Centre for Astro-Particle Physics
UJ CAPP

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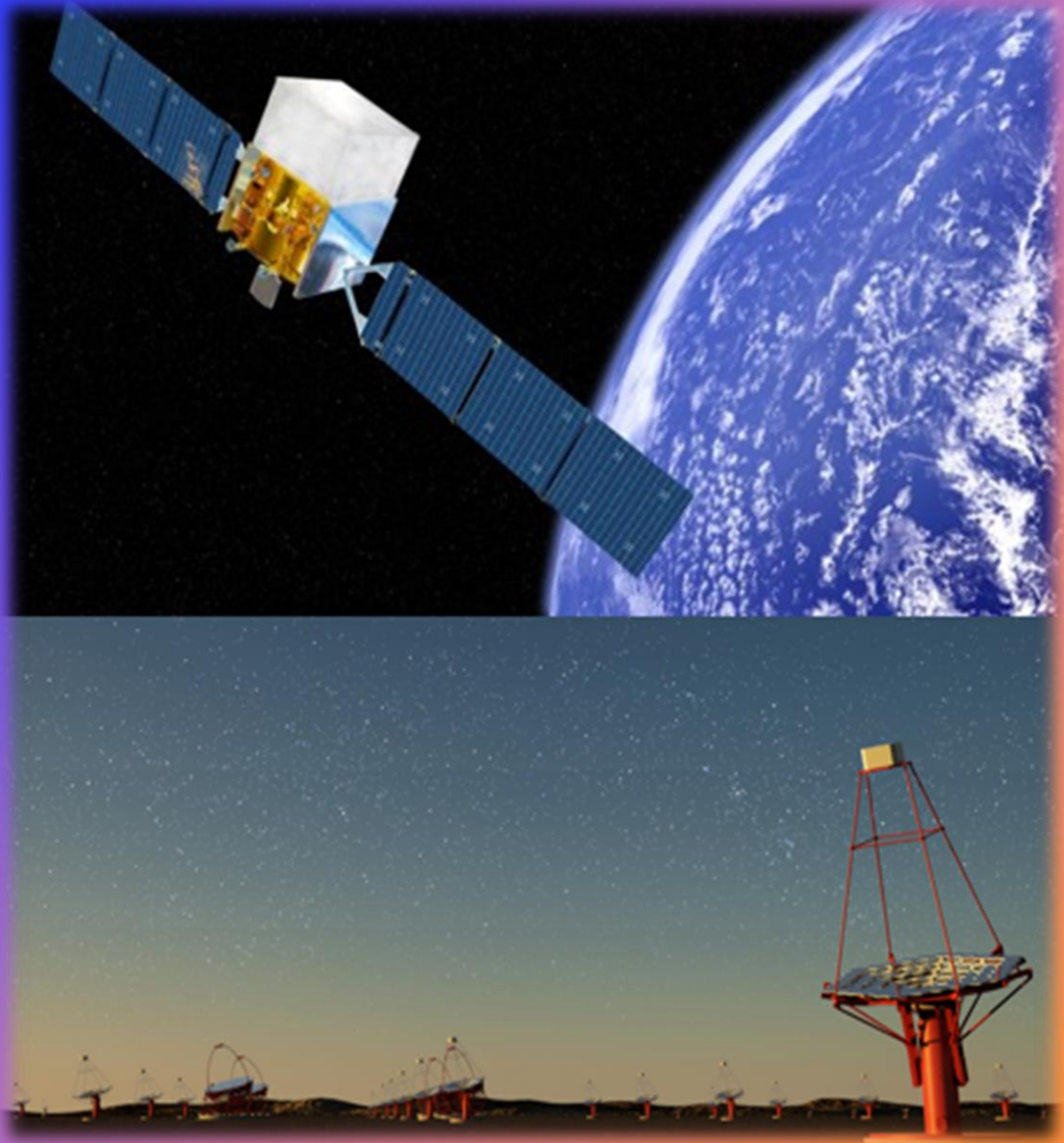
MACHINE LEARNING APPROACH TO PROBE GAMMA-RAY BURSTS AS COSMOLOGICAL STANDARD CANDLES

Presenting by: Tamador Khalil Mansoor Aldowma

Supervisor Prof. Soebur Razzaque

OUTLINE

- Brief Introduction : Gamma-ray Bursts (GRB) and Machine Learning.
- GRB data selection.
- Estimation redshift of GRBs.
- Preliminary Results.
- Summary.



