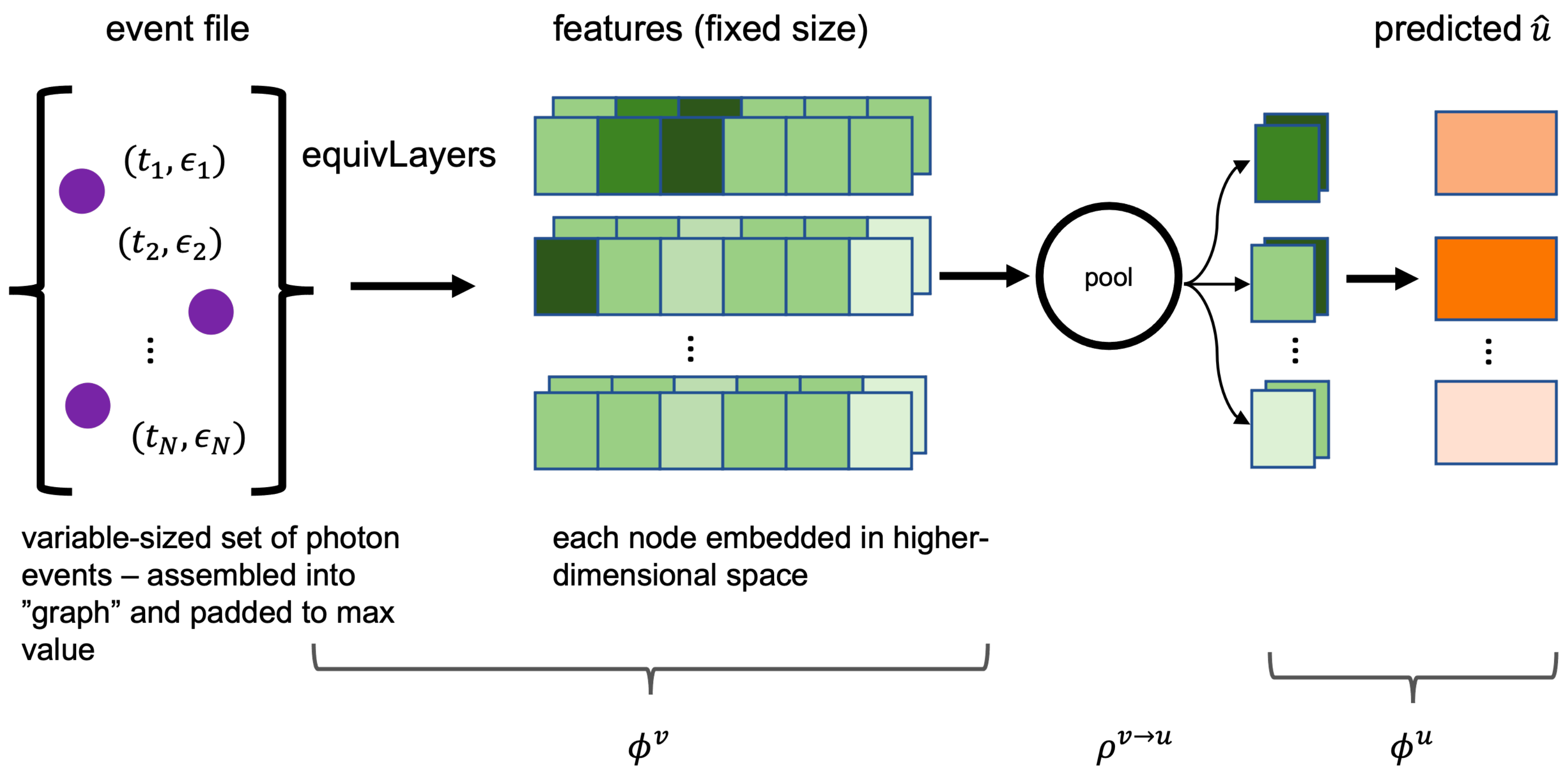
Multi-messenger counterparts and other transients in X-ray datasets

Rafael Martínez-Galarza
With Lucas T. Makinen, R. Di Stefano,

CENTER FOR ASTROPHYSICS
HARVARD & SMITHSONIAN

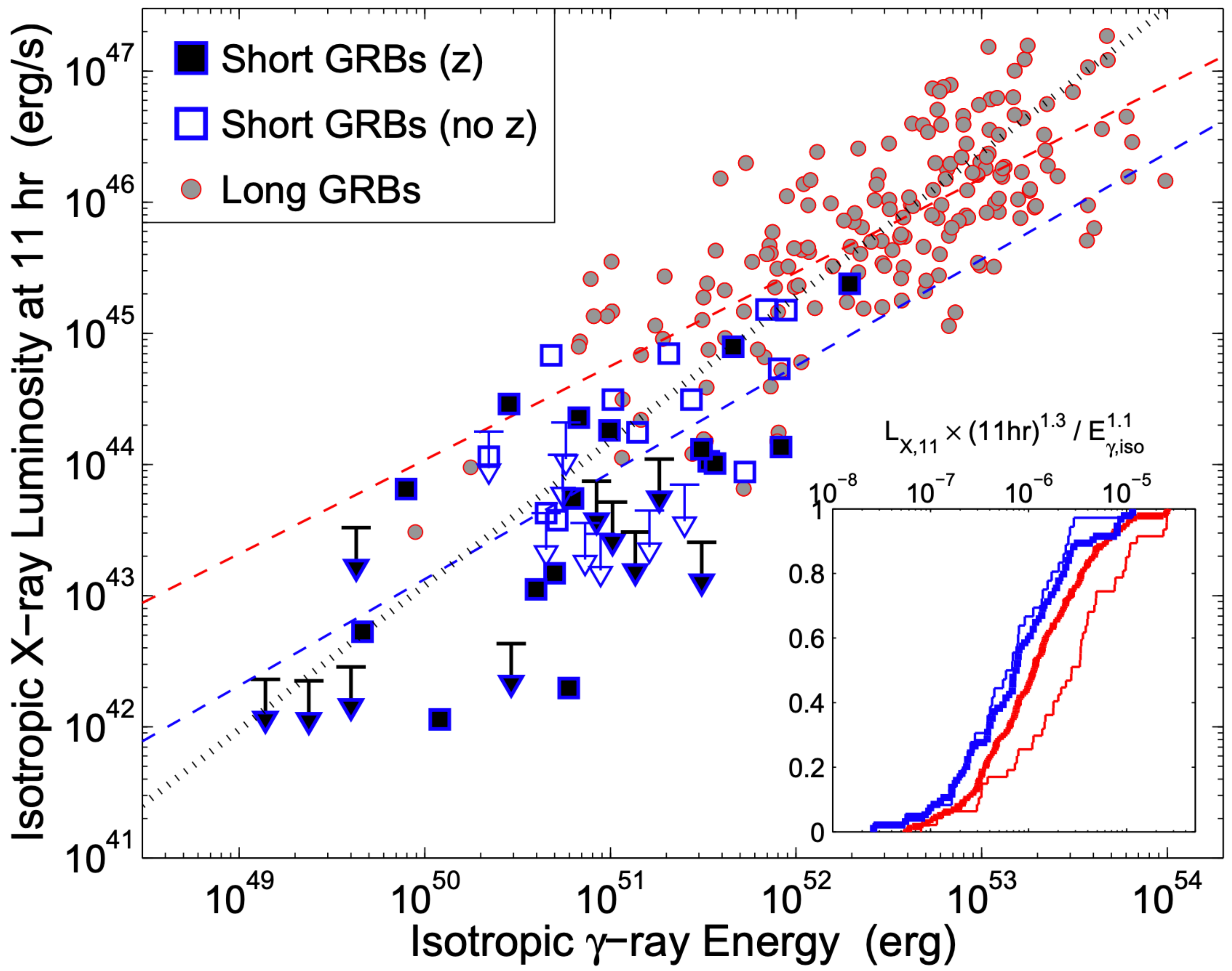
Imperial College London



TDAMM workshop,

Time domain in X-rays

- Transient behavior in X-ray observations provide physical insight. Because most x-ray sources are associated with accretion phenomena, so are transients.
- Sudden increase in accretion rate in X-ray binaries. Parameters are stellar masses, binary and disk dynamics, etc.
- Gravitational collapse. Thermonuclear explosions.
- Synchrotron afterglow in NS mergers. Relativistic shocks due to interaction between jet and merger ejecta.
- **At least some fast (few ks in duration) X-ray transients might be associated with this latter phenomenon.**



Berger 2013

X-ray (exotic) transients. Why bother?

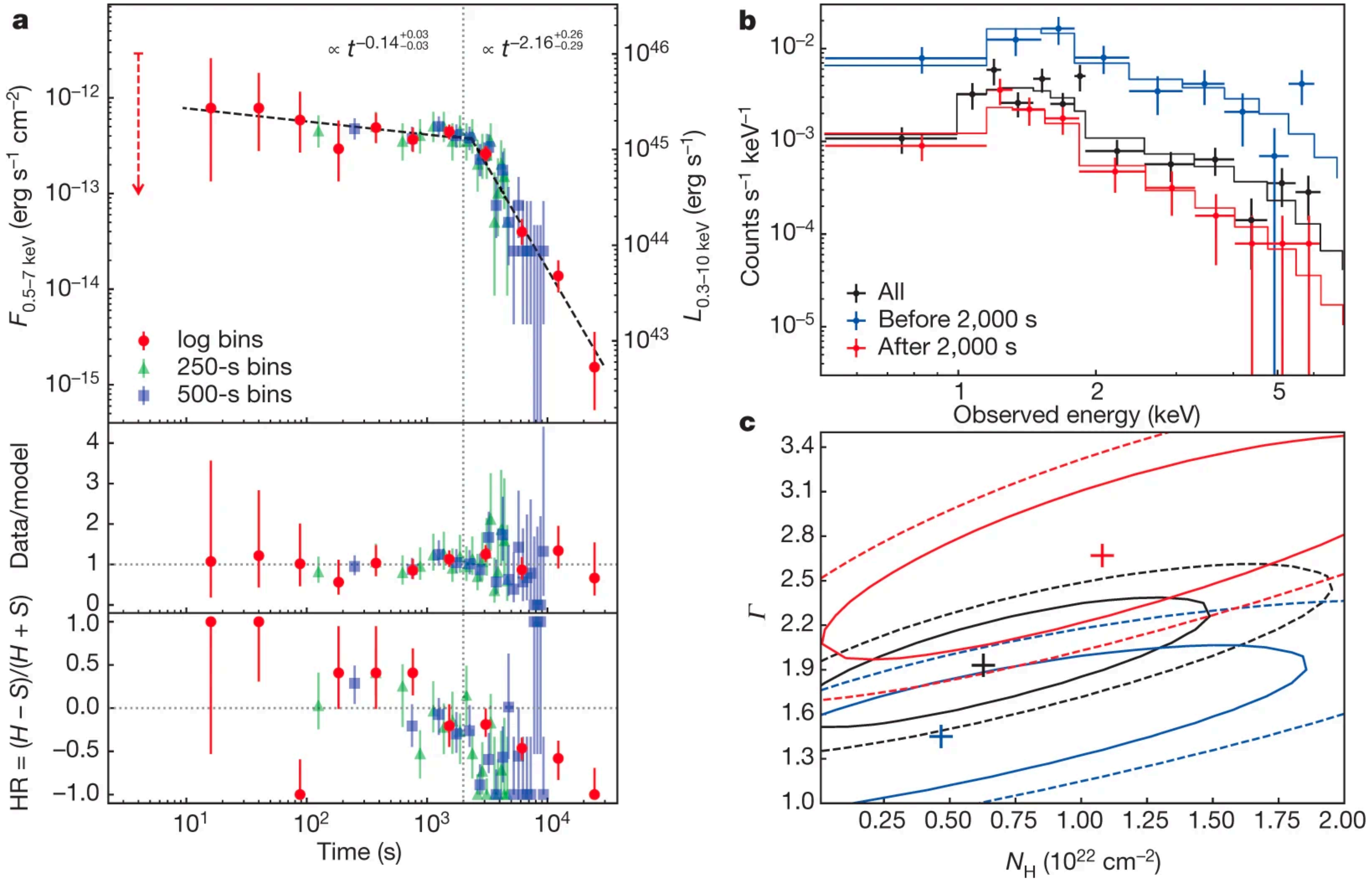
- It has been argued (Zhang, 2013) that BNS mergers resulting in a massive rapidly spinning magnetar produce X-ray afterglows with higher solid angles compared to the sGRB.

- Such afterglows can be used to probe EM counterparts to GW events that lack a γ-ray counterpart, and to search for massive millisecond magnetars.

