AI Gamma-Ray Burst Classification: Methodology/Preliminary Results

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Abstract. Artificial intelligence (AI) classifiers can be used to classify unknowns, refine existing classification parameters, and identify/screen out ineffectual parameters. We present an AI methodology for classifying gamma-ray bursts, along with some preliminary results.

METHODOLOGY

Gamma-ray burst (GRB) subclassification is difficult due to complex burst spectral and temporal behaviors [2]. Few long-standing classification attributes have been known except for those identified on the basis of duration and spectral hardness [6]. Recent evidence suggests that (a) bursts can contain high-energy peaks (with emission above 300 keV), non-high-energy peaks [11] or both, (b) excessive low-luminosity GRB emission is correlated with spectral hardness and duration for a sample of long, bright bursts [4], (c) the spectral break energy vs. intensity relation [8] might indicate that GRB pulse decay is governed by radiative cooling, and (d) significant emission below 10 keV exists in 10-15% of bursts [12].

We are developing a tool to automate GRB classification using the AI technique of knowledge discovery in databases (KDD). This technique has already been used successfully in optical/infrared astronomy [15]: a 300% increase in survey classification was obtained, even though the AI classifier used in this study found only eight of 40 input attributes to be important.

KDD is usually seen as a four step process: data selection, data pre-processing and transformation, data mining, and interpretation/evaluation.

Step 1: Data Selection. The choice of attributes can affect the outcome of classification analysis, since AI classifiers cannot make informed decisions with insufficient information. Moreover, few GRB attributes are useful in a raw (unprocessed) format. Although preprocessed data is initially being drawn from the
TABLE 1. Some Potentially Important Classification Data Available For Each Burst.

| duration | fluence     | hardness ratios (e.g. HR21, HR32, HR43) |
|----------|-------------|----------------------------------------|
| peak flux| location    | burst duration from time range of peaks |
| number of peaks |          | spectral indices in different energy ranges |
| ILF power-law index |       | distribution of peaks by spectral hardness |
| spectral break energy |    | low-energy flux (below 10 keV) |
| peak fluxes in different energy bands | | spectral evolution summary |

BATSE database, future expansion to other databases is planned.

Step 2: Data Pre-Processing and Transformation. Table 1 indicates some preprocessed attributes that can be used as AI classifier input. These range from single elements, to arrays, and to more complex data structures. This list is not exhaustive, but merely indicates the size of the database that can be introduced for classification purposes.

Step 3: Data Mining. Data Mining is the application of one or more pattern identification algorithms to a specific data set. It produces a classification structure representative of the concept classes identified; these are used to document relationships, verify previous knowledge, and predict future outcome. Unknown instances are classified by using the classification structure with an appropriate interpretive algorithm. Classifiers are supervised (decision trees [13] and rule sets are trained with known classification instances), unsupervised (concept hierarchies [3] require learning to be performed without training examples), or both (neural networks [5]).

Step 4: Interpretation/Evaluation. We have modified existing KDD techniques by combining them with the scientific method. By using this approach, we are attempting to address errors (such as statistical errors and instrumental biases) leading to improperly-identified subclasses/substructures.

Unsupervised learning is first used to determine if well-defined burst classes can be discovered. Several unsupervised classifiers are used for comparative analysis. After an unsupervised classifier identifies a concept class, the class instances are presented to supervised learning models so that classification structures can be identified depicting the named concepts.

Next, classification success is evaluated. Unsupervised classification methodology relies on internal checks such as inter-class difference checks, intra-class prototype similarity checks, and instance-by-instance classification comparisons. Success is evaluated in a supervised environment by a variety of “goodness-of-fit” parameters including predictiveness scores (statistical pull of an attribute relative to the class mean value), classification correctness (number of correctly classified instances relative to total number of set instances), and attribute correlations (to eliminate related attributes).

The subclasses and/or classification substructures identified are carefully studied to determine the extent to which they can be attributed to instrumental effects and/or observational biases. We rely on our expertise in working with GRB data
and on our use of datasets obtained from a variety of GRB experiments to identify these biases.

When the data have been corrected for biases, the process begins anew from the point of unsupervised classification. We believe that this process will allow us to successfully identify properties of gamma-ray burst classes, and to optimize differentiation between known or suspected burst subclasses.

