Classification of long gamma-ray transients from INTEGRAL data using machine learning approach*

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Abstract. In this paper we use 19 years of data from INTEGRAL detectors to train classification model for gamma-ray bursts. We present algorithms for automated processing of the light curve of gamma-ray bursts, consisting of a background approximation, distinguishing an event from background, and duration calculation. Candidates are crossmatched with several catalogues of transient events. This provided us labels for supervised machine learning. Gradient boosting classifier is employed for training to find Solar flares and gamma-ray bursts. Estimated accuracy is $\sim 91\%$ for latter events. Similar machine learning approach can be applied to other types of transients.

Keywords: Machine learning · Crossmatching · Gamma-ray bursts · INTEGRAL.

1 Introduction

Gamma-ray bursts (GRB) where discovered in 1973 as a sudden and rapid increase in gamma-ray flux[21]. Since then GRB trigger algorithms rely on search for excess of signal above background on short timescale; for example, the trigger scale in IBAS varies from 0.05 to 5 seconds[30]. This works well for usual short (duration less than 2 seconds) and long (greater that 2 seconds) gamma-ray bursts, but can be problematic in case of events with large signal rise time and/or duration. An example of such an event is ultralong gamma-ray bursts[15]: their duration varies from hundreds up to tens thousands of seconds[5] and may consist of several episodes. Also, it was reported[37] that duration distribution of long bursts is skewed, possibly, because of not found long events with duration $\gtrsim 100$ seconds.

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There is a way to fill this gap in long events - "offline" blind search, carried out on archival data. It is named blind, because search procedure does not have information about presence of known transient at any given time. One of them is Bayesian blocks[35], it is well suited for observatories with stable background, such as Konus-WIND (KW)[7]. A more conventional approach when working with more variable background is using running averages and search for excesses on different timescales[34]. More precise background approximation can be achieved by modeling based on physical properties of observatory and environment. It can be conducted by either physical approach[9] or by training a Neural Network[13]. After that search algorithm can be applied: simple significance threshold or, for example, FOCuS-Poisson[40]. A step further would be using Recurrent Neural Networks, perfectly suited for sequential data, for both background approximation and anomaly detection[33,28].

Determining origin of detected transients is the main problem, especially for detectors without imaging and spectral capabilities. Often, transients are distinguished by a set of different parameters in several dimensions, such as comparison of flux in different detectors or shape of the light curve. It can be carried out by traditional machine learning approaches (for example, random forest [25,14,41]) or by deep learning[33]. Classification requires labels, which are usually derived from catalogues of transients via crossmatching procedure.

In this paper we present our approach to problem of classification long transients using INTEGRAL data. We employ new method, that combines statistical approach to background modeling and data processing with Gradient Boosting classifier.

2 Instruments and data processing

2.1 INTEGRAL

INTEGRAL was launched in 2002 on highly elliptical orbit, with apogee about 150000 km[18]. We use data from almost every detector onboard observatory, namely SPectrometer of INTEGRAL (SPI), SPI AntiCoincidence Shield (SPI-ACS), INTEGRAL Radiation Environment Monitor (IREM), JEM-X, Imager on-Board the INTEGRAL Satellite (IBIS) consisting of Integral Soft Gamma-Ray Imager (ISGRI) and Pixellated Caesium-Iodide Telescope (PICsIT). SPI-ACS is a scintilator, which main purpose is to protect SPI from background photons outside its field of view (FOV), but it has been proven as an effective separate gamma-ray detector[32,39]. Its main disadvantage is lack of imaging and spectral capabilities. IREM is a semiconductor detector, aimed at monitoring radiation environment and prevent damage to other instruments[17]. It can also be used as a full-fledged detector of charged particles. Among 15 channels we use only TC3. It is sensitive to electrons from 0.8 MeV and protons from 12 MeV and has the widest energy range and sensitivity. JEM-X[26], SPI[38] and IBIS[24,23,29] are imaging detectors, that differ in operating energy range: from low energy X-ray in JEM-X to gamma-ray in SPI. Information from all these detectors can give a broad insight about transients spectra, temporal structure in high energy range (from 3 keV and above), and its origin (either radiation or particles).

