

### USING MACHINE LEARNING TO ESTIMATE FERMI GRB REDSHIFTS

#### PRESENTING BY: TAMADOR KHALIL SUPERVISOR PROF. SOEBUR RAZZAQUE

Fermi Summer School June, 6, 2023 Delaware, USA

## OUTLINE

- Brief Introduction.
- Estimation redshift of GRBs:
  - GRB data selection Fermi & Konus-winds.
  - Preliminary Results.
- Summary.

+

0

#### Probing Gamma-ray Bursts as Possible Cosmological Standard Candles using Machine Learning

• High-quality of GRBs data from different satellite instruments are now available (e.g., *Fermi, Konus-Wind, INTEGRAL, SWIFT*, and other) followed by ground-based optical telescope and gamma-ray telescopes such as *H.E.S.S* and *MAGIC*.

#### Motivation

Supernova Type Ia:

- Observed only up to z = 2.
- Have been used as standard candles.
- Can be determine the relatively predictable intrinsic brightness based on their light curve shape.

Use GRBs as standard candles Just like SNe Ia

- High redshift: z = 9.2
- Energy dominated in range of KeV-MeV.
- Gamma rays from GRBs do not suffer dust extinction when they propagate to us, unlike optical emission from the SNe Ia.

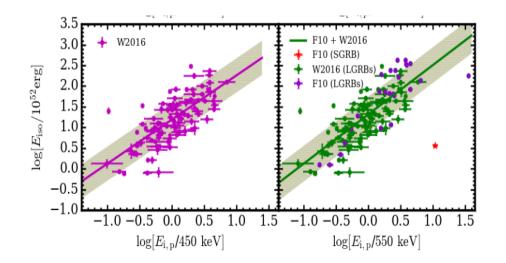
**Duration of GRBs - :** The duration of GRBs is less than a second to a maximum of a few minutes.

 $T_{90}$ : the time to detect 90% of GRBs fluence.

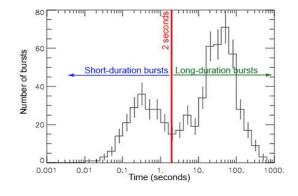
Use GRBs as standard candles just like SNe Ia – Phenomenological relations

Is relation between two or more parameters found from spectral modelling.

Amati correlation (2002) for example:  $\frac{E_{iso}}{10^{52} erg} = 10^k \left(\frac{E_{i}, peak}{E_o keV}\right)^m$ LGRBs

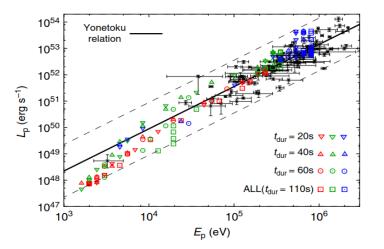


Dirirsa, F.F, Razzaque, S., and Piron, F., et al. 2018, 2019



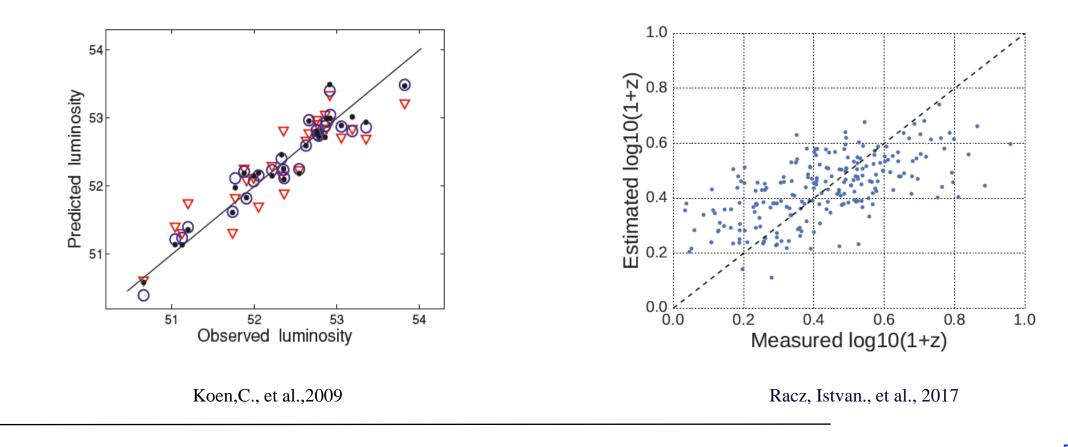
Credit: NASA/L. Rozzella





**GRBs and Machine Learning :** New method to find set of observables that best fit the cosmological indicator.

- Calibrate GRBs as cosmological indicators using different correlations.
- To get a **pseudo redshifts**\* of GRBs.



\* Atteia, J.L et al,. 2003.

□ Spectral analysis: Joint fit for Fermi-LAT and GBM data : from 2018 – up to date. Start with Rmfit – 3ML.

https://threeml.readthedocs.io/en/stable/



Extract spectral lag : Using cross-correlation (crosscrr) tool from heaSoft 6.19 – https://heasarc.gsfc.nasa.gov/xanadu /xronos /xronos.html



Estimation GRBs redshift :

- Fermi-GBM data: gmb-tools.
- Konus-wind data.
- Regression algorithms in neural networks.

