FRAUDOLENT TRANSACTION CLASSIFICATION

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BIG DATA COMPUTING COURSE A.A. 2021/2022

OVERVIEW

1. **Introduction**
   A brief presentation of the addressed problem
2. **Dataset**
   A brief description of the dataset used in the project
3. **Explore and Feature Engineering**
   How the dataset was modified
4. **Machine Learning Models**
   The ML models and Pipelines applied for the task
5. **Results**
   A description of the results obtained from the previous step

I ADDRESSED PROBLEM

Financial fraud is a problem that has a huge impact on the financial industry

Credit card fraud detection is a challenge mainly due to 2 problems that it poses

- Both profiles of fraudolent and normal behaviours change
- Usually used datasets are highly skewed

The goal of the task is to create a Machine Learning model that, given a set of samples of fraudolent and not fraudolent transactions, is capable of classifying whether a new transaction is fraudolent or not.

~709 MiB

Divided into identity.csv and transaction.csv

590540 entries

434 features

Target feature is «isFraud». 0 means not fraudolent, 1 otherwise

2 THE DATASET

The Dataset is available on Kaggle

3 EXPLORE AND FEATURE ENGINEERING OUTLINE

Merging

- Transaction.csv and identity.csv have been merged together

Label Distributrion

- The dataset is highly unbalanced

Missing Values

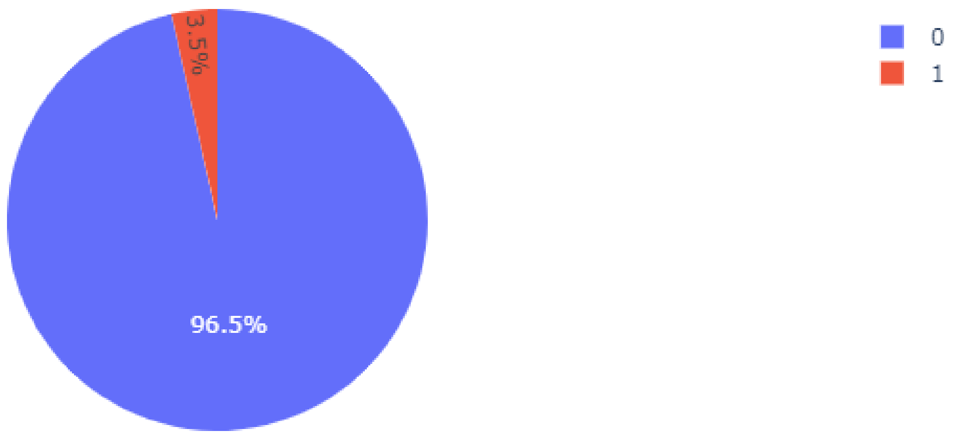
- The dataset has a huge number of missing values

Feature Engineering

- Drop some features
- «Standardizing»
- Apply «Imputing»
- Use Pearson Correlation

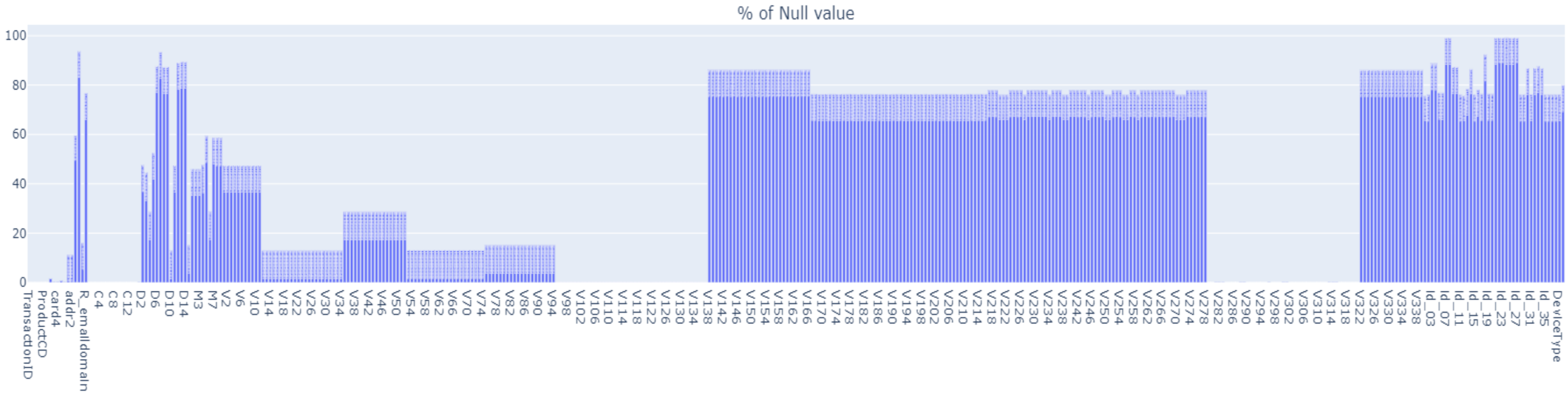
3 .1 - LABEL DISTRIBUTION

- With respect to the target label «isFraud» the dataset results highly unbalanced
- ~96.5 % are not-fraudolent transactions
- ~3.5 % are fraudolent transactions
- We have to handle this problem when splitting the dataset for training and testing the various ML models



