ARTICLE TYPE

The Fermi GBM GRBs’ multivariate statistics

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Studying the GRBs’ gamma-ray spectra may reveal some physical information of Gamma-ray Bursts. The Fermi satellite observed more than two thousand GRBs. The FERMIGBRST catalog contains GRB parameters (peak energy, spectral indices, intensity) estimated for both the total emission (fluence), and the emission during the interval of the peak flux. We found a relationship with linear discriminant analysis between the spectral categories and the model independent physical data. We compared the Swift and Fermi spectral types. We found a connection between the Fermi fluence spectra and the Swift spectra but the result of the peak flux spectra can be disputable. We found that those GRBs which were observed by both Swift and Fermi can similarly discriminate as the complete Fermi sample. We concluded that the common observation probably did not mean any trace of selection effects in the spectral behavior of GRBs.

KEYWORDS:
gamma rays: bursts, techniques: spectroscopic, methods: statistical, catalogs

1 INTRODUCTION

Gamma-ray bursts (GRBs) are the most energetic transients in the Universe (Kumar & Zhang, 2015), and their spectral energy distribution (SED) represents basic information on the physical processes responsible for the observed characteristics of these objects (Sari, Piran, & Narayan, 1998). If we study the gamma energy range of the SED, it can be well approximated by a combination of a small number of power law functions (Ghirlanda, Bosnjak, Ghisellini, Tavecchio, & Firmani, 2007; Uhm & Zhang, 2014), which show that the nonthermal (synchrotron, inverse Compton) processes play probably a fundamental role in the radiation (Massaro & Grindlay, 2011; Mészáros et al., 2015; B. Zhang & Mészáros, 2002). Sometimes we can find trace of the presence of a thermal component in the SED (Mészáros, Ramirez-Ruiz, Rees, & Zhang, 2002; Ryde & Petroian, 2002; Ryde & Svensson, 2002).

The Fermi Gamma-ray Space Telescope (FGST, Fermi satellite) provides the scientific community a wealth of high quality data on several astrophysical objects. The Fermi was launched in 2008 into a Low Earth orbit of ≈565 km and it has two instruments: the all-sky Gamma-ray Burst Monitor (GBM) can detect GRBs in the 8 keV to 40 MeV range (Bhat et al., 2009; Bissaldi et al., 2009; von Kienlin et al., 2014) and the Large Area Telescope (LAT) can observe the 20 MeV to 300 GeV energy range photons (Atwood et al., 2009; Cameron & Fermi LAT Collaboration, 2009). The Neil Gehrels Swift Observatory (formally known as ‘Swift’ Space Telescope) (Barthelmy et al., 2005; Burrows et al., 2005; Roming et al., 2005) has three different instruments: the Burst Alert Telescope (BAT), the X-ray Telescope (XRT), and the UV/Optical Telescope (UVOT). The instruments can detect in the energy ranges of 15–150 keV, 0.3–10 keV, and 170–600nm for the BAT, XRT, and UVOT, respectively. In contrary to GBM the BAT only have 1.4 sr field of view, but the position accuracy is a magnitude better than as of the Fermi GBM (a few arcminutes vs some degrees).

In general we can use the Band function (Band et al., 1993; Briggs et al., 1999) to describe the observed SED within the limits of the statistical inference, but several GRBs can be well approximated by simpler functional forms (power law, cutted power law, Comptonized) (Kaneko et al., 2006; Ryde, 1999; Thompson, 1994; Titarchuk, Farinelli, Frontera, & Amati, 2006).
Several attempts were made in fitting more complex spectra to the observed gamma energy distributions, but in most cases they were not really successful (Chhotray & Lazatzi 2015; Lazatzi & Begelman 2010; B.-B. Zhang et al. 2011). However, the Band function at the bright long GRBs’ prompt radiation is often inadequate to fit the data (Burgess, Preece, Connaughton, et al. 2014). It is worth mentioning that these analytic models do not really have a physical background, although, they can be used to interpret some physical parameters (e.g. low- and high-energy spectral index or peak energy).

The single power law has two free parameters: the \( \alpha \) spectral index and the \( A \) amplitude. To normalize the model to the energy range under consideration a pivot energy \( (E_{\text{piv}}) \) can be defined. It was fixed at 100 keV for GRBs detected by GBM.

The Comptonized model is an exponentially cutoff power law, a subset of the Band function in the limit when \( \beta \to \infty \). It has three free parameters: the \( \alpha \) low-energy spectral index, the \( A \) amplitude and \( E_{\text{peak}} \). Similarly to the power-law model \( E_{\text{piv}} \) is again fixed at 100 keV.

