

# Early SNIa classification using active learning

*Marco Leoni*

Rubin LSST-France, LPNHE

29 November 2022

Paris



# Introduction

**Who :**



*E. Ishida*  
LPC, Clermont

*A. Moller*  
ANU, Swinburne



*J. Peloton*  
IJCLAB, UPSaclay

**What :** Early discovery of supernovae (no need to say why SNIa are relevant !)

**Why Machine Learning :** huge amount of data from LSST hence the need for making ‘automatic’ reliable predictions

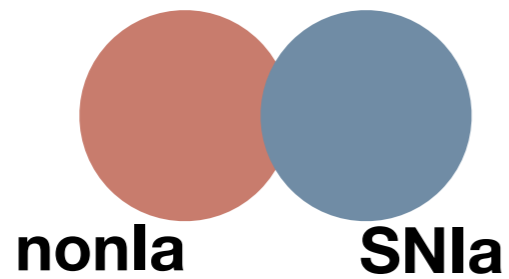
**When :** focus on 2021-2022 using ZTF data

**Where :** <https://doi.org/10.1051/0004-6361/202142715>

A&A, **Volume** 663, July 2022

# What is active ML ?

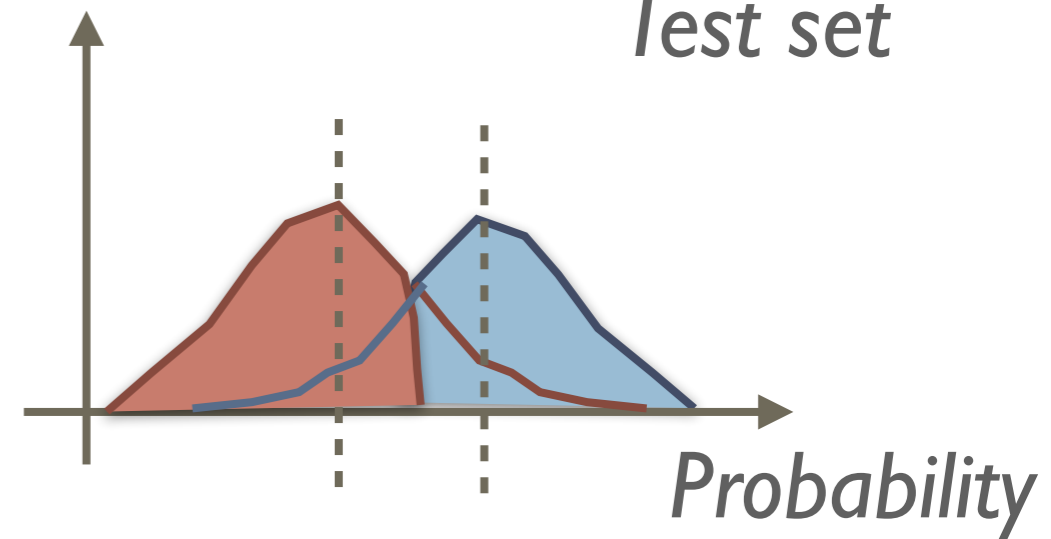
*Train set*



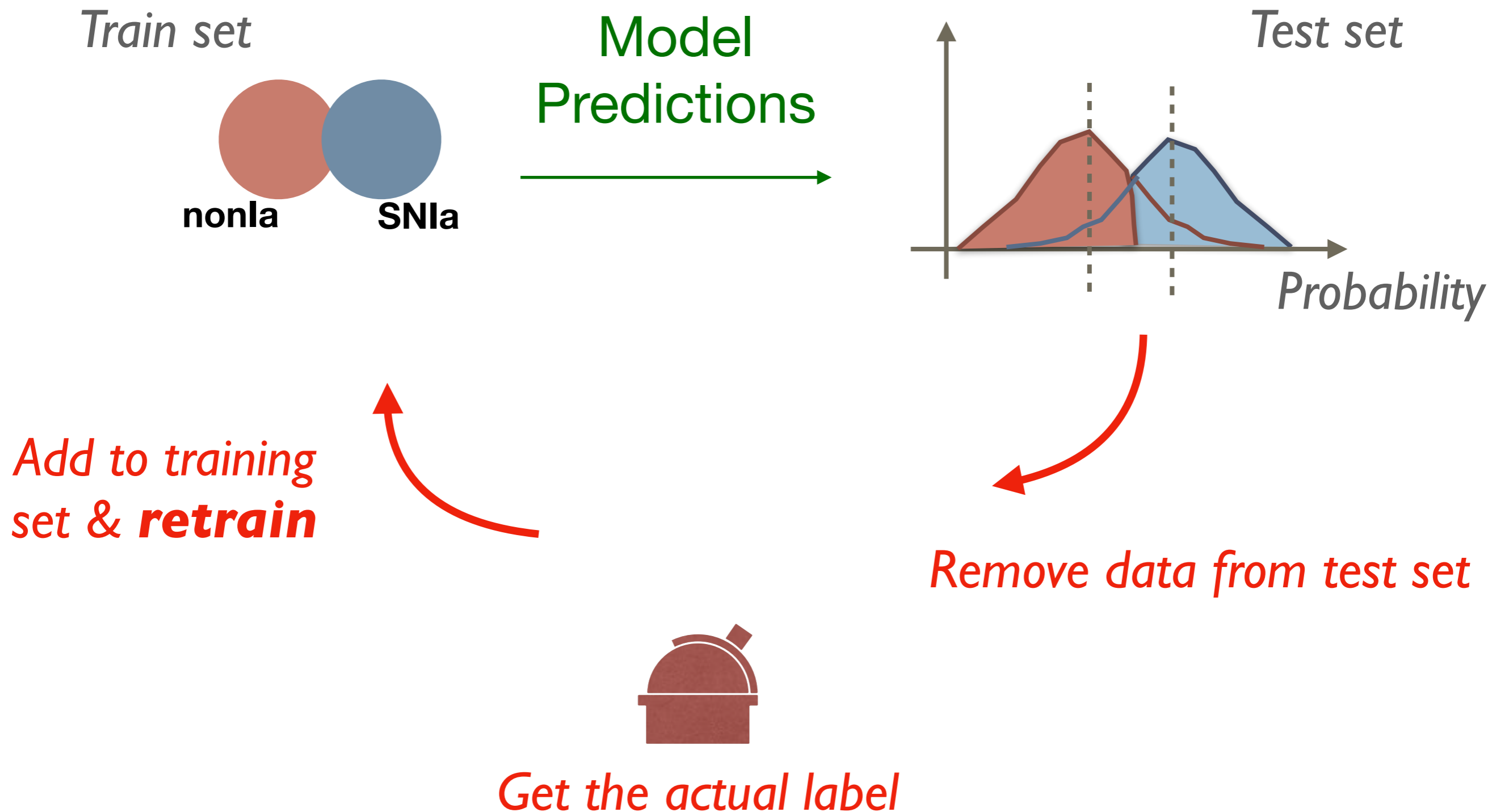
Model  
Predictions



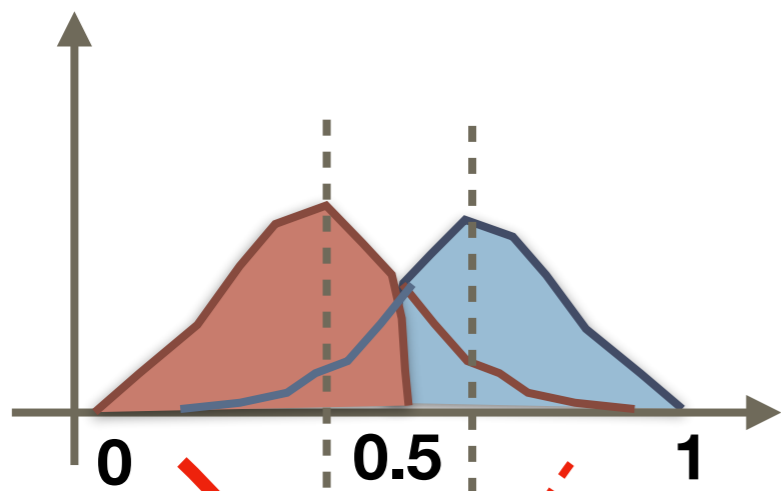
*Test set*



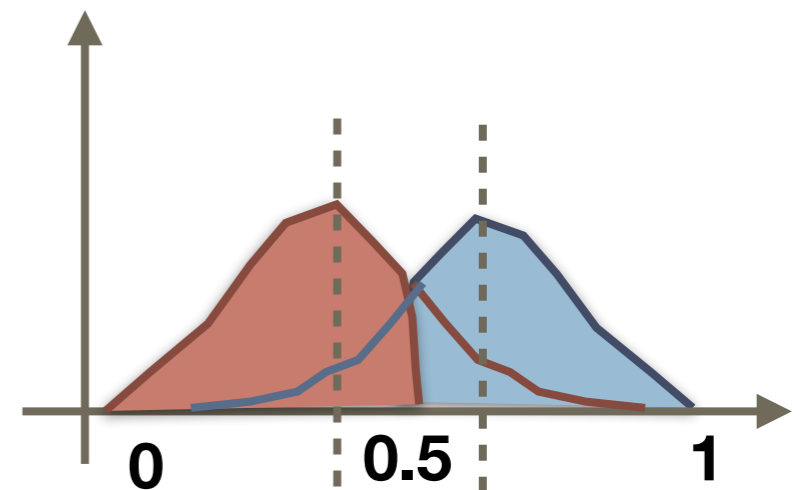
# What is active ML ?



