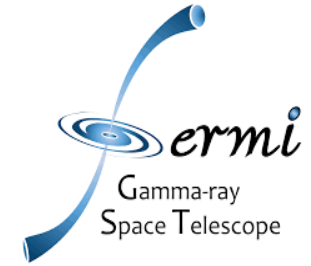




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Constraints on Cosmological Parameters Using a Large Sample of Gamma-Ray Bursts with their redshift derived by Machine Learning

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JOHANNESBURG**

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Outline



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Estimations of GRB Redshift

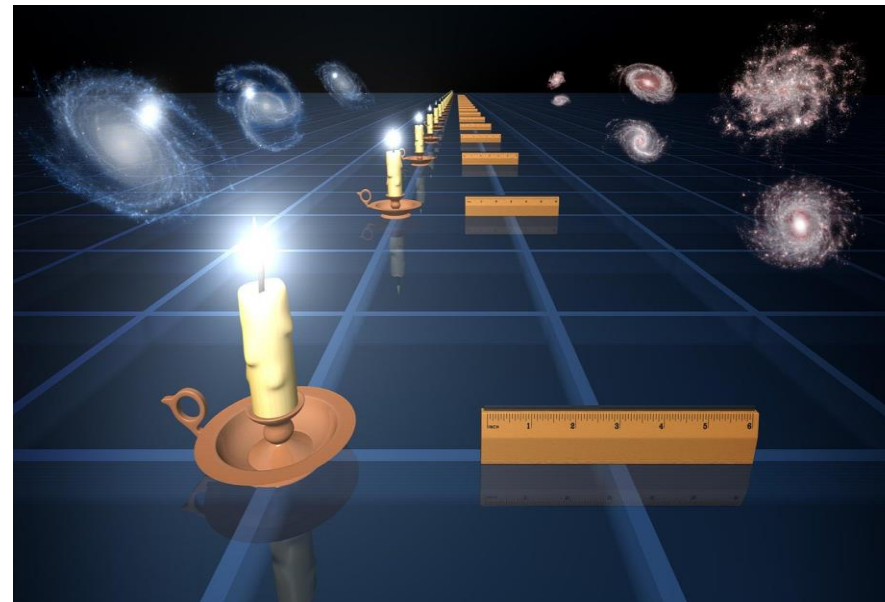
**Preliminary results:
Constraints on Cosmological Parameters**

Summary

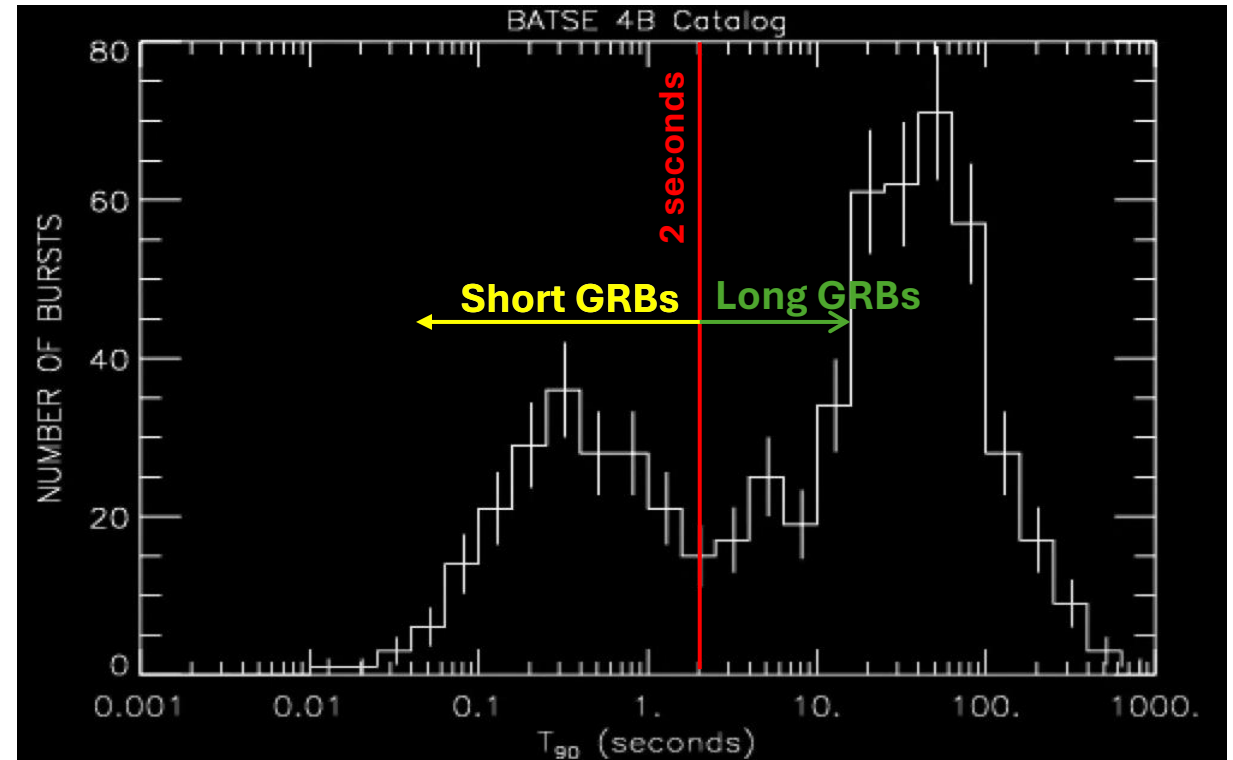
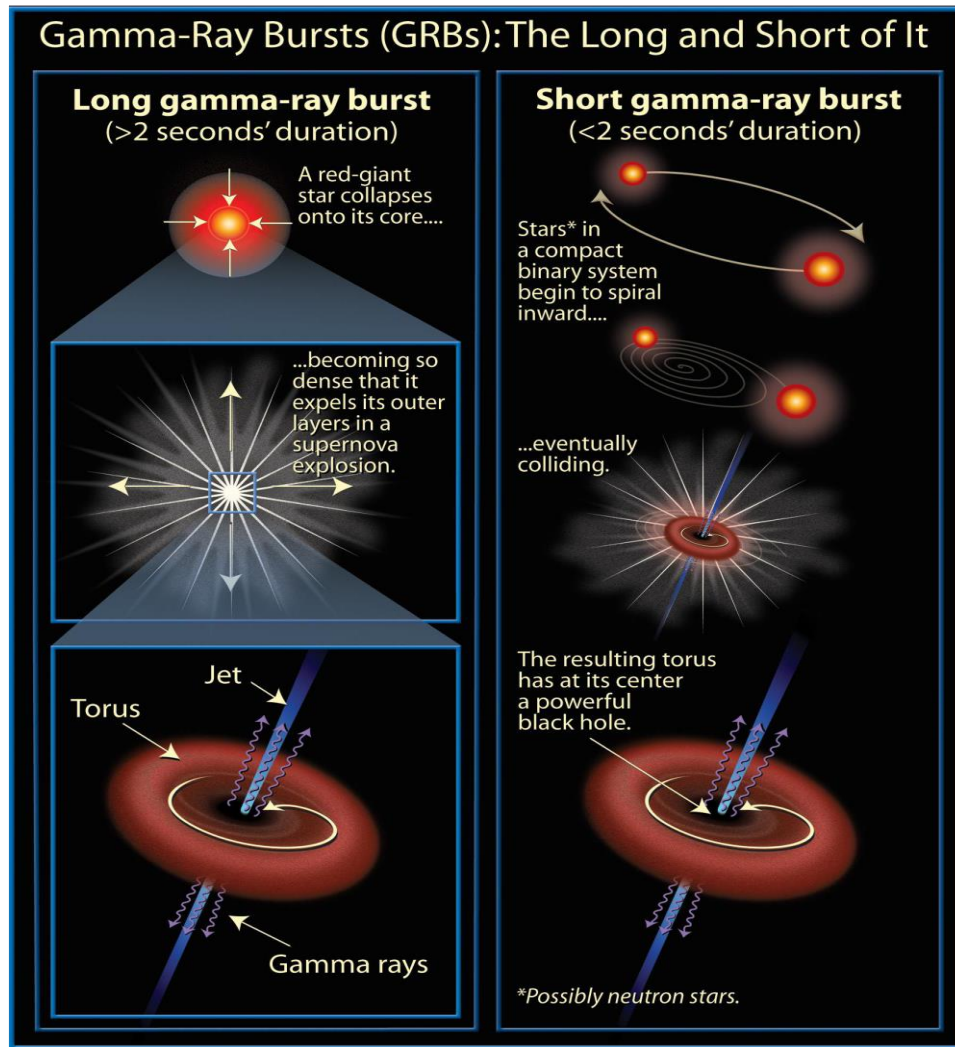
Introduction