#### **Estimation redshift of GRBs** - Data selection

- The datasets : from the Fermi GRB Monitor (Fermi-GBM) Catalog and Konus-winds\*:
- Energy band used in Fermi-GBM (10 1000 keV) and Konus-wind (80 1200 keV).
  - From 2008 to 2018 (Fermi-GBM) 2005 2018 (KW) with known redshift.
  - Spectral fitting parameters from two models:
  - **Band:** with indices  $\alpha$ ,  $\beta$ , and spectral peak energy  $E_p$  in keV.

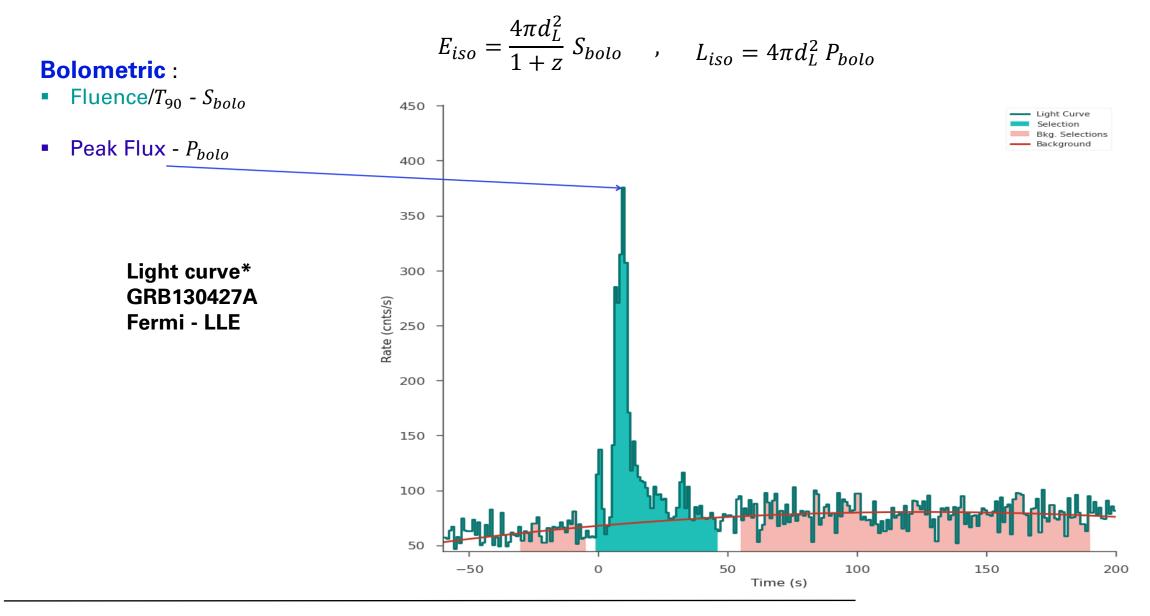
$$N_{Band}(E) = A_{Band} \begin{cases} \left(\frac{E}{100 \ keV}\right)^{\alpha} exp\left[-\frac{E(2+\alpha)}{E_p}\right] & \text{if } E \leq E_b \\ \left(\frac{E}{100 \ keV}\right)^{\beta} exp(\beta-\alpha) \left[-\frac{E_p}{100 \ keV} \frac{\alpha-\beta}{2+\alpha}\right]^{\alpha-\beta} & \text{if } E > E_b, \end{cases}$$
Band D et al., 1993

• **Comptonized**: the photon index  $\gamma$ , and the peak energy  $E_p$ .

$$N_{Comp} = A_{Comp} \left(\frac{E}{100 \ keV}\right)^{\gamma} \exp\left[-(2+\gamma)\frac{E}{E_p}\right]$$

Steiner J. F. et al., 2009

#### **Estimation redshift of GRBs – Data selection**



\* Light curve produced by 3ML.

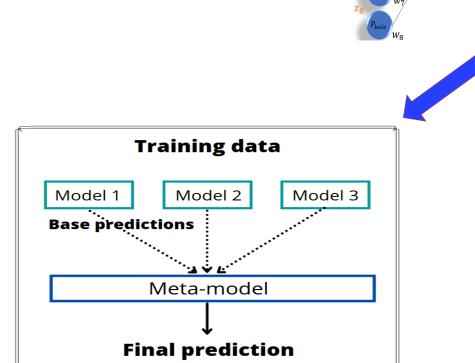
#### **Estimation redshift of GRBs**

**Ensemble Stacking** 

Wang, L., et al. 2020

Regression - Deep Neural Networks (DNNs)

Spectral Parameters		
Bolometric	Peak Flux	Fluence/T <sub>90</sub>
Band	$\alpha, \beta, E_p, P_{bolo}$	$\alpha, \beta, E_p, S_{bolo}$
Comptonized	$\alpha_{index}, E_p, P_{bolo}$	$\alpha_{index}, E_p, S_{bolo}$