# Uncertainty vs Random Sampling



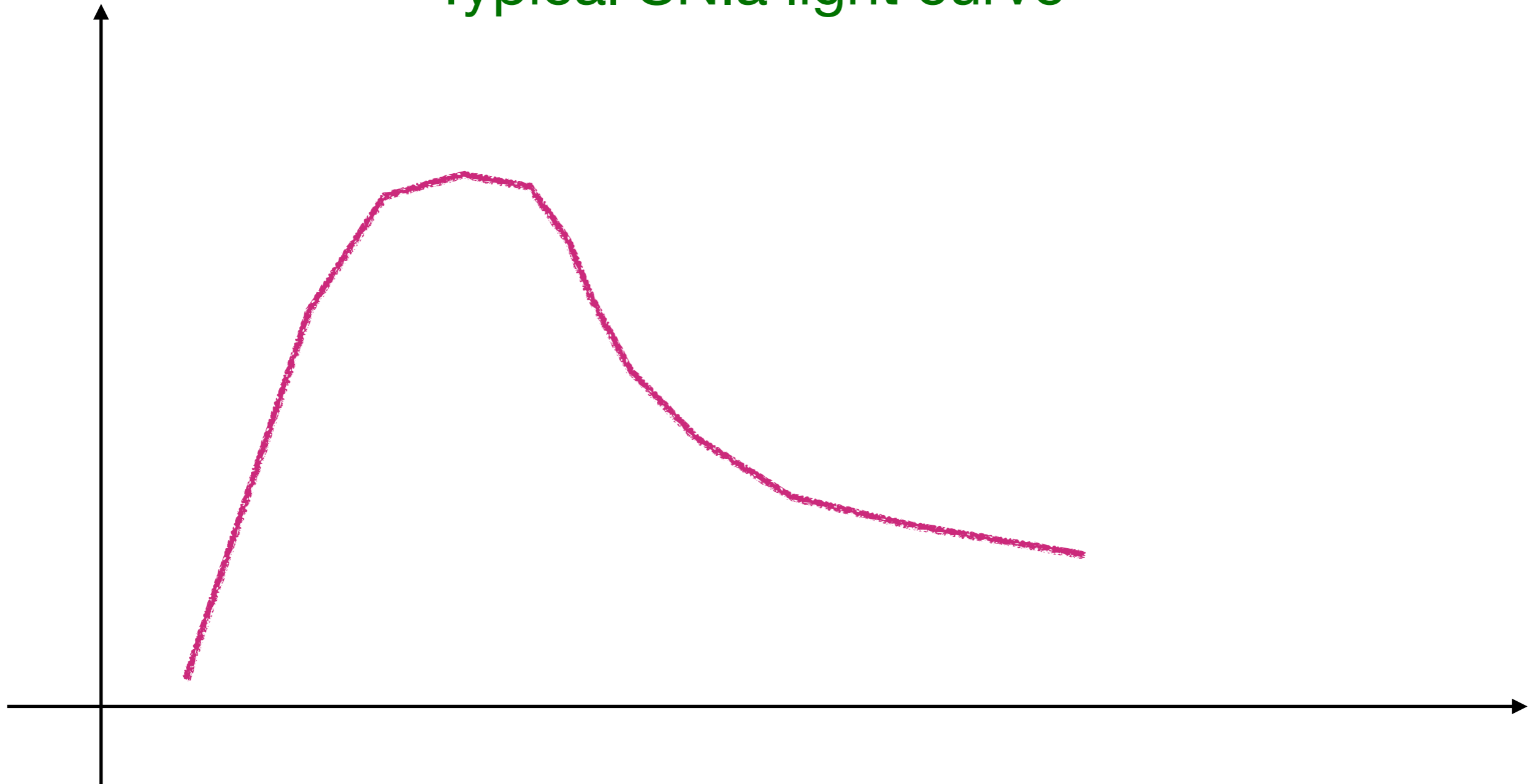
*Random sampling*



*Uncertainty sampling*

# Learning from light curves

Typical SNIa light curve



# Learning from light curves

Early discovery of SNIa

