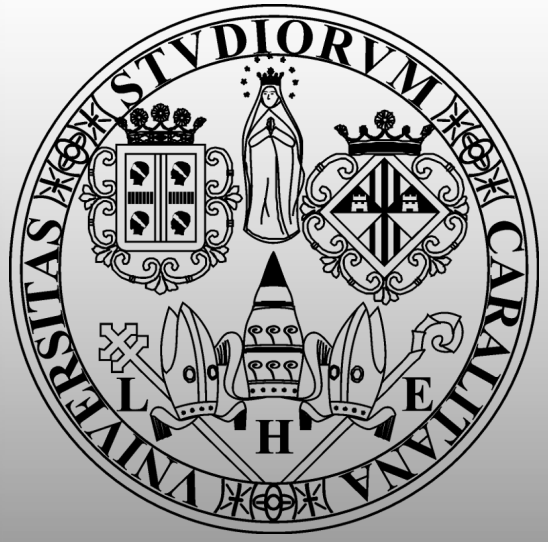

An Entropy Based Algorithm for Credit Scoring

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Outline

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- **Intuition**
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- **Implementation**
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- **Results**
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OVERVIEW

Introduction

- The main aim of **credit scoring models** is the classification of the loan applications 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*[1]
  - *Linear Discriminant*[2]
  - *Logistic Regression*[3]
  - *Neural Networks*[4]
  - *Genetic Program*[5]
  - *Decision-tree*[6]
  - … and many more

State of the Art

- Regardless of the adopted technique, the definition of effective *Credit Scoring* models represents a **hard challenge** due to several factors

- The most important of which is the **Imbalanced class distribution**[7]

Limits

- The **Imbalanced class distribution** exists because the number of *default* cases (*non-refunded loans*) is **much smaller** than that of the *non-default* ones (*refunded loans*)
- This reduces the **effectiveness** of the most widely used approaches[8]

NON-DEFAULT CASES **VS** DEFAULT CASES

INTUITION

Idea

- Since the **Shannon Entropy** (from now on referred simply as *entropy*) increases as the data becomes equally probable and decreases otherwise
- We exploit this concept in order to evaluate a new loan application (from now on referred simply as *instance*)

Idea

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- We exploit this concept in order to evaluate a new loan application (from now on referred simply as *instance*)

The idea is to measure the *entropy* in the set of the past non-default instances, **before** and **after** we added to it a new instance to evaluate

Usage

- We calculate the **Local Maximum Entropy** (LME) which give us information about the entropy achieved by each **instance*** feature in the set of non-default cases

  (*Differences between instances in terms of single features*)

- We also calculate the **Global Maximum Entropy** (GME) which represents a meta-feature based on the *integral* of the area under the curve of the LME values

  (*Differences between instances in terms of all features*)

* It contains several information about the applicant, e.g., **gender**, **age**, **marital status**, **income**, **loan amount**, **other loans**, etc.

Usage

- Finally we define the **Difference in Maximum Entropy** (DME) approach that allows us to classify a new instance as *accepted* o *rejected*
- It was performing by exploiting the previous *Local* and *Global Maximum Entropy* (**LME** and **GME**) information
- It is based on the observation of **how changes** the **LME** and **GME** values when we add a *new* (*unevaluated*) instance to the set of the *past* non-default instances

Usage

A **larger** entropy indicates that the added new instance contains similar data in the features, increasing their level of equiprobability

Otherwise, a **lower** entropy indicates different data in the instance, and we consider it as a potential *default case*

Advantages

- The adoption of the proposed entropy-based approach presents several advantages:
  - It **overcomes** the imbalance class distribution issue by using only a class of data (*non-default instances*)
  - The use of only *non-default* cases, allows us to operate in a **proactive** way
  - It reduces the problems related to the **cold-start** issue[9]

