



A Novel GRB Progenitor Classifier Based on Fermi-GBM Prompt Emission Properties

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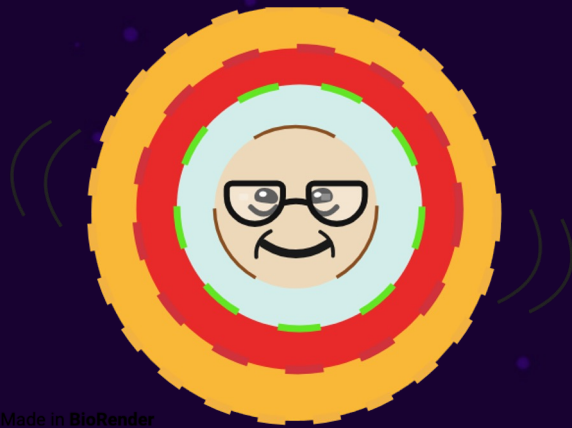
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“GRB Progenitor Classification from Gamma-Ray Burst Prompt and Afterglow Observations”, 2024. doi:10.48550/arXiv.2407.08857 (in press)

There are two widely-accepted GRB progenitors generally attributed to two observational classes

The massive stellar collapsar



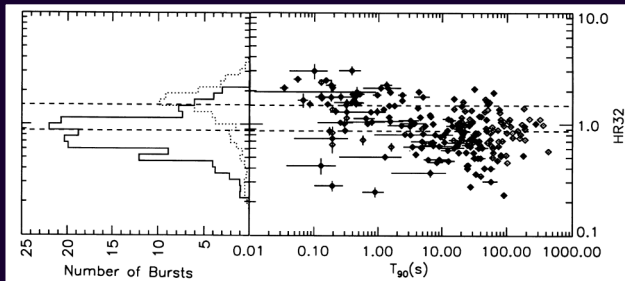
The compact merger
(including at least one neutron star)



Many ways to observe the different classes

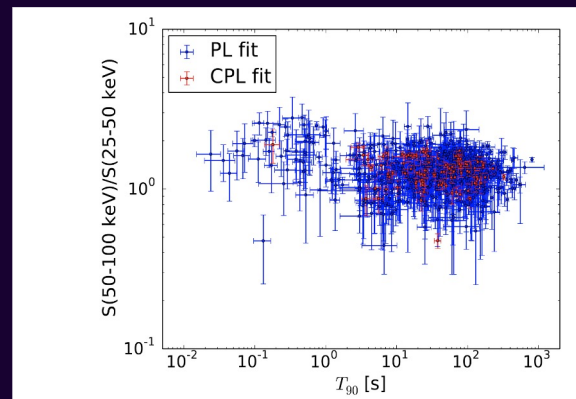
Collapsars	Mergers
mid-Z elements created through nuclear fusion and photodisintegration in Type Ibc supernovae	high-Z elements created via r-process nucleosynthesis associated with kilonovae
dense environments produced by the shedding of the star's outer layer	less dense environments—tend to move out of their stellar nurseries
very young stars in star-forming regions	older objects typically in the outskirts of their older, redder host galaxies
tend towards softer spectra	harder spectra in general
most long (>5 seconds) duration	most short (<5 seconds) duration
for GBM, use 4.2 s from GBM GRB Catalog (von Kienlin et al., 2020)	

Hardness Ratio and Duration Typically Used to Discriminate



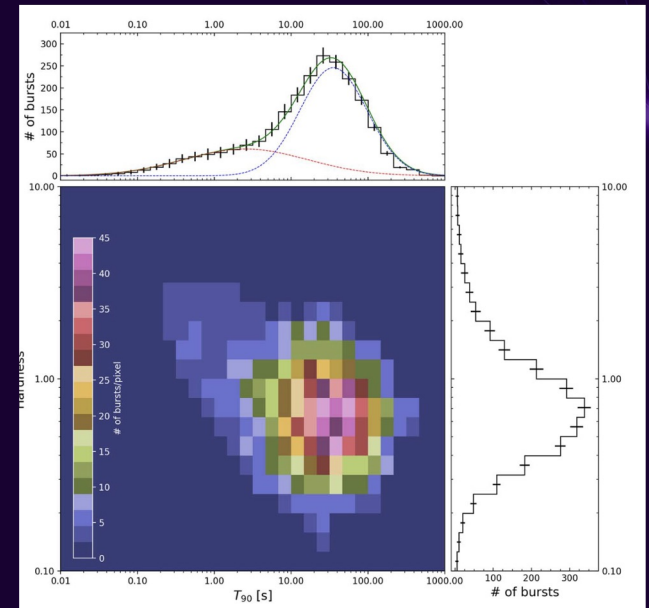
Kouveliotou et al. (1993)

