NASA, ESA, and A. Riess (STScI/JHU); SH0ES Team

Rubin Project and Community Workshop, August 2023

First Impressions

Early SN Classification with Host Information and Shallow Learning

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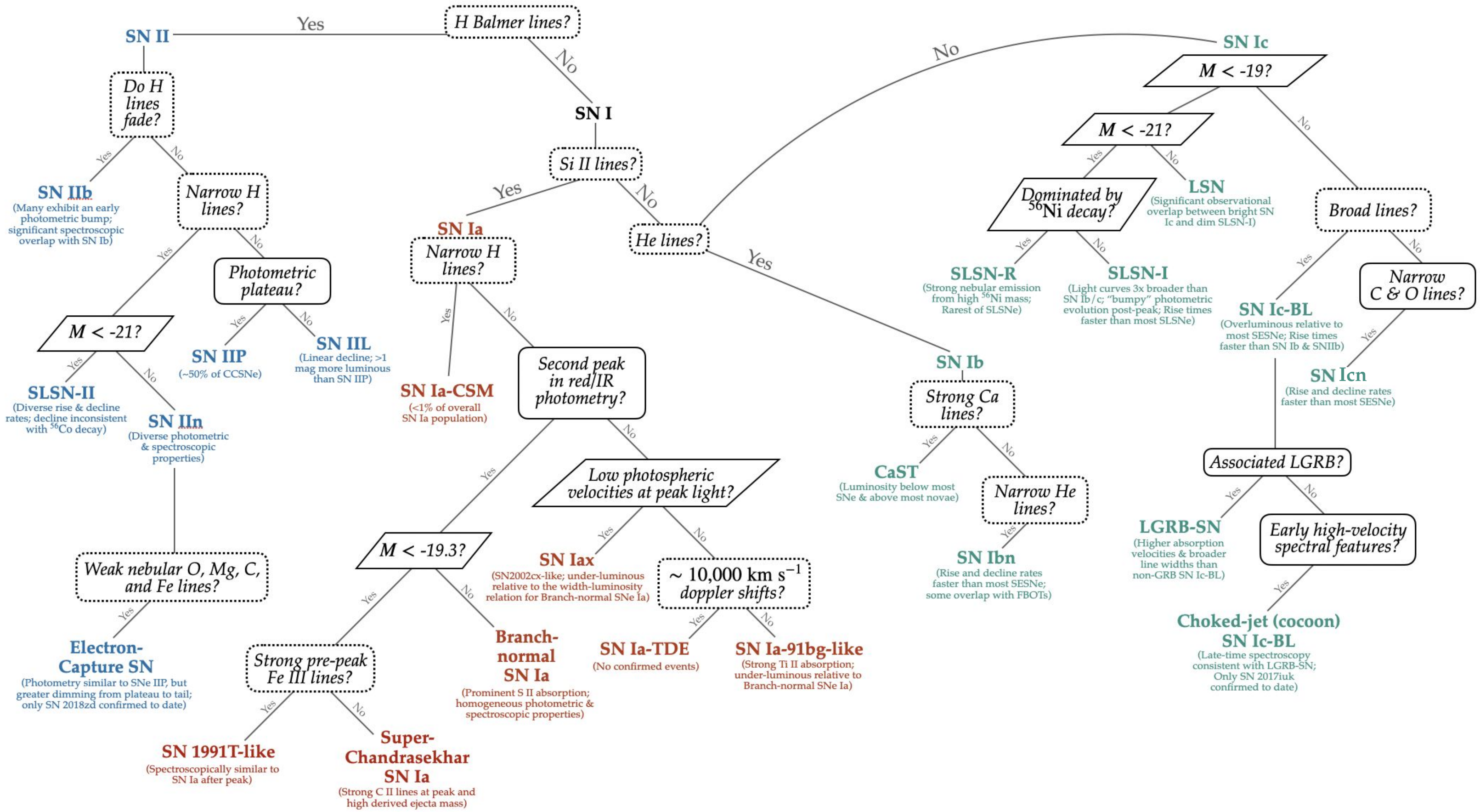
TAXONOMY OF TERMINAL TRANSIENTS