- ❖ Gamma-ray Bursts (GRBs) are the most powerful explosions in electromagnetic wavebands ever discovered.
- ❖ Emitting in high energy range (keV to GeV) in gamma-ray within durations less than 1 second to few minutes.
- ❖ Detected at high redshift up to ~ 9.4 .
- ❖ GRBs can be visible at a very large distance, because of their high luminosities ($L_{\text{iso}} \sim 10^{52} \text{ erg s}^{-1}$).
- ❖ Are extremely bright and release an enormous isotropic equivalent radiated energy ($E_{\text{iso}} \sim 10^{54} \text{ erg}$) in a few hundreds of seconds.

They have the potential to be used as cosmological standard candles.



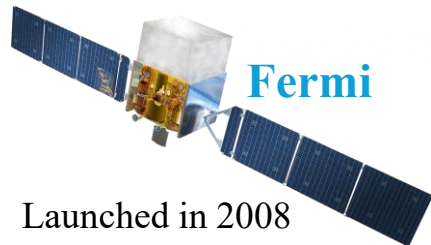
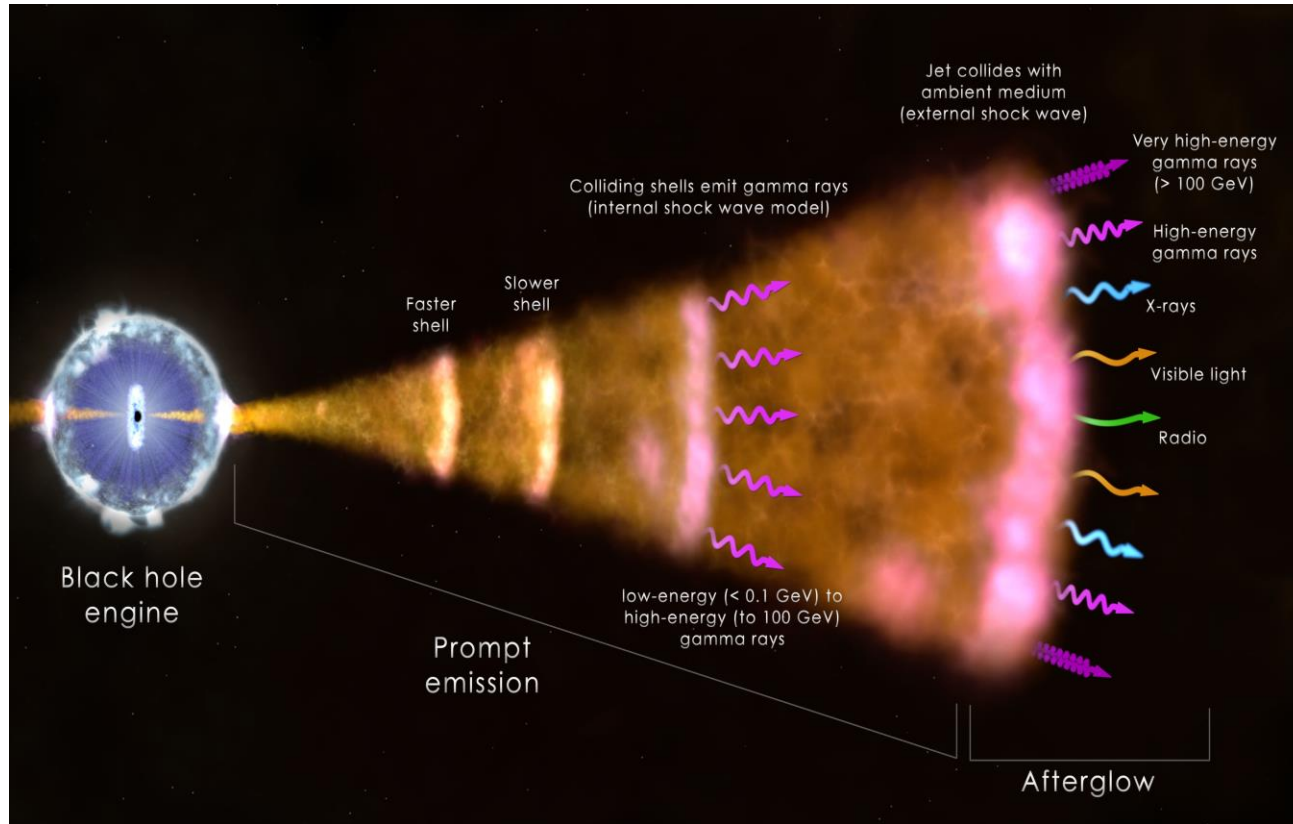
Introduction



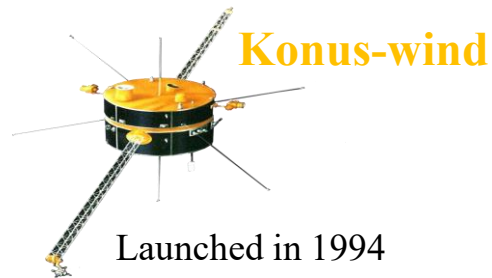
<https://gammaray.nsstc.nasa.gov/batse/grb/duration/>

Credit: NASA and A. Feild (STScI)

Introduction



Launched in 2008



Launched in 1994



Launched in 2004



High Energy Stereoscopic System (H.E.S.S.)



