

# POLAR background prediction

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November 2, 2023

# Overview

## 1 Introduction

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- Related work
- Our work

## 2 Methodology

- Background model
- Poor predictions
- Cluster and cluster intersections

## 3 Results & discussion

## 4 Conclusion

# Gamma Ray Bursts (GRBs)

- What are GRBs?
  - ▶ Intense, energetic, and extra-galactic explosions
  - ▶ Bursts of high-energy photons, gamma rays
- Lead to spikes in photon counts/rates

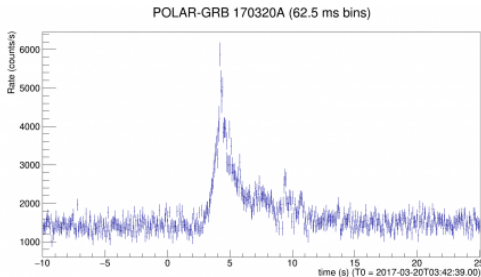


Figure: A light-curve containing a Gamma Ray Burst<sup>1</sup>

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<sup>1</sup><https://www.astro.unige.ch/polar/grb-light-curves>

# What are astrophysicists interested in?

- Better understand GRBs
- For this purpose, there's a need for:
  - ▶ Data taking → POLAR or POLAR-2 detector

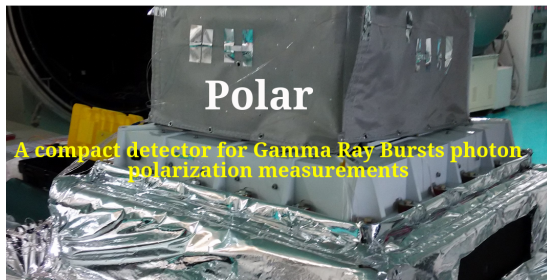


Figure: Picture taken from <https://www.astro.unige.ch/polar/>.

# What are astrophysicists interested in?

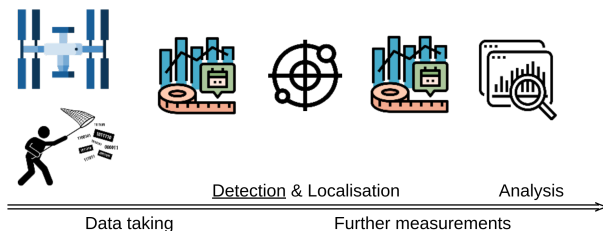


Figure: Process<sup>2</sup>.

<sup>2</sup>Icons were taken from <https://www.flaticon.com/free-icons/>. More accurate attributions in the credits.

- Koziol's master thesis [1]: HAGRID<sup>3</sup>
  - ▶ Fast real-time GRB detection and localization using ML
  - ▶ In particular, for GRB detection, he used:
    - ★ Labeled simulated data with simulated GRBs
    - ★ From past 60 [s] simulated light-curves + energy info.
    - ★ Predict the occurrence of a GRB at time  $t$

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<sup>3</sup>High Accuracy GRB Rapid Inference with Deep Learning in Space

## Related work

- Koziol's master thesis [1]: HAGRID<sup>4</sup>
  - ▶ Possible data distribution mismatch
  - ▶ But low miss-detection: correctly detected all real GRBs within 10 days of POLAR data.
  - ▶ Does not account for other measurements

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<sup>4</sup>High Accuracy GRB Rapid Inference with Deep Learning in Space

# Our work

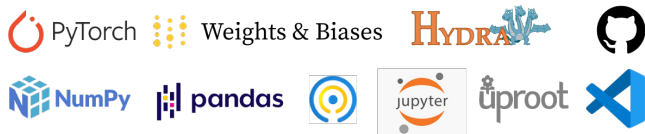
Would like to

- Train our model from real POLAR data
  - ▶ No longer have access to labels
  - ▶ → Background model
- Explicitly account for other measurements
  - ▶ → Predict photon rates from diverse measurements
- Reduce complexity barrier to model interpretability
  - ▶ → Multi-Layer Perceptron (MLP)
- Try to interpret our trained model
  - ▶ → Gradients w.r.t input variables



# Methodology

- Train background model **without** 25 known GRBs<sup>5</sup>.
- Apply our model to everything
- Extract time intervals based on the residuals
- Peek at model interpretability using Jacobian matrices
- A few technologies:



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<sup>5</sup>25 of 55 known GRBs [2] happening within our data

# Background model

- Multi-Layer Perceptron (MLP) background model<sup>6</sup>

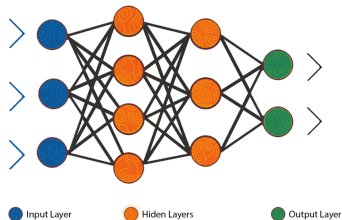


Figure: Multi-Layer Perceptron high-level

- $3 \times 200$  hidden units with ReLUs.
- Trained to minimize a weighted MSE

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<sup>6</sup>Picture taken from <https://medium.com/unpackai/from-anns-artificial-neural-networks-to-rnns-recurrent-neural-networks-93b638772fd1>

# Poor predictions

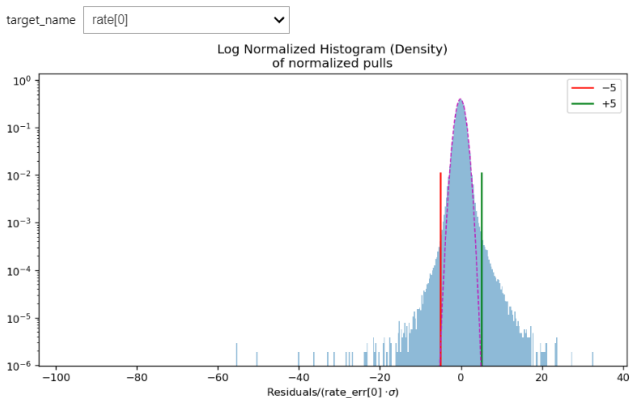
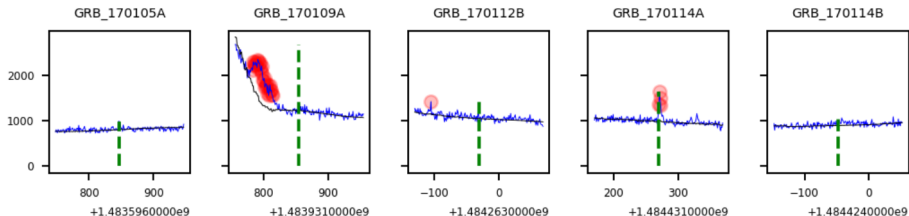


Figure: Normalized pulls for rate[0]

# Cluster and cluster intersections

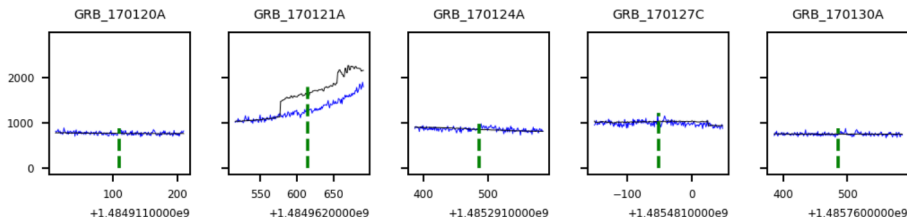
- Aggregating extracted data-points  $\rightarrow$  clusters
- GRBs should be visible in different energy bins
- Cluster of data points extracted using different energy bins:
  - ▶ Each from the same set of energy bins
  - ▶ Or each satisfying same conditions (e.g. number of energy bins)

# Results & discussion: Known GRBs



**Figure:** Energy bin 0, time windows of  $\pm 100$  [s] around 5 known GRB trigger times [2], based on pulls with  $k = 5$ . Predictions are in black.

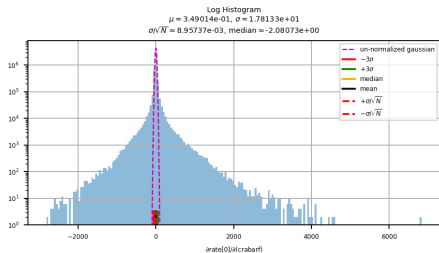
# Results & discussion: Known GRBs



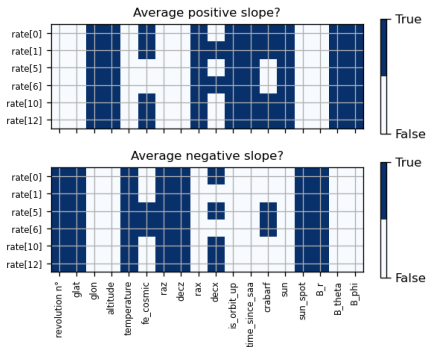
**Figure:** Energy bin 0, time windows of  $\pm 100$  [s] around 5 other known GRB trigger times [2], based on pulls with  $k = 5$ .



