Time-domain astronomy in the era of LSST

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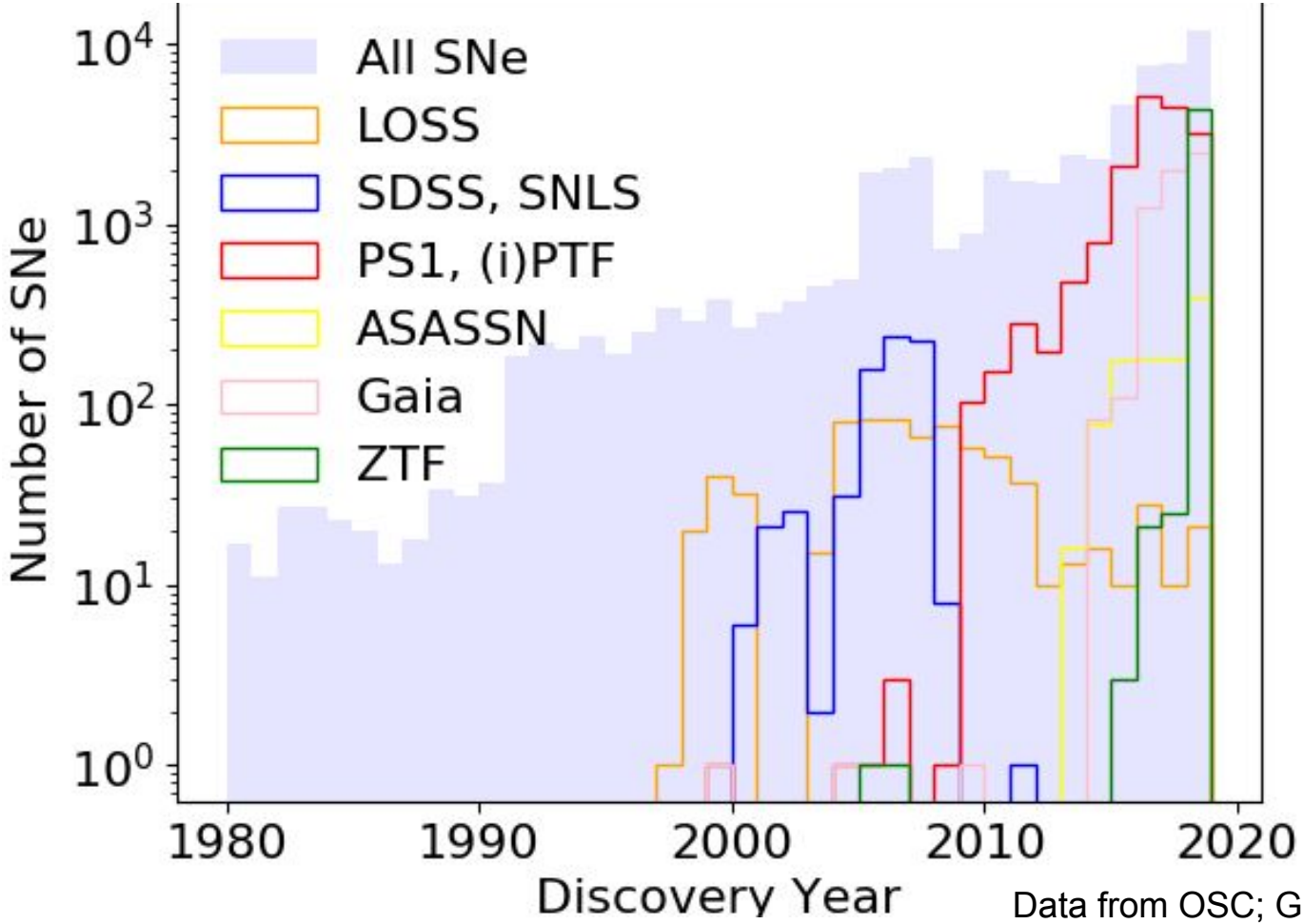
