Entrega1

Loading data and Sample selection

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Carregar les dades

Les dades es diuen adult.data i es troben en el directori actual.

```
df<-read.table("adult.data",header=F, sep=",",fill=FALSE,
strip.white=TRUE,na.string="?")
names(df)<-c("age", "type.employer", "fnlwgt", "education",
"education.num","marital", "occupation",
             "relationship", "race","sex", "capital.gain",
"capital.loss",
             "hr.per.week", "country", "y.bin")
```

Selecció de la mostra

Inicialitzem un generador aleatori, amb una llavor que es igual a la data de neixament d'un dels integrants del grup, i agafem 5000 observacions de les dades totals

```
set.seed(14121997)
sam<-sort(sample(1:nrow(df),5000))



str(df)

## 'data.frame':    32561 obs. of  15 variables:
##  $ age          : int  39 50 38 53 28 37 49 52 31 42 ...
##  $ type.employer: Factor w/ 8 levels "Federal-gov",..: 7 6 4 4
4 4 4 6 4 4 ...
##  $ fnlwgt       : int  77516 83311 215646 234721 338409 284582
160187 209642 45781 159449 ...
##  $ education    : Factor w/ 16 levels "10th","11th",..: 10 10
12 2 10 13 7 12 13 10 ...
##  $ education.num: int  13 13 9 7 13 14 5 9 14 13 ...
##  $ marital      : Factor w/ 7 levels "Divorced","Married-AF-
spouse",..: 5 3 1 3 3 3 4 3 5 3 ...
##  $ occupation   : Factor w/ 14 levels "Adm-clerical",..: 1 4 6
6 10 4 8 4 10 4 ...
##  $ relationship : Factor w/ 6 levels "Husband","Not-in-
family",..: 2 1 2 1 6 6 2 1 2 1 ...
##  $ race         : Factor w/ 5 levels "Amer-Indian-Eskimo",..:
5 5 5 3 3 5 3 5 5 5 ...
##  $ sex          : Factor w/ 2 levels "Female","Male": 2 2 2 2
1 1 1 2 1 2 ...
##  $ capital.gain : int  2174 0 0 0 0 0 0 0 14084 5178 ...
##  $ capital.loss : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ hr.per.week  : int  40 13 40 40 40 40 16 45 50 40 ...
##  $ country      : Factor w/ 41 levels "Cambodia","Canada",..:
39 39 39 39 5 39 23 39 39 39 ...
```

```
##  $ y.bin       : Factor w/ 2 levels "<=50K",">50K": 1 1 1 1 1 
1 1 2 2 2 ...
```

```
# Select sample
df<-df[sam,]
```

Guardar la mostra

Guardarem la mostra com a mostra.RData, en el directori actua, aquest pas el podriem evitar, no obstant el fem perquè creiem que es important saber guardar les dades.

```
save(list="df",file="mostra.RData")
```

Fitxa de dades del cens

Descripció

variables d'entrada:

1. age: continuous.
2. workclass: Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked.
3. fnlwgt: continuous.
4. education: Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool.
5. education-num: continuous.
6. marital.status: Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse.
7. occupation: Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces.
8. relationship: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried.
9. race: White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black.
10. sex: Female, Male.
11. capital.gain: continuous.
12. capital.loss: continuous.
13. hours.per.week: continuous. Numeric target.
14. native.country: United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy,

Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands.

15. y.bin: Making more than $50K per year. Binary target.

Carrega de paquets

Carregarem tots els paquets necessaris per utilitzar al llarg de la pràctica.

```
options(contrasts=c("contr.treatment","contr.treatment"))

requiredPackages <- c("effects","FactoMineR","car",
"factoextra","ggplot2","dplyr","ggmap","ggthemes","knitr")
missingPackages <- requiredPackages[!(requiredPackages %in%
installed.packages()[,"Package"])]
if(length(missingPackages)) install.packages(missingPackages)

## Installing package into '/usr/local/lib/R/site-library'
## (as 'lib' is unspecified)

## also installing the dependency 'jpeg'

## Warning in install.packages(missingPackages): installation of
package
## 'jpeg' had non-zero exit status

## Warning in install.packages(missingPackages): installation of
package
## 'ggmap' had non-zero exit status

lapply(requiredPackages, require, character.only = TRUE)

## Loading required package: effects

## Loading required package: carData

## lattice theme set by effectsTheme()
## See ?effectsTheme for details.

## Loading required package: FactoMineR

## Loading required package: car

## Registered S3 methods overwritten by 'car':
##   method                          from
##   influence.merMod                lme4
##   cooks.distance.influence.merMod lme4
##   dfbeta.influence.merMod         lme4
##   dfbetas.influence.merMod        lme4
```

```
## Loading required package: factoextra

## Loading required package: ggplot2

## Welcome! Related Books: `Practical Guide To Cluster Analysis
in R` at https://goo.gl/13EFCZ

## Loading required package: dplyr

##
## Attaching package: 'dplyr'

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

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

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

## Loading required package: ggmap

## Warning in library(package, lib.loc = lib.loc, character.only
= TRUE,
## logical.return = TRUE, : there is no package called 'ggmap'

## Loading required package: ggthemes

## Loading required package: knitr

## [[1]]
## [1] TRUE
##
## [[2]]
## [1] TRUE
##
## [[3]]
## [1] TRUE
##
## [[4]]
## [1] TRUE
##
## [[5]]
## [1] TRUE
##
## [[6]]
## [1] TRUE
##
## [[7]]
```

```
## [1] FALSE
## 
## [[8]]
## [1] TRUE
## 
## [[9]]
## [1] TRUE
```

Carregar mostra

Carreguem el model previament creat.

```
# Clear objects
rm(list=ls())
# Clear plots
if(!is.null(dev.list())) dev.off()

## null device 
##           1

# Command or Windows-like method
load("mostra.RData")
summary(df)

##       age                   type.employer      fnlwgt       
##  Min.   :17.0   Private         :3468   Min.   :  18827  
##  1st Qu.:27.0   Self-emp-not-inc: 376   1st Qu.: 118008  
##  Median :37.0   Local-gov       : 327   Median : 178950  
##  Mean   :38.7   State-gov       : 205   Mean   : 192215  
##  3rd Qu.:48.0   Self-emp-inc    : 175   3rd Qu.: 241215  
##  Max.   :90.0   (Other)         : 141   Max.   :1268339  
##                 NA's            : 308                    
##         education    education.num                    marital      

##  HS-grad     :1621   Min.   : 1.00   Divorced             :
701  
##  Some-college:1096   1st Qu.: 9.00   Married-AF-spouse    :
1  
##  Bachelors   : 793   Median :10.00   Married-civ-
spouse   :2283  
##  Masters     : 271   Mean   :10.04   Married-spouse-absent:
72  
##  Assoc-voc   : 228   3rd Qu.:12.00   Never-
married        :1606  
##  11th        : 185   Max.   :16.00   Separated            :
167  
##  (Other)     : 806                   Widowed              :
170  
##            occupation           relationship          
race      
##  Prof-specialty : 635   Husband       :1987   Amer-Indian-
```

```
Eskimo:  45
##  Exec-managerial: 624   Not-in-family :1315   Asian-Pac-
Islander: 154
##  Craft-repair   : 595   Other-relative: 169   Black
: 507
##  Adm-clerical   : 591   Own-child     : 758   Other
:  34
##  Sales          : 565   Unmarried     : 505   White
:4260
##  (Other)        :1682   Wife          : 266

##  NA's           : 308

##      sex        capital.gain    capital.loss      hr.per.week

##  Female:1681   Min.   :    0   Min.   :   0.00   Min.   : 1.00

##  Male  :3319   1st Qu.:    0   1st Qu.:   0.00   1st Qu.:40.00

##                Median :    0   Median :   0.00   Median :40.00

##                Mean   : 1073   Mean   :  94.46   Mean   :40.43

##                3rd Qu.:    0   3rd Qu.:   0.00   3rd Qu.:45.00

##                Max.   :99999   Max.   :3900.00   Max.   :99.00

##

##           country       y.bin
##  United-States:4488   <=50K:3800
##  Mexico       :  94   >50K :1200
##  Germany      :  27
##  Philippines  :  26
##  Canada       :  24
##  (Other)      : 253
##  NA's         :  88
```

Algunes funcions útils

Definim totes les funcions que ens podràn ser utils al llarg de la pràctica.

```
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], q2=s.x[3],
```

```
       q3=s.x[5], max=s.x[6], mouts=s.x[5]+1.5*iqr,
souts=s.x[5]+3*iqr ) }

countNA <- function(x) {
  mis_x <- NULL
  for (j in 1:ncol(x)) {mis_x[j] <- sum(is.na(x[,j])) }
  mis_x <- as.data.frame(mis_x)
  rownames(mis_x) <- names(x)
  mis_i <- rep(0,nrow(x))
  for (j in 1:ncol(x)) {mis_i <- mis_i + as.numeric(is.na(x[,j]))
}
  list(mis_col=mis_x,mis_ind=mis_i) }
```

Preparació de les dades

Preparació de les dades, separem entre aquelles variables que tenen un valor numéric i aquelles que són descriptives.

```
vars_con<-names(df)[c(1,3,5,11:13)];
vars_dis<-names(df)[c(2,4,6:10,14:15)];

summary(df[,vars_con]) # Example of descriptive for numeric
variables

##       age           fnlwgt        education.num
capital.gain
##  Min.   :17.0   Min.   :  18827   Min.   : 1.00   Min.   :
0
##  1st Qu.:27.0   1st Qu.: 118008   1st Qu.: 9.00   1st Qu.:
0
##  Median :37.0   Median : 178950   Median :10.00   Median :
0
##  Mean   :38.7   Mean   : 192215   Mean   :10.04   Mean   :
1073
##  3rd Qu.:48.0   3rd Qu.: 241215   3rd Qu.:12.00   3rd Qu.:
0
##  Max.   :90.0   Max.   :1268339   Max.   :16.00
Max.   :99999
##   capital.loss      hr.per.week
##  Min.   :   0.00   Min.   : 1.00
##  1st Qu.:   0.00   1st Qu.:40.00
##  Median :   0.00   Median :40.00
##  Mean   :  94.46   Mean   :40.43
##  3rd Qu.:   0.00   3rd Qu.:45.00
##  Max.   :3900.00   Max.   :99.00

summary(df[,vars_dis])

##           type.employer         education
marital
```

```
##  Private         :3468   HS-grad     :1621   Divorced
: 701
##  Self-emp-not-inc: 376   Some-college:1096   Married-AF-spouse
:   1
##  Local-gov       : 327   Bachelors   : 793   Married-civ-
spouse   :2283
##  State-gov       : 205   Masters     : 271   Married-spouse-
absent:  72
##  Self-emp-inc    : 175   Assoc-voc   : 228   Never-married
:1606
##  (Other)         : 141   11th        : 185   Separated
: 167
##  NA's            : 308   (Other)     : 806   Widowed
: 170
##            occupation           relationship
race
##  Prof-specialty : 635   Husband       :1987   Amer-Indian-
Eskimo:  45
##  Exec-managerial: 624   Not-in-family :1315   Asian-Pac-
Islander: 154
##  Craft-repair   : 595   Other-relative: 169   Black
: 507
##  Adm-clerical   : 591   Own-child     : 758   Other
:  34
##  Sales          : 565   Unmarried     : 505   White
:4260
##  (Other)        :1682   Wife          : 266

##  NA's           : 308

##      sex                 country       y.bin
##  Female:1681   United-States:4488   <=50K:3800
##  Male  :3319   Mexico       :  94   >50K :1200
##                Germany      :  27
##                Philippines  :  26
##                Canada       :  24
##                (Other)      : 253
##                NA's         :  88
```

