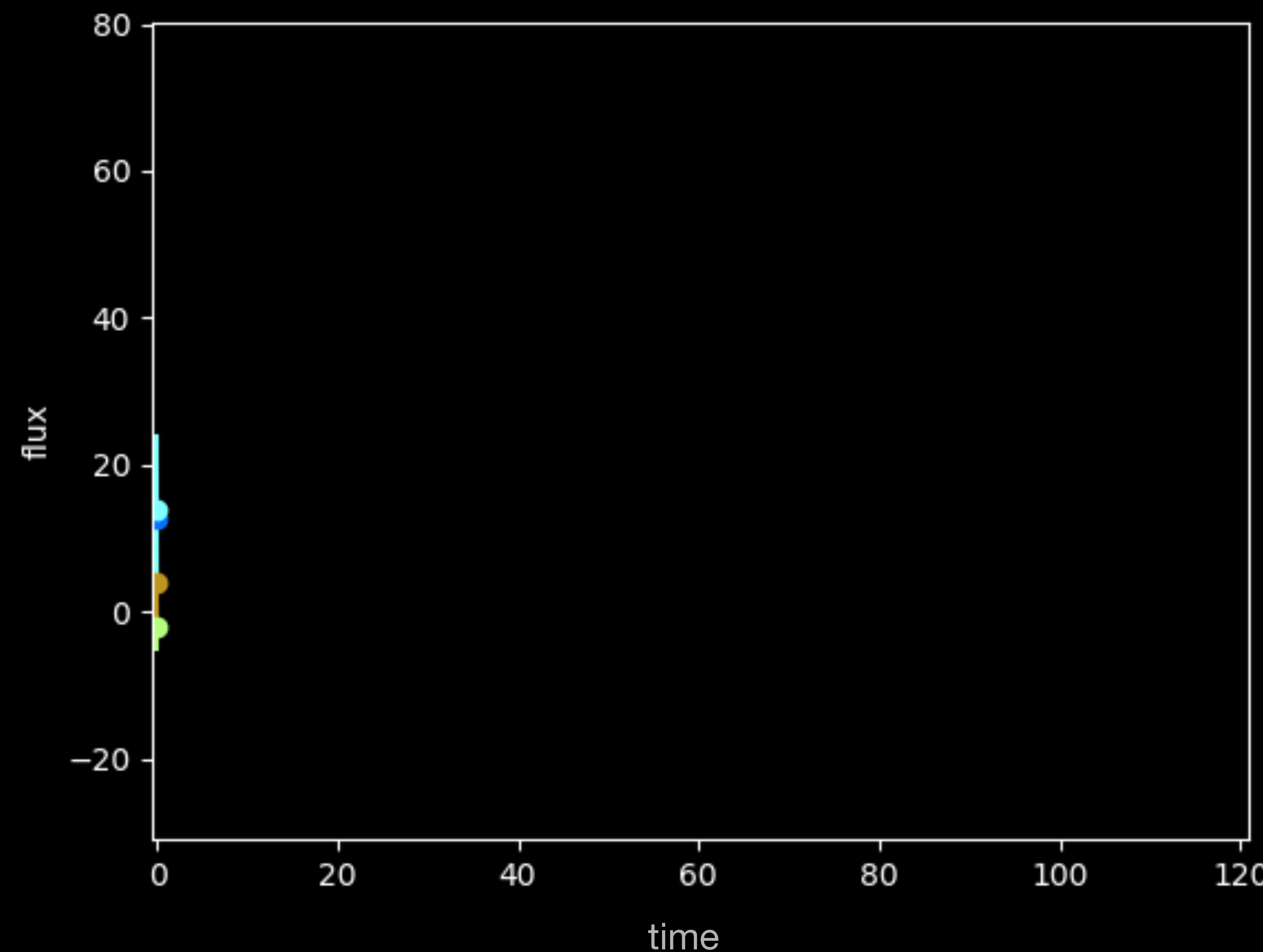
ML classifiers: brokers and towards SN samples for cosmology with Bayesian probabilities

Anais Möller
CNRS / LPC

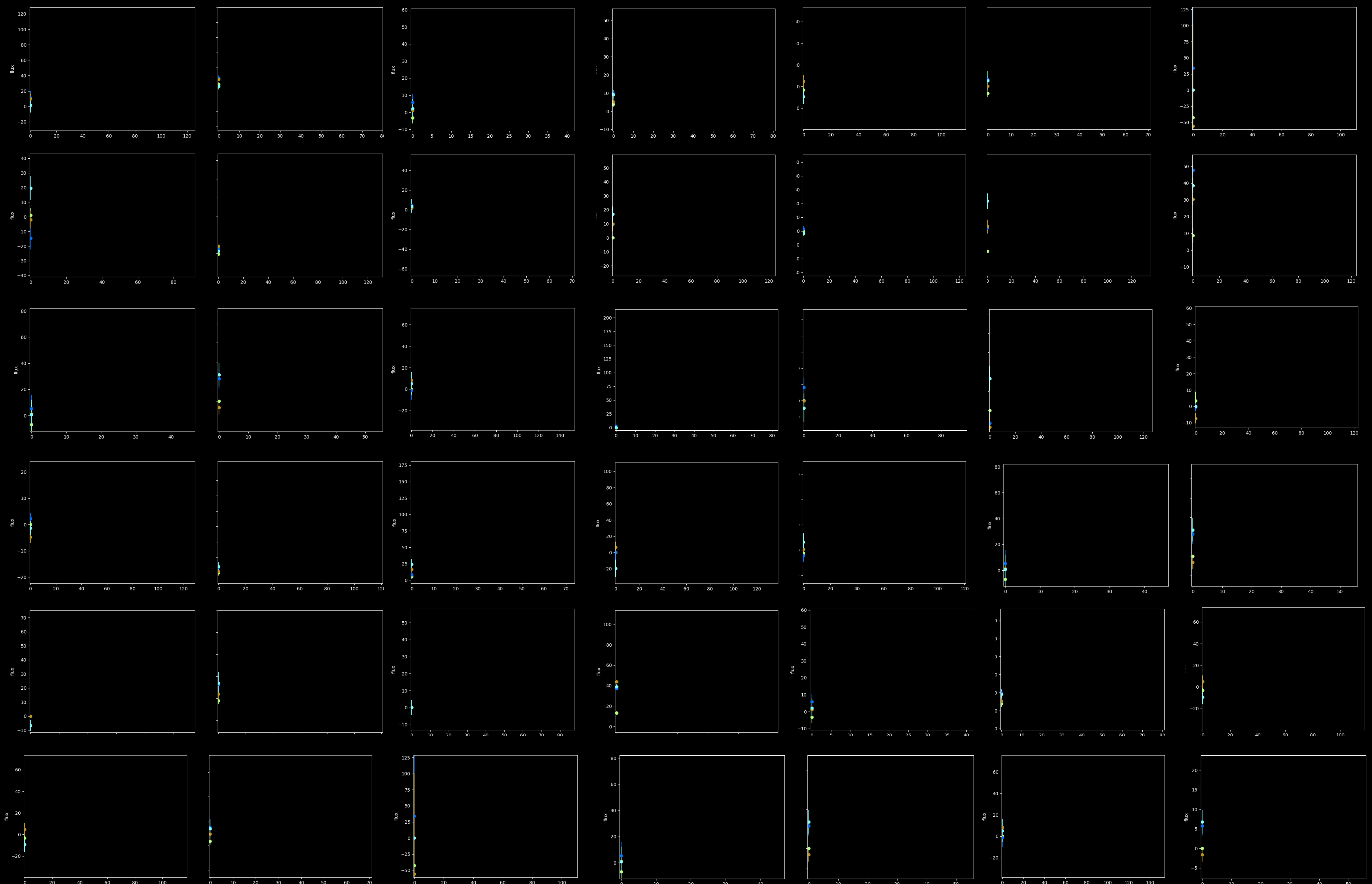
LSST-France,
Clermont 2019

The challenge

(time-domain + SN cosmology)



The challenge



The challenge

(time-domain + SN cosmology)

How can we maximise our science output with LSST?

Data:
- Nature
- Size
- Timeliness

Limited resources:
- Spectroscopic
- Photometric
- Human

Science analyses:
- Robustness
- Selection effects

How can we maximise our science output with LSST?