The smoothly broken power law spectra is characterized by one breakpoint with flexible curvature and is able to fit spectra with sharp or smooth transitions between the low- and high-energy power laws. This model has five parameters and was introduced by Ryde (1999).

Finally, Band’s GRB function is usually considered as the standard for fitting GRB spectra. This function has four free parameters: \( \alpha \) and \( \beta \) the low- and high energy spectral indices, respectively, the \( A \) amplitude, and the \( E_{\text{peak}} \) energy.

In our recent work (Rácz, Balázs, Horvath, Tóth, & Bagoly, 2018) we revealed an ordering of the spectra into a power law – Comptonized – smoothly broken power law – Band series with contingency and correspondence analysis. There are some model independent quantities such as the duration, fluence and flux bear important physical information, all these can be obtained from analyzing the observed gamma radiation (Fenimore, in ‘t Zand, Norris, Bonnell, & Nemiroff 1995; Kumar & Panaitescu 2000). In the following we try to find relationships between the spectral data and model independent quantities (Burgess, Preece, Ryde, et al. 2014).

The GBM has recorded a break in the majority of the GRBs’ spectral energy distribution (Gruber et al. 2014; Narayana Bhat et al. 2016). This break depends on the photon flux quantity, therefore we cannot fit faint sources well with functions that differ from the power law.

In this work we studied the relationship between the GRBs’ model-independent parameters and spectral properties. We compared the Swift and Fermi observations and analyzed the correspondence of the best fitted models.

### 2 GBM SPECTRAL DATA

There is a big catalog from the GBM observations which were classified as GRBs. There are two types of spectra in the Fermi data: one referring to the peak flux (designated with \( \text{pflux} \)) and the other one to the fluence (designated with \( \text{flnc} \)). The peak flux spectra relates to the photons collected in the time bin around the intensity peak of the prompt emission (the time bin equals to 1024 ms at the bursts of \( T90 > 2s \) duration and 64 ms if \( T90 < 2s \)). Both in the \( \text{pflux} \) and \( \text{flnc} \) spectra four different model spectra were fitted to every burst event and the best fitting model was indicated by a likelihood-based statistic. The four fitted model spectra are the power law, the Comptonized, the Band and the smoothly broken power law.

The FERMIGRBST[1] catalog (Goldstein et al. 2012; Paciesas et al. 2012) contains several physical parameters derived from the rough data delivered by the Fermi GBM detectors. The database used in our paper contains more than 2200 records (number of GRBs). One set of the data (e.g. duration, peak flux, fluence) is related to the burst in general and the other one were obtained from fitting the models, along with the best fitted one.

Only the best fitted models in both sets (pflux and flnc) of model spectra were taken into account in our analysis, ignoring the remaining three spectra and their estimated parameters. As for the model independent parameters we used the \( T50 \) and \( T90 \) durations, the \( 64/256/1024 \) ms flux in the \( 10–1000 \) keV energy range, the \( 64/256/1024 \) ms (BATSE standard) flux in the \( 50–300 \) keV energy range, the \( 10–1000 \) keV energy band fluence, and the \( 50–300 \) keV energy band BATSE fluence.

### 3 MULTIVARIATE ANALYSIS OF THE DATA

#### 3.1 Analysis of the contingency tables

There are \( N \) observations with several variables for each observation, and all events were classified into one of ‘A’ mutually exclusive categories and one of ‘B’ mutually exclusive categories. Then we can make the contingency table (an \( A \times B \) matrix) by cross-tabulating the data. Unassociated row and column variables are referred to as independent.

The definition for independence is that

\[
P(\text{row}_i, \text{column}_j) = P(\text{row}_i) \cdot P(\text{column}_j)
\]

for all \( i, j \), where \( P \) is the probability. In our case pflux and flnc spectral categories can be considered as independent so we can

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[1] https://heasarc.gsfc.nasa.gov/W3Browse/fermi/fermigbrst.html
test our null-hypothesis \((H_0)\) with the following chi-square test statistic:

\[
\chi^2 = \sum_{i=1}^{rows} \sum_{j=1}^{columns} \frac{(O_{ij} - E_{ij})^2}{E_{ij}} \tag{2}
\]

where \(O_{ij}\) is the observed and \(E_{ij}\) is the expected number of events (frequencies).

