

# Prompt GRB recognition through Waterfalls and Deep Learning

*International Conference on Machine Learning for Astrophysics*  
Catania, 10/07/2024

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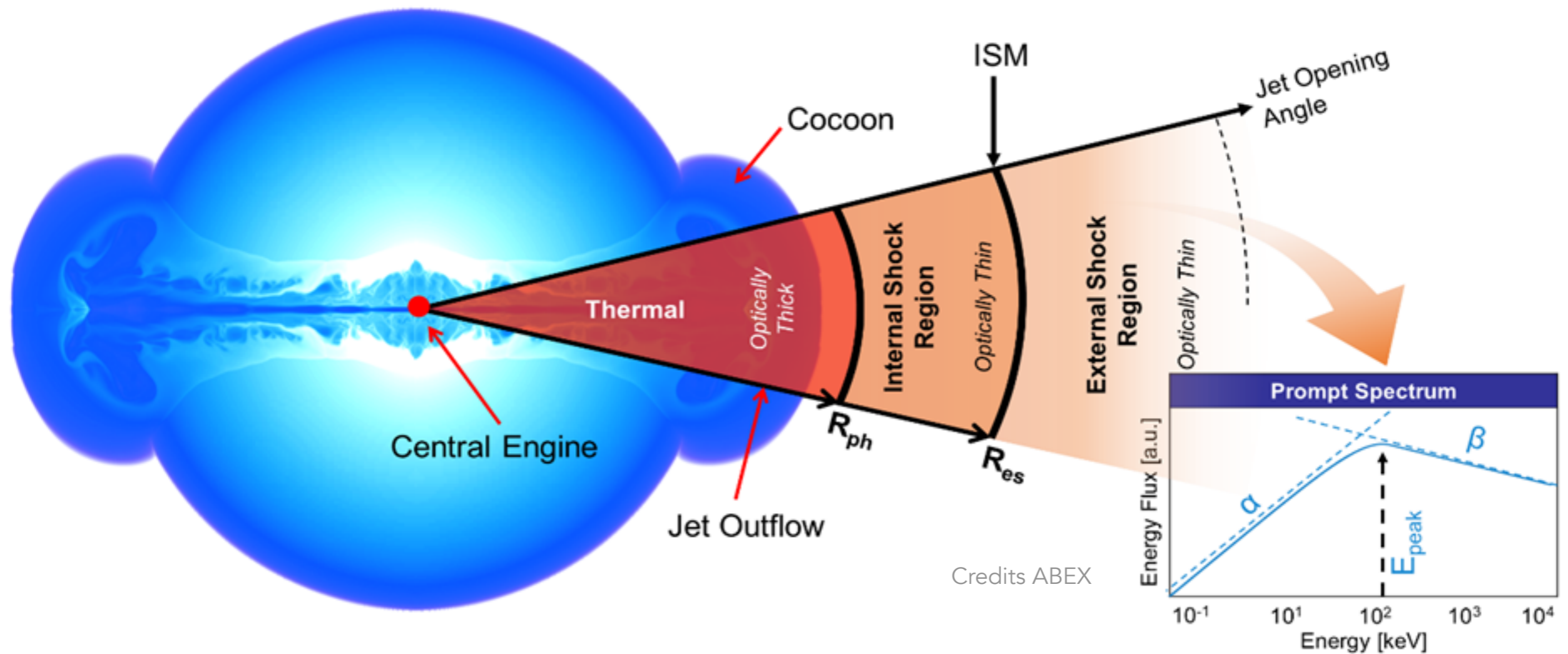
On behalf of the team:

M. Negro, E. Burns, J. Wood, A. Goldstein, T. Del Canton



# Gamma Ray Bursts

Gamma-Ray Bursts (GRBs) are among the most energetic events known in the universe

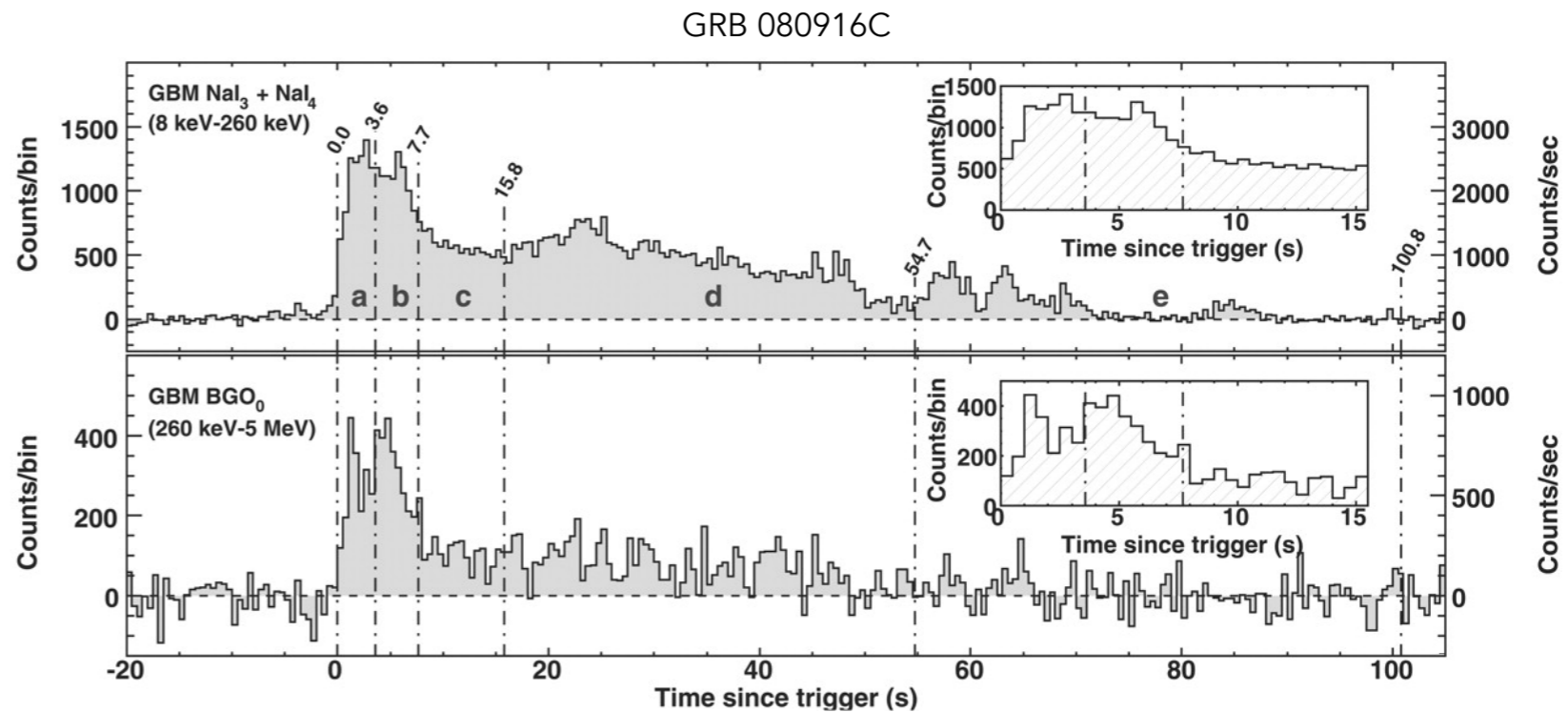


Prompt, multiwavelength, and multimessenger observations allow us to probe physics in extremes which cannot be achieved in terrestrial laboratories

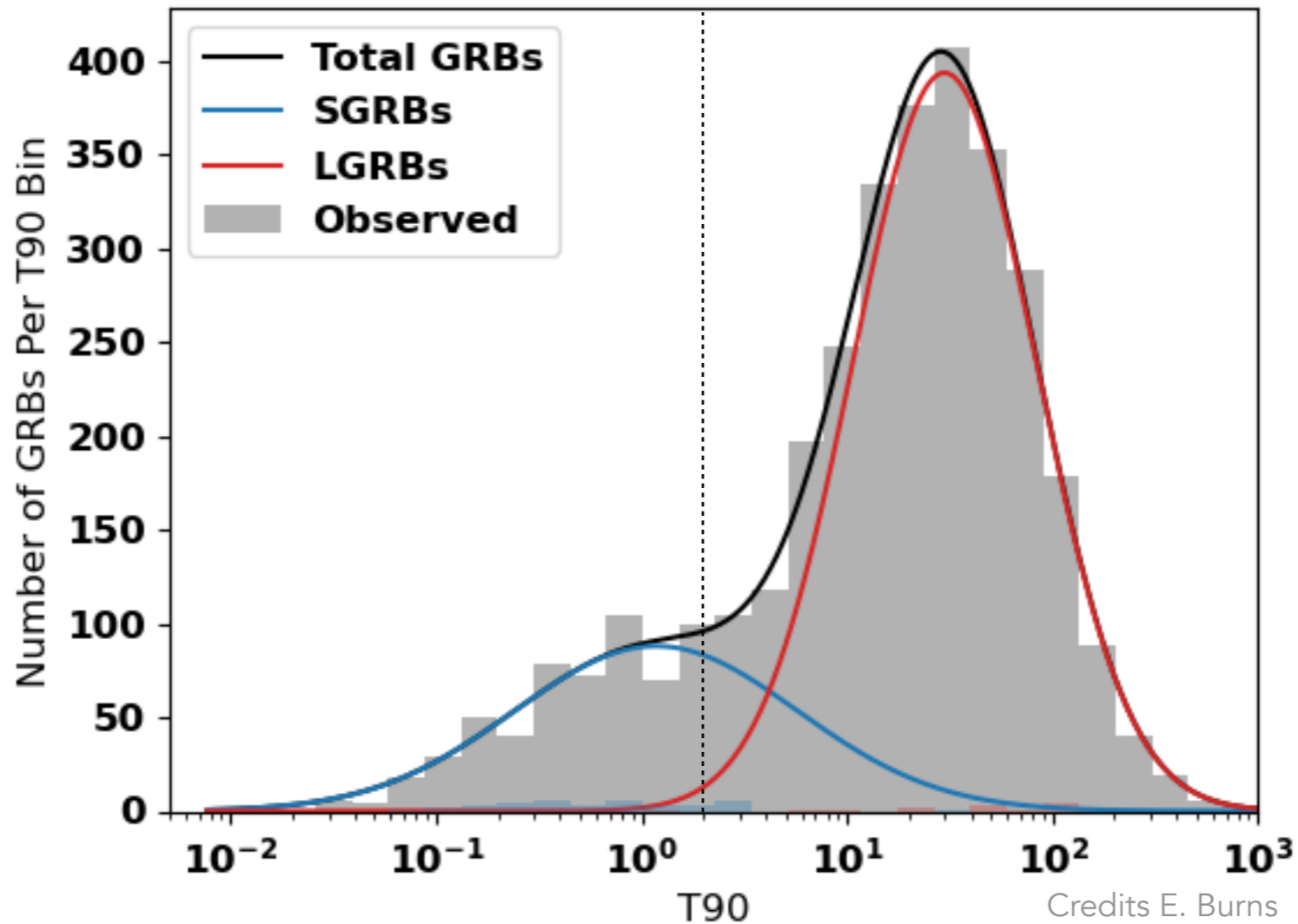
# Fermi Gamma-ray Burst Monitor (GBM)



