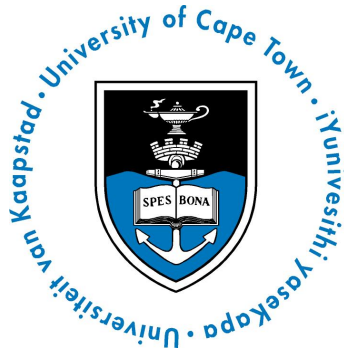




SALT SPECTROSCOPY AND CLASSIFICATION OF SUPERNOVA SPECTRA USING BAYESIAN TECHNIQUES

By

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Abstract

In this thesis, we present the Southern African Large Telescope spectroscopic follow-up programme for supernova candidates discovered by the international Dark Energy Survey, the goals of which are to measure the expansion history of the Universe and shed light on the mysterious nature of dark energy. In total, we took spectra for 36 supernova candidates. These were classified using a new Bayesian Supernova spectra classifier, **SuperNovaMC**, that we developed to address limitations with existing algorithms. **SuperNovaMC** simultaneously finds the best fitting supernova and host galaxy using Bayesian model selection, fitting the entire spectrum with Monte Carlo Markov Chain methods which allow estimation of the entire parameter posterior distributions, and hence principled statistical analysis even at low signal-to-noise. After extensive testing of **SuperNovaMC** against simulations and literature data, we use it to classify 20 of our Dark Energy Survey candidates as Type Ia supernovae. We further performed equivalent width measurements of two Type Ia supernova spectral features: Ca II H&K and Si II 4000, using a sub-sample of the 20 Type Ia supernovae. We compared our results to those of a similar study conducted on a low-redshift ($z < 0.1$) Type Ia supernova sample and found the two sets of results to be consistent, suggesting no redshift evolution in the equivalent widths of the two spectral features in the redshift range $0.1 < z < 0.3$ that we conducted the study in.

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Chapter 1

Introduction

1.1 Overview

Follow-up observational programmes for astronomical transient events have wide spread applications in the study of the origin, dynamics and fate of the Universe. A transient is an astronomical source that displays variability in the amount of radiation it emits as detected by an instrument on the ground or in space. Examples of transients include variable stars, active galactic nuclei, novae and supernovae (SNe). A study of a group of supernova (SN) transients known as type Ia supernovae (SNe Ia) gave the first evidence in 1998 that not only the Universe has been expanding, but the expansion has also been accelerating (Riess et al. 1998; Perlmutter et al. 1999).

Following this discovery, many astronomical surveys have been dedicated to the search for SN events to increase the sample of SNe Ia used in the 1998 study in order to (repeatedly) verify the discovery, improve its accuracy and increase our understanding of the dynamics of the Universe. Some of these surveys include the Lick Observatory Supernova Search (LOSS, Filippenko et al. 2001), Supernova Legacy Survey (SNLS, Astier et al. 2006), Sloan Digital Sky Survey Supernova Survey (SDSS-SN, Frieman et al. 2008), Panoramic Survey Telescope and Rapid Response System (PanSTARRS, Young et al. 2008), Palomar Transient Factory (PTF, Law et al. 2009) and now recently the Dark Energy Survey (DES, Bernstein et al. 2012). The discovery that the universe has an accelerated expansion suggests the existence of some form of cosmic energy with a tendency to work in opposition to the gravitational force (Bahcall et al. 1999). To this day, we do not fully understand the physical properties of such an energy or its source and it is for this reason that we refer to it as “dark energy”, to denote our lack of a better understanding of its nature.

Current and future imaging or photometric surveys such as DES and the Large Synoptic Survey Telescope (LSST, Ivezić et al. 2008) aim to study the expansion history of the universe by observing large areas of the sky to search for, among others, SN candidates, and probe the large scale structures in the Universe, with an overall objective of pinning down the exact nature of dark energy and whether or not it evolves with time. The predictions made about the size and shape of the Universe using SNe Ia data are affected by potential uncertainties in the typing of the discovered SNe and uncertainties in the shapes of their light curves (Phillips 1993). The former is crucial in that inclusion of *non-SNe Ia* into a sample of SNe Ia used for cosmological parameter estimation will lead to a false representation of the true geometry of the Universe and its composition.

The challenge therefore is to ensure that no contamination of other SN types occurs in the SNe Ia sample. One way to address this challenge is to obtain an optical spectrum of each discovered SN candidate. Using a well-observed spectrum, one can usually easily distinguish among the various types of SNe unambiguously. SNe Ia are identified from certain observed features in their spectra that are not seen in the spectra of other SN types, with one such feature being the silicon absorption line Si II that occurs at a wavelength of $6150\text{\AA}$ in the SN's rest-frame.

Another challenge facing supernova cosmologists today is that SN candidates are being discovered at an unprecedented rate. Obtaining a spectrum for each of them for a more accurate typing purpose has become highly unfeasible due to a world-wide scarcity of large telescope time to conduct such exercises. As a result, the classification of the majority of the discovered SN candidates is performed using photometric methods, where the SN *typing* and redshift z are estimated from light-curve data of SN candidates (Sako et al. (2011), Baum (1962) for some of the earlier work that led to the development of such methods). The photometric classification of SN candidates is however plagued by a number of factors, including photometric calibration uncertainties, a high chance of contamination from *non-SNe Ia* and extinction of SN light by dust.

It is for this reason that a reasonable sample of spectroscopically confirmed SNe is crucial to large scale SN search programs, as it provides a framework in which the rather less accurate photometric classification algorithms can be tweaked to improve their performance in order to yield classification results that are as close to the more accurate spectroscopic classification results as possible. This provides some way of mitigating the above-stated classification hurdles that reduces the accuracy of photometric SN classification.

1.2 This Thesis

The thesis is organised as follows: In Chapter 1, we provide a general introduction, starting with an overview of the current role of Supernova Cosmology in understanding the dynamics of the Universe as well as the challenges the field currently faces. We move on to reviewing the concepts of the magnitude scale and, provide a brief account of the SN types and subtypes and continue with a more in-depth review of the photometric and spectroscopic properties of SNe Ia. We then give a brief account of Einstein’s theory of General Relativity and how this applies to Cosmology. We then narrow down the discussion to Supernova Cosmology and DES and end the chapter with a review of existing SN spectral classification algorithms.

In Chapter 2, we give a theoretical background of Bayesian Inference and an account of Markov Chain Monte Carlo as a tool for solving Bayesian Inference problems that have no analytical solutions. We detail the workings of **SNMC** in Chapter 3 and demonstrate how well it classifies simulated and real (literature) spectra in Chapter 4, making comparisons of its classification efficiency to that of **SNID** in both chapters. We discuss in Chapter 5 the **SALT** and **DES** observations, their photometric and spectroscopic setups, respectively, and then briefly touch on the **SALT** spectroscopic data reduction process.

In Chapter 6, we present **SNMC**’s classification results of **SALT** spectra for 36 **DES** SN candidates, the challenges the classifier initially faced and the mitigation measures we employed in resolving them. We then make a comparison of the results to those of both **SNID** and **Superfit** classifiers obtained from their classification of the same spectra of the 36 SN candidates. We end Chapter 6 with the results of our equivalent width (EW) measurements of two SN Ia spectral features for the 21 SN candidates we classified as SNe Ia and how they compare to the results of a similar study conducted using a low-redshift ($z < 0.1$) SN Ia sample. We then end the thesis with Chapter 7, where we provide a discussion and conclusion of our findings as well as plans for future work.

1.3 The magnitude scale

The magnitude scale provides a way of quantifying the brightnesses of astronomical sources. It works by assigning small numbers to objects that are brighter and large numbers to those that are fainter. Historically, the magnitude scale was such that the brightest stars to the naked eye were assigned a first magnitude (i.e. a magnitude of 1), the second brightest star the second magnitude and so on. The modern definition is that a magnitude difference of 5 between two astronomical sources translates into a factor of

100 brightness difference between the two sources (Carroll & Ostlie, 2006).

Unless otherwise stated, we use in this thesis the *UBV* (Vega) based magnitude system, whose basis we do not discuss in detail, except that it is a system where the bright star Vega (α Lyrae) has a magnitude of zero in each of the *UBV* filters, i.e. $U = B = V = 0$ for Vega. Bessell (2005) and references therein provide a review of the various magnitude systems, including the *UBV* and Sloan Digital Sky Survey $u'g'r'i'z'$ magnitude systems.

The brightness of an astronomical source measured by a detecting instrument on the ground or in space is called the ‘apparent magnitude’ of the source. If we let m_1 and m_2 represent apparent magnitudes for two astronomical sources, and f_1 and f_2 their fluxes, the formula

$$m_1 - m_2 = -2.5 \log_{10} \left(\frac{f_1}{f_2} \right), \quad (1.1)$$

or

$$\frac{f_1}{f_2} = 100^{\left(\frac{m_2 - m_1}{5}\right)} \quad (1.2)$$

gives the relation between magnitude and flux. Another quantity known as the absolute magnitude M of an astronomical source is sometimes used to represent the source’s brightness. M is defined as the apparent magnitude an astronomical source would have if it were located at a distance of 10 pc ($1 \text{ pc} = 3.086 \times 10^{13} \text{ km}$). Substituting m_2 with a known value of M for a particular source (e.g. the Sun) and its corresponding flux measured from a distance of 10 pc, the value of $m_1 = m$ in Equation (1.1) for a given source can be determined from its measured flux f_1 as follows:

$$m - M = -2.5 \log_{10} \left(\frac{f_1}{F_{10\text{pc}}} \right). \quad (1.3)$$

The quantity $m - M$ is called the distance modulus, denoted μ .

1.4 Supernova types and subtypes

Certain stars go through a catastrophic explosive event at the end of their lives. Such explosions are referred to as ‘supernova events’ and are so bright that in some cases, a single event can outshine the combined light output of its host galaxy. There exists two

types of supernovae (SNe): (i) Type I (SN I) and (ii) Type II (SN II). The SN I type show a presence of hydrogen in their spectra, whereas the spectra of the SN II type have no hydrogen in them. A further sub-division of the two types is made: The SN I that have Silicon in their spectra are classified as Type Ia (SN Ia) and the SN I with no Silicon in their spectra undergo a further sub-classification as follows: (i) those with Helium in their spectra are classified as Type Ib (SN Ib) and those with no Helium in their spectra as Type Ic (SN Ic) (Filippenko 1997, hereafter FP97, Chevalier & Soderberg 2010).

The SN II type is also sub-divided into the following subtypes: (i) SN IIP, (ii) SN IIL, (iii) SN IIn and (vi) SN IIb (FP97, Chevalier & Soderberg 2010). A few weeks after explosion of the SN IIP subtype sees its expanding ejecta temperature decreasing to ~ 5000 K, at which it stays approximately constant for tens of days (FP97). During such a time frame, a plateau is observed in the light-curve of a SN IIP, the origin of “P” in the naming (FP97, Maguire et al. 2012). The light-curve of a SN IIL subtype decays linearly after maximum brightness, the origin of “L” in the naming and the “n” in the naming of the SN IIn subtype originated from the strong emission lines that dominate the SN IIn spectra, especially H_{α} , with narrow profiles.

The SN IIb subtype is slightly peculiar in that despite not showing the presence of hydrogen in their spectra, the spectra resemble those of the SN Ib subtype several weeks after explosion (Chevalier and Soderberg 2010), and hence the “b” in the naming. The subtypes SN Ic and SN IIn are sometimes referred to as “hypernovae”, due to the highly energetic broad lines observed in their spectra, linked to very high expansion velocities (Cappellaro & Turatto 2001).

SN Ia events are referred to as “thermonuclear explosions” whereas the events of the rest of the SN subtypes are collectively referred to as “core-collapse explosions”. We discuss the physical mechanisms that lead to the two kinds of explosions in the next two subsections.

1.4.1 Physical mechanism of thermonuclear SN explosions

Two scenarios are currently proposed as possible explanations of thermonuclear SN explosions. One is called the ‘accretion (or single-degenerate, SD) scenario’ and the other the ‘merger scenario’ (also known as the double-degenerate (DD) scenario). It is believed that through the Roche lobe overflow concept (Förster et al. 2006), a carbon-oxygen (CO) white dwarf (WD) in a binary system with a companion star accretes matter from the

companion up to a point where its mass reaches the Chandrasekhar limit ($\sim 1.40 M_{\odot}$). Upon reaching this mass limit, its carbon component ignites and starts a ‘thermonuclear runaway reaction’ which culminates into a total disruption of the entire WD (Yungelson & Livio 2000). The process is preceded by the inability of the CO WD to support itself against gravitational collapse due to the suppression of its electron degeneracy pressure caused by the rise in its accreted mass up to the Chandrasekhar limit.

The merger scenario, on the other hand, is characterised by two WDs in a binary system orbiting each other and losing angular momentum to gravitational radiation, which results in shrinkage of their orbit overtime. It is estimated that after a period of 2×10^5 to 5×10^8 years of this process, a massive disk forms around the bigger WD of the two. This then initiates the accretion process by the bigger WD, which eventually leads to a thermonuclear reaction upon reaching the Chandrasekhar limit, culminating into a SN Ia explosion (Iben & Tutukov 1984).

1.4.2 Physical mechanism of core-collapse SN explosions

Our understanding of the nature by which a core-collapse SN event occurs is that the core of a parent star becomes unstable as soon as nuclear fusion stops, leading to gravitational collapse. This sees the compression of the core up to a level that triggers nuclei degeneracy pressure, which counteracts further compression (Janka et al. 2007). The result of this process is an in-falling of the outer core material and the stellar envelope, which ends up bouncing off the hard nuclei degeneracy core, causing a shock-wave that drives the in-falling material backwards (Burrows et al. 2007). The generated shock-wave is believed to lose energy with increasing distance from the centre of the core as it encounters the in-falling material. However, it is believed that the shock-wave receives an energy boost from sufficiently energetic neutrinos that diffuses from the compact dense core, which re-energizes the shock-wave. The end result of this process is an annihilation of the entire star, leaving a compact object at the centre (Janka et al. 2007).

Figure 1.1 summarizes the above discussion of the SN types and subtypes.

1.5 Type Ia supernova photometry and spectroscopy

We continue our review of SN events but only focussing on the photometric and spectroscopic properties of SNe Ia—this is the (sub)type we are concerned with in terms of science in this thesis.

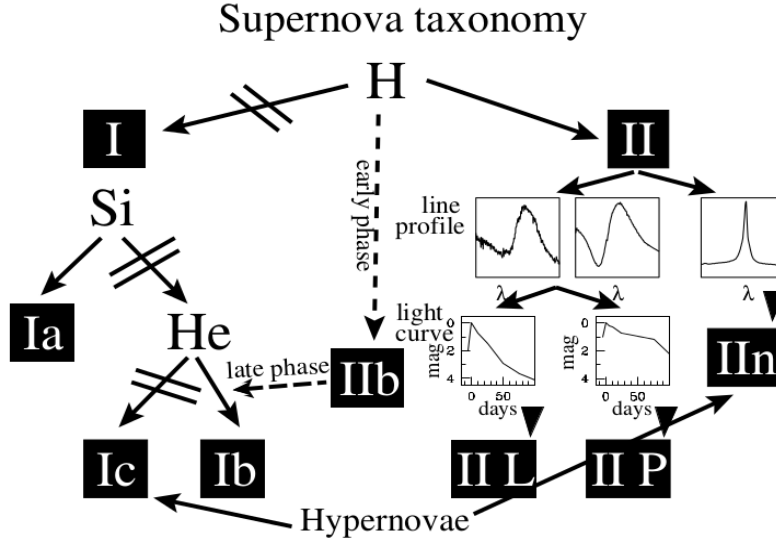


Figure 1.1: SN types and subtypes classified on the basis of their observed spectral properties, and also light-curve properties for the SN II type. As discussed in the text, the two SN types SN I and SN II have the subtypes SN Ia, SN Ib, SN Ic, and SN IIP, SN IIL, SN IIn and SN IIb, respectively. Notice the linear decay after maximum brightness and the plateau in the light curves of SN IIL and SN IIP, respectively, as discussed in the text. Despite not showing a presence of hydrogen in the spectra at the time of explosion, the spectra of the SN IIb subtype resemble those of the SN Ib subtype several weeks after explosion. The SN Ic and SN IIn subtypes are sometimes referred to as ‘hypernovae’, due to broad lines observed in their spectra that are linked to very high expansion velocities.

Figure from Cappellaro & Turatto (2001).

1.5.1 Photometric properties of SNe Ia

The light curves—plots of the brightness (represented in the form of flux or magnitude) of astronomical sources versus time (usually in days)—of SNe Ia enable us to determine their photometric properties, including magnitude and colour of the SN Ia. Figure 1.2 shows examples of typical SN Ia Light Curves (LCs).

The decay of radioactive isotopes ^{56}Ni ($^{56}\text{Nickel}$) and ^{56}Co , synthesised in the deepest and densest regions of a white dwarf star at the time of its explosion (Howell 2011; Hillebrandt et al. 2013) powers the observed SN Ia LCs. The observed luminosity during the early phase of the LC defined by 5-20 days after explosion is the result of the decay of ^{56}Ni into ^{56}Co , whereas the late phase of the LC occurring between 35-65 days after explosion is powered by the exponential decay of $^{56}\text{Co} \rightarrow ^{56}\text{Fe}$ (Colgate & McKee 1969). The amount of energies released in each $^{56}\text{Ni} \rightarrow ^{56}\text{Co}$ and $^{56}\text{Co} \rightarrow ^{56}\text{Fe}$ decay process are 1.72 MeV and an average of 3.59 MeV respectively, as Figure 1.3 shows.

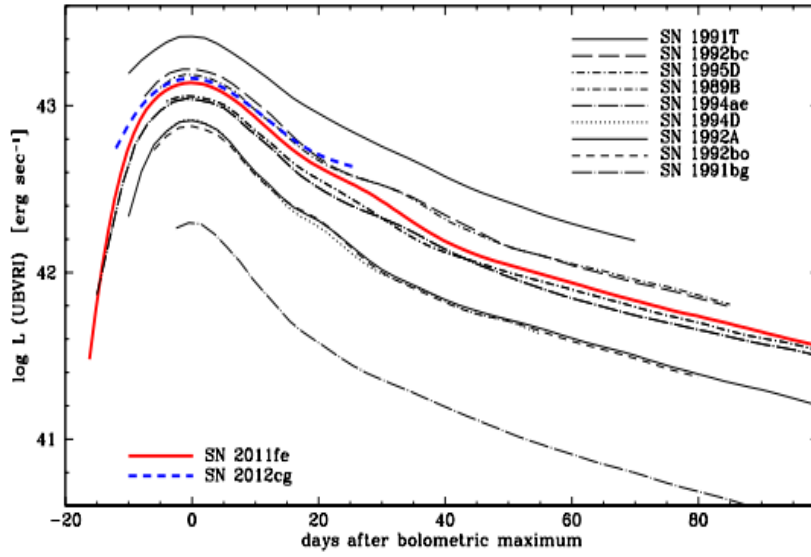


Figure 1.2: Bolometric (multi-band) LCs of SN 2011fe and SN 2012cg compared to those of other SNe Ia observed in previous years. While SNe Ia are known to display remarkable homogeneity in their LCs, the figure shows observed variations in the shapes of the LCs, with the LC of the peculiar SN ‘SN 1991T’ representing the over-luminous group of SN Ia LC and that of the other peculiar SN ‘SN 1991bg’ representing the under-luminous group. The majority of SN Ia LCs constitute normal SN Ia events and lie in the middle region of the plot. Figure from Munari et al. (2013).

Despite the general observed homogeneity in the LCs of SNe Ia, variations in the shapes of LCs for some of them, referred to as peculiar SNe Ia, have been observed. The light curve properties exhibited at similar epochs or phases by such peculiar events are different from those seen in the majority ($\sim 70\%$ and referred to as normal events, see Figure 1.4) of the SN Ia population. Examples of the peculiar events are (i) the 1991T-likes which have similar LC properties to the overluminous “SN 1991T”, (ii) the 1991bg-likes, whose properties resemble those observed in the LC of the underluminous “SN 1991bg” and (iii) the 2002-cx likes, whose properties relate closely to those observed in the LC of “SN 2002-cx” (Li et al. (2003, 2011b)). Figure 1.2 compares the LCs of two SNe Ia “SN 2011fe and SN 2012cg” to those of other SNe Ia, where the LCs for the overluminous SN 1991T and underluminous SN 1991bg can also be seen. Figure 1.4 shows the % distribution of the SN Ia population into normals, 1991T-likes, 1991bg-likes and 2002cx-lines, from a local Universe volume-limited sample studied by Li et al. (2011b).

Among the properties that can be determined from a SN Ia LC are (i) the rise and fall times of the LC (time in days the LC takes to reach maximum brightness and then decline to the minimum detection threshold in a given colour band), and (ii) the $\Delta m_{15}(B)$

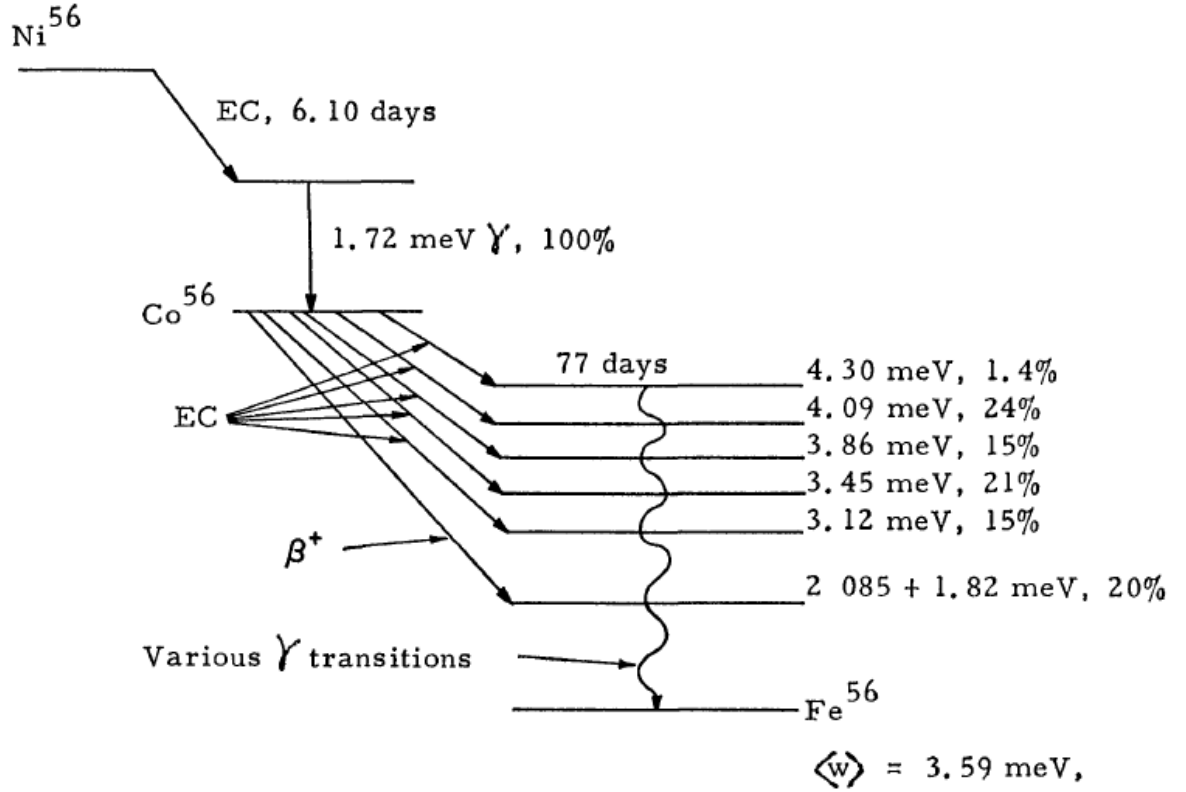


Figure 1.3: The radioactive decay process $^{56}\text{Ni} \rightarrow ^{56}\text{Co} \rightarrow ^{56}\text{Fe}$, depicting the three different decay processes and associated released energies: Electron capture (EC), positron decay (β^+) and gamma decay (γ). Figure from Lederer et al. (1967).

parameter, the change in blue band magnitude of the SN Ia in 15 days after maximum brightness (Phillips 1993; Riess et al. 1999; Phillips et al. 1999).

1.5.2 Spectroscopic properties of SNe Ia

SNe Ia spectra are found to display remarkable homogeneity, as can be seen in Figure 1.5, supporting the claim that their progenitor stars explode on reaching the same mass limit known as the Chandrasekhar limit of $1.4 M_{\odot}$. Their early-time (~ 1 week past maximum brightness in the blue band) spectra are characterised by broad features (also referred to as broad lines) due to the high velocities of the SN ejecta (FP97). Strong silicon absorption lines are observed near maximum light as deep troughs at wavelength 6150Å (in the SN Ia's rest-frame), believed to be caused by the blueshifting of Si II $\lambda 6355$ (F97), as Figure 1.5 shows.

A blend of iron (Fe) emission lines with some cobalt (Co) lines are seen in the late

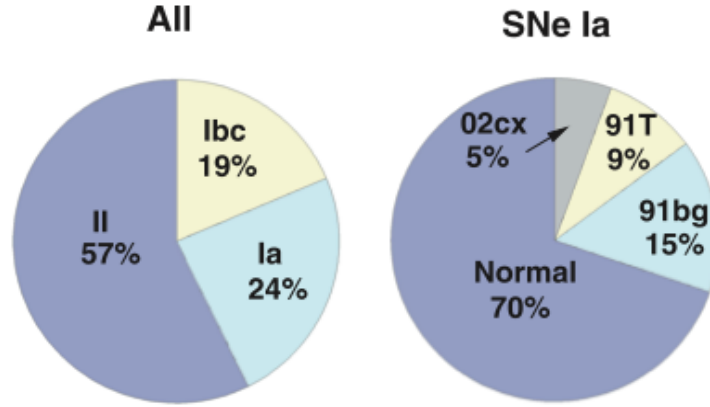


Figure 1.4: Left: A distribution of 180 SNe in a volume-limited sample in the local Universe out to 60 Mpc for SNe II and SNe Ib/c, and 80 Mpc for SNe Ia, compiled by Li et al. (2011b). Right: A breakdown of the 24% SNe Ia population into normals, 02cx-likes, 91T-likes and 91bg-likes. Figure from Li et al. (2011b).

time (4 months or more after maximum brightness in the blue band) spectra (F97), as the spectrum of ‘SN 1987L’ in Figure 1.6 shows.

Properties that can be determined from SN Ia spectra include equivalent widths of spectral features (which provides further tests of the claimed homogeneity of SNe Ia—see Chapter 6 for more on this), accurate estimation of the SN’s redshift as well as the nature of dust extinction and reddening of light by the SN’s host galaxy, albeit this last property is not such a trivial exercise, as discussed in Chapter 6.

1.6 General Relativity and Cosmology

1.6.1 The Einstein and Cosmological Field Equations

The mathematical basis of Einstein’s theory of general relativity—which postulates that gravity is a result of curvature of the spacetime fabric caused by the presence of matter—rests on Einstein’s gravitational field equations, expressed in the form

$$G_{\mu\nu} = -\frac{8\pi G}{c^4}T_{\mu\nu} \quad (1.4)$$

where $G_{\mu\nu} = \mathcal{R}_{\mu\nu} - \frac{1}{2}g_{\mu\nu}\mathcal{R}$ is the Einstein tensor, G the gravitational constant and $T_{\mu\nu}$ the energy-momentum tensor. The $\mathcal{R}_{\mu\nu}$, $g_{\mu\nu}$ and $\mathcal{R}$ in $G_{\mu\nu}$ are the Ricci tensor, metric tensor and Ricci scalar, respectively (Hobson et al. 2006, hereafter HEL06). The subscripts $\mu, \nu = \{0, 1, 2, 3\}$. We do not discuss the various components of these

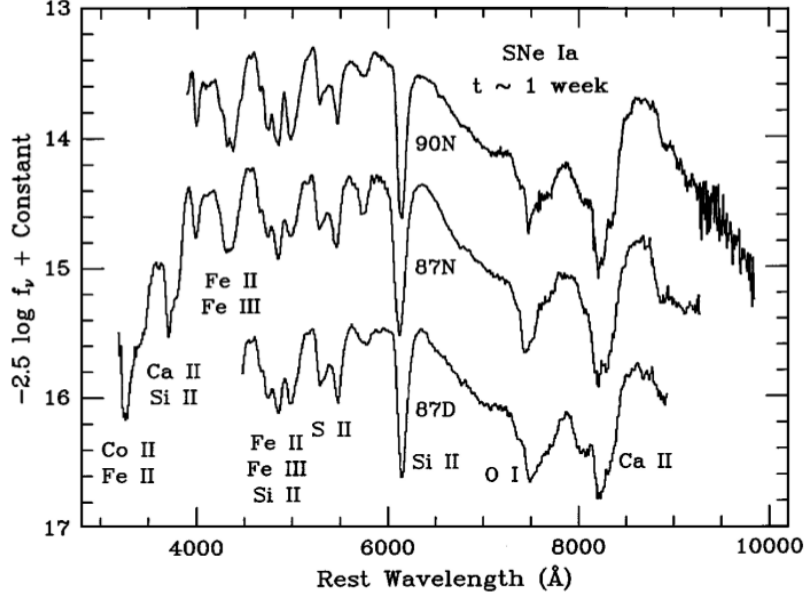


Figure 1.5: SNe Ia spectra at approximately one week past maximum brightness, with host galaxies and their redshifts (kms^{-1}) given as follows: 90N (NGC 4639; 970), 87N (NGC 7606; 2171), and 87D (MCG+00-32-01; 2227). Figure from F97.

equations in detail but touch only on aspects of them that are relevant to this work in our subsequent discussions.

The Einstein equations in Equation (1.4) describe a Universe that is explicitly governed by a gravitational force induced by matter and radiation. The equations are not unique and therefore can be modified by adding additional terms to the left hand side (LHS) of Equation (1.4) and they still remain consistent. This is in fact what Einstein did, where he added to the LHS of Equation (1.4) an additional term called the ‘cosmological constant’ Λ to enable him to have a static Universe as a solution, which he later discarded upon learning of Edwin Hubble’s discovery of an expanding Universe.

With an additional Λ term, Equation 1.4 is rewritten as

$$G_{\mu\nu} + \Lambda g_{\mu\nu} = -\frac{8\pi G}{c^4} T_{\mu\nu}. \quad (1.5)$$

By using the contracted form of Equation (1.5), we can rewrite them as:

$$\mathcal{R}_{\mu\nu} = -\frac{8\pi G}{c^4} (T_{\mu\nu} - \frac{1}{2} T g_{\mu\nu}) + \Lambda g_{\mu\nu}, \quad (1.6)$$

(HEL06). When we view the cosmos on small scales, structure in the Universe appear to have irregular distribution but when we focus our view on larger and large scales,

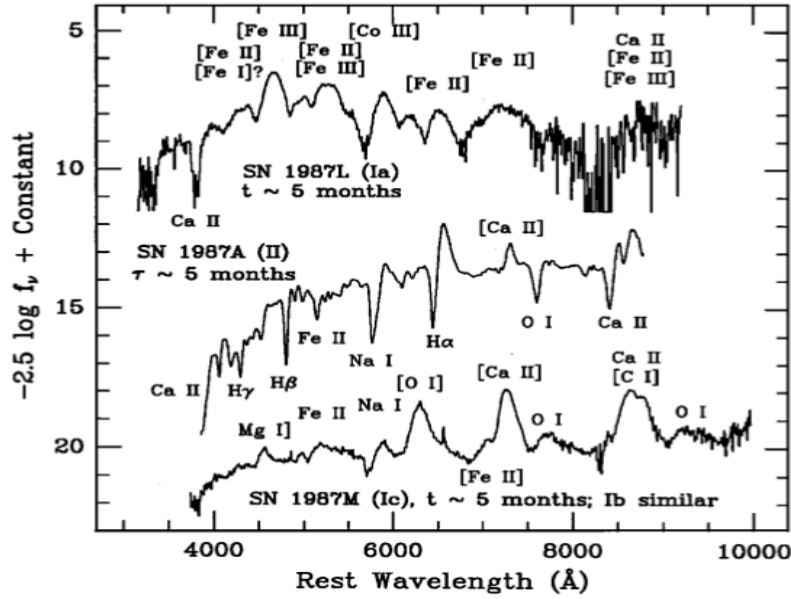


Figure 1.6: Late time SN spectra, at ~ 5 months after peak brightness for SN 1987L showing the ubiquitous presence of Fe. Also shown are the spectra for two core-collapse SNe I. Figure from F97.

the distribution appears more uniform. This implies the Universe appears to have no preferred centre and has a uniform matter distribution in all directions at any given time, i.e. the Universe is isotropic (HEL06). The absence of a preferred centre in an isotropic Universe implies the Universe is also homogeneous. Coupling these two concepts leads to what is called the ‘cosmological principle’, an assumption which states that “*at any particular time the universe looks the same from all positions in space at a particular time and all directions in space at any point are equivalent*” (HEL06). The first part of the principle speaks about *homogeneity* and the second part *isotropy* of the Universe.

We seek the forms of Equation (1.6) for the case of a homogeneous and isotropic Universe. To achieve that, a model of the energy-momentum tensor of matter in the Universe is needed. This matter is assumed to be a *perfect fluid* and modelled as such, defined only by its proper density ρ and pressure p in the rest-frame. The energy-momentum tensor has the following formulation (HEL06):

$$T^{\mu\nu} = \left(\rho + \frac{p}{c^2} \right) u^\mu u^\nu - p g^{\mu\nu}, \quad (1.7)$$

where u^μ is the 4-velocity of the fluid.

The spacetime interval ds , in polar coordinates (r, θ, ϕ, t) , between two adjacent events defined by comoving coordinates (i.e. the spatial coordinates of objects located

at the two events are fixed in space) x^i ($i = r, \theta, \phi$) in a Friedman-Robertson-Walker (FRW) Universe (see discussion below about the FRW Universe) is expressed in the form

$$ds^2 = c^2 dt^2 - a^2(t) \left[\frac{dr^2}{1 - kr^2} + r^2(d\theta^2 + \sin^2 \theta d\phi^2) \right], \quad (1.8)$$

where $a(t)$ is the scale factor of the Universe and k is the curvature constant. The scale factor $a(t)$ is a dimensionless time-dependent quantity used in cosmology as a measure of the size of the Universe and is defined in terms of the redshift z as

$$1 + z = \frac{a(t_o)}{a(t_e)}, \quad (1.9)$$

where $a(t_e)$ is the size of the Universe when an object located at redshift z emitted light and $a(t_o)$ is the size of the Universe when the light from such an object is observed (Hogg 1999). The curvature constant k takes on a value of -1 if the spatial part of Equation (1.8) has negative curvature; 0 if the spatial part has zero curvature, or 1 if the spatial part has positive curvature (HEL06). Equation (1.8) is known as the FRW metric, which can also be expressed as

$$ds^2 = \sum_{\mu, \nu} g_{\mu\nu} dx^\mu dx^\nu, \quad (1.10)$$

where $g_{\mu\nu}$ is the metric tensor, whose matrix representation is diagonal with the following components:

$$g_{00} = c^2, \quad g_{11} = -\frac{a^2(t)}{1 - kr^2}, \quad g_{22} = -a^2(t)r^2, \quad g_{33} = -a^2(t)r^2 \sin^2 \theta.$$

Computing the matrix components of the Ricci tensor in Equation (1.6) involves the calculation of affine connections (Christoffel Symbols) which reveal that the off-diagonal elements are zero. The final diagonal elements of the Ricci tensor are:

$$R_{00} = 3\ddot{a}/a,$$

$$R_{11} = -(a\ddot{a} + 2\dot{a}^2 + 2c^2k)c^{-2}/(1 - kr^2),$$

$$R_{22} = -(a\ddot{a} + 2\dot{a}^2 + 2c^2k)c^{-2}r^2,$$

$$R_{33} = -(a\ddot{a} + 2\dot{a}^2 + 2c^2k)c^{-2}r^2 \sin^2 \theta.$$

The stress-energy tensor is:

$$T_{\mu\nu} = (\rho c^2 + p)c^2 \delta_\mu^0 \delta_\nu^0 - p g_{\mu\nu} \quad (1.11)$$

and

$$T = T^\mu_\mu = (\rho + \frac{p}{c^2})c^2 - p\delta^\mu_\mu = \rho c^2 - 3p, \quad (1.12)$$

where δ_μ^ν is the Kronecker delta function, defined as 1 if $\mu = \nu$ and 0 if $\mu \neq \nu$. Multiplying Equation (1.12) with $1/2g_{\mu\nu}$, and subtracting the result from Equation (1.11), we obtain the final expression for the term in parentheses on the RHS of Equation (1.6):

$$T_{\mu\nu} - \frac{1}{2}Tg_{\mu\nu} = (\rho c^2 + p)c^2 \delta_\mu^0 \delta_\nu^0 - \frac{1}{2}(\rho c^2 - p)g_{\mu\nu}. \quad (1.13)$$

By the definition of the Kronecker delta function and the fact that the FRW metric tensor $g_{\mu\nu}$ is diagonal, Equation 1.11 reveals that the RHS of Equation (1.6) yields zero for $\mu \neq \nu$. Substituting in Equation (1.6) the non-zero components of the RHS of Equation (1.6) and the above derived diagonal elements of the Ricci tensor on the LHS of Equation (1.6), we get

$$3\ddot{a}/a = -\frac{4\pi G}{c^4}(\rho c^2 + 3p)c^2 + \Lambda c^2,$$

$$-(a\ddot{a} + 2\dot{a}^2 + 2c^2k)c^{-2}/(1 - kr^2) = -\left[\frac{4\pi G}{c^4}(\rho c^2 - p) + \Lambda\right]a^2/(1 - kr^2),$$

$$-(a\ddot{a} + 2\dot{a}^2 + 2c^2k)c^{-2}r^2 = -\left[\frac{4\pi G}{c^4}(\rho c^2 - p) + \Lambda\right]a^2r^2,$$

$$-(a\ddot{a} + 2\dot{a}^2 + 2c^2k)c^{-2}r^2 \sin^2 \theta = -\left[\frac{4\pi G}{c^4}(\rho c^2 - p) + \Lambda\right]a^2r^2 \sin^2 \theta.$$

We note that the last three equations, i.e. the spatial equations, are equivalent. This is a direct result of the homogeneity and isotropy inherent in the FRW metric that we have considered in solving Equation (1.6). Performing some basic algebraic manipulations to one of the spatial equations and subtracting it from the time equation to eliminate $\ddot{a}$ from the former and then re-arrange, we obtain the so-called *cosmological field equations* (HEL06), which provide a relation between the time evolution of the scale factor a and the density, pressure and curvature of the FRW Universe:

$$\ddot{a} = -\frac{4\pi G}{3} \left(\rho + \frac{3p}{c^2} \right) a + \frac{1}{3} \Lambda c^2 a, \quad (1.14)$$

$$\dot{a}^2 = \frac{8\pi G}{3} \rho a^2 + \frac{1}{3} \Lambda c^2 a^2 - c^2 k. \quad (1.15)$$

1.6.2 Cosmological Density Parameters

The total mass and energy content of the Universe is postulated to be made out of three components, which are *matter*, *radiation* and the *vacuum*, with each having a characteristic equation of state parameter w . This is mathematically expressed in the form

$$\rho(t) = \rho_m(t) + \rho_r(t) + \rho_\Lambda(t), \quad (1.16)$$

where $\rho(t)$ is the total equivalent mass density and $\rho_i(t)$, $i = (m, r, \Lambda)$ the individual density contributions to $\rho(t)$ by the three components. Each component i is modelled as a perfect fluid with an equation of state that takes the form

$$p_i = w_i \rho_i c^2 \quad (1.17)$$

The *matter* component is modelled as dust with zero pressure, thus its equation-of-state parameter is $w = 0$, whereas the *radiation* and *vacuum* components are modelled with equations of state parameters $w = \frac{1}{3}$ and $w = -1$, respectively (HEL06). The density of component i scales as

$$\rho_i \propto a^{-3(1+w_i)} \quad (1.18)$$

where a is the scale factor at time t and index i has the same meaning as in Equation (1.16). The three density components in Equation (1.16) may also be written in terms of their present-day components using Equation (1.18) and the three different values of w for *matter*, *radiation* and *vacuum* given above, giving the following form of the total equivalent mass density:

$$\rho(t) = \rho_{m,0} \left[\frac{a_0}{a(t)} \right]^3 + \rho_{r,0} \left[\frac{a_0}{a(t)} \right]^4 + \rho_{\Lambda,0}, \quad (1.19)$$

By specifying the values of the equivalent mass densities at some particular cosmic time t_* , we are able to learn about the Universe's history and determine the size of its

scale factor $a(t_*)$ at any cosmic time. t_* is usually taken to be the present-day cosmic time t_0 and so the three equivalent mass densities

$$\rho_{\text{m},0}, \quad \rho_{\text{r},0}, \quad \rho_{\Lambda,0} \quad (1.20)$$

enable fixing the cosmological model of the Universe (HEL06).

Cosmologists commonly express ρ_{m} , ρ_{r} and ρ_{Λ} in terms of dimensionless quantities called density parameters, defined as

$$\Omega_i(t) \equiv \frac{8\pi G}{3H^2(t)} \rho_i(t), \quad (1.21)$$

where $H(t)$ is the Hubble parameter and as before, $i = \{\text{m}, \text{r}, \Lambda\}$. Another important parameter that observational cosmologists are interested in quantifying is the curvature parameter k , given in Equation (1.15). Its formulation in terms of the dimensionless parameters in Equation (1.21) is obtained by dividing a^2 through Equation (1.15) and remembering that $H = \dot{a}/a$. Doing so, we obtain

$$\frac{\dot{a}^2}{a^2} = \frac{8\pi G}{3} \rho + \frac{1}{3} \Lambda c^2 - \frac{c^2 k}{a^2}, \quad (1.22)$$

which simplifies into

$$1 = \Omega_{\text{m}} + \Omega_{\Lambda} - \frac{c^2 k}{H^2 a^2}, \quad (1.23)$$

after dividing H^2 through Equation (1.22) and then applying Equation (1.21). The negative term on the RHS of Equation (1.23) is defined as the ‘dimensionless curvature density parameter’ Ω_k , so that

$$\Omega_k(t) = -\frac{c^2 k}{H^2(t) a^2(t)}. \quad (1.24)$$

Substitution of Equation (1.24) into Equation (1.23) yields the following relation:

$$\Omega_{\text{m}} + \Omega_{\Lambda} + \Omega_k = 1. \quad (1.25)$$

Observations over the past years, including the recent and most accurate ones by the Planck experiment of temperature fluctuation measurements in the cosmic microwave background (Tauber et al. 2004) have shown that we live in a Universe that is almost spatially flat. The Planck Collaboration et al. (2016) constrained the spatial curvature density of our Universe today to $\Omega_k = -0.005^{+0.0016}_{-0.017}$ at 95% confidence limit. Equation (1.25) thus becomes

$$\Omega_m + \Omega_\Lambda \approx 1 \quad (1.26)$$

The cosmological model of the Universe can be fixed with the following four present-day parameters (HEL06):

$$H_0, \quad \Omega_{m,0}, \quad \Omega_{r,0}, \quad \Omega_{\Lambda,0}. \quad (1.27)$$

Modern-day observational cosmologists strive to determine as accurately as possible the true values of these cosmological parameters and other parameters. The best observational constraints we have to date on the values of the parameters in Equation (1.27) are the recent Planck experiment results (Planck Collaboration et al. 2016), which are:

$$\begin{aligned} H_0 &= (67.8 \pm 0.9) \text{ kms}^{-1}\text{Mpc}^{-1}, & \Omega_{m,0} &= 0.308 \pm 0.012, \\ \Omega_{r,0} &= 9.10066 \times 10^{-5}, & \Omega_{\Lambda,0} &= 0.692 \pm 0.012, \end{aligned} \quad (1.28)$$

consistent with the most recent results for the same parameters obtained from the joint light-curve analysis sample of the SDSS and SNLS SNe Ia (Betoule et al. 2014).

1.7 Supernova Cosmology and the Dark Energy Survey

The field of Supernova Cosmology is concerned with the determination of the cosmological parameters discussed in the previous section, using SN Ia observed data. Supernova Cosmology became more popular following the discovery in 1998 that the Universe was not only expanding but also that the expansion has been accelerating. The discovery culminated in the award of the Nobel prize in Physics for 2011 to two groups that conducted it independently, namely the Supernova Cosmology Project (Riess et al. 1998), and the High-Redshift Supernova Search team (Perlmutter et al. 1999).

From here on, we use w (introduced in the previous section) to denote the equation of state parameter for dark energy, as we no longer discuss the cases for matter and radiation components in this section. There are several possibilities for the (numerical) value of w . One is that $w = -1$, which corresponds to Einstein's cosmological constant. This scenario implies that dark energy is a property of the vacuum and does not change in an expanding Universe like matter and radiation. Another possibility is that $w < -1$, implying that the density of dark energy grows continuously in an expanding Universe with its fate ending in a scenario called the “big rip”, where all matter in the Universe (clusters, galaxies, stars, atoms, etc) disband and are ripped apart by this continuous

growth. Another model is called “quintessence”, where $w > -1$. In this model, w is taken to be a scalar field whose value evolves over cosmic time.

Other considerations in attempting to explain the observed accelerated expansion of the Universe are made in modified gravity theories, where it is argued that Einstein’s theory of general relativity might not apply on cosmological scales, prompting modifications to the Einstein field equations in an effort to reconcile the observational data. In the next subsection, we discuss efforts directed at placing stronger constraints on the value of w by the Dark Energy Survey whose Supernova Program is the source of data we use in this work.

1.7.1 Measurements of w by the Dark Energy Survey

The Dark Energy Survey (DES) is an international photometric experiment whose focus is to measure the expansion history of the Universe in order to constrain the equation of state parameter for dark energy w to within an accuracy of $\sim 1\%$. DES aims to accomplish its empirical determination of w via four independent probes chosen by the dark energy “Figure of Merit Task Force” (Albrecht et al. 2006). In alphabetical order, the probes are (i) Baryon Acoustic Oscillations, (ii) Galaxy Clusters, (iii) Supernova Observations and (vi) Weak Gravitational Lensing. We discuss the first three of these probes in a bit more detail, mainly highlighting the basic concepts of the manner in which they are utilised to place tight constraints on the value of w .

1.7.1.1 Baryon Acoustic Oscillations

Baryon Acoustic Oscillations (BAO) are the acoustic (sound) waves imprinted or frozen in the distribution of galaxies in the Universe (see Bassett & Hlozek 2010 for a review). The imprint occurred roughly 380 000 years after the Big Bang, when the Universe was cool enough to permit the recombination of protons and electrons from the plasma state they were in prior to the time. The recombination led to the decoupling of the once tightly coupled photons and baryons (protons and electrons), leaving the former free-streaming across the cosmos. The temperature fluctuations in these photons have been detected with space borne experiments such as the COsmic Background Explorer (COBE, Mather 1982), Wilkinson Microwave Anisotropy Probe (Bennett et al. 2003) and now recently with the experiment (Tauber et al. 2004). The distance that the acoustic waves travelled before freezing out at recombination is known as the sound horizon and is given by the product of the speed of sound and age of the Universe at recombination.

Figure 1.7 illustrates the processes that occurred between baryons, photons and dark

matter prior to the recombination era, which led to the imprint of the BAO signal in the baryons.

The BAO feature is detected as a bump at a comoving separation $r \approx 150$ Mpc, as shown in the top panel of Figure 1.8, after computing the galaxy correlation function $\xi(r)$. Notice the change in units from Mpc to h^{-1} Mpc between Figures 1.7 and the top of Figure 1.8, respectively, which results in a shift of the bump to the left in the latter figure. The Fourier transform of $\xi(r)$ yields the galaxy power spectrum and in it, the BAO bump turns into a number of oscillations, seen as wiggles in the fitted curves to the ‘LRG’ and ‘Main’ data samples in the bottom panel of Figure 1.8.

Measurements of the BAO signature along the light-of-sight and tangential directions provide estimates of the Hubble parameter $H(z)$ and angular diameter distance $d_A(z)$, respectively. d_A in the FRW geometry is defined as the quotient of the proper diameter l of an object and the angular diameter $\Delta\theta$ the object subtends on the sky (HEL06), i.e.

$$d_A = \frac{l}{\Delta\theta} \quad (1.29)$$

Both $H(z)$ and $d_A(z)$ provide a way (we do not dwell on exact details) of placing constraints on the equation of state parameter for dark energy $w(z)$.

1.7.1.2 Galaxy Clusters

Galaxy clusters are the largest gravitationally bound systems and serve as massive laboratories for investigations of structure formation and evolution in the Universe. Given a set of cosmological parameters, N -body simulations are able to predict precisely the growth of dark matter haloes (distributions of dark matter enclosures around visible structures in the Universe) the sizes of clusters, as a function of redshift. The results of the simulations are then compared to observational data to obtain constraints on cosmological parameters.

One such comparison can be made with a cluster redshift survey that detects cluster systems of mass M at redshift z and with efficiency $f(M, z)$. The observed number function in this case is given by

$$\frac{d^2 N(z)}{dz d\Omega} = \frac{c}{H(z)} d_A^2 (1+z)^2 \int_0^\infty f(M, z) \frac{dn(z)}{dM} dM, \quad (1.30)$$

where $d\Omega$, c , $H(z)$, d_A and $dn(z)/dM$ are solid angle of the detection, speed of light, Hubble parameter, angular diameter distance and the evolution of the number density

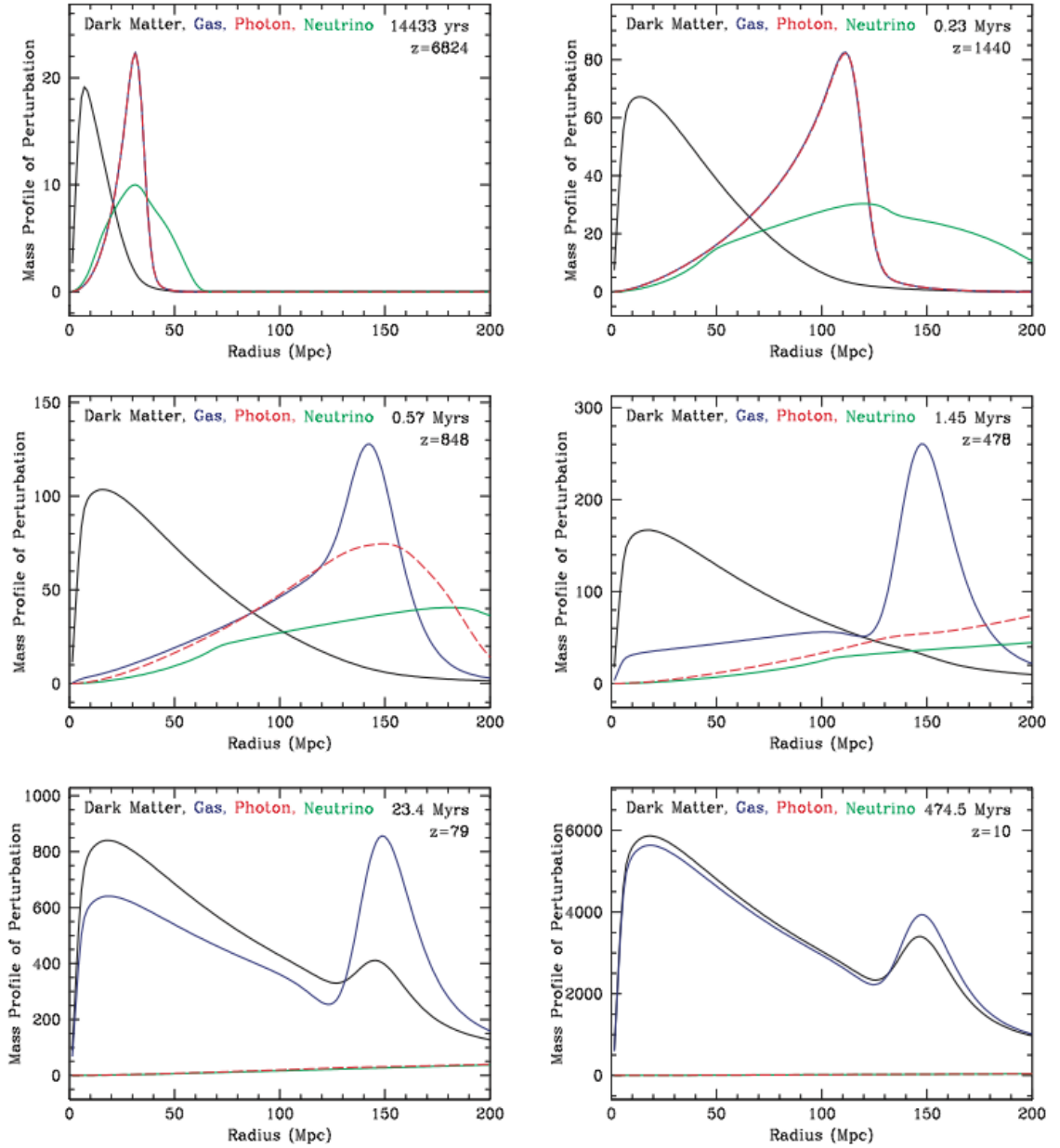


Figure 1.7: Snapshots of the evolution of radial mass profiles (given in arbitrary units) for dark matter (black), gas/baryons (blue), photons (red) and neutrinos (green) vs comoving radius for an initial perturbed point-like overdensity located at the origin. Each panel shows the redshift and time (Myrs) after the Big Bang for each process. The description of each panel is as follows: *Top left:* Near the origin, photons and baryons are tightly coupled and the density perturbation makes them travel outward in unison. *Top right:* Because dark matter interacts only gravitationally, it lags behind the motion of the coupled photons and baryon plasma towards recombination, only responding to the gravitational drag introduced by the plasma. *Middle left:* At recombination, photons free stream away leaving the baryons behind. *Middle right:* The end of recombination (middle right panel) culminates in dark matter and baryonic perturbations near the origin and at ~ 150 Mpc, respectively. In the bottom left panel, gravitational interaction between dark matter and the baryons results in the formation of overdensities near the origin and around 150 Mpc (bottom right panel). This characteristic length scale of the two overdensities set by the sound horizon is imprinted in the large scale structure of the Universe. Figure from Eisenstein et al. (2007).

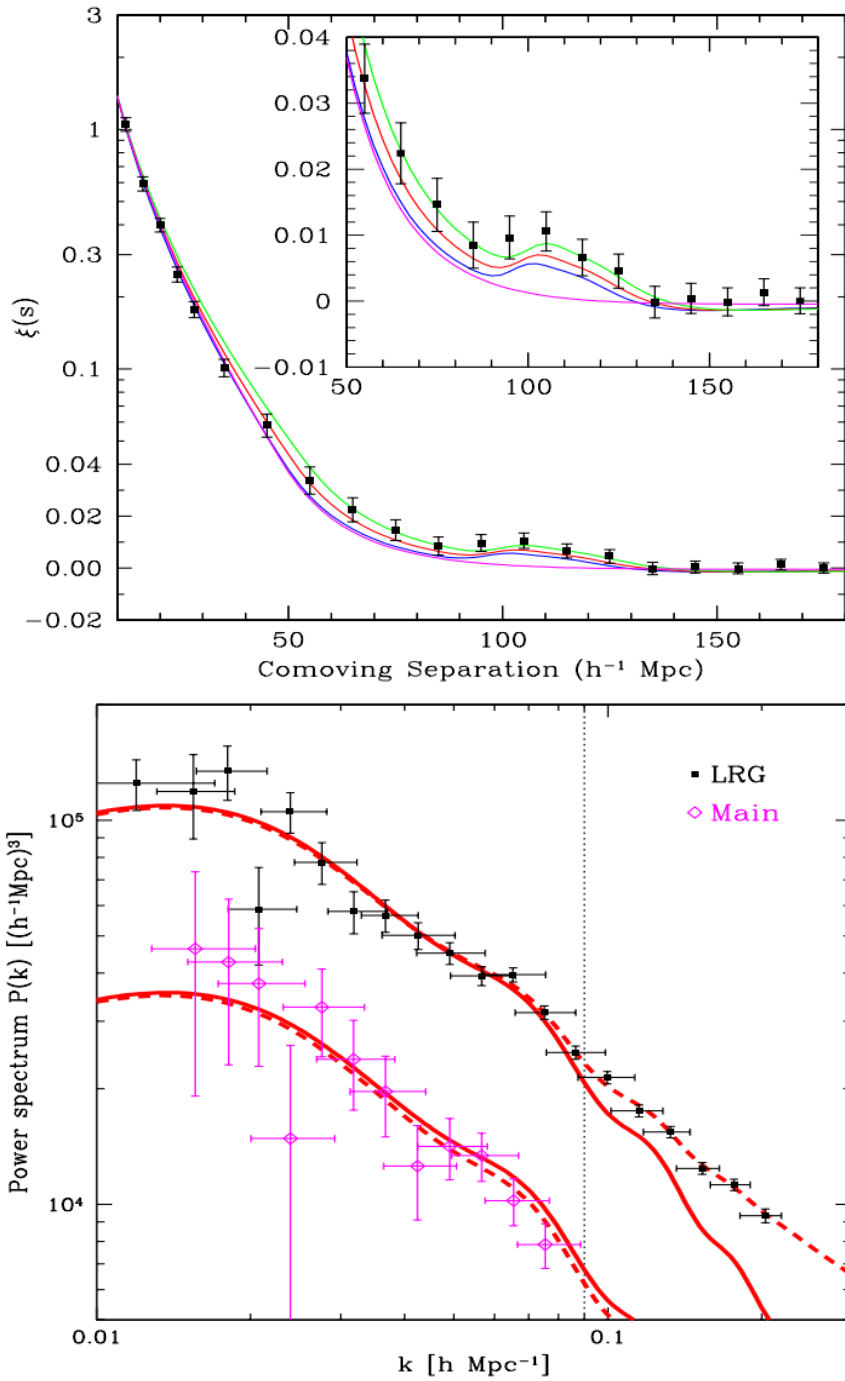


Figure 1.8: *Top:* Correlation function of the Sloan Digital Sky Survey (SDSS) Luminous Red Galaxy (LRG) sample. The fitted curves to the data are for the models $\Omega_m h^2 = 0.12$ (green curve), 0.13 (red curve) and 0.14 (blue curve). All 3 models adopt a baryon energy density and spectral index (power law index of the primordial power spectrum of curvature perturbations, Komatsu et al. (2011)) values of $\Omega_b h^2 = 0.024$ and $n = 0.98$ respectively. The magenta curve lacking the BAO bump represents a pure CDM model with $\Omega_m h^2 = 0.105$. Figure from Eisenstein et al. (2005). *Bottom:* Galaxy power spectra computed for the main SDSS galaxy sample (magenta) and full LRG sample (black). The red solid curves represent fits of the Λ CDM linear theory to WMAP3 data provided in Table 5 of Spergel et al. (2007), whereas the dotted curve fits have been corrected for nonlinear effects discussed by Cole et al. (2005). The effect of the nonlinear corrections is evident and more so with the LRG sample for $k \gtrsim 0.09 h/\text{Mpc}$, as the vertical dotted line indicates. Figure from Tegmark et al. (2006).

of clusters, respectively (The Dark Energy Survey Collaboration 2005). For some cluster observable O , Equation (1.30) can be rewritten as

$$\frac{d^2 N(z)}{dz d\Omega} = \frac{c}{H(z)} d_A^2 (1+z)^2 \int_{O_{min}}^{\infty} f(O, z) dO \int_0^{\infty} g(O|M, z) \frac{dn(z)}{dM} dM, \quad (1.31)$$

with O_{min} representing the z -dependent observable threshold corresponding to an ideal case that results in the detection probability $f(O, z)$ being a step function and $g(O|M, z)$ the intrinsic mass-observable relation¹. The important cluster physics information is contained in the intrinsic mass-observable relation $g(O|M, z)$. Precise theoretical predictions for $dn(z)/dM$ and the halo mass function as well as controlled understanding of $g(O|M, z)$ and $f(O, z)$ are needed for probing dark energy with clusters.

Knowledge of the form of $g(O|M, z)$ and $f(O, z)$, their scatter and redshift evolution is required in deriving cosmological parameters from observations of cluster properties.

1.7.1.3 Supernova Observations

Observations of SNe Ia at various redshifts enable the study of the expansion history of the Universe. Their peak luminosities have been found to show discrepancies of up to a factor of 10 and more in some cases (see Figure 1.2). Phillips (1993) found a method of correlating the rise and fall time of a SN Ia’s brightness with its luminosity. Using such a relation, measurements of the widths of SN Ia light curves are utilised to correct for the observed discrepancies in their peak luminosities and for this reason, SNe Ia are referred to as “standardizable candles”.

The correction uses what is called the “stretch factor” s to stretch or compress the width of a SN Ia light-curve template to produce a best-fit to the SN Ia light-curve from which s is determined (Perlmutter et al. 1999). The stretch factor s and the decline rate parameter $\Delta m_{15}(B)$ (defined in Section 1.5) are directly proportional. Phillips (1993) also found that redder SN Ia events have the fastest light-curve decline rates compared to the other events. Figure 1.9 shows a plot of the absolute magnitudes in B , V and I versus decline rate parameters $\Delta m_{15}(B)$ for 9 SNe Ia events studied by Phillips (1993), where the reddest (underluminous) event “SN 1991bg” has the highest $\Delta m_{15}(B)$ value, and the overluminous event “SN 1991T” has the lowest $\Delta m_{15}(B)$ value.

