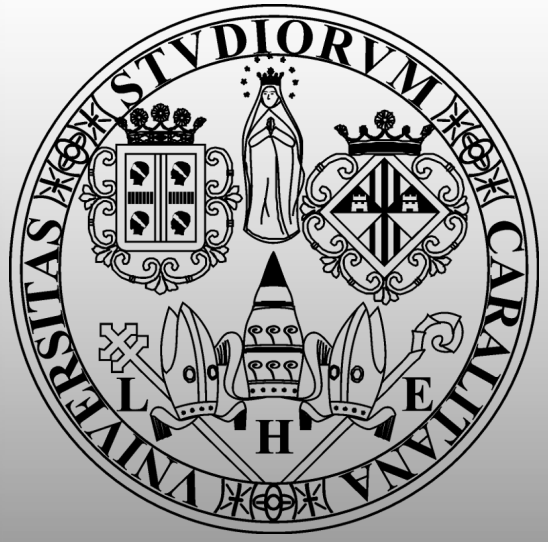

A Discrete Wavelet Transform Approach to Fraud Detection

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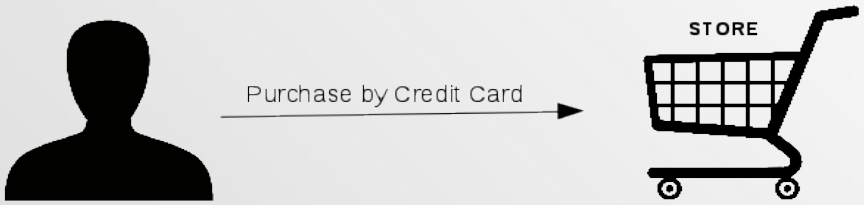
Outline

- **Overview**
  Introduction ▪ State of the Art ▪ Limits
- **Intuition**
  Idea ▪ Formalization ▪ Advantages
- **Implementation**
  Data Definition ▪ Data Evaluation ▪ Data Classification
- **Results**
  Experiments ▪ Conclusions ▪ Future Work

OVERVIEW

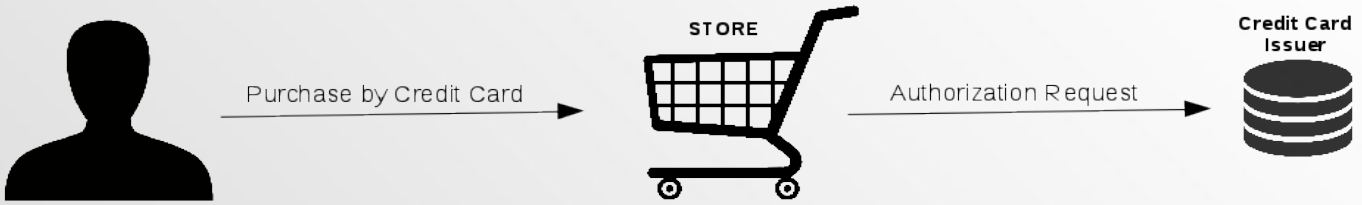
Introduction

- A **Fraud Detection** process is aimed to classify a new credit card transaction as *legitimate* or *fraudulent*



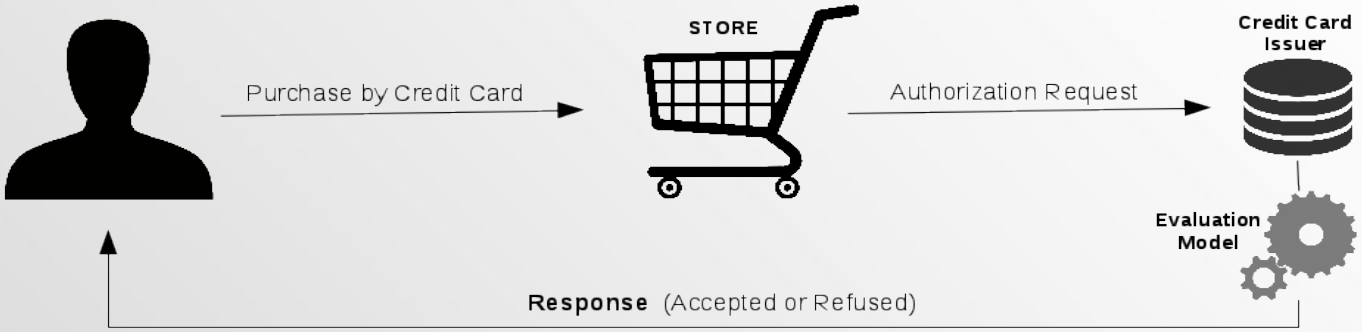
Introduction

- This happens when the **authorization request** arrives at the credit card issuer



