Considerations for optimizing photometric classification of supernovae from the Rubin Observatory

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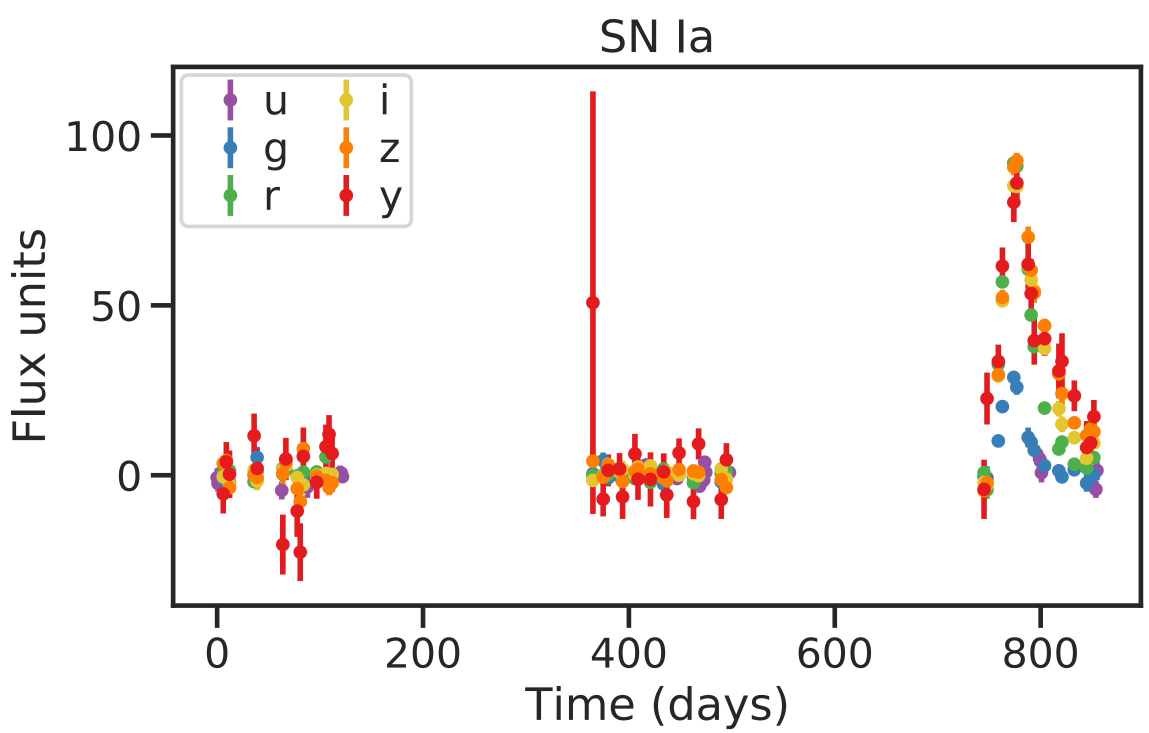
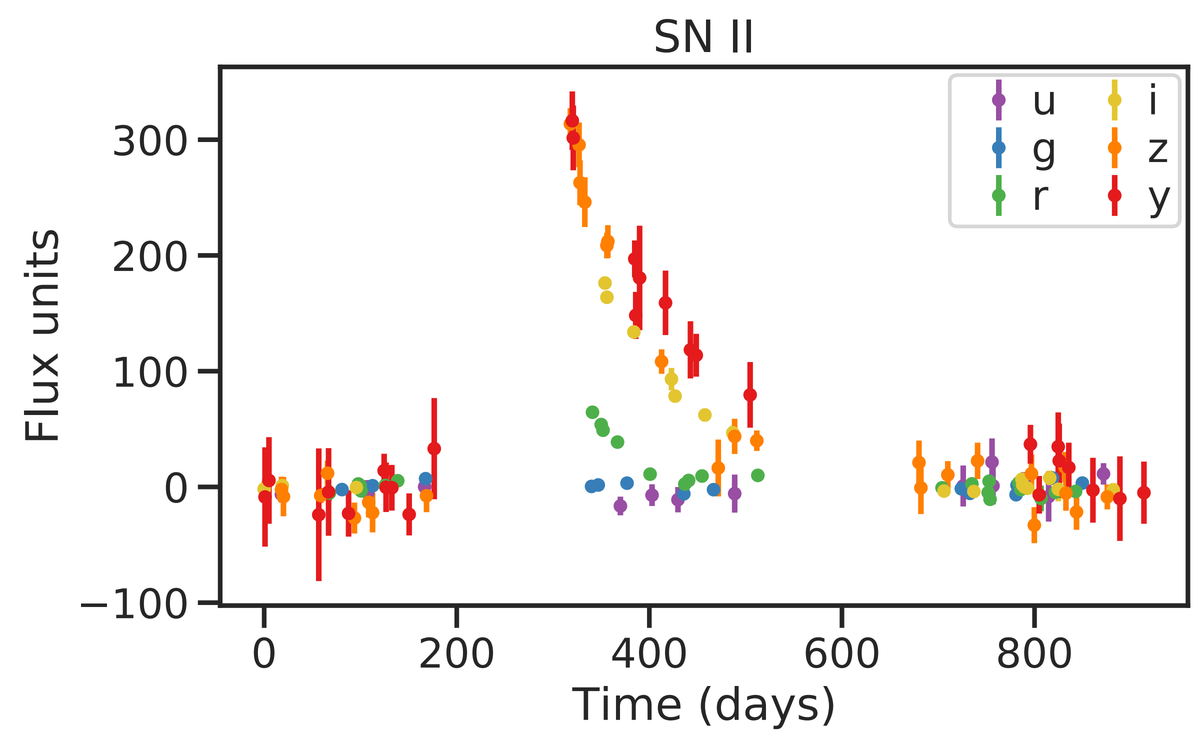
Motivation

