Modeling Supernovae Light Curves

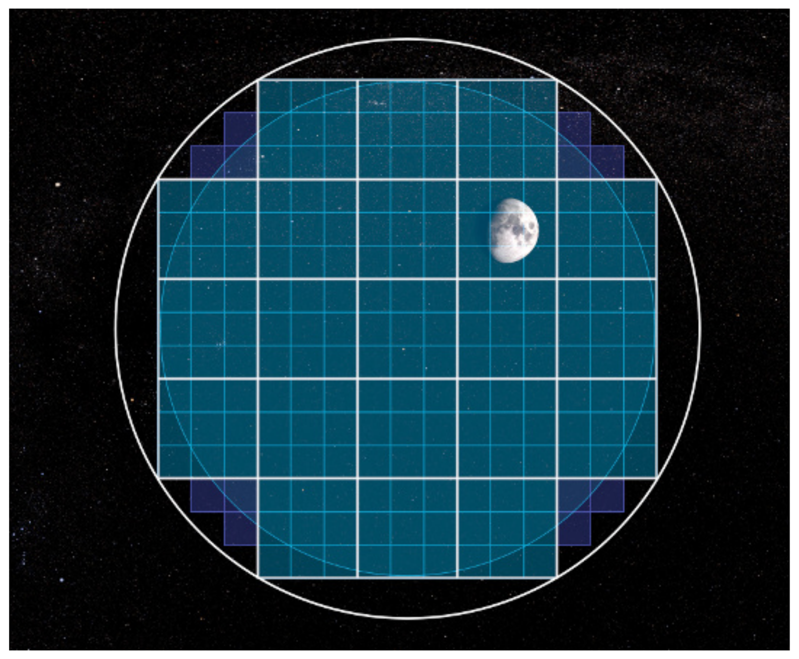
Ethan Marx[1], Adam Miller[1,2]

1. Center for Interdisciplinary Exploration and Research in Astrophysics (CIERA)/Northwestern University

2. Adler Planetarium

Introduction

In a few years, the Large Synoptic Survey Telescope (LSST) will start its 10 year survey of the night sky, delivering a massive 30 terabytes of data, and discovering over 2,000 new supernovae each night. Because LSST discovers supernovae so quickly, it is impossible to gather the spectral information for each of these exploding stars. Thus, classification of supernovae solely through the analysis of their spectra will be nowhere near exhaustive. With this issue in mind, we must look to other methods for classifying supernovae, such as analysis of their photometry, that will allow us to fully take advantage of LSST's large data set. Unfortunately, classification through photometric observations is not as straightforward as through spectra. Photometry does not have visibly discerning features for classification purposes. We will use the tools of machine learning for the purposes of supernovae classification through photometry, and eventually, for outlier detection.



The field of view for LSST – one shot is 40 times the size of the full moon. image credit: SLAC

Why Model Light Curves?

One problem with solely analyzing the photometric data of supernovae is the gaps between observations. To develop a machine learning algorithm to classify supernovae based on their photometry, we need to create a smoother curve on which to run our machine learning algorithm. A method to create accurate models of light curves given limited sets of photometric observations must be developed.

