The 7th international conference on particle physics and astrophysics ICPPA–2024

Uncovering Anomalies in Gamma-Ray Bursts

A Deep Learning Analysis of X-Ray Afterglows

Moscow, 25 October 2024

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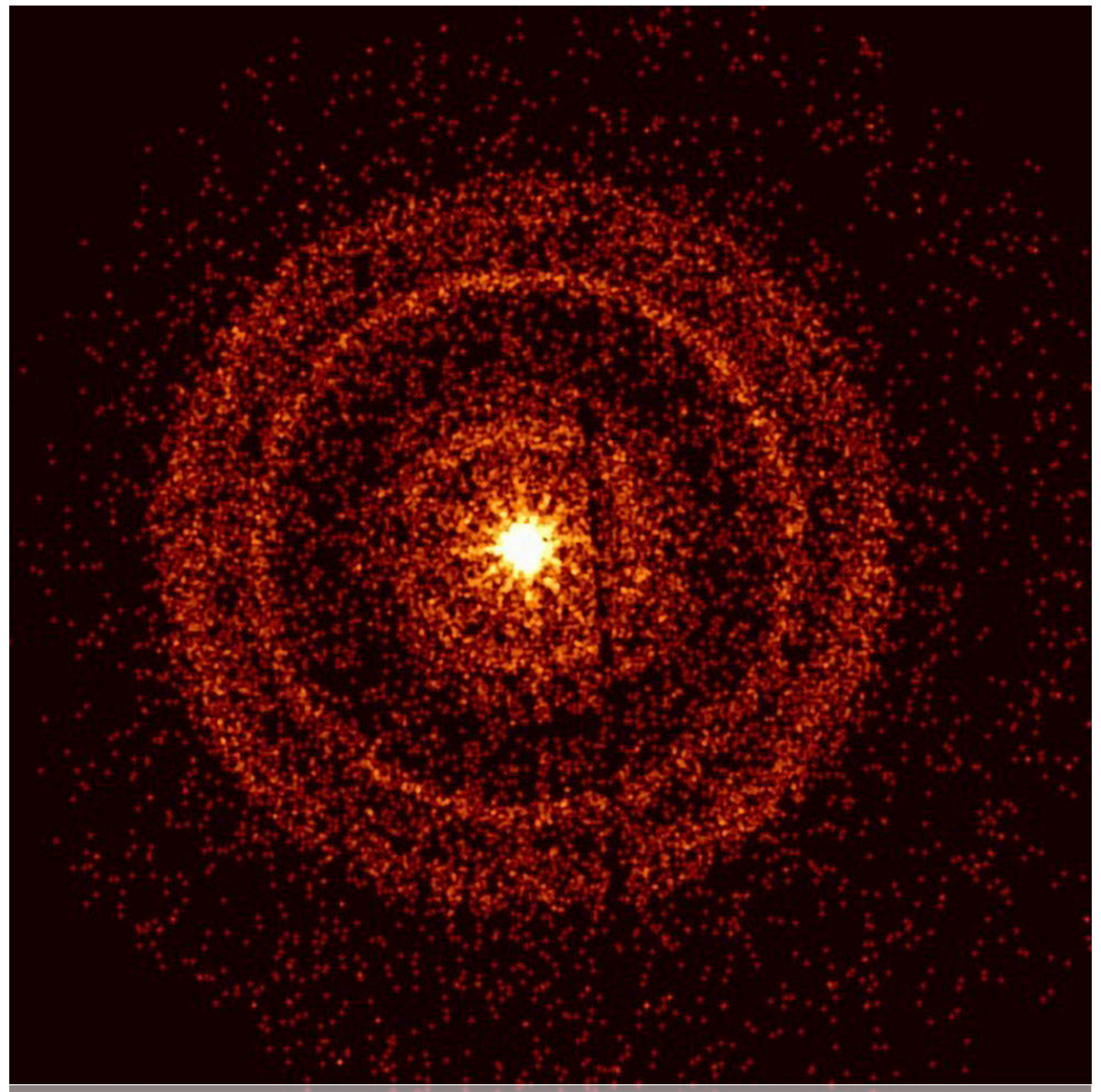
Introduction

Gamma-Ray Bursts (GRBs)



- ✦ Very energetic (up to ~10^{57} erg)

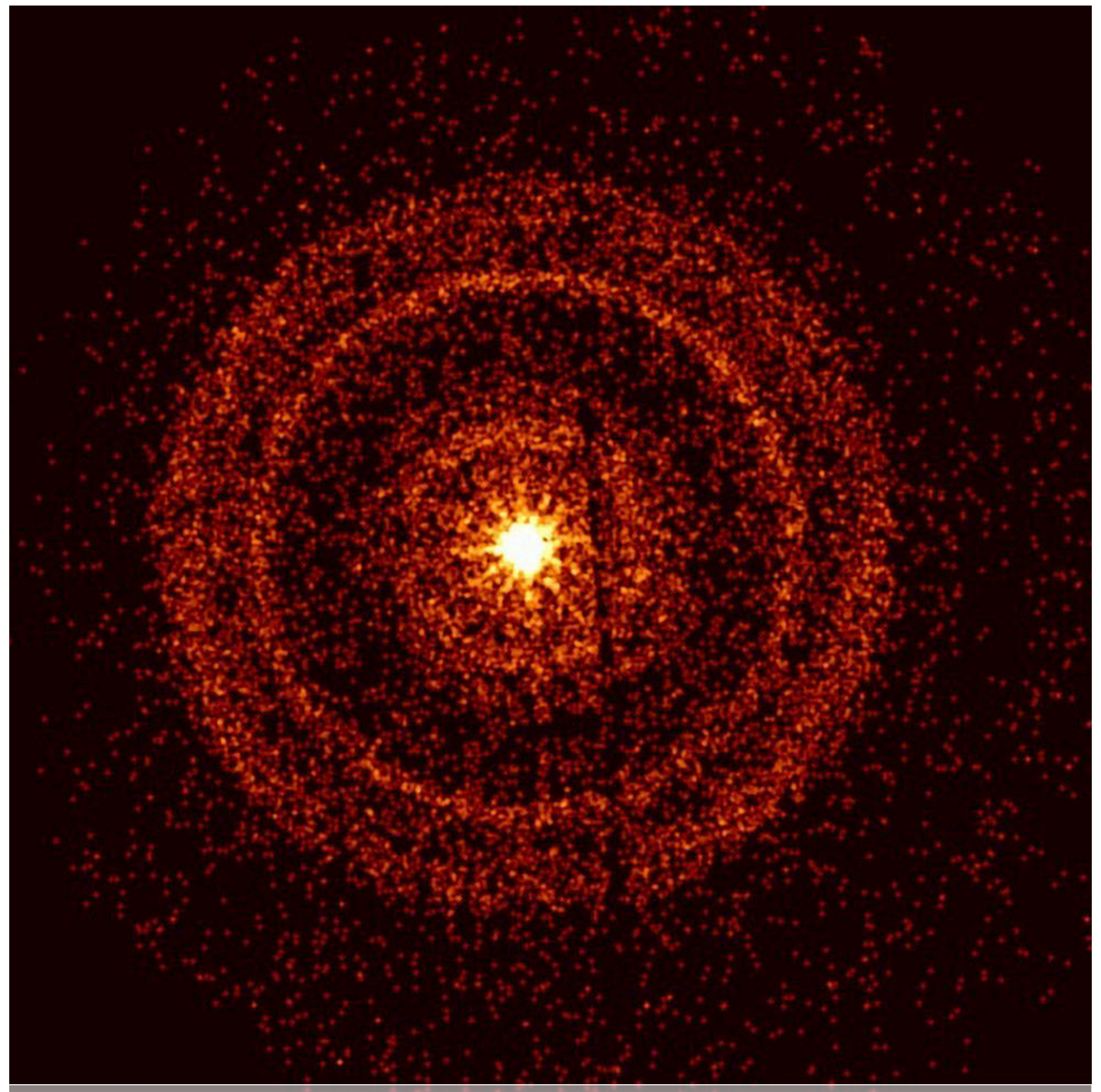
  & cosmologically-distant (z ~ 1) events
- ✦ O(10^3) events detected to date
- ✦ The GRB physics is not yet completely understood:

  at least 2 mechanisms, but there is strong evidence for >2 mechanisms
- ✦ GRB = *Prompt* emission [the burst itself, typically keV…GeV range] +

  + *Afterglow* emission [long-lasting, Gamma/X-rays+optical+radio]

Introduction

Gamma-Ray Bursts (GRBs)



- *Prompt* emission: high variability!

    difficult to analyze statistically

- *Afterglow* emission: high universality!

    statistical analysis is possible, but still difficult

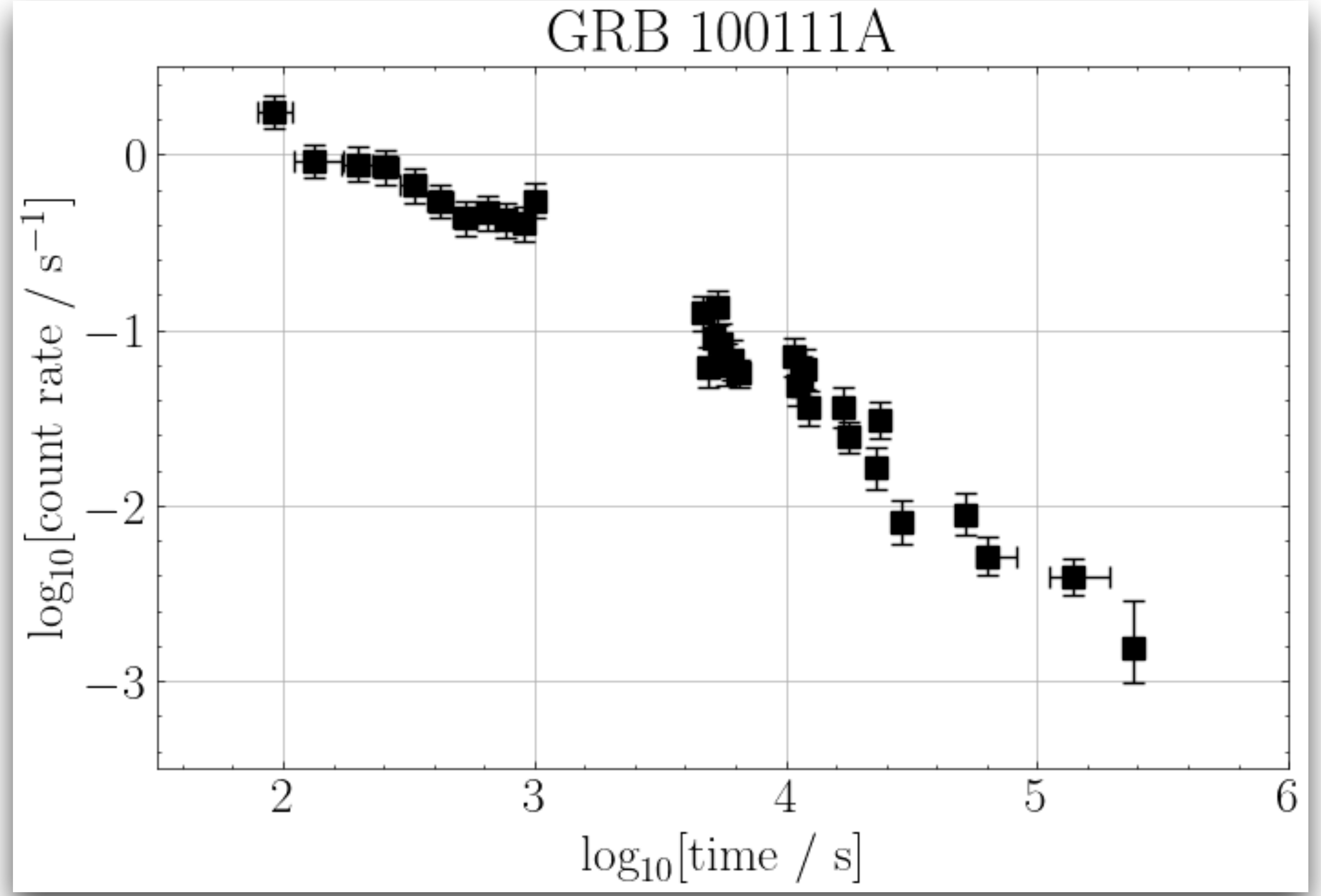
- State-of-the-art approaches are mostly phenomenological