- The Rubin Observatory Legacy Survey of Space and Time (LSST) will discover 3-4 million supernovae (SNe)
- Limited spectroscopic resources → photometric classification
- Photometric classification performance depends on the survey observing strategy
- **First study to analyze the impact of the LSST observing strategy on SNe classification**

PLAsTiCC

- **P**hotometric **L**SST **As**tronomical **Ti**me-Series **C**lassification **C**hallenge
- Simulated multi-band light curves for 3 years of LSST
- Realistic observing conditions but outdated observing strategy
- Simulated spectroscopically-confirmed training set biased towards nearby, brighter events → non-representative

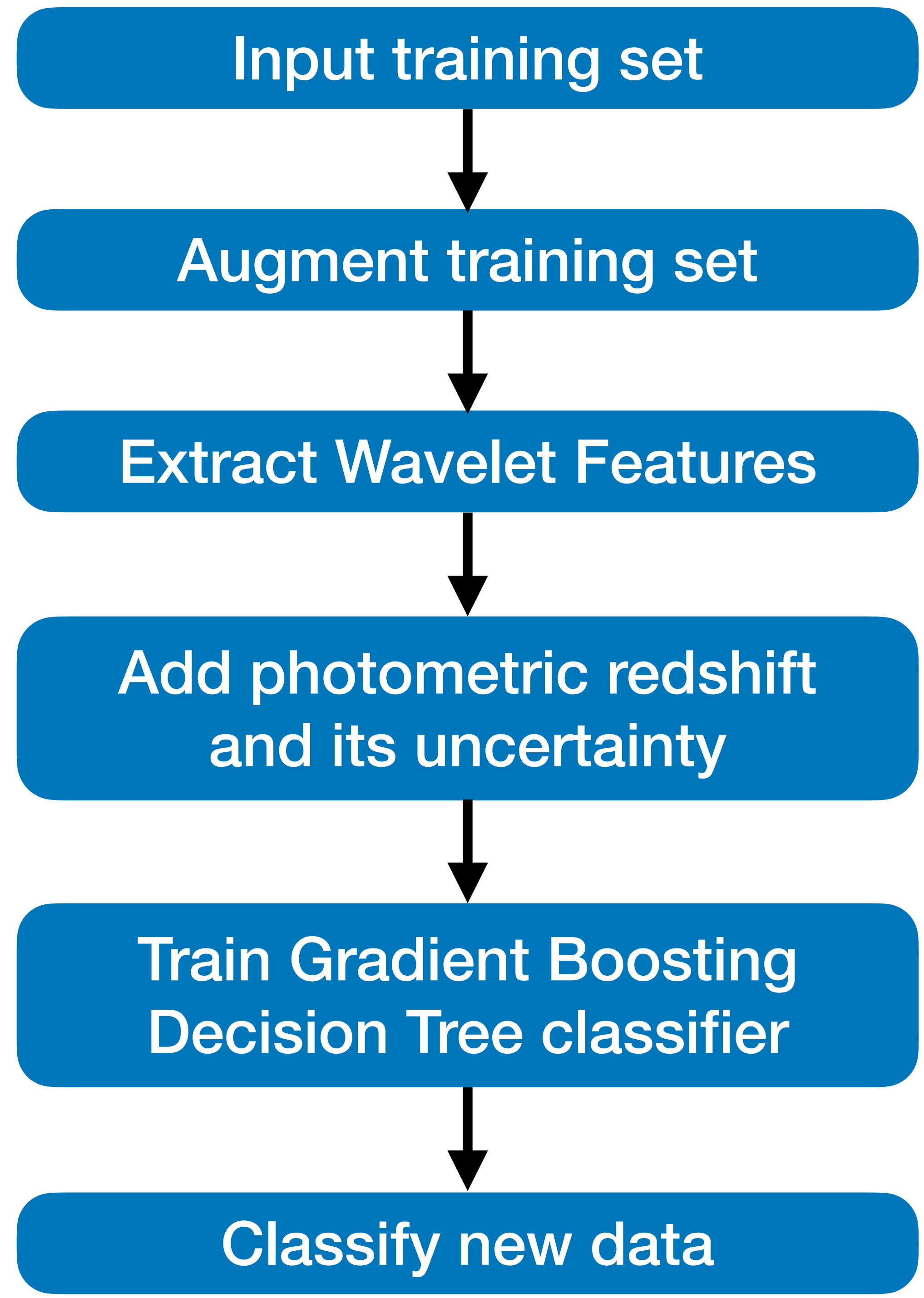




The PLAsTiCC team et al. 2018; PLASTICC Team & PLASTICC Modelers 2019

snmachine pipeline

- Build a classifier using the photometric transient classification library snmachine (Lochner et al. 2016)
- Original version of snmachine used in Lochner et al. (2016), Narayan et al. (2018), Malz et al. (2019), Carrick et al. (2020), Sooknunan et al. (2021)
- snmachine upgraded for use with LSST data
- Public release with the accompanying paper soon