3 .2 – MISSING VALUES

- The dataset has a high number of features with a huge percentage of missing values
- The average range of percentages is ~70-90%
- I handled this during the Feature Engineering step



3.3 – FEATURE ENGINEERING

Features Dropping

- Drop features with percentage value of missing values grater or equal to 90%

Standardization

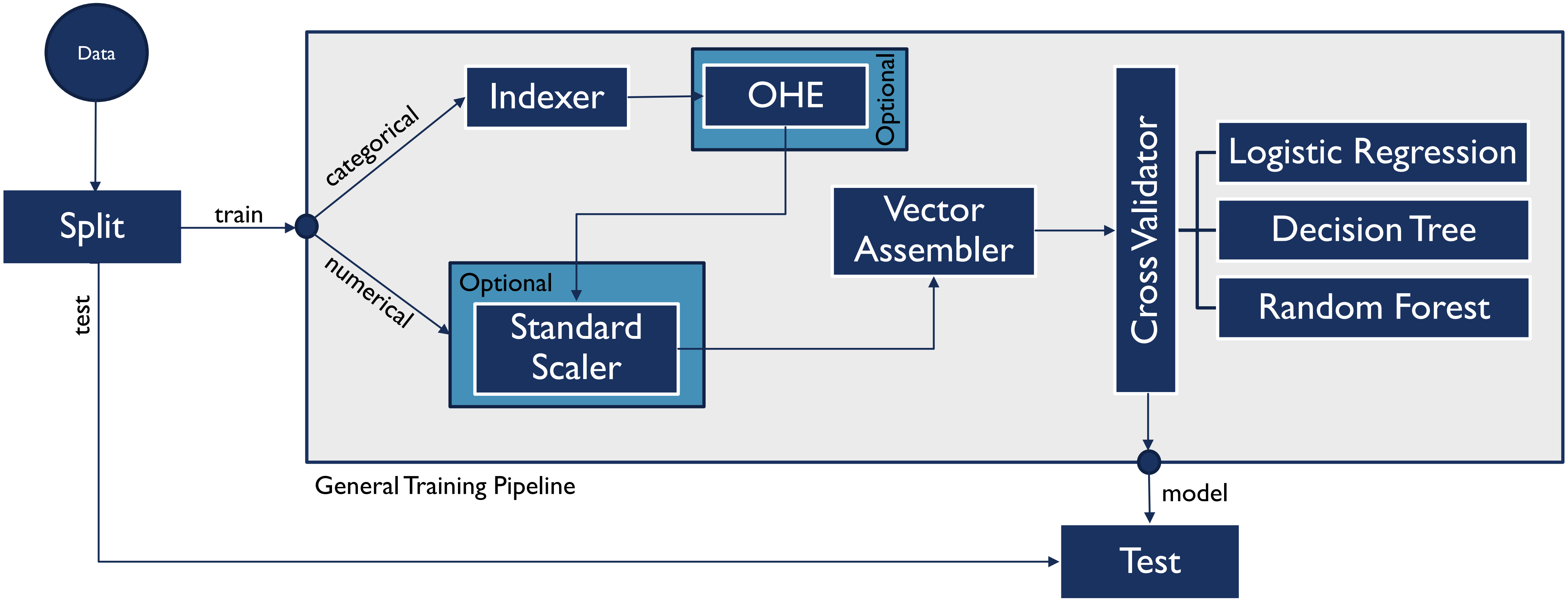
- Standardize certain features
- Given different values for the same feature but with equal meaning, replace with a single more general value
- Take *yahoo.co.jp*, *yahoo.co.uk* and *yahoo.net*, I replace it with *yahoo*

Imputing

- Use the imputer to replace null values in the dataset according to a specific strategy
- Discrete values use strategy *mean*
- Nulls in categorical values have been replaced with «N»

