Unbalanced Data Classification in Fraud Detection by Introducing a Multidimensional Space Analysis

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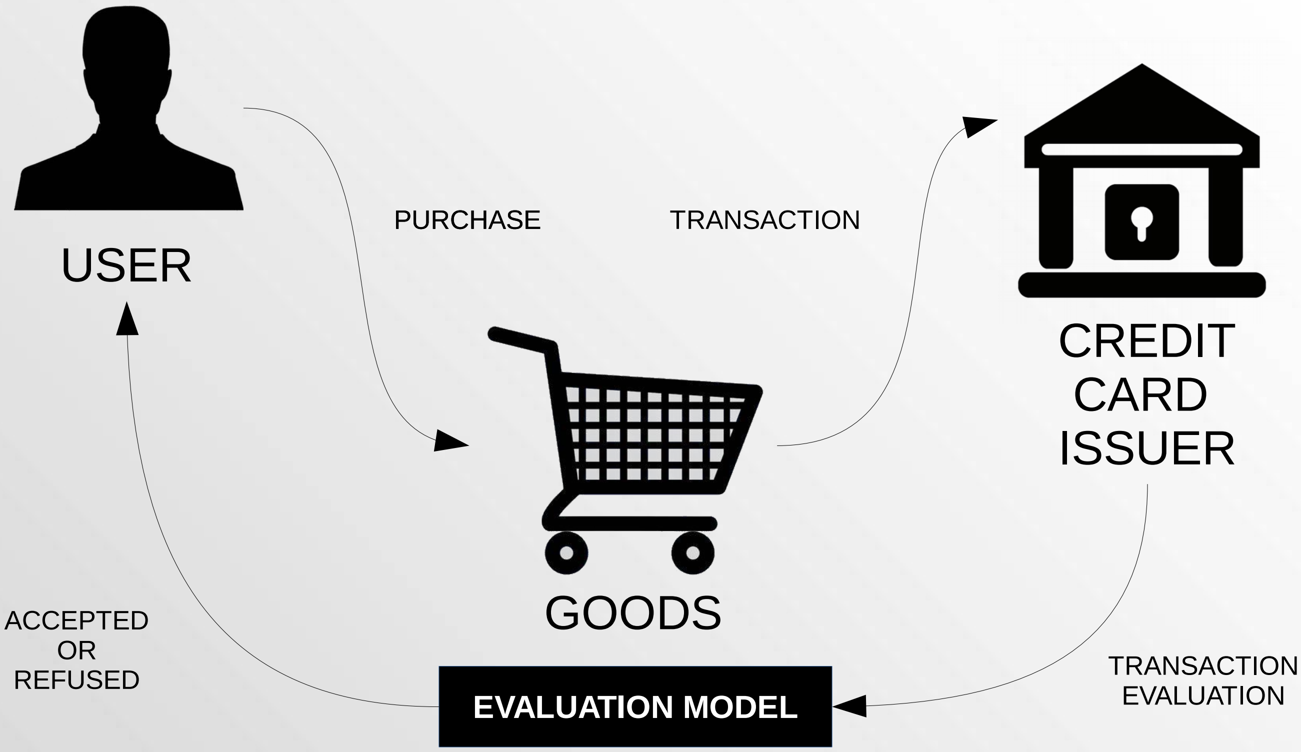
OVERVIEW

Introduction

A **Fraud Detection** task is aimed to classify a financial transaction as *legitimate* or *fraudulent*

Introduction

Such operation is performed by defining an **evaluation model** on the basis of the previous user transactions

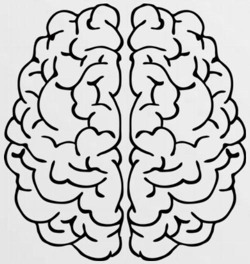


State of the Art

A large number of **state-of-the-art techniques** have been designed to address this problem

Machine Learning [3]

Artificial Intelligence [2]



Data Mining [1]

And so on . . .

