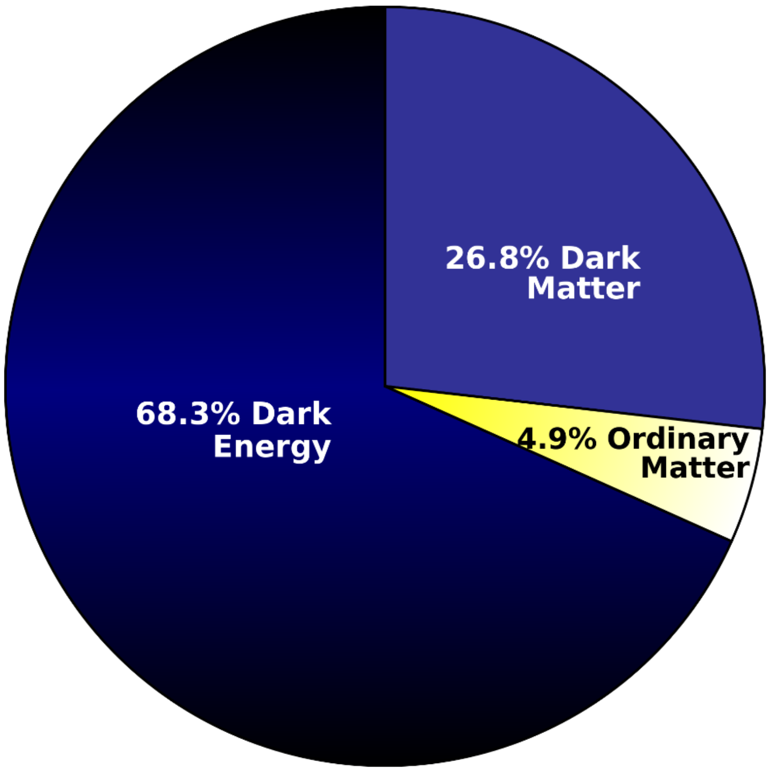
DASH
Deep Automated Supernova and Host spectral classification

Daniel Muthukrishna

Australian National University

Dark Energy

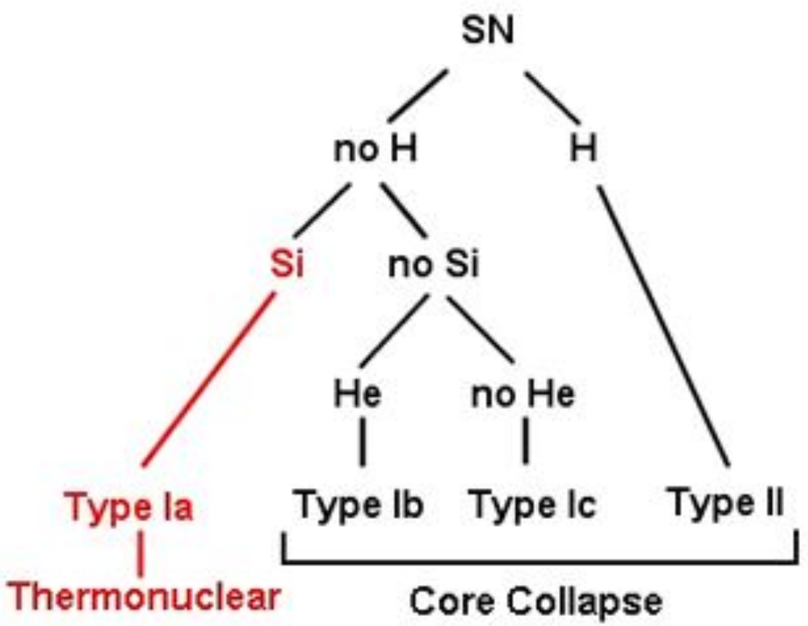
- 2011 Nobel Prize
  - Schmidt (ANU), Riess, Perlmutter
  - The universe's expansion is accelerating…
- This leaves a few options
  - Einstein's theory of gravity is wrong on cosmological scales?
  - A fifth fundamental force?
  - Most of our universe's energy comes from Dark Energy?
- ΛCDM fits very well – but mysterious, and has tensions in datasets



Type Ia Supernovae

- Type Ia Supernovae have provided the most compelling evidence of cosmic acceleration
- Standardizable Candles
- Several surveys are aiming to increase the dataset to understand Dark Energy/modified theories of gravity

