



A data driven framework for searching long faint astronomical high-energy transients



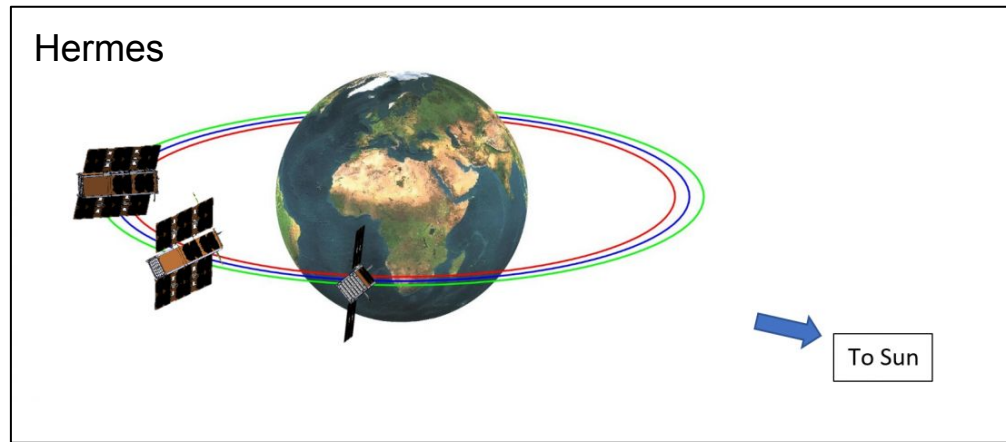
Riccardo Crupi, Giuseppe Dilillo, Fabrizio Fiore, Andrea Vacchi

14 September 2022

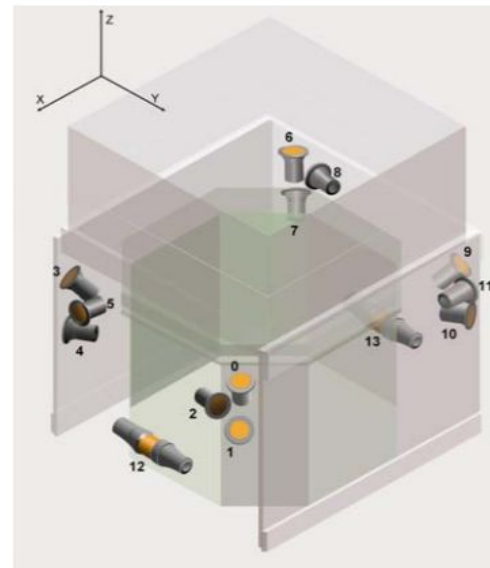
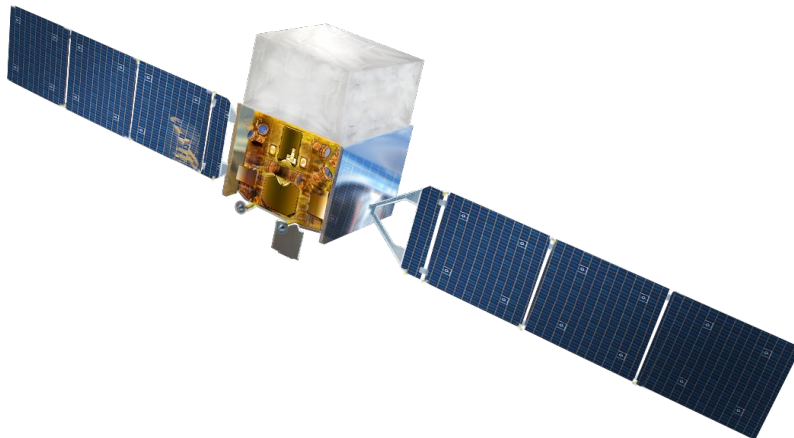
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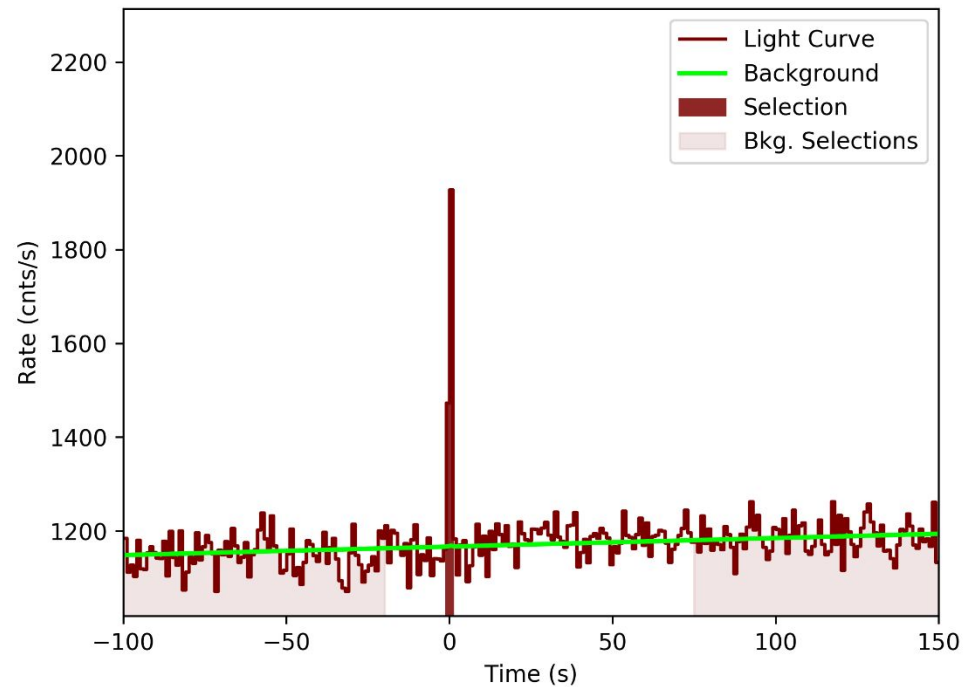
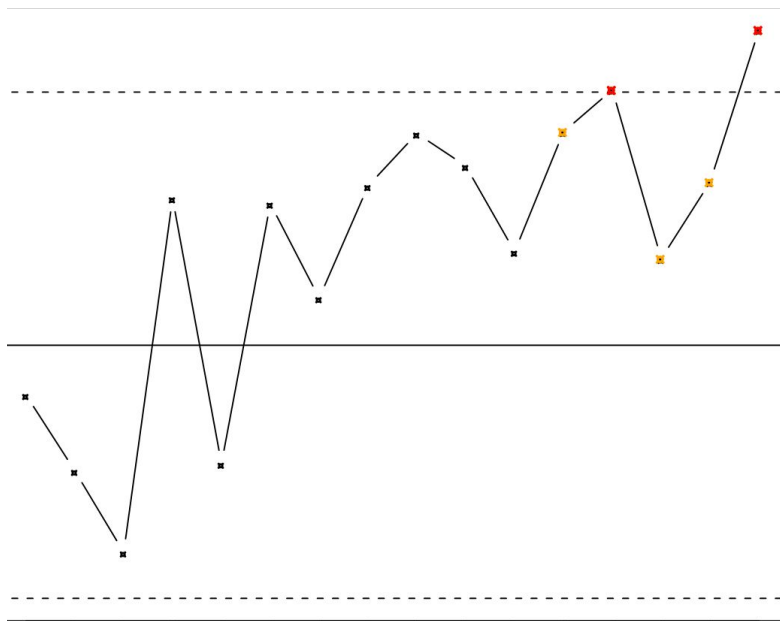
Satellites for X-Gamma ray



Fermi GBM



Background estimation



Background estimation

Background physical model*:

- Detector Response Matrices (DRMs)
- Earth albedo
- South Atlantic Anomaly (SAA)
- point sources (e.g., the Sun)
- extended sources (e.g., cosmic gamma-ray background)
- Other factors...

*Bjorn Biltzinger, Felix Kunzweiler, Jochen Greiner, Kilian Toelge, and J Michael Burgess.
A physical background model for the fermi gamma-ray burst monitor. *Astronomy & Astrophysics*, 640:A8, 2020.

ML Background estimation

Input variables:

- Latitude satellite
- Longitude satellite
- Altitude satellite
- Detectors pointing
- SSA zone
- Sun position
- McIlwain L-parameter
- ...

ML Background estimation

Input variables:

- Latitude GBM
- Longitude GBM
- Altitude GBM
- Detectors pointing
- SSA zone
- Sun position
- ...