State of the Art ■■

- Regardless of the adopted technique, the definition of effective *Fraud Detection* models represents a **hard challenge** for several factors

- The most important of which is the **Data Imbalance** [4]

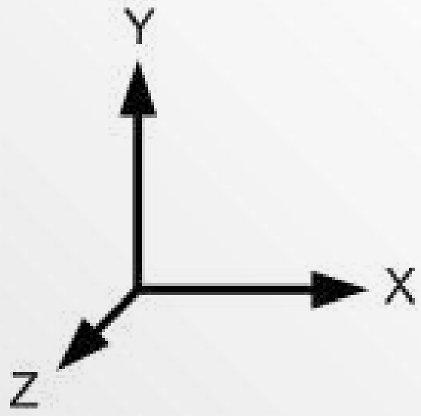
Limits

- **Data Imbalance** refers to a classification problem given by the fact that the classes are *not represented equally*
- Such configuration reduces the **effectiveness** of the state-of-the-art approaches [4]

INTUITION

Idea

- The main intuition on which the proposed approach relies is to perform the data analysis in a **three-dimensional space**, which is given by three different metrics of similarity



- It allows us to obtain a **better characterization** (wrt the state-of-the-art approaches) of each transaction in one of the two possible classes of destination (i.e., *legitimate* or *fraudulent*)

Formalization

- **Step 1 - Metrics Definition**: definition of three metrics aimed to compare two transactions in terms of different *similarity aspects*
- **Step 2 - Evaluation Criteria**: formalization of criteria used to evaluate a new transaction in the *three-dimensional space* given by the metrics
- **Step 3 - Algorithm Formulation**: formulation of an algorithm able to classify a new transaction as *legitimate* or *fraudulent*

Advantages

The adoption of a multidimensional similarity space approach leads toward some advantages:

- It offers a **better characterization** of each transaction in one of the two possible classes of destination (*legitimate* or *fraudulent*)
- It is able to operate in different real-world **data scenarios**, in terms of **size** and degree of **data imbalance**

IMPLEMENTATION

Metrics

The adopted similarity metrics are the following:

1. **Transactions Global Similarity Metric**: it measures the global similarity between two transaction vectors

2. **Features Local Similarity Metric**: it measures the similarity between transactions in terms of the weighted sequence of their features

3. **Features Global Similarity Metric**: it measures the global difference between two transactions in terms of their feature values

Metrics

They represent the **X**, **Y**, and **Z** dimensions:

X → 1

$$TGS(V_1, V_2) = \frac{V_1 \cdot V_2}{\|V_1\| \cdot \|V_2\|}$$

Y → 2

$$FLS(V^{(1)}, V^{(2)}) = TGS\left(idx\left(\overline{\overline{V^{(1)}}}\right), idx\left(\overline{\overline{V^{(2)}}}\right)\right)$$

