

Towards Precision Photometric Supernova Cosmology with Machine Learning

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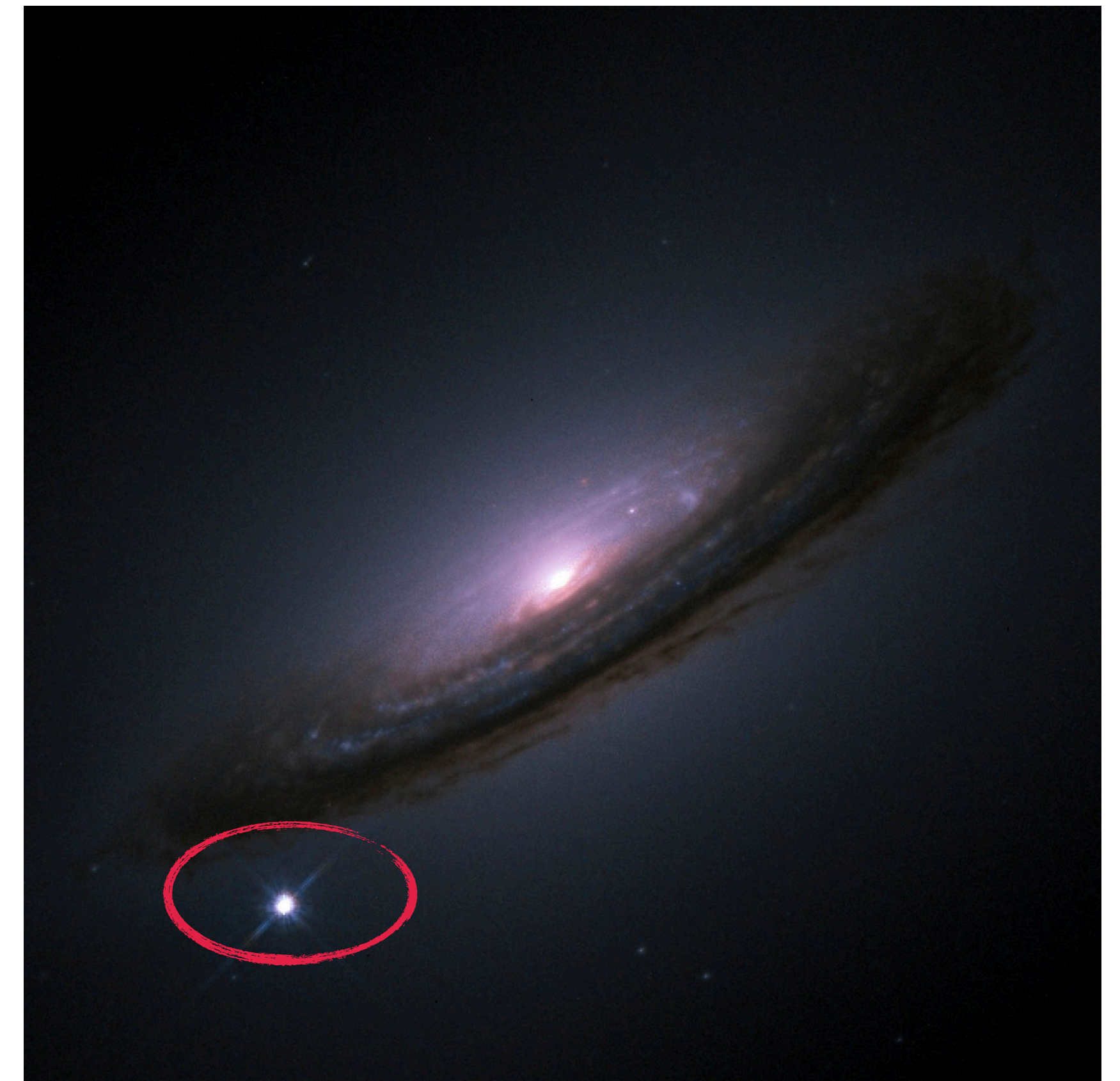
Type Ia supernovae are standard(izable) candles

- *standard(izable) candles*: events that (can be systematically corrected to) occur with the same luminosity every time
- measure brightness \longrightarrow know distance!



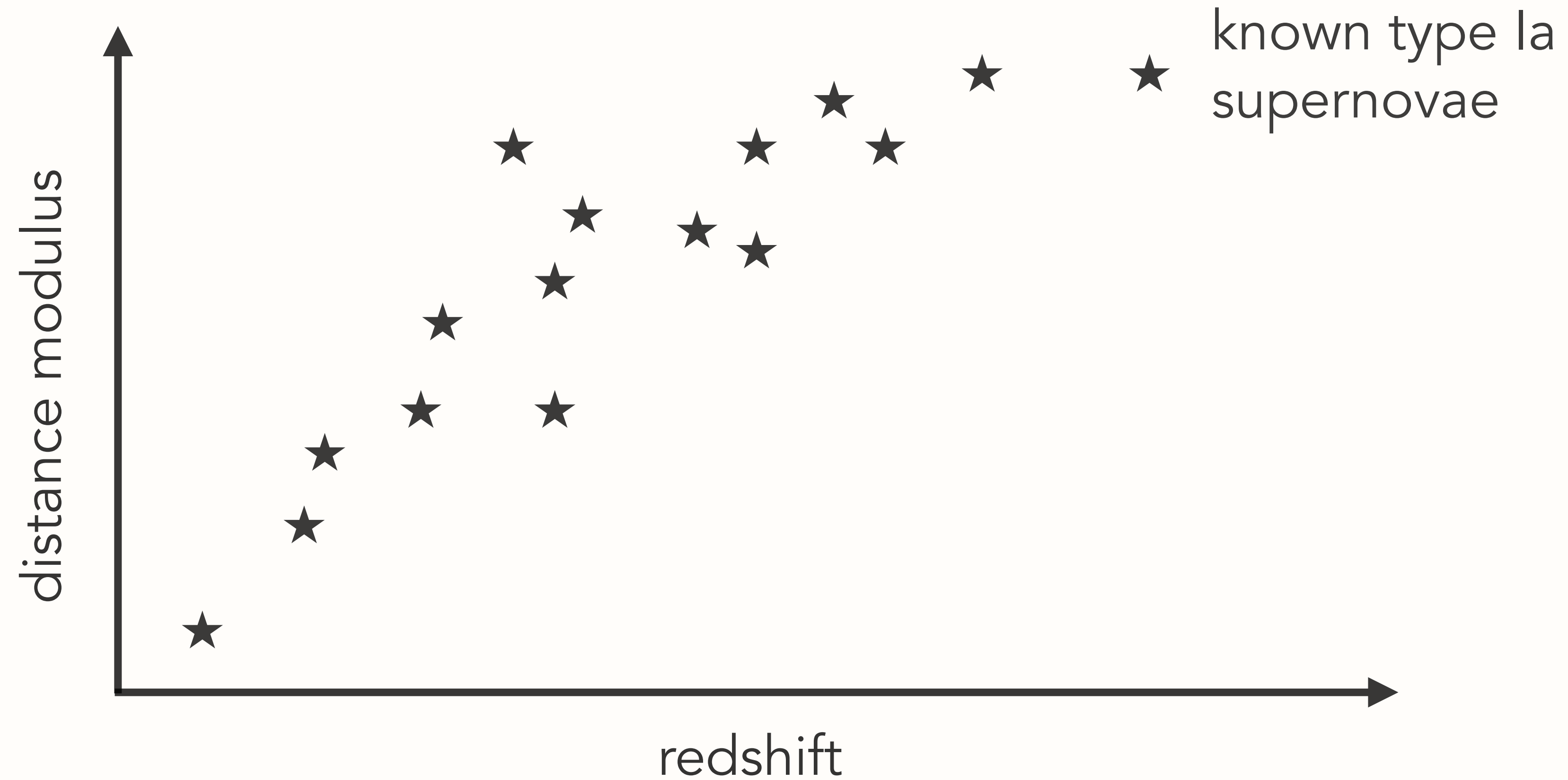
Type Ia supernovae are standard(izable) candles

- *standard(izable) candles*: events that (can be systematically corrected to) occur with the same luminosity every time
- measure brightness \longrightarrow know distance!
- bonus: they're also as bright as a whole galaxy (so Rubin can detect out to $z > 1$)

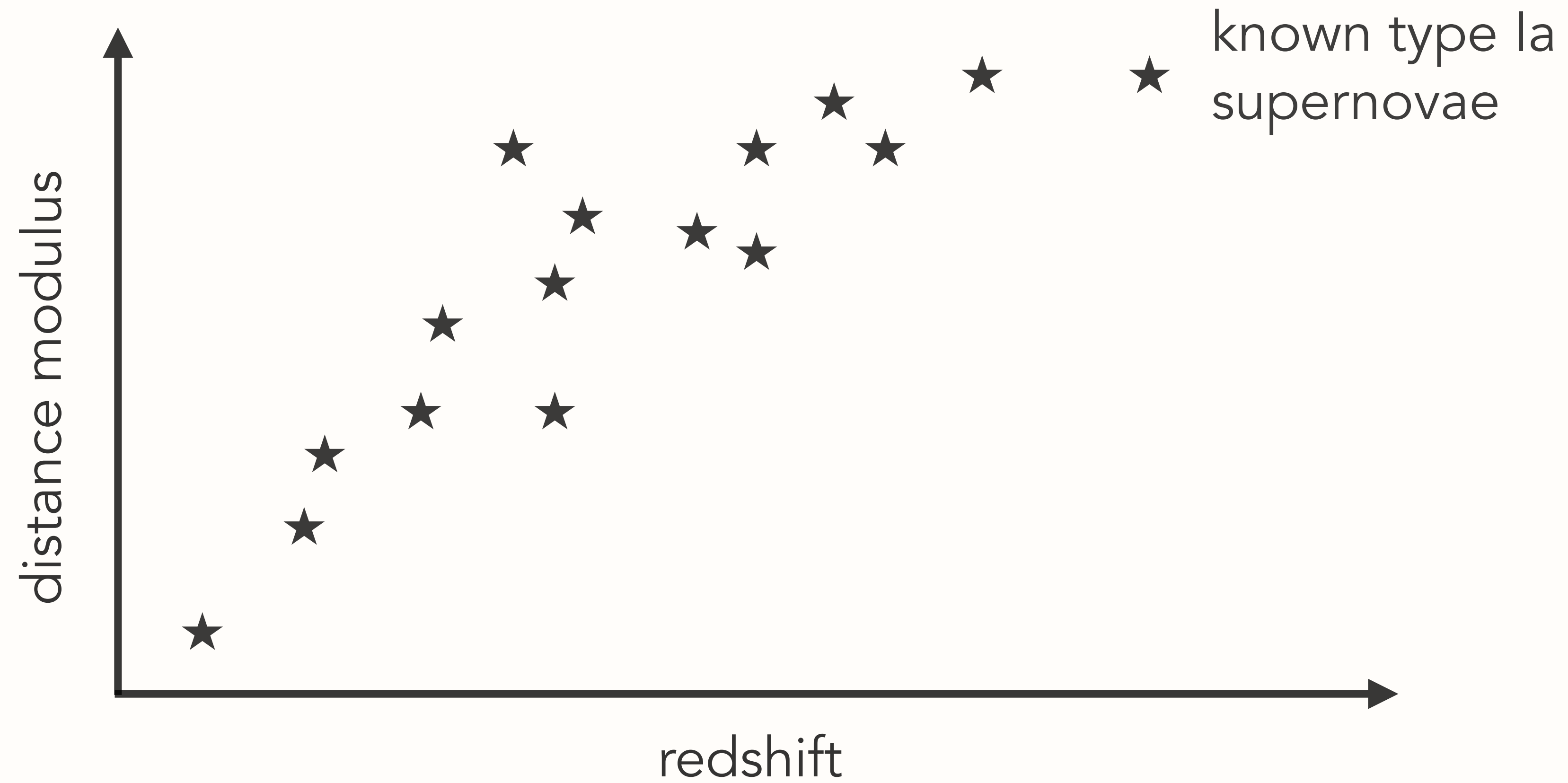


The Hubble Diagram

Standard candles can tell us about cosmology!

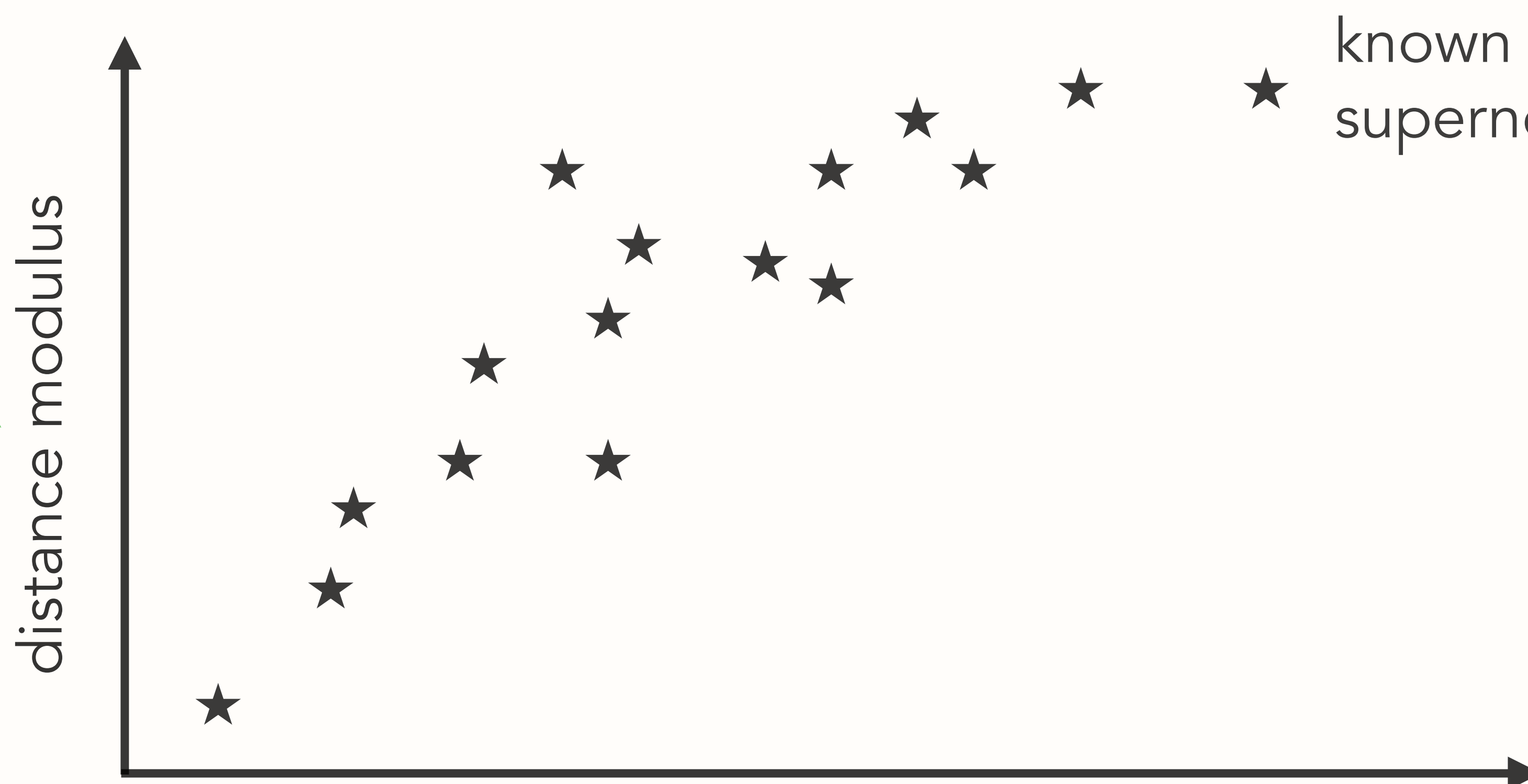
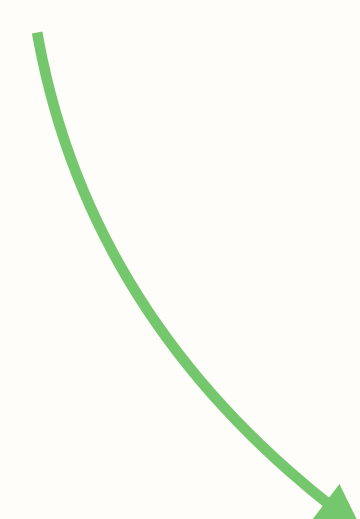


How do we know these quantities?



How do we know these quantities?

standardized
luminosity +
corrections



known type Ia
supernovae

supernova
spectra



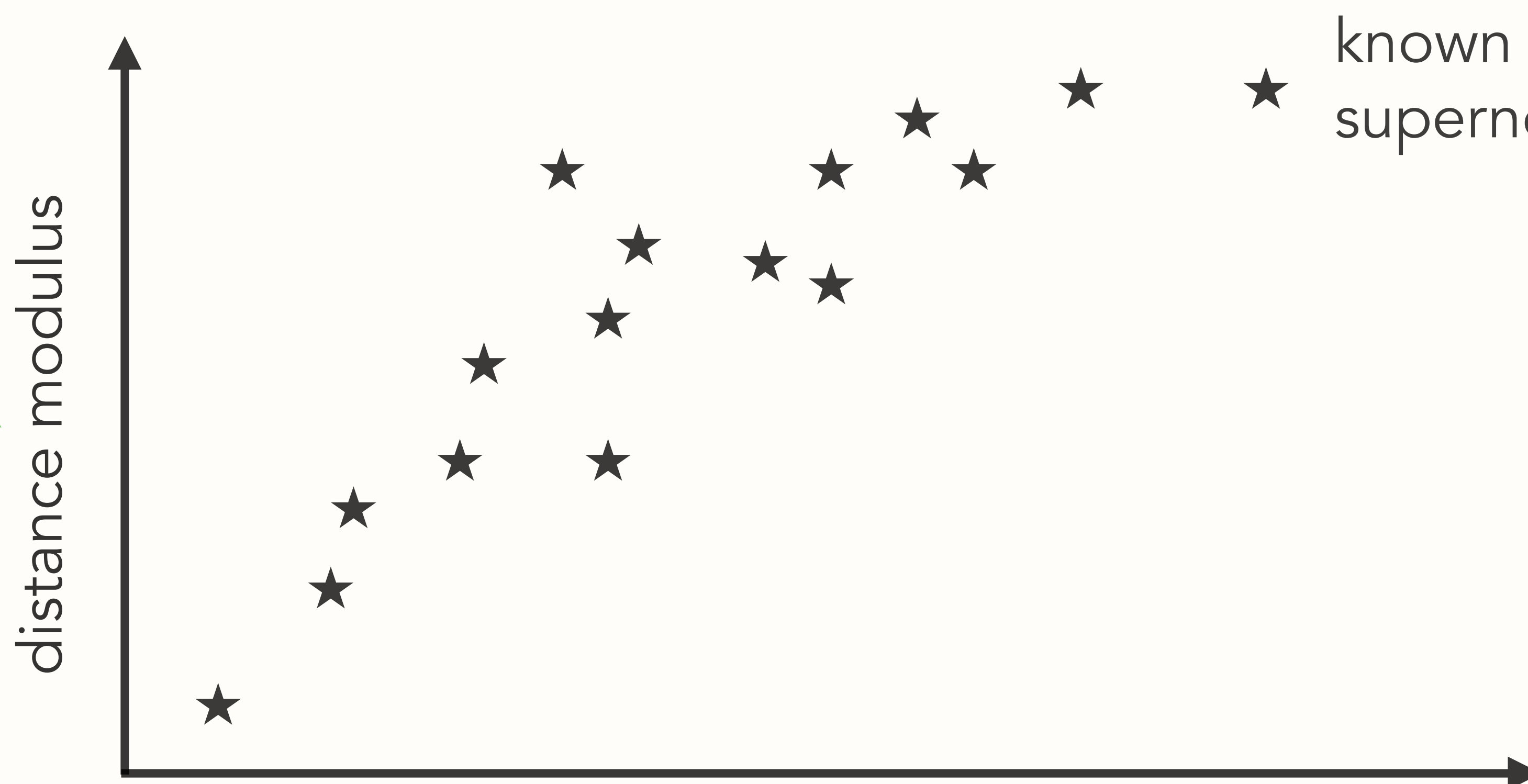
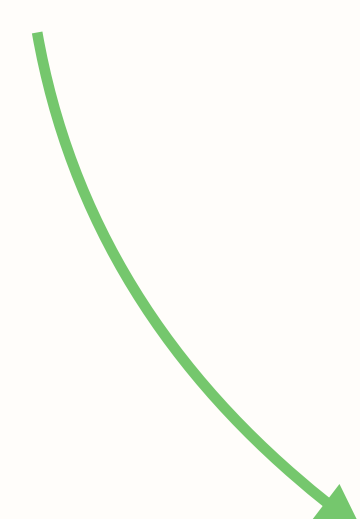
redshift

supernova / galaxy
spectra



How do we know these quantities in the Rubin era?

