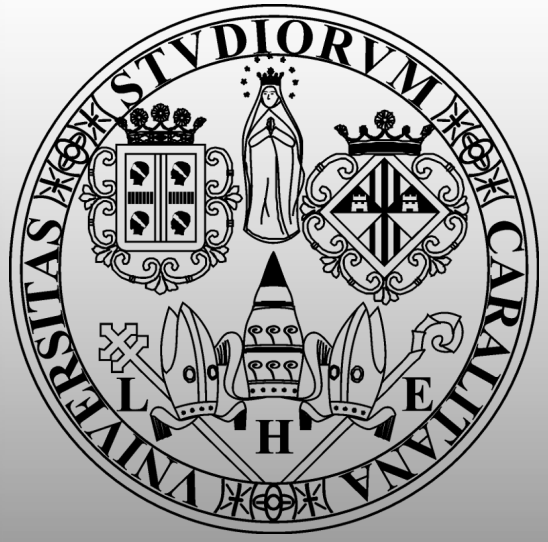

A Wavelet-based Data Analysis to Credit Scoring

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Outline

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- **Idea**
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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**[1]

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[2]

NON-DEFAULT CASES **VS** DEFAULT CASES

IDEA

Intuition

- Overcome the **imbalanced class distribution** issue by using a single class of data (reliable instances) 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 instance in a novel way
- It is made by exploiting the **Discrete Wavelet Transformation**[3], applying it on the values assumed by the **instances***
- We perform this operation by considering these values as a **time series**

* They contain information about the instance, e.g., applicant age, job, loan purpose, 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 Credit Scoring 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 Credit Scoring 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 class of information taken into account

* The Haar wavelet represents the simplest possible wavelet.

Advantages

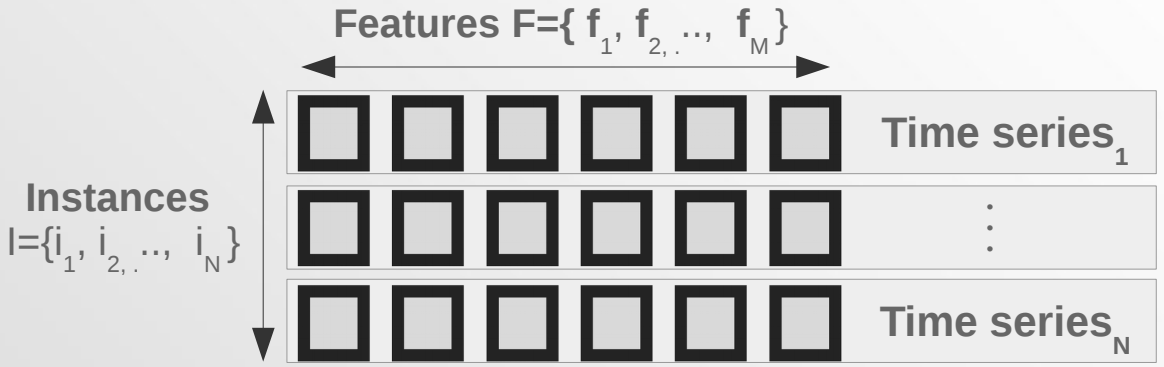
- The adoption of a model based on the wavelet leads toward some advantages:
  - It **overcomes** the imbalance class distribution issue by using only a class of data (previous reliable instances)
  - The use of only *reliable* cases, allows us to operate in a **proactive** way
  - It also reduces the problems related to the **cold-start** issue[4]

IMPLEMENTATION

Implementation

Input Data Definition

- Definition of the **time series** in terms of values assumed by the features of an instance



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

Implementation

Similarity Metrics Definition

We compare two instances in terms of *three metrics of similarity*:

- **Cosine Similarity** (Θ)
  Time-series vectors similarity

- **Features Weighted Sequence Similarity** (Φ)
  Time-series similarity in terms of weighted sequence of the features

- **Normalized Magnitude Similarity** (μ)
  Similarity in terms of magnitude between the DWT output of two time-series

