

Multi-Model Framework for Reconstructing Gamma-Ray Burst Light Curves

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Abstract

Mitigating data gaps in Gamma-ray bursts (GRBs) light curves (LCs) holds immense value for its application in cosmological research because it provides more precise measurements of the parameter of interest of the two-dimensional Dainotti relation which is a relation among the end time of the plateau emission, T_a , its respective luminosity, L_a which is calculated from the fluxes at the end of the plateau, F_a . This study extends the work done by Dainotti et al. 2023c; Manchanda et al. 2024 on the 545 GRB sample by introducing six different models: Deep Gaussian Process (DGP), Temporal Convolutional Network (TCN), Hybrid model of Convolutional Neural Network with Long Short-Term Memory (CNN-LSTM), Bayesian Neural Network (BNN), Polynomial Curve Fitting and Isotonic Regression. Our findings demonstrate that Isotonic Regression achieves the highest uncertainty reduction for all three parameters (36.3% for $\log T_a$, 36.1% for $\log F_a$, and 43.6% for α) outperforming all the other models. The CNN-LSTM model shows consistent improvements across all GRB parameters with the lowest outlier rate for α (0.550%), surpassing the performance of the LSTM model in Manchanda et al. 2024. The DGP model offers reliable uncertainty reduction across all parameters and improves upon the single-layer GP baseline. These advancements are essential for using GRBs as theoretical model discriminators via the parameters of their LCs and standard candles in cosmology, investigating theoretical models, and predicting GRB redshifts through recent cutting-edge machine-learning analysis (Dainotti et al., 2024a,b; Narendra et al., 2024).

Keywords: γ -ray bursts— statistical methods—machine learning— light curve reconstruction

1. Introduction

GRBs are among the most luminous transients in the universe, observed up to redshift $z = 9.4$ (Cucchiara et al., 2011), making them valuable probes of the early universe. Crucial details regarding the Population III stars can also be gained from a detailed study of GRBs.

GRBs have traditionally been divided into two types based on how long their gamma-ray prompt episode lasted, as mea-

sured by T_{90} . This measure shows how long it took to capture 90% of all background-deducted counts, starting after the first 5% of counts were found (Mazets et al., 1981; Kouveliotou et al., 1993). The mergers of compact objects are usually linked to short GRBs (SGRBs), which are characterised as $T_{90} \leq 2$ s (Duncan and Thompson, 1992; Narayan et al., 1992; Usov, 1992; Thompson, 1994; Levan et al., 2008; Metzger et al., 2011; Bucciantini et al., 2012; Perna et al., 2016). On the other hand, the collapse of large stars is associated with long GRBs (LGRBs), which have $T_{90} \geq 2$ s (Woosley, 1993; Paczyński, 1998; MacFadyen and Woosley, 1999; Bloom et al., 2002; Hjorth et al., 2003; Woosley and Bloom, 2006; Woosley and Heger, 2006; Kumar et al., 2008; Hjorth and Bloom, 2012;

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Bucciantini et al., 2008; Cano et al., 2017; Lyman et al., 2017; Perna et al., 2018; Aloy and Obergaulinger, 2021; Ahumada et al., 2021).

The high energy prompt phase has been interpreted by internal shell collision or magnetic reconnection (Vestrand et al., 2005; Blake et al., 2005; Beskin et al., 2010; Gorbovskoy et al., 2012; Vestrand et al., 2014) and the long-lasting multi-wavelength afterglow phase as the interaction of the shells with the circumburst medium (Costa et al., 1997; van Paradijs et al., 1997; Piro et al., 1998; Gehrels et al., 2009). Instruments on board the Neil Gehrels Swift Observatory (Swift, Gehrels et al. 2004), BAT, XRT, and UVOT, have been crucial for rapidly identifying GRBs and enabling follow-up across X-ray to optical bands (Barthelmy et al., 2005; Burrows et al., 2005; Roming et al., 2005). Furthermore, novel features of GRB LCs have been discovered by Swift’s quick multi-wavelength afterglow follow-up (Tagliaferri et al., 2005; Nousek et al., 2006; Troja et al., 2007).

Most of the X-ray LCs exhibit a plateau after the prompt phase (Zhang et al., 2006; O’Brien et al., 2006; Nousek et al., 2006; Sakamoto et al., 2007; Liang et al., 2007; Willingale et al., 2007; Dainotti et al., 2008, 2010, 2016, 2017; Dereli-Bégué et al., 2024), which can be modeled using a broken power-law (BPL) (Zhang et al., 2006, 2007; Racusin et al., 2009), a smoothly BPL, or the phenomenological model proposed by (W07, Willingale et al. 2007). Section 2.2 details the W07 and the critical parameters. The plateau phase is particularly noteworthy and is frequently explained using the framework of the magnetar model (Zhang and Mészáros, 2001; Rowlinson et al., 2014; Rea et al., 2015; Stratta et al., 2018), where precise measurements of T_a (time at the end of plateau) are necessary to confirm this model’s validity. Moreover, a significant anti-correlation between rest-frame time $T_{X,a}^*$ and the corresponding X-ray luminosity L_X , known as the Dainotti 2D relation, has been identified (Dainotti et al., 2008, 2010, 2011; Dainotti et al., 2013; Dainotti et al., 2015, 2017; Tang et al., 2019; Wang et al., 2022; Zhao et al., 2019; Liang et al., 2007; Li et al., 2018).

This 2D L-T relation is further developed into the 3D Dainotti relation (Dainotti et al., 2016, 2017, 2020a, 2022b), incorporating prompt luminosity $L_{X,peak}$, and aiding cosmological parameter constraints (Dainotti et al., 2023b; Dainotti et al., 2022g; Dainotti et al., 2022b; Cao et al., 2022a,b). The reduction of the uncertainties plateau parameter by 47.5% could match the cosmological precision of Ω_M from SNe Ia (Dainotti et al., 2020b) within 8 years (Dainotti et al., 2022g; Betoule et al., 2014), compared to the 16 years required at current observation rates (Dainotti et al., 2022g), highlighting the prospects of a practical LC reconstruction (LCR) approach.

A critical barrier in utilizing GRBs for population studies or cosmology lies in the presence of observational gaps in light curves, caused by instrumental constraints or follow-up delays. These gaps hinder reliable model testing, such as the standard fireball model (Panaiteescu and Kumar, 2000; Piran, 1999) or evaluating closure relations (Willingale et al., 2007; Evans et al., 2009; Racusin et al., 2009; Kumar and Duran, 2010; Srinivasaragavan et al., 2020; Dainotti et al., 2021; Ryan et al.,

2020; Tak et al., 2019). LCR methods have emerged as a powerful solution to this problem.

Previous works such as Dainotti et al. 2023c and Sourav et al. 2023, have introduced probabilistic and deep learning techniques, such as Gaussian Processes (GP) (Rasmussen, 2003) and Long Short-Term Memory (LSTM; Hochreiter and Schmidhuber 1997a), to reconstruct the temporal gaps in the LCs. Manchanda et al. 2024 expanded upon these approaches by evaluating ten different models for LCR. Building upon these advancements, we extend the LCR framework by introducing six more models: Deep Gaussian Process (DGP), Temporal Convolutional Network (TCN), Hybrid model of Convolutional Neural Network with Long Short-Term Memory (CNN-LSTM), Bayesian Neural Network (BNN), Polynomial Curve Fitting and Isotonic Regression.

This paper is organized as follows: Section §2 offers an in-depth description of the dataset used and the different models applied to reconstruct GRB LCs. The uncertainty, performance, and outliers in Sec. §3. Sec. §4 provides the synopsis and conclusions on the observed efficacy of each model.

2. Methodology

This section outlines the methodology adopted for the reconstruction of GRB LCs. We first motivate the selection of the models, then describe the data set and preprocessing steps, followed by a detailed explanation of the theoretical framework and implementation of each model.

2.1. Motivation for the models

A brief description as well as the motivation for selecting these models are provided below.

2.1.1. DGP

Deep Gaussian Processes (DGPs) represent another powerful approach and we expect that they might perform better than the GP or the GP-Random Forest (GP-RF) hybrid model for reconstructing the GRB LCs. Although single GP models are good for handling basic patterns and are faster to train, they may miss the deeper, complex structures in the LCs. DGPs work in layers, learning more abstract and detailed features step by step, and they also give a clear idea of how confident the model is in its predictions.