standardized
luminosity +
corrections



known type Ia
supernovae

supernova
spectra



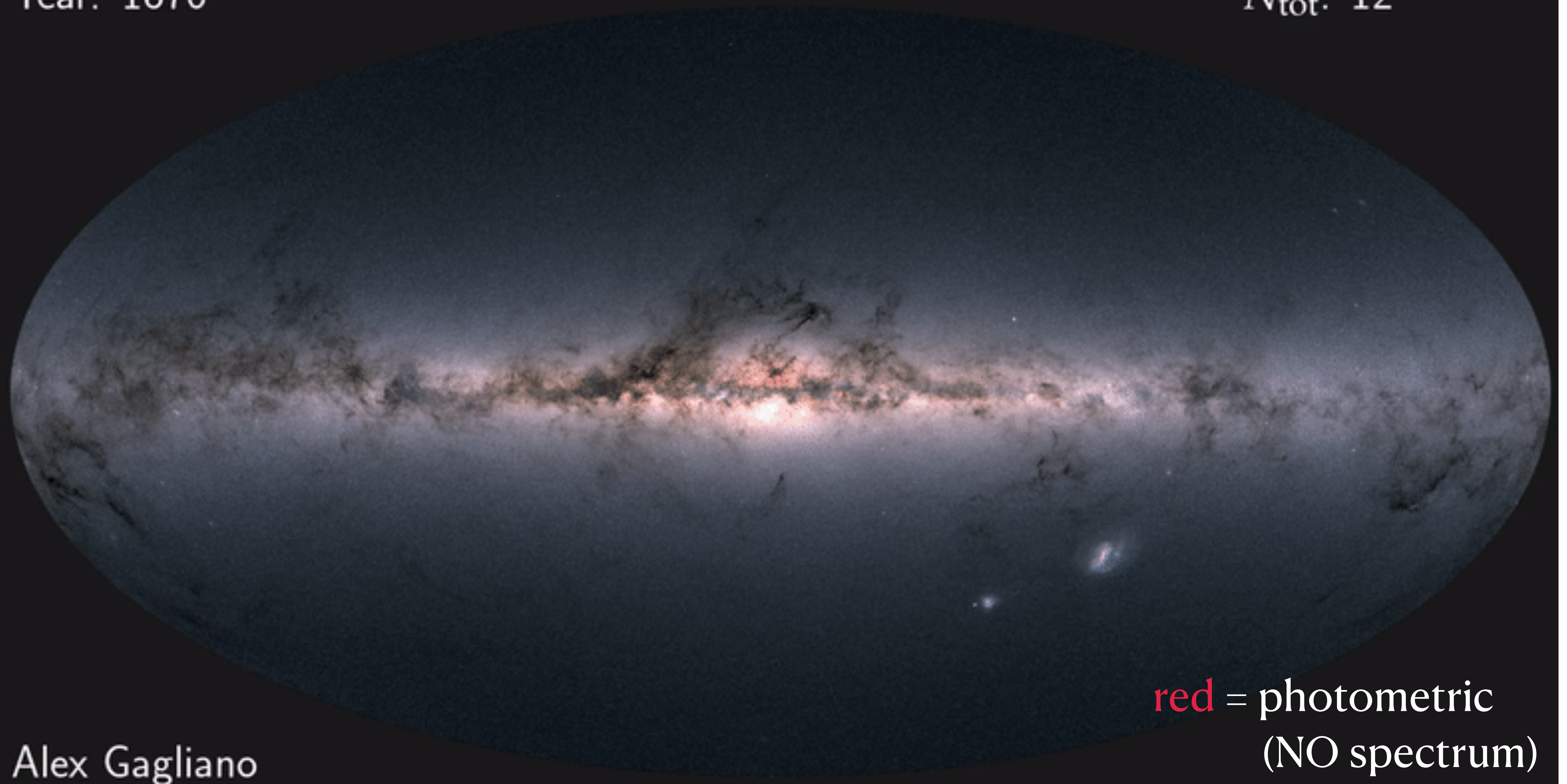
redshift

supernova / galaxy
spectra



s
Year: 1870

N_{tot} : 12



Alex Gagliano

red = photometric
(NO spectrum)

blue = spectroscopic

Year: 1870

N_{tot} : 12

<0.1% of LSST SNe will have spectra!

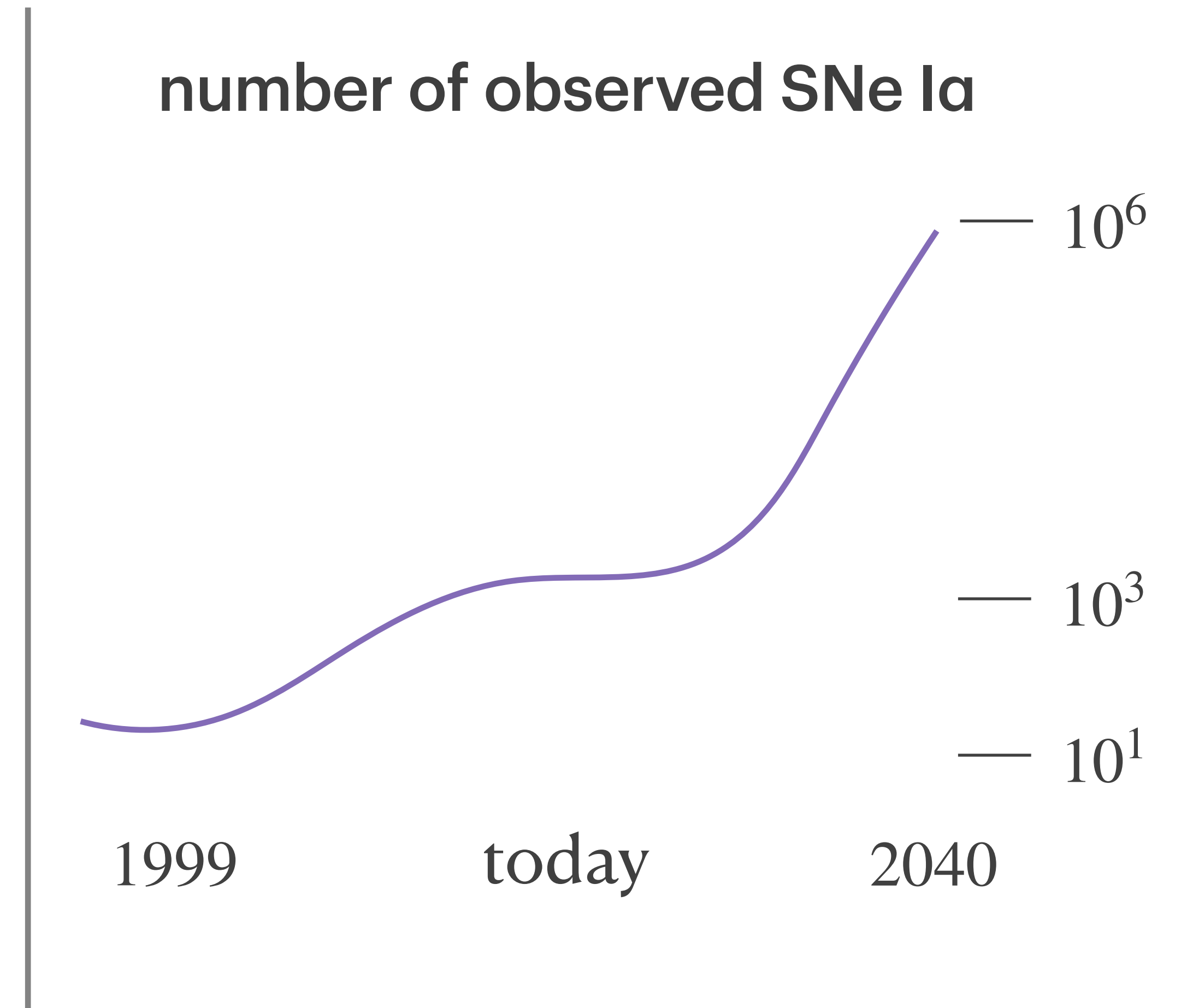
Alex Gagliano

red = photometric

blue = spectroscopic

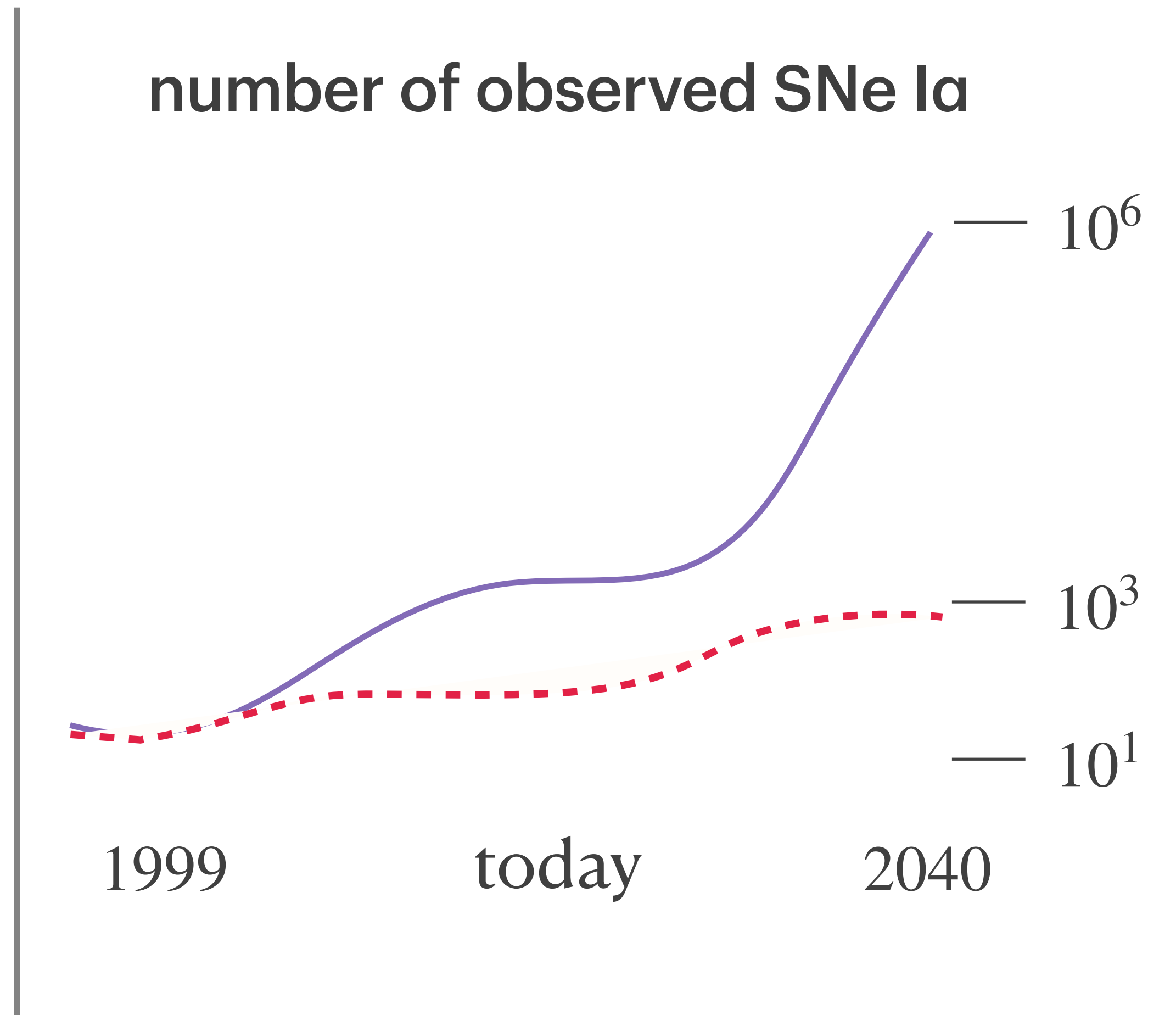
Cosmology in the Rubin era cannot depend on spectra

- Number of **photometrically observed SNe Ia** will skyrocket in the Rubin era



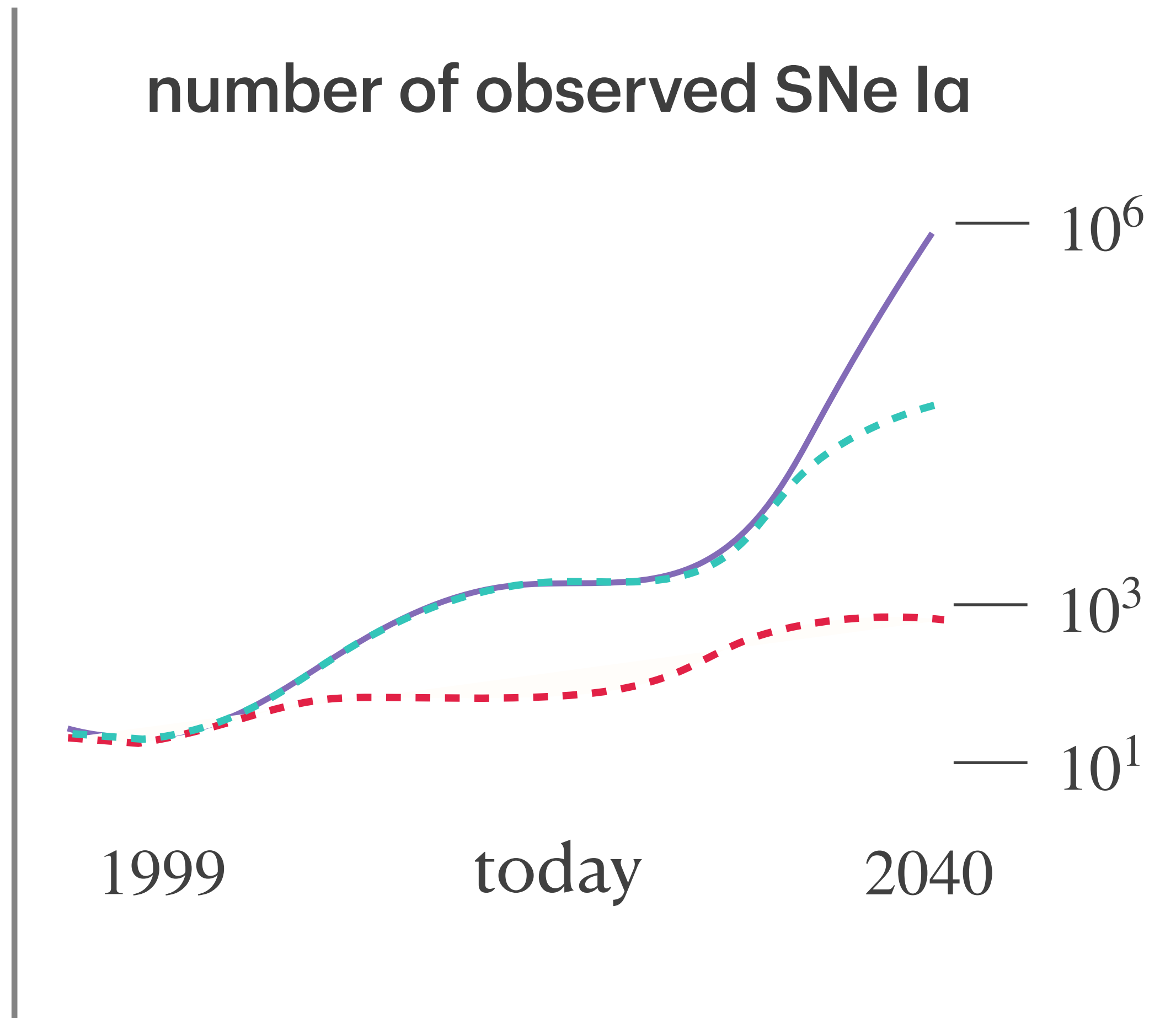
Cosmology in the Rubin era cannot depend on spectra

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 - **SNe Ia with spectra** already make up only $<10\%$ of current sample (5-year Dark Energy Survey, DES5YR)



Cosmology in the Rubin era cannot depend on spectra

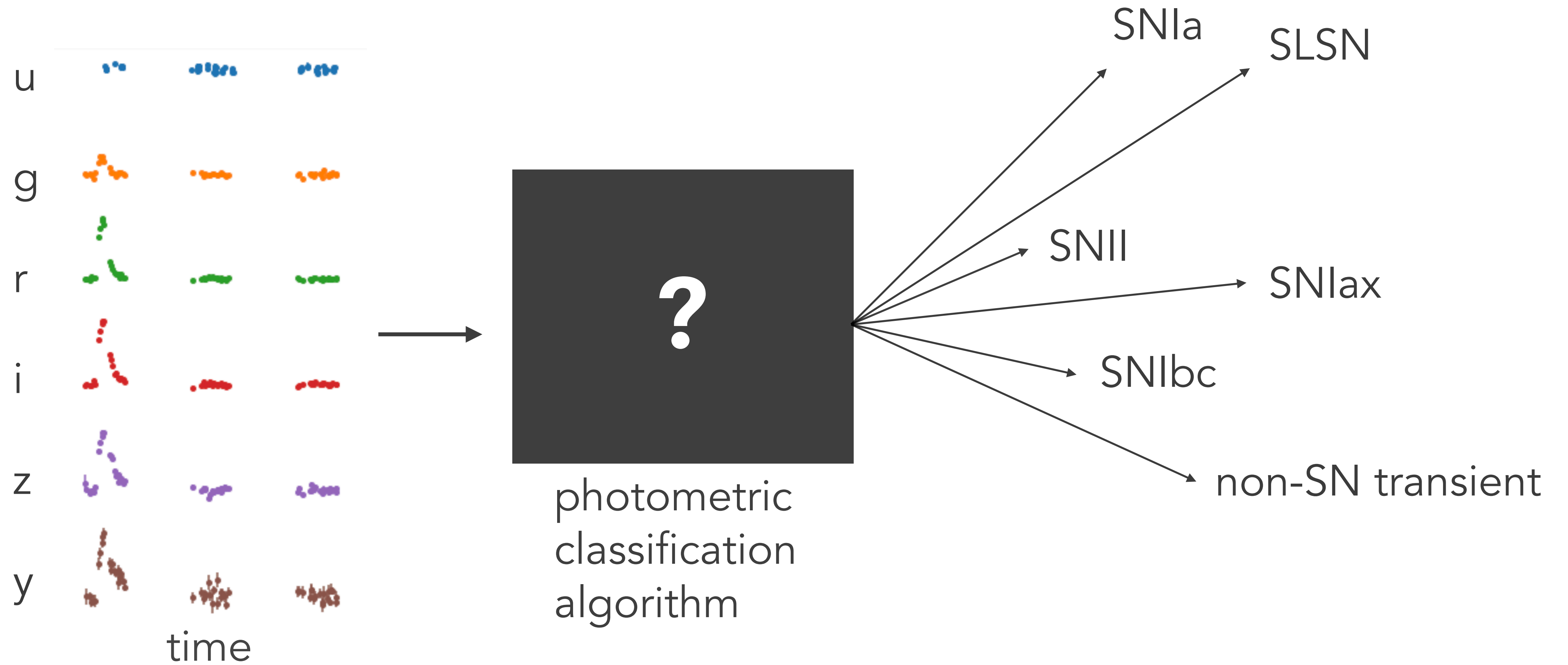
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 - **SNe Ia with spectra** already make up only $<10\%$ of current sample (5-year Dark Energy Survey, DES5YR)
 - **SN host galaxies with spectra** make up 100% of the DES5YR sample (**HQ+23**), but will not scale to Rubin data volumes