2.2 Dataset

As a dataset we use sample of 4364 transient events found in SPI-ACS data with more than 3σ significance between 2003 and 2021. One fraction of these events are random fluctuations, while another are real Solar and astrophysical events. Distribution by detection year is presented in Fig. 1. The number of detections is correlated with the Solar activity cycle. This is expected due to increasing instability of particle environment and number of flares in this period.

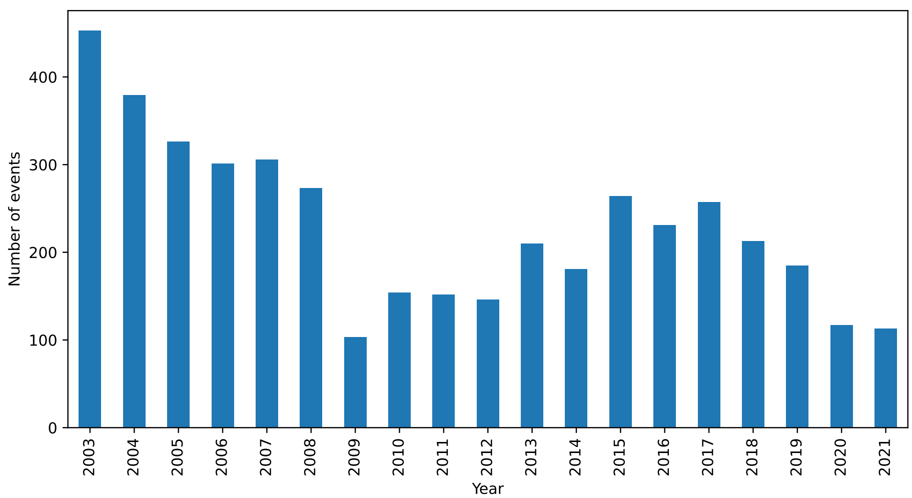

Fig. 1. Distribution of triggered events by year.

2.3 Data processing

Preprocessing procedure is needed to determine duration and flux for each detector, which will be the main features of the model. These parameters can be found in almost every existing catalog of gamma-ray transients, which allows the model to be applied to them without additional processing.

The duration is calculated using the SPI-ACS light curve according to the procedure whose block schema is presented in Fig. 2.

Algorithm requires initial timescale, that varies from 20 to 200 seconds and is selected individually for each event. Firstly, the light curve is binned into current (initial) timescale t_{curr}. Then follows the main part, background subtraction and event extraction. In this section an array of $\{(t_i, c_i)\}$ is referred to as event. On the first iteration this array is empty. Algorithm consists of 3 steps:

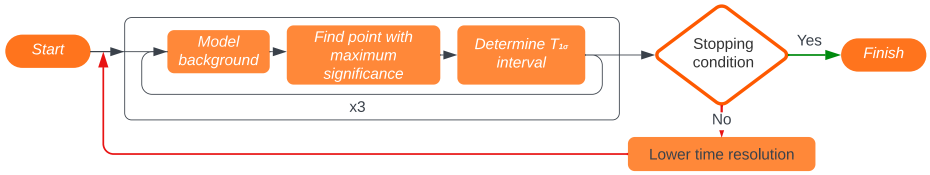

Fig. 2. Procedure of processing SPI-ACS light curve.

