SuperNNova

open source photometric classification

Bayesian Neural Network lightcurve classification

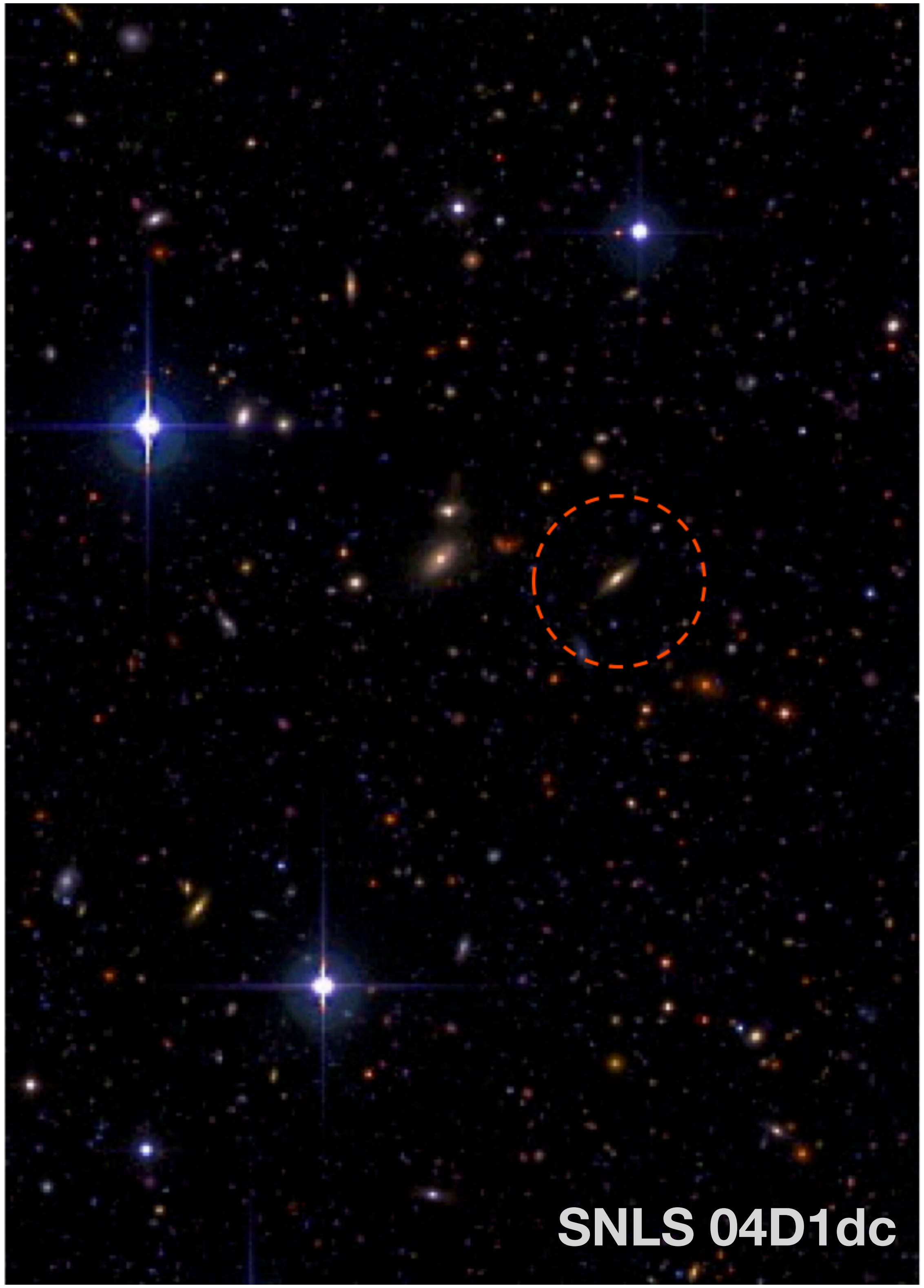
Anais Möller
CNRS / LPC Clermont

Garching, July 21st 2019

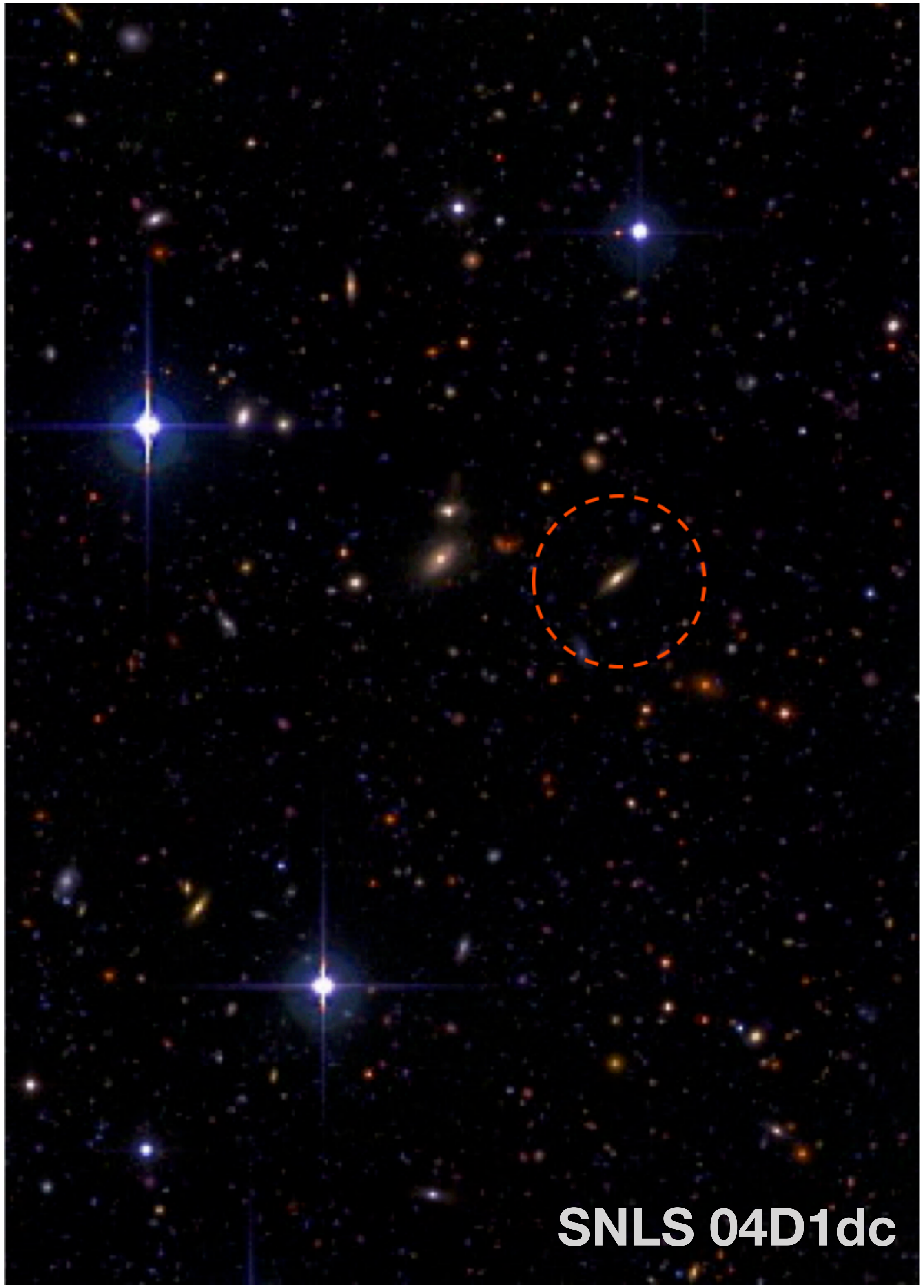
cnrs

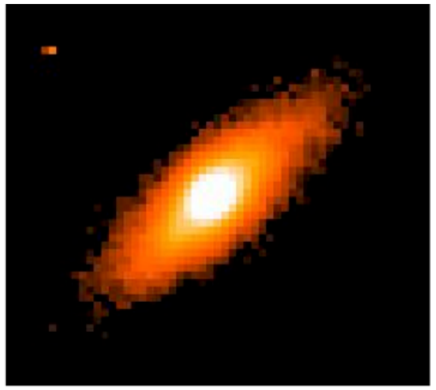
LPC Particules pLasmas Univers applicationS
Laboratoire de Physique de Clermont

