

# ZTF SNIa: legacy photo DR 3 4 5 ...

Collect *all* SNe Ia with *sufficient*  
lightcurves for cosmology.



# DR3

Fall 2026

This will be the legacy  
ZTF SN Ia sample



O(10k) SN Ia (Spectro)

O(30k) SN Ia (Photo)

Initial sample (same?) to be defined

SPECTRA

SEDm & Non SEDm: To be gathered

REDSHIFTS

SNID & DESI: that all set up ?

LIGHTCURVES

photometry: forced & scene

HOST

Identification & Properties: who?

Classification:

Sciences (DR3 spectra)

Sciences

A.I. for Photo-typing

Rates

Cosmo

SNID Automated

Bumps and co.

Spectra feature based

Low-metallicity hosts

Standardisation

Sample defined  
Spectra gathered  
SNID Ran

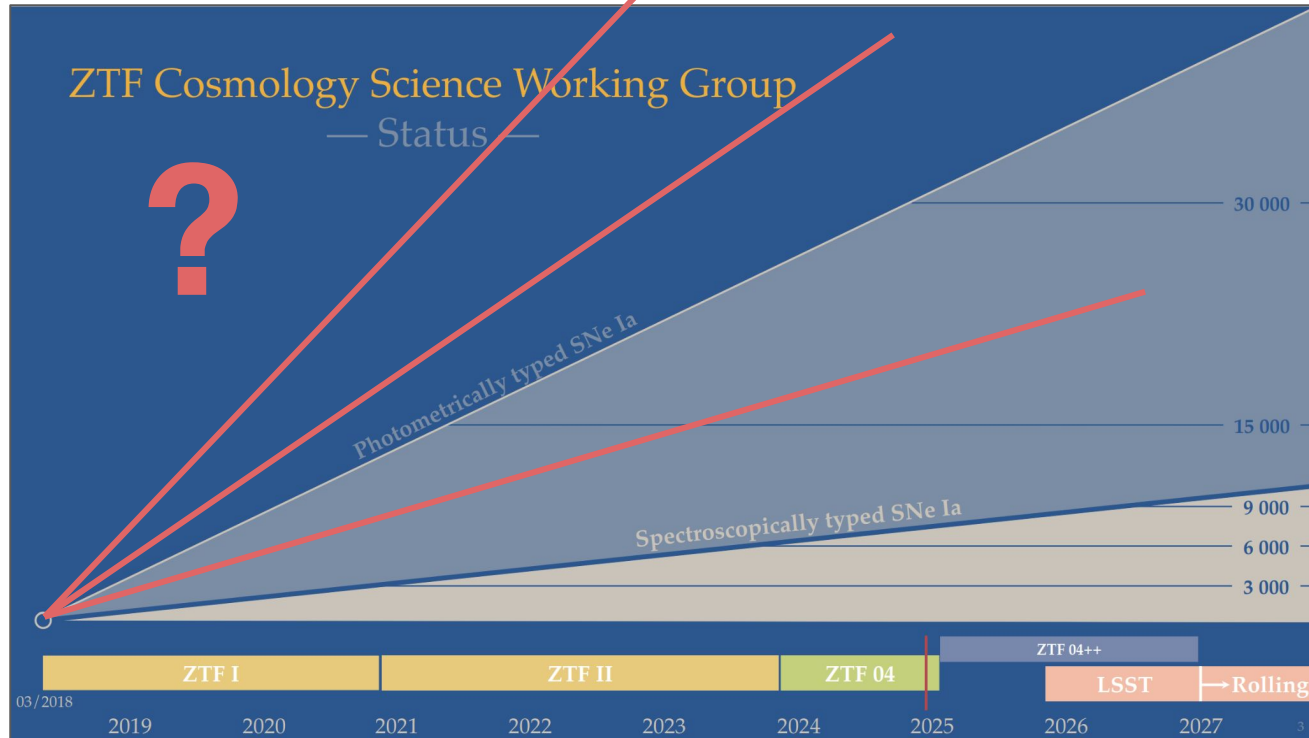
Host matching and  
Their properties Done

Post Cleaning  
DR3 spectrum  
data study starts

01/2025

06/2025

# What to expect



# The masterlist v270724

## Selection process:

- Outside MW, 4+ detections, mag>18.5, isdiffpos
- Accepted by TimeDistributionFilter: No star in PS/Gaia, duration<365d after outlier rejection.

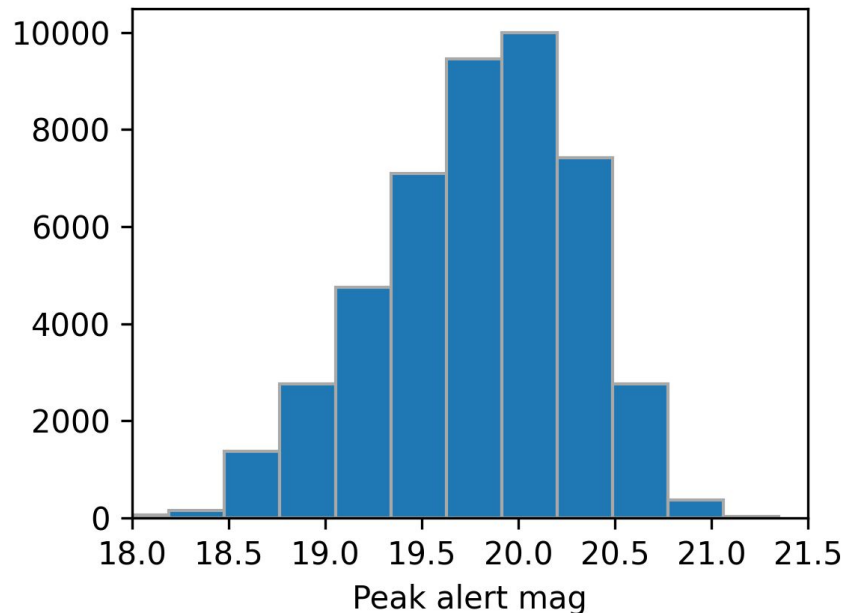
Intended to be easy match with simulations.