Major Atmospheric Gamma-ray Imaging Cherenkov (MAGIC)

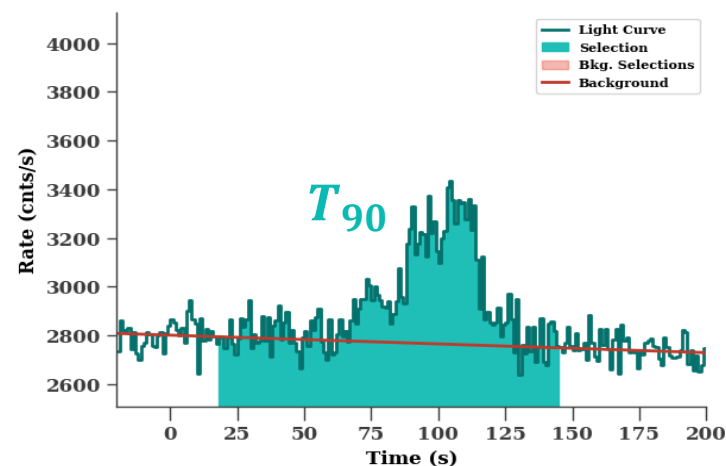
Phenomenological Correlations

❖ Amati (2002): (LGRBs - $*T_{90} > 2 \text{ s}$)

$$\frac{E_{iso}}{10^{52} \text{ erg}} = 10^k \left(\frac{E_{i,peak}}{E_o \text{ keV}} \right)^m$$

$$E_{iso} = \frac{4\pi d_L^2}{1+z} S_{bolo} \text{ , } E_{i,peak} = E_p(1+z)$$

$$S_{bolo}(E_1, E_2, z) = T_{90} \int_{E_1(1+z)}^{E_2(1+z)} EN(E) dE$$

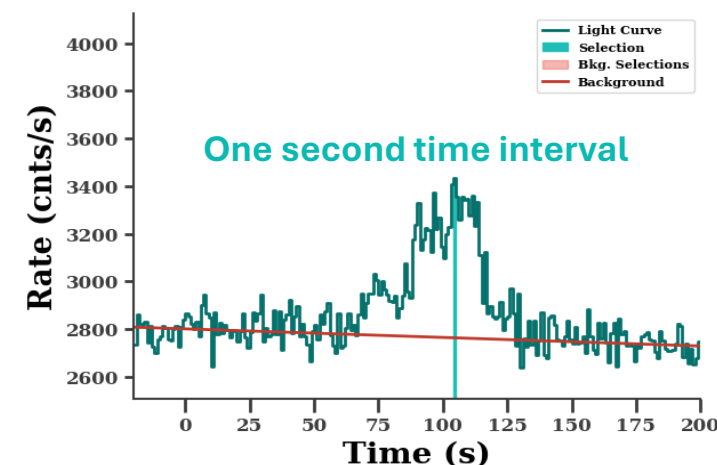


❖ Yonetoku (2007): (SGRBs - LGRBs)

$$\frac{L_{iso}}{10^{51}} = 10^k \left(\frac{E_{i,peak}}{E_o \text{ keV}} \right)^m$$


$$L_{iso} = 4\pi d_L^2 P_{bolo}$$

$$P_{bolo}(E_1, E_2, z) = \int_{E_1/(1+z)}^{E_2/(1+z)} EN(E) dE$$



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

Phenomenological Correlations

$$d_L = (1+z) \frac{c}{H_0} \int_0^z \frac{dz'}{\sqrt{(1-\Omega_\Lambda)(1+z')^3 + \Omega_\Lambda}}$$


$H_0 = 67.3 \text{ km s}^{-1} \text{ Mpc}^{-1}$ and $\Omega_\Lambda = 0.685$ (Planck Collaboration et al., 2018)

From the H_0 and Ω_Λ if one can predict (E_{iso}, L_{iso}) by measuring the peak of spectra then it possible to use GRBs as standard candles because of this d_L .

Redshift

- The redshift of the GRBs can be obtained from the absorption or emission lines.
- GRB 970508 from the few absorption lines, the redshift was determined to be $z = 0.8$ Frail et al., 1997.
- Swift satellite is well studied the localization of GRBs, enabling Swift follow-up observations and facilitating timely redshift measurements Gehrels et al., 2009.
- From photometric and spectroscopy, many GRBs have been identified and can be found in many GRBs catalogs such as Fermi-GBM von Kienlin et al., 2020, and Kouns-Wind Tsvetkova et al., 2021.
- The farthest GRB identified is GRB 090429B $z \approx 9.4$ Cucchiara et al., 2011.

Machine Learning Models

Estimations of GRB Redshift

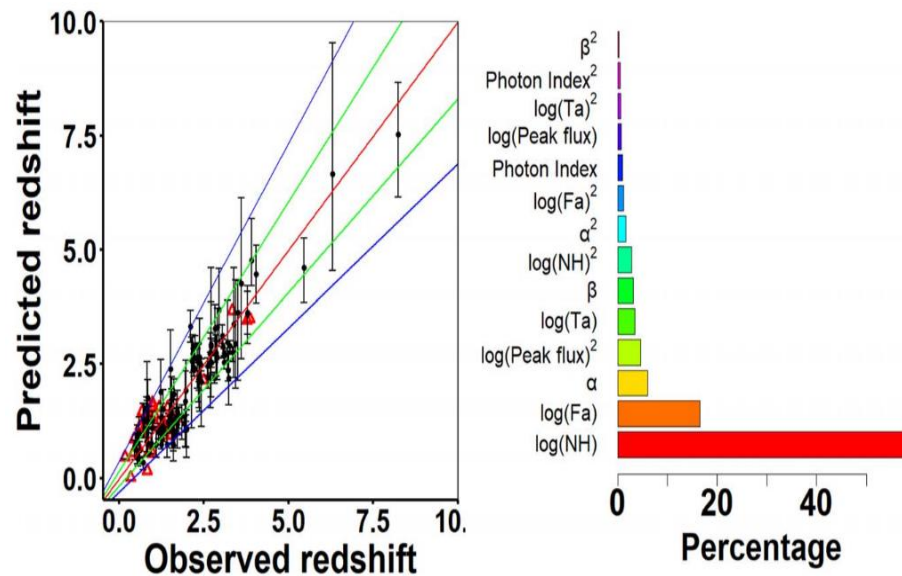
SuperLearner:

An ensemble learning technique that improves predictive accuracy by combining the outputs of multiple statistical models.

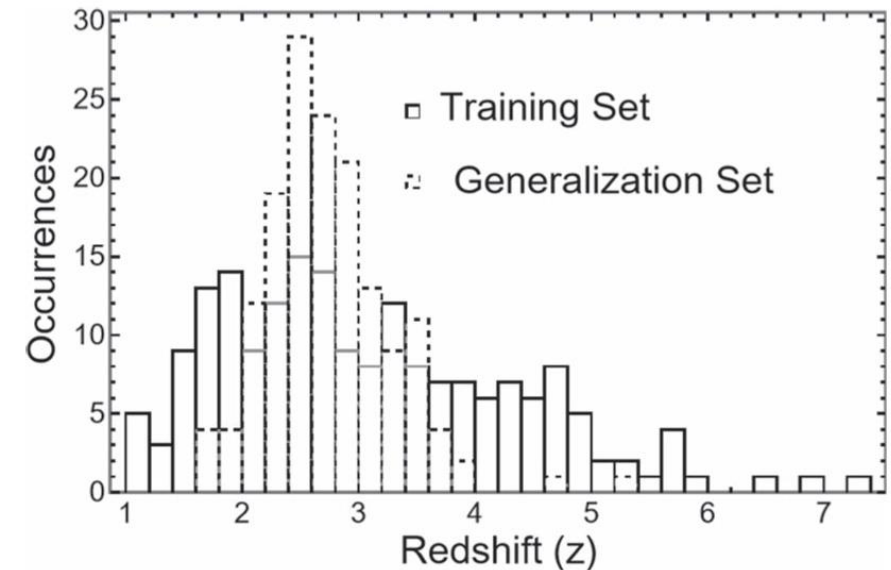
Trains various **supervised models**:

such as generalized additive models and random forests

Observed redshifts with predicted redshifts for 103 GRBs



Dainotti et al. 2024



Dainotti et al. 2024

- A sample of Swift GRBs based on their observed prompt and afterglow.