transient lightcurves



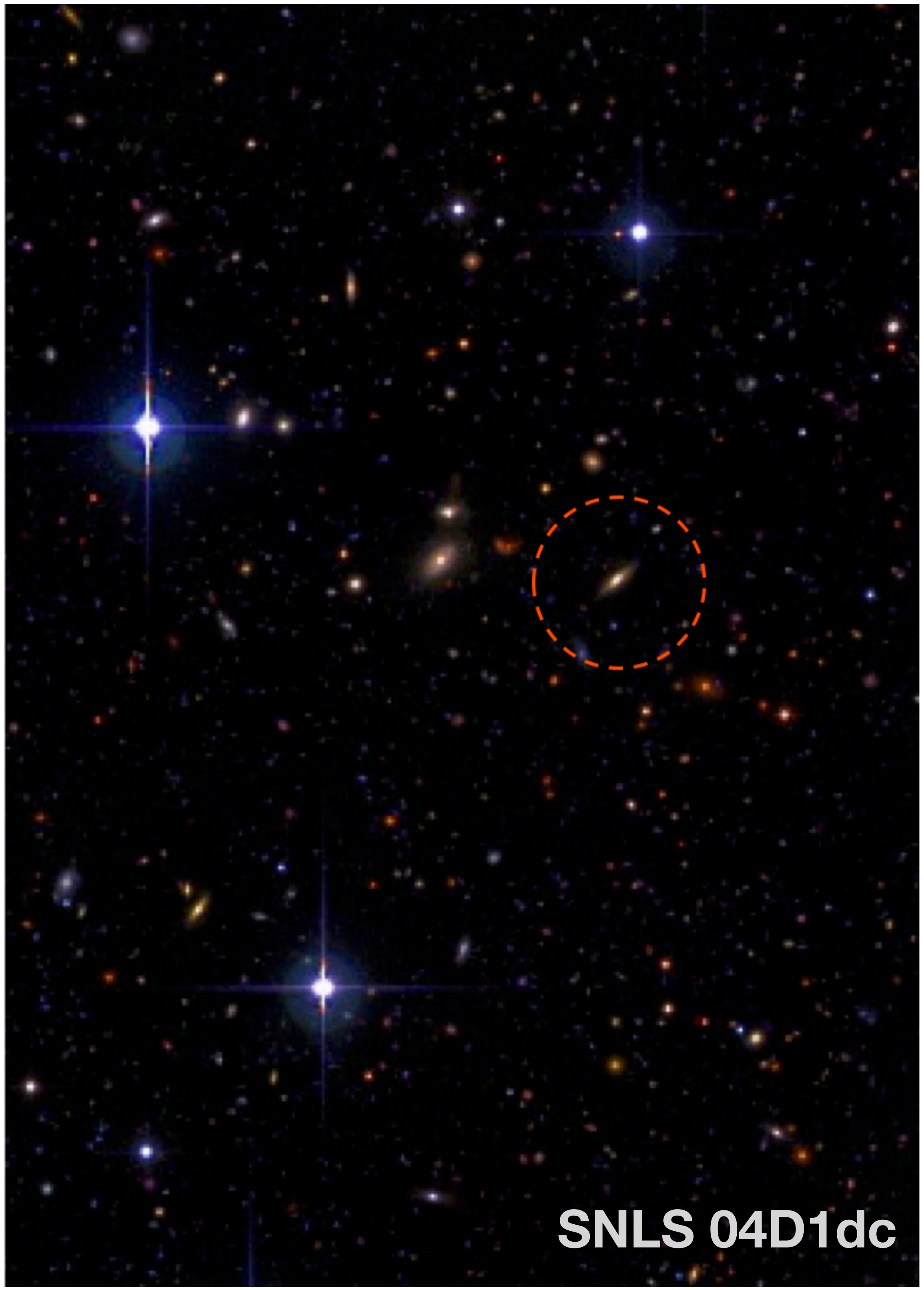
transient lightcurves

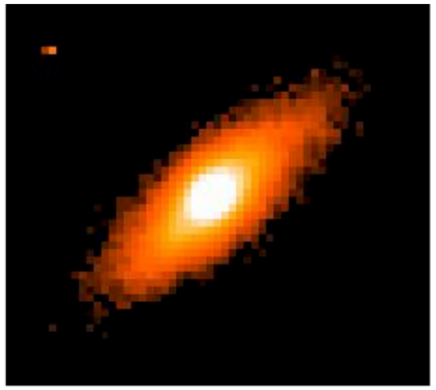




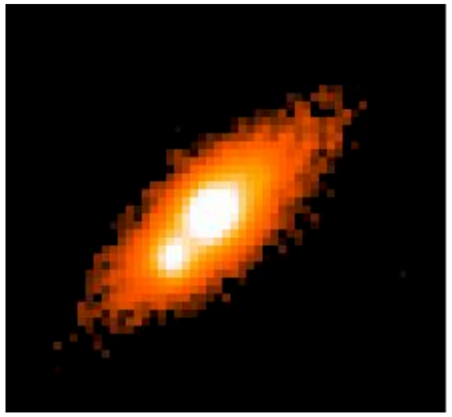
a week ago

transient lightcurves



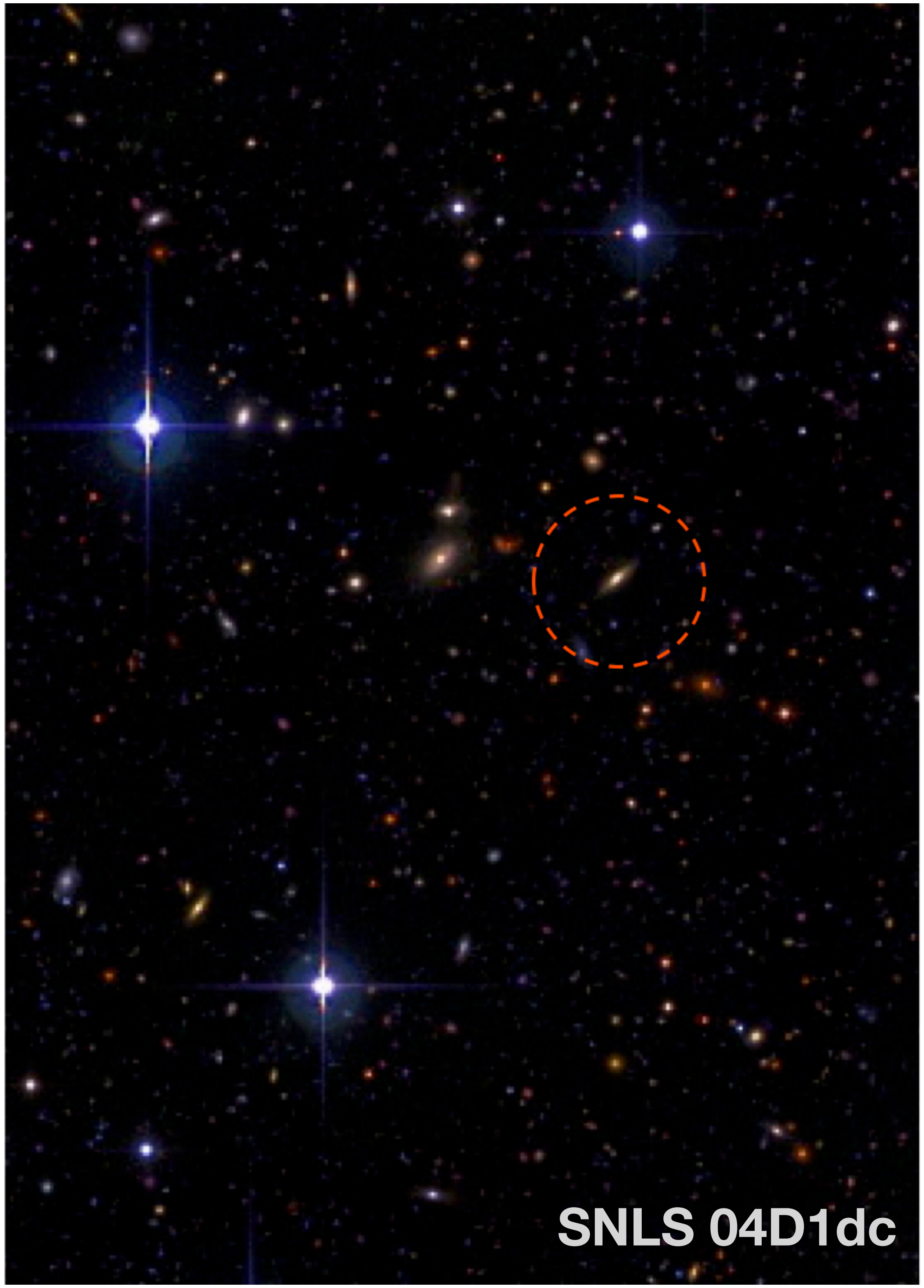


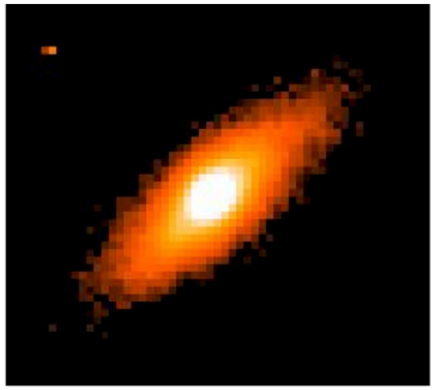
a week ago



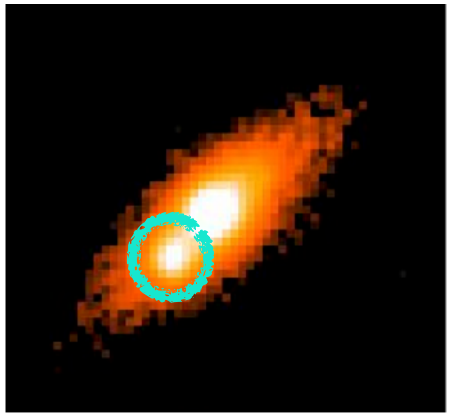
today

transient lightcurves



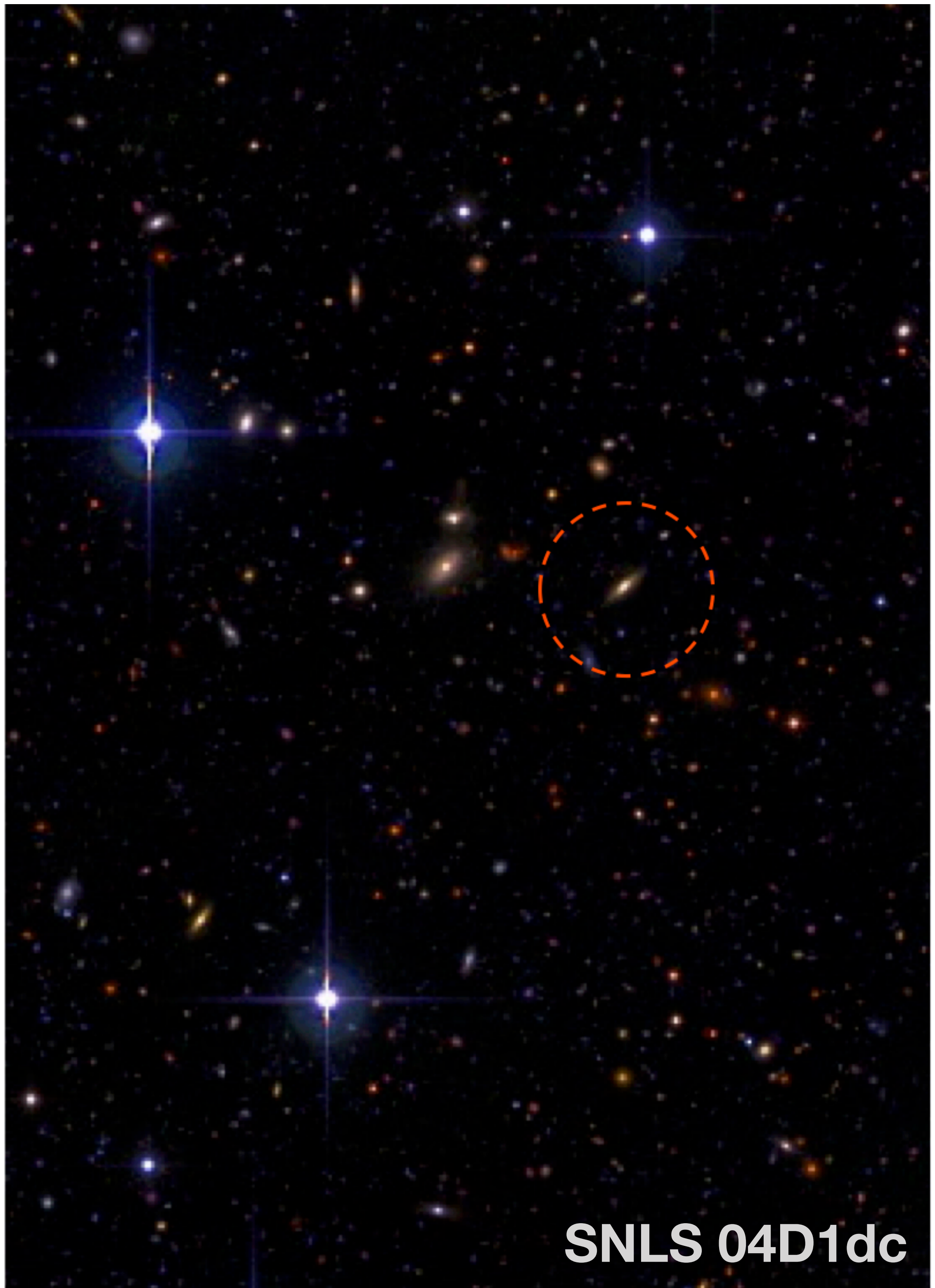


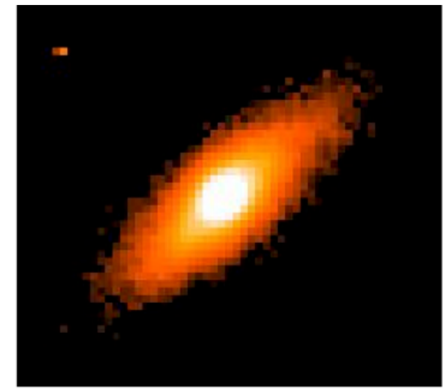
a week ago



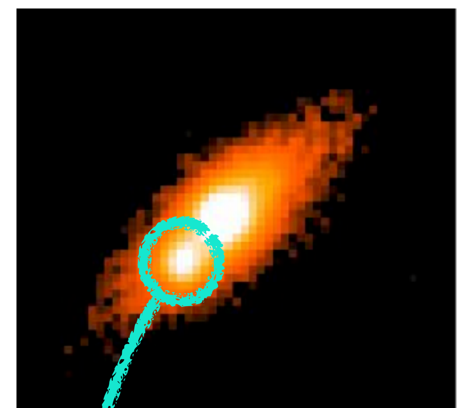
today

transient lightcurves

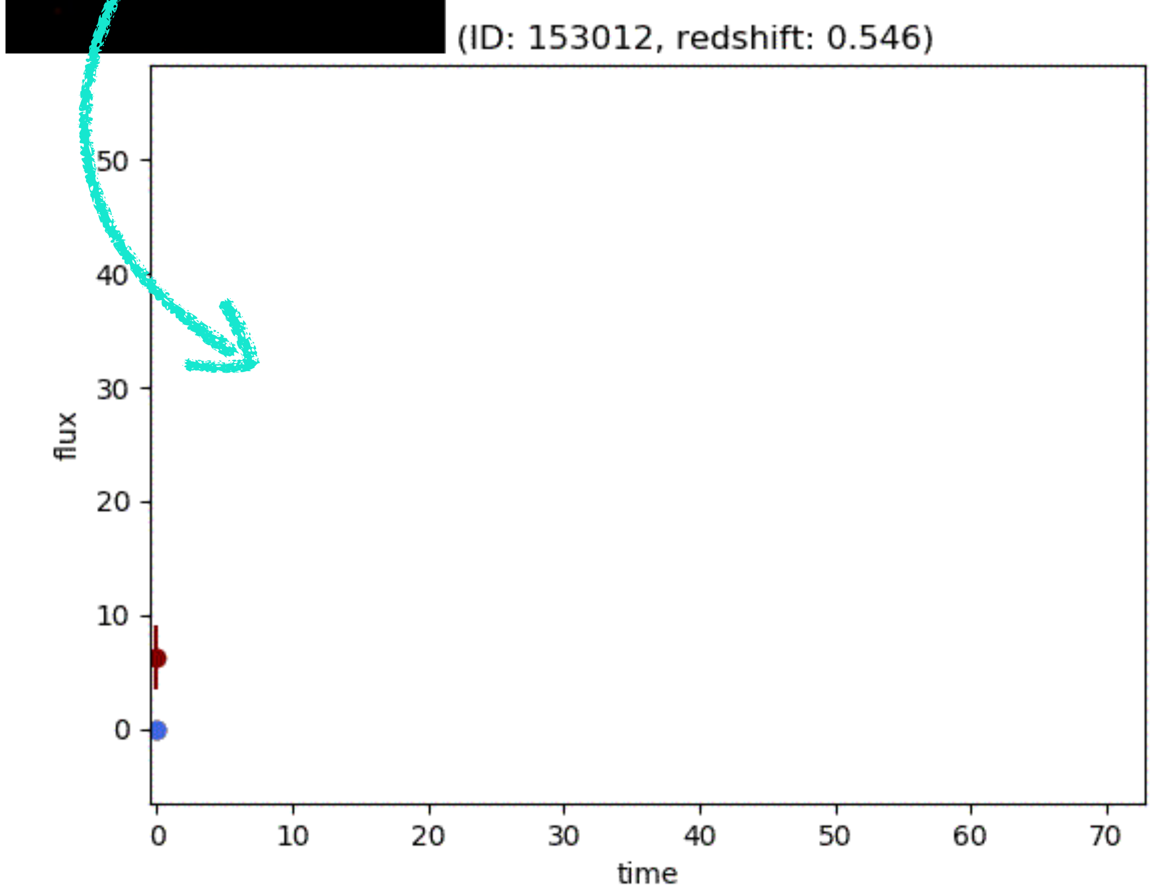




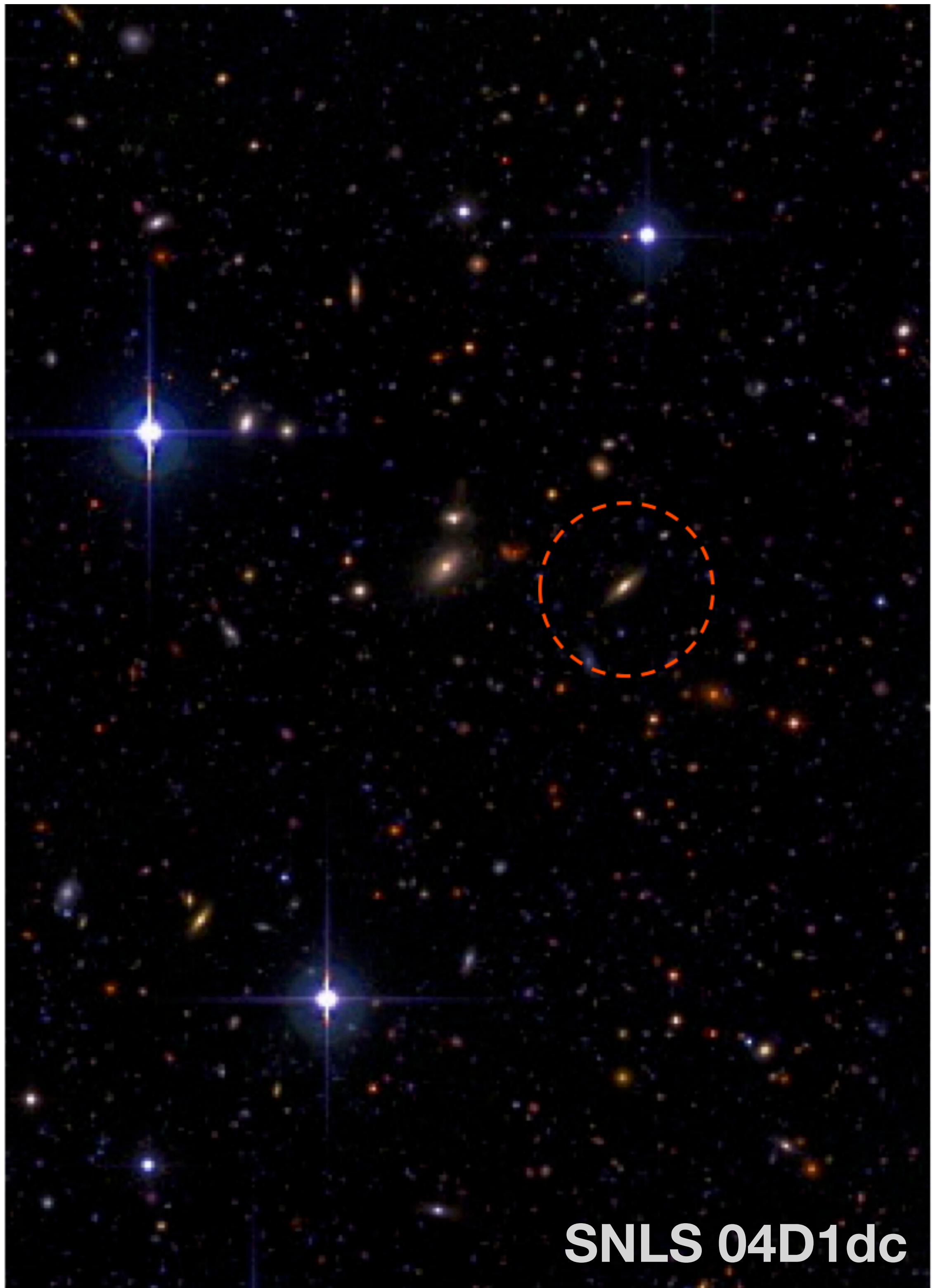
