The future of the redshift estimation of GRBs

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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 $z \approx 0.8$ (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
Two types of redshifts:
- Spectroscopic: accurate, longer measurement
- Photometric: easier measurement, bigger uncertainty

Number of measurements:
- Spectroscopic: $\approx 500$
- Photometric: $\approx 100$

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’):

<table>
<thead>
<tr>
<th>Wavelength</th>
<th>Wavelength range</th>
<th>Redshift</th>
</tr>
</thead>
<tbody>
<tr>
<td>UV</td>
<td>0.1 – 0.4(\mu m)</td>
<td>2 – 3</td>
</tr>
<tr>
<td>Optical</td>
<td>0.4 – 0.7(\mu m)</td>
<td>3 – 7</td>
</tr>
<tr>
<td>NIR</td>
<td>0.7 – 2.5(\mu m)</td>
<td>7 – 26</td>
</tr>
<tr>
<td>MID</td>
<td>2.5 – 20(\mu m)</td>
<td>26 →</td>
</tr>
</tbody>
</table>
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 $\Rightarrow$ 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).
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)
Machine learning for redshift estimation

Data

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:
- $\gamma$-flux
- X-ray fluxes (early, 11hours, 24hours)
- UVOT parameters
- $N(H)_{\text{intrinsic}}$ (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).
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.

<table>
<thead>
<tr>
<th>Number of cases</th>
<th>$z &lt; 4$</th>
<th>$z \geq 4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measured (real)</td>
<td>231</td>
<td>22</td>
</tr>
<tr>
<td>Predicted (known)</td>
<td>195</td>
<td>58</td>
</tr>
<tr>
<td>Predicted (unknown)</td>
<td>242</td>
<td>152</td>
</tr>
</tbody>
</table>
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.)
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
Thank you for your attention!

- Breiman L., 2001, Machine Learning, 45, 5
- Racz, I. I. et al., 2017, PoS(IFS2017),079
- Racz, I. I. et al., 2021, in prep