Photometric classification of supernovae with ‘noisification’

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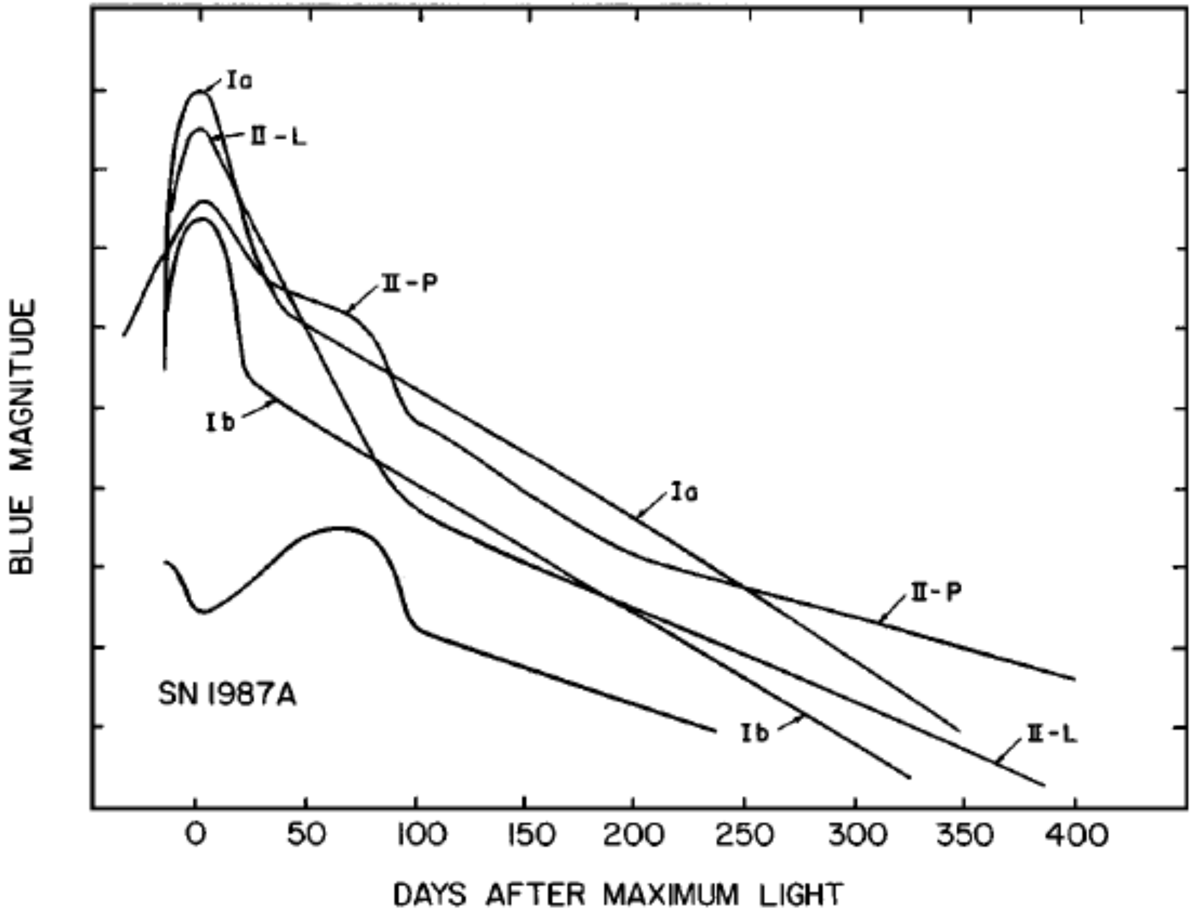
Introduction to ZTF

- The Zwicky Transient Facility (**ZTF**) is a wide-field, optical telescope in Palomar, searching for transients such as supernovae.
- The Bright Transient Survey (**BTS**) is a survey carried out by ZTF, which aims to spectroscopically classify supernovae brighter than ~19 mag.

What do we want to do?

- There are ~ 3000 **Type Ia supernovae** (SNe Ia) recorded in BTS.
- However, in the ZTF archive, there are likely thousands more! They just don't have a spectrum (because they are fainter than BTS follow up criteria).
- How else can we know?
- *… light curves!*

Filippenko (2017)



What do we want to do?

- **Photometric classification**: identifying the type of supernova based on the light curve, using **machine learning**.
- **Training sample**: labelled (i.e. with a spectrum and classification) BTS light curves.