1. Approximate background with 3rd degree polynomial using all bins in light curve, except event. Resulting model is subtracted from original data.
2. Determine point (t_{max}, c_{max}) with maximum statistical significance. Statistical significance above background is determined as $\frac{F}{\sqrt{D}}$, where F is number of counts in a bin after background subtraction and D is the dispersion, calculated on the background intervals from previous stage (1).
3. Calculate $T_{1\sigma}$. In this paper $T_{1\sigma}$ is number of seconds between first and second bin with significance more than 1σ without gaps. We compared 1σ values to manually calculated duration parameters T_{50}, T_{90}, T_{100} of sample of bursts with extended emission[27]. In majority of cases ($\sim 65\%$) value of $T_{1\sigma}$ is between T_{50} and T_{100}. The remaining events belong to the case when the burst consists of several episodes.

Steps (1) - (3) are repeated 3 times. On second and third step bins corresponding to event (calculated from previous steps) are taken into account (excluded) in the process of background modeling (1), which increases quality if approximation.

After that, event is checked on two stopping conditions: limit value of t_{curr} is reached or event has 10 or more bins. Latter condition is introduced to save computation time in case of long transients. If neither of this conditions are met, then algorithm is repeated from the beginning with $t_{curr} = \frac{t_{curr}}{2}$. Also on the first step $T_{1\sigma}$ interval is excluded from background approximation.

Finally, background subtracted integral flux over $T_{1\sigma}$ interval is calculated. We also want to add light curve shape to feature space. Therefore we bin light curve into 10 bins. Their duration varies for different events, because it depends on $T_{1\sigma}$. After binning counts are normalized to be in range [0,1] and added as separate features.

For other detectors procedure is much simpler. Background model is a 1st degree polynomial, calculated on light curve except for the $T_{1\sigma}$ interval. Then, we calculate background subtracted integral flux in this interval. All code is written in Python and can be found at Github. Final dataset is composed of 21 feature: duration $T_{1\sigma}$, mean distance to Earth in $T_{1\sigma}$ interval, 10 bins for light curve shape and 9 integral fluxes of INTEGRAL detectors: SPI-ACS, IBIS veto[29], IREM TC3, ISGRI (20-100 keV), JMX 1 and 2 (3-20 keV), PICsIT (event mode and spectrum mode, 175-500 keV) and SPI (20-500 keV).

3 Crossmatching and labeling

To train a classifier our dataset must be labeled. This is done by crossmatching our events with events from different catalogues of confirmed events. In this paper we consider 3 classes of transients: gamma-ray bursts, Solar flares and background fluctuation, is the class which represents either absence of an event or presence of an unknown background activity. For gamma-ray bursts we use K. Hurleys "masterlist"[3], compilation of confirmed GRB from different catalogues up to 2021. The reason we chose Konus-WIND lies in its position. Location in L2 point guarantees stable background, which is important for detecting long events with duration $\gtrsim$ 100 seconds. Difficulties in detecting long and ultra-long events with near-Earth observatories are described for example in [9,13]. For Solar flares we use GOES[1] and RHESSI[4] catalogues as well as Konus-WIND SF catalog[2]. It has close to SPI-ACS energy range (unlike former ones working in X-ray) so we eliminate coincide triggers. Events crossmatched only with GOES and RHESSI catalogues are marked as potential Solar flares and are not used in training process. There are several types of events, that has non-radiative nature: SEPEs[31], electron clusters in magnetosphere tail[22], crossing of van Allens belts[17] etc.. These events has unstable radiation environment and background model could not describe it well. Therefore we classify all events with background $\chi^2/d.o.f. > 3$ as background events.

For crossmatching we use trigger times and duration $T_1\sigma$ of the event. An event is crossmatched with catalog if time interval of candidate intersects with time interval of catalog event. If duration or time interval is not provided, we check if catalog time belongs to $T_{1\sigma}$ interval. One event can belong to multiple classes: this may happen by accident, when gamma-ray burst coincide with Solar flare, or confirmed event may be surrounded by an unstable background. This is physically impossible and show imperfection of our crossmatching algorithm. In this case we consider one event belonging to several classes, which can be represented as duplicates in a dataset with different labels.