with

$$\overline{\overline{V}} = \{|v_1| \leq |v_2| \leq \ldots \leq |v_M|\}$$

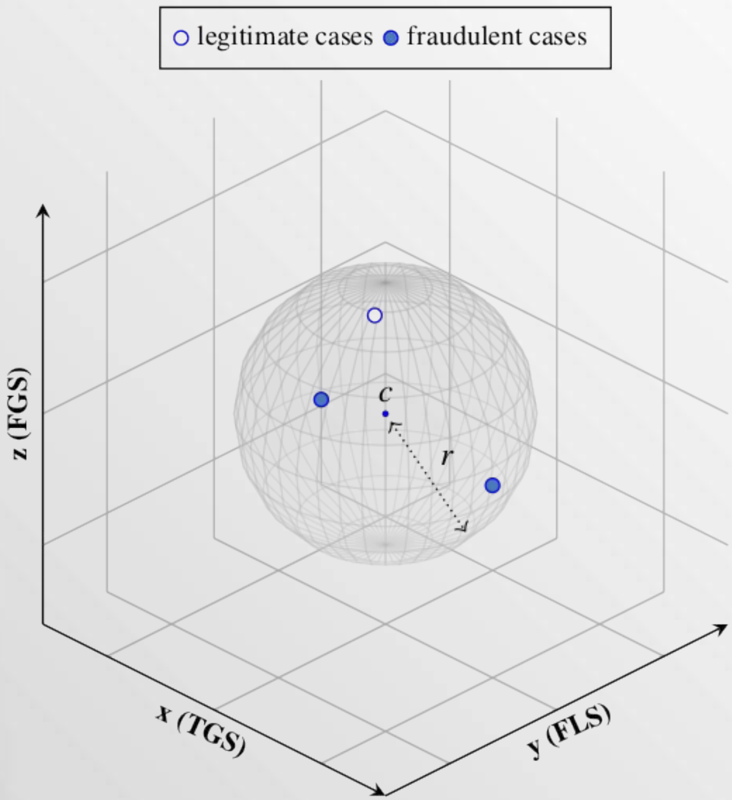
Z → 3

$$FGS(V^{(1)}, V^{(2)}) = 1 - \frac{\text{RMSE}}{max(\text{RMSE})}$$

with

$$\text{RMSE} = \sqrt{\sum_{m=1}^{M}\left(v_m^{(1)} - v_m^{(2)}\right)^2}$$

Classification



* The **radius** r is defined experimentally

1. We define a **center** c in our 3D space at the coordinates:

   ```
   max(TGS) − r
   max(FLS) − r
   max(FGS) − r
   ```

   by **comparing** the transaction to evaluate to the previous ones

2. The classification depends on the **nature** of the transactions bounded by the sphere of radius r* and center c

3. A transaction is **classified** as *legitimate* when the number of legitimate transactions bounded by the sphere is greater than that of the fraudulent ones, otherwise it is classified as *fraudulent*

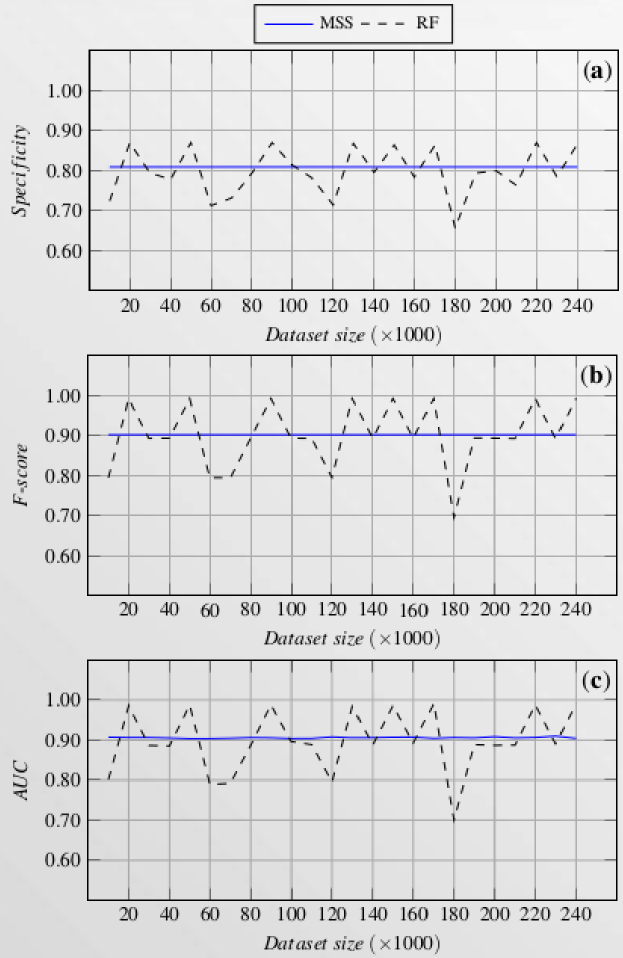
Classification

- The previous example shows a case where the evaluated transaction has been **classified as fraudulent**, because the number of fraudulent transactions bounded by the sphere of radius r and center c is greater than that of the legitimate ones

- In this process we adopt a **prudential criterion**, since the cases with equal number of legitimate and fraudulent transactions bounded by the sphere lead toward a fraudulent classification