## Current status:

- 74185 candidats from 2018-23 (ZTFI/II).
- IPAC forced photometry **completed**.
- ~10% failures (bad pixels, no reference, close to edge, ...)

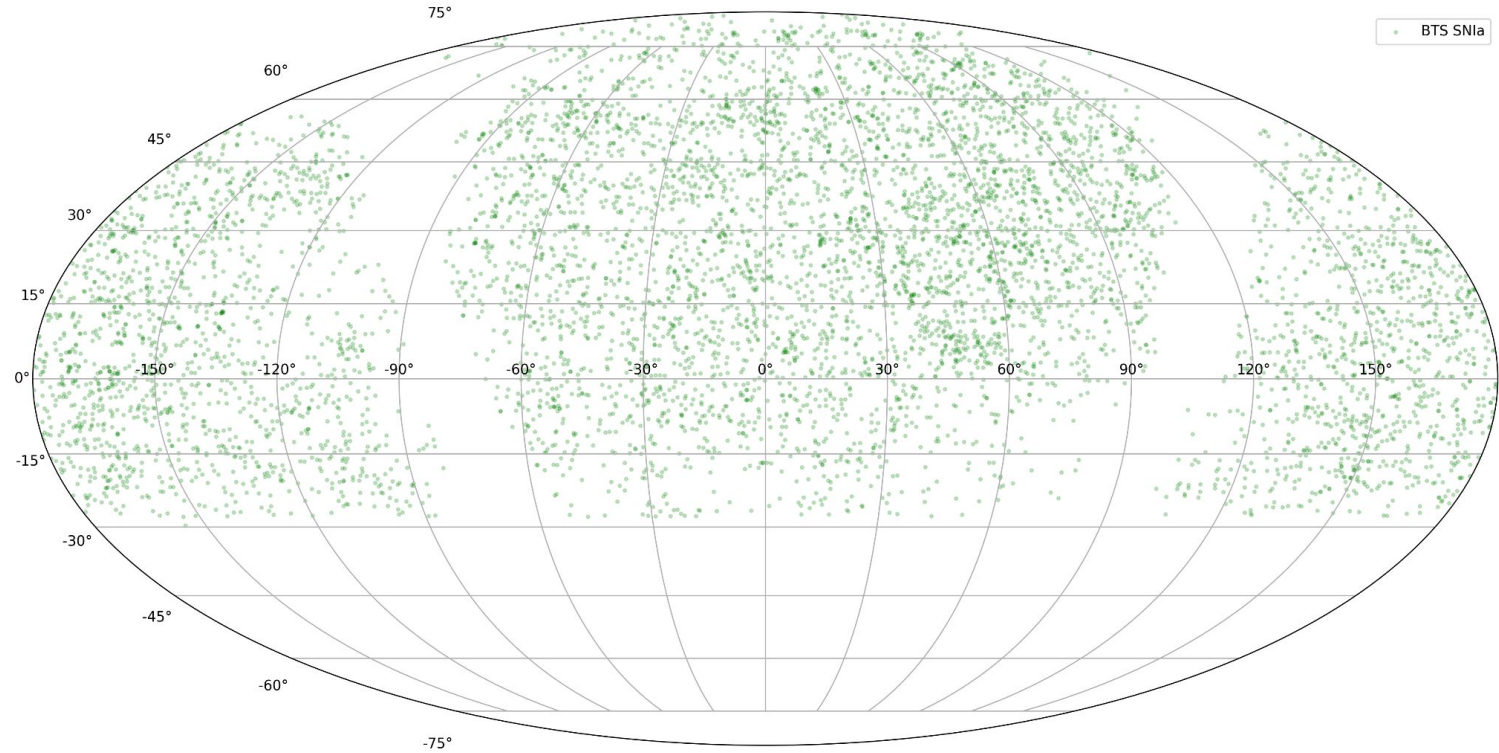
## The Test sample:

- 142 lightcurves in field 600



# ZTF BTS SNIa sample

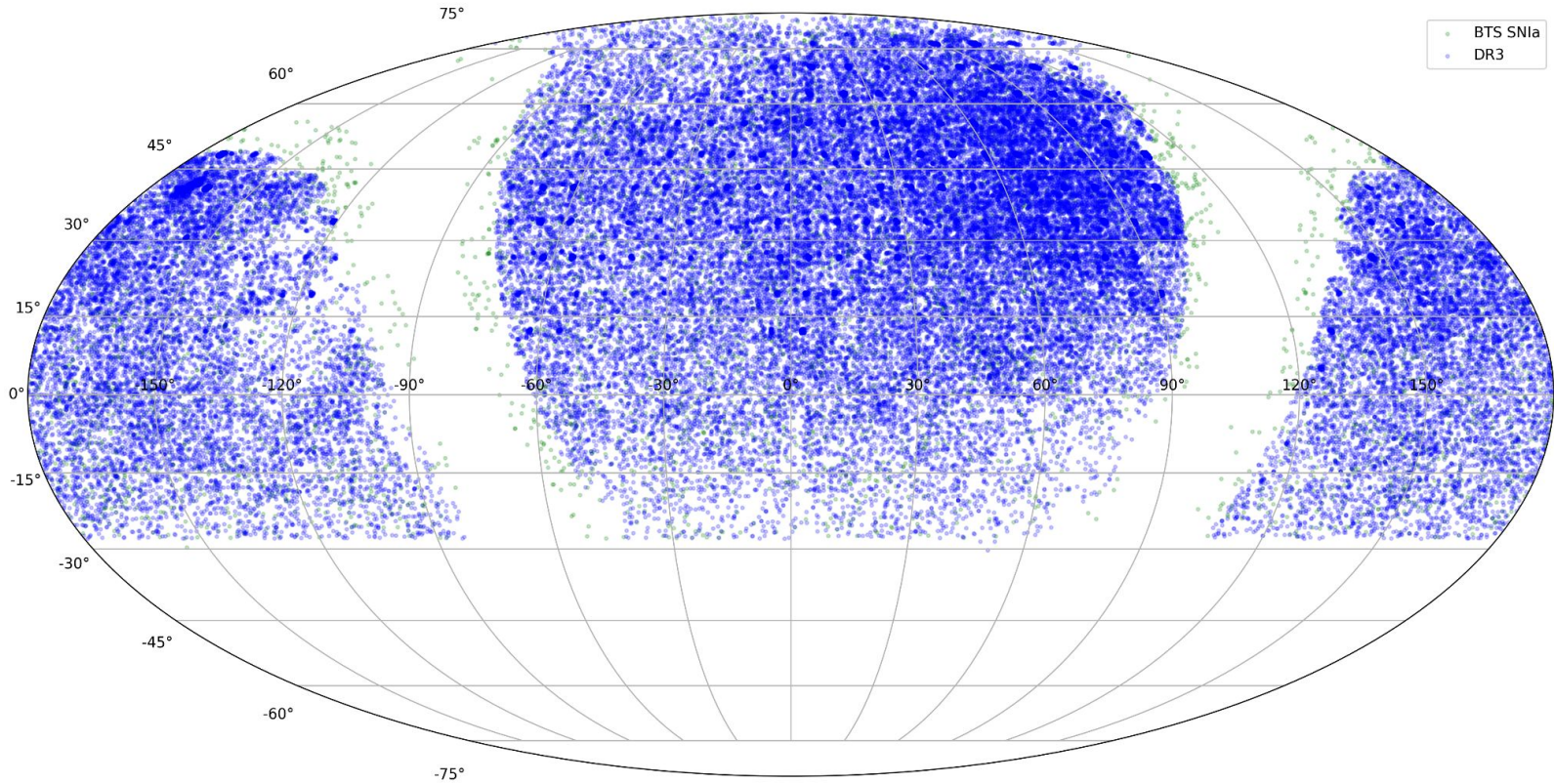
~7000 SNe Ia up to  $z \sim 0.07$





# The masterlist

>70000 transients up to  $z \sim 0.12$



# The *motherlist*

**Will** contain join of:

- Alerts selected as the masterlist until end of 2024 (March 2025).
- Full BTS dataset (what about BTSdeep?).

**Similar incompleteness!**

(MW, close to stars, prior variability, ...)

Presumably we will also do a legacy list (**maggotlist?**) covering period until LSST starts.

# Expected sample size

Field 600 identified as test sample (high cadence).

Processed through classification pipeline:

- Candidates found: 163
- IPAC FP returned: 142
- Baseline correction succeed: 111
- Some host z found: 64
- Salt fit pass cosmo criteria: 41

If we assume that FP, baseline & host z can be fixed:  
~ 65% cosmo SNIa (quite positive)

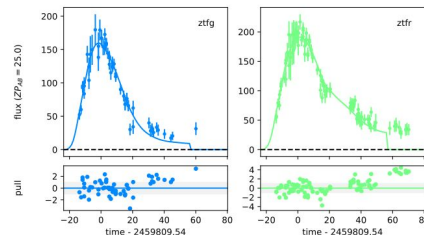
... or if we have to live with all of these losses:  
~ 25% cosmo SNIa (quite negative)

Expected number in the range: **25k-60k SNe Ia!**

181221045 salt2 T2DigestRedshifts  
chisq 359.38  
ndof 151

$z = 0.13225721$   
 $t_0 = 2459809.5$   
 $x_0 = 2.3966914 \times 10^{-4}$

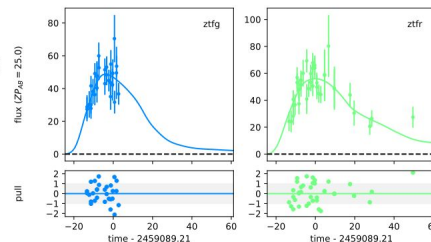
$x_1 = 1.3277280$   
 $c = 0.19368372$



349789091 salt2 T2DigestRedshifts  
chisq 64.40  
ndof 63

$z = 0.22357322$   
 $t_0 = 2459089.2$   
 $x_0 = 7.2986487 \times 10^{-5}$

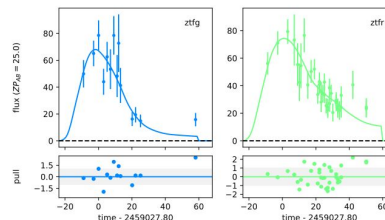
$x_1 = 2.7963875$   
 $c = 0.11034422$



256581283 salt2 T2DigestRedshifts  
chisq 55.70  
ndof 46

$z = 0.18085423$   
 $t_0 = 2459027.8$   
 $x_0 = 9.9878937 \times 10^{-5}$

$x_1 = 1.5589466$   
 $c = 0.10200622$





# Host redshifts

Full list included in DESI transient host program.