BATSE



Lien et al. (2016)

Swift-BAT



von Kienlin et al. (2020)

Fermi-GBM

Bursts Outside this Paradigm

Long Mergers (KN detected)

1. GRB 230307A
 - $T_{90}=35s$, KN detected
 - Bulla et al. 2023
2. GRB 211211A
 - $T_{90}=34s$, KN detected
 - Troja et al. 2022
3. GRB 111005A
 - $T_{90}=26 s$, KN detected
 - Wang et al. 2017
4. GRB 060614
 - $T_{90}=102s$, KN detected
 - Yang et al. 2015

Short Collapsars (SN detected)

1. GRB 200826A
 - $T_{90}=1.1s$, SN detected
 - Ahumada et al. 2021

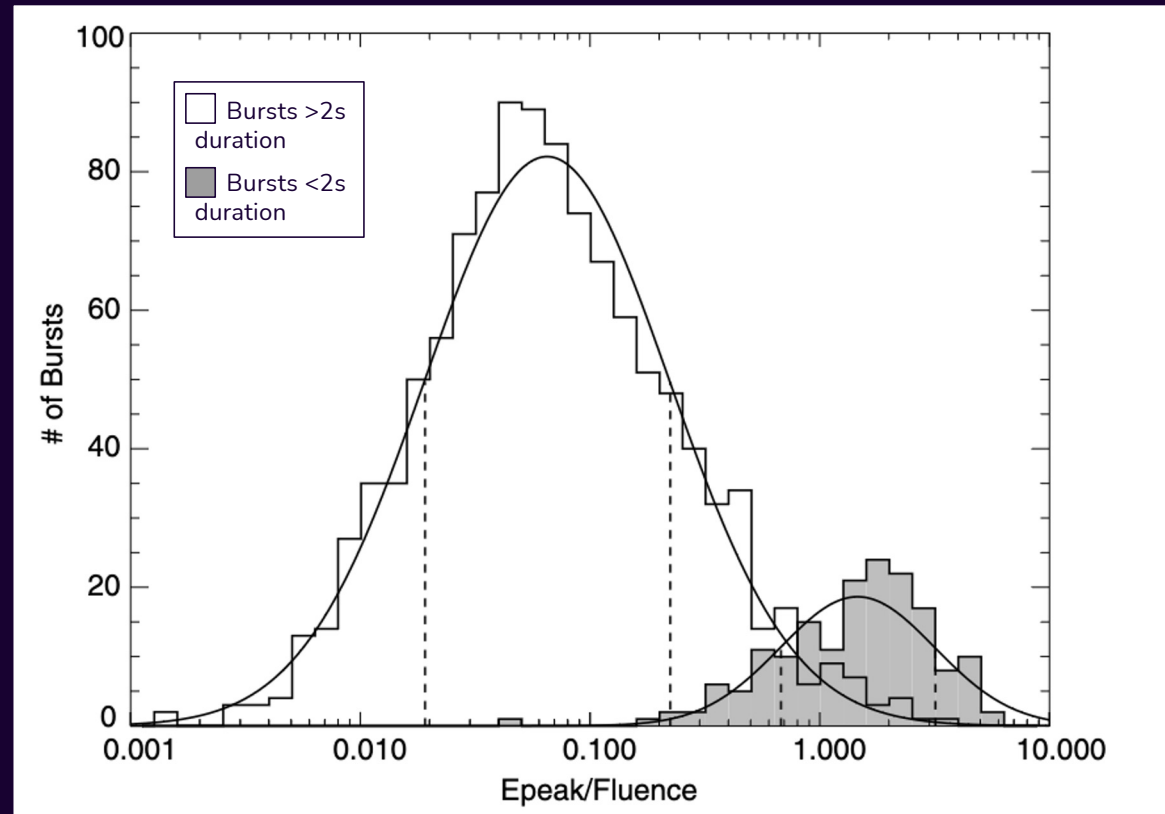
Unclear Progenitor (Both KN and SN features)

1. GRB 210704A
 - $T_{90}=4.7s$, optical excess, long lag, soft spectrum, and possible old galaxy localization
 - Becerra et al. 2023