The instrument response is optimal in the energy range between 8 keV and 40 MeV



# GRBs progenitors



Binary NS merger

Collapsars

Binary BH-NS merger

Tidal disruptive events

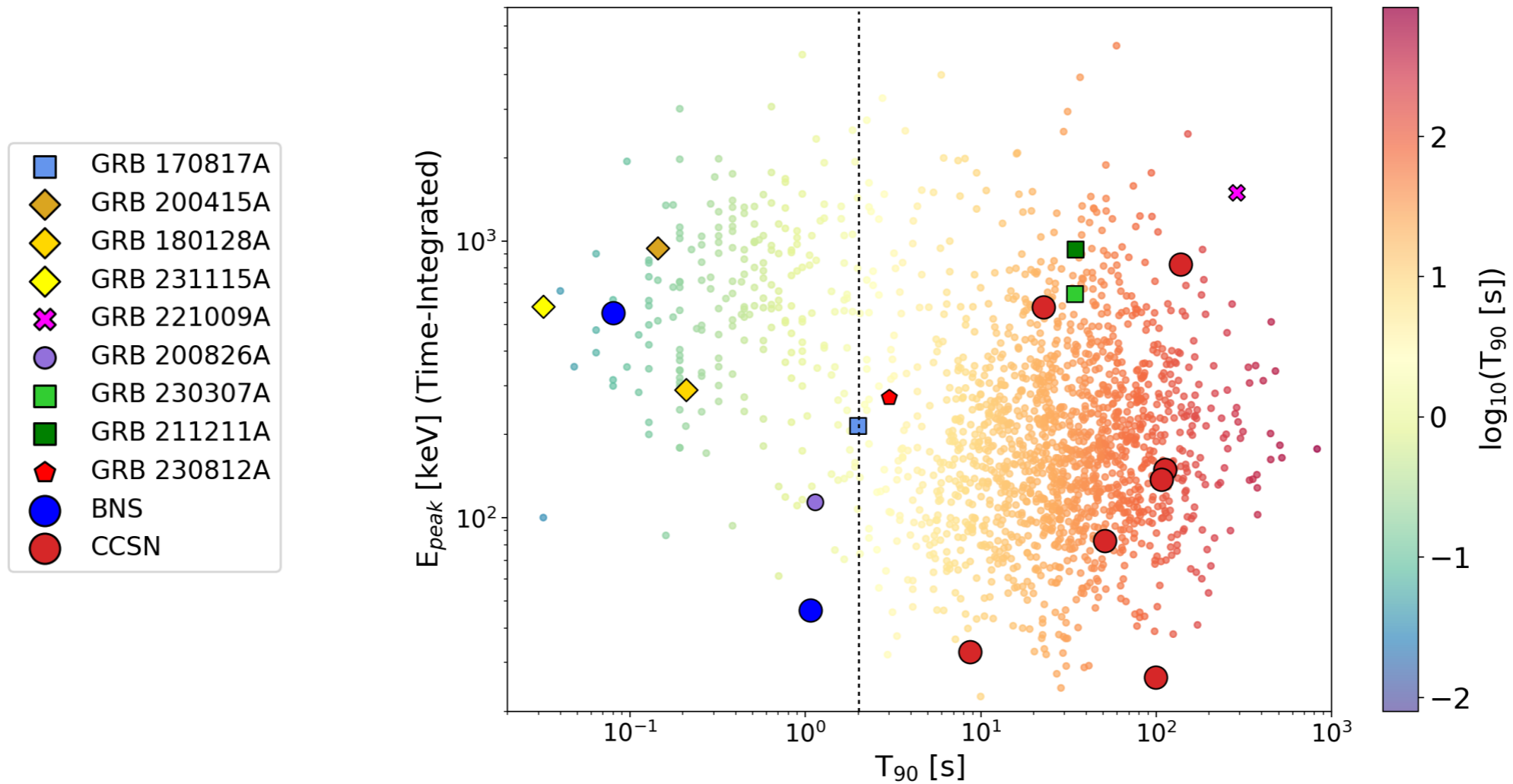
X-ray flashes

Magnetar Giant Flares

Long mergers

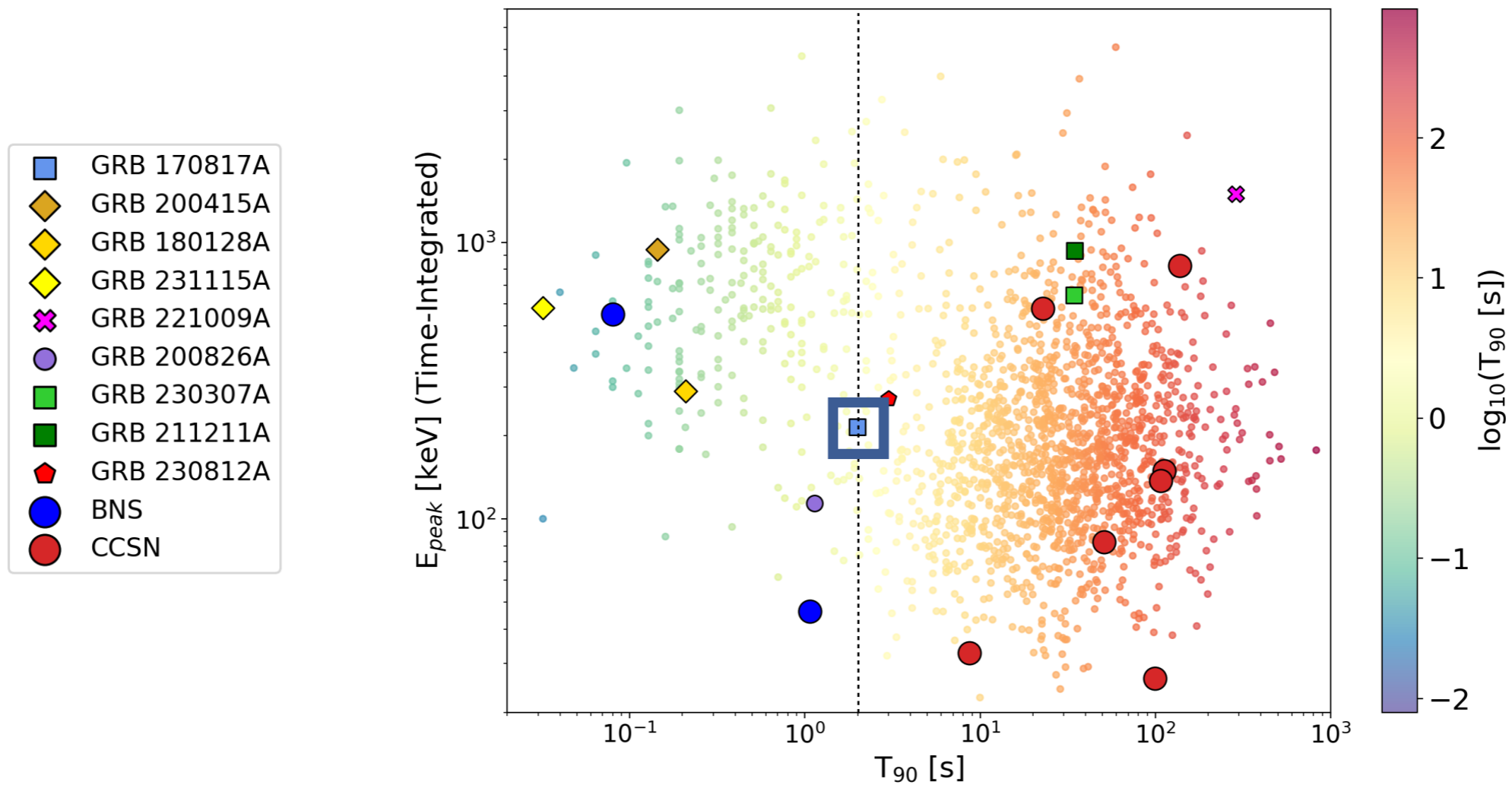
# GRBs classification

Categorization of GRBs is not trivial  
Recent discoveries challenge the traditional classification



# GRBs classification

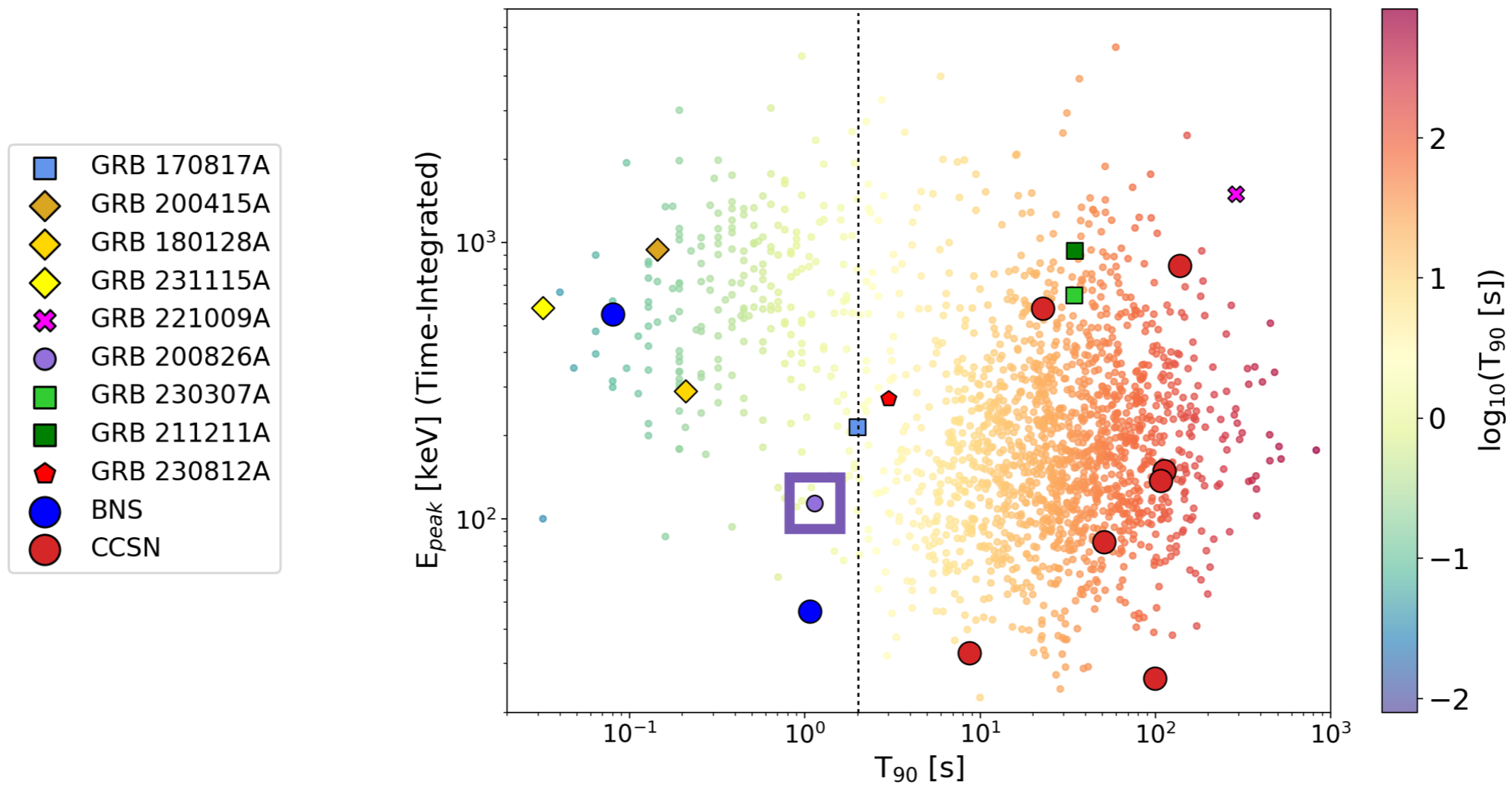
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GRB 170817A: A confirmed BNS merger on the 2s threshold

