DASH
Deep learning for the spectral classification of supernovae

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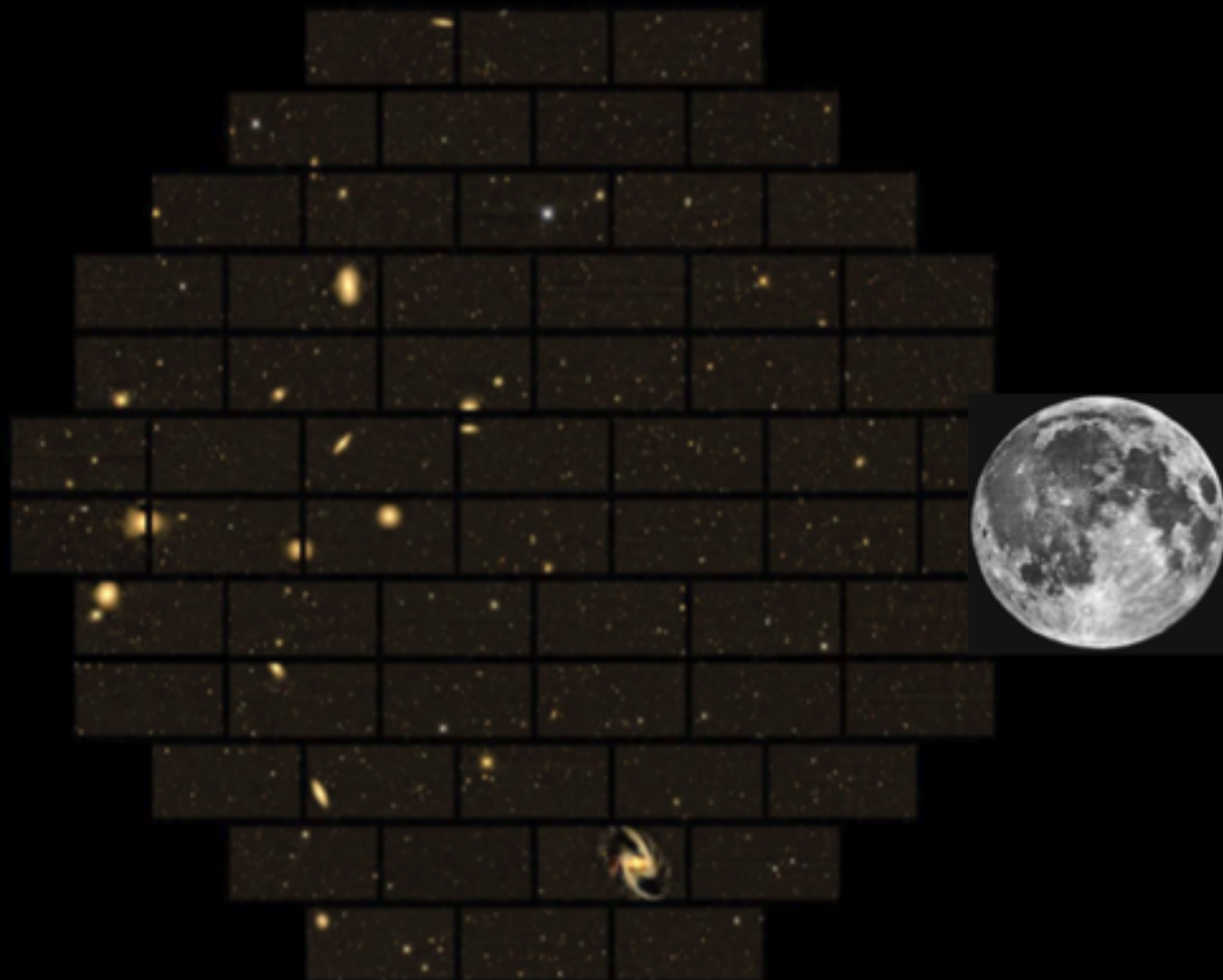

The Dark Energy Camera
(Blanco telescope, Chile)

THE DARK ENERGY SURVEY

Shallow field search for SNe Ia

Graphics: C. D'Andrea

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THE DARK ENERGY SURVEY

Shallow field search for SNe Ia

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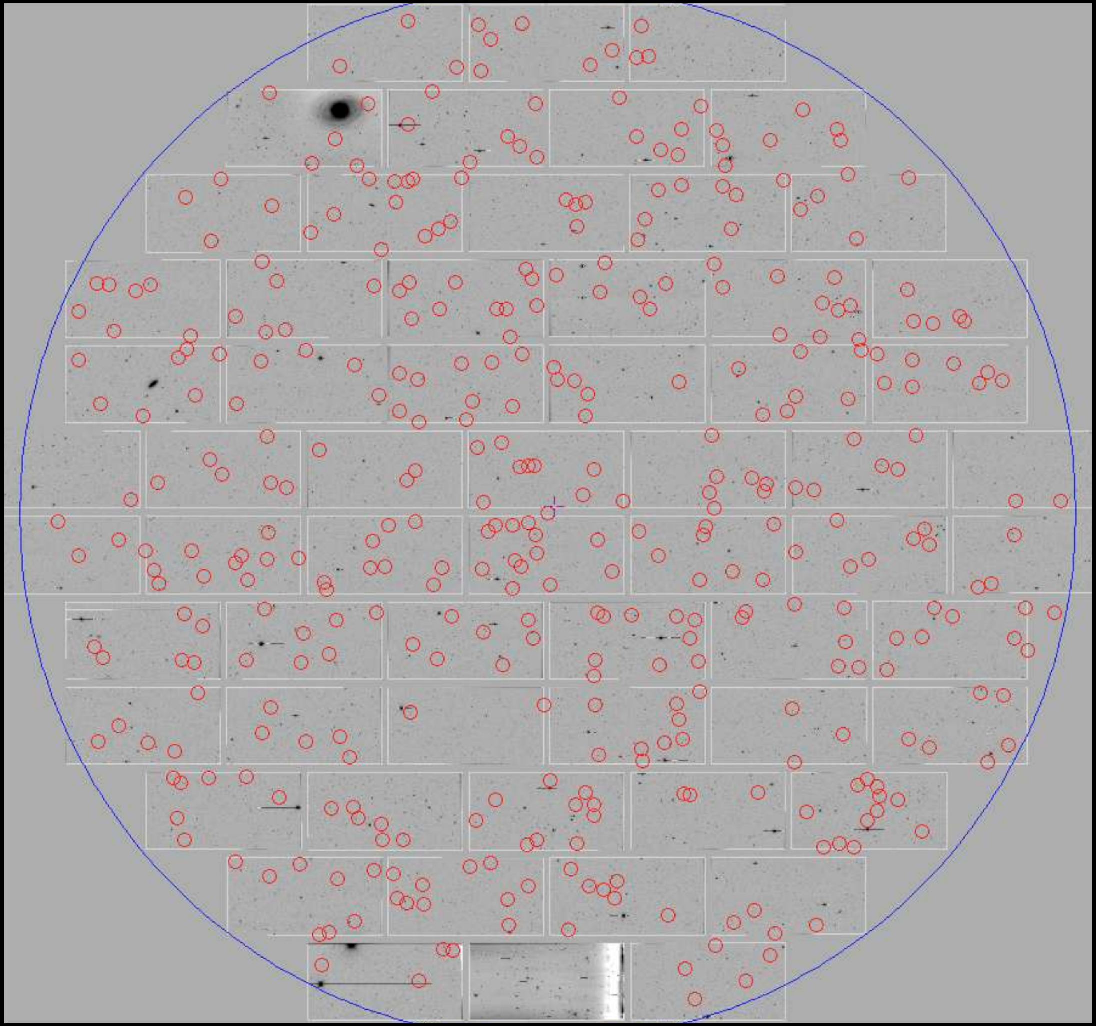
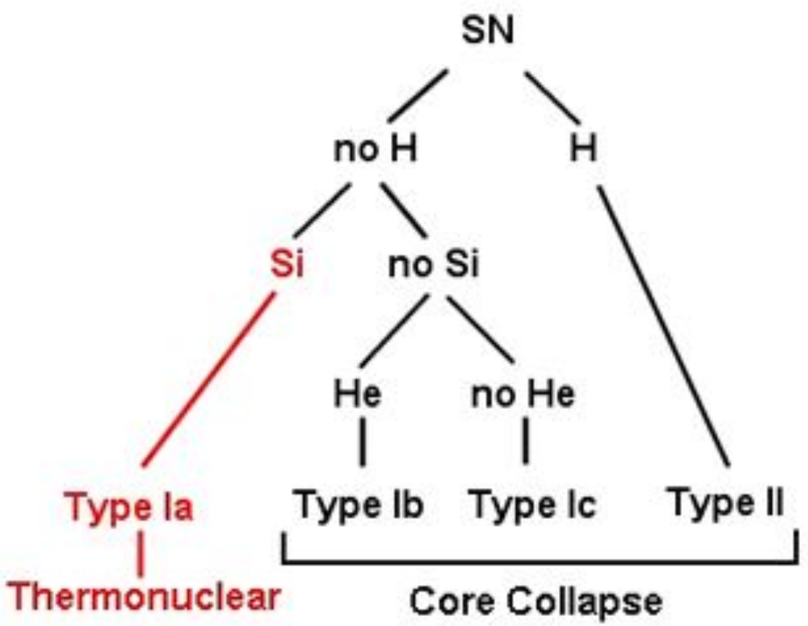
2 degree field
spectrograph
(Anglo-Australian
Telescope)