Cosmology in the Rubin era will depend on photometry

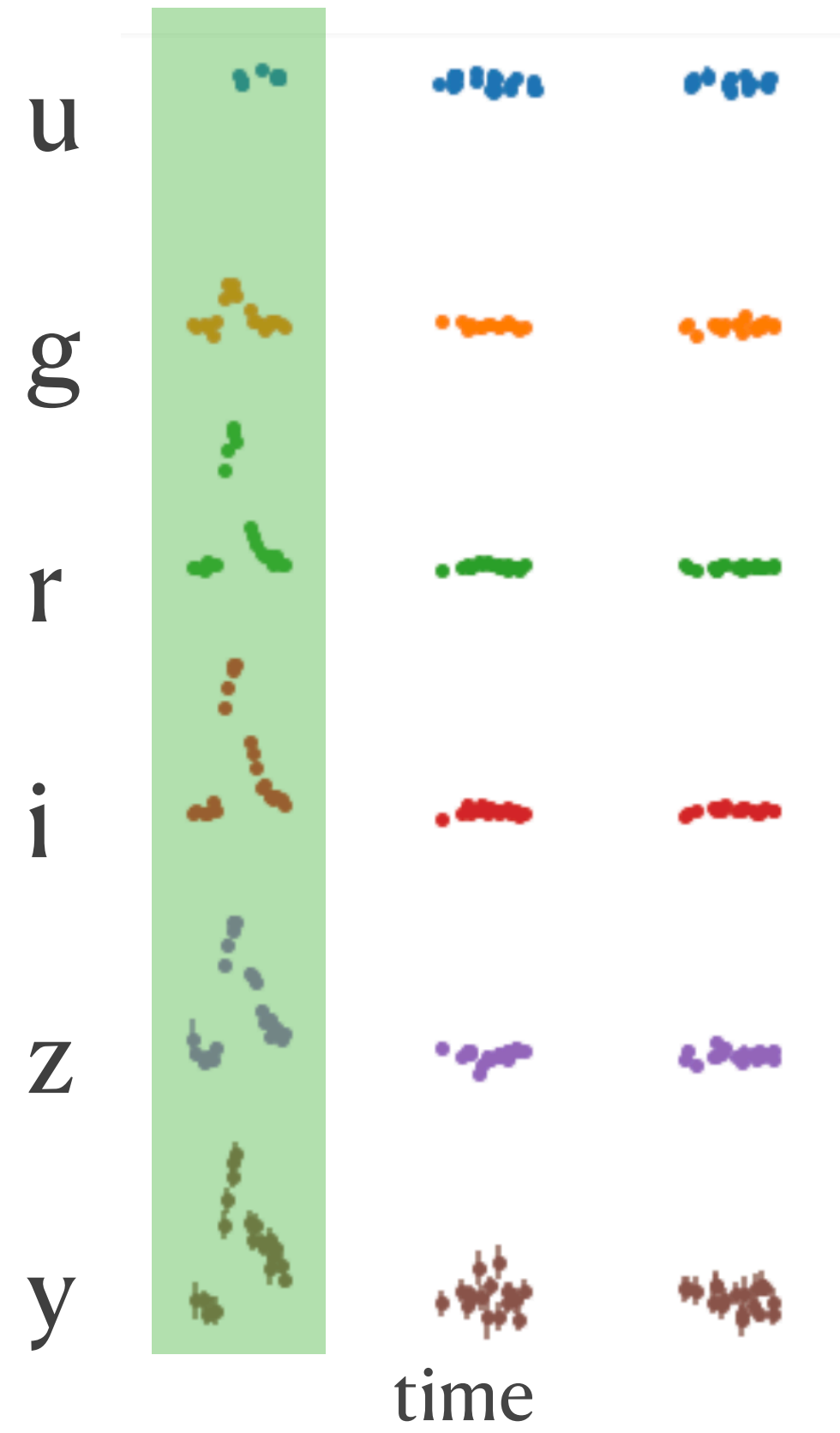
- Number of photometrically observed SNe Ia will skyrocket in the Rubin era
 - SNe Ia with spectra already make up only $<10\%$ of current sample (5-year Dark Energy Survey, DES5YR) \longrightarrow **photometric classification**
 - SN host galaxies with spectra make up 100% of the DES5YR sample (**HQ**+23), but will not scale to Rubin data volumes \longrightarrow **photometric redshift estimation**

SN Photometric Classification



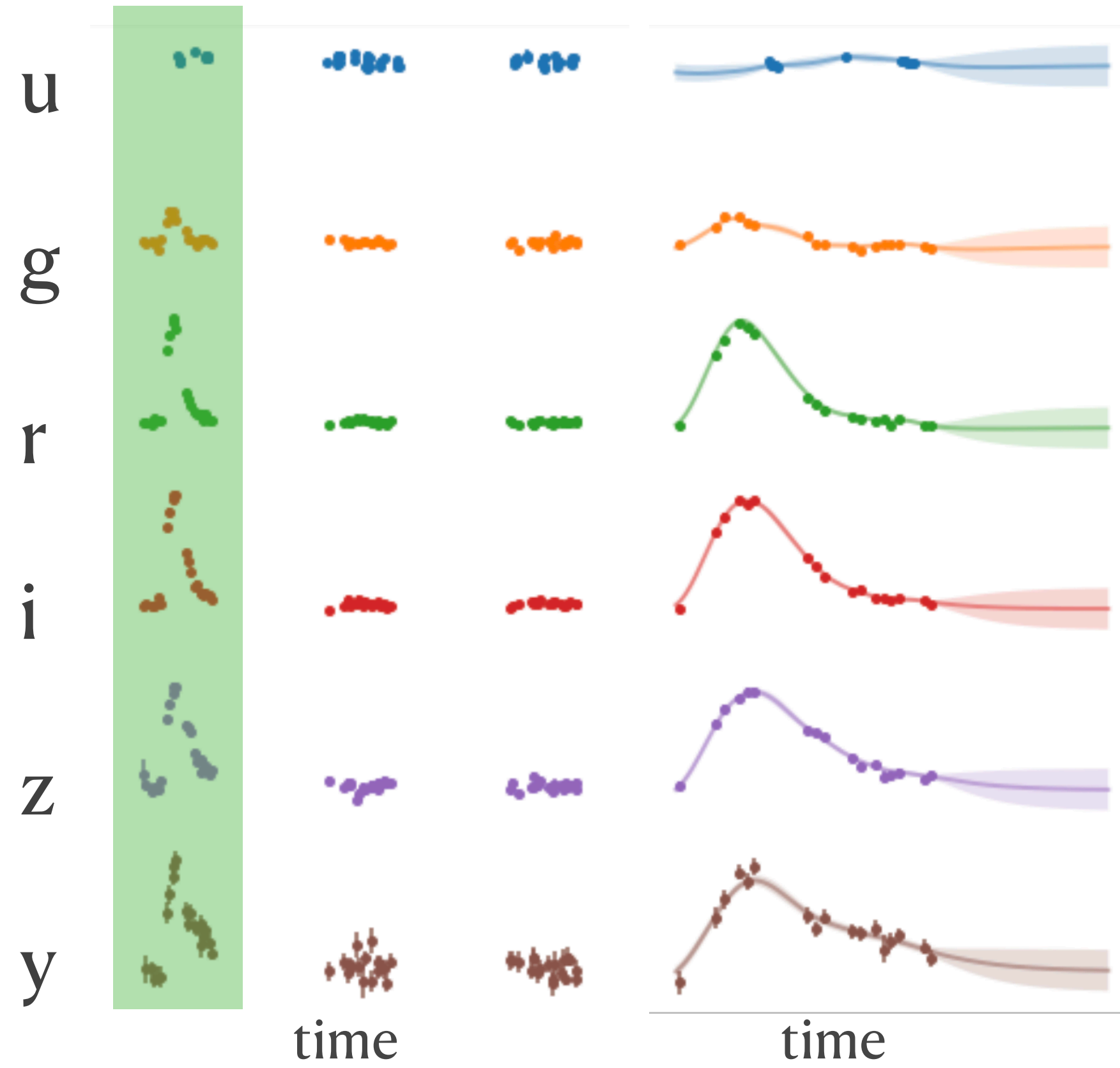
SCONE

Convolutional Neural Network for Supernova Classification



SCONE

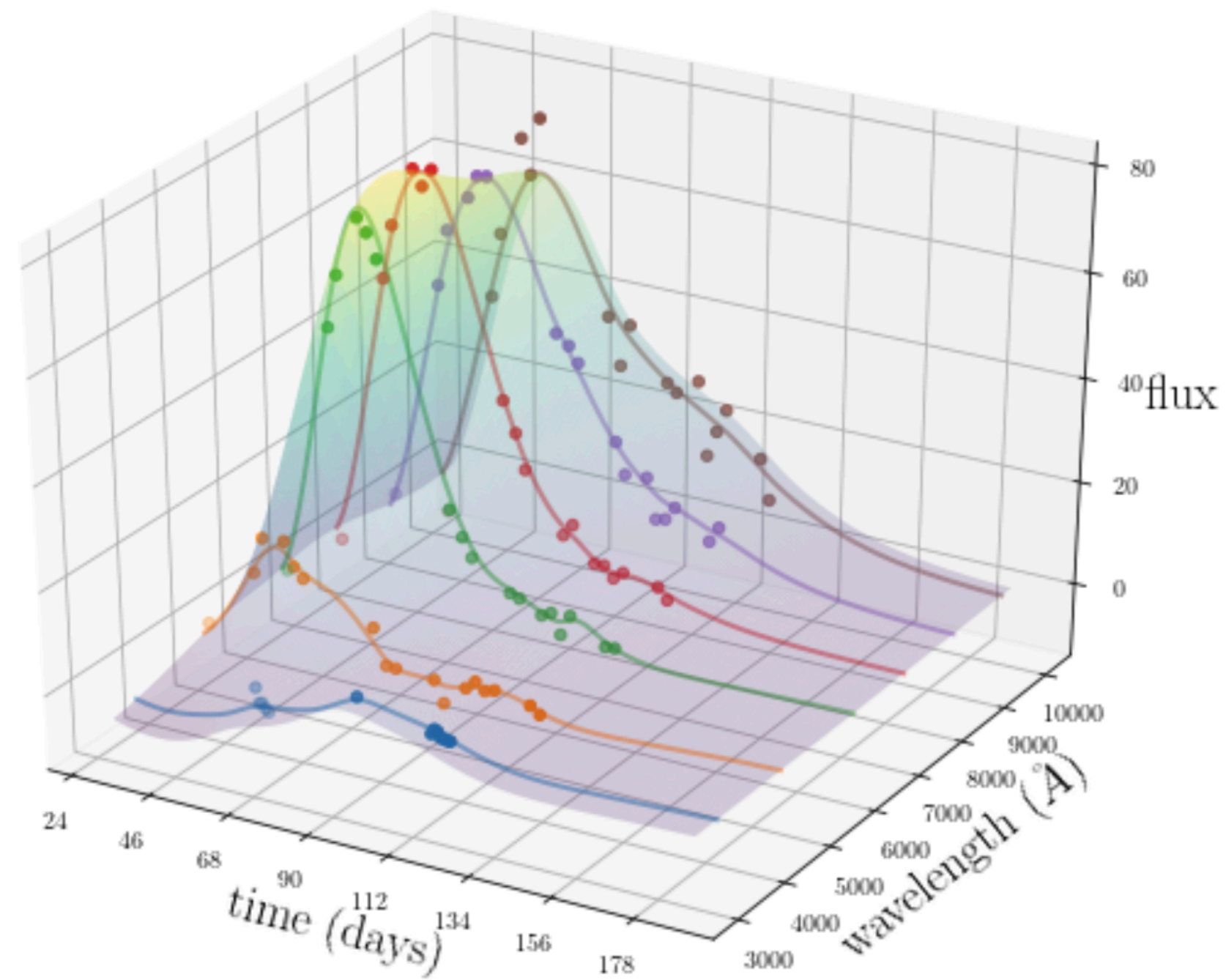
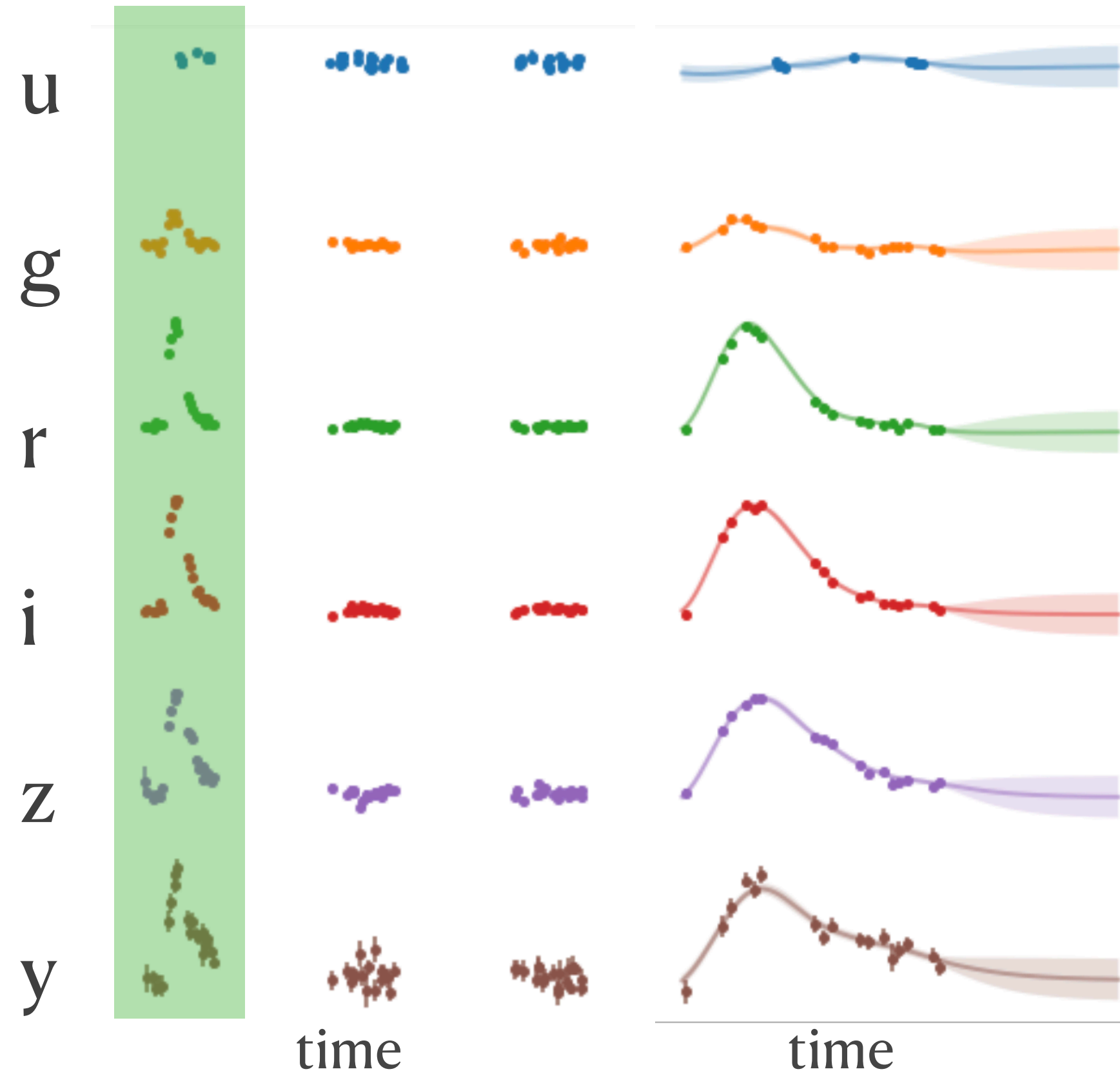
Convolutional Neural Network for Supernova Classification



Gaussian process (time)

SCONE

Convolutional Neural Network for Supernova Classification

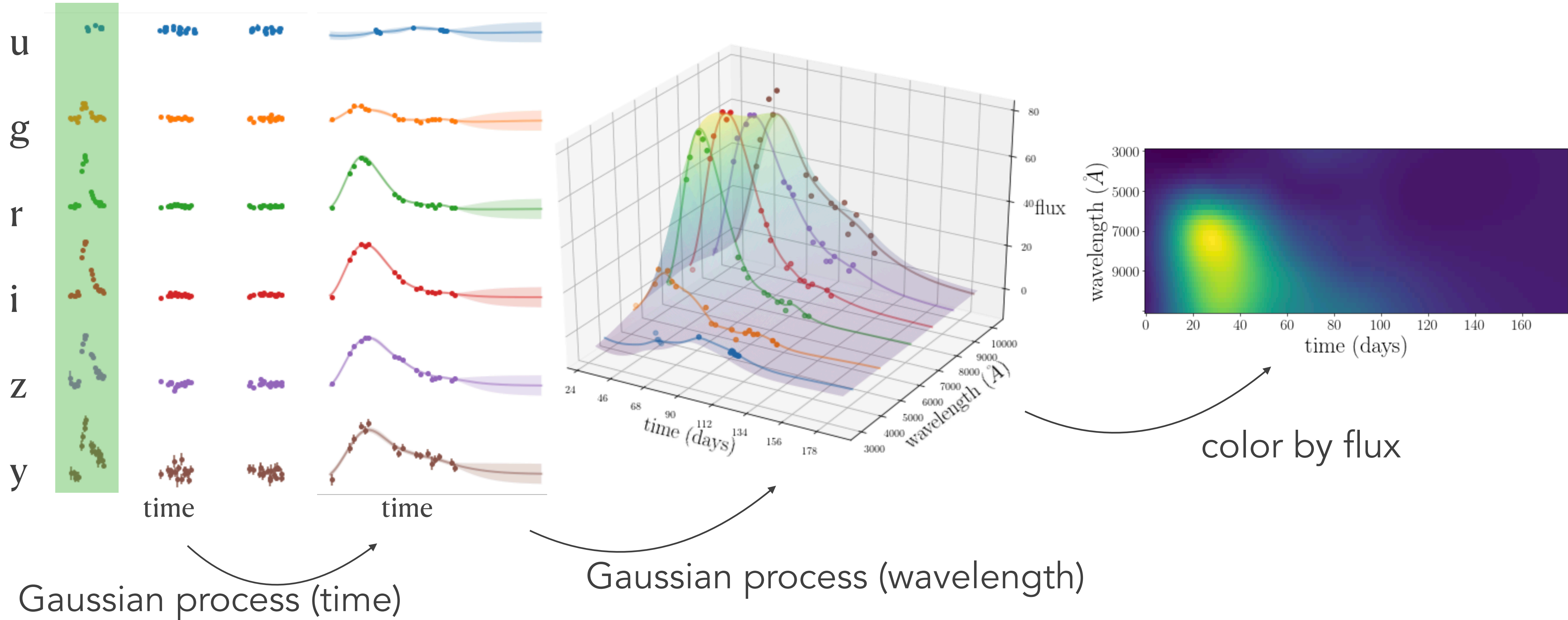


Gaussian process (time)

Gaussian process (wavelength)