Introduction

- The **response** depends on an **evaluation model** previously defined by using the user's past transactions



State of the Art

- Many state-of-the-art **approaches** have been designed to perform the ***Fraud Detection*** task, by exploiting several techniques, such as:
  - *Data Mining*[1]
  - *Artificial Intelligence*[2]
  - *Fuzzy Logic*[3]
  - *Machine Learning*[4]
  - *Genetic Programming*[5]
  - … and many more

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 **Imbalanced class distribution**[6]

Limits

- The **imbalanced class distribution** exists because the number of *fraudulent* cases is usually **much smaller** than that of the legitimate ones
- This reduces the **effectiveness** of the most widely used approaches[6]

LEGITIMATE CASES **vs** FRAUDULENT CASES

INTUITION

Idea

- Overcome the **imbalanced class distribution** issue by using a single class of data (*legitimate transactions*) during the model definition
- Define this model in a **new domain** that allows us to well characterize this class of data
- This goal is achieved thanks to the **different point of view** on data offered by the new domain

Formalization

- We propose a **transformed-domain-based pattern mining** process able to evaluate a new transaction in a novel way
- It is made by exploiting the **Discrete Wavelet Transformation**[7], applying it on the values assumed by the transaction **features***
- We perform this operation by considering these values as a **time series**

* They contain several information about a credit card transaction, e.g., **place**, **amount**, **date**, etc.

Formalization

- The first interesting property of the new data representation is the **dimensionality reduction**
- The DWT process can reduce the time-series data, offering a **compact representation** that preserves the original information
- This allows a Fraud Detection system to reduce the **computational complexity** of the involved processes

Formalization

- The second interesting property of the new data representation is the **multiresolution analysis**
- The DWT process allows us to define **several time series** on the basis of the original one, preserving the information
- A Fraud Detection system can exploit this property to obtain two **different point of views** on data:
  - **approximated** (*data overview*)
  - **detailed** (*data changing*)

Formalization

- Our approach exploits **both** the aforementioned properties
- The original time series are transformed by using the **Haar wavelet***
- It offers us an approximated point of view on data that allows us to **model** the considered class of information

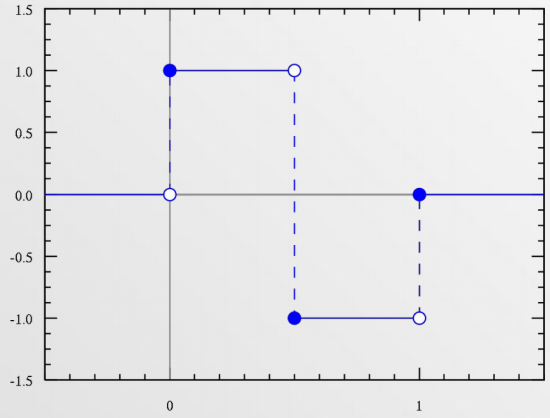
* The Haar wavelet represents the simplest possible wavelet.

Advantages

Haar wavelet is a sequence of rescaled *square-shaped* functions which represent a **wavelet family**

They are based on the following **Mother** and **Father** (*scaling*) functions:

$$\psi(t) = \begin{cases} 1 & 0 \le t < \frac{1}{2}, \\ -1 & \frac{1}{2} \le t < 1, \\ 0 & \text{otherwise.} \end{cases} \qquad \varphi(t) = \begin{cases} 1 & 0 \le t < 1, \\ 0 & \text{otherwise.} \end{cases}$$



Advantages

Suppose we have a **time series** (**TS**) composed by **N** values (where **N** is even)

TS = (6, 12, 15, 15, 14, 12, 120, 116)

We calculate the **pair-wise average** $\mathbf{S}_k = (TS_{2k} + TS_{2k+1}) / 2$ for k=0, …, N/2 -1

TS = (6, 12, 15, 15, 14, 12, 120, 116) → **S** = (9, 15, 13, 118)

We also calculate the **directed distances** $\mathbf{D}_k = (TS_{2k} - TS_{2k+1}) / 2$ for k=0, …, N/2 -1

TS = (6, 12, 15, 15, 14, 12, 120, 116) → **D** = (-3, 0, 1, 2)

