

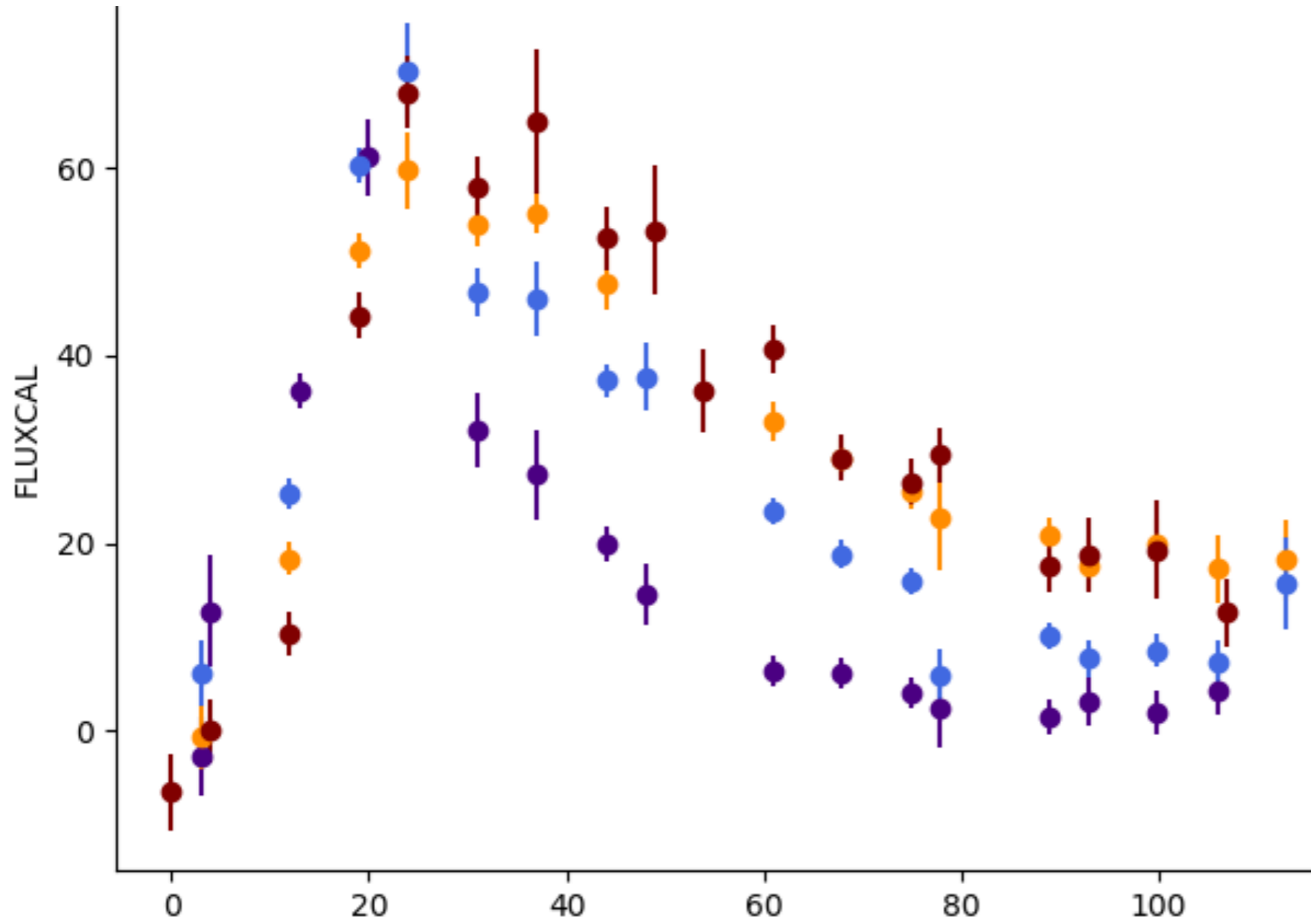


*Möller & de Boissière 2019*    arXiv : 1901.06384

**Anais Möller**  
**TransiXplore 2019**

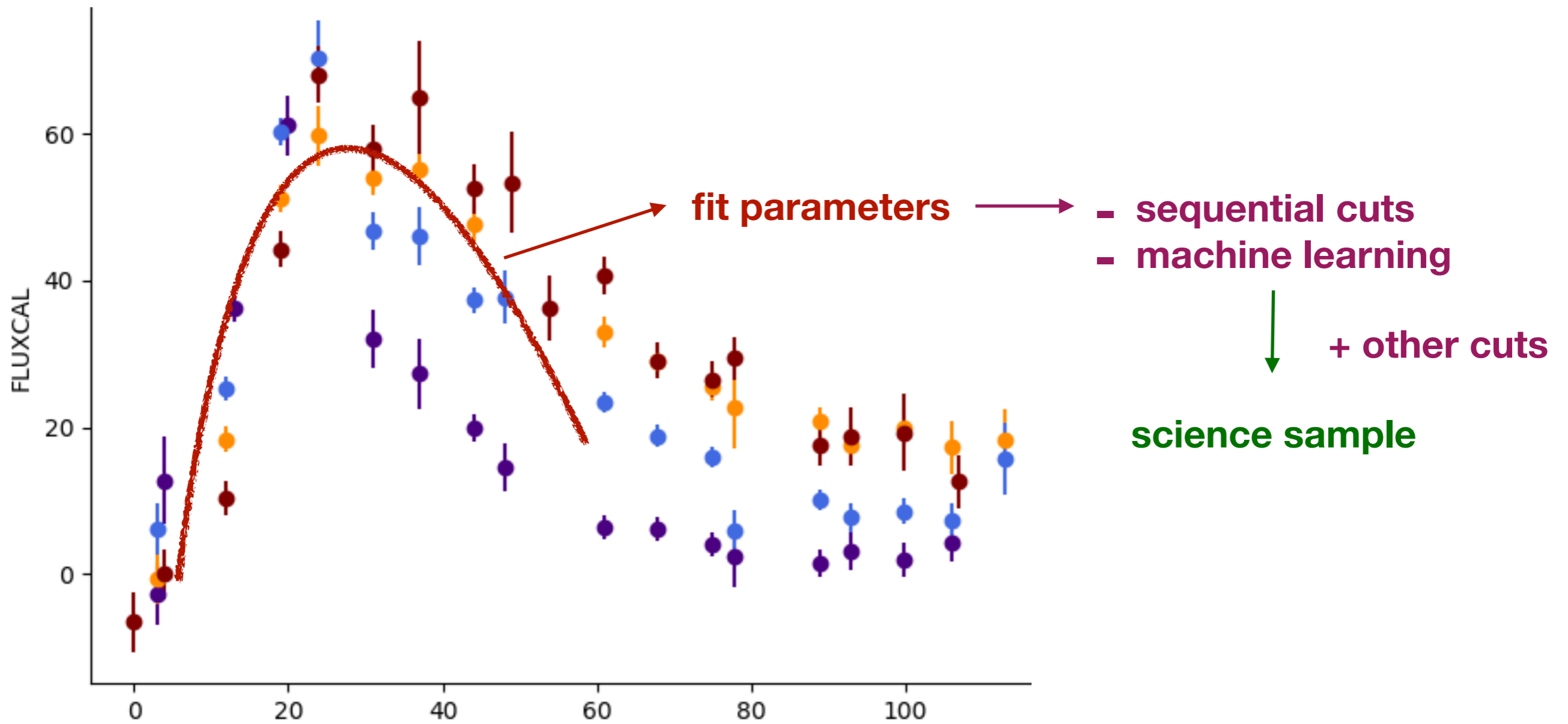


# photometric classification

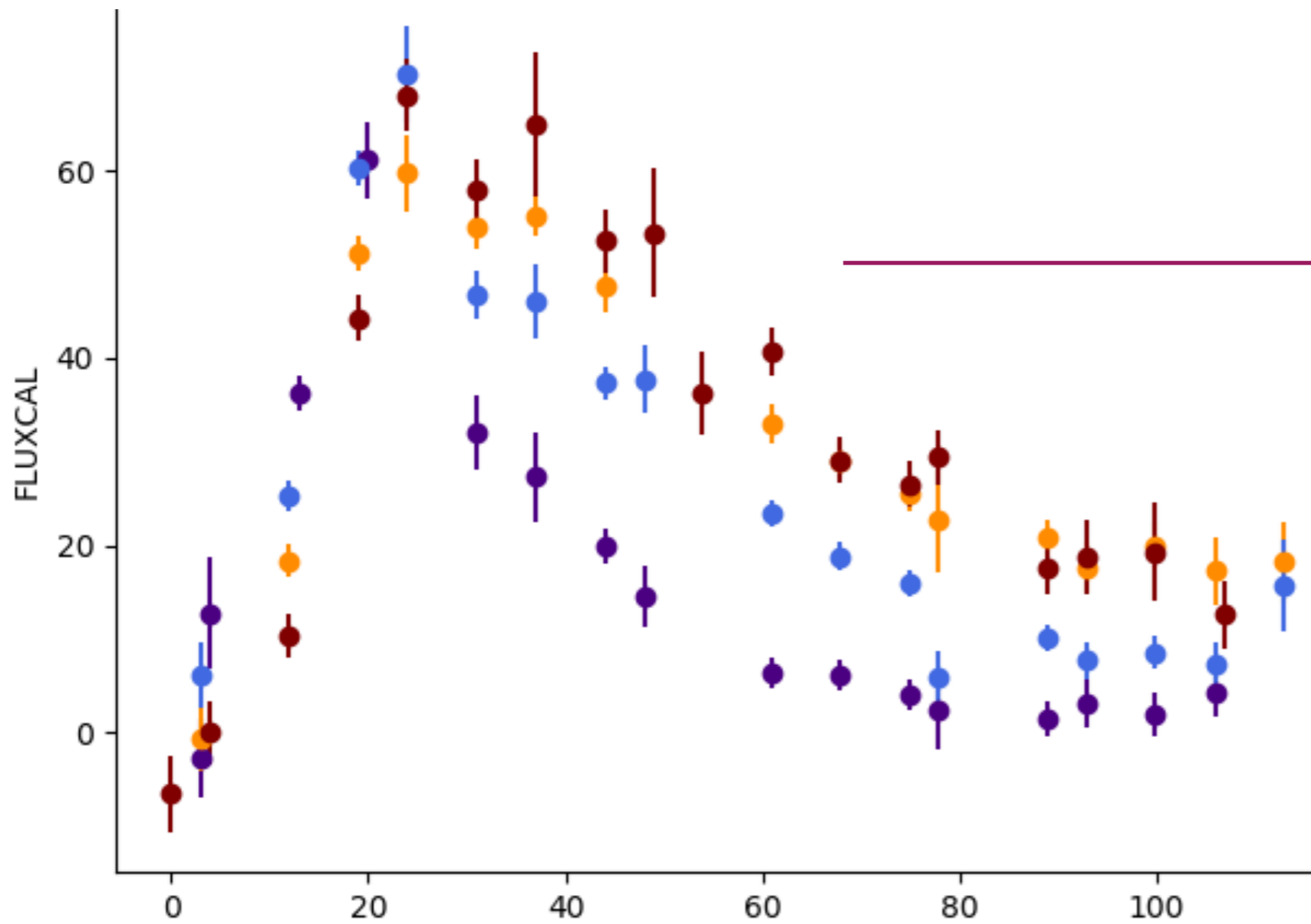


# photometric classification

## most approaches

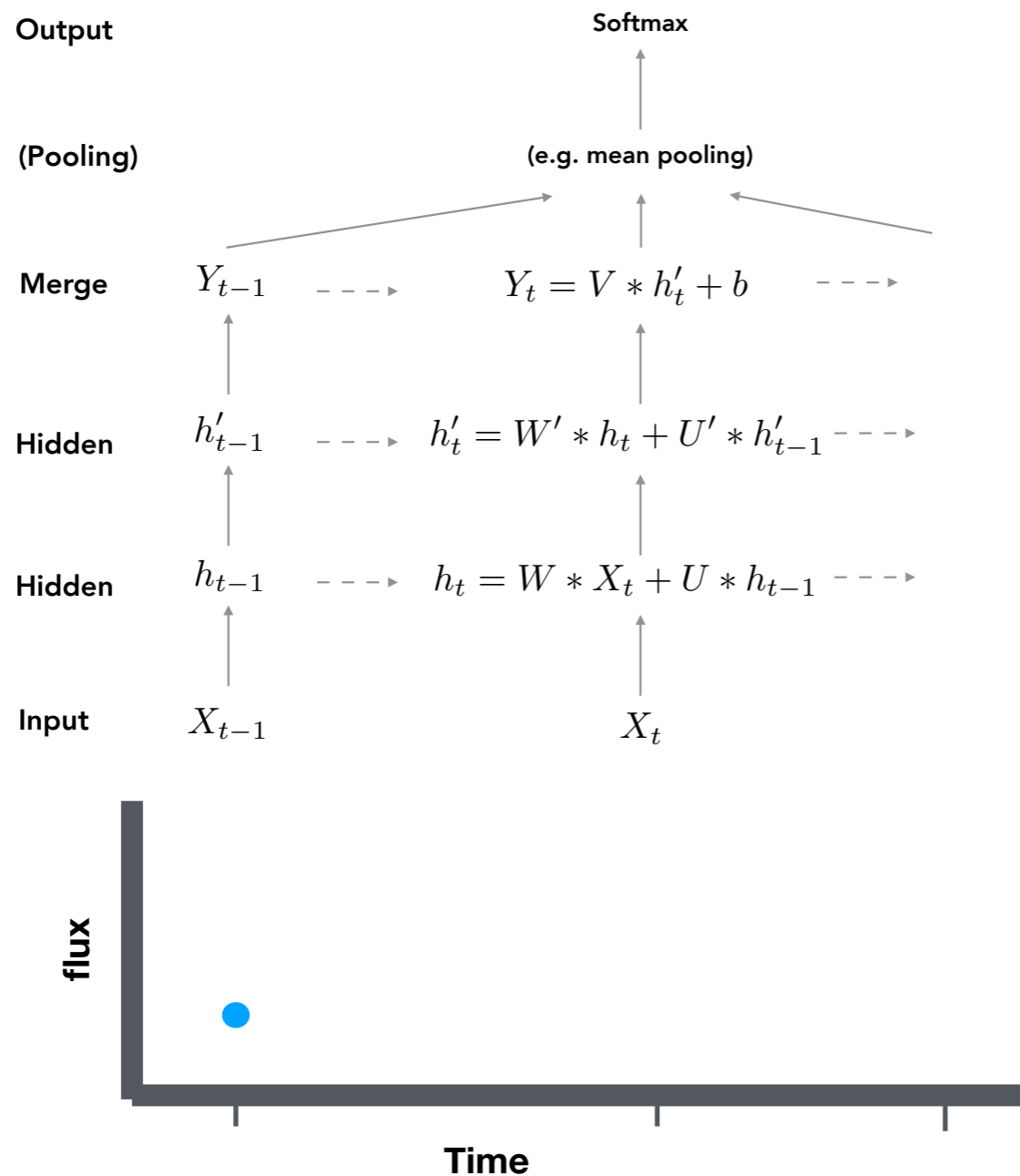


# photometric classification



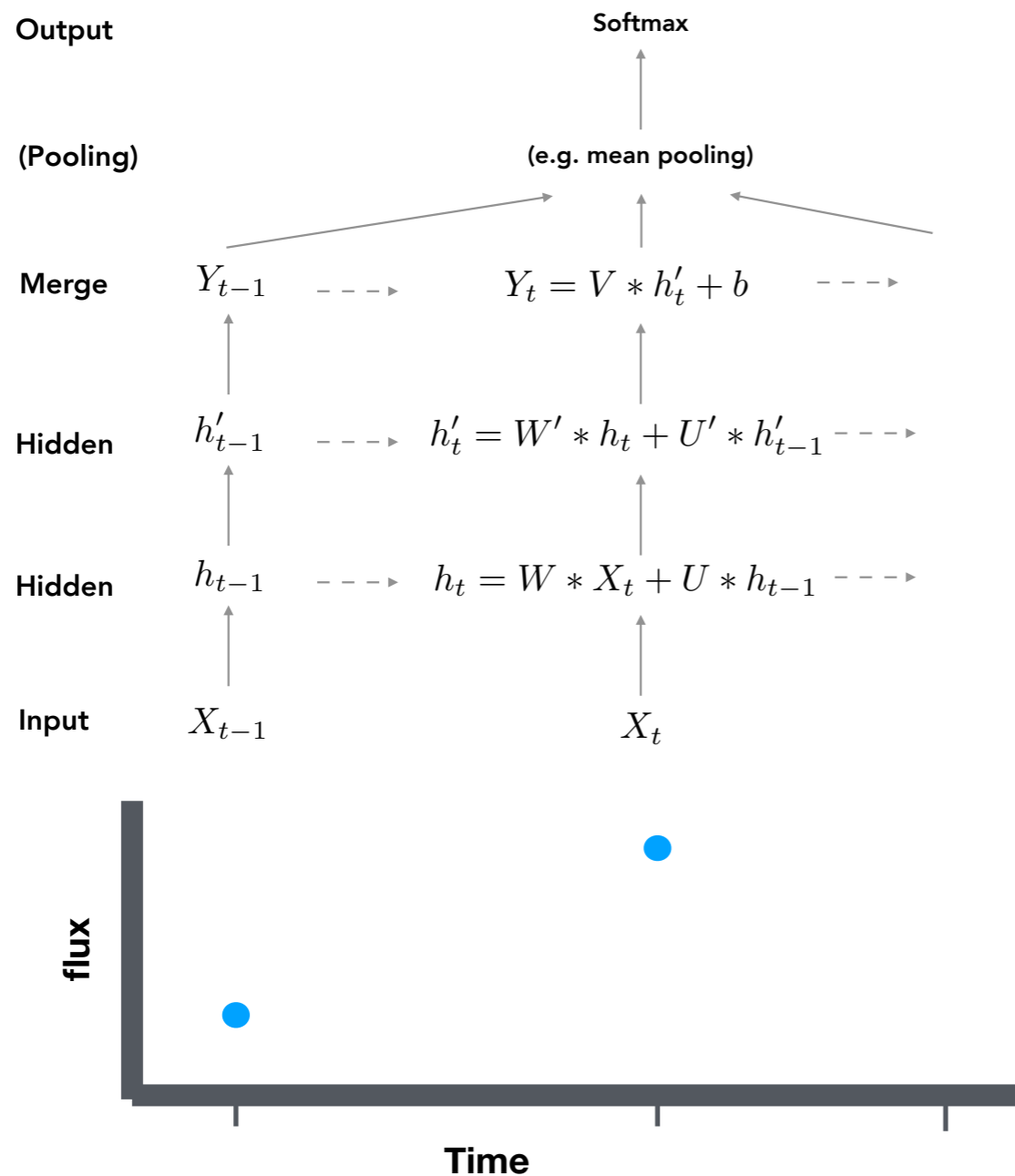
machine learning

science sample