2.1.2. TCN

Temporal Convolutional Networks (TCNs) are used for GRB LCR because they are proficient in identifying intricate temporal trends and long-range dependencies in time-series data (Bai et al., 2018a). GRB LCs often feature sudden bursts and fluctuations across various time scales. TCNs are well-suited to handle this kind of data because they avoid issues like the weights of the model either increasing exponentially or going toward zero, namely exploding or vanishing gradients, which can occur in traditional models like Recurrent Neural Networks (RNNs). They can learn patterns in GRB data more efficiently, making them particularly useful for predicting the evolution of LCs over time.

2.1.3. CNN-BiLSTM

CNN-LSTM models integrate the advantages of convolutional neural networks and long short-term memory networks. We use this hybrid CNN-LSTM model with the expectation that it would perform better than the standard Bi-LSTM in reconstructing GRB LCs. The CNN component first detects and emphasizes important local features in the data, such as rapid bursts, while the LSTM network then models how these features evolve. This separation of feature extraction and sequence modeling can make CNN-LSTM more focused and reliable, especially in noisy LCs. In contrast, Bi-LSTM processes the entire sequence bidirectionally without explicitly identifying which input parts are most relevant, making it computationally heavier and less effective at filtering noise.

2.1.4. BNN

Bayesian Neural Networks (BNNs) are chosen for GRB LCR because they offer a way to estimate uncertainty in predictions. Since GRB data can be noisy, sparse, and unpredictable, it's crucial to understand the confidence level of the model's predictions. BNNs allow for uncertainty estimation by incorporating probabilistic distributions over the model's parameters (Blundell et al., 2015). This helps in situations where data is limited or uncertain, providing a more reliable model for LCR by quantifying both the mean and variance of predictions.

2.1.5. Polynomial Curve Fitting

Polynomial Curve Fitting is used to fit a polynomial function to the data and is particularly effective when the LC does not exhibit rapid fluctuations or irregular bursts. Polynomial fitting can capture the general trend of the LC, making it a simple yet useful approach when the data is relatively well-behaved or to serve as a baseline model for more complex methods.

2.1.6. Isotonic Regression

Isotonic regression is a non-parametric method that can fit a monotonic curve to the data, which makes it well-suited for situations where the relationship between time and intensity is not linear but still follows a consistent trend (Barlow et al., 1972). This method is flexible and can handle noisy data better than simple linear regression, making it useful for reconstructing the LCs in GRBs with flares and breaks.

2.2. Dataset and the Willingale model

This study utilizes the same dataset as described in Dainotti et al. 2023c; Manchanda et al. 2024, comprising 545 GRBs. The data originates from the Swift BAT-XRT repository (Evans et al., 2009, 2007) and has been previously presented in Srinivasaragavan et al. 2020; Dainotti et al. 2020a; Dainotti et al. 2024c,b; Narendra et al. 2024. All light curves exhibit temporal gaps, with a minimum gap size of 0.03 in the log-time scale adopted for the reconstruction task.

The W07 function has been used to model LCs of GRBs, defined in Eq. 1 and introduced by Willingale et al. 2007:

$$f(t) = \begin{cases} F_i \exp\left(\alpha_i\left(1 - \frac{t}{T_i}\right)\right) \exp\left(-\frac{t_i}{t}\right) & \text{for } t < T_i, \\ F_i \left(\frac{t}{T_i}\right)^{-\alpha_i} \exp\left(-\frac{t_i}{t}\right) & \text{for } t \geq T_i. \end{cases} \quad (1)$$

Here, the symbols T_i and F_i refer to the time and flux, respectively. This corresponds to the end of the plateau phase, denoted with a ; α_i is the represented temporal index parameter associated with T_i . The parameter t_i corresponds to the onset of the rising phase, and the afterglow emission is represented by t_a .

The LCs analyzed in this study have been curated to remove the prompt emission segment due to its significant variability and the challenges in modeling it effectively.

The GRBs are classified into four distinct classes as mentioned in Dainotti et al. 2023a; Manchanda et al. 2024; Dainotti et al. 2023c:

- **Good GRBs:** GRBs aligning closely with the W07 model and represent 55.3% of the dataset.
- **Flares/Bumps:** GRBs showing flares and bumps throughout the afterglow phase, account for 24.06% of the dataset.
- **Break:** GRBs with a single break towards the end of the LC, making up 13.14% of the sample.
- **Flares/Bumps + Double Break:** GRBs that display a combination of flares/bumps and a double break constitute 7.5% of the dataset.

The parameters for each GRB LC has been derived from the work of Srinivasaragavan et al. 2020. Fig. 1 illustrates the LCs for the four identified classes and their corresponding W07 model fits. The blue points refer to the observed data that has been trimmed of the prompt emission.

2.3. Dataset Preprocessing

We follow the same preprocessing and training pipeline as described in Dainotti et al. 2023c; Manchanda et al. 2024, which ensures consistency across all models and facilitates a fair comparison. We used a random subset of 16 GRBs, four from each GRB category, to tune our model by minimizing the Mean Squared Error (MSE) loss. This tuning was conducted using optuna framework Akiba et al. (2019) and the parameters obtained were used for the reconstruction of the entire 545 GRBs dataset. After obtaining the parameters, each model is trained independently on individual GRB LCs, using the \log_{10} -transformed time and flux values. The data is scaled to [0,1] using min-max normalization, described in Eq. 2:

$$X_i = \frac{X_i - X_{min}}{X_{max} - X_{min}}; i \in D, \quad (2)$$

where X_{min} and X_{max} are the minimum and the maximum value in D .

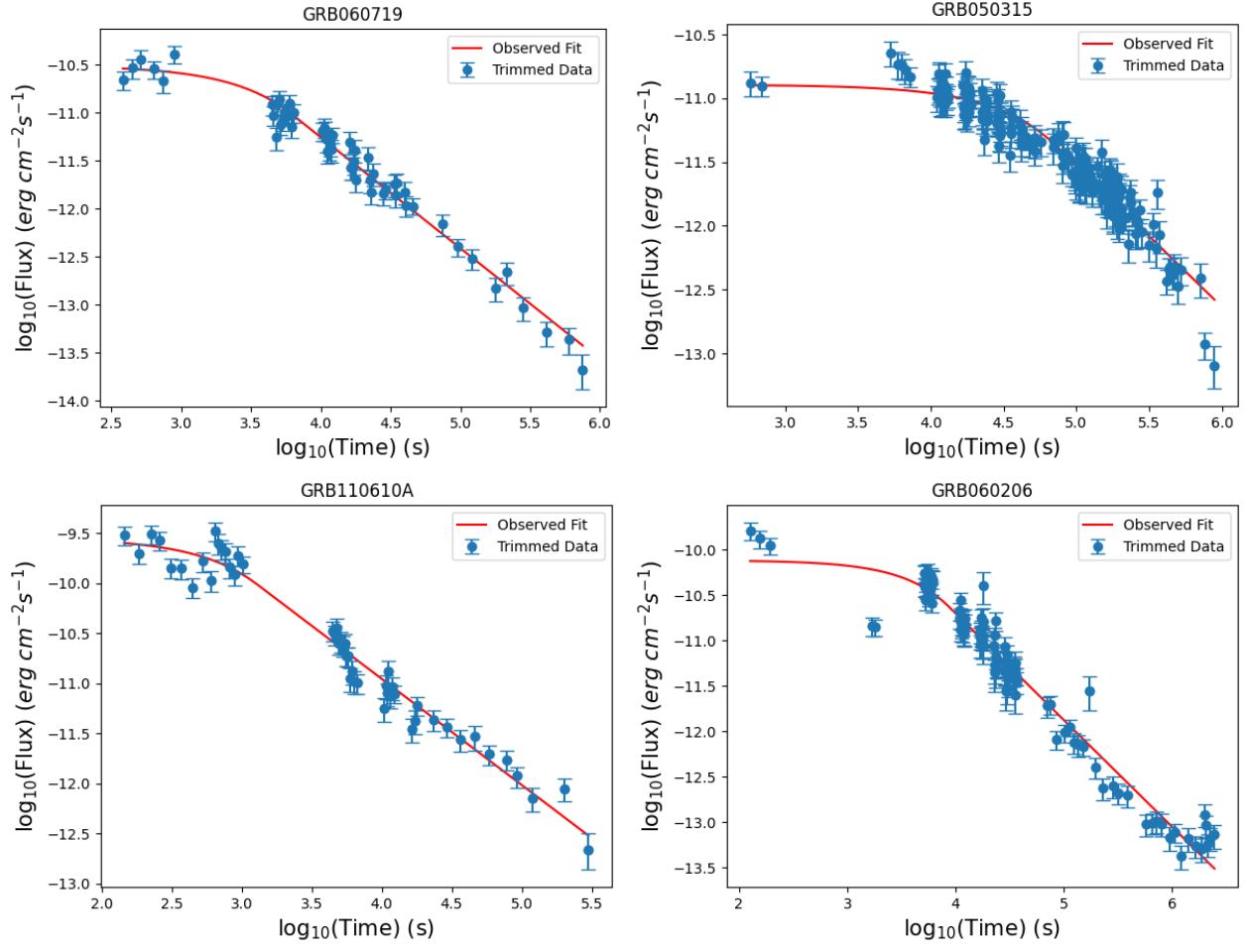


Figure 1: The GRB LCs can be classified into four types based on the afterglow feature: i) Good GRBs (upper left); ii) GRB LCs that have a break in the terminal end (upper right); iii) Flares or Bumps in the afterglow (bottom left); iv) Flares or Bumps that have Double Break at the end of the LC (bottom right). References: [1] Sakamoto et al. 2008; [2] Bi et al. 2018; [3] Dainotti et al. 2022a.