Supernova Types



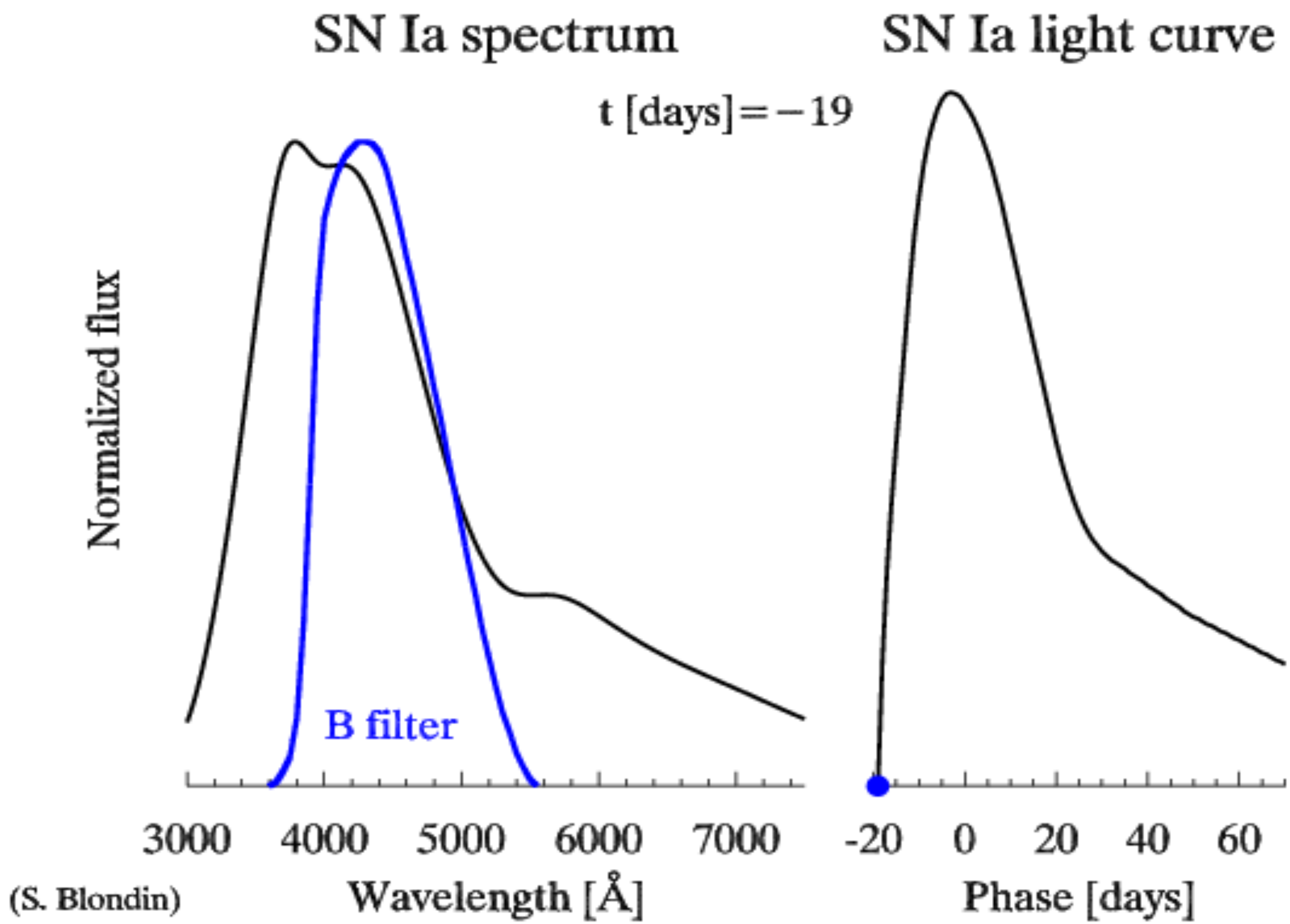
SNIa: Ia-norm, Ia-91T, Ia-91bg, Ia-02cx, Ia-csm, Ia-pec

