Deliverable Final

Guillem Valls, Sergio Mazzariol

Table of Contents

Preparación de la muestra

Establecemos el directorio de trabajo, luego importamos todos los datos del archivo csv bank-additional-full y establecemos una semilla para obtener siempre la misma muestra "aleatoria". Obtenemos 5000 individuos que se usarán para el análisis a lo largo de toda la asignatura. Partimos siempre del mismo fichero, data-INI.RData, para asegurarnos que se usa siempre la misma muestra ya generada.

```
#setwd("C:/Users/Sergio/Dropbox/UPC/FIB/Analisis de datos y explotacion de la informacion (ADEI)/FIB-ADEI-Big-Data-Analysis")
setwd("C:/Users/usuario/Documents/ADEI/FIB-ADEI-Big-Data-Analysis")

# Data file alread
df<-read.table('bank-additional-full.csv',header=TRUE,sep=";")

# Select your 5000 register sample (random sample)
set.seed(19101990)
llista<-sample(size=5000,x=1:nrow(df),replace=FALSE)
llista<-sort(llista)

#llista
df<-df[llista,]
dim(df)

## [1] 5000   21

#save.image("set-datos.RData")
load("data-INI.RData")
```

Inicializamos datos y funciones

Creamos un dataframe que llamamos data quality report "dqr" para almacenar missings, errors, outliers. También creamos uno para los datos individuales "dqri". Inicializamos el "dqr" todo a 0, y el dqri lo inicializamos a 0 pero después de eliminar los individuos que nos dan outliers o errores en las variables target. Declaramos la función calcQ que nos permitirá discriminar los outliers leves y severos en los boxplots. Para poder tratar los datos con mayor facilidad separamos las variables en tres grupos, las variables target "duration, y", las variables categóricas "job", "marital", "education", "default", "housing", "loan", "contact", "month", "day_of_week", "poutcome" y las variables númericas "age", "campaign", "pdays", "previous", "emp.var.rate", "cons.price.idx", "cons.conf.idx", "euribor3m", "nr.employed"

```
dqr <- data.frame(variable=character(), missings=integer(), errors=integer(), outliers=integer())
```

```
dqr[length(names(df)),2:4]<-0
dqr$variable <-names(df)
dqr[,2:4]<-0

dqri <- data.frame(missings=integer(), errors=integer(), outliers=integer
())

calcQ <- function(x) {
  s.x <- summary(x)
  iqr<-s.x[5]-s.x[2]
  list(souti=s.x[2]-3*iqr, mouti=s.x[2]-1.5*iqr, min=s.x[1], q1=s.x[2], q
2=s.x[3],
       q3=s.x[5], max=s.x[6], mouts=s.x[5]+1.5*iqr, souts=s.x[5]+3*iqr )
}

df[1,]

##    age        job marital education default housing loan   contact mon
th
## 20  39 management  single  basic.9y unknown      no   no telephone   m
ay
##    day_of_week duration campaign pdays previous    poutcome emp.var.ra
te
## 20         mon      195        1   999        0 nonexistent          1
.1
##    cons.price.idx cons.conf.idx euribor3m nr.employed  y
## 20         93.994         -36.4     4.857        5191 no

vars_target<-c("duration","y");vars_target

## [1] "duration" "y"

vars_cat<-c("job", "marital", "education", "default", "housing", "loan",
"contact", "month", "day_of_week", "poutcome");vars_cat

##  [1] "job"         "marital"     "education"   "default"     "housing"
##  [6] "loan"        "contact"     "month"       "day_of_week" "poutcome
"

vars_num<-c("age", "campaign", "pdays", "previous", "emp.var.rate", "cons
.price.idx", "cons.conf.idx", "euribor3m", "nr.employed");vars_num

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

Análisis y exploración de datos

Empezamos con la exploración de datos, verificamos los nombres de las variables, también un summary para comprobar que los datos son correctos.

```
summary(df)
```

```
##       age                 job           marital
##  Min.   :18.00   admin.     :1285   divorced: 584
##  1st Qu.:32.00   blue-collar:1130   married :2995
##  Median :38.00   technician : 816   single  :1413
##  Mean   :40.18   services   : 451   unknown :   8
##  3rd Qu.:47.00   management : 352
##  Max.   :92.00   retired    : 223
##                  (Other)    : 743
##                education       default        housing          loan
##  university.degree  :1469   no     :3949   no     :2244   no     :4141
##  high.school        :1142   unknown:1051   unknown: 113   unknown: 113
##  basic.9y           : 756   yes    :   0   yes    :2643   yes    : 746
##  professional.course: 610
##  basic.4y           : 510
##  basic.6y           : 271
##  (Other)            : 242
##       contact          month      day_of_week    duration
##  cellular :3207   may    :1682   fri: 960    Min.   :   0.0
##  telephone:1793   jul    : 866   mon:1058    1st Qu.: 103.0
##                   aug    : 767   thu:1008    Median : 179.0
##                   jun    : 617   tue: 954    Mean   : 263.3
##                   nov    : 514   wed:1020    3rd Qu.: 322.0
##                   apr    : 322               Max.   :4199.0
##                   (Other): 232
##     campaign          pdays          previous             poutcome
##  Min.   : 1.000   Min.   :  0.0   Min.   :0.0000   failure    : 546
##  1st Qu.: 1.000   1st Qu.:999.0   1st Qu.:0.0000   nonexistent:4298
##  Median : 2.000   Median :999.0   Median :0.0000   success    : 156
##  Mean   : 2.579   Mean   :964.3   Mean   :0.1784
##  3rd Qu.: 3.000   3rd Qu.:999.0   3rd Qu.:0.0000
##  Max.   :56.000   Max.   :999.0   Max.   :6.0000
##
##   emp.var.rate      cons.price.idx  cons.conf.idx      euribor3m
##  Min.   :-3.40000   Min.   :92.20   Min.   :-50.80   Min.   :0.634
##  1st Qu.:-1.80000   1st Qu.:93.08   1st Qu.:-42.70   1st Qu.:1.334
##  Median : 1.10000   Median :93.44   Median :-41.80   Median :4.857
##  Mean   : 0.05264   Mean   :93.56   Mean   :-40.54   Mean   :3.585
##  3rd Qu.: 1.40000   3rd Qu.:93.99   3rd Qu.:-36.40   3rd Qu.:4.961
##  Max.   : 1.40000   Max.   :94.77   Max.   :-26.90   Max.   :5.045
##
##   nr.employed     y
##  Min.   :4964   no :4455
##  1st Qu.:5099   yes: 545
##  Median :5191
##  Mean   :5166
##  3rd Qu.:5228
##  Max.   :5228
##
```

Tratamiento de las Variables target

En primer lugar trataremos las variables target porque de estas se pueden desprender errores y outliers que implicarán eliminación de individuos ya que estos errores no pueden imputarse, sería falsificación de la variable target. Tenemos dos variables targets, una categórica y otra numérica, empezamos con la categórica.

Y

Hacemos un summary de la variable y podemos ver que los únicos valores que toma es yes o no, de los cuales podemos decir que no hay errores, outliers o missings.

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

```
##   no  yes
## 4455  545
```

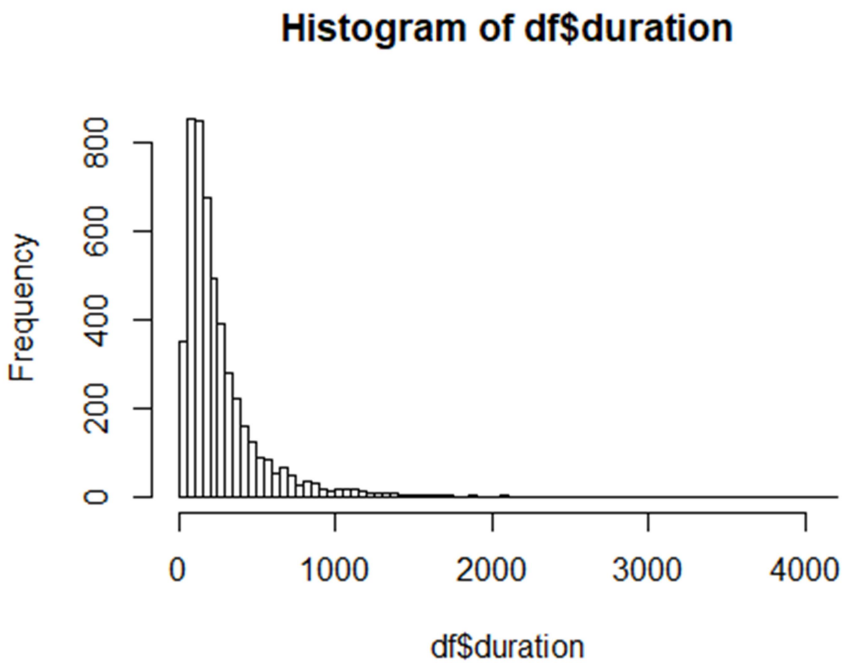
Duration

Vemos que hay valores muy pequeños, incluso 0, también valores muy grandes. Miramos distribución en el histograma. De él se desprende que las llamadas son mayormente de aproximadamente 250 minutos, como ya anticipaba el summary. Hacemos boxplot para ver outliers y solo se contemplan outliers superiores con la función calcQ que fija límite soft y extremo. Detectar outliers aplicando el linde proporcionado por calcQ echaría a perder la muestra, así que mejor se revisan los 10 valores más extremos y vemos que los últimos 6 abarcan un intervalo superior de duración al resto de la muestra, es decir, 4994 individuos están en el intervalo [0,2078] mientras que estos 6 abarcan un intervalo más extenso, [2079,4199]. Hacemos boxplot nuevamente para ver el resultado el cual almacenamos en nuestro data frame. Luego procedemos a revisar los errores, los cuales consideramos que pueden ser llamadas con una duración inferior a 5 segundos. Tanto errores como outliers son eliminados de la muestra.

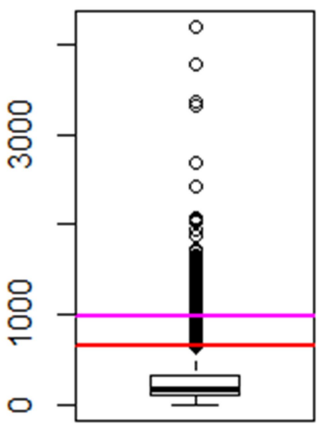
```
summary(df$duration)
```

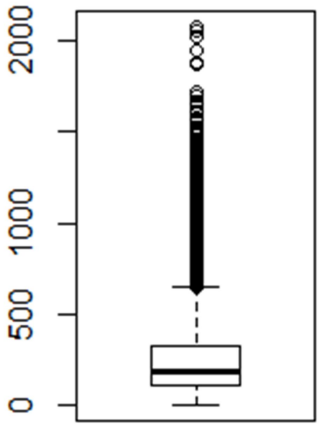
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##     0.0   103.0   179.0   263.3   322.0  4199.0
```

```
hist(df$duration,100)
```




```
par(mfrow=c(1,2))
boxplot(df$duration)
aux<-calcQ(df$duration)
abline(h=aux[8],col="red",lwd=2)
abline(h=aux[9],col="magenta",lwd=2)
aux<-order(df$duration,decreasing=TRUE)[1:10];df[aux,'duration']

##  [1] 4199 3785 3366 3322 2692 2420 2078 2053 2028 1946

df<-df[-aux[1:6],]
boxplot(df$duration)
```






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

aux<-which(df$duration<5);length(aux);df[aux,'duration']

## [1] 4

## [1] 0 4 0 1

df<-df[-aux,]

dqr[dqr$variable=="duration","outliers"]<-6
dqr[dqr$variable=="duration","errors"]<-length(aux)

# Inicializamos el dqri ya que en este punto hemos eliminado todos los in
dividuos que se consideraban como outliers o errores en las variables tar
get.
dqri[nrow(df),]<-0
dqri[,]<-0
```

Tratamiento de variables no-Target Categóricas

Análisis de errores y missings

Primero realizamos un summary de todas las variables categóricas, para analizar sus valores. En este análisis podemos ver que la variable default tiene una cantidad alta de valores unknows, por lo que nos da indicios de que esta variable no nos será útil. Vemos que todas los factores con niveles unknow, menos “default” se pueden

considerar como missings, por lo que procedemos a pasar estos valores a NA´s, para esto utilizamos un bucle for. Para evitar realizar el cambio de variables que tengan una cantidad de uknowns mayor a 300, ya que en estos casos debe permanecer como un nivel más, como lo es en el caso de la variable “default”.

```
for(i in vars_cat){
  cat("################ ",i," ##################\n")
  print(summary(df[,i]))
}
```

```
## ################  job  ##################
##        admin.   blue-collar  entrepreneur     housemaid    management 
##          1281          1128           189           119           351 
##       retired self-employed      services       student    technician 
##           222           166           451           109           815 
##    unemployed       unknown 
##           114            45 
## ################  marital  ##################
## divorced  married   single  unknown 
##      583     2988     1411        8 
## ################  education  ##################
##            basic.4y            basic.6y            basic.9y 
##                 508                 271                 756 
##         high.school          illiterate professional.course 
##                1138                   1                 609 
##   university.degree             unknown 
##                1466                 241 
## ################  default  ##################
##      no unknown     yes 
##    3940    1050       0 
## ################  housing  ##################
##      no unknown     yes 
##    2239     113    2638 
## ################  loan  ##################
##      no unknown     yes 
##    4132     113     745 
## ################  contact  ##################
##  cellular telephone 
##      3203      1787 
## ################  month  ##################
##  apr  aug  dec  jul  jun  mar  may  nov  oct  sep 
##  321  764   18  865  616   63 1680  513   80   70 
## ################  day_of_week  ##################
##  fri  mon  thu  tue  wed 
##  957 1058 1005  952 1018 
## ################  poutcome  ##################
##     failure nonexistent     success 
##         545        4289         156
```

```
for(i in vars_cat){
  aux<-which(df[,i]=="unknown")
  if(length(aux)>0 && length(aux)<300){ # Solo si como máximo la variable
tiene 300 unknowns (Para filtrar a default)
    cat(i, " -- ", length(aux), "\n")
    df[aux,i]<-NA
    dqri[aux,"missings"]<-dqri[aux,"missings"]+1
    df[,i]<-factor(df[,i])
  }
}

## job  --  45
## marital  --  8
## education  --  241
## housing  --  113
## loan  --  113

# Para el data análisis guardamos los missings de las variables categóric
as
for(i in vars_cat){
  dqr[dqr$variable==i,"missings"]<-sum(is.na(df[,i]))
}
```

Ahora realizamos la imputación de las variables categóricas. Contrastamos los summmaries originales e imputados, para comprobar que la imputación se hizo correctamente. Vemos que todo ha sido correcto y aceptamos estos datos, por lo que procedemos a almacenarlo en nuestro data frame que, por seguridad, solo sobrescribimos aquellas variables que han sido modificadas.

```
aux2<-imputeMCA(df[,vars_cat],ncp=10)

for(i in vars_cat){
  cat("################ ",i," ##################\n")
  print(summary(df[,i]))
  print("--- --- --- ---")
  print(summary(aux2$completeObs[,i]))
}

## ################  job  ##################
##        admin.   blue-collar  entrepreneur     housemaid    management
##          1281          1128           189           119           351
##       retired self-employed      services       student    technician
##           222           166           451           109           815
##    unemployed          NA's
##           114            45
## [1] "--- --- --- ---"
##        admin.   blue-collar  entrepreneur     housemaid    management
##          1296          1156           189           119           351
##       retired self-employed      services       student    technician
##           222           166           451           109           817
##    unemployed
```

```
##           114
## ################  marital  ##################
## divorced  married   single     NA's
##      583     2988     1411        8
## [1] "--- --- --- ---"
## divorced  married   single
##      583     2996     1411
## ################  education  ##################
##            basic.4y            basic.6y            basic.9y
##                 508                 271                 756
##         high.school          illiterate professional.course
##                1138                   1                 609
##   university.degree                NA's
##                1466                 241
## [1] "--- --- --- ---"
##            basic.4y            basic.6y            basic.9y
##                 515                 271                 810
##         high.school          illiterate professional.course
##                1196                   1                 633
##   university.degree
##                1564
## ################  default  ##################
##      no unknown     yes
##    3940    1050       0
## [1] "--- --- --- ---"
##      no unknown
##    3940    1050
## ################  housing  ##################
##   no  yes NA's
## 2239 2638  113
## [1] "--- --- --- ---"
##   no  yes
## 2279 2711
## ################  loan  ##################
##   no  yes NA's
## 4132  745  113
## [1] "--- --- --- ---"
##   no  yes
## 4245  745
## ################  contact  ##################
##  cellular telephone
##      3203      1787
## [1] "--- --- --- ---"
##  cellular telephone
##      3203      1787
## ################  month  ##################
##  apr  aug  dec  jul  jun  mar  may  nov  oct  sep
##  321  764   18  865  616   63 1680  513   80   70
## [1] "--- --- --- ---"
##  apr  aug  dec  jul  jun  mar  may  nov  oct  sep
```

```
##  321  764   18  865  616   63 1680  513   80   70
## ################  day_of_week  ##################
##  fri  mon  thu  tue  wed
##  957 1058 1005  952 1018
## [1] "--- --- --- ---"
##  fri  mon  thu  tue  wed
##  957 1058 1005  952 1018
## ################  poutcome  ##################
##     failure nonexistent     success
##         545        4289         156
## [1] "--- --- --- ---"
##     failure nonexistent     success
##         545        4289         156

no_imputadas<-c("poutcome","day_of_week","month","contact","default")
df[,setdiff(vars_cat,no_imputadas)]<-aux2$completeObs[,setdiff(vars_cat,n
o_imputadas)]
```

Creación de nuevos niveles de los factores

Agrupamos subcategorías en menos categorías. El resumen anterior de las variables categóricas nos sirve como referencia para ver como reagruparlas. En jobs realizamos la agrupación en función del posible ingreso monetario. Finalmente vemos la reagrupación final la cual no ha quedado uniformemente distribuida, sin embargo los grupos tienen una relación más significativa.

```
# Job

table(df$job)

##
##        admin.   blue-collar  entrepreneur     housemaid    management
##          1296          1156           189           119           351
##       retired self-employed      services       student    technician
##           222           166           451           109           817
##    unemployed
##           114

df$f.job <- 4
# 1 level - Admin-Managment
aux<-which(df$job %in% c("admin.", "management"))
df$f.job[aux] <-1

# 2 level - Entrep-Retired-selfEmpl
aux<-which(df$job %in% c("entrepreneur", "retired", "self-employed"))
df$f.job[aux] <-2

# 3 level - Not working
aux<-which(df$job %in% c("housemaid","unemployed","student"))
df$f.job[aux] <-3
```

```
# 4 level - Serv-Tech-BlueC
aux<-which(df$job %in% c("services","technician","blue-collar"))
df$f.job[aux] <-4

df$f.job<-factor(df$f.job,levels=1:4,labels=c("Admin-Managment", "Entrep-
Retired-selfEmpl", "Not-working", "Serv-Tech-BlueC"))
levels(df$f.job)<-paste0("f.job.",levels(df$f.job))
summary(df$f.job)

##         f.job.Admin-Managment f.job.Entrep-Retired-selfEmpl
##                          1647                           577
##             f.job.Not-working         f.job.Serv-Tech-BlueC
##                           342                          2424
```

En months realizamos la agrupación en función de las temporadas aunque no tan estrictamente.

```
# Months to groups
table(df$month)

##
##  apr  aug  dec  jul  jun  mar  may  nov  oct  sep
##  321  764   18  865  616   63 1680  513   80   70

df$f.season <- 3
# 1 level - mar-may
aux<-which(df$month %in% c("mar","apr","may"))
df$f.season[aux] <-1

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

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

summary(df$f.season)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   1.000   2.000   1.723   2.000   3.000

df$f.season<-factor(df$f.season,levels=1:3,labels=c("Mar-May","Jun-Aug","
Sep-Dec"))
levels(df$f.season)<-paste0("f.season.",levels(df$f.season)) # Hacemos la
s etiquetas más informativas
summary(df$f.season)

## f.season.Mar-May f.season.Jun-Aug f.season.Sep-Dec
##             2064             2245              681
```

En Education realizamos la agrupación en función del nivel de estudios de cada individuo. Hemos puesto la categoría illiterate dentro de la que consideramos que el nivel de estudios es inferior. Al realizar la agrupación los niveles quedaron relativamente bien equilibrados.

```
#Education
table(df$education)

##
##            basic.4y            basic.6y            basic.9y
##                 515                 271                 810
##         high.school          illiterate professional.course
##                1196                   1                 633
##   university.degree
##                1564

df$f.education <- 3
# 1 level - Basic
aux<-which(df$education %in% c("illiterate","basic.4y","basic.6y","basic.
9y"))
df$f.education[aux] <-1

# 2 level - High School
aux<-which(df$education %in% c("high.school"))
df$f.education[aux] <-2

# 3 level - Professional
aux<-which(df$education %in% c("professional.course","university.degree")
)
df$f.education[aux] <-3

df$f.education<-factor(df$f.education,levels=1:3,labels=c("Basic","High S
chool","Professional"))
table(df$f.education);

##
##        Basic  High School Professional
##         1597         1196         2197
```

Tratamiento de variables no-Target Numéricas

Age

Consideramos que no presenta ningún outlier, ya que las edades comprendidas entre 18 y 92 años, son considerados normal.

Campaing

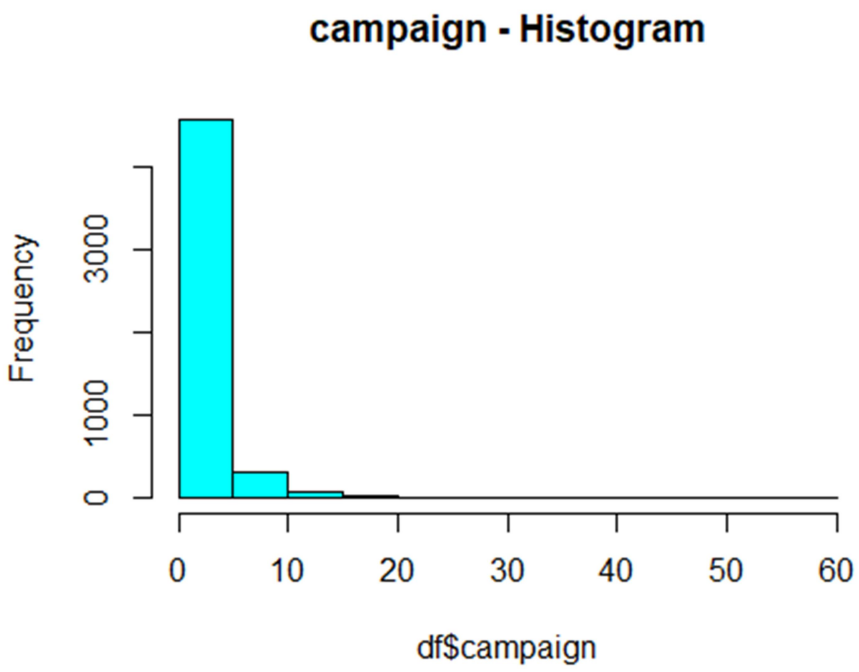
Para sopesar los outliers consideramos que en los 10 meses que dura la campaña, un máximo de 20 contactos es aceptable puesto que eso implica una media de un

contacto cada 15 días. Como errores se han buscado aquellos valores menores a 1 ya que se incluye la presente campaña. No se han detectado errores.

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

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##   1.000   1.000   2.000   2.575   3.000  56.000
```

```
  hist(df$campaign,col="cyan",main="campaign - Histogram")
```




```
  par(mfrow=c(1,2))
  boxplot(df$campaign, labels=row.names(df))
  aux<-calcQ(df$campaign);
  abline(h=aux[8],col="red",lwd=2)
  abline(h=aux[9],col="magenta",lwd=2)
  aux<-which(df$campaign<1);aux  # Si se incluye el último contacto, este valor no puede ser 0
```

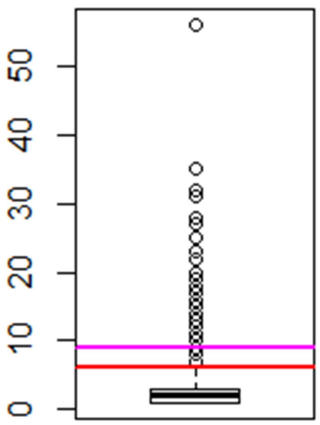
```
## integer(0)
```

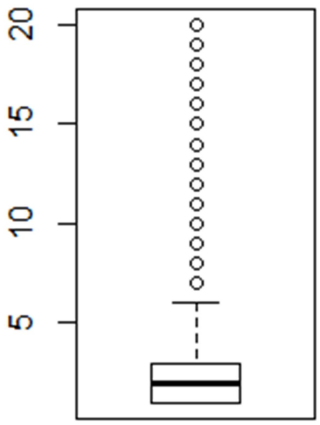
```
  aux<-which(df$campaign>20);length(aux);df[aux,'campaign']
```

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

```
##  [1] 23 25 56 32 35 31 28 27 22 28 25
```

```
  df[aux,"campaign"]<-NA
  boxplot(df$campaign)
```






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

  # Para el data analisis guardamos los missings
  dqr[dqr$variable=='campaing','missings']<-sum(is.na(df[,"campaign"]))
  # Para los individuales
  dqri[aux,'missings']<-dqri[aux,'missings']+1
```

Verificación de inconsistencias en pdays/previous/poutcome

Para pdays/previous/poutcome debería existir la relación directa entre previous=0, outcome=nonexistent y pdays=999 por lo que podemos detectar errores. Al ver el resultado podemos decir que hay inconsistencias entre el pdays y previous, ya que todos los que son pdays = 999, deberían ser previous = nonexistent, lo que en este caso nos dan 526 individuos que no cumplen esta condición. Como suponen más de un 10% de la muestra y nuestro trabajo no es exhaustivo vamos a ignorarlo.

```
  rel_pdays<-which(df$pdays==999)
  rel_previous<-which(df$previous==0)
  rel_poutcome<-which(df$poutcome=='nonexistent')
  length(setdiff(rel_poutcome, rel_previous))

## [1] 0

  length(setdiff(rel_previous, rel_poutcome))

## [1] 0
```

```
  length(setdiff(rel_previous, rel_pdays))
```

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

```
  length(setdiff(rel_pdays,    rel_previous))
```

```
## [1] 526
```

```
  summary(df[setdiff(rel_pdays,rel_previous),c('previous','poutcome')]) #
Miramos el perfil de esos individuos
```

```
##     previous            poutcome
##  Min.   :1.000   failure    :526
##  1st Qu.:1.000   nonexistent:  0
##  Median :1.000   success    :  0
##  Mean   :1.118
##  3rd Qu.:1.000
##  Max.   :5.000
```

Pdays

Con el summary podemos ver que no tenemos outliers ni errores, tampoco missings.

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

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##     0.0   999.0   999.0   964.2   999.0   999.0
```

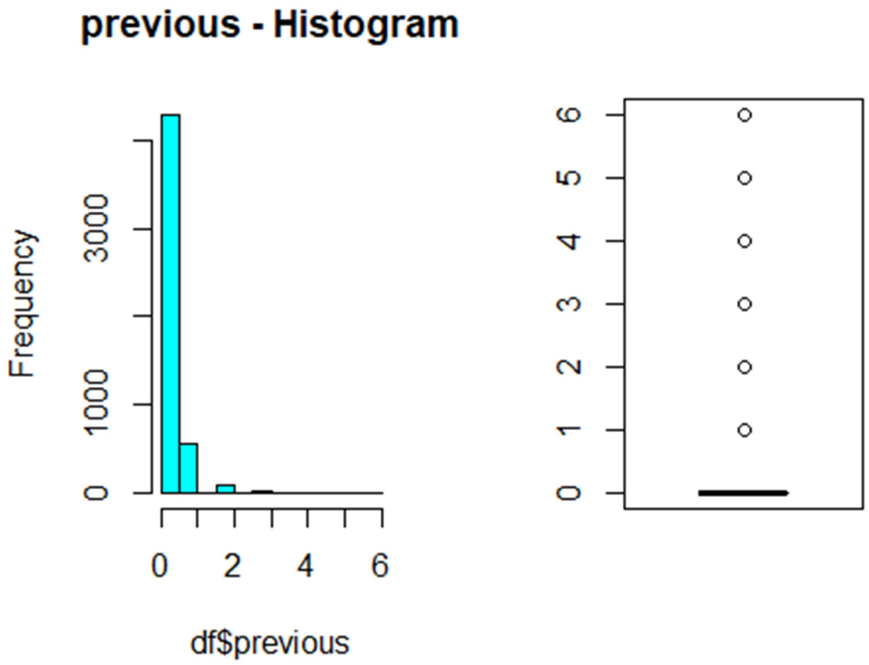
Previous

Consideramos que para esta variable no hay outliers, ya que por los valores se ve que pueden haber sido contactado hasta en 6 campañas previas, lo que tiene sentido.

```
  summary(df$previous)#Vemos que gran parte de los valores es 0
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.0000  0.0000  0.1786  0.0000  6.0000
```

```
  par(mfrow=c(1,2))
  hist(df$previous,col="cyan",main="previous - Histogram")
  boxplot(df$previous, labels=row.names(df))
```




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

Comprobación de inconsistencias en los índices trimestrales/mensuales

Para los índices trimestrales/mensuales (emp.var.rate/nr.employed/cons.prize.idx/ cons.conf.idx) cabe esperar que tengan los mismos valores para cada mes, de lo contrario pueden considerarse errores. Aparecen muchas discordancias, ya que para cada individuo y para un mismo mes el valor debería ser el mismo y en este caso no lo son. Nuestro trabajo no es exhaustivo, así que vamos a ignorar esta inconsistencia. A continuación se muestra, para cada variable y para cada mes el número de niveles, que en el caso ideal debería haber un solo nivel.

```
  aux<-c('emp.var.rate','nr.employed','cons.price.idx','cons.conf.idx')
  for(i in aux){
    cat("################ ",i," ##################\n")
    for(j in levels(df$month)){
      #cat("-- ",j,"--\n")
      aux2<-unique(df[which(df$month==j),i])
      cat(j,": ",aux2,"\n")
    }
  }
```

```
## ################  emp.var.rate  ##################
## apr :  -1.8
## aug :  1.4 -2.9 -1.7
## dec :  -0.2 -3
## jul :  1.4 -2.9 -1.7
```

```
## jun :  1.4 -2.9 -1.7
## mar :  -1.8
## may :  1.1 -1.8
## nov :  -0.1 -3.4 -1.1
## oct :  -0.1 -3.4 -1.1
## sep :  -3.4 -1.1
## ################  nr.employed  ##################
## apr :  5099.1 5008.7
## aug :  5228.1 5076.2 4991.6
## dec :  5176.3 5023.5
## jul :  5228.1 5076.2 4991.6
## jun :  5228.1 5076.2 4991.6
## mar :  5099.1 5008.7
## may :  5191 5099.1 5008.7
## nov :  5195.8 5017.5 4963.6
## oct :  5195.8 5017.5 4963.6
## sep :  5017.5 4963.6
## ################  cons.price.idx  ##################
## apr :  93.075 93.749
## aug :  93.444 92.201 94.027
## dec :  92.756 92.713
## jul :  93.918 92.469 94.215
## jun :  94.465 92.963 94.055
## mar :  92.843 93.369
## may :  93.994 92.893 93.876
## nov :  93.2 92.649 94.767
## oct :  93.798 92.431 94.601
## sep :  92.379 94.199
## ################  cons.conf.idx  ##################
## apr :  -47.1 -34.6
## aug :  -36.1 -31.4 -38.3
## dec :  -45.9 -33
## jul :  -42.7 -33.6 -40.3
## jun :  -41.8 -40.8 -39.8
## mar :  -50 -34.8
## may :  -36.4 -46.2 -40
## nov :  -42 -30.1 -50.8
## oct :  -40.4 -26.9 -49.5
## sep :  -29.8 -37.5
```

Emp.var.rate,cons.price.idx, cons.conf.idx, euribor3m, nr.employed

Necesitamos saber cómo se han obtenido estos datos para poder validarlos, como no tenemos esa información solo podemos comprobar los missings values. En este caso al hacer summary de cada variable, podemos ver que no existen missings.

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

##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -3.40000 -1.80000  1.10000  0.05212  1.40000  1.40000
```

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

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   92.20   93.08   93.44   93.56   93.99   94.77

  summary(df$cons.conf.idx)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  -50.80  -42.70  -41.80  -40.54  -36.40  -26.90

  summary(df$euribor3m)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.634   1.334   4.857   3.585   4.961   5.045

  summary(df$nr.employed)

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

Realizamos la imputación de las variables numéricas y comparamos los datos imputados con los originales. Observamos que da valores razonados, solamente que debemos redondearlos en ambos casos ya que se trata de "número de contactos" de las variables 'previous' y 'campaign'. Igual que en el caso anterior, solo se sobrescriben las variables imputadas en nuestro df.

```
  vars_num_imp<-imputePCA(df[,vars_num],npc=5)

  summary(df[,vars_num])

##       age           campaign          pdays          previous
##  Min.   :18.00   Min.   : 1.000   Min.   :  0.0   Min.   :0.0000
##  1st Qu.:32.00   1st Qu.: 1.000   1st Qu.:999.0   1st Qu.:0.0000
##  Median :38.00   Median : 2.000   Median :999.0   Median :0.0000
##  Mean   :40.18   Mean   : 2.514   Mean   :964.2   Mean   :0.1786
##  3rd Qu.:47.00   3rd Qu.: 3.000   3rd Qu.:999.0   3rd Qu.:0.0000
##  Max.   :92.00   Max.   :20.000   Max.   :999.0   Max.   :6.0000
##                  NA's   :11
##   emp.var.rate      cons.price.idx  cons.conf.idx      euribor3m
##  Min.   :-3.40000   Min.   :92.20   Min.   :-50.80   Min.   :0.634
##  1st Qu.:-1.80000   1st Qu.:93.08   1st Qu.:-42.70   1st Qu.:1.334
##  Median : 1.10000   Median :93.44   Median :-41.80   Median :4.857
##  Mean   : 0.05212   Mean   :93.56   Mean   :-40.54   Mean   :3.585
##  3rd Qu.: 1.40000   3rd Qu.:93.99   3rd Qu.:-36.40   3rd Qu.:4.961
##  Max.   : 1.40000   Max.   :94.77   Max.   :-26.90   Max.   :5.045
##
##   nr.employed
##  Min.   :4964
##  1st Qu.:5099
##  Median :5191
##  Mean   :5166
##  3rd Qu.:5228
```

```
##  Max.   :5228
##
```

```
  summary(vars_num_imp$completeObs)
```

```
##       age           campaign          pdays          previous
##  Min.   :18.00   Min.   : 1.000   Min.   :  0.0   Min.   :0.0000
##  1st Qu.:32.00   1st Qu.: 1.000   1st Qu.:999.0   1st Qu.:0.0000
##  Median :38.00   Median : 2.000   Median :999.0   Median :0.0000
##  Mean   :40.18   Mean   : 2.515   Mean   :964.2   Mean   :0.1786
##  3rd Qu.:47.00   3rd Qu.: 3.000   3rd Qu.:999.0   3rd Qu.:0.0000
##  Max.   :92.00   Max.   :20.000   Max.   :999.0   Max.   :6.0000
##   emp.var.rate      cons.price.idx  cons.conf.idx      euribor3m
##  Min.   :-3.40000   Min.   :92.20   Min.   :-50.80   Min.   :0.634
##  1st Qu.:-1.80000   1st Qu.:93.08   1st Qu.:-42.70   1st Qu.:1.334
##  Median : 1.10000   Median :93.44   Median :-41.80   Median :4.857
##  Mean   : 0.05212   Mean   :93.56   Mean   :-40.54   Mean   :3.585
##  3rd Qu.: 1.40000   3rd Qu.:93.99   3rd Qu.:-36.40   3rd Qu.:4.961
##  Max.   : 1.40000   Max.   :94.77   Max.   :-26.90   Max.   :5.045
##   nr.employed
##  Min.   :4964
##  1st Qu.:5099
##  Median :5191
##  Mean   :5166
##  3rd Qu.:5228
##  Max.   :5228
```

```
  df[,vars_num]<-vars_num_imp$completeObs[,vars_num]
  aux<-c('previous','campaign')
  df[,aux]<-round(df[,aux])
```

Resumen del Data Quality Report y Ranking

A continuación se muestra el ranking de missings, errors y outliers para cada variable que tiene por lo menos algún missing, error o outlier. Vemos que el valor más destacable, los missings de education, no alcanza el 5% de la muestra.

```
aux<-which(dqr$missings>0 | dqr$errors>0 | dqr$outliers>0)
dqr_subset<-dqr[aux,]
dqr_subset[order(-dqr_subset$missings),]
```

```
##     variable missings errors outliers
## 4  education      241      0        0
## 6    housing      113      0        0
## 7       loan      113      0        0
## 2        job       45      0        0
## 3    marital        8      0        0
## 11  duration        0      4        6
```

```
dqr[dqr$variable=="education",'missings']/nrow(df)
```

```
## [1] 0.04829659
```

Para el data quality report de individuales cabe destacar que se han ignorado errores y ouliers de la variable target duration, pues estos individuos se han eliminado resultando una muestra de 4990. Dicho esto, y viendo los resultados anteriores, bastará con supervisar los missings individuales. El summary revela poca incidencia con un escaso 0.1 missings de media, pero sí vemos que hay individuos con hasta 3 missings. Con prop.table se observa un 5% de la muestra con 1 missing, un 2,5% con dos y un 0,24% con tres. Lo consideramos valores razonables.

```
summary(dqri$missings)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.0000  0.0000  0.1064  0.0000  3.0000

prop.table(table(dqri$missings))

##
##          0          1          2          3
## 0.92244489 0.05110220 0.02404810 0.00240481
```

Creación de factores adicionales para cada variable cuantitativa

Age

Primero miramos cuan distribuidos quedan aplicando unos cortes según los cuartiles, como estos no difieren demasiado con los niveles naturales (20 añeros, 30 añeros...) preferimos quedarnos con los niveles naturales.

