Comparisons of Type Ia Supernova Light Curves in the UV and Optical with the Swift Ultra-violet/Optical Telescope

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Abstract

We examine the light-curve parameters of 97 nearby Type Ia supernovae (SN Ia) in the ultraviolet and optical using observations from the Swift Ultra-violet/Optical Telescope. Our light-curve models used linear combinations of templates, which were based on functional principal component analysis of the optical photometry of SN Ia. The weights for each principal component used in the fit capture certain aspects of the light-curve properties. We find that there is little difference in the overall variability of principal component scores across filters. We also find correlations between certain filters and PC components, indicating that the UV and optical properties seem to be tied together. This is a promising step in UV SN Ia analysis and suggests that UV light curves may be used to infer optical properties, paving the way for future cosmological studies.

1. Introduction

Type Ia supernovae (SN Ia) are useful as cosmological tools due to their highly uniform optical luminosity, which correlates strongly with their optical light-curve profile and color (Pskovskii 1977; Phillips 1993; Riess et al. 1996; Phillips et al. 1999). This has led to their use in studies for distance measurements and constraints on cosmological parameters (Riess et al. 1998; Perlmutter et al. 1999). In optical wavelengths, SN Ia have a strong relationship between their peak luminosity and luminosity decline rate, leading to their widespread usage as standardizable candles (Riess et al. 1996; Perlmutter et al. 1999; Garnavich et al. 2004). Another common method is measuring the stretch of a light curve when fitting to a template (Goldhaber et al. 2001).

The luminosity–width relation shows that more luminous SN Ia have broader light curves. The cause of this relation is believed to be the production of $^{56}$Ni during the SN Ia explosion, and the change in the temperature and ionization evolution as a result (Nugent et al. 1995; Höflich et al. 1996; Mazzali et al. 2001; Kasen & Woosley 2007). $^{56}$Ni drives much of the SN Ia luminosity, and the light-curve shape is greatly affected by opacity effects from $^{56}$Ni and Fe group elements (Mazzali et al. 2007).

Subsequent studies have looked beyond the optical to see if these strong correlations still hold true at other wavelengths. For example, the near-infrared (NIR) luminosity has been shown to be less susceptible to the effects of interstellar extinction while also having a diminished dependence on the shape of the light curve (Krisiunas et al. 2000; Wood-Vasey et al. 2008; Mandel et al. 2011; Kattner et al. 2012). Meanwhile, studies in the near-UV have shown that the correlations have a much larger scatter (Jha et al. 2006; Kessler et al. 2009; Brown et al. 2010, 2017; Milne et al. 2010). Understanding the scatter at shorter wavelengths will be an important task, as it enables us to better predict SN Ia properties at larger distances where their rest-frame UV emission will be redshifted into the optical.

One issue with analyzing the UV light curves of SN Ia is the lack of empirical templates at those wavelengths. In the optical, the most common optical fitting techniques are MLCS (Riess et al. 1996; Jha et al. 2007) and SALT3 (Kenworthy et al. 2021). MLCS directly models the light-curve data using vectorized templates over a hypothesized grid, whereas SALT3 uses spectral energy distributions to model light curves. Here, we use templates based on functional principal component analysis (FPCA) of optical SN Ia light curves (He et al. 2018). We apply these templates to UV and optical observations of 97 SN Ia to examine how well this technique can characterize light curves in a regime that it was not trained in, and if the fitted parameters can shed new light on the diversity of SN Ia in the UV.

In Section 2 we describe our observations and methodology for template fitting. Then in Section 3 we apply statistical tests to compare the diversity and correlation of our fitted parameters in the UV and optical regimes. Finally, in Section 4 we examine our results in detail and summarize our work in Section 5.

