FINAL Deliverable

Montserrrat Martinez i Aleix Costa

11 de Juny de 2019

INDEX

----------- *DELIVERABLE 1* ------------

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’)

Package loading and set Working directory

Carreguem els paquets necessaris i definim el nostre directori de treball

Loading data

Upload and select data

A partir del banc de dades proposat, hem de seleccionar una mostra de 5000 registres de manera aleatoria per poder començar a analitzar les nostres dades

```
#setwd("C:/Users/montserrat.martinez.santamaria/Documents/ADEI/bank-
additional/bank-additional")
#dirwd<-"C:/Users/montserrat.martinez.santamaria/Documents/ADEI/bank-
additional/bank-additional"

setwd("/Users/montsee/Desktop/ADEI/bank-additional/bank-additional")
dirwd<-"/Users/montsee/Desktop/ADEI/bank-additional/bank-additional"

# Data file already

df<-read.table(paste0(dirwd,"/bank-additional-
full.csv"),header=TRUE,sep=";",na.strings = "999")

# Select your 5000 register sample (random sample)

#nrow(df)
#ncol(df)
#dim(df)

set.seed(25071997)
mostra<-as.vector(sort(sample(1:nrow(df),5000)))
df<-df[mostra,]

#Verificacio i guardat de la mostra

dim(df) #Mostra la dimensi? de la mostra

## [1] 5000   21

names(df) #Mostra els noms de les variables de la mostra

##  [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"
```

```r
summary(df)
```

```
##       age                    job            marital
##  Min.   :17.00   admin.      :1315   divorced: 574
##  1st Qu.:32.00   blue-collar:1157   married :3029
##  Median :38.00   technician : 789   single  :1390
##  Mean   :40.16   services   : 477   unknown :   7
##  3rd Qu.:47.00   management : 348
##  Max.   :98.00   retired    : 212
##                  (Other)    : 702
##                education       default         housing          loan
##  university.degree   :1503   no     :3958   no     :2206   no     :
4055
##  high.school         :1133   unknown:1042   unknown: 129   unknown:
129
##  basic.9y            : 765   yes    :   0   yes    :2665   yes    :
816
##  professional.course: 600
##  basic.4y            : 514
##  basic.6y            : 268
##  (Other)             : 217
##       contact          month      day_of_week    duration
##  cellular :3148   may    :1633   fri: 979    Min.   :   1.0
##  telephone:1852   jul    : 911   mon:1039    1st Qu.: 102.0
##                   aug    : 754   thu:1064    Median : 180.0
##                   jun    : 663   tue: 911    Mean   : 264.7
##                   nov    : 514   wed:1007    3rd Qu.: 329.0
##                   apr    : 282               Max.   :3253.0
##                   (Other): 243
##     campaign          pdays           previous            poutcome
##  Min.   : 1.000   Min.   : 0.000   Min.   :0.000   failure    : 502
##  1st Qu.: 1.000   1st Qu.: 3.000   1st Qu.:0.000   nonexistent:4330
##  Median : 2.000   Median : 5.000   Median :0.000   success    : 168
##  Mean   : 2.598   Mean   : 5.821   Mean   :0.169
##  3rd Qu.: 3.000   3rd Qu.: 6.000   3rd Qu.:0.000
##  Max.   :40.000   Max.   :20.000   Max.   :5.000
##                   NA's   :4816
```

```
##   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 :93.92   Median :-41.80   Median :4.857
##  Mean   : 0.1184   Mean   :93.59   Mean   :-40.45   Mean   :3.661
##  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 :4394
##  1st Qu.:5099   yes: 606
##  Median :5191
##  Mean   :5168
##  3rd Qu.:5228
##  Max.   :5228
##

save.image("DadesBank_5000.RData")
```

Inicialització dels vectors de missings, errors i outliers

Inicialitzarem tres vectors per poder tenir un recompte del total dels errors, missings i outliers:

```
num_total_missings<-rep(0,21)
num_total_errors<-rep(0,21)
num_total_outliers<-rep(0,21)
```

Inicialitzem les variables de contadors individuals per missings, errors i outliers:

```
df$missings_indiv <- 0
df$errors_indiv <- 0
df$outliers_indiv <- 0
```

Univariate Descriptive Analysis & Data Quality Report

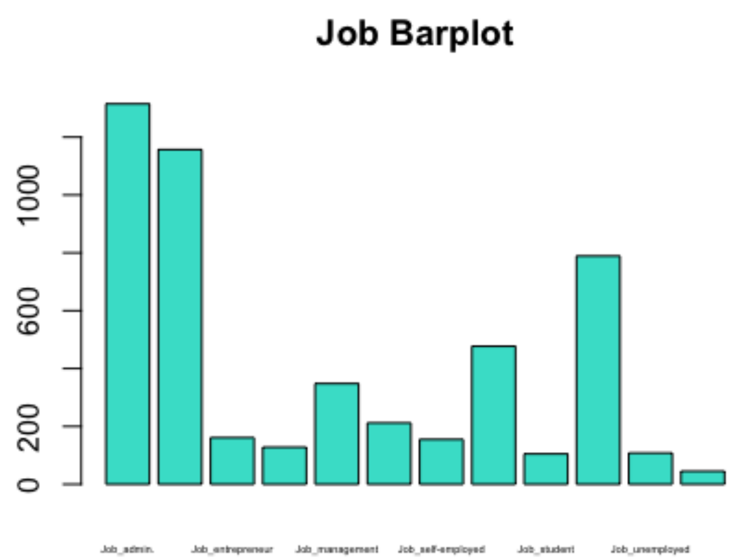
Qualitative Variables (Factors) / Categorical

Hem de fer un analisi de totes les variables per poder identificar missings, errors i els outliers. Tamba tractarem de factoritzar cada variable per a que sigui mes facil entendre la mostra

2. Job

Type of job?

```
df$job<-factor(df$job)
levels(df$job)<-paste("Job_",sep="",levels(df$job))
summary(df$job)

##        Job_admin.   Job_blue-collar  Job_entrepreneur
Job_housemaid
##              1315              1157               161
128
##    Job_management       Job_retired Job_self-employed
Job_services
##               348               212               155
477
##       Job_student    Job_technician    Job_unemployed
Job_unknown
##               105               789               108
45

barplot(summary(df$job),main="Job Barplot",col =
"turquoise",cex.names=0.35)
```




```
#Amb la comanda "factor" el que estem fent es factoritzar la variable
que li passem i el valor que surt amb el "levels" es el numero total
de les nostres 5000 observacions que tenen cada tipus de job i com
```

```
podem veure tots els factors tenen valor i no tenim cap NA (data
missing)
```

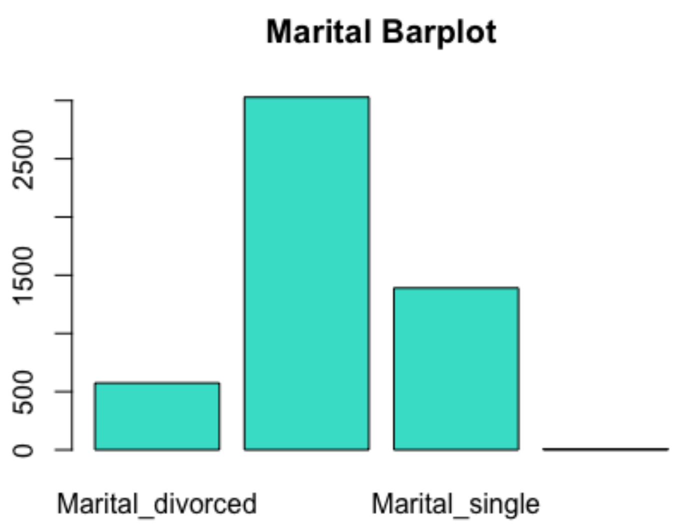
3. Marital

Marital status?

```r
df$marital<-factor(df$marital)
levels(df$marital)<-paste("Marital_",sep="",levels(df$marital))
summary(df$marital)
```

```
## Marital_divorced  Marital_married   Marital_single  Marital_unknown
##              574             3029             1390                7
```

```r
barplot(summary(df$marital),main="Marital Barplot",col = "turquoise")
```




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

```
## [1] 7
```

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

```
## Marital_divorced  Marital_married   Marital_single  Marital_unknown
##              574             3029             1390                0
##             NA's
##                7
```

```
#Podem veure que de la nostra mostra no tenim cap factor incorrecte i
com en la nostra mostra la variable "marital_unkown" es molt petita
s'han de posar com a NA
```

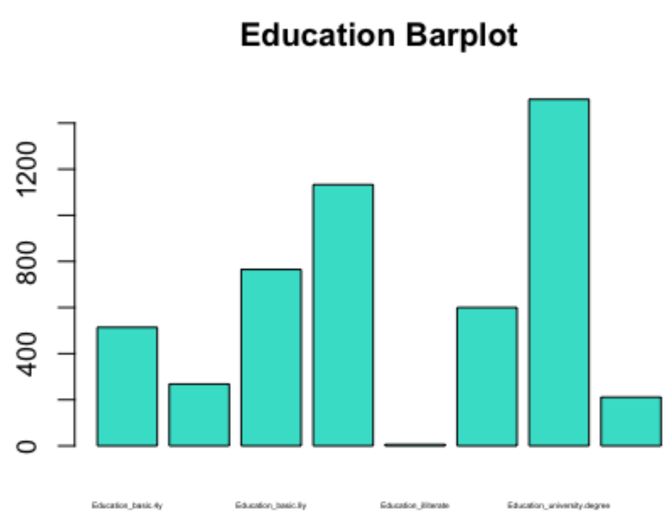
4. Education

Type of education?

```
df$education<-factor(df$education)
levels(df$education)<-paste("Education_",sep="",levels(df$education))
summary(df$education)
```

```
##             Education_basic.4y             Education_basic.6y
##                            514                            268
##             Education_basic.9y           Education_high.school
##                            765                           1133
##          Education_illiterate Education_professional.course
##                              6                            600
##    Education_university.degree              Education_unknown
##                           1503                            211
```

```
barplot(summary(df$education),main="Education
Barplot",col="turquoise",cex.names = 0.3)
```




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

```
## [1] 211
```

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

```
##              Education_basic.4y              Education_basic.6y
##                             514                             268
##              Education_basic.9y            Education_high.school
##                             765                            1133
##            Education_illiterate Education_professional.course
##                               6                             600
##    Education_university.degree               Education_unknown
##                            1503                               0
##                            NA's
##                             211
```

```r
#Quan observem tots els factors ens podem adonar que no hi ha cap NA
(data missing) ni cap factor no contemplat, llavors no tenim cap error
```

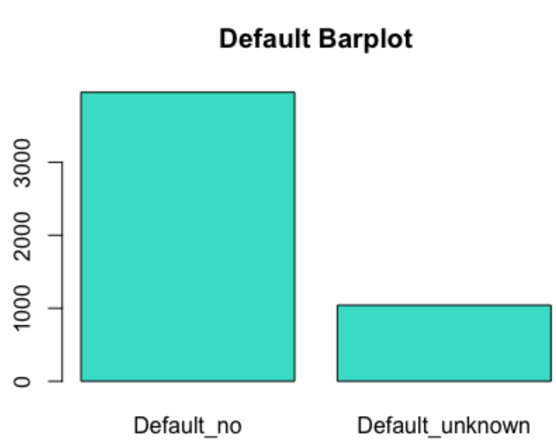
5. Default

Has credit in default?

```r
df$default<-factor(df$default)
levels(df$default)<-paste("Default_",sep="",levels(df$default))
summary(df$default)
```

```
##      Default_no Default_unknown
##            3958            1042
```

```r
barplot(summary(df$default),main="Default Barplot",col = "turquoise")
```



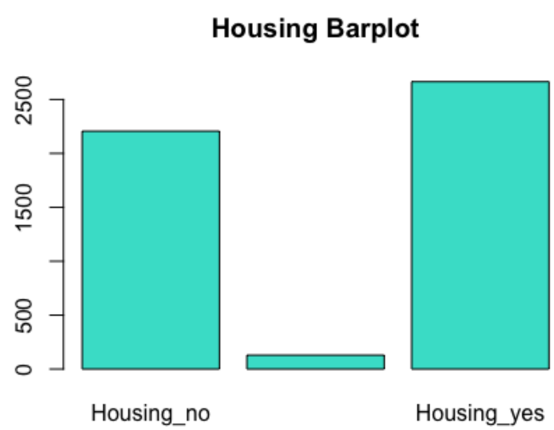

```r
#Quan acabem d'analitzar la mostra veiem que com en els casos
anteriors no tenim cap NA (data missing) ni cap factor incomplet,
```

```
llavors la nostra mostra es correcta i com en els casos anteriors hem
posat nom al nostre barplot per tenir una millor visualitzacio
```

6. Housing

Has housing loan?

```r
df$housing<-factor(df$housing)
levels(df$housing)<-paste("Housing_",sep="",levels(df$housing))
summary(df$housing)

##      Housing_no Housing_unknown     Housing_yes
##            2206             129            2665

barplot(summary(df$housing),main="Housing Barplot",col = "turquoise")
```

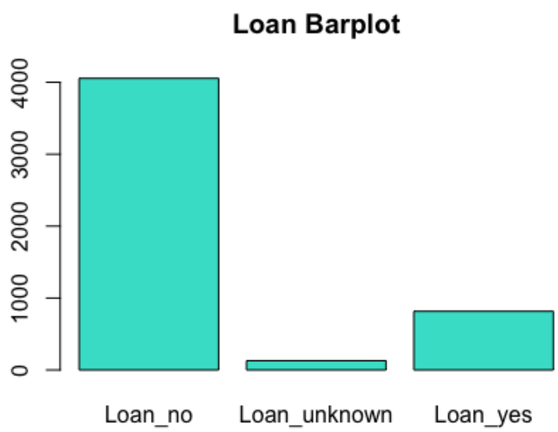



```
#Com podem veure anteriorment tampoc tenim cap data missing ni cap
factor amb valors estranys, pero podem veure que el factor
"Housing_unknown" podria ser un possible outlier
```

7. Loan

Has personal loan?

```r
df$loan<-factor(df$loan)
levels(df$loan)<-paste("Loan_",sep="",levels(df$loan))
summary(df$loan)

##      Loan_no Loan_unknown     Loan_yes
##         4055          129          816

barplot(summary(df$loan),main="Loan Barplot",col = "turquoise")
```

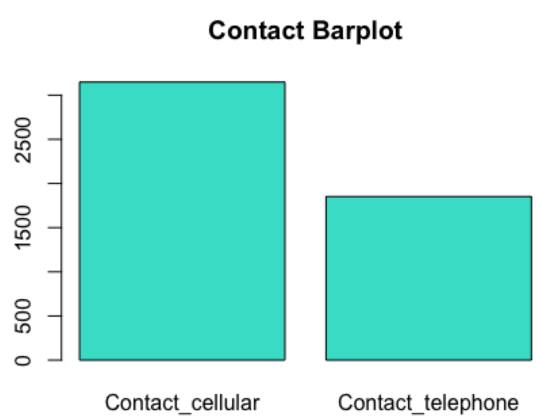



```
#Quan acabem d'analitzar la mostra veiem que com en els casos
anteriors no tenim cap NA (data missing) ni cap factor incomplet,
llavors la nostra mostra es correcta i com en els casos anteriors hem
posat nom al nostre barplot per tenir una millor visualitzacio
```

8. Contact

Contact communication type?

```
df$contact<-factor(df$contact)
levels(df$contact)<-paste("Contact_",sep="",levels(df$contact))
summary(df$contact)

##   Contact_cellular Contact_telephone
##               3148              1852

barplot(summary(df$contact),main="Contact Barplot",col = "turquoise")
```

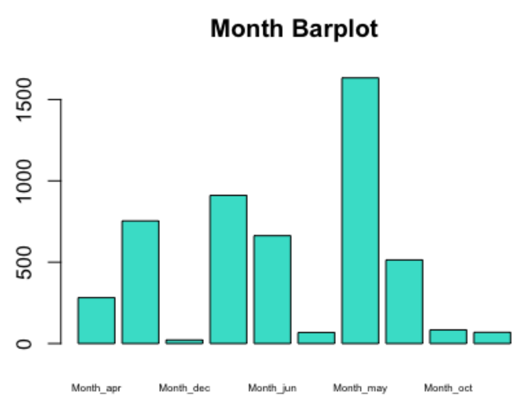


```
#Quan acabem d'analitzar la mostra veiem que com en els casos anteriors no tenim cap NA (data missing) ni cap factor incomplet, llavors la nostra mostra es correcta i com en els casos anteriors hem posat nom al nostre barplot per tenir una millor visualitzacio
```

9. Month

Last contact month of the year?

```
df$month<-factor(df$month)
levels(df$month)<-paste("Month_",sep="",levels(df$month))
summary(df$month)

## Month_apr Month_aug Month_dec Month_jul Month_jun Month_mar
Month_may
##       282       754        22       911       663        68
1633
## Month_nov Month_oct Month_sep
##       514        84        69

barplot(summary(df$month),main="Month Barplot",col =
"turquoise",cex.names = 0.5)
```



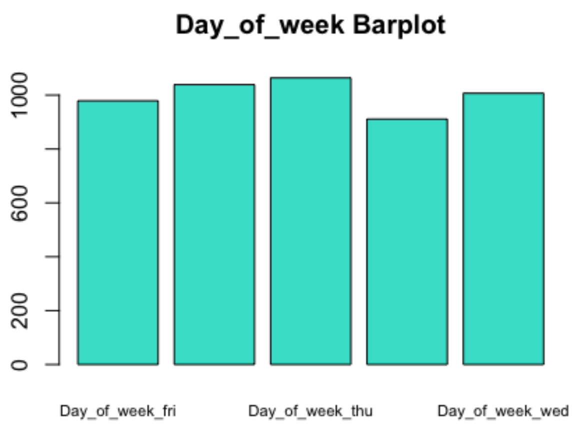
10. Day_of_week

Last contact day of the week?

```
df$day_of_week<-factor(df$day_of_week)
levels(df$day_of_week)<-
paste("Day_of_week_",sep="",levels(df$day_of_week))
summary(df$day_of_week)

## Day_of_week_fri Day_of_week_mon Day_of_week_thu Day_of_week_tue
##             979            1039            1064             911
```

```
## Day_of_week_wed
##            1007
```

```
barplot(summary(df$day_of_week),main="Day_of_week Barplot",col =
"turquoise",cex.names=0.7)
```



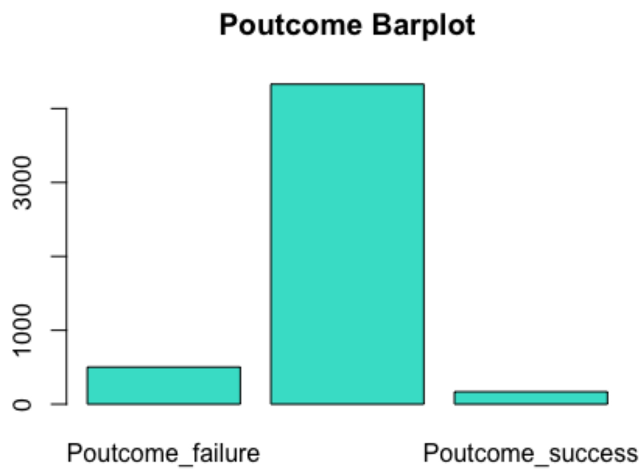
15. Poutcome

Outcome of the previous marketing campaign?

```
df$poutcome<-factor(df$poutcome)
levels(df$poutcome)<-paste("Poutcome_",sep="",levels(df$poutcome))
summary(df$poutcome)
```

```
##     Poutcome_failure Poutcome_nonexistent     Poutcome_success
##                  502                 4330                  168
```

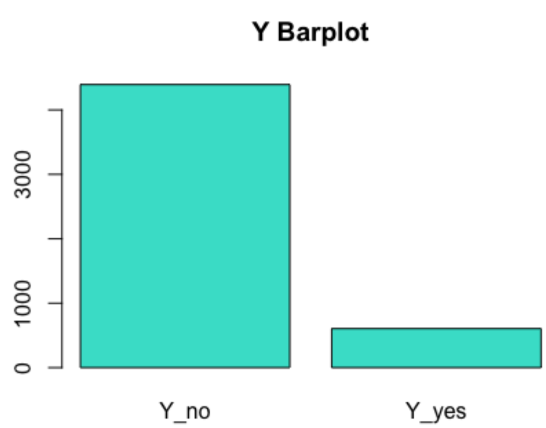
```
barplot(summary(df$poutcome),main="Poutcome Barplot",col =
"turquoise")
```



21. Y

Has the client subscribed a term deposit?

```
df$y<-factor(df$y)
levels(df$y)<-paste("Y_",sep="",levels(df$y))
summary(df$y)

##  Y_no Y_yes
##  4394   606

barplot(summary(df$y),main="Y Barplot",col = "turquoise")
```

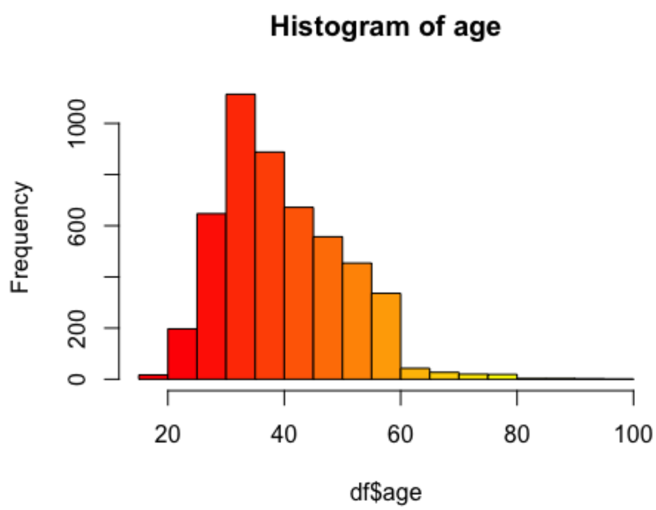


Quantitative Variables (Numerical)

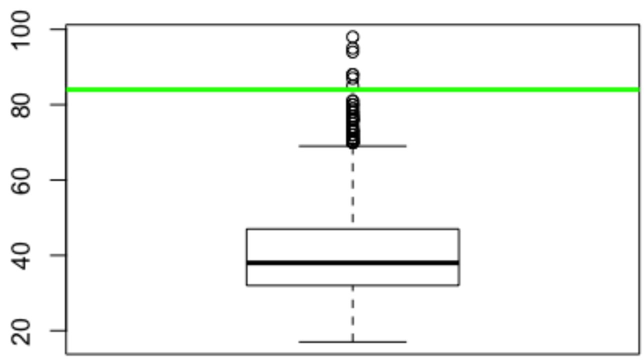
Hem de fer un analisi de totes les variables per poder identificar missings, errors i els outliers. Tambe farem una serie de boxplots i histogrames per analitzar i visualitzar millor les dades de la nostra mostra

1. Age

```
summary(df$age)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   17.00   32.00   38.00   40.16   47.00   98.00

hist(df$age,15,main="Histogram of age",col=heat.colors(17,alpha=1))
```




```
#A partir del summary veiem que no hi ha cap mostra que contingui un
NA (missing data) ni tampoc cap possible error ja que l'edat minima
(17) i la maxima (98) son valors que s'adhereixen a la realitat.
boxplot(df$age)
abline(h=84,col="green",lwd=3)
```

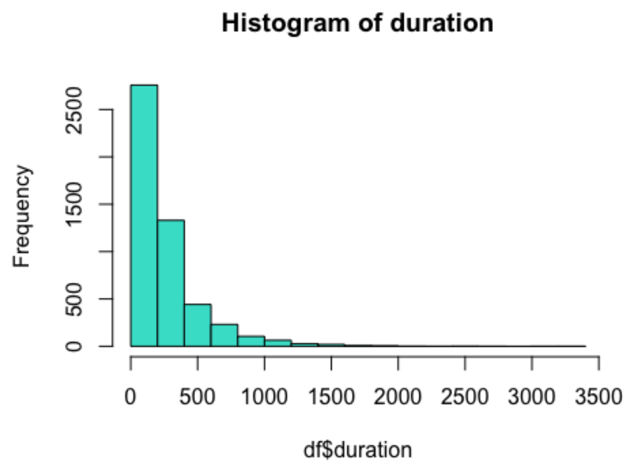



```
#Amb la comanda abline el que volem fer es poder identificar de una
manera mes facil els possibles outliers i poder tenir una millor
visualitzacio, per aixo marco a l'altura dels 84 anys la nostra
mostra, ja que aquests valors son els que s'allunyen una mica de la
resta, llavors s'ahuran de fer una serie d'imputacions

sel <- which(df$age >= 84);length(sel);sel

## [1] 7

## [1] 3434 3436 3439 4564 4646 4714 4781

summary(df$age)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##   17.00   32.00   38.00   40.16   47.00   98.00

num_total_outliers[1] <- length(sel)
df[sel, "age"] <- NA
#Cuando eliminamos nuestros outliers lo que nos queda es que la edad
máxima ahora es de 81 años y tenemos 7 NA's

df[sel, "outliers_indiv"] <- df[sel, "outliers_indiv"] + 1
summary(df$age)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##   17.00   32.00   38.00   40.09   47.00   81.00       7

#Un cop els hem identificat, actualitzem les variables de control per
tal de portar un seguiment correcte de la mostra i eliminem els 7
outliers considerats.
```

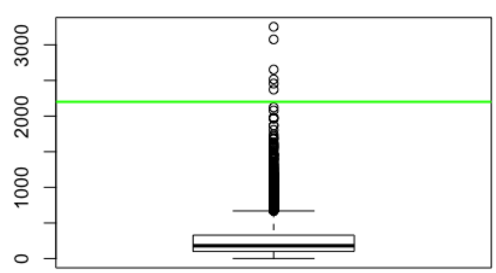
11. Duration

Last contact duration?

```r
summary(df$duration)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##     1.0   102.0   180.0   264.7   329.0  3253.0

hist(df$duration,15,main="Histogram of duration",col="turquoise")
```




```r
#A partir del summary executat podem observar que el temsp minim de la durada de una trucada es d'1 segon, i ja ens podem adonar que aquest valor no te molt sentit a l'hora de tractar-se una trucada no? No dona temps que el client escolti i penji i la durada maxima es de 3253 segons que son aproximadament uns 54 minuts i pot ser un valor real

boxplot(df$duration)
abline(h=2200,col="green",lwd=2)
```

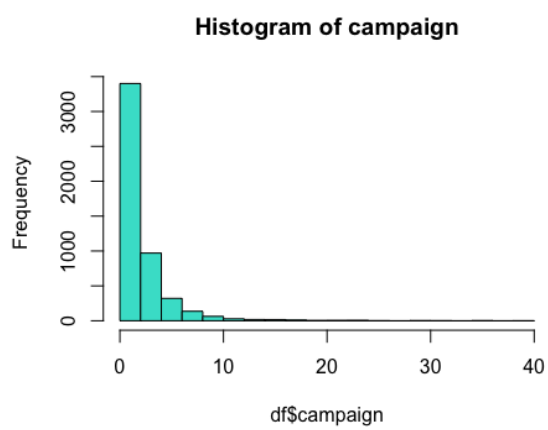


```r
#Per tal d'identificar possibles outliers utilitzem l'eina Boxplot,
tinguent en compte el significat de la variable marquem amb una linia
vermella el valor 2200, a partir del qual definim els possibles
outliers ja que considerem que les observacions que prenen un valor a
partir de 2200 es desvien significativament de la resta

sel <- which(df$duration >= 2200);length(sel);sel

## [1] 6

## [1] 1013 1140 2197 2919 2969 3440

num_total_outliers[11] <- length(sel)
df[sel, "outliers_indiv"] <- df[sel, "outliers_indiv"] + 1
df <- df[-sel,]
summary(df$duration)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##     1.0   102.0   180.0   261.8   328.0  2122.0

#Un cop els hem identificat, actualitzem les variables de control per
tal de portar un seguiment
#correcte de la mostra i eliminem els 18 outliers del nostre traget
num?ric.
```

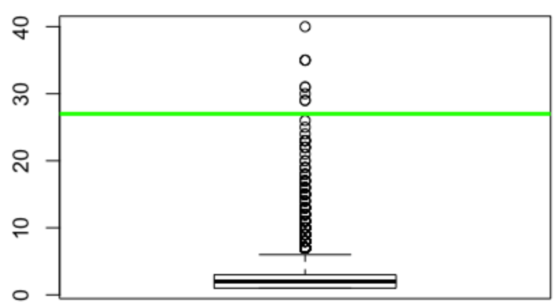
12. Campaign

Number of contacts performed during this campaign?

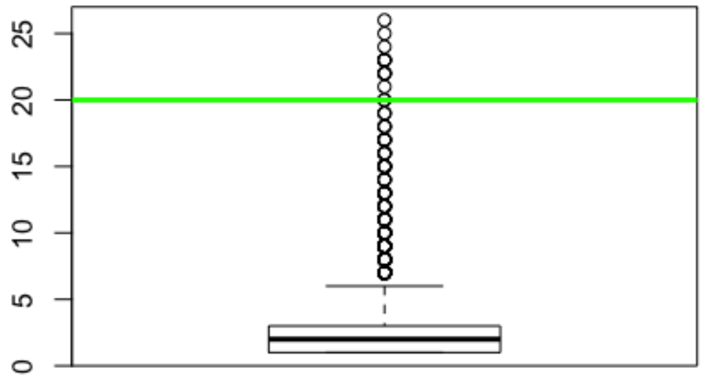
```r
summary(df$campaign)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   1.000   2.000   2.599   3.000  40.000

hist(df$campaign,15,main="Histogram of campaign",col="turquoise")
```



```r
#Quan fem el summary i el boxplot veiem que no hi ha cap mostra que contingui un NA (missing data) pero amb el boxplot si que veiem que hi han alguns valors que poden no ser molt realistes, ja que es una mica estrany que una campanya es contacti unes 40 vegades amb una mateixa persona, comptant que la mitjana són dues vegades, llavors eliminarem a partir d'unes 27 vegades/persona que es el que te mes sentit comu i es on veiem que disten de la resta
#Aquestes dades de la mostra les considerem errors i les eliminarem de la mostra

boxplot(df$campaign)
abline(h=27,col="green",lwd=3)
```




```r
sel <- which(df$campaign > 27)
length(sel);sel

## [1] 9

## [1]  509 1116 1216 1278 1279 2311 2312 2318 2325

num_total_errors[12] <- length(sel)
df[sel, "campaign"] <- NA
df[sel, "errors_indiv"] <- df[sel, "errors_indiv"] + 1

boxplot(df$campaign)
abline(h=20,col="green",lwd=3)
```

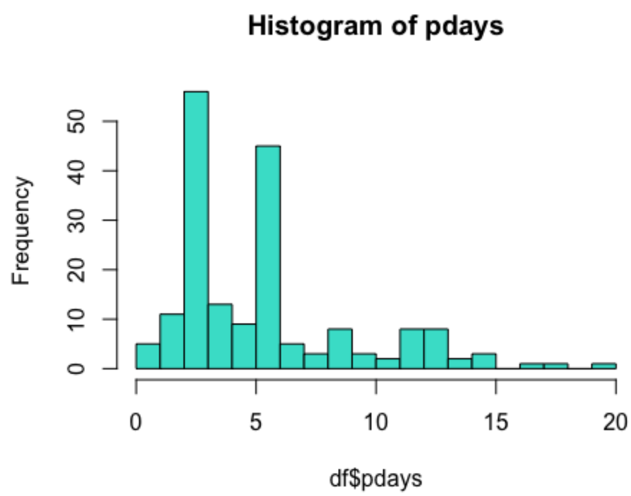



```r
#Després de fer l'analisi de la mostra podem arribar a la conclusio
que no es molt normal rebre contacte de la mateixa campanya mes de 15
cops, llavors haurem d'eliminar els possibles outliers de la mostra
per tenir correcte el nostre traget numeric i veiem que eliminem 57
observacions

sel <- which(df$campaign >= 15)
length(sel);sel

## [1] 48

##  [1]  326  418  452  467  484  665  710  778  874  875  908  922
979 1005
## [15] 1039 1181 1219 1241 1276 1283 1284 1353 1401 1433 1458 1565
1651 1787
## [29] 2049 2095 2128 2155 2179 2182 2214 2242 2246 2270 2276 2279
2314 2321
## [43] 2795 2886 2908 2917 3685 4183

num_total_outliers[12] <- length(sel)
df[sel, "campaign"] <- NA
df[sel, "outliers_indiv"] <- df[sel, "outliers_indiv"] + 1
df<-df[-sel,]
summary(df$campaign)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   1.000   1.000   2.000   2.388   3.000  14.000       9
```

13. Pdays

Number of days that passed by after the client was last contacted from a previous campaign?

```
summary(df$pdays)

##     Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    0.000   3.000   5.000   5.821   6.000  20.000    4762

hist(df$pdays,15,main="Histogram of pdays",col="turquoise")
```




```
#Si analitzem aquesta variable veiem que tenir valor 0 significa que
no ha passat cap dia des de que s'ha finalitzat la campanya anterior i
s'ha contactat amb l'individu per aquesta campanya la qual cosa
considerem que es tracta de un error per aixo procedim a identificar i
comptabilitzar l'esmentat error a continuacio.

sel <- which(df$pdays == 0)
length(sel);sel

## [1] 2

## [1] 4844 4847

#A partir del summary veiem que hi han 2 observacions que tenen valor
0.
num_total_errors[13] = length(sel)
df[sel, "pdays"] <- NA
df[sel, "errors_indiv"] <- df[sel, "errors_indiv"] + 1
```

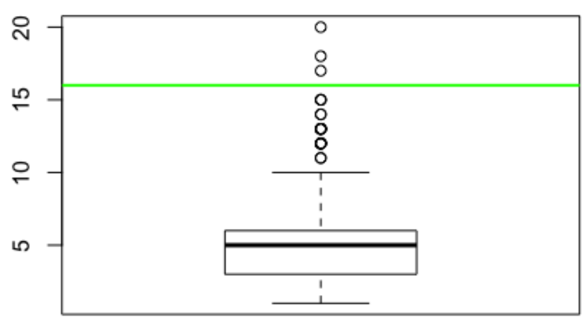
```r
#Tambe podem observem que aquesta variable te un nombre molt elevat de
NA's(missing data) aquestes situacions signifiquen que no s'ha
contactat amb l'individu previament en cap altre campanya per aixo no
pot existir cap valor amb els dies des de la ultima vegada que es va
contactar.

sel <- which(is.na(df$pdays))
length(sel);#sel
```

```
## [1] 4764
```

```r
num_total_missings[13] = length(sel)
df[sel, "missings_indiv"] <- df[sel, "missings_indiv"] + 1
summary(df$pdays)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   1.000   3.000   5.000   5.885   6.000  20.000    4764
```

```r
boxplot(df$pdays)
abline(h=16,col="green",lwd=2)
```




```r
sel <- which(df$pdays >= 16)
length(sel);sel
```

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

```
## [1] 4846 4870 4912
```

```r
num_total_outliers[13] = length(sel)
df[sel, "pdays"] <- NA
df[sel, "outliers_indiv"] <- df[sel, "outliers_indiv"] + 1
summary(df$pdays)
```

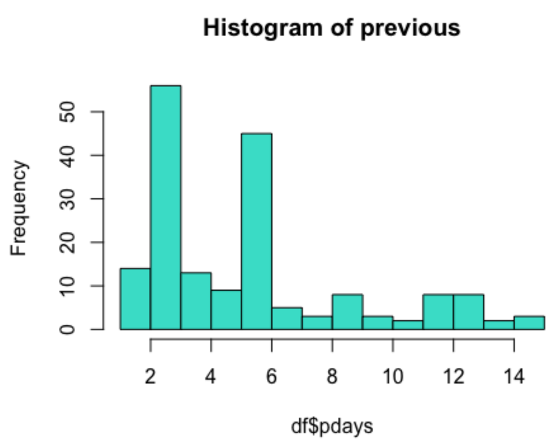
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##   1.000   3.000   5.000   5.676   6.000  15.000    4767
```

```
#Un cop els hem identificat, actualitzem les variables de control per tal de portar un seguiment
#correcte de la mostra i eliminem els outliers del nostre target numeric.
```

14. Previous

Number of contacts performed before this campaign and for this client?

```
summary(df$previous)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##  0.0000  0.0000  0.0000  0.1708  0.0000  5.0000

hist(df$pdays,15,main="Histogram of previous",col="turquoise")
```




```
#A partir del summary efectuat sobre la variable "Previous" podem veure que no tenim cap NA i podriem considerar que tampoc error perque ja que el nombre minim de ocntactes previs a la campanya actual amb l'individu es 0 i el maxim trobat es 5, que poden ser valors reals

#Quan observem el boxplot i el summary veiem que la majoria de les nostres observacions son 0 i llavors no podem tenir o identificar rapidament els possibles outliers
```

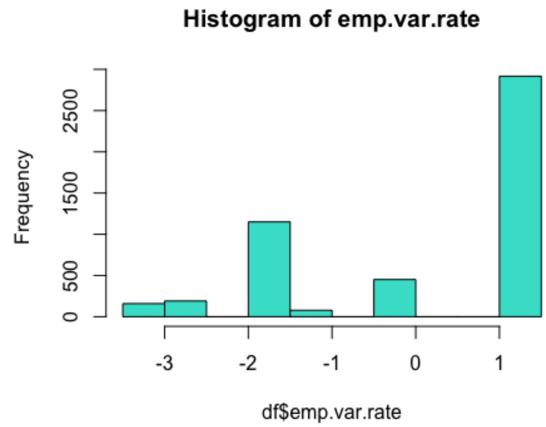
16. Emp.var.rate

Employment variation rate?

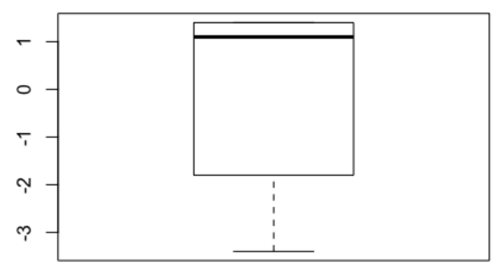
```
summary(df$emp.var.rate)
```

```
## 	Min. 1st Qu.  Median 	Mean 3rd Qu. 	Max.
## -3.4000 -1.8000  1.1000  0.1074  1.4000  1.4000
```

```
hist(df$emp.var.rate,15,main="Histogram of
emp.var.rate",col="turquoise")
```




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




```
#A partir del summary, l'histograma i el boxplot podem afirmar que no
tenim cap missing ni error ni outlier, perque tots els valors agafats
son realistes
```

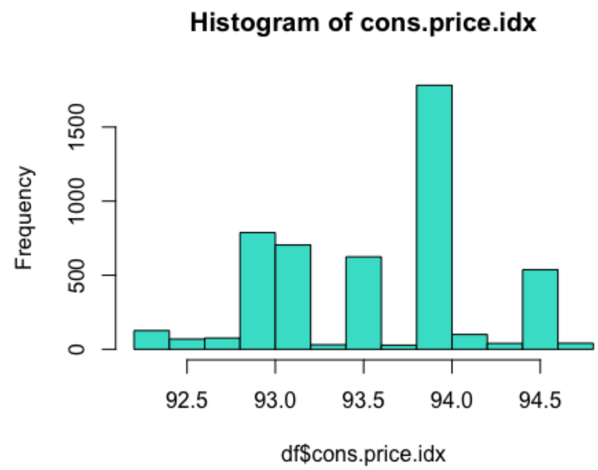
17. Cons.price.idx

Consumer price index - monthly indicator?

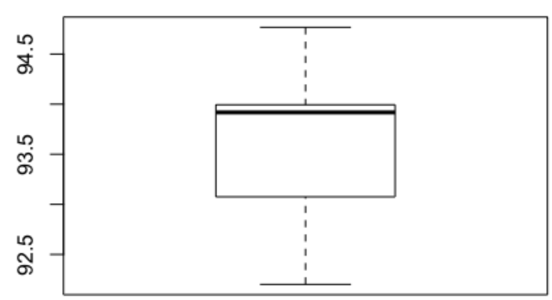
```
summary(df$cons.price.idx)
```

```
## 	Min. 1st Qu.  Median 	Mean 3rd Qu. 	Max.
##   92.20   93.08   93.92   93.59   93.99   94.77
```

```r
hist(df$cons.price.idx,15,main="Histogram of
cons.price.idx",col="turquoise")
```




```r
boxplot(df$cons.price.idx)
```



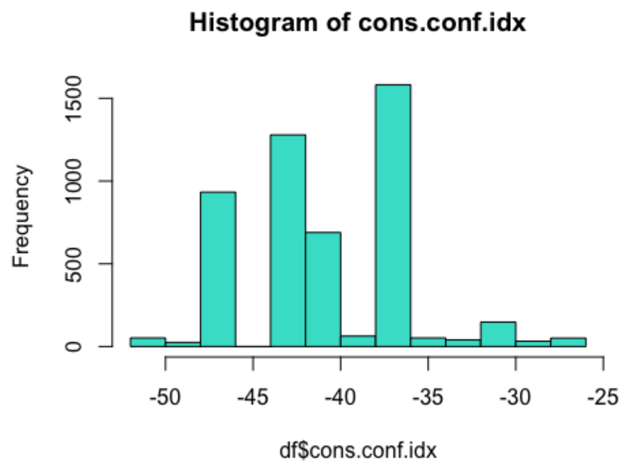

```r
#A partir del summary, l'histograma i el boxplot podem afirmar que no
tenim cap missing ni error ni outlier, perque tots els valors agafats
son realistes
```

18. Cons.conf.idx

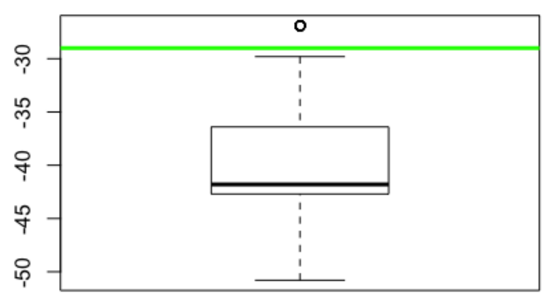
Consumer confidence index - monthly indicator?

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

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  -50.80  -42.70  -41.80  -40.44  -36.40  -26.90
```

```r
hist(df$cons.conf.idx,15,main="Histogram of
cons.conf.idx",col="turquoise")
```




```r
boxplot(df$cons.conf.idx)
#Com podem veure després del boxplot hi han algunes observacions que
podrien considerarse possibles outliers, llavors marquem -29 amb el
abline

abline(h=-29,col="green",lwd=3)
```




```r
sel <- which(df$cons.conf.idx >= -29)
length(sel);sel

## [1] 51

##  [1] 4561 4562 4563 4564 4565 4566 4567 4568 4569 4570 4571 4572
4573 4574
## [15] 4575 4576 4577 4578 4579 4580 4581 4582 4583 4584 4585 4586
```

```
4587 4588
## [29] 4589 4590 4591 4592 4593 4594 4595 4596 4597 4598 4599 4600
4601 4602
## [43] 4603 4604 4605 4606 4607 4608 4609 4610 4611
```

```
num_total_outliers[18] = length(sel)
df[sel, "cons.conf.idx"] <- NA
df[sel, "outliers_indiv"] <- df[sel, "outliers_indiv"] + 1
summary(df$cons.conf.idx)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##  -50.80  -42.70  -41.80  -40.58  -36.40  -29.80      51
```

```
#Ara el que hem fet es veure que hi han uns 51 possibles outliers,
llavors el que hem de fer es imputar-los i posar-los com a NA (missing
values) i llavors els posem en el vector creat per tenir tots els
outliers a ma i després incrementem el contador d'outliers
```

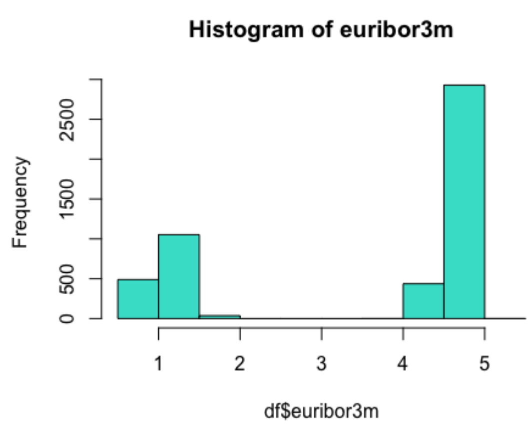
19. Euribor3m

Euribor 3 month rate - daily indicator?

