FRAUDOLENT TRANSACTION CLASSIFICATION

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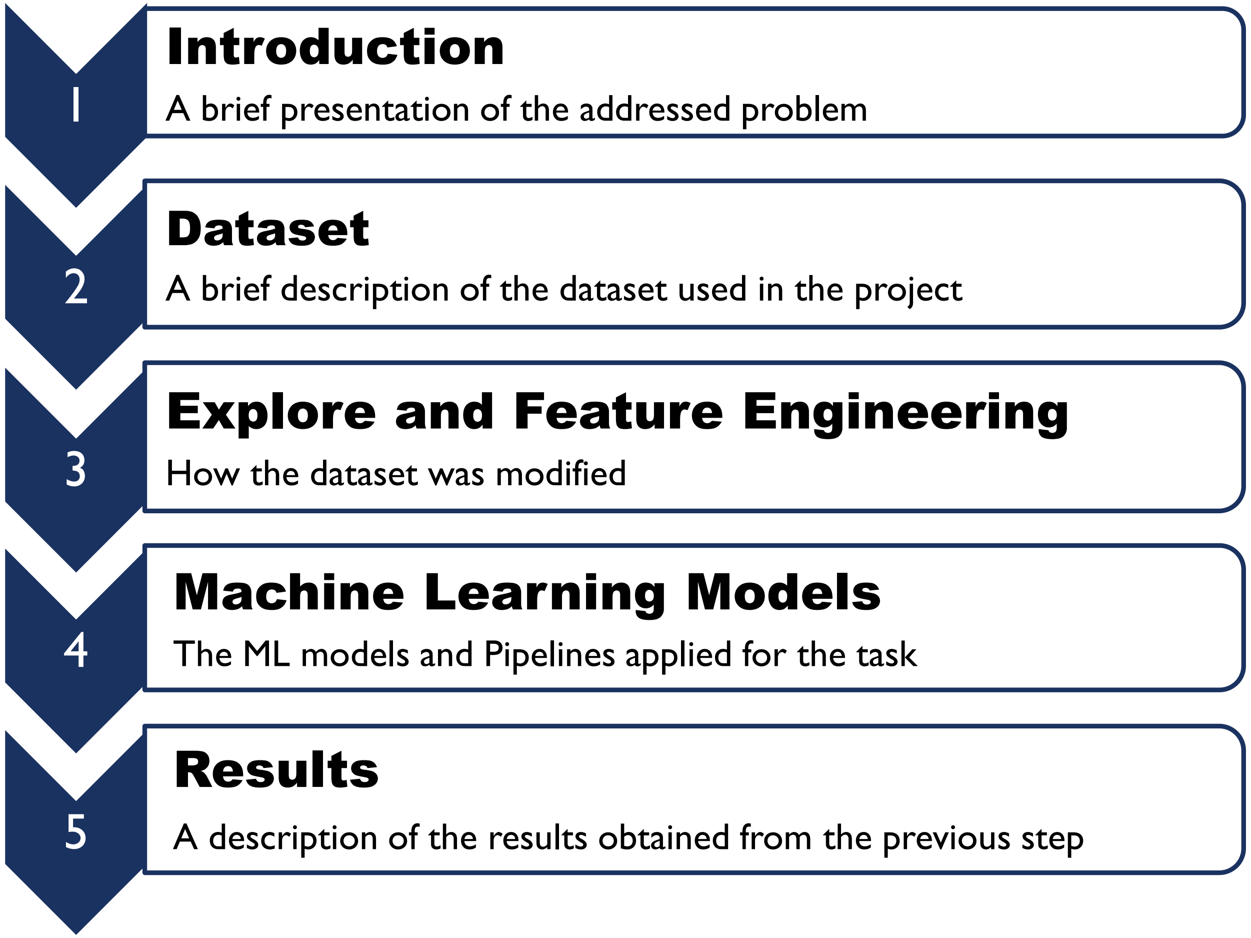
BIG DATA COMPUTING COURSE A.A. 2021/2022