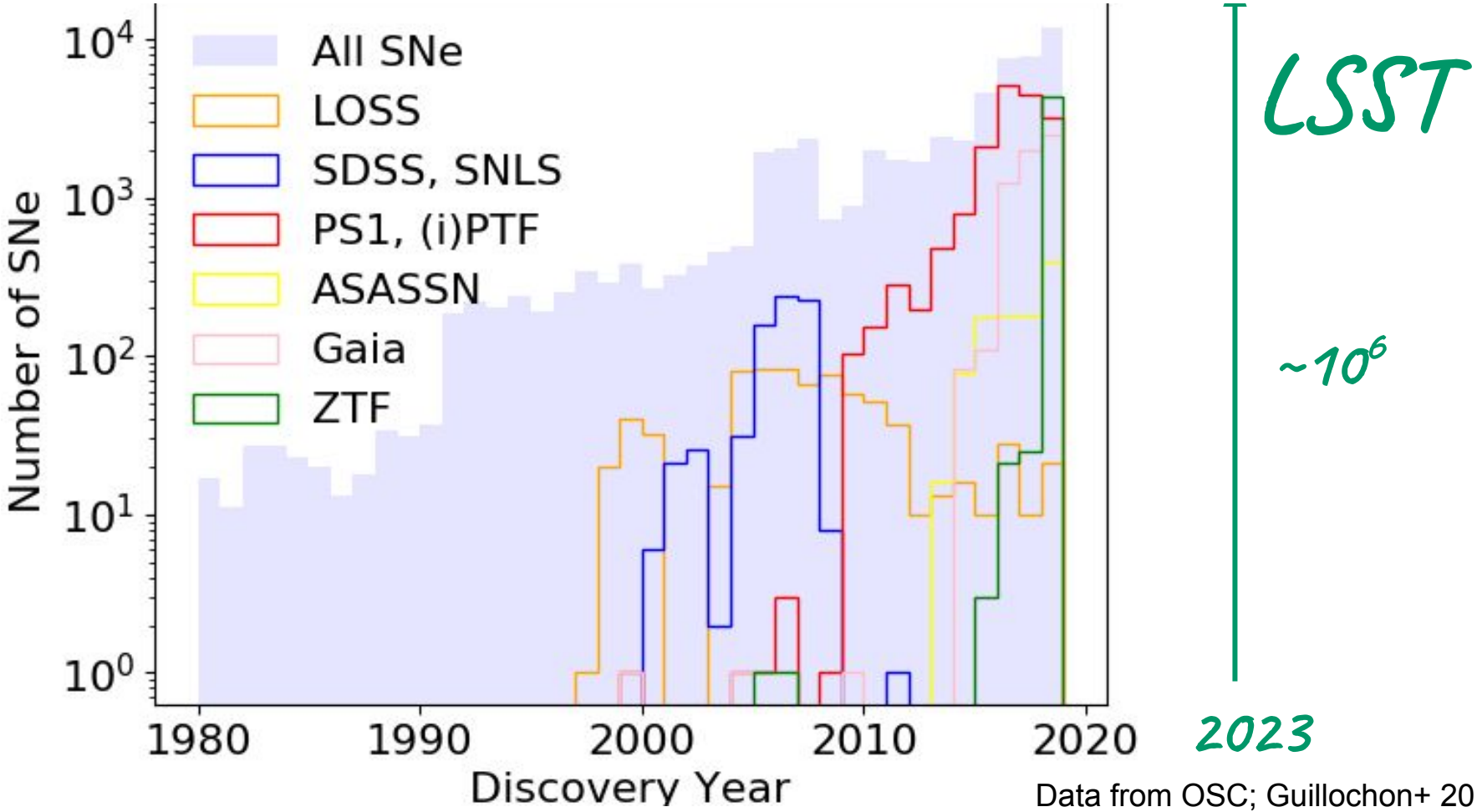
With thanks to: E. Berger, M. Nicholl, J. Guillochon, PS1 Collaboration