S and **D** allow us to recover the original information in **TS**

This process can be repeated **recursively**

and it allows us to define a **more stable** model of evaluation

Advantages

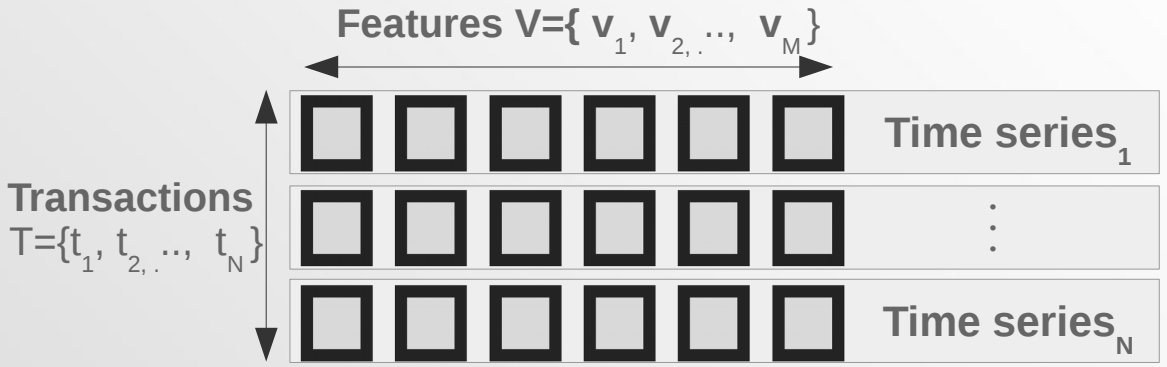
- The adoption of a model based on the wavelet leads toward some advantages:
  - It **overcomes** the imbalance class distribution issue by using only a class of data (previous legitimate transactions)
  - The use of only *legitimate* cases, allows us to operate in a **proactive** way
  - It also overcomes the problems related to the **cold-start** issue[9]

IMPLEMENTATION

Implementation

Step 1 of 3 - Data Definition

- Definition of the **time series** in terms of values assumed by the features of a transaction



- Each time series is processed by using a **Discrete Wavelet Transform** process

Implementation

Step 2 of 3 – Data Evaluation

- Comparison of the **wavelet patterns** of two transactions
- It is performed in terms of **cosine similarity** between the output vectors of the wavelet processes

$$\Delta = Cosim(F(t), F(\hat{t})), \;\; with \;\; c = \begin{cases} \Delta \geq \alpha, & \text{legitimate} \\ \Delta < \alpha, & \text{fraudulent} \end{cases}$$

α is a threshold experimentally defined

Implementation

Step 3 of 3 – Data Classification

- Definition of an **algorithm** able to classify a new transaction as *legitimate* or *fraudulent*, on the basis of the *previous comparison process*
- It takes into account the **cosine similarity** between the new transaction to evaluate and each previous legitimate transaction
- The **classification** of the new transaction is based on the average of these results

Require: T_+=Legitimate previous transactions, $\hat{t}$=Unevaluated transaction, α=Threshold
Ensure: β=Classification of the transaction $\hat{t}$

```
1: procedure TRANSACTIONEVALUATION(T+, t̂)
2:     ts1 ← getTimeseries(t̂)
3:     sp1 ← getDWT(ts1)
4:     for each t in T+ do
5:         ts2 ← getTimeseries(t)
6:         sp2 ← getDWT(ts2)
7:         cos ← cos + getCosineSimilarity(sp1, sp2)
8:     end for
9:     avg ← cos / |T+|
10:    if avg > α then β ← true else β ← false
11:    return β
12: end procedure
```

RESULTS

Experiments

- We conducted the **experiments** by adopting the *k-fold cross validation* criterion, with *k=10*
- We used a **real-world dataset**(*) with 284,807 transactions and a *strong imbalanced* data distribution (only 492 fraud cases)
- The selected competitor was **Random Forests**, since it represents one of the most performing state-of-the-art approach in this field[11]