photometric classification

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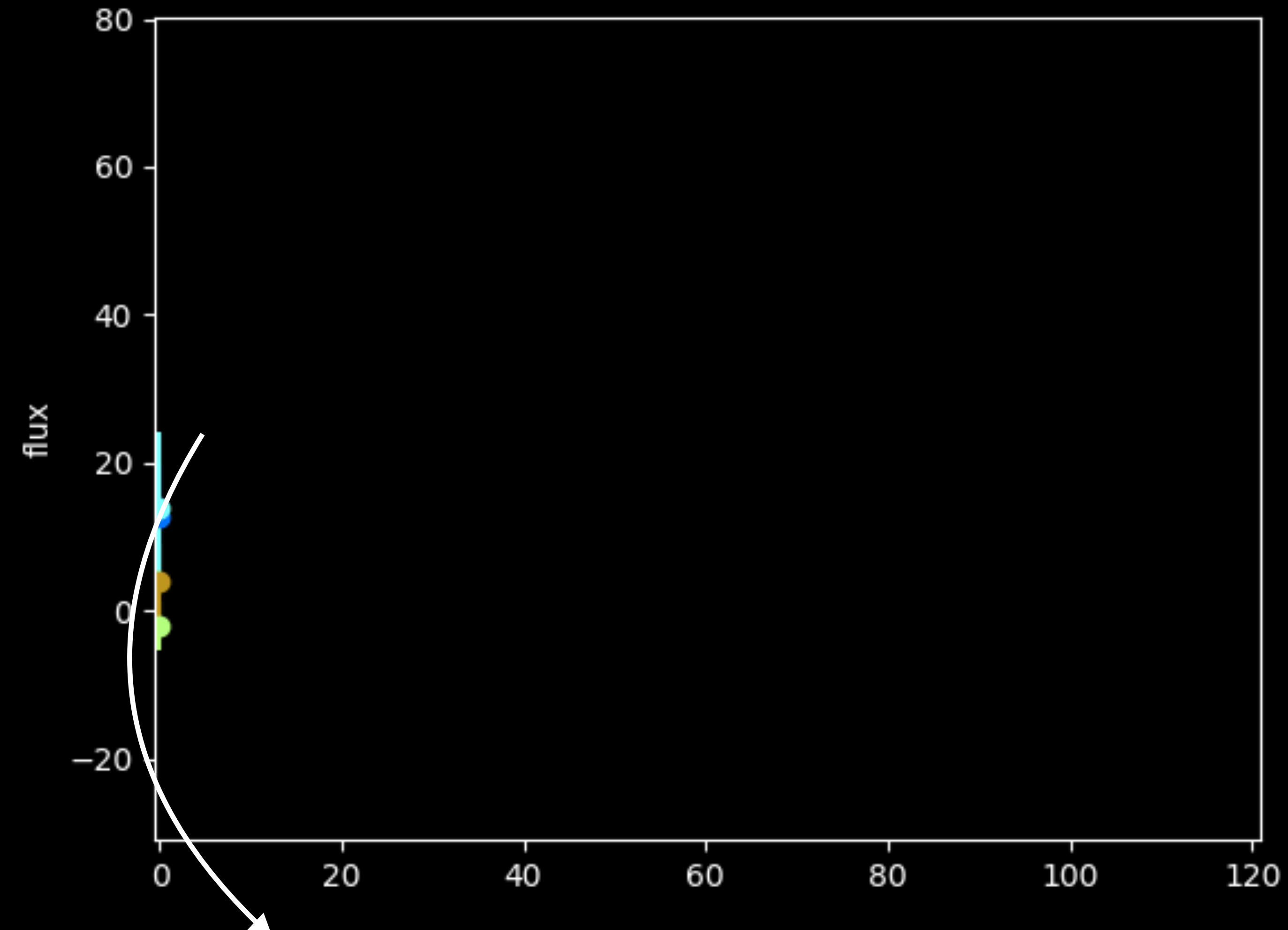
photometric classification



Early classification :

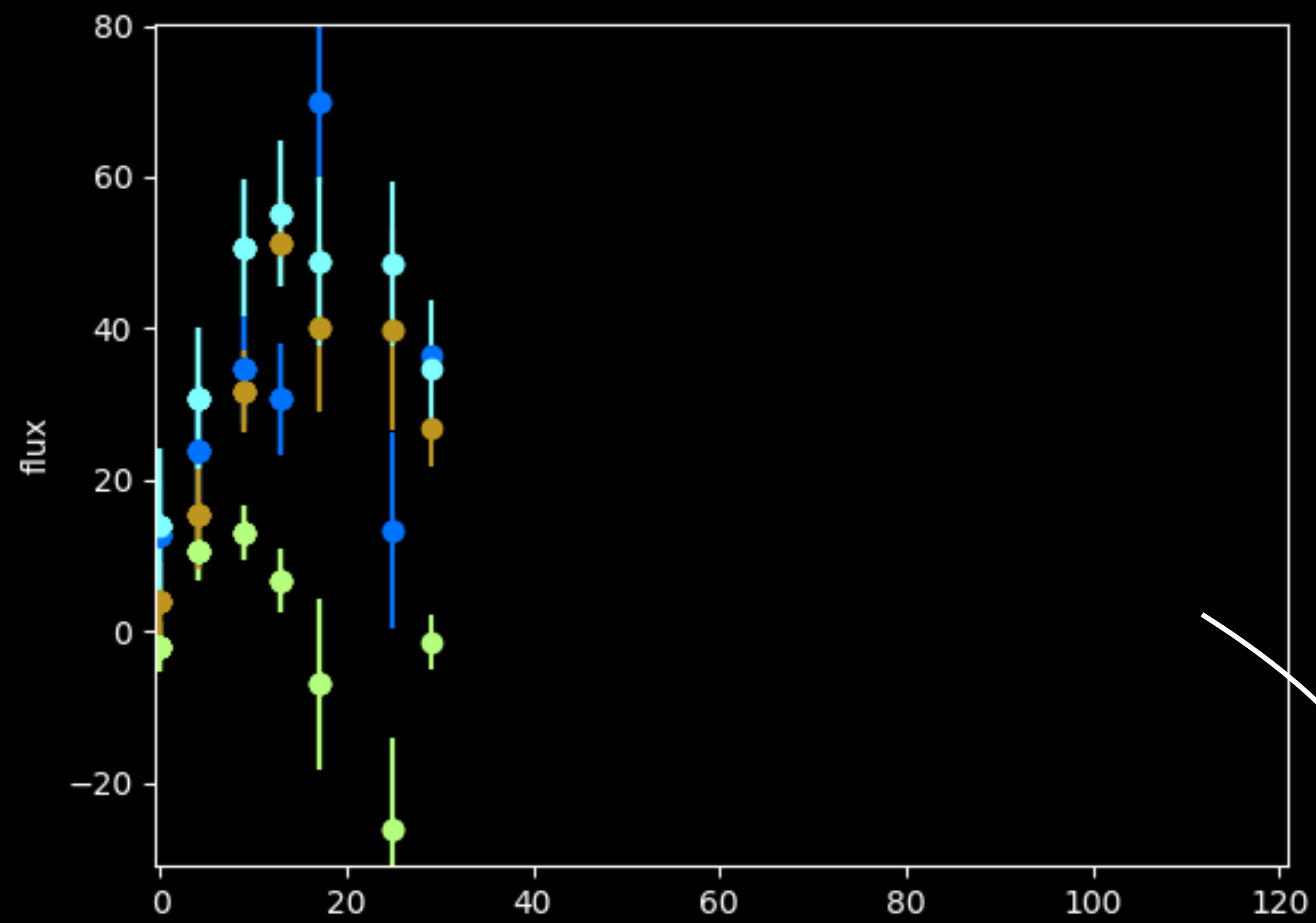
brokers *see next talks*

follow-up: spectroscopic, multi wavelength

(not a new idea, we already do some selection for spectroscopic fup)

How can we maximise our science output with LSST?

photometric classification



Complete light-curve classification: science samples for statistical analyses

Does not need spectroscopic classification, larger samples, probing new parameter space

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 $z_{\rm ph}$[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, H. Lampeitl, M. Kunz, P. Patel (JEDI group[h])	JEDI Combo	yes/no	no	10	Boosted decision trees + Hubble KDE (3+4)
S. Philip, V. Bhatnagar,	MGU+DU-1[i]	no/yes	no	< 1	light curve slopes & Neural Network (2)
A. Singhal, A. Rai, A. Mahabal, K. Indulekha	MGU+DU-2	no/yes	no	< 1	light curve slopes & Random Forests (2)
H. Campbell, B. Nichol,	Portsmouth χ^2	yes/no	no	1	SALT2–χ_r^2 & 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)

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

PELICAN: deeP architecturE for the LIght Curve ANalysis

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

Kernel PCA for type Ia supernovae photometric classification

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

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[13], 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[17,18], 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[19], 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 PROBABILISTIC APPROACH TO CLASSIFYING SUPERNOVAE USING PHOTOMETRIC INFORMATION

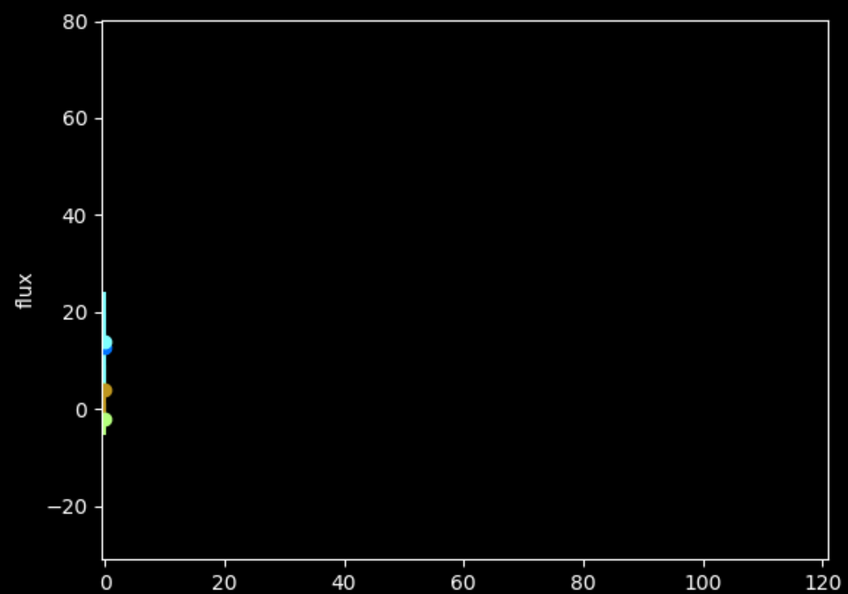
Natalia V. Kuznetsova[1] and Brian M. Connolly[2]
Received 2006 October 9; accepted 2006 December 8

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]

Photometric samples 101

(e.g. SN Ia cosmology)