Machine Learning Models

- We used data from **Fermi Gamma-ray Monitor (Fermi-GBM)** von Kienlin et al., 2020 catalogue, **128 GRBs (2008-2018)** with known redshift.
- **Kouns-Wind** Tsvetkova et al., 2021 catalogue, **338 GRBs (2005-2018)** with known redshift.

Aldowma, T., and Razzaque, S., MNRAS, 2024

Bolometric	Peak Flux	Fluence
Band Model	$\alpha, \beta, E_p, P_{\text{bolo}}$	$\alpha, \beta, E_p, S_{\text{bolo}}$
Comptonized Model	$\alpha, E_p, P_{\text{bolo}}$	$\alpha, E_p, S_{\text{bolo}}$

We excluded:

- All SGRBs.
- GRBs with errors on spectral parameters exceeding 100% and those without E_p values across all spectral models were excluded.
- GRBs best-fitted with the Band model showing $\beta \geq -2$, indicating no peak, were also excluded.
- These applied to both GBM and KW data, regardless of redshift availability.

- **Band** : Band D. et al., 1993.
with indices α , β , and spectral peak energy E_p in keV.

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

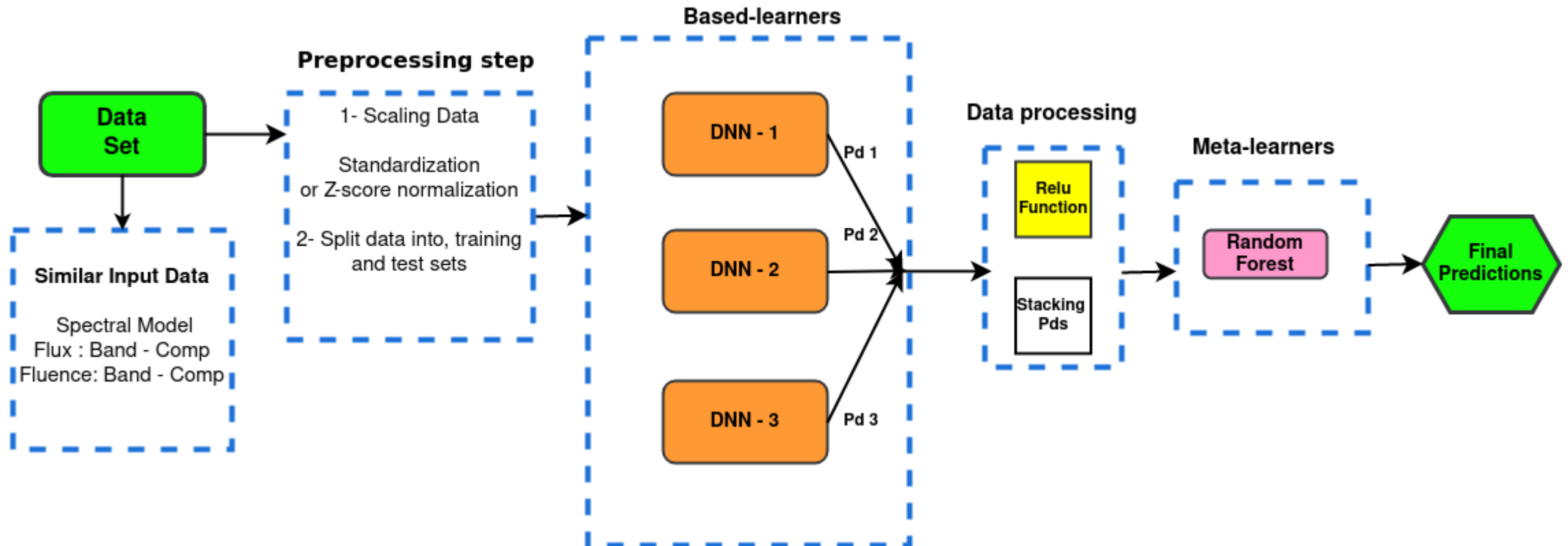
- **Comptonized** : Steiner J. F. et al., 2009.

The photon index γ , and the peak energy E_p .

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

Machine Learning Models

Ensemble Stacking

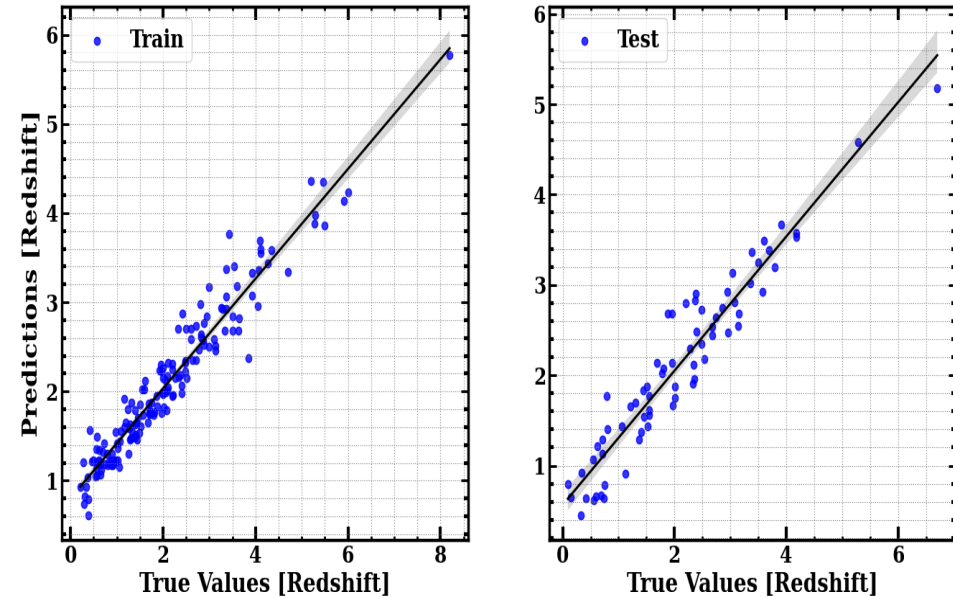


Aldowma, T., and Razzaque, S., MNRAS, 2024

Estimations of GRB Redshift

❖ Results from ensemble model with true redshift

GBM data	Train	Test
	R^2 - MAE	R^2 - MAE
Band fluence	0.812 - 0.383	0.724 - 0.555
Band flux	0.819 - 0.450	0.798 - 0.290
Comp fluence	0.827 - 0.439	0.801 - 0.392
Comp flux	0.823 - 0.384	0.812 - 0.437
Band fluence and flux	0.844 - 0.370	0.821 - 0.498
Comp fluence and flux	0.831 - 0.424	0.823 - 0.343
KW-GBM data	Train	Test
	R^2 - MAE	R^2 - MAE
Band fluence	0.858 - 0.431	0.838 - 0.433
Band flux	0.846 - 0.430	0.839 - 0.413
Comp fluence	0.857 - 0.409	0.836 - 0.433
Comp flux	0.860 - 0.337	0.852 - 0.364
Band fluence and flux	0.851 - 0.418	0.838 - 0.406
Comp fluence and flux	0.861 - 0.369	0.860 - 0.397
KW data	Train	Test
	R^2 - MAE	R^2 - MAE
Band fluence	0.838 - 0.543	0.804 - 0.615
Band flux	0.827 - 0.503	0.766 - 0.457
Comp fluence	0.826 - 0.480	0.810 - 0.509
Comp flux	0.842 - 0.441	0.831 - 0.361
Band fluence and flux	0.846 - 0.463	0.812 - 0.551
Comp fluence and flux	0.838 - 0.406	0.829 - 0.512



Predicted redshift from the ensemble models (DNNs + Random Forest) vs. true redshift for train and test samples from the combined KW-GBM data with known redshift. The regression lines are shown with 95% CL.

