Classification of supernovae with machine learning

DEX 2019

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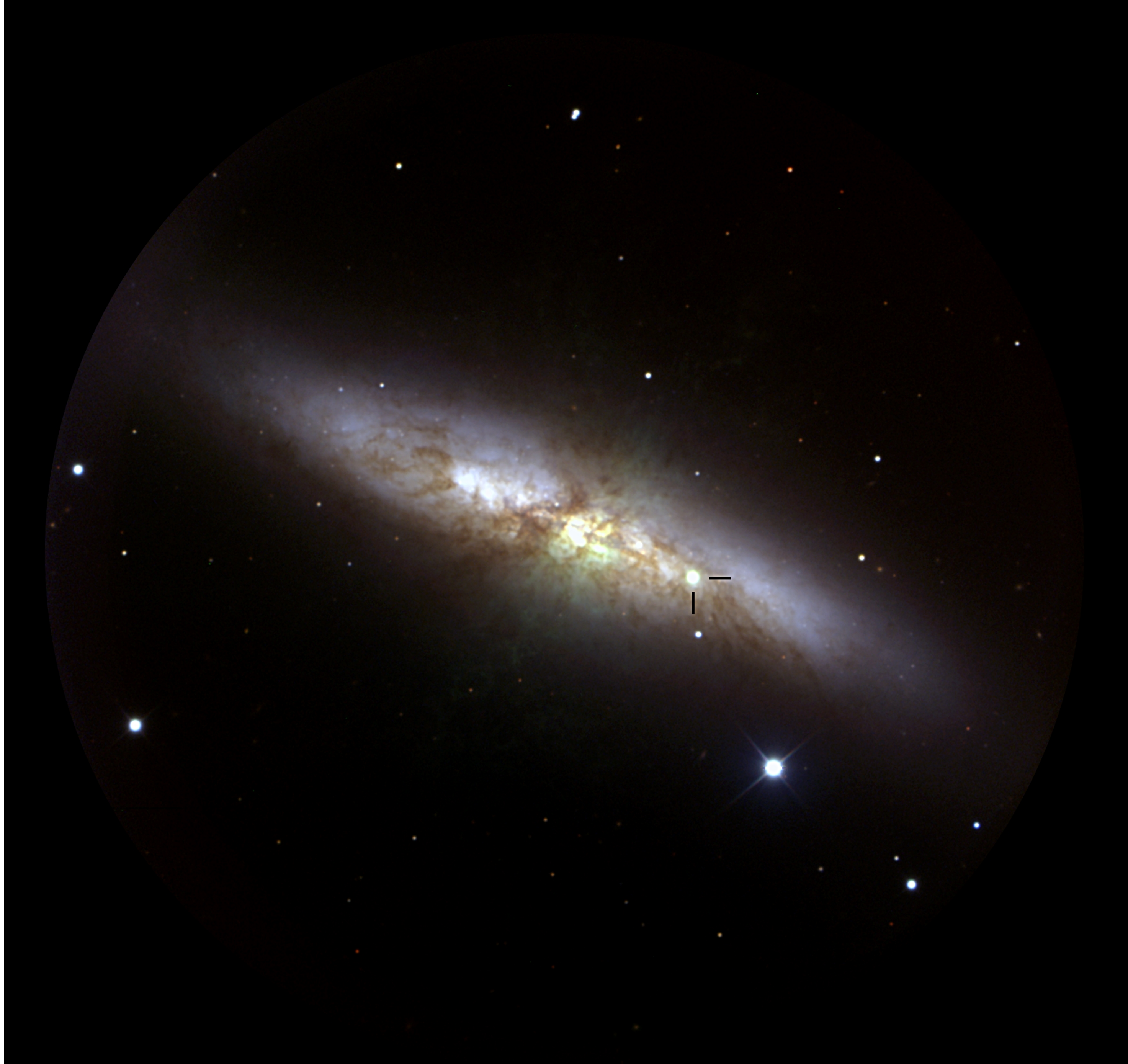
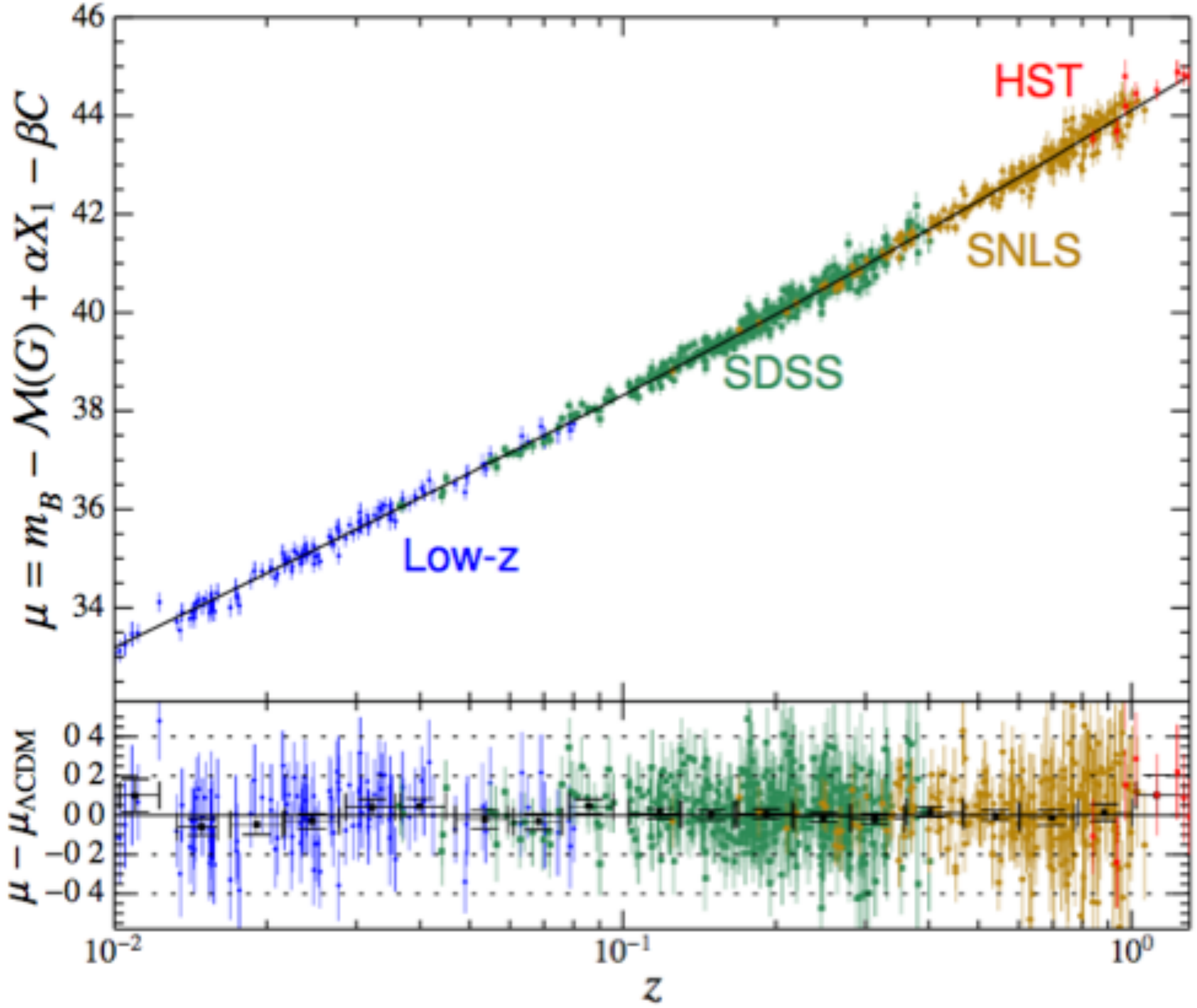