Photometric samples 101

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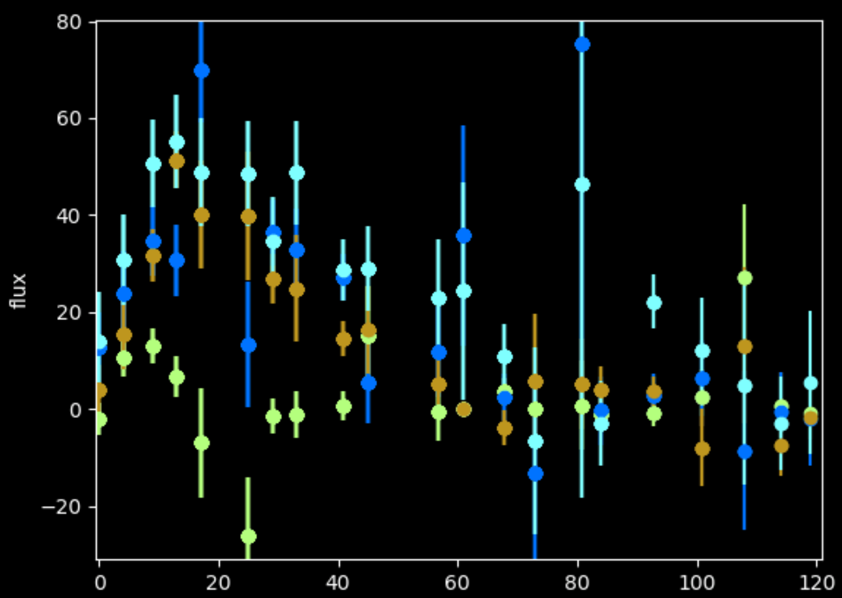
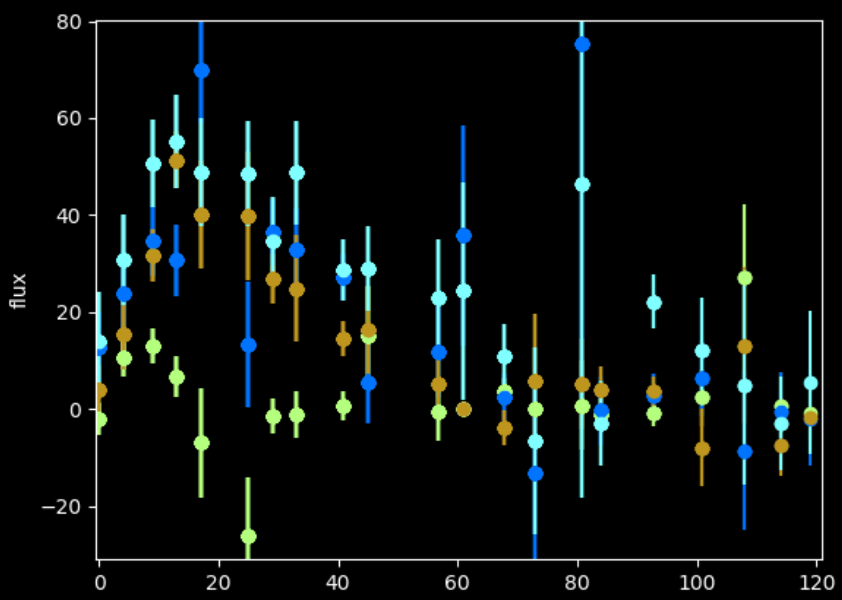


classifier

Photometric samples 101

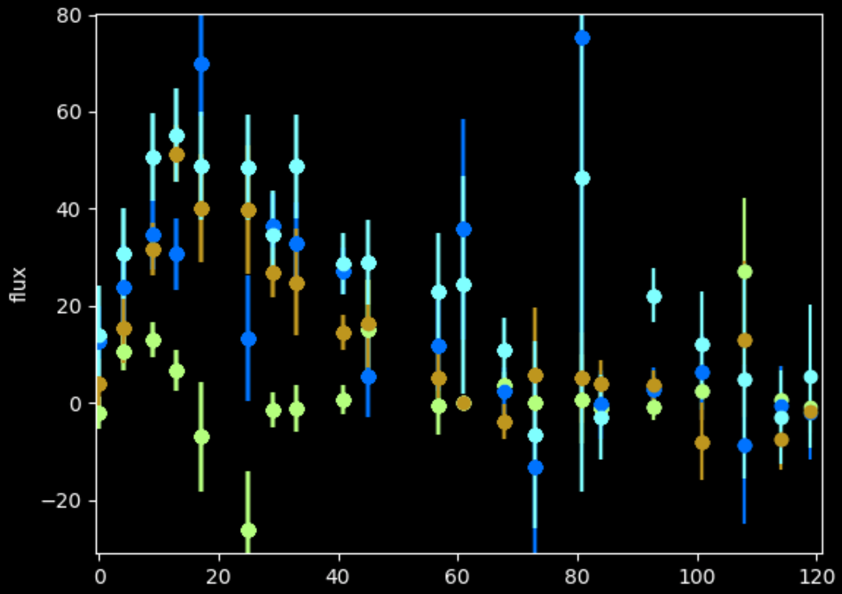
(e.g. SN Ia cosmology)



→ classifier → p(SN Ia)

Photometric samples 101

(e.g. SN Ia cosmology)



classifier → p(SN Ia) → cut on p(SN Ia) → select photometric SN Ia

SuperNNova

open source photometric classification

Möller & de Boissière arXiv: 1901.06384

github: supernnova/SuperNNova

SuperNNova

open source photometric classification

- Core algorithm: **Recurrent Neural Networks** (RNN)
  - Recurrent Neural Network:
    - LSTM
    - GRU
  - Bayesian RNNs
    - Variational (Gal+2016)
    - Bayes by Backprop (Fortunato+2017)
  - Convolutional NN (soon!)

- Trained & tested with supernovae simulations (DES based)

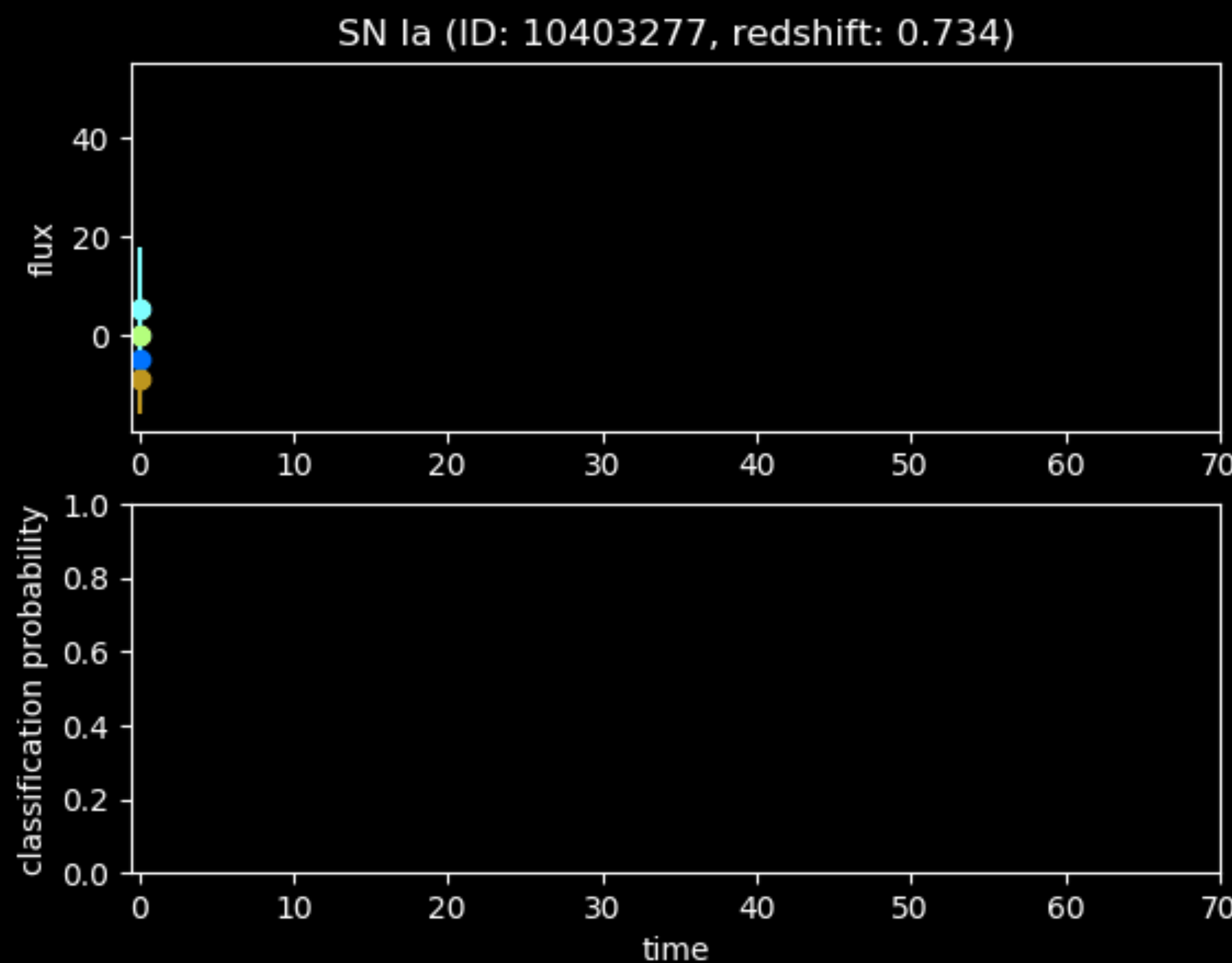
SuperNNova

open source photometric classification

input:

- fluxes + errors
- time
- (redshift)

if available from host-galaxy catalogues

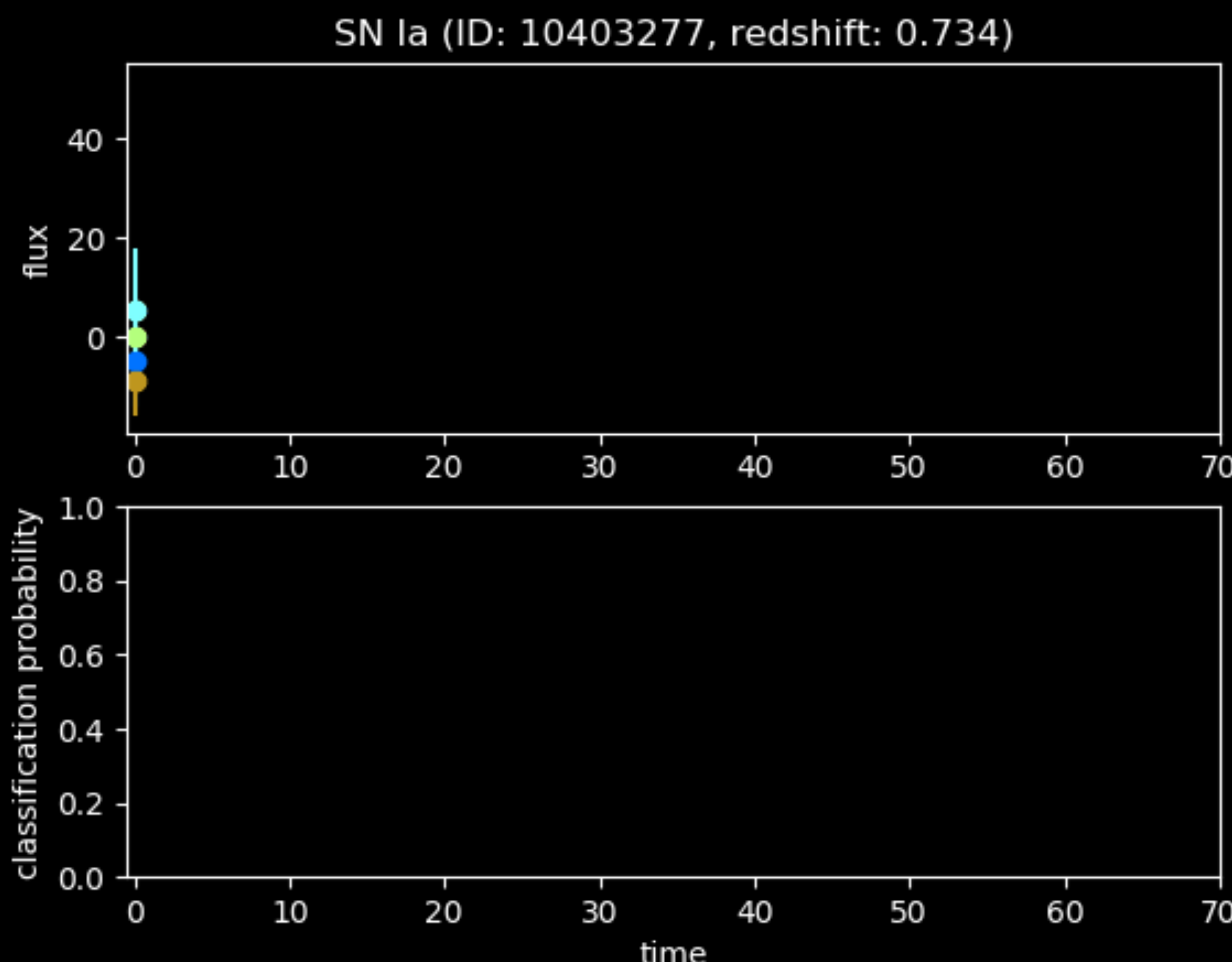


SuperNNova
open source photometric classification

input:
- fluxes + errors
- time
- (redshift)

if available from host-galaxy catalogues

Classification speed: 2,000 light-curves/ second!



SuperNNova

open source photometric classification

SNe Ia vs. Non Ia accuracy

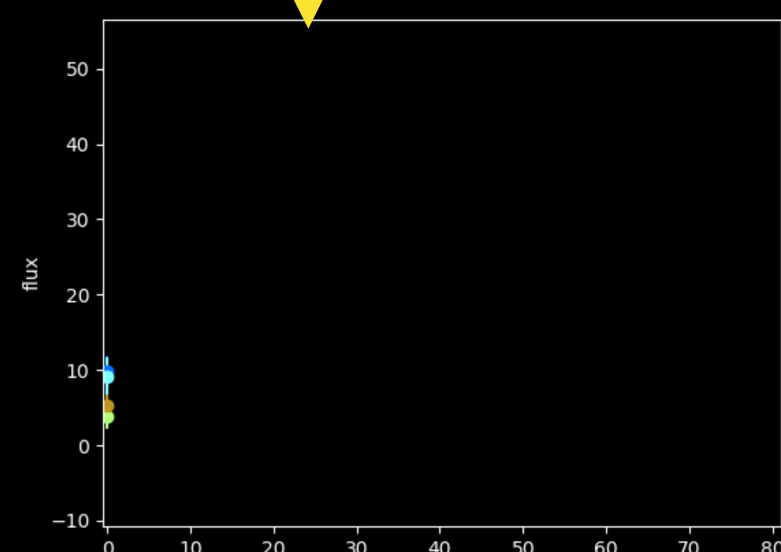
SuperNNova

open source photometric classification

SNe Ia vs. Non Ia accuracy

Early classification

redshift	-2	0	+2
None	86.47 ± 0.16	87.59 ± 0.13	88.68 ± 0.11
zpho	93.56 ± 0.06	94.25 ± 0.07	94.84 ± 0.06
zspe	93.36 ± 0.15	94.09 ± 0.14	94.66 ± 0.14



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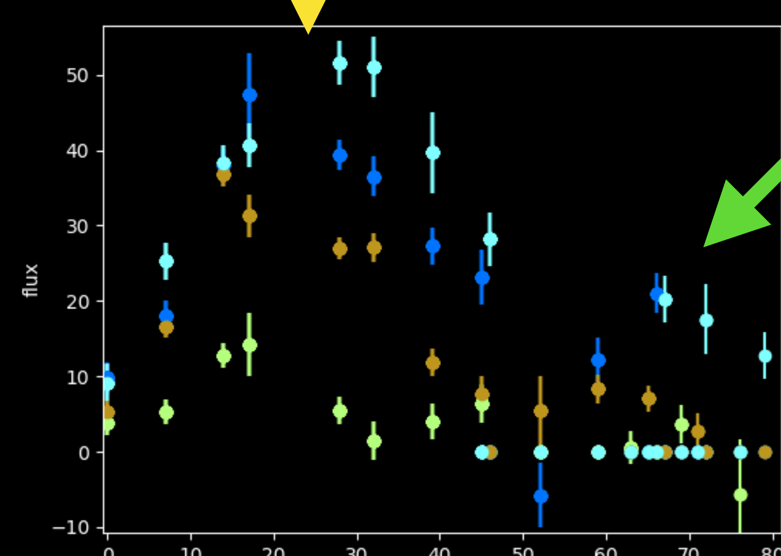
SNe Ia vs. Non Ia accuracy

	Early classification			Complete
redshift	-2	0	+2	all
None	86.47 ± 0.16	87.59 ± 0.13	88.68 ± 0.11	96.97 ± 0.06
zpho	93.56 ± 0.06	94.25 ± 0.07	94.84 ± 0.06	**98.83** ± **0.02**
zspe	93.36 ± 0.15	94.09 ± 0.14	94.66 ± 0.14	98.43 ± 0.07



purities up to 98%!