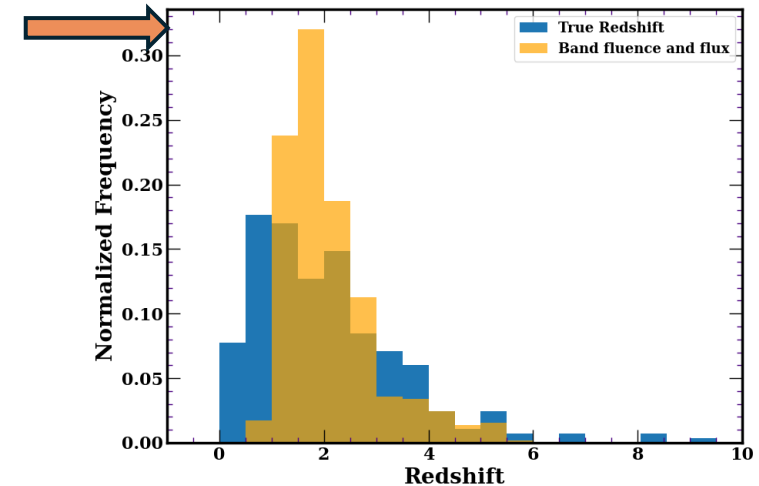
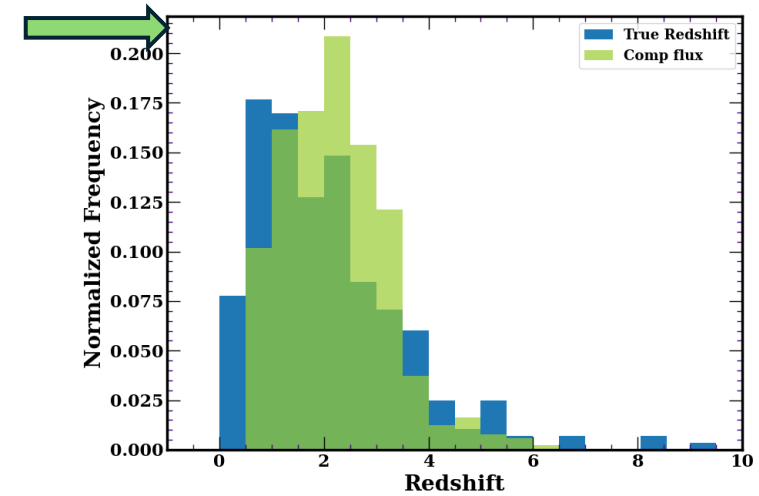
Aldowma, T., and Razzaque, S., MNRAS, 2024

Estimations of GRB Redshift

Pseudo-redshifts compare with the samples of GRBs with true redshifts

GBM data	p-value
Band fluence	0.1532
Band flux	0.0681
Comp fluence	0.1531
Comp flux	0.5713
Band fluence and flux	0.1532
Comp fluence and flux	0.1531
KW-GBM data	p-value
Band fluence	0.0681
Band flux	0.0681
Comp fluence	0.0948
Comp flux	0.8319
Band fluence and flux	0.5713
Comp fluence and flux	0.1745

Kolmogorov-Smirnov (KS) Hodges, 1958 test between the GRB samples with measured redshift and estimated pseudo redshift for GBM data without measured redshift.



Estimations of GRB Redshift



Results of the Amati (Amati et al., 2002) and Yonetoku (Yonetoku et al., 2004) correlation fits applied to the KW-GBM samples of GRBs with true redshift and GBM sample of GRBs with pseudo redshift. To see if may help to constrain the cosmological parameters.

$$x = \log_{10}\left(\frac{E_{i,p}}{E_o}\right), y = \log_{10}\left(\frac{E_{iso}}{erg/s}\right)$$

Or $\log_{10}\left(\frac{L_{iso}}{erg/s}\right)$

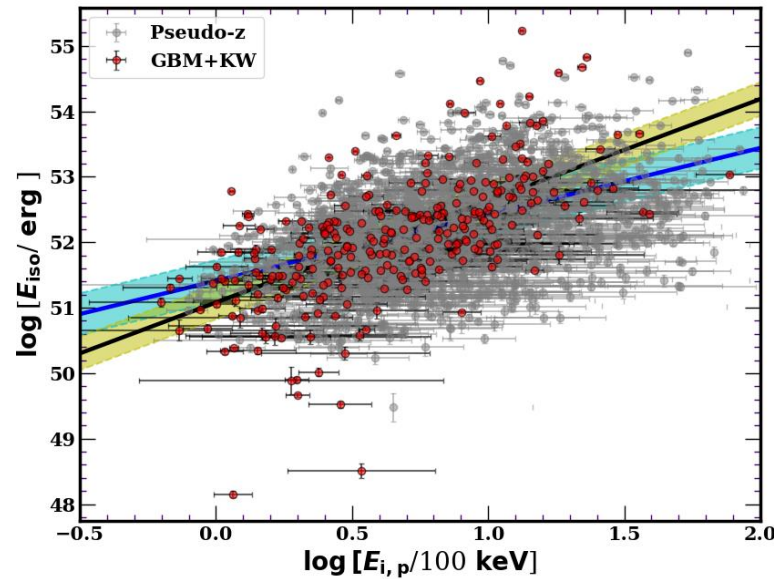
To get the error in y we followed:

$$\sigma_y = \sqrt{\sigma_k^2 + m^2 \sigma_x^2 + \sigma_m^2 + \sigma_{ext}^2}$$

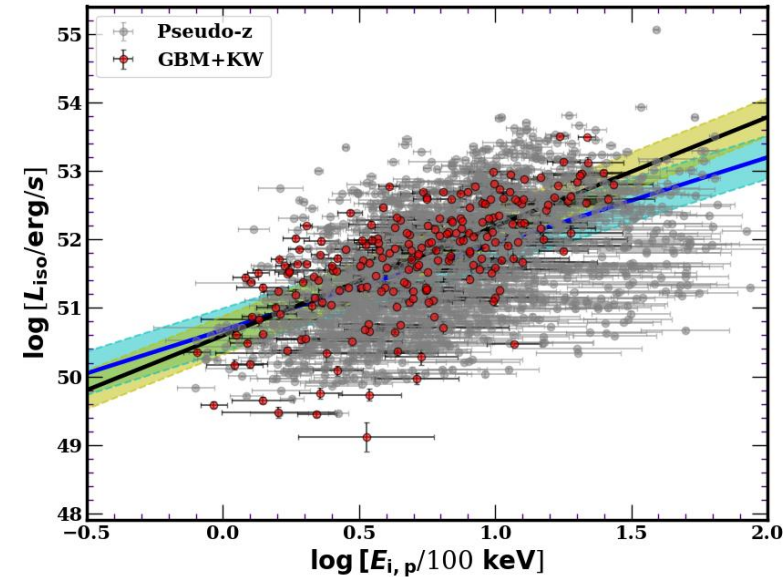
Max-likelihood function used to determine the parameters (k, m, σ_{ext})

$$L(m, k, \sigma_{ext}) = \frac{1}{2} \sum_i^N \ln(\sigma_{ext}^2 + \sigma_{yi} + m^2 \sigma_{xi}) + \frac{1}{2} \sum_i^N \frac{(y_i - mx_i - k)^2}{(\sigma_{ext}^2 + \sigma_{yi} + m^2 \sigma_{xi})}$$

