Machine-Learning Insights into Gamma-ray Burst X-ray Emission

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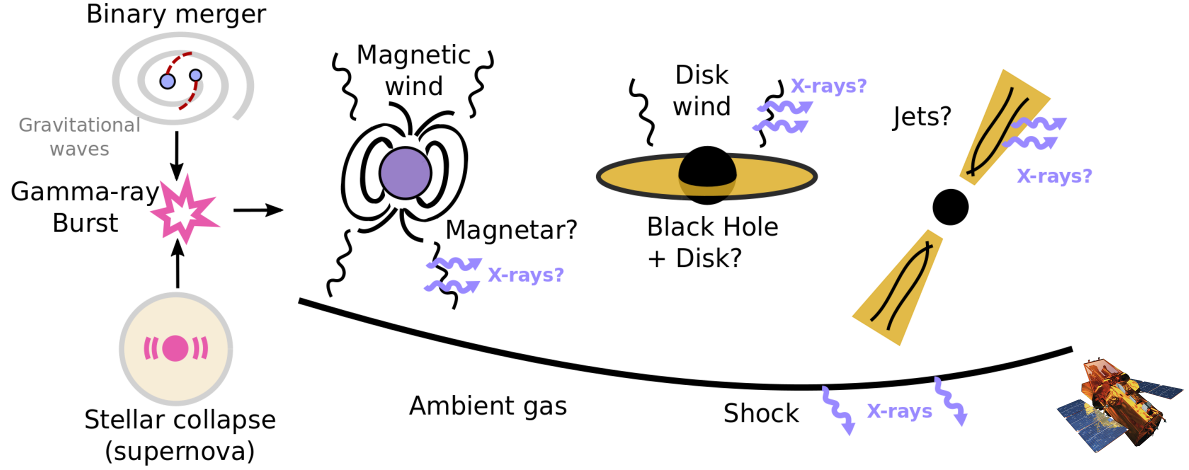
Are there hidden physical parameters in the properties of **Gamma-ray bursts**, the most energetic explosions in the Universe? We study X-ray observations of 1300 gamma-ray bursts (this slide). We train autoencoders to search for such hidden patterns in the data (slide 2). We find no clear evidence for the traditional classification categories with ML-based clustering methods (slides 3-4).

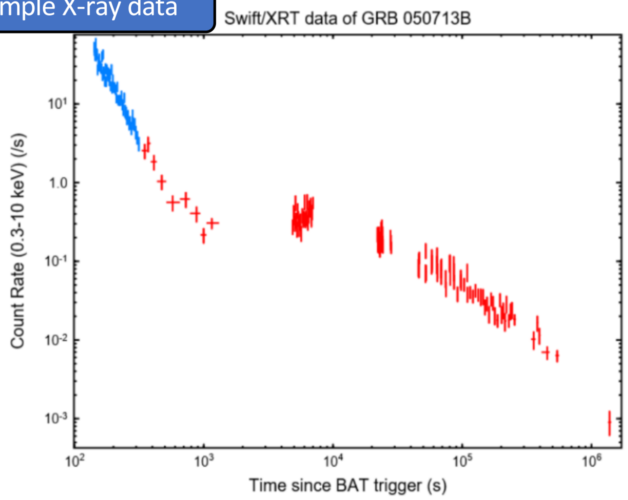
The Physics

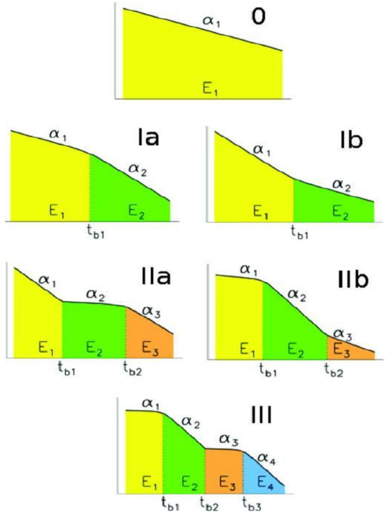


Gamma-ray bursts (GRBs) are bright flashes of gamma-rays, signalling the death of stars. These are followed by fast-fading X-ray emission, which has multiple potential sources (e.g. black hole, magnetar, shocks). The *Swift* satellite is discovering roughly 100 GRBs every year, autonomously slewing to capture their X-ray light within minutes. *Swift's* quick sleuthing has revealed an inexplicably large diversity in the X-ray brightness evolution ("light curves"). What makes the X-rays?

