Finanziato dall'Unione europea NextGenerationEU
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Italiadomani PIANO NAZIONALE DI RIPRESA E RESILIENZA
ICSC Centro Nazionale di Ricerca in HPC, Big Data and Quantum Computing

Anomaly Detection with Machine Learning on Time Series: Unveiling Lost Transients Data

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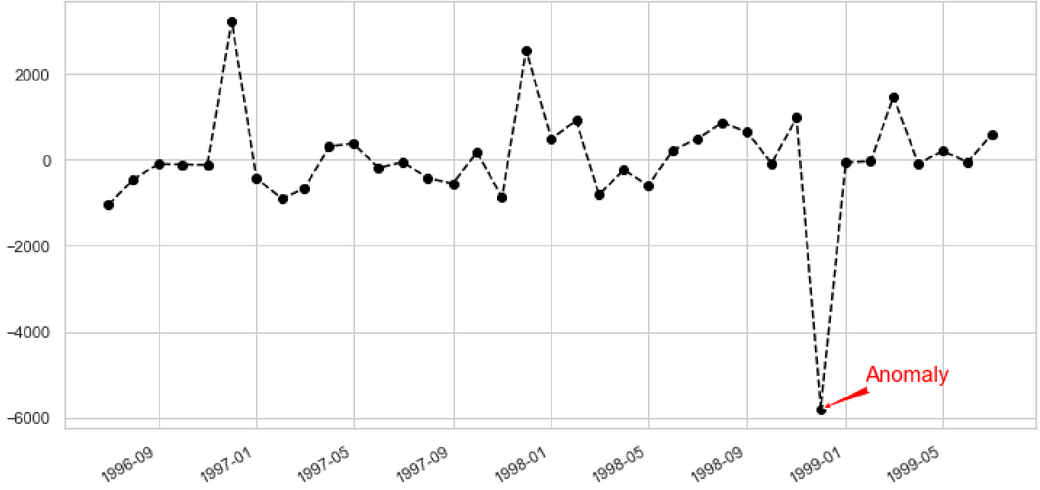
Sexten, 30-06-2025 – 04-07-2025

Our Aims



- To develop an Anomaly Detection algorithm for Time Series data using Machine Learning techniques and efficient triggering algorithm;

- Apply it to create a pipeline for the astrophysical data from the Fermi Anti-Coincidence Detector (ACD) to find astrophysical transients (GRBs, FRB, SGR);

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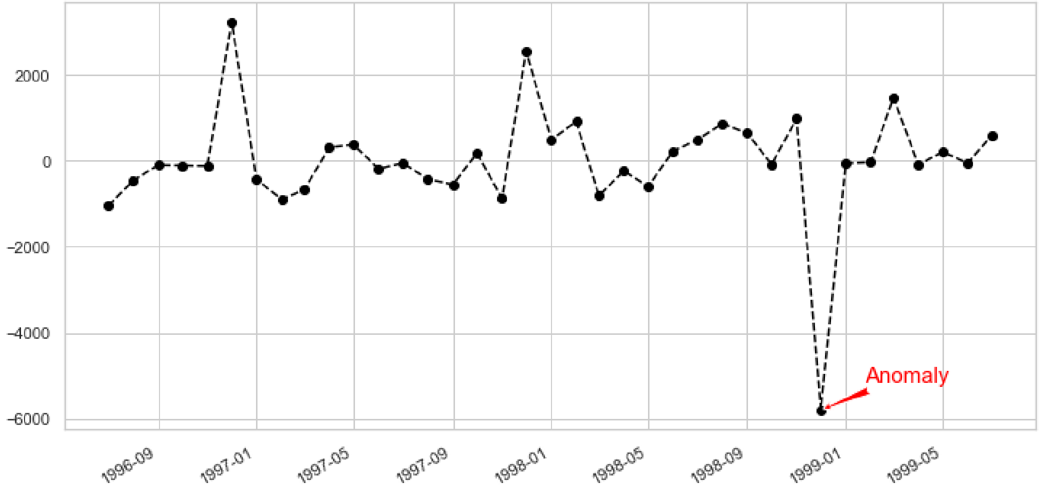

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Methodology

The functionality of this framework can be summarized in two points:

1. **Get a baseline prediction $\widehat{Y}$ of a signal Y, given a set of context variables X and a corresponding value of $\widehat{Y} = f(X)$.**

2. **To use the prediction for the background of Y to find significant deviations in the signal with an efficient algorithm.**

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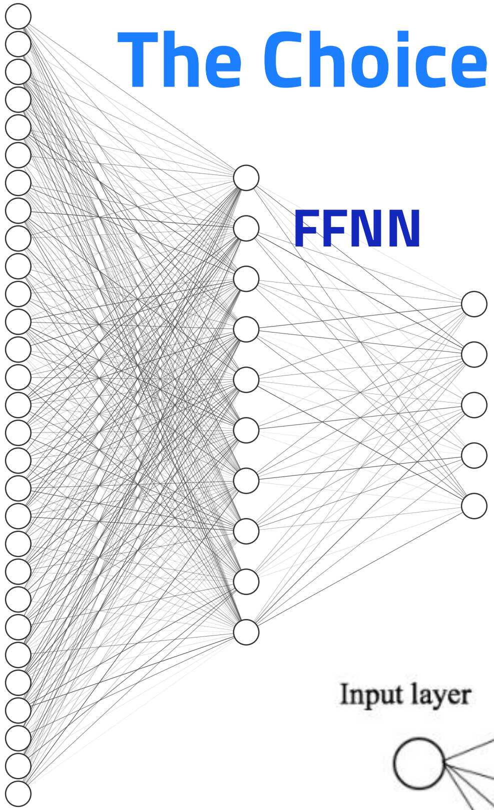
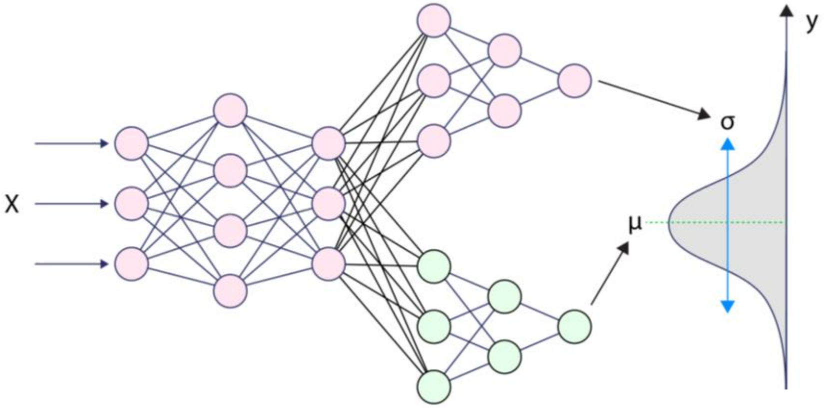
The Choice of the NN based on the Model

