SPECTROSCOPIC DETERMINATION OF THE LOW-REDSHIFT TYPE Ia SUPERNOVA RATE FROM THE SLOAN DIGITAL SKY SURVEY

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Abstract

Supernova rates (SNRs) are directly coupled to high-mass stellar birth and evolution. As such, they are one of the few direct measures of the history of cosmic stellar evolution. In this paper, we describe a probabilistic technique for identifying supernovae within spectroscopic samples of galaxies. We present a study of 52 Type Ia supernovae ranging in age from −14 days to +40 days extracted from a parent sample of ∼350,000 spectra from the SDSS DR5. We find an SNR of 0.47±0.08 (Statistical)±0.10 (Systematic) at a redshift of ⟨z⟩ = 0.1. This value is higher than other values at low redshift at the 1σ level, but is consistent at the 3σ level. In this paper, we demonstrate the potential for the described approach to detect supernovae in future spectroscopic surveys.

Key words: methods: statistical - supernovae: general - techniques: spectroscopic

Online-only material: color figures

1. INTRODUCTION

Over the last decade, the study of the properties of Type Ia supernovae (abbreviated SNe in captions and equations) has become one of the fundamental tools used in observational cosmology. With peak luminosities on the order of $M_V \sim -19.3$, Type Ia supernovae can be observed out to redshifts of $z > 1$. This enables a broad range of science: enrichment of the interstellar medium (Sivanandam et al. 2009), characterization of the expansion history of the universe (Schmidt et al. 1998; Perlmutter et al. 1999), and understanding the physics of how progenitors transition into supernovae (Mannucci et al. 2006). This scientific potential has led to a number of surveys of supernovae in the local and distant universe (Wood-Vasey et al. 2004; Pritchet for The Snls Collaboration 2005; Hamuy et al. 2006; Miknaitis et al. 2007; Frieman et al. 2008; Hicken et al. 2009).

The primary method for detecting and characterizing supernovae is through repeated imaging of the same region of the sky spread over several months or years. By difference imaging multiple epochs (Alard & Lupton 1998), host galaxies can be subtracted, revealing candidate supernovae that can then be classified by additional imaging or spectroscopy. Madgwick et al. (2003) demonstrated that supernovae can also be identified in an analogous way from spectroscopic observations by subtracting the underlying host galaxy spectrum. In this case, the detection and classification of the supernova can be derived from a single observation, with a direct measure of the redshift, type, and age of the supernova. While less efficient than imaging techniques (as the observational cost of obtaining the spectroscopic data is much larger), this approach can be applied serendipitously to any spectroscopic survey to study, for example, supernovae rates (SNRs) in the local and distant universe.

Madgwick et al. (2003) found a local SNR of $R_{3\nu}(z < 0.25) = 0.4 \pm h^2$SNu,8 which is consistent with existing measures but was based on only 19 supernovae. In this paper, we expand upon this work to undertake a systematic study of Type Ia supernovae as found in the Sloan Digital Sky Survey (SDSS) main galaxy sample. We consider the statistical and systematic uncertainties that arise when classifying supernovae from the SDSS spectra, the efficiency of the detection technique (as a function of redshift, galaxy type, and signal-to-noise ratio ($S/N$)), and discuss ways to minimize the impact of systematics due to misclassification of narrow and broad emission-line galaxies. Applying these techniques to the 362,431 spectra from the SDSS DR5 sample, we characterize the supernova population and SNRs for redshifts $z < 0.1$. For calculations dependent on cosmology, we use $\Omega_m = 0.3$, $\Omega_\Lambda = 0.7$, and $H_0 = 70$ km s$^{-1}$ Mpc$^{-1}$ throughout this paper.

2. SPECTROSCOPIC SAMPLES

Throughout this paper, we use galaxy samples based on the DR5 (Adelman-McCarthy et al. 2007) release of the SDSS. The SDSS spectra are observed through 3′′ diameter fibers using a multi-object spectrograph with a spectral resolution of $R \approx 1800$ and a wavelength range of 3800–9200 Å. Galaxy spectroscopic target selection (Strauss et al. 2002) is based on imaging from the SDSS camera (Gunn et al. 1998) using the 2.5 m telescope (Gunn et al. 2006) at Apache Point Observatory. A discussion of the photometric and spectroscopic pipelines and the spectrophotometric calibration can be found in Stoughton et al. (2002). The SDSS photometric system is described in detail in Fukugita et al. (1996), Hogg et al. (2001), Smith et al. (2002), Ivezić et al. (2004), Tucker et al. (2006), and

8 $SNu = 1/10^{15}L_{B}/100yr$ is the definition for the $B$-band-weighted supernova rate used throughout this paper.
Padmanabhan et al. (2008); the filter response curves are given in Fukugita et al. (1996). The astrometric calibration is described in Pier et al. (2003).

For the purpose of this work, we assume that the SDSS spectra have accurate relative spectrophotometric calibration. Discussion of the quality of the SDSS spectrophotometric calibration can be found in Adelman-McCarthy et al. (2007). For this paper, however, we note that the rms dispersion in the absolute spectrophotometry for the SDSS is $\sigma = 0.04$ mag based on the differences between photometric fiber magnitudes and magnitudes synthesized from the SDSS spectrophotometry (http://www.sdss.org/DR6/products/spectra/spectrophotometry .html) and that, at worst, the spectra show a 5% variation in the relative spectrophotometric calibration at the blue end of the spectrum. All spectra are shifted to the rest frame and corrected for Galactic extinction using the dust maps of Schlegel et al. (1998) and applying the reddening curve from Cardelli et al. (1989) with near ultraviolet updates by O’Donnell (1994). The spectra are re-sampled to 3 Å linear bins to match the resolution of the available supernova templates.

Two galaxy samples were constructed for use in this paper (see Table 1 for a synopsis of these samples). We applied the following criteria to the 1,048,960 spectra in the DR5 database: a redshift limit of $z < 0.2$, a positive redshift, and the requirement that type derived from the spectrum was not “STAR.” The redshift limit for these data was applied in order to exclude the high-redshift luminous red galaxy (LRG) population. We wish to avoid segments of the sample dominated by LRGs as this population would have significantly different eigenspectra compared to the low-redshift galaxy sample.