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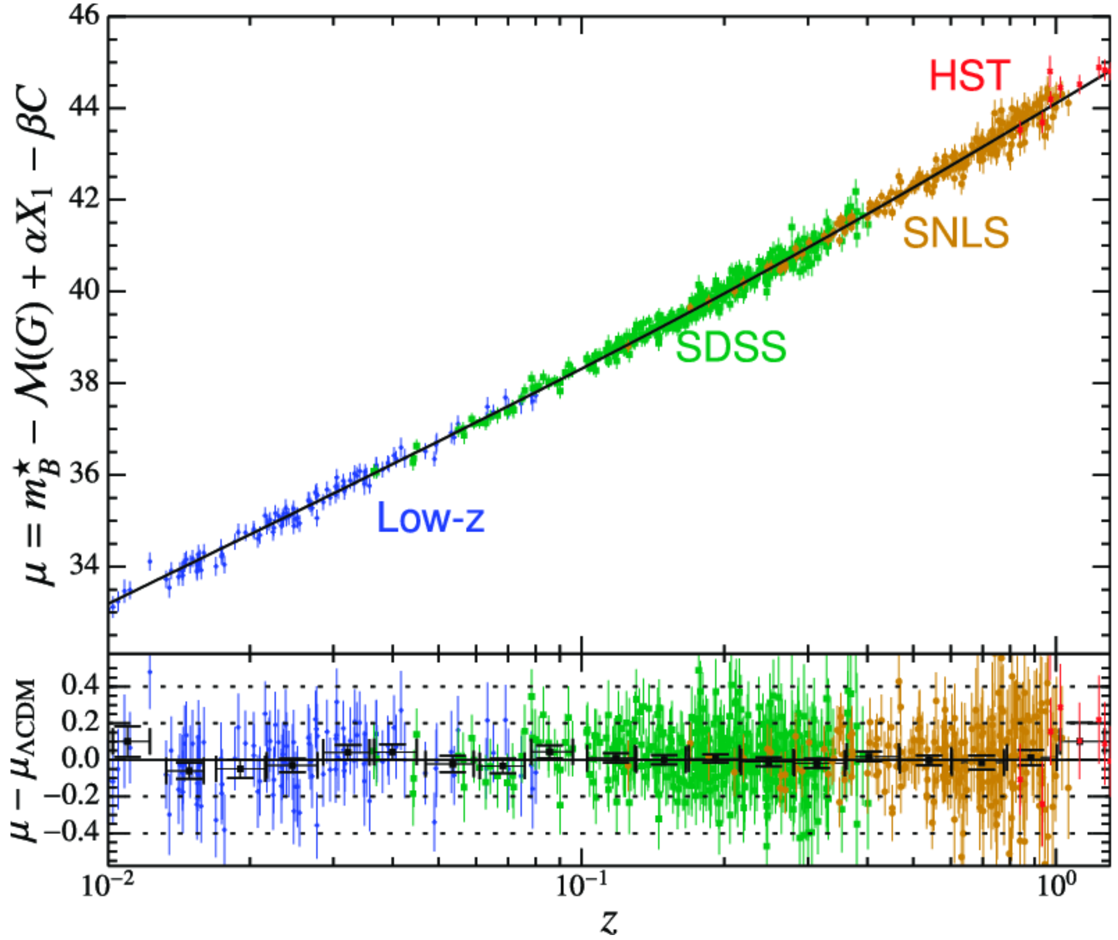
BUT, our final test set (unclassified objects in ZTF archive) will be higher *z*, fainter and noisier than the training sample.

- **Solution**: augment the training sample to be at higher *z*, and add noise (**noisification**).

Why do we want to do it?

- Create a SNe Ia sample more than 2 times larger than BTS, which is important for cosmology studies!
  - Cosmological parameters like H_0, w, σ_8
  - Mapping the universe, i.e. structure growth

Betoule, M., et al. (2014)



How are we going to do it?