Completeness depends on host properties:

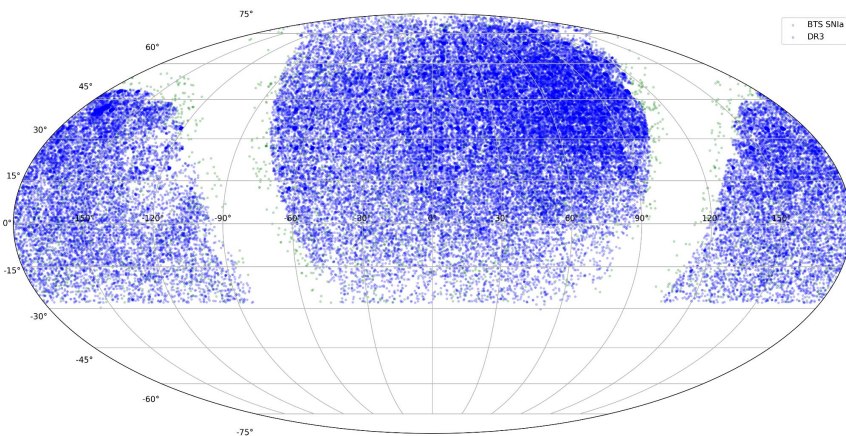
- Does it exist?
- Brightness
- Emission lines?

Do we need a **dedicated host z campaign**?

- Systematics across types
- Completeness across sky

Todo:

- Evaluate first batch of DESI results.
- Our host identification pipeline.



# Classifier results

Key aspect that we will **test** classifier performance on real data.

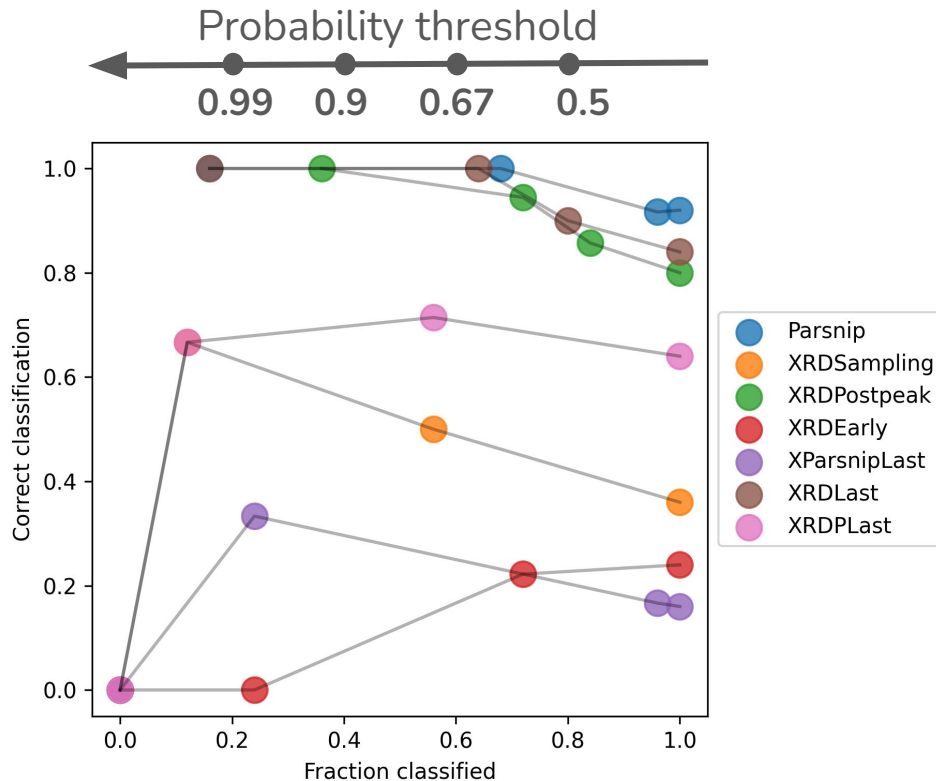
Case study from the September ZTF experiment:

- Attempt to classify fainter transients.
- **Alert photometry.**
- **Small sample.**

Different classifier behaviour:

- **Probability threshold?**
- **Use abs mag?**

More studies coming...



# Alert classification

Try classifiers on individual SN alert photometry:

[https://github.com/AmpelAstro/Ampel-HU-astro/blob/parsnipRisedecline/notebooks/classifiy\\_sn\\_from\\_alert.ipynb](https://github.com/AmpelAstro/Ampel-HU-astro/blob/parsnipRisedecline/notebooks/classifiy_sn_from_alert.ipynb)

