Background Estimation in Fermi Gamma-ray Burst Monitor lightcurves through a Neural Network

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Abstract

The aim of this work is to provide a data-driven approach to estimate a background model for the Gamma-Ray Burst Monitor (GBM) of Fermi satellite. We employ a Neural Network (NN) to estimate each detector background signal given the information of the satellite: position, velocity, direction of the detectors, etc. The estimated background can be employed into a triggering algorithm to discover significant long/weak events that are not previously detected by other approaches. We show the potential of the model by estimating the background on GBM data for Gamma-Ray Bursts (GRBs) present in GBM catalog, the long GRB 190320 and ultra-long GRB 091024. The proposed approach is straightforwardly generalizable to estimate the background model of other satellites.

Introduction

Gamma-Ray Bursts (GRBs) originates in extraordinarily energetic explosions taking place in distant galaxies. They are detected as irregular pulses of X and γ-ray radiation in high-energy detectors by satellites such as BATSE, SWIFT, Fermi Gamma-ray Space Telescope and in future HERMES-TP/SP [3].

The Fermi Gamma-ray Space Telescope hosts the Gamma-ray bursts Monitor (GBM) and Large Area Telescope (LAT) experiments. GBM is composed of 14 different scintillation detectors, 12 NaI (efficient from 8 keV to 1 MeV) and 2 BGO (efficient from 0.2 to 40 MeV) [2]. In this work Fermi GBM Data Tools [4] is employed: it is an Application Programming Interface (API) for GBM data written in Python. It allows to download, analyse and visualise GBM data.

To trigger an event an algorithm should decide if the foreground counts is statistically higher than the background counts. We refer to *foreground* to indicate the counts of the photons received by the detector and to *background* the expected counts in the absence of γ/X-ray events. The background consists in different components such as cosmic Gamma-ray background (CGB), secondary cosmic ray-produced photons, Earth gamma-ray albedo, geomagnetic latitude etc. [6, 1], that are not know a priori, and cannot be measured in isolation with respect to γ/X-ray events, thus an estimation is needed to "clean" the foreground counts factoring out the background.

Objective

Estimating the background with a physical model such as in [1] can improve background estimation and reveal long/weak signals, in the next section we try to reach the same result, but doing it in a data-driven way. The data driven way is more flexible, since can be applied to any satellite data, at least in principle.

Data

The detectors considered are only the twelve NaI: n0, n1, n2, n3, n4, n5, n6, n7, n8, n9, na, nb.

In this work, for sake of memory consumption, computation and focusing on long GRB, the counts lightcurve are binned at 4.096 seconds and binned in energy range of 3 category: 28-50 keV (r0), 50-300 keV (r1), 300-500 keV (r2). These integrals over time and energy are performed with GBM Data Tools. 12 counts rate (in 4.096s) times 3 energy range. In total 36 columns.

$col\_range = [n0\_r0, n0\_r1, n0\_r2, n1\_r0, n1\_r1, n1\_r2, n2\_r0, n2\_r1, n2\_r2, n3\_r0, n3\_r1, n3\_r2, n4\_r0, n4\_r1, n4\_r2,, n5\_r0, n5\_r1, n5\_r2, n6\_r0, n6\_r1, n6\_r2, n7\_r0, n7\_r1, n7\_r2, n8\_r0, n8\_r1, n8\_r2, n9\_r0, n9\_r1, n9\_r2, na\_r0, na\_r1, na\_r2, nb\_r0, nb\_r1, nb\_r2]$

Thanks to the Fermi Data Tools package it is possible to retrieve information of the satellite in a particular timestamp: position of Fermi in Earth inertial coordinates, Fermi attitude quaternions, position of Fermi in Earth latitude, position of Fermi in Earth East longitude, altitude of Fermi in orbit, velocity of Fermi in Earth inertial coordinates, angular velocity of Fermi, sun visibility (True/False), sun location in Right Ascension, sun location in Declination, if Fermi is in an SAA passage (True/False), approximate McIlwain L value as determined by the orbital position of Fermi.

$col\_sat\_pos = [pos\_x, pos\_y, pos\_z, a, b, c, d, lat, lon, alt, vx, vy, vz, w1, w2, w3, sun\_vis, sun\_ra, sun\_dec, earth\_r, earth\_ra, earth\_dec, saa, l]$

Information relative to the detectors are also available: pointing of a GBM detector in equatorial coordinates, if a detector FOV is occulted by the Earth.