Supernova SN2014J in M82, taken from the William Herschel Telescope

Type Ia Supernovae

- Standardisable candles
- Parametrise Universe expansion
- Cosmological distance indicators - can be used to test models e.g. ΛCDM

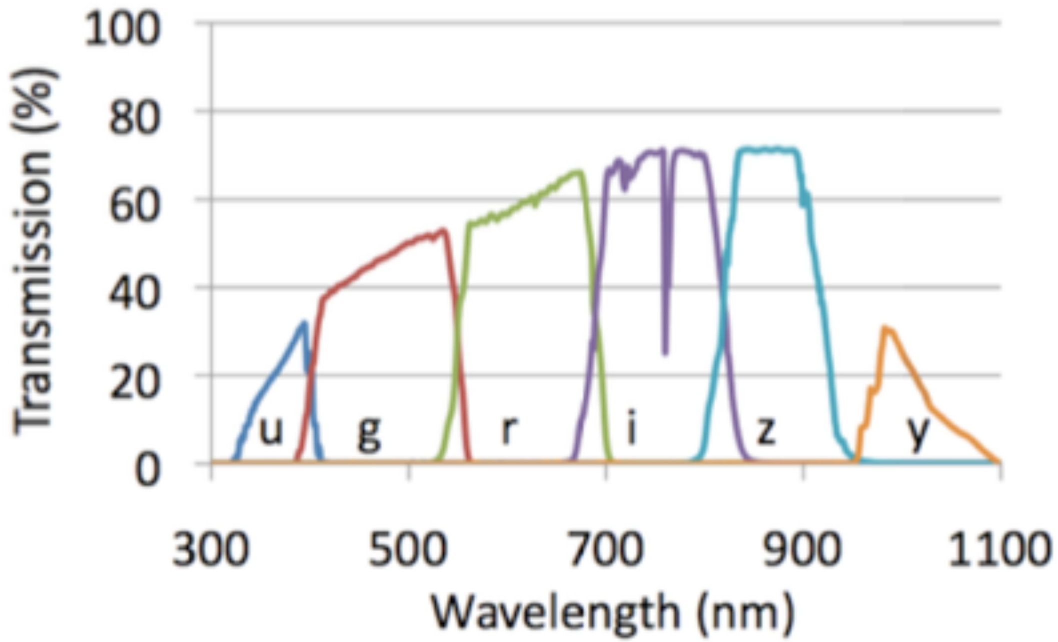


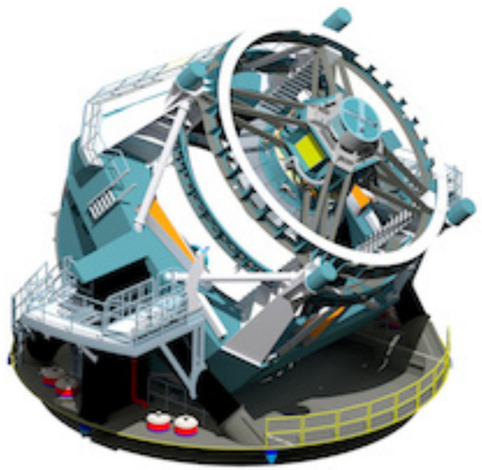
Betoule et al. 2014

The Large Synoptic Survey Telescope (LSST)

- Will cover the whole night sky every 3-4 days.
- 15 TB of data per night.
- ~100,000 Type Ia Supernovae (SNe) per year, depending on survey strategy.
- Impossible to get spectra for all transient discoveries…