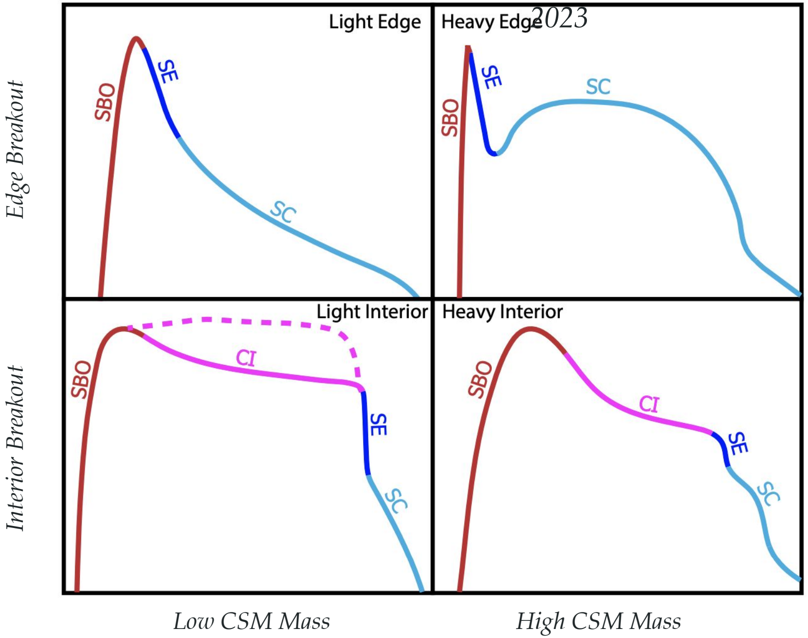
Squeezing Blood From A Stone

The Vera C. Rubin Observatory (2025-2035) will discover 3-4 million SNe among 18,000 deg, breaking exponential scaling for the first time.

Rubin median inter-night gap, Wide-Fast-Deep, rolling cadence:

- 24.96 days in *u*
- 22.93 days in *g*
- 6.92 days in *r*
- 7.93 days in *i*
- 8.03 days in *z*
- 13.96 days in *y*

