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Machine Learning approach to Background Estimation in Fermi/GBM lightcurves

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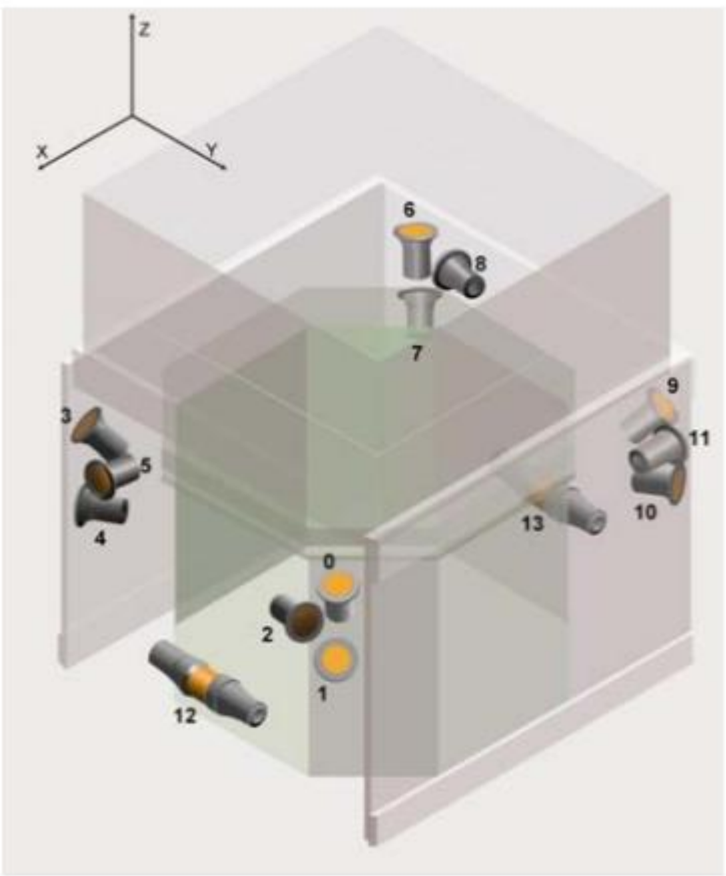
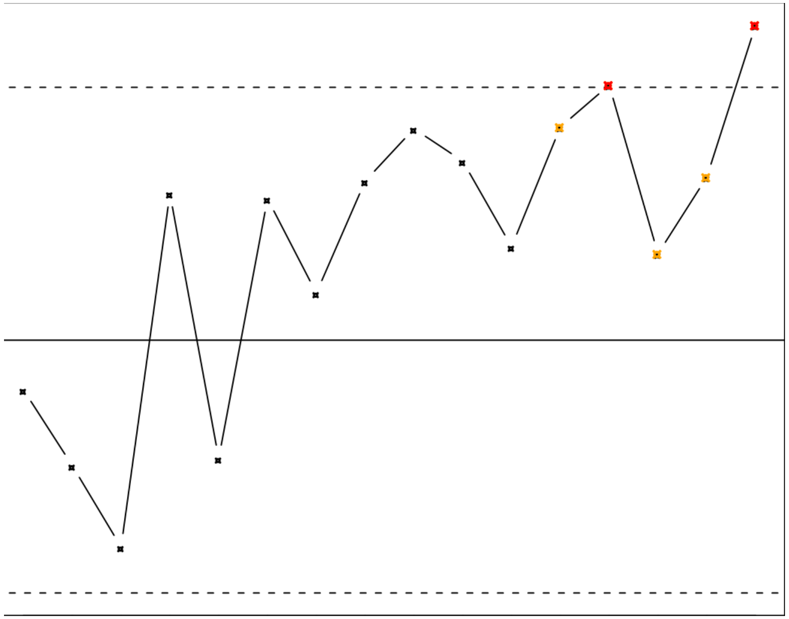
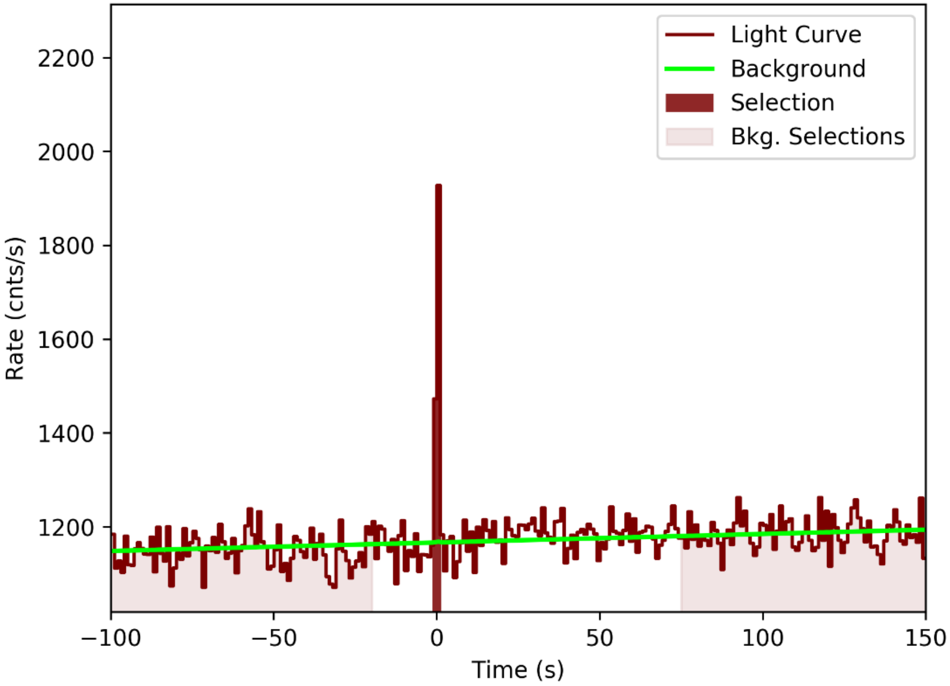
21 February 2022