```
aux<-quantile(df$age,seq(0,1,0.25),na.rm=TRUE) # Niveles por quartiles
aux<-factor(cut(df$age,breaks=aux,include.lowest=T))
table(aux)

## aux
## [18,32] (32,38] (38,47] (47,92]
##    1328    1188    1287    1187

tapply(df$age,aux,median)

## [18,32] (32,38] (38,47] (47,92]
##      30      35      43      54

aux2<-c(18,30,40,50,92) # Niveles "naturales"
aux<-factor(cut(df$age,breaks=aux2,include.lowest=T))
table(aux)

## aux
## [18,30] (30,40] (40,50] (50,92]
##     870    1991    1253     876

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

```
## [18,30] (30,40] (40,50] (50,92]
##      28      35      45      56

df$f.age<-factor(cut(df$age,breaks=aux2,include.lowest=T))
levels(df$f.age)<-paste0("f.age-",levels(df$f.age))
summary(df$f.age)

## f.age-[18,30] f.age-(30,40] f.age-(40,50] f.age-(50,92]
##           870          1991          1253           876
```

Duration

Hemos buscado una distribución más o menos equilibrada y hemos conseguido separarlo en niveles de 2min, 3min, 5min, y el resto.

```
# Para duration
aux<-quantile(df$duration,seq(0,1,0.25),na.rm=TRUE)#Niveles por quartiles
aux<-factor(cut(df$duration,breaks=aux,include.lowest=T))
table(aux)

## aux
##        [5,103]      (103,178]      (178,321] (321,2.08e+03]
##           1255           1240           1249           1246

tapply(df$duration,aux,median)

##        [5,103]      (103,178]      (178,321] (321,2.08e+03]
##             68            140            240            488

aux2<-c(5,120,180,300,2100)#Niveles "naturales"
aux<-factor(cut(df$duration,breaks=aux2,include.lowest=T))
table(aux)

## aux
##       [5,120]     (120,180]     (180,300] (300,2.1e+03]
##          1557           966          1090          1377

tapply(df$duration,aux,median)

##       [5,120]     (120,180]     (180,300] (300,2.1e+03]
##            77           150           235           461

df$f.duration<-factor(cut(df$duration,breaks=aux2,include.lowest=T))#Nos
quedamos con los niveles naturales
levels(df$f.duration)<-paste0("f.duration-",levels(df$f.duration))#Hacemo
s las etiquetas más informativas
summary(df$f.duration)

##       f.duration-[5,120]     f.duration-(120,180]     f.duration-(180,
300]
##                     1557                      966
1090
```

```
## f.duration-(300,2.1e+03]
##                     1377
```

Campaign

Como para esta variable la mayoría de los valores están entre 0 y 1, no se puede hacer la separación por cuartiles. Hemos realizado una factorización manual viendo la cantidad de valores en cada nivel.

```
aux<-levels(factor(df$campaign))
aux<-factor(cut(df$campaign,breaks=aux,include.lowest=T))
table(aux)

## aux
##   [1,2]   (2,3]   (3,4]   (4,5]   (5,6]   (6,7]   (7,8]   (8,9]  (9,10
]
##    3380     676     334     190     117      86      60      31      2
3
## (10,11] (11,12] (12,13] (13,14] (14,15] (15,16] (16,17] (17,18] (18,19
]
##      17      21       9      11       8       6       8       7
4
## (19,20]
##       2

tapply(df$campaign,aux,median)

##   [1,2]   (2,3]   (3,4]   (4,5]   (5,6]   (6,7]   (7,8]   (8,9]  (9,10
]
##       1       3       4       5       6       7       8       9      1
0
## (10,11] (11,12] (12,13] (13,14] (14,15] (15,16] (16,17] (17,18] (18,19
]
##      11      12      13      14      15      16      17      18      1
9
## (19,20]
##      20

aux2<-c(0,1,2,20)
aux<-factor(cut(df$campaign,breaks=aux2,include.lowest=T))
table(aux)

## aux
##  [0,1]  (1,2] (2,20]
##   2121   1259   1610

df$f.campaign<-factor(cut(df$campaign,breaks=aux2,include.lowest=T))
levels(df$f.campaign)<-paste0("f.campaign-",levels(df$f.campaign))
summary(df$f.campaign)

##  f.campaign-[0,1]  f.campaign-(1,2] f.campaign-(2,20]
##              2121              1259              1610
```

Pdays

Como en pdays hay 4815 valores de 999 que significa que no se han contactado en campañas previas, esto sería un 96% de los individuos por lo que decidimos realizar la agrupación en solo dos niveles, contactados y no-contactados.

```
aux2<-c(0,998,999)
pdays_cutted<-factor(cut(df$pdays,breaks=aux2,include.lowest=T))
table(pdays_cutted)

## pdays_cutted
##   [0,998] (998,999]
##       175      4815

tapply(df$pdays,pdays_cutted,median)

##   [0,998] (998,999]
##         6       999

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

##   f.pdays-[0,998] f.pdays-(998,999]
##               175              4815
```

Previous

Vemos que esta variable solo tiene 6 niveles por lo decidimos pasarlos a los tres niveles más relevantes, sin que sea binaria. Ya que pensamos que el grupo de individuos con un solo contacto en una campaña previa podría ser significativo con respecto a la variable target Y.

```
aux2<-c(0,0.9,1,6)
previous_cutted<-factor(cut(df$previous,breaks=aux2,include.lowest=T))
table(previous_cutted)

## previous_cutted
## [0,0.9] (0.9,1]   (1,6]
##    4289     564     137

tapply(df$previous,previous_cutted,median)

## [0,0.9] (0.9,1]   (1,6]
##       0       1       2

df$f.previous<-previous_cutted
levels(df$f.previous)<-paste0("f.previous-",levels(df$f.previous))
summary(df$f.previous)

## f.previous-[0,0.9] f.previous-(0.9,1]   f.previous-(1,6]
##               4289                564                137
```

Profiling

Nombres de niveles más informativos

Para poder hacer profiling, necesitamos darle nombres a los subniveles de los factores, para esto hacemos un bucle que recorre cada variable categórica y le añade el nombre de la variable más un "." y el nombre del nivel. Luego procedemos a ejecutar la función condes con la variable target duration, la cual se encuentra en la posición 11 de nuestro data frame. Usamos una probabilidad de 0.01 que consideramos puede mostrarnos el resultado que queremos. Para la función catdes usamos la variable "Y" la cual se encuentra en la posición 21 de nuestro data frame.

```
vars_cat_con_y<-c(vars_cat,"y")
for (i in vars_cat_con_y){
  levels(df[,i])<-paste0(i,".",levels(df[,i]))
}
```

Resultado del CONDES

```
condes(df,11,proba=0.01)
```

```
## $quanti
##          correlation      p.value
## campaign -0.05940135 2.683764e-05
##
## $quali
##                       R2       p.value
## f.duration 0.621168787  0.000000e+00
## y          0.177066645 2.228224e-213
## f.campaign 0.003783221  7.858324e-05
## month      0.004450289  8.185248e-03
##
## $category
##                               Estimate       p.value
## f.duration-(300,2.1e+03]  310.35106  0.000000e+00
## y.yes                     170.13318 2.228224e-213
## f.campaign-(1,2]           23.01041  3.895001e-05
## month.apr                  35.25783  4.865526e-03
## f.season.Mar-May           13.19170  6.782891e-03
## month.aug                 -25.22225  7.943838e-03
## f.campaign-(2,20]         -17.35164  3.316706e-03
## f.duration-(180,300]      -20.50721  3.927333e-04
## f.duration-(120,180]     -106.75355  5.404997e-53
## y.no                     -170.13318 2.228224e-213
## f.duration-[5,120]       -183.09030 1.278559e-312
```

```
tapply(df$duration,df$f.dur,mean)
```

```
##       f.duration-[5,120]     f.duration-(120,180]     f.duration-(180,
300]
##                 73.39306                149.72981                235.9
```

```
7615
## f.duration-(300,2.1e+03]
##                566.83442

summary(df$duration)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##     5.0   103.0   178.5   259.9   321.0  2078.0

tapply(df$duration,df$y,mean)

##     y.no    y.yes
## 222.8923 563.1587
```

En el resultado de la correlación cuantitativa, podemos ver que la única variable posiblemente relacionada es campaing. Campaing aun estando inversamente relacionada con duration, su correlación es muy pequeña pues no llega al 6%. Traducido al lenguaje natural podemos decir: "hay indicios de que cuantas más campañas ha participado el individuo más corta será la duración de la llamada". Además el pvalor nos indica que la probabilidad de que la correlación sea cero, es muy baja, tanto es así que nos da cierta confianza de que la correlación indicada es la real.

Para las variables cualitativas, podemos ver que los factores de duration están muy relacionados lo cual tiene total sentido ya que se está comparando con ella misma. Para la variable Y, podemos ver que hay una relación con duration aunque 0.177 comparado con 1 es aparentemente poco, en este tipo de estudios es una relación relevante que cabe destacar. Además el pvalor es casi nulo, que nos da mucha confianza sobre este indicador. Para f.campaing y month, presentan ciertos indicios de relación pero con pvalores bastante ajustados.

Mirando el análisis por categorías que nos muestra condes, vemos en primer lugar que el f.duration con intervalo entre (300,2.1e+03] tiene una media estimada de 310 segundos sobre la media global lo cual no deja de ser una obviedad. Sin embargo, si nos fijamos en el y.yes podemos ver que los individuos están 170 segundos por encima de la media global, cosa que viene apoyada por la confianza de un pvalor casi nulo. Con esto podemos decir que los individuos propensos a comprar el producto, resulta que duran más tiempo al teléfono. Sin más información sobre el proceso de contacto en las campañas, nos hace pensar que puede ser por el hecho de que al comprar el producto, estos individuos deben permanecer más tiempo para poder dar todos sus datos.

Si comparamos los meses de abril y agosto podemos ver que en abril, los individuos duran un poco más de tiempo al teléfono respecto a la media, y esto, asumiendo lo anteriormente dicho, puede que sea un mes más propenso a la venta del producto. En cambio en el mes de agosto estos duraron menos tiempo al teléfono, podemos intuir que puede ser debido a las vacaciones.

Resultado del CATDES

```
prop.table(table(df$y)) # y
```

```
##
##      y.no     y.yes
## 0.8913828 0.1086172

prop.table(table(df$f.duration)) # f.duration

##
##       f.duration-[5,120]     f.duration-(120,180]     f.duration-(180,
300]
##                0.3120240                0.1935872                0.218
4369
## f.duration-(300,2.1e+03]
##                0.2759519

prop.table(table(df$f.duration,df$y),1)

##
##                                   y.no      y.yes
##   f.duration-[5,120]       0.98715478 0.01284522
##   f.duration-(120,180]     0.95445135 0.04554865
##   f.duration-(180,300]     0.90000000 0.10000000
##   f.duration-(300,2.1e+03] 0.73202614 0.26797386

prop.table(table(df$f.duration,df$y),2)

##
##                                   y.no      y.yes
##   f.duration-[5,120]       0.34554856 0.03690037
##   f.duration-(120,180]     0.20728417 0.08118081
##   f.duration-(180,300]     0.22054856 0.20110701
##   f.duration-(300,2.1e+03] 0.22661871 0.68081181

catdes(df,21,proba=0.01)

##
## Link between the cluster variable and the categorical variables (chi-s
quare test)
## ================================================================
===========
##                    p.value df
## f.duration  1.038223e-118  3
## poutcome    5.738265e-111  2
## f.pdays     9.773367e-110  1
## month        7.431682e-53  9
## f.previous   4.536325e-49  2
## job          1.524734e-25 10
## contact      1.007104e-18  1
## f.age        1.378066e-12  3
## default      4.342743e-12  1
## f.job        8.884797e-12  3
## f.season     4.127488e-08  2
## f.campaign   1.868723e-06  2
```

```
## f.education  7.638741e-05  2
## education    5.054754e-04  6
## marital      1.381426e-03  2
##
## Description of each cluster by the categories
## =============================================
## $y.no
##                                          Cla/Mod    Mod/Cla    Global
## f.duration=f.duration-[5,120]          98.71548 34.5548561 31.202405
## f.pdays=f.pdays-(998,999]              91.00727 98.5161871 96.492986
## f.previous=f.previous-[0,0.9]          91.11681 87.8597122 85.951904
## poutcome=poutcome.nonexistent          91.11681 87.8597122 85.951904
## contact=contact.telephone              94.34807 37.9046763 35.811623
## f.duration=f.duration-(120,180]        95.44513 20.7284173 19.358717
## default=default.unknown                95.04762 22.4370504 21.042084
## f.job=f.job.Serv-Tech-BlueC            92.07921 50.1798561 48.577154
## job=job.blue-collar                    93.85813 24.3929856 23.166333
## month=month.may                        92.55952 34.9595324 33.667335
## f.campaign=f.campaign-(2,20]           92.17391 33.3633094 32.264529
## f.age=f.age-(40,50]                    92.41820 26.0341727 25.110220
## education=education.basic.9y           92.71605 16.8839928 16.232465
## f.education=Basic                      91.42142 32.8237410 32.004008
## job=job.services                       93.56984  9.4874101  9.038076
## f.age=f.age-(30,40]                    90.85886 40.6699640 39.899800
## f.season=f.season.Jun-Aug              90.69042 45.7733813 44.989980
## marital=marital.married                90.22029 60.7688849 60.040080
## f.age=f.age-[18,30]                    86.43678 16.9064748 17.434870
## marital=marital.single                 86.60524 27.4730216 28.276553
## education=education.university.degree 86.70077 30.4856115 31.342685
## f.education=Professional               87.07328 43.0080935 44.028056
## f.campaign=f.campaign-[0,1]            86.89298 41.4343525 42.505010
## month=month.apr                        80.37383  5.8003597  6.432866
## f.previous=f.previous-(0.9,1]          82.80142 10.4991007 11.302605
## f.job=f.job.Entrep-Retired-selfEmpl    82.84229 10.7464029 11.563126
## job=job.student                        72.47706  1.7760791  2.184369
## f.season=f.season.Sep-Dec              82.81938 12.6798561 13.647295
## month=month.sep                        62.85714  0.9892086  1.402806
## f.age=f.age-(50,92]                    83.21918 16.3893885 17.555110
## month=month.mar                        55.55556  0.7868705  1.262525
## month=month.oct                        57.50000  1.0341727  1.603206
## job=job.retired                        71.62162  3.5746403  4.448898
## default=default.no                     87.56345 77.5629496 78.957916
## contact=contact.cellular               86.23166 62.0953237 64.188377
## f.previous=f.previous-(1,6]            53.28467  1.6411871  2.745491
## f.pdays=f.pdays-[0,998]                37.71429  1.4838129  3.507014
## poutcome=poutcome.success              33.97436  1.1915468  3.126253
## f.duration=f.duration-(300,2.1e+03]    73.20261 22.6618705 27.595190
##                                            p.value     v.test
## f.duration=f.duration-[5,120]          2.229911e-64  16.941339
## f.pdays=f.pdays-(998,999]              7.719766e-64  16.868133
```

```
## f.previous=f.previous-[0,0.9]          6.319513e-24  10.086802
## poutcome=poutcome.nonexistent          6.319513e-24  10.086802
## contact=contact.telephone              2.596533e-20   9.234435
## f.duration=f.duration-(120,180]        2.258505e-14   7.634983
## default=default.unknown                8.276549e-14   7.465847
## f.job=f.job.Serv-Tech-BlueC            6.563448e-11   6.530308
## job=job.blue-collar                    5.519353e-10   6.203578
## month=month.may                        1.337581e-08   5.681193
## f.campaign=f.campaign-(2,20]           1.119511e-06   4.869376
## f.age=f.age-(40,50]                    8.643837e-06   4.448584
## education=education.basic.9y           1.987893e-04   3.720550
## f.education=Basic                      3.022238e-04   3.613386
## job=job.services                       8.082497e-04   3.349954
## f.age=f.age-(30,40]                    1.346805e-03   3.205815
## f.season=f.season.Jun-Aug              1.383606e-03   3.198049
## marital=marital.married                2.776091e-03   2.991502
## f.age=f.age-[18,30]                    5.943641e-03  -2.750874
## marital=marital.single                 3.906851e-04  -3.546297
## education=education.university.degree 2.321260e-04  -3.681214
## f.education=Professional               3.492236e-05  -4.138737
## f.campaign=f.campaign-[0,1]            1.327080e-05  -4.355592
## month=month.apr                        1.663724e-06  -4.790493
## f.previous=f.previous-(0.9,1]          1.344587e-06  -4.833047
## f.job=f.job.Entrep-Retired-selfEmpl    1.134068e-06  -4.866823
## job=job.student                        1.088887e-06  -4.874854
## f.season=f.season.Sep-Dec              7.466144e-08  -5.379576
## month=month.sep                        6.365587e-09  -5.806859
## f.age=f.age-(50,92]                    3.842509e-09  -5.890834
## month=month.mar                        9.598941e-12  -6.812392
## month=month.oct                        2.600541e-13  -7.313613
## job=job.retired                        1.403012e-13  -7.396044
## default=default.no                     8.276549e-14  -7.465847
## contact=contact.cellular               2.596533e-20  -9.234435
## f.previous=f.previous-(1,6]            3.828645e-27 -10.790222
## f.pdays=f.pdays-[0,998]                7.719766e-64 -16.868133
## poutcome=poutcome.success              5.851631e-64 -16.884494
## f.duration=f.duration-(300,2.1e+03]    2.022672e-97 -20.946423
##
## $y.yes
##                                          Cla/Mod   Mod/Cla    Global
## f.duration=f.duration-(300,2.1e+03]   26.797386 68.081181 27.595190
## poutcome=poutcome.success             66.025641 19.003690  3.126253
## f.pdays=f.pdays-[0,998]               62.285714 20.110701  3.507014
## f.previous=f.previous-(1,6]           46.715328 11.808118  2.745491
## contact=contact.cellular              13.768342 81.365314 64.188377
## default=default.no                    12.436548 90.405904 78.957916
## job=job.retired                       28.378378 11.623616  4.448898
## month=month.oct                       42.500000  6.273063  1.603206
## month=month.mar                       44.444444  5.166052  1.262525
## f.age=f.age-(50,92]                   16.780822 27.121771 17.555110
```

```
## month=month.sep                             37.142857  4.797048  1.402806
## f.season=f.season.Sep-Dec                   17.180617 21.586716 13.647295
## job=job.student                             27.522936  5.535055  2.184369
## f.job=f.job.Entrep-Retired-selfEmpl         17.157712 18.265683 11.563126
## f.previous=f.previous-(0.9,1]               17.198582 17.896679 11.302605
## month=month.apr                             19.626168 11.623616  6.432866
## f.campaign=f.campaign-[0,1]                 13.107025 51.291513 42.505010
## f.education=Professional                    12.926718 52.398524 44.028056
## education=education.university.degree       13.299233 38.376384 31.342685
## marital=marital.single                      13.394755 34.870849 28.276553
## f.age=f.age-[18,30]                         13.563218 21.771218 17.434870
## marital=marital.married                      9.779706 54.059041 60.040080
## f.season=f.season.Jun-Aug                    9.309577 38.560886 44.989980
## f.age=f.age-(30,40]                          9.141135 33.579336 39.899800
## job=job.services                             6.430155  5.350554  9.038076
## f.education=Basic                            8.578585 25.276753 32.004008
## education=education.basic.9y                 7.283951 10.885609 16.232465
## f.age=f.age-(40,50]                          7.581804 17.527675 25.110220
## f.campaign=f.campaign-(2,20]                 7.826087 23.247232 32.264529
## month=month.may                              7.440476 23.062731 33.667335
## job=job.blue-collar                          6.141869 13.099631 23.166333
## f.job=f.job.Serv-Tech-BlueC                  7.920792 35.424354 48.577154
## default=default.unknown                      4.952381  9.594096 21.042084
## f.duration=f.duration-(120,180]              4.554865  8.118081 19.358717
## contact=contact.telephone                    5.651931 18.634686 35.811623
## f.previous=f.previous-[0,0.9]                8.883190 70.295203 85.951904
## poutcome=poutcome.nonexistent                8.883190 70.295203 85.951904
## f.pdays=f.pdays-(998,999]                    8.992731 79.889299 96.492986
## f.duration=f.duration-[5,120]                1.284522  3.690037 31.202405
##                                                 p.value     v.test
## f.duration=f.duration-(300,2.1e+03]   2.022672e-97  20.946423
## poutcome=poutcome.success             5.851631e-64  16.884494
## f.pdays=f.pdays-[0,998]               7.719766e-64  16.868133
## f.previous=f.previous-(1,6]           3.828645e-27  10.790222
## contact=contact.cellular              2.596533e-20   9.234435
## default=default.no                    8.276549e-14   7.465847
## job=job.retired                       1.403012e-13   7.396044
## month=month.oct                       2.600541e-13   7.313613
## month=month.mar                       9.598941e-12   6.812392
## f.age=f.age-(50,92]                   3.842509e-09   5.890834
## month=month.sep                       6.365587e-09   5.806859
## f.season=f.season.Sep-Dec             7.466144e-08   5.379576
## job=job.student                       1.088887e-06   4.874854
## f.job=f.job.Entrep-Retired-selfEmpl   1.134068e-06   4.866823
## f.previous=f.previous-(0.9,1]         1.344587e-06   4.833047
## month=month.apr                       1.663724e-06   4.790493
## f.campaign=f.campaign-[0,1]           1.327080e-05   4.355592
## f.education=Professional              3.492236e-05   4.138737
## education=education.university.degree 2.321260e-04   3.681214
## marital=marital.single                3.906851e-04   3.546297
```

```
## f.age=f.age-[18,30]                    5.943641e-03   2.750874
## marital=marital.married                2.776091e-03  -2.991502
## f.season=f.season.Jun-Aug              1.383606e-03  -3.198049
## f.age=f.age-(30,40]                    1.346805e-03  -3.205815
## job=job.services                       8.082497e-04  -3.349954
## f.education=Basic                      3.022238e-04  -3.613386
## education=education.basic.9y           1.987893e-04  -3.720550
## f.age=f.age-(40,50]                    8.643837e-06  -4.448584
## f.campaign=f.campaign-(2,20]           1.119511e-06  -4.869376
## month=month.may                        1.337581e-08  -5.681193
## job=job.blue-collar                    5.519353e-10  -6.203578
## f.job=f.job.Serv-Tech-BlueC            6.563448e-11  -6.530308
## default=default.unknown                8.276549e-14  -7.465847
## f.duration=f.duration-(120,180]        2.258505e-14  -7.634983
## contact=contact.telephone              2.596533e-20  -9.234435
## f.previous=f.previous-[0,0.9]          6.319513e-24 -10.086802
## poutcome=poutcome.nonexistent          6.319513e-24 -10.086802
## f.pdays=f.pdays-(998,999]              7.719766e-64 -16.868133
## f.duration=f.duration-[5,120]          2.229911e-64 -16.941339
##
##
## Link between the cluster variable and the quantitative variables
## ================================================================
##                       Eta2       P-value
## duration       0.177066645 2.228224e-213
## nr.employed    0.108627691 9.588810e-127
## pdays          0.099363145 1.586887e-115
## euribor3m      0.080172702  1.211844e-92
## emp.var.rate   0.074526086  5.345604e-86
## previous       0.045463793  2.111426e-52
## cons.price.idx 0.013909243  6.368783e-17
## campaign       0.006362358  1.679586e-08
## age            0.004721065  1.184599e-06
## cons.conf.idx  0.003722772  1.610540e-05
##
## Description of each cluster by quantitative variables
## ======================================================
## $y.no
##                    v.test Mean in category  Overall mean sd in categor
y
## nr.employed     23.279681     5174.2504272 5165.87569138     65.975653
2
## pdays           22.264832      984.2796763  964.18517034    119.945851
2
## euribor3m       19.999540        3.7572383    3.58457355      1.662919
6
## emp.var.rate    19.282392        0.2024505    0.05212425      1.500410
9
## cons.price.idx   8.330259       93.5875852   93.56373427      0.561839
8
```

```
## campaign         5.633986        2.5807104    2.51503006      2.429261
1
## cons.conf.idx   -4.309630      -40.6408273  -40.54192385      4.412224
6
## age             -4.853184       39.9267086   40.17755511      9.842648
1
## previous       -15.060507        0.1411871    0.17855711      0.412085
5
## duration       -29.721802      222.8923112  259.85110220    201.971895
2
##                 Overall sd       p.value
## nr.employed     72.7919889 7.122275e-120
## pdays          182.6196113 8.102628e-110
## euribor3m        1.7469207  5.558249e-89
## emp.var.rate     1.5774788  7.550292e-83
## cons.price.idx   0.5793439  8.066566e-17
## campaign         2.3588988  1.760909e-08
## cons.conf.idx    4.6436681  1.635282e-05
## age             10.4585324  1.214948e-06
## previous         0.5020810  2.945210e-51
## duration       251.6124483 4.014694e-194
##
## $y.yes
##                    v.test Mean in category  Overall mean sd in categor
y
## duration        29.721802      563.1586716  259.85110220    380.638506
0
## previous        15.060507        0.4852399    0.17855711      0.906497
6
## age              4.853184       42.2361624   40.17755511     14.395684
8
## cons.conf.idx    4.309630      -39.7302583  -40.54192385      6.166449
5
## campaign        -5.633986        1.9760148    2.51503006      1.572766
5
## cons.price.idx  -8.330259       93.3679982   93.56373427      0.675713
9
## emp.var.rate   -19.282392       -1.1815498    0.05212425      1.651576
2
## euribor3m      -19.999540        2.1675756    3.58457355      1.774772
0
## pdays          -22.264832      799.2767528  964.18517034    398.074416
1
## nr.employed    -23.279681     5097.1472325 5165.87569138     88.102466
2
##                 Overall sd       p.value
## duration       251.6124483 4.014694e-194
## previous         0.5020810  2.945210e-51
## age             10.4585324  1.214948e-06
## cons.conf.idx    4.6436681  1.635282e-05
```

```
## campaign          2.3588988  1.760909e-08
## cons.price.idx    0.5793439  8.066566e-17
## emp.var.rate      1.5774788  7.550292e-83
## euribor3m         1.7469207  5.558249e-89
## pdays           182.6196113 8.102628e-110
## nr.employed      72.7919889 7.122275e-120
```

En la descripción por categorías catdes nos da la relación que tiene cada categoría con nuestro target yes o no, de los cuales nos vamos a focalizar en los que respondieron yes.

Aquí de nuevo se corrobora lo que ya nos anticipaba el condes, ya que la categoría que contiene la mayor duración de tiempo de las llamadas, es la que esta más relacionada con que el individuo compre el producto.

Esto lo interpretamos de la columna Mod/Cla en la cual aquellos que compraron el producto, un 68% eran de las llamadas más prolongadas, sin embargo, y esto viene reflejado en la columna Cla/Mod, no podemos decir que todos los que duran un tiempo prolongado en el telefono, vayan a comprar el producto, pues solo un 26% de estos aceptaron el producto, que no es poco.

De la categoría de poutcome, podemos ver que aquellos que aceptaron en una campaña previa el producto, aceptarán con una probabilidad de un 66% el producto de esta campaña. Esto apoya la tesis que pregona el marketing: “Si el individuo ya es cliente de la empresa esto le da confianza para comprar de nuevo”.

En la misma línea nos indica la categoría f.pdays[0,988] que a fin de cuentas tiene el mismo significado que el poutcome y que previous, salvo como hemos visto en el anterior análisis hay ciertos individuos de pdays que no son consistentes con el poutcome.

Otro valor que nos llama la atención es el que da la categoría job, en su nivel retired, podemos ver que un 28% aceptó el producto, lo que es un buen indicador de que este es un tipo de individuo de interés.

En los meses de marzo y octubre, vemos un incremento relevante en las ventas, aunque vemos que estos meses son una muestra poco representativa de nuestra muestra (esto lo podemos ver en la columna global, donde estos meses tienen un valor inferior al 1.7% del total de individuos) lo que nos puede decir que no son valores muy representativos. En cambio para el mes de abril podemos ver que es una muestra mayor, con un 6% con respecto a la muestra global, de este porcentaje casi un 20% aceptó el producto, lo cual nos puede indicar, que sea un mes más propenso a la aceptación del mismo.

Además parece ser que la franja de edad más propensa a la compra corresponde al intervalo de más larga edad que es de mayores de 50 años.

Después de analizar estos datos, podemos crear algunos perfiles que pueden ser propensos a aceptar futuros productos.

Perfil de persona más propensa a que acepte el producto:

1- Persona entre 50 y 92 años, que esté retirada, que haya sido contactada en una campaña previa. 2- Persona mayor de 40 años, profesional, soltero, que haya sido contactada en una campaña previa.

Perfil de llamada más propensa a que se acepte el producto:

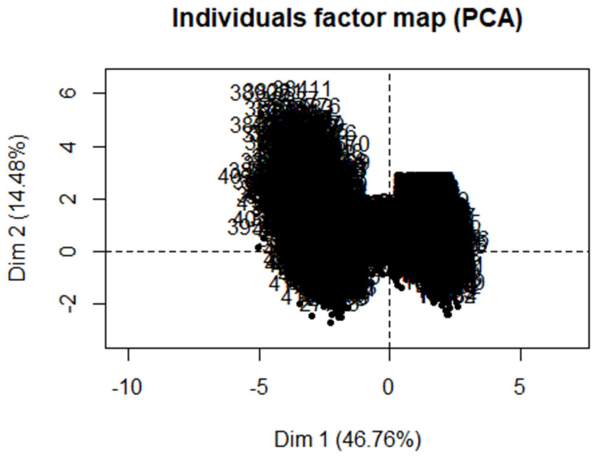
1- Abril, duración larga (más de 300 segundos) y hechas a un móvil.

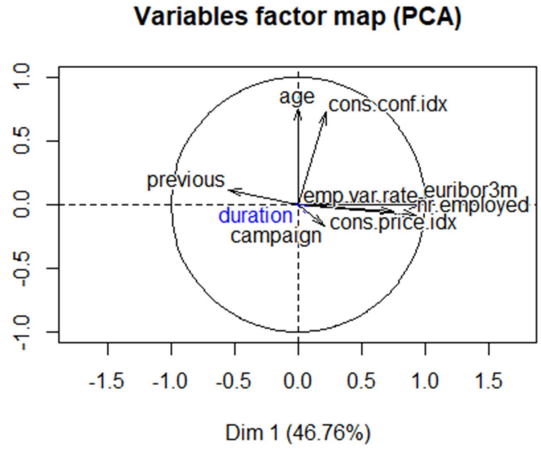
Valores propios y ejes dominantes

Eigenvalues and dominant axes analysis. How many axes we have to interpret according to Kaiser and Elbow's rule?

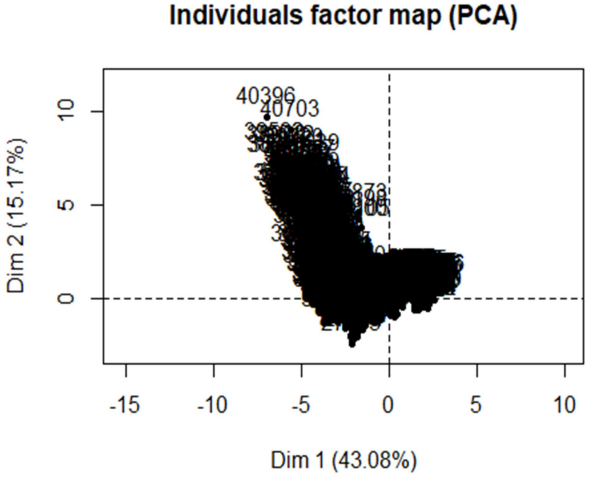
Hemos decidido probar como se ve el PCA sin y con la variable pdays, ya que consideramos que es una variable con bastantes missings, aún así aporta información por lo tanto la vamos a considerar.

```
vars_num_sin_pday = vars_num[-3];
res2.pca<-PCA(df[,c('duration',vars_nu
```



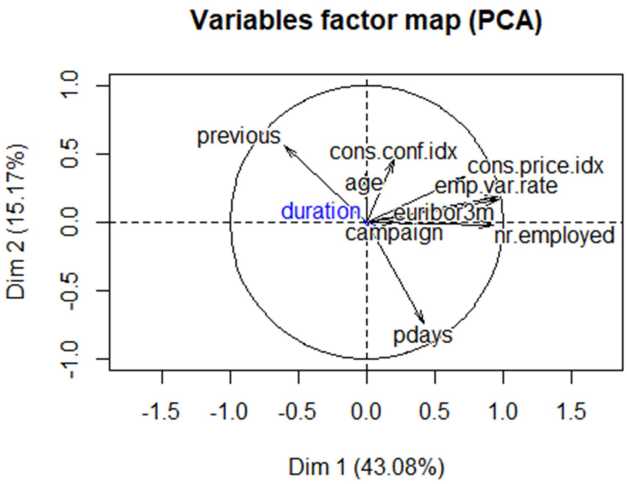



```
m_sin_pday)],quanti.sup=1)
```




```
res.pca<-PCA(df[,c('duration',va
rs_num)],quanti.sup=1)
```

Vemos que con pdays existe una relación inversa con previous, respecto a los dos ejes factoriales, sin pdays se puede ver que la contribución de la variable age con el segundo eje factorial es mayor, ya que gráficamente tiene mayor magnitud además que las variables socio económicas, se ven mejor representadas en el primer eje factorial.



Por la ley de Kaiser, deberíamos utilizar los 3 primeros ejes factoriales, los cuales son mayores a 1. Por la ley de ElBow, al realizar el gráfico podemos ver que la gráfica empieza a ser plana a partir de la 2da dimensión, es decir que se cogen las 2 primeras dimensiones.

Si tomamos en cuenta el criterio del 80% se deberían coger las 4 primeras dimensiones.

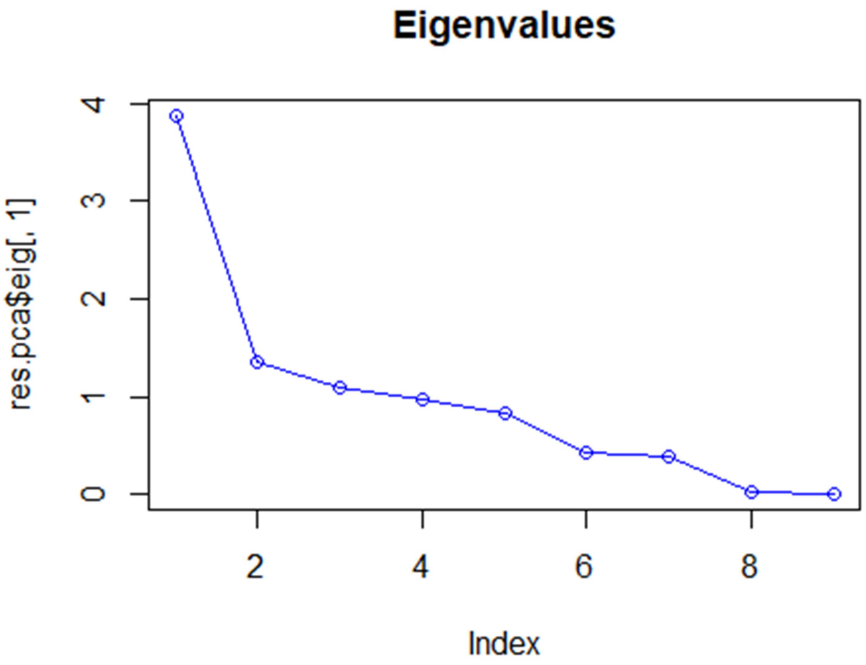
Para realizar el futuro análisis, conviene utilizar dimensiones pares, por lo que decidimos solo usar 2.

