ASTR 288C
Homework 3

Due: 3:30pm, Sept. 25, 2017

- **Write everything in this homework assignment in a LaTeX file using the LaTeX template from `/n/ursa/A288C/alien/lab03_latex/Homework3_latex_form/`.**
- **Print out BOTH the original LaTeX file and the output pdf file and turn them in.**

1. Copy the folder `/n/ursa/A288C/alien/lab03_latex/Homework3_latex_form/` to your home directory or your own computer. Fill out your answers to the following questions in the LaTeX template called `Homework3_latex_form.tex`. Note that this is a different template than the one you used in the lab.

2. [**10 points**] Make the following table using LaTeX.

Table 1: Summary of the *Swift* GRBs in each category.

GRB category	Number of bursts (percentage)
Long	850 (84.49%)
Short	90 (8.95%)
Short with Extended Emission	12 (1.19%)
Ultra long ($T_{90} \gtrsim 1000$ s)	16 (1.59%)
Bursts with un-constrained durations	66 (6.56%)

3. [**10 points**] Write the following equation using LaTeX.

$$\left(\frac{\mathrm{T}}{1\ \mathrm{Ms}}\right)^{1/2} = 2.86 \times 10^{-11}\ [\mathrm{erg\ s^{-1}\ cm^{-2}}]\ \frac{4\pi \mathrm{D_L^2}}{\mathrm{L_{band,rest}}}. \tag{1}$$

4. [**15 points for each proposal; 30 points total**] Proposal reviews:

   Attached are two proposals that were submitted to the *Swift* Guest Investigator Program[1]. These proposals request funding of $\sim \$40,000$ for a one-year research project.

[1] `https://swift.gsfc.nasa.gov/proposals/swiftgi.html`

Each proposal contains 4 pages of science justification (to convince the committee that this research is important and worthy to be funded) and another page or less of budget narrative (to show how the funding will be spent).

Imaging you were one of the reviewers, read these proposals, and review each proposal by answering the following questions in the LaTeX template.

(a) [**3 points for each proposal**] Summarize the goal of the proposal in a few sentences.

(b) [**6 points for each proposal**] List three strengths of this proposal that you find.

(c) [**6 points for each proposal**] List three weaknesses of this proposal that you find.

Judge the proposal strength and weakness based on the following criteria:
(These should be clearly stated in the proposal, regardless of reviewer's background.)

- Does the proposal clearly explain the scientific motivation and the adopted methods of this project?
- Is the science proposed in this project important?
- Is the proposed project timely? That is, is the project better to be done now than in a few years?
- Is the proposed project tightly related to the *Swift* mission?
- Is the project doable in the proposed timeline?
- Is the budget arrangement reasonable?

Note that each strength or weakness should address different points. For example, if you find three typos in a proposal, you can say "there are several typos in the proposals, which makes it difficult to read and understand.". But you should not list each typo as an individual weakness.

Your review for each proposal should be less than one page in the compiled pdf file. We will discuss these proposals based on your review in the next lab.

5. Compile your LaTeX file into a pdf file. Print out and turn in BOTH the original LaTeX file and the output pdf file.

   - Tips: If you are in the Unix/Linux system, you can use command *lpr* to print. For example, type "lpr Homework3_latex_form.tex".

QUANTIFYING THE INSTRUMENTAL EFFECTS AND SYSTEMATIC UNCERTAINTIES IN THE DURATIONS OF *SWIFT*/BAT GAMMA-RAY BURSTS

1. Abstract

The pulse durations of gamma-ray bursts (GRBs) hold the key to crucial information in understanding the underlying physics. In particular, the widely-adopted classification of long and short GRBs, with the separation of ~ 2 sec in the burst durations, has been commonly used to infer the different origins of GRBs. However, the observed burst duration can suffer from different degrees of instrumental and observational biases, and thus might not reflect the true intrinsic duration. We propose to study the biases of the burst durations in the GRB sample from the *Swift* Burst Alert Telescope (BAT), and quantify the instrumental effects and systematic uncertainties on those durations. The proposed study will utilize a code we developed that is capable of simulating *Swift*/BAT GRBs with accurate instrumental response and the BAT trigger algorithm.

2. Description of the Proposed Program

A) Scientific Rationale:

The importance of the observed burst durations to understanding GRB physics

Gamma-ray bursts (GRBs) are one of the most energetic explosions in the universe, and can be observed across a wide range of wavelengths (from radio to GeV). Therefore, GRBs provide a rich environment to study astrophysics and a unique probe of cosmology. GRBs are conventionally categorized into two groups, long and short bursts, based on the burst duration with the separation of ~ 2 sec. The burst duration is usually quantified in terms of the duration that encloses 90% (or 50%) of the burst emissions, T_{90} (or T_{50}). The most common way (adopted by many missions that observe GRBs, such as *CGRO*/BATSE, *Swift*/BAT, and *Fermi*/GBM) defines T_{90} to start at the time when 5% of the total fluence is detected, and end at the time when 95% of the total fluence is observed. Similarly, the start and end time of T_{50} correspond to the time at which 25% and 75% of the total fluence are measured, respectively.