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 GBM
- Longitude GBM
- Altitude GBM
- Detectors pointing
- SSA zone
- Sun position
- …

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output variables:

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

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ML Background estimation

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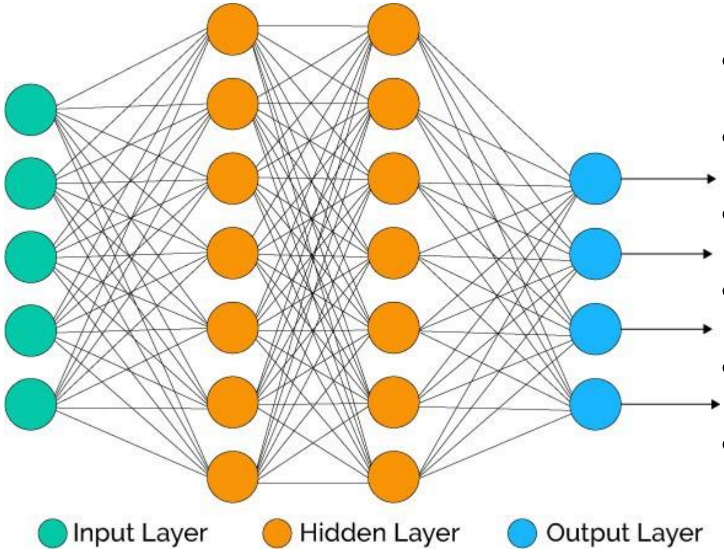

output variables:

- 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]