The light-curve standardization therefore also includes a colour correction to account for the observed differences in the light-curve decline rates (Riess et al. 1996). Fitting for

¹<https://www.noao.edu/meetings/decam/media/DES-science-program.pdf>

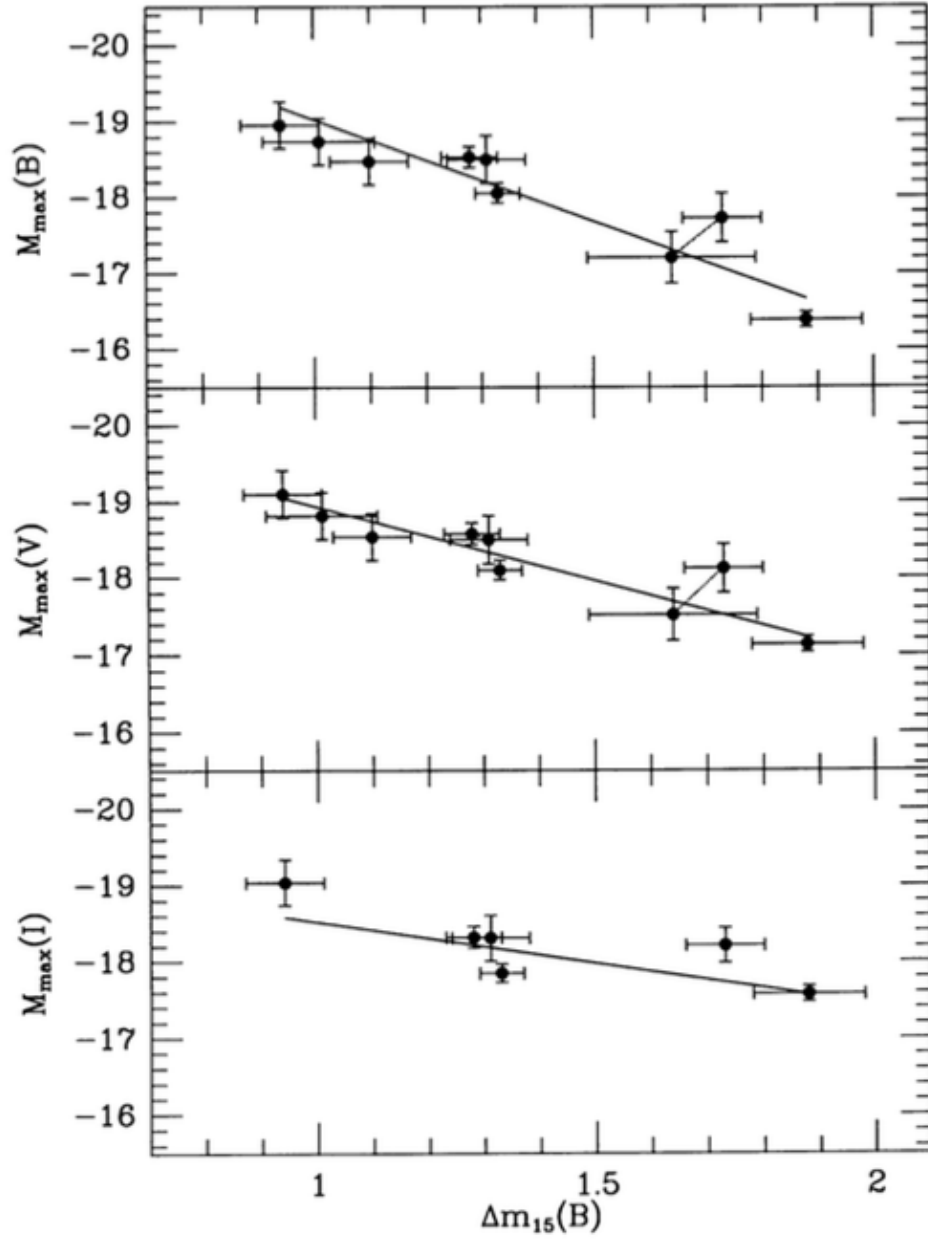


Figure 1.9: The decline rate–peak luminosity relation, also known as “the Phillips relation” for 9 well-observed SNe Ia. The figure shows plots of the absolute magnitudes in B , V and I for 9 SNe Ia for B and V and only 6 SNe Ia for I vs. their decline rate parameter $\Delta m_{15}(B)$ values. The plots show that for all 3 colour bands, the underluminous event SN 1991bg has the fastest B -band light-curve decline rate within 15 days after peak brightness compared to the rest and that the overluminous event SN 1991T have the slowest decline rate in the same colour band compared to the other events. The I -band absolute magnitudes for three of the SNe Ia were not available. Figure from Phillips (1993).

cosmological parameters using SN Ia data is performed by first estimating the distance modulus μ of each SN Ia in the sample, using the following linear parametrisation:

$$\mu_B = m_B^* - M + \alpha(s - 1) - \beta c, \quad (1.32)$$

where m_B^* is the observed peak B -band magnitude, s the stretch factor and c the colour parameter, which are all derived from the fit to a light-curve as discussed above (Astier et al. 2006; Guy et al. 2007). The absolute magnitude M , α and β are nuisance parameters in the cosmological fit, which is performed through the following minimisation with respect to θ , α , β and M :

$$\chi^2 = \frac{(\mu_B - 5\log_{10}(d_L(\theta, z)/1\text{Mpc}) + 25)^2}{\sigma^2(\mu_B) + \sigma_{int}^2}, \quad (1.33)$$

where d_L is the luminosity distance with its argument θ representing the fitted model's defined cosmological parameters, $\sigma^2(\mu_B)$ the variance and σ_{int} the absolute magnitude intrinsic dispersion (Riess et al. 1998; Astier et al. 2006). The information about cosmological parameters is encoded in d_L via its dependence on redshift, as the following equation shows:

$$d_L(z_1) = \frac{c(1+z)}{H_0|\Omega_k|^{-1/2}} \text{sinn} \left\{ |\Omega_k|^{1/2} \int_0^{z_1} [(1+z)^2(1+\Omega_M z) - z(2+z)\Omega_\Lambda]^{-1/2} dz \right\}, \quad (1.34)$$

where ‘sinn’ is defined as ‘sin’ if $\Omega_k < 0$ (closed Universe), ‘sinh’ if $\Omega_k > 0$ (open Universe) and $\text{sinn}(x) = x$ if $\Omega_k = 0$ (see Carroll et al. 1992), with the dimensionless density parameters, Ω_k , Ω_M and Ω_Λ , as defined in Equations (1.24) and (1.21).

We highlight that the determination of the distance modulus in Equation (1.29) and its subsequent use in the fitting for cosmological parameters is specifically based on the Spectral Adaptive Light-curve Template fitting method (SALT/SALT2, see Guy et al. 2005, Guy et al. 2007), which outputs the three values m_B^* , s and c that are utilised in its estimation. There exist other light-curve fitting methods used in determining the LHS of Equation (1.29), such as the multi shape light curve method (MLCS/MLCS2K2, see Riess et al. 1996; Jha et al. 2007), which performs the distance estimation in a slightly different way compared to SALT/SALT2.

The DES SN Program aims to measure ~ 4000 high-quality SN Ia light curves out to redshift $z \sim 1.2$, simultaneously providing the largest SN Ia sample, higher redshifts, improved calibration and better colour constraints than the current state-of-the-art Supernova Legacy Survey (SNLS) and joint light-curve analysis (JLA) (Bernstein et al.

2012, Betoule et al. 2014). The gathered sample will enable the DES SN cosmologists to perform robust SN Ia spectrophotometric analyses and place the best constraints to date on the value of w .

1.8 Existing Classification Methods of Supernova Spectra

Spectroscopic follow-up observations of SNe allow a more accurate classification of these objects as well as a more accurate determination of their redshifts, compared to the classification performed using their photometric data. The process of classifying SN spectra involves fitting several template spectra at various phases (time (in days) at which the spectra are taken in relation to the date of maximum brightness of the SN or time that has elapsed since the first day of the SN explosion) to an observed spectrum. The the best fit SN template spectrum gives the SN typing of the observed spectrum as well as the best estimate of its redshift. Several SN spectral fitting methods are in existence. Examples of these include the Supernova Identification program (SNID, Blondin & Tonry 2007), **Superfit** (Howell et al. 2005), **Gelato** (<https://gelato.tng.iac.es/>) and Zheng’s hybrid SN spectral classification technique (Zheng et al. 2008).

The third method—**GELATO**, which is online-based (i.e. it requires Internet connectivity to operate)—has not proven to be user-friendly as it lacks proper documentation on how to use it. The fourth method (Zheng’s hybrid technique) is a variant of **SNID**. We therefore only review the first two of the four methods. Additionally and more importantly, the comparison of our SN spectral classification results obtained with our classification algorithm **SNMC** (see the next Section for details) is made to the results of these two classification methods.

1.8.1 SNID

The **SNID** classification process is based on the cross-correlation technique developed by Tonry & Davids (1979) originally to determine the redshifts of galaxies. Blondin & Tonry (2007), hereafter BT07, extended the technique to determining the redshifts of observed SNe from spectra as well as typing the spectra and determining their spectroscopic ages (epochs/phases). The technique works by computing a cross-correlation function $c(n) = s(n) * t(n)$, where $*$ is the cross-correlation product, $s(n)$ the observed SN spectrum and $t(n)$ the template spectrum whose SN type and age are known and its redshift is zero. A plot of $c(n)$ reveals a characteristic peak (referred to as correlation peak) from which the best-fit redshift z_{cor} is determined.

A quantity known as the “r-value” (also called the correlation height-noise ratio, BT07), defined as the ratio of the height h of the highest correlation peak to the root-mean-square (rms) of the symmetric component of $c(n)$, measures the quality of the fit for z_{cor} (see Figure 1.10).

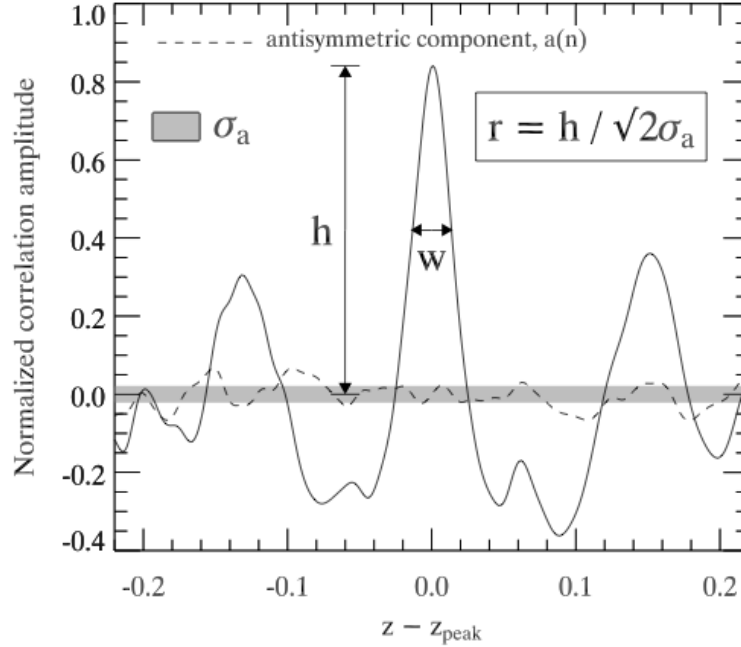


Figure 1.10: The correlation height-noise ratio (r-value) about the redshift z_{cor} (z_{peak} in the figure) corresponding to the correlation peak. The peak width w is utilised in the computation of the error in the estimated redshift z_{cor} . Figure from BT07.

The accepted best-fit redshift z_{cor} corresponds to an r-value greater than 3. Additionally, a large overlap in wavelength between $s(n)$ and $t(n)$ is a requirement for ascertaining a significant measurement of z_{cor} (BT07). One caveat about SNID is that it re-bins the input and template spectra onto a common wavelength logarithmic scale and then continuum subtract them. Additionally, the low- and high-frequency residuals that result from the continuum subtraction are removed using a bandpass filter (BT07). All these operations result in a loss of important information from a spectrum, including host galaxy extinction information that is also recoverable from a spectrum.

At the end of a classification run, SNID outputs a list of the best fit templates to the observed input SN spectrum in a graphical user interface (GUI) that makes use of the PGPLOT plotting package² (see example in Figure 1.11), illustrating the SN type, redshift and possible age in order of the best fit to the least fit SN template.

²<https://people.lam.fr/blondin.stephane/software/snid/>

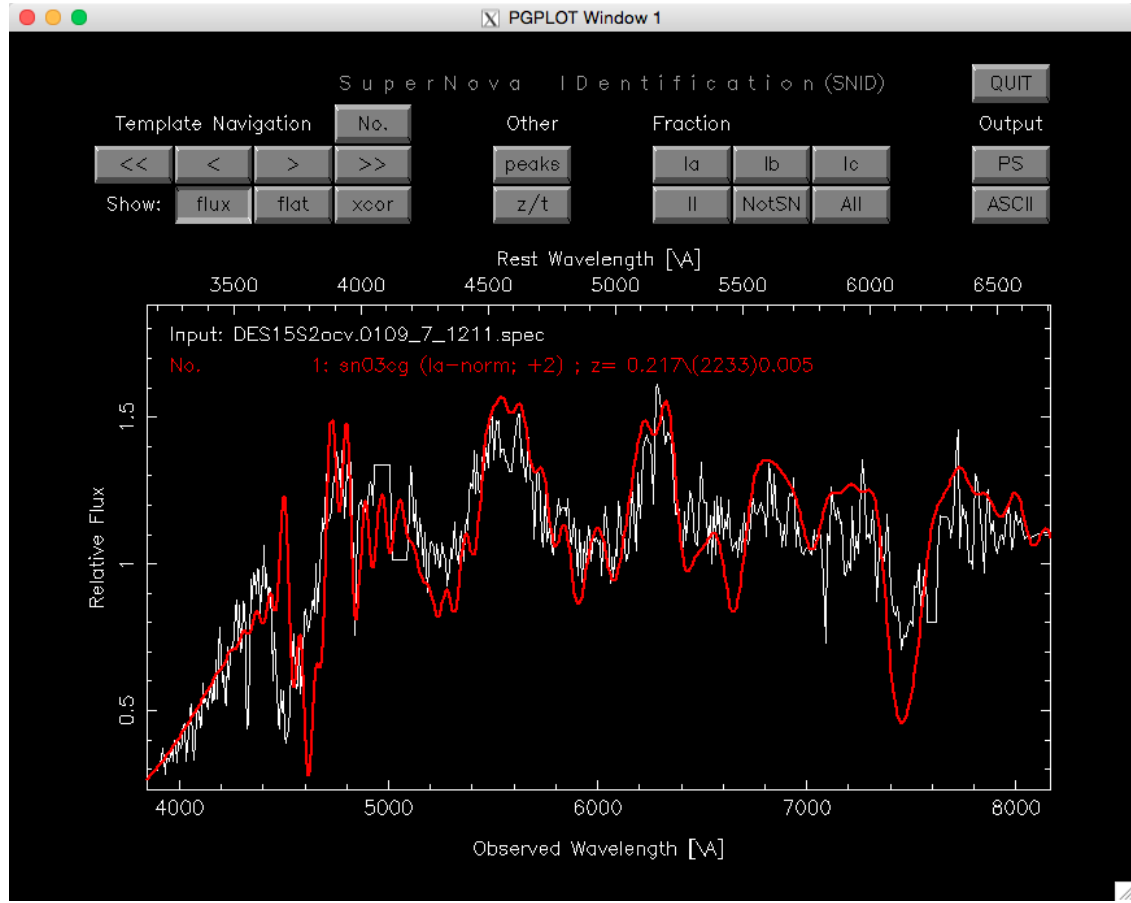


Figure 1.11: Example of a SNID output at the end of a classification run, showing the best fit SN template spectrum (SN03cg, red) to the input spectrum (DES15S2ocv, white), along with its type (SN Ia normal) and age (+2, which means 2 days after peak brightness of the input SN in the Blue filter) as well as the redshift ($z = 0.217 \pm 0.005$). Shown in the top left corner are the ‘Template Navigation’ buttons, which enables the user to step through all the fitted SN templates, from the first best fit to least best fit.

The online SNID manual³ provides descriptions of the meanings of the various output options seen in the SNID output GUI. While the typing and redshift estimation are reasonably accurately performed, the returned age is not always as accurate. SNID works well for SN candidates that are very bright and well separated from their host galaxies (see top row of Figure 1.12).

For faint SN candidates with low signal-to-noise ratio (SNR) and not well separated from their host galaxies, the observed spectra of such candidates suffer significant host light contamination (bottom row of Figure 1.12). This is the *blended spectra problem*.

³<https://people.lam.fr/blondin.stephane/software/snid/howto.html>

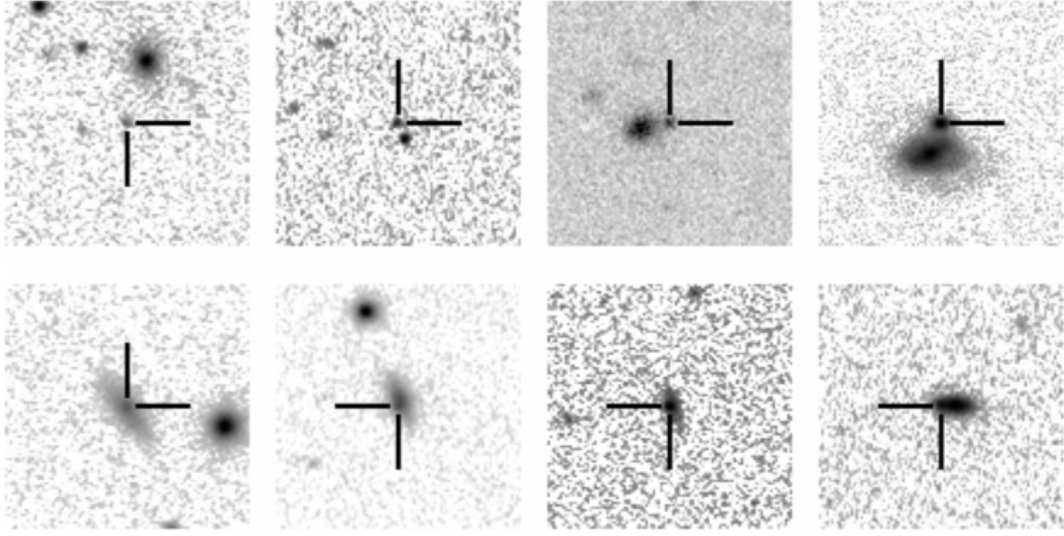


Figure 1.12: A sample of *clean* (bright and well separated from host) and *heavily contaminated* SNe from the SDSS-II SN Survey, in the top and bottom rows, respectively. Figure from Zheng et al. (2008).

When faced with a blended SN spectrum, using **SNID** becomes a challenge as it has no framework of fitting for both the SN type and host galaxy type simultaneously. A different method is thus required in fitting for both SN and galaxy types in blended spectra. This is a major motivation of this thesis.

1.8.2 Superfit

Superfit fits for both the SN type and galaxy type (to within its limitations) in an observed spectrum by comparing the spectrum to SN template and galaxy template libraries. The working mechanism of **Superfit** is discussed by Howell et al. (2005). We provide a summary of the algorithm's classification process.

Superfit utilises χ^2 fitting to isolate SN and host galaxy light in an observed spectrum. It then performs SN typing using the isolated SN spectrum. The χ^2 fitting performs a comparison of each observed SN spectrum to a library of template SNe of all types spanning a range of epochs. During the fitting, the amount of host galaxy light contamination, redshift and reddening are allowed to vary in order to find the best fitting parameters. The code performs the fitting at a given redshift z by computing

$$\chi^2 = \sum \frac{[O(\lambda) - aT(\lambda; z)10^{cA_\lambda} - bG(\lambda; z)]^2}{\sigma(\lambda)^2}, \quad (1.35)$$

where O is the observed spectrum, T the SN template spectrum, G the host galaxy

template spectrum, A_λ the reddening law, σ the error on the observed spectrum and a , b and c are coefficients that are allowed to vary in order to find the best fit template SN, template host galaxy and reddening law, respectively.

The template galaxy spectra utilised by **Superfit** are those of Kinney et al. (1996) and Fioc & Rocca-Volmerange (1997), which consist of the following 11 types⁴: E, S0, Sa, Sb, Sc and SB1-6 (starburst galaxies). The SN template library consist of over 100 SN Ia spectra, over 70 *SN Ibc* spectra and about 50 *SN II* spectra, all selected to have good S/N and cover a wide range of epochs and spectral range. A later version of **Superfit** now also includes the types and subtypes SLSNe (superluminous SNe), 2002cx-like, SN2007bi, SN2002bj⁴, with a splitting of the *SNe Ib/c* into *SN Ib* and *SN Ic*.

Superfit outputs a list of the best fit SN templates, host galaxy templates, redshifts and reddening. The algorithm is not fully automated and thus requires the user's involvement to scrutinise the output and make the final SN typing. The estimated SN type is allocated to one of six confidence indexes, which corresponds to the estimated type and associated classification uncertainty: (i) *Certain Ia*, (ii) *Highly probable Ia*, (iii) *Probably Ia*, (iv) *Unknown*, (v) *Probably not Ia* and (vi) *Not Ia* (see Section 5 of Howell et al. (2005) for the descriptions of each of the six indexes). **Superfit** uses the weighted mean of the best 5 epochs to determine the final spectroscopic epoch of an observed SN spectrum, done to dilute outlier effects and to smooth out the SN Ia spectral diversity. **Superfit** cannot include light-curve or prior information in its classification, which forms another motivation for this thesis.

1.9 Conclusion

We end this chapter with a discussion of why our new Bayesian SN spectral classifier **SupernovaMC** is needed. As discussed above, spectroscopic follow-up observations of SNe play an important role in cross-checking the results of photometric methods obtained from classifying newly discovered SNe. This is so because spectroscopic data yield more accurate classification parameters than photometric data. However, due to the world-wide scarcity of telescopes dedicated to SN spectroscopic follow-up activities, the majority of observed SNe from experiments such as the Dark Energy Survey (DES) have to be classified photometrically, rendering the lesser samples of spectroscopically classified SNe very crucial to the success of photometric classification efforts.

While the above is true, not all spectroscopically observed SNe form part of the

⁴<http://www.dahowell.com/uploads/2/2/4/7/22474426/instructions.pdf>

spectroscopic samples needed in aiding photometric methods. In fact, close to half of the spectroscopically observed SNe Ia do not make it into a cosmological analysis sample (Zheng et al. 2008), because their spectra are not well classified using existing SN spectral classifiers due to either (i) heavy contamination of host galaxy light or (ii) low signal to noise ratio (SNR), which prevents the achievement of unambiguous classification. This was the case with close to half of the SALT spectra from our spectroscopic follow-up campaign of DES SN candidates at the end of the first DES observing season in February 2014. We used **SNID** to classify the spectra and estimate the relevant parameters.

Previous attempts to deal with the problem of classifying spectra that are heavily contaminated with light from their host galaxies or have low SNR have been made. **Superfit** discussed in subsection 1.8.2 was one such attempt. However, **Superfit** is a grid-search template fitting algorithm, which means it is computationally expensive in the case of multi-dimensional parameter fitting, as the computational time grows exponentially with the number of parameters fitted. Additionally, **Superfit** does not provide error bars for all its fitted parameters, which one can achieve with the computation of full posterior probabilities of the parameters. Another **Superfit** drawback is that it is not accessible to the wider Astronomy community, as the IDL language in which it is written is not open source.

Motivated by the above reasons, we developed a Bayesian inference python-based alternative to **Superfit**, **SuperNovaMC** (**SNMC**), which uses the Metropolis Hastings Markov Chain Monte Carlo algorithm (discussed in more detail in Chapter 2). With **SNMC**, we have the capability to perform multi-dimensional parameter fitting simultaneously without introducing an increase in the total computational time by a big margin compared to the grid-search approach. **SNMC** also enables the computation of full posterior distributions of the fitted parameters from which error bars for all parameters can be determined. Another two ways **SNMC** differs from other algorithms is that it uses the full spectrum, not just the deviation from the continuum, and it also allows principled model selection for the classification using the *Bayesian Information Criterion* (discussed further in Chapter 4) or the Bayesian evidence.

In the next chapter, we discuss Bayesian Inference and Markov Chain Monte Carlo Techniques—the foundations over which **SNMC** is built.

Chapter 2

Bayesian Inference and Markov Chain Monte Carlo Techniques

2.1 Introduction

We review in this chapter the key concepts of Bayesian statistics and provide a light treatment of the theory of Markov chains, which are both key to **SNMC**'s classification capabilities (discussed in the next two chapters). We start with the definition of Bayes' theorem, which is central to any Bayesian Inference exercise. We then discuss Markov Chain Monte Carlo (MCMC) techniques, which are part of an important suite of techniques to solving Bayesian Inference problems that have no analytical solutions, covering a reasonable amount of their theoretical aspect. We conclude the chapter by mentioning the various MCMC sampling algorithms, discussing in more detail the Metropolis-Hastings algorithm which, as discussed at the end of Chapter 1, **SNMC** makes use of. Unless otherwise stated, the bulk of the content presented in Section 2.4 was summarized from Pishro-Nik (2014).

2.2 Bayesian Inference

The use of Bayesian statistics as a statistical inference tool rests fundamentally on Bayes' theorem, which mathematically is written as follows (see e.g. Trotta 2008):

$$p(B|A, I) = \frac{p(A|B, I)p(B|I)}{p(A|I)} \quad \text{Bayes' theorem.} \quad (2.1)$$

We discuss the various components of Bayes' theorem in more detail, mostly summarising material from Trotta (2008), which comprehensively discusses the theorem and provides practical examples of the theorem's applications. The left-hand side (LHS) of

(2.1) is obtained from the product rule of the joint probability of two events A and B conditional on some piece of information I taken to be true. The rule has the following mathematical expression:

$$p(A, B|I) = p(A|B, I)p(B|I). \quad (2.2)$$

Since the product rule is commutative, we have

$$p(A, B|I) = p(B, A|I) = p(B|A, I)p(A|I). \quad (2.3)$$

Bayes theorem then follows from Equations (2.2) and (2.3). The vertical bar in the equations means the probability is assigned by taking into consideration the information given on its right side. If we substitute A and B in Equation (2.1) with some observed data d and hypothesis $\mathcal{H}$ that we wish to test, then we re-write it in the form:

$$p(\mathcal{H}|d, I) = \frac{p(d|\mathcal{H}, I)p(\mathcal{H}|I)}{p(d|I)}. \quad (2.4)$$

The quantity on the LHS of Equation (2.4) is known as the posterior probability of $\mathcal{H}$ given d and I . It tells us about our degree of belief of $\mathcal{H}$, after our consideration of the information encoded in d . On the right-hand side (RHS) of the same equation, the two probability factors in the numerator are the sampling distribution for the data, and the hypothesis' prior probability respectively. For observed data, the sampling distribution is referred to as the likelihood function of the hypothesis, denoted $\mathcal{L}(H)$. The denominator is called the marginal likelihood and also known as the Bayesian evidence. The prior probability and Bayesian evidence have the following respective mathematical expressions:

$$p(\mathcal{H}|I) = \sum_d p(d, \mathcal{H}|I), \quad (2.5)$$

and

$$p(d|I) = \sum_{\mathcal{H}} p(d|I, \mathcal{H}). \quad (2.6)$$

In both equations, the sums are performed over all possible outcomes for d and $\mathcal{H}$ respectively. The Bayesian evidence is mostly utilised in the selection of a best fitting model from a collection of various model fits to the data.

Parameter inference under a Bayesian formalism involves an initial selection of a model that has a set of hypotheses represented as a vector of parameters. These parameters would usually describe some physical aspect of a chosen model such as the redshift of a supernova or the amount of host galaxy extinction that light from a supernova suffers. Next is the selection of our prior knowledge about the model parameters. This is a summary of what we already know about the values of our chosen parameters from prior measurements. If, for example, our parameter prior knowledge was derived in a study that employed a Bayesian formalism, then our chosen values for the priors would be the posterior distributions of the parameters that the study determined. Following the selection of a model, model parameters and priors is the construction of a likelihood function for our measurements, which, as described above, is a representation of the sampling distribution function for our measured data.

We provide a practical example of Bayes' theorem, summarising the application of the theorem to independent and depended probability events involving the use of (i) two unbiased coins C and C' for the former and (ii) one unbiased coin C and one biased coin C_b for the latter. The practical example summarised from Puga et al. (2015) estimates the iterative probabilities of toss outcomes (heads or tails) from the two sets of coins. For the case of C and C' , the probability that the toss outcome is heads (H) or tails (T) is independent of the choice of the coin and it is always $P(H) = 0.5$. The joint probability that either C or C' is chosen and that the toss outcome of the chosen coin is for example H is given by the product of their marginal (individual) probabilities $P(C)$ and $P(H)$ respectively, i.e.

$$P(C, H) = P(C) \times P(H) \quad (2.7)$$

For the case of C and C_b , suppose C_b has a toss outcome of heads 75% of the time. Choosing C_b therefore makes the toss outcomes dependent on the fact that the coin is biased. The two conditional probabilities for C and C_b are expressed as $P(H|C) = 0.5$ and $P(H|C_b) = 0.75$, respectively. To determine the probability that the coin is biased upon obtaining a H toss outcome, i.e. $P(C_b|H)$, the joint probability of choosing C_b and obtaining a H toss outcome is first written:

$$P(C_b, H) = P(C_b|H) \times P(H). \quad (2.8)$$

Since, Equation (2.8) is symmetric (from Equation 2.3), we have

$$P(C_b|H) \times P(H) = P(H|C_b) \times P(C_b). \quad (2.9)$$

Rearranging Equations (2.8) and (2.9) leads to Bayes' theorem:

$$P(C_b|H) = \frac{P(H|C_b) \times P(C_b)}{P(H)}. \quad (2.10)$$

The posterior probability $P(C_b|H)$ in Equation (2.10) is calculated by first determining the value of $P(H)$, since the probability values for $P(H|C_b)$ and $P(C_b)$ are known, i.e. $P(H|C_b) = 0.75$, $P(C_b) = 0.5$ as both C and C_b have an equal chance of being selected the first time. $P(H)$ is determined by considering all possible ways in which a H toss outcome can be obtained from C and C_b , i.e. $P(H) = P(H|C) \times P(C) + P(H|C_b) \times P(C_b) = 0.5 \times 0.5 + 0.75 \times 0.5 = 0.625$. Substituting the probability values on the RHS of Equation (2.10), we get $P(C_b|H) = 0.6$.

The process of updating prior information of existing parameters can be done in this way using Bayes' theorem, as new knowledge of the parameter values becomes available. An example in this case is obtaining more information by tossing the same coin one more time and then updating the prediction that the coin is biased using the toss outcome. The probability $P(C_b)$ is not 0.5 the second time the coin is tossed as the suggestion from the first toss is that C_b has a higher chance of being picked than C . The posterior $P(C_b|H)$ calculated in the first toss is set as the updated prior for the probability of selecting C_b , i.e. $P(C_b) = 0.6$, which means the probability of selecting C for the second toss is $P(C) = 1 - P(C_b) = 0.4$. If the outcome of the second toss is again H , then $P(H) = 0.5 \times 0.4 + 0.75 \times 0.6 = 0.65$, and Bayes' theorem gives $P(C_b|HH) = 0.75 \times 0.6 / 0.65 = 0.69$. Repeating this process several times refines the prediction that the coin is biased further.

Moving on, our measurements may sometime include what are known as nuisance parameters, which are parameters we do not need at all but are somehow inherently also present in the data that we measure. The joint posterior probability for both our set of parameters of interest and the set of all nuisance parameters is determined and then the nuisance parameters are marginalised over. We demonstrate the concept of marginalising over nuisance parameters with the following example. Consider a hypothetical case of a chosen model $\mathcal{M}$ that describes a certain physical phenomenon of the Universe such as the 'equation of state parameter for dark energy'. Let us assume that $\mathcal{M}$ has a set of hypotheses both in the form of our parameters of interest represented by a vector ϕ , and nuisance parameters represent by a vector ψ . We use Bayes' theorem to obtain the joint posterior probability for $\theta = (\phi, \psi)$ like so:

$$p(\theta|d, \mathcal{M}) = \mathcal{L}(\theta) \frac{p(\theta|\mathcal{M})}{p(d|\mathcal{M})}, \quad (2.11)$$

where as defined before, $p(\theta|d, \mathcal{M})$ is the posterior probability of all the parameters θ given the data d and conditional on model $\mathcal{M}$, $\mathcal{L}(\theta)$ is the likelihood function of all the parameters, $p(\theta|\mathcal{M})$ and $p(\theta|\mathcal{M})$ the prior probability of the parameters and Bayesian evidence respectively, both conditional on model $\mathcal{M}$. Notice that we have expressed the data sampling distribution in the form of a likelihood function of the parameters i.e. $\mathcal{L}(\theta) \equiv p(d|\theta, \mathcal{M})$. It is worth noting here that if we are only concerned with parameter estimation and not with model fitting to determine the best-fit model to a given data set, then the Bayesian evidence plays no role and is set to unity. To marginalise over nuisance parameters under parameter inference, we re-write Equation (2.11) in the form

$$p(\phi|d, \mathcal{M}) \propto \int \mathcal{L}(\phi, \psi) p(\phi, \psi|\mathcal{M}) d\psi, \quad (2.12)$$

i.e. the integration is performed wrt to the nuisance parameters ψ . The estimated values of our parameters of interest ϕ are obtained from the integral in Equation (2.12) and presented through the use of basic statistical methods such as the mode, median or the mean or through plotting histograms of the individual parameters that make up the set of all our parameters of interest. Two-dimensional contour plots of the parameters are also used in presenting estimates of the posterior probabilities of our parameters of interest.

An analytical solution to the integral in Equation (2.12) usually does not exist. This necessitates the use of numerical methods to determine the value of the likelihood, which coupled with the prior, then provides an approximation of the posterior probability of the parameters. The Markov Chain Monte Carlo (MCMC) numerical techniques are quite popular for this purpose. The use of an MCMC technique offers a wide range of advantages, including its ability to handle multi-dimensional parameter spaces with minimal computational resources.

In the next two sections, we discuss some of the properties of the MCMC technique and give a brief account of its theoretical framework.

2.3 Markov Chain Monte Carlo Sampling Techniques

The application of MCMC techniques in Bayesian inference has become wider, as many problems that involve the determination of the value of the posterior in Equation (2.12) have no analytical solutions. As the name suggests, MCMC operates by constructing what is called a Markov chain, which is a random collection of 1 or n-dimensional variables drawn from a well-defined state space. A Markov chain satisfies the Markov Property,

which states that the distribution of the next state or variable in the chain is only dependent on the current state and not on any past state (Feller 2008).

The chain meanders within the parameter space growing longer in size, with its overall length influenced by the number of samples the user specifies prior to running an MCMC process. The jumps from one state to the next in the chain are governed a transition kernel, which describes the probability of the chain jumping to a new state given the current state of the chain (Chib & Greenberg 1995). In theory, a Markov chain of a correctly designed MCMC algorithm will converge to the target distribution (the posterior probability) as the number of samples tends to infinity. Convergence to the target distribution means that any successive samples in the chain are effectively drawn from the true posterior probability of our hypothesis.

2.4 Some properties of Markov chains and MCMC algorithms

2.4.1 Transition probability matrix

The transition kernel mentioned above is also known as the probability transition matrix. Each Markov chain has a probability matrix P associated with it, whose entries are the transition probabilities of the various states in a Markov chain. To understand this better, if the set $\{X_1, X_2, \dots, X_m\}$ represents elements of a Markov chain, then from the Markov Property described above, the probability of the chain jumping from state X_m to X_{m+1} is only dependent on X_m and not on any of the previous states $X_0, X_1, \dots, X_{m-1}$. Mathematically, this is represented as

$$P(X_{m+1} = j | X_m = i, X_{m-1} = i_{m-1}, \dots, X_0 = i_0) = P(X_{m+1} = j | X_m = i), \quad (2.13)$$

where i, j represent the chain states and m the time corresponding to state i . The values of Equation (2.13) are the transition probabilities of the states and are assumed to be time independent, i.e. Equation (2.13) has no dependency on m . Elements of the transition probability matrix are defined by the mathematical expression

$$p(i, j) = P(X_{m+1} = j | X_m = i), \quad (2.14)$$

with i, j and m as defined in Equation (2.13).

2.4.2 Ergodicity

Convergence of a Markov chain to the target or stationary distribution enables us to use ordinary Monte Carlo integration techniques to obtain estimates of the quantities we are interested in. Despite the fact that there exists a dependency between successive elements of a Markov chain, evaluating them using Monte Carlo methods which demand independent variables (Geyer 2011), is still feasible via the ‘Ergodic theorem’ (Gilks et al. 1996) or, ergodicity, as it is sometimes referred to. The theorem states that given N elements $\theta_1, \theta_2, \dots, \theta_N$ of a Markov chain that is irreducible, aperiodic and positive recurrent with expectation value $\langle g(\theta) \rangle < \infty$ for some function of the parameters $g(\theta)$, then we have with probability 1 that

$$\frac{1}{M} \sum_{i=1}^M g(\theta_i) \rightarrow \int g(\theta) \pi(\theta) d(\theta) \quad (2.15)$$

as $M \rightarrow \infty$. π represents the stationary distribution. Here, we provide brief discussions of the meanings of irreducibility, aperiodicity and positive recurrence properties referred to in the theorem.

2.4.2.1 Irreducibility

The ‘irreducibility’ property of a Markov chain is the notion that irrespective of the present state in the chain, any other state can be reached in a finite time. Two states i and j are said to be *accessible*, if going from i to j and vice versa is possible. States i and j are also said to communicate with each other. Irreducibility of a Markov chain can therefore be rephrased as a quality in which communication among all states of the chain is plausible.

2.4.2.2 Aperiodicity

The ‘aperiodicity’ property of a Markov chain refers to the period of occurrence of state i in the chain. For example, if state i has a period of 3, it means the chain advances to this state at times $m = 3, 6, 9$, and so on. If however, the chain returns to state i after a steps and also after b steps, and a and b are co-prime (i.e. their greatest common divisor is 1), then state i is aperiodic. If the chain is irreducible and state i is aperiodic, then the chain is said to be aperiodic.

2.4.2.3 Positive Recurrence

A state in Markov chain is recurrent if the probability of returning to that state at some point equals one. Mathematically, this is represented as follows: if we denote the probability for Markov chain to return to state i by f_{ii} , i.e.

$$f_{ii} = P(X_n = i, n \in \{1, 2, \dots\} | X_0 = i), \quad (2.16)$$

then state i is a recurrent state if $f_{ii} = 1$. X_0 represents state i at time $m = 0$ and X_n is state i at time $m = n$. State i is *positive recurrent* if the expected return time of the chain to it is finite. A Markov chain is therefore ‘positive recurrent’ if all its states are positive recurrent.

2.4.3 Detailed balance

Detailed balance is associated with a Markov chain that is *reversible*. To understand this better, we revisit the following discussion. A stochastic process $X(t) = \{X(t_1), \dots, X(t_n)\}$ in some finite state space $\mathcal{S}$ with time $t \in \mathcal{T}$ is said to have a stationary distribution π if $X(t + \tau) = \{X(t_1 + \tau), \dots, X(t_n + \tau)\}$ has the same distribution as $X(t)$ for all $t_1, \dots, t_n, \tau \in \mathcal{T}$. $\mathcal{T}$ is the set of integers $\mathbb{Z}$ for a discrete-time stochastic process and the set of reals $\mathbb{R}$ for a continuous-time stochastic process (Kelly 2011). $X(t)$ is *reversible* if $X(\tau - t) = \{X(\tau - t_1), \dots, X(\tau - t_n)\}$ has the same distribution as $X(t)$ for all $t_1, \dots, t_n, \tau \in \mathcal{T}$ (Kelly 2011). A reversible stochastic process is also stationary.

Recall that if $X(t)$ is a Markov chain, then we have its transition probability from state i to state j defined as

$$p(i, j) = P(X(t + 1) = j | X(t) = i) \quad (2.17)$$

where P is the chain’s transition probability matrix. *Detailed balance* is the notion that given an existence of a set of positive numbers $\pi(i)$, $i \in \mathcal{T}$ whose summation is unity, we have

$$\pi(i)p(i, j) = \pi(j)p(j, i) \quad i, j \in \mathcal{T}. \quad (2.18)$$

A Markov chain is *reversible* if and only if it satisfies the detailed balance conditions in Equation (2.18) (Kelly 2011). Existence of such a collection of positive numbers $\pi(i)$, $i \in \mathcal{T}$ in Equation (2.18) implies that π is the “equilibrium distribution” of the process (Kelly 2011), which is the same as the stationary distribution π in Equation (2.15).

2.4.4 Burn-in

The time taken by a Markov chain to converge to the target distribution varies and somewhat is influenced by the chain's starting point. It is sometimes practical to throw away a set of the first initial samples of the chain in order to remain with samples that approximate the target distribution more reasonably. This is done in an attempt to avoid a potential bias that inclusion of such initial samples may introduce on posterior inference, as the chain usually starts far from the target distribution. This set of first starting samples discarded from the total number of samples is referred to as burn-in.

2.4.5 Thinning

Thinning is needed if the chain elements are correlated. It reduces the autocorrelation of the chain elements. This action is useful for chains that are correlated and do not mix very well, i.e. chains that do not sufficiently explore the target distribution fast enough, which directly impacts the rate of convergence (Toft et al. 2007).

2.4.6 Acceptance rate

The acceptance rate of a MCMC algorithm is the fraction of the total number of jumps in parameter space that are accepted. A high acceptance rate is indicative of a chain not mixing very well, i.e. the chain does not explore the full parameter space too well and too quickly, whereas a low acceptance rate is suggestive of a chain taking larger jumps and therefore rejecting too many samples. If the proposal distribution (akin to the above discussed data sampling distribution) is Gaussian, a high acceptance rate means its variance is too small and vice versa. A general rule of thumb is to have a proposal distribution whose variance results in the fractional acceptance rate of between 0.2 and 0.6 of the jumps (Roberts et al. 1997).

2.5 MCMC Sampling methods

Various MCMC algorithms are in use and the popular ones include Gibbs sampling, Hamiltonian Monte Carlo and the Metropolis-Hastings algorithm. In this thesis, we only use the Metropolis-Hastings, which we now discuss in depth.

2.5.1 Metropolis-Hastings algorithm

The Metropolis-Hastings (MH) algorithm is one of most popular and widely used MCMC sampling methods (Trotta 2008; Robert 2015). The algorithm's developmental history

dates back to as far as 1946, where Stanislaw Ulam, while playing the games of solitaire, pondered the chances of a ‘Canfield’ solitaire game laid out with 52 cards coming out successfully (Eckhardt 1987). Ulam’s thoughts gave birth to a novel way of performing numerical approximations for problems that involved a multitude of integrals (tens to hundreds of integrals) which conventional numerical techniques of the time were unable to handle. This new technique was codenamed ‘Monte Carlo’, a name that Nicholas Metropolis, a colleague of Ulam, coined (Metropolis 1987). Shortly thereafter, Metropolis et al. (1953) published a modified version of the Monte Carlo integration technique to investigate equations of states of interacting molecules in substances. Hastings (1970) generalised the Metropolis et al. (1953) Monte Carlo sampling technique, where he gave an account of the various aspects of the algorithm, including its theoretical framework, assessment of errors involved in Monte Carlo estimates and the associated difficulties in assessing such errors. It is this revised version of the Metropolis Monte Carlo method that is referred to today as the ‘Metropolis-Hastings algorithm’.

The MH algorithm operates in the following manner. It draws random jumps from a jump or sampling distribution (usually a mean-zero Gaussian). At each step it compares the ratio of the posterior probabilities at the proposed new position in parameter space to that of the previous point. If the new point is better (higher posterior probability) it accepts that step. However, if the posterior probability is lower there is still a chance to accept the worse step. This helps the algorithm escape from local maxima to find the global best fit.

In detail, the MH algorithm is:

1. Pick a starting point θ_0 for the chain and compute the posterior at this point $P(\theta_0)$.
2. Repeat the following for N steps:
 - (a) Make a jump to the next proposed point $\mathbf{u}$, given by $\mathbf{u} = \theta_i + \Delta\theta_i$, where $\Delta\theta_i$ is the jump drawn from the proposal distribution.
 - (b) Compute the ratio of the posterior at $\mathbf{u}$ to that at θ_i :

$$R = \min(1, P(\mathbf{u})/P(\theta_0)).$$
 - (c) Draw a uniform random number, r , from $[0, 1]$:
 - i. If $r < R$ accept the step and set $\theta_{i+1} = \mathbf{u}$.
 - ii. If $r \geq R$ reject the step and set $\theta_{i+1} = \theta_i$.

The number of steps N must be chosen sufficiently large to ensure the chain has converged. In this thesis, we typically choose $N = 2.5 \times 10^5$ steps. Convergence is

typically a problem for multi-modal posteriors, a problem that we do indeed face here. We address this by first running our optimisation algorithm many times to find the best fitting parameters and using those values as the starting point for our MCMC chains.

2.6 Conclusion

We conclude the chapter by highlighting that Bayes' theorem, model selection and parameter estimation have broad applications across many disciplines, including Biology, Economics, Medicine and Physics. Moreover, the ability of a Markov chain to converge to a target distribution means that the Markov Chain Monte Carlo (MCMC) algorithm is a powerful way to explore high-dimensional parameter estimation since it scales only approximately linearly with the number of parameters, compared to the exponential growth of computing time needed in grid-search methods. As a result MCMC has become the standard parameter inference tool in cosmology and other areas.

SNMC utilises Bayes' theorem and the MCMC algorithm presented in this chapter to estimate parameters of interest and classify SALT DES SN spectra. The use of prior knowledge of the parameters fitted for strongly benefits SNMC's performance, as two of our four parameters of interest, the epoch t and extinction A_V parameters (see Appendix A.3 for an elaborate discussion of these parameters), are reasonably well constrained from other methods.

We then make use of such knowledge by setting reasonably tight prior ranges centred on their prior known values. The prior information on the t parameter is obtained quite accurately from the light curve of a supernova candidate and that of the A_V parameter has been accurately determined using various extinction laws at any given (RA and DEC) location in the Milky Way galaxy. The latter sets the floor for the A_V values we expect to measure at given SN candidate locations.

In the next chapter, we look at the working mechanism of SNMC in more detail, assessing its classification and parameter estimation capabilities using simulated SN spectra.

Chapter 3

The Working Mechanism of *SuperNovaMC*

3.1 Introduction

In this chapter, we discuss the working mechanism of **SuperNovaMC** (SNMC), which uses the Metropolis-Hastings algorithm built into an MCMC package called ‘PyMC’ (Patil et al. 2010), discussed in some detail in Appendix A. We start with showing SNMC classification examples of heavily contaminated simulated SN spectra and how the results compare to SNID’s classification results of the same spectra. We then discuss SNMC’s *Model Selection* and *Parameter Estimation* phases and describe the SN and galaxy templates we use in creating the simulated SN spectra for testing SNMC’s performance as a SN spectral classifier (see Chapter 4). We show in the last section before concluding the chapter one example of SNMC’s classification of a SALT observed SN spectrum and again make a comparison of the results to the SNID classification results of the same spectrum, which reveals that SNMC is as competent in classifying SN spectra as SNID is and outperforms SNID in its estimation of some of the parameters. We also discuss in that section the artifacts present in all our SALT SN spectra and how they are dealt with prior to classification of the spectra.

3.2 SNMC example classification of heavily contaminated spectra and comparison to SNID results

We show in Figures (3.1) to (3.3), the SNID and SNMC classification results of four heavily contaminated (i.e. 70% host galaxy flux) simulated spectra generated using the following input parameters: (i) $\alpha, z, t, A_V, SNR = (0.3, 0.3, 20, 0.5, 5)$, (ii) $\alpha, z, t, A_V, SNR =$

(0.3, 0.3, 20, 0.5, 10), (iii) $\alpha, z, t, A_V, SNR = (0.3, 0.3, 20, 0.5, 100)$.

Because the spectra have more galaxy flux in them than SN flux, SNID finds it difficult to return the correct SN typing as the figures show, especially for low SNR cases. In the case of the $SNR = 100$ simulated spectrum, SNID returns the correct SN Ia typing but incorrect SN Ia sub-typing as the best-fit spectrum is that of ‘SN 91T-like’ and not the input normal SN Ia subtype. Also, the SNID recovered redshifts are incorrect in the last three of the four simulated spectra. SNMC on the other hand performs the typing correctly in all four simulated spectra and recovers the corresponding input parameters accurately in all cases.

We have not gone into the details of how SNMC obtains the results we have presented in this section. This is what we discuss in the next section, where we present the two SNMC stages of determining the SN and host galaxy types (model selection) in an observed SN spectrum and the estimation of the associated parameters (parameter estimation), i.e. the four parameters α, z, t , and A_V discussed above.

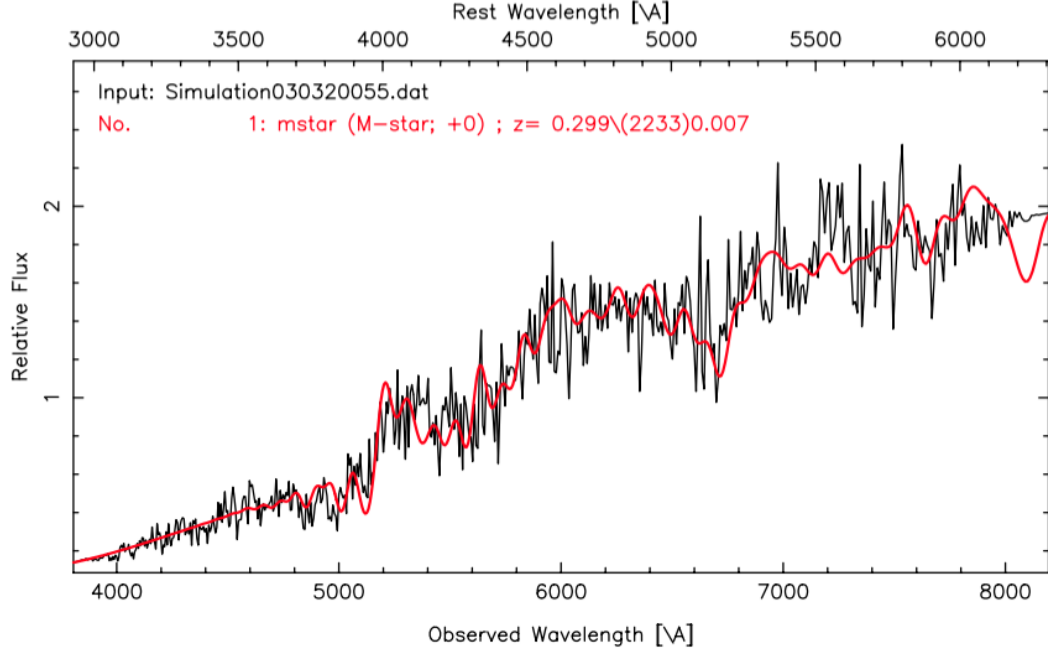
3.3 SNMC Model Selection and Parameter Estimation

Figure 3.4 shows a flow chart of SNMC’s model selection and parameter estimation stages:

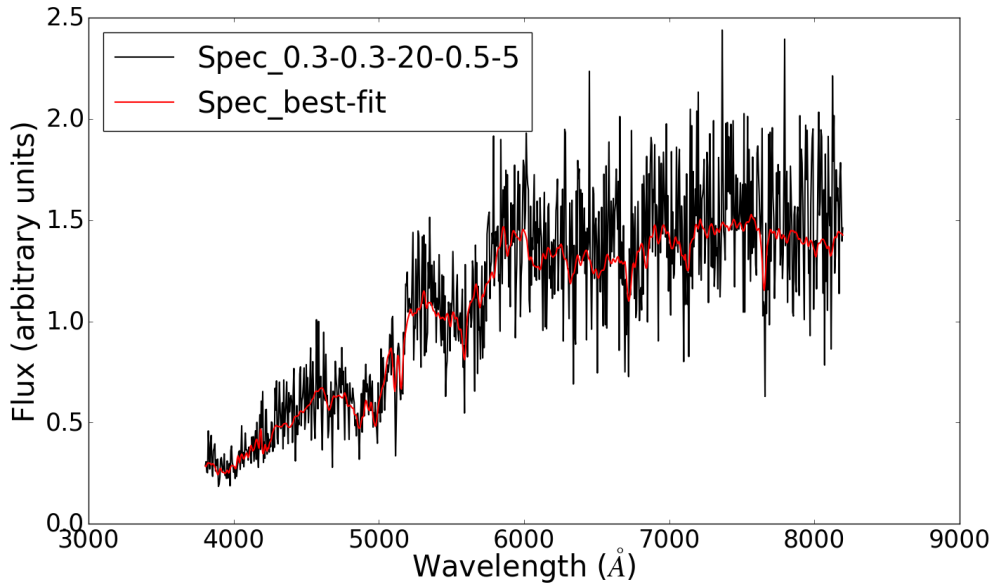
3.3.1 Model Selection

During model selection, SNMC identifies the best-fit SN type and host galaxy type by fitting eight different types of SN templates (with each type comprising templates at different epoch values t) and five different types of host galaxy templates to an observed input spectrum. Fitting of the SN and galaxy templates to an input spectrum is done simultaneously. Details of these templates are presented in Section 3.4. SNMC uses the ‘Nelder-Mead’ optimization algorithm (also known as the Simplex downhill or amoeba algorithm, Nelder & Mead 1965), available in the ‘scipy.optimize’ package, during this stage of the fitting. This is rebuild in PyMC as the class “pymc.MAP”, where MAP stands for *maximum a posterior* (Patil et al. 2010).

The best-fit model—defined by the best-fit SN and galaxy templates and associated parameters—to the spectrum is approximated using the *Bayesian Information Criterion* (BIC, see Kass & Raftery 1995 for details) by applying it to all models fitted to the input spectrum. The BIC provides a way of discriminating among the multiple models fitted to the data. It has the following mathematical formulation:

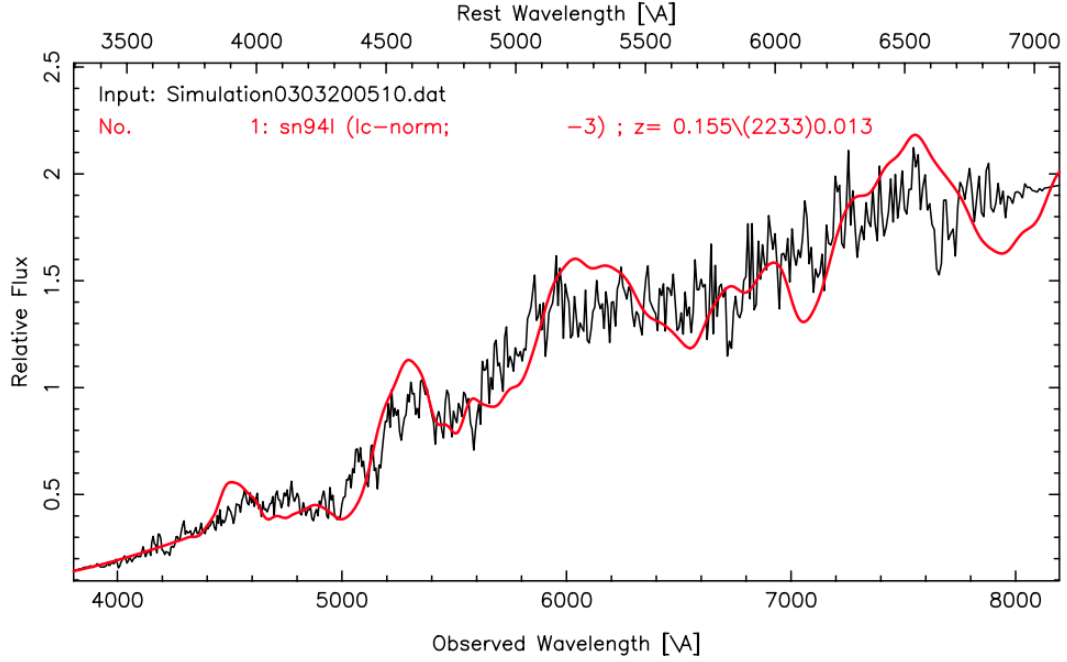


(a) Comparison of SNID's best-fit spectrum (red) to the simulated spectrum (black) generated with the input parameters $\alpha, z, t, A_V, SNR = (0.3, 0.3, 20, 0.5, 5)$, using a SN Ia template and an E0 galaxy template. SNID incorrectly types the spectrum to be that of a 'M-star', albeit the recovered parameters for $z = 0.299 \pm 0.007$, phase $\tau = 0$ (equivalent to epoch $t = 19$ days), are reasonably correctly. The significant host contamination coupled with a low SNR leads SNID into thinking the spectrum is that of a M-star.

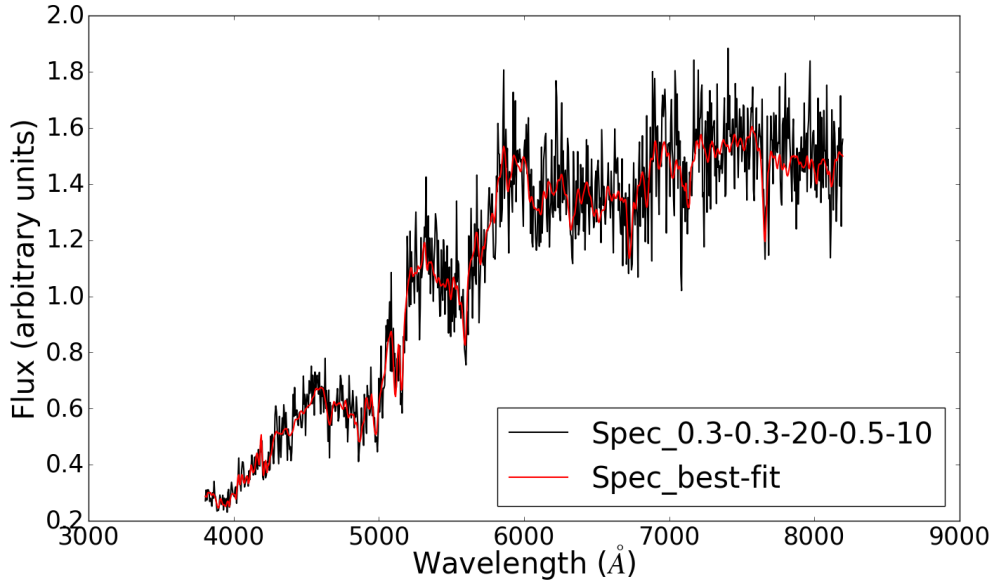


(b) Same as (a) but for SNMC, which types the spectrum to be that of a 'SN Ia' and the host galaxy type as E0, with the following best-fit parameters: $\alpha = 0.30 \pm 0.05$, $z = 0.298 \pm 0.003$, $t = 21 \pm 3$ (equivalent to $\tau = +2$), $A_V = 0.5 \pm 0.4$. The results reveal that SNMC does the typing of the simulated spectrum correctly and recovers the spectrum's input parameters more accurately than SNID.

Figure 3.1

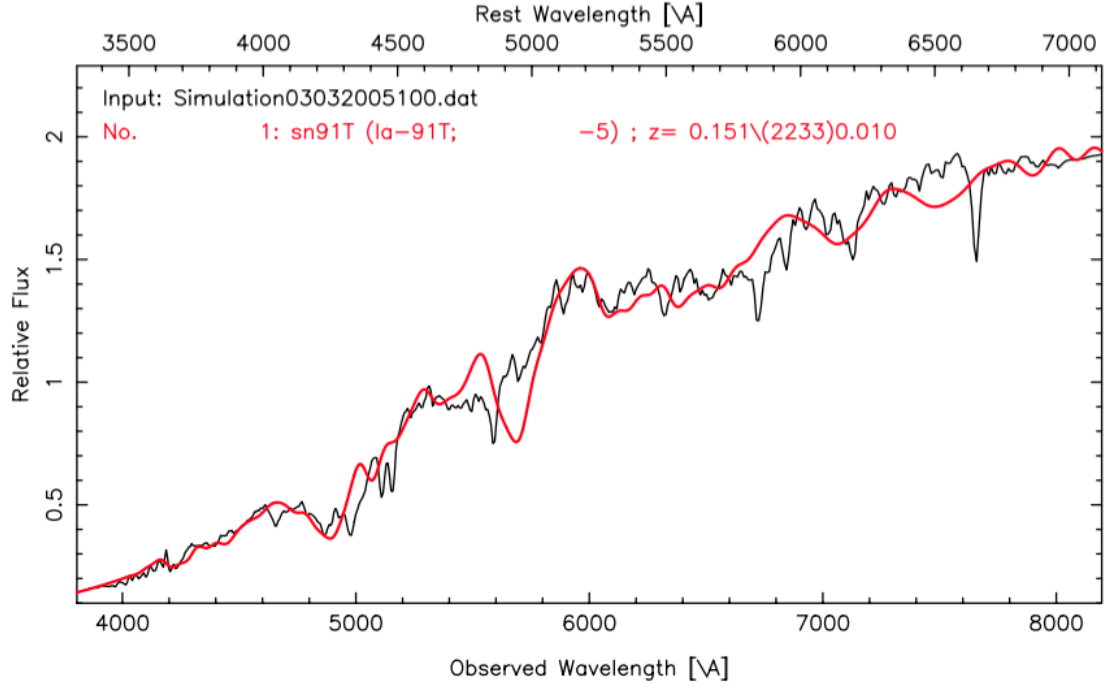


(a) Same as Figure (3.1)(a) but with $SNR = 10$. Here, SNID mistakes the typing for a normal SN Ic instead of a normal SN Ia, and recovers the following parameters: $z = 0.155 \pm 0.013$, $\tau = -3$ (equivalent to epoch $t = 16$ days)—both incorrect.

