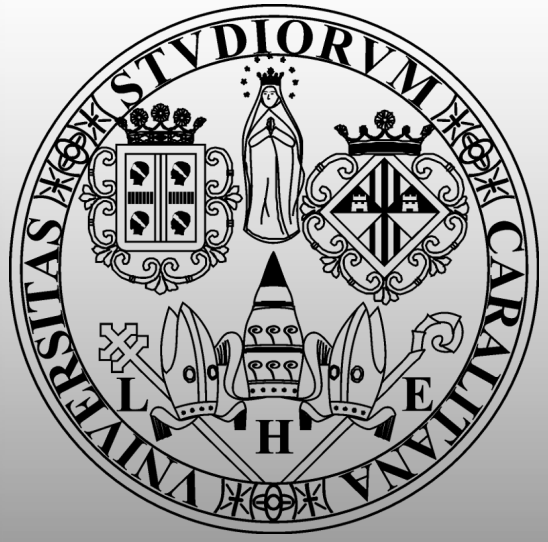

A Frequency-domain-based Pattern Mining for Credit Card Fraud Detection

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Outline

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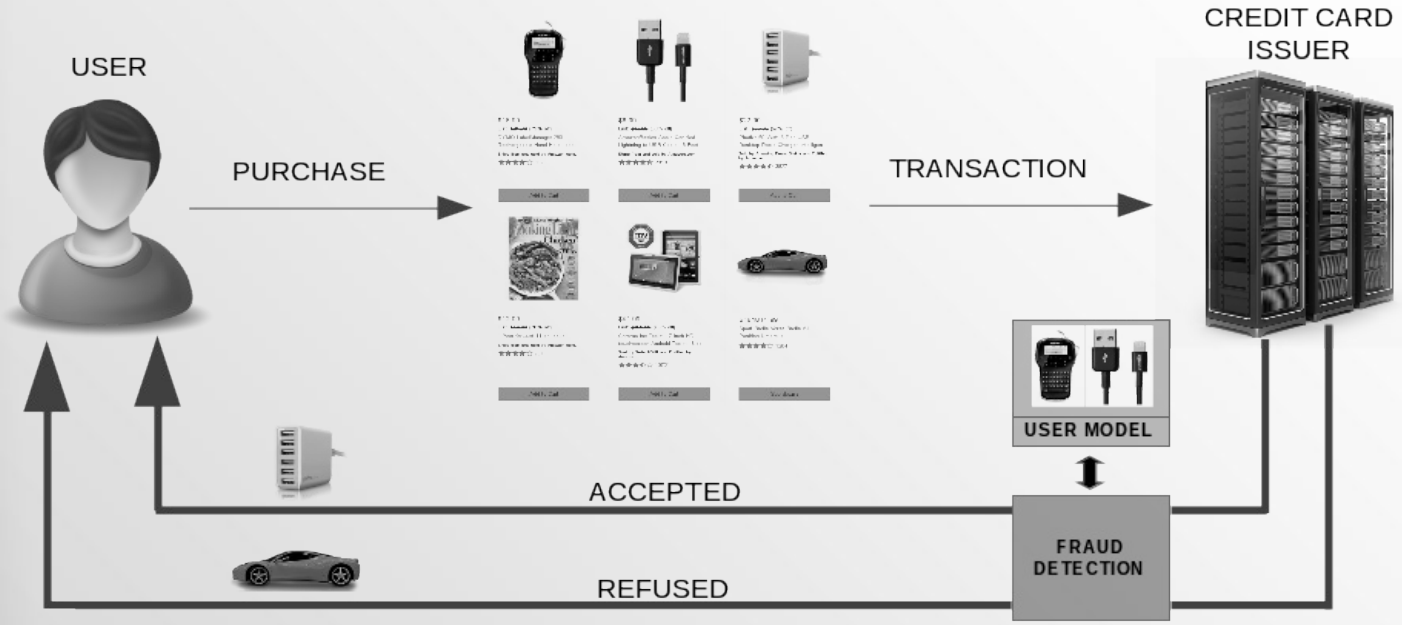
OVERVIEW

Introduction

- The main aim of a **Fraud Detection** task is the classification of a financial transaction as *legitimate* or *fraudulent*

Introduction

- It is usually performed on the basis of a **model** defined by using the previous transactions of a user



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]