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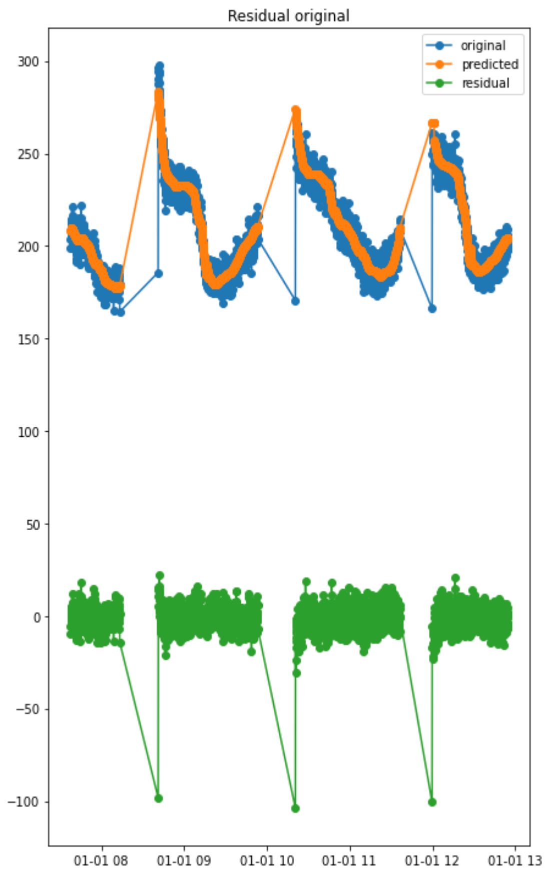
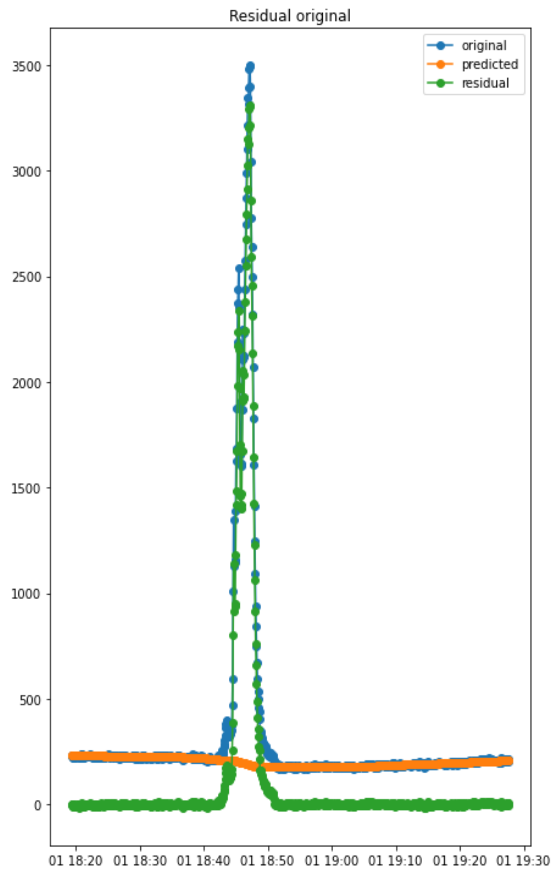
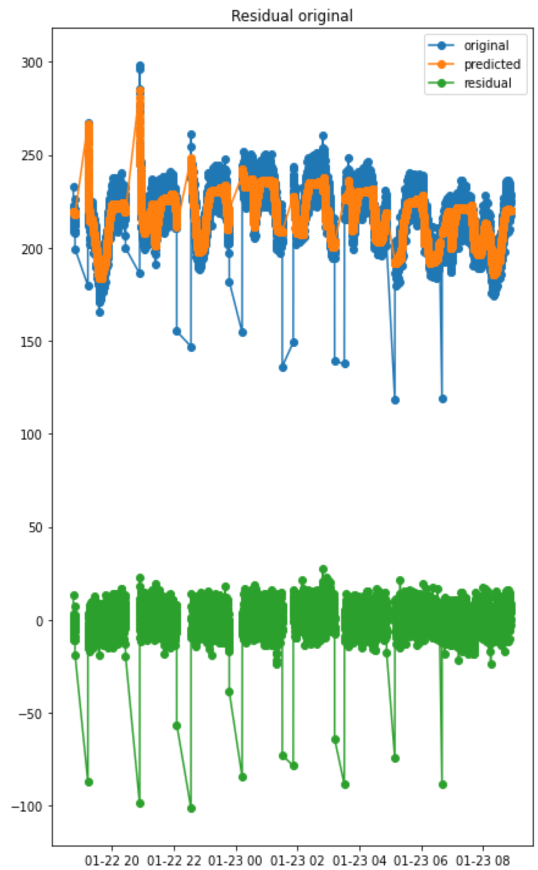
Partial input - output