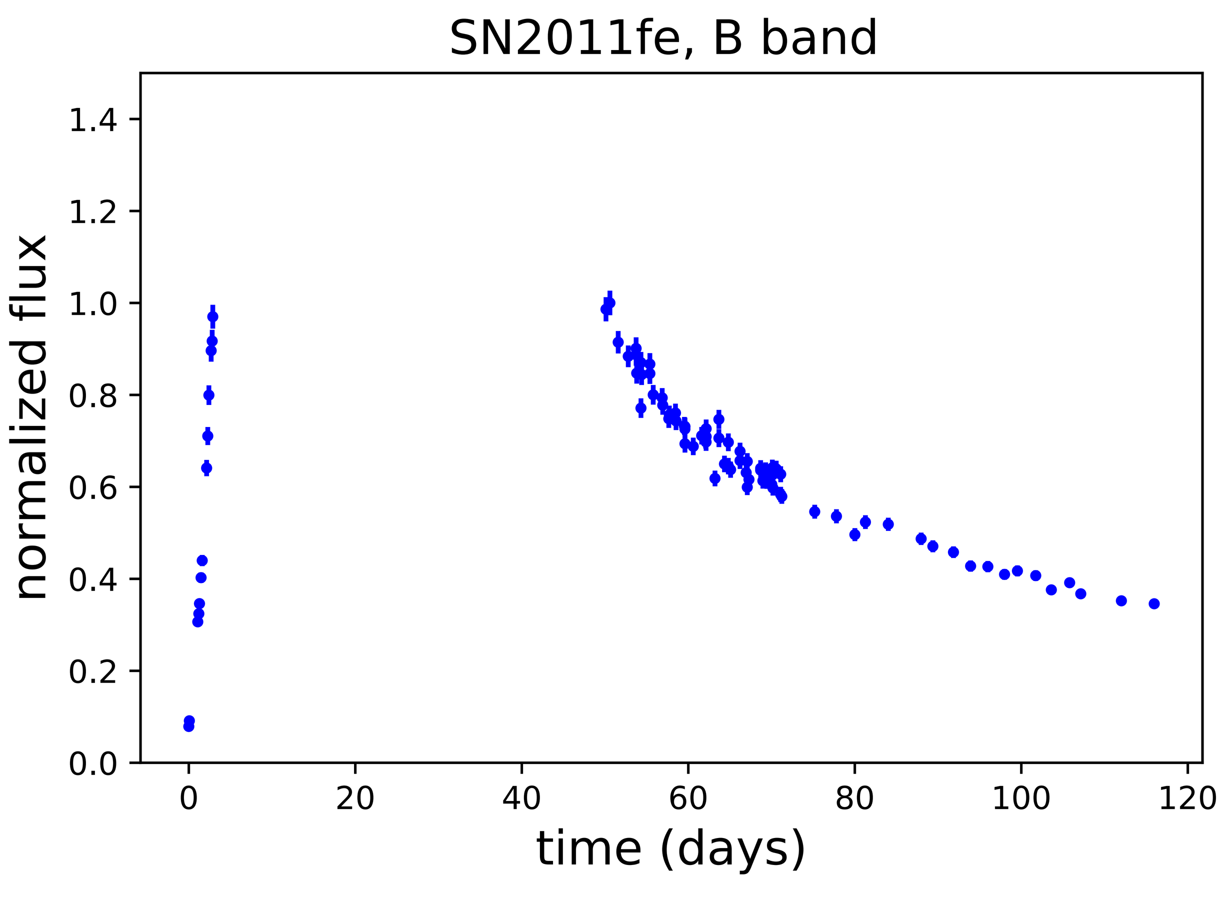


Figure 1

B Band photometry data for SN2011fe, one of the most extensively studied supernovae to date. Still, there is a clear gap in data between the rise and fall due to detector saturation.

Modeling Techniques

All data used was gathered from the Open Supernovae Catalog (Guillochon et al. 2017) For interpolation, we fitted both parametric models (Karpenka et al. 2013, Bazin et al. 2009) and Gaussian processes. Parametric fits force the model upon a given structure, but Gaussian processes uses relationships between the data points themselves (through a covariance function) to model both long term and short term behaviors. We compared the accuracy of several polynomial fits, two different parametric fits, and two Gaussian processes on 386 different supernovae including 747 different light curves across several filters.