Preparació dels factors

En aquest apartat realitzarem la reagrupació d'aquells factors en classes més generals, això només ho farem per aquelles variables que hem cregut necesaries, de reagrupar en altres clases.

type.employer

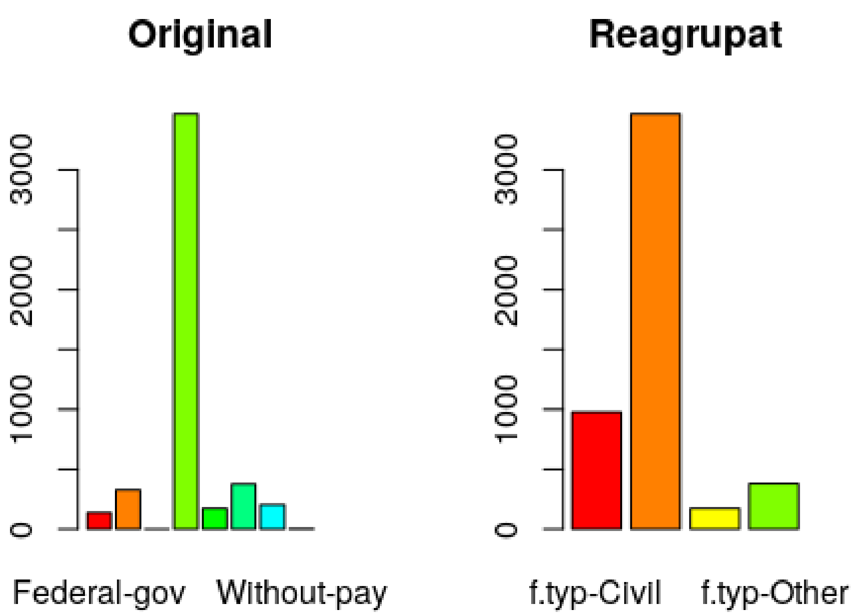
Desició conceptual:

1. Civil => Federal, local and state gov

2. Private
3. SelfEm => Treballadors autonoms amb ingresos.
4. Other => Self-emp-not-inc, Never-worked, Without-pay

```
par(mfrow=c(1,2))

levels(df$type.employer)

## [1] "Federal-gov"      "Local-gov"        "Never-worked"
## [4] "Private"          "Self-emp-inc"     "Self-emp-not-inc"
## [7] "State-gov"        "Without-pay"

barplot(table(df$type.employer),main="Original",col=rainbow(12))
table(df$type.employer)

##
##      Federal-gov        Local-gov     Never-worked
Private
##              138              327                0
3468
##     Self-emp-inc Self-emp-not-inc        State-gov
Without-pay
##              175              376              205
3

tapply(df$hr.per.week,df$type.employer,mean)

##      Federal-gov        Local-gov     Never-worked
Private
##         39.83333         40.99694               NA
40.30421
##     Self-emp-inc Self-emp-not-inc        State-gov
Without-pay
##         48.96000         44.19149         40.10244
25.66667

df$f.type<-1
ll<-which(df$type.employer == "Private");length(ll)

## [1] 3468

df$f.type[ll]<-2
ll<-which(df$type.employer == "Self-emp-inc");length(ll)

## [1] 175

df$f.type[ll]<-3
ll<-which(df$type.employer %in% c("Self-emp-not-inc","Never-
worked","Without-pay"));length(ll)

## [1] 379
```

```
df$f.type[ll]<-4


df$f.type<-
factor(df$f.type,levels=1:4,labels=paste0("f.typ-",c("Civil","Pri
vate","SelfEm","Other")))

summary(df$f.type)

##   f.typ-Civil f.typ-Private  f.typ-SelfEm   f.typ-Other
##           978          3468           175           379

summary(df$type.employer)

##      Federal-gov        Local-gov     Never-worked
Private
##              138              327                0
3468
##     Self-emp-inc Self-emp-not-inc        State-gov
Without-pay
##              175              376              205
3
##             NA's
##              308

barplot(table(df$f.type),main="Reagrupat",col=rainbow(12))
```

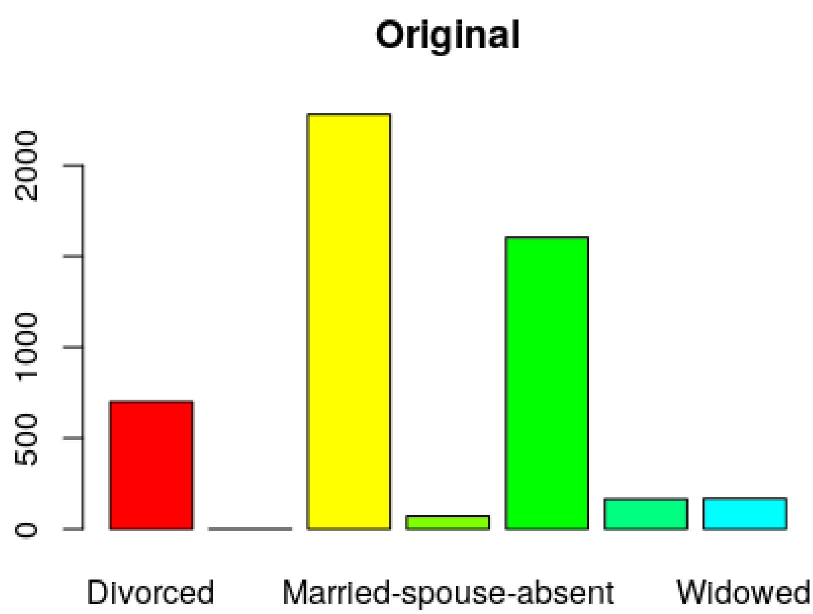


marital

Desició conceptual:

1. Married => tots aquells que esan casats
2. No-married=> Divorced i Separated
3. Never-Married
4. Widowed

```
levels(df$marital)

## [1] "Divorced"              "Married-AF-spouse"     "Married-
civ-spouse"
## [4] "Married-spouse-absent" "Never-married"
"Separated"
## [7] "Widowed"

barplot(table(df$marital),main="Original",col=rainbow(12))
```




```
table(df$marital)

##
##              Divorced     Married-AF-spouse    Married-civ-
spouse
##                   701                     1
2283
## Married-spouse-absent         Never-married
Separated
```

```
##                     72                    1606                  
167 
##               Widowed 
##                   170 
```

```r
tapply(df$hr.per.week,df$marital,mean)
```

```
##              Divorced     Married-AF-spouse    Married-civ-
spouse 
##              40.99572              44.00000              
43.41086 
## Married-spouse-absent         Never-married             
Separated 
##              38.40278              37.18991              
38.13174 
##               Widowed 
##              31.65294 
```

```r
df$f.marital<-1
ll<-which(df$marital %in% c ("Divorced","Separated")); length(ll)
```

```
## [1] 868
```

```r
df$f.marital[ll]<-2
ll<-which(df$marital == "Never-married"); length(ll)
```

```
## [1] 1606
```

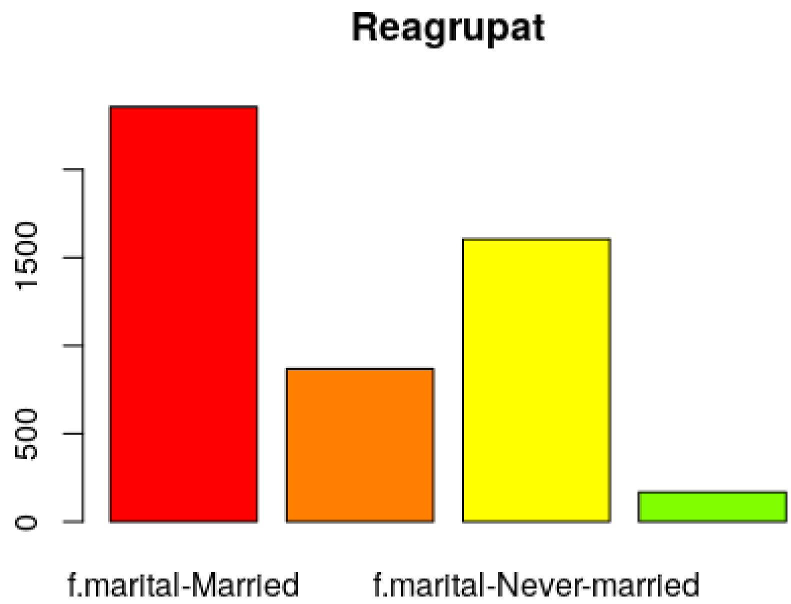
```r
df$f.marital[ll]<-3
ll<-which(df$marital == "Widowed"); length(ll)
```

```
## [1] 170
```

```r
df$f.marital[ll]<-4

df$f.marital<-
factor(df$f.marital,levels=1:4,labels=paste0("f.marital-",c("Married","No- Married","Never-married","Widowed")))

summary(df$f.marital)
```

```
##       f.marital-Married   f.marital-No- Married f.marital-
Never-married 
##                    2356                     868                    
1606 
##       f.marital-Widowed 
##                     170 
```

```r
barplot(table(df$f.marital),main="Reagrupat",col=rainbow(12))
```