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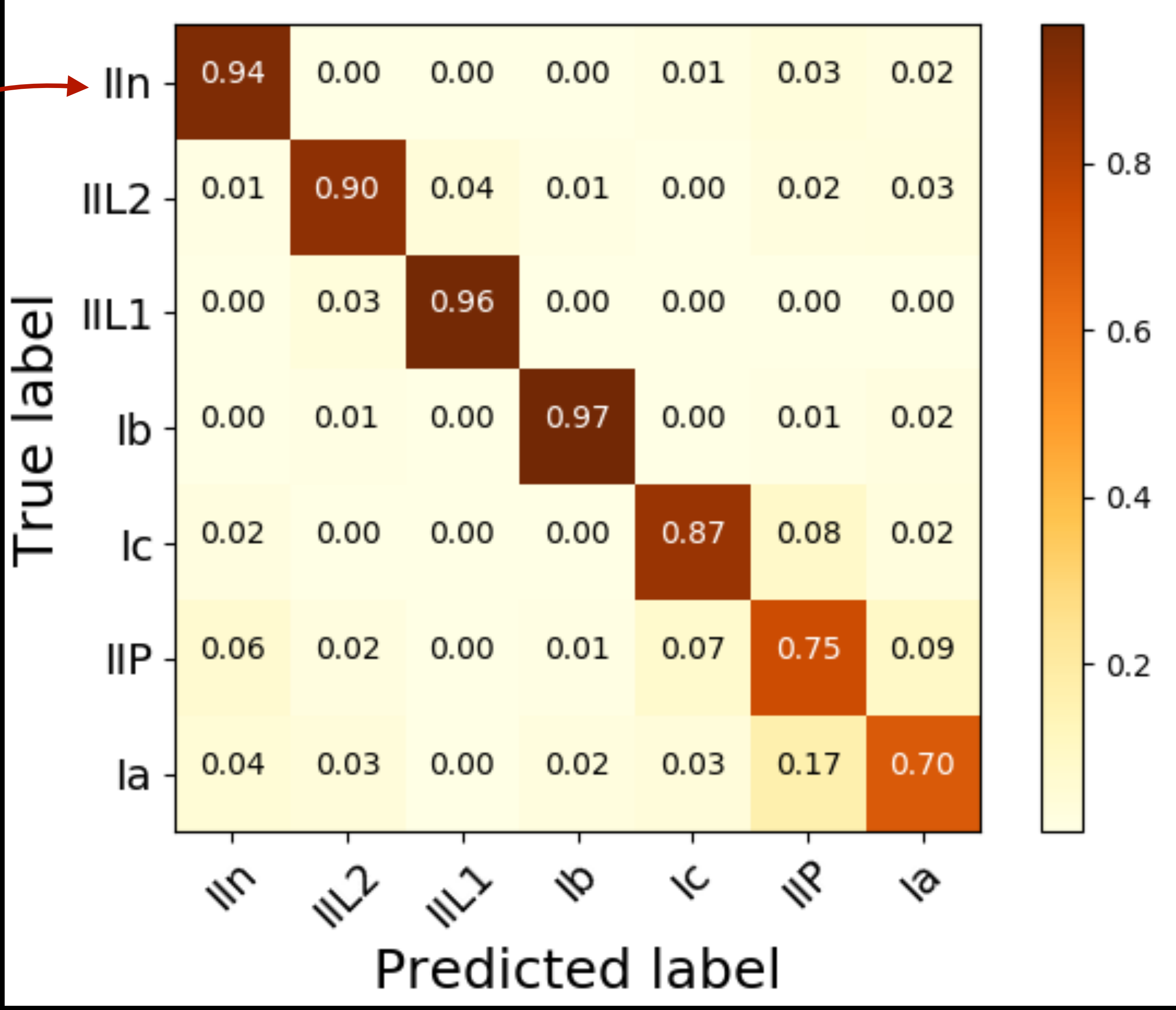
Many SN types accuracy

redshift	-2	0	+2	all
None	57.2 ± 0.31	60.08 ± 0.34	62.99 ± 0.32	86.89 ± 0.2
zpho	64.69 ± 0.21	67.32 ± 0.26	69.96 ± 0.25	90.02 ± 0.14
zspe	63.99 ± 0.58	66.74 ± 0.62	69.43 ± 0.65	**90.14 ± 0.47**



Bayesian RNNs

implementations: variational (Gal+2016), Bayes by Backdrop (Fortunato+2017)

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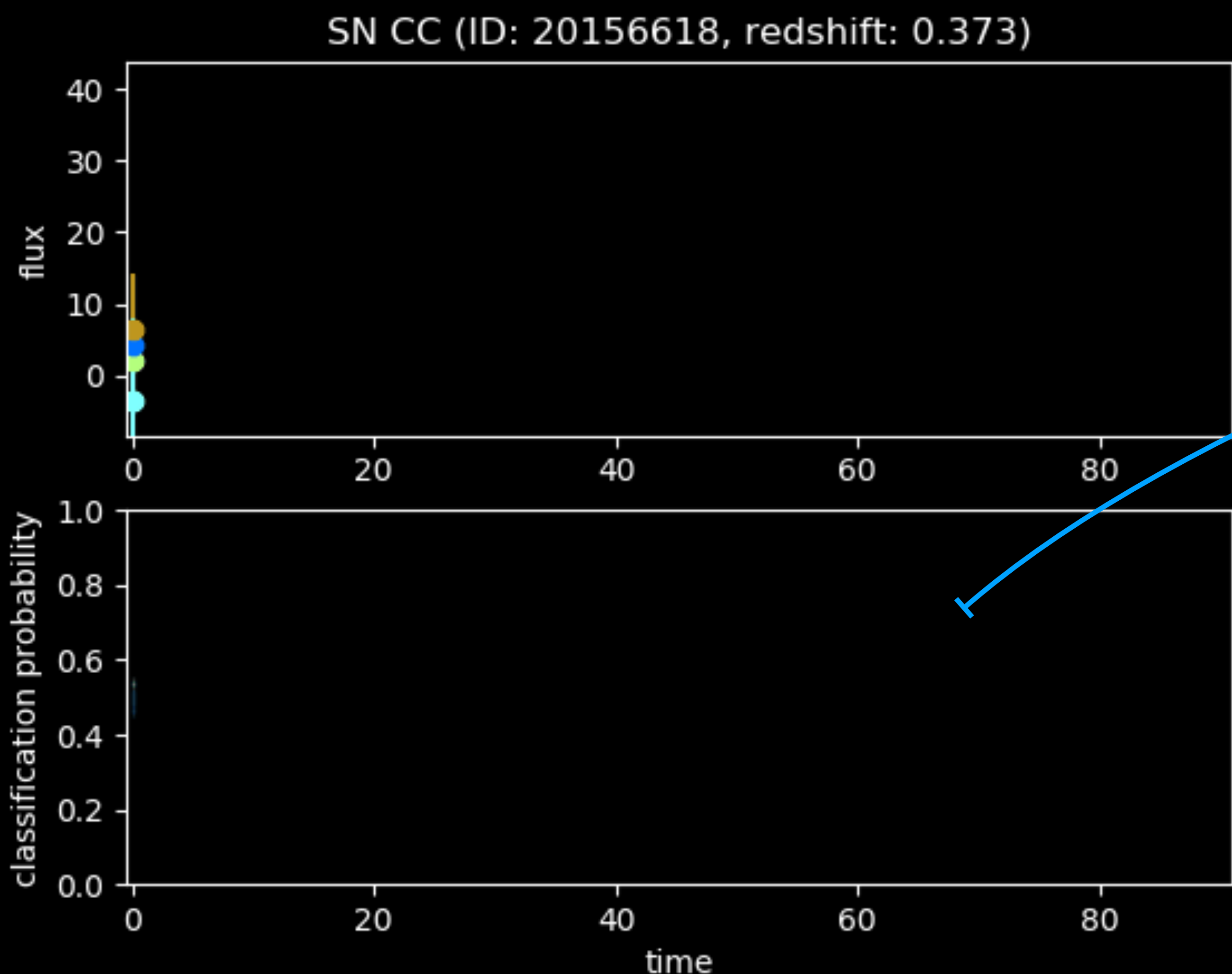
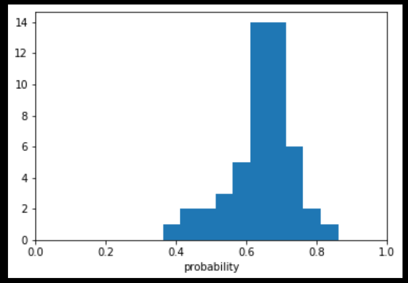


Posterior that provides epistemic uncertainties



Epistemic uncertainties:

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

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Bayesian RNNs Representativeness

Model 1: representative model

Model 2: train non-representative model

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Bayesian RNNs Representativeness

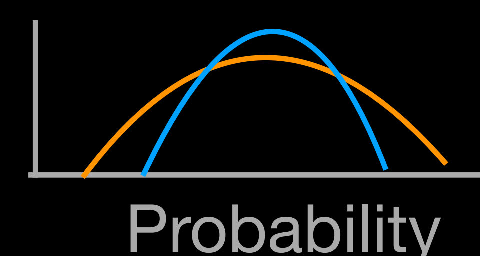
Model 1: representative model

classify representative sample

Model 2: train non-representative model

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

non-representative models give larger uncertainties!



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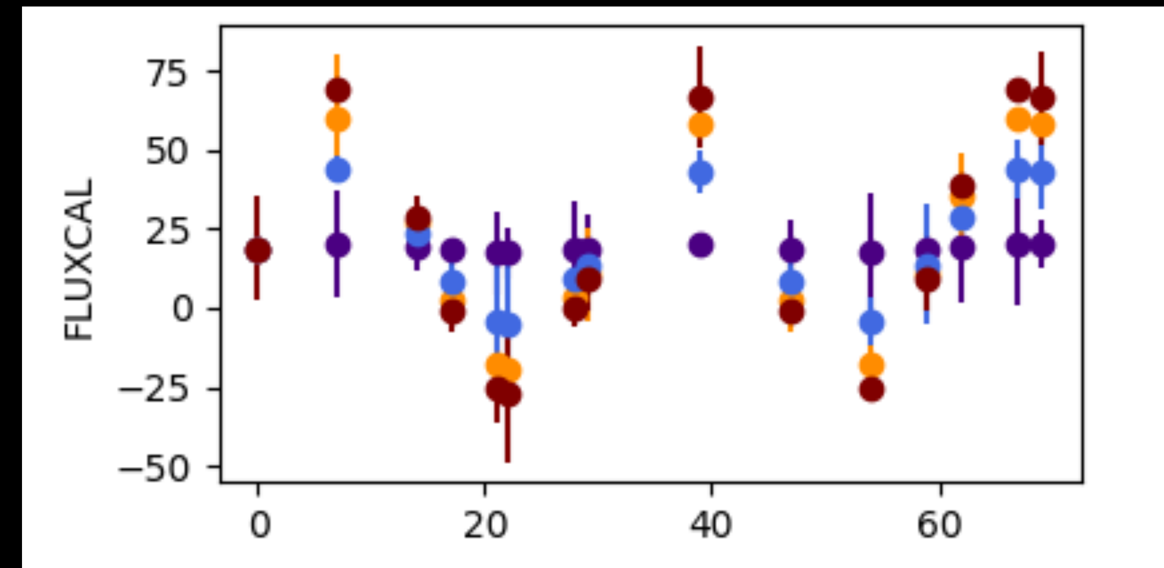
Bayesian RNNs