- The lack of reliable feature extraction technique is a motivation

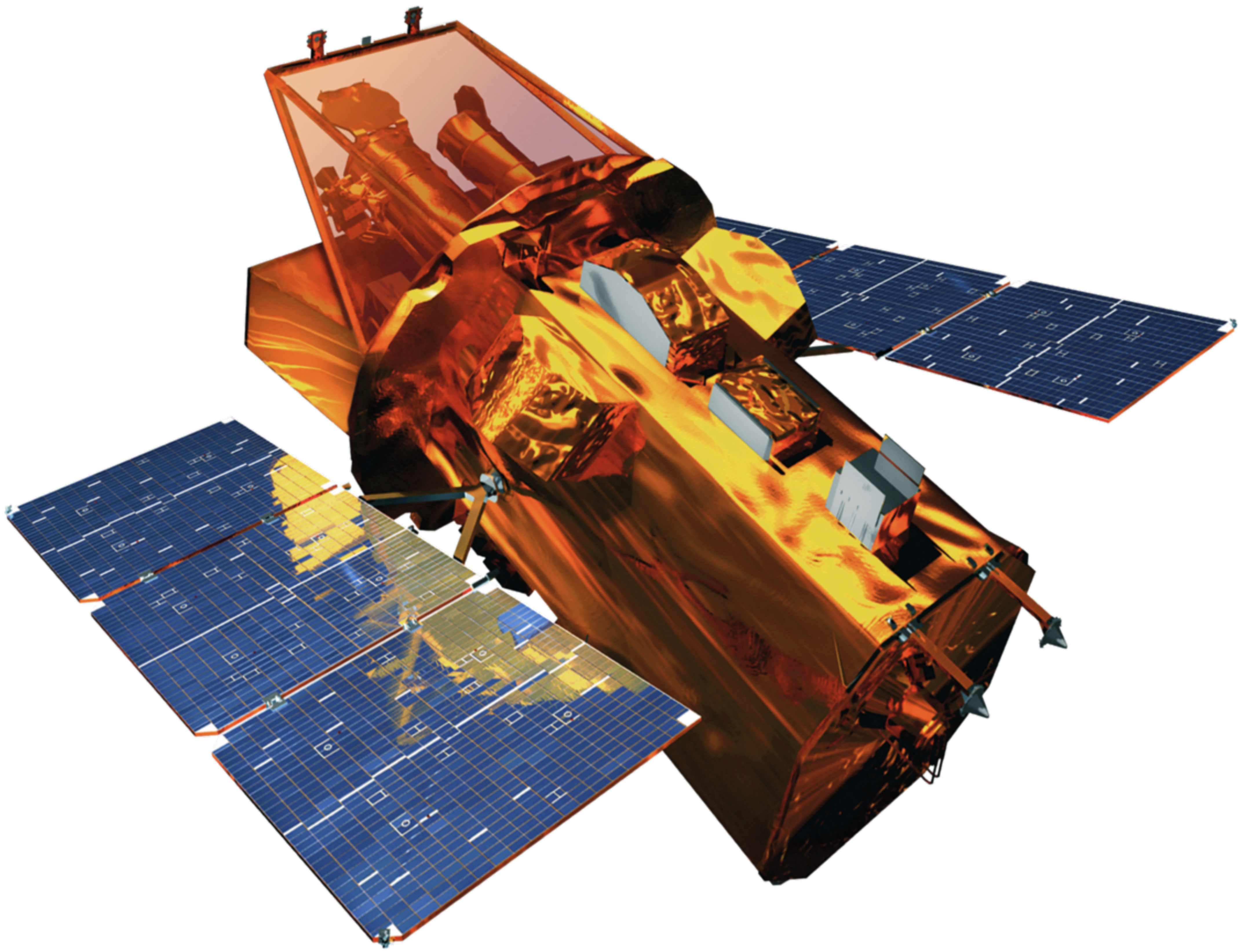
    to implement a Deep Learning

GRB X-Ray Afterglow Light Curves

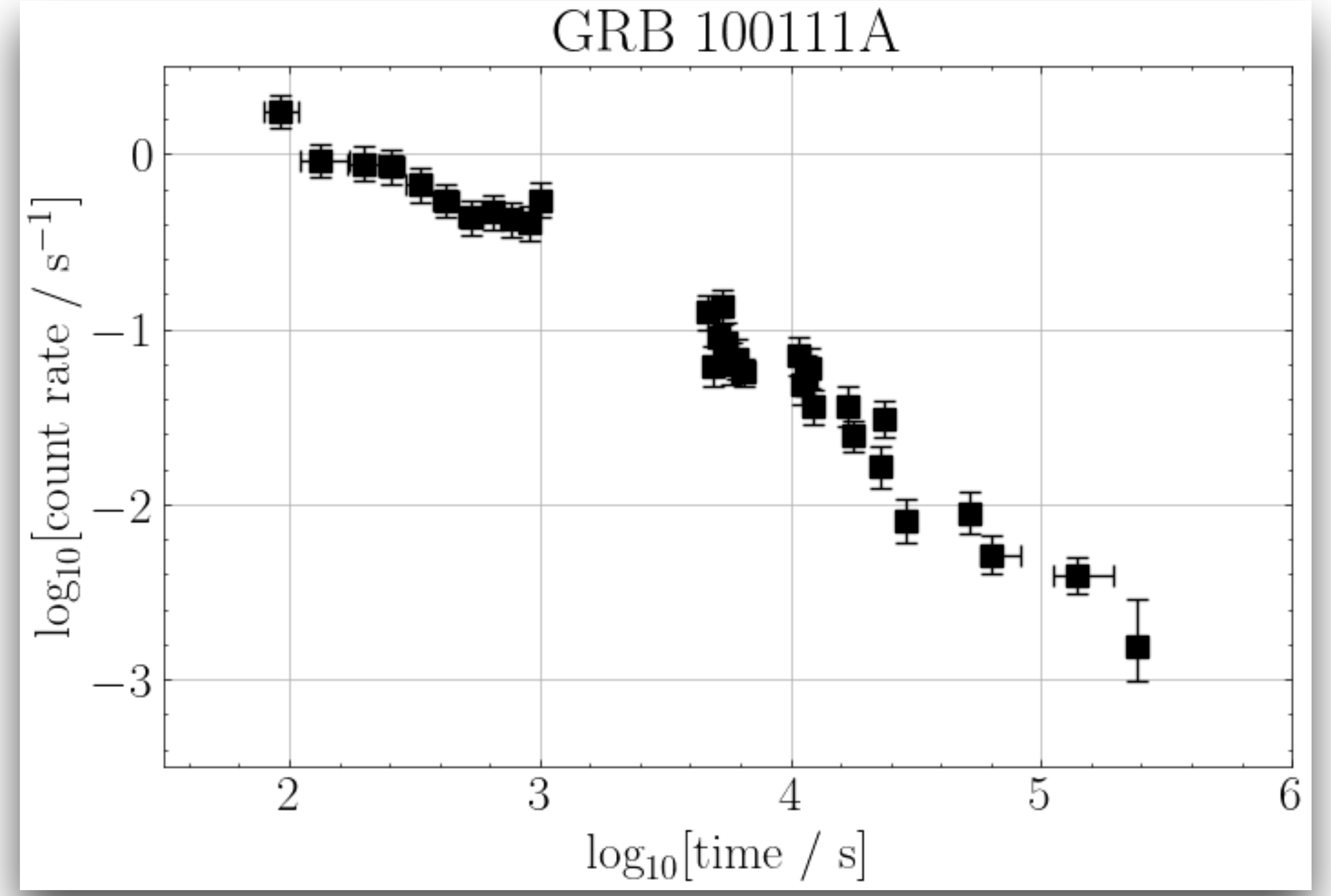
Swift–X-Ray Telescope light curve repository [www.swift.ac.uk/xrt_curves/]