a week ago

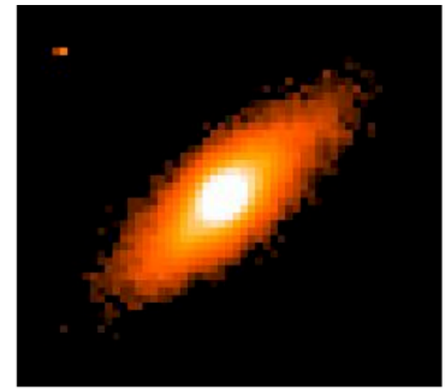


today

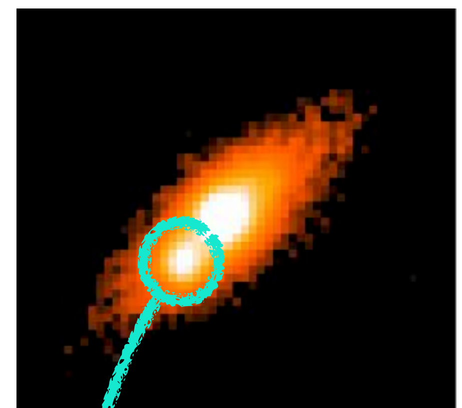


transient lightcurves

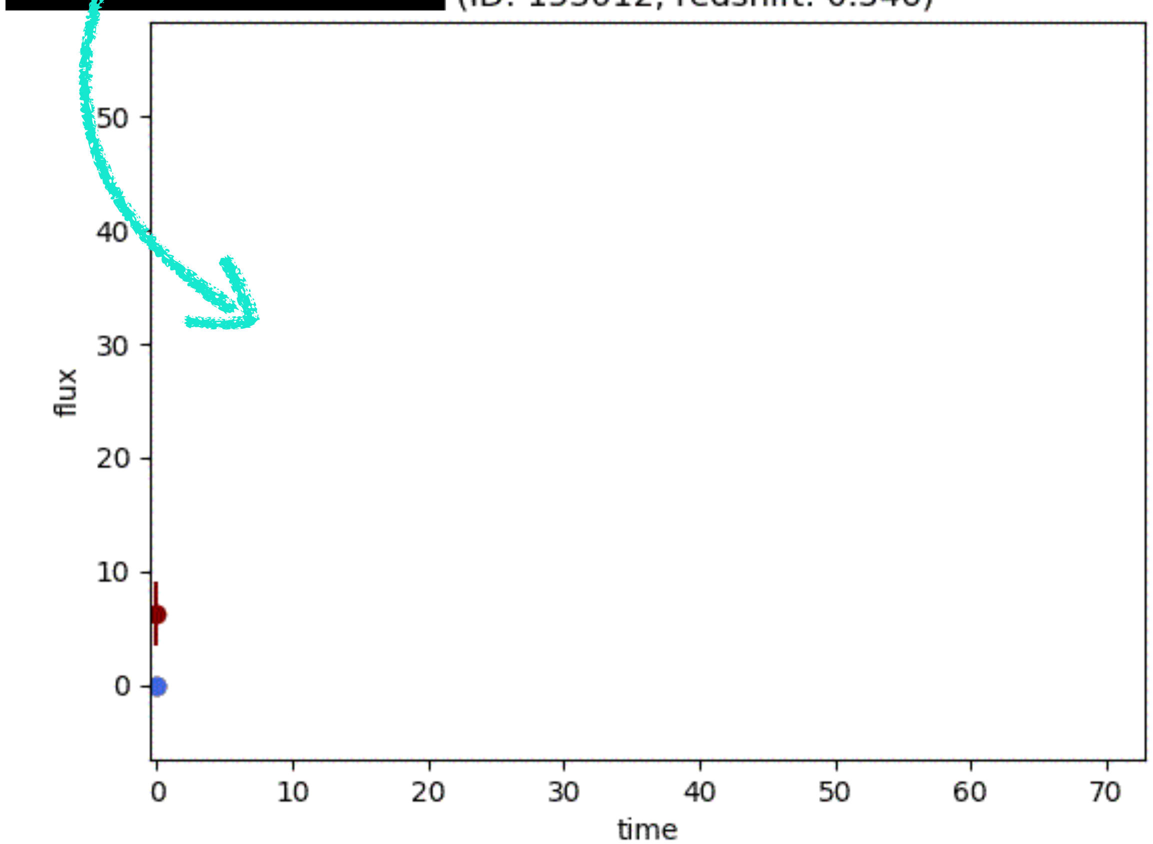




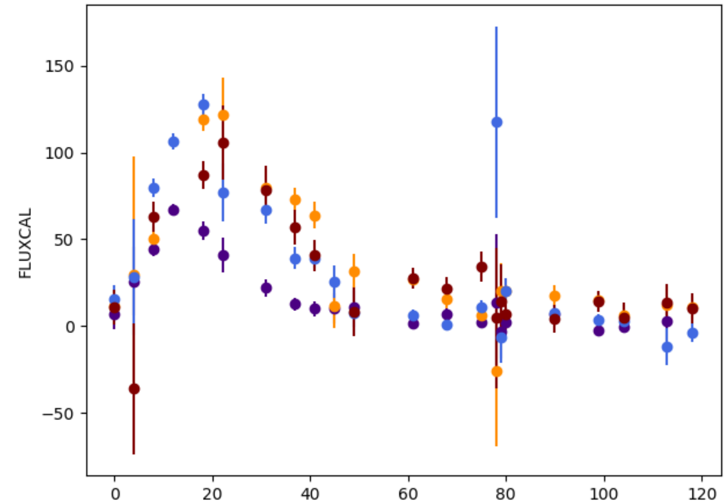
a week ago



today

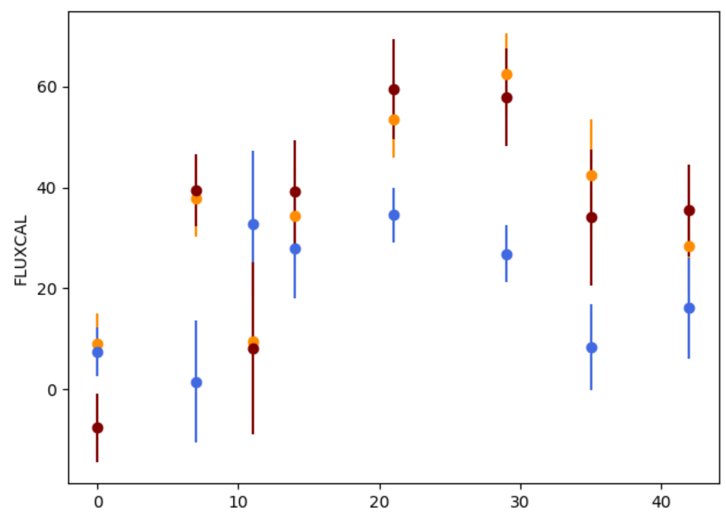


transient lightcurves

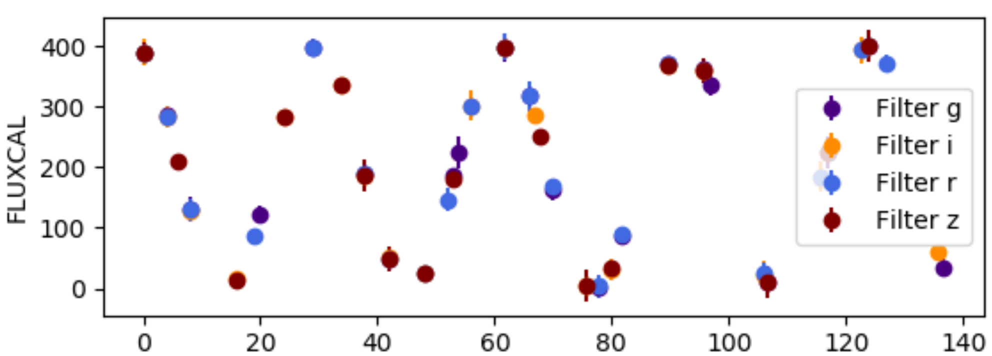


Supernovae

Types Ia, Ib, Ic, II, II-L, II-P, IIn, …



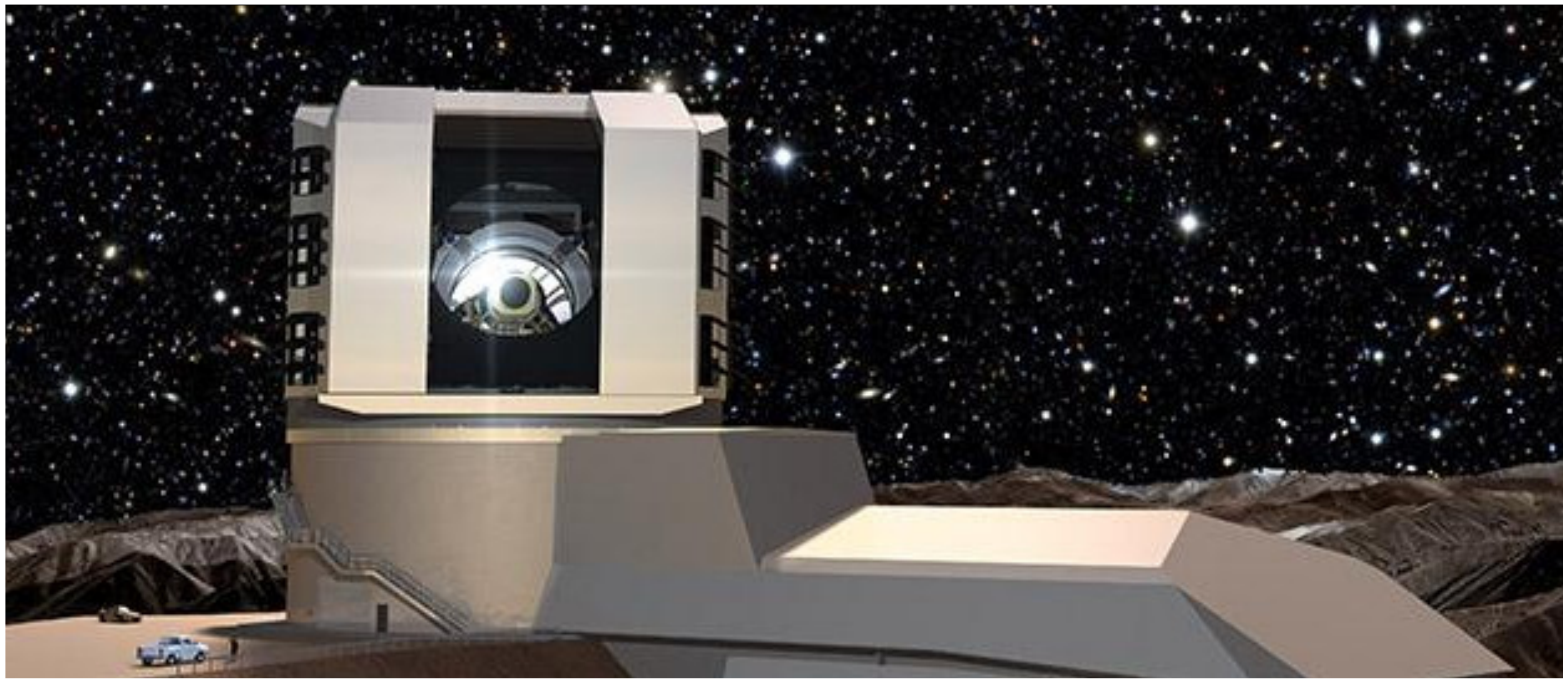
AGNs



Variable stars

kilonovae, transiting exoplanets, microlensing events, flares, CV, …

future surveys: large synoptic survey telescope



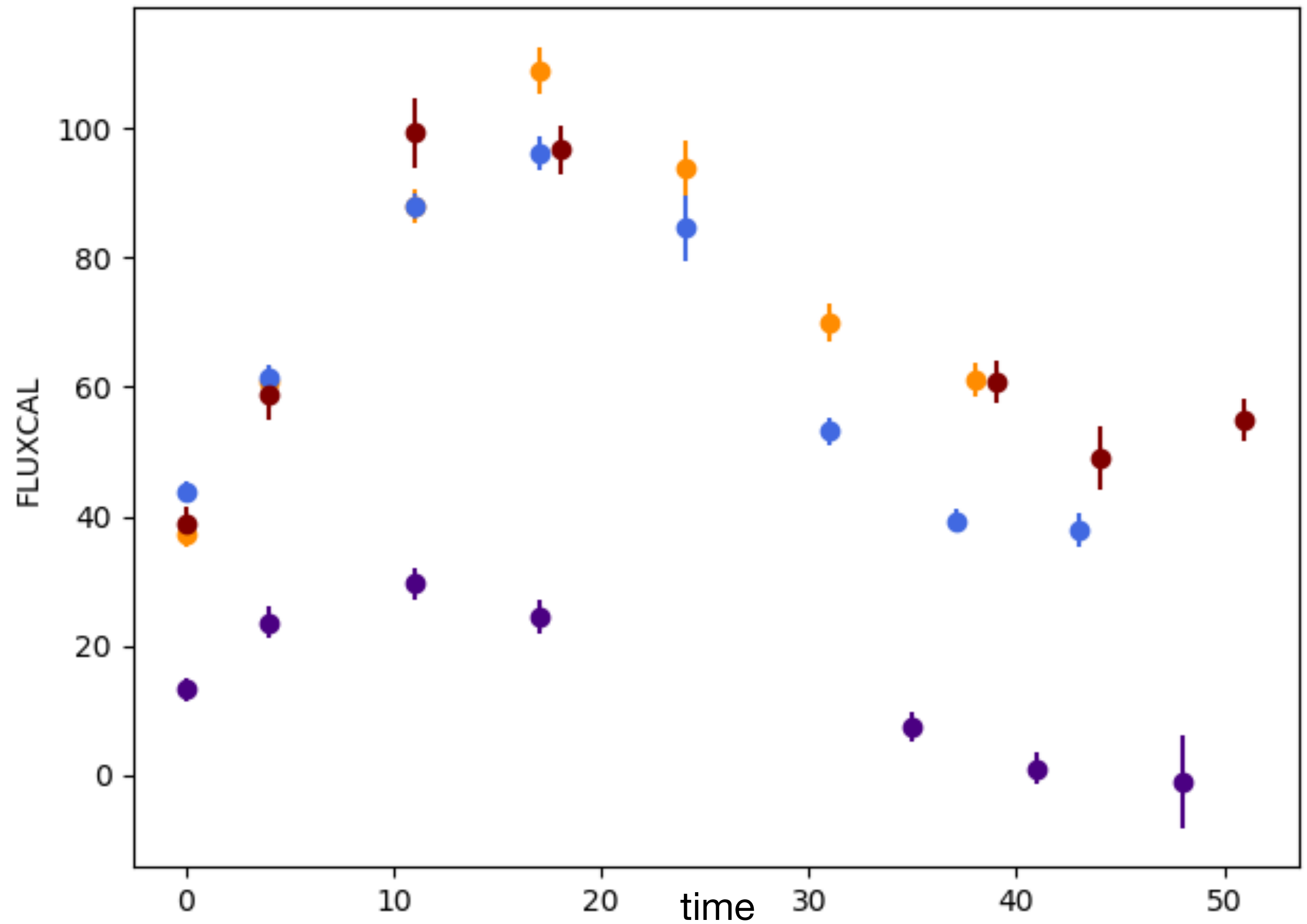
In numbers:

* 10-year survey, starting 2022

* 1,000 images/night = 15 TB/night

* 10,000 alerts/30 seconds = 1 GB / 30 s

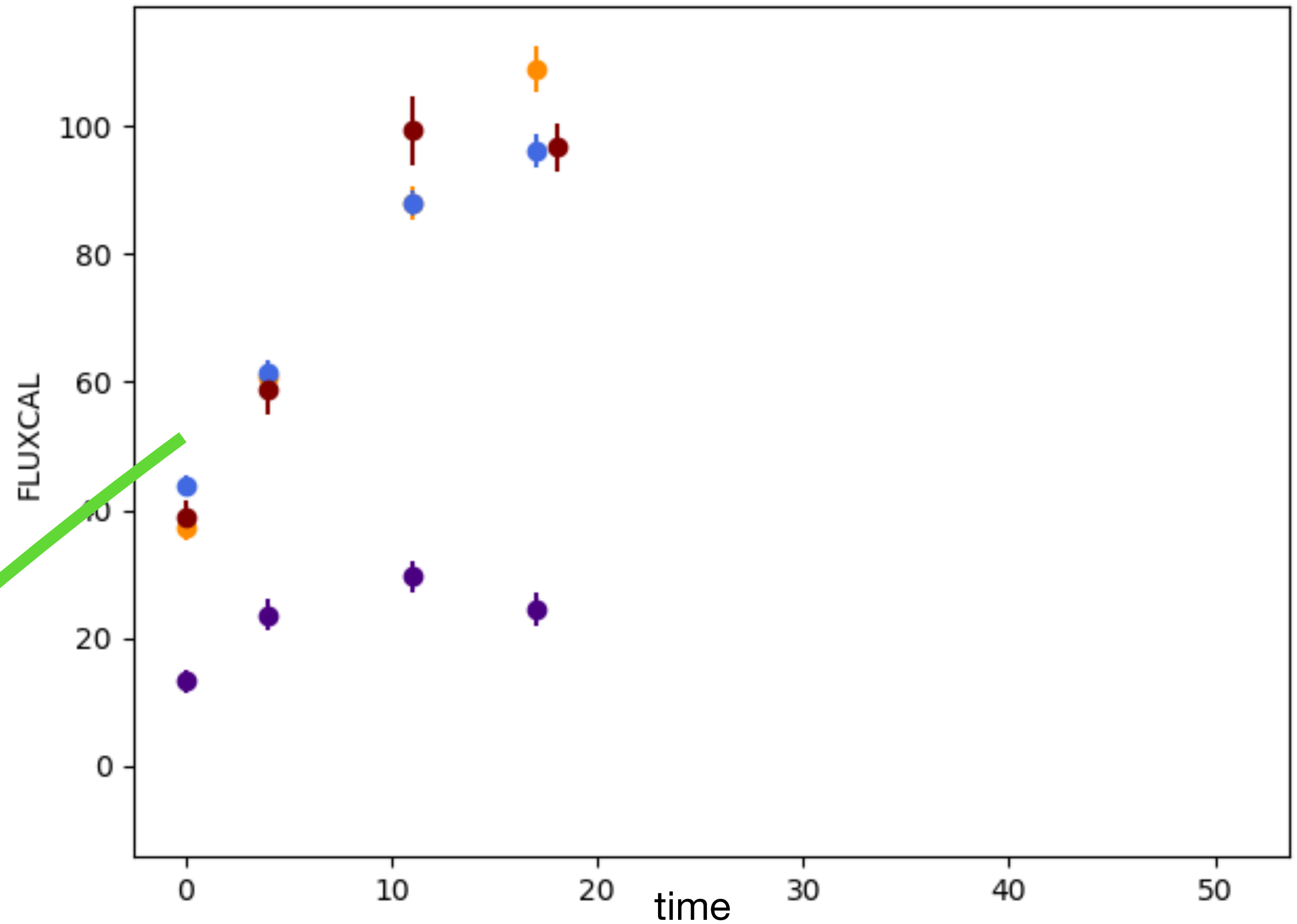
photometric classification



classification

Instead of spectra, we just see the evolution on brightness in some wavelengths

photometric classification

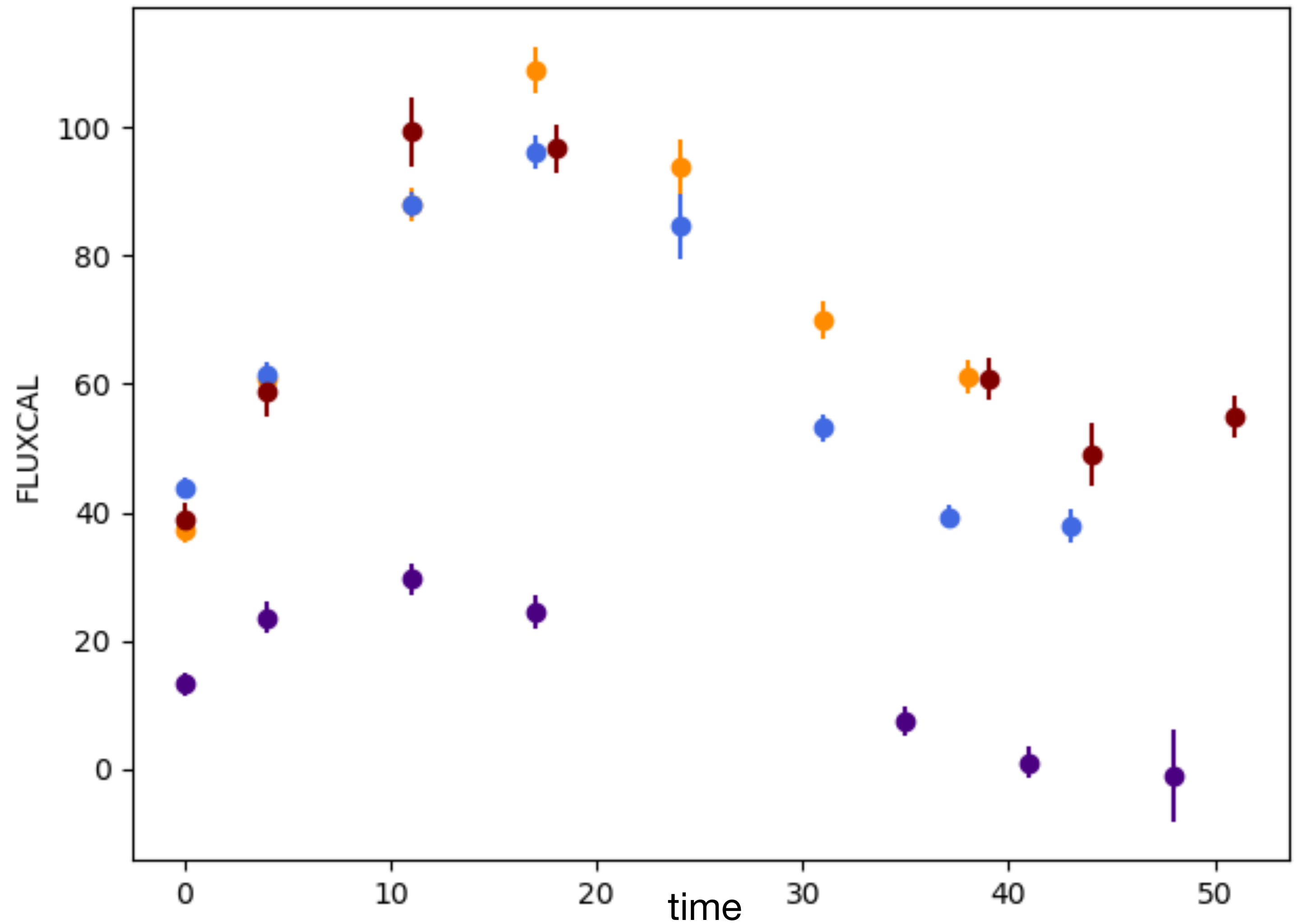


Early classification

brokers

spectroscopic/photometric follow-up

photometric classification



Complete light-curve classification

larger & more reliable samples,
probing new parameter space

photometric classification

Results from the Supernova Photometric Classification Challenge

Richard Kessler,[1,2] Bruce Bassett,[3,4,5] Pavel Belov,[6] Vasudha Bhatnagar,[7] Heather Campbell,[8]
Alex Conley,[9] Joshua A. Frieman,[1,2,10] Alexandre Glazov,[6] Santiago González-Gaitán,[11]
Renée Hlozek,[12] Saurabh Jha,[13] Stephen Kuhlmann,[14] Martin Kunz,[15] Hubert Lampeitl,[8]
Ashish Mahabal,[16] James Newling,[3] Robert C. Nichol,[8] David Parkinson,[17]
Ninan Sajeeth Philip,[18] Dovi Poznanski,[19,20] Joseph W. Richards,[20,21]
Steven A. Rodney,[22] Masao Sako,[23] Donald P. Schneider,[24]
Mathew Smith,[25] Maximilian Stritzinger,[26,27,28]
and Melvin Varughese[29]

Participants	Abbreviation[a]	Classified +Z[b]/noZ[c]	SN z_{ph}[d]	CPU[e]	Description (strategy class[f])
P. Belov and S. Glazov	Belov & Glazov	yes/no	no	90	light curve χ^2 test against Nugent templates (2)
S. Gonzalez	Gonzalez	yes/yes	no	120	cuts on SiFTO fit χ^2 and fit parameters (1)
J. Richards, Homrighausen, C. Schafer, P. Freeman	InCA[g]	no/yes	no	1	Spline fit & nonlinear dimensionality reduction (4)
J. Newling, M. Varuguese,	JEDI-KDE	yes/yes	no	10	Kernel Density Evaluation with 21 params (4)
B. Bassett, R. Hlozek,	JEDI Boost	yes/yes	no	10	Boosted decision trees (4)
D. Parkinson, M. Smith,	JEDI-Hubble	yes/no	no	10	Hubble diagram KDE (3)
H. Campbell, M. Hilton,	JEDI Combo	yes/no	no	10	Boosted decision trees + Hubble KDE (3+4)
H. Lampeitl, M. Kunz,					
P. Patel (JEDI group[h])					
S. Philip, V. Bhatnagar,	MGU+DU-1[i]	no/yes	no	< 1	light curve slopes & Neural Network (2)
A. Singhal, A. Rai,	MGU+DU-2	no/yes	no	< 1	light curve slopes & Random Forests (2)
A. Mahabal, K. Indulekha					
H. Campbell, B. Nichol,	Portsmouth χ^2	yes/no	no	1	SALT2–χ^2_r & False Discovery Rate Statistic (1)
H. Lampietl, M .Smith	Portsmouth-Hubble	yes/no	no	1	Deviation from parametrized Hubble diagram (3)
D. Poznanski	Poz2007 RAW	yes/no	yes	2	SN Automated Bayesian Classifier (SN–ABC) (2)
	Poz2007 OPT	yes/no	yes	2	SN–ABC with cuts to optimize $\mathcal{C}_{\rm FoM-Ia}$ (2).
S. Rodney	Rodney	yes/yes	yes	230	SN Ontology with Fuzzy Templates (2)
M. Sako	Sako	yes/yes	yes	120	χ^2 test against grid of Ia/II/Ibc templates (2)
S. Kuhlmann, R. Kessler	SNANA cuts	yes/yes	yes	2	Cut on MLCS fit probability, S/N & sampling (1)

Classification of Multiwavelength Transients with Machine Learning

K. Sooknunan[1], M. Lochner[2,3,5], Bruce A. Bassett[1,2,3,4], H. V. Peiris[5,6], R. Fender[7,9], A. J. Stewart[7,8], M. Pietka[7], P. A. Woudt[9], J. D. McEwen[10], O. Lahav[5]

MODELS AND SIMULATIONS FOR THE PHOTOMETRIC LSST ASTRONOMICAL TIME SERIES CLASSIFICATION CHALLENGE (PLAsTiCC)

R. Kessler[1,2], G. Narayan[3], A. Avelino[4], E. Bachelet[5], R. Biswas[6], P. J. Brown[7], D. F. Chernoff[8], A. J. Connolly[9], M. Dai[10], S. Daniel[9], R. Di Stefano[4], M. R. Drout[11], L. Galbany[12], S. González-Gaitán, M. L. Graham[9], R. Hložek[11,14], E. E. O. Ishida[15], J. Guillochon[4], S. W. Jha[10], D. O. Jones[16], K. S. Mandel, D. Muthukrishna[17], A. O'Grady[11,14], C. M. Peters[14], J. R. Pierel[19], K. A. Ponder[20], A. Prša[21], S. Rodney,
V. A. Villar[4]
(The LSST Dark Energy Science Collaboration and the Transient and Variable Stars Science Collaboration)

Semi-supervised learning for photometric supernova classification★

Joseph W. Richards,[1,2]† Darren Homrighausen,[3] Peter E. Freeman,[3] Chad M. Schafer[3] and Dovi Poznanski[1,4]

Photometric classification and redshift estimation of LSST Supernovae

Mi Dai,[1]★ Steve Kuhlmann,[2] Yun Wang[3] and Eve Kovacs[2]

Machine-learning-based Brokers for Real-time Classification of the LSST Alert Stream

Gautham Narayan[1,13], Tayeb Zaidi[2], Monika D. Soraisam[3], Zhe Wang[4], Michelle Lochner[5,6,7], Thomas Matheson[3], Abhijit Saha[3], Shuo Yang[4], Zhenge Zhao[4], John Kececioglu[4], Carlos Scheidegger[4], Richard T. Snodgrass[4], Tim Axelrod[8], Tim Jenness[9,10], Robert S. Maier[11], Stephen T. Ridgway[3], Robert L. Seaman[12], Eric Michael Evans[4], Navdeep Singh[4], Clark Taylor[4], Jackson Toeniskoetter[4], Eric Welch[4], and Songzhe Zhu[4]
(The ANTARES Collaboration)

A recurrent neural network for classification of unevenly sampled variable stars

Brett Naul, Joshua S. Bloom, Fernando Pérez, Stéfan van der Walt

November 30, 2017

Deep-Learnt Classification of Light Curves

A Mahabal*, K Sheth†, F Gieseke‡, A Pai‡, S G Djorgovski*, A J Drake§, M J Graham*, and CSS/CRTS/PTF Teams
*Center for Data-Driven Discovery, California Institute of Technology, Pasadena, CA, 91125
†Indian Institute of Technology Gandhinagar, Palaj, Gandhinagar, 382355, India
‡Department of Computer Science, University of Copenhagen, Copenhagen, Denmark
§Cahill Center for Astronomy and Astrophysics, California Institute of Technology, Pasadena, CA, 91125

A PROBABILISTIC APPROACH TO CLASSIFYING SUPERNOVAE USING PHOTOMETRIC INFORMATION

Natalia V. Kuznetsova[1] and Brian M. Connolly[2]
Received 2006 October 9; accepted 2006 December 8

Deep Recurrent Neural Networks for Supernovae Classification

Tom Charnock* and Adam Moss†
School of Physics & Astronomy
University of Nottingham,
Nottingham, NG7 2RD, England
(Dated: October 31, 2016)

PELICAN: deeP architecturE for the LIght Curve ANalysis

Johanna Pasquet[1], Jérôme Pasquet[2], Marc Chaumont[3] and Dominique Fouchez[1]

PHOTOMETRIC SUPERNOVA CLASSIFICATION WITH MACHINE LEARNING

Michelle Lochner[1], Jason D. McEwen[2], Hiranya V. Peiris[1], Ofer Lahav[1], and Max K. Winter[1]
[1] Department of Physics and Astronomy, University College London, Gower Street, London WC1E 6BT, UK; dr.michelle.lochner@gmail.com
[2] Mullard Space Science Laboratory, University College London, Surrey RH5 6NT, UK
Received 2016 March 15; revised 2016 July 6; accepted 2016 July 6; published 2016 August 23

Deep Learning for Image Sequence Classification of Astronomical Events

Rodrigo Carrasco Davis[1,7], Guillermo Cabrera-Vives[2,7], Francisco Förster[6,7], Pablo A. Estévez[1,7], Pablo Huijse[3,7], Pavlos Protopapas[5], Ignacio Reyes[1,7], Jorge Martínez[4,6,7] and Cristóbal Donoso[2]

Kernel PCA for type Ia supernovae photometric classification

E. E. O. Ishida[1,2]★ and R. S. de Souza [3,1,2]

Photometric classification of type Ia supernovae in the SuperNova Legacy Survey with supervised learning

A. Möller,[a,b,c] V. Ruhlmann-Kleider,[c] C. Leloup,[c] J. Neveu,[c,d] N. Palanque-Delabrouille,[c] J. Rich,[c] R. Carlberg,[e] C. Lidman[f,b] and C. Pritchet[g]