Throughout the history of GRB studies, the burst duration plays a crucial rule in understanding GRB origins and the relevant physics. The total burst duration provides important clues of the total energy released from a burst, and the time profile of the pulse encloses information of the underlying mechanism that powers the burst. Long GRBs are found to be associated with the death of massive stars (e.g., MacFadyen & Woosley 1999; Gehrels & Mészáros 2012, and reference therein), and thus are useful tools for studying stellar evolution and star-formation history, particularly in the early universe due to the extraordinary brightness of GRBs. The origin of the short GRBs remains mysterious. Current studies suggest that they might be generated from compact object mergers (e.g., see reviews and references in Berger et al. 2003), which makes them strong candidates of gravitational wave sources. As a results, short GRBs are of particular interest in light of the recent detections of gravitational wave by Advanced LIGO (Abbott et al. 2015; Abbott et al. 2016).

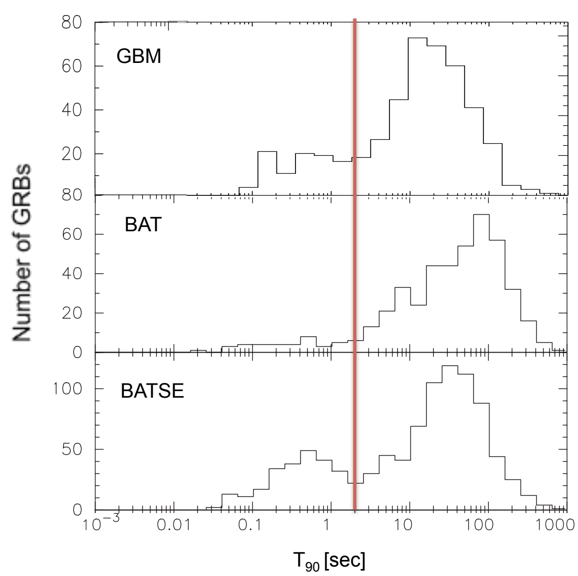

Figure 1: The distributions of GRB duration T_{90} for three different GRB instruments: *Fermi*/GBM, *Swift*/BAT, and *CGRO*/BATSE. The red line marks the 2 second separation for long and short bursts. The top panel is adopted from Fig. 2 in Paciesas et al. 2012. The lower two panels are adopted from Fig. 7 in Sakamoto et al. 2011.

Instrumental and observational biases in GRB durations

Despite the importance of the GRB durations to studying the GRB origins and their intrinsic properties, it is well-recognized that the burst durations are likely to suffer from different degrees of biases and uncertainties. In particular, the observed GRB durations are coupled with the time dilation that in turn depends on the redshift of the burst. However, only $\sim 30\%$ of the BAT-detected GRBs have redshift measurements. Moreover, different instrumental effects, such as background noise and the detector sensitivity at different energies, can bias the burst durations.

The conventional GRB classification is based on burst durations measured from the BATSE sample, which show an obvious double-peaked distribution (see the bottom panel of Fig. 1). However, many studies have shown that the observed burst distributions are instrumental dependent (e.g., Sakamoto et al. 2011, Bromberg et al. 2012, Kocevski & Petrosian 2013). As shown in Fig. 1, the distributions of burst durations for GRBs detected by different instruments can be very different. Short bursts compose of a larger fraction in the BATSE GRB sample ($\sim 26\%$), in comparison to the fractions detected by the *Fermi*/GBM ($\sim 17\%$) and *Swift*/BAT ($\sim 10\%$). In fact, Bromberg et al. (2012) suggests that different missions should adopt different durations that separate the short and long GRBs in order to reflect the correct correspondence to the physical origins of the bursts (i.e., compact-object mergers versus core-collapses of massive stars).

Furthermore, the background noise could hide an unknown fraction of the burst, which is sometimes referred to as the "tip-of-the-iceberg" effect. As shown in Fig. 2 (adopted from Kocevski & Petrosian 2013), Fig 3, and Fig 4, some fraction of the burst can be buried under the background noise and become undetectable as the burst becomes dimmer. Kocevski & Petrosian (2013) demonstrates the importance of this effect, and quantified the hidden fraction of a single-pulse burst as the burst becomes fainter at larger redshifts. These authors use the instrumental response of BATSE and adopt a single-pulse time profile, in order to examine the observed burst duration at different redshift and explain the lack of time-dilation signature in the GRB light curves.

Figure 2 presents plots adopted from Kocevski & Petrosian (2013), which show some of the main results in their study. The left panel demonstrates how the observed burst duration for a single-pulse GRB can actually become shorter at large redshift because the "tip-of-the-iceberg" effect dominates over the time-dilation effect. The right panel shows that when the signal-to-noise ratio drops, a larger fraction of the pulse will be hidden under the background noise. As seen in these plots, the observed burst duration can miss as much as 90% of the intrinsic pulse. These authors adopt a slightly modified way to quantify the burst duration, which is noted as T_{KP} and encloses a time range when the pulse count is larger than the background variation ($\sqrt{N}$, where N is the number of count of the pre-burst background; see Kocevski & Petrosian 2013 for detailed definition).

