# Deriving an Analytical Expression for the Rise of Type Ia Supernovae with Symbolic Regression

**Mark Kanex**
Department of Physics
Massachusetts Institute of Technology
Cambridge, MA 02139, USA.

**Qinan Wang**
Kavli Institute for Astrophysics and Space Research,
Massachusetts Institute of Technology
Cambridge, MA 02139, USA.

## Abstract

Early excess emission in Type Ia supernovae light curves provides a direct clue to the progenitor systems and explosion mechanism of these standardizable candles. Yet the traditional baseline model, i.e., the empirical 'power-law' model developed from low cadence data, is increasingly limited for modern high cadence data due to its restricted time coverage and sensitivity to the chosen fitting window. Here we use symbolic regression to search for compact analytic descriptions of sub-hour-cadence SNe Ia light curves observed by *TESS* and *Kepler*, and examine whether events with early excess emission occupy a distinct region of the learned parameter space. We find that a model combining quadratic and sinusoidal terms provides the best description of the observed rise. These preliminary results demonstrate the potential of symbolic regression as an interpretable, data-driven approach for discovering empirical structure in astronomical data.

## 1 Introduction

With their relatively uniform luminosity evolution, Type Ia supernovae (SNe Ia) have been serving as the standard candles for cosmological distance measurements and have provided the primary evidence for the universe's accelerating expansion and the existence of dark energy [1, 2]. Nevertheless, the exact explosion mechanism and progenitor system of SNe Ia remain elusive, and associated systematic uncertainties might influence cosmological measurements (see summary by [3]). Clues to their progenitors could hide in their earliest signals, occasionally in the form of early excess flux on top of the normal baseline rise in some SNe Ia. Traditionally, the baseline model for 'normal' SNe Ia is believed to be a simple empirical power-law model ($L \propto t^{\alpha}$ with index $\alpha \sim 2$, [4, 5]) up to $40 - 60\%$ of the maximum luminosity. A handful of SNe Ia have been discovered with early excess features above the power-law rise (e.g., [6–15]), especially in the high cadence data coming from surveys such as *Kepler* and *TESS*. Distinguishing excess signals from different models requires high fidelity analysis on the early rise of SNe Ia, which is severely hampered by the inaccuracy and arbitrariness of the baseline power-law model. This issue may contribute to the variation in reported early-excess rates across different statistical samples, which can range from a few percents [16] to as high as $\sim 30\%$ [17].

In search of a fiducial analytic model for SNe Ia rise, we turn to a symbolic regression algorithm [18], which is designed to derive an analytical and interpretable function between multiple observables and variables, rather than black-box models built from other machine learning techniques. On the other hand, astronomers have been uncovering empirical laws from astronomical data since the era of Ptolemy, and symbolic regression can extend that effort in a more systematic way: it does not pre-specify a certain functional form, but instead searches a broad functional space for the best-match mathematical expressions. In this way, it can reduce human bias toward favored analytical forms or oversimplified equations, and thus has the potential to discover higher order structure in the correlations. This technique has already been used in multiple astronomical studies as emulators for

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numerical simulations [e.g., 19], though few studies so far have used it to discover new laws from large data sets. Our model may further provide a rule of thumb for distinguishing the SNe Ia with and without an extra component, and for exploring whether they form two distinct subpopulations or instead lie along a continuum. All code for this paper is made publicly available on GitHub[1].

## 2 Data and Methodology

We collect a complete list of SNe Ia covered in the footprint of *Kepler* and K2 mission as well as *TESS* Sector 1–90, and retrieved their light curves from the Mikulski Archive for Space Telescopes (MAST). The photometry were reduced following the data reduction routine described in [9, 20, 21] and [14–16] for *Kepler* and *TESS* data, respectively. We then selected a 'golden sample' consisting of 10 SNe Ia with redshift $z \lesssim 0.02$, sufficient S/N, and no prominent instrumental artifacts, such as the scattered light from the Earth and Moon, background noise, or major downlink breaks around the time of explosion, as *TESS* data are heavily influenced by those systematics. The remaining data are used for validation. We caution that only two normal SNe Ia in *Kepler* and *TESS*, SN 2018oh and SN 2023bee, have been confirmed with early excess. The data are binned to 6-hour cadence for robust photometric accuracy and uncertainty estimation with minimal impact on the later analysis.

We designed a framework based on the state-of-the-art symbolic regression algorithm `PySR`[2] for modeling early supernova light curves in a consistent, stable, and interpretable way. Our framework uses residual symbolic regression approach, invariance-based data augmentation, and bootstrapping for model selection to identify symbolic form(s) that can either universally describe or distinguish the sub-populations within the broader family of normal SNe Ia light curves analyzed in this paper. In practice, we use the operator set $\{+, -, \times, \div, \sin, \exp\}$, with corresponding complexities $\{1, 1, 2, 3, 5, 5\}$, and enforce constraints that prevent the $\sin$ and $\exp$ from nesting within one another (e.g., $\sin(\exp(x_0)))$. Such forms can behave like rapid oscillations and often indicate overfitting behavior related to random noise or Nyquist-related artifacts.

