

POLAR background prediction

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Overview

1 Introduction

- Gamma Ray Bursts
- 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?

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

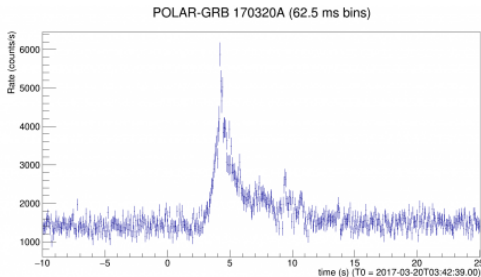


Figure: A light-curve containing a Gamma Ray Burst¹

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What are astrophysicists interested in?

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

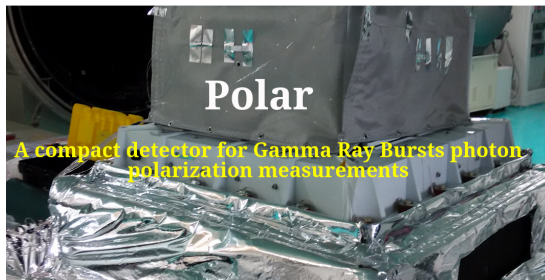


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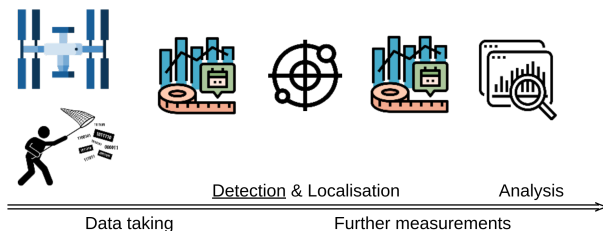


Figure: Process².

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

Related work

- Koziol's master thesis [1]: HAGRID³

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 - ★ Predict the occurrence of a GRB at time t

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 - ▶ Possible data distribution mismatch

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- Koziol's master thesis [1]: HAGRID⁴
 - ▶ 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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- Try to interpret our trained model
 - ▶ → Gradients w.r.t input variables

Methodology

- Train background model **without** 25 known GRBs⁵.

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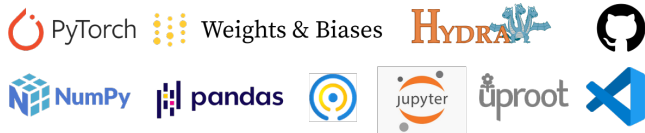
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- Peek at model interpretability using Jacobian matrices

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- A few technologies:



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Background model

- Multi-Layer Perceptron (MLP) background model⁶

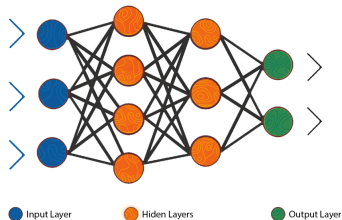


Figure: Multi-Layer Perceptron high-level

- 3×200 hidden units with ReLUs.

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

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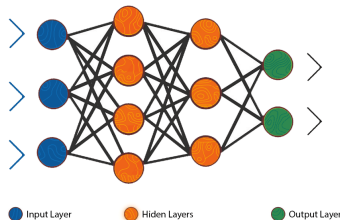


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- 3×200 hidden units with ReLUs.
- Trained to minimize a weighted MSE

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Poor predictions

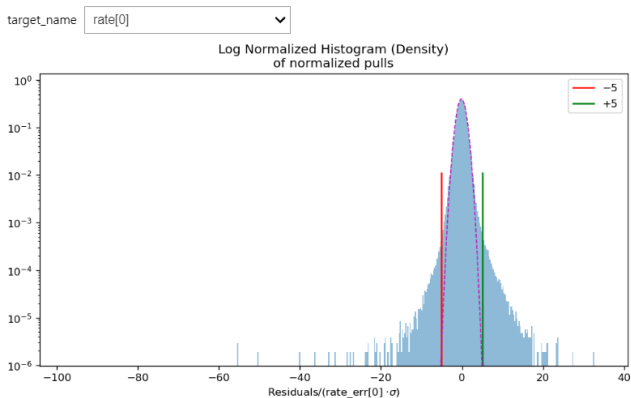


Figure: Normalized pulls for rate[0]