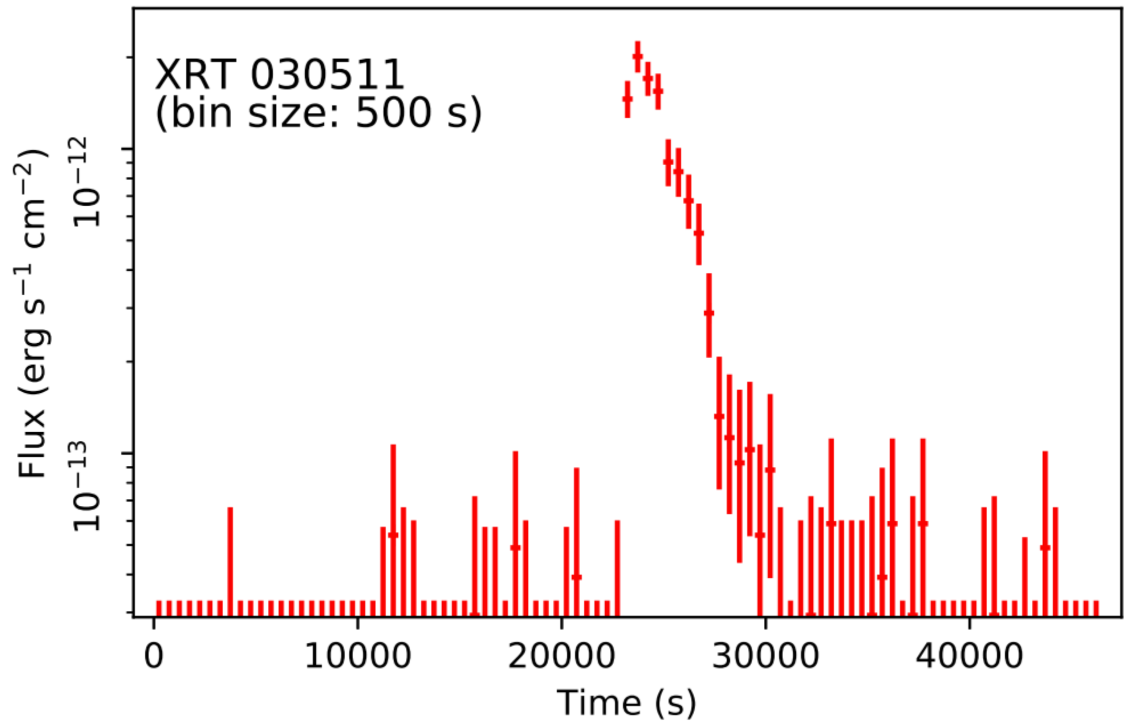
- Some searches have found afterglow candidates resulting from BNS mergers with a magnetar as the end product (Xue et al. 2019, Lin et al. 2022)

- Light curve profile consistent with spin down luminosity of a rapidly spinning magnetar.

Xue et al. 2019

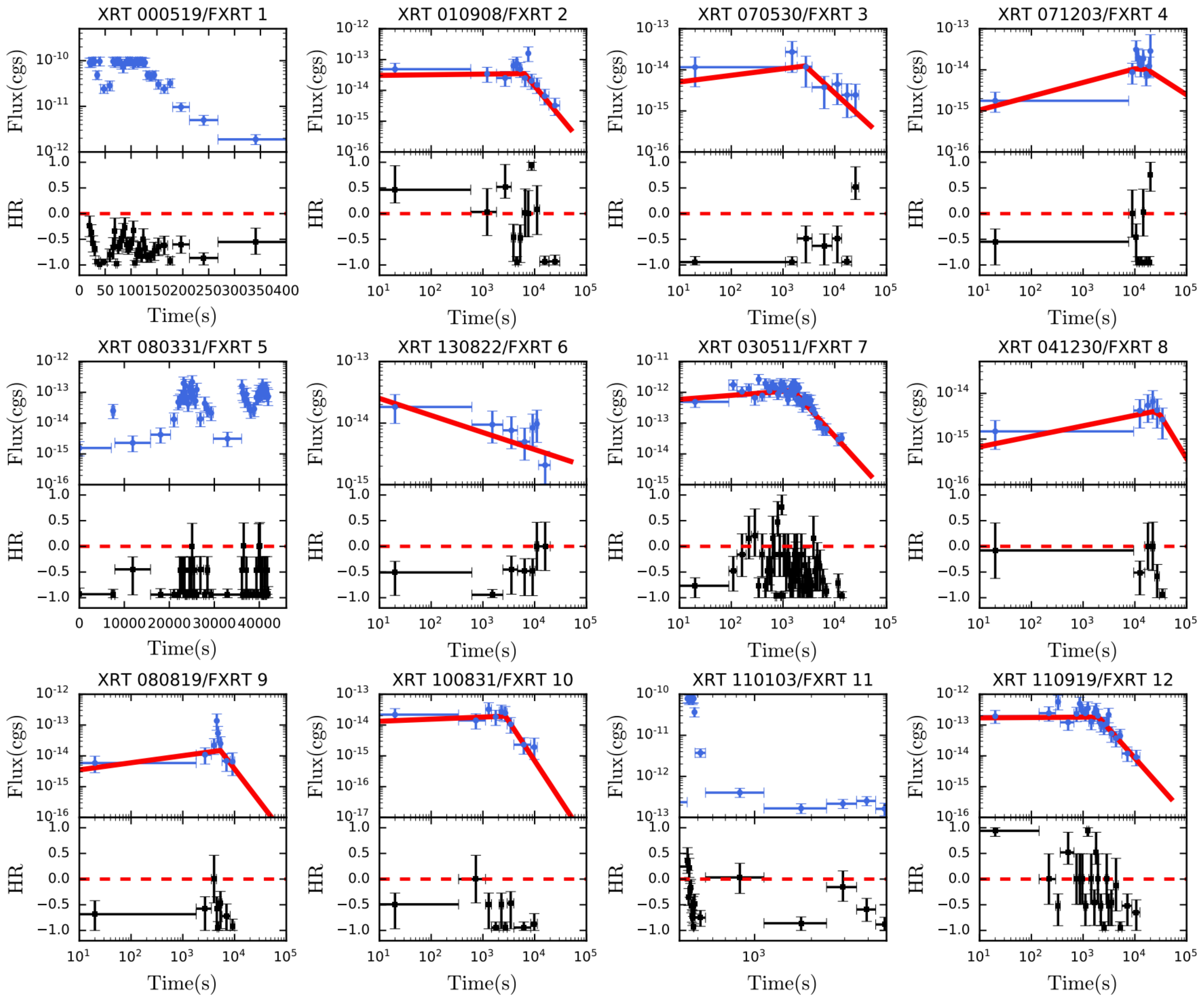


Serendipitous FXT found in Chandra data.



Lin et al.

Successful systematic searches for FXRTs in the CSC



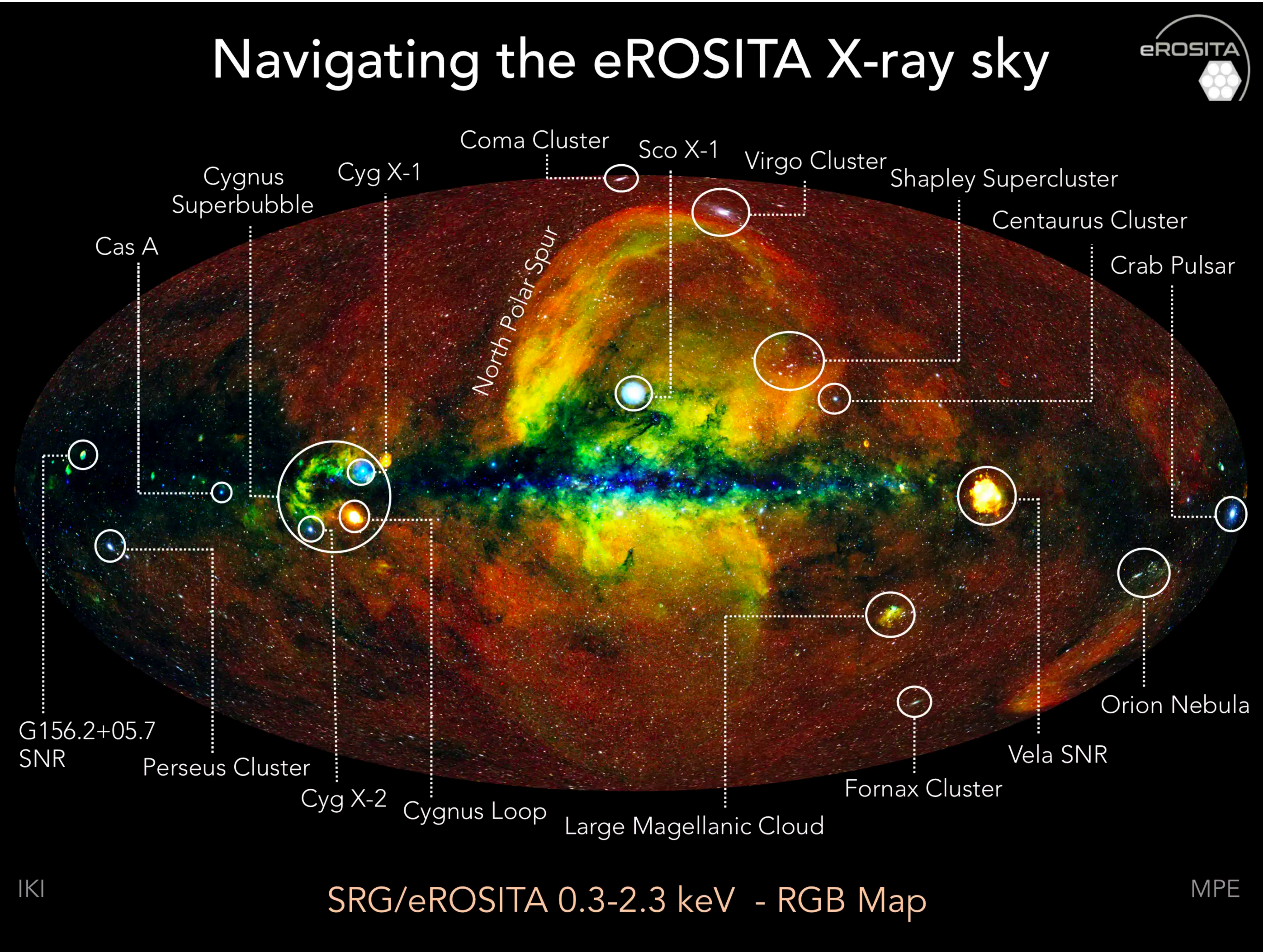
Quirola-Vásquez et al. 2022
See also Yang et al. 2019

- 14 FXRTs that are consistent with extragalactic origin
- None detected as a sGRB.
- Majority consistent with XRBs, ULXs, via association with optical counterparts, X-ray luminosity
- For at least 3 FXRTs, their lack of optical counterparts, luminosity range consistent with off-axis GRBs, or TDEs
- "…progress here will crucially hinge upon the ability of current and future X-ray observatories to carry out efficient strategies for (onboard) detection and alert generation to trigger follow-up campaigns "

The need for systematic and automatic searches

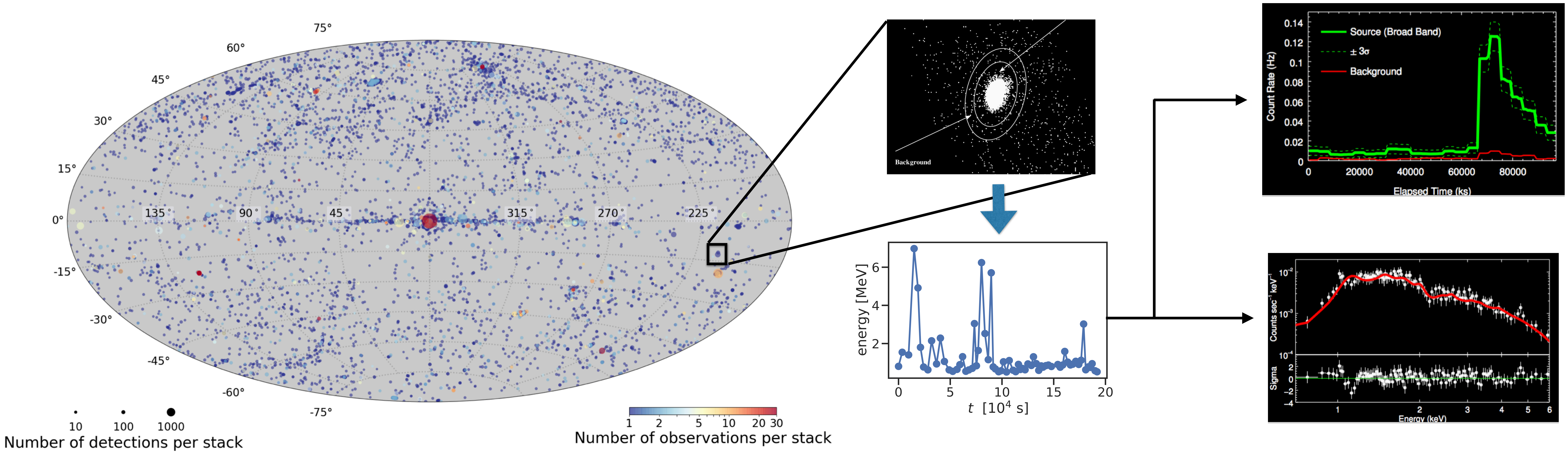
- What avenues of inquire are more likely to result in a sustained rate of discovery?
- X-ray afterglow candidates can be found in existing and upcoming datasets, and can be used to constrain merger models.
- Other types of events might signal the presence of GW event precursors. This includes, for example, lensing events in X-rays, resulting from compact objects in orbit around each other.
- X-ray observatories are not yet suited for alert generation (at least not for transient events of the sort that are interesting for the multi-messenger community)

X-ray astronomy from a data perspective



- Data volume: 600/MB per day over a period of ~7yr: 1.5TB.
- Time domain aspect: about 1000 sq deg of the sky near the poles will be visited more than 30 times in the first 4 years.
- The first full sweep of the sky contains ~1 million sources, and about 165 GB of raw data, that are transformed into **event files**
- X-ray catalogs of properties and data products for non all-sky missions (Chandra, XMM) also have considerable sizes
- **But… X-ray datasets not yet treated from a data science perspective**

The Chandra Source Catalog 2.0: a learning ground



The catalog

1.Over 315,000 individual sources (over 450,000 in CSC 2.1)

2. About 1 million individual detections (Over 1.5 million on CSC 2.1)

3. Tabulated astrometric, photometric, spectroscopic, and variability properties.

4. **Data products: spectra, light curves, event files, background maps, etc. SDSS cross-match catalog available.**

The algorithms

1. Short term variability is estimated probabilistically using the Gregory-Loredo algorithm.

2.Light curves are weighted averages over different binning of the arrival times.