$col\_det\_pos = [n0\_ra, n0\_dec, n0\_vis, n1\_ra, n1\_dec, n1\_vis, n2\_ra, n2\_dec, n2\_vis, n3\_ra, n3\_dec, n3\_vis, n4\_ra, n4\_dec, n4\_vis, n5\_ra, n5\_dec, n5\_vis, n6\_ra, n6\_dec, n6\_vis, n7\_ra, n7\_dec, n7\_vis, n8\_ra, n8\_dec, n8\_vis, n9\_ra, n9\_dec, n9\_vis, na\_ra, na\_dec, na\_vis, nb\_ra, nb\_dec, nb\_vis]$

Method

We formulate the problem as a typical supervised Machine Learning estimation, where input X are the variables in col_sat_pos and col_det_pos and the output Y the variables in col_range.

If we are interested in estimating the photons in absence of events, in Machine Learning the formulation of the problem is the following: The model requires to estimate an F such that $Y \approx F(X)$. Here we are dealing with a multi-output regression.

The model employed is a feed forward neural network [5] with 3 hidden dense layers and 3 dropouts, one per each hidden layer. In the experiment, we employed 2048 neurons in the first two layers, and 1024 in the third, the last (output) layer has 36 neurons, one per each target variable. The probability parameter for the droupts is 0.05. The optimizer used is Nadam with learning rate 0.005, β_1 0.8, β_2 0.8 and ϵ 1e-07. We run the fitting for 64 epochs with a batch size of 2048. The Neural Network is implemented in Tensorflow.

The data in input where standardised, the instances in SSA were deleted. The splitting procedure divides the dataset in 75% train, 25% test; 30% of the training set is further kept as validation set. The resulting splitting is: 52% train, 23% validation and 25% test. The instances inside these sets are taken randomly. The loss function is the Mean Absolute Error (MAE)

$$\text{MAE}(x, y) = \frac{1}{n}\sum_{i=1}^{n} |y_i - x_i| \quad (1)$$

In the settings of multi-output regression, the overall loss L is

$$L = \min_i(\text{MAE}(f_i(X), Y_i)), \text{where i in col\_range} \quad (2)$$

To compare the background estimation with another approach in next section is shown an application on the period of GRB 091024.

Results

To present a benchmark in terms of background estimation, it is analysed period of the ultra-long GRB 091024 , for which the work of [1] provides the same analysis. In figure 1 are shown detectors n0, n6 and n8 in the three energy band specified in Data section. In black are shown the data and in red the background estimation of a Neural Network trained and tested over a period of 3 months, from September to November 2009, that consists of 1.63 million of samples.

In figure 2 the event is GRB 190320, the background estimation is the output of an Neural Network trained and tested in a period of 3 months, from March to May 2019, that consists of 1.69 million of samples.

