Distinguishing short and long Fermi gamma-ray bursts

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ABSTRACT
Two classes of gamma-ray bursts (GRBs), short and long, have been determined without any doubts, and are usually ascribed to different progenitors, yet these classes overlap for a variety of descriptive parameters. A subsample of 46 long and 22 short Fermi GRBs with estimated Hurst Exponents (HEs), complemented by minimum variability time-scales (MVTS) and durations ($T_{90}$) is used to perform a supervised machine learning and Monte Carlo simulation using a support vector machine algorithm. It is found that while $T_{90}$ itself performs very well in distinguishing short and long GRBs, the overall success ratio is higher when the training set is complemented by MVTS and HE. These results may allow us to introduce a new (non-linear) parameter that might provide less ambiguous classification of GRBs.

Key words: methods: data analysis – methods: statistical – gamma-rays: general.

1 INTRODUCTION
Gamma-ray bursts (GRBs) are highly energetic events that often are brighter than all other γ-ray objects visible on the sky combined, with an emission peak in the 200–500 keV region (for recent reviews, see Nakar 2007; Zhang 2011; Gehrels & Razzaque 2013; Berger 2014; Mészáros & Rees 2015). GRBs were detected by military satellites Vela in late 1960’s. Mazets et al. (1981) first observed a bimodal distribution of $T_{90}$ (time during which 90 per cent of the burst’s fluence is accumulated) drawn for 143 events detected in the KONUS experiment. Burst and Transient Source Experiment (BATSE) onboard the Compton Gamma-ray Observatory (Meegan et al. 1992) allowed to confirm the hypothesis (Klebesadel, Strong & Olson 1973) that GRBs are of extragalactic origin due to isotropic angular distribution in the sky. However, a more complete sample of BATSE short GRBs were shown to be distributed anisotropically and cosmological consequences were discussed lately by Mészáros & Rees (2015). BATSE 1B data release was followed by further investigation of the $T_{90}$ distribution (Kouveliotou et al. 1993) that lead to establishing the common classification of GRBs into short ($T_{90} < 2$ s) and long ($T_{90} > 2$ s), and based on which GRBs are most commonly classified. The progenitors of long GRBs are associated with supernovae (Woosley & Bloom 2006) related with collapse of massive stars. Progenitors of short GRBs are thought to be NS–NS or NS–BH mergers (Nakar 2007), and no connection between short GRBs and supernovae has been proven (Zhang et al. 2009).

Despite initial isotropy, short GRBs were shown to be distributed anisotropically on the sky, while long GRBs are distributed isotropically (Balázs, Mészáros & Horváth 1998; Magliocchetti, Ghirlanda & Celotti 2003; Vavrek et al. 2008, see also Mészáros & Štoček 2003 for an analysis that revealed anisotropy in a set of long GRBs). Since long a possibility that GRBs may be divided into more than two classes was put forward as there are GRBs that do not fall easily into one class or another (Gehrels et al. 2006; Zhang et al. 2007; Bromberg et al. 2013). Horváth (1998, 2002) investigated GRBs from the BATSE catalogue (Meegan et al. 1996; Paciesas et al. 1999) by a univariate approach and concluded that the probability that the peak at intermediate values of log $T_{90}$ is a result of random fluctuations is much less than 1 per cent. Also in Swift data evidence for a third component in log $T_{90}$ was found (Zhang et al. 2007; Horváth et al. 2008a,b; Hujta & Řípa 2009; Hujta, Mészáros & Řípa 2009; Horváth et al. 2010). Other data sets, i.e. RHESSI (Řípa et al. 2009, 2012), or BeppoSAX (Horváth 2009), also show evidence for an intermediate class. It is worth to note that the intermediate GRBs are distributed anisotropically on the sky (Mészáros, Bagoly & Vavrek 2000a; Mészáros et al. 2000b; Vavrek et al. 2008). The origin and existence of an intermediate class remains elusive as theoretical models still need to account for an apparent bimodality in duration distribution (Janiuk et al. 2006; Nakar 2007). Finally, not only the existence of an intermediate class was investigated (and remains unsettled), but also subclass classifications of long GRBs were proposed (Gao, Lu & Zhang 2010).