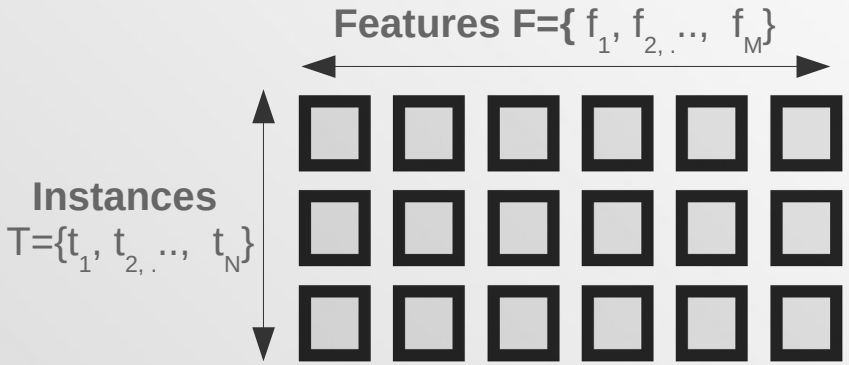
IMPLEMENTATION

Implementation

Step 1 of 3 – Local Maximum Entropy

We define a set **Λ** that contains the maximum value of entropy **H** achieved by each feature **f** in the non-default instances set **T**

$$\Lambda = \{\lambda_1 = max(H(f_1)), \lambda_2 = max(H(f_2)), \ldots, \lambda_M = max(H(f_M))\}$$

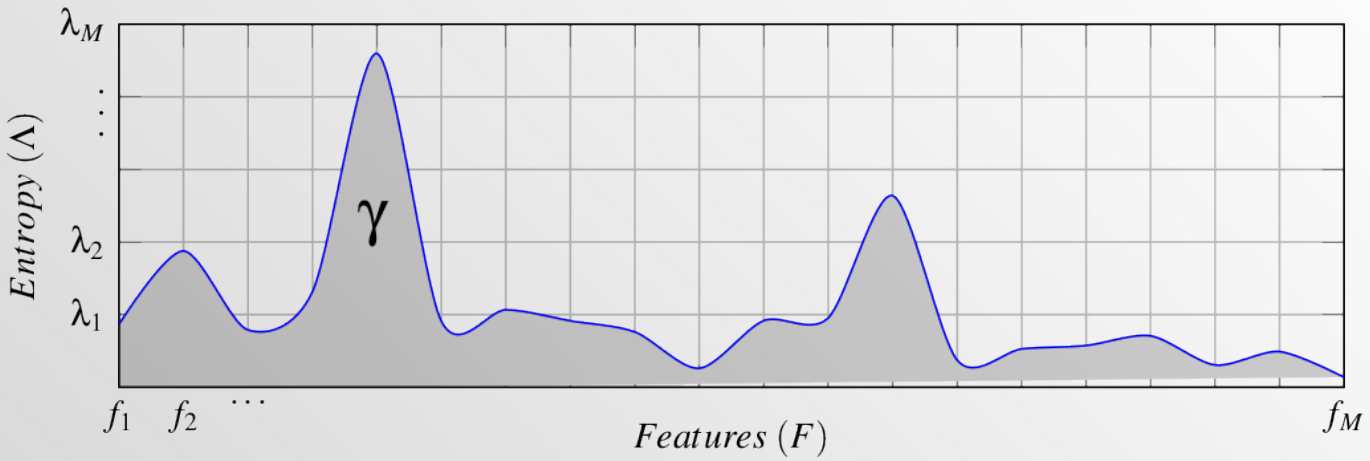


Implementation

Step 2 of 3 – Global Maximum Entropy

Subsequently, we calculate the integral γ of the area under the curve given by the previous set Λ