SuperNNova

open source photometric classification

Möller & de Boissière 2019 ***arXiv: 1901.06384***

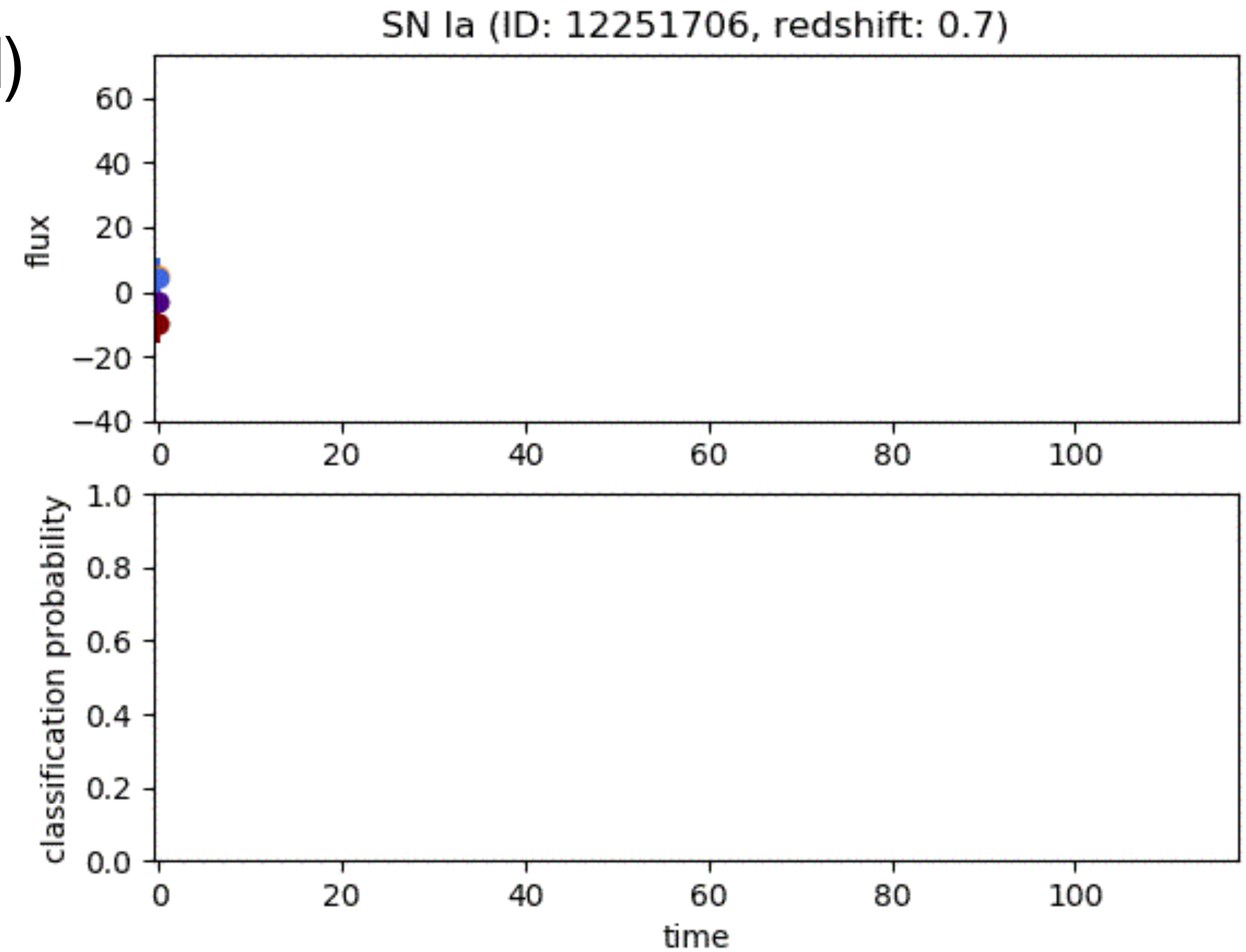
github: supernnova/SuperNNova

Deep Learning

SuperNNova
open source photometric classification

Recurrent Neural Networks (RNN)

- Recurrent Neural Network:
  - LSTM
  - GRU
- Bayesian RNNs
  - MC dropout (Gal+2016)
  - Bayes by Backprop (Fortunato+2017)
- Convolutional NN (soon!)



Deep Learning

SuperNNova
open source photometric
classification

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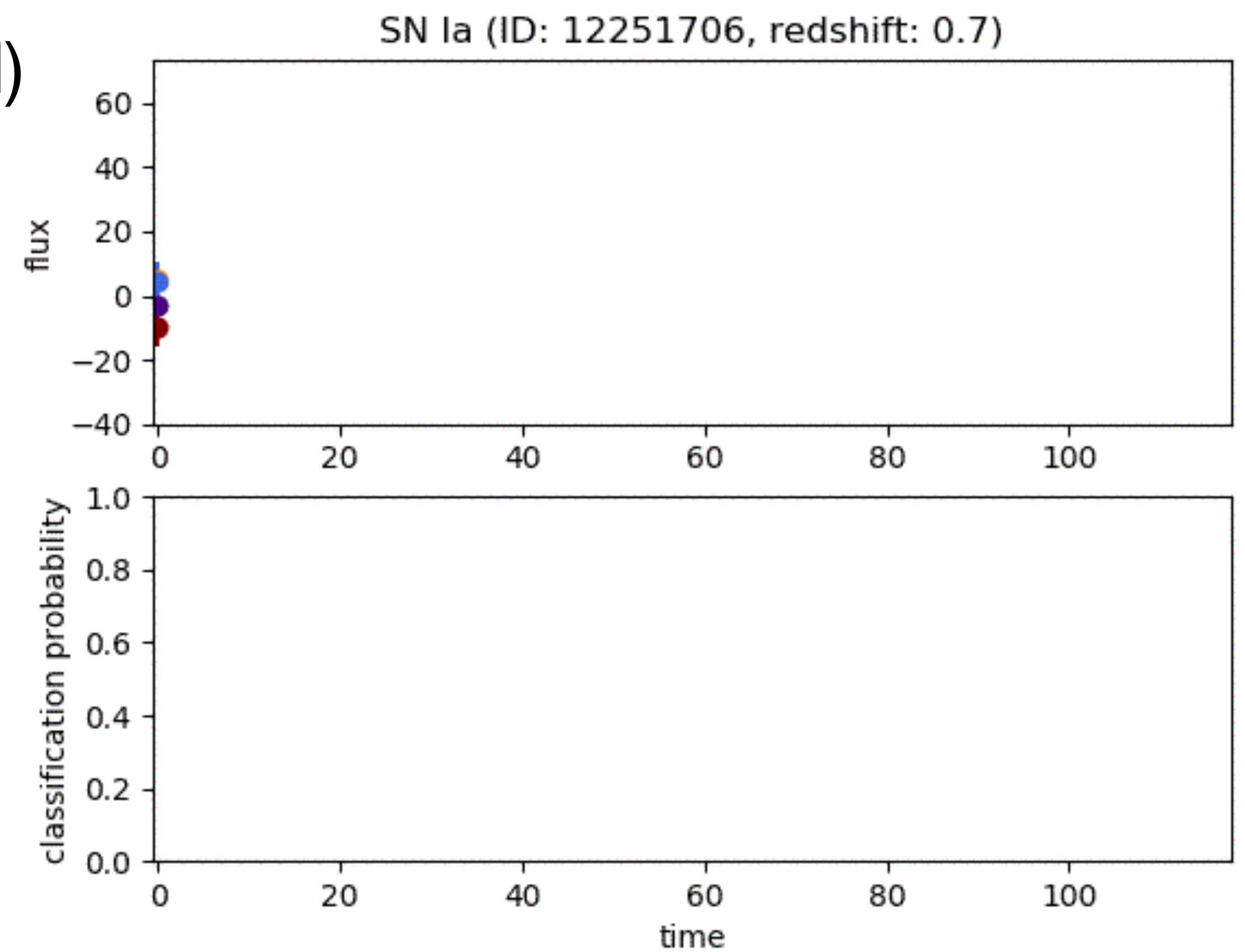


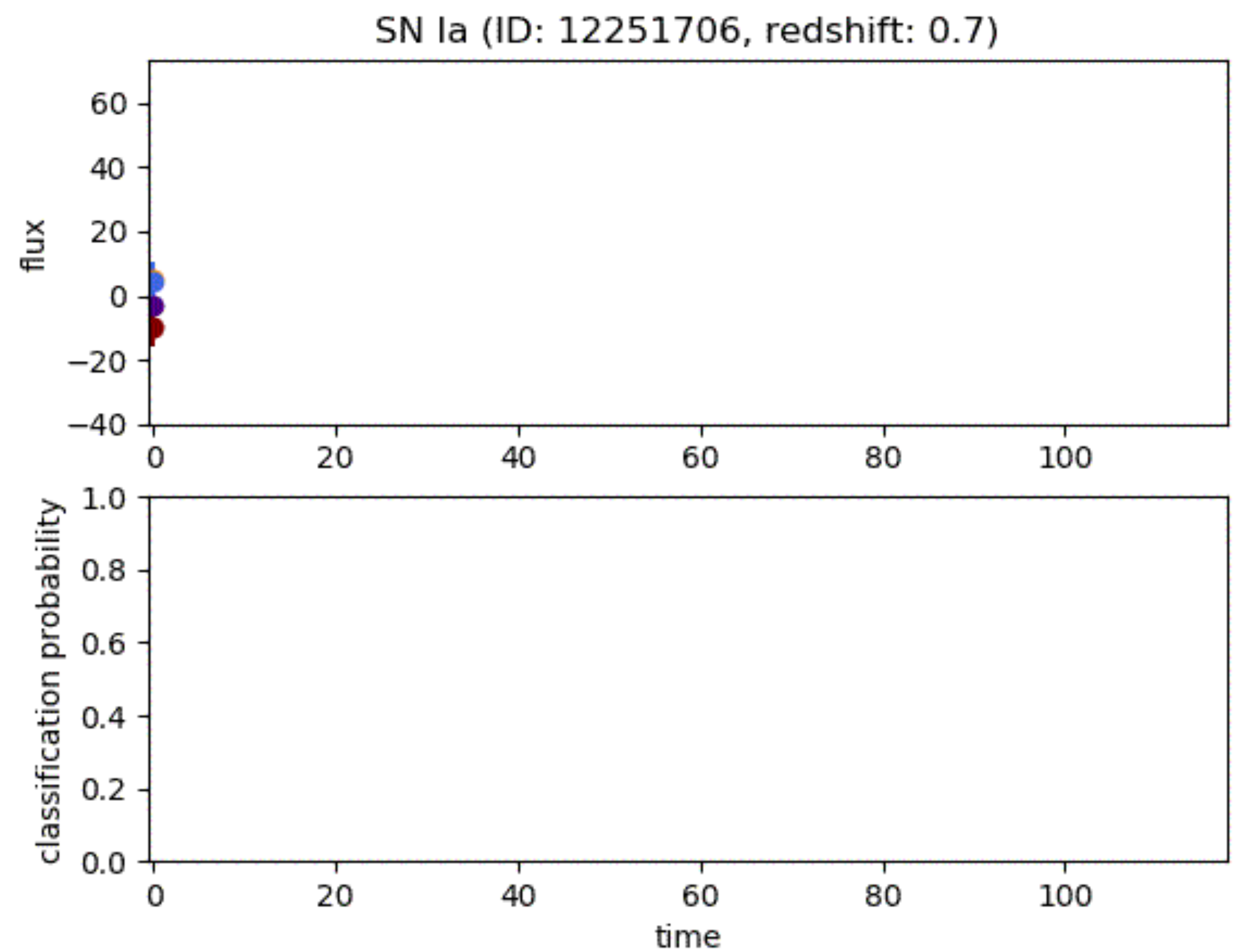
lightcurve classification

SuperNNova
open source photometric classification

Fast: can classify up to 2,000 lcs/s

No interpolation necessary

Classification at any time step



inputs:

- flux & errors
- time
- other if available (e.g. redshifts)

lightcurve classification

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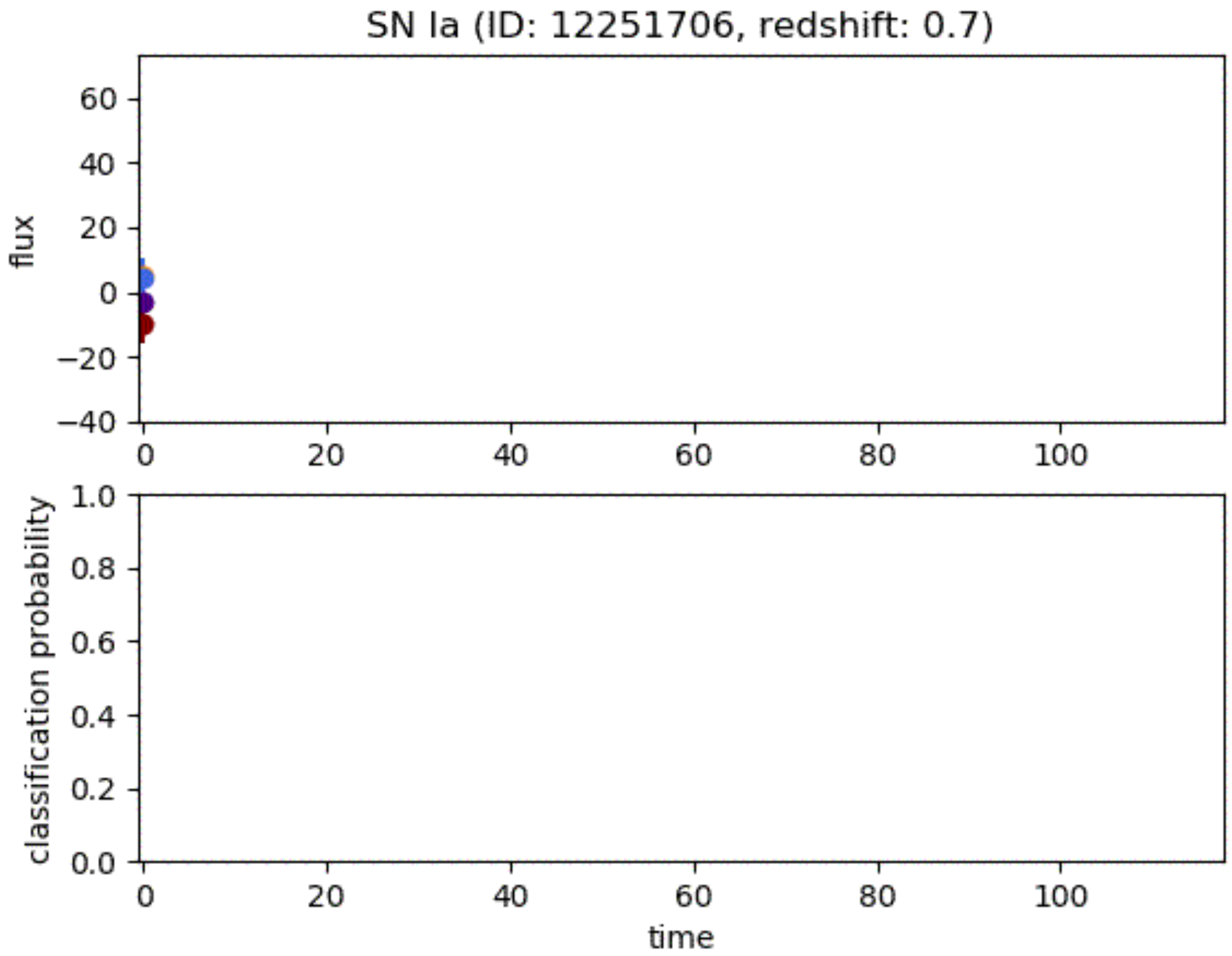