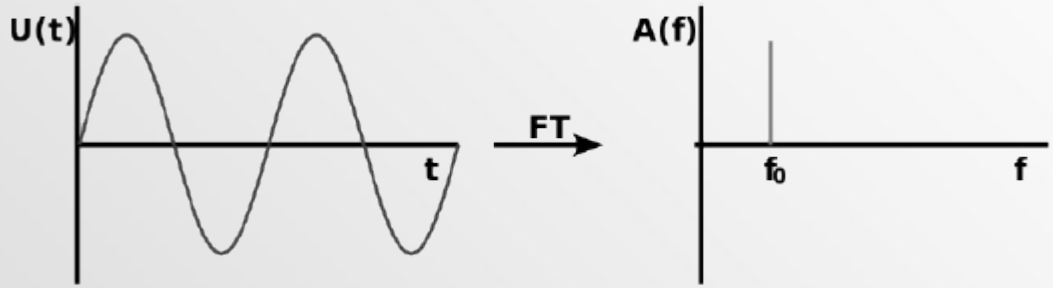
LEGITIMATE CASES **VS** FRAUDULENT CASES

INTUITION

Idea

- Overcome the **imbalanced class distribution** issue by using a single class of data (*legitimate transactions*) during the model definition

- Perform this operation through a model able to well characterize the legitimate transactions, defining it in the **frequency domain**



We move the data analysis from the canonical domain to the frequency one in order to obtain a **more stable** model

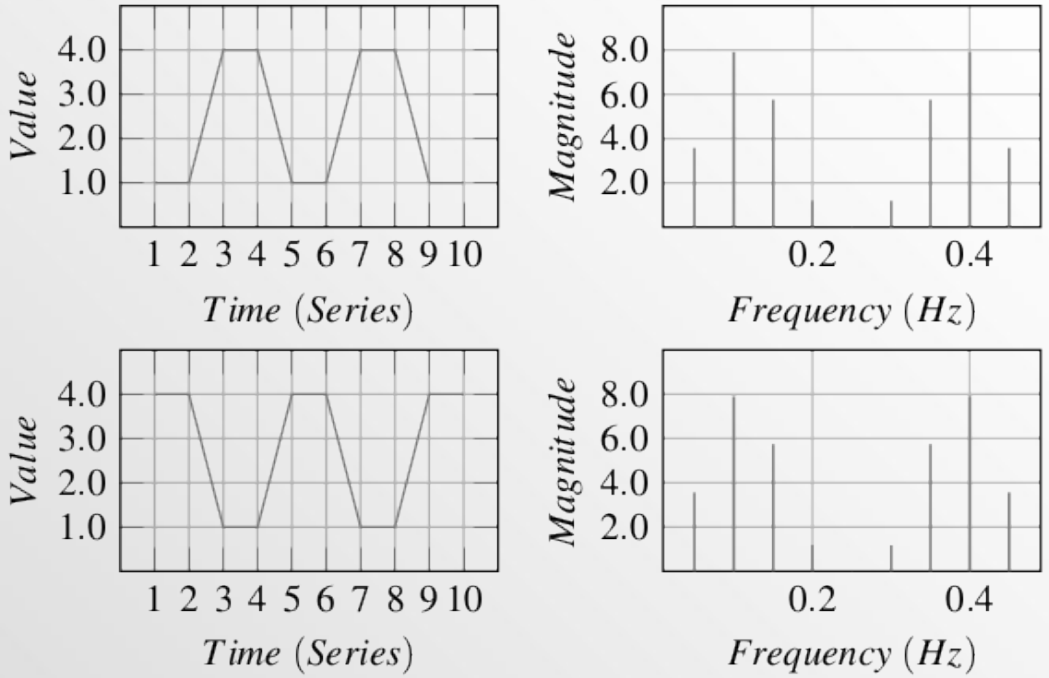
Formalization

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

* It contains several information about the credid card transaction, e.g., **place**, **amount**, **date**, etc.