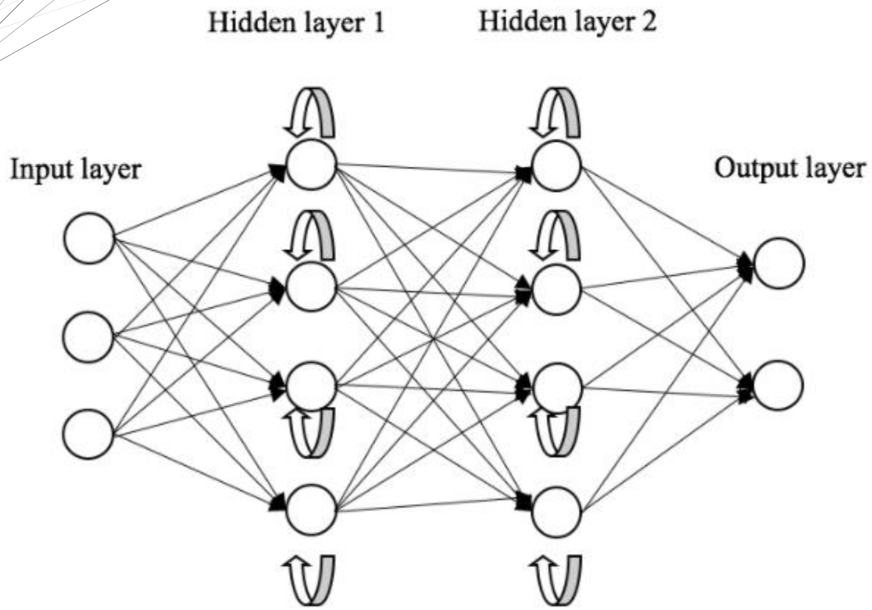


FFNN

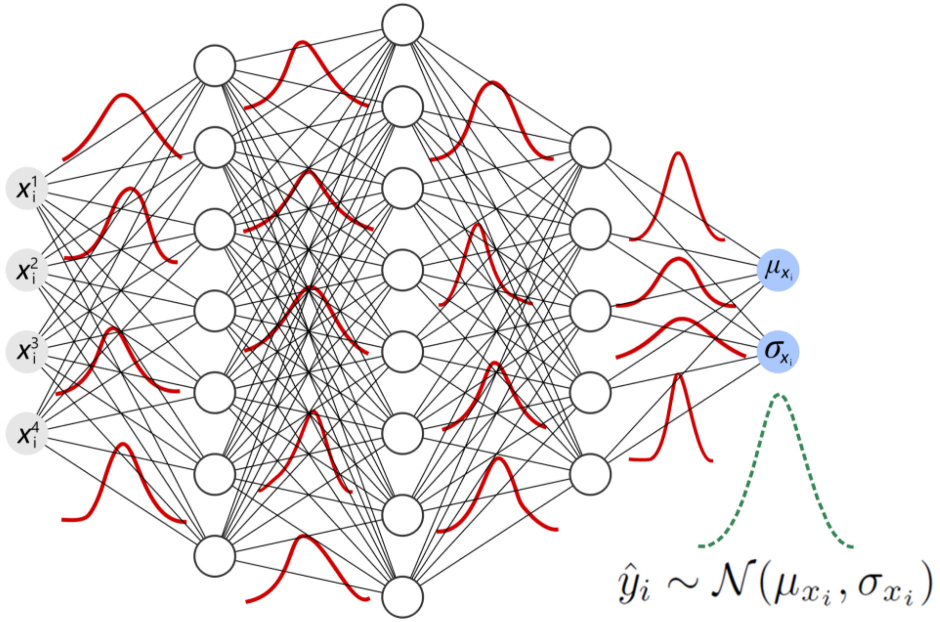


BNN

RNN



PBNN



Triggering Algorithm

The optimal choice would be a triggering algorithm sensitive to transients of different time scales, and that does not require predefined window sizes for background estimation or fixed thresholds for anomaly detection.

Triggering Algorithm: FOCuS

The Functional Online CuSUM (FOCuS) is a fast and efficient algorithm based on the computation of the cumulative sum of the significance of the data.

***Efficient*: computes the sum of score statistics and compares it to a threshold. Efficient at identifying change points in the data set.**

***Fast*: only records score statistics of data points that deviate from the distribution.**

$$S(s,n) = \sum_{i=s+1}^{N} H(x_i, \mu_0)$$

Very powerful to estimate the start of an anomaly, before the cumulative sum is above the threshold.

Triggering Algorithm: FOCuS

The Functional Online CuSUM (FOCuS) is a fast and efficient algorithm based on the computation of the cumulative sum of the significance of the data.

Can be used in *flavours*:
-Poisson-FOCuS: assumes a Poisson-like distribution of data; can be used for count rates data.

-Gaussian-FOCuS: assumes a Gaussian distribution; can be used for continuous signals (flux…)

-Non-parametric-FOCuS: no assumptions on the type of data.

Anomaly Detection Software

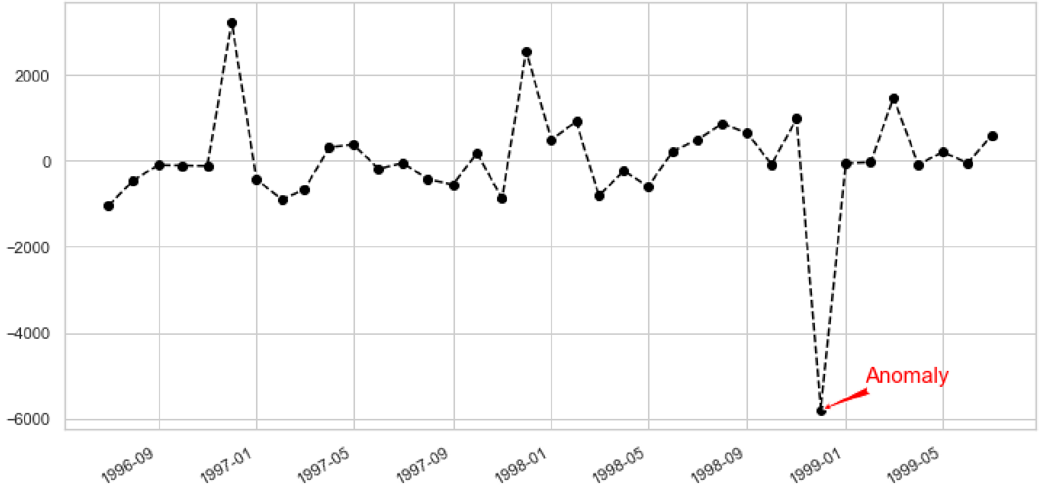
Can be used in the form of an online/offline pipeline to analyse time series data.

The documentation is available (needs constant updating), together with a set of examples, both in modular form and in the form of a pipeline.

You can also find a poster on its application on the Fermi ACD data.