Out-of-distribution



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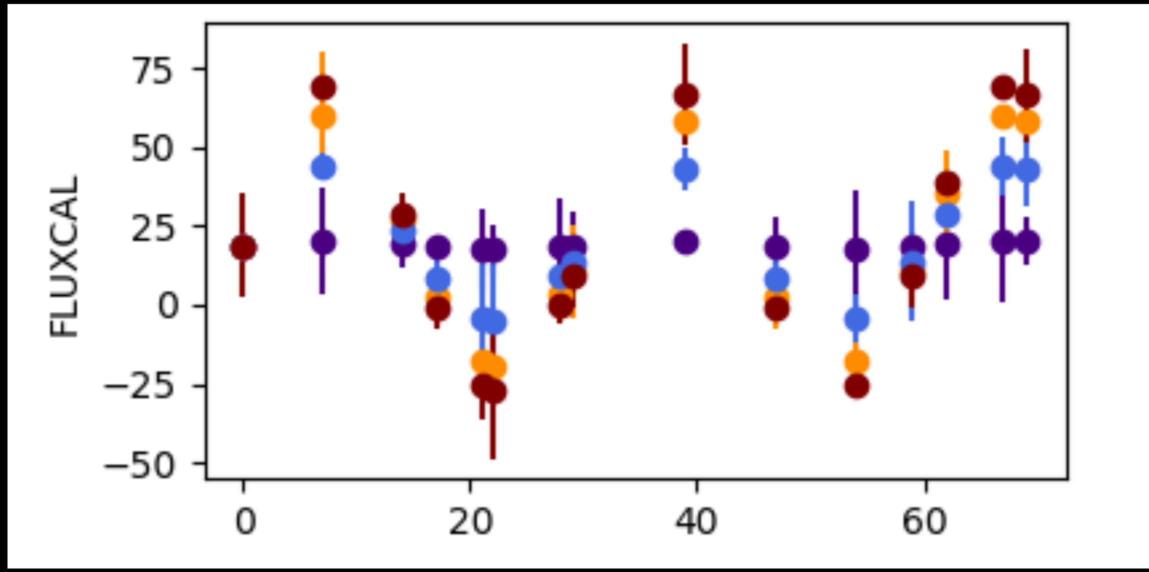
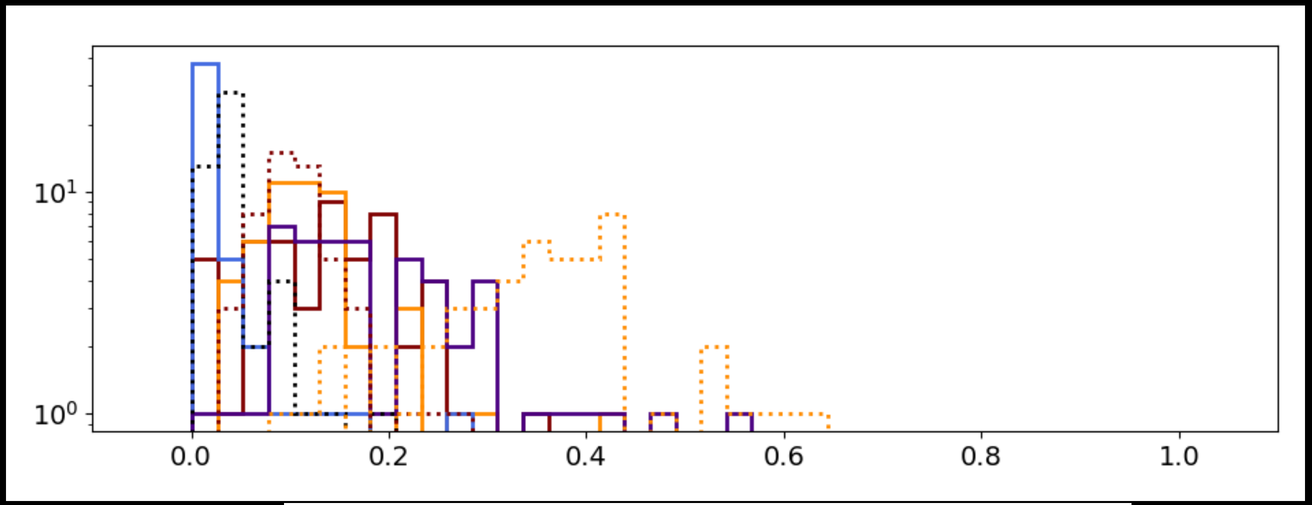
Bayesian RNNs   Out-of-distribution



low probability for any class



classification probability

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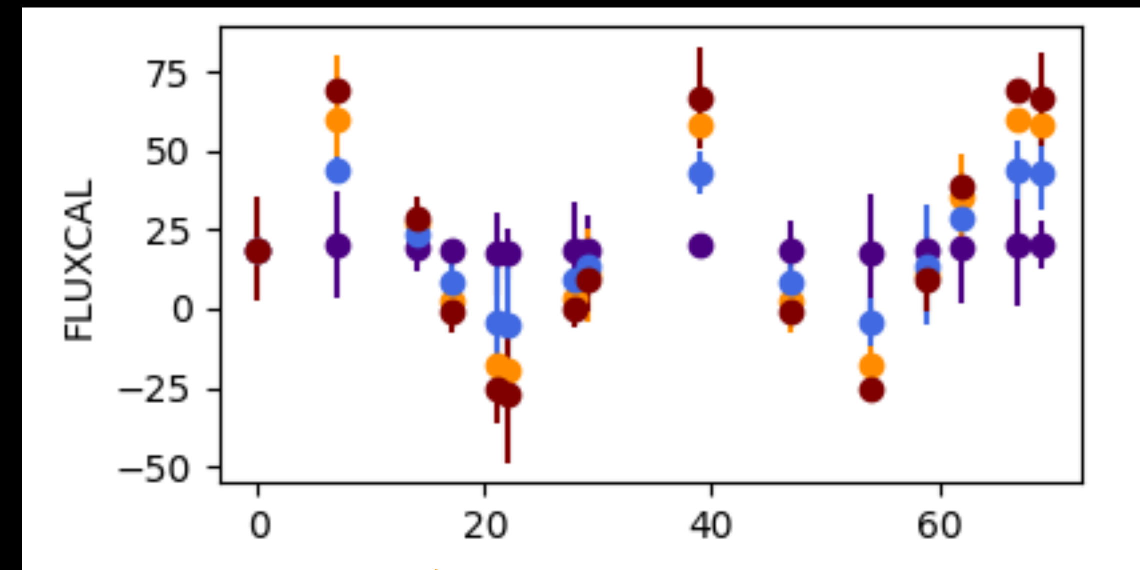
Bayesian RNNs

Out-of-distribution



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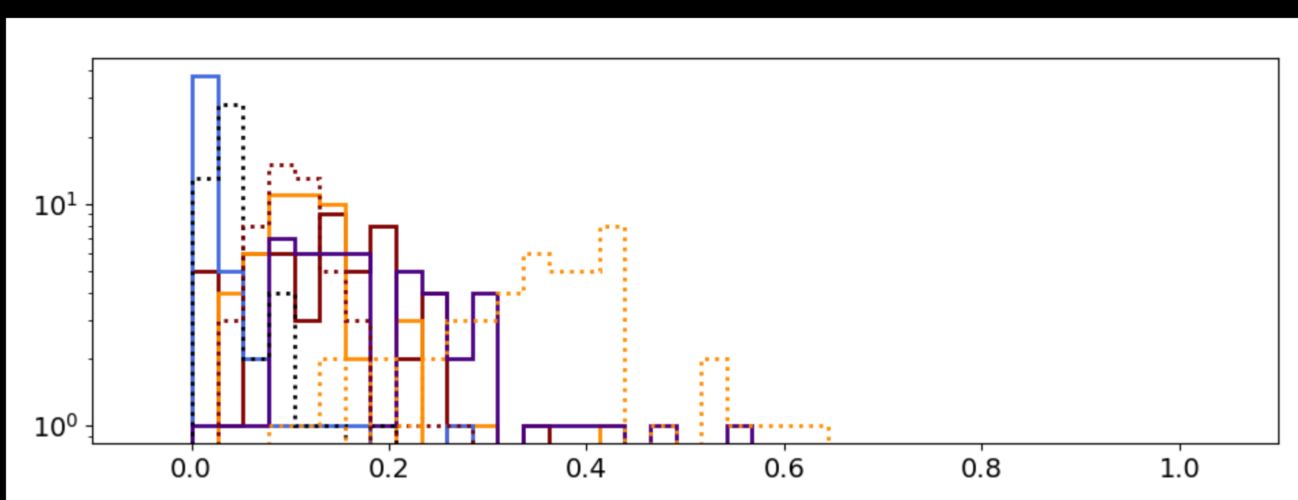
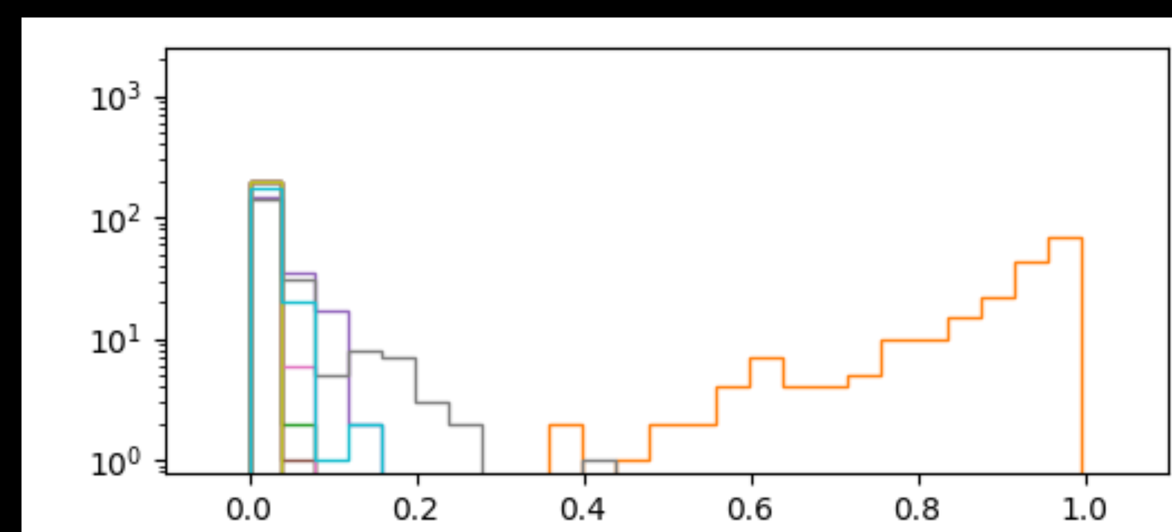