The research conducted on Fermi data (Gruber et al. 2014; von Kienlin et al. 2014) are consistent with a bimodal duration distribution (Zhang et al. 2012) as well as with the existence of an intermediate class (Horváth et al. 2012); however, even a bimodal structure was not present in some energy bands in the examined sample of 315 GRBs (not to mention trimodality) and may be due to an instrumental selection effect (Qin et al. 2013). It is important to note that in all mentioned research, only a mixture of standard normal distributions (Gaussians) was fitted to the observed log $T_{90}$ distributions. By examining the duration distribution it was shown that the third class is unlikely to be present in the Fermi data (Tarnopolski 2015c), and that a mixture of two intrinsically skewed distributions follows better the log $T_{90}$ distribution of...
Fermi GRBs than a mixture of three standard Gaussians (Tarnopolski 2015b).

The Fermi data set has been examined widely for other reasons, too. Its redshift distribution was investigated (Ackermann et al. 2013) confirming the observation that short GRBs have lower redshifts than long GRBs. The Amati correlation was investigated (Gruber 2012; Basak & Rao 2013; Heussaff, Atteia & Zolnierowski 2013) and a link between short and long GRBs was discovered (Muccino et al. 2013). It gave insight into the GRB afterglow population (Racusin et al. 2011), allowed to observe a number of high-energy GRBs (with photon energies exceeding 100 MeV, or even 10 GeV; Atwood et al. 2013), and provided a verification of the short–long classification (Zhang et al. 2012).

Other parameters, despite $T_{90}$ durations (e.g. similarly defined $T_{32}$ or hardness ratios for various bands) were used to classify GRBs for different satellite data bases as well. A distinction in the hardness ratio $H_{92}$ of all three classes was formulated early (Mukherjee et al. 1998; Horváth et al. 2004). Minimum variability time-scale (MVTS; MacLachlan et al. 2012, 2013a,b; Bhat 2013) was used as a distinctive parameter for differentiating GRB light curves based on their temporal structure. It is a non-parametric feature, such as the Hurst exponent (HE, denoted $H$) (Hurst 1951; Mandelbrot & van Ness 1968), which is a quantitative measure of the persistence of the signal, i.e. it reveals a temporal trend in the overall behaviour in the data, and was suggested to be applicable in GRB classifications (MacLachlan et al. 2013b).

Among many existing computational algorithms for estimating $H$ [Rescaled Range Analysis (Mandelbrot & Wallis 1969), Detrended Fluctuation Analysis (Peng et al. 1994, 1995), wavelet approach (Simonsen, Hansen & Nes 1998), Detrended Moving Average (Allessio et al. 2002), to mention only a few], their extraction for the Fermi GRB sample was performed by the wavelet approach with the Haar wavelet as a basis (for further details, see MacLachlan et al. 2013b and Section 2.3 herein for a brief description). It was found that there is an offset between means of $H$ distributions of long and short GRBs that may serve as a criterion for distinguishing these two classes. Moreover, it was proposed that the overlap region of HE distribution may be related to the third class of GRBs (possibly intermediate). However, the region where short and long GRBs overlap is significant due to a large dispersion in $H$, and the union distribution is skewed towards values less than 0.5.

Additional parameters have been defined and proposed for GRB classification as well. Examples are $\varepsilon = E_{\gamma,iso,52}/E_{p,\gamma,7,2}$ (where $E_{\gamma, iso, 52}$ is the isotropic $\gamma$-ray energy given in $10^{52}$ erg, and $E_{p,\gamma,7,2}$ is the cosmic rest-frame spectral peak energy in units of 100 keV) unambiguously dividing short and long GRBs (Lü et al. 2010), MVTS (MacLachlan et al. 2012, 2013a,b; Bhat 2013; Golkhou & Butler 2014; Golkhou, Butler & Littlejohns 2015) or HE (MacLachlan et al. 2013b). However, providing a set of parameters that could classify GRBs with high accuracy remains a desired objective. Unsupervised machine learning (ML) algorithms, trained on a data set containing these parameters, yield a possibility of attaining this goal. Before that, performance of supervised ML with arbitrary number of classes needs to be tested.

