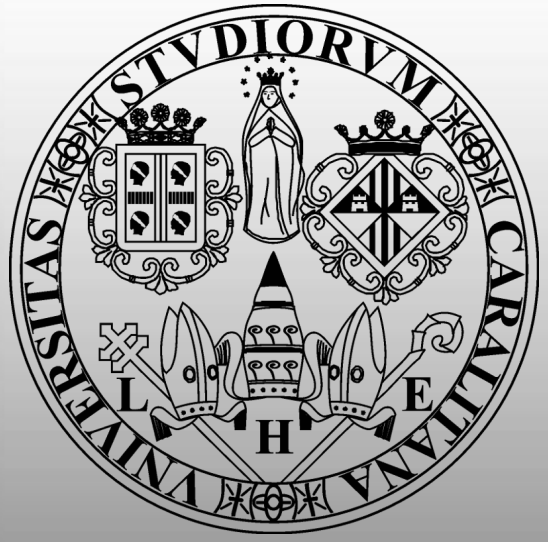

A Discretized Enriched Technique to Enhance Machine Learning Performance in Credit Scoring

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Outline

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OVERVIEW

Introduction

- The main aim of **credit scoring models** is the classification of the loan applications (from now on named as ***instances***) as *reliable* or *unreliable*

Introduction

- They are usually **designed** on the basis of the past loan applications
- They represent a **crucial** instrument for the financial operators

State of the Art

- Many **techniques** have been designed to address the *Credit Scoring* problem, by exploiting several models, such as:
  - *Statistical* and *Data Mining*
  - *Linear Discriminant*
  - *Logistic Regression*
  - *Neural Networks*
  - *Genetic Program*
  - *Decision-tree*
  - … and many more

State of the Art

- Regardless of the adopted technique, the definition of effective *Credit Scoring* models represents a **hard challenge** for several factors
- The most important of which is the **Imbalanced class distribution**

Open Problems

- The **Imbalanced class distribution** exists because the number of un*reliable* instances (*non-refunded loans*) is **much smaller** than that of the *reliable* ones (*refunded loans*)
- This reduces the **effectiveness** of the most widely used approaches

RELIABLE CASES **VS** UNRELIABLE CASES

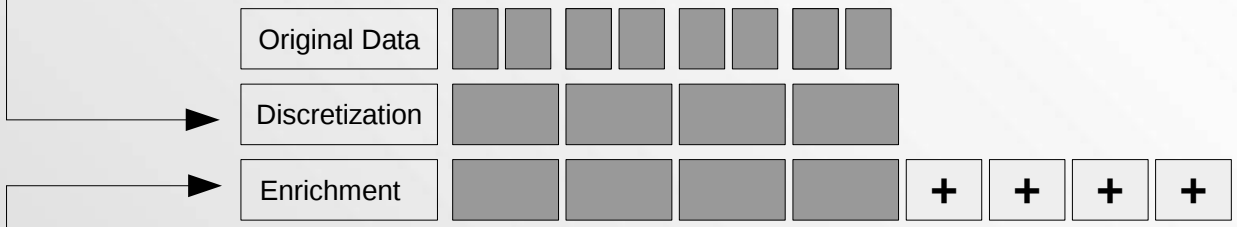
INTUITION

Idea

- The data unbalance issue can be reduced by improving the **instance** classes (i.e. reliable and unreliable cases) characterization
- We proposed a *Discretized Enriched Data* (**DED**) model able to face the heterogeneity of the event patterns
- This because the data domain is characterized by a **number of features** that could be very different, even when they define the same class of information

Formalization

Through a discretization process we **reduce** the instance patterns by grouping the similar ones in terms of feature values



Through an enrichment process we **improve** the instance characterization by adding a series of additional information

IMPLEMENTATION

Implementation

Step 1 of 3 - Discretization

On the basis of a η value experimentally defined, we perform the **data discretization** process $\xrightarrow{\Delta}$

$$\{f_1, f_2, \ldots, f_N\} \xrightarrow{\Delta} \{d_1, d_2, \ldots, d_N\}, \ \forall \ i \in I$$

Where f_1, f_2, ..., f_N denotes the original feature values of an instance i, and d_1, d_2, ..., d_N denotes these values after the discretization process

Implementation

Step 2 of 3 - Enrichment

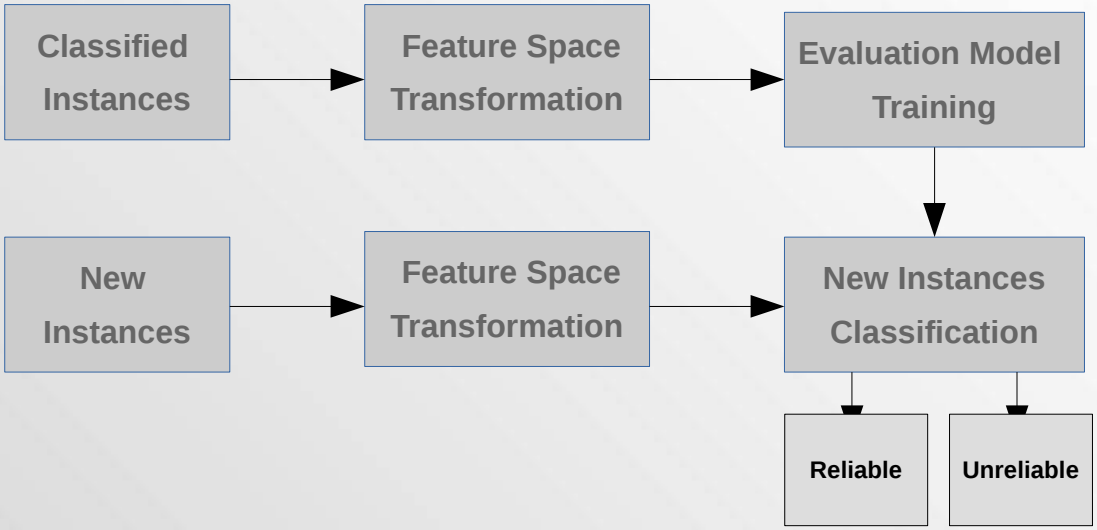
The discretized data are then enriched by adding to them the **Minimum** (m), **Maximum** (M), **Average** (A), and **Standard Deviation** (S) meta-information