# Results & discussion: Model interpretability



(a) Histogram of  $\frac{\partial \text{rate}[0]}{\partial \text{crabarf}}$  (un-normalized features)



(b) Avg slope  $\mu$  greater (lesser) than its (negative) standard error  $\frac{\sigma}{\sqrt{N}}$ ?

- Need for further analysis



# Results & discussion

Table 6: Mean  $\pm$  standard deviation (over 10 different seeds) number of positive/negative cluster intersections for different sets of energy bins  $bs$  or conditions<sup>29</sup>. This time, there's a discard window of 30 seconds.

$bs$ or condition	negative	positive	$bs$ or condition	negative	positive	$bs$ or condition	negative	positive
# inter > 0	5762.1 $\pm$ 965.708	6487.6 $\pm$ 826.131	0,2	6.9 $\pm$ 2.726	10.7 $\pm$ 4.111	1,3	15.6 $\pm$ 6.398	51.2 $\pm$ 42.695
# inter > 1	4802.8 $\pm$ 822.34	5450.6 $\pm$ 752.954	0,2,3	6.0 $\pm$ 3.432	7.1 $\pm$ 1.37	1,3,4	1.0*	–
# inter > 2	3493.8 $\pm$ 610.247	4083.5 $\pm$ 564.85	0,2,3,4	8.0*	–	1,3,4,5	1.333 $\pm$ 0.577	1.5 $\pm$ 0.577
# inter > 3	3238.4 $\pm$ 602.769	3821.5 $\pm$ 538.957	0,2,3,4,5	212.2 $\pm$ 42.158	242.7 $\pm$ 65.109	1,3,5	–	5.5 $\pm$ 6.364
# inter > 4	1150.2 $\pm$ 232.379	1595.0 $\pm$ 202.499	0,2,3,5	1.0 $\pm$ 0.0	3.5 $\pm$ 3.536	1,4	1.0*	3.0*
# inter > 5	791.3 $\pm$ 165.14	1135.2 $\pm$ 149.199	0,2,4	1.5 $\pm$ 0.707	1.0*	1,4,5	2.125 $\pm$ 1.356	5.5 $\pm$ 3.742
0	23.8 $\pm$ 8.23	71.6 $\pm$ 18.368	0,2,4,5	5.8 $\pm$ 4.367	15.8 $\pm$ 5.095	1,5	–	2.0 $\pm$ 0.0
0,1	16.6 $\pm$ 6.059	62.3 $\pm$ 45.631	0,2,5	1.0 $\pm$ 0.0	2.5 $\pm$ 2.38	2	734.8 $\pm$ 169.59	939.8 $\pm$ 235.236
0,1,2	4.0 $\pm$ 2.0	15.2 $\pm$ 9.739	0,3	1.0*	3.0 $\pm$ 1.414	2,3	2459.9 $\pm$ 493.897	3265.5 $\pm$ 779.499
0,1,2,3	12.4 $\pm$ 3.806	30.5 $\pm$ 17.219	0,3,4,5	1.667 $\pm$ 1.155	1.75 $\pm$ 0.957	2,3,4	114.8 $\pm$ 335.669	11.75 $\pm$ 12.395
0,1,2,3,4	23.0*	2.5 $\pm$ 0.707	0,4	2.0*	–	2,3,4,5	3156.9 $\pm$ 657.884	4049.1 $\pm$ 676.033
0,1,2,3,4,5	791.3 $\pm$ 165.14	1135.2 $\pm$ 149.199	0,4,5	2.25 $\pm$ 1.753	11.6 $\pm$ 3.062	2,3,5	60.444 $\pm$ 11.479	225.0 $\pm$ 392.74
0,1,2,3,5	1.0 $\pm$ 0.0	3.667 $\pm$ 4.899	0,5	1.0*	1.75 $\pm$ 1.5	2,4	18.333 $\pm$ 38.563	2.333 $\pm$ 1.751
0,1,2,4	1.0*	3.0*	1	52.6 $\pm$ 15.16	104.0 $\pm$ 118.135	2,4,5	212.3 $\pm$ 59.913	244.9 $\pm$ 73.942
0,1,2,4,5	2.8 $\pm$ 1.751	11.2 $\pm$ 7.315	1,2	3.444 $\pm$ 1.424	8.5 $\pm$ 4.143	2,5	9.8 $\pm$ 6.356	55.5 $\pm$ 127.411
0,1,2,5	1.0*	2.667 $\pm$ 2.082	1,2,3	56.1 $\pm$ 19.221	115.1 $\pm$ 41.391	3	1206.3 $\pm$ 282.876	1633.0 $\pm$ 282.032
0,1,3	1.25 $\pm$ 0.5	4.875 $\pm$ 7.2	1,2,3,4	14.75 $\pm$ 27.5	1.4 $\pm$ 0.548	3,4	6.25 $\pm$ 9.215	1.0 $\pm$ 0.0
0,1,3,4,5	2.5 $\pm$ 2.811	2.25 $\pm$ 0.5	1,2,3,4,5	413.5 $\pm$ 141.535	714.4 $\pm$ 132.802	3,4,5	19.7 $\pm$ 8.166	16.5 $\pm$ 4.503
0,1,3,5	–	1.0*	1,2,3,5	2.167 $\pm$ 0.753	9.667 $\pm$ 19.268	3,5	1.889 $\pm$ 0.782	21.0 $\pm$ 58.877
0,1,4	1.0*	6.0*	1,2,4	–	4.0*	4	9.333 $\pm$ 20.174	3.833 $\pm$ 4.167
0,1,4,5	2.875 $\pm$ 1.959	5.9 $\pm$ 4.202	1,2,4,5	3.143 $\pm$ 2.673	4.889 $\pm$ 3.333	4,5	123.5 $\pm$ 30.395	124.0 $\pm$ 31.383
0,1,5	2.0*	2.0*	1,2,5	–	3.0*	5	7.3 $\pm$ 3.302	88.1 $\pm$ 234.779