superimposed on



The Dark Energy Camera
(Blanco telescope, Chile)

Why is this a difficult problem?
Supernova Types



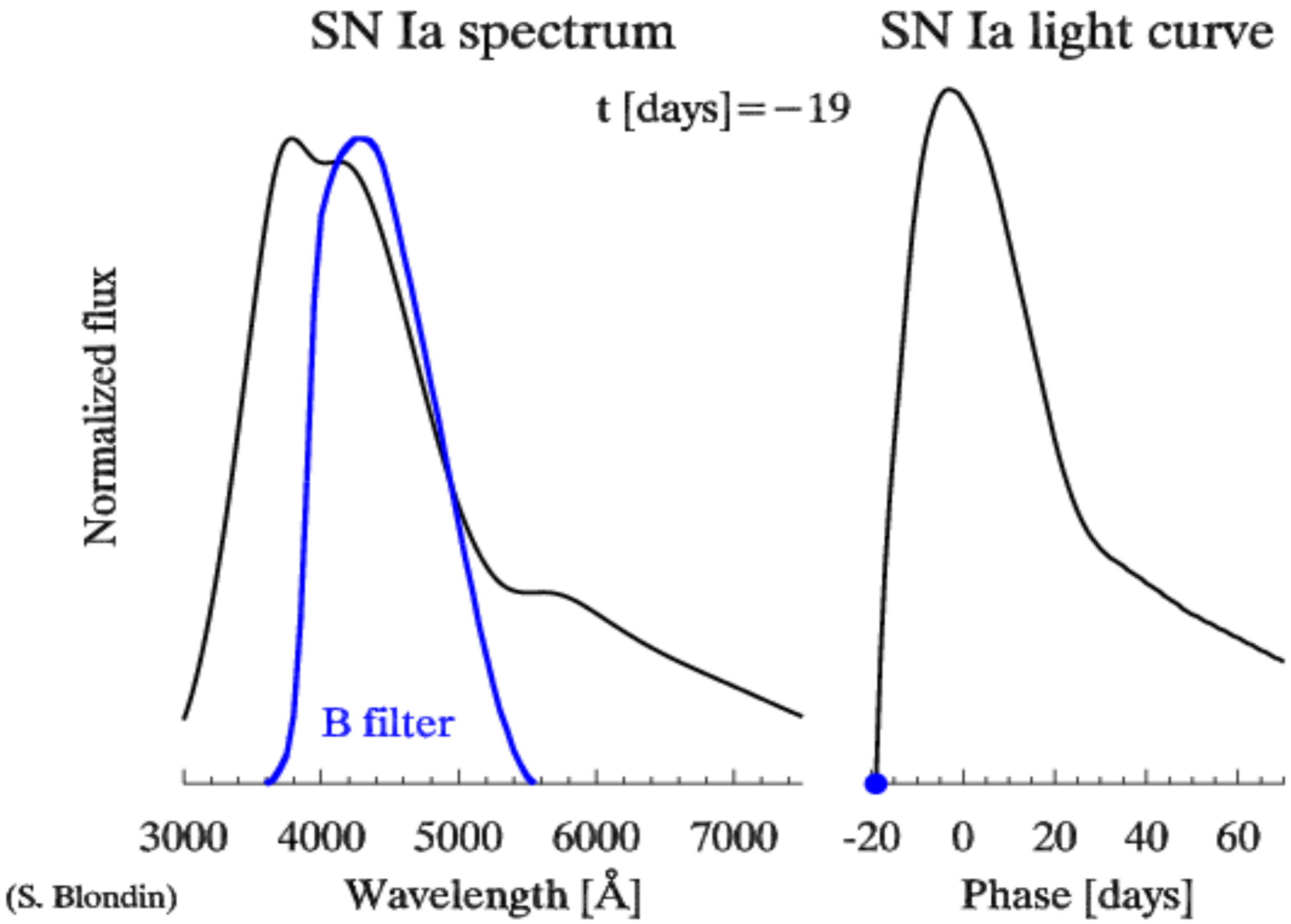
SNIa: Ia-norm, Ia-91T, Ia-91bg, Ia-02cx, Ia-csm, Ia-pec

