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Need for Time-Based Classification of Supernovae

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Motivation

There are key characteristics that could contribute to supernovae classification that cannot be spotted at the spectrum at peak, but rather have to be observed throughout epochs. We illustrate this need to examine sequences of spectra rather than a single spectrum at peak in the following poster, and we also propose an approach to this examination.

Introduction

Supernovae (SNe) are violent explosions at the end of a star's life. Their duration is of the order of ~ 100 days and their apparent magnitude can reach that of an entire galaxy. The physical nature of these explosions is not yet fully understood, though it is accepted that there are several types of SNe whose underlying physical processes are distinct, as their spectra vary widely. All major SNe classes can be defined based on the peak spectral properties (Gal-Yam, 2017), and so the current classification relies on a single spectrum, usually near peak magnitude. This scheme disregards some characteristics during the evolution of the transient and so we see a need to develop a classification scheme that would relay on the entirety of the *spectral-temporal* energy distribution of the object.

Superfit is a tool which uses χ^2 statistics for the spectroscopic classification of supernovae within a host galaxy. Superfit is designed to classify a supernova at a specific point in time, meaning it looks at a particular spectrum and from a library of templates chooses the best fit object to match.

Method

We used 75 well-documented-in-time SNe. We interpolated each through time and from this interpolation took equally-spaced-in-time spectra to classify with Superfit. From each supernova we took about 50 spectra. We classified each spectrum separately and looked at the classification Superfit assigned to it to determine the recovery fraction for the correct SN type. We see that as time goes by the recovery fraction for type Ia and type II SNe does not significantly vary, however, when we look at type Ib, Ic, IIn or IIb it varies more significantly.