## classifiers:

- Recurrent Neural Networks (RNNs):
  - LSTM
  - GRU
- Bayesian RNNs
  - MC dropout (Gal+2016)
  - Bayes by Backprop (Fortunato+2017)
- Convolutional Neural Networks
- (Random Forest w. SALT2 fit parameters)



## classifiers:

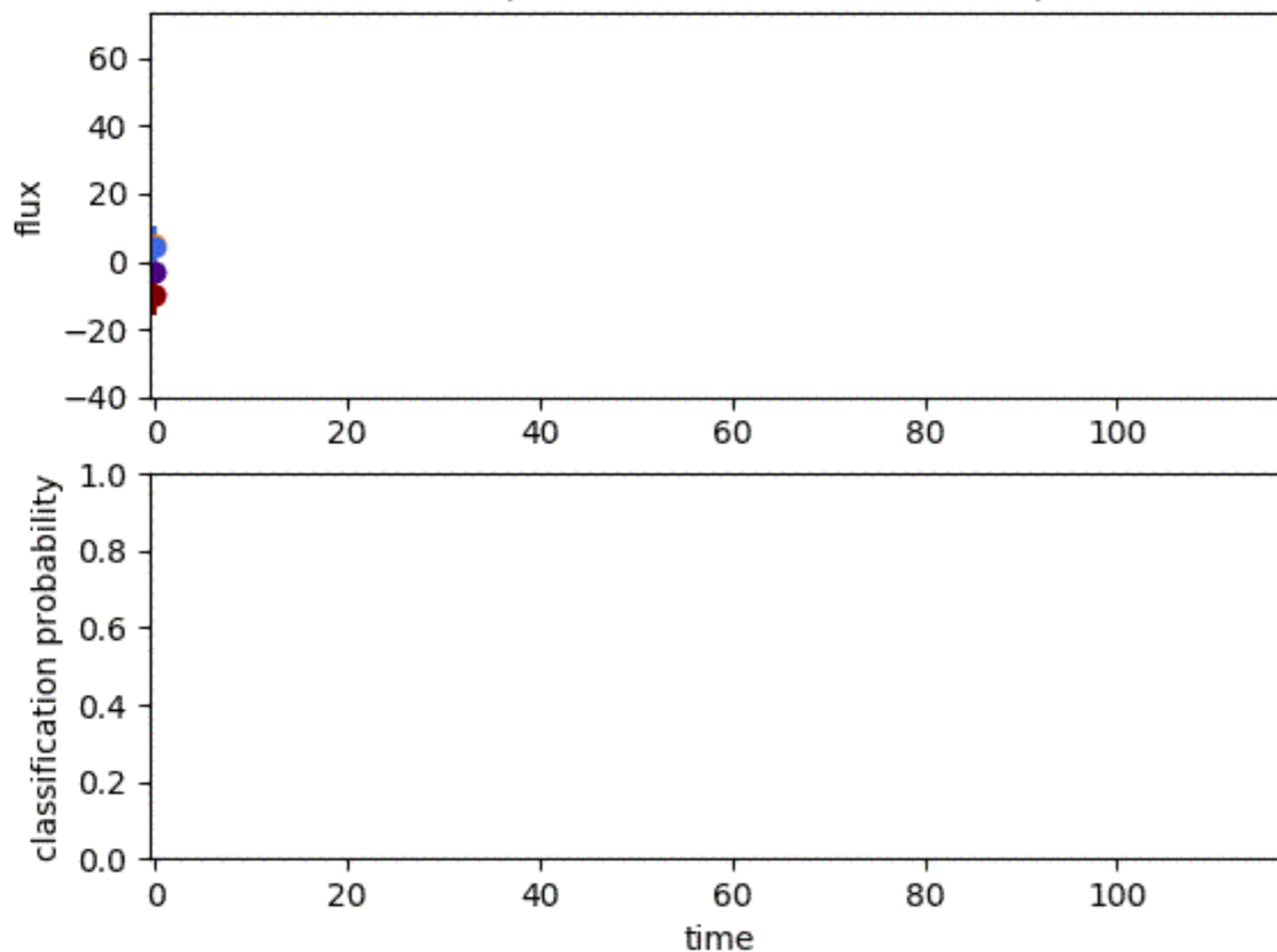
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# SuperNNova

open source photometric  
classification

uses observed data

SN Ia (ID: 12251706, redshift: 0.7)