(*) https://kaggle.com/dalpozz/creditcardfraud

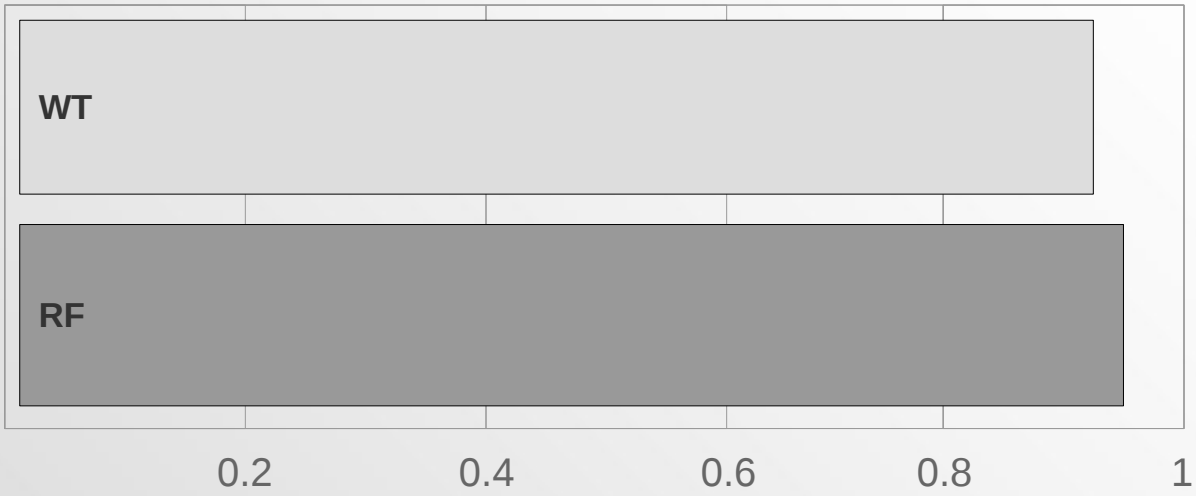
Experiments

- The *first series of* experiments shows the *general performance* achieved by our approach and Random Forests, in terms of ***F-score***
- The *second series of* experiment is instead aimed to evaluate our predictive model in terms of Area Under the ROC* Curve (**AUC**)

(*) Receiver Operating Characteristic

Experiments

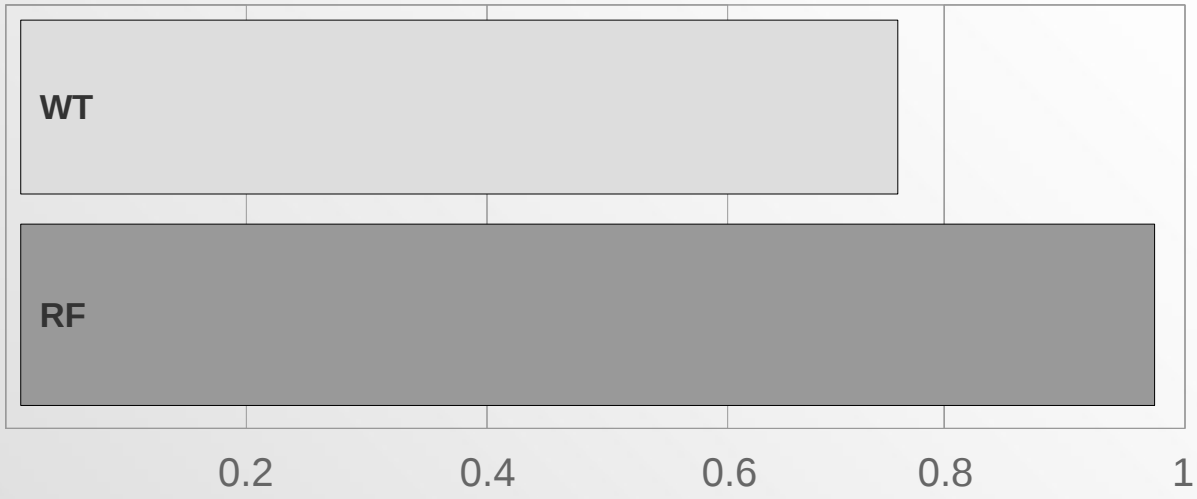
- The general performance of our **WT** approach in terms of ***F-score*** is close to that of *Random Forests* (**RF**)



- In spite of the fact that we did **not use** any past default instance to train the evaluation model

Experiments

- The last set of experiments measures the predictive model performance in terms of **AUC**



- Also in this case, the performance of our *predictive model* is quite close to that of **RF**

Conclusions

- **Fraud Detection** techniques cover a crucial role in many financial contexts
- The proposed approach allows a Fraud Detection system to face some well-known issues, such as the **unbalanced distribution of data** and the **cold-start**
- It is made by adopting a proactive strategy based on an evaluation model defined by exploiting the **Wavelet Transformation**

Conclusions

- Such **proactive** approach is not designed to replace the existing **retroactive** state-of-the-art approaches
- It is aimed to face some well-known problems that affect them, such as the **cold-start** and the **data unbalance** ones
- It can be used to define **hybrid** fraud detection approaches able to operate in all real-world scenarios

Future Work

- A future work will be the definition and evaluation of a **hybrid fraud detection approach** that exploits both previous *legitimate* and *fraudulent* cases
- We are also considering the evaluation of our approach in **different scenarios** (e.g., those related to the *credit scoring* tasks)

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