2. Methods

2.1. Observations

Observations were done with the Ultra-violet Optical Telescope (UVOT; Roming et al. 2005) at the Neil Gehrels Swift Observatory (Gehrels et al. 2004). Observations were usually performed in all six medium-band UVOT filters: UVW2, UVM2, UBV1, U, B, and V. See Poole et al. (2008) for calibration and filter curve details, and Brown et al. (2010) for the effective throughput for an SN Ia. In total, 219 SN Ia were observed by Swift UVOT between 2005 March and 2016 October (SN Ia 2005am through 2016gxp, inclusive) with...
Figure 1. Examples of the effect that each PC template has on the light curve for a range of common $B$-band PC score weights. The PC1 template mostly controls the late-phase decline rate, the PC2 template controls the overall stretch of the light curve and the postpeak decline rate, and the PC3 template plays a role in the prepeak rise rate and the late-phase flux.

Figure 2. Swift observations of SN2011by (blue) and the three-template model (orange) with 1σ errors (red). A phase of 0 in each subplot corresponds to the date of the modeled peak brightness for each band.
photometry available through the Swift Optical Ultra-violet Supernova Archive (SOUSA; Brown et al. 2014). A 3" or 5" aperture was used to maximize the signal-to-noise ratio, and zero-points were based on the updated calibration of Breeveld et al. (2011) and the time sensitivity correction from 2015 July.

Upon manual inspection of the galaxy-subtracted UVOT light curves, we selected 110 SN Ia which had at least four data points in the UVW1 filter covering the peak and early decline. Due to the faintness of SN Ia in the mid-UV, some did not have adequate light curves in UVW2 and UVM2, and some were saturated in the $U$, $B$, and $V$ filters at peak. The light curves were initially fit following the procedure in Brown et al. (2017). Template light curves were fit to our data using the peak magnitude, time of maximum, and stretch (linear scaling in the time axis) as free parameters. We used the $B$ and $V$ template curves from MLCS2k2 (Jha et al. 2007) and the UVW2, UVM2, and UVW1 light curves

| Filter Type | Training Set Sample Size | Testing Set Sample Size | 3 Template Mean | 3 Template $\sigma$ | 4 Template Mean | 4 Template $\sigma$ |
|-------------|--------------------------|-------------------------|-----------------|-----------------|-----------------|-----------------|
| W2          | 22                       | 10                      | 5.4             | 0.7             | 12.3            | 0.7             |
| M2          | 18                       | 8                       | 6.3             | 1.4             | 17.0            | 1.8             |
| W1          | 18                       | 9                       | 4.9             | 1.3             | 12.8            | 1.4             |
| U           | 23                       | 10                      | 3.5             | 1.4             | 10.4            | 1.5             |
| B           | 23                       | 10                      | 3.0             | 1.7             | 9.6             | 1.9             |
| V           | 16                       | 8                       | 4.0             | 1.5             | 14.0            | 1.6             |

Note. Taken from 100 random samples of SN2011by data. In general, a lower AIC score indicates a more favorable model.

![Figure 3. The $R^2$ values of modeled SN Ia in each band. This value measures the amount of variance in the data that is explained by the model on a scale of 0–1. This measurement is done without accounting for the known observational error in the data, and is thus a lower limit on the true $R^2$ value. The notches on each box plot indicate the uncertainty in the median, and the whiskers indicate 1.5 $\times$ IQR distance.](image)

### Table 2

| Band | Interquartile Range | Brown–Forsythe Statistic | Brown–Forsythe P-Value |
|------|---------------------|--------------------------|------------------------|
| W2   | 2.062               | 0.169                    | 0.682                  |
| M2   | 2.235               | 0.012                    | 0.913                  |
| W1   | 1.913               | 0.112                    | 0.738                  |
| U    | 2.679               | 0.118                    | 0.732                  |
| B    | 2.320               | ...                      | ...                    |
| V    | 2.597               | 1.516                    | 0.221                  |

Note. Similar IQR scores and P-values $>0.05$ would suggest that there is no statistical difference in the variability between the bands.

