# Data Processing and Cleaning

TeenTox Team

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#### 1 Introduction

This document presents a **systematic procedure** for handling missing values. The objective is to:

- Minimize information loss.
- Reduce biases due to missing data.
- Maintain the *statistical consistency* of variables.

Throughout the process, different imputation methods (e.g., MICE and kNN) are employed, chosen based on the percentage of missing data in each variable.

## 2 Initial Analysis of Missing Values

## 2.1 Calculating NA Percentages

The first step is to calculate the proportion of missing values (NA) for each variable, in order to:

- 1. Determine the severity of missing data in each column.
- 2. Choose the most appropriate imputation method.

An example of R code:

This generates a dataframe with two columns: Variable and Missing\_Percentage, identifying variables with high levels of NA (e.g., around 30%) versus others with minimal values (5%–10%).

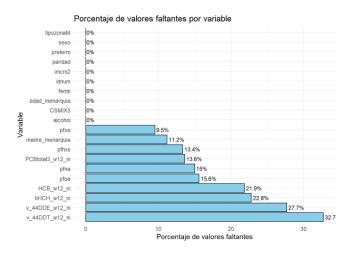


Figure 1: Table of missing values in percentage

#### 2.2 25% Threshold

Based on the previous results, a 25% threshold for missing values is established, dividing the variables into:

- Less than 25% missing: can be imputed with methods like MICE.
- More than 25% missing: kNN or additional techniques are used to avoid significant biases.

This division is based on the idea that, beyond a certain level of missingness, some imputation methods (e.g., MICE) may be significantly affected, increasing statistical distortion in the data.

## 3 Handling Variables with Less than 25% Missing Values

## 3.1 Multiple Imputation by Chained Equations (MICE)

For variables below the 25% threshold, *Multiple Imputation by Chained Equations* (MICE) is used. The general process:

- 1. Identify a model for each variable with NA.
- 2. Perform multiple iterations (chained equations) to *predict* and sequentially re-impute missing values.
- 3. Combine the results (multiple imputed datasets) into a unified dataset.

We compare various methods within MICE (pmm, rf, cart). The RMSE (Root Mean Squared Error) and MAE (Mean Absolute Error) were calculated for each case, determining that rf (Random Forest) generally offers the lowest error. The R loop for this comparison is as follows:

```
methods <- c("pmm", "rf", "cart")
results <- list()</pre>
```

```
for(m in methods){
  imp <- mice(df[vars_below_25], method = m, ...)
  # Calculate RMSE, MAE, etc.
  results[[m]] <- list(rmse=..., mae=...)
}</pre>
```

## 4 Handling Variables with More than 25% Missing Values

#### 4.1 k-Nearest Neighbors (kNN)

Variables exceeding 25% NA are handled using **kNN** (k-Nearest Neighbors), utilizing the **kNN()** function from the VIM package. This procedure involves:

- Testing different values of k (1, 3, 5, 7, 9, ...).
- Evaluating RMSE and MAE for each k.
- Choosing the configuration that best preserves the variable's distribution shape and maintains a low error.

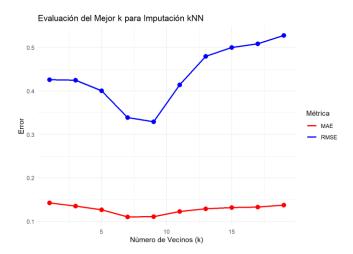


Figure 2: Evaluation graph for the best "k"

## 5 Validation and Final Evaluation

### 5.1 Error Metrics (RMSE, MAE)

For MICE and kNN, imputed values and actual observations (or reference methods) are compared using metrics such as:

- RMSE (Root Mean Squared Error): Square root of the mean squared errors.
- MAE (Mean Absolute Error): Average of absolute differences.

#### 5.2 Distribution Verification

In addition to error metrics, *density plots*, *histograms*, and *boxplots* are examined to confirm that the overall shape of the distribution has not been significantly affected.

#### 5.3 Final Results

Finally, it is verified that the columns no longer contain NA.

```
colSums(is.na(df[vars_below_25])) # Expected to be 0
colSums(is.na(df[vars above 25])) # Expected to be 0
```

### 6 Conclusions

The proposed missing values treatment process is based on:

- An **initial analysis** to identify columns with higher or lower incidence of NA.
- The selection of MICE (with rf method) for variables with less than 25% missing data.
- The use of kNN for those with more than 25%, adjusting the value of k based on error metrics.

**Note:** Additional adjustments could be made depending on the nature of the data (e.g., categorical variables, outliers).