Known Correlations in the Context of Progenitor Outliers

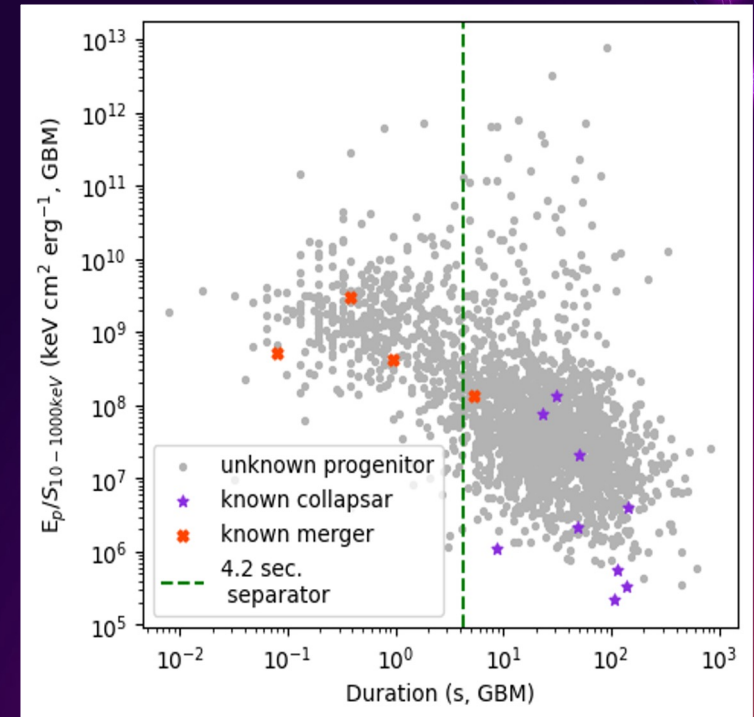
$$\frac{E_{peak}}{S_{\gamma}} \sim T_{90}$$

Goldstein et al. (2010)



Sample Selection

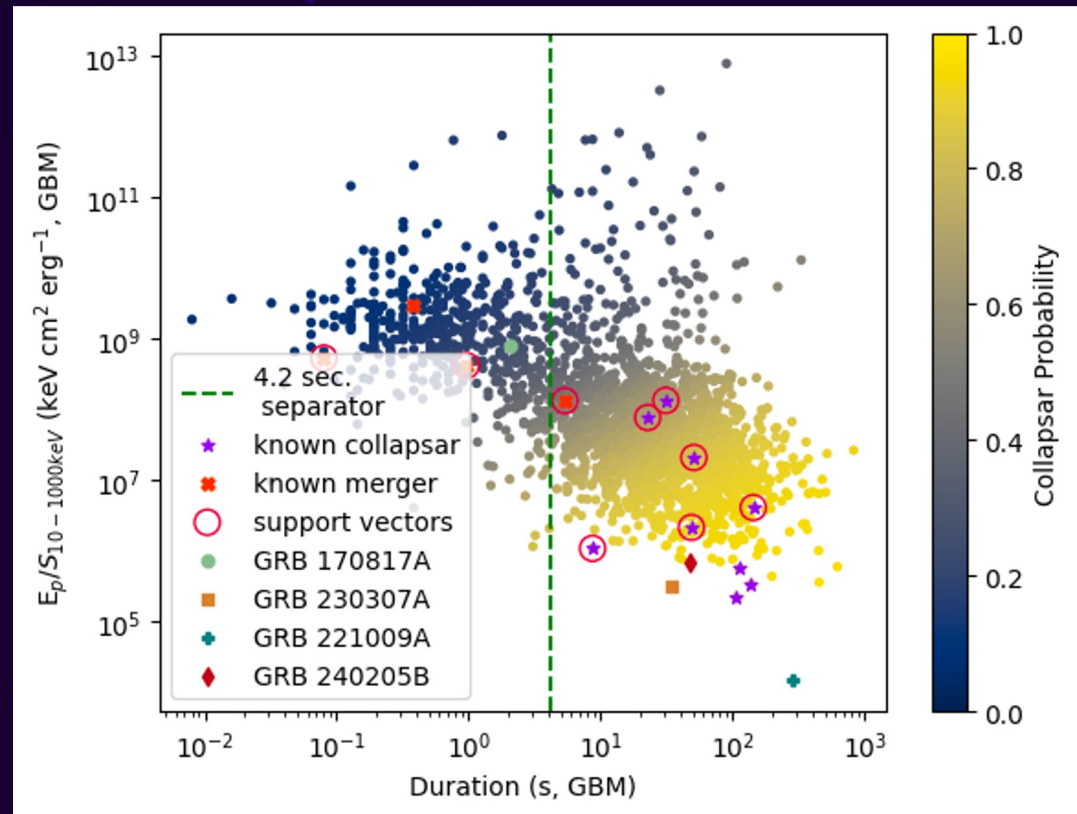
- Every *Fermi*-GBM GRB through 05/2023 (von Kienlin et al., 2020) (3527 bursts)
 - Eliminated any without peak energy, e.g. best fit by power law (2310 bursts left)
- Known progenitors (63 bursts)
 - mergers (21 bursts)
 - correlated kilonova (9 bursts)
 - likely kilonova (3 bursts)
 - in the outskirts of their host galaxies via Fong et al. (2022) (8 bursts)
 - low spectral lag (Jiang et al., 2023, 1 burst)
 - collapsars (42 bursts)
 - correlated supernova mostly from Dainotti et al. (2022), GRBs 200826A, 211023A, and 150210A from individual papers