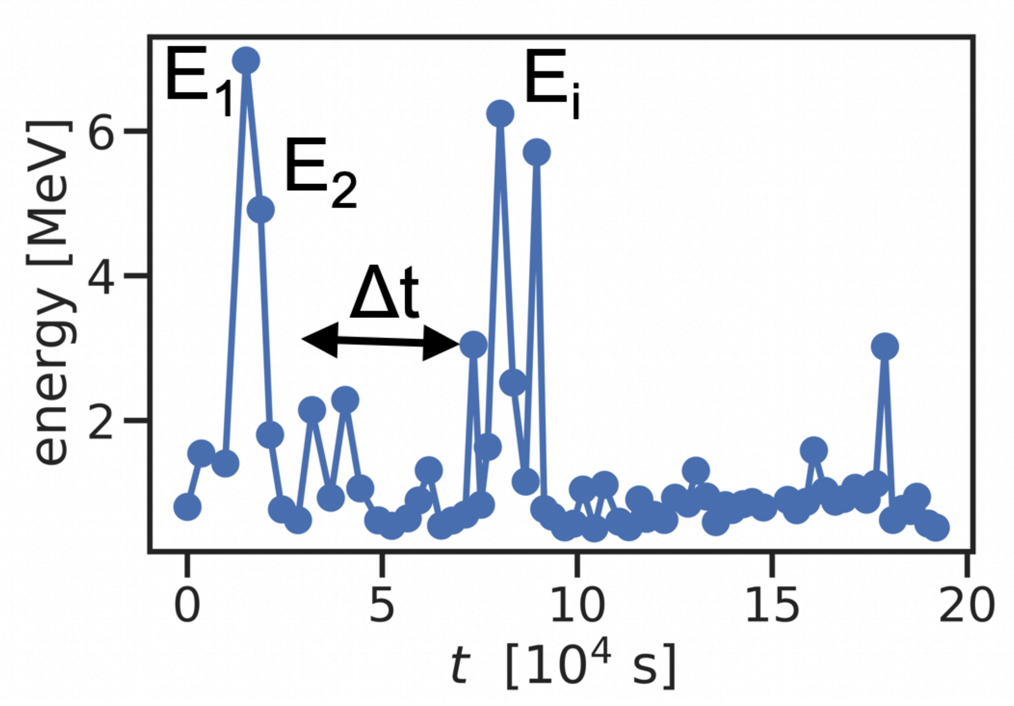
3. Spectra is reduced by applying a redistribution matrix file and an auxiliary response file.

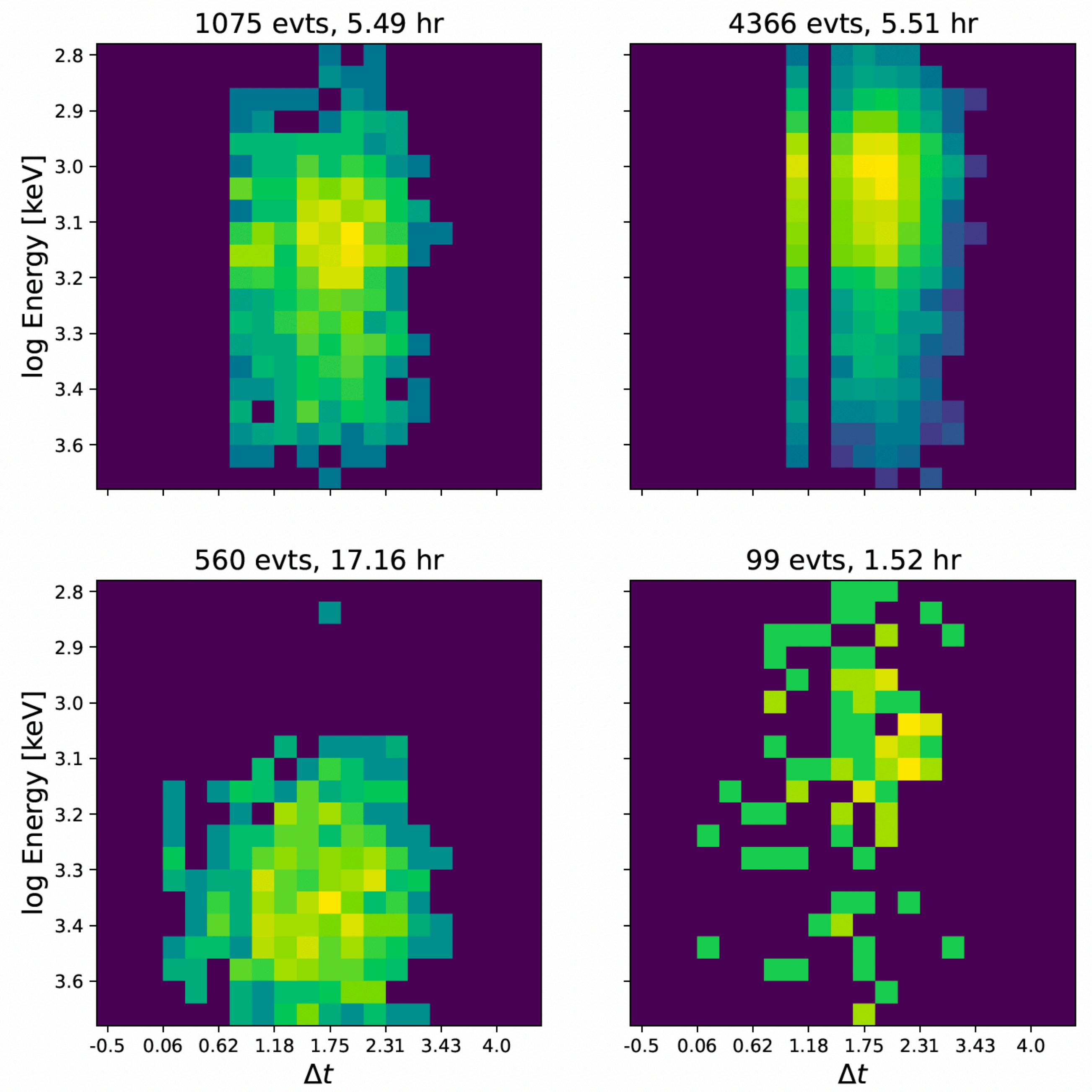
4. They are complex functions that map the events into complex quantities.

https://cxc.cfa.harvard.edu/csc/threads/all.html

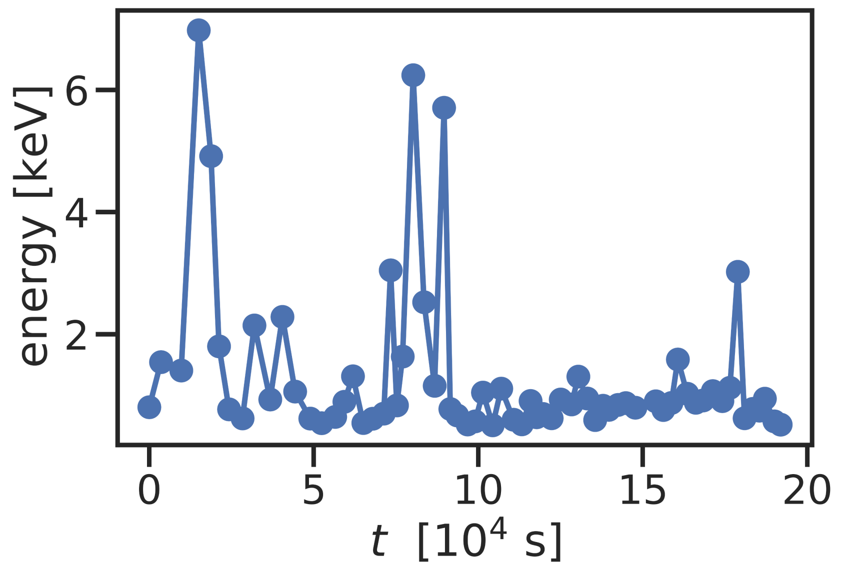
New data representations for transient identification

Edt map representation: a 2D histogram of the event energies and arrival time differences. Takes the form of an image. Visual representation of variability and spectral hardness. Good input for CNN approaches.

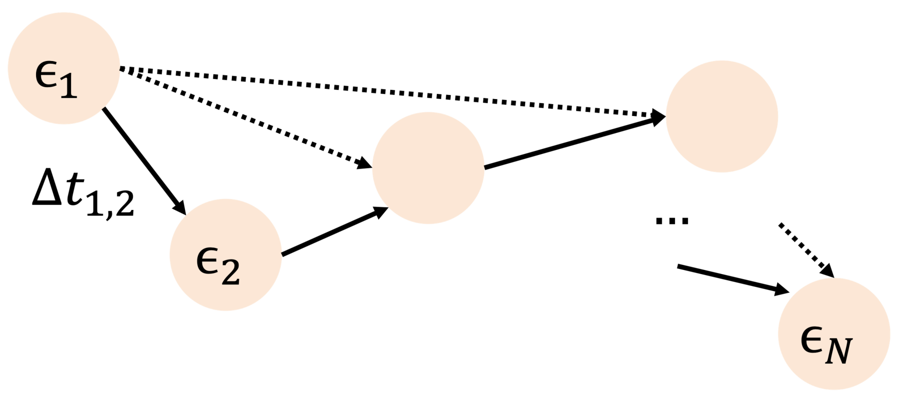




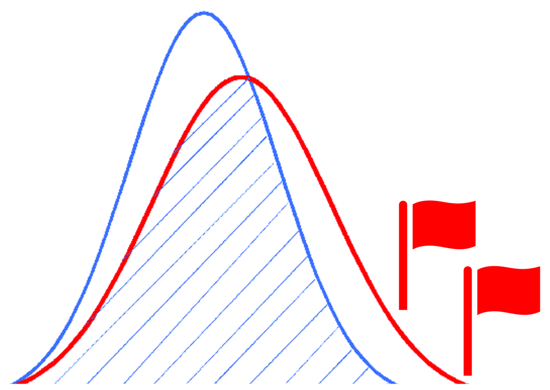
Graph representation: a set of objects (nodes), where some of the pairs are related. Event file pairs (photons energies) can be related via their difference in arrival times. No information loss due to binning. Summary statistics (HRs, variabilities) can be associated to each graph.



Step 1: Assemble (connected) variable-length graph from timeseries. Nodes are photon energies (and x, y positions) and connected by Δt_{ij}

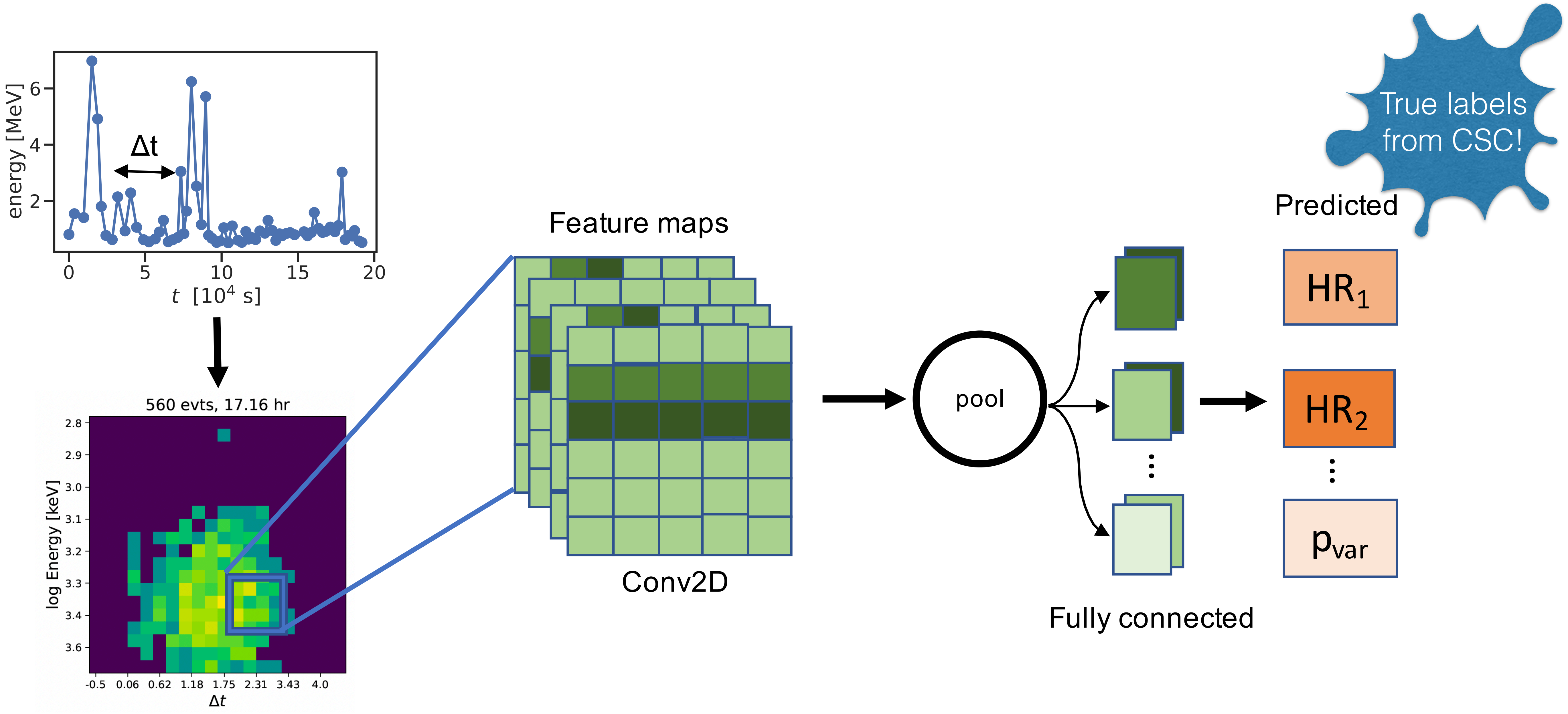


Step 2: Use Graph Neural Networks (GNNs) to regress to known summary statistics like hardness ratios and variabilities to learn posterior mean



Step 3: Pass test data through network and flag outliers in prediction or latent space