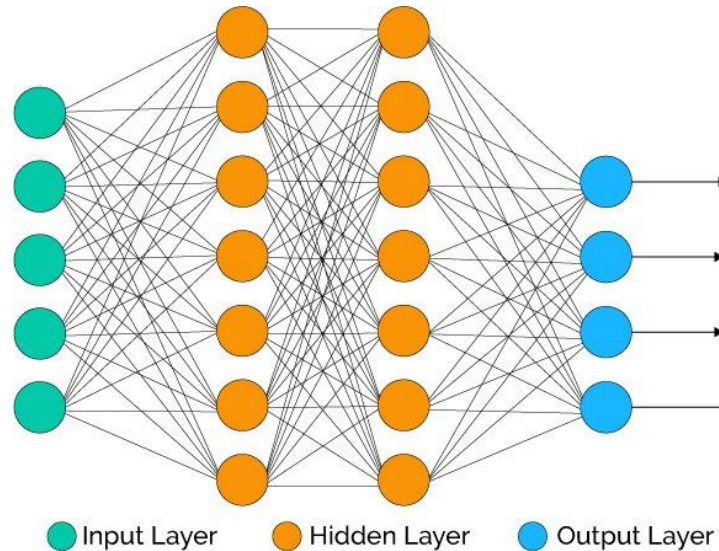
output variables:

- Counts det n0
- Counts det n1
- ...
- Counts det n9
- Counts det na
- Counts det nb

ML Background estimation

Input variables:

- Latitude GBM
- Longitude GBM
- Altitude GBM
- Detectors pointing
- SSA zone
- Sun position
- ...



output variables:

- Counts det n0
- Counts det n1
- ...
- Counts det n9
- Counts det na
- Counts det nb

4 seconds bin

Energy range (KeV): [28, 50], [50, 300], [300, 500]

Partial input - output

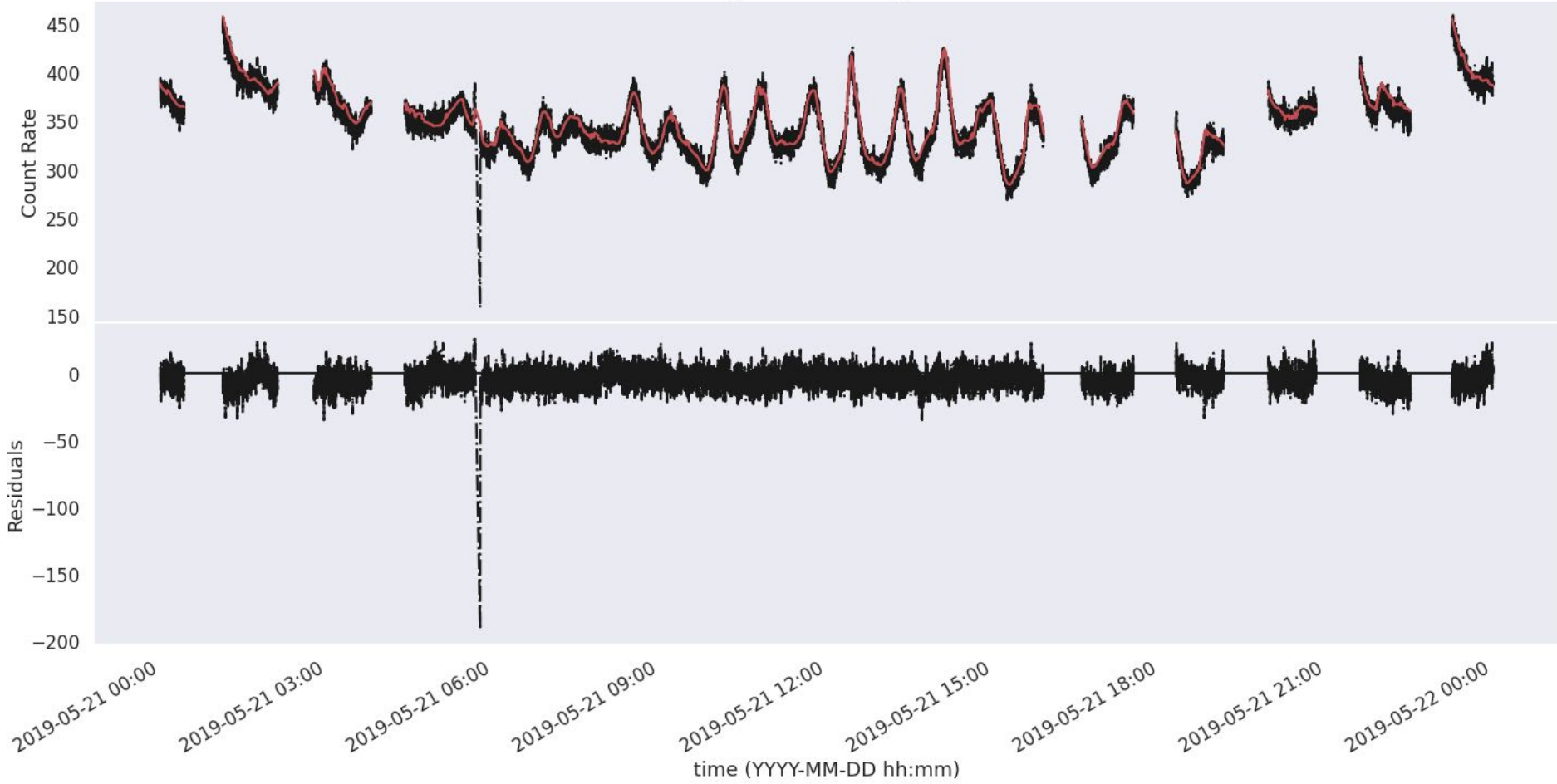
lat	lon	alt	n0_dec	n0_ra
-21.74720	16.13370	536687.34686	-60.61029	193.13023
-21.68540	16.38606	536703.44551	-60.45834	193.21557
-21.62316	16.63820	536719.48134	-60.30667	193.30146
-21.56049	16.89012	536734.64282	-60.15521	193.38776
-21.49737	17.14180	536750.18760	-60.00350	193.47457
-21.43384	17.39325	536765.63889	-59.85207	193.56186
-21.36987	17.64446	536780.25793	-59.70084	193.64969
-21.30547	17.89543	536795.28120	-59.54942	193.73788
-21.24065	18.14616	536809.89110	-59.39822	193.82666
-21.17541	18.39666	536825.25390	-59.24726	193.91585
-21.10975	18.64692	536840.85849	-59.09606	194.00553
-21.04367	18.89693	536855.23207	-58.94514	194.09561
-20.97716	19.14671	536869.53731	-58.79449	194.18599
-20.91025	19.39625	536884.27429	-58.64356	194.27703
-20.84292	19.64555	536898.11610	-58.49301	194.36832
-20.77518	19.89461	536911.85559	-58.34254	194.46017
-20.70703	20.14341	536925.07311	-58.19195	194.55239
-20.63847	20.39198	536939.09638	-58.04163	194.64502
-20.56950	20.64031	536952.73061	-57.89151	194.73807
-20.50013	20.88840	536965.88525	-57.74122	194.83153

n0_r0	n0_r1	n0_r2
131.84344	275.56137	46.64100
274.10376	548.45300	91.94076
280.94550	541.39386	92.78934
280.45737	535.99884	95.24504
280.56808	537.93964	94.87277
266.68027	535.44684	97.44323
264.70062	534.06450	100.62796
265.55270	535.52313	97.31207
262.96994	521.39954	92.15605
266.53240	521.16160	93.38451
265.80035	529.88270	95.71757
263.83970	521.91174	91.17808
264.19520	509.61572	90.19204
267.47410	504.76535	93.12515
270.79575	513.12540	91.04234
257.90674	513.11414	89.93607
249.80258	503.28592	89.44306
257.17477	505.39258	91.40993
253.60439	498.98840	87.97018
252.25041	490.51416	83.91988