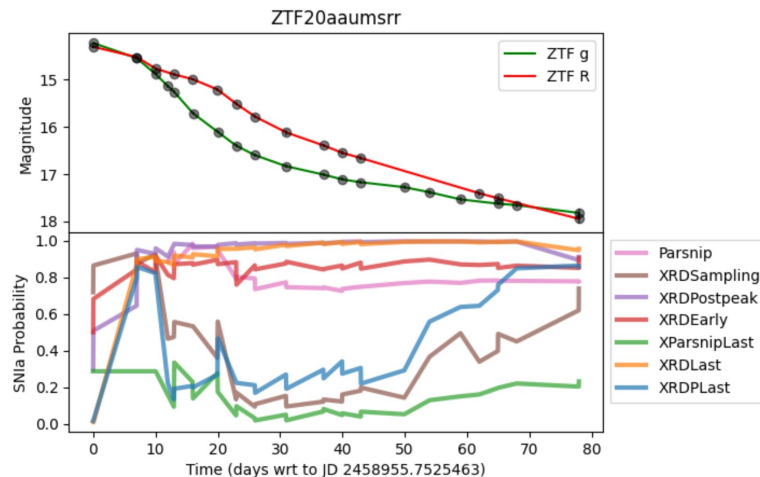
Retrieve photometry, load classifiers, evaluate  $P(\text{SNIa})$  vs time:

```
jupyter classify_sn_from_alert Last Checkpoint: 8 days ago
File Edit View Run Kernel Settings Help
+ ✂ 📄 📄 ▶ ⏪ ⏩ Code ▾

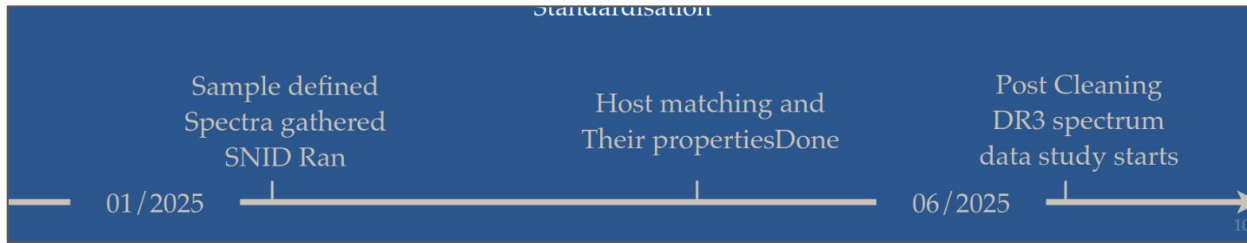
This notebook will:
• Download ZTF alerts for a named SN from the DESY archive.
• Load a set of AMPEL feature extraction and ML classification units.
• Apply these to each phase of the transient, using an assumed redshift.
• Plot the evolution of SNIa probability provided by each classifier.

[1]: # Name (ZTF ID) of transient and redshift to use (when relevant)
      sname = "ZTF20aamsrr" # Ia
      #sname = "ZTF24abhzjl" # Ia
      #sname = "ZTF24abiesnr" # Ibn
      z_assumed = 0.01

[2]: import os
      import requests
      import warnings
```



# Timeline



## 2025:

- **ML classifier paper (v1)**
- **Masterlist classification paper (similar to DR1)**
- **Simulation framework**
- **Host identification + DESI evaluation**
- **Alt classifiers (e.g. snnova trained)**
- **Start obtaining SMP ...**

## 2026:

- **Completeness enhanced DR2.5 cosmology?**
- **Selection / simulation paper**
- **Photometric classifier summary / evaluation paper**
- **... done getting SMP**
- **New cosmology inference tool papers?**
- **Possibly getting more host redshifts?**

## 2027:

- **Legacy release of candidates and classifications**
- **Cosmology ....**

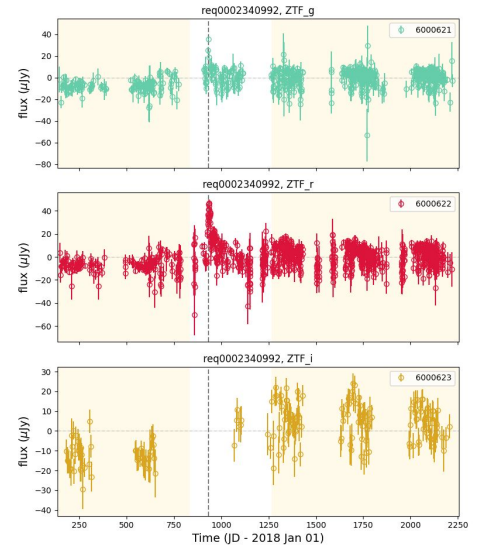
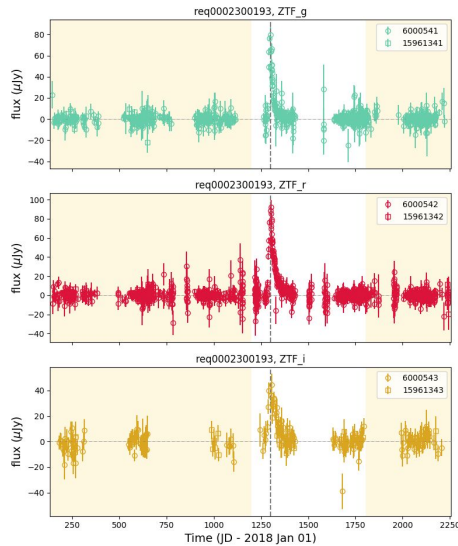
# Additional topics

## Internal lightcurve release?

- Baseline correction
- Siblings, outbursts
- Blinding
- Distribution

FPbot

LS4, LSST, ULTRASAT



# Current status

The ZTF photometric legacy sample will consist of 25k-65k SNe Ia, enabling a range of new studies.

Base list of candidates defined, with alert and forced photometry. SMP required eventually, list is not final.

We have a first generation of operational classifiers, which are being tested on real data.