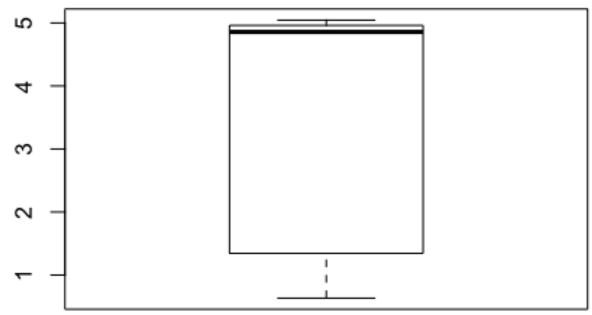
```
summary(df$euribor3m)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.634   1.344   4.857   3.649   4.961   5.045
```

```
hist(df$euribor3m,15,main="Histogram of euribor3m",col="turquoise")
```




```
boxplot(df$euribor3m)
```

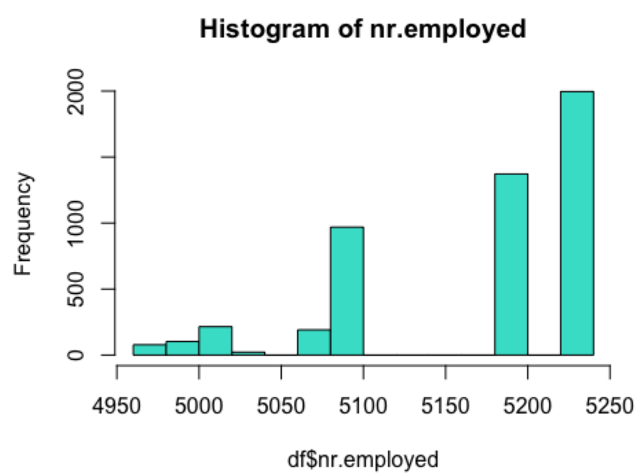



```
#A partir del boxplot efectuat podem veure que els valors obtinguts
son majoritariament menors que 5 i com s'observa la mitjana es troba
molt a prop del maxim obtingut
```

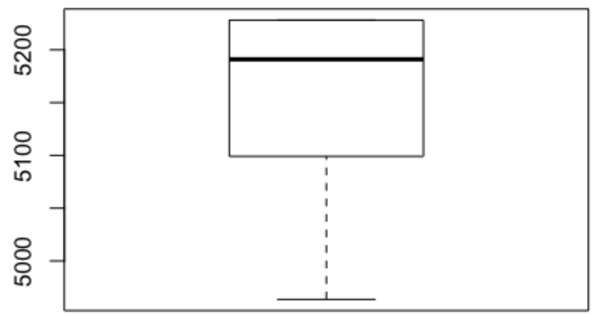
20. Nr.employed

Number of employees - quarterly indicator?

```
summary(df$nr.employed)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    4964    5099    5191    5168    5228    5228

hist(df$nr.employed,15,main="Histogram of
nr.employed",col="turquoise")
```




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




```
#A partir del summary, l'histograma i el boxplot podem afirmar que no
tenim cap missing ni error ni outlier.
```

CONTAR NA's

```
#Hem de contar el numero de NA's despres d'analitzar les dades i
marcta els outliers, missings i errors
miss_row <- rowSums(is.na(df))
miss_col <- colSums(is.na(df))
miss_col

##             age             job         marital       education
default
##               7               0               7             210
0
##         housing            loan         contact           month
day_of_week
##               0               0               0               0
0
##        duration        campaign           pdays        previous
poutcome
##               0               9            4767               0
0
##    emp.var.rate  cons.price.idx   cons.conf.idx       euribor3m
nr.employed
##               0               0              51               0
0
##               y  missings_indiv    errors_indiv  outliers_indiv
##               0               0               0               0

#Podem veure el numero de NA que tenim per cada variable
summary(miss_row)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   1.000   1.000   1.021   1.000   3.000
```

Rank of variables

Com hem fet abans ja tenim creades les variables on tenim emmagatzemats els errors, missing values i els outliers i ara el que farem es un ranking amb aquestes variables

Per individuals:

```
#errors (la majoria de registres no tenen errors i els que tenen errors com a maxim nomes en tenen 1 )
summary(df$errors_indiv)

##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## 0.000000 0.000000 0.000000 0.002224 0.000000 1.000000

#outliers (el registres amb outliers com a maxim tenen 2 variables amb outlier)
summary(df$outliers_indiv)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.00000 0.00000 0.00000 0.01233 0.00000 2.00000

#missings abans d'introduir manualment NA's per cada registre, nomes la variable pdays tenia missings des de un principi
summary(df$missings_indiv)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  1.0000  1.0000  0.9632  1.0000  1.0000

#despres de depurar les dades i introduir els NA`s
#miss_col<-colSums(is.na(df))
NAs_indiv <- rowSums(is.na(df))
summary(df$NAs_indiv)

## Length  Class   Mode 
##      0   NULL   NULL
```

Per variable:

```
#Després de calcular tots el missings, outliers i errors fem el resum d'ells

#num total missings
data <- t(c(num_total_missings[13]))
data

##      [,1]
## [1,] 4764
```

```r
barplot(data, main="Total missings", col=("turquoise"))
```

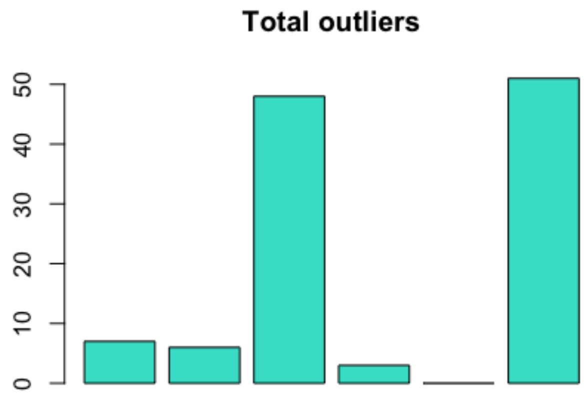

```r
#num total errors
data <- t(c(num_total_errors[12:13]))
data
```

```
##      [,1] [,2]
## [1,]    9    2
```

```r
barplot(data, main="Total errors", col=("turquoise"))
```


```r
#num total outliers
data <-
t(c(num_total_outliers[1],num_total_outliers[11:14],num_total_outliers
[18]))
data
```

```
##      [,1] [,2] [,3] [,4] [,5] [,6]
## [1,]    7    6   48    3    0   51

barplot(data, main="Total outliers", col=("turquoise"))
```



Imputation

Ara farem l'estudi per variables i tractarem d'imoutar les observacions que siguin necesasaries

```
library(missMDA)

# Numeric imputation
vars_con<-names(df)[c(1,11:14,16:20)]
vars_dis<-names(df)[c(2:10,15,21)] #solo 21
summary(df[,vars_con])

##       age           duration          campaign           pdays       
##  Min.   :17.00   Min.   :   1.0   Min.   : 1.000   Min.   : 1.000  
##  1st Qu.:32.00   1st Qu.: 104.0   1st Qu.: 1.000   1st Qu.: 3.000  
##  Median :38.00   Median : 182.0   Median : 2.000   Median : 5.000  
##  Mean   :40.05   Mean   : 262.8   Mean   : 2.388   Mean   : 5.676  
##  3rd Qu.:47.00   3rd Qu.: 329.0   3rd Qu.: 3.000   3rd Qu.: 6.000  
##  Max.   :81.00   Max.   :2122.0   Max.   :14.000   Max.   :15.000  
##  NA's   :7                        NA's   :9        NA's   :4767    
##     previous       emp.var.rate      cons.price.idx  cons.conf.idx  
##  Min.   :0.0000   Min.   :-3.4000   Min.   :92.20   Min.   :-50.80  
##  1st Qu.:0.0000   1st Qu.:-1.8000   1st Qu.:93.08   1st Qu.:-42.70  
##  Median :0.0000   Median : 1.1000   Median :93.92   Median :-41.80  
##  Mean   :0.1708   Mean   : 0.1074   Mean   :93.59   Mean   :-40.58  
##  3rd Qu.:0.0000   3rd Qu.: 1.4000   3rd Qu.:93.99   3rd Qu.:-36.40  
```

```
##  Max.   :5.0000   Max.   : 1.4000   Max.   :94.77   Max.   :-29.80
##                                                      NA's   :51
##    euribor3m      nr.employed
##  Min.   :0.634   Min.   :4964
##  1st Qu.:1.344   1st Qu.:5099
##  Median :4.857   Median :5191
##  Mean   :3.649   Mean   :5168
##  3rd Qu.:4.961   3rd Qu.:5228
##  Max.   :5.045   Max.   :5228
##
```

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

```
##                job                     marital
##  Job_admin.     :1301   Marital_divorced: 562
##  Job_blue-collar:1144   Marital_married :3000
##  Job_technician : 784   Marital_single  :1377
##  Job_services   : 473   Marital_unknown :   0
##  Job_management : 345   NA's            :   7
##  Job_retired    : 206
##  (Other)        : 693
##                            education                 default
##  Education_university.degree  :1486   Default_no     :3914
##  Education_high.school        :1120   Default_unknown:1032
##  Education_basic.9y           : 759
##  Education_professional.course: 595
##  Education_basic.4y           : 502
##  (Other)                      : 274
##  NA's                         : 210
##             housing                 loan                      contact
##  Housing_no     :2179   Loan_no     :4020   Contact_cellular :3128
##  Housing_unknown: 126   Loan_unknown: 126   Contact_telephone:1818
##  Housing_yes    :2641   Loan_yes    : 800
##
##
##
##
##        month              day_of_week                    poutcome
##  Month_may:1620   Day_of_week_fri: 967   Poutcome_failure    : 502
##  Month_jul: 893   Day_of_week_mon:1029   Poutcome_nonexistent:4276
##  Month_aug: 749   Day_of_week_thu:1049   Poutcome_success    : 168
##  Month_jun: 648   Day_of_week_tue: 903
##  Month_nov: 514   Day_of_week_wed: 998
```

```
##  Month_apr: 281
##  (Other)  : 241
##      y
##  Y_no :4349
##  Y_yes: 597
##
##
##
##
##
```

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

res.impn<-imputePCA(df[,vars_con],ncp=5) #vars_con=numericas
#res.impn<-imputePCA(df[,vars_dis],ncp=5)
attributes(res.impn)
```

```
## $names
## [1] "completeObs" "fittedX"
```

```
#data.frame with all NA imputed: res.impn$completeObs
#summary(res.impn$completeObs)

df[,"age"] <- res.impn$completeObs[,"age"]
df[,"campaign"] <- res.impn$completeObs[,"campaign"]
#df[,"pdays"] <- res.impn$completeObs[,"pdays"]
df[,"cons.conf.idx"] <- res.impn$completeObs[,"cons.conf.idx"]
df[,"euribor3m"] <- res.impn$completeObs[,"euribor3m"]
miss_row <- rowSums(is.na(df))
miss_col <- colSums(is.na(df))
```

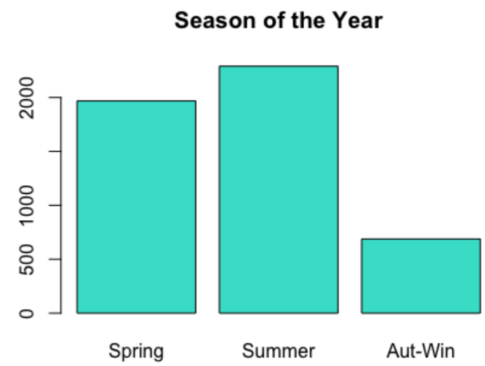
```
summary(df$month)
```

```
## Month_apr Month_aug Month_dec Month_jul Month_jun Month_mar
Month_may
##       281       749        22       893       648        67
1620
## Month_nov Month_oct Month_sep
##       514        83        69
```

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

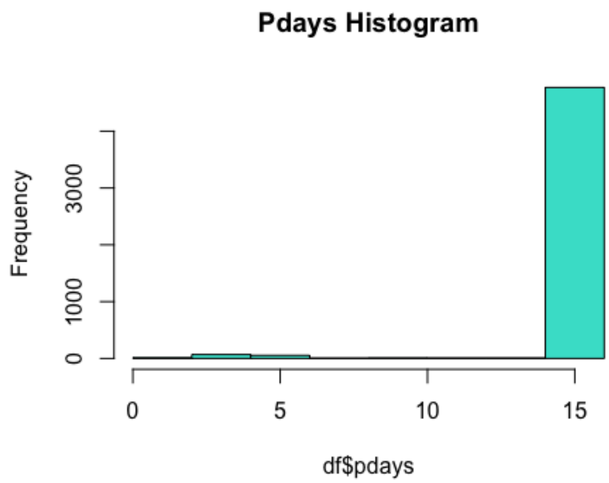
```
##
## Month_apr Month_aug Month_dec Month_jul Month_jun Month_mar
Month_may
##       281       749        22       893       648        67
```

```
1620
## Month_nov Month_oct Month_sep
##       514        83        69

# Define new factor categories: 1- Spring 2-Summer 3-Resta
df$season <- 3
summary(df$season)

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

# 1 level - spring
sel<-which(df$month %in% c("Month_mar","Month_apr","Month_may"))
df$season[sel] <-1

# 2 level - Summer
sel<-which(df$month %in% c("Month_jun","Month_jul","Month_aug"))
df$season[sel] <-2

table(df$season)

##
##    1    2    3
## 1968 2290  688

summary(df$season)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   1.000   2.000   1.741   2.000   3.000

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

barplot(summary(df$season), main="Season of the Year",
col=("turquoise"))
```




```
#IMPUTATION Pdays (Manual)

table(df$pdays)

##
##  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15
##  3 11 56 13  9 45  5  3  8  3  2  8  8  2  3

summary(df$pdays)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   1.000   3.000   5.000   5.676   6.000  15.000    4767

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

length(sel)

## [1] 4767

df[sel, "pdays"] <- 16
table(df$pdays)

##
##    1    2    3    4    5    6    7    8    9   10   11   12   13
14   15
##    3   11   56   13    9   45    5    3    8    3    2    8    8
2    3
##   16
## 4767

summary(df$pdays)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1.00   16.00   16.00   15.63   16.00   16.00
```

```r
hist(df$pdays, 10, main = "Pdays Histogram", col = "turquoise")
```



Discretitzation

Ara el que farem será la discretització de les variables numeriques i aixo ho farem convertint en factors els diferents rangs que tenim de les observacions corresponents a una variable numerica per tenir una visualitzacio mes clara

```r
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"
```

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

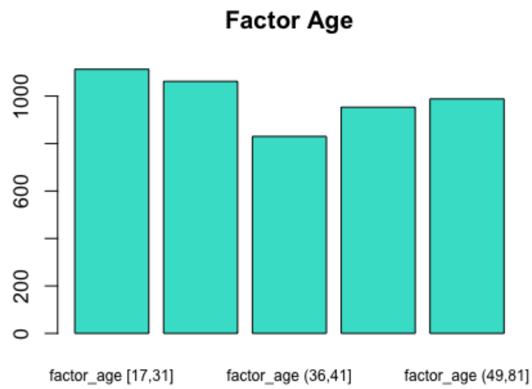
```
##       age           duration         campaign          pdays
##  Min.   :17.00   Min.   :   1.0   Min.   : 1.000   Min.   : 1.00
##  1st Qu.:32.00   1st Qu.: 104.0   1st Qu.: 1.000   1st Qu.:16.00
##  Median :38.00   Median : 182.0   Median : 2.000   Median :16.00
##  Mean   :40.05   Mean   : 262.8   Mean   : 2.389   Mean   :15.63
##  3rd Qu.:47.00   3rd Qu.: 329.0   3rd Qu.: 3.000   3rd Qu.:16.00
##  Max.   :81.00   Max.   :2122.0   Max.   :14.000   Max.   :16.00
##     previous        emp.var.rate      cons.price.idx  cons.conf.idx
##  Min.   :0.0000   Min.   :-3.4000   Min.   :92.20   Min.   :-50.80
##  1st Qu.:0.0000   1st Qu.:-1.8000   1st Qu.:93.08   1st Qu.:-42.70
##  Median :0.0000   Median : 1.1000   Median :93.92   Median :-41.80
##  Mean   :0.1708   Mean   : 0.1074   Mean   :93.59   Mean   :-40.62
##  3rd Qu.:0.0000   3rd Qu.: 1.4000   3rd Qu.:93.99   3rd Qu.:-36.40
```

```
## Max.   :5.0000   Max.   : 1.4000   Max.   :94.77   Max.   :-29.80
##    euribor3m      nr.employed
## Min.   :0.634   Min.   :4964
## 1st Qu.:1.344   1st Qu.:5099
## Median :4.857   Median :5191
## Mean   :3.649   Mean   :5168
## 3rd Qu.:4.961   3rd Qu.:5228
## Max.   :5.045   Max.   :5228
```

Factor Age

```
# Trend and dispersion statistics
quantile(df$age,na.rm=TRUE)

##   0%  25%  50%  75% 100%
##   17   32   38   47   81

quantile(df$age,seq(0,1,0.2),na.rm=TRUE)

##   0%  20%  40%  60%  80% 100%
##   17   31   36   41   49   81

#Es crea una variable auxiliar per tenir els diferents rangs d'edat i
fem els intervals per a que sigui mes sencilla i facil la
visualitzacio de les diferents mostres
df$varauxiliar<-
factor(cut(df$age,include.lowest=T,breaks=c(17,31,36,41,49,81)))
summary(df$varauxiliar)

## [17,31] (31,36] (36,41] (41,49] (49,81]
##    1113    1062     830     953     988

#Fem la mitjana amb els valors de les edats i els nostres intervals
tapply(df$age,df$varauxiliar,median)

## [17,31] (31,36] (36,41] (41,49] (49,81]
##      29      34      39      45      55

#Ara li posem el nom de "factor_age" a la nostra variable per poder
tenir una millor interpretacio i tornem a fer el mateix proces
df$factor_age<-
factor(cut(df$age,include.lowest=T,breaks=c(17,31,36,41,49,81)))
levels(df$factor_age)<-paste("factor_age
",levels(df$factor_age),sep="")
table(df$factor_age)

##
## factor_age [17,31] factor_age (31,36] factor_age (36,41]
##                1113               1062                830
```

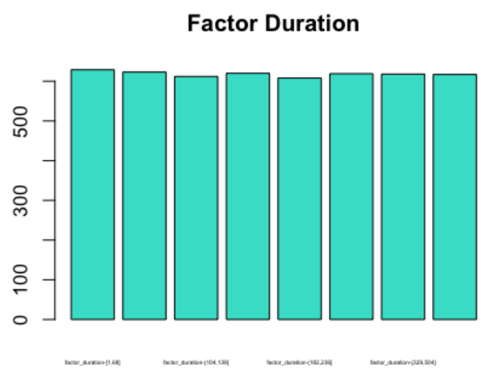
```
## factor_age (41,49] factor_age (49,81]
##                 953               988

barplot(summary(df$factor_age), main="Factor
Age",col=("turquoise"),cex.names=0.75)
```



Factor Duration

```
# Trend and dispersion statistics
quantile(df$duration,seq(0,1,0.125),na.rm=TRUE)

##     0%  12.5%    25%  37.5%    50%  62.5%    75%  87.5%   100%
##      1     68    104    139    182    236    329    504   2122

df$factor_duration<-
factor(cut(df$duration,include.lowest=T,breaks=c(1,68,104,139,182,236,
329,504,2122)))
summary(df$factor_duration)

##          [1,68]        (68,104]       (104,139]       (139,182]
(182,236]
##             629             623             612             620
608
##       (236,329]       (329,504] (504,2.12e+03]
##             619             618            617

tapply(df$duration,df$factor_duration,median)

##          [1,68]        (68,104]       (104,139]       (139,182]
(182,236]
##              44              86             122             160
206
##       (236,329]       (329,504] (504,2.12e+03]
##             277             396            716
```

```r
levels(df$factor_duration)<-
paste("factor_duration-",levels(df$factor_duration),sep="")
table(df$factor_duration)

##
##         factor_duration-[1,68]       factor_duration-(68,104]
##                            629                            623
##      factor_duration-(104,139]      factor_duration-(139,182]
##                            612                            620
##      factor_duration-(182,236]      factor_duration-(236,329]
##                            608                            619
##      factor_duration-(329,504] factor_duration-(504,2.12e+03]
##                            618                            617

barplot(summary(df$factor_duration), main="Factor
Duration",col=("turquoise"),cex.names=0.3)
```



Factor Campaign

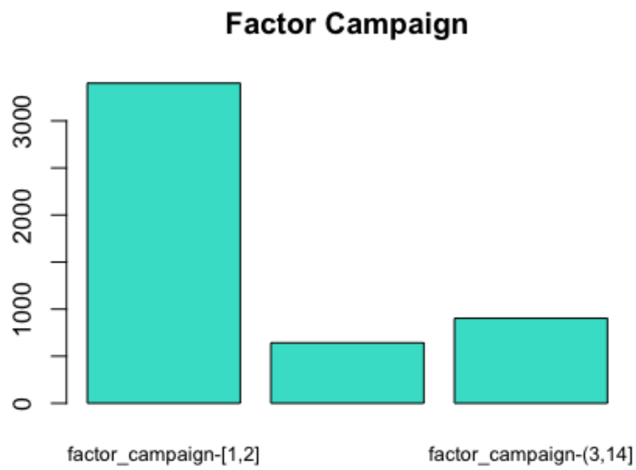
```r
# Trend and dispersion statistics
quantile(df$campaign,seq(0,1,0.2),na.rm=TRUE)

##   0%  20%  40%  60%  80% 100%
##    1    1    1    2    3   14

df$factor_campaign<-
factor(cut(df$campaign,include.lowest=T,breaks=c(1,2,3,14)))

summary(df$factor_campaign)

##  [1,2]  (2,3] (3,14]
##   3401    642    903

tapply(df$campaign,df$factor_campaign,median)
```

```
##  [1,2]  (2,3] (3,14]
##      1      3      5
```

```
levels(df$factor_campaign)<-
paste("factor_campaign-",levels(df$factor_campaign),sep="")
table(df$factor_campaign)
```

```
##
##  factor_campaign-[1,2]  factor_campaign-(2,3] factor_campaign-
(3,14]
##                   3401                    642
903
```

```
barplot(summary(df$factor_campaign), main="Factor
Campaign",col=("turquoise"),cex.names=0.8)
```



Factor PDays

```
quantile(df$pdays,seq(0,1,0.25),na.rm=TRUE)
```

```
##   0%  25%  50%  75% 100%
##    1   16   16   16   16
```

```
df$factor_Pdays<-
factor(cut(df$pdays,include.lowest=T,breaks=c(0,15,17)))

summary(df$factor_Pdays)
```

```
##  [0,15] (15,17]
##     179    4767
```

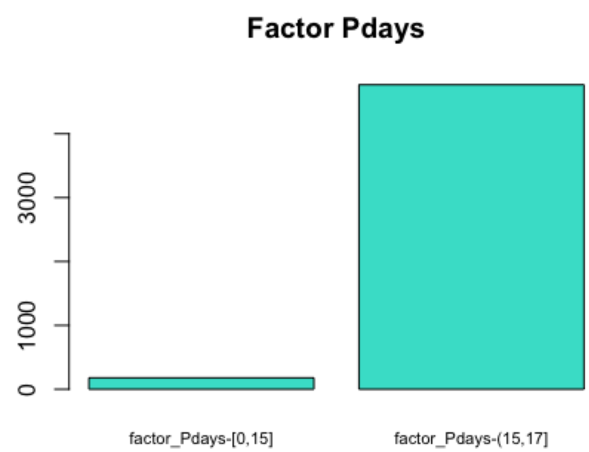
```
tapply(df$pdays,df$factor_Pdays,median)
```

```
##  [0,15] (15,17]
##       5      16
```

```
levels(df$factor_Pdays)<-
paste("factor_Pdays-",levels(df$factor_Pdays),sep="")
table(df$factor_Pdays)
```

```
##
##  factor_Pdays-[0,15] factor_Pdays-(15,17]
##                  179                 4767
```

```
barplot(summary(df$factor_Pdays), main="Factor
Pdays",col=("turquoise"),cex.names=0.7)
```



Factor Previous

```
quantile(df$previous,seq(0,1,0.1),na.rm=TRUE)
```

```
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##    0    0    0    0    0    0    0    0    0    1    5
```

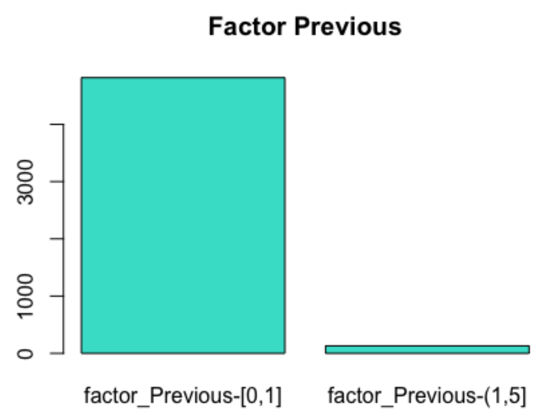
```
df$factor_Previous<-
factor(cut(df$previous,include.lowest=T,breaks=c(0,1,5)))

summary(df$factor_Previous)
```

```
## [0,1] (1,5]
##  4815   131
```

```
tapply(df$previous,df$factor_Previous,median)
```

```
## [0,1] (1,5]
##     0     2
```

```
levels(df$factor_Previous)<-
paste("factor_Previous-",levels(df$factor_Previous),sep="")
table(df$factor_Previous)

##
## factor_Previous-[0,1] factor_Previous-(1,5]
##                  4815                   131

barplot(summary(df$factor_Previous), main="Factor
Previous",col=("turquoise"),cex.names=1.0)
```

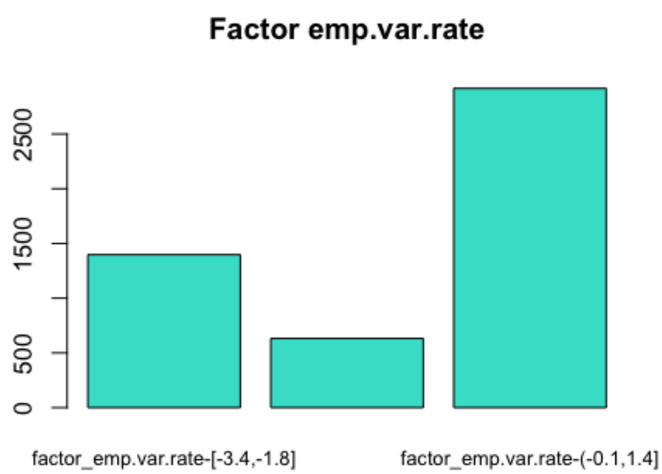



```
#Amb aquesta discretitzacio podem comprobar que el nombre de cops que
s'ha contactat previament amb l'individu es majoritariament 0 o 1 i
com a maxim una mitja de 5 cops.
```

Factor emp.var.rate

```
quantile(df$emp.var.rate,seq(0,1,0.2),na.rm=TRUE)

##   0%  20%  40%  60%  80% 100%
## -3.4 -1.8 -0.1  1.4  1.4  1.4

df$factor_emp.var.rate<-
factor(cut(df$emp.var.rate,include.lowest=T,breaks=c(-3.4,-1.8,-0.1,1.
4)))

summary(df$factor_emp.var.rate)

## [-3.4,-1.8] (-1.8,-0.1]  (-0.1,1.4]
##        1397         632        2917

tapply(df$emp.var.rate,df$factor_emp.var.rate,median)

## [-3.4,-1.8] (-1.8,-0.1]  (-0.1,1.4]
##        -1.8        -0.1         1.4
```

```
levels(df$factor_emp.var.rate)<-
paste("factor_emp.var.rate-",levels(df$factor_emp.var.rate),sep="")
table(df$factor_emp.var.rate)

##
## factor_emp.var.rate-[-3.4,-1.8] factor_emp.var.rate-(-1.8,-0.1]
##                            1397                             632
##  factor_emp.var.rate-(-0.1,1.4]
##                            2917

barplot(summary(df$factor_emp.var.rate), main="Factor
emp.var.rate",col=("turquoise"),cex.names=0.8)
```



Factor cons.price.idx

```
quantile(df$cons.price.idx,seq(0,1,0.2),na.rm=TRUE)

##     0%    20%    40%    60%    80%   100%
## 92.201 92.963 93.444 93.918 93.994 94.767

df$factor_cons.price.idx<-
factor(cut(df$cons.price.idx,include.lowest=T,breaks=c(92.201,92.963,9
3.444,93.918,93.994,94.767)))

summary(df$factor_cons.price.idx)

##   [92.2,93]   (93,93.4] (93.4,93.9]   (93.9,94]   (94,94.8]
##        1059        1359         889         921         718

tapply(df$cons.price.idx,df$factor_cons.price.idx,median)
```

```
##    [92.2,93]    (93,93.4] (93.4,93.9]    (93.9,94]    (94,94.8]
##       92.893       93.200       93.918       93.994       94.465
```

```
levels(df$factor_cons.price.idx)<-
paste("factor_cons.price.idx-",levels(df$factor_cons.price.idx),sep=""
)
table(df$factor_cons.price.idx)
```

```
##
##   factor_cons.price.idx-[92.2,93]   factor_cons.price.idx-(93,93.4]
##                              1059                              1359
## factor_cons.price.idx-(93.4,93.9]   factor_cons.price.idx-(93.9,94]
##                               889                               921
##   factor_cons.price.idx-(94,94.8]
##                               718
```

```
barplot(summary(df$factor_cons.price.idx), main="Factor
cons.price.idx",col=("turquoise"),cex.names=0.5)
```

Factor cons.conf.idx

```
quantile(df$cons.conf.idx,seq(0,1,0.2),na.rm=TRUE)
```

```
##     0%    20%    40%    60%    80%   100%
## -50.8 -46.2 -42.0 -40.3 -36.4 -29.8
```

```
df$factor_cons.conf.idx<-
factor(cut(df$cons.conf.idx,include.lowest=T,breaks=c(-50.8,-46.2,-42,
-40.3,-36.4,-29.8)))

summary(df$factor_cons.conf.idx)
```

```
## [-50.8,-46.2]   (-46.2,-42]   (-42,-40.3] (-40.3,-36.4]
(-36.4,-29.8]
##          1026          1304           666          1052
898
```

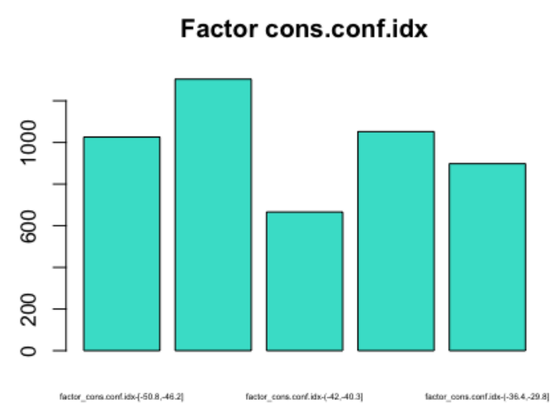
```r
tapply(df$cons.conf.idx,df$factor_cons.conf.idx,median)
```

```
## [-50.8,-46.2]   (-46.2,-42]   (-42,-40.3] (-40.3,-36.4]
(-36.4,-29.8]
##         -46.2         -42.7         -41.8         -36.4
-36.1
```

```r
levels(df$factor_cons.conf.idx)<-
paste("factor_cons.conf.idx-",levels(df$factor_cons.conf.idx),sep="")
table(df$factor_cons.conf.idx)
```

```
##
## factor_cons.conf.idx-[-50.8,-46.2]   factor_cons.conf.idx-
(-46.2,-42]
##                               1026
1304
##   factor_cons.conf.idx-(-42,-40.3] factor_cons.conf.idx-
(-40.3,-36.4]
##                                666
1052
## factor_cons.conf.idx-(-36.4,-29.8]
##                                898
```

```r
barplot(summary(df$factor_cons.conf.idx), main="Factor
cons.conf.idx",col=("turquoise"),cex.names=0.4)
```



Factor euribor3m

```r
quantile(df$euribor3m,seq(0,1,0.15),na.rm=TRUE)
```

```
##     0%    15%    30%    45%    60%    75%    90%
## 0.634 1.266 1.415 4.856 4.864 4.961 4.964
```

```
df$factor_euribor3m<-
factor(cut(df$euribor3m,include.lowest=T,breaks=c(0.634,1.266,1.415,4.
856,4.864,4.961,4.964)))

summary(df$factor_euribor3m)
```

```
## [0.634,1.266] (1.266,1.415] (1.415,4.856] (4.856,4.864]
(4.864,4.961]
##           817           673           784           755
719
## (4.961,4.964]          NA's
##           792           406
```

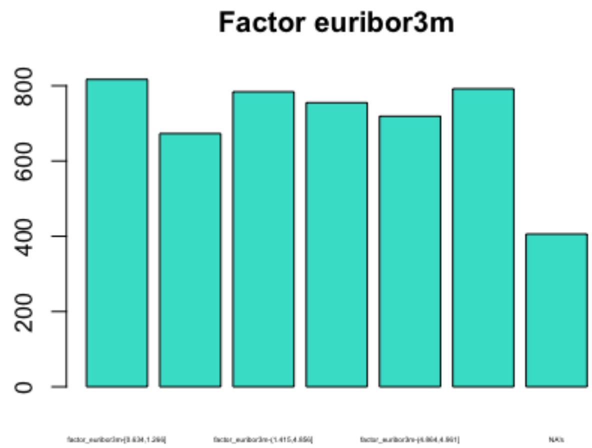
```
tapply(df$euribor3m,df$factor_euribor3m,median)
```

```
## [0.634,1.266] (1.266,1.415] (1.415,4.856] (4.856,4.864]
(4.864,4.961]
##         0.884         1.334         4.153         4.858
4.960
## (4.961,4.964]
##         4.963
```

```
levels(df$factor_euribor3m)<-
paste("factor_euribor3m-",levels(df$factor_euribor3m),sep="")
table(df$factor_euribor3m)
```

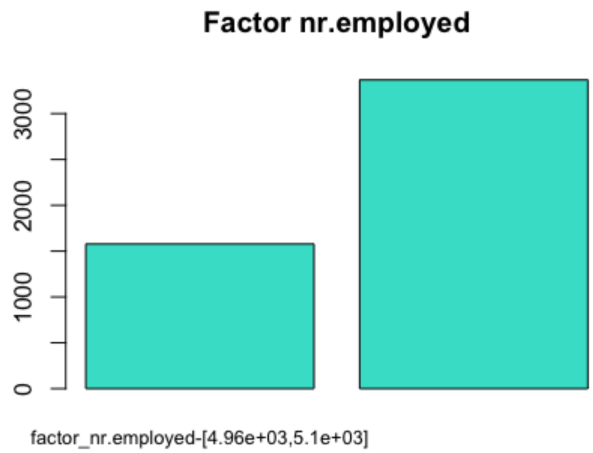
```
##
## factor_euribor3m-[0.634,1.266] factor_euribor3m-(1.266,1.415]
##                            817                            673
## factor_euribor3m-(1.415,4.856] factor_euribor3m-(4.856,4.864]
##                            784                            755
## factor_euribor3m-(4.864,4.961] factor_euribor3m-(4.961,4.964]
##                            719                            792
```

```
barplot(summary(df$factor_euribor3m), main="Factor
euribor3m",col=("turquoise"),cex.names=0.3)
```



Factor nr.employed

```
quantile(df$nr.employed,seq(0,1,0.3),na.rm=TRUE)

##     0%    30%    60%    90% 
## 4963.6 5099.1 5228.1 5228.1

df$factor_nr.employed<-
factor(cut(df$nr.employed,include.lowest=T,breaks=c(4963.6,5099.1,5228
.1)))

summary(df$factor_nr.employed)

## [4.96e+03,5.1e+03] (5.1e+03,5.23e+03] 
##               1578               3368

tapply(df$nr.employed,df$factor_nr.employed,median)

## [4.96e+03,5.1e+03] (5.1e+03,5.23e+03] 
##             5099.1             5228.1

levels(df$factor_nr.employed)<-
paste("factor_nr.employed-",levels(df$factor_nr.employed),sep="")
table(df$factor_nr.employed)

## 
## factor_nr.employed-[4.96e+03,5.1e+03] 
##                                  1578 
## factor_nr.employed-(5.1e+03,5.23e+03] 
##                                  3368

barplot(summary(df$factor_nr.employed), main="Factor
nr.employed",col=("turquoise"),cex.names=0.8)
```



PROFILING

Numeric target (Duration)

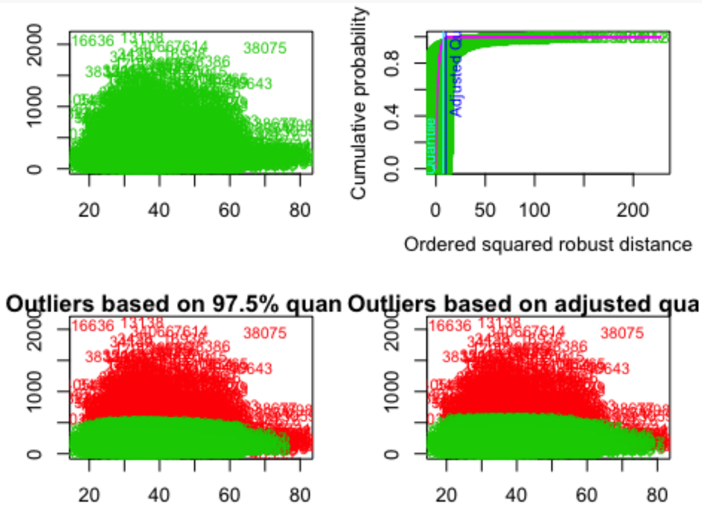
El profiling s'utilitza per acabar de perfilar la nostra mostra

Ara procedirem a fer el profiling que ens demana del nostre target numeric (duration) i llavors hem d'utilitzar les variables originals i els factors menys el factor_duration, ja que es una variable que prove de la variable original i no volem aquesta informacio

Per tal de observar la relacio del nostre target numeric amb les altres variables utilitzem la eina condes que ens proporciona informacio de les relacions entre les variables indicades i el target.

```
df$varauxiliar <- NULL #borrem la variable auxiliar creada
df$aux <- NULL
#Despres de discretitzar les nostres variables tenim un total de 35
variables
#names(df)

#Description continuous by quantitative variables and/or by
categorical variables
library(FactoMineR)

library(mvoutlier)

vars_resu <-names(df)[c(1,11)]
vars_resu

## [1] "age"      "duration"
```

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

aq.plot(df[,vars_resu])
```




```
## $outliers


#vars_res<-names(df)[c(11,21)]
vars<-unique(c(vars_con,vars_dis))
#vars

condes(df, which(names(df) == "duration"))

## $quanti
##                correlation      p.value
## previous        0.02859224 4.435374e-02
## errors_indiv   -0.03476735 1.447588e-02
## nr.employed    -0.03619203 1.091224e-02
## campaign       -0.04179341 3.284450e-03
## pdays          -0.06147234 1.516945e-05
## missings_indiv -0.07328498 2.474678e-07
##
## $quali
##                                 R2       p.value
## factor_duration       0.8271873066  0.000000e+00
## y                     0.1863696068 9.891372e-224
## factor_Pdays          0.0051824450  4.017238e-07
## poutcome              0.0041874670  3.132625e-05
## month                 0.0073478185  3.327154e-05
```

```
## factor_cons.price.idx 0.0039803615  5.696640e-04
## factor_Previous       0.0019228074  2.038492e-03
## day_of_week           0.0029955473  5.075577e-03
## factor_cons.conf.idx  0.0026002247  1.194404e-02
## contact               0.0011105265  1.909343e-02
## default               0.0009897216  2.693284e-02
## factor_campaign       0.0013152237  3.866909e-02
##
## $category
##                                      Estimate       p.value
## factor_duration-(504,2.12e+03]      547.162252  0.000000e+00
## Y_yes                               169.675531 9.891372e-224
## factor_duration-(329,504]           138.462468  3.985182e-48
## factor_Pdays-[0,15]                  49.355073  4.017238e-07
## Poutcome_success                     62.641078  7.933875e-06
## factor_cons.price.idx-(93.4,93.9]    27.117765  2.010384e-04
## Month_jul                            12.946601  2.986551e-04
## factor_Previous-(1,5]                34.966136  2.038492e-03
## Contact_cellular                      8.850090  1.909343e-02
## Default_no                            9.913335  2.693284e-02
## Month_dec                           104.090396  2.868142e-02
## Day_of_week_tue                      14.917687  4.872420e-02
## Education_illiterate                178.585152  4.932974e-02
## Education_university.degree         -38.308971  3.857651e-02
## factor_cons.conf.idx-(-36.4,-29.8]  -13.574401  3.768483e-02
## factor_cons.conf.idx-(-42,-40.3]    -17.926886  2.695593e-02
## Default_unknown                      -9.913335  2.693284e-02
## Contact_telephone                    -8.850090  1.909343e-02
## Month_jun                           -37.404273  1.736971e-02
## factor_campaign-(3,14]              -16.741883  1.148865e-02
## Job_technician                      -25.341033  1.106827e-02
## Day_of_week_mon                     -19.239047  7.577039e-03
## Month_aug                           -39.248662  5.073298e-03
## factor_cons.price.idx-(93,93.4]     -19.809889  2.312144e-03
## factor_Previous-[0,1]               -34.966136  2.038492e-03
## factor_Pdays-(15,17]                -49.355073  4.017238e-07
## factor_duration-(182,236]           -56.414720  8.764699e-09
## factor_duration-(139,182]          -103.067426  8.297196e-27
## factor_duration-(104,139]          -141.910732  3.245807e-49
## factor_duration-(68,104]           -177.221056  2.195363e-78
## factor_duration-[1,68]             -222.636796 8.250905e-127
## Y_no                               -169.675531 9.891372e-224
```

```
#S'utilitza per fer totes les combinacions possibles de variables numeriques i factorials
#Tindrem les variables que tenen un pvalor a partir d'un llindar del pvalor acceptat. No ens surten totes les variables estudiades, només les que tenen una mena de relació
#Con el p valor muy bajo entonces rechazamos la hipotesi nula

#$quanti: Com podem observar la variable pdays es la que te mes relacio amb la nostra variable target (duration), es a dir, quant mes gran sigui la duracio de la trucada tenim una correlacio mes gran amb aquesta i veiem que com a relacio inversament proporcional tenim campaign
#$quali: La variable qualitativa que te mes realcio amb el nostre target es el seu mateix factor (factor_duration) com es obvi, pero seguidament tenim el factor_Pdays i la nostra variable y
#$category: Podem observar que tenim una relacio dependent molt forta dels mesos i ultims contactes, podem veure que ha tingut exit i majoritariament la y es yes
```

Y (target qual)

Per analitzar les relacions de la nostre variable qualitativa utilitzem l'eina catdes que de la mateixa manera que el condes ens mostrar? les seves relacions.

```
df_catdes<-df[c(1:21)]
catdes(df_catdes,21)

##
## Link between the cluster variable and the categorical variables (chi-square test)
## ===========================================================================
##                    p.value df
## poutcome    2.884978e-155  2
## month        2.020968e-82  9
## contact      8.049707e-27  1
## job          5.149262e-24 11
## default      7.888260e-14  1
## education    1.246599e-05  7
## marital      4.868728e-03  3
## day_of_week  3.137547e-02  4
##
## Description of each cluster by the categories
## =============================================
## $Y_no
```

```
##                                             Cla/Mod    Mod/Cla
Global
## poutcome=Poutcome_nonexistent           91.01964 89.4918372
86.4537000
## contact=Contact_telephone               94.44444 39.4803403
36.7569753
## default=Default_unknown                 94.67054 22.4649345
20.8653457
## month=Month_may                         92.83951 34.5826627
32.7537404
## job=Job_blue-collar                     92.74476 24.3964130
23.1298019
## education=Education_basic.9y            92.09486 16.0726604
15.3457339
## month=Month_jul                         90.92945 18.6709588
18.0549939
## education=Education_basic.6y            93.28358  5.7484479
5.4185200
## marital=Marital_married                 88.96667 61.3704300
60.6550748
## job=Job_services                        91.54334  9.9563118
9.5632835
## job=Job_technician                      90.17857 16.2566107
15.8511929
## day_of_week=Day_of_week_mon             89.79592 21.2462635
20.8046907
## education=NA                            83.33333  4.0239135
4.2458552
## education=Education_professional.course 85.21008 11.6578524
12.0299232
## day_of_week=Day_of_week_tue             85.16058 17.6822258
18.2571775
## education=Education_university.degree   85.93540 29.3630720
30.0444804
## marital=Marital_single                  85.47567 27.0636928
27.8406793
## poutcome=Poutcome_failure               83.26693  9.6114049
10.1496159
## job=Job_admin.                          85.16526 25.4771212
26.3040841
## month=Month_apr                         78.29181  5.0586342
5.6813587
## month=Month_dec                         45.45455  0.2299379
0.4448039
## job=Job_student                         65.71429  1.5865716
2.1229276
```

```
## job=Job_retired                            72.81553  3.4490688
4.1649818
## month=Month_mar                            50.74627  0.7817889
1.3546300
## month=Month_sep                            50.72464  0.8047827
1.3950667
## default=Default_no                         86.15227 77.5350655
79.1346543
## month=Month_oct                            48.19277  0.9197517
1.6781237
## contact=Contact_cellular                   84.14322 60.5196597
63.2430247
## poutcome=Poutcome_success                  23.21429  0.8967579
3.3966842
##                                                p.value     v.test
## poutcome=Poutcome_nonexistent             3.543373e-50  14.895160
## contact=Contact_telephone                 1.650430e-29  11.279842
## default=Default_unknown                   6.847442e-16   8.073209
## month=Month_may                           1.529311e-14   7.685055
## job=Job_blue-collar                       2.309977e-09   5.974358
## education=Education_basic.9y              6.478104e-05   3.994682
## month=Month_jul                           1.804548e-03   3.120646
## education=Education_basic.6y              3.345680e-03   2.934052
## marital=Marital_married                   5.727878e-03   2.762966
## job=Job_services                          8.657080e-03   2.625307
## job=Job_technician                        3.216891e-02   2.142305
## day_of_week=Day_of_week_mon               3.661258e-02   2.090058
## education=NA                              4.459048e-02  -2.008497
## education=Education_professional.course 3.369438e-02  -2.123710
## day_of_week=Day_of_week_tue               5.704442e-03  -2.764304
## education=Education_university.degree   5.300406e-03  -2.788186
## marital=Marital_single                    1.198449e-03  -3.239249
## poutcome=Poutcome_failure                 1.167715e-03  -3.246651
## job=Job_admin.                            4.654028e-04  -3.499917
## month=Month_apr                           2.649823e-06  -4.696249
## month=Month_dec                           1.944834e-06  -4.759074
## job=Job_student                           2.045387e-09  -5.994161
## job=Job_retired                           1.710143e-09  -6.023188
## month=Month_mar                           6.474585e-14  -7.498107
## month=Month_sep                           2.609525e-14  -7.616349
## default=Default_no                        6.847442e-16  -8.073209
## month=Month_oct                           6.812368e-19  -8.877918
## contact=Contact_cellular                  1.650430e-29 -11.279842
```

```
## poutcome=Poutcome_success                   2.944669e-88 -19.916208
##
## $Y_yes
##                                                Cla/Mod   Mod/Cla
Global
## poutcome=Poutcome_success                   76.785714 21.608040
3.3966842
## contact=Contact_cellular                    15.856777 83.082077
63.2430247
## month=Month_oct                             51.807229  7.202680
1.6781237
## default=Default_no                          13.847726 90.787270
79.1346543
## month=Month_sep                             49.275362  5.695142
1.3950667
## month=Month_mar                             49.253731  5.527638
1.3546300
## job=Job_retired                             27.184466  9.380235
4.1649818
## job=Job_student                             34.285714  6.030151
2.1229276
## month=Month_dec                             54.545455  2.010050
0.4448039
## month=Month_apr                             21.708185 10.217755
5.6813587
## job=Job_admin.                              14.834743 32.328308
26.3040841
## poutcome=Poutcome_failure                   16.733068 14.070352
10.1496159
## marital=Marital_single                      14.524328 33.500838
27.8406793
## education=Education_university.degree       14.064603 35.008375
30.0444804
## day_of_week=Day_of_week_tue                 14.839424 22.445561
18.2571775
## education=Education_professional.course 14.789916 14.740369
12.0299232
## education=NA                                16.666667  5.862647
4.2458552
## day_of_week=Day_of_week_mon                 10.204082 17.587940
20.8046907
## job=Job_technician                           9.821429 12.897822
15.8511929
## job=Job_services                             8.456660  6.700168
9.5632835
```

```
## marital=Marital_married                        11.033333 55.443886
60.6550748
## education=Education_basic.6y                    6.716418  3.015075
5.4185200
## month=Month_jul                                 9.070549 13.567839
18.0549939
## education=Education_basic.9y                    7.905138 10.050251
15.3457339
## job=Job_blue-collar                             7.255245 13.902848
23.1298019
## month=Month_may                                 7.160494 19.430486
32.7537404
## default=Default_unknown                         5.329457  9.212730
20.8653457
## contact=Contact_telephone                       5.555556 16.917923
36.7569753
## poutcome=Poutcome_nonexistent                   8.980355 64.321608
86.4537000
##                                                     p.value     v.test
## poutcome=Poutcome_success                      2.944669e-88  19.916208
## contact=Contact_cellular                       1.650430e-29  11.279842
## month=Month_oct                                6.812368e-19   8.877918
## default=Default_no                             6.847442e-16   8.073209
## month=Month_sep                                2.609525e-14   7.616349
## month=Month_mar                                6.474585e-14   7.498107
## job=Job_retired                                1.710143e-09   6.023188
## job=Job_student                                2.045387e-09   5.994161
## month=Month_dec                                1.944834e-06   4.759074
## month=Month_apr                                2.649823e-06   4.696249
## job=Job_admin.                                 4.654028e-04   3.499917
## poutcome=Poutcome_failure                      1.167715e-03   3.246651
## marital=Marital_single                         1.198449e-03   3.239249
## education=Education_university.degree          5.300406e-03   2.788186
## day_of_week=Day_of_week_tue                    5.704442e-03   2.764304
## education=Education_professional.course        3.369438e-02   2.123710
## education=NA                                   4.459048e-02   2.008497
## day_of_week=Day_of_week_mon                    3.661258e-02  -2.090058
## job=Job_technician                             3.216891e-02  -2.142305
## job=Job_services                               8.657080e-03  -2.625307
## marital=Marital_married                        5.727878e-03  -2.762966
## education=Education_basic.6y                   3.345680e-03  -2.934052
## month=Month_jul                                1.804548e-03  -3.120646
## education=Education_basic.9y                   6.478104e-05  -3.994682
## job=Job_blue-collar                            2.309977e-09  -5.974358
```

```
## month=Month_may                              1.529311e-14  -7.685055
## default=Default_unknown                      6.847442e-16  -8.073209
## contact=Contact_telephone                    1.650430e-29 -11.279842
## poutcome=Poutcome_nonexistent                3.543373e-50 -14.895160
##
##
## Link between the cluster variable and the quantitative variables
## ================================================================
##                       Eta2       P-value
## duration       0.186369607 9.891372e-224
## nr.employed    0.139052649 5.557605e-163
## pdays          0.124416618 7.349696e-145
## euribor3m      0.104758799 5.493737e-121
## emp.var.rate   0.099078243 3.487741e-114
## previous       0.070648755  9.329422e-81
## cons.price.idx 0.019937283  1.907193e-23
## campaign       0.005057924  5.536389e-07
##
## Description of each cluster by quantitative variables
## =====================================================
## $Y_no
##                    v.test Mean in category Overall mean sd in
category
## nr.employed     26.222421     5177.8744999 5167.8073595
64.2441089
## pdays           24.804035       15.8919292   15.6263647
1.1098761
## euribor3m       22.760322        3.8560536    3.6487535
1.6188731
## emp.var.rate    22.134632        0.2901587    0.1073999
1.4661991
## cons.price.idx   9.929243       93.6160205   93.5857345
0.5562445
## campaign         5.001143        2.4413845    2.3891187
2.0381577
## previous       -18.691123        0.1230168    0.1708451
0.3957657
## duration       -30.357828      221.8063923  262.7672867
200.3541053
##                 Overall sd       p.value
## nr.employed     72.8658491 1.475237e-151
## pdays            2.0320681 8.109757e-136
## euribor3m        1.7286683 1.134100e-114
## emp.var.rate     1.5670994 1.467071e-108
```

```
## cons.price.idx   0.5789159  3.106051e-23
## campaign         1.9835304  5.699132e-07
## previous         0.4856692  5.846876e-78
## duration       256.0881160 1.980616e-202
##
## $Y_yes
##                    v.test Mean in category Overall mean sd in
category
## duration         30.357828       561.157454  262.7672867
386.8354045
## previous         18.691123         0.519263    0.1708451
0.8216383
## campaign         -5.001143         2.008375    2.3891187
1.4727896
## cons.price.idx   -9.929243        93.365109   93.5857345
0.6835676
## emp.var.rate    -22.134632        -1.223953    0.1073999
1.6338789
## euribor3m       -22.760322         2.138623    3.6487535
1.7527742
## pdays           -24.804035        13.691792   15.6263647
4.5804350
## nr.employed     -26.222421      5094.470687 5167.8073595
88.3423897
##                 Overall sd       p.value
## duration       256.0881160 1.980616e-202
## previous         0.4856692  5.846876e-78
## campaign         1.9835304  5.699132e-07
## cons.price.idx   0.5789159  3.106051e-23
## emp.var.rate     1.5670994 1.467071e-108
## euribor3m        1.7286683 1.134100e-114
## pdays            2.0320681 8.109757e-136
## nr.employed     72.8658491 1.475237e-151
```

```
save.image("DadesBank1_5000.RData")
```

———— DELIVERABLE 2 ————-

Principal Component Analysis (PCA)

L'analisi de components principals (a partir d'ara PCA) es una tecnica utilitzada per reduir la dimensionalitat d'un conjunt de dades per a poder-les representar graficament en grafics de dues o tres dimensions agrupant diverses variables de les dades en factors, o components, compostos per l'agrupacio de diverses variables.