## inputs:

- observed fluxes + errors
- time
- optional: host galaxy redshifts

**no rest-frame, dust, ... corrections**

**No feature engineering** necessary!  
Handles **irregular sampled** time series!



# SuperNNova

open source photometric  
classification

## is deep learning

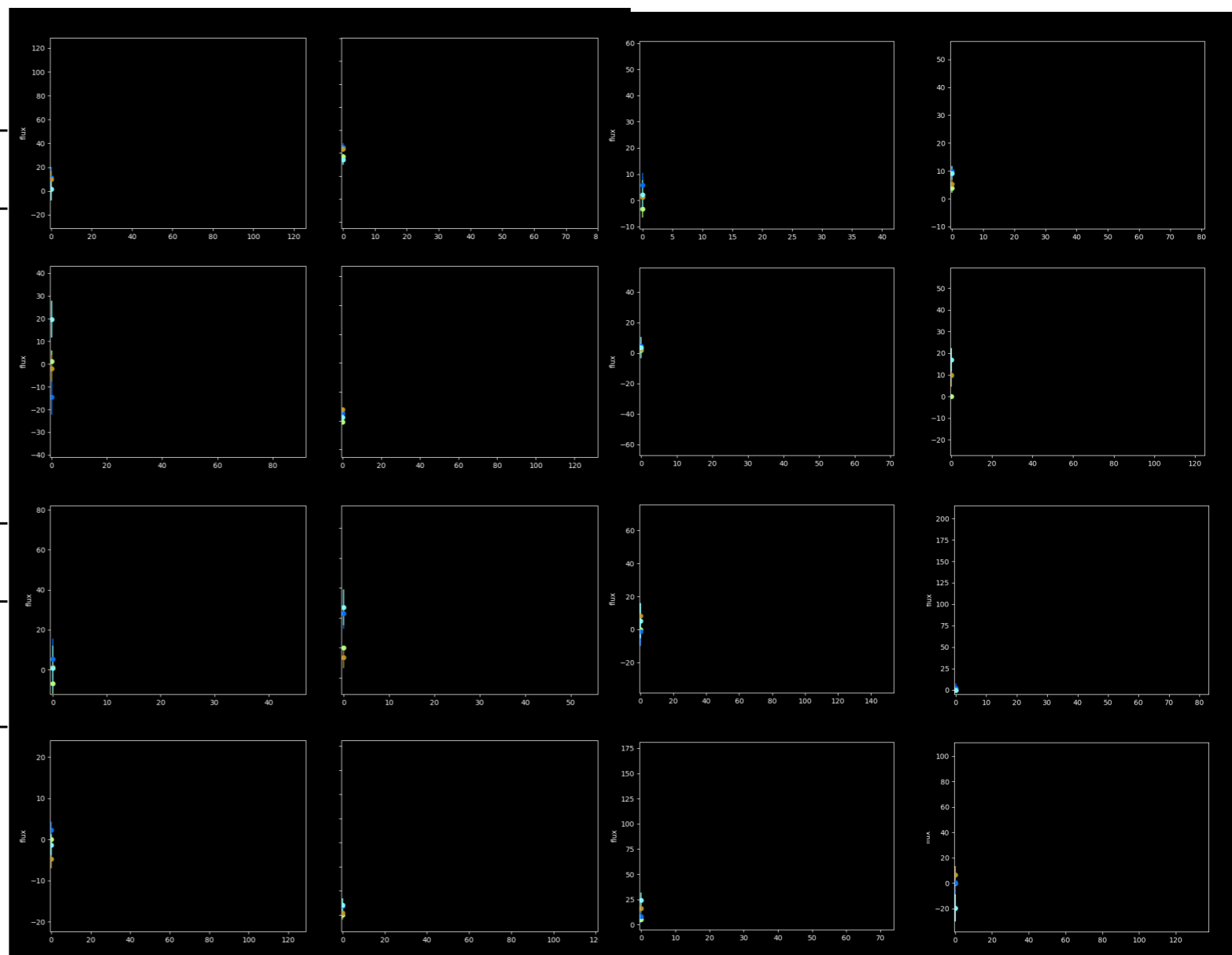
### Simulated supernovae

SN type	SALT2 fitted	complete dataset
Ia	402,786	912,691
Ib	140,197	181,454
Ic	70,811	90,485
IIP	94,994	296,523
IIn	3,249	154,614
IIL	93,535	189,615

### IILs by template

IIL1	26,717	100,827
IIL2	66,818	88,788

*Möller + 2019*

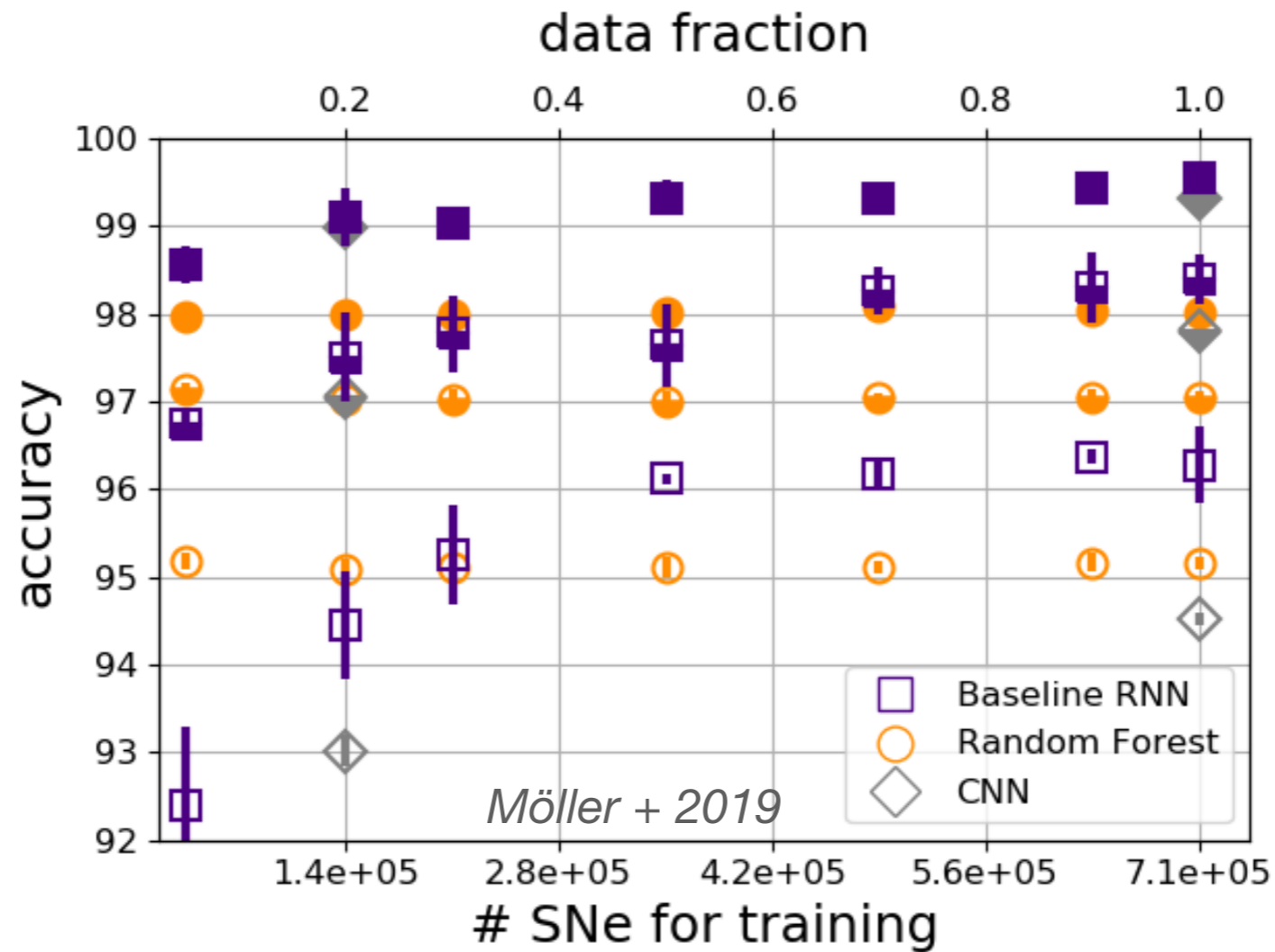




# SuperNNova is deep learning

open source photometric classification

Needs large training samples to achieve peak performance

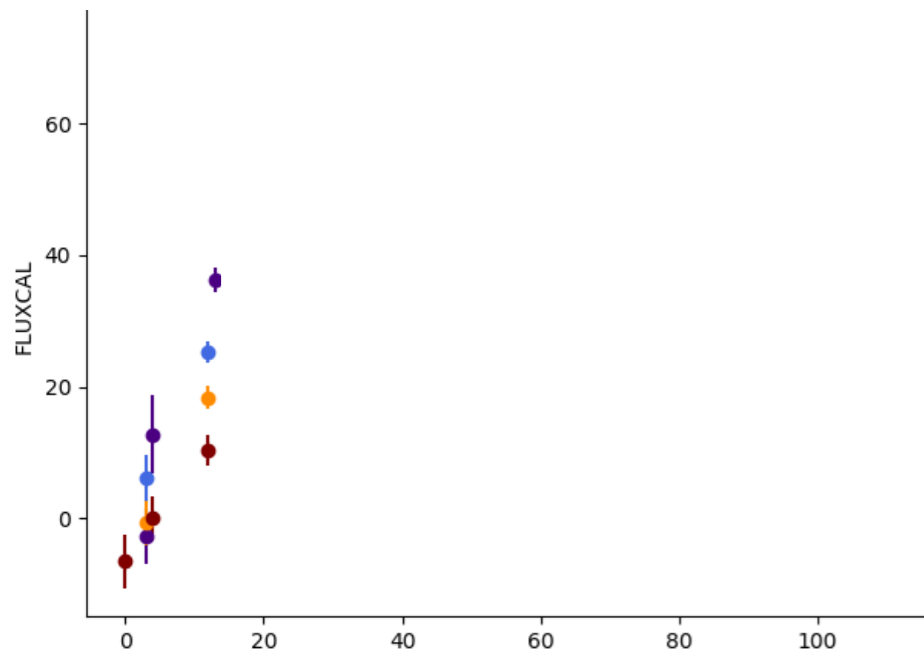




**for spectroscopic /  
photometric follow-up?**

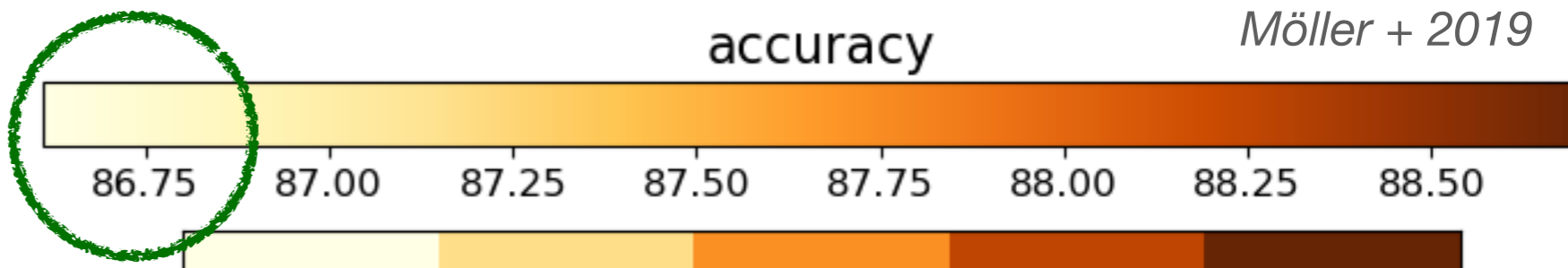
**Early  
light curves**

- to optimise spectroscopic resources
- to select SNe to improve photometric classification?
- for brokers