accurate classification

SuperNNova
open source photometric classification

trained & tested with supernovae simulations: SNe type Ia vs. Non Ia

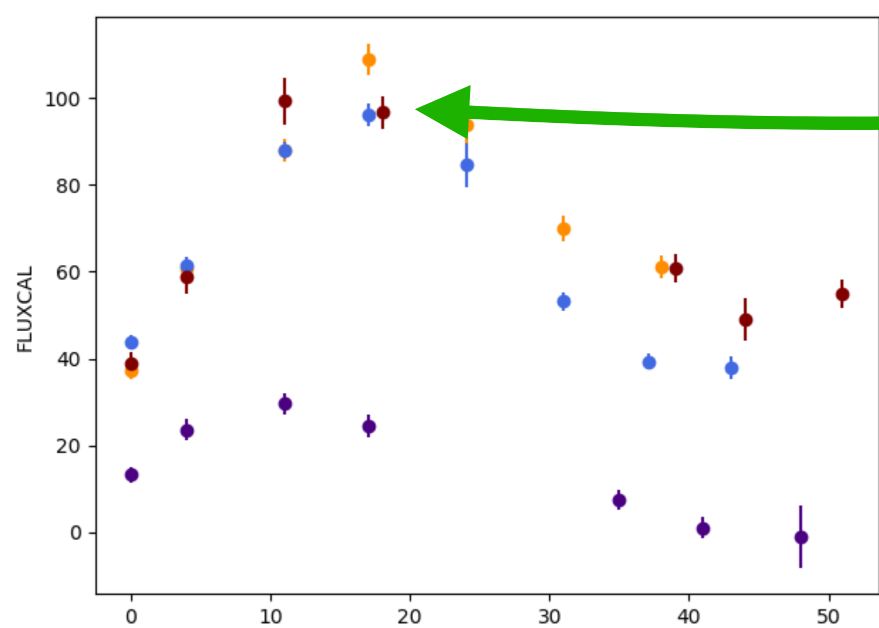
accurate classification

SuperNNova
open source photometric classification

trained & tested with supernovae simulations: SNe type Ia vs. Non Ia

flux+time

early 87.59 ± 0.13

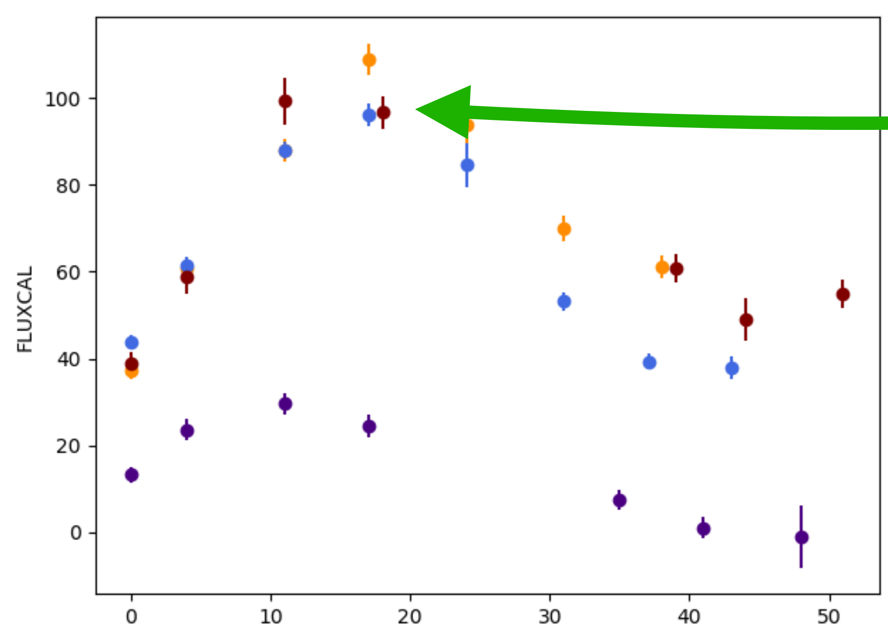


accurate classification

SuperNNova
open source photometric classification

trained & tested with supernovae simulations: SNe type Ia vs. Non Ia

	flux+time	flux+time+redshift
early	87.59 ± 0.13	94.25 ± 0.07

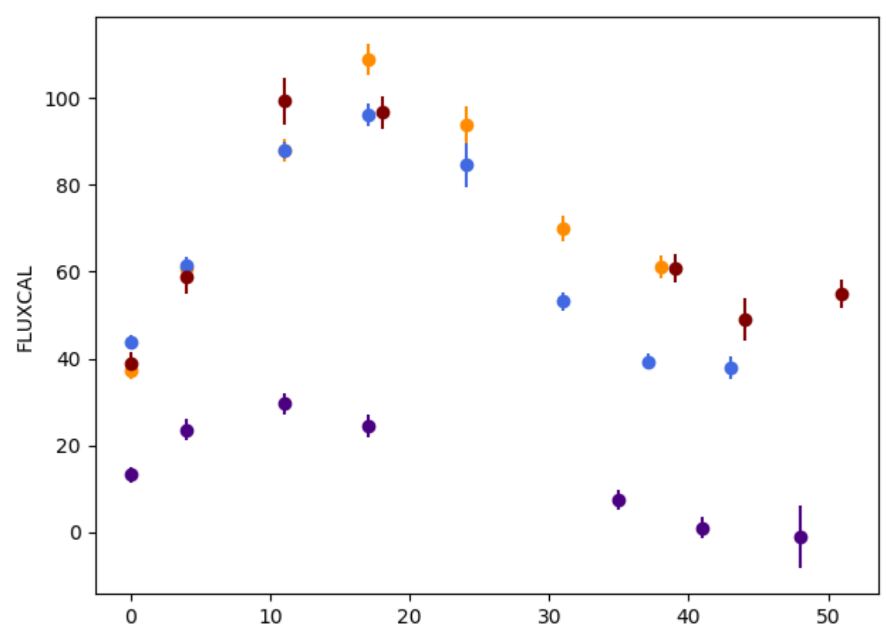


accurate classification

SuperNNova
open source photometric classification

trained & tested with supernovae simulations: SNe type Ia vs. Non Ia

	flux+time	flux+time+redshift
early	87.59 ± 0.13	94.25 ± 0.07
complete	96.97 ± 0.06	$\mathbf{98.83 \pm 0.02}$



bayesian NNs

$$\mathcal{P}\left(\mathbf{y}|\mathbf{X},\mathbf{w}\right)$$

Categorical distribution

Target
(SN type)

data
(lightcurves)

Network weights

bayesian NNs

$$\mathcal{P}\left(\mathbf{y}|\mathbf{X},\mathbf{w}\right)$$

Categorical distribution

Target (SN type)

data (lightcurves)

Network weights

$$\mathcal{P}(\hat{\mathbf{y}}\,|\,\mathbf{x}) = \int \mathcal{P}(\hat{\mathbf{y}}\,|\,\mathbf{X},\mathbf{w})\mathcal{P}\left(\mathbf{w}\,|\,\mathcal{D}\right) d\mathbf{w}$$

untractable for NNs

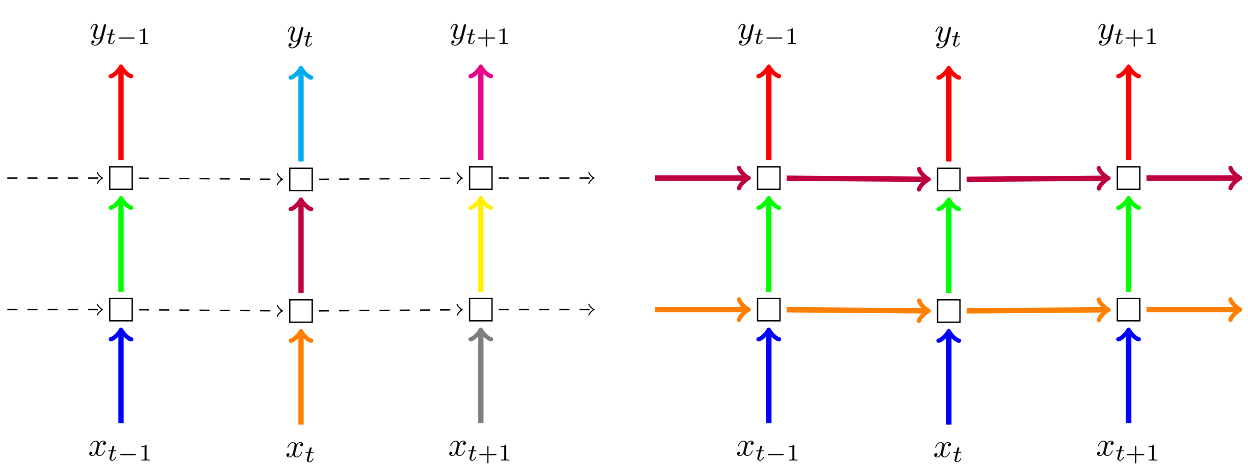
$$\mathcal{P}(\mathbf{w}\,|\,\mathcal{D}) \approx q(\mathbf{w}\,|\,\theta)$$ variational distribution

bayesian RNNs

SuperNNova
open source photometric classification

Approximating the variational distribution

1. MC dropout
Gal & Ghahramani 2016



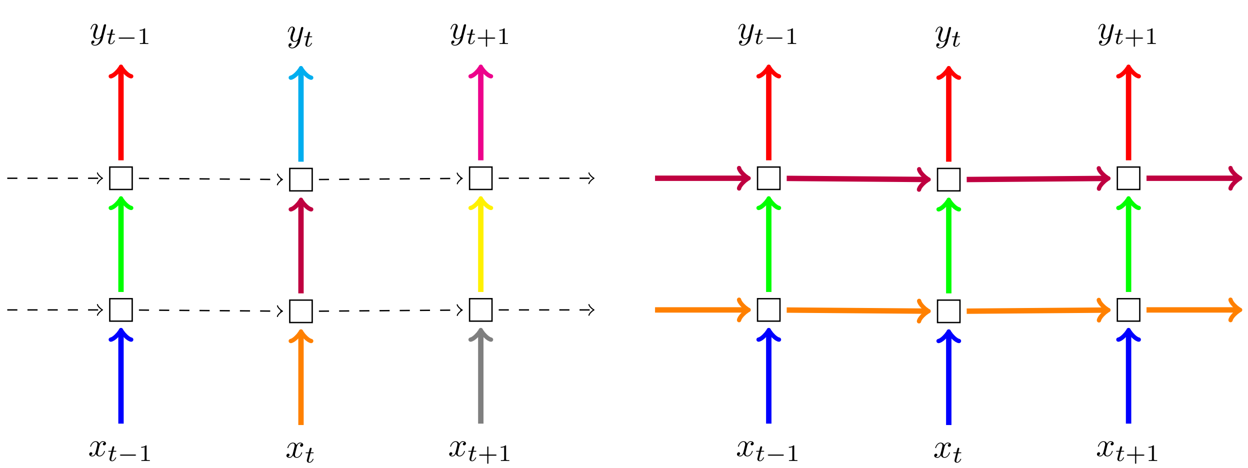
(a) Naive dropout RNN (b) Variational RNN