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

##
## Call:
## PCA(X = df[, c("duration", vars_num)], quanti.sup = 1)
##
##
## Eigenvalues
##                        Dim.1  Dim.2  Dim.3  Dim.4  Dim.5  Dim.6  Dim.7
## Variance                3.88   1.36   1.10   0.97   0.83   0.43   0.39
## % of var.              43.08  15.17  12.28  10.74   9.25   4.82   4.29
## Cumulative % of var.   43.08  58.24  70.52  81.26  90.50  95.33  99.62
##                        Dim.8  Dim.9
## Variance                0.02   0.01
## % of var.               0.27   0.12
## Cumulative % of var.   99.88 100.00
##
## Individuals (the 10 first)
##                    Dist   Dim.1   ctr  cos2   Dim.2   ctr  cos2   Dim.3
## 20              |  1.74 |  1.29  0.01  0.55 |  0.44  0.00  0.06 |  0.41
## 21              |  1.99 |  1.30  0.01  0.42 |  0.18  0.00  0.01 | -0.13
## 30              |  2.24 |  1.28  0.01  0.33 |  0.90  0.01  0.16 |  1.38
## 33              |  1.93 |  1.29  0.01  0.44 |  0.73  0.01  0.14 |  1.02
## 48              |  1.74 |  1.29  0.01  0.55 |  0.47  0.00  0.07 |  0.47
## 56              |  2.24 |  1.28  0.01  0.33 |  0.90  0.01  0.16 |  1.38
## 61              |  1.85 |  1.29  0.01  0.48 |  0.67  0.01  0.13 |  0.90
```

```
## 62              |  2.02 |  1.29  0.01  0.41 |  0.78  0.01  0.15 |  1.14
## 65              |  1.89 |  1.29  0.01  0.46 |  0.70  0.01  0.14 |  0.96
## 84              |  1.93 |  1.29  0.01  0.44 |  0.73  0.01  0.14 |  1.02
##                  ctr  cos2   Dim.4   ctr  cos2
## 20              0.00  0.06 | -0.81  0.01  0.22 |
## 21              0.00  0.00 | -1.06  0.02  0.28 |
## 30              0.03  0.38 | -0.38  0.00  0.03 |
## 33              0.02  0.28 | -0.54  0.01  0.08 |
## 48              0.00  0.07 | -0.79  0.01  0.21 |
## 56              0.03  0.38 | -0.38  0.00  0.03 |
## 61              0.01  0.23 | -0.60  0.01  0.10 |
## 62              0.02  0.32 | -0.49  0.00  0.06 |
## 65              0.02  0.26 | -0.57  0.01  0.09 |
## 84              0.02  0.28 | -0.54  0.01  0.08 |
##
## Variables
##                  Dim.1   ctr  cos2   Dim.2   ctr  cos2   Dim.3   ctr
cos2
## age            | -0.01  0.00  0.00 |  0.35  8.93  0.12 |  0.67 40.10
0.44
## campaign       |  0.21  1.13  0.04 |  0.00  0.00  0.00 | -0.23  4.74
0.05
## pdays          |  0.42  4.63  0.18 | -0.74 40.21  0.55 |  0.28  7.10
0.08
## previous       | -0.60  9.37  0.36 |  0.56 22.84  0.31 | -0.30  8.38
0.09
## emp.var.rate   |  0.96 23.97  0.93 |  0.19  2.54  0.03 | -0.11  1.00
0.01
## cons.price.idx |  0.72 13.43  0.52 |  0.33  8.11  0.11 | -0.30  8.08
0.09
## cons.conf.idx  |  0.20  1.06  0.04 |  0.46 15.36  0.21 |  0.58 30.44
0.34
## euribor3m      |  0.97 24.20  0.94 |  0.16  1.98  0.03 | -0.01  0.01
0.00
## nr.employed    |  0.93 22.20  0.86 | -0.02  0.03  0.00 | -0.04  0.16
0.00
##                  Dim.4   ctr  cos2
## age            |  0.28  8.23  0.08 |
## campaign       |  0.93 89.89  0.87 |
## pdays          |  0.04  0.17  0.00 |
## previous       | -0.02  0.05  0.00 |
## emp.var.rate   | -0.06  0.39  0.00 |
## cons.price.idx | -0.06  0.41  0.00 |
## cons.conf.idx  | -0.04  0.13  0.00 |
## euribor3m      | -0.07  0.51  0.00 |
## nr.employed    | -0.05  0.24  0.00 |
##
## Supplementary continuous variable
##                  Dim.1  cos2   Dim.2  cos2   Dim.3  cos2   Dim.4  cos2
```

```
## duration       | -0.02  0.00 |  0.02  0.00 |  0.00  0.00 | -0.05  0.00
|
```

```
plot(res.pca$eig[,1],main="Eigenvalues",type="o", col="blue")
```

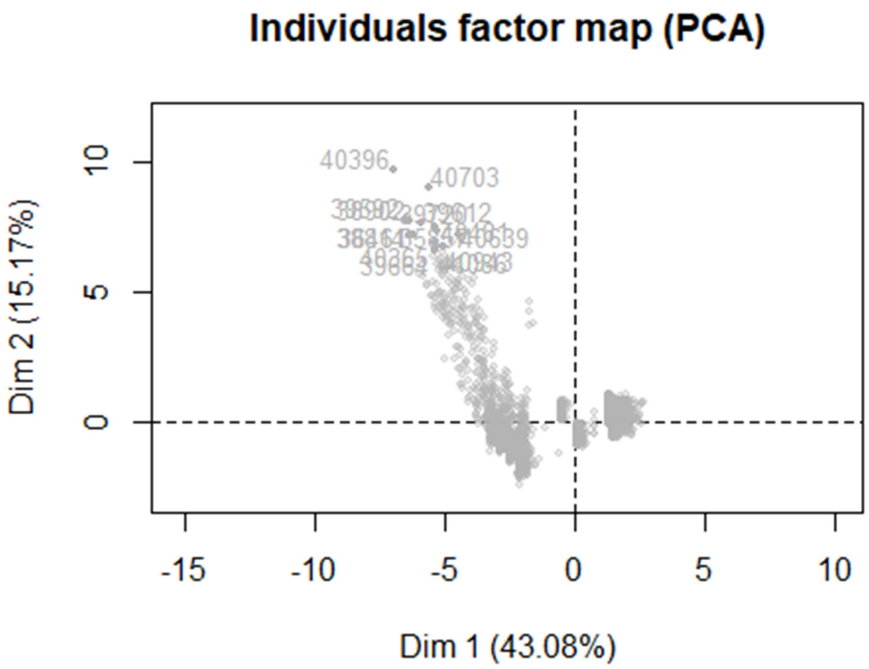


Individuals point of view: Are they any individuals “too contributive”? To better understand the axes meaning use the extreme individuals. Detection of multivariant outliers and influent data.

Primero graficamos en rp los 15 individuos más contributivos en ambos ejes, luego analizamos los 5 individuos más contributivos en la dimensión 1 y 2. Al ver si estos tienen alguna relación significativa, podemos decir que para los 5 individuos de la dimension 1, vemos que principalmente son gente mayor de 45años, todos han comprado el producto, han sido contactados mediante el móvil, han sido contactados previamente, comprado un producto en una campaña anterior y la duración de la llamada ha sido mayor a los 300s.

Para la dimensión 2 podemos ver prácticamente las mismas características menos la duración que ha sido menor. Cabe destacar sin embargo que hay dos individuos que son muy contributivos en ambos ejes, eso hace pensar que pueden ser posibles outliers pero de igual forma los dejamos en los datos.

```
plot.PCA(res.pca, choix=c("ind"),cex=0.8,col.ind="grey70",select="contrib
15",axes=c(1,2))
```




```
mas_ctr_dim1 <- sort(res.pca$ind$contrib[,1], decreasing = TRUE)[1:5]
mas_ctr_dim2 <- sort(res.pca$ind$contrib[,2], decreasing = TRUE)[1:5]
df[names(mas_ctr_dim1),]
```

```
##       age         job          marital                   education
## 40396  48  job.admin. marital.divorced education.university.degree
## 39592  24 job.student   marital.single       education.high.school
## 38902  83 job.retired marital.divorced          education.basic.4y
## 38814  65 job.retired  marital.married education.university.degree
## 36461  55 job.retired  marital.married          education.basic.4y
##          default     housing    loan          contact     month
## 40396 default.no  housing.no loan.no contact.cellular month.aug
## 39592 default.no housing.yes loan.no contact.cellular month.may
## 38902 default.no  housing.no loan.no contact.cellular month.nov
## 38814 default.no  housing.no loan.no contact.cellular month.nov
## 36461 default.no  housing.no loan.no contact.cellular month.jun
##           day_of_week duration campaign pdays previous         poutcom
e
## 40396 day_of_week.thu      172        3     3        6 poutcome.succes
s
## 39592 day_of_week.wed      258        1     3        5 poutcome.succes
s
## 38902 day_of_week.tue      242        1     3        3 poutcome.succes
s
## 38814 day_of_week.fri      226        1     3        3 poutcome.succes
s
## 36461 day_of_week.tue      553        2     3        4 poutcome.failur
```

```
e
##       emp.var.rate cons.price.idx cons.conf.idx euribor3m nr.employed
## 40396         -1.7         94.027         -38.3     0.904      4991.6
## 39592         -1.8         93.876         -40.0     0.672      5008.7
## 38902         -3.4         92.649         -30.1     0.716      5017.5
## 38814         -3.4         92.649         -30.1     0.714      5017.5
## 36461         -2.9         92.963         -40.8     1.262      5076.2
##           y                          f.job         f.season
## 40396 y.yes         f.job.Admin-Managment f.season.Jun-Aug
## 39592 y.yes             f.job.Not-working f.season.Mar-May
## 38902 y.yes f.job.Entrep-Retired-selfEmpl f.season.Sep-Dec
## 38814 y.yes f.job.Entrep-Retired-selfEmpl f.season.Sep-Dec
## 36461  y.no f.job.Entrep-Retired-selfEmpl f.season.Jun-Aug
##                    f.education         f.age               f.duration
## 40396 f.education.Professional f.age-(40,50]     f.duration-(120,180]
## 39592  f.education.High School f.age-[18,30]     f.duration-(180,300]
## 38902        f.education.Basic f.age-(50,92]     f.duration-(180,300]
## 38814 f.education.Professional f.age-(50,92]     f.duration-(180,300]
## 36461        f.education.Basic f.age-(50,92] f.duration-(300,2.1e+03]
##              f.campaign        f.pdays       f.previous
## 40396 f.campaign-(2,20] f.pdays-[0,22] f.previous-(1,6]
## 39592  f.campaign-[0,1] f.pdays-[0,22] f.previous-(1,6]
## 38902  f.campaign-[0,1] f.pdays-[0,22] f.previous-(1,6]
## 38814  f.campaign-[0,1] f.pdays-[0,22] f.previous-(1,6]
## 36461  f.campaign-(1,2] f.pdays-[0,22] f.previous-(1,6]

df[names(mas_ctr_dim2),]

##       age            job          marital                    education
## 40396  48     job.admin. marital.divorced education.university.degree
## 40703  82    job.retired  marital.married education.university.degree
## 39592  24    job.student   marital.single       education.high.school
## 38902  83    job.retired marital.divorced          education.basic.4y
## 39612  52 job.technician  marital.married education.university.degree
##                default     housing    loan           contact     month
## 40396      default.no  housing.no loan.no contact.cellular month.aug
## 40703 default.unknown  housing.no loan.no contact.cellular month.sep
## 39592      default.no housing.yes loan.no contact.cellular month.may
## 38902      default.no  housing.no loan.no contact.cellular month.nov
## 39612      default.no  housing.no loan.no contact.cellular month.may
##           day_of_week duration campaign pdays previous         poutcom
e
## 40396 day_of_week.thu      172        3     3        6 poutcome.succes
s
## 40703 day_of_week.mon       81        3     3        4 poutcome.succes
s
## 39592 day_of_week.wed      258        1     3        5 poutcome.succes
s
## 38902 day_of_week.tue      242        1     3        3 poutcome.succes
s
```

```
## 39612 day_of_week.thu      211        1     3        4 poutcome.succes
s
##       emp.var.rate cons.price.idx cons.conf.idx euribor3m nr.employed
## 40396         -1.7         94.027         -38.3     0.904      4991.6
## 40703         -1.1         94.199         -37.5     0.879      4963.6
## 39592         -1.8         93.876         -40.0     0.672      5008.7
## 38902         -3.4         92.649         -30.1     0.716      5017.5
## 39612         -1.8         93.876         -40.0     0.677      5008.7
##           y                          f.job         f.season
## 40396 y.yes         f.job.Admin-Managment f.season.Jun-Aug
## 40703  y.no f.job.Entrep-Retired-selfEmpl f.season.Sep-Dec
## 39592 y.yes             f.job.Not-working f.season.Mar-May
## 38902 y.yes f.job.Entrep-Retired-selfEmpl f.season.Sep-Dec
## 39612 y.yes         f.job.Serv-Tech-BlueC f.season.Mar-May
##                    f.education         f.age           f.duration
## 40396 f.education.Professional f.age-(40,50] f.duration-(120,180]
## 40703 f.education.Professional f.age-(50,92]   f.duration-[5,120]
## 39592  f.education.High School f.age-[18,30] f.duration-(180,300]
## 38902        f.education.Basic f.age-(50,92] f.duration-(180,300]
## 39612 f.education.Professional f.age-(50,92] f.duration-(180,300]
##              f.campaign        f.pdays       f.previous
## 40396 f.campaign-(2,20] f.pdays-[0,22] f.previous-(1,6]
## 40703 f.campaign-(2,20] f.pdays-[0,22] f.previous-(1,6]
## 39592  f.campaign-[0,1] f.pdays-[0,22] f.previous-(1,6]
## 38902  f.campaign-[0,1] f.pdays-[0,22] f.previous-(1,6]
## 39612  f.campaign-[0,1] f.pdays-[0,22] f.previous-(1,6]
```

Interpreting the axes: Variables point of view coordinates, quality of representation, contribution of the variables

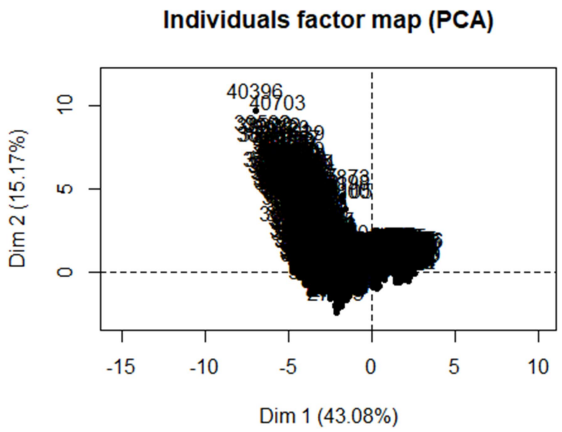
Al hacer el PCA con la variable target duration como suplementaria, podemos ver que su módulo es prácticamente nulo, esto quiere decir que la variable no se ve representada en niguno de los ejes factoriales.

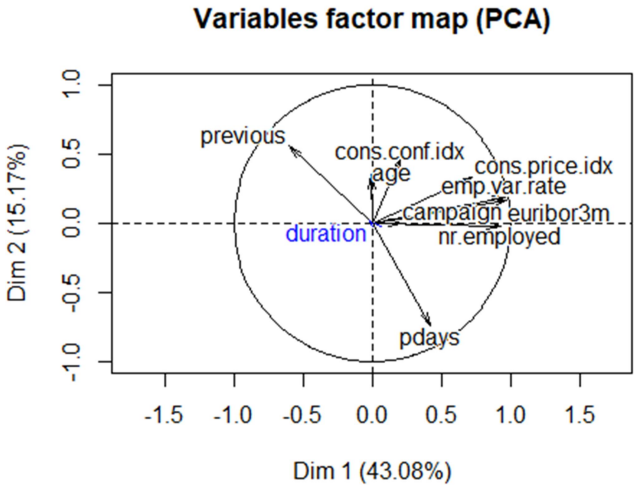
El eje horizontal está muy relacionado con las variables socio económicas, mirando el cos2 del summary podemos ver que las variables que están mejor representadas con la dimensión 1 son: euribor3m, emp.var.rate, nr.emplyed Para el eje vertical: pdays y previous

Para el eje vertical, podemos decir que está relacionado con las campañas previas.

Al hacer el PCA con la variable target Y como suplementaria, podemos ver que en el gráfico de rp, el factor NO, esta muy cerca del centro, por lo que no se ve representada en estos ejes factoriales. En cambio el factor SI, está a una distancia mayor del centro, aunque poco significativa.

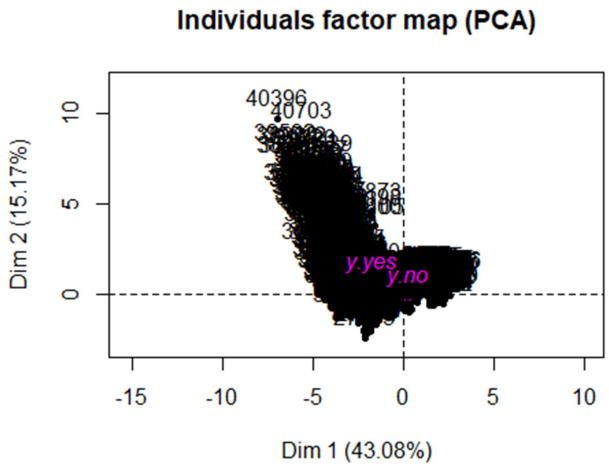
```
res.pca<-PCA(df[,c('duration',vars_num)],quanti.sup=1)
```

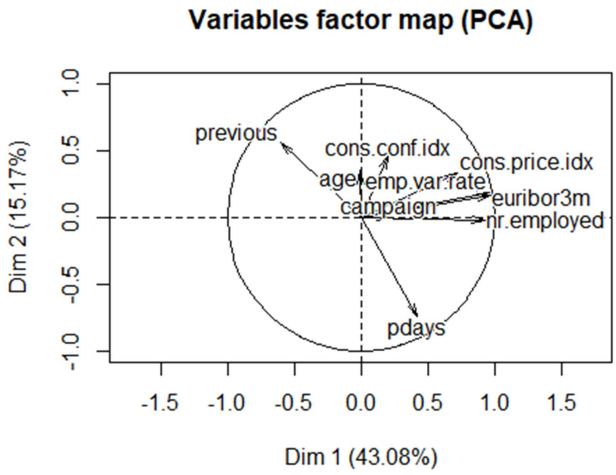





```
summary(res.pca,ncp=4,nb.dec=2)

##
## Call:
## PCA(X = df[, c("duration", vars_num)], quanti.sup = 1)
##
##
## Eigenvalues
##                        Dim.1  Dim.2  Dim.3  Dim.4  Dim.5  Dim.6  Dim.7
## Variance                3.88   1.36   1.10   0.97   0.83   0.43   0.39
## % of var.              43.08  15.17  12.28  10.74   9.25   4.82   4.29
## Cumulative % of var.   43.08  58.24  70.52  81.26  90.50  95.33  99.62
##                        Dim.8  Dim.9
## Variance                0.02   0.01
## % of var.               0.27   0.12
## Cumulative % of var.   99.88 100.00
##
## Individuals (the 10 first)
##                    Dist   Dim.1   ctr  cos2   Dim.2   ctr  cos2   Dim.3
## 20              |  1.74 |  1.29  0.01  0.55 |  0.44  0.00  0.06 |  0.41
## 21              |  1.99 |  1.30  0.01  0.42 |  0.18  0.00  0.01 | -0.13
## 30              |  2.24 |  1.28  0.01  0.33 |  0.90  0.01  0.16 |  1.38
## 33              |  1.93 |  1.29  0.01  0.44 |  0.73  0.01  0.14 |  1.02
## 48              |  1.74 |  1.29  0.01  0.55 |  0.47  0.00  0.07 |  0.47
## 56              |  2.24 |  1.28  0.01  0.33 |  0.90  0.01  0.16 |  1.38
## 61              |  1.85 |  1.29  0.01  0.48 |  0.67  0.01  0.13 |  0.90
## 62              |  2.02 |  1.29  0.01  0.41 |  0.78  0.01  0.15 |  1.14
## 65              |  1.89 |  1.29  0.01  0.46 |  0.70  0.01  0.14 |  0.96
## 84              |  1.93 |  1.29  0.01  0.44 |  0.73  0.01  0.14 |  1.02
##                    ctr  cos2   Dim.4   ctr  cos2
## 20                0.00  0.06 | -0.81  0.01  0.22 |
## 21                0.00  0.00 | -1.06  0.02  0.28 |
## 30                0.03  0.38 | -0.38  0.00  0.03 |
## 33                0.02  0.28 | -0.54  0.01  0.08 |
```

```
## 48               0.00  0.07 | -0.79  0.01  0.21 |
## 56               0.03  0.38 | -0.38  0.00  0.03 |
## 61               0.01  0.23 | -0.60  0.01  0.10 |
## 62               0.02  0.32 | -0.49  0.00  0.06 |
## 65               0.02  0.26 | -0.57  0.01  0.09 |
## 84               0.02  0.28 | -0.54  0.01  0.08 |
##
## Variables
##                   Dim.1   ctr  cos2   Dim.2   ctr  cos2   Dim.3   ctr
cos2
## age             | -0.01  0.00  0.00 |  0.35  8.93  0.12 |  0.67 40.10
0.44
## campaign        |  0.21  1.13  0.04 |  0.00  0.00  0.00 | -0.23  4.74
0.05
## pdays           |  0.42  4.63  0.18 | -0.74 40.21  0.55 |  0.28  7.10
0.08
## previous        | -0.60  9.37  0.36 |  0.56 22.84  0.31 | -0.30  8.38
0.09
## emp.var.rate    |  0.96 23.97  0.93 |  0.19  2.54  0.03 | -0.11  1.00
0.01
## cons.price.idx |  0.72 13.43  0.52 |  0.33  8.11  0.11 | -0.30  8.08
0.09
## cons.conf.idx   |  0.20  1.06  0.04 |  0.46 15.36  0.21 |  0.58 30.44
0.34
## euribor3m       |  0.97 24.20  0.94 |  0.16  1.98  0.03 | -0.01  0.01
0.00
## nr.employed     |  0.93 22.20  0.86 | -0.02  0.03  0.00 | -0.04  0.16
0.00
##                   Dim.4   ctr  cos2
## age             |  0.28  8.23  0.08 |
## campaign        |  0.93 89.89  0.87 |
## pdays           |  0.04  0.17  0.00 |
## previous        | -0.02  0.05  0.00 |
## emp.var.rate    | -0.06  0.39  0.00 |
## cons.price.idx | -0.06  0.41  0.00 |
## cons.conf.idx   | -0.04  0.13  0.00 |
## euribor3m       | -0.07  0.51  0.00 |
## nr.employed     | -0.05  0.24  0.00 |
##
## Supplementary continuous variable
##                   Dim.1  cos2   Dim.2  cos2   Dim.3  cos2   Dim.4  cos2
## duration        | -0.02  0.00 |  0.02  0.00 |  0.00  0.00 | -0.05  0.00
|

res.pca<-PCA(df[,c('y',vars_num)],quali.sup=1)
```






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

##
## Call:
## PCA(X = df[, c("y", vars_num)], quali.sup = 1)
##
##
## Eigenvalues
##                        Dim.1  Dim.2  Dim.3  Dim.4  Dim.5  Dim.6  Dim.7
## Variance                3.88   1.36   1.10   0.97   0.83   0.43   0.39
## % of var.              43.08  15.17  12.28  10.74   9.25   4.82   4.29
## Cumulative % of var.   43.08  58.24  70.52  81.26  90.50  95.33  99.62
##                        Dim.8  Dim.9
## Variance                0.02   0.01
## % of var.               0.27   0.12
## Cumulative % of var.   99.88 100.00
##
## Individuals (the 10 first)
##                    Dist   Dim.1   ctr  cos2   Dim.2   ctr  cos2   Dim.3
## 20              |  1.74 |  1.29  0.01  0.55 |  0.44  0.00  0.06 |  0.41
## 21              |  1.99 |  1.30  0.01  0.42 |  0.18  0.00  0.01 | -0.13
## 30              |  2.24 |  1.28  0.01  0.33 |  0.90  0.01  0.16 |  1.38
## 33              |  1.93 |  1.29  0.01  0.44 |  0.73  0.01  0.14 |  1.02
## 48              |  1.74 |  1.29  0.01  0.55 |  0.47  0.00  0.07 |  0.47
## 56              |  2.24 |  1.28  0.01  0.33 |  0.90  0.01  0.16 |  1.38
## 61              |  1.85 |  1.29  0.01  0.48 |  0.67  0.01  0.13 |  0.90
## 62              |  2.02 |  1.29  0.01  0.41 |  0.78  0.01  0.15 |  1.14
## 65              |  1.89 |  1.29  0.01  0.46 |  0.70  0.01  0.14 |  0.96
## 84              |  1.93 |  1.29  0.01  0.44 |  0.73  0.01  0.14 |  1.02
##                    ctr  cos2   Dim.4   ctr  cos2
## 20              0.00  0.06 | -0.81  0.01  0.22 |
```

```
## 21              0.00  0.00 | -1.06  0.02  0.28 |
## 30              0.03  0.38 | -0.38  0.00  0.03 |
## 33              0.02  0.28 | -0.54  0.01  0.08 |
## 48              0.00  0.07 | -0.79  0.01  0.21 |
## 56              0.03  0.38 | -0.38  0.00  0.03 |
## 61              0.01  0.23 | -0.60  0.01  0.10 |
## 62              0.02  0.32 | -0.49  0.00  0.06 |
## 65              0.02  0.26 | -0.57  0.01  0.09 |
## 84              0.02  0.28 | -0.54  0.01  0.08 |
##
## Variables
##                  Dim.1   ctr  cos2   Dim.2   ctr  cos2   Dim.3   ctr
cos2
## age            | -0.01  0.00  0.00 |  0.35  8.93  0.12 |  0.67 40.10
0.44
## campaign       |  0.21  1.13  0.04 |  0.00  0.00  0.00 | -0.23  4.74
0.05
## pdays          |  0.42  4.63  0.18 | -0.74 40.21  0.55 |  0.28  7.10
0.08
## previous       | -0.60  9.37  0.36 |  0.56 22.84  0.31 | -0.30  8.38
0.09
## emp.var.rate   |  0.96 23.97  0.93 |  0.19  2.54  0.03 | -0.11  1.00
0.01
## cons.price.idx |  0.72 13.43  0.52 |  0.33  8.11  0.11 | -0.30  8.08
0.09
## cons.conf.idx  |  0.20  1.06  0.04 |  0.46 15.36  0.21 |  0.58 30.44
0.34
## euribor3m      |  0.97 24.20  0.94 |  0.16  1.98  0.03 | -0.01  0.01
0.00
## nr.employed    |  0.93 22.20  0.86 | -0.02  0.03  0.00 | -0.04  0.16
0.00
##                  Dim.4   ctr  cos2
## age            |  0.28  8.23  0.08 |
## campaign       |  0.93 89.89  0.87 |
## pdays          |  0.04  0.17  0.00 |
## previous       | -0.02  0.05  0.00 |
## emp.var.rate   | -0.06  0.39  0.00 |
## cons.price.idx | -0.06  0.41  0.00 |
## cons.conf.idx  | -0.04  0.13  0.00 |
## euribor3m      | -0.07  0.51  0.00 |
## nr.employed    | -0.05  0.24  0.00 |
##
## Supplementary categories
##                     Dist    Dim.1   cos2 v.test    Dim.2   cos2 v.test
## y.no           |   0.23 |   0.21   0.84  21.77 |  -0.08   0.13 -14.15
|
## y.yes          |   1.89 |  -1.74   0.84 -21.77 |   0.67   0.13  14.15
|
##                  Dim.3   cos2 v.test    Dim.4   cos2 v.test
```

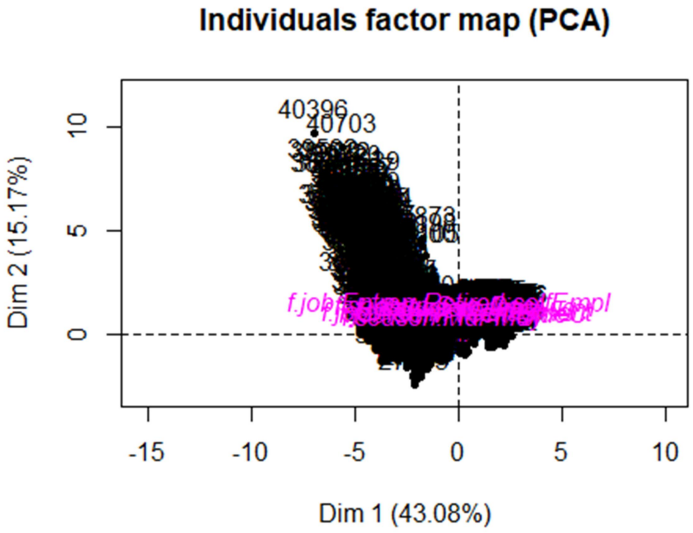
```
## y.no            -0.01    0.00  -1.74 |    0.01    0.00    1.09 |
## y.yes            0.07    0.00   1.74 |   -0.04    0.00   -1.09 |
```

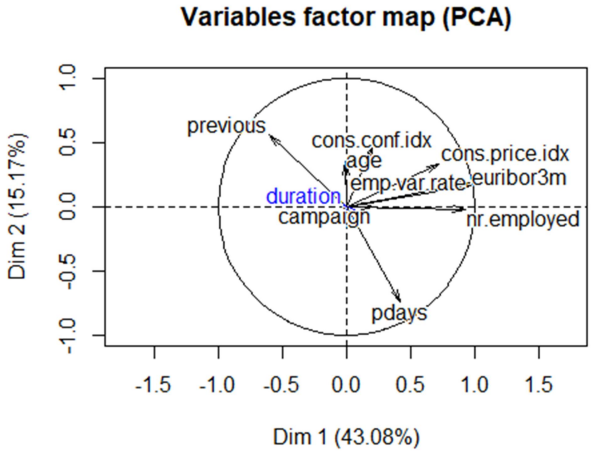
Perform a PCA taking into account also supplementary variables the supplementary variables can be quantitative and/or categorical

Hemos dividido el plot en diferentes partes, para así poder entender y ver mejor el resultado. Para la primera dimensión podemos ver que para los niveles mejor representados son: f.season.jun-aug, f.previous-(0.9,1], y.no, y.yes.

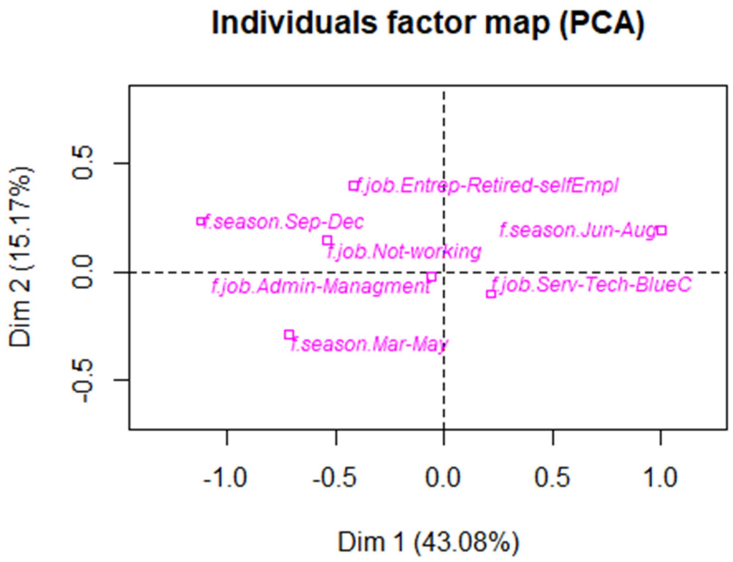
Para la segunda dimsensión, las que se ven mejor representadas son: f.pdays-[0,22],f.pdays-(22,23], f.previous-(1,6]

```
vars_factorizadas<- c("f.job","f.season","f.education","f.age","f.duration","f.campaign","f.pdays","f.previous","y");

res.pca<-PCA(df[,c('duration',vars_num, "f.job","f.season")],quanti.sup=1, quali.sup = c(11:12))
```

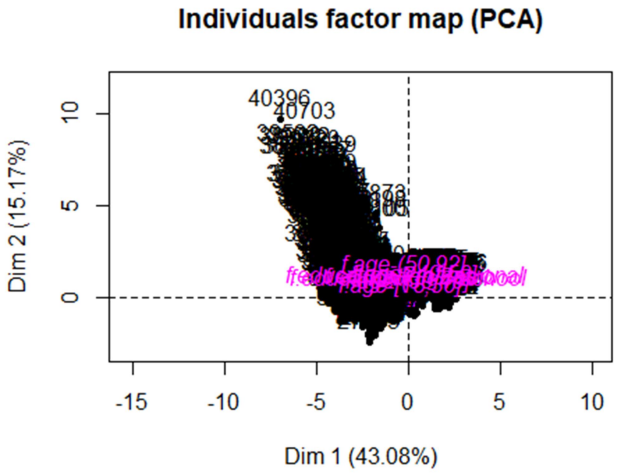


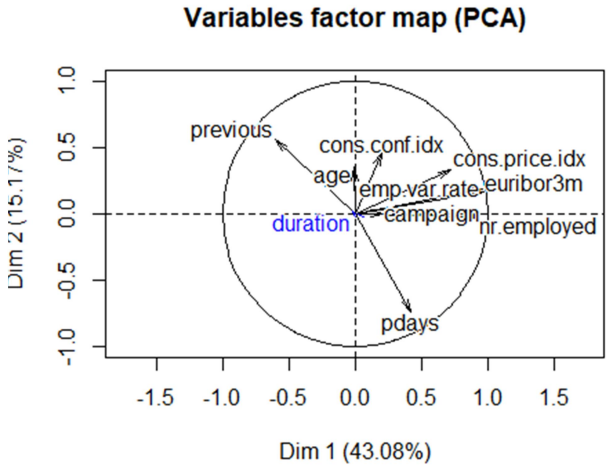



```
plot.PCA(res.pca,choix="ind",invisible="ind",cex=0.75)
```

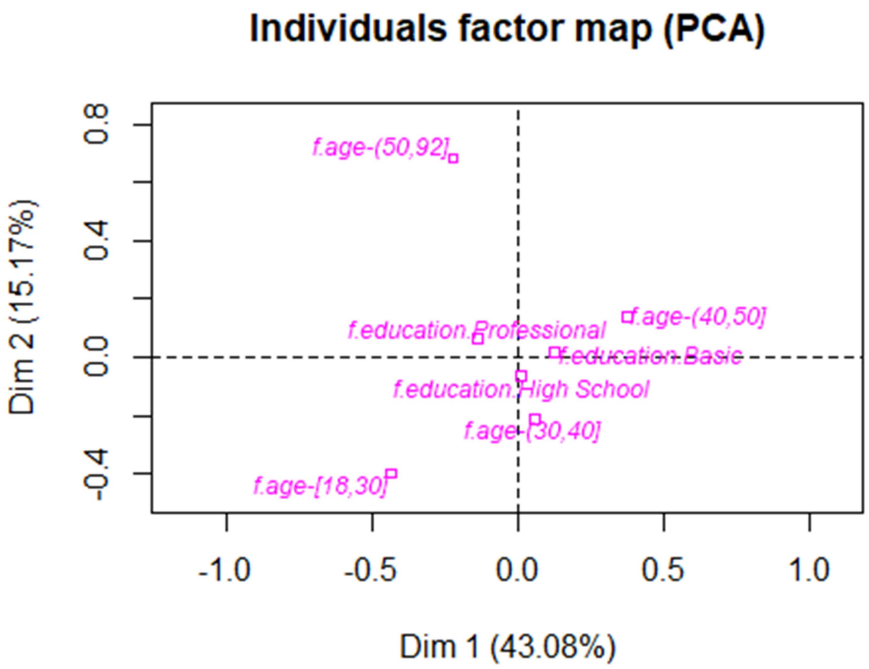



```
res.pca<-PCA(df[,c('duration',vars_num,"f.education","f.age")],quanti.sup
=1, quali.sup = c(11:12))
```

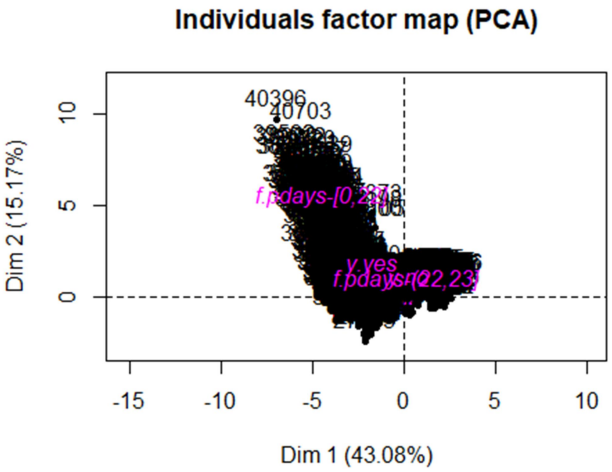


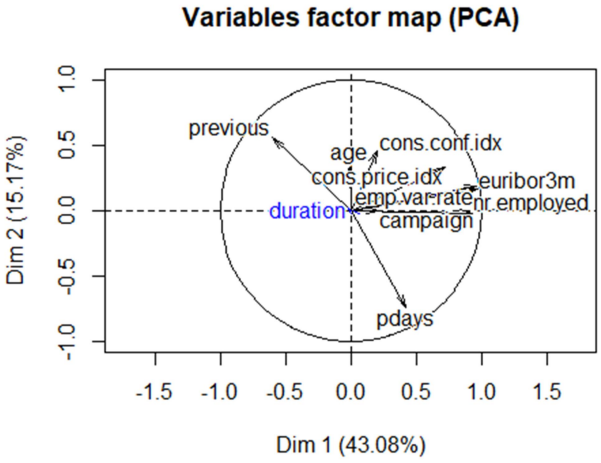



```
plot.PCA(res.pca,choix="ind",invisible="ind",cex=0.75)
```

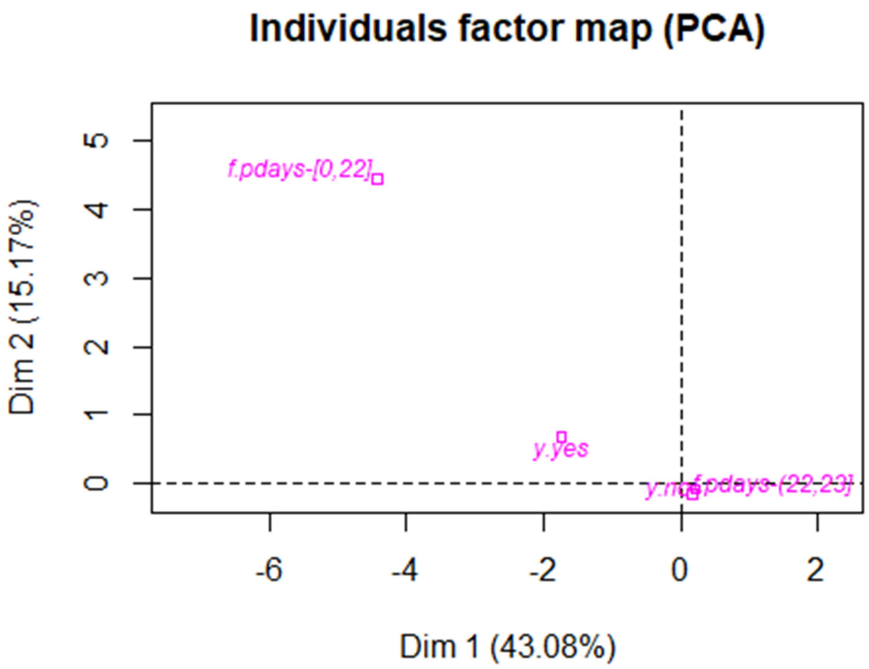



```
res.pca<-PCA(df[,c('duration',vars_num,"f.pdays","y")],quanti.sup=1, quali.sup = c(11:12))
```