SNIb: Ib-norm, Ibn, IIb, Ib-pec

SNIc: Ic-norm, Ic-broad, Ic-pec

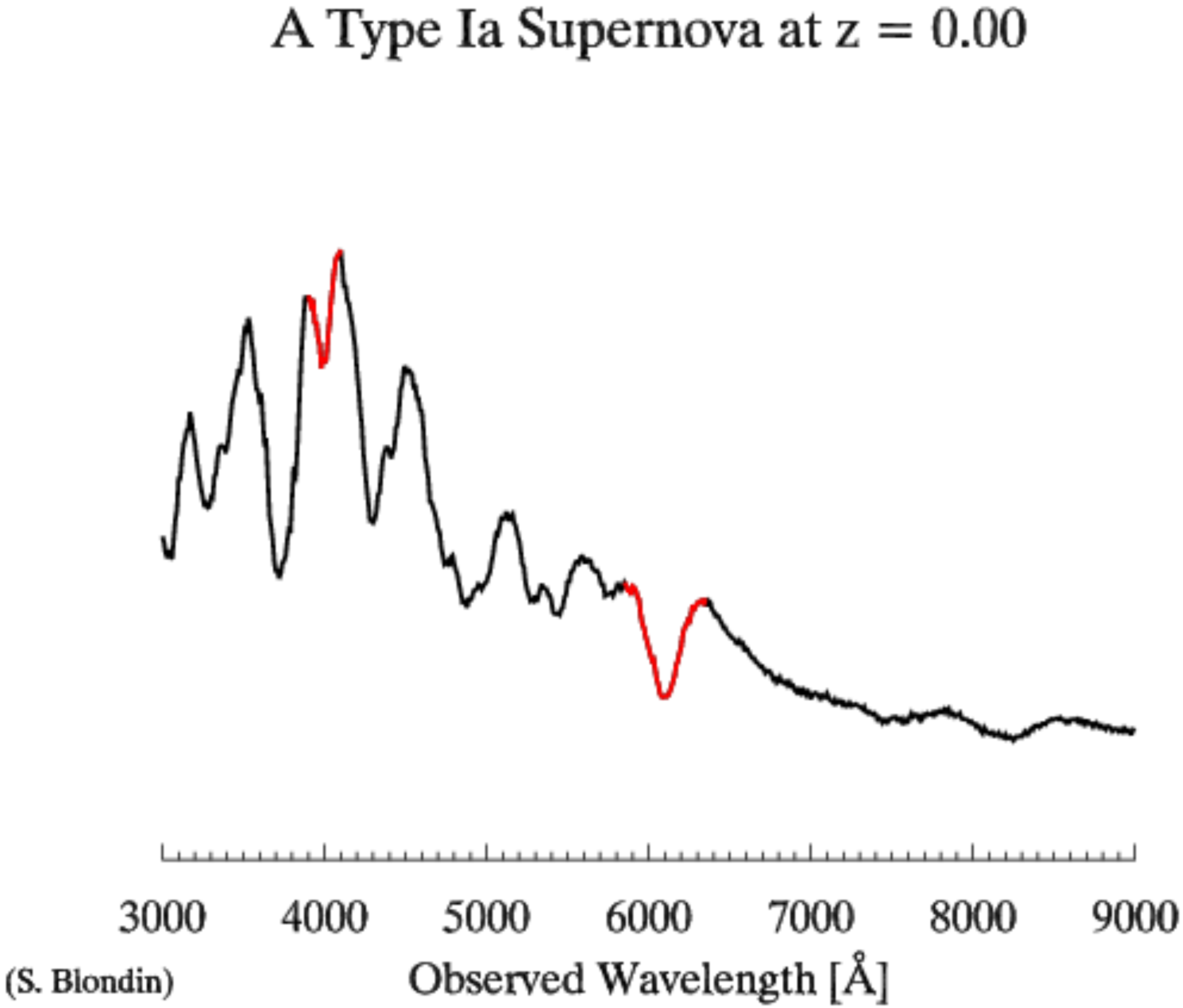
SNII: IIP, IIL, IIn, II-pec

Why is this a difficult problem?
Age

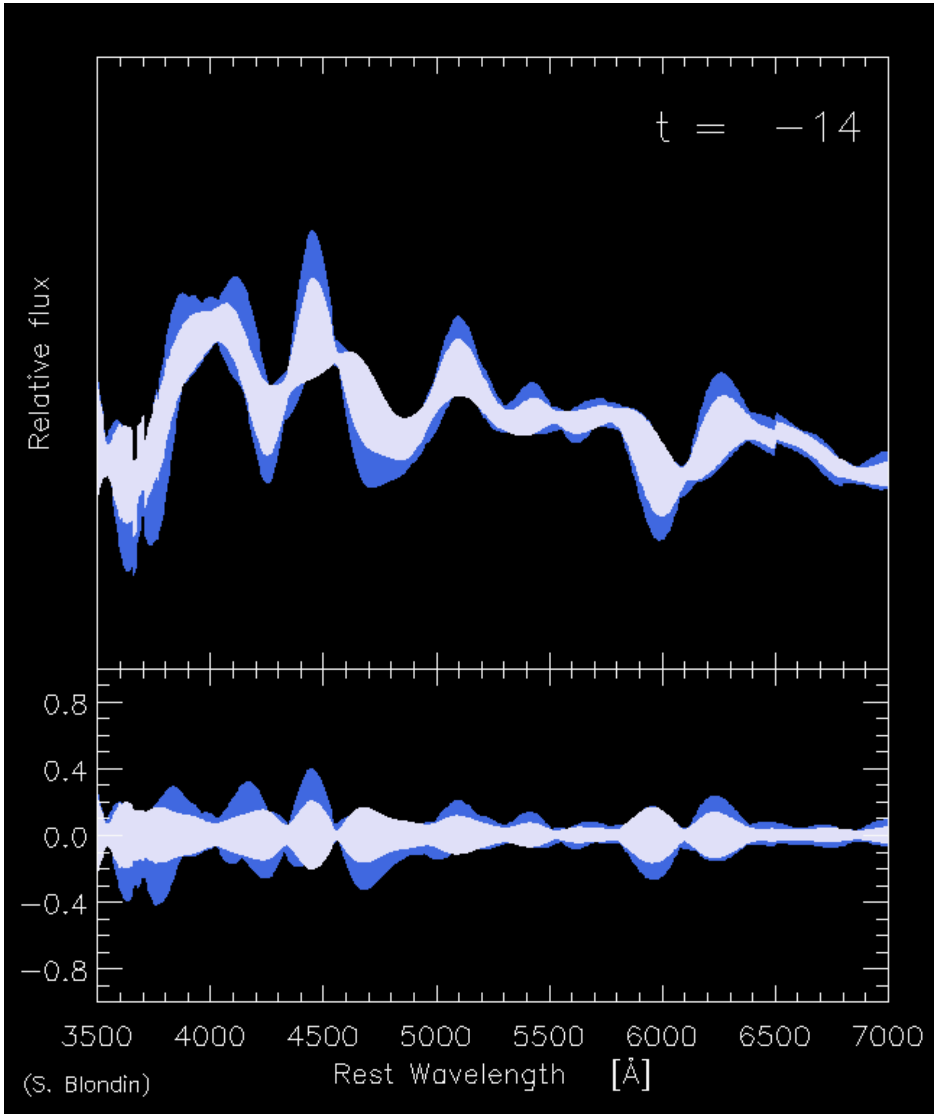


Why is this a difficult problem?