### Table 3

| Band | Interquartile Range | Brown–Forsythe Statistic | Brown–Forsythe P-Value |
|------|---------------------|--------------------------|------------------------|
| W2   | 1.304               | 0.426                    | 0.516                  |
| M2   | 1.731               | 3.118                    | 0.082                  |
| W1   | 1.110               | 0.359                    | 0.550                  |
| U    | 1.095               | 0                        | 0.983                  |
| B    | 0.900               | ...                      | ...                    |
| V    | 0.581               | 10.731                   | 0.001                  |

Note. Similar IQR scores and P-values $>0.05$ would suggest that there is no statistical difference in the variability between the bands.

### Table 4

| Band | Interquartile Range | Brown–Forsythe Statistic | Brown–Forsythe P-Value |
|------|---------------------|--------------------------|------------------------|
| W2   | 0.861               | 7.804                    | 0.007                  |
| M2   | 0.925               | 13.237                   | 0.001                  |
| W1   | 1.444               | 28.489                   | 0                      |
| U    | 1.075               | 21.533                   | 0                      |
| B    | 0.448               | ...                      | ...                    |
| V    | 0.481               | 0.062                    | 0.804                  |

Note. Similar IQR scores and P-values $>0.05$ would suggest that there is no statistical difference in the variability between the bands.

### Table 5

| Band | Interquartile Range | Brown–Forsythe Statistic | Brown–Forsythe P-Value |
|------|---------------------|--------------------------|------------------------|
| W2   | 0.350               | 0.008                    | 0.930                  |
| M2   | 0.473               | 0.107                    | 0.745                  |
| W1   | 0.367               | 0.533                    | 0.219                  |
| U    | 0.337               | 0.031                    | 0.861                  |
| B    | 0.363               | ...                      | ...                    |
| V    | 0.188               | 9.904                    | 0.002                  |

Note. Similar IQR scores and P-values $>0.05$ would suggest that there is no statistical difference in the variability between the bands.
of SN 2011fe (Brown et al. 2012). The UVW1 light curve of SN 2011fe was also used to fit the $U$-band light curves due to the similarity of the mean light curves of $U$ and UVW1 bands found by Milne et al. (2010) and the saturation of the Swift $U$-band light curve of SN 2011fe near the peak.

### 2.2. FPCA Model

To model our sample, we used templates constructed from functional principal component analysis (FPCA, He et al. 2018), a statistical method that uses a linear combination of a mean function and a few principal component (PC) functions to
represent the light curve. The coefficients associated with these functions are called PC scores. The mean light-curve function and PC functions were trained using a data set of light-curve photometry for 111 SN Ia in the BVRI bands. A four-PC template was created for each band, as well as a generic (band-vague) template that combined the training data across bands that can be used to model light curves in any filter.

To retrain the FPCA model to include UV photometry would require more quality observations and an amount of work beyond the scope of this paper. Rather, we take the would require more quality observations and an amount of work beyond the scope of this paper.

To determine how many principal components were needed to ensure a good quality fit for our data set, we employed several tests of model selection. From the preliminary modeling as our zero-point.

\[
\text{Phase}_i = \frac{\text{MJD}_i - \text{MJD}_{\text{peak}}}{1 + z}.
\] (1)

We then removed data points that occur 10 days before the peak or 40 days after the peak, as those are outside of the domain of the template. We ensured that there was at least one data point before the peak and one at least 15 days after the peak, and that there was a minimum of five data points. The template models were then linearly interpolated to match the phases of the observations, and linearly combined to match the observed light curve with weights for the templates determined by the curve_fit package from the SciPy library in Python (Virtanen et al. 2020). The program attempts to fit the function to the data by minimizing the nonlinear least squared errors. Equation (2) is an example of the function,

\[
\text{LC}(p) = M_{\text{peak}} + \text{Mean}_{\text{template}}(p) + \sum_{i=1}^{N} W_i \ast \text{PC}_i(p)
\] (2)

where \( p \) is the phase, \( M_{\text{peak}} \) is the peak magnitude (a free parameter, but given an initial guess based on the preliminary modeling estimates), \( \text{Mean}_{\text{template}} \) is the mean light curve from the template, and \( W_i \) is the weight of each principal component as determined by curve_fit.