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

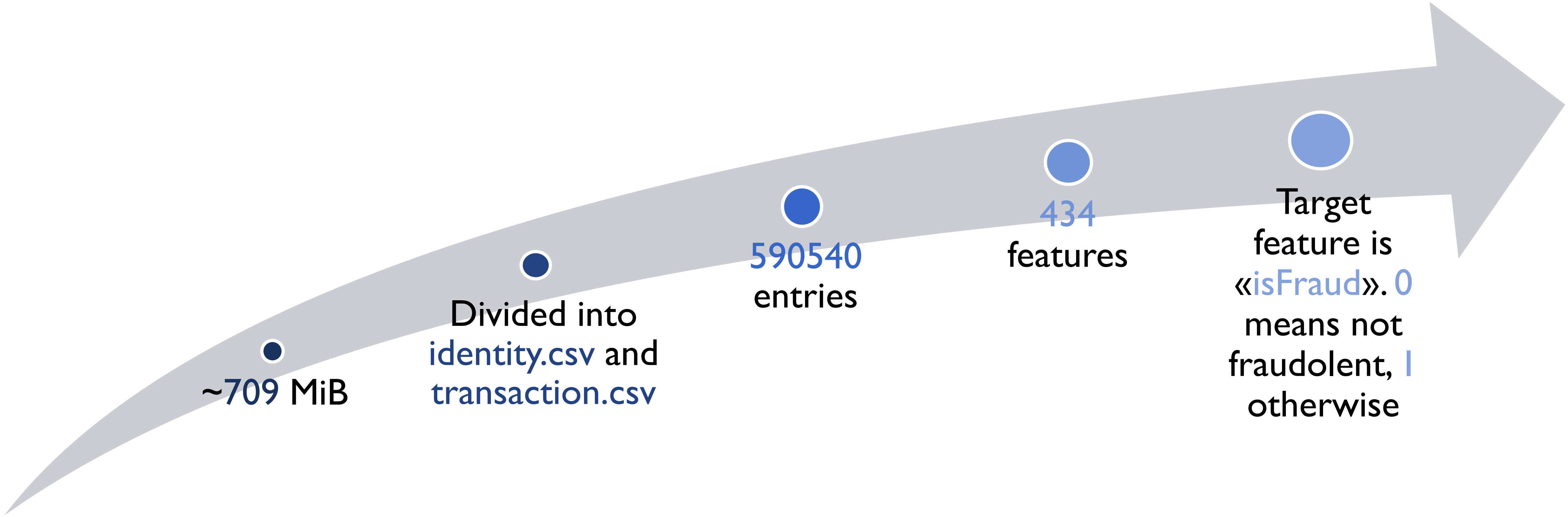
1 ADDRESSED PROBLEM

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

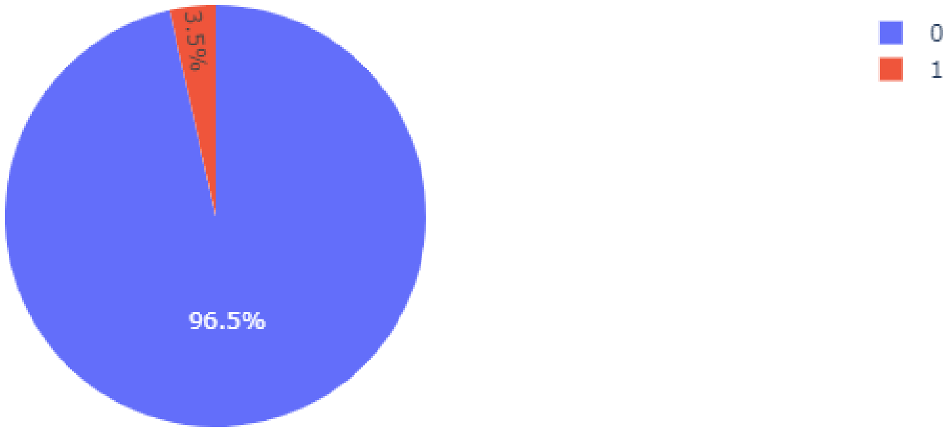
- The dataset has a huge number of missing values