Brief introduction

A Gamma-Ray Burst (GRB) is the most energetic explosion yet discovered. Most of the energy is emitted in the keV to MeV range.

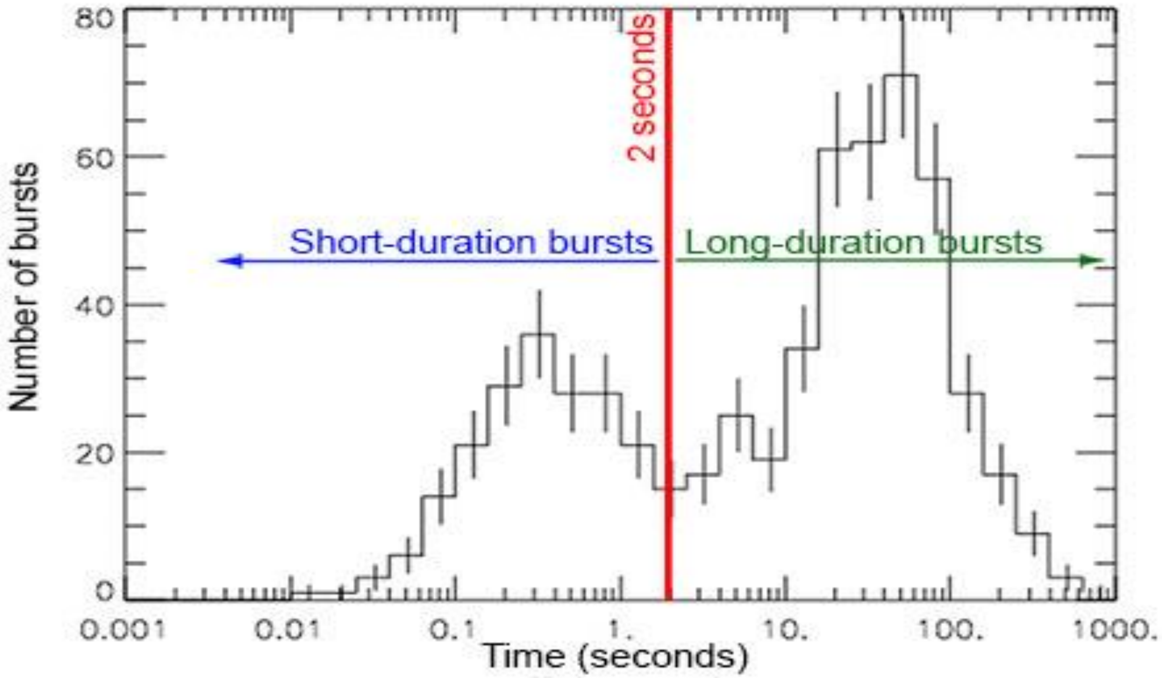
- GRBs have been detected to a high redshift of $z = \mathbf{9.2}$.
- High-quality of GRBs data from different satellite instruments are now available (e.g., *Fermi, Konus-Wind, INTEGRAL, SWIFT,* and other) followed by ground-based optical telescope and gamma-ray telescopes such as *H.E.S.S* and *MAGIC*.
- The duration of GRBs is less than a second to a maximum of a few minutes.

Brief introduction

Duration of GRBs - $\boldsymbol{T_{90}}$

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

$T_{90} > 2\,s$ Long GRB (LGRBs) ___ $T_{90} < 2\,s$ Short GRB (SGRBs)



Credit: NASA/L. Rozzella

Brief introduction

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)

Yonetoku correlation (2004) : $$\frac{L_{iso}}{10^{52}} = 10^{k}\left(\frac{E_{i,peak}}{E_{o}\,keV}\right)^{m}$$ → (LGRBs - SGRBs)

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.