Further we define a statistical sample for use in determining the cosmic SNR using the selection criteria used to create the Pitt-CMU Value Added Catalog (VAC; http://nvogre.astro.washington.edu/vac). In the SDSS, each observed spectrum has a set of binary flags set either by the data acquisition system or the reduction pipeline. The statistical sample was assembled using the flags associated with the redshift measurement of the object. These redshift flags being set can indicate problems with the spectrum and are for this reason eliminated from the sample. See Stoughton et al. (2002) for complete descriptions of the flags. These criteria are as follows:

1. Spectroscopically classed as a galaxy (SPECTCLASS = 2).
2. The following redshift flags are set to zero:
   - Z_WARNING _LOC—confidence is low,
   - Z_WARNING_NO_SPEC—no spectrum,
   - Z_WARNING_NO_BLUE—no blue side spectrum,
   - Z_WARNING_NO_RED—no red side spectrum.
3. Redshift status flags not set to 0 or 1 (0 = not measured, 1 = failed).
4. Redshift confidence level greater than 70%.
5. The spectrum is the highest S/N example of the object.

This statistical sample contains 362,431 unique objects. We note that these criteria are less strict than those employed in building the SDSS main galaxy sample (Strauss et al. 2002) and provide more objects for analysis. All derived attributes (e.g., apparent magnitudes, absolute magnitudes, and signal-to-noise measurements) are taken from the VAC. In the redshift range $0.1 < z < 0.2$, the VAC is 4% larger than the main sample using the same criteria. Although the two samples are selected using different criteria, a contributing factor to the VAC being larger is that the main sample is magnitude limited to $m_{\text{fiber}} < 19.0$ where the VAC has no such limit.

We randomly select a subset of galaxies from the statistical sample to determine the efficiency and systematics of the supernova detection and classification method. No attempt was made to avoid spectra with supernova contribution already present. This should not, however, affect efficiency or systematics estimates, since only 0.025% of galaxies are expected to contain a supernova. The model sample is constructed by randomly selecting two thirds of the runs in the DR5 release which provides enough galaxies to capture the statistical properties of the statistical sample but saves compute and storage resources. This model sample consists of 234,638 galaxies.

For each galaxy in the model sample, a Type Ia supernova template is added to the galaxy spectrum (with the supernova age chosen at random from an interval of $-20$ to $+50$ days from peak brightness). The absolute luminosity of the supernova is sampled from the distribution of $B$-band peak brightnesses given in Dahlen et al. (2004). The luminosity is scaled to the observation time using the parameterization of the light curve introduced in Goldhaber et al. (2001). We assume a stretch factor $s = 1$ for all synthetic supernovae. The spectra are then shifted and dimmed based on the redshift of the host galaxy.

Host galaxy extinction and reddening are applied by choosing a $V$-band absorption in magnitudes, $A_V$, from an exponential distribution, $P(A_V) = e^{-A_V/m}$, with the scaling parameter, $m = 0.33 \pm 0.09$, and using the Cardelli et al. (1989) reddening curve with updates to the near ultraviolet by O’Donnell (1994). Galactic reddening is applied using the Schlegel et al. (1998) Galactic reddening maps. As before, we assume a Cardelli et al. (1989) with O’Donnell (1994) reddening curve. We do not attempt to correlate supernova properties with host spectral properties.

3. METHOD

As described in Madgwick et al. (2003), our goal is to identify supernova within SDSS spectra. In this section, we describe our extension of the initial work of Madgwick et al. (2003). We approach this problem by requiring that our technique must satisfy the following attributes.

1. Computational efficiency. It must be computationally tractable to classify spectra in real time.
2. Efficient and complete detection. Detection must produce a few false positives and reject none of the candidates with more than four matched spectral features above the noise in the spectrum.
3. Quantifiable selection effects. No method will be exact, but to be useful, the method must have uncertainties which can be quantified.

| Sample | Number of Spectra | $N_{\text{SNe}}$ | Notes |
|--------|-------------------|------------------|-------|
| Statistical sample | 362,431 | 52 | G = 7, S = 7, B = 43 |
| Model sample | 234,638 | N/A | |

Notes. The first column gives the name of the sample as used in the text. Column 2 gives the sample size. In Column 3, we report the number of supernova candidates in the sample. This is the total number of candidates. The number listed here includes all selection criteria listed in Section 3.1. This number increases to 57 if no age cutoff is applied. Any notes are given in Column 4. In particular, the number of gold (G), silver (S), and bronze (B) candidates are noted. For a description of how the gold, silver, and bronze candidates are defined, see Section 3.1.
Principal component analysis (PCA) of galaxy spectra has shown that, in the visible regime, spectral energy distributions (SEDs) are inherently low dimensional (Connolly et al. 1995; Fekkes et al. 1996; Yip et al. 2004a). The spectra can, therefore, be represented by a small set of orthogonal components or eigenspectra. Yip et al. (2004a) demonstrated that between eight and eleven components are sufficient to fully describe the spectral variation within galaxy spectra in the SDSS (York et al. 2000). This results in a reduction in the complexity or dimensionality of the spectroscopic data by a factor of 400 and means that it is computationally tractable to fit host galaxy spectra jointly with any additional components (e.g., template supernovae Ia spectra). Alternative approaches such as fitting a spectral synthesis model (e.g., Bruzual & Charlot 2003) can be computationally expensive due to the breadth of the phase space that must be searched.

Based on the PCA approach, we express each spectrum as a linear combination of eigenspectra, \( e_{ij} \), scaled by an expansion coefficient, \( a_i \), where \( j \) indexes the wavelength bins. In this way the spectrum, \( f_j \), is represented by

\[
\hat{f}_j = \sum_{i=0}^{n-1} a_i e_{ij},
\]

where \( n \) is the number of spectral eigencomponents used. If the number of spectral components is less than the dimensionality of the data, the reconstructed spectrum is said to be a “lossy” compression. However, as the PCA is a variance-weighted statistic, this truncated expansion preferentially suppresses the noise within a spectrum.

We use the first eight (\( n = 8 \)) eigenspectra from Yip et al. (2004a) to fit the galaxy contribution. Figure 1 shows the first six galaxy eigenspectra and the two QSO eigenspectra used in the fitting. At this level of truncation, the contribution from higher order eigenspectra is typically less than 1% of the total flux.

From this expansion, we calculate the error-weighted log likelihood (\( \log(L) \)) value for each spectrum:

\[
\log(L) = \sum_{j=0}^{m} (f_j - \hat{f}_j)/\sigma_j^2,
\]

where \( f_j \) and \( \hat{f}_j \) are the spectrum flux and the reconstructed flux, respectively, and \( \sigma_j \) is the rms error as a function of wavelength.