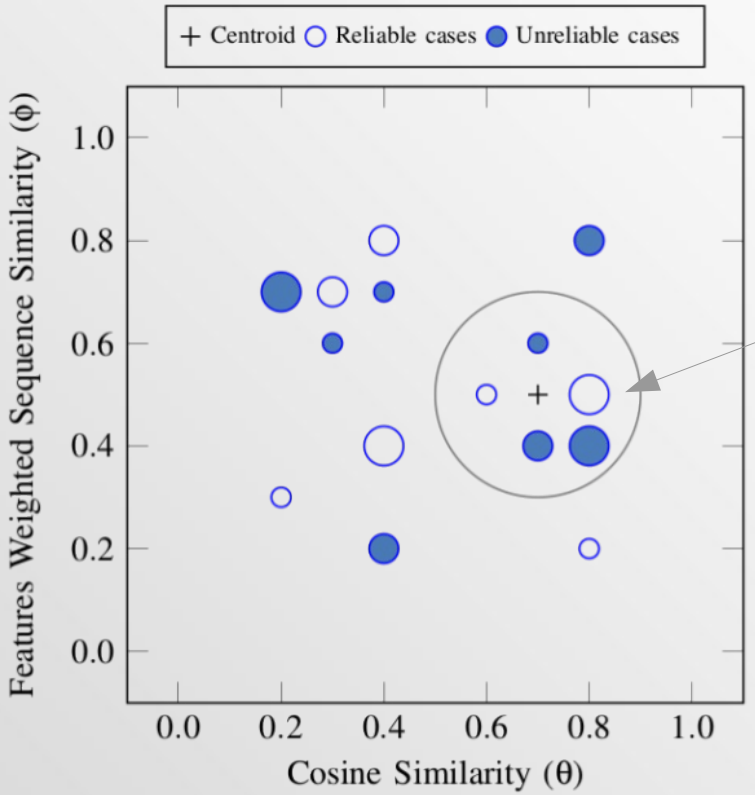
Implementation

Instance Classification

- We define a **radius (ρ)** value experimentally
- We define a **centroid** at coordinates **max(Cosine Similarity) − ρ** and **max(Features Weighted Sequence Similarity) − ρ**, (**max** *has been calculated between the instance to evaluate and all the instances in the training set*)
- A new instance is classified as reliable if the weight (in terms of **Normalized Magnitude Similarity**) of the selected *reliable* instances within the **radius ρ** is greater than that of the *unreliable* ones, otherwise it is classified as unreliable.

Implementation

Instance Classification



The size of circle represent s the *Normalized Magnitude Similarity* (**μ**)

In this case the instance under evaluation **is classified as unreliable**, since the sum of the weight of the **three unreliable instances** within the **radius** is **greater** than that of the other **two reliable ones.**

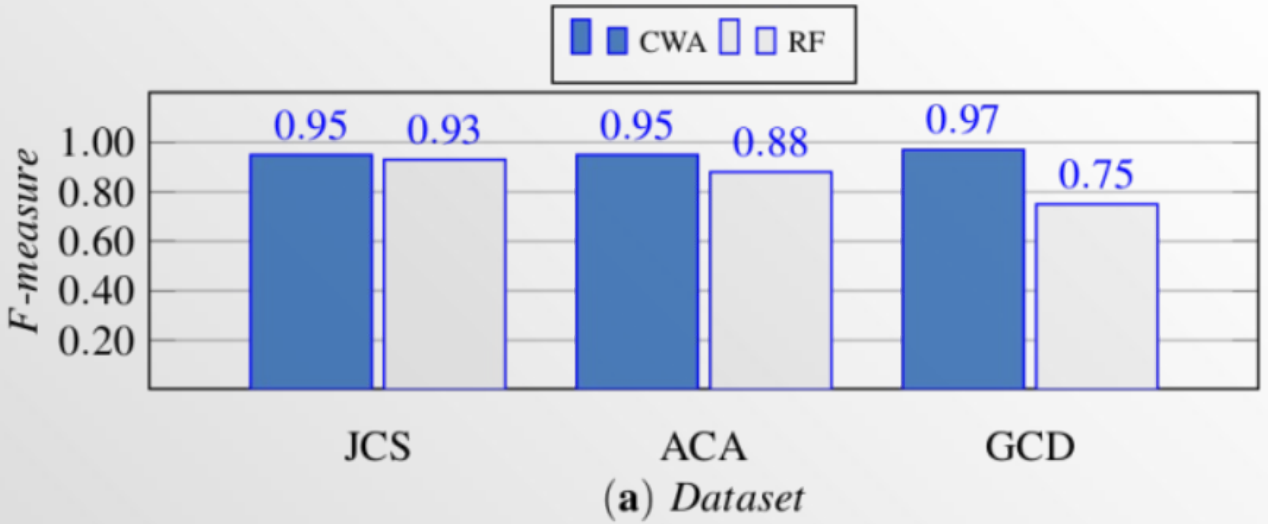
RESULTS

Experiments

- We conducted the **experiments** by using three **real-world datasets** that reproduce different data scenarios (for number of instances and class balancing)
- The selected competitor was **Random Forests**, since it represents one of the most performing state-of-the-art approach in this field[5]
- The first experiment evaluates the general performance (**F-measure**), while the second one evaluates our predictive model (**AUC**)