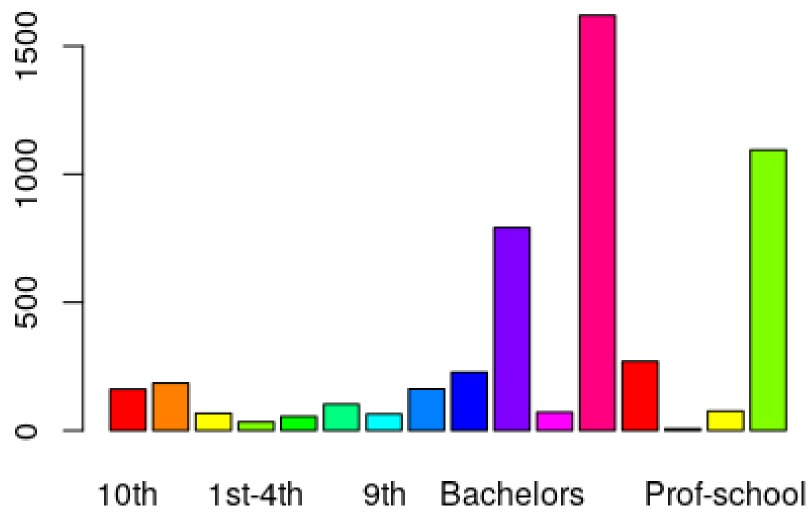


education

Desició conceptual:

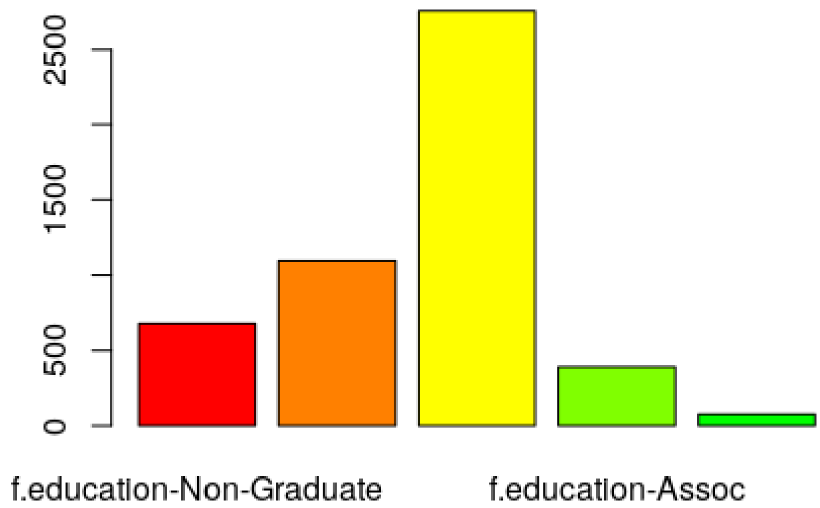
1. Non-Graduatee => tots aquells que no han superat res més que els estudis obligatoris, o bé que no ho han fet
2. Some-college
3. University-Or-More => Doctorate, Bachelors, HS-grad, Masters
4. Assoc => Assoc-acdm, Assoc-voc
5. Prof-school

```
levels(df$education)

##  [1] "10th"         "11th"         "12th"         "1st-4th"
##  [5] "5th-6th"      "7th-8th"      "9th"          "Assoc-acdm"
##  [9] "Assoc-voc"    "Bachelors"    "Doctorate"    "HS-grad"
## [13] "Masters"      "Preschool"    "Prof-school"  "Some-
college"

barplot(table(df$education),col=rainbow(12))
```




```
table(df$education)

##
##         10th         11th         12th      1st-4th      5th-
6th
##          161          185           68           34
56
##      7th-8th          9th   Assoc-acdm    Assoc-voc
Bachelors
##          104           65          162          228
793
##    Doctorate      HS-grad      Masters    Preschool  Prof-
school
##           72         1621          271            7
77
## Some-college
##         1096

tapply(df$hr.per.week,df$education,mean)

##         10th         11th         12th      1st-4th      5th-
6th
##     37.32919     33.69189     38.10294     33.11765
36.80357
##      7th-8th          9th   Assoc-acdm    Assoc-voc
Bachelors
##     39.76923     37.24615     40.93827     42.50439
```

```
42.46784
##    Doctorate      HS-grad      Masters    Preschool  Prof-
school
##     49.41667     40.55706     43.71587     32.42857
47.11688
## Some-college
##     38.82208

df$f.education<-1
ll<-which(df$education == "Some-college")
df$f.education[ll]<-2
ll<-which(df$education %in% c("Doctorate","Bachelors","HS-
grad","Masters"))
df$f.education[ll]<-3
ll<-which(df$education %in% c("Assoc-acdm","Assoc-voc"))
df$f.education[ll]<-4
ll<-which(df$education == "Prof-school")
df$f.education[ll]<-5


df$f.education<-
factor(df$f.education,levels=1:5,labels=paste0("f.education-",c("
Non-Graduate","Some-college","University-Or-More","Assoc","Proof-
school")))

summary(df$f.education)

##       f.education-Non-Graduate       f.education-Some-college
##                            680                           1096
## f.education-University-Or-More             f.education-Assoc
##                           2757                            390
##       f.education-Proof-school
##                             77

barplot(table(df$f.education),col=rainbow(12))
```



Discretització de variables numèriques

En aquest apartat reagruparem totes aquelles variables númeriques en categories més generals, segons el nostre criteri pròpi.

Age

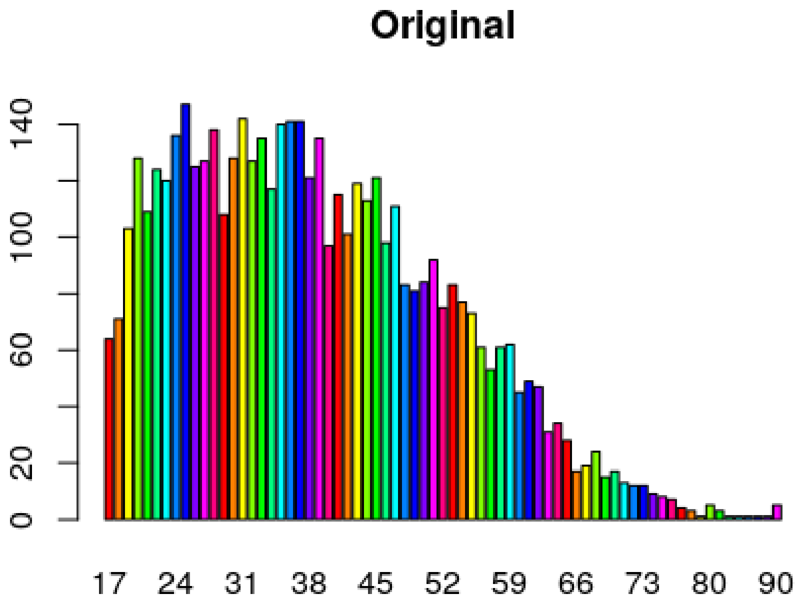
Agruparem el terme edat en els valors de tall que ens donen els quartils de la mostra.

Desició conceptual:

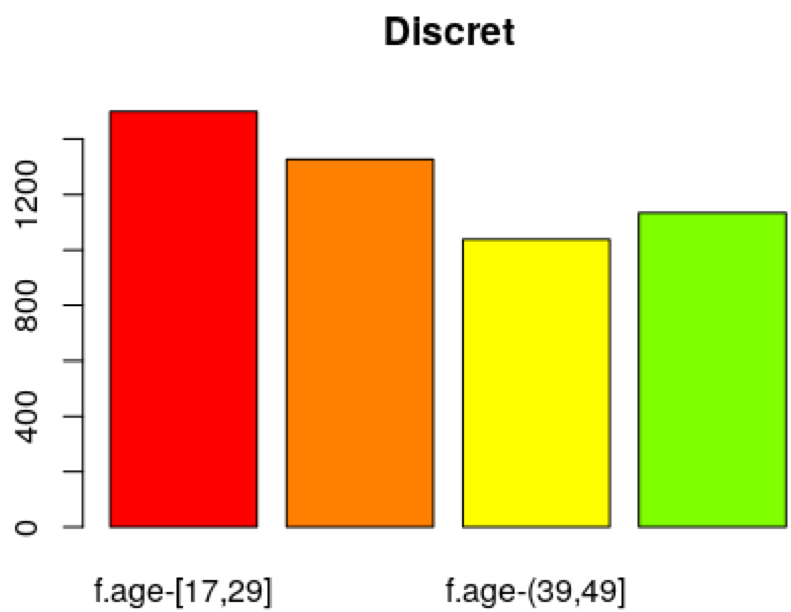
1. [17-29]
2. [30,39]
3. [40,49]
4. [50,90]

```
summary(df$age)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    17.0    27.0    37.0    38.7    48.0    90.0

df$f.age<-factor(cut(df$age,c(17,29,39,49,90),include.lowest =
T))
summary(df$f.age)

## [17,29] (29,39] (39,49] (49,90]
##    1500    1327    1039    1134
```

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

barplot(table(df$age),main="Original",col=rainbow(12))
```




```
barplot(table(df$f.age),main="Discret",col=rainbow(12))
```



capital.gain & capital.loss

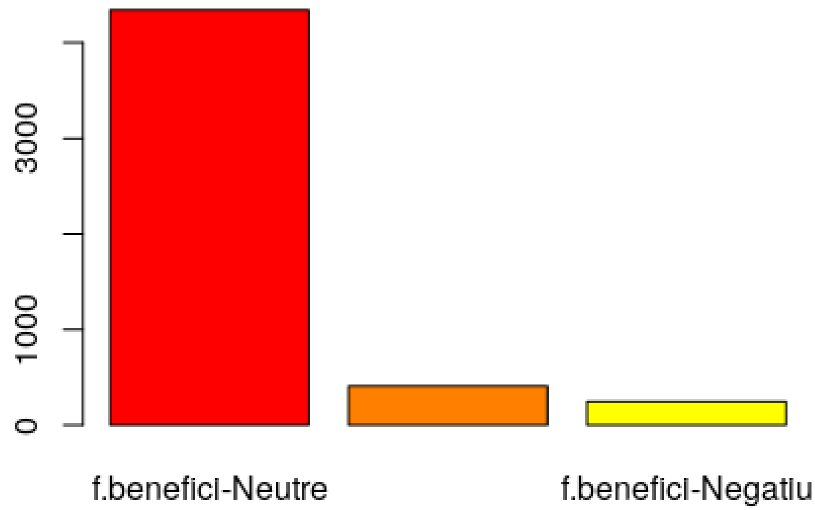
Hem cregut que aquestes variables tenen una relació gran que sería el benefici, es a dir capital.gain - capital.loss.

Desició conceptual:

1. Neutre
2. Positiu
3. Negatiu

```
df$f.benefici<-1 #Neutre
ll<-which((df$capital.gain - df$capital.loss) > 0)
df$f.benefici[ll]<-2 #positiu
ll<-which((df$capital.gain-df$capital.loss) < 0)
df$f.benefici[ll]<-3


df$f.benefici<-
factor(df$f.benefici,levels=1:3,labels=paste0("f.benefici-",c("Ne
utre","Positiu","Negatiu")))

summary(df$f.benefici)

##  f.benefici-Neutre f.benefici-Positiu f.benefici-Negatiu
##               4345                407                248
```

```
par(mfrow=c(1,1))
barplot(table(df$f.benefici),col=rainbow(12))
```




```
par(mfrow=c(1,2))
```

Qualitat de les dades

En aquest apartat, per cada variable contarem el nombre d'errors, missings i outliers. Per definir els outliers i errors, en cada categoria s'establiran valors limits en els que considerarem que a apartir d'allà ja són valors que poden comprometrer la qualitat de les dades. I per cada individu calcularem el nombre total d'errors + missings + outliers i s'afegira com una variable extra del dataframe.

No obstant, per les variables discretes només es calcula el nombre de missings i errors (considerar outliers no té sentit). Considerarem que un error en una variable discreta és tot aquell valor que pren i que no es considera com a possible valor a prendre (tal i com queda explicat a la definició de les dades).