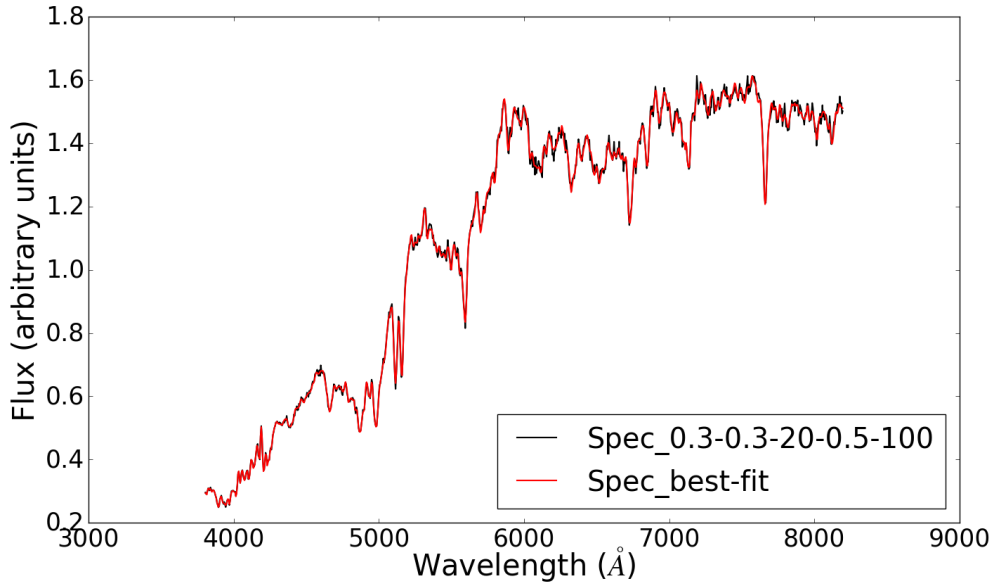


(b) Comparison of SNMC's best-fit spectrum (red) to the simulated spectrum (black) generated with the input parameters $\alpha, z, t, A_V, SNR = (0.3, 0.3, 20, 0.5, 10)$, using a SN Ia template and an E0 galaxy template. SNMC types the spectrum to be that of a 'SN Ia' and the host galaxy type as elliptical, with the following best-fit parameters: $\alpha = 0.30 \pm 0.02$, $z = 0.2996 \pm 0.0004$, $t = 20.1 \pm 0.4$ (equivalent to $\tau = +1$), $A_V = 0.5 \pm 0.2$. Unlike SNID, SNMC correctly classifies the supernova and host and obtains the correct parameters.

Figure 3.2



(a) Comparison of SNID's best-fit spectrum (red) to the simulated spectrum (black) generated with the input parameters α , z , t , A_V , $SNR = (0.3, 0.3, 20, 0.5, 100)$, using a SN Ia template and an elliptical galaxy template. Here, SNID types the spectrum to be that of a 'SN 91T-like', with the following recovered parameters: $z = 0.151 \pm 0.010$ and $\tau = -5 \pm 0.1$ (equivalent to $t = 14$ days). While the typing is correct, the subtyping into a SN Ia-91T-like is wrong as the input SN template is SN Ia. The two recovered parameters are also incorrect.



(b) Same as (a) but for SNMC, which recovers the correct input SN and galaxy templates, with the following best-fit parameters: $\alpha = 0.300 \pm 0.001$, $z = 0.29998 \pm 0.00002$, $t = 20.02 \pm 0.02$ (equivalent to $\tau = +1$), $A_V = 0.49 \pm 0.02$.

Figure 3.3

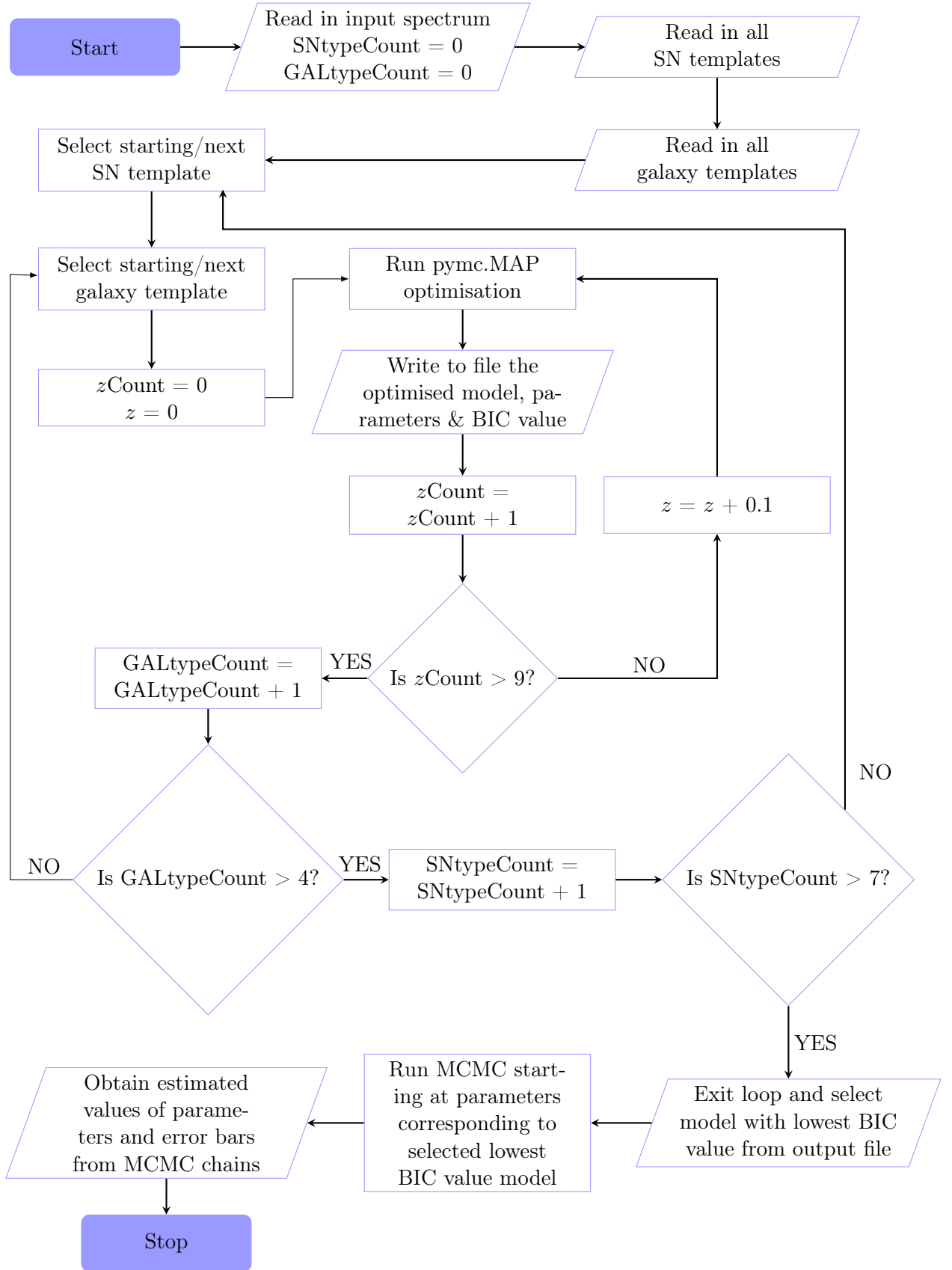


Figure 3.4: Flow chart of SNMC's process of classifying a SN spectrum and estimating relevant parameters. In the flow chart, 'pymc.MAP' is the optimisation algorithm whose output we select the best fitting model from, using the 'Bayesian Inference Criterion' (BIC) discussed in the text. Out of all the optimised fitted models, the best-fit model is that characterised by the lowest BIC value, which gets passed on to an MCMC sampler for parameter estimation in a more rigorous way.

$$BIC = -2 \cdot \ln \mathcal{L}_* + k \cdot \ln n \quad (3.1)$$

where $\mathcal{L}_*$ is the maximised value of the likelihood function of the parameters, k is the number of parameters being fitted for and n the number of data points. In our case, k is the same for all models and thus minimising Equation (3.1) is equivalent to maximising the likelihood $\mathcal{L}$ of the parameters for every model. Equation (3.1) is an approximation to the full Bayesian evidence and we use it over the latter to improve computational speed given the large number of SN and galaxy template combinations—which for **SNMC**’s current setup are 400 in total. These result from 8 SN templates, 5 galaxy templates and 10 different redshift starting positions—starting at $z = 0$ and incrementing by $\delta z = 0.1$ —aimed at increasing the probability of accurate redshift recovery.

3.3.2 Parameter Estimation

During parameter estimation, **SNMC** runs a long MCMC chain to fit for parameters of interest in the input spectrum using the best-fit model obtained from the model selection phase. The parameters fitted for are exactly the same as those that maximises the likelihood L_* during model selection. The values of such parameters corresponding to the best-fit model are used as starting values for the MCMC chain in the parameter estimation phase. The said parameters are (i) fraction of SN flux in the spectrum α , (ii) SN redshift z , (iii) SN epoch t and (iv) the extinction parameter A_V , with t defined as the time elapsed since SN explosion.

At the end of an MCMC run, we estimate the values of the parameters using the mean or median of the returned single parameter MCMC chains, quoting the associated error bars. We make a visual illustration of the full posterior distributions of the parameters using 1-D histograms and 1σ level contour plots.

3.4 Description of templates employed in this work

In this section, we describe the nature of the SN and galaxy templates used by **SNMC** in this work, focussing on their sources and providing details of how they were constructed.

3.4.1 Supernova templates

We use the Nugent SN templates¹, which comprise 8 different SN types: (i) Type Ia Branch-normal (SN Ia), (ii) Type Ia 1991T-like (SN 91T-like), (iii) Type Ia 1991bg-like

¹Available from https://c3.lbl.gov/nugent/_templates.html

Table 3.1: Available epochs for the 8 different Nugent SN templates

SN type	Available epochs t (days after SN explosion)	Peak brightness epoch t^*
SN Ia	0–90 (every day)	19
SN 91T-like	0–93 (every day)	24
SN 91bg-like	0–113 (every day)	15
SN Ibc	0–85 (every day)	19
SN Ibc-hv	1, 7, 12, 17, 22, 27, 32, 37, 47, 57, 67, 117	17
SN IIP	1, 6, 11, 16, 21, 36, 61, 86, 111, 136	11
SN IIL	1, 6, 11, 16, 21, 36, 61, 86, 111, 136	11
SN IIn	1, 2, 3, 4, 6, 9, 14, 20, 31, 46, 59, 81, 97, 128	6

Notes

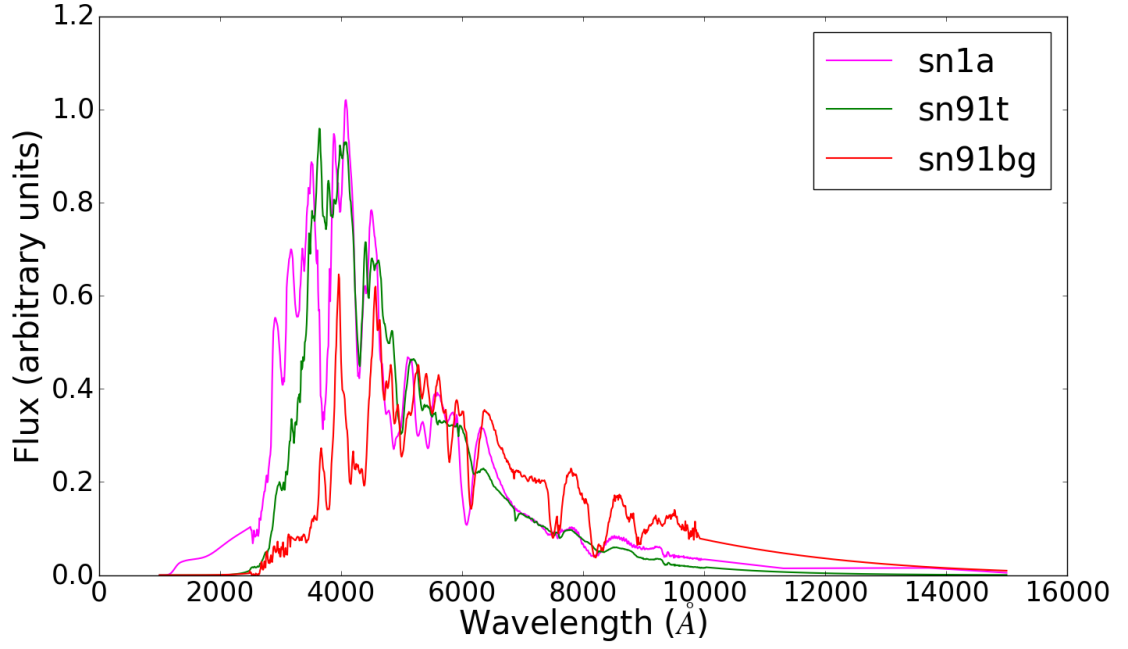
* - the peak brightness epochs are obtained by summing fluxes falling within our SALT spectroscopic follow-up spectral range of 3800Å to 8200Å. The epoch with the highest summed flux value within the specified spectral range for a given template is adopted to be the peak brightness epoch.

(SN 91bg-like), (iv) Type Ib/c (SN Ibc), (v) Type Ib/c high velocity - Hypernovae (SN Ibc - hv), (vi) Type IIP (SN IIP), (vii) Type IIL (SN IIL) and (viii) Type IIn (SN IIn) (see Chapter 1, Section 1.4 for a schematic representation the SN types). Table 3.1 shows the available epochs for each of the 8 different Nugent SN template types. We deliberately exclude the epochs $t = 411$ for the SN IIP/IIL templates and $t = 137, 227$ for the SN IIn templates from Table 3.1, as our SN observations are mostly all around peak brightness and do not stretch that far in epoch space.

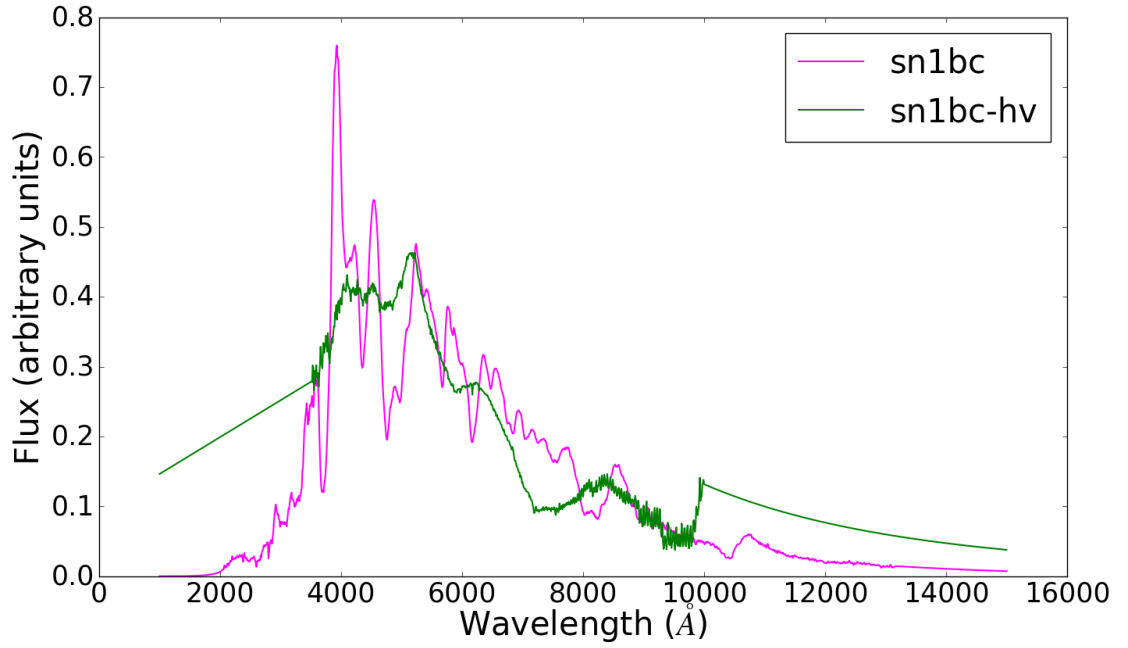
The templates were mostly made using data available from the online supernova database SUSPECT². Nugent scales and shifts the templates as described in his web page³. All templates have a spectral range of 1000Å–25000Å with 10Å resolution. Figures 3.5 and 3.6 show examples of the 8 SN spectral templates, plotted at epochs of their peak brightnesses (Table 3.1). We only plot the templates up to a wavelength of 15000Å, as the upper bound of the spectral range in our analysis is less than 15000Å.

²<https://www.nhn.ou.edu/~suspect/>

³https://c3.lbl.gov/nugent/nugent_templates.html

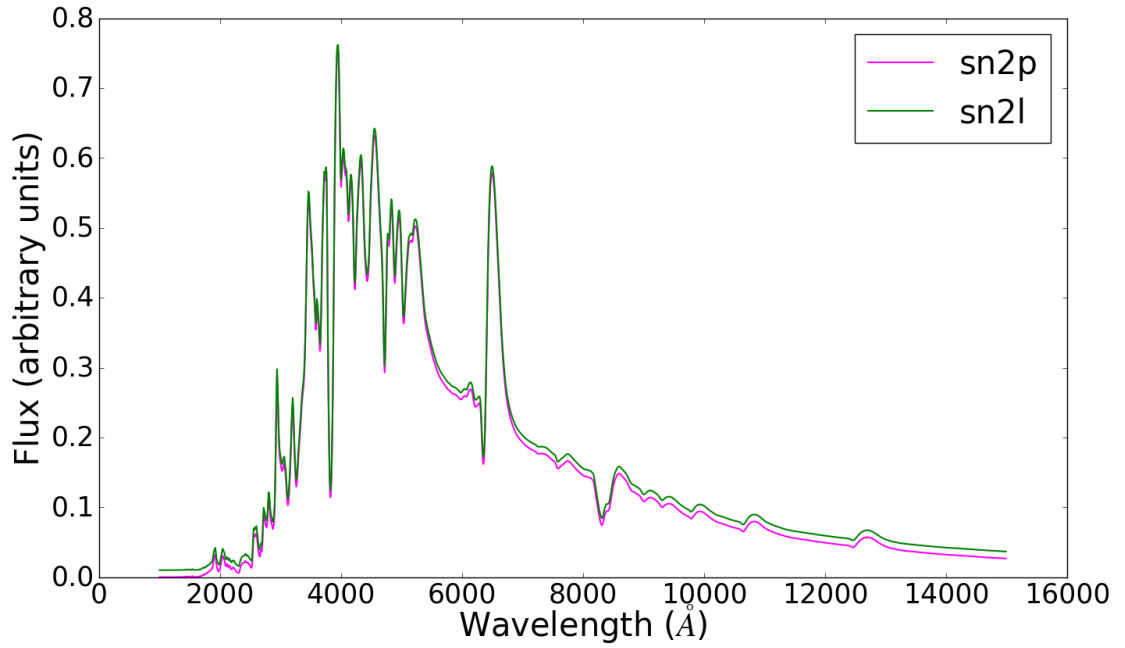


(a) The Type Ia Branch-normal (sn1a), Type Ia - 1991T-like (sn91t) and Type Ia - 1991bg-like templates plotted at epoch $t = 19$ days, 24 days and 15 days, respectively.

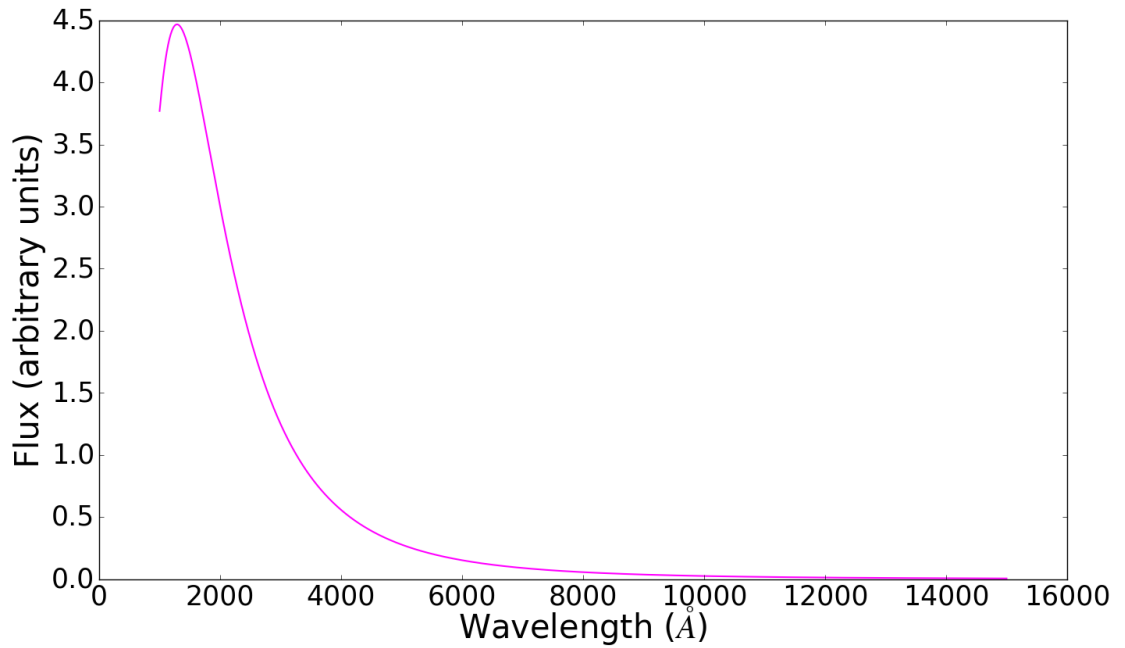


(b) The Type Ibc (sn1bc) and Type Ibc high-velocity templates plotted at epochs $t = 19$ days for the former and $t = 17$ days for the latter.

Figure 3.5



(a) The Type IIP (sn2p) and Type IIL (sn2l) templates both plotted at $t = 11$ days. The two templates have been constructed to have the same spectral shape at peak brightness. The sn2l template has been scaled upwards by a value of 0.01 for purposes of visualisation.



(b) The Type IIn (sn2n) template (resembling a blackbody curve as discussed in the text) plotted at $t = 6$ days.

Figure 3.6

3.4.2 Galaxy templates

The template galaxy spectra from which we selected a sample used in this work are based on a set of observed spectra (Coleman et al. 1980; Kinney et al. 1996) used by Crawford et al. (2006, 2009). There are thirteen in total and comprise the following types: (i) Elliptical (E0), (ii) S0 (lenticular galaxy), (iii) Sa, (iv) Sb, (v) Sc, (vi) Seyfert 1 (SY1), (vii) Seyfert 2 (SY2), (viii) Starburst 1 (SB1), (ix) Starburst 2 (SB2), (x) Starburst 3 (SB3), (xi) Starburst 4 (SB4), (xii) Starburst 5 (SB5) and (xiii) Starburst 6 (SB6). Figures 3.7 to 3.13 show plots of the 13 templates.

Due to computational reasons, we only select 5 out of the total 13 templates to use in the classification, which are (i) E0, (ii) Sb, (iii) SY2, (iv) SB1 and (v) SB4. The time **SNMC** takes for one MAP run (subsection 3.3.1) using all 8 different SN types and one galaxy template is approximately 60 seconds. After identifying the model that returns the lowest BIC value, running MCMC to perform parameter estimation takes between 300 and 360 seconds, for 250 000 steps. This is the minimum number of steps we selected for parameter estimation. Running MAP using all 13 templates translates into approximately 780 seconds. As will be discussed in Section 4.3, we find from simulations that running MAP several times improves model recovery, with $N = 5$ being sufficient to recover the correct model. With $N = 5$, this implies a model selection total computational time of 3900 seconds for every input spectrum using all 8 different SN templates and all 13 different galaxy templates. Coupled with an MCMC run of ~ 360 seconds, this gives ~ 4260 seconds, which is quite time intensive. It is for this reason that we select only 5 galaxy templates from the total 13 templates to reduce on the lengthy computational time to approximately 1600 seconds for both MAP and MCMC runs. Using more galaxy templates is simply a matter of more computing power, which could be achieved by running **SNMC** on a cluster.

Our selection of the 5 templates is done on the basis of attempting to have a representative sample across the whole range of the 13 templates in terms of their shapes. Our motivation in this regard is as follows. The shapes of the E0 and S0 templates in Figure 3.7 closely resemble each other and for this reason, we select only the E0 template to represent both two templates during classification. Similarly, the ‘Sa’ and ‘Sb’ templates in Figure 3.8 closely resemble each other (with the exception of what appears to be emission line features at blue and UV wavelengths for the Sb template). For this reason, we select the Sb template to represent both templates during classification. We do not consider the inclusion of the Sc and SY1 templates, as their wavelength coverage fall short of that of our SALT observed SN spectra at the red end, i.e. the maximum

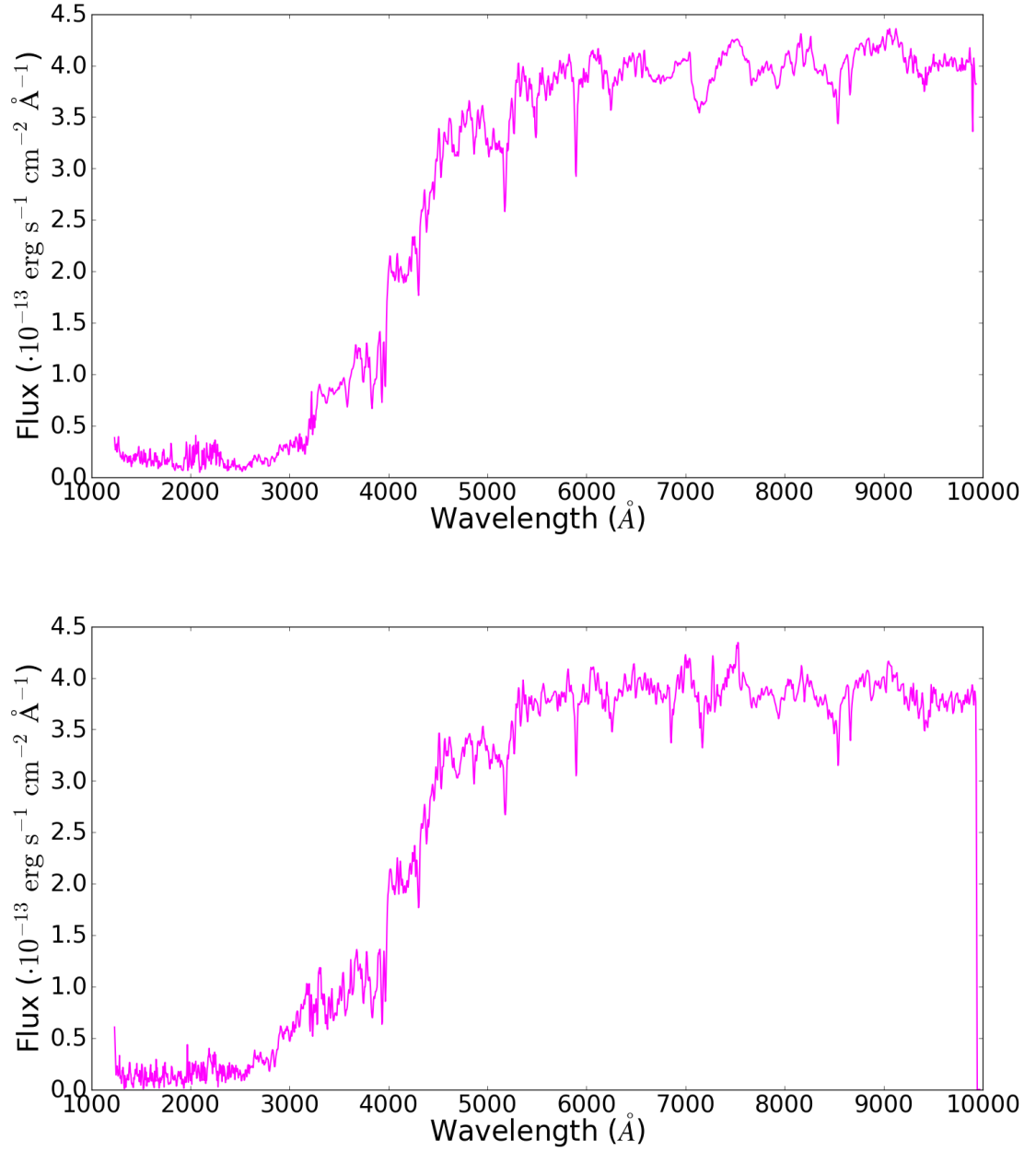


Figure 3.7: The shapes of the E0 (*top*) and S0 (*bottom*) galaxy templates, showing a striking resemblance between them. Of the two templates presented in this figure, only the ‘E0’ was included in the final 5 templates used for all our SNMC classifications in this work. The origin of both templates is Crawford et al. (2006, 2009).

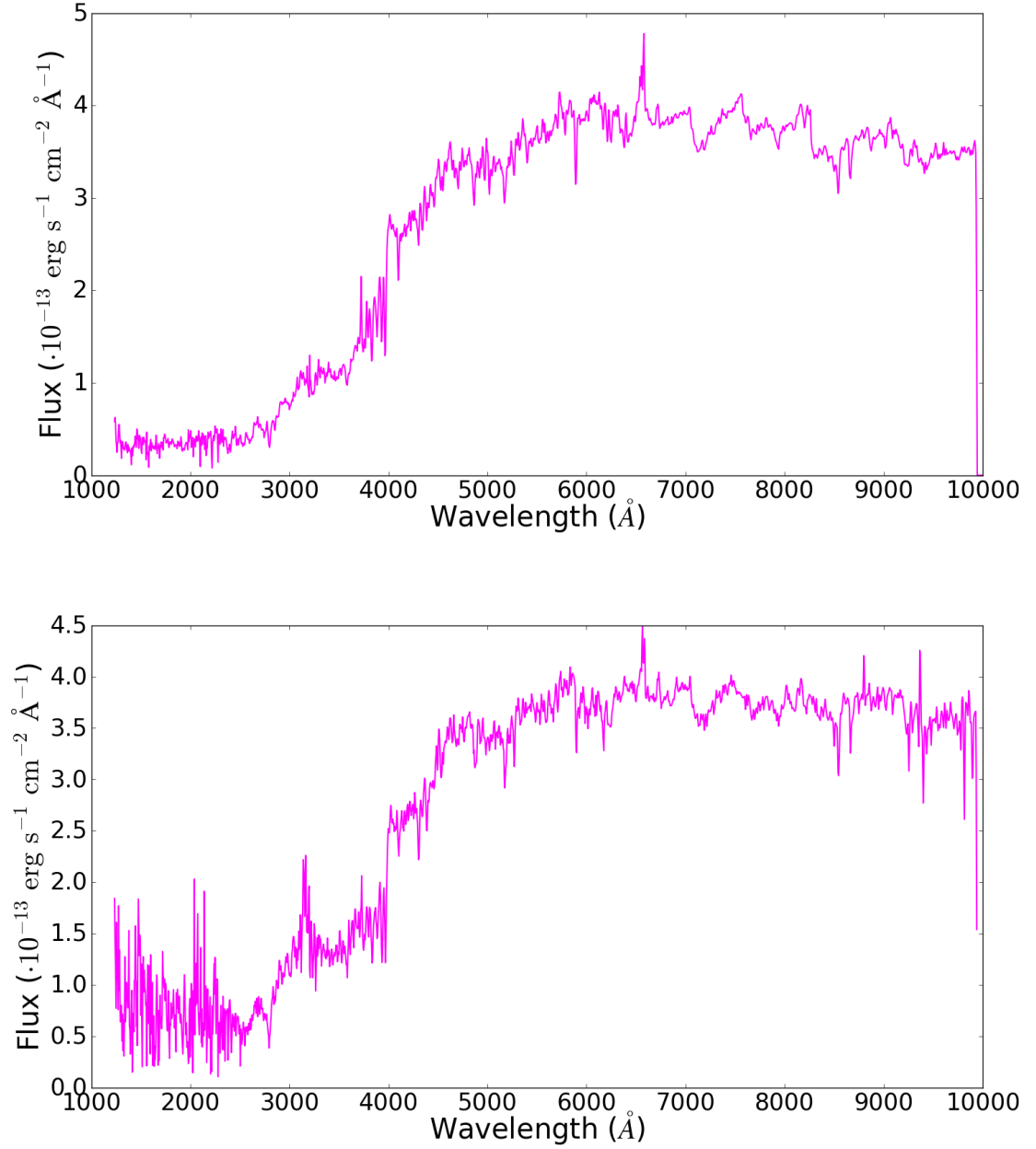


Figure 3.8: The shapes of the ‘Sa’ (*top*) and ‘Sb’ (*bottom*) galaxy templates. The two templates appear to be similar in shape, with the exception of what appears to be emission features at UV and blue wavelengths in the Sb template. Of the two templates presented in this figure, only the ‘Sb’ was part of the final 5 templates used for all our SNMC classifications in this thesis. The origin of both templates is Crawford et al. (2006, 2009).

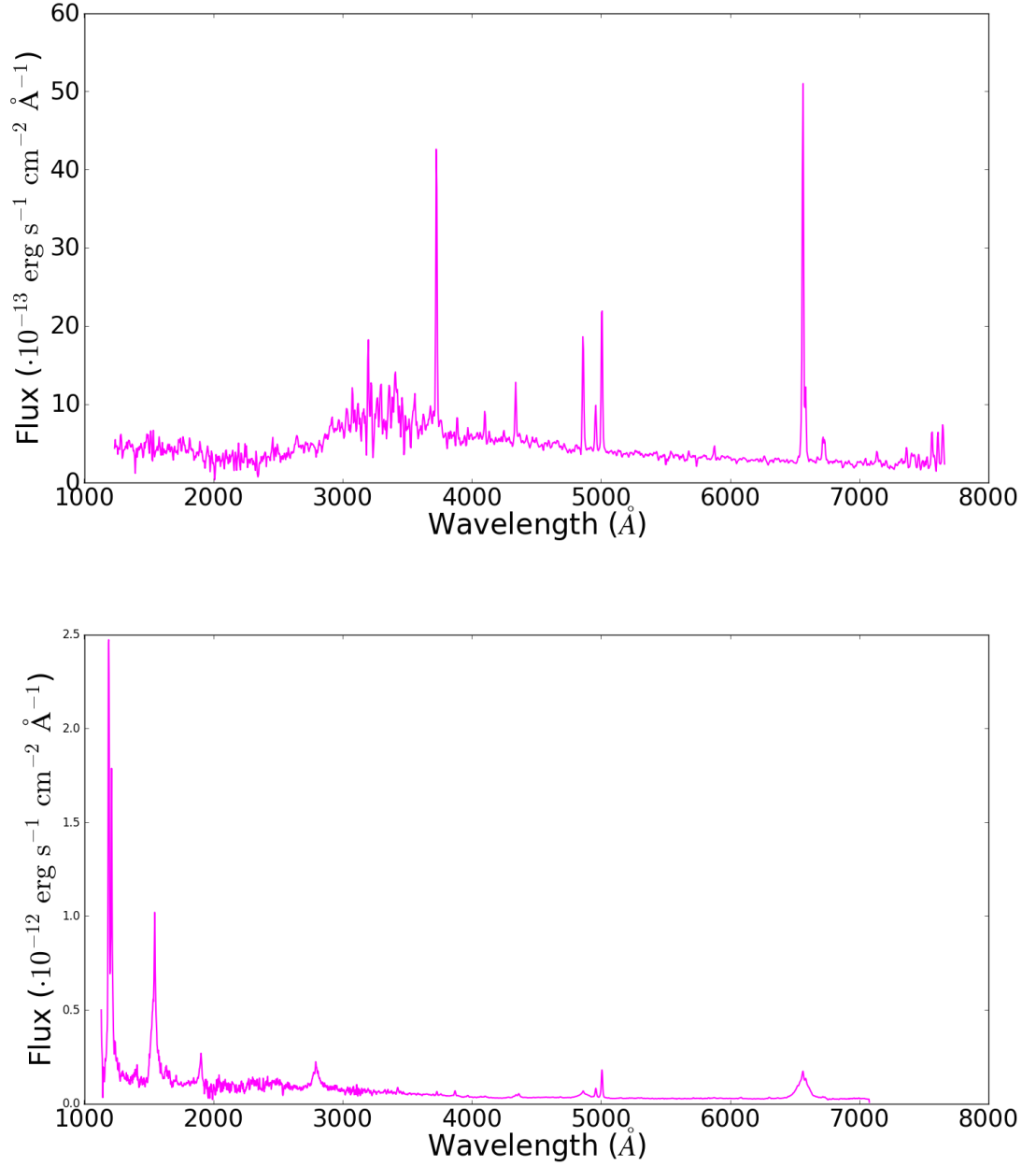


Figure 3.9: The shapes of the Sc (*top*) and SY1 (*bottom*) galaxy templates. Both templates have a maximum wavelength coverage of less than 8000Å, making them unsuitable for our SALT SN simulated and real spectra, both of which have a maximum wavelength coverage of $\sim 8200\text{Å}$. None of the two templates presented in this figure were included in the final 5 templates used for all our SNMC classifications in this thesis. The origin of both templates is Crawford et al. (2006, 2009).

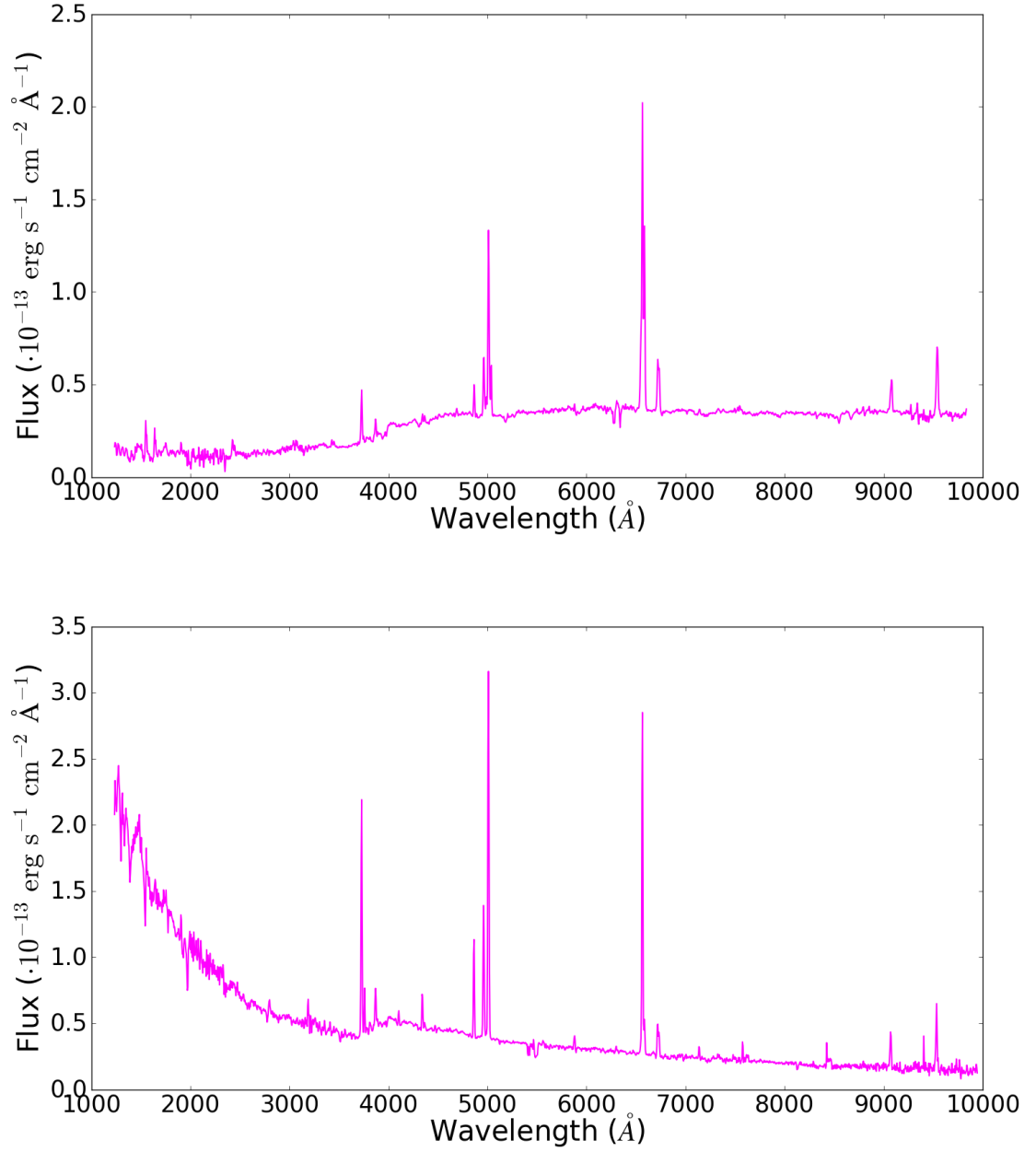


Figure 3.10: The shapes of the SY2 (*top*) and SB1 (*bottom*) galaxy templates, which are quite distinct. Of the two templates presented in this figure, only the ‘SY2’ was part of the final 5 templates used for all our SNMC classifications. The origin of both templates is Crawford et al. (2006, 2009).

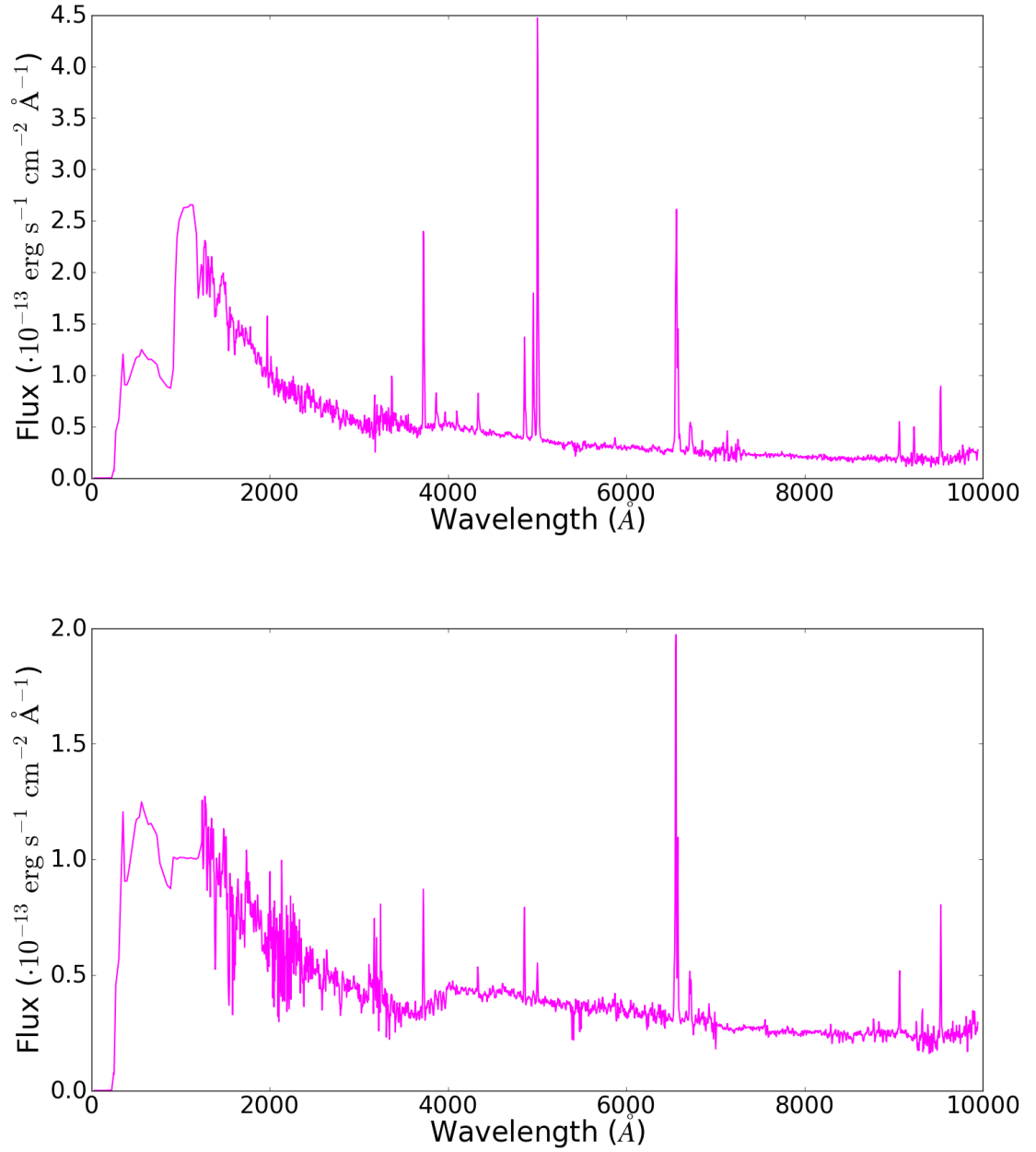


Figure 3.11: The shapes of the SB2 (*top*) and SB3 (*bottom*) galaxy templates. Aside from the high UV-flux seen in the SB1 template in the previous figure, the shapes of these two templates quite closely resemble that of SB1, and it is for this reason that we choose the SB2 template to represent all 3 templates in our selection of only 5 galaxy templates to use in the runs due to computational reasons, as discussed in the text. Of the two templates presented in this figure, only the ‘SB2’ was included in the final 5 templates used for all our SNMC classifications in this work. The origin of both templates is Crawford et al. (2006, 2009).

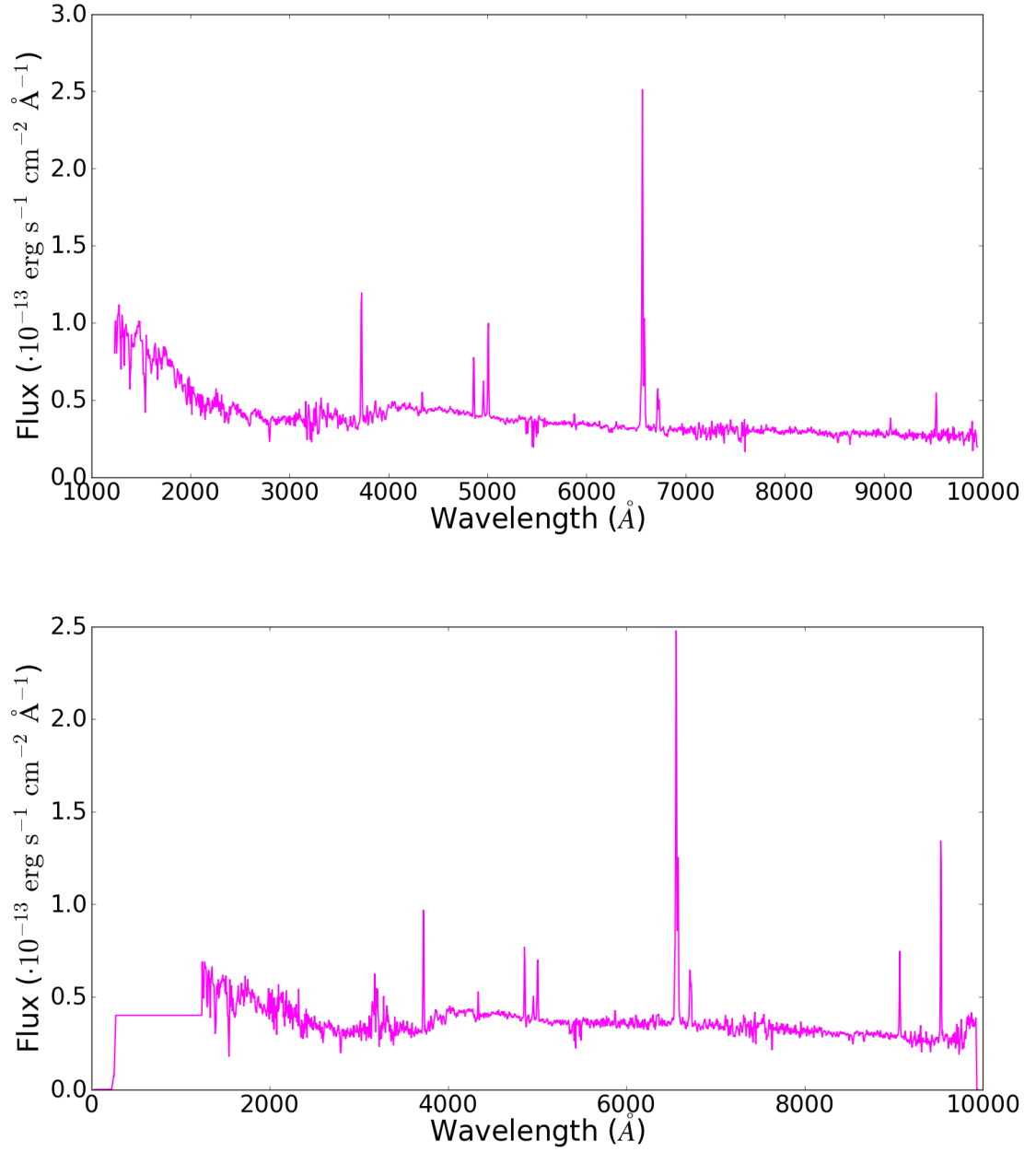


Figure 3.12: The shapes of the SB4 (*top*) and SB5 (*bottom*) galaxy templates. Aside from a high flux seen in the UV of the SB4 template, the two templates shows a striking resemblance. Of the two templates presented in this figure, only the ‘SB4’ was part of the final 5 templates used for all our *SNMC* classifications. The origin of both templates is Crawford et al. (2006, 2009).

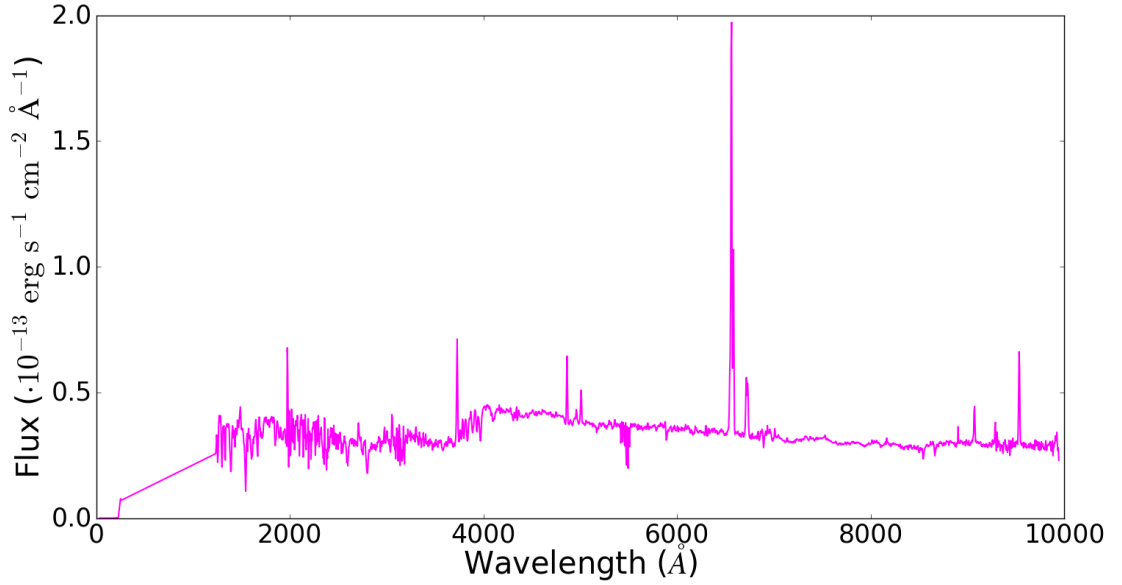


Figure 3.13: The shape of the SB6 galaxy template. Aside from the high UV flux seen in the SB4 template, this template resembles both the SB4 and SB5 templates in the previous figure. It is for this reason that the SB4 template is included in the selection of the 5 templates to use in the runs, due to computational reasons discussed in the text. This template was not part of the final 5 templates used for all our SNMC classifications in this thesis. The origin of the template is Crawford et al. (2006, 2009).

wavelength coverage for the Sc and SY1 templates are 7760Å and 7078Å, respectively, whereas our SALT observed SN spectra have a maximum wavelength coverage of $\sim 8200\text{Å}$. We consider including in the classification the SY2 template, shown in the top panel of Figure 3.10, as it has a distinct shape not seen in all other 13 templates. Finally, we consider the SB1 template to represent the first 3 starburst templates, as its shape resembles those of SB2 and SB3, despite having a high flux component in the UV compared to SB2 and SB3. Similarly, we select SB4 to represent the last 3 starburst templates in the classification, as these last 3 templates also show a striking resemblance, again with the exception of a high UV flux component seen in the SB4 template.

We currently weight the different galaxy templates equally but a more flexible approach is to add a prior probability for each galaxy template based on observed host galaxies for supernovae. For example, if SN were very rare in some class of galaxies the corresponding prior for that class could be made very small.

3.5 SNMC real SALT spectrum classification example and comparison to SNID

In this section, we demonstrate the capabilities of SNMC in classifying the SN spectrum of ‘DES15S2ocv’ observed by SALT on the 9th of January 2016. We perform the classification using the SN and galaxy templates discussed in the last section. Our goal here is to quickly demonstrate that SNMC is able to classify SN spectra in the same way that SNID is able to and better in some instances (as we shall see in subsequent chapters), before delving into testing SNMC’s classification efficiency using simulated spectra. Prior to the discussion of classification and parameter estimation of a true SALT DES SN spectrum, we briefly discuss the two main artifacts we encounter in our SALT spectra and their removal prior to performing classification of the extracted 1-D SN spectra.

3.5.1 Artifacts in SALT SN spectra

The Robert Stobie Spectrograph (RSS, see subsection 5.3.3 for more details) on SALT comprises a three CCD⁴ mosaic (see subsection B.2.1 for elaborate details), resulting in two CCD gaps, as Figure (B.1) shows. The gap on the left side, known as the ‘Blue Chip CCD gap’ covers the wavelength range 4927.0Å - 5100.1Å, whereas that on the right side known as the ‘Red Chip CCD gap’ covers the wavelength range 8179.1Å - 8350.5Å. In addition to this, the spectra are also affected by a telluric absorption line⁵ which has a wavelength range 7595.055Å - 7663.588Å⁶.

Before performing classification and parameter estimation, portions of spectra that overlap the two CCD gaps are excluded, i.e. their wavelengths and corresponding fluxes are physically removed from the 1-D spectral data files. While some methods of correcting for the telluric absorption lines have been suggested, they come with a host of challenges, including resolution mismatches between a template spectrum and an observed spectrum, variations in atmospheric constituents (water vapour, ozone, etc) with time and altitude, which results in potential misalignments between a template and an observed spectrum (Wood 2003). For this reason, we do not correct for the above-mentioned telluric feature but also physically remove it from the spectra in the same way that we remove sections of spectra overlapping the CCD gaps.

⁴CCD stands for Charge Coupled Device, a photon detector made out of thin silicon wafer and predominantly used in modern cameras. See <http://www.microscopyu.com/articles/digitalimaging/ccdintro.html> for more details on CCD technology

⁵http://www.astro.caltech.edu/~tb/ipac_staff/tab/makeewww-2005/Atmosphere/

⁶http://www.astro.caltech.edu/~tb/ipac_staff/tab/makeewww-2005/Atmosphere/atmabs.txt

3.5.2 Model selection and parameter estimation

SNID classified the spectrum of DES15S2ocv as ‘sn1a (Type Ia Branch-normal)’ at redshift $z = 0.217 \pm 0.005$ with phase $\tau = +2$, i.e. two days after the SN reached peak brightness in the *blue filter* (the B -band). The term *phase* is another descriptor of the time at which a SN spectrum is taken and is measured relative to the time the SN reaches peak brightness in the B -band as opposed to the term *epoch* which gets measured relative to the time of the SN explosion. As an example, a phase of $\tau = +2$ is equivalent to an epoch of $t = 21$ days for the Nugent SN templates⁷.

From its model selection (subsection 3.3.1), SNMC finds the best-fit model to ‘DES15S2ocv’ to consist of the ‘sn1a (Type Ia Branch-normal)’ template and the E0 galaxy template. The best-fit model is then passed on to MCMC sampling in the parameter estimation phase (subsection 3.3.2), performed within the PyMC module, to estimate the posterior probabilities of the four parameters α, z, t and A_V . As stated in subsection 3.3.1, the starting values for the four parameters in the MCMC chain are those corresponding to the best-fit model. In Figure 3.14, generated with the “corner.py” code (Foreman-Mackey 2016), we plot the recovered values for the four parameters, in the form of 1-D histograms and 1σ -level contours, at the end of the MCMC run.

Shown in Figure (3.14) are the 2-D marginalised plots of α, z, t and A_V . Marginalisation—discussed in detail in Section 2.2—is done automatically in PyMC by appropriate histogramming of the MCMC chains. At the end of an SNMC parameter estimation run, PyMC produces marginalised posterior probabilities as defined in Equation (2.11) for all fitted parameters as single MCMC chains, which we then plot in the form shown in the figure.

We show in Figures (3.15a) and (3.15b) comparisons of SNMC’s and SNID’s best-fit spectra, respectively, to the spectrum of DES15S2ocv.

The typing and redshift recovery are consistent between the two classifiers, whereas the epoch is more accurately recovered by SNMC than SNID. DES15S2ocv’s estimated date of peak brightness was $MJD = 57390$ (see Chapter 7 for details of how dates of peak brightness are estimated from light-curve data), which is equivalent to 2016-01-03. Since DES15S2ocv is a normal SN Ia (i.e. peaks at $t = 19$ days) and SALT observed it on 2016-01-09 (6 days post peak brightness), we expect the epoch of the SALT spectrum to be $t = 25$ days. Given that the epoch recovered by SNMC’s is $t = 27.8 \pm 0.2$ and that recovered by SNID is $t = 21$ days, SNMC thus gives a more accurate estimation compared to SNID.

⁷We shall report the phase τ values returned by SNID in terms of epoch values t using the following conversion formula: $t = 19 + \tau$

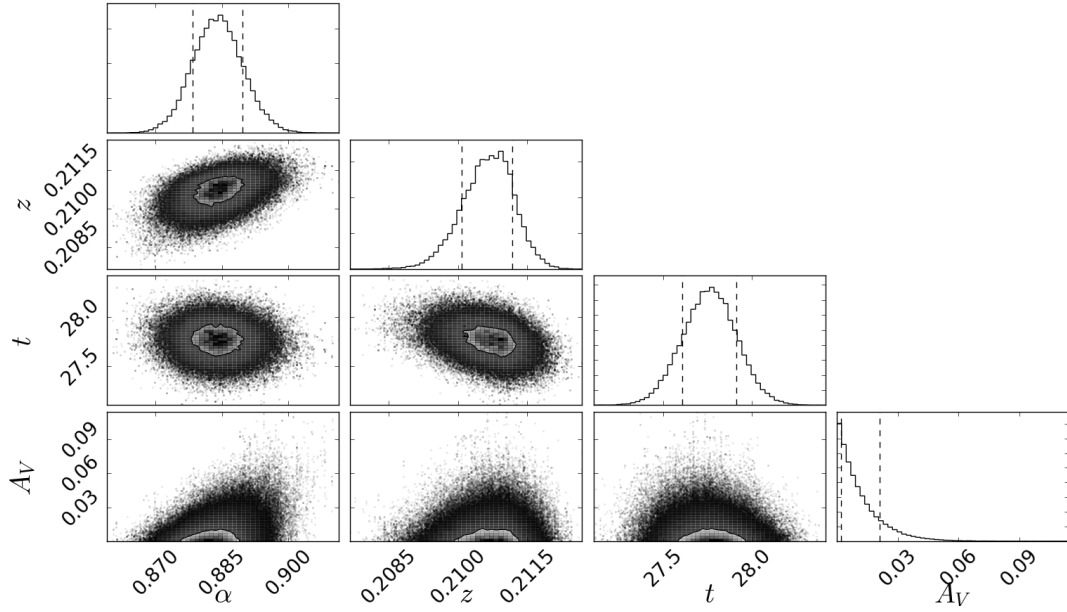
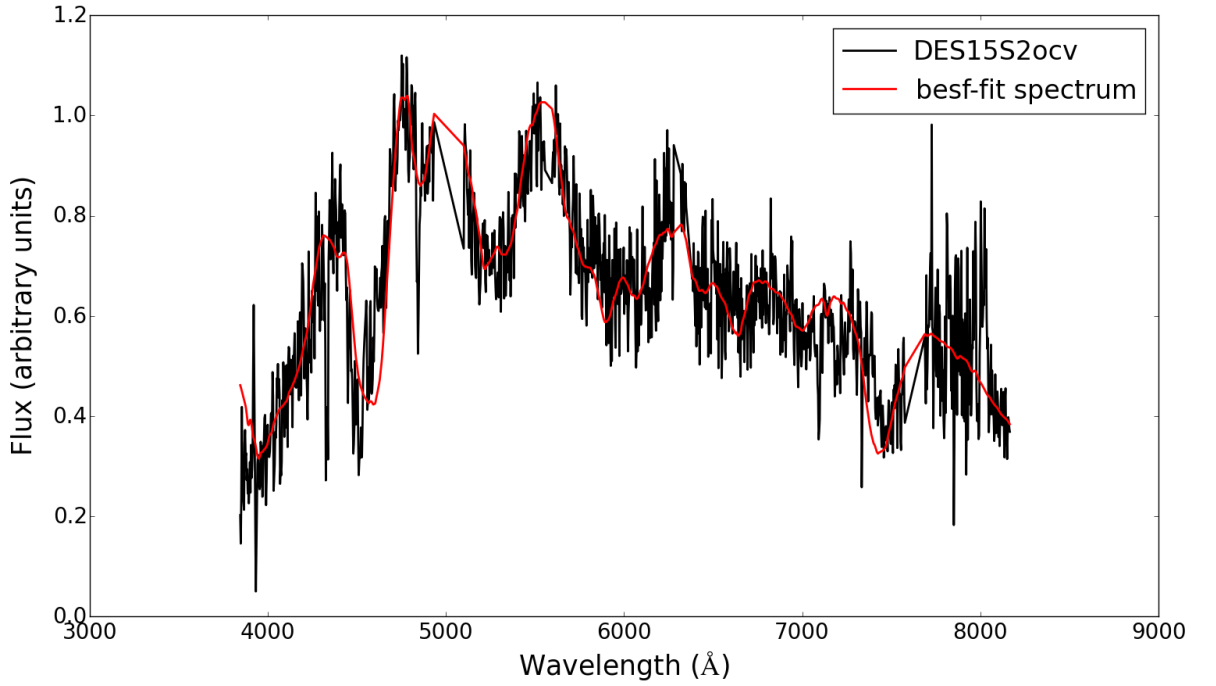


Figure 3.14: Corner plot of the SALT spectrum of ‘DES15S2ocv’, showing 1-D histograms and 1σ -level contours of **SNMC**’s estimated posterior distributions of the four parameters: α , z , t and A_V . At the end of an **SNMC** parameter estimation run, **PyMC** automatically produces these marginalised posterior probabilities as single MCMC chains that we then plot as shown in this figure. The vertical dotted lines in the 1-D histograms represent the 1σ confidence levels.