A convolutional regressor for X-ray properties

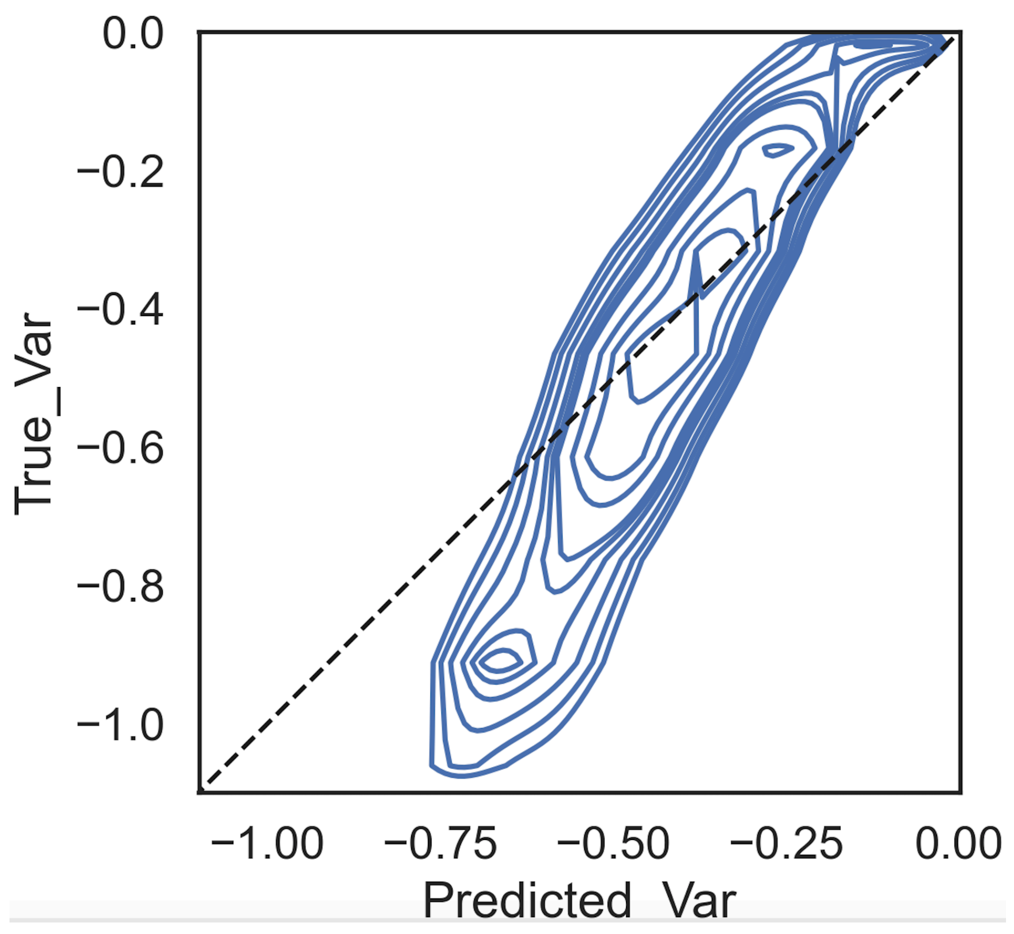


A Convolutional Neural Network

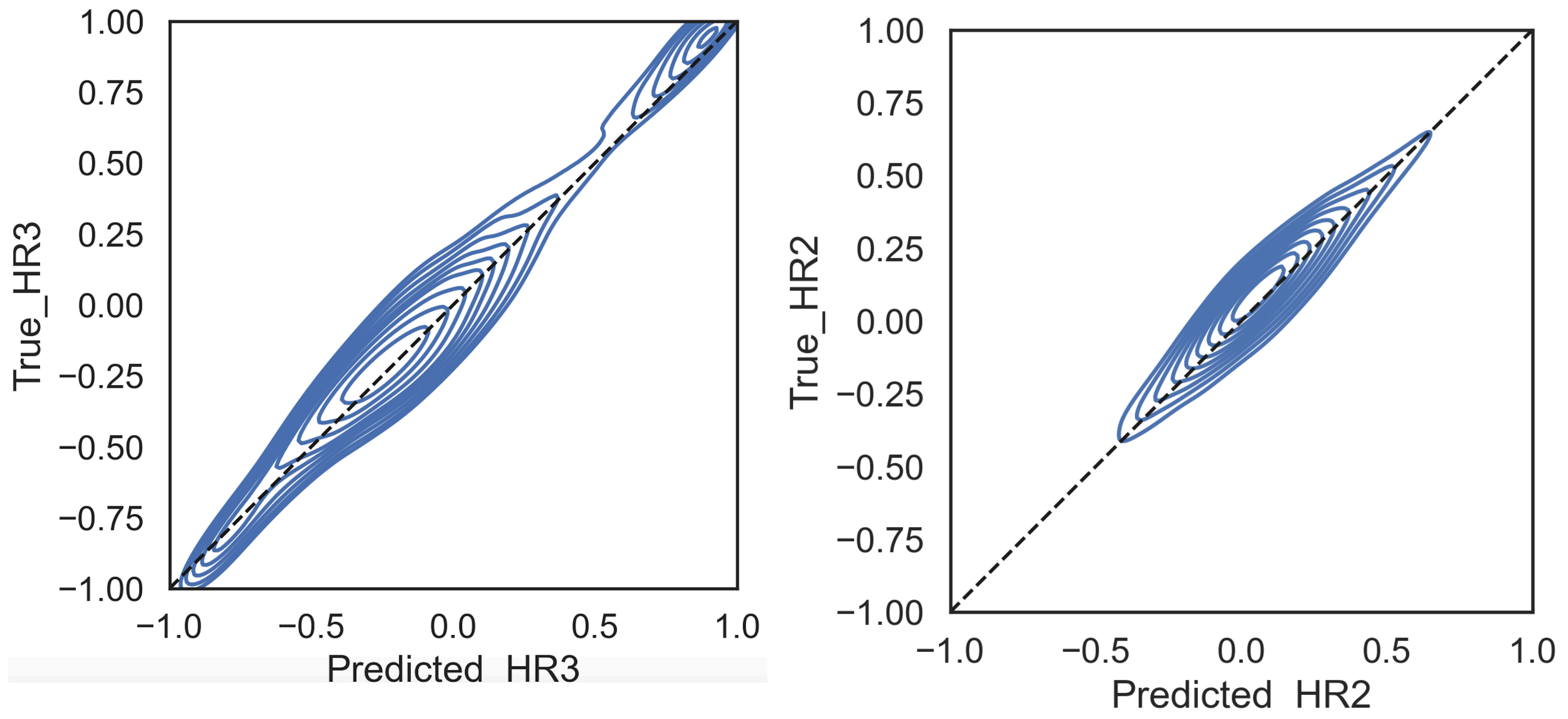
1. The input are Edt maps.
2. Single convolutional layer, followed by single dense, fully connected layer.
3. Activation function are either logistic or tanh, which naturally adapt to the probabilistic nature of the target quantities
4. ADAM optimizer, MSE loss.

Regression results: A simple CNN architecture learns a mapping from event files to physically relevant quantities, such as hardness ratios and variabilities. For a given X-ray detection, this by-passes a relatively complex detection+source properties pipeline. Incorporate into automatic processing?

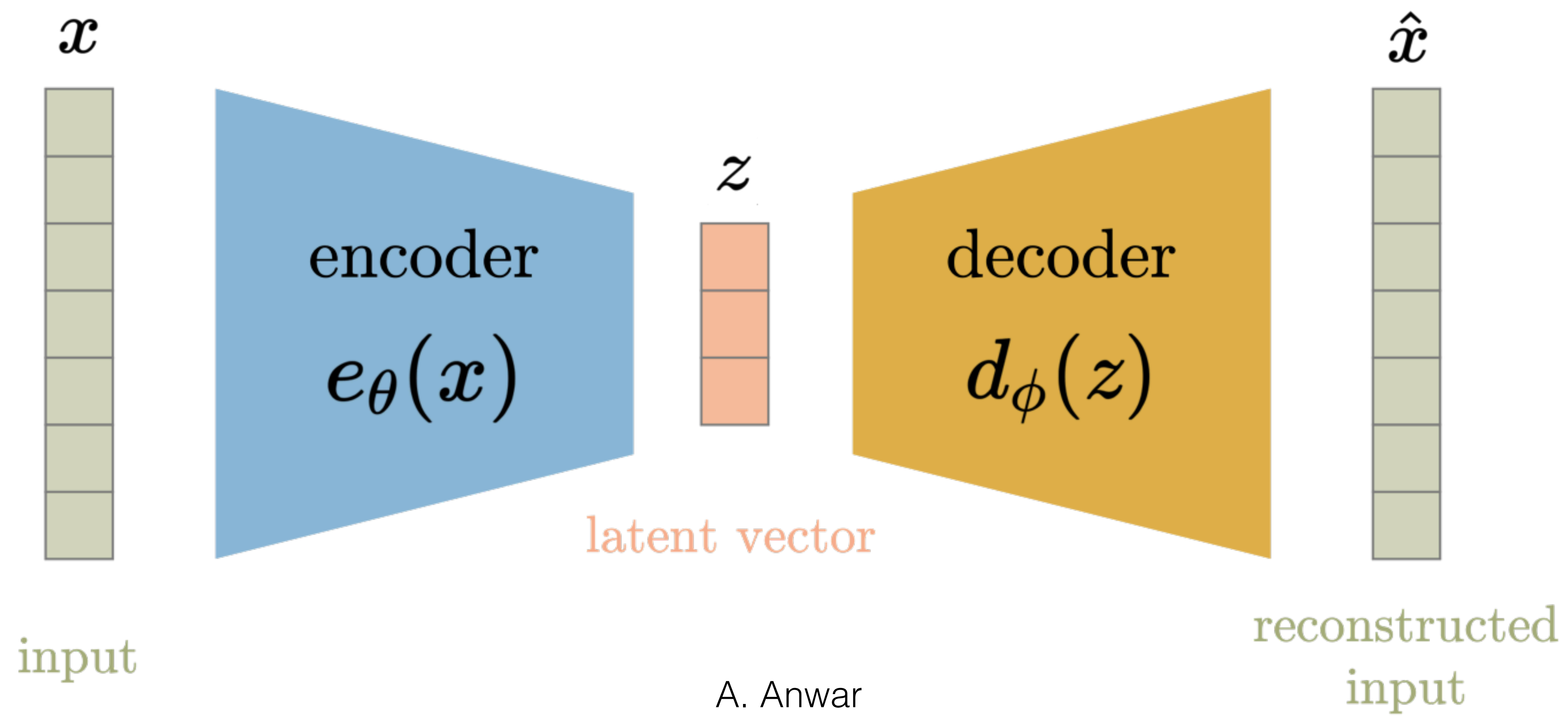
Variability



Hardness ratios



Anomaly detection using an auto encoder



A. Anwar

$$loss = \|x - \hat{x}\|_2 = \|x - d_\phi(z)\|_2 = \|x - d_\phi(e_\theta(x))\|_2$$

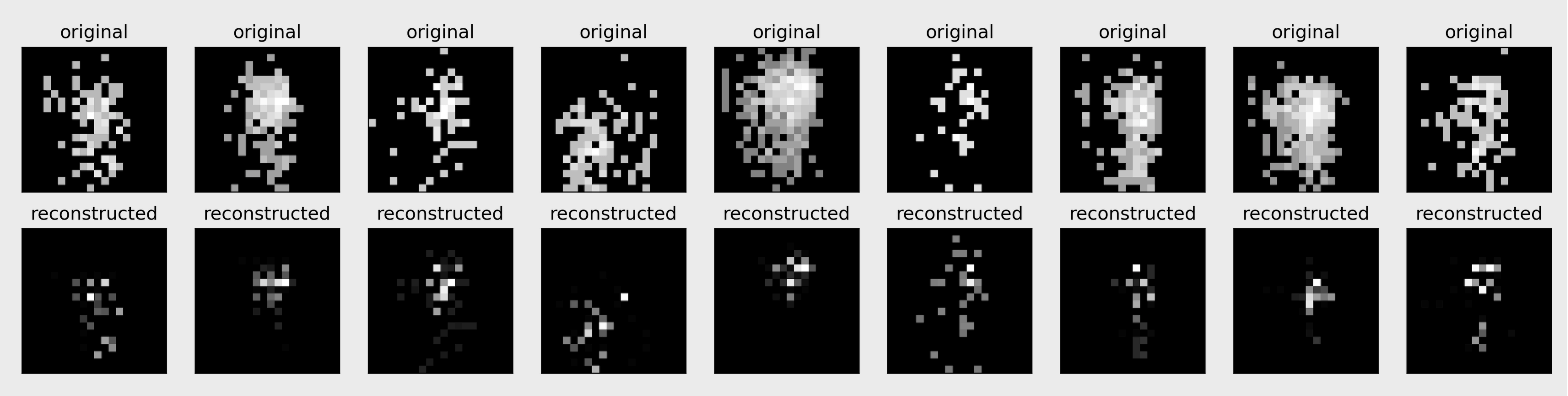
A recipe for anomaly detection in X-ray datasets.