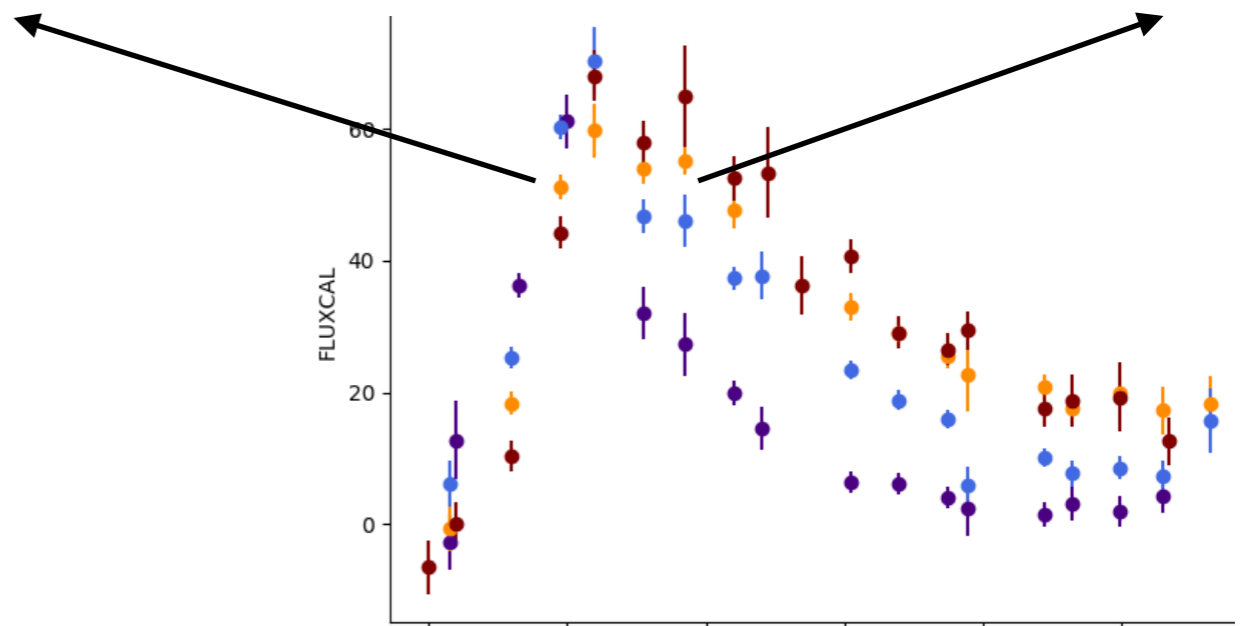
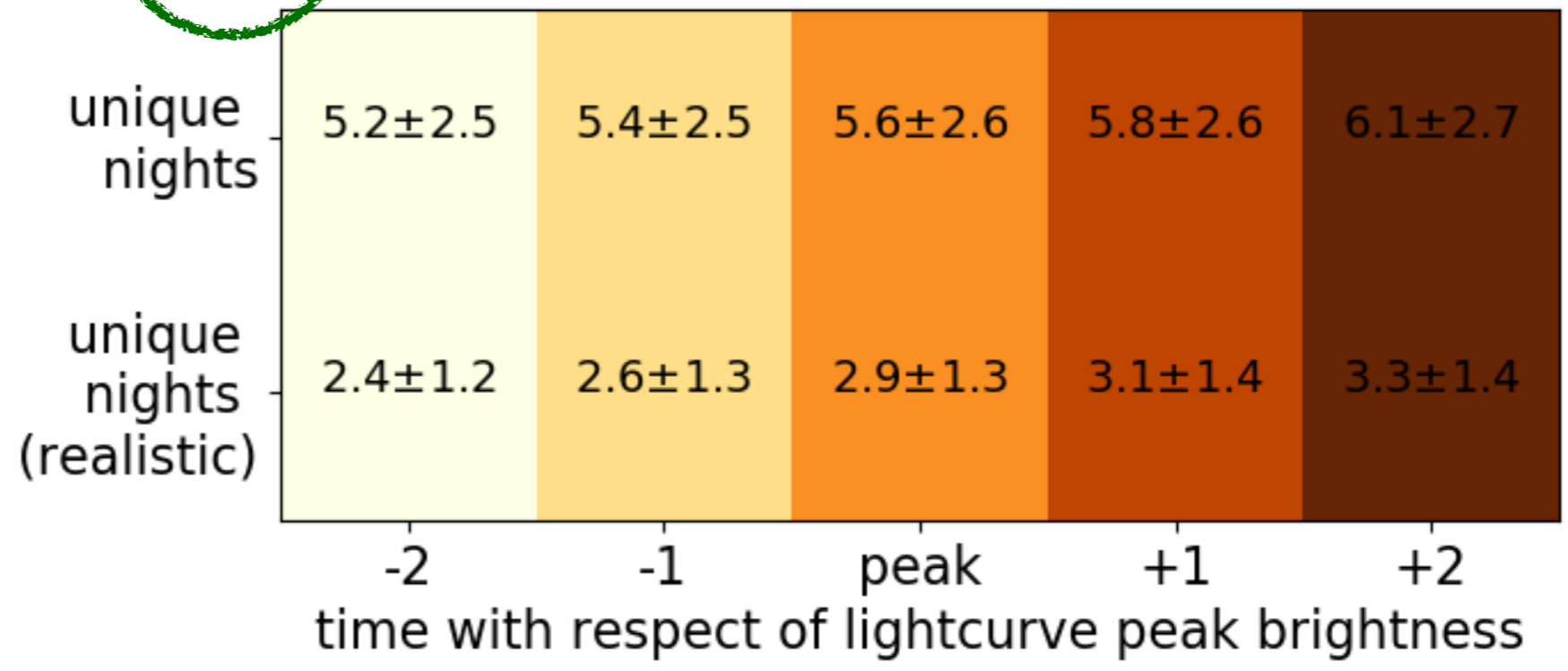