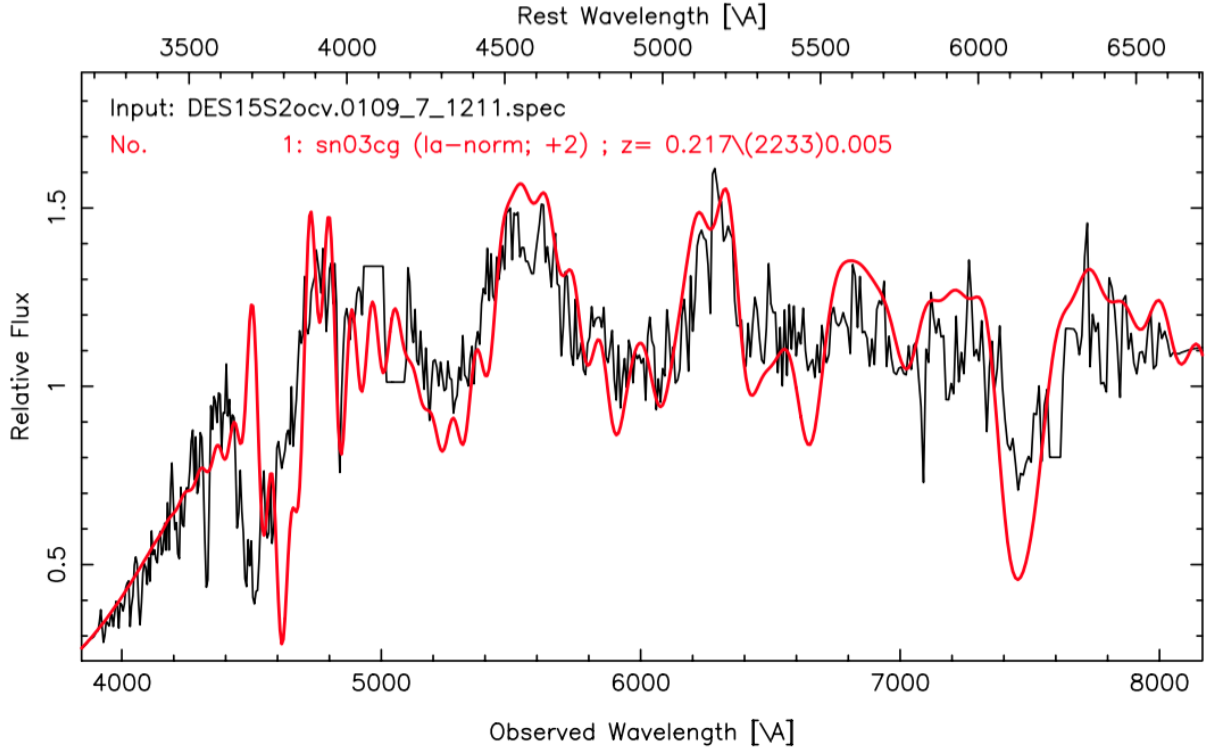
3.6 Conclusion

PyMC has become an extremely useful python package for doing Bayesian statistical inference in the last few years, with its current version ‘**PyMC3**’ now including functions and classes for ‘Probabilistic Machine Learning’ (Salvatier et al. 2015). As stated in Section 3.1, **SNMC** is centrally build on **PyMC** (version 2) which includes two popular MCMC algorithms: ‘Gibbs sampling’ and ‘Metropolis-Hastings (MH) algorithm’ (Patil et al. 2010), the latter being the algorithm **SNMC** uses. The MH algorithm is quite popular, simple to use and easily understood, and offers a robust platform for performing rigorous parameter estimation.

SNMC has demonstrated tremendous ability to handle classification scenarios involving heavily contaminated spectra, containing up to three-quarters of the host galaxy light, and down to a SNR of 5. Classification and parameter estimation by **SNID** did not yield the correct results for such a level of host galaxy contamination. However, it is our intention to repeat this exercise beyond the thesis, using **SNID**’s template libraries. This will give us a more appropriate comparison of the results by the two classifiers



(a) Comparison of SNMC's best-fit spectrum to the input spectrum of DES15S2ocv (black). The best-fit model comprises a normal SN Ia template and E0 galaxy template with the following best-fit MCMC parameters: $\alpha = 0.88 \pm 0.03$, $z = 0.211 \pm 0.004$, $t = 27.8 \pm 0.4$ and $A_V = 0.01 \pm 0.01$.



(b) Same as (a) but for SNID, where the best-fit SN template is a normal SN Ia with the following best-fit parameters: $z = 0.217 \pm 0.005$, $t = 21$ days.

Figure 3.15: Since the spectrum of DES15S2ocv was taken 6 days after its estimated date of peak brightness, i.e. $t \approx 25$ days (see text), SNMC estimates the epoch more accurately than SNID. Other than that, both classifiers agree on the SN typing and redshift recovery.

for the case of simulated spectra, as **SNMC** currently uses the same templates that the simulated spectra are created from during its classification and parameter estimation phases, whereas **SNID** does not.

Through its *maximum a posteriori* (MAP) object, **PyMC** discriminates among the models to select the best-fit one (i.e. the best-fitting SN template and galaxy template). For our default setup of using only 5 galaxy templates with 8 different SN templates, we have a total of 40 models from which **SNMC** selects only one during a MAP run. The *Bayesian Information Criterion* is used in the selection of the best-fit model.

Classification of a real SALT spectrum also reveals that **SNMC** is a competitive spectral classifier, as, in addition to performing the typing and recovering the redshift correctly, it also recovers the epoch more accurately compared to **SNID**. A current challenge we face is how to model the two artifact types discussed in subsection 3.5.1, in our extracted 1-D SALT SN spectra, instead of simply removing areas of a spectrum that overlaps the CCD gaps and the $7595.055\text{\AA}$ - $7663.588\text{\AA}$ telluric feature. Our current approach in dealing with the said artifacts may have led to effects that could have affected the quality of classification of our SALT spectra and the subsequent parameter estimation. Studying such effects in detail, if there are any, and how they may affect our classification results forms another one of our areas of investigation beyond the thesis, as an integral part of our plans to improve **SNMC**'s performance.

In the next chapter, we test **SNMC**'s classification efficiency further, using simulated SN spectra with different combinations of the four parameters α, z, t and A_V discussed in subsection A.3, at 5 *SNR* values.

Chapter 4

SNMC Classification of Simulated and Literature SN Spectra

4.1 Introduction

In this Chapter, we showcase the results of our code *SuperNovaMC*'s (**SNMC**) performance using simulated data with various combinations of input parameters. For each SN spectrum, we create several realisations with a different Gaussian noise added to the flux, as in (4.1). For the computational reasons discussed in Chapter 3, we use only the 5 galaxy templates (E0, Sb, SY2, SB1 and SB4) and all 8 different SN templates for model selection in our classification of both the simulated and real spectra. We show that for $SNR \geq 5$, **SNMC** performs model selection and parameter estimation well. In the last section of the chapter, we test **SNMC**'s efficiency in classifying SN spectra from the literature and find similar classification results as those in the literature for some of the spectra and interesting inconsistencies with the others. We also find that **SNID** does not particularly perform better than **SNMC** in classifying the five spectra, as it also could not recover some of the literature parameter values of the five spectra.

4.2 Simulations

In this section, we describe the process of creating a simulated SN spectrum which resembles a typical SN spectrum that SALT would observe. We gauge **SNMC**'s performance in classifying such spectra.

4.2.1 Simulated SN spectra

We begin creating a simulated SN spectrum by specifying a fraction of SN flux α we intend to have in the spectrum. We assume that the overall flux in a real observed SN spectrum is made entirely of flux from the SN and that of its host galaxy. As described in subsection 3.3.2, the other input parameters are z , t , and A_V . Given the mismatch between the spectral resolutions of the SN and galaxy templates, we interpolate the SN templates wavelength scale onto the wavelength scale of the galaxy templates, prior to adding the SN and galaxy template fluxes to produce a theoretical or model flux F_{mod} . This is to enable the combination of the SN and galaxy template fluxes in producing simulated spectra and also when fitting SN and galaxy templates to an input spectrum during model selection.

We then multiply the created common wavelength vector by the factor $1 + z$ to shift the templates to the observer's frame. We restrict the spectral range of the simulated SN spectra to that of our SALT SN observational programme, which falls between 3800Å and 8200Å. Because the SN and galaxy templates have different flux scalings, as shown in Chapter 3, Figures 3.1 to 3.7, we normalise both templates to unity at 5500Å.

For the classification to be performed in a consistent manner, F_{mod} has to be normalised to unity at 5500Å as well. Finally, we apply some scatter to F_{mod} in the form of gaussian noise, in order to approximate and include some degree of randomness involved in actual SN spectral observations. This produces our observed flux in a simulated spectrum F_{obs} . The noise in F_{obs} is inversely proportional to the signal-to-noise-ratio (SNR) and modelled by Equation (4.1).

We summarise below the process of creating the above described simulated SN spectrum:

- Select a given epoch SN template and galaxy template, e.g. Type Ia Branch-normal template with $t = 20$ days and an E0 galaxy template.
- From the selected templates, create a simulated SN spectrum using the input parameters α , z , t and A_V , and a simulated galaxy spectrum using the parameters $1 - \alpha$ and z only, as a galaxy spectrum template does not change on a timescale of days and is assumed to be extinction-free.
- Normalise the fluxes F_{SN} and F_{GAL} of the created SN and galaxy spectra, respectively, to unity at 5500Å and sum them up to produce the model flux F_{mod} .

- Normalise F_{mod} to unity at 5500Å and apply Gaussian noise as in Equation (4.1) to produce the simulated observed flux F_{obs} . Restrict the spectral range to 3800Å–8200Å.

Mathematically, F_{obs} is represented as

$$F_{obs} = F_{mod} + F_{mod} \times \mathcal{N}\left(0, \frac{1}{(SNR)^2}\right), \quad (4.1)$$

where F_{mod} has the following mathematical representation:

$$F_{mod} = \alpha((1+z) \cdot F_{SN}) \cdot 10^{-0.4A_\lambda} + (1-\alpha)((1+z) \cdot F_{GAL}). \quad (4.2)$$

A_λ in Equation (4.2) represents the absolute extinction at any wavelength (Cardelli et al. 1989), parameterised as

$$\left\langle \frac{A_\lambda}{A_V} \right\rangle = a(x) + \frac{b(x)}{R_V}, \quad (4.3)$$

where the coefficients a and b are wavelength-dependent and fitted with a polynomial in inverse wavelength x in units of μm^{-1} . The wavelength-dependence of $a(x)$ and $b(x)$ are as follows: for the optical/NIR regime that our data sample falls in, i.e. the interval $1.1 \mu\text{m}^{-1} \leq x \leq 3.3 \mu\text{m}^{-1}$, with $y = x - 1.82$, $a(x)$ and $b(x)$ have the following expressions¹:

$$\begin{aligned} a(x) = & 1 + 0.17699y - 0.50447y^2 - 0.02427y^3 + 0.72085y^4 \\ & + 0.01979y^5 - 0.77530y^6 + 0.32999y^7; \end{aligned} \quad (4.4)$$

$$\begin{aligned} b(x) = & 1.41338y + 2.28305y^2 + 1.07233y^3 - 5.38434y^4 \\ & - 0.62251y^5 + 5.30260y^6 - 2.09002y^7. \end{aligned} \quad (4.5)$$

The error on F_{obs} is

$$\sigma_{F_{obs}} = \frac{F_{obs}}{SNR}. \quad (4.6)$$

We conducted a number of classification test cases using simulated spectra with different combinations of SN fractions α and the other 3 parameters at different SNR values, during SNMC's developmental stages. However, in the thesis, we only show simulated

¹See Cardelli et al. (1989) for the expressions in other wavelength regimes

spectra for four chosen cases and their classification and parameter estimation results. These four cases are representative of an average heavily contaminated SN spectrum ($\alpha = 0.3$) and a lightly contaminated one ($\alpha = 0.8$). Figure 4.1 shows an example of a simulated spectrum, created from a SN Ia template and E0 galaxy template using two different values of $\alpha = (0.3, 0.8)$, each combined with the following values of the other four parameters: $(z, t, A_V, SNR) = (0.3, 20, 0.5, 1)$ and $(z, t, A_V, SNR) = (0.3, 20, 2.1, 1)$. We show in Appendix C in Figures C.1 to C.4, simulated spectra generated with the same parameter values as those in Figure 4.1, except for the cases of $SNR = (5, 10, 20, 100)$.

The basis for our choice of the five SNR values, i.e. $SNR = (1, 5, 10, 20, 100)$ was mostly influenced after running various tests using SNR values between 1 and 10 and then between 10 and 20 during SNMC’s developmental stages. The value $SNR = 100$ was merely used a ‘control value’, in our classification of the simulated spectra, as observational data with such a high SNR are rare in SN studies. We then specifically selected the above five SNR values to showcase at these five values the classification and parameter estimation results for the four cases of input parameters shown in Table 4.1.

In the next Section, we test how well SNMC can classify the above simulated spectra, looking specifically at its efficiency in recovering the correct input SN and galaxy templates as well as the four input parameters α , t , z , and A_V , at each of the five SNR values.

4.3 SNMC classification of simulated spectra and results

To test SNMC’s efficiency in classifying the simulated SN spectra in Figures 4.1 to C.4, we run twenty realisations of the ‘model selection’ and ‘parameter estimation’ phases discussed in Chapter 3 on each spectrum. During each realisation, we run the model selection phase $N = 5$ number of times, whereas the parameter estimation phase we run only once, with 250000 MCMC steps and a burn-in of 25000 steps.

The number of times N we run model selection is arbitrary. We find that increasing N improves the recovery of the correct model and find $N = 5$ sufficient in most cases. Below are the model selection and parameter estimation results of the twenty realisation runs.

4.3.1 Model selection results

Figure 4.2 shows SNMC’s model selection results at the five SNR values.

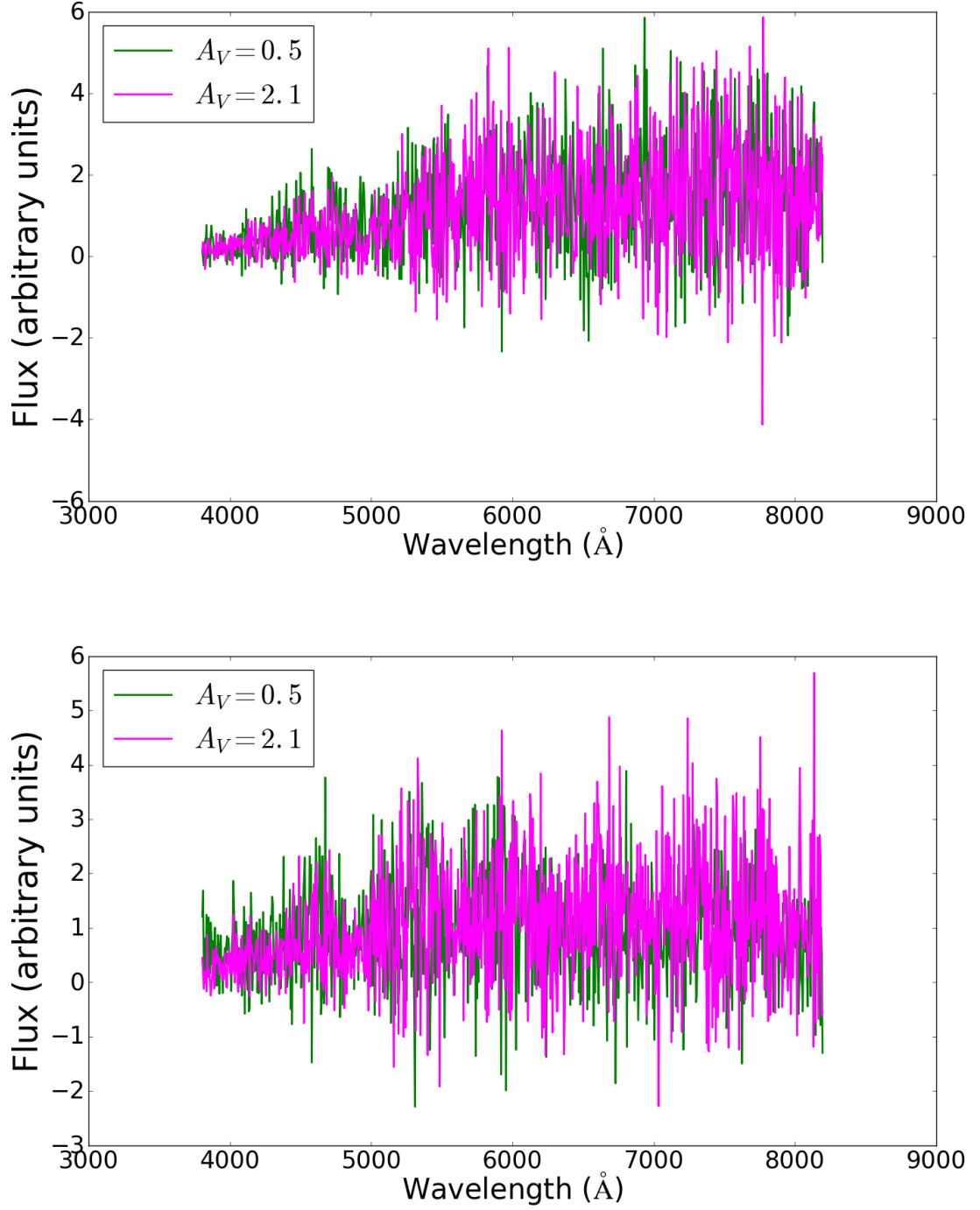


Figure 4.1: *Top:* Examples of simulated SN spectra created from a Type Ia Branch-normal SN (SN Ia) template and the E0 galaxy template, using the parameters $\alpha = 0.3$, $z = 0.3$, $t = 20$ days, $SNR = 1$, with $A_V = 0.5$ for the green spectrum and $A_V = 2.1$ for the magenta spectrum. Both spectra have been normalized to unity at $\lambda = 5500\text{\AA}$. *Bottom:* Same as *Top* but for $\alpha = 0.8$. At such a low SNR , there is no clear effect of the extinction.

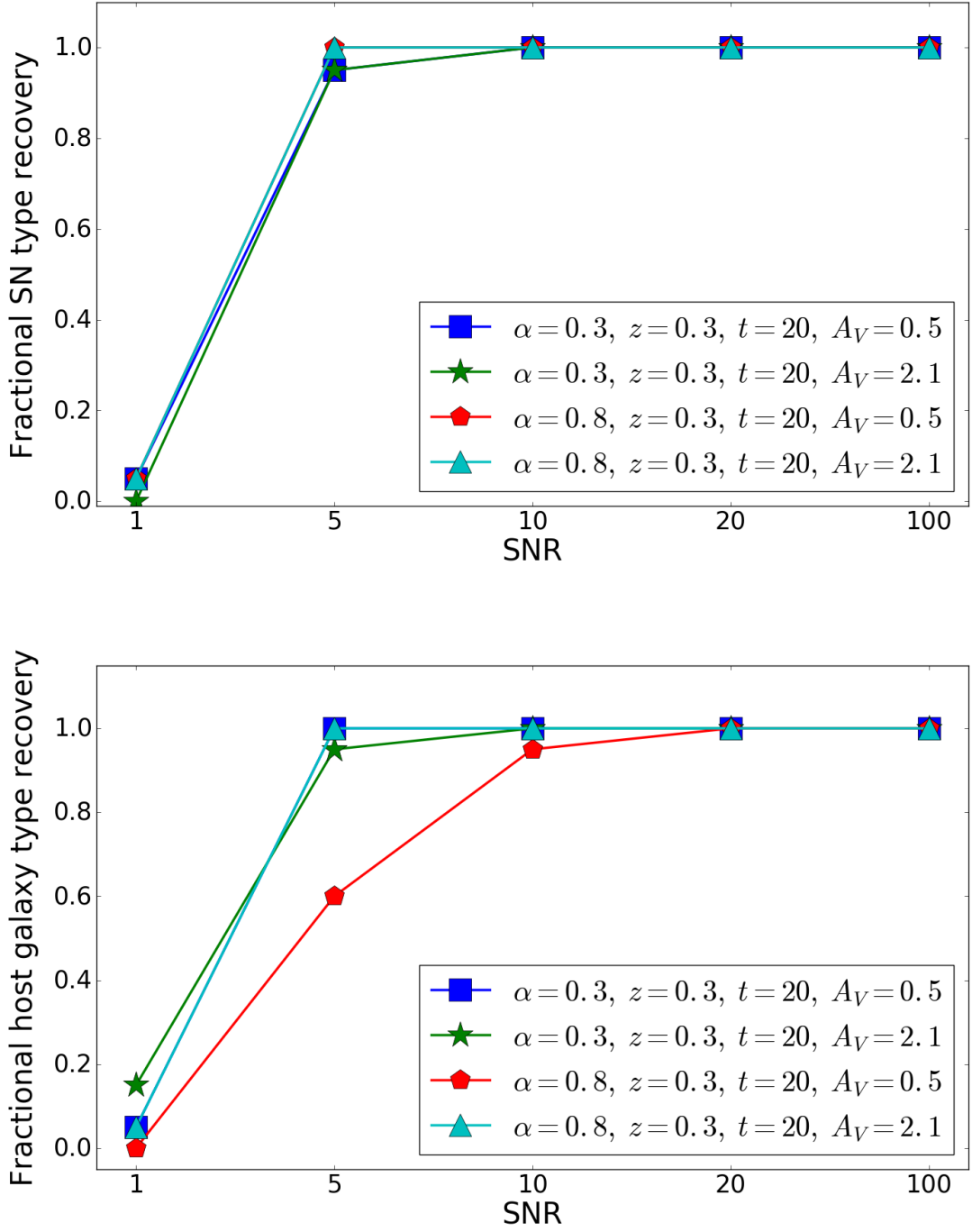


Figure 4.2: *Top:* SNMC's recovery efficiency of the correct input SN type in a simulated observed spectrum as a function of SNR. The efficiency is tested using the twenty different simulated spectra in Figures 4.1 to C.4, where SNMC attempts to recover the correct input SN spectrum from the twenty classification realisations performed at each of the 5 SNR values: 1, 5, 10, 20, 100; *Bottom:* Same as *Top* but for the recovery of input galaxy template. Here, we used the number of model selections runs $N = 5$ and the normal SN Ia and E0 galaxy as input templates.

At $SNR = 1$, SNMC has very little chance of recovering the correct SN type from a simulated spectrum irrespective of the parameters. As expected, the recovery efficiency increases with increasing SNR , reaching over 80% recovery of the correct SN type for all four curves—95% for the blue ($\alpha, z, t, A_V = (0.3, 0.3, 20, 0.5)$) and green ($\alpha, z, t, A_V = (0.3, 0.3, 20, 2.1)$) curves and 100% for the red ($\alpha, z, t, A_V = (0.8, 0.3, 20, 0.5)$) and cyan ($\alpha, z, t, A_V = (0.8, 0.3, 20, 2.1)$) curves—at $SNR = 5$ and 100% recovery for all four curves at $SNR \geq 10$. We also see 100% recovery of the correct galaxy type, for the blue and cyan curves at $SNR \geq 5$ and 95% at $SNR = 5$ for the green curve, reaching 100% at $SNR \geq 10$. However, the red curve in the recovery of the correct galaxy template only reaches 100% recovery at $SNR \geq 20$, having only 60% recovery at $SNR = 5$ and 95% at $SNR = 10$.

We provide in Table 4.1 a summary of the model selection results for the four cases displayed in the legends of the top and bottom panes of Figure 4.2.

4.3.2 Parameter estimation results

Given SNMC's inability to recover the correct SN type and galaxy type from simulated spectra at $SNR = 1$ as demonstrated in the previous subsection, we only test parameter estimation at $SNR \geq 5$. Before we present the results, we first test for bias involved in SNMC's recovery of the input values of the four parameters α, z, t and A_V in the simulated spectra, using the twenty realisations for each spectrum, as discussed above. For each realisation, a simulated SN spectrum is created using the exact same input parameters for a given case (of the four cases) with the only difference being the Gaussian noise added to the flux, as in Equation (4.1). We compute the bias B involved in the recovery of the j th parameter θ_j as follows:

$$B_{\theta_j} = \text{mean} \left[(\text{median}(\hat{\theta}_j))_i - \theta_{j,true} \right], \quad (4.7)$$

where $\text{median}(\hat{\theta}_j)$ is the median of the MCMC chain $\hat{\theta}_j$ for the j th parameter ($\theta_j = \alpha, z, t, A_V$) after removing the burn-in, $\hat{\theta}_{j,true}$ the j th parameter's true value and $i = 0, 1, \dots, 19$. We show in Figures 4.3 and 4.4 plots of B_{θ_j} with error bars versus SNR for the four parameters.

The error bars on the determined B_{θ_j} values are just the standard deviations of the difference $(\text{mean}(\hat{\theta}_j))_i - \theta_{j,true}$ in square brackets in Equation (4.7). Table 4.2 provides a summary of the determined biases and their error bars for all four parameters for the four cases of input parameters presented in Table 4.1.

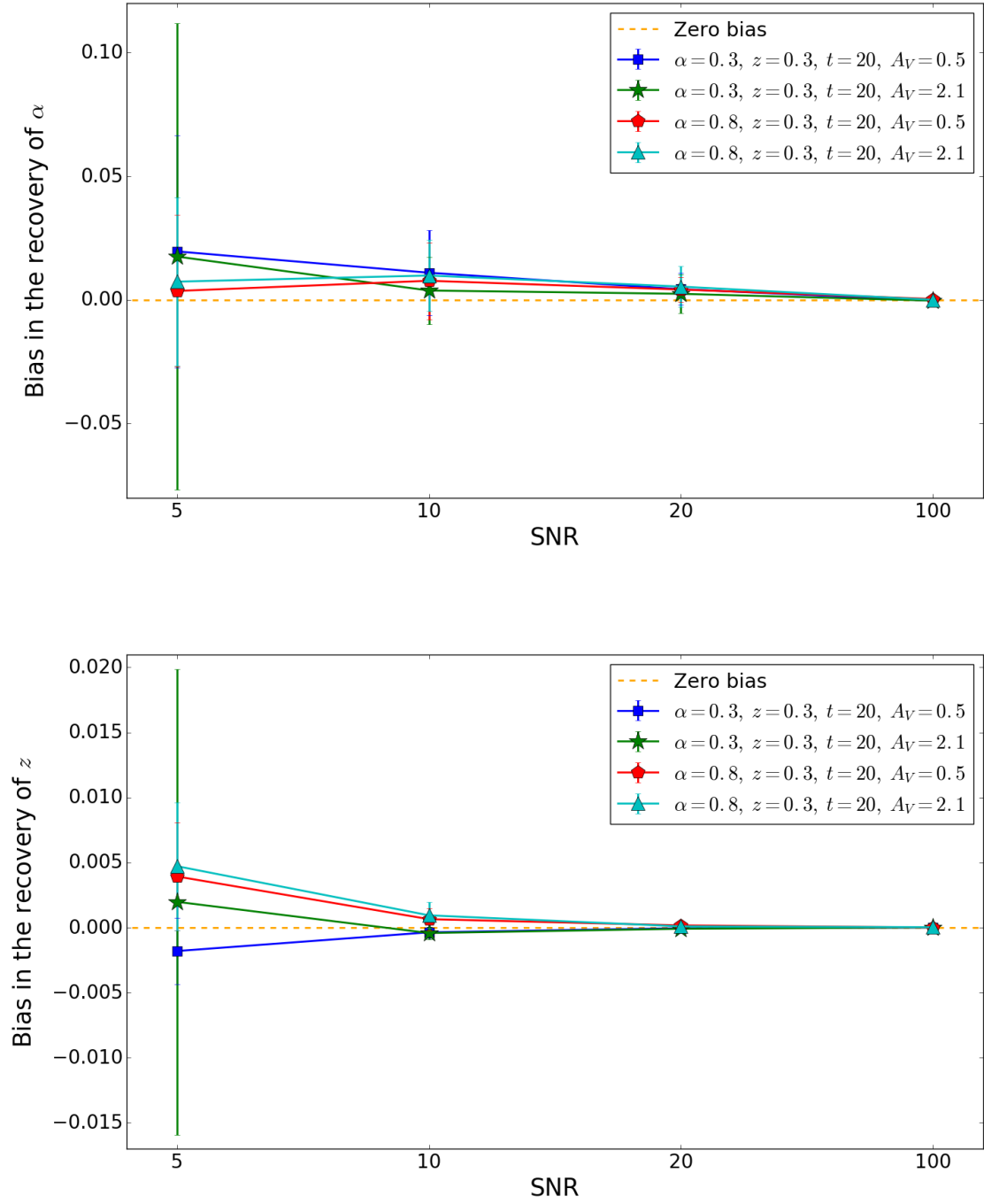


Figure 4.3: *Top:* Bias in SNMC's recovery of α from the simulated spectra in Figures C.1 to C.4, computed at four SNR values: 5, 10, 20, 100. *Bottom:* Same as *Top* but for the z parameter.

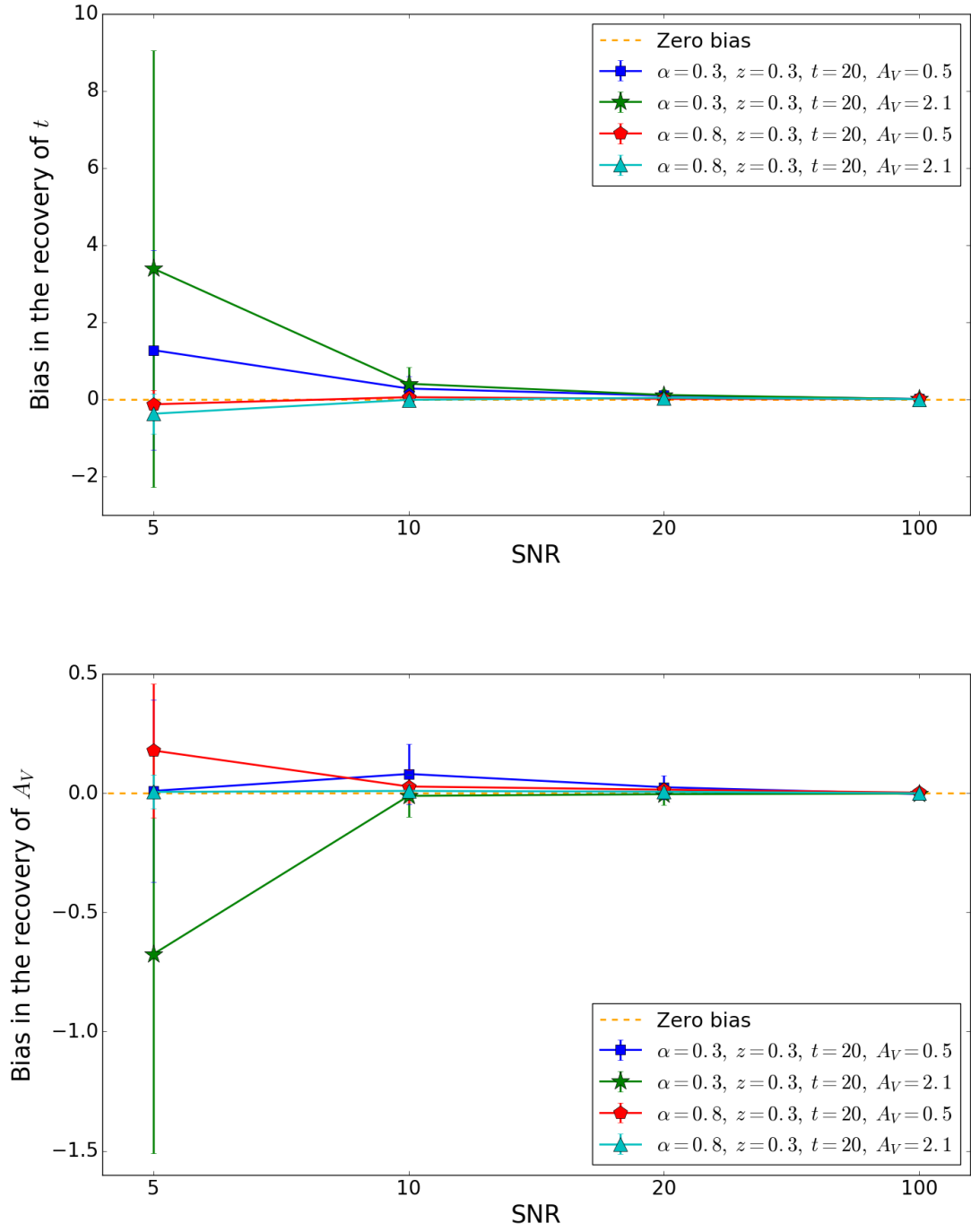


Figure 4.4: *Top:* Bias in SNMC's recovery of t (in days) from the simulated spectra in Figures C.1 to C.4, computed at four SNR values: 5, 10, 20, 100. *Bottom:* Same as *Top* but for the A_V parameter.

Table 4.1: SNMC’s fractional efficiency in recovering the correct input SN type (SN Ia) and galaxy type (E0 galaxy) from the simulated spectra in Figures 4.1 to C.4, done for the following 4 cases of input parameters: Case 1: $(\alpha, z, t, A_V) = (0.3, 0.3, 20, 0.5)$; Case 2: $(\alpha, z, t, A_V) = (0.3, 0.3, 20, 2.1)$; Case 3: $(\alpha, z, t, A_V) = (0.8, 0.3, 20, 0.5)$ and Case 4: $(\alpha, z, t, A_V) = (0.8, 0.3, 20, 2.1)$. Twenty classification realisations were performed at each of the five SNR values: 1, 5, 10, 20, 100; with $N = 5$.

SNMC’s fractional recovery of the correct input SN template				
SNR	Case 1	Case 2	Case 3	Case 4
1	0.05	0.00	0.05	0.05
5	0.95	0.95	1.00	1.00
10	1.00	1.00	1.00	1.00
20	1.00	1.00	1.00	1.00
100	1.00	1.00	1.00	1.00

SNMC’s fractional recovery of the correct input galaxy template				
SNR	Case 1	Case 2	Case 3	Case 4
1	0.05	0.15	0.00	0.15
5	1.00	0.95	0.60	1.00
10	1.00	1.00	0.95	1.00
20	1.00	1.00	1.00	1.00
100	1.00	1.00	1.00	1.00

We see in Table 4.2 that the error bars on the parameters decrease with increasing SNR as expected. Additionally, we also see that all error bars quoted on the determined biases are bigger than the recovered parameter values themselves, i.e. the z -score of each recovered parameter value in Table 4.2 is less than 1. This gives good evidence that SNMC is not biased in recovering the true parameters from simulated data generated using the four cases of input parameters in Table 4.1.

For purposes of further demonstrations of how SNMC works in practise, we show in Figure 4.5a the SNMC’s parameter estimation results in the form of 1-D histograms and contour plots of posterior distributions of the recovered parameters for the first of the four cases for which we have presented bias results in Table 4.2. We only illustrate the results and plots for the case of $SNR = 100$. The contours represent the 68% credible regions whereas the blue vertical and horizontal lines represent the true values of the

Table 4.2: SNMC's bias in the recovery of the four parameters α , z , t and A_V from the simulated spectra in Figures C.1 to C.4, done for the following 4 cases of input parameters: Case 1: $(\alpha, z, t, A_V) = (0.3, 0.3, 20, 0.5)$; Case 2: $(\alpha, z, t, A_V) = (0.3, 0.3, 20, 2.1)$; Case 3: $(\alpha, z, t, A_V) = (0.8, 0.3, 20, 0.5)$ and Case 4: $(\alpha, z, t, A_V) = (0.8, 0.3, 20, 2.1)$.

Bias from SNMC's recovery of α				
SNR	Case 1	Case 2	Case 3	Case 4
5	0.02 ± 0.05	-0.02 ± 0.09	0.00 ± 0.03	0.01 ± 0.03
10	0.01 ± 0.02	0.00 ± 0.01	0.01 ± 0.02	0.01 ± 0.01
20	0.004 ± 0.006	0.002 ± 0.008	0.004 ± 0.005	0.005 ± 0.008
100	-0.0004 ± 0.0009	-0.000 ± 0.002	0.0003 ± 0.0006	-0.0000 ± 0.0008

Bias from SNMC's recovery of z				
SNR	Case 1	Case 2	Case 3	Case 4
5	-0.002 ± 0.003	-0.00 ± 0.02	0.004 ± 0.004	0.005 ± 0.005
10	-0.0004 ± 0.0004	-0.0004 ± 0.0005	0.0006 ± 0.0008	0.000 ± 0.001
20	-0.0001 ± 0.0001	-0.0001 ± 0.0001	0.0002 ± 0.0003	0.0000 ± 0.0002
100	-0.00000 ± 0.00001	-0.00000 ± 0.00002	-0.00000 ± 0.00004	0.00002 ± 0.00003

Bias from SNMC's recovery of t				
SNR	Case 1	Case 2	Case 3	Case 4
5	1 ± 3	3 ± 6	-0.1 ± 0.4	-0.4 ± 0.5
10	0.3 ± 0.3	0.4 ± 0.4	0.1 ± 0.1	-0.02 ± 0.09
20	0.1 ± 0.1	0.1 ± 0.1	0.00 ± 0.05	0.03 ± 0.07
100	0.00 ± 0.01	0.00 ± 0.02	0.005 ± 0.008	0.001 ± 0.008

Bias from SNMC's recovery of A_V				
SNR	Case 1	Case 2	Case 3	Case 4
5	0.0 ± 0.4	-0.7 ± 0.8	0.2 ± 0.3	0.00 ± 0.07
10	0.1 ± 0.1	-0.01 ± 0.09	0.03 ± 0.07	0.01 ± 0.03
20	0.02 ± 0.05	-0.01 ± 0.05	0.01 ± 0.02	0.00 ± 0.02
100	-0.00 ± 0.01	-0.00 ± 0.01	0.002 ± 0.003	-0.001 ± 0.004

parameters.

We present in Appendix C the results for the other three cases at $SNR = 100$, in Figures C.5a to C.7a. From the comparisons of the best-fit spectra (red) to the input simulated spectra (black) in Figures 4.5b to C.7b, we see good approximations of the true models and parameters for the simulated data, as the best-fit spectra fit the data quite well. The recovered values of z and t in Figure C.7a are within the 2σ contour and not inside the 1σ like their counterparts in Figures 4.5a to C.6a. This is an expected outcome, as we expect about 32% of simulations to be outside the 1σ contour and about 5% to be outside the 2σ contour on average.

In the next section, we discuss the process of determining the error bars quoted on parameters that SNMC recovers from real SN spectra.

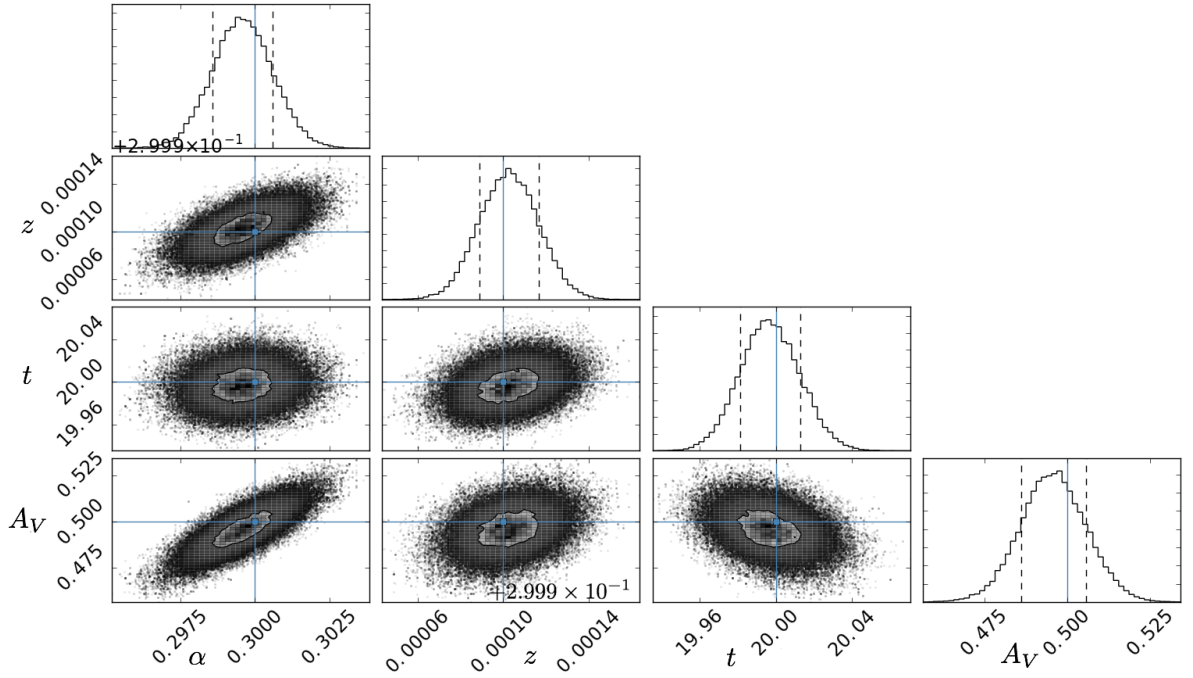
4.4 SNMC error bar determination for parameters estimated from real spectra

The errors, σ_B , quoted on the bias values in Table 4.2 constitute the minimum error bars quoted on the corresponding parameters that SNMC recovers from the literature spectra (discussed in the next section) and the SALT spectra (discussed in Chapter 6). The final error bar σ_{θ_j} quoted on the recovered value of the j th parameter θ_j ($\theta_j = \alpha, z, t, A_V$) from real spectra is the quadrature sum of the standard deviation $\sigma_{\theta_j, PyMC}$ of the parameter’s marginalised posterior probability (the parameter’s PyMC chain) and $\sigma_{B_{\theta_j}}$

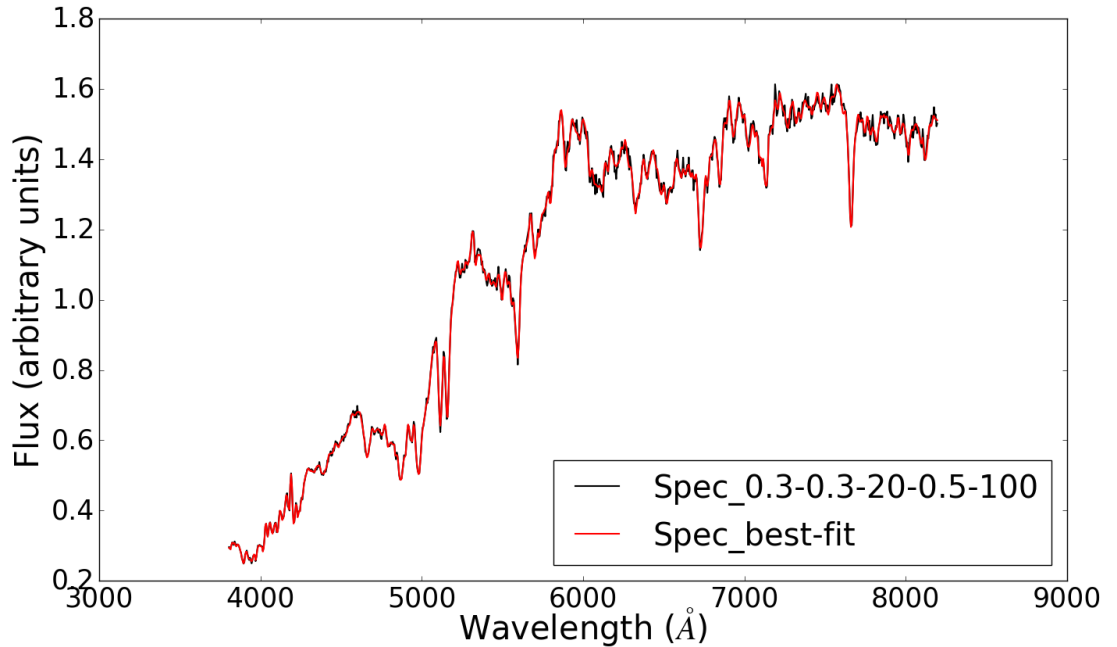
$$\sigma_{\theta_j} = (\sigma_{\theta_j, PyMC}^2 + \sigma_{B_{\theta_j}}^2)^{1/2} \quad (4.8)$$

Linear interpolation is used to determine $\sigma_{B_{\theta_j}}$ at any given $SNR \in [5, 100]$ using the values in Table 4.2. Since SNR varies across the spectral range of a SN spectrum, we use the average value (rounded to the nearest unit) for each spectrum to determine $\sigma_{B_{\theta_j}}$ in Equation (4.8). Figure (4.6) and (4.7) show the interpolated values of $\sigma_{B_{\theta_j}}$ in between the four SNR values in Table 4.2 for each parameter.

For spectra with average $SNR > 100$, their $\sigma_{B_{\theta_j}}$ in Equation (4.8) are capped to the values evaluated at $SNR = 100$. We illustrate how the final error bars on the parameters recovered from real spectra are computed, where we use the example of “SNMC real SALT spectrum classification” in Section 3.5. The SNMC recovered values and errors from the marginalisation $\sigma_{\theta_j, PyMC}$, from the spectrum of ‘DES15S2ocv’ for α, z, t and A_V are 0.88 ± 0.01 , 0.211 ± 0.001 , 27.8 ± 0.2 , and 0.01 ± 0.01 , respectively.



(a) Histograms and 2-D-contour plots of SNMC's estimated posterior distributions of the four parameters, from a simulated spectrum generated with the values $\alpha, z, t, A_V = (0.3, 0.3, 20, 0.5)$ for $SNR = 100$, using a SN Ia template and an E0 galaxy template. The recovered parameters are $\alpha = 0.300 \pm 0.001$, $z = 0.30000 \pm 0.00001$, $t = 20.00 \pm 0.02$, $A_V = 0.4959 \pm 0.0099$. We see that even at high SNR , the resulting errors recovered are within the contours from PyMC.



(b) Comparison of SNMC's best-fit spectrum (red) to the simulated spectrum (black) described in (a). The best-fit spectrum appears to approximate the shape of the input spectrum, which implies SNMC performed the model selection and parameter estimation quite accurately.

Figure 4.5

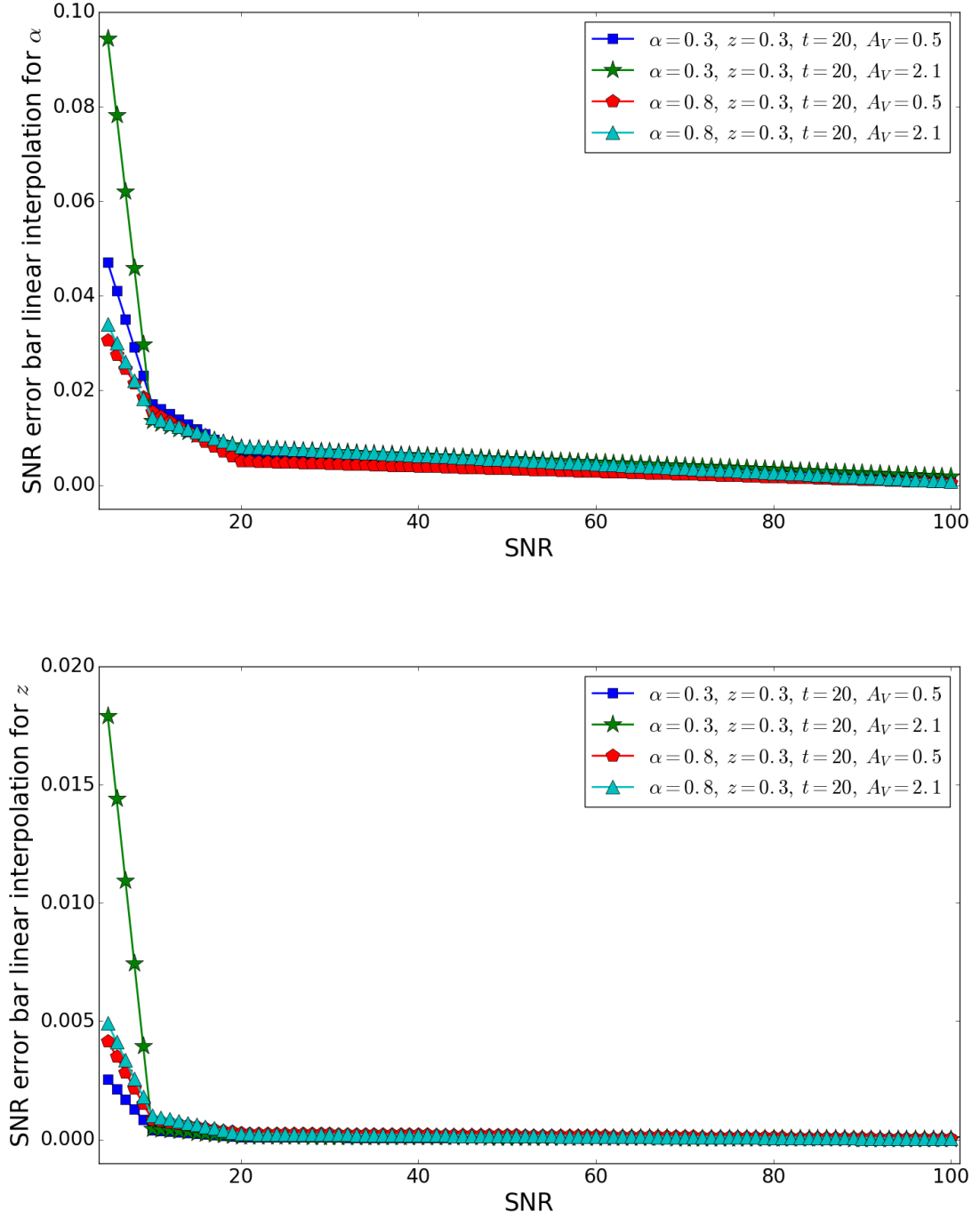


Figure 4.6: The interpolated bias error bars $\sigma_{B_{\theta_\alpha}}$ in between the four SNR values in column 1 of Table 4.2 for the α parameter. The intention of the linear interpolation is to provide a manner in which the $\sigma_{B_{\theta_\alpha}}$ can be estimated at any $SNR \in [5, 100]$. *Bottom:* Same as *Top* but for the z parameter.

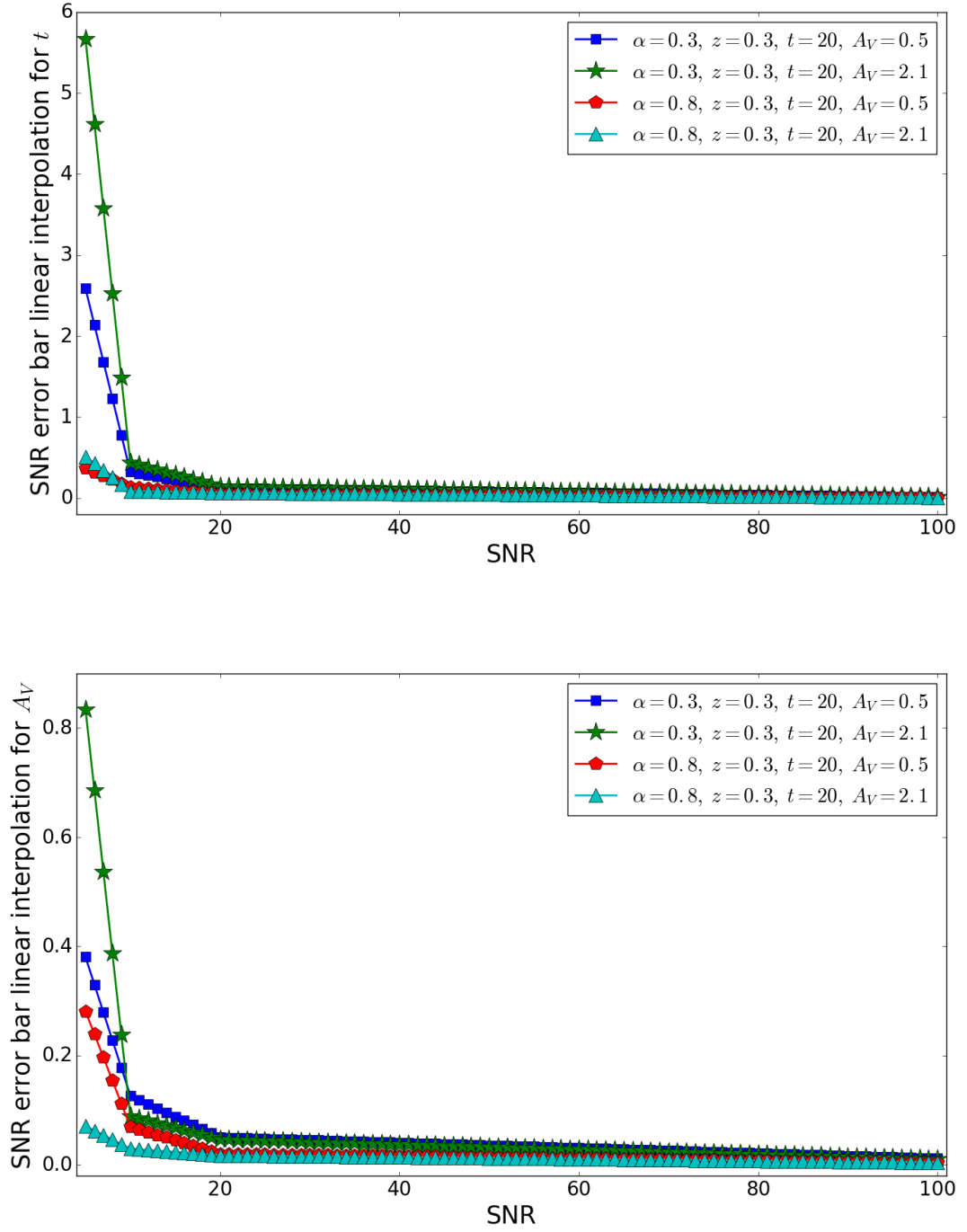


Figure 4.7: The interpolated bias error bars $\sigma_{B_{\theta_t}}$ in between the four SNR values in column 1 of Table 4.2 for the t parameter. The intention of the linear interpolation is to provide a manner in which the $\sigma_{B_{\theta_t}}$ can be estimated at any $SNR \in [5, 100]$. *Bottom:* Same as *Top* but for the A_V parameter.

The average SNR determined from the spectrum of DES15S2ocv is 6. The recovered parameters are closest to our case 3 simulations, so we use the SNR - σ relationship for each parameter derived from such simulations. Thus, the final error bars quoted on the recovered parameters for α , z , t and A_V (as seen in Figure 3.15(a)) are 0.03, 0.004, 0.4 and 0.01, respectively.

In the next section, we test SNMC's efficiency in classifying SN spectra from the literature.

4.5 SNMC classification of literature spectra

To test SNMC's performance in classifying real data, we select some literature spectra for which we know the results and use all SN and the five selected galaxy templates as discussed in Chapter 3 to classify them. Our selection criteria of the literature spectra were that the spectrum

- has a redshift of $z < 0.3$;
- falls within the epoch range $-3 \leq \text{phase} \leq +3$; and
- closely match the SALT spectral range of $3800 < \lambda < 8200 \text{\AA}$.

We strongly prefer spectra for which there is host galaxy information (morphological or spectral type) although this was not always available. Additionally, we demanded that none of the spectra are for candidates that have been previously classified with SNID. This removes any selection bias in choosing examples where SNID is known to perform badly. To that end, we found five SN spectra within a reasonable search time to this for spectra meeting such criteria. Our choice of $z = 0.3$ corresponds to the expected redshift upper bound for our SALT spectroscopic follow-up campaign of DES SN candidates and the intended science of equivalent widths of SN Ia spectral features that we use our SALT spectroscopic SN Ia sample of DES candidates for (see Chapter 6).

4.5.1 Descriptions of the five literature spectra

We sourced the five SN spectra from the online SN database *SUSPECT*² and the *Online Supernova Catalogue*³ (Guillochon et al. 2017). Below are short descriptions of the five literature SNe, specifically focussing on their discovery and typing.

²<https://www.nhn.ou.edu/~suspect/>

³<https://sne.space>

4.5.1.1 SN 2004S

SN 2004S was discovered by Ralph Martin in images taken with the 0.61-m Perth/Lowell Automated Telescope on Feb. 3.542 and 4.560 UT (Martin & Biggs 2004). A spectrum of it taken with the CTIO⁴ 1.5-m telescope was typed as that of a SN Ia (Suntzeff et al. 2004).

4.5.1.2 SN 1998S

SN 1998S was discovered by Zhou Wan in images taken with the 0.60-m BAO (Beijing Astronomical Observatory) telescope on Mar. 3 UT (Li et al. 1998). From their observation of prominent H and He emission lines on the blue part of a low-resolution spectrum taken with the Keck-2 telescope, Filippenko and Moran typed SN 1998S as a Type IIn SN (Filippenko & Moran 1998).

4.5.1.3 SNLS-03D4cj

SNLS-03D4cj was discovered by the SNLS on the 22nd of August 2003 (Neill et al. 2006). Its spectrum taken by the Gemini-north telescope on the 26th of August 2003 was classified as a SN Ia by Howell et al. (2005), using the *Superfit* classifier discussed in Chapter 1.

4.5.1.4 SN 1998bw

SN 1998w was discovered by Galama et al. (1998) through a comparison of images taken between April 28.4 UT and May 1.3 UT by the ESO⁵ New Technology Telescope. Chris Lidman et al. analysed spectra of SN 1998w taken between May 1.4 and May 6.4 UT by various telescopes and found the object to be puzzling as they could not classify it as a SN II or a regular SN Ia due to an absence of H lines and lack of Si at 6150 Å, respectively (Galama et al. 1998). At peak brightness, SN 1998bw's luminosity resembled that of a SN Ia, while its spectral appearance was more comparable to that of a SN Ic, despite not showing all SN Ic features (Patat et al. 2001). The spectrum began resembling those of other SN Ibc events only after one year (Patat et al. 2001).

4.5.1.5 SN 2008es

SN 2008es was discovered by Yuan et al. (2008a) on April 26.23 UT in images obtained with the 0.45-m ROTSE-IIb telescope at MacDonald Observatory, Texas. With no luck

⁴Cerro Tololo Inter-America Observatory, <http://www.ctio.noao.edu/noao/>

⁵European Southern Observatory

Table 4.3: Literature values of five SN spectra obtained from *SUSPECT* and the *OSC*

SN candidate	SN type	Host galaxy type	z	Phase τ^c	Epoch t^d	Colour excess $E(B - V)^b$
SN2004S	SN Ia	Sc ^a	0.0091	+1	20	0.0857 ± 0.0014
SN1998S	SN IIn	Sc ^a	0.0028	-2	4	0.0202 ± 0.0009
SNLS-03D4cj	SN Ia	Unknown ^b	0.27	-1.57	17.43	0.0225 ± 0.0008
SN 1998bw	SN Ibc	SB ^a	0.0085	+3	22	0.0494 ± 0.0011
SN 2008es	SN IIL	Unknown ^b	0.202	2.75	13.75	0.0102 ± 0.0005

Notes

^a - source: Asiago Supernova Catalogue (<http://graspa.oapd.inaf.it/cgi-bin/sncat.php>)

^b - source: <https://sne.space/>

^c - number of days before (-) or after (+) B -band peak brightness.

^d - number of days elapsed since SN explosion. The conversion from phase (which we represent herein with τ) to epoch (which we represent with t) is to enable an easier comparison between the literature spectra and the Nugent SN templates. While a phase of $\tau = 0$ corresponds to peak brightness, peak brightness epoch for the Nugent templates occurs at different values of t for the different SN types (Table 3.1). The conversion from the former to the latter is performed using the relation $t = \tau + t_{peak}$, where t_{peak} is peak brightness epoch for a given SN type, as shown in column 3 of Table 3.1.

in classifying the early time observed spectra of SN 2008es conclusively, Yuan et al. (2008b) classified a late-time spectrum of the SN taken with the Keck-I telescope as SN II, using SNID.

Table 4.3 provides a summary of the parameters of the five spectra.

4.5.2 SNMC and SNID classification results

In fitting for the A_V parameter in each of the 5 literature spectra, we first compute the Galactic A_V value at the location of each spectrum using the “Galactic Dust Reddening and Extinction” calculator⁶, with the RA and DEC of each spectrum being the only inputs. These Galactic A_V values serve as the lower bounds of our prior knowledge of the A_V parameter for each spectrum. This is because the A_V term in the absolute extinction formulation A_λ in Equation (4.3) that applies to SN flux in Equation (4.2) includes the Galactic A_V component.