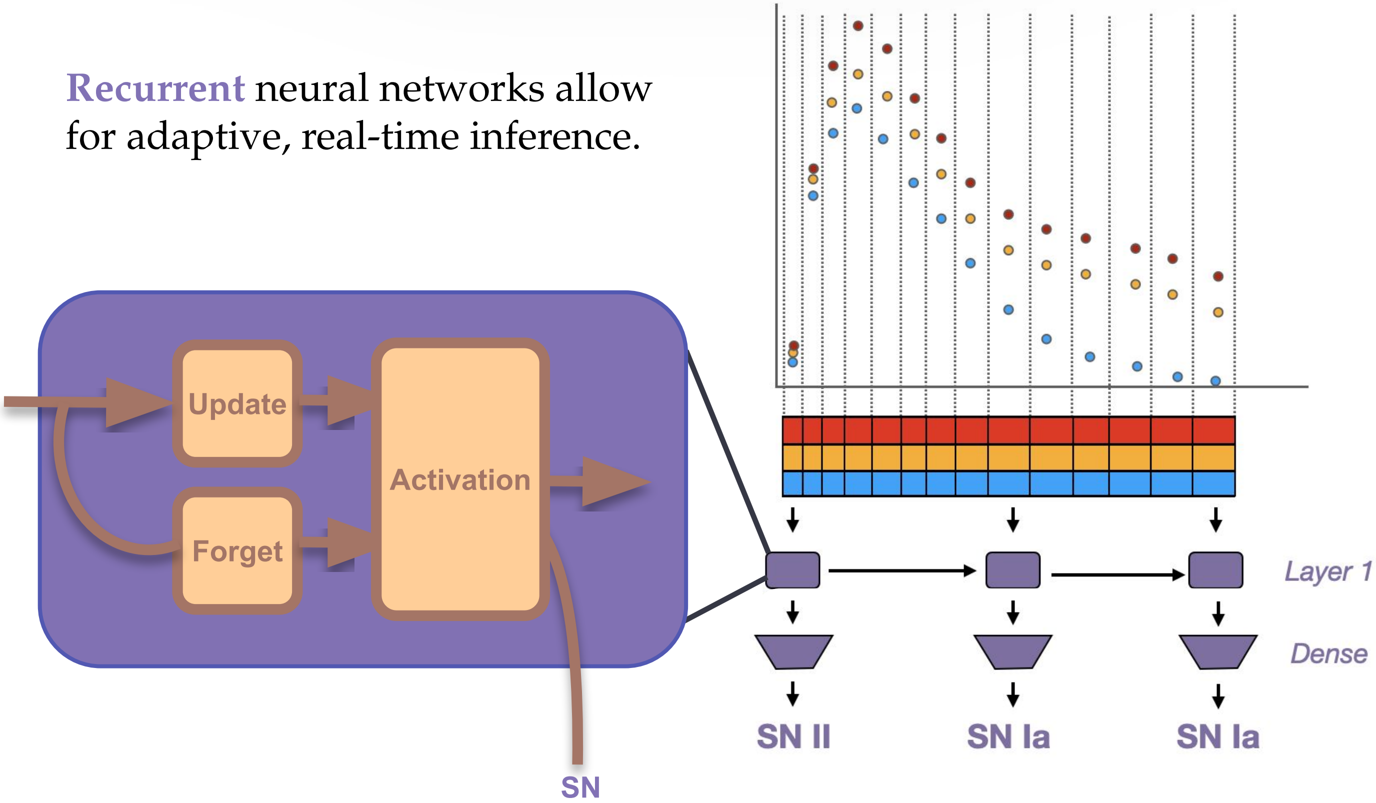
Khatami & Kasen, 2023



SN characterization now pushes *far* beyond classification to timescales of ~hours and wavelengths across the EM spectrum.

Neural Networks Have Become Commonplace for Real-Time Classification…

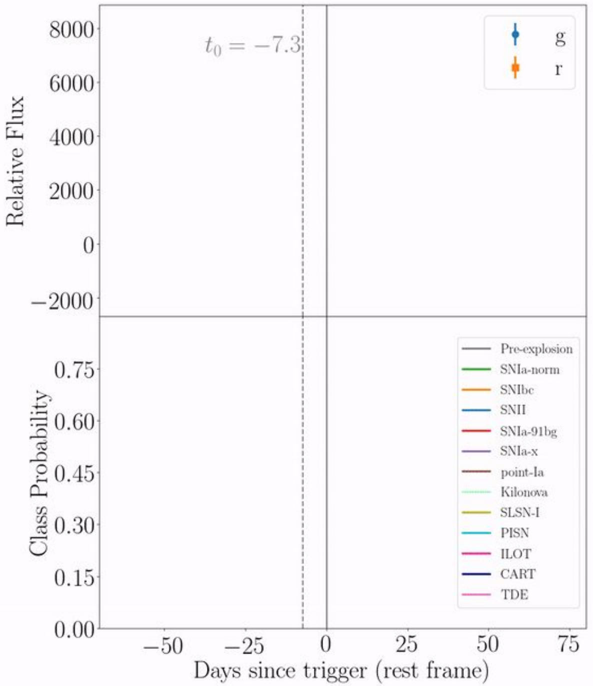
Recurrent neural networks allow for adaptive, real-time inference.



…But Obstacles Remain For Rubin-Era Processing.

1. **Ensuring classification performance on *observed* partial-phase supernovae.**

Performance has been validated on simulated samples from the Photometric LSST Astronomical Time-Series Classification Challenge (e.g., *Muthukrishna+2019; Möller+2019; Qu+2021*).

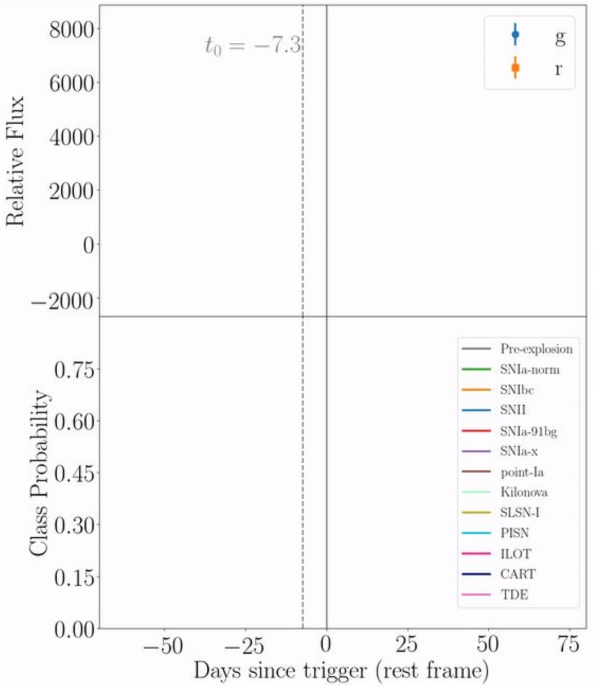


Muthukrishna+2019

Obstacles to Rubin-Era Processing

1. **Ensuring classification performance on *observed* partial-phase supernovae.**
2. **Scaling to 10 million alerts per night.**