Focus  
on rising  
Part

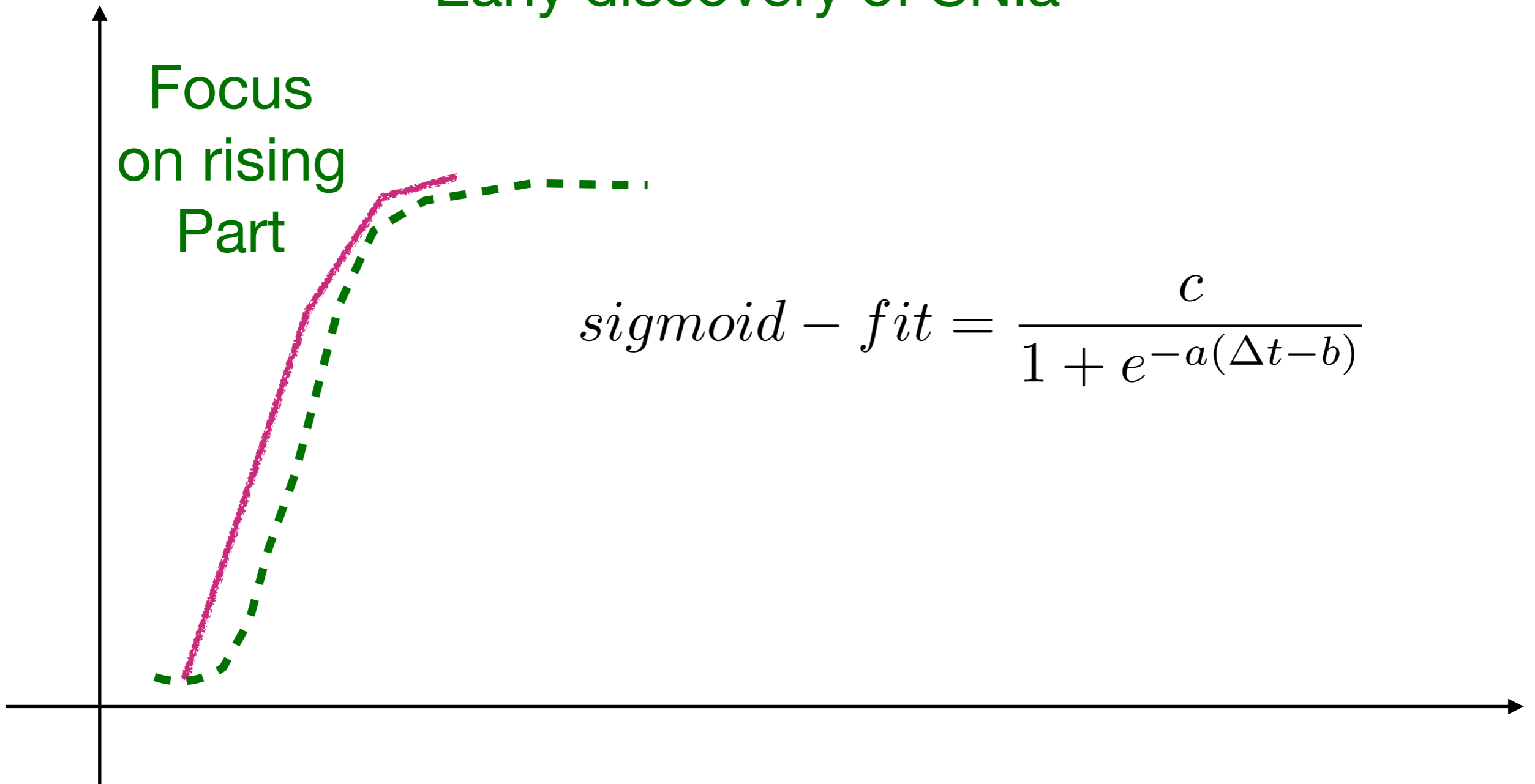


# Learning from light curves

Early discovery of SNIa

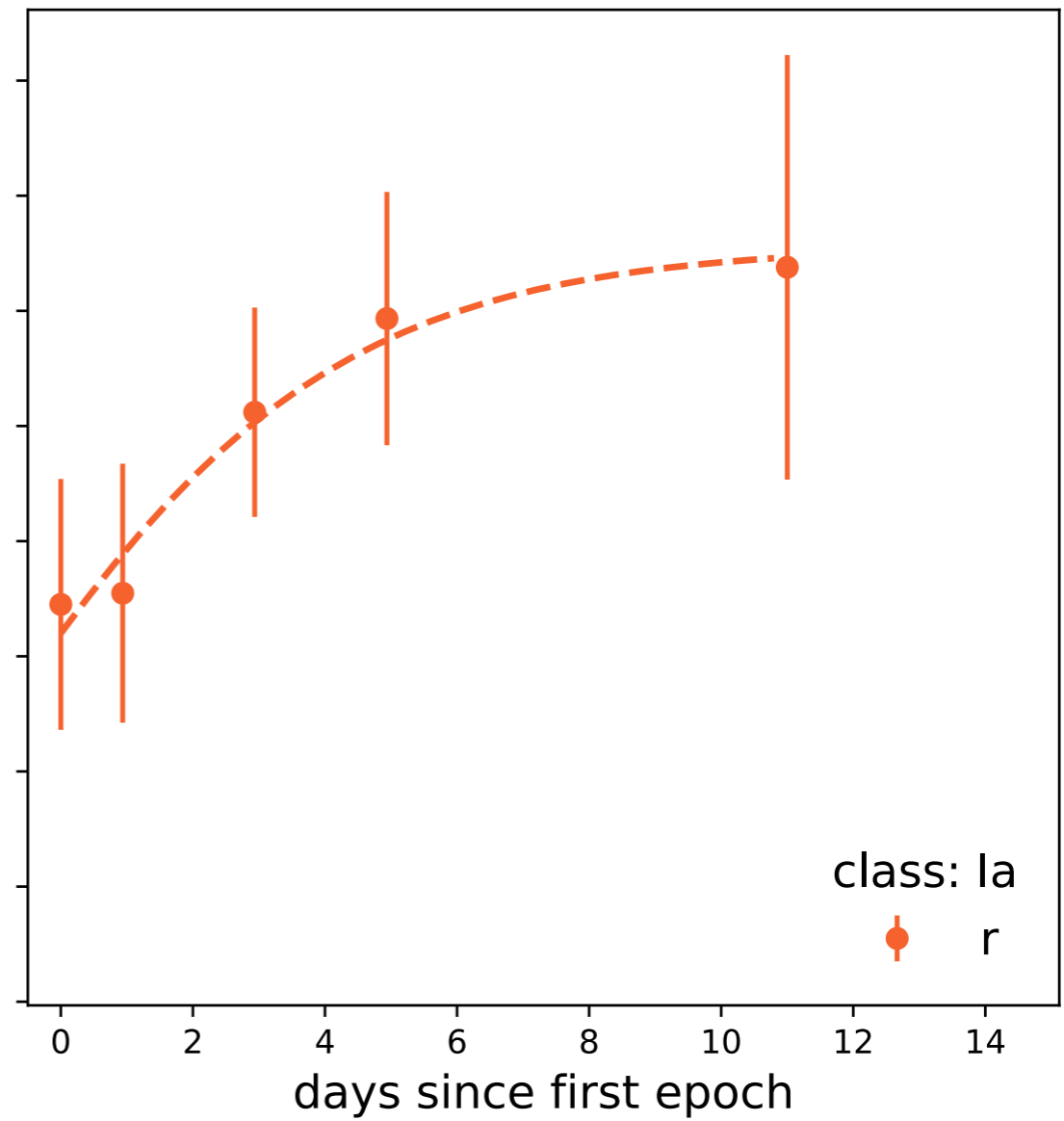
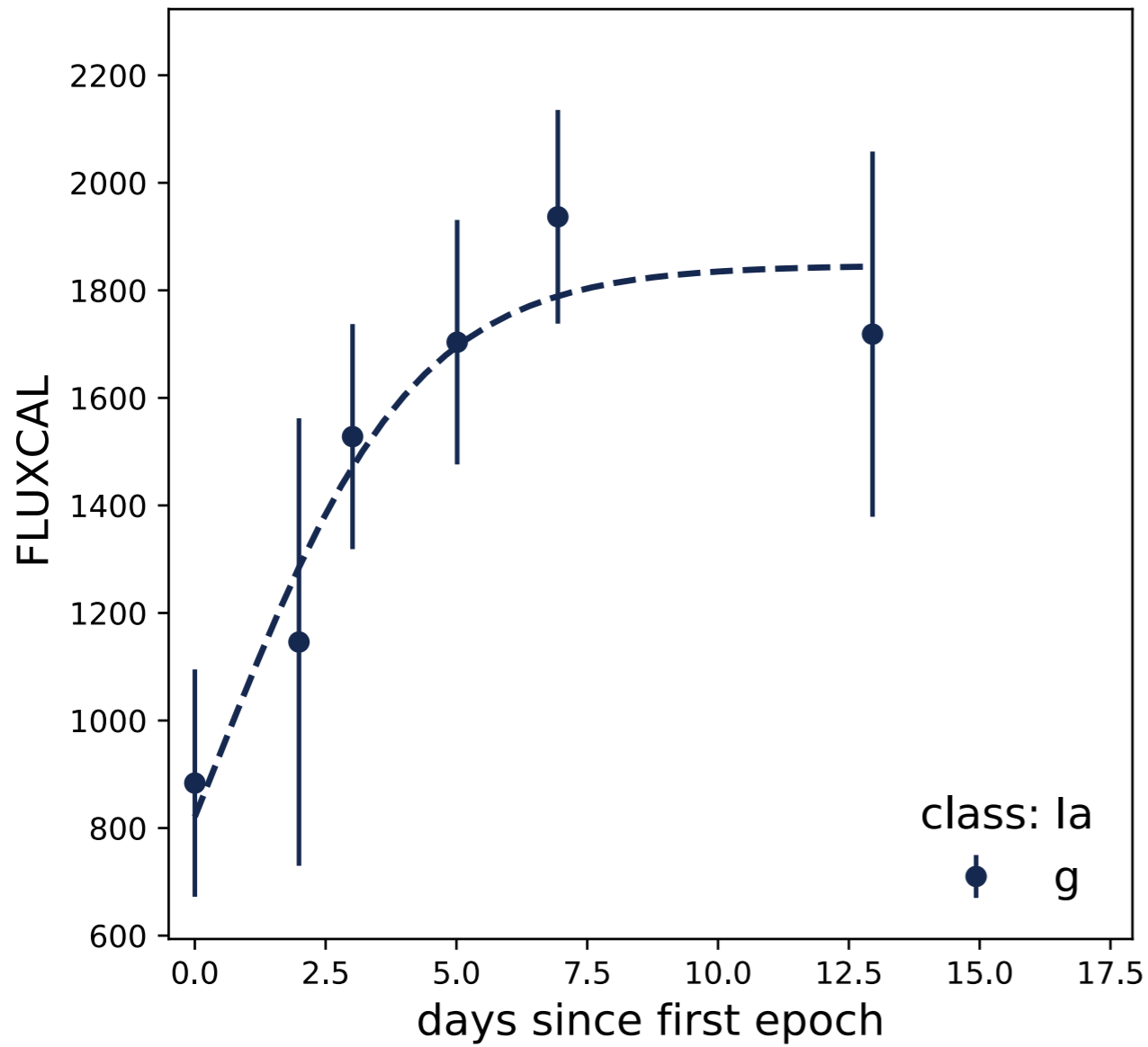
Focus  
on rising  
Part