Traditional classification

Sample X-ray data





Above: A traditional phenomenological classification scheme for GRB X-ray light curves. The brightness declines as a power law with time ($F \propto t^{\alpha}$). Different power law slopes (α) and transitions between them may encode information about the physical processes producing the X-rays. From Margutti et al. (2013).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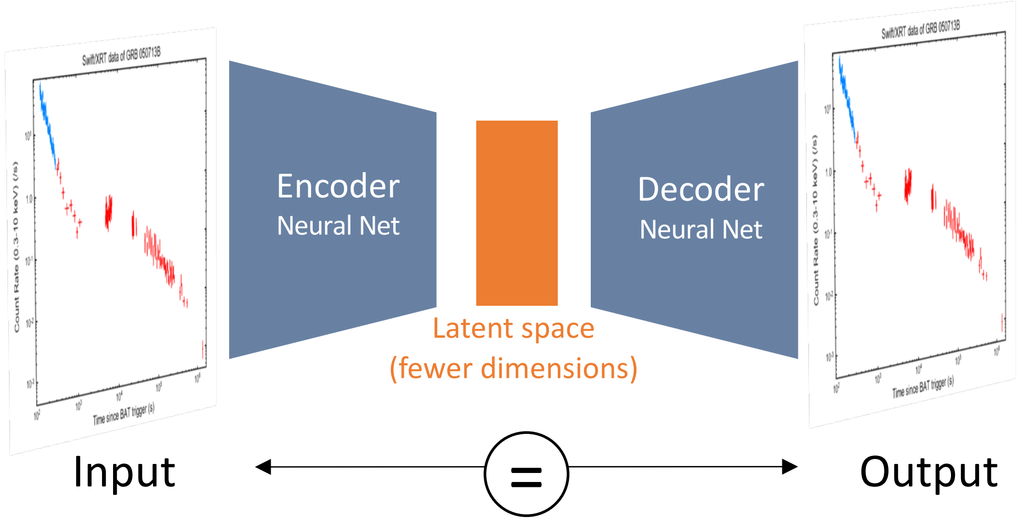
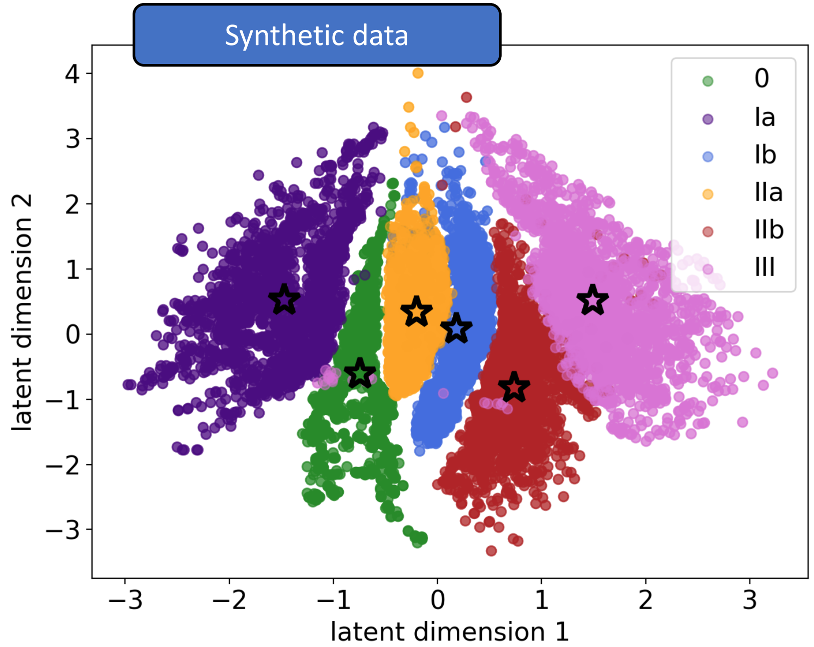
We use autoencoders to reduce each gamma-ray burst X-ray light curve to a set of parameters (i.e., a point) in a lower dimensional ("latent") space. We then test whether we can recover the traditional classifications of the light curve shapes by searching for clusters in these parameters.

Architecture and implementation

Autoencoder



Above: Schematic of our autoencoder for modelling GRB X-ray light curves. The encoder and decoder are both convolutional neural networks (CNN) that have shown great performance for image and time-series processing.