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

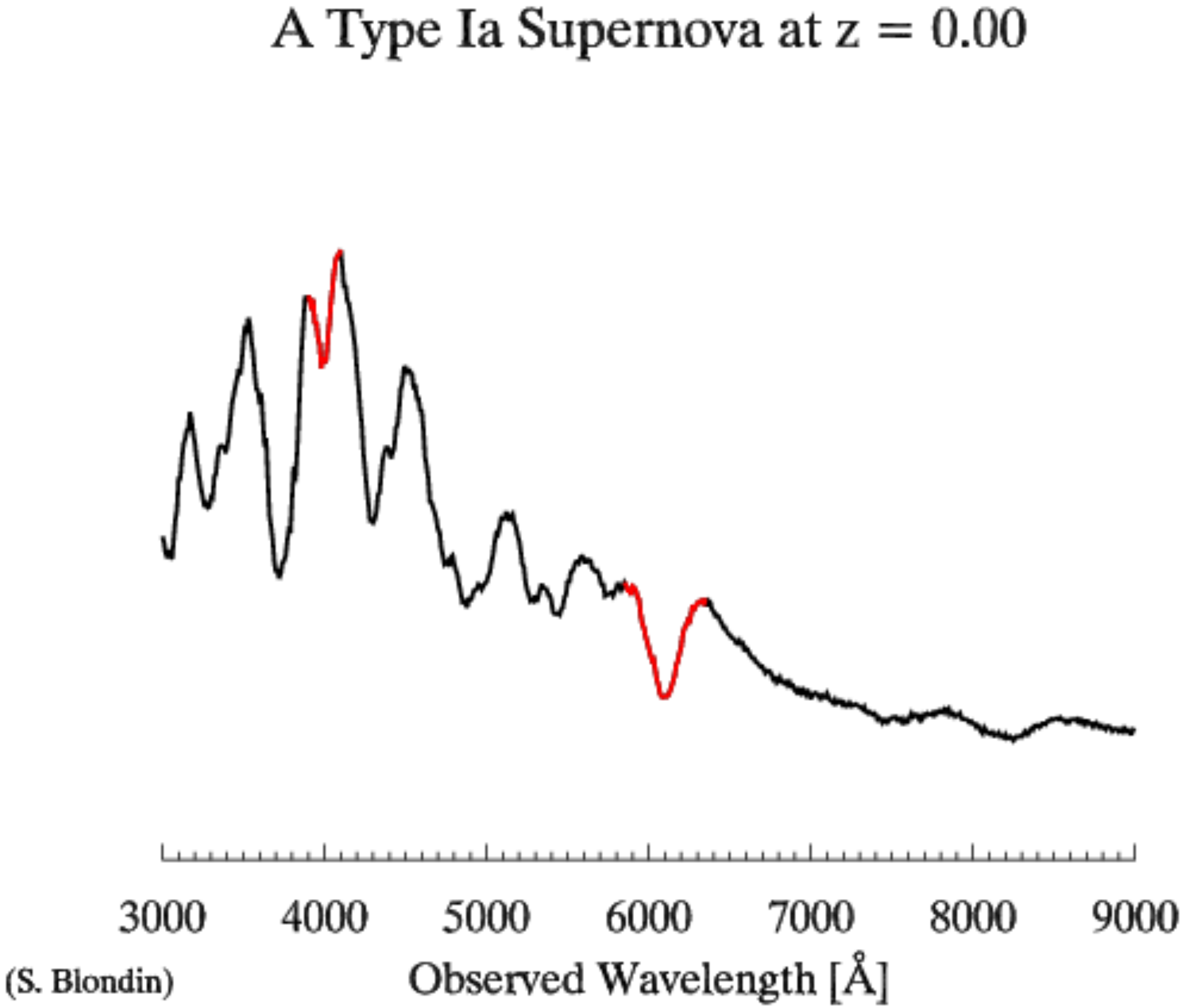
SNIc: Ic-norm, Ic-broad, Ic-pec

SNII: IIP, IIL, IIn, II-pec

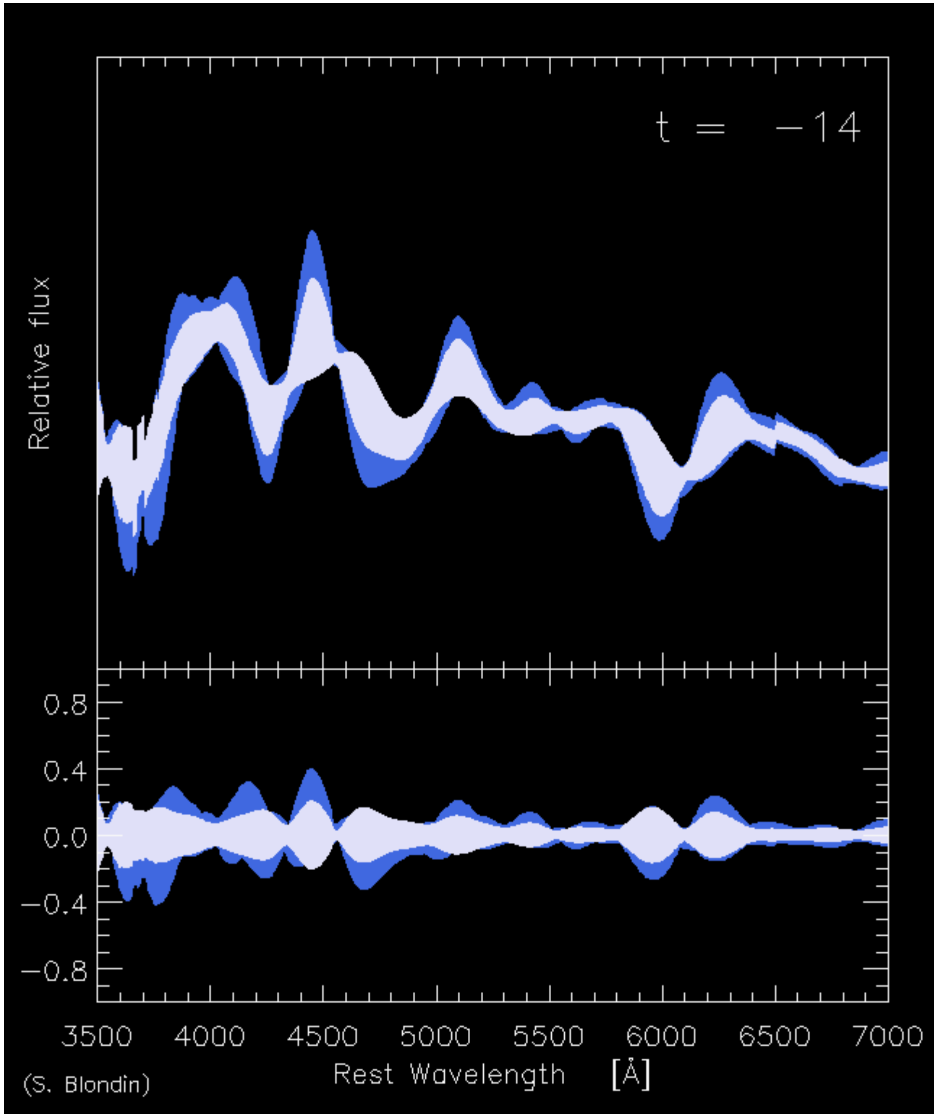
Why is this a difficult problem?
Age