Intuïtivament, la tècnica serveix per determinar el nombre de factors explicatius d'un conjunt de dades que determinen en major grau la variabilitat d'aquestes dades. Llavors podrem sintetitzar i visualitzar informacio util en un conjunt de dades que contindra observacions descrites per multiples variables quantitatives correlacionades.

Com hem pogut observar a la nostra mostra o conjunt de dades, tenim un elevat nombre de variables i aixo ens dificulta la visualitzacio de la informacio que volem tractar en un espai multi-dimensional.

Gracies al procediment explicat aconseguirem reduir la dimensionalitat de les nostes dades en un baix nombre de components que podrem visualitzar graficament amb la menor perdua de informacio i variança possible.

Data format & analysis

Abans de res, prepararem les dades necessaries per realitzar l'analisi de components principals. Escollirem les variables actives que ens permetran realitzar el PCA i tambe seleccionarem un conjunt de variables suplementaries.

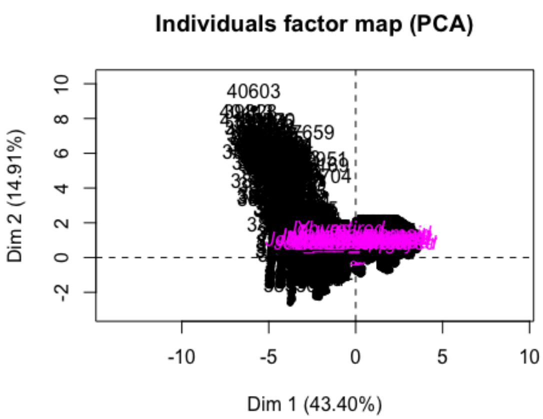
Create PCA

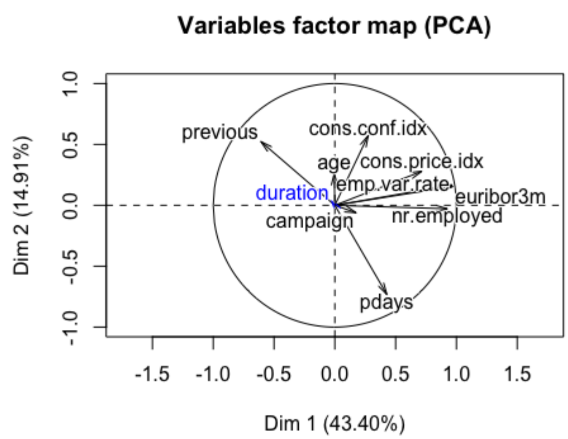
Hem agrupat totes les variables numeriques, les quals utilitzarem com a variables actives menys el target numeric "duration" i com a variables suplementaries tenim "y", "marital" y "job", encara que havíem també seleccionat "education", però la mostra no era del tot concluent.

```
names(df)
```

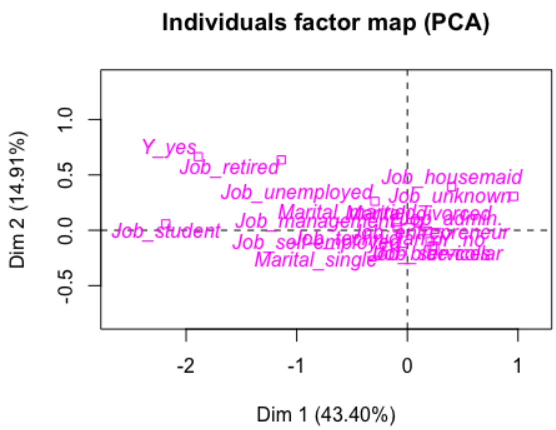
```
##  [1] "age"                  "job"
##  [3] "marital"              "education"
##  [5] "default"              "housing"
##  [7] "loan"                 "contact"
##  [9] "month"                "day_of_week"
## [11] "duration"             "campaign"
## [13] "pdays"                "previous"
## [15] "poutcome"             "emp.var.rate"
## [17] "cons.price.idx"       "cons.conf.idx"
## [19] "euribor3m"            "nr.employed"
## [21] "y"                    "missings_indiv"
## [23] "errors_indiv"         "outliers_indiv"
## [25] "season"               "factor_age"
## [27] "factor_duration"      "factor_campaign"
## [29] "factor_Pdays"         "factor_Previous"
## [31] "factor_emp.var.rate"  "factor_cons.price.idx"
## [33] "factor_cons.conf.idx" "factor_euribor3m"
## [35] "factor_nr.employed"
```

```r
vars_conaux <- names(df)[c(1,12:14,16:20)]
vars_conaux

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

res.pca<-
PCA(df[,c("duration","y","marital","job",vars_conaux)],quanti.sup =
1,quali.sup = 2:4)

## Warning in PCA(df[, c("duration", "y", "marital", "job",
vars_conaux)], :
## Missing values are imputed by the mean of the variable: you should
use the
## imputePCA function of the missMDA package
```

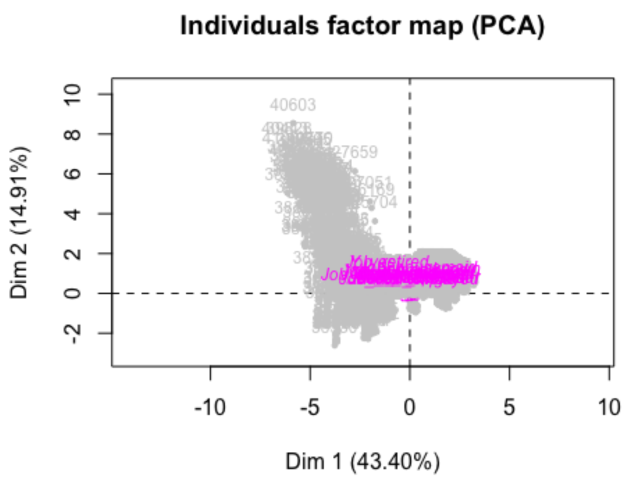





```r
#LES VARIABLES ACTIVES NO PODEN SER FACTORS!

plot.PCA(res.pca,choix = "ind", invisible = "ind")
```




```
plot(res.pca,choix="ind", cex=0.75, col.ind="grey80")
```




```
#par(mfrow=c(1,2)) poner dos graficos juntos!
```

La funcio PCA() ha realitzat el PCA del nostre conjunt de dades. Visualitzarem dos grafics, tenim el “Variables factor map” i el “Individuals factor map” que detallarem amb més profunditat posteriorment.

En el grafic “Variables factor map” podem observar que les variables “previous”" i “pdays” es troben totalment oposades i tambe veiem que el nostre target (variable quantitativa suplementaria) “duration” no te res a veure amb les variables numeriques ja que la fetxa es molt curta.

Eigenvalues and dominant axes Analysis

En aquest apartat utilitzarem valors propis (Eigenvalues) per determinar quins components principals considerarem per el nostre analisi (denominat axes).

Concretament els valors propis mesuren la quantitat de variança proporcionada per cada component principal. A partir d'aquesta informacio i les regles de Kaiser i Elbow podrem determinar, com hem dit, els components a considerar i les dimensions necessaries a agafar.

Kaiser Rule

```
res.pca$eig

##        eigenvalue percentage of variance cumulative percentage of
variance
## comp 1 3.90643762             43.4048625
43.40486
## comp 2 1.34224472             14.9138303
58.31869
## comp 3 1.03534030             11.5037811
69.82247
## comp 4 0.98070837             10.8967597
80.71923
## comp 5 0.84014761              9.3349735
90.05421
## comp 6 0.46176101              5.1306779
95.18488
## comp 7 0.39576928              4.3974364
99.58232
## comp 8 0.02438733              0.2709704
99.85329
## comp 9 0.01320375              0.1467083
100.00000
```

Quan executem aquesta comanda podem visualitzar una taula on observem els valors propis (eigenvalues) de cada component principal.

La primera columna mostra el valor propi per cada component, la suma de tots els valors propis ens dona una variança de 9. En la segona columna podem observar la proporcio de variança de cada component i en la tercera el percentatge acomulat de variança obtingut a partir de la suma dels successius components.

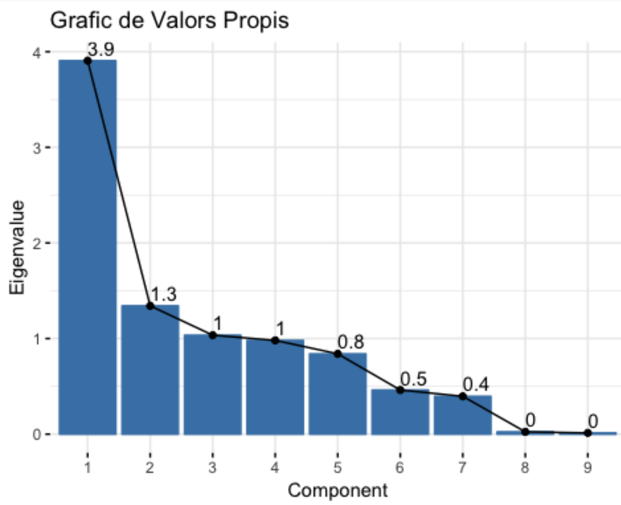
La regla de Kaiser diu que un valor propi (eigenvalue) amb valor superior a 1 indica que les components principals compten amb mes variança que una de les variables originals en dades estandaritzades.

Després de la execució, a partir de la taula de valors propis i seguint la regla de Kaiser hem decidit tenir en compte les 4 primeres components principals. Com podem veure el valor propi de la component numero 4 no supera el valor 1, però el seu valor es de 0.9807 que es molt proxim a 1, llavors tambe es podria considerar agafar-la. Amb el nostre percentatge de variança (69.822) podem dir que quasi tres quarts (75%) de les nostres dades queden representades amb aquestes 3 components principals i si agafessim les 4 components seria una mica mes de tres quarts de les nostres dades (80.719).

Elbow Rule

Tambe tenim un altre metode d'interpretacio i validacio de les nostres components i aquest es el "Elbow Rule", que utilitza un grafic dels valors propis ordenats de major a menor i determina el nombre de components principals a considerar fins al punt del grafic en el qual el valor propi es relativament petit.

```
fviz_eig(res.pca, choice = "eigenvalue", addlabels = TRUE, main =
"Grafic de Valors Propis", xlab = "Component", ylab = "Eigenvalue")
```



Com podem observar al grafic dels valors propis, segons la regla d'elbow hauriem de considerar les 7 primeres components principals. Tot i així, en el nostre cas, decidim considerar les 3 primeres components principals ja que ens proporcionen una variança totalment acceptable (80.71%) i en el cas d'utilitzar les 7 components obtindrem una dimensionalitat massa elevada, fet que no ens interessa molt.

Individuals point of view

En aquest apartat estudiarem diferents aspectes del nostre conjunt de dades i de les nostres components principals a partir del individus de la nostra mostra.

Individuals contribution

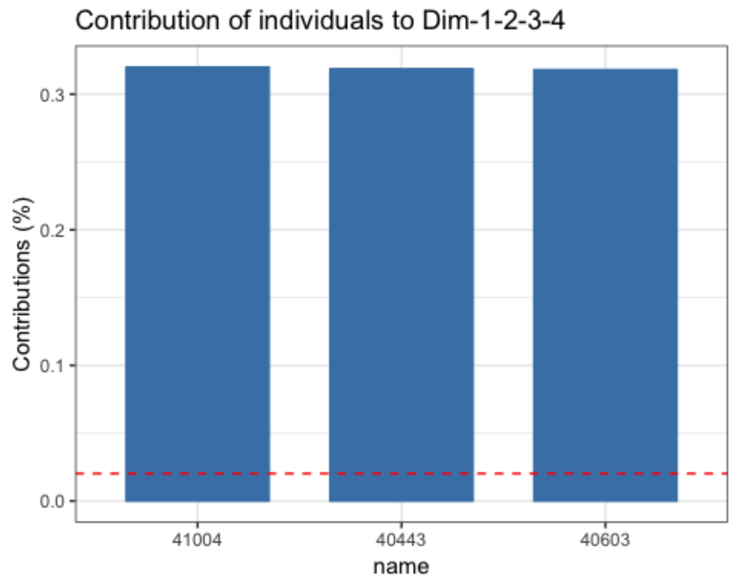
Ara el que farem es estudiar les possibles contribucions per part d'alguns individus.

```
#Hacemos esto para poder ver los tres más contributivos al segundo eje
de las 4 dimensiones que hemos cogido

sort(res.pca$ind$contrib[,1],decreasing = TRUE)[1:3]
```

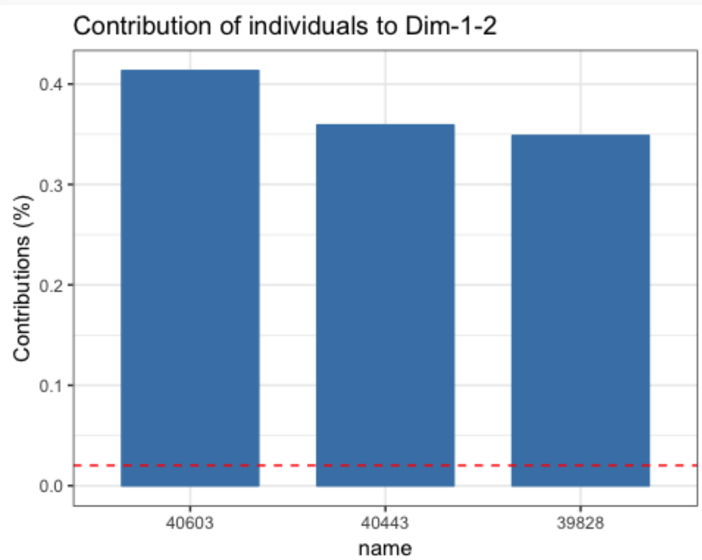
```
##     40443     41004     38275
## 0.2035832 0.2016805 0.1941485

#Se ha de hacer con which
df["40443",]

##       age        job        marital                   education    default
## 40443  26 Job_admin. Marital_single Education_university.degree Default_no
##          housing    loan           contact     month     day_of_week
## 40443 Housing_no Loan_no Contact_cellular Month_aug Day_of_week_mon
##       duration campaign pdays previous         poutcome emp.var.rate
## 40443      242        1     6        5 Poutcome_success         -1.7
##       cons.price.idx cons.conf.idx euribor3m nr.employed     y
## 40443         94.027         -38.3     0.904      4991.6 Y_yes
##       missings_indiv errors_indiv outliers_indiv season           factor_age
## 40443              0            0              0 Summer factor_age [17,31]
##                 factor_duration       factor_campaign        factor_Pdays
## 40443 factor_duration-(236,329] factor_campaign-[1,2] factor_Pdays-[0,15]
##             factor_Previous             factor_emp.var.rate
## 40443 factor_Previous-(1,5] factor_emp.var.rate-(-1.8,-0.1]
##                 factor_cons.price.idx                factor_cons.conf.idx
## 40443 factor_cons.price.idx-(94,94.8] factor_cons.conf.idx-(-40.3,-36.4]
##                     factor_euribor3m                    factor_nr.employed
## 40443 factor_euribor3m-[0.634,1.266] factor_nr.employed-[4.96e+03,5.1e+03]

sort(res.pca$ind$contrib[,2],decreasing = TRUE)[1:3]

##     40603     39828     40443
## 1.1009452 0.8130194 0.8116665

df["40603",]

##       age          job         marital                        education
## 40603  59 Job_services Marital_married Education_professional.course
##          default     housing    loan           contact     month
## 40603 Default_no Housing_yes Loan_no Contact_cellular Month_sep
##           day_of_week duration campaign pdays previous         poutcome
## 40603 Day_of_week_fri      251        3     2        4 Poutcome_success
##       emp.var.rate cons.price.idx cons.conf.idx euribor3m nr.employed    y
## 40603         -1.1         94.199         -37.5     0.883      4963.6 Y_no
##       missings_indiv errors_indiv outliers_indiv  season
## 40603              0            0              0 Aut-Win
##                factor_age           factor_duration       factor_campaign
## 40603 factor_age (49,81] factor_duration-(236,329] factor_campaign-(2,3]
##              factor_Pdays       factor_Previous
## 40603 factor_Pdays-[0,15] factor_Previous-(1,5]
##                   factor_emp.var.rate           factor_cons.price.idx
## 40603 factor_emp.var.rate-(-1.8,-0.1] factor_cons.price.idx-(94,94.8]
##                     factor_cons.conf.idx               factor_euribor3m
## 40603 factor_cons.conf.idx-(-40.3,-36.4] factor_euribor3m-[0.634,1.266]
##                          factor_nr.employed
## 40603 factor_nr.employed-[4.96e+03,5.1e+03]
```

```r
sort(res.pca$ind$contrib[,3],decreasing = TRUE)[1:3]

##     40930     41004     37819
## 0.7201366 0.5128497 0.4860395

df["40930",]

##       age         job        marital education    default     housing
## 40930  20 Job_student Marital_single      <NA> Default_no Housing_yes
##          loan          contact     month     day_of_week duration
## 40930 Loan_yes Contact_cellular Month_oct Day_of_week_tue      187
##       campaign pdays previous         poutcome emp.var.rate cons.price.idx
## 40930        1     3        4 Poutcome_success         -1.1         94.601
##       cons.conf.idx euribor3m nr.employed     y missings_indiv
## 40930         -49.5     0.982      4963.6 Y_yes              0
##       errors_indiv outliers_indiv  season        factor_age
## 40930            0              0 Aut-Win factor_age [17,31]
##                 factor_duration       factor_campaign        factor_Pdays
## 40930 factor_duration-(182,236] factor_campaign-[1,2] factor_Pdays-[0,15]
##             factor_Previous             factor_emp.var.rate
## 40930 factor_Previous-(1,5] factor_emp.var.rate-(-1.8,-0.1]
##                 factor_cons.price.idx              factor_cons.conf.idx
## 40930 factor_cons.price.idx-(94,94.8] factor_cons.conf.idx-[-50.8,-46.2]
##                     factor_euribor3m                     factor_nr.employed
## 40930 factor_euribor3m-[0.634,1.266] factor_nr.employed-[4.96e+03,5.1e+03]

sort(res.pca$ind$contrib[,4],decreasing = TRUE)[1:3]

##     35442     33741     11630
## 0.6914135 0.6822475 0.6640766

df["35442",]

##       age        job         marital             education         default
## 35442  36 Job_admin. Marital_married Education_high.school Default_unknown
##          housing    loan          contact     month     day_of_week
## 35442 Housing_no Loan_no Contact_cellular Month_may Day_of_week_mon
##       duration campaign pdays previous             poutcome emp.var.rate
## 35442       11       14    16        0 Poutcome_nonexistent         -1.8
##       cons.price.idx cons.conf.idx euribor3m nr.employed    y
## 35442         92.893         -46.2     1.244      5099.1 Y_no
##       missings_indiv errors_indiv outliers_indiv season        factor_age
## 35442              1            0              0 Spring factor_age (31,36]
##              factor_duration        factor_campaign         factor_Pdays
## 35442 factor_duration-[1,68] factor_campaign-(3,14] factor_Pdays-(15,17]
##             factor_Previous             factor_emp.var.rate
## 35442 factor_Previous-[0,1] factor_emp.var.rate-[-3.4,-1.8]
##                 factor_cons.price.idx              factor_cons.conf.idx
## 35442 factor_cons.price.idx-[92.2,93] factor_cons.conf.idx-[-50.8,-46.2]
##                     factor_euribor3m                     factor_nr.employed
## 35442 factor_euribor3m-[0.634,1.266] factor_nr.employed-[4.96e+03,5.1e+03]
```

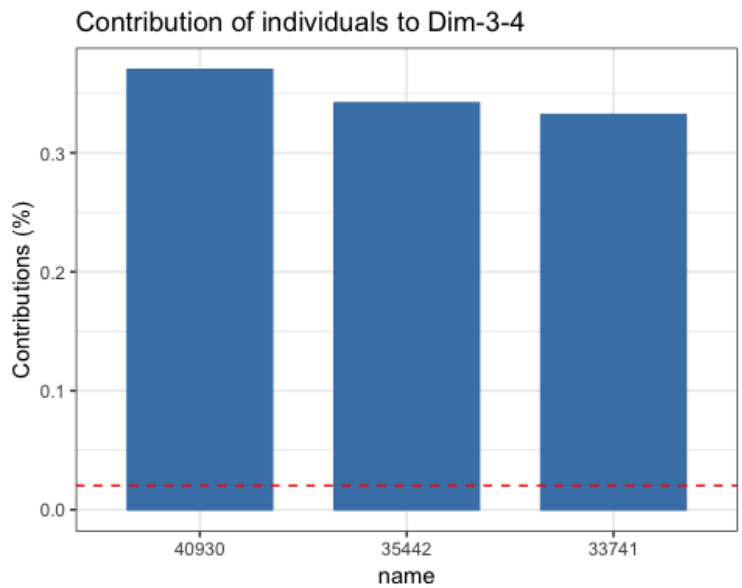
```r
#fviz_pca_var(res.pca)
fviz_contrib(res.pca, choice = "ind", axes = 1:4, top = 3)+theme_bw()
```




```r
#Aqui fem el mateix pero separant les dimensions per fer-ho en dos
grafics diferents
fviz_contrib(res.pca, choice = "ind", axes = 1:2, top = 3)+theme_bw()
```




```r
fviz_contrib(res.pca, choice = "ind", axes = 3:4, top = 3)+theme_bw()
```



A partir dels dos grafics anteriors veiem que per cada parell de dimensions hi ha individus determinats que tenen una contribucio elevada.

Individuals best representation

Ara veurem els individuals que tenen una millor representació

```
#Millor representats

sort(res.pca$ind$cos2[,1],decreasing = TRUE)[1:3]

##     38571     38490     38345
## 0.8867685 0.8752577 0.8582645

df["38571",]

##       age            job        marital                      education
## 38571  34 Job_technician Marital_single Education_university.degree
##          default    housing    loan          contact     month
## 38571 Default_no Housing_no Loan_no Contact_cellular Month_oct
##           day_of_week duration campaign pdays previous          poutcome
## 38571 Day_of_week_thu      136        1    16        1 Poutcome_failure
##       emp.var.rate cons.price.idx cons.conf.idx euribor3m nr.employed
## 38571         -3.4         92.431     -42.33883     0.722      5017.5
##           y missings_indiv errors_indiv outliers_indiv  season
## 38571 Y_yes              1            0              1 Aut-Win
##                 factor_age           factor_duration       factor_campaign
## 38571 factor_age (31,36] factor_duration-(104,139] factor_campaign-[1,2]
##                 factor_Pdays        factor_Previous
## 38571 factor_Pdays-(15,17] factor_Previous-[0,1]
##                     factor_emp.var.rate           factor_cons.price.idx
## 38571 factor_emp.var.rate-[-3.4,-1.8] factor_cons.price.idx-[92.2,93]
```

```
##                   factor_cons.conf.idx               factor_euribor3m
## 38571 factor_cons.conf.idx-(-46.2,-42] factor_euribor3m-[0.634,1.266]
##                          factor_nr.employed
## 38571 factor_nr.employed-[4.96e+03,5.1e+03]
```

```r
sort(res.pca$ind$cos2[,2],decreasing = TRUE)[1:3]
```

```
##     40603     39181     39505
## 0.5929517 0.5861391 0.5856818
```

```r
df["40603",]
```

```
##       age          job         marital                      education
## 40603  59 Job_services Marital_married Education_professional.course
##          default     housing    loan          contact     month
## 40603 Default_no Housing_yes Loan_no Contact_cellular Month_sep
##           day_of_week duration campaign pdays previous         poutcome
## 40603 Day_of_week_fri      251        3     2        4 Poutcome_success
##       emp.var.rate cons.price.idx cons.conf.idx euribor3m nr.employed    y
## 40603         -1.1         94.199         -37.5     0.883      4963.6 Y_no
##       missings_indiv errors_indiv outliers_indiv  season
## 40603              0            0              0 Aut-Win
##               factor_age           factor_duration       factor_campaign
## 40603 factor_age (49,81] factor_duration-(236,329] factor_campaign-(2,3]
##              factor_Pdays       factor_Previous
## 40603 factor_Pdays-[0,15] factor_Previous-(1,5]
##                   factor_emp.var.rate           factor_cons.price.idx
## 40603 factor_emp.var.rate-(-1.8,-0.1] factor_cons.price.idx-(94,94.8]
##                     factor_cons.conf.idx               factor_euribor3m
## 40603 factor_cons.conf.idx-(-40.3,-36.4] factor_euribor3m-[0.634,1.266]
##                          factor_nr.employed
## 40603 factor_nr.employed-[4.96e+03,5.1e+03]
```

```r
sort(res.pca$ind$cos2[,3],decreasing = TRUE)[1:3]
```

```
##     37819     27018     26458
## 0.7361513 0.6887437 0.6855514
```

```r
df["37819",]
```

```
##       age         job         marital          education    default
## 37819  80 Job_retired Marital_married Education_basic.4y Default_no
##           housing    loan          contact     month     day_of_week
## 37819 Housing_yes Loan_no Contact_cellular Month_aug Day_of_week_wed
##       duration campaign pdays previous             poutcome emp.var.rate
## 37819      323        1    16        0 Poutcome_nonexistent         -2.9
##       cons.price.idx cons.conf.idx euribor3m nr.employed     y
## 37819         92.201         -31.4     0.834      5076.2 Y_yes
##       missings_indiv errors_indiv outliers_indiv season         factor_age
## 37819              1            0              0 Summer factor_age (49,81]
##                  factor_duration       factor_campaign          factor_Pdays
## 37819 factor_duration-(236,329] factor_campaign-[1,2] factor_Pdays-(15,17]
##             factor_Previous             factor_emp.var.rate
```

```
## 37819 factor_Previous-[0,1] factor_emp.var.rate-[-3.4,-1.8]
##                factor_cons.price.idx             factor_cons.conf.idx
## 37819 factor_cons.price.idx-[92.2,93] factor_cons.conf.idx-(-36.4,-29.8]
##                    factor_euribor3m                   factor_nr.employed
## 37819 factor_euribor3m-[0.634,1.266] factor_nr.employed-[4.96e+03,5.1e+03]
```

```
sort(res.pca$ind$cos2[,4],decreasing = TRUE)[1:3]
```

```
##     26278     16663     12711
## 0.8875421 0.8809677 0.8802130
```

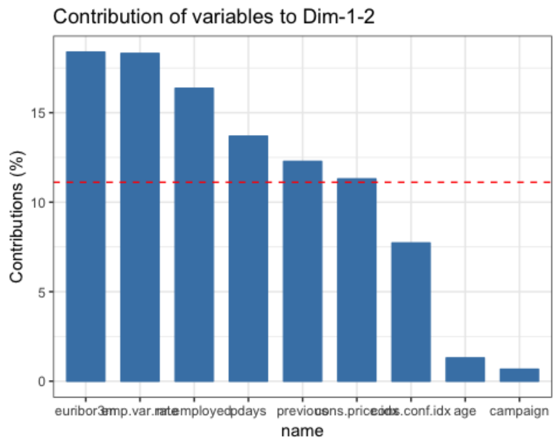
```
df["26278",]
```

```
##       age             job         marital          education
## 26278  47 Job_blue-collar Marital_married Education_basic.9y
##              default     housing    loan           contact     month
## 26278 Default_unknown Housing_yes Loan_no Contact_telephone Month_nov
##          day_of_week duration campaign pdays previous
## 26278 Day_of_week_thu       76        9    16        0
##                  poutcome emp.var.rate cons.price.idx cons.conf.idx
## 26278 Poutcome_nonexistent         -0.1           93.2           -42
##       euribor3m nr.employed    y missings_indiv errors_indiv
## 26278     4.076      5195.8 Y_no              1            0
##       outliers_indiv  season         factor_age          factor_duration
## 26278              0 Aut-Win factor_age (41,49] factor_duration-(68,104]
##              factor_campaign         factor_Pdays       factor_Previous
## 26278 factor_campaign-(3,14] factor_Pdays-(15,17] factor_Previous-[0,1]
##                   factor_emp.var.rate           factor_cons.price.idx
## 26278 factor_emp.var.rate-(-1.8,-0.1] factor_cons.price.idx-(93,93.4]
##                   factor_cons.conf.idx                factor_euribor3m
## 26278 factor_cons.conf.idx-(-46.2,-42] factor_euribor3m-(1.415,4.856]
##                         factor_nr.employed
## 26278 factor_nr.employed-(5.1e+03,5.23e+03]
```

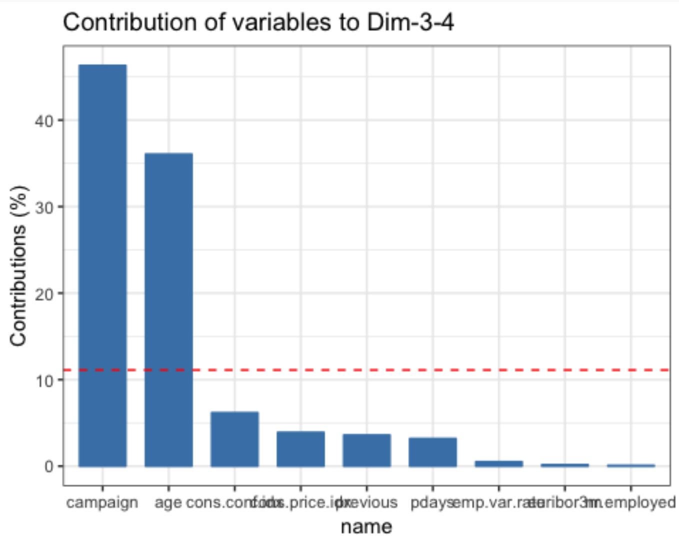
```
# Quality of individuals
# head(res.pca$ind$cos2)
```

Variables contribution

```
fviz_contrib(res.pca, choice = "var", axes = 1:2)+theme_bw()
```




```
fviz_contrib(res.pca, choice = "var", axes = 3:4)+theme_bw()
```




```
#fviz_contrib(res.pca, choice = "var", axes = 1:4)+theme_bw()
```

Com podem veure en els grafics que surten despres d'executar les comandes anteriors, podem veure que les variables que tenen mes contribucio o els individuals mes contributius son els corresponents a les variables "euribor3m", "emp.var.rate", i "nr.employed", aixo pel que fa a la dim 1-2 i a la dim 3-4 tenim les variables "campaign" i "age" com les mes destacades.

Interpreting the axes

```
# summary(res.pca, nb.dec = 2,ncp = 4)

dimdesc(res.pca, axes = 1:4)
```

```
## $Dim.1
## $Dim.1$quanti
##                 correlation       p.value
## euribor3m        0.97012135  0.000000e+00
```

```
## emp.var.rate    0.96596055  0.000000e+00
## nr.employed     0.92622181  0.000000e+00
## cons.price.idx  0.71732355  0.000000e+00
## pdays           0.42778256 2.747395e-219
## cons.conf.idx   0.27475758  2.220057e-86
## campaign        0.17647126  6.925306e-36
## duration       -0.02789008  4.984006e-02
## previous       -0.60838071  0.000000e+00
##
## $Dim.1$quali
##                  R2       p.value
## y       0.125386566 4.727704e-146
## job     0.050547845  1.431720e-48
## marital 0.006555608  4.090296e-07
##
## $Dim.1$category
##                    Estimate       p.value
## Y_no             1.07413334 4.727704e-146
## Job_blue-collar  0.38172472  1.578463e-06
## Marital_married  0.31200050  1.111008e-05
## Job_unknown      1.09681411  1.361795e-03
## Job_technician   0.31629473  5.350108e-03
## Job_services     0.36150713  9.057754e-03
## Job_housemaid    0.53511934  2.165660e-02
## Marital_single  -0.03928771  2.479330e-08
## Job_retired     -1.00385338  2.180033e-17
## Job_student     -2.04730655  1.106798e-30
## Y_yes           -1.07413334 4.727704e-146
##
##
## $Dim.2
## $Dim.2$quanti
##                correlation      p.value
## cons.conf.idx   0.57422055 0.000000e+00
## previous        0.52363024 0.000000e+00
## cons.price.idx  0.28034870 5.339409e-90
## age             0.26095722 8.309706e-78
## emp.var.rate    0.16716817 2.513370e-32
## euribor3m       0.15421659 1.052205e-27
## duration        0.04037167 4.515730e-03
## nr.employed    -0.02841696 4.567319e-02
## campaign       -0.06123050 1.638747e-05
```

```
## pdays          -0.73167488 0.000000e+00
##
## $Dim.2$quali
##                 R2      p.value
## y       0.04515955 1.302046e-51
## job     0.02376411 3.195565e-20
## marital 0.01239773 2.598827e-13
##
## $Dim.2$category
##                       Estimate      p.value
## Y_yes                0.377861724 1.302046e-51
## Job_retired          0.538789877 6.759304e-16
## Marital_single       0.004356898 2.903848e-14
## Marital_married      0.287205205 6.730200e-10
## Job_housemaid        0.295587120 1.140921e-04
## Job_unemployed       0.164414804 1.813003e-02
## Job_self-employed -0.286908713 4.048030e-02
## Job_services        -0.237667993 5.602952e-03
## Job_blue-collar     -0.243007374 1.206646e-06
## Y_no                -0.377861724 1.302046e-51
##
##
## $Dim.3
## $Dim.3$quanti
##                correlation       p.value
## age              0.82888610  0.000000e+00
## cons.conf.idx    0.34042071 1.951278e-134
## pdays            0.24888801  1.013084e-70
## duration        -0.03380074  1.744413e-02
## emp.var.rate    -0.09882178  3.278995e-12
## campaign        -0.11007792  8.282436e-15
## previous        -0.26339058  2.783976e-79
## cons.price.idx -0.27971856  1.379085e-89
##
## $Dim.3$quali
##                  R2       p.value
## job     0.178569210 2.700620e-201
## marital 0.108636234 7.136894e-123
## y       0.002560617  3.706473e-04
##
## $Dim.3$category
##                     Estimate       p.value
```

```
## Job_retired       1.68149671 5.680668e-154
## Marital_married   0.20097034  4.022987e-60
## Marital_divorced  0.32318275  1.363916e-14
## Job_management    0.21386530  7.974613e-09
## Job_housemaid     0.26294711  7.749768e-05
## Y_no              0.07902348  3.706473e-04
## Job_unknown       0.32659224  6.931541e-03
## Job_technician   -0.19259908  2.190366e-03
## Job_blue-collar  -0.17391611  1.561623e-03
## Y_yes            -0.07902348  3.706473e-04
## Job_admin.       -0.19544362  1.450930e-05
## Job_services     -0.28666694  1.024159e-05
## Job_student      -1.31635556  2.904328e-36
## Marital_single   -0.52342349 6.555178e-124
##
##
## $Dim.4
## $Dim.4$quanti
##               correlation      p.value
## campaign       0.96002062 0.000000e+00
## age            0.20031553 6.085712e-46
## previous       0.05584528 8.510511e-05
## duration      -0.03555363 1.239946e-02
## nr.employed   -0.03657601 1.009608e-02
## pdays         -0.04772882 7.858589e-04
## euribor3m     -0.05064684 3.662674e-04
## cons.conf.idx -0.09302262 5.577676e-11
##
## $Dim.4$quali
##                  R2      p.value
## marital 0.006967409 1.511213e-07
## job     0.008422687 1.773990e-05
##
## $Dim.4$category
##                    Estimate      p.value
## Job_retired       0.3107102 3.526031e-07
## NA                0.5653440 4.474349e-02
## Job_student      -0.3084071 3.956014e-03
## Marital_married -0.1436551 2.306144e-04
## Marital_single  -0.3104477 3.333871e-08
```

Ara comentarem a partir de les comandes executades anteriorment quines variables son mes explicatives segons cada dimensio:

A la dimensio 1 les variables mes explicatives son les que mostren els diferents indicadors relacionats amb l'individu i l'estat de l'economia. Tambe podem veure que la variable previous (numero de cops que s'ha contactat amb el client anteriorment) es inversament proporcional.

A la dimensio 2 la variable mes clarament explicativa es "cons.conf.idx", que es l'index de confiança del consumidor.

A la dimensio 3 veiem que "age", "cons.conf.idx" i "pdays" tenen una alta contribucio, les dues variables relacionades amb la confiança i amb aspectes especifics d'aquest client abans de realitzar l'actual campanya.

Finalment a la dimensio 4, veiem que "campaign" i "age" son les variables mes explicatives.

K-Means Classification

Ara farem un nou metode d'agrupament, que es el clustering i ens permetra buscar dins de les nostres observacions grups d'individus amb caracteristiques similars.

```
# Fixed number of groups/clusters

dclu<-res.pca$ind$coord[,1:4] # Significant axes
kcla <- kmeans(dclu,7) # No less than 6 groups

#names(kcla)
#summary(kcla)
table(kcla$cluster)

##
##    1    2    3    4    5    6    7
##  312 1744  828  166 1245  376  275

kcla$totss #inercia total

## [1] 35931.36

kcla$betweenss #inercia entre grups

## [1] 28960.27

kcla$withinss #inercia intra grups

## [1]  809.6068 1638.6338  875.0929  811.3854 1164.1523  822.3318
849.8907

#Set clusters m'expliquen una mica mes d'un 80% de l'informacio, es la
qualitat de la representacio
info<-kcla$betweenss/kcla$totss
info
```

```
## [1] 0.8059886
```

Sabem que no hi ha una manera del tot correcte per determinar el nombre de clusters, pero sabem que no hem d'agafar menys de 6, pero sabem que s'han d'agafar un minim per a que el nombre de clusters sigui mes optim i poder veure una bona representacio dels nostres clusters. Podem comprobar que amb set clusters tenim una mica més d'un 80% de qualitat en la representació de l'informació i aixo ho sabem amb la nostra nova variable creada "info".