In this work, focus is laid on performance of HEs, complemented by MVTS (both being wavelet-based parameters new in GRB classification) and $T_{90}$, being a classical GRB type indicator, in classifying short and long GRBs. This paper is organized in the following manner. In Section 2, a description of the data is provided. In Section 3, a statistical analysis of the available data set of GRBs with computed HEs is conducted. In Section 4, ML is applied to ($H$, MVTS, $T_{90}$) singles, pairs and triples, and a Monte Carlo simulation provides statistics of the success ratio. Section 5 contains discussion of the results, and Section 6 gives concluding remarks. A computer algebra system MATHEMATICA® v10.0.2 is used throughout this paper.

## 2 THE SAMPLE

### 2.1 Selection criteria

The data are taken from MacLachlan et al. (2013a,b), and are complemented by Golkhou & Butler (2014) and Golkhou, Butler & Littlejohns (2015). They consist of 46 long and 22 short GRBs detected by the Fermi satellite. According to MacLachlan et al. (2013a), the selection criteria for the GRB sample examined in MacLachlan et al. (2013b) are two-fold. The following condition on the ratio of variances for one or more octaves $j$, $\beta_j(\text{preburst}) < 0.75,$

was required, where $\beta_j(\text{preburst})$ corresponds to a certain time interval before the burst, used as a surrogate for the background variance, and $\beta_j(\text{burst})$ expresses the variability of the burst. The variances were computed according to

$\beta_j = \frac{1}{n_j} \sum_{k=0}^{n_j-1} |d_{j,k}|^2,$

where $d_{j,k}$ are the wavelet transform coefficient (for further details, see MacLachlan et al. 2013b and Section 2.3 herein for a brief explanation). Additionally, it was required that the light curve fits a $K^2_{\text{reduced}} < 2$.

### 2.2 Duration $T_{90}$

The duration $T_{90}$ is the time during which the cumulative counts increase from 5 to 95 per cent above background, encompassing 90 per cent of the total fluence detected. This way of measuring the duration is independent of the intensity for a given instrument (Kouveliotou et al. 1993). The detection is triggered when the signal exceeds a certain threshold.

Fermi has a time resolution of 2 µs; the light curves are extracted at a binning of 200 µs. Time intervals that are far before and far after the main burst are selected as background and subtracted from the light curve. The procedure is described in detail by Koshut et al. (1996).

The durations used herein come from the Fermi GRB Burst Catalogue as cited in MacLachlan et al. (2013b). They are also available in the online catalogue. The $T_{90}$ distribution of GRBs examined herein is displayed in Fig. 1.

### 2.3 Hurst exponent

The HE describes the level of statistical self-similarity of a time series. A time series $X(t)$ with $N$ data points $t_i$ is called self-similar (or self-affine) with a Hurst exponent $H$ if, after a rescaling $t \rightarrow \lambda t$, it satisfies the following relation

$X(t) \propto \lambda^{-H}X(\lambda t),$

for long GRBs, the pre-burst was defined to start 20 s and finish 5 s before the trigger, and for short GRBs, these were 15 and 1 s, respectively.

1. [http://heasarc.gsfc.nasa.gov/W3Browse/fermi/fermiburst.html](http://heasarc.gsfc.nasa.gov/W3Browse/fermi/fermiburst.html) (Gruber et al. 2014; von Kienlin et al. 2014).
where $\equiv$ denotes equality in distribution. The HEs under study were calculated by MacLachlan et al. (2013b) with the fast wavelet transform using the Haar wavelet as the basis. The basis is obtained from a mother wavelet, $\psi(t)$, by

$$
\psi(t) \rightarrow \psi_{j,k}(t) = \frac{1}{2^{j/2}} \psi \left( \frac{t - k}{2^j} \right),
$$

where $j$ represents the octave (time-scale) and $k$ the position of the wavelet. The wavelet transform coefficient is defined as

$$
d_{j,k} = \langle X, \psi_{j,k} \rangle.
$$

By inserting equation (3) into equation (5), one gets the relation between the variance of the wavelet coefficients $d_{j,k}$ and the scale $j$:

$$
\log_2 \text{var}(d_{j,k}) = (2H + 1)j + \text{const}.
$$

The HE is obtained by fitting a line to the linear part of the $\log_2 \text{var}(d_{j,k})$ versus $j$ relation. For further details, the reader is referred to MacLachlan et al. (2013b).