Solution: photometric classification with machine learning



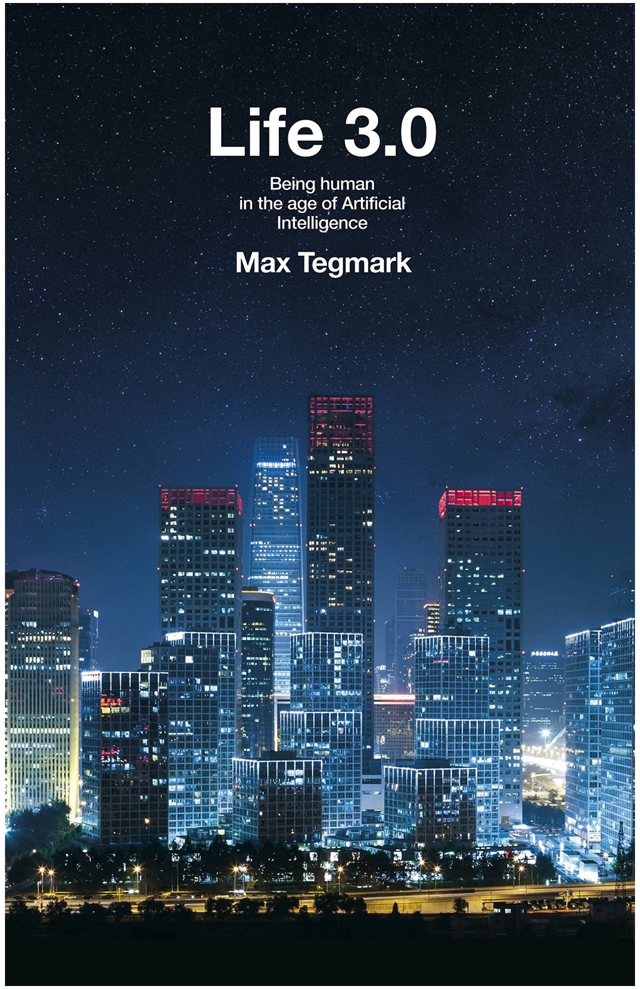


lsst.org

A very brief introduction to machine learning

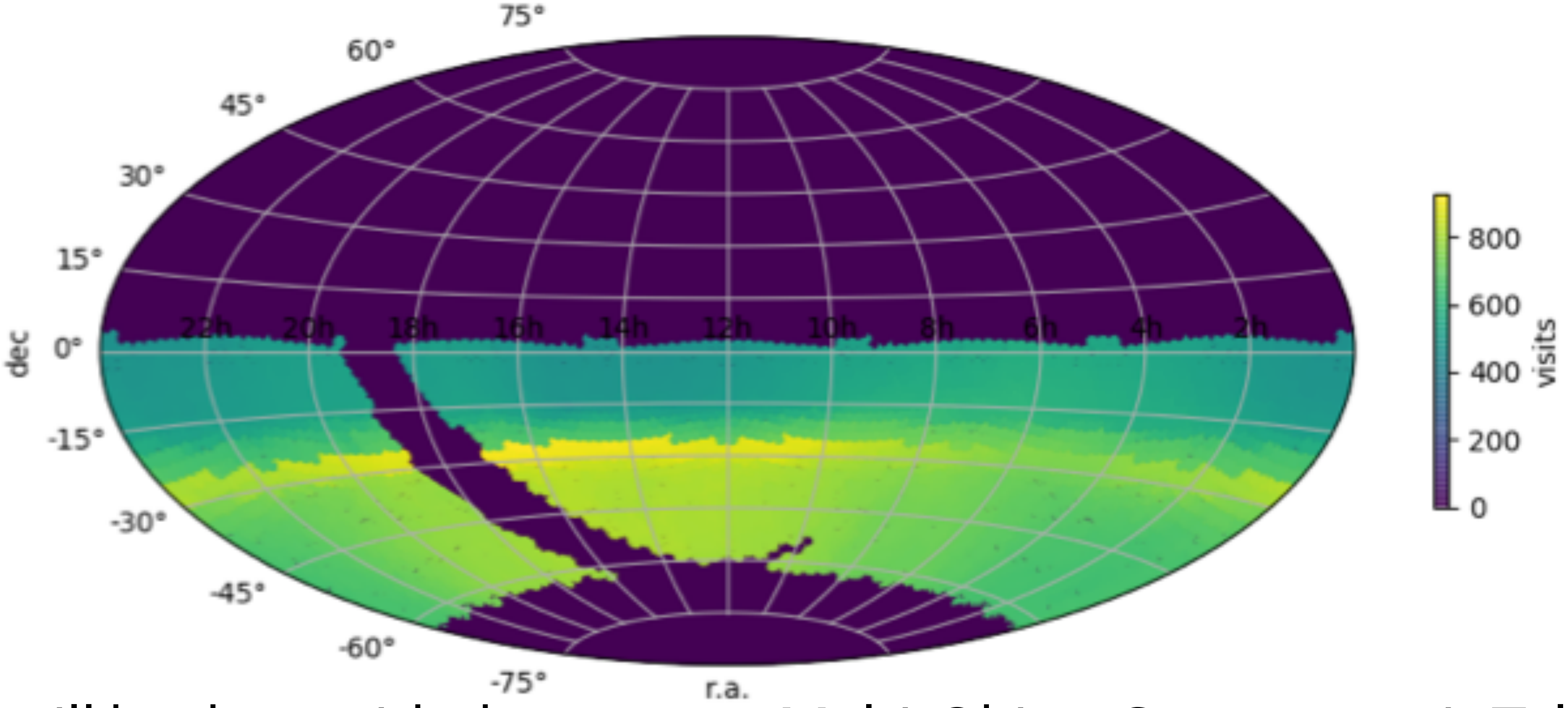
‘The 4th Industrial Revolution’

- Subset of artificial intelligence
- Program which learns to classify based on specific ‘features’
- Alternative to *deep learning* which attempts to automatically learn summary features
- A training set of data is required for the program to learn before it can reliably classify input data



Creating a training sample

- Rapid spectroscopic follow-up will provide the training sample for machine learning to classify subsequent LSST transient discoveries.
- In the Time-Domain Extragalactic Survey (TiDES) we are working to maximise survey overlap with LSST to obtain many, good quality SNe light curves.

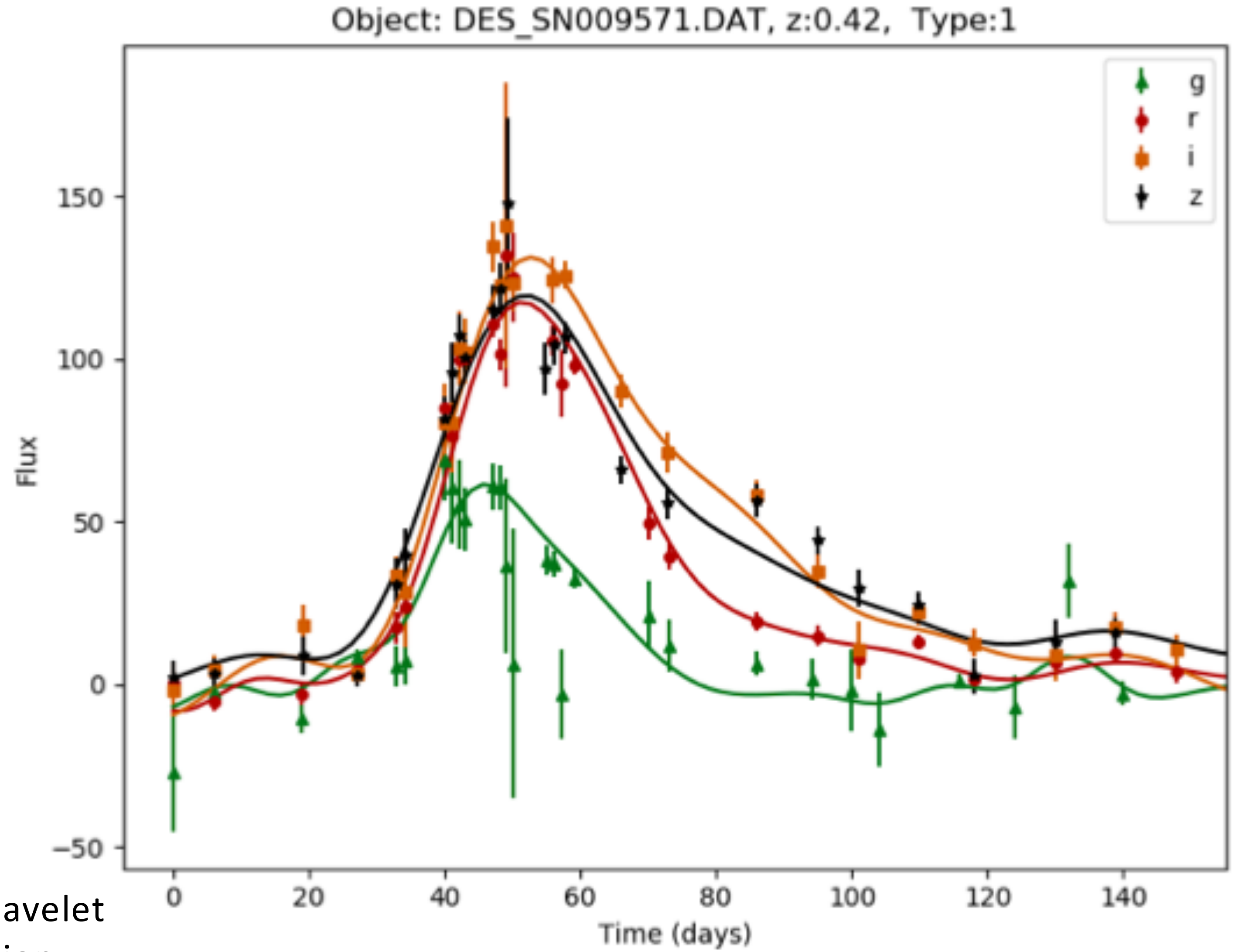


LSST: example of rolling cadence (mothra_2045)

This will be done with the 4-metre Multi-Object Spectroscopic Telescope (4MOST) in the first few years of LSST's observations.