Nuessle et al. 2024, our sample

Classification Method

- Supervised Machine Learning
 - Support Vector Machine (SVM)
 - trained on known progenitors
 - minimizes training set
 - creates dividing hyperplane
- uniform response over sizes of training data
- Platt Scaling makes it gives you Bayesian probability



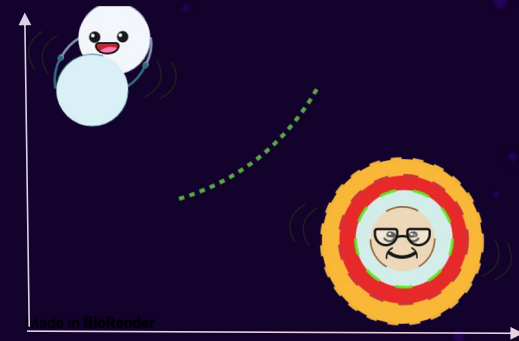
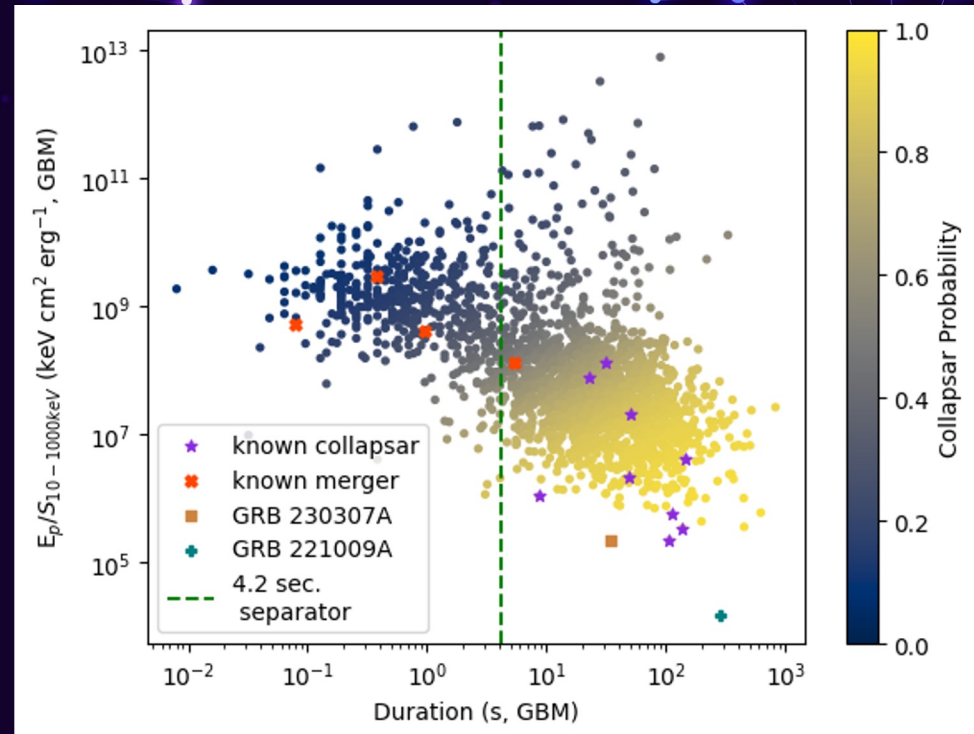
Testing for selection effects

- prompt fluence dependence
- redshift-dependence
- simulated distance dependence
- afterglow plateau fluence dependence
- bootstrap analysis of the number of progenitors in the training sample
- tested if some ambiguous cases could be due to a short spike with extended emission

Correlation persisted, and it appeared to discriminate on classes—more details in paper