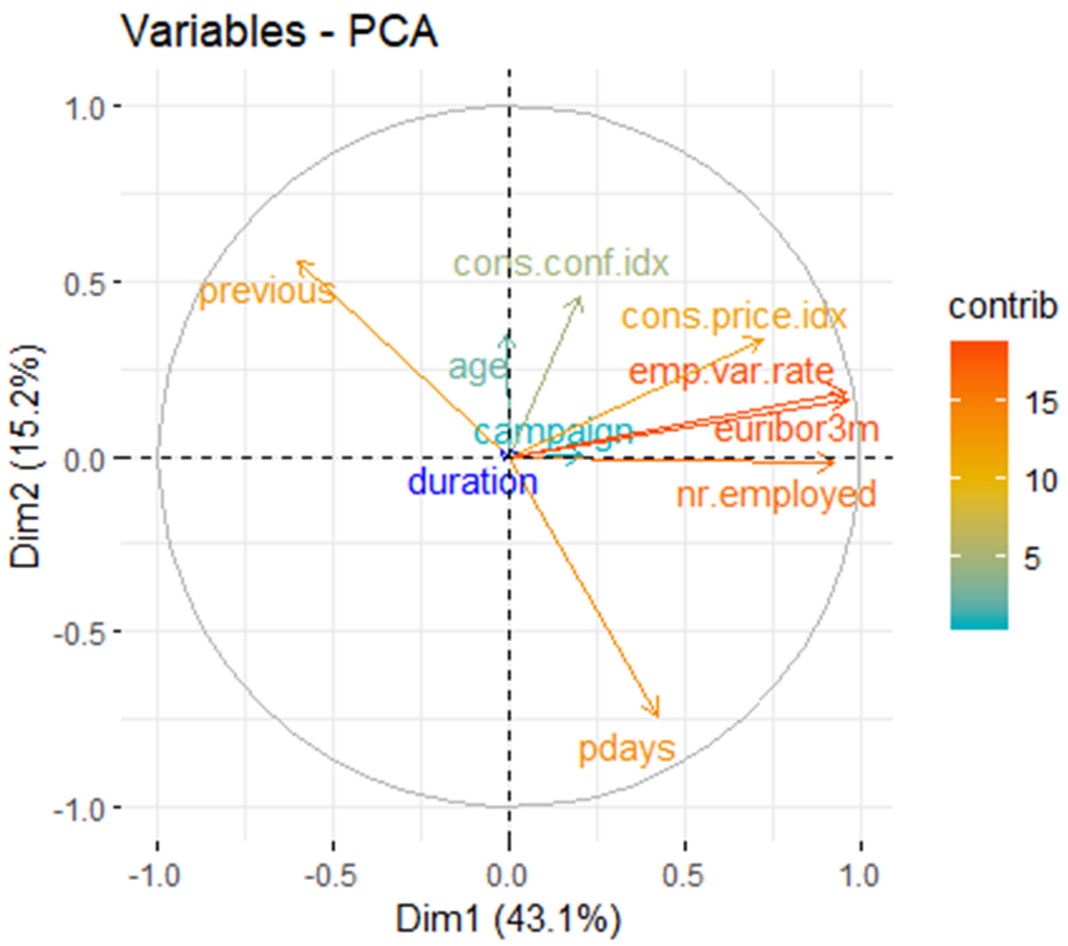





```
plot.PCA(res.pca,choix="ind",invisible="ind",cex=0.75)
```




```
res.pca<-PCA(df[,c('duration',vars_num,vars_factorizadas)],quanti.sup=1,
quali.sup = c(11:19),graph=FALSE)

fviz_pca_var(res.pca, col.var = "contrib",gradient.cols = c("#00AFBB", "#
E7B800", "#FC4E07"),repel = TRUE)
```




```
summary(res.pca,dig = 2, nbelements= 30, nbind=3, ncp=2)

##
## Call:
## PCA(X = df[, c("duration", vars_num, vars_factorizadas)], quanti.sup =
1,
##      quali.sup = c(11:19), graph = FALSE)
##
##
## Eigenvalues
##                        Dim.1   Dim.2   Dim.3   Dim.4   Dim.5   Dim.6
## Variance               3.877   1.365   1.105   0.966   0.832   0.434
## % of var.             43.078  15.166  12.276  10.736   9.246   4.823
## Cumulative % of var.  43.078  58.244  70.521  81.257  90.503  95.326
##                        Dim.7   Dim.8   Dim.9
## Variance               0.386   0.024   0.010
## % of var.              4.291   0.266   0.116
## Cumulative % of var.  99.618  99.884 100.000
##
## Individuals (the 3 first)
##                                   Dist    Dim.1    ctr   cos2    Dim.2    ct
```

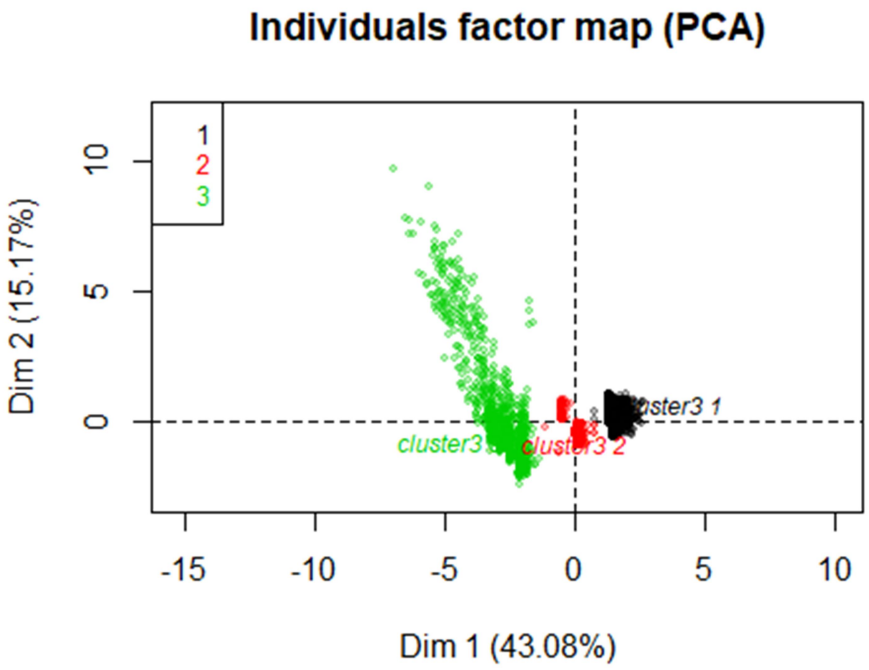
```
r
## 20                               | 1.739 | 1.291 0.009 0.551 | 0.441 0.00
3
## 21                               | 1.990 | 1.295 0.009 0.424 | 0.184 0.00
0
## 30                               | 2.240 | 1.284 0.009 0.328 | 0.898 0.01
2
##                                   cos2
## 20                               0.064 |
## 21                               0.009 |
## 30                               0.161 |
##
## Variables
##                                     Dim.1    ctr   cos2    Dim.2    ctr
## age                              | -0.009  0.002  0.000 |  0.349  8.933
## campaign                         |  0.210  1.132  0.044 |  0.003  0.001
## pdays                            |  0.424  4.633  0.180 | -0.741 40.212
## previous                         | -0.603  9.366  0.363 |  0.558 22.836
## emp.var.rate                     |  0.964 23.967  0.929 |  0.186  2.544
## cons.price.idx                   |  0.722 13.431  0.521 |  0.333  8.109
## cons.conf.idx                    |  0.203  1.063  0.041 |  0.458 15.356
## euribor3m                        |  0.969 24.202  0.938 |  0.164  1.978
## nr.employed                      |  0.928 22.205  0.861 | -0.020  0.030
##                                   cos2
## age                              0.122 |
## campaign                         0.000 |
## pdays                            0.549 |
## previous                         0.312 |
## emp.var.rate                     0.035 |
## cons.price.idx                   0.111 |
## cons.conf.idx                    0.210 |
## euribor3m                        0.027 |
## nr.employed                      0.000 |
##
## Supplementary continuous variable
##                                     Dim.1   cos2    Dim.2   cos2
## duration                         | -0.022  0.000 |  0.017  0.000 |
##
## Supplementary categories
##                                        Dist     Dim.1    cos2  v.test
## f.job.Admin-Managment            |   0.125 |  -0.061   0.237  -1.532 |
## f.job.Entrep-Retired-selfEmpl    |   1.020 |  -0.418   0.168  -5.418 |
## f.job.Not-working                |   0.690 |  -0.541   0.615  -5.266 |
## f.job.Serv-Tech-BlueC            |   0.272 |   0.217   0.637   7.570 |
## f.season.Mar-May                 |   0.793 |  -0.719   0.821 -21.657 |
## f.season.Jun-Aug                 |   1.026 |   1.002   0.954  32.508 |
## f.season.Sep-Dec                 |   1.257 |  -1.125   0.801 -16.040 |
## f.education.Basic                |   0.294 |   0.125   0.181   3.071 |
## f.education.High School          |   0.155 |   0.010   0.005   0.285 |
## f.education.Professional         |   0.255 |  -0.140   0.300  -3.384 |
```

```
## f.age-[18,30]                  |   1.312 |  -0.436   0.111  -7.188 |
## f.age-(30,40]                  |   0.485 |   0.055   0.013   1.600 |
## f.age-(40,50]                  |   0.606 |   0.373   0.380   7.755 |
## f.age-(50,92]                  |   1.667 |  -0.225   0.018  -3.730 |
## f.duration-[5,120]             |   0.274 |   0.190   0.483   4.596 |
## f.duration-(120,180]           |   0.138 |   0.076   0.299   1.332 |
## f.duration-(180,300]           |   0.222 |  -0.180   0.658  -3.418 |
## f.duration-(300,2.1e+03]       |   0.166 |  -0.126   0.571  -2.781 |
## f.campaign-[0,1]               |   0.707 |  -0.356   0.254 -10.989 |
## f.campaign-(1,2]               |   0.221 |  -0.006   0.001  -0.127 |
## f.campaign-(2,20]              |   1.083 |   0.474   0.192  11.738 |
## f.pdays-[0,22]                 |   6.580 |  -4.417   0.451 -30.206 |
## f.pdays-(22,23]                |   0.239 |   0.161   0.451  30.206 |
## f.previous-[0,0.9]             |   0.543 |   0.487   0.804  43.179 |
## f.previous-(0.9,1]             |   2.787 |  -2.633   0.893 -33.713 |
## f.previous-(1,6]               |   6.104 |  -4.396   0.519 -26.498 |
## y.no                           |   0.231 |   0.212   0.844  21.769 |
## y.yes                          |   1.892 |  -1.738   0.844 -21.769 |
##                                  Dim.2    cos2  v.test
## f.job.Admin-Managment          -0.020   0.027  -0.869 |
## f.job.Entrep-Retired-selfEmpl   0.399   0.153   8.730 |
## f.job.Not-working               0.143   0.043   2.353 |
## f.job.Serv-Tech-BlueC          -0.101   0.139  -5.958 |
## f.season.Mar-May               -0.288   0.132 -14.633 |
## f.season.Jun-Aug                0.194   0.036  10.604 |
## f.season.Sep-Dec                0.234   0.035   5.626 |
## f.education.Basic               0.015   0.003   0.613 |
## f.education.High School        -0.066   0.180  -3.025 |
## f.education.Professional        0.062   0.059   2.527 |
## f.age-[18,30]                  -0.400   0.093 -11.108 |
## f.age-(30,40]                  -0.213   0.193 -10.495 |
## f.age-(40,50]                   0.139   0.053   4.874 |
## f.age-(50,92]                   0.682   0.168  19.031 |
## f.duration-[5,120]             -0.094   0.118  -3.822 |
## f.duration-(120,180]            0.014   0.010   0.414 |
## f.duration-(180,300]            0.085   0.147   2.721 |
## f.duration-(300,2.1e+03]        0.029   0.030   1.081 |
## f.campaign-[0,1]                0.003   0.000   0.167 |
## f.campaign-(1,2]                0.014   0.004   0.486 |
## f.campaign-(2,20]              -0.015   0.000  -0.627 |
## f.pdays-[0,22]                  4.435   0.454  51.122 |
## f.pdays-(22,23]                -0.161   0.454 -51.122 |
## f.previous-[0,0.9]             -0.181   0.111 -27.027 |
## f.previous-(0.9,1]              0.442   0.025   9.534 |
## f.previous-(1,6]                3.839   0.396  38.998 |
## y.no                           -0.082   0.126 -14.153 |
## y.yes                           0.671   0.126  14.153 |
```

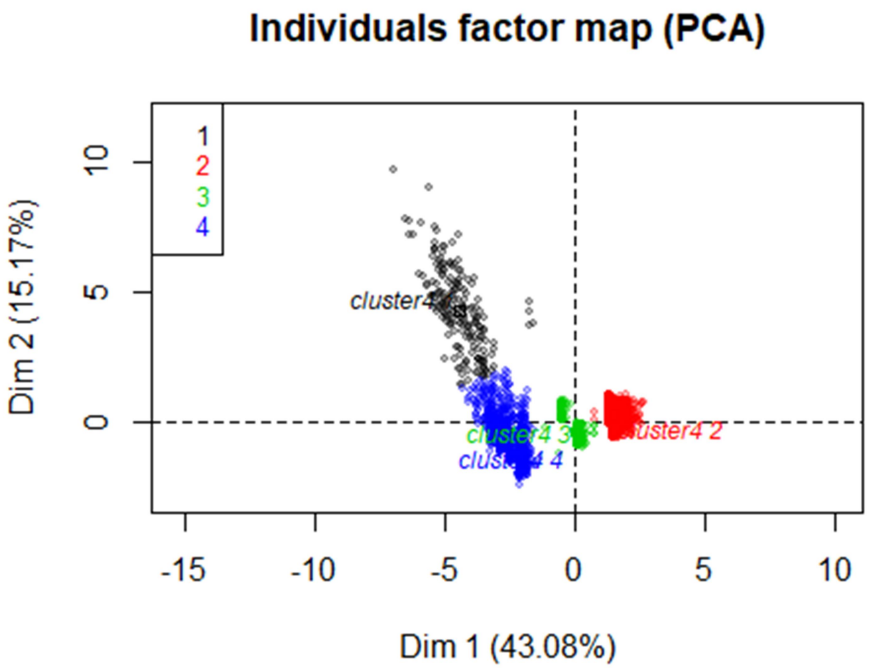
K-Means Classification

Hemos graficado los grupos separados en 3, 4, 5 y 6 clusters, para los cuales nos parece que gráficamente con 4 clusters los grupos están bien definidos, por lo que decidimos usar 4 clusters los cuales analizaremos seguidamente.

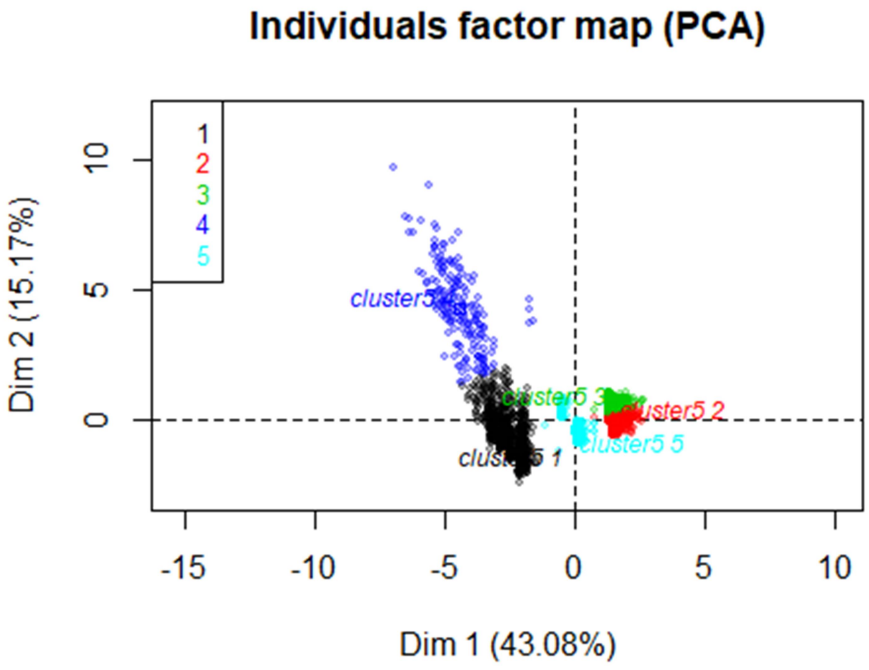
```
dclu<- res.pca$ind$coord[,1:2]; # los dos ejes

kcla<- kmeans(dclu,4);

df$cluster3 = factor(kmeans(dclu,3)$cluster);
df$cluster4 = factor(kmeans(dclu,4)$cluster);
df$cluster5 = factor(kmeans(dclu,5)$cluster);
df$cluster6 = factor(kmeans(dclu,6)$cluster);

res.pca<-PCA(df[,c('duration',vars_num, "cluster3")],quanti.sup=1, quali.
sup = 11, graph=FALSE)
plot.PCA(res.pca,choix="ind",habillage=11,select=0 ,cex=0.75)
```



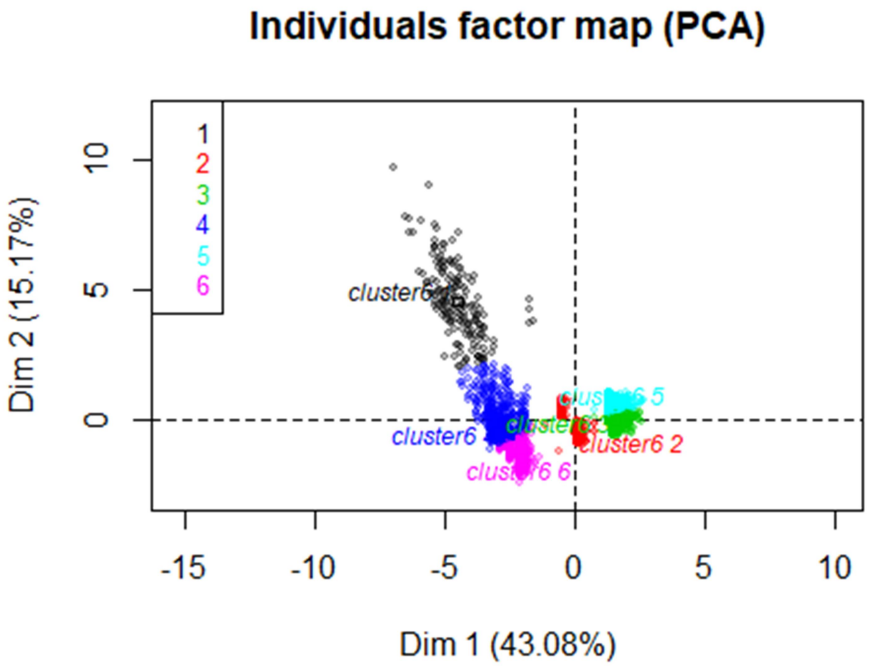

```
res.pca<-PCA(df[,c('duration',vars_num, "cluster4")],quanti.sup=1, quali.
sup = 11, graph=FALSE)
plot.PCA(res.pca,choix="ind",habillage=11,select=0 ,cex=0.75)
```




```
res.pca<-PCA(df[,c('duration',vars_num, "cluster5")],quanti.sup=1, quali.
sup = 11, graph=FALSE)
plot.PCA(res.pca,choix="ind",habillage=11,select=0 ,cex=0.75)
```



```
res.pca<-PCA(df[,c('duration',vars_num, "cluster6")],quanti.sup=1, quali.
sup = 11, graph=FALSE)
plot.PCA(res.pca,choix="ind",habillage=11,select=0 ,cex=0.75)
```




```
df <- df[,c(1:29, 31)] # guardamos la clasificación en 4 clusters
```

Description of clusters

Viendo el chi-square test, podemos saber qué variables se utilizarán para caracterizar nuestros 4 clusters. Viendo las categorías donde el P-value es casi 0 podemos ver que las categorías que cumplen estas caracteristicas son: month (y por extensión también f.season), poutcome, f.pdays, f.previous, contact, y, job(f.job), default, f.age, f.campaign, marital. Ahora veremos que categorías de estas variables son las que caracterizan estos clusters.

Para el catdes del cluster 1, hemos podido ver las categorías que mejor lo definen, la temporada de verano es la que mejor lo caracteriza, f.season.Jun-Aug, tenemos también un poutcome que nos indica que ninguno de los individuos ha sido contactado previamente, podemos ver que y.no representa el 95% de este cluster, han sido contactados en su mayoría por teléfono fijo, también podemos ver que este cluster está ligeramente relacionado con la categoría f.job.Serv-Tech-BlueC. En conclusión podemos decir que este cluster está caracterizado por: - Meses de jun-Ago - No han sido contactados previamente - Han sido contactados más de una vez en la campaña actual - Contactados por teléfono fijo - Trabajo normalmente es, servicio, técnicos o blue collar. - No compraron el producto en su mayoría.

Para el cluster 2, tenemos: - La temporada de mar-may están sobrerepresentadas en este cluster - Han sido contacados en su mayoría por teléfono móvil - No han comprado el producto en campañas anteriores - Han sido contacados en camapañas previas - La categoría student está sobrerepresentada - La aceptación del producto está sobrerepresentada también

Para el cluster 3, tenemos: - Temporada de Sep-Dec - Contactados por móvil en su mayoría - La categoría de job.management está sobrerepresentada - No han adquirido el producto - Una gran cantidad de individuos rechazó el producto (y.no)

Para el cluster 4, podemos ver que aglutina individuos muy bien caracterizados por las siguientes variables: - Han sido contactados previamente f.pdays[0,22] - Han comprado el producto en una campaña previa - Han comprado el producto y.yes - Temporada de Sep-Dec - Han sido contactados por móvil - Una parte importante son job.retired - Una edad de f.age-(50,92]

```
catdes(df, 30, proba = 0.001)
```

```
##
## Link between the cluster variable and the categorical variables (chi-s
quare test)
## ================================================================
===========
##                    p.value df
## month         0.000000e+00 27
## poutcome      0.000000e+00  6
## f.season      0.000000e+00  6
## f.pdays       0.000000e+00  3
## f.previous    0.000000e+00  6
## contact     4.750967e-213  3
## y           3.629487e-144  3
## job          4.108692e-67 30
## default      6.986972e-43  3
## f.age        1.030850e-26  9
## f.campaign   6.092760e-24  6
## f.job        1.806095e-19  9
## marital      1.705029e-16  6
## f.duration   1.919242e-10  9
## education    5.661192e-09 18
## f.education  8.669827e-09  6
## housing      1.403613e-07  3
## day_of_week  4.039589e-04 12
##
## Description of each cluster by the categories
## ============================================
## $`1`
##                                          Cla/Mod   Mod/Cla    Global
## f.pdays=f.pdays-[0,22]                96.5714286 88.947368  3.507014
## poutcome=poutcome.success             96.1538462 78.947368  3.126253
## f.previous=f.previous-(1,6]           75.1824818 54.210526  2.745491
```

```
## y=y.yes                                  21.0332103 60.000000 10.861723
## f.previous=f.previous-(0.9,1]            15.4255319 45.789474 11.302605
## f.season=f.season.Sep-Dec                11.1600587 40.000000 13.647295
## month=month.oct                          32.5000000 13.684211  1.603206
## contact=contact.cellular                  5.4011864 91.052632 64.188377
## default=default.no                        4.6954315 97.368421 78.957916
## job=job.retired                          15.7657658 18.421053  4.448898
## month=month.sep                          25.7142857  9.473684  1.402806
## f.age=f.age-(50,92]                       7.4200913 34.210526 17.555110
## month=month.mar                          20.6349206  6.842105  1.262525
## job=job.student                          15.5963303  8.947368  2.184369
## f.job=f.job.Entrep-Retired-selfEmpl       7.6256499 23.157895 11.563126
## f.duration=f.duration-(180,300]           6.0550459 34.736842 21.843687
## poutcome=poutcome.failure                 7.3394495 21.052632 10.921844
## f.education=f.education.Professional      5.4347826 44.736842 31.342685
## education=education.university.degree     5.4347826 44.736842 31.342685
## f.job=f.job.Not-working                   8.1871345 14.736842  6.853707
## f.campaign=f.campaign-[0,1]               4.9504950 55.263158 42.505010
## month=month.jun                           1.6233766  5.263158 12.344689
## f.education=f.education.Basic             2.5046963 21.052632 32.004008
## f.season=f.season.Mar-May                 2.7131783 29.473684 41.362725
## marital=marital.married                   3.0040053 47.368421 60.040080
## f.age=f.age-(40,50]                       1.9952115 13.157895 25.110220
## f.season=f.season.Jun-Aug                 2.5835189 30.526316 44.989980
## education=education.basic.9y              1.3580247  5.789474 16.232465
## f.campaign=f.campaign-(2,20]              2.0496894 17.368421 32.264529
## month=month.jul                           1.1560694  5.263158 17.334669
## month=month.may                           1.8452381 16.315789 33.667335
## f.duration=f.duration-[5,120]             1.7341040 14.210526 31.202405
## f.job=f.job.Serv-Tech-BlueC               1.9801980 25.263158 48.577154
## job=job.blue-collar                       0.8650519  5.263158 23.166333
## default=default.unknown                   0.4761905  2.631579 21.042084
## contact=contact.telephone                 0.9513151  8.947368 35.811623
## y=y.no                                    1.7086331 40.000000 89.138277
## f.previous=f.previous-[0,0.9]             0.0000000  0.000000 85.951904
## poutcome=poutcome.nonexistent             0.0000000  0.000000 85.951904
## f.pdays=f.pdays-(22,23]                   0.4361371 11.052632 96.492986
##                                                p.value     v.test
## f.pdays=f.pdays-[0,22]                   1.259643e-281  35.860546
## poutcome=poutcome.success                3.796871e-240  33.092604
## f.previous=f.previous-(1,6]              1.553305e-129  24.214815
## y=y.yes                                   2.494385e-64  16.934745
## f.previous=f.previous-(0.9,1]             1.156226e-34  12.280262
## f.season=f.season.Sep-Dec                 3.391033e-20   9.205810
## month=month.oct                           3.163903e-18   8.705424
## contact=contact.cellular                  4.127348e-18   8.675225
## default=default.no                        4.787962e-14   7.537574
## job=job.retired                           2.103831e-13   7.342027
## month=month.sep                           5.701121e-11   6.551371
## f.age=f.age-(50,92]                       1.767166e-08   5.633375
```

```
## month=month.mar                             5.214842e-07   5.018235
## job=job.student                              6.469157e-07   4.976658
## f.job=f.job.Entrep-Retired-selfEmpl          4.357820e-06   4.593544
## f.duration=f.duration-(180,300]              3.266772e-05   4.154025
## poutcome=poutcome.failure                    3.513520e-05   4.137342
## f.education=f.education.Professional         8.193961e-05   3.938655
## education=education.university.degree        8.193961e-05   3.938655
## f.job=f.job.Not-working                      1.066886e-04   3.874854
## f.campaign=f.campaign-[0,1]                  3.261253e-04   3.593612
## month=month.jun                              9.887768e-04  -3.293701
## f.education=f.education.Basic                6.774908e-04  -3.398530
## f.season=f.season.Mar-May                    5.767248e-04  -3.442331
## marital=marital.married                      3.331185e-04  -3.588083
## f.age=f.age-(40,50]                          4.090062e-05  -4.102332
## f.season=f.season.Jun-Aug                    3.480205e-05  -4.139528
## education=education.basic.9y                 1.044307e-05  -4.407790
## f.campaign=f.campaign-(2,20]                 2.688717e-06  -4.693270
## month=month.jul                              4.872344e-07  -5.031273
## month=month.may                              5.199683e-08  -5.444343
## f.duration=f.duration-[5,120]                4.101428e-08  -5.486428
## f.job=f.job.Serv-Tech-BlueC                  2.251008e-11  -6.688740
## job=job.blue-collar                          1.081400e-11  -6.795230
## default=default.unknown                      4.787962e-14  -7.537574
## contact=contact.telephone                    4.127348e-18  -8.675225
## y=y.no                                       2.494385e-64 -16.934745
## f.previous=f.previous-[0,0.9]               2.196177e-173 -28.071291
## poutcome=poutcome.nonexistent               2.196177e-173 -28.071291
## f.pdays=f.pdays-(22,23]                     1.259643e-281 -35.860546
##
## $`2`
##                                                 Cla/Mod      Mod/Cla     Glob
al
## f.season=f.season.Jun-Aug                    87.0824053  68.47635727 44.98998
00
## f.previous=f.previous-[0,0.9]                66.5656330 100.00000000 85.95190
38
## poutcome=poutcome.nonexistent                66.5656330 100.00000000 85.95190
38
## contact=contact.telephone                    86.6256295  54.22066550 35.81162
32
## month=month.jul                              93.5260116  28.33625219 17.33466
93
## f.pdays=f.pdays-(22,23]                      59.2938733 100.00000000 96.49298
60
## month=month.aug                              82.3298429  22.03152364 15.31062
12
## y=y.no                                       61.0161871  95.06129597 89.13827
66
## month=month.jun                              83.9285714  18.10858144 12.34468
94
```

```
## default=default.unknown                75.8095238  27.88091068 21.04208
42
## f.campaign=f.campaign-(2,20]           67.0807453  37.82837128 32.26452
91
## f.age=f.age-(40,50]                    65.5227454  28.75656743 25.11022
04
## f.job=f.job.Serv-Tech-BlueC            62.1699670  52.78458844 48.57715
43
## marital=marital.married                60.8144192  63.81786340 60.04008
02
## housing=housing.no                     61.6498464  49.21190893 45.67134
27
## job=job.technician                     63.7698898  18.24868651 16.37274
55
## job=job.blue-collar                    62.2837370  25.21891419 23.16633
27
## f.education=f.education.Basic          61.1145899  34.18563923 32.00400
80
## job=job.housemaid                      72.2689076   3.01225919  2.38476
95
## f.education=f.education.Professional   53.7084399  29.42206655 31.34268
54
## education=education.university.degree  53.7084399  29.42206655 31.34268
54
## f.job=f.job.Not-working                47.6608187   5.70928196  6.85370
74
## month=month.may                        53.4523810  31.45359019 33.66733
47
## f.job=f.job.Entrep-Retired-selfEmpl    48.5268631   9.80735552 11.56312
63
## job=job.retired                        41.8918919   3.25744308  4.44889
78
## month=month.dec                         0.0000000   0.00000000  0.36072
14
## f.age=f.age-[18,30]                    48.6206897  14.81611208 17.43486
97
## housing=housing.yes                    53.4857986  50.78809107 54.32865
73
## marital=marital.single                 49.8936924  24.65849387 28.27655
31
## job=job.student                        14.6788991   0.56042032  2.18436
87
## f.campaign=f.campaign-[0,1]            49.6463932  36.88266200 42.50501
00
## month=month.mar                         0.0000000   0.00000000  1.26252
51
## month=month.oct                         2.5000000   0.07005254  1.60320
64
## month=month.sep                         0.0000000   0.00000000  1.40280
56
```

```
## default=default.no                       52.2588832  72.11908932 78.95791
58
## f.previous=f.previous-(1,6]               0.0000000   0.00000000  2.74549
10
## y=y.yes                                  26.0147601   4.93870403 10.86172
34
## poutcome=poutcome.success                 0.0000000   0.00000000  3.12625
25
## f.season=f.season.Mar-May                43.5077519  31.45359019 41.36272
55
## f.pdays=f.pdays-[0,22]                    0.0000000   0.00000000  3.50701
40
## month=month.apr                           0.0000000   0.00000000  6.43286
57
## month=month.nov                           0.0000000   0.00000000 10.28056
11
## poutcome=poutcome.failure                 0.0000000   0.00000000 10.92184
37
## f.previous=f.previous-(0.9,1]             0.0000000   0.00000000 11.30260
52
## contact=contact.cellular                 40.8054948  45.77933450 64.18837
68
## f.season=f.season.Sep-Dec                 0.2936858   0.07005254 13.64729
46
##                                                p.value     v.test
## f.season=f.season.Jun-Aug                 0.000000e+00        Inf
## f.previous=f.previous-[0,0.9]            3.019215e-293  36.598522
## poutcome=poutcome.nonexistent            3.019215e-293  36.598522
## contact=contact.telephone                1.051844e-235  32.782323
## month=month.jul                          1.306801e-149  26.051114
## f.pdays=f.pdays-(22,23]                   4.293494e-67  17.305259
## month=month.aug                           3.823967e-57  15.931608
## y=y.no                                    8.988442e-55  15.586531
## month=month.jun                           2.951209e-51  15.060372
## default=default.unknown                   8.402225e-45  14.043849
## f.campaign=f.campaign-(2,20]              1.196425e-22   9.793857
## f.age=f.age-(40,50]                       4.665985e-12   6.915384
## f.job=f.job.Serv-Tech-BlueC               5.923144e-12   6.881486
## marital=marital.married                   3.139148e-10   6.291746
## housing=housing.no                        6.199688e-09   5.811280
## job=job.technician                        3.130573e-05   4.163754
## job=job.blue-collar                       6.671792e-05   3.987697
## f.education=f.education.Basic             1.296174e-04   3.827184
## job=job.housemaid                         6.364492e-04   3.415586
## f.education=f.education.Professional      7.361711e-04  -3.375741
## education=education.university.degree     7.361711e-04  -3.375741
## f.job=f.job.Not-working                   2.382353e-04  -3.674586
## month=month.may                           1.335878e-04  -3.819748
## f.job=f.job.Entrep-Retired-selfEmpl       8.231372e-06  -4.459076
## job=job.retired                           2.872930e-06  -4.679701
```

```
## month=month.dec                              2.215519e-07  -5.180281
## f.age=f.age-[18,30]                          2.026128e-08  -5.609755
## housing=housing.yes                          6.199688e-09  -5.811280
## marital=marital.single                       6.116596e-11  -6.540860
## job=job.student                              2.122476e-20  -9.255993
## f.campaign=f.campaign-[0,1]                  1.628849e-20  -9.284227
## month=month.mar                              3.477079e-24 -10.145300
## month=month.oct                              8.502567e-27 -10.716652
## month=month.sep                              8.041008e-27 -10.721815
## default=default.no                           8.402225e-45 -14.043849
## f.previous=f.previous-(1,6]                  2.340302e-52 -15.227016
## y=y.yes                                      8.988442e-55 -15.586531
## poutcome=poutcome.success                    1.057860e-59 -16.295757
## f.season=f.season.Mar-May                    8.078887e-61 -16.452266
## f.pdays=f.pdays-[0,22]                       4.293494e-67 -17.305259
## month=month.apr                             1.591937e-125 -23.831058
## month=month.nov                             3.512409e-207 -30.715702
## poutcome=poutcome.failure                   2.239752e-221 -31.760980
## f.previous=f.previous-(0.9,1]               6.871049e-230 -32.371692
## contact=contact.cellular                    1.051844e-235 -32.782323
## f.season=f.season.Sep-Dec                   8.033924e-278 -35.615604
##
## $`3`
##                                               Cla/Mod    Mod/Cla    Global
## f.season=f.season.Sep-Dec                   66.079295 100.000000 13.647295
## month=month.nov                             86.549708  98.666667 10.280561
## contact=contact.cellular                    12.425851  88.444444 64.188377
## job=job.management                          17.948718  14.000000  7.034068
## f.pdays=f.pdays-(22,23]                      9.345794 100.000000 96.492986
## default=default.no                          10.076142  88.222222 78.957916
## y=y.no                                       9.622302  95.111111 89.138277
## poutcome=poutcome.failure                   14.311927  17.333333 10.921844
## f.campaign=f.campaign-[0,1]                 11.032532  52.000000 42.505010
## f.duration=f.duration-[5,120]               11.560694  40.000000 31.202405
## f.previous=f.previous-(0.9,1]               13.829787  17.333333 11.302605
## f.education=f.education.Professional        11.125320  38.666667 31.342685
## education=education.university.degree       11.125320  38.666667 31.342685
## job=job.entrepreneur                        16.402116   6.888889  3.787575
## education=education.basic.4y                 5.048544   5.777778 10.320641
## job=job.retired                              2.702703   1.333333  4.448898
## f.age=f.age-[18,30]                          5.747126  11.111111 17.434870
## job=job.student                              0.000000   0.000000  2.184369
## job=job.blue-collar                          5.795848  14.888889 23.166333
## y=y.yes                                      4.059041   4.888889 10.861723
## f.previous=f.previous-(1,6]                  0.000000   0.000000  2.745491
## f.education=f.education.Basic                6.199123  22.000000 32.004008
## f.campaign=f.campaign-(2,20]                 6.211180  22.222222 32.264529
## poutcome=poutcome.success                    0.000000   0.000000  3.126253
## default=default.unknown                      5.047619  11.777778 21.042084
## f.pdays=f.pdays-[0,22]                       0.000000   0.000000  3.507014
```

```
## month=month.apr                              0.000000   0.000000  6.432866
## month=month.jun                              0.000000   0.000000 12.344689
## contact=contact.telephone                    2.909905  11.555556 35.811623
## month=month.aug                              0.000000   0.000000 15.310621
## month=month.jul                              0.000000   0.000000 17.334669
## month=month.may                              0.000000   0.000000 33.667335
## f.season=f.season.Mar-May                    0.000000   0.000000 41.362725
## f.season=f.season.Jun-Aug                    0.000000   0.000000 44.989980
##                                                   p.value     v.test
## f.season=f.season.Sep-Dec                    0.000000e+00        Inf
## month=month.nov                              0.000000e+00        Inf
## contact=contact.cellular                     4.457861e-34  12.170601
## job=job.management                           4.606444e-08   5.465869
## f.pdays=f.pdays-(22,23]                      4.814305e-08   5.458036
## default=default.no                           8.895002e-08   5.347962
## y=y.no                                       3.321039e-06   4.649895
## poutcome=poutcome.failure                    1.761402e-05   4.293170
## f.campaign=f.campaign-[0,1]                  2.207930e-05   4.242754
## f.duration=f.duration-[5,120]                3.465489e-05   4.140500
## f.previous=f.previous-(0.9,1]                6.332305e-05   4.000073
## f.education=f.education.Professional         5.526671e-04   3.453839
## education=education.university.degree        5.526671e-04   3.453839
## job=job.entrepreneur                         9.628257e-04   3.301170
## education=education.basic.4y                 4.140424e-04  -3.530968
## job=job.retired                              1.504256e-04  -3.790366
## f.age=f.age-[18,30]                          1.055513e-04  -3.877463
## job=job.student                              2.982402e-05  -4.174806
## job=job.blue-collar                          5.480188e-06  -4.545512
## y=y.yes                                      3.321039e-06  -4.649895
## f.previous=f.previous-(1,6]                  1.972148e-06  -4.756258
## f.education=f.education.Basic                9.408844e-07  -4.903616
## f.campaign=f.campaign-(2,20]                 9.107926e-07  -4.909994
## poutcome=poutcome.success                    3.093148e-07  -5.117681
## default=default.unknown                      8.895002e-08  -5.347962
## f.pdays=f.pdays-[0,22]                       4.814305e-08  -5.458036
## month=month.apr                              2.294108e-14  -7.632967
## month=month.jun                              8.435071e-28 -10.928369
## contact=contact.telephone                    4.457861e-34 -12.170601
## month=month.aug                              6.622682e-35 -12.325263
## month=month.jul                              6.599006e-40 -13.221438
## month=month.may                              8.848336e-86 -19.628385
## f.season=f.season.Mar-May                   8.311269e-112 -22.469179
## f.season=f.season.Jun-Aug                   2.151192e-125 -23.818443
##
## $`4`
##                                 Cla/Mod    Mod/Cla     Global
## f.season=f.season.Mar-May     53.779070 74.2474916 41.3627255
## month=month.apr               96.261682 20.6688963  6.4328657
## contact=contact.cellular      41.367468 88.6287625 64.1883768
## poutcome=poutcome.failure     78.348624 28.5618729 10.9218437
```

```
## f.previous=f.previous-(0.9,1] 70.744681 26.6889632 11.3026052
## month=month.may               44.702381 50.2341137 33.6673347
## y=y.yes                       48.892989 17.7257525 10.8617234
## default=default.no            32.969543 86.8896321 78.9579158
## f.pdays=f.pdays-(22,23]       30.924195 99.5986622 96.4929860
## job=job.student               69.724771  5.0836120  2.1843687
## month=month.mar               79.365079  3.3444816  1.2625251
## month=month.sep               74.285714  3.4782609  1.4028056
## marital=marital.single        37.774628 35.6521739 28.2765531
## f.age=f.age-[18,30]           40.574713 23.6120401 17.4348697
## f.campaign=f.campaign-[0,1]   34.370580 48.7625418 42.5050100
## month=month.oct               60.000000  3.2107023  1.6032064
## housing=housing.yes           32.312800 58.5953177 54.3286573
## month=month.dec               72.222222  0.8695652  0.3607214
## housing=housing.no            27.161036 41.4046823 45.6713427
## f.season=f.season.Sep-Dec     22.466960 10.2341137 13.6472946
## job=job.technician            22.888617 12.5083612 16.3727455
## marital=marital.married       27.202937 54.5150502 60.0400802
## f.campaign=f.campaign-(2,20]  24.658385 26.5551839 32.2645291
## f.age=f.age-(40,50]           22.984836 19.2642140 25.1102204
## poutcome=poutcome.success      3.846154  0.4013378  3.1262525
## f.pdays=f.pdays-[0,22]         3.428571  0.4013378  3.5070140
## default=default.unknown       18.666667 13.1103679 21.0420842
## month=month.jun               14.448052  5.9531773 12.3446894
## y=y.no                        27.652878 82.2742475 89.1382766
## month=month.aug               12.696335  6.4882943 15.3106212
## month=month.nov                7.797271  2.6755853 10.2805611
## f.previous=f.previous-[0,0.9] 24.761017 71.0367893 85.9519038
## poutcome=poutcome.nonexistent 24.761017 71.0367893 85.9519038
## month=month.jul                5.317919  3.0769231 17.3346693
## contact=contact.telephone      9.513151 11.3712375 35.8116232
## f.season=f.season.Jun-Aug     10.334076 15.5183946 44.9899800
##                                     p.value     v.test
## f.season=f.season.Mar-May    1.214684e-211  31.047983
## month=month.apr              2.443356e-153  26.378112
## contact=contact.cellular     7.335999e-138  24.992718
## poutcome=poutcome.failure    5.641457e-137  24.911094
## f.previous=f.previous-(0.9,1] 3.761358e-101  21.351684
## month=month.may               2.068828e-57  15.969971
## y=y.yes                       9.791179e-23   9.814096
## default=default.no            1.504249e-20   9.292699
## f.pdays=f.pdays-(22,23]       7.889588e-20   9.114690
## job=job.student               6.601535e-18   8.621617
## month=month.mar               5.354652e-16   8.103167
## month=month.sep               1.931681e-14   7.655096
## marital=marital.single        7.928406e-14   7.471503
## f.age=f.age-[18,30]           1.851132e-13   7.359130
## f.campaign=f.campaign-[0,1]   5.524740e-09   5.830543
## month=month.oct               2.441289e-08   5.577408
## housing=housing.yes           7.419015e-05   3.962432
```

```
## month=month.dec                  2.959629e-04   3.618808
## housing=housing.no                7.419015e-05  -3.962432
## f.season=f.season.Sep-Dec         2.698987e-06  -4.692491
## job=job.technician                8.712805e-07  -4.918684
## marital=marital.married           2.090160e-07  -5.191135
## f.campaign=f.campaign-(2,20]      1.226294e-08  -5.696030
## f.age=f.age-(40,50]               2.434489e-10  -6.331081
## poutcome=poutcome.success         4.435265e-17  -8.400779
## f.pdays=f.pdays-[0,22]            7.889588e-20  -9.114690
## default=default.unknown           1.504249e-20  -9.292699
## month=month.jun                   1.863347e-21  -9.512388
## y=y.no                            9.791179e-23  -9.814096
## month=month.aug                   1.221397e-33 -12.088058
## month=month.nov                   8.917776e-38 -12.847202
## f.previous=f.previous-[0,0.9]     4.885281e-80 -18.944683
## poutcome=poutcome.nonexistent     4.885281e-80 -18.944683
## month=month.jul                   1.393898e-85 -19.605278
## contact=contact.telephone        7.335999e-138 -24.992718
## f.season=f.season.Jun-Aug        1.401958e-178 -28.493704
##
##
## Link between the cluster variable and the quantitative variables
## ================================================================
##                         Eta2       P-value
## pdays           0.833431759  0.000000e+00
## previous        0.501141537  0.000000e+00
## emp.var.rate    0.949447313  0.000000e+00
## cons.price.idx 0.574427755  0.000000e+00
## euribor3m       0.989874994  0.000000e+00
## nr.employed     0.866883329  0.000000e+00
## cons.conf.idx   0.167721928 3.916150e-198
## campaign        0.027687626  3.757869e-30
## age             0.008632187  2.197904e-09
##
## Description of each cluster by quantitative variables
## =====================================================
## $`1`
##                      v.test Mean in category  Overall mean sd in categor
y
## previous         45.971997        1.8210526    0.17855711      0.956737
3
## cons.conf.idx     6.937479      -38.2494737  -40.54192385      7.116295
2
## age               5.645279       44.3789474   40.17755511     16.985863
4
## campaign         -4.322398        1.7894737    2.51503006      1.259864
1
## cons.price.idx   -4.817260       93.3651368   93.56373427      0.834190
6
## emp.var.rate    -19.115707       -2.0936842    0.05212425      0.856530
```

```
4
## euribor3m      -21.054798        0.9672263    3.58457355      0.512139
4
## nr.employed    -27.122883     5025.3821053 5165.87569138     51.334073
0
## pdays          -64.481704        7.8473684   22.41362725      6.445142
5
##                Overall sd       p.value
## previous        0.5020810  0.000000e+00
## cons.conf.idx   4.6436681  3.991593e-12
## age            10.4585324  1.649135e-08
## campaign        2.3588988  1.543422e-05
## cons.price.idx  0.5793439  1.455430e-06
## emp.var.rate    1.5774788  1.868722e-81
## euribor3m       1.7469207  2.066633e-98
## nr.employed    72.7919889 5.290316e-162
## pdays           3.1744936  0.000000e+00
##
## $`2`
##                   v.test Mean in category  Overall mean sd in category
## emp.var.rate    64.85040         1.304588    0.05212425     0.14415633
## euribor3m       62.64096         4.924314    3.58457355     0.05025276
## nr.employed     56.70185      5216.408091 5165.87569138    17.23254124
## cons.price.idx  52.54683        93.936445   93.56373427     0.32429720
## cons.conf.idx   25.36681       -39.099755  -40.54192385     3.04458233
## pdays           15.08725        23.000000   22.41362725     0.00000000
## campaign        11.60168         2.850088    2.51503006     2.73344964
## previous       -29.04787         0.000000    0.17855711     0.00000000
##                Overall sd       p.value
## emp.var.rate    1.5774788  0.000000e+00
## euribor3m       1.7469207  0.000000e+00
## nr.employed    72.7919889  0.000000e+00
## cons.price.idx  0.5793439  0.000000e+00
## cons.conf.idx   4.6436681 5.863605e-142
## pdays           3.1744936  1.964506e-51
## campaign        2.3588988  4.040627e-31
## previous        0.5020810 1.637199e-185
##
## $`3`
##                    v.test Mean in category Overall mean sd in category
## nr.employed      9.115196      5195.713333  5165.875691     1.29710789
## euribor3m        6.818350         4.120207     3.584574     0.11552217
## pdays            4.107565        23.000000    22.413627     0.00000000
## campaign        -4.708571         2.015556     2.515030     1.58527328
## cons.conf.idx   -6.997289       -42.003111   -40.541924     0.30057591
## cons.price.idx -13.833237        93.203342    93.563734     0.06359003
##                Overall sd      p.value
## nr.employed    72.7919889 7.852866e-20
## euribor3m       1.7469207 9.209193e-12
## pdays           3.1744936 3.998529e-05
```

```
## campaign        2.3588988 2.494597e-06
## cons.conf.idx   4.6436681 2.609633e-12
## cons.price.idx  0.5793439 1.606263e-43
##
## $`4`
##                    v.test Mean in category  Overall mean sd in categor
y
## previous        12.312403        0.3123746    0.17855711      0.510178
1
## pdays            8.075532       22.9685619   22.41362725      0.568705
9
## age             -4.052007       39.2602007   40.17755511     12.043615
9
## campaign        -7.780683        2.1177258    2.51503006      1.682743
5
## cons.conf.idx  -25.921260      -43.1475585  -40.54192385      5.978130
1
## cons.price.idx -46.092491       92.9856876   93.56373427      0.431589
9
## nr.employed    -55.611005     5078.2481605 5165.87569138     38.102052
3
## emp.var.rate   -60.712801       -2.0210702    0.05212425      0.535674
7
## euribor3m      -63.124684        1.1974843    3.58457355      0.246900
9
##                Overall sd       p.value
## previous        0.5020810  7.767580e-35
## pdays           3.1744936  6.718328e-16
## age            10.4585324  5.078016e-05
## campaign        2.3588988  7.213395e-15
## cons.conf.idx   4.6436681 3.835830e-148
## cons.price.idx  0.5793439  0.000000e+00
## nr.employed    72.7919889  0.000000e+00
## emp.var.rate    1.5774788  0.000000e+00
## euribor3m       1.7469207  0.000000e+00
```