Formalization

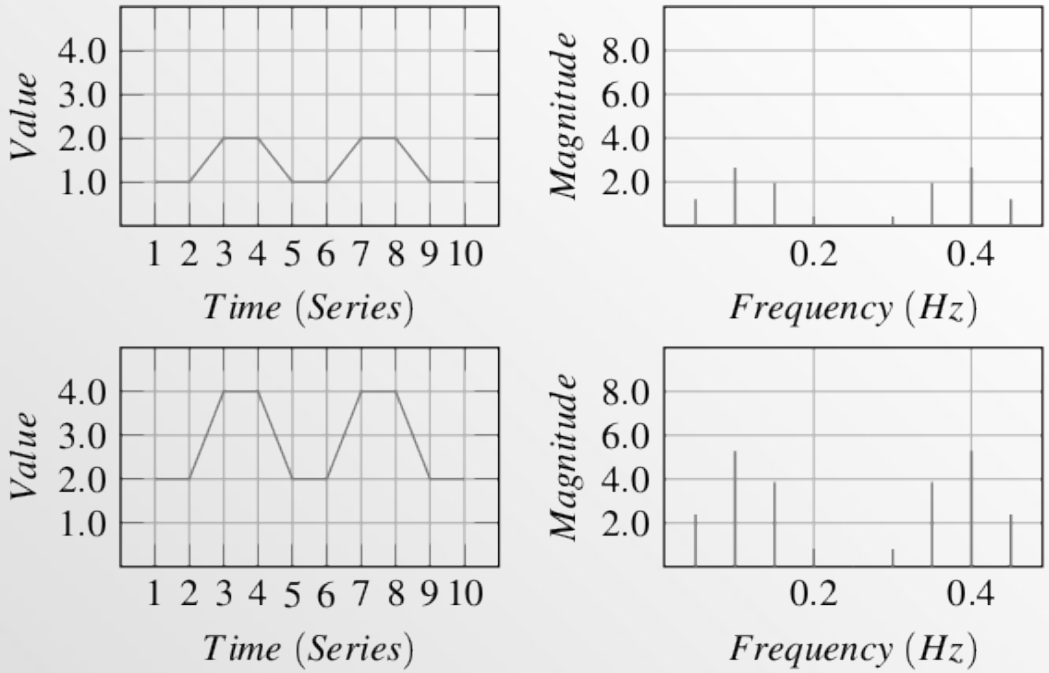
- The first interesting property of the new data representation is the **phase invariance**



- This allows us to detect **specific patterns**, also when they shift along the transaction features

Formalization

- The second interesting property of the new data representation is the **amplitude correlation**



- This grants that our model is able to differentiate same patterns with different feature values

Advantages

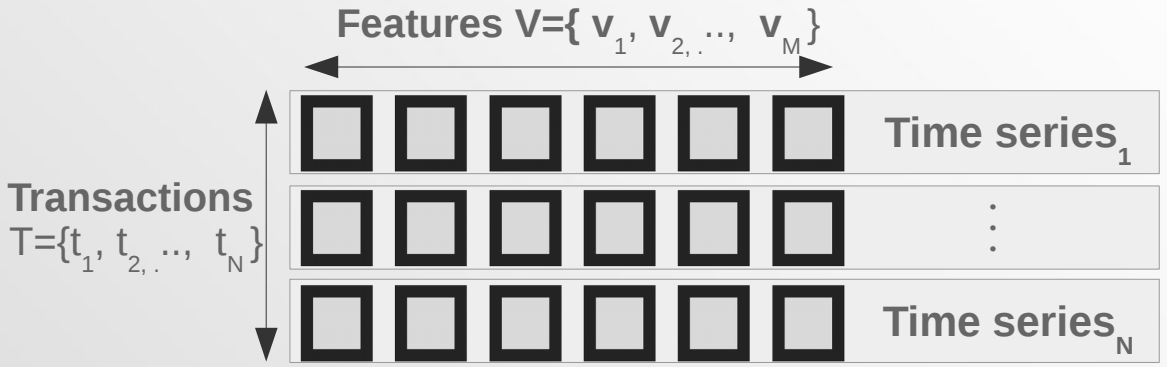
- The adoption of a model based on the frequency pattern leads toward some advantages:
  - It **overcomes** the imbalance class distribution issue by using only a class of data (previous legitimate transactions)
  - The use of only *legitimate* cases, allows us to operate in a **proactive** way
  - It 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 Fourier Transform** process

Implementation

Step 2 of 3 – Data Evaluation

- Comparison of the **frequency patterns** of two transactions
- It is performed by measuring the difference **Δ** between the **magnitude** of each frequency component **f*** of the pattern

$$\Delta = \left(|f_x^1| - |f_x^2| \right), \ with \ |f_x^1| \geq |f_x^2|$$

*f_x^1 and f_x^2 denote, respectively, the same component of the two transactions

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 counts how many times the **magnitude** of each frequency component of a new transaction is below or above that of each previous legitimate transaction
- The **classification** of the new transaction is made on the basis of the final result* of this operation

* A tolerance can be taken into account

CONCLUSIONS

Applications

- **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 the **frequency pattern** of the transactions

Future Work

- After a validation of our approach by using real-world datasets, a possible follow up of this work could be the definition of an **hybrid approach** that exploits both the previous *legitimate* and *fraudulent* cases

- We also consider the evaluation of our approach in **heterogeneous scenarios** that involve different types of financial data, such as those of the e-commerce environment

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