Summary

- new classification method
 - based on standard prompt emission properties (in GRB catalogs)
 - probabilistic
 - has limitations—misclassifies the known merger GRB 230307A
- related studies using different methods: Dimple et al. (2023, 2024), Negro et al. (2024), and Zhu et al. (2024)
- our classifier is on GitHub:
https://github.com/PiNuessle/Novel_SVM_GRB_Progenitor_Classifier



Backup

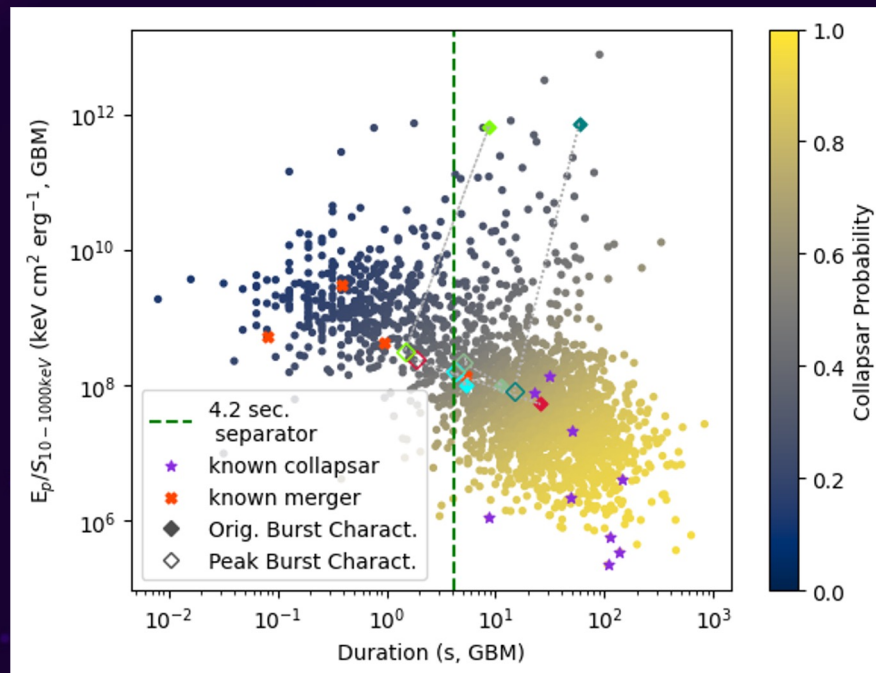
Several Possible Contributors to Overlap

- Some Wolf-Rayet stars form in binary or more systems and may be triggered through collision rather than collapse
 - We still refer to these as collapsars
- At least some binaries may contain one non-neutron star massive companion at the time of collision
 - hypothesized WD channel
 - Dense environments
- Selection bias for observed length and progenitor of GRBs

Analysis of BOAT and SBOAT spectra

- Both GRBs have issues with their fitted spectra--221009A because it was so bright, 230307A because it was so long
 - 221009A: Lesage et al. (2023), Table 1, peak energy in stage IVc, about mean time, (300 s) about mean value (1400 keV)
 - The duration and fluence were taken as the values calculated in this paper
 - 230307A: Levan et al (2023), we took the peak energy at 20s, (682.4 keV) as it was halfway through the measured interval
 - Again, authors calculated fluence and duration