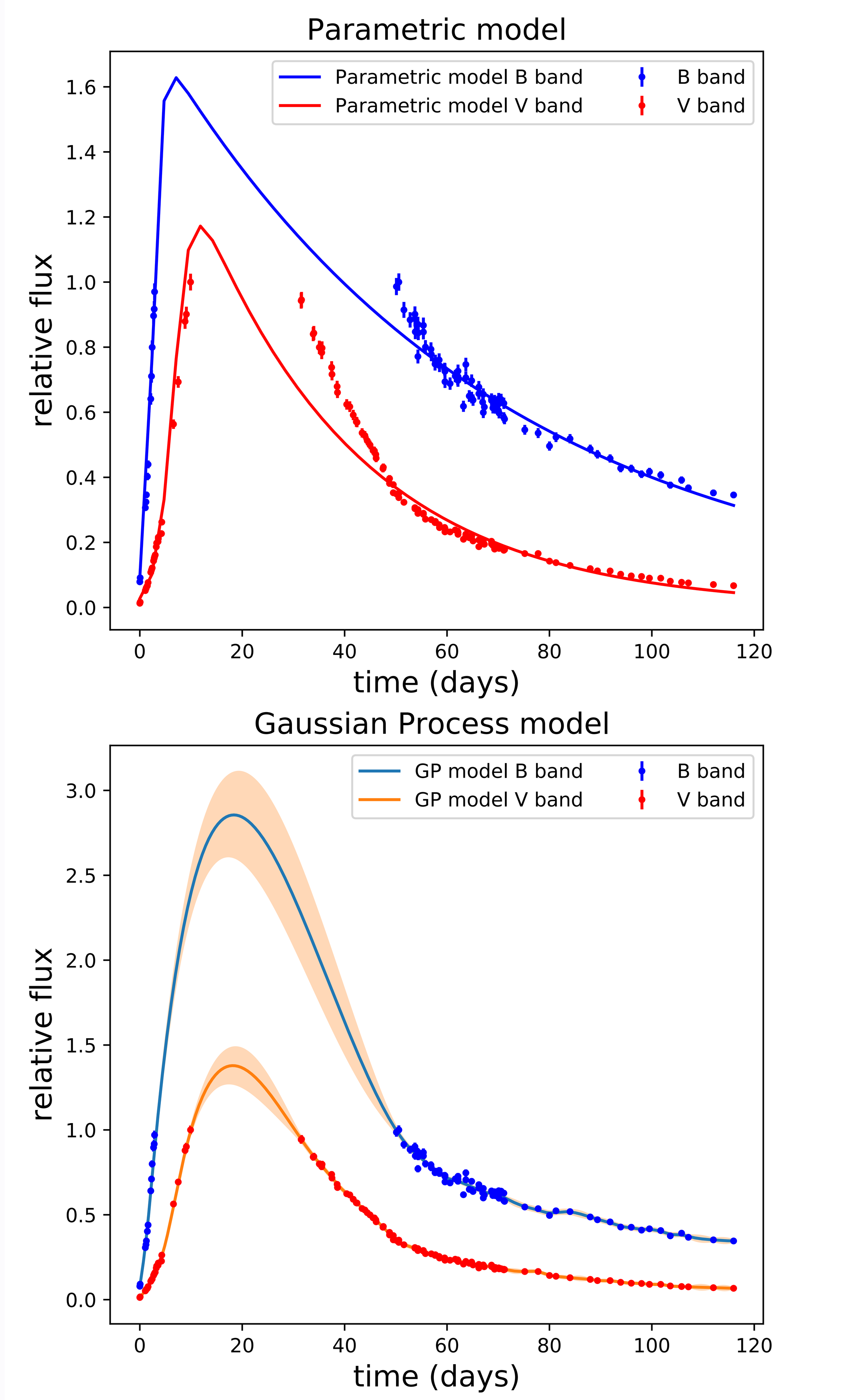


Figure 2

Comparison of a parametric model versus a Gaussian process. The Gaussian process more accurately describes the observed data.

Model Evaluation

Each model was evaluated using 'leave one out' cross validation. Looping over the data points, each iteration would remove one of the data points. We would then fit, and evaluate the model at the point in time of the missing data point, creating a set of predicted values. We used the summary statistic given below to measure how closely the predicted values determined by the models, matched the observed values gathered from the Open Supernovae Catalog.

$$\xi_i = \frac{y_{pred,i} - y_{obs,i}}{\sigma_{f,i}}$$

Equation 1

The formula used to evaluate the accuracy of the model at the point in time of the removed data point. The most accurate models minimize these values.

$$\zeta = \frac{1}{n}\sum_{1}^{n} \xi_i^2 \qquad \text{Median}\left(\xi\right)$$

Equations 2 ;3

Summary statistics calculated from the ξ values. ζ, is the LOO CV RNMSE (leave one out cross validation root normalized mean squared error) , an overall metric of how well the model reproduces missing observations. Lower values of ζ represent a better fit to the data. The median statistic was used to account for the effect of outliers on the ζ values.