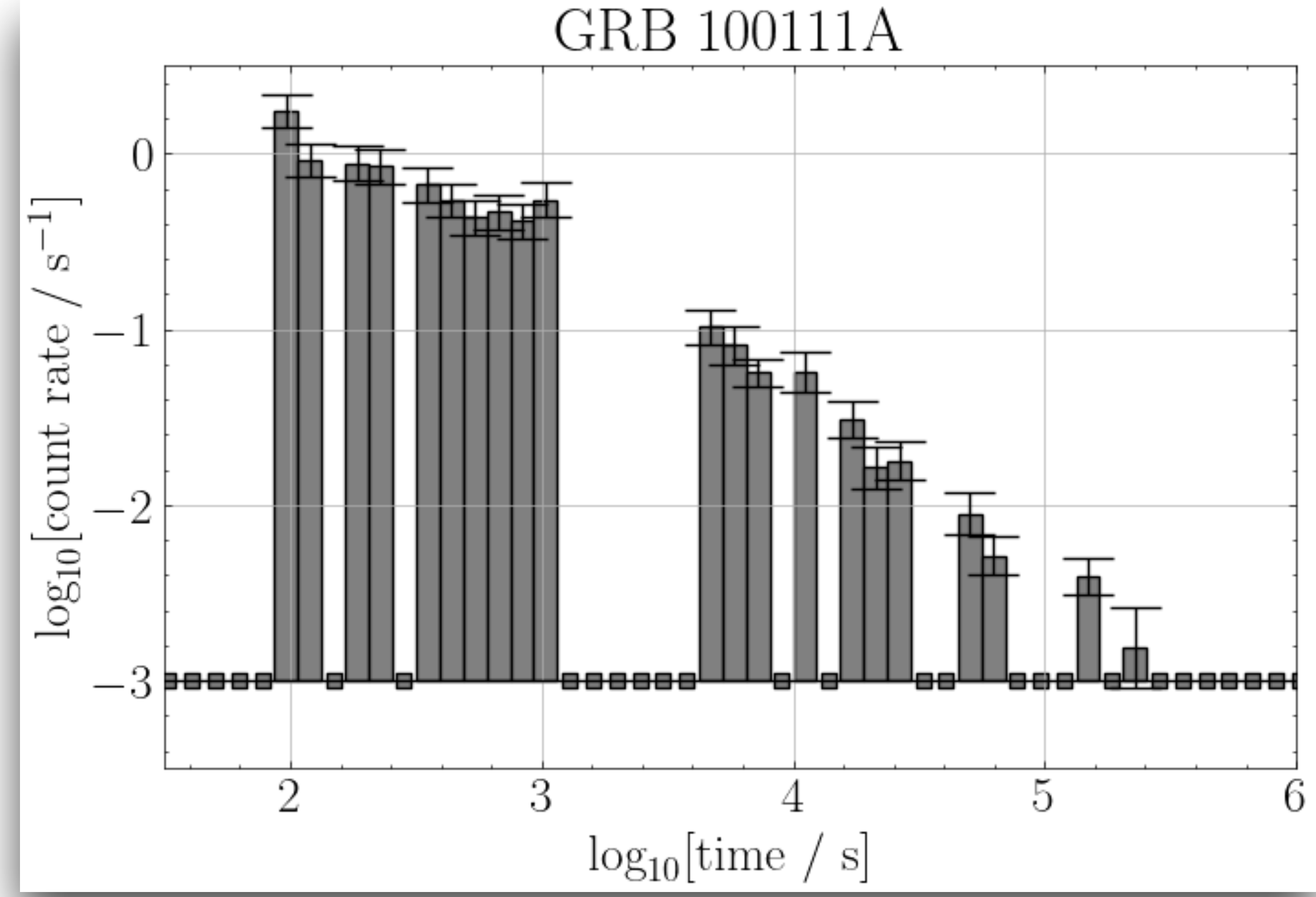
0.3–10 keV count rate vs trigger time



Data preprocessing

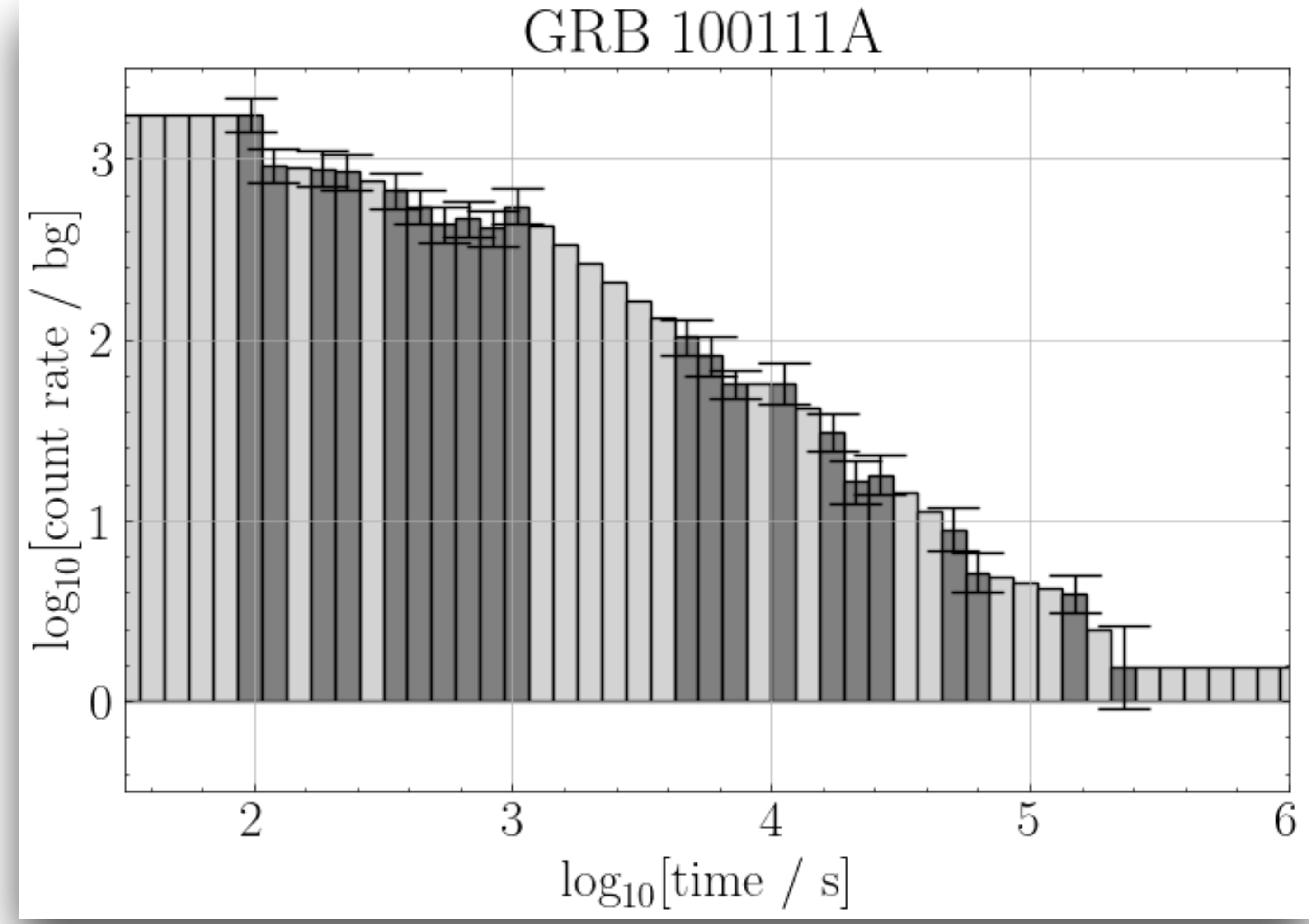


(1) rebinning to a regular grid



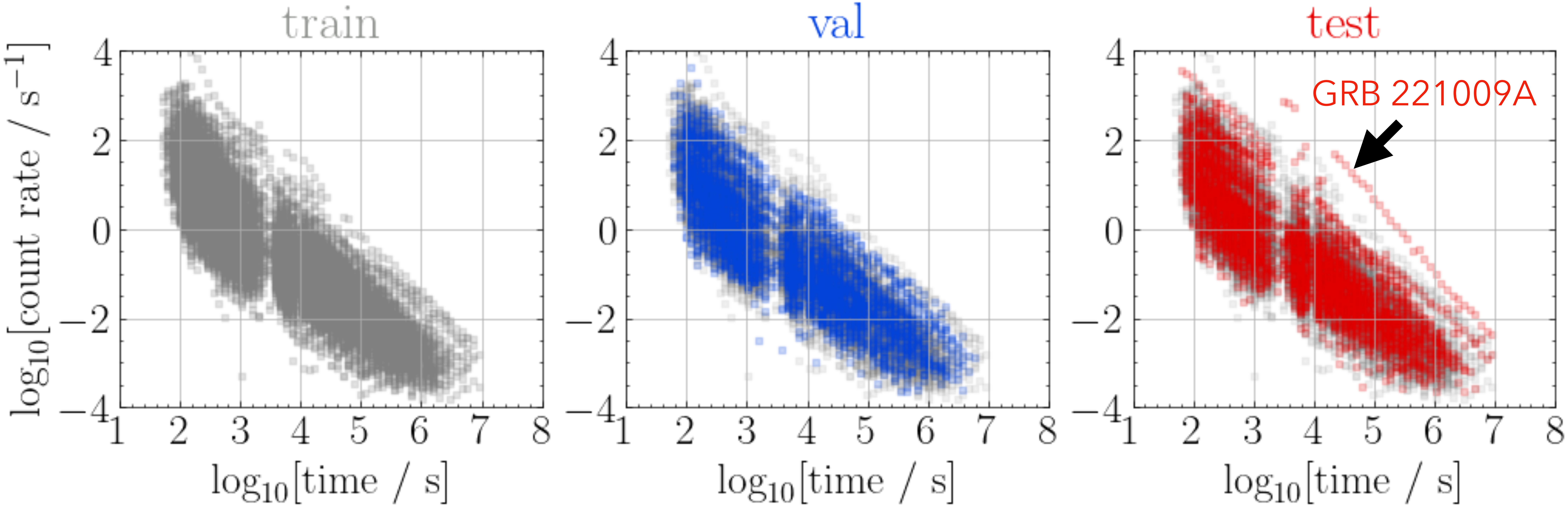
(2) filtering bad entries and interpolation

(3) log[count rate * s] → log[count rate / bg]



Dataset train–val–test split

812 ÷ 174 ÷ 175 light curves (~ 0.70 ÷ 0.15 ÷ 0.15)



We maintain a uniform distribution by the year of detection

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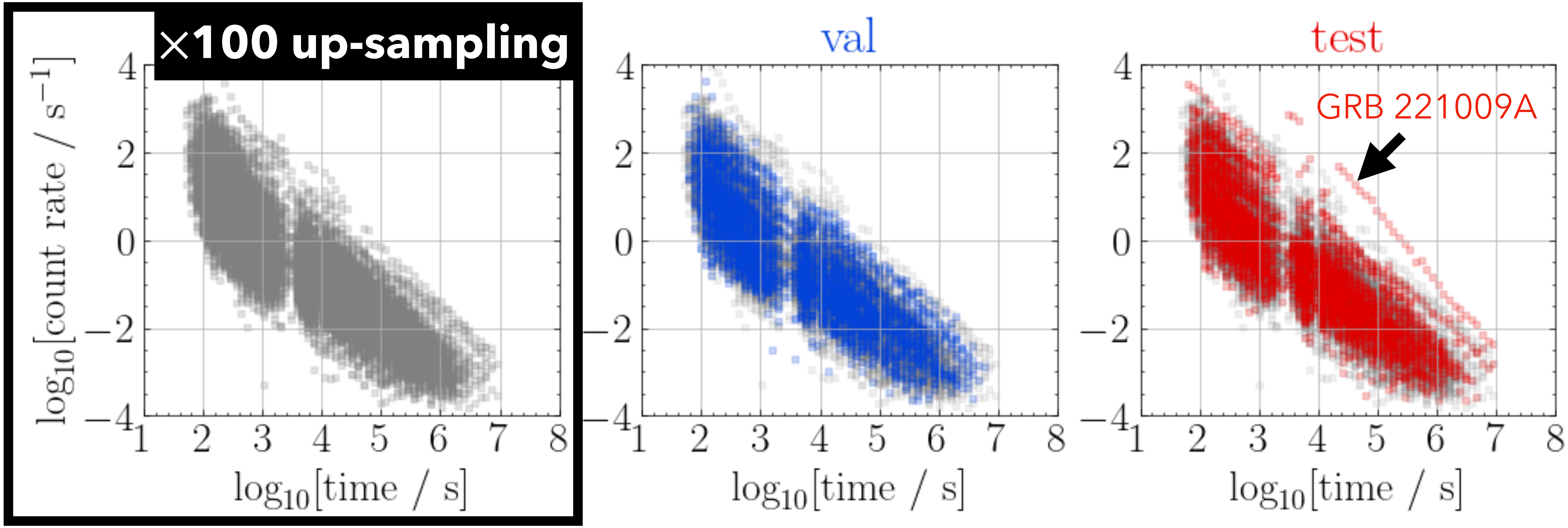