SCAN ME

Our Aims



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Fermi ACD application

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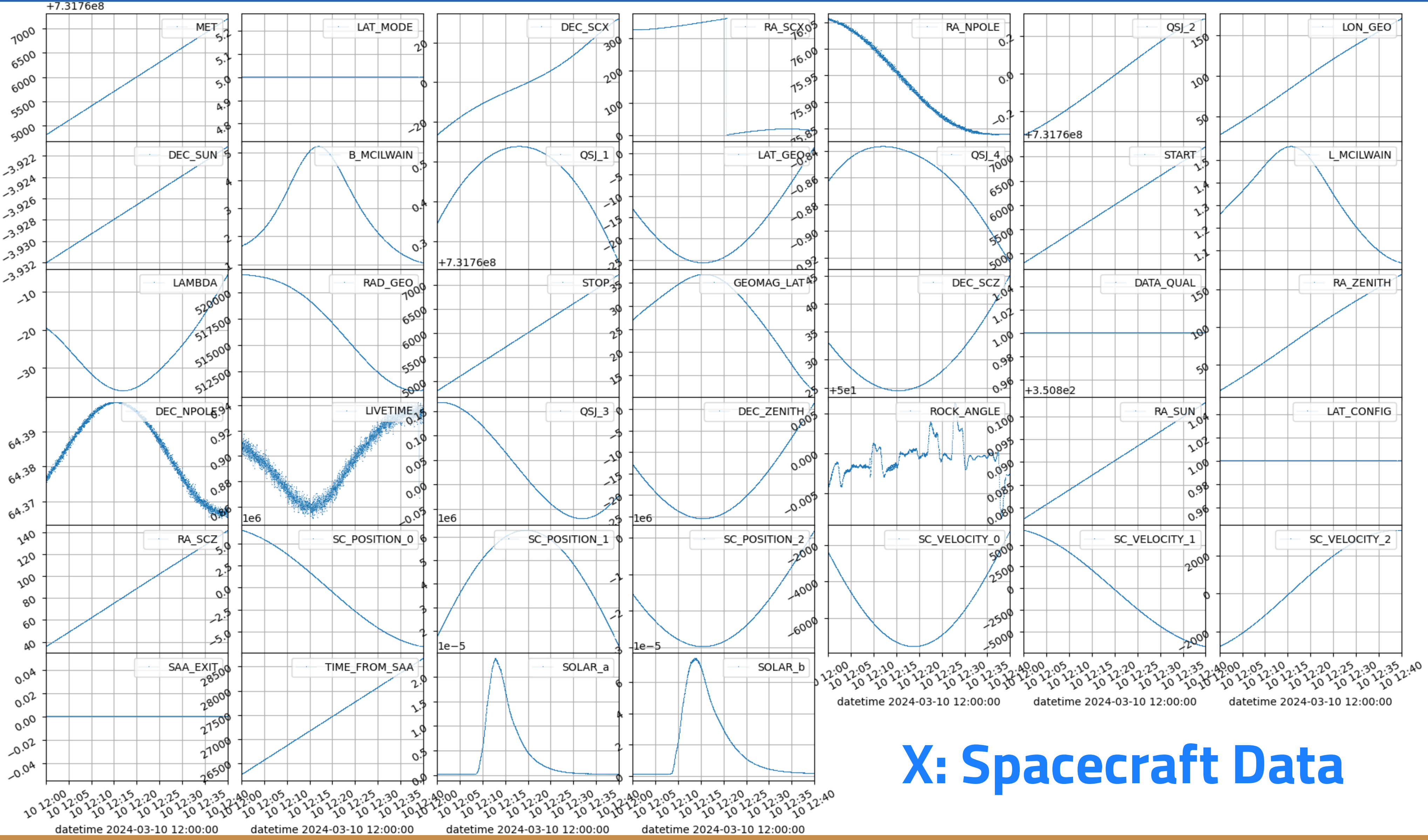
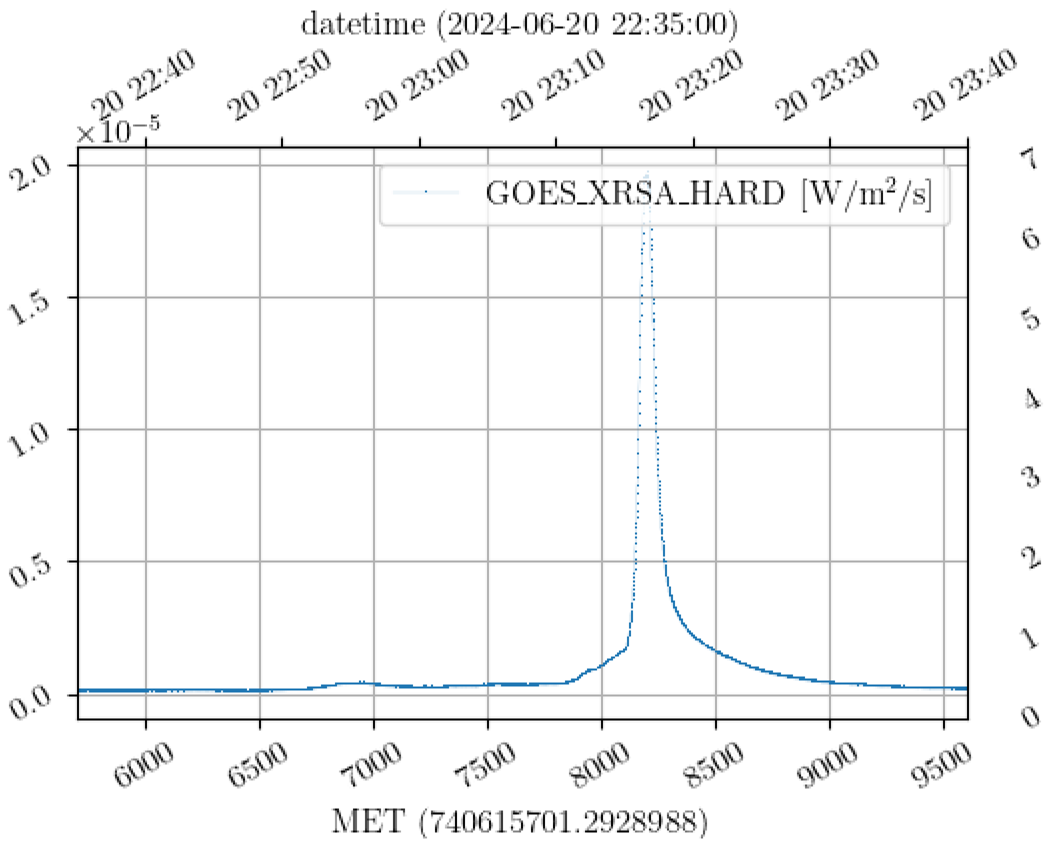
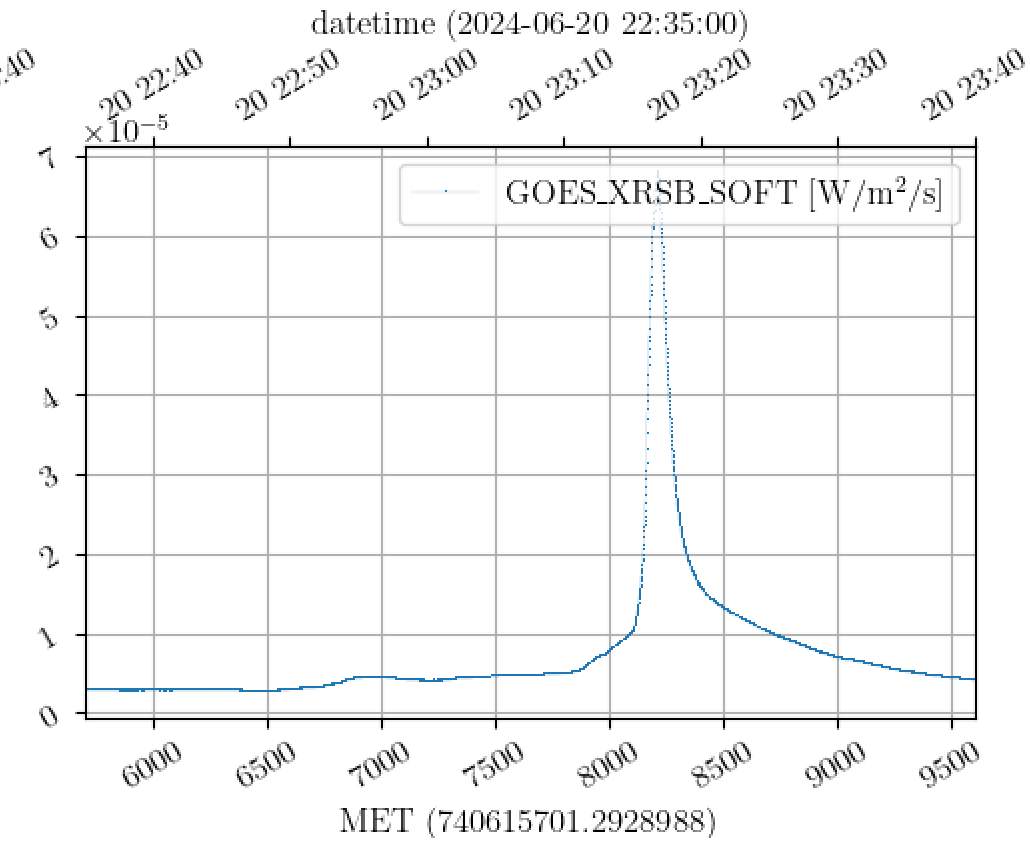


X: Spacecraft Data

X: Solar Activity Data from GOES X-Ray Sensor (XRS)

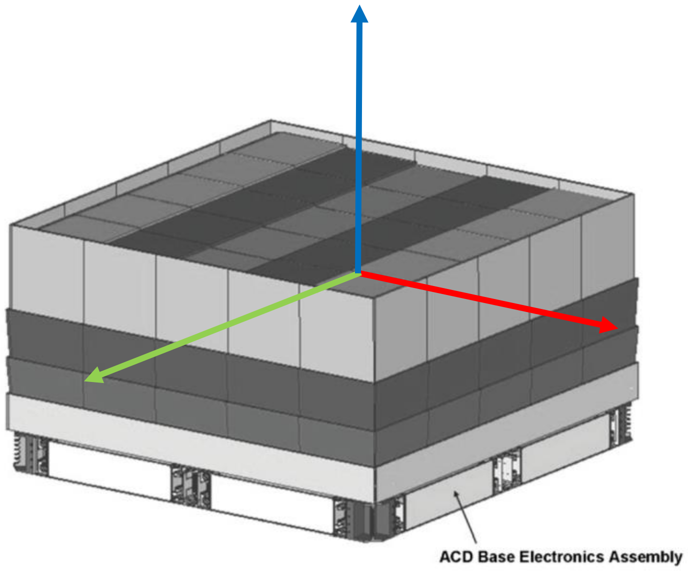
It describes the flux of X-rays coming from the Sun.