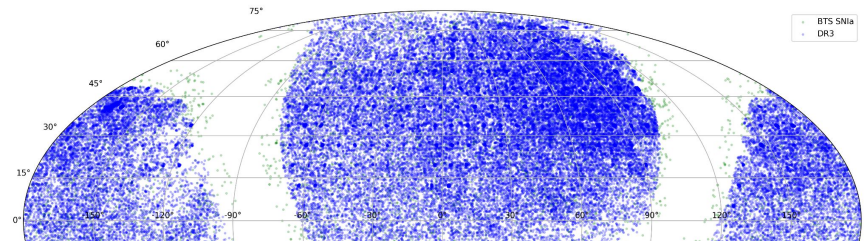
Candidate hosts are scheduled for DESI observations. The completeness still needs to be determined, as well as whether we should propose for further host obs. We need to automate our host determination and characterization tools.

Simulations are needed! Both for training deep neural networks as well as for studying the selection function.

Do we need new statistical inference tools (lc, s8) accepting a classification uncertainty?

ML very active: new models every month, ZTF-ML discussions etc.

# wg-photoclass





# NoiZTF + ParSNIP

For photometric classification with ML, we need a **representative** training sample.

However... current sample of classified ZTF transients is **biased** to brighter, lower  $z$  objects. It is also unbalanced, i.e. majority of the sample is SN Ia. ML classifiers performed poorly on the 'raw' dataset.

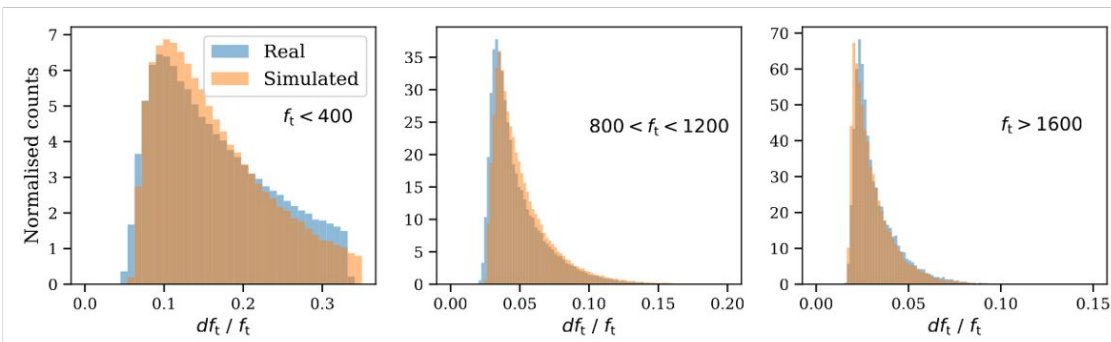
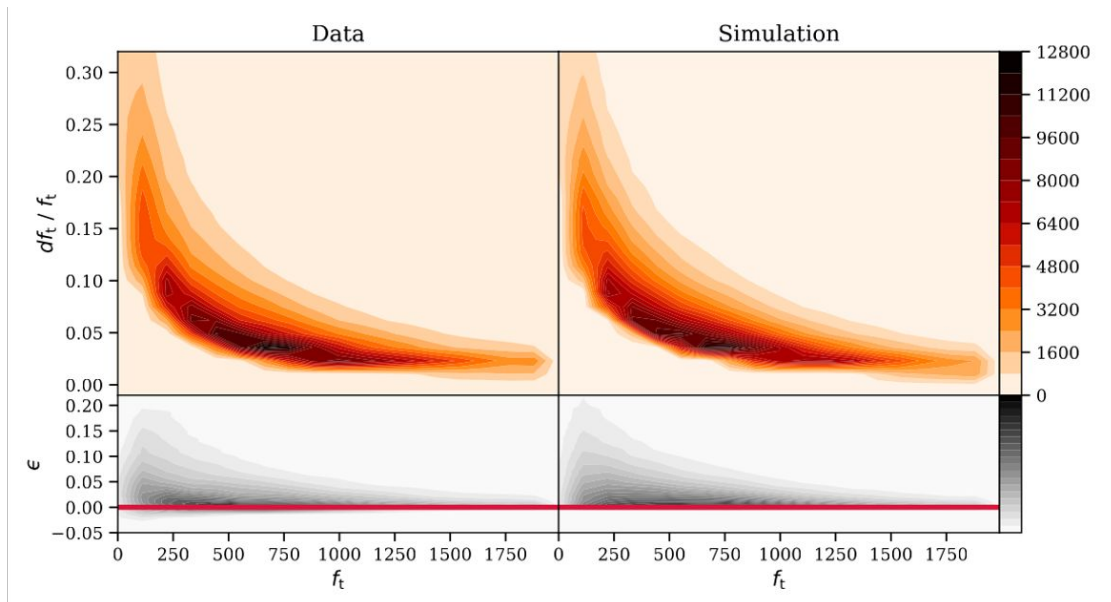
→ **Solution:** augment the training sample by creating copies of the original ZTF data with a higher redshift and additional noise (NoiZTF).