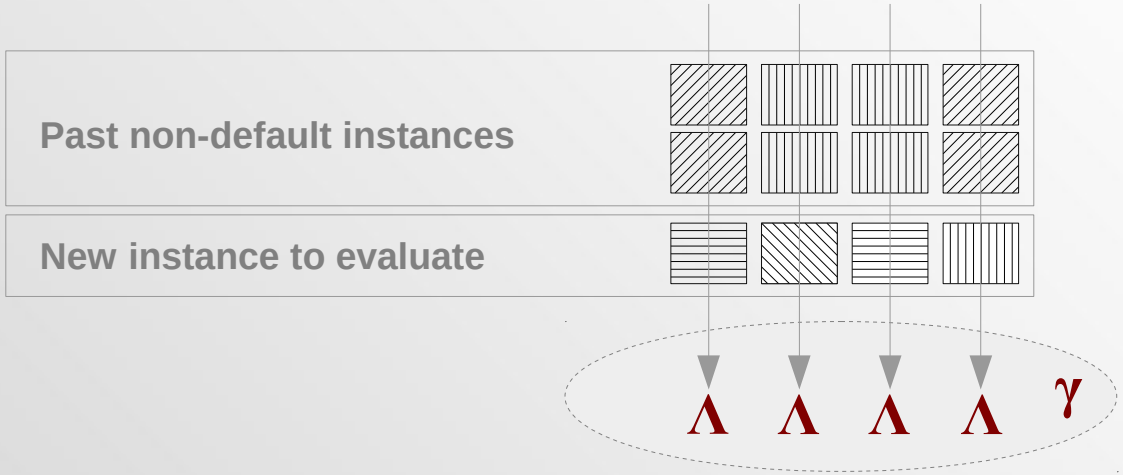
$$\gamma = \int_{\lambda_1}^{\lambda_M} f(x)\,dx \approx \frac{\Delta x}{2} \sum_{k=1}^{|\Lambda|} \left(f(x_{k+1}) + f(x_k)\right) \quad \textbf{with} \quad \Delta x = \frac{(\lambda_M - \lambda_1)}{|\Lambda|}$$



Implementation

Step 3 of 3 – Difference in Maximum Entropy

A new instance is classified as *accepted* or *rejected* on the basis of the Λ and γ values, compared them before and after that we added to the set of non-default past instances **T** the instance to evaluate



Lower values of Λ and γ indicate that the new instance contains different data in its features

RESULTS

Experiments

The **experiments** were performed by following the *k-fold cross validation* criterion, with *k=10*

- We used two **real-world datasets**[10] characterized by a *strong imbalanced* data distribution
- As competitor we use **Random Forests**, one of the most performing state-of-the-art approaches in this field[11]

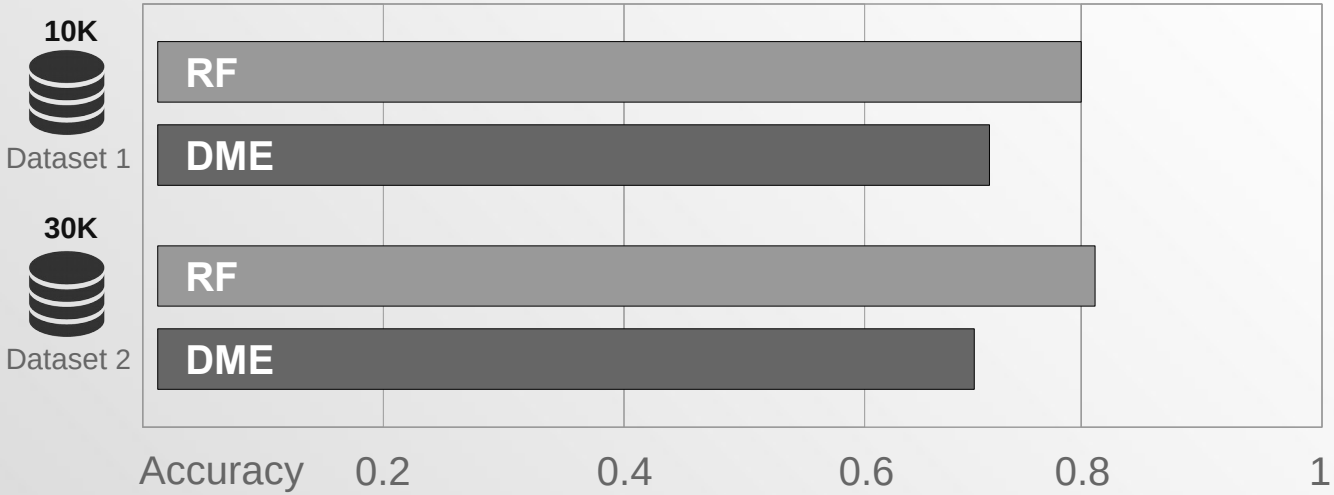
Experiments

- The *first two* experiments show the *general performance* achieved by our **DME** approach and Random Forests, in terms of ***Accuracy*** and ***F-score***
- The *third* experiment is instead aimed to evaluate our predictive model in terms of **AUC***

