FITTING EARLY LIGHT CURVES OF EXPLOSIVE ASTROPHYSICS

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ABSTRACT

We have attempted to compute useful light curve features giving the rise rate and blackbody temperature for an early light curve of an explosive event such as a supernova. We fit two families of functions: an exponential in time multiplied by a blackbody spectrum; and a Bazin rise-fall function multiplied by blackbody. We have computed these best fits on 60 simulated LSST light curves from the Plasticc dataset; not just once but at every epoch that new data arrives.

1 Introduction

We have benchmarked a feature set for observations of early explosive transients, based on fitting parametric functions simultaneously in both time and wavelength. It will work best when observations are with many filters, to provide a range of wavelengths: the target is LSST, where we expect 6 filters ($ugrizy$). While there has been much work on modelling post-peak supernova light curves, there seems to be much less on useful features from the pre-peak light curve.

The LSST project will release large numbers of alert each night[1], and the UK transient broker Lasair[2] will add value to the stream, and filter out precisely what each user wants. The filters are built from *features* of the light curve, that should capture some essence of a light curve, features that can be used in the SQL-based statement of a filter. We prefer features to classification, so that Lasair is a platform for scientists to ask questions, rather than a provider of answers. But in both cases, feature or classifier, it is important for the system to be able to say *I don't know*, rather than sometimes providing a useless number.

Under the leadership of Eric Bellm, the LSST project is considering a number of published features[3], mostly concentrated on periodic and stochastic variables. The "Light-Curve-Features" library[4] has another selection of features, many built from curve fitting. We note in passing that there are not many "multi-wavelength" features of light curves. Early transient surveys used one filter, or no filter, so a light curve was necessarily a scalar plot of flux against time. ZTF had 3 filters, but LSST will have six filters; therefore colour information becomes much more useful. We shall be modelling the light curve as a "spectrumcurve" – where flux is a function of both time and wavelength.

In this note, however, we try to search for and characterise explosive transients, such as supernovae, kilonovae, tidal disruption events, etc. There are two main characteristics of these: (1) A host galaxy in which the explosion resides, although sometimes it can be too faint to be seen. (2) They are not variable sources; rather the light curve starts suddenly, as soon as its flux is 5σ above the reference sky, and the survey reports an alert. We are interested in finding unusual supernovae, where a rapid follow-up is crucial for the science; these are characterised by the rise rate of the flux before peak, and the fall rate after peak. The six filters of LSST will allow us to fit also in this direction, producing a black-body temperature. These are the features we would like to extract from an early light curve: rise and fall rates, and effective black body temperature.

Sako et.al.[6] fit historical observed light curves of different types of supernovae, to classify a new supernova. Guillochon et.al.[7] built MOSFiT, an architecture and collection of models, so that light curves can interoperate with classification software.

There are many ways to convert a time-wavelength light curve into an image, so that the power of machne learning can be brought to bear. Conley et.al.[8] fit sophisticated complete light curves, including colour information, to high redshift SNIa candidates. Vincenzi et.al.[9] use gaussian process fitting to create a library of time-wavelength images, and use these to classify full light curves of supernovae. `SNGuess` from Miranda et.al.[10] uses some 27 features of the light curve and sky context, with a machine learning system, to make classifications. Mahabal's dm/dt plots are images that can also be used for classification, created for example by the light-curve-dmdt-exec code[11]. In the following, we model time-wavelength flux data with a product of a black body flux and either a Bazin[5] or exponential in time.

2 Modeling the Light Curve

We model the flux as a function of

- time in days, with the zero of time at or near the peak flux, and
- wavelength in microns, ranging from g at 0.5 micron to y at 1.0 micron.

The model splits into a product of a function of time and a function of wavelength. We note that this implies no heating or cooling as the supernova progresses, which is simple but unphysical. In this work, the function of wavelength is a blackbody spectrum. The flux from LSST is expressed in Jansky, or flux per unit frequency:

$$B(\nu;T) = \frac{2h\nu^3}{c^2}\frac{1}{\exp(h\nu/kT) - 1} \tag{1}$$

This can be converted for use with wavelengths using $\nu = c/\lambda$:

$$B(\lambda;T) = \frac{2hc}{\lambda^3}\frac{1}{\exp(Q/\lambda T) - 1]} \tag{2}$$

If λ is measured in microns, and the temperature in thousands of Kelvin, then $Q = hc/k = 14.387$. This function is shown as Figure 1, together with the wavelengths of the five filters we will use. For temperatures much higher than 4000K, the flux decreases with wavelength, and for temperatures much less than 4000K, the flux increases with wavelength. In these cases, a linear relation would suffice between wavelength and flux, but at 4000K, the flux rises then falls with wavelength. For the time component of the fitting model, we consider first the Bazin model[5], a simple