1. Start with a data set of Edt maps.

2. Train an auto encoder model to encode the relevant information in a latent vector and reconstruct the original image.

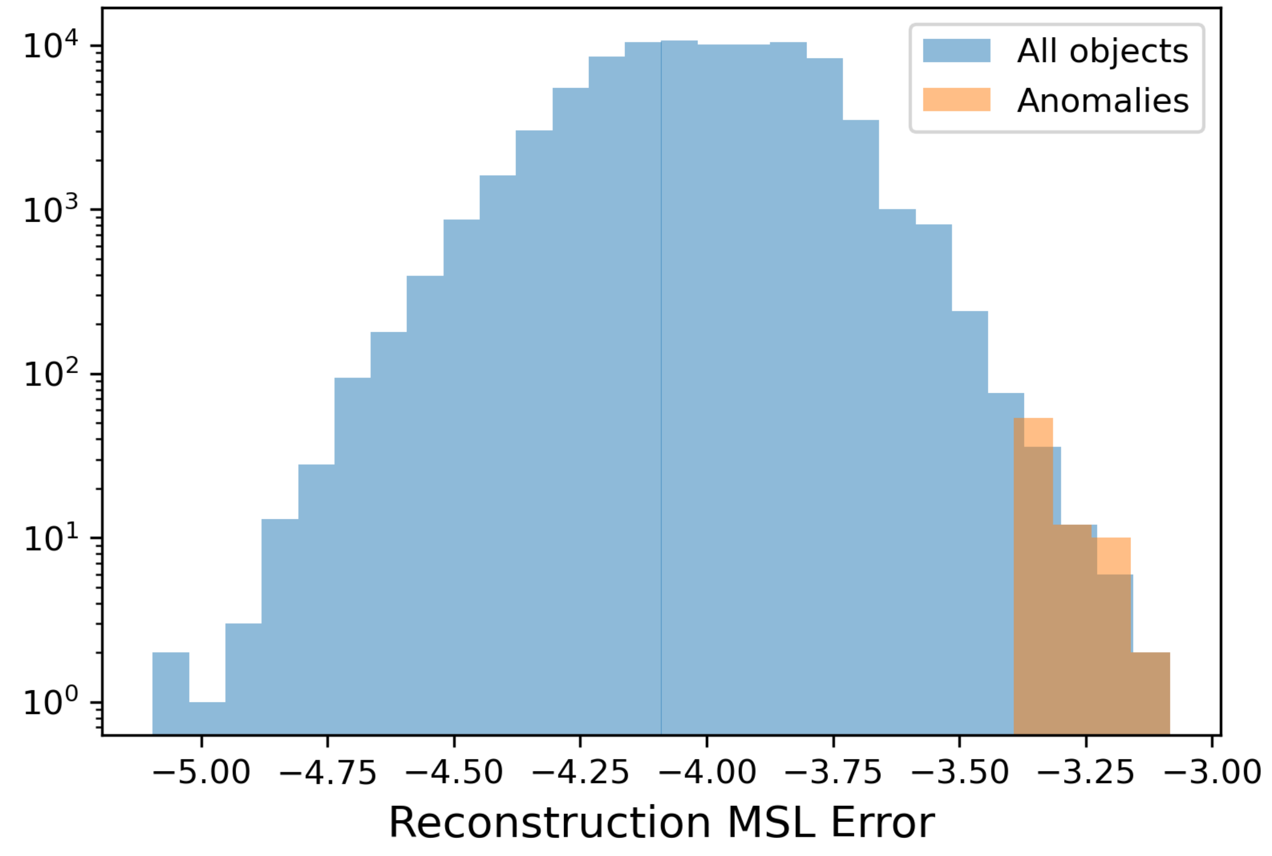
3. Use the reconstruction errors to flag objects as anomalies, i.e. those that the algorithm has more trouble reconstructing.

4. What are typical anomalous behaviors?

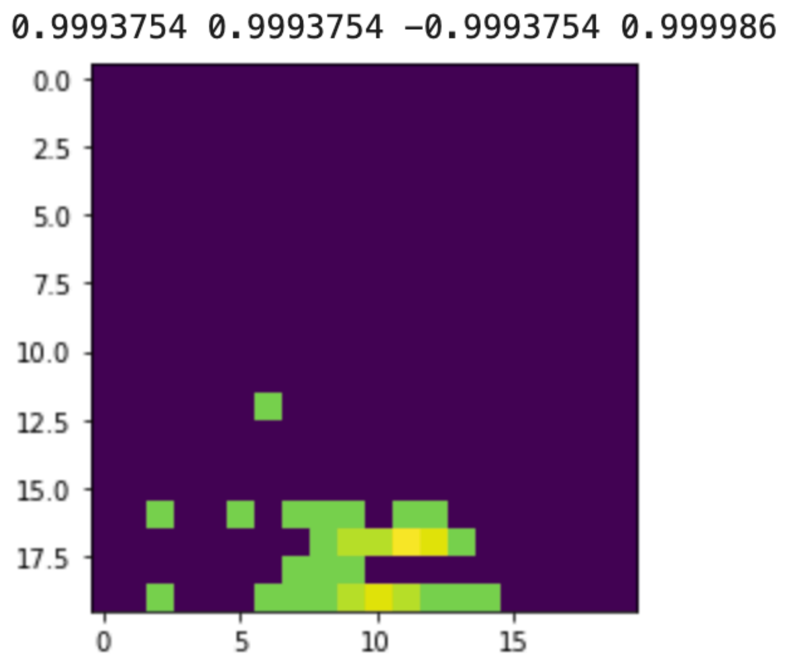


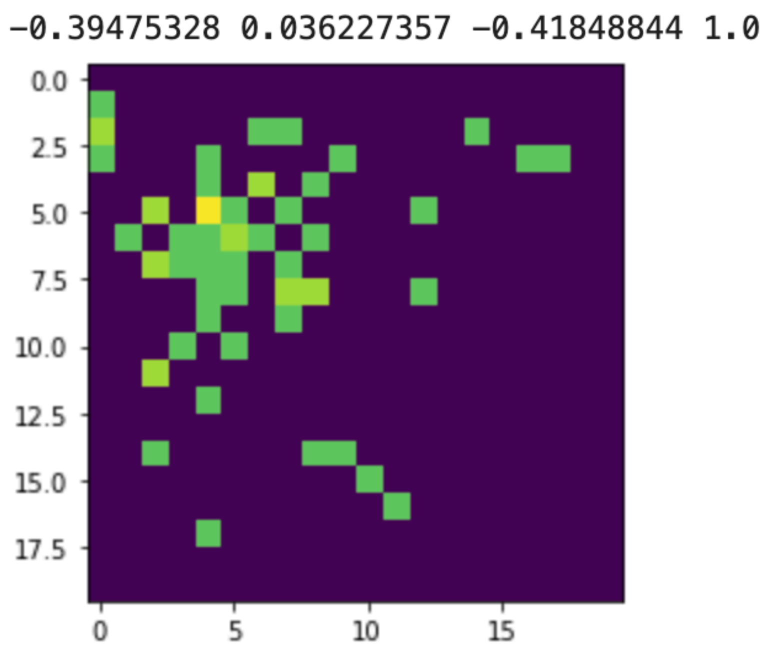
Reconstruction error as an anomaly score

Objects that are less common in the dataset are harder to reconstruct with the auto encoder.

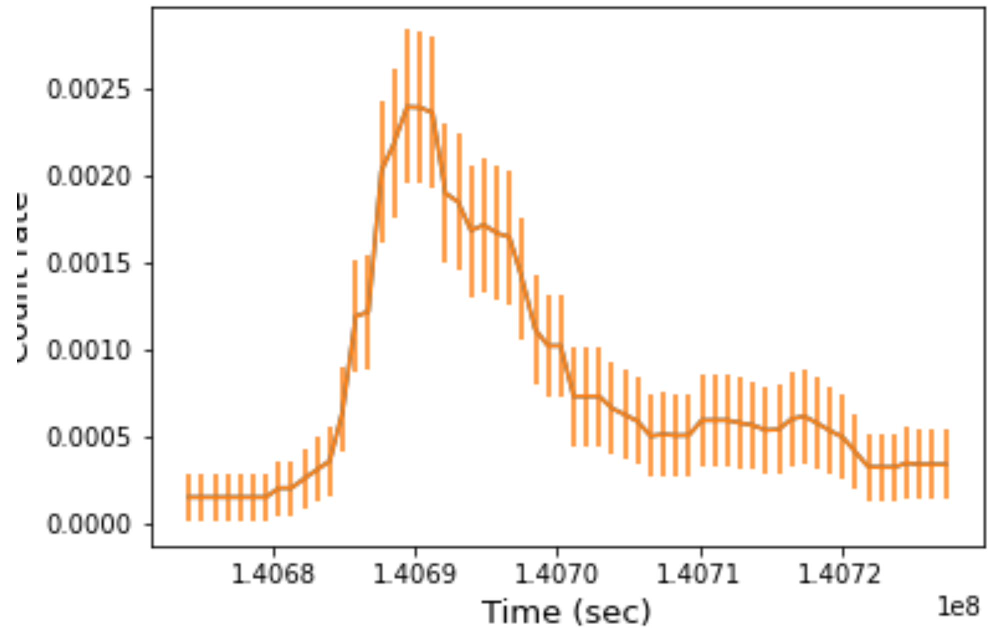


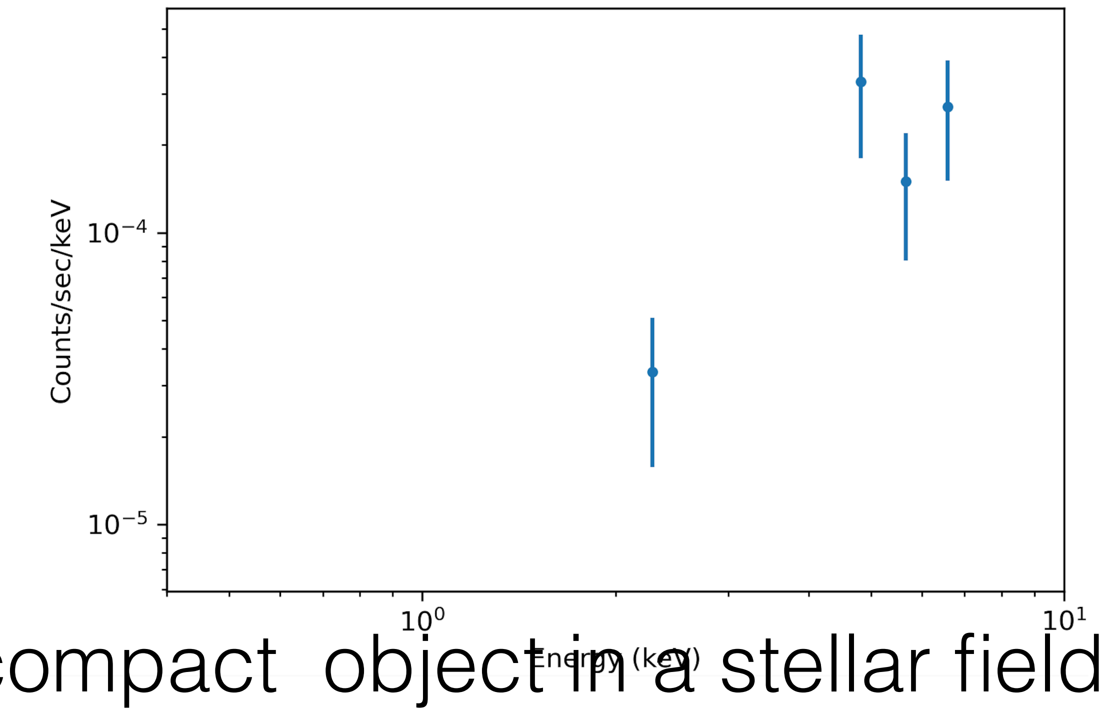
Anomalies are….