We present in Tables 4.4 and 4.5 the SNMC and SNID classification results, respectively, of the five literature spectra. Note that we do not include the recovered values of α in

⁶<http://irsa.ipac.caltech.edu/applications/DUST/>

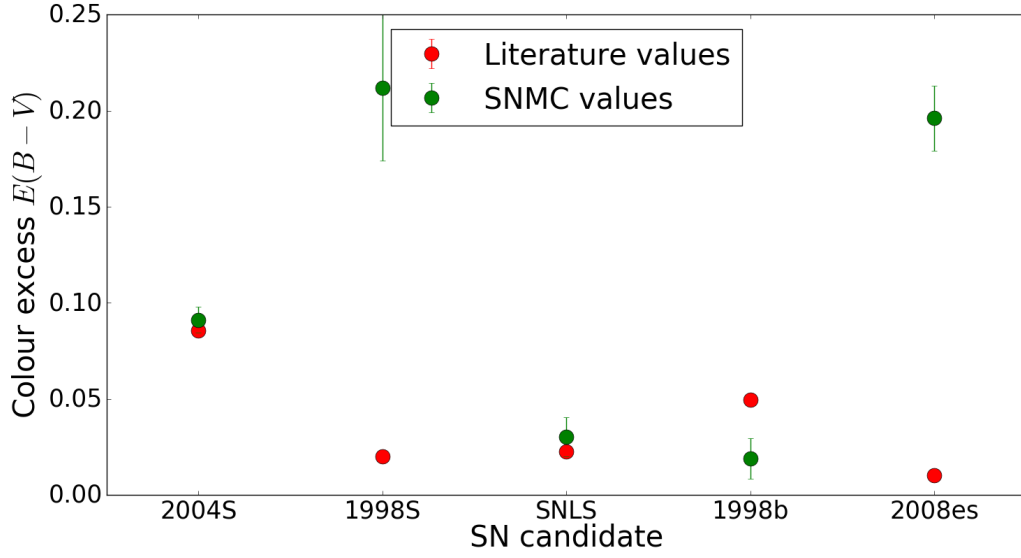


Figure 4.8: Comparison of SNMC recovered colour excess vs the literature values for the 5 spectra.

Table 4.4 but only those that correspond to the literature parameters of the five spectra (i.e. z , t and A_V and the SN and host types). Instead, we present the α values in the notes of the table.

SNMC does not recover any of the host galaxy types for the three spectra. We have seen from simulations that a lower galaxy fraction—which from the five recovered values of α for all five literature spectra (Table 4.4) is less than 5%—coupled with very low SNR drastically reduces the probability of recovering the correct galaxy type. While the SNR is not very low in this case, the $< 5\%$ galaxy fraction alone could result in an incorrect host typing for all five spectra. Figure (4.8) shows a comparison plot of the SNMC recovered colour excess values versus the literature values for the spectra.

Figure (4.8) shows only two of the SNMC determined colour excess values’ uncertainty limits overlap those of the literature values. It is not immediately clear as to what the cause of the observed discrepancy between the two sets of values for the other three SN candidates is. Gaining a good understanding of the cause of that forms part of our future work plans.

4.5.3 Discussion and comparison of the results

For each of the five spectra, we discuss how the SNMC and SNID results compare to the type and parameters and then show plots of how our selected best-fit spectrum by each

Table 4.4: SNMC's classification results of the five literature SN spectra

SN candidate	SN type	Host galaxy type	z	Epoch	Phase ^a	A_V	$E(B - V)^b$
SN 2004S	SN Ia	E	0.0059 ± 0.0004	20.00 ± 0.03	+1	0.2826 ± 0.0209	0.0912 ± 0.0067
SN 1998S	SN IIn	SY2	0.0029 ± 0.0003	8 ± 3	+2	0.6568 ± 0.1177	0.2119 ± 0.0380
SNLS-03D4cj	SN 91T-like	SB1	0.268 ± 0.001	17.9 ± 0.2	-6.1	0.0935 ± 0.0312	0.0302 ± 0.0101
SN 1998bw	SN Ibc-hv	E	0.0051 ± 0.0001	19.5 ± 0.2	+2.5	0.0587 ± 0.0324	0.0189 ± 0.0105
SN 2008es	SN IIn	SB4	0.3691 ± 0.0004	3.1 ± 0.8	-2.9	0.6078 ± 0.0525	0.1961 ± 0.0169

Notes ^a - The Phase τ is obtained from Epoch t using the linear relation $\tau = t - t_{peak}$, where t_{peak} is the peak brightness epoch for a given SN type, as shown in column 3 of Table 3.1.

^b - The colour excess $E(B - V)$ is obtained from the A_V by assuming a reddening color ratio of $A_V/E(B - V) = 3.1$.

The SNMC recovered values of α for the five SNe are as follows: **SN2004S**: 0.993 ± 0.004 , **SN1998S**: 0.968 ± 0.006 , **SNLS - 03D4cj**: 0.999 ± 0.001 , **SN1998bw**: 0.949 ± 0.004 , **SN2008es**: 0.962 ± 0.005 .

Table 4.5: SNID's classification results of the five literature SN spectra

SN candidate	SN type	z	Phase	Epoch ^c
SN 2004S	SN Ia	0.009 ± 0.002	+1	20
SN 1998S	SN IIn	0.004 ± 0.003	-2	4
SNLS-03D4cj	SN 91T-like	0.266 ± 0.008	0	24
SN 1998bw	Ic - broad	0.310 ± 0.015	+9	28
SN 2008es	SN IIP	0.428 ± 0.003	+382	393

Notes

^c - The Epoch t is obtained from Phase τ using the linear relation $t = \tau + t_{peak}$, where t_{peak} is the peak brightness epoch for a given SN type, as illustrated in column 3 of Table 3.1.

classifier compares.

4.5.3.1 SN 1998S

SNMC correctly classifies the candidate as SN IIn and recovers its redshift and epoch accurately and reasonably accurately, respectively, as Figure 4.9a shows.

All of SNID's twenty-nine SN template fits to SN 1998S have incorrect redshifts bigger than $z = 0.3$, compared to the redshift of SN 1998S provided in the literature. The best-fitting template is also incorrect, as Figure 4.9b shows. However, after removing the telluric absorption feature at around $7600\text{\AA}$, SNID recovers the correct SN type and phase for SN 1998S but a slightly higher z value, as Figure 4.10 shows.

Interestingly, the best-fit SNID SN template this time is a spectrum of the SN itself that SNID has as part of its SN IIn template library. Other than this SN template of SN 1998S itself, no templates belonging to other SNe IIn are returned by SNID in this classification.

Our conclusion from the classification of the spectrum of SN 1998S with phase $\tau = -2$ is that we are not certain whether or not the provided parameters were obtained by classifying the spectrum with the telluric feature present, as removing the feature changes the recovered parameters compared to the provided literature parameters. We see from Figure 4.9a that with the presence of the telluric feature in the spectrum, SNMC recovers the literature parameters.

4.5.3.2 SN 2004S

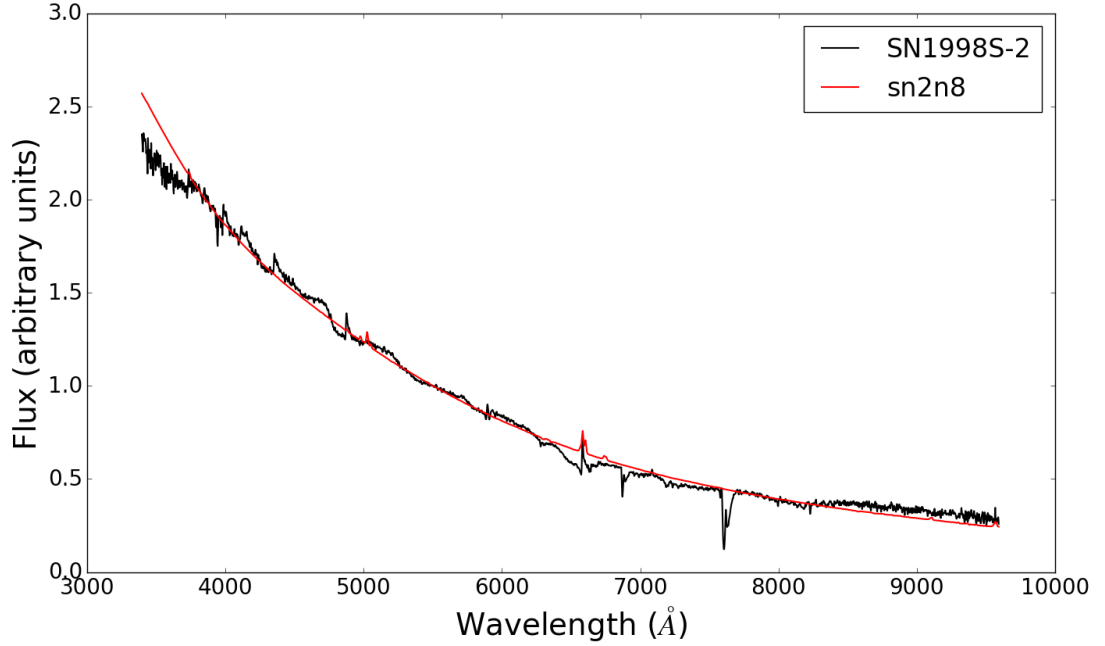
While SNMC recovers the other parameters accurately, the redshift recovery is slightly less accurate, i.e. $z = 0.0059 \pm 0.0004$ compared to the literature value of $z_{lit} = 0.0091$. A visual scan of SNMC overall model selection output (arranged in terms of increasing BIC value) shows that the model that returns the closest estimate of z_{lit} is defined by the following:

1. Templates

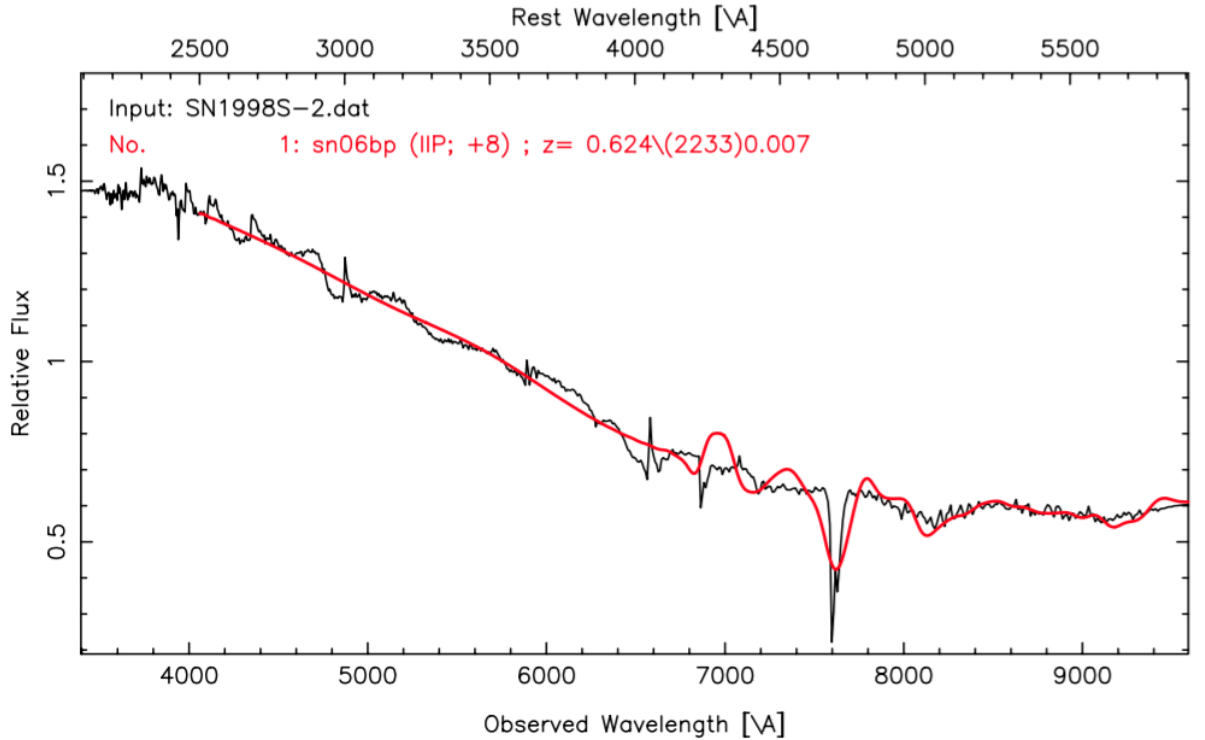
- SN type: SN 91T-like; Galaxy type: Sb

2. Parameters

- $\alpha = 0.967$, $z = 0.0095$, $t = 18.00$ days ($\tau = -6$), $A_V = 0.6331$



(a) Comparison of SNMC's best-fit spectrum (red) to the spectrum of SN 1998S (black), which appears to be quite a good fit. The recovered parameters are: $z = 0.0029 \pm 0.0003$, $t = 8 \pm 3$. SNMC correctly types the spectrum to be that of a SN IIn and recovers the redshift accurately, as the recovered value lies within 1σ of the literature value 0.0028. The epoch however, is less accurately recovered but still lies within 2σ of the literature value of $t = 4$ days. Here, we have converted the phase given in the literature as $\tau = -2$ days (Table 4.3) to the epoch $t = 4$ days that it equates to for the Nugent SN IIn templates, which peak at $t = 6$ days (see Table 3.1).



(b) Same as (a) but for SNID, with the recovered parameters shown in red above the plots (SN type and phase τ given in parentheses). The fit looks bad as a small portion of the spectrum at $\lambda < 4000\text{\AA}$ is not fit. We also see that SNID gets the SN typing wrong and the recovered redshift and epoch parameters are also wrong.

Figure 4.9

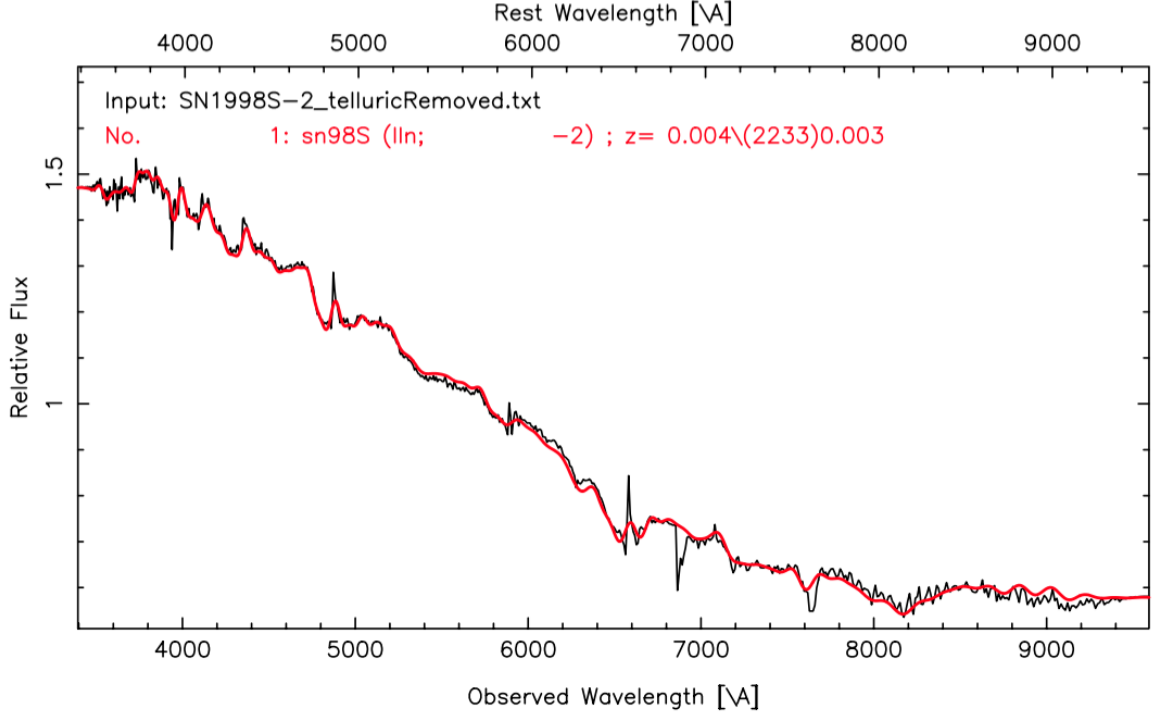
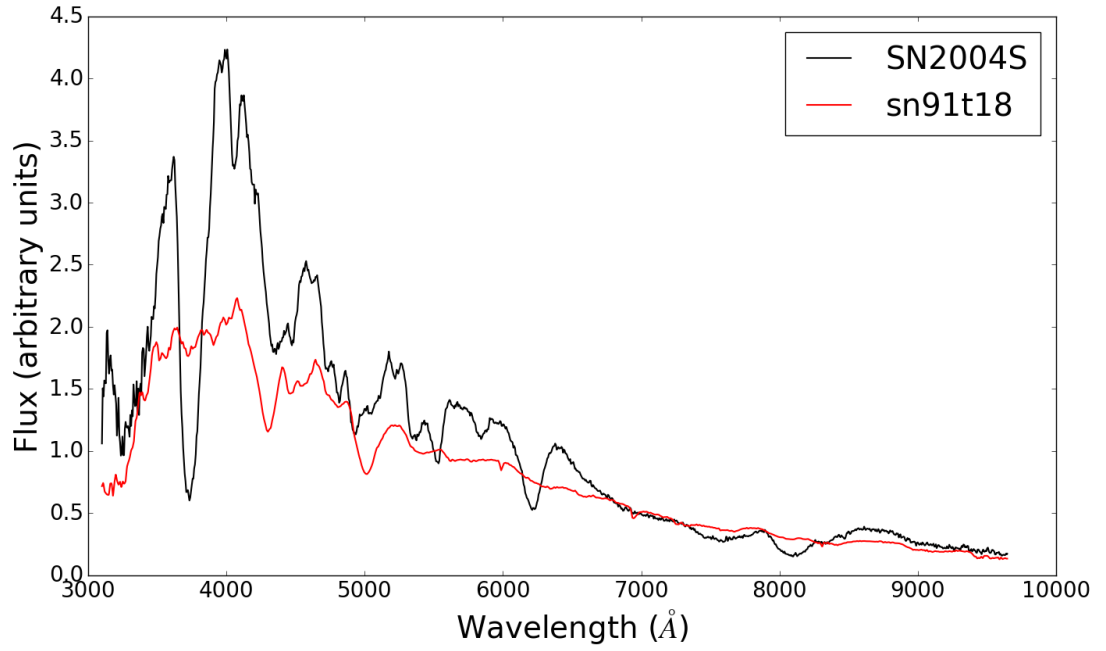


Figure 4.10: Comparison of SNID’s best-fit spectrum (red) to the telluric absorption corrected spectrum of SN 1998S (black). The SN typing and recovered parameters for z and τ are shown in red above the plots. After removal of the telluric absorption feature seen at $\sim 7600\text{\AA}$ in Figure 4.9b, SNID then types the spectrum correctly and recovers both the redshift and phase accurately.

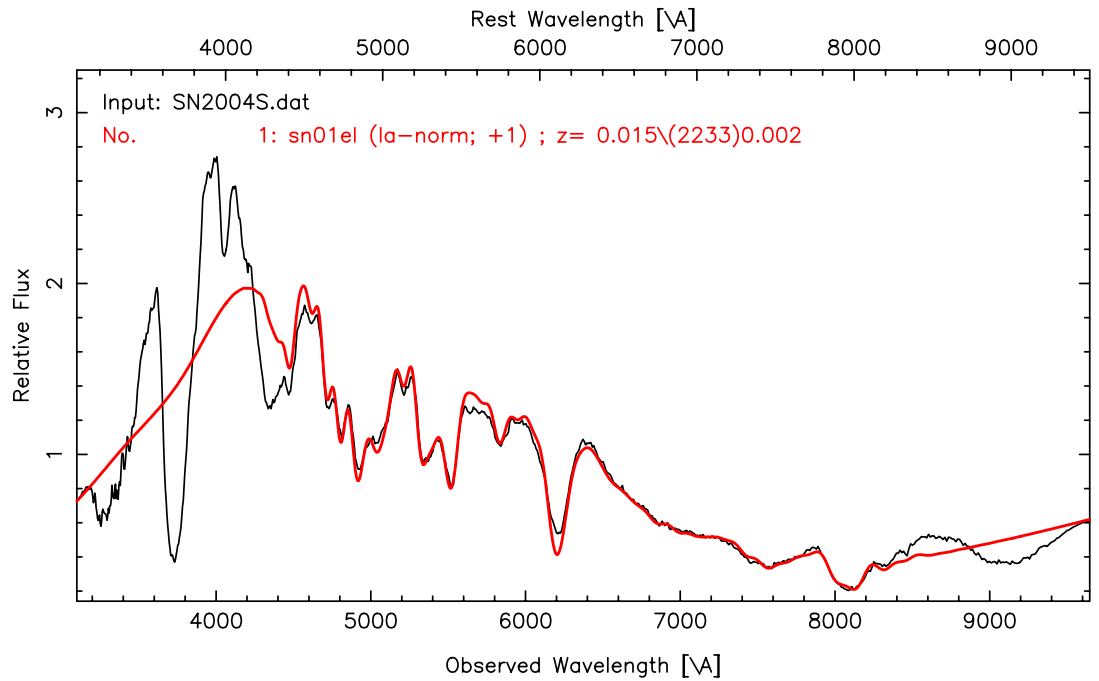
However, performing parameter estimation using this model and parameters does not return a good fit to SN 2004S, as Figure 4.11a shows.

We therefore do not consider this model and parameters a good representation of SN 2004S’s true model and parameters. In the SNID classification results of SN 2004S, we note that while the typing and epoch are correctly recovered, the redshift is not, as Figure 4.11b shows. However, stepping through all of SNID’s fitted SN templates, we find that a more accurate recovery is characterised by the following:

1. Template
 - SN type: SN Ia
2. Parameters
 - $z = 0.009 \pm 0.003$, $\tau = 0$ ($t = 19$)



(a) Comparison of SNMC's spectrum (red) yielded by the SN model (SN 91T-like) that recovers the closest literature redshift of SN 2004S (black). The recovered parameters are $z = 0.0095 \pm 0.0002$, $t = 18.00 \pm 0.01$ ($\tau = -1$).



(b) Same as (a) but for SNID, with the recovered parameters shown in red above the plots (SN type and phase τ given in parentheses).

Figure 4.11

We show in Figures 4.12a and 4.12b how our selected best-fit spectra of both **SNMC** and **SNID**, respectively, compare to the spectrum of SN 2004S.

In the classification of the remaining three literature spectra, we only show in the comparison plots of Figures C.8 to Figure C.10 the best-fit model (or SN template for **SNID**) and parameters that we select from the output of all models fitted to the spectra by both classifiers.

4.5.3.3 SNLS-03D4cj

SNMC classifies SNLS-03D4cj as a SN 91T-like and not SN Ia but recovers its redshift and epoch reasonably accurately (Table 4.4). **SNID** also types the candidate as a SN 91T-like and recovers the redshift and epoch quite accurately as well. Figures C.8a and C.8b illustrate how the best-fit spectra by **SNMC** and **SNID**, respectively, compare to the SNLS-03D4cj spectrum.

4.5.3.4 SN 1998bw

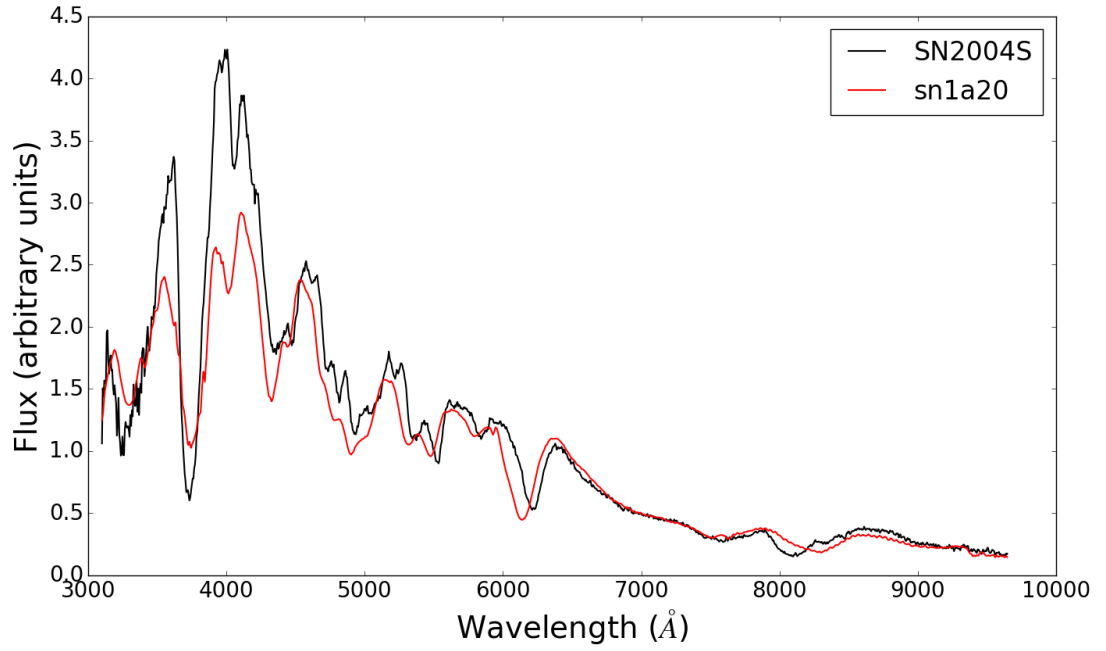
SNMC types SN 1998bw as a SN I b/c high-velocity, albeit the recovered redshift is less accurate. While **SNID** correctly types SN 1998bw as SN Ic - broad (Table 4.5), all its eleven template fits have redshifts $z > 0.27$, i.e. **SNID** is unable to reasonably recover the literature redshift for SN 1998bw. Figures C.9a and C.9b illustrate how the best-fit spectra of both **SNMC** and **SNID**, respectively, compare to the spectrum of SN 1998bw.

4.5.3.5 SN 2008es

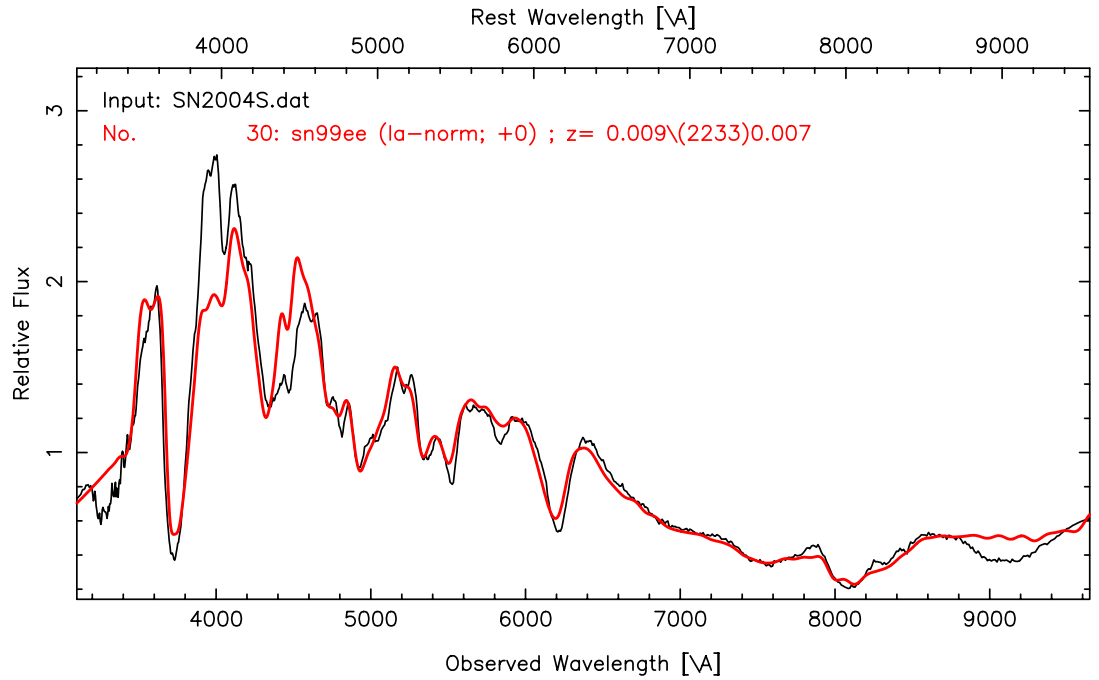
SNMC types SN 2008es as a SN IIn and not SN IIL, and the recovered redshift is higher than the literature redshift. **SNID** also recovers the wrong type of this candidate (none of the 17 **SNID** fits return the correct type), the wrong redshift (all 17 returned fits have redshifts $z > 0.350$) and a largely incorrect phase of $\tau = +382$. Both classifiers are not successful at recovering the literature parameters of this SN candidate. Figures C.10a and C.10b show how our selected best-fit spectra of **SNMC** and **SNID**, respectively, compare to the spectrum of SN 2008es.

4.6 Conclusion

SNMC's ability to include prior knowledge about our parameters of interest allows it to narrow down the range of possibilities in finding the true parameters. **SNMC** has the ability



(a) Comparison of SNMC's best-fit spectrum (red) to the input spectrum of SN 2004S (black). The recovered parameters are $z = 0.0060 \pm 0.0002$, $t = 20.00 \pm 0.03$ ($\tau = +1$)



(b) Same as (a) but for SNID, with the recovered parameters shown in red above the plots (SN type and phase τ given in parentheses).

Figure 4.12: Here, SNID appears to provide a better fit than SNMC.

to put a strong prior on the t parameter derived from the light-curve (where the peak is often clear) allowing tighter constraints on the other parameters as a result.

Overall, SNMC was able to return the parameters of simulated spectra relatively well, although there were some issues with the A_V parameter at low signal to noise. In the recovery of the correct galaxy template from the simulated spectra at $SNR = 5$ (Table 4.1), we expect the success rate for case 3 ($A_V = 0.5$) to be larger than that of case 4 ($A_V = 2.1$), given that an increase in the A_V parameter translates into a higher extinction and therefore a decrease in the overall signal, leading to a reduced success rate. Instead, we see the opposite, where the success rate is 100% for case 4 and only 60% for case 3. We intend to investigate this further as part of our future work, by conducting more tests to gauge the average behaviour in order to gain a better understanding of the cause.

A similar observation is made in the bias determination of the A_V parameter in the bottom panel of Figure (4.4). While we expect the determined bias values for all parameters to asymptote to zero with increasing SNR , we observe the opposite for the A_V parameter between a SNR change from 5 to 10. While this may be a random result by the algorithm, we intend to investigate the observation further, beyond the thesis, using an approach similar to that outlined for the odd success rate behaviour for the correct galaxy template, in order to have more insight into the real cause of such a trend. Additionally, in Figures (4.5) and (C.5a) to (C.7a), it appears that A_V and α are positively correlated. This is another one of our areas that requires further investigation to understand the cause of such an outcome.

Conversion of the SNMC's recovered A_V values for the 5 literature spectra into colour excess $E(B - V)$ values shows that only the uncertainty limits of the SNMC determined colour excess for 'SN 2004S' and 'SNLS-03D4cj' overlap the uncertainty limits of the corresponding literature values, as Figure (4.8) illustrates. Investigating the cause of the observed discrepancy between the SNMC recovered values and the literature values for the other three spectra forms part of our future work plans for improving SNMC's performance.

The next chapter gives a general overview of the DES and SALT observations as well as the SALT data reduction process, to set stage for the following chapter after it, where we use SNMC and everything we now about its classification mechanism, to classify all SALT spectra of DES SN candidates.

Chapter 5

DES and SALT observations

5.1 Introduction

In this Chapter, we provide an overview of the Dark Energy Survey (DES) supernova (SN) detection strategy and the manner in which such information is stored for access and further use by all relevant members of the DES Supernova Program. Unlike the discussion provided in Section 1.7, here we specifically describe the DES observing instruments as well as the locations in the sky in which DES conducts its photometric observations to detect SN candidates. We then discuss the overall manner in which the Southern African Large Telescope (SALT) conducts spectroscopic follow-up observations of the detected DES SN candidates, highlighting the various SALT tools utilised in the follow-up operations; and end the Chapter by briefly touching on the process of reducing and calibrating all the SALT follow-up spectral data.

5.2 DES photometric observations

The DES photometric observations are conducted from the Cerro-Tololo Inter-American Observatory (CTIO) in Chile, using the Blanco 4 m telescope¹. DES conducts its search of SNe by observing ten 3 deg² fields repeatedly in four filters, namely g , r , i and z , with approximately one week cadence (Kessler et al. 2015). The ten fields comprise eight shallow and two deep fields and are located within previously well observed fields. Two shallow fields called E1 and E2 are located in “ELAIS-S1”, the southern of the four fields that make up the European Large Area ISO² Survey (ELAIS, see Rowan-Robinson et al. 1999; Berta et al. 2006 for details). Table 5.1—adapted from Kessler et al. (2015)—

¹<http://www.ctio.noao.edu/noao/content/Victor-Blanco-4-m-Telescope>

²Infrared Space Observatory, <https://www.cosmos.esa.int/web/iso>

gives the characteristic of the rest of the fields along with the names of the well known previously observed fields that they are located in. Also given in Table 5.1 are details of the exposure times for each field.

Table 5.1: The DES SN fields and summary of exposures

Name	DES Name	Field Centre (deg)		filters	Exposure ^e (sec)
		RA	DEC		× number of visits
Elais S1	E1 shallow	7.8356	-42.9860	griz ^d	(175,175,200,200) × (1,1,1,2)
	E2 shallow	9.5000	-43.9980	griz	(175,175,200,200) × (1,1,1,2))
XMM-LSS ^a	X1 shallow	34.6356	-3.6880	griz	(175,175,200,200) × (1,1,1,2)
	X2 shallow	34.6356	-5.7120	griz	(175,175,200,200) × (1,1,1,2)
	X3 deep	36.3000	-4.7000	griz	(200,400,360,330) × (3,3,5,11)
Stripe 82 ^b	S1 shallow	49.1000	0.0000	griz	(175,175,200,200) × (1,1,1,2)
	S2 shallow	47.4356	-1.0120	griz	(175,175,200,200) × (1,1,1,2)
CDFS ^c	C1 shallow	54.2644	-27.0000	griz	(175,175,200,200) × (1,1,1,2)
	C2 shallow	54.2644	-29.1120	griz	(175,175,200,200) × (1,1,1,2)
	C3 deep	52.6000	-28.1000	griz	(200,400,360,330) × (3,3,5,11))

^a - X-ray Multi Mirror for Large Scale Structure (<http://wela.astro.ulg.ac.be/themes/spatial/xmm/LSS/>)

^b - Sloan Digital Sky Survey region lying along the celestial equator in the Southern Galactic Hemisphere, covering about 290 deg² and bounded by an RA and DEC range of 22h 24m < α < 04h 08m, -1.27° < δ < +1.27° (Sesar et al. 2007)

^c - Chandra Deep Field South (<http://cxc.harvard.edu/cdo/cdfs.html>)

^d - The filter central wavelengths (Å) are: $g = 4830$, $r = 6430$, $i = 7830$, $z = 9180$

^e - Exposure time in each of the four filters

Observations are conducted with the DES camera ‘DECam’ (Honscheid & DePoy 2008; Flaugher et al. 2015), a 570 mega pixel CCD camera with a low-noise electronic readout system and wide-field optical corrector. The camera consists of 72 CCDs which have a thickness of roughly ten times that of conventional CCDs that reduces fringing in the red and increases the efficiency in the detection of high redshift sources. Figures 6.1 and 6.2 show images of DECam and its science array CCDs, respectively.

Of the total 72 CCDs, 62 are 2048 × 4096 science array CCDs, 4 are 2048 × 2048 guider CCDs and the remaining 8 are 2048 × 2048 focus and alignment CCDs. DECam has a 2.2 degree field of view with a pixel scale of 0.27"/pixel.

DES has an allocation of 525 nights of observations on the 4m Blanco telescope and aims to measure about 4000 high quality SN Ia light curves out to redshift $z \sim 1.2$ in a period of 5 years (Bernstein et al. 2012). The DES SN Program started with ‘science verification’ observations in November 2012, which were conducted till February 2013 and then commenced science observations from August 2013.

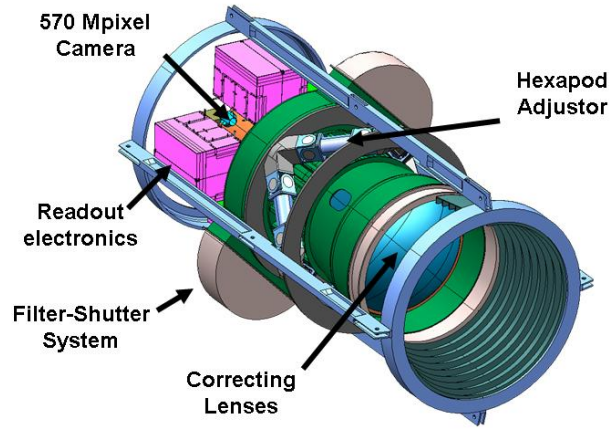


Figure 5.1: A schematic diagram of DECam, illustrating the locations of its various components.
Credit: Fermilab

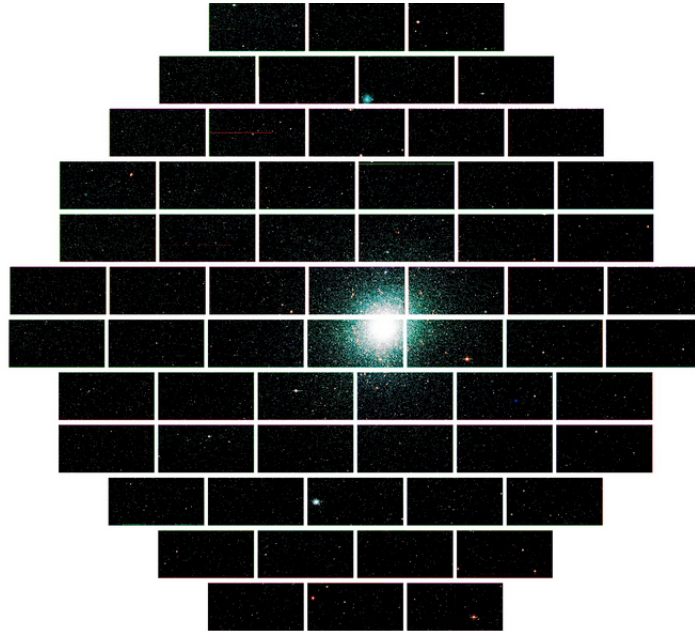


Figure 5.2: DECam 2048×4096 science array CCDs, showing a composite image of the globular star cluster 47 Tucanae that was observed during science verification. *Image credit: Fermilab, DES Collaboration.*

5.2.1 Detection of SN candidates

The detection of SN candidates in observed images is performed by a difference imaging pipeline (`DiffImg`). Kessler et al. (2015) give full details of how `DiffImg` works. The key idea is that a high signal to noise image referred to as ‘the reference image’ or ‘template’ is subtracted from every observed image, known as ‘the search image’. Since both the template and search images are taken from the same patch of the sky, the difference image obtained from the subtraction should only contain transient sources, including SN candidates, if the subtraction is performed correctly.

Correct subtraction means individual objects in the two images have matching pixel coordinates, i.e. the objects must be aligned, and the seeing in both images must be as closely identical as possible, such that when a pixel to pixel subtraction is performed, all that is left are new or varying sources. Following the steps above is `autoScan`, a machine learning algorithm developed by Goldstein et al. (2015) to identify artifacts (cosmic rays, optical ghosts, star halos, defective pixels, near-field objects, CCD edge effects) in the images. `autoScan` uses a random forest algorithm to distinguish between artifacts and no-artifacts. During classification, `autoScan` assigns a score τ to each object, a parameter which impacts both the ‘False Positive Rate’ (fraction of artifacts predicted to be legitimate detections in the validation set) and the ‘Missed Detection Rate’ (fraction of non-artifacts predicted to be artifacts in the validation set). At the end of a classification run, objects with scores $\tau = 5$ or higher are classified as non-artifacts and those with scores of $\tau < 5$ as artifacts (see Goldstein et al. 2015 for further details).

To identify SN candidates for follow-up spectroscopy, the results of `DiffImg` are passed on to a photometric supernova identification software (`PSNID`, Sako et al. (2011)) to identify the types of SN candidates found by assigning to them probabilities of belonging to a certain type. SN candidates that `PSNID` assigns higher probabilities to as being SNe Ia and backed up by a visual examination of their light curves, are then made available for follow-up spectroscopy to various telescopes, including SALT.

5.3 SALT spectroscopic follow-up and data reduction

The SALT spectroscopic follow-up of DES SN candidates begins with accessing an on-line DES page, where all discovered SN candidates are displayed with their relevant properties. Also accessible from the page is information about observatories involved in conducting follow-up spectroscopy. Table 5.2 (sourced from the online page) lists the details of the current DES spectroscopic follow-up telescopes, with the sizes of their mirrors

Table 5.2: Observatories around the world involved in conducting spectroscopic follow-up of SN candidates discovered by DES

Observatory ID	Name	Longitude	Latitude	Height (m)
AAT	Anglo-Australian Telescope (3.9m)	+149:03:57.9	-31:16:37.3	1164.0
GEMINI-N	Gemini North (8.1m)	-155:28:11.4	+19:49:26.3	4213.0
GEMINI-S	Gemini South (8.1m)	-70:44:11.7	-30:14:26.6	2722.0
GTC	Gran Telescopio Canarias (10.4m)	-17:53:31.3	+28:45:23.8	2275.0
HET	Hobby-Eberly Telescope (9.2m)	-104:00:53.0	+30:40:53.2	2026.0
KECK	Keck Observatory (10m)	-155:28:28.1	+19:49:35.0	4160.0
LBT	Large Binocular Telescope (2x8.4m)	-109:53:09	+32:42:05	3182.0
LICK	Lick Observatory (3m)	-121:38:13.7	+37:20:34.9	1283.0
MAGELLAN	Magellan Telescopes (6.5m)	-70:41:32.6	-29:00:51.0	2516.0
MDM	MDM Observatory (2.4m)	-111:37:00	+31:57:00	1939.0
MMT	MMT (6.5m)	-110:53:06	+31:41:18	2606.0
NTT	New Technology Telescope (3.6m)	-70:44:01.5	-29:15:32.1	2375.0
SALT	South African Large Telescope (10m)	+20:48:38.4	-32:22:33.6	1798.0
SOAR	Southern Astrophysical Research Telescope (4.1m)	-70:44:01.11	-30:14:16.41	2738.0
VLT	Very Large Telescope (4x8.2m)	-70:24:15	-24:37:38	2635.0

given in parentheses in column 2.

The DES “spectroscopic marshal” assigns the discovered SN candidates to various telescopes including SALT for spectroscopic follow-up, based on certain properties of a given telescope available to the marshal. Such properties for SALT are mainly the magnitude observing limit of the SN targets in the r -band of $r < 21.5$ and the target visibility window to SALT. Candidates that fulfil the SALT observing requirement are then automatically tagged to it for spectroscopic follow-up.

One of the main advantages of SALT in the DES SN program is its flexibility to conduct follow-up observations rapidly—under an hour following notification—a feature that not all follow-up telescopes in the DES SN program (such as the AAT) possess. Additionally, SALT is well suited to observe in the redshift range $0.1 < z < 0.3$, which traditionally has fewer SN observations compared to those conducted at $z < 0.1$ (e.g. Bailey et al. 2009) and by high redshift surveys (Kessler et al. 2009), thereby increasing

the numbers in this redshift range, which assists greatly in the realisation of the DES SN program ambitious goals.

Some of the information accessible from the above mentioned DES online page are finder charts of the discovered SN candidates. Figure 5.3 shows an example of a typical DES finder chart for one of the discovered SN candidates.

The chart entails the standard details (e.g. the object's RA and DEC, etc) as well as nearby stars that make the acquisition of a SN candidate by the telescope easier. The standard SALT follow-up process involves providing an additional *SALT finder chart*, generated using the *SALT Finder Chart Generator*³. Figure 5.4 shows an example of the *SALT Finder chart* of the same SN candidate on the *DES finder chart* in Figure 5.3.

The above information about a SN candidate obtained from the online DES page is then fed into the SALT Principal Investigator Proposal Tool⁴ to place an object in the queue for an observation. All SALT follow-up observations of DES SN candidates are made in *Target of Opportunity (ToO)* mode, which means they have the highest observing priority. Unless the SALT observing queue contains other *ToO* programmes that are higher priority, all follow-up observations of DES SN candidates take precedence over other observing programmes in the queue.

5.3.1 SN candidate visibility and SALT tracking time

All 10 DES fields are visible to SALT for varying durations during the DES SN observing season, which typically runs from early August in one year to early February in the following year. Some fields stay visible longer than others, depending on their RA and DEC coordinates. The E fields have the shortest visibility span over the duration of the observing season, followed by the X and then S fields, with the C fields having the longest visibility span compared to the other 3 sets. Figure 5.5 shows an example of the nightly visibility of the E1 field at the start (~1st of August) and end (~7th of February) of the SN observing season for each DES year, generated with the *SALT visibility calculator*⁵.

After obtaining the details for a given SN candidate presented above, its window of visibility with SALT is computed using the SALT visibility calculator. The length of time that SALT can observe the object is dependent on the length of time the object spends inside the annular region of the diagram shown in Figure 5.6.

The time it takes a celestial object to cross the above-discussed annular region is

³http://pysalt.salt.ac.za/finder_chart/

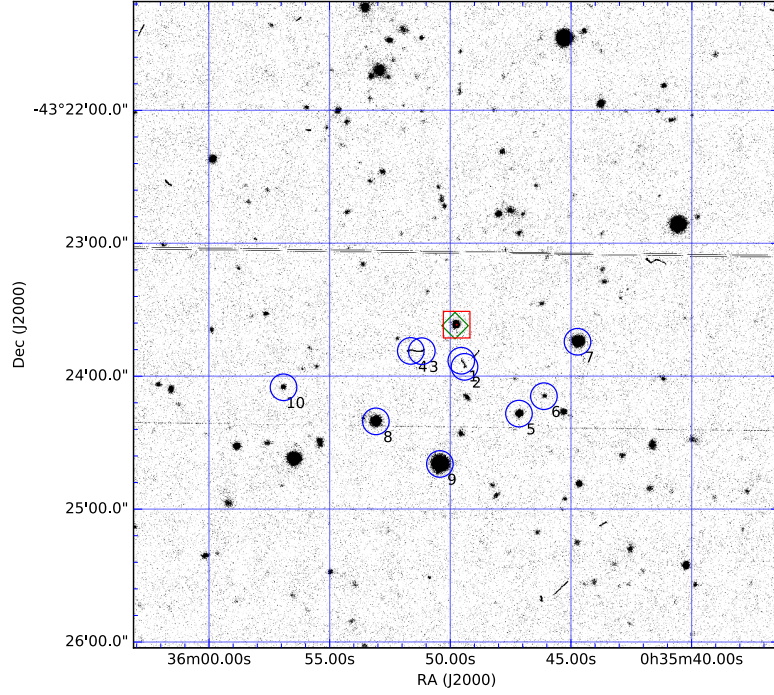
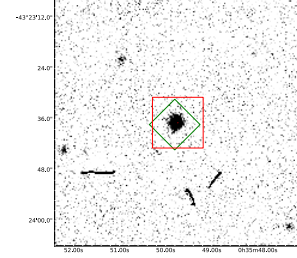
⁴<http://pysalt.salt.ac.za/pipt-manual/pdf/pipt-manual.pdf>

⁵<http://astronomers.salt.ac.za/software/#VisibilityCalculator>

DES16E1ciy (20.2)

00:35:49.737 -43:23:36.78

◇ (host) 00:35:49.803 -43:23:37.23
 Offset (arcsec) 0.9
 P.A. from Target (degrees) 122.0
 E/W from Target (arcsec) 0.7 E
 N/S from Target (arcsec) 0.5 S



Label	Mag.	R.A.	Dec.	Offset (arcsec)	P.A. from Target (degrees)	E/W to Target (arcsec)	N/S to Target (arcsec)
1	21.1	00:35:49.545	-43:23:53.05	16.4	187.3	2.1 E	16.3 N
2	21.3	00:35:49.411	-43:23:55.82	19.4	190.6	3.6 E	19.0 N
3	21.4	00:35:51.181	-43:23:48.74	19.8	127.2	15.7 W	12.0 N
4	20.9	00:35:51.637	-43:23:48.63	23.9	119.8	20.7 W	11.8 N
5	19.6	00:35:47.156	-43:24:16.92	49.0	215.0	28.1 E	40.1 N
6	21.5	00:35:46.122	-43:24:09.07	50.9	230.7	39.4 E	32.3 N
7	17.4	00:35:44.730	-43:23:44.48	55.1	262.0	54.6 E	7.7 N
8	18.1	00:35:53.083	-43:24:20.42	56.9	140.1	36.5 W	43.6 N
9	15.9	00:35:50.431	-43:24:39.65	63.3	173.1	7.6 W	62.9 N
10	21.1	00:35:56.908	-43:24:05.03	83.1	109.9	78.2 W	28.3 N

Figure 5.3: An example finder chart produced by DES for the candidate *DES16E1ciy*, showing, among other properties, the candidate's estimated peak magnitude in the *R*-band ($m_R = 20.2$) and its RA and DEC. The sources highlighted with blue circles in the image represent bright objects—whose properties are given in the table below—that can be used as references in the correct positioning the slit on a target. Also shown in the centre of the image is the host galaxy inside the green rhombus. The SN candidate is located at the centre of the enclosing red square.

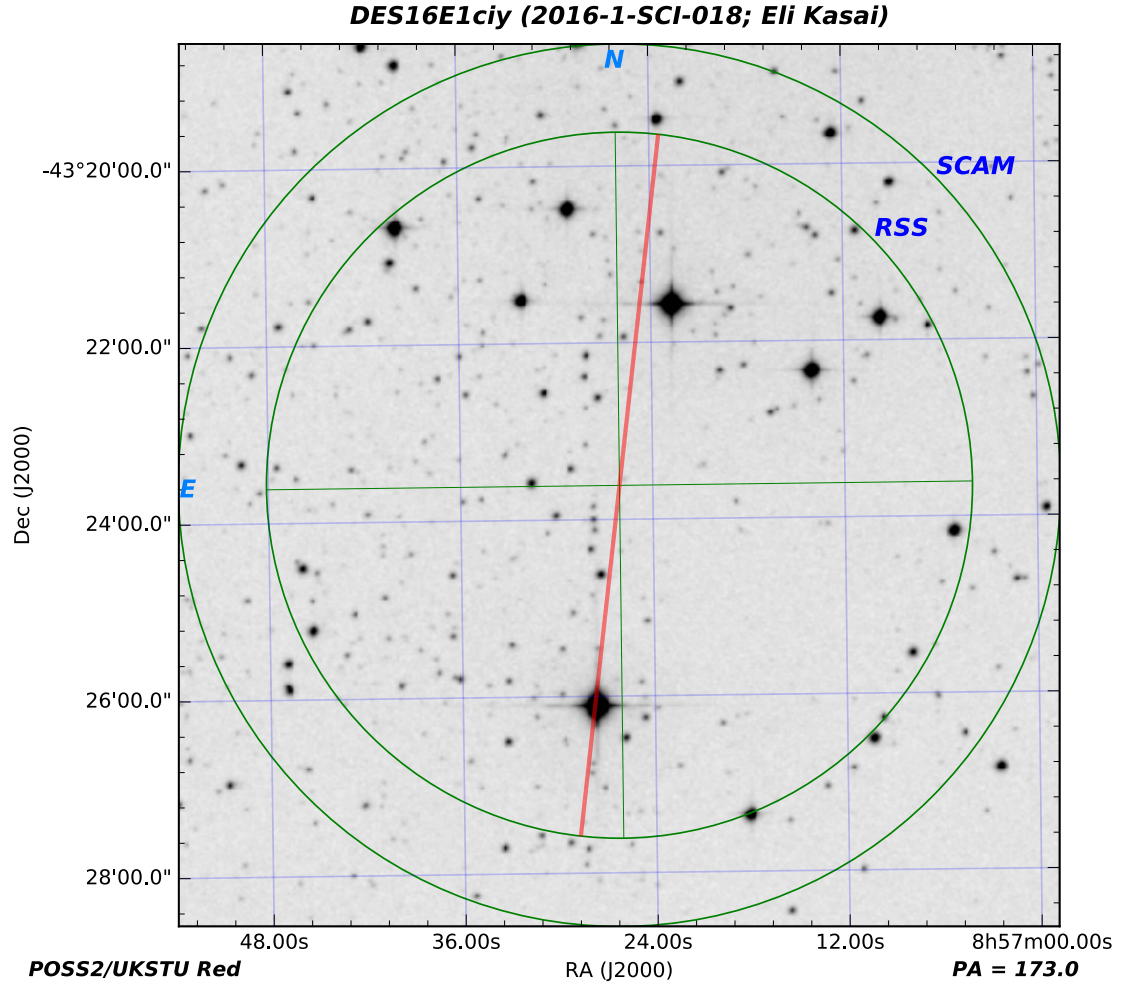
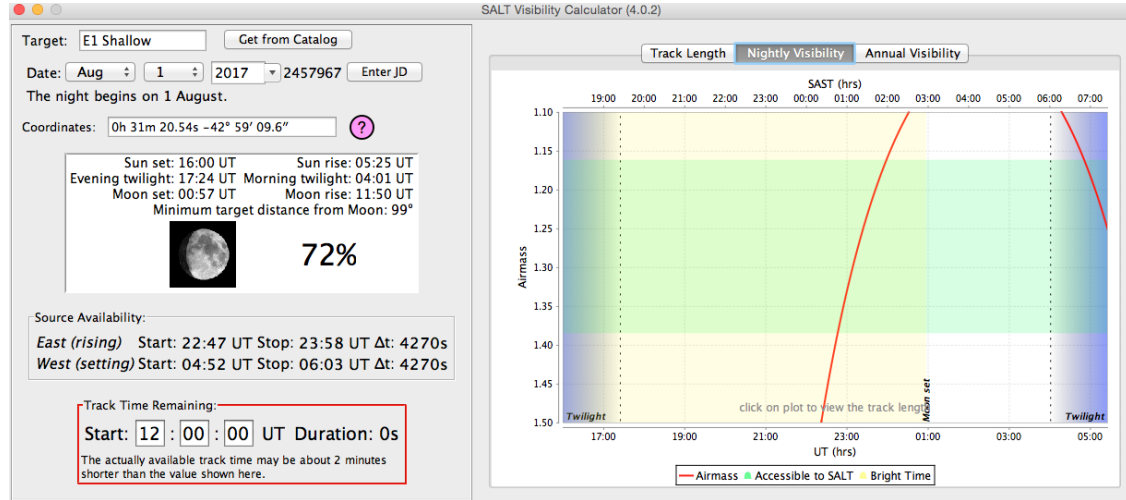
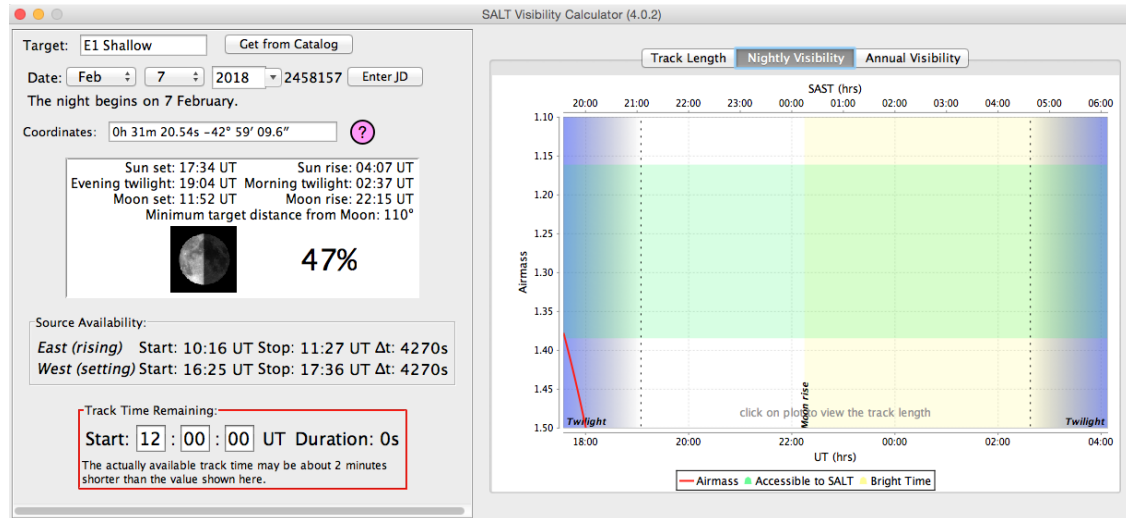


Figure 5.4: The SALT finder chart version of the same object given in the DES finder chart in Figure 5.3, produced by the SALT finder chart generator discussed in the text. The red line in the chart represents the slit placed on the SN candidate, which is located at the centre of the image. The 9th object in Figure 5.3 has been used as the reference in positioning the slit on *DES16E1ciy*.



(a) Nightly visibility of the DES E1 field at the start of the DES SN observing season, early August in a year. Shown in the top left are the dates of the object's visibility to SALT, its RA and DEC coordinates and some self-explanatory information about the moon brightness, sunrise and sunset times, moon rise and moon set times as well as the times of the morning and evening twilights. Most importantly are the times that the source enters and exits the SALT observing window the first time (East, rising) and the second time (West, setting). Also shown are the time durations that the object can be tracked by the telescope, but as discussed below, SALT can only track objects for about 1 hour. Shown on the right is an illustration of how the object traverses the SALT observing window, indicated with the red curve.



(b) Same as (a) but at the end of the DES observing season, early February in a year. We can clearly see how the object sets quite early during twilight as the portion of its red curve in the 'Nightly Visibility' plot shows.

Figure 5.5: Nightly visibility of the DES E1 field at the start and end of a SN observing season.

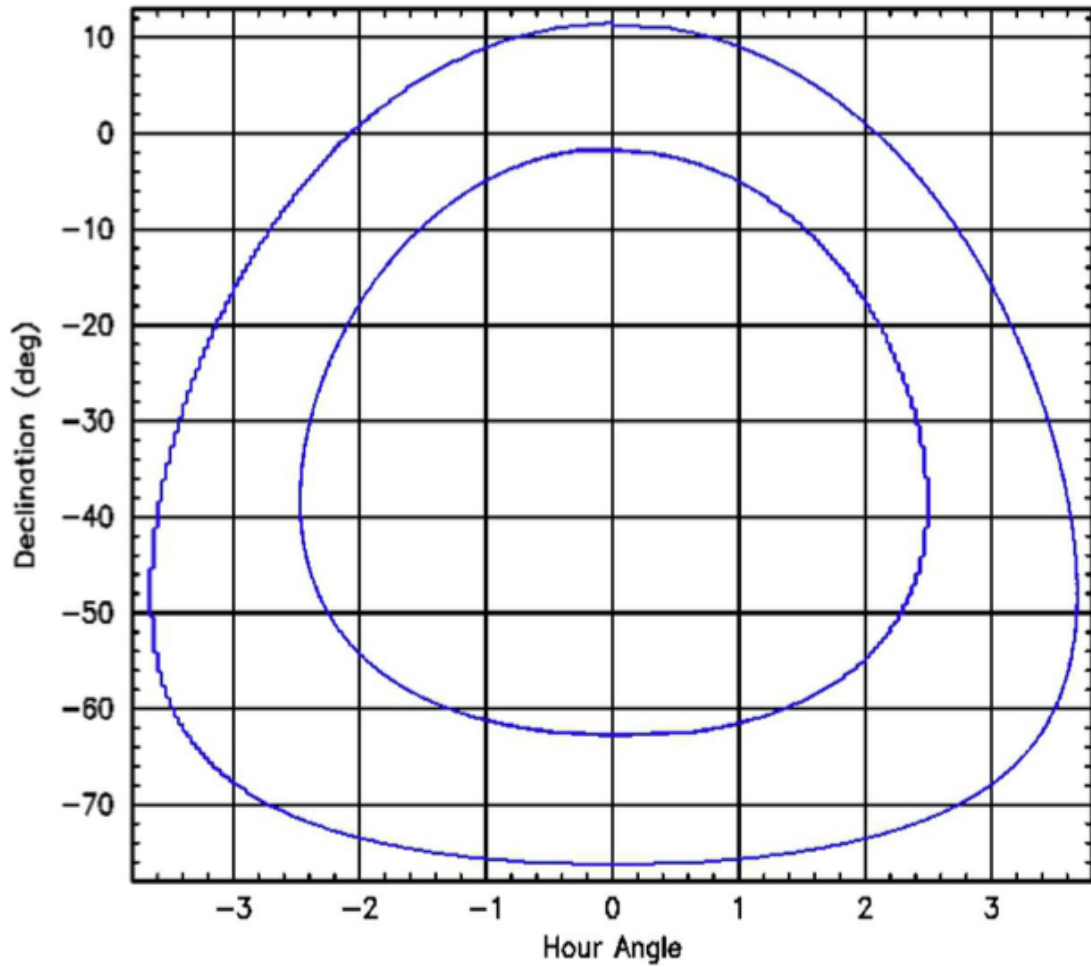


Figure 5.6: The SALT visibility annular region. Only objects located inside the annular region are observable by SALT at any given time of the night. Objects are typically visible twice each night. Figure from http://pysalt.salt.ac.za/proposal_calls/current/ProposalCall.pdf.

dependant on its Declination. As Figure 5.6 shows, objects located in equatorial zones (i.e. $\delta \sim 0^\circ$) and those far in the south (i.e. $\delta \sim 70^\circ$) have longer annulus crossing times than those at other declinations. However, SALT’s observation of an object is done by the tracker located on the telescope’s payload, which only has a maximum observing or tracking time of about 1 hour (including overheads), without having to re-acquire the object by moving the telescope structure⁶.