Hierarchical Clustering

Al hacer el HCPC podemos ver que el gráfico de ganancia de inercia nos da la mayoría en dos variables, y luego dos picos más pequeños.

Ahora vemos el clustering no supervisado. Vamos a clasificar estos clusters.

Para el cluster 1:
- Está caracterizado por personas que han sido contactados previamente
- Han aceptado el producto
- Se han contactado en f.season.Sep-Dec
- Tienen una sobrerepresentación de f.job.Entrep-Retired-selfEmpl
- Llamadas de duración mayor a 3min

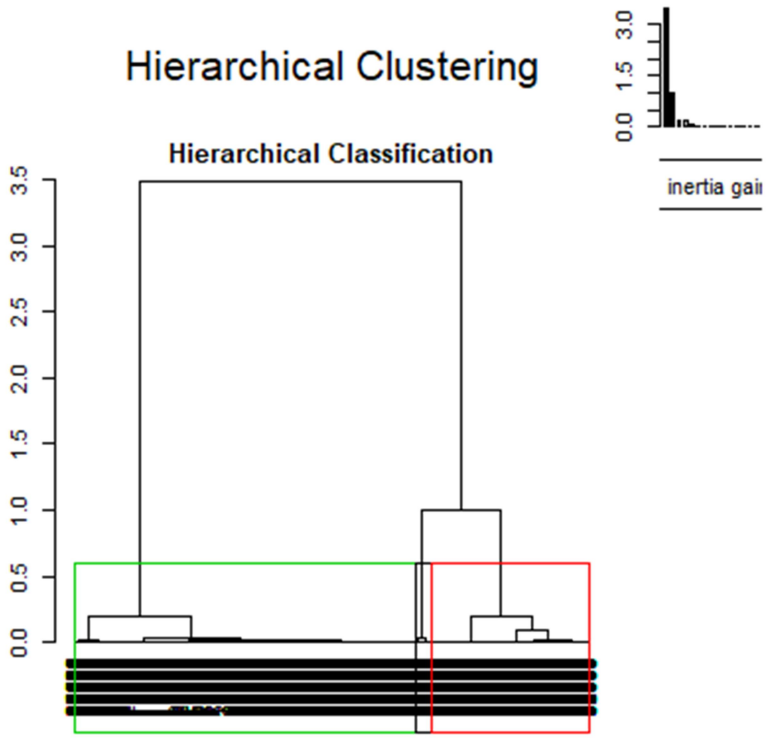
Para el cluster 2:
- Han sido contactados f.season.Mar-May
- Han sido contactados en campañas previas
- Han aceptado el producto (y.yes)

Para el cluster 3:
- Han sido contactados previamente
- No han sido contactados en campañas previas
- Han sido contactados en la temporada de f.season.Jun-Aug
- Han rechazado el producto
- Tienen una leve representación de f.job.Serv-Tech-BlueC

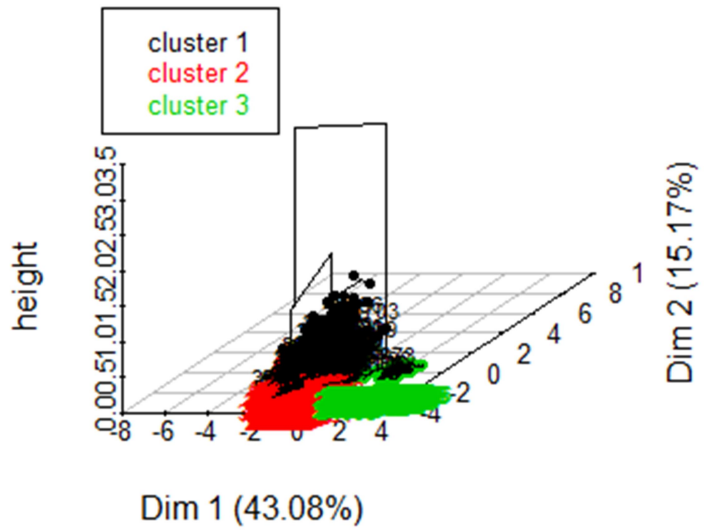
Además vemos que los parengones tienen mucho parecido a lo descrito para cada cluster.

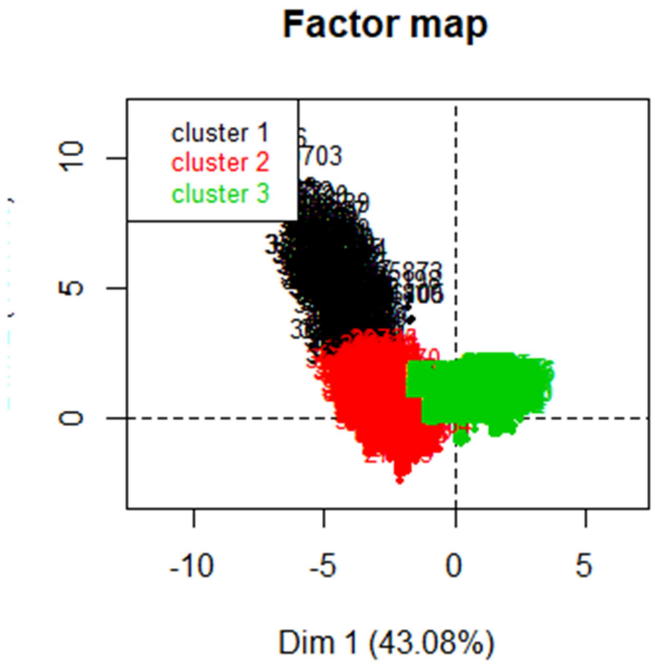
Utilizamos el atributo nb.clust=3, después de haber visto que era el mejor corte.

```
res.pca<-PCA(df[,c('duration',vars_num,vars_factorizadas)],quanti.sup=1,
quali.sup = c(11:19), ncp=2, graph=FALSE)
res.hcpc<-HCPC(res.pca,order=TRUE, nb.clust = 3)
```



Hierarchical clustering on the factor map






```
attributes(res.hcpc)

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

summary(res.hcpc$data.clust)

##     duration           age           campaign          pdays
##  Min.   :   5.0   Min.   :18.00   Min.   : 1.000   Min.   : 0.00
##  1st Qu.: 103.0   1st Qu.:32.00   1st Qu.: 1.000   1st Qu.:23.00
##  Median : 178.5   Median :38.00   Median : 2.000   Median :23.00
##  Mean   : 259.9   Mean   :40.18   Mean   : 2.515   Mean   :22.41
##  3rd Qu.: 321.0   3rd Qu.:47.00   3rd Qu.: 3.000   3rd Qu.:23.00
##  Max.   :2078.0   Max.   :92.00   Max.   :20.000   Max.   :23.00
##     previous       emp.var.rate      cons.price.idx  cons.conf.idx
##  Min.   :0.0000   Min.   :-3.40000   Min.   :92.20   Min.   :-50.80
##  1st Qu.:0.0000   1st Qu.:-1.80000   1st Qu.:93.08   1st Qu.:-42.70
##  Median :0.0000   Median : 1.10000   Median :93.44   Median :-41.80
##  Mean   :0.1786   Mean   : 0.05212   Mean   :93.56   Mean   :-40.54
##  3rd Qu.:0.0000   3rd Qu.: 1.40000   3rd Qu.:93.99   3rd Qu.:-36.40
##  Max.   :6.0000   Max.   : 1.40000   Max.   :94.77   Max.   :-26.90
##    euribor3m      nr.employed                              f.job
##  Min.   :0.634   Min.   :4964   f.job.Admin-Managment        :1647
##  1st Qu.:1.334   1st Qu.:5099   f.job.Entrep-Retired-selfEmpl: 577
```

```
##  Median :4.857   Median :5191   f.job.Not-working            : 342
##  Mean   :3.585   Mean   :5166   f.job.Serv-Tech-BlueC        :2424
##  3rd Qu.:4.961   3rd Qu.:5228
##  Max.   :5.045   Max.   :5228
##             f.season                      f.education
##  f.season.Mar-May:2064   f.education.Basic       :1597
##  f.season.Jun-Aug:2245   f.education.High School :1829
##  f.season.Sep-Dec: 681   f.education.Professional:1564
##
##
##
##           f.age                          f.duration
##  f.age-[18,30]: 870   f.duration-[5,120]      :1557
##  f.age-(30,40]:1991   f.duration-(120,180]    : 966
##  f.age-(40,50]:1253   f.duration-(180,300]    :1090
##  f.age-(50,92]: 876   f.duration-(300,2.1e+03]:1377
##
##
##             f.campaign              f.pdays                  f.previo
us
##  f.campaign-[0,1] :2121   f.pdays-[0,22] : 175   f.previous-[0,0.9]:42
89
##  f.campaign-(1,2] :1259   f.pdays-(22,23]:4815   f.previous-(0.9,1]: 5
64
##  f.campaign-(2,20]:1610                          f.previous-(1,6]  : 1
37
##
##
##
##     y        clust
##  y.no :4448   1: 190
##  y.yes: 542   2:1497
##               3:3303
##
##
##
```

```
attributes(res.hcpc$desc.var)
```

```
## $names
## [1] "test.chi2"  "category"   "quanti.var" "quanti"     "call"
##
## $class
## [1] "catdes" "list "
```

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

```
##                   p.value df
## f.pdays      0.000000e+00  2
## f.previous   0.000000e+00  4
```

```
## f.season    3.418306e-239  4
## y           2.373371e-145  2
## f.age        4.054913e-27  6
## f.job        5.294443e-17  6
## f.campaign   6.236440e-15  4
## f.duration   2.126018e-09  6
## f.education  7.523481e-04  4

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

## $`1`
##                                        Cla/Mod  Mod/Cla    Global
## f.pdays=f.pdays-[0,22]               96.5714286 88.94737  3.507014
## f.previous=f.previous-(1,6]          75.1824818 54.21053  2.745491
## y=y.yes                              21.0332103 60.00000 10.861723
## f.previous=f.previous-(0.9,1]        15.4255319 45.78947 11.302605
## f.season=f.season.Sep-Dec            11.1600587 40.00000 13.647295
## f.age=f.age-(50,92]                   7.4200913 34.21053 17.555110
## f.job=f.job.Entrep-Retired-selfEmpl   7.6256499 23.15789 11.563126
## f.duration=f.duration-(180,300]       6.0550459 34.73684 21.843687
## f.education=f.education.Professional  5.4347826 44.73684 31.342685
## f.job=f.job.Not-working               8.1871345 14.73684  6.853707
## f.campaign=f.campaign-[0,1]           4.9504950 55.26316 42.505010
## f.duration=f.duration-(300,2.1e+03]   4.9382716 35.78947 27.595190
## f.age=f.age-[18,30]                   5.0574713 23.15789 17.434870
## f.age=f.age-(30,40]                   2.8126570 29.47368 39.899800
## f.education=f.education.Basic         2.5046963 21.05263 32.004008
## f.season=f.season.Mar-May             2.7131783 29.47368 41.362725
## f.age=f.age-(40,50]                   1.9952115 13.15789 25.110220
## f.season=f.season.Jun-Aug             2.5835189 30.52632 44.989980
## f.campaign=f.campaign-(2,20]          2.0496894 17.36842 32.264529
## f.duration=f.duration-[5,120]         1.7341040 14.21053 31.202405
## f.job=f.job.Serv-Tech-BlueC           1.9801980 25.26316 48.577154
## y=y.no                                1.7086331 40.00000 89.138277
## f.previous=f.previous-[0,0.9]         0.0000000  0.00000 85.951904
## f.pdays=f.pdays-(22,23]               0.4361371 11.05263 96.492986
##                                           p.value     v.test
## f.pdays=f.pdays-[0,22]               1.259643e-281  35.860546
## f.previous=f.previous-(1,6]          1.553305e-129  24.214815
## y=y.yes                               2.494385e-64  16.934745
## f.previous=f.previous-(0.9,1]         1.156226e-34  12.280262
## f.season=f.season.Sep-Dec             3.391033e-20   9.205810
## f.age=f.age-(50,92]                   1.767166e-08   5.633375
## f.job=f.job.Entrep-Retired-selfEmpl   4.357820e-06   4.593544
## f.duration=f.duration-(180,300]       3.266772e-05   4.154025
## f.education=f.education.Professional  8.193961e-05   3.938655
## f.job=f.job.Not-working               1.066886e-04   3.874854
## f.campaign=f.campaign-[0,1]           3.261253e-04   3.593612
## f.duration=f.duration-(300,2.1e+03]   1.193267e-02   2.514129
```

```
## f.age=f.age-[18,30]                    4.007463e-02   2.052979
## f.age=f.age-(30,40]                    2.422784e-03  -3.032822
## f.education=f.education.Basic          6.774908e-04  -3.398530
## f.season=f.season.Mar-May              5.767248e-04  -3.442331
## f.age=f.age-(40,50]                    4.090062e-05  -4.102332
## f.season=f.season.Jun-Aug              3.480205e-05  -4.139528
## f.campaign=f.campaign-(2,20]           2.688717e-06  -4.693270
## f.duration=f.duration-[5,120]          4.101428e-08  -5.486428
## f.job=f.job.Serv-Tech-BlueC            2.251008e-11  -6.688740
## y=y.no                                 2.494385e-64 -16.934745
## f.previous=f.previous-[0,0.9]         2.196177e-173 -28.071291
## f.pdays=f.pdays-(22,23]               1.259643e-281 -35.860546
##
## $`2`
##                                   Cla/Mod    Mod/Cla    Global       p.v
alue
## f.season=f.season.Mar-May     53.779070 74.1482966 41.362725 9.639926e
-211
## f.previous=f.previous-(0.9,1] 70.921986 26.7201069 11.302605 8.620072e
-102
## y=y.yes                       48.892989 17.7020708 10.861723  1.228275
e-22
## f.pdays=f.pdays-(22,23]       30.965732 99.5991984 96.492986  7.200421
e-20
## f.age=f.age-[18,30]           40.574713 23.5804943 17.434870  2.310583
e-13
## f.campaign=f.campaign-[0,1]   34.464875 48.8309953 42.505010  3.637684
e-09
## f.job=f.job.Not-working       37.134503  8.4836339  6.853707  3.388459
e-03
## f.duration=f.duration-[5,120] 28.066795 29.1917168 31.202405  4.431130
e-02
## f.job=f.job.Serv-Tech-BlueC   28.135314 45.5577822 48.577154  5.209983
e-03
## f.season=f.season.Sep-Dec     22.760646 10.3540414 13.647295  5.972406
e-06
## f.campaign=f.campaign-(2,20]  24.658385 26.5197061 32.264529  9.621448
e-09
## f.age=f.age-(40,50]           22.984836 19.2384770 25.110220  1.946669
e-10
## f.pdays=f.pdays-[0,22]         3.428571  0.4008016  3.507014  7.200421
e-20
## y=y.no                        27.697842 82.2979292 89.138277  1.228275
e-22
## f.previous=f.previous-[0,0.9] 24.784332 71.0086840 85.951904  1.676131
e-80
## f.season=f.season.Jun-Aug     10.334076 15.4976620 44.989980 3.526427e
-179
##                                   v.test
## f.season=f.season.Mar-May      30.981263
```

```
## f.previous=f.previous-(0.9,1]  21.420424
## y=y.yes                         9.791202
## f.pdays=f.pdays-(22,23]         9.124596
## f.age=f.age-[18,30]             7.329474
## f.campaign=f.campaign-[0,1]     5.899879
## f.job=f.job.Not-working         2.930106
## f.duration=f.duration-[5,120]  -2.011134
## f.job=f.job.Serv-Tech-BlueC    -2.793756
## f.season=f.season.Sep-Dec      -4.527364
## f.campaign=f.campaign-(2,20]   -5.737271
## f.age=f.age-(40,50]            -6.365490
## f.pdays=f.pdays-[0,22]         -9.124596
## y=y.no                         -9.791202
## f.previous=f.previous-[0,0.9] -19.000910
## f.season=f.season.Jun-Aug     -28.542041
##
## $`3`
##                                      Cla/Mod    Mod/Cla    Global
## f.previous=f.previous-[0,0.9]       75.21567  97.668786 85.951904
## f.season=f.season.Jun-Aug           87.08241  59.188616 44.989980
## f.pdays=f.pdays-(22,23]             68.59813 100.000000 96.492986
## y=y.no                              70.59353  95.065092 89.138277
## f.age=f.age-(40,50]                 75.01995  28.458977 25.110220
## f.campaign=f.campaign-(2,20]        73.29193  35.725098 32.264529
## f.job=f.job.Serv-Tech-BlueC         69.88449  51.286709 48.577154
## f.duration=f.duration-[5,120]       70.19910  33.091129 31.202405
## f.duration=f.duration-(180,300]     62.66055  20.678171 21.843687
## f.duration=f.duration-(300,2.1e+03] 63.03558  26.279140 27.595190
## f.job=f.job.Entrep-Retired-selfEmpl 58.92548  10.293672 11.563126
## f.job=f.job.Not-working             54.67836   5.661520  6.853707
## f.campaign=f.campaign-[0,1]         60.58463  38.904027 42.505010
## f.age=f.age-[18,30]                 54.36782  14.320315 17.434870
## f.previous=f.previous-(1,6]          0.00000   0.000000  2.745491
## y=y.yes                             30.07380   4.934908 10.861723
## f.pdays=f.pdays-[0,22]               0.00000   0.000000  3.507014
## f.previous=f.previous-(0.9,1]       13.65248   2.331214 11.302605
## f.season=f.season.Mar-May           43.50775  27.187405 41.362725
##                                           p.value     v.test
## f.previous=f.previous-[0,0.9]       6.011990e-240  33.078726
## f.season=f.season.Jun-Aug           3.447463e-187  29.180312
## f.pdays=f.pdays-(22,23]              7.182640e-86  19.638980
## y=y.no                               2.742424e-74  18.234602
## f.age=f.age-(40,50]                  8.378911e-15   7.761714
## f.campaign=f.campaign-(2,20]         1.432305e-13   7.393298
## f.job=f.job.Serv-Tech-BlueC          8.211297e-08   5.362423
## f.duration=f.duration-[5,120]        5.127384e-05   4.049743
## f.duration=f.duration-(180,300]      5.558862e-03  -2.772728
## f.duration=f.duration-(300,2.1e+03]  3.761527e-03  -2.897497
## f.job=f.job.Entrep-Retired-selfEmpl  1.078588e-04  -3.872197
## f.job=f.job.Not-working              4.940469e-06  -4.567300
```

```
## f.campaign=f.campaign-[0,1]          6.903561e-13  -7.181332
## f.age=f.age-[18,30]                  1.568440e-15  -7.971434
## f.previous=f.previous-(1,6]          6.723232e-67 -17.279410
## y=y.yes                              2.742424e-74 -18.234602
## f.pdays=f.pdays-[0,22]               7.182640e-86 -19.638980
## f.previous=f.previous-(0.9,1]       1.915585e-167 -27.580337
## f.season=f.season.Mar-May           1.553439e-179 -28.570715

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

##                        Eta2       P-value
## pdays          0.833431720  0.000000e+00
## previous       0.492162105  0.000000e+00
## emp.var.rate   0.887391268  0.000000e+00
## cons.price.idx 0.451020756  0.000000e+00
## euribor3m      0.972756054  0.000000e+00
## nr.employed    0.859965803  0.000000e+00
## cons.conf.idx  0.137891619 2.106281e-161
## campaign       0.018064870  1.813245e-20
## age            0.008646255  3.945874e-10

res.hcpc$desc.var$quanti

## $`1`
##                    v.test Mean in category  Overall mean sd in categor
y
## previous        45.971997        1.8210526    0.17855711      0.956737
3
## cons.conf.idx    6.937479      -38.2494737  -40.54192385      7.116295
2
## age              5.645279       44.3789474   40.17755511     16.985863
4
## duration         2.110371      297.6368421  259.85110220    204.056157
7
## campaign        -4.322398        1.7894737    2.51503006      1.259864
1
## cons.price.idx  -4.817260       93.3651368   93.56373427      0.834190
6
## emp.var.rate   -19.115707       -2.0936842    0.05212425      0.856530
4
## euribor3m      -21.054798        0.9672263    3.58457355      0.512139
4
## nr.employed    -27.122883     5025.3821053 5165.87569138     51.334073
0
## pdays          -64.481704        7.8473684   22.41362725      6.445142
5
##                 Overall sd       p.value
## previous         0.5020810  0.000000e+00
## cons.conf.idx    4.6436681  3.991593e-12
## age             10.4585324  1.649135e-08
```

```
## duration       251.6124483  3.482644e-02
## campaign         2.3588988  1.543422e-05
## cons.price.idx   0.5793439  1.455430e-06
## emp.var.rate     1.5774788  1.868722e-81
## euribor3m        1.7469207  2.066633e-98
## nr.employed     72.7919889 5.290316e-162
## pdays            3.1744936  0.000000e+00
##
## $`2`
##                    v.test Mean in category  Overall mean sd in categor
y
## previous        12.347248        0.3126253    0.17855711      0.510210
6
## pdays            8.083856       22.9686039   22.41362725      0.568327
0
## age             -4.063321       39.2585170   40.17755511     12.035711
6
## campaign        -7.817387        2.1162325    2.51503006      1.682114
6
## cons.conf.idx  -25.982635      -43.1512358  -40.54192385      5.974981
3
## cons.price.idx -46.161007       92.9853808   93.56373427      0.431383
1
## nr.employed    -55.580906     5078.3791583 5165.87569138     38.244662
8
## emp.var.rate   -60.699472       -2.0186373    0.05212425      0.539433
6
## euribor3m      -63.098140        1.2007649    3.58457355      0.262553
2
##                Overall sd       p.value
## previous        0.5020810  5.040624e-35
## pdays           3.1744936  6.275018e-16
## age            10.4585324  4.837945e-05
## campaign        2.3588988  5.393129e-15
## cons.conf.idx   4.6436681 7.782048e-149
## cons.price.idx  0.5793439  0.000000e+00
## nr.employed    72.7919889  0.000000e+00
## emp.var.rate    1.5774788  0.000000e+00
## euribor3m       1.7469207  0.000000e+00
##
## $`3`
##                    v.test Mean in category  Overall mean sd in categor
y
## euribor3m       69.642425       4.81553255    3.58457355      0.281558
4
## emp.var.rate    66.534303       1.11407811    0.05212425      0.499256
3
## nr.employed     64.815247    5213.61292764 5165.87569138     17.506356
1
## cons.price.idx  46.665983      93.83728217   93.56373427      0.392426
```

```
8
## cons.conf.idx   22.363260     -39.49118983  -40.54192385      2.998622
8
## pdays           18.255882      23.00000000   22.41362725      0.000000
0
## campaign         9.321541       2.73751135    2.51503006      2.623136
0
## previous       -30.559574       0.02331214    0.17855711      0.150893
0
##                Overall sd       p.value
## euribor3m       1.7469207  0.000000e+00
## emp.var.rate    1.5774788  0.000000e+00
## nr.employed    72.7919889  0.000000e+00
## cons.price.idx  0.5793439  0.000000e+00
## cons.conf.idx   4.6436681 8.971345e-111
## pdays           3.1744936  1.857861e-74
## campaign        2.3588988  1.146631e-20
## previous        0.5020810 4.219155e-205

### desc.ind ###
### C. 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
##      36296      36721      40892      41007      36907
## 0.03946875 0.05735028 0.13237750 0.21737224 0.22738201
## ------------------------------------------------------------
## Cluster: 2
##      30951      36346      36347      36427      36864
## 0.06134805 0.09336824 0.09336824 0.09552183 0.09624810
## ------------------------------------------------------------
## Cluster: 3
##       1467       1752        331       6185      18926
## 0.01424926 0.01424926 0.01478019 0.01478019 0.01491243

res.hcpc$desc.ind$dist

## Cluster: 1
##     40396     40703     39592     38902     39612
## 11.543929 10.404680  9.652239  9.431592  9.270355
## ------------------------------------------------------------
## Cluster: 2
##    37956    38026    38148    37904    38051
## 4.742178 4.688806 4.646346 4.645320 4.644823
## ------------------------------------------------------------
## Cluster: 3
```

```
##    11696     8484    11485    11056    10761
## 5.265453 5.246245 5.197173 5.138562 5.009706
```

CA analysis for your data should contain your factor version of the numeric target (duration) in K= 7 (maximum 10) levels and 2 factors:

Eigenvalues and dominant axes analysis. How many axes we have to consider are there any row categories that can be combined/avoided to explain Duration target.

Para experimentar y para que tenga más sentido el análisis de correspondencias, refactorizaremos a 8 niveles la variable duration.

Ahora hacemos el análisis de correspondencias entre nuestra nueva duration factorizada y f.age. Para saber cuantas dimensiones debemos considerar, obtenemos la media de los eigenvalues. Vemos que solamente tiene sentido considerar el primer eje, ya que este es el único valor mayor a la media (kaiser).

Al graficar el CA, podemos ver que los 2 niveles con menores edades, son los que menos representados en ese eje. Para duration, los niveles mejor representados en el eje son los de mayor y menor duración.

Al ejecutar la función del chisq.test podemos ver que el pvalue es muy grande, lo que nos puede decir que la probabilidad de que no tengan relación es muy grande.