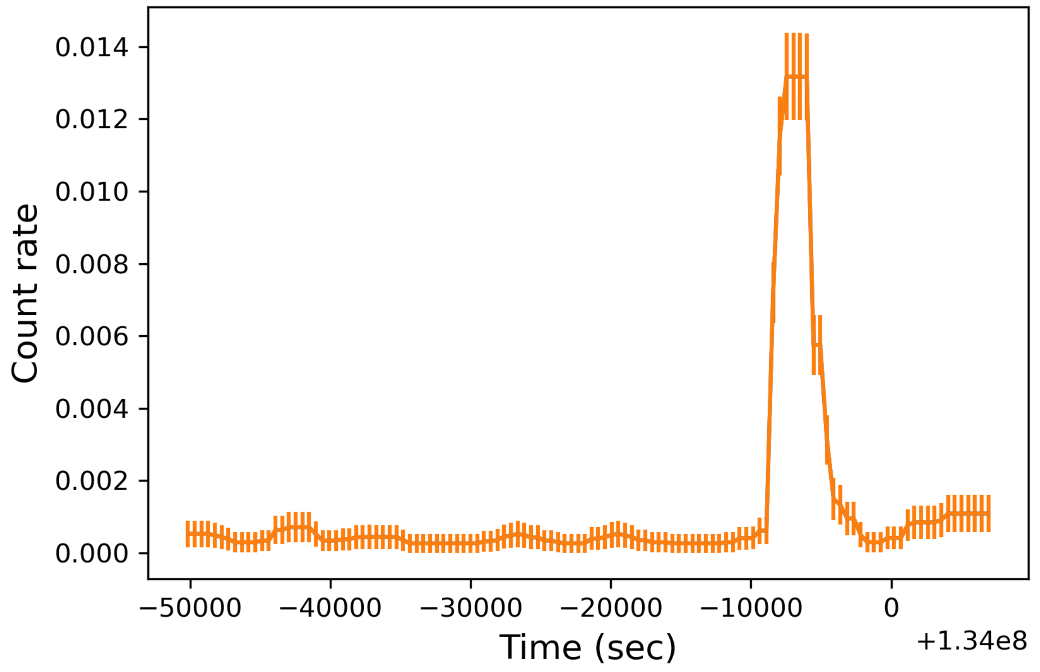


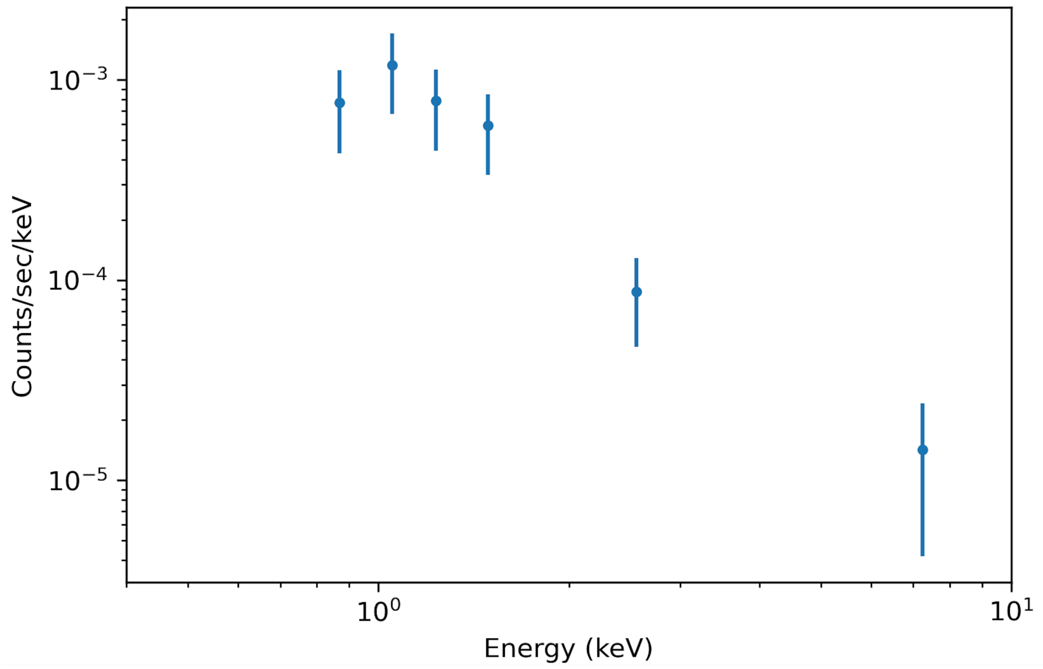
Hard flare from a young star in W51



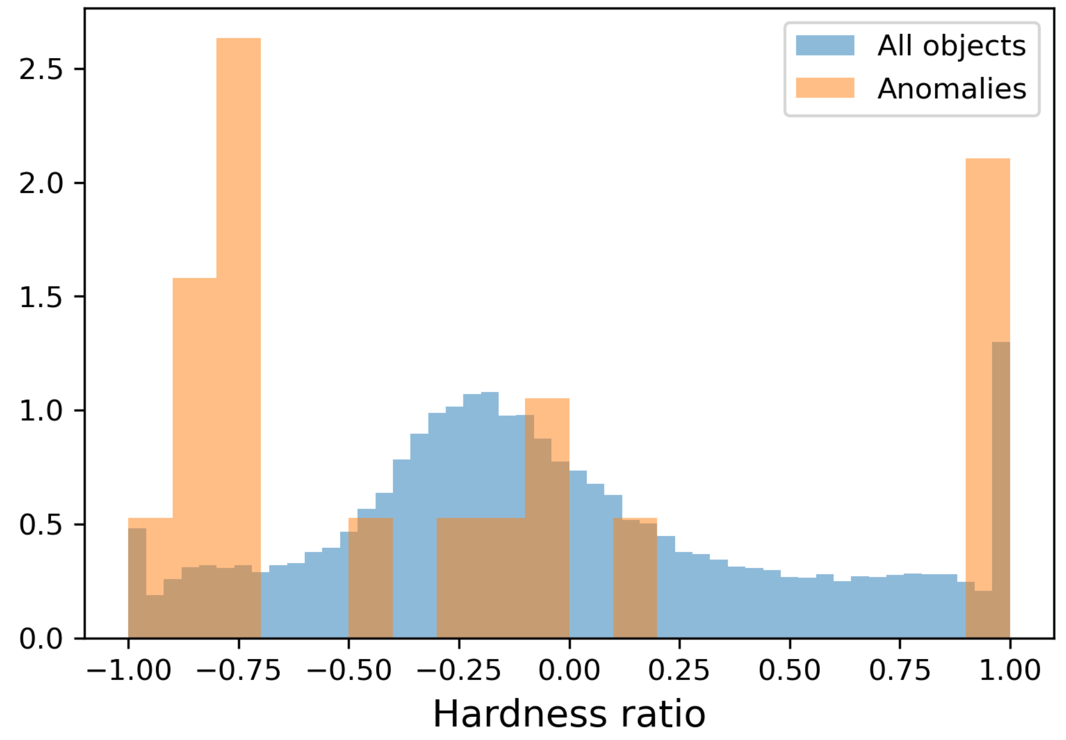


A soft flare associated with a compact object in a stellar field

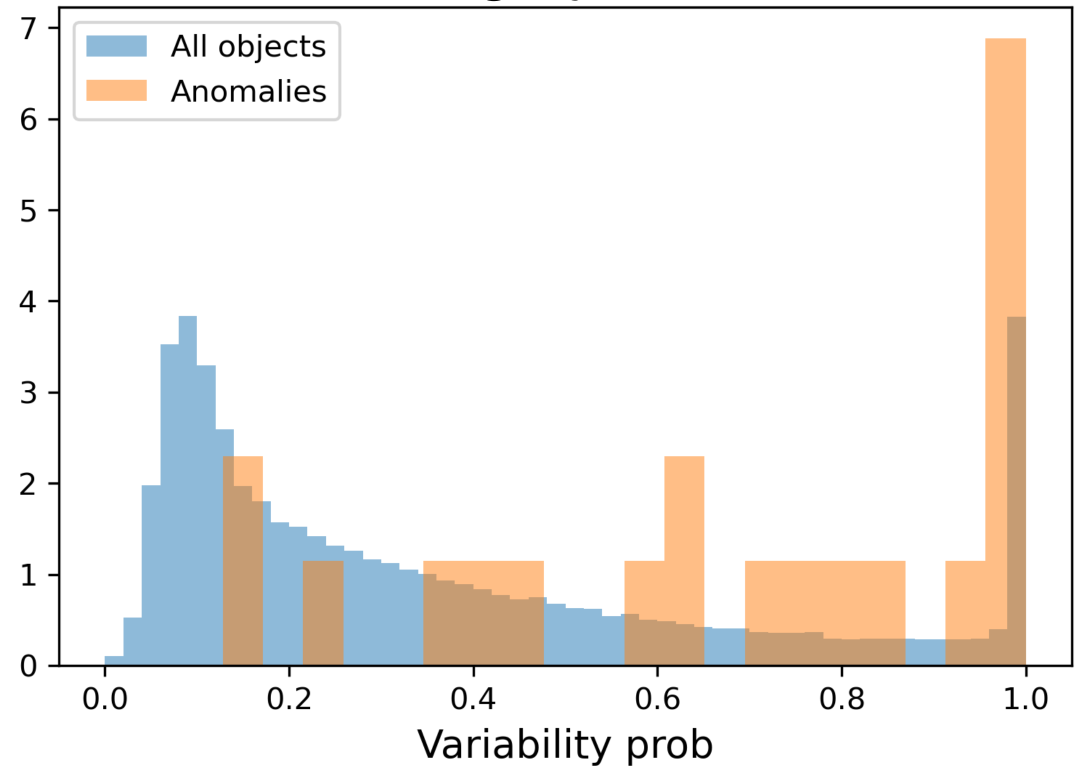




Spectrally extreme

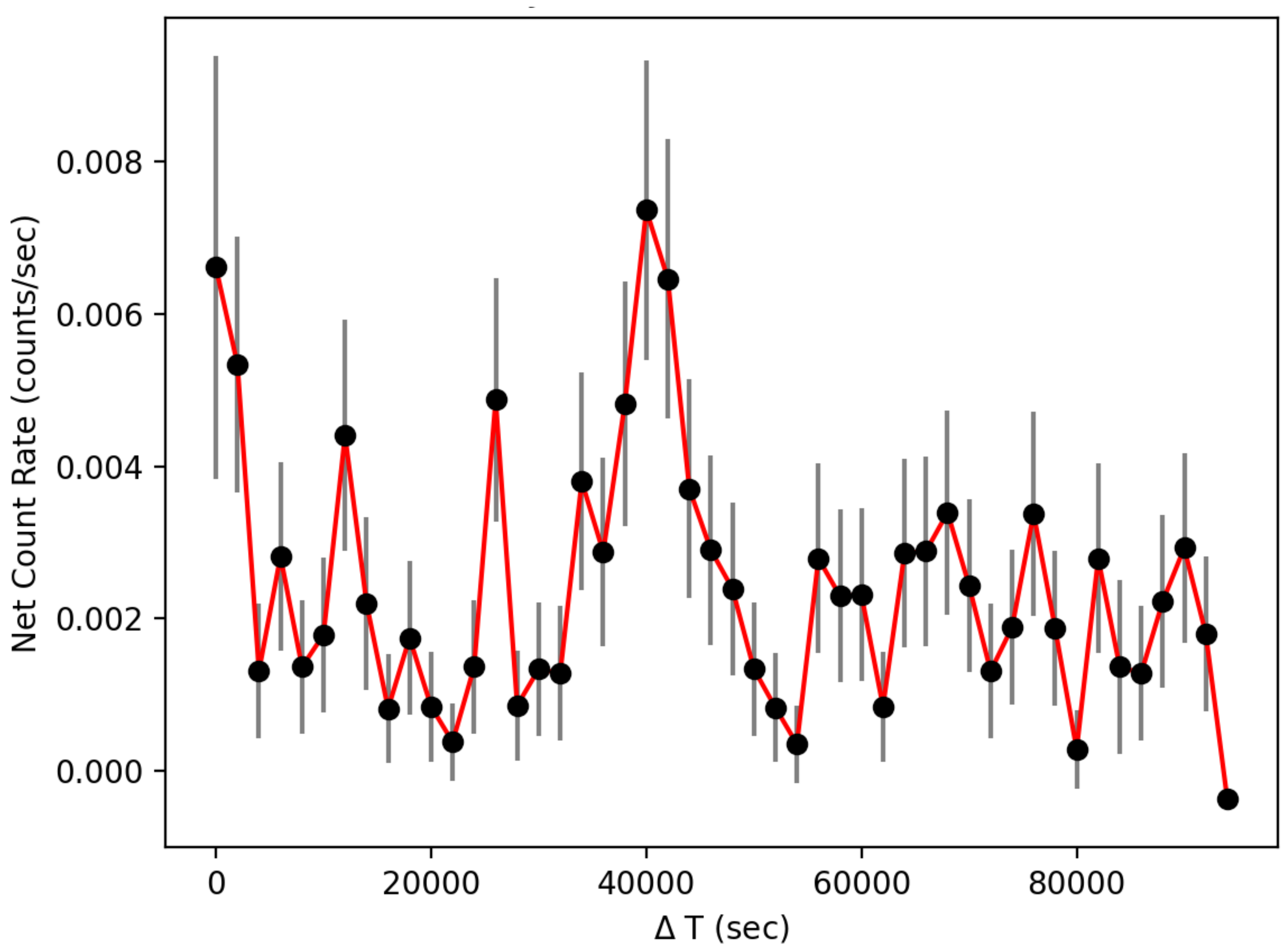


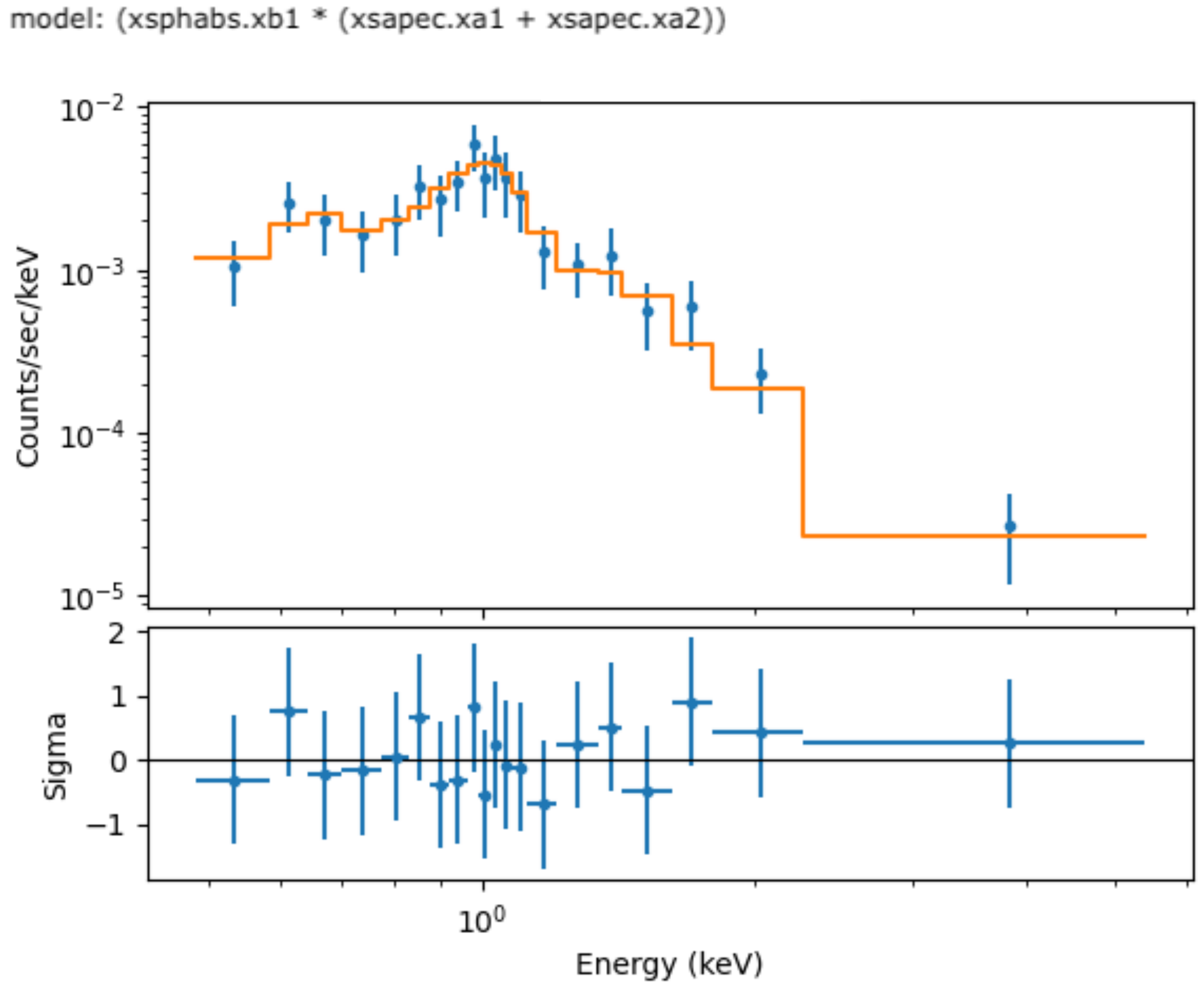
Highly variable

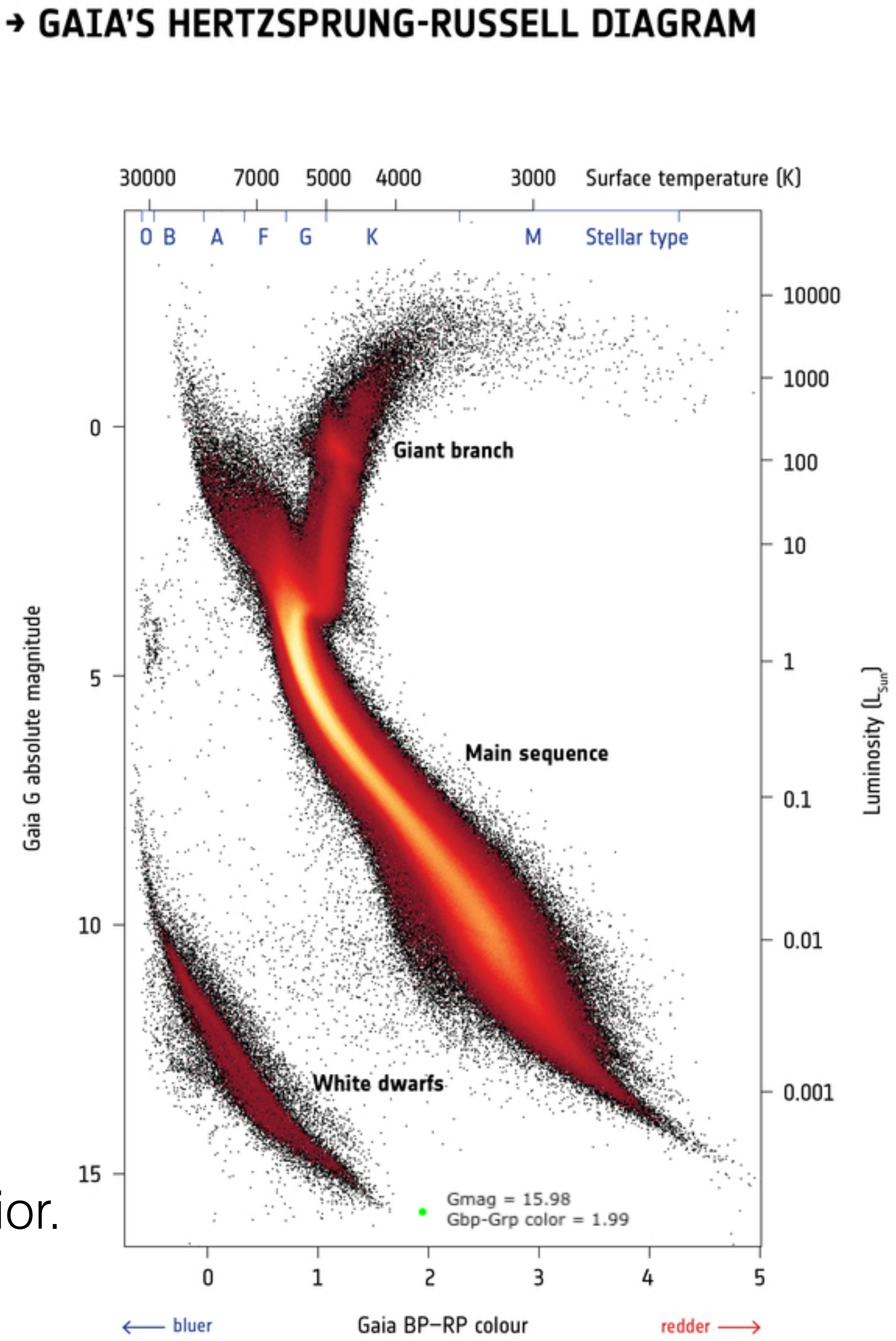


- Transients show up as anomalies in an exploratory search of the Edt maps using neural networks.
- A large fraction of these identified transients are not reported.