met	lat	lon	alt	n0_dec	n0_ra	saa	n0_r0	n0_r1	n0_r2
599443696.64426	-21.74720	16.13370	536687.34686	-60.61029	193.13023	False	131.84344	275.56137	46.64100
599443700.73996	-21.68540	16.38606	536703.44551	-60.45834	193.21557	False	274.10376	548.45300	91.94076
599443704.83571	-21.62316	16.63820	536719.48134	-60.30667	193.30146	False	280.94550	541.39386	92.78934
599443708.93181	-21.56049	16.89012	536734.64282	-60.15521	193.38776	False	280.45737	535.99884	95.24504
599443713.02792	-21.49737	17.14180	536750.18760	-60.00350	193.47457	False	280.56808	537.93964	94.87277
599443717.12403	-21.43384	17.39325	536765.63889	-59.85207	193.56186	False	266.68027	535.44684	97.44323
599443721.22012	-21.36987	17.64446	536780.25793	-59.70084	193.64969	False	264.70062	534.06450	100.62796
599443725.31622	-21.30547	17.89543	536795.28120	-59.54942	193.73788	False	265.55270	535.52313	97.31207
599443729.41231	-21.24065	18.14616	536809.89110	-59.39822	193.82666	False	262.96994	521.39954	92.15605
599443733.50841	-21.17541	18.39666	536825.25390	-59.24726	193.91585	False	266.53240	521.16160	93.38451
599443737.60451	-21.10975	18.64692	536840.85849	-59.09606	194.00553	False	265.80035	529.88270	95.71757
599443741.70060	-21.04367	18.89693	536855.23207	-58.94514	194.09561	False	263.83970	521.91174	91.17808
599443745.79670	-20.97716	19.14671	536869.53731	-58.79449	194.18599	False	264.19520	509.61572	90.19204
599443749.89279	-20.91025	19.39625	536884.27429	-58.64356	194.27703	False	267.47410	504.76535	93.12515
599443753.98890	-20.84292	19.64555	536898.11610	-58.49301	194.36832	False	270.79575	513.12540	91.04234
599443758.08501	-20.77518	19.89461	536911.85559	-58.34254	194.46017	False	257.90674	513.11414	89.93607
599443762.18111	-20.70703	20.14341	536925.07311	-58.19195	194.55239	False	249.80258	503.28592	89.44306
599443766.27720	-20.63847	20.39198	536939.09638	-58.04163	194.64502	False	257.17477	505.39258	91.40993
599443770.37330	-20.56950	20.64031	536952.73061	-57.89151	194.73807	False	253.60439	498.98840	87.97018
599443774.46939	-20.50013	20.88840	536965.88525	-57.74122	194.83153	False	252.25041	490.51416	83.91988