In total, there were 97 SN Ia that had a fitted light curve in at least one filter, and 14 SN Ia that had a fitted light curve in every filter (see Figure 2 for example). The UVM2 filter had the fewest well-fit light curves due to the lower S/N of observations compared to other filters. Uncertainties in our model fits were determined by examining the full covariance matrix that results in output by the curve_fit package. We measured the \( R^2 \) values for the modeled SN Ia (Figure 3) as a test of goodness-of-fit, and find that the majority of SN Ia behavior is well explained by our model. The U and UVW1 curves (which were not included in the training of the band-vague fitting) are fit with similar accuracy to the B and V band, respectively, and the PC fits explain 95% of the points for 75% of the mid-UV (UVM2 and UVW2) light curves.

2.4. Model Selection

To determine how many principal components were needed to ensure a good quality fit for our data set, we employed several tests of model selection. From the 14 SN Ia with fits in all six bands, we selected four that had a relatively large number of observations (SN2005ke, SN2007af, SN2007on, SN2011by) to serve as test cases. Using the train_test_split package in the scikit-learn library in Python (Pedregosa et al. 2011), we performed 100 bootstrap draws from each SN Ia with a 70/30 split between the training and testing sample sizes (Figure 4). This allowed us to test the robustness of our fit with light curves that have sparse or inconsistent sampling, which is a more realistic case for the majority of our observations.

The Akaike information criterion (AIC; Akaike 1974) was calculated for each bootstrap sample and the mean AIC score for the two-, three-, and four-PC models were compared. The AIC score is a comparison test that measures how well a model fits a data set given a certain level of model complexity. In general, a lower AIC score indicates a better model. We employed a modified version of the AIC to account for the
relatively small sample size, as shown in Equation (3).

\[
\text{AIC} = 2k - 2\ln(\hat{L})
\]

\[
\text{AIC}_{\text{small sample}} = \text{AIC} + \frac{2k^2 + 2k}{n - k - 1}.
\]  

(3)

\(\hat{L}\) is the maximum value of the likelihood function of the model, \(k\) is the number of parameters, and \(n\) is the sample size. We also explored using the Bayesian information criterion, but determined that our sample sizes were too small for an accurate assessment.

Overall, we found that the two-PC and three-PC models had the lowest mean AIC scores in all six filters, signifying them as more appropriate models than the four-PC model to use for our analysis. Between the two-PC and three-PC models, neither one had a significant difference when examining the larger data set. Future work with the FPCA template fitting could include individualized fitting for each SN Ia and filter with more rigorous testing, but for uniform fitting we chose the three-PC model. It added robustness to our modeling by improving our estimates of the rise of the light curves, with a minor risk of overfitting certain SN Ia.

### 3. Analysis and Results

We employed a series of statistical tests to examine the similarity in the distribution of PC scores across the different bands. The Brown–Forsythe test (Brown & Forsythe 1974) examines the differences in the variance of two data sets by examining the distribution around the median. The null hypothesis for this test is that there is no statistical difference in the variance, while a \(P\)-Value below 0.05 would indicate there is a difference in variance.

Additionally, we visually inspected the data variability with box plots (Figure 5; Tukey 1977). Box plots allow us to identify quickly and assess outliers, while also being less susceptible to issues such as sample size and skewness that may bias \(p\)-values. In particular, we examined the interquartile range (IQR) of the different PC scores in each band. Similar IQR scores would suggest that the populations have similar variances. Visual analysis of the outliers revealed that many had models with acceptable fit quality, indicating that our model is capable of fitting the full diversity of our sample.