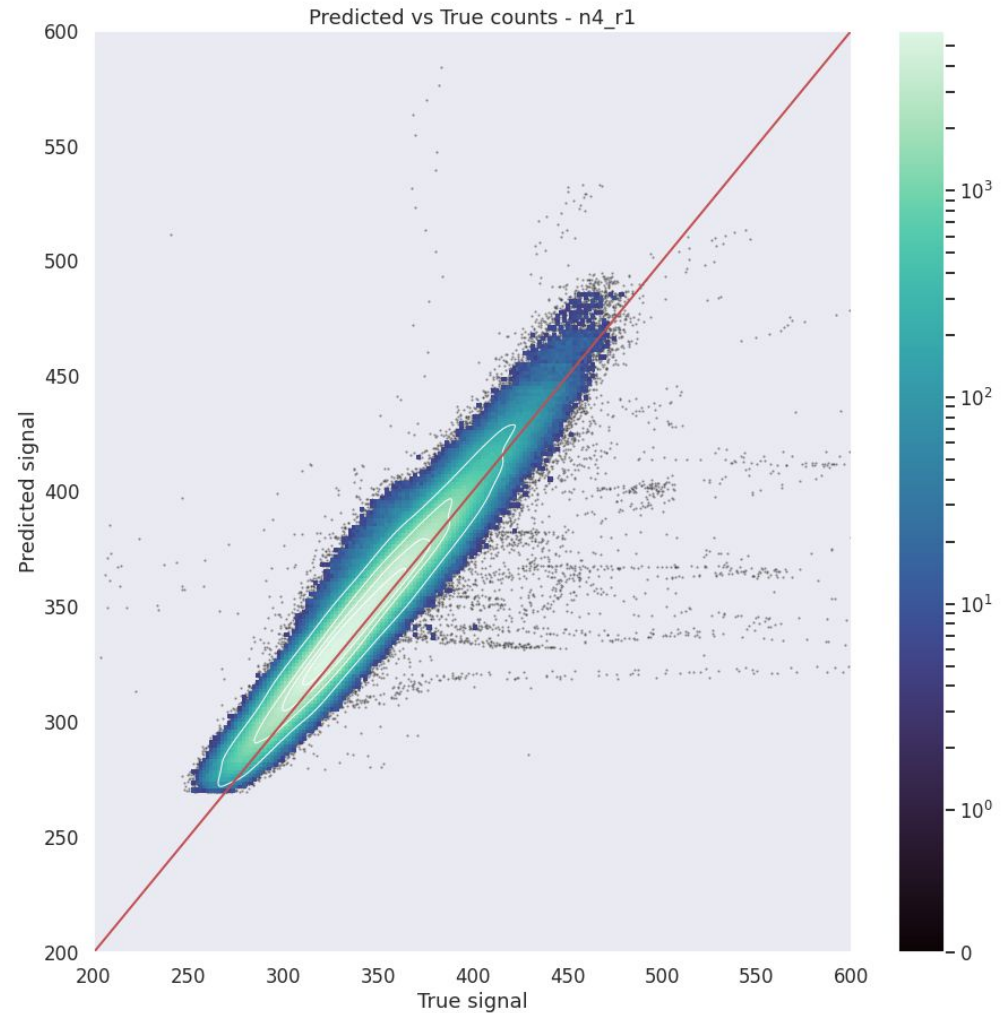
n4_r1 2019-05-21 00:00:01.977903

foreground and background



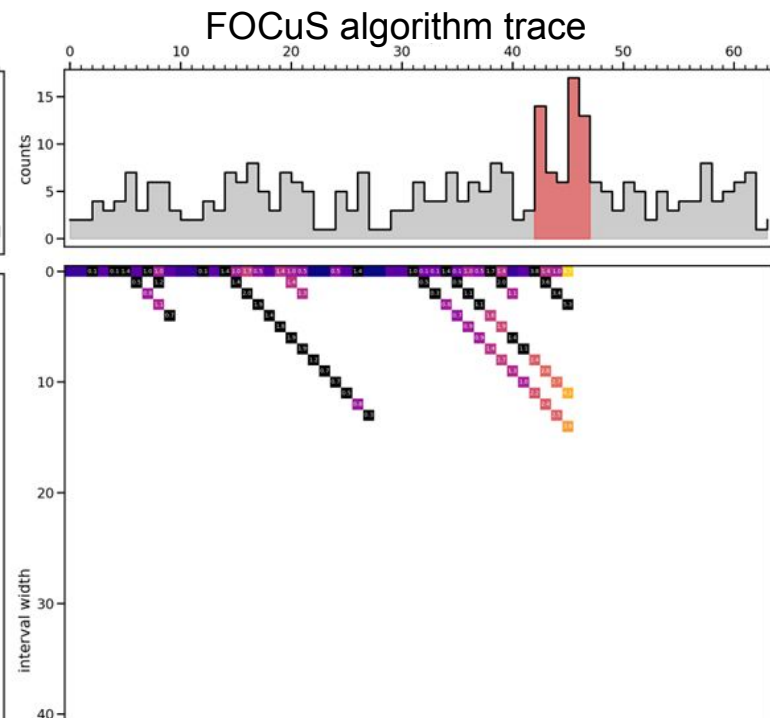
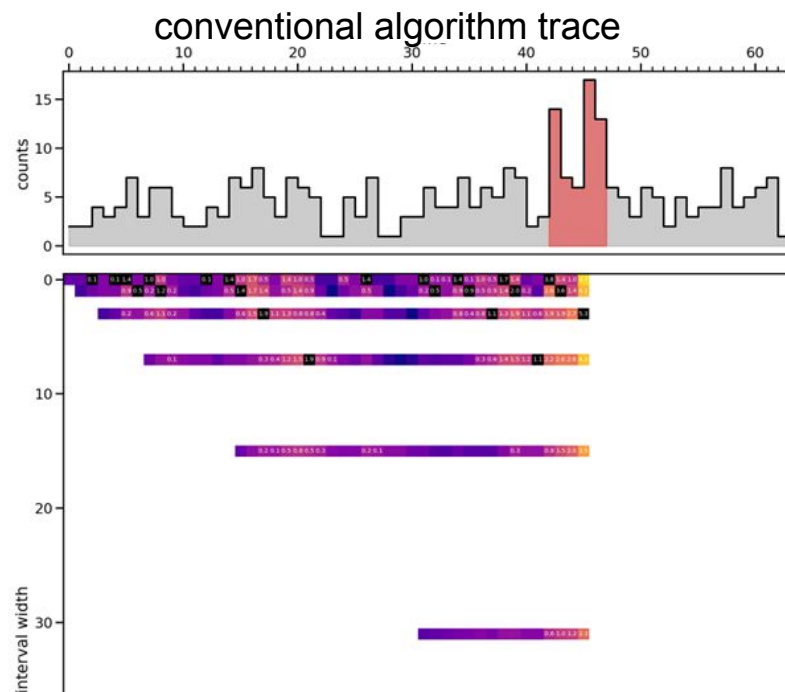