After training the model and reconstructing the temporal gaps, we estimate the aleatoric uncertainty in the reconstructed flux values in a similar way as Dainotti et al. 2023c; Manchanda et al. 2024. For each model, we perform 1000 Monte Carlo simulations by adding noise sampled from a Gaussian distribution, fitted to the residuals between the original and reconstructed fluxes. This captures the inherent data variability of the LCs. The 95% confidence interval (CI) is computed using the 2.5th and 97.5th percentiles of the distribution of the reconstructed values at each time point, providing a reliable estimate of the aleatoric uncertainty.

2.4. The Machine-Learning Approach

This section provides a brief overview of various ML-based models for LC reconstruction.

2.4.1. Deep Gaussian Model

This method layers the GP (Rasmussen and Williams, 2006) regression technique, enabling deep learning for probabilistic outputs tailored to regression tasks. A Deep Gaussian Process (DGP) Damianou and Lawrence 2013 extends the traditional GP framework by stacking multiple GP layers, where each layer models latent functions whose outputs serve as inputs to the next. Unlike a single-layer GP, which assumes a joint Gaussian distribution between inputs and outputs, a DGP introduces intermediate layers of latent variables—unobserved, inferred quantities that capture complex underlying structure—breaking the joint Gaussianity. This hierarchical setup enables the model to capture increasingly complex patterns in LC data by learning a distribution over the latent space at each layer. As shown in Fig. 2, we can view the DGP as a form of Markov Chain, where each layer conditionally depends only on its immediate predecessor, thus simplifying the propagation of uncertainty through the network.

$$p(\mathbf{a}|\mathbf{g}) = p(\mathbf{a}|y_4)p(y_4|y_3)p(y_3|y_2)p(y_2|y_1)p(y_1|\mathbf{g})$$

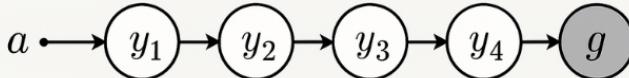


Figure 2: Deep GP as a Markov chain

In our model, we use two DGP layers, each consisting of a scalable single-layer approximate GP. The model is implemented using GPyTorch, a Gaussian Process library built on top of PyTorch. The input is standardized using Eq. 2 before training to ensure stable optimization. For smooth and effective transitions, we use the Radial Basis Function (RBF) kernel with a length scale of 2.0. The RBF kernel, also known as the squared exponential kernel, measures similarity between inputs based on their Euclidean distance and assumes that points closer in the input space are more strongly correlated. Within a single-layer GP, we employ a GPyTorch-enabled Cholesky variational strategy to learn the optimal inducing point locations. Inducing points are a small set of representative inputs

that help approximate the full GP, making it faster and more scalable. The Cholesky strategy improves stability and efficiency by factorizing the covariance matrix, allowing the model to handle larger datasets without sacrificing performance. We use 50 inducing points in the first layer and 30 for the second layer, selected through manual hyperparameter tuning on different GRB types. We tested several combinations on all types of GRBs and selected the configuration that minimized reconstruction error while maintaining computational efficiency. All evaluations were done under consistent training settings and preprocessing steps to ensure a fair comparison. Each layer outputs a latent distribution whose mean is passed as input to the next layer, modeling a two-layered function:

$$\mathbf{y} = g(h(\mathbf{x})).$$

This hierarchical formulation allows the model to capture complex, non-linear behaviors that might be missed by a shallow GP model.

To model the observed log flux values, we use a Gaussian likelihood:

$$p(\mathbf{y} | \mathbf{f}) = \mathcal{N}(\mathbf{y} | \mathbf{f}, \sigma_n^2 \mathbf{I}),$$

where \mathbf{y} denotes the observed outputs, \mathbf{f} represents the latent function outputs, σ_n^2 is the learnable noise variance, and \mathbf{I} is the identity matrix, assuming Gaussian noise. The noise is initialized at 0.01 and constrained within the interval $[10^{-4}, 0.05]$ to prevent the model from overfitting or underfitting the noise levels across different GRB types.

Training is performed over 500 iterations with an initial learning rate of 0.005. To stabilize optimization and prevent oscillations or overshooting, we apply a StepLR learning rate scheduler that reduces the learning rate at fixed intervals.

This model configuration performs well across most GRBs. Notably, adding a third GP layer improves performance for 34 GRBs with a large number of data points, as deeper latent representations can be learned.

Compared to standard GPs, DGPs can model non-stationary, non-Gaussian, and multi-modal behavior more effectively. While GPs are limited in expressiveness, DGPs offer greater flexibility at the cost of increased computational complexity.

2.4.2. Temporal Convolutional Neural Network

The Temporal Convolutional Network (TCN) (Bai et al., 2018b) is a convolutional neural network architecture designed for sequence modeling tasks. TCN uses causal convolutions, where the output at time step t is computed exclusively from elements at time t and earlier, preventing information leakage from future time steps and enhancing convolutions through dilation, where filters (learnable weights that detect patterns) are applied with regularly spaced gaps across the input sequence, as illustrated in Fig. 3(b). For a 1D input sequence $\mathbf{x} \in \mathbb{R}^n$ and a filter $f : \{0, \dots, k-1\} \rightarrow \mathbb{R}$, the dilated convolution F at position s is given by:

$$F(s) = (\mathbf{x} *_d f)(s) = \sum_{i=0}^{k-1} f(i) \cdot \mathbf{x}_{s-d \cdot i}. \quad (3)$$

Residual connections (He et al., 2016) involve adding the input of a layer directly to its output, skipping one or more intermediate layers as shown in Fig. 3(a). This technique allows the model to learn identity mappings, which helps prevent the vanishing gradient problem and facilitates more stable gradient flow during backpropagation. The TCN uses residual connections to improve training stability and ensure efficient convergence.

Unlike RNNs, which process sequences step by step, TCNs operate over the entire sequence in parallel. This parallelism improves computational efficiency and reduces training time. In terms of resource efficiency, TCNs generally require less memory during training compared to gated RNNs such as LSTMs (Hochreiter and Schmidhuber, 1997b) and GRUs (Cho et al., 2014). This is because TCNs share convolutional filters across time steps and do not need to store internal states or gate activations.

In this study, the TCN was implemented using the `keras-tcn` library in combination with Keras' Functional API. The network was created with 64 filters, a kernel size of 5, a dropout rate of 0.1, a single stack of residual blocks, and dilation factors set to (1, 2, 4, 8, 16, 32). The TCN output was passed to a Dense layer with a linear activation function. The input shape was (1, 1, 1).

Hyperparameter optimization was performed through grid search on a randomly selected subset of GRB data, using the following ranges:

- `nb_filters_range` = [16, 32, 64, 128]
- `kernel_size_range` = [1, 3, 5]
- `dropout_range` = [0.1, 0.5, 0.7]

The ideal set of values for all GRBs was determined by combining the values that performed the best on this subset. Using the Adam optimizer with a batch size of 8 and MSE as the loss function, the model was trained across 100 epochs. Both input features and target values were normalized using Min-MaxScaler to ensure consistent scaling.