# GRBs classification

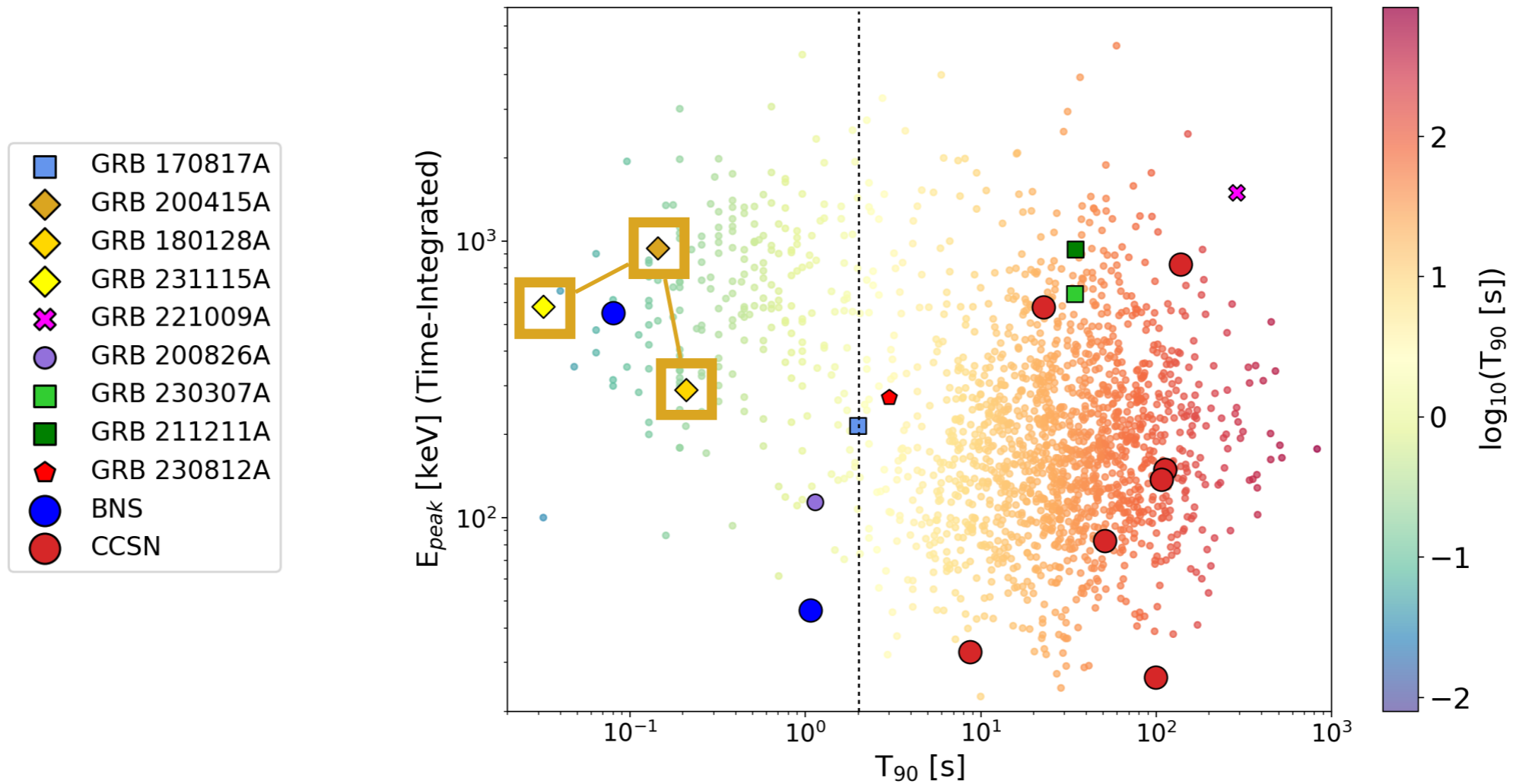
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GRB 200826A: a collapsar GRB under the 2s threshold

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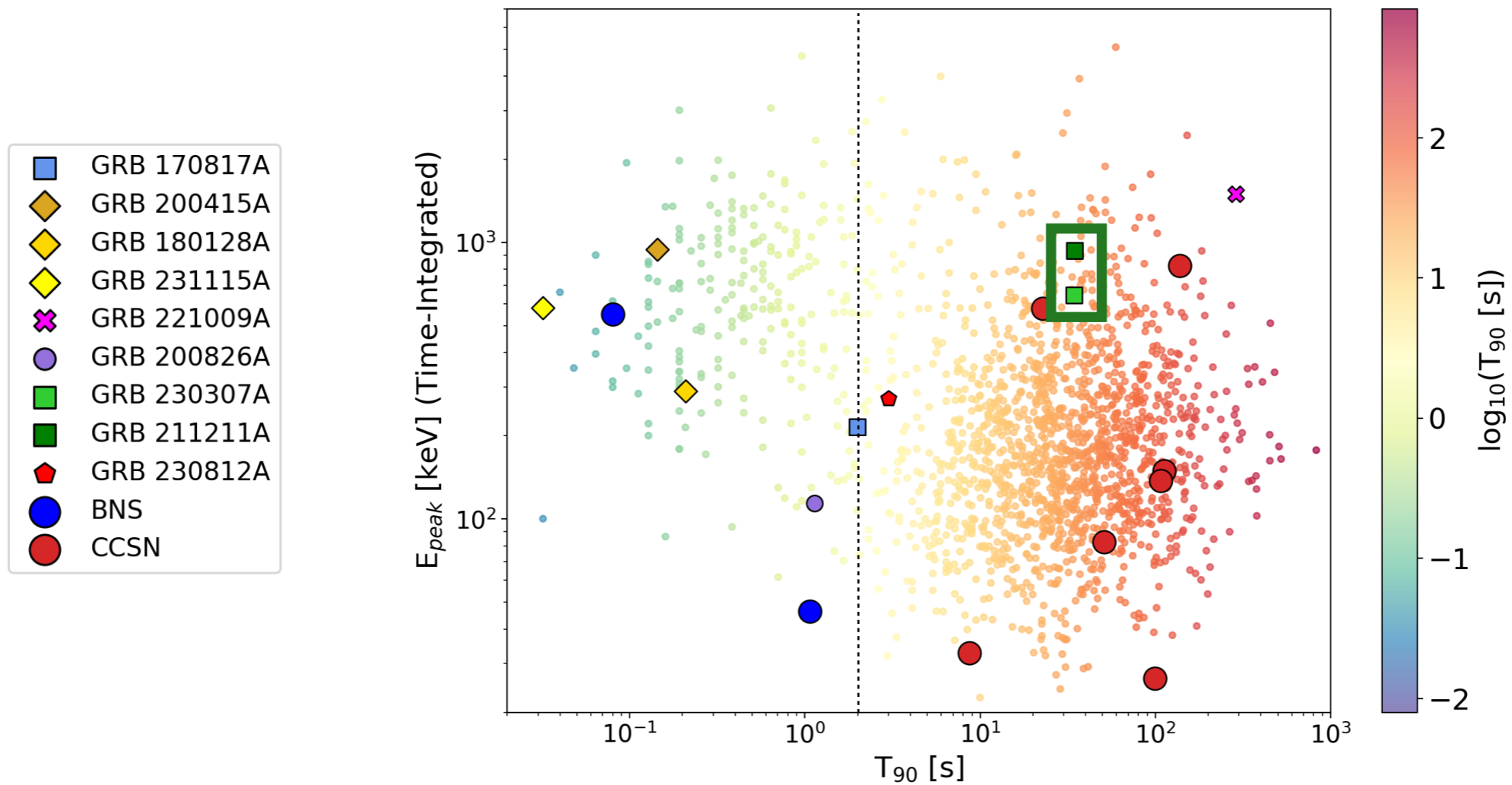


Magnetar Giant Flares candidates: indistinguishable from short GRBs



# GRBs classification

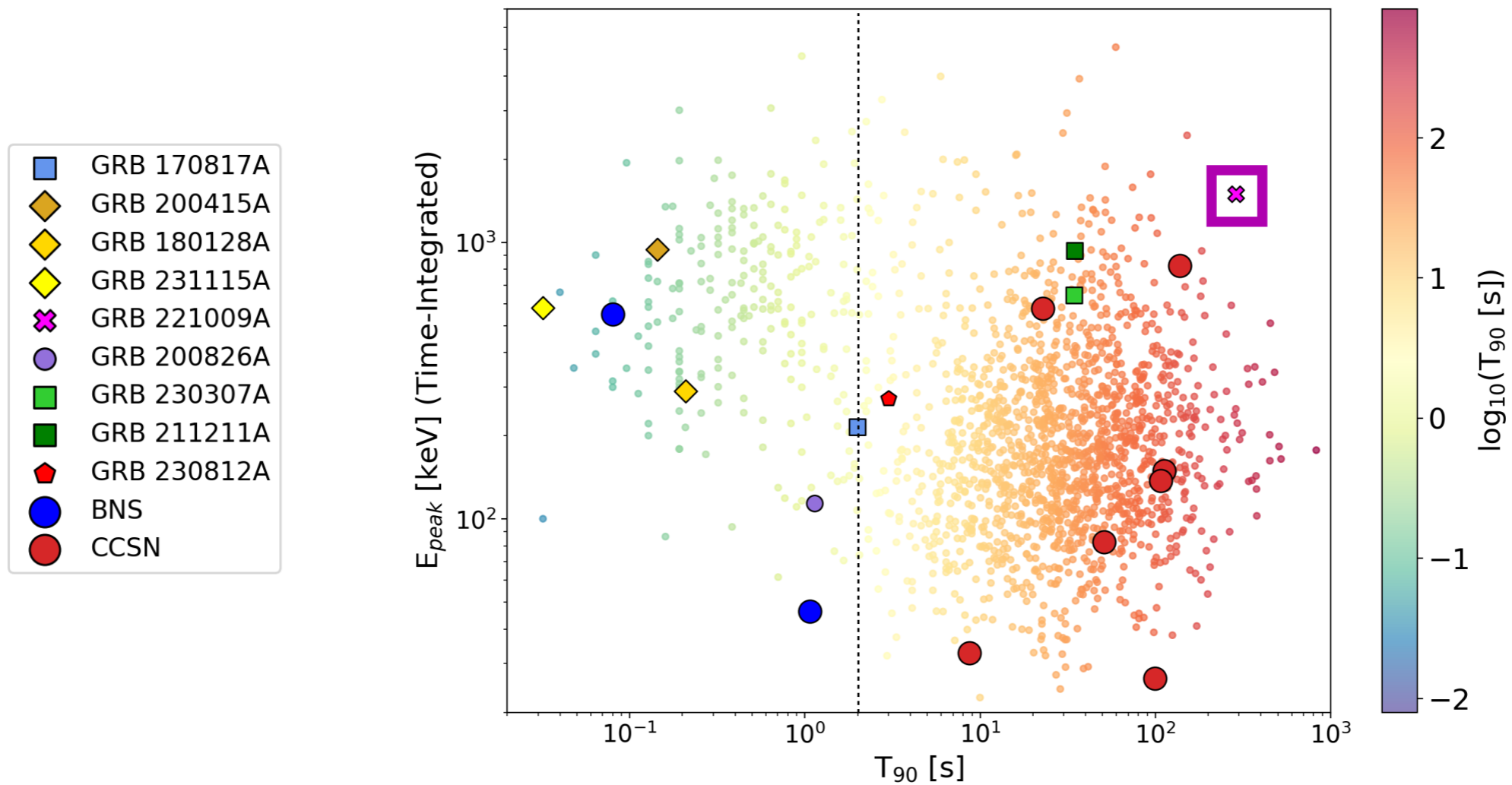
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GRBs 230207A and 211211A: the long mergers