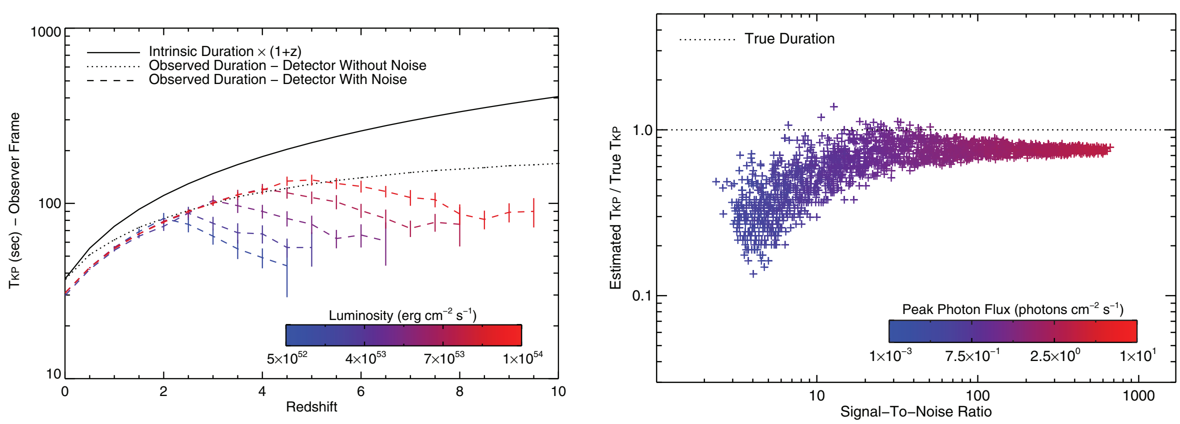

Figure 2: Figures adopted from Kocevski & Petrosian (2013). The left panel shows how the observed durations can diverge from the intrinsic durations for bursts at larger redshifts. The right panel demonstrates that bursts with lower signal-to-noise ratios can suffer from significant impact of the "tip-of-the-iceberg" effect, with up to $\sim 90\%$ of the intrinsic pulse structure buried under the noise.

In our proposed project, we plan to generalize the studies conducted in Kocevski & Petrosian (2013). We will perform a population study including GRBs with different pulse shapes, along with many other GRB characteristics, such as fluxes, spectral properties, and burst incident angles relative to the detector plane. Moreover, we will focus on the *Swift*/BAT GRBs and adopt the instrumental response of the BAT. *The goal of this project is to quantify the instrumental effects and systematic uncertainties in the burst durations for GRBs detected by the BAT.*

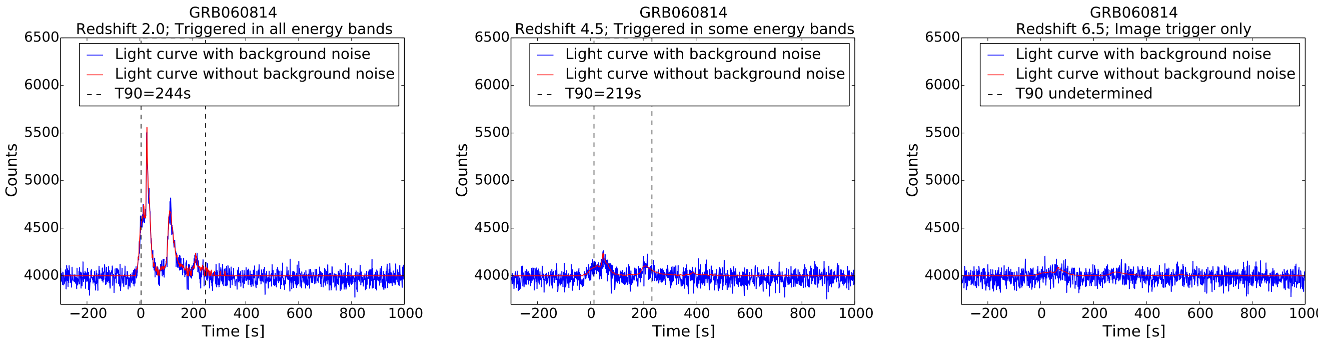

Figure 3: Simulated light curves for the same bursts at different redshifts. This example uses the pulse shape from GRB060814, and shows the observed burst duration T_{90} can change as the burst becomes fainter and a larger fraction of the burst is buried under the background noise. The T_{90} determined by the standard pipeline "battblocks" is also labeled in each plot.