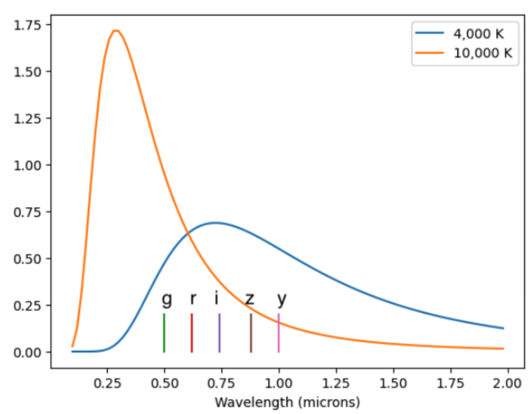

Figure 1: Blackbody flux at 4000 and 10000 Kelvin, with wavelengths of five filters

function that increases exponentially for large negative times, and decreases exponentially for large positive times. It is characterised by a rise rate k_r and a fall rate k_f:

$$b(\tau) = \exp(-k_f\tau)/[1 + \exp(-k_r\tau)] \tag{3}$$

As noted above, when τ is large and negative, the Bazin curve is approximated by an exponential with $k = k_r - k_f$:

$$e(\tau) = \exp(k\tau) \tag{4}$$

We combine $B(\lambda;T)$ and either $b(\tau)$ or $e(\tau)$ as a fitting function for the flux-light curves measured through multiple filters:

$$F_b(t,\lambda) = AB(\lambda,T)b(t - t_0)$$
$$F_e(t,\lambda) = AB(\lambda,T)e(t)$$

The first version (Bazin) has five free parameters: A, T, t_0, k_f, and k_r, and the second (Exponential) version has three free parameters: A, T, k.

Figure 3 shows the transition from fitting with a 3-parameter exponential to fitting with the 5-parameter Bazin. The green diamonds in the top panel show the idealised light curve, an equally-spaced Bazin with $k_r = 2.5$ and $k_f = 0.5$. We imagine the data comes in from left to right, with increasing time, and for each data point we fit with an exponential,

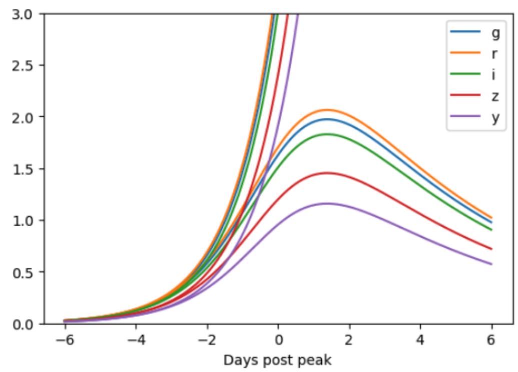

Figure 2: Bazin and exponential functions of time, multiplied by 4000K blackbody, at five wavelengths.

as shown with the red blobs below. Each blob represents an exponential fit to the data above and to the left. At first, the fitted value is exactly as the mathematics predicts: $k = k_r - k_f = 2.0$. But as we approach the peak of the Bazin data, the fitted k falls. The blue blobs at the right show the true Bazin parameters. We will see the same behaviour in the fits described below: the fitted exponential rate falls as peak approaches, which splits into two Bazin dates – rise and fall – at and past the peak.

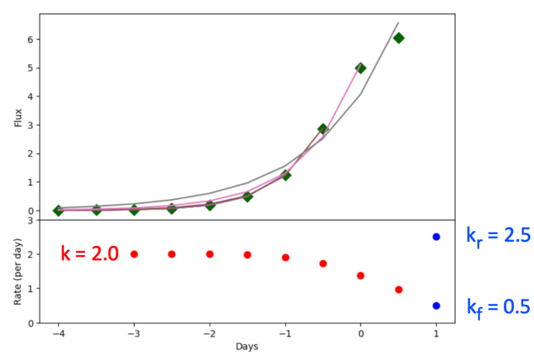

Figure 3: Fitting a Bazin light curve with exponentials.

3 Simulated LSST Data

In order to test our fitting procedure, and its ability to make useful light-curve features, we want to test it on real explosive transients, as recorded by a suitable transient survey. This means multiple filters, where the number is greater than the two filters provided by the ZTF public survey, more like the six that will be provided by LSST.