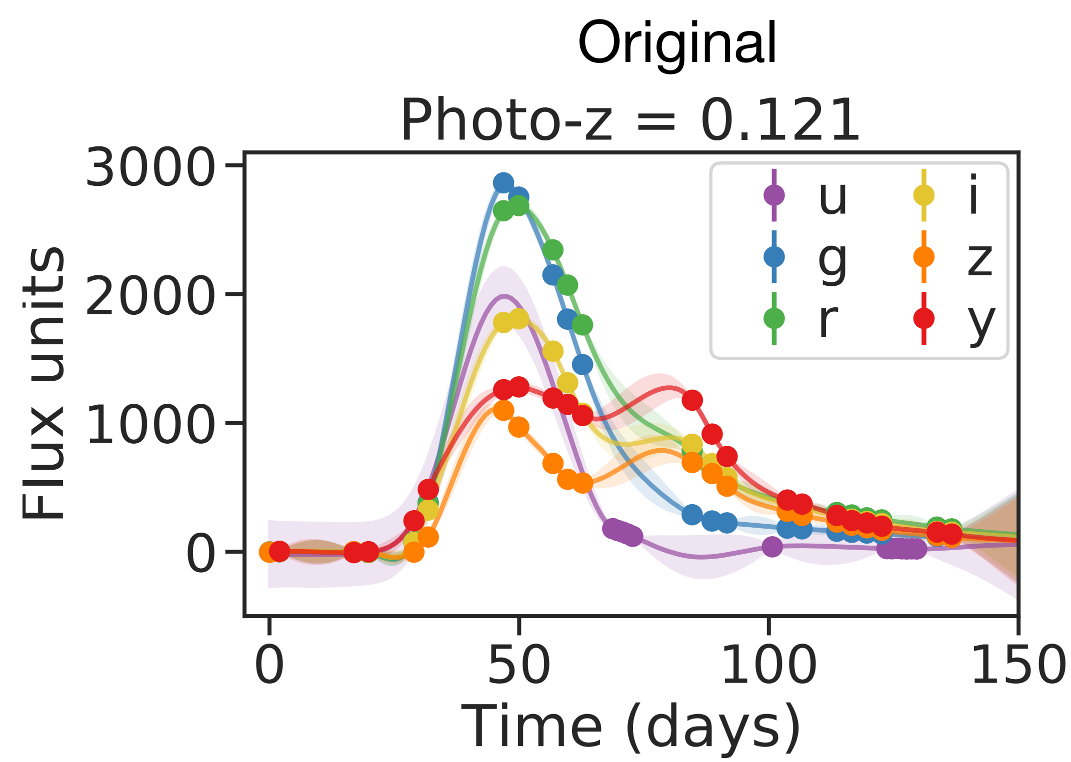


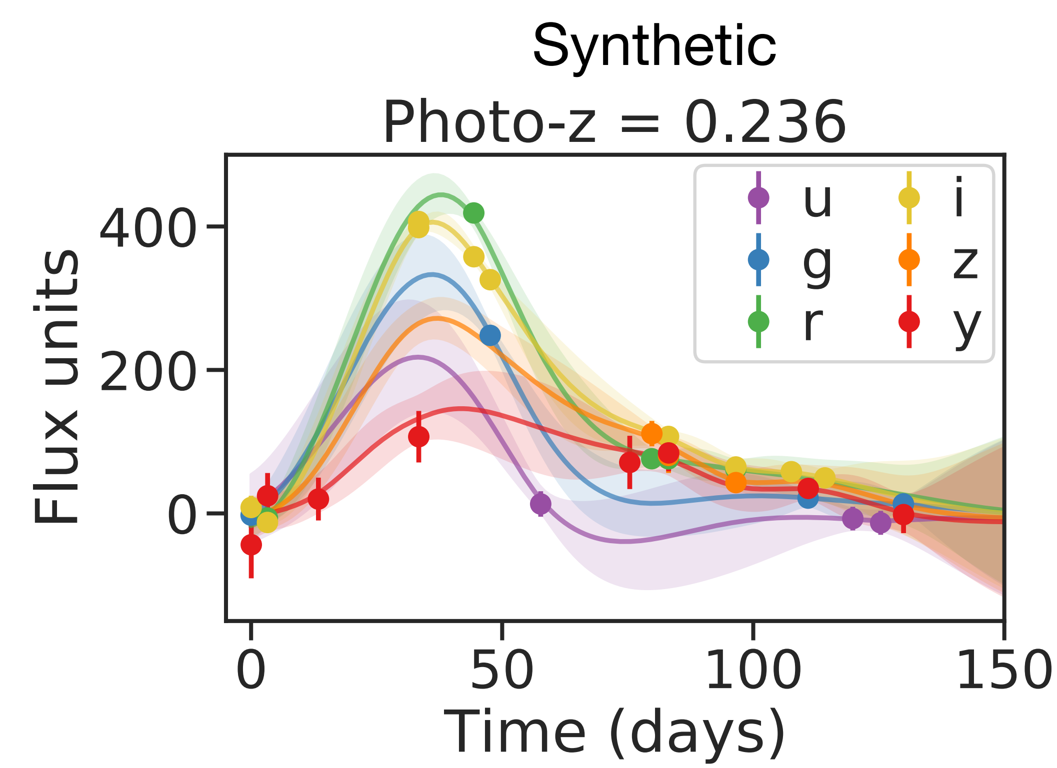
Training set augmentation

- Augment the simulated training set to be representative of
  - the photometric redshift distribution per SNe class,
  - the cadence of observations,
  - and the flux uncertainty distribution of the test set

- New light curves from 2D Gaussian processes (based on Boone, 2019)

- Same number of augmented events from **each SN class**





Wavelet features

- Wavelet features are model independent