We currently discover ~10,000 SNe annually



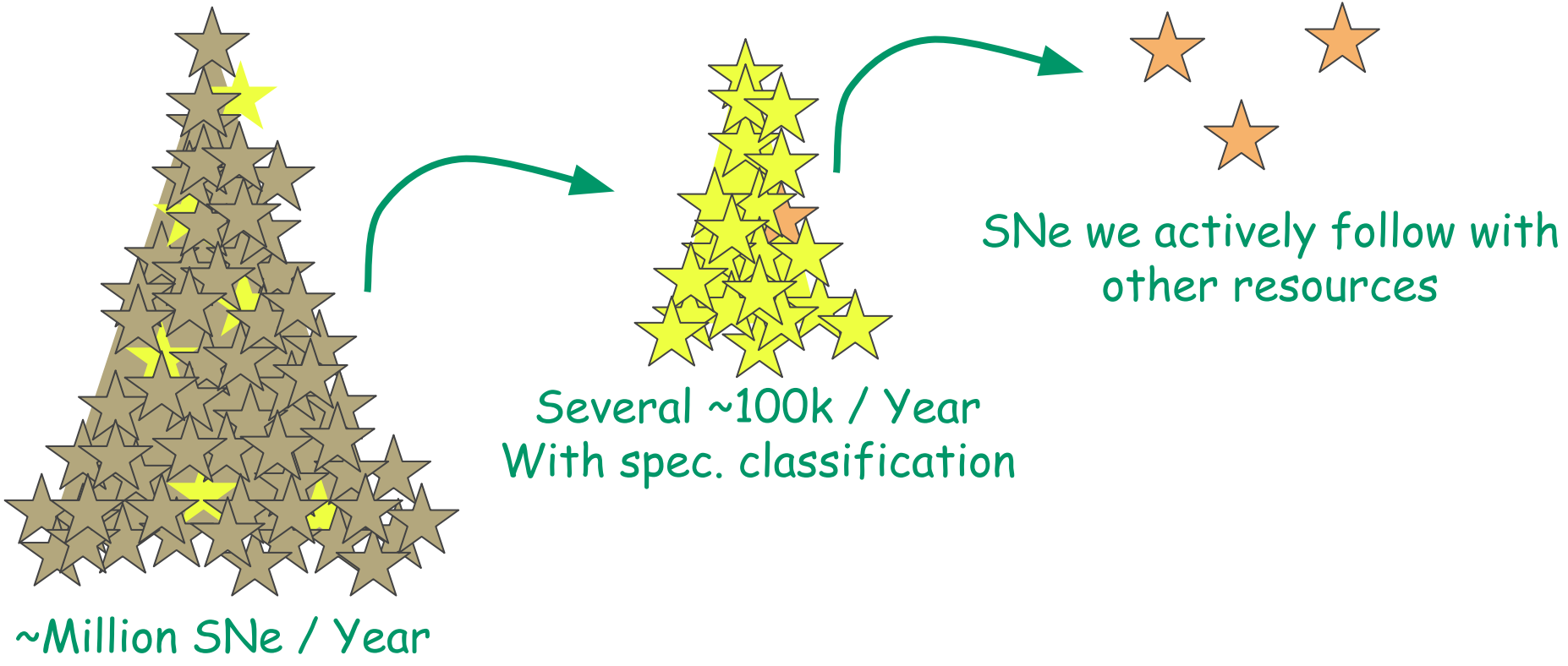
Data from OSC; Guillochon+ 2018

LSST may discover 1 million SNe annually!