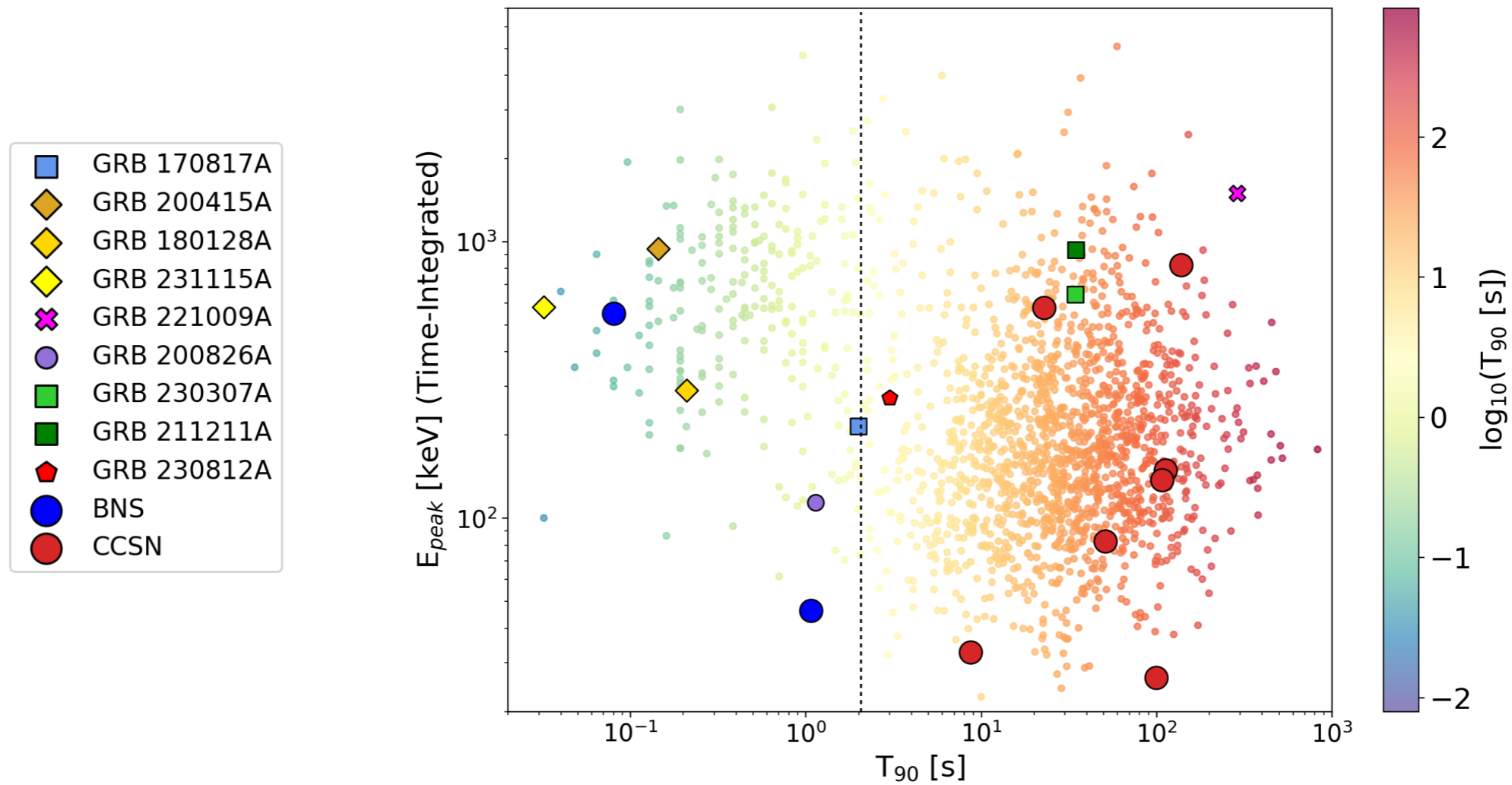
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GRB 221009A: the BOAT

# GRBs classification



## Ultimate goal

Rapid identification of the progenitor of a given event, allowing for specific follow-up observations to occur