Machine learning on SNe light curves

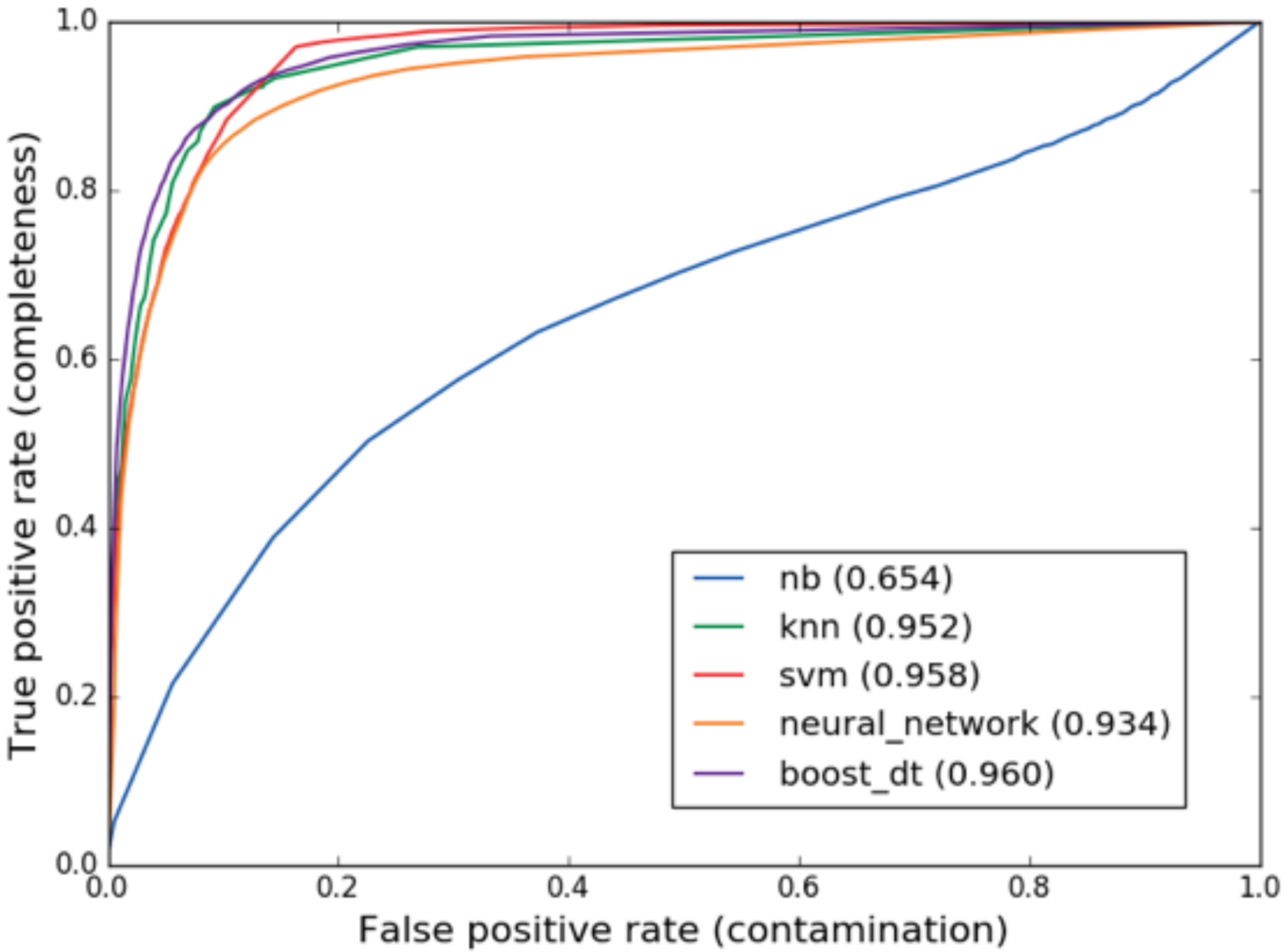
- *snmachine* (Lochner et al. 2016)
- Extract light curve features
- Train algorithms to recognise features as belonging to specific classes (i.e. type Ia, Ibc, II)
- Classify new data based on their features



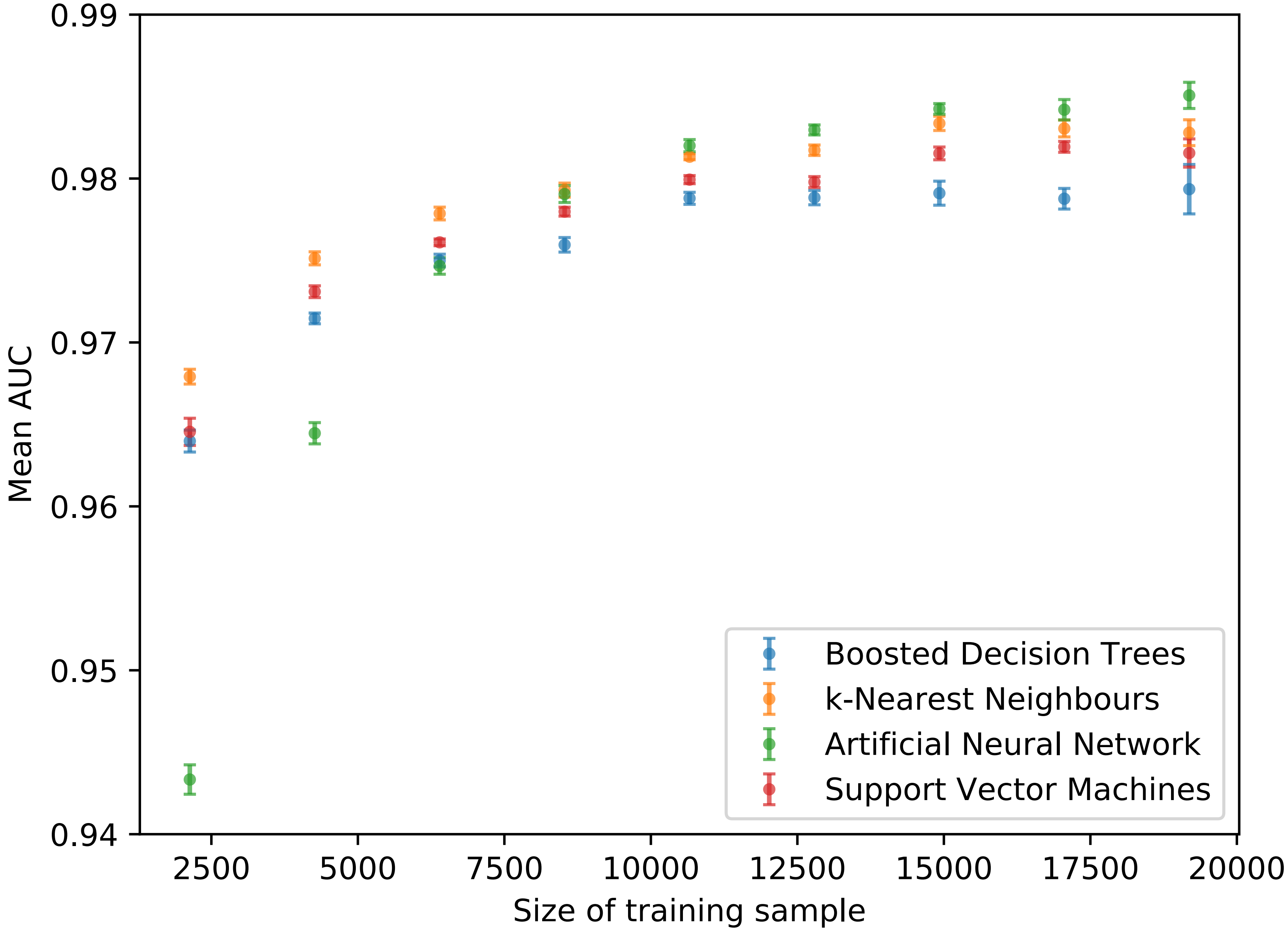
A type Ia light curve fit after wavelet decomposition feature extraction

Classification performance – ROC curves

- Receiver Operating Characteristic curves
- Binary classification of SNe (Ia vs non-Ia)
- Depends on many variables in training, such as sample size, representativeness, magnitude cut-off