We maintain a uniform distribution by the year of detection

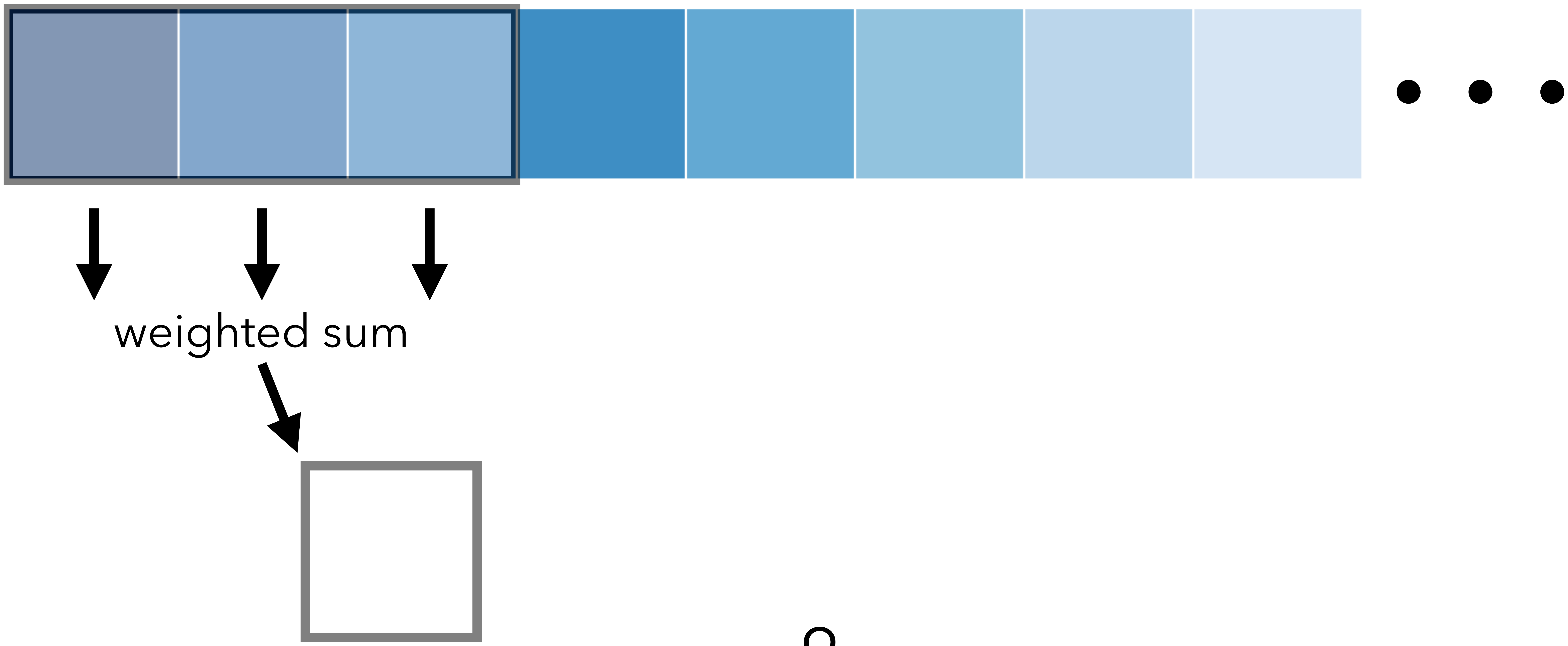
Auto-encoder with 1D Convolutional layers

The aim is to encode the most important features + reconstruct the LC

log [count rate / bg] time series

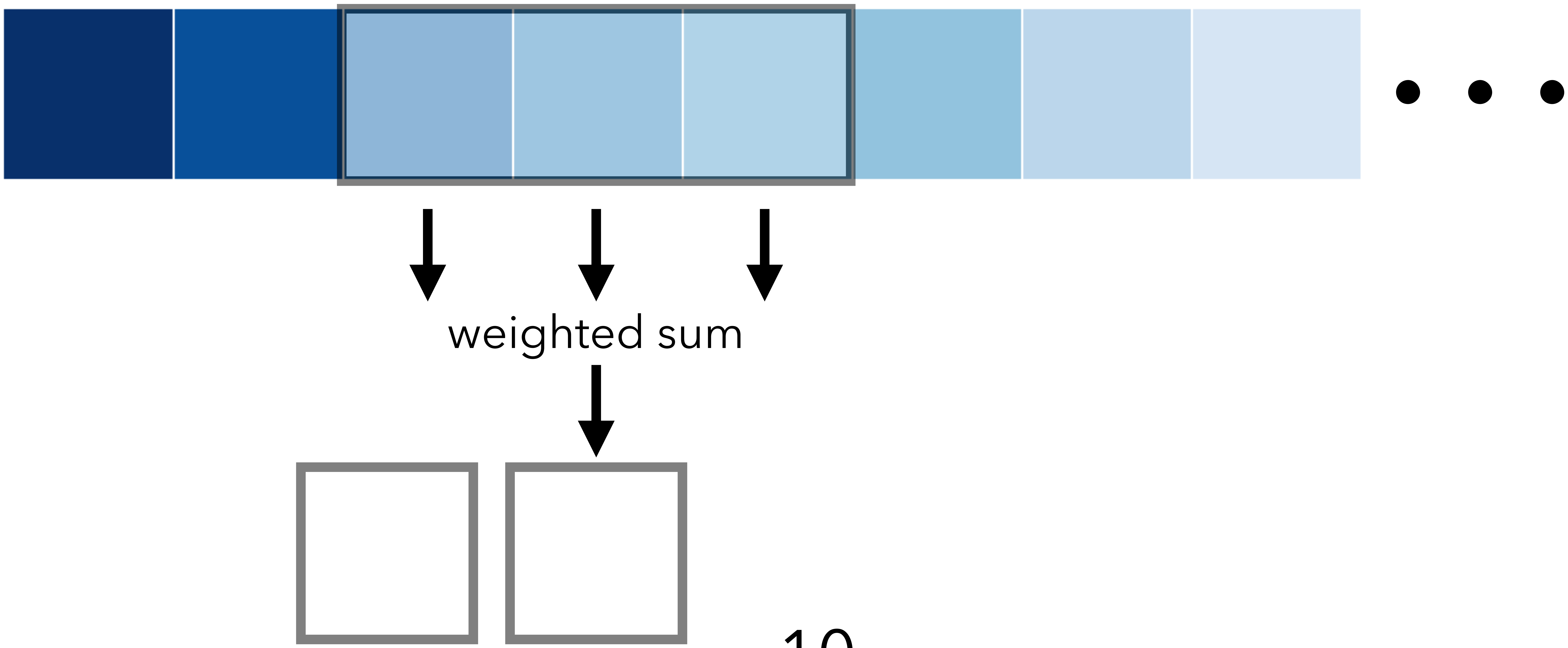
Auto-encoder with 1D Convolutional layers

The aim is to encode the most important features + reconstruct the LC



Auto-encoder with 1D Convolutional layers

The aim is to encode the most important features + reconstruct the LC



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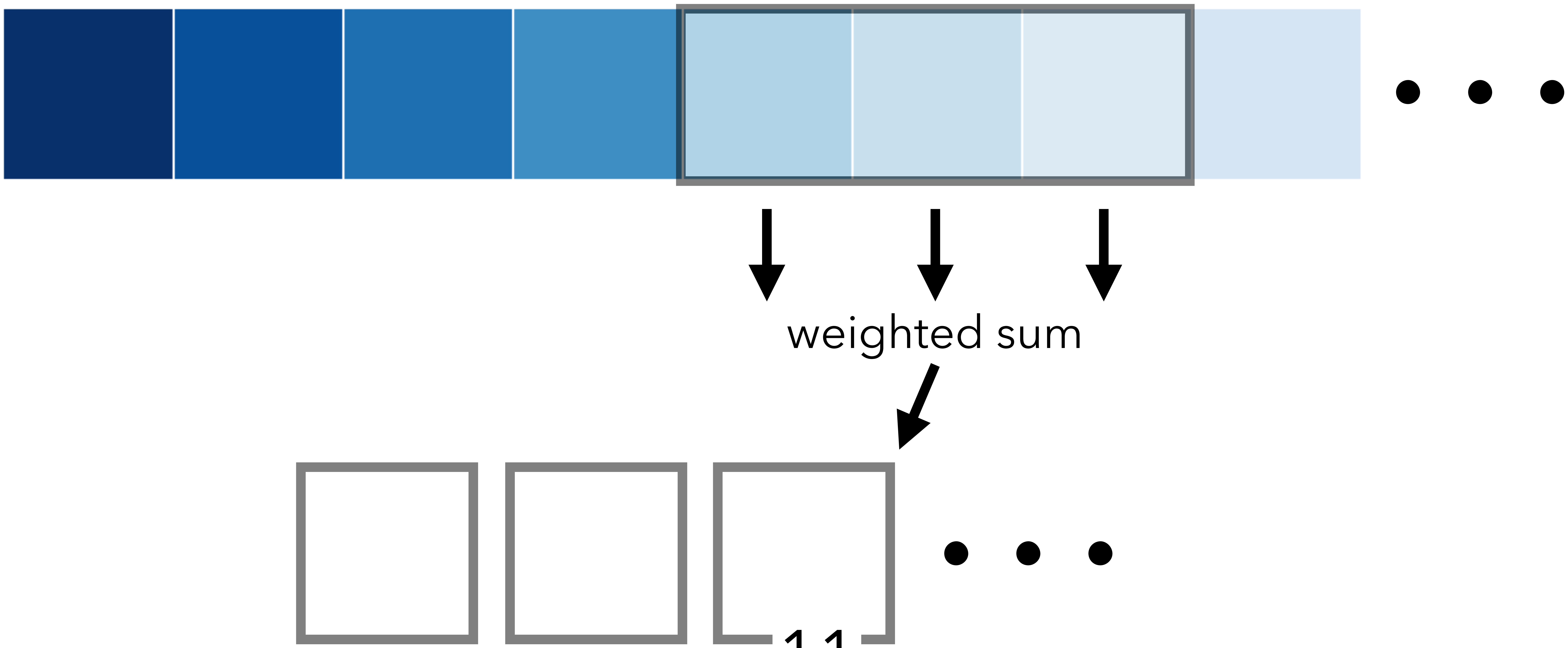
The aim is to encode the most important features + reconstruct the LC



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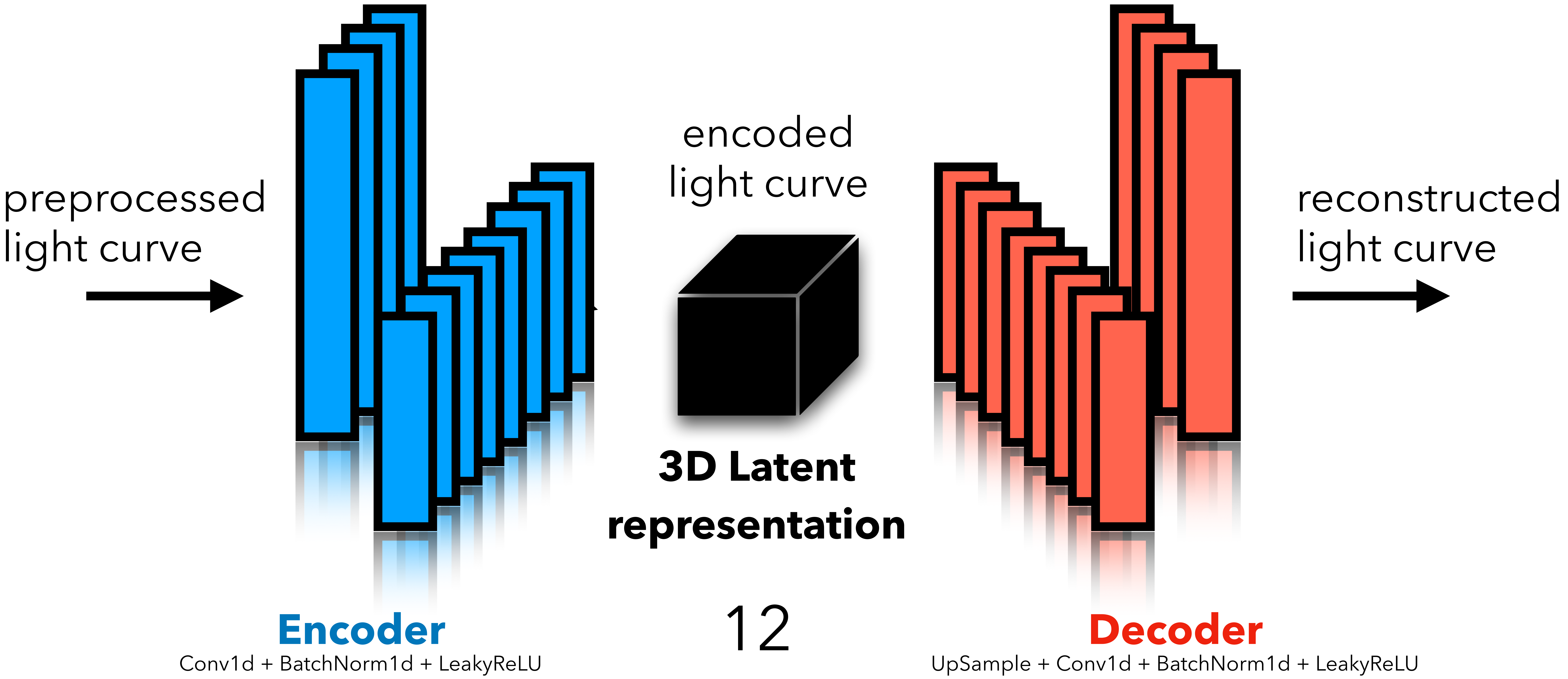
The aim is to encode the most important features + reconstruct the LC