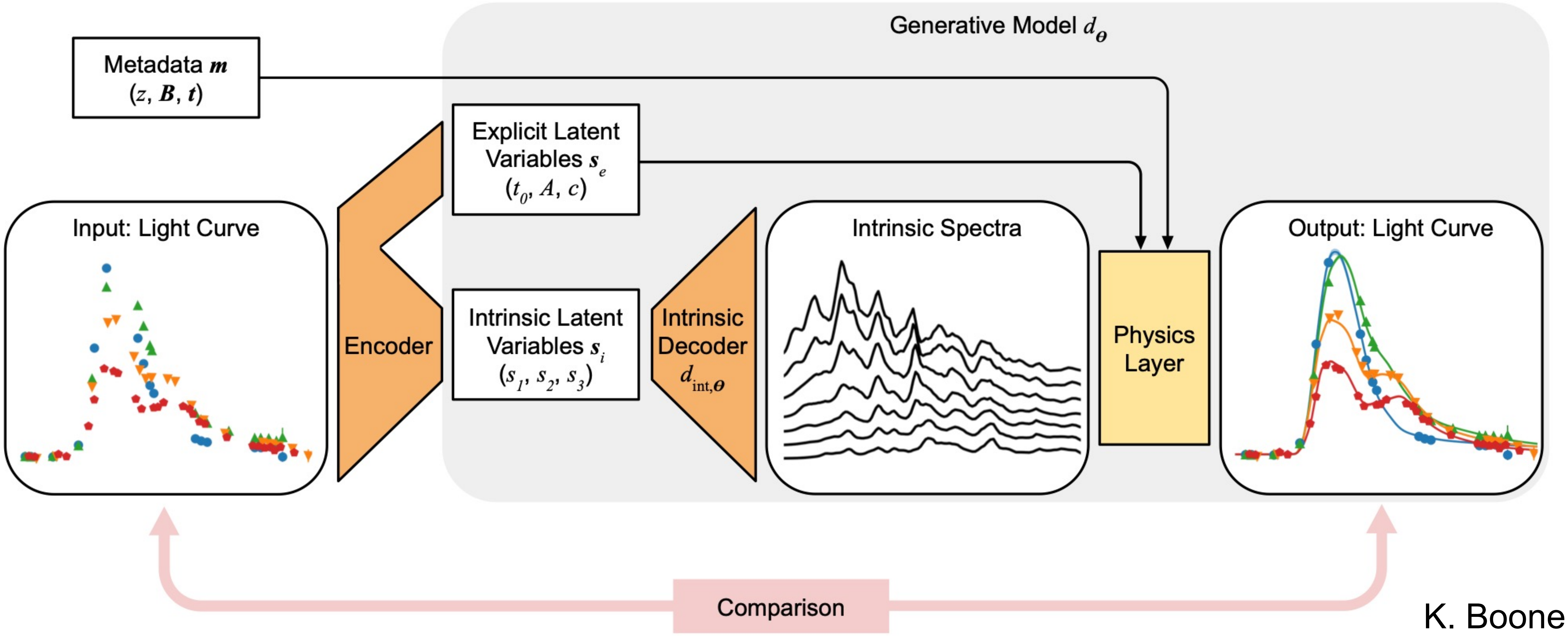
- Train a deep learning model using BTS light curves augmented with added noise.

ParSNIP – Parametrization of SuperNova Intrinsic Properties

(K. Boone, 2021)

- Test classification predictions with follow-up (for SNe with $z \sim 0.1$) and incorporate this into a statistical cosmological framework.

The ParSNIP model

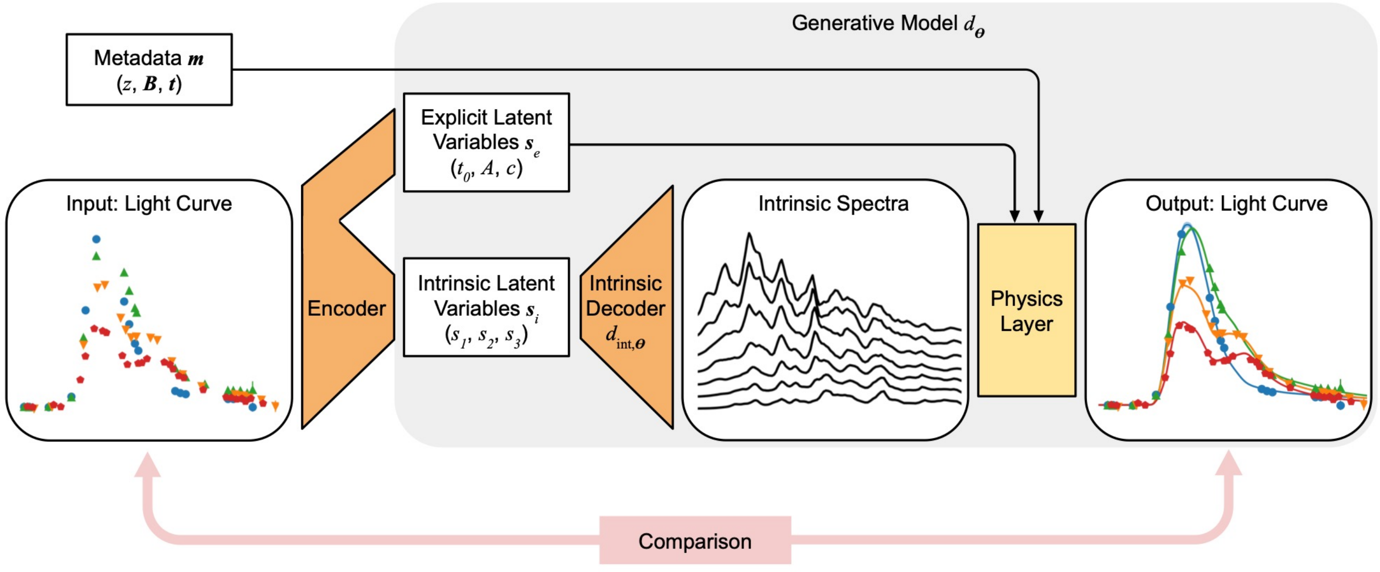


K. Boone, 2021

The ParSNIP model

- A modified version of a variational autoencoder (VAE)
  - Intrinsic variables (functional form is not known) – modelled with NN.
  - Extrinsic variables (A, c, t_0) – modelled with known functional form.

