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Analysis of the observed and intrinsic durations of *Swift*/BAT gamma-ray bursts

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HIGHLIGHTS

- Duration distribution of *Swift*/BAT gamma-ray bursts (GRBs) is investigated.
- For GRBs with known z, the analysis is performed in the observer and rest frames.
- Mixtures of two and three log-normal distributions are fitted.
- Maximum log-likelihood, Akaike and Bayesian information criterion are employed to choose the best fit.
- It is found that the data is better followed by a two-Gaussian.

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ABSTRACT

The duration distribution of 947 GRBs observed by *Swift*/BAT, as well as its subsample of 347 events with measured redshift, allowing to examine the durations in both the observer and rest frames, are examined. Using a maximum log-likelihood method, mixtures of two and three standard Gaussians are fitted to each sample, and the adequate model is chosen based on the value of the difference in the log-likelihoods, Akaike information criterion and Bayesian information criterion. It is found that a two-Gaussian is a better description than a three-Gaussian, and that the presumed intermediate-duration class is unlikely to be present in the *Swift* duration data.

1. Introduction

Gamma-ray bursts (GRBs) were detected by military satellites *Vela* in late 1960's. Mazets et al. (1981) first pointed out hints for a bimodal distribution of T_b (taken to be the time interval within which fall 80%–90% of the measured GRB's intensity) drawn for 143 events detected in the KONUS experiment. Burst and Transient Source Explorer (BATSE) onboard the Compton Gamma Ray Observatory (*CGRO*) provided data that were further investigated by Kouveliotou et al. (1993), and led to establishing the common classification of GRBs into short ($T_{90} < 2\,\mathrm{s}$) and long ($T_{90} > 2\,\mathrm{s}$), where T_{90} is the time during which 90% of the burst's fluence is accumulated, referred to as the duration of a GRB. The progenitors of long GRBs are associated with supernovae related with collapse of massive stars (Woosley and Bloom, 2006). 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). It was observed that durations T_{90} seem to exhibit log-normal distributions which were thereafter fitted to short and long GRBs (McBreen et al., 1994; Koshut et al., 1996; Kouveliotou et al., 1996; Horváth, 2002).

The existence of an intermediate-duration GRB class, consisting of GRBs with T_{90} in the range 2–10 s, was put forward (Horváth, 1998; Mukherjee et al., 1998) based on the analysis of BATSE 3B data. It was supported (Horváth, 2002; Chattopadhyay et al., 2007) with the use of the complete BATSE dataset. Evidence for a third log-normal component was also found in *Swift*/BAT data (Horváth et al., 2008; Zhang and Choi, 2008; Huja et al., 2009; Horváth et al., 2010). Interestingly, Zitouni et al. (2015) re-examined the BATSE current catalog as well as the *Swift* dataset, and found that a mixture of three Gaussians (3-G) fits the $\log T_{90}$ data from *Swift* better than a two-Gaussian (2-G), while in the case of BATSE statistical tests did not support the presence of a third component (hereinafter, the $\log T_{90}$ distributions are considered, and are shortly referred to as durations as well). Regarding *Fermi*/GBM (Gruber et al., 2014; von Kienlin et al., 2014), a 3-G is a better fit than a 2-G,[1] however the presence of a

[1] Adding parameters to a nested model always results in a better fit (in the sense of a lower χ^2 or a higher maximum log-likelihood) due to more freedom given to the model to follow the data, i.e. due to introducing more free parameters.

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third group in the duration distribution was found to be unlikely (Tarnopolski, 2015a; 2015b), which was based on the fact that the $\log T_{90}$ distribution is bimodal, i.e. it exhibits two local maxima (Tarnopolski, 2015a), and that a mixture of two skewed components follows the data better than a standard three-Gaussian (Tarnopolski, 2015b).

The *Swift* data were re-examined by Bromberg et al. (2013), and they found that a limit of 0.8 s is more suitable for the GRBs observed by *Swift* than the conventional 2 s limit of Kouveliotou et al. (1993). It should be stressed that Bromberg et al. (2013) applied a different approach than Kouveliotou et al. (1993) and Tarnopolski (2015c): a functional form of the T_{90} distribution different from the commonly used phenomenological log-normal distribution, coming from a physical model for the short duration collapsar distribution, and by means of exceeding a probability threshold that a GRB with a given T_{90} is a non-collapsar. Interestingly, the limits for BATSE and *Fermi* data are consistent with the 2 s limit, and also with the results obtained by Tarnopolski (2015c), where based on the well-established conjecture that durations T_{90} are log-normally distributed, the limit between short and long GRBs may be placed at the local minimum, which is detector-dependent. Finally, many works in which a 2-G was fitted to the $\log T_{90}$ distribution showed a significant overlap of components corresponding to short and long GRBs (McBreen et al., 1994; Koshut et al., 1996; Horváth, 2002; Zhang and Choi, 2008; Huja et al., 2009; Bromberg et al., 2013; Barnacka and Loeb, 2014; Tarnopolski, 2015c; Zitouni et al., 2015).