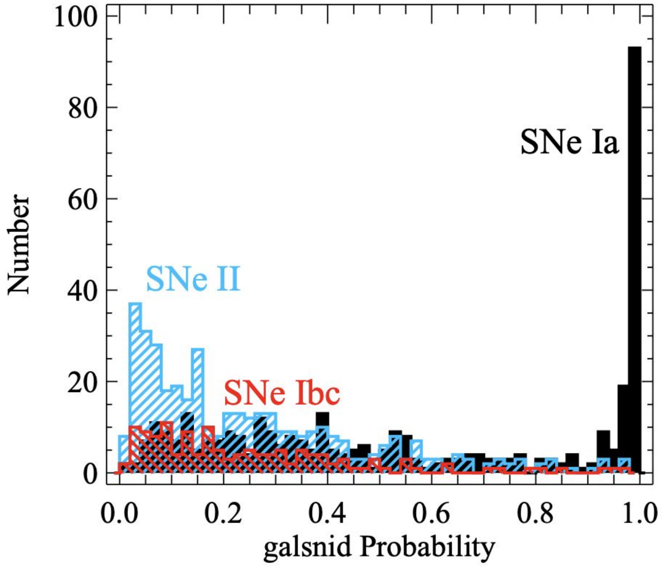
A significant computational bottleneck is simply loading the model into memory (*Allam Jr., 2023*).



Muthukrishna+2019

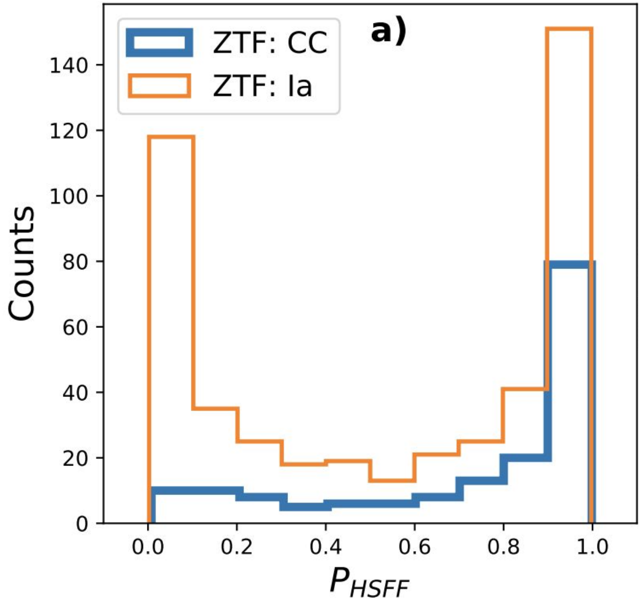
Ensuring Performance without Transient Photometry

SN Ia probability as odds ratio over host galaxy morphology, color, luminosity, and offset.