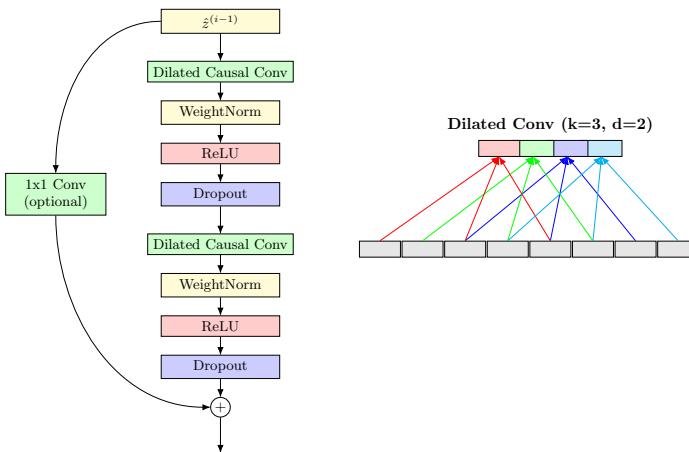


Figure 3: (a) Residual block of a Temporal Convolutional Network. (b) Expanded view of a dilated convolution layer

2.4.3. Convolutional Neural Network - Long Short Term Memory

Convolutional Neural Networks (CNNs) (LeCun et al., 1998; Zhang et al., 2019) and Bidirectional Long Short-Term Memory (Bi-LSTM) networks have individually demonstrated strong performance in extracting spatial and temporal features, respectively, making their hybrid combination particularly powerful for sequential pattern learning. CNN-BiLSTM models leverage this synergy by integrating convolutional feature extraction with temporal sequence modeling, enabling superior performance in tasks involving complex and noisy time-series data (Wang et al., 2017; Yao et al., 2017).

In the CNN-BiLSTM architecture, the input LC is initially passed through one or more convolutional layers that act as localized feature detectors. These layers apply multiple filters to capture short-range dependencies and local patterns such as flares, peaks, or breaks in GRB LCs. Filters are like pattern detectors that slide over the input data and look for patterns in a local region of the input. This local processing is effective in denoising the signal and emphasizing key morphological structures relevant for downstream reconstruction (Kiranyaz et al., 2021). A typical convolution operation in a 1D CNN can be defined as:

$$y_i = \sum_{j=0}^{k-1} w_j \cdot x_{i+j}, \quad (4)$$

where w_j are the filter weights, x is the input sequence, k is the kernel size, and i indexes the position in the output feature map.

The compressed feature maps from the CNN are then fed into a Bi-LSTM block that processes the sequence in both forward and backward directions. This dual perspective allows the model to capture long-range dependencies while incorporating context from both past and future time steps (Graves et al., 2005). For GRB LCs, where information from both earlier and later intervals can improve reconstruction accuracy, especially in the presence of complex events like multiple flares, this bidirectional processing is critical.

The Bi-LSTM component consists of three stacked layers, each with 100 hidden units. Within each LSTM cell, an input gate (i_t), forget gate (f_t), and output gate (o_t) regulate information flow:

$$i_t = \sigma(W_i[x_t, h_{t-1}] + b_i), \quad (5)$$

$$f_t = \sigma(W_f[x_t, h_{t-1}] + b_f), \quad (6)$$

$$o_t = \sigma(W_o[x_t, h_{t-1}] + b_o). \quad (7)$$

These gates control what information is written to, retained in, and released from the cell state, enabling stable learning of long-term dependencies.

Each Bi-LSTM layer returns a full sequence of hidden states in both directions, which are concatenated at each time step:

$$h_t^{\text{Bi-LSTM}} = [h_t^{\rightarrow}; h_t^{\leftarrow}]. \quad (8)$$

In our implementation, we use:

- A 1D convolutional layer with 64 filters, kernel size $k = 3$, ReLU activation, He-uniform initialization, and L_2 -regularization.

- A max-pooling layer with pool size 1 to preserve sequence length.
- Three stacked Bi-LSTM layers (100 units each).
- A final dense layer with a single unit to reconstruct the flux value.

We use the Adam optimizer with a learning rate of 0.0001 for training. This hyperparameter was determined during the hyperparameter tuning phase as mentioned in the section 2.3.

Fig. 4 illustrates the end-to-end workflow of our CNN-BiLSTM architecture.

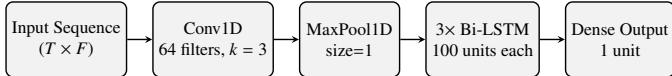


Figure 4: Workflow of the CNN-BiLSTM model for GRB light-curve reconstruction.

2.4.4. Bayesian Neural Network

Bayesian neural networks (BNNs) are made up of a neural network and a stochastic model. The latter introduces either a stochastic activation or a stochastic weight. It is possible to simulate multiple models of parameters θ with an associated probability distribution $p(\theta)$. Comparing their predictions shows uncertainty: agreement indicates low uncertainty; disagreement indicates high uncertainty. Training a BNN involves computing a posterior distribution over the weights given data, denoted as $p(\theta | D)$, where θ represents the weights and D is the training dataset. Exact inference is intractable, so variational inference is used. By minimizing the Kullback–Leibler divergence, a variable distribution $q(\theta)$ chosen from a family of distributions approximates the posterior $p(\theta | D)$:

$$\text{KL}(q(\theta) \| p(\theta | D)). \quad (9)$$

This converts the inference problem into an optimization one, often using reparameterization tricks to enable backpropagation through stochastic variables. Dropout-based approximations, such as Monte Carlo Dropout, implement a form of variational inference where dropout is applied at test time, sampling from an implicit posterior over the weights. These samples generate predictive distributions from which uncertainty can be estimated.

Prediction involves marginalizing over the posterior:

$$p(y | x, D) = \int p(y | x, \theta) p(\theta | D) d\theta, \quad (10)$$

for an input vector x and predicted output y .

Since this integral is intractable, it is approximated via Monte Carlo sampling for T samples:

$$p(y | x, D) \approx \frac{1}{T} \sum_{t=1}^T p(y | x, \theta_t), \quad \theta_t \sim q(\theta). \quad (11)$$

This ensemble of predictions allows the computation of predictive mean and variance.

The model is implemented using PyTorch and `torchbnn`, structured with hidden layers (`num_layers`). Each hidden layer is a `BNNHiddenLayer`, which wraps a `BNNLinear` layer with trainable Gaussian-distributed weights and biases. The hidden layers are defined by an activation function (Leaky ReLU, Tanh, or Swish) and include dropout for regularization. The output consists of two parallel linear heads - one for the predictive and another for the log-variance. Hyperparameters such as the number of layers, hidden units, dropout rate, and activation function are optimized using Optuna. The values of `PRIOR_MU` and `PRIOR_SIGMA` are set to 0.0 and 0.1 respectively. The training process involves forward propagation with stochastic weight sampling, minimizing a composite loss function consisting of:

- The negative log-likelihood of the Gaussian output.
- A KL-divergence term that regularizes the learned weights by penalizing deviations from a standard normal prior.

$$\mathcal{L}(\theta) = \underbrace{-[\log p(D | \theta)]}_{\text{Negative Log-Likelihood}} + \underbrace{\text{KL}(q(\theta) \| p(\theta))}_{\text{KL Divergence}}. \quad (12)$$

The KL-divergence term is scaled by a fixed multiplicative factor $\lambda_{\text{KL}} = 10^{-3}$ to balance model fit and uncertainty. After hyperparameter optimization, the model is retrained on the full LC of every GRB separately. For prediction, multiple stochastic forward passes are conducted to generate a distribution of outputs, from which prediction intervals and uncertainty estimates are derived.

Hyperparameter	Optuna Values/Range
Number of layers	(1, 2, 3)
Hidden Unit 1	(32, 64, 128)
Hidden Unit 2	(32, 64, 128)
Hidden Unit 3	(16, 32, 64)
Dropout Rate	(0.1, 0.2, 0.3, 0.4)

Table 1: Hyperparameter ranges used in Optuna optimization

2.5. The statistical approach

This section provides a brief overview of various statistical-based models for LC reconstruction

2.5.1. Polynomial Curve Fitting

In previous sections, we experimented with various sophisticated approaches. However, now, we aim to simplify the curve-fitting process. Our approach involves fitting an n-degree polynomial to the LC, starting with an initial fine-tuning phase. Similar polynomial regression techniques have been employed in previous studies, as noted by (AlShammari, 2024). An n-degree polynomial can be defined as:

$$y = c_1 + c_2 x + c_3 x^2 \dots c_n x^{n-1}. \quad (13)$$

We deliberately use a general polynomial form without imposing any specific curve function, allowing the model to capture the underlying trend in GRBs without bias toward a predefined shape. Importantly, the choice of a general curve does not

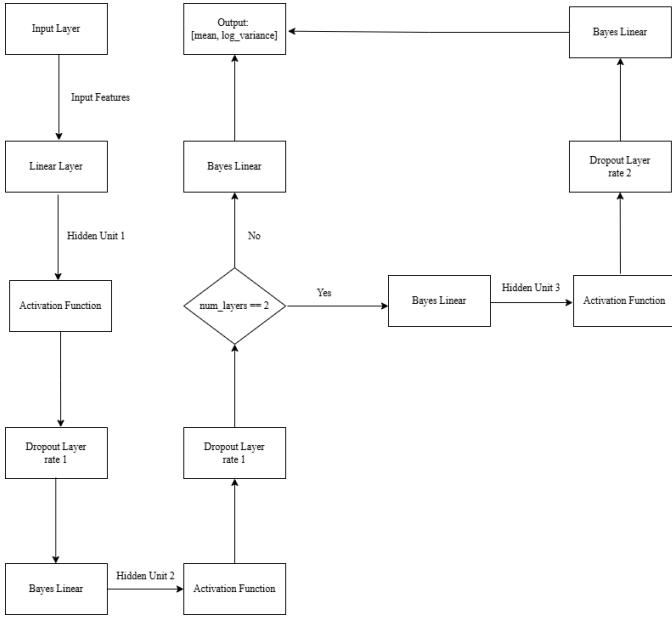


Figure 5: BNN architecture for GRB light-curve reconstruction

contradict or attempt to draw definitive conclusions about the physical interpretations or trends established in GRB-related literature.