Loss function

$$\text{Loss} = \left\langle \frac{(y_t^{\text{reco}} - y_t)^2}{\sigma_{y_t}^2} \right\rangle + \delta \cdot \left\langle \left| y_{t+\Delta t}^{\text{reco}} - y_t^{\text{reco}} \right| \right\rangle + \kappa \cdot \text{KL Divergence Loss}\,(y^{\text{latent}})$$

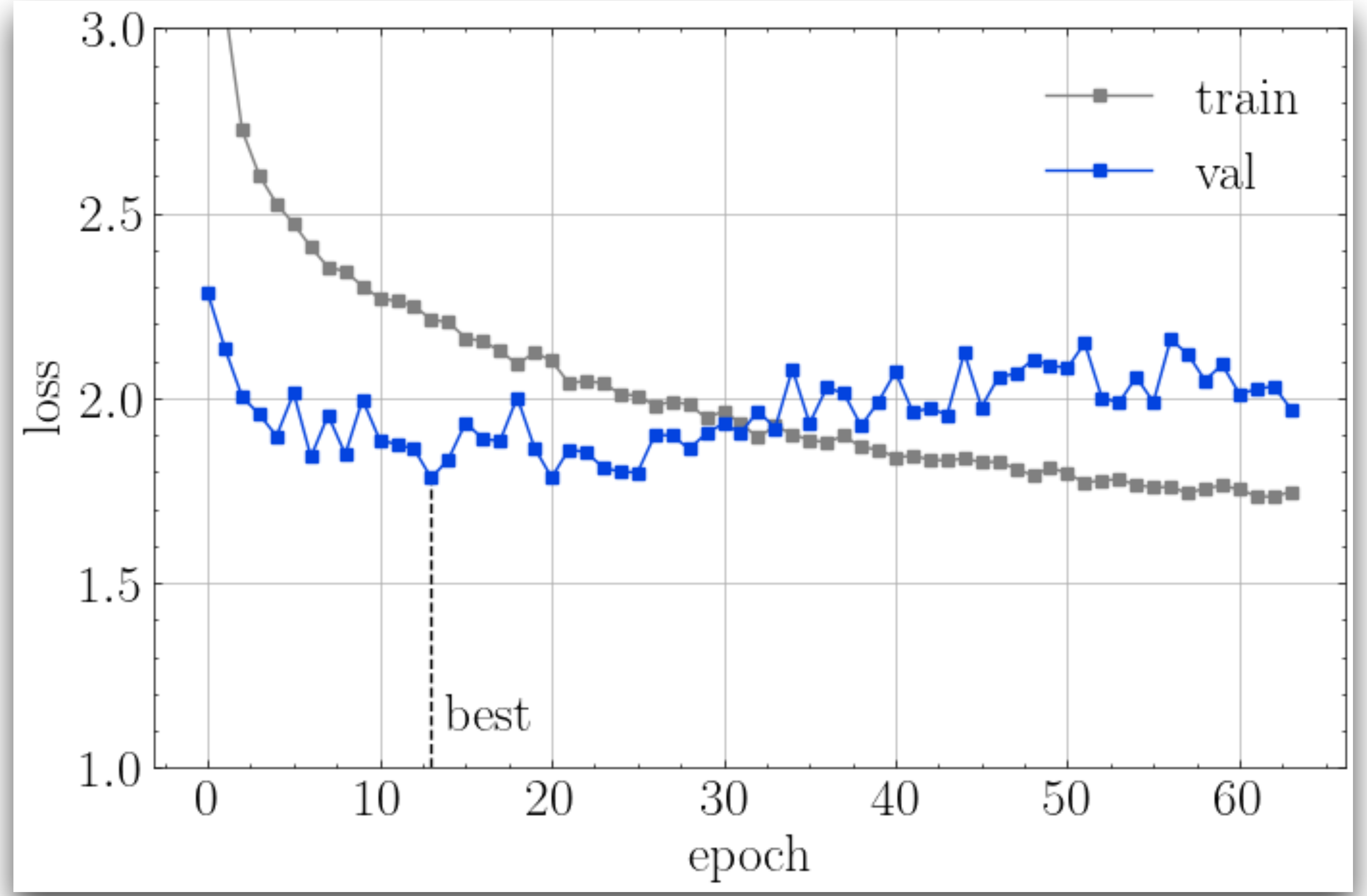
Reconstruction error: Weighted MSE Loss (average over non-empty time bins in a batch)

L1-regularization of the reconstructed LC (average over all time bins in a batch)

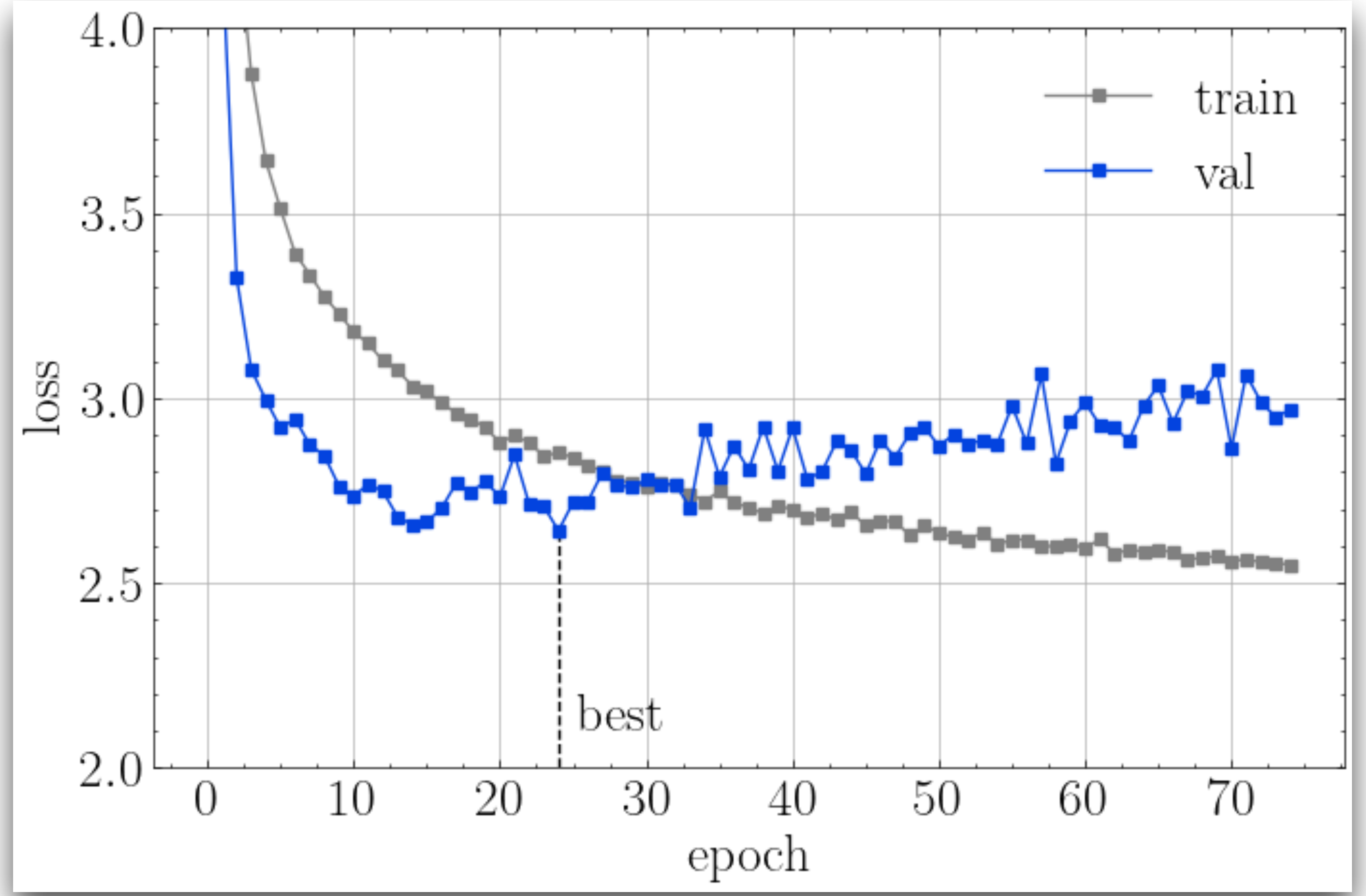
Gaussian distribution in the latent space (only for VAE)