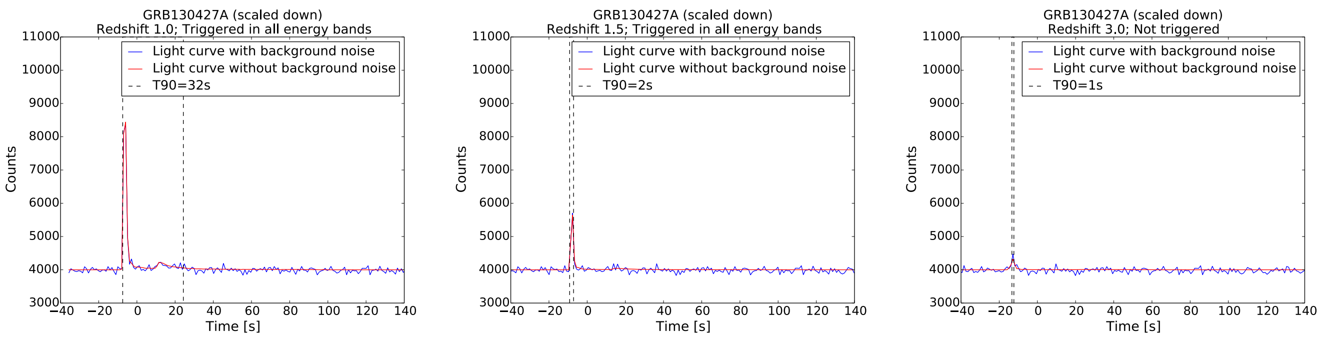

Figure 4: Similar to Fig. 3, but using the pulse shape from GRB130427A. Due to the extraordinary brightness of this burst, the flux is scaled down from the original one by a factor of ~ 10 to better demonstrate the instrumental effects as the burst is moved to larger redshifts.

B) Immediate Objective:

We have developed a code that is capable of generating GRB light curves in count rate by accounting for the instrumental response of BAT, and simulating its complex trigger algorithm to determine whether the burst is detectable (Lien et al. 2014). The code is capable of simulating GRBs with different input physical properties such as the luminosity, redshift, spectrum, and spectral evolution. In addition, the code also takes into account different input parameters related to various instrumental effects, including the burst incident angle relative to the detector plane and the number of active detectors.

We propose to utilize this code to perform systematic studies of the instrumental effects on the burst durations for GRBs detected by BAT. Our primary goal is to perform a population study to quantify the systematic uncertainties of the burst durations in the BAT GRB sample, and to study how these uncertainties affect the the burst-duration distribution. Ultimately, we would like to provide the systematic uncertainties of the burst durations for the BAT-detected GRBs, which will likely depend on some GRB properties, such as the GRB flux, signal-to-noise ratio, the complexity of the pulse shape (e.g., number of pulses), and GRB spectrum (e.g., photon index or hardness ratio).

Figure 3 and 4 show examples of simulated light curves at different redshifts using the code we developed, with the light curve shapes from GRB060814 and GRB130427A, respectively. The detectability of the burst in each scenario is also determined by our "trigger-simulator" code. The burst durations are estimated from the standard pipeline, "battblocks[1]", which determines the burst durations via the Bayesian Block method. We will use battblocks to determine burst durations in this proposed study. Fig. 3 shows that as the burst is moved to higher redshifts, some fractions of the burst gradually sink under the background noise and are thus missed by the T_{90} estimated by battblocks. Moreover, this burst can still be detectable at $z \sim 6.5$ via the "image trigger" algorithm of BAT[2] even

[1] https://heasarc.gsfc.nasa.gov/ftools/caldb/help/battblocks.html

[2] The BAT adopts two different trigger algorithms: the "rate trigger" based on changes in photon-count rate, and "image trigger" based on searches in the image created with longer exposure time ($\gtrsim$ minute; detail descriptions can be found in Lien et al. 2014).

when the burst structure become un-recognizable by the standard pipeline. Fig. 4 presents similar "tip-of-the-icberg" effect as the burst becomes fainter, and shows that a intrinsically long burst can become a short burst observationally.

Specifically, we plan to study the instrumental effects and systematic uncertainties of the burst durations through the following two approaches:

(1) Observational approach: exploring the potential confusion in the distribution of the GRB burst durations

We will first use the sample of the BATSE-detected GRBs, to see whether it is possible to reproduce the double-peaked distribution using the BAT energy band, instrumental response, and backgrounds. Particularly, we will perform the studies in two different methods: (1) Using the pulse shapes and fluxes in the energy ranges that overlaps with the BAT ($\sim$ 15 to 350 keV). (2) Retaining the pulse shape in the whole BATSE energy range ($\sim$ 10 keV to $\sim$ 20 MeV; Goldstein et al. 2013), but scaling the flux to the BAT energy range based on the burst spectrum. We will then explore how much distortion in the burst-duration distribution that would be introduced by each of these two methods. We will also perform the same studies on *Fermi*/GBM and other instruments for which data are available.

(2) Theoretical approach: providing quantifiable systematic uncertainties of the burst durations

Because all the observed bursts will suffer from different degrees of instrumental and observational biases in their burst-duration measurements, we propose to study the systematic uncertainty of the burst durations via a theoretical approach. We will create two different kinds of libraries of intrinsic GRB light curves: (a) A library of purely theoretical light curves. Many studies have suggested possible functional forms to described a single-pulse light curve (e.g., Norris et al. 2005; Hakkila & Preece 2014). We will try one or more of these functional forms, and create a random sample of light curves with different number of pulses by adding up the single-pulse function with different amplitudes and different time separations between pulses. (b) A library of observational-based pulses. Due to the complexity of the GRB pulse shapes, it is possible that the theoretical functions might not correctly capture or mimic all of the pulse shapes. Therefore, we will also create an alternative library from the observed GRBs. We will select a sample of bright (i.e., high signal-to-noise ratio) GRBs with low redshifts (potentially with $z \lesssim 1$), in order to create a sample of GRBs that suffer less from the "tip-of-the-iceberg" effect.

For each GRB pulse shape in the libraries, we will systematically adjust the burst flux and spectrum. We will quantify the uncertainty of the burst duration, and how the uncertainty depends on different GRB properties (e.g., fluxes, number of pulses, photon index, and/or hardness ratio).