CA - duration vs f.age

```
# Para duration
aux2<-c(5,60,120,150,180,240,300,1200,2100) # Niveles "naturales"
duration_k8<-factor(cut(df$duration,breaks=aux2,include.lowest=T))
table(duration_k8)
```

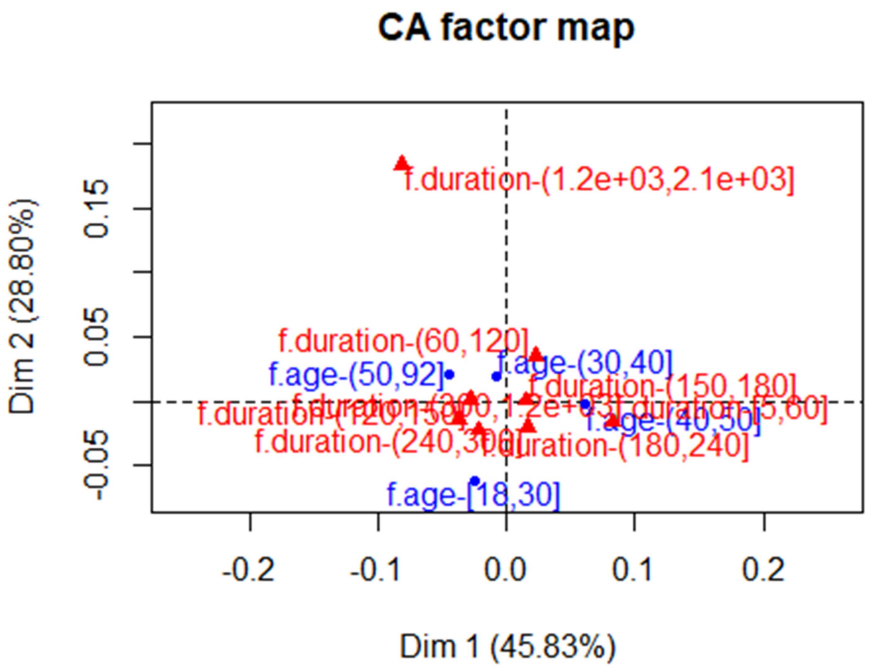
```
## duration_k8
##            [5,60]          (60,120]         (120,150]         (150,180
]
##               490              1067               496               47
0
##         (180,240]         (240,300]     (300,1.2e+03] (1.2e+03,2.1e+03
]
##               606               484              1311                6
6
```

```
levels(duration_k8)<-paste0("f.duration-",levels(duration_k8)) # Hacemos
las etiquetas más informativas
summary(duration_k8)
```

```
##            f.duration-[5,60]          f.duration-(60,120]
##                          490                         1067
##         f.duration-(120,150]         f.duration-(150,180]
```

```
##                             496                             470
##         f.duration-(180,240]         f.duration-(240,300]
##                             606                             484
##     f.duration-(300,1.2e+03] f.duration-(1.2e+03,2.1e+03]
##                            1311                              66
```

```
res.ca<-CA(table(df$f.age,duration_k8))
```




```
attributes(res.ca)
```

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

```
res.ca$eig
```

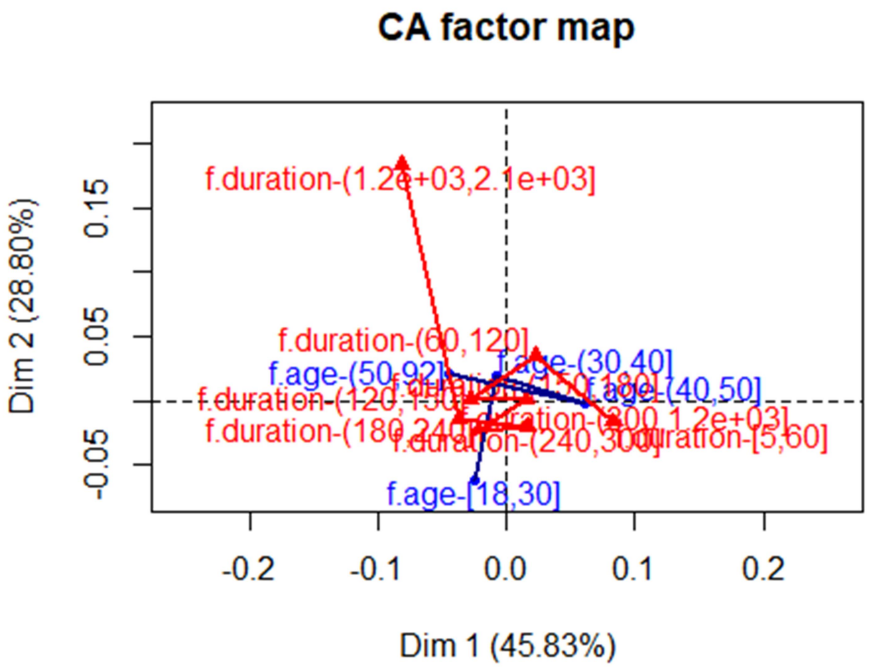
```
##         eigenvalue percentage of variance
## dim 1 0.0014130984               45.82949
## dim 2 0.0008880983               28.80273
## dim 3 0.0007821856               25.36778
##       cumulative percentage of variance
## dim 1                           45.82949
## dim 2                           74.63222
## dim 3                          100.00000
```

```
mean(res.ca$eig[,1])  # Mean of eigenvalues
```

```
## [1] 0.001027794

sum(res.ca$eig[,1])  # Total inertia

## [1] 0.003083382

# Rows
res.ca$row

## $coord
##                       Dim 1        Dim 2       Dim 3
## f.age-[18,30] -0.024672376 -0.061587071  0.00515479
## f.age-(30,40] -0.007883325  0.019128850  0.02866207
## f.age-(40,50]  0.060905585 -0.002487498 -0.01655528
## f.age-(50,92] -0.044696383  0.021246627 -0.04658344
##
## $contrib
##                     Dim 1      Dim 2      Dim 3
## f.age-[18,30]  7.510490 74.4623554  0.5922851
## f.age-(30,40]  1.754758 16.4394554 41.9059874
## f.age-(40,50] 65.916230  0.1749504  8.7985988
## f.age-(50,92] 24.818522  8.9232388 48.7031287
##
## $cos2
##                      Dim 1       Dim 2       Dim 3
## f.age-[18,30] 0.13746379 0.856535696 0.006000512
## f.age-(30,40] 0.04973439 0.292830101 0.657435510
## f.age-(40,50] 0.92975389 0.001550884 0.068695230
## f.age-(50,92] 0.43249165 0.097726640 0.469781706
##
## $inertia
## [1] 0.0007720623 0.0004985776 0.0010018363 0.0008109061

# Columns: the same
res.ca$col

## $coord
##                                       Dim 1         Dim 2         Dim 3
## f.duration-[5,60]              0.08319396 -0.0161245945  2.458294e-02
## f.duration-(60,120]            0.02249525  0.0348536919 -2.577791e-02
## f.duration-(120,150]          -0.02735408  0.0013898644  1.373241e-02
## f.duration-(150,180]           0.01565127  0.0006091358  6.835979e-05
## f.duration-(180,240]          -0.02116464 -0.0227191287  4.705510e-02
## f.duration-(240,300]           0.01669583 -0.0202658085  3.700409e-04
## f.duration-(300,1.2e+03]      -0.03694459 -0.0143453208 -2.112106e-02
## f.duration-(1.2e+03,2.1e+03] -0.08146358  0.1836311251  1.153212e-01
##
## $contrib
##                                     Dim 1       Dim 2        Dim 3
## f.duration-[5,60]              48.095757  2.87482957 7.586705e+00
## f.duration-(60,120]             7.657254 29.24828562 1.816559e+01
```

```
## f.duration-(120,150]           5.263239  0.02162046 2.396431e+00
## f.duration-(150,180]           1.632767  0.00393518 5.627155e-05
## f.duration-(180,240]           3.849653  7.05820696 3.437761e+01
## f.duration-(240,300]           1.913324  4.48550815 1.697988e-03
## f.duration-(300,1.2e+03]      25.376484  6.08781771 1.498386e+01
## f.duration-(1.2e+03,2.1e+03]   6.211521 50.21979635 2.248806e+01
##
## $cos2
##                                    Dim 1       Dim 2        Dim 3
## f.duration-[5,60]             0.8889838 0.033395490 7.762072e-02
## f.duration-(60,120]           0.2121463 0.509274053 2.785796e-01
## f.duration-(120,150]          0.7970605 0.002057746 2.008818e-01
## f.duration-(150,180]          0.9984686 0.001512388 1.904743e-05
## f.duration-(180,240]          0.1409384 0.162401758 6.966599e-01
## f.duration-(240,300]          0.4042264 0.595574996 1.985675e-04
## f.duration-(300,1.2e+03]      0.6767699 0.102037507 2.211926e-01
## f.duration-(1.2e+03,2.1e+03] 0.1236833 0.628458833 2.478578e-01
##
## $inertia
## [1] 7.645138e-04 5.100466e-04 9.331130e-05 2.310800e-05 3.859799e-04
## [6] 6.688615e-05 5.298621e-04 7.096744e-04
```

```r
# Link levels in rows
plot.CA(res.ca)
lines(res.ca$row$coord[,1],res.ca$row$coord[,2],lwd=2,col="darkblue")
lines(res.ca$col$coord[,1],res.ca$col$coord[,2],lwd=2,col="red")
```



```r
# Phi2 = Intensity of the association Chisq/nbobservations
sum(res.ca$eig[,1]) # Total Inertia = Phi2
```

```
## [1] 0.003083382
```

```r
# H0: f.duration - f.age independency
chisq.test(table(df$f.age,duration_k8))
```

```
##
##  Pearson's Chi-squared test
##
## data:  table(df$f.age, duration_k8)
## X-squared = 15.386, df = 21, p-value = 0.8031
```

CA - Education vs f.duration

Para la segunda prueba decidimos utilizar duration junto con education. Para education usaremos la variable original con todos sus niveles menos el nivel illiterate el cual nos puede causar inconvenientes.

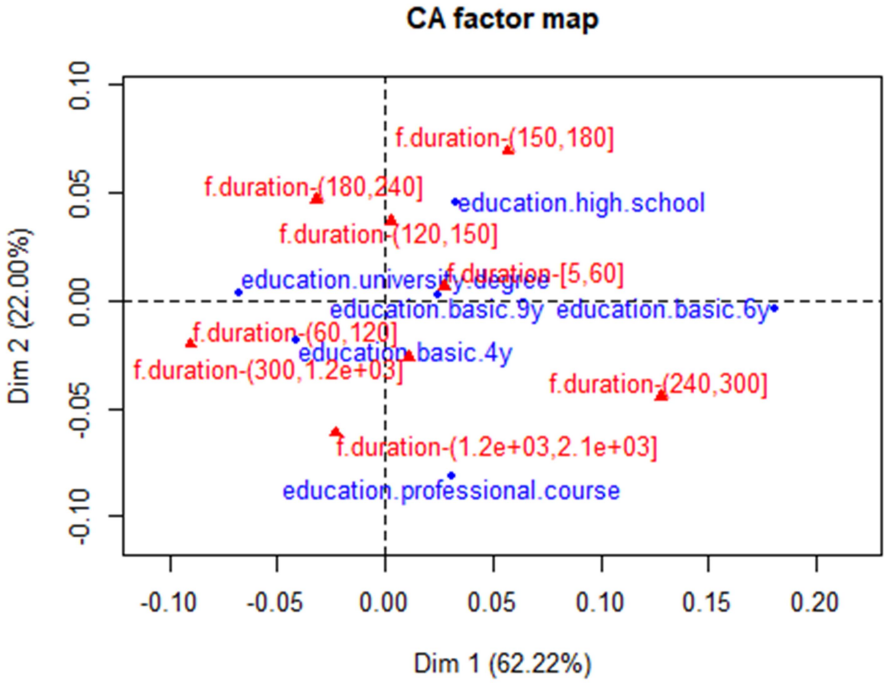
Por kaiser vemos que las primeras dos dimensiones están por encima de la media, por lo que son las que cogemos.

Podemos ver que para la primera dimensión los valores más lejanos del centro son los niveles de education.basic_6y, education.university.degree, para la primera dimensión. Para la segunda tenemos, f.duration(150,180], education.professioal.course, esto nos puede decir qué niveles se ven mejor representados en las dimensiones.

```r
#Education
table(df$education)
```

```
##
##            education.basic.4y            education.basic.6y
##                           515                           271
##            education.basic.9y         education.high.school
##                           810                          1196
##          education.illiterate education.professional.course
##                             1                           633
##   education.university.degree
##                          1564
```

```r
education_k6<-df$education
education_k6[which(education_k6=="education.illiterate")]<-"education.bas
ic.4y"
education_k6=factor(education_k6)

par(cex=0.8)
res.ca<-CA(table(education_k6,duration_k8))
```




```
res.ca$eig
```

```
##         eigenvalue percentage of variance
## dim 1 3.865234e-03             62.2179391
## dim 2 1.366656e-03             21.9987982
## dim 3 7.963697e-04             12.8190136
## dim 4 1.318112e-04              2.1217398
## dim 5 5.234014e-05              0.8425093
##       cumulative percentage of variance
## dim 1                           62.21794
## dim 2                           84.21674
## dim 3                           97.03575
## dim 4                           99.15749
## dim 5                          100.00000
```

```
mean(res.ca$eig[,1])
```

```
## [1] 0.001242482
```

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

```
## $coord
##                                  Dim 1        Dim 2        Dim 3
## education.basic.4y           -0.04133205 -0.018121606 -0.058412332
## education.basic.6y            0.18102401 -0.004110569  0.042729415
## education.basic.9y            0.02483545  0.002685184 -0.027046691
## education.high.school         0.03234069  0.045050136 -0.004194745
```

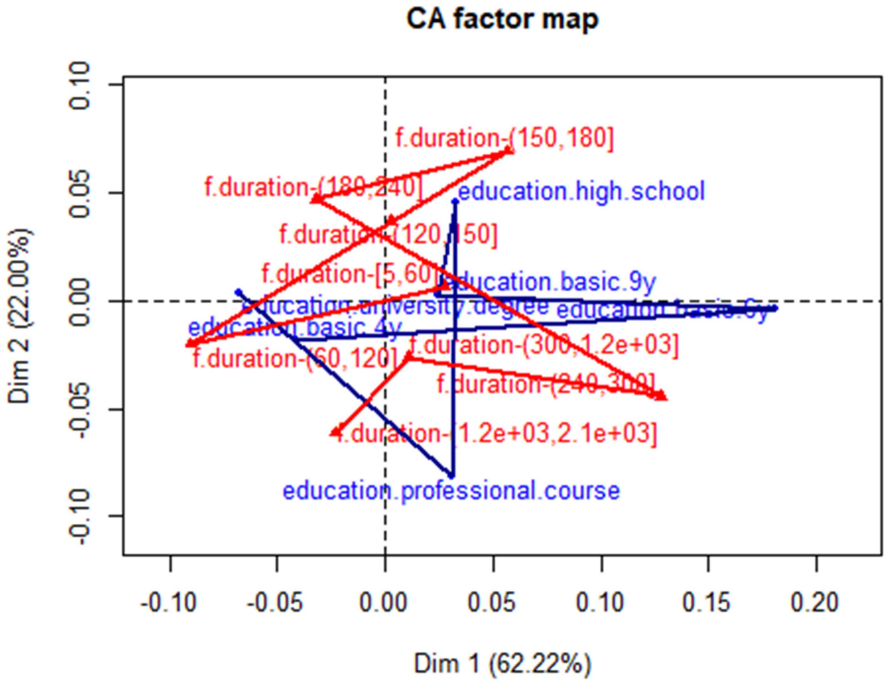
```
## education.professional.course  0.03069724 -0.081359937  0.007155999
## education.university.degree   -0.06774789  0.003779150  0.026186751
##                                      Dim 4        Dim 5
## education.basic.4y             0.010678244 -0.012189412
## education.basic.6y            -0.003590873 -0.018490687
## education.basic.9y            -0.022417259  0.003721054
## education.high.school          0.010664921  0.005274952
## education.professional.course  0.008039829  0.008059669
## education.university.degree   -0.002700335 -0.001997413
##
## $contrib
##                                     Dim 1       Dim 2      Dim 3      Di
m 4
## education.basic.4y             4.570327  2.48475408 44.3040567  8.9453
332
## education.basic.6y            46.043183  0.06714497 12.4511048  0.5312
717
## education.basic.9y             2.590316  0.08563935 14.9106984 61.8866
872
## education.high.school          6.485648 35.59293113  0.5295743 20.6820
512
## education.professional.course  3.092616 61.44198967  0.8156972  6.2207
761
## education.university.degree   37.217909  0.32754080 26.9888687  1.7338
807
##                                     Dim 5
## education.basic.4y            29.354847
## education.basic.6y            35.476433
## education.basic.9y             4.294194
## education.high.school         12.741859
## education.professional.course 15.743551
## education.university.degree    2.389116
##
## $cos2
##                                     Dim 1       Dim 2       Dim 3
## education.basic.4y            0.2991135 0.057498362 0.597408243
## education.basic.6y            0.9371554 0.000483218 0.052214742
## education.basic.9y            0.3295023 0.003851787 0.390789233
## education.high.school         0.3233541 0.627439873 0.005439900
## education.professional.course 0.1217065 0.854941382 0.006613871
## education.university.degree   0.8658182 0.002694161 0.129359520
##                                      Dim 4        Dim 5
## education.basic.4y            0.0199646527 0.0260152290
## education.basic.6y            0.0003687563 0.0097778938
## education.basic.9y            0.2684598606 0.0073968422
## education.high.school         0.0351637465 0.0086023464
## education.professional.course 0.0083485069 0.0083897596
## education.university.degree   0.0013755312 0.0007526117
##
## $inertia
```

```
## [1] 0.0005905913 0.0018990198 0.0003038576 0.0007752660 0.0009821731
## [6] 0.0016615026

# Columns: the same
res.ca$col
```

```
## $coord
##                                       Dim 1        Dim 2        Dim 3
## f.duration-[5,60]              0.027029115  0.006192711  0.035619391
## f.duration-(60,120]           -0.090112862 -0.020538411  0.017086167
## f.duration-(120,150]           0.002502632  0.036564696 -0.049483431
## f.duration-(150,180]           0.056880902  0.069080817  0.004342747
## f.duration-(180,240]          -0.032420109  0.046836380  0.019636428
## f.duration-(240,300]           0.127883956 -0.044401648  0.030160547
## f.duration-(300,1.2e+03]       0.010833855 -0.026353481 -0.028797208
## f.duration-(1.2e+03,2.1e+03] -0.023054621 -0.061622025 -0.029181692
##                                       Dim 4        Dim 5
## f.duration-[5,60]              0.0049402640  0.001195881
## f.duration-(60,120]           -0.0054537007  0.003195489
## f.duration-(120,150]          -0.0047413221  0.015186085
## f.duration-(150,180]          -0.0004840916 -0.004166702
## f.duration-(180,240]           0.0067808780 -0.005449376
## f.duration-(240,300]          -0.0044409552  0.006544906
## f.duration-(300,1.2e+03]      -0.0015812648 -0.007781878
## f.duration-(1.2e+03,2.1e+03]  0.0922854018  0.011622914
##
## $contrib
##                                        Dim 1      Dim 2      Dim 3
Dim 4
## f.duration-[5,60]              1.85602333  0.2755485 15.6442142  1.81
820805
## f.duration-(60,120]           44.92226773  6.5999164  7.8385985  4.82
496535
## f.duration-(120,150]           0.01610644  9.7240230 30.5622963  1.69
522671
## f.duration-(150,180]           7.88414319 32.8891869  0.2230549  0.01
674558
## f.duration-(180,240]           3.30236637 19.4930424  5.8800674  4.23
634841
## f.duration-(240,300]          41.03941655 13.9921319 11.0792023  1.45
126036
## f.duration-(300,1.2e+03]       0.79779697 13.3511603 27.3582403  0.49
837825
## f.duration-(1.2e+03,2.1e+03]  0.18187944  3.6749905  1.4143262 85.45
886729
##                                    Dim 5
## f.duration-[5,60]              0.2683099
## f.duration-(60,120]            4.1716088
## f.duration-(120,150]          43.7963518
## f.duration-(150,180]           3.1242607
```

```
## f.duration-(180,240]          6.8901823
## f.duration-(240,300]          7.9381048
## f.duration-(300,1.2e+03]     30.3973777
## f.duration-(1.2e+03,2.1e+03]  3.4138039
##
## $cos2
##                                     Dim 1      Dim 2       Dim 3
## f.duration-[5,60]             0.354045576 0.01858477 0.614849014
## f.duration-(60,120]           0.915064957 0.04753484 0.032897861
## f.duration-(120,150]          0.001548393 0.33053014 0.605350244
## f.duration-(150,180]          0.402214863 0.59325319 0.002344522
## f.duration-(180,240]          0.283613187 0.59192152 0.104045298
## f.duration-(240,300]          0.847459925 0.10216102 0.047137383
## f.duration-(300,1.2e+03]      0.068871807 0.40752236 0.486604635
## f.duration-(1.2e+03,2.1e+03] 0.038426381 0.27452723 0.061565082
##                                      Dim 4        Dim 5
## f.duration-[5,60]             1.182758e-02 0.0006930612
## f.duration-(60,120]           3.351668e-03 0.0011506756
## f.duration-(120,150]          5.557584e-03 0.0570136422
## f.duration-(150,180]          2.913267e-05 0.0021582909
## f.duration-(180,240]          1.240707e-02 0.0080129231
## f.duration-(240,300]          1.021974e-03 0.0022196981
## f.duration-(300,1.2e+03]      1.467184e-03 0.0355340175
## f.duration-(1.2e+03,2.1e+03] 6.157147e-01 0.0097666035
##
## $inertia
## [1] 0.0002026283 0.0018975163 0.0004020629 0.0007576562 0.0004500643
## [6] 0.0018717928 0.0004477408 0.0001829489
```

```r
# Link levels in rows
plot.CA(res.ca)
lines(res.ca$row$coord[,1],res.ca$row$coord[,2],lwd=2,col="darkblue")
lines(res.ca$col$coord[,1],res.ca$col$coord[,2],lwd=2,col="red")
```




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

```
## [1] 0.00621241
```

```
chisq.test(table(education_k6,duration_k8))
```

```
## Warning in chisq.test(table(education_k6, duration_k8)): Chi-squared
## approximation may be incorrect
```

```
##
##  Pearson's Chi-squared test
##
## data:  table(education_k6, duration_k8)
## X-squared = 31, df = 35, p-value = 0.6617
```

```
# Traditional analysis
table(df$y,duration_k8)
```

```
##        duration_k8
##         f.duration-[5,60] f.duration-(60,120] f.duration-(120,150]
##   y.no                490                1047                  481
##   y.yes                 0                  20                   15
##        duration_k8
##         f.duration-(150,180] f.duration-(180,240] f.duration-(240,300]
##   y.no                  441                  550                  431
##   y.yes                  29                   56                   53
##        duration_k8
```

```
##         f.duration-(300,1.2e+03] f.duration-(1.2e+03,2.1e+03]
##   y.no                       983                           25
##   y.yes                      328                           41
```

```
chisq.test(table(df$y,duration_k8))
```

```
##
##  Pearson's Chi-squared test
##
## data:  table(df$y, duration_k8)
## X-squared = 643.03, df = 7, p-value < 2.2e-16
```

Modelización con target numérico

Modelización con variables explicativas numéricas

Modelo simple

El primer paso es decidir con cuantas variables contamos para el modelo. Si tuviéramos muchas variables explicativas podríamos utilizar el resultado del condes para saber cuáles de ellas utilizar, aunque también sería posible seleccionarlas a partir del análisis de componentes principales. Dado que tenemos poca cantidad de variables usamos todas.

Empezamos utilizando **lm** para crear un modelo inicial del cual podemos ir descartando aquellas variables explicativas que nos parecen irrelevantes. Después contrastaremos nuestra selección usando el método Akaike o BIC, que en una sucesión de pasos va descartando variables.

```
m1<-lm(duration~.,data=df[,c("duration",vars_num)])
summary(m1)
```

```
##
## Call:
## lm(formula = duration ~ ., data = df[, c("duration", vars_num)])
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -328.23 -154.46  -82.08   61.30 1842.65
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)     777.28481 2613.90120   0.297   0.7662
## age               0.03205    0.34459   0.093   0.9259
## campaign         -6.21960    1.53172  -4.061 4.97e-05 ***
## pdays            -2.37020    1.40614  -1.686   0.0919 .
## previous        -17.62769    9.52959  -1.850   0.0644 .
## emp.var.rate      3.48261   13.07499   0.266   0.7900
## cons.price.idx   11.61303   15.53269   0.748   0.4547
```

```
## cons.conf.idx    -0.51158    1.24917  -0.410   0.6822
## euribor3m         3.62210   16.39663   0.221   0.8252
## nr.employed      -0.30339    0.28145  -1.078   0.2811
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 251.1 on 4980 degrees of freedom
## Multiple R-squared:  0.006393,   Adjusted R-squared:  0.004597
## F-statistic:  3.56 on 9 and 4980 DF,  p-value: 0.0002021
```

```
Anova(m1)
```

```
## Anova Table (Type II tests)
##
## Response: duration
##                   Sum Sq   Df F value    Pr(>F)
## age                  545    1  0.0087   0.92589
## campaign          1039241    1 16.4879 4.971e-05 ***
## pdays              179087    1  2.8413   0.09193 .
## previous           215671    1  3.4217   0.06440 .
## emp.var.rate         4472    1  0.0709   0.78998
## cons.price.idx      35233    1  0.5590   0.45471
## cons.conf.idx       10571    1  0.1677   0.68216
## euribor3m            3076    1  0.0488   0.82518
## nr.employed         73240    1  1.1620   0.28111
## Residuals      313891375 4980
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Viendo este volcado, vemos que todas las variables menos, campaign tienen un p-value superior al 0.05, sin embargo, pdays y previous están por debajo de 0.1 lo que podríamos llegar a incorporarlas al modelo. El r-square es de 0.006393 lo que nos dice que nuestro modelo no se ajusta bien.

Al ver el resultado de Anova, podemos ver resultados muy parecidos.

Ahora probaremos seleccionando las variables a partir de la criba anterior:

```
m2<-lm(duration~campaign+pdays+previous,data=df)
summary(m2)
```

```
##
## Call:
## lm(formula = duration ~ campaign + pdays + previous, data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -264.50 -156.27  -82.24   61.80 1840.02
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept)  344.591     32.204  10.700  < 2e-16 ***
## campaign      -6.304      1.513  -4.167 3.14e-05 ***
## pdays         -2.991      1.377  -2.172   0.0299 *
## previous     -10.391      8.726  -1.191   0.2337
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 251.1 on 4986 degrees of freedom
## Multiple R-squared:  0.004472,   Adjusted R-squared:  0.003873
## F-statistic: 7.465 on 3 and 4986 DF,  p-value: 5.52e-05
```

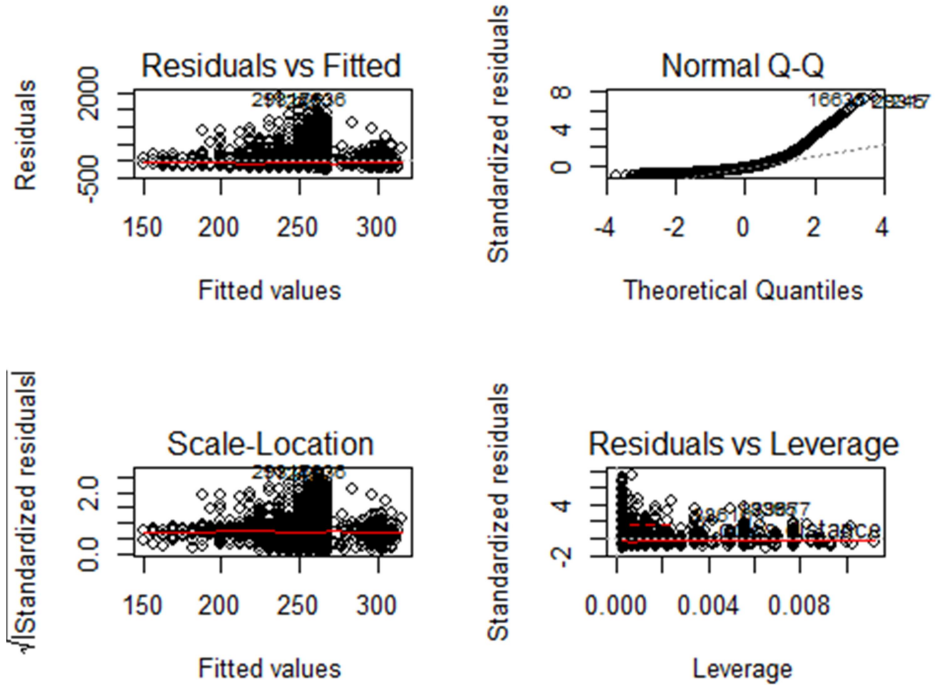
```
m3<-lm(duration~campaign+pdays,data=df)
summary(m3)
```

```
##
## Call:
## lm(formula = duration ~ campaign + pdays, data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -263.02 -156.25  -82.58   60.87 1840.89
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  321.114     25.467  12.609  < 2e-16 ***
## campaign      -6.183      1.510  -4.095 4.28e-05 ***
## pdays         -2.040      1.122  -1.818   0.0691 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 251.2 on 4987 degrees of freedom
## Multiple R-squared:  0.004189,   Adjusted R-squared:  0.003789
## F-statistic: 10.49 on 2 and 4987 DF,  p-value: 2.848e-05
```

```
vif(m3)
```

```
## campaign    pdays
## 1.003138 1.003138
```

```
par(mfrow=c(2,2))
plot(m3)
```




```
par(mfrow=c(1,1))
m=m3;
```

Viendo el resultado del lm con estas variables, podemos ver que previous da por encima de 0.2, por lo que también descartamos esta variable. También podemos ver que el r-square sigue siendo muy bajo.

Al realizar nuevamente el lm con estas dos variables restantes, vemos que su p-value es inferior al 0.1, por lo que daríamos por concluida la criba.

Finalmente hacemos el análisis de residuos con vif, el cual nos dice si existen problemas de colinealidad es decir si existen variables que pueden explicar a otras. Si nos da valores por debajo de 3 son buenos y por encima de 5 que las variables elegidas tienen redundancia y que inflará las varianzas. En nuestro caso, el resultado de las dos variables es inferior a 3.

Viendo el plot de la normal Q-Q, vemos que los valores distan mucho de la recta de referencia, con que podemos decir que su distribución no es para nada normal.

Para quitar las variables redundantes probamos con la versión bayesiana del step (del BIC):

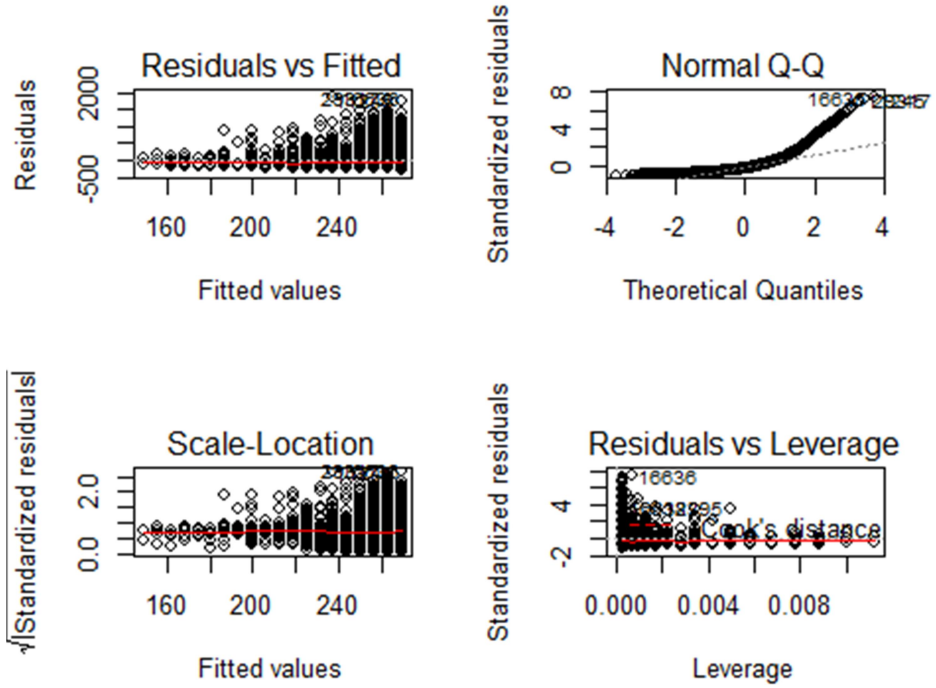
```
m5<-step(m,k=log(nrow(df)))

## Start:  AIC=55172.94
## duration ~ campaign + pdays
##
```

```
##            Df Sum of Sq       RSS   AIC
## - pdays     1    208524 314796334 55168
## <none>                  314587810 55173
## - campaign  1   1058016 315645826 55181
##
## Step:  AIC=55167.73
## duration ~ campaign
##
##            Df Sum of Sq       RSS   AIC
## <none>                  314796334 55168
## - campaign  1   1114698 315911032 55177
```

```
summary(m5)
```

```
##
## Call:
## lm(formula = duration ~ campaign, data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -264.45 -156.69  -82.45   61.14 1840.23
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  275.786      5.199  53.051  < 2e-16 ***
## campaign      -6.336      1.508  -4.203 2.68e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 251.2 on 4988 degrees of freedom
## Multiple R-squared:  0.003529,   Adjusted R-squared:  0.003329
## F-statistic: 17.66 on 1 and 4988 DF,  p-value: 2.684e-05
```

```
par(mfrow=c(2,2))
plot(m5)
```




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

La versión bayesiana es conveniente usarla en casos de muestras grandes. En este caso vemos que se queda con una sola variable (campaign), ya que en el primer step del volcado vemos que sin la variable p-days el valor AIC, en este caso BIC, es menor.

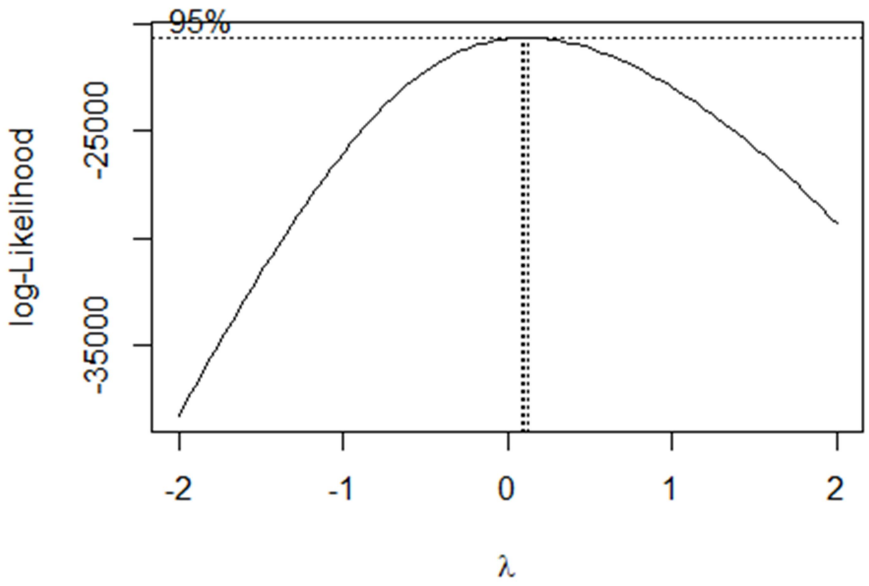
En este caso no podemos hacer el análisis de residuos con vif porque solo tenemos 1 variable.

Al igual que en nuestro caso nos da una plot Q-Q totalmente desviada de las dist normal.

Modelo con transformaciones

Mediante la función boxcox descartamos la posibilidad de elevar el target al cuadrado, pero sí contemplamos aplicarle el logaritmo, pues el pico de la curva está entre 0 y 1, bastante cerca del 0.

```
boxcox(m,data=df)
```



Ahora procedemos a la transformación polinómica.

Como solo tenemos una variable explicativa podemos empezar desde cero, pero si tuviéramos ya un modelo no volveríamos a empezar.

```
m6<-lm(log(duration)~.,data=df[,c("duration",vars_num)])
Anova(m6)

## Anova Table (Type II tests)
##
## Response: log(duration)
##                Sum Sq   Df  F value  Pr(>F)
## age               0.1    1   0.1176 0.73162
## campaign         97.4    1 120.3195 < 2e-16 ***
## pdays             4.0    1   4.9361 0.02635 *
## previous          0.2    1   0.1873 0.66523
## emp.var.rate      0.2    1   0.1976 0.65665
## cons.price.idx    0.4    1   0.4944 0.48201
## cons.conf.idx     0.1    1   0.1082 0.74227
## euribor3m         1.6    1   1.9413 0.16359
## nr.employed       2.7    1   3.3650 0.06666 .
## Residuals      4030.4 4980
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Viendo el resultado del Anova, procedemos a descartar las variables cuyo valor de Pr es mayor a 0.1

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

```
##
## Call:
## lm(formula = log(duration) ~ campaign + pdays + nr.employed,
##     data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.6815 -0.5509 -0.0106  0.5858  2.6860
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  6.3887200  0.9445802   6.764  1.5e-11 ***
## campaign    -0.0598301  0.0054664 -10.945  < 2e-16 ***
## pdays       -0.0135538  0.0042873  -3.161  0.00158 **
## nr.employed -0.0001463  0.0001888  -0.775  0.43843
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9007 on 4986 degrees of freedom
## Multiple R-squared:  0.02798,    Adjusted R-squared:  0.0274
## F-statistic: 47.84 on 3 and 4986 DF,  p-value: < 2.2e-16
```

```r
Anova(m7)
```

```
## Anova Table (Type II tests)
##
## Response: log(duration)
##             Sum Sq   Df  F value  Pr(>F)
## campaign      97.2    1 119.7932 < 2e-16 ***
## pdays          8.1    1   9.9945 0.00158 **
## nr.employed    0.5    1   0.6005 0.43843
## Residuals   4044.5 4986
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Viendo los p-values, nos encontramos que la variable nr.employed es mayor a 0.1, por lo que procedemos a eliminarla de nuestro modelo.

Relativo al gráfico, podemos ver como la Normal Q-Q ha mejorado bastante acercándose a la recta ideal.

Ahora procedemos a quitar nr.employed.

