Imputació de dades faltants

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2025-10-04

```
library(readr)
library(dplyr)
```

```
## Warning: package 'dplyr' was built under R version 4.4.3
```

```
##
## Adjuntando el paquete: 'dplyr'
```

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

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

```
data <- read_csv("train.csv", col_types = cols(...1 = col_skip()))
```

```
## New names:
## * `` -> `...1`
```

```
for(i in 1:ncol(data)){
  if(is.character(data[[i]])==TRUE){
    data[[i]] = as.factor(data[[i]])
  }
}

data$HasCrCard <- as.factor(data$HasCrCard)
data$IsActiveMember <- as.factor(data$IsActiveMember)
data$SavingsAccountFlag <- as.factor(data$SavingsAccountFlag)
data$Exited <- as.factor(data$Exited)
```

Podrem veure els valors faltants de la nostra base de dades de forma visual:

```
visdat::vis_dat(data)
```

Veiem només tenim dos tipus de variables (Factor i numèriques) però que tenim una barbaritat de NAs a les nostres variables. Anem a arreglar-ho.

Imputació de valors faltants Univariants:

Mirarem primerament si hi han valors extrems que s'hagin de considerar NAs per haver estat incorrectament afegits a la base de dades:

```
summary(data)
```

```
##      Tenure          Gender          EducationLevel        LoanStatus
##  Min.   : 0.000   Female:2233   High School :1658   Active loan :1416
##  1st Qu.: 3.000   Male  :2667   Other       : 217   Default risk: 492
##  Median : 5.000   NA's  :2100   Postgraduate: 736   No loan     :2992
##  Mean   : 5.021                 University  :2289   NA's        :2100
##  3rd Qu.: 7.000                 NA's        :2100
##  Max.   :10.000
##  NA's   :2100
##  NetPromoterScore TransactionFrequency    Surname          Age
##  Min.   : 0.000   Min.   :13.00        Walker :  21   Min.   :18.00
##  1st Qu.: 4.000   1st Qu.:26.00        Scott  :  17   1st Qu.:32.00
##  Median : 8.000   Median :30.00        Martin :  16   Median :37.00
##  Mean   : 6.482   Mean   :30.06        Smith  :  16   Mean   :39.01
##  3rd Qu.: 9.000   3rd Qu.:34.00        Graham :  15   3rd Qu.:44.00
##  Max.   :10.000   Max.   :52.00        (Other):4815   Max.   :92.00
```

```
##  NA's   :2100     NA's   :2100         NA's   :2100   NA's   :2100
##    Geography    ComplaintsCount  HasCrCard   EstimatedSalary     IsActiveMember
##  France :2445   Min.   :0.0000   0   :1462   Min.   :    11.58   0   :2357
##  Germany:1232   1st Qu.:0.0000   1   :3438   1st Qu.: 51271.41   1   :2543
##  Spain  :1223   Median :0.0000   NA's:2100   Median :100218.21   NA's:2100
##  NA's   :2100   Mean   :0.3588               Mean   :100405.20
##                 3rd Qu.:0.0000               3rd Qu.:149613.87
##                 Max.   :5.0000               Max.   :199862.75
##                 NA's   :2100                 NA's   :2100
##  AvgTransactionAmount       CustomerSegment  MaritalStatus
##  Min.   : 19.60       Affluent      :1415   Divorced: 711
##  1st Qu.: 70.19       High Net Worth: 932   Married :2538
##  Median : 98.60       Mass Market   :2553   Single  :1427
##  Mean   :111.35       NA's          :2100   Widowed : 224
##  3rd Qu.:137.32                             NA's    :2100
##  Max.   :581.79
##  NA's   :2100
##  DigitalEngagementScore       ID        CreditScore   SavingsAccountFlag
##  Min.   :  5.00         Min.   :   1   Min.   :350    0   :1650
##  1st Qu.: 50.00         1st Qu.:1760   1st Qu.:583    1   :3250
##  Median : 60.00         Median :3530   Median :651    NA's:2100
##  Mean   : 59.61         Mean   :3515   Mean   :650
##  3rd Qu.: 70.00         3rd Qu.:5266   3rd Qu.:717
##  Max.   :100.00         Max.   :6999   Max.   :850
##  NA's   :2100           NA's   :2100   NA's   :2100
##     Balance       NumOfProducts  Exited
##  Min.   :     0   Min.   :1.00   0:5550
##  1st Qu.:     0   1st Qu.:1.00   1:1450
##  Median : 97576   Median :1.00
##  Mean   : 76733   Mean   :1.53
##  3rd Qu.:127652   3rd Qu.:2.00
##  Max.   :250898   Max.   :4.00
##  NA's   :2100     NA's   :2100
```

Busquem valors tant extrems que siguin irreals i s'hagin de considerar faltants; algú amb 500 anys, una satifacció del client de 13 cuan la variable es mou entre el 0 i el 10, ingresos negatius o variables binàries amb valors diferents a 1 o 0. Per aquesta base de dades no hem trobat valors d'aquest tipus, per tant començarem directament amb la imputació dels valors que ja tenim faltants.

Primerament comprovarem la aleatòrietat de les dades faltants amb el test de Little per a MCAR:

```
naniar::mcar_test(data)
```

```
## # A tibble: 1 x 4
##   statistic     df p.value missing.patterns
##       <dbl>  <dbl>   <dbl>            <int>
## 1   112066. 112035   0.473             6858
```

Comprovem que per un P-valor de 0.4730255 els nostres Missings are Completly generated At Random.