```
iout<-rep(0,nrow(df))
jout<-rep(0,length(vars_con))

ierr<-rep(0,nrow(df))
jerr<-rep(0,ncol(df))
```

```
imiss<-rep(0,nrow(df))
jmiss<-rep(0,ncol(df))

dfaux<-df
```

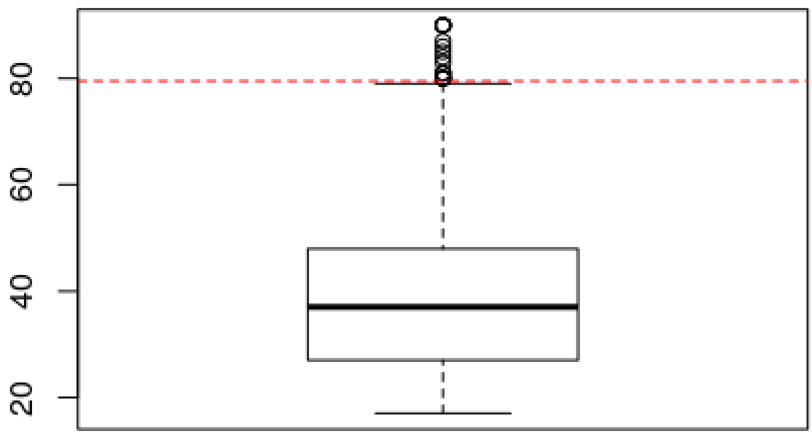
Hem creat un dataframe auxiliar que serà una copia del dataframe original, per poder fer en tot moment la compartiva del que són les dades reals i les dades que anem tractant.

age

Per a la variable "age", establim que tota edat que sigui 0 o bé sigui negatia serà considerada com a error.

```
#Calcul missing data
missingData<-which(is.na(dfaux$age)); length(missingData) #no
missing data

## [1] 0

#Calcul errors (que assignem com NA per a la inputation)
sel<-which(df$age <= 0); length(sel) # errors

## [1] 0

if(length(sel)>0){
  dfaux[sel,"age"]<-NA
}
outers <- calcQ(dfaux$age)

outlier<-which(dfaux$age > outers$souts);length(outlier)

## [1] 0

dfaux[outlier ,"age"]<-NA

outlier<-which(dfaux$age < outers$souti);length(outlier)

## [1] 0

dfaux[outlier ,"age"]<-NA

# 0 outliers severs, es adir que per la variable age no tenim ni
errors ni miss

outlier<-which(dfaux$age > outers$mouts);length(outlier)

## [1] 18

outlier<-which(dfaux$age < outers$mouti);length(outlier)
```

```
## [1] 0

#tenim 0 outliers inferiors.

par(mfrow=c(1,1))
boxplot(df$age)
# A continuació veiem per on tallarien els outliers la mostra
d'entrada.
abline(h= outers$mouts,col="red",lty=2)
```



Per aquesta variable, hem decidit que no hi hauran outliers, ja que els outliers que ens dona la teoria de quartils, creiem que no representen la diversitat d'aquest cens. Per tant mostrem un boxplot on es veu per on hauriem de tallar segons els valors teorics, no obstant per desició pròpia decidim no fer-ho.

workclass

Per aquesta variable, hem establert que com a errors tractarem com a errors a tots aquells valors que no formin part de les categories d'entrada definides al inici.

```
missingData<-which(is.na(dfaux$type.employer));
length(missingData)

## [1] 308
```

```
imiss[missingData]<- imiss[missingData] +1
jmiss[2] <- jmiss[2]+ length(missingData)

#Tractarem com a error tot allo que no pertanyi al rang de valors
que contemplem
sel<-which(df$type.employer != 'Private' & df$type.employer !=
'Self-emp-not-inc' &
             df$type.employer != 'Self-emp-inc' &
df$type.employer != 'Federal-gov' &
             df$type.employer != 'Local-gov' & df$type.employer !
= 'State-gov' &
             df$type.employer != 'Without-pay' & df$type.employer
!= 'Never-worked'); length(sel) # errors
```

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

```
if(length(sel)>0){
  dfaux[sel,"type.employer"]<-NA
}

#Tenim 0 errors
```

Com podem observar no hi han ni errors, no obstant si que tenim algun NA.

fnlwgt

En aquest cas, considerem errors aquells valors iguals o menor a 0. Amb aquesta variable no te sentit calcular els outliers perque ens és inútil.

```
missingData<-which(is.na(dfaux$fnlwgt)); length(missingData) #no
missing data
```

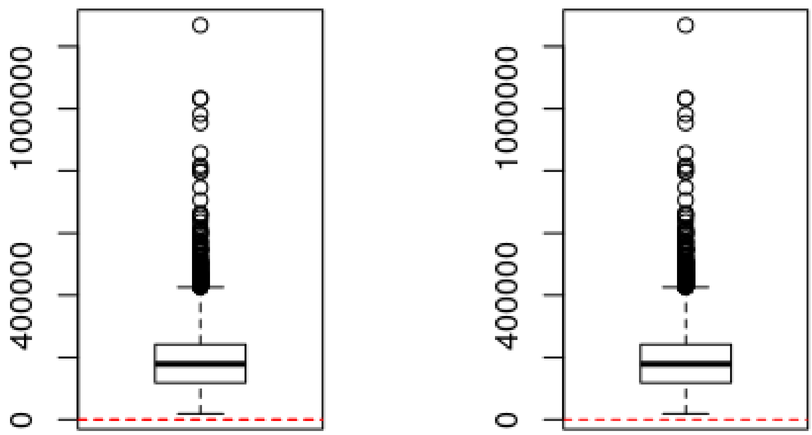
```
## [1] 0
```

```
#no tenim missing data

sel<-which(dfaux$fnlwgt <= 0); length(sel) # errors
```

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

```
if(length(sel)>0){
  dfaux[sel,"fnlwgt"]<-NA
}

par(mfrow=c(1,2))
boxplot(dfaux$fnlwgt)
abline( h= outers$mouts, col="red", lty= 2)
abline( h= outers$souts, col="red", lty= 2)
```

```
boxplot(df$fnlwgt)
abline( h= outers$mouts, col="red", lty= 2)
```



Reportem que no tenim cap missing value ni errors.

education

Seguim l'esquema inicial pel càlcul de missings i errors a variables discretes.

```
missingData<-which(is.na(dfaux$education)); length(missingData)

## [1] 0

#no tenim missing data
sel<-which(df$education != 'Bachelors' & df$education != 'Some-
college' &
             df$education != '11th' & df$education != 'HS-grad' &
             df$education != 'Prof-school' & df$education !=
'Assoc-acdm' &
             df$education != 'Assoc-voc' & df$education != '9th'
&
             df$education != '7th-8th' & df$education != '12th' &
             df$education != 'Masters' & df$education != '1st-
4th' &
             df$education != '10th' & df$education != 'Doctorate'
&
```

```
             df$education != '5th-6th' & df$education !=
'Preschool'); length(sel) # errors

## [1] 0

if(length(sel)>0){
  dfaux[sel,"education"]<-NA
}
#no tenim errors
```

No tenim ni missing data ni errors.

education.num

Veiem que aquesta variable sembla ser una discretització de la variable “education” (o que estan bastant lligades).

```
df %>% slice (1:20) %>% select(education,education.num)

##       education education.num
## 1          11th             7
## 2  Some-college            10
## 3       HS-grad             9
## 4     Assoc-voc            11
## 5   Prof-school            15
## 6       HS-grad             9
## 7  Some-college            10
## 8       7th-8th             4
## 9       HS-grad             9
## 10    Doctorate            16
## 11    Assoc-voc            11
## 12 Some-college            10
## 13      HS-grad             9
## 14      HS-grad             9
## 15    Assoc-voc            11
## 16    Bachelors            13
## 17 Some-college            10
## 18      HS-grad             9
## 19      HS-grad             9
## 20      Masters            14

summary(dfaux$education.num)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1.00    9.00   10.00   10.04   12.00   16.00

misingData<-which(is.na(dfaux$education.num));length(missingData)

## [1] 0
```

```
# no hi ha errors
sel<- which(dfaux$education.num < 1 | dfaux$education.num >
99);length(sel)

## [1] 0

#no hi ha errors
```

No tenim ni missing data ni errors. Com veiem al summary, no hi ha valors extrems i per tant considerem que no hi ha outliers.

marital status

Repetim càlcul de missing i errors per variables discretes.

```
missingData<-which(is.na(dfaux$marital)); length(missingData)

## [1] 0

sel<-which(df$marital != 'Married-civ-spouse' & df$marital !=
'Divorced' &
             df$marital != 'Never-married' & df$marital !=
'Separated' &
             df$marital != 'Widowed' & df$marital != 'Married-
spouse-absent' &
             df$marital != 'Married-AF-spouse'); length(sel) #
errors

## [1] 0

if(length(sel)>0){
  dfaux[sel,"marital"]<-NA
}
```

No tenim ni missing data ni errors.

occupation

Repetim càlcul de missing i errors per variables discretes.