To determine the best-fit supernova spectrum, we refit each SED using the same eigenspectra together with a series of supernova templates taken from Nugent et al. (1997). These 91 supernova templates range in age, defined as the rest-frame time from peak brightness, from \(-20 \) days to \(+70 \) days. An example of supernova templates is shown in Figure 2. For each of the supernova templates, we recalculate the \( \log(L) \) value and take the minimum \( \log(L) \) to be the best-fit age. An example of this procedure is shown in Figure 3 together with the resulting residuals after subtracting the galaxy model.

In cases where there is strong nuclear activity, the galaxy eigenspectra underfit broad emission line features. Due to a conspiracy between Si II and O I absorption, Type Ia supernova spectra (Branch et al. 1982) produce an apparent emission feature at \( \sim 6500 \) Å. This effect creates false positives from confusion between this absorption feature and broad Hα emission in Type 1 Seyfert-like galaxies. Even though the fraction of the active galactic nucleus is small (5%-10%), this leads to several tens of thousands of false positives. We therefore include an additional component in the galaxy model based on the first two QSO eigenspectra from Yip et al. (2004b). The QSO component fits the broad and narrow emission which decreases the number of false positives by an order of magnitude.

### 3.1. Selection Criteria for Supernova Candidates

To determine the low-redshift SNR, we must discriminate reliably between those galaxy spectra that contain supernovae and those that do not. To accomplish this, we consider two
We define the signal to noise as

\[ S/N = \frac{\sum_{j=4500\text{Å}}^{6000\text{Å}} R_j}{\sqrt{\sum_{j=4500\text{Å}}^{6000\text{Å}} \sigma_j^2}}, \]

where \( R_j = f_j - \sum_{i=0}^{n} a_i e_{ij} \) is the residual flux after subtracting the underlying galaxy and QSO components, and \( n \) is the number of eigenspectra used to model the galaxy and QSO spectra (in our case the first two QSO components were used). The signal to noise is measured over the wavelength interval 4500–6000 Å in order to exclude contamination of the flux due to H\( \alpha \).

Following the method outlined in Richards et al. (2004), we use a nonparametric Bayes classifier (NBC) to select supernova candidates. For a general two class system, the NBC can be written as

\[ P(C_1|x) = \frac{p(x|C_1)P(C_1)}{p(x|C_1)P(C_1) + p(x|C_2)P(C_2)}. \]

For our problem, \( C_1 \) is the supernova candidate class (SN) and \( C_2 \) is the class of galaxies without supernovae (GAL). The variable \( x \) is the two-dimensional location of a source within the \( 5\sigma - \log(L) \) space. The priors \( P(C_1) \) and \( P(C_2) \) are the probability of drawing a galaxy with a supernova \((P(SN))\) and without a supernova \((P(GAL))\), respectively. We choose \( P(SN) = 3/10000 \). This value is consistent with estimates from historical SNR calculations and with the numbers we see when the algorithm is run on the statistical sample. This is a two class system, so \( P(GAL) = 1 - P(SN) \).

We estimate the relative likelihoods for the NBC using the statistical and model samples described in the previous section. Figure 4 shows the probability density distributions of the statistical and model samples within the \( 5\sigma - \log(L) \) space. The light color corresponds to high probability density and the dark color corresponds to low probability density. Overlaid
on these plots are contours of the value of $P(SN | \log(L))$ corresponding to $3\sigma$, $4\sigma$, and $5\sigma$ confidence levels that a source contains a supernova.

Probability density functions for the samples have been estimated by fitting a mixture of Gaussians using the FastMix package (Moore 1999). The probability $P(SN|x)$ is then derived from $P(SN | \log(L)/GAL)$ and $P(SN | \log(L)/SN)$. For our current work, we choose to classify a galaxy as a supernova candidate if $P(SN | \log(L)) \geq 0.9973$. This corresponds to a $3\sigma$ threshold. We further define a subset of supernovae the bronze, silver, and gold candidates (see Section 5) using thresholds of $3\sigma$, $4\sigma$, and $5\sigma$, respectively.

In addition to a cutoff in $P(SN | \log(L))$, the available supernovae template models require that all supernovae span $-20 < \text{Age} < 70$ (i.e., the template spectra used in the model sample span a finite range in supernova age). To mitigate potential edge effects, we include only those supernovae with ages $-14 < \text{Age} < 40$ within our final candidates.

Finally, a cutoff is placed in both $\log(L)$ and $S/N$ to avoid catastrophic failures in the algorithm. These are generally due to objects that are not fit well by either galaxy or supernova templates. By inspection, conservative boundaries are set that exclude objects with both $\log(L) > 4$ and $S/N < 150$ (see Figure 5). This region is populated by extreme emission line galaxies where the emission lines influence the $\chi^2$-statistic such that a good fit is impossible, and objects for which the spectral calibration failed for one reason or another. These points are not rejected by the $P(SN | \log(L))$ cutoff because neither training set samples this area of parameter space well.

Together, these selection criteria provide a fully automated and probabilistic approach for selection of supernovae from galaxy spectra.

4. SIMULATED SPECTRA AND THE EFFICIENCY OF SUPERNOVA DETECTION

The statistical and systematic properties of our supernova detection and classification technique are determined through a Monte Carlo simulation using the model sample described in Section 2 (and Table 1).

4.1. Efficiency of Supernova Detection in SDSS Spectra

Host galaxy properties have a large influence on our algorithm’s ability to detect the resident supernova. Herein, we examine these properties and discuss their impact on measuring SNRs. Efficiencies are calculated by applying the selection criteria introduced in the previous section, i.e., we require that the output age is $-14 < \text{Age} < 40$, $P(SN | \log(L)) \geq 0.9973$, and the region with catastrophic failures is avoided. In the following sections, we examine the impact of host galaxy luminosity, redshift, supernova age, host galaxy color, and $S/N$ on the efficiency of the method.

4.2. Efficiency as Functions of Observables

Figure 6 shows the efficiency, defined as the ratio of the number of detected supernovae to the number of input supernovae, as a function of $r$-band absolute magnitude through the fiber, galaxy rest-frame color, age of the supernova, and redshift of the host galaxy.