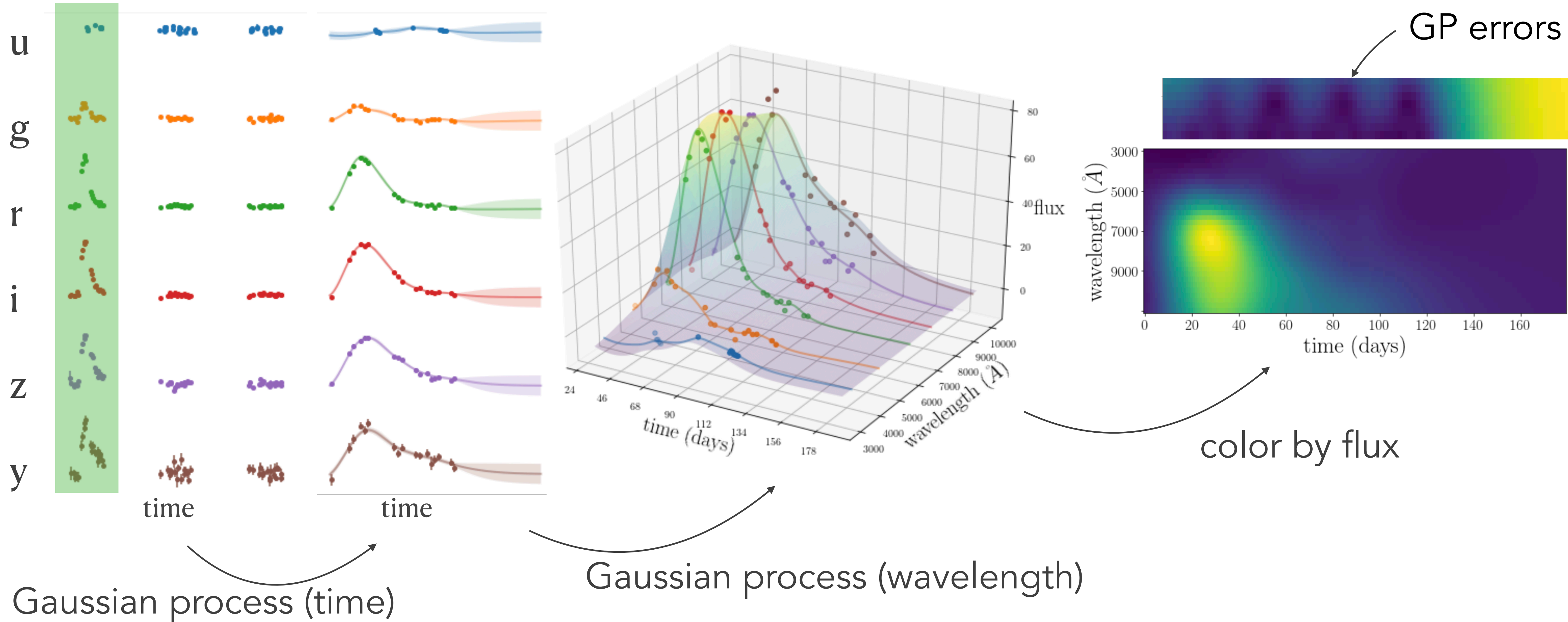
SCONE

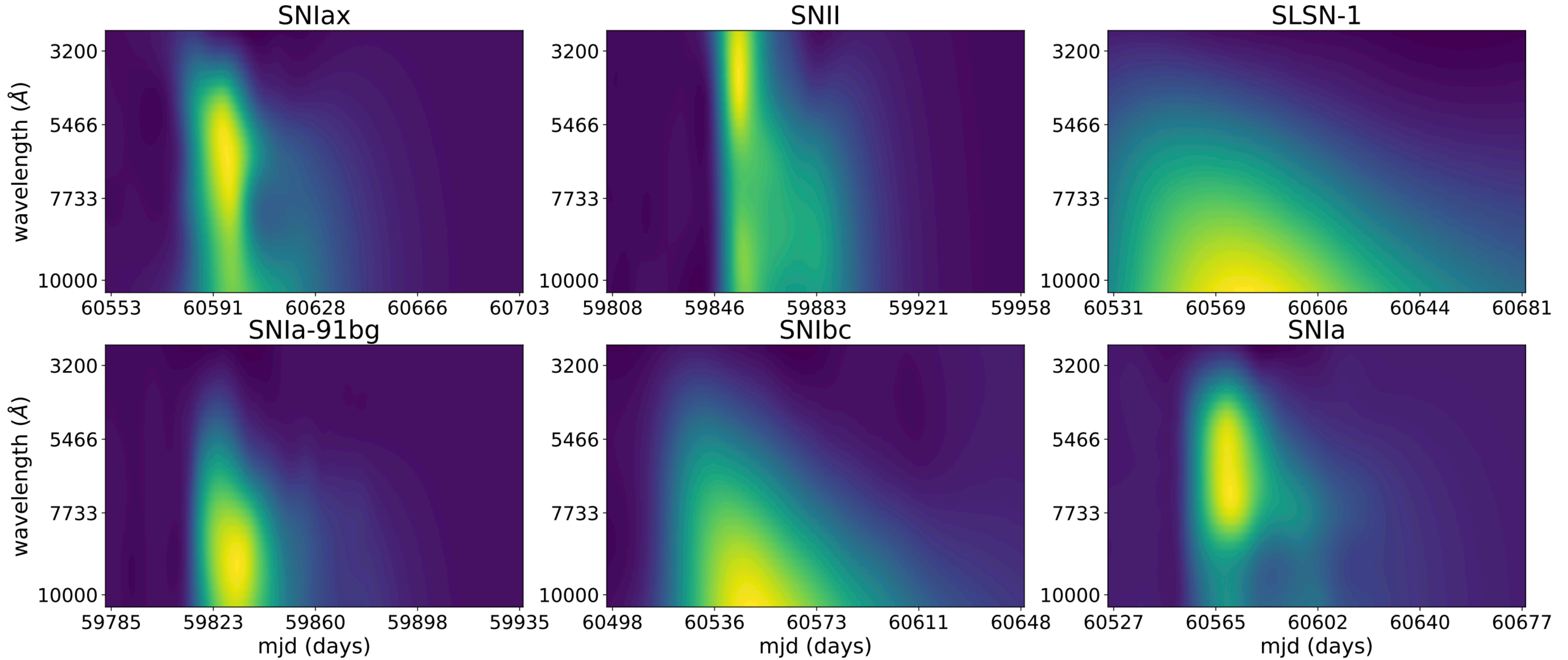
Convolutional Neural Network for Supernova Classification



SCONE

Convolutional Neural Network for Supernova Classification





SCONE performs well on simulations + real data

SN Ia vs. non-Ia classification

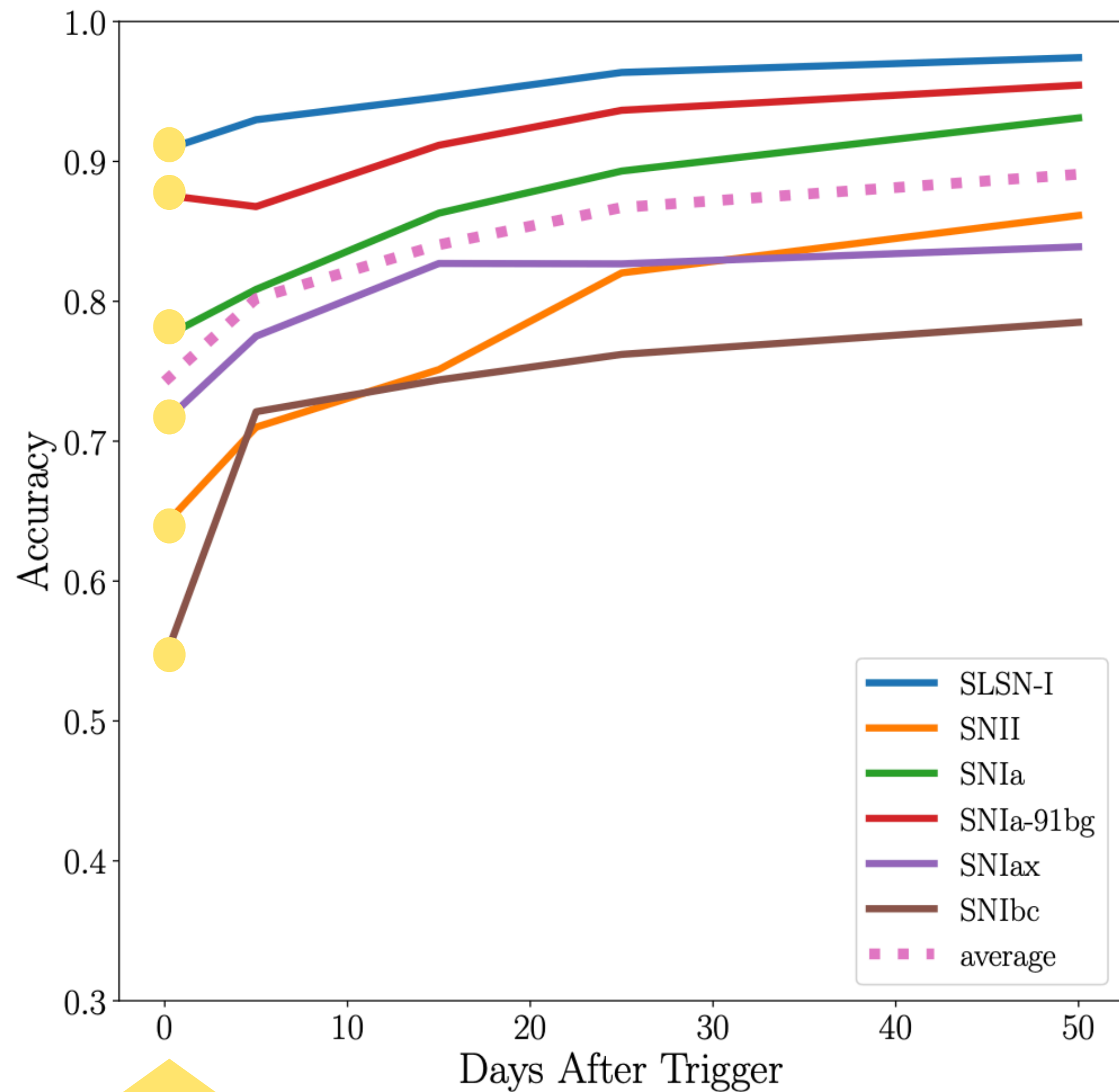
Actual Type	SN Ia	0.9978 ± 0.002	0.0022 ± 0.002
	non-Ia	0.0033 ± 0.0033	0.9967 ± 0.0033
		SN Ia	non-Ia
		Predicted Type	

- **accurate:**
 - >99% accuracy on simulations
 - 93% on 568 spectroscopic DES SNe
- **fast:** trained w/ 40k SNe (15 min on GPU)
- other approaches require millions of SNe, >10hr to train!
- used in DES, LSST, Roman analyses

SCONE for Early-Time Classification

- *early-time*: as soon after detection as possible
- vital for optimal allocation of limited spectroscopic resources

SCONE for Early-Time Classification

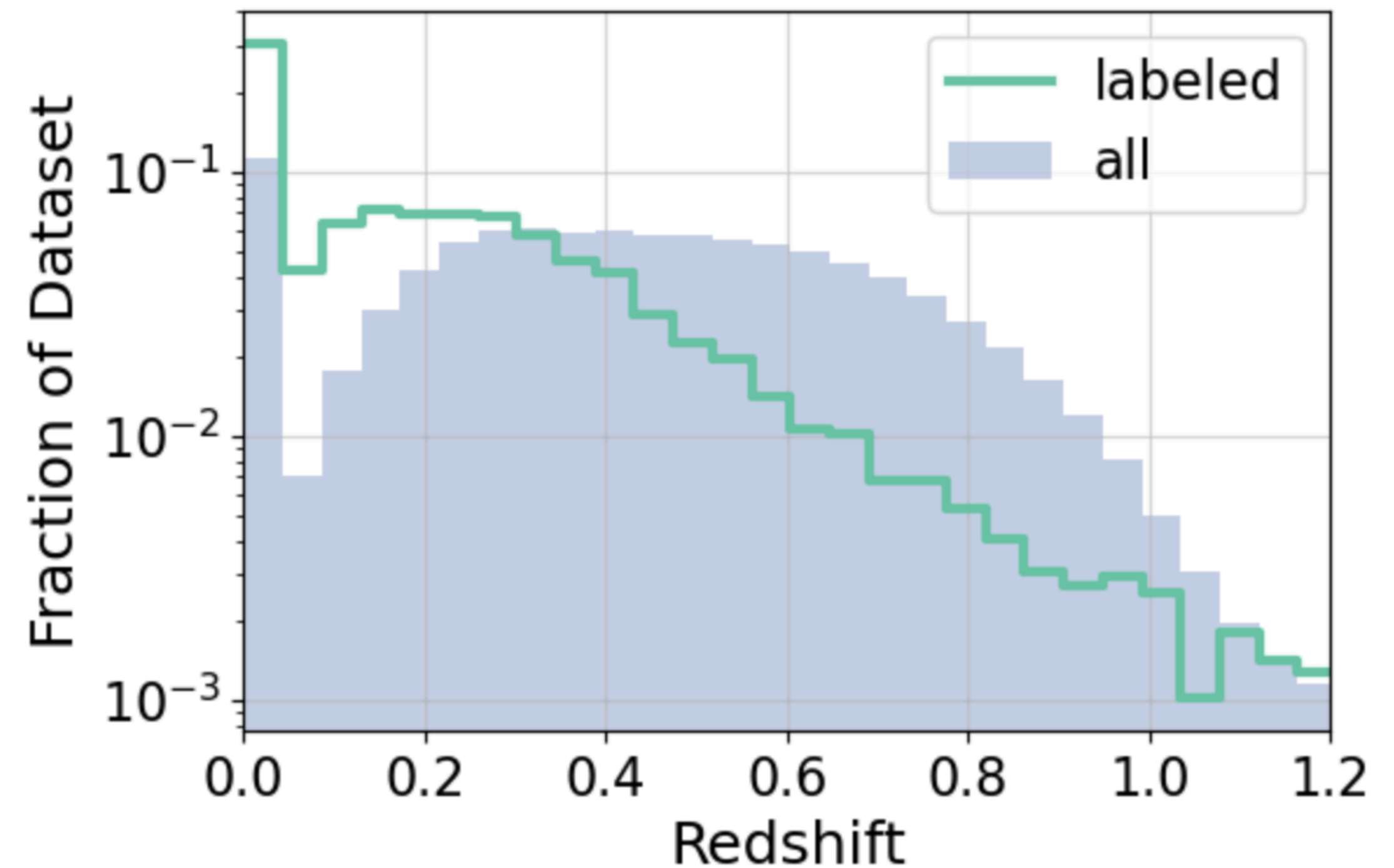


75% average accuracy (with redshift)
on the night of trigger

Training a model with real data

Task: PLAsTiCC classification (14 transient/variable types)

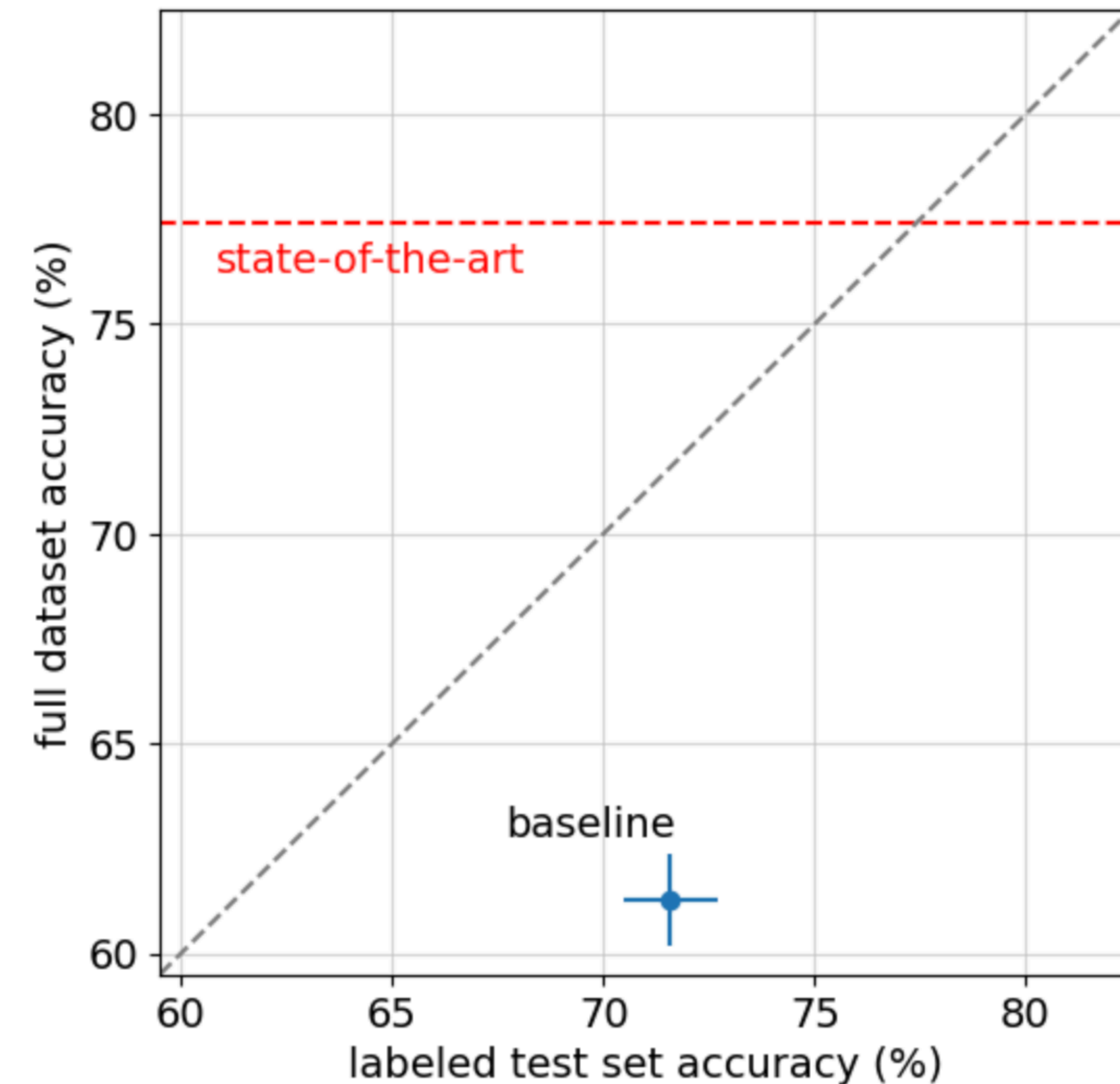
- Very **little** labeled data ($\sim 0.1\%$, ~ 7000 lightcurves)
- Labeled (spectroscopic) subset very **unrepresentative** of full dataset — bad for training!



Training a model with real data

Task: Classify 14 transient/variable object types

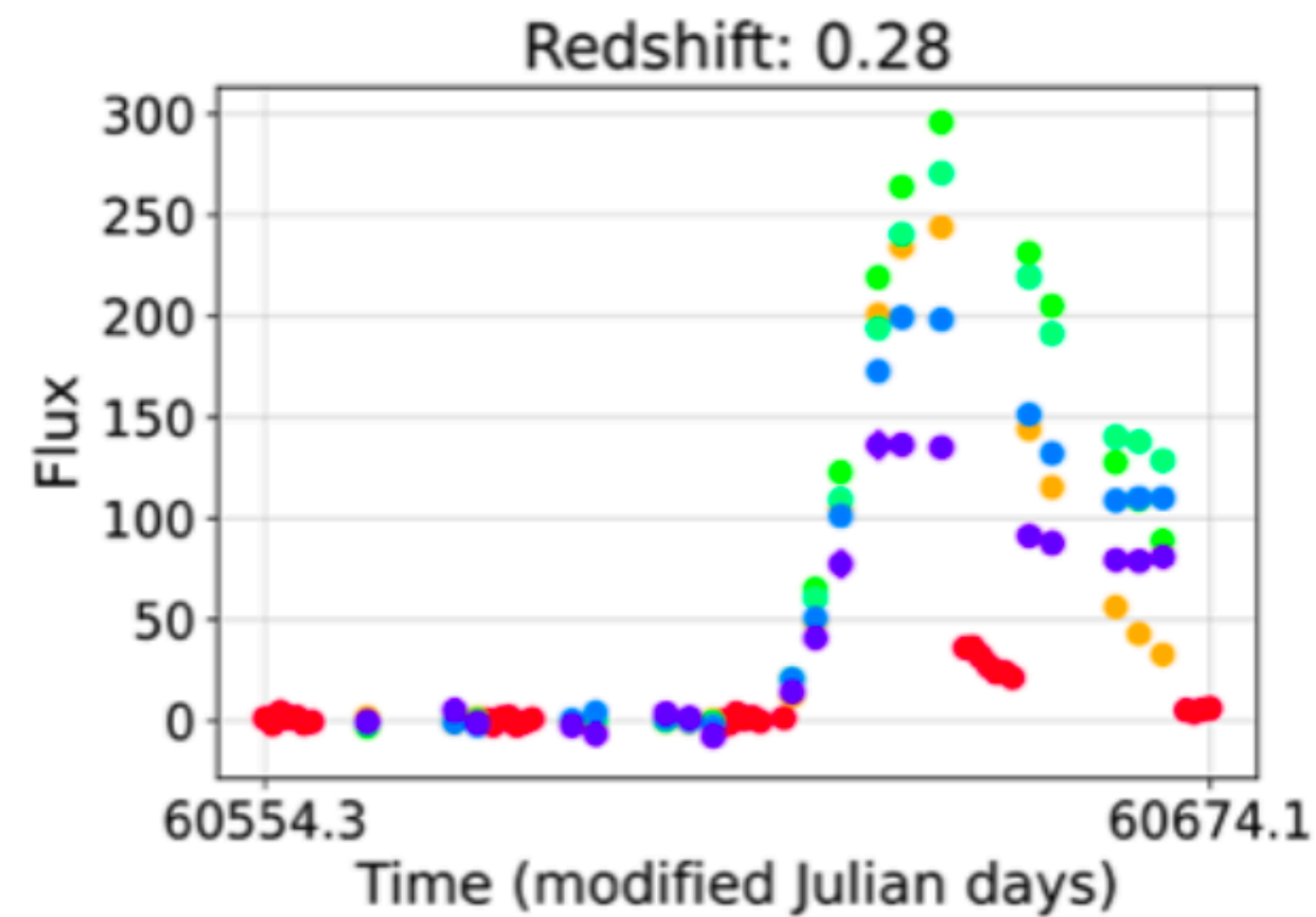
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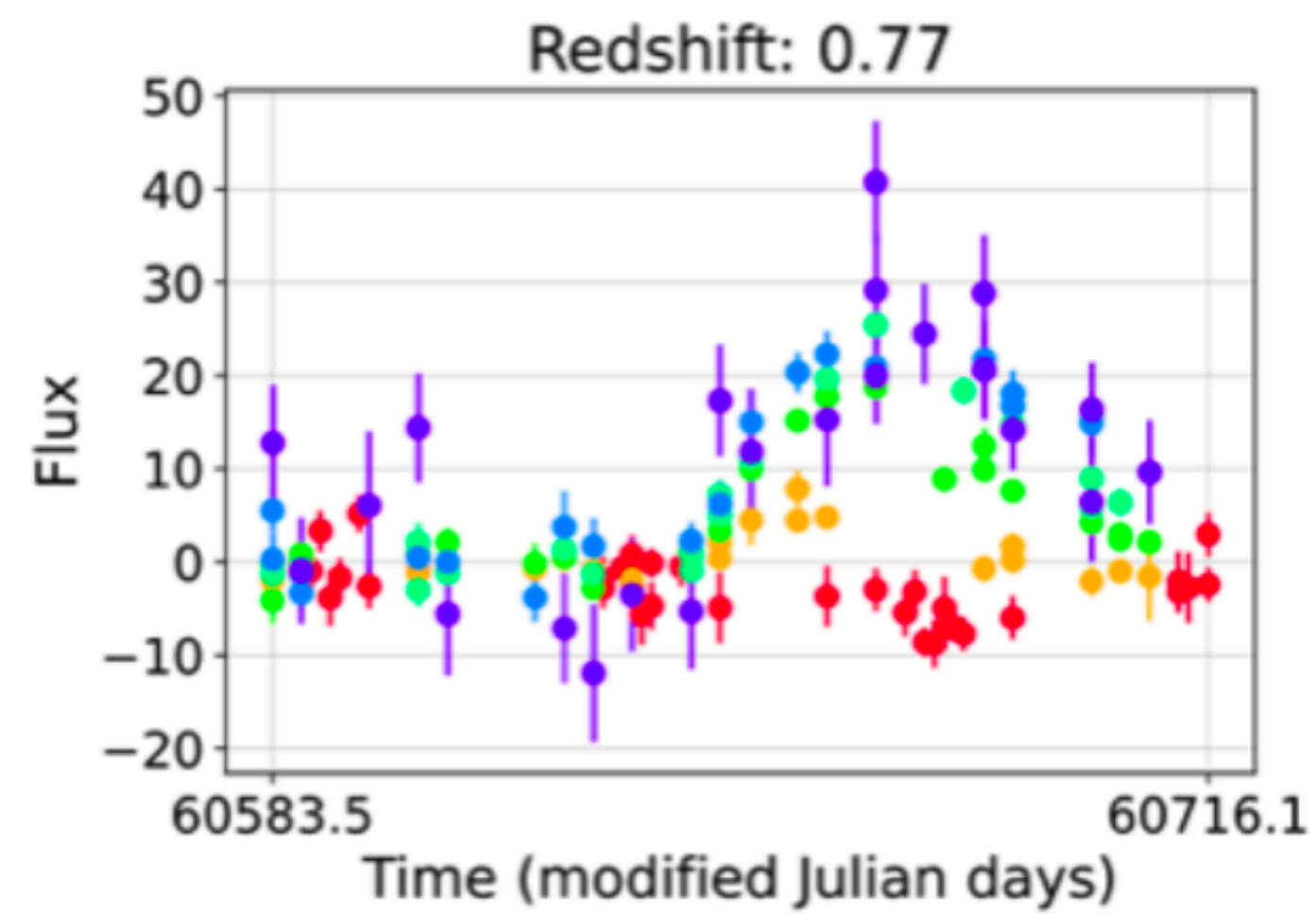
Training a model with real data