- Localised both in time and frequency
- General features → can characterise many classes of transients
- Successful for general transient classification (e.g. Varughese et al. 2015; Lochner et al. 2016; Gautham Narayan et al. 2018; Sooknunan et al. 2021)
- Approach not previously used by the winning PLAsTiCC entries

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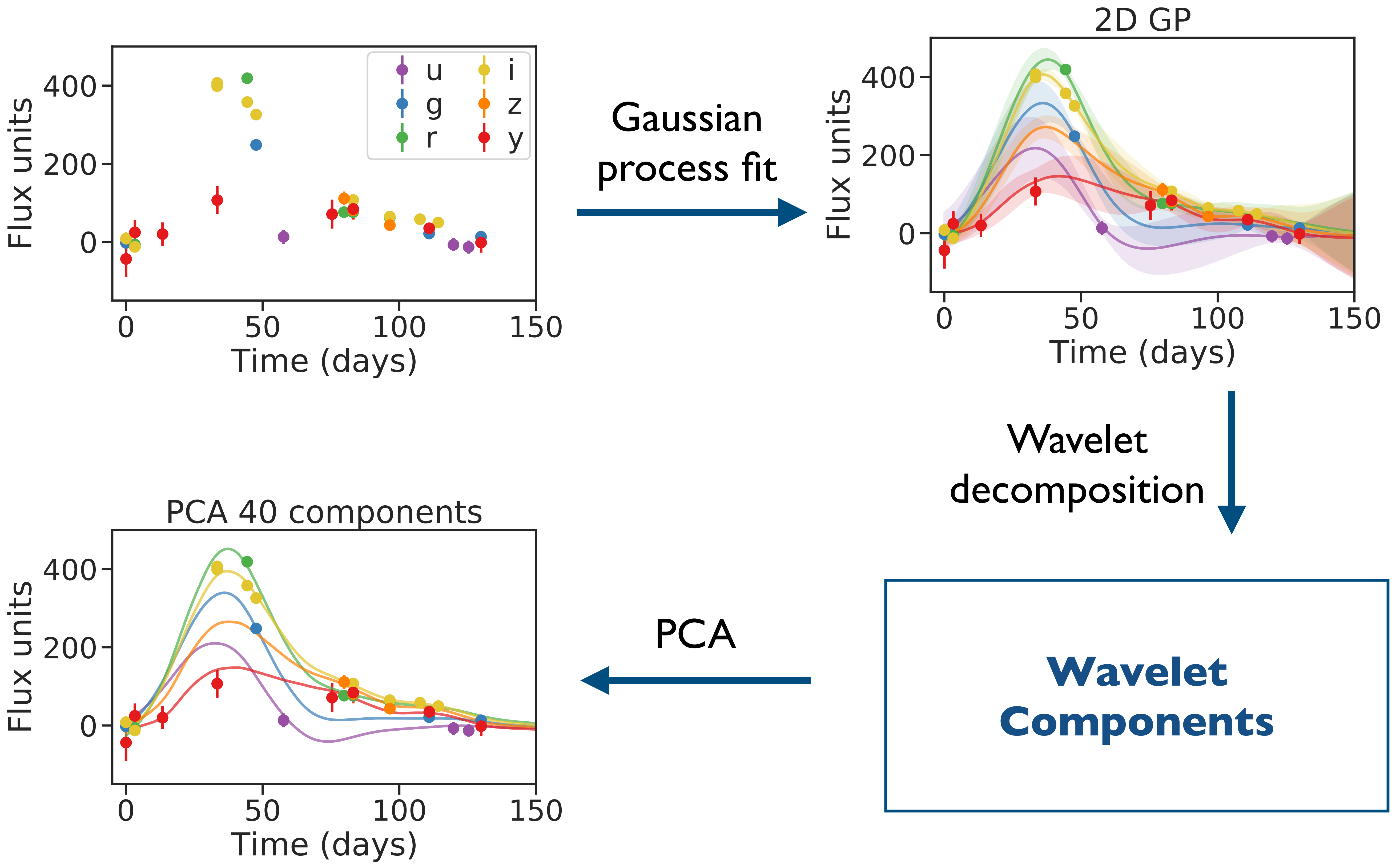
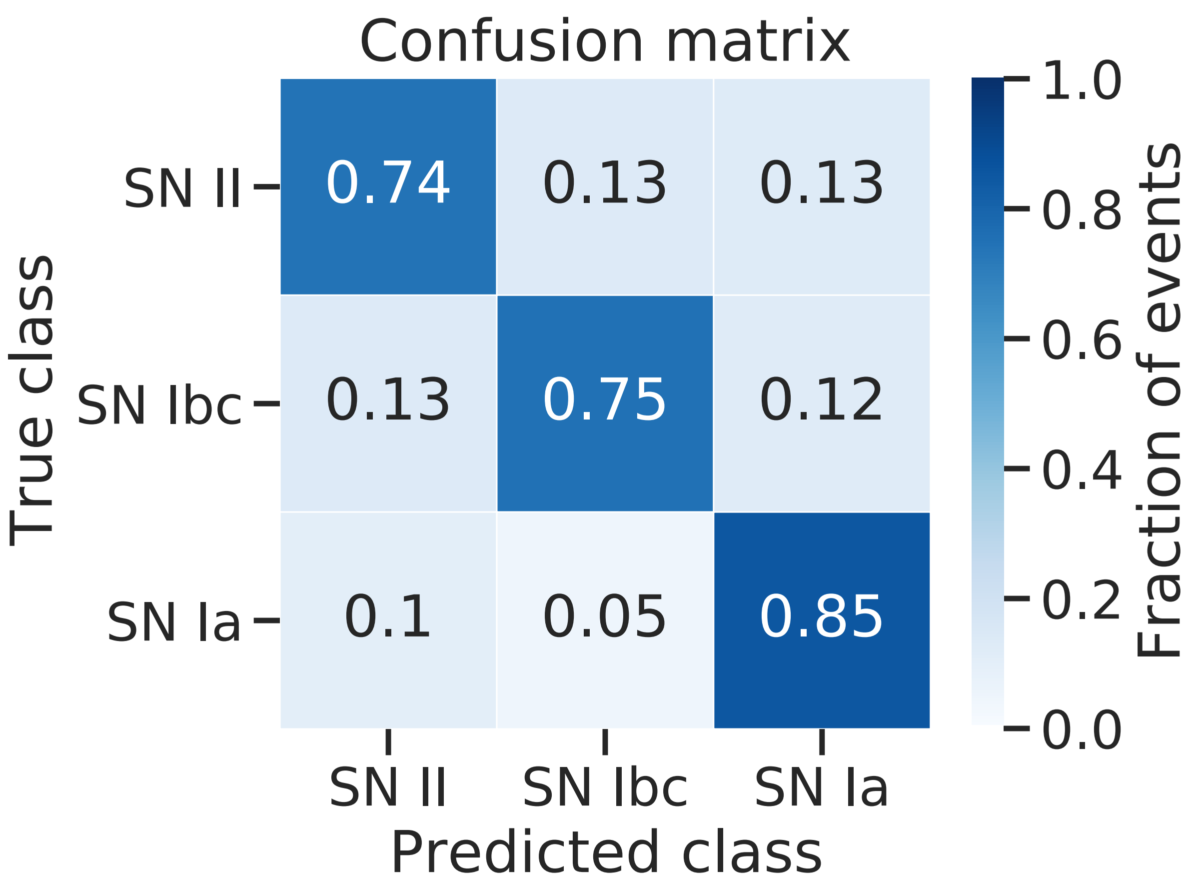
How do we extract wavelet features?

