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Estimating GRBs' cosmological distances

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Abstract. Several thousand gamma-ray bursts have been observed but more than 500 events have known distances. Numerous papers have shown huge structures in the Universe based on GRBs. We want to examine the distribution of the GRBs' distances, to give an estimation on the distances of those GRBs which have no measured redshifts. The GRB catalogs contain more than 100 physical parameters among which there can be parameters dependent on distance. In this work we examined the distances of Swift GRBs with machine learning methods. For the regression of the distances we used both Random Forest and XGBoost regression algorithms. We found an 0.76 strength correlation between the regressed and measured redshift.

Key words: methods: numerical – gamma-ray burst: general – cosmology: observations

1. Introduction

The Gamma-ray bursts (GRBs) are the most energetic explosions in the far Universe (Mészáros, 2006; Kumar & Zhang, 2015). Two main models can explain GRB events: the collapse of the most massive stars (collapsar model) (MacFadyen & Woosley, 1999; Zhang & Mészáros, 2002) and the merging of compact stars as black holes or neutron stars (Eichler et al., 1989). The discovery of GW170814/GRB170814A had validated the second model (Abbott et al., 2017; Goldstein et al., 2017; Bagoly et al., 2016, 2017; Horváth et al., 2018).

It seems that we can distinguish between the two models based on the duration or hardness of the burst. The collapsing events are typically longer and softer than the star merging ones. A third group was identified by Horváth (1998) based on the duration–hardness plane (Horváth et al., 2004, 2006; Kóbori et al., 2020). The physical model of this intermediate group could not be perfectly determined but it seems that the X-ray flash events could have a connection to the intermediate GRBs (Horváth et al., 2010; Veres et al., 2010; Pinter et al., 2017; Bi et al., 2018). Balazs et al. (1998) showed that the sky distribution of GRBs not isotropic, since then, more and more signs indicate that the sky distribution of GRBs shows significant anisotropies (Balázs et al., 1999; Mészáros et al., 2000a,b; Vavrek et al., 2008; Pérez-Ramírez et al., 2010; Hakkila et al., 2018; Horváth et al., 2019; Tóth et al., 2019; Horvath et al., 2020).

Several thousand GRBs were discovered but only a few hundred redshifts are known. The first redshift measurement was taken in 1997 (GRB970508) (Metzger et al., 1997b,a; Reichart, 1998) in spite of the first GRB event being discovered in the 2nd of July, 1967 (Klebesadel et al., 1973). For the spectroscopy redshift measurement the precise position of the transient is necessary which we can get from the afterglow because the position errors of gamma detectors are usually several arcminutes. To examine the spatial distribution of the GRBs it is an essential question to determine their distances (Mészáros et al., 2000b,a; Horvath et al., 2022). Balázs et al. (2015) and Horváth et al. (2014) discovered two massive structures, the Giant GRB Ring and the Hercules-Corona Borealis Great Wall, which were formed by gamma-ray bursts. As of our current understanding, these objects are the largest cosmic structures in the Universe (Horváth et al., 2015; Balázs et al., 2018).

The highest spectroscopic redshift GRB was published by Tanvir et al. (2009), that time it was the the most distant object in the Universe (Bagoly et al., 2019). We think that the GRB redshift distribution extending at least to $z \approx 10$ and their association with explosive death of massive stars (therefore the GRBs) can be unique and powerful tool for cosmology (Tanvir et al., 2021). Two fresh projects (e.g. Space Variable Objects Monitor (SVOM) and Transient High-Energy Sky and Early Universe Surveyor (THESEUS) satellites) will try to answer these key questions locating hundreds of GRBs, including those which have high redshift ($z > 6$) (Zhao et al., 2012; Amati et al., 2018b).