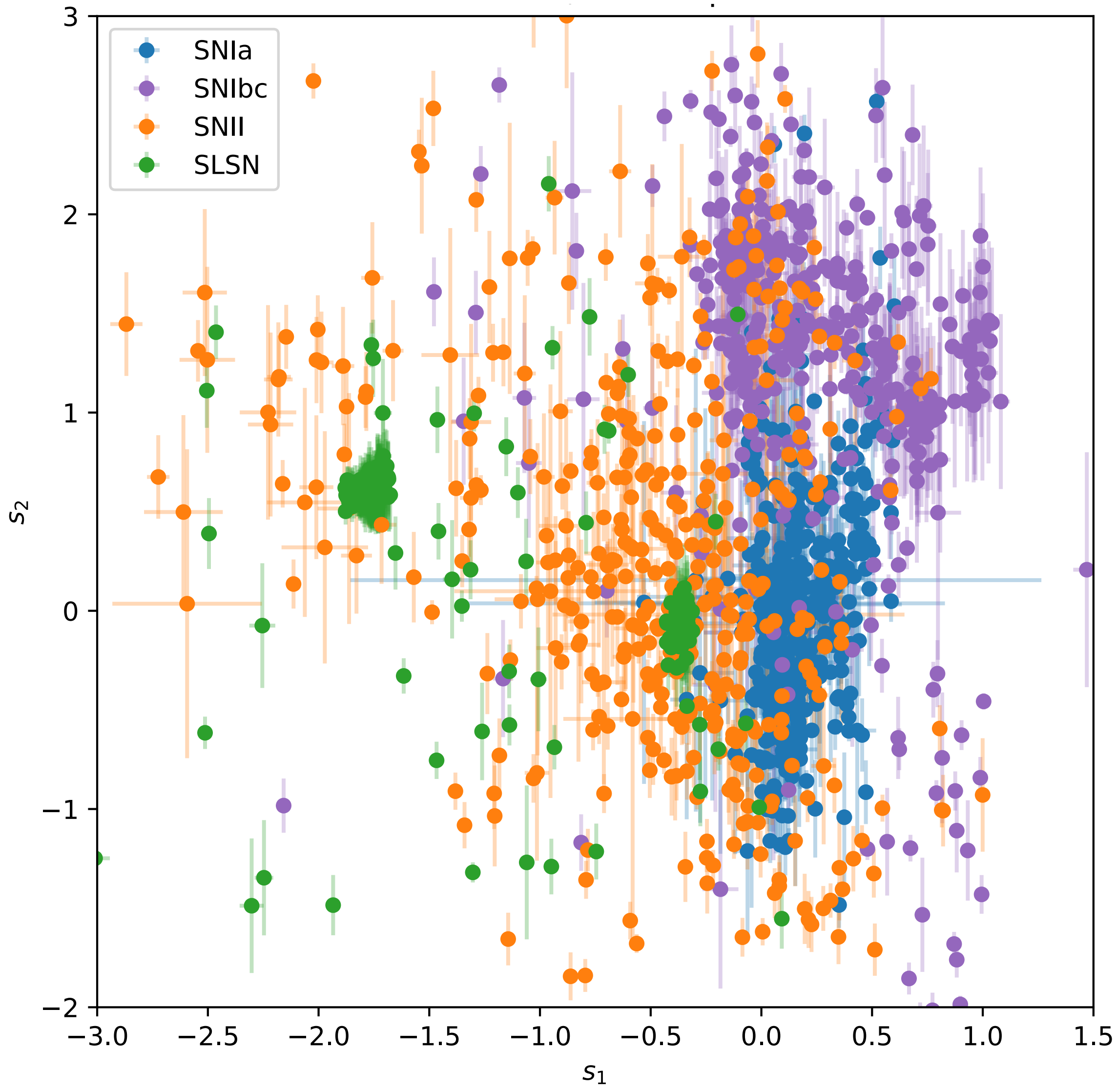
1. Uses a NN to predict the intrinsic spectra as a function of three intrinsic latent variables (s_1, s_2, s_3).
2. Intrinsic spectra are passed through a physics layer that models how the light propagates.
3. The physics layer also implements the explicit latent variables and metadata describing the observing conditions.



K. Boone, 2021

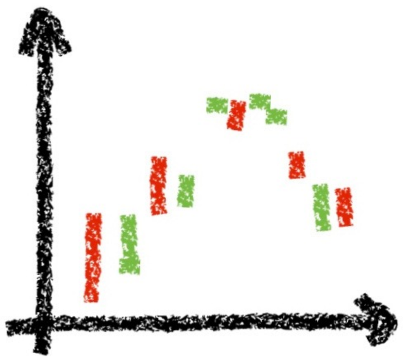
Classification

- **Currently**: using a Gradient Boosting Decision Tree to classify based on the intrinsic (s_1, s_2, s_3) and extrinsic (t_0, A, c) latent variables.
- **Future plans**: combine other information such as host galaxy info, light curve fit outputs and rates of SN types.