Predicted vs Detected



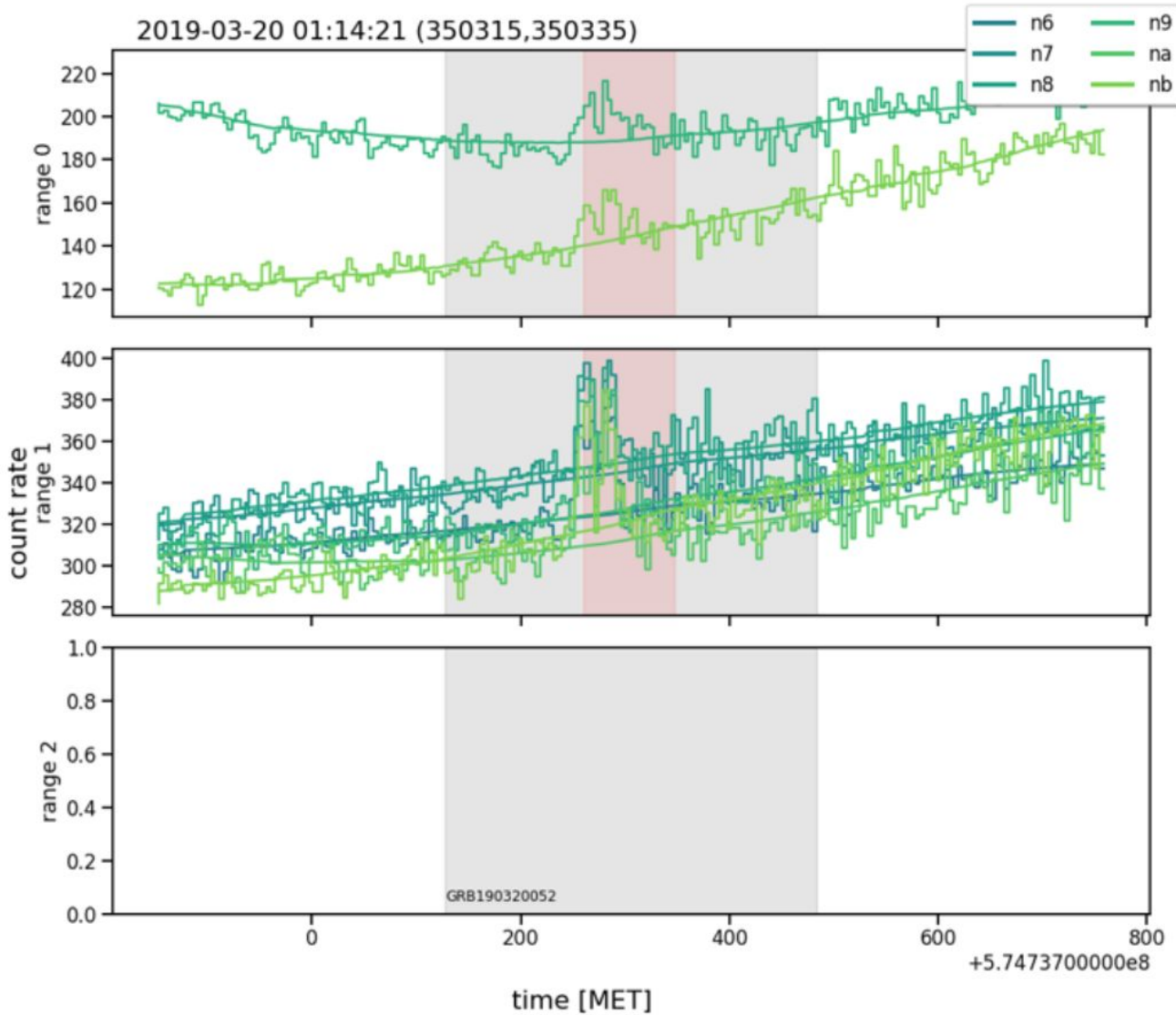
Trigger algorithm: FOCuS

- Conventional algorithms checks for counts excess over pre-defined timescales.
- FOCuS tests for count excess over timescales which are optimal and dynamically assessed.
- Faster and more accurate (less false negatives).