For the majority of our fields, the typical track length of SALT is about 1 hour. While it is possible to extend the tracking time of an object beyond the stated maximum time,

⁶http://pysalt.salt.ac.za/proposal_calls/current/ProposalCall.pdf

doing so requires stepping the telescope in azimuth and re-acquiring the object, which incurs all of the normal overheads of acquiring a target and repositioning the telescope⁸. It is therefore recommended that block times are limited to available track times. In the event of signal-to-noise ratio (SNR) requirements demanding exposures longer than 1 hour, multiple observations of the object should rather be conducted on separate nights and then stacked. Our experience has however shown that this does not work out well, as the co-adding did not always produce the amount of SNR specified in our observing conditions. This prompted us to limit our maximum r -band observing requirement to $r = 21.2$ magnitudes, from an initial value of $r = 21.9$ magnitudes, a change that has shown to produce the right level of the SNR we require in a single observation.

5.3.2 The Moving Pupil and Calibrations

As objects gets tracked across the visibility annular region, the pupil moves along as well. This results in a constant changing of the telescope's effective area. It is for this reason that absolute photometry and spectroscopy are not easy to achieve with SALT. Only relative spectral calibration is feasible, which is accomplished through the use of spectrophotometric standard stars⁷.

5.3.3 The RSS Configuration for follow-up spectroscopy

Full details about the optical design and working of the SALT Robert Stobie Spectrograph (RSS) are presented by Burgh et al. (2003). The type of slit we use for follow-up observations of the DES SN candidates is the RSS *longslit* 'PLN0150N001', which has a width and height of 1.5 arc seconds and 8 arc minutes, respectively. For the grating, we use *pg0300*, which has a wavelength coverage of 3700–9000Å with a spectral resolution of $\sim 3\text{\AA}$. Our choice of such a spectroscopic setup is to enable a successful observation of both the Si II 4000Å Si II 6150Å SN Ia spectral features at $0.1 < z < 0.3$. A successful measurement of the two features is key to the science aspect of our work. Other RSS configurations for our follow-up campaign include a camera station and grating angle of 11.5° and 5.75° , respectively, as Figure 5.7 shows.

Other key properties shown in Figure 5.7 include the wavelengths corresponding the positions of the CCD gaps on the blue and red chips, the wavelengths corresponding to the chip centres and edges, the resolutions corresponding to the blue and red chip centres and the slit's central wavelength. We use 2×2 CCD binning for all our observations and the

⁷http://pysalt.salt.ac.za/proposal_calls/current/ProposalCall.pdf

RSS Configuration

Name:

Cycles: ?

RSS Mode:

Slit Type:

Longslit:

Grating:

Camera Station: 11.5 deg

Grating Angle: deg

Order Blocking Filter: (show) ?

	Wavelength	Resolution
Blue Chip Edge	1,862.1 Å	
Blue Chip Center	3,387.7 Å	192
Blue Chip Gap	4,927.0 Å – 5,100.1 Å	
Central Wavelength	6,643.2 Å	376
Red Chip Gap	8,179.1 Å – 8,350.5 Å	
Red Chip Center	9,867.0 Å	558
Red Chip Edge	11,356.2 Å	

Central Dispersion: 1.52 Å per unbinned pixel
 Error Estimate for the Wavelengths: 30 Å
 Spatial Plate Scale: 0.127 arcsec per unbinned pixel

Figure 5.7: A *PIPT* snapshot of the RSS Configuration for a typical SN candidate follow-up exercise, showing the slit type, camera and grating angle and the order blocking filter used in our DES SN candidates follow-up campaign. Other properties shown include the wavelengths and corresponding resolutions for the blue and red chip centres and spatial plate scale value.

pc03850 order blocking filter, which blocks out *UV*-light⁸ that would otherwise overlap a portion of our spectral range. This causes an undesirable result as the resultant *UV* spectrum gets superimposed on our desired spectrum⁹ falling within the spectral range defined by our choice of the grating.

5.3.4 Data Reduction

The data reduction of our follow-up spectral data for all DES SN candidates, including wavelength and flux calibrations, is performed with the PySALT software (Crawford et al. 2010). As stated in the introduction of this chapter, PySALT is an automated SALT data reduction pipeline, which mostly uses the IRAF data reduction commands written in the PyRAF software. Step-by-step details of how PySALT performs the reduction are given in Appendix B. We present below a summary of the steps:

1. **Basic data reduction.** This includes (i) *gain correction*, which corrects for fluctuations in the amplifier readout speeds and gain settings; (ii) *crosstalk correction*,

⁸http://pysalt.salt.ac.za/proposal_calls/current/ProposalCall.pdf

⁹http://sbo.colorado.edu/SBO_OLD_SITE/sbo/manuals/24inch/obfilters.pdf

which corrects for the crosstalk effect between neighbouring readout amplifiers in the CCD, and (iii) *bias correction*, which corrects for the bias signal detected by the CCDs, which results from the imperfect functioning of the telescope and the CCDs themselves. The PySALT tasks ‘saltgain’, ‘saltxtalk’ and ‘saltbias’ perform the three corrections, respectively.

2. **Cosmic ray removal.** This step removes cosmic rays from all observed 2-D spectra (see Figures B.3 and B.4), accomplished with the PySALT task ‘saltcrlean’.
3. **Flat-fielding.** This is similar to bias correction but goes a step further to correct for pixel to pixel sensitivities. While the bias correction uses data from the overscan region of the observations (Figure B.2), flat-fielding uses dome flats to do the correction. Three PySALT tasks are involved in this correction, namely ‘saltcombine’, ‘saltillum’ and ‘saltflat’.
4. **Wavelength calibration.** This step mainly involves converting the 2-D spectrum from pixel scale to wavelength. Four PySALT tasks are involved in this process, namely ‘specidentify’, ‘specrectify’, ‘specsky’ and ‘specextract’ (see Section B.5 for elaborate details of each task).
5. **Flux calibration.** This step involves the conversion of flux of wavelength-calibrated spectra from pixel counts to real flux units, i.e. $\text{erg s}^{-1} \text{cm}^{-2} \text{\AA}$. Two PySALT tasks are involved in the calibration, namely ‘specsens’ and ‘speccal’ (see Section B.6 for elaborate details).

5.4 Conclusion

DES was allocated 525 nights on the Blanco 4m telescope at CTIO in Chile, to conduct observations over a period of 5 years aimed at measuring the expansion history of the Universe in order to constrain the equation of state parameter for dark energy to 1% accuracy. DES commenced science observations in the 2nd half of 2013. By the end of the 5 years, the DES SN Program aims to measure up to ~ 4000 high-quality SN Ia light curves by conducting search observations in SN 10 fields, two of which are deep and 8 are shallow. DES uses DECam for its observations, which is a 570 Mega pixel camera characterised by a low-noise electronic readout system, among other properties.

To find SN candidates from the photometric images, a difference imaging pipeline developed called `DiffImg` is used to perform image subtraction from which SN candidates are then eventually discovered, after a series of additional intermediate processes.

Include in the intermediate processes is an algorithm called `autoScan`, which is nested into `DiffImg` and its job is to remove all kinds of artifacts from images. A final algorithm called `PSNID` identifies the most likely subtype that a discovered SN candidate belongs to. The above results are then passed on to the DES spectroscopic marshall, which tags the resultant SN candidates for spectroscopic follow-up telescopes (including SALT) whose observing requirements match those of the discovered SN candidates.

Several tools are used by SALT in conducting follow-up observations of the DES SN candidates. These include DES finder charts of new SN candidates, SALT visibility calculator and SALT finder chart generator. These 3 play an important role in placing SN in the SALT observing queue, SN candidates tagged to SALT by the DES spectroscopic marshall for spectroscopic follow-up.

One limitation we experience is the maximum tracking time of objects by SALT of about 1 hour, due to the telescope's design. This means that if our requirement is to observe a SN target for longer than an hour, the observation has to be broken into two sets and then co-add them. In practice, this has not proven to work well. The co-adding was not always yielding the desired result. It was for this reason that we capped the r -band observing limit from the initial value of $r = 21.9$ to $r = 21.2$, which proved sufficient in acquiring in a single observation a reasonable level of the SNR we require.

Lastly, we reduce the follow-up spectral data of all DES SN candidates using the PySALT software discussed in the text. The PySALT reductions include gain, crosstalk and bias corrections, cosmic ray removal, flat-fielding, wavelength calibration and flux calibration.

In the next chapter, we present `SNMC`'s classification and parameter estimation results of the 36 SALT spectra of DES SN candidates and measurements of equivalent widths using a sub-sample of candidates classified as SNe Ia.

Chapter 6

Classification and Equivalent Width Science with SALT Spectra

6.1 Introduction

In this chapter, we use **SNMC** to classify a total of thirty-six (36) spectra of supernova candidates discovered by the Dark Energy Survey (DES), taken with the Southern African Large Telescope (SALT) between October 2013 and February 2016. The 36 spectra include high signal-to-noise ratio (*SNR*) spectra, heavily contaminated spectra as well as low *SNR* spectra, with the high *SNR* spectra accounting for the majority. The availability of light curves for all 36 spectra from which a more accurate determination of the epoch parameter t is made for each spectrum is an added advantage in this work, as it enables the cross-checking of epoch parameters t that **SNMC** recovers from each spectrum. In the event that **SNMC**'s recovers an unreasonable value of t , i.e. several days prior to or post the more accurately predicted value from the light-curve t_{lc} for a given SN candidate, we apply a 10-day prior range centred on t_{lc} and re-run the classification. We the chapter with a discussion of the model selection and parameter estimation of the 36 spectra, the prior ranges applied on t during parameter estimation using prior information obtained from light curves and then the results of re-running the classifications after applying the said prior epoch information. The chapter ends with equivalent width (EW) measurements of two selected SN Ia spectral features and how the results compare to the literature.

6.2 Model selection and parameter estimation

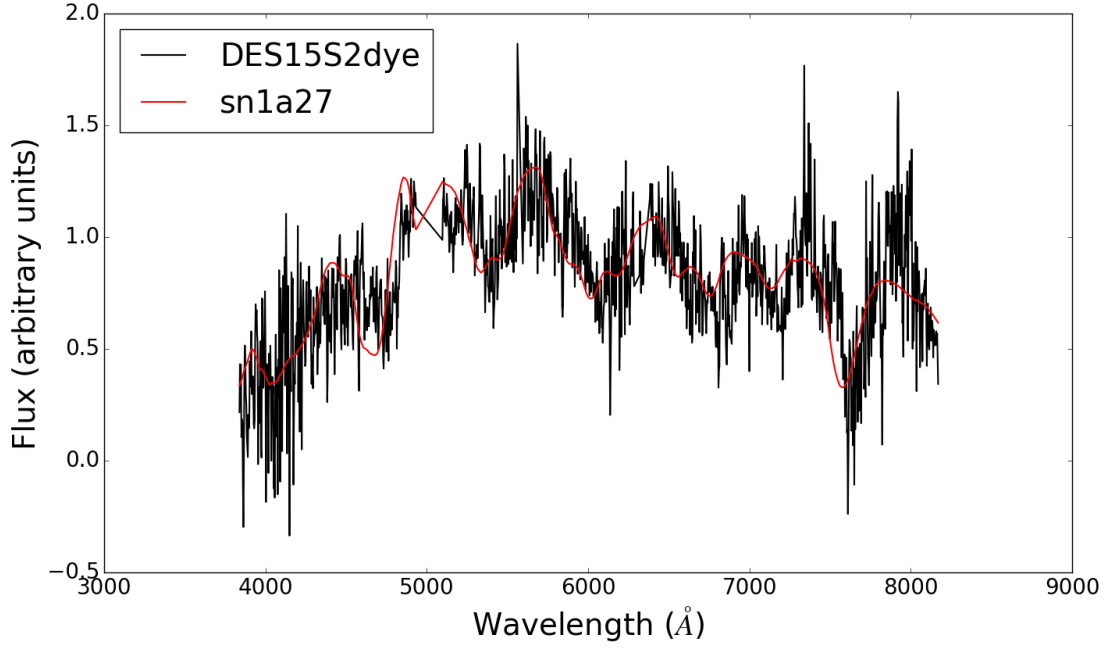
We start the classification of each SALT spectrum by using all 8 Nugent SN template types discussed in Chapter 3, but restricting the use of all their available epochs (Table 3.1) to a maximum range of 80 days for all templates. We put this restriction on the epoch as the DES SN candidates we follow-up are around peak brightness, i.e. $t = 19$ days and do not deviate from that by weeks. We use the 5 galaxy templates, also discussed in Chapter 3, during the classification of the 36 spectra. We show in Figure 6.1 and Appendix C, Figures C.11 to C.13, four of some of SNMC’s well classified spectra along with their corner plots (1-D histograms and 1σ level contour plots) of the recovered parameter posterior distributions and in Table 6.1, the model selection and parameter estimation results of all 36 spectra.

As stated in the Introduction, recovery of the correct epoch parameter t by SN spectroscopic classifiers is less accurate compared to its determination from the SN light curves. SNMC is no exception to this as it recovers low t values for some spectra and high t values for others, compared to the t_{lc} values. One example of a spectrum for which SNMC returns a lower t value compared to that obtained from the light-curve is the spectrum of the SN candidate “DES13C1feu” taken by SALT on 2013-10-08. The time of B -band maximum brightness estimated from its light-curve was 2013-10-05 ($MJD = 56570.0$, see Table 6.2), which corresponds to $t = 22$ days for the SN templates used in this work.

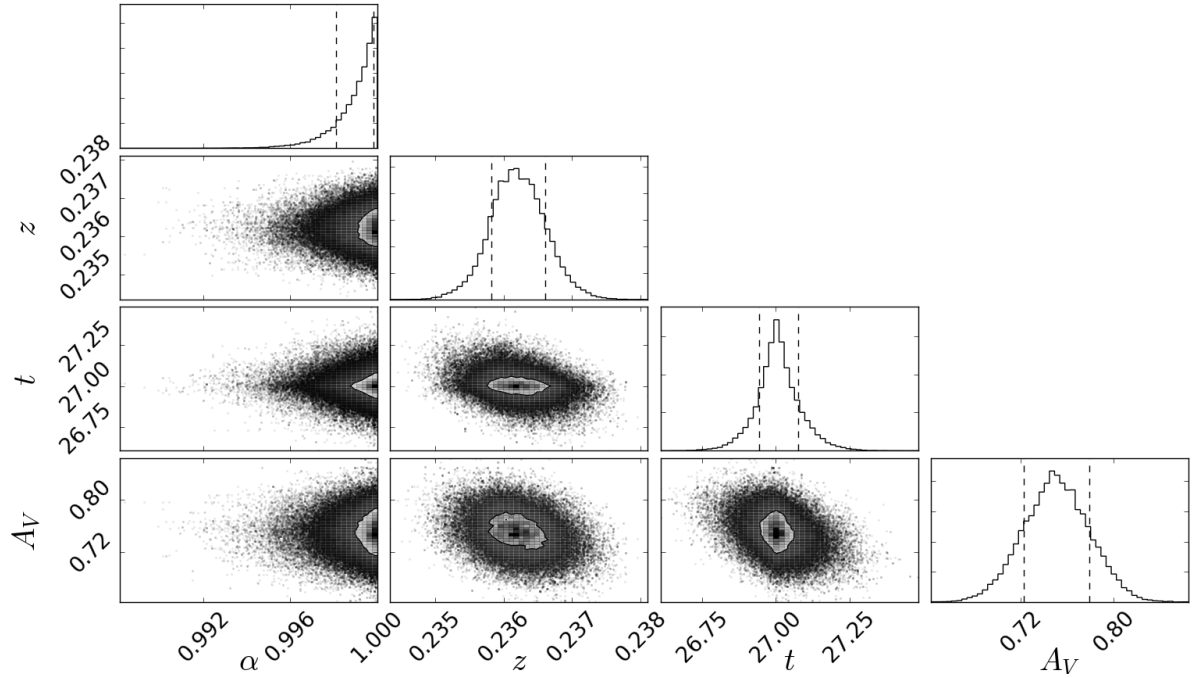
The estimation of the times of maximum B -band brightness $t_{B,max,est}$ —given in columns 4, 6 and 8 of Table 6.2—from the light curves of all 36 DES SN candidates considered in this thesis was performed by our DES SN photometric classification team, using the *Photometric SuperNova IDentification software (PSNID)*, developed by Sako et al. (2011). Also shown in Table 6.2 are the Bayesian probabilities (PBAYES, also derived by *PSNID* from the light curves) that a candidate is a *SN Ia*, *SN Ibc* or *SN II*. It is the light-curve models of these three subtypes that the $t_{B,max,est}$ discussed above are determined from.

We compare the date of SALT’s observation of each SN candidate to its light-curve determined $t_{B,max,est}$ and easily work out whether or not the observation was conducted prior to, during or post maximum brightness and if prior to or post maximum brightness, by how many days. That then gives us a good estimate of the true epoch $t_{est,true}$ and given in column 4 of Table 6.3 for all 36 DES SN spectra considered in this work. Using the $t_{est,true}$ values, we place strong prior ranges of 10 days centred on $t_{est,true}$.

Using DES13C1feu again for an example, its $t_{est,true} = 22$ days (which is post maximum brightness), hence its *10-day top-hat prior range* centred on its $t_{est,true}$ is $17 \leq$



(a) Comparison of SNMC's best-fit spectrum (red) to the spectrum of the SN candidate DES15S2dye (black). The recovered SN type and galaxy type are SN Ia and SB4 respectively, with the following corresponding MCMC best-fit parameters: $\alpha = 1.00 \pm 0.03$, $z = 0.236 \pm 0.004$, $t = 27.0 \pm 0.5$, $A_V = 0.8 \pm 0.3$. The label for the best-fit spectrum 'sn1a27' means the recovered SN type and epoch t are SN Ia and 27 days, respectively.



(b) 1-D histograms and 1σ level contour plots of SNMC's posterior distributions for α , z , t and A_V , estimated from the spectrum of DES15S2dye in (a). The vertical dotted lines represent the 1σ levels.

Figure 6.1

Table 6.1: SALT spectra of DES SN candidates observed between October 2013 and February 2016 and classified with **SNMC**. *SN type* and *Galaxy type* represent the recovered types of the SN and host galaxy from the spectrum; α , z , t and A_V represent the associated MCMC *best-fit* parameters.

SN candidate	Date of observation	Model selection		Parameter estimation			
		<i>SN type</i>	<i>Galaxy type</i>	α	z	t	A_V
DES13C1feu	2013-10-08	SN Ibc	E0	0.48 ± 0.01	0.0593 ± 0.0001	8.6 ± 0.2	0.46 ± 0.06
DES13X1cpt	2013-10-23	SN Ibc	E0	0.79 ± 0.01	0.2185 ± 0.0003	7.79 ± 0.07	0.50 ± 0.03
DES13X1kae	2013-10-29	SN 91T-like	Sb	0.972 ± 0.008	0.1384 ± 0.0003	31.00 ± 0.05	0.73 ± 0.02
DES13C1juw	2013-10-29	SN 91T-like	E0	0.81 ± 0.03	0.189 ± 0.004	39.2 ± 0.5	0.0 ± 0.3
DES13C3absw	2014-01-25	SN Ibc	SB4	0.83 ± 0.02	0.0687 ± 0.0008	7.6 ± 0.1	1.52 ± 0.03
DES13C2acmj	2014-02-02	SN IIIn	SB1	0.671 ± 0.003	0.0019 ± 0.0001	89.9 ± 0.1	0.21 ± 0.01
DES13C3adnw	2014-02-06	SN Ibc	SY2	0.87 ± 0.03	0.181 ± 0.003	7.9 ± 0.4	0.4 ± 0.2
DES13C2ahyt	2014-02-07	SN Ia	Sb	0.99 ± 0.09	0.582 ± 0.006	2.9 ± 0.9	0.2 ± 0.3
DES14X1oes	2014-12-23	SN 91T-like	Sb	0.92 ± 0.03	0.458 ± 0.004	19.3 ± 0.6	0.0 ± 0.3
DES14E2rpm	2014-12-25	SN Ibc-hv	E0	0.85 ± 0.03	0.004 ± 0.004	24.5 ± 0.4	0.2 ± 0.3
DES14E1rph	2014-12-30	SN 91T-like	SB1	0.92 ± 0.09	0.2641 ± 0.0009	18.5 ± 0.1	0.00 ± 0.07
DES14S1rwf	2015-01-16	SN Ibc	E0	0.433 ± 0.006	0.0754 ± 0.0001	4.99 ± 0.09	0.50 ± 0.04
DES14C3kzd	2015-01-18	SN IIIn	SB1	1.000 ± 0.001	0.6891 ± 0.0004	8.01 ± 0.05	1.184 ± 0.005
DES14C3vwl	2015-02-09	SN Ibc-hv	E0	0.59 ± 0.03	0.060 ± 0.004	10 ± 1	0.6 ± 0.3
DES15C2ir	2015-08-24	SN Ibc	SB1	0.969 ± 0.004	0.0579 ± 0.0002	13.86 ± 0.04	0.00 ± 0.02
DES15C2sj	2015-09-08	SN Ia	SB1	1.00 ± 0.03	0.74 ± 0.02	2.0 ± 0.4	0.4 ± 0.3
DES15C2eaz	2015-09-15	SN IIIn	SY2	0.92 ± 0.01	0.6618 ± 0.0008	2.1 ± 0.1	0.57 ± 0.05
DES15E2dzb	2015-09-16	SN Ibc	SY2	0.81 ± 0.02	0.098 ± 0.004	5.0 ± 0.2	0.7 ± 0.2
DES15S2dye	2015-09-20	SN Ia	SB4	0.99 ± 0.04	0.258 ± 0.004	2.1 ± 0.5	2.12 ± 0.08
DES15S1flj	2015-09-25	SN IIIn	SB1	1.00 ± 0.03	0.74 ± 0.02	2.0 ± 0.5	0.4 ± 0.3
DES15C3efn	2015-10-04	SN Ia	E0	0.95 ± 0.01	0.0773 ± 0.0006	9.33 ± 0.07	0.67 ± 0.05
DES15X3kqv	2015-10-04	SN Ia	Sb	0.65 ± 0.02	0.142 ± 0.002	26.2 ± 0.2	0.2 ± 0.1
DES15X1ith	2015-10-09	SN Ibc	E0	0.71 ± 0.01	0.2197 ± 0.0003	7.99 ± 0.05	1.01 ± 0.02
DES15E1kwg	2015-10-11	SN Ia	SB1	0.742 ± 0.007	0.1075 ± 0.0003	15.26 ± 0.07	0.39 ± 0.03

Table 6.1 continued

SN candidate	Date of observation	Model selection		Parameter estimation			
		<i>SN type</i>	<i>Galaxy type</i>	α	z	t	A_V
DES15E2kvn	2015-10-12	SN Ibc	E0	0.38 ± 0.01	0.2069 ± 0.0001	11.0 ± 0.1	0.79 ± 0.06
DES15S2eaq	2015-10-15	SN 91T-like	SB1	0.74 ± 0.01	0.0674 ± 0.0006	19.1 ± 0.1	2.25 ± 0.03
DES15S2kqw	2015-10-16	SN Ibc-hv	E0	0.67 ± 0.03	0.035 ± 0.004	26.8 ± 0.4	0.0 ± 0.2
DES15X2mei	2015-11-13	SN Ia	E0	0.74 ± 0.03	0.2320 ± 0.003	27.5 ± 0.3	0.3 ± 0.2
DES15S2max	2015-11-13	SN Ibc	E0	0.85 ± 0.02	0.277 ± 0.002	7.3 ± 0.3	0.1 ± 0.2
DES15S2mau	2015-11-13	SN Ibc	SB4	0.745 ± 0.006	0.1338 ± 0.0003	8.07 ± 0.05	0.56 ± 0.02
DES15C3mpk	2015-12-05	SN Ia 91T-like	E0	0.78 ± 0.02	0.1644 ± 0.0009	33.3 ± 0.2	0.29 ± 0.08
DES15S1mvv	2015-12-09	SN Ia 91T-like	SB4	0.84 ± 0.04	0.253 ± 0.004	31.2 ± 0.4	0.3 ± 0.3
DES15X3nad	2015-12-09	SN Ia 91T-like	SB1	1.00 ± 0.03	0.0221 ± 0.004	39.0 ± 0.4	0.0 ± 0.3
DES15S2mpg	2015-12-03	SN 91T-like	Sb	0.81 ± 0.02	0.1798 ± 0.0009	26.8 ± 0.2	0.00 ± 0.07
DES15S2ocv	2016-01-09	SN Ia	E0	0.88 ± 0.03	0.211 ± 0.004	27.8 ± 0.4	0.0 ± 0.2
DES15S2okl	2016-01-13	SN 91T-like	Sb	0.99 ± 0.02	0.163 ± 0.002	31.4 ± 0.2	0.0 ± 0.2

Table 6.2: The *PSNID* $t_{B,max,est}$ (TMAX) and probabilities (PBAYES, i.e. Bayesian probabilities, also derived by *PSNID* from the light curves) that a candidate is a *SN Ia* (*IA*), *SN Ibc* (*IBC*) or *SN II* (*II*). We have made the highest probabilities in columns 3, 5 and 7 bold in order to highlight them.

Transient							
name	z	PBAYES _{IA}	TMAX _{IA} (<i>MJD</i>)	PBAYES _{IBC}	TMAX _{IBC} (<i>MJD</i>)	PBAYES _{II}	TMAX _{II} (<i>MJD</i>)
DES13C1feu	0.060	0.00000	56566.0	1.00000	56570.0	0.00000	56567.0
DES13X1cpt	0.151	1.00000	56547.0	0.00000	56551.0	0.00000	56550.0
DES13X1kae	0.149	1.00000	56592.0	0.00000	56595.0	0.00000	56592.0
DES13C1juw	0.196	1.00000	56582.0	0.00000	56588.0	0.00000	56585.0
DES13C3absw	0.069	1.00000	56668.0	0.00000	56675.0	0.00000	56672.0
DES13C2acmj	0.114	1.00000	56652.0	0.00000	56664.0	0.00000	56654.0
DES13C3adnw	0.181	0.20690	56692.0	0.32410	56692.0	0.46900	56693.0
DES13C2ahyt	0.375	1.00000	56685.0	0.00000	56684.0	0.00000	56683.0
DES14X1oes	0.289	1.00000	57002.0	0.00000	57019.0	0.00000	57005.0
DES14E2rpm	0.322	1.00000	57015.0	0.00000	57022.0	0.00000	57020.0
DES14E1rph	0.105	1.00000	57014.0	0.00000	57019.0	0.00000	57017.0
DES14S1rwf	0.075	1.00000	57017.0	0.00000	57022.0	0.00000	57020.0
DES14C3kzd	0.078	0.00000	56986.0	0.00000	56982.0	1.00000	56978.0
DES14C3vwl	0.061	0.05855	57053.0	0.74600	57057.0	0.19540	57060.0
DES15C2ir	0.060	1.00000	57257.0	0.00000	57260.0	0.00000	57252.0
DES15C2sj	0.071	1.00000	57265.0	0.00000	57275.0	0.00000	57229.0
DES15C2eaz	0.066	0.01955	57292.0	0.00000	57291.0	0.98050	57289.0
DES15E2dzb	0.260	1.00000	57285.0	0.00000	57290.0	0.00000	57289.0
DES15S2dye	0.250	1.00000	57278.0	0.00000	57285.0	0.00000	57283.0
DES15S1flj	0.171	1.00000	57284.0	0.00000	57287.0	0.00000	57288.0
DES15C3efn	0.078	1.00000	57293.0	0.00000	57302.0	0.00000	57294.0
DES15X3kqv	0.142	1.00000	57301.0	0.00000	57304.0	0.00000	57303.0
DES15X1ith	0.156	1.00000	57297.0	0.00000	57312.0	0.00000	57303.0
DES15E1kwg	0.105	1.00000	57314.0	0.00000	57319.0	0.00000	57317.0
DES15E2kvn	0.208	1.00000	57307.0	0.00000	57314.0	0.00000	57313.0

Table 6.2 continued

Transient name	z	PBAYES _{IA}	TMAX _{IA} (<i>MJD</i>)	PBAYES _{IBC}	TMAX _{IBC} (<i>MJD</i>)	PBAYES _{II}	TMAX _{II} (<i>MJD</i>)
DES15S2eq	0.068	0.00000	57341.0	0.00000	57340.0	1.00000	57333.0
DES15S2kqw	0.237	1.00000	57304.0	0.00000	57319.0	0.00000	57306.0
DES15X2mei	0.232	1.00000	57335.0	0.00000	57341.0	0.00000	57338.0
DES15S2max	0.267	1.00000	57336.0	0.00000	57342.0	0.00000	57342.0
DES15S2mau	0.134	1.00000	57336.0	0.00000	57341.0	0.00000	57340.0
DES15C3mpk	0.181	1.00000	57357.0	0.00000	57360.0	0.00000	57357.0
DES15S1mvv	0.250	1.00000	57362.0	0.00000	57370.0	0.00000	57364.0
DES15X3nad	0.100	0.99180	57383.0	0.00000	57383.0	0.00824	57384.0
DES15S2mpg	0.186	1.00000	57354.0	0.00000	57358.0	0.00000	57356.0
DES15S2ocv	0.215	1.00000	57390.0	0.00000	57402.0	0.00000	57394.0
DES15S2okl	0.160	1.00000	57397.0	0.00000	57403.0	0.00000	57400.0

Table 6.3: A comparison of the two classification scenarios for all 36 spectra for the cases of (i) using all SN templates and up to $t = 80$ days of all available epochs and (ii) using only epochs that are 5 days prior to and 5 days after $t_{est,true}$. Also shown are the SALT observation dates for each SN, the **SNMC** recovered epochs as well as their corresponding BIC values for each scenario.

SN candidate	SALT observation date	Estimated date of B -band max brightness	Estimated true epoch $t_{est,true}$ (days)	Recovered epoch without prior on t	Recovered epoch with prior on t	BIC value without prior on t	BIC value with prior on t
DES13C1feu	2013-10-08	2013-10-05	22	8.6 ± 0.2	24.0 ± 0.2	-3439	-3259
DES13X1cpt	2013-10-23	2013-09-16	56	7.79 ± 0.07	59.5 ± 0.3	-402	42
DES13X1kae	2013-10-29	2013-10-27	21	31.00 ± 0.05	26.00 ± 0.04	3650	7204
DES13C1juw	2013-10-29	2013-10-17	31	39.2 ± 0.5	29.6 ± 0.5	-281	-52
DES13C3absw	2014-01-25	2014-01-11	33	7.6 ± 0.1	29.1 ± 0.1	-2728	-1945
DES13C2acmj	2014-02-02	2013-12-26	38	89.9 ± 0.1	36.7 ± 0.2	706249	709181
DES13C3adnw	2014-02-06	2014-02-04	21	7.9 ± 0.4	18.2 ± 0.4	-1473	-1372
DES13C2ahyt	2014-02-07	2014-01-28	29	2.9 ± 0.9	28 ± 2	357	9240
DES14X1oes	2014-12-23	2014-12-11	31	19.3 ± 0.6	27.2 ± 0.4	357	377
DES14E2rpm	2014-12-25	2014-12-24	20	24.5 ± 0.4	24.4 ± 0.4	-419	-409
DES14E1rph	2014-12-30	2014-12-23	26	18.5 ± 0.1	22.0 ± 0.1	1267	1720
DES14S1rwf	2015-01-16	2014-12-26	40	4.99 ± 0.09	36.00 ± 0.09	2281	5129
DES14C3kzd	2015-01-18	2014-11-17	81	8.01 ± 0.05	84 ± 2	116288	258000
DES14C3vwl	2015-02-09	2015-02-04	24	10 ± 1	19 ± 1	-1756	-1728
DES15C2ir	2015-08-24	2015-08-23	20	13.86 ± 0.04	26.00 ± 0.04	41969	54589
DES15C2sj	2015-09-08	2015-09-01	21, 27, 44 ^a	2.0 ± 0.4	23.2 ± 0.4	-906	811
DES15C2eaz	2015-09-15	2015-09-24	1,2 ^b	2.1 ± 0.1	2.1 ± 0.1	-1454	-1391

Notes

^a - DSCT classification of the candidate is *uncertain* (Table 6.4). **SNMC** classifies the candidate as SN Ia without imposing a prior on t (Table 6.1). We thus list the derived $t_{est,true}$ values for all 3 SN sub-types

^b - DSCT classification: SN II, **SNMC** classification: SN IIn. Since $t_{B,max,est}$ occurred 9 days after observation date (see Table 6.2 for SN II), $t_{est,true}$ is $t = 2$ days for SN II, since both SN IIP and IIL peak at $t = 11$ days (Table 3.1). However, we are uncertain what epoch value $t_{est,true}$ corresponds to for the SN IIn templates since their peak brightness occurs at $t = 6$ days. From the SN IIn available epochs in Table 3.1, 9 days prior to $t = 6$ days would be $t = 1$ day since this is the lowest epoch value for these templates.

Table 6.3 continued

SN candidate	SALT observation date	Estimated date of B -band max brightness	Estimated true epoch $t_{est,true}$ (days)	Recovered epoch without prior on t	Recovered epoch with prior on t	BIC value without prior on t	BIC value with prior on t
DES15E2dzb	2015-09-16	2015-09-18,25	17, 8 ^c	5.0 ± 0.2	7.0 ± 0.2	-1673	-1596
DES15S2dye	2015-09-20	2015-09-13	26	2.1 ± 0.5	27.0 ± 0.5	223	577
DES15S1flj	2015-09-25	2015-09-18	26	2.0 ± 0.5	23.9 ± 0.4	-906	-773
DES15C3efn	2015-10-04	2015-09-28	25	9.33 ± 0.07	28.8 ± 0.1	-1122	-1122
DES15X3kqv	2015-10-04	2015-10-06	17	26.2 ± 0.2	22.0 ± 0.2	-1794	-1437
DES15X1ith	2015-10-09	2015-10-02	26	7.99 ± 0.05	23.2 ± 0.1	-207	178
DES15E1kwg	2015-10-11	2015-10-19	11	15.26 ± 0.07	15.26 ± 0.07	9072	9132
DES15E2kvn	2015-10-12	2015-10-12,19	19, 26 ^c	11.0 ± 0.1	15.0 ± 0.1	-3341	-2115
DES15S2eaq	2015-10-15	2015-11-07,14,15	42, 49, 50 ^d	19.1 ± 0.1	46.1 ± 0.1	462	1442
DES15S2kqw	2015-10-16	2015-10-09, 24	26,34 ^c	26.8 ± 0.4	26.8 ± 0.4	-1182	-1181
DES15X2mei	2015-11-13	2015-11-09	23	32.8 ± 0.2	27.5 ± 0.3	-1759	-1759
DES15S2max	2015-11-13	2015-11-10,16	16, 22 ^c	7.3 ± 0.3	24.7 ± 0.5	-1566	-1447
DES15S2mau	2015-11-13	2015-11-10,15	16, 21 ^c	8.07 ± 0.05	12.00 ± 0.05	1094	6101
DES15C3mpk	2015-12-05	2015-12-01	23	33.3 ± 0.2	24.0 ± 0.1	-2241	-1475
DES15S1mvv	2015-12-09	2015-12-06	22	31.3 ± 0.4	26.5 ± 0.5	-1051	-983
DES15X3nad	2015-12-09	2015-12-27,28	1, 2 ^e	39.0 ± 0.4	6 ± 3	66622	83955
DES15S2mpg	2015-12-03	2015-11-28	24	26.9 ± 0.1	26.8 ± 0.2	-2061	-2047
DES15S2ocv	2016-01-09	2016-01-03,15	25,13 ^c	27.8 ± 0.4	27.8 ± 0.4	-2266	-2266
DES15S2okl	2016-01-13	2016-01-10	22	31.4 ± 0.2	26.4 ± 0.2	-1260	-926

Notes

^c - DSCT classification: SN Ia; SNMC classification: SN Ibc high velocity. We thus adopt the two values for $t_{est,true}$ derived for the SN Ia and SN Ibc sub-types

^d - Same as ^a on the previous page

^e - DSCT classification: SN II but using an *Anglo-Australian Telescope (AAT)* spectrum of the candidate–SALT spectrum returned an uncertain classification), SNMC classification: SN 91T-like. The two $t_{est,true}$ values are thus adopted for the two sub-types

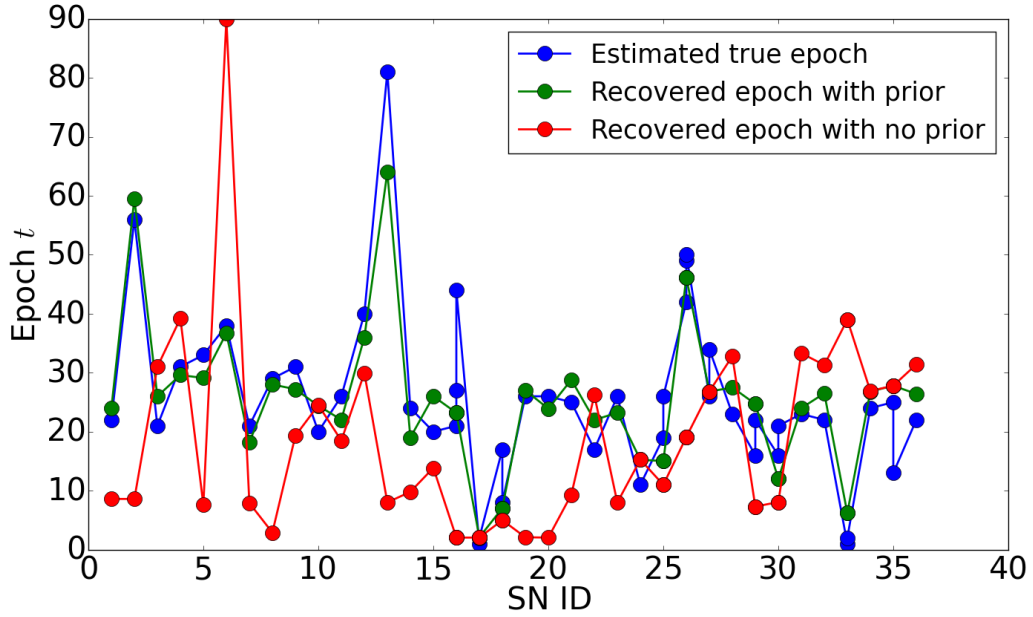


Figure 6.2: Comparison of the ‘true epoch’ derived from the light curves and dates of observations of the SN candidates to the two epochs returned by SNMC with and without applying a prior range on the t parameter during parameter estimation. The SN candidates are numbered from 1 to 36 as ‘SN ID’ on the horizontal axis, in the order that they are given in column 1 of Table 6.2, from top to bottom. The figure shows that the majority of the epochs are underestimated when no prior range is applied, as the red curve illustrates.

$$t_{est,true} \leq 27.$$

For an easier comparison of the date SALT took a spectrum of an SN candidate and its $t_{B,max,est}$, we include in column 2 of Table 6.3, the SALT observation dates for all candidates. We also include in the table the BIC values for the fits with and without applying ‘10-day top-hat prior ranges’ centred on $t_{est,true}$ and the recovered t parameter values for each scenario. Figure 6.2 shows a plot of the three epochs given in Table 6.2 to allow easier comparison.

We use the BIC values to demonstrate goodness of fit between the two classification scenarios. The DES SN spectroscopic classification team (DSCT) provided independent spectroscopic classification results of all SALT spectra of the 36 DES SN candidates, which are presented in Table 6.4. DSCT predominantly performed the classification using the *Superfit* classifier and for a minority of the candidates, using *SNID*. Our determination of $t_{est,true}$, given in column 4 of Table 6.3, is based on the following criteria:

- if the DSCT *typing* result of a spectrum is the same as that of SNMC for the same

spectrum, $t_{est,true}$ is determined using $t_{B,max,est}$ from Table 6.2 corresponding to the recovered *type* of the spectrum and SALT’s observation date of the spectrum;

- if the *typing* result described in the first bullet is different between SNMC and DSCT, then more than one $t_{B,max,est}$ is adopted in determining $t_{est,true}$, i.e. two $t_{est,true}$ values are adopted; and
- lastly, if DSCT’s *typing* is uncertain for a given candidate, then all 3 $t_{B,max,est}$ in Table 7.3 are used in the determination of $t_{est,true}$, yielding three values for that candidate.

Again using DES13C1feu as an example, its SNMC classification finds the best-fit spectrum (red in Figure 6.3) to be that of a ‘SN Ibc’ with the following best-fit parameters: $\alpha = 0.48 \pm 0.01$, $z = 0.0593 \pm 0.0001$, $t = 8.6 \pm 0.1$ days and $A_V = 0.46 \pm 0.04$ (Table 6.1). As stated above, the numeric character(s) at the end of the label for the best-fit spectra in Figure 6.3 and similar figures represent the recovered value of t . While the SN type and recovered redshifts are the same as those found with SNID for this candidate (see ATel 5463, Smith et al. 2013), the recovered epoch is lower than what we expect, i.e. we expect the epoch to be in the range $17 \text{ days} \leq t_{est,true} \leq 27 \text{ days}$, as demonstrated above.

We therefore ignore the recovered epoch t of this classification, impose a *10-day top-hat prior range* on the t parameter centred on $t_{est,true}$ (as discussed above) and rerun the classification. Doing so, we find the best-fit spectrum (magenta in Figure 6.3) to have the same SN typing as in the first classification but with the following best-fit parameters: $\alpha = 0.361 \pm 0.008$, $z = 0.0586 \pm 0.0001$, $t = 24.0 \pm 0.2$ days and $A_V = 0.003 \pm 0.003$. The recovered epoch in the second classification is more reasonable than in the first classification, even though its determined uncertainty interval does not contain the expected value of t (i.e. $t_{est,true} = 22$ days). Table 6.5 shows the results of re-running the classifications with the application of the above-defined *10-day top-hat prior range* on t centred on the determined $t_{est,true}$ for each SN candidate (column 4 of Table 6.3). This resulted in the following typing: (i) 20 SNe Ia and (ii) 16 core-collapse SNe.

Table 6.4: Results of spectroscopic classification of all SALT DES SN spectra by DSCT using **Superfit** as the main classifier.

SN	Classification results			SN	Classification results		
Candidate	Typing	z_{sn}	z_{host}	Candidate	Typing	z_{sn}	z_{host}
DES13C1feu	SNIc		0.059	DES15S2dye	SNIa	0.25	
DES13X1cpt	galaxy		0.1498	DES15S1fj	uncertain		
DES13X1kae	SNIa		0.149	DES15X3kqv	SNIa		0.1421
DES13C1juw	SNIa	0.199		DES15C3efn	SNIa		0.077
DES13C3absw	SNIc	0.07	0.0699	DES15X1lith	galaxy		0.155
DES13C2acmj	SNIa	0.115		DES15E1kwg	SNIa		0.1049
DES13C3adnw	SNIbc		0.18	DES15E2kvn	SNIa		0.208
DES13C2ahyt	uncertain			DES15S2eaq	SNII?		0.068
DES14X1oes	SNIa	0.297		DES15S2kqw	SNIa		0.237
DES14E2rpm	SNIa?			DES15X2mei	SNIa	0.232	
DES14E1rph	SNIa	0.111		DES15S2mau	SNIa		0.134
DES14S1rwf	SNIa ^a	0.07 ^a		DES15S2max	SNIa	0.27	
DES14C3kzd	uncertain			DES15S2mpg	SNIa		0.186
DES14C3vwl	uncertain			DES15C3mpk	SNIa	0.18	
DES15C2ir	SNIa		0.058	DES15S1mvv	SNIa	0.25	
DES15C2sj	SNIa?	0.07		DES15X3nad	SNII ^b	0.1 ^b	
DES15C2eaz	SNII		0.062	DES15S2ocv	SNIa	0.215	
DES15E2dzb	SNIa	0.26		DES15S2okl	SNIa	0.17	

Notes

^a - *typing* and z classification obtained from the Okayama telescope spectrum of the candidate. The SALT spectrum returned an uncertain classification.

^b - *typing* and z classification obtained from the AAT spectrum of the candidate. The SALT spectrum returned an uncertain classification.

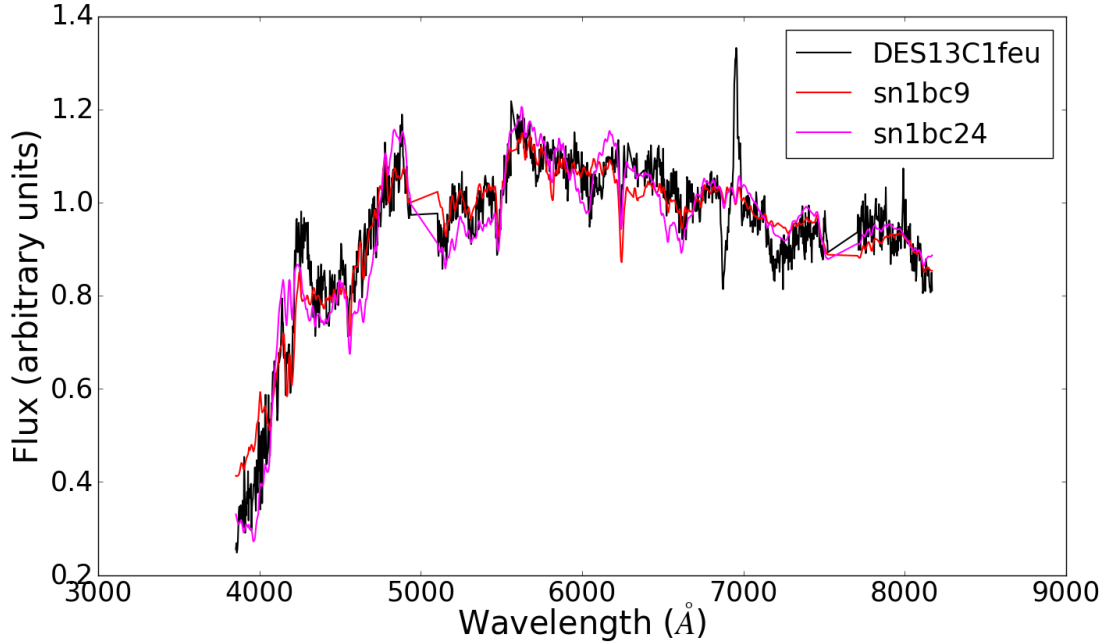


Figure 6.3: *Red:* Best-fit spectrum (red) to the spectrum of DES13C1feu (black) for the case of fitting all 8 different SN types with epochs up to $t = 80$ days. The best-fit spectrum is that of a SN Ibc with the corresponding MCMC best-fit parameters: $\alpha = 0.48 \pm 0.01$, $z = 0.0593 \pm 0.0001$, $t = 8.6 \pm 0.2$ days and $A_V = 0.46 \pm 0.06$. *Magenta:* Same as *Red* except a 10-day top-hat prior range (centred on $t_{est,true}$) is applied on the t parameter, where only the epochs between 17 and 27 days (inclusive) are considered during the fitting for all 8 different SN types. The following are the MCMC best-fit parameters: $\alpha = 0.361 \pm 0.008$, $z = 0.0586 \pm 0.0001$, $t = 24.0 \pm 0.2$ days and $A_V = 0.003 \pm 0.003$.

From the above, we conclude that while SNMC performs the SN typing and redshift recovery reasonably well, the epoch t is not well estimated, just as is the case with SNID and Superfit. This is not inherent to SNMC because we showed in Chapter 4 that the epoch recovery is unbiased using simulated data. Hence, if statistically significant, the bias must be due to some unknown systematic—perhaps the range of templates we used is insufficient. However, because SNMC is a Bayesian algorithm, we are able to use prior information of the epoch from the light-curve, which the other classifiers cannot do in a statistically principled way, and this improves SNMC’s recovery of all parameters of interest, and particularly the epoch parameter as seen above.

In the next section, we present results of EW measurements of two SN Ia spectral features that we conducted using our typed SN Ia sample

Table 6.5: SALT spectra of 36 DES SN candidates observed between February 2013 and February 2016 and classified with SNMC after applying the *10-day top-hat prior range* on t discussed in the text. *SN type* and *Galaxy type* represent the recovered types of the SN and host galaxy from the spectrum, respectively; α , z , t and A_V represent the associated MCMC best-fit parameters.

SN candidate	Date of observation	Model selection		Parameter estimation			
		<i>SN type</i>	<i>Galaxy type</i>	α	z	t	A_V
DES13C1feu	2013-10-08	SN Ibc	Sb	0.361 ± 0.008	0.0586 ± 0.0001	24.0 ± 0.2	0.003 ± 0.003
DES13X1cpt	2013-10-23	SN Ibc-hv	E0	0.47 ± 0.01	0.0326 ± 0.0003	59.5 ± 0.3	0.84 ± 0.06
DES13X1kae	2013-10-29	SN 91T-like	SB1	0.984 ± 0.004	0.1386 ± 0.0003	26.00 ± 0.04	0.61 ± 0.02
DES13C1juw	2013-10-29	SN 91T-like	SB1	0.98 ± 0.03	0.358 ± 0.004	29.6 ± 0.5	0.01 ± 0.01
DES13C3absw	2014-01-25	SN 91T-like	SY2	0.79 ± 0.01	0.0686 ± 0.0009	29.1 ± 0.1	2.47 ± 0.03
DES13C2acmj	2014-02-02	SN IIn	SB1	0.418 ± 0.004	0.1097 ± 0.0001	36.7 ± 0.2	2.50 ± 0.03
DES13C3adnw	2014-02-06	SN 91bg-like	E0	0.48 ± 0.05	0.0003 ± 0.0002	18.2 ± 0.4	0.03 ± 0.03
DES13C2ahyt	2014-02-07	SN IIL	Sb	0.98 ± 0.04	0.378 ± 0.006	28 ± 2	0.2 ± 0.2
DES14X1oes	2014-12-23	SN Ibc-hv	E0	0.84 ± 0.04	0.001 ± 0.005	27.2 ± 0.4	1.8 ± 0.1
DES14E2rpm	2014-12-25	SN Ibc-hv	E0	0.85 ± 0.03	0.004 ± 0.004	24.4 ± 0.4	0.2 ± 0.2
DES14E1rph	2014-12-30	SN 91T-like	SB1	0.89 ± 0.09	0.2553 ± 0.0009	22.0 ± 0.1	0.001 ± 0.001
DES14S1rwf	2015-01-16	SN 91T-like	E0	0.323 ± 0.006	0.0742 ± 0.0001	36.00 ± 0.09	1.73 ± 0.04
DES14C3kzd	2015-01-18	SN IIn	SB1	1.0000 ± 0.0006	0.0037 ± 0.0002	84 ± 2	0.616 ± 0.004
DES14C3vwl	2015-02-09	SN Ibc-hv	E0	0.58 ± 0.03	0.060 ± 0.004	19 ± 1	0.2 ± 0.2
DES15C2ir	2015-08-24	SN Ia	Sb	0.889 ± 0.004	0.0584 ± 0.0002	26.00 ± 0.04	0.28 ± 0.02
DES15C2sj	2015-09-08	SN 91bg-like	E0	0.58 ± 0.04	0.075 ± 0.004	23.2 ± 0.4	1.2 ± 0.3
DES15C2eaz	2015-09-15	SN IIn	Sb	0.98 ± 0.01	0.533 ± 0.001	2.1 ± 0.1	0.97 ± 0.05
DES15E2dzb	2015-09-16	SN Ibc-hv	Sb	0.73 ± 0.02	0.089 ± 0.003	7.0 ± 0.2	1.86 ± 0.06
DES15S2dye	2015-09-20	SN Ia	SB4	1.00 ± 0.03	0.236 ± 0.004	27.0 ± 0.5	0.8 ± 0.3
DES15S1fj	2015-09-25	SN 91T-like	Sb	0.91 ± 0.04	0.005 ± 0.005	23.9 ± 0.4	0.6 ± 0.3
DES15C3efn	2015-10-04	SN Ia	E0	0.95 ± 0.01	0.0773 ± 0.0006	28.8 ± 0.1	0.67 ± 0.05
DES15X3kqv	2015-10-04	SN Ia	Sb	0.64 ± 0.02	0.143 ± 0.002	22.0 ± 0.2	0.5 ± 0.1
DES15X1ith	2015-10-09	SN Ibc-hv	E0	0.508 ± 0.008	0.2192 ± 0.0001	23.2 ± 0.1	0.001 ± 0.001
DES15E1kwg	2015-10-11	SN Ia	SB1	0.742 ± 0.007	0.1075 ± 0.0003	15.26 ± 0.07	0.39 ± 0.03

Table 6.5 continued

SN candidate	Date of observation	Phase 1 classification		Phase 2 classification			
		<i>SN type</i>	<i>Galaxy type</i>	α	z	t	A_V
DES15E2kvn	2015-10-12	SN Ibc	E0	0.268 ± 0.007	0.2071 ± 0.0001	15.0 ± 0.1	0.28 ± 0.06
DES15S2eaq	2015-10-15	SN IIn	SB4	0.71 ± 0.01	0.0675 ± 0.0006	46.1 ± 0.1	0.87 ± 0.03
DES15S2kqw	2015-10-16	SN Ibc-hv	E0	0.69 ± 0.03	0.035 ± 0.004	26.8 ± 0.4	0.03 ± 0.03
DES15X2mei	2015-11-13	SN Ia	E0	0.74 ± 0.03	0.2319 ± 0.0004	27.5 ± 0.3	0.3 ± 0.1
DES15S2max	2015-11-13	SN Ibc-hv	E0	0.51 ± 0.02	0.097 ± 0.001	24.7 ± 0.5	1.1 ± 0.2
DES15S2mau	2015-11-13	SN 91bg-like	SB4	0.604 ± 0.006	0.1338 ± 0.0003	12.00 ± 0.05	0.55 ± 0.02
DES15C3mpk	2015-12-05	SN 91T-like	SY2	1.00 ± 0.01	0.173 ± 0.001	24.0 ± 0.1	1.53 ± 0.03
DES15S1mvv	2015-12-09	SN 91T-like	SB4	0.85 ± 0.04	0.253 ± 0.004	26.5 ± 0.5	0.8 ± 0.3
DES15X3nad	2015-12-09	SN Ibc	SB1	1.00 ± 0.03	0.098 ± 0.004	6 ± 3	0.9 ± 0.8
DES15S2mpg	2015-12-03	SN Ia	Sb	0.81 ± 0.02	0.1798 ± 0.003	26.8 ± 0.2	0.002 ± 0.002
DES15S2ocv	2016-01-09	SN Ia	E0	0.88 ± 0.03	0.211 ± 0.004	27.8 ± 0.4	0.01 ± 0.01
DES15S2okl	2016-01-13	SN Ia	SB4	0.97 ± 0.02	0.167 ± 0.002	26.4 ± 0.2	0.001 ± 0.001

6.3 Measurements and Science of Equivalent Widths

As discussed in Chapter 1, one way of probing SN Ia evolution as a function of redshift is through the measurements of EW of SN Ia spectral features. The method we employ in conducting such measurements is that described by Kasai et al. (2016) (originally adapted from Folatelli 2004). We provide below a summary of the main steps of the method:

- Fit a straight line (referred to as a ‘pseudo-continuum’) between two local maxima of a spectral absorption feature to be measured, as Figure 6.4 shows.
- Ensure that the locations of the local maxima (or feature boundaries) for the various absorption features shown in Figure 6.4, are within their defined wavelength regions given in Table 6.6 and do not exceed those limits.
- Select the feature boundaries in a way that maximises the wavelength range covered by a given feature without crossing the boundaries of adjacent features.
- Measure the EW of the absorption feature of interest using the following equation:

$$EW = \sum_{i=1}^N \left(1 - \frac{f_{\lambda}(\lambda_i)}{f_c(\lambda_i)} \right) \Delta\lambda_i, \quad (6.1)$$

where λ_i are the centres of the wavelength bins of sizes $\Delta\lambda_i$, $f_{\lambda}(\lambda_i)$ is the flux in bin i and $f_c(\lambda_i)$ the flux determined from the pseudo-continuum at λ_i .

- Determine the uncertainty in the measured EW using the following equation:

$$\sigma_{EW}^2 = \sum_{i=1}^N \left(\left\{ \frac{\sigma_f(\lambda_i)}{f_c(\lambda_i)} \right\}^2 + \left\{ \frac{f_{\lambda}(\lambda_i)}{f_c(\lambda_i)^2} \right\}^2 \cdot \sigma_{ci}^2 \right) \Delta\lambda_i^2, \quad (6.2)$$

where σ_f and σ_{ci} (derived via error propagation of the estimated errors in the slope and intercept of the fitted pseudo-continuum) are the uncertainties in the measured fluxes f_{λ} and f_c , respectively.

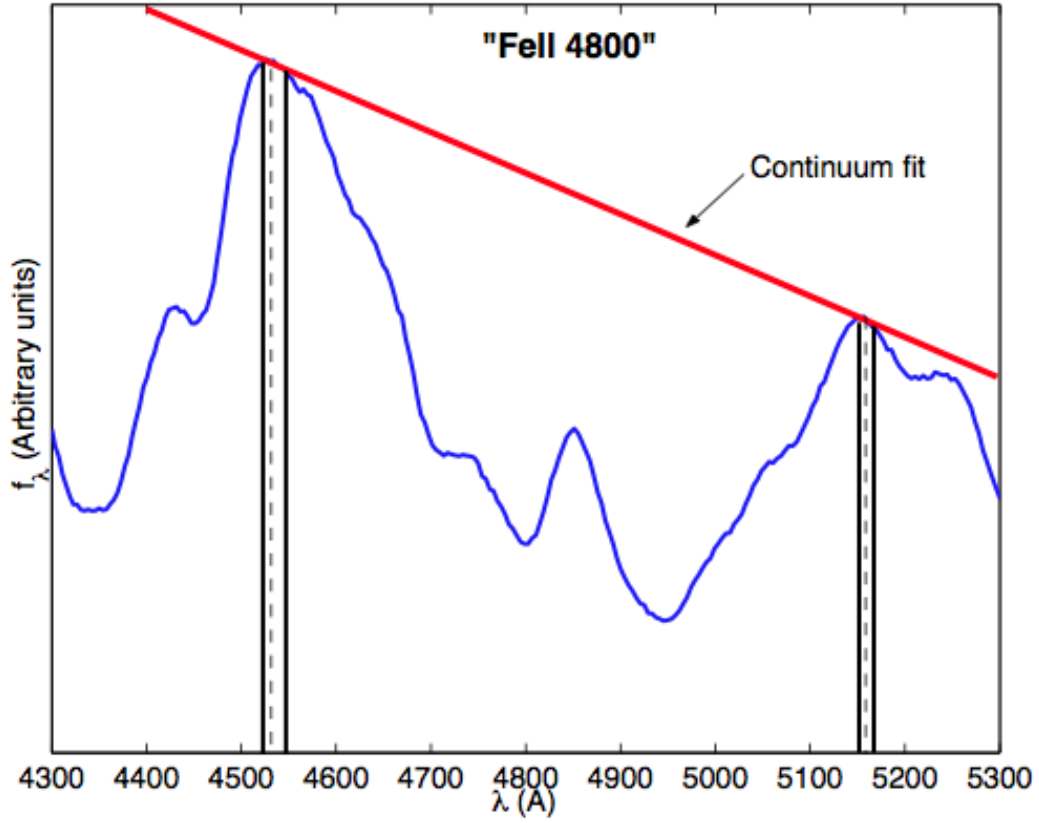


Figure 6.4: The Fe II 4800Å absorption feature of a SN Ia spectrum (blue), showing the fitted pseudo-continuum (red) passing through two points located within the regions bounded by the two solid vertical lines on each side of the feature. Shown with the dashed lines inside the two vertical lines on each side of the feature are the feature limits for this absorption feature, discussed in the second bullet above, that are not to be exceeded when fitting a pseudo-continuum. Figure from Folatelli (2004).

Table 6.6: SN Ia absorption features with their blue-ward and red-ward wavelength limits as defined by Folatelli (2004). The table is reproduced from Garavini et al. (2007).

Feature Number	Mnemonic Label	Blue-ward Limit (Å)	Red-ward Limit (Å)
1	“Ca II H&K”	3500–3800	3900–4100
2	“Si II 4000”	3900–4000	4000–4150
3	“Mg II 4300”	3900–4150	4450–4700
4	“Fe II 4800”	4500–4700	5050–5550
5	“S II W”	5150–5300	5500–5700
6	“Si II 5800”	5550–5700	5800–6000
7	“Si II 6150”	5800–6000	6200–6600
8	“Ca II IR”	7500–8000	8200–8900

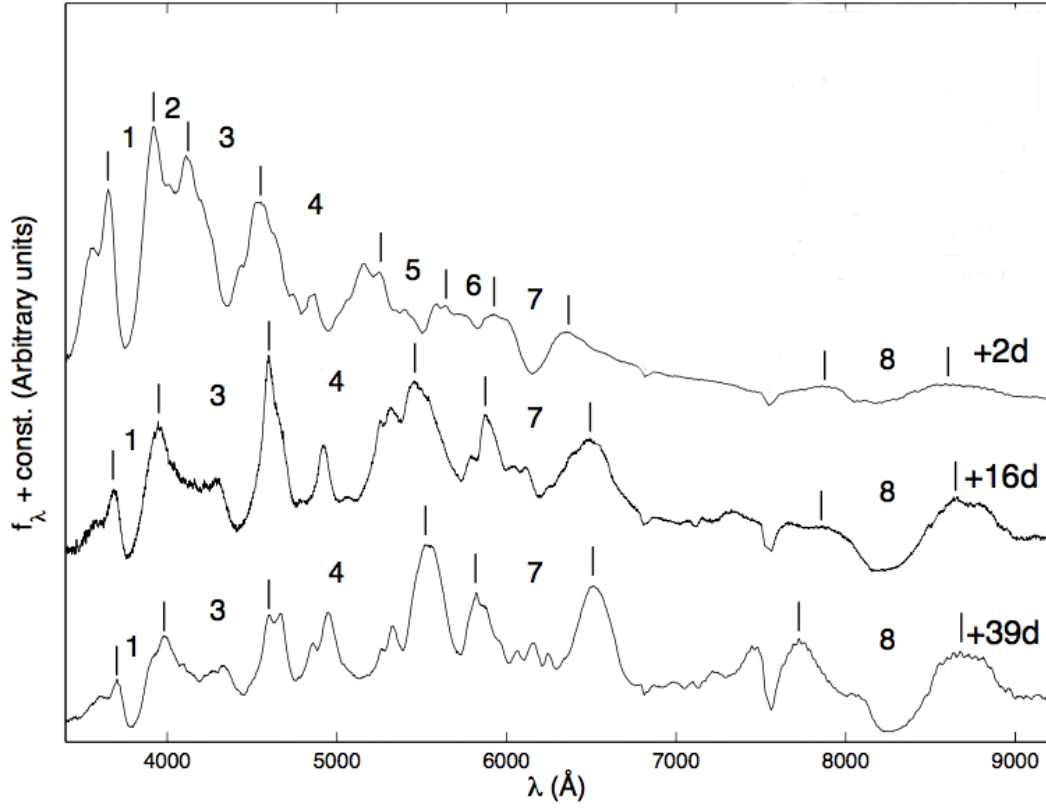


Figure 6.5: Absorption features of a SN Ia spectrum shown at phases $\tau = 2, 16$ and 39 days after maximum brightness. As shown in Table 6.6, the numbers 1 to 8 represent the following features: 1— “Ca II H&K”; 2— “Si II 4000”; 3— “Mg II 4300”; 4— “Fe II 4800”; 5— “S II W”; 6— “Si II 5800”; 7— “Si II 6150”; 8— “Ca II IR”. Figure adapted from Folatelli (2004).