The objective is to select the degree n such that the model achieves an optimal balance between flexibility and generalization. To do this, we apply *MinMaxScaling* given by the Eq. 2 and then randomly sample four instances from each GRB class and determine the polynomial degree that minimizes MSE loss while maintaining model simplicity. In our experiments, a third-degree polynomial yielded the best performance. Apart from choosing the polynomial degree, we also fine-tune the initial parameters c_1 , c_2 , and c_3 , which serve as the starting point for optimization. The resulting polynomial equation takes the form:

$$y = -0.354 + 0.796x - 0.0255x^2. \quad (14)$$

This polynomial is then fitted to the data using the `scipy.optimize.curve_fit` function, which estimates the optimal coefficients $\{c_1, c_2, c_3\}$ for each GRB.

Fig. 6 presents an overview of the entire process.

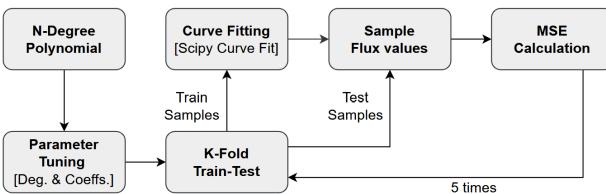


Figure 6: Workflow of the Polynomial Curve Fit model for GRB light-curve reconstruction.

2.5.2. Isotonic regression

This approach uses a statistical, non-parametric method to estimate monotonic (either decreasing or increasing) one-dimensional data. Unlike classical regression which assumes a linear functional form, the non-parametric approach does not presume the structure. Therefore, this method is more flexible than standard regression and fits the data more accurately as it is displayed in Fig. 7.

Given that the LCs generally show a decreasing trend over time, in our implementation, a non-increasing isotonic regression model is applied (Best and Chakravarti, 1990).

Let $(x_1, y_1), \dots, (x_n, y_n)$ be observations such that $x_1 < x_2 < \dots < x_n$, and for any $i > j$, it holds that $y_j \geq y_i$. With such assumption, the isotonic regression seeks a non-increasing function $f : X \rightarrow \mathbb{R}$ that minimizes the weighted least squares criterion:

$$\min_f \sum_{j=1}^n w_j (y_j - f(y_j))^2, \quad (15)$$

where $w_j \geq 0$ is added weight to the observation.

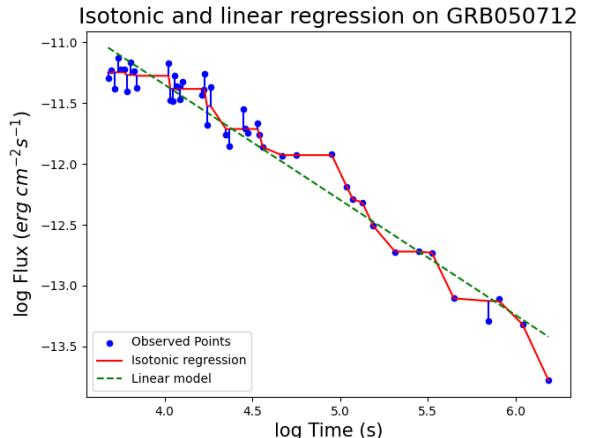


Figure 7: Weighted least-square method minimizes the residuals which are marked with blue lines

Typically, weights are set to 1, but in our implementation, we assign a weight of 0.1 for the outliers to reduce their influence on the fitted curve.

To find the most optimal function f the pool adjacent violators (PAV) algorithm is used. This procedure is implemented in Python `sklearn` package in `IsotonicRegression` in the fitting method (de Leeuw et al., 2009). Let us present this algorithm briefly.

Let $\hat{y}_1, \hat{y}_2, \dots, \hat{y}_n$ denote the fitted values obtained from isotonic regression corresponding to x_1, \dots, x_n , respectively. Consequently, the function defined by the Eq. 15 is expressed as:

$$f(x_i) = \hat{y}(x_i) = \hat{y}_i. \quad (16)$$

In our case, we perform non-increasing isotonic regression, which imposes the condition:

$$\hat{y}_i \geq \hat{y}_{i+1} \quad \text{for all } i = 1, \dots, n-1. \quad (17)$$

The algorithm proceeds as follows:

- 1. Initialization:** Set the initial fitted values equal to the observed values:

$$\hat{y}_i = y_i \quad \text{for all } i = 1, \dots, n. \quad (18)$$

- 2. Check for monotonicity:** For each pair $(\hat{y}_i, \hat{y}_{i+1})$, verify whether the non-increasing condition holds:

$$\hat{y}_{i+1} \leq \hat{y}_i. \quad (19)$$

- 3. Merge in case of violation:** If the condition is violated (i.e., $\hat{y}_{i+1} > \hat{y}_i$), merge the two values using a weighted average:

$$\hat{y}_{\text{merged}} = \frac{w_i \cdot \hat{y}_i + w_{i+1} \cdot \hat{y}_{i+1}}{w_i + w_{i+1}}. \quad (20)$$

Replace both \hat{y}_i and \hat{y}_{i+1} with \hat{y}_{merged} , therefore $\hat{y}_i = \hat{y}_{i+1} = \hat{y}_{\text{merged}}$ and treat them as a single block with combined weight $w_i + w_{i+1}$ (i.e., validate the next steps of the algorithm with \hat{y}_{merged} and the updated weight.)

- 4. Iterative verification of merged values:** After merging, verify whether the updated values violate the non-increasing condition with the preceding values. If a violation occurs, continue merging recursively to the left.

5. Repeat until no violations remain.

Therefore the sequence $\hat{y}_1, \dots, \hat{y}_n$ are the fitted values resulting from isotonic regression, such that they satisfy the monotonicity $\hat{y}_1 \geq \hat{y}_2 \geq \dots \geq \hat{y}_n$.

After training the model, the procedure of predicting new value x is given by:

$$\hat{y}(x) = \begin{cases} \hat{y}_1 & \text{if } x \leq x_1, \\ \hat{y}_i + \frac{x - x_i}{x_{i+1} - x_i}(\hat{y}_i - \hat{y}_{i+1}) & \text{if } x_i \leq x \leq x_{i+1}, \\ \hat{y}_n & \text{if } x \geq x_n, \end{cases} \quad (21)$$

where x_1, x_2, \dots, x_n are the data points used to fit the isotonic regression, satisfying the strictly increasing order $x_1 < x_2 < \dots < x_n$.

3. Results

Decreasing the uncertainty associated with the model parameters is an objective of LCR. To evaluate this, the error fractions, symbolized by EF , are calculated for every model parameter in both the primary datasets and after reconstructing them using the model. Eq. 22, 23, and 24 reflect the error fractions for the three parameters as stated in Dainotti et al. 2023c:

$$EF_{\log_{10}(T_a)} = \left| \frac{\Delta \log_{10}(T_a)}{\log_{10}(T_a)} \right|, \quad (22)$$

$$EF_{\log_{10}(F_a)} = \left| \frac{\Delta \log_{10}(F_a)}{\log_{10}(F_a)} \right|, \quad (23)$$

$$EF_{\alpha_a} = \left| \frac{\Delta \alpha_a}{\alpha_a} \right|. \quad (24)$$

We compute the reduction in the percentage of the error fractions in order to evaluate the enhancement in fit post reconstruction.

$$\%_{DEC} = \frac{|EF_X^{\text{after}}| - |EF_X^{\text{before}}|}{|EF_X^{\text{before}}|} \times 100. \quad (25)$$

The reconstruction for each category of GRBs for all models is shown in Fig. 8, and the histogram distribution of the relative percentage decrease for the three parameters is illustrated in Fig. 9.