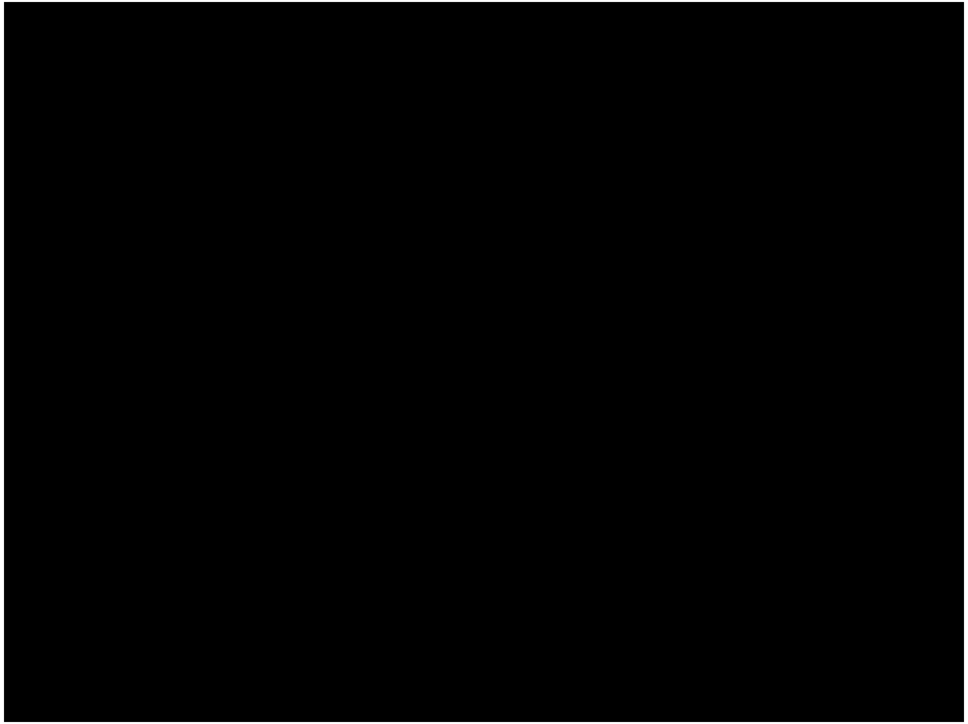
(Foley & Mandel, 2013)

Random-forest model trained to classify hosts as highly star-forming (within 0.3 Gyr) or not.



(Baldeschi+2020)

Combining SN+Host Photometry: The "First Impressions" Classifier



Improvements over prior methods:

1. *Lightweight model architecture - 10% of RAPID (Muthukrishna+2019), 75% of SCONE (Qu+2021)*
2. *Use of contextual information (host-galaxy photometry)*
3. *Validated on observed samples from ZTF.*

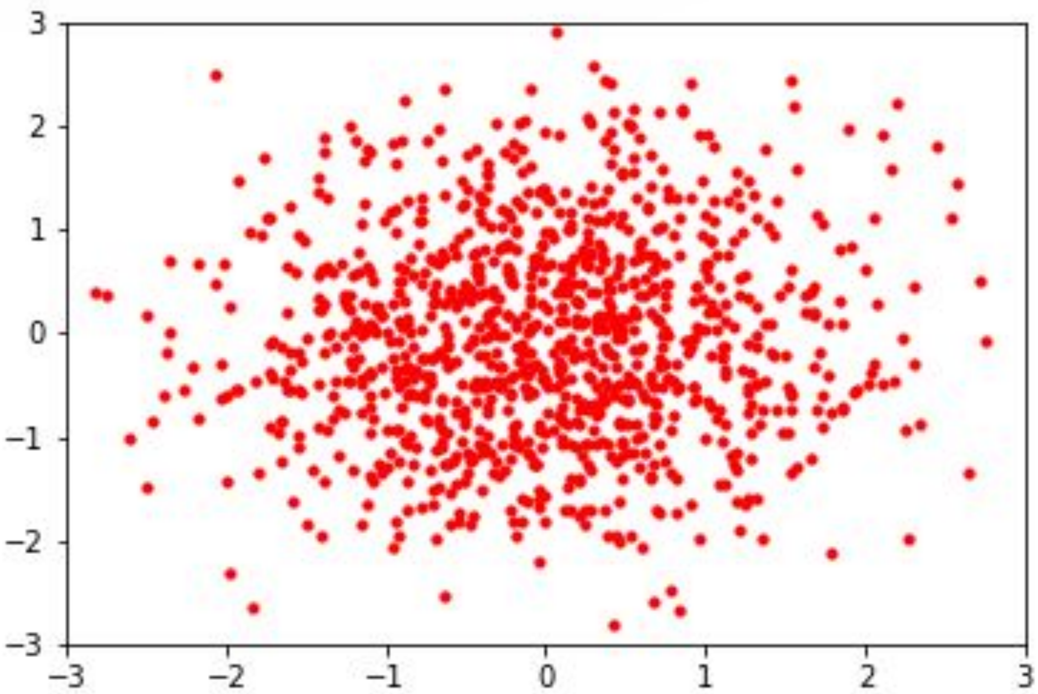
Host-Galaxy Photometry From Normalizing Flows

We want to sample from a multivariate distribution p(x), but don't know how.