# Error modelling

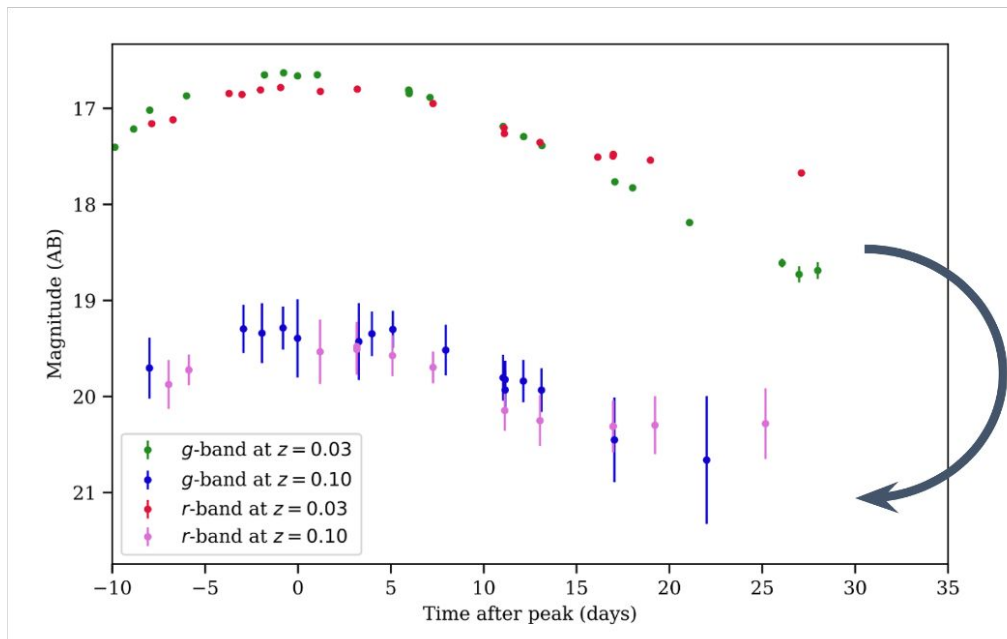
- To accurately simulate SNe at higher redshifts, we need to model the photometric errors in ZTF.

$$\frac{df}{f} = \sqrt{\frac{1}{f} + \frac{e_b^2}{f^2}} + \epsilon + \delta \quad \epsilon \sim \text{Exp}(\lambda_f)$$

where  $e_b$  and  $\delta$  are constants,  $\epsilon$  is a random exponential term with a scale factor linearly dependant on the flux ( $\lambda_f$ ).



# Creating the training sample



Using the BTS sample with forced photometry data.

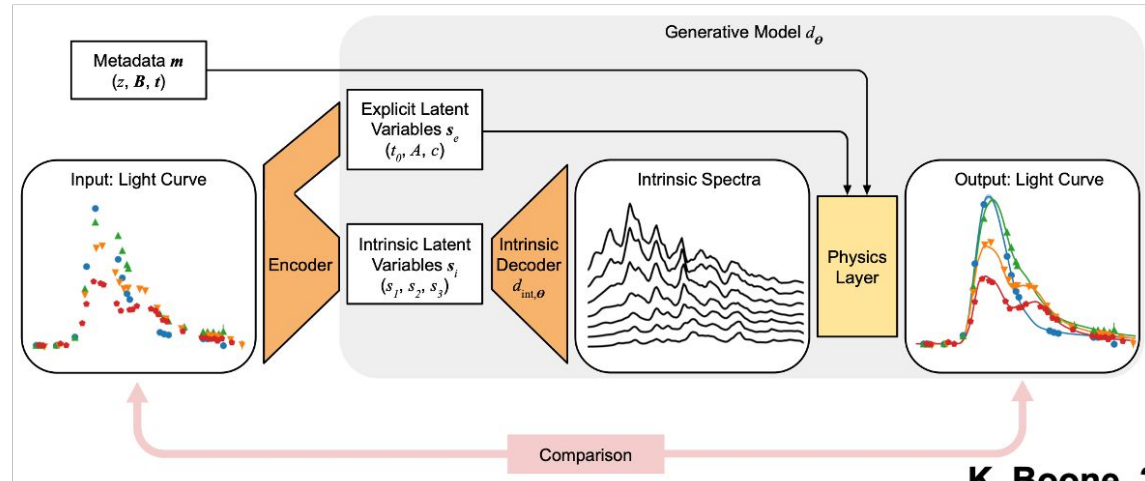
1. **Select new redshift** (in this case, from  $z = 0.03$  to  $0.10$ ) and scale flux and errors. Additional scatter is added. K-correction is also applied.
2. **S/N cut** applied (at least 5 detections with  $S/N > 5$ ).
3. **Drop data points** according to their 'local density' first, then drop points randomly.

The number of augmented copies generated is chosen to balance the classes.

# Classifier

- We use *ParSNIP* (Parametrization of SuperNova Intrinsic Properties, Boone 2021) to produce models for the transients.
- *ParSNIP* is a modified version of a variational autoencoder (VAE), it uses:

- a neural network to model the unknown **intrinsic** diversity of transients (latent variables;  $s_1, s_2, s_3$ )
- an **explicit** physics-based model of how light travels through the universe and is observed ( $A, c, t_0$ ).