$$\text{sigmoid} - \text{fit} = \frac{c}{1 + e^{-a(\Delta t - b)}}$$

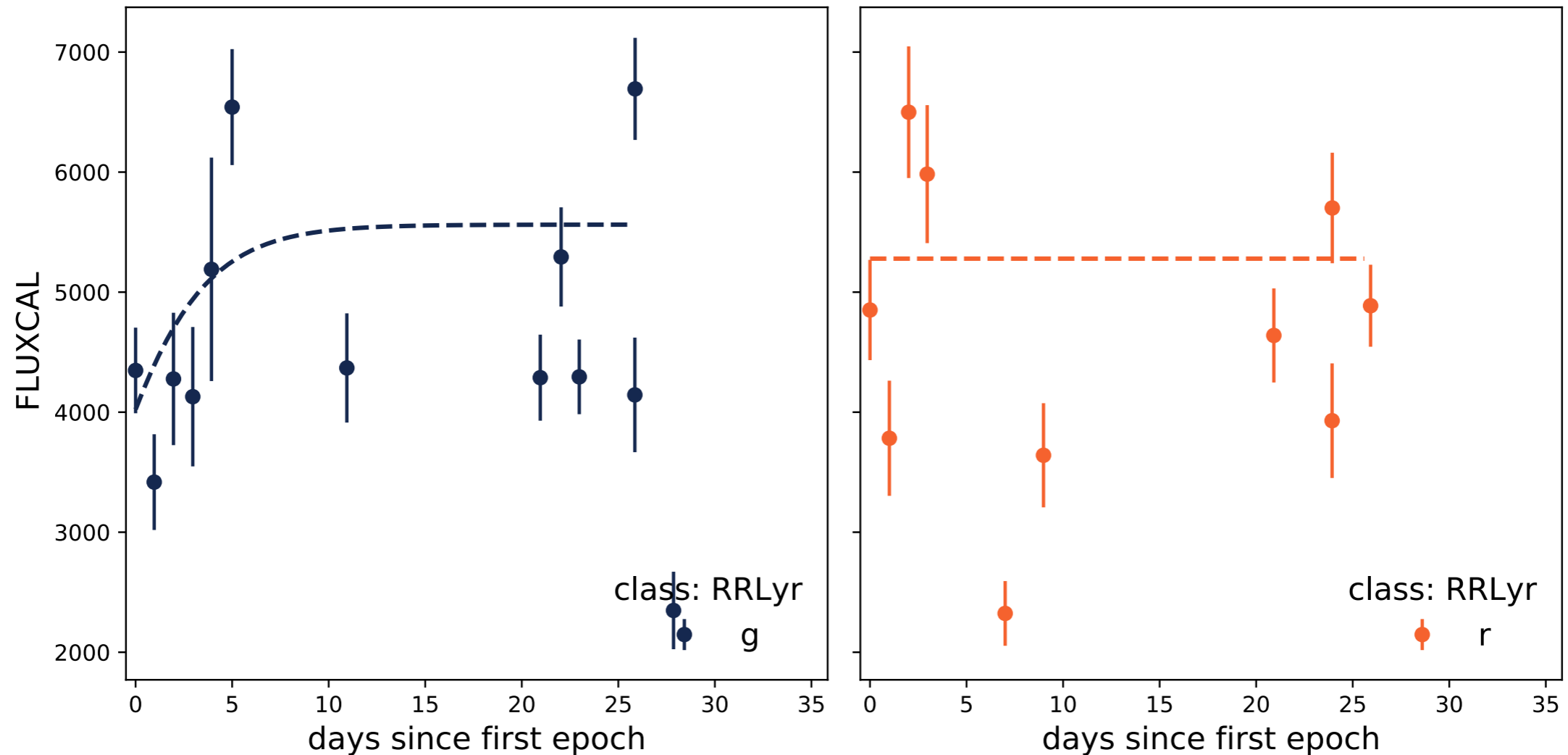




# Actual data for SNIa



# ...and for nonla



Luckily nonla objects are very diverse hence the fit of such light curves is pretty bad.

A feature  $\chi^2 = \sum_{i=1}^k \frac{(o_i - e_i)^2}{e_i}$  describes the goodness of the fit