It became clear shortly after the first redshift measurement that the distance of the GRBs show a relation to their duration (Katz & Canel, 1996; Piran, 2004). The observed sample shows that the harder, short GRBs are located closer than the softer, long GRBs (D'Avanzo, 2015; Horvath et al., 2022). This is not necessarily a statement about where short bursts occur versus where long bursts occur. Instead, it merely illustrates how challenging it is to spot a brief burst. The detection process is less sensitive to short bursts, so triggering on a shorter (and thus noisier) window for a short burst is much complicated. Additionally, since the detection of afterglow is so crucial to the identification of hosts and redshifts – which is also more difficult for short events – thus less is known about the distribution of short bursts. Also Rácz et al. (2018) examined redshift distributions within GRB spectral groups and discovered no distinction between spectral types within the bounds of statistical inference. Since there aren't any concrete proof that the closer peak of the short GRB is just a selection effect, this question is left unanswered. Moreover, this effect is well understandable because the star forming rate is decreasing in time; the timescale to have extremely high mass stars is shorter than the timescale needed to have already compact objects. However, high SFR is needed to form supermassive stars.

Understanding the high-z Universe is one of the main open issues in cosmology. The already mentioned THESEUS project will examine e.g., the star formation rate and metallicity evolution of the inter-stellar and inter-galactic medium, signatures of Pop III stars, sources and physics of re-ionization, and the faint end of the galaxy luminosity function by observing distant GRBs and other γ- and X-ray sources up to the redshift of ≈ 10 (Stratta et al., 2018; Amati et al., 2018a).

In this article, I focus on estimating the redshift of GRBs using machine learning methods, which can bring us closer to a more efficient investigation of the spatial distribution of these bursts and the identification of high-redshift GRBs.

We explain the GRB catalogs and parameters used in Sec. 2. In Sec. 3 we show two machine-learning algorithms which can be used for both regression and classification. Our results can be seen in Sec. 4. We discuss the results in Sec 5. Finally, in Sec. 6 a short summary can be read.

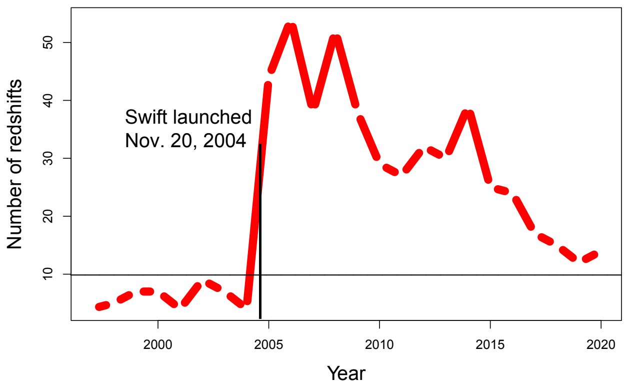

Figure 1. The regressive tendency is clearly seen from the peak after the launching of Swift. In a few years redshift measurements will be made for only a few GRBs every year.

1.1. Annual distribution of redshift measurement

Everyone knows that most of GRBs with redshifts can be found among the GRBs detected by the Swift telescope. By 2023, the Swift telescope detected about 1500 GRBs, performed XRT X-ray measurements in 80 percent cases, and a third of cases identified with also the UVOT instrument. We conducted a survey to examine the relationship between the number of observations and the number of redshift measurements. We examined about 1350 Swift bursts, including 408 cases of spectroscopic redshift measurements with ground-based telescopes. Interesting fact that among that GRBs with redshift measurements there were only 22 cases when UVOT observations hasn't been involved. 386

GRBs, or almost 95 percent of GRBs, were observed by UVOT. The typical error of the celestial coordinates given by UVOT is a few arcseconds, which is already accurate enough for ground-based observers to perform spectroscopic measurements. So it is clear that the accurate localization of GRBs is an essential issue for ground-based observers, who can be do the spectroscopic redshift measurements.