```
missingData<-which(is.na(dfaux$occupation)); length(missingData)

## [1] 308

imiss[missingData]<- imiss[missingData] +1
jmiss[7]<- jmiss[7] + length(missingData)

sel<-which(df$occupation != 'Tech-support' & df$occupation !=
'Craft-repair' &
             df$occupation != 'Other-service' & df$occupation !=
'Sales' &
             df$occupation != 'Exec-managerial' & df$occupation !
```

```
= 'Prof-specialty' &
             df$occupation != 'Handlers-cleaners' & df$occupation
!= 'Machine-op-inspct' &
             df$occupation != 'Adm-clerical' & df$occupation !=
'Farming-fishing' &
             df$occupation != 'Transport-moving' & df$occupation
!= 'Priv-house-serv' &
             df$occupation != 'Protective-serv' & df$occupation !
= 'Armed-Forces'); length(sel) # errors

## [1] 0

if(length(sel)>0){
  dfaux[sel,"occupation"]<-NA
}
```

En aquest cas tenim 308 missing values i cap error.

relationship

Repetim càlcul de missing i errors per variables discretes.

```
missingData<-which(is.na(dfaux$relationship));
length(missingData)

## [1] 0

sel<-which(df$relationship != 'Wife' & df$relationship != 'Own-
child' &
             df$relationship != 'Husband' & df$relationship !=
'Not-in-family' &
             df$relationship != 'Other-relative' &
df$relationship != 'Unmarried'); length(sel) # errors

## [1] 0

if(length(sel)>0){
  dfaux[sel,"relationship"]<-NA
}
```

No tenim ni missing data ni errors.

race

Repetim càlcul de missing i errors per variables discretes.

```
missingData<-which(is.na(dfaux$race)); length(missingData)

## [1] 0

sel<-which(df$race != 'White' & df$race != 'Asian-Pac-Islander' &
             df$race != 'Amer-Indian-Eskimo' & df$race != 'Other'
```

```
&
             df$race != 'Black'); length(sel) # errors
```

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

```
if(length(sel)>0){
  dfaux[sel,"race"]<-NA
}
```

No tenim ni missing data ni errors.

sex

Repetim càlcul de missing i errors per variables discretes.

```
missingData<-which(is.na(dfaux$sex)); length(missingData)
```

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

```
sel<-which(df$sex != 'Female' & df$sex != 'Male'); length(sel) #
errors
```

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

```
if(length(sel)>0){
  dfaux[sel,"race"]<-NA
}
```

No tenim ni missing data ni errors.

capital.gain

Considerem errors aquells valors inferiors a 0 o iguals a 99999. D'altra banda, calculem els outliers i per aquells valors considerats com a "several outlier" els posem a NA per a que posteriorment siguin inputats.

```
summary(dfaux$capital.gain)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##       0       0       0    1073       0   99999
```

```
#Calcul missing data
missingData<-which(is.na(dfaux$capital.gain));
length(missingData) #no missing data
```

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

```
sel<-which(dfaux$capital.gain < 0 | dfaux$capital.gain == 99999);
length(sel) # errors
```

```
## [1] 25
```

```
ierr[sel]<-ierr[sel] +1
jerr[11]<- jerr[11]+length(sel)

if(length(sel)>0){
  dfaux[sel,"capital.gain"]<-NA
}

aux<- sort(dfaux[dfaux$capital.gain >
0,"capital.gain"],decreasing=TRUE); aux[1:30]
```

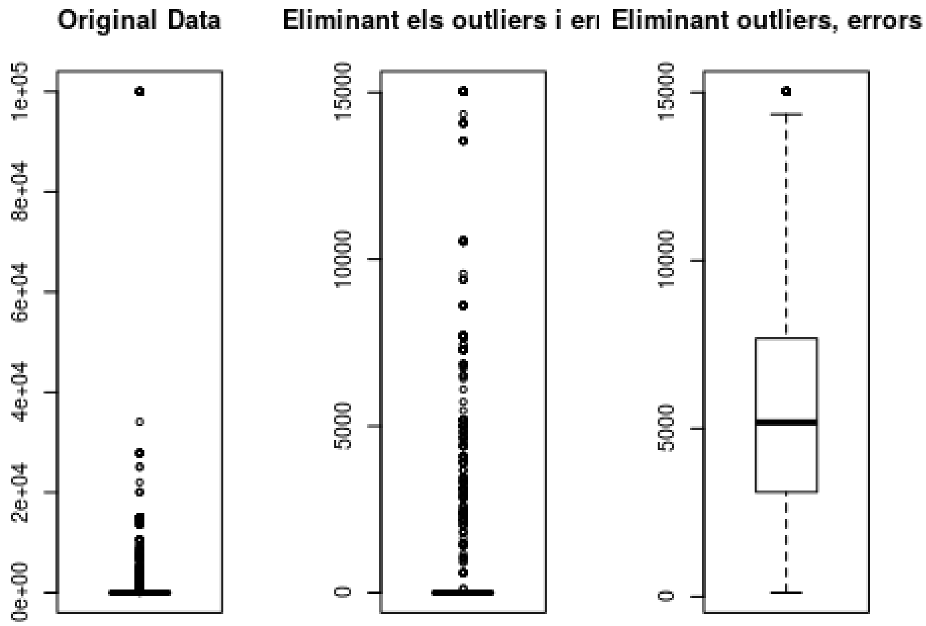
```
##  [1] 34095 27828 27828 27828 27828 27828 27828 27828 27828
25124 25124
## [12] 22040 20051 20051 20051 15024 15024 15024 15024 15024
15024 15024
## [23] 15024 15024 15024 15024 15024 15024 15024 15024
```

Decidim per el criteri propi establir que tot capital gain superior a 20000 serà considerat outlier. No considerem outlier inferior, perque les dades que siguin negatives(si hi ha), hauran estat tractades com a errors.

```
outlimit <- 20000

outlier<-which(dfaux$capital.gain > outlimit);length(outlier)
```

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

```
ierr[outlier] <- ierr[outlier]+1
jerr[11]<- jerr[11] + length(outlier)
dfaux[outlier ,"capital.gain"]<-NA


par(mfrow=c(1,3))
boxplot(df$capital.gain,main="Original Data")
boxplot(dfaux$capital.gain, main= "Eliminant els outliers i
errors")
boxplot(dfaux[dfaux$capital.gain>0,"capital.gain"], main=
"Eliminant outliers, errors i 0")
```



En el primer boxplot no veiem res al respecte, ja que la majoria de dades són 0, per tant mostrem que si treiem les que són 0 del segon boxplot, on hem posat els outliers a NA, ens queda un boxplot bastant bonic.

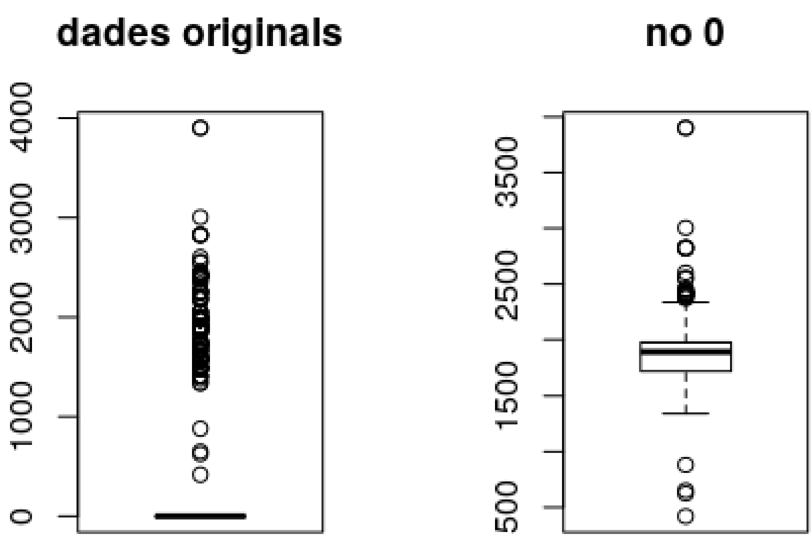
No tenim errors pero tenim 407 missing data. Els several outliers han estat posats a NA.

capital.loss

Calculem errors, missings i outliers de manera anàloga a com s'ha fet amb la variable capital.loss

```
summary(dfaux$capital.loss)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00    0.00    0.00   94.46    0.00 3900.00

missingData<-which(is.na(dfaux$capital.loss));
length(missingData) #no missing data

## [1] 0

sel<-which(df$capital.loss < 0 | df$capital.los == 99999);
length(sel) # errors

## [1] 0
```

```
if(length(sel)>0){
  dfaux[sel,"capital.loss"]<-NA
}
#no hi han errors

aux<- sort(dfaux[dfaux$capital.loss >
0,"capital.loss"],decreasing=TRUE); aux[1:30]

##  [1] 3900 3900 3004 2824 2824 2824 2824 2603 2559 2547 2457
2444 2444 2415
## [15] 2415 2415 2415 2415 2415 2415 2415 2415 2415 2415 2415
2415 2392 2377
## [29] 2377 2339

par(mfrow=c(1,2))
boxplot(df$capital.loss,main="dades originals")
boxplot(dfaux[dfaux$capital.loss>0,"capital.loss"],main="no 0")
```



No tenim errors pero tenim 248 missing data. En aquesta variable no tenim en compte outliers, ja que després d’analitzar les dades hem vist que no hi ha cap valor tant extrem com per a considerar-lo outlier.

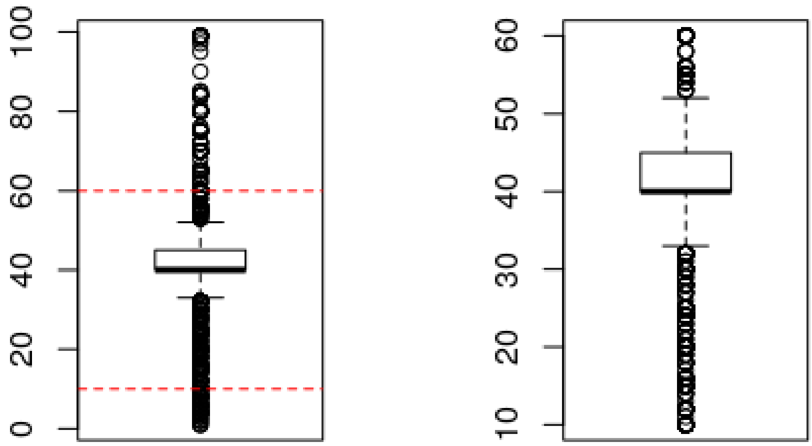
hr.per.week

Considerem errors aquells valors que siguin menor o igual a 0 o iguals a 99.