Checking for observational selection effects

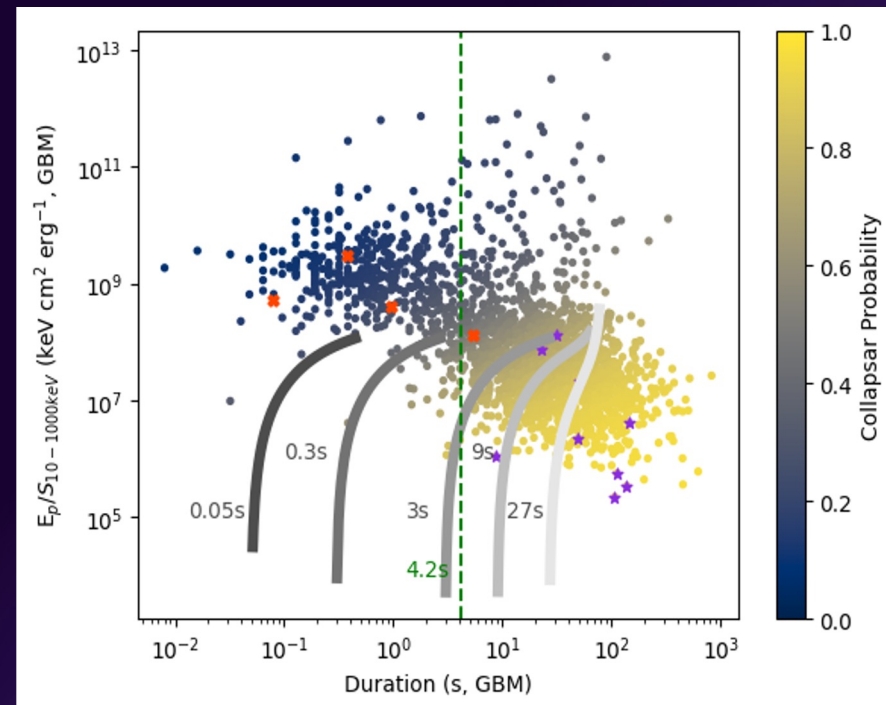


Subtracting “Extended Emission”

- EE selected by eye
- removal did not improve classification
- changed classification in one case

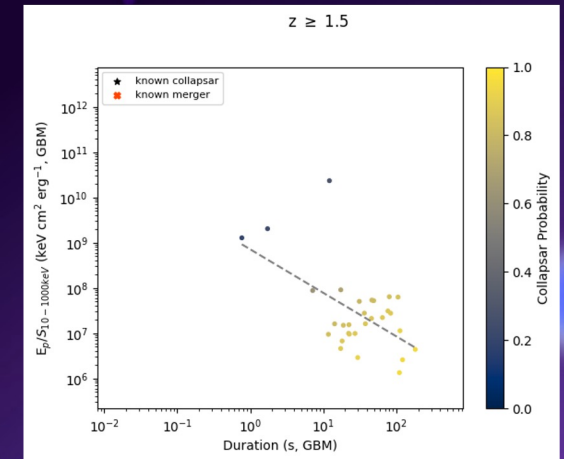
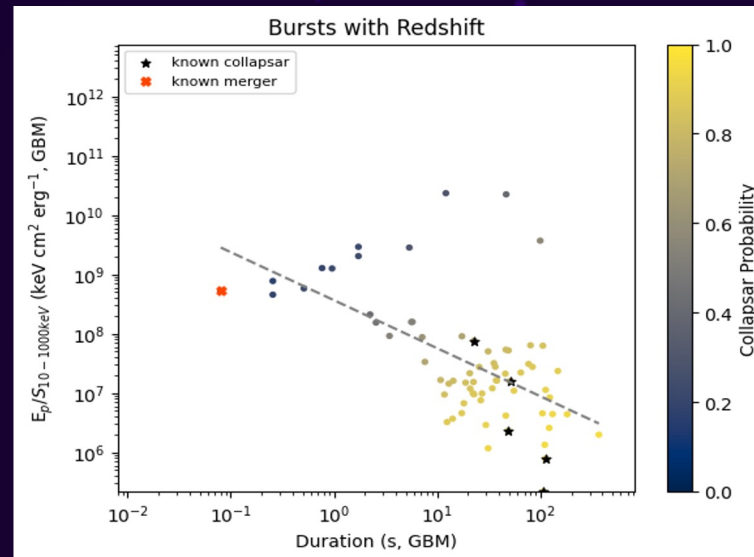
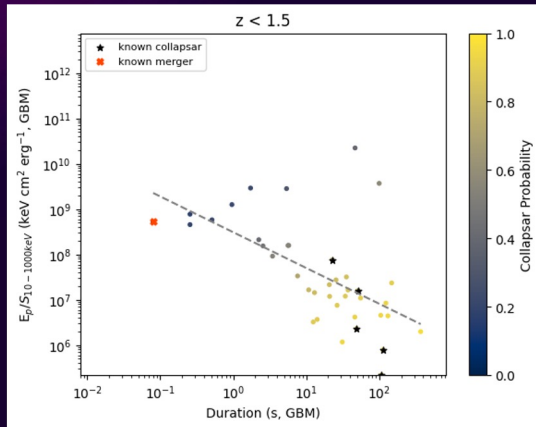
Checking for observational selection effects

- All simulated bursts have same energetics
- Each grey line same duration
- explained data spread, not classification