* Area Under the (Receiver Operating Characteristic) Curve

Experiments

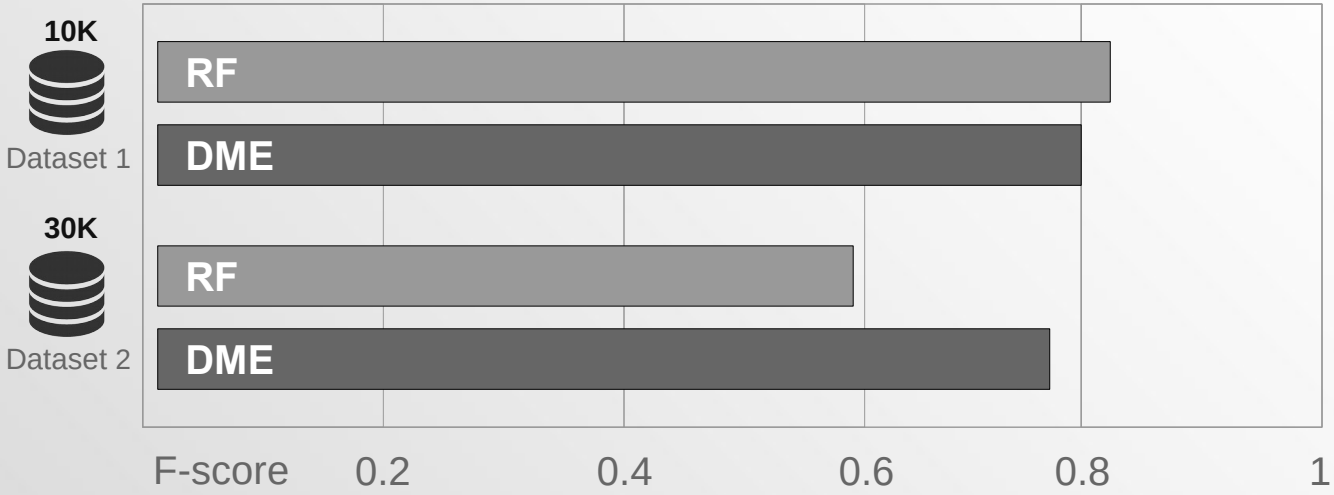
- The general performance of our **DME** approach in terms of *accuracy* is very close to those of Random Forests (**RF**)



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

Experiments

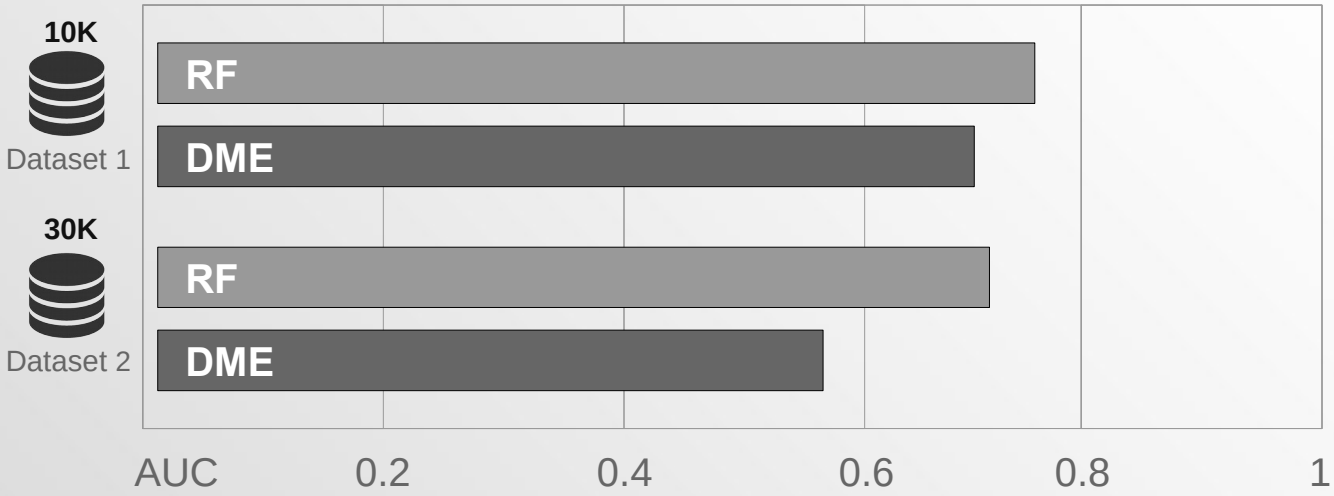
- Also in terms of *F-score*, the general performance of our **DME** approach is very close to those of Random Forests (**RF**)