As shown in Figure 6(a), supernova detection efficiency decreases with redshift (as the $S/N$ of the underlying spectra will decrease and the sampled galaxy populations will be intrinsically more luminous). The efficiency decreases rapidly beyond a redshift of $z > 0.07$, reaching 50% efficiency at around $z = 0.11$. From the efficiency–$S/N$ relation shown in Figure 7, we find that this rapid drop in efficiency corresponds to a median per pixel $r$-band $S/N$ of 50. This value is calculated by computing the $S/N$ for each pixel of the spectrum covered by the $r$-band filter and taking the median value over all pixels. At $z = 0.1$, the fraction of galaxy spectra with $S/N > 50$ is only 3%.

As expected, the efficiency of detection depends on the intrinsic luminosity of the host galaxy; as the luminosity of the host galaxy increases, the efficiency of isolating the supernovae decreases. The intrinsic peak luminosity for Type Ia supernovae reaches $M_V = -19.5$ (Gallagher et al. 2008) with underluminous supernovae scattering to $M_V \simeq -17.5$. At the bright end of the distribution the supernova dominates the luminosity of a typical galaxy. On the dim end, the typical galaxy dominates the total flux even when the supernova is at peak brightness. Figure 6(c) demonstrates this effect, showing the decrease in the efficiency of detecting supernovae remaining at about 75% to $M_{\text{fiber},e} = -18$ and then dropping quickly to 30% at $M_{\text{fiber},e} = -20$ (at which point the galaxy is contributing about 50% more light than the peak brightness SN).

One might expect the detection of supernovae to be independent of the color of the galaxy as there are spectral features distributed throughout the optical spectral range. Figure 6(b) shows, however, a color dependence in the detection efficiency such that supernova detection in red galaxies has a lower efficiency than for blue galaxies. This is due to the correlation between luminosity and intrinsic galaxy color. If the model sample is binned in absolute magnitude and the efficiencies replotted as a function of rest-frame color, the efficiency curve is flat but the normalization of that curve decreases with luminosity.
We also consider the efficiency as a function of supernova age in Figure 6(d). The integral of this histogram is the control time, $\tau$, which dictates the temporal window over which a supernova is detectable. As shown in Figure 6(d), the impact on efficiency occurs at early and late times when the supernova luminosity is closest to a minimum in our templates. For ages $-10 < \text{days} < +20$, the efficiency of supernova detection remains above 50%.

4.3. Signal-to-Noise Ratio

Based on the results described above, the most important efficiency indicator for the rate of supernova detection is that of the $S/N$ of the measured spectrum. The $S/N$ incorporates all of the dependencies on galaxy and supernova properties in the efficiency calculation. In each of the previous results, the drop in efficiency was related to a decrease in supernova $S/N$ (either absolute or relative to the galaxy luminosity). We therefore approximate the $S/N$ of the measured spectrum (including the supernova) as the median of the $S/N$s of the spectral bins in the $r$ passband. Figure 7 shows this efficiency as a function of median $r$-band $S/N$. As expected, the efficiency decreases with lower $S/N$, but remains above 50% down to $S/N = 23$ (which represents 70% of galaxies in the statistical sample).

5. APPLICATION TO SDSS

The algorithm described in Section 3 and the criteria from Section 3.1 were applied to the SDSS spectra from the DR5 statistical sample. To quantify the effectiveness of these techniques, we define subsamples of supernovae as a function of their classification probability. These supernovae, gold ($P(SN|L, \log(L)) > 0.99999943$), silver ($P(SN|L, \log(L)) > 0.99999943$), and bronze ($P(SN|L, \log(L)) > 0.99999943$), are identified with different colors and symbols in Figure 8.
Figure 8. Six examples of supernova candidates selected using the algorithm presented in this paper. The top two panes are for the “gold” sample, the middle two panes are for the “silver” sample, and the bottom two panes are for the “bronze” sample. The residual after the galaxy component subtracted is shown in black. The best-fit template is plotted in red and the rms uncertainty as reported by the pipeline is plotted in gray. The plate, MJD, and fiber are provided in the upper right of each pane.

(0.999937) and bronze \( (P(SN|S, \log(L)) > 0.9973) \), are shown in Figure 5. Visual inspection of these supernova candidates shows that gold candidates have many (greater than four) spectral features in the residual fit that are coincident with the best-fit template, silver candidates have at least three features that match the template and exceed the noise in the spectrum, and bronze class sources have at least three well-fit features, but with the per pixel signal at the level of the per pixel error. Figure 8 shows examples of these three classes. The bronze candidate spectra were smoothed with a five bin top-hat filter to show more clearly how the low-frequency signal matches the template spectra.

For reference, we show the distribution in color and redshift for the statistical and candidate samples. Figure 9(a) shows that the color distribution is similar for both populations. The redshift distributions, however, are quite different. As seen in Figure 9(b), the candidate supernova population has a much flatter distribution than the parent population. This is likely due simply to the increased efficiency of finding supernovae in nearby galaxies. Note that the redshift distribution is truncated at \( z = 0.2 \). In Figure 10, we show the distribution of measured ages from the peak for the candidate supernovae. Obviously, the number of candidates is not large enough to fully sample the range of templates, but we do recover supernovae over essentially the entire window of possible ages.

5.1. Direct Confirmation of Supernovae

To validate the accuracy of the detection algorithm we undertake a number of tests on the derived spectra. The first of these is a comparison of the fiber magnitudes measured from the photometry with synthetic magnitudes calculated from the observed spectra. The fiber magnitudes are computed by placing a \( 3'' \) diameter aperture at the centroid of the seeing convolved object. The synthetic magnitudes are calculated by integrating the product of the filter transmission curves and the observed spectrum. We obtain the fiber and synthetic magnitudes in the \( r \) band for all objects in the full sample. In the absence of transient events, one would expect the two values to be equivalent. Figure 11 shows the difference between the fiber and synthetic magnitudes in the \( r \) band for all objects in the full sample. In the absence of transient events, one would expect the two values to be equivalent. Figure 11 shows the difference between the fiber and synthetic magnitudes as a function of fiber magnitude (for the statistical sample). The supernova candidates are plotted as circles. Yellow symbols are gold candidates, gray symbols are silver candidates, and red symbols are bronze candidates.

Figure 9. Comparison of supernova candidate distributions to the distribution of the statistical sample. (a) Comparison of fiber \( u-r \) color distribution for the statistical sample (solid line) and supernovae (dotted line). The magnitudes are absolute \( k \)-corrected fiber magnitudes. (b) Comparison of redshift distribution for the statistical sample (solid line) and supernovae (dotted line).
Figure 10. Distribution of measured rest-frame ages for the 52 SN candidates used in the rate calculation.