6.3.1 Measurements of Ca II H&K and Si II 4000 features

Of the 8 SN Ia spectral features shown in Figure 6.5, we only study the first two in this work: Ca II H&K and Si II 4000. An example of the two features is shown in Figure 6.6 as the green and magenta filled-in regions in one of our 20 spectra classified as SN Ia.

In selecting a SN Ia sample for EW measurements, the following points are taken into consideration:

- Spectra classified as uncertain by the DES Spectroscopic Classification Team (DSCT, using both **Superfit** and **SNID**) but as SNe Ia by **SNMC** are included in the sample.
- Spectra classified as SNe Ia by DSCT but as core-collapse subtypes by **SNMC** are included in the sample. Due to their diverse and versatile SN templates, if **Superfit** and **SNID** are both in agreement about the typing of a given SN candidate, we trust

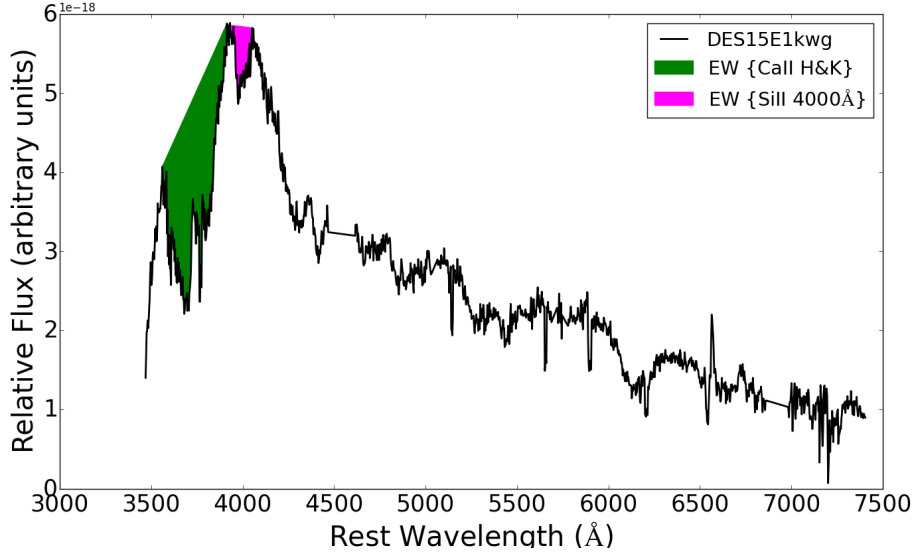


Figure 6.6: A SALT spectrum of the SN candidate “DES15E1kwg” highlighting in green and magenta filled-in regions the SN Ia Ca II H&K and Si II 4000 absorption features, respectively. Figure from Kasai et al. (2016).

the typing to be correct. We assume the inadequacy in numbers of the Nugent SN templates to be responsible for the difference in the *typing* obtained by SNMC and DSCT *typing* for the same SN candidate. This assumption will be verified in work beyond the scope of this thesis, where we add a functionality to SNMC to make use of the SNID and Superfit templates. However, not all such spectra show the Ca II H & K and Si II 4000 features distinctly, making their EW measurements difficult. Examples of such spectra are *DES15E2kvn* and *DES15S2max*, which we exclude from the EW measurement sample. The rest of the spectra falling in this category and included in the sample are those of *DES13C2acmj*, *DES14X1oes*, *DES15E2dzb*, and *DES15S2kqw*.

- Spectra classified as SNe Ia after applying the *10-day top-hat prior range* on the t parameter, which initially were not classified as such without applying the *10-day top-hat prior range* on the t parameter, and also not classified as SNe Ia by DSCT, are not included in the EW measurement sample.
- Where a host galaxy redshift z_{host} is available for a given SN Ia candidate, we use it in the EW measurement of that candidate, given that z_{host} is more accurately determined (from the host’s prominent emission lines) than z_{sn} .

- Where a discrepancy of more than 2% between the z_{sn} recovered by SNMC and that recovered by DSCT is encountered, the latter's recovered z_{sn} is adopted in the EW measurement of the SN Ia candidate for the same reasons provided in the second bullet. Examples in this category are the spectra for *DES13C1juw*, *DES14X1oes*, *DES14E1rph*, *DES15E2dzb* and *DES15S2dye*.

We provide in Table 6.7, the EW measurement results for our classified SN Ia sample meeting the above criteria.

Note that the epoch values we provide in Table 6.7 are the $t_{est,true}$ discussed in Section 6.2 and provided in Table 6.3, since, as previously discussed, those are more accurately estimated using light-curve data than the estimations of spectral classifiers. For comparison, we include in column 4 of Table 6.7, the epochs t recovered by SNMC (which are the same as those provided in column 6 of Table 6.3).

6.3.2 Comparison of results to the literature

In Figure 6.7, we compare our results of the Ca II H&K and Si II 4000 EW measurements to those of Chotard et al. (2011) (hereafter C11) performed on a low-redshift sample ($z < 0.1$) of 76 SNe Ia, where we plot the correlation of the two features as shown in the figure.

The C11 76 SNe Ia spectral sample falls within 2.5 days of maximum brightness in the B -band. However, as column 3 of Table 6.7 shows, only a small fraction of our EW measurement SN Ia sample has epochs t falling within 2.5 days of maximum brightness (i.e. 2.5 days pre or post $t = 19$ days after SN explosion for Nugent SN Ia templates).

To increase our sample, we consider all SNe Ia with epochs falling within 5 days of maximum brightness, which gives us a sample of 8 candidates, whose measured EWs are shown with red pentagon symbols in Figure 6.7. The C11 measurements are shown with grey circles in the same figure. While our SN Ia sample may be hampered by small number statistics, the overall comparison seems to imply no redshift evolution in SN Ia spectra in terms of the measured EW values for the 8 candidates in the redshift range $0.1 < z < 0.3$.

6.4 Conclusion

The initial SNMC classification and parameter estimation runs resulted in low recovered values of the epoch parameter t for many SN candidates compared to the more accurate t values obtained from the light curves of each SN candidate. It is not very clear as to

Table 6.7: EW measurements of 15 SALT spectra of DES SNe Ia taken between October 2013 and February 2016.

SN candidate	Observation date	$t_{est,true}^a$	SNMC recovered t^a	z	EW _{Ca} (Å)	EW _{Si} (Å)
DES13X1kae	2013-10-29	21	26.00 ± 0.04	0.1386 ± 0.0003	101.5 ± 3.8	10.2 ± 4.2
DES13C1juw	2013-10-29	31	29.6 ± 0.5	0.199 ± 0.005	50.7 ± 3.1	19.5 ± 8.5
DES13C2acmj	2014-02-02	38	36.7 ± 0.2	0.115 ± 0.006	97.3 ± 2.5	71.5 ± 4.3
DES14X1oes	2014-12-23	31	27.2 ± 0.4	0.297 ± 0.010	129.2 ± 4.5	27.7 ± 4.7
DES14E1rph	2014-12-30	26	22.0 ± 0.1	0.111 ± 0.006	146.8 ± 6.1	31.5 ± 7.9
DES15S1rwf	2015-01-16	40	36.00 ± 0.09	0.0742 ± 0.0001	49.6 ± 5.8	17.9 ± 4.4
DES15C2ir	2015-08-24	20	26.00 ± 0.04	0.0584 ± 0.0002	114.7 ± 8.4	16.9 ± 2.5
DES15C2sj	2015-09-08	21	23.2 ± 0.4	0.075 ± 0.004	134.6 ± 4.0	18.8 ± 5.7
DES15E2dzb	2015-09-16	11	7.0 ± 0.2	0.262 ± 0.006	117.7 ± 1.0	26.5 ± 27.2
DES15S2dye	2015-09-20	26	27.0 ± 0.5	0.0784 ± 0.0001	44.2 ± 2.5	20.1 ± 10.2
DES15C3efn	2015-10-04	25	28.8 ± 0.1	0.227 ± 0.001	85.0 ± 6.6	46.6 ± 3.5
DES15X3kqv	2015-10-04	17	22.0 ± 0.2	0.143 ± 0.002	121.1 ± 2.8	14.5 ± 3.1
DES15E1kwg	2015-10-11	11	15.26 ± 0.07	0.1075 ± 0.0003	119.0 ± 3.1	11.5 ± 1.8
DES15S2kqw	2015-10-16	26	26.8 ± 0.4	0.237 ± 0.007	107.3 ± 3.3	33.0 ± 19.1
DES15X2mei	2015-11-13	23	27.5 ± 0.3	0.2357 ± 0.0004	89.1 ± 3.5	33.8 ± 20.5
DES15S2mau	2015-11-13	16	12.00 ± 0.05	0.1407 ± 0.0001	90.2 ± 5.1	14.4 ± 2.1
DES15C3mpk	2015-12-05	23	24.0 ± 0.1	0.173 ± 0.001	84.3 ± 2.3	25.1 ± 2.2
DES15S1mvv	2015-12-09	22	26.5 ± 0.5	0.253 ± 0.004	70.1 ± 2.4	29.7 ± 12.8
DES15S2mpg	2015-12-03	24	26.8 ± 0.2	0.1798 ± 0.0003	119.3 ± 2.9	16.8 ± 2.0
DES15S2ocv	2016-01-09	25	27.8 ± 0.4	0.211 ± 0.004	137.7 ± 2.3	22.3 ± 31.1
DES15S2okl	2016-01-13	22	26.4 ± 0.2	0.1765 ± 0.0002	67.7 ± 2.9	11.9 ± 3.0

Notes

^a - Relative to the date of SN explosion

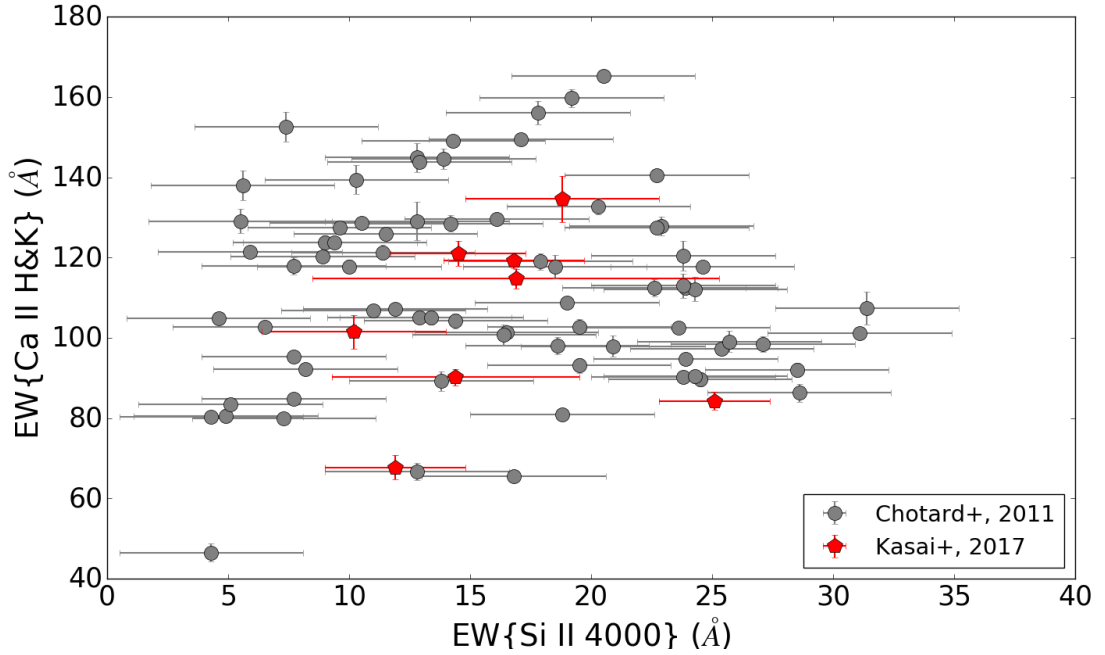


Figure 6.7: Correlation of the Chotard et al. (2011) EW measurements of the Ca II H&K and Si II 4000 features (grey) versus our measurements (red) for 8 candidates of our SN Ia sample.

why the model selection phase preferred such low epoch SN templates. The great advantage of the Bayesian approach is that we can seamlessly include the light curve information as a strong prior on the t parameter. We used a top-hat prior centered on the light-curve best fit with a 10-day width. This was particularly powerful since all 36 DES SN candidates in this thesis have well-sampled DES light curves and hence accurate peak estimates.

Rerunning the classifications with a strong prior on the t parameter resulted in more reasonable epoch recoveries, even though the resultant BIC values of the chosen models this time was higher than in the first runs. This is typical when the best fit does not coincide with the peak of the prior. Nevertheless we checked that the resulting parameters still give good spectral fits to the SALT data. However, the recovery of the correct t parameter via spectral classification in general is not trivial and it is for this reason that our DES spectroscopic classification team (DSCT) does not include their recovered t values in their classification results in Table 6.4. The SN typing and redshift recovery are key outputs of a spectral classification and parameter estimation exercise, the reason we see the DSCT results in Table 6.4 consisting of only these two outputs. DSCT used a combination of `Superfit` and `SNID` to classify the 36 SALT DES SN spectra.

Of the 36 SALT spectra of DES SN candidates, **DSCT** typed four of them as ‘uncertain’, two as galaxies, two as ‘probable SNe Ia’ and one as ‘probable SN II’. Omitting only the uncertain and galaxy classifications, this leaves 30 **DSCT** classified SALT spectra of DES SN candidates that we compare the **SNMC** classification and parameter estimation results to. Out of the 30 **DSCT** classified spectra, we find 19 to have the same typing as that obtained by **DSCT** and 22 to have redshifts that are consistent with the **DSCT** recovered redshifts.

We are uncertain about the sources of the inconsistencies seen in the typing and redshift recovery in the 11 and 8 remaining SN candidates, respectively, between the **SNMC** and **DSCT** results. The sources of the experienced inconsistencies could range from the quality of the SN and galaxy templates we use, the quality of our SALT spectra, the accuracy of our data reduction or it could be caused by some other effects that are currently unknown to us. Identifying the exact sources of the observed discrepancy forms a strong area of future work, to better understand the potential complexities of the algorithm’s performance in different settings.

In our EW measurements of the Ca II H&K and Si II 4000 SN Ia spectral features, because **SNMC** is still in its early stages, we took a decision to include in the EW SN Ia sample candidates that **SNMC** does not classify as SNe Ia but are classified as such by **DSCT**. We find our measured EW values of the two spectral features to consistent with the results obtained by Chotard et al. (2011), for a similar study conducted in the local Universe, i.e. at $z < 0.1$.

One caveat we experience is that while our initial intention of EW measurements was to obtain a sample of SNe Ia that has the same characteristics as that of Chotard et al. (2011) to enable an appropriate comparison, i.e. all our SNe Ia spectra for such measurements ought to be within 2.5 days of peak brightness, this was not the case as we only have a handful of such spectra in our EW SN Ia sample. Obtaining such candidates from DES was not always practical and when it was, the follow-up observing conditions were not met at the SALT observatory, or some other factors would prevent a speedy and timely follow-up of the candidate before going out of such an epoch observing window. As result, we only have fewer of such candidates that we managed to follow-up timely.

Other than the above, **SNMC** has proven to be competent in classifying and estimating the parameters of interest of the 36 SALT DES SN spectra reasonably well. As a fundamentally Bayesian algorithm, **SNMC** has a natural, rigorous way to incorporate prior information into the parameter estimation and typing. Our above-mentioned rival spectral classifiers do not have such an advantage.

In the next chapter, we summarise the thesis, providing conclusions and highlighting areas of future work.

Chapter 7

Conclusions and Future Work

7.1 Introduction

In this chapter, we bring to a close all aspects of the work done in this thesis. We summarise our findings, contrasting between **SNMC**'s classification results and the results of other classifiers. We begin by reviewing the goals for developing **SNMC**'s, move on with a further discussion of our findings and then provided some conclusions at the end of the chapter.

7.2 Goals of **SNMC**'s development

The goals of developing **SNMC** were:

- To develop a formalism to undertake SN classification and parameter estimation in a rigorous way using Bayesian methods. This is critical for doing accurate science with low SNR spectra. Using **PyMC** as a base we undertake classification by minimising the Bayesian Information Criterion (BIC) while parameter estimation is achieved via MCMC.
- To be able to seamlessly incorporate additional information such as multiple spectra or light curve information into the spectral analysis. This is particularly important in the era of LSST where light curve information will be very high quality. This extra data can be included trivially in **SNMC** either by incorporating the extra data into the likelihood function or as priors on the parameters. Neither **SNID** nor **Superfit** can achieve this in a statistically rigorous way. In particular, the likelihood for light curve information can be computed since for each SN template we can compute the flux in different bands. While we only include light curve

information in this thesis through a prior on the epoch, t , the approach to include all the light curve information is straightforward.

- To handle significant host contamination of the spectrum, something which SNID, for example, cannot do. We do this by including five general galaxy templates alongside the eight SN classes and fitting for α , the fraction of SN light in the spectrum.
- To handle dust contamination, quantified by the A_V parameter. In SNMC A_V is marginalised over in the MCMC analysis as a nuisance parameter.

In addition, we were interested in exploring the issues around using all the available spectral information rather than first subtracting the continuum. SNID, for example, subtracts the continuum which throws away useful information. However, this also makes SNID more robust to wavelength-dependent effects that have not been modelled correctly. Within the Bayesian approach such effects can be treated in a straight-forward way by introducing a nuisance polynomial that multiplies the spectrum and whose parameters are marginalised over in the MCMC. This will help deal with any incorrect calibrations of spectra. Implementing this marginalisation, as well as including more SN templates into our library, is left for future work and may help significantly in dealing with some of the cases for which SNMC struggled.

7.3 Discussion

One of our interesting SNMC's classification findings is the recovery of the epoch parameter t . As discussed in Chapter 6, despite SNMC correct SN *typing* and redshift recovery for many of our 36 SN sample, the recovery of the epoch parameter was somewhat inaccurate. The recovered epochs for the majority of the candidates were lower than what we expected for the case of classifying the spectra using all 8 different Nugent SN templates and all 5 galaxy templates discussed in Chapter 3. As discussed in the previous chapter, this is a challenge experienced by existing SN spectroscopic classifiers as well. In an attempt to have SNMC recover the correct value of t , we place a *10-day prior-range* on the t parameter, centred on the estimated true value of t , $t_{est,true}$. $t_{est,true}$ is obtained from the *PSNID* predicted time of maximum brightness $t_{B,max,est}$ and the SALT observation date for a given spectrum.

The DES Spectroscopic Classification Team (DSCT) found an *uncertain* classification of the SALT spectrum for *DES14S1rwf*. SNMC on the other hand classified the spectrum

to be that of a SN Ia at $z = 0.0742 \pm 0.0001$, the same classification result obtained by DSCT using *DES14S1ruf*'s spectrum taken by the *Okayama* telescope (Table 6.4). This is another demonstration of SNMC's ability to correctly classify some SALT spectra that neither **Superfit** nor **SNID** classifiers are able to classify conclusively. Additionally, DSCT also finds an *uncertain* classification of *DES13C2ahyt*'s SALT spectrum with no redshift recovery, whereas SNMC's redshift recovery ($z = 0.378 \pm 0.006$) is consistent with that derived from the candidate's light-curve data ($z = 0.375$) by *PSNID*, albeit SNMC's *typing* result is *SN IIL* whereas the *PSNID typing* is SN Ia, as deduced from the candidate's derived *PBAYES_{IA}* of 1 (Tables 6.2 and 6.4).

Equivalent width (EW) measurements of the Ca II H&K and Si II 4000 spectral features using our EW SN Ia sample (Section 6.3) show evidence of evolution in such features as a function of redshift. At the end of the of the DES SN Program, we expect to have double the size of our current EW SN Ia sample, which will allow us to address this observation with more statistical significance.

7.4 Conclusions

We have developed a SN spectral classification algorithm **SuperNovaMC** (SNMC) that utilises Bayesian techniques to classify SN spectra using the full shape of a spectrum. While there are popular SN spectral classification algorithms already in existence such as **Superfit** and **SNID**, they are grid-search algorithms that return only the maximum likelihood values of their fitted parameters and not full posterior distributions of the parameters. For the first time, we are now able to obtain—through Bayesian inference and MCMC fitting—full posterior distributions with SNMC of the fitted parameters in SN spectral classification, enabling us to put error bars on all our fitted parameters.

SNMC is built on a python MCMC engine called **PyMC**¹—a well-tested and robust MCMC algorithm for solving problems that involves the use of Bayesian Inference techniques. As discussed and demonstrated in the various chapters and sections, especially Section 4.5 and 6, SNMC has shown advantages and disadvantages over **Superfit** and **SNID** (as used by the DES Spectroscopic Classification Team) in classifying both literature spectra and the SALT spectra used in this thesis. SNMC therefore adds a new additional tool to the existing SN spectral classification tools.

All in all, SNMC is a thriving software that has demonstrated promising results in classifying SN spectra. It is a work in progress classifier with a great potential of improving

¹<https://pymc-devs.github.io/pymc/>

its current classification efficiency, which forms a greater part of our plans for future work. In addition to being able to obtain additional information (e.g. error bars on all recovered parameters) that **Superfit** and **SNID** do not provide, **SNMC** also has the ability to fit for SN host galaxy information (such as the type of host galaxy) as well as host galaxy dust extinction.

7.5 Future Work

In this section, we highlight some of the areas of future work that we discussed in the chapters, which we believe are crucial to enhancing **SNMC**'s current level of performance. We list them in bullet point form, in no particular order.

- Parallelise the **SNMC** code to improve its current total running time in performing model selection and parameter estimation;
- Investigate the cause of the observed discrepancy between the colour excess $E(B - V)$ literature values and those recovered by **SNMC** for the 3 other literature spectra in Section 4.4;
- Investigate why the success rate for the recovery of the correct galaxy template is lower for case 3 and higher for case 4 in Table 4.1, when we expect it to be the opposite;
- Investigate the cause of **SNMC**'s apparent preference for low epoch SN templates, in the absence of a strong prior range on t . We showed in Chapter 4 that the epoch parameter was not biased in simulations so this may be due to a lack of templates or another systematic;
- Investigate the cause of the increase in the bias value for A_V at $SNR = 10$, when what we expect is a decrease in the bias value as SNR changes from 5 to 10; and
- Investigate further the cause of what appears to be a positive correlation between A_V and α , shown in Figures (4.5) and (C.5a) to (C.7a), given that we do not expect such a correlation between the two parameters.

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Appendix A

PyMC

A.1 Introduction

In this appendix, we discuss PyMC in some detail, highlighting the key concepts that are relevant to SNMC. PyMC is the python engine that SNMC employs and has more than one MCMC algorithm build into it, including the Metropolis-Hastings (MH) algorithm discussed in subsection 2.5.1, which SNMC uses. We summarise the main concepts of how this MCMC engine works (focussing on the MH algorithm) from Patil et al. (2010), specifically tailoring them to the SNMC spectral fitting process.

A.2 PyMC prior definitions of the parameters

The priors for all parameters we fit for are defined and made known to PyMC. Various options are available for the prior distribution function, e.g. uniform distribution, gaussian distribution, etc. We use the uniform distribution in defining the prior ranges for all our parameters, i.e. a ‘top hat’ prior distribution is employed for all parameters. Below is a code snippet showing an example of how this is specified in PyMC for one of our 4 parameters of interest α :

```
import pymc
import numpy
alpha = pymc.Uniform('alpha', lower limit, upper limit, value\,
(optional), observed (Boolean))
```

PyMC requires the *numpy* module to run (Patil et al. 2010). In the above code snippet, *pymc.Uniform* tells PyMC to uniformly select a random value of $\alpha \in (lower\ limit, upper\ limit)$. The optional *value* parameter specifies the starting point of the MCMC chain for α . If not given, the chain starts at a random point $p \in (lower\ limit, upper\ limit)$. Lastly, the parameter *observed*

controls whether or not PyMC varies α in the fitting. If set to *False*, PyMC fits for α whereas if set to *True*, α is set to a constant value given by the *value* parameter during the fitting.

A.3 PyMC definition of other objects: F_{mod} , F_{obs} , $\sigma_{F_{obs}}$

The theoretical flux defined in Equation (4.2) in Chapter 4, is passed to PyMC using the decorator '@pymc.deterministic' as in the following code snippet:

```
import pymc
import numpy
@pymc.deterministic
def F_mod(alpha, z, t, A_V, T_SN, T_GAL):
    return alpha * F_SN * 10**(-0.4A_lambda) + (1 - alpha)*F_GAL
```

See subsection 4.2.1 for the relationship between A_λ and A_V . The parameters α , z , t , and A_V represent the fraction of SN flux in the spectrum, the SN redshift, the SN epoch (defined as the time elapsed since SN explosion) and the extinction parameter, respectively (see subsection 3.3.2 for a further discussion of these parameters).

As discussed in subsection 4.2.1, these parameters are inputs in generating SN flux F_{SN} from the SN templates T_{SN} (subsection 3.4.1). In generating the desired galaxy flux F_{GAL} from the galaxy templates T_{GAL} (subsection 3.4.2), only the redshift z and the difference $1 - \alpha$ are required as inputs. The @pymc.deterministic decorator tells PyMC that F_{mod} is a deterministic variable, i.e. its value can be determined absolutely from its provided arguments or parents (Patil et al. 2010). Next, we define the error function τ , to represent the error $\sigma_{F_{obs}}$ in our simulated observed flux F_{obs} as a PyMC object. For our simulations, $\sigma_{F_{obs}}$ is the quotient of F_{obs} and SNR (Equation (4.6)). Representing $\sigma_{F_{obs}}$ as a PyMC object is performed in a similar manner as for F_{mod} , using a decorator, i.e.

```
import pymc
import numpy
@pymc.deterministic
def tau(sigmaF_obs):
    return pow(sigmaF_obs,-2)
```

Again, this tells PyMC that the values of τ are determined with certainty from its provided argument $\sigma_{F_{obs}}$.

A.3.1 PyMC definition of the likelihood function

As a last step, we relate our simulated observed data F_{obs} to all the above defined PyMC objects: parameter prior definitions, F_{mod} , and τ . We define the following PyMC object ‘y’ to represent our data sampling distribution:

```
y = pymc.Normal('F_obs', mu=F_mod, tau=tau, value = F_obs, observed = True)
```

Our chosen sampling distribution in this case is the Normal distribution. We choose this distribution to be the appropriate likelihood since we have many photons contributing to a spectrum and the central limit theorem assures us that the Gaussian is the appropriate limit of the Poisson distribution. Its *observed* parameter is set to *True* to notify PyMC that the values of F_{obs} are not to be varied during the fitting. The variables *mu* and *tau* that F_{mod} and τ are equated to, respectively, represent their internal labelings in PyMC by the likelihood function ‘y’.

A.4 PyMC Model

All the above defined PyMC variables and objects are then nested into what is referred to as a “PyMC Model”, accessed via the command *pymc.Model* that is then passed to the MCMC to perform the sampling (Patil et al. 2010). Below is a snippet of the syntax that accomplishes this process:

```
import pymc
import numpy as np
model=pymc.Model([alpha, z, t, A_V, F_mod, tau, y])
MCMC=pymc.MCMC(model)
MCMC.sample(iter, burn(optional), thin(optional))
```

The variables *model* and *MCMC* used to represent the model and the MCMC sampler are arbitrarily chosen. The arguments *iter*, *burn* and *thin* represent the number of MCMC steps, the amount of burn-in we require (subsubsection 2.4.4), as well as our thinning requirement for the chain (subsubsection 2.4.5), respectively. As indicated, the latter two are both optional.

Appendix B

The SALT Spectroscopic Data Reduction

B.1 Introduction

In this appendix, we provide an overview of the SALT longslit data reduction process performed with PySALT, the SALT data reduction pipeline developed by Crawford et al. (2010). PySALT runs inside PyRAF, an IRAF¹ python wrapper, and reduces our SN spectral data in three stages: (i) PySALT basic data reduction, cosmic ray removal and flat-fielding, (ii) PySALT wavelength calibration and (iii) Pysalt flux calibration. We discuss each of the three stages in detail.

B.2 PySALT basic data reduction

This stage involves correcting the raw data (original data frames taken by the telescope) for gain of the different CCD amplifiers, crosstalk between the amplifiers during readout of the CCD chips and CCD bias. We provide brief descriptions of the three corrections.

B.2.1 Gain correction

The gain G of a CCD amplifier refers to the ratio of the number of electrons in each CCD pixel, n_e to the data number DN , i.e. $G = n_e/DN$. The data number (also known as the Analogue to Digital Unit - ADU) is obtained by performing an analogue to digital conversion of n_e . A gain of 2 means the number of electrons n_e is twice the data number DN .

The RSS has a three CCD mosaic, as Figure B.1 shows, with each CCD possessing two

¹IRAF is the Image Reduction and Analysis Facility, a general purpose software system for the reduction and analysis of astronomical data. IRAF is written and supported by the National Optical Astronomy Observatories, operated by the Association of Universities for Research in Astronomy (AURA), Inc. under cooperative agreement with the National Science Foundation

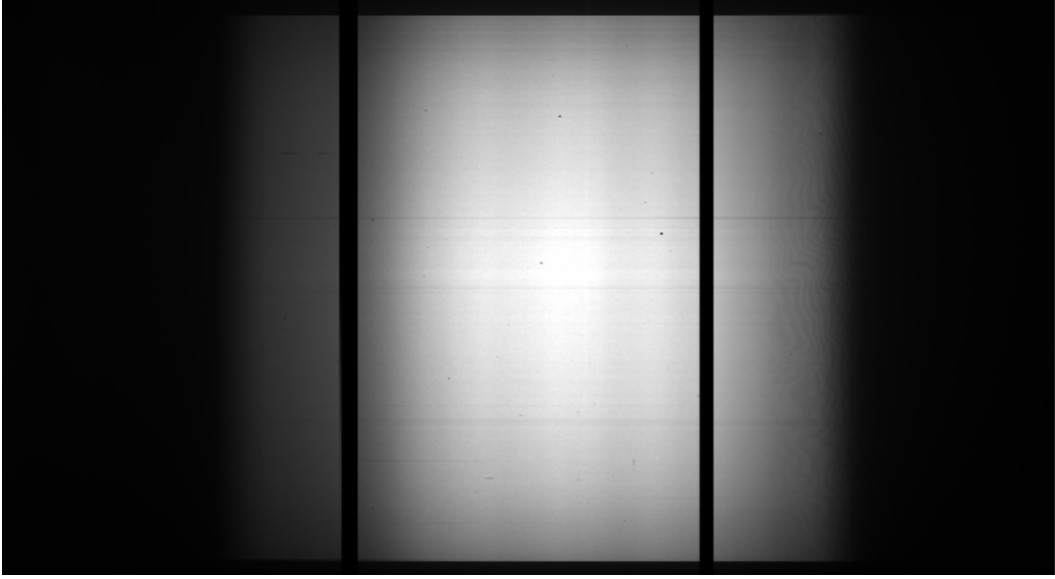


Figure B.1: A typical dome flat taken by the RSS, showing the three-CCD mosaic, with two CCD gaps (the middle two thick vertical lines) separating the three individual CCDs.

readout amplifiers. Each amplifier has a specific gain factor that fluctuates slowly with time. Factors that influence such fluctuations include CCD readout speed and gain setting. These fluctuations manifest themselves in observational data and are corrected for using a stored ascii table containing all possible gain permutations. The PySALT task “saltgain” performs this correction.

B.2.2 Crosstalk correction

The discussion provided in this subsection has mostly been summarized from the PySALT ‘crosstalk’ help file. The signal from each readout amplifier on a given CCD interferes or talks into its neighbouring amplifier and vice versa. This is known as “crosstalk” and results in the appearance of ghost sources in an image along the boundaries of the two amplifiers. The ghost sources seen are actually mirror images of bright sources. The PySALT task “saltxtalk” corrects for this effect by subtracting a scaled image of one amplifier from that of its neighbouring amplifier using scaling factors provided in the image headers.

B.2.3 Bias correction

Telescopes and CCDs do not work perfectly, i.e. CCD pixels have different sensitivities, CCD illumination by the telescope does not occur homogeneously, and so on. The end result is a biased signal detected by the CCD and this differs for each data frame. In PySALT, the bias

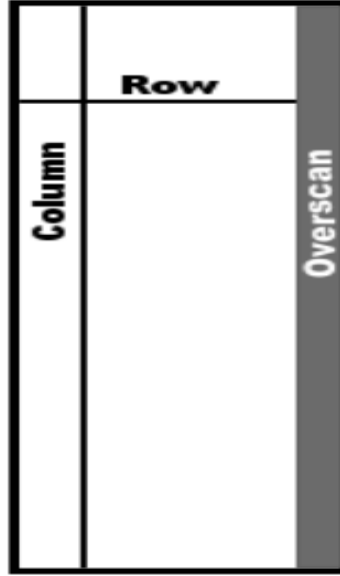


Figure B.2: A diagram illustrating the overscan region in a data frame, taken from Massey (1997)

in the signal is subtracted using data in the overscan region - a region created by performing a few empty readout cycles prior to reading the CCD. Figure B.2 shows a diagram of an overscan region. The PySALT task “saltbias” performs the bias correction.

B.3 PySALT cosmic ray removal

Cosmic rays are energetic particles originating from the sun, from the remains of exploding stars (supernova remnants) and from high energy process occurring within and outside of the Milky way². Cosmic rays reveal themselves in data frames as bright isolated points with varying shapes. Figure B.3 shows an example of cosmic rays highlighted with dotted red circles in a data frame taken by the RSS.

The PySALT task “saltclean” performs cosmic ray cleaning on the data frames. The task provides three cosmic ray cleaning methods: (i) fast, (ii) median and (iii) edge cosmic ray detection. For our analysis, we use the third method which utilizes the “L.A.Cosmic” cosmic ray rejection algorithm. The L.A.Cosmic algorithm is based on a method known as “Laplacian edge detection” utilized in digital images to highlight boundaries (see Van Dokkum 2001 for a comprehensive discussion of the algorithm). Figure B.4 shows a cosmic ray cleaned data frame.

²<http://helios.gsfc.nasa.gov/cosmic.html>

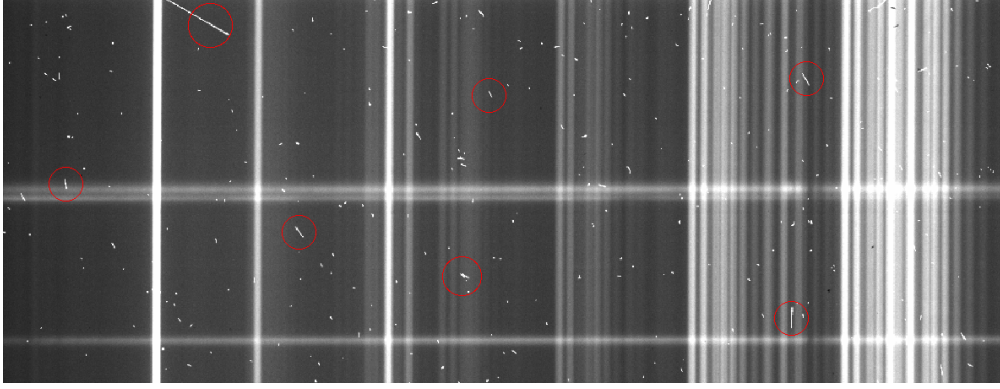


Figure B.3: A section of an RSS 2-D spectrum illustrating the presence of cosmic rays. Their varying shapes are highlighted with the dotted red circles.

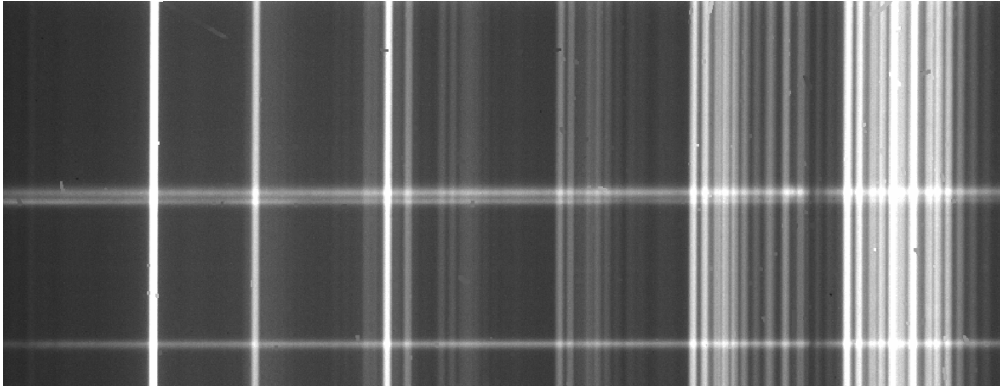


Figure B.4: Same as Figure B.3 but with cosmic rays removed.

B.4 PySALT flat-fielding

As discussed in subsection B.2.3, the sensitivity of pixels on a CCD detector respond to light detection differently. The flat-fielding process aims to correct for such pixel to pixel sensitivity variations. For spectroscopy, the correction is performed in the spatial direction—i.e. the direction perpendicular to the dispersion axis (the axis parallel to the column axis in Figure B.2)—and gets rid of sensitivity variations in adjacent pixels falling along a spatial row defined by the same wavelength of light from a source (Zwitter & Munari, 2000).

For our analysis, flat-fielding is performed using 5 dome flats (exposures taken from a flat white surface inside the dome) that are median combined into one masterflat. The reason for median combining is to filter out stray cosmic rays (Zwitter & Munari 2000). This however does not make a difference in our case as dome flats are not exposed to cosmic ray interference. Prior to normalizing our science frame with the created masterflat, the masterflat first undergoes

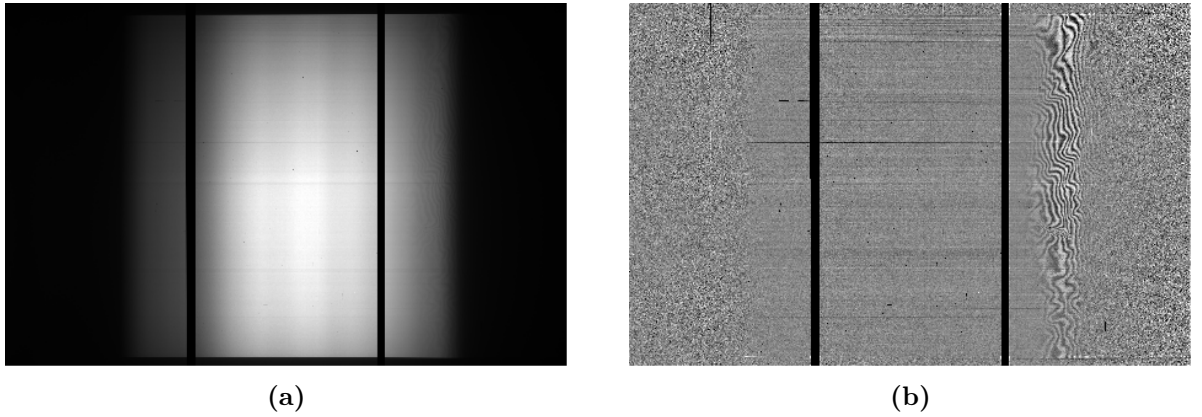


Figure B.5: (a) Combined masterflat obtained by median combining 5 dome flats, (b) normalized illumination corrected masterflat obtained by performing illumination correction on (a) and normalizing the resultant frame by the average of its pixel values.

“illumination” correction, which attempts to remove any gradients that may be present along the spatial direction (Massey 1997). The objective is to obtain a masterflat that has an average of unity across the entire frame (Zwitter & Munari 2000). The illumination corrected masterflat is therefore normalized by the mean of its pixel values in order to obtain a normalized illumination corrected masterflat whose average is unity. The normalized illumination corrected masterflat is then divided into the science frames to complete the flat-fielding. The PySALT tasks “saltcombine”, “saltillum” and “saltflat” are used in this process. Figure B.5 shows examples of a median combined and normalized illumination corrected masterflats.

B.5 PySALT wavelength calibration

Longslit spectral wavelength calibration involves correcting the spectral data for geometrical distortions that arise when a source covers a considerable length of the slit, which results in spectral resolution degradation (Massey et al., 1992), and converting the spectrum from a pixel scale to a wavelength scale. For our case of the SALT DES SN spectra, we make use of the following PySALT tasks: (i) `specidentify`, (ii) `specrectify`, (iii) `specsky` and (iv) `specextract`, in performing the calibration. We provide a summary of how each task performs its function.

B.5.1 Specidentify

The wavelength calibration process starts by running this task on a comparison arc spectrum. This task works in exactly the same way as the IRAF task *identify*. Some of the well known comparison arc spectra include Neon, Argon and Xenon. The initial comparison spectrum coordinates are pixel coordinates. The process involves identifying a number of lines interactively

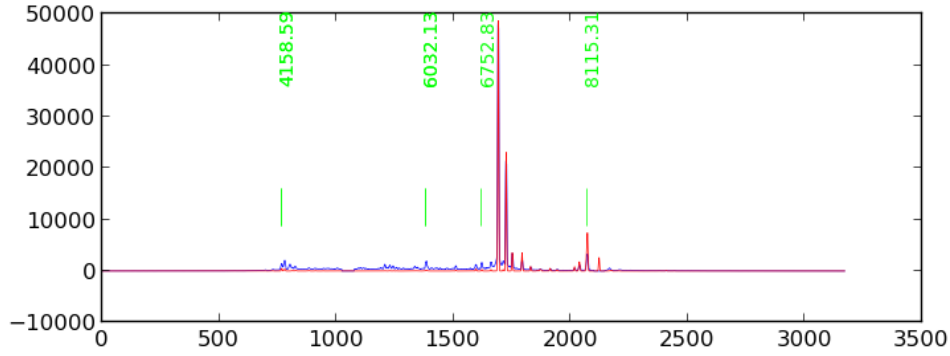


Figure B.6: Plot of the Argon comparison arc spectrum (blue curve) in PySALT, showing 4 selected features highlighted in green with their approximate wavelengths. *Specidentify* makes a fit between the comparison arc spectrum and the line list, with a polynomial of an appropriate order using the 4 selected features to obtain the first mapping of pixel coordinates to wavelength coordinates. The superimposed red curve is a plot of the artificial spectrum of the line list. The vertical and horizontal axes are both in pixel scale.

along the comparison spectrum (as shown in Figure B.6) and providing approximate wavelength values for each.

The approximate wavelengths provided are obtained from what is called a line list, which contains precise laboratory wavelength measurements of the emission lines (features). After identifying and marking a few lines (minimum of 4 are required in PySALT) and providing their approximate wavelengths, a fit is made between the comparison arc spectrum and the line list as a function of pixel number. The choice of functions for the fitting are chebyshev, legendre (both polynomials), spline1 (linear spline) or spline3 (cubic spline), with an appropriate order. The fit attempts to map pixel coordinates to wavelength coordinates. After the fitting function is established, other lines are identified automatically by the task and a refitting is done. The process is repeated a number of times until a good fit is obtained. Obtaining a good fit may involve changing the fitting function or its order (Massey et al. 1992).

Specidentify also includes the IRAF task *reidentify*, which makes use of the first solution obtained with *identify* to determine wavelength solutions for other dispersion lines. The first time *specidentify* derives a wavelength solution using the comparison spectrum, it does this for the middle dispersion line (by default), shown in Figure B.7. However, we do not use the *reidentify* task in our calibration of the SALT DES SN spectra, as it does not always yield a good solution. We instead only derive solutions for dispersion lines chosen at appropriate locations at the top and bottom, as Figures B.8 and B.9 show, in addition to the middle line.

Figure B.10 shows the ‘Argon’ lamp 2-D spectrum (*top*), from which we derive a wavelength

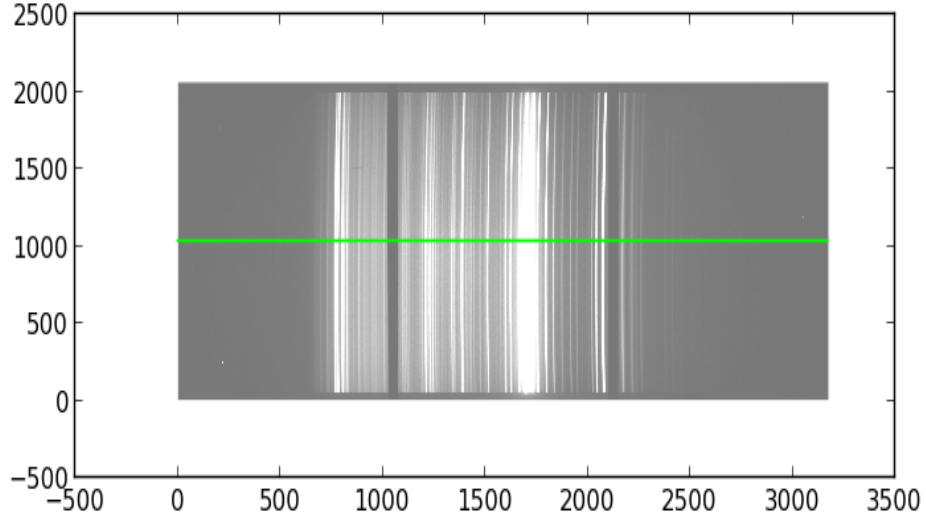


Figure B.7: Image of the Argon comparison arc spectrum generated in PySALT, showing the middle dispersion line used by *specidentify* in creating the first wavelength solution. Both axes have pixel scales.

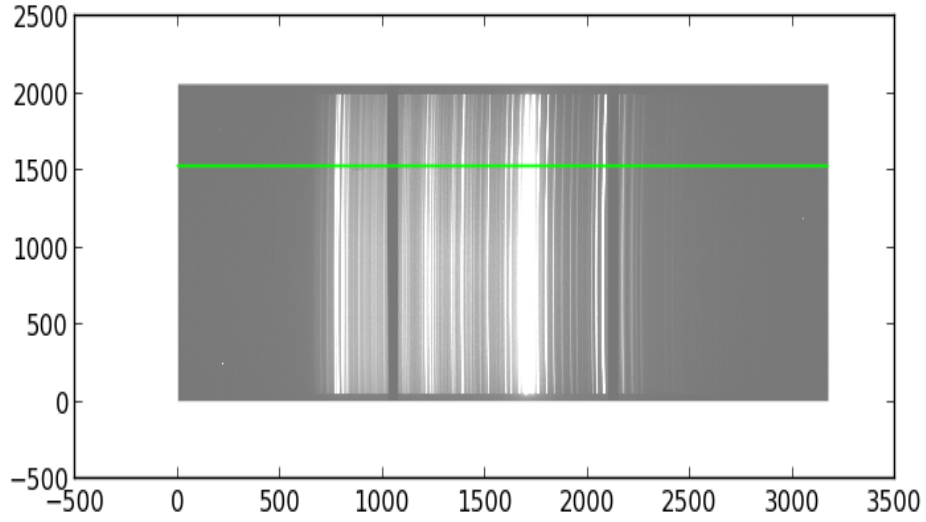


Figure B.8: Same image as Figure B.7 except the dispersion line is located at the top of the frame at 500 pixels from the centre. *Specidentify* uses the solution obtain in Figure B.7 as a starting point to derive the solution at this dispersion line.

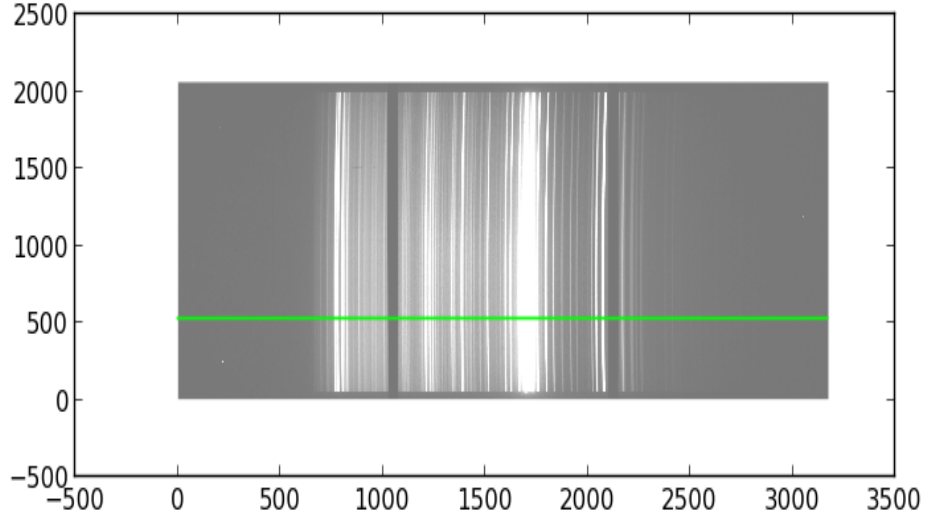


Figure B.9: Same as Figure B.7 except the dispersion line is located at the bottom of the frame at 500 pixels from the centre. *Specidentify* uses the solution from Figure B.8 as a starting point for deriving the wavelength solution at this dispersion line.

solution for performing wavelength calibration on our science images. The line distortions present in the arc spectrum are corrected for using the derived wavelength solution and the resultant spectrum is shown in the *Bottom* panel of the figure.

B.5.2 Specrectify

This task applies the wavelength solution derived by *Specidentify* task to the science data frames. Reference to the database containing the wavelength solution is made in the header of the science frame. If the calibration is performed correctly, the shape of the sky lines in the resultant science image should resemble those seen in the corrected arc spectrum in Figure ??.

B.5.3 Specskey

This task works in a similar way as the IRAF *background* task. It measure the sky brightness background in a specified region of the image and subtracts this from the rest of the image. The purpose for doing this is to exclude the contribution of light intensity from the sky in our spectral data.

B.5.4 Specextract

This task extracts the 1-D wavelength corrected spectrum from the sky subtracted image. The region to be extracted is specified to the task.

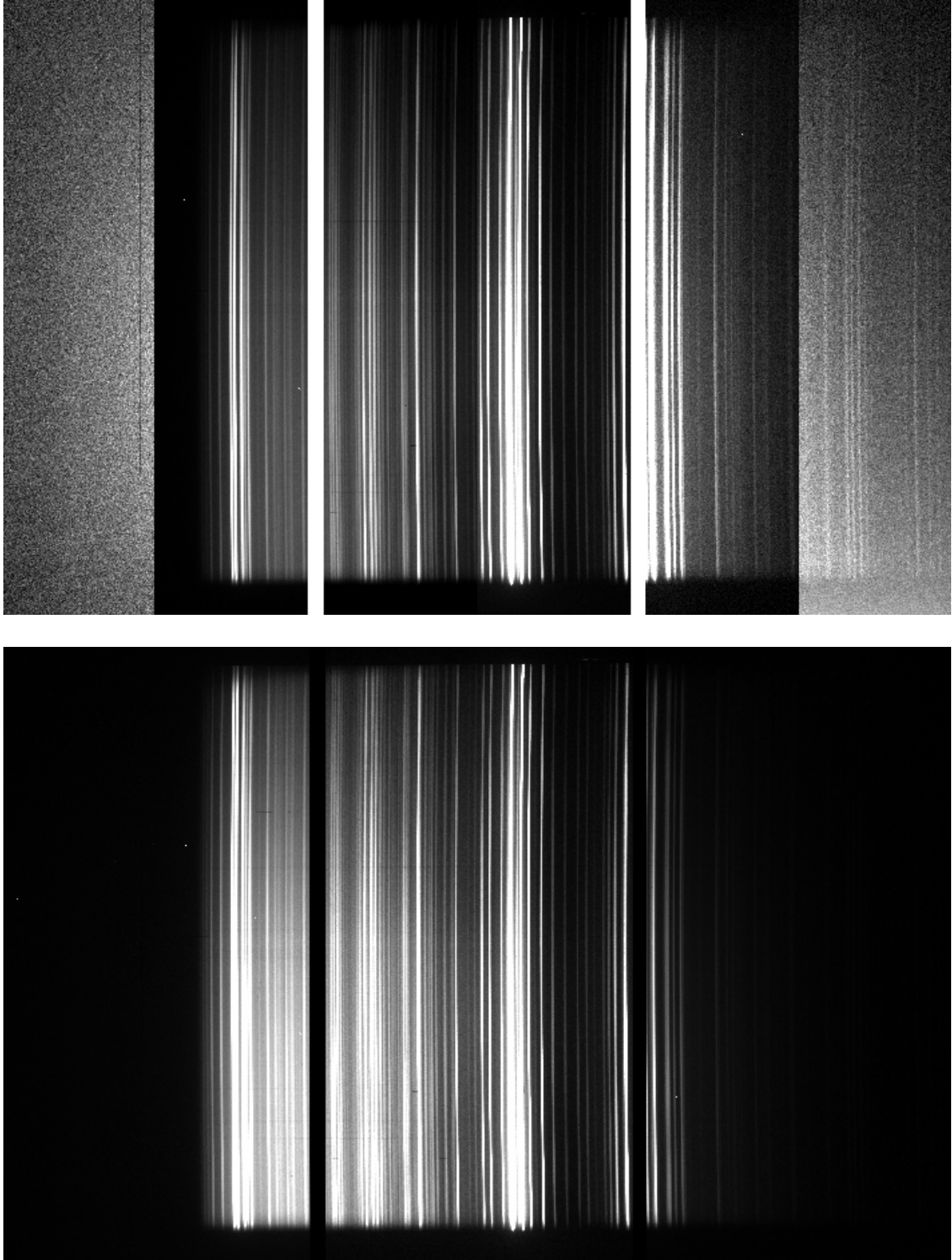


Figure B.10: *Top:* The Argon arc lamp spectrum taken with the RSS using the PG0300 grating that we use to obtain the wavelength calibration solution for science images observed on the same night as the arc lamp. *Bottom:* Same as *Top* but corrected for distortions in the lines seen in the top frame and wavelength calibrated using the wavelength solution derived with *Specidentify*. The two gaps seen in both the *Top* (in white color) and *Bottom* (in black colour) of the two 2-D spectra are CCD gaps.

B.6 PySALT flux calibration

Flux calibration involves calibrating our extracted spectra into real flux units. This is accomplished via observation of a spectrophotometric standard star (a star with a known spectrum and magnitude). In PySALT, flux calibration is performed via the tasks *specsens* and *speccal* in the Saltspec package.

B.6.1 Specsens

This task calculates a calibrated sensitivity curve using as inputs the output from *specextract*, a file containing calibrated magnitudes for the spectrophotometric standard star, an extinction curve for the observing site, airmass and exposure time for the observed standard star.

B.6.2 Speccal

This task uses the output from *specsens*, *specextract*, the extinction curve for the observing site, airmass and exposure time for an observed science image as inputs to produce a flux calibrated spectrum for an object of interest. SALT however currently does not produce absolute flux units for the sources but relative flux units, i.e. the produced flux solution yields a spectrum that has the right shape but not exact flux values.

Appendix C

Additional Figures from Chapters 4 and 6

C.1 Introduction

In this appendix, we show additional figures from Chapters 4 and 6 that further demonstrate the capabilities of *SNMC* as a SN spectral classifier.

C.2 Additional Figures from Chapter 4

Figures C.1 to C.4 show examples of simulated spectra, created from a SN Ia template and E0 galaxy template using different values of the four parameters α , z , t , A_V , with each combination of them yielding a spectrum at each of the four *SNR* values: 5, 10, 20, 100.

Figures C.5a to C.7a, show *SNMC*'s parameter estimation results in the form of 1-D histograms and contour plots of posterior distributions of the recovered parameters for the last three cases for which bias results were presented in Table 4.2. However, this is only for the case of *SNR* = 100, where we determined the least bias values for all four cases in Table 4.2 and at all four *SNR* values. Figures C.5b to C.7b show comparisons of the best-fit spectra (red) to the input simulated spectra (black). The contours represent the 68% credible regions whereas the blue vertical and horizontal lines represent the true values of the parameters.

Figures C.8 to C.10 show the best-fit model (or SN template for *SNID*) and parameters selected from the output of all models fitted to the three literature spectra of the SN candidates ‘SNLS-03D4cj’, ‘SN 1998bw’ and ‘SN 2008es’ by both *SNMC* and *SNID*.

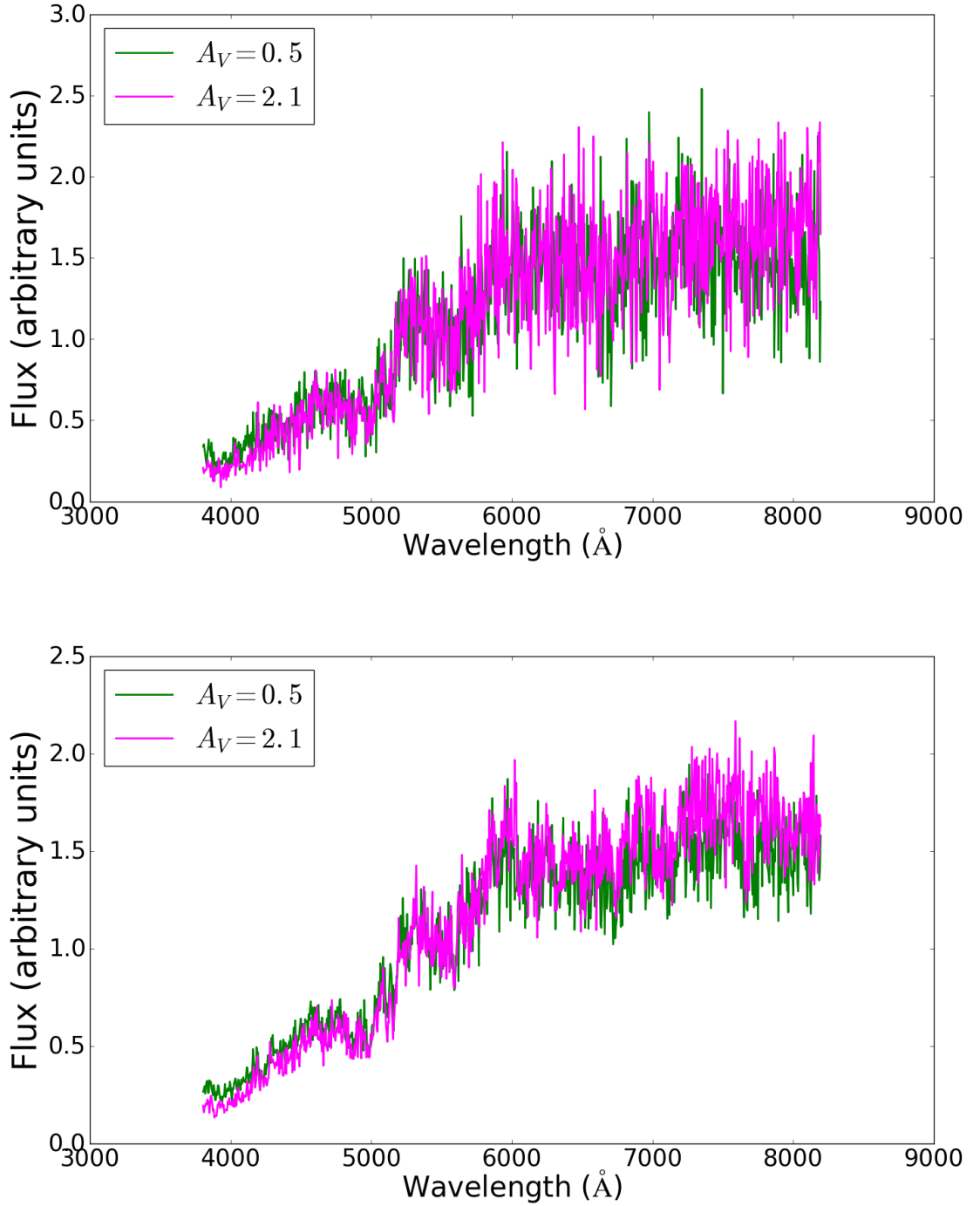


Figure C.1: *Top:* Examples of simulated SN spectra created from a SN Ia template and the E0 galaxy template, using the parameters $\alpha = 0.3$, $z = 0.3$, $t = 20$ days, $SNR = 5$, with $A_V = 0.5$ for the green spectrum and $A_V = 2.1$ for the magenta spectrum. Both spectra have been normalized to unity at $\lambda = 5500\text{\AA}$. *Bottom:* Same as *Top* but for $SNR = 10$. While the effect of the extinction is hard to see in the top panel, it is clearer in the bottom panel.