Simulated Distance

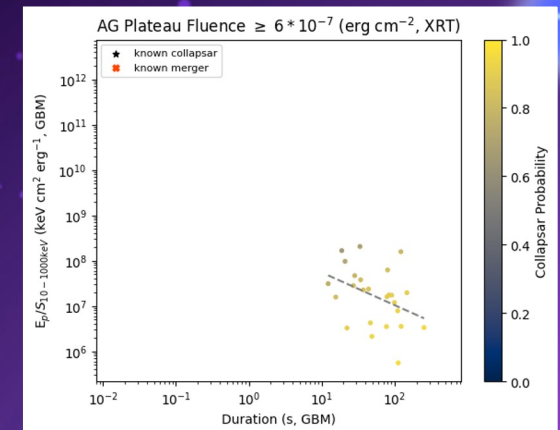
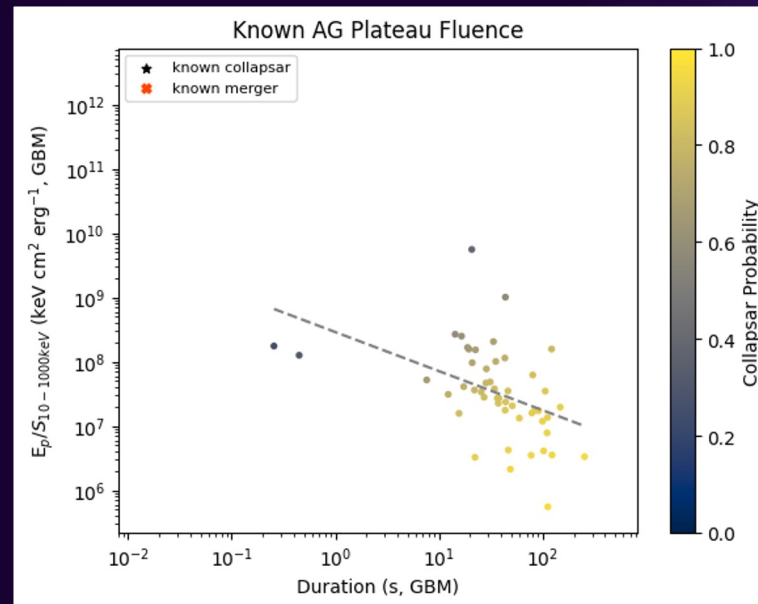
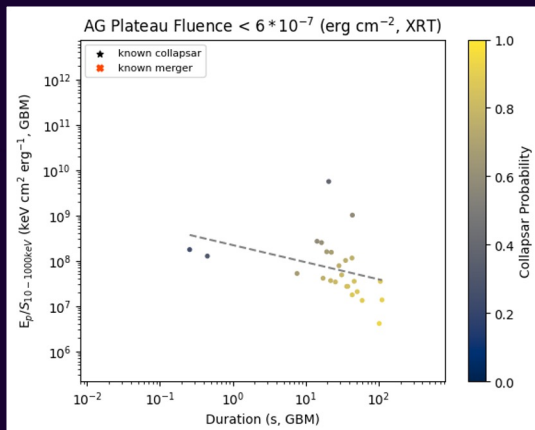
Checking for observational selection effects



- Redshift subsample statistically cannot be rejected as representing full sample
- All three graphs statistically similar, confidence level 0.01 and effect size 0.5
- All redshift progenitors at low redshift

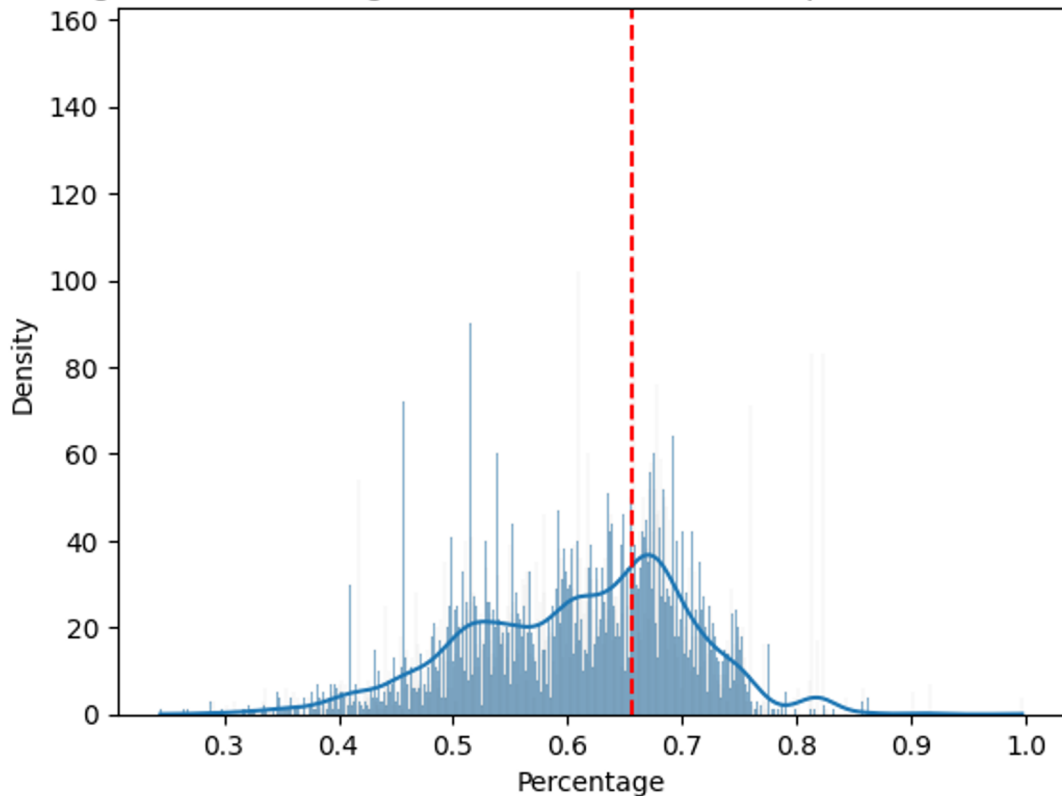
Checking for observational selection effects