Augment lightcurves from spectroscopic data to resemble full dataset

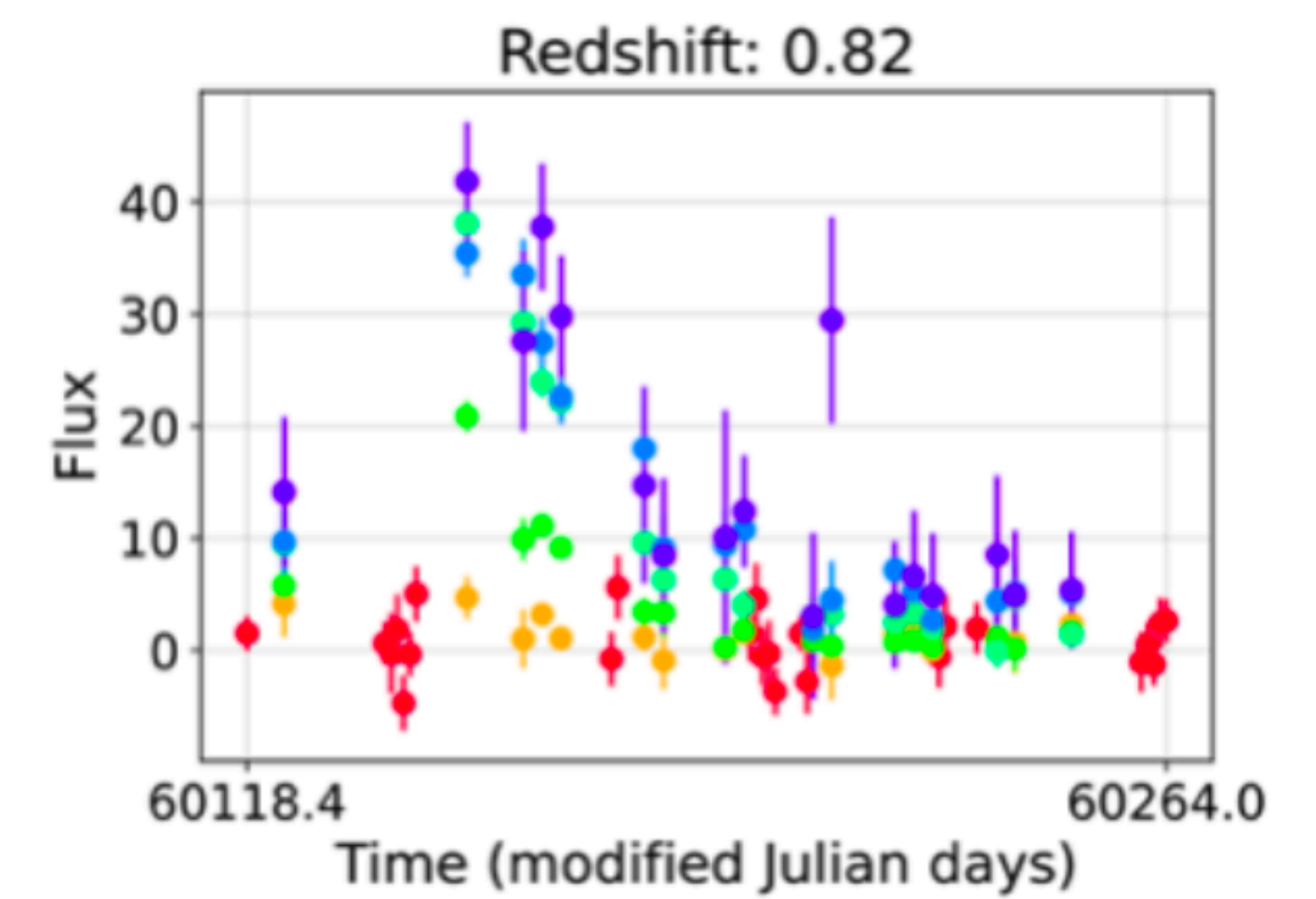
from spectroscopic data



redshifting
augmentation

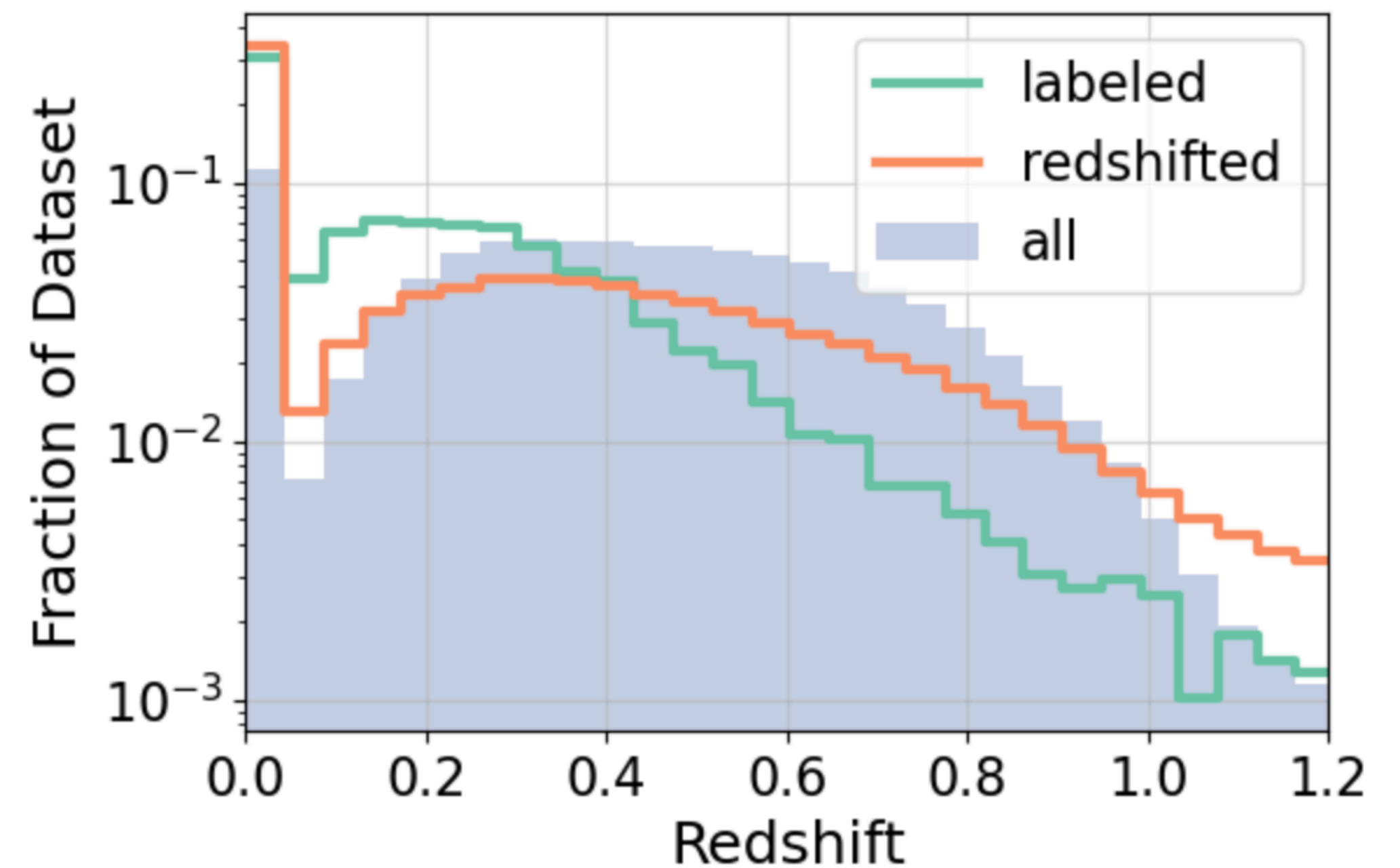
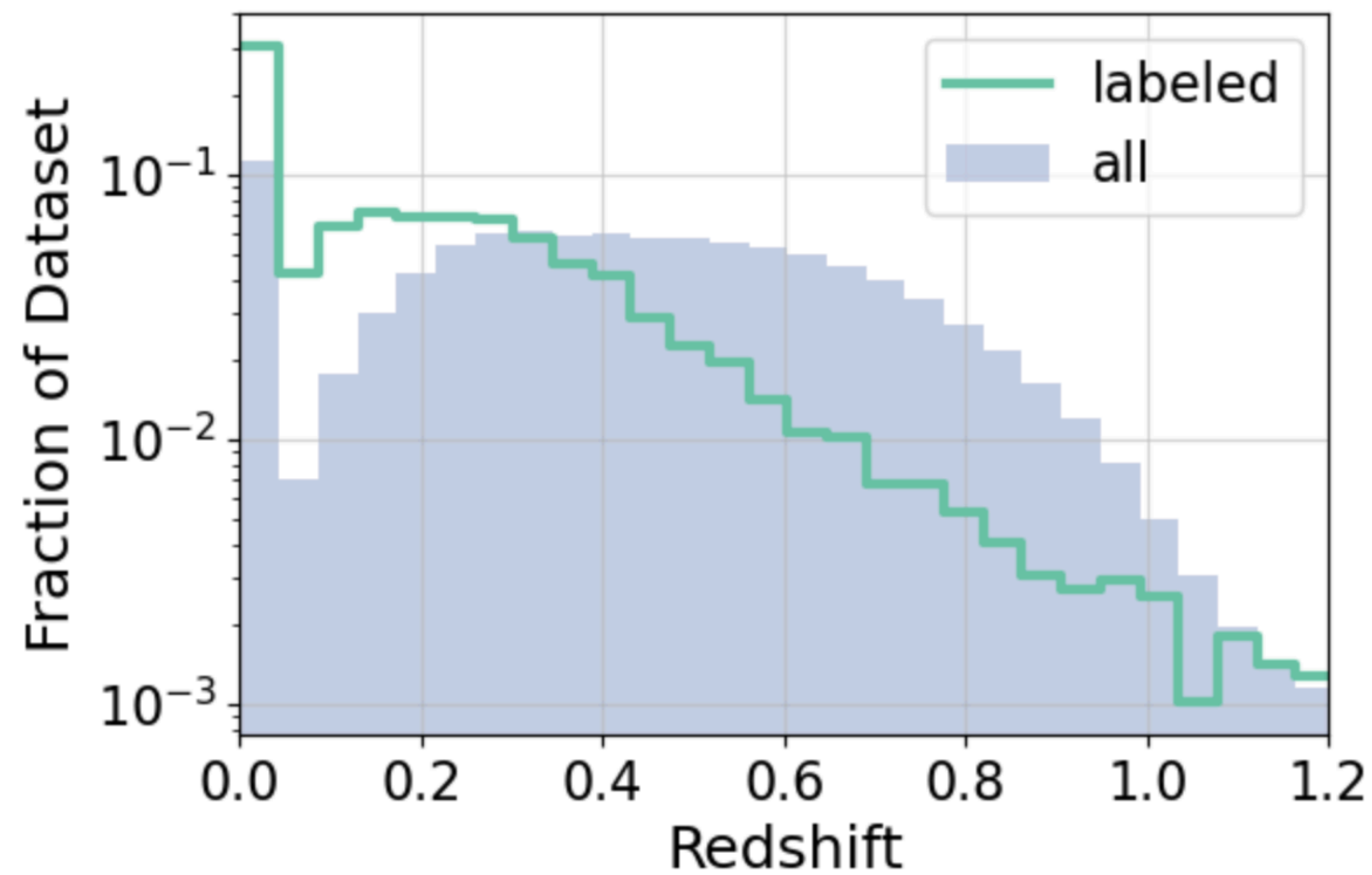


from full dataset



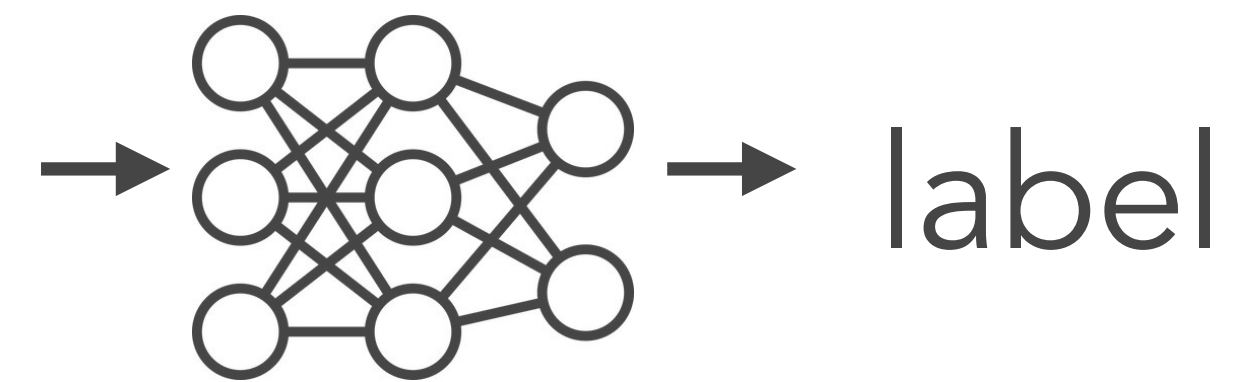
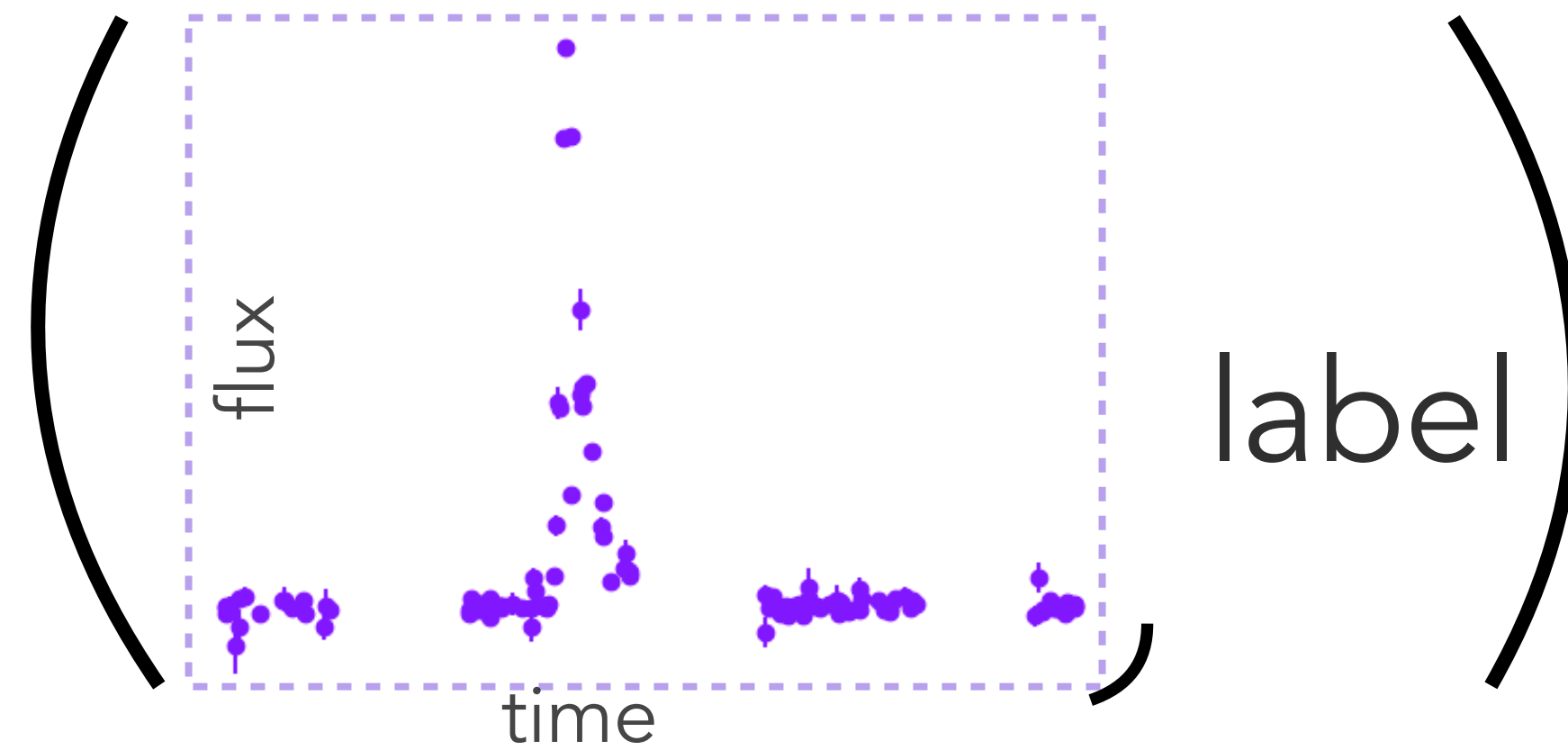
Training a model with real data

