Self-Organising Networks for Classification: developing Applications to Science Analysis for Astroparticle Physics

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Abstract

Physics analysis in astroparticle experiments requires the capability of recognizing new phenomena; in order to establish what is new, it is important to develop tools for automatic classification, able to compare the final result with data from different detectors. A typical example is the problem of Gamma Ray Burst detection, classification, and possible association to known sources: for this task physicists will need in the next years tools to associate data from optical databases, from satellite experiments (EGRET, GLAST), and from Cherenkov telescopes (MAGIC, HESS, CANGAROO, VERITAS).

Key words: SOM, Classification, Clustering, GRB

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1 Introduction

Clustering of features is an important problem in many physics experiments. Such an analysis task can be performed:

- in a supervised way, when the analyst has some examples, for which the correct classification is known. This can be done, for example, in most problems related to particle physics at accelerators, where there is a generally good knowledge of detectors and of the underlying physics, and good simulations are available.
- in an unsupervised way, when the events are partitioned into classes of similar elements, without using additional information. This is the case especially for fields operating in a discovery regime, as, e.g., astroparticle physics.
The idea of automatic classification is not new in particle and astroparticle physics. Cleaning up the signal and separating concurrent signals when nonlinear effects and high-order correlations are important is a standard in particle physics since the analysis of the branching fraction of the Z boson into $b\bar{b}$ pairs by DELPHI [1].

An important literature exists for the use of automatic classifiers in astroparticle physics (see for example [2] and references therein). Such a classification was mostly done with the use of Multilayer Perceptrons, while the bulk of the works based on unsupervised classification uses Independent Component Analysis (see for example [3] and references therein). Studies based on Self-Organized Maps and Growing Self-Organizing Networks [4,5,7,8,9] have recently started [10], but a general framework for multiwavelength classification is still missing.

2 A case study in astroparticle physics

Gamma-ray astroparticle physics is a relatively new science; it has as a counterpart optical astrophysics, one of the oldest sciences. Many of the objects we observe in the gamma sky, sensitive to the phenomena of high-energy physics, have an optical counterpart or clear relations to optical objects. Finding what is a signature of a new phenomenon requires the ability to classify observations, and the ability to recognize what is not new.

Astrophysical databases contain large amounts of data; one example is given by the growing number of experiments studying Gamma Ray Bursts (GRBs). Data sets can be found in several archives (see e.g. Ref. [11]).

Large datasets are available from systematic sky surveys. The size of such databases is now of the order of $10^{12}$ bytes, but in the near future it will grow by three orders of magnitude thanks to the technological development of telescopes and detectors. Surveys are done on a wide energy range (from $10^{-7}$ to $10^{14}$ eV), and they are heterogeneous (mission-oriented, platform and instrument dependent). The attributes registered are variable (polarization etc.); numerical simulations have to be matched to real data.

Such a complexity poses nontrivial data management issues (see [12]); moreover, we need uniform interfaces to access complex data. A few projects started in the last years with the simple purpose of making the data readable.
3 The project at the University of Udine

At the University of Udine we are developing a project involving data organization, data mining and analysis tools for the analysis of gamma sources (Gamma Ray Bursts in particular: most of the EGRET sources were unidentified).

The sources detected by GLAST [14] and MAGIC [15] will be compared with existing databases to detect what is new. What is new can be then classified based on an unsupervised classifier.

Another important analysis tool is a powerful visualization package: the idea is to visually present many variables together offering a degree of control over a number of different visual properties. High dimensionality of data set and visual properties such as color, size can be added to the position property for proper visualization purposes. Multiple views can be used by linking all separate views together when the use of these properties makes it difficult.

3.1 Classification of GRBs

The kernel of the analysis is the strategy for the classification. With the growing number of experiments dedicated to GRBs [16] it is essential to optimize the techniques for the complex task of classification. Artificial Intelligence-(AI-) based pattern recognition algorithms are one possible candidate: automated linear classification of vector data into a given number (or an arbitrary number) of classes is a well established technique in the field of machine learning. Several varieties of AI-based classifiers exist [10].

Clustering is the unsupervised classification of patterns [6] (observations, data items or feature vectors) into groups called clusters. Clustering is useful in several exploratory pattern analysis, grouping, decision making and machine learning situations including data mining, document retrieval, image segmentation and pattern classification.

Self-Organising Neural Networks [4,5,7,8,9] are often used to cluster input data. Similar patterns are grouped by the network and are represented by a single unit. This grouping is done automatically on the basis of data correlations. Well-known examples of Self-Organising Artificial Neural Networks (ANN) used for clustering include Kohonen’s self-organising maps, Self-Organising Tree Algorithm (SOTA), Growing Cell Structures (GCS).

In our prototype, Self-Organizing Maps (SOM) were used.
4 Research Perspectives

One promising area where the potential of self-organizing networks has not been fully exploited is certainly data mining and knowledge discovery. Clustering huge data sets without knowing in advance the number of clusters is something such strategy should excel at.

Making hybrid neural networks (combining various self-organizing networks) can result in an efficient clustering.

Visualisation has an important role in cluster analysis. Advanced Visualisation techniques [13] such as Galaxies, Correlation Tool, OmniViz Pro, Hypercube, play an important role in analyzing clusters. Integrating these techniques with neural networks can provide interesting results.

GRB classification [10] could be a case study to use as a benchmark. Possible applications could be tested on data sets from the GRB catalogs, for example using light curves or band-spectral parameters.

Separation of gamma from hadrons is another important and difficult problem in Gamma-Ray experiments. The classification problem has been addressed with supervised neural networks. The network separation is based on the study of simulated data. It is very likely that severe adjustments have to be made to the simulation to better reflect the data, and the network training has to be redone with the improved simulation. The disadvantage of this approach is the output ambiguity and the network should be refined constantly to improve the separation of the output. Applying Self-Organizing Networks would be useful as the classification could be automatic and model-independent.

The final research perspective is a library of Science Tools for AstroParticle Physics. Such library should include tools for data mining, tools for optimizing the features selection (physical characteristics which can be extracted from different detectors, in particular GLAST, MAGIC, and X-ray detectors like INTEGRAL, CHANDRA, SWIFT), and a powerful visualization package.

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