The aim of this paper is to analyze the current dataset of *Swift*/BAT GRBs, and to test whether a greater sample of 947 events leads to conclusions other than Zitouni et al. (2015) arrived at for a set of 757 events. Moreover, a relevant increase of GRBs with measured redshift—347 compared to 248 GRBs examined by Zitouni et al. (2015)—provides an opportunity for a re-evaluation of the GRB properties that are, after moving to the rest frame, not affected by cosmological factors. This paper is organized in the following manner. In Section 2 the datasets, fitting method and statistical criteria used to infer the validity of the models applied are described. Section 3 presents the results of fitting a 2-G and 3-G to the whole sample of 947 GRBs, as well as a subsample of 347 events in both the observer and rest frames. Section 4 is devoted to discussion, and gathers concluding remarks.

2. Methods

2.1. Dataset

The *Swift* dataset contains 947 GRBs[2] with measured duration T_{90}, of which 9% are short (87 events). 347 GRBs have their redshift known, and those constitute the second sample examined herein. It consists of 324 long GRBs and 23 short ones. A scatter plot of this subsample on a $\log T_{90} - z$ plane is drawn in Fig. 1. The median redshift for short and long GRBs is equal to $\tilde{z}_{\rm short} = 0.72$ and $\tilde{z}_{\rm long} = 1.90$, respectively. The intrinsic durations are calculated according to

$$T_{90}^{\rm int} = \frac{T_{90}^{\rm obs}}{1+z}. \quad (1)$$

Distributions of the $\log T_{90}$ for the observed and intrinsic durations are examined hereinafter, and are displayed together with the distribution of the whole sample in Fig. 2.

The important question is whether this improvement is statistically significant, and whether the model is justified.

[2] http://swift.gsfc.nasa.gov/archive/grb_table.html, accessed on September 30, 2015.

2.2. Fitting method

Two standard fitting techniques are commonly applied: χ^2 fitting (Voinov et al., 2013) and maximum likelihood (ML, Kendall and Stuart 1973). For the first, data needs to be binned, and despite various binning rules are known (e.g. Freedman–Diaconis, Scott, Knuth etc.), they still leave place for ambiguity, as it might happen that the fit may be statistically significant on a given significance level for a number of binnings (Huja et al., 2009; Koen and Bere, 2012; Tarnopolski, 2015a). The ML method is not affected by this issue and is therefore applied herein. However, for display purposes, the binning was chosen based on the Freedman–Diaconis rule.

Having a distribution with a probability density function (PDF) given by $f = f(x;\theta)$ (possibly a mixture), where $\theta = \{\theta_i\}_{i=1}^{p}$ is a set of parameters, the log-likelihood function is defined as

$$\mathcal{L}_p(\theta) = \sum_{i=1}^{N} \ln f(x_i;\theta), \quad (2)$$

where $\{x_i\}_{i=1}^{N}$ are the datapoints from the sample to which a distribution is fitted. The fitting is performed by searching a set of parameters $\hat{\theta}$ for which the log-likelihood is maximized. When nested models are considered, the maximal value of the log-likelihood function $\mathcal{L}_{\rm max} \equiv \mathcal{L}_p(\hat{\theta})$ increases when the number of parameters p increases.

A mixture of k standard normal (Gaussian) distributions:

$$f_k(x) = \sum_{i=1}^{k} \frac{A_i}{\sqrt{2\pi}\,\sigma_i} \exp\left(-\frac{(x-\mu_i)^2}{2\sigma_i^2}\right), \quad (3)$$

is considered. It is described by $p = 3k-1$ free parameters: k pairs (μ_i, σ_i) and $k-1$ weights A_i, satysfying $\sum_{i=1}^{k} A_i = 1$ due to normalization of a PDF. Therefore, $p = 5$ for a 2-G, and $p = 8$ for a 3-G.

2.3. Statistical criteria

If one has two fits such that $\mathcal{L}_{p_2,\rm max} > \mathcal{L}_{p_1,\rm max}$, then twice their difference, $2\Delta\mathcal{L}_{\rm max} = 2(\mathcal{L}_{p_2,\rm max} - \mathcal{L}_{p_1,\rm max})$, is distributed like $\chi^2(\Delta p)$, where $\Delta p = p_2 - p_1 > 0$ is the difference in the number of parameters (Kendall and Stuart, 1973; Horváth, 2002). If a p-value associated with the value of $\chi^2(\Delta p)$ does not exceed the significance level α, one of the fits (with higher $\mathcal{L}_{\rm max}$) is statistically better than the other. For instance, for a 2-G and a 3-G, $\Delta p = 3$, and despite that, according to Footnote 1, $\mathcal{L}_{\rm max,\,3-G} > \mathcal{L}_{\rm max,\,2-G}$ holds always, twice their difference provides a decisive p-value.

For nested as well as non-nested models, the Akaike information criterion (*AIC*) (Akaike, 1974; Burnham and Anderson, 2004; Liddle, 2007) may be applied. The *AIC* is defined as

$$AIC = 2p - 2\mathcal{L}_{p,\rm max}. \quad (4)$$

A preferred model is the one that minimizes *AIC*. The formulation of *AIC* penalizes the use of an excessive number of parameters, hence discourages overfitting. It prefers models with fewer parameters, as long as the others do not provide a substantially better fit. The expression for *AIC* consists of two competing terms: the first measuring the model complexity (number of free parameters), and the second measuring the goodness of fit (or more precisely, the lack of thereof). Among candidate models with AIC_i, let $AIC_{\rm min}$ denote the smallest. Then,

$$Pr_i = \exp\left(-\frac{\Delta_i}{2}\right), \quad (5)$$