Descripició dels clusters

```
nbcluster <- 7
df$CLUSTER <- nbcluster
df[names(kcla$cluster),"CLUSTER"]<-kcla$cluster

df$f.CLUSTER <- factor(df$CLUSTER, labels =
c("CLUSTER-1","CLUSTER-2","CLUSTER-3","CLUSTER-4","CLUSTER-5","CLUSTER
-6","CLUSTER-7"))

#df$kcla<-factor(kcla$cluster)
#names(df)
#catdes(df,34,prob=0.005)
#res.pca<-
PCA(df[,c("duration","y","kcla",vars_con)],quanti.sup=1,quali.sup=2:3,
ncp=4)
#plot.PCA(res.pca,choix="ind", habillage=3)

names(df)

##  [1] "age"                   "job"
##  [3] "marital"               "education"
##  [5] "default"               "housing"
##  [7] "loan"                  "contact"
##  [9] "month"                 "day_of_week"
## [11] "duration"              "campaign"
## [13] "pdays"                 "previous"
## [15] "poutcome"              "emp.var.rate"
## [17] "cons.price.idx"        "cons.conf.idx"
## [19] "euribor3m"             "nr.employed"
## [21] "y"                     "missings_indiv"
## [23] "errors_indiv"          "outliers_indiv"
## [25] "season"                "factor_age"
## [27] "factor_duration"       "factor_campaign"
## [29] "factor_Pdays"          "factor_Previous"
## [31] "factor_emp.var.rate"   "factor_cons.price.idx"
## [33] "factor_cons.conf.idx"  "factor_euribor3m"
```

```
## [35] "factor_nr.employed"    "CLUSTER"
## [37] "f.CLUSTER"

sel <- c(1:21)

vars_km <- names(df[sel])

vars <- c(vars_km,"f.CLUSTER")
targ <- which(vars == "f.CLUSTER")
catdes(df[,vars],targ)

##
## Link between the cluster variable and the categorical variables
(chi-square test)
##
======================================================================
===========
##                    p.value df
## month         0.000000e+00 54
## poutcome      0.000000e+00 12
## y            7.309361e-189  6
## job          2.405672e-165 66
## contact      1.740516e-145  6
## marital       4.107931e-75 18
## default       1.164839e-52  6
## education     1.497215e-20 42
## day_of_week   3.433224e-05 24
##
## Description of each cluster by the categories
## =============================================
## $`CLUSTER-1`
##                                             Cla/Mod    Mod/Cla
Global
## job=Job_retired                           44.660194 29.4871795
4.1649818
## poutcome=Poutcome_failure                 21.115538 33.9743590
10.1496159
## y=Y_yes                                   17.420436 33.3333333
12.0703599
## contact=Contact_cellular                   8.663683 86.8589744
63.2430247
## month=Month_sep                           40.579710  8.9743590
1.3950667
## default=Default_no                         7.332652 91.9871795
79.1346543
```

```
## month=Month_dec                             50.000000  3.5256410
0.4448039
## education=Education_basic.4y                12.350598 19.8717949
10.1496159
## month=Month_oct                             24.096386  6.4102564
1.6781237
## month=Month_mar                             25.373134  5.4487179
1.3546300
## marital=Marital_married                      7.566667 72.7564103
60.6550748
## month=Month_apr                             12.455516 11.2179487
5.6813587
## day_of_week=Day_of_week_tue                  9.191584 26.6025641
18.2571775
## month=Month_aug                              9.212283 22.1153846
15.1435503
## job=Job_management                           9.565217 10.5769231
6.9753336
## marital=Marital_divorced                     8.718861 15.7051282
11.3627173
## education=Education_university.degree  7.402423 35.2564103
30.0444804
## day_of_week=Day_of_week_wed                  4.809619 15.3846154
20.1779216
## job=Job_student                              0.952381  0.3205128
2.1229276
## day_of_week=Day_of_week_thu                  4.575786 15.3846154
21.2090578
## education=Education_high.school              4.553571 16.3461538
22.6445613
## poutcome=Poutcome_success                    1.190476  0.6410256
3.3966842
## job=Job_technician                           3.571429  8.9743590
15.8511929
## education=Education_basic.9y                 3.425560  8.3333333
15.3457339
## month=Month_jun                              2.932099  6.0897436
13.1014962
## job=Job_services                             1.902748  2.8846154
9.5632835
## month=Month_may                              3.641975 18.9102564
32.7537404
## job=Job_blue-collar                          2.797203 10.2564103
23.1298019
## default=Default_unknown                      2.422481  8.0128205
20.8653457
```

```
## month=Month_jul                          1.791713  5.1282051
18.0549939
## marital=Marital_single                   2.614379 11.5384615
27.8406793
## contact=Contact_telephone                2.255226 13.1410256
36.7569753
## poutcome=Poutcome_nonexistent            4.770814 65.3846154
86.4537000
## y=Y_no                                   4.782709 66.6666667
87.9296401
##                                              p.value     v.test
## job=Job_retired                         2.741695e-59  16.237431
## poutcome=Poutcome_failure               7.003146e-33  11.943706
## y=Y_yes                                 1.093042e-24  10.257677
## contact=Contact_cellular                8.513033e-22   9.593520
## month=Month_sep                         1.333337e-16   8.270558
## default=Default_no                      2.409876e-10   6.332649
## month=Month_dec                         2.114315e-08   5.602377
## education=Education_basic.4y            1.043361e-07   5.319005
## month=Month_oct                         1.381825e-07   5.267648
## month=Month_mar                         5.658811e-07   5.002512
## marital=Marital_married                 4.005160e-06   4.611114
## month=Month_apr                         8.740549e-05   3.923131
## day_of_week=Day_of_week_tue             1.658807e-04   3.766005
## month=Month_aug                         7.213479e-04   3.381334
## job=Job_management                      1.486789e-02   2.435581
## marital=Marital_divorced                1.655982e-02   2.396338
## education=Education_university.degree 4.049047e-02   2.048710
## day_of_week=Day_of_week_wed             2.592471e-02  -2.227338
## job=Job_student                         9.145980e-03  -2.606549
## day_of_week=Day_of_week_thu             7.514420e-03  -2.673143
## education=Education_high.school        4.743381e-03  -2.823963
## poutcome=Poutcome_success               1.357037e-03  -3.203637
## job=Job_technician                      2.717358e-04  -3.640853
## education=Education_basic.9y            1.566510e-04  -3.780282
## month=Month_jun                         3.957147e-05  -4.109968
## job=Job_services                        2.723397e-06  -4.690649
## month=Month_may                         2.011190e-08  -5.611036
## job=Job_blue-collar                     1.784928e-09  -6.016260
## default=Default_unknown                 2.409876e-10  -6.332649
## month=Month_jul                         4.182234e-12  -6.930882
## marital=Marital_single                  7.887592e-13  -7.163095
## contact=Contact_telephone               8.513033e-22  -9.593520
```

```
## poutcome=Poutcome_nonexistent         7.915205e-23  -9.835527
## y=Y_no                                1.093042e-24 -10.257677
##
## $`CLUSTER-2`
##                                    Cla/Mod    Mod/Cla     Global
## poutcome=Poutcome_nonexistent   39.663237 97.2477064 86.4537000
## month=Month_jul                 58.230683 29.8165138 18.0549939
## contact=Contact_telephone       46.149615 48.1077982 36.7569753
## marital=Marital_single          46.550472 36.7545872 27.8406793
## y=Y_no                          37.686825 93.9793578 87.9296401
## month=Month_jun                 53.240741 19.7821101 13.1014962
## month=Month_nov                 47.859922 14.1055046 10.3922362
## job=Job_services                43.974630 11.9266055  9.5632835
## education=Education_high.school 39.821429 25.5733945 22.6445613
## day_of_week=Day_of_week_wed     39.979960 22.8784404 20.1779216
## job=Job_technician              40.051020 18.0045872 15.8511929
## education=Education_basic.9y    39.789196 17.3165138 15.3457339
## day_of_week=Day_of_week_thu     38.036225 22.8784404 21.2090578
## marital=NA                       0.000000  0.0000000  0.1415285
## month=Month_aug                 32.042724 13.7614679 15.1435503
## day_of_week=Day_of_week_mon     32.458698 19.1513761 20.8046907
## job=Job_management              27.246377  5.3899083  6.9753336
## marital=Marital_divorced        28.291815  9.1169725 11.3627173
## month=Month_dec                  0.000000  0.0000000  0.4448039
## job=Job_student                 13.333333  0.8027523  2.1229276
## education=Education_basic.4y    22.709163  6.5366972 10.1496159
## month=Month_oct                  4.819277  0.2293578  1.6781237
## marital=Marital_married         31.466667 54.1284404 60.6550748
## month=Month_mar                  0.000000  0.0000000  1.3546300
## month=Month_sep                  0.000000  0.0000000  1.3950667
## y=Y_yes                         17.587940  6.0206422 12.0703599
## month=Month_may                 24.012346 22.3050459 32.7537404
## poutcome=Poutcome_success        0.000000  0.0000000  3.3966842
## contact=Contact_cellular        28.932225 51.8922018 63.2430247
## job=Job_retired                  1.456311  0.1720183  4.1649818
## poutcome=Poutcome_failure        9.561753  2.7522936 10.1496159
## month=Month_apr                  0.000000  0.0000000  5.6813587
##                                     p.value     v.test
## poutcome=Poutcome_nonexistent   9.983079e-74  18.163820
## month=Month_jul                 2.245179e-54  15.527928
## contact=Contact_telephone       6.123716e-34  12.144659
## marital=Marital_single          1.820325e-24  10.208297
```

```
## y=Y_no                             5.068766e-24  10.108435
## month=Month_jun                    9.092724e-24  10.051014
## month=Month_nov                    5.691155e-10   6.198755
## job=Job_services                   3.921572e-05   4.112052
## education=Education_high.school 3.071926e-04   3.609158
## day_of_week=Day_of_week_wed        5.232636e-04   3.468556
## job=Job_technician                 2.386167e-03   3.037415
## education=Education_basic.9y       4.834718e-03   2.817845
## day_of_week=Day_of_week_thu        3.473033e-02   2.111489
## marital=NA                         4.755159e-02  -1.981354
## month=Month_aug                    4.458324e-02  -2.008565
## day_of_week=Day_of_week_mon        3.396930e-02  -2.120436
## job=Job_management                 1.036131e-03  -3.280528
## marital=Marital_divorced           1.985520e-04  -3.720852
## month=Month_dec                    6.832667e-05  -3.982039
## job=Job_student                    3.773708e-07  -5.080032
## education=Education_basic.4y       1.595910e-10  -6.395913
## month=Month_oct                    3.086689e-11  -6.642375
## marital=Marital_married            4.856257e-12  -6.909716
## month=Month_mar                    1.742771e-13  -7.367178
## month=Month_sep                    7.194562e-14  -7.484271
## y=Y_yes                            5.068766e-24 -10.108435
## month=Month_may                    6.732938e-32 -11.754030
## poutcome=Poutcome_success          3.848356e-33 -11.993388
## contact=Contact_cellular           6.123716e-34 -12.144659
## job=Job_retired                    3.356116e-35 -12.379936
## poutcome=Poutcome_failure          5.197520e-44 -13.914149
## month=Month_apr                    9.136003e-56 -15.731946
## 
## $`CLUSTER-3`
##                                Cla/Mod    Mod/Cla     Global
p.value
## month=Month_apr            71.5302491 24.2753623  5.6813587
9.058650e-100
## contact=Contact_cellular   23.8171355 89.9758454 63.2430247
4.766994e-80
## month=Month_may            28.7654321 56.2801932 32.7537404
3.770219e-53
## default=Default_no         18.8298416 89.0096618 79.1346543
4.585452e-16
## job=Job_student            49.5238095  6.2801932  2.1229276
5.110953e-15
## marital=Marital_single     23.3841685 38.8888889 27.8406793
```

```
3.735231e-14
## month=Month_mar             52.2388060  4.2270531  1.3546300
2.449652e-11
## y=Y_yes                     23.9530988 17.2705314 12.0703599
1.377677e-06
## job=Job_blue-collar         19.8426573 27.4154589 23.1298019
1.594152e-03
## poutcome=Poutcome_failure   21.7131474 13.1642512 10.1496159
2.243483e-03
## month=Month_oct             30.1204819  3.0193237  1.6781237
2.366941e-03
## day_of_week=Day_of_week_fri 19.3381593 22.5845411 19.5511524
1.728303e-02
## job=Job_unknown              4.6511628  0.2415459  0.8693894
2.069975e-02
## marital=Marital_divorced    13.3451957  9.0579710 11.3627173
1.957459e-02
## education=NA                10.9523810  2.7777778  4.2458552
1.717205e-02
## job=Job_housemaid            6.3492063  0.9661836  2.5475131
5.317520e-04
## y=Y_no                      15.7507473 82.7294686 87.9296401
1.377677e-06
## job=Job_retired              4.3689320  1.0869565  4.1649818
3.200463e-08
## marital=Marital_married     14.2666667 51.6908213 60.6550748
9.627802e-09
## month=Month_jun              8.3333333  6.5217391 13.1014962
4.302173e-11
## poutcome=Poutcome_success    0.0000000  0.0000000  3.3966842
2.391195e-14
## default=Default_unknown      8.8178295 10.9903382 20.8653457
4.585452e-16
## month=Month_nov              0.9727626  0.6038647 10.3922362
7.650679e-36
## month=Month_aug              1.6021362  1.4492754 15.1435503
2.014127e-47
## month=Month_jul              2.0156775  2.1739130 18.0549939
2.454945e-53
## contact=Contact_telephone    4.5654565 10.0241546 36.7569753
4.766994e-80
##                                v.test
## month=Month_apr              21.202484
## contact=Contact_cellular     18.945973
## month=Month_may              15.345946
```

```
## default=Default_no               8.122005
## job=Job_student                  7.824151
## marital=Marital_single           7.569896
## month=Month_mar                  6.676351
## y=Y_yes                          4.828207
## job=Job_blue-collar              3.156975
## poutcome=Poutcome_failure        3.055950
## month=Month_oct                  3.039852
## day_of_week=Day_of_week_fri      2.380631
## job=Job_unknown                 -2.313416
## marital=Marital_divorced        -2.334404
## education=NA                    -2.383003
## job=Job_housemaid               -3.464230
## y=Y_no                          -4.828207
## job=Job_retired                 -5.530101
## marital=Marital_married         -5.737159
## month=Month_jun                 -6.593279
## poutcome=Poutcome_success       -7.627624
## default=Default_unknown         -8.122005
## month=Month_nov                -12.498048
## month=Month_aug                -14.465066
## month=Month_jul                -15.373761
## contact=Contact_telephone      -18.945973
##
## $`CLUSTER-4`
##                                          Cla/Mod    Mod/Cla
Global
## poutcome=Poutcome_success             88.0952381 89.1566265
3.3966842
## y=Y_yes                               20.1005025 72.2891566
12.0703599
## month=Month_sep                       31.8840580 13.2530120
1.3950667
## contact=Contact_cellular               4.7953964 90.3614458
63.2430247
## month=Month_oct                       22.8915663 11.4457831
1.6781237
## job=Job_student                       16.1904762 10.2409639
2.1229276
## default=Default_no                     3.9856924 93.9759036
79.1346543
## month=Month_dec                       31.8181818  4.2168675
0.4448039
## month=Month_mar                       13.4328358  5.4216867
```

```
1.3546300
## job=Job_retired                            7.7669903  9.6385542
4.1649818
## education=Education_professional.course  5.3781513 19.2771084
12.0299232
## job=Job_admin.                            4.5349731 35.5421687
26.3040841
## education=Education_university.degree    4.3741588 39.1566265
30.0444804
## job=Job_unemployed                        8.4112150  5.4216867
2.1633643
## job=Job_self-employed                     0.6578947  0.6024096
3.0731905
## job=Job_services                          1.6913319  4.8192771
9.5632835
## education=Education_basic.6y              1.1194030  1.8072289
5.4185200
## education=Education_basic.9y              1.5810277  7.2289157
15.3457339
## month=Month_jul                           1.2318029  6.6265060
18.0549939
## job=Job_blue-collar                       1.1363636  7.8313253
23.1298019
## default=Default_unknown                   0.9689922  6.0240964
20.8653457
## month=Month_may                           0.8641975  8.4337349
32.7537404
## contact=Contact_telephone                 0.8800880  9.6385542
36.7569753
## y=Y_no                                    1.0577144 27.7108434
87.9296401
## poutcome=Poutcome_nonexistent             0.0000000  0.0000000
86.4537000
##                                               p.value     v.test
## poutcome=Poutcome_success                8.703859e-239  32.997907
## y=Y_yes                                   1.563077e-76  18.514996
## month=Month_sep                           1.485214e-16   8.257688
## contact=Contact_cellular                  6.857204e-16   8.073035
## month=Month_oct                           1.540670e-11   6.744017
## job=Job_student                           5.601823e-08   5.431067
## default=Default_no                        7.923004e-08   5.368873
## month=Month_dec                           5.003774e-06   4.564629
## month=Month_mar                           4.144742e-04   3.530692
## job=Job_retired                           1.826039e-03   3.117158
## education=Education_professional.course  6.245827e-03   2.734589
```

```
## job=Job_admin.                              7.620775e-03   2.668425
## education=Education_university.degree    1.092935e-02   2.544950
## job=Job_unemployed                         1.223931e-02   2.505168
## job=Job_self-employed                      3.827209e-02  -2.071929
## job=Job_services                           2.484116e-02  -2.243864
## education=Education_basic.6y               2.234725e-02  -2.284413
## education=Education_basic.9y               1.505217e-03  -3.173676
## month=Month_jul                            1.791942e-05  -4.289353
## job=Job_blue-collar                        1.542134e-07  -5.247457
## default=Default_unknown                    7.923004e-08  -5.368873
## month=Month_may                            5.514070e-14  -7.519133
## contact=Contact_telephone                  6.857204e-16  -8.073035
## y=Y_no                                     1.563077e-76 -18.514996
## poutcome=Poutcome_nonexistent             2.421178e-153 -26.378457
##
## $`CLUSTER-5`
##                                           Cla/Mod     Mod/Cla
Global
## poutcome=Poutcome_nonexistent         28.531338 97.99196787
86.4537000
## default=Default_unknown               40.794574 33.81526104
20.8653457
## marital=Marital_married               30.833333 74.29718876
60.6550748
## month=Month_aug                       42.723632 25.70281124
15.1435503
## contact=Contact_telephone             34.103410 49.79919679
36.7569753
## y=Y_no                                27.408600 95.74297189
87.9296401
## education=Education_basic.4y          38.247012 15.42168675
10.1496159
## marital=Marital_divorced              34.875445 15.74297189
11.3627173
## month=Month_nov                       34.435798 14.21686747
10.3922362
## job=Job_management                    34.782609  9.63855422
6.9753336
## job=Job_housemaid                     39.682540  4.01606426
2.5475131
## month=Month_may                       28.024691 36.46586345
32.7537404
## job=Job_retired                       34.951456  5.78313253
4.1649818
```

```
## job=Job_unknown                         46.511628  1.60642570
0.8693894
## education=Education_university.degree 23.216689 27.71084337
30.0444804
## job=Job_services                        20.084567  7.63052209
9.5632835
## education=Education_high.school         21.785714 19.59839357
22.6445613
## job=Job_admin.                          21.983090 22.97188755
26.3040841
## month=Month_dec                          0.000000  0.00000000
0.4448039
## month=Month_jul                         20.156775 14.45783133
18.0549939
## month=Month_jun                         17.129630  8.91566265
13.1014962
## month=Month_oct                          3.614458  0.24096386
1.6781237
## month=Month_mar                          0.000000  0.00000000
1.3546300
## month=Month_sep                          0.000000  0.00000000
1.3950667
## job=Job_student                          0.952381  0.08032129
2.1229276
## poutcome=Poutcome_success                0.000000  0.00000000
3.3966842
## y=Y_yes                                  8.877722  4.25702811
12.0703599
## contact=Contact_cellular                19.980818 50.20080321
63.2430247
## default=Default_no                      21.052632 66.18473896
79.1346543
## poutcome=Poutcome_failure                4.980080  2.00803213
10.1496159
## month=Month_apr                          0.000000  0.00000000
5.6813587
## marital=Marital_single                   8.932462  9.87951807
27.8406793
##                                              p.value     v.test
## poutcome=Poutcome_nonexistent         5.574912e-57  15.908020
## default=Default_unknown               5.398614e-36  12.525739
## marital=Marital_married               3.498103e-31  11.614012
## month=Month_aug                       1.826830e-30  11.471863
## contact=Contact_telephone             1.065106e-27  10.907179
## y=Y_no                                9.633353e-27  10.705093
```

```
## education=Education_basic.4y          8.065390e-12   6.837381
## marital=Marital_divorced              4.841989e-08   5.457017
## month=Month_nov                       7.075034e-07   4.959293
## job=Job_management                    3.671864e-05   4.127213
## job=Job_housemaid                     2.952524e-04   3.619430
## month=Month_may                       1.339529e-03   3.207374
## job=Job_retired                       1.408222e-03   3.192961
## job=Job_unknown                       2.534928e-03   3.019141
## education=Education_university.degree 3.722773e-02  -2.083258
## job=Job_services                      6.367842e-03  -2.728213
## education=Education_high.school       2.729912e-03  -2.996619
## job=Job_admin.                        1.857985e-03  -3.112041
## month=Month_dec                       1.669487e-03  -3.143486
## month=Month_jul                       1.045039e-04  -3.879889
## month=Month_jun                       1.688691e-07  -5.230700
## month=Month_oct                       1.281132e-07  -5.281525
## month=Month_mar                       3.135831e-09  -5.924325
## month=Month_sep                       1.739524e-09  -6.020432
## job=Job_student                       1.572260e-12  -7.067962
## poutcome=Poutcome_success             2.613913e-22  -9.714554
## y=Y_yes                               9.633353e-27 -10.705093
## contact=Contact_cellular              1.065106e-27 -10.907179
## default=Default_no                    5.398614e-36 -12.525739
## poutcome=Poutcome_failure             3.398883e-36 -12.562395
## month=Month_apr                       2.489983e-37 -12.767508
## marital=Marital_single                6.416022e-69 -17.545698
##
## $`CLUSTER-6`
##                                 Cla/Mod     Mod/Cla    Global
p.value
## poutcome=Poutcome_nonexistent  8.793265 100.0000000 86.453700
1.600430e-25
## month=Month_jul               15.117581  35.9042553 18.054994
8.156780e-18
## contact=Contact_telephone     10.561056  51.0638298 36.756975
4.194641e-09
## y=Y_no                         8.254771  95.4787234 87.929640
2.174139e-07
## month=Month_jun               12.500000  21.5425532 13.101496
2.371417e-06
## default=Default_unknown       10.174419  27.9255319 20.865346
6.895477e-04
## loan=Loan_no                   8.059701  86.1702128 81.277800
9.349510e-03
```

```
## day_of_week=Day_of_week_thu    9.246902  25.7978723 21.209058
2.638068e-02
## job=Job_student              2.857143   0.7978723  2.122928
4.699588e-02
## marital=Marital_single         6.390704  23.4042553 27.840679
4.362357e-02
## loan=Loan_yes                5.625000  11.9680851 16.174687
1.794441e-02
## month=Month_mar              0.000000   0.0000000  1.354630
4.822099e-03
## month=Month_sep              0.000000   0.0000000  1.395067
4.107437e-03
## month=Month_oct              0.000000   0.0000000  1.678124
1.333768e-03
## default=Default_no           6.923863  72.0744681 79.134654
6.895477e-04
## month=Month_nov              3.307393   4.5212766 10.392236
2.222579e-05
## poutcome=Poutcome_success      0.000000   0.0000000  3.396684
1.341034e-06
## y=Y_yes                      2.847571   4.5212766 12.070360
2.174139e-07
## month=Month_may              4.876543  21.0106383 32.753740
1.827153e-07
## contact=Contact_cellular       5.882353  48.9361702 63.243025
4.194641e-09
## month=Month_apr              0.000000   0.0000000  5.681359
1.135353e-10
## poutcome=Poutcome_failure      0.000000   0.0000000 10.149616
6.087260e-19
##                                 v.test
## poutcome=Poutcome_nonexistent 10.441628
## month=Month_jul               8.597364
## contact=Contact_telephone       5.876329
## y=Y_no                        5.183797
## month=Month_jun               4.718884
## default=Default_unknown        3.393702
## loan=Loan_no                  2.599002
## day_of_week=Day_of_week_thu    2.220561
## job=Job_student              -1.986337
## marital=Marital_single        -2.017690
## loan=Loan_yes                -2.366763
## month=Month_mar              -2.818684
## month=Month_sep              -2.869791
## month=Month_oct              -3.208613
```

```
## default=Default_no           -3.393702
## month=Month_nov              -4.241271
## poutcome=Poutcome_success    -4.833574
## y=Y_yes                      -5.183797
## month=Month_may              -5.216114
## contact=Contact_cellular     -5.876329
## month=Month_apr              -6.447733
## poutcome=Poutcome_failure    -8.890430
##
## $`CLUSTER-7`
##                                 Cla/Mod    Mod/Cla    Global
## poutcome=Poutcome_failure    39.0438247 71.2727273 10.149616
## contact=Contact_cellular      7.9283887 90.1818182 63.243025
## month=Month_may               9.8148148 57.8181818 32.753740
## marital=Marital_single        7.9883805 40.0000000 27.840679
## default=Default_no            6.2595810 89.0909091 79.134654
## month=Month_apr              12.0996441 12.3636364  5.681359
## job=Job_student              16.1904762  6.1818182  2.122928
## y=Y_yes                       9.2127303 20.0000000 12.070360
## month=Month_oct              14.4578313  4.3636364  1.678124
## poutcome=Poutcome_success    10.7142857  6.5454545  3.396684
## month=Month_sep              13.0434783  3.2727273  1.395067
## day_of_week=Day_of_week_fri   7.1354705 25.0909091 19.551152
## month=Month_jun               3.0864198  7.2727273 13.101496
## marital=Marital_married       4.5666667 49.8181818 60.655075
## y=Y_no                        5.0586342 80.0000000 87.929640
## job=Job_retired               0.4854369  0.3636364  4.164982
## education=Education_basic.4y  1.9920319  3.6363636 10.149616
## default=Default_unknown       2.9069767 10.9090909 20.865346
## month=Month_nov               1.5564202  2.9090909 10.392236
## month=Month_aug               1.6021362  4.3636364 15.143550
## month=Month_jul               1.4557671  4.7272727 18.054994
## contact=Contact_telephone     1.4851485  9.8181818 36.756975
## poutcome=Poutcome_nonexistent  1.4265669 22.1818182 86.453700
##                                    p.value     v.test
## poutcome=Poutcome_failure    6.338765e-145  25.634232
## contact=Contact_cellular      1.723673e-25  10.434584
## month=Month_may               1.748450e-18   8.772434
## marital=Marital_single        7.703282e-06   4.473269
## default=Default_no            8.466879e-06   4.453025
## month=Month_apr               1.392197e-05   4.345088
## job=Job_student               6.909637e-05   3.979376
```

```
## y=Y_yes                          1.089450e-04   3.869755
## month=Month_oct                  2.487692e-03   3.024835
## poutcome=Poutcome_success        7.460265e-03   2.675568
## month=Month_sep                  1.778430e-02   2.370079
## day_of_week=Day_of_week_fri      2.036235e-02   2.319603
## month=Month_jun                  1.754083e-03  -3.128990
## marital=Marital_married          1.843993e-04  -3.739483
## y=Y_no                           1.089450e-04  -3.869755
## job=Job_retired                  8.641328e-05  -3.925880
## education=Education_basic.4y     4.226314e-05  -4.094746
## default=Default_unknown          8.466879e-06  -4.453025
## month=Month_nov                  1.900719e-06  -4.763703
## month=Month_aug                  6.200589e-09  -5.811256
## month=Month_jul                  1.745944e-11  -6.725830
## contact=Contact_telephone        1.723673e-25 -10.434584
## poutcome=Poutcome_nonexistent 7.515621e-142 -25.357039
##
##
## Link between the cluster variable and the quantitative variables
## ================================================================
##                       Eta2      P-value
## age            0.474040466 0.000000e+00
## campaign       0.558436885 0.000000e+00
## pdays          0.892215906 0.000000e+00
## previous       0.560755628 0.000000e+00
## emp.var.rate   0.894046500 0.000000e+00
## cons.price.idx 0.453861592 0.000000e+00
## cons.conf.idx  0.352386993 0.000000e+00
## euribor3m      0.973955527 0.000000e+00
## nr.employed    0.869891520 0.000000e+00
## duration       0.006155359 3.146859e-05
##
## Description of each cluster by quantitative variables
## =====================================================
## $`CLUSTER-1`
##                    v.test Mean in category Overall mean sd in
category
## age              24.992876       54.1040262   40.0525729
12.9633587
## cons.conf.idx   12.408521      -37.6166907  -40.6182329
6.8636111
## previous         8.392611        0.3942308    0.1708451
0.5787631
```

```
## pdays              3.182317       15.9807692   15.6263647
0.1951710
## campaign          -5.053737        1.8397436    2.3891187
1.2785047
## cons.price.idx -24.309345       92.8144647   93.5857345
0.5526930
## euribor3m      -28.297286        0.9678942    3.6487535
0.2725778
## nr.employed    -28.712276     5053.1480769 5167.8073595
40.2045371
## emp.var.rate   -30.784863       -2.5365385    0.1073999
0.7128929
##                Overall sd       p.value
## age            10.2585844 7.307003e-138
## cons.conf.idx   4.4137411  2.349529e-35
## previous        0.4856692  4.754639e-17
## pdays           2.0320681  1.461020e-03
## campaign        1.9835304  4.332492e-07
## cons.price.idx  0.5789159 1.561416e-130
## euribor3m       1.7286683 3.732084e-176
## nr.employed    72.8658491 2.680973e-181
## emp.var.rate    1.5670994 4.178487e-208
##
## $`CLUSTER-2`
##                    v.test Mean in category Overall mean sd in
category
## euribor3m       34.964558       4.81339966    3.6487535
0.2864047
## nr.employed     33.750774    5215.19466743 5167.8073595
17.0298403
## emp.var.rate    33.469955       1.11806193    0.1073999
0.5129521
## cons.price.idx  26.054971      93.87637787   93.5857345
0.4030072
## pdays            9.542349      16.00000000   15.6263647
0.0000000
## cons.conf.idx    6.040870     -40.10447248  -40.6182329
2.8899983
## campaign       -13.047872       1.89042626    2.3891187
1.0282696
## previous       -15.315055       0.02752294    0.1708451
0.1636014
## age            -31.388217      33.84805046   40.0525729
5.1452934
##                Overall sd       p.value
```

```
## euribor3m       1.7286683 7.781109e-268
## nr.employed    72.8658491 1.041496e-249
## emp.var.rate    1.5670994 1.319276e-245
## cons.price.idx  0.5789159 1.181688e-149
## pdays           2.0320681  1.396325e-21
## cons.conf.idx   4.4137411  1.532856e-09
## campaign        1.9835304  6.534699e-39
## previous        0.4856692  6.066061e-53
## age            10.2585844 2.930161e-216
##
## $`CLUSTER-3`
##                    v.test Mean in category Overall mean sd in
category
## pdays             5.797820       16.0000000   15.6263647
0.0000000
## previous         -2.545245        0.1316425    0.1708451
0.3381017
## campaign         -9.699313        1.7789855    2.3891187
1.1102043
## age             -13.699771       35.5955424   40.0525729
7.7075184
## cons.price.idx -31.605862       93.0054674   93.5857345
0.3555162
## nr.employed    -34.897408     5087.1652174 5167.8073595
31.8350959
## cons.conf.idx  -35.509624      -45.5887066  -40.6182329
3.1682232
## emp.var.rate   -40.362573       -1.8985507    0.1073999
0.3905253
## euribor3m      -43.244710        1.2779831    3.6487535
0.1943923
##                Overall sd       p.value
## pdays           2.0320681  6.718246e-09
## previous        0.4856692  1.092011e-02
## campaign        1.9835304  3.035350e-22
## age            10.2585844  1.018447e-42
## cons.price.idx  0.5789159 3.067183e-219
## nr.employed    72.8658491 8.138904e-267
## cons.conf.idx   4.4137411 3.491769e-276
## emp.var.rate    1.5670994  0.000000e+00
## euribor3m       1.7286683  0.000000e+00
##
## $`CLUSTER-4`
##                    v.test Mean in category Overall mean sd in
```

```
category
## previous          42.528318        1.7469880    0.1708451
0.9228475
## cons.conf.idx      7.824800      -37.9827704  -40.6182329
6.0515896
## duration           4.547735      351.6385542  262.7672867
274.7841904
## campaign          -4.202564        1.7530120    2.3891187
1.0553178
## cons.price.idx  -5.128640       93.3591687   93.5857345
0.8261510
## emp.var.rate    -18.831759       -2.1445783    0.1073999
0.8798621
## euribor3m       -20.520883        0.9417771    3.6487535
0.5259618
## nr.employed     -26.293197     5021.6084337 5167.8073595
49.4738746
## pdays           -66.391579        5.3313253   15.6263647
3.3588376
##                 Overall sd       p.value
## previous          0.4856692  0.000000e+00
## cons.conf.idx     4.4137411  5.084663e-15
## duration        256.0881160  5.422624e-06
## campaign          1.9835304  2.639083e-05
## cons.price.idx    0.5789159  2.918428e-07
## emp.var.rate      1.5670994  4.147513e-79
## euribor3m         1.7286683  1.401424e-93
## nr.employed      72.8658491 2.293978e-152
## pdays             2.0320681  0.000000e+00
##
## $`CLUSTER-5`
##                   v.test Mean in category Overall mean sd in
category
## age              34.592509      48.75341365   40.0525729
6.0606902
## euribor3m        27.183291       4.80089398    3.6487535
0.2850300
## emp.var.rate     25.150085       1.07373494    0.1073999
0.5016688
## nr.employed      23.561540    5209.90128514 5167.8073595
17.9321967
## cons.conf.idx    19.380080     -38.52096386  -40.6182329
2.8913196
## cons.price.idx   13.001943      93.77028514   93.5857345
0.3715335
```

```
## pdays             7.499251      16.00000000   15.6263647
0.0000000
## duration         -2.122793     249.43855422  262.7672867
242.1298277
## campaign         -8.964372       1.95315496    2.3891187
1.0831782
## previous        -12.660989       0.02008032    0.1708451
0.1402751
##                 Overall sd       p.value
## age              10.2585844 3.274542e-262
## euribor3m         1.7286683 1.023658e-162
## emp.var.rate      1.5670994 1.410167e-139
## nr.employed      72.8658491 9.560810e-123
## cons.conf.idx     4.4137411  1.136703e-83
## cons.price.idx    0.5789159  1.192733e-38
## pdays             2.0320681  6.418366e-14
## duration        256.0881160  3.377118e-02
## campaign          1.9835304  3.120553e-19
## previous          0.4856692  9.726559e-37
##
## $`CLUSTER-6`
##                   v.test Mean in category Overall mean sd in
category
## campaign       50.728690         7.377660    2.3891187
2.2493334
## emp.var.rate   14.853947         1.261436    0.1073999
0.3583756
## euribor3m      14.426375         4.885128    3.6487535
0.2632639
## nr.employed    14.060411      5218.600266 5167.8073595
16.9326584
## cons.price.idx 12.194694        93.935734   93.5857345
0.3601197
## pdays           3.708759        16.000000   15.6263647
0.0000000
## cons.conf.idx   2.580999       -40.053457  -40.6182329
2.9787704
## age             2.265504        41.204787   40.0525729
8.8773006
## previous       -7.095467         0.000000    0.1708451
0.0000000
##                Overall sd      p.value
## campaign        1.9835304 0.000000e+00
## emp.var.rate    1.5670994 6.559004e-50
```

```
## euribor3m       1.7286683 3.531615e-47
## nr.employed    72.8658491 6.649921e-45
## cons.price.idx  0.5789159 3.317468e-34
## pdays           2.0320681 2.082779e-04
## cons.conf.idx   4.4137411 9.851477e-03
## age            10.2585844 2.348177e-02
## previous        0.4856692 1.289158e-12
##
## $`CLUSTER-7`
##                   v.test Mean in category Overall mean sd in
category
## previous        25.936115        0.9090909    0.1708451
0.6052115
## campaign         9.978225        3.5490909    2.3891187
2.4643548
## duration        -2.048501      232.0218182  262.7672867
238.7423097
## age             -8.119420       35.1709091   40.0525729
7.8079138
## cons.price.idx -11.740027       93.1874073   93.5857345
0.5662071
## cons.conf.idx  -13.746299      -44.1741210  -40.6182329
4.2645317
## emp.var.rate   -21.377494       -1.8560000    0.1073999
0.4394112
## nr.employed    -23.275177     5068.4105455 5167.8073595
48.7286468
## euribor3m      -24.465933        1.1700255    3.6487535
0.2279239
##                 Overall sd       p.value
## previous         0.4856692 2.608160e-148
## campaign         1.9835304  1.898329e-23
## duration       256.0881160  4.051090e-02
## age             10.2585844  4.684180e-16
## cons.price.idx   0.5789159  7.946097e-32
## cons.conf.idx    4.4137411  5.360204e-43
## emp.var.rate     1.5670994 2.164450e-101
## nr.employed     72.8658491 7.911039e-120
## euribor3m        1.7286683 3.406047e-132
```

Ara procedirem a l'explicació de cada cluster:

Cluster 1: En aquest cluster veiem que el nombre de cops que s'ha contactat anteriorment es superior a la mitjana i tambe es pot observar que es caracteritza perque s'ha contactat durant els mesos d'hivern, sobretot desembre.

Cluster 2: En aquest segon cluster veiem que no hi ha hagut cap mena de campanya de marqueting anteriorment i que principalment es caracteritza pels mesos d'estiu, ja que son els que tenen un v.test major, també podem dir que destaquen els individus que estan solters.

Cluster 3: Aquest cluster es caracteritza perque s'ha contactat durant els mesos de la primavera (abril, maig) a la majoria d'individus i les persones d'aquest cluster son la majoria estudiants.

Cluster 4: Aquest cluster es caracteritza perque s'ha contactat durant els mesos de septembre i octubre a la majoria d'individus i veiem que hi ha hagut una campanya de marqueting exitosa anteriorment.

Cluster 5: Aquest cluster es caracteritza perque s'ha contactat durant el mes d'agost principalment i la major part estan casats i a molts els han contactat a traves del mobil.

Cluster 6: Aquest cluster es caracteritza per un tipus d'individu el qual s'ha contactat a traves del mobil i el nombre de contactes realitzats durant aquesta campanya i per a aquest individus es superior a la mitjana.

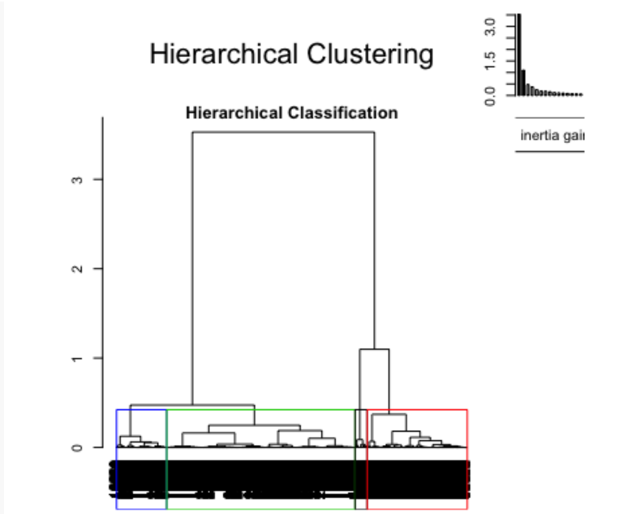
Cluster 7: En aquest cluster veiem que el nombre de cops que s'ha contactat anteriorment es superior a la mitjana i la majoria d'aquest individus estan solters.

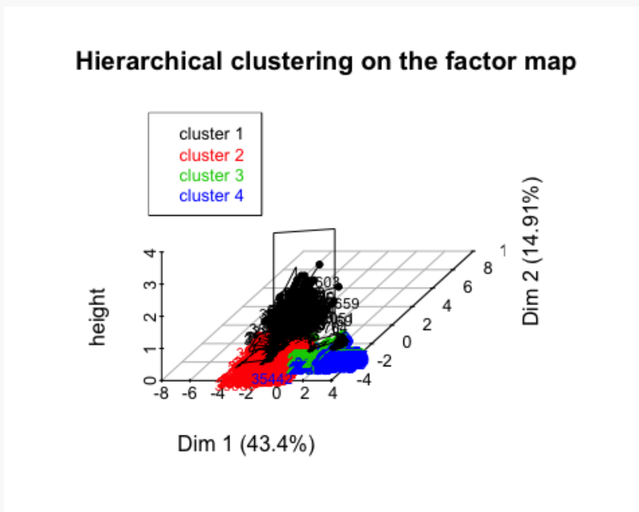
Hierarchical Clustering

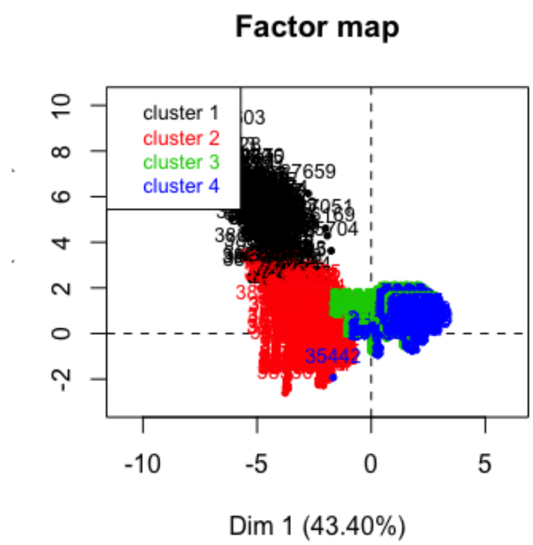
Ara el que farem sera aplicar la classificacio jerarquica de clustering.

Seguidament executem una comanda especifica per poder veure quin es el nombre de clusters mes adequat, ja que aixi podrem veure un grafic on podrem seleccionar com volem agrupar els clusters.

```
res.hcpc <- HCPC(res.pca, nb.clust = 4, order =TRUE) #Hay que cortar
en un punto que no haya muchos saltos apartir de ahi cerca del cero, a
primera vista podemos ver que, deberiamos ver grupos uniformes, pero
no salen limpias las particiones.
```


Hierarchical Clustering
Hierarchical Classification
inertia gai


Hierarchical clustering on the factor map
cluster 1
cluster 2
cluster 3
cluster 4
height
Dim 1 (43.4%)
Dim 2 (14.91%)




```r
attributes(res.hcpc) #Tiene esas listas
```

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

```r
summary(res.hcpc$data.clust) #Nos dice el tamaño de cada cluster
```

```
##     duration           y                     marital
##  Min.   :   1.0   Y_no :4349   Marital_divorced: 562
##  1st Qu.: 104.0   Y_yes: 597   Marital_married :3000
##  Median : 182.0                Marital_single  :1377
##  Mean   : 262.8                NA's            :   7
##  3rd Qu.: 329.0
##  Max.   :2122.0
##
##                 job             age            campaign          pdays
##  Job_admin.      :1301   Min.   :17.00   Min.   : 1.000   Min.   :
1.00
##  Job_blue-collar:1144   1st Qu.:32.00   1st Qu.: 1.000   1st Qu.:
16.00
##  Job_technician : 784   Median :38.00   Median : 2.000   Median :
16.00
##  Job_services   : 473   Mean   :40.05   Mean   : 2.389   Mean   :
15.63
##  Job_management : 345   3rd Qu.:47.00   3rd Qu.: 3.000   3rd Qu.:
16.00
```

```
##  Job_retired    : 206   Max.   :81.00   Max.   :14.000   Max.   :
16.00
##  (Other)        : 693
##     previous       emp.var.rate     cons.price.idx  cons.conf.idx
##  Min.   :0.0000   Min.   :-3.4000   Min.   :92.20   Min.   :-50.80
##  1st Qu.:0.0000   1st Qu.:-1.8000   1st Qu.:93.08   1st Qu.:-42.70
##  Median :0.0000   Median : 1.1000   Median :93.92   Median :-41.80
##  Mean   :0.1708   Mean   : 0.1074   Mean   :93.59   Mean   :-40.62
##  3rd Qu.:0.0000   3rd Qu.: 1.4000   3rd Qu.:93.99   3rd Qu.:-36.40
##  Max.   :5.0000   Max.   : 1.4000   Max.   :94.77   Max.   :-29.80
##
##    euribor3m      nr.employed   clust
##  Min.   :0.634   Min.   :4964   1: 180
##  1st Qu.:1.344   1st Qu.:5099   2:1401
##  Median :4.857   Median :5191   3:2713
##  Mean   :3.649   Mean   :5168   4: 652
##  3rd Qu.:4.961   3rd Qu.:5228
##  Max.   :5.045   Max.   :5228
##
```

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

```
##               p.value df
## y       5.654668e-177  3
## job      6.528644e-45 33
## marital  6.394260e-06  9
```

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

```
##                       Eta2       P-value
## campaign       0.523277769  0.000000e+00
## pdays          0.844684307  0.000000e+00
## previous       0.483134285  0.000000e+00
## emp.var.rate   0.886188857  0.000000e+00
## cons.price.idx 0.443420176  0.000000e+00
## euribor3m      0.972728324  0.000000e+00
## nr.employed    0.862075267  0.000000e+00
## cons.conf.idx  0.178928568 6.471519e-211
## duration       0.004360341  7.907623e-05
## age            0.001841458  2.786614e-02
```

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

```
## $`1`
##                  v.test Mean in category Overall mean sd in
category
## previous        44.747785        1.7611111    0.1708451
0.9089914
## cons.conf.idx    7.085967      -38.3296660  -40.6182329
6.1337026
## duration         4.545145      347.9388889  262.7672867
273.7414263
## cons.price.idx  -3.937550       93.4189333   93.5857345
0.8322883
## campaign        -4.173711        1.7833333    2.3891187
1.1891874
## emp.var.rate   -19.056038       -2.0777778    0.1073999
0.8795552
## euribor3m      -21.375733        0.9448556    3.6487535
0.5073431
## nr.employed    -27.925157     5018.9133333 5167.8073595
50.1367856
## pdays          -64.626980        6.0166667   15.6263647
4.0599329
##                 Overall sd       p.value
## previous         0.4856692  0.000000e+00
## cons.conf.idx    4.4137411  1.380767e-12
## duration       256.0881160  5.489737e-06
## cons.price.idx   0.5789159  8.231785e-05
## campaign         1.9835304  2.996782e-05
## emp.var.rate     1.5670994  5.854424e-81
## euribor3m        1.7286683 2.247650e-101
## nr.employed     72.8658491 1.320822e-171
## pdays            2.0320681  0.000000e+00
##
## $`2`
##                  v.test Mean in category Overall mean sd in
category
## previous        14.010599         0.324768    0.1708451
0.5230112
## pdays            7.336442        15.963597   15.6263647
0.3826571
## age             -2.098021        39.565714   40.0525729
11.9152285
## campaign        -5.633923         2.136331    2.3891187
1.6501597
## cons.conf.idx  -29.535606       -43.567123  -40.6182329
5.4810779
```

```
## cons.price.idx -45.687783        92.987431   93.5857345
0.4524177
## nr.employed    -55.147107      5076.909707 5167.8073595
39.0431169
## emp.var.rate   -60.532277        -2.038401    0.1073999
0.5550071
## euribor3m      -62.859907         1.190700    3.6487535
0.2529861
##                Overall sd       p.value
## previous        0.4856692  1.342670e-44
## pdays           2.0320681  2.193465e-13
## age            10.2585844  3.590331e-02
## campaign        1.9835304  1.761553e-08
## cons.conf.idx   4.4137411 1.005224e-191
## cons.price.idx  0.5789159  0.000000e+00
## nr.employed    72.8658491  0.000000e+00
## emp.var.rate    1.5670994  0.000000e+00
## euribor3m       1.7286683  0.000000e+00
##
## $`3`
##                   v.test Mean in category Overall mean sd in
category
## euribor3m       51.50287       4.79738150    3.6487535
0.2961639
## emp.var.rate    48.14380       1.08075931    0.1073999
0.5264601
## nr.employed     47.78941    5212.73276815 5167.8073595
17.5946210
## cons.price.idx  32.15316      93.82588058   93.5857345
0.3977156
## cons.conf.idx   19.13856     -39.52841872  -40.6182329
2.9848752
## pdays           14.25192      16.00000000   15.6263647
0.0000000
## previous       -22.97193       0.02690748    0.1708451
0.1618131
## campaign       -27.58456       1.68322202    2.3891187
0.7827272
##                Overall sd       p.value
## euribor3m       1.7286683  0.000000e+00
## emp.var.rate    1.5670994  0.000000e+00
## nr.employed    72.8658491  0.000000e+00
## cons.price.idx  0.5789159 7.978769e-227
## cons.conf.idx   4.4137411  1.205556e-81
```

```
## pdays             2.0320681  4.361442e-46
## previous          0.4856692 8.897223e-117
## campaign          1.9835304 1.704849e-167
##
## $`4`
##                    v.test Mean in category Overall mean sd in
category
## campaign        50.391249         6.036810    2.3891187
2.3318009
## emp.var.rate    20.351770         1.271319    0.1073999
0.3024787
## euribor3m       19.794810         4.897537    3.6487535
0.2113150
## nr.employed     18.610074      5217.294939 5167.8073595
17.2495005
## cons.price.idx 15.733815        93.918144   93.5857345
0.3546711
## cons.conf.idx    7.263154       -39.448313  -40.6182329
3.0538591
## pdays            5.038317        16.000000   15.6263647
0.0000000
## previous        -9.639132         0.000000    0.1708451
0.0000000
##                Overall sd      p.value
## campaign        1.9835304 0.000000e+00
## emp.var.rate    1.5670994 4.478120e-92
## euribor3m       1.7286683 3.299949e-87
## nr.employed    72.8658491 2.662485e-77
## cons.price.idx  0.5789159 8.870154e-56
## cons.conf.idx   4.4137411 3.781682e-13
## pdays           2.0320681 4.696423e-07
## previous        0.4856692 5.464823e-22
```

Amb la comanda del “chi2” podem observar que les variables “y”, “job” i “marital” son les que mes caracteritzen la particio en els quatre clusters que utilitzarem en el nostre analisi i tambe es podria fer amb 5 clusters, pero com no canviava molt hem vist mes convenient agafar o fer la particio en 4 clusters pel nostre estudi.