Why is this a difficult problem?
Redshift and Noise

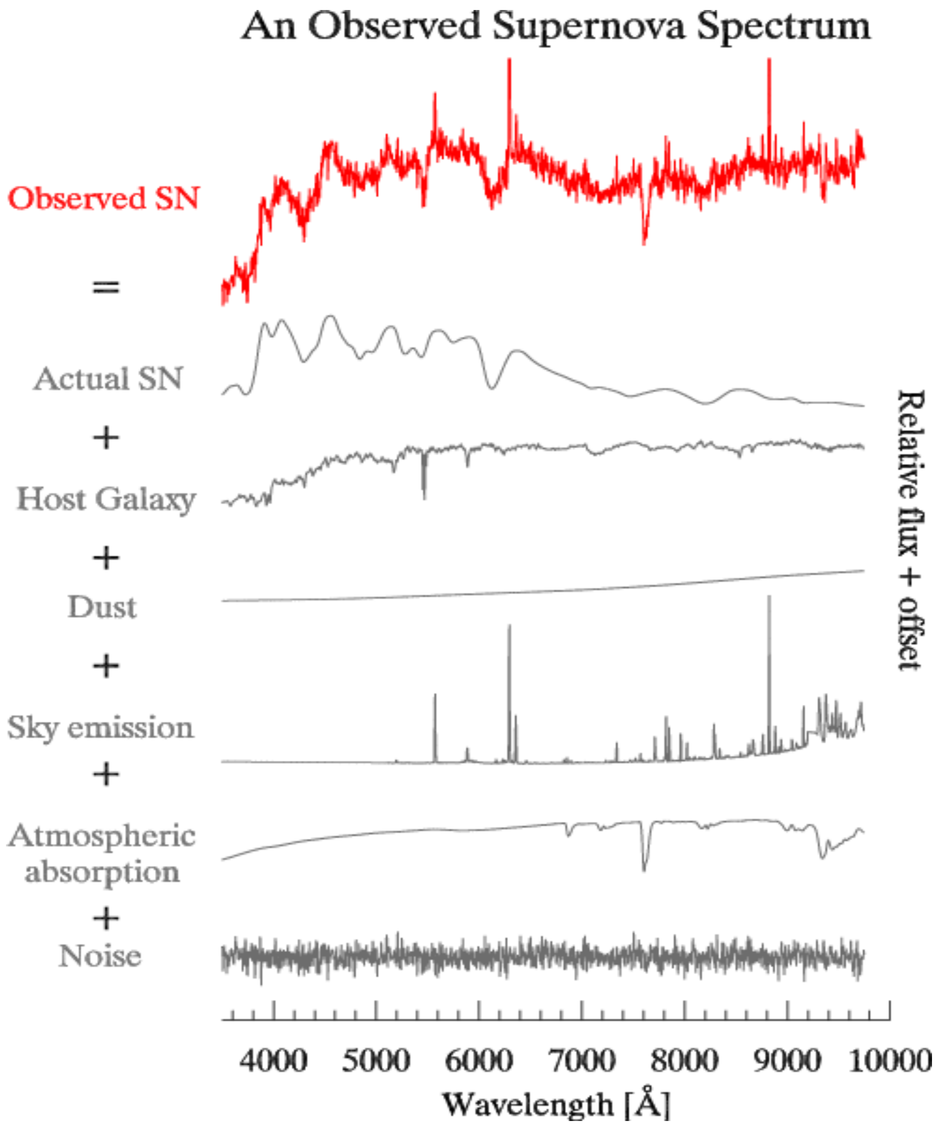


Why is this a difficult problem?
Variations in data



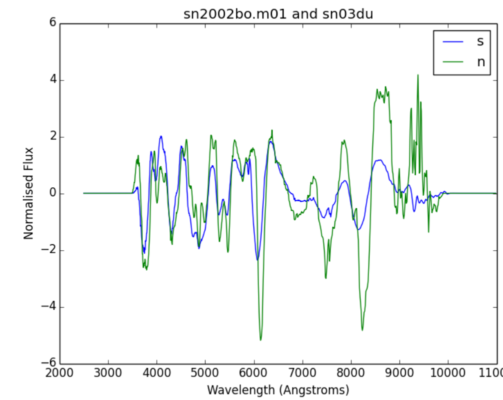
CAASTRO
ARC CENTRE OF EXCELLENCE FOR ALL-SKY ASTROPHYSICS