bayesian RNNs

SuperNNova
open source photometric classification

Approximating the variational distribution

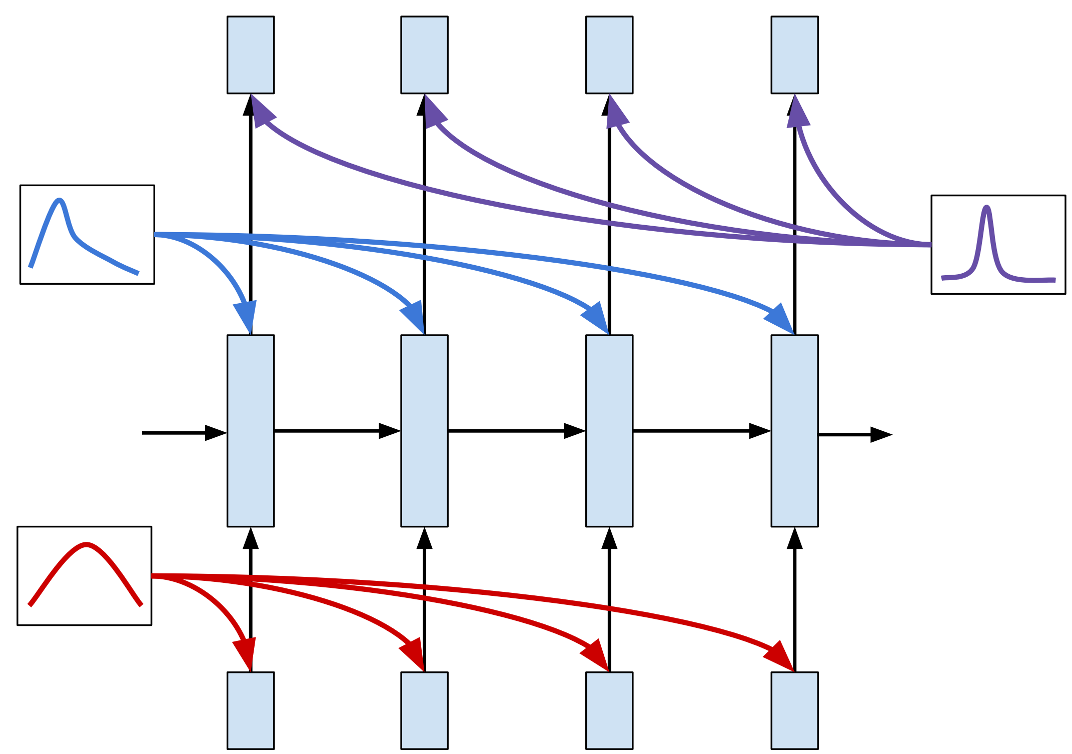
1. MC dropout
Gal & Ghahramani 2016



(a) Naive dropout RNN

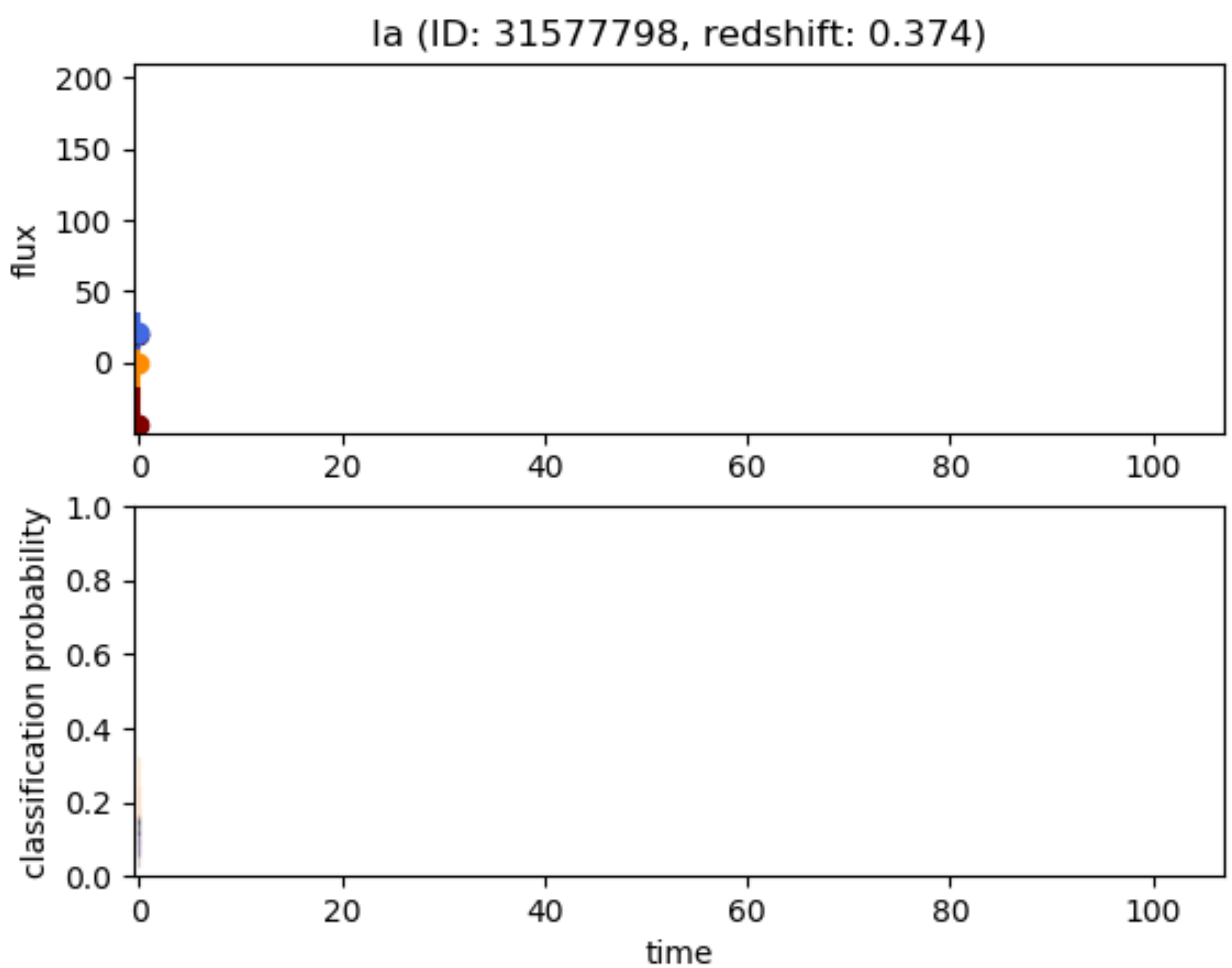
(b) Variational RNN

2. Bayes by Backprop
Fortunato+ 2017



bayesian RNNs

SuperNNova
open source photometric classification



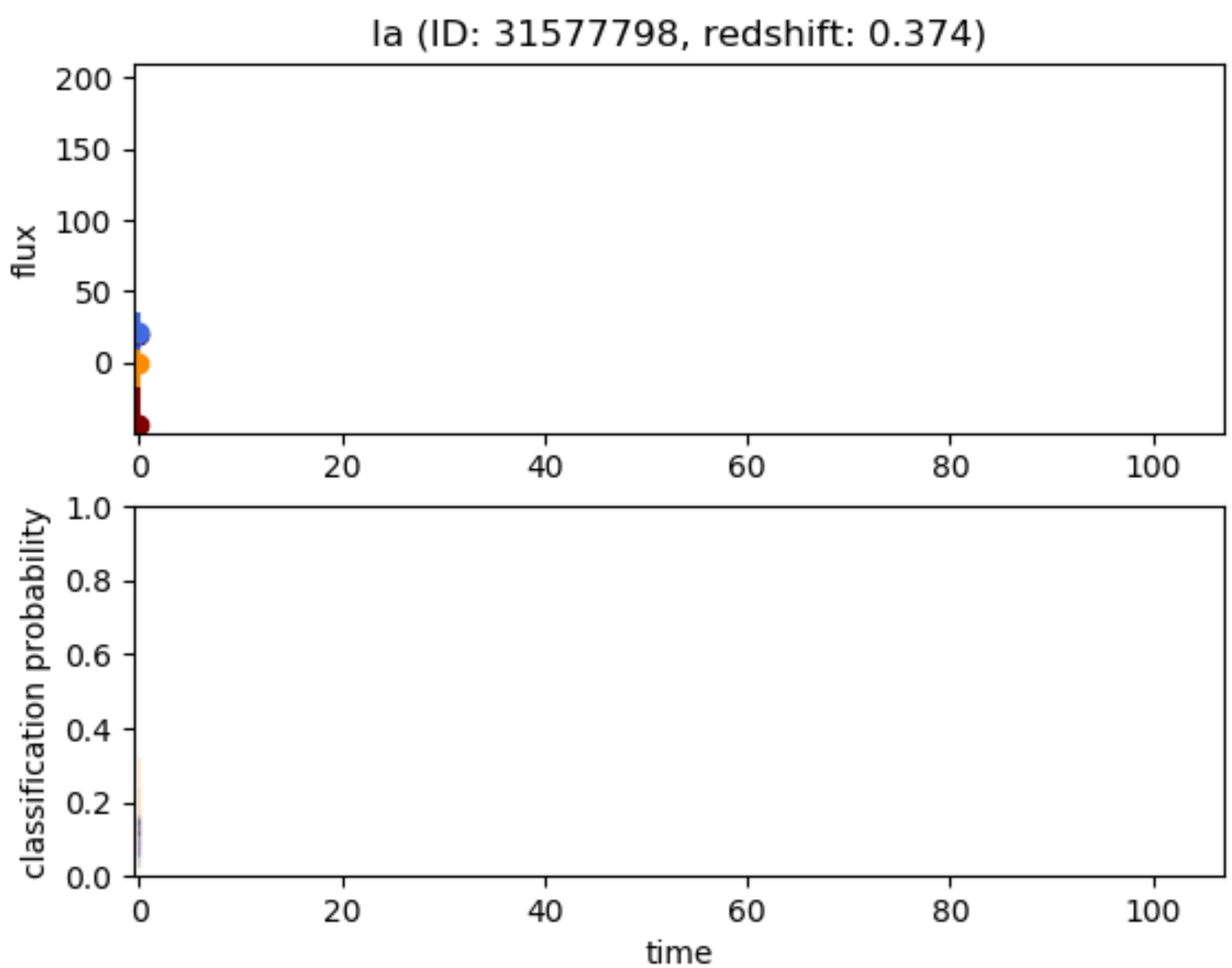
Posterior that provides epistemic uncertainties

Epistemic uncertainties:

express our <u>ignorance about the model</u> that generated the data.

bayesian RNNs

SuperNNova
open source photometric classification



Posterior that provides epistemic uncertainties

Epistemic uncertainties:

express our <u>ignorance about the model</u> that generated the data.

bayesian RNNs

Current lightcurve classification limitations

Training sets are:

1. not representative

2. incomplete (we don't know/can't simulate)

3. ML probabilities as thresholds?

1. representativity

Distribution of properties of SNe

Simplistic simulation

peak brightness *i*

data

peak brightness *i*

1. representativity

SuperNNova open source photometric classification *with BNNs*

Simplistic simulation

peak brightness *i*

Model 1

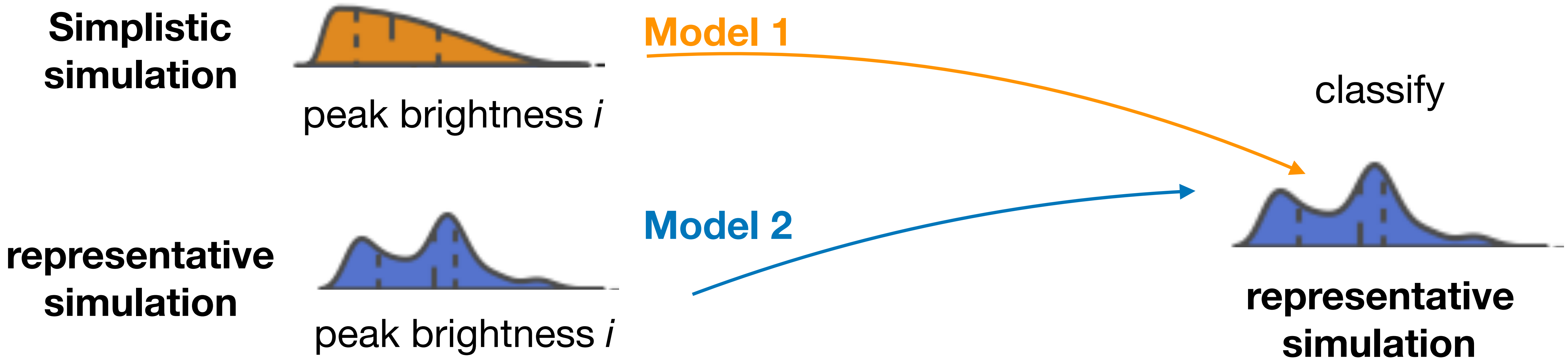
representative simulation

peak brightness *i*

Model 2

1. representativity

SuperNNova open source photometric classification *with BNNs*



1. representativity

SuperNNova *with BNNs*
open source photometric classification

Simplistic simulation

peak brightness *i*

Model 1

classify

representative simulation

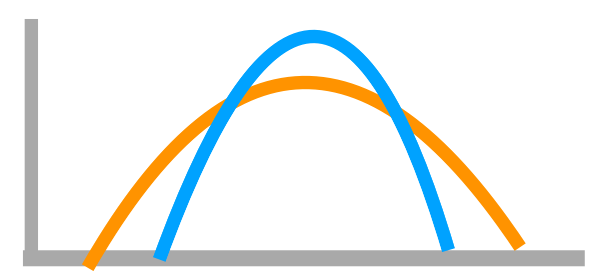
peak brightness *i*

Model 2

representative simulation

accuracy changes slightly (<prob> are not the most indicative)

non-representative models give larger uncertainties!



2. incompleteness

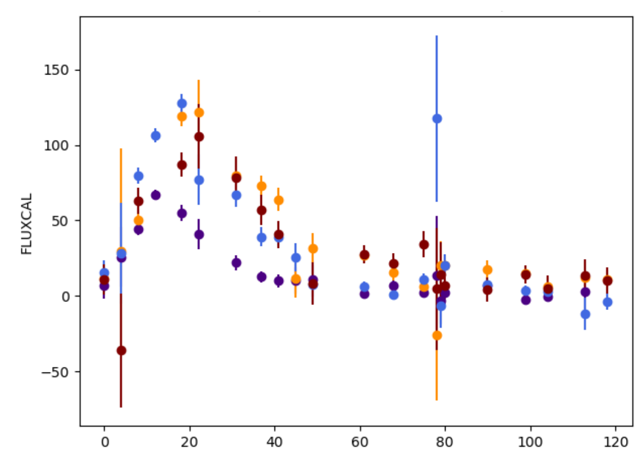
training set

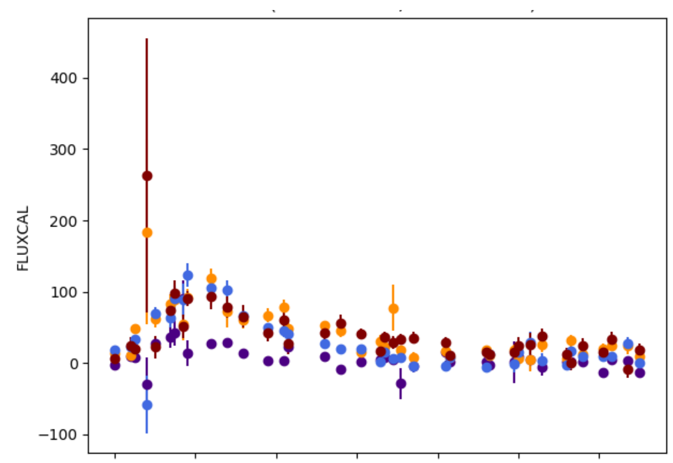
to classify

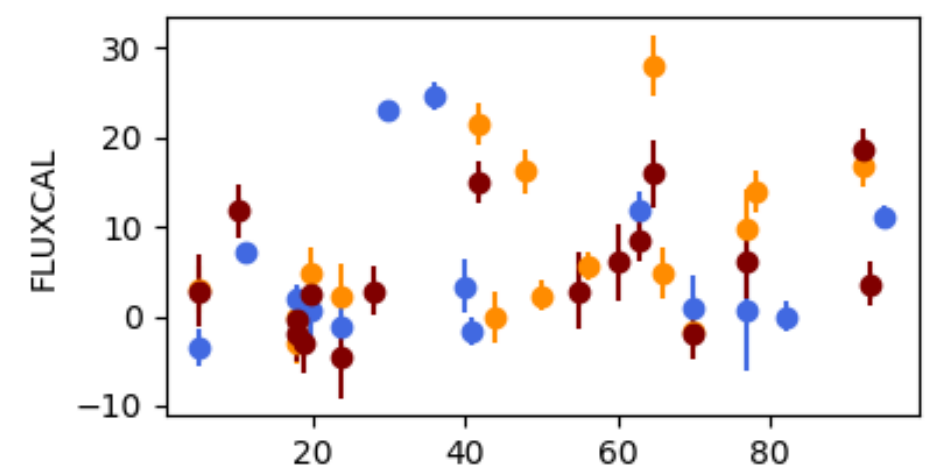
2. incompleteness

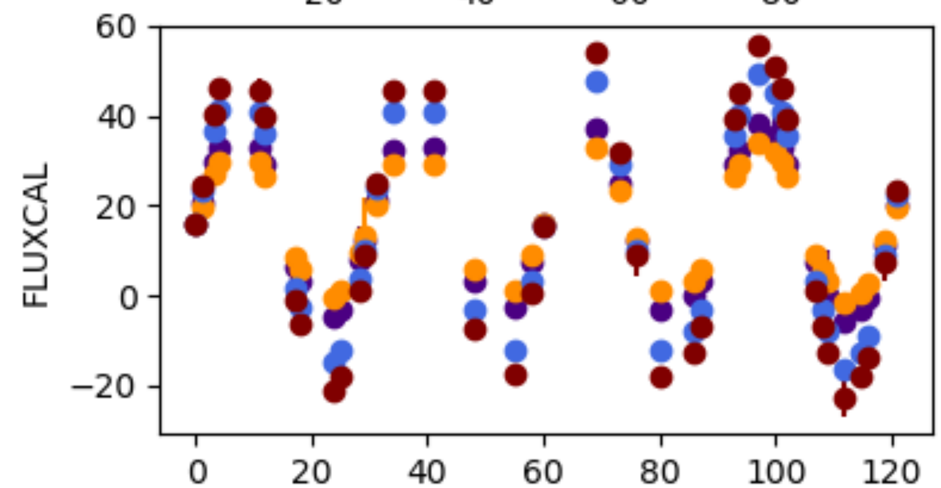
training set

to classify





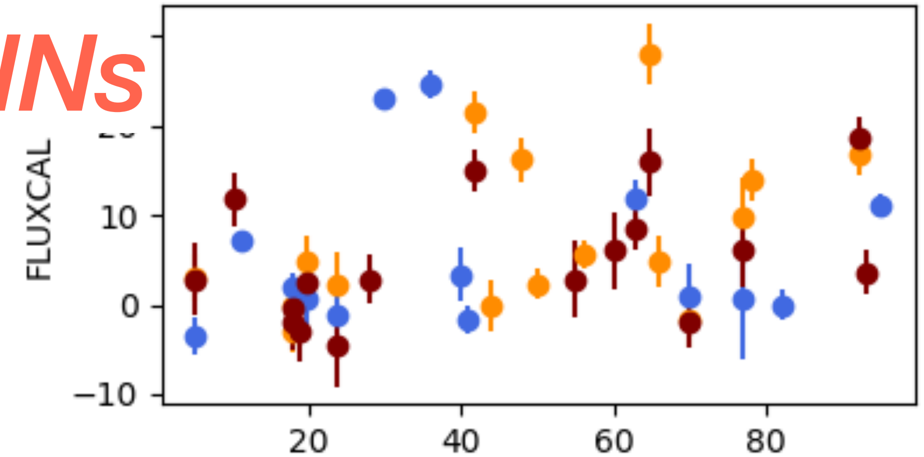




2. incompleteness

SuperNNova
open source photometric classification

with BNNs



2. incompleteness

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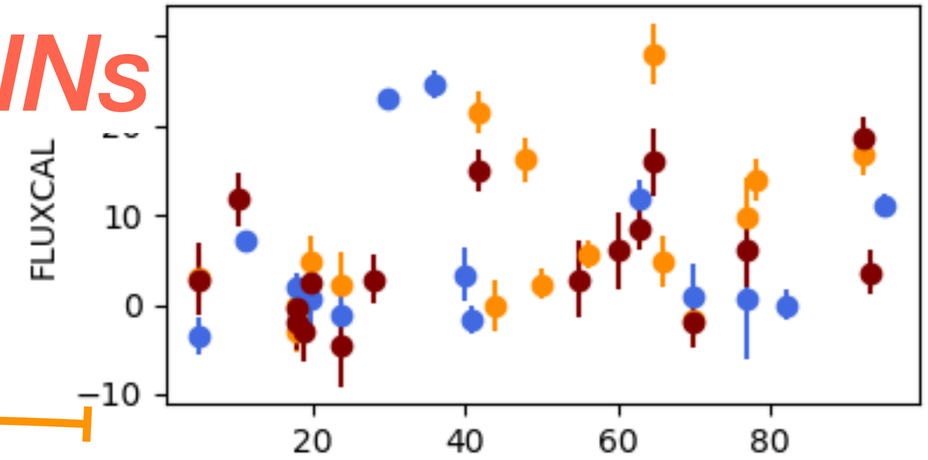
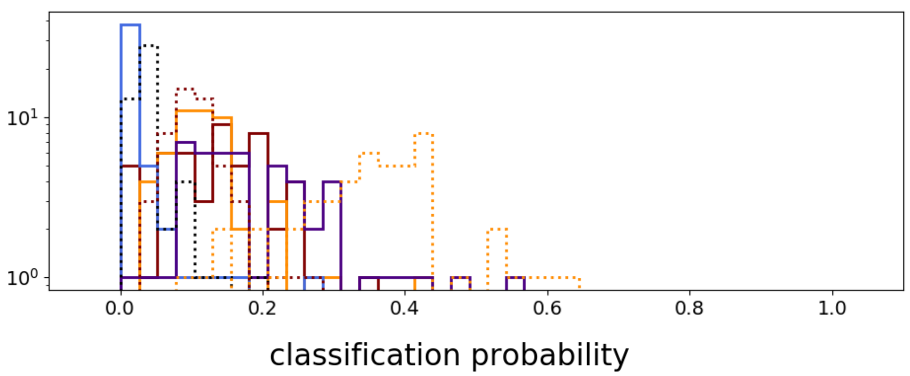


