Classifying Stripped Envelope Supernovae with Properly Synthesized Low-Resolution Spectra

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Abstract

After first light for the Rubin Observatory, millions of transient events and hundreds of supernovae are discovered each night. As a result, observatories around the world will have the chance to photographically and spectroscopically classify each supernova. While certain supernova can be classified through photometry alone, stripped envelope core collapse supernova must be classified through spectroscopy. Therefore, when it comes to the classifying power, R, of new spectrographs, it is important to know the minimum R necessary to classify these supernova to arbitrary accuracy. This work attempts to identify a critical spectral resolution R = 44/1 at which spectral classification of subtypes of supernovae becomes impossible. In the process, we provide a rigorous method to degrade space to simulate future low-resolution observations from existing high-resolution data. To classify the spectra we follow previous work of Williamson (2019) and first perform Principal Component Analysis (PCA) on spectra taken at similar phases of the supernova’s evolution. Subsequently, a Support Vector Machine (SVM) classifier is used on some of the principal components (PCs). The SVM score for each group of supernovae is recorded as we artificially degrade the spectra. We confirm that even at R = 5, the SVM score remains at -0.50, significantly above what would be expected for a random guess. -0.25. Further work includes measuring the performance of different data-driven classifiers as a function of spectral resolution.

Methodology

The entire dataset of well observed stripped envelope supernovae (SnIb, Type Ic, Type Ic-bl, and Type Ib) was obtained from work on by Williamson (2019) who provided an entirely data-driven classification scheme for stripped envelope supernovae and on prior work of our group (Zubair’s UofD Masters Thesis, Stripped Evelope Supenovae Classification at Low Spectral Resolution). Notably, in our group’s first exploration of the question, Zubair observed no critical spectral resolution below which the classifier was only as good as a random guess.

We attempt to reproduce the results of this thesis by examining the same dataset with the same classifier while using an adjusted method for degrading the spectra. The original method for degrading the spectra did not take the spectral PSF into account and instead simply re-binned the fluxes in order to maintain the original signal-to-noise ratio and also to avoid excessive information loss. The method we employ consorts the spectrum with a Gaussian with a FWHM that is proportional to the wavelength bin size and is inversely proportional to the degraded spectral resolution. R. The Gaussian serves as a generic spectral PSF, which enables the results of this work to be informative for those seeking to build new spectrographs.

SVM-PCA (Williamson 2019) is a machine learning based classifier that performs Principal Component Analysis (PCA) on the dataset. The result of the PCA is the principal components (PCs) and the PC coefficients. SVM-PCA feeds these PC coefficients into a linear support vector machine (SVM) classifier which constructs hyperplanes in the feature space which optimally classify the spectra.

The first five PCs explain ~80% of the variance of the data, and as a result we do not consider any other PCs. However, while Williamson selected two optimal components from the top five by visual inspection to build the SVM classifier, we improve on this method by performing classification in the 5-dimensional feature space of the top five PCs.

Results

In an effort to assess the minimum resolution required for stripped envelope supernova classification, we build on previous work by our group with the following improvements: (1) we performed the classification using the first five PCs while Williamson (2019) used two PCs for each phase which we shown to produce the best SVM score.

As expected, utilizing more PCs leads to a higher SVM score at every epoch and at every spectral resolution (see Figure 3), although an analysis of the feature space like what was done in Williamson & Morrell & Bianco (2019) becomes impossible.

The SVM scores for the classification of spectra at the native resolution were taken for all five PCs are:

<table>
<thead>
<tr>
<th>Phase</th>
<th>SVM Score</th>
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<tbody>
<tr>
<td>0</td>
<td>0.79 ± 0.10</td>
</tr>
<tr>
<td>1</td>
<td>0.79 ± 0.10</td>
</tr>
<tr>
<td>2</td>
<td>0.77 ± 0.09</td>
</tr>
<tr>
<td>3</td>
<td>0.77 ± 0.09</td>
</tr>
<tr>
<td>4</td>
<td>0.77 ± 0.09</td>
</tr>
<tr>
<td>5</td>
<td>0.77 ± 0.09</td>
</tr>
</tbody>
</table>

As the amount of information in the spectra is reduced as the resolution tends to 0, we expect the classifier to have no classifying power. That is, the random guess classification power which takes dataset imbalance into account is calculated by inputting only random noise into the SVM which yields 0.19 ± 0.09 ± 0.10 ± 0.23 ± 0.10 ± 0.22 ± 0.09 for each phase, respectively. In future work we will look at alternative classification techniques such as the work of Marcolli (2009) a deep learning based classifier, in order to further investigate the critical spectral resolution, as well as understand how accurate a classifier can be at this task.

Figure 2: A still from a GIF (animated GIF at the QR code on the right) shows each step of the classification for the original spectrum is shown in black, and the resulting convolution is shown in yellow. The kernel at each step is shown in blue, the peak of the kernel is denoted by the horizontal dashed black line, and the peak of the kernel is procedurally plotted in gray. Note how the kernel gets wider as it moves to the right.

Figure 3: The SVM score for the classifier is plotted as a function of the spectral resolution, R, of the degraded spectra. Each panel represents supernova of epochs 0.5, 5, 5.5, 10.5, and 15.5 days from top to bottom, respectively. The blue curves represent the SVM score when only two principal components were used. According Williamson (2019), the best two of the first five principal components were used as features in the classifier. The red curves represent the SVM score when all of the first five principal components were used. As a result, we are unable to find a minimum spectral resolution below which the SVM score is worse than chance. -0.25.

Conclusion

The results of this work surprisingly indicates that even at low resolution we retain some classification power. While there is an obvious degradation of the classification accuracy at R < 30 we continue to retain more accuracy than a random guess (~0.25). Even with four spectra bins our classification power is 0.4 ± 0.5 there are only four wavelength bins remaining in the spectra, which is less information than is contained in a photometric survey with the typical five passbands.

More work is required to test the limits of this observation. Adding more supernova to the dataset and trying different classifiers could help assess how robust this finding is.

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