We find little statistical difference between the spread of PC1 and PC2 scores for both the UV and optical bands when compared to the \(B\)-band PC scores. For PC3 weights, only the \(V\) band has a similar spread in values to the \(B\) band, all other bands
show a much larger spread in potential values. As both the PC1 and PC2 scores relate to the near-peak decline rate, neither can be solely used as a proxy for \( \Delta m_{15} \). However, the full model can be used to directly estimate the \( \Delta m_{15} \), and the derived values show similar diversity to the \( B \)-band values (except for the \( V \) band, which has a much tighter spread of values).

To examine the one-to-one correlations between filters, we plotted the parameter values in each filter versus the \( B \)-band value (Figures 6 and 7–10). We then estimated the Spearman rank-order coefficient (Kokoska & Zwilinger 2000), a nonparametric measure of two sets for a monotonic relationship. For parameters that have a \( P \)-Value below 0.05, we test whether a linear model can describe the relationship. While the true relationship may not be linear, having the linear fit can be a useful visual representation of the correlation and distribution of parameters. To perform this linear regression we employed the Python routine LINMIX, which uses Bayesian inference to return random draws from the posterior distribution (Kelly 2007). The routine uses a 1000 iteration Markov Chain Monte Carlo (MCMC) procedure to converge on the posterior. The benefit of using this routine is its ability to handle uncertainties in both the independent and dependent variables as well as intrinsic scatter. From the iterations, we take the average value of the slope and intercept as our best fit parameters, and estimate the \( r^2 \) value to see how well the linear fit describes the correlation. The \( r^2 \) value is based on the total sum of squares (\( SS_{\text{tot}} \)) and the sum of squared residuals (\( SS_{\text{res}} \)) of the observed \( (y) \) and modeled \( (f) \) data, where

\[
SS_{\text{tot}} = \sum_i (y_i - \bar{y})^2
\]
\[
SS_{\text{res}} = \sum_i (y_i - f_i)^2
\]
\[
r^2 = 1 - \frac{SS_{\text{res}}}{SS_{\text{tot}}}.
\]

We find that while the optical properties (\( U \) and \( V \) bands) are highly related to the \( B \)-band properties, only the PC2 weights (Figure 8) show a consistent correlation between the mid-UV and near-UV bands and the \( B \) band. For PC1 (Figure 7), there is a strong correlation between the UVW2 band and the \( B \) band, which may be due to the relatively higher quality and quantity of data compared to the UVM2 and UVW1 bands.

There is little to no statistical correlation for the PC3 weights (Figure 9) between the UV bands and the \( B \) band, although the
UVW1 could be a statistical edge case that lacks enough quality data to make a solid statement. The $\Delta m_{15}$ (Figure 10) shows a strong correlation and a relatively tight linear relation with the $B$ band in both the UV and the optical.

Finally, we examined the differences in the peak magnitude phase between the $B$ band and the other filters, using a similar analysis to the PC score distributions. We find (Figure 11) that the $U$-band and UVW2-band light curves have a tight spread of peaks phases at around 2 days before the $B$-band peak, and the $V$ band has a tight spread at around 2 days after the $B$-band peak (Figure 11). The UVM2 and UVW1-band light curves also seem to peak earlier than the $B$-band light curves, although there is a much larger spread in the distribution of peak phases.

Examining the outliers, we find that SN Ia that peak in the UV 4 or more days before the B band peak were more likely to be classified as overluminous in the literature. The most extreme outliers, SN2011aa (Kamiya 2012), SN2012dn (Copin et al. 2012), and LSQ12gdj (Scalzo et al. 2014), are all super-Chandrasekhar mass candidates. Thus, the difference in the time of the peak in the UV and optical may be a useful metric for subtype classification.

4. Discussion

We successfully fit UV observations of SN Ia using templates constructed from functional principal component analysis of optical photometry. While the quality of fit is better for the optical observations, the quality of the UV fits was sufficient to perform a statistical analysis of the SN Ia light-curve properties. With improved UV observations and a larger data set, it should be possible to create filter-specific UV templates that will greatly improve future analysis of SN Ia light curves.