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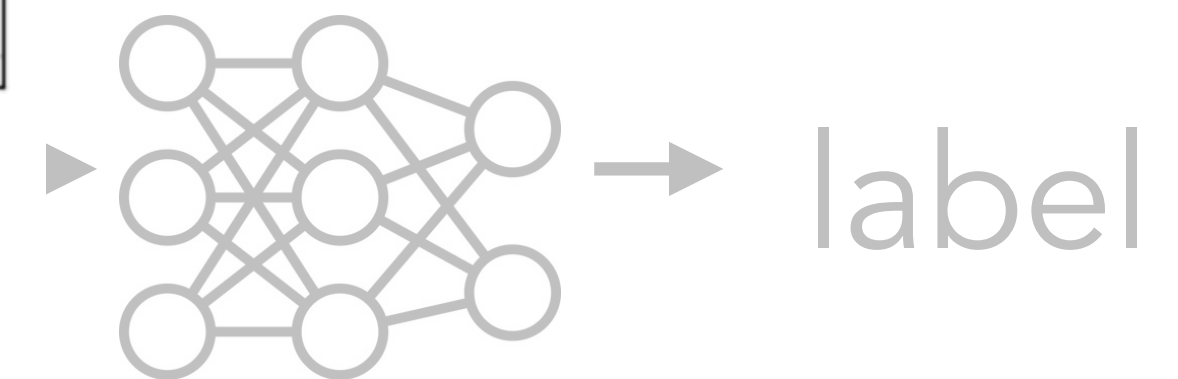
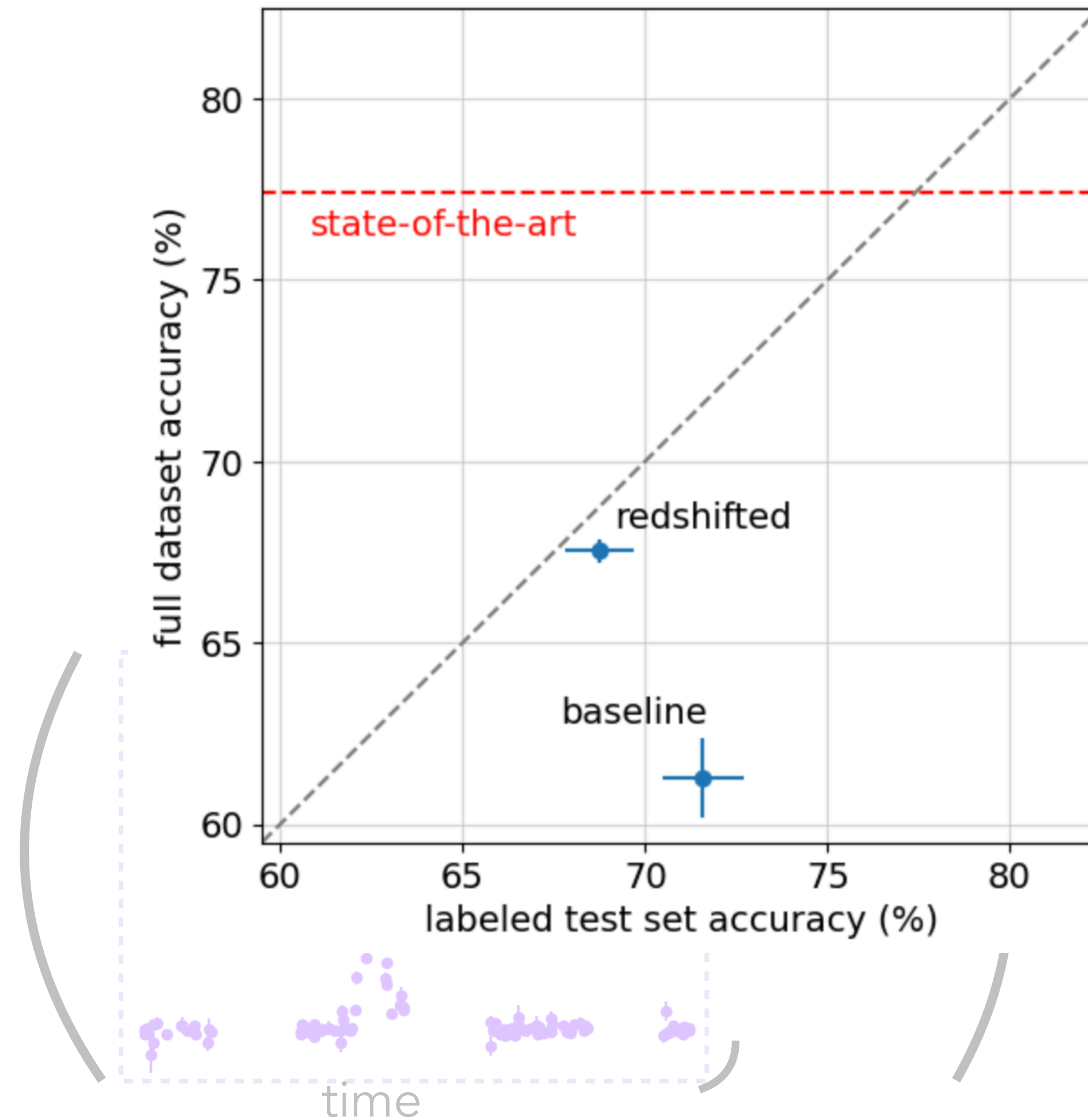
Training a model with real data

train w/
redshifted
labeled data



Training a model with real data

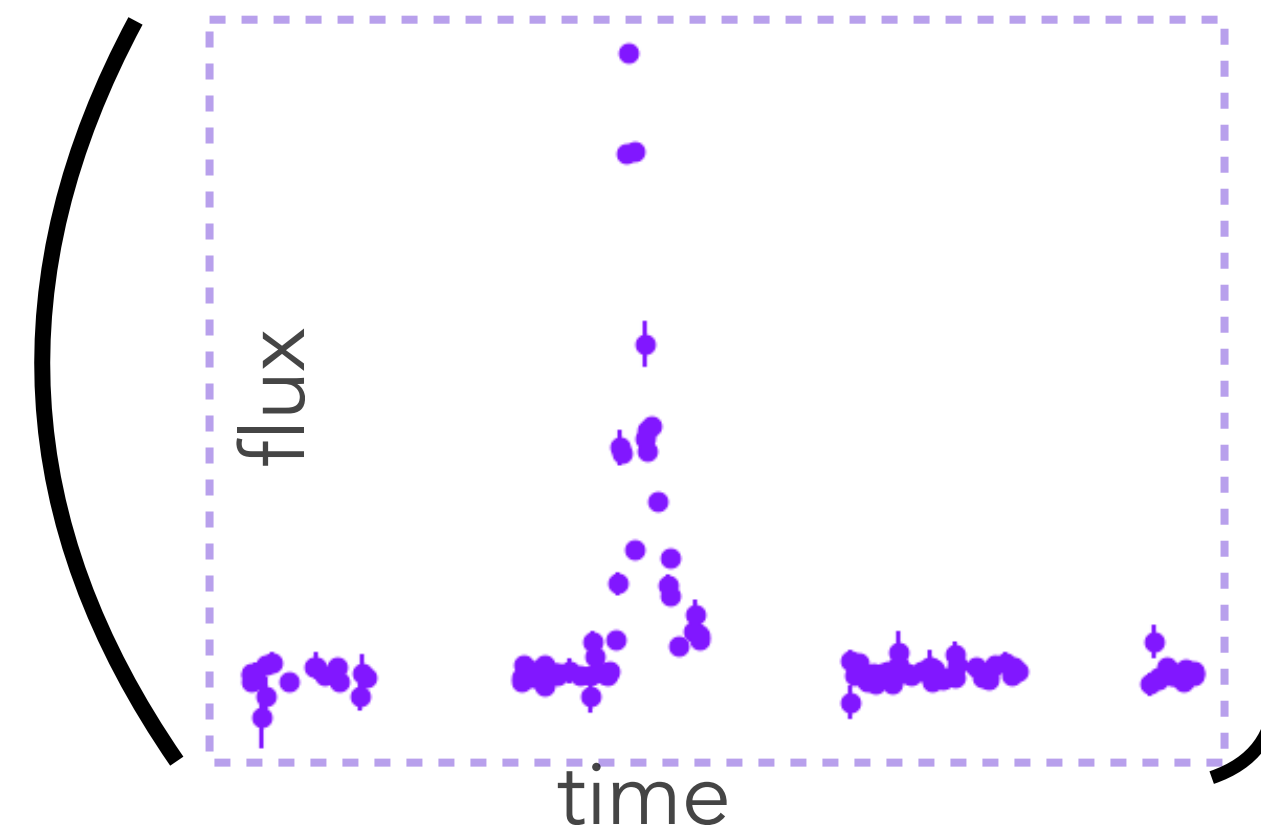
train w/
redshifted
labeled data



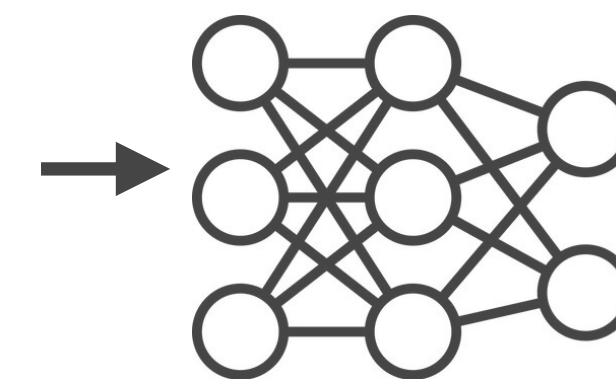
Training a model with real data

this was 0.1%...
**what about the
other 99.9%?**

train w/
redshifted
labeled data



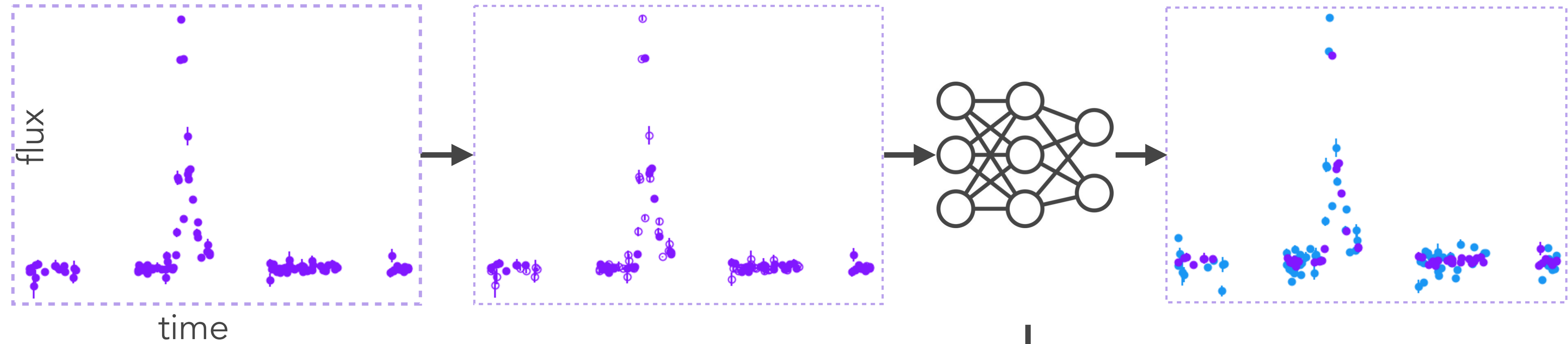
label



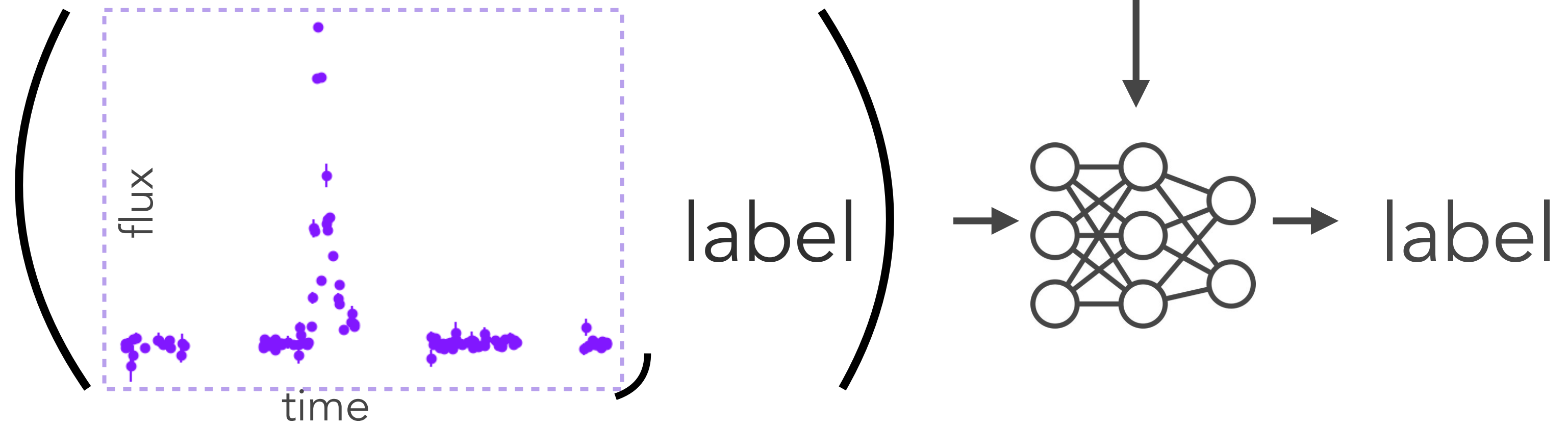
label

Connect Later: Incorporates Labeled + Unlabeled Data

① pretrain w/
all data

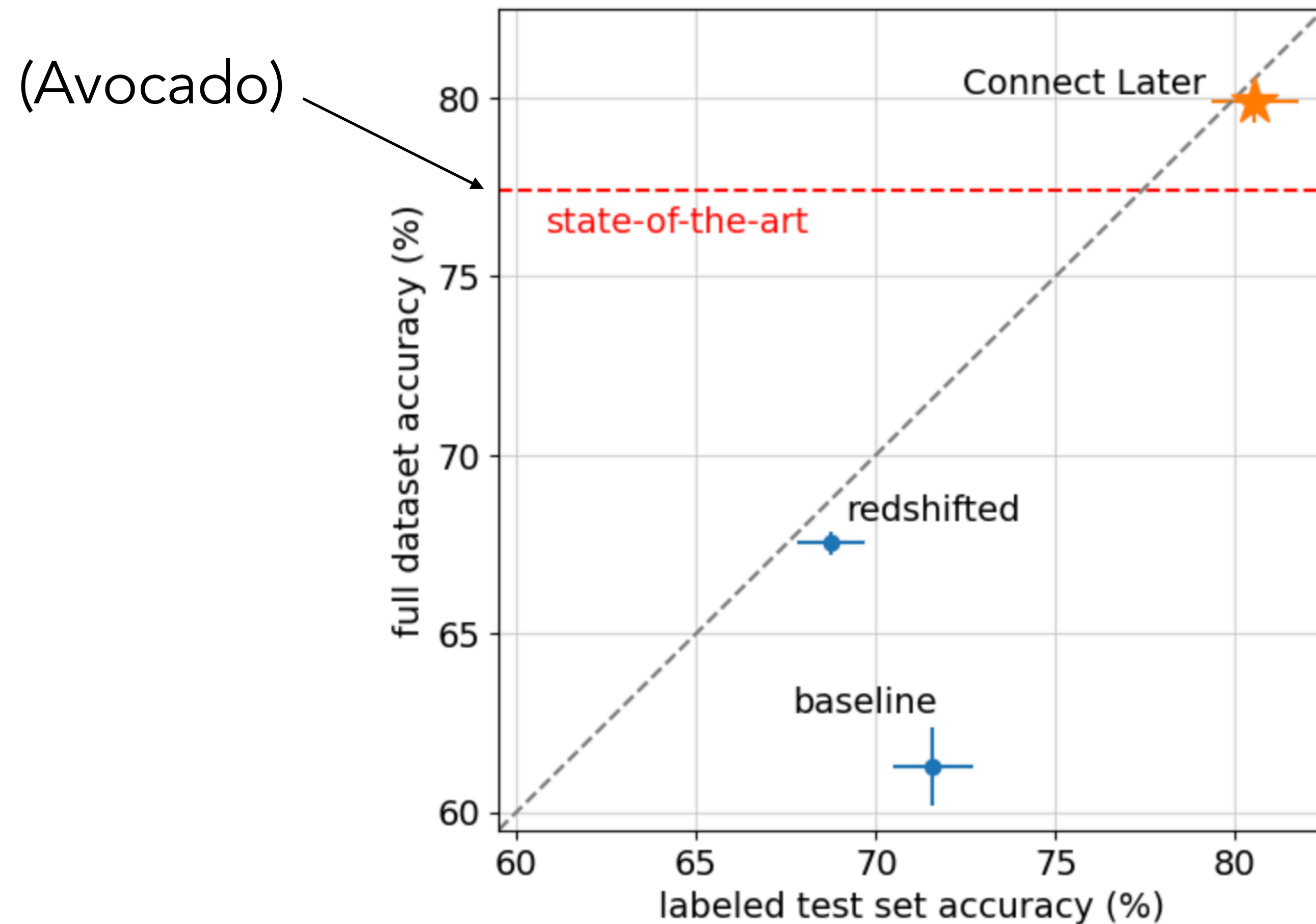


② train w/
redshifted
labeled data



Connect Later outperforms all variants for

Task: PLAsTiCC classification (14 transient/variable types)