- Differently from **RF**, the effectiveness of **DME** increases with the number of instances

Experiments

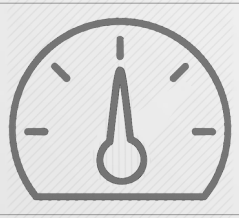
- The last set of experiments measures the performance in terms of **AUC** (*Area Under ROC Curve*)



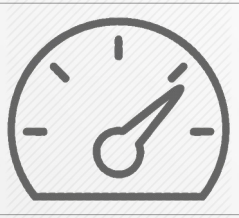
- Also in this case, the performance of our *predictive model* is very close to those of **RF**

Conclusions

- We proposed a novel approach of ***Credit Scoring*** that exploits an *entropy-based* criterion
- The experiments show **two** main results:



By using a small dataset, our performance is **similar** to one of the most performing state-of-the-art approach (*RF*), in spite of the fact that we do not use the past default instances



By using a larger dataset, our approach **outperforms** its competitor (*RF*), while continuing to not use past default instances during the training

Conclusions

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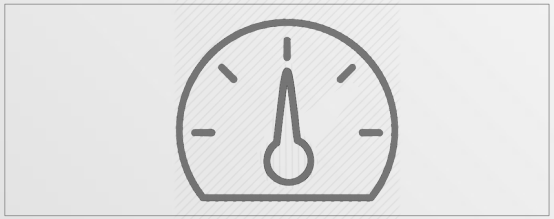
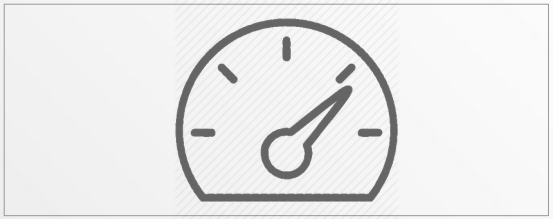
- The experiments show **two** main results:



Proactivity



Improvement

Future Work

- A possible follow up of this work could be a new series of experiments performed by using **both** the *past default* and *non-default* cases
- This will allow us to investigate about the advantages and disvantages related to a **non-proactive** approach
- We also consider to test our approach in **heterogeneous** scenarios that involve different types of financial data

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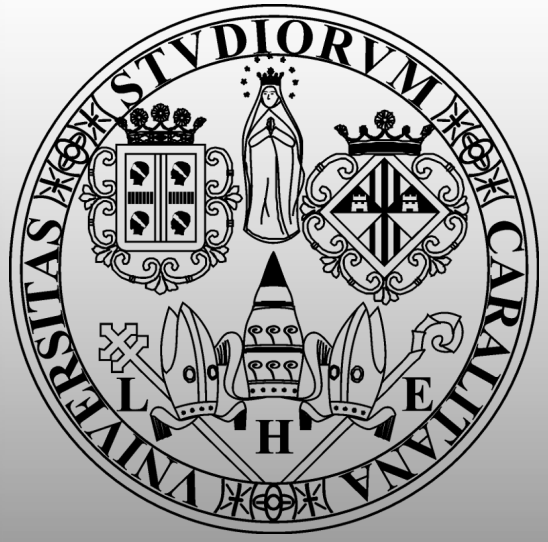

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