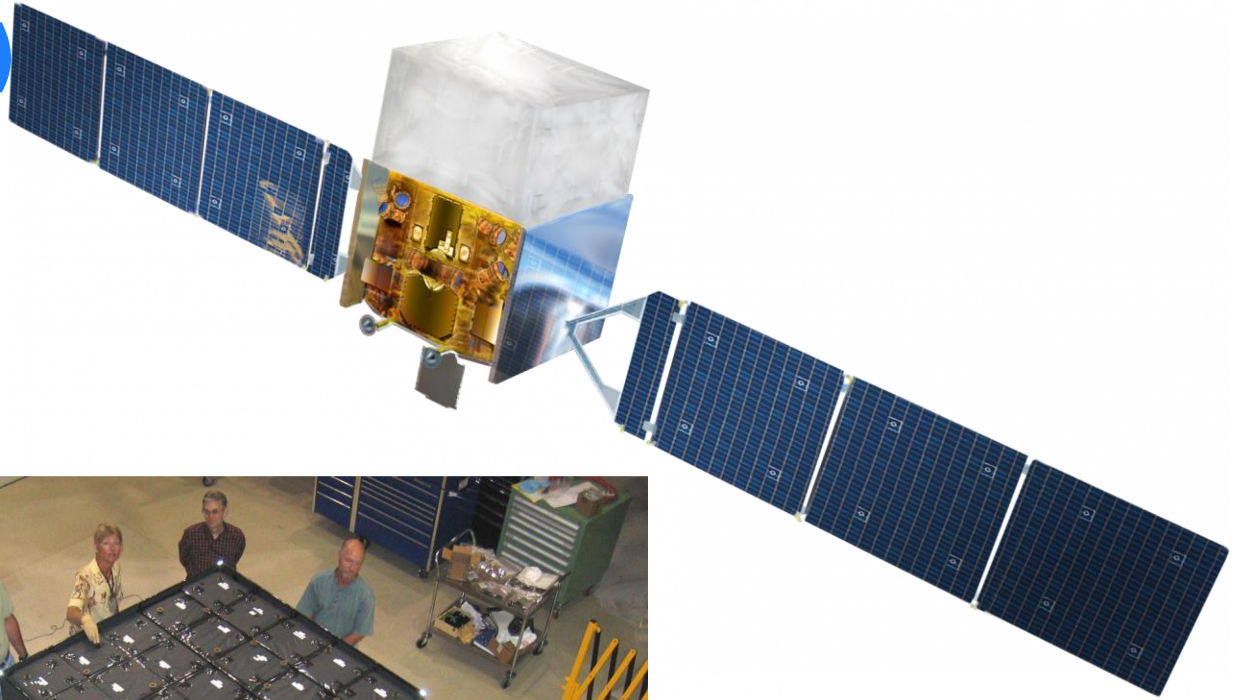




Y: ACD Data (~1 yr of data, 2024)

- -top (Z)
- -Xpos (X+)
- -Xneg (X-)
- -Ypos (Y+)
- -Yneg (Y-)





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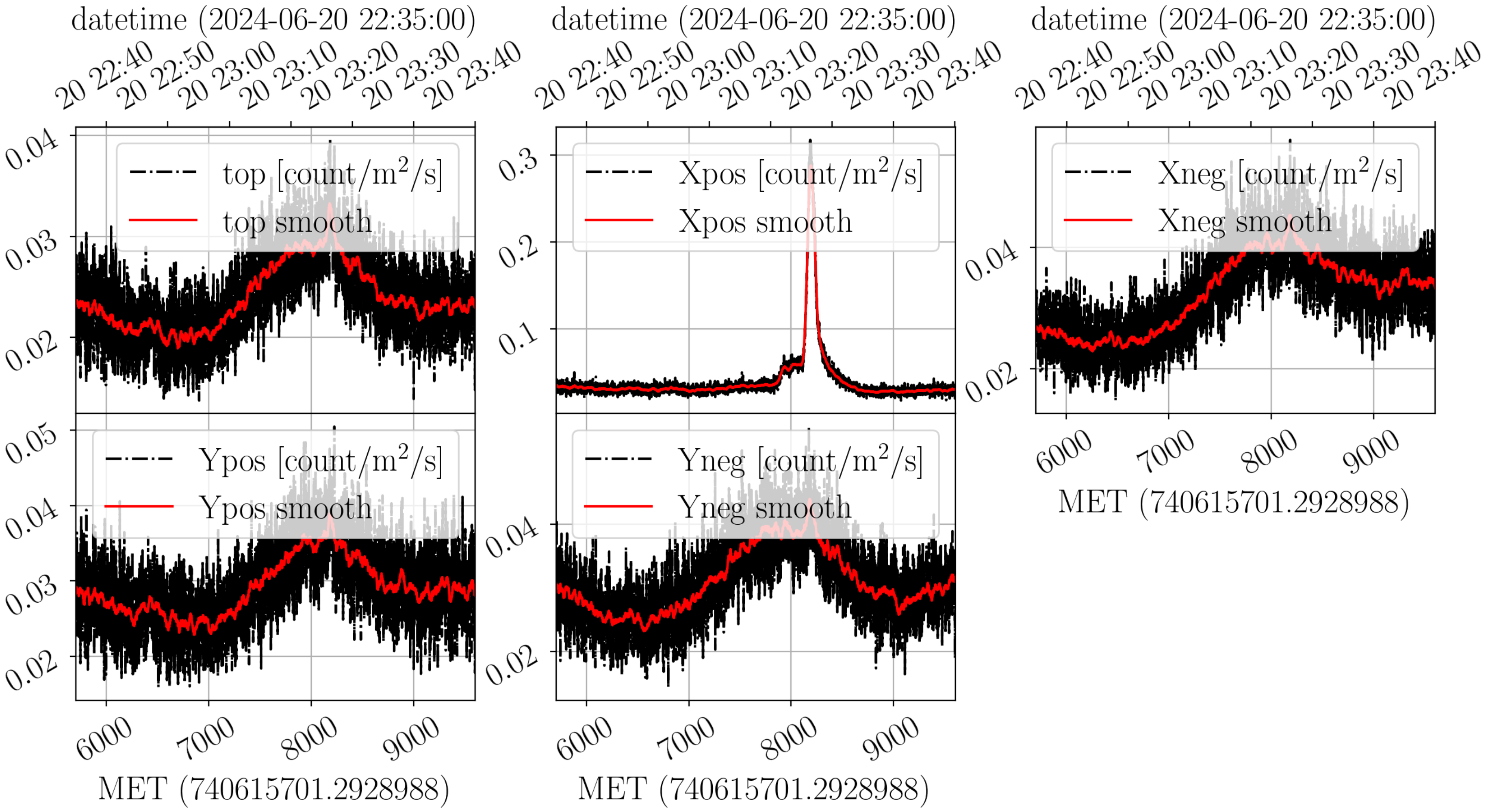

Y: ACD Data

-top (Z)

-Xpos (X+)

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-Ypos (Y+)

-Yneg (Y-)

The ACD data are sampled with the same trigger rate of the Large Area Telescope:

1) The trigger rate depends on the region of the sky that the LAT is observing;
2) If an event is observed by the LAT, the trigger rate increases.