We will apply the systematic uncertainties of the burst durations to the real BAT-detected GRBs. This will provide further information of the intrinsic GRB durations, and help determine the possibility that a short GRB is truly short.

4. Report on Previous Swift and Related Programs

As mentioned before, we developed a code that generates GRB light curves in count rate by taking into account accurate instrumental response, and simulates the complex BAT-trigger algorithm (Lien et al. 2014). We have used this code to perform studies of the cosmic GRB rate and luminosity distribution for the long bursts (Lien et al. 2014; Graff et al. 2015). Our proposals for using this trigger simulator code to study high redshift GRBs and short bursts, was accepted in the Swift GI cycle 9 and 10 program, respectively. Fig. 3 and 4 are made by codes written by the summer intern, Kevin Chen, who was supported by the Swift GI cycle 9 grant. Furthermore, this trigger simulator is revised for public use via support from the Swift GI cycle 9 grant, and is available on the public webpage[3].

6. Applicant's Most Relevant Publications

See those that are bold-faced in the References.

7. References

Abbott, B. P., et al. 2016, PRL, 116, 061102; Abbott, B. P., PRL, 116, 241103; Berger E., et al. 2003, ARAA, 52, 43; Bromberg, O.,et al. 2012, ApJ, 749, 110; Gehrels, N., & Mészáros, P., 2012, Science, 337, 932; Goldstein, A. et al., 2013, ApJS, 208, 21 Hakkila, J., & Preece, R. D. 2014, ApJ, 783, 88 **Kocevski, D., & Petrosian, V., 2013, ApJ, 765, 116; Lien, A. et al. 2014, ApJ, 783, 24;** MacFadyen A, & Woosley S., 1999, ApJ 524, 262; Norris, J. P., et al. 2005, ApJ, 627, 324; Paciesas, W. S. et al. 2012, ApJS, 199, 18; Sakamoto, T. et al. 2011, ApJS, 195, 2; Graff, P. B. et al. 2016, ApJ, 818, 55.

[3] `http://userpages.umbc.edu/~alien/Index.html`

8. Cost Overview

We request a total amount of \$40K for this proposal. Among the requested funds, \$33K will be used to support partial salary for a graduate student who participates in this project. The graduate student will use the trigger simulator and BAT data analysis pipelines to conduct the simulations. Additionally, the student will participate in the analysis to quantify the instrumental effects and systematic uncertainties of the burst durations. The PI and other Co-Is are fully funded by their institutions, and agreed to dedicate their time to this project.

The rest of the budget will cover travel to facilitate the on-going collaboration between different institutes (\$3K), present the results at a national conference (\$2K), and publication costs (\$2K). Table 1 presents a summary of the requested budget. Overhead costs are included in our estimates.

Table 1: Summary of Budget Allocation

Amount of money required	Purpose of the budget requirement
33,000	Partial salary for a graduate student ($\sim$0.55 FTE including overhead)
5,000	Travel between institutes and to a national conference
2,000	Publication charges

EXPLORING THE CONNECTION OF SWIFT LONG GRB POPULATIONS TO THE STAR FORMATION RATE

1. Abstract

Long GRBs may provide a strong probe of star formation history in the early universe. However it remains difficult to draw inferences about the intrinsic population from observed GRB rates. This is partly due to the *Swift* 's complex trigger algorithm. We have recently developed a machine learning approach to quickly approximate the output of a full simulation of *Swift* 's response to simulated data and demonstrate that this enables Bayesian study of the GRB rate as a function of redshift. Our recent results provide evidence for differences between the observed star formation rate and the long GRB rate. These differences may be realted to an assocation long GRBs and low-metalicity environments which are less common at low redshift. We extend our studies to explore of the relationship between star formation rate, metalicity and the long GRB rate by performing Bayesian model selection comparisons to compare population models updating our data set with more recent Swift data.

2. Description of the Proposed Program

A) Scientific Rationale:

Gamma-ray Bursts (GRBs) are among the most energetic astrophysical phenomena. Their extraordinary luminosities make them rare objects that can be seen beyond redshift $z \sim 6$. To date, the highest spectroscopically-confirmed redshift of a detected GRB is $z \sim 8.2$ for GRB 090423 (Tanvir et al 2009, Salvaterra et al. 2009), while a photometrically measured redshift suggests that GRB 090429B occurred at $z \sim 9.4$ (Cucchiara et al. 2011). Both observational evidence and theoretical studies suggest that GRBs are related to the death of stars (e.g., Galama et al. 1998; Heger et al. 2003). The detection of these high redshift GRBs provide a unique probe tracing the star-formation history in the early universe, but even at lower redshifts there remain interesting questions about the relationship between GRBs the star formation rate (SFR).

While short GRBs (bursts with observational durations < 2s) are believed to be related to the merger of compact objects such as Neutron stars, long GRBs are expected to result from the explosion of massive stars with a powerful central engine such as a black hole. Additionally, observations have shown that at least some long GRBs are found to be accompanied by Type Ic supernovae (SNe) (e.g., Campana et al. 2006) and may be associated with low-metalicity environments where larger stars are likely to form (e.g. Kocevski et al. 2009).