$$\mu = \begin{cases} m = min(d_1, d_2, \ldots, d_N) \\ M = max(d_1, d_2, \ldots, d_N) \\ A = \frac{1}{N} \sum_{n=1}^{N} (d_n) \\ S = \sqrt{\frac{1}{N-1} \sum_{n=1}^{N} (d_n - \bar{d})^2} \end{cases}$$

Implementation

Step 3 of 3 – Instance Classification

Our approach classifies the **new instances** as ***reliable*** or **unreliable** in the new feature space



RESULTS

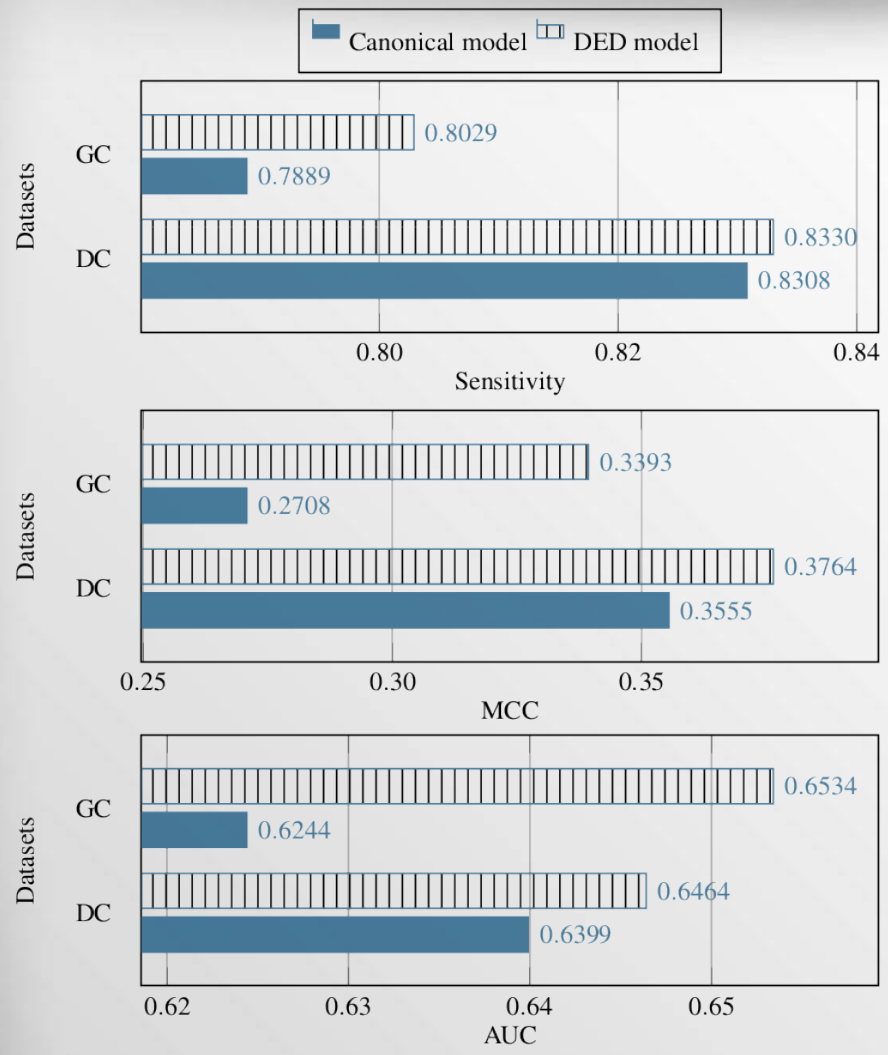
Experiments

- In addition to a canonical *k-fold cross validation* criterion, we **validated** our approach by dividing the dataset into two parts:
  - **In-sample part**, which has been used to select the internal algorithms parameters
  - **Out-of-sample part**, which has been used to evaluate the performance
- The *German Credit* (**GC**) and the *Default of Credit Card Clients* (**DC**) are the real-world dataset used in order to evaluate the performance of the proposed approach
- Our competitor, experimentally selected on the basis of its performance, is **Gradient Boosting**

Experiments

- We used the *50%* of each dataset as **in-sample** data, using the remaining *50%* as **out-of-sample** data
- We evaluated our predictive model in terms of **Sensitivity**, **Matthews Correlation Coefficient**, and **AUC**

Experiments



The results show that our **DED** model **outperforms** the canonical one in terms of *Sensitivity*, *MCC*, and *AUC* metrics, in both datasets

Conclusions

- The proposed model proved that the transformation of the original feature space, made by applying a discretization and an enrichment process, improves the performance of one of the most performing machine learning algorithm (i.e., Gradient Boosting)
- A possible **future work** would be the experimentation of such a model in the context of different classification algorithms configured through an ensemble strategy

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THANK YOU FOR YOUR ATTENTION

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