- Afterglow subsample rejected as representative of whole, $\alpha=0.01$, $\beta=0.5$
- Bright and dim statistically different
- No progenitors to compare with



Bootstrapping our SVM model to check for dependence on training set size

Histogram of Percentage of Bursts Sorted as Collapsars with Density Plot

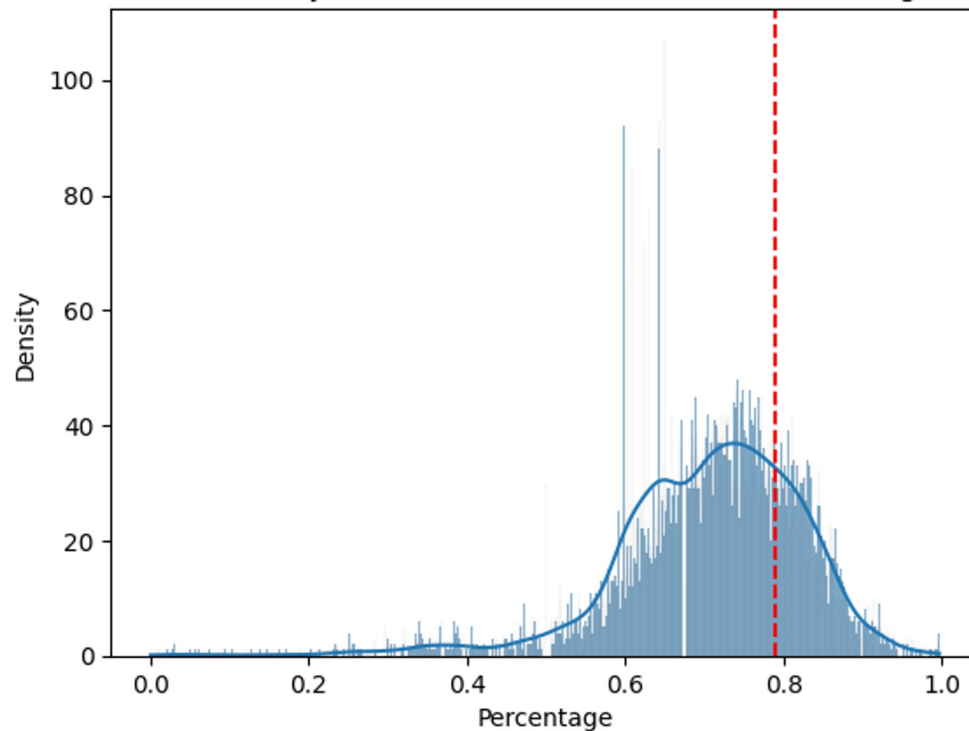


- High variance
- model likely missed some collapsars

Bootstrapping our SVM model to check for dependence on training set size

- 10^4 models, original was on the high end
- likely need more mergers

Histogram of Percent Similarity Between GRB170817A and Known Mergers with Density Plot



Bootstrapping our SVM model to check for dependence on training set size

- The majority of the 10^4 models misclassify 230307A
 - small bump at merger
- More likely a problem with physical model

Histogram of Percent Similarity Between GRB230307A and Known Mergers with Density Plot