Down sampling the data will result in a dataset proportional to the flux of particles hitting the tiles of the ACD at a constant sampling rate, independent of the triggering rate of the LAT.

Y: ACD Data

-top (Z)

-Xpos (X+)

-Xneg (X-)

-Ypos (Y+)

-Yneg (Y-)

An additional step has been added to the pre-processing of the data:

For each hit tracked in the ACD we know the (deposited) energy (in the sample interval of the trigger rate -> PILE-UP)

This makes it possible to split the time series into three energy ranges, for each face of the ACD:

- LOW: $E < 0.01$ MeV
- MIDDLE: $0.01 \text{ MeV} < E < 0.5$ MeV
- HIGH: $E > 0.5$ MeV

Higher potential to analyse anomalies.

Y: ACD Data

-top (Z) x3

-Xpos (X+) x3

-Xneg (X-) x3

-Ypos (Y+) x3

-Yneg (Y-) x3

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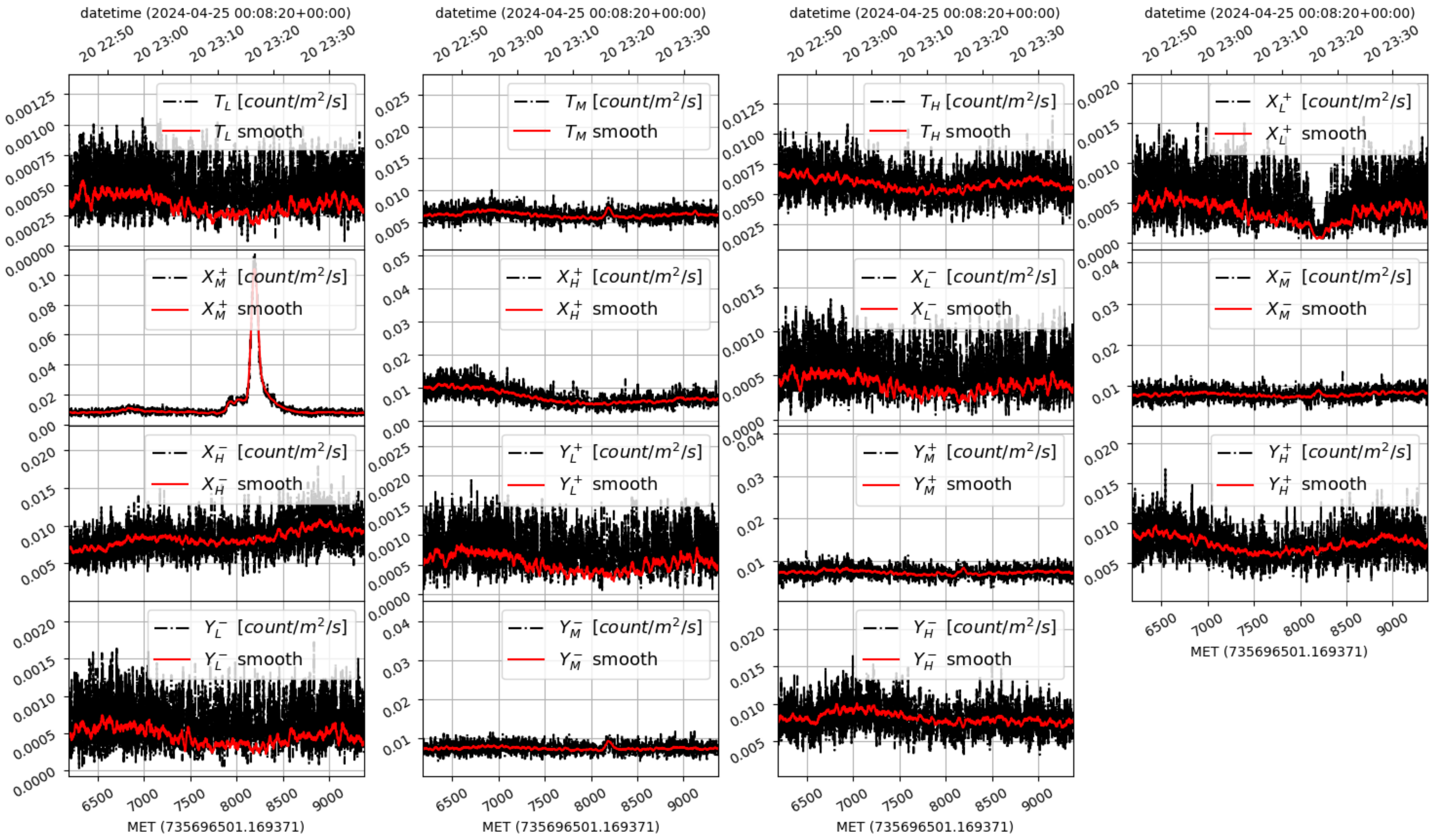
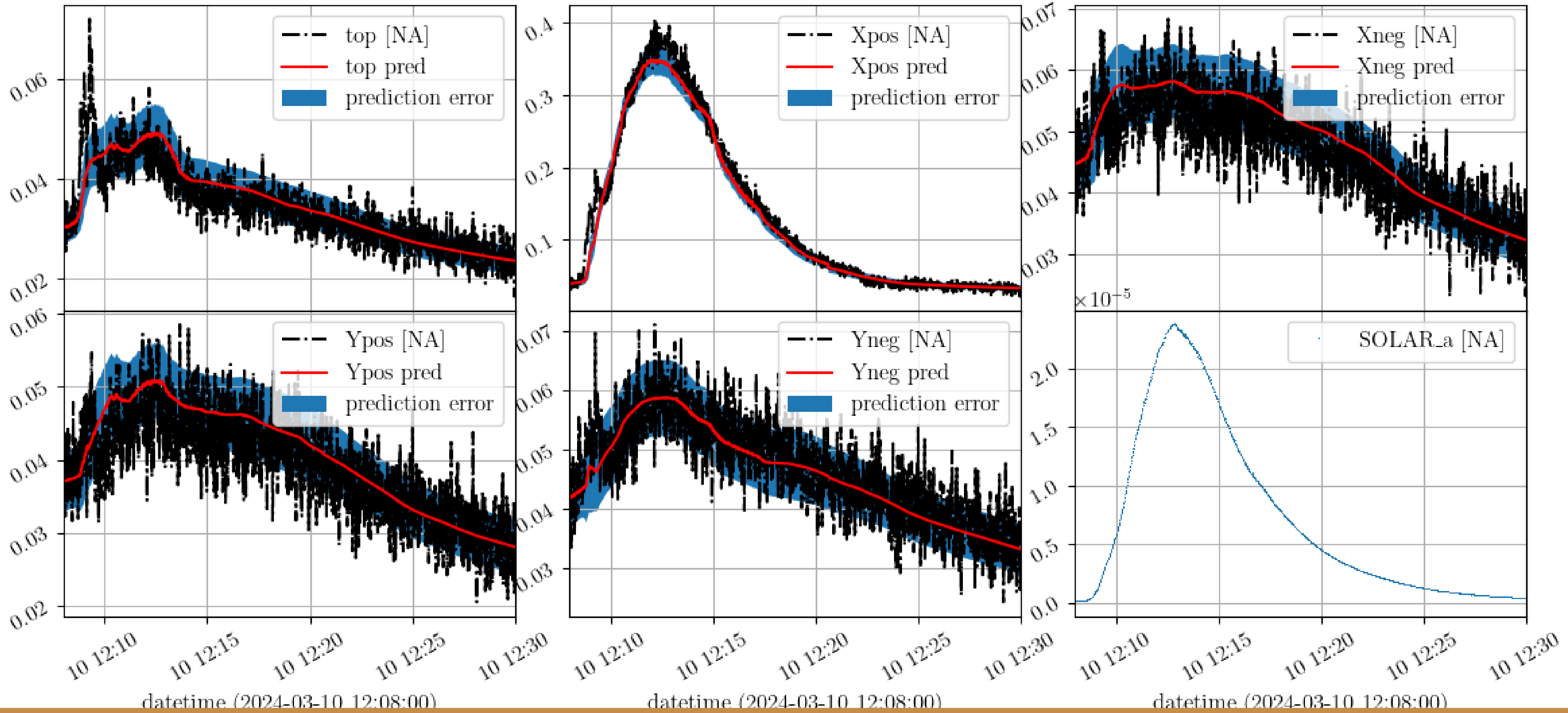


BNN Results

This is the prediction of the model for the Xpos signal.