Figure 11. For all detected supernovae, we plot the difference in the $r$-band fiber and synthetic magnitudes against the $r$-band fiber magnitude. Fiber magnitudes are aperture magnitudes calculated from the photometry. Synthetic magnitudes are calculated by integrating the observed spectrum convolved with fiducial filter curves. The density plot is the entire SDSS DR5 spectroscopic sample. Gold candidates are plotted in yellow (diamonds), silver in gray (squares), and bronze in red (circles). In general, the spectra are brighter than their photometric counterparts, suggesting an extra flux contribution.

(A color version of this figure is available in the online journal.)

Of the 52 supernovae used in the rate calculation, all show a brightening in the synthetic magnitude as compared to the fiber magnitude. This is consistent with additional flux contribution from transient sources.

Of the 52 supernova candidates, all show a brightening in the spectrum relative to the photometry and multi-epoch spectroscopic observations showing supernova signatures, strongly indicate that the algorithm is selecting real supernova signatures.

6. TYPE IA LUMINOSITY-WEIGHTED SUPERNOVA RATE

Based on the efficiency calculations in Section 4 and the supernovae identified in the statistical sample, we calculate the
SNR for galaxies at a mean redshift of $z = 0.1$. The luminosity-weighted SNR ($r_L$) is traditionally defined as

$$\langle N_{SN} \rangle = r_L \times S,$$

(5)

where $\langle N_{SN} \rangle$ is the expected number of Type Ia supernovae and $S$ is the sum of the probability of detecting a supernova in a given galaxy, weighted by the luminosity in the $B$ band, in units of $L_\odot$:

$$S = \sum_{i=1}^{N_{gal}} L_i \epsilon_i \tau_i.$$

(6)

The sum runs over all galaxies in the statistical sample. $L_i$ is the rest-frame $B$-band luminosity in units of $L_\odot$, and $\tau_i$ is the time period we are sensitive to identify supernova. The efficiency $\epsilon$ is a function of redshift, apparent magnitude, luminosity, galaxy type, seeing, and other observables. As in Dilday et al. (2008), we avoid the complexity involved in modeling the efficiency as a joint distribution of all characteristics by using the efficiency as a function of $S/N$. The control time $\tau$ is then defined as

$$\tau = \sum_{z=0.0}^{z=0.2} \epsilon(z) \times \int_{t_1}^{t_2} \epsilon(t, z) dt,$$

(7)

where $t$ is the age of the supernova with peak brightness occurring at $t = 0$ and $\epsilon(t)$ is the efficiency as a function of supernova age. We use the window $-14 \leq z \leq 40$ as this is the interval over which $\epsilon(t)$ was evaluated. We use a redshift-averaged value of $\tau$ using the redshift distribution for the statistical sample (see Figure 5) to obtain the typical detection window for the survey as a whole. We evaluate this integral to obtain the fraction of a year over which the algorithm is sensitive to detecting Type Ia supernovae. For this survey $\tau = 0.1$ yr.

We calculate the luminosity weight in two ways. First, we consider only the contribution of flux from within the fiber. This takes a local view of the luminosity weighting by allowing for only stellar light encompassed by the fiber. A second approach is to rescale the luminosity by the covering factor of the fiber relative to the galaxy total flux. This covering factor is calculated as

$$cf = 10^{(M_{model} - M_{fiber})/2.5}.$$

(8)

In the above equation, the $k$-corrected, absolute magnitudes may be in any band but, as the galaxy sample is $r$-band-selected, we use the $r$ band to calculate the covering factor. In some cases, however, the fiber magnitude is brighter than the model magnitude due to blending of overlapping galaxies. In order to avoid these issues, we discard galaxies where $M_{fiber} < M_{model}$. This situation is encountered in $0.5\%$ of the galaxy sample. This results in $360,698$ galaxies used in the covering factor method of calculating the rate.

In general, using the flux through the fiber is preferable since there is no dependence on photometric model fitting. The model fitting could potentially introduce a bias in the covering factor as a function of galaxy morphology. For this reason, we use the fiber-based $B$-band luminosity-weighted rate for comparison to other published values and in reporting the rate as a function of galaxy color.

We further subdivide the sample into red and blue subsets using a color cutoff of $M_a - M_r = 2.2$ to estimate the SNR as a function of galaxy spectral type.strateva et al. (2001) suggest that a value of 2.2 gives optimal separation between early- and late-type galaxies. We use this value to separate the statistical sample into an early (red) and late (blue) galaxy sample. In this case, these values have been calculated using the measured fiber flux in order to maximize the size of the supernova sample.

Solving Equation (5) for $r_L$, and applying the calculated values of $S$ and $\langle N_{SN} \rangle$, we obtain a value of $r_L$ given a value from Equation (4). In order to get the best estimate of the rate, given the variance inherent in the sample, we select many values of the cutoff: $0.9973 \leq P(SN|\frac{r_L}{\epsilon z}, \log(L)) \leq 1.0$. The lower limit corresponds to $3\sigma$ and is the cutoff used in producing the plots presented in Figures 6 and 7. In practice, new efficiency curves are calculated for each selected value of the probability cutoff. We calculate the rate for 100 different selections of the selection cutoff. We then find the inverse variance weighted mean of the rates. This weighting was chosen with the expectation that more stringent cutoffs would produce less candidates but be less likely to include false positives. If there is no contamination from interlopers, even at the $3\sigma$ level, the inverse variance weighting should have no impact on the mean. See Section 6.1.4 for the discussion of systematic error contribution of varying the threshold. The weighted mean yields $r_L = 0.472 \pm 0.08 h_70^{\text{SNu}}$ which assumes that the SNR is proportional to the rest-frame $B$-band galaxy luminosity. The statistical error is the central 68.3% Poisson confidence interval assuming the median number of supernova candidates (45) for the 100 data points. The SNR values and details of the errors are summarized in Table 2. The SNRs for the red and blue samples are $r_L(\text{red}) = 0.379 \pm 0.08$ and $r_L(\text{blue}) = 0.394 \pm 0.12$, respectively. As seen in other samples, the luminosity-weighted rate from blue galaxies is higher than that from red galaxies; however, they are consistent within errors.

6.1. Systematic Errors in Supernovae Rates

We consider potential systematics in our derived values of $r_L$.