GRBs data

- The datasets are from the Fermi GRB Monitor (**Fermi-GBM) Catalog*:**
- Energy band used in Fermi-GBM (10-1000 keV).
    - From 2008 to 2018.
    - 129 LGRBs with known redshift.
    - Spectral fitting parameters from two models:

    - **Band**: with indices α, β, and spectral peak energy $E_p$in keV.

$$\boldsymbol{N_{Band}(E) = A_{Band}} \begin{cases} \left(\frac{E}{100\ keV}\right)^{\alpha} exp\left[-\frac{E(2+\alpha)}{E_p}\right] & if\ E \le E_b \\ \left(\frac{E}{100\ keV}\right)^{\beta} exp(\beta-\alpha)\left[-\frac{E_p}{100\ keV}\frac{\alpha-\beta}{2+\alpha}\right]^{\alpha-\beta} & if\ E > E_b, \end{cases}$$

Band D et al ,. 1993

    - **Comptonized**: the photon index γ, and the peak energy E_p.

Steiner J. F. et al., 2009

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

* https://heasarc.gsfc.nasa.gov

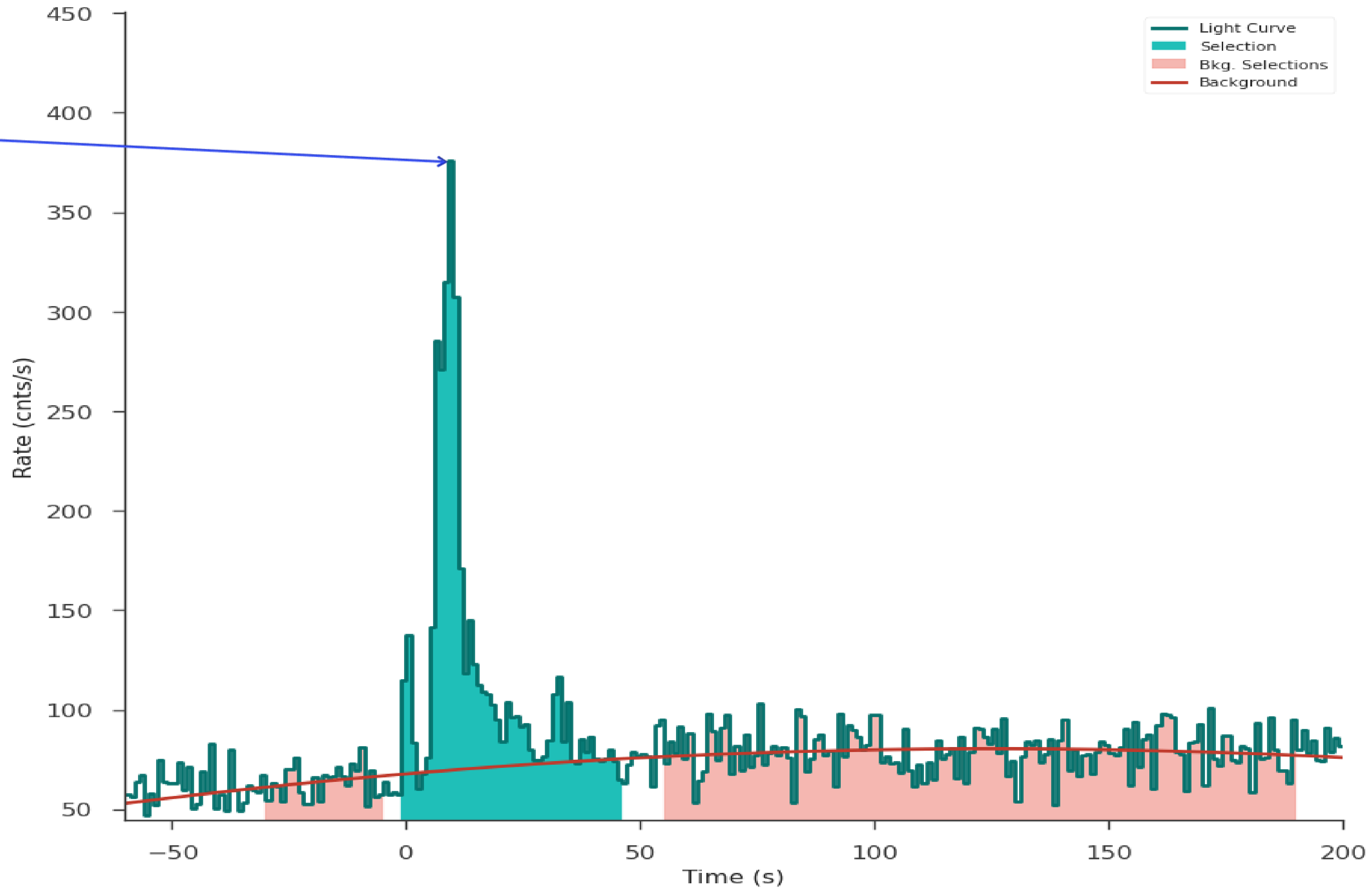
GRBs data

$$E_{iso} = \frac{4\pi d_L^2}{1+z}\, S_{bolo} \quad , \quad L_{iso} = 4\pi d_L^2\, P_{bolo}$$

Bolometric :