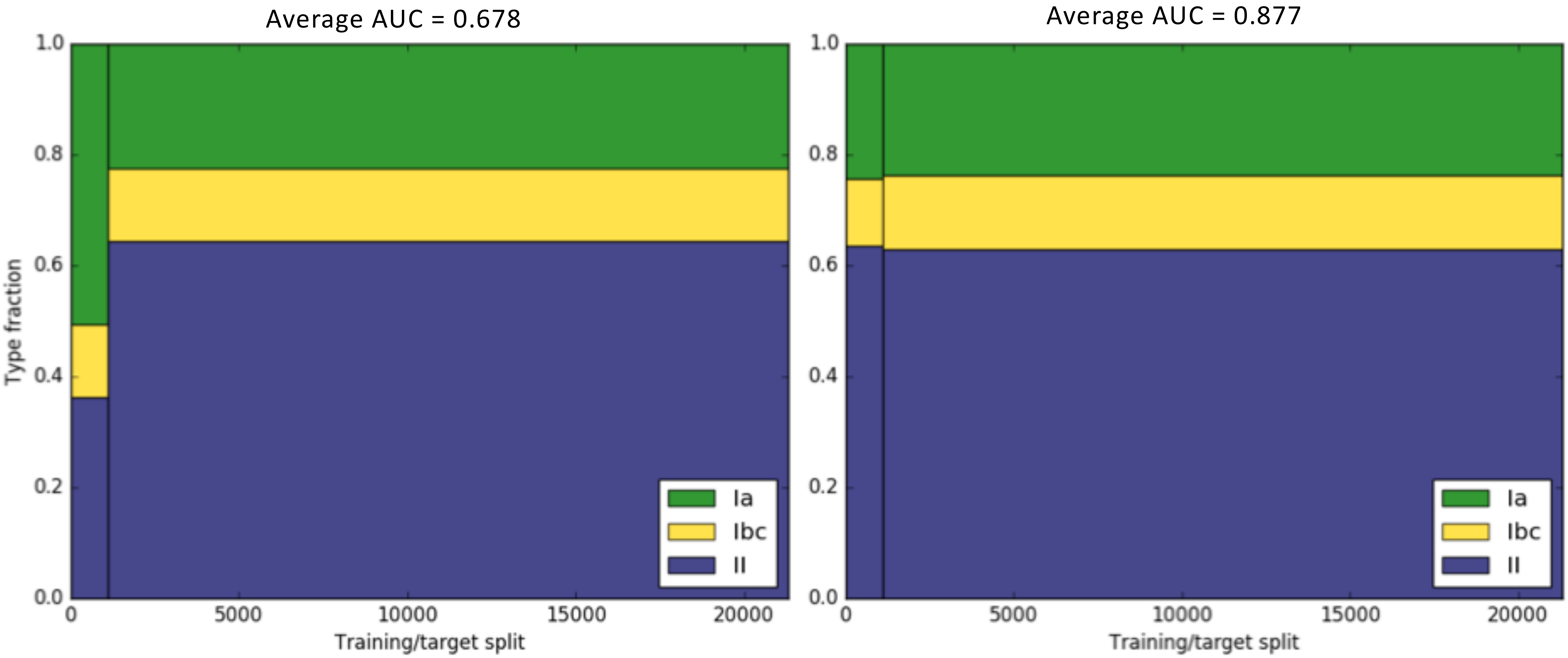


Size of training sample



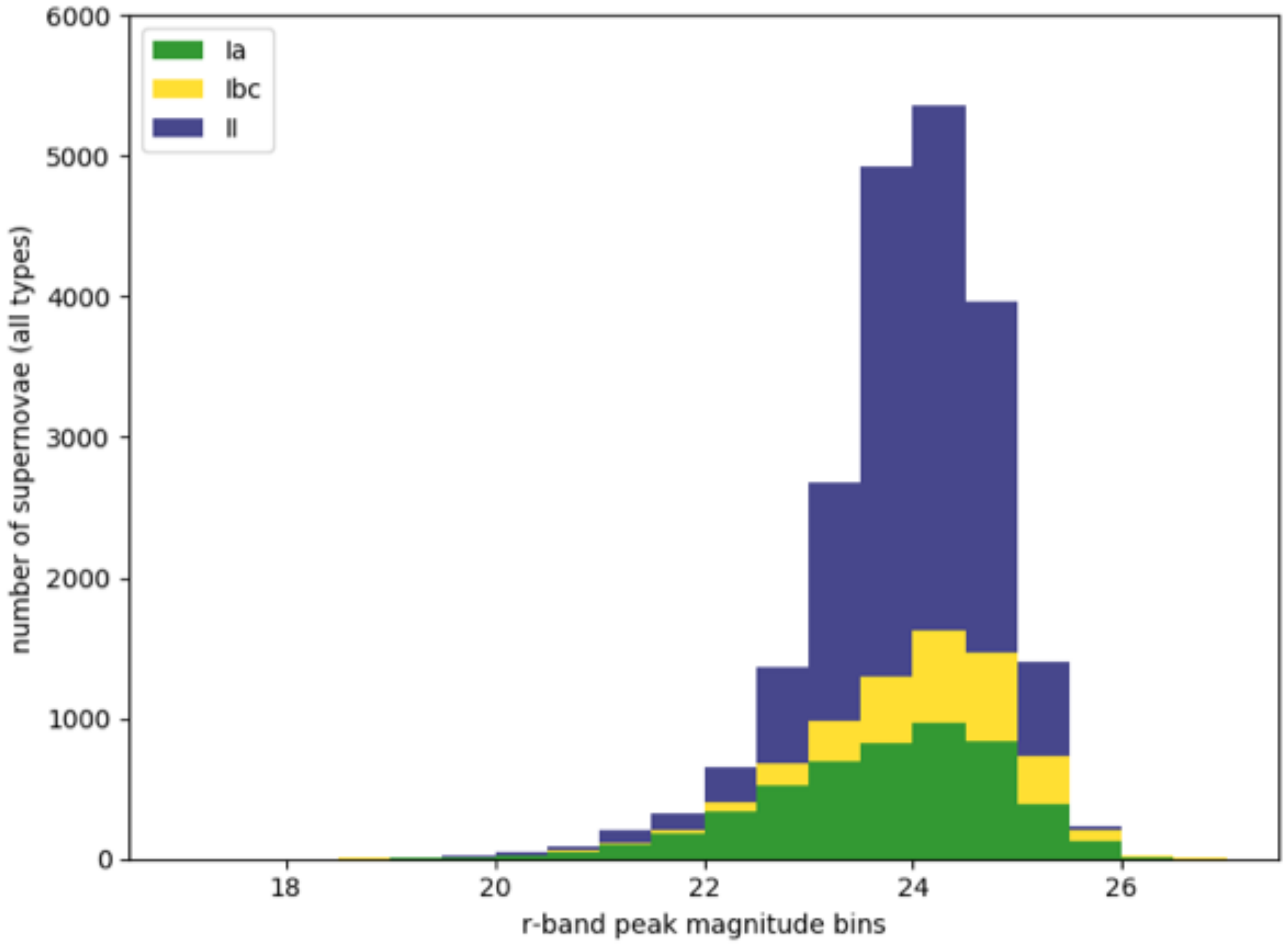
Representativeness

Compare original training (non-representative) against same size but class-representative