Feature Engineering

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

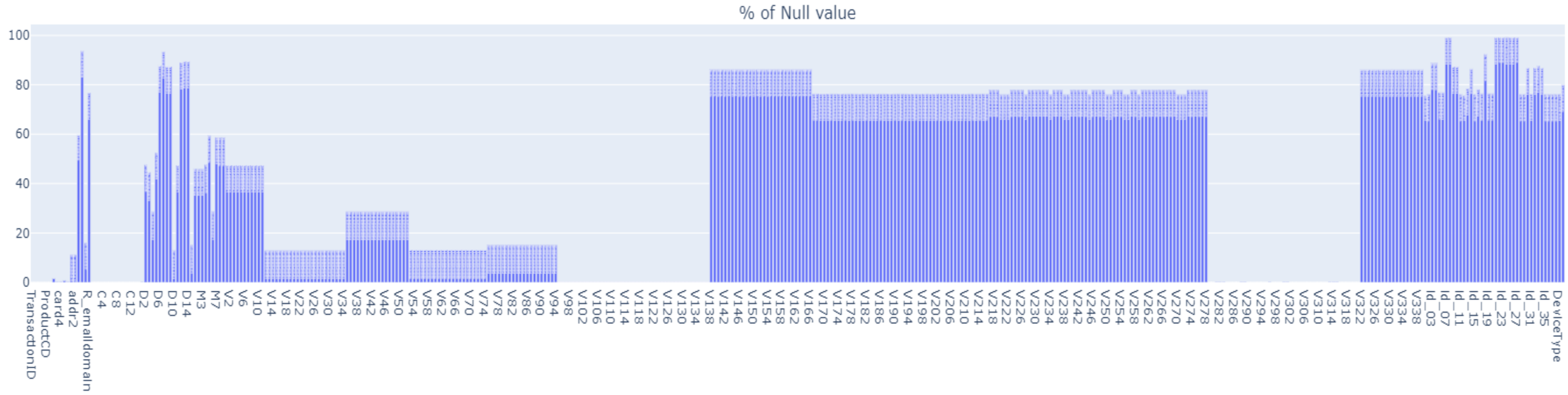
3.1 - LABEL DISTRIBUTION

- 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

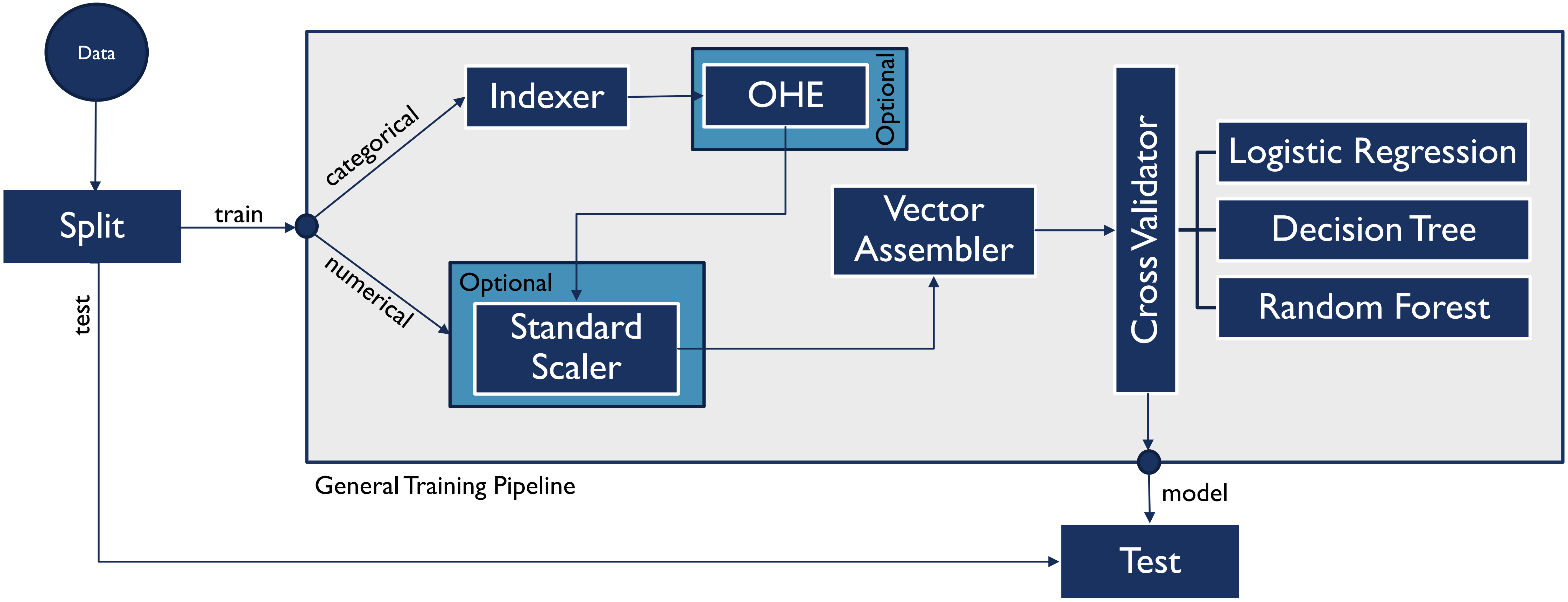
- Standardize certain features
- Given different values for the same feature but with equal meaning, replace with a single more general value
- Take *yahoo.co.jp*, *yahoo.co.uk* and *yahoo.net*, I replace it with *yahoo*