Table 3 shows how effectively the models' reconstructed data performs in comparison to the initial observed data for all GRBs. Although the models perform well for most GRB reconstructions, a few outliers are observed in the W07 parameters. We classify outliers as instances where the relative percentage decrease exceeds 100%.

4. Summary and Conclusion

We showcase the efficacy of the proposed methods in modeling LCs and bridging the temporal gaps in the GRB LCs. The main conclusions of our studies are outlined below:

- The isotonic regression model achieved strong reductions in uncertainty - 36.3% for $\log T_a$, 36.1% for $\log F_a$, and 43.6% for α . These reductions are among the highest, particularly for α , where it outperformed several deep learning models. Isotonic regression remains a satisfactory baseline, particularly strong for the α parameter. This model achieved a 3.80% improvement for the α parameter over the Bi-Mamba model.
- The TCN model achieved moderate improvements in $\log T_a$ and $\log F_a$ parameters, but showed a notable reduction of 38.7% in the uncertainty of the α parameter.
- For the α parameter specifically, TCN performs slightly better than the MLP Manchanda et al. 2024, with a 2.60% improvement. However, it exhibits the highest number of outliers among all models. This suggests that although TCN performs well on seen data, it may struggle with generalization, particularly when applied to gaps in GRB LC.
- The DGP model effectively models the uncertainties in the data. It performs notably well for the 218 good GRBs, achieving 31.7% reduction in $\log(T_a)$, 32.6% in $\log(F_a)$, and 41.0% in α . It also maintains outlier percentages of 7.24% ($\log(T_a)$), 6.86% ($\log(F_a)$), and 1.48% (α), indicating reliable generalization performance. Its performance is also comparable to the Bi-Mamba model, showcasing similar uncertainty values for $\log(T_a)$, $\log(F_a)$, and α parameters.
- On comparison with the GP model used in Dainotti et al. 2023c; Manchanda et al. 2024 for the 545 sample, we observe that the DGP model performs better across all three uncertainty reduction parameters, highlighting the importance of introducing layers that are able to capture complex

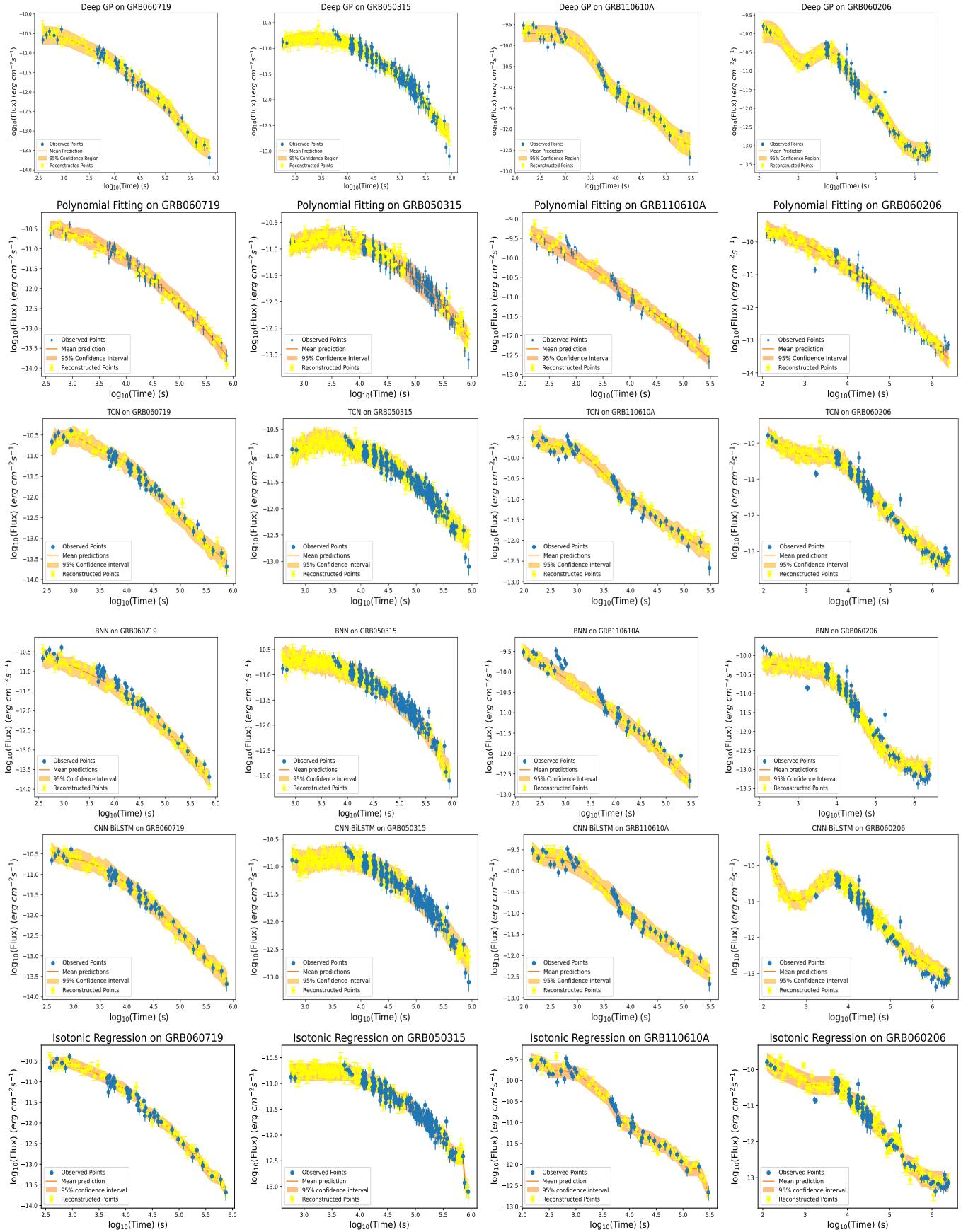


Figure 8: Reconstruction of LCs for all four varieties of GRBs are shown with four types of GRBs (left to right): i) Good GRBs (Column 1); ii) a GRB LC with a break towards the end (Column 2); iii) flares or bumps in the afterglow (Column 3); iv) flares or bumps with a double break towards the end of the LC (Column 4) and the models (top to bottom): i) Deep GP (Row 1); ii) Polynomial Fitting Model (Row 2); iii) TCN Model (Row 3); BNN Model (Row 4); CNN-BiLSTM Model (Row 5); Isotonic Regression Model (Row 6).