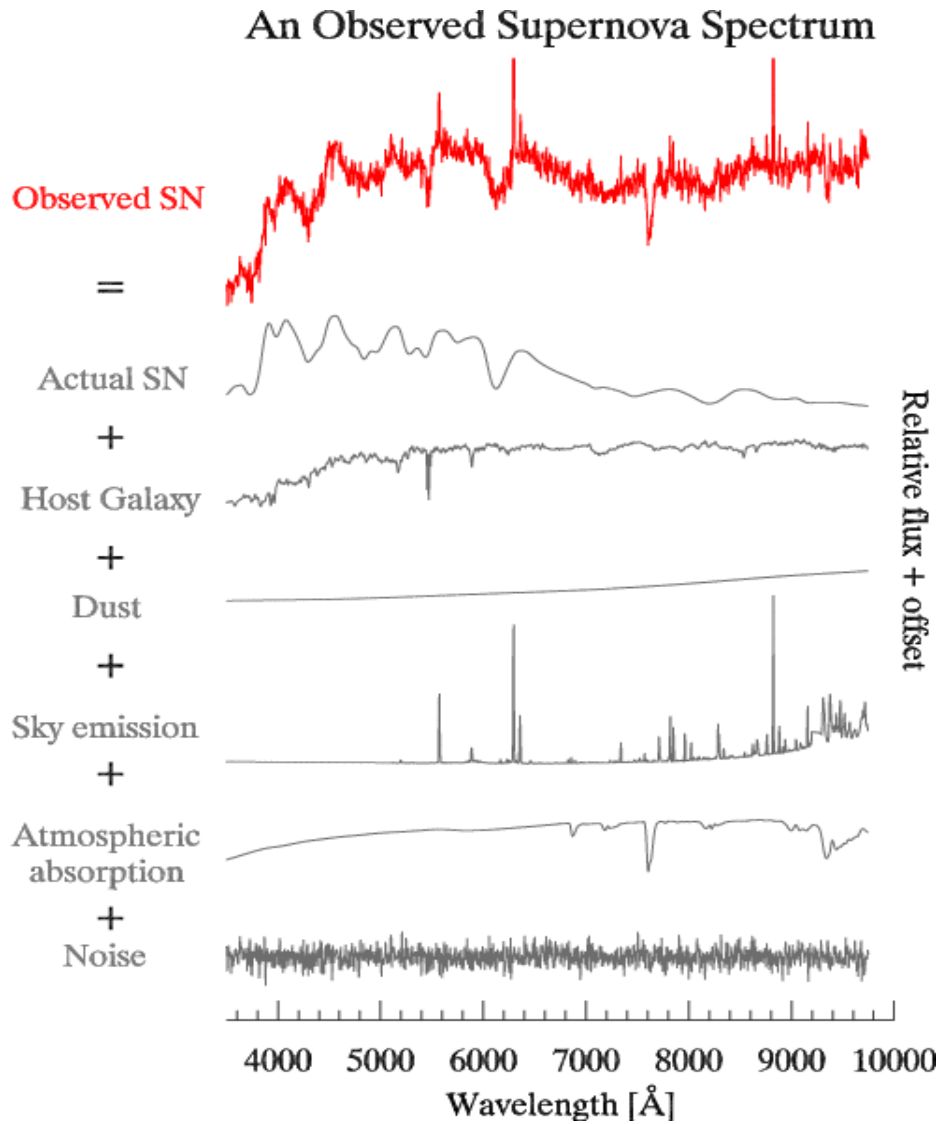
Redshift and Noise



Why is this a difficult problem?
Variations in data

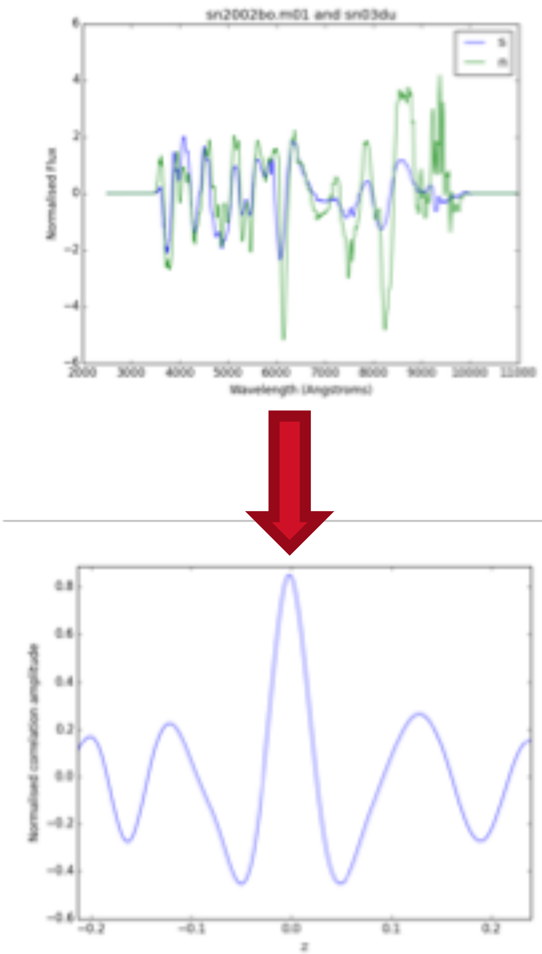


What do we observe?