In contrast, there is also an interesting trend that can be observed in the annual decrease of redshift measurements. It is clear that when Swift started in 2004, the number of sightings had a drastic increase, but it has been slowing down exponentially ever since. In our personal opinion, the decreasing interest in GRBs is the reason behind that. The trend shows that by the middle of the decade we will reach a few observations a year, evoking times before Swift. Unfortunately, the decrease in ground-based observations cannot be ignored, but it would still be necessary for efficiently examine the GRBs to know their exact celestial location. It is an obvious fact that the measured physical parameters depend on distance, but the impact is relatively smaller than the GRB's own variability, and the mechanism is very complex so it is hard to specify with simple statistical methods. The machine learning techniques may help amplifying the underlying subtle relations between the observed physical parameters and the distance.

2. Data

The *Neil Gehrels Swift Observatory* (formerly known as 'Swift' Space Telescope) is a robotic spacecraft which was launched into orbit on 20 November, 2004, four years after the mission of the Compton Gamma Ray Observatory has ended.

Swift, being a multi-wavelength space observatory, is dedicated to the study of GRBs. It has three instruments with different energy ranges to observe GRBs together with their afterglows in the gamma-ray (Barthelmy et al., 2005), X-ray (Burrows et al., 2005), ultraviolet and optical wavebands (Roming et al., 2005). The Swift discovered more than 1500 GRBs from which more than one thousand X-ray afterglows were detected. In this work we studied these events.

2.1. Main Swift GRB catalogs

The Swift Gamma-Ray Burst Table is a public catalog of the Swift GRB observations. This table is available on the webpage of NASA[1]. The catalog contains the most γ parameters as well as some X-ray and UV-optical parameters and comments from all three Swift instruments. Every GRB has a name from the observation date, a trigger number, gamma position and position error. The following parameters have been recorded in the table: duration of gamma radiation (T90), γ fluence, γ 1-sec peak photon flux and the photon index and spectrum

[1] https://swift.gsfc.nasa.gov/archive/grb_table/

type (calculated from the γ spectrum) which can be simple power-law or cutoff power-law. On both the X-ray and the UV-optical observations the time to first observation in seconds is available, which are essential values. If this duration is too long the afterglow observation is probably incomplete because the telescope turned on the target more slowly, so the beginning of the observation was lost. The table contains 6 further X-ray parameters and 7 UV-optical magnitudes (X-ray early/11hours/24hours flux, initial temporal index, spectral index, intrinsic hydrogen column density, V, B, U, UVW1, UVW2, UVM2, White magnitude).

The mission was developed in a joint partnership as an international consortium from the United States, the United Kingdom, and Italy. The XRT observations are being analyzed by the U.K. partners. There is a similar public catalog 'The Swift-XRT GRB Catalogue'[2] from the UK Swift Science Data Centre (UKSSDC), where all XRT light curves and spectra data are published. Both official Swift catalogs contain the redshift values but we used other sources to validate these data.

2.2. GRB distances

We used two additional catalogs of redshift measurements. The Jochen Greiner's GRB table [3] is a subjective collection of information on the results of GRBs. The Gamma-Ray Burst Online Index (GRBox) [4] gives what appears to be the most likely redshift, but there are some possibilities for these catalogs to have mistyping or other errors. To eliminate the errors we compared the redshifts from the different sources and in several cases we needed to check the GCN (Gamma-ray Coordinates Network) notes to make sure we used the right redshift data. Earlier Balázs et al. (2015, 2018) and Horváth et al. (2015) have published a similar dataset which can be considered complete until September 2015. We completed this list with the newer redshift measurements.

2.3. Catalog merging

We joined the above data sources and for the best results we checked exhaustively the numerical values in the catalog and in the merged dataframe. We added more indicator variables instead of the not numerical information e.g. the upper limits vs. precise measurement or the forms of the X-ray light curves.

3. Methods

Machine learning uses statistical techniques to give computer systems the ability to progressively improve performance on a specific task with data. In this article we tried to estimate the redshift of GRBs with the physical parameters.

