University of Public Service, Budapest, Hungary
Eötvös University, Budapest, Hungary
ELKH CSFK Konkoly Observatory, Budapest, Hungary

The future of the redshift estimation of GRBs

István I. Rácz

With the contribution of Z. Bagoly, I. Csabai, I. Horváth, L. G. Balázs, L. V. Tóth, S. Pinter

THESEUS CONFERENCE
2021

Outline

Spatial distribution of GRBs

Redshift measurements

Machine learning for redshift estimation

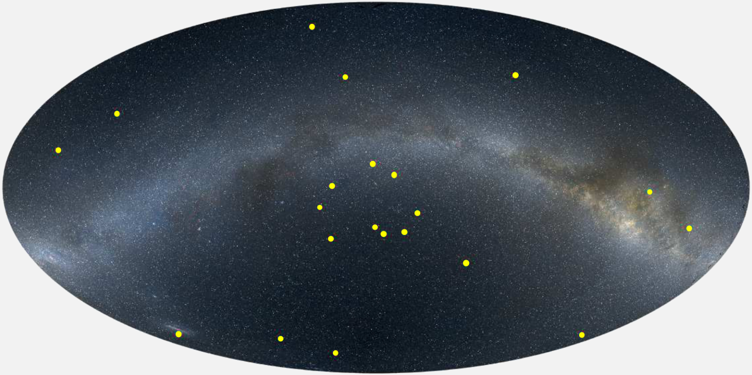
Summary

Spatial distribution of GRBs

Are the spatial distribution of GRBs homogeneous and isotropic?

Giant GRB ring at z≈0.8 (Balázs et al., 2015 and 2018)

- from 21 GRBs with redshift between 0.78 and 0.86
- 9 GRBs form a 1.72 Gpc diameter ring-like structure



Redshift measurements
Overview

Two types of redshifts:

- Spectroscopic: accurate, longer measurement
- Photometric: easier measurement, bigger uncertainty

Number of measurements:

- Spectroscopic: ≈ 500
- Photometric: ≈ 100

Positions errors of different instruments (i.e.):

- Fermi GBM: few degrees
- Swift BAT: few arcmins

The exact source is difficult to identify for the ground-based follow-up observations

Redshift measurements
Afterglow

Afterglows' time evolution:

- X-Ray
- UV and optical, i.e. Swift – UVOT
- IR, i.e. Theseus – IRT (see Poster by L. G. Balazs)
- Radio

Lyman limit at 912Å is almost completely absorbed

Lyman-break shifting ('detection limit'):

Wavelength	Wavelenght range	Redshift
UV	$0.1 - 0.4\mu m$	$2 - 3$
Optical	$0.4 - 0.7\mu m$	$3 - 7$
NIR	$0.7 - 2.5\mu m$	$7 - 26$
MID	$2.5 - 20\,\mu m$	$26 \rightarrow$

Redshift measurements
Statistics

Swift GRB Statistics:

- 1443 GRBs detected
- 1168 X-Ray (XRT) measurements
- 454 UVOT measurements

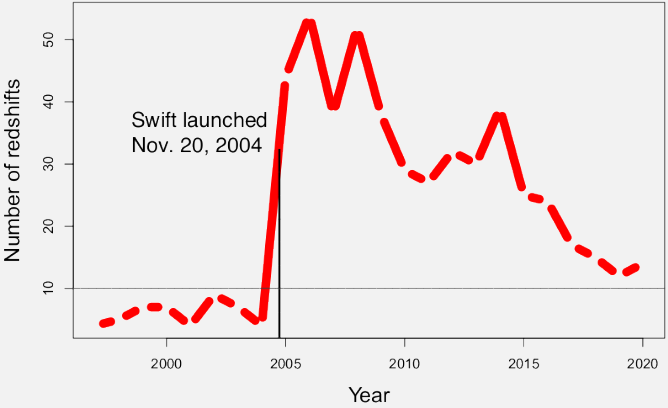
The frequency of redshift detections of Swift GRBs (spring of 2020):

- 1346 Swift GRBs
- 408 ground-based spectroscopic redshift measurements
- From which only 22 did not have UVOT detections (under 6%)

Precise localizations $\Longrightarrow$ spectroscopic redshift measurements

Redshift measurements

Changing over time



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 (see Poster by I. Horvath).