We have chosen a simulated transient survey "The Photometric LSST Astronomical Time-Series Classification Challenge" (PLAsTiCC) [12] that has been used for classification challenges in the past. In addition to providing fluxes at many wavelengths, it also provides a training set with each light curve labelled by the type of explosive event – SNIa, SNII, SLSN, KN, etc. The simulated light curves are provided in six filters, follow the expected LSST cadence, and effects of redshift and galactic extinction are included. Of the types of explosive events, we have chosen six, each listed with their abbreviation, description and responsible authors:

- SNIa – WD detonation, Type Ia SN (R.Kessler)
- PecSNIax – Peculiar SNIax (S.Jha, M.Dai)
- SNIbc – Core Collapse, Type Ibc SN (A.Villar, R.Kessler, J.Pierel)
- SNII – Core Collapse, Type II SN (S.González-Gaitán, L.Galbany, R.Kessler, J. Pierel, A.Villar)
- SLSN – Super-Luminous SN (magnetar) (A.Villar)
- TDE – Tidal Disruption Event (A.Villar)

Figure 4 is an example of a SNIa light curve from Plasticc. We have not used the u-filter, as its fluxes seem unreliable, but only the five $grizy$ filters. Each light curve from Plasticc has a long section of essentially zero flux before the

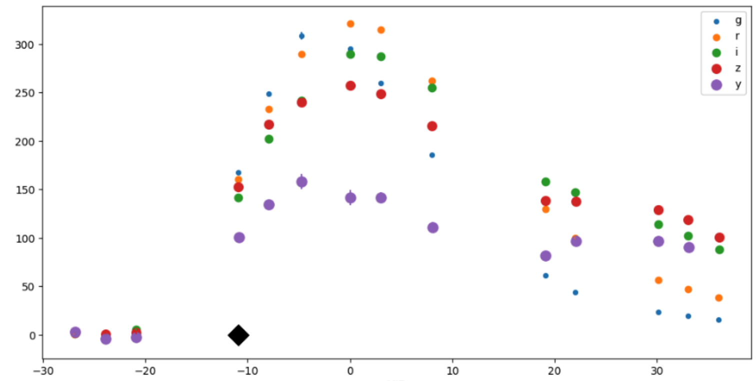

Figure 4: A simulated light curve from Plasticc, id=29088.

explosive event starts, whereas the LSST will not report these quiescent detections: the first alert is sent only when the flux rises above background. This is marked with the black diamond in Figure 4. In this work, we search for this “discovery” as a 7σ deviation from the previous background. LSST will also deliver some forced photometry from before the discovery time, which we have simulated by allowing all data after 20 days pre-discovery.

4 Fitting the Simulated Data

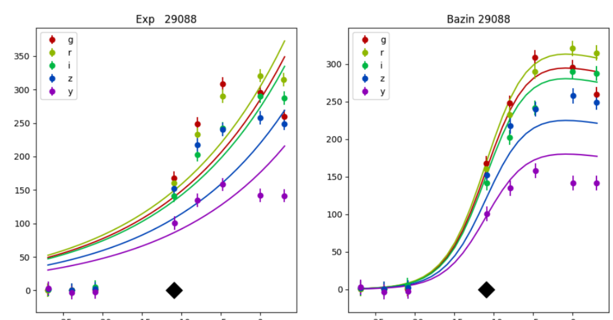

Figure 5: Early light curve from Plasticc (id=29088), fitted with both exponential (left) and Bazin (right).

We have used the curve fitting package `scipy.leastsq` to minimise the sum of the squares of the residuals, over a two-dimensional time-wavelength space. The return from this process is: (a) the best fit, and (b) the covariance matrix, that can be converted to error bars on the fitted parameters – see Figure 6 for these, where a few of the parameters have error bars bigger than the size of the marker. Sometimes the curve fitting doesn’t converge; for example when trying to fit a Bazin curve well before the peak it is intuitively obvious that there is no available information about the fall rate. Figure 5 shows how the exponential and Bazin models can be used to fit the light curve of Figure 4. We have removed the data for $t > 5$, so we are fitting an event just past peak, with 40 photometric measurements. The Bazin is the best fit – see below for the criterion.

From the thousands of light curves in the Plasticc training set, we picked about 60 by eye, with about equal numbers from the five categories listed above. We chose those light curves that start with flux near zero, then have a rise, a peak, and a fall. We did not choose those that seemed to be just jagged noise, nor did we choose those where there is only a pre-peak or post-peak light curve.