Descripcio dels clusters

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

```
## $`1`
##                             Cla/Mod    Mod/Cla    Global      p.value
## y=Y_yes                  20.9380235 69.4444444 12.070360 2.066147e-76
```

```
## job=Job_student       17.1428571 10.0000000  2.122928 3.138518e-08
## job=Job_retired        9.2233010 10.5555556  4.164982 1.951846e-04
## job=Job_admin.         4.9961568 36.1111111 26.304084 3.190110e-03
## job=Job_unemployed     9.3457944  5.5555556  2.163364 6.838252e-03
## job=Job_self-employed  0.6578947  0.5555556  3.073190 2.588876e-02
## job=Job_services       1.6913319  4.4444444  9.563283 1.061796e-02
## job=Job_blue-collar    1.1363636  7.2222222 23.129802 9.936978e-09
## y=Y_no                 1.2646585 30.5555556 87.929640 2.066147e-76
##                           v.test
## y=Y_yes                18.499963
## job=Job_student         5.533529
## job=Job_retired         3.725169
## job=Job_admin.          2.948799
## job=Job_unemployed      2.704620
## job=Job_self-employed  -2.227876
## job=Job_services       -2.555027
## job=Job_blue-collar    -5.731801
## y=Y_no                -18.499963
##
## $`2`
##                          Cla/Mod    Mod/Cla     Global      p.value
## y=Y_yes                 49.74874 21.1991435 12.0703599 2.352298e-32
## job=Job_student         65.71429  4.9250535  2.1229276 1.147770e-15
## job=Job_retired         48.05825  7.0663812  4.1649818 9.670365e-10
## marital=Marital_single  33.69644 33.1192006 27.8406793 2.569686e-07
## job=Job_unknown         11.62791  0.3568879  0.8693894 1.005915e-02
## job=Job_housemaid       17.46032  1.5703069  2.5475131 4.501339e-03
## job=Job_technician      23.85204 13.3476089 15.8511929 2.166634e-03
## marital=Marital_married 26.13333 55.9600286 60.6550748 2.309388e-05
## y=Y_no                  25.38515 78.8008565 87.9296401 2.352298e-32
##                            v.test
## y=Y_yes                 11.842536
## job=Job_student          8.009926
## job=Job_retired          6.114758
## marital=Marital_single   5.152550
## job=Job_unknown         -2.573790
## job=Job_housemaid       -2.840709
## job=Job_technician      -3.066386
## marital=Marital_married  -4.232665
## y=Y_no                 -11.842536
##
## $`3`
##                          Cla/Mod     Mod/Cla     Global
```

```
p.value
## y=Y_no                  59.14003 94.80280133 87.9296401
1.640791e-61
## marital=Marital_married 56.56667 62.55068190 60.6550748
2.650603e-03
## job=Job_entrepreneur    64.37500  3.79653520  3.2349373
1.346392e-02
## job=Job_services        59.83087 10.43125691  9.5632835
2.190374e-02
## job=Job_blue-collar     57.69231 24.32731294 23.1298019
2.760138e-02
## job=Job_technician      58.29082 16.84482123 15.8511929
3.477799e-02
## job=Job_unknown         69.76744  1.10578695  0.8693894
4.818052e-02
## marital=NA              14.28571  0.03685957  0.1415285
4.004320e-02
## marital=Marital_single  50.10893 25.43309989 27.8406793
3.229271e-05
## job=Job_retired         32.52427  2.46959086  4.1649818
4.817695e-11
## job=Job_student         12.38095  0.47917435  2.1229276
5.264065e-20
## y=Y_yes                 23.61809  5.19719867 12.0703599
1.640791e-61
##                            v.test
## y=Y_no                  16.548523
## marital=Marital_married  3.005597
## job=Job_entrepreneur     2.471257
## job=Job_services         2.292033
## job=Job_blue-collar      2.202906
## job=Job_technician       2.110934
## job=Job_unknown          1.975773
## marital=NA              -2.053303
## marital=Marital_single  -4.156665
## job=Job_retired         -6.576463
## job=Job_student         -9.158465
## y=Y_yes                -16.548523
##
## $`4`
##                  Cla/Mod    Mod/Cla    Global      p.value
v.test
## y=Y_no         14.210163 94.7852761 87.929640 3.150217e-10
6.291200
```

```
## job=Job_student  4.761905  0.7668712  2.122928 4.802179e-03
-2.820012
## y=Y_yes          5.695142  5.2147239 12.070360 3.150217e-10
-6.291200
```

Cluster 1: Els individus que pertanyen al cluster numero 1 es detaquen perque tenen la variable “y = yes”, per tant, aixo vol dir que son individus que SI que contracten el producte i a mes tambe podem observar que la majoria d’aquests individus son estudiants.

Cluster 2: Els individus que pertanyen al cluster numero 2 es detaquen perque tenen la variable “y = yes”, per tant, aixo vol dir que son individus que SI que contracten el producte i a mes tambe podem observar que la majoria d’aquests individus son estudiants i estan solters.

Cluster 3: Els individus que pertanyen al cluster numero 3 es detaquen perque tenen la variable “y = no”, per tant, aixo vol dir que son individus que NO contracten el producte i a mes tambe podem observar que la majoria d’aquests individus treballen com empresaris o en el sector de serveis i que estan casats.

Cluster 4: Els individus que pertanyen al cluster numero 4 es detaquen perque tenen la variable “y = no”, per tant, aixo vol dir que son individus que NO contracten el producte i a mes tambe podem observar que la majoria d’aquests individus son estudiants.

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

## [1] "para" "dist"

res.hcpc$desc.ind$para  #Close to center of gravity

## Cluster: 1
##     36910     40420     40457     40031     39208
## 0.8996255 0.9520736 1.0182792 1.0842884 1.1687768
## --------------------------------------------------------
## Cluster: 2
##     34135     31328     31002     32850     32962
## 0.7368927 0.7400291 0.7406566 0.7427179 0.7427179
## --------------------------------------------------------
## Cluster: 3
##     24034      4467      4473       726      5358
## 0.6391974 0.6502367 0.6502367 0.6503246 0.6503246
## --------------------------------------------------------
## Cluster: 4
##      5296      7006      3322      6693      1049
## 0.6445766 0.6572942 0.6627406 0.6627473 0.6627498

res.hcpc$desc.ind$dist
```

```
## Cluster: 1
##    41004    40603    40930    40443    39828
## 11.14194 10.75528 10.61921 10.42103 10.07574
## --------------------------------------------------------
## Cluster: 2
##    37819    38061    38985    38677    38583
## 6.455196 6.447230 6.406478 6.351079 6.344856
## --------------------------------------------------------
## Cluster: 3
##    18895    23309    22214    14894    19305
## 3.303387 3.303373 3.303371 3.265879 3.249192
## --------------------------------------------------------
## Cluster: 4
##    18491    11713    11630    23559    35442
## 6.349686 6.335066 6.315248 6.301241 6.048853
```

```r
# NO ES NECESSARI!

#### Characteristic individuals
para1<-which(rownames(res.pca$ind$coord)
%in%names(res.hcpc$desc.ind$para[[1]]))
para2<-which(rownames(res.pca$ind$coord)
%in%names(res.hcpc$desc.ind$para[[2]]))
para3<-which(rownames(res.pca$ind$coord)
%in%names(res.hcpc$desc.ind$para[[3]]))
para4<-which(rownames(res.pca$ind$coord)
%in%names(res.hcpc$desc.ind$para[[4]]))
# to be completed... as many as cluster you choose

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

Correspondence Analysis (CA)

En la part final del nostre estudi el que farem sera l'analisi de correspondencies simples (CA) per poder analitzar les relacions entre 2 factors de les dades de la nostra mostra.

Per fer l'analisi de correspondencies simples utilitzarem com a target el factor discretitzat factor_duration i realitzarem dues taules de contingencia per comparar aquest target amb 2 variables qualitatives mes. Aquestes dues variables seran "job" i "factor_age".

Factor_age i Factor_duration

```
# Contingency tables - Complex : solo cuentan con los target
discretizados
names(df)

##  [1] "age"                 "job"
##  [3] "marital"             "education"
##  [5] "default"             "housing"
##  [7] "loan"                "contact"
##  [9] "month"               "day_of_week"
## [11] "duration"            "campaign"
## [13] "pdays"               "previous"
## [15] "poutcome"            "emp.var.rate"
## [17] "cons.price.idx"      "cons.conf.idx"
## [19] "euribor3m"           "nr.employed"
## [21] "y"                   "missings_indiv"
## [23] "errors_indiv"        "outliers_indiv"
## [25] "season"              "factor_age"
## [27] "factor_duration"     "factor_campaign"
## [29] "factor_Pdays"        "factor_Previous"
## [31] "factor_emp.var.rate" "factor_cons.price.idx"
## [33] "factor_cons.conf.idx" "factor_euribor3m"
## [35] "factor_nr.employed"  "CLUSTER"
## [37] "f.CLUSTER"

# Target factor_duration vs job
# Podemos elegir la variable que queramos con la de f_duration y en
este caso hemos elegido job para este ejemplo

table(df$factor_age, df$factor_duration)

##
##                     factor_duration-[1,68] factor_duration-(68,104]
##   factor_age [17,31]                   129                      127
##   factor_age (31,36]                   155                      137
##   factor_age (36,41]                   104                      112
##   factor_age (41,49]                   119                      108
##   factor_age (49,81]                   122                      139
##
##                     factor_duration-(104,139] factor_duration-(139,182]
##   factor_age [17,31]                      143                       140
##   factor_age (31,36]                      125                       123
##   factor_age (36,41]                      101                       105
```

```
##   factor_age (41,49]                        124                       117
##   factor_age (49,81]                        119                       135
##
##                        factor_duration-(182,236] factor_duration-(236,329]
##   factor_age [17,31]                        135                       135
##   factor_age (31,36]                        126                       139
##   factor_age (36,41]                        101                       110
##   factor_age (41,49]                        126                       119
##   factor_age (49,81]                        120                       116
##
##                        factor_duration-(329,504]
##   factor_age [17,31]                        148
##   factor_age (31,36]                        127
##   factor_age (36,41]                        114
##   factor_age (41,49]                        110
##   factor_age (49,81]                        119
##
##                        factor_duration-(504,2.12e+03]
##   factor_age [17,31]                              156
##   factor_age (31,36]                              130
##   factor_age (36,41]                               83
##   factor_age (41,49]                              130
##   factor_age (49,81]                              118
```

```
#Le digo que calcule unas probabilidades en la dimension 1, calculo
los perfiles por fila que tenemos
#Calculo los perfiles de fila y la suma tendria que dar mas o menos 1
y tenemos que ver si es equivalente al perfil marginal fila
prop.table(table(df$factor_age, df$factor_duration), 1) # Por filas
```

```
##
##                        factor_duration-[1,68] factor_duration-(68,104]
##   factor_age [17,31]              0.1159030                0.1141060
##   factor_age (31,36]              0.1459510                0.1290019
##   factor_age (36,41]              0.1253012                0.1349398
##   factor_age (41,49]              0.1248688                0.1133263
##   factor_age (49,81]              0.1234818                0.1406883
##
##                        factor_duration-(104,139] factor_duration-(139,182]
##   factor_age [17,31]                 0.1284816                 0.1257862
##   factor_age (31,36]                 0.1177024                 0.1158192
##   factor_age (36,41]                 0.1216867                 0.1265060
##   factor_age (41,49]                 0.1301154                 0.1227702
##   factor_age (49,81]                 0.1204453                 0.1366397
##
##                        factor_duration-(182,236] factor_duration-(236,329]
##   factor_age [17,31]                 0.1212938                 0.1212938
##   factor_age (31,36]                 0.1186441                 0.1308851
##   factor_age (36,41]                 0.1216867                 0.1325301
##   factor_age (41,49]                 0.1322141                 0.1248688
##   factor_age (49,81]                 0.1214575                 0.1174089
##
```

```
##                         factor_duration-(329,504]
##   factor_age [17,31]                    0.1329739
##   factor_age (31,36]                    0.1195857
##   factor_age (36,41]                    0.1373494
##   factor_age (41,49]                    0.1154250
##   factor_age (49,81]                    0.1204453
##
##                         factor_duration-(504,2.12e+03]
##   factor_age [17,31]                         0.1401617
##   factor_age (31,36]                         0.1224105
##   factor_age (36,41]                         0.1000000
##   factor_age (41,49]                         0.1364113
##   factor_age (49,81]                         0.1194332
```

```
#Marginal row profile
prop.table(table(df$factor_duration))
```

```
##
##        factor_duration-[1,68]       factor_duration-(68,104]
##                     0.1271735                      0.1259604
##      factor_duration-(104,139]      factor_duration-(139,182]
##                     0.1237364                      0.1253538
##      factor_duration-(182,236]      factor_duration-(236,329]
##                     0.1229276                      0.1251516
##      factor_duration-(329,504] factor_duration-(504,2.12e+03]
##                     0.1249495                      0.1247473
```

```
#Esta proporcion se mantiene en cualquiera de los colectivos mirados
anteriormente? Se tiene que hacer la comparacion

#Podemos comprobar ahora los perfiles columna
#Column profile
prop.table(table(df$factor_age, df$factor_duration), 2) # dim 2
```

```
##
##                         factor_duration-[1,68] factor_duration-(68,104]
##   factor_age [17,31]                 0.2050874                0.2038523
##   factor_age (31,36]                 0.2464229                0.2199037
##   factor_age (36,41]                 0.1653418                0.1797753
##   factor_age (41,49]                 0.1891892                0.1733547
##   factor_age (49,81]                 0.1939587                0.2231140
##
##                         factor_duration-(104,139] factor_duration-(139,182]
##   factor_age [17,31]                    0.2336601                 0.2258065
##   factor_age (31,36]                    0.2042484                 0.1983871
##   factor_age (36,41]                    0.1650327                 0.1693548
##   factor_age (41,49]                    0.2026144                 0.1887097
##   factor_age (49,81]                    0.1944444                 0.2177419
##
##                         factor_duration-(182,236] factor_duration-(236,329]
##   factor_age [17,31]                    0.2220395                 0.2180937
```

```
##   factor_age (31,36]                0.2072368                   0.2245557
##   factor_age (36,41]                0.1661184                   0.1777060
##   factor_age (41,49]                0.2072368                   0.1922456
##   factor_age (49,81]                0.1973684                   0.1873990
##
##                     factor_duration-(329,504]
##   factor_age [17,31]                0.2394822
##   factor_age (31,36]                0.2055016
##   factor_age (36,41]                0.1844660
##   factor_age (41,49]                0.1779935
##   factor_age (49,81]                0.1925566
##
##                     factor_duration-(504,2.12e+03]
##   factor_age [17,31]                      0.2528363
##   factor_age (31,36]                      0.2106969
##   factor_age (36,41]                      0.1345219
##   factor_age (41,49]                      0.2106969
##   factor_age (49,81]                      0.1912480
```

```
#Marginal colum profile
prop.table(table(df$factor_age))
```

```
##
## factor_age [17,31] factor_age (31,36] factor_age (36,41]
##          0.2250303          0.2147190          0.1678124
## factor_age (41,49] factor_age (49,81]
##          0.1926810          0.1997574
```

```
#El perfil columna de les diferents columnes es pot considerar
diferent que el marginal? Evidentment SI

# HO: factor_duration -factor_age independency
chisq.test(table(df$factor_age, df$factor_duration))
```

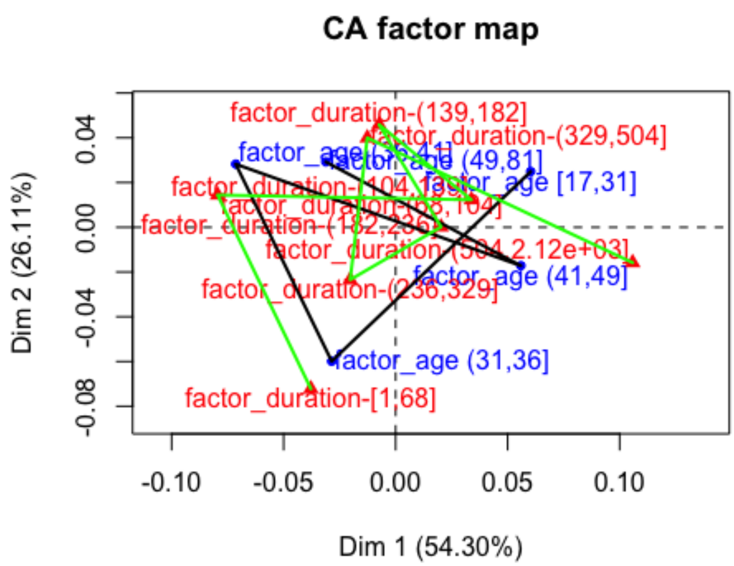
```
##
##  Pearson's Chi-squared test
##
## data:  table(df$factor_age, df$factor_duration)
## X-squared = 24.084, df = 28, p-value = 0.6771
```

```
# Accepto la hipotesi nula porque el pvalor es 0.6771
```

En aquesta part de la nostra investigacio podem veure que la hipotesi nula s'accepta perque el pvalor es 0.6771, es mes gran que un 5%. Llavors, podem dir que la durada de la trucada no depen de l'edat del nostre individu.

```
# CA - factor_duration vs factor_age
res.ca <- CA(table(df$factor_age, df$factor_duration))
# Interpretacio numerica: Com mes lluny estigui la rodona (blau) hace
referencia al factor que esta en las filas y el rojo a las columnas,
```

```
entonces como mas lejos este del centro de gravedad, quiere decir que
es mas remarcables, es decir, mas raro es, los que estan mas cerca no
me aporta nada

#Link levels in row
#plot.CA(res.ca)
lines(res.ca$row$coord[,1], res.ca$row$coord[,2],lwd=2)
#No tenemos que ver nada porque hemos visto que no tienen nada que ver

#Link levels in columns
lines(res.ca$col$coord[,1], res.ca$col$coord[,2],lwd=2, col = "green")
```



Com podem veure a l'hora de l'execució tenim que el factor_duration-(182,236] es el que mes destaca en que no ens aporta cap mena d'informacio ja que es troba mes a prop del centre de gravetat, A partir de les taules de contingencia i els seus diferents perfils intentem observar si hi pot haver alguna relacio de dependencia entre els dos factors, tot i aixi visualtment ens resulta complicat.

Eigenvalues and dominant axes analysis

En aquest subapartat realitzarem un estudi dels valors propis i dels eixos dominants per tal de determinar quantes dimensions tindrem en compte.

```
#attributes(res.ca)
res.ca$eig

##          eigenvalue percentage of variance
## dim 1 0.0026443419              54.304636
```

```
## dim 2 0.0012712615              26.106835
## dim 3 0.0006783276              13.930247
## dim 4 0.0002755277               5.658282
##       cumulative percentage of variance
## dim 1                           54.30464
## dim 2                           80.41147
## dim 3                           94.34172
## dim 4                          100.00000
```

```
#No es extraño que los eigenvalues sean pequeños, cojemos tantas
dimensiones como las que tengan un valor propio > mitjana de este
valor
mean(res.ca$eig[,1]) #Mean eigenvalue
```

```
## [1] 0.001217365
```

```
#KAISER: take as many as dimensions as eigenvalue > mean eig
sum(res.ca$eig[,1]) #Total inertia, contra mas grande hay mas realcion
entre las variables
```

```
## [1] 0.004869459
```

```
#Rows
res.ca$row
```

```
## $coord
##                            Dim 1       Dim 2        Dim 3        Dim 4
## factor_age [17,31]  0.06028947  0.02489821  0.016824123 -0.017911266
## factor_age (31,36] -0.02855663 -0.05990896  0.001849387 -0.011976354
## factor_age (36,41] -0.07137954  0.02821861  0.035431074  0.012368421
## factor_age (41,49]  0.05590097 -0.01718799 -0.006454706  0.027347518
## factor_age (49,81] -0.03117779  0.02922096 -0.044479508 -0.003718468
##
## $contrib
##                        Dim 1     Dim 2      Dim 3     Dim 4
## factor_age [17,31] 30.931887 10.973430  9.3900174 26.201633
## factor_age (31,36]  6.621655 60.620433  0.1082646 11.177750
## factor_age (36,41] 32.333583 10.511397 31.0565438  9.317238
## factor_age (41,49] 22.769835  4.477691  1.1834564 52.300922
## factor_age (49,81]  7.343039 13.417048 58.2617178  1.002457
##
## $cos2
##                        Dim 1      Dim 2        Dim 3       Dim 4
## factor_age [17,31] 0.7481200 0.12759233 0.0582576789 0.066029941
## factor_age (31,36] 0.1791707 0.78856386 0.0007514654 0.031513932
## factor_age (36,41] 0.6979823 0.10908582 0.1719751003 0.020956822
## factor_age (41,49] 0.7422793 0.07017444 0.0098965007 0.177649715
## factor_age (49,81] 0.2545863 0.22363176 0.5181605763 0.003621366
##
```

```
## $inertia
## [1] 0.0010933337 0.0009772756 0.0012249745 0.0008111667 0.0007627082

#Tenemos las coordenadas, las contribuciones, el cos2 (indica la
calidad de la representacion de cada una de las categorias en el eje
que toca), inertia

#Cols
res.ca$col

## $coord
##                                    Dim 1         Dim 2        Dim 3
## factor_duration-[1,68]        -0.037838157 -0.0722213624 -0.003223726
## factor_duration-(68,104]      -0.079484346  0.0144258906 -0.032136966
## factor_duration-(104,139]      0.033810408  0.0122767778  0.007661304
## factor_duration-(139,182]     -0.007382708  0.0458581152 -0.028290026
## factor_duration-(182,236]      0.020271631  0.0001678354 -0.004295253
## factor_duration-(236,329]     -0.020308835 -0.0234604264  0.030890479
## factor_duration-(329,504]     -0.012654910  0.0399387089  0.047274023
## factor_duration-(504,2.12e+03]  0.105787697 -0.0158309148 -0.017544387
##                                    Dim 4
## factor_duration-[1,68]        -0.007649896
## factor_duration-(68,104]      -0.009047632
## factor_duration-(104,139]      0.013727248
## factor_duration-(139,182]      0.001523774
## factor_duration-(182,236]      0.031880042
## factor_duration-(236,329]      0.009810846
## factor_duration-(329,504]     -0.019119842
## factor_duration-(504,2.12e+03] -0.020319730
##
## $contrib
##                                  Dim 1        Dim 2      Dim 3
## factor_duration-[1,68]          6.8855540 5.217867e+01  0.1948379
## factor_duration-(68,104]       30.0939744 2.061979e+00 19.1780380
## factor_duration-(104,139]       5.3490977 1.467004e+00  1.0706886
## factor_duration-(139,182]       0.2583755 2.073648e+01 14.7898845
## factor_duration-(182,236]       1.9103338 2.723842e-04  0.3343393
## factor_duration-(236,329]       1.9520412 5.418430e+00 17.6054166
## factor_duration-(329,504]       0.7567194 1.567789e+01 41.1661239
## factor_duration-(504,2.12e+03] 52.7939041 2.459281e+00  5.6606712
##                                  Dim 4
## factor_duration-[1,68]          2.7011103
## factor_duration-(68,104]        3.7422993
## factor_duration-(104,139]       8.4625062
## factor_duration-(139,182]       0.1056364
## factor_duration-(182,236]      45.3442221
## factor_duration-(236,329]       4.3720403
## factor_duration-(329,504]      16.5782111
## factor_duration-(504,2.12e+03] 18.6939743
##
## $cos2
```

```
##                                     Dim 1        Dim 2       Dim 3
## factor_duration-[1,68]         0.2131635 7.765763e-01 0.001547281
## factor_duration-(68,104]       0.8268767 2.723722e-02 0.135172172
## factor_duration-(104,139]      0.7418214 9.780641e-02 0.038089380
## factor_duration-(139,182]      0.0184129 7.104333e-01 0.270369437
## factor_duration-(182,236]      0.2842387 1.948377e-05 0.012760955
## factor_duration-(236,329]      0.2048606 2.733758e-01 0.473955531
## factor_duration-(329,504]      0.0367676 3.662142e-01 0.513088482
## factor_duration-(504,2.12e+03] 0.9201376 2.060604e-02 0.025308058
##                                        Dim 4
## factor_duration-[1,68]         0.0087129229
## factor_duration-(68,104]       0.0107138956
## factor_duration-(104,139]      0.1222828325
## factor_duration-(139,182]      0.0007843904
## factor_duration-(182,236]      0.7029808969
## factor_duration-(236,329]      0.0478080704
## factor_duration-(329,504]      0.0839297108
## factor_duration-(504,2.12e+03] 0.0339483217
##
## $inertia
## [1] 0.0008541689 0.0009624017 0.0001906772 0.0003710622 0.0001777230
## [6] 0.0002519696 0.0005442359 0.0015172202

#Durada mes curta es la que te mes contribucio!

#Phi2 = Intensity of the association Chisq/nobservations
sum(res.ca$eig[,1]) #Total inertia = Phi2

## [1] 0.004869459

chisq.test(table(df$factor_age, df$factor_duration))

##
##  Pearson's Chi-squared test
##
## data:  table(df$factor_age, df$factor_duration)
## X-squared = 24.084, df = 28, p-value = 0.6771

#24.084/4946 porque son las observaciones
```

Job i Factor_duration

```
# Contingency tables - Complex : solo cuentan con los target
discretizados
names(df)

##  [1] "age"                        "job"
##  [3] "marital"                    "education"
##  [5] "default"                    "housing"
##  [7] "loan"                       "contact"
##  [9] "month"                      "day_of_week"
```

```
## [11] "duration"              "campaign"
## [13] "pdays"                 "previous"
## [15] "poutcome"              "emp.var.rate"
## [17] "cons.price.idx"        "cons.conf.idx"
## [19] "euribor3m"             "nr.employed"
## [21] "y"                     "missings_indiv"
## [23] "errors_indiv"          "outliers_indiv"
## [25] "season"                "factor_age"
## [27] "factor_duration"       "factor_campaign"
## [29] "factor_Pdays"          "factor_Previous"
## [31] "factor_emp.var.rate"   "factor_cons.price.idx"
## [33] "factor_cons.conf.idx"  "factor_euribor3m"
## [35] "factor_nr.employed"    "CLUSTER"
## [37] "f.CLUSTER"
```

```
# Target factor_duration vs job
# Podemos elegir la variable que queramos con la de f_duration y en
este caso hemos elegido job para este ejemplo

table(df$job, df$factor_duration)
```

```
##
##                    factor_duration-[1,68] factor_duration-(68,104]
##   Job_admin.                          162                      169
##   Job_blue-collar                     131                      141
##   Job_entrepreneur                     18                       17
##   Job_housemaid                        14                       14
##   Job_management                       47                       35
##   Job_retired                          18                       29
##   Job_self-employed                    20                       25
##   Job_services                         75                       61
##   Job_student                           8                       17
##   Job_technician                      109                       96
##   Job_unemployed                       20                       14
##   Job_unknown                           7                        5
##
##                    factor_duration-(104,139] factor_duration-(139,182]
##   Job_admin.                             164                       167
##   Job_blue-collar                        133                       135
##   Job_entrepreneur                        12                        18
##   Job_housemaid                           22                        17
##   Job_management                          39                        47
##   Job_retired                             24                        33
##   Job_self-employed                       23                        20
##   Job_services                            52                        52
##   Job_student                             10                         7
##   Job_technician                         116                       105
##   Job_unemployed                          10                        16
```

```
##   Job_unknown                          7                       3
##
##                      factor_duration-(182,236] factor_duration-(236,329]
##   Job_admin.                         150                     157
##   Job_blue-collar                    137                     157
##   Job_entrepreneur                    24                      21
##   Job_housemaid                       16                      19
##   Job_management                      53                      45
##   Job_retired                         21                      28
##   Job_self-employed                   12                      13
##   Job_services                        54                      57
##   Job_student                         13                      19
##   Job_technician                     111                      85
##   Job_unemployed                      10                      15
##   Job_unknown                          7                       3
##
##                      factor_duration-(329,504]
##   Job_admin.                         167
##   Job_blue-collar                    165
##   Job_entrepreneur                    18
##   Job_housemaid                       10
##   Job_management                      43
##   Job_retired                         29
##   Job_self-employed                   17
##   Job_services                        64
##   Job_student                         14
##   Job_technician                      82
##   Job_unemployed                       5
##   Job_unknown                          4
##
##                      factor_duration-(504,2.12e+03]
##   Job_admin.                              165
##   Job_blue-collar                         145
##   Job_entrepreneur                         32
##   Job_housemaid                            14
##   Job_management                           36
##   Job_retired                              24
##   Job_self-employed                        22
##   Job_services                             58
##   Job_student                              17
##   Job_technician                           80
##   Job_unemployed                           17
##   Job_unknown                               7
```

```r
#Le digo que calcule unas probabilidades en la dimension 1, calculo
los perfiles por fila que tenemos
#Calculo los perfiles de fila y la suma tendria que dar mas o menos 1
y tenemos que ver si es equivalente al perfil marginal fila
prop.table(table(df$job, df$factor_duration), 1) # Por filas
```

```
##
##                      factor_duration-[1,68] factor_duration-(68,104]
```

```
##   Job_admin.                        0.12451960               0.12990008
##   Job_blue-collar                   0.11451049               0.12325175
##   Job_entrepreneur                  0.11250000               0.10625000
##   Job_housemaid                     0.11111111               0.11111111
##   Job_management                    0.13623188               0.10144928
##   Job_retired                       0.08737864               0.14077670
##   Job_self-employed                 0.13157895               0.16447368
##   Job_services                      0.15856237               0.12896406
##   Job_student                       0.07619048               0.16190476
##   Job_technician                    0.13903061               0.12244898
##   Job_unemployed                    0.18691589               0.13084112
##   Job_unknown                       0.16279070               0.11627907
##
##                     factor_duration-(104,139] factor_duration-(139,182]
##   Job_admin.                           0.12605688                0.12836280
##   Job_blue-collar                      0.11625874                0.11800699
##   Job_entrepreneur                     0.07500000                0.11250000
##   Job_housemaid                        0.17460317                0.13492063
##   Job_management                       0.11304348                0.13623188
##   Job_retired                          0.11650485                0.16019417
##   Job_self-employed                    0.15131579                0.13157895
##   Job_services                         0.10993658                0.10993658
##   Job_student                          0.09523810                0.06666667
##   Job_technician                       0.14795918                0.13392857
##   Job_unemployed                       0.09345794                0.14953271
##   Job_unknown                          0.16279070                0.06976744
##
##                     factor_duration-(182,236] factor_duration-(236,329]
##   Job_admin.                           0.11529593                0.12067640
##   Job_blue-collar                      0.11975524                0.13723776
##   Job_entrepreneur                     0.15000000                0.13125000
##   Job_housemaid                        0.12698413                0.15079365
##   Job_management                       0.15362319                0.13043478
##   Job_retired                          0.10194175                0.13592233
##   Job_self-employed                    0.07894737                0.08552632
##   Job_services                         0.11416490                0.12050740
##   Job_student                          0.12380952                0.18095238
##   Job_technician                       0.14158163                0.10841837
##   Job_unemployed                       0.09345794                0.14018692
##   Job_unknown                          0.16279070                0.06976744
##
##                     factor_duration-(329,504]
##   Job_admin.                           0.12836280
##   Job_blue-collar                      0.14423077
##   Job_entrepreneur                     0.11250000
##   Job_housemaid                        0.07936508
##   Job_management                       0.12463768
##   Job_retired                          0.14077670
##   Job_self-employed                    0.11184211
##   Job_services                         0.13530655
##   Job_student                          0.13333333
##   Job_technician                       0.10459184
```

```
##   Job_unemployed                   0.04672897
##   Job_unknown                      0.09302326
##
##                      factor_duration-(504,2.12e+03]
##   Job_admin.                               0.12682552
##   Job_blue-collar                          0.12674825
##   Job_entrepreneur                         0.20000000
##   Job_housemaid                            0.11111111
##   Job_management                           0.10434783
##   Job_retired                              0.11650485
##   Job_self-employed                        0.14473684
##   Job_services                             0.12262156
##   Job_student                              0.16190476
##   Job_technician                           0.10204082
##   Job_unemployed                           0.15887850
##   Job_unknown                              0.16279070
```

```r
#Marginal row profile
prop.table(table(df$factor_duration))
```

```
##
##         factor_duration-[1,68]        factor_duration-(68,104]
##                      0.1271735                       0.1259604
##       factor_duration-(104,139]       factor_duration-(139,182]
##                      0.1237364                       0.1253538
##       factor_duration-(182,236]       factor_duration-(236,329]
##                      0.1229276                       0.1251516
##       factor_duration-(329,504] factor_duration-(504,2.12e+03]
##                      0.1249495                       0.1247473
```

```r
#Esta proporcion se mantiene en cualquiera de los colectivos mirados
anteriormente? Se tiene que hacer la comparacion

#Podemos comprobar ahora los perfiles columna
#Column profile
prop.table(table(df$job, df$factor_duration), 2) # dim 2
```

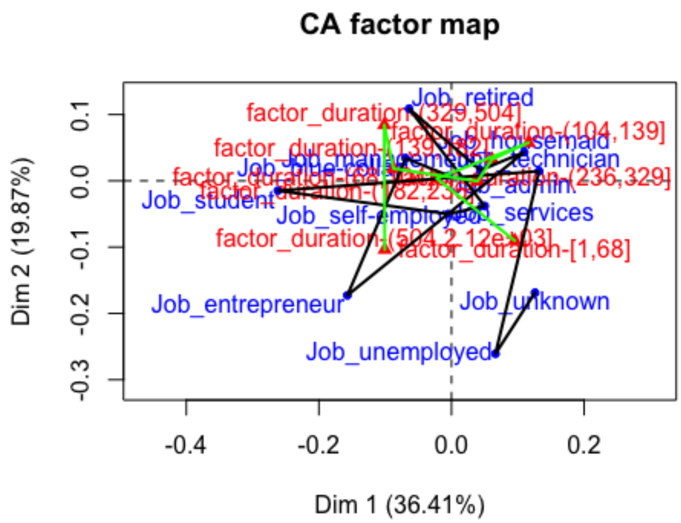
```
##
##                      factor_duration-[1,68] factor_duration-(68,104]
##   Job_admin.                    0.257551669              0.271268058
##   Job_blue-collar               0.208267091              0.226324238
##   Job_entrepreneur              0.028616852              0.027287319
##   Job_housemaid                 0.022257552              0.022471910
##   Job_management                0.074721781              0.056179775
##   Job_retired                   0.028616852              0.046548957
##   Job_self-employed             0.031796502              0.040128411
##   Job_services                  0.119236884              0.097913323
##   Job_student                   0.012718601              0.027287319
##   Job_technician                0.173290938              0.154093098
##   Job_unemployed                0.031796502              0.022471910
##   Job_unknown                   0.011128776              0.008025682
```

```
##
##                     factor_duration-(104,139] factor_duration-(139,182]
##   Job_admin.                      0.267973856               0.269354839
##   Job_blue-collar                 0.217320261               0.217741935
##   Job_entrepreneur                0.019607843               0.029032258
##   Job_housemaid                   0.035947712               0.027419355
##   Job_management                  0.063725490               0.075806452
##   Job_retired                     0.039215686               0.053225806
##   Job_self-employed               0.037581699               0.032258065
##   Job_services                    0.084967320               0.083870968
##   Job_student                     0.016339869               0.011290323
##   Job_technician                  0.189542484               0.169354839
##   Job_unemployed                  0.016339869               0.025806452
##   Job_unknown                     0.011437908               0.004838710
##
##                     factor_duration-(182,236] factor_duration-(236,329]
##   Job_admin.                      0.246710526               0.253634895
##   Job_blue-collar                 0.225328947               0.253634895
##   Job_entrepreneur                0.039473684               0.033925687
##   Job_housemaid                   0.026315789               0.030694669
##   Job_management                  0.087171053               0.072697900
##   Job_retired                     0.034539474               0.045234249
##   Job_self-employed               0.019736842               0.021001616
##   Job_services                    0.088815789               0.092084006
##   Job_student                     0.021381579               0.030694669
##   Job_technician                  0.182565789               0.137318255
##   Job_unemployed                  0.016447368               0.024232633
##   Job_unknown                     0.011513158               0.004846527
##
##                     factor_duration-(329,504]
##   Job_admin.                      0.270226537
##   Job_blue-collar                 0.266990291
##   Job_entrepreneur                0.029126214
##   Job_housemaid                   0.016181230
##   Job_management                  0.069579288
##   Job_retired                     0.046925566
##   Job_self-employed               0.027508091
##   Job_services                    0.103559871
##   Job_student                     0.022653722
##   Job_technician                  0.132686084
##   Job_unemployed                  0.008090615
##   Job_unknown                     0.006472492
##
##                     factor_duration-(504,2.12e+03]
##   Job_admin.                           0.267423015
##   Job_blue-collar                      0.235008104
##   Job_entrepreneur                     0.051863857
##   Job_housemaid                        0.022690438
##   Job_management                       0.058346840
##   Job_retired                          0.038897893
##   Job_self-employed                    0.035656402
##   Job_services                         0.094003241
```

```
##   Job_student                          0.027552674
##   Job_technician                       0.129659643
##   Job_unemployed                       0.027552674
##   Job_unknown                          0.011345219

#Marginal colum profile
prop.table(table(df$job))

##
##        Job_admin.   Job_blue-collar  Job_entrepreneur     Job_housemaid
##       0.263040841       0.231298019       0.032349373       0.025475131
##    Job_management       Job_retired Job_self-employed      Job_services
##       0.069753336       0.041649818       0.030731905       0.095632835
##       Job_student    Job_technician    Job_unemployed       Job_unknown
##       0.021229276       0.158511929       0.021633643       0.008693894

#El perfil columna de les diferents columnes es pot considerar
diferent que el marginal? Evidentment SI

# HO: factor_duration -factor_age independency
chisq.test(table(df$job, df$factor_duration))

##
##  Pearson's Chi-squared test
##
## data:  table(df$job, df$factor_duration)
## X-squared = 95.774, df = 77, p-value = 0.07247

# Accepto la hipotesi nula porque el pvalor es 0.07247
```

En aquesta part de la nostra investigacio podem veure que rebutgem la hipotesi nula perque el pvalor es 0.07247, encara que sigui una mica mes gran que un 5%. Llavors, podem dir que la durada de la trucada podria dependre del treball o a que es dediqui el nostre individu.

```
# CA - factor_duration vs factor_age
res.ca <- CA(table(df$job, df$factor_duration))

#Link levels in row
#plot.CA(res.ca)
lines(res.ca$row$coord[,1], res.ca$row$coord[,2],lwd=2)
#No tenemos que ver nada porque hemos visto que no tienen nada que ver

#Link levels in columns
lines(res.ca$col$coord[,1], res.ca$col$coord[,2],lwd=2, col = "green")
```



Com podem veure a l'hora de l'execució tenim que el Job_admin, Job_management i factor_duration-(68,104] son els que mes destaquen en que no ens aporta cap mena d'informacio ja que es troba mes a prop del centre de gravetat, A partir de les taules de contingencia i els seus diferents perfils intentem observar si hi pot haver alguna relacio de dependencia entre els dos factors.