- Possible nature? Fast X-ray transients, x-ray binary flares, gravitational lensing events,
- A fraction of them show dips instead of flares.

A transient (lensing?) candidate

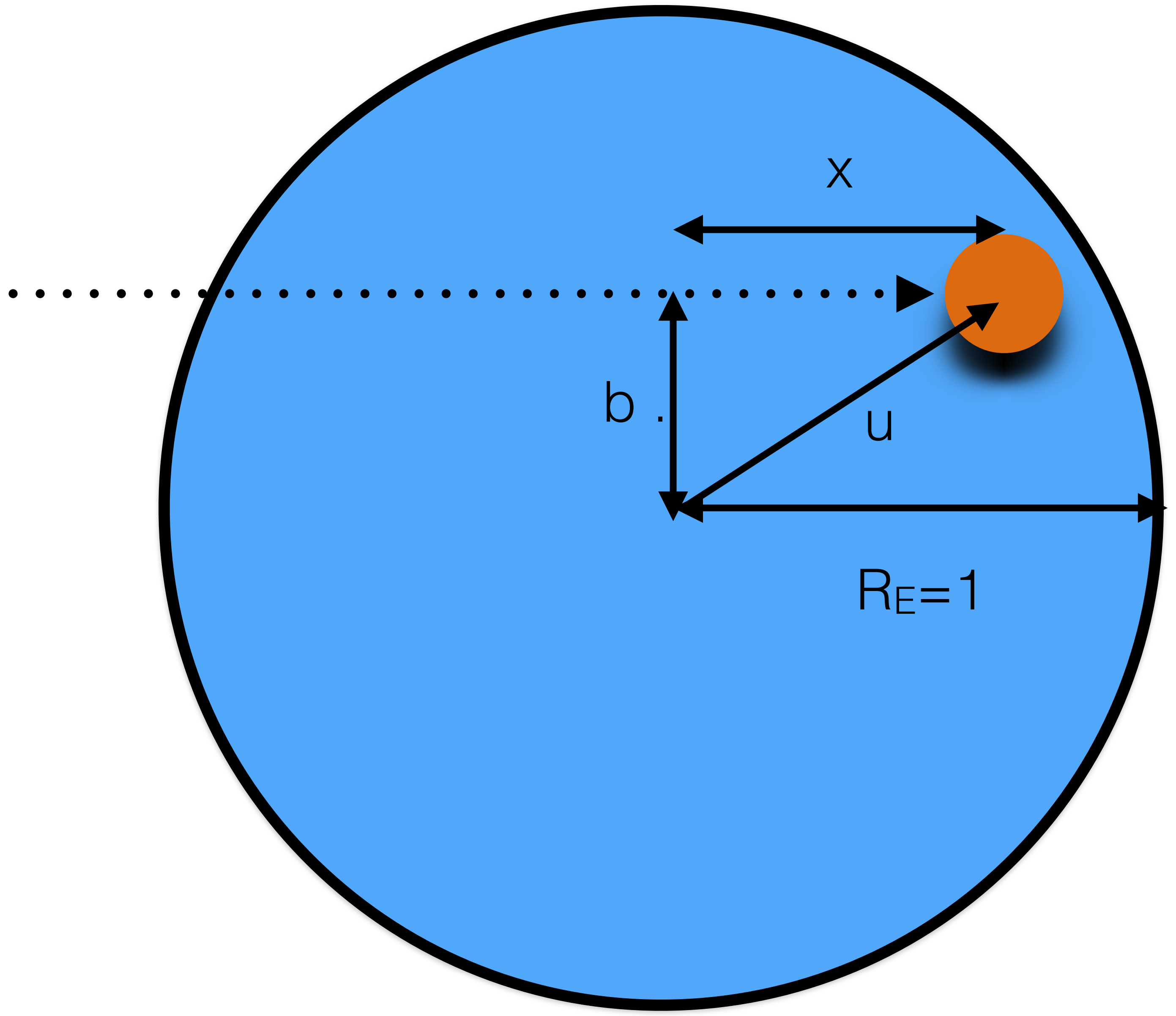






- This transient is very likely real (i.e, the variability peak is statistically very significant)
- Soft spectrum, better fitted with APEC plasma with T ~ 0.2 keV.
- Optical counterpart is a dim white dwarf, so a symbiotic is unlikely.
- No sign of spectral variability during transient, which disfavors flaring behavior.
- We are investigating a potential lensing event.