Learning curves

The state with the best loss on validation data is logged



AutoEncoder



Variational AutoEncoder

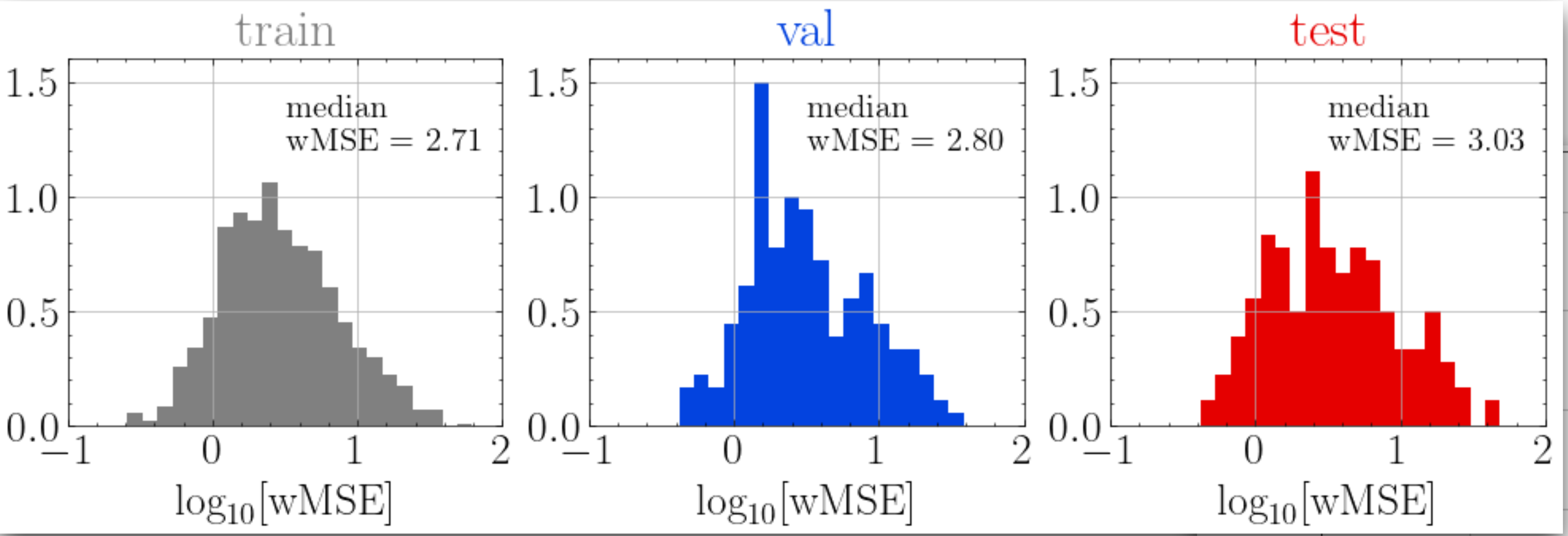
Results: weighted MSE

AutoEncoder

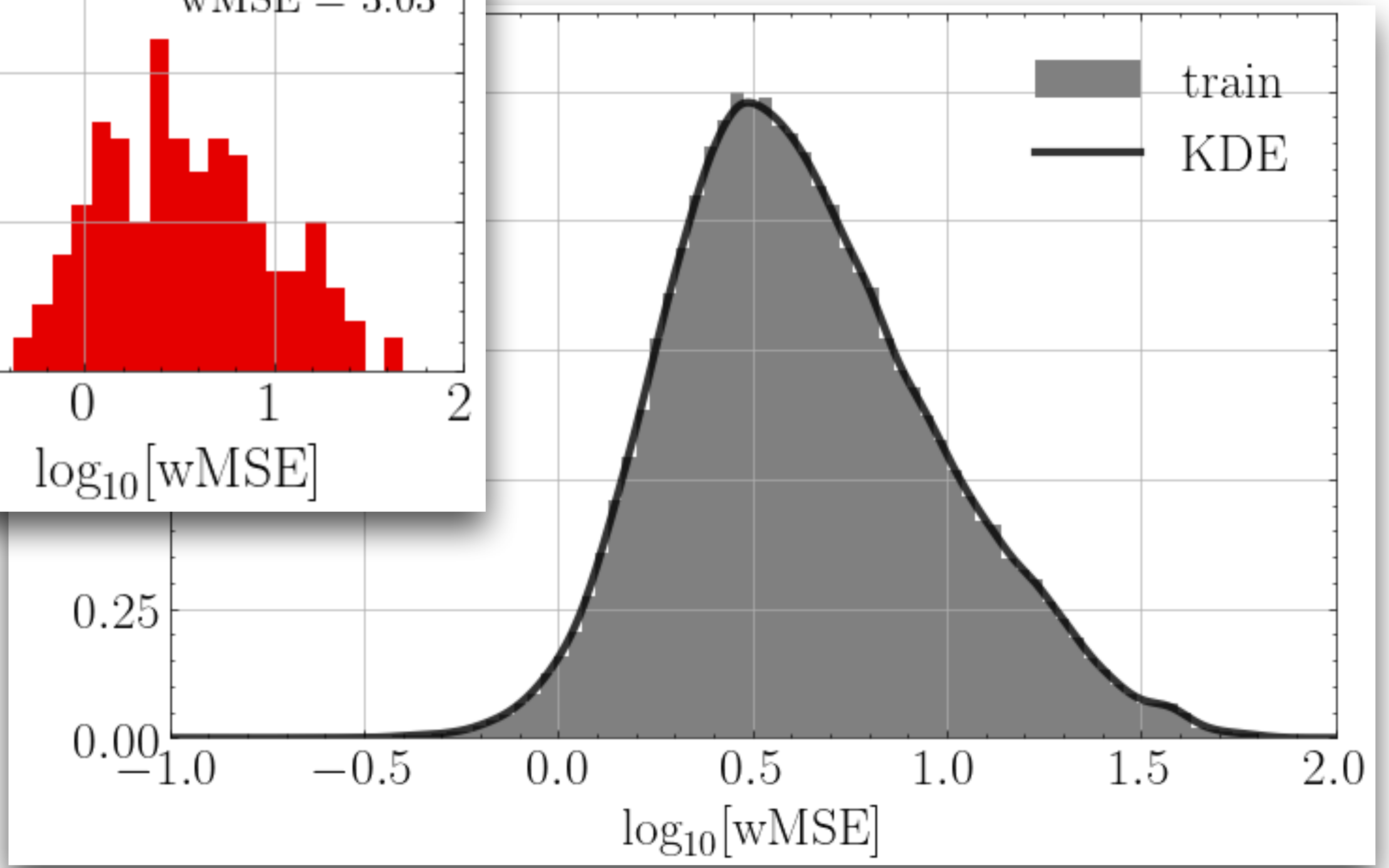
< 1σ: ~10% of events

< 2σ: ~60% of events

< 3σ: ~80% of events



KDE of log[reconstruction error] distribution → p–value



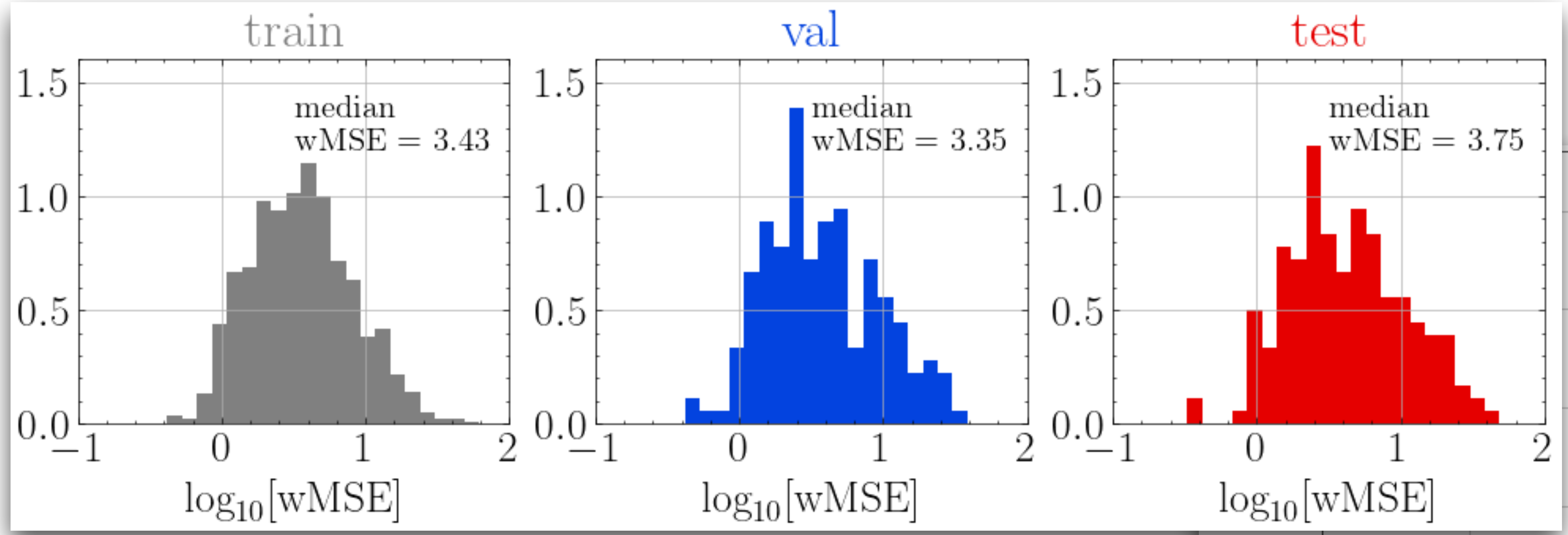
Results: weighted MSE

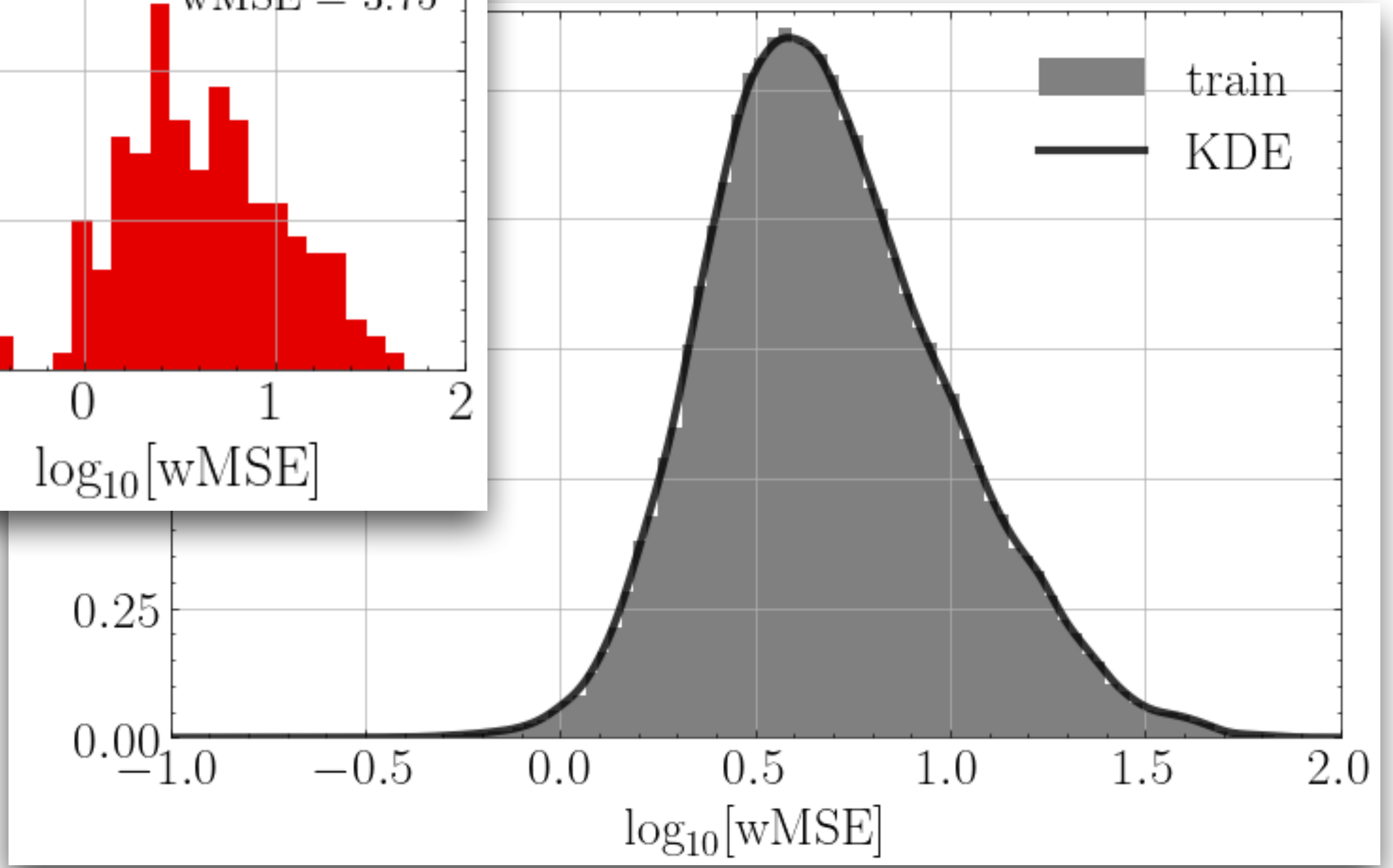
Variational AutoEncoder

$< 1\sigma$: ~ 5% of events