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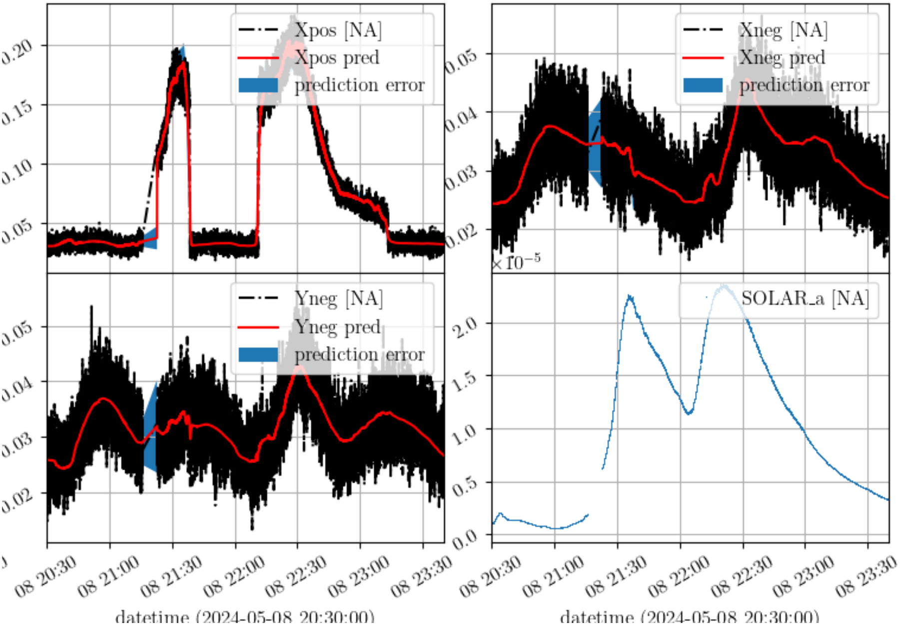
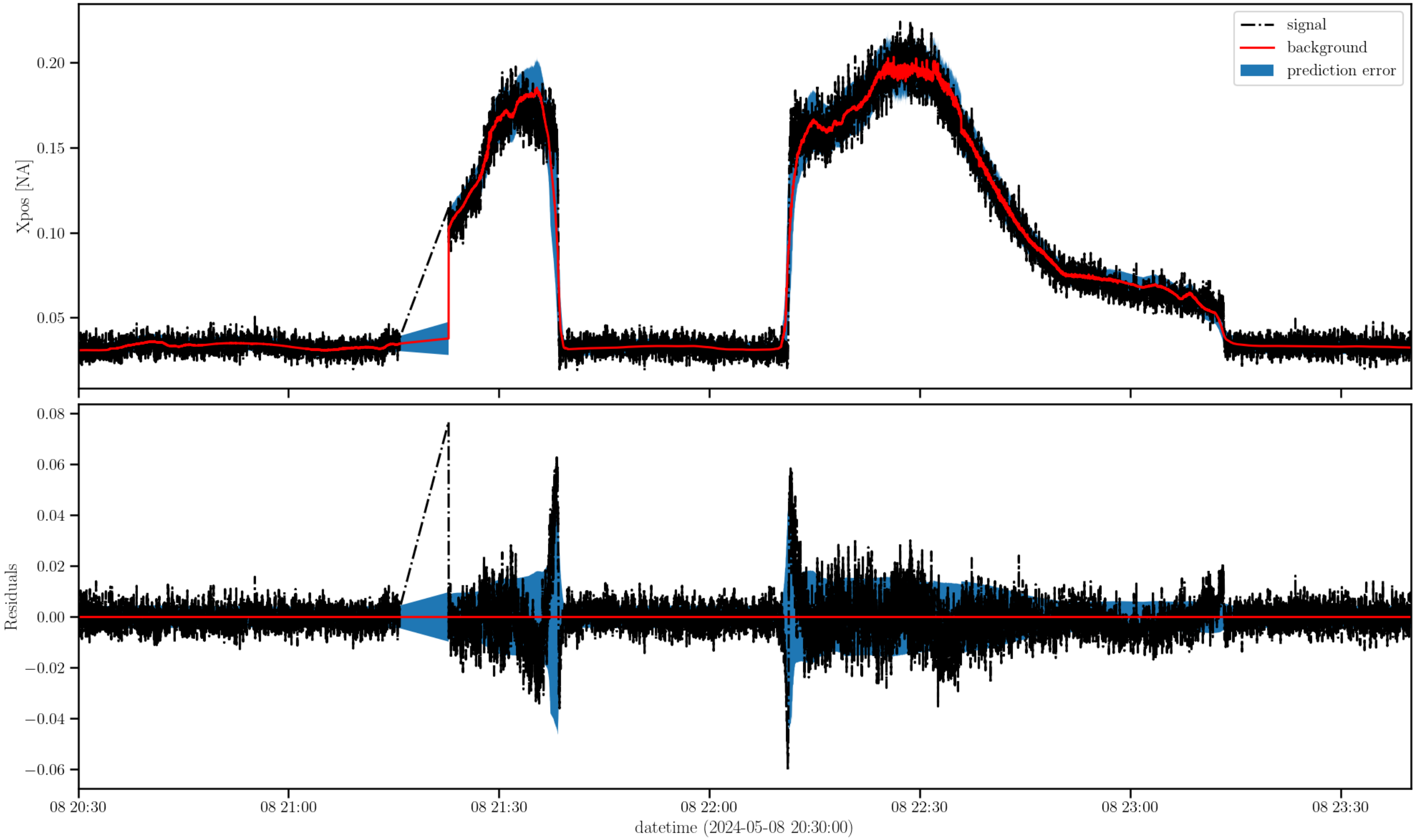




Comparing with Catalogs

We are comparing the events with catalogs from different instruments:

- **Fermi GBM Triggers Catalog (+ Fermi GBM OnlyGRBs Catalog)**
- **Space Variable Objects Monitor (SVOM) GRM (from GCN)**
- **Einstein Probe (EP) (from GCN)**
- **Swift BAT Catalog**

Gaussian-FOCuS Results (PRELIMINARY)