Above: Autoencoders compress their input into a low-dimensional "latent space", mapping input samples with greatest similarity close to one another. We validate of our model with synthetic GRB X-ray light curves generated using the traditional classes. Cluster centres (stars) are clearly separated in the autoencoder's 2D latent space.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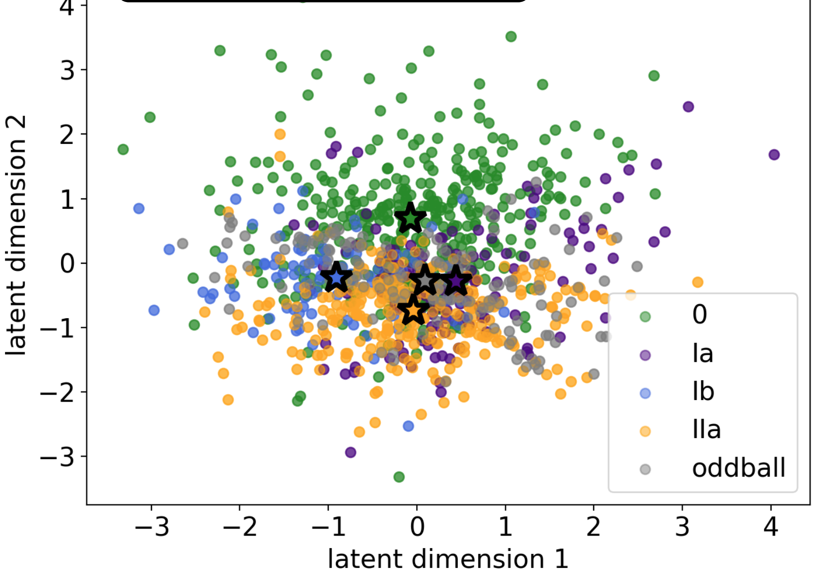
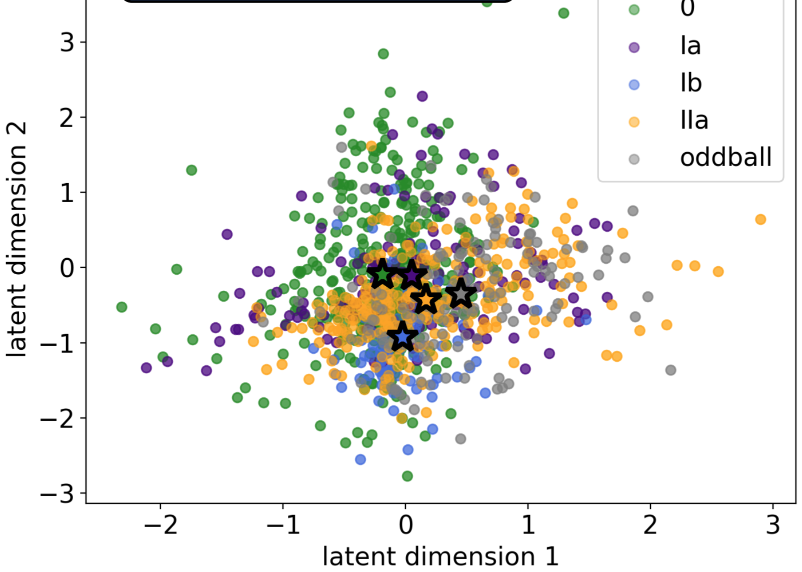
We expect clusters in the latent space if the classification scheme is relevant. We investigate this by (i) training the autoencoder on real data and (ii) using a model pre-trained on synthetic data. **No classes are evident.**

Analysis and Results 1/2

Real data



Pre-trained model



Left: A CNN autoencoder trained on real X-ray light curves reveals no clusters in the latent space.

Right: No clusters are visible in the GRB data even when using an autoencoder that has been pre-trained using a large synthetic dataset (slide 2). This suggests that that the traditional phenomenological classification scheme may be arbitrary.