classification probability

high probability for "less-known" class

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

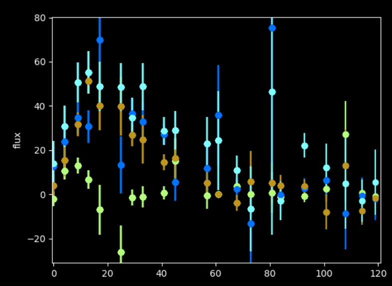


classification probability

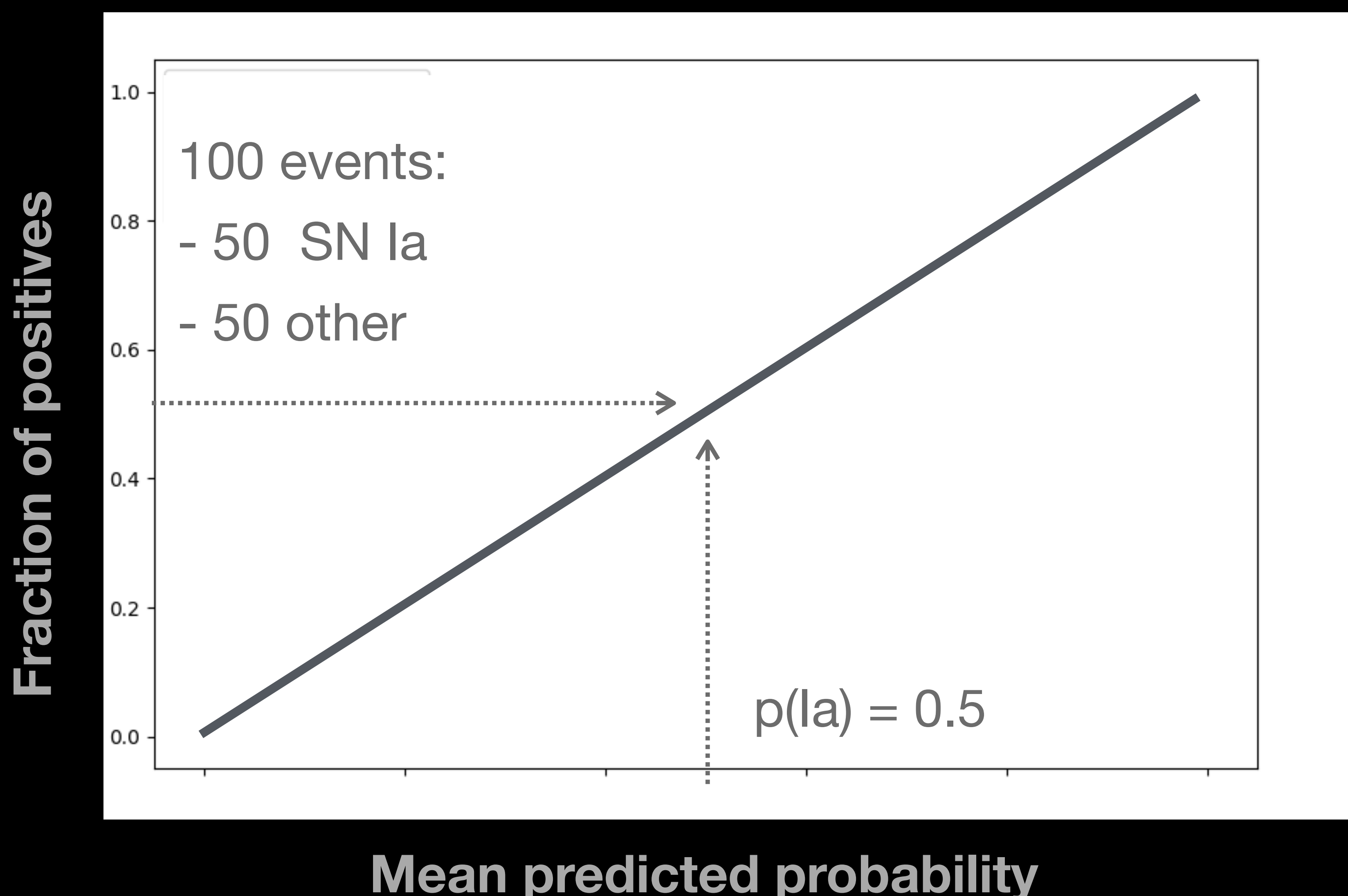
SuperNNova

open source photometric classification

Selecting photometric samples for statistical studies

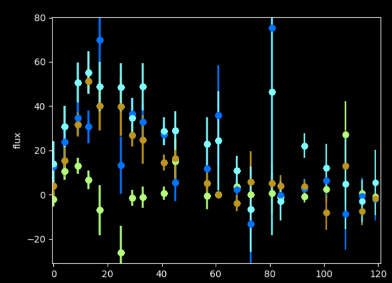


→ classifier → p(SN Ia) → cut on p(SN Ia)



SuperNNova
open source photometric classification

Selecting photometric samples for statistical studies



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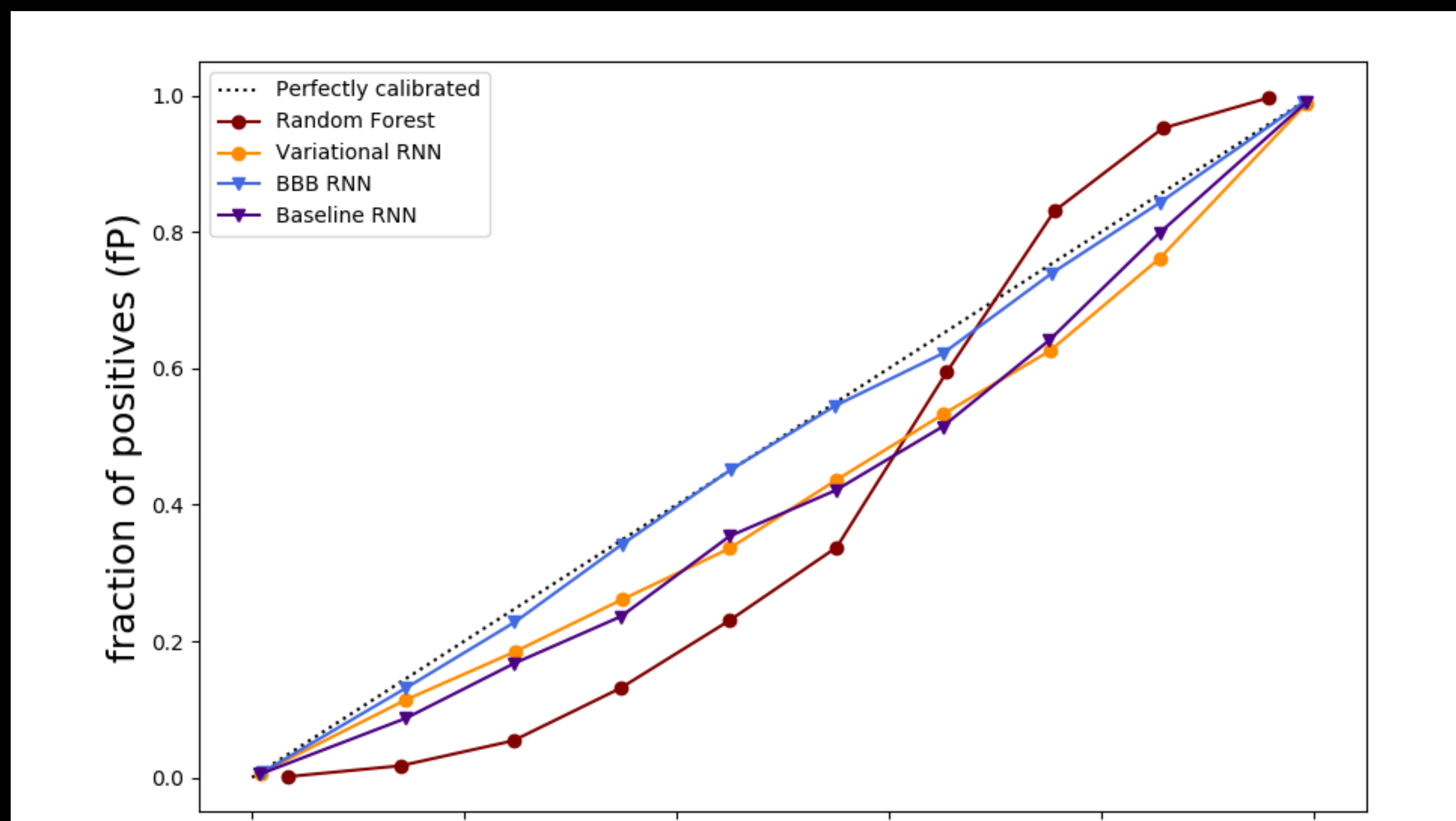