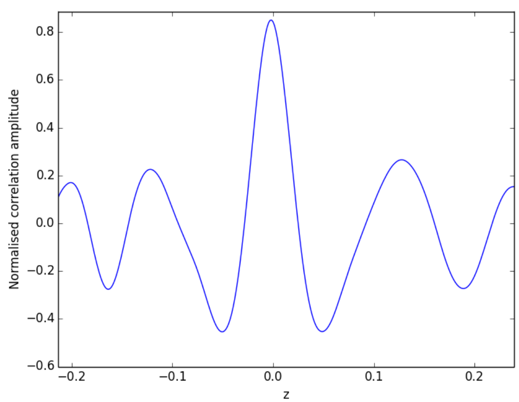
What do we observe?



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

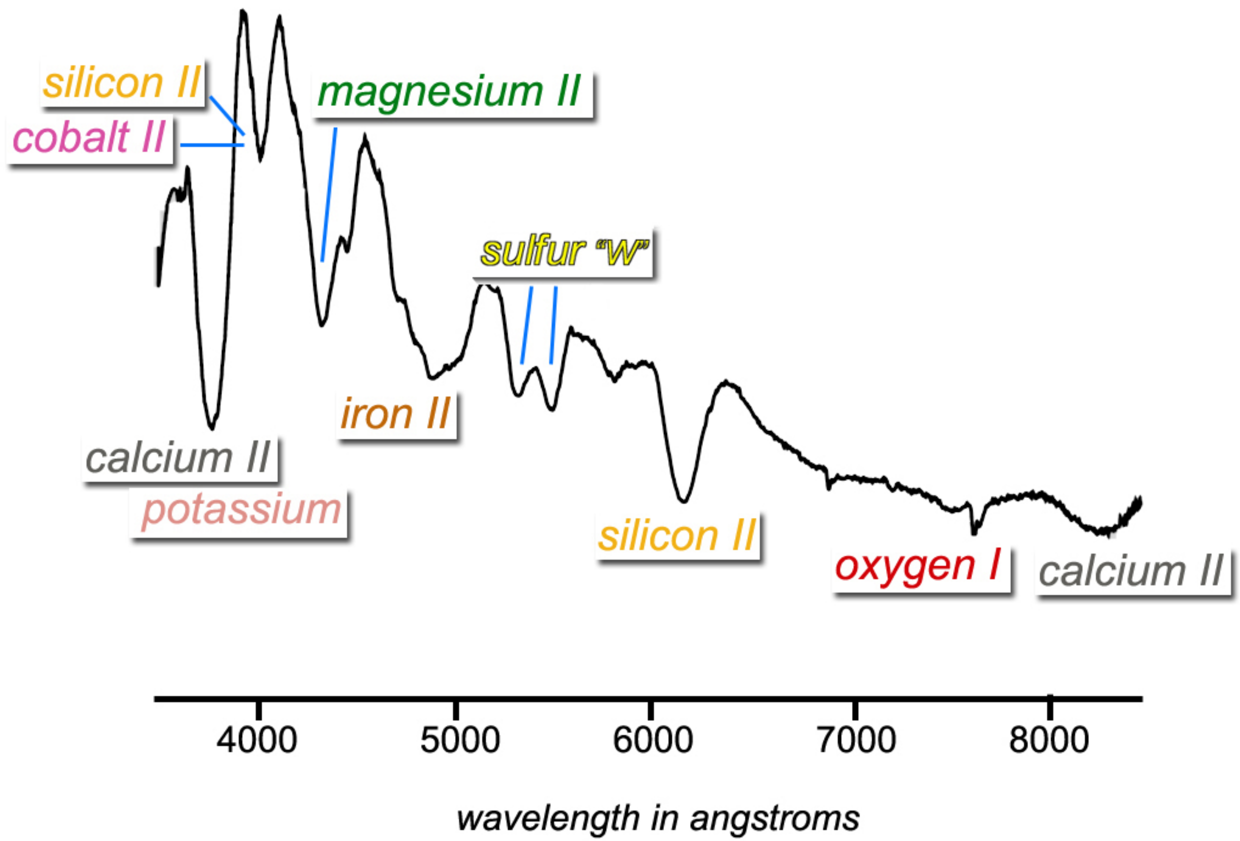




Problems with current methods

- 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?