Training data

1. Get forced photometry light curves from classified objects in BTS (Simeon’s FPBot).



Training data

1. Get forced photometry light curves from classified objects in BTS (Simeon's FPBot).
2. Create higher redshift copies of the forced photometry light curves.
   - New z are selected randomly from a z^3 distribution (with a maximum of $z_{\mathrm{orig}} + 0.1$)
   - Light curve magnitudes are scaled to observed values at new z
   - Errors are scaled and noise is added
   - K-correction (where possible)

Training data

1. Get forced photometry light curves from classified objects in BTS (Simeon's FPBot).
2. Create higher redshift copies of the forced photometry light curves.
3. Apply a signal to noise cut.
   - At least 5 data points (including the peak) with S/N > 5.

■ = Optional

Training data

1. Get forced photometry light curves from classified objects in BTS (Simeon's FPBot).
2. Create higher redshift copies of the forced photometry light curves.
3. Apply a signal to noise cut.
4. Remove data points according to the 'density' of detections.
   - A sliding window of 5 days calculates the density of detections (per band).
   - Probabilistically remove points with high density, according to some threshold.

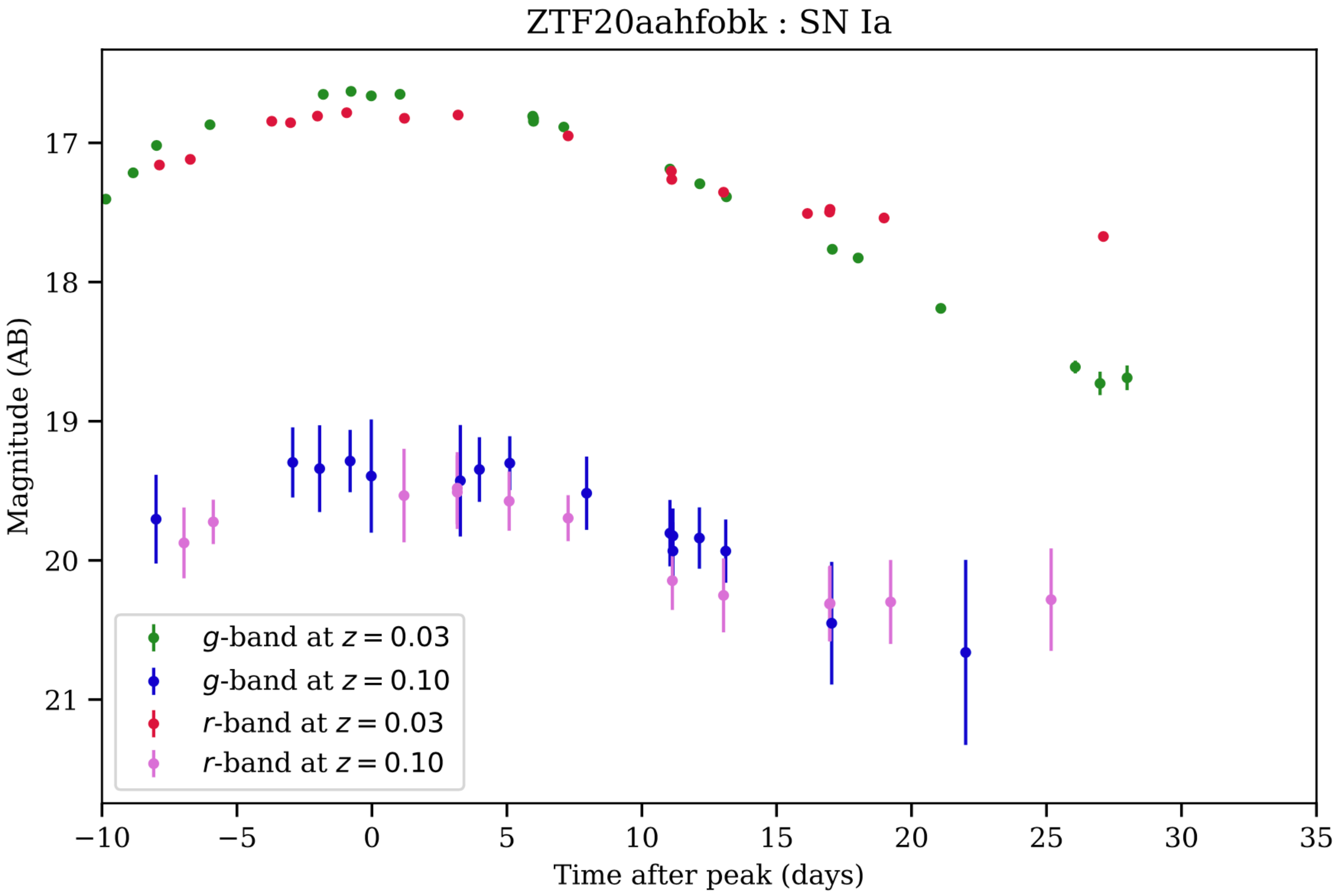
= Optional

Training data

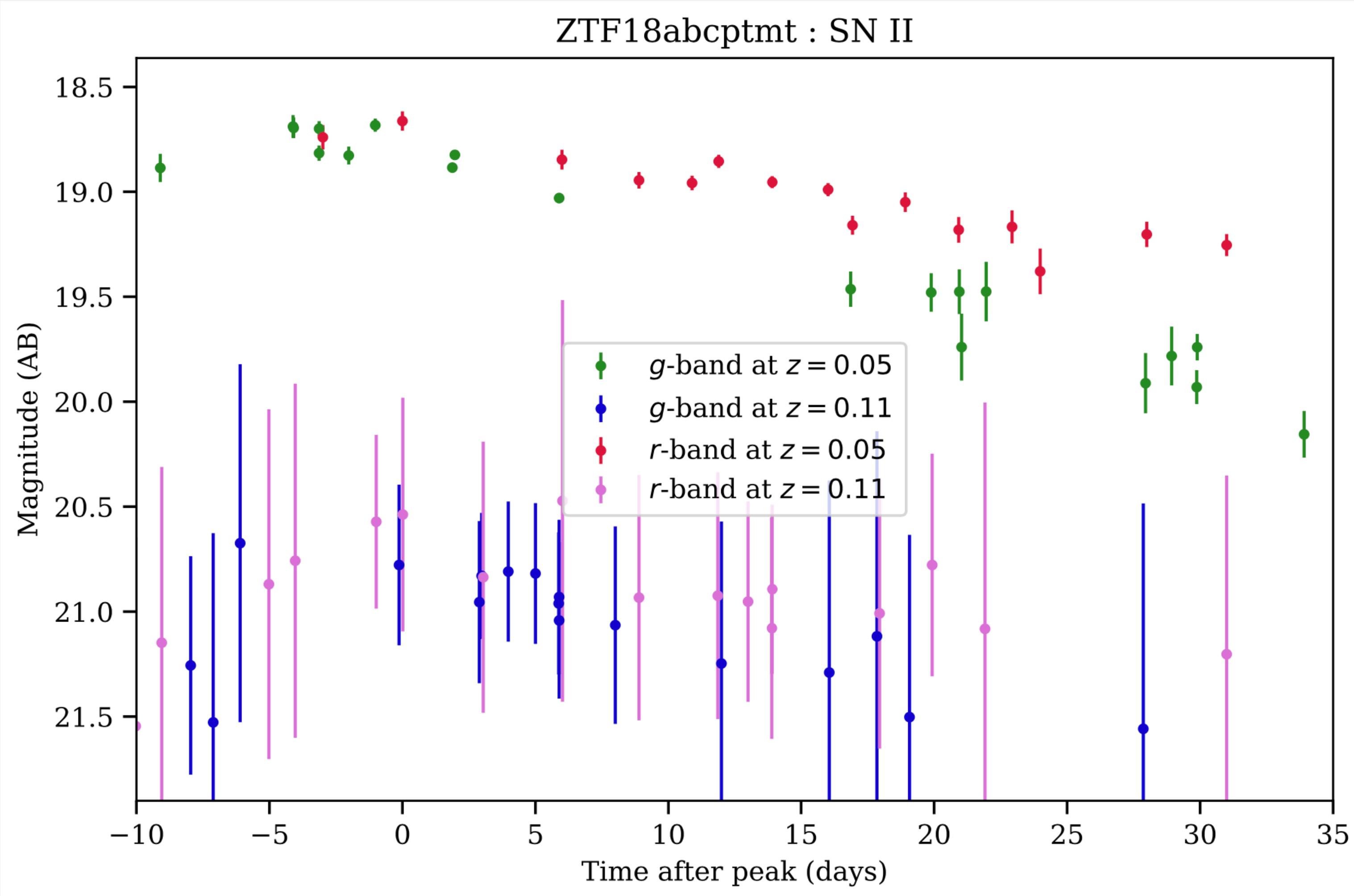
1. Get forced photometry light curves from classified objects in BTS (Simeon's FPBot).
2. Create higher redshift copies of the forced photometry light curves.
3. Apply a signal to noise cut.
4. Remove data points according to the 'density' of detections.
5. Remove data points randomly.
    - Number of data points removed is according to some fraction: 'subsampling rate'.