```r
m9<-lm(log(duration)~campaign+pdays,data=df)
summary(m9)
```

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

```
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.6522 -0.5521 -0.0090  0.5858  2.6797
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  5.660184   0.091319  61.982  < 2e-16 ***
## campaign    -0.060418   0.005413 -11.161  < 2e-16 ***
## pdays       -0.014703   0.004023  -3.655  0.00026 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9006 on 4987 degrees of freedom
## Multiple R-squared:  0.02786,    Adjusted R-squared:  0.02747
## F-statistic: 71.47 on 2 and 4987 DF,  p-value: < 2.2e-16
```

```
Anova(m9)
```

```
## Anova Table (Type II tests)
##
## Response: log(duration)
##           Sum Sq   Df F value    Pr(>F)
## campaign   101.0    1  124.57 < 2.2e-16 ***
## pdays       10.8    1   13.36 0.0002597 ***
## Residuals 4045.0 4987
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
vif(m9)
```

```
## campaign    pdays
## 1.003138 1.003138
```

Viendo el valor final del r-square, podemos ver que este no es un buen modelo. También los que no puede decir es que las variables no representan a nuestro target, esto ya lo pudimos ver en el deliverable2.

El resultado del vif nos da valores aceptables, diciendo que no hay colinealidad entre variables.

Modelo de regresión polinómica

Ahora podemos probar con las versiones cuadráticas de las variables explicativas, partiendo de nuestro mejor modelo:

```
m20<-lm(log(duration)~poly(campaign,2)+poly(pdays,2),data=df)
summary(m20)
```

```
##
## Call:
```

```
## lm(formula = log(duration) ~ poly(campaign, 2) + poly(pdays,
##     2), data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.6353 -0.5534 -0.0100  0.5842  2.6431
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)          5.17868    0.01274 406.451  < 2e-16 ***
## poly(campaign, 2)1 -10.03807    0.90154 -11.134  < 2e-16 ***
## poly(campaign, 2)2  -1.79572    0.90036  -1.994 0.046158 *
## poly(pdays, 2)1     -3.34605    0.90176  -3.711 0.000209 ***
## poly(pdays, 2)2     -1.90923    0.90014  -2.121 0.033968 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9 on 4985 degrees of freedom
## Multiple R-squared:  0.02951,    Adjusted R-squared:  0.02873
## F-statistic: 37.89 on 4 and 4985 DF,  p-value: < 2.2e-16
```

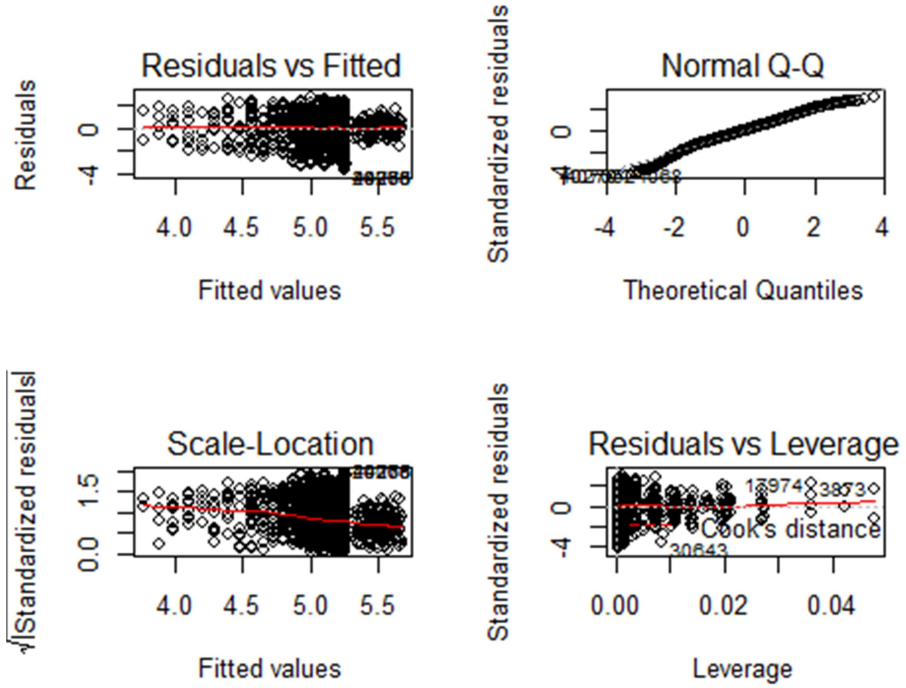
```
Anova(m20)
```

```
## Anova Table (Type II tests)
##
## Response: log(duration)
##                   Sum Sq   Df F value    Pr(>F)
## poly(campaign, 2)  103.7    2 64.0104 < 2.2e-16 ***
## poly(pdays, 2)      14.8    2  9.1263 0.0001106 ***
## Residuals         4038.2 4985
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
vif(m20)
```

```
##                      GVIF Df GVIF^(1/(2*Df))
## poly(campaign, 2) 1.004062  2        1.001014
## poly(pdays, 2)    1.004062  2        1.001014
```

```
par(mfrow=c(2,2))
plot(m20)
```




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

Modelización con variables explicativas numéricas y categóricas

Creamos una variable que contiene las variables categóricas y categóricas factorizadas además de las categóricas.

```
vars_cat_total = c(vars_cat, names(df[,22:29]))
condes(df[,c("duration",vars_cat_total)],1, proba= 0.05)
```

```
## $quali
##                       R2      p.value
## f.duration 0.621168787 0.000000e+00
## f.campaign 0.003783221 7.858324e-05
## month      0.004450289 8.185248e-03
## poutcome   0.001675246 1.528736e-02
## f.pdays    0.001120416 1.805086e-02
## f.season   0.001469523 2.555430e-02
##
## $category
##                                 Estimate       p.value
## f.duration-(300,2.1e+03]  310.351061  0.000000e+00
## f.campaign-(1,2]           23.010415  3.895001e-05
## month.apr                  35.257830  4.865526e-03
## f.season.Mar-May           13.191703  6.782891e-03
## poutcome.success           38.426383  1.231875e-02
## f.pdays-[0,22]             22.891544  1.805086e-02
```

```
## day_of_week.wed             14.619928  3.788283e-02
## job.retired                 34.239467  3.904250e-02
## marital.divorced           -15.444147  4.653367e-02
## f.season.Jun-Aug            -6.204726  4.445499e-02
## f.pdays-(22,23]            -22.891544  1.805086e-02
## month.aug                  -25.222251  7.943838e-03
## f.campaign-(2,20]          -17.351641  3.316706e-03
## f.duration-(180,300]       -20.507215  3.927333e-04
## f.duration-(120,180]      -106.753548  5.404997e-53
## f.duration-[5,120]        -183.090298 1.278559e-312
```

Al hacer condes, con todas las variables categóricas, contemplamos el uso de f.campaign y month para nuestro modelo, ya que la probabilidad de que no tengan relación con el target está por debajo del 0.01. Como nos sale la versión categórica de campaign que también nos sale en el modelo numérico, debemos elegir entre una u otra, pero nunca las dos a la vez.

En vista de que la variable numérica pdays aporta una información errante ya que aquellos que no fueron contactados tienen asignados un valor que no les corresponde, decidimos utilizar f.pdays porque contiene una información más rigurosa, ya que se clasifican entre contactados y no contactados.

Debido a que la variable month es una variable con muchos niveles y eso no es bueno para la modelización, decidimos reagruparla.

```
#chunk 115
# Months to groups
df$f.influentMonth <- 3
# 1 level - mar-may
aux<-which(df$month %in% c("month.apr","month.jun","month.aug"))
df$f.influentMonth[aux] <-1

# 2 level - jun-ago
aux<-which(df$month %in% c("month.sep","month.may","month.jul"))
df$f.influentMonth[aux] <-2

# 3 level - aug-feb
aux<-which(df$month %in% c("month.mar","month.dec","month.oct","month.nov
"))
df$f.influentMonth[aux] <-3

df$f.influentMonth<-factor(df$f.influentMonth,levels=1:3,labels=c("apr-ju
n-aug","sep-may-jul","mar-dec-oct-nov"))
levels(df$f.influentMonth)<-paste0("f.influentMonth.",levels(df$f.influen
tMonth)) # Hacemos las etiquetas m?s informativas
summary(df$f.influentMonth)

##     f.influentMonth.apr-jun-aug     f.influentMonth.sep-may-jul
##                            1701                            2615
```

```
## f.influentMonth.mar-dec-oct-nov
##                             674
```

Contrastamos un modelo con campaign o con f.campaign para ver cuál es mejor.

```
m22<-lm(log(duration)~campaign+f.pdays+f.influentMonth,data=df)
m23<-lm(log(duration)~f.pdays+f.campaign+f.influentMonth,data=df)
BIC(m23,m22)

##     df      BIC
## m23  7 13214.68
## m22  6 13150.71

# Ya que nos quedamos con el modelo m22
Anova(m22)

## Anova Table (Type II tests)
##
## Response: log(duration)
##                 Sum Sq   Df  F value    Pr(>F)
## campaign         102.8    1 126.9775 < 2.2e-16 ***
## f.pdays           15.2    1  18.7951 1.484e-05 ***
## f.influentMonth    8.4    2   5.1938  0.005581 **
## Residuals       4033.9 4985
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Haciendo BIC para comparar modelos, podemos ver que el que da un menor BIC es m22, por lo que decidimos quedarnos con este modelo. Viendo el resultado del Anova, podemos ver que los p-values son inferiores a 0.1

Interacciones

```
m30<-lm(log(duration)~(campaign+f.pdays+f.influentMonth)^2,data=df)
Anova(m30)

## Anova Table (Type II tests)
##
## Response: log(duration)
##                           Sum Sq   Df  F value    Pr(>F)
## campaign                   103.1    1 127.5736 < 2.2e-16 ***
## f.pdays                     15.0    1  18.5584  1.68e-05 ***
## f.influentMonth              8.5    2   5.2517  0.005268 **
## campaign:f.pdays             2.2    1   2.7306  0.098506 .
## campaign:f.influentMonth     5.2    2   3.1929  0.041136 *
## f.pdays:f.influentMonth      1.2    2   0.7427  0.475884
## Residuals                 4025.4 4980
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Vemos que la interacción entre campaign y nuestra nueva variable factor month es significativa, por lo tanto, creamos un nuevo modelo m31 con esa interacción. Por otro

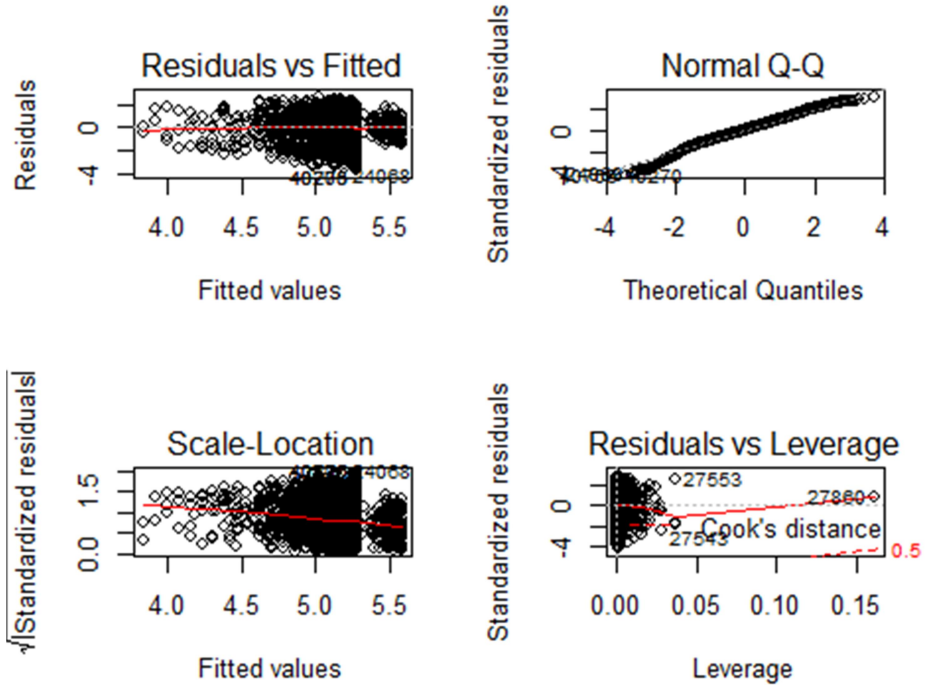
lado, aunque f.pdays con f.influentMoth tiene un p-value muy alto de 0.4, realizamos la interacción porque lo pide el enunciado.

```
#chunk 140
m31<-lm(log(duration)~(f.influentMonth*campaign+f.pdays),data=df)
Anova(m31)

## Anova Table (Type II tests)
##
## Response: log(duration)
##                           Sum Sq   Df  F value    Pr(>F)
## f.influentMonth             8.4    2   5.1981  0.005557 **
## campaign                  102.8    1 127.0831 < 2.2e-16 ***
## f.pdays                    15.0    1  18.5535 1.684e-05 ***
## f.influentMonth:campaign    5.0    2   3.0728  0.046377 *
## Residuals                4028.9 4983
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

m32<-lm(log(duration)~(f.influentMonth*f.pdays+campaign),data=df)
Anova(m32)

## Anova Table (Type II tests)
##
## Response: log(duration)
##                          Sum Sq   Df  F value    Pr(>F)
## f.influentMonth            8.4    2   5.1932  0.005584 **
## f.pdays                   15.2    1  18.7930 1.486e-05 ***
## campaign                 103.1    1 127.4200 < 2.2e-16 ***
## f.influentMonth:f.pdays    1.2    2   0.7228  0.485455
## Residuals               4032.7 4983
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Vemos que el modelo 31 es aceptable, sus p-values son aceptables, mientras como ya era previsible el modelo m32 lo descartamos.

Validación

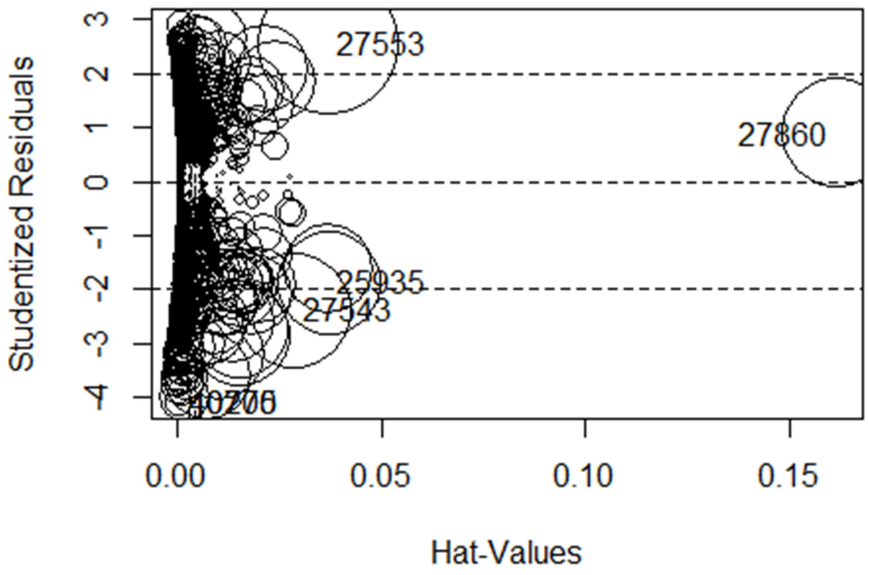
```
par(mfrow=c(2,2))
plot(m31)
```




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

Analizando los gráficos:
- Residual VS Fitted. En este gráfico muestra los residuos de los valores predichos. Lo deseable es que los puntos estén uniformemente dispersos, para poderlo contrastar el gráfico está provisto de una recta smoother que conviene que sea horizontal, y uniforme. A pesar de que podemos ver un patrón en el gráfico, podemos decir que el resultado no es aceptable. - Normal Q-Q. Este plot nos muestra la tendencia a una distribución normal de los residuos, esta provista de una recta diagonal de referencia en la que se espera que los residuos se ajusten lo máximo posible. En nuestro caso, apreciamos ciertas desviaciones en los extremos de la recta, aunque si lo comparamos con plots anteriores, se acerca más a la normal, pero sigue siendo poco aceptable. - Scale-Location. Este plot hace referencia a la varianza de los valores de la predicción, si se mantiene constante implica homocedasticidad, de lo contrario heterocedasticidad que se vería reflejada en una nube de puntos en forma de cono. Para nuestro caso, podemos ver que el gráfico tiene una tendencia a cono que además se evidencia con la desviación de la smoother line. Pero es una heterocedasticidad que es imposible de corregir de manera fácil, es una réplica del primer plot. - Residuals Vs Leverage. Vemos que hay un individuo con mucho leverage, el 27860. Utilizaremos el influencePlot para poder ver con más detalles los individuos influyentes.

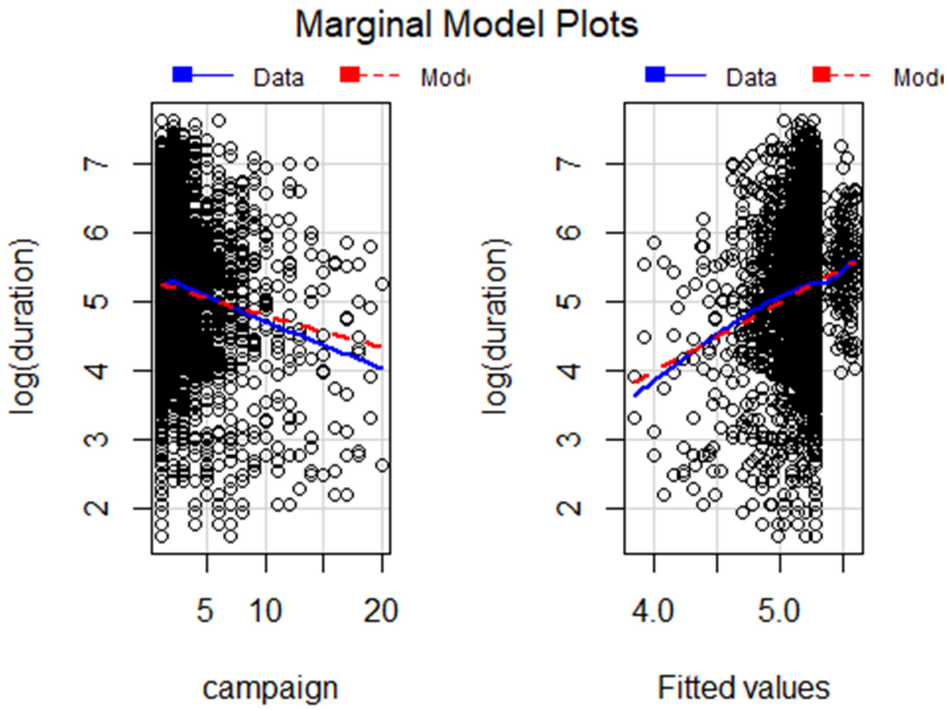
```
#chunk 150
influencePlot(m31)
```




```
##          StudRes          Hat       CookD
## 25935 -1.866796 0.0369674028 0.019101054
## 27543 -2.380400 0.0286710547 0.023871117
## 27553  2.548824 0.0369674028 0.035586127
## 27860  0.882873 0.1613511871 0.021424449
## 40270 -4.092113 0.0005533216 0.001320216
## 40705 -4.092113 0.0005533216 0.001320216
```

```
marginalModelPlots(m31)
```

```
## Warning in mmps(...): Interactions and/or factors skipped
```




```
which(row.names(df)==27860)
```

```
## [1] 3329
```

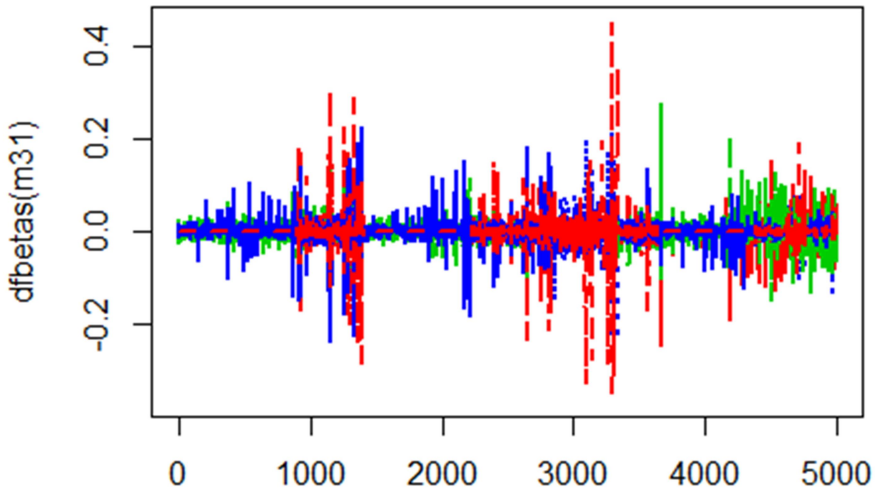
```
which(row.names(df)==27553)
```

```
## [1] 3293
```

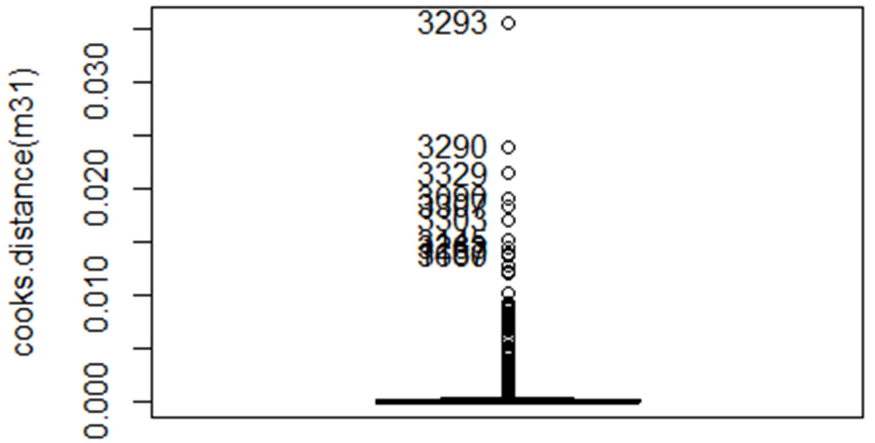
- InfluenPLot. Nos muestra los individuos más influentes, esto se puede ver gráficamente a través del radio de las circunferencias. En nuestro caso, viendo el gráfico podemos ver que hay individuos bastante influyentes, el 3329 y 3293 que para nuestra muestra serían los individuos.
- MarginalModelPlot. Nos muestra las discrepancias entre las predicciones de nuestro modelo y los resultados reales de nuestras observaciones desglosado por variables, utiliza dos líneas de soporte, una roja para la tendencia del modelo y otra azul referente a cada variable. Podemos ver que, para nuestro modelo, las líneas tienen un poco de desviación entre ellas, pero nada muy relevante.

Trabajamos con el mejor modelo obtenido, y vemos que individuos influyen más en nuestros datos para saber si están afectando nuestro resultado.

```
matplot(dfbetas(m31), type="l", col=2:4,lwd=2)
```



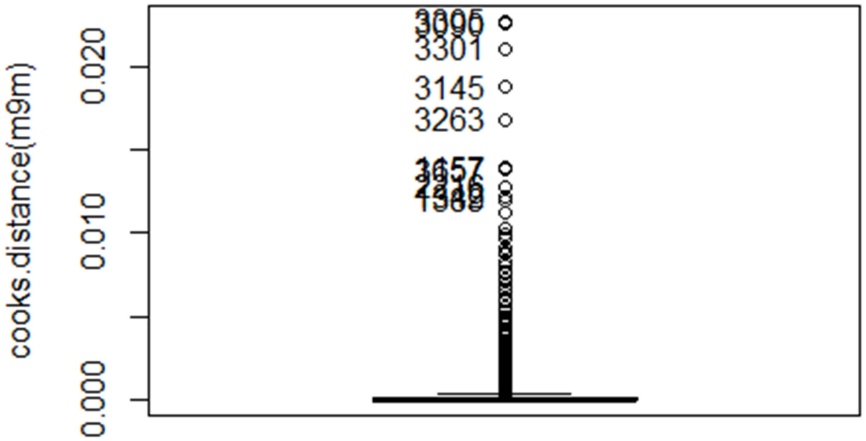

```
Boxplot(cooks.distance(m31))
```




```
##  [1] 3293 3290 3329 3090 3307 3303 3145 3263 1157 3660
```

Consideramos que hay un individuo que repercute demasiado en los datos (3293), aun así, no lo eliminaremos.

```
m9m<-lm(log(duration)~(f.influentMonth*campaign+f.pdays),data=df[c(-3293,
-3290,-3329),])

 Boxplot(cooks.distance(m9m))
```




```
##  [1] 3305 3090 3301 3145 3263 1157 3657 2216 1342 1389

summary(m9m)

##
## Call:
## lm(formula = log(duration) ~ (f.influentMonth * campaign + f.pdays),
##     data = df[c(-3293, -3290, -3329), ])
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.6728 -0.5449 -0.0105  0.5877  2.6092
##
## Coefficients:
##                                                    Estimate
## (Intercept)                                        5.631270
## f.influentMonthf.influentMonth.sep-may-jul         0.001571
## f.influentMonthf.influentMonth.mar-dec-oct-nov    -0.057482
## campaign                                          -0.078799
## f.pdaysf.pdays-(22,23]                            -0.300195
```

```
## f.influentMonthf.influentMonth.sep-may-jul:campaign      0.028354
## f.influentMonthf.influentMonth.mar-dec-oct-nov:campaign  0.011485
##                                                        Std. Error t v
alue
## (Intercept)                                              0.073735  76
.372
## f.influentMonthf.influentMonth.sep-may-jul               0.040830   0
.038
## f.influentMonthf.influentMonth.mar-dec-oct-nov           0.066125  -0
.869
## campaign                                                 0.008971  -8
.784
## f.pdaysf.pdays-(22,23]                                   0.069722  -4
.306
## f.influentMonthf.influentMonth.sep-may-jul:campaign      0.011481   2
.470
## f.influentMonthf.influentMonth.mar-dec-oct-nov:campaign  0.025573   0
.449
##                                                        Pr(>|t|)
## (Intercept)                                             < 2e-16 ***
## f.influentMonthf.influentMonth.sep-may-jul               0.9693
## f.influentMonthf.influentMonth.mar-dec-oct-nov           0.3847
## campaign                                                < 2e-16 ***
## f.pdaysf.pdays-(22,23]                                  1.7e-05 ***
## f.influentMonthf.influentMonth.sep-may-jul:campaign      0.0136 *
## f.influentMonthf.influentMonth.mar-dec-oct-nov:campaign  0.6534
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.8983 on 4980 degrees of freedom
## Multiple R-squared:  0.03195,    Adjusted R-squared:  0.03078
## F-statistic: 27.39 on 6 and 4980 DF,  p-value: < 2.2e-16

summary(m31)

##
## Call:
## lm(formula = log(duration) ~ (f.influentMonth * campaign + f.pdays),
##     data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.6728 -0.5452 -0.0098  0.5884  2.6092
##
## Coefficients:
##                                                         Estimate
## (Intercept)                                             5.631659
## f.influentMonthf.influentMonth.sep-may-jul              0.001578
## f.influentMonthf.influentMonth.mar-dec-oct-nov         -0.077716
## campaign                                               -0.078797
```

```
## f.pdaysf.pdays-(22,23]                                          -0.300603
## f.influentMonthf.influentMonth.sep-may-jul:campaign      0.028353
## f.influentMonthf.influentMonth.mar-dec-oct-nov:campaign  0.022602
##                                                         Std. Error t v
alue
## (Intercept)                                               0.073805  76
.304
## f.influentMonthf.influentMonth.sep-may-jul                0.040870   0
.039
## f.influentMonthf.influentMonth.mar-dec-oct-nov            0.063074  -1
.232
## campaign                                                  0.008980  -8
.775
## f.pdaysf.pdays-(22,23]                                    0.069788  -4
.307
## f.influentMonthf.influentMonth.sep-may-jul:campaign       0.011493   2
.467
## f.influentMonthf.influentMonth.mar-dec-oct-nov:campaign   0.022954   0
.985
##                                                          Pr(>|t|)
## (Intercept)                                               < 2e-16 ***
## f.influentMonthf.influentMonth.sep-may-jul                  0.9692
## f.influentMonthf.influentMonth.mar-dec-oct-nov              0.2180
## campaign                                                  < 2e-16 ***
## f.pdaysf.pdays-(22,23]                                   1.68e-05 ***
## f.influentMonthf.influentMonth.sep-may-jul:campaign         0.0137 *
## f.influentMonthf.influentMonth.mar-dec-oct-nov:campaign     0.3248
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.8992 on 4983 degrees of freedom
## Multiple R-squared:  0.03173,    Adjusted R-squared:  0.03057
## F-statistic: 27.22 on 6 and 4983 DF,  p-value: < 2.2e-16
```

Podemos ver que el nuevo modelo sin los individuos influyentes tiene una mejora en el r-square, aunque este sigue siendo muy bajo.

Modelización con target binario

Empezamos dividiendo nuestra muestra en una muestra de trabajo y una muestra de testeo, para ello seleccionaremos aleatoriamente el 25% de la muestra para crear la muestra de testeo.

```
set.seed(19101990)
sam <-sample(1:nrow(df),0.75*nrow(df))

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

Modelización con variables explicativas numéricas

Modelo simple

Para empezar, hacemos un catdes con todas las variables numéricas para ver cuáles son las que están más relacionadas con nuestro target. Las utilizamos para hacer un modelo lineal general con variables explicativas numéricas. Este modelo es de la familia binomial ya que nuestro target es binario.

```
catdes(dfw[,c("y",vars_num,"duration")],1)
```

```
##
## Link between the cluster variable and the quantitative variables
## ================================================================
##                       Eta2       P-value
## duration       0.176628371 4.526217e-160
## nr.employed    0.107146172  3.620826e-94
## pdays          0.098200453  4.721537e-86
## euribor3m      0.077763912  8.384377e-68
## emp.var.rate   0.072681695  2.518903e-63
## previous       0.043535295  4.410367e-38
## cons.price.idx 0.012743864  4.345713e-12
## campaign       0.006955344  3.241195e-07
## age            0.004418712  4.712507e-05
## cons.conf.idx  0.003847937  1.464648e-04
##
## Description of each cluster by quantitative variables
## ======================================================
## $y.no
##                    v.test Mean in category Overall mean sd in category
## nr.employed     20.020835     5174.1172673 5165.6679316     66.5132140
## pdays           19.166844       22.7627628   22.4142170      2.0015446
## euribor3m       17.056225        3.7481483    3.5760190      1.6726437
## emp.var.rate    16.489458        0.1990691    0.0485302      1.5112677
## cons.price.idx   6.904694       93.5892261   93.5660259      0.5683953
## campaign         5.100975        2.5990991    2.5299305      2.4284226
## cons.conf.idx   -3.794092      -40.6458859  -40.5445216      4.4151245
## age             -4.065760       39.8219219   40.0652058      9.8012900
## previous       -12.761878        0.1405405    0.1774452      0.4123568
## duration       -25.705383      219.4867868  255.9438803    196.7693288
##                 Overall sd       p.value
## nr.employed     73.3850752  3.625944e-89
## pdays            3.1621071  7.003107e-82
## euribor3m        1.7548478  3.142184e-65
## emp.var.rate     1.5874850  4.368514e-61
## cons.price.idx   0.5842716  5.031186e-12
## campaign         2.3578875  3.379091e-07
## cons.conf.idx    4.6456264  1.481848e-04
## age             10.4049243  4.787623e-05
## previous         0.5028450  2.676679e-37
```

```
## duration       246.6183107 1.017624e-145
##
## $y.yes
##                    v.test Mean in category Overall mean sd in category
## duration        25.705383      550.6092233  255.9438803     376.687736
## previous        12.761878        0.4757282    0.1774452       0.906767
## age              4.065760       42.0315534   40.0652058      14.230300
## cons.conf.idx    3.794092      -39.7252427  -40.5445216       6.140692
## campaign        -5.100975        1.9708738    2.5299305       1.574717
## cons.price.idx  -6.904694       93.3785097   93.5660259       0.670650
## emp.var.rate   -16.489458       -1.1682039    0.0485302       1.662956
## euribor3m      -17.056225        2.1847791    3.5760190       1.783746
## pdays          -19.166844       19.5970874   22.4142170       7.036851
## nr.employed    -20.020835     5097.3759709 5165.6679316      88.965074
##                 Overall sd       p.value
## duration       246.6183107 1.017624e-145
## previous         0.5028450  2.676679e-37
## age             10.4049243  4.787623e-05
## cons.conf.idx    4.6456264  1.481848e-04
## campaign         2.3578875  3.379091e-07
## cons.price.idx   0.5842716  5.031186e-12
## emp.var.rate     1.5874850  4.368514e-61
## euribor3m        1.7548478  3.142184e-65
## pdays            3.1621071  7.003107e-82
## nr.employed     73.3850752  3.625944e-89
```

```
gm1<-glm( y ~
            duration +
            nr.employed +
            pdays +
            euribor3m +
            emp.var.rate +
            previous +
            cons.price.idx +
            campaign +
            age +
            cons.conf.idx, family = binomial, data = dfw)
summary(gm1)
```

```
##
## Call:
## glm(formula = y ~ duration + nr.employed + pdays + euribor3m +
##     emp.var.rate + previous + cons.price.idx + campaign + age +
##     cons.conf.idx, family = binomial, data = dfw)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.6937  -0.3319  -0.1897  -0.1238   2.9794
##
## Coefficients:
```

```
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)    -3.530e+01  5.242e+01  -0.673  0.50070
## duration        5.008e-03  2.518e-04  19.887  < 2e-16 ***
## nr.employed    -5.899e-03  4.944e-03  -1.193  0.23281
## pdays          -1.205e-01  1.702e-02  -7.079 1.45e-12 ***
## euribor3m       3.016e-02  2.839e-01   0.106  0.91542
## emp.var.rate   -6.405e-01  2.289e-01  -2.797  0.00515 **
## previous       -3.306e-01  1.316e-01  -2.512  0.01201 *
## cons.price.idx  6.955e-01  3.308e-01   2.102  0.03553 *
## campaign       -1.280e-01  4.381e-02  -2.922  0.00348 **
## age             1.356e-02  5.361e-03   2.530  0.01141 *
## cons.conf.idx   3.157e-02  1.987e-02   1.589  0.11208
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2594.9  on 3741  degrees of freedom
## Residual deviance: 1584.3  on 3731  degrees of freedom
## AIC: 1606.3
##
## Number of Fisher Scoring iterations: 6
```

```
Anova(gm1)
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: y
##                LR Chisq Df Pr(>Chisq)
## duration         563.62  1  < 2.2e-16 ***
## nr.employed        1.44  1   0.230622
## pdays             55.07  1  1.161e-13 ***
## euribor3m          0.01  1   0.915436
## emp.var.rate       7.77  1   0.005314 **
## previous           6.63  1   0.010024 *
## cons.price.idx     4.29  1   0.038251 *
## campaign           9.81  1   0.001740 **
## age                6.38  1   0.011547 *
## cons.conf.idx      2.52  1   0.112437
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Viendo el resultado de summary, podemos ver variables que tienen el p-value mayor a 0.1 (cons.cinf.idx, euribor3m), por lo que procedemos a quitarlas de nuestro modelo. Podemos ver que el deviance es inferior al null deviance.

```
gm2<-glm( y ~
            duration +
            nr.employed +
            pdays +
            emp.var.rate +
```

```
            previous +
            campaign +
            age +
            cons.conf.idx, family = binomial, data = dfw)
vif(gm2)
```

```
##      duration   nr.employed         pdays  emp.var.rate      previous
##      1.283771      3.979725      1.829567      3.518890      2.048827
##      campaign           age cons.conf.idx
##      1.029761      1.037190      1.057214
```

Haciendo vif podemos ver que emp.var.rate tiene un valor mayor a 3, por lo que decidimos sacarla de nuestro modelo.

```
gm3<-glm( y ~
            duration +
            nr.employed +
            pdays +
            previous +
            campaign +
            age +
            cons.conf.idx, family = binomial, data = dfw)
vif(gm3)
```

```
##      duration   nr.employed         pdays      previous      campaign
##      1.241533      1.496925      1.820608      2.031438      1.021478
##           age cons.conf.idx
##      1.034254      1.056345
```

Modelo de regresión polinómica

Hacemos un tanteo aplicando una transformación polinómica de segundo grado a cada una de las variables.

```
gm4<-glm(y~
           poly(duration,2) +
            poly(nr.employed,2) +
            poly(pdays,2) +
            poly(previous,2) +
            poly(campaign,2) +
            poly(age,2) +
            poly(cons.conf.idx,2), family = binomial, data = dfw
           )
summary(gm4)
```

```
##
## Call:
## glm(formula = y ~ poly(duration, 2) + poly(nr.employed, 2) +
##     poly(pdays, 2) + poly(previous, 2) + poly(campaign, 2) +
##     poly(age, 2) + poly(cons.conf.idx, 2), family = binomial,
##     data = dfw)
```

```
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.8033  -0.3187  -0.1672  -0.1044   2.9358
##
## Coefficients:
##                           Estimate Std. Error z value Pr(>|z|)
## (Intercept)               -3.3334     0.1132 -29.449  < 2e-16 ***
## poly(duration, 2)1        82.4000     3.9367  20.931  < 2e-16 ***
## poly(duration, 2)2       -24.3172     3.0845  -7.884 3.18e-15 ***
## poly(nr.employed, 2)1    -61.5257     5.4420 -11.306  < 2e-16 ***
## poly(nr.employed, 2)2      4.9535     3.9118   1.266 0.205411
## poly(pdays, 2)1          -26.0379     3.5679  -7.298 2.92e-13 ***
## poly(pdays, 2)2           -0.9880     2.5784  -0.383 0.701581
## poly(previous, 2)1       -16.9490     4.7079  -3.600 0.000318 ***
## poly(previous, 2)2         8.2807     3.2481   2.549 0.010790 *
## poly(campaign, 2)1       -12.3096     5.9479  -2.070 0.038493 *
## poly(campaign, 2)2        10.7221     5.9999   1.787 0.073929 .
## poly(age, 2)1              5.7959     3.6339   1.595 0.110721
## poly(age, 2)2              6.4103     3.3367   1.921 0.054714 .
## poly(cons.conf.idx, 2)1    4.8461     3.7665   1.287 0.198225
## poly(cons.conf.idx, 2)2    5.7061     3.7847   1.508 0.131638
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2594.9  on 3741  degrees of freedom
## Residual deviance: 1523.1  on 3727  degrees of freedom
## AIC: 1553.1
##
## Number of Fisher Scoring iterations: 7
```