Wavelet features extraction



Classification and performance

- Use the augmented training set to train a classifier with the features:
  - wavelet features (40 PCA components)
  - photometric redshift + its uncertainty
- Use the PLAsTiCC weighted log-loss metric (Malz et al. 2019)
- Performance comparable to that obtained by the top three submissions to PLAsTiCC



Observing strategy

- **What are the implications for observing strategy?**

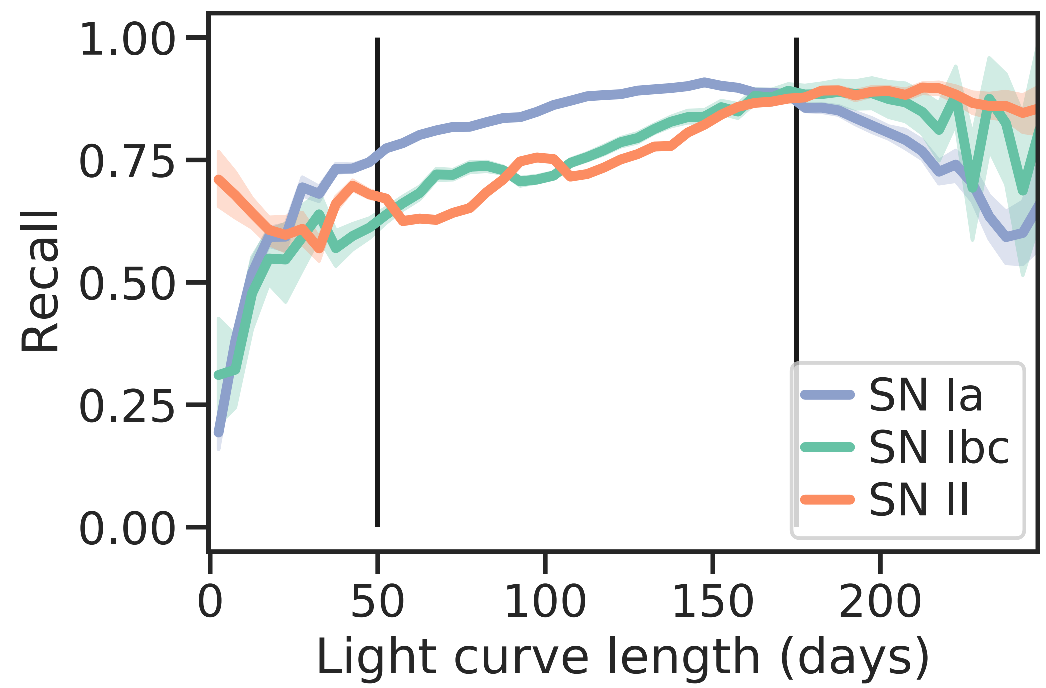
- We study classification performance for SNe with different properties within the single simulated observing strategy that is available in PLAsTiCC