# Unsupervised learning for GRBs classification

The application of unsupervised ML techniques for GRBs classification is not new

*Chattopadhyay & Maitra 2017*

*Acuner & Ryde 2018*

*Jespersen et al. 2020*

*Steinhardt et al. 2023*

*Garcia-Cifuentes et al. 2023*

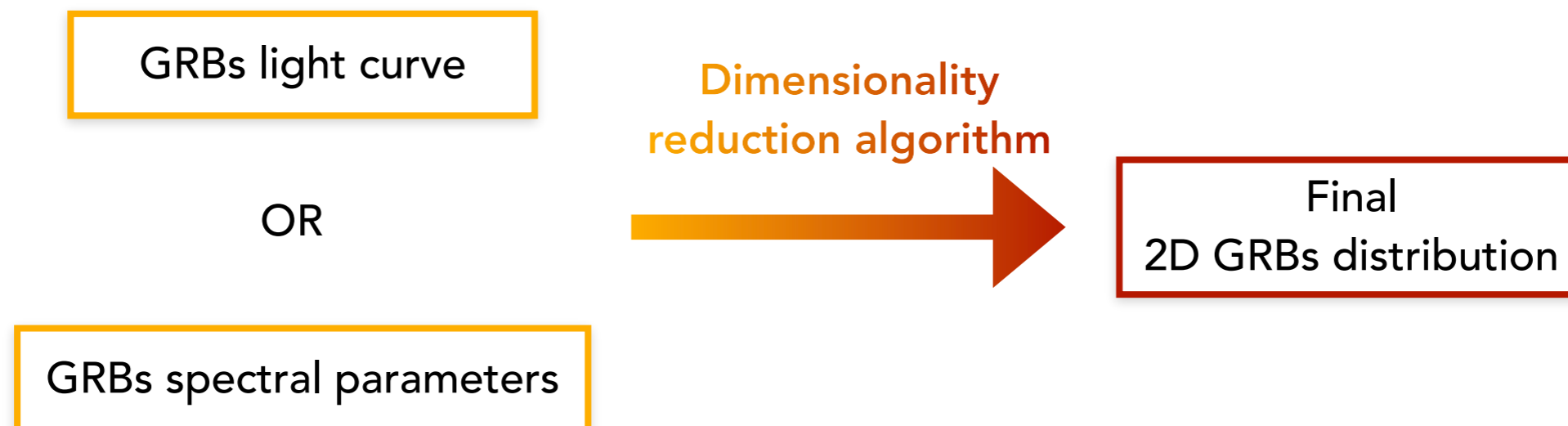
*Dimple et al. 2023*

*Chen et al. 2023*

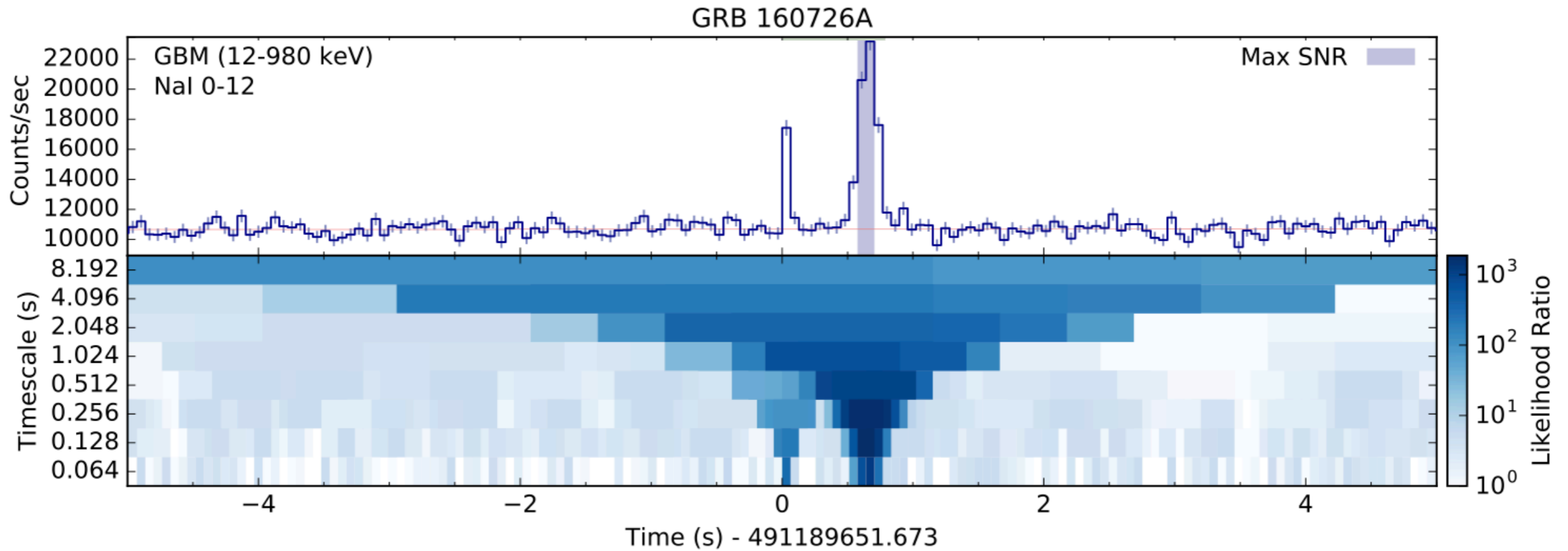
*Mehta & Iyyani 2024*

*Zhu et al. 2024*

*and more!*



# A new input: Waterfall plots



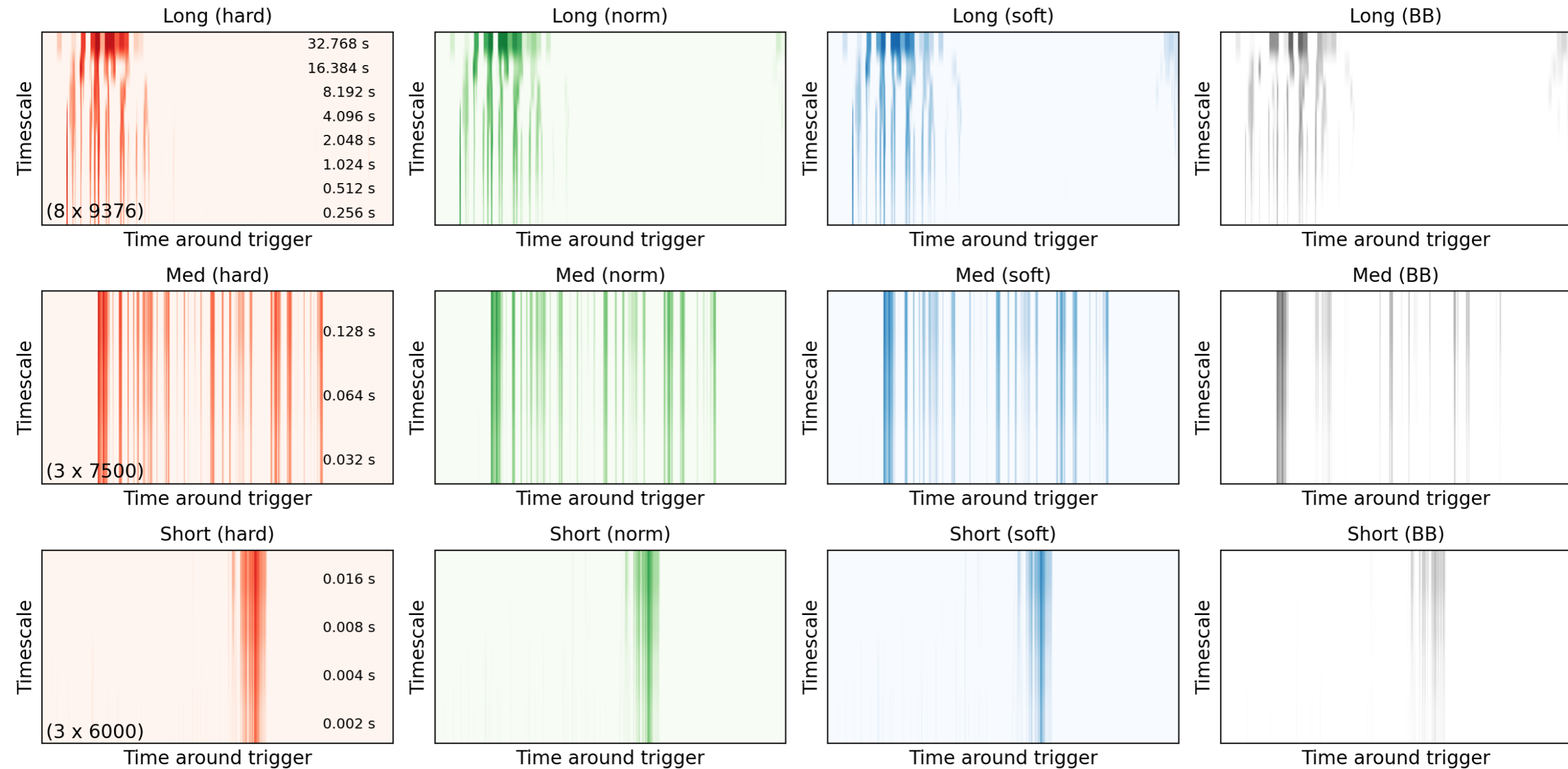
Probability of observed counts being from a source of amplitude  $S$   $P(c|S)$

Probability of observed counts being from the background ( $S=0$ )  $P(c|B)$

Likelihood Ratio  $\ln \left[ \frac{P(c|S)}{P(c|B)} \right]$

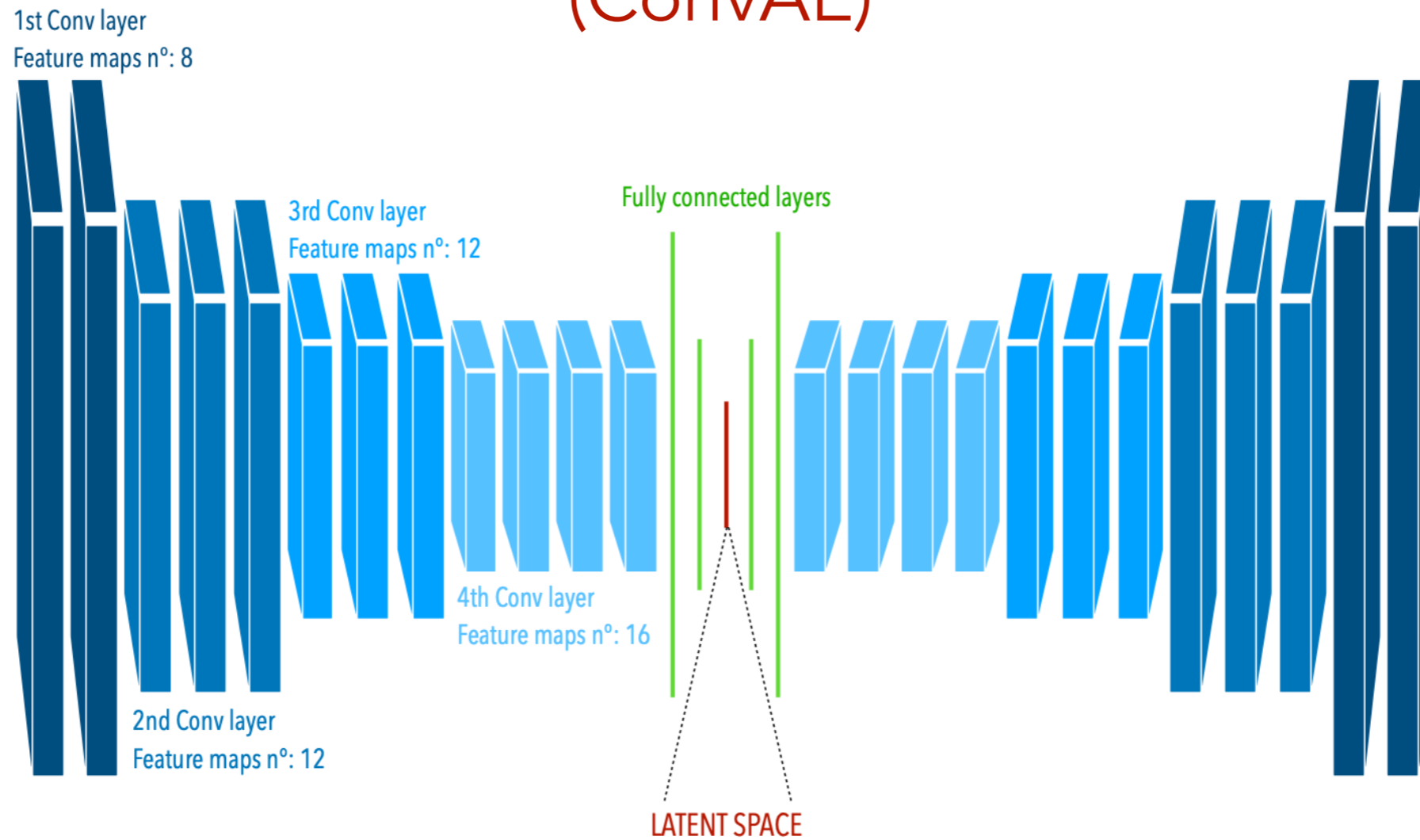
Different spectral shapes representative of typical GRB spectra  
Hard - Normal - Soft - Blackbody

# Waterfall plots for a single GRB



They contain core prompt information relevant for GRB classification, such as duration, temporal variation, pulse structure, spectral hardness and evolution, and how these parameters relate

# Convolutional Autoencoders (ConvAE)



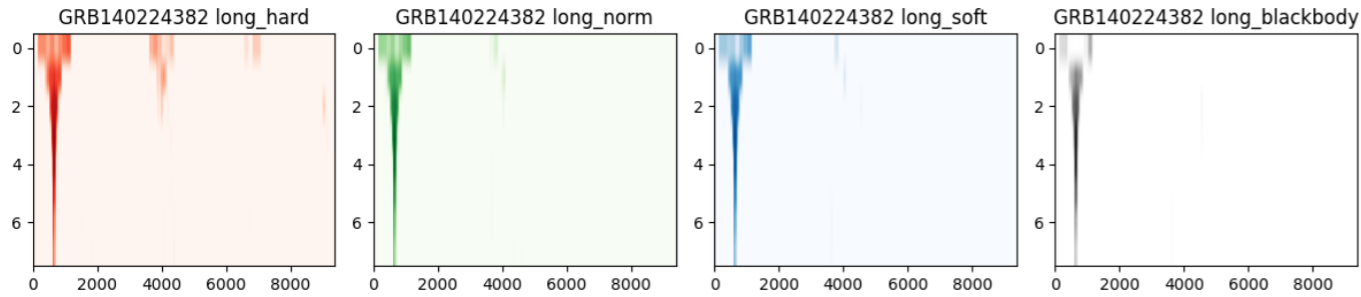
$$Loss = ||x - \hat{x}||^2$$

Input  $\leftarrow$   $x$        $\hat{x}$   $\rightarrow$  Output

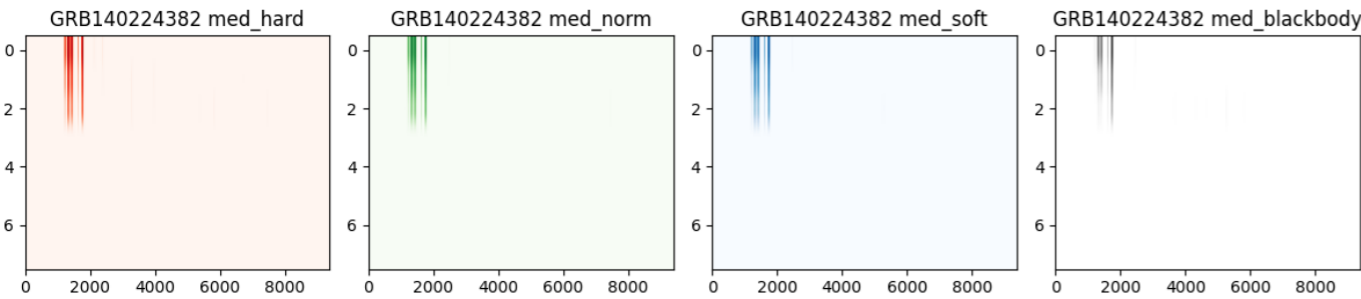
Main goal:  
Learn input images representations in a lower dimensionality latent space  
(latent space dimension = 10D)

# Our model

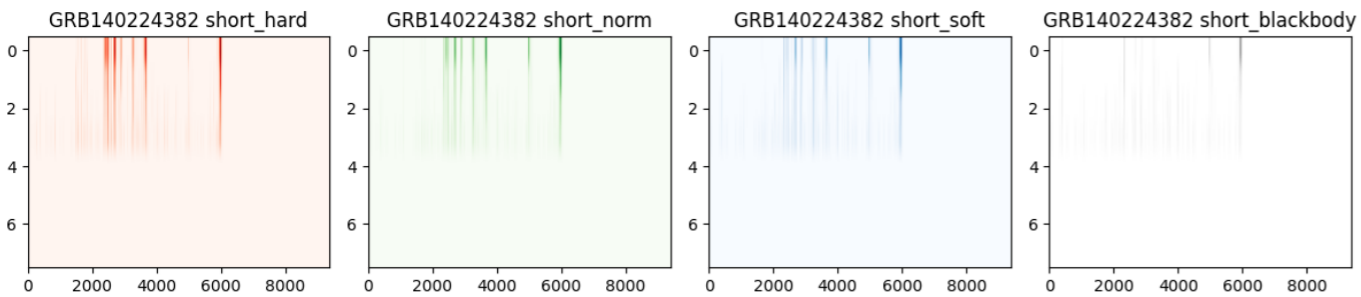
Dataset: 2371 GRBs (all GBM triggers from Jan 2013 to May 2023)