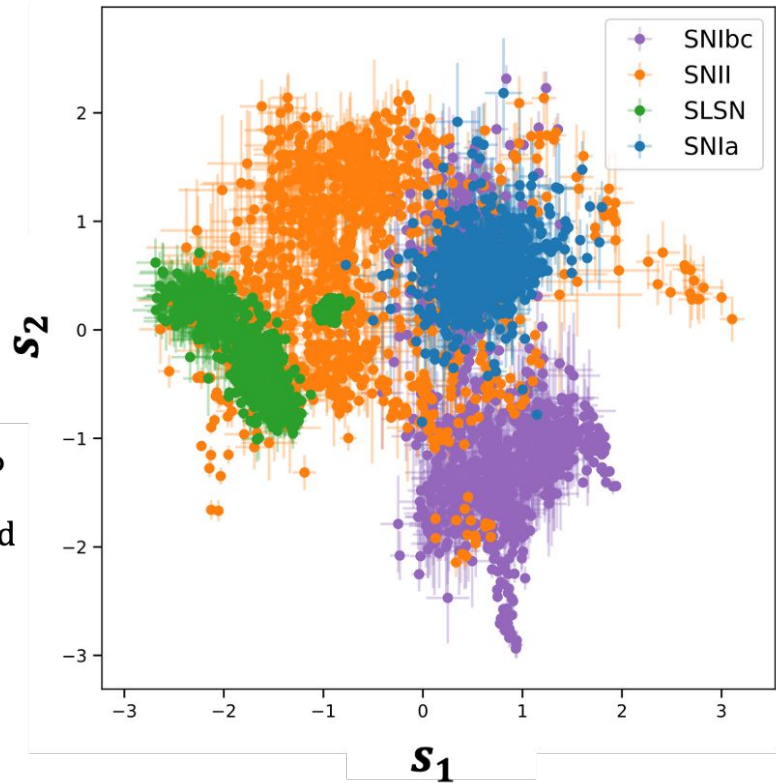


K. Boone, 2021

# Classifier

- We extract the features from ParSNIP.

An example of how two of the ParSNIP features (intrinsic latent variables  $s_1$  and  $s_2$ ) vary for the classes.



# Classifier

- We extract the features from ParSNIP.
- We also extract additional light curve features (e.g. with colour, time, slope information).

We use the features included in *SNGuess* (Miranda et al. 2022) with additional improvements.

Name	Type	Description
tPredetect	Time	Time between final good upper limit and first detection.
tLC	Time	Duration (time between first and most recent detection).
ndet	Int	Number of significant detections.
peaked	Bool	Is the lc estimated to be declining?
pure	Bool	No significant nondetections after first detection.
rising	Bool	Max brightness close to the most recent detection.
norise	Bool	No (significant) detected rise.
hasgaps	Bool	The light curve has a gap between detections of at least 30 days.
mPeak	Mag	Magnitude at peak light (any band). Only calculated if peaked==True.
mDet	Mag	Magnitude at first detection (any band).
mLast	Mag	Magnitude of the current (i.e. latest) detection (any band).
cPeak	<i>g-r</i>	Color at peak (if peaked and with <i>g</i> and <i>r</i> ).
cDet	<i>g-r</i>	Color at detection (if with <i>g+r</i> ).
cLast	<i>g-r</i>	Color at last detection (if with <i>g+r</i> ).
slopeRise <i>g,r</i>	Mag/time	<i>g</i> or <i>r</i> mag slope between detection and peak (None if norise).
slopeDecline <i>g,r</i>	Mag/time	<i>g/r</i> magnitude slope between peak and last detection (None unless peaked).

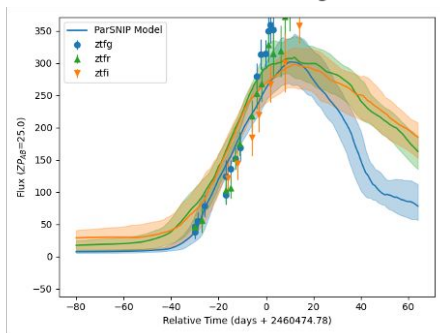




# Live testing

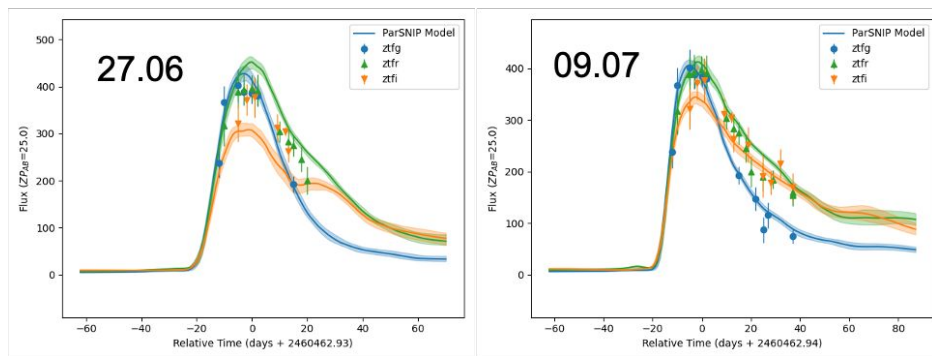
- We have a live classification project ongoing with ePESSTO+ (until the end of the program, ~ September '25).
- So far, ~40 objects classified (plus sample of 7 from P200 run in Dec '23).

## ZTF24aaowjlv



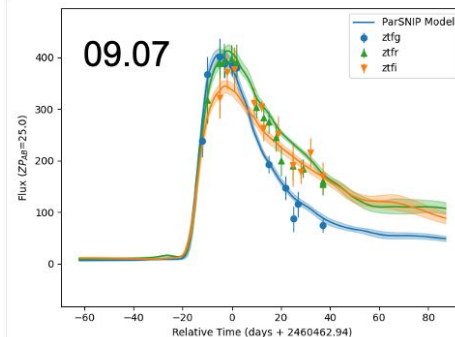
P(SLSN) = 86%  
Classified as SLSN-I

## ZTF24aaooxcd



P(SNIa) = 82%

Classified as SNI



P(SNII) = 65%

# Future work

- Continuing live testing to get a good sample ( $N \sim 50-100$ ) of objects to test performance of classifier.
- Include host information as a feature in classifier (e.g.  $M_i$  and  $g-i$  from BTS catalogue).
- Add simulated data (e.g. for SLSN, TDEs, etc.) to the training data set.
- Retraining retraining retraining
- Finishing the paper!