Cluster and cluster intersections

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- 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

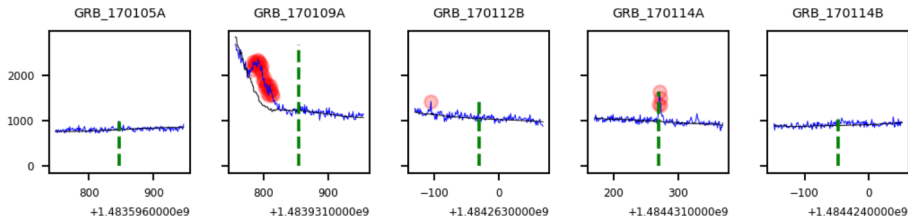


Figure: Energy bin 0, time windows of ± 100 [s] around 5 known GRB trigger times [2], based on pulls with $k = 5$. Predictions are in black.

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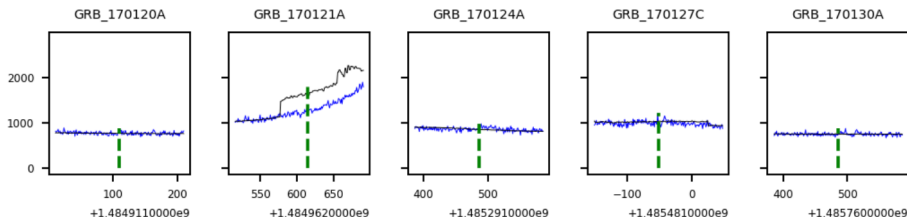
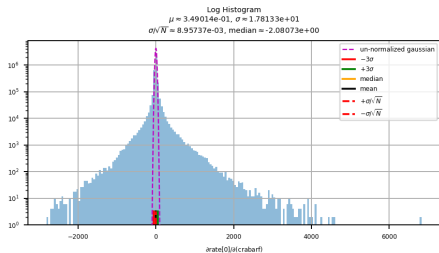
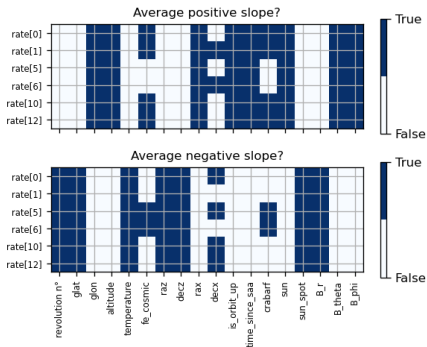


Figure: Energy bin 0, time windows of ± 100 [s] around 5 other known GRB trigger times [2], based on pulls with $k = 5$.

Results & discussion: Model interpretability

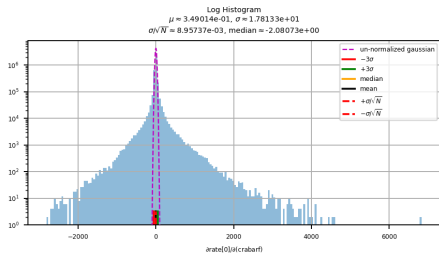


(a) Histogram of $\frac{\partial \text{rate}[0]}{\partial \text{crabarf}}$ (un-normalized features)

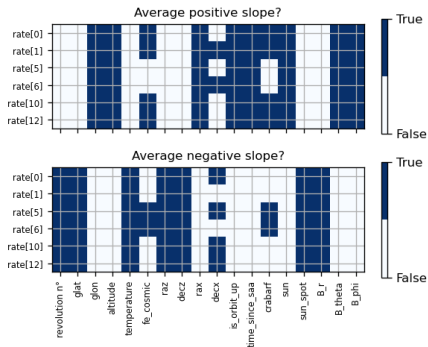


(b) Avg slope μ greater (lesser) than its (negative) standard error $\frac{\sigma}{\sqrt{N}}$?

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



(b) Avg slope μ 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 conditions²⁹. 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	4802.1 \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
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- Need an analysis of clusters' stability due to initial seeds

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- Used poor predictions to extract time intervals
- Brief peek at model interpretability using partial derivatives of output w.r.t. input

Conclusion: Possible improvements

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 - ▶ 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>
- Analysis icons created by monkik - Flaticon:
<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.



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

Overview of the GRB observation by POLAR.

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