Design Decisions
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

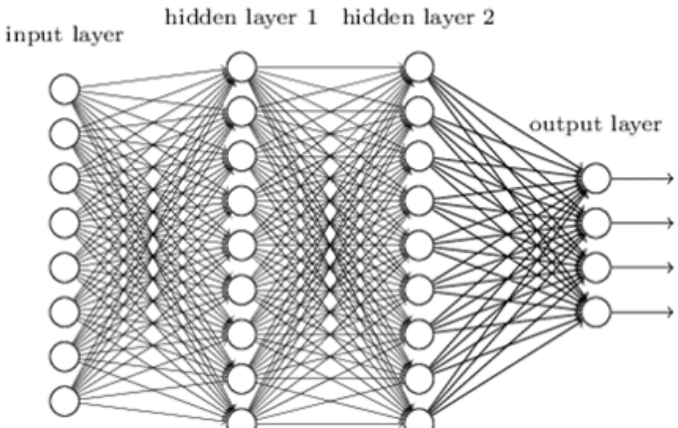
SNIb: Ib-norm, Ibn, IIb, Ib-pec

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

SNII: IIP, IIL, IIn, II-pec

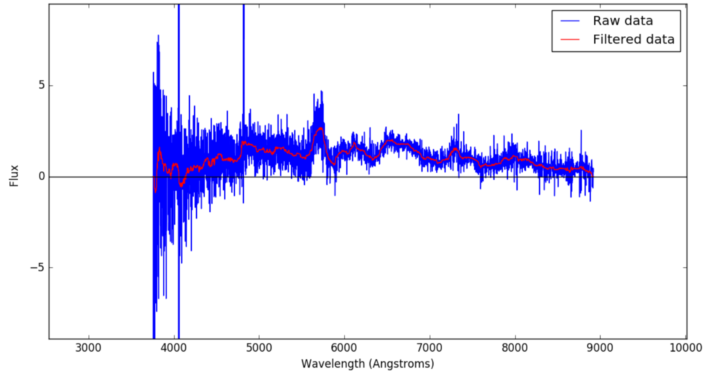
Why Deep Learning?

- Deep Learning has had success in a range of new Big Data problems:
  - Image, speech, language recognition. Beating grandmasters at Chess and Go
- 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