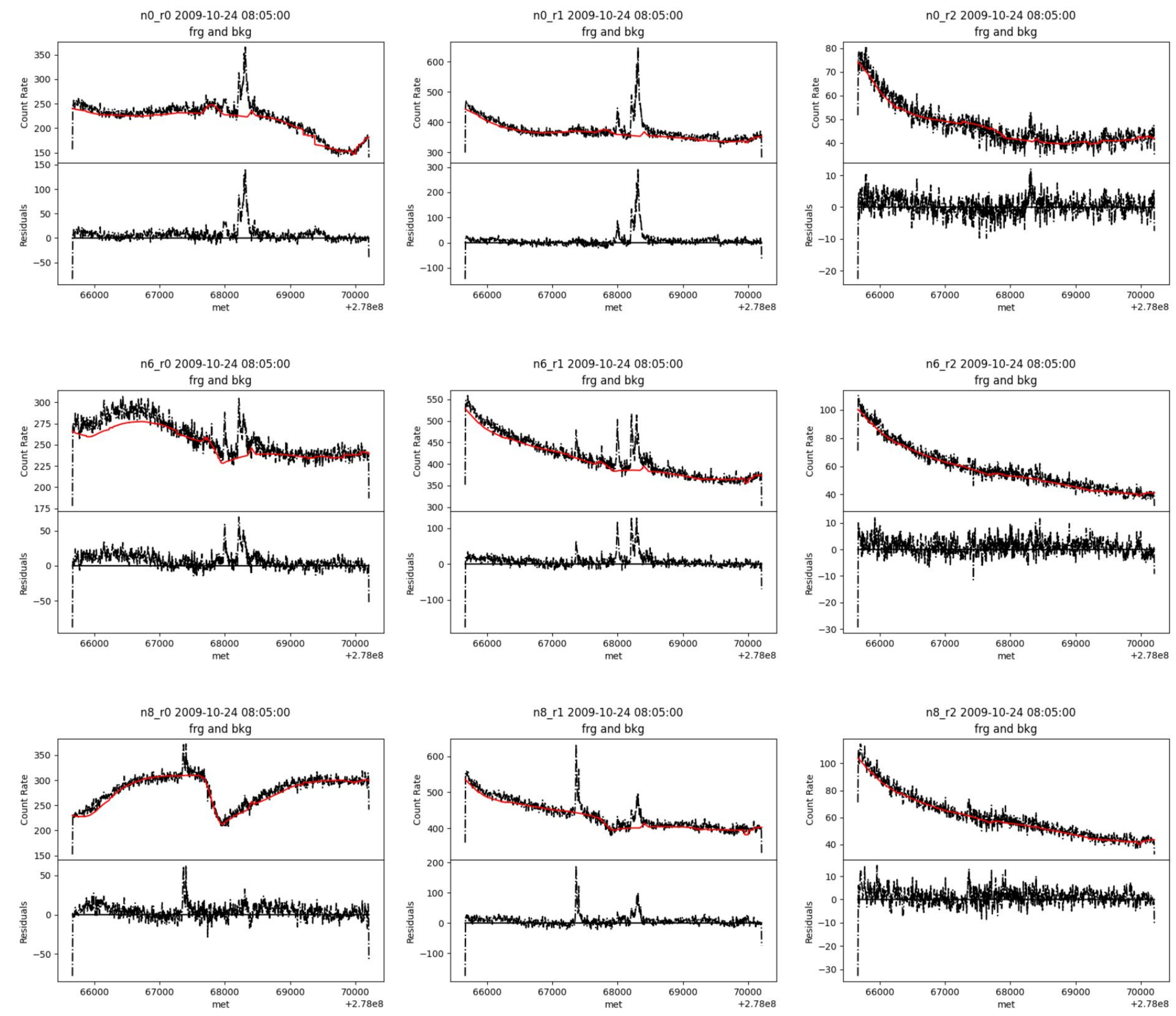

Figure 1: Foreground and background fit around the event GRB 091024. This figure can be compared with figure 18 of [1].

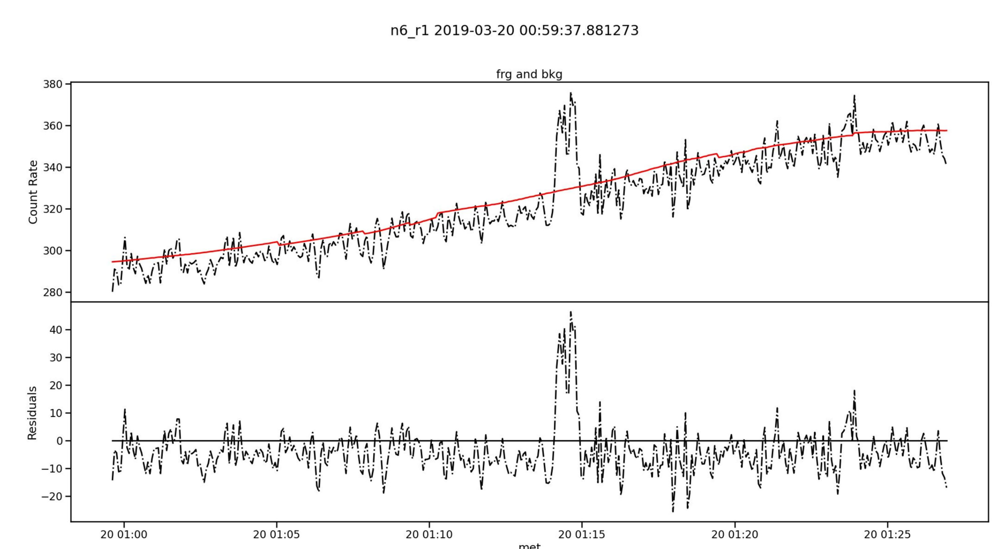

Figure 2: Foreground and background fit around the event GRB 190320 for detector n6 in energy range r1.

Conclusion

A new method to provide a data-driven estimation of the γ/X-ray background is provided given the data of the satellite and a Neural Network that performs a multi-output regression. The tests are performed on GBM data for the events GRB 190320 and GRB 091024, the latter shows results in line with a physical background estimator, despite the method is agnostic with respect to any physical assumption. This method could be employed in recreating the background of other satellites, such as Hermes, then applying a trigger algorithm to efficiently recover astronomical transient events.

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