



Data Glacier

Week 8: Deliverables

Group Name: Solo Analyst

Name: Munirah Alfahaid

Email: munirah9hamad@gmail.com

Country: Saudi Arabia

Specialization: Data Analyst

Problem Description

XYZ Credit Union in Latin America has been successful in selling individual banking products like credit cards, deposit accounts, and retirement accounts. However, they are facing a challenge in cross-selling, as existing customers are typically not purchasing more than one product. The goal of this project is to analyze the current situation and suggest strategies to increase cross-selling opportunities among existing customers without relying on machine learning solutions.

What type of data do you have for analysis?

The dataset consists of a mix of data types:

- **Numerical Data:** These include columns like `ncodpers`, `age`, `ind_nuevo`, `antiguedad`, `indrel`, `tipodom`, `cod_prov`, and `ind_actividad_cliente`. These are mostly integers, representing counts, IDs, or numerical values.
- **Categorical Data:** These include columns like `sexo`, `ind_empleado`, `pais_residencia`, `segmento`, and others, which are represented as text strings and indicate categories or groups.
- **Date/Time Data:** Columns like `fecha_dato` and `fecha_alta` appear to be dates, which can be useful for time-based analysis.

What are the problems in the data?

The dataset has several issues:

- **Missing Values:**
 - **High Missingness:** Columns like `ult_fec_cli_1t` and `conyuemp` have an extremely high percentage of missing values, with over 99% of their data missing.
 - **Moderate Missingness:** Columns like `canal_entrada`, `cod_prov`, `nomprov`, and `segmento` have missing values but to a lesser extent.

- **Low Missingness:** Columns like `sexo`, `indrel_1mes`, and `tiprel_1mes` have very few missing values.
- **Mixed Data Types Warning:** There's a warning about mixed data types in the `conyuemp` column, which could lead to issues during analysis.
- **Potential Outliers:** Without seeing the actual distribution, certain columns (like `age` and `renta`) might have outliers, which can skew analysis results.

3. What approaches are you trying to apply to overcome problems like NA values, outliers, etc., and why?

To address these problems:

- **Handling Missing Values:**
 - **Drop Columns:** Consider dropping columns like `ult_fec_cli_1t` and `conyuemp` due to the overwhelming amount of missing data.
 - **Imputation:** For columns with moderate or low missing values, you can impute the missing values using the median or mode, depending on the data type. For example:
 - **Categorical Data:** Impute with the most frequent category.
 - **Numerical Data:** Impute with the median, especially if the data is skewed.
- **Mixed Data Types:** Convert the `conyuemp` column to a consistent data type if it's necessary for analysis, or consider dropping it if it's not valuable.
- **Handling Outliers:** Once identified, outliers can be managed by either capping them to a maximum value or transforming the data (e.g., log transformation) to reduce their impact.

4. Why are you applying these approaches?

- **Dropping Columns with High Missingness:** Columns with over 99% missing data are likely to be unreliable and contribute little to the analysis. Removing them helps streamline the dataset and avoids introducing noise.
- **Imputation:** Imputing missing values ensures that you don't lose valuable data from rows where only a few values are missing, which helps maintain the dataset's integrity and allows for more robust analysis.
- **Handling Outliers:** Outliers can distort statistical analyses and machine learning models. By managing them appropriately, you ensure that your analysis is more representative of the true data distribution.