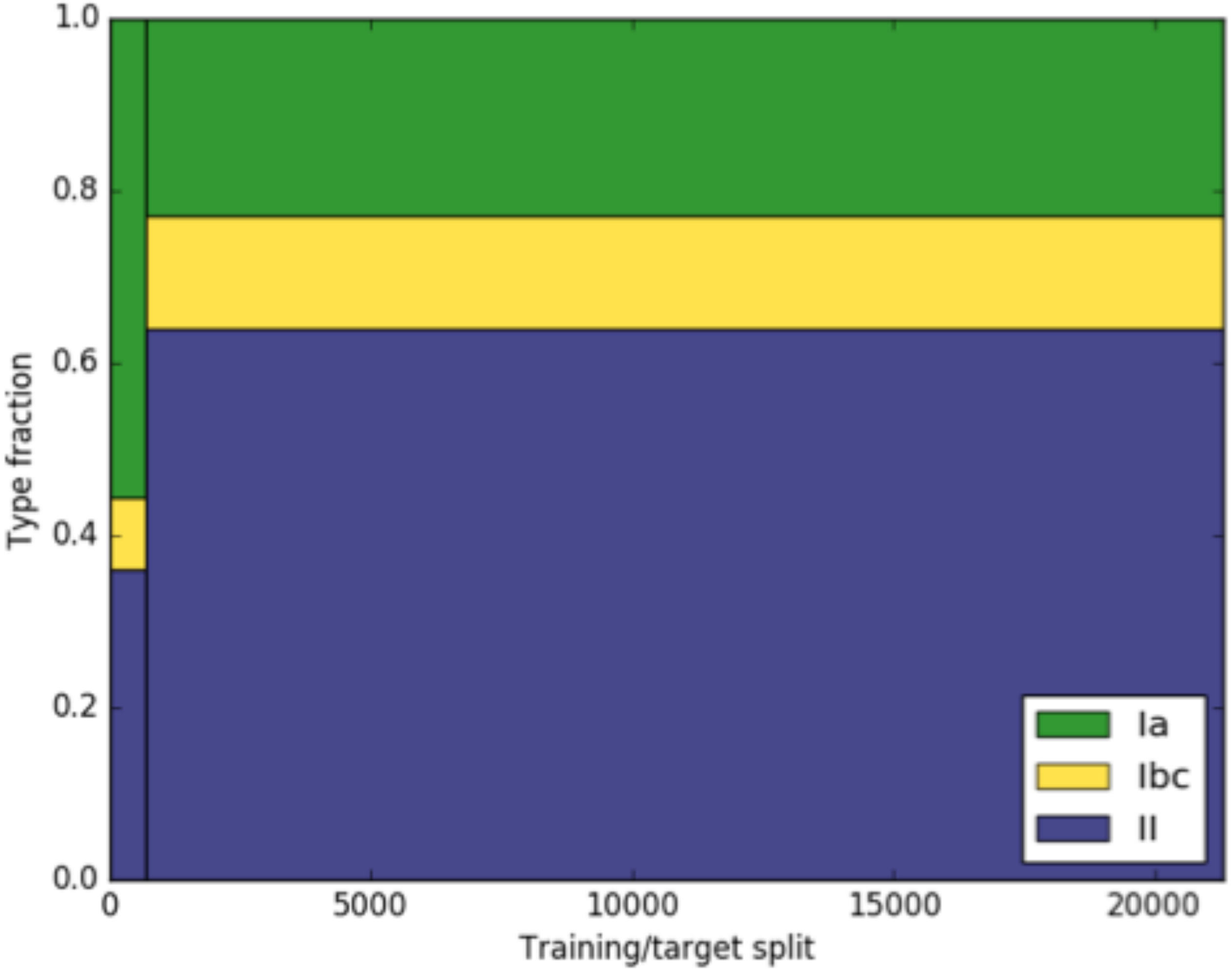
(All magnitudes)