Mean predicted probability

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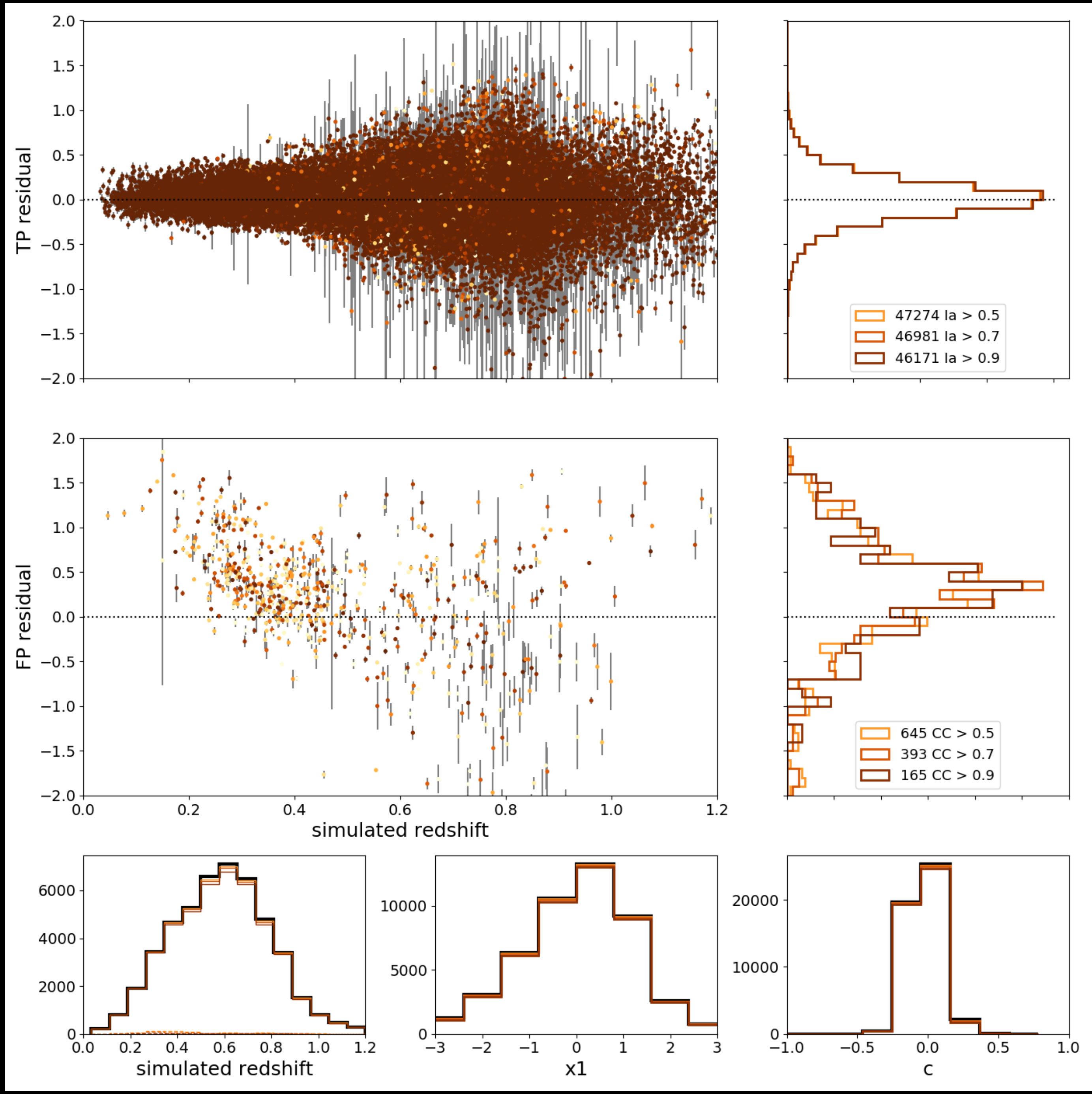
Selecting photometric samples for cosmology



Dark Energy Survey

SURVEY	SNe Ia	wErr (stat + sys)
JLA (2014)	740	0,054
Pantheon (2018)	1049	0,040
DES 3YR (2018) spec	**334**	**0,057**
DES 5YR spec	~500	?
DES 5YR photo	~2000	?

SuperNNova
open source photometric classification

Photometric classification is an excellent option to maximise our science output with LSST

Classification: early (brokers), complete (cosmology)

Fast, reliable, statistically sound.

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Accurate: Early >86%, complete > 97% *SN Ia cosmology (<2% contamination)*

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Bayesian RNNs = classification model uncertainty

great to detect anomalies, asses representativity, select events poorly characterised with current model

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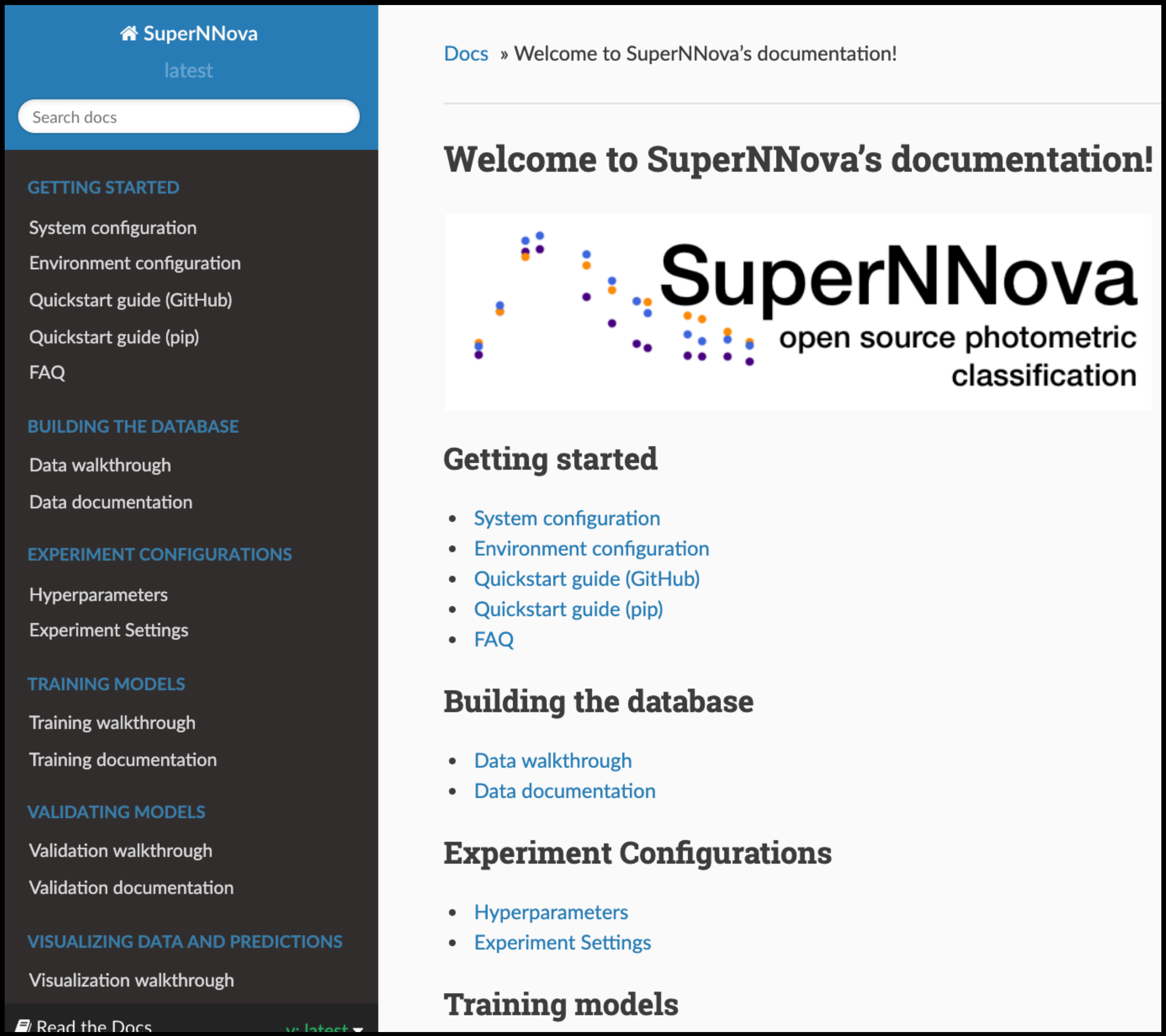
Real data: Dark Energy Survey 5-year supernova sample

github: supernnova/SuperNNova



Available algorithms:

- Recurrent Neural Network
- Bayesian RNNs
  - Variational (Gal+2016)
  - Bayes by Backprop (Fortunato+2017)
- Convolutional NN (soon!)