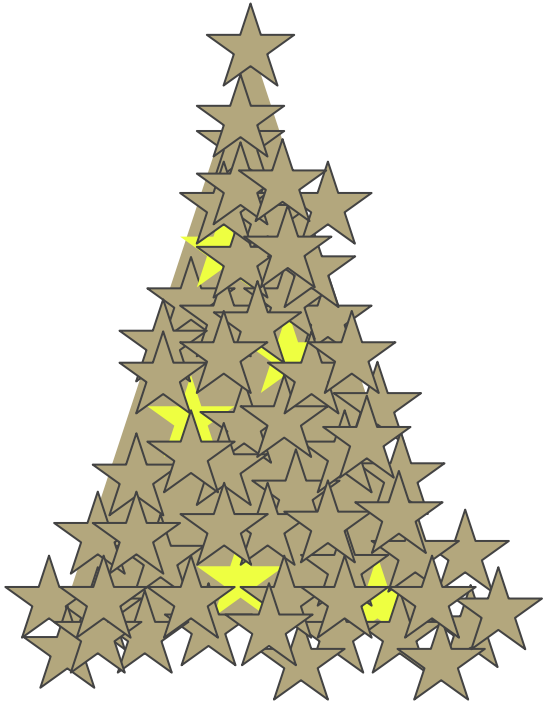


Data from OSC; Guillochon+ 2018

The Needles & the Haystack



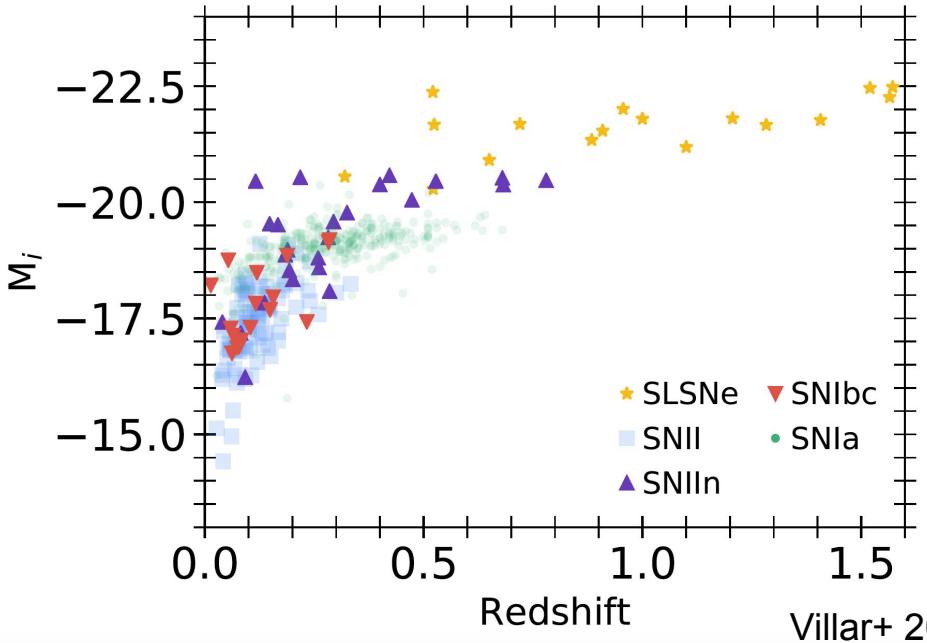
The Needles & the Haystack



~Million SNe / Year

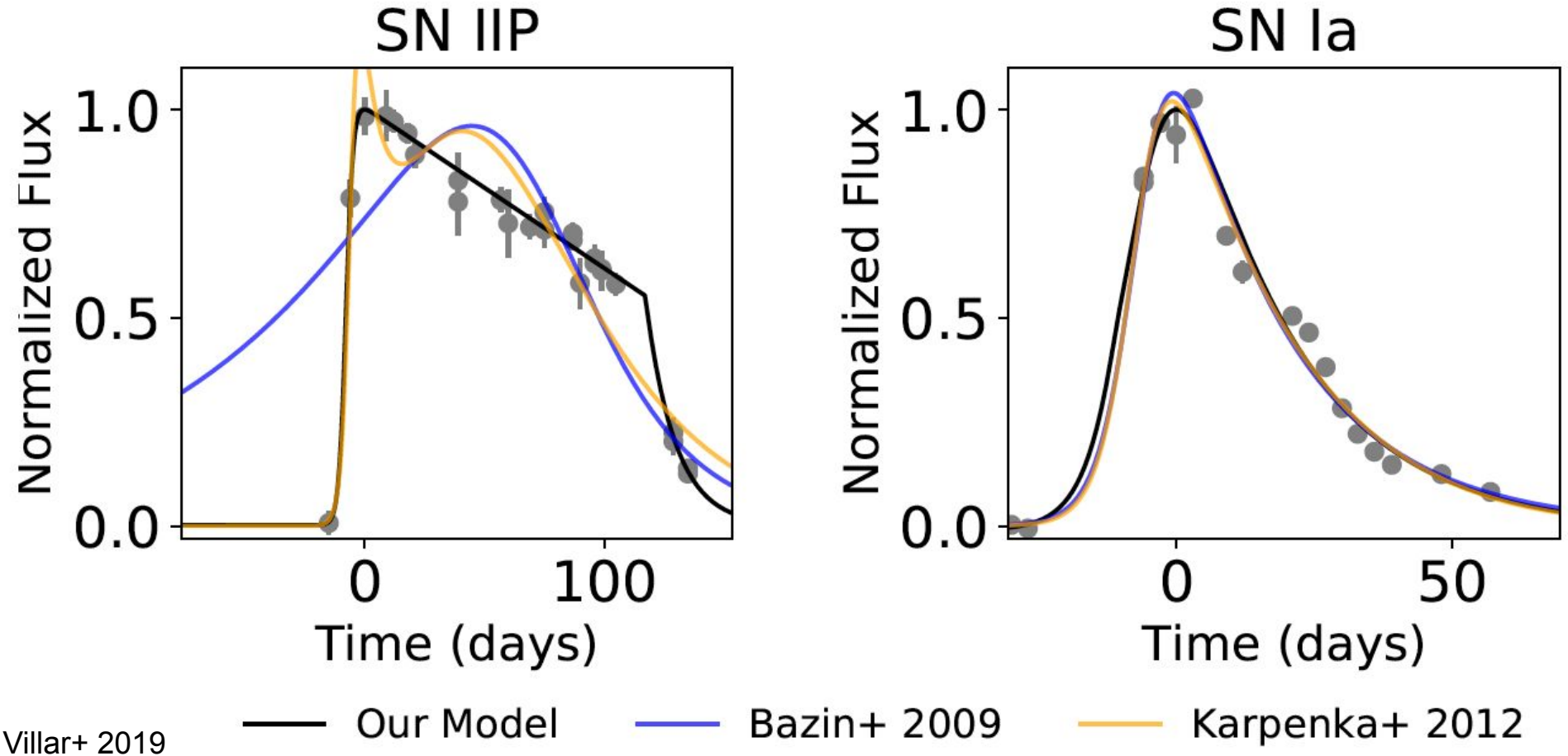
Can we classify SNe into their spectroscopic subtypes, given a complete multiband light curve and redshift?

- ~ 5200 SNe-like transients in PS1 Medium Deep Survey (Jones+2017)
- ~ 3100 have host redshift measurements
- 518 SNe are spectroscopically classified with host redshift measurements