 $\left(\sum_{i=1}^{n} x_{i}w_{i} + b\right) f \xrightarrow{f\left(\sum_{i=1}^{n} w_{i}x_{i} + b\right)} \xrightarrow{Redshift} y$   $y = Activation \left(\sum(wight.inputs) + bias\right)$ Activation functions: Relu: Rectified linear units.  $Relu(z) = \max(0, z)$   $f(x) = (0, w_{0} + w_{1} + w_{2} + ... + w_{m} + b)$   $h_{w,b}(X) = \max(X.w + b, 0)$ 

 $\sum_{i=1}^{n} x_{i} w_{i} = w_{1} x_{1} + w_{2} x_{2} + \dots + w_{n} x_{n} + b$ 

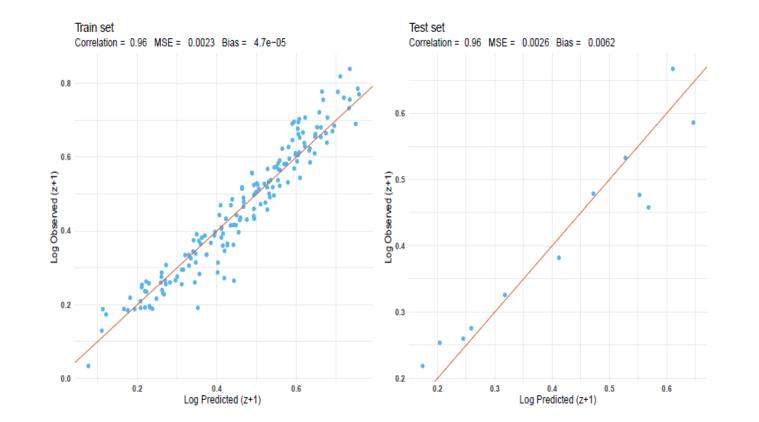
Neural Networks – Band model

 $W_3$ 

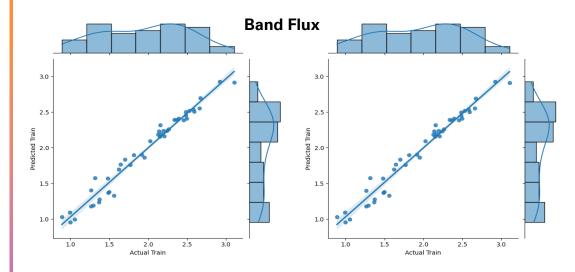
#### **Estimation redshift of GRBs – Pervious work**

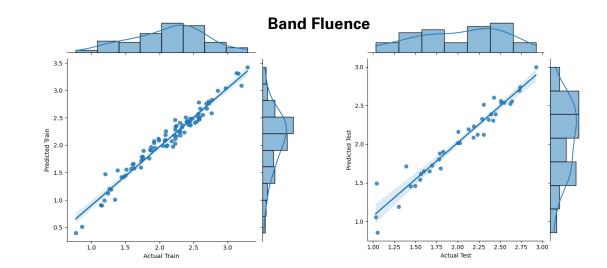
Several previous works used supervised machine learning algorithms, e.g., SuperLearner, to estimate possible non-linear relations between the redshift and GRB properties ( $T_{90}$ , photon index, hydrogen column density, fluence, peak flux, etc.).

This was done using existing data from 171 *Swift* GRBs collected from January 2005 until January 2019 with a known redshift obtained a correlation coefficient of 0.96 and a mean squared error of 0.003 between actual and predicted redshifts (*Maria Dainotti et al, 2019*).

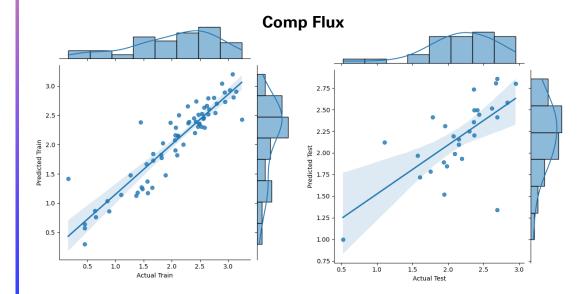


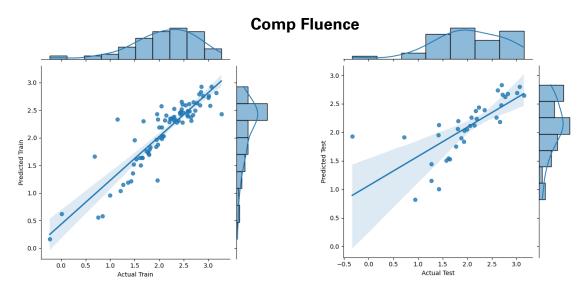
#### **Estimation redshift of GRBs - Preliminary Results**





+





# SUMMARY

Obtaining pseudo redshift is useful to standardize GRBs as cosmological probes, we use a different tools or techniques in machine learning (Regression-DNN) as different supervised tools used in the previous works. The best fit is obtained using the training and test set alone with band models depend on the  $R^2$  and *MAE*.