6.1.1. Color Corrections to a $B$-band Luminosity

We compare the derived $B$ luminosity for the host galaxies using two relations for color transformations between the SDSS and Johnson $B$ passbands. These color corrections are taken from Jester et al. (2005) and those done by Robert Lupton9 for the SDSS. Specifically, the corrections are

$$B = g + 0.33 \times (g - r) + 0.20$$

Jester et al. (2005),

$$B = g + 0.3130 \times (g - r) + 0.2271.$$

(9)

(10)

The difference between these solutions amounts to $\pm 3\%$ in the derived luminosities.

6.1.2. Type Ib/c Contamination

Since we use only Type Ia templates for candidate selection, it is possible that Type Ib/c supernovae could be a source of false positives. To test how sensitive this algorithm is to Type Ib/c interlopers, we simulate perfect galaxy subtraction by fitting our set of Type Ia templates directly to Type Ib/c templates (Levan et al. 2005) at various signal-to-noise levels. We can then plot the results of the fit directly in the same space as that used for candidate selection. Figure 13 shows where the Type Ib/c spectra fall on the log$(L) - S/N$ space. Many are excluded by

9 http://www.sdss.org/dr7/algorithms/sdssUBVRITransform.htmlk#Lupton2005
the Type Ib candidates in the region of the discriminate space occupied are well separated from the candidates in our sample. If we select candidates. Many of the candidates are ruled out by the threshold.

Figure 13. Type Ia candidates (circles) plotted with the results of fitting Type Ib/c spectra with Type Ia templates (stars). The size of the point indicates the age of the Type Ib/c candidate. The dotted line is the 3σ threshold applied when selecting candidates. Many of the candidates are ruled out by the threshold.

6.1.3. Efficiency Uncertainty

The efficiency histogram has an intrinsic uncertainty due to shot noise (based on the number of galaxies in each bin). Propagating Poisson errors on the S/N efficiency shows an uncertainty of not more than 2% in the rate calculation when 1σ errors are considered. We adopt a value of 2% for the contribution of uncertainty in efficiency.  

6.1.4. Uncertainty in Threshold Cutoff

The value of Equation (4) gives a good discriminant for distinguishing SN candidates, but the choice of the cutoff value influences the calculated value of the rate. To get a handle on how much this affects the rate value, we calculate rates using 100 different choices for the cutoff. We then calculate the inverse variance-weighted mean of the rate given the 100 data points. We then quantify the scatter by calculating the standard deviation of the sample greater than the mean and the standard deviation of the sample less than the mean. This analysis gives a positive scatter of 9.5% and a negative scatter of 7.5%. The fact that

the scatter to higher values of the rate is larger than the scatter to lower values suggests that there is some contamination from interlopers, but that when several values of the cutoff are taken, the effect on the measured rate is small.

Adding these contributions in quadrature, this estimate of the systematic error corresponds to +10.2% -8.3%.

7. COMPARISON TO MODELS

Many Type Ia supernova rate (SNR\text{Ia}) measures have recently appeared in the literature, often at higher redshift than previously sampled. Measures at high redshift (z > 1) are generally given in units of the co-moving volumetric element. In order to directly compare the rate derived in this paper with those in the literature, we convert luminosity-weighted rates to volumetric rates using the B-band luminosity density. As in Horesh et al. (2008) we use the redshift-dependent form \( f_B(z) = (1.03 + 1.76 \times z) \times 10^8 \text{L}_\odot \text{Mpc}^{-3} \) from Botticella et al. (2008). Table 3 is a collation of SNR\text{Ia} from the literature. We have ordered them in mean redshift to facilitate comparison of values at similar distances.

The cosmic SNR is notoriously difficult to measure as the number of events is usually small, the systematics are numerous and hard to correct for, and even the data on a per object basis can be less than ideal because of their transient nature. All these factors contribute to large errors, which make differentiation between different predictions difficult.

Two formulations of the analytic SNR\text{Ia} are typically used. The delay time distribution (DTD) formulation can be expressed using the notation of Greggio (2005); the SNR\text{Ia}(t) is defined as:

\[
\text{SNR}_{\text{Ia}}(t) = k_\nu \int_{\tau_i}^{\min(t, \tau_e)} A_{\text{Ia}}(t - \tau) \rho(t - \tau) f_{\text{Ia}}(\tau) d\tau,  \tag{11}
\]

where \( k_\nu \) is the normalization of the initial mass function (taken to be 2.83 for the Salpeter IMF), \( A_{\text{Ia}} \) is the efficiency of the progenitor channel, \( \rho \) is the cosmic star formation rate, and \( f_{\text{Ia}} \) is the distribution of times between birth and explosion also denoted as DTD\text{Ia}. \( A_{\text{Ia}} \) is typically taken to be constant with time, but in general can evolve with the stellar population.

The “A+B” model formalized in Sullivan et al. (2006) scales a tardy component and a prompt component based on the integrated stellar mass buildup and instantaneous star formation rate, respectively. Using the notation of Hopkins & Beacom (2006),

\[
\text{SNR}_{\text{Ia}} = A \rho_\star(t) + B \dot{\rho}_\star(t). \tag{12}
\]

Both the DTD and “A+B” methods can have short and long timescale contributions to the total SNR\text{Ia} at any given time, but the DTD formulation allows much more latitude in the spectrum of the delay times. Hopkins & Beacom (2006) modified the

### Table 2

| Method     | Value (SNu) | System Error (SNu) | Statistical Error (SNu) | N\text{SN} | N\text{SN} |
|------------|-------------|--------------------|-------------------------|------------|------------|
| Covering factor | 0.454       | +0.046             | -0.038                  | 44         | 51         |
| Fiber      | 0.472       | +0.048             | -0.039                  | 45         | 52         |
| Red        | 0.379       | +0.039             | -0.031                  | 32         | 36         |
| Blue       | 0.394       | +0.040             | -0.033                  | 13         | 16         |