After the crossmatching step, 2420 events are labeled, remaining 1944 events are not found in the used catalogues and have stable background. The duration distribution is shown in Fig. 3. As expected the Solar flares generally longer than the gamma-ray bursts[16,36]. Also, number of background (1909) events is bigger then GRB and, especially, Solar events. Such imbalance needs to be taken into account during training.

4 Model

In this paper we use gradient boosting as classifier. It is one of universal algorithms which has proven to be one of the best for tabular data [20]. It requires less data than NN, which is important due to our relatively small dataset (only 3198 events). Hyperparameter optimization is fulfilled via optuna[6] package with objective to maximize precision of predicting gamma-ray bursts. Therefore we use $F_\beta = (1+\beta^2) \cdot \frac{precision \cdot recall}{(\beta^2 \cdot precision) + recall}$ score [8] with $\beta = 0.5$. Two commonly

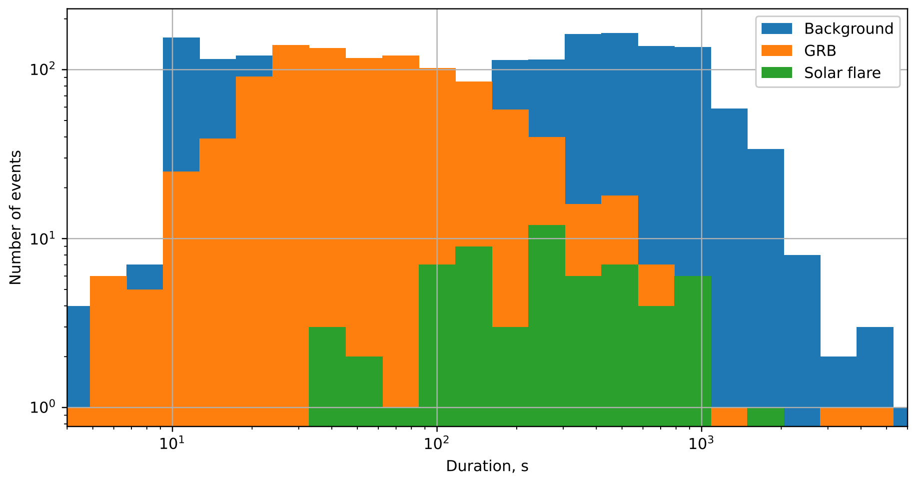

Fig. 3. Duration distribution of labeled events.

used values for β are 2, which weighs recall higher than precision, and 0.5, which weighs recall lower than precision. We perform 500 iteration, each time generating new train and test splits in ratio of 80 to 20. Optimal parameters are then used during training. Training is executed on 80% of data, the rest is used to control accuracy metrics. In Fig.4 we present a ROC (Receiver Operating Characteristic), which binds the True positive rate to the False positive rate and can be used to evaluate the quality of prediction as follows: the closer the area under ROC curve (ROC AUC) to 1 the better. ROC AUC for gamma-ray bursts is 0.97.

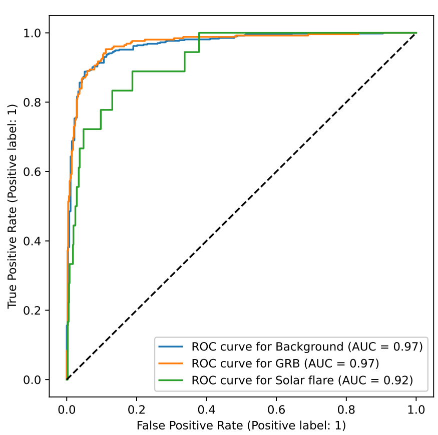

Fig. 4. ROC curve for classificator.