**PRELIMINARY RESULTS**

We have begun applying the KDD process to the BATSE 4B Catalog. We have constructed a test dataset of 954 bursts for which we have chosen six basic preprocessed attributes: T90 duration, 1024 ms peak flux, channel 2+3 fluence, and three hardness ratios (HR21, HR32, and HR43).

The duration bimodality (short bursts have durations < 2 seconds; long ones have durations ≥ 2 seconds) is the one natural division expected in this dataset, producing two corresponding “subclasses” of slightly differing HR32 hardness ratios (e.g. [6]). It should be noted that a clean division does not exist between these subclasses; there is considerable overlap in the distributions (a histogram of HR32 does not produce strong evidence of two subclasses; [14]). We have included as Figure 1 a plot of HR32 vs. duration, so that the reader might verify the efficacy of this classification.

Initially, we used the unsupervised classifier CLASSIT to identify subclasses. Surprisingly, CLASSIT did not create concept clusters that clearly defined “long” and “short” subclasses. The classifier did not ignore duration and hardness in making its decision; rather it concluded that there were more statistically significant subsets in the data than this particular one. We are currently investigating this result in greater detail.

We trained the benchmark supervised learning program C4.5 with 25 short and

![Figure 1. HR32 vs. duration diagram. Long and short bursts train the supervised classifier C4.5, even though there is not a clean subclass separation.](image)
25 long bursts. C4.5 built a decision tree to be used for classifying new instances of unknown duration, as well as a set of rules representing decision tree paths. The rules were used to classify the remaining 904 bursts; these were correctly classified as long or short 89.7% of the time.

We concluded that duration information was being included in the fluence attribute, and subsequently retrained the classifier after having removed the fluence attribute. *The classifier still correctly classified the unknowns 77.2% of the time without any duration information.* The rule set is simply:

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\text{IF (HR32 > 4.60 OR HR21 > 2.23) THEN SHORT ELSE LONG}
\]

Figure 2 demonstrates the effect of this simple rule on bursts with “unknown” duration classes. From this rule, C4.5 classified the 681 long bursts correctly 77% of the time and the 223 short bursts 78% of the time.

We considered the possibility that relative numbers of long vs. short events might contribute to classification success: in other words, if the knowledge that 75% of the bursts are long and 25% are short was used, then a 75% accuracy could be obtained by guessing that all bursts would be long. To test this, we applied the decision tree to a sample of 223 short bursts (50%) and 223 long ones (50%). The classification accuracy was still 80.5% (78% accuracy for long bursts and 83% accuracy for long ones), although guessing that all bursts would be long would now only produce a 50% accuracy.

The C4.5 results are consistent with those obtained using other supervised classifiers. We subsequently verified the relative importances of the fluence, HR32, and HR21 attributes using the supervised classifier SX-WEB and Bayesian-based Discriminant Analysis.

**FIGURE 2.** HR32 vs. HR21 plot identifying long and short bursts, according to a simple decision tree identified by C4.5 trained on 50 BATSE bursts. The rule set identified allows 77% correct classification of unknown instances, is independent of peak flux and HR43 (which were ignored by the classifier despite the known hardness-intensity correlation), and does not include correlations with duration and fluence (not included for analysis).
CONCLUSIONS AND FUTURE STUDY

The long and short burst substructures [6] do not represent optimum data subclasses, as suggested by inspection of Figure 1 and by results from the unsupervised classifier CLASSIT. Nonetheless, our analysis indicates strong evidence to support the existence of burst groupings that relate hardness to duration. It is quite possible that these groups would be made more distinct by the aid of additional preprocessed attributes.

The two duration groups have distinct fluence differences and correlated hard-nesses, implying that ensemble analyses examining duration and/or hardness for other purposes might not succeed unless these groups are considered separately. Analyses that might be affected include the use of durations to identify cosmological time dilation [10] [9], the use of hardness variations to determine cosmological energy shifts, and the use of fluences (S) in \( \log(N > S) \) vs. \( \log(S) \) to determine the cosmological distance scale [1] [7].

These preliminary results demonstrate the power of applying the KDD process to gamma-ray bursts. The process has been used here to verify the predictive power of an existing subclassification structure; we will apply KDD in the future to verify other subclasses and/or classification substructures and to search for previously unknown ones.

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