Pearson Correlation

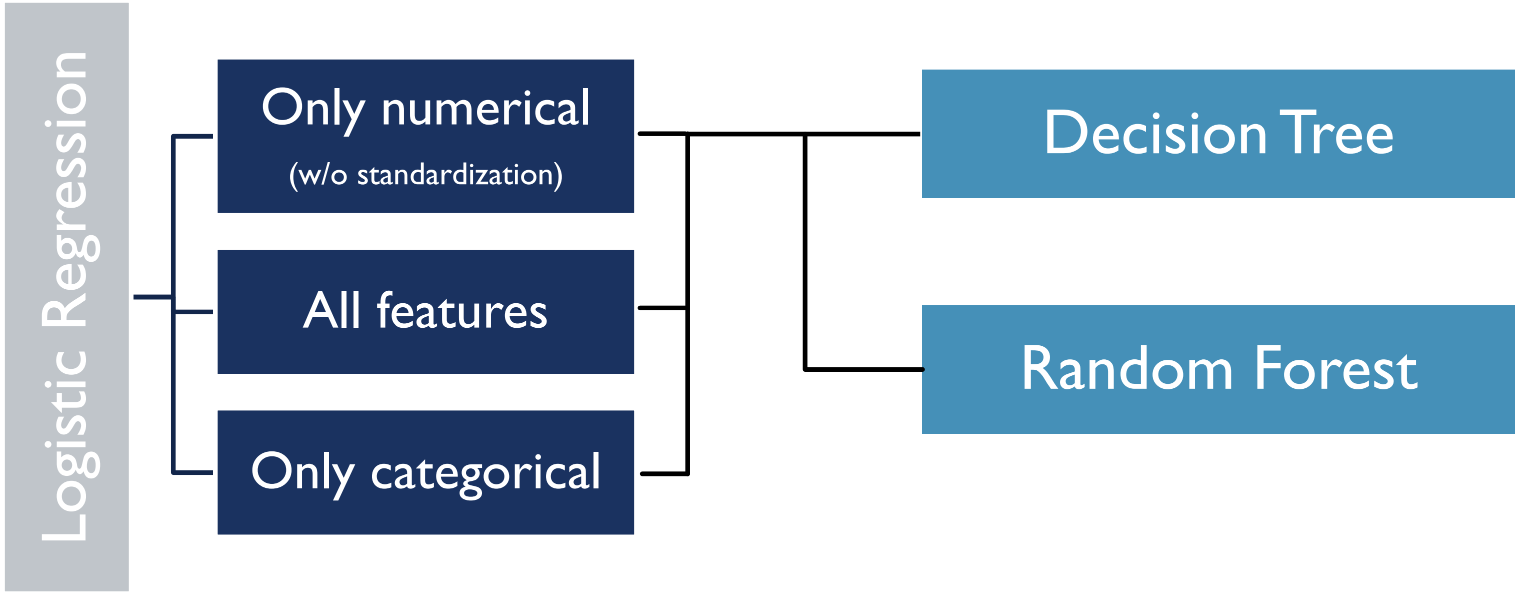
- Drop more features using the Pearson Correlation
- If the PC > .95, then drop that feature
- Avoiding duplicate features



4 MACHINE LEARNING PIPELINE

- The dataset is highly unbalanced, thus we cannot apply a simple random splitting
- This might lead to a poor splitting strategy
  - For instance the test set ends up containing only examples that are labeled with the most representative class
  - In this case such a class is the one for *non-fraudolent transactions*
- For this reason I used the so-called Stratified Random Sampling
  - It guarantees that both the training and the test split follow the same class distribution of the original dataset
  - For the experiments I selected 60% of 0's and 70% of 1's
- After splitting we last with: 357041 x 232 (train set) and 233499 x 232 (test set)

4.1 – DATASET SPLITTING



4.2 - EXPERIMENTS

5.1 - EXPERIMENTAL RESULTS

Accuracy	Numerical (oversample)		All Features (oversample)	Categorical (oversample)
	with standardization	w/out standardize		
Logistic Regression	0.9772 (?)	0.97725 (?)	**0.9777** (?)	0.9733 (?)
Decision Tree	0.9773 (?)	0.9773 (?)	(?)	0.9734 (?)
Random Forest	(?)	(?)	(?)	(?)

AUC ROC	Numerical (oversample)		All Features (oversample)	Categorical (oversample)
	with standardization	w/out standardize		
Logistic Regression	0.832 (?)	0.834 (?)	**0.857** (?)	0.800 (?)
Decision Tree	0.428 (?)	0.428 (?)	(?)	0.7074 (?)
Random Forest	(?)	(?)	(?)	(?)

5.2 - EXPERIMENTAL RESULTS

F1-Score	Numerical (oversample)		All Features (oversample)	Categorical (oversample)
	with standardization	w/out standardize		
Logistic Regression	0.7137 (?)	0.7139 (?)	**0.7227** (?)	0.5897 (?)
Decision Tree	0.7138 (?)	0.7138 (?)	(?)	0.5961 (?)
Random Forest	(?)	(?)	(?)	(?)

P/R	Numerical (oversample)		All Features (oversample)	Categorical (oversample)
	with standardization	w/out standardize		
Logistic Regression	0.853/0.613 (?)	0.852/0.614 (?)	**0.858/0.624** (?)	0.706/0.505 (?)
Decision Tree	0.878/0.601 (?)	0.878/0.601 (?)	(?)	0.732/0.502 (?)
Random Forest	(?)	(?)	(?)	(?)