Photometric Redshift Estimation

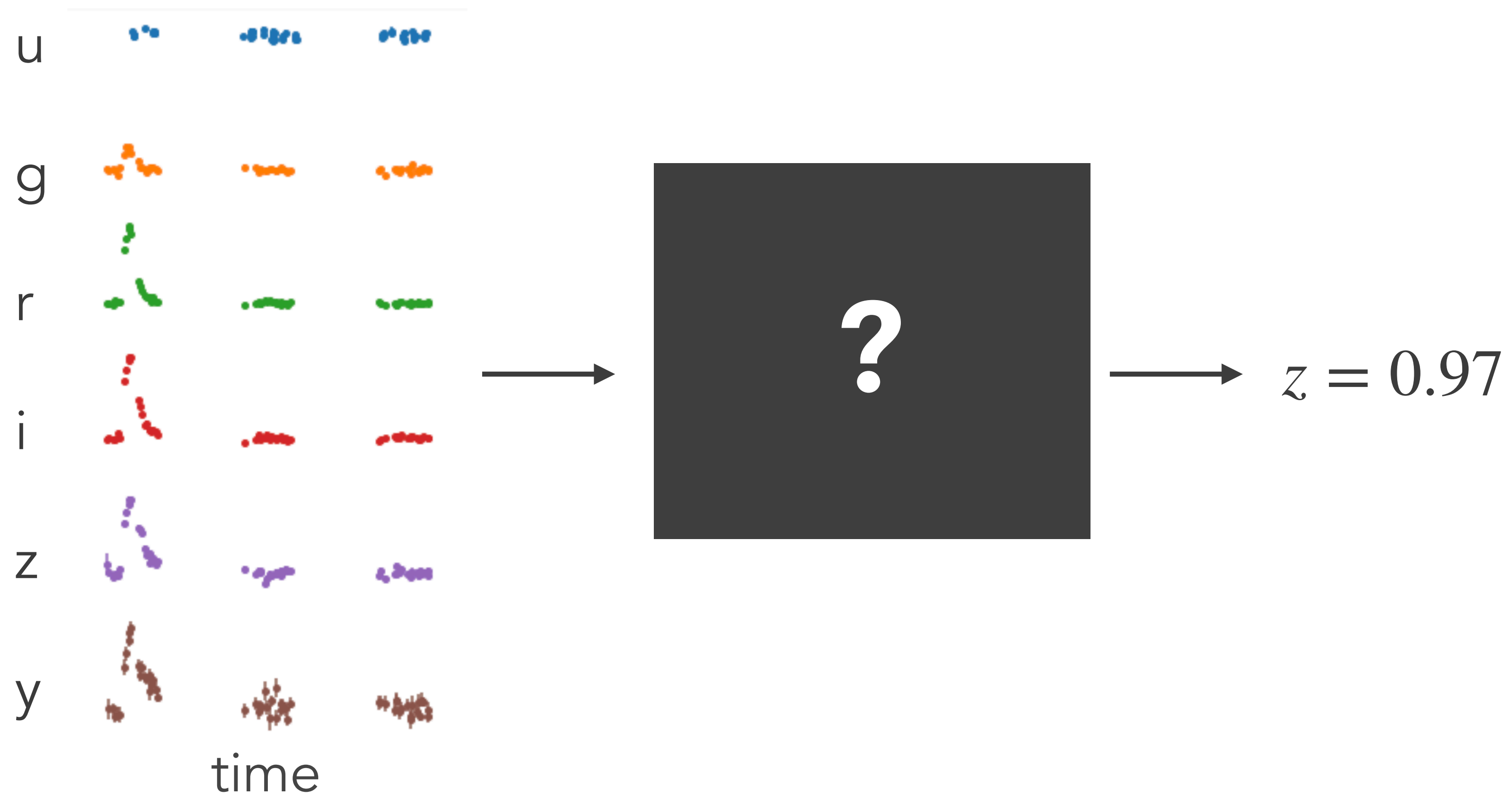


Image Representation Makes Redshift Visible

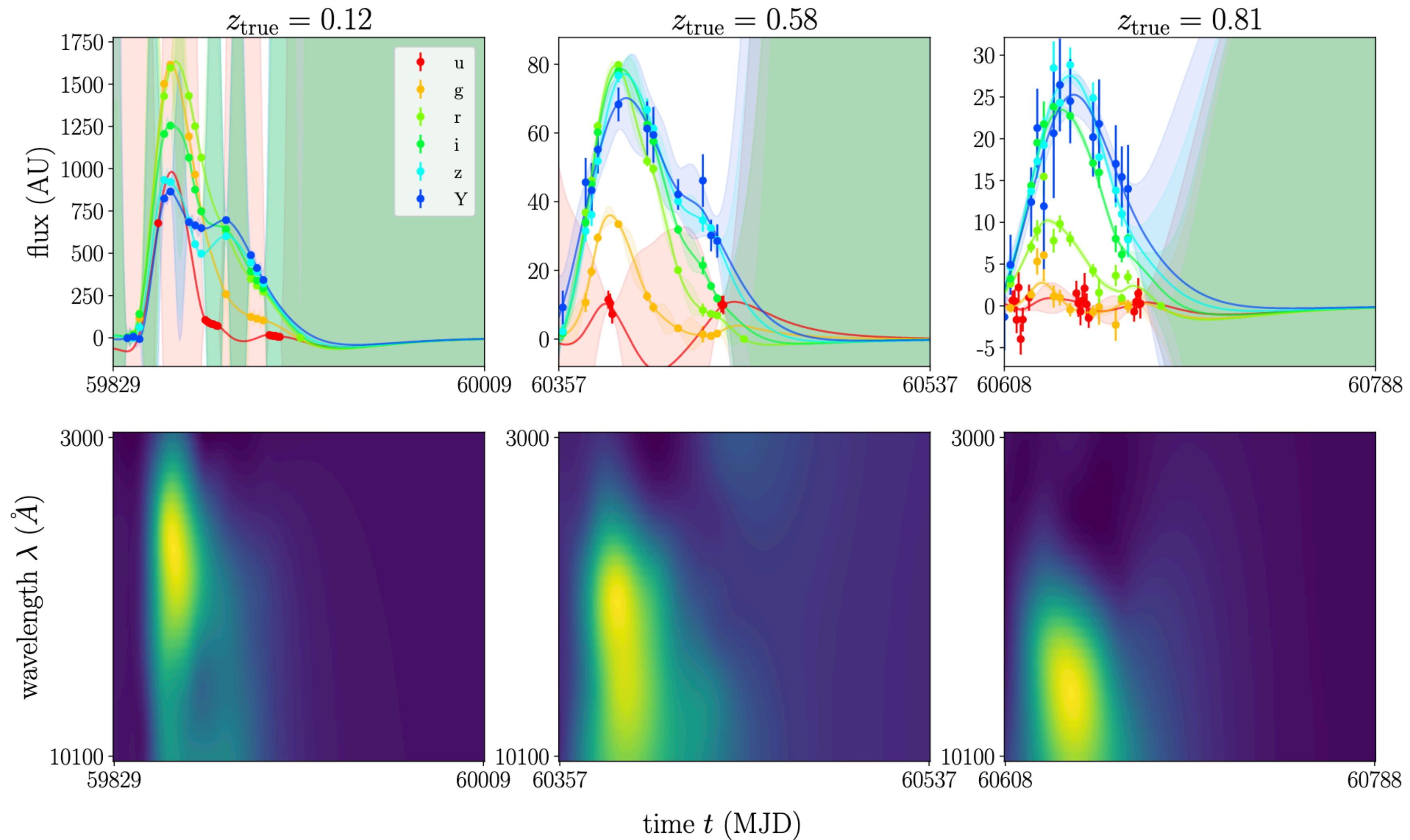
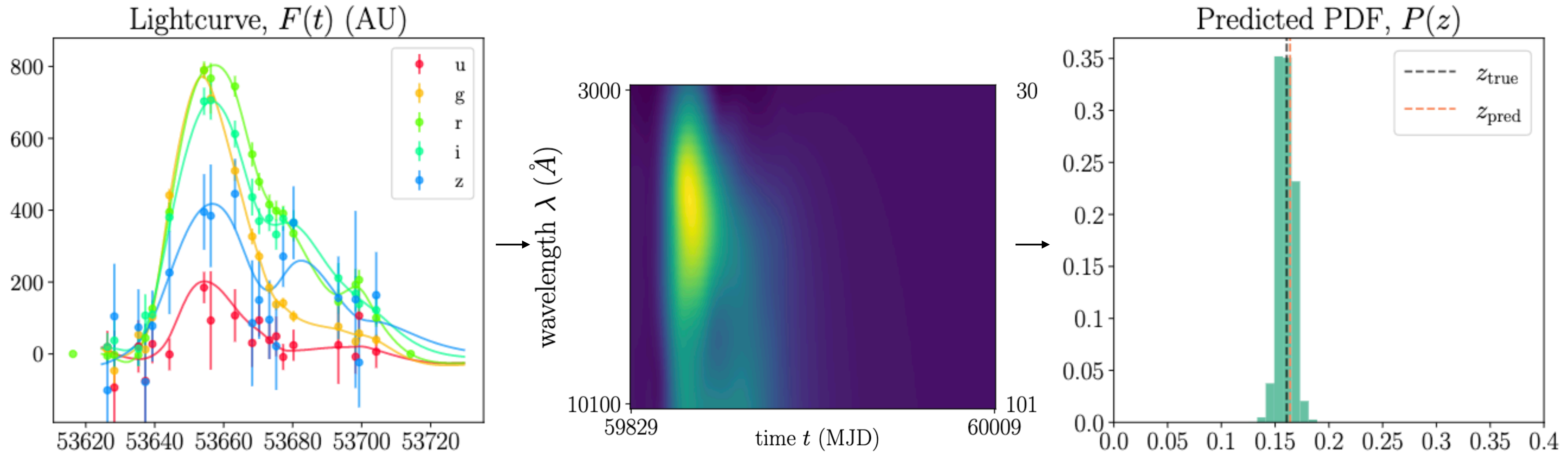
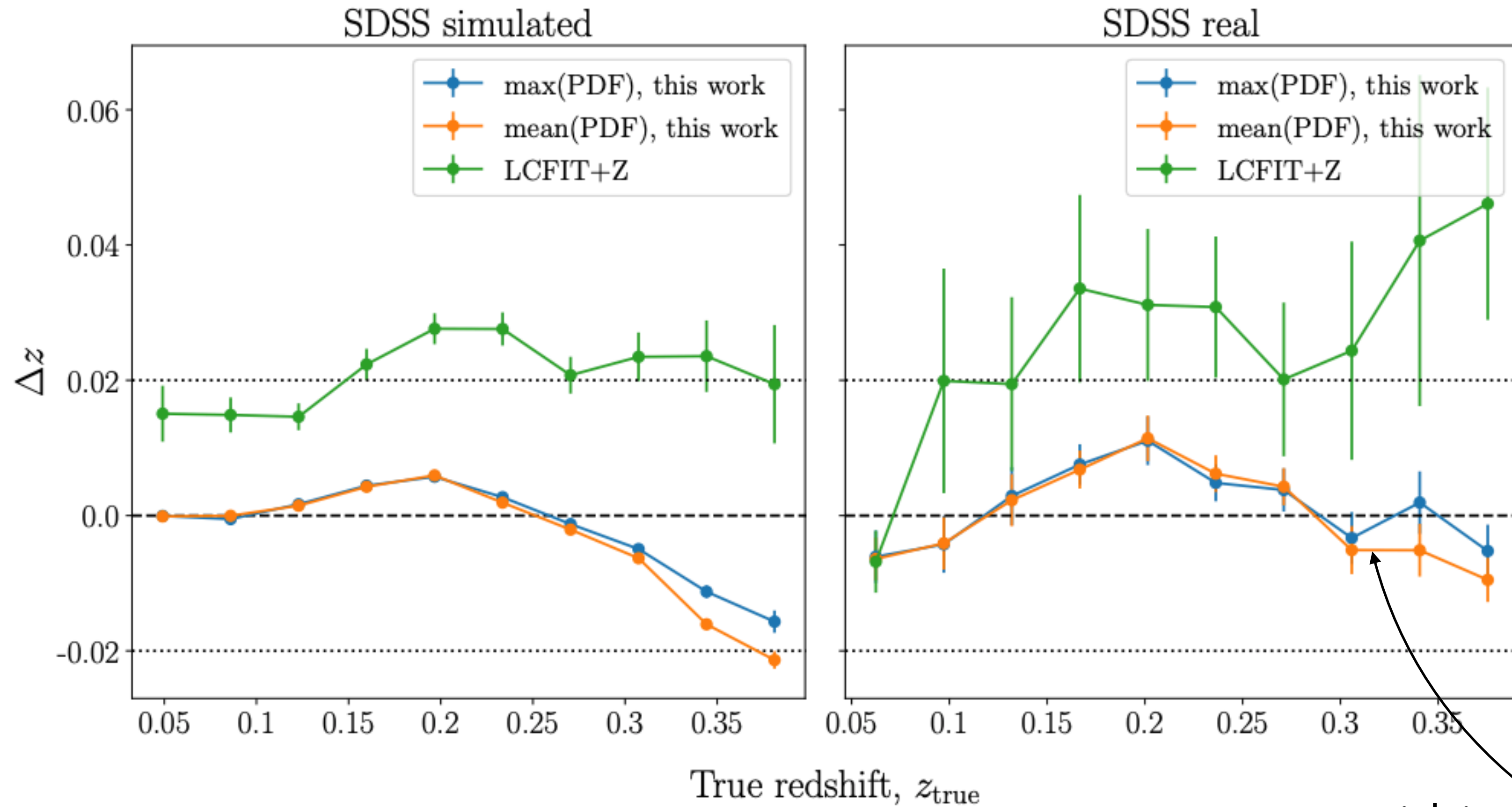


Photo-zSNthesis: Converting SN Ia Lightcurves to Redshift PDFs

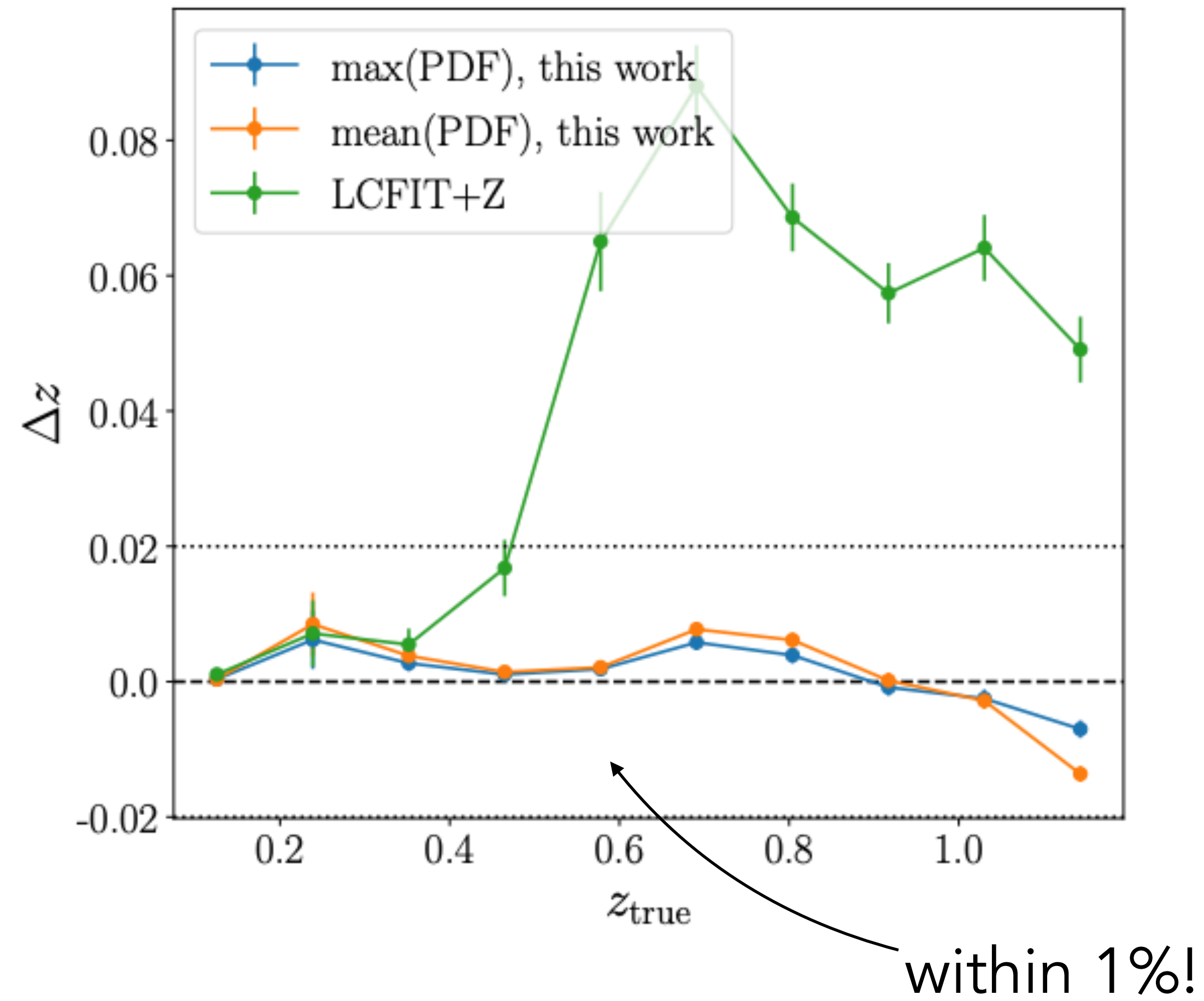


Tested on SDSS simulations + real data



within 1% (similar to best galaxy photo-z's!)

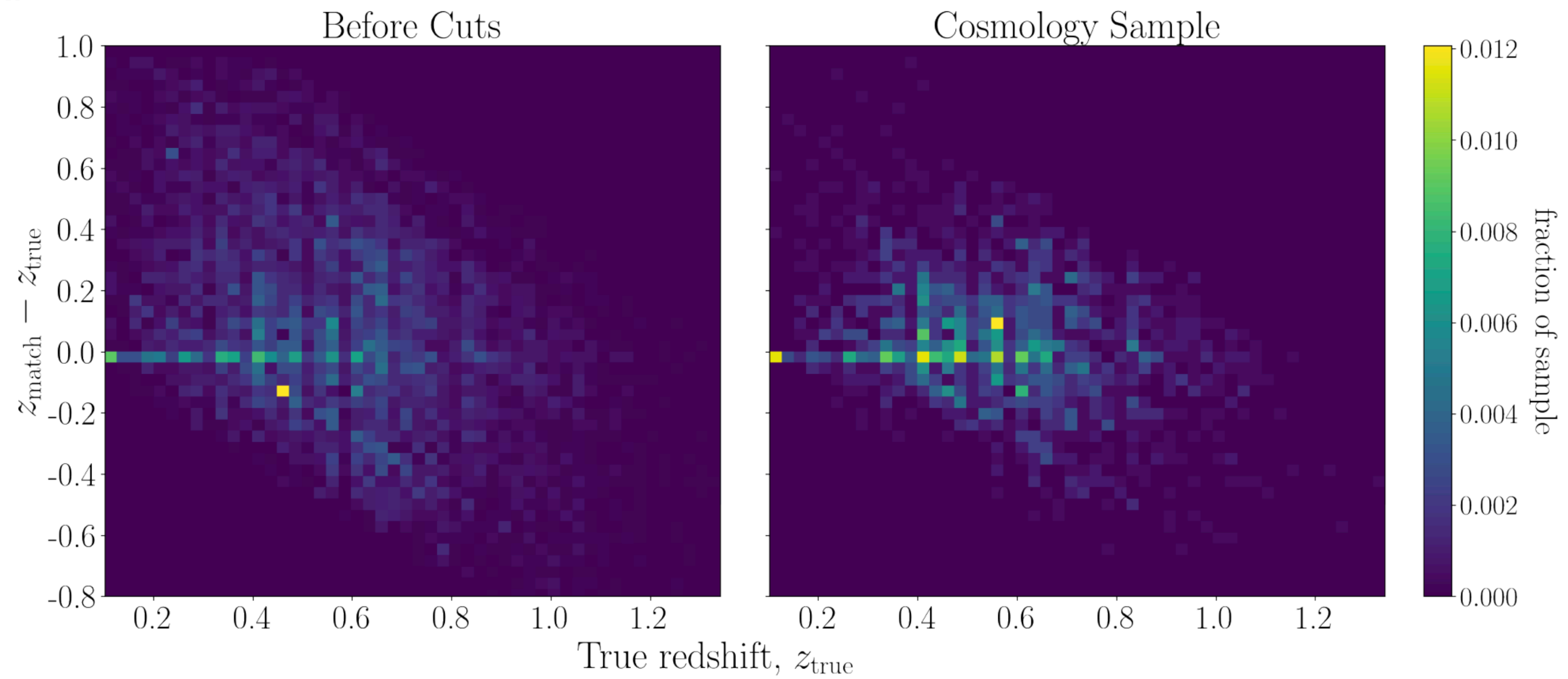
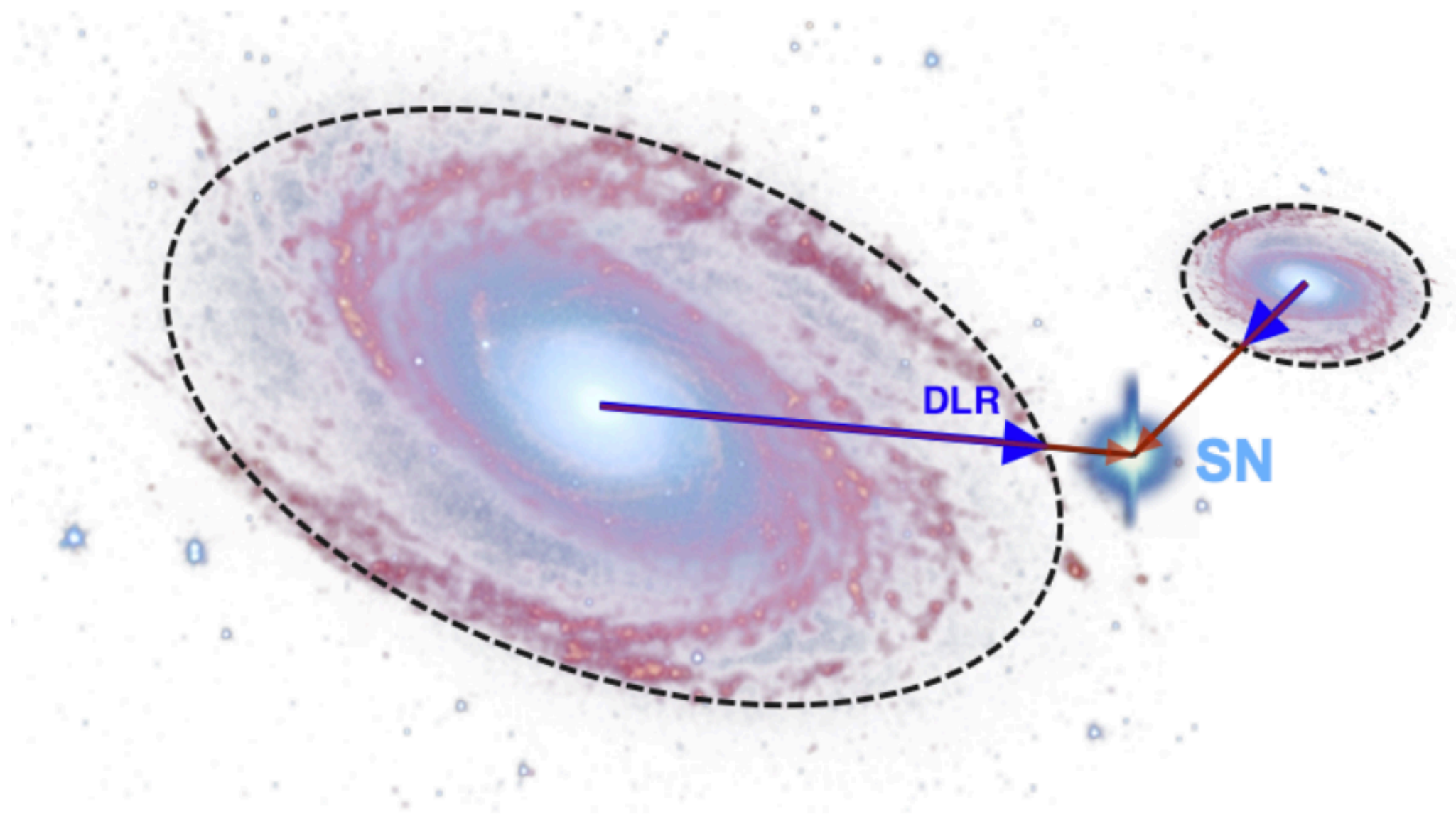
Tested on LSST simulations