We ran the curve-fitting process for each day on which new data appeared, using that data and the data before it, back to 20 days before the discovery time. As can be seen in Figure 4, there are generally many detections at almost the same time, so we only ran the fitting when all the data is in for that day.

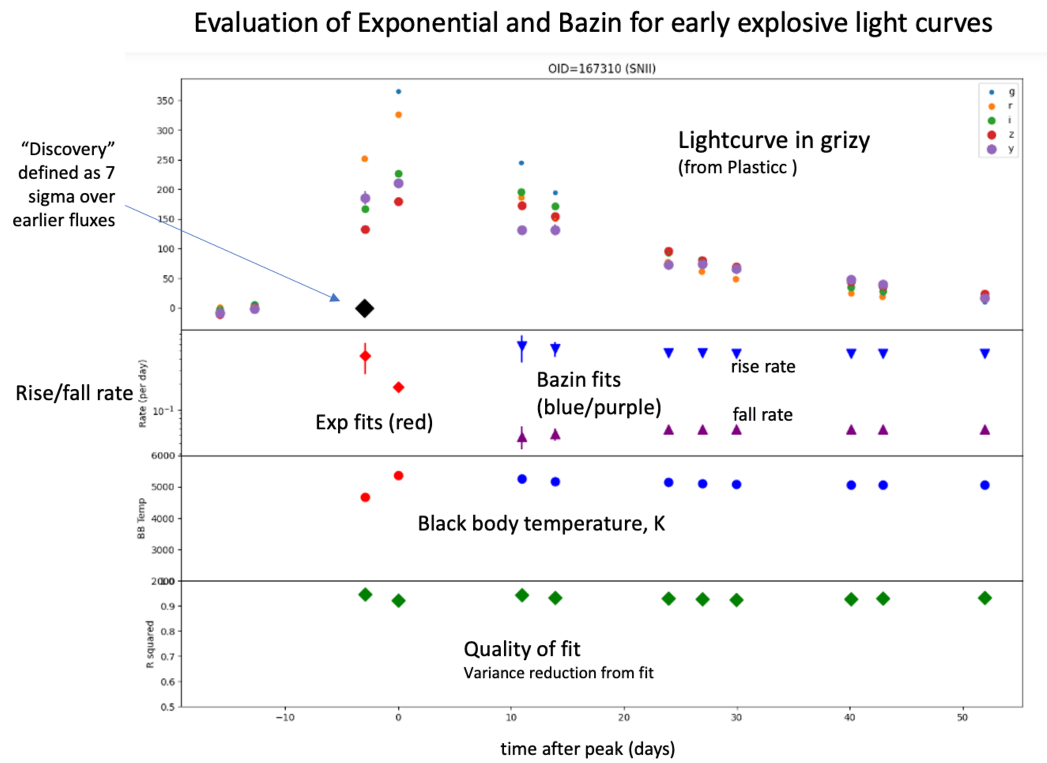

Figure 6: Repeated fitting of a light curve for each day of new data (id=167310). Top of 4: the light curve data; then the best fit rise/fall rates, red for exponential and blie/purple for Bazin; the blackbody temperature fit; bottom the R^2 measure of the quality of fit.

As noted above, one of the objectives of this work is to make useful features from the early light curves of these explosive events; and that implies not quoting a numerical value that is not worth having. Therefore, if the curve-fitting doesn't converge in good time, we simply do not quote a value – value of feature = NULL.

There are other conditions when we judge that there is no sensible result, and do not quote any values:

- if the rise rate or fall rate is negative, or
- if the rise rate or fall rate rate is greater then 2, or
- if the errorbar on a quantity is larger than the magnitude of the quantity itself.

We have defined the quality of the fit with the coefficient of determination, or "R-squared". If SST is the sum of the squares of the difference between the data and its mean, and SSR is the sum of squares of the differences between data and the best fit, then $R^2 = 1 - SSR/SST$. In Figure 5, the R^2 for the exponential (left) is 0.80, and for the Bazin (right), the R^2 is 0.98, which is a better fit, we declare the Bazin to be the best model for fitting at this stage of the light curve.

Figure 6 shows our complete analysis of a light curve from Plasticc, running a best-fit analysis each time new photometry appears. Sometimes our procedure fails to reach a sensible result, and so nothing is shown, as with the first detections before $t = -20$,

The detected fluxes are in the top panel, and the lower three panels show:

- Rise and fall rates: k for the exponential in red; k_r and k_f for the Bazin fit in blue and purple. Error bars are derived from the least squares software used for the fitting, and reflect the curvature of the residual at the minimum.
- The black body temperature from the simultaneous time-wavelength fitting.
- The quality of the fit as given by R-squared.