low probability for any class



2. incompleteness

SuperNNova
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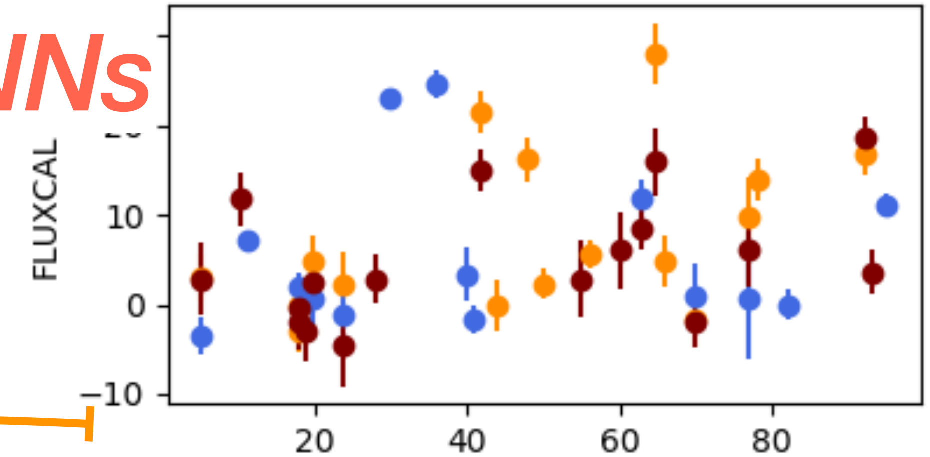
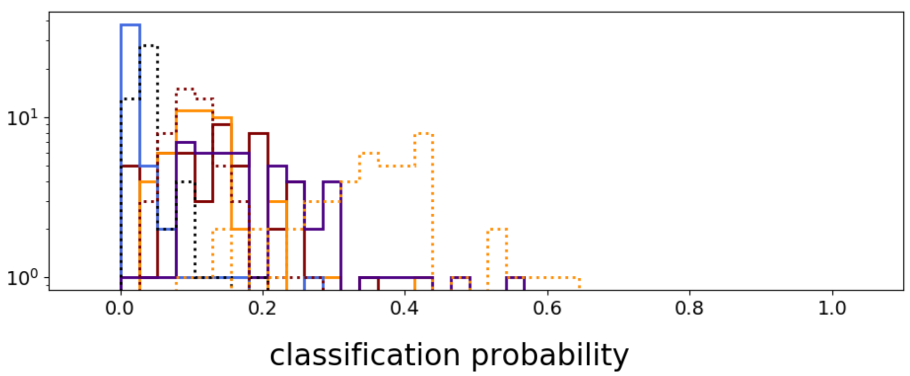
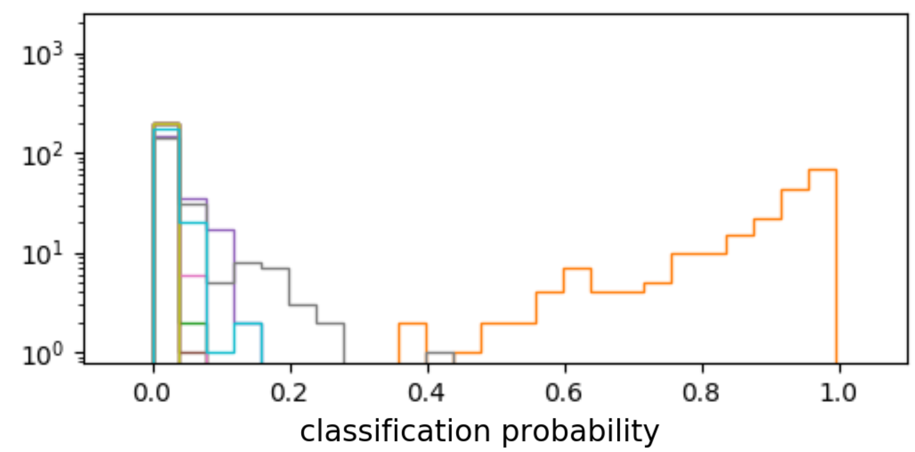


low probability for any class



high probability for “less-known” class

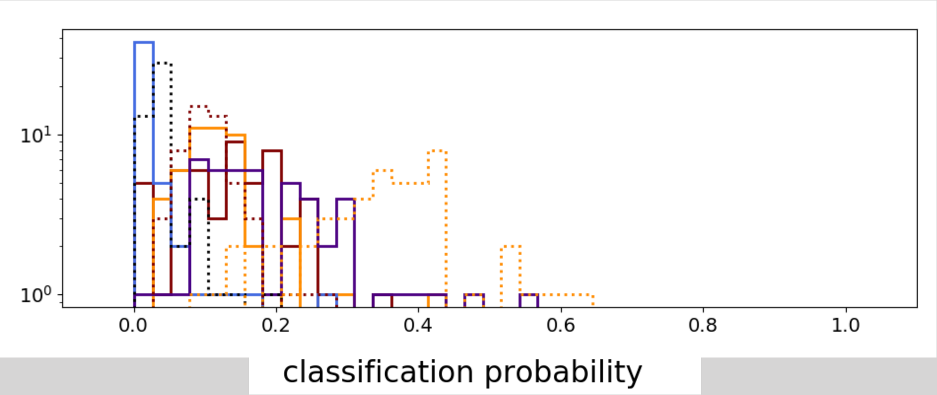


but… BNNs can give us high-probability but large uncertainty

3. ML probabilities as a threshold?

Selecting a transient sample:

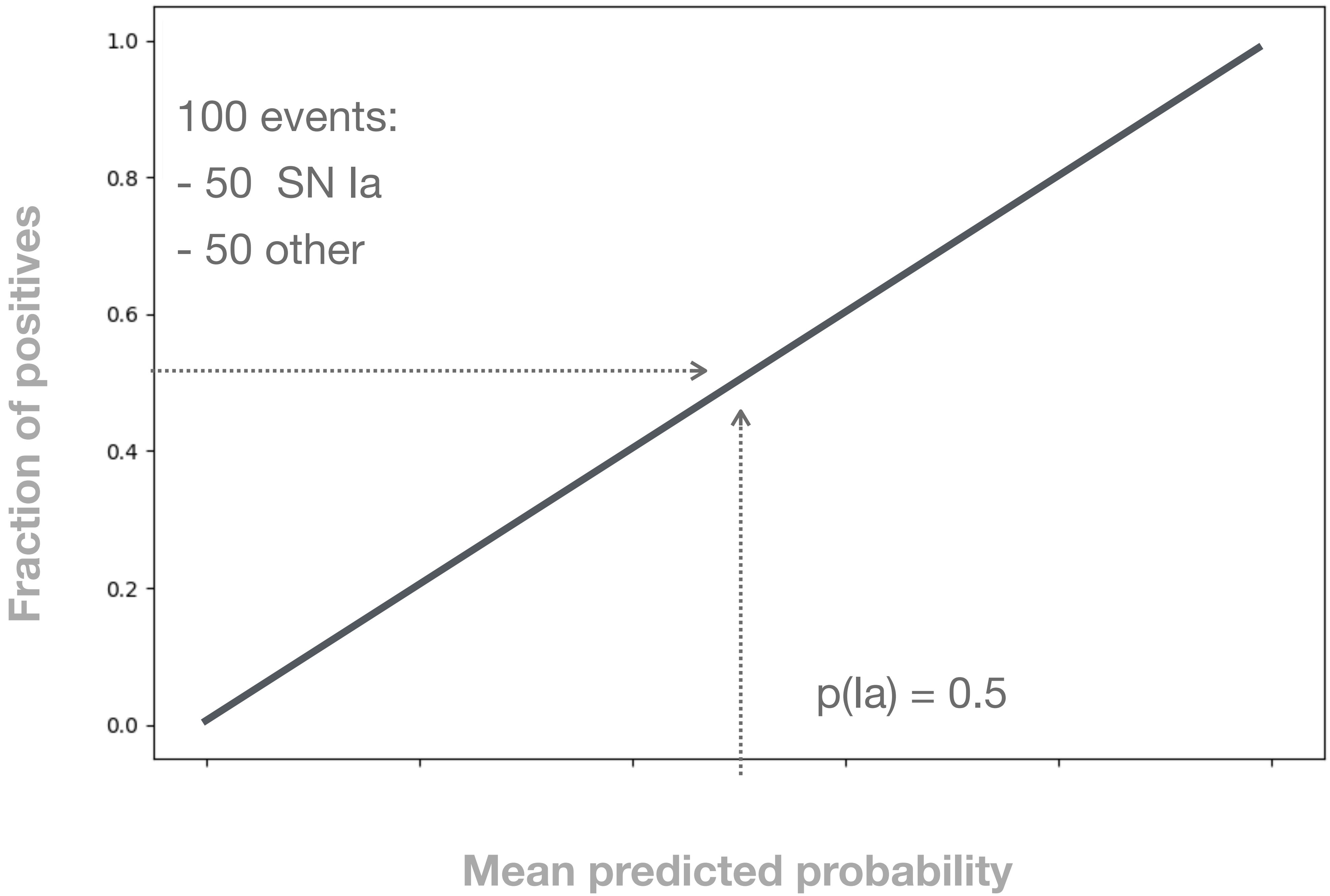
cutting on “classification probabilities” for selection



Can use a “weight” in the analysis using these “classification probabilities” *Jones+2018, Hinton+2018*

3. ML probabilities as a threshold?

De Groot+ 1983, Niculezcu-Mizil+ 2005, Guo+ 2017



3. ML probabilities as a threshold?

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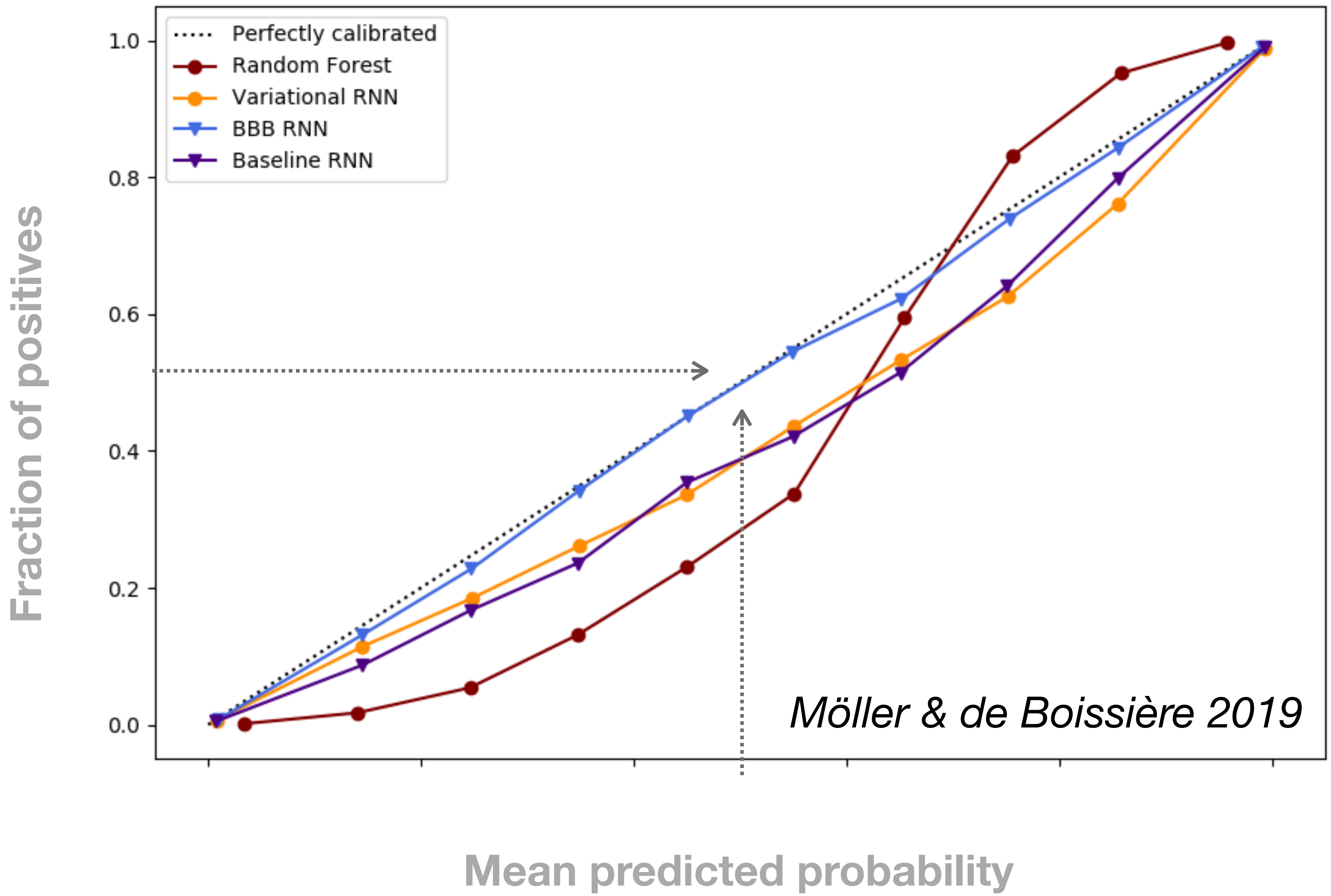

take away

SuperNNova
open source photometric classification

Accurate: Early >86%, complete > 97%
Fast: up to 2,000 lcs/s

Bayesian RNNs

- promising classification method

-> classification model uncertainty

- **Representativity**
- **Anomalies**
- **Reliability**

Can be applied to any lightcurves classification problem

Open source & documented

github: supernnova/SuperNNova