```
summary(dfaux$hr.per.week)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1.00   40.00   40.00   40.43   45.00   99.00

ll<-which(is.na(dfaux$hr.per.week));ll

## integer(0)

#no tenim na
sel<-which(dfaux$hr.per.week <= 0 | dfaux$hr.per.week ==99);
length(sel) # errors

## [1] 15

ierr[sel]<- ierr[sel]+1
jerr[13]<- jerr[13]+length(sel)
dfaux[sel,"hr.per.week"]<-NA
```

Tenint en compte que la jornada labroal màxima es de 40 hores setmanals, establirem el limit a un 150% d'aquesta, es a dir 60 hores. Establim un limit inferior també, ja que considerarem que treballar menys de 10 hores serà outlier

```
outlimit<- 60
outlier<-which(dfaux$hr.per.week > outlimit );length(outlier)
#outliers superiors critics

## [1] 153

ierr[outlier]<- ierr[outlier] +1
jerr[13]<-jerr[13]+length(outlier)
dfaux[outlier,"hr.per.week"]<-NA

outlimit<- 10
outlier<-which(dfaux$hr.per.week < outlimit );length(outlier)
#outliers superiors critics

## [1] 80

ierr[outlier]<- ierr[outlier] +1
jerr[13]<-jerr[13]+length(outlier)
dfaux[outlier,"hr.per.week"]<-NA

par(mfrow=c(1,2))
boxplot(df$hr.per.week)
abline(h= 60,col="red",lty=2)
abline(h= 10,col="red",lty=2)

boxplot(dfaux$hr.per.week)
```



No tenim errors ni missing values. Els several outliers han estat posats a NA.

country

```
missingData<-which(is.na(dfaux$country)); length(missingData)

## [1] 88

imiss[missingData]<- imiss[missingData] + 1
jmiss[14]<-jmiss[14]+length(missingData)

sel<-which(df$country != 'United-States' & df$country !=
'Cambodia' &
             df$country != 'England' & df$country != 'Puerto-
Rico' &
             df$country != 'Canada' & df$country != 'Germany' &
             df$country != 'Outlying-US(Guam-USVI-etc)' &
df$country != 'India' &
             df$country != 'Japan' & df$country != 'Greece' &
             df$country != 'South' & df$country != 'China' &
             df$country != 'Cuba' & df$country != 'Iran' &
             df$country != 'Honduras' & df$country !=
'Philippines' &
             df$country != 'Italy' & df$country != 'Poland' &
             df$country != 'Jamaica' & df$country != 'Vietnam' &
             df$country != 'Mexico' & df$country != 'Portugal' &
             df$country != 'Ireland' & df$country != 'France' &
```

```
             df$country != 'Dominican-Republic' & df$country !=
'Laos' &
             df$country != 'Ecuador' & df$country != 'Taiwan' &
             df$country != 'Haiti' & df$country != 'Columbia' &
             df$country != 'Hungary' & df$country != 'Guatemala'
&
             df$country != 'Nicaragua' & df$country != 'Scotland'
&
             df$country != 'Thailand' & df$country !=
'Yugoslavia' &
             df$country != 'El-Salvador' & df$country !=
'Trinadad&Tobago' &
             df$country != 'Peru' & df$country != 'Hong' &
             df$country != 'Holand-Netherlands'); length(sel) #
errors

## [1] 0

if(length(sel)>0){
  dfaux[sel,"country"]<-NA
}
```

Tenim 88 missing values i no tenim cap error.

y.bin

En aquest cas estem tractant una variable binaria, per tant només té sentit analitzar el nombre de missing values.

```
missingData<-which(is.na(dfaux$y.bin)); length(missingData)

## [1] 0
```

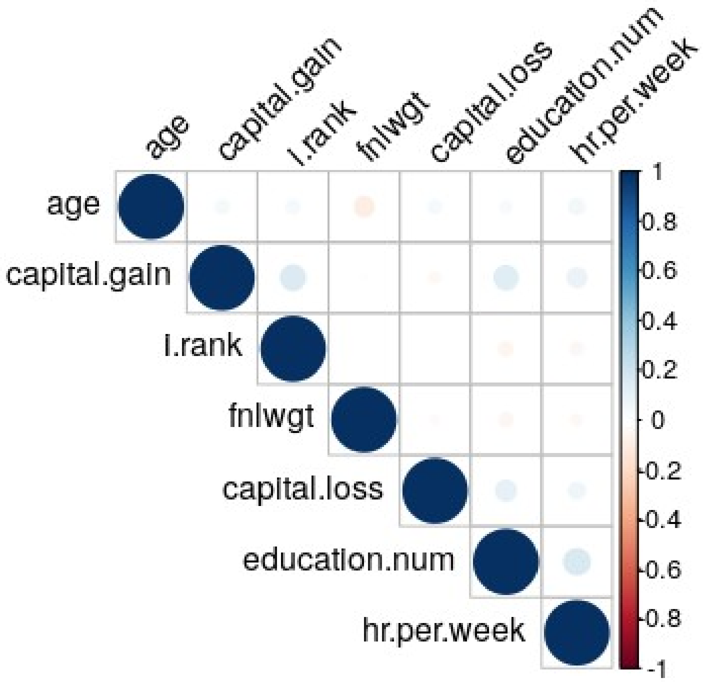
No tenim missing values.   Tot aquest procés es podria fer per les variables reagrupades i discretitzades. No obstant, considerem que no té sentit ja que previament ja estem tractant tots els casos.

Recompte d’errors, per individu

A continuació veurem quants errors te cada individu, i també veurem la mitjana d’error per cada clase. Realitzarem la mitjana fent l suma de error, outliers i missing dividit entre 3, de tal manera que veurem per cada clase quina es la mitjana d’errors outliers i missings.

```
#afegim la variable que es la suma dels errors missings i
outliers al df
dfaux$i.rank<-  ierr + imiss + iout

#realitzar la mitjana de tot per variable.
aux<-(countNA(dfaux)$mis_col)/3
```

```r
install.packages("corrplot")

## Installing package into '/usr/local/lib/R/site-library'
## (as 'lib' is unspecified)

library(corrplot)

## corrplot 0.84 loaded

t<- df[,vars_con]
df$i.rank <- dfaux$i.rank
t$i.rank <- df[,"i.rank"]
corMatrix<-cor(t); corMatrix

##                         age        fnlwgt education.num
capital.gain
## age             1.00000000 -0.0938874683    0.03748753
0.048825838
## fnlwgt         -0.09388747  1.0000000000   -0.04762524
0.008635798
## education.num  0.03748753 -0.0476252438    1.00000000
0.139627539
## capital.gain   0.04882584  0.0086357980    0.13962754
1.000000000
## capital.loss   0.04621191 -0.0225491721    0.10466473 -
0.032178822
## hr.per.week    0.05832764 -0.0306001824    0.16637797
0.089539722
## i.rank         0.04750264 -0.0003940381   -0.05039291
0.151180385
##                capital.loss hr.per.week        i.rank
## age             0.046211911  0.05832764  0.0475026386
## fnlwgt         -0.022549172 -0.03060018 -0.0003940381
## education.num  0.104664731  0.16637797 -0.0503929118
## capital.gain  -0.032178822  0.08953972  0.1511803854
## capital.loss   1.000000000  0.06633876  0.0029919329
## hr.per.week    0.066338758  1.00000000 -0.0419182111
## i.rank         0.002991933 -0.04191821  1.0000000000

corrplot(corMatrix, type = "upper", order = "hclust",
         tl.col = "black", tl.srt = 45)
```



Veiem que la variable i.rank, aquella que resumeix quants errors/missings/outliers hi ha per individu, no te gaire correlació amb les altres variables (numériques).

Imputació de variables

En aquest apartat el que realitzarem és per totes aquelles variables que hem categoritzat com preillosses, és a dir que estan en la categoría err/miss/out, farem una aproximació del valor o categoria, mitjançant imputePCA o imputeMCA, respectivament.

```
install.packages("missMDA")

## Installing package into '/usr/local/lib/R/site-library'
## (as 'lib' is unspecified)

library(missMDA)

# numericas
res.num<-imputePCA(dfaux[,vars_con])
summary(res.num$completeObs)

##       age           fnlwgt         education.num
capital.gain
##  Min.   :17.0   Min.   :  18827   Min.   : 1.00   Min.   :
0.0
```

```
##  1st Qu.:27.0   1st Qu.: 118008   1st Qu.: 9.00   1st Qu.:
0.0
##  Median :37.0   Median : 178950   Median :10.00   Median :
0.0
##  Mean   :38.7   Mean   : 192215   Mean   :10.04   Mean   :
502.9
##  3rd Qu.:48.0   3rd Qu.: 241215   3rd Qu.:12.00   3rd Qu.:
0.0
##  Max.   :90.0   Max.   :1268339   Max.   :16.00
Max.   :15024.0
##   capital.loss      hr.per.week
##  Min.   :   0.00   Min.   :10.00
##  1st Qu.:   0.00   1st Qu.:40.00
##  Median :   0.00   Median :40.00
##  Mean   :  94.46   Mean   :39.84
##  3rd Qu.:   0.00   3rd Qu.:43.03
##  Max.   :3900.00   Max.   :60.00
```

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

```
##       age            fnlwgt         education.num
capital.gain
##  Min.   :17.0   Min.   :  18827   Min.   : 1.00   Min.   :
0.0
##  1st Qu.:27.0   1st Qu.: 118008   1st Qu.: 9.00   1st Qu.:
0.0
##  Median :37.0   Median : 178950   Median :10.00   Median :
0.0
##  Mean   :38.7   Mean   : 192215   Mean   :10.04   Mean   :
499.4
##  3rd Qu.:48.0   3rd Qu.: 241215   3rd Qu.:12.00   3rd Qu.:
0.0
##  Max.   :90.0   Max.   :1268339   Max.   :16.00
Max.   :15024.0
##                                                   NA's   :40

##   capital.loss      hr.per.week
##  Min.   :   0.00   Min.   :10.00
##  1st Qu.:   0.00   1st Qu.:40.00
##  Median :   0.00   Median :40.00
##  Mean   :  94.46   Mean   :39.81
##  3rd Qu.:   0.00   3rd Qu.:45.00
##  Max.   :3900.00   Max.   :60.00
##                    NA's   :248
```

Per a les variables numériques, veiem que no hi ha gran diferència entre el summary de la original, es a dir amb els NA, que a la actual, els valors mean i quartils, no es veuen afectats de gran manera, així que acceptem aquesta imputació.