The usage of this method is beneficial in determining whether there is dependence, but as the strength of that association depends on the degrees of freedom as well as the value of the test statistic, it is not easy to interpret the strength of association.

The Pearson’s residuals (which are also known as Pearson’s contingency coefficient) is one method to provide an easy way to interpret the strength of association. Specifically, it is:

\[
\text{Pearson’s residuals} = \frac{(O_{ij} - E_{ij})}{\sqrt{E_{ij}}} \tag{3}
\]

This residual have approximate Normal distribution with mean 0 (no association).

### 3.2 Discriminant Analysis

Discriminant analysis aims to recognize difference between groups in the multivariate parameter space, orders membership probabilities to the cases and one may use this scheme for classifying additional ones not having assigned group memberships. We use this technique to look for differences in the distributions of GRBs in the parameter space defined by the variables listed in the Fermi GBM catalog.

There are some different methods for the problem stated above. In this case we used linear discriminant analysis (LDA) originally proposed by [Fischer 1936]; see [McLachlan 2004] for a review. Further mathematical background can be found in Sect. 3.3.1 of [Rácz et al. 2018].

LDA presents in all professional statistical software packages. We used the `lda()` procedure available in the `MASS` library [Venables & Ripley 2002] of the R statistical environment.

#### 3.2.1 LDA of the GBM Data

We analyzed more than two thousand GRBs of the the Fermi GBM catalog with the LDA method. We used the the following model independent variables: \(T90\), \(T50\), fluence, batse fluence, 64ms/256ms/1024ms flux, batse 64ms/256ms/1024ms flux. In the analysis we take both types of spectral fitting into account where the categorical variables were the best fitted model of both peak flux and fluence.

The LDA resulted in three discriminant functions (LD1, LD2, LD3) based on the parameters above. The mean values of the discriminant functions within the different spectral types and significance obtained. The significance of the discrimination between the spectral types was shown by the output of this procedure. The Wilks’ lambda parameters can be calculated based on the probability, which is the level of significance.

We may use the complete sample without taking the different uncertainties of the data given in the catalog into consideration, but the Fermi group published a better sample. [Gruber et al. 2014], however, defines a subsample of ‘GOOD’ having uncertainties below a certain limit. For our study we used LDA with the data fulfilling these criteria. These criteria do not differentiate between the classical GRB groups (short, intermediate, and long) [Horváth 2002, Rípa & Mészáros 2016].

Our results obtained from the peak flux and fluence spectra are also shown in Fig. 1. One can see that in both cases the first linear discriminant function (LD1) separates the different spectral types well. The results show that fitting the model spectra on the peak flux is much more efficient for the significance values if we compare the two plots. The Band and the smoothly broken power law merged into each other, but the LDA could separate the power law and the Comptonized types well (in both of the classification types).

The greatest discriminated distances appear to be between the Band and the power law classes, with the remaining two classes being between them [Racz et al. 2015]. The fluence spectra contain much more photons, thus more informations

![FIGURE 1 The 'GOOD' sample GRBs' distribution of the first discriminant function between the spectral classes and types. On the left side the 'peak flux' types and on the right the 'fluence' type models. We found that the difference between the classes are bigger in the 'peak flux' models but both (pflx and flnce) significances are very high.](image)
about the GRBs even though in this work we found the surprising and significant effect that the level of discrimination is higher in case of the peak flux than the fluence spectra.

Performing LDA in this case would result in improved significances, and as we obtained the LD2 of the peak flux spectra became significant as well (sign. level: $< 10^{-3}$). The LDA also show that the duration of the GRB is not a significant discriminator, thus our results are valid for all groups of GRBs.

4 | ASSOCIATING THE SWIFT-FERMI GRBS

Both the Swift and the Fermi satellites detected several thousand events from which more than a thousand were triggered GRBs. It can be declared boldly that the two satellites opened a new area in studying GRBs. There are significant differences in the covered energy range because the Fermi is sensitive from a few keV to a few GeV, in contrast the Swift can observe the radiation up to 150 keV. We can find several GRBs which both Fermi and Swift had detected.

The NASA Swift GRB Table[^1] was made using the GRB observations and contains the trigger time and position data for more than 1100 Swift discovered GRBs until the May of 2018.

We compared the objects presented in the GBM catalog with those recorded by Swift to get the simultaneously detected GRBs. We looked for the closest neighbor in between the two catalogs in position and time to find the matching objects.