Previous classification methods

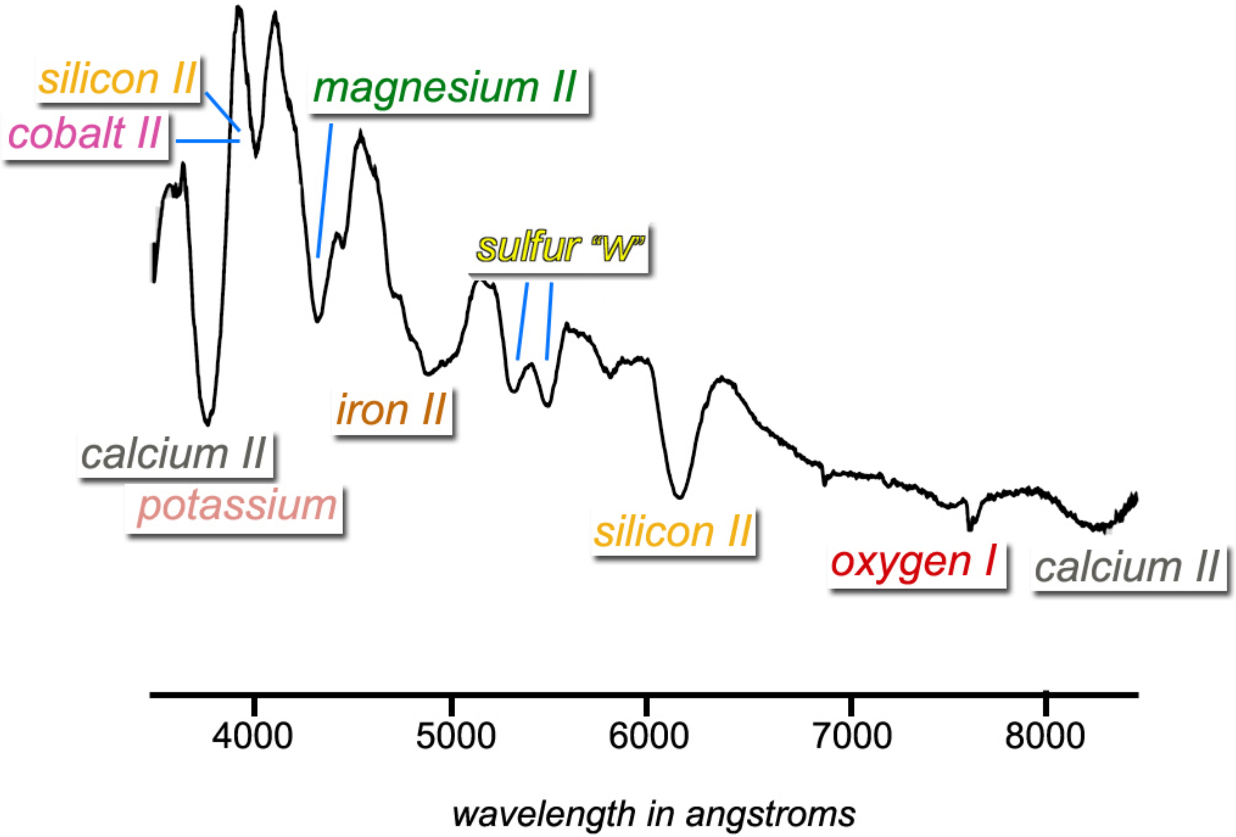
- Currently classification is slow, labour-intensive, and can take tens of minutes for a single supernova spectrum
- SNID – Stephane Blondin (Fortran)
  - Uses a cross-correlation of input with templates
  - Fast
  - Inaccurate with signals that are intermixed with host galaxy light
- Superfit – Andy Howell (IDL)
  - Uses a minimisation of chi-squared
  - Very slow, labour-intensive
  - Can deal with intermixed host galaxy light



Problems with current methods

- All rely on iterative template matching processes
  - Computation time increases linearly with the number of templates
  - Can only compare to one template at a time (rather than the aggregate set of each SN type)
- Chi-squared minimisations are slow
- Not autonomous: requires a lot of human-input

What type of SN is this?



How DASH improves

- Speed
  - Autonomously classify several spectra at once
  - Significantly faster (example: 250 classified spectra in 18 seconds)
- Accuracy
  - DASH classifies based on *features* instead of templates
    - Uses aggregate set of templates rather than a single template
  - Softmax regression probabilities
- Precision
  - More specific classification including age and specific type
- Installation and ease of use
  - Graphical interface and python library
  - Very simple installation and use

Data Description

- Datasets:
  - CfA Supernovae Program (Blondin 2012)
  - Liu, Modjaz 2016
  - BSNIP – Berkeley Supernovae Ia Program (Silverman et al. 2012)
- 4831 spectra across 403 different supernovae
- Separated into 17 different subtypes separated into 4-day age bins

SNIa: Ia-norm, Ia-91T, Ia-91bg, Ia-02cx, Ia-csm, Ia-pec

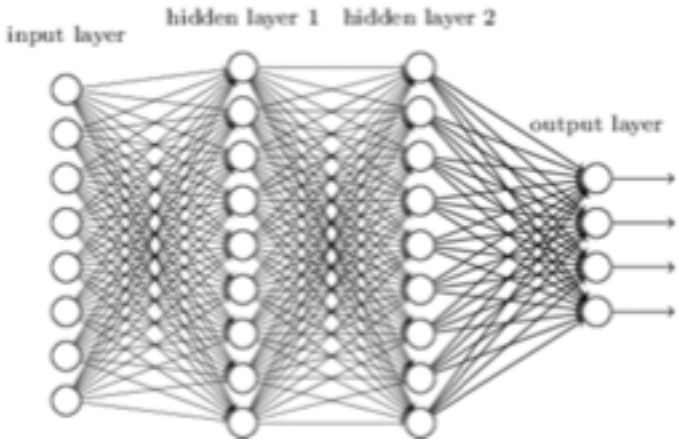
SNIb: Ib-norm, Ibn, IIb, Ib-pec

SNIc: Ic-norm, Ic-broad, Ic-pec

SNII: IIP, IIL, IIn, II-pec

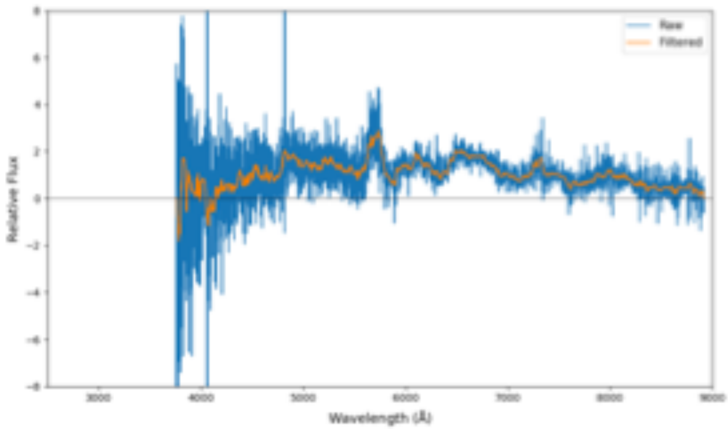
Why Deep Learning?