$< 2\sigma$: ~50% of events

$< 3\sigma$: ~80% of events

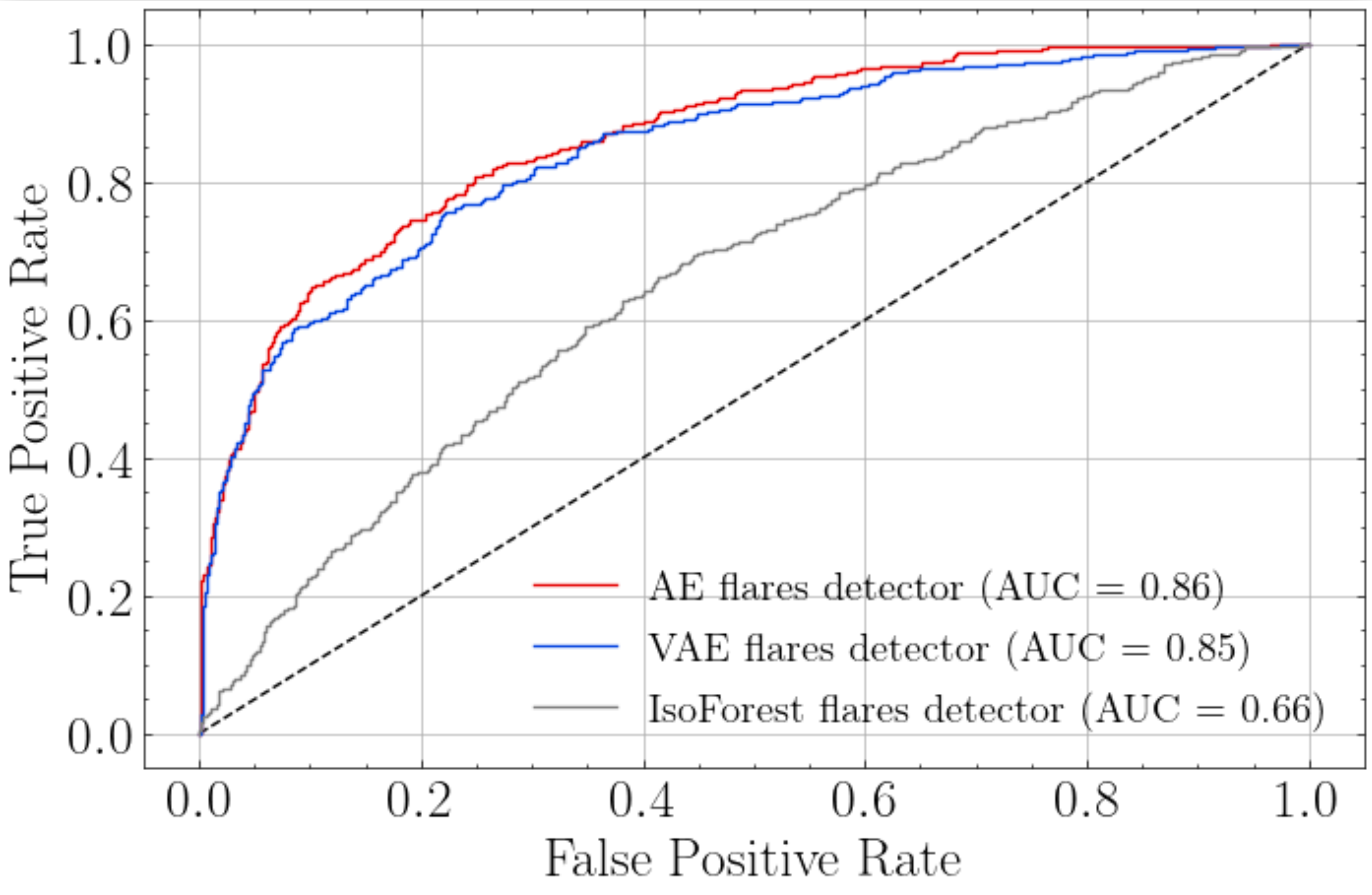




KDE of log[reconstruction error] distribution → p–value

Results: X-Ray flares detection

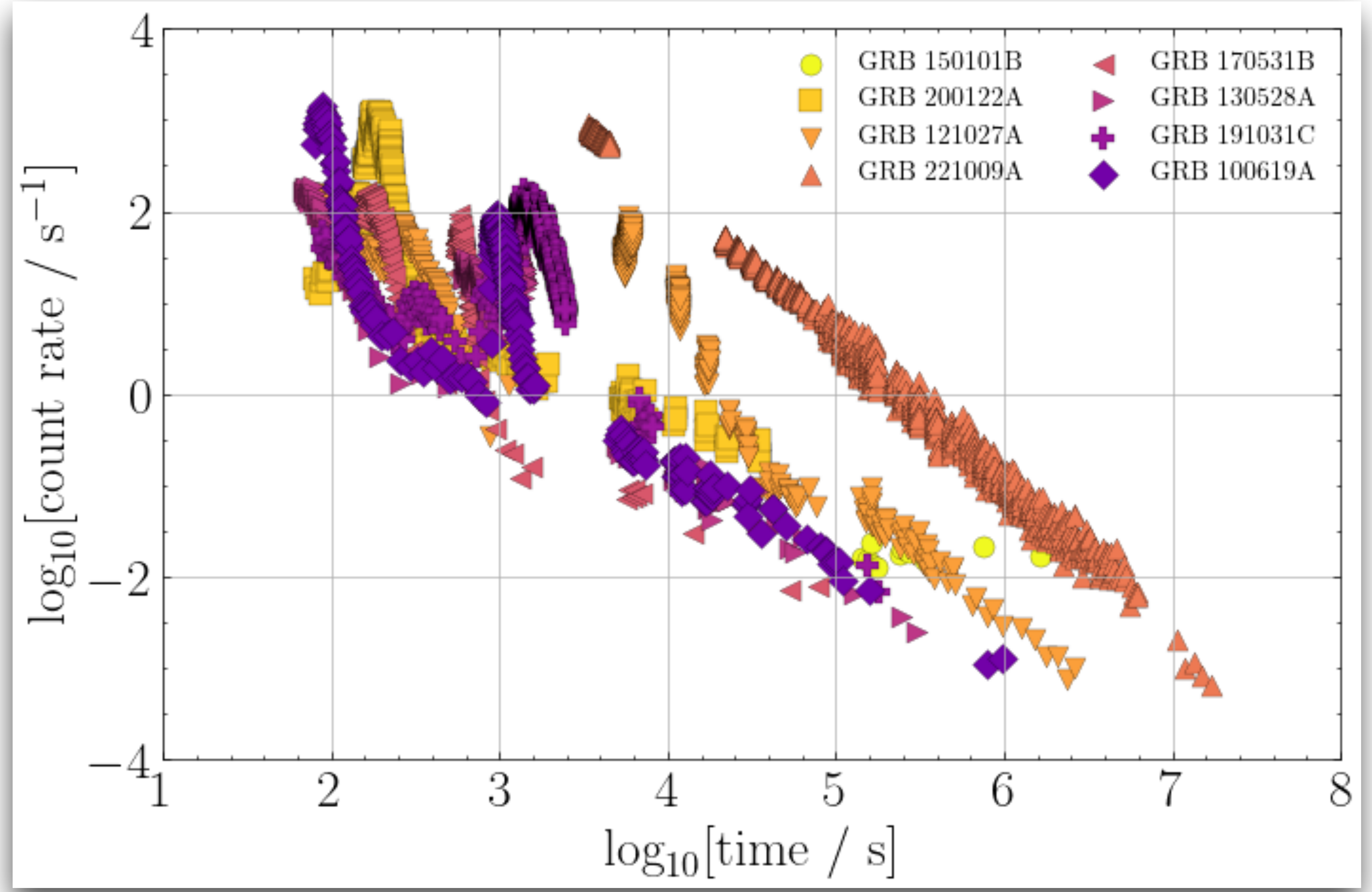
AE / VAE vs Isolation Forest (ML algorithm) ROC–AUC score



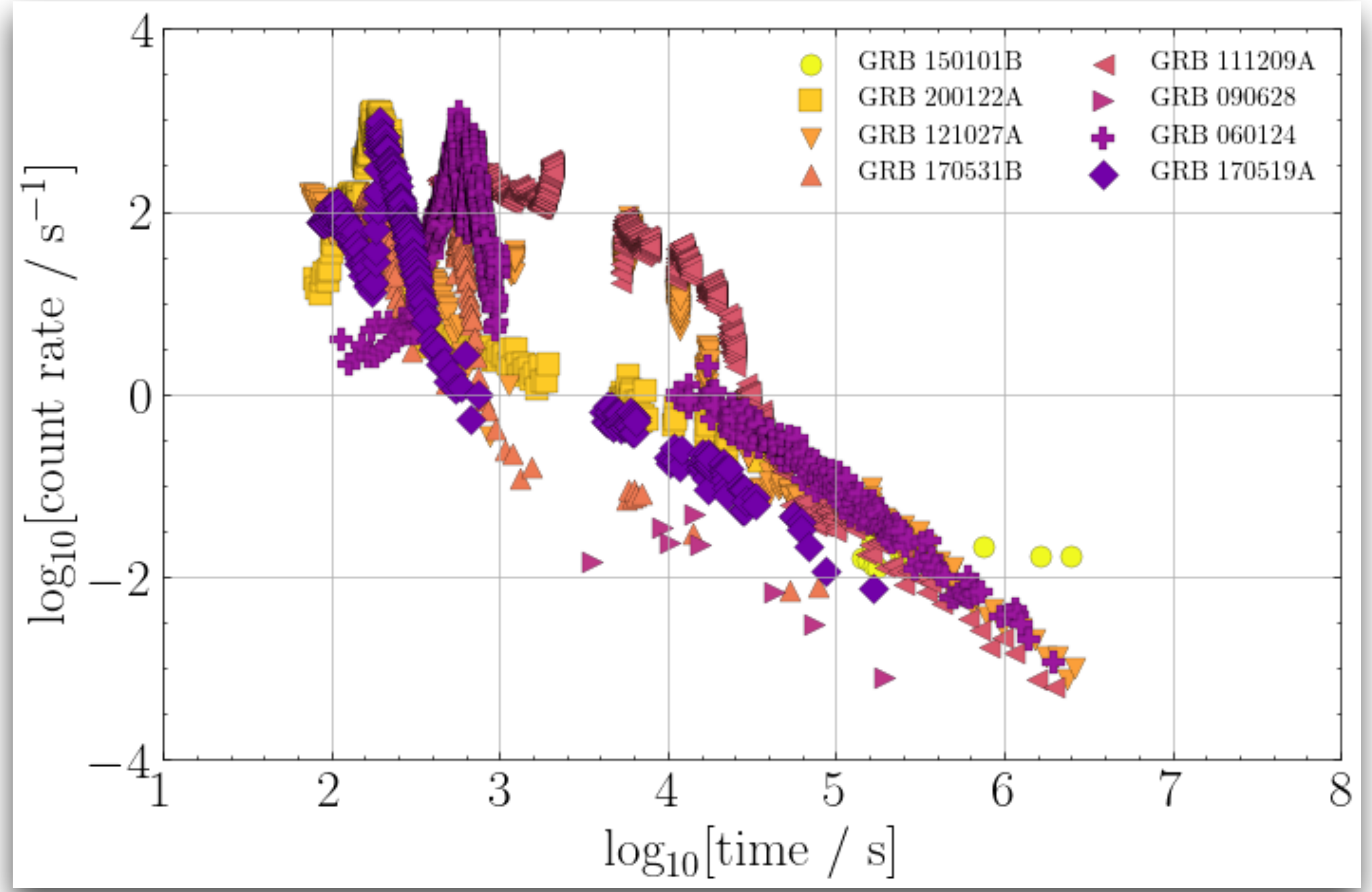
Our model can be probably improved and used instead manual labelling!

Results: "anomalous" light curves

Criterion: p-value < 0.01 / Precision ~ 1.0 / Recall ~ ??