Magnitude cut-off

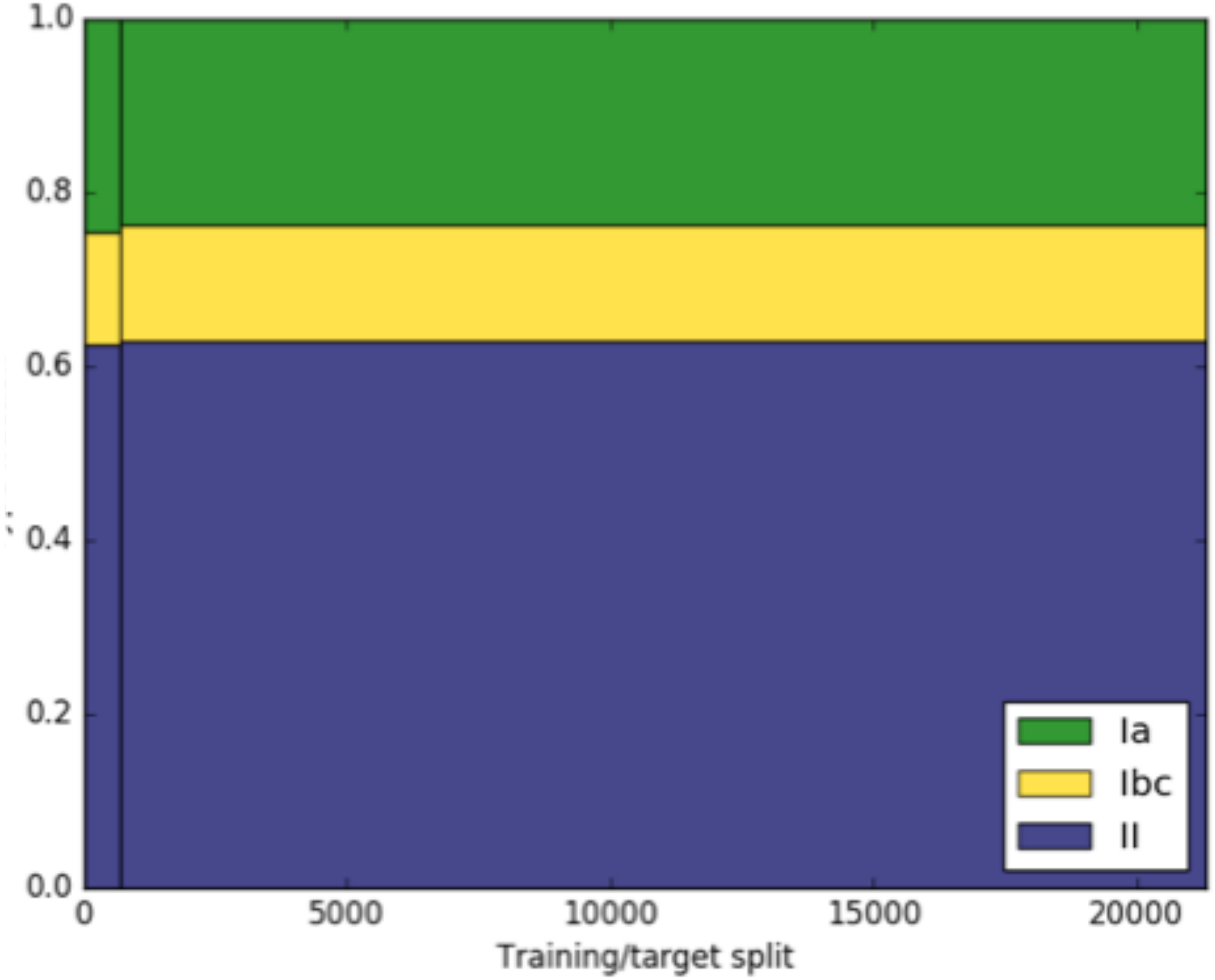


Magnitude cut-off vs no cut-off

All training objects < 22 r mag

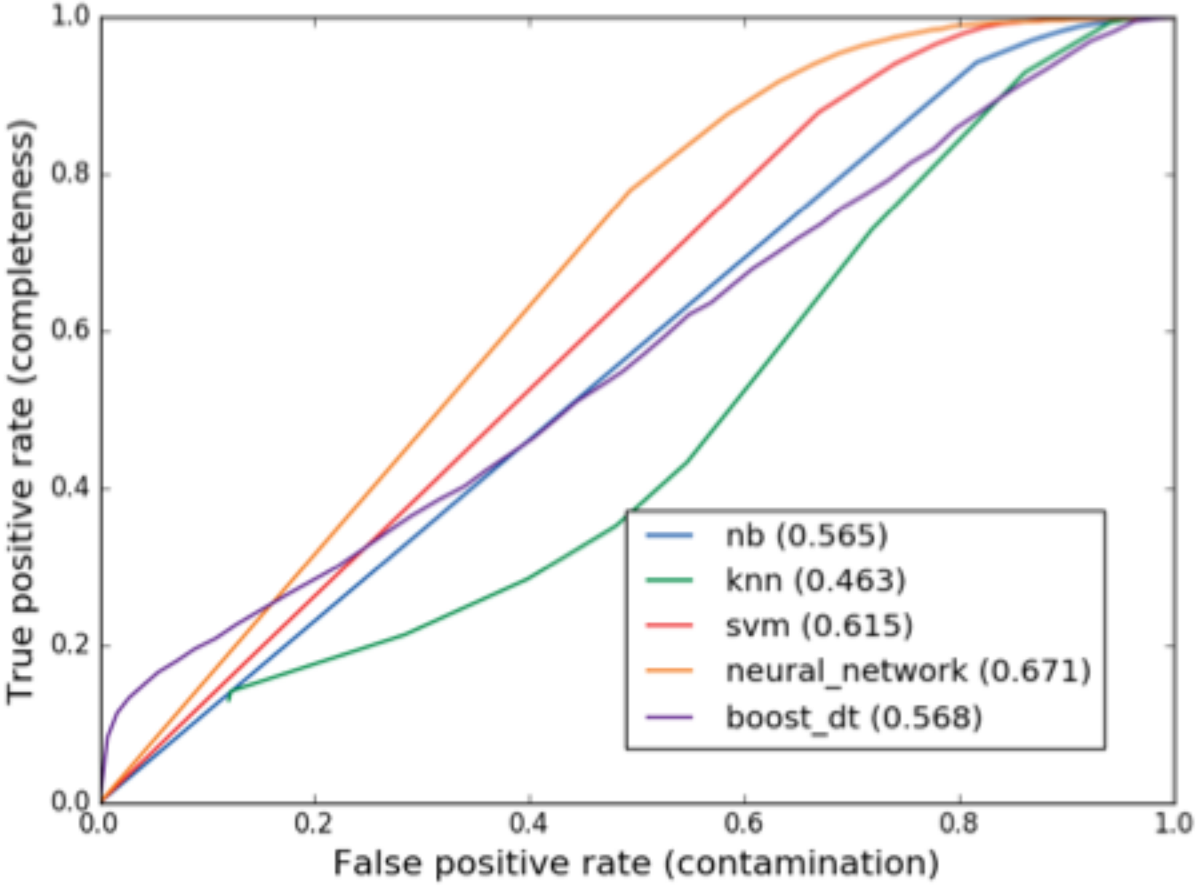


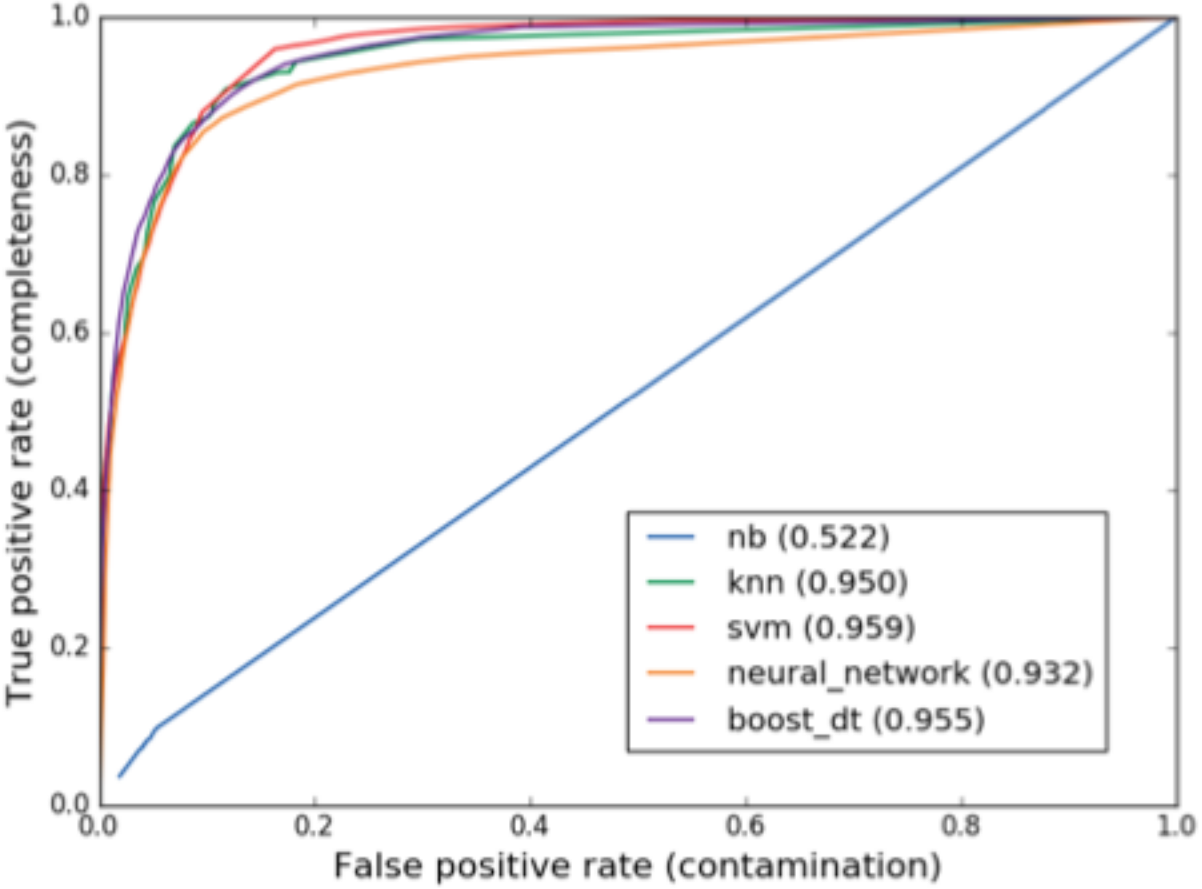
Same size training for all mags (i.e. no mag cut-off)