- Fluence/T_{90} - S_{bolo}
- Peak Flux - P_{bolo}

Light curve*
GRB130427A
Fermi - LLE

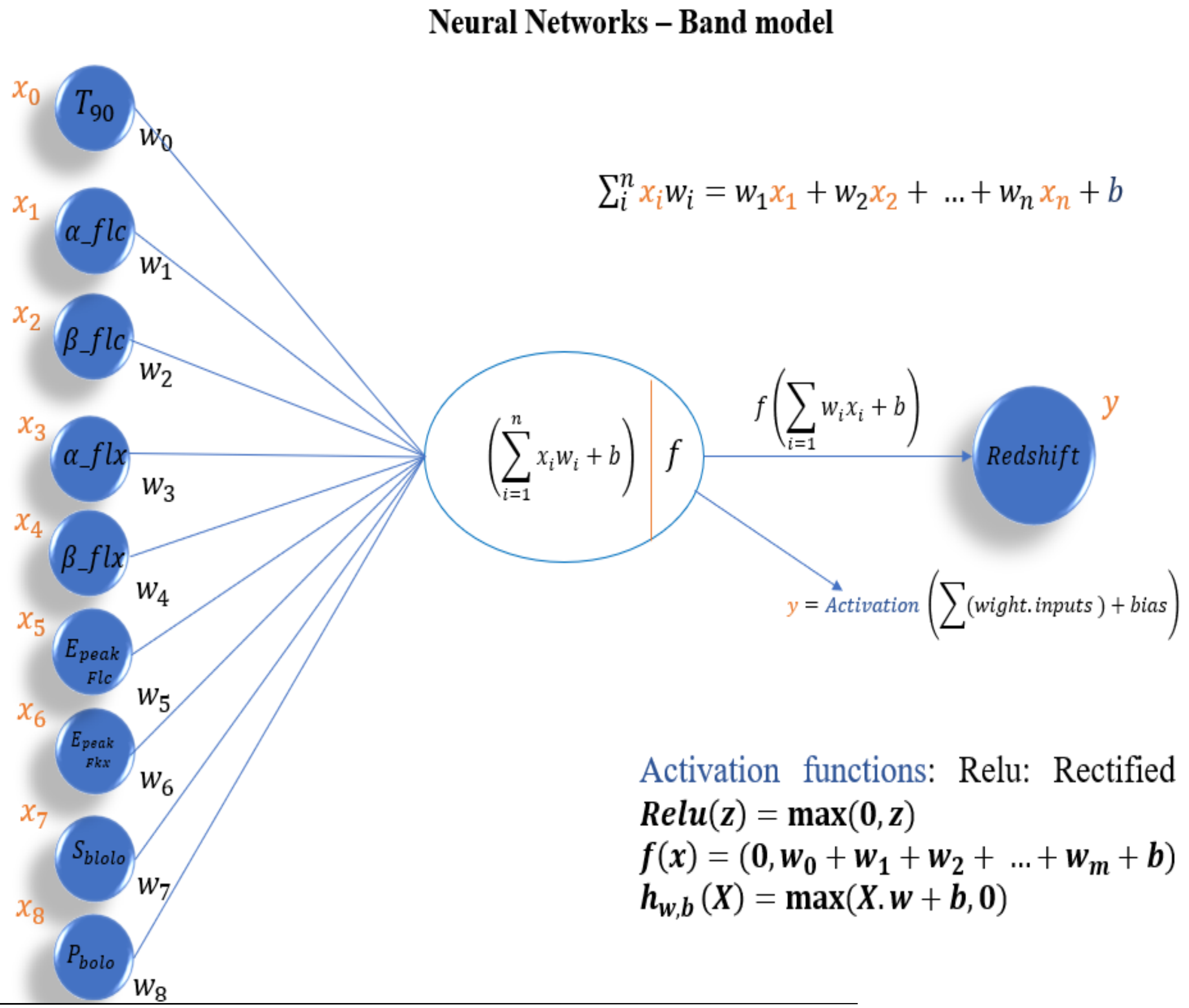


* Light curve produced by 3ML software.

Estimation redshift of GRBs

- Deep learning regression algorithm – using **TensorFlow*: Deep Neural Networks (DNNs)**

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



Activation functions: Relu: Rectified linear units.

$\boldsymbol{Relu(z) = \max(0, z)}$

$\boldsymbol{f(x) = (0, w_0 + w_1 + w_2 + \ldots + w_m + b)}$

$\boldsymbol{h_{w,b}(X) = \max(X.w + b, 0)}$