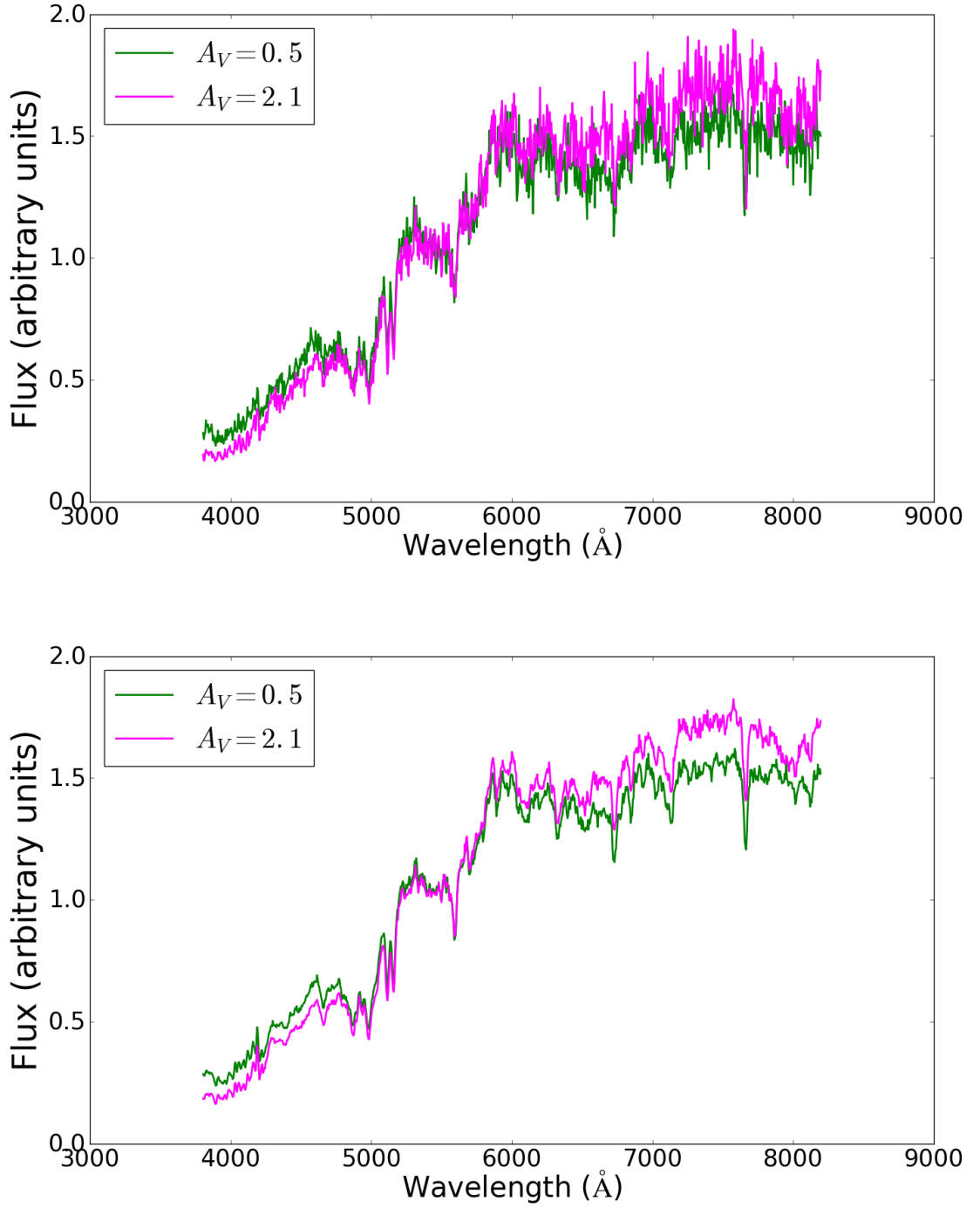


Figure C.2: *Top:* Examples of simulated SN spectra created from a SN Ia template and the E0 galaxy template, using the parameters $\alpha = 0.3$, $z = 0.3$, $t = 20$ days, $SNR = 20$, with $A_V = 0.5$ for the green spectrum and $A_V = 2.1$ for the magenta spectrum. Both spectra have been normalized to unity at $\lambda = 5500\text{\AA}$. *Bottom:* Same as *Top* but for $SNR = 100$. The effect of the extinction in reddening the spectra is clear.

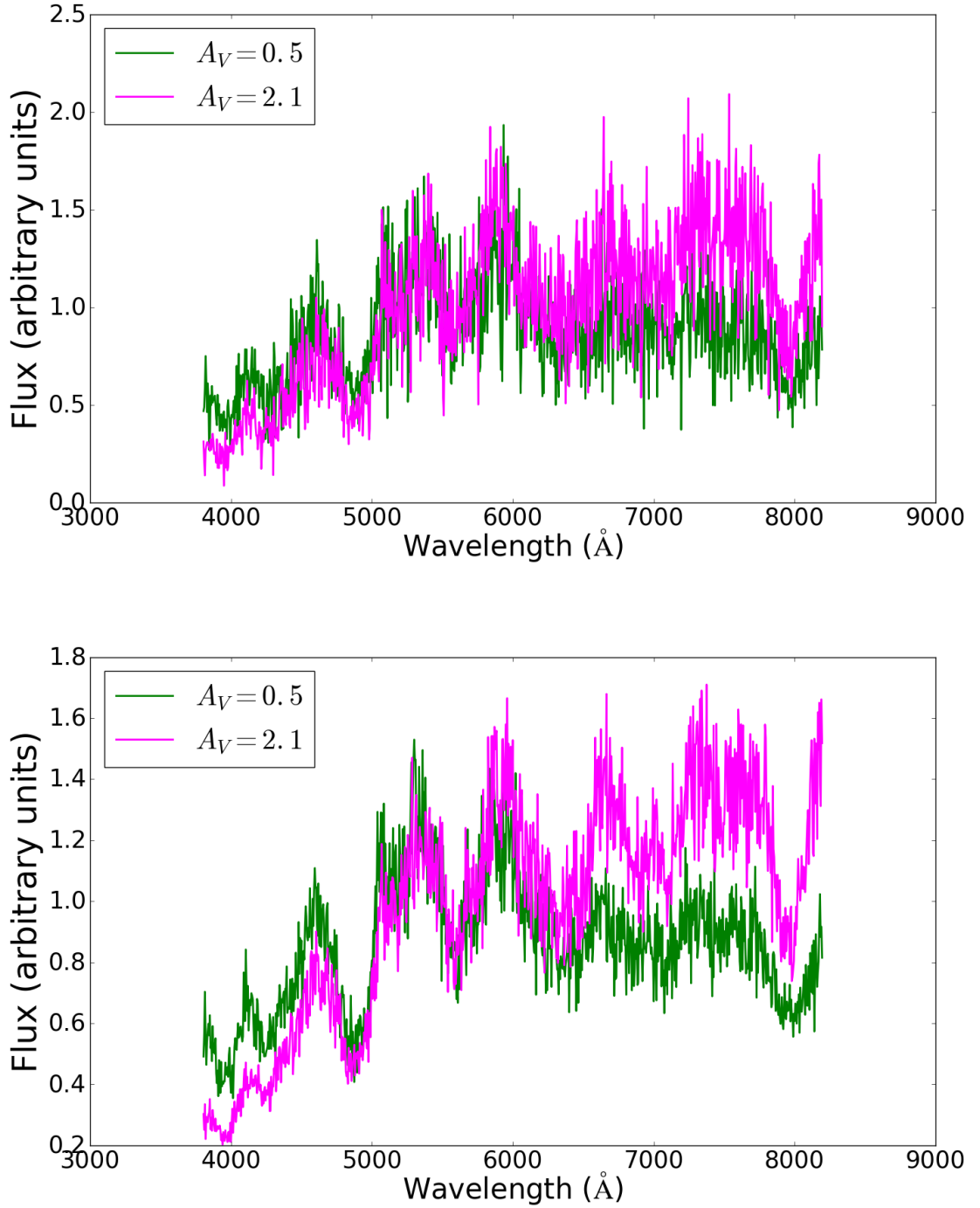


Figure C.3: *Top:* Examples of simulated SN spectra created from a SN Ia template and the E0 galaxy template, using the parameters $\alpha = 0.8$, $z = 0.3$, $t = 20$ days, $SNR = 5$, with $A_V = 0.5$ for the green spectrum and $A_V = 2.1$ for the magenta spectrum. Both spectra have been normalized to unity at $\lambda = 5500\text{\AA}$. *Bottom:* Same as *Top* but for $SNR = 10$. When the SN makes up 80% of the flux, the extinction is much more clearly visible.

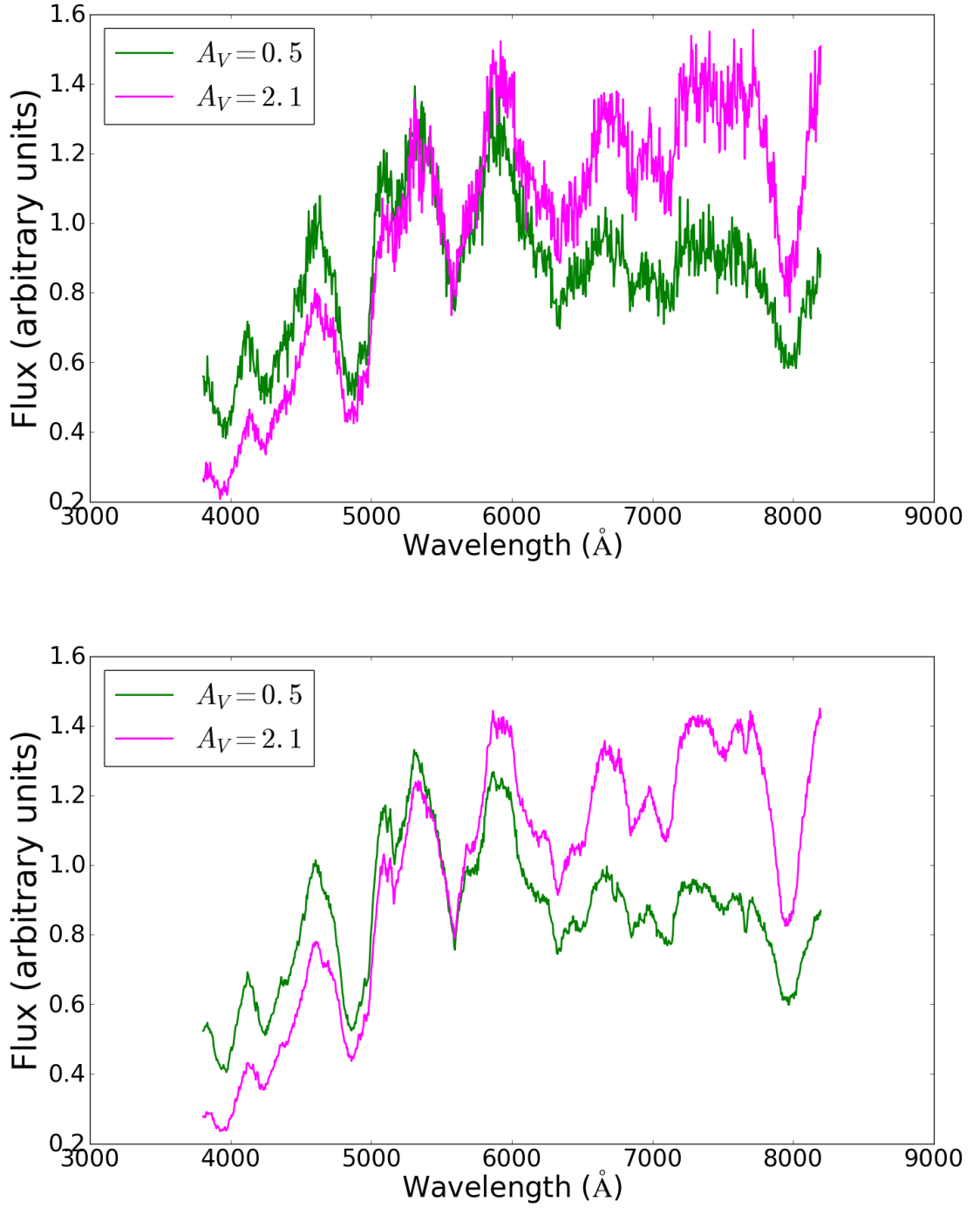
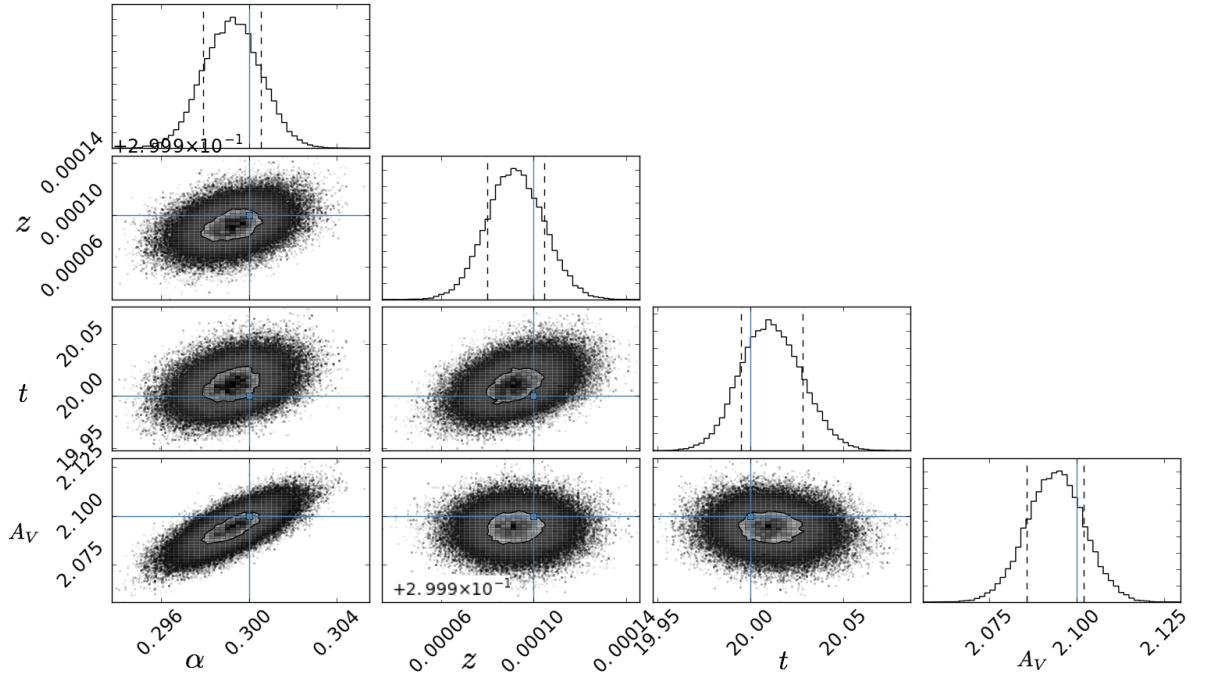
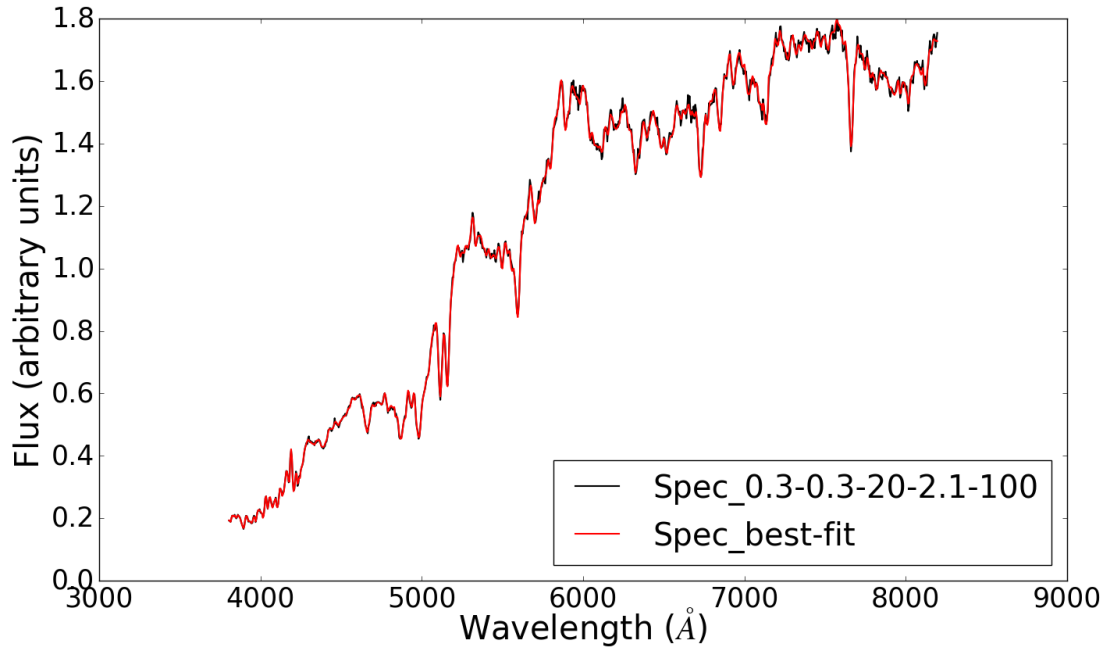


Figure C.4: *Top:* Examples of simulated SN spectra created from a SN Ia template and the E0 galaxy template, using the parameters $\alpha = 0.8$, $z = 0.3$, $t = 20$ days, $SNR = 20$, with $A_V = 0.5$ for the green spectrum and $A_V = 2.1$ for the magenta spectrum. Both spectra have been normalized to unity at $\lambda = 5500\text{\AA}$. *Bottom:* Same as *Top* but for $SNR = 100$.

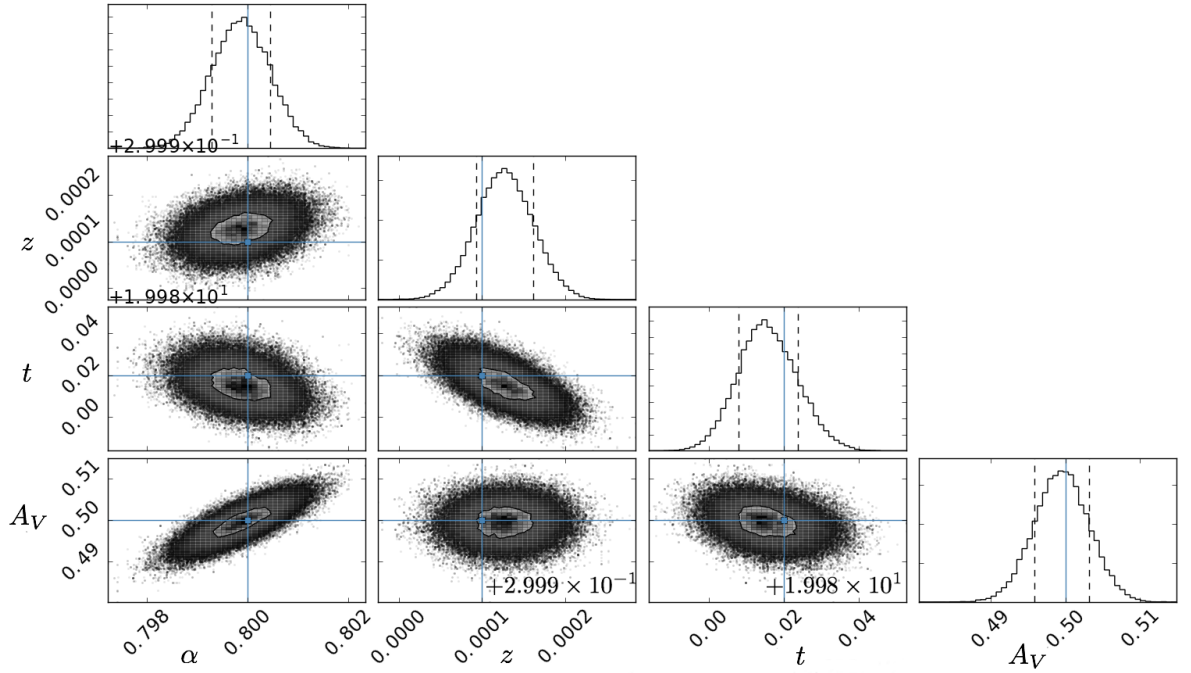


(a) Histograms and 2-D-contour plots of SNMC's estimated posterior distributions of the four parameters, from a simulated spectrum generated with the values $\alpha, z, t, A_V = (0.3, 0.3, 20, 2.1)$ for $SNR = 100$, using a SN Ia template and an E0 galaxy template. The recovered parameters are $\alpha = 0.299 \pm 10^{-3}$, $z = 0.29999 \pm 10^{-5}$, $t = 20.01 \pm 0.02$, $A_V = 2.09 \pm 0.01$.

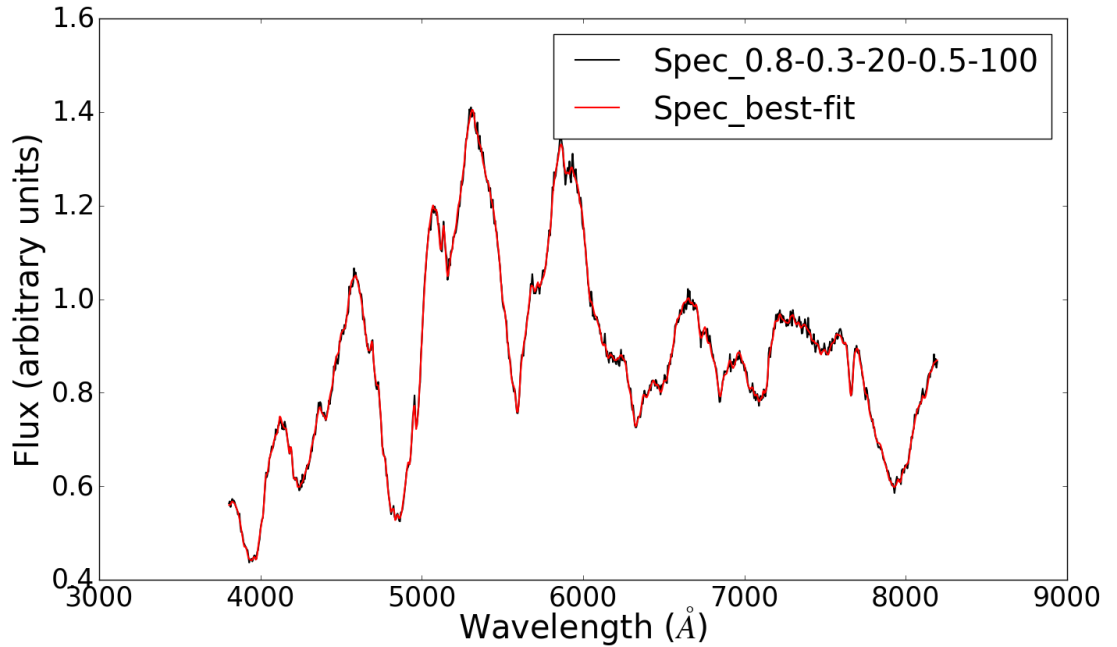


(b) Comparison of SNMC's best-fit spectrum (red) to the simulated spectrum (black) described in (a).

Figure C.5

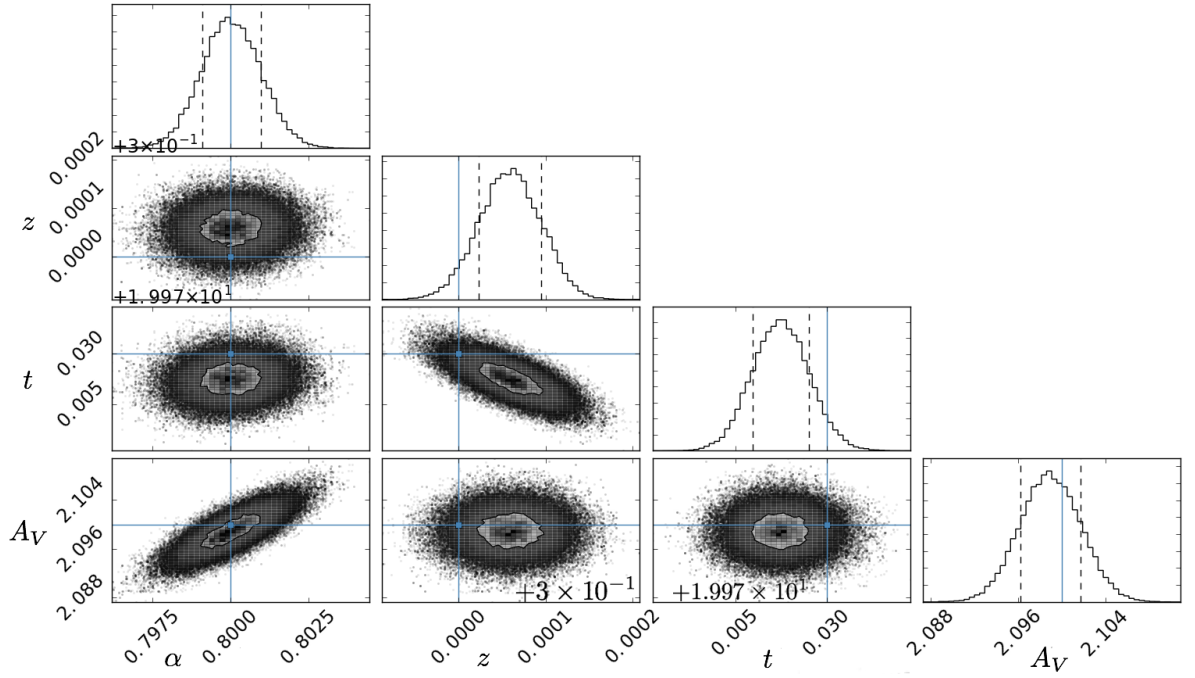


(a) Histograms and 2-D-contour plots of SNMC's estimated posterior distributions of the four parameters, from a simulated spectrum generated with the values $\alpha, z, t, A_V = (0.8, 0.3, 20, 0.5)$ for $SNR = 100$, using a SN Ia template and an E0 galaxy template. The recovered parameters are $\alpha = 0.800 \pm 10^{-3}$, $z = 0.30003 \pm 3 \times 10^{-5}$, $t = 20.00 \pm 0.01$, $A_V = 0.499 \pm 4 \times 10^{-3}$.

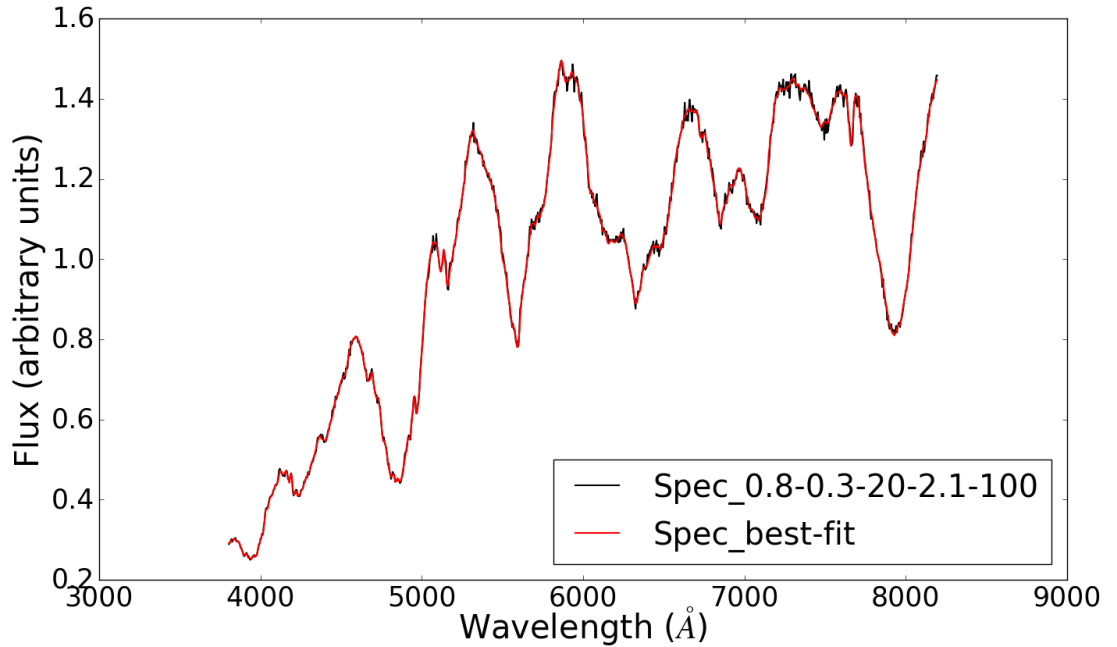


(b) Comparison of SNMC's best-fit spectrum (red) to the simulated spectrum (black) described in (a).

Figure C.6

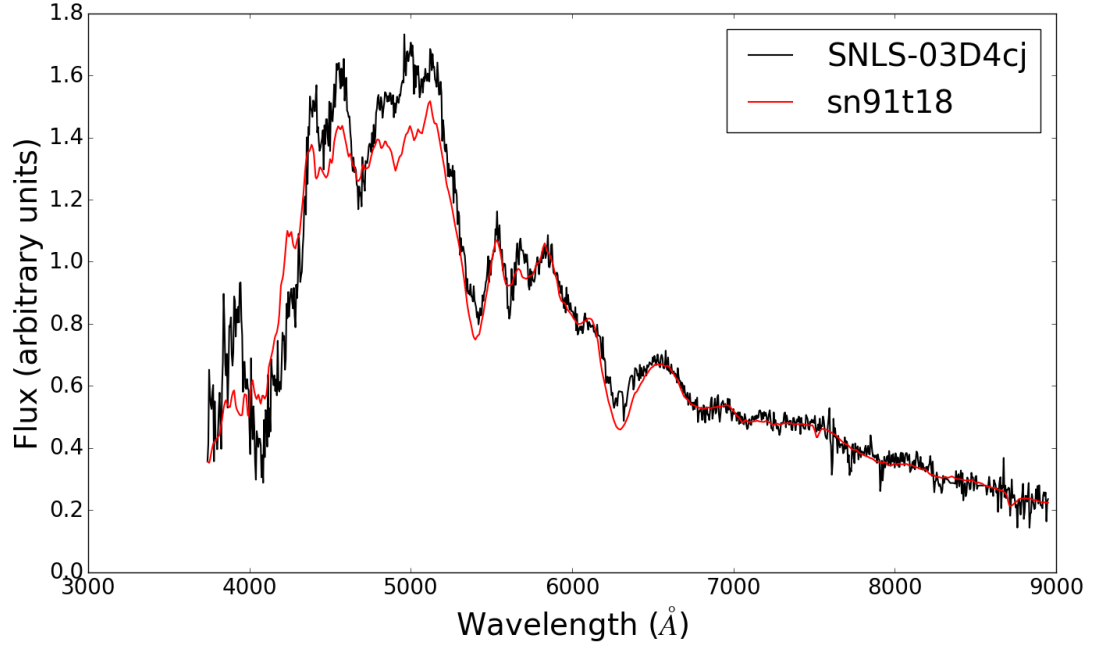


(a) Histograms and 2-D-contour plots of SNMC's estimated posterior distributions of the four parameters, from a simulated spectrum generated with the values $\alpha, z, t, A_V = (0.8, 0.3, 20, 2.1)$ for $SNR = 100$, using a SN Ia template and an E0 galaxy template. The recovered parameters are $\alpha = 0.800 \pm 10^{-3}$, $z = 0.30000 \pm 3 \times 10^{-5}$, $t = 20.00 \pm 0.01$, $A_V = 2.099 \pm 3 \times 10^{-3}$.

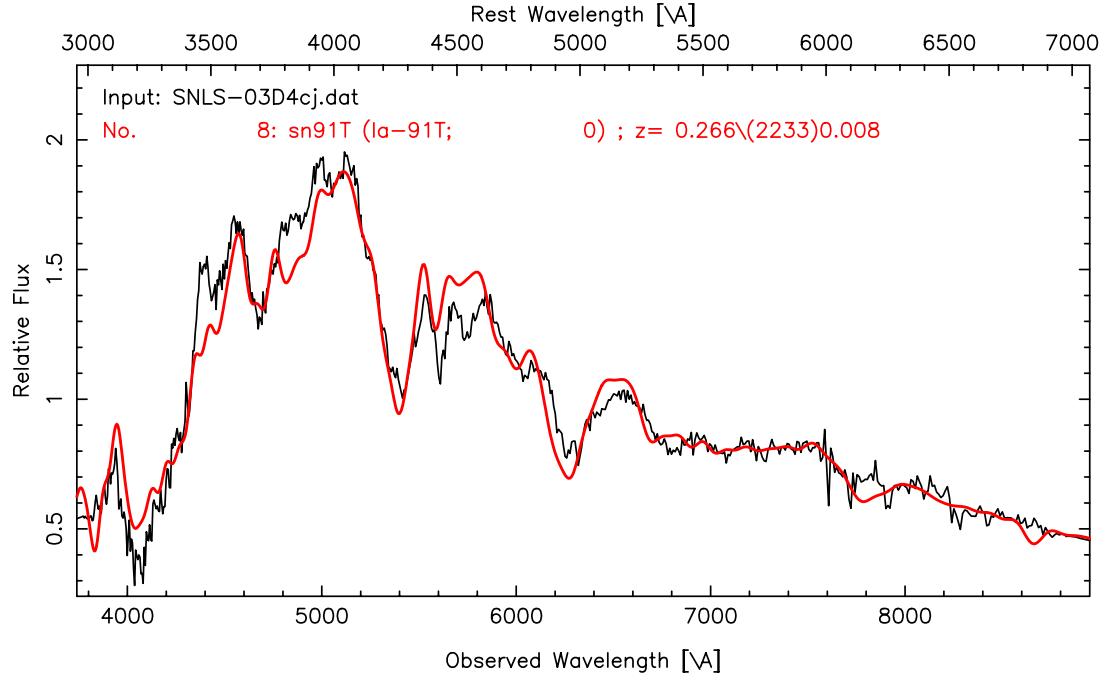


(b) Comparison of SNMC's best-fit spectrum (red) to the simulated spectrum (black) described in (a).

Figure C.7

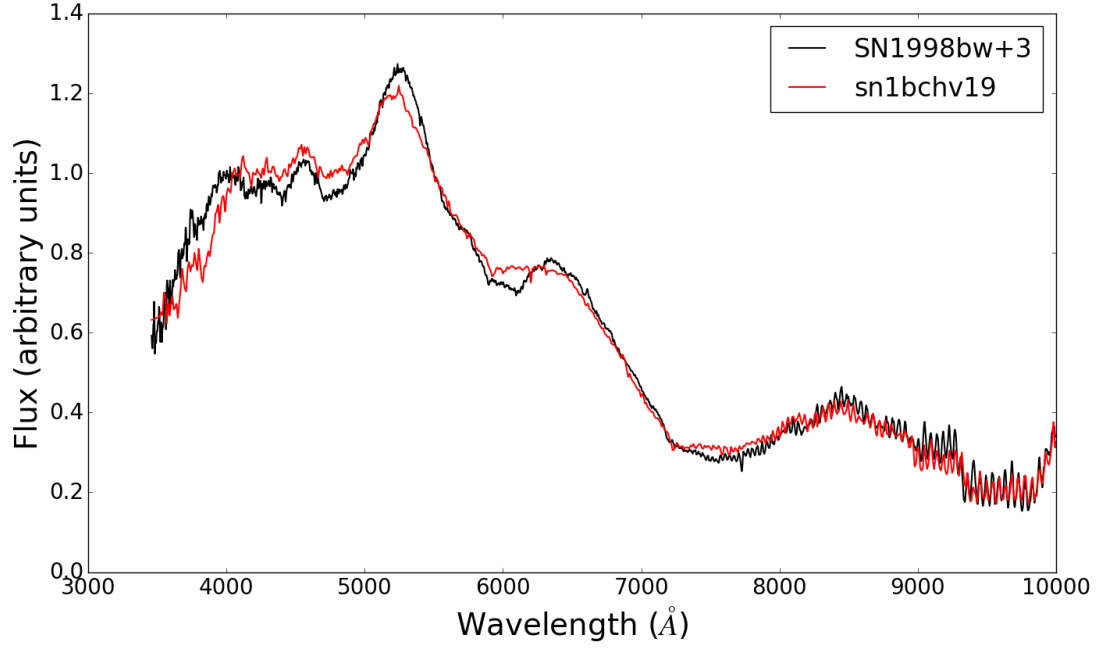


(a) Comparison of SNMC's best-fit spectrum (red) to the spectrum of SNLS-03D4cj (black). The recovered parameters are: $z = 0.268 \pm 0.001$, $t = 17.9 \pm 0.2$.

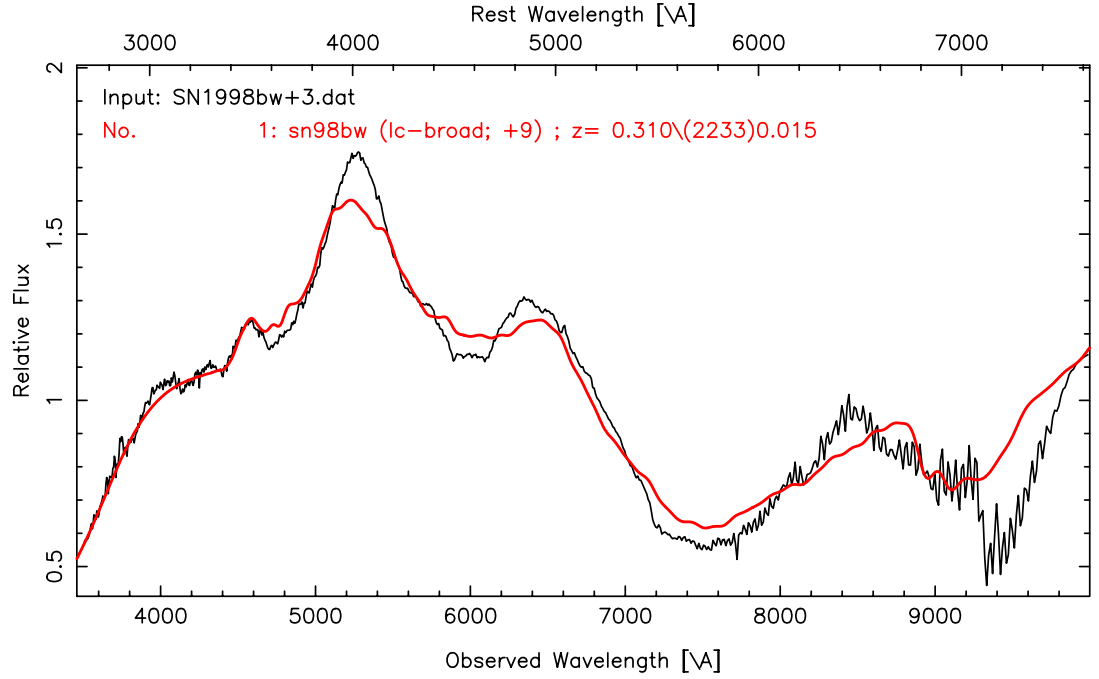


(b) Same as (a) but for SNID, with the recovered parameters shown in red above the plots (SN type and phase τ given in parentheses).

Figure C.8: Here, both classifiers appear to fit the spectrum reasonably well.

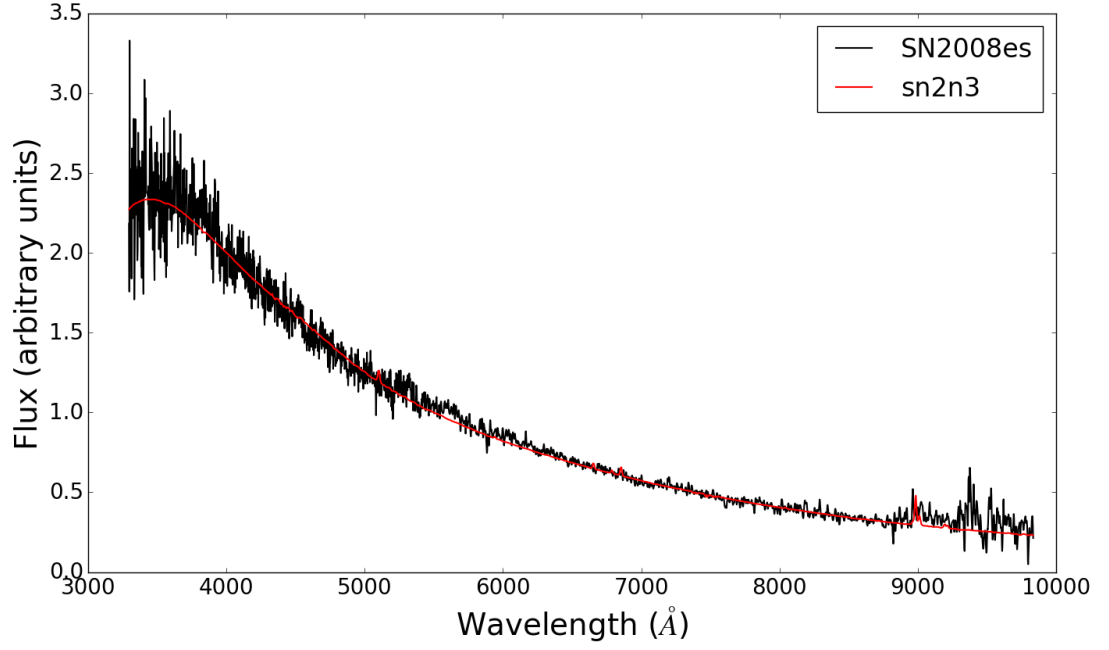


(a) Comparison of SNMC's best-fit spectrum (red) to the spectrum of SN 1998bw (black). The recovered parameters are $z = 0.0051 \pm 0.0001$, $t = 19.5 \pm 0.2$.

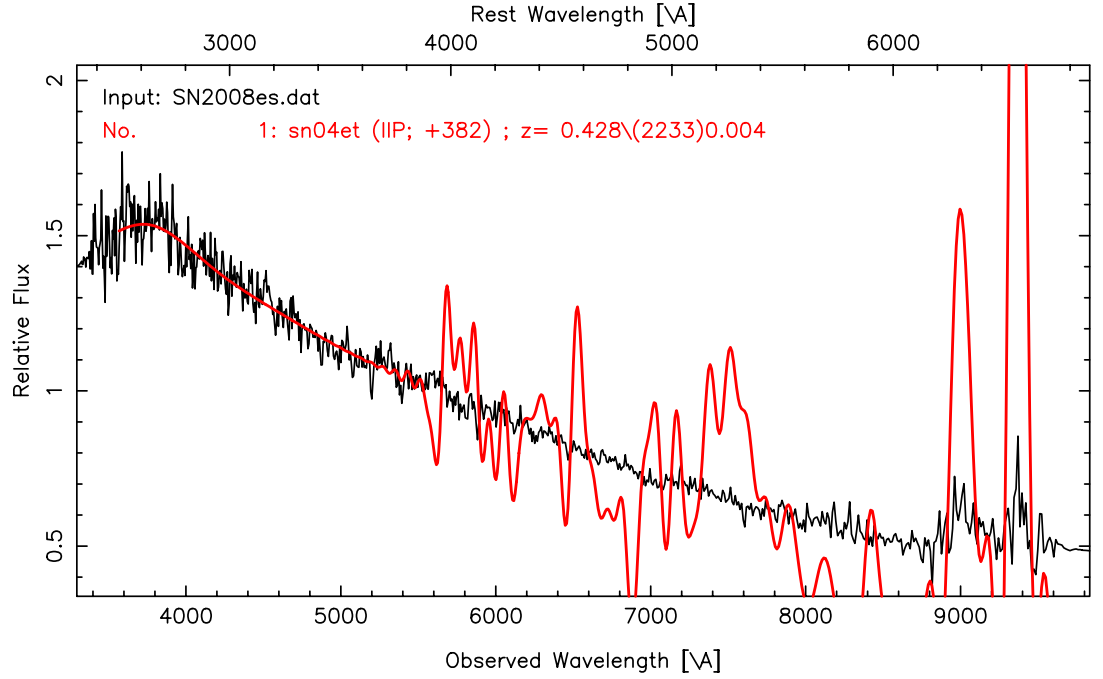


(b) Same as (a) but for the SNID classifier, with the recovered parameters given in red above the plots (SN type and phase τ given in parentheses).

Figure C.9: Here, SNMC provides a better fit than SNID.



(a) Comparison of the SNMC classifier's best-fit spectrum (red) to the input spectrum of SN 2008es (black). The recovered parameters are as shown in Table 4.4: $z = 0.3691 \pm 0.0004$, $t = 3.1 \pm 0.8$

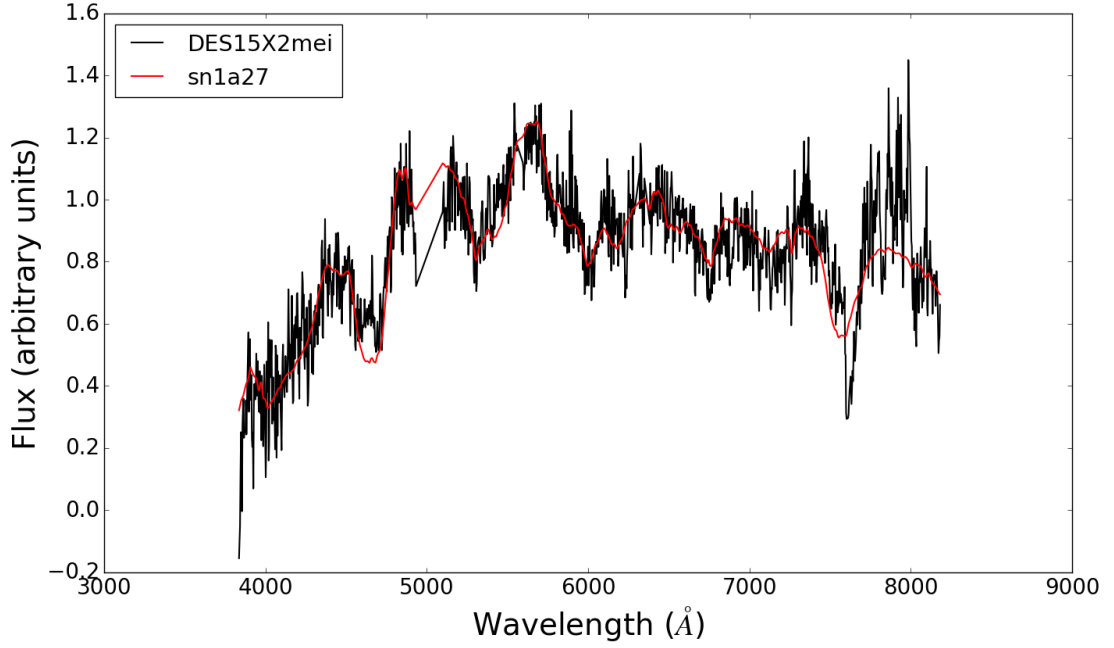


(b) Same as (a) but for SNID, with the recovered parameters shown in red above the plots (SN type and phase τ given in parentheses).

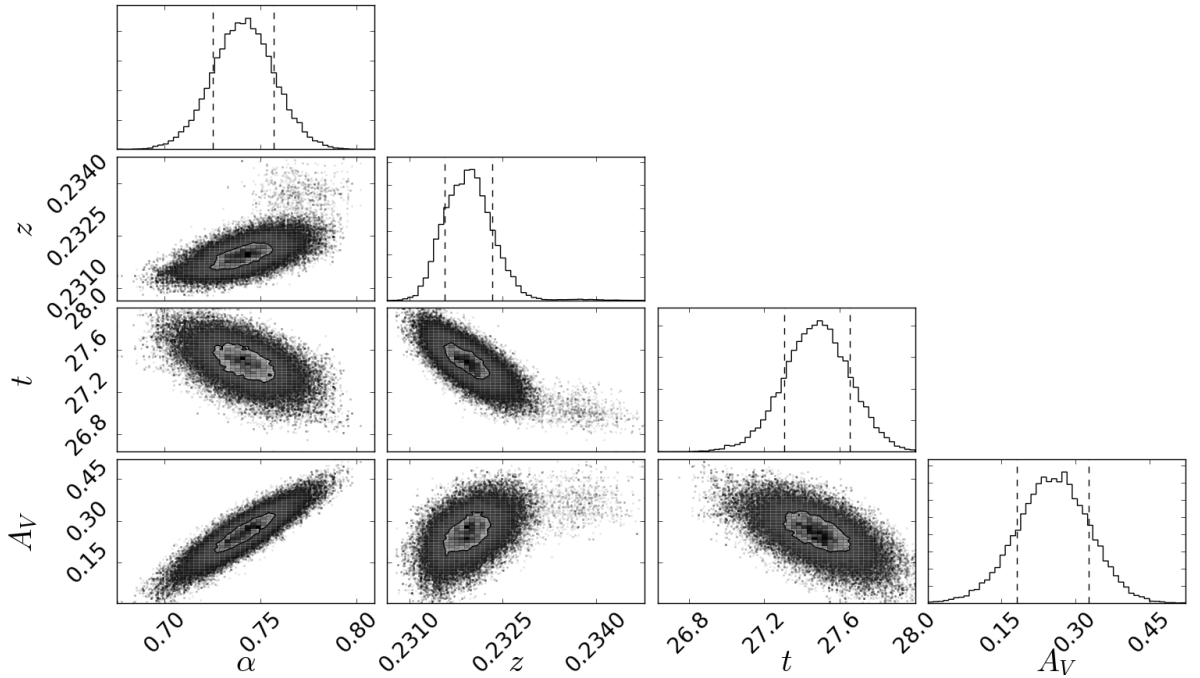
Figure C.10: Here, SNMC fits well while SNID fails badly.

C.3 Additional Figures from Chapter 6

Figures C.11 to C.13 show three of some of SNMC's well classified spectra together with the 1-D histograms and 1σ level contours of their recovered parameters.



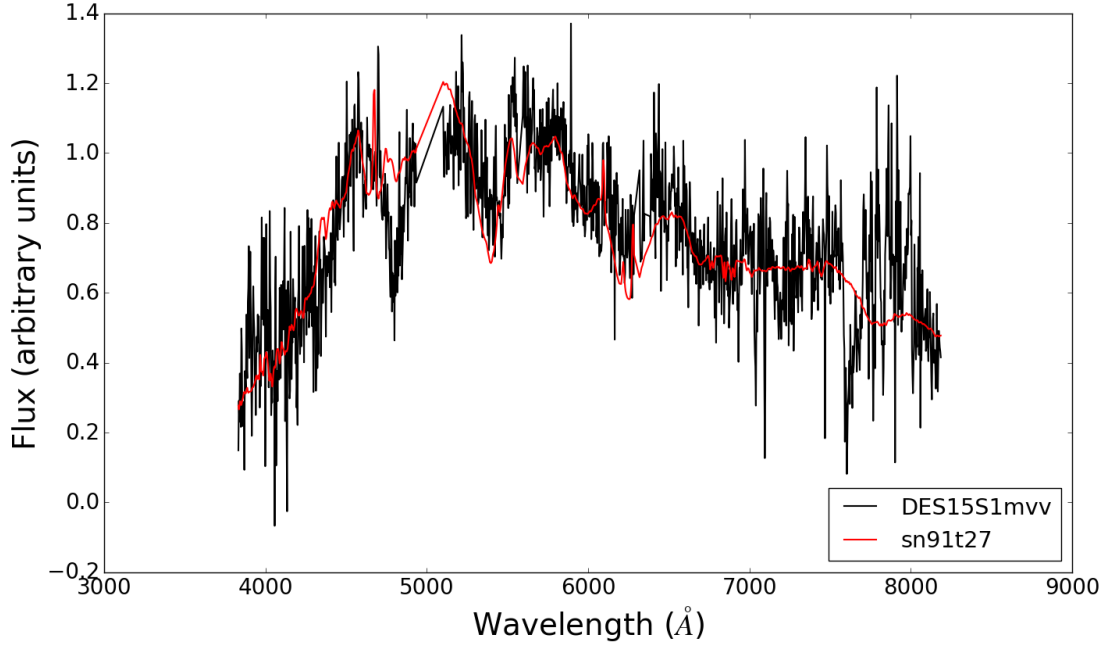
(a) Comparison of SNMC's best-fit spectrum (red) to the spectrum of the SN candidate DES15X2mei (black). The recovered SN type and galaxy type are SN Ia and E0 respectively, with the following corresponding MCMC best-fit parameters: $\alpha = 0.74 \pm 0.03$, $z = 0.2319 \pm 0.0004$, $t = 27.5 \pm 0.3$, $A_V = 0.3 \pm 0.1$. The label 'sn1a24' means the recovered SN type and t are SN Ia and 24 days, respectively.



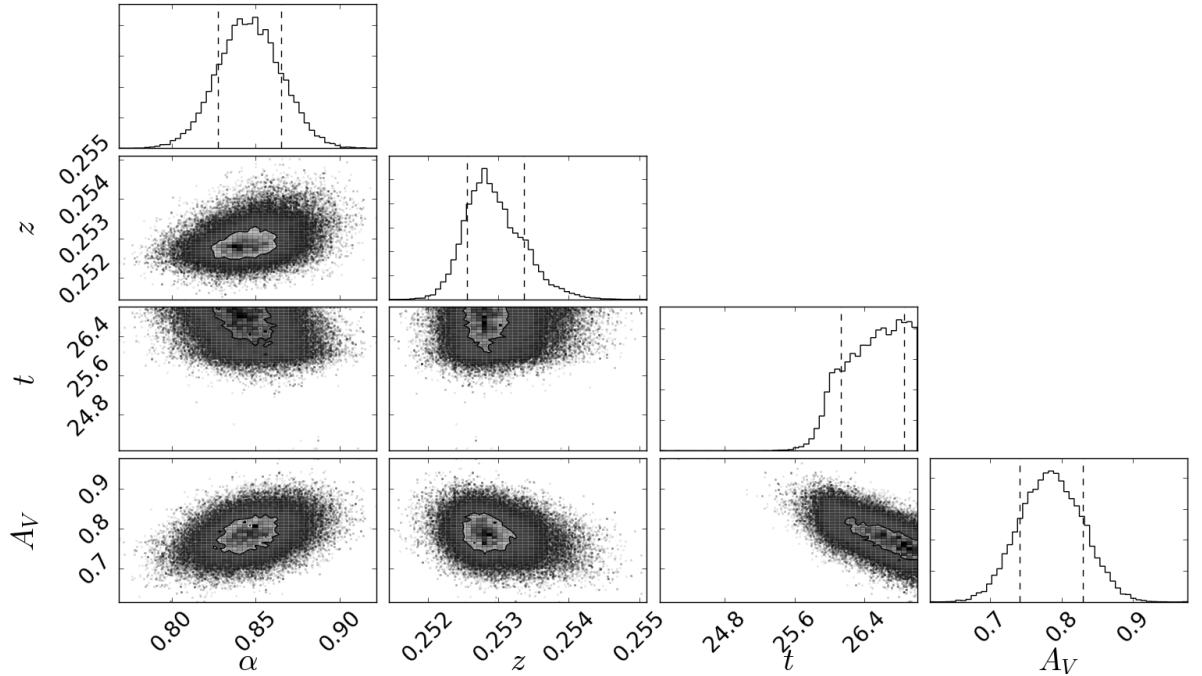
(b) 1-D histograms and 1σ level contour plots of SNMC's posterior distributions for α , z , t and A_V , estimated from the spectrum of DES15X2mei in (a). The vertical dotted lines represent the 1σ levels^a.

^a<http://corner.readthedocs.io/en/latest/pages/sigmas.html>

Figure C.11



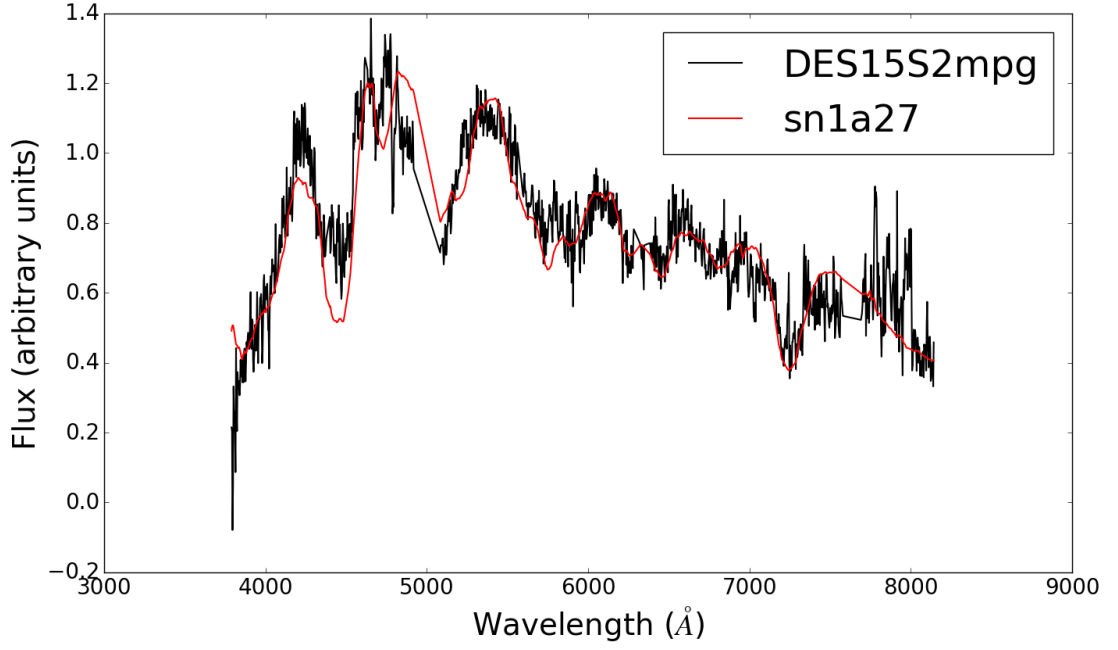
(a) Comparison of SNMC's best-fit spectrum (red) to the spectrum of the SN candidate DES15S1mvv (black). The recovered SN type and galaxy type are SN 91T-like and SB4 respectively, with the following corresponding MCMC best-fit parameters: $\alpha = 0.85 \pm 0.04$, $z = 0.253 \pm 0.004$, $t = 26.5 \pm 0.5$, $A_V = 0.8 \pm 0.3$. The label for the best-fit spectrum 'sn91t27' means the recovered SN type and epoch are SN 91T-like and $t = 27$ days.



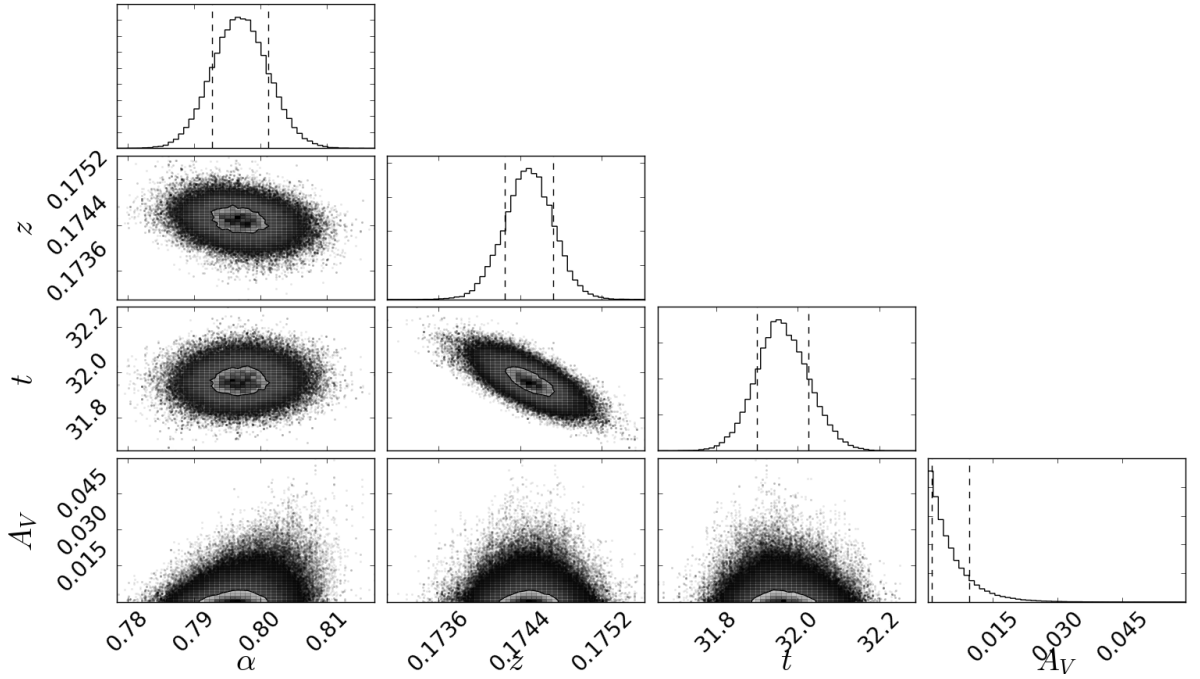
(b) 1-D histograms and 1σ level contour plots of SNMC's posterior distributions for α , z , t and A_V , estimated from the spectrum of DES15S1mvv in (a). The vertical dotted lines represent the 1σ levels^a.

^a<http://corner.readthedocs.io/en/latest/pages/sigmas.html>

Figure C.12



(a) Comparison of SNMC's best-fit spectrum (red) to the spectrum of the SN candidate DES15S2mpg (black). The recovered SN type and galaxy type are SN Ia and Sb respectively, with the following corresponding MCMC best-fit parameters: $\alpha = 0.81 \pm 0.02$, $z = 0.1798 \pm 0.003$, $t = 26.8 \pm 0.2$, $A_V = 0.002 \pm 0.002$.



(b) 1-D histograms and 1σ level contour plots of SNMC's posterior distributions for α , z , t and A_V , estimated from the spectrum of DES15S2mpg in (a). The vertical dotted lines represent the 1σ levels.

Figure C.13