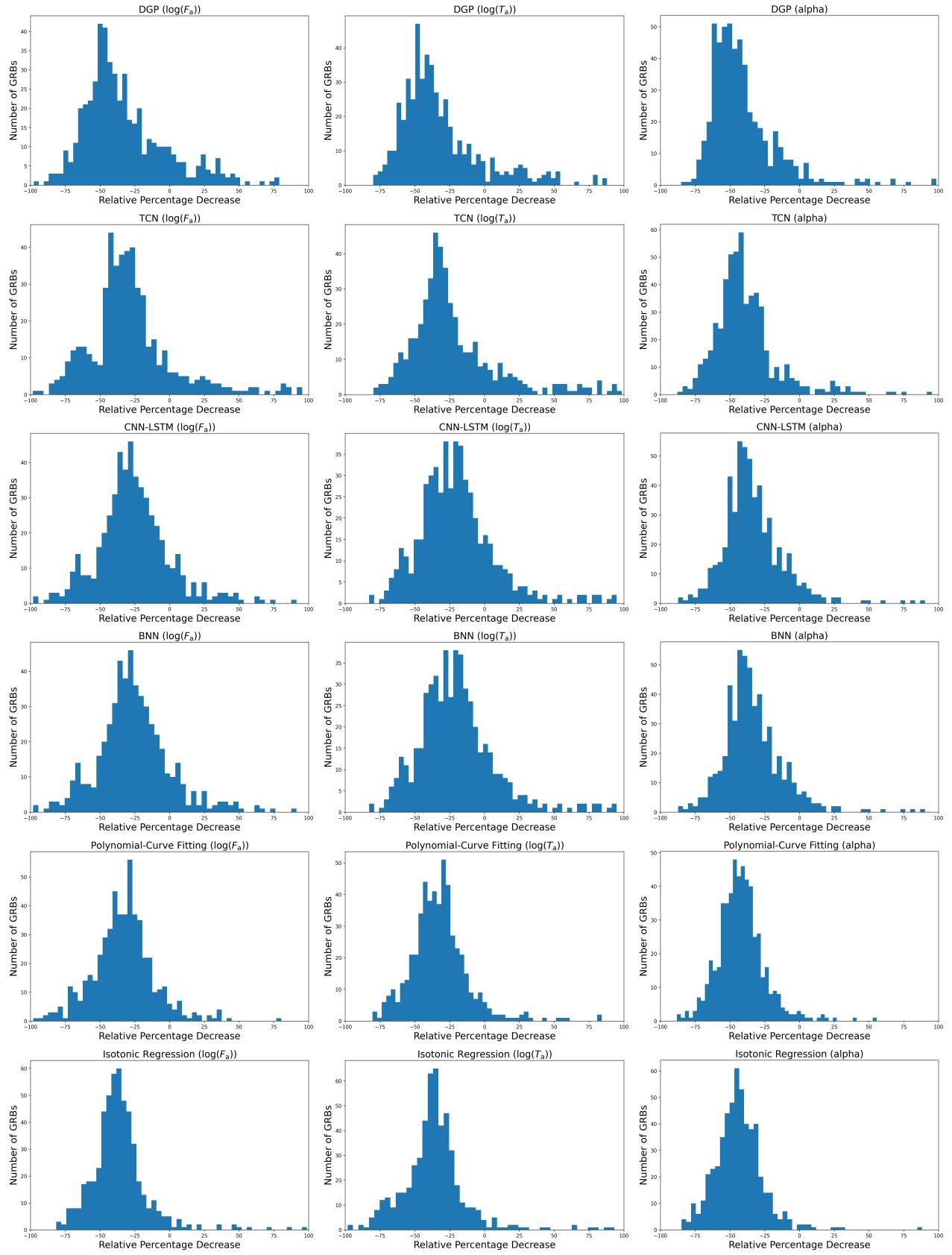


Figure 9: Distribution plot of all three W07 parameters in a grid with parameters (left to right): i) $\log F_a$ (Column 1) ii) $\log T_a$ (Column 2) iii) α (Column 3) and the models (top to bottom): i) Deep GP (Row 1); ii) TCN Model (Row 2); iii) CNN-BiLSTM Model (Row 3); iv) BNN Model (Row 4); v) Polynomial Curve Fitting Model (Row 4); vi) Isotonic Regression Model (Row 6)

GRB ID	$EF_{\log_{10}(T_i)}$	$EF_{\log_{10}(F_i)}$	EF_{α_i}	$EF_{\log_{10}(T_i)}$ RC	$EF_{\log_{10}(F_i)}$ RC	EF_{α_i} RC	$\%_{\log_{10}(T_i)}$	$\%_{\log_{10}(F_i)}$	$\%_{\alpha_i}$
TCN									
070110	0.0268	0.00899	0.0852	0.0245	0.00612	0.0390	-8.80	-31.9	-54.2
070208	0.00623	0.00232	0.0133	0.00484	0.00166	0.00947	-22.3	-28.4	-29.23
070223	0.0126	0.00495	0.0326	0.00912	0.00310	0.0176	-27.9	-37.4	-45.8
070306	0.0409	0.0149	0.0524	0.0181	0.00432	0.0536	-55.6	-71.0	2.28
070802	0.0602	0.0149	0.179	0.0521	0.0106	0.117	-13.4	-28.4	-34.8
070521	0.0058	0.00297	0.0325	0.00352	0.00171	0.0161	-39.2	-42.4	-50.3
070529	0.00393	0.00117	0.00972	0.00285	0.000861	0.00327	-27.3	-26.9	-66.3
CNN-LSTM									
070110	0.0126	0.00495	0.0326	0.00969	0.00336	0.0184	-23.4	-32.1	-43.4
070208	0.0409	0.0149	0.0524	0.0166	0.00442	0.0537	-59.4	-70.3	2.51
070223	0.0480	0.0140	0.0799	0.0294	0.00859	0.0395	-38.8	-38.6	-50.5
070306	0.00580	0.00297	0.0325	0.00448	0.00218	0.0214	-22.6	-26.4	-34.1
070802	0.0602	0.0149	0.179	0.0421	0.00966	0.100	-30.1	-35.1	-43.8
070521	0.0136	0.00489	0.0388	0.00709	0.00271	0.0178	-48.0	-44.6	-54.2
070529	0.0219	0.00538	0.0288	0.0166	0.00435	0.0167	-24.4	-19.1	-41.8
BNN									
070110	0.0126	0.00495	0.0326	0.00734	0.00266	0.0142	-42.0	-46.2	-56.4
070208	0.0409	0.0149	0.0524	0.0136	0.00433	0.0568	-66.6	-70.9	8.49
070223	0.0480	0.0140	0.0799	0.0299	0.00871	0.0533	-37.7	-37.8	-33.2
070306	0.00580	0.00297	0.0325	0.00375	0.00186	0.0181	-35.2	-37.2	-44.2
070802	0.0602	0.0149	0.179	0.0424	0.00941	0.0946	-29.5	-36.8	-47.3
070521	0.0136	0.00489	0.0388	0.00901	0.00307	0.0219	-33.9	-37.3	-43.6
070529	0.0219	0.00538	0.0288	0.0190	0.00480	0.0183	-13.6	-10.8	-36.4
Polynomial Curve Fitting									
070110	0.0126	0.00495	0.0326	0.00816	0.00292	0.0154	-35.5	-41.0	-52.8
070208	0.0497	0.0149	0.0524	0.0126	0.00412	0.0502	-69.2	-72.3	-4.14
070223	0.0480	0.0140	0.0799	0.0360	0.0104	0.0391	-25.1	-25.3	-51.1
070306	0.0058	0.00297	0.0325	0.00409	0.00178	0.0176	-29.5	-40.0	-45.9
070802	0.0602	0.0149	0.179	0.0404	0.00903	0.0936	-32.8	-39.4	-47.8
070521	0.0136	0.00489	0.0388	0.00681	0.00271	0.0173	-50.0	-44.6	-55.4
070529	0.0219	0.005387	0.0288	0.0195	0.00492	0.0187	-10.9	-8.53	-34.9
Isotonic Regression									
070110	-0.00495	0.0126	0.0326	-0.00329	0.00931	0.0173	-33.5	-26.3	-46.6
070208	-0.0149	0.0409	0.0524	-0.00385	0.0125	0.0470	-74.1	-69.4	-10.2
070223	-0.0140	0.0480	0.0799	-0.00726	0.0257	0.0386	-48.1	-46.4	-51.7
070306	-0.00297	0.00579	0.0325	-0.00160	0.00340	0.0155	-46.0	-41.3	-52.3
070802	-0.0149	0.0602	0.179	-0.0120	0.0511	0.111	-19.4	-15.0	-37.9
070521	-0.00489	0.0136	0.0388	-0.00329	0.00789	0.0213	-32.7	-42.1	-45.2
070529	-0.00538	0.0219	0.0288	-0.00362	0.0140	0.0139	-32.7	-36.2	-51.6
DGP									
070110	0.0126	0.00495	0.0326	0.0105	0.00380	0.0181	-16.5	-23.2	-44.2
070208	0.0409	0.0149	0.0524	0.0157	0.00411	0.0509	-61.4	-72.4	-2.82
070223	0.0480	0.0140	0.0799	0.0282	0.00777	0.0484	-41.3	-44.4	-39.4
070306	0.00580	0.00297	0.0325	0.00302	0.00132	0.0123	-47.78	-55.5	-62.0
070802	0.0602	0.0149	0.179	0.0336	0.00743	0.0796	-44.14	-50.1	-55.6
070521	0.0136	0.00489	0.0388	0.00693	0.00270	0.0168	-49.12	-44.6	-56.6
070529	0.0219	0.00538	0.0288	0.0151	0.00405	0.0142	-31.2	-24.7	-50.4

Table 2: Comparison of EF and RC values under different methods and noise levels.