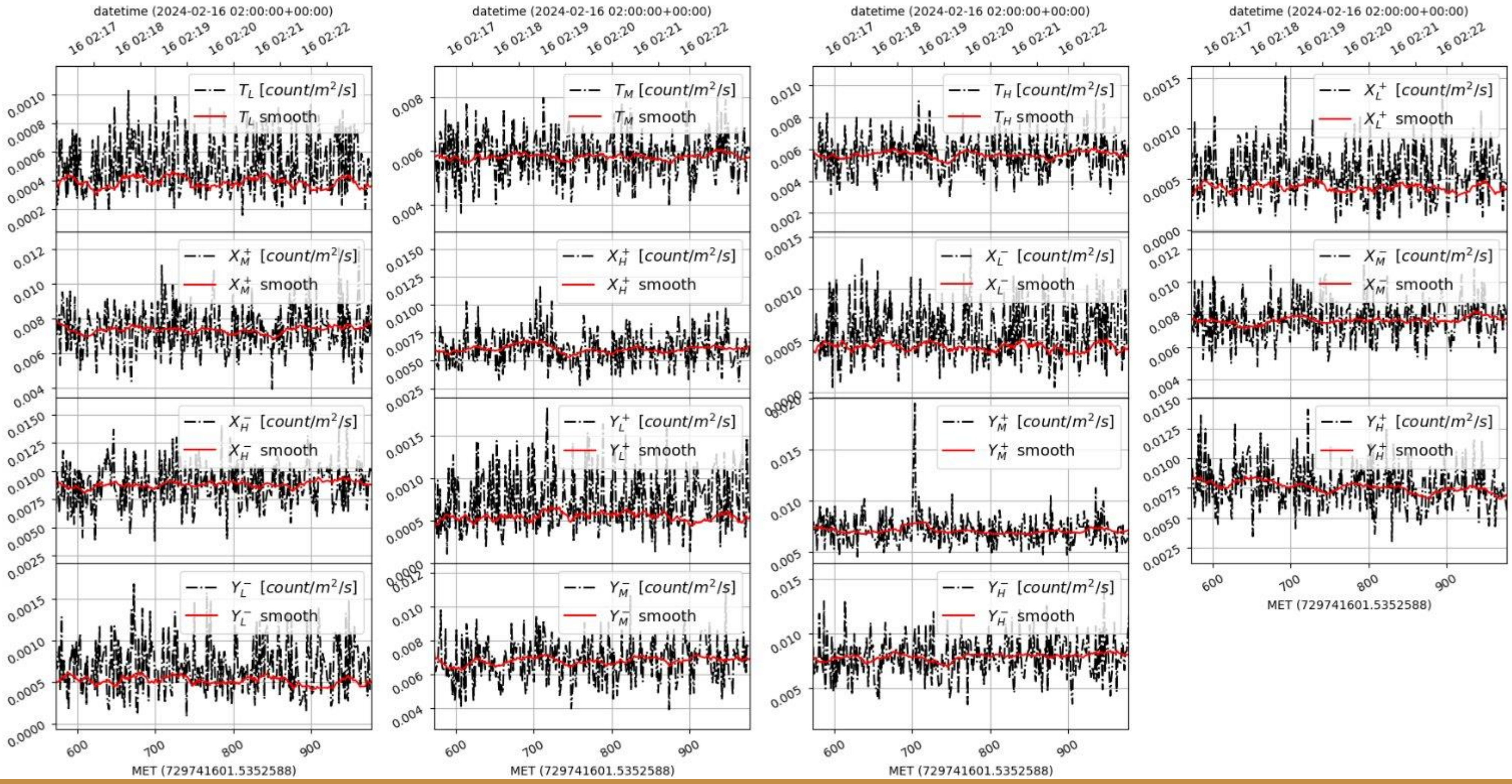
- **FFNN: uses the FFNN as background estimation and a rolling standard deviation to estimate the uncertainty.**

- **MA: uses a moving average as background estimation and a rolling standard deviation to estimate the uncertainty.**

- **BNN: uses the FFNN as background estimation for the background estimation and the BNN outputs to get the uncertainty estimations.**

	FFNN (5σ)	MA (5σ)	FFNN (6σ)	MA (7σ)	BNN
SFLARE	39	54	37	1	?
GRB	13	21	13	0	?
TGF	3	7	3	1	?
SGR	2	0	2	0	?
LOCALPART	13	21	10	2	?
DISTPART	1	5	0	0	?
UNCERT	9	12	9	1	?
TOT w/ c.p.	80	120	74	5	
TOT	23k	40k	20k	1k	