Machine learning for redshift estimation

Measured physical parameters depend on distance, but the impact

- is relatively smaller than the GRB's own variability
- is a complex mechanism
- is hard to specify with simple statistical methods

Machine learning may help amplifying the underlying subtle relations between the observed physical parameters and the distance.

We used two procedures:

- Random Forests
- Gradient Boosted Trees (XGBoost)

Data & Catalogs:

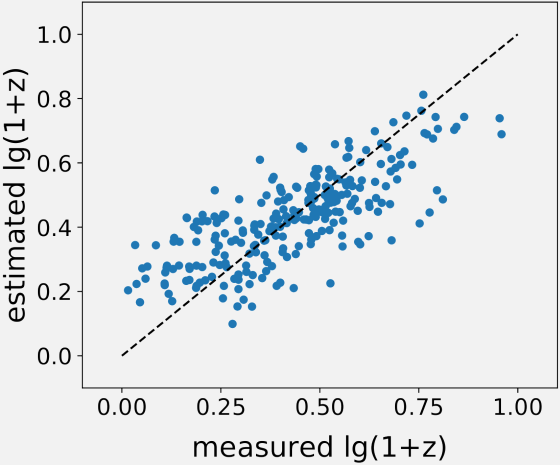
- Swift GRB Catalog
- UKSSDC catalog
- Own redshift catalog, data tables (i.e Jochen Greiner GRBs' table), GCN reports, other found publications

We selected 20 parameters:

- γ-flux
- X-ray fluxes (early, 11hours, 24hours)
- UVOT parameters
- $N(H)_{\mathrm{intrinsic}}$ (both of WT and PC observation mode)

Similar parameters will be available for Theseus (IRT is essential)

The correlation coefficient was 0.759±0.008 (Racz et al., 2017).



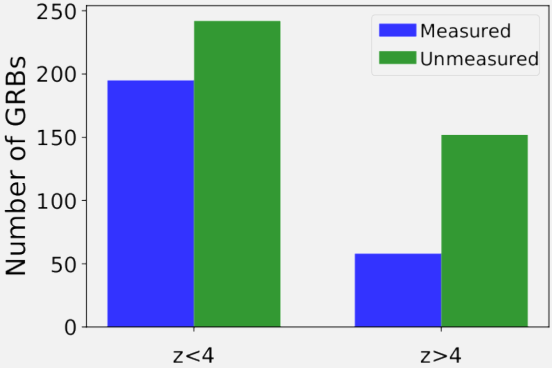
Machine learning for redshift estimationt
Redshift classification

Besides the distance estimation we could separate GRBs into distance ranges.

From the classification we obtained that it is possible to distinguish the z<4 and z>4 GRBs with an almost 90% goodness of estimation.

We classified the GRBs without measured redshift and we found that the group with z<4 contains comparable numbers of GRBs with known and unknown redshifts. In the high-z case three times more unmeasured GRBs were found than measured. This can imply that the distance of GRBs above a given value can strongly reduce the measurement of redshifts.

Number of cases	$z < 4$	$z \geq 4$
Measured (real)	231	22
Predicted (known)	195	58
Predicted (unknown)	242	152



The distribution of high-z GRBs. It is shown that there are three times more high-z GRBs in the population of objects with unmeasured redshifts. (Racz et al., in prep.)

Summary

- Position determination from high precision observation is essential
- Lyman-break cutoff, Optical: $z \approx 5$, NIR: $z \approx 10$
- The number of ground-based redshift measurements are decreasing year by year
- Theseus IRT will be a good solution
- We obtained promising results for redshift estimation by machine learning
- It is possible to distinguish the z<4 and z>4 GRBs with an almost 90% goodness of classification

References

Thank you for your attention!

- Balázs, L. G. et al., 2015, MNRAS, 452, 2236B
- Balázs, L. G. et al., 2018, MNRAS, 473, 3169B
- Breiman L., 2001, Machine Learning, 45, 5
- Horvath, I. et al., 2020, MNRAS, 498, 2544
- Racz, I. I. et al., 2017, PoS(IFS2017),079
- Racz, I. I. et al., 2018, MNRAS, 475, 306
- Racz, I. I. et al., 2021, in prep
- Ukwatta T. N. et al., 2016, MNRAS, 458, 3821
- T. Chen and C. Guestrin, 2016, ArXiv e-prints: 1603.02754