AutoEncoder



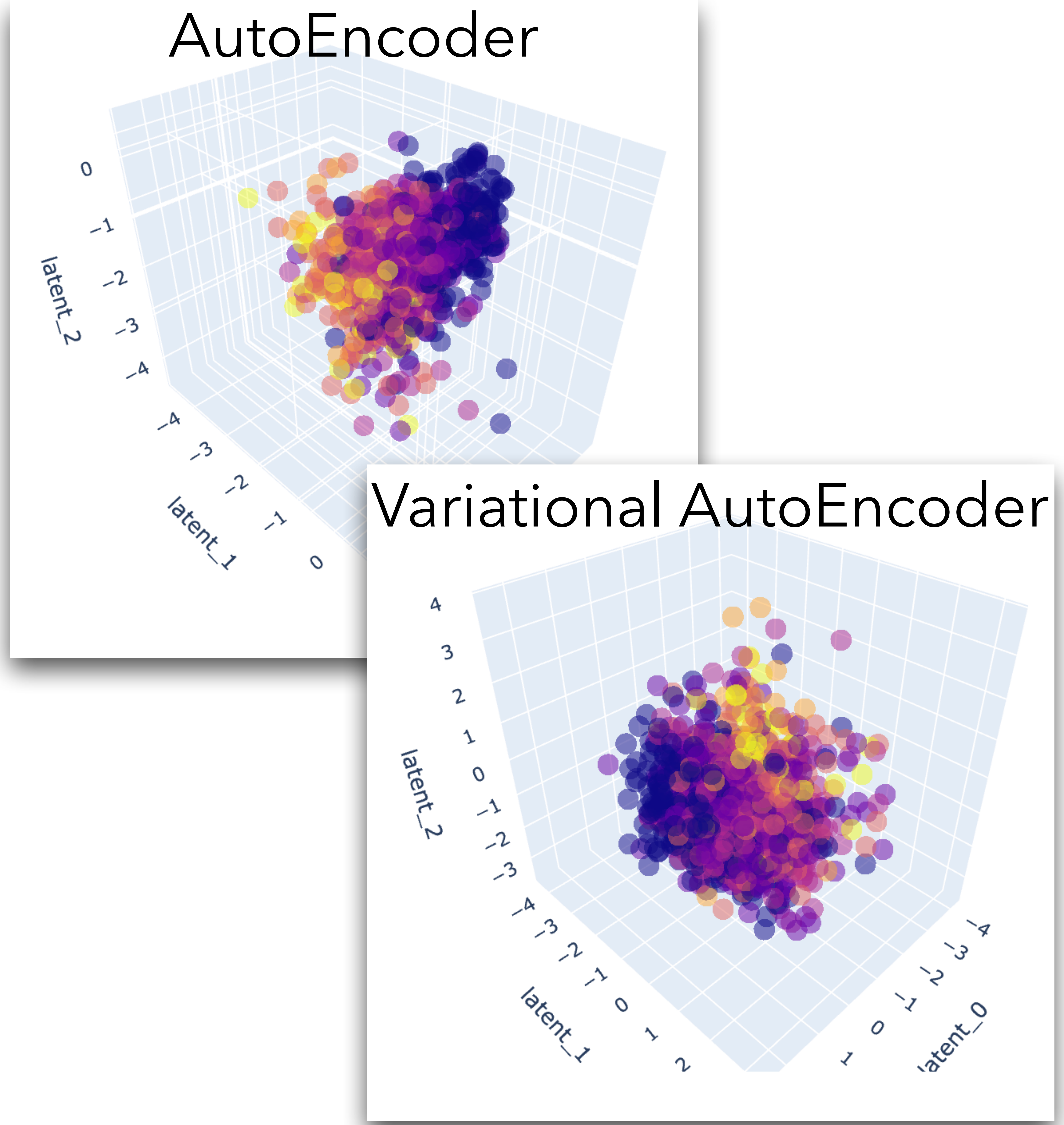
*p-value of GRB 221009A ~ 0.015

Variational AutoEncoder

Results: latent space

latent_dim	numbreaks	has_flares	NH_gal	Redshift
0	-0.66	-0.54	+0.10	+0.15
1	-0.19	+0.10	+0.09	+0.16
2	-0.21	-0.04	+0.03	-0.05

correlation matrix



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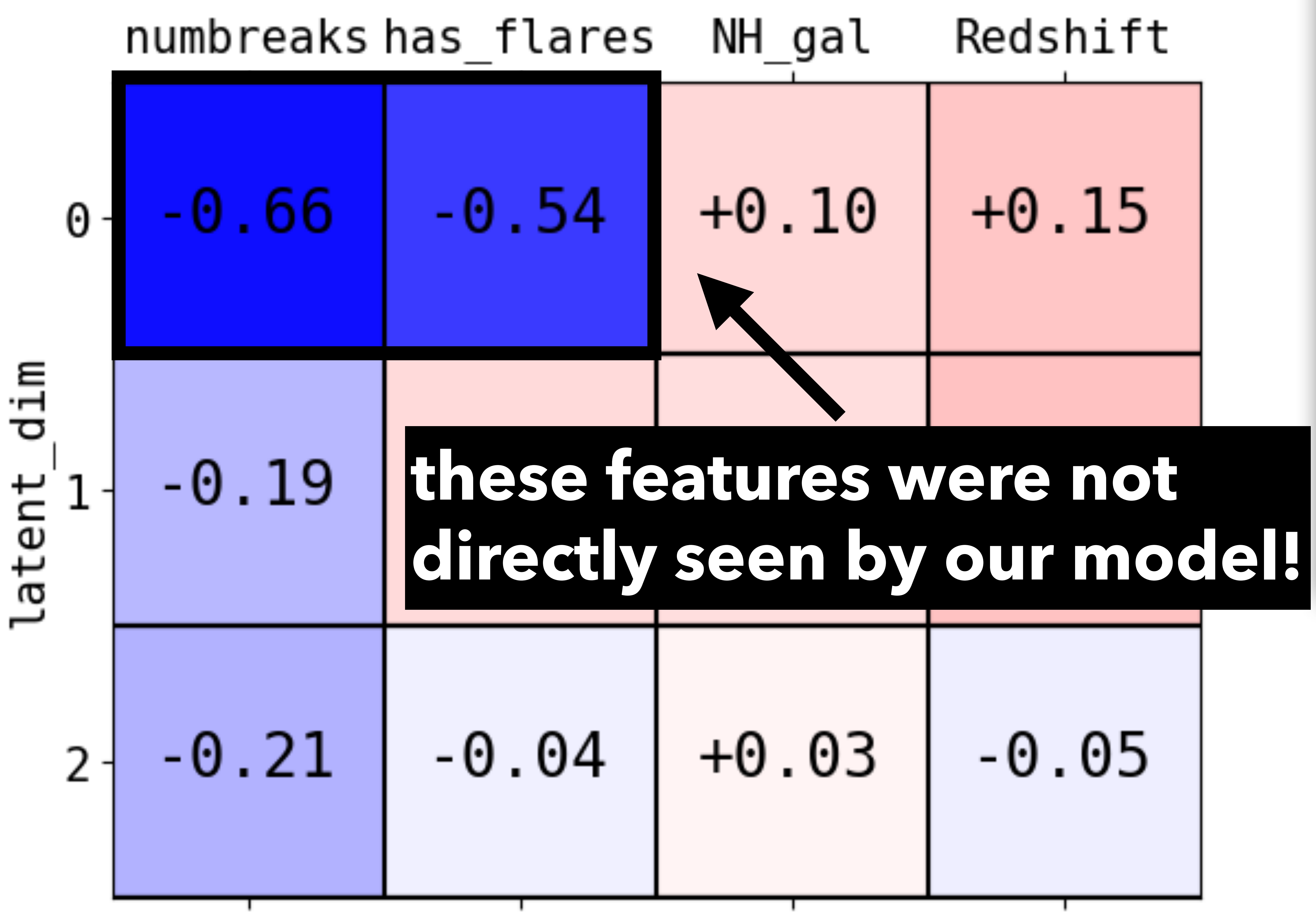

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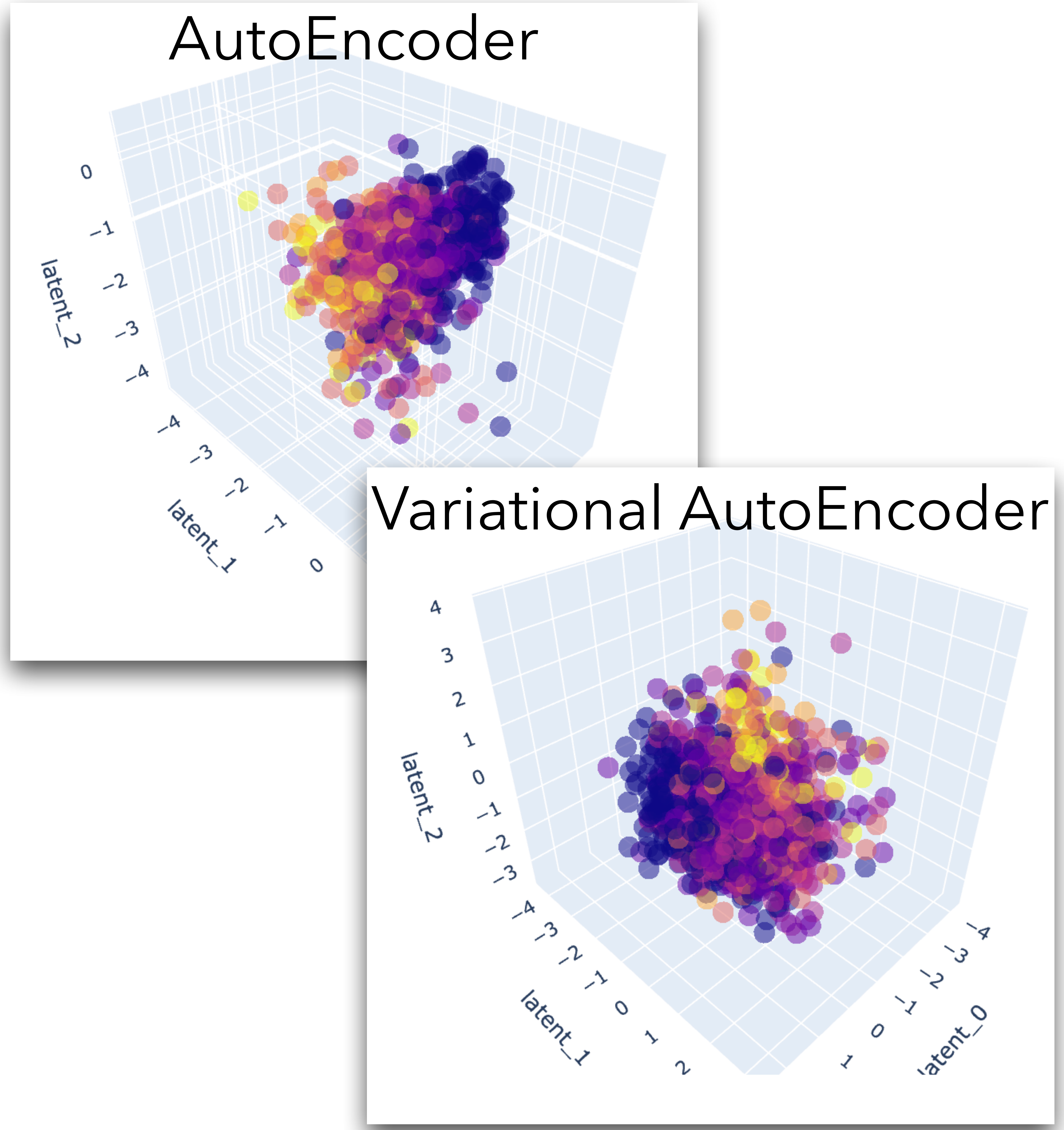

Conclusion

- We trained Convolutional (V)AE model with 3D latent space to reconstruct the GRB X-ray afterglow light curves from *Swift*–XRT online repository
- Almost all light curves are reconstructed within $(2\ldots3)\sigma$
- Using the reconstruction error distribution, we are able to detect X-Ray flares (ROC AUC ~ 0.85) and "anomalous" GRBs (precision ~ 1.0)
- The extracted latent features are correlated with the light curve morphological properties

Most importantly, we demonstrate that DL is a promising tool for GRB analysis!