### 2.1 Residual Symbolic Regression

To make the regression stable and robust while avoiding overfitting issues and numerical artifacts, we use residual symbolic regression to model each light curve as a sum of interpretable components, rather than fitting a single expression to the full data. Our implementation first fits the data and then recursively fits the residual, with the expression complexity constrained to be at most 25, and the final expression is the sum of all resulting expressions. To prevent overfitting, we limit the number of components by allowing symbolic regression to run at most twice and retaining the second component only if it improves the Bayesian Information Criterion (BIC). In practice, adding more than two components does not produce any meaningful change in the fit, as additional terms tend to have very small amplitudes and primarily capture noise rather than real structure.

### 2.2 Invariance-Based Data Augmentations

Physical laws often possess some invariant properties, and incorporating known physical constraints can improve regression quality. In our case, the supernova light curve should be: 1) scale invariant, i.e. the amplitude can vary arbitrarily as it mostly depends on the distance to the supernovae rather than the supernovae physics; and 2) independent of $t_0$ explosion time which is itself uncertain. These invariances may also help us identify characteristic quantities that correlates with the shape of light curve, e.g. characteristic rise time if it exists. In addition, the regression is sensitive to the choice of fitting window, which is influenced largely by temporal coverage and instrumental systematics rather than supernova physics. Thus, we introduce an invariance-based data augmentation scheme to improve robustness and interpretability while reducing the risk of overfitting or unphysical results.

The augmentation is created by generating multiple shifted and scaled versions of the same light curve within the original regression window. For each light curve, to minimize edge effects, we first extend the time window by one day before the time of explosion and after the peak time, and apply random small variations in the window size at the level of $\pm 10\%$. We also randomly apply a time

[1] `https://github.com/Mark-Kanex/SNe-Ia-SR`

[2] `https://github.com/MilesCranmer/PySR`

shift $t_0$ within a range of $\pm 10\%$ of the window size, along with random amplitude scaling factors $A$. That is, we transform the data as

$$(t, f) \longrightarrow (t - t_0,\ Af,\ t_0,\ A)\,,$$

thereby changing the regression problem from modeling a single-variable function to modeling a multivariate one. We make it so the transformed points remain within the same time window as the original data for regression and plotting. This creates multiple snapshots of the same data with different starting and ending points along the curve. Because of the fixed cadence of *Kepler* and *TESS*, the algorithm occasionally encounters Nyquist-related bias, so we also augment the training sample by resampling individual data points, i.e. by marginally shifting them in time and interpolating the corresponding fluxes from nearby points. We then fit `PySR` to all of these transformed light curves at once, which encourages it to learn a single symbolic form that is invariant to time shifts in the bounds and amplitude scalings, rather than one that depends on an arbitrary choice of bounds.

### 2.3 Model Selection

Through the augmentation process, $N = 100$ resampled duplicates are created from each light curve in the training sample. For each light curve, we count how often each general form appears across all runs and set the lower bar on occurrence rate of $\sqrt{N} = 10$ for acceptable models. We further calculate a simple heuristic score to compare candidate models as a weighted combination of three terms: goodness of fit, consistency across bootstrap runs, and model complexity. The score function is defined as follows:

$$w_{R^2}\left[-\log_{10}(1 - R^2)\right] + w_{\rm occ}\,\frac{n_{\rm occ}}{N} - w_{\rm comp}\,C, \tag{1}$$

where $w_{R^2}$, $w_{\rm occ}$ and $w_{\rm comp}$ are the weights assigned to these three terms, respectively. The first term rewards models that fit the data well. The second term favors robust expressions that appear consistently across different resamples and penalizes models that are overly sensitive to perturbations, noise, or violations of the intended invariances. The final term penalizes models with high expression complexity $C$. This score is used to rank candidate symbolic forms that pass the occurrence threshold. When $R^2$ values are similar, the occurrence and complexity terms help distinguish between models, favoring robust, consistent, and simple expressions. The score is not a formal information criterion, but rather a practical way to compare models using relative differences. In practice, candidates with substantially lower scores are effectively disregarded, as they typically correspond to severely overfit, underfit, unnecessarily complex, or unstable expressions. We set ad hoc $w_{R^2} = 1$, $w_{\rm occ} = 1$, and $w_{\rm comp} = 0.10$. The final model for all light curves is selected from their highest-scoring candidates, and we then choose an overall general form that can represent these models across all light curves while retaining the key terms identified by this procedure. This criterion selects forms that are robust against the noise and perturbations and while filtering out run-to-run randomness in individual cases.