Magnitude cut-off vs no cut-off

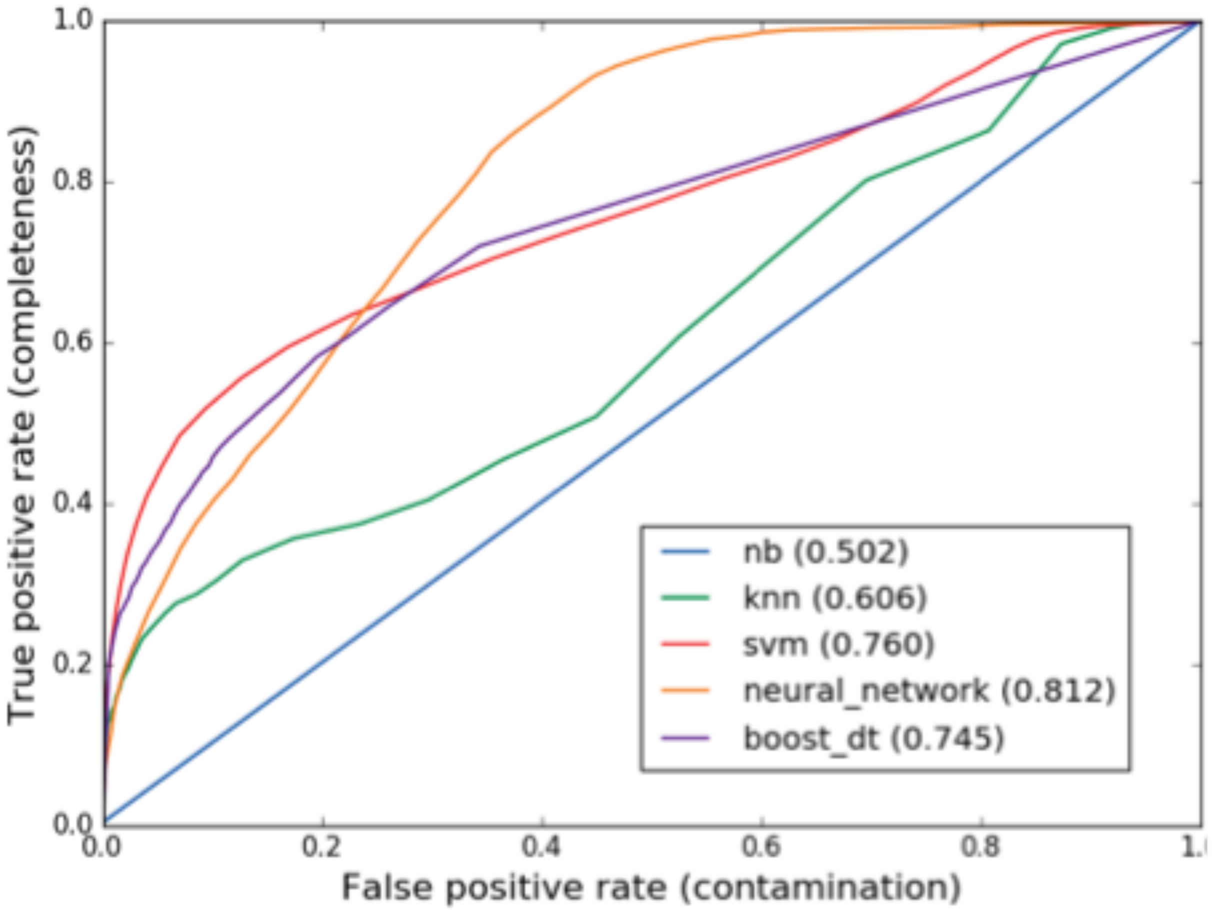
Mag cut-off implies non-representativeness. Therefore we next test a magnitude cut-off against the same cut-off but representative by class

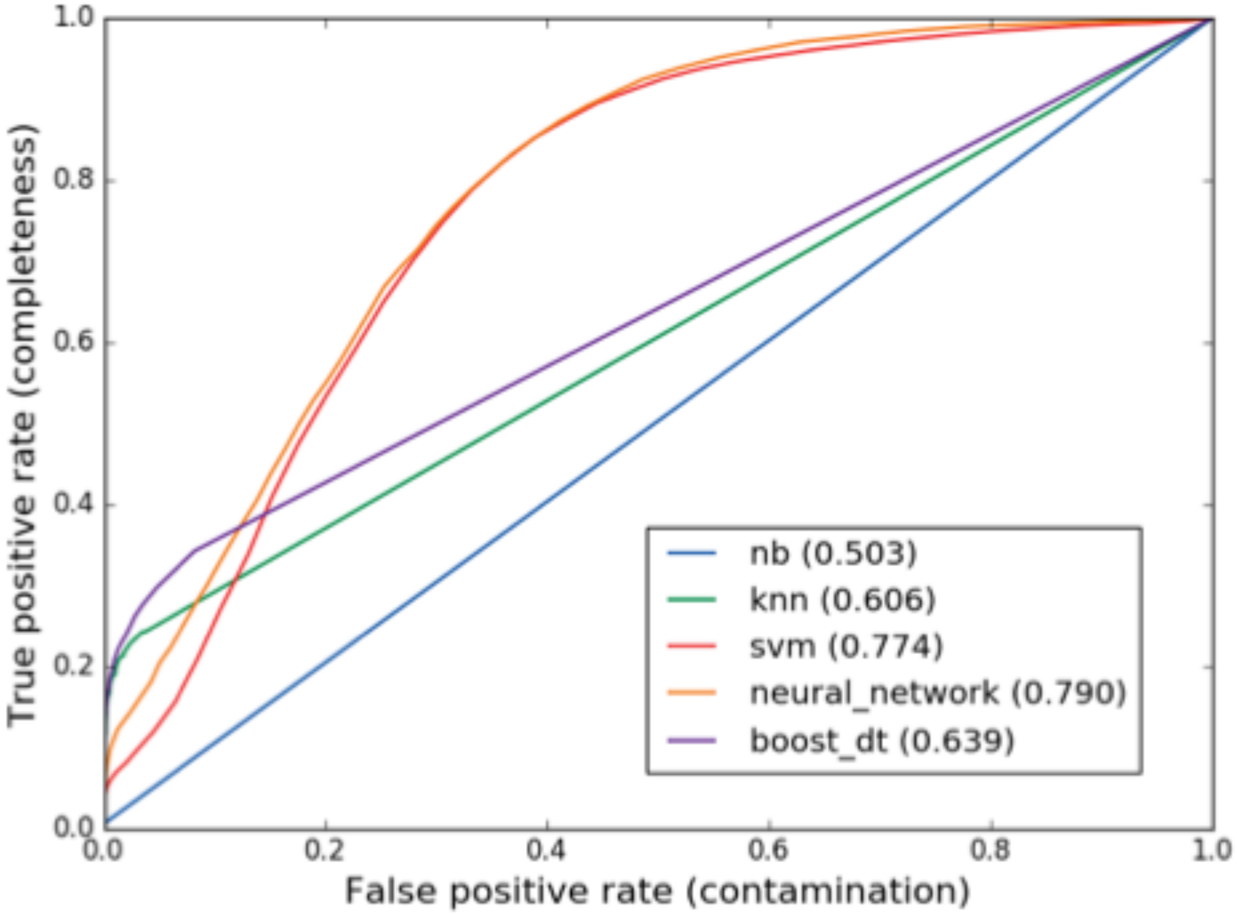




Magnitude cut-off vs representative (by class) cut-off

Same size training set as before, but limit set to 22.5 r mag (training/target split looks the same after down-sample, although the mag cut-off is present in both cases)





What this means…

- Classification performance with wavelet feature extraction is highly dependent on class and magnitude representativeness.
- Introducing a magnitude cut-off shows us that the machine learning struggles with this type of training.
- Going to deeper magnitudes requires more exposure time for getting good spectra. This really affects how many supernova we can realistically get for training.
- A template-fitting method may work better as it will help to normalise the light curves.

Summary – further work

- Supernova classification with machine learning appears highly dependent on dataset size and representativeness in all senses
- A magnitude cut on training may affect classification negatively

Next things to consider:

- Main contaminants
- Partial light curves
- More data (PLAsTiCC)

Example plot of class separation after reducing feature dimensionality