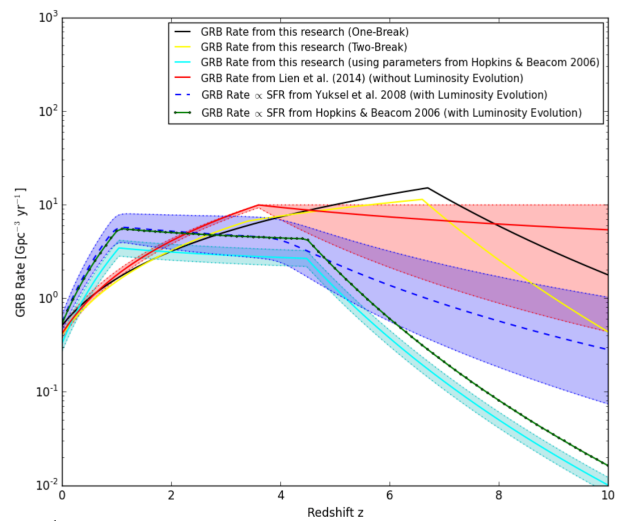

Figure 1: Using our machine-learning model for Swift detection efficiency and Bayesian techniques, we can compare measurements of the cosmic SFR and long GRB rates. Either a one-break or two-break model can provide an equally good fit for the GRB rate, but either shows differnces from the SFR. A GRB rate model constrained to be proportional to the SFR does not fit as well, strongly disfavored with natural log Bayes factor of about 15.

GRBs at redshift $z \gtrsim 4$ are especially important because beyond this redshift other methods of estimating the star formation rate (SFR) become very difficult engendering large uncertainties. As shown in (Yüsel et al 2008) different methods for estimating the SFR can yield results differing more than an order of magnitude. The GRB rate provides an independent and more direct probe of stellar formation at early times. Even at lower redshift $z \sim 1 - 2$ the GRB rate may provide another perspective on star formation in comparison with other estimates. In particular, GRBs offer a unique way to measure the SFR in dim galaxies, which are likely to be missed by other methods based on galaxy observations (Trenti et al 2012). These probe may not probe identical populations though if long GRBs form preferentially in low-metallicity environments (Graham et al 2013 and Trenti et al 2015).

Many studies have tried to use the cosmic GRB rate at high redshift to estimate the cosmic SFR in the early universe (e.g., Butler et al. 2010; Ishida et al. 2011; Robertson & Ellis 2012; Tanvir et al. 2012,Wanderman & Piran 2012). Results from these studies show that the GRB rate at high redshift (especially at $z \gtrsim 6$) indicates a higher SFR than previously expected (see Fig. 1 for related illustration). For example, Kistler et al (2009) conclude that at high redshift the GRB rate does not trace the commonly adopted SFR from Hopkins & Beacom (2006). These authors further state that the higher SFR implied by the GRB rate can be explained when including the star formation from undetectable galaxies at the faint end of the UV luminosity function. More recently Graham and Schady (2016) have elaborated the case that differences in the long GRB rate and the SFR may arise from the the evolution of metalicity with redshift with differences showing up even at redshifts $z < 4$. We will further explore this latter hypothesis applying our Bayesian methodology with an updates unbiased sample of long GRBs with measured redshifts (Perley et al 2016).

Challenges in estimating the GRB rate with Swift, and the new tools we developed:

There are significant challenges understanding of the GRB source population from observational data. Two reasons that it is hard to recover the such parameters as the intrinsic GRB rate based on the detections from *Swift* are the many features of the population that may impact the observed result and the complicated selection effects involved in determining exactly which events *Swift* would detect. The first issue motivates broad Bayesian-like parameter space the potential intrinsic properties of the GRB population, while the latter motivate detailed simluation of the intrumental detection respose.

Most previous studies have estimated the GRB rates using a coarse approximation of the complex trigger algorithm for *Swift*, such as assuming a flux detection threshold. However, this is generally not a good approximation for *Swift*'s trigger algorithm. Unlike previously flown GRB instruments, the Burst Alert Telescope (BAT) of *Swift* adopts over 500 "rate trigger" criteria, based on photon count rates, and additional thresholds for the "image trigger", based on the real image generated for further confirmation and localization.

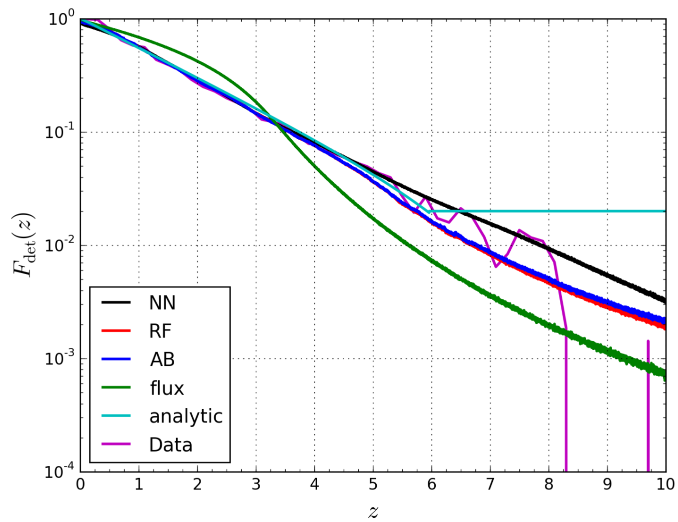

Figure 2: The detection fraction $F_{\rm det}(z)$ as computed by the three different MLAs used as well as the constant flux cut and an analytic form used in (Howell 2014). The detection fraction of all data provided for training and validation is also shown. This is calculated under the assumption of the particular luminosity function used in this study and may change significantly for other choices of the luminosity function parameters.