# Features

I)  $sigmoid - fit = \frac{c}{1 + e^{-a(\Delta t - b)}}$  3 features +

II)  $\chi^2 = \sum_{i=1}^k \frac{(o_i - e_i)^2}{e_i}$  1 feature +

III)  $SNR = \frac{1}{N} \sum_{i=1}^N \frac{o_i}{\Delta o_i}$  1 feature+

IV)  $N$  points in the raising part 1 feature =

---

6 features which we use to train  
RF model

# Training using random forests

an ensemble of  
decision trees

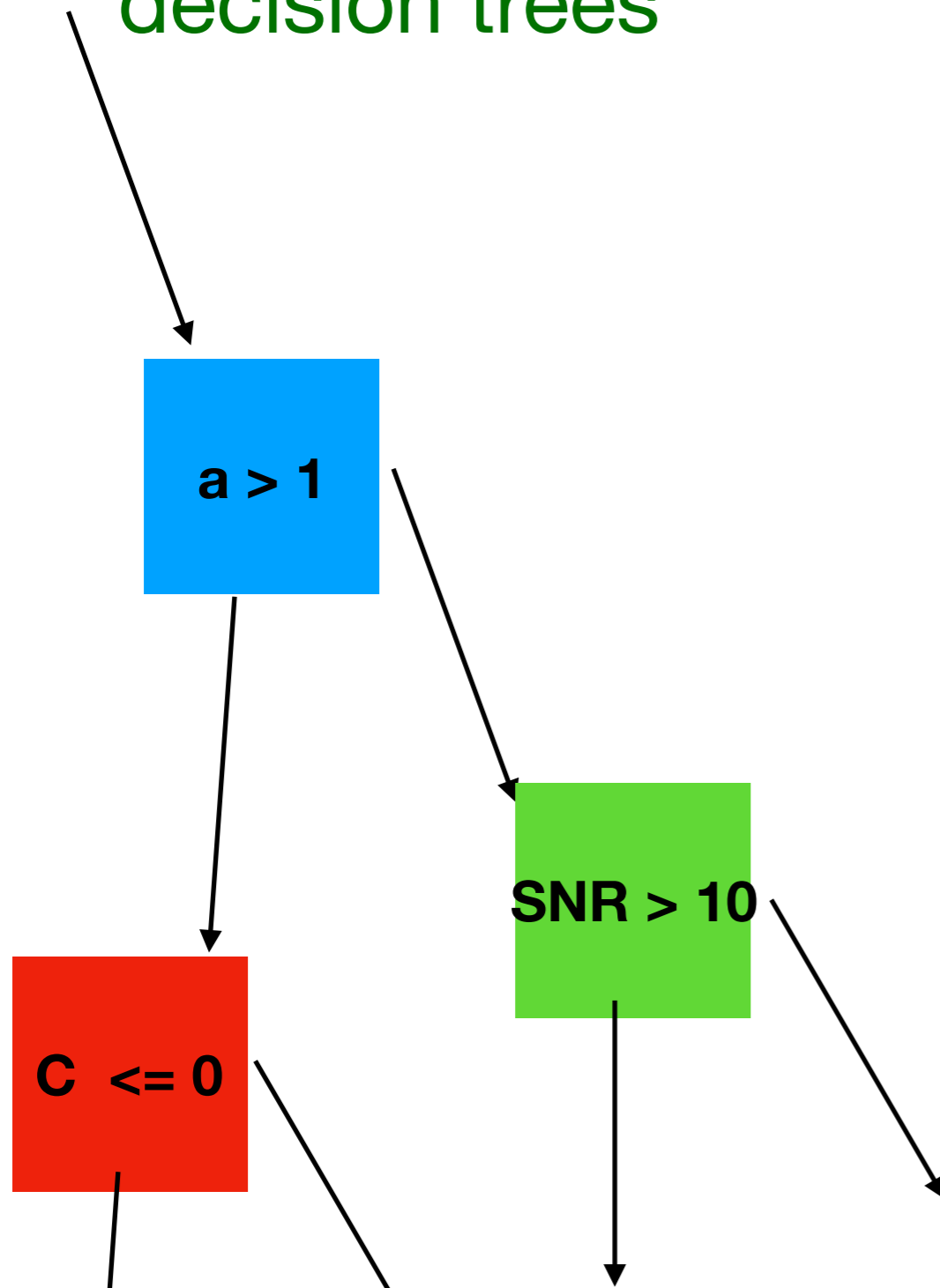
*Parameters for our training*

*N-trees = 1000*

*Train Sample ~ 10 alerts  
(half of which SN1a)*

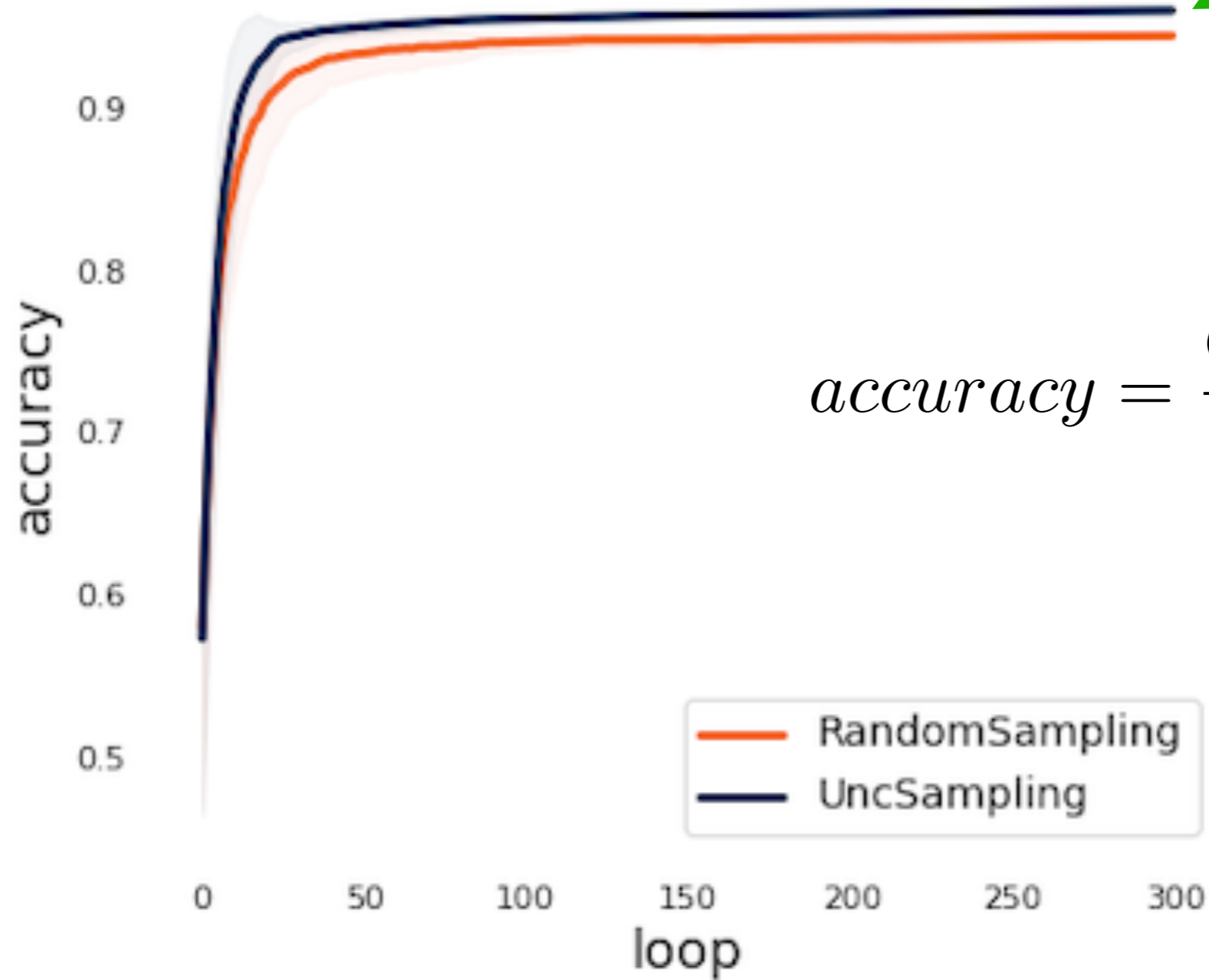
*Test Sample ~ 23000 alerts  
(vast majority of non1a)*