Amati correlation



Yonetoku correlation

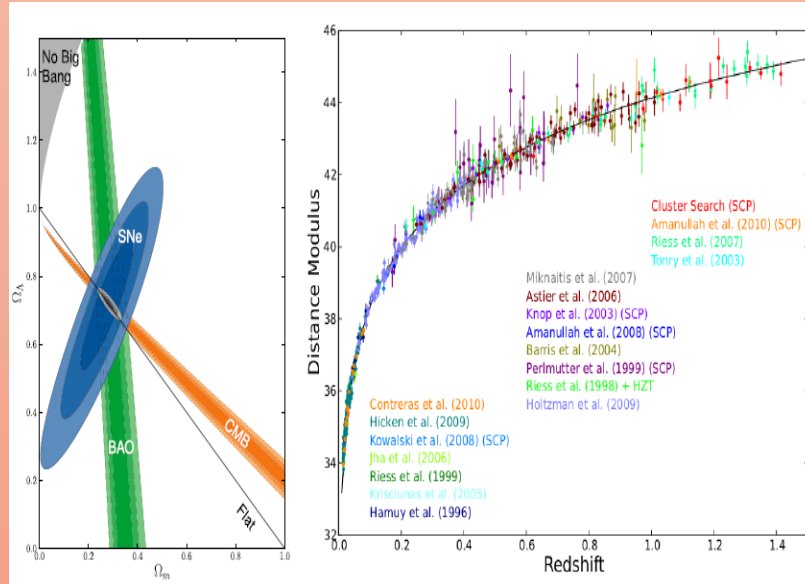


The ensemble model used for predicting pseudo redshift is “*Comp flux*” derived from KW-GBM true-redshift data (KS-test p-value: 0.8319).

Constraints on cosmological parameters

Supernova Type Ia (SNe Ia):

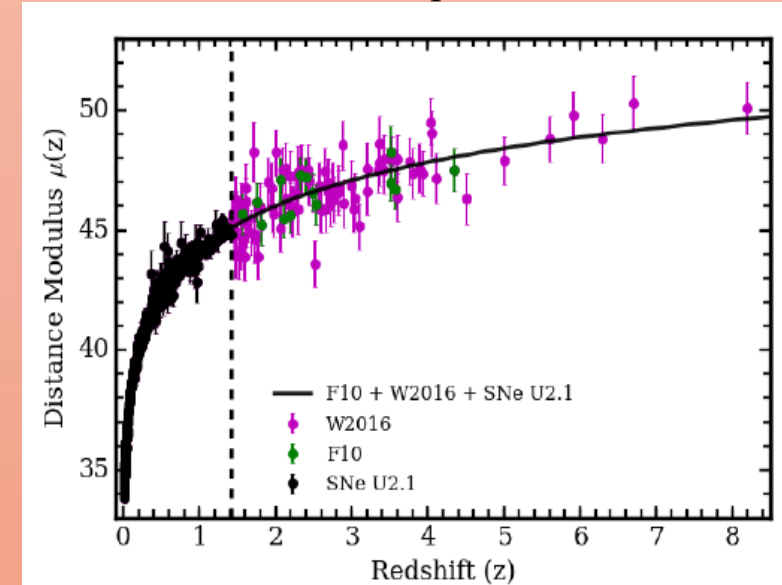
Observed only up to $z = 2$



Suzuki et al., 2012

GRBs

Observed up to $z = 8.2$



Combined SNe and GRB Hubble diagram

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

- ❖ Based on the best fit from the p-value shown in “Comp-flux,” we have published pseudo-redshift dataset: is available on the Zenodo website.

<https://doi.org/10.5281/zenodo.13695954>

- ❖ Once the parameters are obtained by fitting the linearized Yonetoku relation, we can use the GBM data with pseudo-redshift to estimate the cosmological parameters.

Preliminary results

Constraints on cosmological parameters

❖ GBM-GRB data:

True redshift: 116 GRBs, $0.0 < z < 8.2$

Pseudo redshift: 1576 GRBs, $0.6 < z < 6.3$

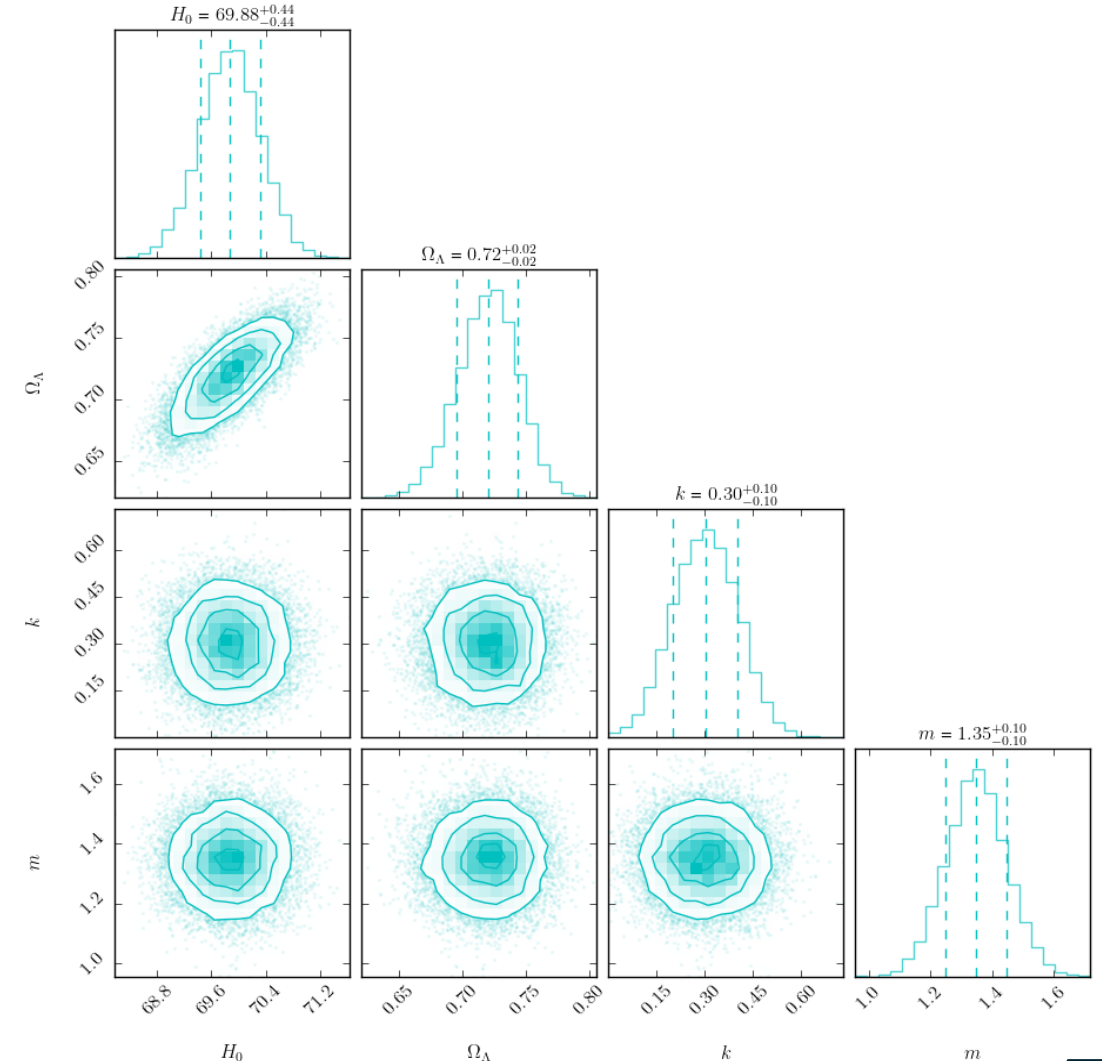
❖ SNe Ia data:

SNe U2.1 Suzuki et al. (2012) : 580, $0.0 < z < 1.4$

Dark Energy Survey (DES) Abbott et al. 2019: 207, $0.02 < z < 0.85$

- ❖ Using the MCMC method for Fermi GRB samples with true and pseudo-redshift. The parameters k , and m , represent the phenomenological parameters of the Yonetoku relation.

$$\chi^2(H_0, \Omega_\Lambda, k, m) = \sum_{i=1}^N \left[\frac{\mu^{obs}(z_i, k, m) - \mu^{th}(z_i, H_0, \Omega_\Lambda, k, m)}{\sigma_{\mu(z_i)}} \right]^2 + \left(\frac{k - k'}{\sigma_k} \right)^2 + \left(\frac{m - m'}{\sigma_m} \right)^2$$



Preliminary results

Constraints on cosmological parameters

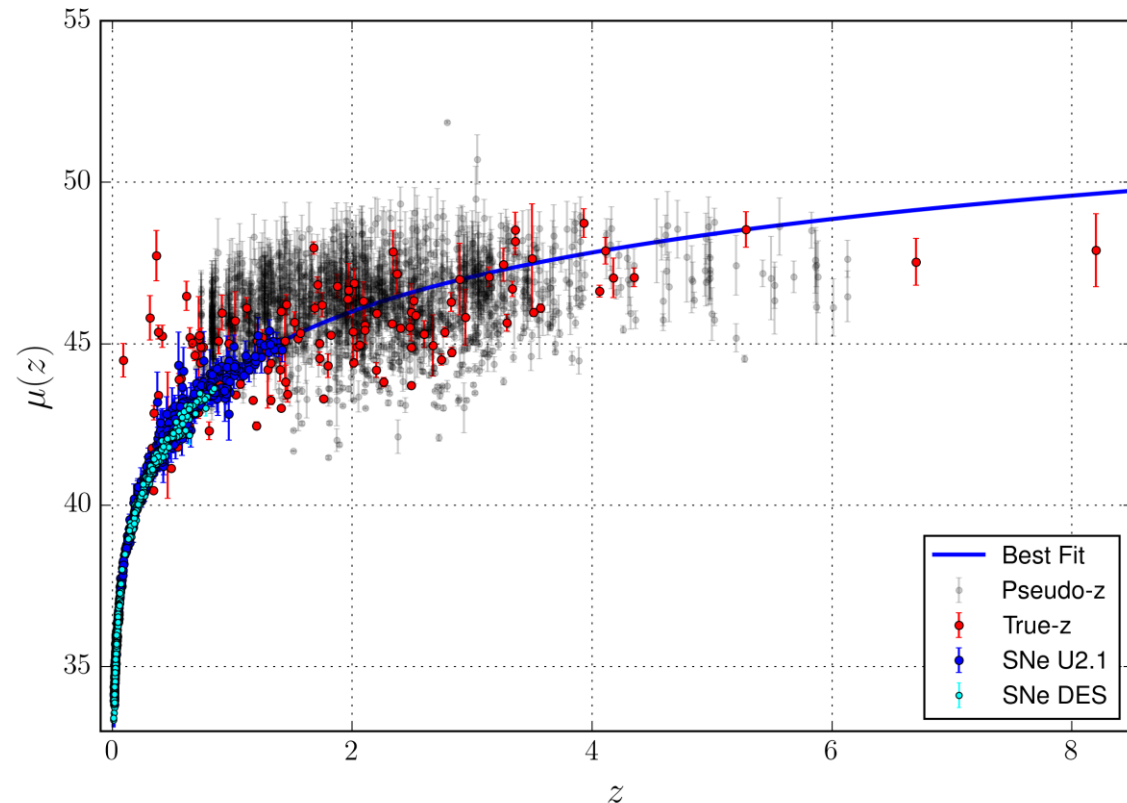
The Distance Modulus given as:

$$\mu = 5 \log \frac{d_l}{Mpc} + 25$$

$$\mu(z) = \frac{5}{2} \log_{10} \left[\frac{1}{4\pi P_{bolo}} \left(\frac{E_{i,p}}{E_0} \right)^m \right] + \frac{5}{2} (k + 51) - 5 \log_{10}(1 \text{ MPC}) + 25$$