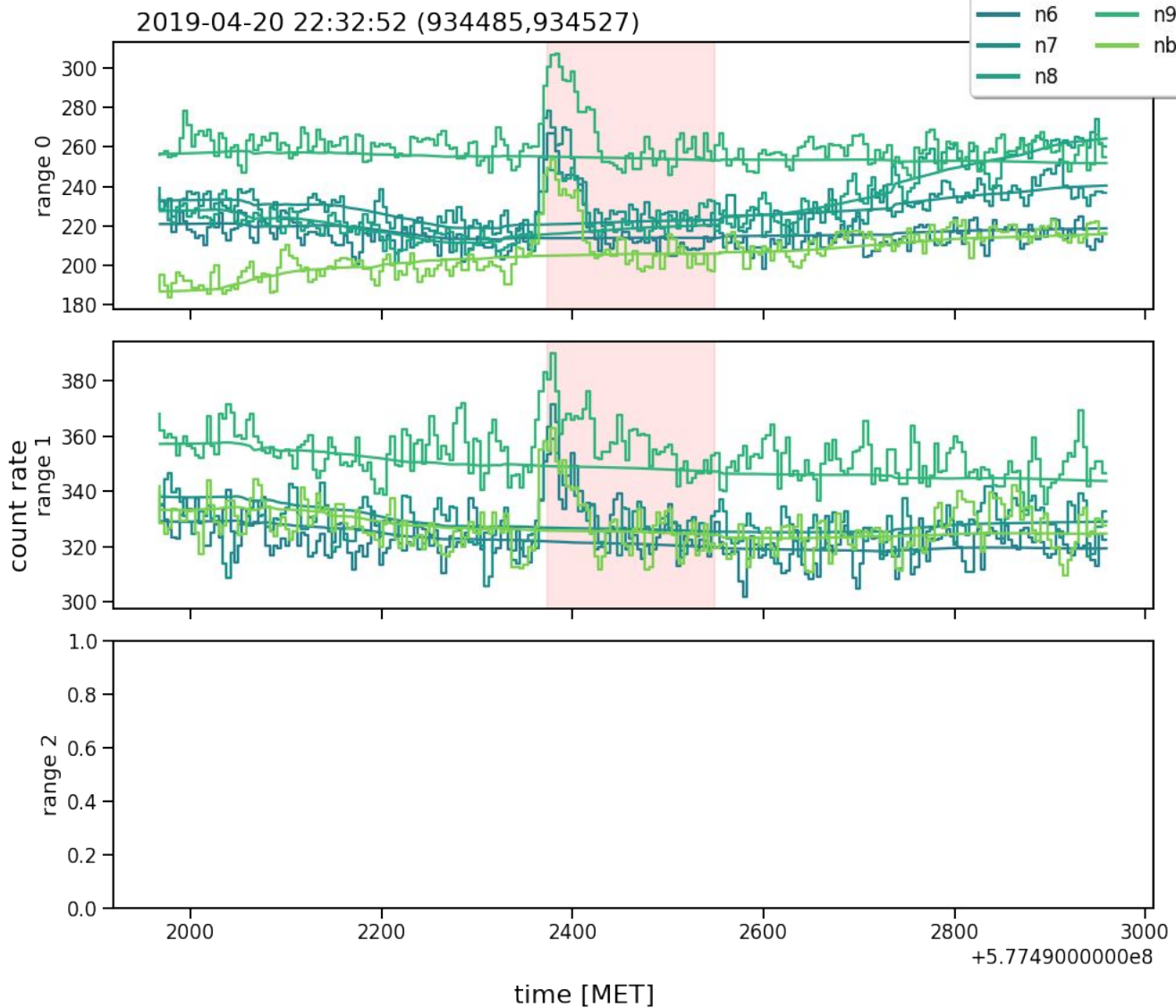


GRB 190320

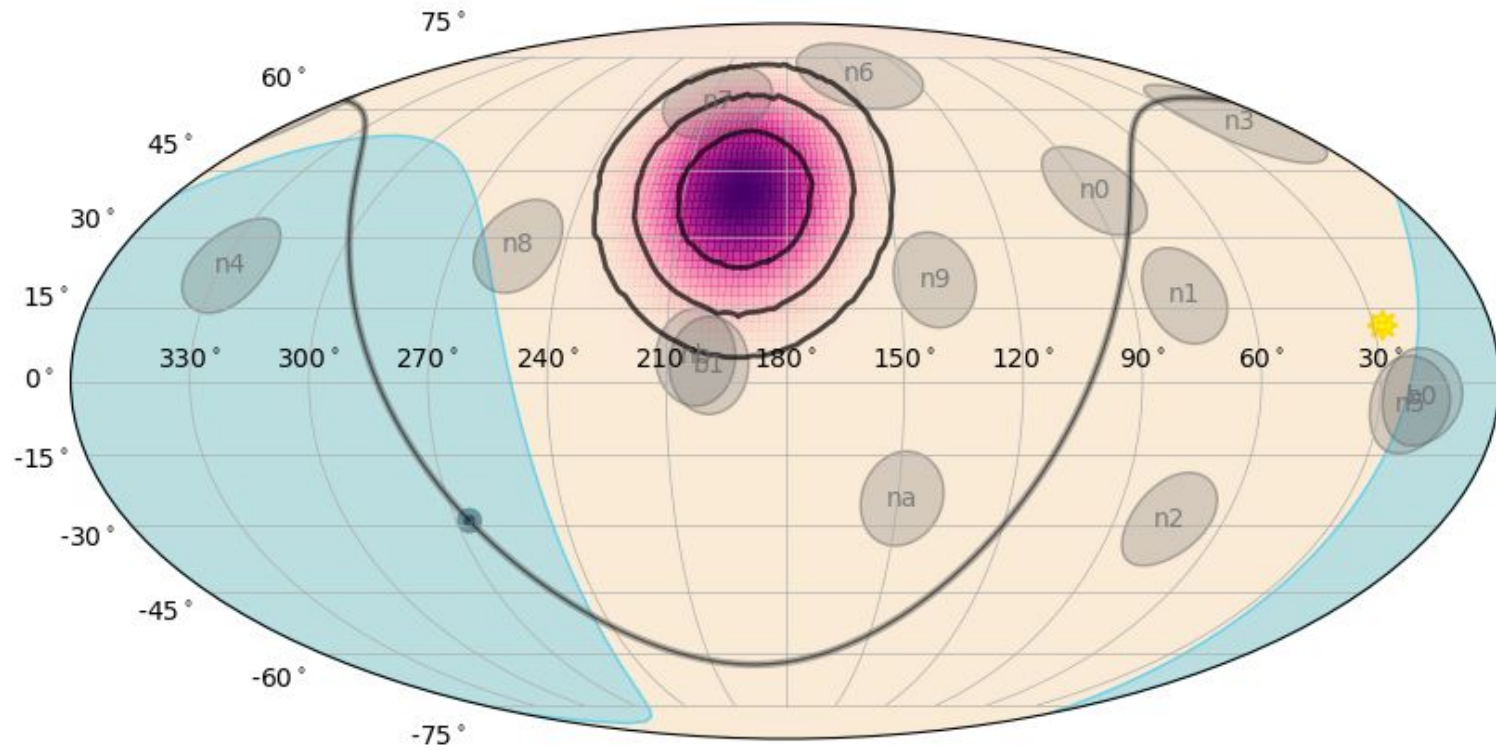




Event 190420*

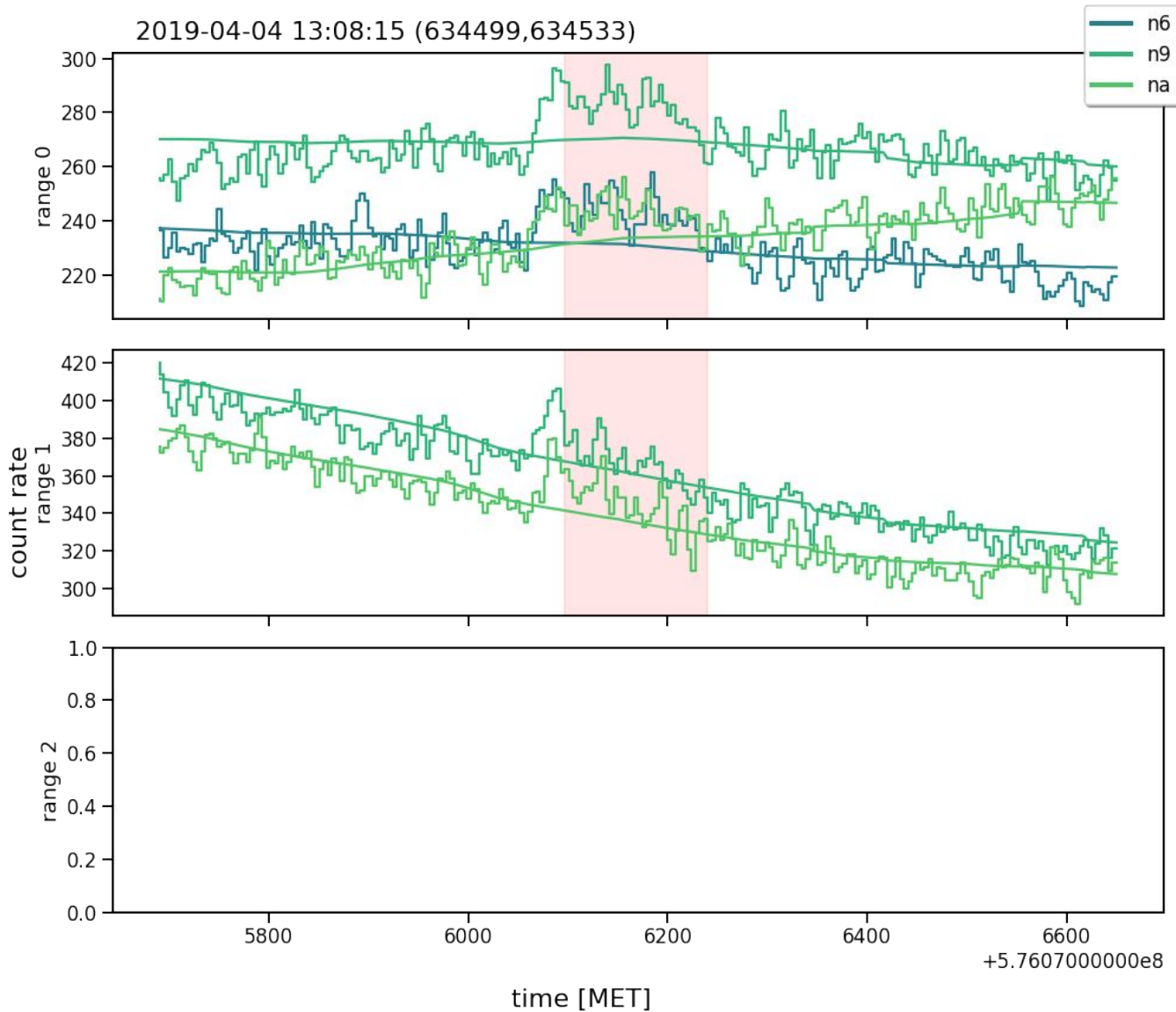


Event 190420*



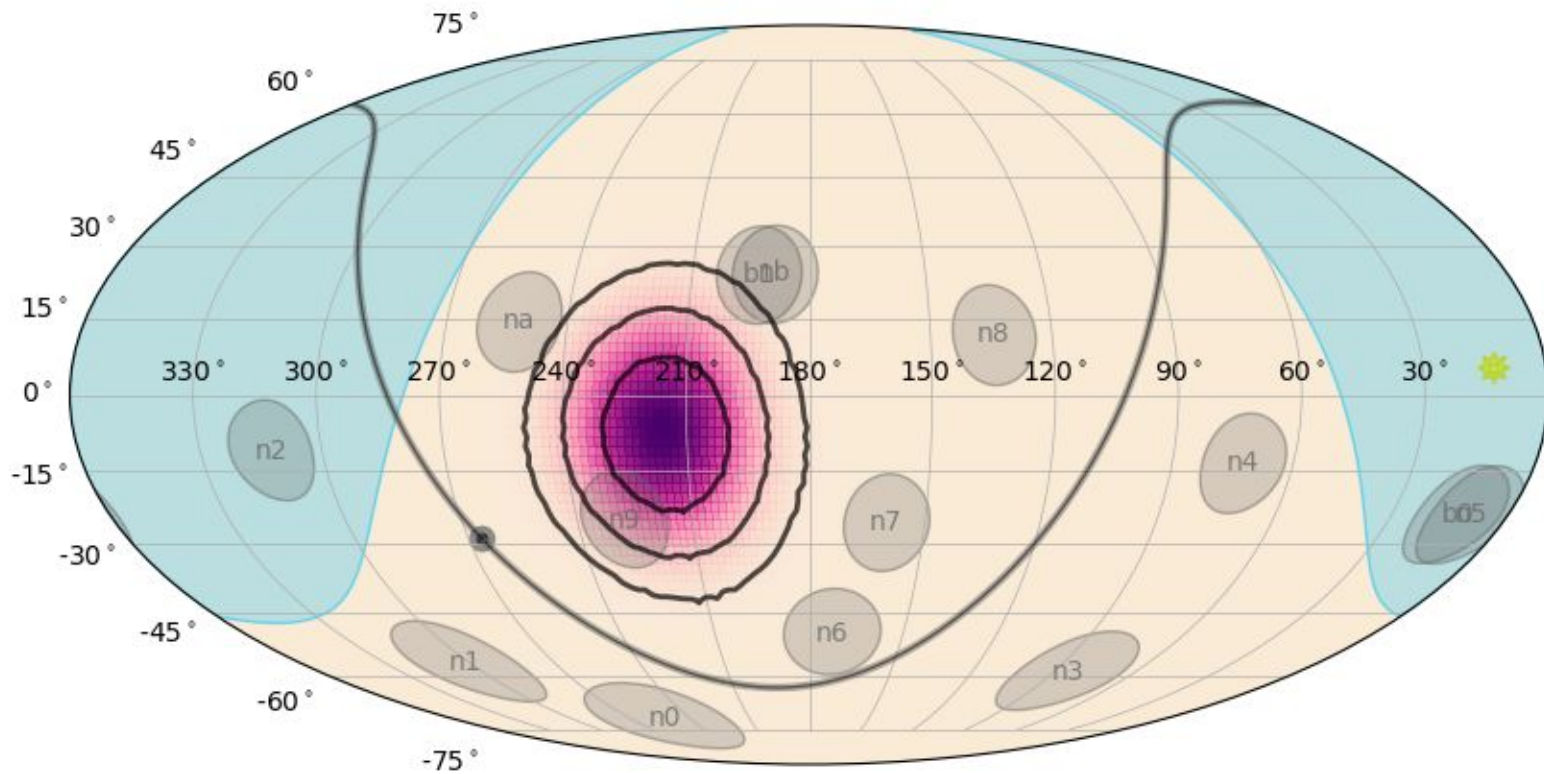


GRB 190404B*



Time start: 2019/04/04 13:08

Localization: 220° ra & -10° dec



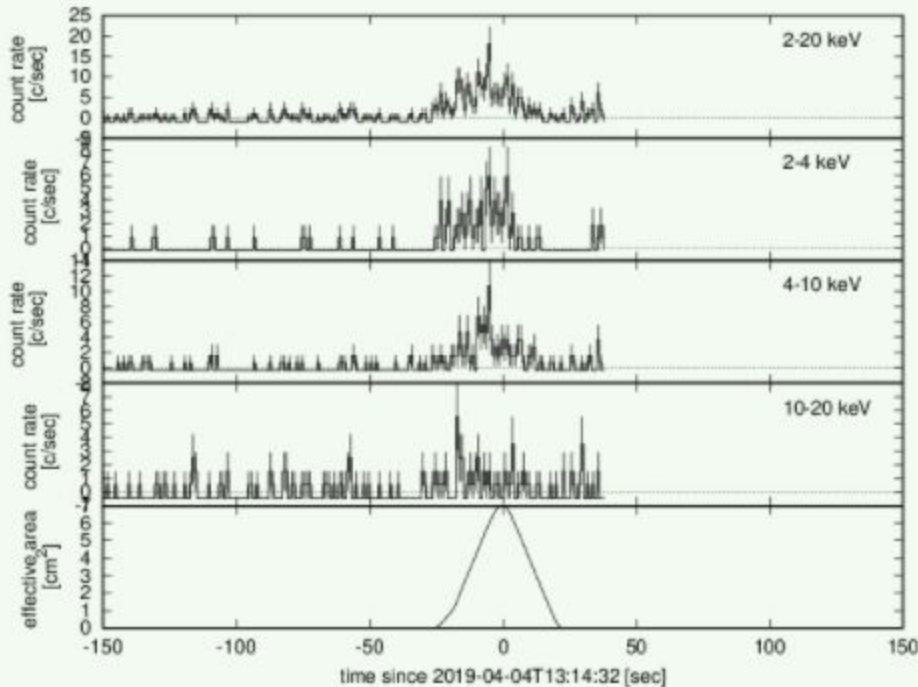
GRB 190404B

Data	med
SN	32.9
Flux ($\times 10^{-8}$ erg cm^{-2} s^{-1})	1.09 ± 0.08
Hardness	0.27 ± 0.06
Time bin	1 sec

<http://maxi.riken.jp/grbs/190404b/>

light curves

no effective area correction



The MAXI/GSC nova alert system triggered on a bright uncatalogued X-ray transient source at 13:14:08 UT on 2019 April 