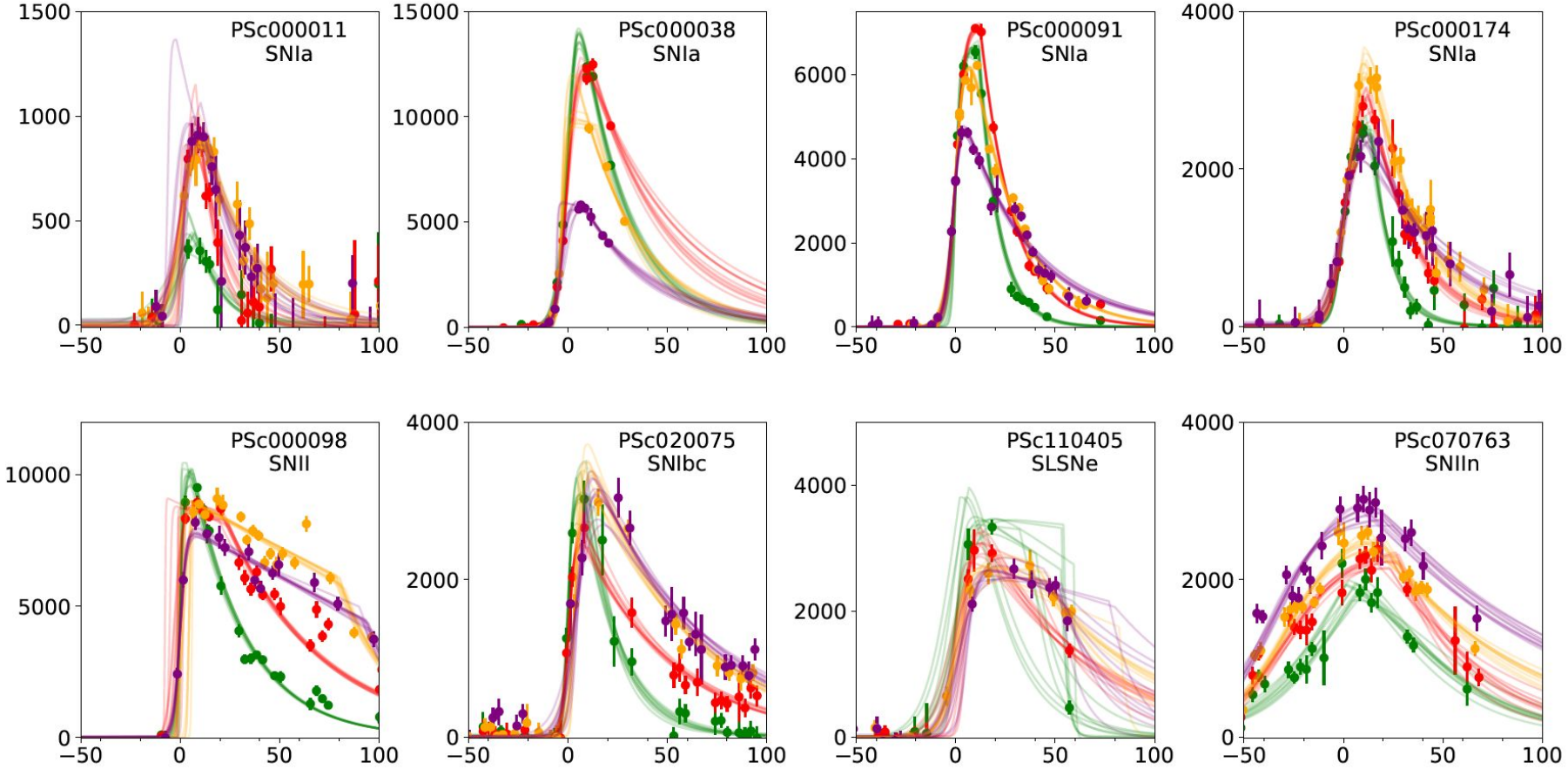
Villar+ 2019

We introduce a new analytical model to better fit all SNe subtypes

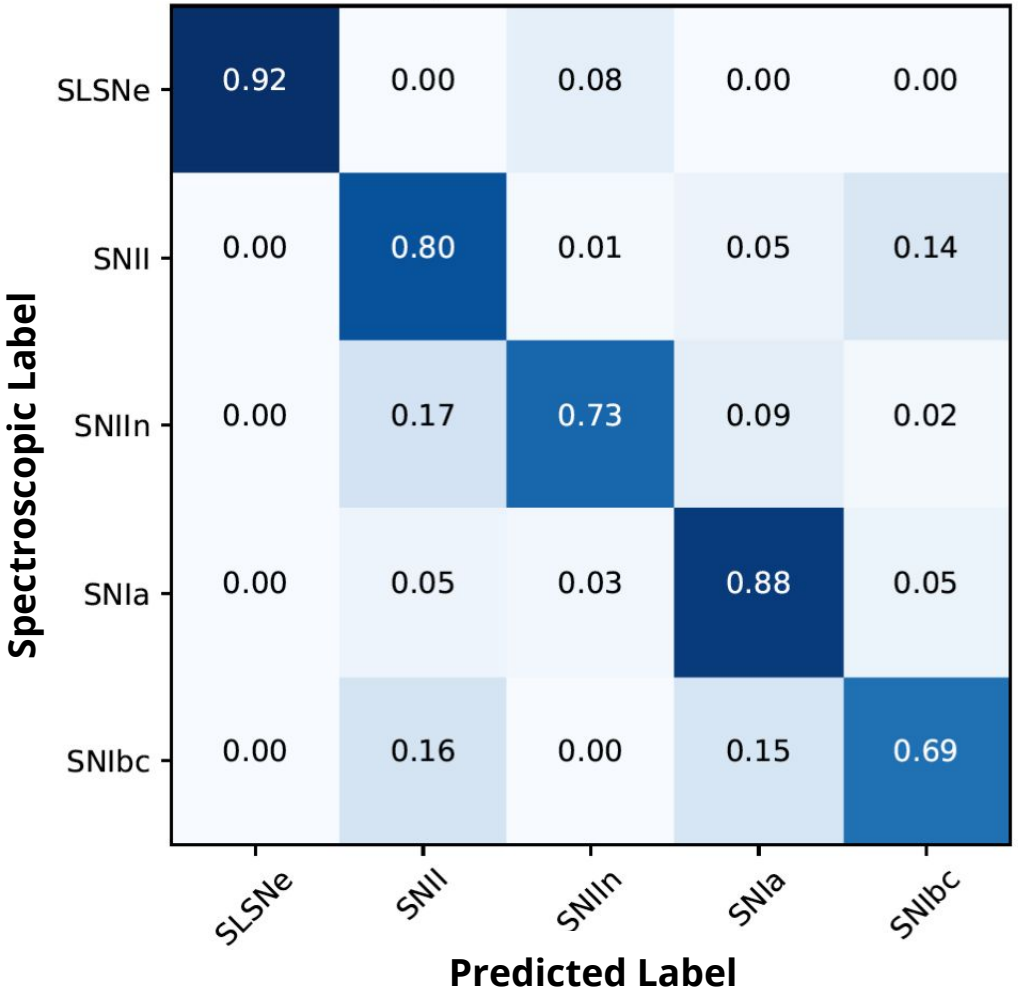


Villar+ 2019

Using posterior draws from an MCMC, we can understand the uncertainty of our classifications



Villar+ 2019



Our classification pipeline performs similarly to:

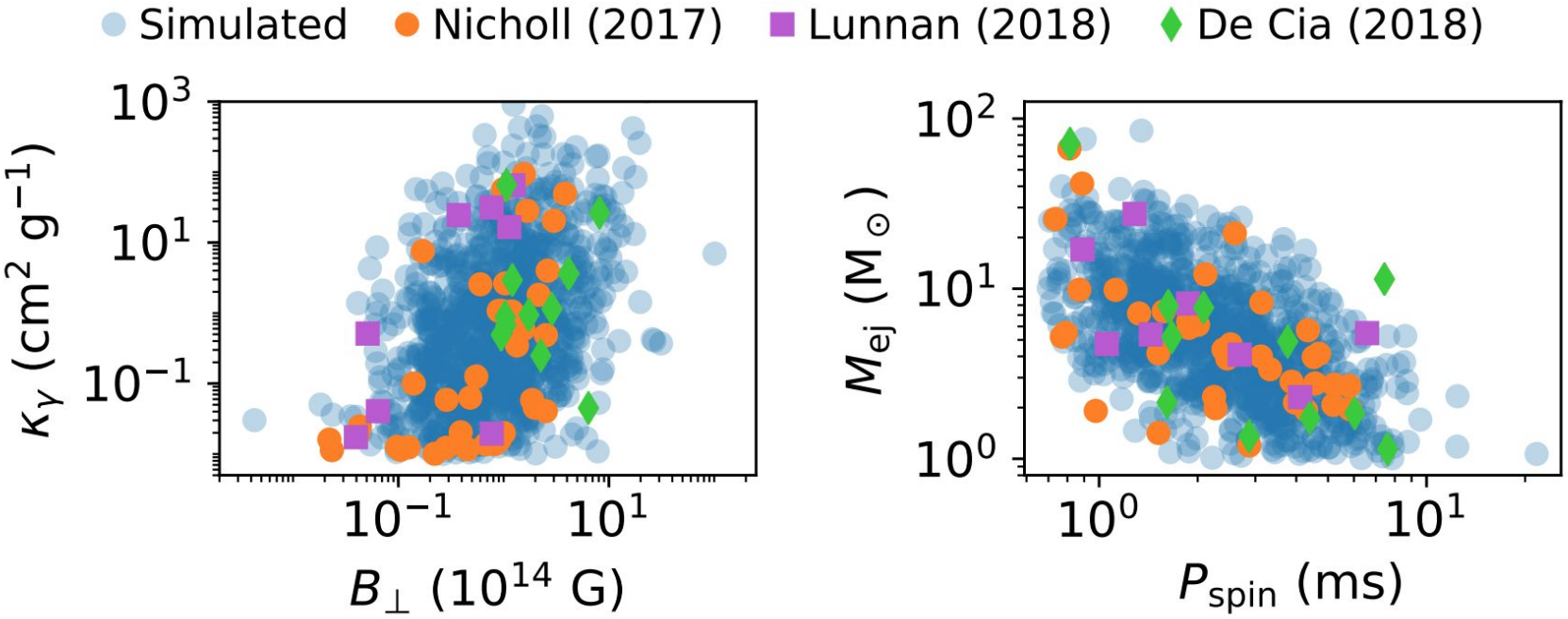
- Ia-vs-nonIa classifiers (e.g., Ishida & de Souza 2013;Charnock & Moss 2017; Jones et al. 2017)
- Classifiers trained on synthetic data (e.g., SNPCC, PLAsTiCC)

Villar+ 2019

Classification is the first step!