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

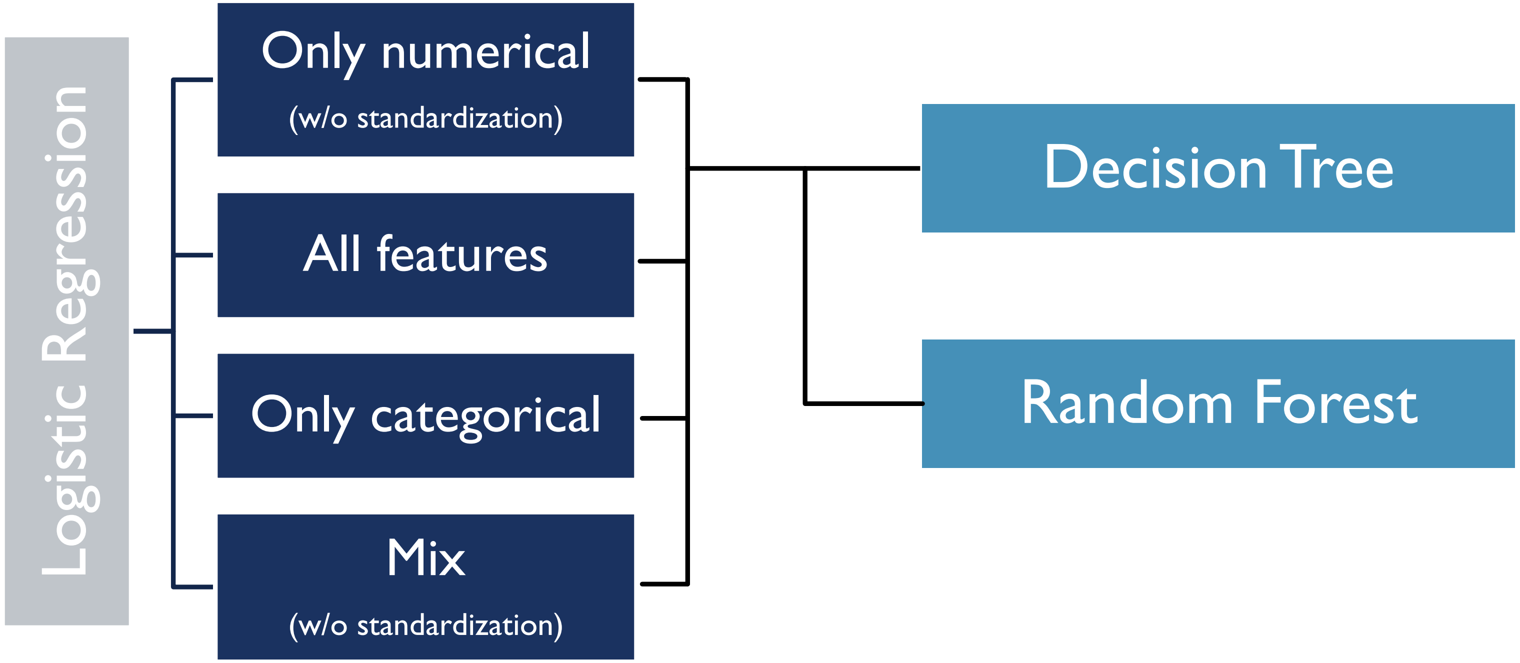


4

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



Logistic Regression

Only numerical
(w/o standardization)

All features

Only categorical

Mix
(w/o standardization)

Decision Tree

Random Forest

4 .2 - EXPERIMENTS

5.1 - EXPERIMENTAL RESULTS

Accuracy	Numerical		All Features	Categorical	Mix	
	with standardization	w/out standardize			with standardization	w/out standardize
Logistic Regression	0.9772	0.97725	**0.9777**	0.9733	0.974	0.974
Decision Tree	0.9773	0.9773		0.9734		
Random Forest						

AUC ROC	Numerical		All Features	Categorical	Mix	
	with standardization	w/out standardize			with standardization	w/out standardize
Logistic Regression	0.832	**0.834**		0.800	0.824	0.824
Decision Tree	0.428	0.428		0.7074		
Random Forest						

5.2 - EXPERIMENTAL RESULTS

F1-Score	Numerical		All Features	Categorical	Mix	
	with standardization	w/out standardize			with standardization	w/out standardize
Logistic Regression	0.7137	**0.7139**		0.5897	0.6352	0.6352
Decision Tree	0.7138	0.7138		0.5961		
Random Forest						

P/R	Numerical		All Features	Categorical	Mix	
	with standardization	w/out standardize			with standardization	w/out standardize
Logistic Regression	0.853/0.613	0.852/0.614		0.706/0.505	0.785/0.533	0.785/0.533
Decision Tree	0.878/0.601	0.878/0.601		0.732/0.502		
Random Forest						