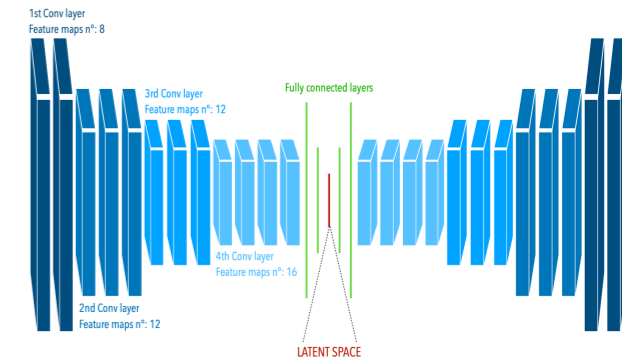
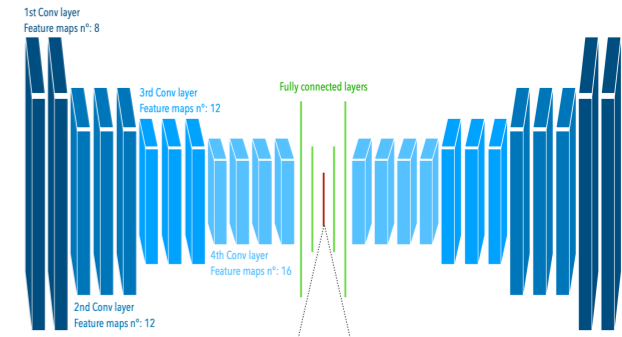
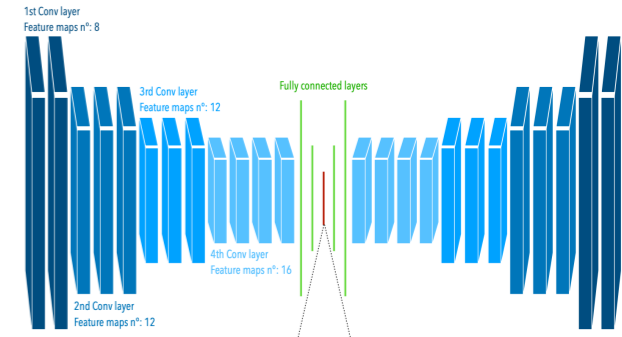
ConvAE 1 — Long timescales  
(4 images, 8x9376)



ConvAE 2 — Medium timescales  
(4 images, 3x7500)



ConvAE 3 — Short timescales  
(4 images, 3x7500)



We train 3 ConvAEs, one for each timescale

Final latent space = Long timescales + Medium timescales + Short timescales

30D = 10D + 10D + 10D

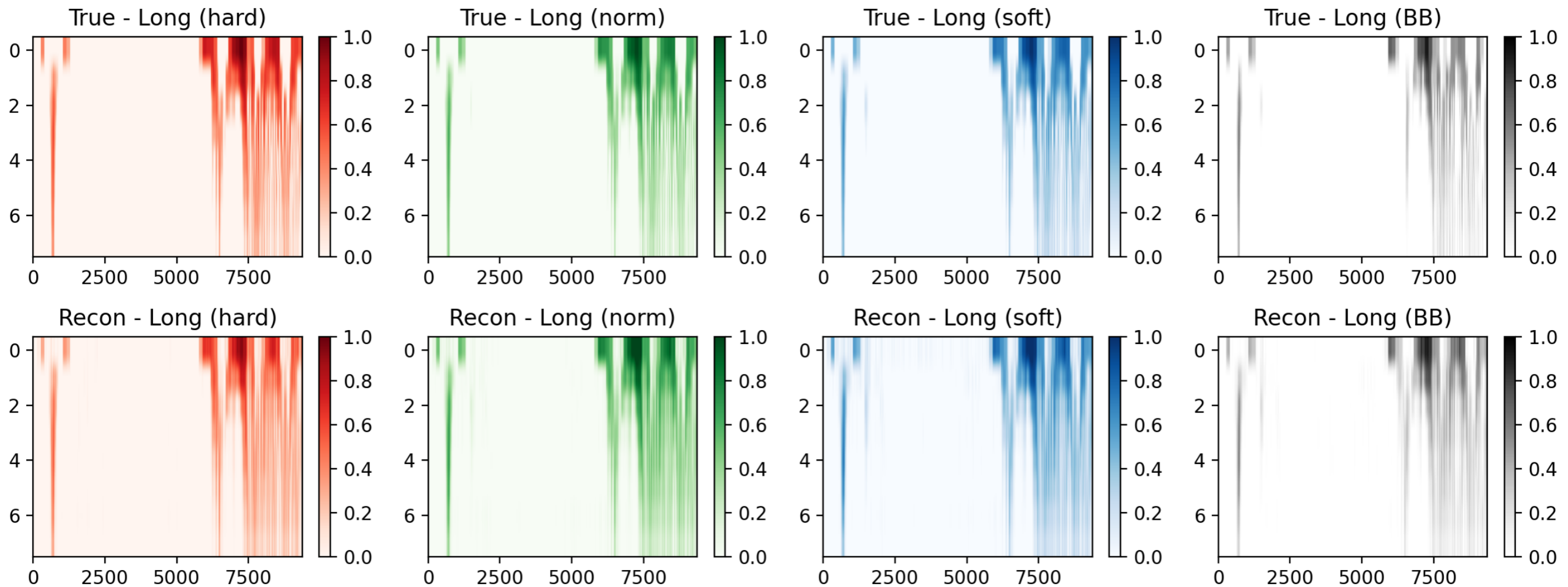


# Evaluate the performances

## QUALITATIVELY

Evaluation of the similarity between the input and output images for random subsamples of the GRBs dataset

### GRB 221009A

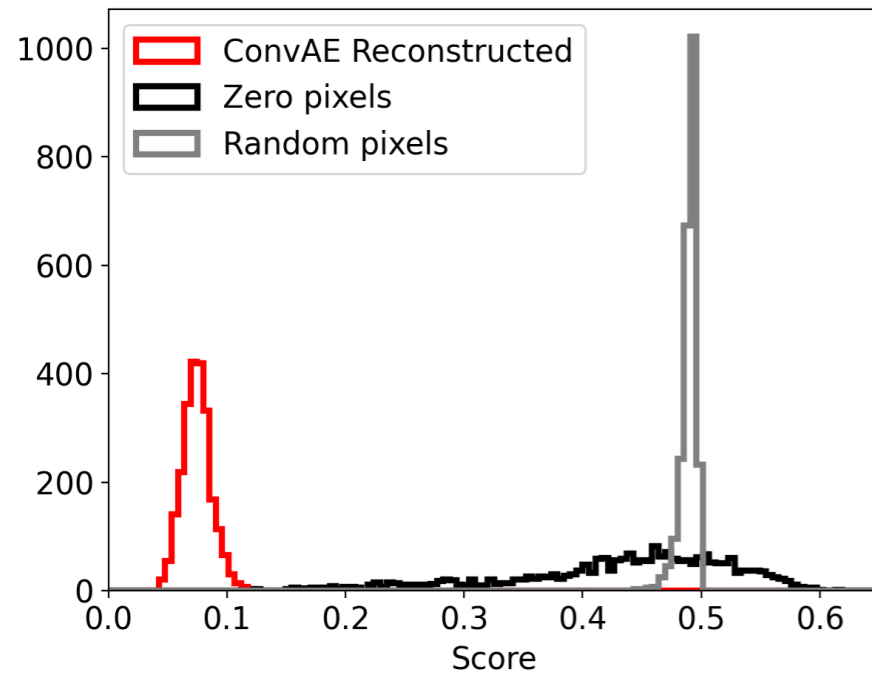


# Evaluate the performance

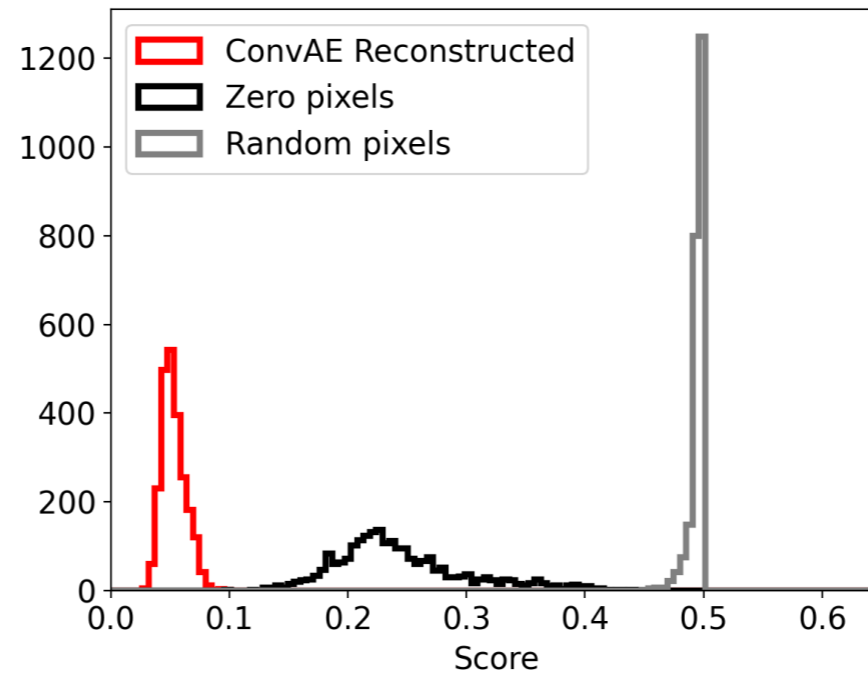
## QUANTITATIVELY

Evaluation of the mean error between original input and reconstructed output for each GRB

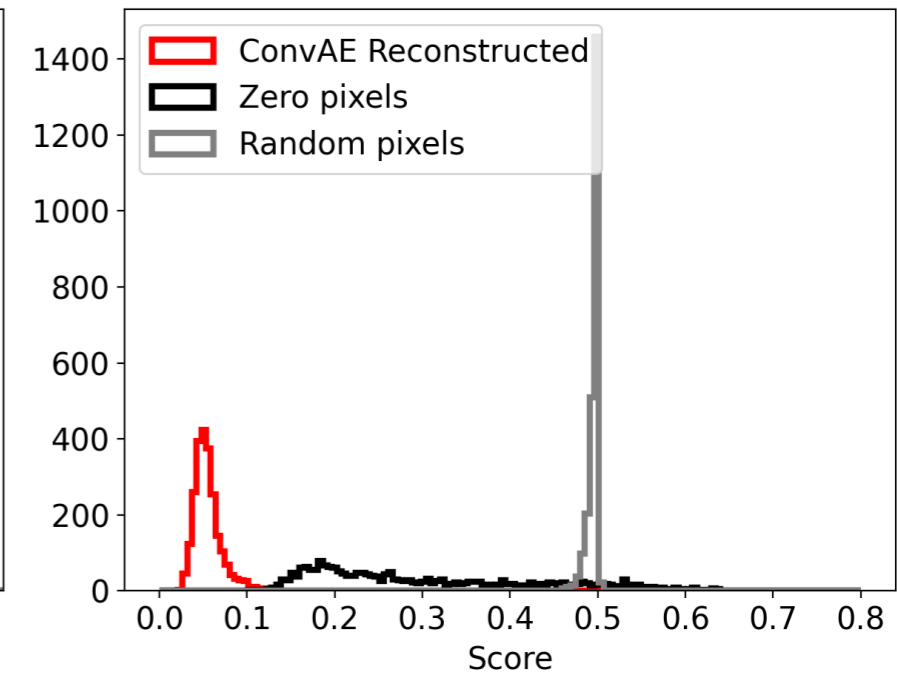
*Long timescales*



*Medium timescales*



*Short timescales*



# Dimensionality reduction with UMAP

Once the ConvAEs are trained, we have 30 variables for each GRB (10 for each timescale)