Experiments

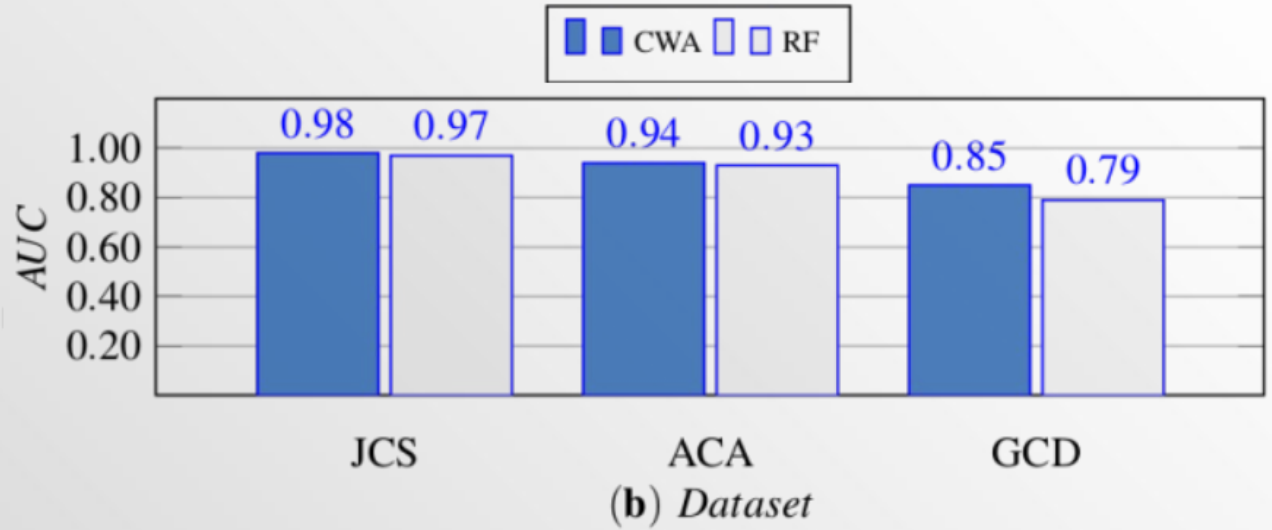
Our *Centroid Wavelet-based Approach* (**CWA**) ouperforms **RF** in terms of *F-measure*, regardless of data size and the level of imbalance



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

Experiments

- Also in terms of *AUC* our **CWA** approach outperforms its competitor **RF**



- It shows the **effectiveness** of its predictive model

Conclusions

- The **Credit Scoring** techniques cover a crucial role in many financial contexts
- The proposed approach allows a Credit Scoring 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 **Discrete 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 Credit Scoring approaches** able to operate in all real-world scenarios

Future Work

- Future work would be oriented to experiment **additional metrics** of similarity, as well as **other wavelet functions** in the *Discrete Wavelet Transformation* process, with the aim to further improve the effectiveness of the classification model

- Another interesting future work would be the experimentation of the proposed approach in **different scenarios**

References

[**1**] He, H. and Garcia, E. A. (2009). Learning from imbalanced data. IEEE Trans. Knowl. Data Eng., 21(9):1263–1284.

[**2**] Japkowicz, N. and Stephen, S. (2002). The class imbalance problem: A systematic study. Intell. Data Anal., 6(5):429–449.

[**3**] Percival, D.B., Walden, A.T.: Wavelet methods for time series analysis. Volume 4. Cambridge university press (2006).

[**4**] Attenberg, J. and Provost, F. J. (2010). Inactive learning?: difficulties employing active learning in practice. SIGKDD Explorations, 12(2):36–41.

[**5**] Lessmann, S., Baesens, B., Seow, H., and Thomas, L. C. (2015). Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research. European Journal of Operational Research, 247(1):124–136.

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