En vista del summary, podemos omitir el termino cuadrático de las variables nr.employed, pdays, age, con.conf.idx.

```
gm5<-glm(y~
           poly(duration,2) +
            nr.employed +
            pdays +
            poly(previous,2) +
            poly(campaign,2) +
            age +
            cons.conf.idx, family = binomial, data = dfw
           )
summary(gm5)
```

```
##
## Call:
## glm(formula = y ~ poly(duration, 2) + nr.employed + pdays + poly(previ
ous,
```

```
##     2) + poly(campaign, 2) + age + cons.conf.idx, family = binomial,
##     data = dfw)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.8321  -0.3202  -0.1672  -0.1022   2.9323
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)         79.166461   5.222892  15.158  < 2e-16 ***
## poly(duration, 2)1  82.458219   3.923723  21.015  < 2e-16 ***
## poly(duration, 2)2 -23.887690   3.100519  -7.704 1.31e-14 ***
## nr.employed         -0.015261   0.001019 -14.975  < 2e-16 ***
## pdays               -0.133120   0.017975  -7.406 1.30e-13 ***
## poly(previous, 2)1 -15.732038   4.526575  -3.475  0.00051 ***
## poly(previous, 2)2   8.049464   3.229608   2.492  0.01269 *
## poly(campaign, 2)1 -12.349248   5.936024  -2.080  0.03749 *
## poly(campaign, 2)2  10.937572   6.001919   1.822  0.06840 .
## age                  0.011624   0.005552   2.094  0.03629 *
## cons.conf.idx        0.028578   0.011999   2.382  0.01724 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2594.9  on 3741  degrees of freedom
## Residual deviance: 1530.6  on 3731  degrees of freedom
## AIC: 1552.6
##
## Number of Fisher Scoring iterations: 7
```

```
Anova(gm5)
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: y
##                   LR Chisq Df Pr(>Chisq)
## poly(duration, 2)   612.00  2  < 2.2e-16 ***
## nr.employed         255.09  1  < 2.2e-16 ***
## pdays                59.71  1  1.102e-14 ***
## poly(previous, 2)    16.12  2  0.0003158 ***
## poly(campaign, 2)    12.48  2  0.0019487 **
## age                   4.38  1  0.0364587 *
## cons.conf.idx         5.67  1  0.0172915 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

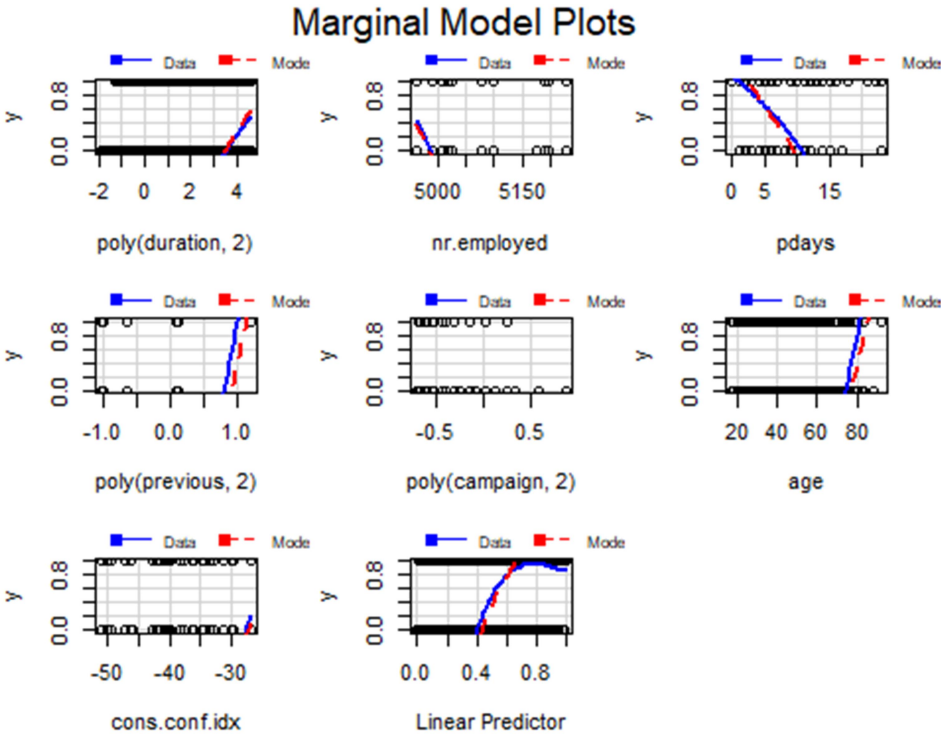
```
vif(gm5)
```

```
##                       GVIF Df GVIF^(1/(2*Df))
## poly(duration, 2) 1.377914  2        1.083442
```

```
## nr.employed        1.641804  1        1.281329
## pdays              1.808186  1        1.344688
## poly(previous, 2) 2.079898  2        1.200910
## poly(campaign, 2) 1.044713  2        1.010996
## age                1.037165  1        1.018413
## cons.conf.idx      1.060481  1        1.029796
```

```
marginalModelPlots(gm5)
```

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



Podemos ver que los p-values son inferiores a 0.1 para todas las variables, también vemos que el resultado del vif no presenta colinealidad.

Generalmente podemos ver que el modelo no se acerca tanto a los valores reales.

Modelización con variables explicativas numéricas y categóricas

```
# duration y f.duration
gm6<-glm(y~
           poly(duration,2) +
            nr.employed +
            pdays +
            poly(previous,2) +
            poly(campaign,2) +
            age +
            cons.conf.idx, family = binomial, data = dfw
           )
```

```r
gm7<-glm(y~
           f.duration +
            nr.employed +
            pdays +
            poly(previous,2) +
            poly(campaign,2) +
            age +
            cons.conf.idx, family = binomial, data = dfw
           )
BIC(gm7,gm6)
```

```
##     df      BIC
## gm7 12 1847.037
## gm6 11 1621.054
```

```r
# pdays y f.pdays
gm8<-glm(y~
           poly(duration,2) +
            nr.employed +
            pdays +
            poly(previous,2) +
            poly(campaign,2) +
            age +
            cons.conf.idx, family = binomial, data = dfw
           )
gm9<-glm(y~
           poly(duration,2) +
            nr.employed +
            f.pdays +
            poly(previous,2) +
            poly(campaign,2) +
            age +
            cons.conf.idx, family = binomial, data = dfw
           )
BIC(gm9,gm8)
```

```
##     df      BIC
## gm9 11 1620.968
## gm8 11 1621.054
```

```r
# previous y f.previous
gm10<-glm(y~
           poly(duration,2) +
            nr.employed +
            pdays +
            poly(previous,2) +
            poly(campaign,2) +
            age +
            cons.conf.idx, family = binomial, data = dfw
           )
gm11<-glm(y~
```

```
           poly(duration,2) +
            nr.employed +
            pdays +
            f.previous +
            poly(campaign,2) +
            age +
            cons.conf.idx, family = binomial, data = dfw
           )
BIC(gm11,gm10)
```

```
##      df      BIC
## gm11 11 1621.220
## gm10 11 1621.054
```

```
# campaign vs f.campaign
gm12<-glm(y~
           poly(duration,2) +
            nr.employed +
            pdays +
            poly(previous,2) +
            poly(campaign,2) +
            age +
            cons.conf.idx, family = binomial, data = dfw
           )
gm13<-glm(y~
           poly(duration,2) +
            nr.employed +
            pdays +
            poly(previous,2) +
            f.campaign +
            age +
            cons.conf.idx, family = binomial, data = dfw
           )
BIC(gm13,gm12)
```

```
##      df      BIC
## gm13 11 1624.202
## gm12 11 1621.054
```

```
# age vs f.age
gm14<-glm(y~
           poly(duration,2) +
            nr.employed +
            pdays +
            poly(previous,2) +
            poly(campaign,2) +
            age +
            cons.conf.idx, family = binomial, data = dfw
           )
gm15<-glm(y~
           poly(duration,2) +
```

```
            nr.employed +
            pdays +
            poly(previous,2) +
            poly(campaign,2) +
            f.age +
            cons.conf.idx, family = binomial, data = dfw
           )
BIC(gm15,gm14)
```

```
##      df      BIC
## gm15 13 1630.939
## gm14 11 1621.054
```

A partir de los resultados de los BICs, nos quedamos con las versiones de las variables numéricas o de factores cuyo valor de BIC es menor.

Con el resultado obtenido anteriormente, creamos un nuevo modelo.

```
gm16<-glm(y~
           poly(duration,2) +
            nr.employed +
            f.pdays +
            poly(previous,2) +
            poly(campaign,2) +
            age +
            cons.conf.idx, family = binomial, data = dfw
           )
summary(gm16)
```

```
##
## Call:
## glm(formula = y ~ poly(duration, 2) + nr.employed + f.pdays +
##     poly(previous, 2) + poly(campaign, 2) + age + cons.conf.idx,
##     family = binomial, data = dfw)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.8290  -0.3203  -0.1678  -0.1034   2.9250
##
## Coefficients:
##                            Estimate Std. Error z value Pr(>|z|)
## (Intercept)              77.867008   5.208078  14.951  < 2e-16 ***
## poly(duration, 2)1       82.135385   3.916635  20.971  < 2e-16 ***
## poly(duration, 2)2      -23.637806   3.097309  -7.632 2.32e-14 ***
## nr.employed              -0.015156   0.001018 -14.892  < 2e-16 ***
## f.pdaysf.pdays-(22,23]   -2.326819   0.314062  -7.409 1.27e-13 ***
## poly(previous, 2)1      -16.405010   4.606619  -3.561 0.000369 ***
## poly(previous, 2)2        9.381292   3.275937   2.864 0.004187 **
## poly(campaign, 2)1      -12.215658   5.905733  -2.068 0.038599 *
## poly(campaign, 2)2       10.952908   5.964041   1.836 0.066285 .
## age                       0.012244   0.005557   2.203 0.027560 *
```

```
## cons.conf.idx            0.028649   0.011975   2.392 0.016738 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2594.9  on 3741  degrees of freedom
## Residual deviance: 1530.5  on 3731  degrees of freedom
## AIC: 1552.5
##
## Number of Fisher Scoring iterations: 7
```

```
Anova(gm16)
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: y
##                    LR Chisq Df Pr(>Chisq)
## poly(duration, 2)   608.02  2  < 2.2e-16 ***
## nr.employed         251.42  1  < 2.2e-16 ***
## f.pdays              59.79  1  1.055e-14 ***
## poly(previous, 2)    17.95  2  0.0001263 ***
## poly(campaign, 2)    12.34  2  0.0020925 **
## age                   4.85  1  0.0276839 *
## cons.conf.idx         5.72  1  0.0167883 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
vif(gm16)
```

```
##                       GVIF Df GVIF^(1/(2*Df))
## poly(duration, 2) 1.374363  2        1.082743
## nr.employed       1.632340  1        1.277631
## f.pdays           1.911480  1        1.382563
## poly(previous, 2) 2.167088  2        1.213303
## poly(campaign, 2) 1.044674  2        1.010986
## age               1.037314  1        1.018486
## cons.conf.idx     1.057644  1        1.028418
```

Comprobamos el resultado y son correctos.

Ahora añadimos el resto de factores, utilizamos un catdes para ver cuales están más relacionadas con nuestro target.

```
catdes(dfw[,c("y",vars_cat)],1)
```

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

```
## poutcome  8.905412e-84  2
## month     9.664852e-42  9
## job       5.444613e-17 10
## contact   2.379692e-14  1
## default   1.290603e-09  1
## marital   8.221254e-04  2
## housing   4.148800e-03  1
## education 8.424425e-03  6
##
## Description of each cluster by the categories
## =============================================
## $y.no
##                                          Cla/Mod    Mod/Cla     Global
## poutcome=poutcome.nonexistent          90.93168 87.9279279 86.0502405
## contact=contact.telephone              94.20074 38.0480480 35.9433458
## default=default.unknown                94.96855 22.6726727 21.2453234
## month=month.may                        92.54210 34.6546547 33.3244254
## job=job.blue-collar                    93.39513 24.2042042 23.0625334
## job=job.services                       94.67456  9.6096096  9.0326029
## marital=marital.married                90.30817 60.7207207 59.8343132
## education=education.basic.9y           92.32026 16.9669670 16.3548904
## housing=housing.no                     90.57259 47.0270270 46.2052378
## month=month.dec                        66.66667  0.3003003  0.4008552
## housing=housing.yes                    87.63040 52.9729730 53.7947622
## education=education.university.degree 86.43042 30.0300300 30.9192945
## marital=marital.single                 85.95506 27.5675676 28.5408872
## month=month.apr                        80.08850  5.4354354  6.0395510
## job=job.student                        70.65217  1.9519520  2.4585783
## month=month.sep                        62.74510  0.9609610  1.3629075
## job=job.retired                        74.56647  3.8738739  4.6231962
## month=month.mar                        54.16667  0.7807808  1.2827365
## default=default.no                     87.37699 77.3273273 78.7546766
## month=month.oct                        54.83871  1.0210210  1.6568680
## contact=contact.cellular               86.06592 61.9519520 64.0566542
## poutcome=poutcome.success              33.33333  1.1711712  3.1266702
##                                            p.value     v.test
## poutcome=poutcome.nonexistent          1.033863e-17   8.570110
## contact=contact.telephone              1.723437e-15   7.959781
## default=default.unknown                6.533397e-11   6.530995
## month=month.may                        4.627585e-07   5.041143
## job=job.blue-collar                    7.948561e-07   4.936626
## job=job.services                       1.615234e-04   3.772649
## marital=marital.married                1.803002e-03   3.120898
## education=education.basic.9y           2.923747e-03   2.975643
## housing=housing.no                     4.058668e-03   2.873566
## month=month.dec                        2.219854e-02  -2.286953
## housing=housing.yes                    4.058668e-03  -2.873566
## education=education.university.degree 9.941775e-04  -3.292169
## marital=marital.single                 2.417762e-04  -3.670817
## month=month.apr                        5.137216e-05  -4.049295
```

```
## job=job.student                           1.134551e-06  -4.866738
## month=month.sep                           8.387879e-07  -4.926119
## job=job.retired                           4.689017e-08  -5.462717
## month=month.mar                           9.910614e-10  -6.110843
## default=default.no                        6.533397e-11  -6.530995
## month=month.oct                           7.066133e-12  -6.856311
## contact=contact.cellular                  1.723437e-15  -7.959781
## poutcome=poutcome.success                 7.526687e-49 -14.689500
##
## $y.yes
##                                             Cla/Mod   Mod/Cla     Global
## poutcome=poutcome.success                 66.666667 18.932039  3.1266702
## contact=contact.cellular                  13.934084 81.067961 64.0566542
## month=month.oct                           45.161290  6.796117  1.6568680
## default=default.no                        12.623006 90.291262 78.7546766
## month=month.mar                           45.833333  5.339806  1.2827365
## job=job.retired                           25.433526 10.679612  4.6231962
## month=month.sep                           37.254902  4.611650  1.3629075
## job=job.student                           29.347826  6.553398  2.4585783
## month=month.apr                           19.911504 10.922330  6.0395510
## marital=marital.single                    14.044944 36.407767 28.5408872
## education=education.university.degree     13.569576 38.106796 30.9192945
## housing=housing.yes                       12.369598 60.436893 53.7947622
## month=month.dec                           33.333333  1.213592  0.4008552
## housing=housing.no                         9.427415 39.563107 46.2052378
## education=education.basic.9y               7.679739 11.407767 16.3548904
## marital=marital.married                    9.691827 52.669903 59.8343132
## job=job.services                           5.325444  4.368932  9.0326029
## job=job.blue-collar                        6.604867 13.834951 23.0625334
## month=month.may                            7.457899 22.572816 33.3244254
## default=default.unknown                    5.031447  9.708738 21.2453234
## contact=contact.telephone                  5.799257 18.932039 35.9433458
## poutcome=poutcome.nonexistent              9.068323 70.873786 86.0502405
##                                               p.value    v.test
## poutcome=poutcome.success                 7.526687e-49 14.689500
## contact=contact.cellular                  1.723437e-15  7.959781
## month=month.oct                           7.066133e-12  6.856311
## default=default.no                        6.533397e-11  6.530995
## month=month.mar                           9.910614e-10  6.110843
## job=job.retired                           4.689017e-08  5.462717
## month=month.sep                           8.387879e-07  4.926119
## job=job.student                           1.134551e-06  4.866738
## month=month.apr                           5.137216e-05  4.049295
## marital=marital.single                    2.417762e-04  3.670817
## education=education.university.degree     9.941775e-04  3.292169
## housing=housing.yes                       4.058668e-03  2.873566
## month=month.dec                           2.219854e-02  2.286953
## housing=housing.no                        4.058668e-03 -2.873566
## education=education.basic.9y              2.923747e-03 -2.975643
## marital=marital.married                   1.803002e-03 -3.120898
```

```
## job=job.services                          1.615234e-04 -3.772649
## job=job.blue-collar                       7.948561e-07 -4.936626
## month=month.may                           4.627585e-07 -5.041143
## default=default.unknown                   6.533397e-11 -6.530995
## contact=contact.telephone                 1.723437e-15 -7.959781
## poutcome=poutcome.nonexistent             1.033863e-17 -8.570110
```

Viendo el resultado del catdes, obtenemos que las variables que están más relacionadas son outcome, month, job, contact, default, marital, housing y education. Como month tiene muchos niveles decidimos usar el month factorizado.

```
gm17<-glm(y~poly(duration,2) +nr.employed +f.pdays +poly(previous,2) +pol
y(campaign,2) +age +cons.conf.idx+poutcome+ f.influentMonth + job+ contac
t+ default+ marital+ housing+ education, family = binomial, data = dfw)
Anova(gm17)

## Analysis of Deviance Table (Type II tests)
##
## Response: y
##                    LR Chisq Df Pr(>Chisq)
## poly(duration, 2)   625.07  2  < 2.2e-16 ***
## nr.employed         177.78  1  < 2.2e-16 ***
## f.pdays               0.02  1   0.895857
## poly(previous, 2)     1.21  2   0.546061
## poly(campaign, 2)     9.00  2   0.011102 *
## age                   6.51  1   0.010722 *
## cons.conf.idx         1.54  1   0.214577
## poutcome              9.22  2   0.009954 **
## f.influentMonth      12.92  2   0.001564 **
## job                  12.51 10   0.252449
## contact               3.60  1   0.057727 .
## default               5.75  1   0.016536 *
## marital               4.60  2   0.100507
## housing               3.43  1   0.063919 .
## education             5.17  6   0.522155
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Seguimos cribando dado el resultado del Anova

```
gm18<-glm(y~poly(duration,2) +nr.employed +poly(campaign,2) +age +poutcom
e+ f.influentMonth + contact+ default+ housing, family = binomial, data =
dfw)
Anova(gm18)

## Analysis of Deviance Table (Type II tests)
##
## Response: y
##                    LR Chisq Df Pr(>Chisq)
## poly(duration, 2)   623.25  2  < 2.2e-16 ***
## nr.employed         213.89  1  < 2.2e-16 ***
```

```
## poly(campaign, 2)     9.65  2   0.008020 **
## age                   8.49  1   0.003566 **
## poutcome             70.85  2  4.116e-16 ***
## f.influentMonth      20.46  2  3.614e-05 ***
## contact               3.80  1   0.051222 .
## default               8.33  1   0.003909 **
## housing               3.21  1   0.073099 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
vif(gm18)
```

```
##                       GVIF Df GVIF^(1/(2*Df))
## poly(duration, 2) 1.447940  2        1.096952
## nr.employed       1.721167  1        1.311932
## poly(campaign, 2) 1.056114  2        1.013743
## age               1.033641  1        1.016681
## poutcome          1.296327  2        1.067035
## f.influentMonth   1.106236  2        1.025562
## contact           1.123197  1        1.059810
## default           1.075544  1        1.037084
## housing           1.010610  1        1.005291
```

Ahora las variables nos dan aceptables, con p-values menores a 0.1 y sin colinealidad.

Ahora hacemos un step con el criterio bayesiano, para validar el modelo

```
gm19<-step(gm18,k=log(nrow(dfw)))
```

```
## Start:  AIC=1601.84
## y ~ poly(duration, 2) + nr.employed + poly(campaign, 2) + age +
##     poutcome + f.influentMonth + contact + default + housing
##
##                      Df Deviance    AIC
## - poly(campaign, 2)  2   1496.3 1595.0
## - housing            1   1489.9 1596.8
## - contact            1   1490.5 1597.4
## <none>                   1486.7 1601.8
## - default            1   1495.0 1601.9
## - age                1   1495.1 1602.1
## - f.influentMonth    2   1507.1 1605.8
## - poutcome           2   1557.5 1656.2
## - nr.employed        1   1700.5 1807.5
## - poly(duration, 2)  2   2109.9 2208.6
##
## Step:  AIC=1595.03
## y ~ poly(duration, 2) + nr.employed + age + poutcome + f.influentMonth
+
##     contact + default + housing
##
##                      Df Deviance    AIC
```

```
## - housing            1   1499.3 1589.8
## - contact            1   1500.8 1591.3
## <none>                   1496.3 1595.0
## - age                1   1505.1 1595.6
## - default            1   1505.2 1595.7
## - f.influentMonth    2   1518.2 1600.4
## - poutcome           2   1567.5 1649.7
## - nr.employed        1   1717.9 1808.4
## - poly(duration, 2)  2   2117.1 2199.4
##
## Step:  AIC=1589.77
## y ~ poly(duration, 2) + nr.employed + age + poutcome + f.influentMonth
+
##     contact + default
##
##                     Df Deviance    AIC
## - contact            1   1504.1 1586.4
## <none>                   1499.3 1589.8
## - age                1   1507.6 1589.8
## - default            1   1508.4 1590.7
## - f.influentMonth    2   1522.0 1596.1
## - poutcome           2   1570.1 1644.2
## - nr.employed        1   1721.4 1803.7
## - poly(duration, 2)  2   2120.4 2194.5
##
## Step:  AIC=1586.4
## y ~ poly(duration, 2) + nr.employed + age + poutcome + f.influentMonth
+
##     default
##
##                     Df Deviance    AIC
## - age                1   1512.3 1586.3
## <none>                   1504.1 1586.4
## - default            1   1514.4 1588.5
## - f.influentMonth    2   1529.8 1595.6
## - poutcome           2   1573.6 1639.5
## - nr.employed        1   1747.3 1821.3
## - poly(duration, 2)  2   2128.2 2194.0
##
## Step:  AIC=1586.33
## y ~ poly(duration, 2) + nr.employed + poutcome + f.influentMonth +
##     default
##
##                     Df Deviance    AIC
## <none>                   1512.3 1586.3
## - default            1   1520.5 1586.3
## - f.influentMonth    2   1539.5 1597.1
## - poutcome           2   1582.0 1639.6
## - nr.employed        1   1767.7 1833.5
## - poly(duration, 2)  2   2136.3 2193.9
```

```
summary(gm19)
```

```
##
## Call:
## glm(formula = y ~ poly(duration, 2) + nr.employed + poutcome +
##     f.influentMonth + default, family = binomial, data = dfw)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.6811  -0.3085  -0.1597  -0.1003   3.0735
##
## Coefficients:
##                                              Estimate Std. Error
## (Intercept)                                   75.15851    5.20488
## poly(duration, 2)1                            83.77127    3.98039
## poly(duration, 2)2                           -24.63315    3.12149
## nr.employed                                   -0.01528    0.00103
## poutcomepoutcome.nonexistent                   0.89824    0.22100
## poutcomepoutcome.success                       2.40968    0.30331
## f.influentMonthf.influentMonth.sep-may-jul    -0.68808    0.15291
## f.influentMonthf.influentMonth.mar-dec-oct-nov  0.06799    0.19438
## defaultdefault.unknown                        -0.57789    0.20843
##                                              z value Pr(>|z|)
## (Intercept)                                   14.440  < 2e-16 ***
## poly(duration, 2)1                            21.046  < 2e-16 ***
## poly(duration, 2)2                            -7.891 2.99e-15 ***
## nr.employed                                  -14.831  < 2e-16 ***
## poutcomepoutcome.nonexistent                   4.064 4.81e-05 ***
## poutcomepoutcome.success                       7.945 1.95e-15 ***
## f.influentMonthf.influentMonth.sep-may-jul    -4.500 6.80e-06 ***
## f.influentMonthf.influentMonth.mar-dec-oct-nov  0.350  0.72651
## defaultdefault.unknown                        -2.773  0.00556 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2594.9  on 3741  degrees of freedom
## Residual deviance: 1512.3  on 3733  degrees of freedom
## AIC: 1530.3
##
## Number of Fisher Scoring iterations: 7
```

Hay que ver que todos los coeficientes sean calculables y que no tengamos ningún NA en el summary, en nuestro caso no tenemos ninguno.

Interacciones

Primero probamos con todas las interacciones posibles de orden 2 para hacernos una idea de las interacciones que podemos usar de muestra.

```
gm20<-glm(y~ (poly(duration,2) +nr.employed +poly(campaign,2) +age +poutc
ome+ f.influentMonth + contact+ default+ housing)^2, family = binomial, d
ata = dfw)

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

Anova(gm20)

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Analysis of Deviance Table (Type II tests)
##
## Response: y
##                                      LR Chisq Df Pr(>Chisq)
## poly(duration, 2)                      606.44  2  < 2.2e-16 ***
## nr.employed                            219.61  1  < 2.2e-16 ***
## poly(campaign, 2)                       11.93  2  0.0025650 **
## age                                      7.41  1  0.0064886 **
## poutcome                                63.00  2  2.083e-14 ***
## f.influentMonth                         16.74  2  0.0002317 ***
## contact                                  6.26  1  0.0123735 *
## default                                  8.37  1  0.0038152 **
## housing                                  4.99  1  0.0255125 *
## poly(duration, 2):nr.employed           12.60  2  0.0018372 **
## poly(duration, 2):poly(campaign, 2)      2.17  4  0.7042833
## poly(duration, 2):age                    0.20  2  0.9040617
## poly(duration, 2):poutcome               3.63  4  0.4578341
## poly(duration, 2):f.influentMonth       16.14  4  0.0028348 **
## poly(duration, 2):contact                0.70  2  0.7038259
## poly(duration, 2):default                1.43  2  0.4886817
## poly(duration, 2):housing                6.20  2  0.0450133 *
## nr.employed:poly(campaign, 2)            2.43  2  0.2968249
## nr.employed:age                          0.00  1  0.9476946
## nr.employed:poutcome                     5.67  2  0.0588327 .
## nr.employed:f.influentMonth              0.84  2  0.6558761
## nr.employed:contact                      0.01  1  0.9381053
## nr.employed:default                      0.48  1  0.4868526
## nr.employed:housing                      0.02  1  0.8895965
## poly(campaign, 2):age                    8.90  2  0.0116869 *
## poly(campaign, 2):poutcome              13.38  4  0.0095456 **
## poly(campaign, 2):f.influentMonth       18.34  4  0.0010595 **
## poly(campaign, 2):contact                1.19  2  0.5509442
```

```
## poly(campaign, 2):default                0.06  2  0.9705383
## poly(campaign, 2):housing                3.48  2  0.1755176
## age:poutcome                             1.69  2  0.4304841
## age:f.influentMonth                      0.46  2  0.7937762
## age:contact                              0.15  1  0.6986240
## age:default                              0.83  1  0.3622380
## age:housing                              3.63  1  0.0567390 .
## poutcome:f.influentMonth                 7.12  4  0.1297656
## poutcome:contact                         3.67  2  0.1594200
## poutcome:default                         3.36  2  0.1866776
## poutcome:housing                         1.76  2  0.4153831
## f.influentMonth:contact                  9.26  2  0.0097760 **
## f.influentMonth:default                  4.77  2  0.0920652 .
## f.influentMonth:housing                  2.12  2  0.3465305
## contact:default                          0.64  1  0.4233159
## contact:housing                          0.30  1  0.5831223
## default:housing                          3.33  1  0.0678341 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Elegiremos una interacción factor por factor y factor por numérica de entre todas las interacciones, cuyos p-values son los más convincentes. Comprobamos la bondad de la interacción factor

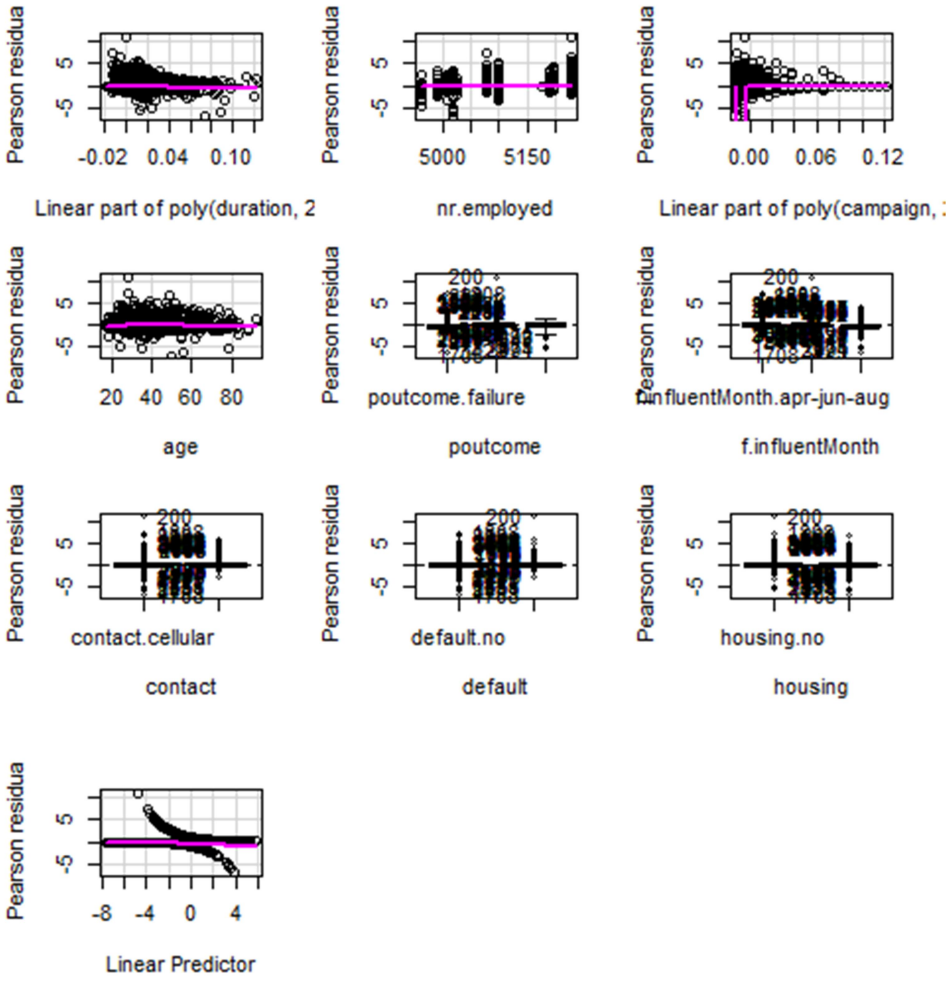
```
gm21<-glm(y~ poly(duration,2) +nr.employed +poly(campaign,2) +age +poutcome+ f.influentMonth*contact+ default+ housing, family = binomial, data = dfw)

gm22<-glm(y~ poly(duration,2) +nr.employed +poly(campaign,2)*f.influentMonth  +age +poutcome+ contact+ default+ housing, family = binomial, data = dfw)

BIC(gm21,gm20)

##      df      BIC
## gm21 16 1613.523
## gm20 88 2052.909

BIC(gm22,gm20)

##      df      BIC
## gm22 18 1618.316
## gm20 88 2052.909
```

Vemos que los dos modelos con interacciones dan mejor que nuestro modelo, entre estos vemos que el de menor BIC es el de la interacción de f.influentMonth*contact.

Validación

Para la validación analizamos los gráficos

```
residualPlots(gm21)
```

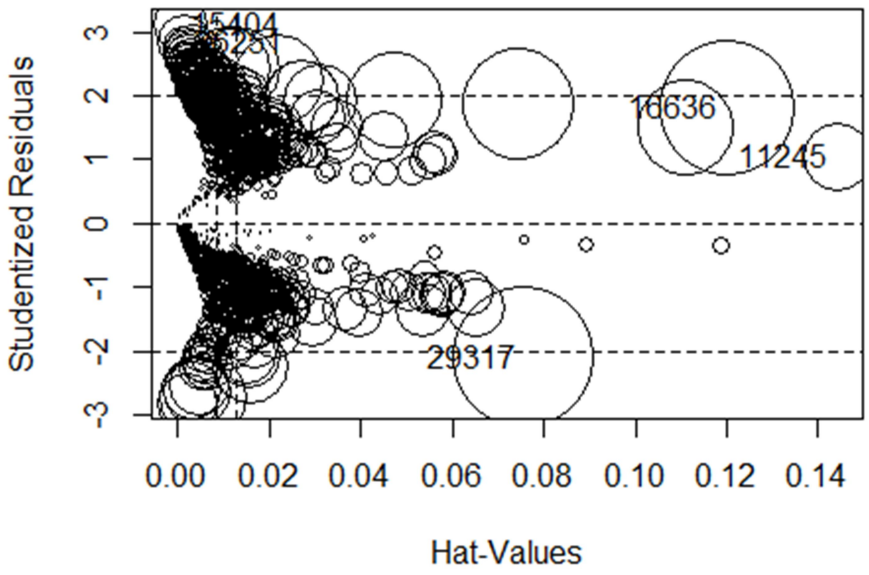



```
##                     Test stat Pr(>|Test stat|)
## poly(duration, 2)
```

```
## nr.employed           0.8698          0.35102
## poly(campaign, 2)
## age                   3.4946          0.06157 .
## poutcome
## f.influentMonth
## contact
## default
## housing
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Con el residualPlots, podemos ver que tenemos una observación en común que es muy influente, como ahora vamos a hacer el influencePlot, podremos determinar si efectivamente esta observación es demasiado influyente.

```
influencePlot(gm21)
```

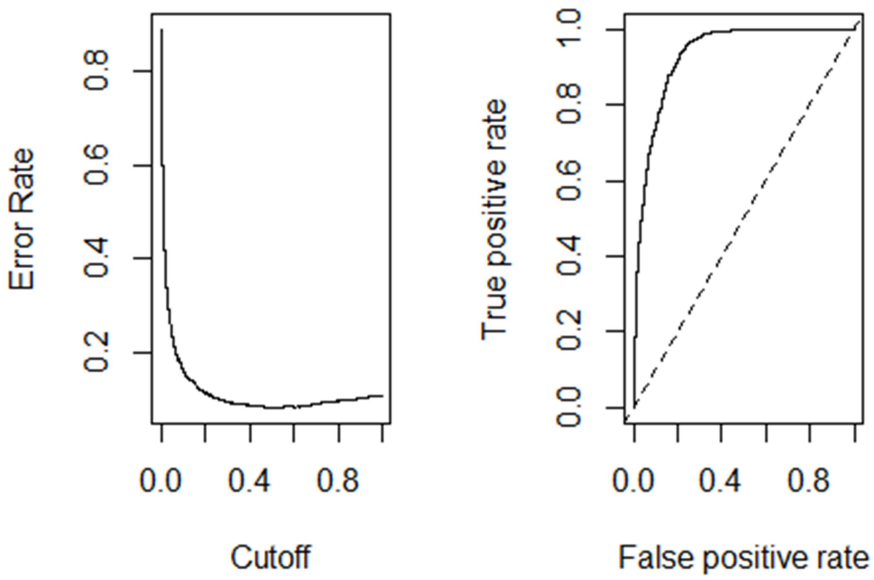



```
##          StudRes           Hat       CookD
## 15404  3.116369 0.0006512188 0.004991063
## 36251  2.835739 0.0015232026 0.005018080
## 11245  1.043963 0.1440726950 0.007802044
## 29317 -2.103560 0.0758185513 0.033909413
## 16636  1.817313 0.1200968043 0.030955448

which(row.names(df)==11245)

## [1] 1317
```

```
which(row.names(df)==16636)

## [1] 1940

which(row.names(df)==29317)

## [1] 3498
```

Viendo el resultado del influentPlot, no vemos al individuo 200, que nos sale en la gráfica de residuos, lo que nos puede decir que no influye demasiado en nuestro modelo.

```
dataroc<-prediction(predict(gm21, type="response"),dfw$y)
par(mfrow=c(1,2))
plot(performance(dataroc,"err"))
plot(performance(dataroc,"tpr","fpr"))
abline(0,1,lty=2)
```



Estamos cogiendo las betas de este modelo y aplicándolos a las variables explicativas del dft, para así obtener las predicciones según nuestro modelo. Montamos una tabla con las predicciones y los datos reales a modo de matriz de confusión, del cual su diagonal nos indica la cantidad de aciertos.

```
p<-factor(ifelse(predict(gm21, dft, type = "response") < 0.4, 0, 1 ))
tabConfusion<-table(p, dft[,"y"])
```

Para calcular la capacidad predictiva del modelo, bastará con sumar la diagonal de la matriz de confusión y dividirla entre el número de observaciones.

```
capacidadPredictiva <- (tabConfusion[1,1] + tabConfusion[2,2])/nrow(dft)
```

Tenemos un 91,42% de aciertos con nuestro modelo.

Nos damos cuenta que por los datos que tenemos no es posible que tengamos una capacidad predictiva tan grande, por lo que decidimos comparar con el modelo null.

```
gmnull<-glm(y~ 1, family = binomial, data = dfw)
pnull<-factor(ifelse(predict(gmnull, dft, type = "response") < 0.4, 0, 1
))
tabConfusionNull<-table(pnull, dft[,"y"])
capacidadPredictivaNull <- (tabConfusionNull[1,1] + 0)/nrow(dft)
```

Con el modelo Null tenemos un 89,58% de aciertos, ahora viendo la diferencia entre nuestro modelo y el null tenemos que

```
MejoraModelo <- capacidadPredictiva - capacidadPredictivaNull
MejoraModelo*100

## [1] 1.842949
```

Tenemos que nuestro modelo es 1.84% mejor que el modelo más básico. El hecho de que la capacidad predictiva sea tan alta en ambos casos, es debido a que la gran mayoría de las observaciones tienen como valor de respuesta “no”, esto hace que cualquier modelo por tonto que sea tenga una buena capacidad predictiva.