One of us recently developed the first code to simulate the complex trigger algorithm adopted by the BAT including simulating hundreds of rate trigger criteria and mimicking the image threshold. Therefore, our program can simulate GRBs found by both the rate trigger and image trigger. Additionally, our program can create a mock sample of observed GRB light curves with many adjustable GRB characteristics,such as the GRB rate and luminosity function, their spectral distributions, and GRB pulse shapes. The first application of this code to explore the features of the intrisic GRB population cosmic GRB rate and the GRB luminosity distribution via a Monte Carlo approach (Lien et al. 2014) showed that our BAT-trigger simulator can detect simulated bursts with flux as low as $\sim 10^{-8}$ erg s^{-1} cm^{-2} for on-axis bursts, and $\sim 10^{-7}$ erg s^{-1} cm^{-2} for off-axis bursts, which agrees extremely well with the flux of real GRBs detected by *Swift*. This work showed the value of the BAT-trigger simulator but also revealed that it is too slow (typically requiring tens of seconds per GRB) for direct application in large scale population studies.

In (Graff et al. 2016) we recently teamed up to realize a practical application of the BAT-trigger simulator building in Bayesian studies of the long GRB population. This collaboration benefits from our combined backgrounds in both Swift GRB observations and practical Bayesian analysis approaches based on experience in gravitational-wave analysis. First we applied machine learning techniques to realize most of the benefit of the BAT-trigger simulator while speeding up the calculation by several orders of magnitude to achieve the speed necessary for broad Bayesian-based GRB population parameter studies. This involved first running the BAT-trigger simulator over a broad range of potential GRB events which may appear with the theoritical population models. Then we applied a variety of popular machine-learning algorithms to effectively learn the behavior of the simulator, training on a large number (> 100000) of simulated observations and tuning the algorithms using 5-fold cross-validation testing, and judging the results by testing on an independent sample. Several machine learning algorithms realized $\gtrsim 97\%$ accuracy with a practical option being the random forest algorithm at 97.5%, significantly improved over the 89.6% accuracy of the optimal flux-cut approach.

Next, we applied a rigorous Bayesian approach to studying the redshift dependence of the GRB rate. After marginalizing over features of the population other than redshift dependence, we derive a likelihood function that depends principally on the expected number of events during some time interval Δt_{obs} as a function of redshift,

$$N_{\text{exp}}(z) = \Delta t_{\text{obs}} R_{\text{GRB};dz}(z, \vec{n}) F_{\text{det}}(z_i) dz. \quad (1)$$

Here $R_{\text{GRB};dz}(z, \vec{n})$ is the intrinsic GRB rate derived from the parameters $\vec{n}$ of some model population, and $F_{\text{det}}(z)$ is the redshift-dependent detection fraction which we compute based on our machine learning model. The log-likelihood function we derive for the log-probability of detecting a set of GRBs with redshifts at $\{z_i\}$ given a population statistically described by some parameters $\vec{n}$ is

$$\mathcal{L}(\vec{n}) = -N_{\text{exp}} + \sum_{\{i\}_{\text{det}}} \log(N_{\text{exp}}(z_i)) \quad (2)$$

where N_{exp} is the integrated expected rate of observations over all redshifts.

In (Graff et al 2016) we applied the full Bayesian analysis based on a nested sampling approach (Graff et al 2013) to address some of the same questions addressed in (Lien et al 2014). Specicaly we studied the parameters of the GRB rate in a one-break logarithmic model for the redshift dependence while assuming a fixed luminosity function of the form in (Wanderman & Piran 2010). Summary results of our Bayesian analysis are shown in the Fig. 3. Not surprisingly the best fit results from (Lien et al 2014) are consistent with the Bayesian results though the new analysis provides a clearer picture of the full range of parameter space of statistical population models which are consistent with the data. With the (Fynbo et al 2009) data we found little constraint on the higher redshift population $z > 4$ though we found tighter constraints on the lower redshift population which points to a need for more GRB data (and redshift information).