Instead, we can approximate *p(x)* as an ***invertible*** function *g* applied to a simple latent distribution (e.g., a Gaussian).

Then, we can sample from *p(x)* by drawing samples *u* and applying *g*.

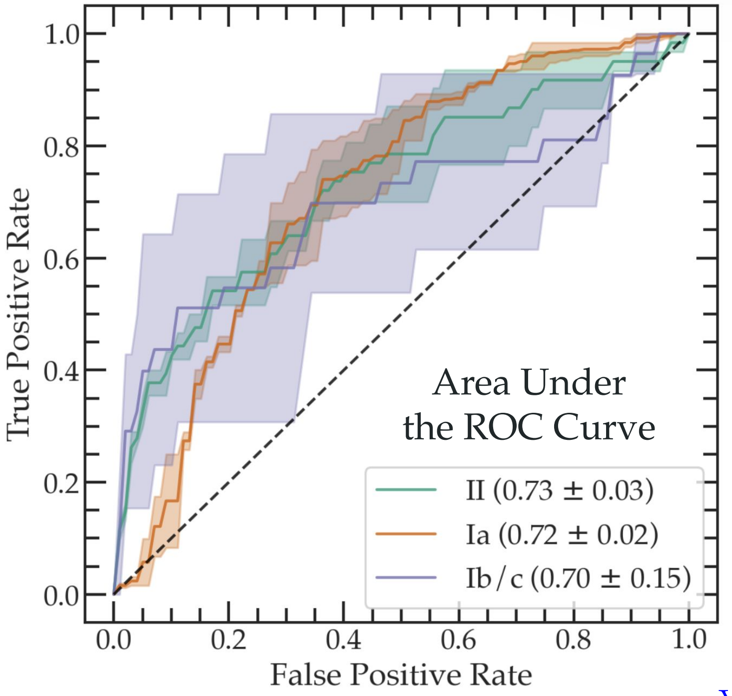
We model *p*(Host *grizy* | z *spec*).



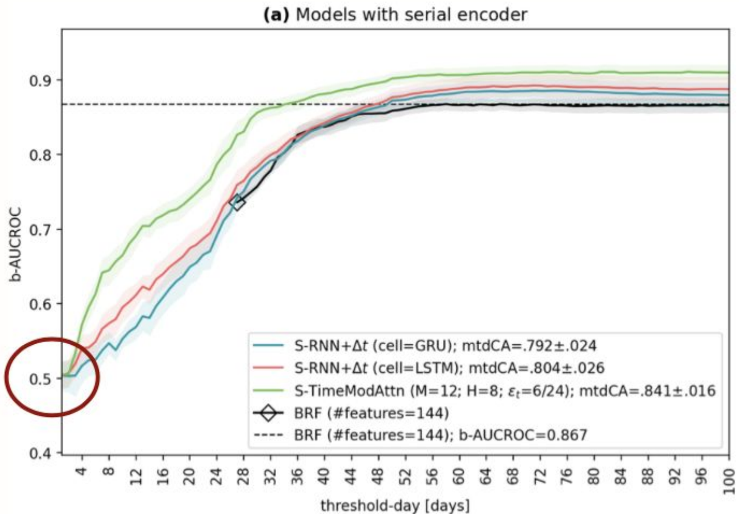
Normalizing Flows, Eric Jang

Day 3 Performance: ZTF BTS

(Fremling+2020,Perley+2020)