Möller + 2019

accuracy

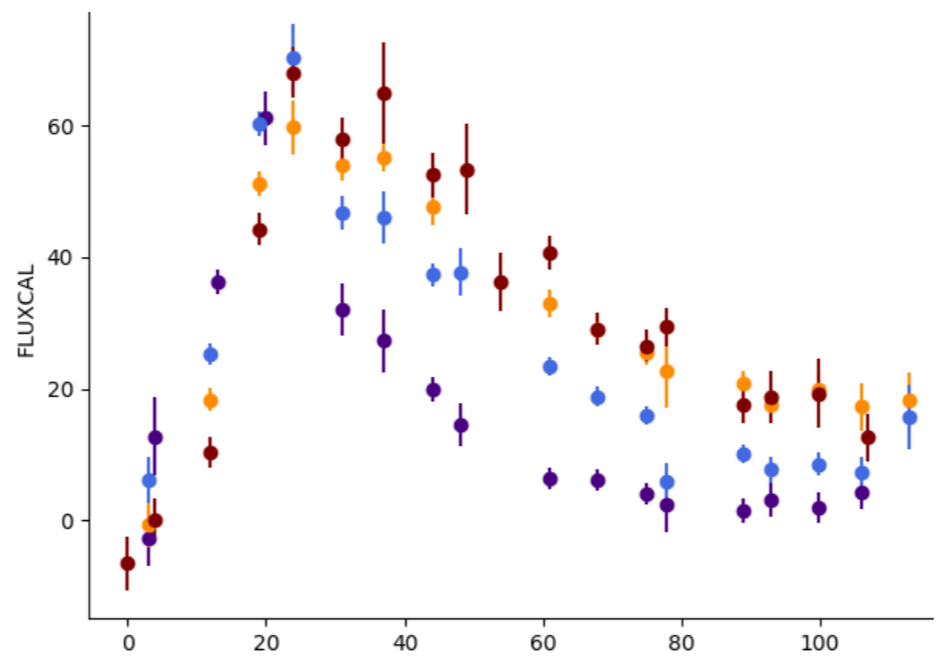


SNe Ia vs. Non Ia, no host-redshift information





# Complete light curves



# SuperNNova **is accurate**

open source photometric classification

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

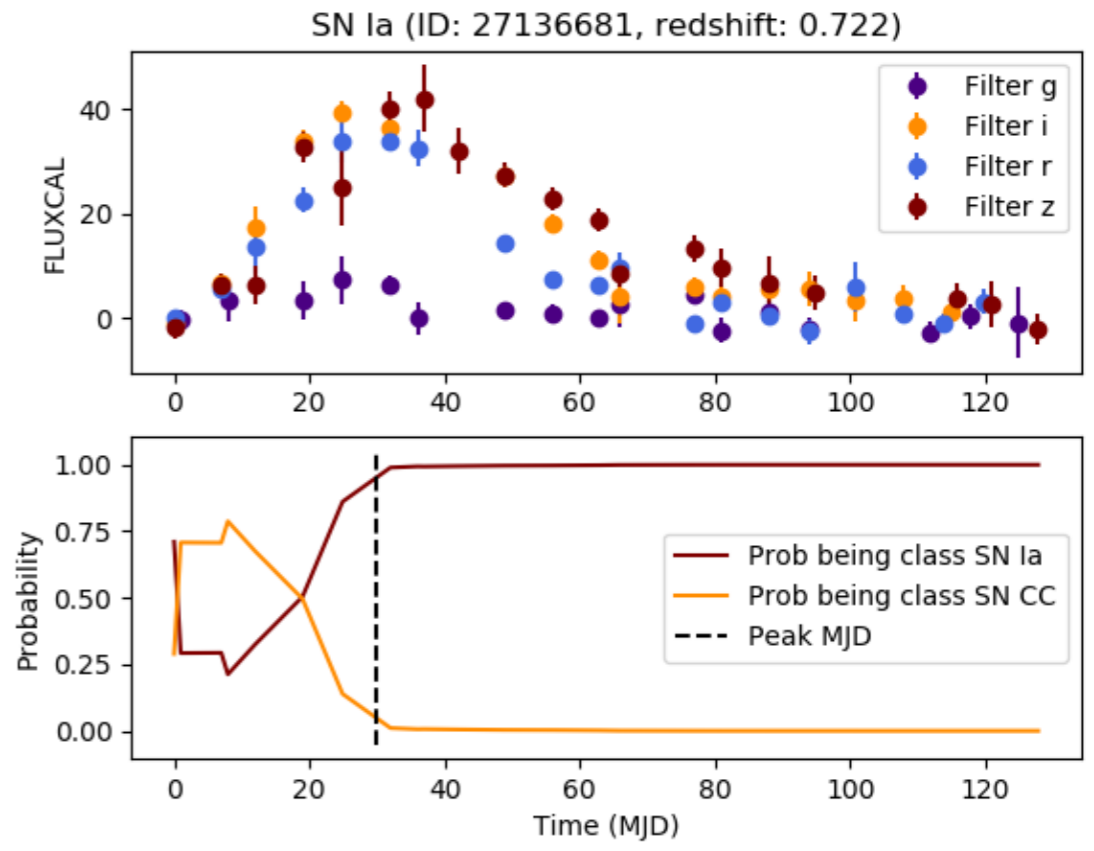
complete Ic

fluxes+ errors

**96.92 ± 0.09**

fluxes+ errors + host z

**98.85 ± 0.04**





is accurate

trained & tested with supernovae simulations: SNe Ia, Ic, Ib, IIa, IIL1, IIL2

7 classes

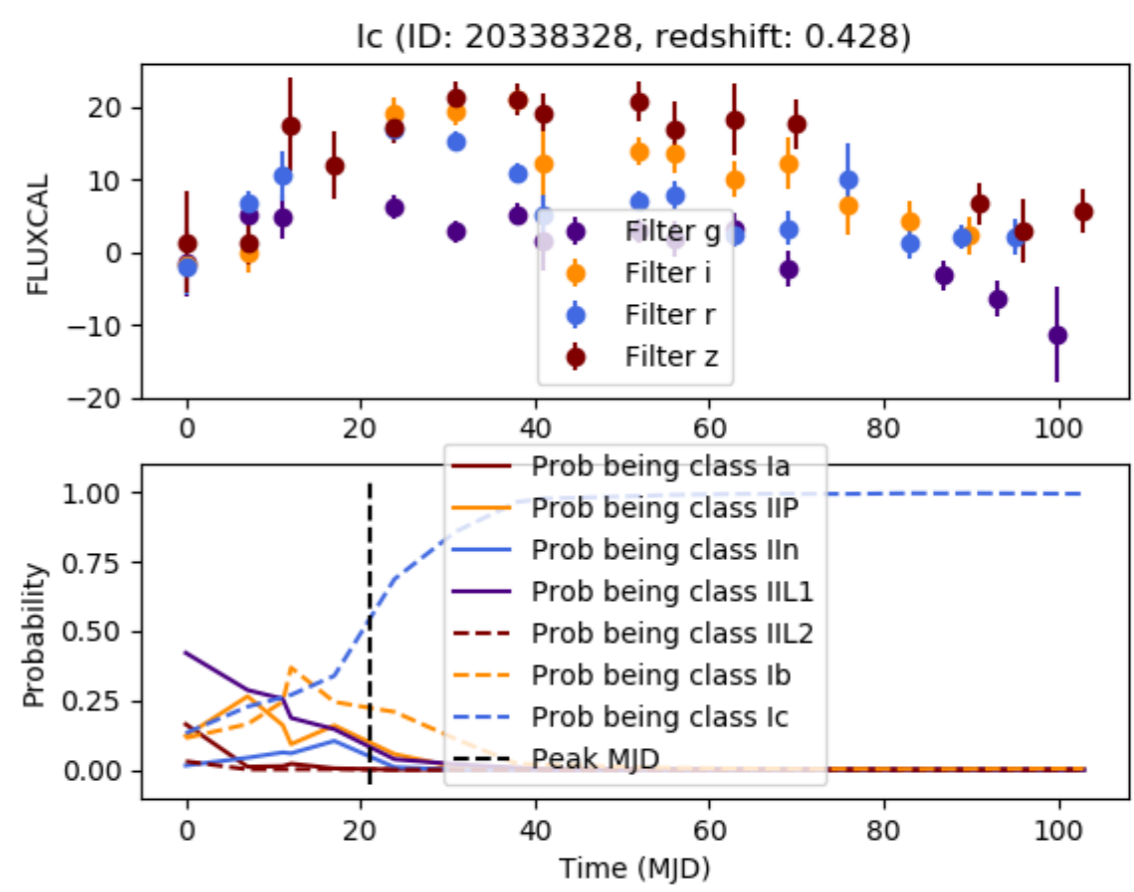
fluxes+ errors

complete Ic

86.8 ± 0.3

fluxes+ errors + host z

90.4 ± 0.4



# photometric classifiers & common pitfalls

# photometric classifiers & common pitfalls

## limitations

### I. Training sets are:

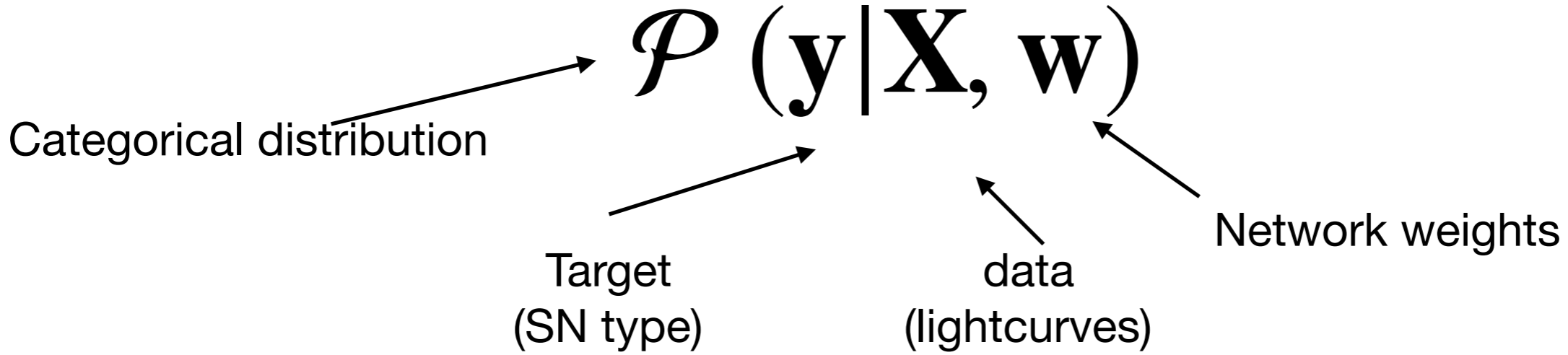
1. not representative
2. incomplete (we don't know/can't simulate)



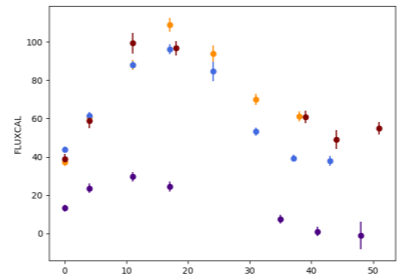


# bayesian RNNs

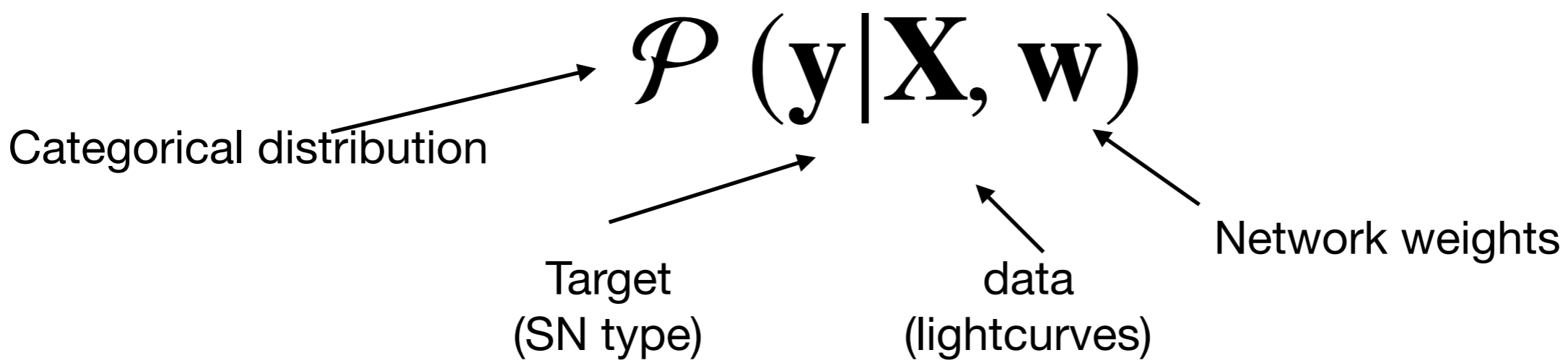
# Bayesian Neural Networks



**Ia vs. Non Ia**

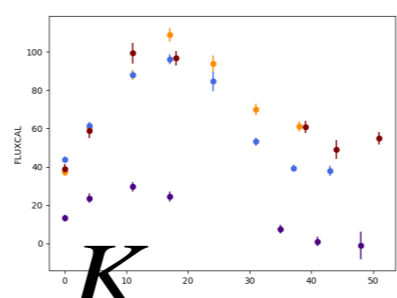


## Bayesian Neural Networks



la vs. Non la

data  $\mathcal{D} = (\mathbf{X}_k, y_k)_{k=1 \dots K}$



Training minimisation  $NLL = \min_{\mathbf{w}} \sum_{k=1}^K -\log \mathcal{P}(y_k | \mathbf{X}_k, \mathbf{w})$

## Bayesian Neural Networks

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

Bayesian: distribution of weights



posterior is intractable for deep neural networks



## Bayesian Neural Networks

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

Bayesian: distribution of weights



posterior is intractable for deep neural networks

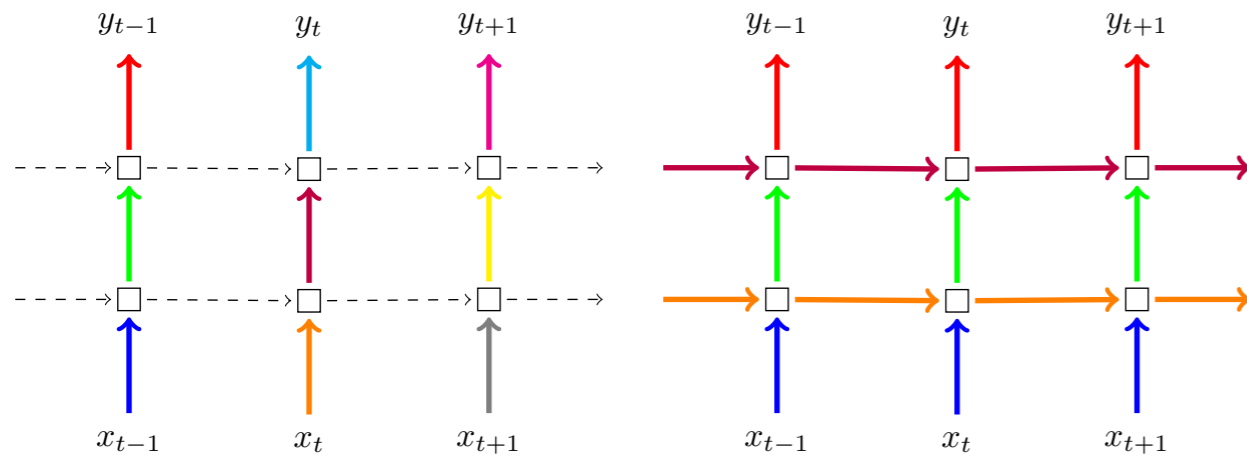


$$\mathcal{P}(\mathbf{w} | \mathcal{D}) \approx q(\mathbf{w} | \theta) \quad \text{variational distribution}$$