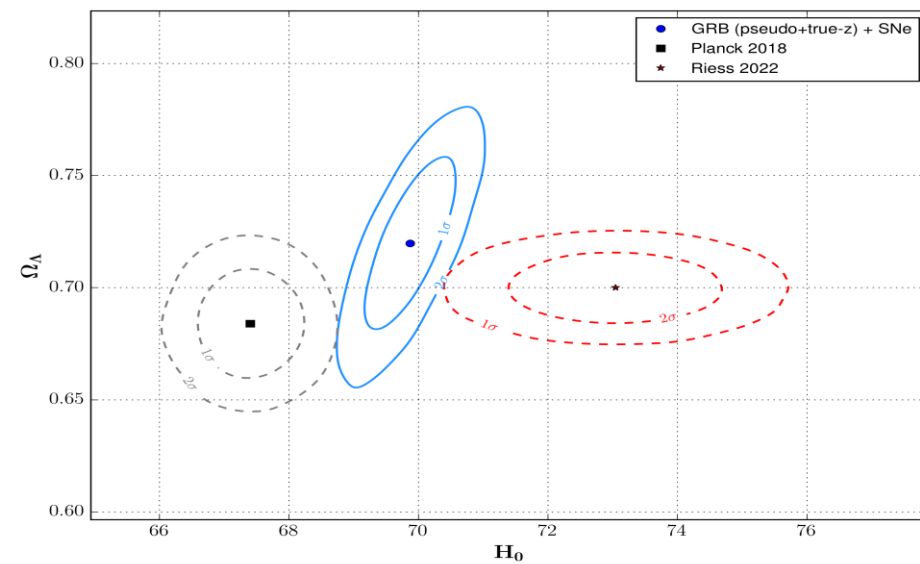
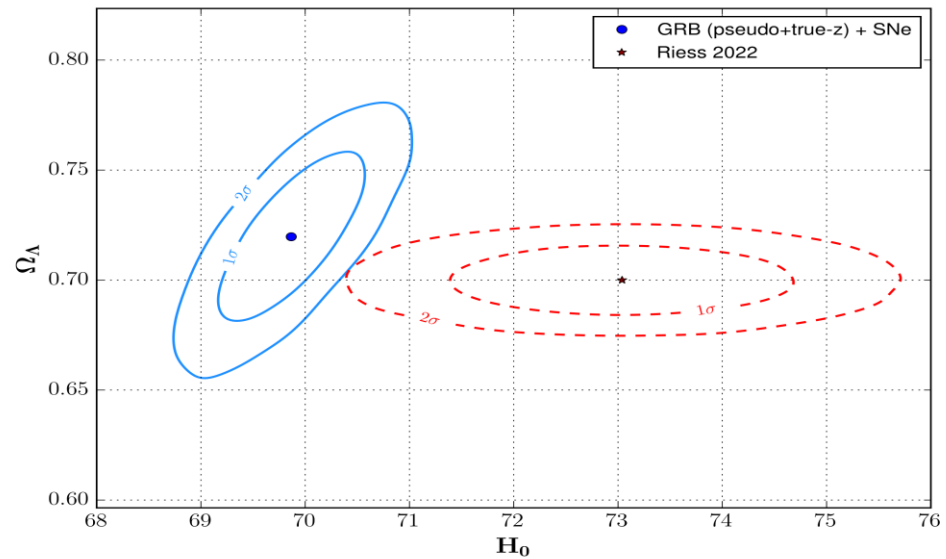
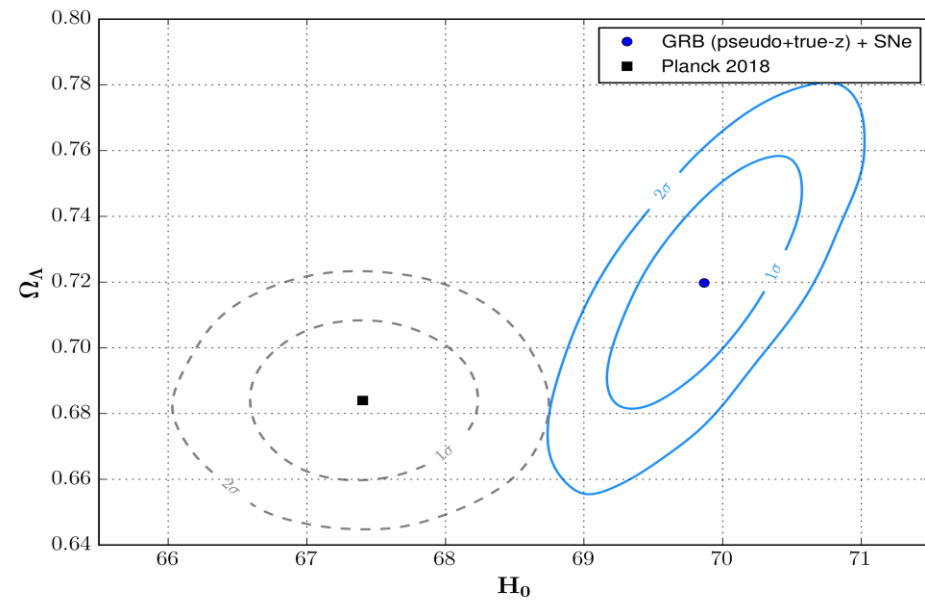
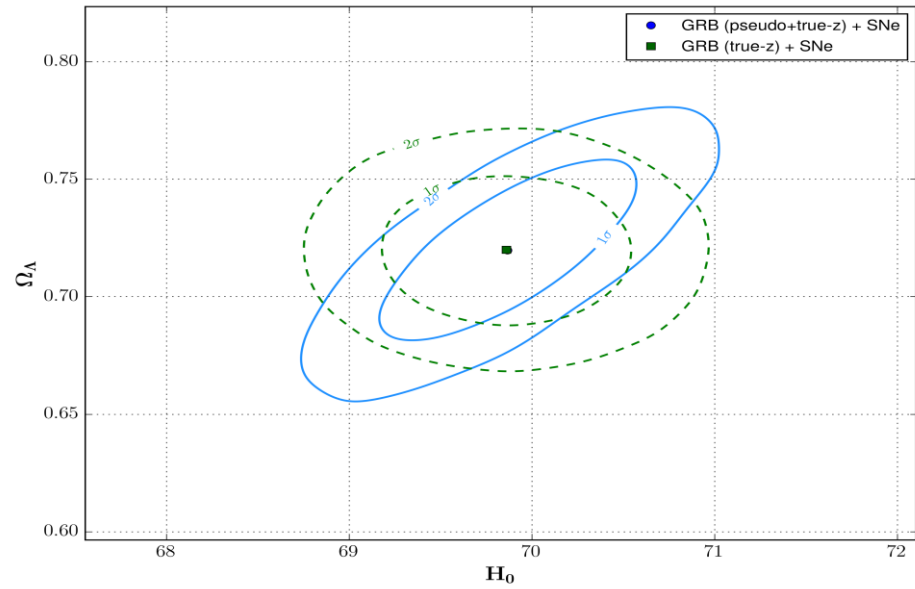
The uncertainty in Distance Modulus:

$$\sigma_{\mu(z)} = \frac{5}{2 \ln 10} \left[\left(\frac{\sigma_{p_{bolo}}}{P_{bolo}} \right)^2 + \left(\frac{m \sigma_{E_{i,p}}}{E_{i,p}} \right)^2 \right]^{1/2}$$



Preliminary results

Constraints on cosmological parameters

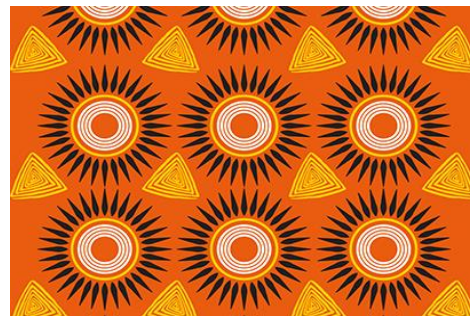


Summary

- We used a large sample of pseudo-redshifts predicted by our machine learning model, which is based on the Yonetoku correlation. This allowed us to explore how large number of GRBs can help constrain cosmological parameters.
- Specifically, we fit the Yonetoku parameters (k, m) simultaneously with the cosmological parameters (H_0, Ω_Λ).
- Our pseudo-redshift sample spans a wide redshift range from $z = 0.6$ to 6.3 . To improve constraints at lower redshifts, we also included GRBs with known redshifts and combined them with SNe Ia data from **Suzuki et al. (2012)** and the **Dark Energy Survey (DES)**.
- We compared our best-fit values of H_0, Ω_Λ with results from other major studied:
 - Our H_0 value higher than Planck 2018, but lower than Riess 2022.
 - For Ω_Λ the all results are consistent within uncertainties.

Source	H_0 (km/s/Mpc)	Ω_Λ	Data	References
GBM pseudo+true z	69.88 ± 0.44	0.72 ± 0.02	GRB + SNe	-
GBM true z	69.86 ± 0.43	0.72 ± 0.02	GRB + SNe	-
WMAP 9	69.3 ± 0.8	0.721 ± 0.015	CMB	Bennett et al. (2013)
F10 + SNe	70 ± 0.6	0.72 ± 0.03	GRB + SNe	Dirirsa et al. (2019)
F10 W2016 + SNe	70 ± 0.5	0.72 ± 0.03	GRB + SNe	Dirirsa et al. (2019)
Planck 2018	67.4 ± 0.5	0.684 ± 0.0073	CMB	Planck Collaboration et al. (2020)
SDSS/BAO+SNe	68.5 ± 1.0	0.70 ± 0.02	BAO + SNe	Alam et al. (2021)
Riess 2022	73.04 ± 1.04	~ 0.70	Cepheids + SNe	Riess et al. (2022)
Cosmic Chronometers	69.0 ± 1.2	0.70 ± 0.02	Galaxy ages	Moresco (2024)

 **Thank you**



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