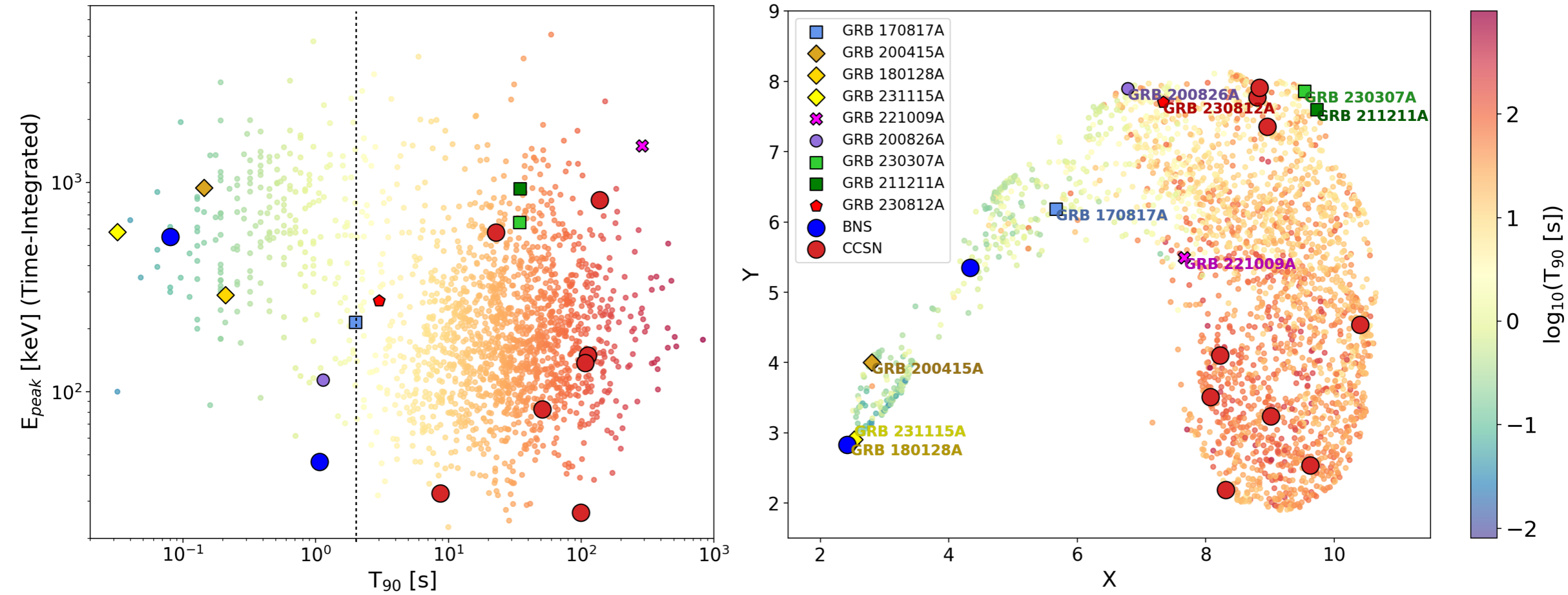
We further reduce the dimensionality of the latent space through UMAP



UMAP reduces dimensionality by preserving data structure through manifold learning and neighbor graphs



# Preliminary results



Interactive plot

[https://nmik.github.io/SmartWaterfalls/plotly/grbs\\_mv5umap\\_plotly\\_v0.html](https://nmik.github.io/SmartWaterfalls/plotly/grbs_mv5umap_plotly_v0.html)

# Future prospects

**Optimization of the waterfall plots generation**  
(polynomial model of the detector background rates, account for the spacecraft motion when building the response matrix)

**Optimization of the ML algorithm**  
(Variational Autoencoder, Adversarial Autoencoder, Semi-supervised clustering)

**Automatization of the pipeline**  
(Fast association of new GRB triggers to its position in the final 2D distribution)

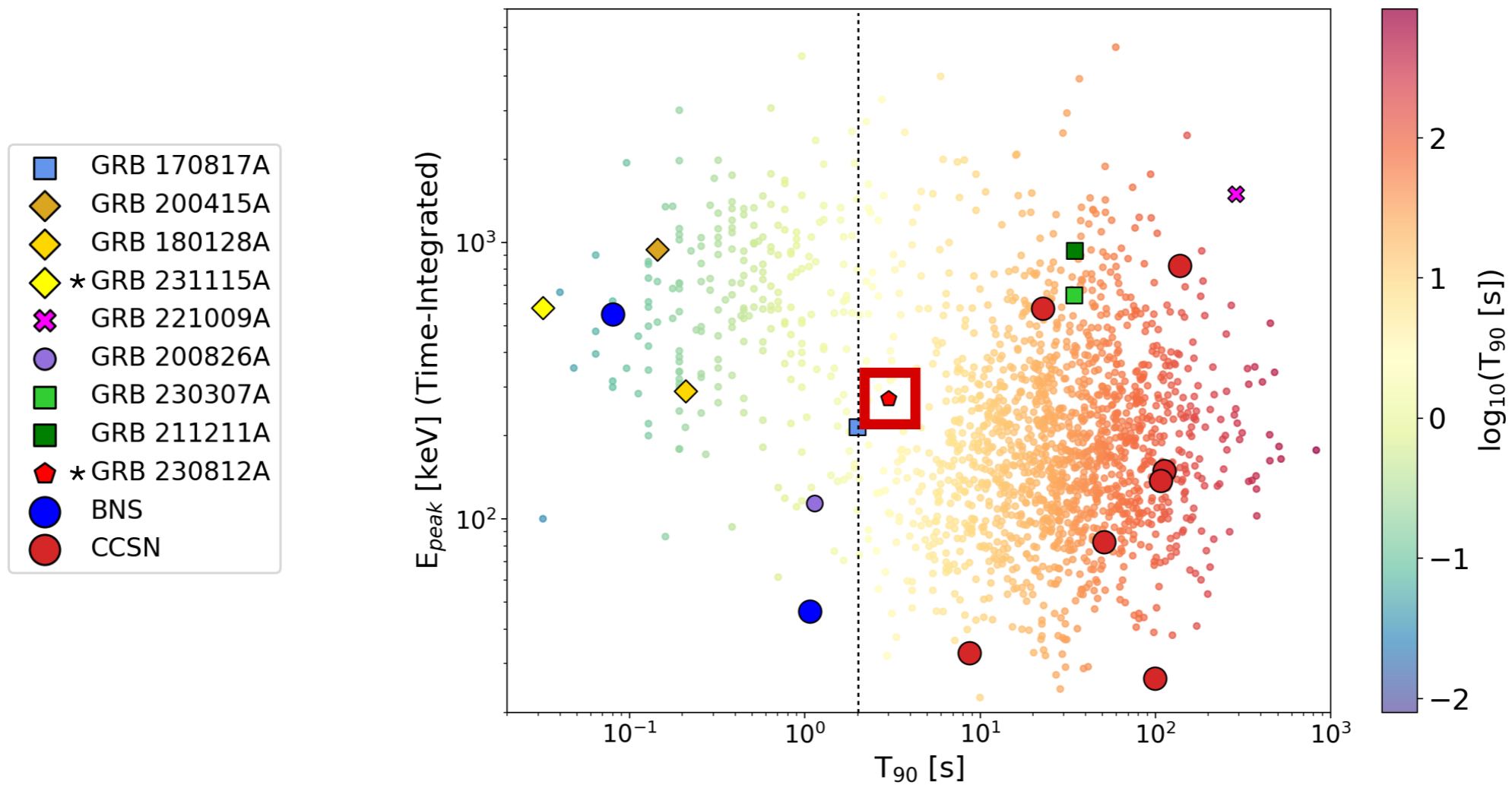
*Prompt GRB recognition through Waterfalls and Deep Learning*