```
# descriptivas
res.des<-imputeMCA(dfaux[,vars_dis])
summary(res.des$completeObs)
```

```
##           type.employer         education
marital
##  Federal-gov     : 138   HS-grad     :1621   Divorced
: 701
##  Local-gov       : 327   Some-college:1096   Married-AF-spouse
:   1
##  Private         :3776   Bachelors   : 793   Married-civ-
spouse   :2283
##  Self-emp-inc    : 175   Masters     : 271   Married-spouse-
absent:  72
##  Self-emp-not-inc: 376   Assoc-voc   : 228   Never-married
:1606
##  State-gov       : 205   11th        : 185   Separated
: 167
##  Without-pay     :   3   (Other)     : 806   Widowed
: 170
##            occupation           relationship
race
##  Adm-clerical   : 716   Husband       :1987   Amer-Indian-
Eskimo:  45
##  Prof-specialty : 681   Not-in-family :1315   Asian-Pac-
Islander: 154
##  Craft-repair   : 643   Other-relative: 169   Black
: 507
##  Exec-managerial: 638   Own-child     : 758   Other
:  34
##  Sales          : 565   Unmarried     : 505   White
:4260
##  Other-service  : 562   Wife          : 266

##  (Other)        :1195

##      sex                country       y.bin
##  Female:1681   United-States:4576   <=50K:3800
##  Male  :3319   Mexico       :  94   >50K :1200
##                Germany      :  27
##                Philippines  :  26
##                Canada       :  24
##                Puerto-Rico  :  22
##                (Other)      : 231
```

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

```
##           type.employer         education
marital
##  Private         :3468   HS-grad     :1621   Divorced
: 701
```

```
##  Self-emp-not-inc: 376   Some-college:1096   Married-AF-spouse
:   1
##  Local-gov       : 327   Bachelors   : 793   Married-civ-
spouse   :2283
##  State-gov       : 205   Masters     : 271   Married-spouse-
absent:  72
##  Self-emp-inc    : 175   Assoc-voc   : 228   Never-married
:1606
##  (Other)         : 141   11th        : 185   Separated
: 167
##  NA's            : 308   (Other)     : 806   Widowed
: 170
##            occupation           relationship
race
##  Prof-specialty : 635   Husband       :1987   Amer-Indian-
Eskimo:  45
##  Exec-managerial: 624   Not-in-family :1315   Asian-Pac-
Islander: 154
##  Craft-repair   : 595   Other-relative: 169   Black
: 507
##  Adm-clerical   : 591   Own-child     : 758   Other
:  34
##  Sales          : 565   Unmarried     : 505   White
:4260
##  (Other)        :1682   Wife          : 266

##  NA's           : 308

##      sex               country       y.bin
##  Female:1681   United-States:4488   <=50K:3800
##  Male  :3319   Mexico       :  94   >50K :1200
##                Germany      :  27
##                Philippines  :  26
##                Canada       :  24
##                (Other)      : 253
##                NA's         :  88
```

El mateix que per les variables numériques, veiem ara amb les descriptives. No hi han grans alteracions de les dades, que ens facin rebutjar la imputació d’aquestes.

Un cop tenim les dades correctes, procedim a modificarles directament en el data frame.

```
dfaux[,vars_con]<- res.num$completeObs
dfaux[,vars_dis]<- res.des$completeObs
```

Profiling

En aquest apartat veurem la rellevància de cada variable, respecte els nostres targets (hr.per.week, i y.bin).

En primer lloc realitzarem el profilling per el target numéric (hr.per.week)

hr.per.week

```
vars<-names(dfaux)[c(13,1,3,5:12,14:21)]


condes(dfaux[,vars],1,prob=0.01)

## $quanti
##                correlation      p.value
## education.num  0.19651751 1.029850e-44
## age            0.09969124 1.605256e-12
## capital.gain   0.08784074 4.916267e-10
## capital.loss   0.05439922 1.188463e-04
## i.rank        -0.09451823 2.130714e-11
##
## $quali
##                       R2       p.value
## relationship 0.110607964 2.669338e-124
## occupation   0.077085618  1.833097e-77
## marital      0.069073334  3.757814e-74
## f.marital    0.065725288  2.552400e-73
## sex          0.060532871  7.785357e-70
## y.bin        0.052782197  6.885118e-61
## f.age        0.048346203  2.166215e-53
## f.education  0.045695922  2.132574e-49
## f.type       0.021378895  2.988465e-23
## f.benefici   0.007718743  3.908575e-09
## race         0.005762989  8.287345e-06
##
## $category
##                                                 Estimate
p.value
## relationship=Husband                           4.7763436
2.237082e-84
## sex=Male                                       2.4804003
7.785357e-70
## y.bin=>50K                                     2.5619753
6.885118e-61
## marital=Married-civ-spouse                     3.0210095
4.213715e-58
## f.marital=f.marital-Married                    3.8513373
2.697405e-55
## occupation=Exec-managerial                     4.0086635
```

```
8.527091e-25
## f.education=f.education-University-Or-More  0.6826905
6.183215e-24
## f.age=f.age-(39,49]                          2.0493493
6.515364e-18
## f.type=f.typ-SelfEm                          4.2681764
9.710092e-17
## f.age=f.age-(29,39]                          1.4820344
3.633890e-14
## occupation=Transport-moving                  3.6494035
5.763996e-08
## f.education=f.education-Proof-school         5.0342136
2.239735e-07
## race=White                                   0.8335159
8.332228e-07
## f.benefici=f.benefici-Positiu                0.9069227
9.040816e-07
## occupation=Prof-specialty                    1.9391430
6.048272e-06
## f.type=f.typ-Other                           0.4693562
1.183258e-05
## relationship=Unmarried                       0.1918107
4.264665e-04
## f.benefici=f.benefici-Negatiu                0.7312630
5.225828e-04
## f.education=f.education-Assoc                0.8552218
2.636731e-03
## occupation=Farming-fishing                   2.5938377
3.037365e-03
## country=Japan                               12.6081484
7.812425e-03
## country=Philippines                         -6.1995439
9.695281e-04
## relationship=Other-relative                 -0.9440270
3.946402e-04
## occupation=Priv-house-serv                  -7.2369833
5.722396e-05
## occupation=Handlers-cleaners                -2.1882230
2.888862e-05
## race=Black                                  -1.5315953
1.843173e-07
## f.type=f.typ-Civil                          -3.0347255
1.184541e-07
## relationship=Wife                           -1.4878873
4.948176e-08
## f.education=f.education-Some-college        -1.9722400
1.585957e-08
## f.benefici=f.benefici-Neutre                -1.6381857
5.015363e-10
## occupation=Adm-clerical                     -2.3764595
```

```
2.437808e-17
## f.marital=f.marital-Widowed                      -4.6553225
1.329083e-18
## marital=Widowed                                   -5.6088598
1.329083e-18
## f.education=f.education-Non-Graduate              -4.5998860
1.949181e-33
## occupation=Other-service                          -4.2514764
2.829742e-35
## f.marital=f.marital-Never-married                 -1.0385328
1.938486e-43
## marital=Never-married                             -1.9920701
1.938486e-43
## f.age=f.age-[17,29]                               -3.1297624
1.464304e-46
## y.bin=<=50K                                       -2.5619753
6.885118e-61
## sex=Female                                        -2.4804003
7.785357e-70
## relationship=Own-child                            -4.1993299
1.172618e-76
```

Veiem que les variables que tenen major correlació amb el target quantitat d'hores treballades, són education.num i relationship. amb correlacions superiors al 0.1.

També observem que hi han variables que tenen importància, no obstant no tanta com les que hem esmentat anteriorment, i per últim tenim aquelles variables que realment no tenen molta relevancia, com seria la raça. Aquesta particularment ens ha sobtat, ja que a priori creiem que anava a ser una de les que anava a tenir major relevància ja que habitualment creiem que la raça ens limita al moment de establir un sou.

No ens ha sorprès que la variable i.rank, la que defineix el nombre de missings i d'errors sigui inversament proporcional al número d'hores treballades, ja a major nombre d'hores treballades indica que hi ha major nombre d'hores d'estudi, amb el que podem concloure que aquelles persones que més anys han estudiat, generen menys errors o no es deixen les dades per completar, en enquestes del tipus que es planteja en aquest informe.

y.bin

```
vars<-names(dfaux)[c(15,1,3,7:10,13:14,16:21)]

catdes(dfaux[,vars],1,prob=0.01)

##
## Link between the cluster variable and the categorical
```

```
variables (chi-square test)
##
==================================================================
================
##                      p.value df
## relationship 4.196083e-224  5
## f.marital    3.478295e-203  3
## occupation   1.431812e-134 13
## f.benefici   1.777278e-106  2
## f.age         2.305331e-85  3
## f.education   2.568685e-66  4
## sex           2.684671e-42  1
## f.type        6.855541e-28  3
## race          1.366388e-13  4
##
## Description of each cluster by the categories
## =============================================
## $`<=50K`
##                                              Cla/Mod
Mod/Cla Global
## f.marital=f.marital-Never-married           94.95641
40.1315789  32.12
## f.age=f.age-[17,29]                         93.53333
36.9210526  30.00
## f.benefici=f.benefici-Neutre                81.17376
92.8157895  86.90
## relationship=Own-child                      99.34037
19.8157895  15.16
## occupation=Other-service                    97.50890
14.4210526  11.24
## sex=Female                                  87.56692
38.7368421  33.62
## f.education=f.education-Non-Graduate        94.26471
16.8684211  13.60
## relationship=Not-in-family                  88.89734
30.7631579  26.30
## f.marital=f.marital-No- Married             91.12903
20.8157895  17.36
## relationship=Unmarried                      94.65347
12.5789474  10.10
## occupation=Adm-clerical                     88.12849
16.6052632  14.32
## race=Black                                  88.95464
11.8684211  10.14
## relationship=Other-relative                 97.04142
4.3157895   3.38
## occupation=Handlers-cleaners                94.22222
5.5789474   4.50
## country=Mexico                              95.74468
2.3684211   1.88
```

```
## f.marital=f.marital-Widowed                      90.58824
4.0526316   3.40
## f.type=f.typ-Private                             77.99885
71.1842105  69.36
## occupation=Machine-op-inspct                     86.46865
6.8947368   6.06
## f.education=f.education-Some-college             80.29197
23.1578947  21.92
## occupation=Priv-house-serv                      100.00000
0.6578947   0.50
## race=Amer-Indian-Eskimo                          93.33333
1.1052632   0.90
## f.age=f.age-(29,39]                              73.17257
25.5526316  26.54
## country=United-States                            75.21853
90.5789474  91.52
## f.age=f.age-(49,90]                              68.16578
20.3421053  22.68
## race=White                                       74.15493
83.1315789  85.20
## f.education=f.education-University-Or-More  71.63584
51.9736842  55.14
## f.type=f.typ-SelfEm                              40.57143
1.8684211   3.50
## relationship=Wife                                46.61654
3.2631579   5.32
## f.age=f.age-(39,49]                              62.84889
17.1842105  20.78
## f.education=f.education-Proof-school             16.88312
0.3421053   1.54
## f.benefici=f.benefici-Negatiu                    42.74194
2.7894737   4.96
## occupation=Prof-specialty                        54.03818
9.6842105  13.62
## sex=Male                                         70.14161
61.2631579  66.38
## occupation=Exec-managerial                       51.88088
8.7105263  12.76
## f.benefici=f.benefici-Positiu                    41.03194
4.3947368   8.14
## relationship=Husband                             55.96376
29.2631579  39.74
## f.marital=f.marital-Married                      56.45161
35.0000000  47.12
##                                                       p.value
v.test
## f.marital=f.marital-Never-married          9.012756e-125
23.758325
## f.age=f.age-[17,29]                              2.817808e-95
20.709945
```