We find that the overall spread of the SN Ia parameters is similar between the UV and optical bands in our sample, particularly for the PC2 template weights which are most directly tied to the stretch and decline rates of the SN Ia light curve. In addition, we offer strong statistical evidence for a correlation between the UV and optical PC2 weights, suggesting that we can directly interpolate the spread of the SN Ia light curve in one band based on the other. This will be highly useful with upcoming large survey telescopes such as the Rubin observatory, which is expected to find millions of SN Ia at a wide range of redshifts. Interpreting the rest-frame UV
light from distant SN Ia will require further understanding of the UV emission from nearby objects.

The lack of a strong correlation in the PC1 weights could suggest that physics behind the UV and optical light curves may be different at later phases ($\geq$20), where the PC1 weights have the largest impact. For phases immediately after the peak the PC2 weights have the strongest effect on the decline rate, resulting in the strong correlation with the $\Delta m_{15}$ rates. The correlations between PC2 weights in different bands suggest a common origin for the near-peak variations in the UV and optical light curves. Further studies with multiepoch UV spectra of SN Ia could provide more details on the emission mechanisms and the variations of SN Ia light curves.

Previous work in the field has focused on rest-frame optical emission, leading to a wealth of robust models and large data sets. In comparison, there is a lack of quality observations and modeling in the UV. Our findings suggest that the UV and optical light-curve properties may be more similar than previously suggested, which suggests the worth of further study into this regime. Future work will greatly constrain the true behavior of UV SN Ia light curves relative to the better understood optical regime.

**Figure 10.** The correlation between the $B$ band and the other Swift UVOT bands for the 15 day decline rate postpeak. The red lines indicate the spread of the MCMC draws from Linmix, and the black line is the mean linear fit from which we calculate the $r^2$ value. The decline rate is calculated from the best fit FPCA model for each individual light curve.

**Figure 11.** A box plot of the peak phases for the light curves in each band relative to the $B$-band peak phase. Both the UVW2 and $U$-band light curves have a narrow distribution of peak phases at around 2 days before the $B$-band peak phase, while the $V$-band light curves have a narrow distribution at around 2 days after the $B$-band peak phase. The UVW1-band light curves seem to peak earlier than the $B$-band light curves, but with a larger spread in the distribution.
These correlations will be important for the study of high redshift SN Ia, whose rest-frame UV and optical emission will be simultaneously observable with upcoming ground-based telescopes such as the Vera Rubin Observatory. In the case that the optical light curve is poorly sampled by telescopes such as the Vera Rubin Observatory, it may be simultaneously observable with upcoming ground-based facilities. The diversity of the UV absolute magnitudes remains poorly constrained, however, hindering cosmological studies based only on UV observations.

5. Conclusion

We modeled the light curves of 97 SN Ia in the UV and optical from the Ultra-violet Optical Telescope on the Neil Gehrels Swift Observatory in order to better understand the correlation of their properties in different wavelength regimes. Modeling was done using a linear combination of band-vague templates, based on the FPCA of a sample of SN Ia in the optical bands. Each principal component is associated with a different light-curve property, making it a useful tool for finding correlations between the filters.

We find that the overall dispersion in the PC1 and PC2 weights in all filters were similar, suggesting that the UV light curves are not as variable as the optical light curves. There is not a strong correlation in the PC1 weights for the UV and optical filters, which would indicate the lack of a strong correlation in the late-phase decline rate. There is a statistically strong correlation between the UV and optical filters for the PC2 weights, which would suggest that the stretch of the light curves and the postpeak decline rates are correlated across the wavelength regimes. This could point to underlying physics that ties the UV and optical flux together, with the bulk of the light-curve shape likely being driven by $^{56}$Ni decay. The differences that do exist are likely due to wavelength-dependent metallicity effects and the opacity of the SN Ia atmosphere. This is the first study to statistically show that the UV and optical-light-curve properties have similar variability, and that the stretch and decline rate of the UV and optical light curves are significantly correlated.

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