<https://arxiv.org/pdf/2406.03643>

# Backup

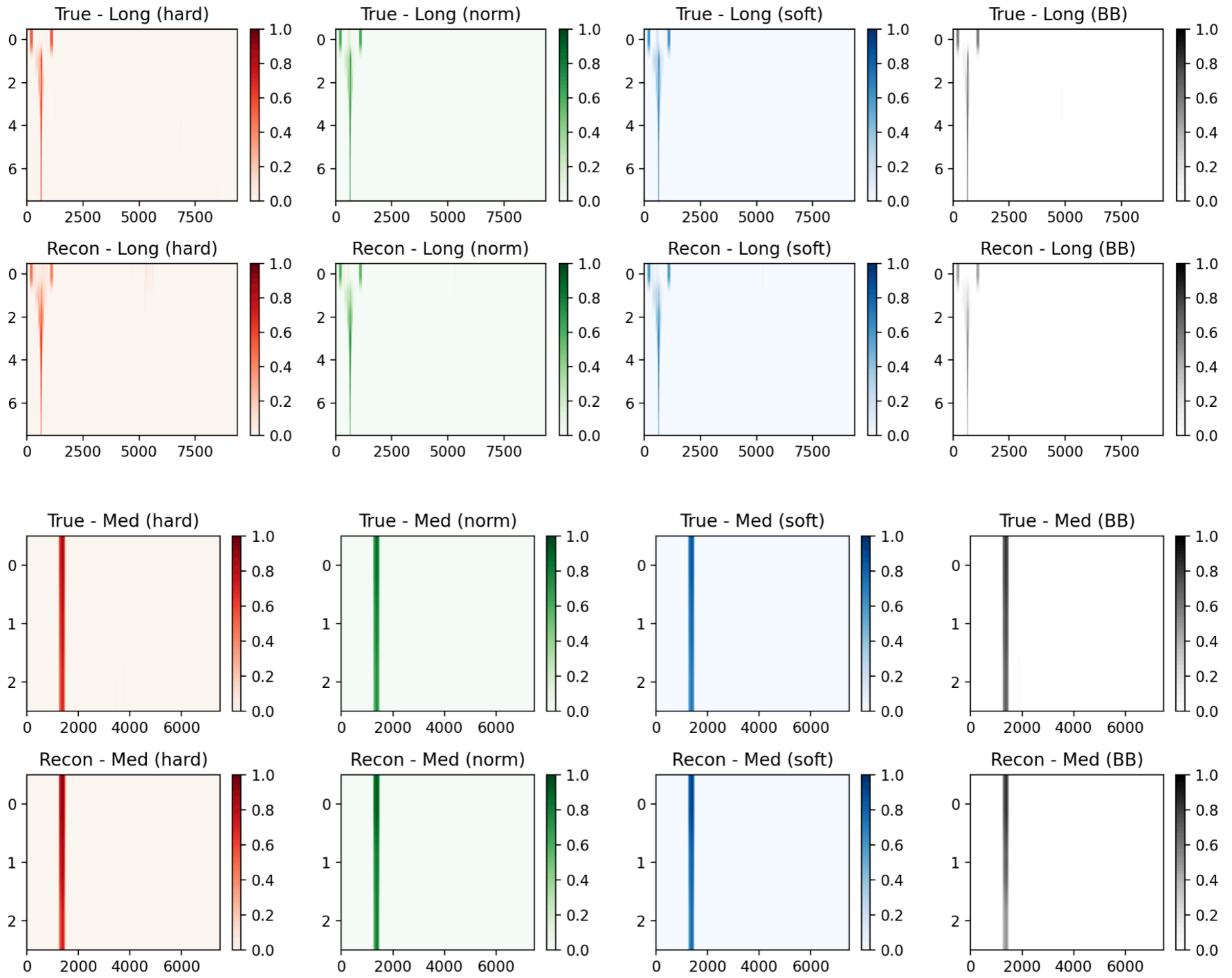
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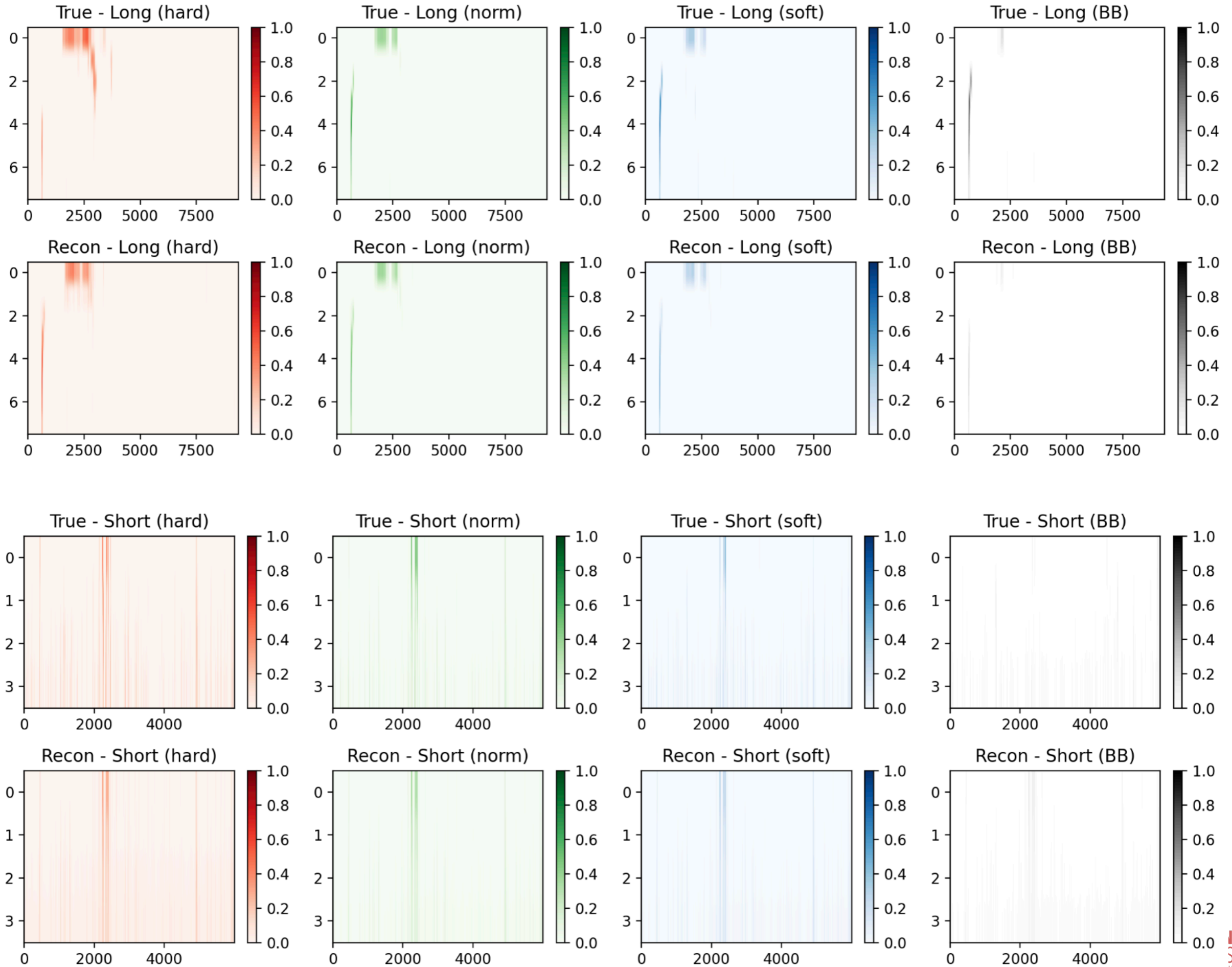
GRB 230812: a close, quite short collapsar

# GRB 200826A

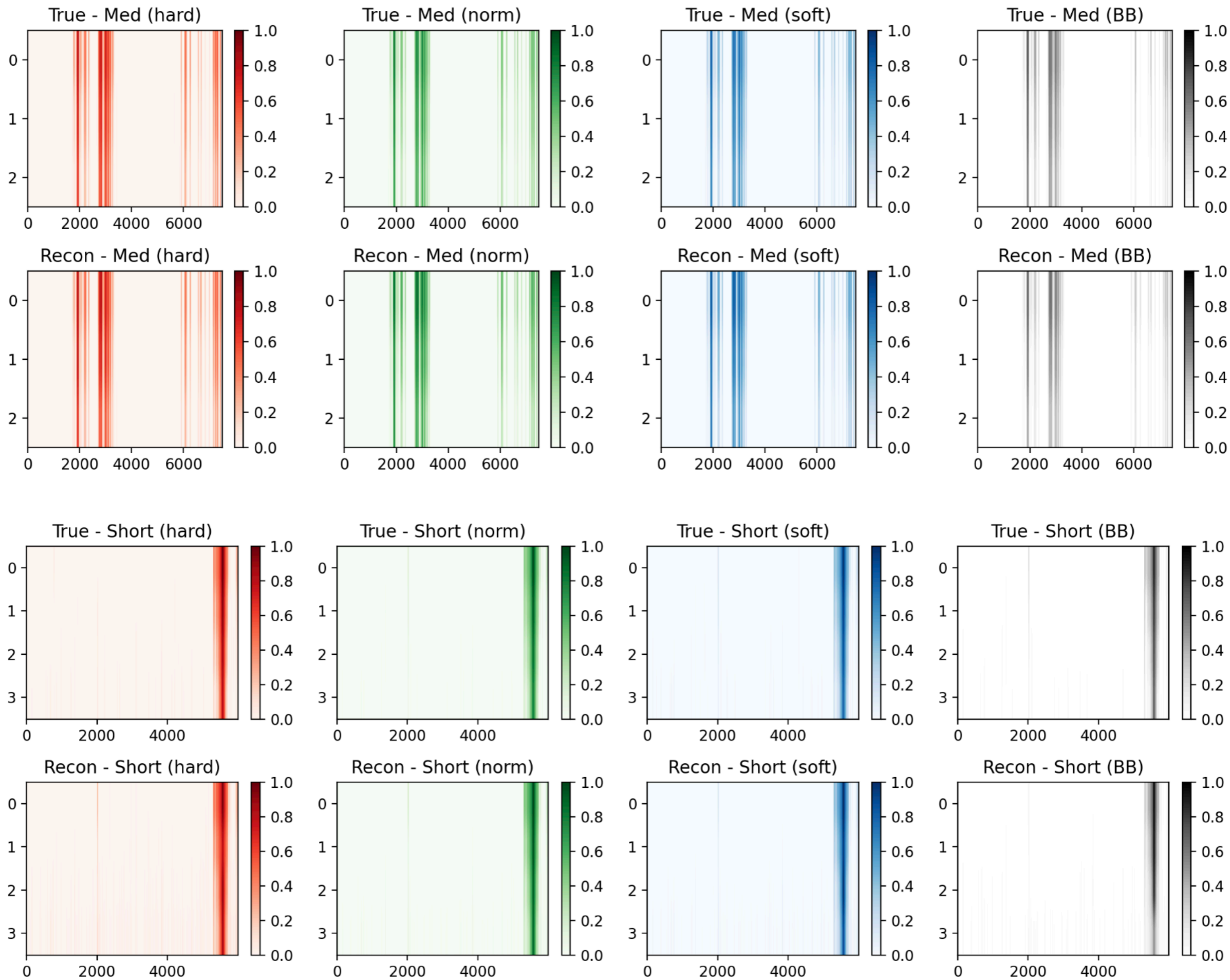




# GRB 170817A



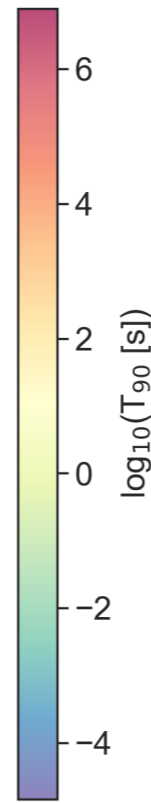
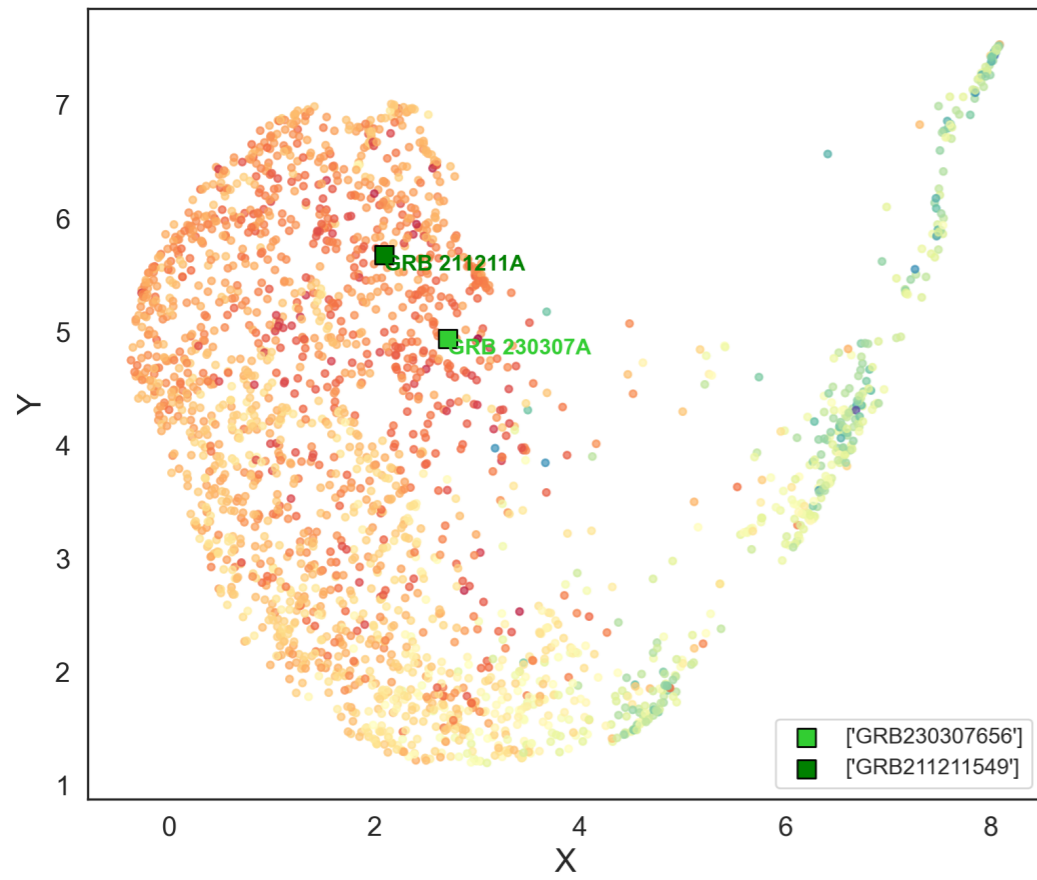
# GRB 211211A



# Single timescale distributions

LONG

MEDIUM



SHORT