■ = Optional

Training data



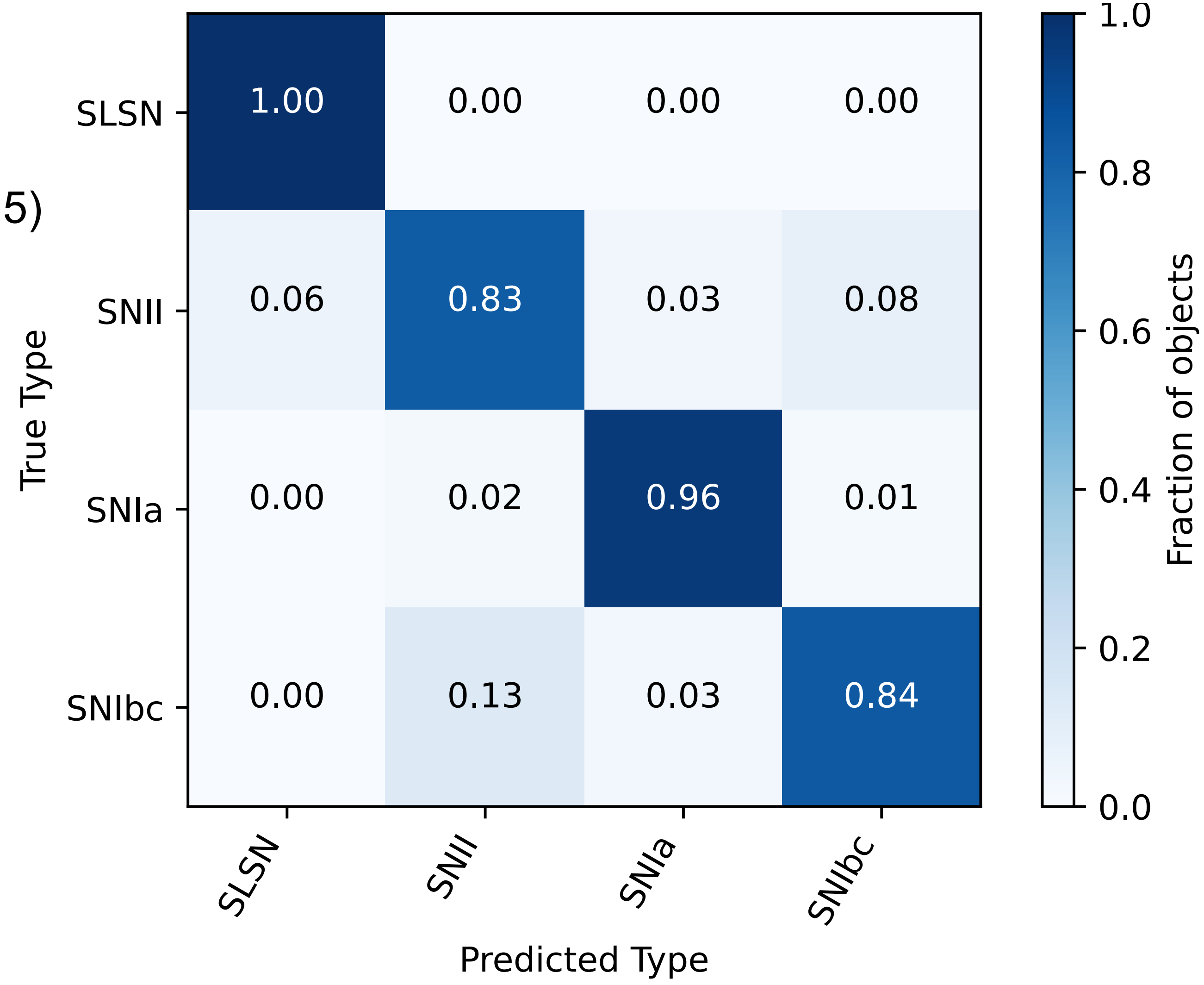
Training data



Initial results

Trained on:
Number per class: ~13000 (SNIa scaled by 5)
Random subsampling rate: 90%