*300 steps of active learning*



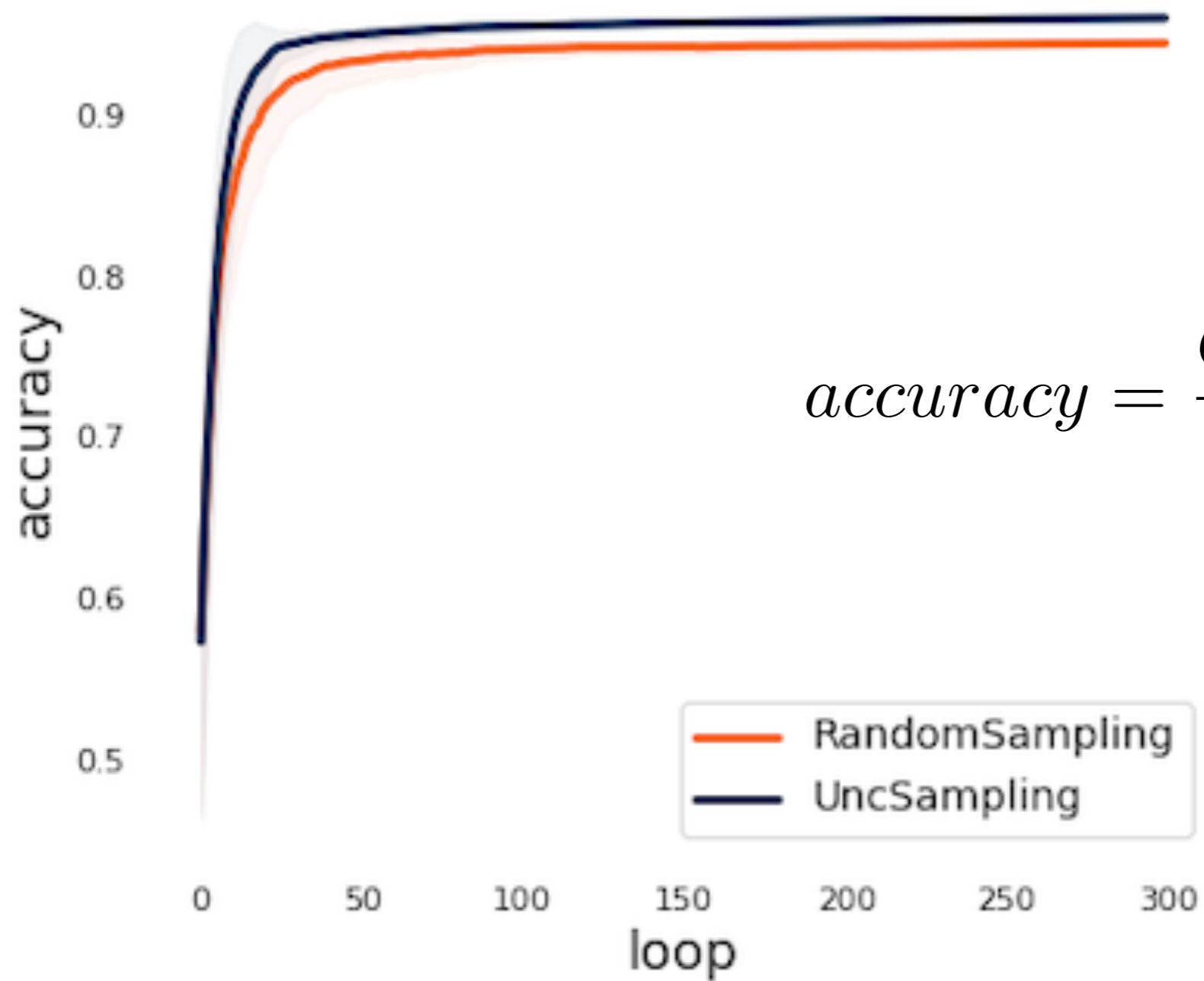
# Results : accuracy

average over  
100 different  
realisations

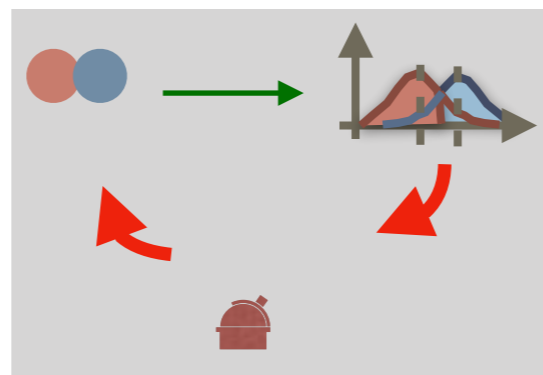


$$accuracy = \frac{C_{Ia} + C_{nonIa}}{N}$$

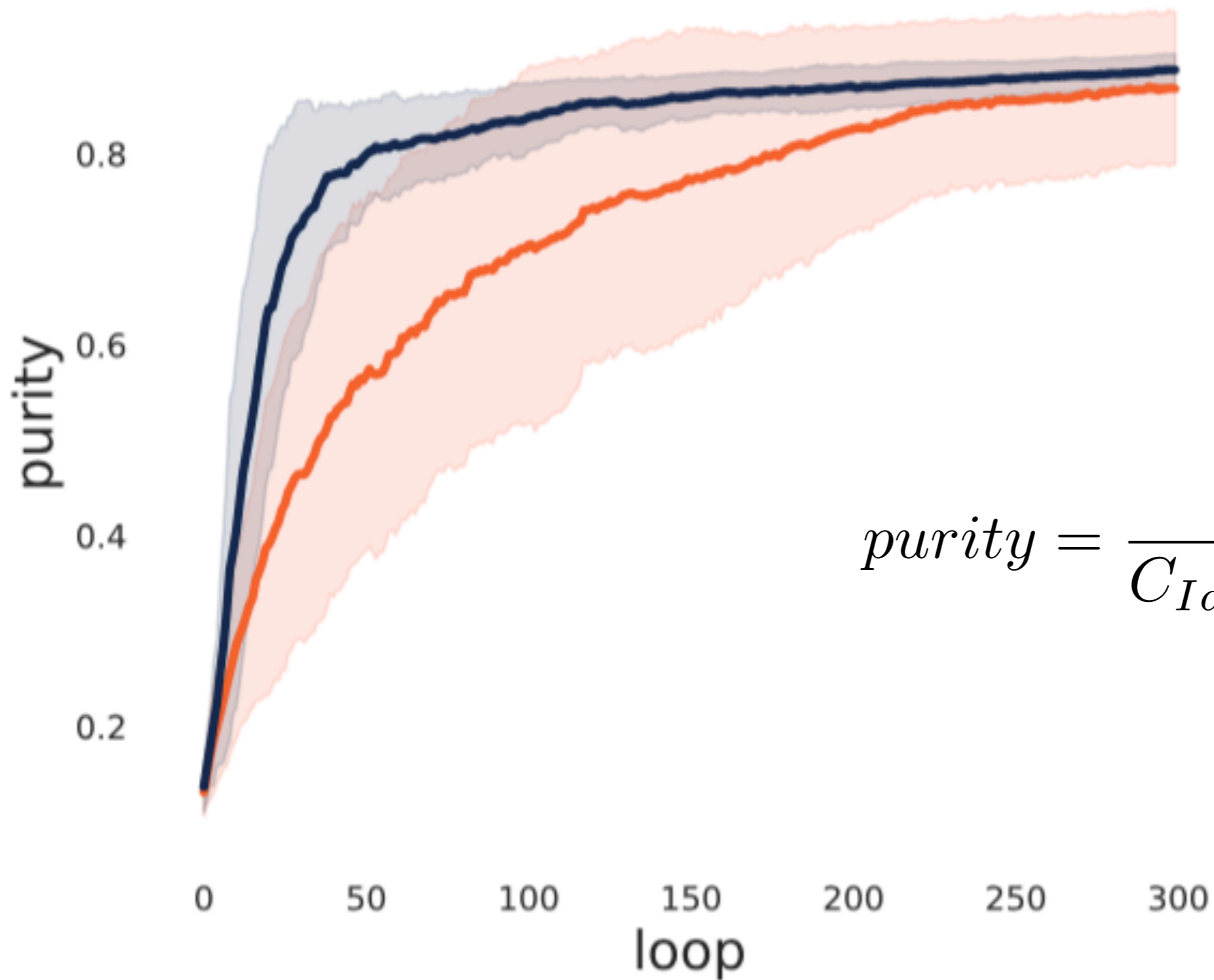
# Results : accuracy



$$accuracy = \frac{C_{Ia} + C_{nonIa}}{N}$$