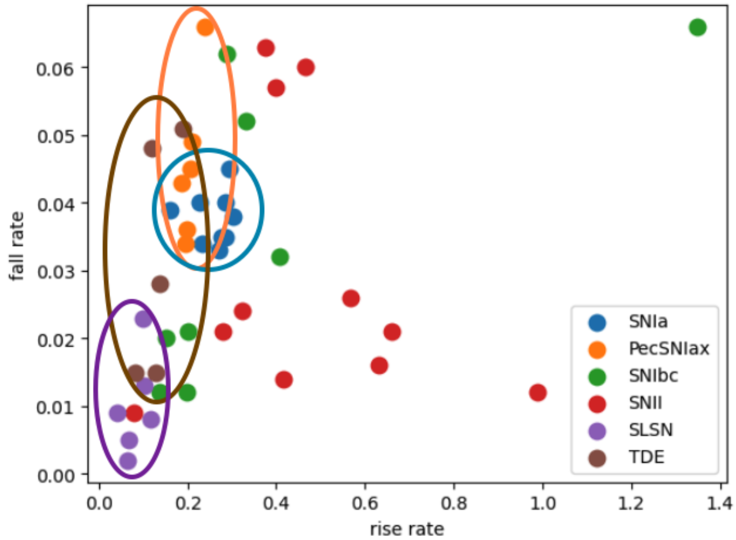

Figure 7: A scatter plot of rise rate and fall rate for the final Bazin fit well after the peak flux.

5 Conclusion

While our objective here is the difficult problem of early light curves, we can show that the fitting method works at least for late light curves. Figure 7 is a scatter plot of the rise rate and fall rate (k_r and k_f) computed at the end of the light curve, for the five different types of supernova. The superluminous supernovae (SLSN) are clearly clustered in the corner with slow rise and slow fall. The SN Ia are tightly clustered with rise rate between 0.2 and 0.4 per day; and the peculiar SNIax are differentiated with a fast fall rate.

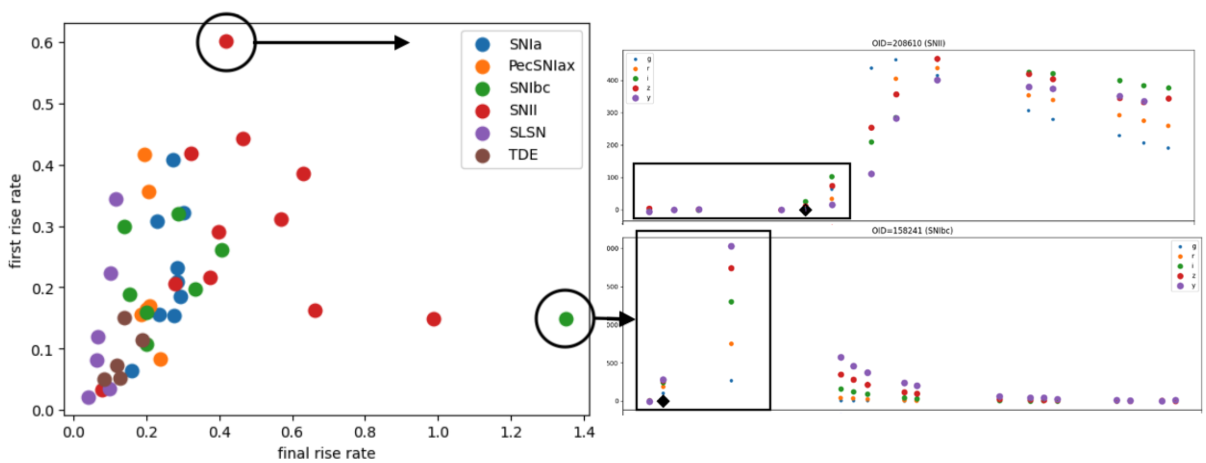

Figure 8: A scatter plot of first (exponential) fit to the rise rate, vs the rise rate for the final Bazin fit – well after the peak flux.

Figure 8 attempts to show how well the first measurement of the rise rate correlates with the final measurement. The first was in each case the exponential fit, based on very little data, and the last can be thought of as the "true" rise rate, determined by the entire post-peak light curve. It is clear there is a strong diagonal on the plot, showing the worth of the feature we have computed. However, there are some outliers, shown in more detail to the right. The top one has a sudden brightening in just 2 days, giving rise to the overestimate of initial rise rate. The bottom one has no date between discovery and peak, making the early determination of rise rate rather difficult.

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