Eigenvalues and dominant axes analysis

En aquest subapartat realitzarem un estudi dels valors propis i dels eixos dominants per tal de determinar quantes dimensions tindrem en compte.

```
res.ca$eig

##        eigenvalue percentage of variance cumulative percentage of
variance
## dim 1 0.007050333              36.409534
36.40953
## dim 2 0.003847258              19.868124
56.27766
## dim 3 0.003249026              16.778713
73.05637
## dim 4 0.002161419              11.162064
84.21844
## dim 5 0.001718252               8.873445
93.09188
## dim 6 0.001041702               5.379590
98.47147
## dim 7 0.000295984               1.528529
100.00000
```

```r
#No es extraño que los eigenvalues sean pequeños, cojemos tantas dimensiones como las que tengan un valor propio > mitjana de este valor
mean(res.ca$eig[,1]) #Mean eigenvalue
```

```
## [1] 0.002766282
```

```r
#KAISER: take as many as dimensions as eigenvalue > mean eig
sum(res.ca$eig[,1]) #Total inertia, contra mas grande hay mas relacion entre las variables
```

```
## [1] 0.01936397
```

```r
#Rows
res.ca$row
```

```
## $coord
##                          Dim 1        Dim 2        Dim 3        Dim 4
## Job_admin.        -0.004186212  0.007701902 -0.028673409 -0.002854957
## Job_blue-collar   -0.069096677  0.033980063  0.012824475 -0.012061634
## Job_entrepreneur  -0.157069320 -0.172777310  0.095319234  0.073797366
## Job_housemaid      0.109639754  0.043116843  0.011457101  0.159644423
## Job_management     0.043596504  0.016129874  0.118496133 -0.013785385
## Job_retired       -0.064052069  0.108786121 -0.065965837  0.053120289
## Job_self-employed  0.050005969 -0.037996065 -0.208308255  0.003606401
## Job_services      -0.004690390 -0.049982823 -0.007662952 -0.096663163
## Job_student       -0.261854900 -0.014852099  0.006879286  0.082853328
## Job_technician     0.132101028  0.014640019  0.023566514  0.012316894
## Job_unemployed     0.066308261 -0.260754891 -0.065825305  0.068094425
## Job_unknown        0.125895275 -0.168760946  0.041355718 -0.024777522
##                          Dim 5
## Job_admin.         0.000286884
## Job_blue-collar    0.001586189
## Job_entrepreneur   0.021690042
## Job_housemaid      0.017201430
## Job_management    -0.044076180
## Job_retired       -0.077827955
## Job_self-employed  0.049353299
## Job_services      -0.007967764
## Job_student        0.094554874
## Job_technician     0.019815606
## Job_unemployed    -0.149509980
## Job_unknown        0.237538144
##
## $contrib
##                        Dim 1      Dim 2       Dim 3       Dim 4
## Job_admin.        0.06538166  0.4055718  6.65623555  0.09919351
## Job_blue-collar  15.66306072  6.9417492  1.17084112  1.55684451
## Job_entrepreneur 11.31980610 25.1008208  9.04635891  8.15095688
## Job_housemaid     4.34353103  1.2310026  0.10292308 30.03896341
## Job_management    1.88043659  0.4717106 30.14534050  0.61328707
## Job_retired       2.42364957 12.8117579  5.57825188  5.43744611
```

```
## Job_self-employed  1.08999261  1.1532285 41.04396339  0.01849262
## Job_services       0.02984114  6.2100805  0.17284073 41.34186280
## Job_student       20.64652601  0.1217193  0.03092208  6.74242469
## Job_technician    39.23419417  0.8830675  2.70956455  1.11256497
## Job_unemployed     1.34913477 38.2334270  2.88510940  4.64102364
## Job_unknown        1.95444563  6.4358644  0.45764881  0.24693979
##                         Dim 5
## Job_admin.         0.001259937
## Job_blue-collar    0.033868409
## Job_entrepreneur   0.885727032
## Job_housemaid      0.438691050
## Job_management     7.886532880
## Job_retired       14.682417960
## Job_self-employed  4.356473625
## Job_services       0.353340345
## Job_student       11.046285370
## Job_technician     3.622345822
## Job_unemployed    28.143834431
## Job_unknown       28.549223139
##
## $cos2
##                        Dim 1       Dim 2        Dim 3        Dim 4
## Job_admin.        0.016594367 0.056171271 0.7785329044 0.0077182245
## Job_blue-collar   0.739280414 0.178790006 0.0254667819 0.0225271988
## Job_entrepreneur  0.315537130 0.381804603 0.1162060750 0.0696545455
## Job_housemaid     0.245681834 0.037995385 0.0026827883 0.5208881086
## Job_management    0.102696948 0.014057762 0.7586868817 0.0102681461
## Job_retired       0.130823433 0.377368975 0.1387577892 0.0899787729
## Job_self-employed 0.048798014 0.028173169 0.8467816202 0.0002538087
## Job_services      0.001699359 0.192978417 0.0045358573 0.7217539703
## Job_student       0.677204963 0.002178584 0.0004673965 0.0677982733
## Job_technician    0.916061394 0.011251113 0.0291543176 0.0079636948
## Job_unemployed    0.040898751 0.632469657 0.0403051494 0.0431318294
## Job_unknown       0.151106062 0.271523191 0.0163055017 0.0058530031
##                         Dim 5
## Job_admin.        7.793471e-05
## Job_blue-collar   3.895871e-04
## Job_entrepreneur  6.017118e-03
## Job_housemaid     6.047363e-03
## Job_management    1.049693e-01
## Job_retired       1.931481e-01
## Job_self-employed 4.753252e-02
## Job_services      4.903883e-03
## Job_student       8.830119e-02
## Job_technician    2.061232e-02
## Job_unemployed    2.079290e-01
## Job_unknown       5.379349e-01
##
## $inertia
##  [1] 0.0002777825 0.0014937470 0.0025292871 0.0012464633 0.0012909540
##  [6] 0.0013061525 0.0015748203 0.0012380548 0.0021494951 0.0030196024
## [11] 0.0023257064 0.0009119086
```

```r
#Tenemos las coordenadas, las contribuciones, el cos2 (indica la
calidad de la representacion de cada una de las categorias en el eje
que toca), inertia

#Cols
res.ca$col

## $coord
##                                      Dim 1         Dim 2        Dim 3
## factor_duration-[1,68]          0.09531274 -0.0902001831  0.004152345
## factor_duration-(68,104]       -0.02226995  0.0035790782 -0.085408752
## factor_duration-(104,139]       0.11616899  0.0575727078 -0.037797854
## factor_duration-(139,182]       0.06103176  0.0322551944 -0.020524250
## factor_duration-(182,236]       0.03929675 -0.0004978809  0.122488603
## factor_duration-(236,329]      -0.08742549  0.0184521454  0.038039160
## factor_duration-(329,504]      -0.10141238  0.0842994678  0.004928502
## factor_duration-(504,2.12e+03] -0.10067398 -0.1036350174 -0.023679053
##                                        Dim 4        Dim 5
## factor_duration-[1,68]         -0.0736844595 -0.023341450
## factor_duration-(68,104]       -0.0007433834  0.016809274
## factor_duration-(104,139]       0.0310640066  0.056862266
## factor_duration-(139,182]       0.0338717427 -0.080127776
## factor_duration-(182,236]       0.0143242316  0.033492169
## factor_duration-(236,329]       0.0421650872 -0.036944879
## factor_duration-(329,504]      -0.0803395322  0.007811121
## factor_duration-(504,2.12e+03]  0.0350721387  0.027175814
##
## $contrib
##                                    Dim 1        Dim 2       Dim 3
## factor_duration-[1,68]         16.386601 2.689429e+01  0.06748859
## factor_duration-(68,104]        0.886059 4.193966e-02 28.28039945
## factor_duration-(104,139]      23.684714 1.066054e+01  5.44099668
## factor_duration-(139,182]       6.622772 3.389889e+00  1.62524571
## factor_duration-(182,236]       2.692484 7.920435e-04 56.76592066
## factor_duration-(236,329]      13.567602 1.107590e+00  5.57372088
## factor_duration-(329,504]      18.226645 2.307983e+01  0.09341381
## factor_duration-(504,2.12e+03] 17.933124 3.482513e+01  2.15281423
##                                      Dim 4      Dim 5
## factor_duration-[1,68]         31.94547451  4.0324168
## factor_duration-(68,104]        0.00322048  2.0713099
## factor_duration-(104,139]       5.52424913 23.2840689
## factor_duration-(139,182]       6.65386009 46.8400112
## factor_duration-(182,236]       1.16695240  8.0250777
## factor_duration-(236,329]      10.29445944  9.9416456
## factor_duration-(329,504]      37.31246714  0.4436845
## factor_duration-(504,2.12e+03]  7.09931680  5.3617852
##
## $cos2
##                                     Dim 1        Dim 2        Dim 3
## factor_duration-[1,68]         0.38193087 3.420563e-01 0.0007248861
## factor_duration-(68,104]       0.05170872 1.335574e-03 0.7605543115
```

```
## factor_duration-(104,139]      0.58668609 1.440982e-01 0.0621097313
## factor_duration-(139,182]      0.25497352 7.121682e-02 0.0288348615
## factor_duration-(182,236]      0.08321936 1.335863e-05 0.8085417008
## factor_duration-(236,329]      0.46736782 2.081979e-02 0.0884798704
## factor_duration-(329,504]      0.42099659 2.909017e-01 0.0009943206
## factor_duration-(504,2.12e+03] 0.41139957 4.359557e-01 0.0227592517
##                                       Dim 4        Dim 5
## factor_duration-[1,68]         2.282625e-01 0.022905431
## factor_duration-(68,104]       5.761707e-05 0.029459366
## factor_duration-(104,139]      4.195080e-02 0.140563863
## factor_duration-(139,182]      7.853412e-02 0.439490460
## factor_duration-(182,236]      1.105742e-02 0.060450181
## factor_duration-(236,329]      1.087148e-01 0.083462456
## factor_duration-(329,504]      2.642136e-01 0.002497602
## factor_duration-(504,2.12e+03] 4.992911e-02 0.029977434
##
## $inertia
## [1] 0.003024919 0.001208115 0.002846243 0.001831278 0.002281069
0.002046699
## [7] 0.003052374 0.003073277

#Durada mes curta es la que te mes contribucio!

#Phi2 = Intensity of the association Chisq/nobservations
sum(res.ca$eig[,1]) #Total inertia = Phi2

## [1] 0.01936397

chisq.test(table(df$job, df$factor_duration))

##
##  Pearson's Chi-squared test
##
## data:  table(df$job, df$factor_duration)
## X-squared = 95.774, df = 77, p-value = 0.07247

#95.774/4946 porque son las observaciones
```

————— DELIVERABLE 3 —————-

Model construction only with numeric explanatory variables

Multivariant Data Analysis

Ara el que farem serà analitzar quines són les variables numèriques més relacionades amb el nostre target duration, per tal de decidir quines d'aquestes utilitzarem en la construcció dels diferents models fins trobar l'òptim.

```r
#En vars_model també tenim la variable "duration" perquè és necessari per poder veure les més relacionades amb aquesta
vars_model<-names(df)[c(1,11:14,16:20)]; vars_model
```

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

```r
# condes(df[,vars_model],which(vars_model == "duration"))
```

A partir d'executar la comanda "condes" podem veure que les variables més relacionades són previous, nr.employed, campaign i pdays, tot i que la correlació que presenten és molt baixa i poc significativa. Tot i així les podem considerar com a candidates a formar part de la construcció del nostre model.

Model Construction

A partir de tot l'anàlisi realitzat fins ara, començarem la construcció dels models, partint d'un model més complexe de totes les variables numèriques. Realitzarem diferents anàlisis per a cada model fins a trobar el model més adient o òptim a la nostra situació o joc de dades.

Initial modelling

```r
names(df)
```

```
##  [1] "age"                 "job"
##  [3] "marital"             "education"
##  [5] "default"             "housing"
##  [7] "loan"                "contact"
##  [9] "month"               "day_of_week"
## [11] "duration"            "campaign"
## [13] "pdays"               "previous"
## [15] "poutcome"            "emp.var.rate"
## [17] "cons.price.idx"      "cons.conf.idx"
## [19] "euribor3m"           "nr.employed"
## [21] "y"                   "missings_indiv"
## [23] "errors_indiv"        "outliers_indiv"
## [25] "season"              "factor_age"
## [27] "factor_duration"     "factor_campaign"
## [29] "factor_Pdays"        "factor_Previous"
## [31] "factor_emp.var.rate" "factor_cons.price.idx"
## [33] "factor_cons.conf.idx" "factor_euribor3m"
## [35] "factor_nr.employed"  "CLUSTER"
## [37] "f.CLUSTER"
```

```
#Las variables socioeconomicas estan relacionadas entre ellas, pero no
tienen nada que ver con el target
#vars_exp<-names(df)[c(1,12:14,16:20)]; vars_exp

vars_conaux #numèriques = vars_exp
```

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

```
#vars_con_aux2 #numeriques (sense age) que es la que utilitzem!
condes(df,11)
```

```
## $quanti
##                correlation      p.value
## previous        0.02859224 4.435374e-02
## errors_indiv   -0.03476735 1.447588e-02
## nr.employed    -0.03619203 1.091224e-02
## CLUSTER        -0.04004368 4.853468e-03
## campaign       -0.04179341 3.284450e-03
## pdays          -0.06147234 1.516945e-05
## missings_indiv -0.07328498 2.474678e-07
##
## $quali
##                                R2       p.value
## factor_duration       0.8271873066  0.000000e+00
## y                     0.1863696068 9.891372e-224
## factor_Pdays          0.0051824450  4.017238e-07
## poutcome              0.0041874670  3.132625e-05
## f.CLUSTER             0.0061553592  3.146859e-05
## month                 0.0073478185  3.327154e-05
## factor_cons.price.idx 0.0039803615  5.696640e-04
## factor_Previous       0.0019228074  2.038492e-03
## day_of_week           0.0029955473  5.075577e-03
## factor_cons.conf.idx  0.0026002247  1.194404e-02
## contact               0.0011105265  1.909343e-02
## default               0.0009897216  2.693284e-02
## factor_campaign       0.0013152237  3.866909e-02
##
## $category
##                                    Estimate       p.value
## factor_duration-(504,2.12e+03]    547.162252  0.000000e+00
## Y_yes                             169.675531 9.891372e-224
## factor_duration-(329,504]         138.462468  3.985182e-48
```

```
## factor_Pdays-[0,15]                      49.355073  4.017238e-07
## CLUSTER-4                                82.017790  5.318613e-06
## Poutcome_success                         62.641078  7.933875e-06
## factor_cons.price.idx-(93.4,93.9]        27.117765  2.010384e-04
## Month_jul                                12.946601  2.986551e-04
## factor_Previous-(1,5]                    34.966136  2.038492e-03
## Contact_cellular                          8.850090  1.909343e-02
## Default_no                                9.913335  2.693284e-02
## Month_dec                               104.090396  2.868142e-02
## Day_of_week_tue                          14.917687  4.872420e-02
## Education_illiterate                    178.585152  4.932974e-02
## CLUSTER-7                               -37.598946  4.049876e-02
## Education_university.degree             -38.308971  3.857651e-02
## factor_cons.conf.idx-(-36.4,-29.8]      -13.574401  3.768483e-02
## CLUSTER-5                               -20.182210  3.375761e-02
## factor_cons.conf.idx-(-42,-40.3]        -17.926886  2.695593e-02
## Default_unknown                          -9.913335  2.693284e-02
## Contact_telephone                        -8.850090  1.909343e-02
## Month_jun                               -37.404273  1.736971e-02
## factor_campaign-(3,14]                  -16.741883  1.148865e-02
## Job_technician                          -25.341033  1.106827e-02
## Day_of_week_mon                         -19.239047  7.577039e-03
## Month_aug                               -39.248662  5.073298e-03
## factor_cons.price.idx-(93,93.4]         -19.809889  2.312144e-03
## factor_Previous-[0,1]                   -34.966136  2.038492e-03
## factor_Pdays-(15,17]                    -49.355073  4.017238e-07
## factor_duration-(182,236]               -56.414720  8.764699e-09
## factor_duration-(139,182]              -103.067426  8.297196e-27
## factor_duration-(104,139]              -141.910732  3.245807e-49
## factor_duration-(68,104]               -177.221056  2.195363e-78
## factor_duration-[1,68]                 -222.636796 8.250905e-127
## Y_no                                   -169.675531 9.891372e-224
```

```r
m1<-lm(duration~previous+euribor3m+campaign+pdays+nr.employed,data=df)
#summary(m1)
Anova(m1)
```

```
## Anova Table (Type II tests)
##
## Response: duration
##                Sum Sq   Df F value    Pr(>F)
## previous        69540    1  1.0663 0.3018273
## euribor3m      393980    1  6.0413 0.0140094 *
```

```
## campaign       441217    1  6.7656 0.0093209 **
## pdays          726966    1 11.1473 0.0008478 ***
## nr.employed    478090    1  7.3310 0.0068008 **
## Residuals   322161286 4940
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Inferential criteria o Bayesian info criteria
# Remove non significant variables

#Les variables que sobran son las que tienen un pvalor por encima del
5%
#Aqui se ponen las que tengan un p valor menor que 5
```

Veiem que aquest model i segurament tots els que realitzarem amb el target numèric tenen una explicabilitat molt baixa (menys del 0.005 del % de les dades),i per tant serà díficil obtenir dades rellevants. Tot i així procedirem a fer un procés metadològic de "Modeling" del target numèric.

Ara el que farem és fer un segon model i només posaré les variables que tenen un p-valor per sota d'un 5%, llavors em queda el mateix model que m1 però sense les variables previous.

```
m2<-lm(duration~euribor3m+campaign+pdays+nr.employed,data=df)
summary(m2)

##
## Call:
## lm(formula = duration ~ euribor3m + campaign + pdays + nr.employed,
##     data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -305.24 -158.09  -83.76   65.34 1858.59
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 2419.0524   788.7005   3.067  0.00217 **
## euribor3m     15.9367     6.5155   2.446  0.01448 *
## campaign      -4.7524     1.8455  -2.575  0.01005 *
## pdays         -6.2056     1.9320  -3.212  0.00133 **
## nr.employed   -0.4075     0.1584  -2.573  0.01012 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 255.4 on 4941 degrees of freedom
```

```
## Multiple R-squared:  0.006577,   Adjusted R-squared:  0.005773
## F-statistic: 8.178 on 4 and 4941 DF,  p-value: 1.434e-06
```

```
Anova(m2)
```

```
## Anova Table (Type II tests)
##
## Response: duration
##                Sum Sq   Df F value   Pr(>F)
## euribor3m      390168    1  5.9827 0.014481 *
## campaign       432446    1  6.6310 0.010051 *
## pdays          672831    1 10.3170 0.001327 **
## nr.employed    431626    1  6.6184 0.010122 *
## Residuals   322230826 4941
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#I ara el que farem serà un vif (variance inflation factor) per veure
les variables explicatives del model que estan correlacionades
vif(m2)
```

```
##   euribor3m    campaign       pdays nr.employed
##    9.620996    1.016309    1.168931   10.105172
```

Ara en el nostre tercer model el que farem és que quan executem el vif veiem que tenim les variables nr.employed i euribor3m amb un vif > 3, llavors això no és vàlid, perquè inflarà la variança de la nostra mostra. Llavors primer el que fem és eliminar nr.employed y després en el model número 4 eliminarem euribor3m també per veure quin és el que té una millor explicabilitat.

```
m3<-lm(duration~campaign+pdays+euribor3m,data=df)
summary(m3)
```

```
##
## Call:
## lm(formula = duration ~ campaign + pdays + euribor3m, data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -319.98 -159.03  -83.08   67.50 1854.92
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  391.323     28.316  13.820  < 2e-16 ***
## campaign      -4.967      1.845  -2.692  0.00712 **
## pdays         -7.505      1.866  -4.023 5.84e-05 ***
```

```
## euribor3m      0.162      2.204   0.074  0.94141
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 255.5 on 4942 degrees of freedom
## Multiple R-squared:  0.005247,   Adjusted R-squared:  0.004643
## F-statistic: 8.688 on 3 and 4942 DF,  p-value: 9.541e-06
```

```
m4<-lm(duration~campaign+pdays+nr.employed,data=df)
summary(m4)
```

```
##
## Call:
## lm(formula = duration ~ campaign + pdays + nr.employed, data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -316.92 -158.62  -83.03   66.73 1857.76
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 604.23452  267.59919   2.258 0.023990 *
## campaign     -4.78623    1.84642  -2.592 0.009565 **
## pdays        -6.93604    1.90973  -3.632 0.000284 ***
## nr.employed  -0.04289    0.05359  -0.800 0.423582
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 255.5 on 4942 degrees of freedom
## Multiple R-squared:  0.005374,   Adjusted R-squared:  0.004771
## F-statistic: 8.901 on 3 and 4942 DF,  p-value: 7.024e-06
```

```
m5<-step(m1, k=log(nrow(df)))
```

```
## Start:  AIC=54873.63
## duration ~ previous + euribor3m + campaign + pdays + nr.employed
##
##               Df Sum of Sq       RSS   AIC
## - previous     1     69540 322230826 54866
## - euribor3m    1    393980 322555266 54871
## - campaign     1    441217 322602503 54872
## - nr.employed  1    478090 322639376 54872
## <none>                     322161286 54874
## - pdays        1    726966 322888252 54876
```

```
##
## Step:  AIC=54866.19
## duration ~ euribor3m + campaign + pdays + nr.employed
##
##                Df Sum of Sq       RSS   AIC
## - euribor3m    1    390168 322620995 54864
## - nr.employed  1    431626 322662452 54864
## - campaign     1    432446 322663273 54864
## <none>                     322230826 54866
## - pdays        1    672831 322903657 54868
##
## Step:  AIC=54863.67
## duration ~ campaign + pdays + nr.employed
##
##                Df Sum of Sq       RSS   AIC
## - nr.employed  1     41810 322662805 54856
## - campaign     1    438650 323059645 54862
## <none>                     322620995 54864
## - pdays        1    861130 323482124 54868
##
## Step:  AIC=54855.81
## duration ~ campaign + pdays
##
##             Df Sum of Sq       RSS   AIC
## - campaign  1    475707 323138512 54855
## <none>                  322662805 54856
## - pdays     1   1134867 323797672 54865
##
## Step:  AIC=54854.59
## duration ~ pdays
##
##          Df Sum of Sq       RSS   AIC
## <none>               323138512 54855
## - pdays  1   1225723 324364235 54865
```

```r
#vif(m5) # Dóna error perquè tenim menys de dos variables!

m6<-lm(duration~campaign+pdays,data=df)
summary(m6)
```

```
##
## Call:
## lm(formula = duration ~ campaign + pdays, data = df)
```

```
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -319.93 -158.86  -82.90   67.12 1855.14
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  391.279     28.307   13.82  < 2e-16 ***
## campaign      -4.953      1.835   -2.70  0.00697 **
## pdays         -7.467      1.791   -4.17  3.1e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 255.5 on 4943 degrees of freedom
## Multiple R-squared:  0.005245,   Adjusted R-squared:  0.004843
## F-statistic: 13.03 on 2 and 4943 DF,  p-value: 2.264e-06
```

```r
vif(m6)
```

```
## campaign    pdays
## 1.003368 1.003368
```

Amb aquesta sortida el que podem comprobar és que les variables que són més significatives són campaign i pdays, però si fem el step veiem que la millor és pdays, però un model amb només una variable és molt poc i no explicaria el suficient, llavors agafem campaign i pdays.

Quan executem el vif en el nostre model definitiu veiem que les dos variables que tenim tenen un vif < 3, llavors això vol dir que el nostre model és correcte i que anem en bona direcció.

Transforming variables

Ara el que farem serà una transformació de les nostres variables per veure si podem explicar més en el nostre model.

```r
m7 <- lm(log(duration)~previous+campaign+nr.employed+pdays,data=df)
Anova(m7)
```

```
## Anova Table (Type II tests)
##
## Response: log(duration)
##             Sum Sq   Df  F value   Pr(>F)
## previous       0.1    1   0.0688   0.7931
## campaign      93.7    1 108.1953 < 2e-16 ***
## nr.employed    0.1    1   0.1424   0.7060
## pdays         17.0    1  19.5908 9.8e-06 ***
## Residuals   4277.7 4941
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
m8<-lm (log(duration)~campaign+pdays,data=df)
summary(m8)
```

```
##
## Call:
## lm(formula = log(duration) ~ campaign + pdays, data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.2586 -0.5401 -0.0011  0.6236  2.7295
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  5.88173    0.10307  57.066  < 2e-16 ***
## campaign    -0.06979    0.00668 -10.447  < 2e-16 ***
## pdays       -0.03458    0.00652  -5.303 1.19e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9303 on 4943 degrees of freedom
## Multiple R-squared:  0.02834,    Adjusted R-squared:  0.02795
## F-statistic: 72.09 on 2 and 4943 DF,  p-value: < 2.2e-16
```

```r
#Polinomic regression
m9 <- lm(log(duration)~poly(campaign,2)+poly(pdays,2), data=df)
summary(m9)
```

```
##
## Call:
## lm(formula = log(duration) ~ poly(campaign, 2) + poly(pdays,
##     2), data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.2184 -0.5456  0.0019  0.6134  2.8100
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)         5.17462    0.01319 392.362  < 2e-16 ***
## poly(campaign, 2)1 -9.69878    0.92913 -10.439  < 2e-16 ***
## poly(campaign, 2)2 -4.30252    0.92758  -4.638  3.6e-06 ***
```

```
## poly(pdays, 2)1    -4.99650    0.92914  -5.378  7.9e-08 ***
## poly(pdays, 2)2    -2.94158    0.92757  -3.171  0.00153 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9275 on 4941 degrees of freedom
## Multiple R-squared:  0.03452,    Adjusted R-squared:  0.03374
## F-statistic: 44.16 on 4 and 4941 DF,  p-value: < 2.2e-16
```

```
Anova(m9)
```

```
## Anova Table (Type II tests)
##
## Response: log(duration)
##                     Sum Sq   Df F value    Pr(>F)
## poly(campaign, 2)  112.3    2  65.273 < 2.2e-16 ***
## poly(pdays, 2)      33.5    2  19.477 3.755e-09 ***
## Residuals          4250.6 4941
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# marginalModelPlots(m9)
```

Com podem observar les nostres variables més significatives del nostre model són campaign y pdays, llavors com a conclusió el nostre model será m8 que té una explicabilitat d'un 2,8%. Però quan fem la transformació logarítmica veiem que té una mica més d'explicabilitat el nostre model, perquè el Multiple R-squared és major, veiem que tenim una explicabilitat d'un 3,4%.

La diferència és sumament petita i fent les diferents execucions que venen a continuació hem vist que no hi ha cap tipus de diferència, com era correcte agafar un d'aquests dos models vam optar per agafar el m8 en comptes del m9. Si que és veritat que hauriem de treballar amb la cuadràtica, però vam seguir el nostre estudi sense ell, ja que no hi havia molta diferència.

CONCLUSIÓ: El Multiple R-squared (variabilitat de les dades) és molt petit i això vol dir que el nostre target és complicat d'interpretar, és a dir, no podem explicar el nostre target (duration, en aquest cas) amb les variables que tenim.

Adding factors as explanatory variables

Ara el que farem és afegir variables factors com a variables explicatives, llavors hem de trobar les que poden ser més significatives i ara a continuació farem aquest estudi.

```
vars_dis2<-names(df)[c(2:10,15,25,26:35)];vars_dis2
```

```
##  [1] "job"                       "marital"
##  [3] "education"                 "default"
##  [5] "housing"                   "loan"
```

```
##  [7] "contact"                "month"
##  [9] "day_of_week"            "poutcome"
## [11] "season"                 "factor_age"
## [13] "factor_duration"        "factor_campaign"
## [15] "factor_Pdays"           "factor_Previous"
## [17] "factor_emp.var.rate"    "factor_cons.price.idx"
## [19] "factor_cons.conf.idx"   "factor_euribor3m"
## [21] "factor_nr.employed"
```

```
# Agafem el nostre millor model que tenim fins ara
m10<-step(m8,k=log(nrow(df)))
```

```
## Start:  AIC=-692.34
## log(duration) ~ campaign + pdays
##
##             Df Sum of Sq    RSS     AIC
## <none>                   4277.8 -692.34
## - pdays      1    24.342 4302.1 -672.78
## - campaign   1    94.458 4372.3 -592.82
```

```
# maux4<-step(m9,k=log(nrow(df))) Con el modelo que usa poly!

condes(df[,c("duration",vars_dis2)],1,proba = 0.01)
```

```
## $quali
##                                R2      p.value
## factor_duration       0.827187307 0.000000e+00
## factor_Pdays          0.005182445 4.017238e-07
## poutcome              0.004187467 3.132625e-05
## month                 0.007347818 3.327154e-05
## factor_cons.price.idx 0.003980361 5.696640e-04
## factor_Previous       0.001922807 2.038492e-03
## day_of_week           0.002995547 5.075577e-03
##
## $category
##                                    Estimate       p.value
## factor_duration-(504,2.12e+03]    547.16225  0.000000e+00
## factor_duration-(329,504]         138.46247  3.985182e-48
## factor_Pdays-[0,15]                49.35507  4.017238e-07
## Poutcome_success                   62.64108  7.933875e-06
## factor_cons.price.idx-(93.4,93.9]  27.11777  2.010384e-04
## Month_jul                          12.94660  2.986551e-04
## factor_Previous-(1,5]              34.96614  2.038492e-03
## Day_of_week_mon                   -19.23905  7.577039e-03
```

```
## Month_aug                               -39.24866  5.073298e-03
## factor_cons.price.idx-(93,93.4]         -19.80989  2.312144e-03
## factor_Previous-[0,1]                   -34.96614  2.038492e-03
## factor_Pdays-(15,17]                    -49.35507  4.017238e-07
## factor_duration-(182,236]               -56.41472  8.764699e-09
## factor_duration-(139,182]              -103.06743  8.297196e-27
## factor_duration-(104,139]              -141.91073  3.245807e-49
## factor_duration-(68,104]               -177.22106  2.195363e-78
## factor_duration-[1,68]                 -222.63680 8.250905e-127
```

Després de l'execució anterior el que hem vist són les variables més correlacionades amb el nostre model que són aquelles que tenen un p-valor << 0.01. Aquestes variables són: factor_Pdays+ poutcome+month+factor_cons.price.idx+ factor_Previous+day_of_week

Llavors ara estudiarem el cas, és a dir, al nostre model li afegim aquests factors.

```
#Avoid numeric and factors simultaneously for the same concept
m11<-
lm(log(duration)~campaign+pdays+poutcome+month+factor_cons.price.idx+
factor_Previous+day_of_week,data = df)
summary(m11) #Take a look to NA estimates

##
## Call:
## lm(formula = log(duration) ~ campaign + pdays + poutcome + month +
##     factor_cons.price.idx + factor_Previous + day_of_week, data =
df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.1845 -0.5552 -0.0061  0.6031  2.6685
##
## Coefficients:
##                                                          Estimate
## (Intercept)                                              5.406988
## campaign                                                -0.069743
## pdays                                                    0.002901
## poutcomePoutcome_nonexistent                             0.009651
## poutcomePoutcome_success                                 0.378327
## monthMonth_aug                                          -0.212340
## monthMonth_dec                                           0.141391
## monthMonth_jul                                          -0.187828
## monthMonth_jun                                          -0.351201
## monthMonth_mar                                          -0.185593
## monthMonth_may                                          -0.345035
```

```
## monthMonth_nov                                           -0.269914
## monthMonth_oct                                           -0.228642
## monthMonth_sep                                           -0.352472
## factor_cons.price.idxfactor_cons.price.idx-(93,93.4]     -0.110456
## factor_cons.price.idxfactor_cons.price.idx-(93.4,93.9]    0.088951
## factor_cons.price.idxfactor_cons.price.idx-(93.9,94]      0.219283
## factor_cons.price.idxfactor_cons.price.idx-(94,94.8]      0.002831
## factor_Previousfactor_Previous-(1,5]                      0.188940
## day_of_weekDay_of_week_mon                                0.060226
## day_of_weekDay_of_week_thu                                0.085789
## day_of_weekDay_of_week_tue                                0.211005
## day_of_weekDay_of_week_wed                                0.150490
##                                                          Std. Error t
value
## (Intercept)                                                 0.306736
17.627
## campaign                                                    0.006710
-10.393
## pdays                                                       0.018666
0.155
## poutcomePoutcome_nonexistent                                0.049726
0.194
## poutcomePoutcome_success                                    0.207580
1.823
## monthMonth_aug                                              0.066472
-3.194
## monthMonth_dec                                              0.214603
0.659
## monthMonth_jul                                              0.114380
-1.642
## monthMonth_jun                                              0.105853
-3.318
## monthMonth_mar                                              0.130310
-1.424
## monthMonth_may                                              0.092767
-3.719
## monthMonth_nov                                              0.069135
-3.904
## monthMonth_oct                                              0.130712
-1.749
## monthMonth_sep                                              0.140611
-2.507
## factor_cons.price.idxfactor_cons.price.idx-(93,93.4]        0.070455
-1.568
## factor_cons.price.idxfactor_cons.price.idx-(93.4,93.9]      0.096588
```

```
0.921
## factor_cons.price.idxfactor_cons.price.idx-(93.9,94]     0.049133
4.463
## factor_cons.price.idxfactor_cons.price.idx-(94,94.8]     0.074668
0.038
## factor_Previousfactor_Previous-(1,5]                     0.098283
1.922
## day_of_weekDay_of_week_mon                               0.041383
1.455
## day_of_weekDay_of_week_thu                               0.041253
2.080
## day_of_weekDay_of_week_tue                               0.042899
4.919
## day_of_weekDay_of_week_wed                               0.041820
3.598
##                                                        Pr(>|t|)
## (Intercept)                                             < 2e-16 ***
## campaign                                                < 2e-16 ***
## pdays                                                  0.876480
## poutcomePoutcome_nonexistent                           0.846126
## poutcomePoutcome_success                               0.068431 .
## monthMonth_aug                                         0.001410 **
## monthMonth_dec                                         0.510022
## monthMonth_jul                                         0.100625
## monthMonth_jun                                         0.000914 ***
## monthMonth_mar                                         0.154438
## monthMonth_may                                         0.000202 ***
## monthMonth_nov                                         9.58e-05 ***
## monthMonth_oct                                         0.080316 .
## monthMonth_sep                                         0.012218 *
## factor_cons.price.idxfactor_cons.price.idx-(93,93.4]   0.117007
## factor_cons.price.idxfactor_cons.price.idx-(93.4,93.9] 0.357133
## factor_cons.price.idxfactor_cons.price.idx-(93.9,94]   8.26e-06 ***
## factor_cons.price.idxfactor_cons.price.idx-(94,94.8]   0.969754
## factor_Previousfactor_Previous-(1,5]                   0.054612 .
## day_of_weekDay_of_week_mon                             0.145640
## day_of_weekDay_of_week_thu                             0.037615 *
## day_of_weekDay_of_week_tue                             9.00e-07 ***
## day_of_weekDay_of_week_wed                             0.000323 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9212 on 4923 degrees of freedom
```

```
## Multiple R-squared:  0.05104,    Adjusted R-squared:  0.0468
## F-statistic: 12.03 on 22 and 4923 DF,  p-value: < 2.2e-16
```

```
#Com no ha sortit cap NA, de moment no tenim cap variable
problemàtica!


Anova (m11)
```

```
## Anova Table (Type II tests)
##
## Response: log(duration)
##                         Sum Sq   Df  F value    Pr(>F)
## campaign                  91.7    1 108.0209 < 2.2e-16 ***
## pdays                      0.0    1   0.0242  0.876480
## poutcome                   2.8    2   1.6624  0.189794
## month                     22.6    9   2.9525  0.001679 **
## factor_cons.price.idx     20.6    4   6.0598 7.335e-05 ***
## factor_Previous            3.1    1   3.6957  0.054612 .
## day_of_week               24.8    4   7.3018 7.367e-06 ***
## Residuals               4177.9 4923
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#Para limpiar! Efectes nets
#Poutcome és problemàtica perquè es 0.1 i les demés veiem que si que
són significatives!
```

A partir d'executar Anova(m11) podem veure quines són les variables significatives llavors agafem el nou model, que el que li hem tret és la variables poutcome i factor_Previous(encara que aquesta última es podria agafar també com a significativa, perquè hi ha un .).

Ara quan tenim el nostre model m8 amb els factors significatius corresponents el que hem de fer és veure si les nostres variables numèriques inicials del nostre model són més explicatives com a numèriques o com a factors.

```
#Our model
m12<-
lm(log(duration)~campaign+pdays+poutcome+month+factor_cons.price.idx+d
ay_of_week,data = df)
summary(m12)
```

```
##
## Call:
## lm(formula = log(duration) ~ campaign + pdays + poutcome + month +
```

```
##     factor_cons.price.idx + day_of_week, data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.2483 -0.5570 -0.0058  0.6015  2.6707
##
## Coefficients:
##                                                        Estimate
## (Intercept)                                            5.531569
## campaign                                              -0.069960
## pdays                                                 -0.003735
## poutcomePoutcome_nonexistent                          -0.013441
## poutcomePoutcome_success                               0.350904
## monthMonth_aug                                        -0.208718
## monthMonth_dec                                         0.163868
## monthMonth_jul                                        -0.193449
## monthMonth_jun                                        -0.370057
## monthMonth_mar                                        -0.185277
## monthMonth_may                                        -0.343337
## monthMonth_nov                                        -0.268959
## monthMonth_oct                                        -0.219786
## monthMonth_sep                                        -0.336518
## factor_cons.price.idxfactor_cons.price.idx-(93,93.4]   -0.110291
## factor_cons.price.idxfactor_cons.price.idx-(93.4,93.9]  0.099605
## factor_cons.price.idxfactor_cons.price.idx-(93.9,94]    0.221876
## factor_cons.price.idxfactor_cons.price.idx-(94,94.8]    0.030606
## day_of_weekDay_of_week_mon                             0.060586
## day_of_weekDay_of_week_thu                             0.086819
## day_of_weekDay_of_week_tue                             0.212060
## day_of_weekDay_of_week_wed                             0.152392
##                                                       Std. Error t value
## (Intercept)                                             0.299894  18.445
## campaign                                                0.006711 -10.424
## pdays                                                   0.018349  -0.204
## poutcomePoutcome_nonexistent                            0.048267  -0.278
## poutcomePoutcome_success                                0.207146   1.694
## monthMonth_aug                                          0.066463  -3.140
## monthMonth_dec                                          0.214343   0.765
## monthMonth_jul                                          0.114374  -1.691
## monthMonth_jun                                          0.105427  -3.510
## monthMonth_mar                                          0.130345  -1.421
## monthMonth_may                                          0.092788  -3.700
## monthMonth_nov                                          0.069152  -3.889
## monthMonth_oct                                          0.130666  -1.682
## monthMonth_sep                                          0.140404  -2.397
## factor_cons.price.idxfactor_cons.price.idx-(93,93.4]     0.070475  -1.565
## factor_cons.price.idxfactor_cons.price.idx-(93.4,93.9]   0.096455   1.033
## factor_cons.price.idxfactor_cons.price.idx-(93.9,94]     0.049128   4.516
## factor_cons.price.idxfactor_cons.price.idx-(94,94.8]     0.073276   0.418
## day_of_weekDay_of_week_mon                              0.041394   1.464
## day_of_weekDay_of_week_thu                              0.041260   2.104
## day_of_weekDay_of_week_tue                              0.042907   4.942
```

```
## day_of_weekDay_of_week_wed                                         0.041820   3.644
##                                                                  Pr(>|t|)
## (Intercept)                                                       < 2e-16 ***
## campaign                                                          < 2e-16 ***
## pdays                                                            0.838711
## poutcomePoutcome_nonexistent                                     0.780664
## poutcomePoutcome_success                                         0.090330 .
## monthMonth_aug                                                   0.001697 **
## monthMonth_dec                                                   0.444597
## monthMonth_jul                                                   0.090828 .
## monthMonth_jun                                                   0.000452 ***
## monthMonth_mar                                                   0.155254
## monthMonth_may                                                   0.000218 ***
## monthMonth_nov                                                   0.000102 ***
## monthMonth_oct                                                   0.092623 .
## monthMonth_sep                                                   0.016577 *
## factor_cons.price.idxfactor_cons.price.idx-(93,93.4]   0.117652
## factor_cons.price.idxfactor_cons.price.idx-(93.4,93.9] 0.301815
## factor_cons.price.idxfactor_cons.price.idx-(93.9,94]   6.44e-06 ***
## factor_cons.price.idxfactor_cons.price.idx-(94,94.8]   0.676204
## day_of_weekDay_of_week_mon                                       0.143350
## day_of_weekDay_of_week_thu                                       0.035414 *
## day_of_weekDay_of_week_tue                                       7.98e-07 ***
## day_of_weekDay_of_week_wed                                       0.000271 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9215 on 4924 degrees of freedom
## Multiple R-squared:  0.05032,    Adjusted R-squared:  0.04627
## F-statistic: 12.43 on 21 and 4924 DF,  p-value: < 2.2e-16

#marginalModelPlots(m12)

#par(mfrow=c(2,2))
#plot(m13)

#Estudi de campaign

# Decide wether campaign should be considered either numeric, or
factor (never both)
maux<-
lm(log(duration)~factor_campaign+pdays+month+factor_cons.price.idx+day
_of_week,data = df)



BIC(m12,maux) #Choose option with minimum BIC
```

```
##      df      BIC
## m12  23 13400.74
## maux 22 13420.62
```

```
#El BIC més petit es el recomanable
#La variable campaign numèrica m'explica més que factor_campaign
perquè el BIC de m12 és més petit que el de maux

# Estudi de pdays

maux2<-
lm(log(duration)~campaign+factor_Pdays+poutcome+month+factor_cons.pric
e.idx+day_of_week,data = df)
BIC(m12,maux2) #Choose option with minimum BIC, for me pdays as
numeric is not an option
```

```
##       df      BIC
## m12   23 13400.74
## maux2 23 13395.80
```

```
#El factor_Pdays m'explica més que la variable numèrica pdays perquè
el BIC de maux2 és més petir que el de m12

maux3<-
lm(log(duration)~factor_campaign+factor_Pdays+poutcome+month+factor_co
ns.price.idx+day_of_week,data = df)
BIC(m12,maux3)
```

```
##       df      BIC
## m12   23 13400.74
## maux3 24 13429.43
```

```
#Hi ha una millor explicabilitat en el maux2!

#Best solution:
m13<-
lm(log(duration)~campaign+factor_Pdays+poutcome+month+factor_cons.pric
e.idx+day_of_week,data = df)
```

Després del nostre estudi, el que podem veure o les conclusions que podem treure és que les nostres variables numèriques del model incial, campaign i pdays, és que campaign és més explicativa sent numèrica mentre que la variable pdays és més explicativa quan s'utilitza com a factor i això es pot comprovar amb la comanda "BIC".

És pot veure com en maux3 tenim un BIC més petit que en el nostre model m12, però si comprobem tots els models auxiliar veiem que el BIC més petit és el que ens dóna el model maux2.

```r
#Try to combine both criteria
Anova(m13) #Check significant variables
```

```
## Anova Table (Type II tests)
##
## Response: log(duration)
##                       Sum Sq   Df  F value    Pr(>F)
## campaign                91.8    1 108.2467 < 2.2e-16 ***
## factor_Pdays             4.2    1   4.9628  0.025943 *
## poutcome                 0.2    2   0.1296  0.878431
## month                   22.5    9   2.9462  0.001715 **
## factor_cons.price.idx   20.6    4   6.0794 7.075e-05 ***
## day_of_week             25.6    4   7.5441 4.692e-06 ***
## Residuals             4176.8 4924
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
m14<-step(m13,k=log(nrow(df))) #I priorize BIC criteria
```

```
## Start:  AIC=-648.84
## log(duration) ~ campaign + factor_Pdays + poutcome + month +
##     factor_cons.price.idx + day_of_week
##
##                         Df Sum of Sq    RSS     AIC
## - month                  9    22.492 4199.3 -698.84
## - poutcome               2     0.220 4177.1 -665.60
## - factor_cons.price.idx  4    20.628 4197.5 -658.50
## - day_of_week            4    25.597 4202.4 -652.65
## - factor_Pdays           1     4.210 4181.1 -652.37
## <none>                               4176.8 -648.84
## - campaign               1    91.822 4268.7 -549.80
##
## Step:  AIC=-698.84
## log(duration) ~ campaign + factor_Pdays + poutcome +
factor_cons.price.idx +
##     day_of_week
##
##                         Df Sum of Sq    RSS     AIC
## - poutcome               2     0.401 4199.7 -715.38
## - day_of_week            4    22.889 4222.2 -705.98
## - factor_Pdays           1     5.071 4204.4 -701.38
## <none>                               4199.3 -698.84
```

```
## - factor_cons.price.idx  4    43.631 4243.0 -681.74
## - campaign               1    94.896 4294.2 -596.82
##
## Step:  AIC=-715.38
## log(duration) ~ campaign + factor_Pdays + factor_cons.price.idx +
##     day_of_week
##
##                         Df Sum of Sq    RSS     AIC
## - day_of_week            4    22.803 4222.5 -722.62
## <none>                               4199.7 -715.38
## - factor_cons.price.idx  4    45.083 4244.8 -696.59
## - factor_Pdays           1    39.056 4238.8 -678.10
## - campaign               1    95.751 4295.5 -612.39
##
## Step:  AIC=-722.62
## log(duration) ~ campaign + factor_Pdays + factor_cons.price.idx
##
##                         Df Sum of Sq    RSS     AIC
## <none>                               4222.5 -722.62
## - factor_cons.price.idx  4    48.066 4270.6 -700.66
## - factor_Pdays           1    40.106 4262.7 -684.37
## - campaign               1   100.169 4322.7 -615.17
```

```r
summary(m14)
```

```
##
## Call:
## lm(formula = log(duration) ~ campaign + factor_Pdays +
factor_cons.price.idx,
##     data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.1686 -0.5522 -0.0012  0.6094  2.6940
##
## Coefficients:
##                                                      Estimate
## (Intercept)                                          5.746773
## campaign                                            -0.072224
## factor_Pdaysfactor_Pdays-(15,17]                    -0.491280
## factor_cons.price.idxfactor_cons.price.idx-(93,93.4]    0.004904
## factor_cons.price.idxfactor_cons.price.idx-(93.4,93.9]  0.219195
## factor_cons.price.idxfactor_cons.price.idx-(93.9,94]    0.189446
## factor_cons.price.idxfactor_cons.price.idx-(94,94.8]   -0.014655
```

```
##                                                        Std. Error t
value
## (Intercept)                                              0.072690
79.059
## campaign                                                 0.006672
-10.824
## factor_Pdaysfactor_Pdays-(15,17]                         0.071729
-6.849
## factor_cons.price.idxfactor_cons.price.idx-(93,93.4]     0.038153
0.129
## factor_cons.price.idxfactor_cons.price.idx-(93.4,93.9]   0.042427
5.166
## factor_cons.price.idxfactor_cons.price.idx-(93.9,94]     0.042045
4.506
## factor_cons.price.idxfactor_cons.price.idx-(94,94.8]     0.044780
-0.327
##                                                        Pr(>|t|)
## (Intercept)                                             < 2e-16 ***
## campaign                                                < 2e-16 ***
## factor_Pdaysfactor_Pdays-(15,17]                       8.34e-12 ***
## factor_cons.price.idxfactor_cons.price.idx-(93,93.4]      0.898
## factor_cons.price.idxfactor_cons.price.idx-(93.4,93.9] 2.48e-07 ***
## factor_cons.price.idxfactor_cons.price.idx-(93.9,94]   6.76e-06 ***
## factor_cons.price.idxfactor_cons.price.idx-(94,94.8]      0.743
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9246 on 4939 degrees of freedom
## Multiple R-squared:  0.04089,    Adjusted R-squared:  0.03973
## F-statistic:  35.1 on 6 and 4939 DF,  p-value: < 2.2e-16

#No tenim NA! -> PERFECTE!

#Anova(m13)

#m15<-
lm(log(duration)~campaign+factor_Pdays+factor_cons.price.idx+day_of_we
ek,data = df)
#summary(m15)
#Anova(m15)

#Ara volem saber els nivells que tenim
summary(df[,c("campaign", "factor_Pdays","factor_cons.price.idx")])
```

```
##     campaign                          factor_Pdays
##  Min.   : 1.000   factor_Pdays-[0,15] : 179
##  1st Qu.: 1.000   factor_Pdays-(15,17]:4767
##  Median : 2.000
##  Mean   : 2.389
##  3rd Qu.: 3.000
##  Max.   :14.000
##                         factor_cons.price.idx
##  factor_cons.price.idx-[92.2,93]  :1059
##  factor_cons.price.idx-(93,93.4]  :1359
##  factor_cons.price.idx-(93.4,93.9]: 889
##  factor_cons.price.idx-(93.9,94]  : 921
##  factor_cons.price.idx-(94,94.8]  : 718
##

#model.matrix(m14)
```

Per aconseguir la nostra matriu he agafat les variables més significatives que m'ha donat la comanda "step", podiem agafar també a partir de fer l'Anova del nostre model final que teníem fins el moment, però hem decidit agafar el model m14 per averiguar els nivells que tenim. Fent l'Anova tenim el model m15 que també posaria en el summary les variables "month" i "day_of_week", mentre que el model m14 ens dóna les variables que tenim en el summary. (Era correcte agafar qualsevol de les dues opcions).