We used the `knn()` procedure from the `class` library of the R environment [Venables & Ripley 2002] to assign every Fermi GRBs a Swift counterpart with the shortest time and spatial differences. With this procedure we got a 2D plane from the difference of observation times and positions where the points on this plane show the closest associations between the Fermi-Swift events. The results can be seen in Fig. 2.

The Model-Based Clustering procedure (Mclust()) from the `mclust` package [Fraley & Raftery 2002, Fraley, Raftery, Murphy, & Scrucca 2012] provided a well separated group, which can also be seen by the naked eye. This group of GRBs is clearly defined by the time difference being less than 30 minutes and the coordinate difference being less than 10 degrees.

Finally, we checked the accidental multiple associations and omitted these 8 events. In our previous work we presented 292 Fermi-Swift pairs from 2069 Fermi and 1122 Swift GRBs, now, after 1 year, we found 316 pairs from 2307 and 1205 GRBs. We note that the Swift GRB Table contains Fermi discovered and Swift observed GRBs, but in that table there are only 52 events.

4.1 | Comparing the Fermi-Swift spectral classes

In contrast to the Fermi, the Swift GRB Table contains only two spectral classes (power law and cutoff power law) and does not distinguish the spectral types (over the peak flux or

[^1]: https://swift.gsfc.nasa.gov/archive/grb_table/
during the duration), therefore we only have two category variables. We studied the relationship between the Fermi and the Swift spectral classes. The results of the contingency analysis – the strength of association (Pearson’s coefficient) – is shown in Fig. 3. The Fermi fluence type spectral classes match well because we cannot see a power law – non-power law (Comptonized, broken, or Band) association. Also, the cut-off power law connected the Band and smoothly broken power law. Contrarily the peak flux type spectra show a surprising Band–power law relationship. The reason of this strange association can probably be that the Swift classified the spectra over the entire burst duration similar to the Fermi fluence type and the spectrum changed in time. Several papers have found similar variability on the spectrum (among others (Kumar & Zhang 2015; Mészáros 2006; Rácz et al., 2018)). The spectral evolution is best shown by the Band spectra, because more GRBs have the Band spectral class over the peak flux time.

4.2 LDA of common GRBs

By using LDA we have examined the GRBs which have been observed by both Swift and Fermi at the same time. Similarly to Sect. 3.2.1, the first linear discriminate function can be seen in Fig. 4. It shows consistency with the previous results from the ‘GOOD’ sample. The Band and the smoothly broken power law spectral classes are merged on the peak flux spectra type, but the peak flux still appears to be a better discriminator. The primary cause of the significant overlap might be the low number of objects, because there are only a few GRBs that both satellites were able to detect, and their best fitted spectral class was the smoothly broken power law. We were unable to find any evidence that the GRBs’ simultaneous observation would cause a selection effect in the spectral classes.

5 SUMMARY

Gamma-ray bursts, which are the brightest transient in the Universe, can be detected – besides the gamma-ray energy range – in almost all wavelengths. Generally the spectral energy distribution can be well-approximated by a small number of power law functions. The Fermi Gamma-ray Space Telescope discovered more than 2000 GRB events, and 2 types of spectra were made from the GRBs: over the time range of the peak flux of the burst (peak flux type, pflx) and over the entire burst duration (fluence type, flnc). 4 spectral classes could be fitted on both types: Band, smoothly broken power law, Comptonized and power law.

The best fitted spectral classes can be seen as category variables, and we are able to study the relationship between the model independent parameters (duration, total energy, peak flux) and these categories. We used the procedure of linear discriminant analysis and we have found a significant separation between the spectral classes on both spectral types. Our results also show that the peak flux spectra can discriminate better, even though the fluence spectra contain much more photons, thus more informations about the GRBs.

We paired Fermi and Swift observations, and we studied the association between the Fermi and Swift spectral classes. The Swift spectra were made over the entire duration of the burst like the Fermi fluence type spectra, these classes were well-matched. In the case of ‘pflx’, we have found the trace of spectral evolution because there is a deficit on the Band – cutoff power law associations.

The LDA method was used to analyze the GRBs which have been detected by both the Swift and the Fermi satellites to test whether the two satellites are observing different populations of GRBs. Our results are similar to the previous ones: we were unable to find any significant evidence of any selection effect. The small difference can be explained with the small number of objects in our sample. Interpretation of data as well as the preparation of the manuscript.

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Author contributions

All authors participated in acquisition, analysis and interpretation of data as well as the preparation of the manuscript.

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Conflict of interest

The authors declare no potential conflict of interests.

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