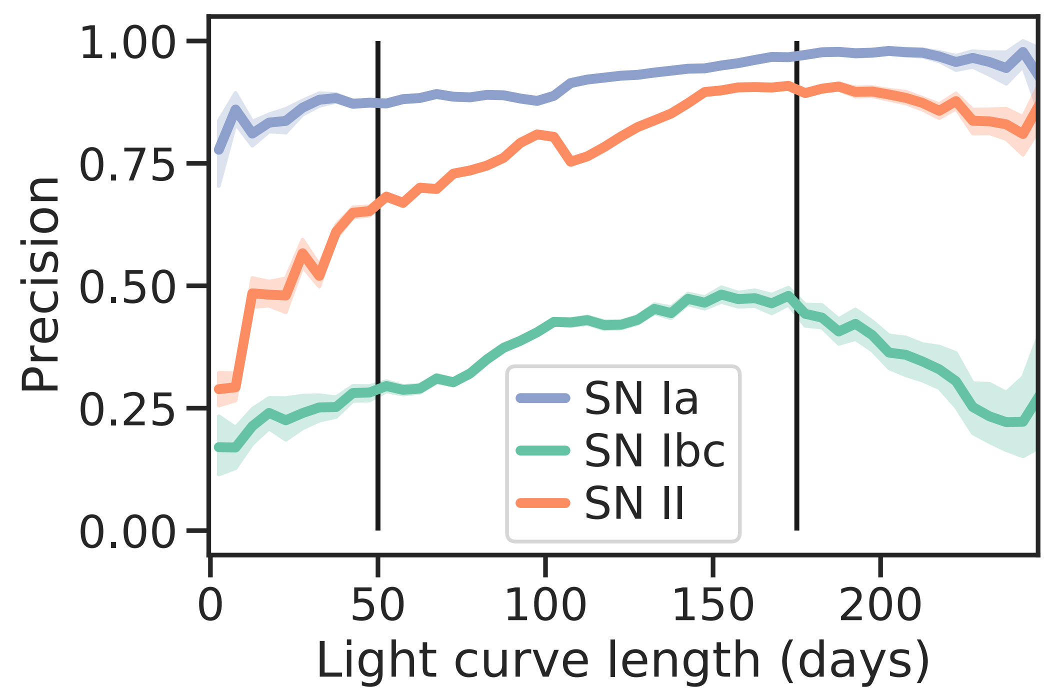
- Measure the performance using:
    - $\text{Recall} = \dfrac{\text{TP}}{\text{TP} + \text{FN}}$
    - $\text{Precision} = \dfrac{\text{TP}}{\text{TP} + \text{FP}}$

		True class	
		Positive (P)	**Negative (N)**
Predicted Class	**P**	True positive (TP)	False positive (FP)
	N	False negative (FN)	True negative (TN)