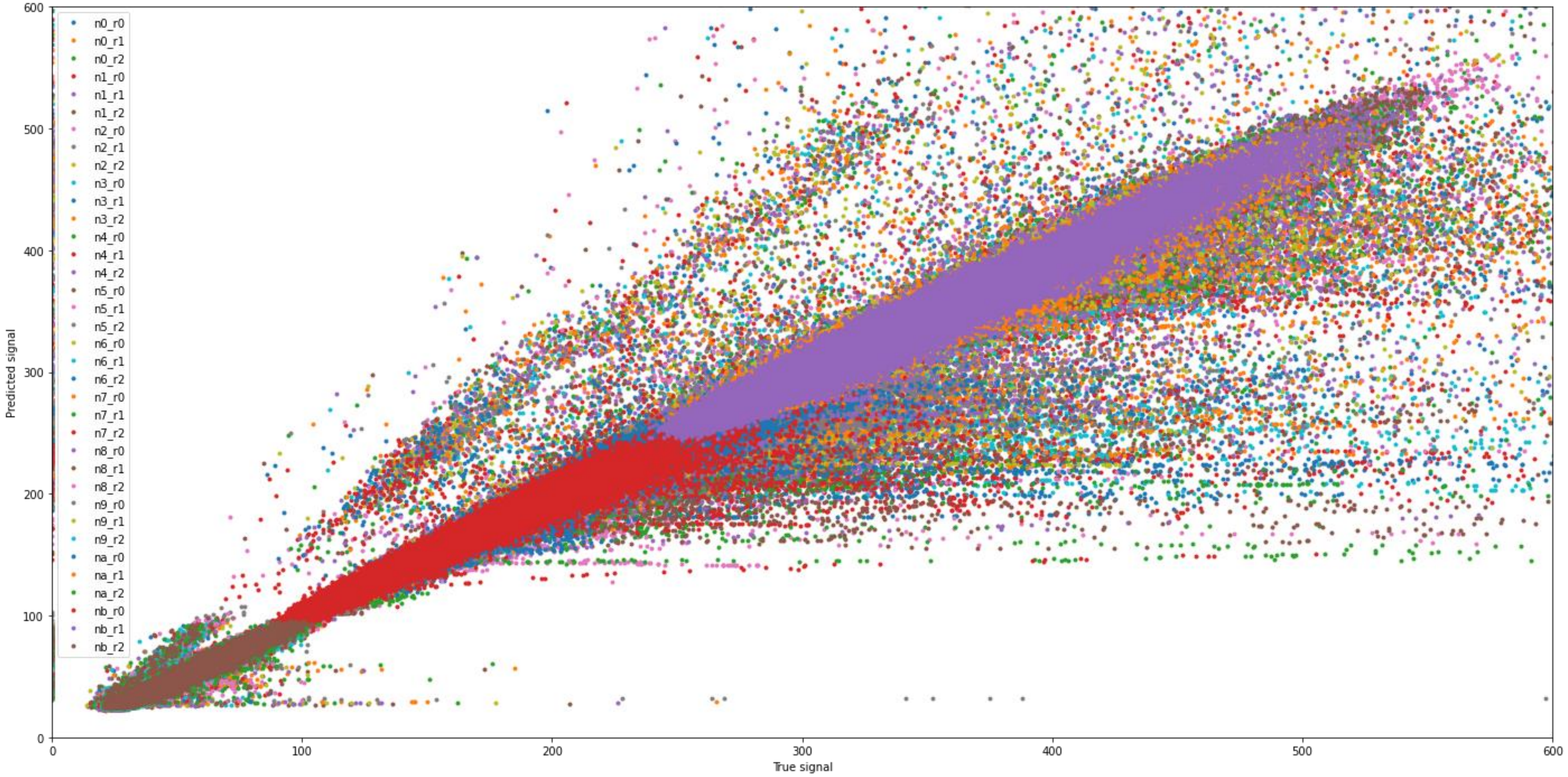
Residuals (28, 50) KeV







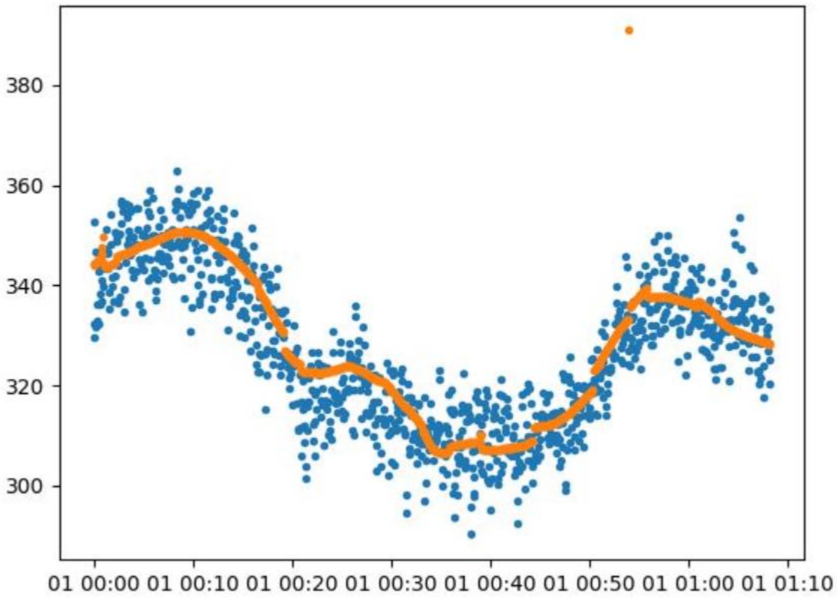
Predicted vs Detected

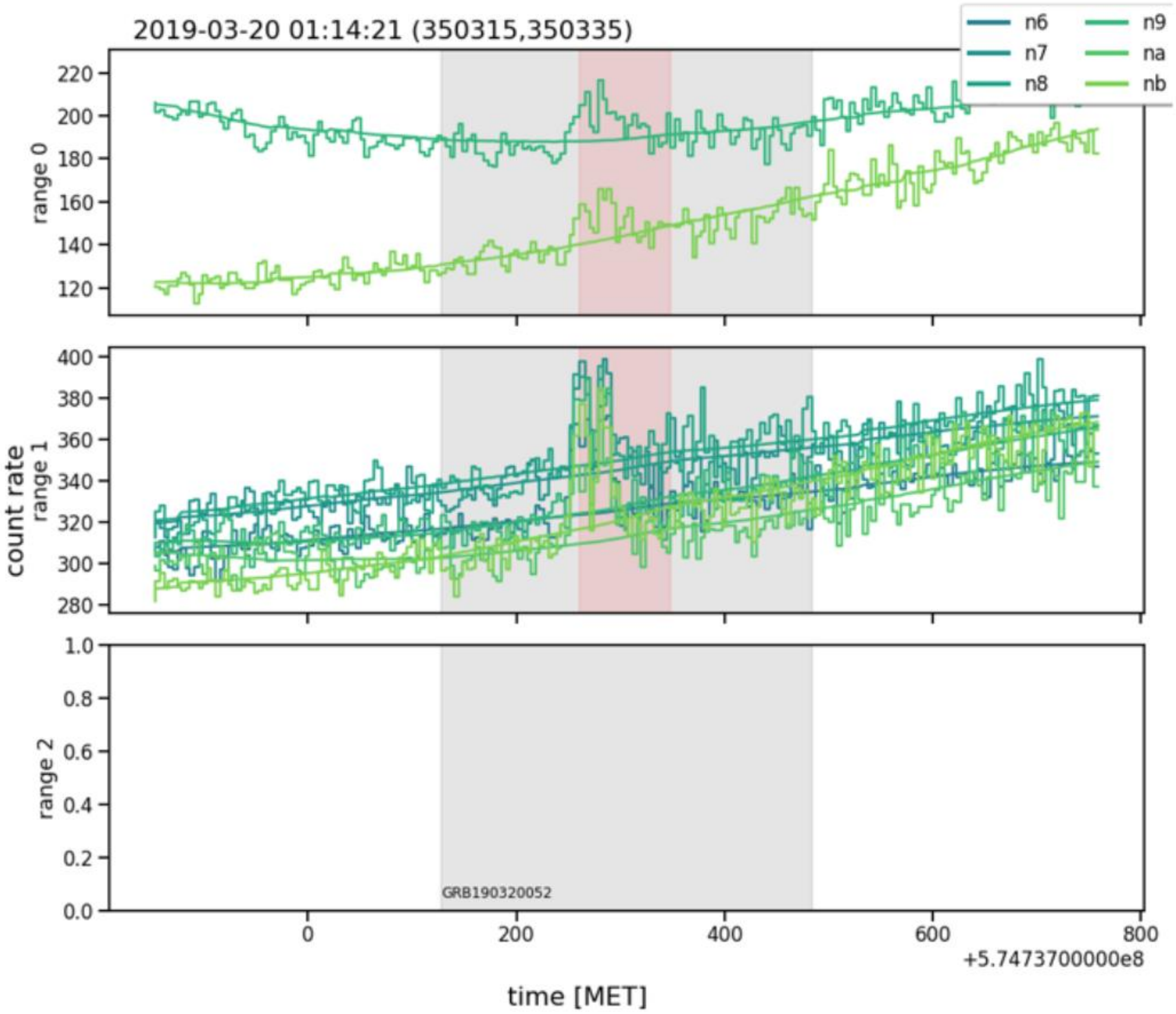


Drowbacks

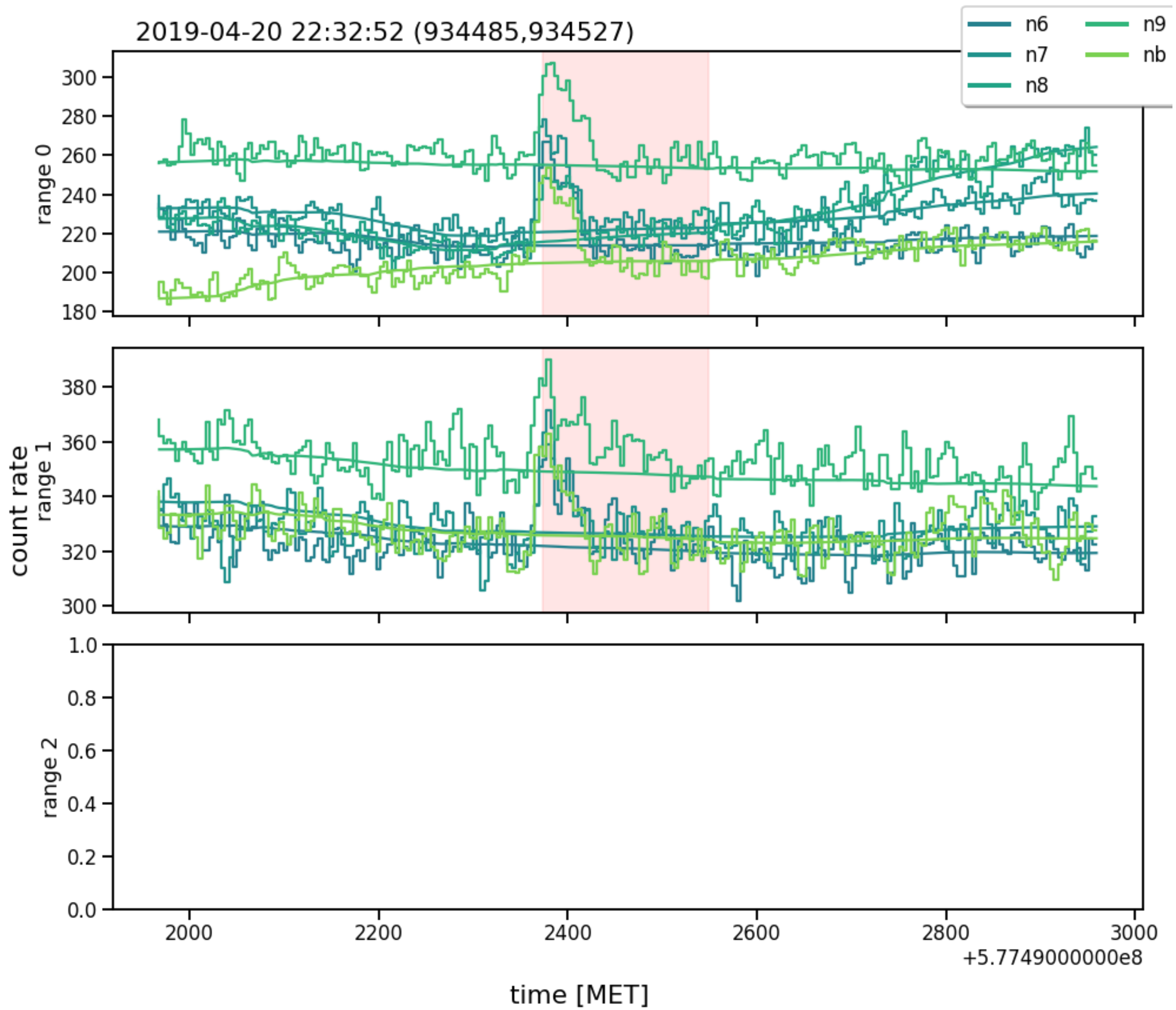
- Discontinuos prediction over time
  Possible solution: change architecture to a recurrent neural network or apply a filter to get a smoother signal

- Difficult to explain why.
  Possibile solution: use algorithm of explainability for black box (what feature was importat for the prediction)





Credits to Giuseppe Dilillo



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Conclusion

- Collect photon counts and data info about the satellite
- Estimate the background with a data drived approach
- Use a trigger algorithm to discover faint long event