- Need an analysis of clusters' stability due to initial seeds

# Conclusion: Summary

- Built a model of the background (light curve) using data collected from the POLAR detector
- Used poor predictions to extract time intervals
- Brief peek at model interpretability using partial derivatives of output w.r.t. input

# Conclusion: Possible improvements

- Future analysis of our extracted time intervals is required
  - ▶ Categorize them into solar events, GRBs and so on
  - ▶ Assess the clusters' stabilities due to initial seeds
- Other possible improvements:
  - ▶ Dive deeper into model interpretability
  - ▶ Change the methodology, e.g. use sequential models
  - ▶ Improve code quality, GPU usage and decrease memory footprint.
- Manual inspection of our clusters by experts can give crucial information telling us what to do next.

# The End

# Credits

- Space station icons created by Freepik - Flaticon:  
<https://www.flaticon.com/free-icons/space-station>
- Collecting icons created by Leremy - Flaticon:  
<https://www.flaticon.com/free-icons/collecting>
- Detection icons created by Freepik - Flaticon:  
<https://www.flaticon.com/free-icons/detection>
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<https://www.flaticon.com/free-icons/analysis>
- Measure icons created by GOWI - Flaticon:  
<https://www.flaticon.com/free-icons/measure>

# References

Figures without references come from author of the slides.



[1] Gilles Koziol, (2023)

HAGRID in Space. *Master's thesis*, University of Geneva.

<https://cernbox.cern.ch/s/X10vZ4iY19vewcV>. Accessed: 2023-09-22.



[2] François Fleuret, (2023)

Deep Learning Course.

<https://fleuret.org/dlc/>. Accessed: 2023-09-22



[2] Shaolin Xiong, Yuanhao Wang, Zhengheng Li, Jianchao Sun, Yi Zhao, Hancheng Li, and Yue Huang, (2017)

Overview of the GRB observation by POLAR.

*ICRC2017*. page 640