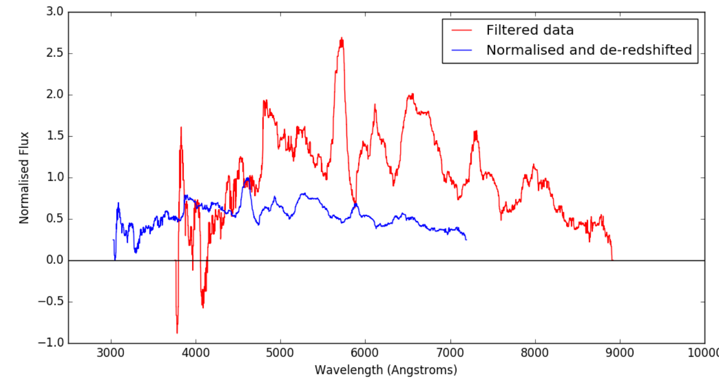


Pre-processing spectra

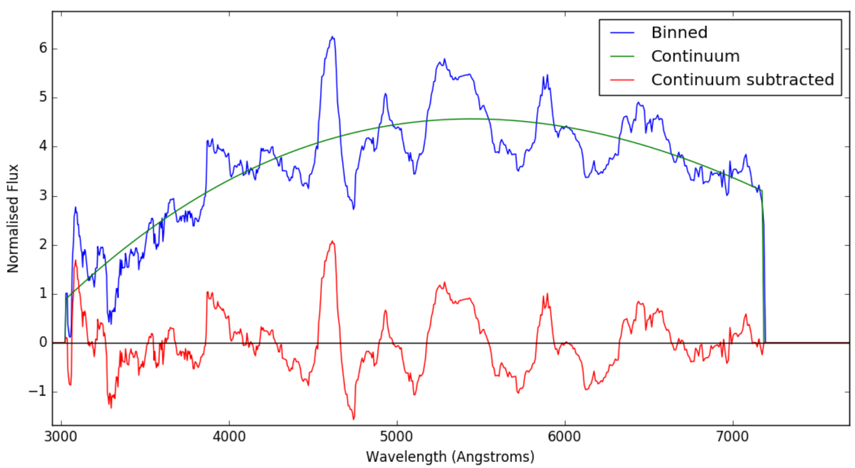
1. Low pass median filtering



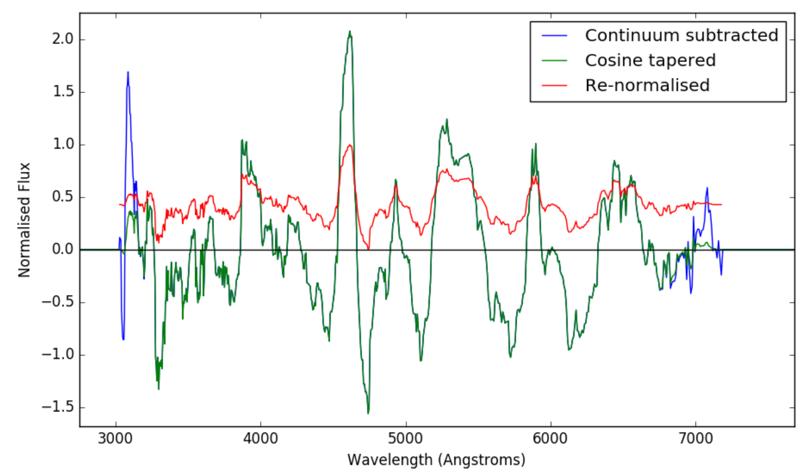
2. Normalising
3. De-redshifting



4. Continuum modelling with spline interpolation
5. Continuum subtraction



6. Log-wavelength-binning
7. Apodising edges

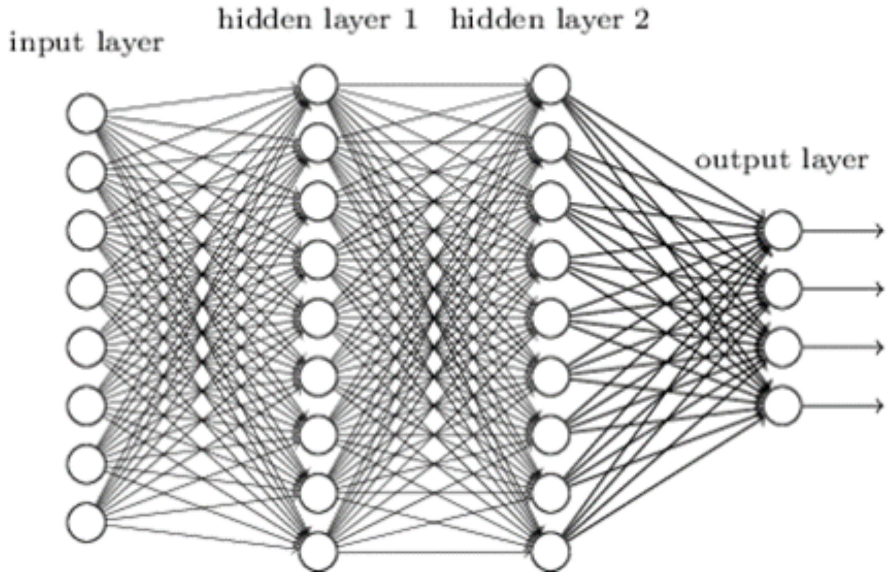


Convolutional Neural Network

- Two layer neural network 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%