* TensorFlow: is a more complex library for distributed numerical computation using data flow graphs.

Estimation redshift of GRBs

- **Overfitting**

Deep learning regression algorithm: will quickly overfit a test data set when the train data set is too well trained, but not on test data.

- **Ensemble Stacking**

Ensemble techniques can be primarily classified into Bagging, Boosting, and **Stacking.**

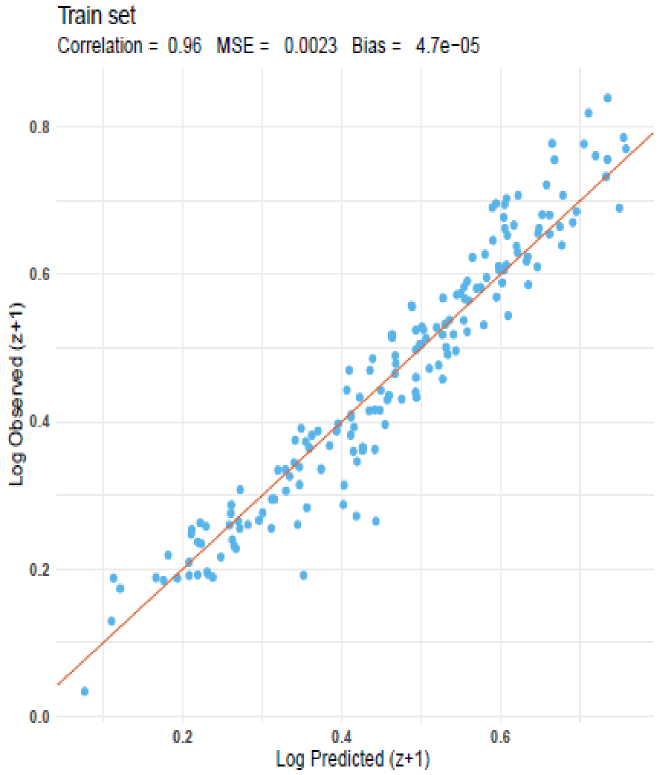
In stacking, an algorithm takes the outputs of sub-models as input and attempts to learn how to best combine the input predictions to make a better output prediction.