[2] http://www.swift.ac.uk/xrt_live_cat/

[3] http://www.mpe.mpg.de/~jcg/grbgen.html

[4] https://sites.astro.caltech.edu/grbox/grbox.php

This work can overlap with computational statistics, too. The machine learning algorithms can be unsupervised and be used to learn and establish baseline behavioral profiles for various entities and then be used to find meaningful anomalies and weak connections.

We need to distinguish between classification problems and regression tasks. If we already have established classes, then placing our data into these classes is called a classification procedure. If we want to estimate a continuous quantity from our existing data, then we use regression analysis.

The machine learning algorithms used by us have different versions for both types of analysis. To measure the goodness of estimation for the regression we calculated the correlation between the estimated and catalog redshift. The more accurate our estimations are, the higher correlation should be shown by the results.

3.1. Random Forest

A Random Forest is an ensemble of decision trees which may be used both for classification and regression (Breiman, 2001). It is a meta estimator that fits a number of decision trees on various bootstrap samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting. The individual trees are further decorrelated by randomly subsampling the variables considered for each split during the growth of the decision trees. Random Forests correct for the habit of decision trees to overfit their training set.

3.2. Gradient boosted trees, XGBoost

Gradient boosted trees, especially an implementation named, eXtreme Gradient Boosting (XGBoost) has recently been dominating machine learning competitions (Chen & Guestrin, 2016). Boosted decision trees are the ensemble of simple decision trees, where trees are added sequentially to the ensemble. Each additional tree is trained to correct the errors made by the ensemble of previous trees. New trees are added until no further improvements can be made on a validation dataset. During the addition of new trees, gradient boosting grows the best trees by optimizing a loss function which is made up of the error of predictions and a regularization term which describes the complexity of the trees.

3.3. Cross-validation

I used the Python 'sklearn.model_selection.KFold' function for cross-validation (Pedregosa et al., 2011). In this function, the 'n_splits' variable specifies the number of parts (folds) into which the original dataset is divided during cross-validation. To train the model, one of these parts (train) is used, while the others (test) are used for model evaluation. This process is repeated several times, ensuring that each part is used for training and evaluation, thus helping estimate the model's performance. Since the choice of the cross-validation value depends on the dataset, the problem, and computational constraints, it's worth experimenting to find the most suitable value. The value I chose was 10, but I also examined cases with 3, 5, and 20. I obtained the best results with a value of 10; beyond this, the efficiency significantly decreased due to the low number of elements.

4. Results

4.1. Input dataframe

The final dataframe contains more than 200 variables for the GRBs including γ-, X-ray and optical physical parameters and observation indicators (like upper limit markers). Based on physical considerations we did not use several parameters (e.g. sky coordinate or galactic column density) which should not affect redshift.

We used multiple steps to improve the correlation starting from the procedure introduced by Ukwatta et al. (2016), these steps are explained in the following subsections.

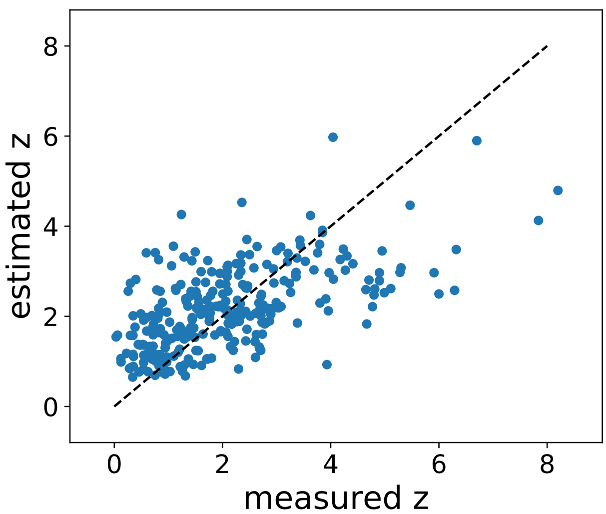

Figure 2. We repeated the method that was published in 2016 (identical data set and method). We obtained the same result; the Pearson's correlation coefficient was 0.57±0.01. The dashed line is the identity function ($y = x$).