The HE is bounded in the interval $[0, 1]$ and is equal to 0.5 for a random walk (Brownian motion). For persistent data $H > 0.5$, while for antipersistent $H < 0.5$. Regular (periodic or quasi-periodic) time series posses $H = 1$. It is related to the fractal dimension of the signal $D = 2 - H$, providing information about its statistical self-similarity. This means that in a persistent process the increments are positive and varies with the light curve. To infer the right binning, a comparison of the variances of the GRB and the background is performed. A ratio of these variances is plotted against the bin-width and the MVTS is the binning at which this ratio is minimized (Bhat 2013).

Expressing this concept in other words, MVTS is a time-scale at which a transition between white noise and a power law is observed in the power density spectrum. This means that MVTS marks the time-scale at which a power-law process and a white noise exchange dominance. As wavelets are sensitive to whichever process dominates at a given time-scale, they are a natural choice to extract the MVTS from the light curves.

The wavelet-based MVTS extraction is carried out similarly to the HE estimation described in Section 2.3. Starting from equation (6), with the background subtraction as described in Section 2.2, the MVTS is calculated at the octave $j_{\text{intersection}}$ at which an intersection of a flat noise spectrum and a linear relation associated with the power-law domain in the log-scale diagram occurs:

$$
\text{MVTS} = T_{\text{bin}} \times 2^{j_{\text{intersection}}},
$$

where $T_{\text{bin}}$ is the finest binning of the data. For further details, the reader is referred to MacLachlan et al. (2013a).

The MVTS used in this study are taken from MacLachlan et al. (2013a), although some values for the short GRBs subsample were not reported there. Hence, the missing values were replaced with the MVTS from Golkhou & Butler (2014) and Golkhou, Butler & Littlejohns (2015). The distribution of the sample under consideration is shown in Fig. 3.

### 2.4 Minimum variability time-scale

If the light curve is binned into too narrow bins, the intrinsic variability is lost in the statistical noise. When the binning is too coarse, the variability might disappear. Hence, the right binning is crucial and varies with the light curve. To infer the right binning, a comparison of the variances of the GRB and the background is performed. A ratio of these variances is plotted against the bin-width and the MVTS is the binning at which this ratio is minimized (Bhat 2013).

Littlejohns (2015). The distribution of the sample under consideration is shown in Fig. 3.

### 3 INDEPENDENCE OF SHORT AND LONG GRBS' HE DISTRIBUTIONS

In Fig. 2, the HE distributions for short and long GRBs from MacLachlan et al. (2013b) are reproduced. While the systematic difference is clearly visible, the histograms overlap strongly. This leads to a question whether they are statistically distinguishable. As most of statistical tests (Kendall & Stuart 1973; Kanji 2006; Press et al. 2007) assume normality, first a Kolmogorov–Smirnov test (Massey 1951) is performed, that resulted in $p$-values of 0.95 and 0.87 for short and long GRBs, respectively. These values are
large, so might lead to a conclusion that both samples are normally distributed. However, in the sample of long GRBs, ties are present, and the p-value is obtained after ignoring them. A mean of hundred Monte Carlo realizations is equal to 0.8735 ± 0.0102, where the error is the standard deviation of the mean. Another trial gave 0.8728 ± 0.0106. To be sure these data are normally distributed two more tests are performed. The Pearson χ² test (Voinov, Nikulin & Balakrishnan 2013) gave p-values equal to 0.75 and 0.81, and the Shapiro–Wilk test (Shapiro & Wilk 1965) gave 0.33 and 0.39 for short and long GRBs, respectively. Despite these values span a quite broad interval, they are all significant enough to ascertain that the HE distributions are normal.