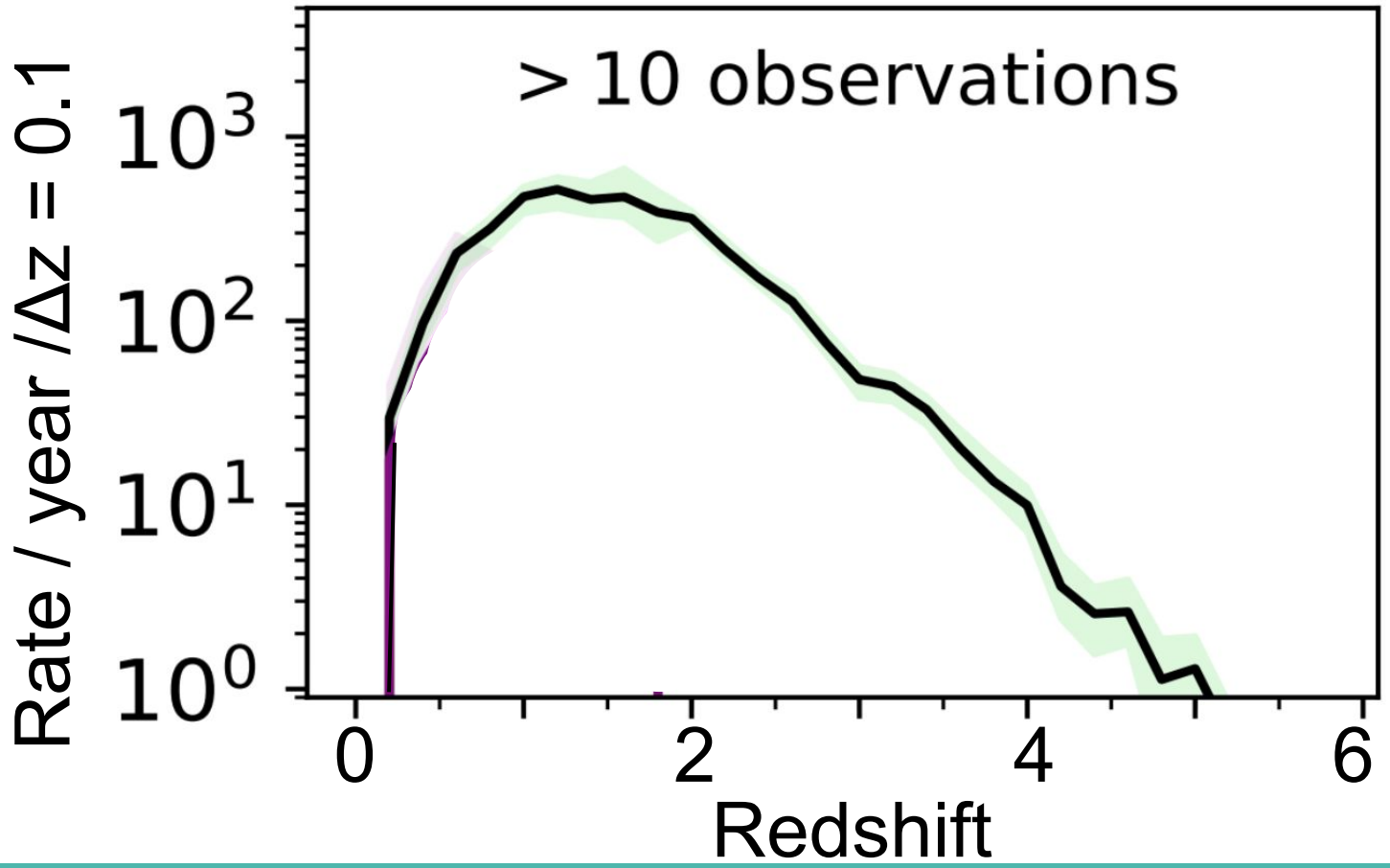
Can we actually gain physical insight with *only* optical light curves?

We model 58 SLSNe from the literature using a magnetar model, use these fits to simulate the SLSNe population & inject them into an LSST simulation (OpSim)



Villar+ 2018b

Redshift distribution



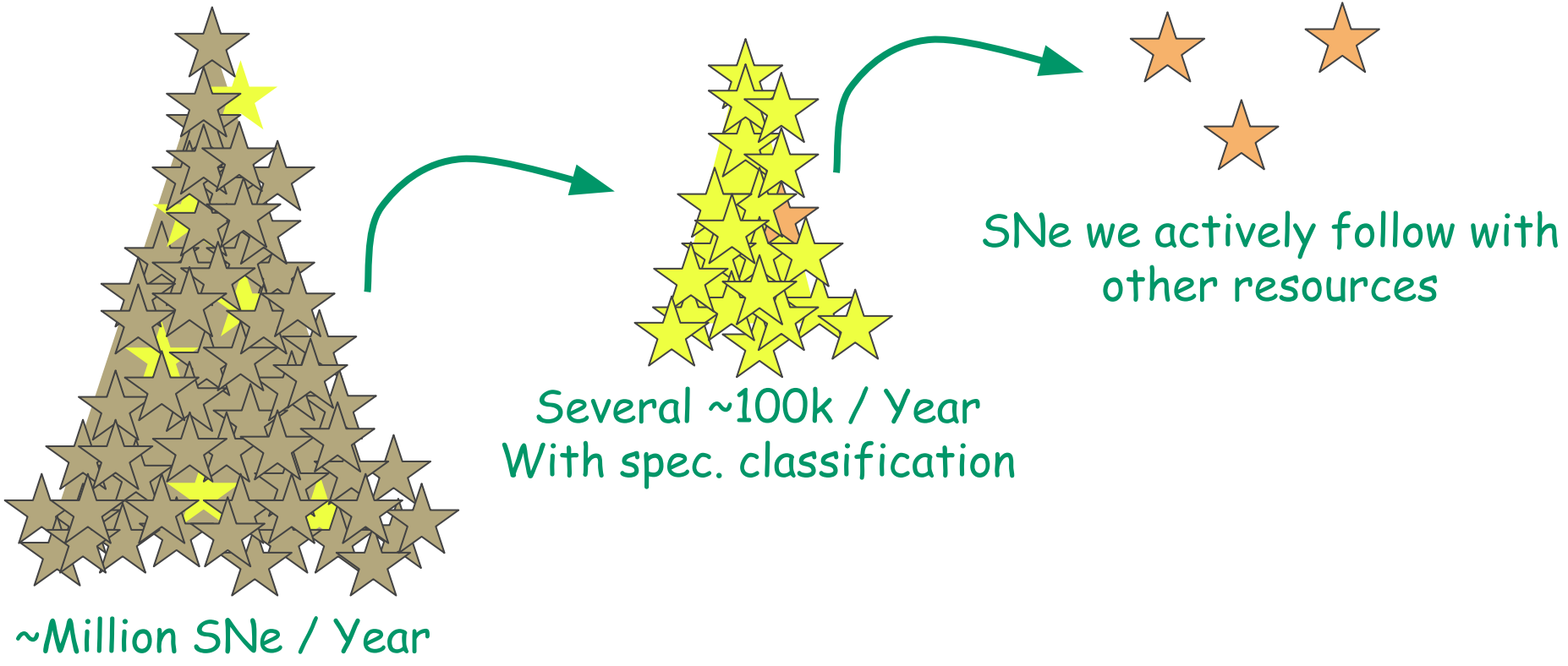
Villar+ 2018b

We uncover the “information content” by refitting our simulated light curves using MOSFiT