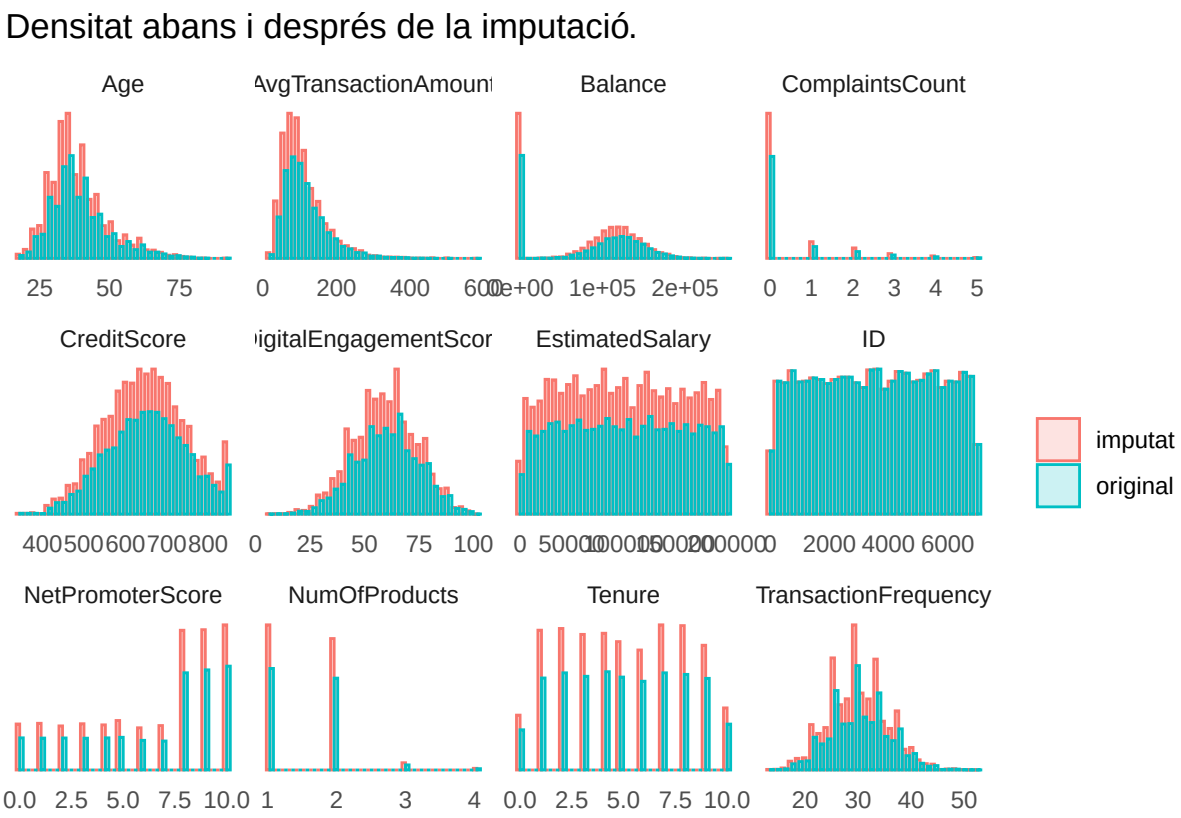
Podrem fer la primera imputació de les dades faltants a través de l'algorisme MICE (Multiple Imputation by Chained Equations):

```r
density_before_after <- function(before, after) {
    require(ggplot2)

    density_df_before <- before |>
        select(where(is.numeric)) |>
        mutate(imputation = "original")

    density_df_after <- after |>
        select(where(is.numeric)) |>
        mutate(imputation = "imputat")

    density_df <- bind_rows(density_df_before, density_df_after) |>
        mutate(imputation = factor(imputation)) |>
        tidyr::pivot_longer(!imputation, names_to = "variable") |>
        filter(!is.na(value))

    ggplot(density_df, aes(x = value, color = imputation, fill = imputation)) +
        facet_wrap(~variable, scales = "free") +
        geom_histogram(alpha = 0.2, width = 0.1, bins = 30, position = "dodge") +
        scale_color_discrete(aesthetics = c("color", "fill"), name = "") +
        scale_y_continuous(breaks = NULL) +
        xlab("") +
        ylab("") +
        ggtitle("Densitat abans i després de la imputació.") +
        theme_minimal() +
        theme(panel.grid = element_blank())
}
mass_before_after <- function(before, after) {
    require(ggplot2)

    mass_df_before <- before |>
        select(where(is.factor)) |>
        mutate(imputation = "original")

    mass_df_after <- after |>
        select(where(is.factor)) |>
        mutate(imputation = "imputat")

    levels_in_order <- lapply(mass_df_before, levels) |> unlist()

    mass_df <- bind_rows(mass_df_before, mass_df_after) |>
        mutate(imputation = factor(imputation)) |>
        tidyr::pivot_longer(!imputation, names_to = "variable") |>
        filter(!is.na(value)) |>
        group_by(imputation, variable) |>
        reframe(prop = proportions(table(value)), category = names(prop)) |>
        mutate(category = factor(category, levels = levels_in_order)) |>
        filter(prop > 0)

    ggplot(mass_df, aes(x = category, y = prop, color = imputation, fill = imputation)) +
        facet_wrap(~variable, scales = "free") +
        geom_col(alpha = 0.2, width = 0.6, position = "dodge") +
        scale_color_discrete(aesthetics = c("color", "fill"), name = "") +
```

```
        scale_y_continuous(breaks = NULL) +
        xlab("") +
        ylab("") +
        ggtitle("Massa abans i després de la imputació") +
        theme_minimal() +
        theme(panel.grid = element_blank(),
              axis.text.x = element_text(angle = 45, hjust = 1))
}
```

```
density_before_after(data, data_imputed)
```

```
## Cargando paquete requerido: ggplot2
```




```
# mass_before_after(data, data_imputed)
```