04. Assuming that the source flux was constant over the transit, we obtain the source position at **(R.A., Dec) = (220.987 deg, -22.632 deg) = (14 43 56, -22 37 55) (J2000)** with a statistical 90% C.L. elliptical error region with long and short radii of 0.13 deg and 0.11 deg, respectively.

GCN:

<https://gcn.gsfc.nasa.gov/gcn3/24049.gcn3>
<https://gcn.gsfc.nasa.gov/other/190404.gcn3>

Swift afterglow:

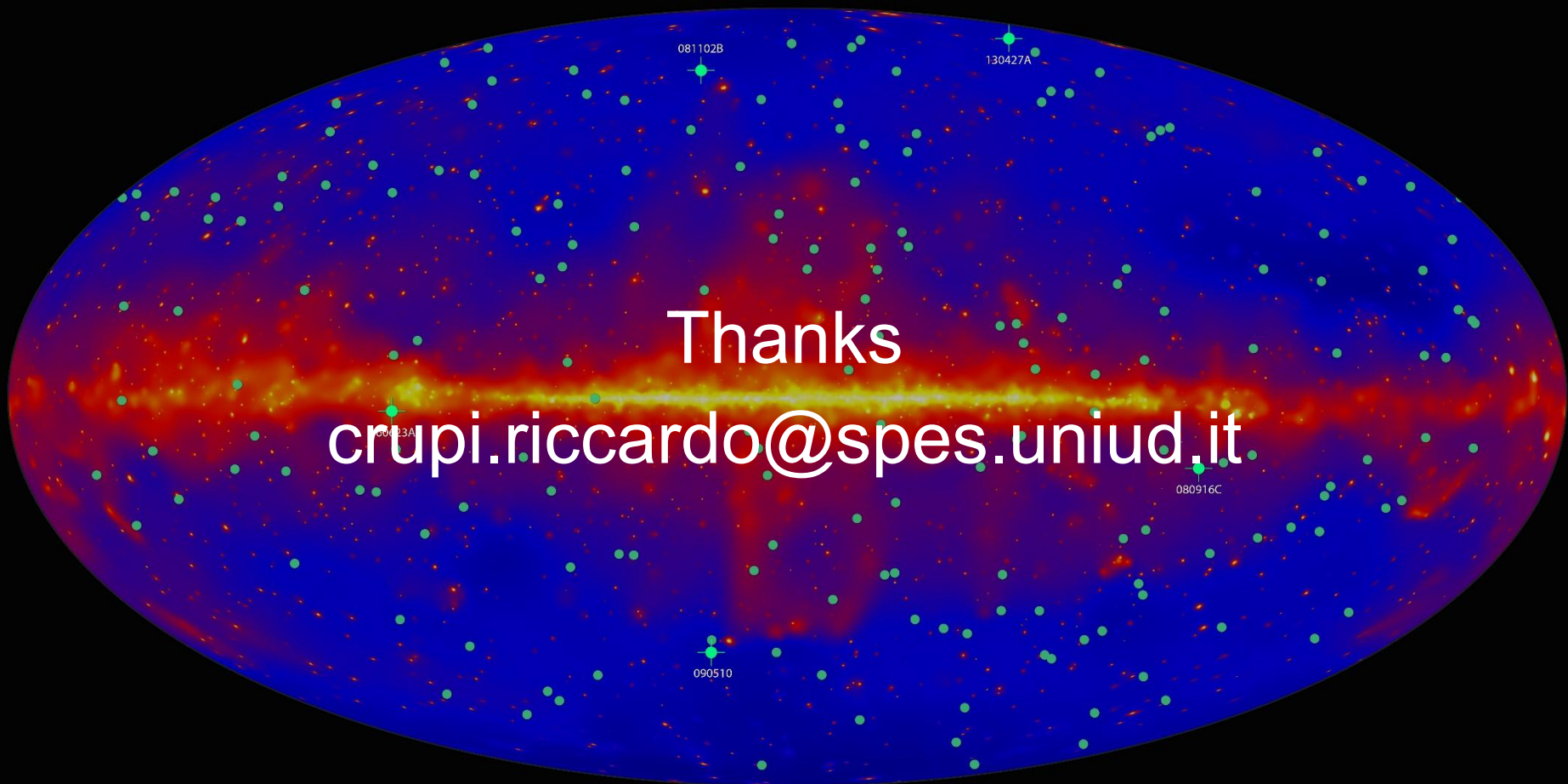
https://www.swift.ac.uk/xrt_live_cat/20887

Summary

- New method to estimate the background via a Neural Network
- Use FOCuS to discover faint long event
- Presented two events out of catalog that are GRB-categorizable