We created a subsample from our catalog which was identical to the published catalog by Ukwatta et al. (2016). In this subsample we used data of the pre 2015 GRBs only, and only from the 'grbtable' catalog. Using the same algorithms and parameters as the aforementioned article we were able to reproduce the same results with a minor change in the cross-validation value from 20% to 10% for the bigger training sample. We varied the earlier statement and found a 0.57 ± 0.02 correlation between the estimated and measured redshift (Fig. 2).

4.2. Results of Machine-z

We also examined several datasets, methods, and settings to improve the results.

We thought that the correlation improves significantly with adding newer observations to our data but using the same parameters as mentioned before. We have about 400 GRBs with measured spectroscopical redshift contrary to the previous steps where about 280 objects were used. We found that increasing the number of observations didn't change the correlation significantly between the estimated and measured redshift.

Then we used XGBoost method besides the simple Random Forest Estimator. We found that the correlation is equal to the result of random forest, 0.57 ± 0.1, but the variance was significantly smaller. It means that the XGBoost method is robust and – in addition – it is also faster.

4.2.1. Using other parameters and data cleaning

We checked the correlation between redshift and other physical parameters and indicators. The correlations were very weak, the highest coefficient was about 0.3 (using the UVOT parameters). We selected 20 parameters which showed the best correlation (Table 1). Because the catalog also contains several similar variables (e.g. X-ray flux from the 'grbtable' and from the UKSSDC catalog) in this step we used only one of them. In the final dataset we used the following parameters: γ flux, X-ray fluxes (early, 11hours, 24hours), all UVOT parameters and the intrinsic hydrogen column densities (both of WT and PC observation mode).

We examined the distribution of the first observation times of both XRT and UVOT. We found that it follows the standard distribution until about 150 sec for XRT and 200 sec for UVOT. It means that the sample can be considered complete, and after that 150 and 200 sec we marked the GRBs outlier and we skipped these records. This step seems valid because the correlation improved significantly to 0.66.

4.2.2. Final setting (Weighted XGBoost)

In the final step we changed the training sample from the redshift to lg(1+z) because this quantity can be interpreted as the physical distance (approximates

Table 1. There are thousands parameters for the GRBs as flux, fluence, spectral components. This table shows that 20 parameters which we used for the regression. UVOT data can be categorized into two groups. We can observe the values measured with the filters ('val') and determine whether this data represents an exact value or just an upper limit ('type').

The selected 20 parameters
BAT 1-sec PeakPhoton Flux
BAT 1-sec PeakPhoton Flux Error
BAT Fluence
XRT Early Flux
XRT Flux 11h
XRT Flux 24h
XRT WT Spec Ave N(H)
XRT PC Spec Ave N(H)
UVOT Magnitude type
UVOT B type
UVOT U val
UVOT U type
UVOT UVW1 val
UVOT UVW1 type
UVOT UVW2 val
UVOT UVW2 type
UVOT UVM2 val
UVOT UVM2 type
UVOT White val
UVOT White type

the co-moving distance well). The best results were obtained when we also used the errors of redshifts as fitting weights. This could be only done with the XGBoost method. I calculated the both Pearson's and Spearman's correlation using the obtained data, which in both cases yielded a value of 0.759 ± 0.0078. In addition, I examined the coefficient of determination, as we are dealing with a rather linear relationship. I obtained a value of 0.47 for R^2. Moreover, assuming this linear relationship between the measured and estimated values, I calculated the covariance matrix, which shows the Eq. 1.

$$Cov(z_{measured}, z_{predicted}) = \begin{pmatrix} 1.578 & 0.758 \\ 0.758 & 0.639 \end{pmatrix} \tag{1}$$

Fig. 3 shows a significant improvement in correlation. Therefore, we fitted the linear conversion line and we executed this re-normalization. This process did not affect the correlation but the results became more plausible and seemingly less affected by systematic errors from the fitting compared to Fig. 2. Finally, we transformed back the lg(1+z) data to the classical redshifts which can be seen in Fig. 4.