~5,000 SLSNe / year with recoverable parameters to within a factor of 2

~2,000 SLSNe / year with recoverable parameters to within 30%

The Needles & the Haystack

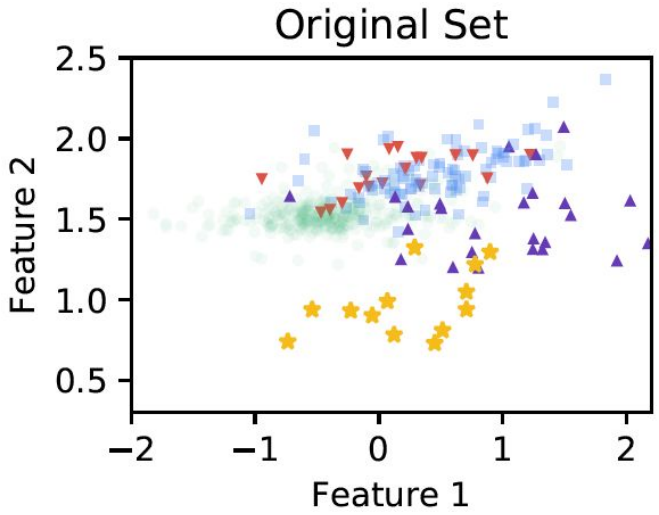


A concluding point about those “needles”

- “Needles” will represent 1/10,000 outliers (given multiwavelength observing/person-hour constraints)
- Anomaly detection (even with state-of-the-art machine learning) is *challenging*, especially when SN LC properties overlap
- More likely than not, machine learning will not *choose* interesting objects for us
- Instead, we can use our domain knowledge to construct simple, physically-motivated cuts to search for the most “interesting” needles
- I’d love to chat more about this!

Conclusions & Thanks!

- LSST will increase transient discovery rate by several orders of magnitude, leaving us to search for needles in a haystack of nightly objects
- In preparation, we train a classifier on the PS1-MDS SNe dataset, utilizing a MCMC to generate simple LCs with extractable features
- We find our classifier performs as well as those trained for on Ia-vs-non Ia classification, and those trained on synthetic datasets
- Using SLSNe as an example, we show that we can extract useful physical information from LCs alone, allowing us to perform population studies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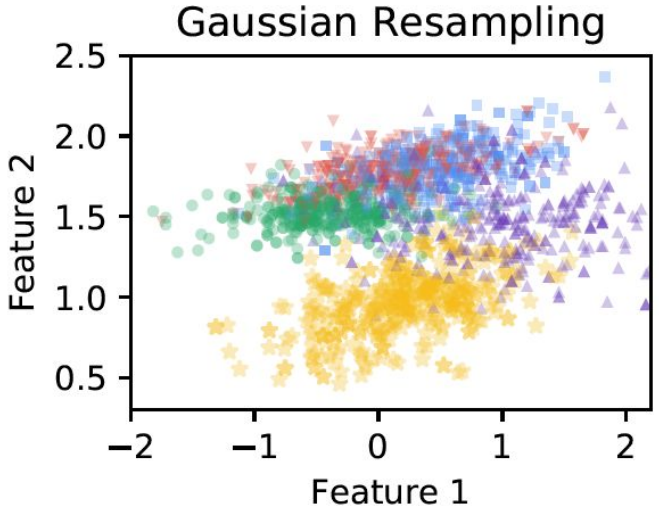
Feature 1
2.5
2.0
1.5
1.0
0.5
−2
−1
0
1
2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Feature 1
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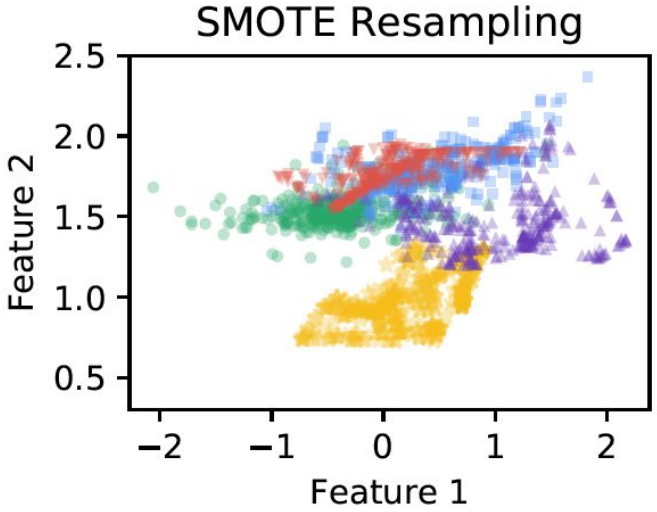
2.0
1.5
1.0
0.5
−2
−1
0
1
2


SMOTE Resampling
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Feature 1
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2.0
1.5
1.0
0.5
−2
−1
0
1
2