Després de tot l'estudi hem vist que nosaltres hem fet un model i un estudi Variable Numèrica VS. Factor Mai es pot donar una interacció entre dos variables numèriques!

```
##Interaction: order 2 no more

m15<-
lm(log(duration)~(campaign+factor_Pdays+factor_cons.price.idx)^2,data
= df)
#summary(m15)
#coef(m15)

m16<-step(m15,k=log(nrow(df)))

## Start:  AIC=-726.41
## log(duration) ~ (campaign + factor_Pdays + factor_cons.price.idx)^2
##
##                                       Df Sum of Sq    RSS     AIC
## - factor_Pdays:factor_cons.price.idx  3     2.215 4163.9 -749.30
```

```
## - campaign:factor_Pdays              1     0.356 4162.0 -734.50
## <none>                                           4161.7 -726.41
## - campaign:factor_cons.price.idx      4    58.796 4220.5 -691.05
##
## Step:  AIC=-749.3
## log(duration) ~ campaign + factor_Pdays + factor_cons.price.idx +
##     campaign:factor_Pdays + campaign:factor_cons.price.idx
##
##                                  Df Sum of Sq    RSS     AIC
## - campaign:factor_Pdays           1     0.454 4164.3 -757.27
## <none>                                        4163.9 -749.30
## - campaign:factor_cons.price.idx  4    58.630 4222.5 -714.17
##
## Step:  AIC=-757.27
## log(duration) ~ campaign + factor_Pdays + factor_cons.price.idx +
##     campaign:factor_cons.price.idx
##
##                                  Df Sum of Sq    RSS     AIC
## <none>                                        4164.3 -757.27
## - campaign:factor_cons.price.idx  4    58.222 4222.5 -722.62
## - factor_Pdays                    1    36.552 4200.9 -722.55
```

```
#Anova(m16)
anova(m16,m15) #Fisher test - Priority to BIC criteria
```

```
## Analysis of Variance Table
##
## Model 1: log(duration) ~ campaign + factor_Pdays +
factor_cons.price.idx +
##     campaign:factor_cons.price.idx
## Model 2: log(duration) ~ (campaign + factor_Pdays +
factor_cons.price.idx)^2
##   Res.Df    RSS Df Sum of Sq      F Pr(>F)
## 1   4935 4164.3
## 2   4931 4161.7  4    2.6684 0.7904 0.5312
```

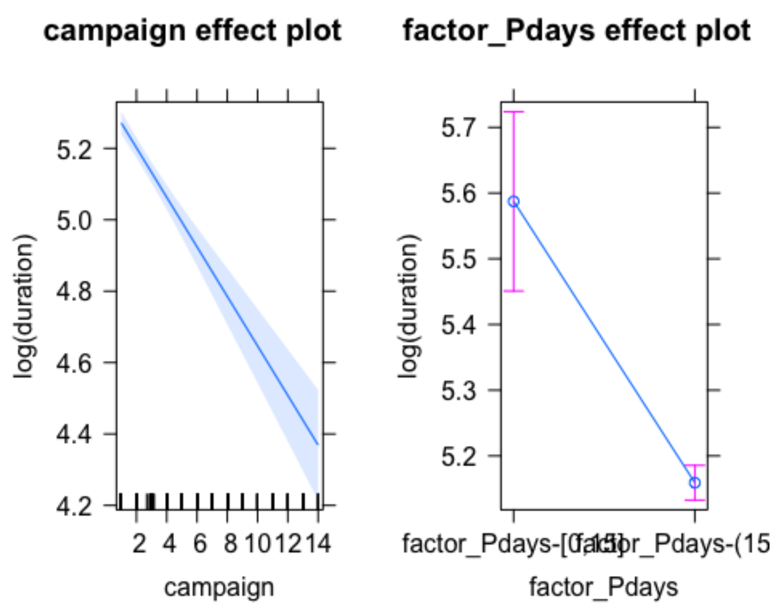
```
#Prioritzo el criteri step per agafar les redundants
```

Després d'aquesta execució podem veure segons el criteri de Fisher que els dos models no són equivalents, i això ho podem saber mirant el p-valor i és molt petit!

Interactions between numeric variables and factors

Model Additiu

```
#Exemple adhoc: Y ~ X+A
m17<-lm(log(duration)~campaign+factor_Pdays,data = df)
summary(m17)

##
## Call:
## lm(formula = log(duration) ~ campaign + factor_Pdays, data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.2555 -0.5417  0.0013  0.6222  2.7306
##
## Coefficients:
##                                    Estimate Std. Error t value Pr(>|
t|)
## (Intercept)                        5.753204   0.070467  81.644  <
2e-16 ***
## campaign                          -0.069384   0.006676 -10.394  <
2e-16 ***
## factor_Pdaysfactor_Pdays-(15,17] -0.428324   0.070898  -6.041
1.64e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9295 on 4943 degrees of freedom
## Multiple R-squared:  0.02997,    Adjusted R-squared:  0.02958
## F-statistic: 76.37 on 2 and 4943 DF,  p-value: < 2.2e-16

#Suport visual
# scatterplot(log(duration)~campaign|factor_Pdays,data=df)

#Interpretation of models through effects library
library(effects)
plot(allEffects(m17))
```



A l'eix de les ordenades tenim el logaritme de "duration" (eix vertical), campaign en aquest cas augmenta, és a dir, el número de campanyes implica una disminució en el logaritme de la durada = efecte negatiu Però el factor_Pdays calcula un valor de confianza segons els intervals que tenim i d'aquesta manera ens ayuda a interpretar el que tenim com a sortida

Llavors ara és hora de interpretar el nostre model: Y ~ X+A i = 1 (que és equivalent al factor_Pdays[0,15]) Yi = Y1 = 5.75-0.069X i = 2 (que és equivalent al factor_Pdays[15,17]) Yi = Y2 = (5.75-0,428)-0.069X

Model Interaccions

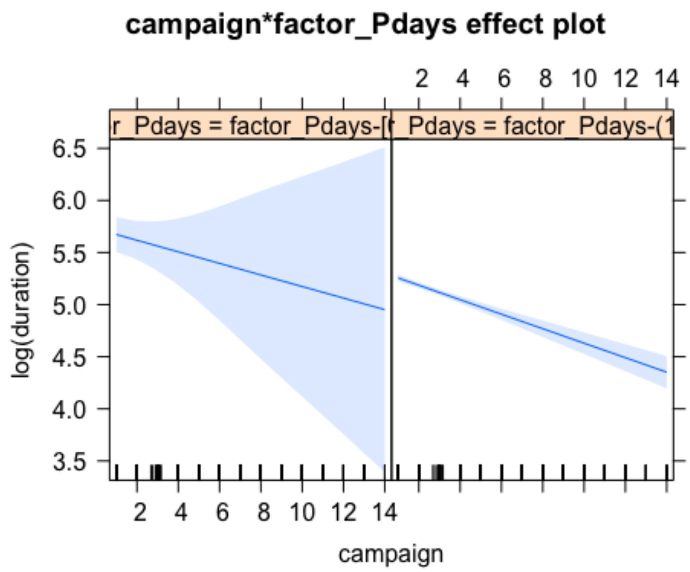
```
# Y ~ X*A (que és equivalent a X+A+A:X)
m18<-lm(log(duration)~campaign*factor_Pdays,data = df) #Concepte
d'interacció ara
summary(m18)

##
## Call:
## lm(formula = log(duration) ~ campaign * factor_Pdays, data = df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -5.2557 -0.5418  0.0014  0.6220  2.7311
##
## Coefficients:
##                                          Estimate Std. Error t
value
## (Intercept)                               5.72867    0.13376
42.828
```

```
## campaign                                      -0.05549    0.06474
-0.857
## factor_Pdaysfactor_Pdays-(15,17]         -0.40343    0.13541
-2.979
## campaign:factor_Pdaysfactor_Pdays-(15,17] -0.01405    0.06509
-0.216
##                                           Pr(>|t|)
## (Intercept)                                 <2e-16 ***
## campaign                                    0.3915
## factor_Pdaysfactor_Pdays-(15,17]            0.0029 **
## campaign:factor_Pdaysfactor_Pdays-(15,17]   0.8291
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9296 on 4942 degrees of freedom
## Multiple R-squared:  0.02998,    Adjusted R-squared:  0.0294
## F-statistic: 50.92 on 3 and 4942 DF,  p-value: < 2.2e-16
```

```
# Las interaccions son rellevants?
anova(m17,m18)
```

```
## Analysis of Variance Table
##
## Model 1: log(duration) ~ campaign + factor_Pdays
## Model 2: log(duration) ~ campaign * factor_Pdays
##   Res.Df    RSS Df Sum of Sq      F Pr(>F)
## 1   4943 4270.6
## 2   4942 4270.6  1  0.040249 0.0466 0.8291
```

```
#pvalue << 0.05 -> HO Rejected -> m18 X*A
#anova(petit, gran)

plot(allEffects(m18))
```




```
# Hi han moltes observacions influents per això hi ha tanta zona blau
clar, per l'interval de confiança que tenim!
```

També el que hem pogut comprobar és si les nostres interaccions són rellevants i amb la comanda "anova" fem com unaména de comparació per veure els dos models que tenim i poder treure com a conclusió que haure d'acceptar la hipòtesi nula, perquè el pvalor que surt és més gran que 0.05 (5%).

Ara és hora d'interpretar el nostre model: Y ~ X*A i = 1 (que és equivalent al factor_Pdays[0,15]) Yi = Y1 = 5.73-0.055X i = 2 (que és equivalent al factor_Pdays[15,17]) Yi = Y2 = (5.73-0.403)+(-0.055-0.014)X

Binary Regression

Explanatory numeric variables

Initial modelling

El que farem al començament de tot és dividir la modelització inicial (que tenim fins ara) en mostres de treball i mostres per testejar. En aquest apartat trobarem el "Eta2", que no el podem interpretar del tot bé ja que s'utilitza més en el MCA i no l'hem pogut fer a classe, però és com un coeficient de determinació quan tenim variables involucrades que són factors. A l'hora d'escollir el nostre millor model, és bona tècnica agafar com a referència també el "Estimate" que ens dóna el pes que se li dóna a cada variable en el model, llavors veiem quines són les més explicatives. I finalment, el “z value” és una aproximació del “Estimate/Std.Error”, valors de la normal estàndard.

```
# Divide into work and test samples

set.seed(123)
sam<-sample(1:nrow(df),0.75*nrow(df)) #Random sample without
replacement

dfw<-df[sam,]
dft<-df[-sam,]

# Numeric variables
vars_con

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

catdes(dfw[,c("y",vars_con)],1) #Numericas relacionadas

##
## Link between the cluster variable and the quantitative variables
## ================================================================
##                      Eta2       P-value
## duration       0.17671414 9.254637e-159
## nr.employed    0.14477732 4.417482e-128
## pdays          0.13675760 1.481722e-120
## euribor3m      0.10793163  4.600661e-94
## emp.var.rate   0.09974083  1.089368e-86
## previous       0.07808778  1.666707e-67
## cons.price.idx 0.01621864  6.967791e-15
## campaign       0.00438049  5.487012e-05
##
## Description of each cluster by quantitative variables
## =====================================================
## $Y_no
##                    v.test Mean in category Overall mean sd in
category
## nr.employed     23.169685     5177.7302797 5.167214e+03
64.7069872
## pdays           22.518818       15.8902551 1.559935e+01
1.1196236
## euribor3m       20.005261        3.8549862 3.641860e+00
```

```
1.6193552
## emp.var.rate    19.231198        0.2851214 9.937989e-02
1.4698800
## cons.price.idx   7.754916       93.6098528 9.358235e+01
0.5538129
## campaign         4.030243        2.4041326 2.356065e+00
1.9968564
## previous       -17.016154        0.1251153 1.763279e-01
0.4006136
## duration       -25.597969      223.6446357 2.640345e+02
203.6701199
##                 Overall sd       p.value
## nr.employed     73.8222624 9.207180e-119
## pdays            2.1010235 2.715126e-112
## euribor3m        1.7326984  4.955848e-89
## emp.var.rate     1.5708408  2.028852e-82
## cons.price.idx   0.5767261  8.840227e-15
## campaign         1.9397909  5.571924e-05
## previous         0.4894910  6.233339e-65
## duration       256.6235243 1.607064e-144
##
## $Y_yes
##                   v.test Mean in category Overall mean sd in
category
## duration        25.597969      552.1666667 2.640345e+02
380.8900798
## previous        17.016154        0.5416667 1.763279e-01
0.8073244
## campaign        -4.030243        2.0131579 2.356065e+00
1.4234264
## cons.price.idx  -7.754916       93.3861820 9.358235e+01
0.6881347
## emp.var.rate   -19.231198       -1.2256579 9.937989e-02
1.6296390
## euribor3m      -20.005261        2.1214627 3.641860e+00
1.7541244
## pdays          -22.518818       13.5241228 1.559935e+01
4.6959610
## nr.employed    -23.169685     5092.1901316 5.167214e+03
89.6674427
##                 Overall sd       p.value
## duration       256.6235243 1.607064e-144
## previous         0.4894910  6.233339e-65
## campaign         1.9397909  5.571924e-05
```

```
## cons.price.idx   0.5767261  8.840227e-15
## emp.var.rate     1.5708408  2.028852e-82
## euribor3m        1.7326984  4.955848e-89
## pdays            2.1010235 2.715126e-112
## nr.employed     73.8222624 9.207180e-119
```

```
# EXEMPLE!
# Model NULL, només tenim una constant
# gm0<-glm(y~1,family=binomial,data = dfw)
# summary(gm0)

# binomial = distribucion que le damos a la variable de respuesta
# Si volem podem utilitzar duration, sino no, si es posa és com fer una mica de trampa, no té sentit utilitzar-la com a variable explicativa, però si volem és pot utilitzar.
gm1<-
glm(y~nr.employed+pdays+euribor3m+emp.var.rate+previous+cons.price.idx+campaign,family=binomial,data = dfw)
# summary(gm1)
# Anova(gm1) #Test efectes nets
vif(gm1)
```

```
##    nr.employed          pdays      euribor3m   emp.var.rate
previous
##      16.957527       1.416024      24.098435      31.623083
1.692257
## cons.price.idx       campaign
##       7.702834       1.027985
```

```
#Saca los problemas de col·linealitat!
#Més gran que 3 SON DOLENTES!

#Remove colinear variables
#Es treuran per separat i la que canviï menys el model s'agafa fins que siguin quasi totes significatives
gm2<-
glm(y~nr.employed+pdays+euribor3m+previous+cons.price.idx+campaign,family=binomial,data = dfw)
# summary(gm2)
vif(gm2)
```

```
##    nr.employed          pdays      euribor3m       previous
cons.price.idx
##      14.181816       1.417321      18.347138       1.684602
2.968792
```

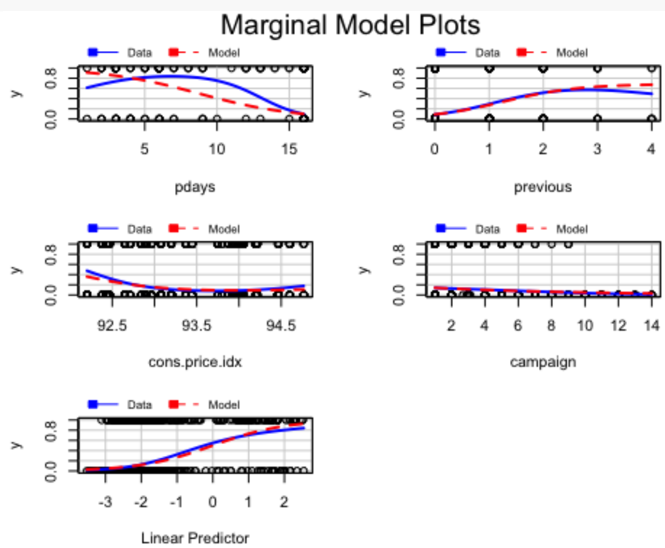
```
##       campaign
##       1.022954

# Anova(gm2)

# gm3<-
glm(y~nr.employed+pdays+previous+cons.price.idx+campaign,family=binomi
al,data = dfw)
# summary(gm3)
# vif(gm3)
# Anova(gm3)

gm4<-glm(y~pdays+previous+cons.price.idx+campaign,family=binomial,data
= dfw)
summary(gm4)

##
## Call:
## glm(formula = y ~ pdays + previous + cons.price.idx + campaign,
##     family = binomial, data = dfw)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.2876  -0.4763  -0.4141  -0.3734   2.5103
##
## Coefficients:
##                Estimate Std. Error z value Pr(>|z|)
## (Intercept)    44.22567    8.67333   5.099 3.41e-07 ***
## pdays          -0.23029    0.02344  -9.824  < 2e-16 ***
## previous        0.49007    0.10292   4.762 1.92e-06 ***
## cons.price.idx -0.45626    0.09254  -4.930 8.21e-07 ***
## campaign       -0.06844    0.03318  -2.063   0.0391 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2765.1  on 3708  degrees of freedom
## Residual deviance: 2406.1  on 3704  degrees of freedom
## AIC: 2416.1
##
## Number of Fisher Scoring iterations: 5

vif(gm4)
```

```
##          pdays       previous cons.price.idx       campaign
##       1.366062       1.394791       1.023703       1.015790
```

```r
Anova(gm4)
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: y
##                LR Chisq Df Pr(>Chisq)
## pdays           120.636  1  < 2.2e-16 ***
## previous         20.643  1  5.535e-06 ***
## cons.price.idx   24.457  1  7.600e-07 ***
## campaign          4.603  1    0.03192 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
marginalModelPlots(gm4) # Some missfit data vs model
```



Ara el que hem fet ha sigut trobar el nostre millor model lineas generalitzat i el que hem fet per aconseguir-ho ha sigut que a partir d'una mostra aleatòria hem anat elaborant els nostres models i amb la comanda "vif" hem anat treient els problemes de col·linealitat, és a dir, les variables que tenien un vif > 3 s'han de treure i anar probant diferents models amb les variables corresponents fins arribar a tenir un model on totes les nostres variables són significatives, però no hi ha cap estratègia òptima per dur a terme aquestes comprovacions.

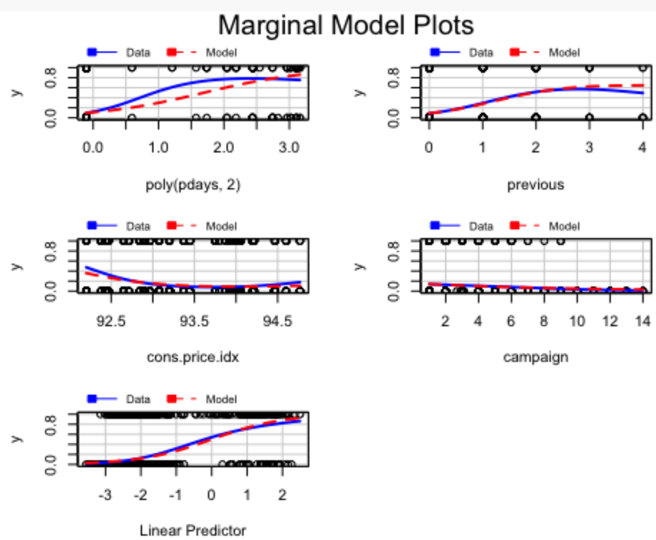
Hem aconseguit disminuir la discrepancia amb el nostre últim model (Residual deviance < Null deviance) i també es pot considerar correcte ja que Grau de llibertat = Num. observacions (3709) - Num. variables (5) = 3704 i una altra manera de veure que anem bé és que la Residual deviance és igual o inferior als graus de llibertat (2232.7 < 3704).

Com podem veure en les nostres transformacions, al model gm3 li hem tret la variable "euribor3m" respecte al model gm2 perquè segons el vif era una variable que afectava molt a la variança, però quan executàvem Anova hem vist que hi havien dos variables que no eren significatives, llavors hem optat per treure la variable "nr.employed" (Que en el model gm2 també sortia amb el vif elevat) que és el nostre model gm4 i ara quan executem Anova(gm4) podem veure que totes les variables implicades en el model són significatives, que és el que buscàvem.

Transforming variables

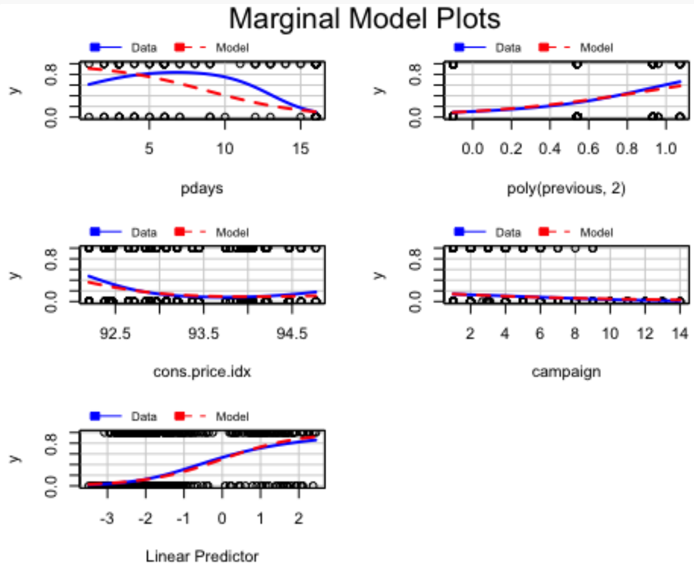
El que farem a continuació és a partir del marginalPlots podem veure on hi ha un desajust entre les observacions i la predicció, llavors hem de trobar la manera d'arreglar-ho:

```
gm5<-glm(y~poly(pdays,
2)+previous+cons.price.idx+campaign,family=binomial,data = dfw)
# summary(gm5)
# Anova(gm5)
marginalModelPlots(gm5)
```




```
gm6<-glm(y~pdays+poly(previous,
2)+cons.price.idx+campaign,family=binomial,data = dfw)
vif(gm6)

##                         GVIF Df GVIF^(1/(2*Df))
## pdays               1.411412  1        1.188028
## poly(previous, 2) 1.616349  2        1.127545
## cons.price.idx      1.151112  1        1.072899
## campaign            1.016208  1        1.008072

marginalModelPlots(gm6)
```

```
## Warning in mmps(...): Splines and/or polynomials replaced by a
fitted
## linear combination
```



Després de fer les comprovacions aplicant el cuadràtic, veiem que en la variable pdays no canvia, sino que provoca un desajust més gran, després era hora de provar-ho amb previous i amb aquesta variable si que hi ha hagut una mica de millora, amb les variables que no són numèriques no fa falta fer-ho perquè mai sortirà res al marginalModelPlots. Llavors el model que ens quedarem serà el gm6 que és el que té menor desajust entre les observacions i les prediccions fetes.

Adding Factors

Seguidament el que hem de fer és agafar el nostre millor model des del punt anterior i introduim els factors. El que s'ha de fer és anar probant totes les variables numèriques del nostre model fins ara com a factors i llavors ens quedem amb la que més t'expliqui segons ens indiqui el BIC.

```
gm10<-glm(y~pdays+poly(previous,
2)+cons.price.idx+campaign,family=binomial,data = dfw)

# First step: Choose between numeric explanatory variable or factor
# Check for all numerical variables: one by one

# Pdays: covariate or factor??
gm10a<-
glm(y~factor_Pdays+previous+cons.price.idx+campaign,family=binomial,da
ta = dfw)
BIC(gm10,gm10a)
```

```
##        df      BIC
## gm10   6 2453.155
## gm10a  5 2421.241

# Explica més com a factor que com a numèrica! (BIC gm10a < BIC gm10)
# L'ordre pot modificar els resultats pero no es pot fer res

# Previous?
gm10b<-
glm(y~factor_Pdays+factor_Previous+cons.price.idx+campaign,family=bino
mial,data = dfw)
BIC(gm10,gm10b)

##        df      BIC
## gm10   6 2453.155
## gm10b  5 2418.271

# Explica més com a factor que com a numèrica! (BIC gm10b < BIC gm10)

# Cons.price.idx?
gm10c<-
glm(y~factor_Pdays+factor_Previous+factor_cons.price.idx+campaign,fami
ly=binomial,data = dfw)
BIC(gm10,gm10c)

##        df      BIC
## gm10   6 2453.155
## gm10c  8 2394.856

# Explica més com a factor que com a numèrica! (BIC gm10c < BIC gm10)

# Campaign?
gm10d<-
glm(y~factor_Pdays+factor_Previous+factor_cons.price.idx+factor_campai
gn,family=binomial,data = dfw)
BIC(gm10,gm10d)

##        df      BIC
## gm10   6 2453.155
## gm10d  9 2406.311

# Explica més com a factor que com a numèrica! (BIC gm10d < BIC gm10)

## MILLOR MODEL FINS ARA:
gm11<-
glm(y~factor_Pdays+factor_Previous+factor_cons.price.idx+factor_campai
gn,family=binomial,data = dfw)
```

Podem veure o arribar a la conclusió després dels resultats que totes les variables del nostre model ideal fins ara que és el gm10 expliquen més com a factors que com a variables numèriques.