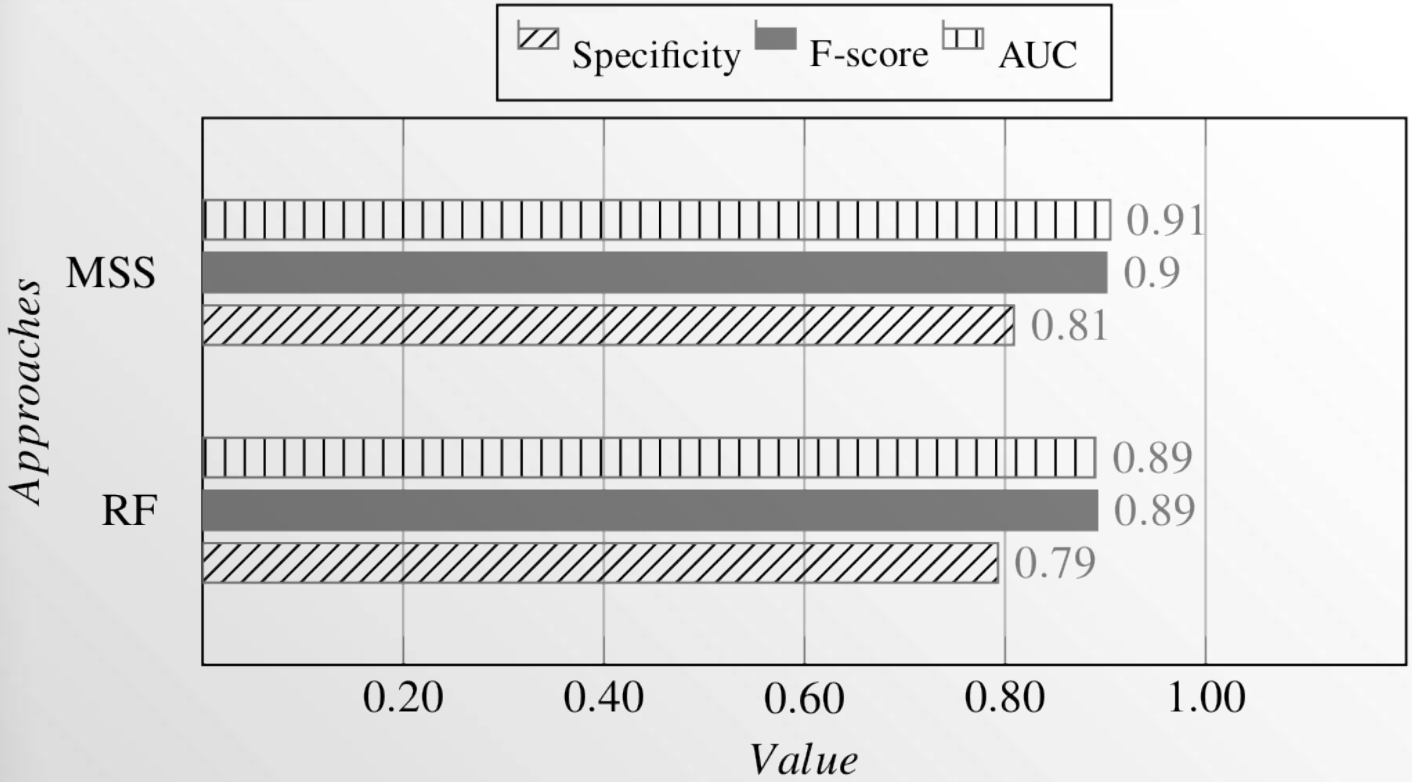
CONCLUSIONS

Experimental Results



- The first observation is related to the capability of our *Multidimensional Similarity Space* (**MSS**) approach to keep **constant** its performance, regardless of the size and the level of data imbalance, differently from its competitor Random Forests (**RF**)
- This mainly depends on the adopted strategy, which is able to better characterize the transactions in a 3D space of evaluation **less influenced** by the size and the level of data imbalance

Experimental Results



AVERAGE PERFORMANCE

Future Work

- Considering that the credit card fraud detection represents only one of the possible contexts where our approach can operate, a future work will be oriented to experiment it in other scenarios characterized by a high degree of data imbalance

- Another interesting future work would be the experimentation of additional metrics of similarity in order to improve the effectiveness of our classification approach

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THANK YOU FOR YOUR ATTENTION

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