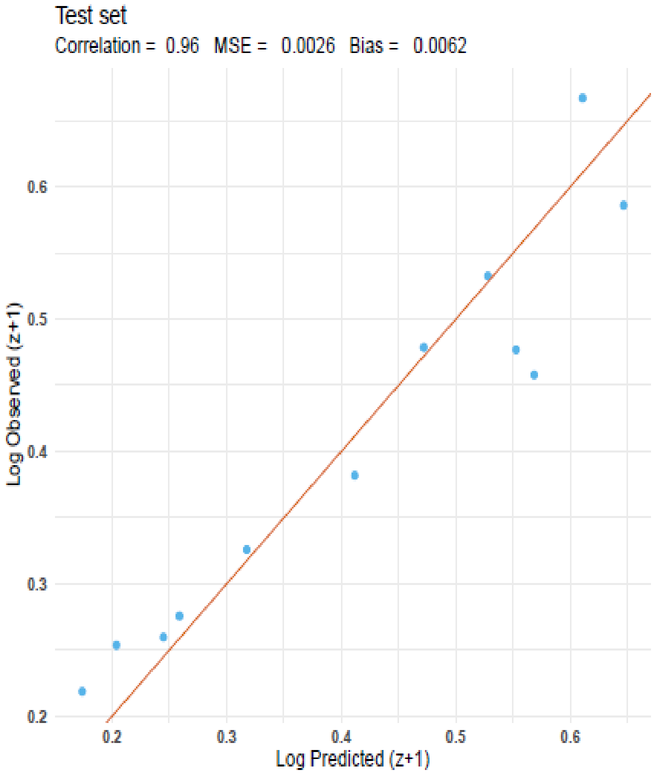
- **Sub-models**

Multilayer Perceptron Model, Random Forest, XGBoost, and linear regression, beside split the train-test data to (k-fold or cross-validation).

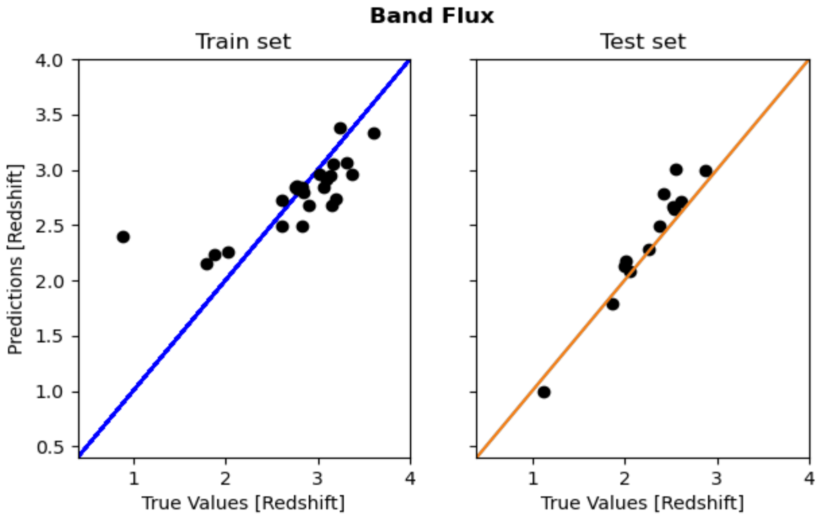
Estimation redshift of GRBs

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*).