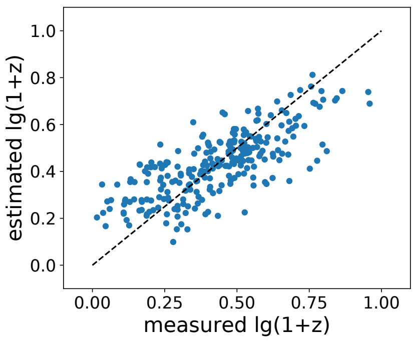

Figure 3. This plot shows the correlation between the regressed and measured redshift. We found the best correlation when we trained the algorithm with the lg(1+z) - which is equivalent the real distance -, weighted redshifts and skipped the outliers. The correlation coefficient in this case was 0.759 ± 0.0078.

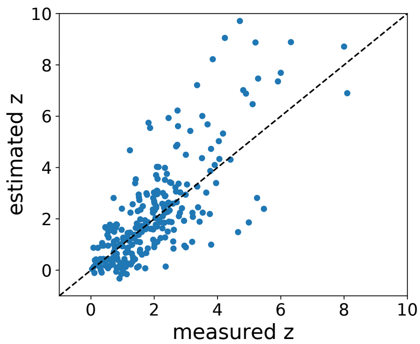

Figure 4. We transformed back the logarithmic values to original data and the correlation between the measured and estimated redshift can be seen. The dashed line shows the identical straight line.

5. Discussion

5.1. Reliability of results

So far we used the Swift XRT spectrum parameters from the UKSSDC catalog. This catalog contained the intrinsic column density values, which we used for both the regression. This physical parameter was calculated from the X-ray spectrum with the fitting method which was published by Evans et al. (2009). In the spectral fitting we can use the redshift information, because the intrinsic hydrogen column density depends on the redshift (see in Section 2, Rácz & Hortobagyi (2018)). As where the redshifts were measured and the redshifts were used in calculating intrinsic hydrogen column density, it could have affected the result of the regression.

We calculated the statistically unified intrinsic hydrogen column densities with the better resolution foreground (Toth et al., 2019; Hatsukade et al., 2019; Kovács et al., 2019; Suleiman et al., 2022). We used the 5 arcminutes foreground which were obtained from Planck measurements (Rácz et al., 2017; Pinter, 2018). We made the fit without the redshift information – with the same other settings as the catalog parameters –, so the hydrogen column densities were statistically comparable. This N(H) showed weak correlation with the redshift as the catalog values.

Then we repeated the regression with the new Planck based N(H) parameter. We found that the prediction was very sensitive to this feature without the UKSSDC column density. The correlation of the prediction decreased from 0.76 to 0.56, but this value will be improve by the new redshift measurements. Comparing the previously used and the newly employed column density data, in some cases, significant discrepancies are observed, which have led to the decrease in the correlation mentioned above. However, a thorough examination of these cases goes beyond the scope of this article, but it is imperative to investigate this direction in the near future.

6. Summary and conclusions

The Swift telescope found roughly 1500 GRBs, measured X-rays in 80% of the cases, and also the UVOT instrument observed the bursts in 30% of the cases. Less than 500 of the thousands of gamma-ray bursts that have been seen have distances that are known. After the peak of the GRBs redshift measurement number (2006-2008), the frequency of observationws shows a constant decrease. In order to provide an estimate for the distances of those GRBs without known redshifts, we wished to look at the distribution of GRB distances. More than 100 physical parameters, including quite a few that depend on distance, may be found in the GRB catalogs. In this study, we used machine learning techniques to investigate the Swift GRBs' distances. We first assembled a common database from various online GRB catalogs, which we then purified of inaccurate information. Both the Random Forest and XGBoost regression techniques were utilized for the regression of the distances. The regressed and measured redshifts showed a 0.76 correlation, according to our research. Finally, we looked at the results' dependability and offered suggestions for how to make them better.

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