To check whether they are separate, first a t-test (Student 1908) is performed, based on which at the 0.01 significance level the hypothesis that the means’ difference is μ_long = μ_short = 0.163 215 cannot be rejected. The means were computed from the samples. Also, the Mann–Whitney test (Mann & Whitney 1947) does not allow to reject the hypothesis that the medians’ difference is m_long − m_short = 0.144 at the 0.01 significance level. Finally, variance tests: Brown–Forsythe (Brown & Forsythe 1974), Fisher Ratio (Press et al. 2007), and Levene (Levene 1960), all gave p-values greater than 0.9. All of these tests imply that the HE distributions indeed are different for short and long GRBs.

4 MACHINE LEARNING

As other schemes of classifying GRBs were proposed, e.g. based on MVTS, it is desired to investigate their efficiency for distinguishing short and long GRBs. As the amount of GRBs classified in such a way is still limited, in the following section focus is paid only to the two classical classes.

4.1 Methods

In order to verify whether H can serve as a GRB type indicator (MacLachlan et al. 2013b), a supervised ML is performed. A support vector machine (SVM) algorithm is employed. It aims at building a potentially non-linear model that is trained over a set of examples that are classified as belonging to one of arbitrarily specified categories (short or long in this case). The training set is represented in a multidimensional space, and the classification is done so that the categories are divided by a gap as wide as possible. After the SVM is trained, a classification probability is derived over the set of applicable parameters. Based on this classification, new examples are mapped into the same space and predicted to belong to one category or another based on which side of the dividing hyperplane they fall on. The probability threshold is set at 50 per cent, and no undetermined classifications are allowed.

The parameter space is three-dimensional, and constitutes of H, MVTS and T90. It is found that the number of mistaken classifications is reduced when using a space of H, log MVTS and log T90, and this semilog space is explored throughout this section. A subsample of the total 22 short and 46 long GRBs is taken to be a training set, while the remaining GRBs serve as a validation set. A subsample is created in the following way. For each training set, 20 out of 22 short GRBs are chosen. The number of these subsets is equal to \((\binom{22}{20}) = 231\). Among long GRBs, 42 out of 46 examples are randomly chosen for each of the short GRBs subsets, and this is repeated 435 times. A total of \(\sim 10^5\) SVM models is built, and they exhaust the number of realizations of short GRBs subsets.\(^3\)

ML is done in seven spaces:

(i) three univariate classifications based on H, log MVTS, and log T90,
(ii) three bivariate classifications based on pairs (H, log MVTS), (H, log T90) and (log MVTS, log T90),
(iii) a trivariate classification based on triples (H, log MVTS, log T90).

For each, a success ratio \(r\) is inferred from the number of correct classifications in the following manner. If both short GRBs from the validation set (consisting of two short and four long GRBs) were classified correctly by an SVM model, the success ratio \(r_{short}\) is equal to 1; if one is correct and the other is false, \(r_{short} = 0.5\); and if both were classified falsely as long GRBs, \(r_{short} = 0\). Similarly for long GRBs, \(r_{long}\) is computed, and takes the values 0, 0.25, 0.5, 0.75 or 1. A total success ratio is defined as

\[r_{tot} = \frac{2r_{short} + 4r_{long}}{6},\]  

and the success ratios are calculated for all \(\sim 10^5\) trials. The relative frequency for each \(r\) is obtained by dividing the counts by the number of trials.

4.2 Results

4.2.1 1D parameter spaces

The results of ML for univariate distributions of parameters under consideration are displayed in Fig. 4. The HEs, suggested to be a candidate for distinguishing between short and long GRBs (MacLachlan et al. 2013b), exhibit a rather poor performance: 57 per cent of short GRBs were classified improperly, and correct matches took place for only 5 per cent of them. On the other hand, 81 per cent of long GRBs were classified correctly. This leads to a peak in total matches at the level of 54 per cent for the success ratio \(r_{tot} = 0.67\). Overall, this is an unsatisfactory result that comes from a large overlap of HEs for short and long GRBs (compare with Fig. 2).