## Approximating the variational distribution

### 1. MC dropout

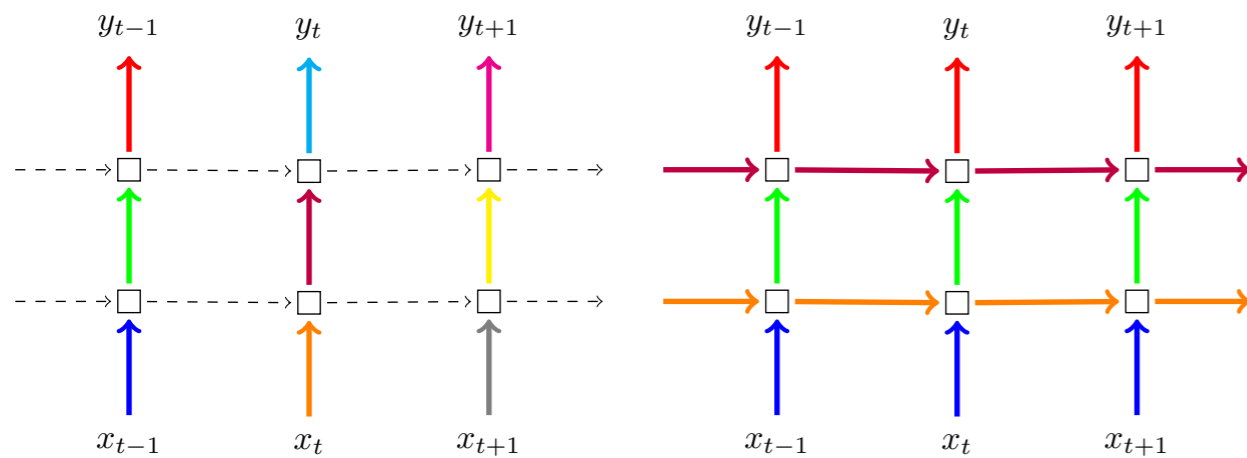
*Gal & Ghahramani 2016*



## Approximating the variational distribution

### 1. MC dropout

*Gal & Ghahramani 2016*

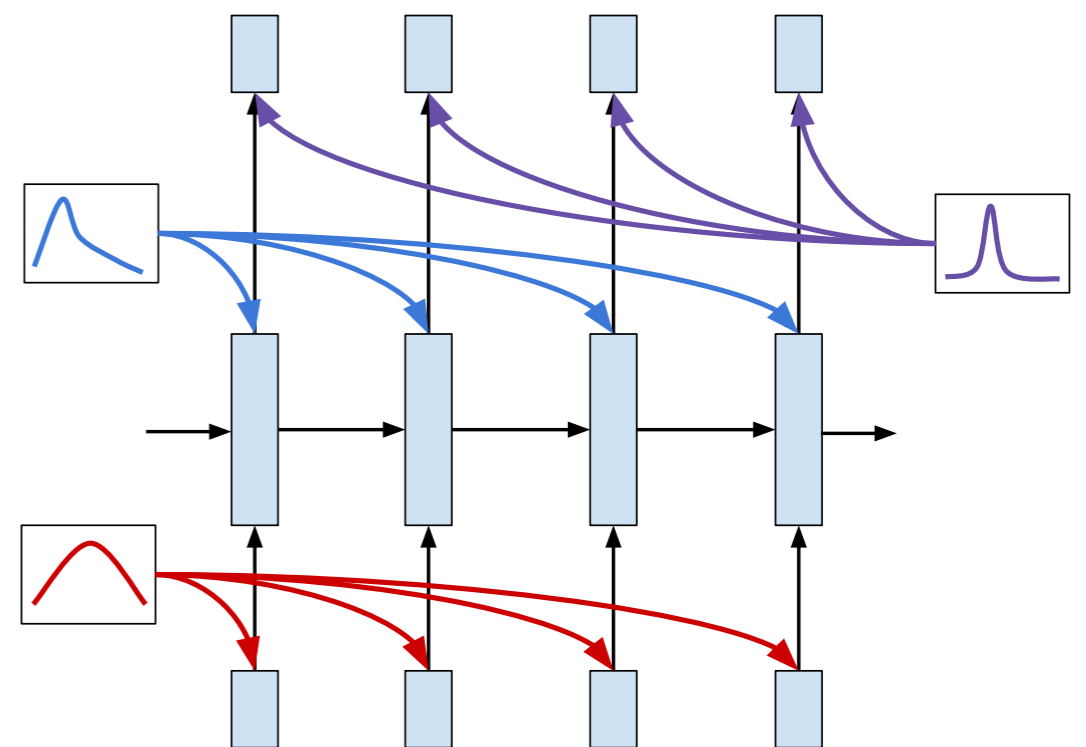


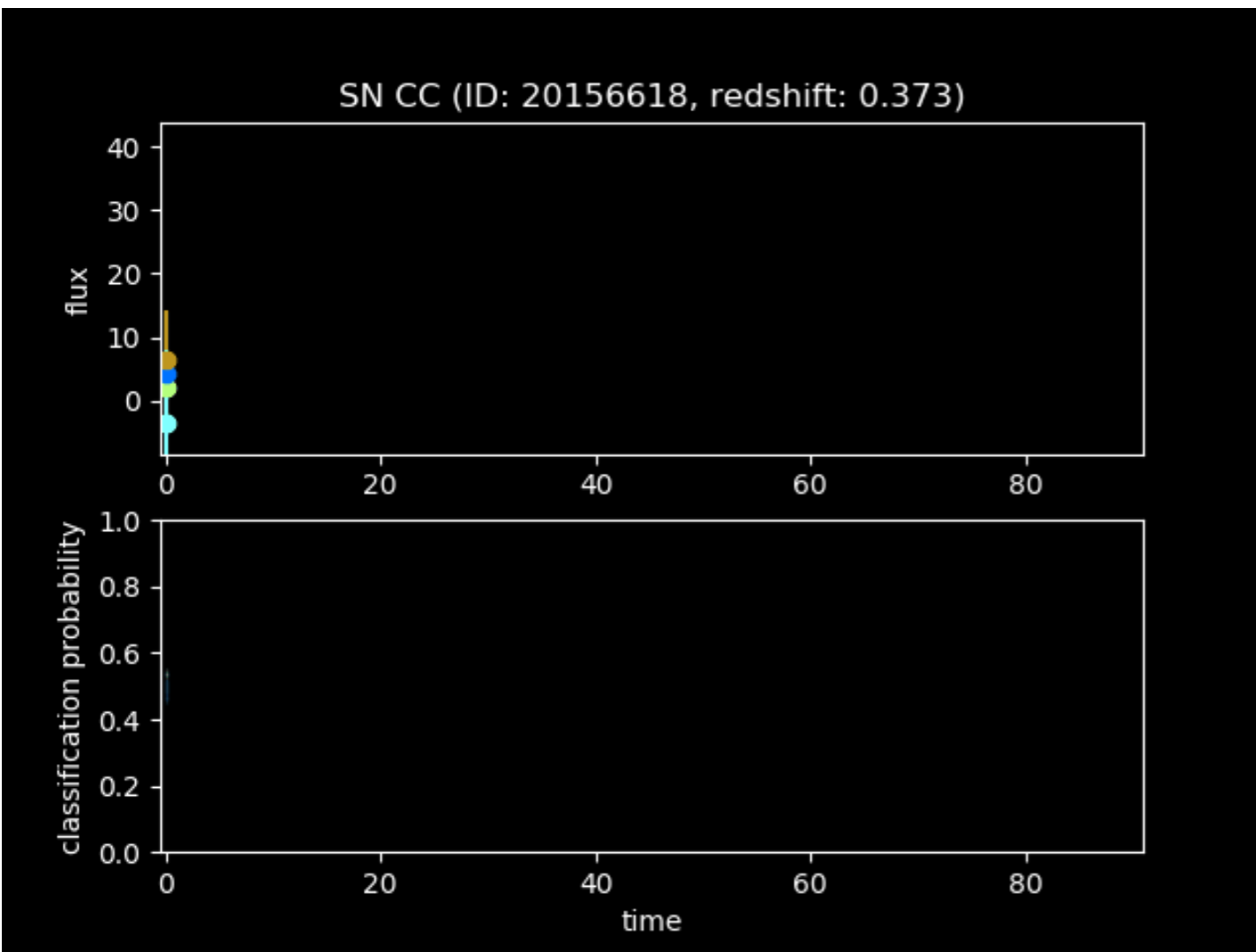
(a) Naive dropout RNN

(b) Variational RNN

### 2. Bayes by Backprop

*Fortunato+ 2017*

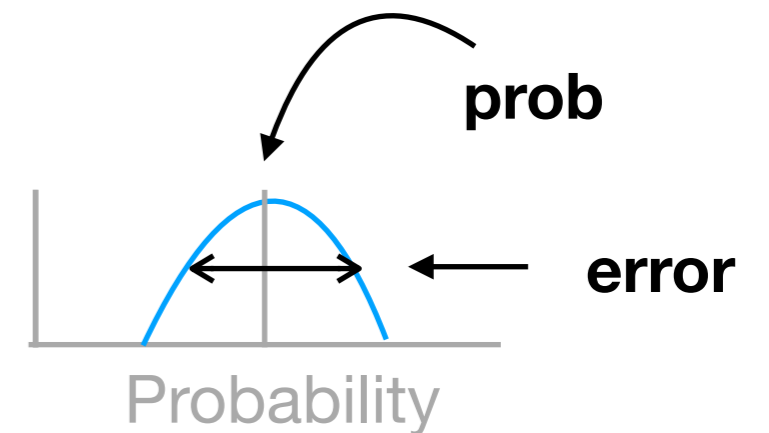




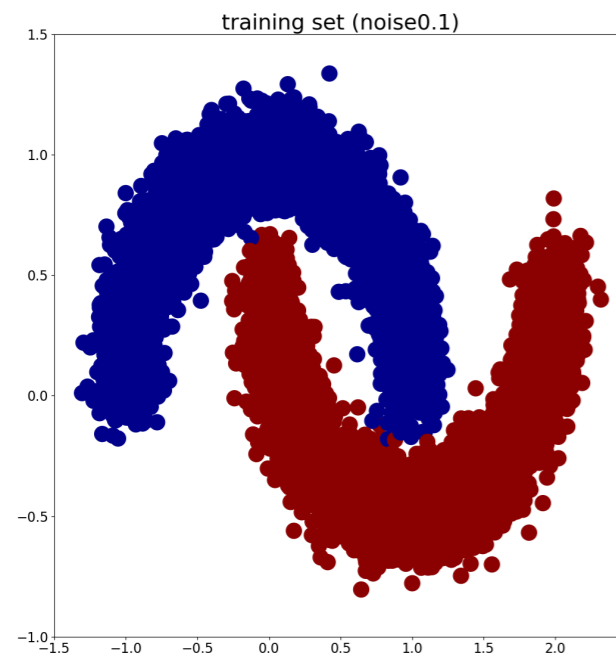
*Posterior that provides epistemic uncertainties*