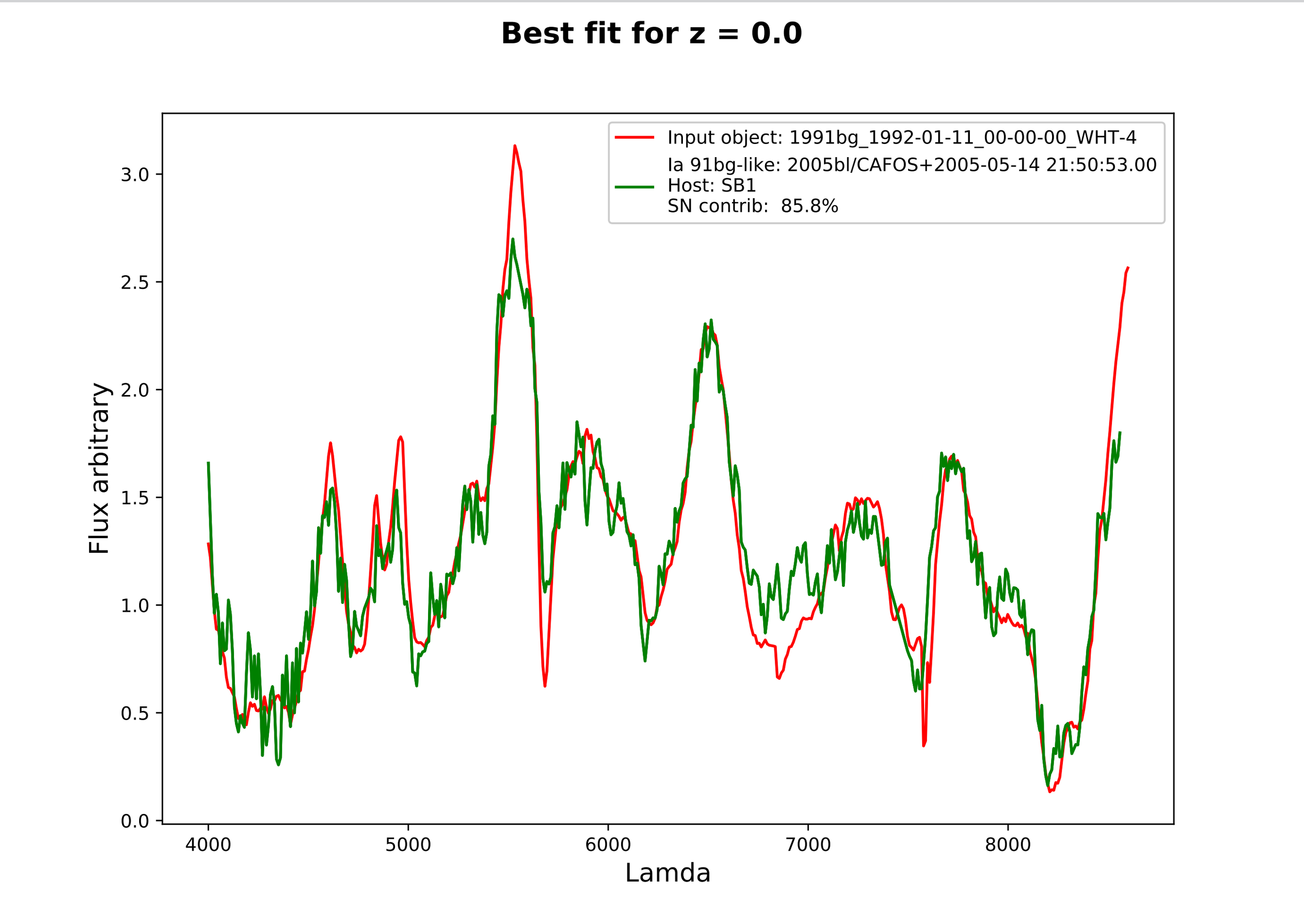

Figure 1: Typical Superfit output

Embedding a SN in 3D Space

Spectra and photometry of a SN are calibrated, dereddened and interpolated – by PyCoCo (Vincenzi et al., 2019) – to achieve an approximation of the entire distribution of energy in wavelength and time, $f(t, \lambda)$, for which we take the wavelength derivative of the logarithm, to emphasise spectral lines and diminish the effect of reddening (Sasdelli et al., 2014). The dimensionality of our data set is reduced using Expectation Maximization Principle Component Analysis (Bailey, 2012). We then build a dissimilarity matrix for this data set, using unsupervised random forest as a similarity measure, a method the has been successfully used for the comparison of spectra (Baron and Poznanski, 2016; Reis et al., 2018). These similarities are then embedded into 3D Euclidean space using tSNE (Maaten and Hinton, 2008).

Conclusions

Because there is a variation on the recovery fraction for SNe of several types we see a need for time-based spectroscopic classification of these types.

As seen in Fig. 2, the similarity measure we used embeds same-type SNe to separable clusters. This is an important test for the use of random forest as a similarity measure for SNe. For future work, it could be wise to test any correlations between the embedded space and physical properties (e.g. ratios of emission/absorption line, equivalent widths).

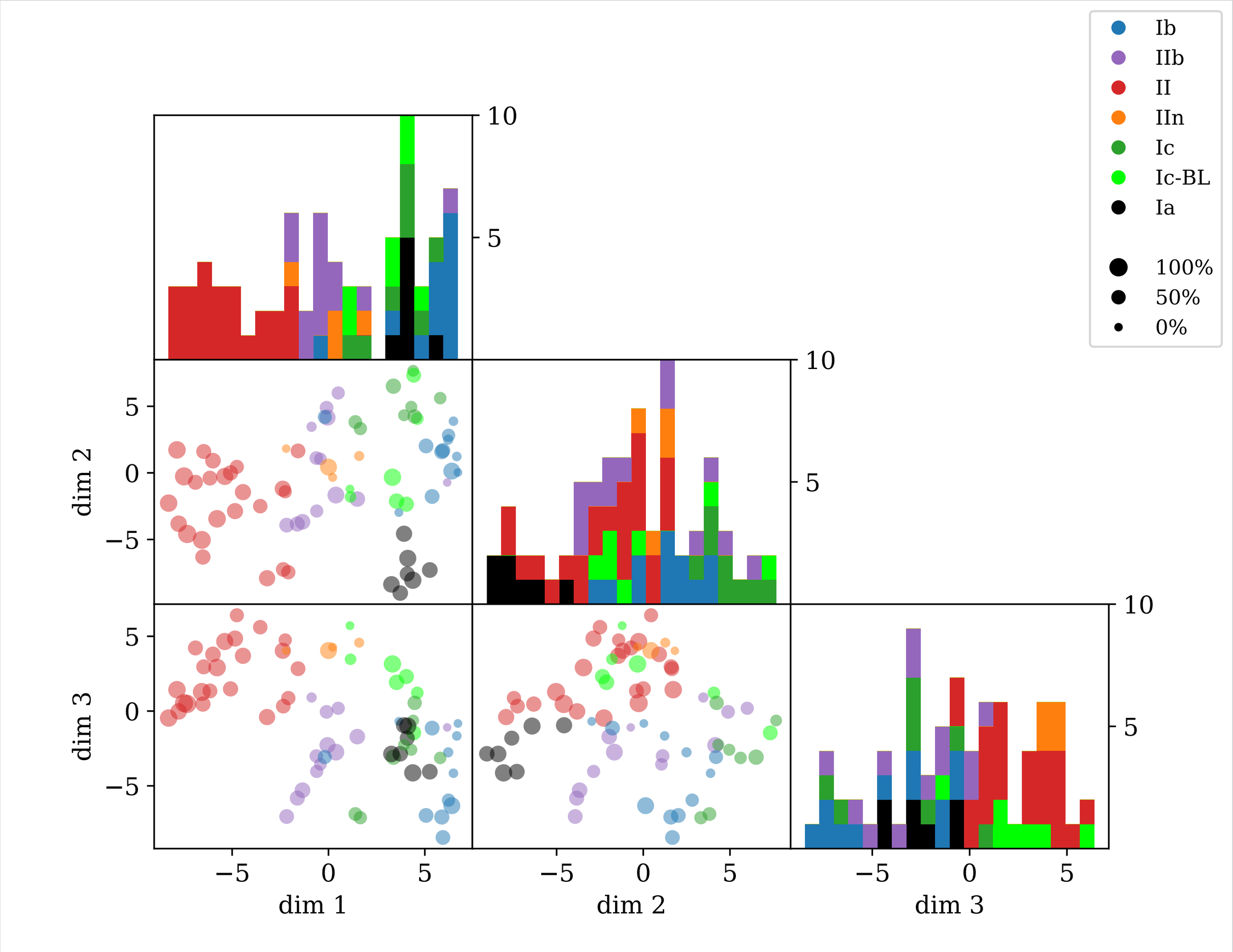

Figure 2: Corner plot of the tSNE embedding of the 75 SNe. Colors represent the type as assigned by a human expert relaying on the spectral sequence of the SN. Size represents the fraction of interpolated spectra correctly classified by Superfit. The axes are a priori meaningless.

References

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