References

- Elisabetta Bissaldi, Andreas von Kienlin, G Lichti, Helmut Steinle, P Narayana Bhat, Michael S Briggs, Gerald J Fishman, Andrew S Hoover, R Marc Kippen, Michael Krumrey, et al. Ground-based calibration and characterization of the fermi gamma-ray burst monitor detectors. *Experimental Astronomy*, 24(1-3):47–88, 2009.
- Charles Meegan, Giselher Lichti, PN Bhat, Elisabetta Bissaldi, Michael S Briggs, Valerie Connaughton, Roland Diehl, Gerald Fishman, Jochen Greiner, Andrew S Hoover, et al. The fermi gamma-ray burst monitor. *The Astrophysical Journal*, 702(1):791, 2009.
- Bjorn Biltzinger, Felix Kunzweiler, Jochen Greiner, Kilian Toelge, and J Michael Burgess. A physical background model for the fermi gamma-ray burst monitor. *Astronomy & Astrophysics*, 640:A8, 2020.
- Kester Ward, Giuseppe Dilillo, Idris Eckley, Paul Fearnhead. Poisson-FOCuS: An efficient online method for detecting count bursts with application to gamma ray burst detection. Submitted, <https://arxiv.org/abs/2208.01494>
- Riccardo Crupi, Giuseppe Dilillo, Fabrizio Fiore, Andrea Vacchi - Work in Progress
- GitHub repository <https://github.com/rcrupi/DeepGRB>, Work in Progress

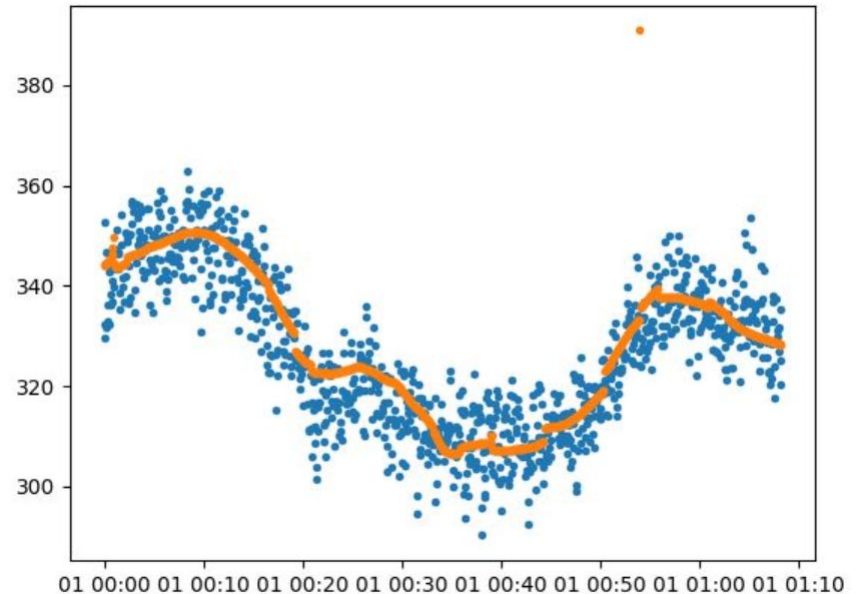


det range	MAE train	MAE test
r0	4.942 ± 0.331	4.953 ± 0.328
r1	6.088 ± 0.167	6.098 ± 0.163
r2	1.790 ± 0.044	1.792 ± 0.045
average	4.273	4.281

Table 1: The NN MAE loss function (\pm standard deviation) per energy range, over the training and the testing datasets, averaged on detectors. The complete table can be found in table 7).

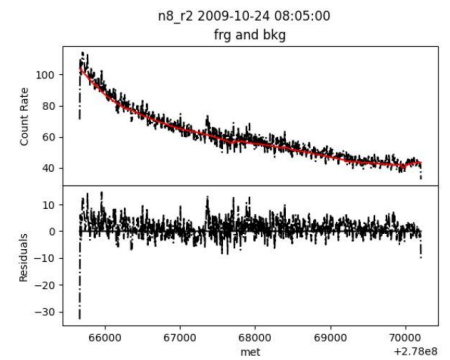
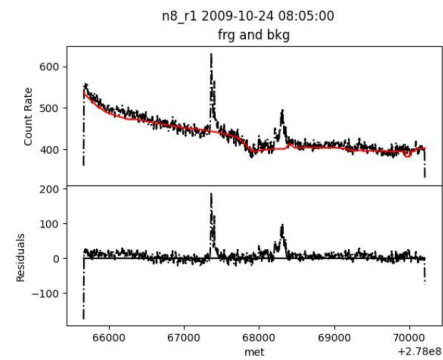
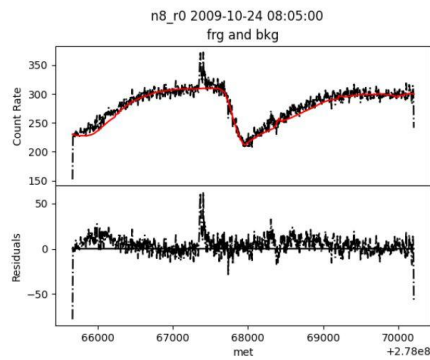
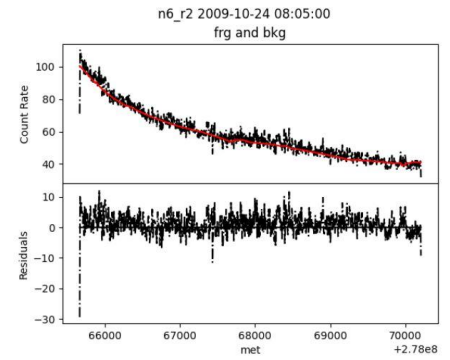
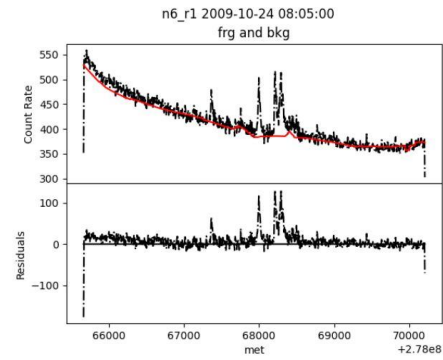
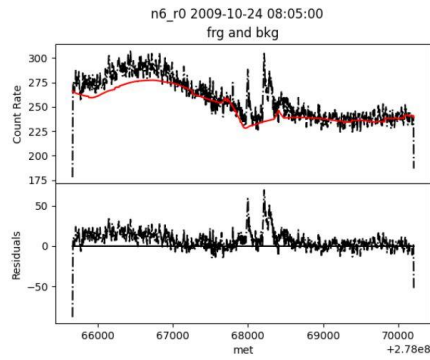
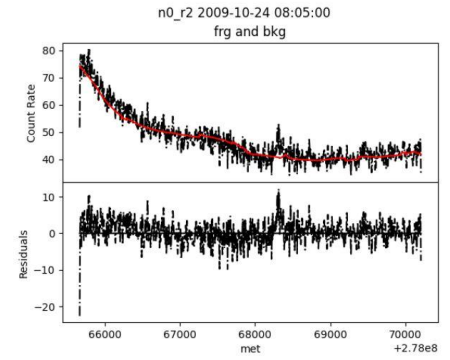
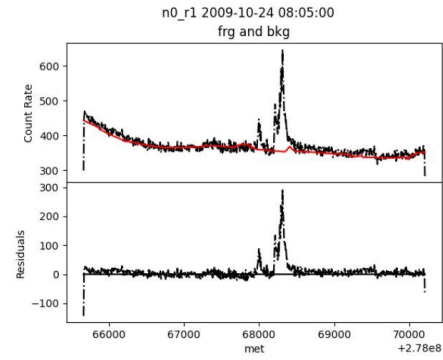
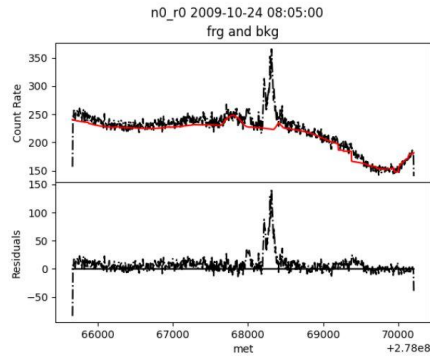
Drawbacks

- Discontinuous prediction over time
Possible solution: change architecture to a recurrent neural network or apply a filter to get a smoother signal
- Difficult to explain why.
Possible solution: use algorithm of explainability for black box (what feature was important for the prediction)
- Overestimate the background.
Possible solution: change the hyperparameter of the NN and train with more data