Light curve length

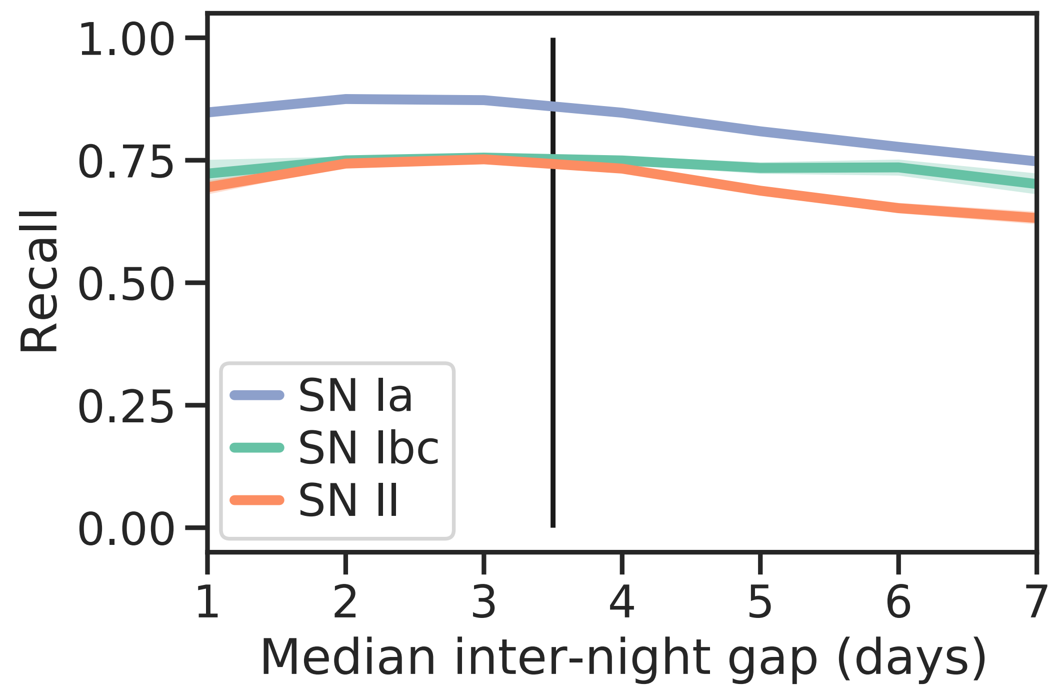
- Season length → tuned by taking additional observations in suboptimal conditions
- Light curve length → proxy for season length
- Focus on light curve lengths between 50–175 days; small-number effects outside that range
- Events observed for longer
  → better characterization by the feature extraction step
  → higher recall and precision

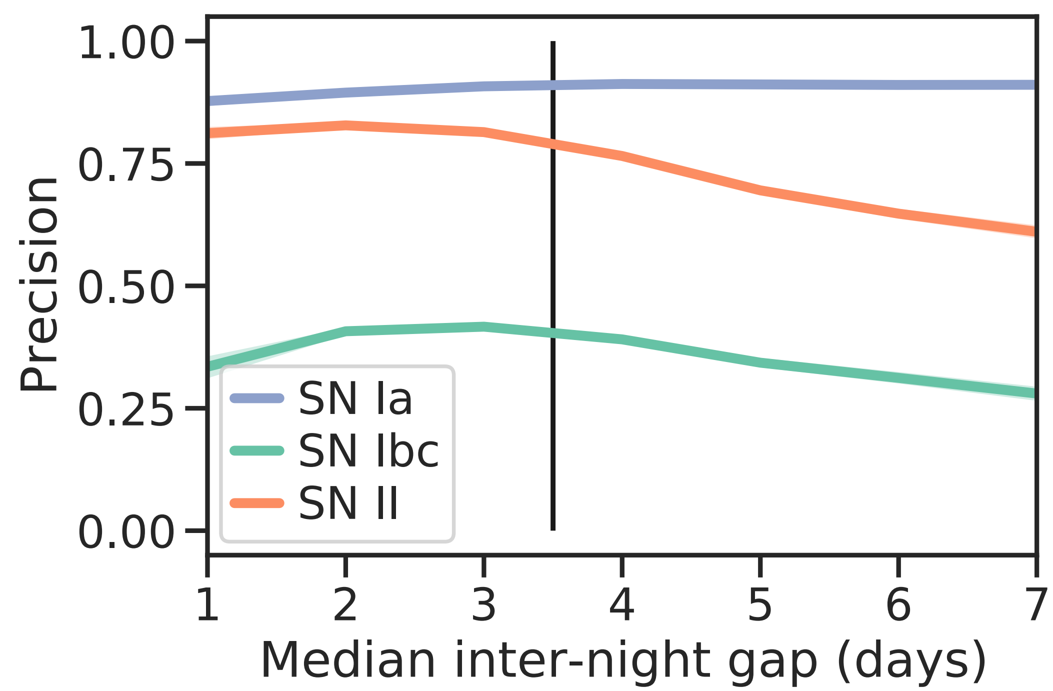




Median inter-night gap

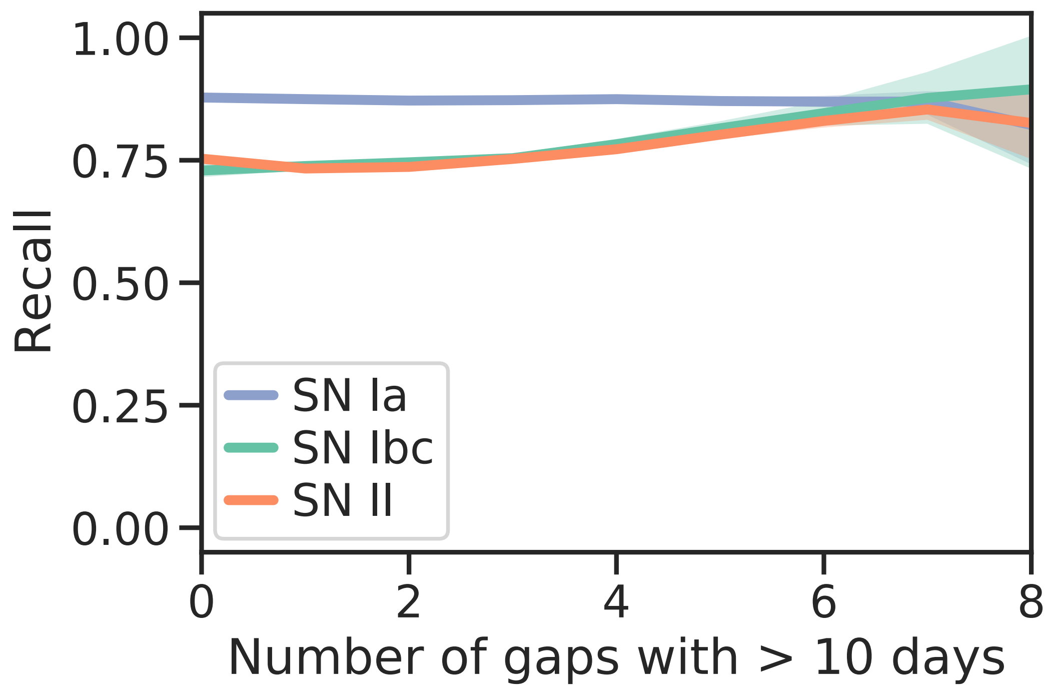
- Cadence of observations → impacts all transient science goals
- Inter-night gap → quantifies the cadence
- Events whose median inter-night gap is < 3.5 days
  → better sampled events
  → higher light curve quality
  → higher recall and precision