## Epistemic uncertainties:

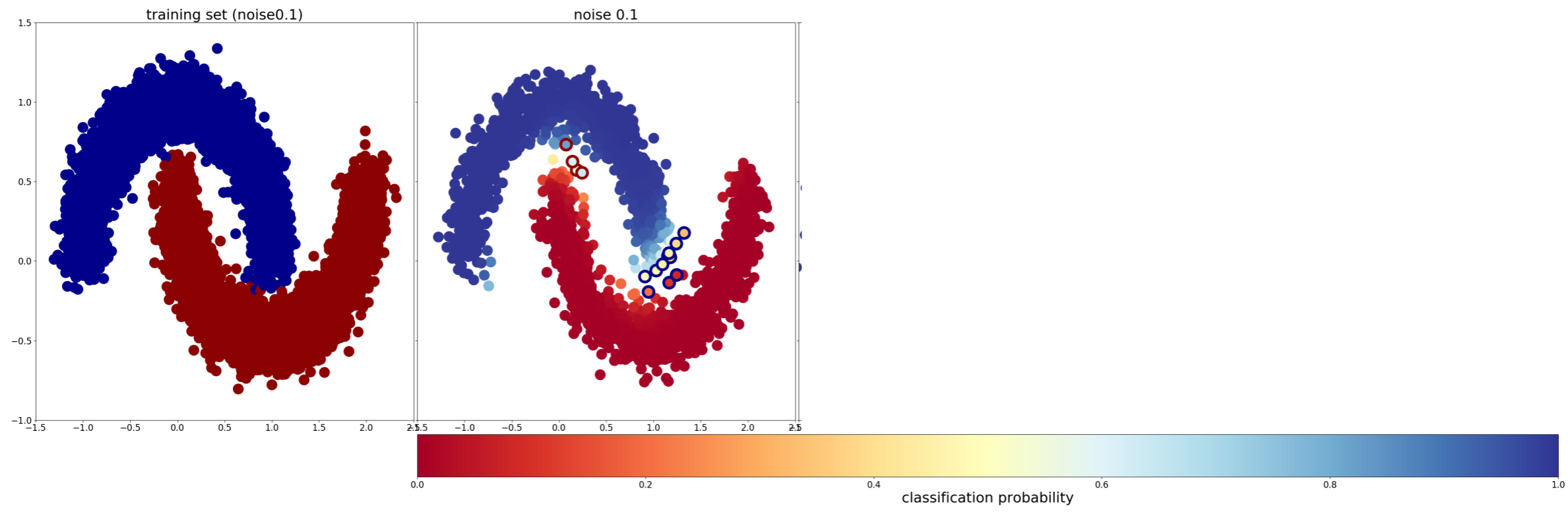
*express our ignorance about the model*



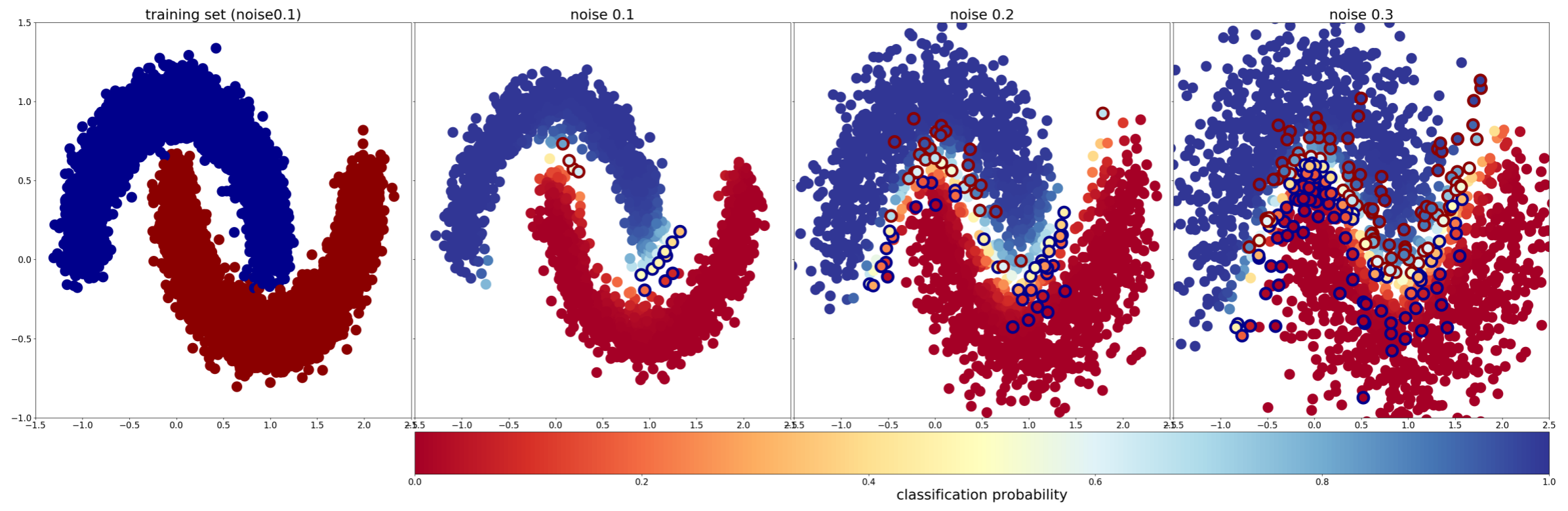




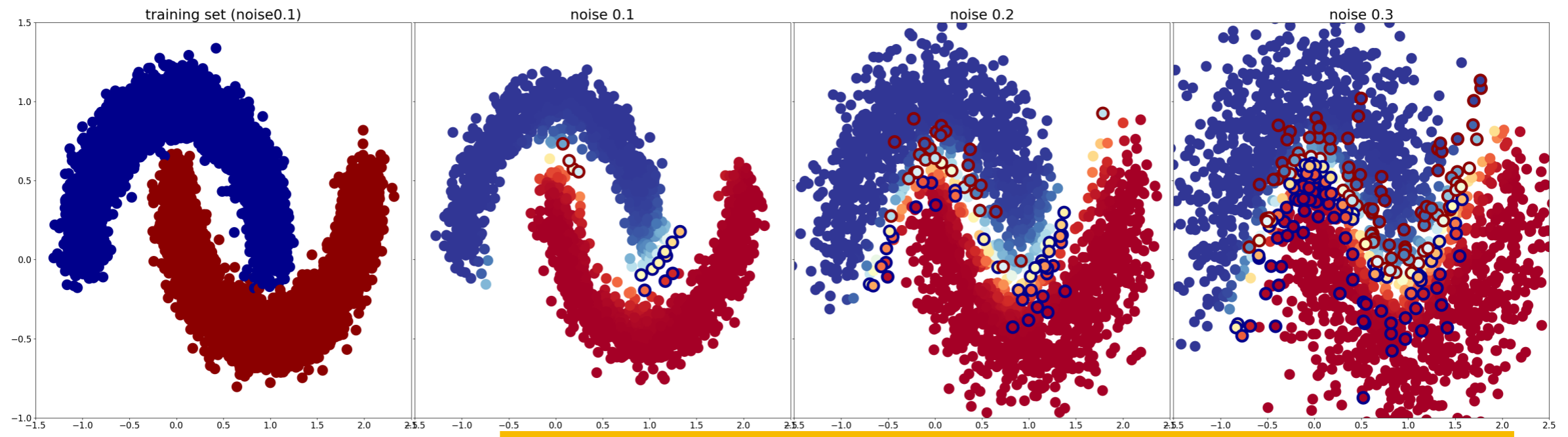
## classification probability



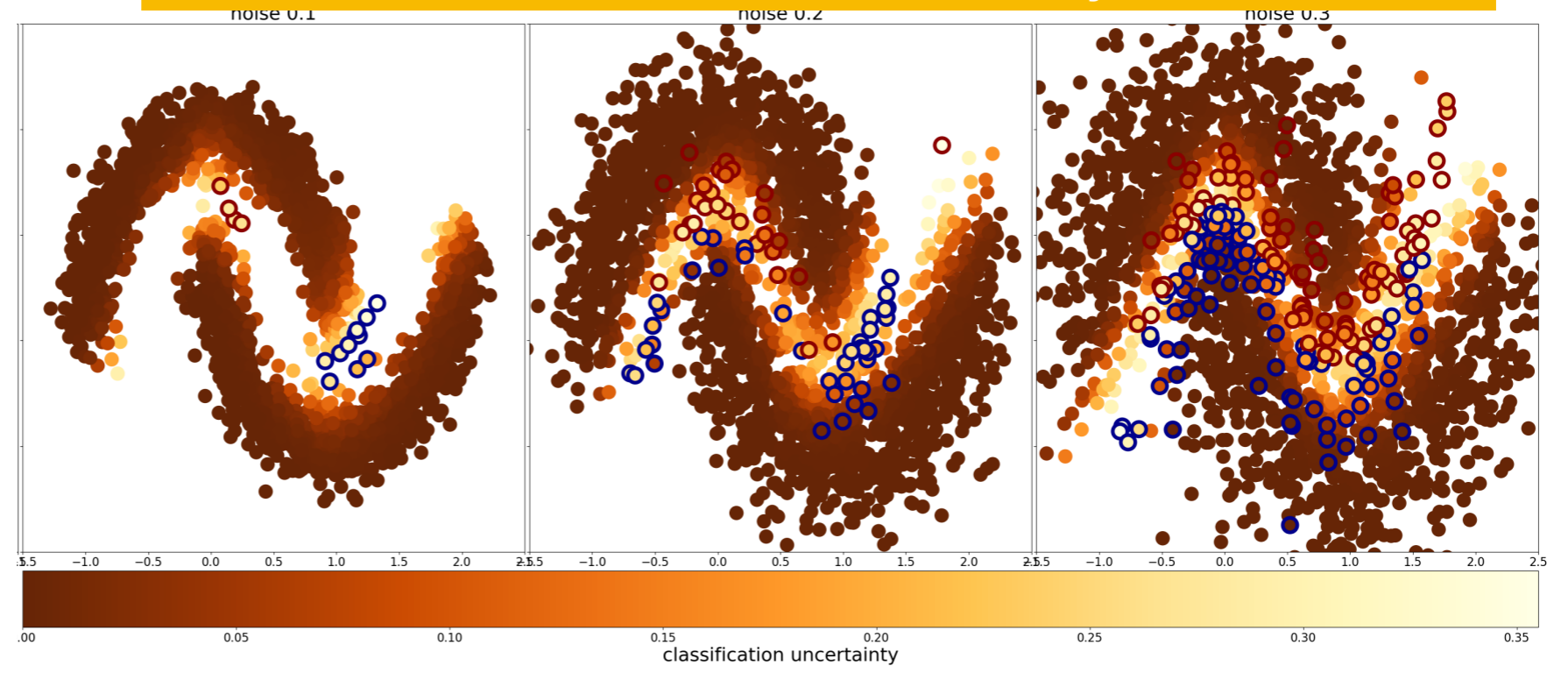
## classification probability



## classification probability



## classification uncertainty



# photometric classifiers & common pitfalls

training sets are:

1. not representative

Model 1: representative model



Model 2: train non-representative model



# photometric classifiers & common pitfalls

training sets are:

1. not representative

Model 1: representative model



Model 2: train non-representative model



classify representative sample



# photometric classifiers & common pitfalls

training sets are:

1. not representative

Model 1: representative model



Model 2: train non-representative model

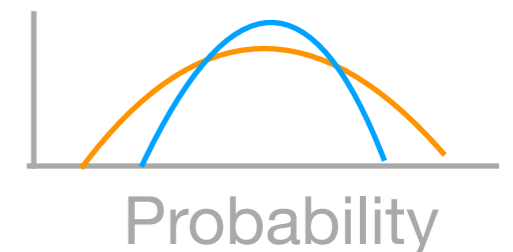


classify representative sample



accuracy changes slightly ( $\langle \text{prob} \rangle$  are not the most indicative)

**non-representative models give larger uncertainties!**



# photometric classifiers & common pitfalls

**training sets are:**

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



# photometric classifiers & common pitfalls

training sets are:

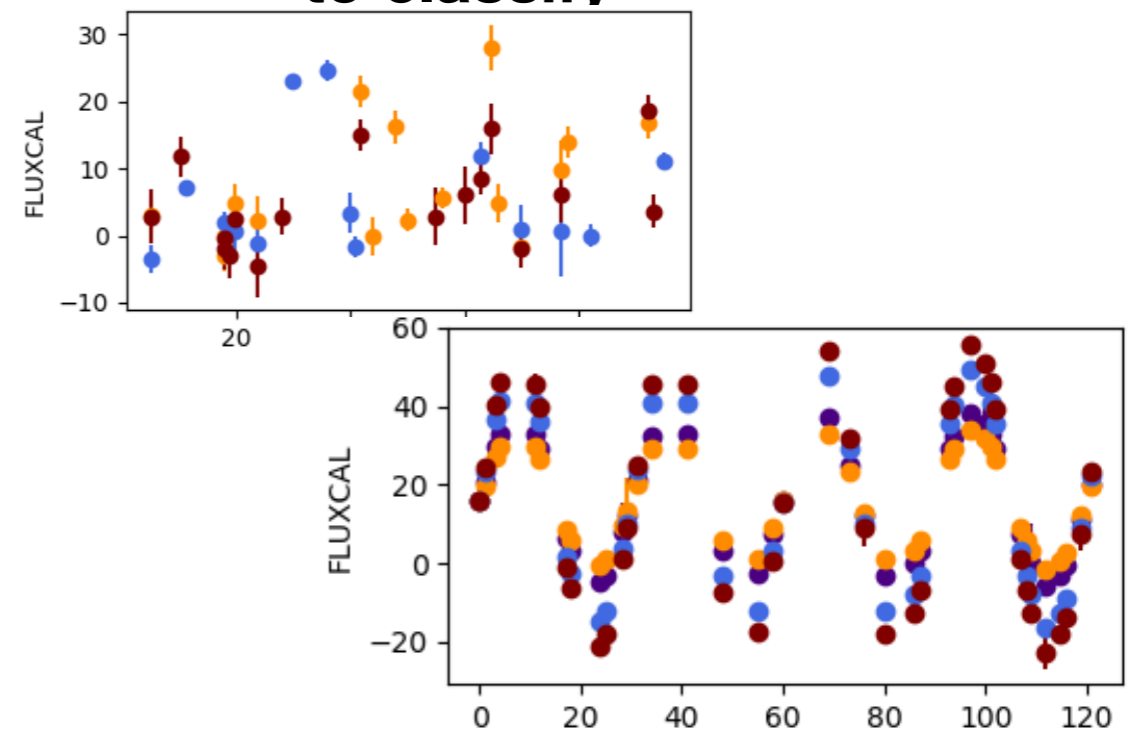
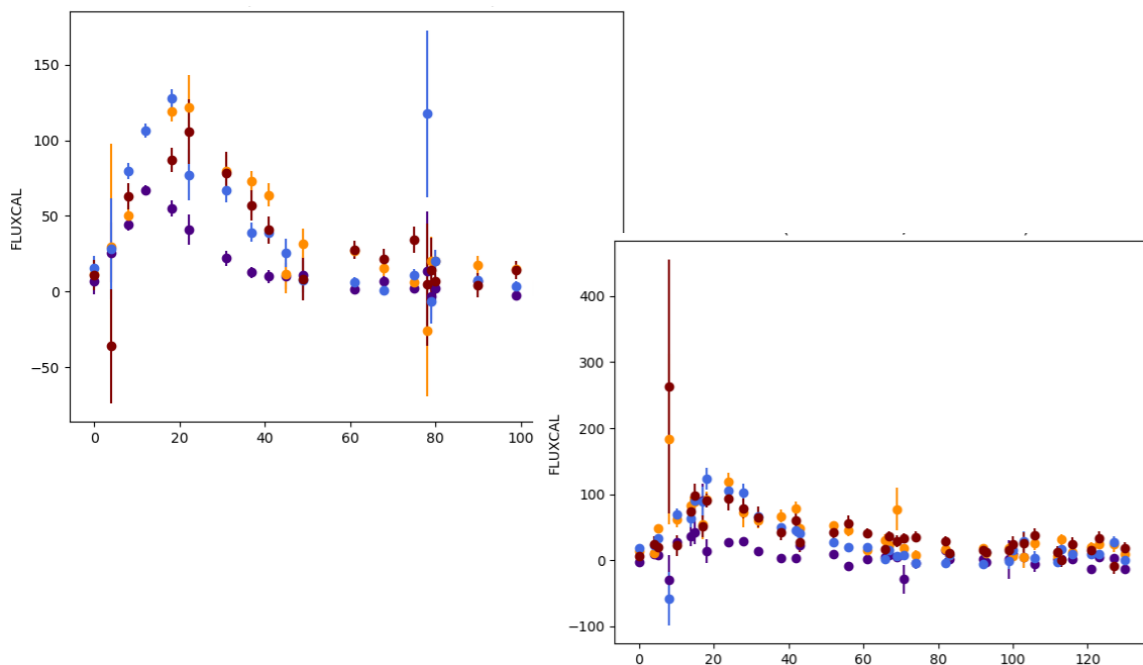
2. **incomplete** (we don't know/can't simulate)



training set



to classify

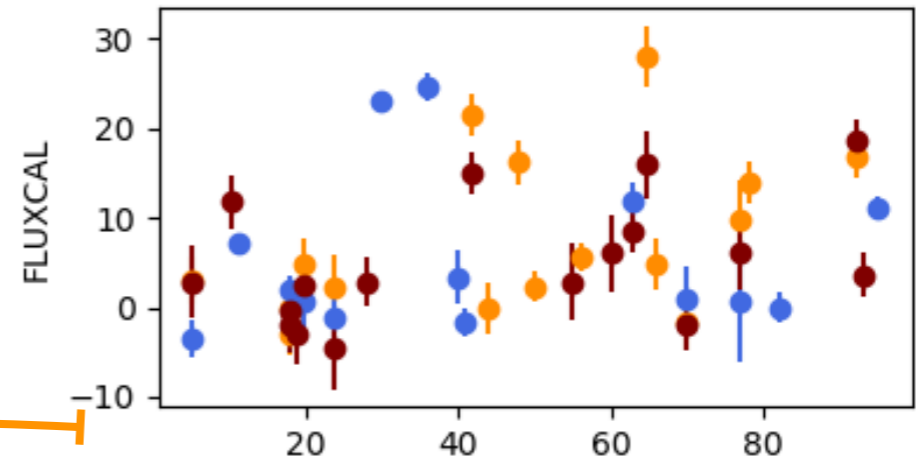


# SuperNNova

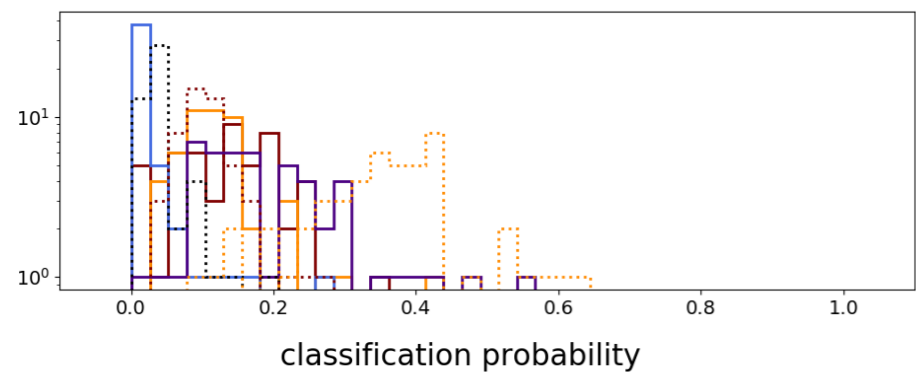
open source photometric classification

## & anomalies

**7-way classification**  
Ia, Ib, Ic, II-n, II-P, IIL1, III2



*low probability for any class*

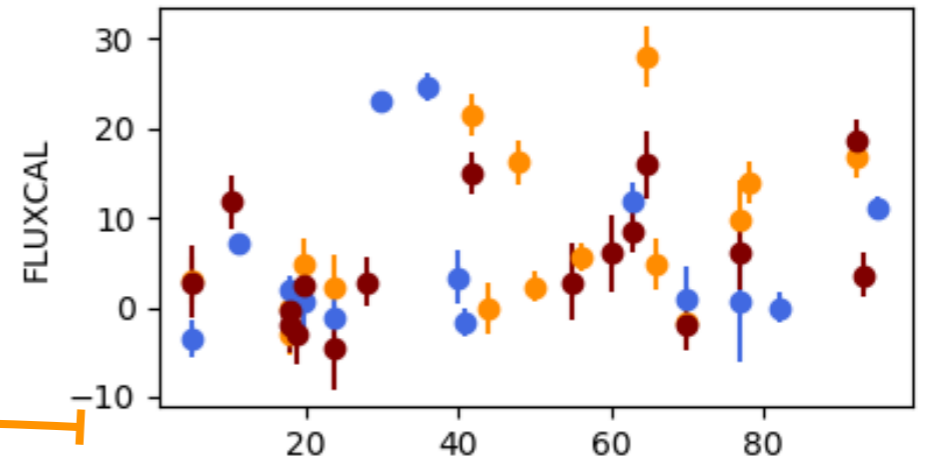


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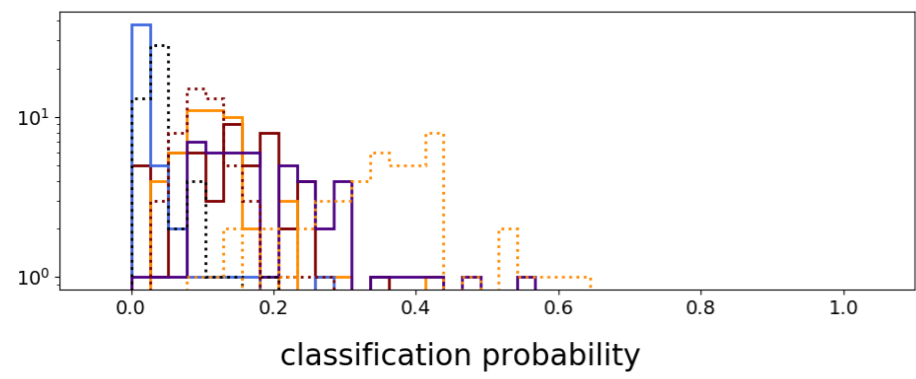
open source photometric classification

## & anomalies

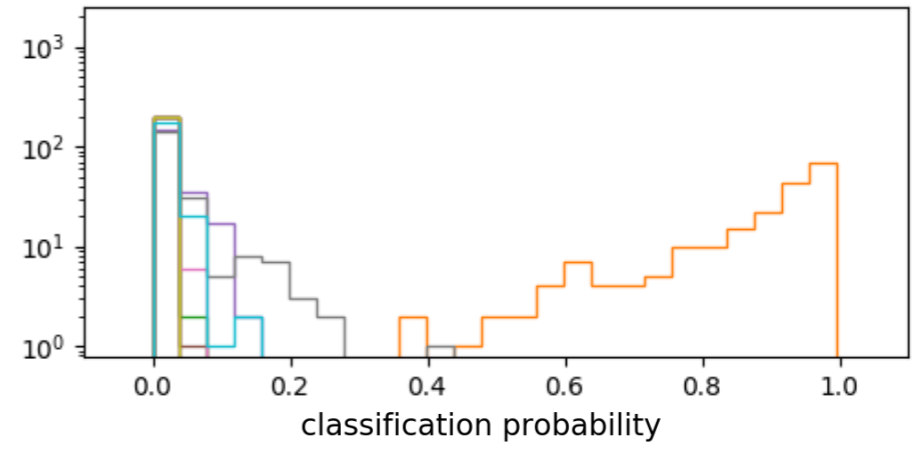
**7-way classification**  
Ia, Ib, Ic, II<sub>n</sub>, II-P, IIL1, III2



*low probability for any class*



*high probability for "less-known" class*



*but... BNNs can give us high-probability but large uncertainty*

*"an increase in average classification uncertainties for these anomalies" Möller + 2019*



# SuperNNova

open source photometric classification

## summary

Möller + 2019

- ingests “observed data”: **no interpolation necessary**
- High accuracy for complete and partial light-curves
- Exploring the use BNNs as meaningful probabilities
- **fast:** can classify up to 2,000 lcs/s

- reproducible: data available 10.5281/zenodo.3265189
- Open source
- Documented!



[supernnova/SuperNNova](https://github.com/supernnova/SuperNNova)

<https://supernnova.readthedocs.io>

SuperNNova latest

Search docs

**GETTING STARTED**

- System configuration
- Environment configuration
- Quickstart guide (GitHub)
- Quickstart guide (pip)
- FAQ

**BUILDING THE DATABASE**

- Data walkthrough
- Data documentation

**EXPERIMENT CONFIGURATIONS**

- Hyperparameters
- Experiment Settings

**TRAINING MODELS**

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- Training documentation

**VALIDATING MODELS**

- Validation walkthrough
- Validation documentation

**VISUALIZING DATA AND PREDICTIONS**

- Visualization walkthrough

Read the Docs

Docs » Welcome to SuperNNova’s documentation!

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