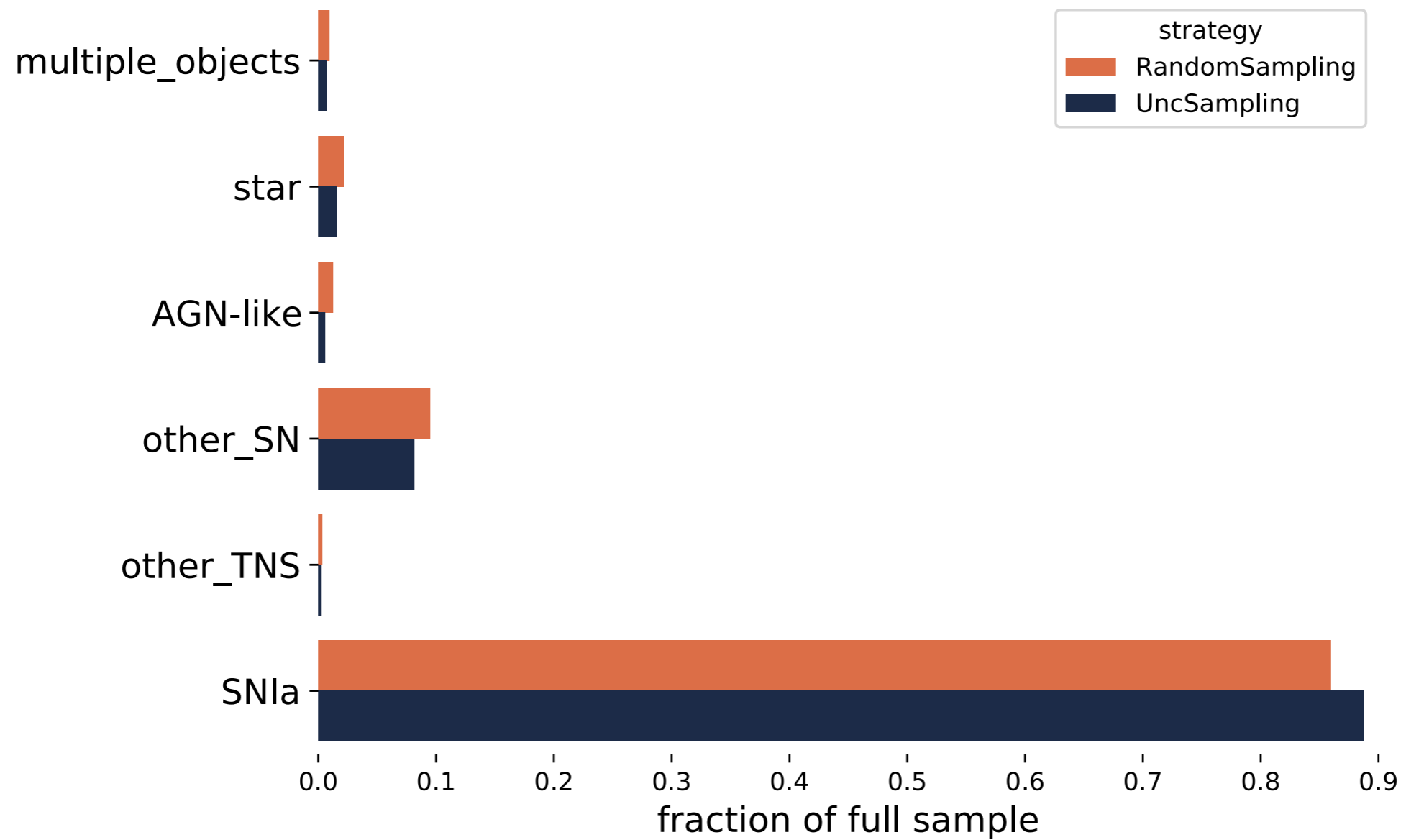


# Results : purity



$$purity = \frac{C_{Ia}}{C_{Ia} + W_{nonIa}}$$

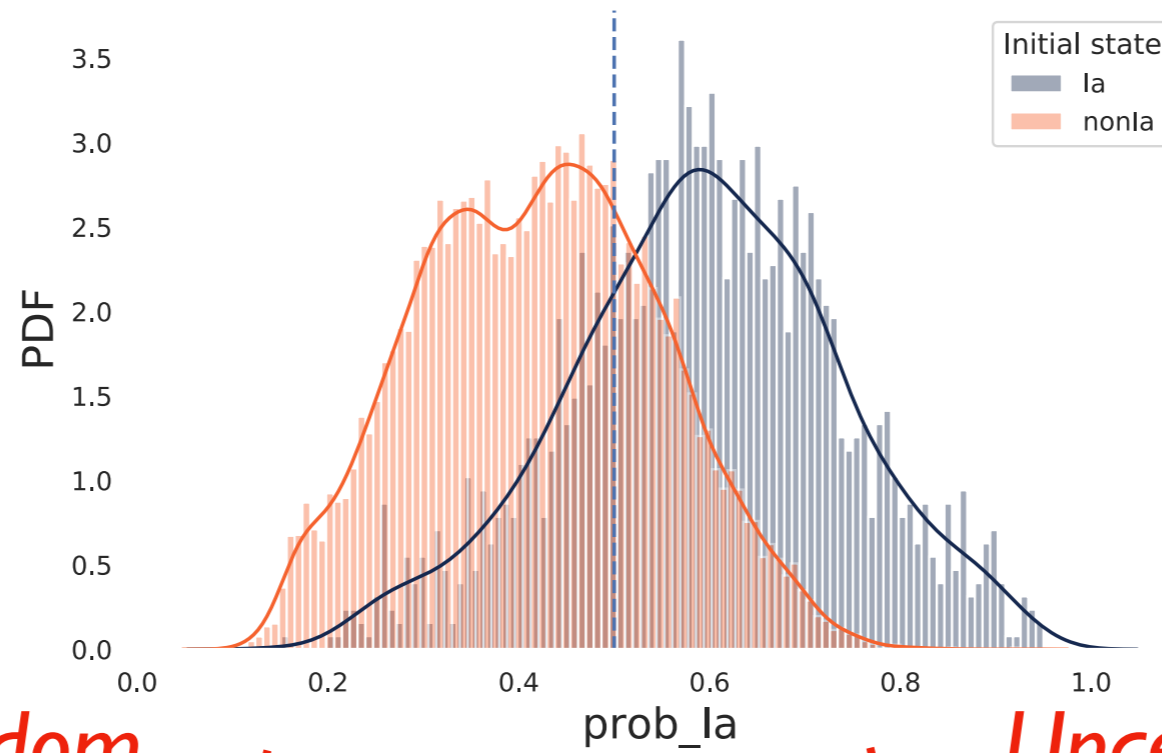
# Results : actual classes





# Results : probability distribution

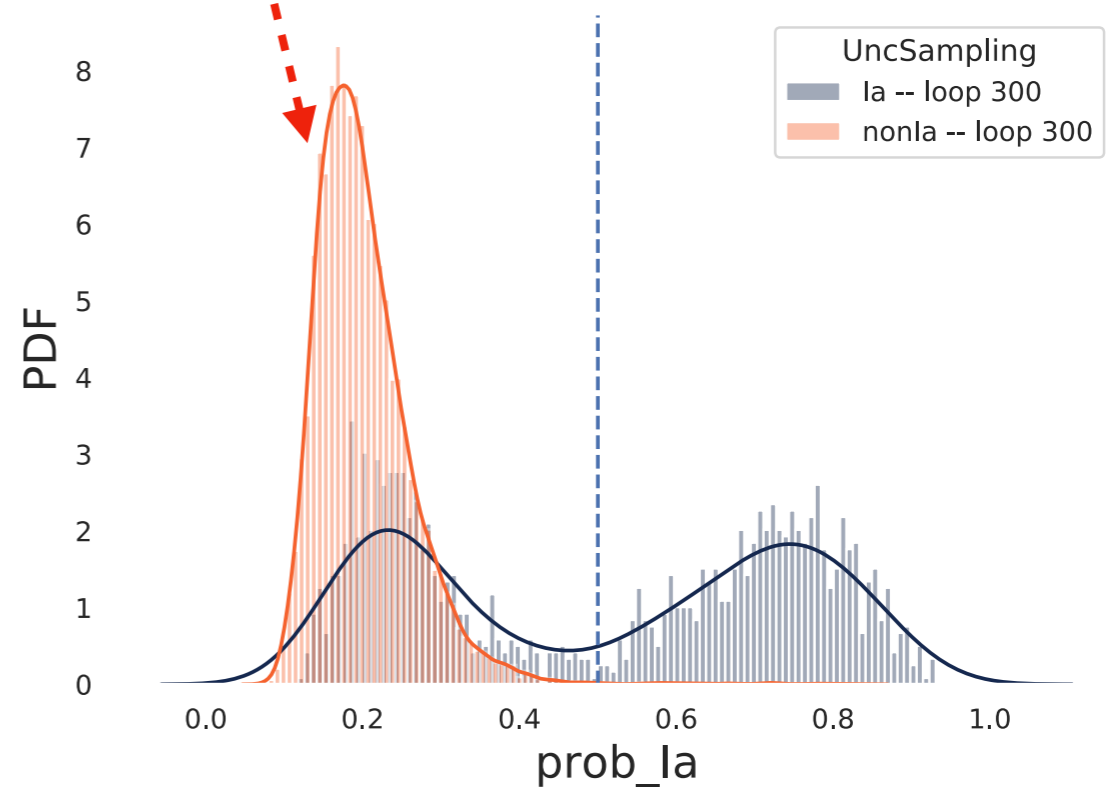
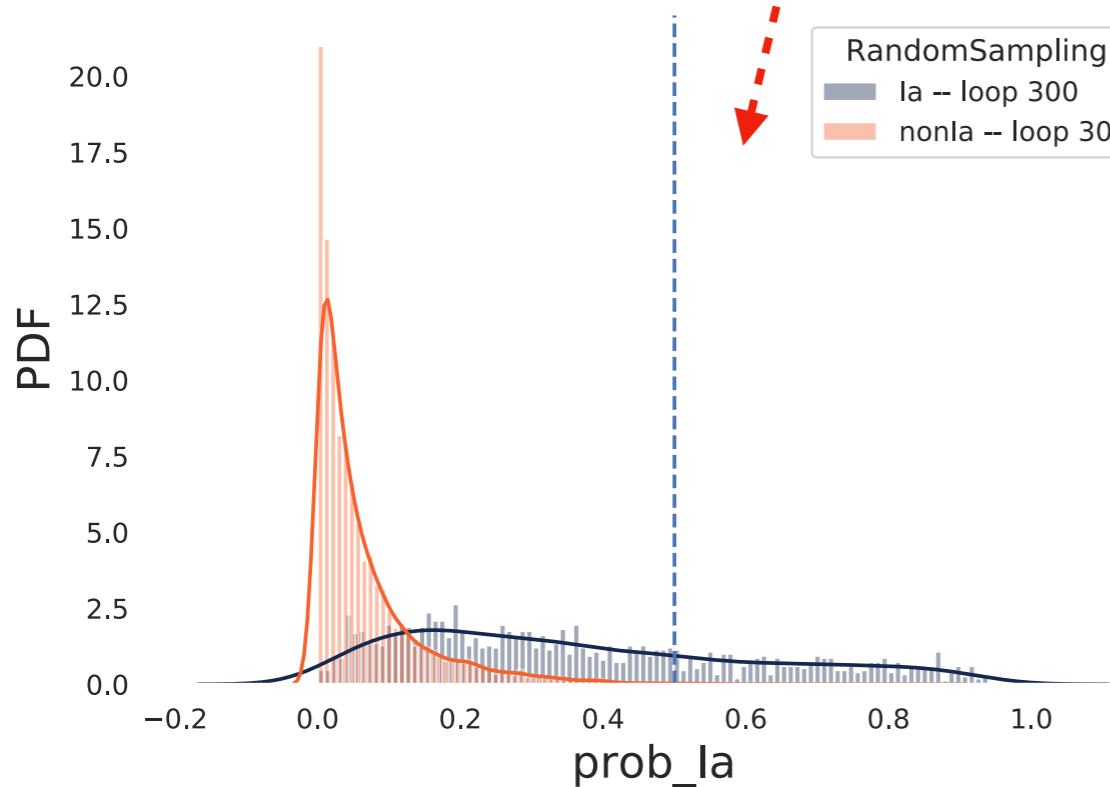
Loop = 0