Using log MVTS similar results are obtained, with an even higher frequency of mismatches for short GRBs, equal to 82 per cent. On the other hand, it performs slightly better in distinguishing long GRBs with an \(r_{long} = 1\) in 88 per cent of validation sets. This leads to a peak of 76 per cent at \(r_{tot} = 0.67\), which is a considerable accuracy.

\(^3\) There is a total of \((\binom{22}{20}) \times \binom{46}{10} \approx 3.77 \times 10^7\) subsets.
Historically, the distinction between short and long GRBs was made based on log $T_{90}$ distribution (Kouveliotou et al. 1993), and the classification is straightforward: if $T_{90} < 2\,\text{s}$ ($T_{90} > 2\,\text{s}$), a GRB is short (long). Nevertheless, given that SVM classification is probability-based, one can expect a lower than 100 per cent accuracy, especially that both short and long GRBs may be arbitrarily close to the limit $T_{90} = 2\,\text{s}$. Indeed, short (long) GRBs were properly recognized in 99.95 per cent (91.64 per cent) cases, what gives a net accuracy of 91.59 per cent (at $r_{\text{tot}} = 1$). However, when HEs are complemented with log $T_{90}$, an accuracy of 100 per cent for long GRBs is attained. For short GRBs, an accuracy of 94 per cent is obtained, what results in a total proper recognition level of also 94 per cent. Note this is a better result than for $H$ and log $T_{90}$ alone.

Distributions in log MVTS have larger overlaps than in $H$, hence the performance of log $T_{90}$ complemented with MVTS is slightly worse than in the previous case: success ratios equal to unity are obtained in 96 and 93 per cent for short and long GRBs, respectively, and $r_{\text{tot}} = 1$ in 88 per cent cases. Considering this space as durations complemented with MVTS, the accuracy is lower. On the other hand, when MVTS are complemented with log $T_{90}$, the performance is much better than for MVTS alone. Again, when the populations overlap strongly, the probabilities favour long GRBs (compare with right-hand column in Fig. 4).

### 4.2.3 3D parameter spaces

When ML is performed on a three-dimensional training set (see right-hand panel in Fig. 6) of triples ($H$, log MVTS, log $T_{90}$), short GRBs are classified properly in 95.18 per cent, long GRBs in 99.99 per cent, and the overall accuracy is higher than 95 per cent.
Comparing with 1D and 2D approaches, this gives a significant improvement (see Fig. 6). Specifically, when \((\log T_{90}, \log \text{MVTS})\) is complemented with HEs, the gain in accuracy is almost 7 per cent. It is not surprising, however, that complementing \((H, \log \text{MVTS})\) with durations gives a significant improvement, as \(T_{90}\) allows to introduce a clear separation between the populations, which are highly mixed otherwise. Moreover, adding \(\log \text{MVTS}\) to \((H, \log T_{90})\) gives an improvement of about 1.5 per cent.

5 DISCUSSION

Unsupervised ML gives hints about the number of classes in a data set. This is, however, a phenomenological approach that does not have to reflect differences in physical processes underlying their origin (Horváth et al. 2006; Nakar 2007; Bromberg et al. 2013). Given the small data set with computed HEs, a supervised ML was performed in order to verify whether the features recently introduced to characterize GRBs, i.e. MVTS (MacLachlan et al. 2006),
2012, 2013a; Bhat 2013) and HE (MacLachlan et al. 2013b), are suitable for automated classification. As the commonly accepted division of GRBs into short and long according to $T_{90}$ is its key, based on which the classes for an SVM classifier were attributed to available MVTS and HE values, a three-dimensional parameter space ($H$, log MVTS, log $T_{90}$) was studied. It was shown that the accuracy was much greater in this parameter space than in a one- or two-dimensional parameter spaces. Especially, complementing (log MVTS, log $T_{90}$) by $H$ lead to a better performance. Therefore, the HE is considered a candidate indicator for distinguishing short and long GRBs, however its performance alone was rather poor. On the other hand, a sample of 22 + 46 = 68 GRBs with calculated HEs is not numerous enough to adjudicate with certainty what is the genuine overlap for the whole population.