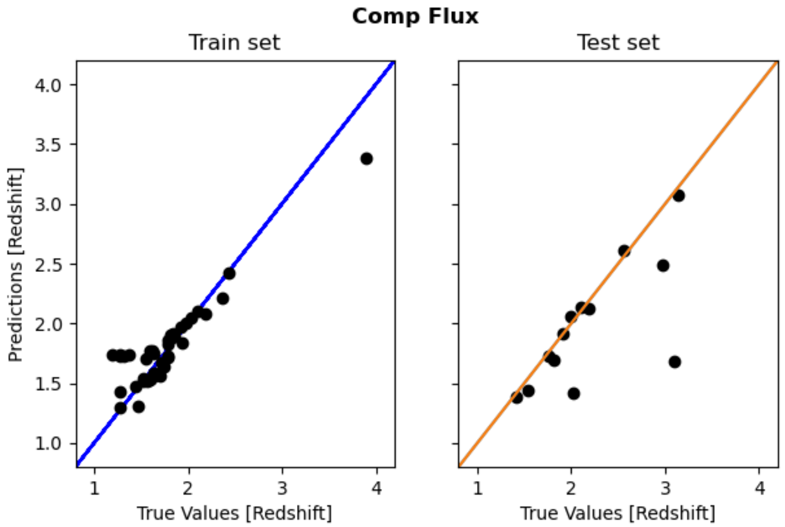




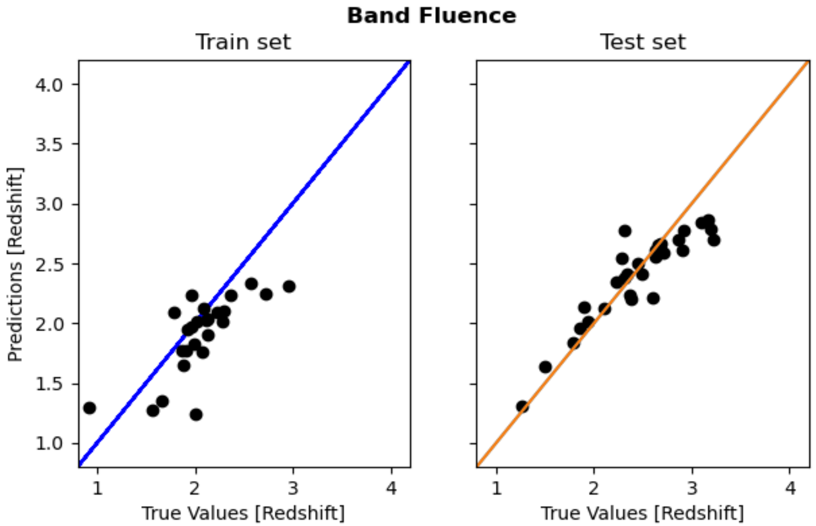
Preliminary Results



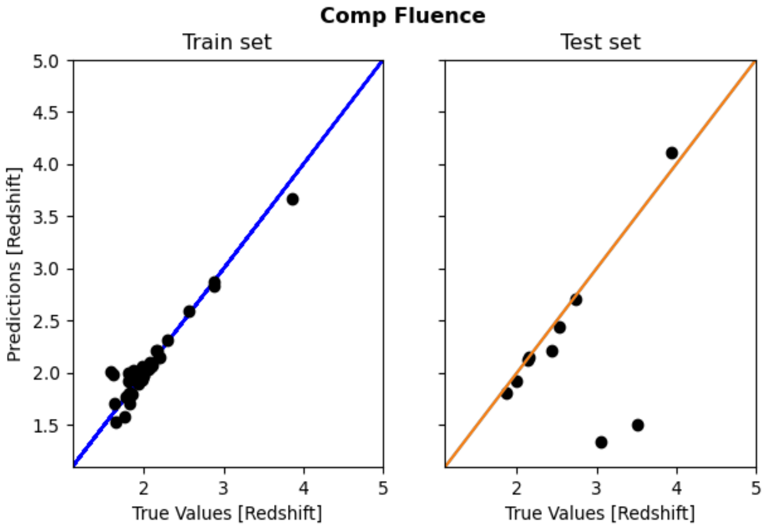
Coefficient R^2: 0.557 – 0.845



Coefficient R^2: 0.804 – 0.310

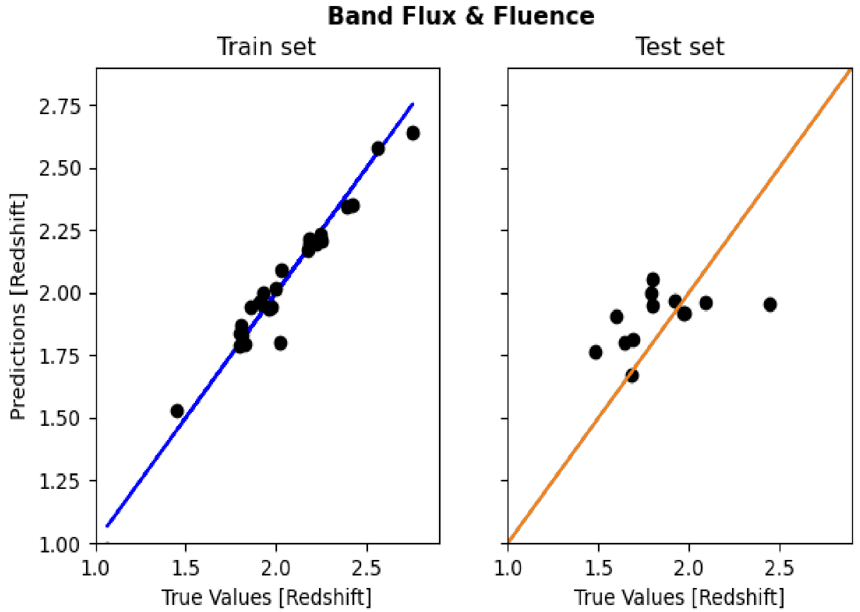


Coefficient R^2: 0.385 – 0.797

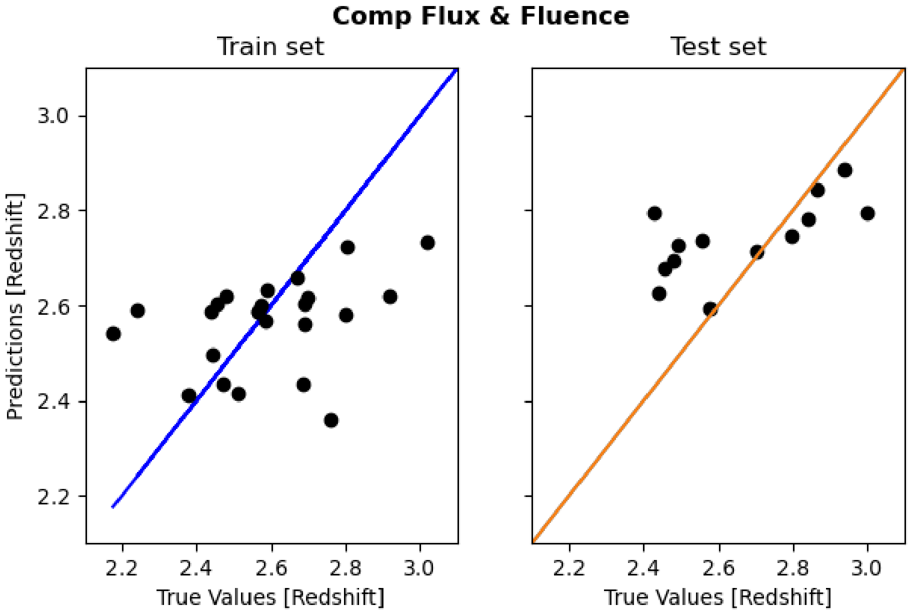


Coefficient R^2: 0.915 – 0.664

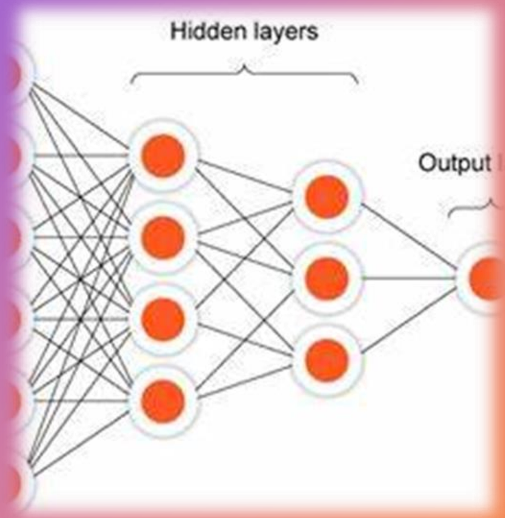
Preliminary Results



Coefficient R^2: 0.960 – 0.182



Coefficient R^2: 0.104 – 0.230



Summary

Obtaining pseudo redshift is useful to standardize GRBs as cosmological probes, we tried to use different tools or techniques in machine learning – deep learning, as different supervised tools from previous works. We got overfitting quickly on the test data set because we use a small data set only from the Fermi-GBM Catalog. The best fit is obtained using the training set alone with all band models.

THANK YOU