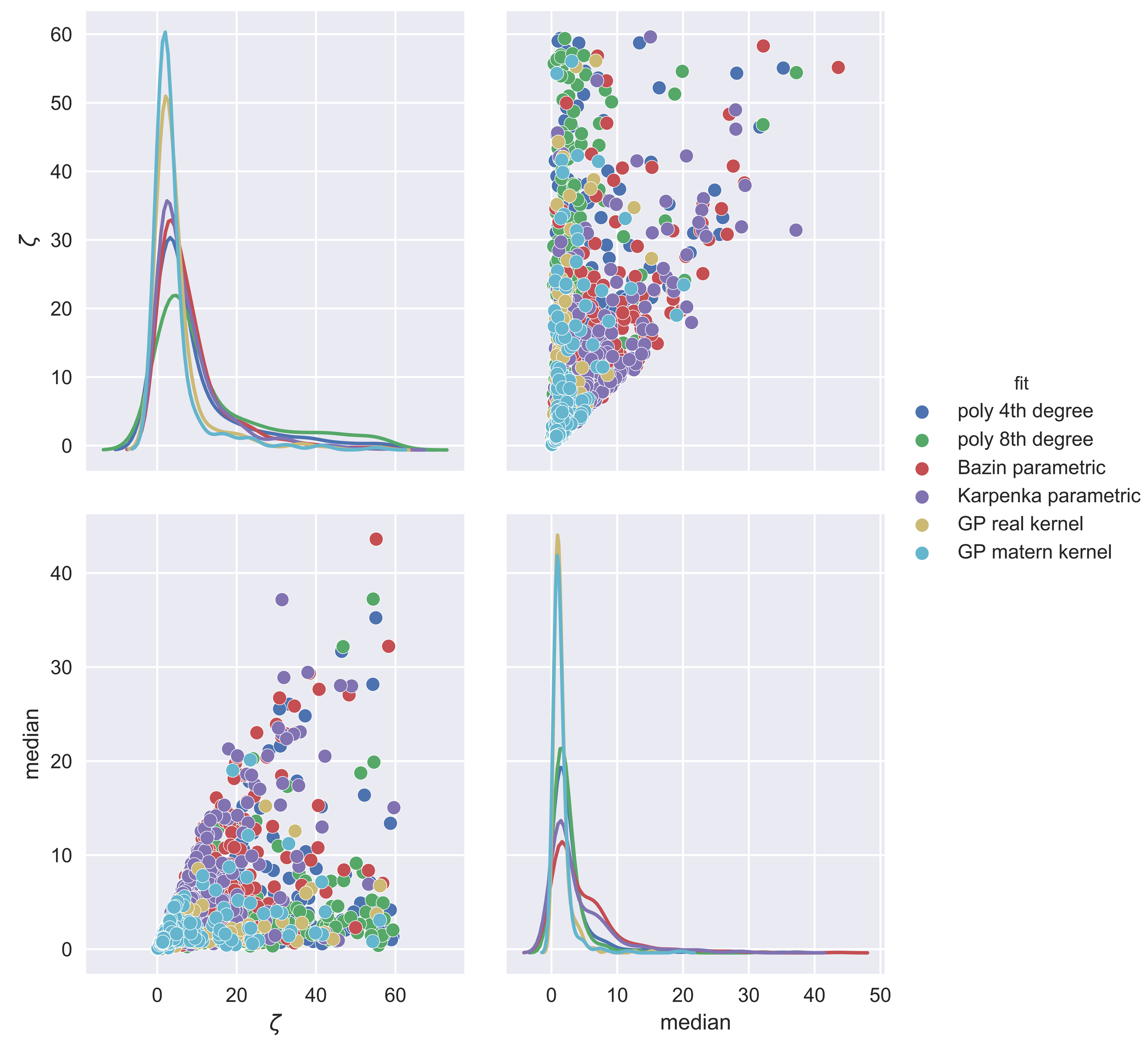


Figure 3

Figure 3 gives a scatter plot of the median vs ζ value, where each color represents a different model. We can see that the parametric models did not interpolate the missing data points as well as the Gaussian processes, confirmed by their larger ζ values.

Moving Forward: Machine Learning

With a reliable method for interpolating supernovae light curves, we have laid the framework for which we can develop a machine learning algorithm. Our next step will use wavelet decomposition, a method for feature extraction, to reduce the dimensionality of our dataset. These features accurately describe each light curve in a much simpler form. Using these features, we will train our algorithm, and use cross validation to test its accuracy.

References

Kapernka, Feroz & Hobson, 2013, MNRAS, 429, 1278
Bazin et all. 2009, A&A, 499, 653
Guillochon et al. 2017, ApJ, 835,64

Acknowledgements

I would like to thank Adam Miller for his guidance and support throughout this research project. I would also like to thank Aaron Geller for the effort he put in to allow undergraduate research programs like this to be run at CIERA. This work was funded by a 2017 LSSTC Enabling Science Grant Award # 2017-UG05, to P.I. Aaron Geller.