Notes. Column 1 describes the method used, the value of the rate is reported in Column 2, and systematic and statistical errors are shown in Columns 3 and 4. Column 5 contains the median number of supernova candidates in the samples used to calculate the weighted mean of the rate. Finally, we report the number of candidates used in each of the methods in Column 6.
Table 3
Compilation of Volumetric Supernova Rates from the Literature

| Min(\(z\)) | Max(\(z\)) | \(\langle z \rangle\) | Rate\(^1\) | Statistical Error | Systematic Error | \(N_{SN}\) | Reference\(^2\) |
|-----------|-----------|----------------|-----------|------------------|-----------------|----------|----------------|
| 0.0       | 0.0       | 0.0            | 2.8       | -0.9             | 0.9             | 70       | g,e            |
| 0.025     | 0.075     | 0.05           | 2.78      | +0.12            | -0.83           | 0.15     | -0.00         | ~15         | p             |
| 0.0       | 0.12      | 0.09           | 2.9       | +0.9             | -0.7            | 0.2      | -0.0          | 17          | f             |
| 0.0       | 0.19      | 0.098          | 3.12      | +1.58            | +1.38           | 19       | h,e           |
| 0.075     | 0.125     | 0.01           | 2.59      | +0.52            | -0.44           | 0.18     | -0.01         | ~25         | p             |
| 0.0       | 0.2       | 0.1            | 5.69      | +0.98            | -0.85           | 0.98     | -0.47         | 52          | q             |
| 0.0       | 0.3       | 0.13           | 2.0       | +0.7             | -0.5            | 0.5      | -0.5          | 14          | e             |
| 0.02      | 0.2       | 0.14           | 3.43      | +2.7             | +1.6            | +1.1     | -0.8          | 4           | i,e           |
| 0.125     | 0.175     | 0.15           | 3.07      | +0.38            | -0.34           | +0.35    | -0.05         | ~100        | p             |
| 0.0       | 0.3       | 0.15           | 3.2       | +2.3             | +2.3            | +0.7     | -0.6          | 1.95        | n             |
| 0.175     | 0.225     | 0.2            | 3.48      | +3.3             | +3.3            | +0.82    | -0.07         | ~175        | p             |
| 0.225     | 0.275     | 0.25           | 3.65      | +0.31            | -0.28           | +1.02    | -0.12         | ~200        | p             |
| 0.0       | 0.5       | 0.25           | 0.0       | +2.4             | -0.0            | 0        | b             |
| 0.18      | 0.37      | 0.25           | 2.86      | 1                | j,e            |
| 0.275     | 0.325     | 0.3            | 4.34      | +0.37            | -0.34           | +3.96    | -0.16         | ~200        | p             |
| 0.3       | 0.4       | 0.35           | 3.4       | +1.9             | -1.9            | +0.7     | -0.3          | 4.01        | n             |
| 0.25      | 0.50      | 0.38           | 6.52      | 3                | k,e           |
| 0.2       | 0.6       | 0.4            | 6.9       | +1.4             | +1.7            | +1.2     | -0.4          | 5.11        | n             |
| 0.2       | 0.6       | 0.4            | 5.3       | +1.9             | +1.7            | 8        | i,e           |
| 0.4       | 0.5       | 0.45           | 3.1       | +1.5             | -1.5            | +1.0     | -0.4          | 5.44        | a             |
| 0.25      | 0.6       | 0.46           | 4.8       | +1.7             | -1.7            | 8        | i,e           |
| 0.2       | 0.6       | 0.47           | 8.0       | +1.7             | +2.7            | +1.6     | -2.6          | 8.8         | c             |
| 0.2       | 0.6       | 0.47           | 4.2       | +0.6             | -0.6            | +1.3     | -0.9          | 73          | d             |
| 0.5       | 0.6       | 0.55           | 3.2       | +1.4             | -1.4            | +0.7     | -0.7          | 6.49        | n             |
| 0.25      | 0.85      | 0.55           | 5.4       | +0.74            | -0.66           | +0.64    | -0.82         | 37          | m             |
| 0.6       | 0.7       | 0.65           | 4.9       | +1.7             | +1.7            | +1.4     | -0.8          | 10.09       | n             |
| 0.7       | 0.8       | 0.75           | 6.8       | +2.1             | -2.1            | +2.3     | -1.4          | 14.29       | n             |
| 0.5       | 1.0       | 0.75           | 4.3       | +1.8             | -3.2            | 5.5      | b             |
| 0.6       | 1.0       | 0.8            | 15.7      | +4.4             | -2.5            | +7.5     | -5.3          | 14          | o             |
| 0.6       | 1.0       | 0.8            | 9.3       | +2.5             | +2.5            | 18.33    | a             |
| 0.6       | 1.0       | 0.83           | 13.0      | +3.3             | +2.7            | +7.3     | -5.1          | 23.5        | c             |
| 0.8       | 0.9       | 0.85           | 7.8       | +2.2             | +2.2            | +3.1     | -1.6          | 15.43       | n             |
| 0.87      | 1.27      | 0.9            | 9.32      | +2.7             | +1.7            | 5        | j,e           |
| 0.9       | 1.0       | 0.95           | 7.6       | +2.5             | +2.1            | +1.2     | -2.6          | 13.21       | n             |
| 1.0       | 1.1       | 1.05           | 7.9       | +2.8             | -2.8            | +3.6     | -4.1          | 11.01       | n             |
| 1.0       | 1.4       | 1.2            | 7.5       | +3.3             | +3.3            | 8.87     | a             |
| 1.0       | 1.4       | 1.2            | 11.5      | +4.7             | -2.6            | +3.2     | -4.4          | 6           | o             |
| 1.0       | 1.4       | 1.21           | 13.2      | +3.6             | -2.9            | +3.8     | -3.2          | 20.2        | c             |
| 1.0       | 1.5       | 1.25           | 10.5      | +4.5             | -5.6            | 10.0     | b             |
| 1.4       | 1.7       | 1.55           | 1.2       | +2.8             | -1.2            | 0.35     | a             |
| 1.4       | 1.8       | 1.6            | 4.4       | +3.2             | -2.5            | +1.4     | -1.1          | 2           | o             |
| 1.4       | 1.8       | 1.61           | 4.2       | +3.9             | -2.1            | +1.4     | -1.4          | 3.1         | c             |
| 1.5       | 2.0       | 1.75           | 8.1       | +2.9             | -6.0            | 3.0      | b             |

Notes. Column 1 shows the minimum redshift, Column 2 the maximum redshift, Column 3 the average redshift, Column 4 the volumetric rate, Column 5 the statistical error, Column 6 the systematic error, Column 7 the number of SNe used in the measurement, and Column 8 contains the reference code (see footnote 2).

1 \(10^{-5}\text{SNe (Mpc/}\text{h}_{100}\text{)}^{-3}\text{yr}^{-1}\).