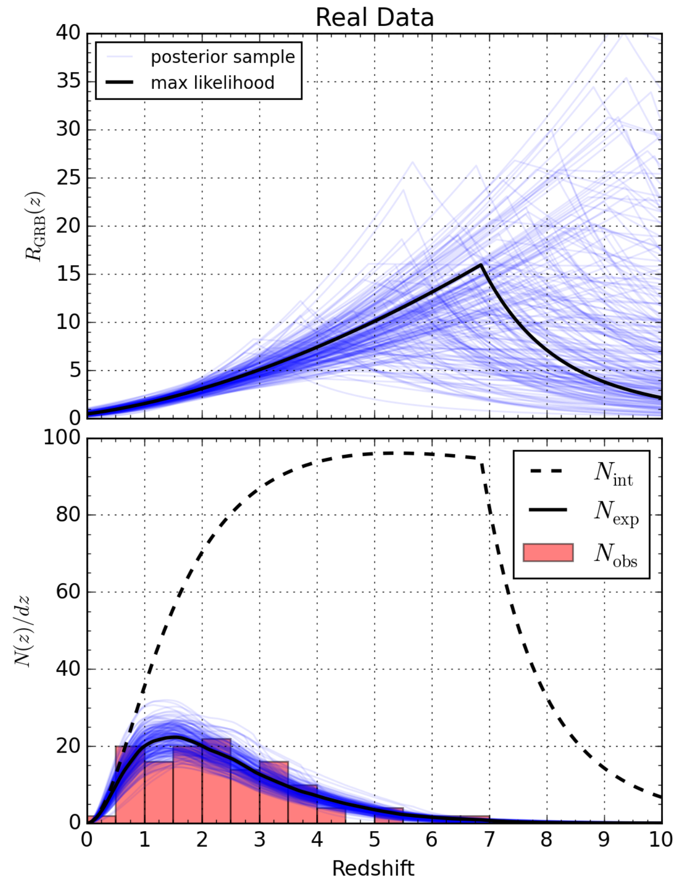

Figure 3: The distribution of model predictions from the posterior (RF) for the real set of 66 *Swift* GRBs (Fynbo et al 2009). 200 models with parameters chosen randomly from the posterior are shown in light blue lines in both panels. The maximum $\mathcal{L}(\vec{n})$ point is shown in black. The upper panel shows the intrinsic model rate $R_{\text{GRB}}(z, \vec{n})$ and the lower panel shows expected observed rate $N_{\text{exp}}(z)/dz$ (Eq. 1. The lower panel also shows the distribution of measured redshifts for observed GRBs and the intrinsic rate for the maximum $\mathcal{L}(\vec{n})$ point in dashed black.

Since then we have further explored differences with the SFR at low redshift (see Fig. 1) that raise questions about the relationship between GRB rates and other SFR measures in this period. Generalizing first to a two-break model for the GRB rate, we found no support for the more complicated model, with a Bayes factor near unity (i.e. equal odds). Then constraining that two break model to be proportional to the SFR as in (Hopkins & Beacome 2006), we quantified the differences, finding strong evidence against SFR-proportional model, with a natural log

Bayes factor near 15 (odds ratio 3 million:1).This study focuses on exploring these differences may be related to metallicity evolution as suggested in (Graham et al 2013, Graham et al 2013 and Trenti et al 2015).

B) Immediate Objective:

We propose a richer set of Bayesian GRB population studies using *Swift* data and the tools and methods developed in (Graff et al 2016) and subsequently. The study has three principal elements.

I Incorporate more recent data in our analysis of the GRB-SFR analysis. Our previous results were based on the Fynbo (2009) unbiased sample of *Swift* long GRBs with measured redshifts, but this included only a small fraction of the *Swift* events to date. We plan to update this incorporate more recent data. The Perley et al (2016) sample seems to be adequate for this purpose including nearly twice as many (110) events. Along with this we will recompute our machine learning models incorporating a larger number of simulated high-redshift events to better constrain the detection fraction beyond (z 5). With the new data and updated MLA models we will reexamine the questions which we have previously studied based on the Fynbo sample.

II Model selection study of GRB models based on low-metalicity cuts. Bayesian model selection provides a clear way to quantitatively compare population models, as we have already demonstrated with the comparison for a general one-break GRB rate model and a model constrained to be directly proportional to the SFR rate. We will follow (Graham et at 2016) in exploring population models based on metalicity dependence. Graham et al 2016 suggest several models based on theoretical assumptions about the evolution of the metalicity, but we will also consider metalicity observations in constraining these models. Using Bayesian methods and the expanded *Swift* long GRB data set we will compare these models with the generic one-break model to better understand if metalicity dependence can explain the relationship between GRB and SFR rates.

III Bayesian model selection studies to explore evidence for GRB luminosity function evolution in the population model. (Lien et al 2014) and previous studies have suggested that GRB lumiosity evolution can allow better agreement of the GRB rate with the redshift evolution seen in other observational approaches. We will apply similar Bayesian techniques to explore this possibility. As before we will study the Bayesian evidence for luminosity function evolution, this time comparing several models, including one-break and two-break rate models as well SFR-constrained models, each with and without luminosity function evolution. Since the observed flux also depends on the luminosity function will will apply a generalization of our previous likelihood function incorporating both redshift z and flux Φ from the data. This will require us to compute the detection fraction as a function of both parameters $F_{\rm det}(z_i, \Phi_i)$.

3. Report on Previous Swift and Related Programs

As mentioned before, we developed a code that generates GRB light curves in count rate by taking into account accurate instrumental response. Moreover, the code simulates the complex BAT-trigger algorithm (Lien et al. 2014).

We have used this code to perform studies of the cosmic GRB rate and luminosity distribution for the long bursts (Lien et al. 2014; Graff et al. 2015). Our proposal to use this trigger simulator for the studies of high redshift GRBs and short bursts, was accepted in the Swift GI cycle 9 and 10 program, respectively.

4. References

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7. Budget Narrative

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