Unsupervised Induction and Gamma-Ray Burst Classification

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Abstract. We use ESX, a product of Information Acumen Corporation, to perform unsupervised learning on a data set containing 797 gamma-ray bursts taken from the BATSE 3B catalog [5]. Assuming all attributes to be distributed logNormally, Mukherjee et al. [6] analyzed these same data using a statistical cluster analysis. Utilizing the logarithmic values for T90 duration, total fluence, and hardness ratio HR321 their results showed the instances formed three classes. Class I contained long/bright/intermediate bursts, class II consisted of short/faint/hard bursts and class III was represented by intermediate/intermediate/soft bursts.

When ESX was presented with these data and restricted to forming a small number of classes, the two classes found by previous standard techniques [1] were determined. However, when ESX was allowed to form more than two classes, four classes were created. One of the four classes contained a majority of short bursts, a second class consisted of mostly intermediate bursts, and the final two classes were subsets of the Class I (long) bursts determined by Mukherjee et al. We hypothesize that systematic biases may be responsible for this variation.

INTRODUCTION

Induction-based learning [4] attempts to extract interesting patterns from data. These patterns form concept classes with each class containing data instances. When the induction is unsupervised, the learning model has no a priori class knowledge. Rather, the learning algorithm uses one or more statistical or symbolic (machine learning) evaluation functions to cluster instances into concept classes.

Mukherjee et al. [6] performed a statistical cluster analysis on a data set containing 797 gamma-ray bursts taken from the BATSE 3B catalog [5]. Assuming all attributes to be distributed logNormally, and utilizing the logarithmic values for T90 duration, total fluence, and hardness ratio HR321 their results showed the instances formed three classes. Class I contained long/bright/intermediate bursts, class II consisted of short/faint/hard bursts and class III was represented by intermediate/intermediate/soft bursts. Table 1 shows the mean and standard deviation...
values for the three classes. Table 2 offers a best defining rule for each class, as determined by ESX [7]. The rule for class I bursts indicates that 82.72% of the bursts in this class have a log T90 value between .70 and 2.66 and a log Fluence between -5.77 and -3.11. The rule also shows that we can be at least 97% confident that a burst with these characteristics is a class I burst. Table 2 shows that the class III rule does not cover its instances as well as the rules for classes I and II.

| Table 1. Mean and Standard Deviations for the Classes found by Mukherjee et al. (1998) |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|
|                                | Class I | Class II | Class III |
|--------------------------------|---------|----------|-----------|
| Number of Bursts               | Long    | Short    | Intermediate | 796 |
| Log T50 (mean)                 | 1.13    | -0.80    | 0.33       | 0.53 |
| (sd)                           | 0.45    | 0.41     | 0.26       | 0.93 |
| Log T90 (mean)                 | 1.55    | -0.42    | 0.71       | 0.93 |
| (sd)                           | 0.40    | 0.44     | 0.32       | 0.94 |
| Log Fluence (mean)             | -5.21   | -6.37    | -6.11      | -5.63 |
| (sd)                           | 0.59    | 0.57     | 0.37       | 0.77 |
| Log P256 (mean)                | 0.21    | 0.14     | -0.08      | 0.15 |
| (sd)                           | 0.48    | 0.38     | 0.33       | 0.45 |
| Log HR32 (mean)                | 0.20    | 0.51     | 0.09       | 0.26 |
| (sd)                           | 0.27    | 0.27     | 0.40       | 0.33 |
| Log HR321 (mean)               | 0.43    | 0.70     | 0.35       | 0.49 |
| (sd)                           | 0.23    | 0.26     | 0.39       | 0.30 |

Attributes log T50, log P256, and log HR32 were not used in the final analysis since each had a high correlation with its respective counterpart (log T90, log fluence, and log H321).

| Table 2. Representative ESX Rules for the Three Classes found by Mukherjee et al. (1998) |
|-----------------------------------|-----------------|-----------------|-----------------|
| Class I                           | (Long Bursts)   | 0.70 <= log T90 <= 2.66 and -5.77 <= log Fluence <= -3.11 |
|                                  | :rule accuracy 97.34% |
|                                  | :rule coverage 82.72% |
| Class II                          | (Short Bursts)   | -1.55 <= log T90 <= 0.41 |
|                                  | :rule accuracy 90.87% |
|                                  | :rule coverage 98.03% |
| Class III                         | (Intermediate Bursts) | 0.46 <= log T90 <= 0.96 and 0.17 <= log T50 <= 0.55 |
|                                  | :rule accuracy 79.17% |
|                                  | :rule coverage 53.27% |

In this paper we use ESX [7], a machine learning model and product of Information Acumen Corporation, to perform unsupervised learning on these same data for the purpose of comparative analysis. We chose ESX for this research since ESX explains its behavior has been shown to perform well in several real-world environments [7].
METHOD

The machine learning component of ESX is an induction-based sequential learning model that creates a concept hierarchy [2] from a set of input instances. ESX uses knowledge contained in its concept hierarchy to generate a set of production rules to help define and explain what has been discovered. Supervised as well as unsupervised learning is supported.

ESX accepts data in the form of instances represented in attribute-value format. When learning is unsupervised, ESX takes one of two possible actions for each newly presented instance: (1) Place the new instance into an existing cluster, or (2) create a new conceptual cluster containing the instance as its only member.