- Deep Learning has had success in a range of new Big Data problems:
  - Image, speech, language recognition.
- Accuracy improves with number of template (does not affect computation time)
- Training process is separate to testing
- Only need to train once. Then only need the trained model instead of the entire template set.
- Train based on the aggregate set of all templates in a particular SN bin
- Disadvantages
  - Deep learning is often position invariant, which makes redshifting difficult.
  - Softmax probabilities are relative, not absolute measures

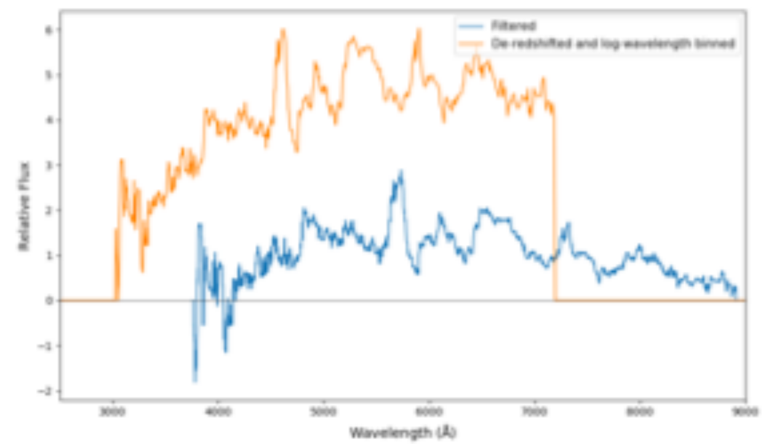


Pre-processing spectra

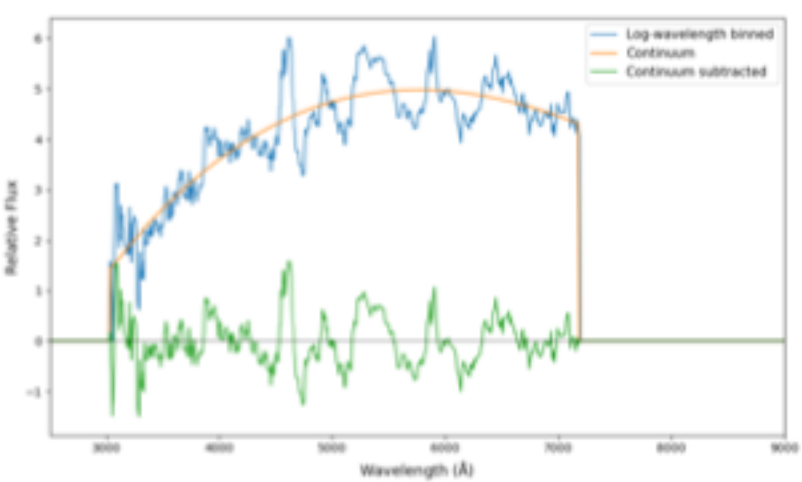
1. Low pass median filtering



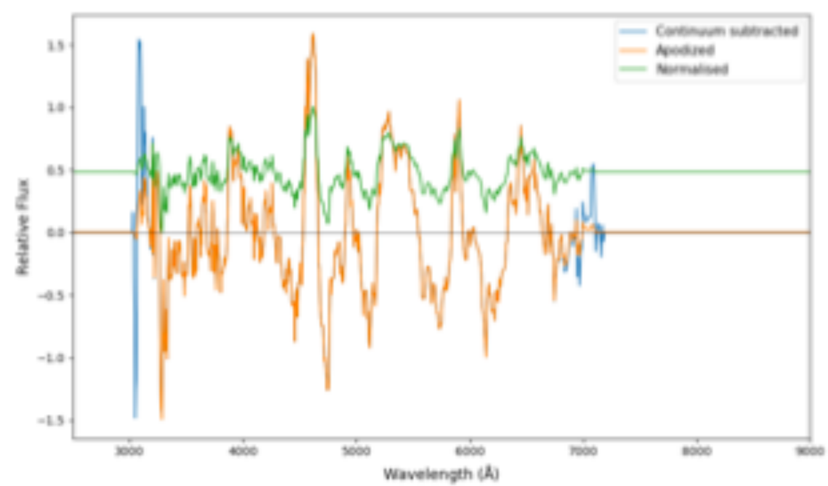
2. De-redshifting (if known)
3. Log-wavelength binning



4. Continuum modelling with spline interpolation
5. Continuum division



6. Apodising edges
7. Normalising



Data Augmentation and oversampling

To ensure the spectra are invariant to shifts and to deal with the imbalanced data we augment and oversample.

1. Add Noise *(up to 200 oversamples)*
2. Add Host galaxy spectra *(11 hosts at 10 fractions)*
3. Cropping *(3 wavelength ranges)*
4. Redshifting *(50 redshifts)*

Increases training set by several thousand times

Convolutional Neural Network

- Softmax Regression

$$\text{evidence}_{\text{i}} = \sum_{i=1}^{1024} W_{i,j} x_j + b_i$$

$$y = \text{Softmax}(\text{evidence})$$ where $$\text{Softmax}(x)_i = \frac{e^{x_i}}{\sum_j e^{x_j}}$$

- Cross-entropy:

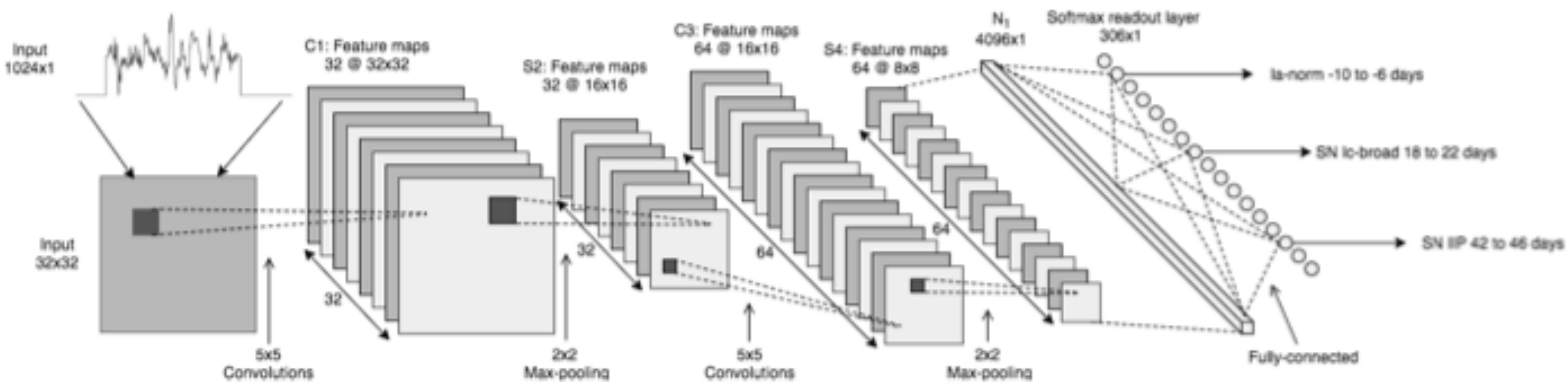
$$H'_y(y) = -\sum_{i=1}^{306} y'_i \log(y_i)$$

  - Minimised with ADAM optimiser
- Building the layers
  - Convolution and Pooling
  - Rectified linear units (ReLU)
  - Dropout layer

Convolutional Neural Network

- Two convolutional layers with Tensorflow
  - 2 layers was over 10-30% better than a single layer
  - 3 layers provided no significant improvement

- 4831 spectra across 403 different supernovae
  - Training set – 80%
  - Validation set – 20%