References

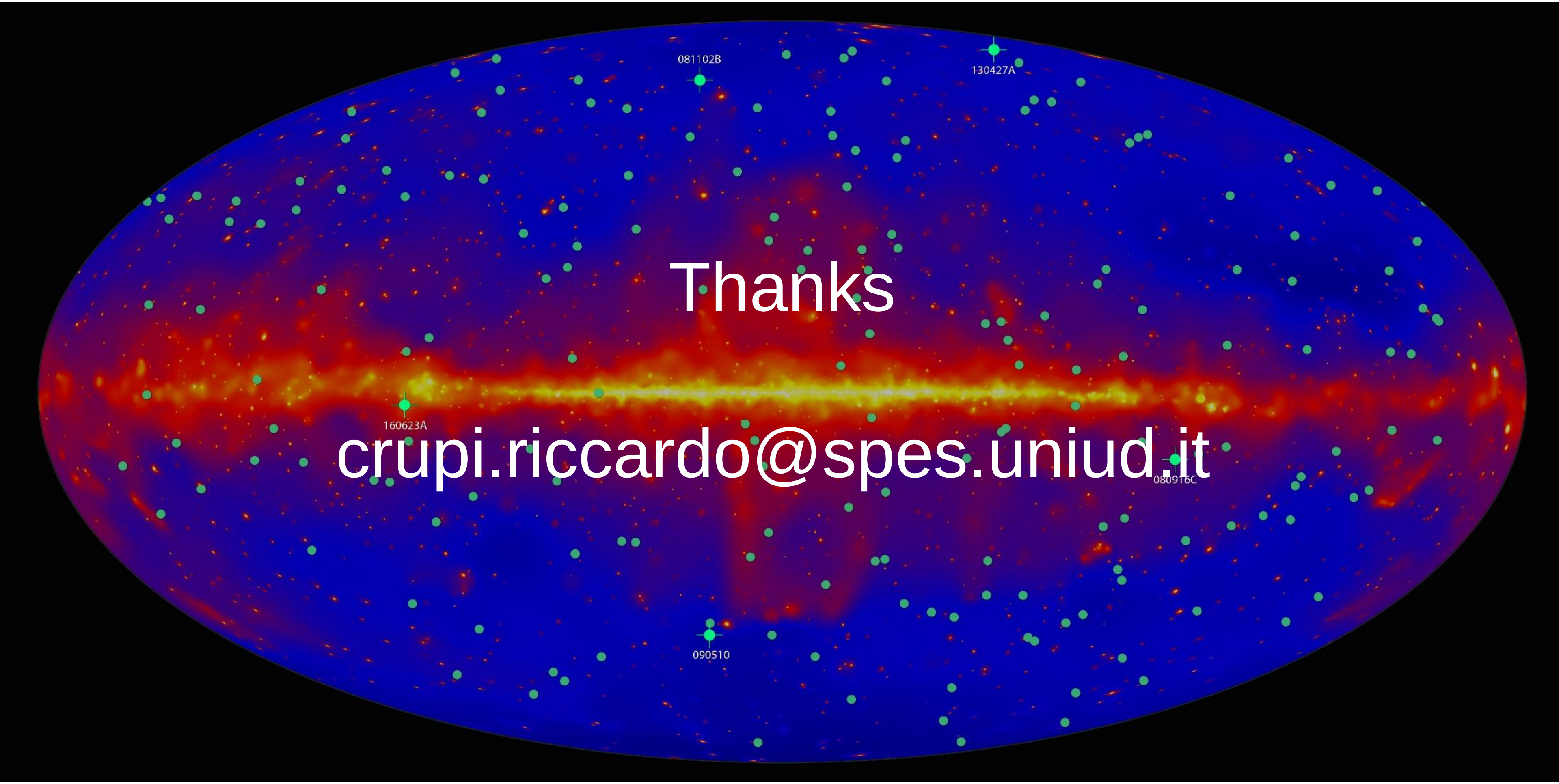
- Elisabetta Bissaldi, Andreas von Kienlin, G Lichti, Helmut Steinle, P Narayana Bhat, Michael S Briggs, Gerald J Fishman, Andrew S Hoover, R Marc Kippen, Michael Krumrey, et al. Ground-based calibration and characterization of the fermi gamma-ray burst monitor detectors. Experimental Astronomy, 24(1-3):47–88, 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.

- Riccardo Crupi, Giuseppe Dilillo, Working in Progress

- GitHub repository, Working in Progress



Thanks

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