Adding new factors

Ara a continuació el que farem serà després del nostre model elaborat fins ara (gm11), li afegirem les variables factors que surtin que són més explicatives al nostre model.

```
# Add to your best model all new factors that are significantly
related "y" according to catdes(). I assume gm10 as the best model at
this point
vars_dis2

##  [1] "job"                      "marital"
##  [3] "education"                "default"
##  [5] "housing"                  "loan"
##  [7] "contact"                  "month"
##  [9] "day_of_week"              "poutcome"
## [11] "season"                   "factor_age"
## [13] "factor_duration"          "factor_campaign"
## [15] "factor_Pdays"             "factor_Previous"
## [17] "factor_emp.var.rate"      "factor_cons.price.idx"
## [19] "factor_cons.conf.idx"     "factor_euribor3m"
## [21] "factor_nr.employed"

catdes(dfw[,c("y",vars_dis2)],1)

##
## Link between the cluster variable and the categorical variables
(chi-square test)
##
======================================================================
===========
##                             p.value df
## poutcome              2.712647e-126  2
## factor_Pdays          3.806493e-126  1
## factor_duration       2.092643e-122  7
## factor_euribor3m      1.068403e-109  6
## factor_nr.employed     1.791399e-80  1
## month                  6.985212e-66  9
## factor_emp.var.rate    6.316792e-57  2
## factor_Previous        1.141518e-51  1
## factor_cons.price.idx  3.525616e-33  4
## contact                1.649866e-19  1
```

```
## job                    6.448891e-15 11
## season                 2.880483e-11  2
## factor_cons.conf.idx   2.949610e-11  4
## factor_age             2.089730e-10  4
## default                1.153536e-09  1
## education              1.675919e-03  7
## factor_campaign        2.204092e-03  2
##
## Description of each cluster by the categories
## =============================================
## $Y_no
##                                                            Cla/Mod
## factor_Pdays=factor_Pdays-(15,17]                         90.29453
## factor_nr.employed=factor_nr.employed-(5.1e+03,5.23e+03] 94.72850
## factor_emp.var.rate=factor_emp.var.rate-(-0.1,1.4]        94.98158
## poutcome=Poutcome_nonexistent                             91.06583
## factor_Previous=factor_Previous-[0,1]                     89.07680
## factor_duration=factor_duration-[1,68]                    99.78947
## contact=Contact_telephone                                 94.25113
## factor_cons.price.idx=factor_cons.price.idx-(93.9,94]     96.43917
## factor_duration=factor_duration-(68,104]                  97.60349
## factor_euribor3m=factor_euribor3m-(4.856,4.864]           95.78755
## month=Month_may                                           92.91139
## factor_duration=factor_duration-(104,139]                 96.19687
## default=Default_unknown                                   94.13299
## factor_cons.conf.idx=factor_cons.conf.idx-(-46.2,-42]     92.84294
## factor_euribor3m=factor_euribor3m-(4.961,4.964]           94.43535
## factor_euribor3m=factor_euribor3m-(4.864,4.961]           94.69835
## factor_duration=factor_duration-(139,182]                 94.88273
## job=Job_blue-collar                                       91.91439
## factor_cons.price.idx=factor_cons.price.idx-(93,93.4]     91.28751
## factor_age=factor_age (36,41]                             92.40924
## factor_euribor3m=factor_euribor3m-(1.415,4.856]           92.22973
## factor_campaign=factor_campaign-(3,14]                    91.42857
## factor_euribor3m=NA                                       93.24324
## factor_age=factor_age (41,49]                             90.90909
## season=Summer                                             89.17346
## season=Spring                                             89.36464
## education=Education_basic.6y                              92.85714
## job=Job_services                                          91.54930
## education=Education_basic.9y                              90.69767
## factor_cons.price.idx=factor_cons.price.idx-(93.4,93.9]   90.24745
```

```
## factor_cons.conf.idx=factor_cons.conf.idx-(-40.3,-36.4]  90.05168
## month=Month_jul                                          90.20468
## education=NA                                             82.09877
## education=Education_professional.course                  84.26966
## marital=Marital_single                                   85.56505
## job=Job_admin.                                           85.19270
## poutcome=Poutcome_failure                                82.64249
## factor_cons.conf.idx=factor_cons.conf.idx-[-50.8,-46.2]  84.28005
## factor_campaign=factor_campaign-[1,2]                    86.54147
## month=Month_apr                                          78.57143
## factor_cons.conf.idx=factor_cons.conf.idx-(-36.4,-29.8]  82.53275
## factor_duration=factor_duration-(329,504]                80.84211
## factor_cons.price.idx=factor_cons.price.idx-(94,94.8]    81.17871
## job=Job_retired                                          74.02597
## month=Month_dec                                          38.88889
## job=Job_student                                          64.93506
## factor_age=factor_age [17,31]                            81.89252
## factor_emp.var.rate=factor_emp.var.rate-(-1.8,-0.1]      78.90467
## month=Month_mar                                          52.83019
## season=Aut-Win                                           78.63720
## default=Default_no                                       86.02991
## month=Month_sep                                          49.12281
## month=Month_oct                                          48.57143
## factor_cons.price.idx=factor_cons.price.idx-[92.2,93]    77.69328
## contact=Contact_cellular                                 84.08044
## factor_Previous=factor_Previous-(1,5]                    39.21569
## factor_emp.var.rate=factor_emp.var.rate-[-3.4,-1.8]      76.72414
## poutcome=Poutcome_success                                21.80451
## factor_duration=factor_duration-(504,2.12e+03]           57.20430
## factor_nr.employed=factor_nr.employed-[4.96e+03,5.1e+03] 72.76560
## factor_Pdays=factor_Pdays-[0,15]                         23.61111
## factor_euribor3m=factor_euribor3m-[0.634,1.266]          60.89030
##                                                            Mod/Cla
## factor_Pdays=factor_Pdays-(15,17]                        98.9548109
## factor_nr.employed=factor_nr.employed-(5.1e+03,5.23e+03] 73.4706425
## factor_emp.var.rate=factor_emp.var.rate-(-0.1,1.4]       63.4183830
## poutcome=Poutcome_nonexistent                            89.3021826
## factor_Previous=factor_Previous-[0,1]                    98.7703658
## factor_duration=factor_duration-[1,68]                   14.5711651
## contact=Contact_telephone                                38.3031048
## factor_cons.price.idx=factor_cons.price.idx-(93.9,94]    19.9815555
## factor_duration=factor_duration-(68,104]                 13.7719029
```

```
## factor_euribor3m=factor_euribor3m-(4.856,4.864]           16.0774670
## month=Month_may                                            33.8456809
## factor_duration=factor_duration-(104,139]                  13.2185675
## default=Default_unknown                                    22.1948970
## factor_cons.conf.idx=factor_cons.conf.idx-(-46.2,-42]      28.7119582
## factor_euribor3m=factor_euribor3m-(4.961,4.964]            17.7374731
## factor_euribor3m=factor_euribor3m-(4.864,4.961]            15.9237627
## factor_duration=factor_duration-(139,182]                  13.6796803
## job=Job_blue-collar                                        23.7626806
## factor_cons.price.idx=factor_cons.price.idx-(93,93.4]      28.9886259
## factor_age=factor_age (36,41]                              17.2148786
## factor_euribor3m=factor_euribor3m-(1.415,4.856]            16.7845066
## factor_campaign=factor_campaign-(3,14]                     18.6904396
## factor_euribor3m=NA                                         8.4844759
## factor_age=factor_age (41,49]                              19.6741469
## season=Summer                                              47.0949892
## season=Spring                                              39.7786658
## education=Education_basic.6y                                5.9944666
## job=Job_services                                            9.9907777
## education=Education_basic.9y                               15.5856133
## factor_cons.price.idx=factor_cons.price.idx-(93.4,93.9]    19.0593298
## factor_cons.conf.idx=factor_cons.conf.idx-(-40.3,-36.4]    21.4263757
## month=Month_jul                                            18.9671073
## education=NA                                                4.0885337
## education=Education_professional.course                    11.5278205
## marital=Marital_single                                     27.6975100
## job=Job_admin.                                             25.8223179
## poutcome=Poutcome_failure                                   9.8063326
## factor_cons.conf.idx=factor_cons.conf.idx-[-50.8,-46.2]    19.6126652
## factor_campaign=factor_campaign-[1,2]                      67.9987704
## month=Month_apr                                             5.0722410
## factor_cons.conf.idx=factor_cons.conf.idx-(-36.4,-29.8]    17.4300646
## factor_duration=factor_duration-(329,504]                  11.8044882
## factor_cons.price.idx=factor_cons.price.idx-(94,94.8]      13.1263449
## job=Job_retired                                             3.5044574
## month=Month_dec                                             0.2151860
## job=Job_student                                             1.5370427
## factor_age=factor_age [17,31]                              21.5493391
## factor_emp.var.rate=factor_emp.var.rate-(-1.8,-0.1]        11.9581924
## month=Month_mar                                             0.8607439
## season=Aut-Win                                             13.1263449
## default=Default_no                                         77.8051030
```

```
## month=Month_sep                                              0.8607439
## month=Month_oct                                              1.0451891
## factor_cons.price.idx=factor_cons.price.idx-[92.2,93]      18.8441439
## contact=Contact_cellular                                    61.6968952
## factor_Previous=factor_Previous-(1,5]                        1.2296342
## factor_emp.var.rate=factor_emp.var.rate-[-3.4,-1.8]        24.6234245
## poutcome=Poutcome_success                                    0.8914848
## factor_duration=factor_duration-(504,2.12e+03]               8.1770673
## factor_nr.employed=factor_nr.employed-[4.96e+03,5.1e+03] 26.5293575
## factor_Pdays=factor_Pdays-[0,15]                             1.0451891
## factor_euribor3m=factor_euribor3m-[0.634,1.266]            11.7737473
##                                                               Global
## factor_Pdays=factor_Pdays-(15,17]                           96.117552
## factor_nr.employed=factor_nr.employed-(5.1e+03,5.23e+03] 68.023726
## factor_emp.var.rate=factor_emp.var.rate-(-0.1,1.4]         58.560259
## poutcome=Poutcome_nonexistent                               86.007010
## factor_Previous=factor_Previous-[0,1]                       97.249933
## factor_duration=factor_duration-[1,68]                      12.806686
## contact=Contact_telephone                                   35.643030
## factor_cons.price.idx=factor_cons.price.idx-(93.9,94]      18.172014
## factor_duration=factor_duration-(68,104]                    12.375303
## factor_euribor3m=factor_euribor3m-(4.856,4.864]            14.720949
## month=Month_may                                             31.949312
## factor_duration=factor_duration-(104,139]                   12.051766
## default=Default_unknown                                     20.679428
## factor_cons.conf.idx=factor_cons.conf.idx-(-46.2,-42]      27.123214
## factor_euribor3m=factor_euribor3m-(4.961,4.964]            16.473443
## factor_euribor3m=factor_euribor3m-(4.864,4.961]            14.747910
## factor_duration=factor_duration-(139,182]                   12.644918
## job=Job_blue-collar                                         22.674575
## factor_cons.price.idx=factor_cons.price.idx-(93,93.4]      27.851173
## factor_age=factor_age (36,41]                               16.338636
## factor_euribor3m=factor_euribor3m-(1.415,4.856]            15.961176
## factor_campaign=factor_campaign-(3,14]                      17.929361
## factor_euribor3m=NA                                          7.980588
## factor_age=factor_age (41,49]                               18.980857
## season=Summer                                               46.319763
## season=Spring                                               39.040173
## education=Education_basic.6y                                 5.661903
## job=Job_services                                             9.571313
## education=Education_basic.9y                                15.071448
## factor_cons.price.idx=factor_cons.price.idx-(93.4,93.9]    18.522513
```

```
## factor_cons.conf.idx=factor_cons.conf.idx-(-40.3,-36.4]  20.868159
## month=Month_jul                                          18.441628
## education=NA                                              4.367754
## education=Education_professional.course                  11.997843
## marital=Marital_single                                   28.390402
## job=Job_admin.                                           26.583985
## poutcome=Poutcome_failure                                10.407118
## factor_cons.conf.idx=factor_cons.conf.idx-[-50.8,-46.2]  20.409814
## factor_campaign=factor_campaign-[1,2]                    68.913454
## month=Month_apr                                           5.661903
## factor_cons.conf.idx=factor_cons.conf.idx-(-36.4,-29.8]  18.522513
## factor_duration=factor_duration-(329,504]                12.806686
## factor_cons.price.idx=factor_cons.price.idx-(94,94.8]    14.181720
## job=Job_retired                                           4.152063
## month=Month_dec                                           0.485306
## job=Job_student                                           2.076031
## factor_age=factor_age [17,31]                            23.078997
## factor_emp.var.rate=factor_emp.var.rate-(-1.8,-0.1]      13.291992
## month=Month_mar                                           1.428957
## season=Aut-Win                                           14.640065
## default=Default_no                                       79.320572
## month=Month_sep                                           1.536802
## month=Month_oct                                           1.887301
## factor_cons.price.idx=factor_cons.price.idx-[92.2,93]    21.272580
## contact=Contact_cellular                                 64.356970
## factor_Previous=factor_Previous-(1,5]                     2.750067
## factor_emp.var.rate=factor_emp.var.rate-[-3.4,-1.8]      28.147749
## poutcome=Poutcome_success                                 3.585872
## factor_duration=factor_duration-(504,2.12e+03]           12.537072
## factor_nr.employed=factor_nr.employed-[4.96e+03,5.1e+03] 31.976274
## factor_Pdays=factor_Pdays-[0,15]                          3.882448
## factor_euribor3m=factor_euribor3m-[0.634,1.266]          16.958749
##
p.value
## factor_Pdays=factor_Pdays-(15,17]
8.869751e-75
## factor_nr.employed=factor_nr.employed-(5.1e+03,5.23e+03]
1.507798e-74
## factor_emp.var.rate=factor_emp.var.rate-(-0.1,1.4]
5.042204e-58
## poutcome=Poutcome_nonexistent
1.973670e-42
## factor_Previous=factor_Previous-[0,1]
```

```
3.468405e-32
## factor_duration=factor_duration-[1,68]
6.379655e-28
## contact=Contact_telephone
1.980375e-21
## factor_cons.price.idx=factor_cons.price.idx-(93.9,94]
1.103609e-17
## factor_duration=factor_duration-(68,104]
9.799768e-16
## factor_euribor3m=factor_euribor3m-(4.856,4.864]
4.572876e-12
## month=Month_may
5.588679e-12
## factor_duration=factor_duration-(104,139]
5.778351e-11
## default=Default_unknown
6.864912e-11
## factor_cons.conf.idx=factor_cons.conf.idx-(-46.2,-42]
1.199456e-09
## factor_euribor3m=factor_euribor3m-(4.961,4.964]
2.049229e-09
## factor_euribor3m=factor_euribor3m-(4.864,4.961]
4.409414e-09
## factor_duration=factor_duration-(139,182]
3.093764e-08
## job=Job_blue-collar
1.147472e-05
## factor_cons.price.idx=factor_cons.price.idx-(93,93.4]
2.232259e-05
## factor_age=factor_age (36,41]
5.330682e-05
## factor_euribor3m=factor_euribor3m-(1.415,4.856]
1.315903e-04
## factor_campaign=factor_campaign-(3,14]
8.490243e-04
## factor_euribor3m=NA
1.321112e-03
## factor_age=factor_age (41,49]
3.150623e-03
## season=Summer
1.132004e-02
## season=Spring
1.330307e-02
## education=Education_basic.6y
1.391403e-02
## job=Job_services
```

```
1.644228e-02
## education=Education_basic.9y
1.667389e-02
## factor_cons.price.idx=factor_cons.price.idx-(93.4,93.9]
2.208263e-02
## factor_cons.conf.idx=factor_cons.conf.idx-(-40.3,-36.4]
2.320824e-02
## month=Month_jul
2.488580e-02
## education=NA
3.411171e-02
## education=Education_professional.course
2.211982e-02
## marital=Marital_single
1.360164e-02
## job=Job_admin.
5.787768e-03
## poutcome=Poutcome_failure
2.174750e-03
## factor_cons.conf.idx=factor_cons.conf.idx-[-50.8,-46.2]
1.710649e-03
## factor_campaign=factor_campaign-[1,2]
1.094741e-03
## month=Month_apr
1.240920e-04
## factor_cons.conf.idx=factor_cons.conf.idx-(-36.4,-29.8]
1.090858e-05
## factor_duration=factor_duration-(329,504]
3.954639e-06
## factor_cons.price.idx=factor_cons.price.idx-(94,94.8]
3.004724e-06
## job=Job_retired
2.283305e-06
## month=Month_dec
1.322665e-06
## job=Job_student
1.832741e-07
## factor_age=factor_age [17,31]
1.347689e-08
## factor_emp.var.rate=factor_emp.var.rate-(-1.8,-0.1]
2.386878e-09
## month=Month_mar
3.535525e-10
## season=Aut-Win
7.720262e-11
## default=Default_no
```

```
6.864912e-11
## month=Month_sep
1.077496e-12
## month=Month_oct
1.064412e-15
## factor_cons.price.idx=factor_cons.price.idx-[92.2,93]
1.225232e-19
## contact=Contact_cellular
1.980375e-21
## factor_Previous=factor_Previous-(1,5]
3.468405e-32
## factor_emp.var.rate=factor_emp.var.rate-[-3.4,-1.8]
7.827988e-34
## poutcome=Poutcome_success
2.315983e-72
## factor_duration=factor_duration-(504,2.12e+03]
2.002945e-74
## factor_nr.employed=factor_nr.employed-[4.96e+03,5.1e+03]
1.507798e-74
## factor_Pdays=factor_Pdays-[0,15]
8.869751e-75
## factor_euribor3m=factor_euribor3m-[0.634,1.266]
1.278016e-86
##                                                             v.test
## factor_Pdays=factor_Pdays-(15,17]                        18.296217
## factor_nr.employed=factor_nr.employed-(5.1e+03,5.23e+03]  18.267281
## factor_emp.var.rate=factor_emp.var.rate-(-0.1,1.4]       16.057787
## poutcome=Poutcome_nonexistent                            13.651647
## factor_Previous=factor_Previous-[0,1]                    11.809932
## factor_duration=factor_duration-[1,68]                   10.953687
## contact=Contact_telephone                                 9.506051
## factor_cons.price.idx=factor_cons.price.idx-(93.9,94]     8.562589
## factor_duration=factor_duration-(68,104]                  8.029341
## factor_euribor3m=factor_euribor3m-(4.856,4.864]           6.918240
## month=Month_may                                           6.889759
## factor_duration=factor_duration-(104,139]                 6.549362
## default=Default_unknown                                   6.523579
## factor_cons.conf.idx=factor_cons.conf.idx-(-46.2,-42]     6.080316
## factor_euribor3m=factor_euribor3m-(4.961,4.964]           5.993856
## factor_euribor3m=factor_euribor3m-(4.864,4.961]           5.868053
## factor_duration=factor_duration-(139,182]                 5.536046
## job=Job_blue-collar                                       4.387337
## factor_cons.price.idx=factor_cons.price.idx-(93,93.4]     4.240295
## factor_age=factor_age (36,41]                             4.040634
```

```
## factor_euribor3m=factor_euribor3m-(1.415,4.856]                  3.823463
## factor_campaign=factor_campaign-(3,14]                            3.336297
## factor_euribor3m=NA                                               3.211354
## factor_age=factor_age (41,49]                                     2.952647
## season=Summer                                                     2.532661
## season=Spring                                                     2.475551
## education=Education_basic.6y                                      2.459475
## job=Job_services                                                  2.398947
## education=Education_basic.9y                                      2.393821
## factor_cons.price.idx=factor_cons.price.idx-(93.4,93.9]           2.288944
## factor_cons.conf.idx=factor_cons.conf.idx-(-40.3,-36.4]           2.269989
## month=Month_jul                                                   2.243171
## education=NA                                                     -2.118749
## education=Education_professional.course                          -2.288304
## marital=Marital_single                                           -2.467615
## job=Job_admin.                                                   -2.759569
## poutcome=Poutcome_failure                                        -3.065268
## factor_cons.conf.idx=factor_cons.conf.idx-[-50.8,-46.2]          -3.136350
## factor_campaign=factor_campaign-[1,2]                            -3.264974
## month=Month_apr                                                  -3.837898
## factor_cons.conf.idx=factor_cons.conf.idx-(-36.4,-29.8]          -4.398332
## factor_duration=factor_duration-(329,504]                        -4.613752
## factor_cons.price.idx=factor_cons.price.idx-(94,94.8]            -4.670497
## job=Job_retired                                                  -4.726582
## month=Month_dec                                                  -4.836318
## job=Job_student                                                  -5.215548
## factor_age=factor_age [17,31]                                    -5.679906
## factor_emp.var.rate=factor_emp.var.rate-(-1.8,-0.1]              -5.969017
## month=Month_mar                                                  -6.273266
## season=Aut-Win                                                   -6.505952
## default=Default_no                                               -6.523579
## month=Month_sep                                                  -7.120227
## month=Month_oct                                                  -8.019194
## factor_cons.price.idx=factor_cons.price.idx-[92.2,93]            -9.066836
## contact=Contact_cellular                                         -9.506051
## factor_Previous=factor_Previous-(1,5]                           -11.809932
## factor_emp.var.rate=factor_emp.var.rate-[-3.4,-1.8]             -12.124560
## poutcome=Poutcome_success                                       -17.990419
## factor_duration=factor_duration-(504,2.12e+03]                  -18.251775
## factor_nr.employed=factor_nr.employed-[4.96e+03,5.1e+03]        -18.267281
## factor_Pdays=factor_Pdays-[0,15]                                -18.296217
## factor_euribor3m=factor_euribor3m-[0.634,1.266]                 -19.726465
```

```
##
## $Y_yes
##                                                                   Cla/Mod
## factor_euribor3m=factor_euribor3m-[0.634,1.266]                 39.1096979
## factor_Pdays=factor_Pdays-[0,15]                                76.3888889
## factor_nr.employed=factor_nr.employed-[4.96e+03,5.1e+03] 27.2344013
## factor_duration=factor_duration-(504,2.12e+03]                  42.7956989
## poutcome=Poutcome_success                                       78.1954887
## factor_emp.var.rate=factor_emp.var.rate-[-3.4,-1.8]             23.2758621
## factor_Previous=factor_Previous-(1,5]                           60.7843137
## contact=Contact_cellular                                        15.9195643
## factor_cons.price.idx=factor_cons.price.idx-[92.2,93]           22.3067174
## month=Month_oct                                                 51.4285714
## month=Month_sep                                                 50.8771930
## default=Default_no                                              13.9700884
## season=Aut-Win                                                  21.3627993
## month=Month_mar                                                 47.1698113
## factor_emp.var.rate=factor_emp.var.rate-(-1.8,-0.1]             21.0953347
## factor_age=factor_age [17,31]                                   18.1074766
## job=Job_student                                                 35.0649351
## month=Month_dec                                                 61.1111111
## job=Job_retired                                                 25.9740260
## factor_cons.price.idx=factor_cons.price.idx-(94,94.8]           18.8212928
## factor_duration=factor_duration-(329,504]                       19.1578947
## factor_cons.conf.idx=factor_cons.conf.idx-(-36.4,-29.8]         17.4672489
## month=Month_apr                                                 21.4285714
## factor_campaign=factor_campaign-[1,2]                           13.4585290
## factor_cons.conf.idx=factor_cons.conf.idx-[-50.8,-46.2]         15.7199472
## poutcome=Poutcome_failure                                       17.3575130
## job=Job_admin.                                                  14.8073022
## marital=Marital_single                                          14.4349478
## education=Education_professional.course                         15.7303371
## education=NA                                                    17.9012346
## month=Month_jul                                                  9.7953216
## factor_cons.conf.idx=factor_cons.conf.idx-(-40.3,-36.4]          9.9483204
## factor_cons.price.idx=factor_cons.price.idx-(93.4,93.9]          9.7525473
## education=Education_basic.9y                                     9.3023256
## job=Job_services                                                 8.4507042
## education=Education_basic.6y                                     7.1428571
## season=Spring                                                   10.6353591
## season=Summer                                                   10.8265425
## factor_age=factor_age (41,49]                                    9.0909091
```

```
## factor_euribor3m=NA                                             6.7567568
## factor_campaign=factor_campaign-(3,14]                           8.5714286
## factor_euribor3m=factor_euribor3m-(1.415,4.856]                  7.7702703
## factor_age=factor_age (36,41]                                    7.5907591
## factor_cons.price.idx=factor_cons.price.idx-(93,93.4]            8.7124879
## job=Job_blue-collar                                              8.0856124
## factor_duration=factor_duration-(139,182]                        5.1172708
## factor_euribor3m=factor_euribor3m-(4.864,4.961]                  5.3016453
## factor_euribor3m=factor_euribor3m-(4.961,4.964]                  5.5646481
## factor_cons.conf.idx=factor_cons.conf.idx-(-46.2,-42]            7.1570577
## default=Default_unknown                                          5.8670143
## factor_duration=factor_duration-(104,139]                        3.8031320
## month=Month_may                                                  7.0886076
## factor_euribor3m=factor_euribor3m-(4.856,4.864]                  4.2124542
## factor_duration=factor_duration-(68,104]                         2.3965142
## factor_cons.price.idx=factor_cons.price.idx-(93.9,94]            3.5608309
## contact=Contact_telephone                                        5.7488654
## factor_duration=factor_duration-[1,68]                           0.2105263
## factor_Previous=factor_Previous-[0,1]                           10.9232049
## poutcome=Poutcome_nonexistent                                    8.9341693
## factor_emp.var.rate=factor_emp.var.rate-(-0.1,1.4]               5.0184162
## factor_nr.employed=factor_nr.employed-(5.1e+03,5.23e+03]  5.2715022
## factor_Pdays=factor_Pdays-(15,17]                                9.7054698
##                                                                    Mod/Cla
## factor_euribor3m=factor_euribor3m-[0.634,1.266]                 53.9473684
## factor_Pdays=factor_Pdays-[0,15]                                24.1228070
## factor_nr.employed=factor_nr.employed-[4.96e+03,5.1e+03] 70.8333333
## factor_duration=factor_duration-(504,2.12e+03]                  43.6403509
## poutcome=Poutcome_success                                       22.8070175
## factor_emp.var.rate=factor_emp.var.rate-[-3.4,-1.8]             53.2894737
## factor_Previous=factor_Previous-(1,5]                           13.5964912
## contact=Contact_cellular                                        83.3333333
## factor_cons.price.idx=factor_cons.price.idx-[92.2,93]           38.5964912
## month=Month_oct                                                  7.8947368
## month=Month_sep                                                  6.3596491
## default=Default_no                                              90.1315789
## season=Aut-Win                                                  25.4385965
## month=Month_mar                                                  5.4824561
## factor_emp.var.rate=factor_emp.var.rate-(-1.8,-0.1]             22.8070175
## factor_age=factor_age [17,31]                                   33.9912281
## job=Job_student                                                  5.9210526
## month=Month_dec                                                  2.4122807
```

```
## job=Job_retired                                                  8.7719298
## factor_cons.price.idx=factor_cons.price.idx-(94,94.8]            21.7105263
## factor_duration=factor_duration-(329,504]                        19.9561404
## factor_cons.conf.idx=factor_cons.conf.idx-(-36.4,-29.8]          26.3157895
## month=Month_apr                                                  9.8684211
## factor_campaign=factor_campaign-[1,2]                            75.4385965
## factor_cons.conf.idx=factor_cons.conf.idx-[-50.8,-46.2]          26.0964912
## poutcome=Poutcome_failure                                        14.6929825
## job=Job_admin.                                                   32.0175439
## marital=Marital_single                                           33.3333333
## education=Education_professional.course                          15.3508772
## education=NA                                                     6.3596491
## month=Month_jul                                                  14.6929825
## factor_cons.conf.idx=factor_cons.conf.idx-(-40.3,-36.4]          16.8859649
## factor_cons.price.idx=factor_cons.price.idx-(93.4,93.9]          14.6929825
## education=Education_basic.9y                                     11.4035088
## job=Job_services                                                 6.5789474
## education=Education_basic.6y                                     3.2894737
## season=Spring                                                    33.7719298
## season=Summer                                                    40.7894737
## factor_age=factor_age (41,49]                                    14.0350877
## factor_euribor3m=NA                                              4.3859649
## factor_campaign=factor_campaign-(3,14]                           12.5000000
## factor_euribor3m=factor_euribor3m-(1.415,4.856]                  10.0877193
## factor_age=factor_age (36,41]                                    10.0877193
## factor_cons.price.idx=factor_cons.price.idx-(93,93.4]            19.7368421
## job=Job_blue-collar                                              14.9122807
## factor_duration=factor_duration-(139,182]                        5.2631579
## factor_euribor3m=factor_euribor3m-(4.864,4.961]                  6.3596491
## factor_euribor3m=factor_euribor3m-(4.961,4.964]                  7.4561404
## factor_cons.conf.idx=factor_cons.conf.idx-(-46.2,-42]            15.7894737
## default=Default_unknown                                          9.8684211
## factor_duration=factor_duration-(104,139]                        3.7280702
## month=Month_may                                                  18.4210526
## factor_euribor3m=factor_euribor3m-(4.856,4.864]                  5.0438596
## factor_duration=factor_duration-(68,104]                         2.4122807
## factor_cons.price.idx=factor_cons.price.idx-(93.9,94]            5.2631579
## contact=Contact_telephone                                        16.6666667
## factor_duration=factor_duration-[1,68]                           0.2192982
## factor_Previous=factor_Previous-[0,1]                            86.4035088
## poutcome=Poutcome_nonexistent                                    62.5000000
## factor_emp.var.rate=factor_emp.var.rate-(-0.1,1.4]               23.9035088
```

```
## factor_nr.employed=factor_nr.employed-(5.1e+03,5.23e+03] 29.1666667
## factor_Pdays=factor_Pdays-(15,17]                         75.8771930
##                                                              Global
## factor_euribor3m=factor_euribor3m-[0.634,1.266]           16.958749
## factor_Pdays=factor_Pdays-[0,15]                           3.882448
## factor_nr.employed=factor_nr.employed-[4.96e+03,5.1e+03] 31.976274
## factor_duration=factor_duration-(504,2.12e+03]            12.537072
## poutcome=Poutcome_success                                  3.585872
## factor_emp.var.rate=factor_emp.var.rate-[-3.4,-1.8]       28.147749
## factor_Previous=factor_Previous-(1,5]                      2.750067
## contact=Contact_cellular                                  64.356970
## factor_cons.price.idx=factor_cons.price.idx-[92.2,93]     21.272580
## month=Month_oct                                            1.887301
## month=Month_sep                                            1.536802
## default=Default_no                                        79.320572
## season=Aut-Win                                            14.640065
## month=Month_mar                                            1.428957
## factor_emp.var.rate=factor_emp.var.rate-(-1.8,-0.1]       13.291992
## factor_age=factor_age [17,31]                             23.078997
## job=Job_student                                            2.076031
## month=Month_dec                                            0.485306
## job=Job_retired                                            4.152063
## factor_cons.price.idx=factor_cons.price.idx-(94,94.8]     14.181720
## factor_duration=factor_duration-(329,504]                 12.806686
## factor_cons.conf.idx=factor_cons.conf.idx-(-36.4,-29.8]  18.522513
## month=Month_apr                                            5.661903
## factor_campaign=factor_campaign-[1,2]                     68.913454
## factor_cons.conf.idx=factor_cons.conf.idx-[-50.8,-46.2]  20.409814
## poutcome=Poutcome_failure                                 10.407118
## job=Job_admin.                                            26.583985
## marital=Marital_single                                    28.390402
## education=Education_professional.course                   11.997843
## education=NA                                               4.367754
## month=Month_jul                                           18.441628
## factor_cons.conf.idx=factor_cons.conf.idx-(-40.3,-36.4]  20.868159
## factor_cons.price.idx=factor_cons.price.idx-(93.4,93.9]  18.522513
## education=Education_basic.9y                              15.071448
## job=Job_services                                           9.571313
## education=Education_basic.6y                               5.661903
## season=Spring                                             39.040173
## season=Summer                                             46.319763
## factor_age=factor_age (41,49]                             18.980857
```

```
## factor_euribor3m=NA                                                7.980588
## factor_campaign=factor_campaign-(3,14]                          17.929361
## factor_euribor3m=factor_euribor3m-(1.415,4.856]                 15.961176
## factor_age=factor_age (36,41]                                   16.338636
## factor_cons.price.idx=factor_cons.price.idx-(93,93.4]           27.851173
## job=Job_blue-collar                                             22.674575
## factor_duration=factor_duration-(139,182]                       12.644918
## factor_euribor3m=factor_euribor3m-(4.864,4.961]                 14.747910
## factor_euribor3m=factor_euribor3m-(4.961,4.964]                 16.473443
## factor_cons.conf.idx=factor_cons.conf.idx-(-46.2,-42]           27.123214
## default=Default_unknown                                         20.679428
## factor_duration=factor_duration-(104,139]                       12.051766
## month=Month_may                                                 31.949312
## factor_euribor3m=factor_euribor3m-(4.856,4.864]                 14.720949
## factor_duration=factor_duration-(68,104]                        12.375303
## factor_cons.price.idx=factor_cons.price.idx-(93.9,94]           18.172014
## contact=Contact_telephone                                       35.643030
## factor_duration=factor_duration-[1,68]                          12.806686
## factor_Previous=factor_Previous-[0,1]                           97.249933
## poutcome=Poutcome_nonexistent                                   86.007010
## factor_emp.var.rate=factor_emp.var.rate-(-0.1,1.4]              58.560259
## factor_nr.employed=factor_nr.employed-(5.1e+03,5.23e+03] 68.023726
## factor_Pdays=factor_Pdays-(15,17]                               96.117552
##
p.value
## factor_euribor3m=factor_euribor3m-[0.634,1.266]
1.278016e-86
## factor_Pdays=factor_Pdays-[0,15]
8.869751e-75
## factor_nr.employed=factor_nr.employed-[4.96e+03,5.1e+03]
1.507798e-74
## factor_duration=factor_duration-(504,2.12e+03]
2.002945e-74
## poutcome=Poutcome_success
2.315983e-72
## factor_emp.var.rate=factor_emp.var.rate-[-3.4,-1.8]
7.827988e-34
## factor_Previous=factor_Previous-(1,5]
3.468405e-32
## contact=Contact_cellular
1.980375e-21
## factor_cons.price.idx=factor_cons.price.idx-[92.2,93]
1.225232e-19
## month=Month_oct
```

```
1.064412e-15
## month=Month_sep
1.077496e-12
## default=Default_no
6.864912e-11
## season=Aut-Win
7.720262e-11
## month=Month_mar
3.535525e-10
## factor_emp.var.rate=factor_emp.var.rate-(-1.8,-0.1]
2.386878e-09
## factor_age=factor_age [17,31]
1.347689e-08
## job=Job_student
1.832741e-07
## month=Month_dec
1.322665e-06
## job=Job_retired
2.283305e-06
## factor_cons.price.idx=factor_cons.price.idx-(94,94.8]
3.004724e-06
## factor_duration=factor_duration-(329,504]
3.954639e-06
## factor_cons.conf.idx=factor_cons.conf.idx-(-36.4,-29.8]
1.090858e-05
## month=Month_apr
1.240920e-04
## factor_campaign=factor_campaign-[1,2]
1.094741e-03
## factor_cons.conf.idx=factor_cons.conf.idx-[-50.8,-46.2]
1.710649e-03
## poutcome=Poutcome_failure
2.174750e-03
## job=Job_admin.
5.787768e-03
## marital=Marital_single
1.360164e-02
## education=Education_professional.course
2.211982e-02
## education=NA
3.411171e-02
## month=Month_jul
2.488580e-02
## factor_cons.conf.idx=factor_cons.conf.idx-(-40.3,-36.4]
2.320824e-02
## factor_cons.price.idx=factor_cons.price.idx-(93.4,93.9]
```

```
2.208263e-02
## education=Education_basic.9y
1.667389e-02
## job=Job_services
1.644228e-02
## education=Education_basic.6y
1.391403e-02
## season=Spring
1.330307e-02
## season=Summer
1.132004e-02
## factor_age=factor_age (41,49]
3.150623e-03
## factor_euribor3m=NA
1.321112e-03
## factor_campaign=factor_campaign-(3,14]
8.490243e-04
## factor_euribor3m=factor_euribor3m-(1.415,4.856]
1.315903e-04
## factor_age=factor_age (36,41]
5.330682e-05
## factor_cons.price.idx=factor_cons.price.idx-(93,93.4]
2.232259e-05
## job=Job_blue-collar
1.147472e-05
## factor_duration=factor_duration-(139,182]
3.093764e-08
## factor_euribor3m=factor_euribor3m-(4.864,4.961]
4.409414e-09
## factor_euribor3m=factor_euribor3m-(4.961,4.964]
2.049229e-09
## factor_cons.conf.idx=factor_cons.conf.idx-(-46.2,-42]
1.199456e-09
## default=Default_unknown
6.864912e-11
## factor_duration=factor_duration-(104,139]
5.778351e-11
## month=Month_may
5.588679e-12
## factor_euribor3m=factor_euribor3m-(4.856,4.864]
4.572876e-12
## factor_duration=factor_duration-(68,104]
9.799768e-16
## factor_cons.price.idx=factor_cons.price.idx-(93.9,94]
1.103609e-17
## contact=Contact_telephone
```

```
1.980375e-21
## factor_duration=factor_duration-[1,68]
6.379655e-28
## factor_Previous=factor_Previous-[0,1]
3.468405e-32
## poutcome=Poutcome_nonexistent
1.973670e-42
## factor_emp.var.rate=factor_emp.var.rate-(-0.1,1.4]
5.042204e-58
## factor_nr.employed=factor_nr.employed-(5.1e+03,5.23e+03]
1.507798e-74
## factor_Pdays=factor_Pdays-(15,17]
8.869751e-75
##                                                             v.test
## factor_euribor3m=factor_euribor3m-[0.634,1.266]          19.726465
## factor_Pdays=factor_Pdays-[0,15]                         18.296217
## factor_nr.employed=factor_nr.employed-[4.96e+03,5.1e+03]  18.267281
## factor_duration=factor_duration-(504,2.12e+03]           18.251775
## poutcome=Poutcome_success                                17.990419
## factor_emp.var.rate=factor_emp.var.rate-[-3.4,-1.8]      12.124560
## factor_Previous=factor_Previous-(1,5]                    11.809932
## contact=Contact_cellular                                  9.506051
## factor_cons.price.idx=factor_cons.price.idx-[92.2,93]     9.066836
## month=Month_oct                                           8.019194
## month=Month_sep                                           7.120227
## default=Default_no                                        6.523579
## season=Aut-Win                                            6.505952
## month=Month_mar                                           6.273266
## factor_emp.var.rate=factor_emp.var.rate-(-1.8,-0.1]       5.969017
## factor_age=factor_age [17,31]                             5.679906
## job=Job_student                                           5.215548
## month=Month_dec                                           4.836318
## job=Job_retired                                           4.726582
## factor_cons.price.idx=factor_cons.price.idx-(94,94.8]     4.670497
## factor_duration=factor_duration-(329,504]                 4.613752
## factor_cons.conf.idx=factor_cons.conf.idx-(-36.4,-29.8]   4.398332
## month=Month_apr                                           3.837898
## factor_campaign=factor_campaign-[1,2]                     3.264974
## factor_cons.conf.idx=factor_cons.conf.idx-[-50.8,-46.2]   3.136350
## poutcome=Poutcome_failure                                 3.065268
## job=Job_admin.                                            2.759569
## marital=Marital_single                                    2.467615
## education=Education_professional.course                   2.288304
```

```
## education=NA                                               2.118749
## month=Month_jul                                            -2.243171
## factor_cons.conf.idx=factor_cons.conf.idx-(-40.3,-36.4]    -2.269989
## factor_cons.price.idx=factor_cons.price.idx-(93.4,93.9]    -2.288944
## education=Education_basic.9y                               -2.393821
## job=Job_services                                           -2.398947
## education=Education_basic.6y                               -2.459475
## season=Spring                                              -2.475551
## season=Summer                                              -2.532661
## factor_age=factor_age (41,49]                              -2.952647
## factor_euribor3m=NA                                        -3.211354
## factor_campaign=factor_campaign-(3,14]                     -3.336297
## factor_euribor3m=factor_euribor3m-(1.415,4.856]            -3.823463
## factor_age=factor_age (36,41]                              -4.040634
## factor_cons.price.idx=factor_cons.price.idx-(93,93.4]      -4.240295
## job=Job_blue-collar                                        -4.387337
## factor_duration=factor_duration-(139,182]                  -5.536046
## factor_euribor3m=factor_euribor3m-(4.864,4.961]            -5.868053
## factor_euribor3m=factor_euribor3m-(4.961,4.964]            -5.993856
## factor_cons.conf.idx=factor_cons.conf.idx-(-46.2,-42]      -6.080316
## default=Default_unknown                                    -6.523579
## factor_duration=factor_duration-(104,139]                  -6.549362
## month=Month_may                                            -6.889759
## factor_euribor3m=factor_euribor3m-(4.856,4.864]            -6.918240
## factor_duration=factor_duration-(68,104]                   -8.029341
## factor_cons.price.idx=factor_cons.price.idx-(93.9,94]      -8.562589
## contact=Contact_telephone                                  -9.506051
## factor_duration=factor_duration-[1,68]                    -10.953687
## factor_Previous=factor_Previous-[0,1]                     -11.809932
## poutcome=Poutcome_nonexistent                             -13.651647
## factor_emp.var.rate=factor_emp.var.rate-(-0.1,1.4]        -16.057787
## factor_nr.employed=factor_nr.employed-(5.1e+03,5.23e+03] -18.267281
## factor_Pdays=factor_Pdays-(15,17]                         -18.296217

# No hem de repetir els factors que ja tenim fins al moment comprovats
i això s'ha de fer agafant el model estudiat anteriorment
gm12<-
glm(y~factor_Pdays+factor_Previous+factor_cons.price.idx+factor_campai
gn+poutcome+month+job+season+default+education,family=binomial,data =
dfw)
# Anova(gm12)
# summary(gm12)

#Amb el summary(gm12) he vist que tinc NA a la meva vostra en la
```

```
variable factor "season" i per això també em surt error en l'execució
del vif, perquè tenia aquesta variable que no era molt redundant,
llavors:

gm12a<-
glm(y~factor_Pdays+factor_Previous+factor_cons.price.idx+factor_campai
gn+poutcome+month+job+default+education,family=binomial,data = dfw)
Anova(gm12a) # Mirem les que ens interessen i les que no!

## Analysis of Deviance Table (Type II tests)
##
## Response: y
##                       LR Chisq Df Pr(>Chisq)
## factor_Pdays             1.112  1    0.29164
## factor_Previous          4.045  1    0.04430 *
## factor_cons.price.idx   57.732  4  8.686e-12 ***
## factor_campaign          1.580  2    0.45392
## poutcome                 6.035  2    0.04892 *
## month                   87.675  9  4.762e-15 ***
## job                     12.743 11    0.31047
## default                  6.003  1    0.01428 *
## education                7.193  6    0.30338
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

vif(gm12a)

##                            GVIF Df GVIF^(1/(2*Df))
## factor_Pdays           9.527644  1        3.086688
## factor_Previous        1.560871  1        1.249348
## factor_cons.price.idx 31.904305  4        1.541634
## factor_campaign        1.055823  2        1.013673
## poutcome              11.555512  2        1.843730
## month                 36.559308  9        1.221331
## job                    3.689568 11        1.061137
## default                1.089252  1        1.043672
## education              3.182190  6        1.101270

#A partir de l'Anova veiem que hi han variables factors no
significatives, que no ens aporten res al model, llavors les treiem:

gm12b<-
glm(y~factor_Previous+factor_cons.price.idx+poutcome+month+default,fam
ily=binomial,data = dfw)
Anova(gm12b)
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: y
##                       LR Chisq Df Pr(>Chisq)
## factor_Previous          7.266  1   0.007027 **
## factor_cons.price.idx   65.835  4  1.716e-13 ***
## poutcome               120.651  2  < 2.2e-16 ***
## month                  109.822  9  < 2.2e-16 ***
## default                  8.504  1   0.003543 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
vif(gm12b)
```

```
##                            GVIF Df GVIF^(1/(2*Df))
## factor_Previous        1.351135  1        1.162383
## factor_cons.price.idx 28.887284  4        1.522609
## poutcome               1.521054  2        1.110545
## month                 28.115574  9        1.203641
## default                1.035864  1        1.017774
```

```
gm13<-step(gm12b,k=log(nrow(dfw)))
```

```
## Start:  AIC=2354.17
## y ~ factor_Previous + factor_cons.price.idx + poutcome + month +
##     default
##
##                         Df Deviance    AIC
## - factor_Previous        1   2213.5 2353.2
## <none>                       2206.2 2354.2
## - default                1   2214.7 2354.5
## - factor_cons.price.idx  4   2272.1 2387.1
## - month                  9   2316.1 2390.0
## - poutcome               2   2326.9 2458.4
##
## Step:  AIC=2353.22
## y ~ factor_cons.price.idx + poutcome + month + default
##
##                         Df Deviance    AIC
## <none>                       2213.5 2353.2
## - default                1   2222.1 2353.6
## - factor_cons.price.idx  4   2278.1 2384.9
## - month                  9   2327.5 2393.3
## - poutcome               2   2374.7 2498.0
```

```
#vif(gm13)

# END POINT: No colinearity, all net effects for factors and numeric
variables should be significant
# colinearity: Se mira con el vig, el apartado GVIF que sean < 3
```

Després de fer el procés de modelització introduint les millores pas a pas, hem pogut observar que el nostre millor model completat amb els factors que faltaven és el model gm12b, i també ho podem comprovar executant la comanda Anova i veiem com totes les variables factors són significatives. Un model també òptim i correcte seria el gm13, ja que aquest surt després d'executar la comanda "step" al model gm12b.

```
# Check your final model at this point: all coefficients should be
available in the summary(model)
summary(gm12b)

##
## Call:
## glm(formula = y ~ factor_Previous + factor_cons.price.idx +
poutcome +
##     month + default, family = binomial, data = dfw)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.3646  -0.4763  -0.3483  -0.2866   2.7158
##
## Coefficients:
##                                                        Estimate
Std. Error
## (Intercept)                                             0.20017
0.29558
## factor_Previousfactor_Previous-(1,5]                    0.79436
0.29289
## factor_cons.price.idxfactor_cons.price.idx-(93,93.4]   -1.65895
0.23230
## factor_cons.price.idxfactor_cons.price.idx-(93.4,93.9] -1.13814
0.31381
## factor_cons.price.idxfactor_cons.price.idx-(93.9,94]   -1.08805
0.26039
## factor_cons.price.idxfactor_cons.price.idx-(94,94.8]   -0.40926
0.23599
## poutcomePoutcome_nonexistent                           -0.03669
```

```
0.17995
## poutcomePoutcome_success                                       2.47038
0.27019
## monthMonth_aug                                                -1.32216
0.25693
## monthMonth_dec                                                -0.30063
0.60409
## monthMonth_jul                                                -1.29686
0.35683
## monthMonth_jun                                                -1.87335
0.34855
## monthMonth_mar                                                 0.07422
0.37630
## monthMonth_may                                                -2.24742
0.31011
## monthMonth_nov                                                -1.31315
0.26964
## monthMonth_oct                                                -0.47742
0.38193
## monthMonth_sep                                                -0.73219
0.41880
## defaultDefault_unknown                                        -0.49048
0.17571
##                                                              z value
Pr(>|z|)
## (Intercept)                                                     0.677
0.498265
## factor_Previousfactor_Previous-(1,5]                            2.712
0.006684
## factor_cons.price.idxfactor_cons.price.idx-(93,93.4]           -7.142
9.23e-13
## factor_cons.price.idxfactor_cons.price.idx-(93.4,93.9]         -3.627
0.000287
## factor_cons.price.idxfactor_cons.price.idx-(93.9,94]           -4.179
2.93e-05
## factor_cons.price.idxfactor_cons.price.idx-(94,94.8]           -1.734
0.082873
## poutcomePoutcome_nonexistent                                   -0.204
0.838448
## poutcomePoutcome_success                                        9.143  <
2e-16
## monthMonth_aug                                                 -5.146
2.66e-07
## monthMonth_dec                                                 -0.498
0.618717
## monthMonth_jul                                                 -3.634
```

```
0.000279
## monthMonth_jun                                                  -5.375
7.67e-08
## monthMonth_mar                                                   0.197
0.843652
## monthMonth_may                                                  -7.247
4.25e-13
## monthMonth_nov                                                  -4.870
1.12e-06
## monthMonth_oct                                                  -1.250
0.211293
## monthMonth_sep                                                  -1.748
0.080411
## defaultDefault_unknown                                          -2.791
0.005248
##
## (Intercept)
## factor_Previousfactor_Previous-(1,5]                           **
## factor_cons.price.idxfactor_cons.price.idx-(93,93.4]   ***
## factor_cons.price.idxfactor_cons.price.idx-(93.4,93.9] ***
## factor_cons.price.idxfactor_cons.price.idx-(93.9,94]   ***
## factor_cons.price.idxfactor_cons.price.idx-(94,94.8]   .
## poutcomePoutcome_nonexistent
## poutcomePoutcome_success                               ***
## monthMonth_aug                                         ***
## monthMonth_dec
## monthMonth_jul                                         ***
## monthMonth_jun                                         ***
## monthMonth_mar
## monthMonth_may                                         ***
## monthMonth_nov                                         ***
## monthMonth_oct
## monthMonth_sep                                         .
## defaultDefault_unknown                                 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2765.1  on 3708  degrees of freedom
## Residual deviance: 2206.2  on 3691  degrees of freedom
## AIC: 2242.2
```

```
##
## Number of Fisher Scoring iterations: 6
```

```
# Month too many levels. Try to use season
gm14<-
glm(y~factor_Previous+factor_cons.price.idx+poutcome+season+default,fa
mily=binomial,data = dfw)
Anova(gm14)
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: y
##                       LR Chisq Df Pr(>Chisq)
## factor_Previous          8.978  1  0.0027321 **
## factor_cons.price.idx   68.010  4  5.969e-14 ***
## poutcome               160.529  2  < 2.2e-16 ***
## season                   9.555  2  0.0084162 **
## default                 13.495  1  0.0002392 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
vif(gm14)
```

```
##                           GVIF Df GVIF^(1/(2*Df))
## factor_Previous       1.302512  1        1.141277
## factor_cons.price.idx 2.507984  4        1.121800
## poutcome              1.457428  2        1.098745
## season                2.328777  2        1.235327
## default               1.022145  1        1.011012
```

```
#Ahora no nos aparecen NA!

#anova(gm12b,gm12) #Test for nested models not equivalent
Anova(gm12b, test="LR")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: y
##                       LR Chisq Df Pr(>Chisq)
## factor_Previous          7.266  1   0.007027 **
## factor_cons.price.idx   65.835  4  1.716e-13 ***
## poutcome               120.651  2  < 2.2e-16 ***
## month                  109.822  9  < 2.2e-16 ***
## default                  8.504  1   0.003543 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#cooks.distance(gm12b)
```

Add to the best model: INTERACTIONS

Un cop utilitzades variables numèriques i factors en la construcció del model, en aquest apartat utilitzarem les interaccions per tal de veure si aquesta eina millora el nostre model. I el model que tenim fins ara és el model gm12b i si surten NA agafem el model gm14, llavors farem les interaccions sobre aquest.

En el primer cas provarem de utilitzar factor_Previous com a interacció:

```
mf1<-glm(y ~
(factor_cons.price.idx+poutcome+month+default)*(factor_Previous),
family = binomial, data = dfw)

Anova(mf1,test="LR")

## Analysis of Deviance Table (Type II tests)
##
## Response: y
##                                       LR Chisq Df Pr(>Chisq)
## factor_cons.price.idx                   58.580  4  5.765e-12 ***
## poutcome                               112.230  2  < 2.2e-16 ***
## month                                  116.016  9  < 2.2e-16 ***
## default                                  7.624  1   0.005759 **
## factor_Previous                          7.266  1   0.007027 **
## factor_cons.price.idx:factor_Previous    2.694  3   0.441214
## poutcome:factor_Previous                 1.244  1   0.264685
## month:factor_Previous                    7.044  9   0.632521
## default:factor_Previous                  0.880  1   0.348089
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

A partir del test d'efectes nets veiem que la interacció amb factor_Previous no aporta res rellevant al model. Continuem amb el model anterior gm12b.

A continuació intentarem una interacció amb poutcome:

```
mf2<-glm(y ~
(factor_Previous+factor_cons.price.idx+month+default)*(poutcome),
family = binomial, data = dfw)
```

```r
Anova(mf2,test="LR")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: y
##                                LR Chisq Df Pr(>Chisq)
## factor_Previous                   2.484  1   0.114983
## factor_cons.price.idx            57.032  4  1.218e-11 ***
## month                           115.339  9  < 2.2e-16 ***
## default                           5.134  1   0.023460 *
## poutcome                        120.651  2  < 2.2e-16 ***
## factor_Previous:poutcome          0.391  1   0.531576
## factor_cons.price.idx:poutcome   10.417  6   0.108173
## month:poutcome                   41.408 18   0.001337 **
## default:poutcome                  1.727  2   0.421763
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
BIC(mf2, gm12b)
```

```
##       df      BIC
## mf2   45 2513.298
## gm12b 18 2354.171
```

Es pot veure que hi ha una interacció que si que és rellevant, que és la month:poutcome

```r
mf3<-step(mf2, k=log(nrow(dfw)))
```

```
## Start:  AIC=2513.3
## y ~ (factor_Previous + factor_cons.price.idx + month + default) *
##     (poutcome)
##
##                                  Df Deviance    AIC
## - month:poutcome                 18   2184.9 2406.8
## - factor_cons.price.idx:poutcome  6   2153.9 2474.4
## - default:poutcome                2   2145.2 2498.6
## - factor_Previous:poutcome        1   2143.9 2505.5
## <none>                                2143.5 2513.3
##
## Step:  AIC=2406.77
```

```
## y ~ factor_Previous + factor_cons.price.idx + month + default +
##     poutcome + factor_Previous:poutcome +
factor_cons.price.idx:poutcome +
##     default:poutcome
##
##                                   Df Deviance    AIC
## - factor_cons.price.idx:poutcome  6   2203.2 2375.8
## - default:poutcome                2   2186.8 2392.3
## - factor_Previous:poutcome        1   2185.0 2398.6
## <none>                                2184.9 2406.8
## - month                           9   2300.2 2448.2
##
## Step:  AIC=2375.77
## y ~ factor_Previous + factor_cons.price.idx + month + default +
##     poutcome + factor_Previous:poutcome + default:poutcome
##
##                            Df Deviance    AIC
## - default:poutcome          2   2205.4 2361.5
## - factor_Previous:poutcome  1   2204.1 2368.4
## <none>                          2203.2 2375.8
## - factor_cons.price.idx     4   2269.2 2408.9
## - month                     9   2315.2 2413.8
##
## Step:  AIC=2361.53
## y ~ factor_Previous + factor_cons.price.idx + month + default +
##     poutcome + factor_Previous:poutcome
##
##                            Df Deviance    AIC
## - factor_Previous:poutcome  1   2206.2 2354.2
## <none>                          2205.4 2361.5
## - default                   1   2213.8 2361.7
## - factor_cons.price.idx     4   2272.0 2395.3
## - month                     9   2316.1 2398.2
##
## Step:  AIC=2354.17
## y ~ factor_Previous + factor_cons.price.idx + month + default +
##     poutcome
##
##                         Df Deviance    AIC
## - factor_Previous        1   2213.5 2353.2
## <none>                       2206.2 2354.2
## - default                1   2214.7 2354.5
## - factor_cons.price.idx  4   2272.1 2387.1
```

```
## - month                     9   2316.1 2390.0
## - poutcome                  2   2326.9 2458.4
##
## Step:  AIC=2353.22
## y ~ factor_cons.price.idx + month + default + poutcome
##
##                          Df Deviance    AIC
## <none>                       2213.5 2353.2
## - default                 1   2222.1 2353.6
## - factor_cons.price.idx  4   2278.1 2384.9
## - month                   9   2327.5 2393.3
## - poutcome                2   2374.7 2498.0
```

```
Anova(mf3,test="LR")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: y
##                        LR Chisq Df Pr(>Chisq)
## factor_cons.price.idx   64.601  4  3.122e-13 ***
## month                  114.026  9  < 2.2e-16 ***
## default                  8.582  1   0.003396 **
## poutcome               161.220  2  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
BIC(mf3, gm12b)
```

```
##       df      BIC
## mf3   17 2353.218
## gm12b 18 2354.171
```

Un cop realitzades les interaccions realitzem una comparació del model de partida sense interaccions (gm12b) i el millor model obtingut a partir de les interaccions. Per poca diferència, però veiem que el model sense interaccions és millor. Per tant continuarem amb el model gm12b.

Model final

Un cop realitzat l'anterior estudi, proposem el model gm14 com a model final, ja que és el mateix que el model gm12b, l'única cosa que agrupa els mesos segons les estacions.

```
#summary(gm12b)
summary(gm14)
```

```
##
## Call:
## glm(formula = y ~ factor_Previous + factor_cons.price.idx +
poutcome +
##     season + default, family = binomial, data = dfw)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.2327  -0.4963  -0.3845  -0.2898   2.7465
##
## Coefficients:
##                                                         Estimate
Std. Error
## (Intercept)                                             -1.47527
0.15932
## factor_Previousfactor_Previous-(1,5]                     0.86497
0.28652
## factor_cons.price.idxfactor_cons.price.idx-(93,93.4]   -0.85528
0.16264
## factor_cons.price.idxfactor_cons.price.idx-(93.4,93.9] -0.46882
0.20044
## factor_cons.price.idxfactor_cons.price.idx-(93.9,94]   -1.60689
0.24339
## factor_cons.price.idxfactor_cons.price.idx-(94,94.8]   -0.18375
0.19862
## poutcomePoutcome_nonexistent                            -0.06729
0.17421
## poutcomePoutcome_success                                 2.71804
0.26050
## seasonSummer                                            -0.24255
0.17346
## seasonAut-Win                                            0.29833
0.17494
## defaultDefault_unknown                                  -0.59889
0.17241
##                                                         z value
Pr(>|z|)
## (Intercept)                                              -9.260  <
2e-16
## factor_Previousfactor_Previous-(1,5]                      3.019
0.002537
## factor_cons.price.idxfactor_cons.price.idx-(93,93.4]    -5.259
1.45e-07
## factor_cons.price.idxfactor_cons.price.idx-(93.4,93.9]  -2.339
0.019337
```

```
## factor_cons.price.idxfactor_cons.price.idx-(93.9,94]    -6.602
4.05e-11
## factor_cons.price.idxfactor_cons.price.idx-(94,94.8]    -0.925
0.354887
## poutcomePoutcome_nonexistent                            -0.386
0.699287
## poutcomePoutcome_success                                10.434  <
2e-16
## seasonSummer                                            -1.398
0.162027
## seasonAut-Win                                            1.705
0.088134
## defaultDefault_unknown                                  -3.474
0.000514
##
## (Intercept)                                            ***
## factor_Previousfactor_Previous-(1,5]                   **
## factor_cons.price.idxfactor_cons.price.idx-(93,93.4]   ***
## factor_cons.price.idxfactor_cons.price.idx-(93.4,93.9] *
## factor_cons.price.idxfactor_cons.price.idx-(93.9,94]   ***
## factor_cons.price.idxfactor_cons.price.idx-(94,94.8]
## poutcomePoutcome_nonexistent
## poutcomePoutcome_success                               ***
## seasonSummer
## seasonAut-Win                                          .
## defaultDefault_unknown                                 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2765.1  on 3708  degrees of freedom
## Residual deviance: 2306.5  on 3698  degrees of freedom
## AIC: 2328.5
##
## Number of Fisher Scoring iterations: 6
```

Interpretació del model final

Y = -1.475 + 0.863factor_Previousfactor_Previous-(1,5] - 0.855factor_cons.price.idxfactor_cons.price.idx-(93,93.4] - 0.469factor_cons.price.idxfactor_cons.price.idx-(93.4,93.9] - 1.607factor_cons.price.idxfactor_cons.price.idx-(93.9,94] + 2.712poutcomePoutcome_success + 0.298seasonAut-Win - 0.598defaultDefault_unknown

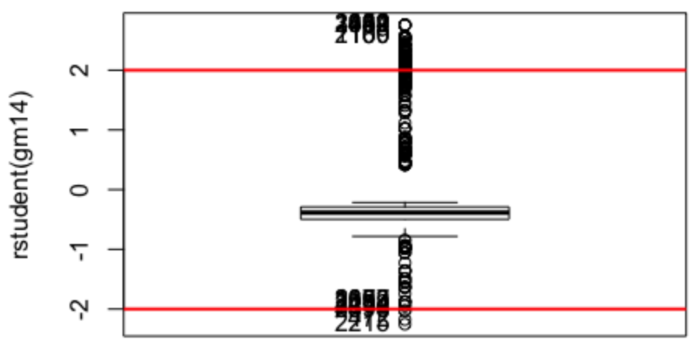
Validació del model

Anàlisi dels residus

```
Boxplot(rstudent(gm14), id.n=2)
```

```
##  [1] 2215  472 2899 3378 2252 2434 1053 1373 2167 2690  144  460
612  932
## [15] 1491 2359 3432  100 1180 2109
```

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

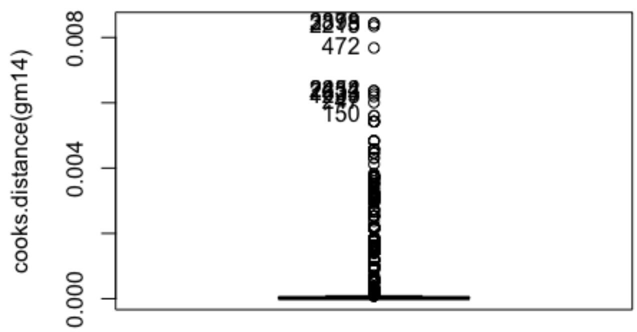



```
out2 <- which(rstudent(gm14) >= 3 | rstudent(gm14) <= -3);length(out2)
```

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

A partir de l'anàlisi de residus veiem que no hi han quasi possibles outliers. Però ens centrarem en buscar si existeix alguna dada influent entre aquests:

```
infl<-Boxplot(cooks.distance(gm14), id.n=4)
```




```
llinfl<-which(abs(cooks.distance(gm14))>3);length(llinfl)
```

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

```
dfw[llinfl,]
```

```
##  [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] missings_indiv         errors_indiv           outliers_indiv
## [25] season                 factor_age             factor_duration
## [28] factor_campaign        factor_Pdays           factor_Previous
## [31] factor_emp.var.rate    factor_cons.price.idx
factor_cons.conf.idx
## [34] factor_euribor3m       factor_nr.employed     CLUSTER
## [37] f.CLUSTER
## <0 rows> (or 0-length row.names)
```

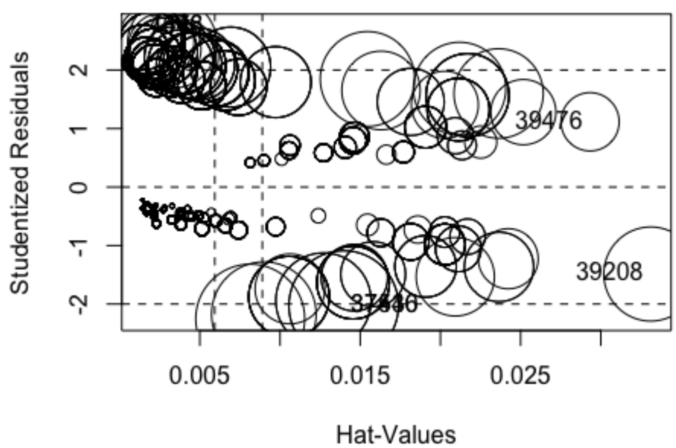
```
influencePlot(gm14,id.n=3)
```

```
## Warning in plot.window(...): "id.n" is not a graphical parameter
```

```
## Warning in plot.xy(xy, type, ...): "id.n" is not a graphical
parameter
```

```
## Warning in axis(side = side, at = at, labels = labels, ...): "id.n"
is not
## a graphical parameter
```

```
## Warning in axis(side = side, at = at, labels = labels, ...): "id.n"
is not
## a graphical parameter

## Warning in box(...): "id.n" is not a graphical parameter

## Warning in title(...): "id.n" is not a graphical parameter

## Warning in plot.xy(xy.coords(x, y), type = type, ...): "id.n" is
not a
## graphical parameter
```




```
##          StudRes         Hat       CookD
## 7446   2.757323 0.001401683 0.005424479
## 4678   2.757323 0.001401683 0.005424479
## 39208 -1.486823 0.033113887 0.006190260
## 37440 -2.027270 0.013967882 0.008433304
## 39476  1.115459 0.029331514 0.002375588
## 37536 -2.027270 0.013967882 0.008433304
```

A partir del gràfic observat a priori es pot veure que les dades més influents són les “39208” i “39476” observant el leverage que hi ha en el plot corresponent.

Predicció

WORK

```
pre1<-predict(gm14,type="response")
pn<- as.numeric(pre1)
summary(df$y)

##  Y_no Y_yes
##  4349   597

pre.y <- factor(ifelse(pn<0.5,0,1),labels=c("pre.Success?-
no","pre.Success?-yes"))

tt<-table(pre.y,dfw$y);tt

##
## pre.y              Y_no Y_yes
##   pre.Success?-no  3224   353
##   pre.Success?-yes   29   103

100*sum(diag(tt))/sum(tt)

## [1] 89.70073
```

TEST

```
pre<-predict(gm14,type="response",newdata=dft)
pn<- as.numeric(pre)
summary(df$y)

##  Y_no Y_yes
##  4349   597

pre.y <- factor(ifelse(pn<0.5,0,1),labels=c("pre.Success?-
no","pre.Success?-yes"))

tt<-table(pre.y,dft$y);tt

##
## pre.y              Y_no Y_yes
##   pre.Success?-no  1086   116
##   pre.Success?-yes   10    25

100*sum(diag(tt))/sum(tt)

## [1] 89.81407
```

En aquest apartat hem realitzat les prediccions per tal de veure les taxes d'encert del nostre model. Tenim una taxa d'encert del 89.814%.

Ara tenim una altra manera de calcular la predicció:

```
library("ROCR")

## Loading required package: gplots

##
## Attaching package: 'gplots'

## The following object is masked from 'package:stats':
##
##     lowess

dadesroc<-prediction(predict(gm14,type="response"),dfw$y)
par(mfrow=c(1,2))
plot(performance(dadesroc,"err"))
plot(performance(dadesroc,"tpr","fpr")) > abline(0,1,lty=2)
```