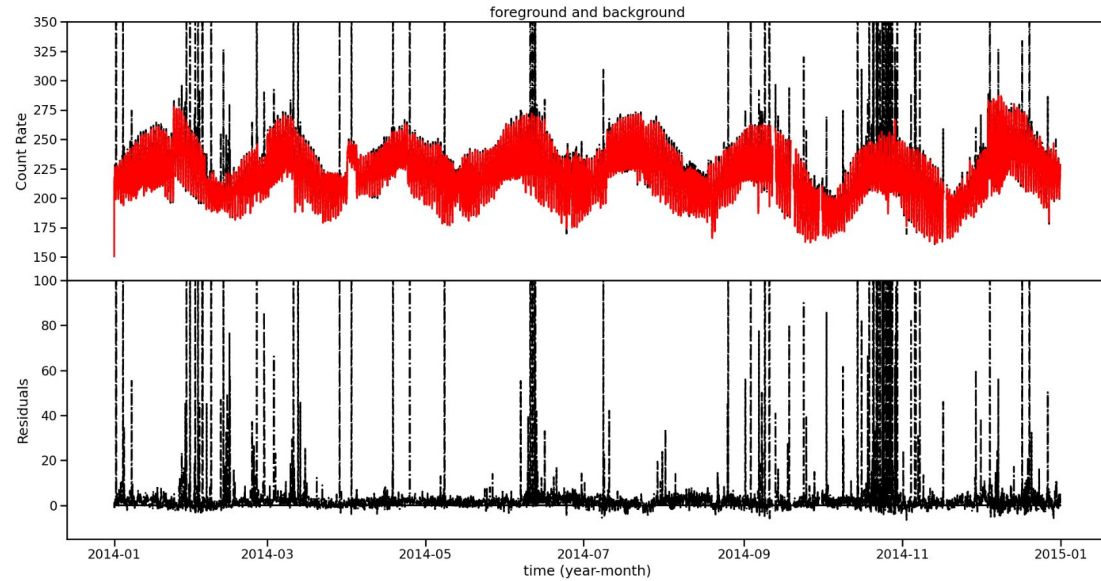
GRB 091024



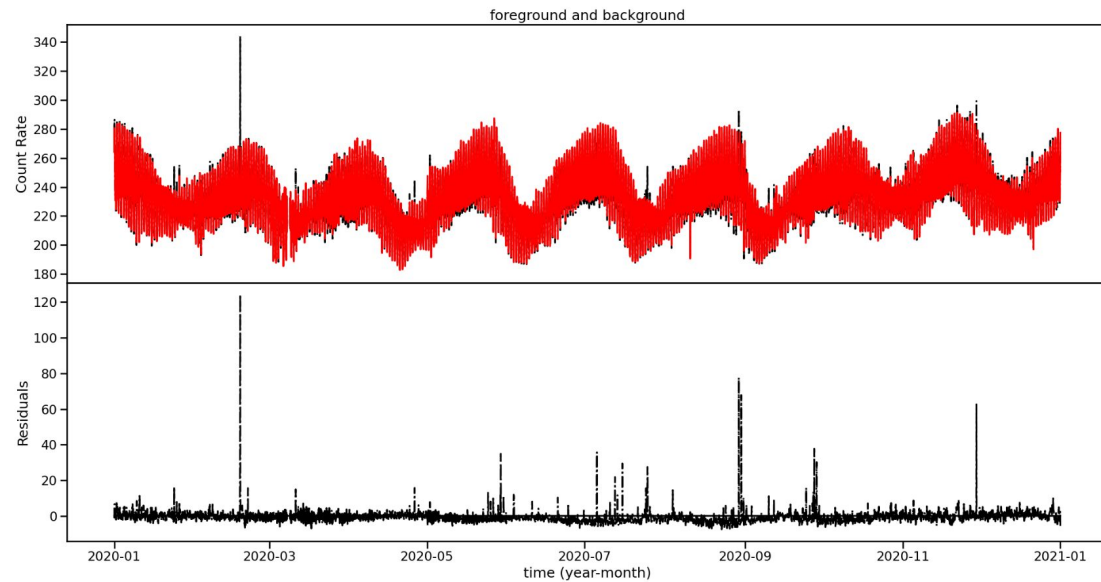


Solar Maxima Minima

n5_r0 2013-12-31 23:59:55.455420



n5_r0 2019-12-31 23:59:55.090142



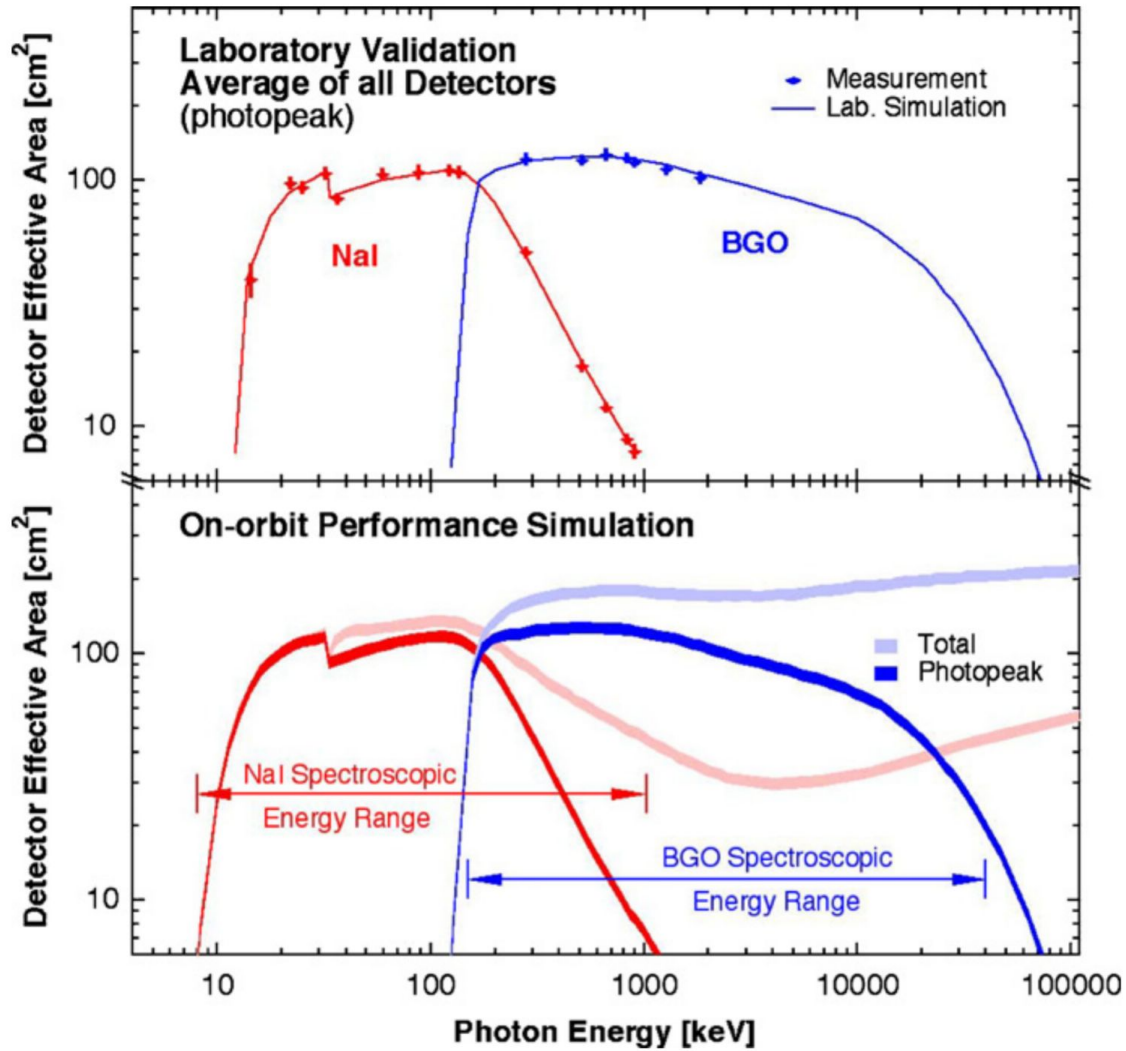


Figure 11. Energy dependence of the effective area at normal incidence, for both detector types. The lower panel includes the simulated effects of the spacecraft for a representative detector.