User Interfaces

```
pip install astrodash
```

- Python 2/3
- Operating Systems: Linux/Mac/Windows

- Available open source: https://github.com/daniel-muthukrishna/DASH/
  - (Muthukrishna et al. 2018 in prep)
- Links with Open Supernova Catalogs

Python Interface

```
pip install astrodash
```

- Python 2/3
- Operating Systems: Unix/Mac/Windows

```
import dash
    classify = dash.Classify([filenames], [knownRedshifts])
    print classify.list_best_matches()
    classify.plot_with_gui(indexToPlot=0)
```

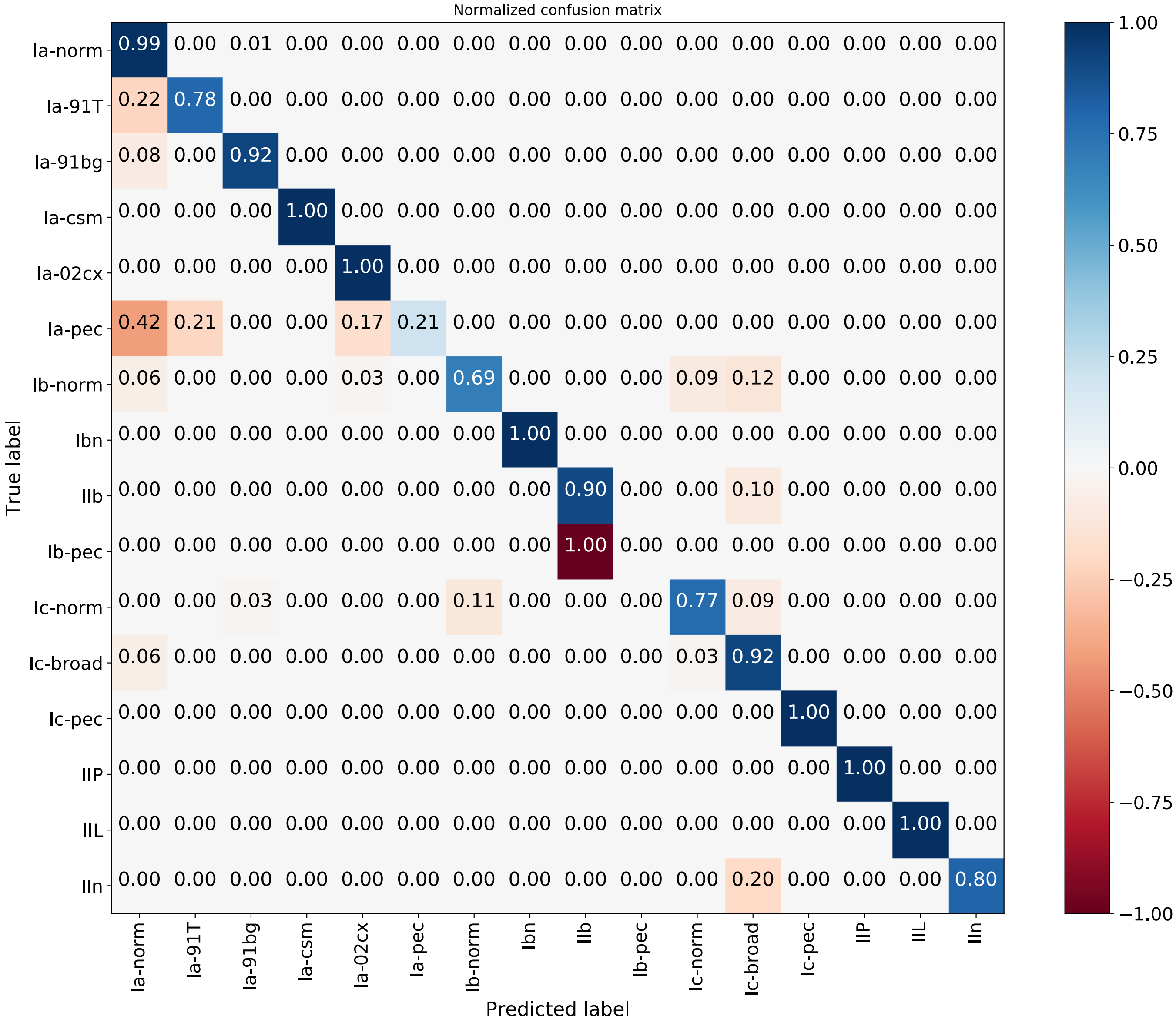
- https://astrodash.readthedocs.io

Validation Set Performance

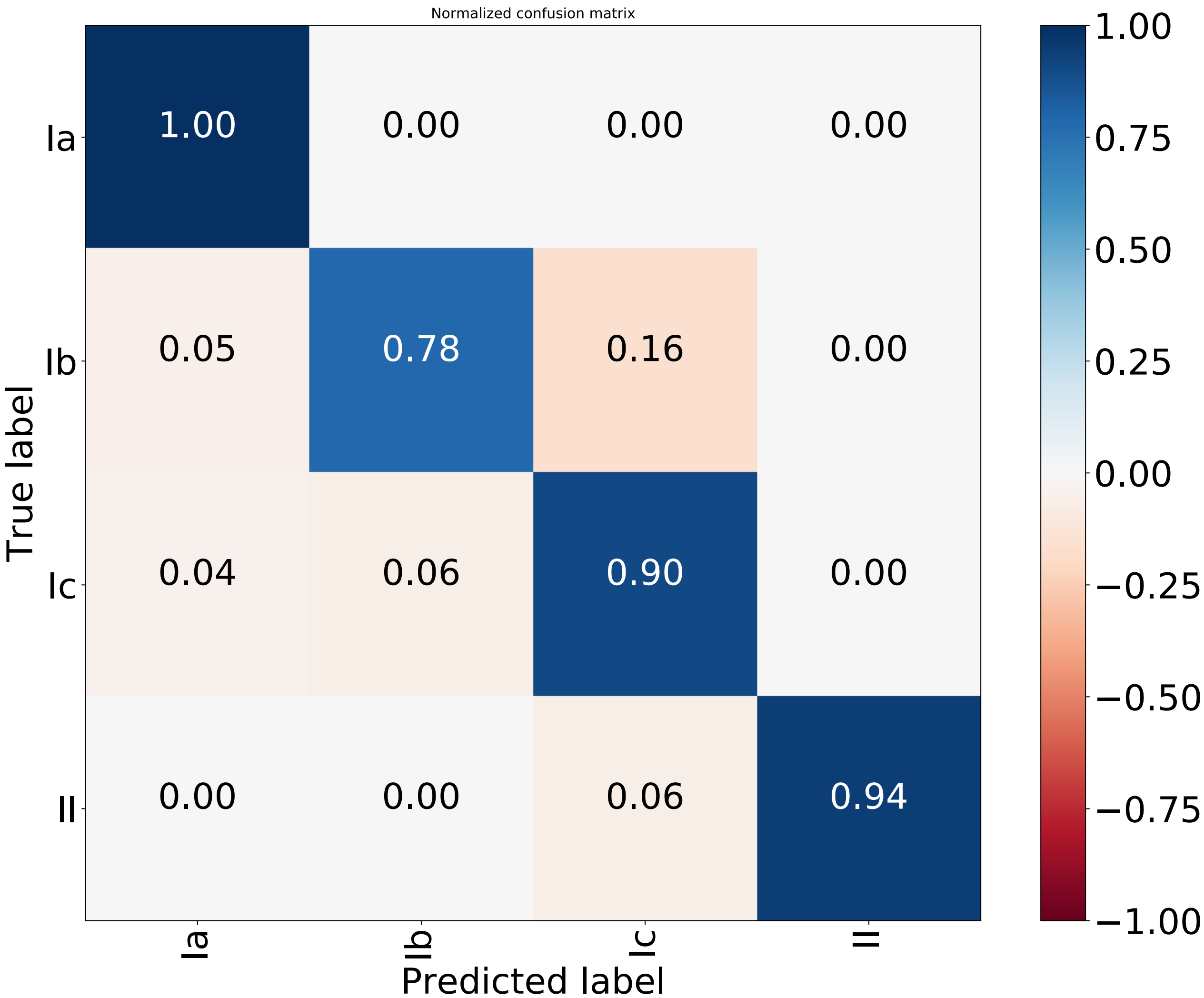
- **Type:** Correct broad type (i.e. Ia, Ibc, II) identified by the matching algorithm.
- **Subtype:** Correct subtype (i.e. Ia-norm, Ib-pec, Ib-norm, etc.) identified.
- **Type and Age:** Correct broad type and the correct age bin identified by the matching algorithm.
- **Subtype and Age:** Correct subtype and the correct age bin identified.