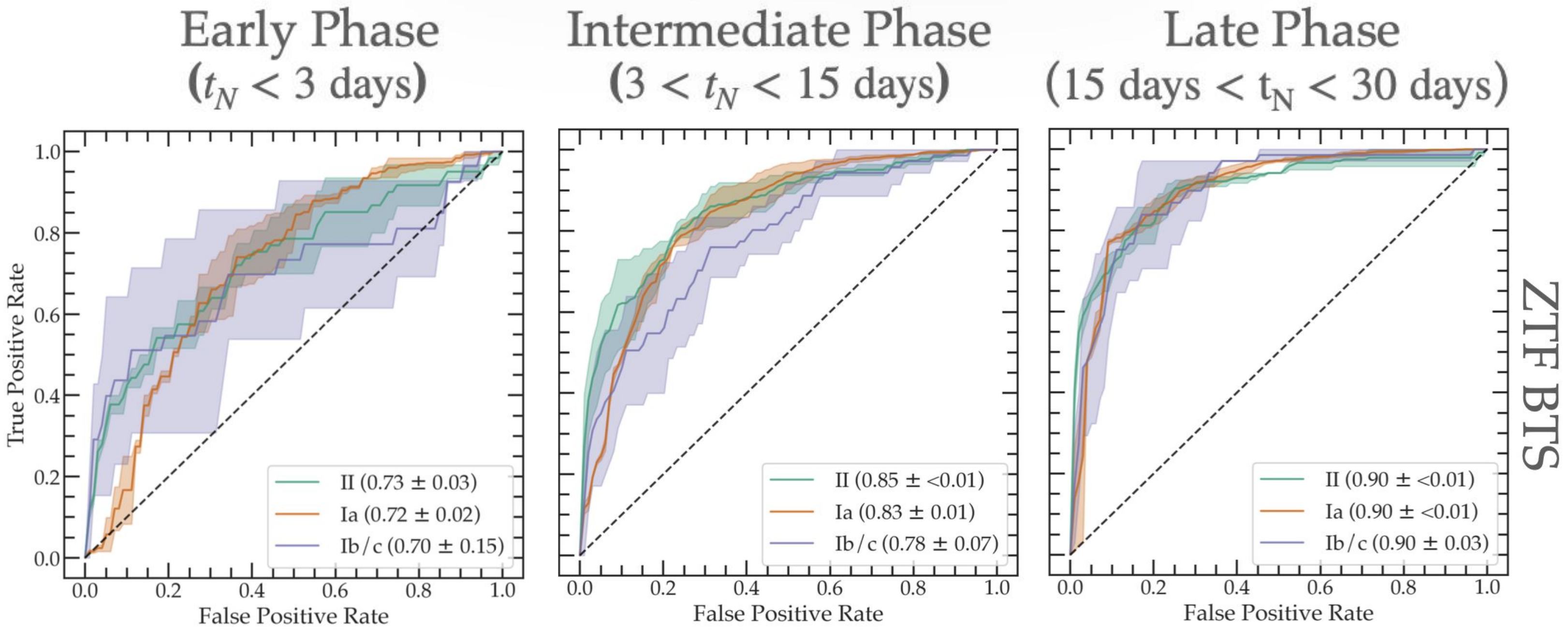
We achieve 82% accuracy and 72% AUROC *within 3 days of discovery*, from ZTF photometry with a ~2 day cadence.



(*Pimentel+2022*)

[*arXiv:2305.08894*](arXiv:2305.08894)

Late-Phase Performance



Performance suggests a later focus on light-curve information - attention networks could confirm!

Framework easily extended to classes with stronger host-galaxy correlations (e.g., TDEs, SLSNe-I).

Validation of Model Architecture and Training

Model	b-AUROC	b-AUPRC	b-Precision	b-Recall	b-F_1 Score	Accuracy
Baseline	0.74 ± 0.04	0.52 ± 0.07	0.58 ± 0.13	0.46 ± 0.09	0.48 ± 0.11	0.82 ± 0.02
No Host	0.72 ± 0.08	0.48 ± 0.09	0.48 ± 0.12	0.41 ± 0.09	0.40 ± 0.08	0.78 ± 0.02
No Primary Training	0.71 ± 0.04	0.45 ± 0.02	0.40 ± 0.18	$0.34 \pm < 0.01$	0.30 ± 0.01	$0.81 \pm < 0.01$
No Adaptive Training	0.65 ± 0.03	0.43 ± 0.02	0.41 ± 0.02	0.39 ± 0.05	0.39 ± 0.03	0.66 ± 0.02

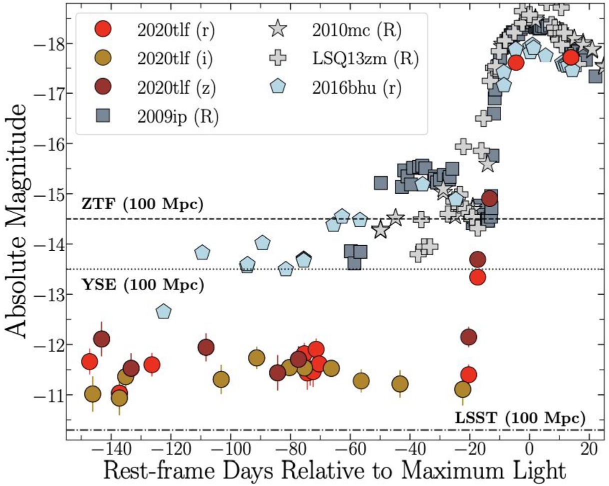
Host-galaxy photometry, balanced training, *and* re-training on real data improves every classification metric.