Reconstruction Model	Uncertainty Decrease			% Outliers		
	% $\log_{10}(T_a)$	% $\log_{10}(F_a)$	% α	% $\log T_a$	% $\log F_a$	% α
545 GRBs						
TCN	-22.6	-28.1	-38.7	13.2	11.6	2.20
DGP	-31.7	-32.6	-41.0	7.24	6.86	1.48
CNN-LSTM	-32.2	-32.8	-39.5	2.57	2.94	0.550
BNN	-20.2	-25.6	-33.4	4.04	4.04	0.550
Polynomial Curve Fitting	-32.3	-33.1	-41.9	2.57	2.57	0.920
Isotonic Regression	-36.2	-36.1	-43.6	3.12	3.30	0.730
Bi-Mamba	-33.3	-33.6	-41.9	2.70	2.70	0.700
MLP	-25.9	-28.6	-37.7	3.60	3.30	0.900
Bi-LSTM	-28.4	-28.2	-36.0	3.80	3.60	1.20
GP (W07)	-22.8	-23.2	-33.5	3.10	3.30	1.10
W07 model (10%)	-24.5	-25.7	-36.2	2.40	2.40	0.900
W07 model (20%)	-21.2	-22.9	-34.7	2.80	2.80	1.50
218 Good GRBs Dainotti et al. (2023c)						
TCN	-20.2	-26.2	-37.8	14.6	10.5	1.37
DGP	-35.4	-36.2	-45.4	3.25	3.25	0.460
CNN-LSTM	-31.7	-32.7	-41.0	0.450	0.450	0
BNN	-17.2	-24.2	-32.4	2.75	2.29	0.450
Polynomial Curve Fitting	-30.3	-32.5	-42.1	0.450	0.450	0.450
Isotonic Regression	-38.8	-37.4	-46.8	0.450	0.450	0
Bi-Mamba	-32.7	-34.3	-43.6	0.400	0.400	0.400
MLP	-24.1	-27.8	-38.9	0.900	0.400	0.400
Bi-LSTM	-26.1	-28.0	-37.3	1.30	1.80	1.30
GP (W07)	-25.6	-27.9	-41.6	0.400	0	0
W07 model (10%)	-33.3	-35.0	-43.3	0	0	0
W07 model (20%)	-29.5	-31.2	-40.6	0	0	0

Table 3: Summary of average uncertainty decrease and outliers for different reconstruction models on 545 GRBs and the 218 good GRBs subset.

patterns that a single-layer GP fails to catch. However, there is a notable increase in the outliers. The differences are demonstrated in Table 4.

- Comparing the DGP model with the hybrid model GP-RF mentioned in Dainotti et al. 2023c; Manchanda et al. 2024 for the entire sample, shows that the DGP model outperforms the hybrid model as well. Although the outliers are slightly higher than GP-RF, the DGP model reduces the outliers for the α parameters slightly. The comparison is shown in Table 4.
- The CNN-LSTM model demonstrates moderate yet consistent performance for all three parameters. It achieves reductions of 32.2%, 32.8%, and 39.5% for $\log(T_a)$, $\log(F_a)$, and α respectively. Notably, it also shows low outlier rates (2.57% and 2.94% for $\log(T_a)$ and $\log(F_a)$), and the lowest outlier percentage for α at just 0.550%, indicating reliability.
- Compared with the LSTM model used in Manchanda et al. 2024, the CNN-LSTM model outperforms it across all three parameters and shows fewer outliers. This highlights the benefit of combining convolutional layers with recurrent structures to effectively capture both local and temporal features in GRB light curves, see Table 5 for a detailed comparison.
- The BNN model reduces the W07 parameters by the lowest percentage for the full dataset as well as the 218 Good GRBs. It achieves reductions of 20.2%, 25.6%, and 33.4% for $\log(T_a)$, $\log(F_a)$, and α respectively. It did show the lowest outlier for the α parameter of 0.550
- Polynomial Curve Fitting demonstrates solid performance in uncertainty reduction, achieving 32.3%, 33.1%, and 41.9% decreases in $\log(T_a)$, $\log(F_a)$, and α , respectively. It retains low outlier rates, particularly 2.57% in both $\log(T_a)$ and $\log(F_a)$, and 0.920% in α . It is on par with the Bi-Mamba model, with an equal decrease of 41.9% in the α parameter.

We consider these $\log T_a$, $\log F_a$, and α as the most important outputs of our reconstruction. The parameter α describes the post-plateau decay behavior, relevant for the testing of the standard fireball model (Piran, 1999), and the reduction of α parameter is crucial to obtain reduced uncertainties on the closure relationship (Dainotti et al., 2021, 2024a). The parameters $\log T_a$ and $\log F_a$ are key for identifying empirical correlations, such as the Dainotti relations in two and three dimensions (Dainotti et al., 2008, 2010, 2011; Dainotti et al., 2013, 2016; Dainotti et al., 2020a,b; Dainotti et al., 2022b; Levine et al., 2022). Among all models tested, Isotonic Regression demonstrates the most significant reduction in error for the three parameters. Thus, we recommend it as the preferred model when accurate estimation of these physically meaningful quantities is the main objective.

These reconstructions achieve a significant reduction in uncertainty, which improves the reliability of the GRB plateau parameters. By achieving reduced uncertainty, the relationships associated with plateau emissions can be considered as standard candles for cosmological research (Dainotti et al., 2022g; Dainotti et al., 2022c, 2023b).

These methods can also be explored in future studies, including cutting-edge deep learning approaches such as neural ordinary differential equations (neural ODEs), Physics Informed Neural Network (PINN), and evolutionary algorithms. Additionally, the potential of transformer architectures and large language models to capture complex temporal patterns warrants investigation. When combined with new observational data, it is anticipated that these methods will greatly improve LCR's accuracy, dependability, and interpretability.

Though we have only used Swift LCs to develop this reconstruction framework thus far, we plan to apply it to other ongoing missions like SVOM (Atteia et al., 2022) and Einstein Probe (Yuan et al., 2022), as well as upcoming missions like THESEUS (Amati et al., 2018) and HiZ-GUNDAM (Yonetoku et al., 2024). Additionally, future analysis will provide data from other wavelengths. Given the availability of the most comprehensive optical catalogue to date, it is particularly appealing to extend this work to optical wavelengths (Dainotti et al., 2020a, 2022b, 2024a,b; Zhang and Mészáros, 2004).

5. Appendix

This section discusses an additional model we experimented with, namely the Time-aware Neural Ordinary Differential Equation (ODE). Although this model did not yield satisfactory outcomes for our particular application, we believe it may prove more beneficial in other hybrid configurations or in future research endeavors.

5.1. Time-aware Neural ODE (TN-ODE)

We developed the **TN-ODE** model to handle time-series data in which the measurements are irregular, as is frequently the case with GRB light curves. The model consists of three main components:

1. **Encoder:** After reading the supplied data, this module compresses it into a representation with fewer dimensions. It uses a time-aware LSTM network (Baytas et al., 2017), a variant of RNNs that incorporates the time gaps between observations to control how much past information is retained or forgotten.
2. **Neural ODE Block:** The compressed latent representation from the encoder is then passed into a Neural ODE block (Chen et al., 2018). This component models the continuous-time dynamics of the latent state, simulating how it evolves over time. The neural ODE enables interpolation and extrapolation at arbitrary time points, even between known data samples (Rubanova et al., 2019).
3. **Decoder:** Finally, the evolved latent representation is decoded into predictions of the original signal (e.g., GRB light intensity) at specified time points.

Parameters	DGP	GP	% Improvement	GP-RF	% Improvement
% Uncertainty Decrease					
$\log F_a$	-31.7	-22.8	39.0	-27.5	15.3
$\log T_a$	-32.6	-23.2	40.5	-25.0	30.4
α	-41.0	-33.5	22.4	-34.7	18.2
% Outliers					
$\log F_a$	7.24	3.10	-134	5.30	-36.6
$\log T_a$	6.86	3.30	-108	5.60	-22.5
α	1.48	1.10	-25.7	2.30	55.4

Table 4: Comparison between DGP & GP and DGP & GP-RF

Parameters	CNN-LSTM	Bi-LSTM	% Improvement
% Uncertainty Decrease			
$\log T_a$	-32.2	-28.4	13.4
$\log F_a$	-32.8	-28.2	16.3
α	-39.5	-36.0	9.72
% Outliers			
$\log T_a$	2.57	3.80	32.4
$\log F_a$	2.94	3.60	18.3
α	0.550	1.20	54.2

Table 5: Comparison between CNN-LSTM and Bi-LSTM

To incorporate uncertainty and improve generalization, we employ **variational sampling** (Kingma et al., 2013) during encoding. Stochasticity is introduced into the latent vectors via sampling from a training-learned distribution. This step allows the model to generate a distribution over possible outputs, enabling it to produce not only point forecasts but also confidence intervals, which quantify the model’s uncertainty.

During training and inference, the full process is repeated multiple times with different random samples. This Monte Carlo sampling technique provides probabilistic forecasts and confidence bounds.

In our experiments, TN-ODE demonstrated strong performance in modeling and forecasting GRB LCs with irregular time intervals. However, due to the model’s complexity and large number of parameters, careful hyperparameter tuning was required to prevent overfitting and mitigate sensitivity to noise. While the uncertainty estimates were generally informative, they were sometimes unstable because of the stochastic sampling process.

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