Criteria	Correctly Classified
Type	99.2%
Subtype	96.0%
Type and Age	95.7%
Subtype and Age	93.3%

Validation Set Performance



Validation Set Performance



Results with OzDES Data

- OzDES data from some published ATels
- Matches Superfit in 100% of confirmed cases
- Classified all 23 spectra in <10 seconds!
- Able to classify more spectra
  - Precise likelihood measurements (from softmax regression)
  - More precise measurement (with age and specific type)

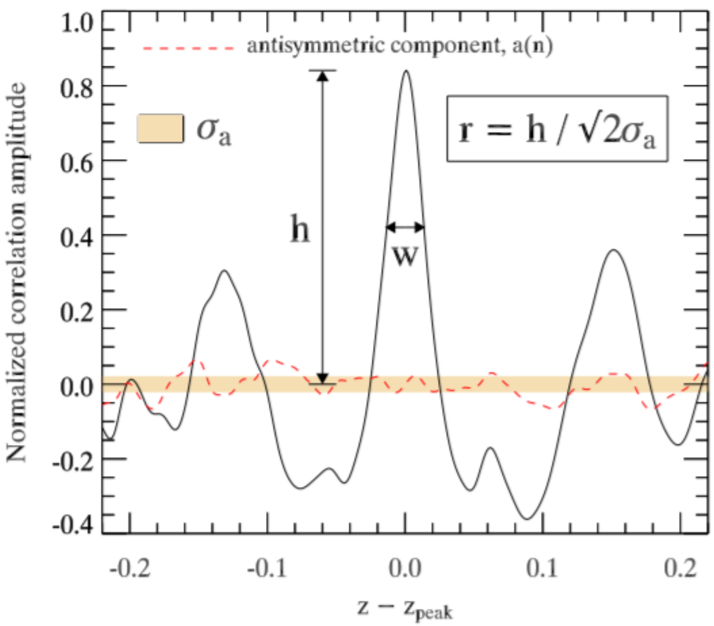
Name	Redshift	ATEL Classification	DASH Classification	DASH Probability	Match?
DES16E1de	0.292	Ia? (+2)	Ia-pec (+2 to +10)	91%	✓
DES16E2dd	0.0746	Ia (+3)	Ia-norm (+2 to +6)	89%	✓
DES16X3km	0.0542	II (+)	IIP (+6 to +10)	99.7%	✓
DES16X3er	0.167	Ia (+2)	Ia-91T (-2 to +6)	86%	✓
DES16X3hj	0.308	Ia (0)	Ia-norm (-2 to +2)	90%	✓
DES16X3es	0.554	Ia? (0)	IIP (+22 to +26)	92%	x
DES16X3jj	0.238	II? (+)	Ic-pec (-2 to 2)	37%	x
DES16C3fv	0.322	Ia (-6)	Ia-norm (-10 to +2)	99.8%	✓
DES16C3bq	0.241	Ia (+0)	Ia-norm (-2 to +6)	99.6%	✓
DES16E1md	0.178	Ia (0)	Ia-norm (-6 to +2)	99%	✓
DES16E1ah	0.149	II (+)	Ia-91T (+14 to +22)	75%	x
DES16C3ea	0.217	Ia (+)	Ia-norm (+10 to +26)	88%	✓
DES16X1ey	0.076	II (+)	IIb (+2 to +6)	38%	✓
DES16C3bq	0.237	Ia (+)	Ia-norm (-2 to +6)	97%	✓
DES16E2aoh	0.403	Ia (+)	Ia-norm (-2 to +6)	88%	✓
DES16X3aqd	0.033	IIP (+)	IIb (-6 to +2)	99%	✓
DES16X3biz	0.24	Ia (-)	Ia-norm (-14 to +2)	98%	✓
DES16C2aiy	0.182	Ia (+)	Ia-norm (-2 to +6)	99.99%	✓
DES16C2ma	0.24	Ia (+)	Ia-norm (+14 to +22)	99.2%	✓
DES16X1ge	0.25	Ia (+)	Ia-norm (+14 to +22)	99.7%	✓
DES16X2auj	0.144	Ia (0)	Ia-norm (-6 to +6)	84%	✓
DES16E2bkg	0.478	Ia (0)	Ia-norm (-2 to +6)	99%	✓
DES16E2bht	0.392	Ia (+3)	Ia-norm (-6 to +2)	58%	✓

False Positive Rejection

Reliability scores

1. Low rlap warning
   - Cross-correlation with best fit templates
   - Ensure that rlap > 5 (Blondin & Tonry 2007)

2. Inconsistent classification warning
   - Check top ranked matches for consistency



Blondin & Tonry (2007)

Conclusions

- DASH makes use of a CNN with Tensorflow
- Over 100 times faster and more precise than previous methods because it classifies based on aggregate features instead of individual templates
- Two interfaces:
  - Graphical interface, Python library
- Easy installation
  - pip install astrodash
- Open Source
  - astrodash.readthedocs.io
- Currently being used by OzDES for implementation in the Y6 run

Early photometric classification