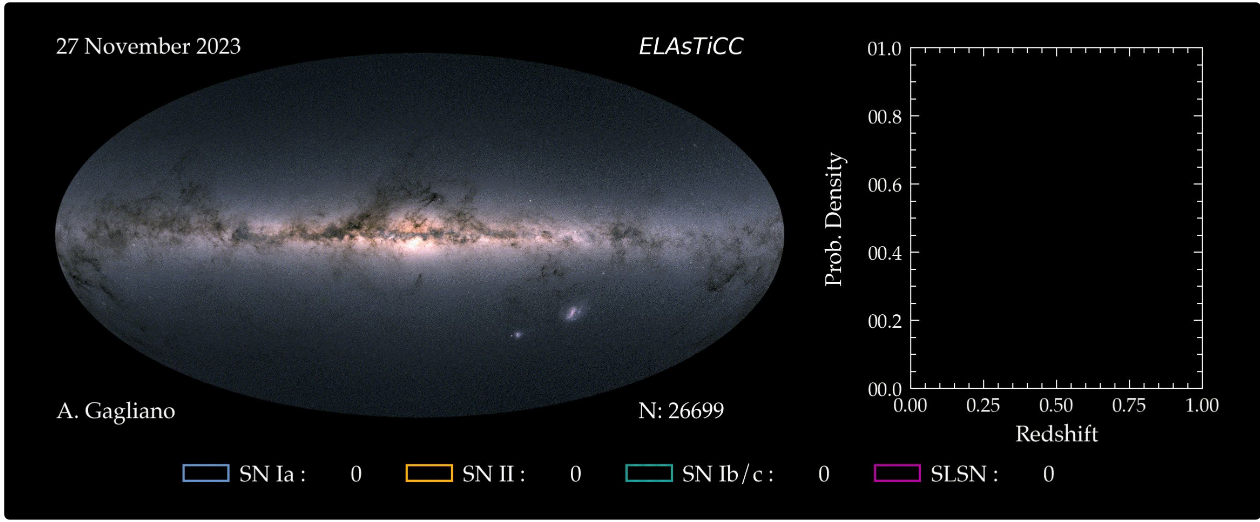
(Mandel & Foley, 2013)

	Exclusively Using Observable		
Observable	Peak FoM	Improvement Factor	Difference in Medians
Baseline[a]	0.121	N/A	N/A
Using All Galaxy Data[b]	0.269	2.23	0.34
Morphology	0.262	2.18	0.15
Color	0.128	1.06	0.10
Luminosity	0.135	1.12	0.07
Effective Offset	0.122	1.02	0.03
Pixel Rank	0.123	1.02	0.00

Incorporating (even small) postage stamps will further improve performance.

Proactive Supernova classification with Rubin





(Jacobson-Galán+2022)

Deep, precise photometry with LSST will enable **broad pre-explosion variability studies**, further revolutionizing our transient taxonomy.

Drivers for Supernova Science with Rubin

(TVS Roadmap, Hambleton+2022; Data to Software to Science, Breivik+2022; DESC Science Overview, 2023)

1. **In-Depth Studies of Fast Phenomena**
2. **Refined Progenitor Theories**
3. **Expanding the Supernova Classification Schema**
4. **Understanding Transient-Host Galaxy Correlations**

These demand:

- *Automation of the Discovery and Analysis Chain*
- *Accurate Identification of Host Galaxies*
- *Realistic Precursor Datasets*

Simple, context-aware models bring us closer to realizing these goals.

Conclusions

Contextual information can aid early Ia/Ibc/II classification, when SN photometry is minimal, but models should be adaptive to new data *(Gagliano+2023)*.

Simple, scalable inference models will be essential for both population-level and single-object studies of Rubin supernovae. **We should validate them now.**