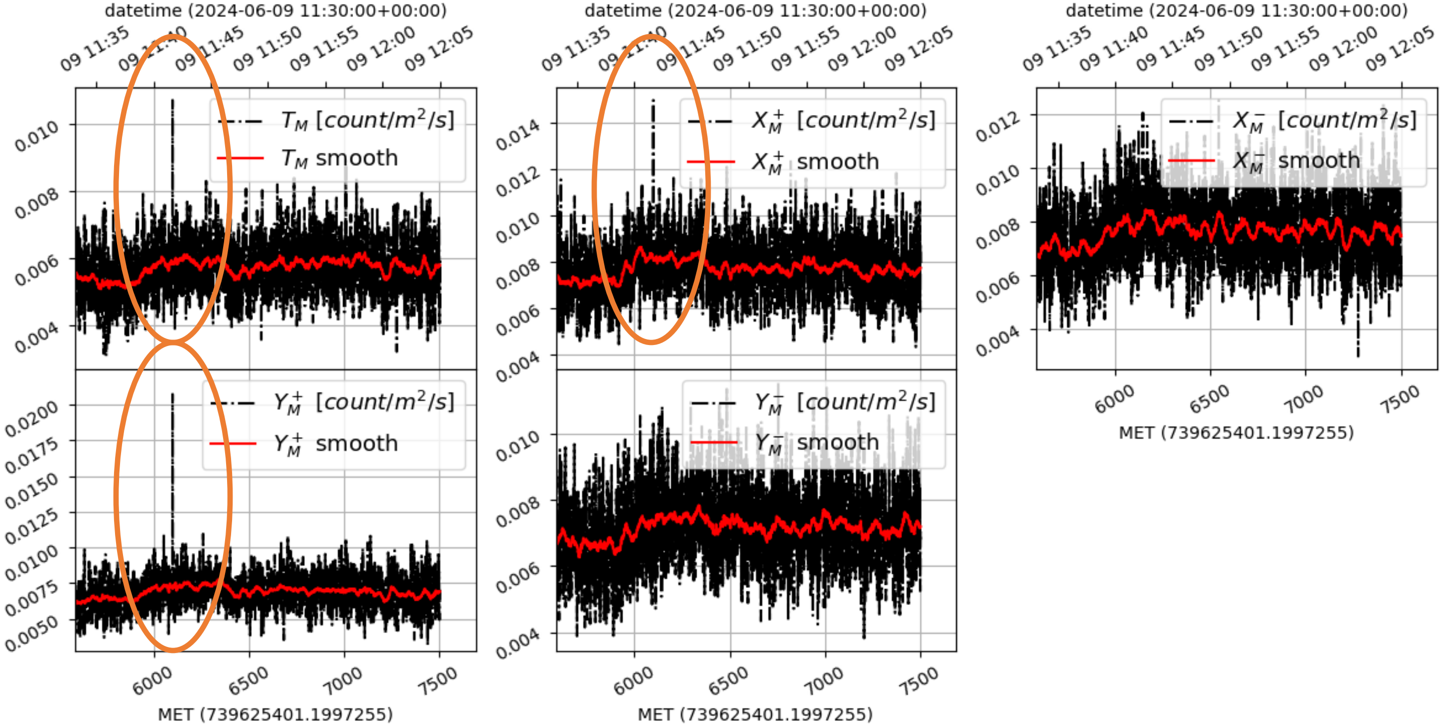
Unknown events

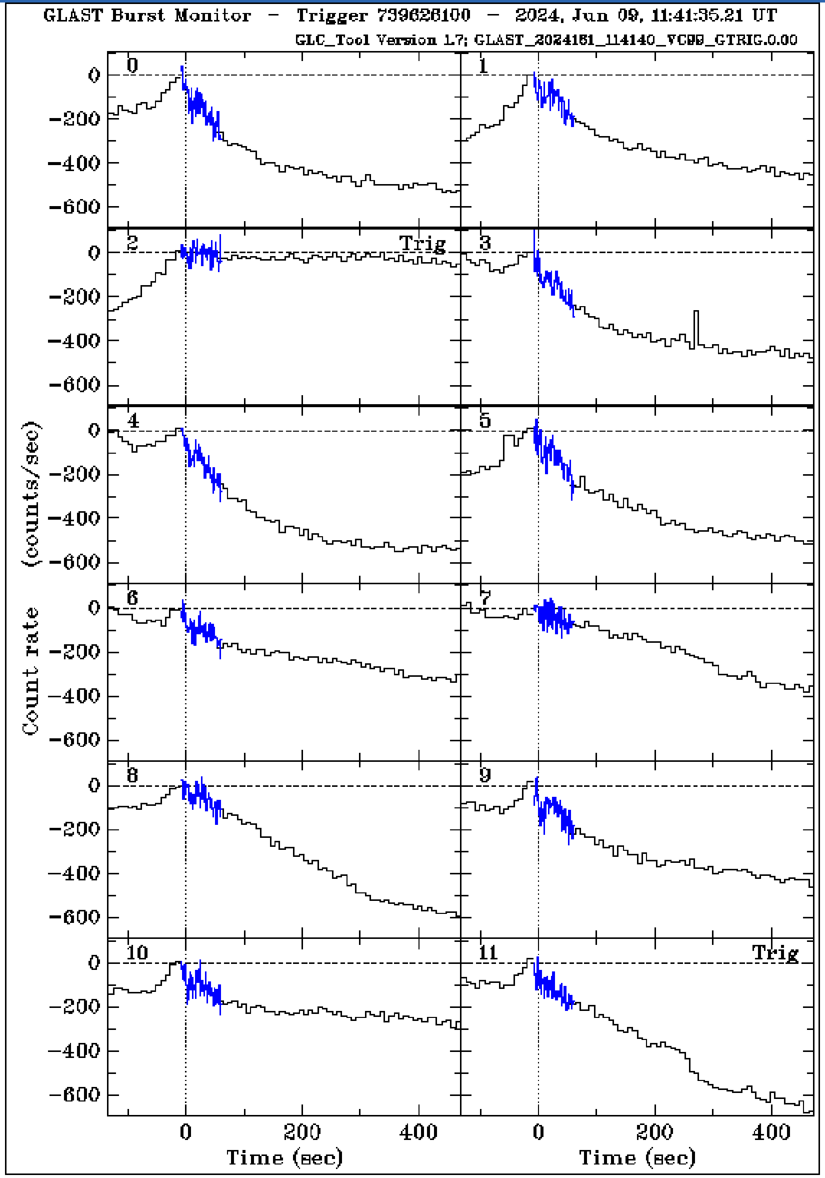


Localization

Use the magnitudes of the fluxes in the faces along the 3 axes to obtain the (θ, ϕ) angles in order to compare it with the localization the known events.

e.g. LOCLPAR2406094 (θ, ϕ) = 0.0474°, 258.8200°





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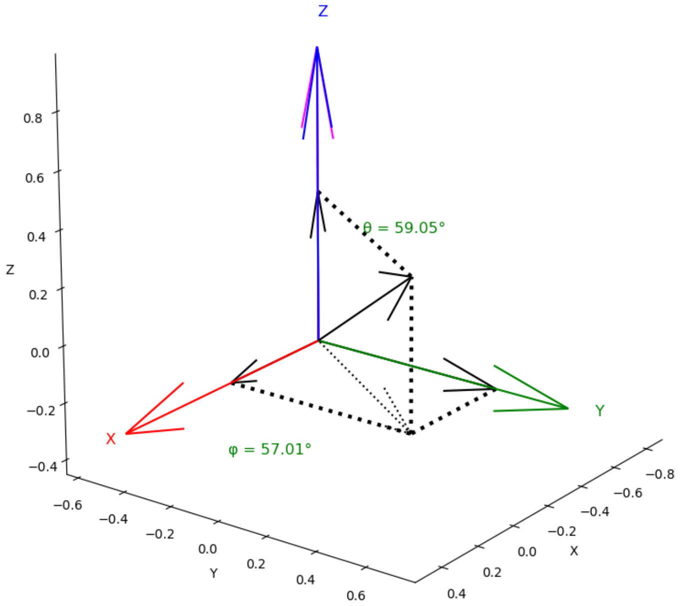
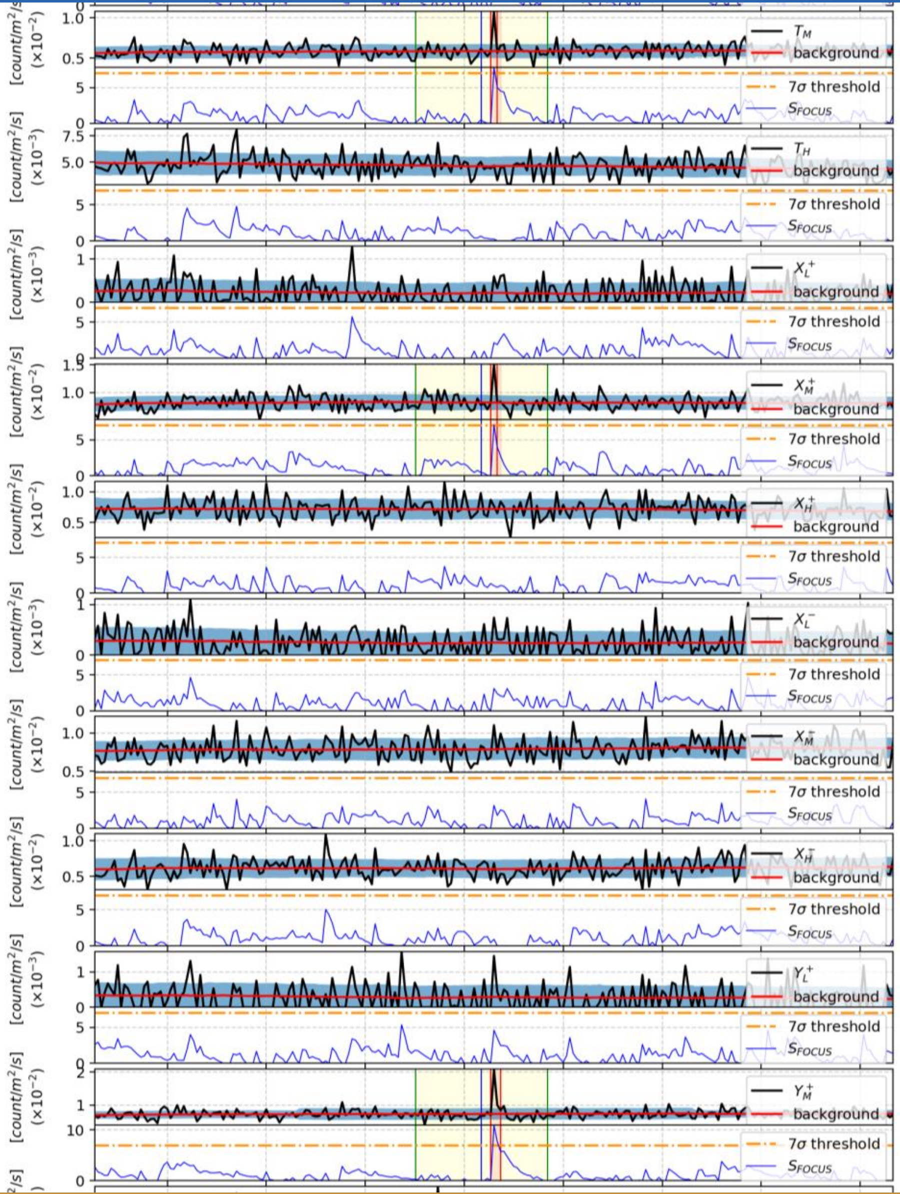
(θ, ϕ) = 59.052°, 57.005°





Next Steps

- Complete the dataset with the whole 2024 and up until today. (IN PROGRESS)
- Check for BNS/BBH mergers counterparts
- Localization of events using the triggered faces to check the consistency with localizations in catalogs. (IN PROGRESS)
- Classification of the events (!) (IN PROGRESS, thanks to localization and energy characterizations)
- Implement the framework as an online pipeline for the ACD data (!)

Thank You