2 References. (a) Kuznetsova et al. 2008; (b) Poznanski et al. 2007; (c) Dahlen et al. 2008; (d) Neill et al. 2006; (e) Blanc et al. 2004; (f) Dilday et al. 2008; (g) Cappellaro et al. 1999; (h) Madgwick et al. 2003; (i) Hardin et al. 2000; (j) Gal-Yam et al. 2002; (k) Pain et al. 1996; (l) Tonry et al. 2003; (m) Pain et al. 2002; (n) Rodney & Tonry 2010; (o) Dahlen et al. 2004; (p) Dilday et al. 2010; (q) This paper.
both low and high redshifts, except for the point at 1.6, which was excluded by theory and data, overpredicts the rate at low redshift, but is within the error bars of all of them. A possible explanation of the higher measurement is that systematic effects tend to drive efficiency down. This leads to lower predicted rate measurements if these effects are not taken into account. This argues for a greater level of correction in the measurement from this paper as compared to others for 

\[ \text{SNR}_{\text{Ia}} = B \rho(t - \tau), \] 

where \( \tau \) is the delay time and is 3 Gyr.

Most DTD models rely on white dwarf binary systems as progenitors of Type Ia supernovae. However, it is not yet clear what the companion star is in these binary systems (Branch et al. 1995; Parthasarathy et al. 2007). Many groups have attempted to constrain DTDs (see Valiante et al. 2009; Rui et al. 2009; Totani et al. 2008; Hachisu et al. 2008; Greggio et al. 2008; and others). Recent measurements and models of the Type Ia DTD imply a featureless power law. The two main channels for Type Ia supernova progenitors are the single degenerate (SD; white dwarf with non-degenerate star, Whelan & Iben 1973) and double degenerate (DD; white dwarf binary, Iben & Tutukov 1984) scenarios. Models of the DD path show that a featureless power law is in agreement with the predicted DTD from the DD contribution (Totani et al. 2008, and references therein). Recently, it was shown that the SD path can produce a power-law DTD when both white dwarf + main sequence and white dwarf + red giant systems are considered (Hachisu et al. 2008). Direct measurements also support power-law DTDs for Type Ia supernovae (Totani et al. 2008; Pritchet et al. 2008). The power-law DTD is attractive because of its simplicity and the fact that it has contributions from both prompt and tardy components.

There is much discussion about which model for the evolution of the cosmic Type Ia SNR is the most appropriate, but even for power-law DTD models, the exponent of the power law \( \alpha \) is under debate. Theoretical values seem to point to a steep power law \( \alpha \approx -1.0 \) from both SD and DD channels (Hachisu et al. 2008; Yungelson & Livio 2000; Greggio 2005). The value as measured from data in Totani et al. (2008) agrees well with \( \alpha = -1.0 \), although Pritchet et al. (2008) find a shallower power law with \( \alpha \approx -0.5 \).

Changing from cosmic time to redshift and substituting a power law for the DTD model, we produce the following formula:

\[ \text{SNR}_{\text{Ia}}(z) = k_a \int_{0.3}^{t(z)} A_{\text{Ia}} \rho_a(t(z) - \tau) \tau^\alpha d\tau, \] 

where \( t(z) \) is the cosmic time at redshift \( z \), \( \rho_a \) is the cosmic star formation rate, \( t \) is the delay time, and \( \alpha \) is the slope of the power law. The product of \( k_a A_{\text{Ia}} \) is the constant for which we fit. It should be noted that we are not attempting to pin down any physical constants to higher precision than is already reported in the literature. The error bars used are statistical in all cases. No attempt has been made to cull the data of unreliable data points as the model fitting is intended to be illustrative rather than diagnostic. Figure 14 shows the data from the literature fit using the above models with \( \alpha = -1.0 \) (dashed line). This model, supported by theory and data, overpredicts the rate at both low and high redshifts, except for the point at \( z = 1.2 \) from Poznanski et al. (2007), who question the sharp decline in SNR at \( z \approx 1.5 \).

The A+B model appears to be too flat to account for both the rise in rate from \( z = 0 \) to \( z \approx 1.0 \) and the decline after \( z = 1.5 \). Since a large part of the best-fit A+B model is contributed by the prompt (\( \rho_a \)) component which does not peak until \( z \approx 2 \), it is not surprising that it continues to rise at high redshift. As mentioned above, Hopkins & Beacom (2006) noticed that a modified A+B model with \( \alpha = -1.0 \) and a delta function DTD do just as well in describing the observed downturn at \( z \approx 1 \). Figure 14 shows the best-fit Scannapieco & Bildsten (2005) model with a fixed delay time \( \tau_a = 3 \) Gyr. In this scenario, the accumulated stellar mass contributes nothing to the cosmic SNR. Instead, Type Ia supernovae arise after a fixed waiting period after a star formation event. This model is certainly an oversimplification as a broad distribution of assembly times surely exist for both the SD and DD scenarios.

The result from this work is higher than other measurements at low redshift, but is within the error bars of all of them. A possible explanation of the higher measurement is that systematic effects tend to drive efficiency down. This leads to lower predicted rate measurements if these effects are not taken into account. This argues for a greater level of correction in the measurement from this paper as compared to others for \( z \approx 0.3 \). The model that is closest to the low-redshift values is that of the constant delta function delay time model.

Current models for the DTD of Type Ia supernovae show good agreement with the data despite DTDs as different as power law and delta functions. The ability for observed SNRs to distinguish between these models will depend on reliable SNR measurements at \( z = 2.0 \).
Despite our measurement being slightly higher than others at similar redshift, there is still a significant rise in the Type Ia rate from our value at \( z = 0.1 \) to redshift of unity. One possible explanation for this trend is that we were able to incorporate many contributors to the efficiency calculation including realistic estimates of host extinction and peak supernova luminosity. Almost any modeled physical effect will tend to drive efficiency down resulting in higher recovered rate measurements. This study is based on one of the largest samples of supernovae in the local universe. Subdividing the galaxy population into red and blue components, we find no evidence for a difference in SNR as a function of host galaxy rest-frame color within errors.

The success of this study demonstrates that spectroscopic surveys can be used to identify and classify supernova and SNRs in the local and distant universe in a serendipitous manner. In the next generation of wide field spectroscopic surveys like BOSS (Schlegel et al. 2009), we will have the potential to detect thousands of supernovae in a much larger volume than that sampled by the SDSS spectroscopic sample.

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