## 3 Results and conclusion

Across all supernovae, the highest-scoring and most frequently recovered functions follow a common structure consisting of a smooth linear or quadratic component plus a single sinusoidal term. Expressions containing multiple sinusoidal terms and cross terms, such as $x_0 \sin(x_0)$, occasionally occur. Including these extra terms to account for subtle structures in the data can modestly increase $R^2$, but also penalized by a dramatic increase in complexity. Given both their low recurrence in the symbolic regression results and their more complicated functional form, these expressions are not well motivated as preferred models for individual light curves under our score system. They are even less suitable as candidates for a single general form to describe all of the light curves together. Therefore, we conclude that

$$at^2 + bt + c + d\sin(et + f) \tag{2}$$

is the common model. This expression captures the main behavior of the light curves in our training sample without unnecessary complexity. It is reassuring that the selected model is consistent with previous early-time power-law descriptions of Type Ia supernova light curves over the first $\sim$ week (see Figure 1) and then gradually flattens by around $\sim 18$ days [16]. Moreover, the traditional power-law model requires an additional Gaussian or skewed-Gaussian component to fit the SNe Ia with an early excess (e.g., SN 2018oh [9] and SN 2023bee [15]). Our results place it into a single

general form that applies across multiple light curves at once as the change in sinusoidal phase $f$ can mimic the occurrence of the extra component of the early time for both SN 2018oh (see Figure 1) and SN 2023bee. Whether this is a complete description for all early excess feature for SNe Ia, however, requires larger sample for validation.

We further validate this model by fitting the complete normalized *Kepler* and *TESS* light curve sample with lower S/N and incomplete data coverage [16] to test whether the derived symbolic model can serve as a reasonable analytic model among the general Type Ia supernova population, especially in the low S/N limit. During this step we exclude objects without enough data ($< 30$ data points after binning). After fitting we utilize t-SNE method to visualize the distribution in parameter space. In t-SNE space, we identify a major branch containing most of the objects including all of the training sample, separated from two minor clusters likely originating from instrumental systematics. We then derive a most representative model with the kernel density estimation (KDE) method from the targets on the major branch. The best-fit results for individual supernovae and the KDE peak model are shown in Figure 1.

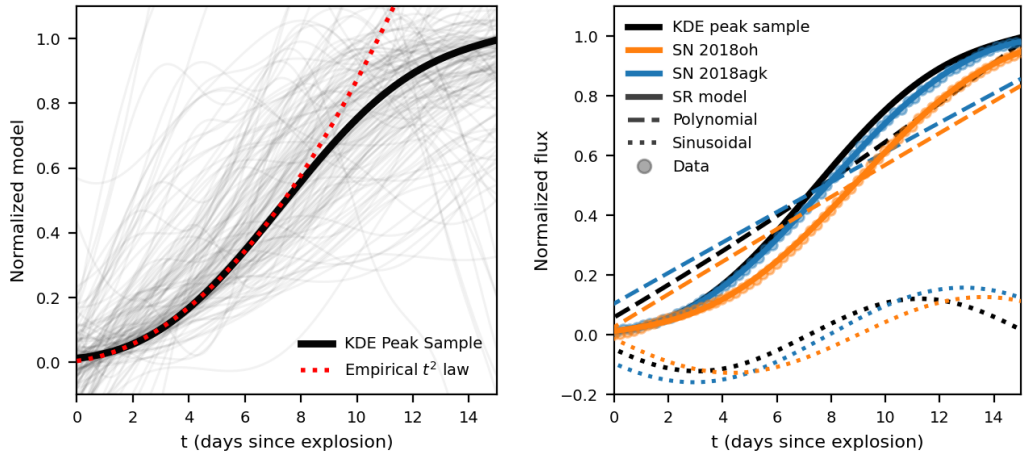


Figure 1: **Left:** The best-fit models to individual supernovae in training and validation sample, with the most representative model of SNe Ia rise defined by the KDE peak in parameter space. Red dotted line shows the empirical power-law model which can only approximate the rise for the first $\sim 8$ days. **Right:** The KDE peak model of SNe Ia rise, in comparison with two representative SNe Ia in training sample, SN 2018oh, an SNe Ia confirmed with an early excess, and SN 2018agk, an SNe Ia confirmed with a smooth power-law. The model derived by SR and two major components are plotted in different line styles. Notice that despite its relatively long rise, the flattening at the beginning of SN 2018oh's light curve indicates an early excess with amplitude of $\sim 3\%$ of its peak luminosity.

To summarize, we find that a combined quadratic and sinusoidal function can robustly fit the single-band, high-cadence light curves of SNe Ia from the time of explosion to peak using the symbolic regression algorithm alone, without prior assumptions. This analytic model will provide a useful framework for characterizing the early-time evolution of SNe Ia in upcoming high-cadence surveys, including PLATO and ULTRASAT. The resulting model is consistent with the widely used empirical power-law model describing the evolution of luminosity within the first few days after explosion, while offering additional advantage of covering the full rising phase without an arbitrary choice in the fitting range. This demonstrates the potential of the symbolic regression algorithm to uncover the hidden analytical relationship in large astronomical datasets with minimal reliance on human intuition, observation, or prior empirical assumptions.

In parameter space, SNe Ia previously confirmed with and without early excess features fall onto the same major branch, with only minor difference in the parameter range. Such a result could indicate that there is no clear distinction between the SNe Ia with and without the early excess feature, or the symbolic regression method we adopt is not sufficiently sensitive to distinguish the two classes. Our analysis is largely limited by the number of SNe Ia that are confirmed with early excess features and weak amplitude of the excess in these events, and more high-fidelity light curve samples will help further resolve the related problem.

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