In addition, ESX allows the user to set a learning parameter so as to encourage or discourage the creation of new clusters. For a given domain, a best value for this parameter can be determined experimentally.

RESULTS

For our first experiment, we set the ESX learning parameter so as to restrict the formation of new classes. As a result, ESX clustered the data into the two classes found by previous standard techniques [1]. Table 3 shows a representative rule for each class. Notice that both clusters are well-defined.

| Class I (Long Bursts) | 0.54 <= log T90 <= 2.66 |
|-----------------------|-------------------------|
|                       | :rule accuracy 98.03%   |
|                       | :rule coverage 96.99%   |

| Class II (Short Bursts) | -1.55 <= log T90 <= 0.38 |
|-------------------------|--------------------------|
|                         | :rule accuracy 98.14%    |
|                         | :rule coverage 90.95%    |

For our second experiment, we allowed ESX to form a best set of three or more clusters. The results of this experiment showed the formation of four clusters. One of the four clusters contained a majority of intermediate bursts (class 1); a second cluster consisted of mostly short bursts (class 2). The remaining two clusters (classes 3 and 4) were subsets of the Mukherjee class I bursts. The class mean and standard deviation values for each of the six burst attributes are shown in Table 4.

Table 5 offers representative rules for each of the four clusters. Figures 1 and 2 as well as Table 4 indicate that class 3 contains mostly long/soft bursts and class 4 contains long/bright bursts. The following rule represents a covering rule for the cluster formed by combining the class 3 and class 4 bursts.

1.19 <= log T90 <= 2.66
:rule accuracy 90.26%
:rule coverage 92.68%
TABLE 4. Mean and Standard Deviations for the ESX Four Class Clustering

|                      | Class 1         | Class 2         | Class 3         | Class 4         | Domain |
|----------------------|-----------------|-----------------|-----------------|-----------------|--------|
|                      | Intermediate    | Short           | Long/Soft       | Long/Bright     |        |
| Number of Bursts     | 182             | 205             | 195             | 215             | 796    |
| Log T50 (mean)       | 0.44            | -0.78           | 1.27            | 1.18            | 0.53   |
| (sd)                 | 0.44            | 0.44            | 0.37            | 0.44            | 0.93   |
| Log T90 (mean)       | 0.85            | -0.41           | 1.67            | 1.62            | 0.93   |
| (sd)                 | 0.37            | 0.46            | 0.32            | 0.38            | 0.94   |
| Log Fluence (mean)   | -5.87           | -6.36           | -5.50           | -4.84           | -5.63  |
| (sd)                 | 0.45            | 0.59            | 0.37            | 0.61            | 0.77   |
| Log P256 (mean)      | 0.04            | 0.13            | -0.07           | 0.48            | 0.15   |
| (sd)                 | 0.43            | 0.38            | 0.22            | 0.51            | 0.45   |
| Log HR32 (mean)      | 0.11            | 0.54            | -0.03           | 0.38            | 0.26   |
| (sd)                 | 0.27            | 0.30            | 0.24            | 0.16            | 0.33   |
| Log HR321 (mean)     | 0.36            | 0.73            | 0.24            | 0.59            | 0.49   |
| (sd)                 | 0.27            | 0.29            | 0.21            | 0.14            | 0.30   |

TABLE 5. Representative Rules Taken from the Four Class ESX Clustering

| Class 1 (Intermediate) | 0.29 <= log T90 <= 1.20 :rule accuracy 75.00% :rule coverage 74.18% | 0.21 <= log T50 <= 0.63 and 0.29 <= log T90 <= 1.09 :rule accuracy 89.02% :rule coverage 40.11% |
| Class 2 (Short)        | -1.55 <= log T90 <= 0.42 and -1.92 <= log T50 <= -0.02 :rule accuracy 93.20% :rule coverage 93.66% | -7.80 <= log Fluence <= -6.63 and -1.92 <= log T50 <= -0.02 :rule accuracy 95.95% :rule coverage 34.63% |
| Class 3 (Long/Soft)    | 1.19 <= log T90 <= 2.66 :rule accuracy 90.26% | 0.02 <= log HR321 <= 0.08 :rule accuracy 77.36% :rule coverage 21.03% |
| Class 4 (Long/Bright)  | :rule coverage 92.68% | -4.85 <= log Fluence <= -3.11 :rule accuracy 90.91% :rule coverage 51.16% |

CONCLUSIONS

We used ESX to cluster data about 797 gamma ray bursts. When restricted to forming a small number of classes, two classes were determined. However, when allowed to form more than two classes, four classes were created. Two of the clusters were similar to the class II and class III bursts determined by Mukherjee et al. [6]. Taken together, the two remaining clusters represent the class I Mukherjee et al. bursts. ESX differentiated the class I bursts by brightness and hardness. The separation of long bursts into two classes may be due in part to the fact that ESX makes no a priori assumptions about data distribution.

We hypothesize that systematic effects may cause some class I bursts to take on class III characteristics [3]. Systematic biases may explain why class I bursts have been separated into two groups by ESX. Our future work will focus on testing these hypotheses with the help of additional induction-based techniques.
FIGURE 1. 3/21 Hardness Ratio vs. ch 2 + 3 fluence

FIGURE 2. 3/21 Hardness Ratio vs. T90 duration

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