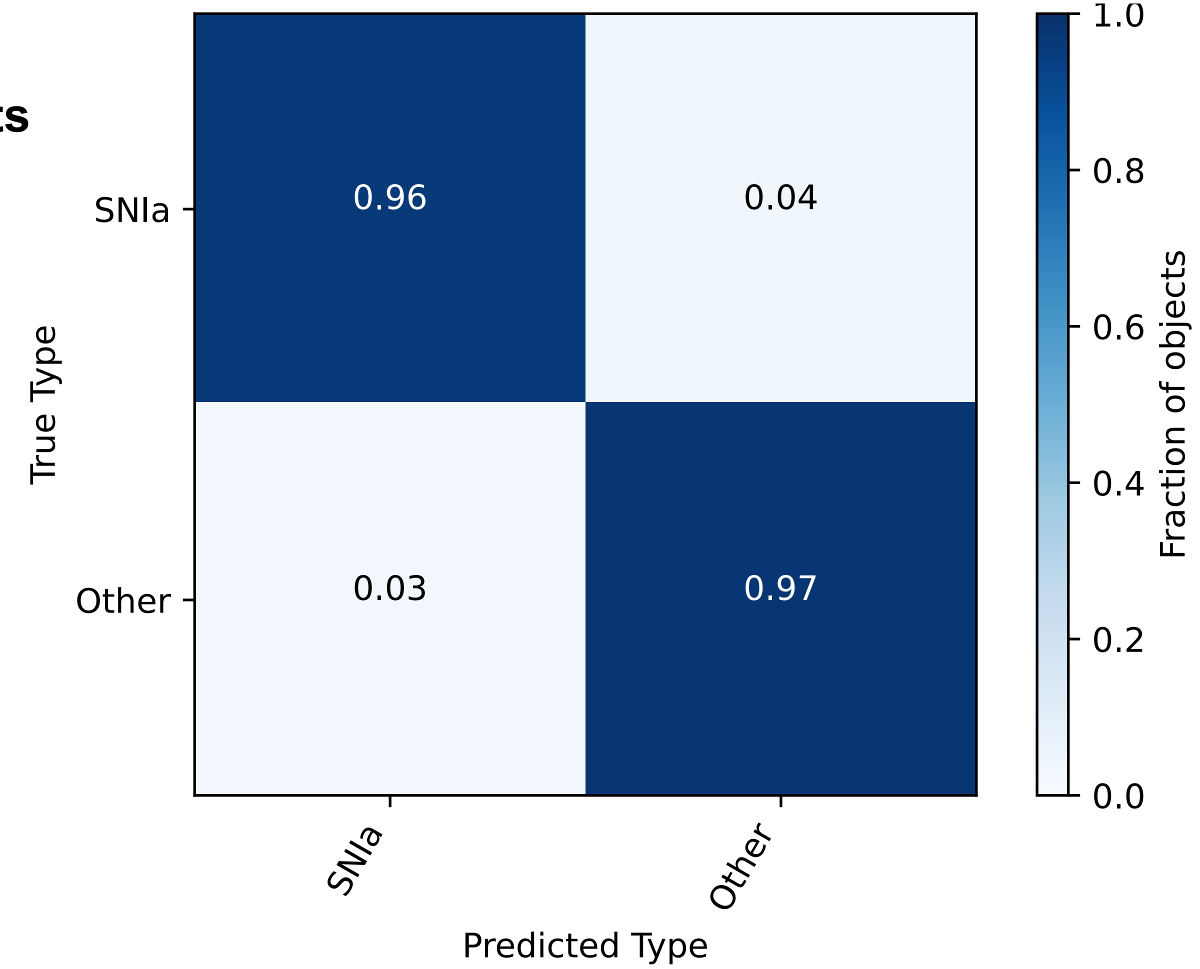
Tested on:
BTS + augmented transients (balanced, ~13000 per class)



Initial results – SN Ia

SNIa classifier tested on BTS + augmented transients

For cosmology, the classification **uncertainty** must be incorporated into the cosmological fitting procedure.

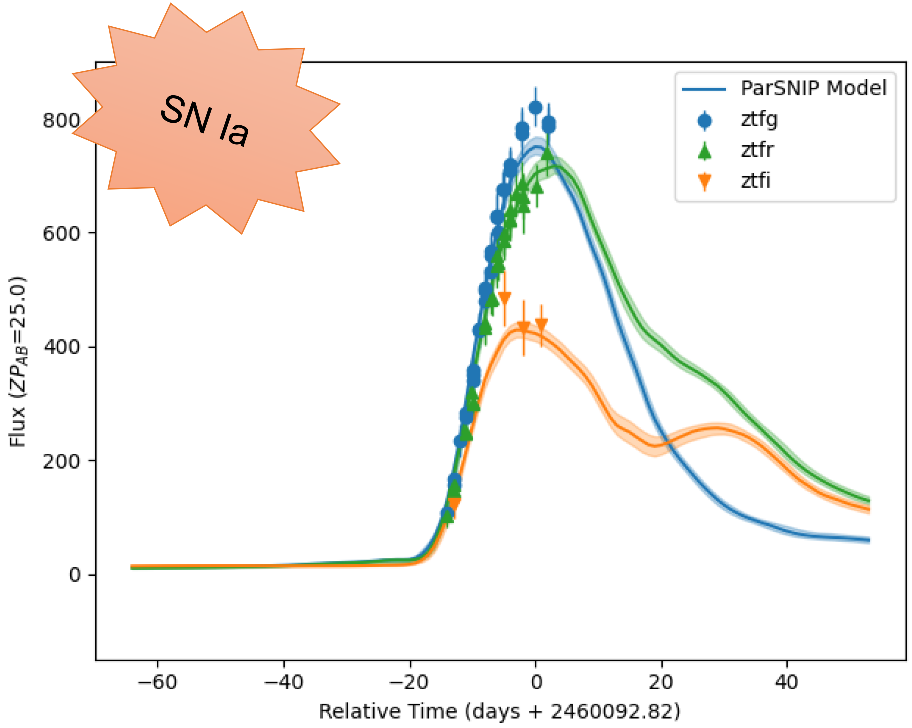


Live testing

We have started live testing!

… but only on one test object so far (giving us a 100% success rate!)

- Use spectroscopic time for follow-up to confirm/deny the predictions.
- Misclassified transients can be fed into training data for new model.
- Can develop a statistical model for the **classification uncertainty.**



Summary

- Promising classification results so far, but there are lots of parameters we can still tweak!
- Live testing is just starting…
- Very happy to hear comments/ideas for improvement from ML people