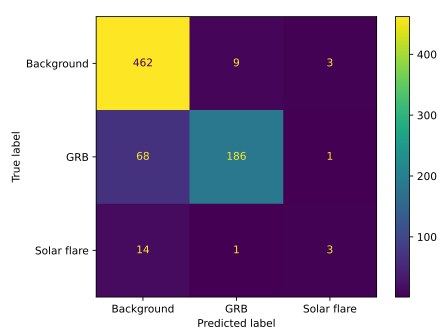

Fig. 5. Confusion matrix for the classification on test set.

We calculate custom probability thresholds for GRB and Solar flares maximizing F_β score. The optimal probability thresholds are 0.828 for GRB and 0.5 for Solar flares.

We applied similar training and evaluation procedures for other models: Logistic Regression [10] and Random Forest [12]. The results are presented in the Table 1. Gradient boosting outperforms both of the models and is much faster than Random Forest classifier (possibly due to different implementations).

Table 1. Comparison of different ML models. sklearn implementation of Logistic Regression and Random Forest is used.

Model	f_β	Balanced Accuracy
Logistic Regression	0.51	0.38
Random Forest	0.87	0.60
Gradient Boosting	0.90	0.67

We also checked whether the model is overfitting. One model is trained as described above and another one with early stopping: 10% of training data is allocated for validation set, which is used to stop training when metrics stop improving for 100 rounds. Then the results are compared. No significant difference is found between this models, all metrcis are withing margin of errors.

5 Results

We analyzed feature importances of our model, i.e., the relative values, describing impact of each feature on the final prediction. It is calculated via LightGBM [20] embedded functions based on Gini impurity[11]. Top 4 important features are total fluence in SPI-ACS, duration, ISGRI and IREM fluence. It is explained by strong distinction of events by duration and the fact, that background fluctuations tend to be more faint than real GRB (for the same duration). Moreover, importance of IREM fluence indicate that background events, unlike GRB, may consist of charged particles.

Confusion matrix for test set is presented in Fig. 5. The number in each square in the confusion matrices represents the overall classification for each event type compared to the actual classification obtained through crossmatching procedure. To evaluate the accuracy of our classifier, we use the method of cross-fold validation on 10 folds. One fold consist of 10 sets, nine are used for training, last one uses the created model to classify the remaining sample set. This procedure is repeated for each fold and metrics are averaged. Total accuracy is $91 \pm 4\%$ for gamma-ray bursts. Such high accuracy is achieved at the cost of recall, its value is $\sim 73\%$. This fact does not contradict the goals of our work, to make reliable classification model. For Solar flares accuracy is $35 \pm 32\%$. Such low value can be a result of low amount of samples, only 61 event for both training and test samples. Also, it can be low due to high similarity between

GRB and Solar flares with gamma-ray emission. INTEGRAL detectors could lack sensitivity to pick out differences in the spectrum. The last reason might be the crossmatching procedure. We compare events based only on time intervals, which does not negate possible coincidences.

We checked the hypothesis that hyperparameter selection created a bias towards GRB and lowered precision for Solar flares. We repeated hyperparameter optimization for 2 more cases with objectives of maximizing F_β for Solar flares and maximizing sum of F_β scores for SF and GRB. Neither of this approaches show significantly better results, all metrics were within margin of error.

6 Conclusion

Our model shows consistent result in classification of gamma-ray bursts with accuracy $\sim 91\%$ on test set. This makes it possible to classify events in the absence of data from other observatories. Accuracy can be improved by several ways. Firstly, we can expand our training dataset; it can include more known confirmed gamma-ray bursts and Solar flares. Secondly, we can enrich feature space with new parameters. We can expand usage of the shape of transient on all events and apply Furie Transform with dimensionality reduction to use them as features[19]. Thirdly, use more complex algorithm, for example ensemble of multiple machine learning models or Neural Network. Also we can make use of imaging detectors: if transient is seen inside FOV we can use Convolutional Neural Network to help with classification.

The method, proposed in this work can be extended to any observatory, having a sufficient set of detectors. The more detectors with non-overlapping energy ranges it has, the better should be the accuracy for different classes of events.

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