Another issue is to construct the training set; specifically, to unambiguously attribute classes to the objects observed. The conservative limit of $T_{90}$ = 2 s was shown to be appropriate for BATSE GRBs, but for Swift data a division at $T_{90}$ = 0.8 s is more suitable (Bromberg et al. 2013). The plausible limits were derived (by means of a local minimum of a bimodal distribution of $T_{90}$ durations) for a number of catalogues by Tarnopolski (2015a) and gave values in the range 2.05–3.38 s, hence the classification is detector dependent.4 Note that the short and long associations for the current study were taken from MacLachlan et al. (2013a), MacLachlan et al. (2013b), Golkhou & Butler (2014), and Golkhou, Butler & Littlejohns (2015), and are based on the classical limit of 2 s. Moreover, GRBs classified as short often are of collapsar origin and those classified as long are recognized as having non-collapsar progenitors (Nakar 2007; Bromberg et al. 2013). Other properties commonly used as indicators are the hardness ratio, spectral lag, peak energy etc. (Bagoly et al. 1998; Borgonovo & Björnsson 2006; Zhang et al. 2009), but they are still selected phenomenologically. It was also suggested that GRBs may be generated by a third mechanism, most likely shock break out (Bromberg, Nakar & Piran 2011).

It was shown in a number of research, for BATSE data (Horváth et al. 2006) as well as for Swift sample (Horváth et al. 2010; Veres et al. 2010), that while the GRB separation by duration or hardness ratio alone is ambiguous, the joint distribution in a two-dimensional space of log $H_{32}$ versus log $T_{90}$ allows a sharper differentiation between the GRB types. In the spirit of these findings, and in light of the proposition that HEs may serve as a GRB type indicator (MacLachlan et al. 2013b), it was verified that complementing the sets of log $T_{90}$ and (log MVTS, log H) by HEs increases the success rate defined in equation (8). The fact that HE and MVTS alone, i.e. without $T_{90}$, are less convenient is not fully new, but the main result herein is that HEs help in distinguishing GRBs of different types.

SVM performs well in distinguishing short and long GRBs with data complemented by HEs. After setting the number of physically different GRB classes (at least two, and possibly three), which will require a working model that may hopefully predict the distributions (univariate, i.e. durations, hardness ratio, etc., as well as multivariate) of characteristic features, a supervised ML might then be applied to automated classification of GRBs observed in the future.

6 CONCLUSIONS

In this paper, GRBs observed by Fermi were investigated. Among ~1600 GRBs, there are 68 GRBs with calculated HE values, and a supervised ML was performed on this subsample. The SVM method is applied to singles, pairs and triples of ($H$, log MVTS, log $T_{90}$). The HE and MVTS (parameters new in GRB classification) alone perform rather poor in distinguishing between short and long GRBs due to a large overlap in their distributions. However, when the pairs (log MVTS, log $T_{90}$) are complemented by HEs, the accuracy of classification increases by 7 per cent and exceeds 95 per cent, i.e. introduction of $H$ in the classification scheme gives more accurate results. Hence, HEs are suggested as indicator candidates for distinguishing short and long GRBs, however not alone, as it is commonly done with durations $T_{90}$, but as part of an association of parameters. Particularly, in this paper an association of three parameters ($H$, MVTS, $T_{90}$) was examined.

It is suggested that HEs will be useful in classifying GRBs after the number of their classes is unambiguously determined, possibly by constructing a working model rather than by a phenomenological approach. As the shape of the HE distribution could not be determined accurately due to a small sample (consisting of 68 GRBs), a bigger, preferably complete, sample of Fermi GRBs might reveal new properties of the GRB population that could either challenge present theoretical models, or give hints on how to construct them.

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4 It appears that the Fermi data set has a limit of 2.05 s (Tarnopolski 2015a), very close to the conventional limit derived by Kouveliotou et al. (1993).
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