*Random sampling*

*Uncertainty sampling*

Loop = 300

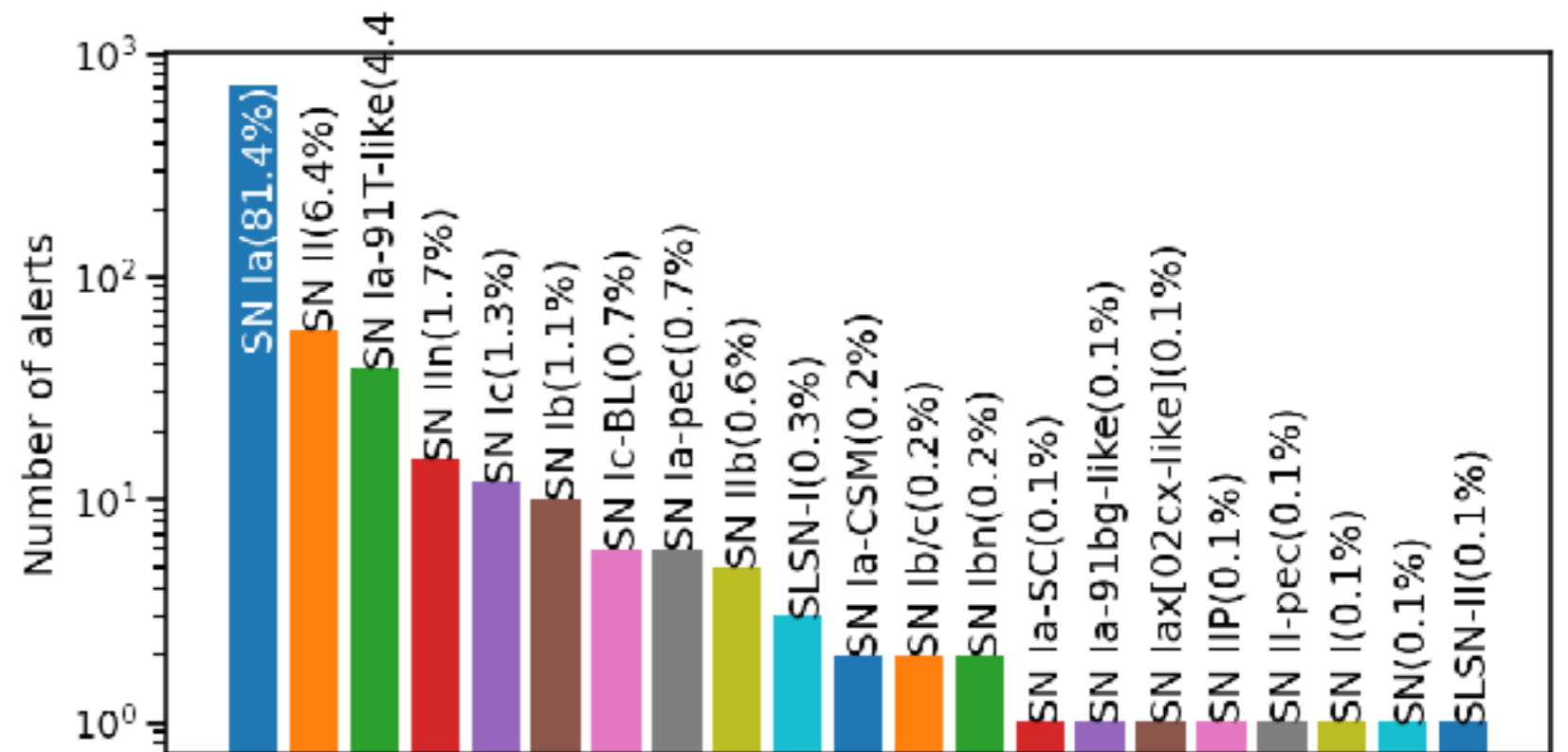


# Results : in prod

predictions are matched with those from Bayesian Neural Network models (Anais Moller).

If both models agree predictions are sent out.

from November/2020  
to November/2022  
Fink communicated  
1,533 early  
SNIa candidates to TNS.



908 (59%) of which : followed-up & spectroscopically by facilities  
around the world

788 (86%) of which : correctly classified as SNIa

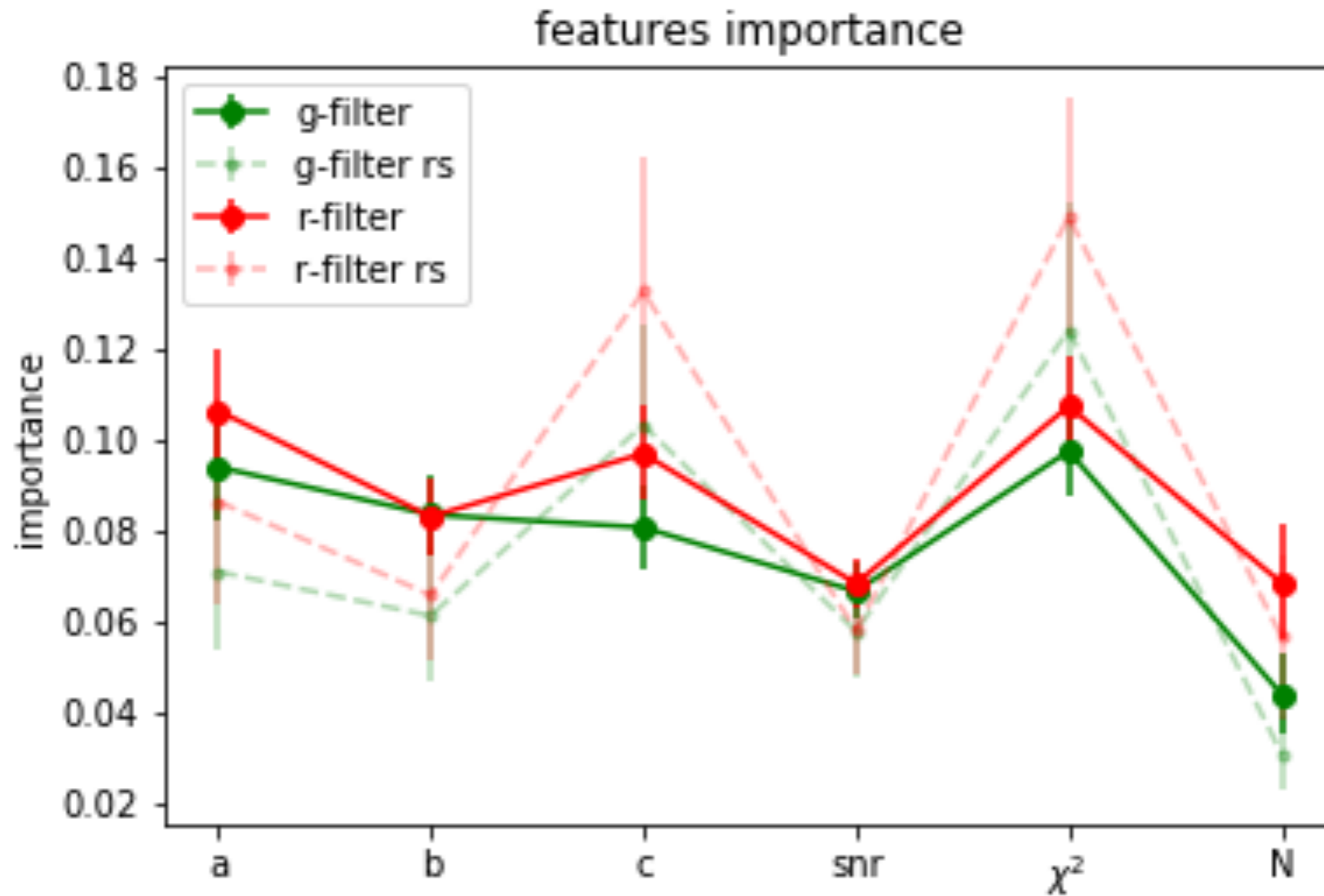
**Thanks, for your attention!**

**Backup**

# Early discovery: difficulties

- i) from ZTF simulations, we have to reconstruct a dataset of rising light curves.
- ii) *Bazin's* fit does not work well with a few data points (more later)
- iii) sometimes there are seasonal gaps in the time series (telescope off for a season etc. )
- iv) some of the data points for the flux are negative (with values below -10)

# Features importance



# Estimate of how many days before max ?

1. typical length of a light curve last ? : 30 data points
2. typical length of rising part ? (1/3 of the light curve i.e. 10 points)
3. Typical prediction sent out ? (probably 5 points on average)
4. Typical N points before max ? ( $10 - 5 = 5$ )
5. Confirm with predicted data from the broker ?