Looking for precursors: Gravitational self-lensing

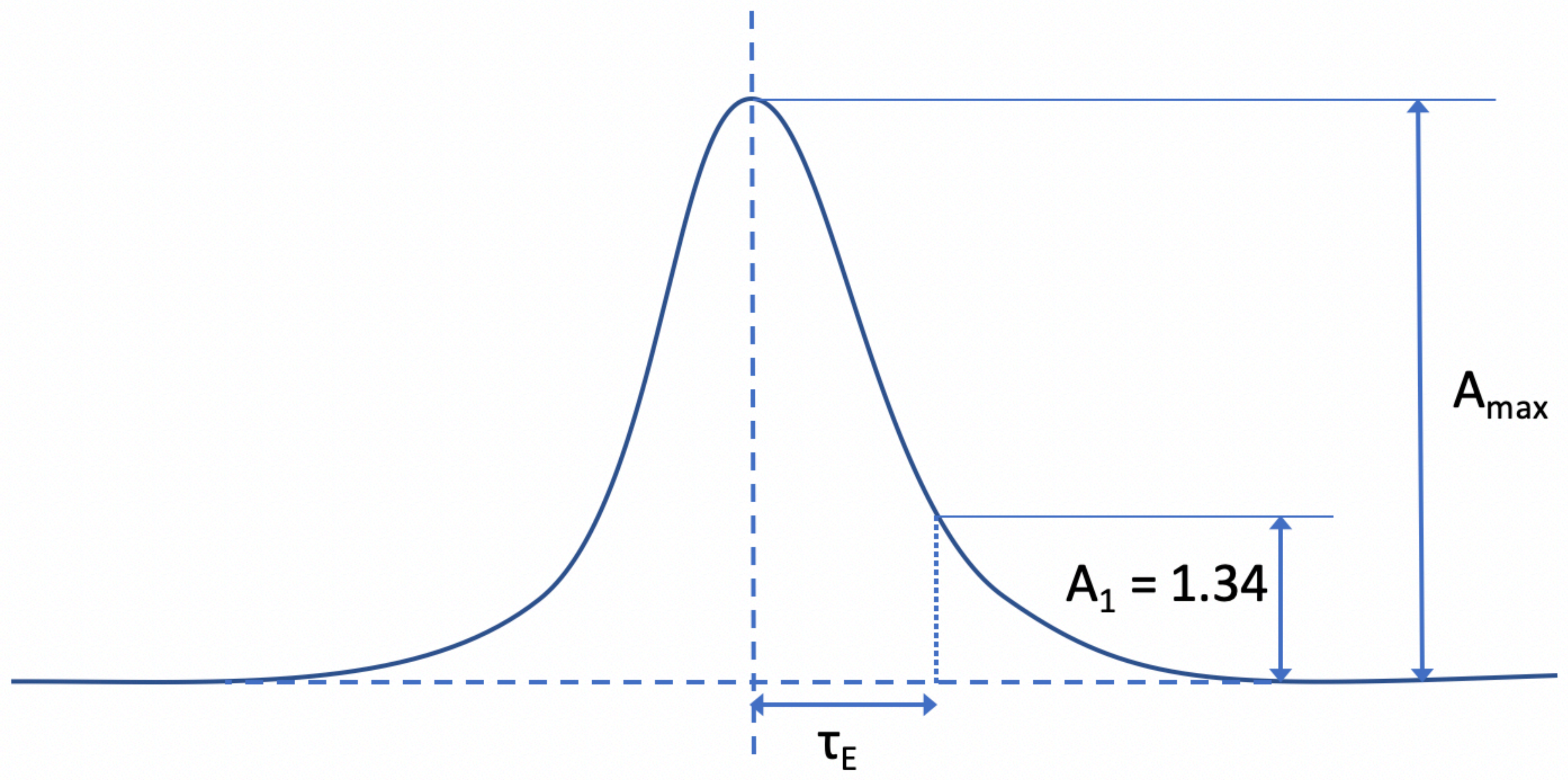


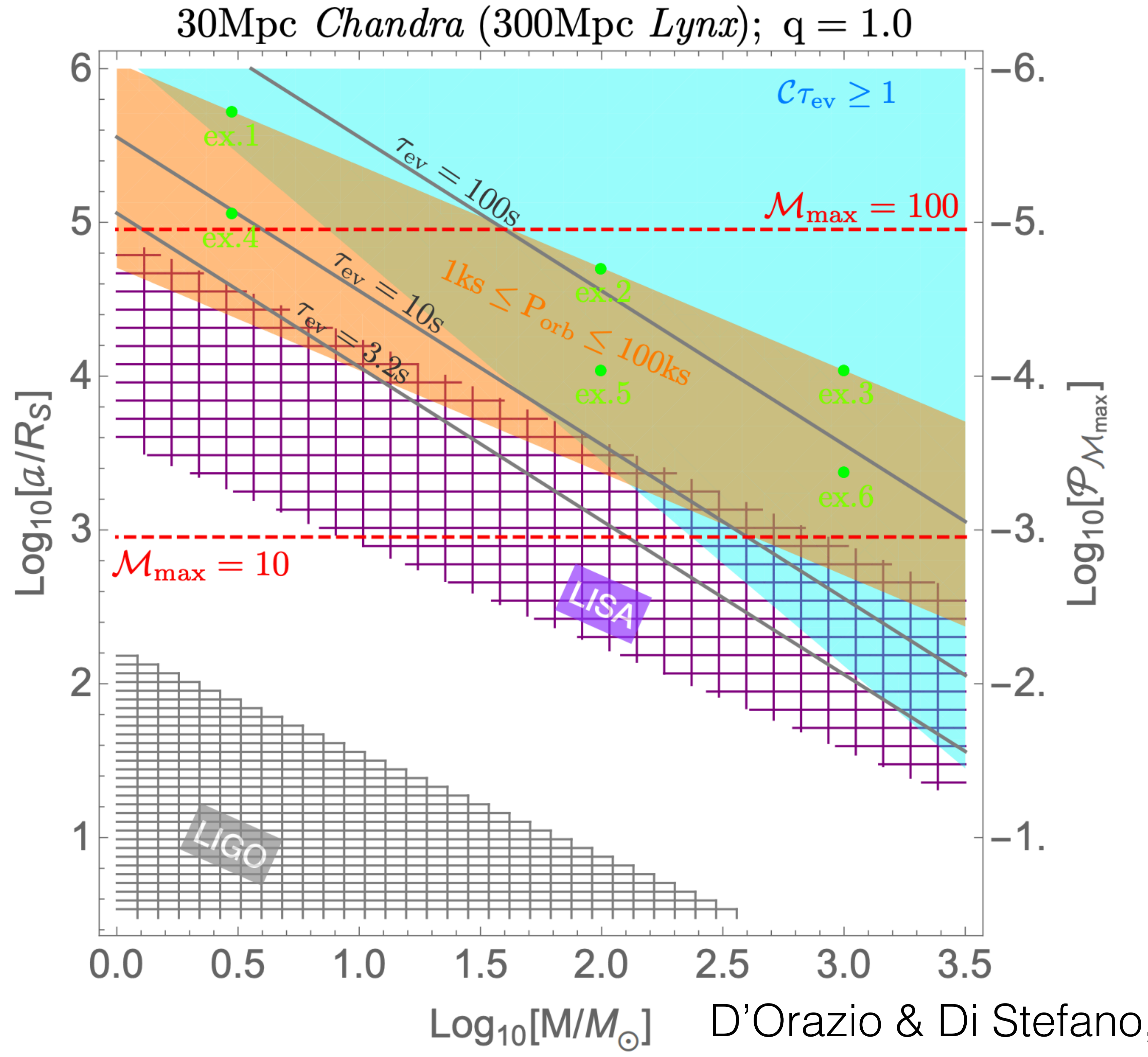
$$A = \frac{u^2+2}{u\sqrt{u^2+4}}$$

$$x = (t - t_0)v$$

$$v = R_E/\tau_E$$

$$A_{\max} = A_0 = \frac{b^2+2}{b\sqrt{b^2+4}} \approx \frac{1}{b}$$





D'Orazio & Di Stefano, 2021

- Periodic lensing signature of binaries within the LIGO frequency band can be detected with current X-ray observations, including Chandra (at 30 Mpc, or with Lynx at 300 Mpc).
- Systematic searches of archival and upcoming Chandra, XMM-Newton, etc. can unveil more candidates.

A few final thoughts…

- X-ray transient detection is of astrophysical relevance for multi-messenger studies, as well as the study of accretion phenomena

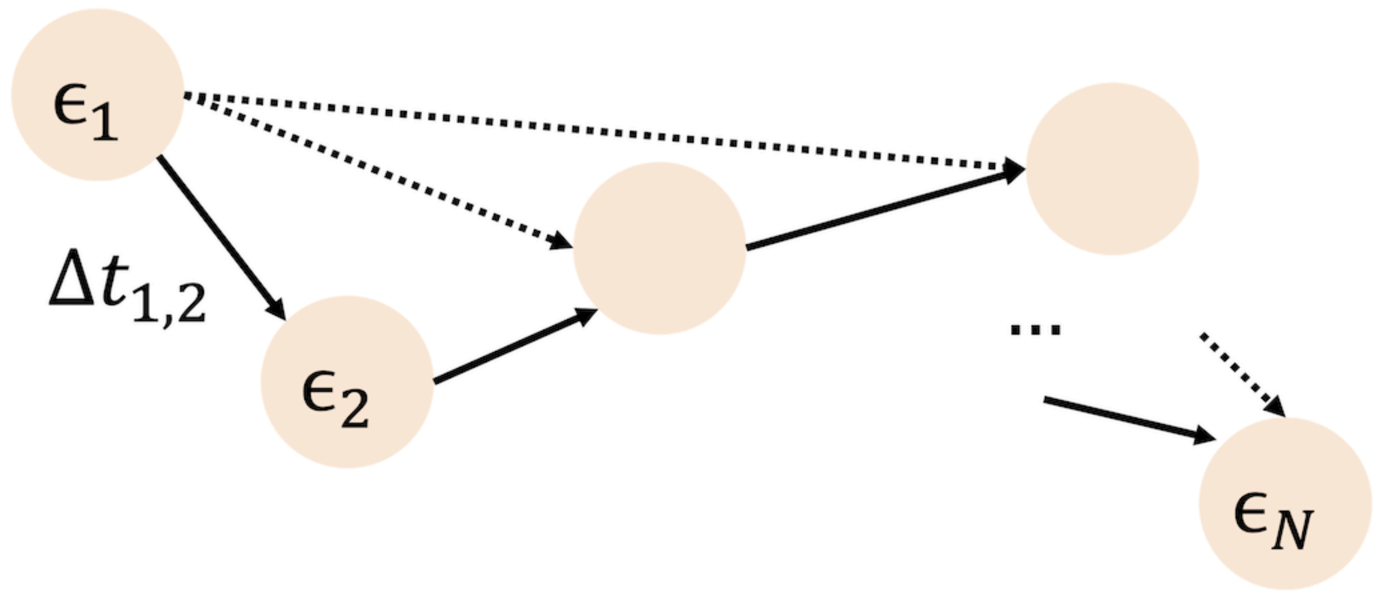
- No automatic detection of transients happen as part of regular automatic processing in Chandra or other X-ray observatories, but this needs to change soon.

- We can learn directly from the event files in a number of ways, leveraging knowledge compiled in X-ray catalogs.

- Spectrally hard/soft transients naturally come as anomalies. A trained algorithm can spot them on the flight during regular processing for new data.

- Trained algorithms for transient finding can be easily incorporated in the automatic processing flow.

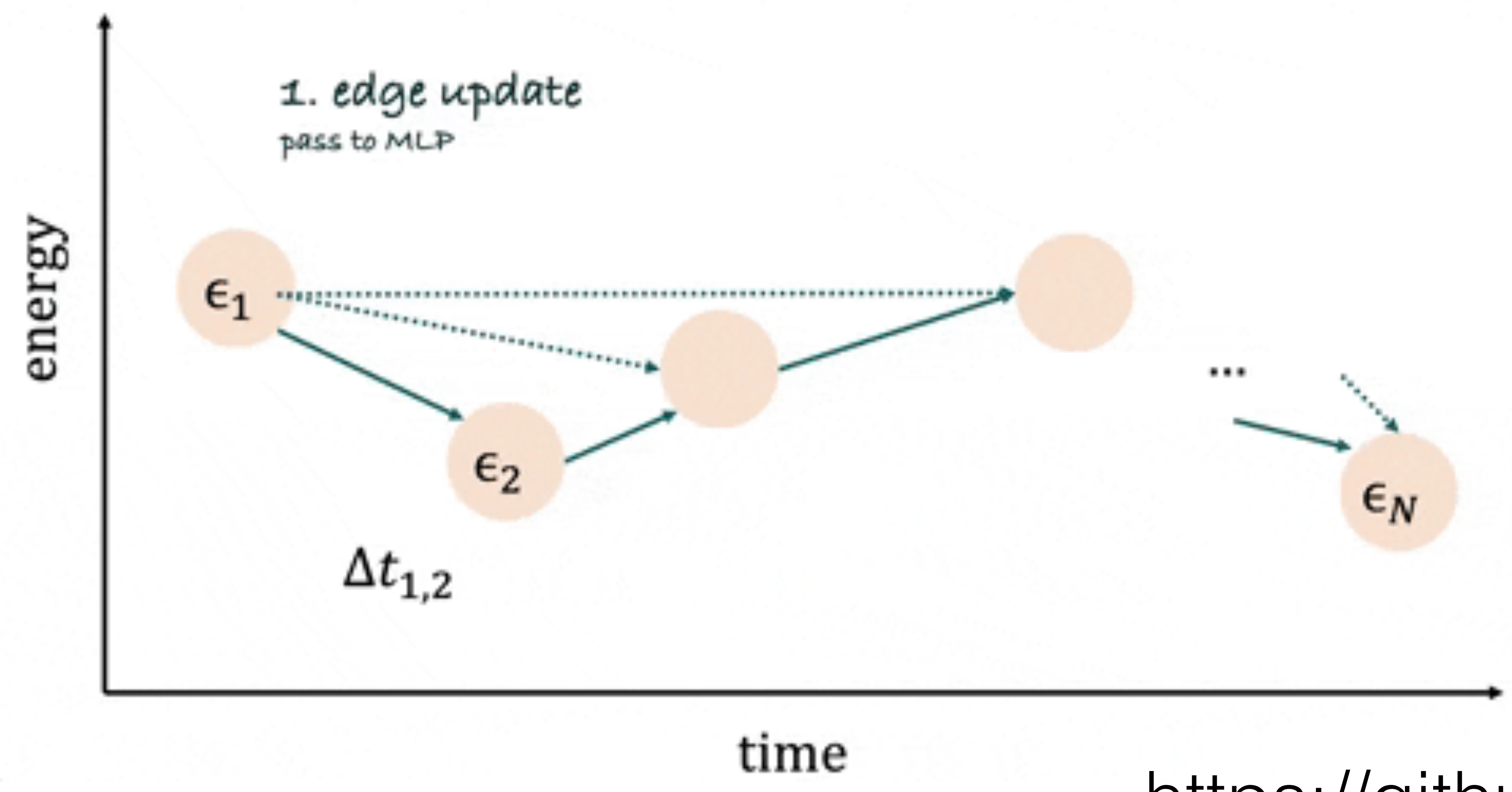
XANDER:Anomaly detection using a graph regressor

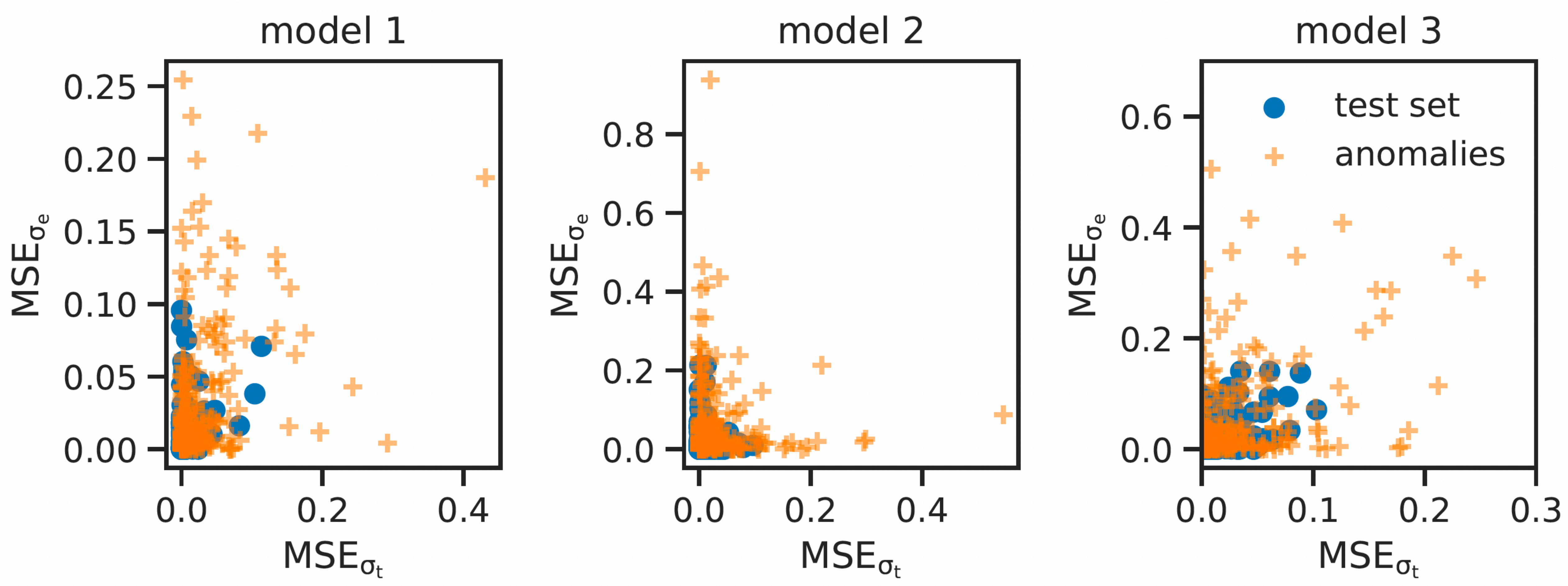


Step 2: Use Graph Neural Networks (GNNs) to regress to known summary statistics like hardness ratios and variabilities to learn posterior mean

A Graph Neural Network

1. The input event files represented as graphs.
2. A graph neural network is built by:
    1. Updating nodes and edges by passing then and their connections through an MLP
    2. Aggregating the updated edges and nodes into a vector with the desired dimension.
    3. Do a global update status with a neural networks operating on the aggregate
    4. Predict for the summary statistics and use prediction error to find anomalies.





https://github.com/tlmakinen/xander

Some recent examples of related research…

- Supervised classification of X-ray sources - Yang et al. 2021(https://baas.aas.org/pub/2021n6i132p02).
- Automatic detection of Chandra background photons (R. Nevin et al.)
- Resolving X-ray source confusion using spatial, temporal, and spectral information (eBASCS, Meyer et al. 2021)
- Recurrent neural networks applied to X-ray datasets for time-domain analysis (Orwat-Kapola et al. 2021)
- See the CDO Chandra Data Science Workshop for more (https://cxc.harvard.edu/cdo/cds2021/)