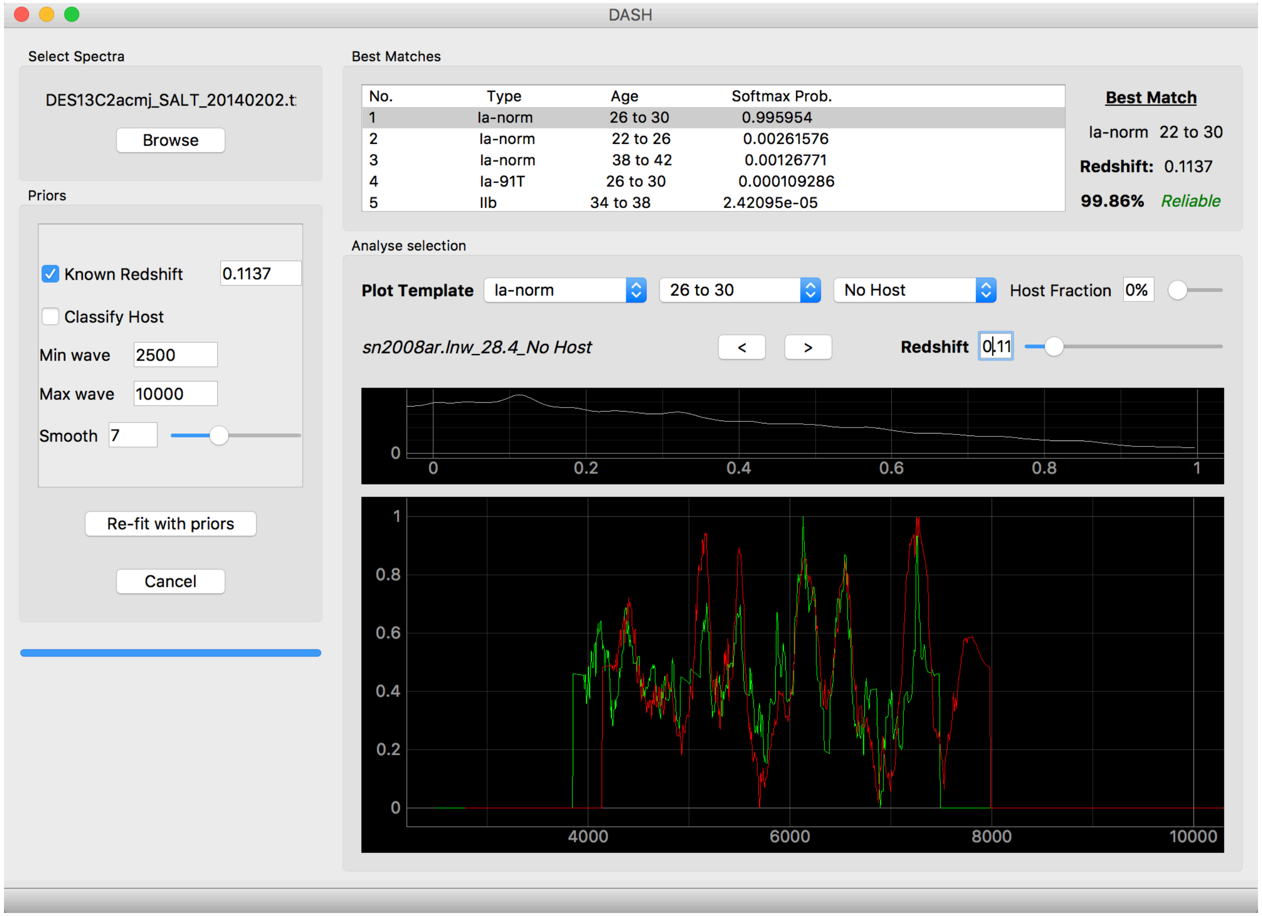
- Need to oversample



User Interfaces

`pip install astrodash`

- Python 2/3
- Operating Systems: Linux/Mac/Windows
- Available open source at: https://github.com/daniel-muthukrishna/DASH
  - (Paper in preparation)



Validation Set Performance

- **Type:** Correct broad type (i.e. Ia, Ib, Ic, 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	93.3%
Subtype and Age	95.7%

Conclusions

- Supernovae are the most powerful probe for probing the nature of dark energy
- DASH makes use of a 2 layer neural network 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
  - https://github.com/daniel-muthukrishna/DASH
- Currently being tested by OzDES for implementation in the Y5 run

Results with OzDES Data

- OzDES data from the last couple of runs at the end of 2016.
- 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%	✓

Template distribution

	-20 to -18	-18 to -14	-14 to -10	-10 to -6	-6 to -2	-2 to 2	2 to 6	6 to 10	10 to 14	14 to 18	18 to 22	22 to 26	26 to 30	30 to 34	34 to 38	38 to 42	42 to 46	46 to 50
Ia-norm	0	2	46	176	216	280	271	229	181	156	110	93	86	81	50	61	47	28
Ia-91T	0	0	18	44	49	35	18	24	17	26	23	21	17	13	10	8	10	14
Ia-91bg	0	0	0	10	24	26	38	24	23	20	19	10	10	13	2	2	6	5
Ia-csm	0	0	1	0	0	1	1	2	1	1	0	0	1	1	0	3	2	2
Ia-02cx	0	0	0	10	14	7	1	0	3	4	6	8	3	1	1	2	2	0
Ia-pec	0	0	5	5	7	15	11	17	8	6	4	7	5	7	6	6	1	1
Ib-norm	1	11	14	20	21	26	16	14	19	12	10	6	7	10	5	7	2	5
Ibn	0	0	0	0	0	0	3	6	3	2	3	1	1	3	1	1	2	1
IIb	4	14	13	9	13	13	18	13	15	12	9	6	4	6	8	7	2	3
Ib-pec	0	0	2	1	2	0	0	0	1	5	0	0	0	0	0	0	1	0
Ic-norm	0	1	1	11	21	16	15	12	6	12	6	14	6	12	6	8	2	6
Ic-broad	0	0	4	15	31	39	27	25	14	17	16	11	12	6	4	2	3	9
Ic-pec	0	0	0	0	3	9	7	0	1	0	4	3	0	2	0	0	0	2
IIP	0	0	0	1	8	19	13	15	6	8	3	8	5	3	7	4	2	2
IIL	0	0	0	0	0	0	0	3	4	0	0	0	0	0	0	1	2	0
IIn	0	0	2	0	0	4	1	2	3	1	0	0	0	3	0	2	3	1
II-pec	1	3	2	3	2	2	2	3	3	3	4	2	3	2	1	6	3	2

Why Deep Learning?

	Deep Learning	Cross-correlation matching	Chi-squared matching
Classification technique	Matches based on the combined 'features' of all templates	Iteratively compares to templates	Iteratively compares to templates
Speed	Very Fast (no change in speed with templates)	Fast (but increases linearly with number of templates)	Slow (increases linearly with number of templates)
Noise	Can train with noise	Cannot classify low S/N	OK with low S/N
Redshifting	Redshifting is unreliable	Very good at redshifting	OK redshifting
Goodness of Fit	Relative	Absolute	Absolute