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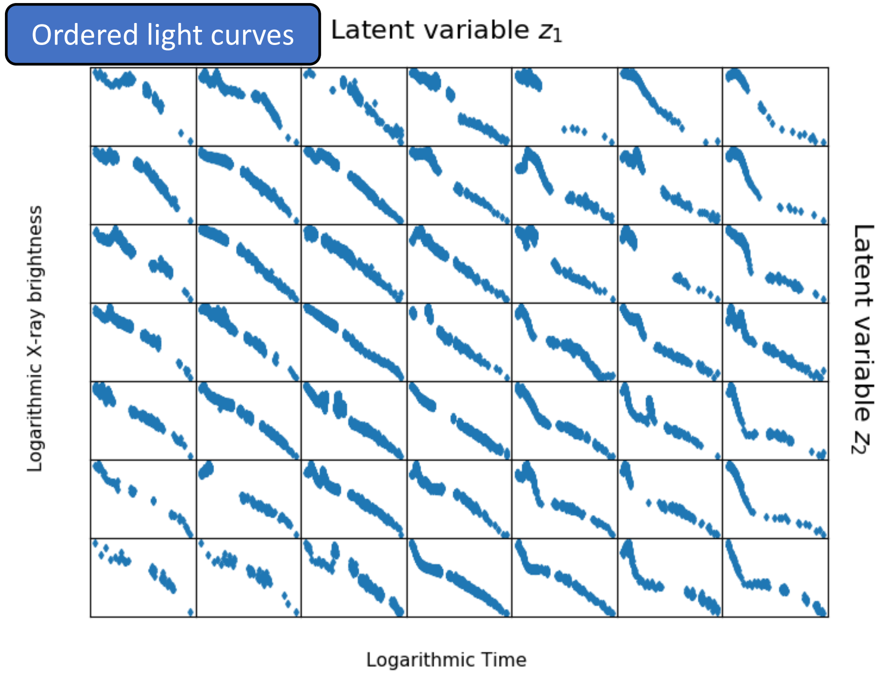
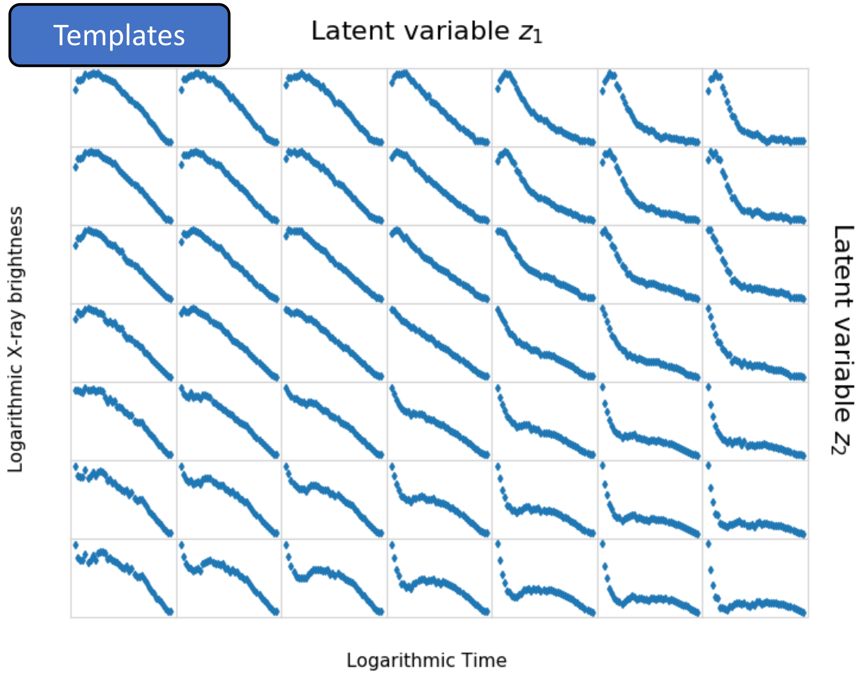
Since an autoencoder is a **generative model**, we can make synthetic light-curves by picking a point in the latent space and feeding it to the decoder. Generated templates from the latent-space representation of the data reveal that **light curve morphology spans a continuum.**

Analysis and Results 2/2

Ordered light curves



Templates



Left: Sample GRB X-ray light curves arranged by their mapped position in the latent space.
Right: Synthetic template light curves generated by sampling the latent space at the same locations. The central single power law light curve can be smoothly transformed into the others, suggesting new underlying physical processes, such as the presence of competing emission components.

Conclusions: There is a large diversity in X-ray afterglow light curves, and no clear evidence for traditional categories when using ML-based clustering methods. The inferred continuum of light curves may be representative of a competition between multiple underlying physical processes. ML recovers clusters for large enough data sets (>1k samples / label); such data sets may be feasible with future instruments (e.g. SVOM, Athena).

Future work:

- Improved pre-processing steps
- Data augmentation
- Other clustering algorithms (t-SNE, SOM)