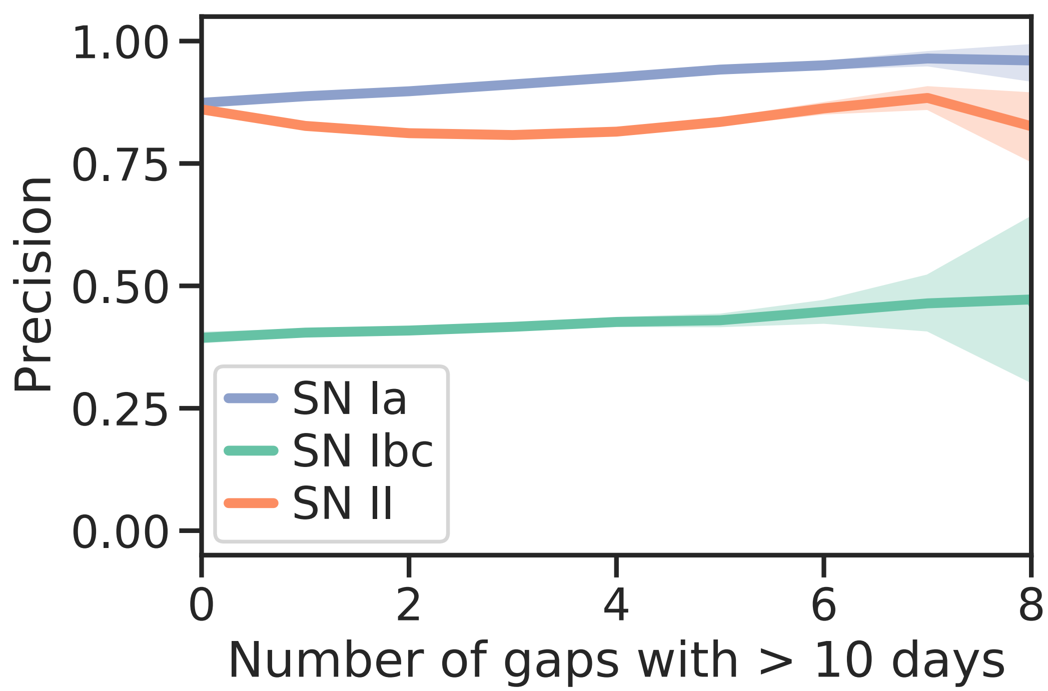




Large inter-night gaps

- Effect of the number of large gaps in events with a median inter-night gap < 3.5 days
- GP fits can interpolate large gaps if median inter-night gap < 3.5 days → recall and precision independent of the number of large gaps
- Results show that a median inter-night gap of < 3.5 days is sufficient for photometric classification





Conclusion

- Augmentation is crucial to obtain a representative training set
- First study of how observing strategy impacts photometric classification:
  - longer light curves → higher performance
  - median inter-night gap of $<$ 3.5 days → higher performance
  - number of inter-night gaps $>$ 10 days → no impact
- The results provide guidance for further refinement of the LSST observing strategy on the question of SNe photometric classification
- Public release of `snmachine`

PLAsTiCC metric

$$\textbf{Log-loss} = -\left(\frac{\sum_{i=1}^{M} w_i \cdot \sum_{j=1}^{N_i} \frac{y_{ij}^*}{N_i} \cdot \ln p_{ij}}{\sum_{i=1}^{M} w_i} \right)$$

- where M is the total number of classes, N_i is the number of events in class i, y_{ij}^* is 1 if observation j belongs to type i and 0 otherwise, p_{ij} is the predicted probability that event j belongs to class i and w_i is the weight of the class i. The weights can be changed to give different importances to different classes. (Malz et al. 2019)

- Following the PLAsTiCC challenge, we gave the same weight to every SNe class.

Best performance

- Transient part of the light curve
- 2D Gaussian Process fit with Matern-3/2 kernel
- 40 PCA components from wavelets
- Photometric redshift + its error as features
- Augmented training set
- Balanced training classes