```
## f.benefici=f.benefici-Neutre                1.023816e-92
20.423976
## relationship=Own-child                      1.064373e-89
20.081814
## occupation=Other-service                    5.499322e-51
15.019169
## sex=Female                                  1.146411e-45
14.184277
## f.education=f.education-Non-Graduate        1.326698e-41
13.512107
## relationship=Not-in-family                  1.722531e-41
13.492874
## f.marital=f.marital-No- Married             1.046142e-35
12.473145
## relationship=Unmarried                      6.071266e-32
11.762765
## occupation=Adm-clerical                     2.420233e-18
8.735760
## race=Black                                  1.022517e-14
7.736424
## relationship=Other-relative                 1.448749e-14
7.691980
## occupation=Handlers-cleaners                1.132376e-13
7.424464
## country=Mexico                              2.048243e-07
5.194905
## f.marital=f.marital-Widowed                 8.112097e-07
4.932651
## f.type=f.typ-Private                        8.381738e-07
4.926262
## occupation=Machine-op-inspct                3.447791e-06
4.642164
## f.education=f.education-Some-college        1.338104e-04
3.819338
## occupation=Priv-house-serv                  1.028205e-03
3.282693
## race=Amer-Indian-Eskimo                     2.821914e-03
2.986499
## f.age=f.age-(29,39]                         5.232697e-03  -
2.792348
## country=United-States                       9.802713e-06  -
4.421480
## f.age=f.age-(49,90]                         6.429593e-12  -
6.869791
## race=White                                  1.197214e-14  -
7.716336
## f.education=f.education-University-Or-More  7.217966e-16  -
8.066775
## f.type=f.typ-SelfEm                         2.616307e-24 -
10.173034
```

```
## relationship=Wife                              2.464475e-26 -
10.617743
## f.age=f.age-(39,49]                            5.134904e-27 -
10.763211
## f.education=f.education-Proof-school           4.016679e-28 -
10.995503
## f.benefici=f.benefici-Negatiu                  1.139926e-30 -
11.512597
## occupation=Prof-specialty                      4.052161e-42 -
13.599132
## sex=Male                                       1.146411e-45 -
14.184277
## occupation=Exec-managerial                     1.721208e-46 -
14.316693
## f.benefici=f.benefici-Positiu                  2.478837e-56 -
15.814317
## relationship=Husband                          3.419847e-159 -
26.883554
## f.marital=f.marital-Married                   2.216248e-219 -
31.616131
##
## $`>50K`
##                                                 Cla/Mod
Mod/Cla Global
## f.marital=f.marital-Married                   43.5483871
85.5000000  47.12
## relationship=Husband                          44.0362355
72.9166667  39.74
## f.benefici=f.benefici-Positiu                 58.9680590
20.0000000   8.14
## occupation=Exec-managerial                    48.1191223
25.5833333  12.76
## sex=Male                                      29.8583911
82.5833333  66.38
## occupation=Prof-specialty                     45.9618209
26.0833333  13.62
## f.benefici=f.benefici-Negatiu                 57.2580645
11.8333333   4.96
## f.education=f.education-Proof-school          83.1168831
5.3333333   1.54
## f.age=f.age-(39,49]                           37.1511068
32.1666667  20.78
## relationship=Wife                             53.3834586
11.8333333   5.32
## f.type=f.typ-SelfEm                           59.4285714
8.6666667   3.50
## f.education=f.education-University-Or-More 28.3641639
65.1666667  55.14
## race=White                                    25.8450704
91.7500000  85.20
```

```
## f.age=f.age-(49,90]                            31.8342152
30.0833333  22.68
## country=United-States                          24.7814685
94.5000000  91.52
## f.age=f.age-(29,39]                            26.8274303
29.6666667  26.54
## race=Amer-Indian-Eskimo                         6.6666667
0.2500000   0.90
## occupation=Priv-house-serv                      0.0000000
0.0000000   0.50
## f.education=f.education-Some-college           19.7080292
18.0000000  21.92
## occupation=Machine-op-inspct                   13.5313531
3.4166667   6.06
## f.type=f.typ-Private                           22.0011534
63.5833333  69.36
## f.marital=f.marital-Widowed                     9.4117647
1.3333333   3.40
## country=Mexico                                  4.2553191
0.3333333   1.88
## occupation=Handlers-cleaners                    5.7777778
1.0833333   4.50
## relationship=Other-relative                     2.9585799
0.4166667   3.38
## race=Black                                     11.0453649
4.6666667  10.14
## occupation=Adm-clerical                        11.8715084
7.0833333  14.32
## relationship=Unmarried                          5.3465347
2.2500000  10.10
## f.marital=f.marital-No- Married                 8.8709677
6.4166667  17.36
## relationship=Not-in-family                     11.1026616
12.1666667  26.30
## f.education=f.education-Non-Graduate            5.7352941
3.2500000  13.60
## sex=Female                                     12.4330756
17.4166667  33.62
## occupation=Other-service                        2.4911032
1.1666667  11.24
## relationship=Own-child                          0.6596306
0.4166667  15.16
## f.benefici=f.benefici-Neutre                   18.8262371
68.1666667  86.90
## f.age=f.age-[17,29]                             6.4666667
8.0833333  30.00
## f.marital=f.marital-Never-married               5.0435866
6.7500000  32.12
##                                                      p.value
v.test
```

```
## f.marital=f.marital-Married                    2.216248e-219
31.616131
## relationship=Husband                           3.419847e-159
26.883554
## f.benefici=f.benefici-Positiu                   2.478837e-56
15.814317
## occupation=Exec-managerial                      1.721208e-46
14.316693
## sex=Male                                        1.146411e-45
14.184277
## occupation=Prof-specialty                       4.052161e-42
13.599132
## f.benefici=f.benefici-Negatiu                   1.139926e-30
11.512597
## f.education=f.education-Proof-school            4.016679e-28
10.995503
## f.age=f.age-(39,49]                             5.134904e-27
10.763211
## relationship=Wife                               2.464475e-26
10.617743
## f.type=f.typ-SelfEm                             2.616307e-24
10.173034
## f.education=f.education-University-Or-More  7.217966e-16
8.066775
## race=White                                      1.197214e-14
7.716336
## f.age=f.age-(49,90]                             6.429593e-12
6.869791
## country=United-States                           9.802713e-06
4.421480
## f.age=f.age-(29,39]                             5.232697e-03
2.792348
## race=Amer-Indian-Eskimo                         2.821914e-03  -
2.986499
## occupation=Priv-house-serv                      1.028205e-03  -
3.282693
## f.education=f.education-Some-college            1.338104e-04  -
3.819338
## occupation=Machine-op-inspct                    3.447791e-06  -
4.642164
## f.type=f.typ-Private                            8.381738e-07  -
4.926262
## f.marital=f.marital-Widowed                     8.112097e-07  -
4.932651
## country=Mexico                                  2.048243e-07  -
5.194905
## occupation=Handlers-cleaners                    1.132376e-13  -
7.424464
## relationship=Other-relative                     1.448749e-14  -
7.691980
```

```
## race=Black                                      1.022517e-14  -
7.736424
## occupation=Adm-clerical                         2.420233e-18  -
8.735760
## relationship=Unmarried                          6.071266e-32 -
11.762765
## f.marital=f.marital-No- Married                 1.046142e-35 -
12.473145
## relationship=Not-in-family                      1.722531e-41 -
13.492874
## f.education=f.education-Non-Graduate            1.326698e-41 -
13.512107
## sex=Female                                      1.146411e-45 -
14.184277
## occupation=Other-service                        5.499322e-51 -
15.019169
## relationship=Own-child                          1.064373e-89 -
20.081814
## f.benefici=f.benefici-Neutre                    1.023816e-92 -
20.423976
## f.age=f.age-[17,29]                             2.817808e-95 -
20.709945
## f.marital=f.marital-Never-married              9.012756e-125 -
23.758325
##
##
## Link between the cluster variable and the quantitative
variables
##
================================================================
##                   Eta2      P-value
## hr.per.week 0.05278220 6.885118e-61
## age         0.04774912 4.083489e-55
##
## Description of each cluster by quantitative variables
## =====================================================
## $`<=50K`
##                v.test Mean in category Overall mean sd in
category
## age         -15.44985         37.01421     38.70380
14.164738
## hr.per.week -16.24371         38.60780     39.83755
9.657673
##             Overall sd      p.value
## age          13.759406 7.562039e-54
## hr.per.week   9.525189 2.474817e-59
##
## $`>50K`
##               v.test Mean in category Overall mean sd in
category
```

```
## hr.per.week 16.24371         43.73175     39.83755
7.920081
## age         15.44985         44.05417     38.70380
10.761640
##             Overall sd      p.value
## hr.per.week   9.525189 2.474817e-59
## age          13.759406 7.562039e-54
```

Per a la variable si cobren mes de 50 mil anuals o no, veiem que per exemple la mitjana d'edat que tenen un sou inferior a 50 mil es menor a la que els tenen major, de 37 anys de mitjana a 44. és a dir que l'edat te una gran importància en el que ve a ser el fet de tenir un sou més elevat, probablement aixó es degut a que una persona d'edat major té més experiència, i per tant té millor remuneració en el seu àmbit de treball.

També tenim una dada important que són les hores de treball de mitjana, la majoria de persones que cobren més de 50mil són aquelles que setmanalment excedeixen el límit de 40 hores establert a Espanya. Amb el que majoritariament podem dir que aquelles persones que treballen més hores acustumen a tenir un sou més elevat.

També podem veure variables importants com els estudis, la gran part de les persones que no tenen estudis, o que tenen uns estudis baixos, acustumen a tenir un sou menor a 50mil anuals. No obstant les persones més preparades, si que tenen un percentatge més alt de cobrar un sou més elevat no obstant no son la majoria que tenen un sou elevat.