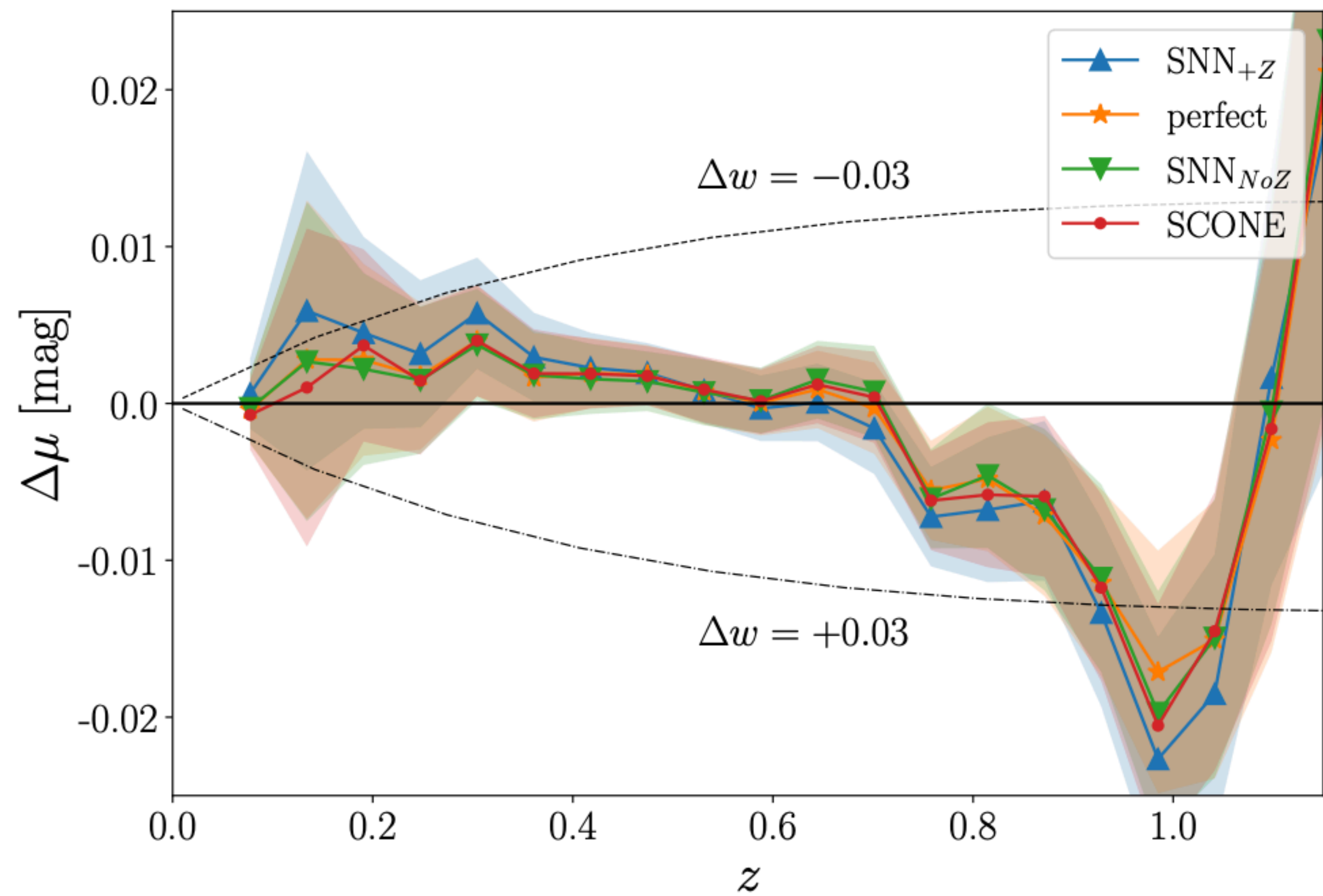
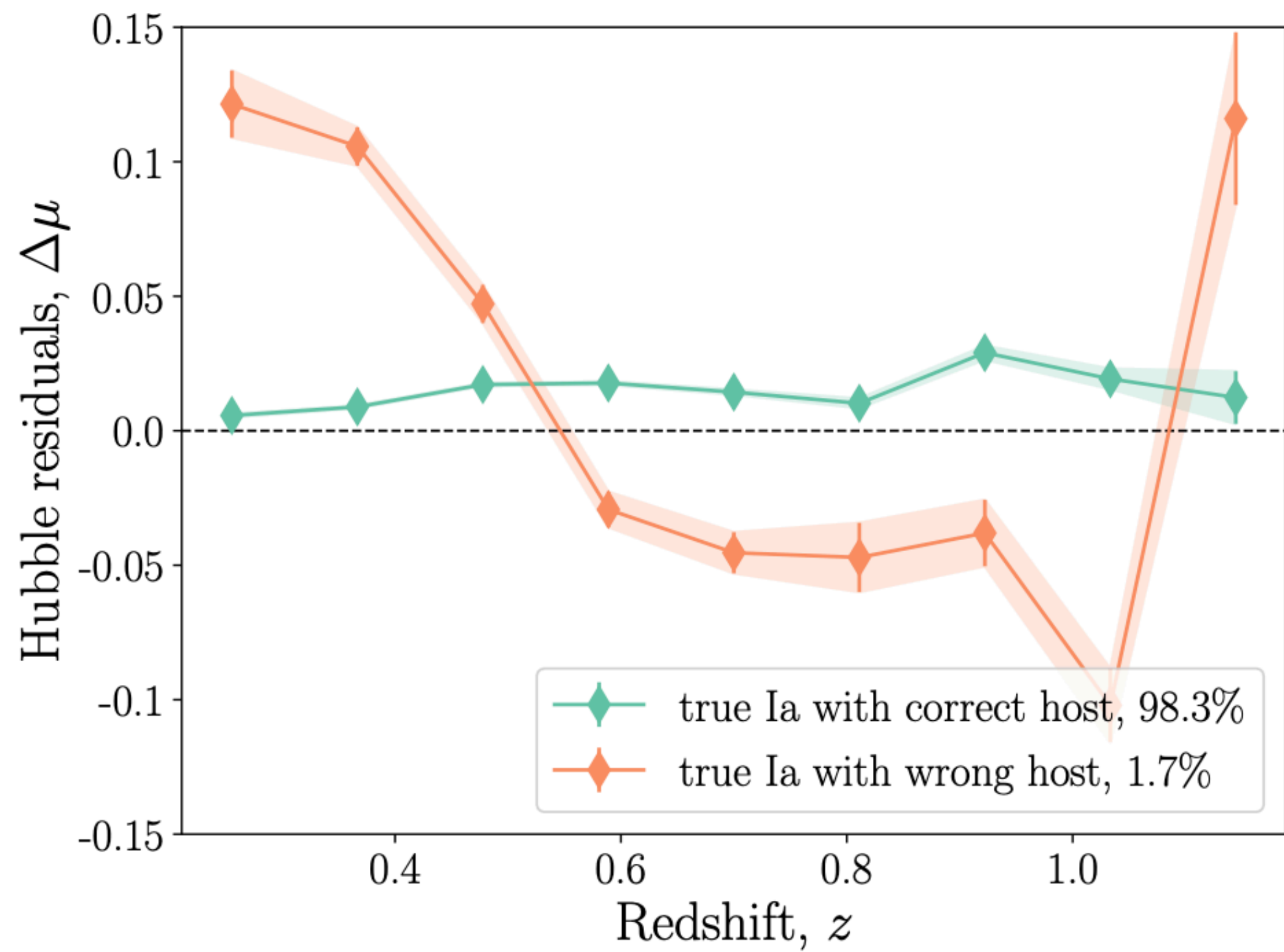


Summary

- Rubin SN cosmology will depend on photometric estimates of SN type & redshift
 - *Photometric classification:* **SCONE**
 - *Photometric redshift estimation:* **Photo-zSNthesis**

Appendix



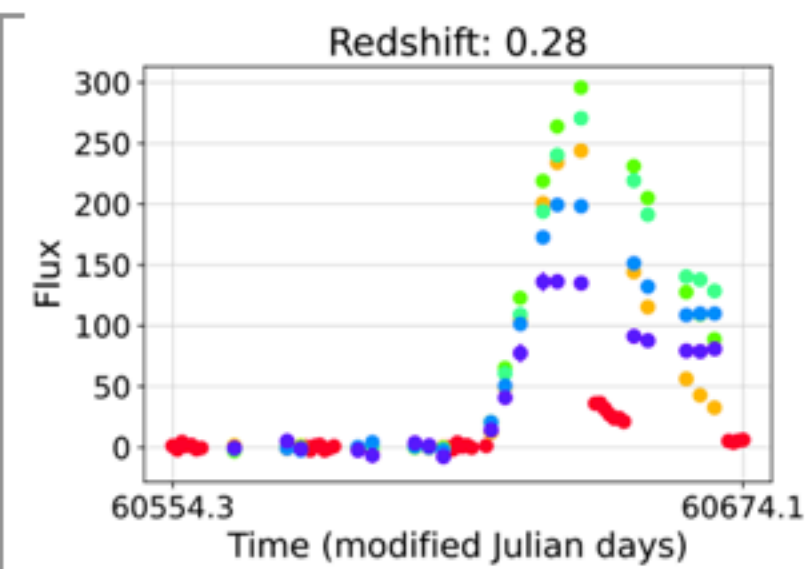


Why pretraining?

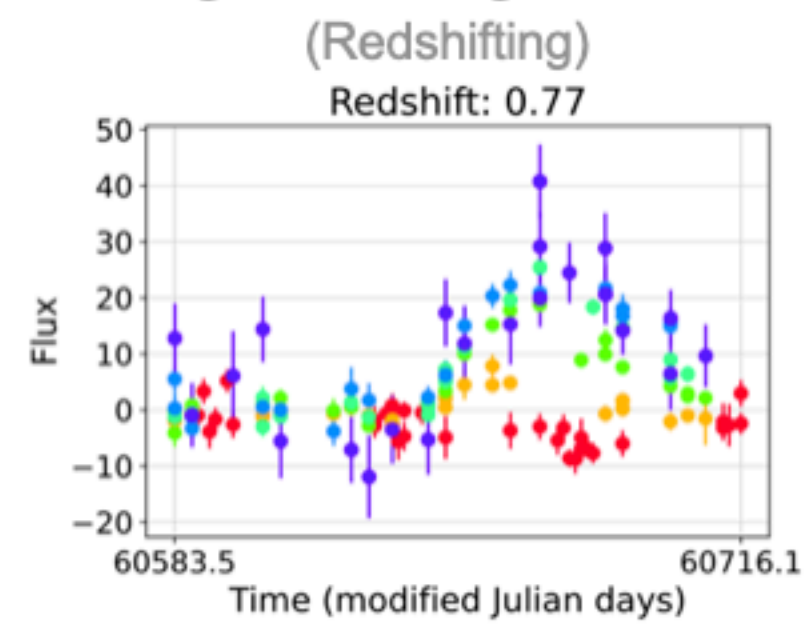
- Out-of-the-box pretraining objectives have been shown to be more effective for unsupervised domain adaptation (UDA) than methods tailored for UDA (e.g., DANN, CORAL) [Shen et al., 2022]
- Generally, much more unlabeled data is available than labeled data
- pretrained models can be reused for multiple downstream tasks (AstroClassification and Redshifts in our paper)

AstroClassification +
Redshifts

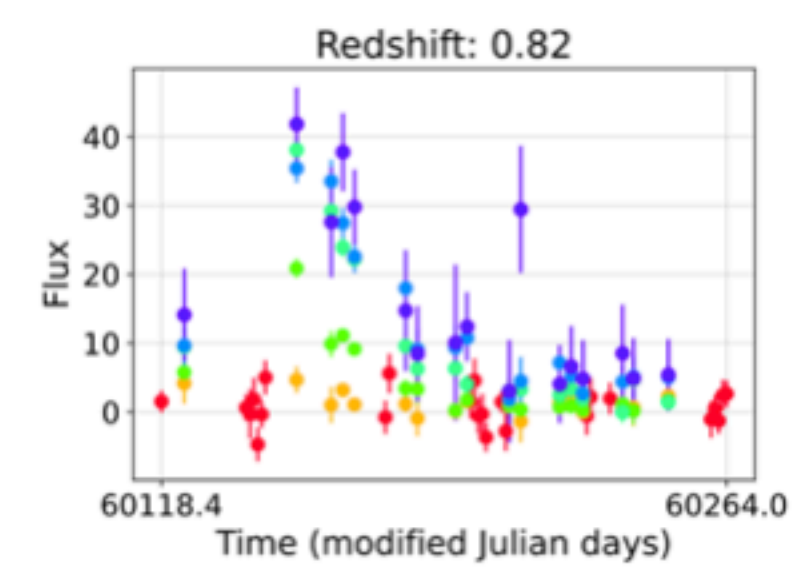
Source



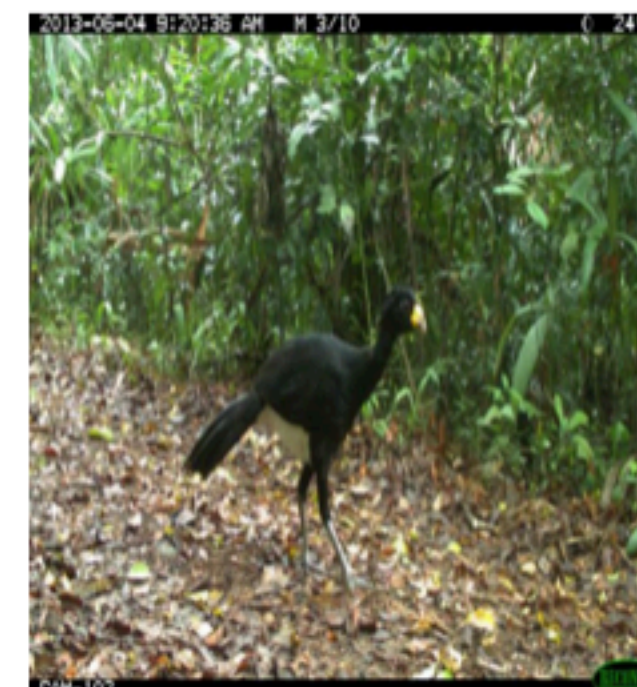
Targeted Augmentation (Redshifting)



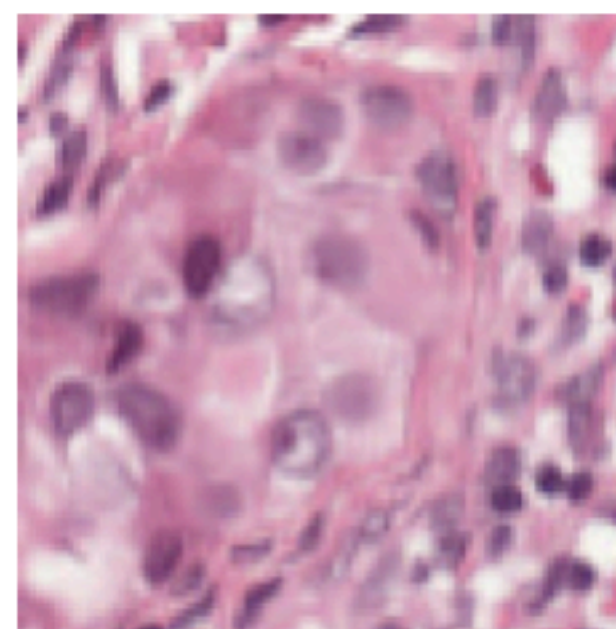
Target



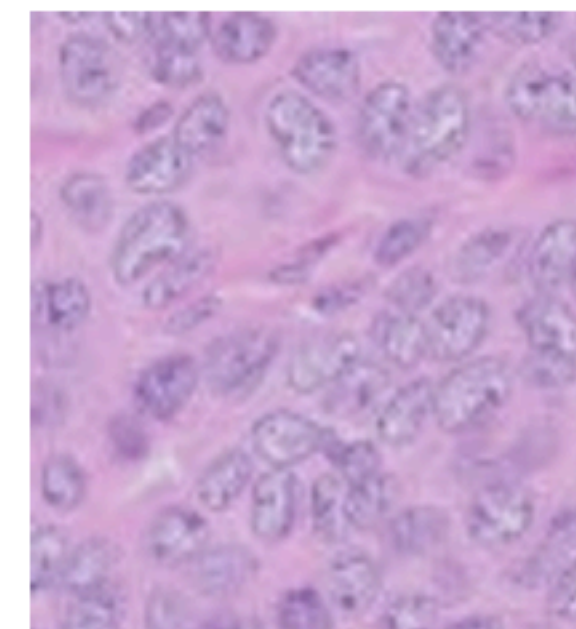
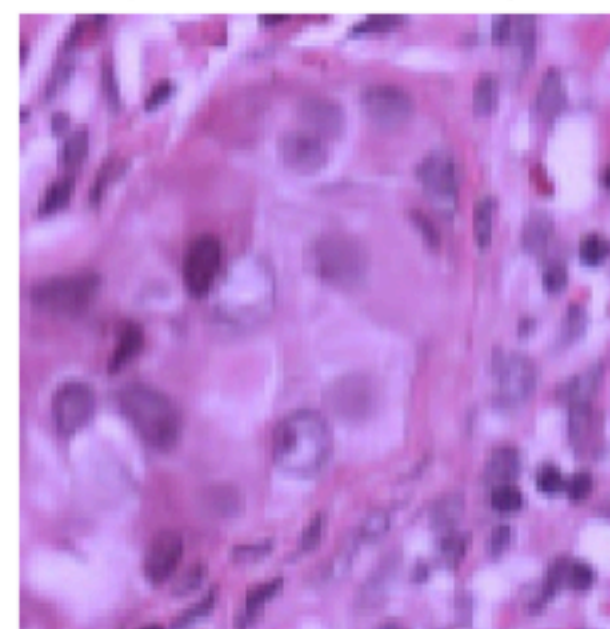
iWildCam



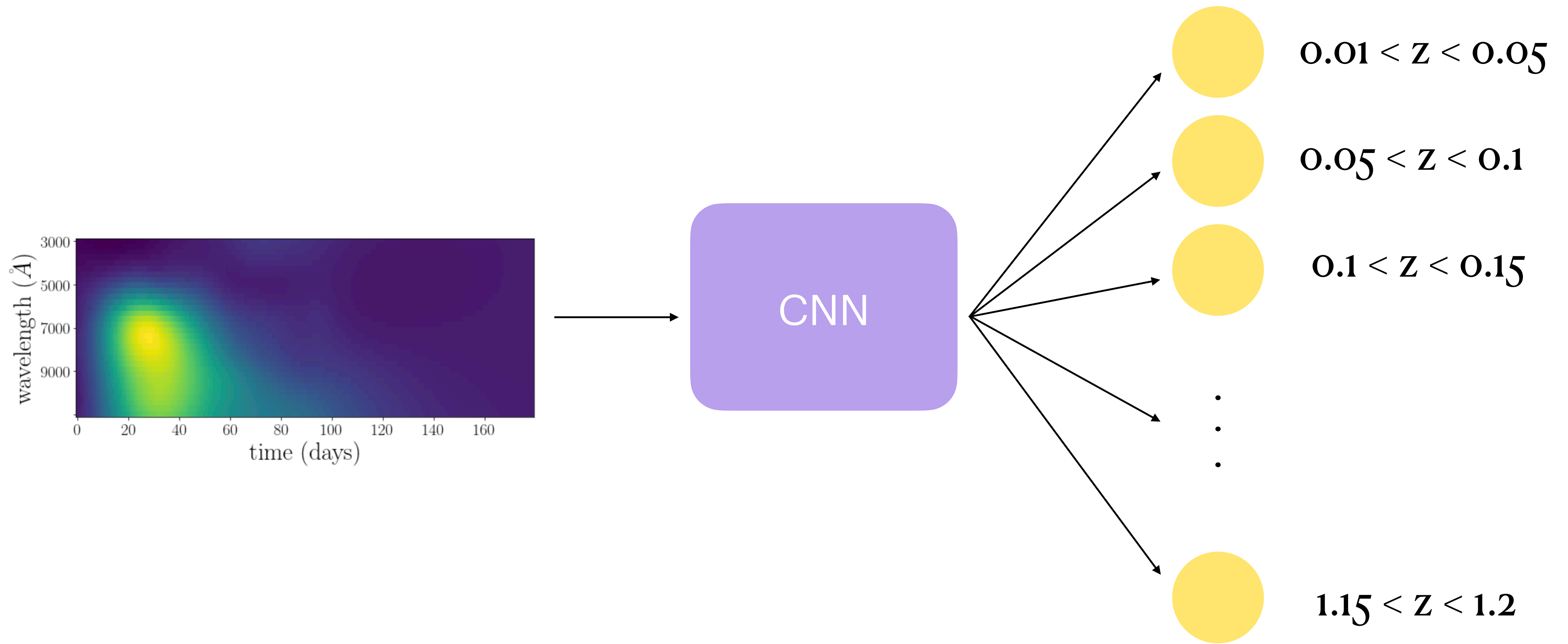
Camelyon17



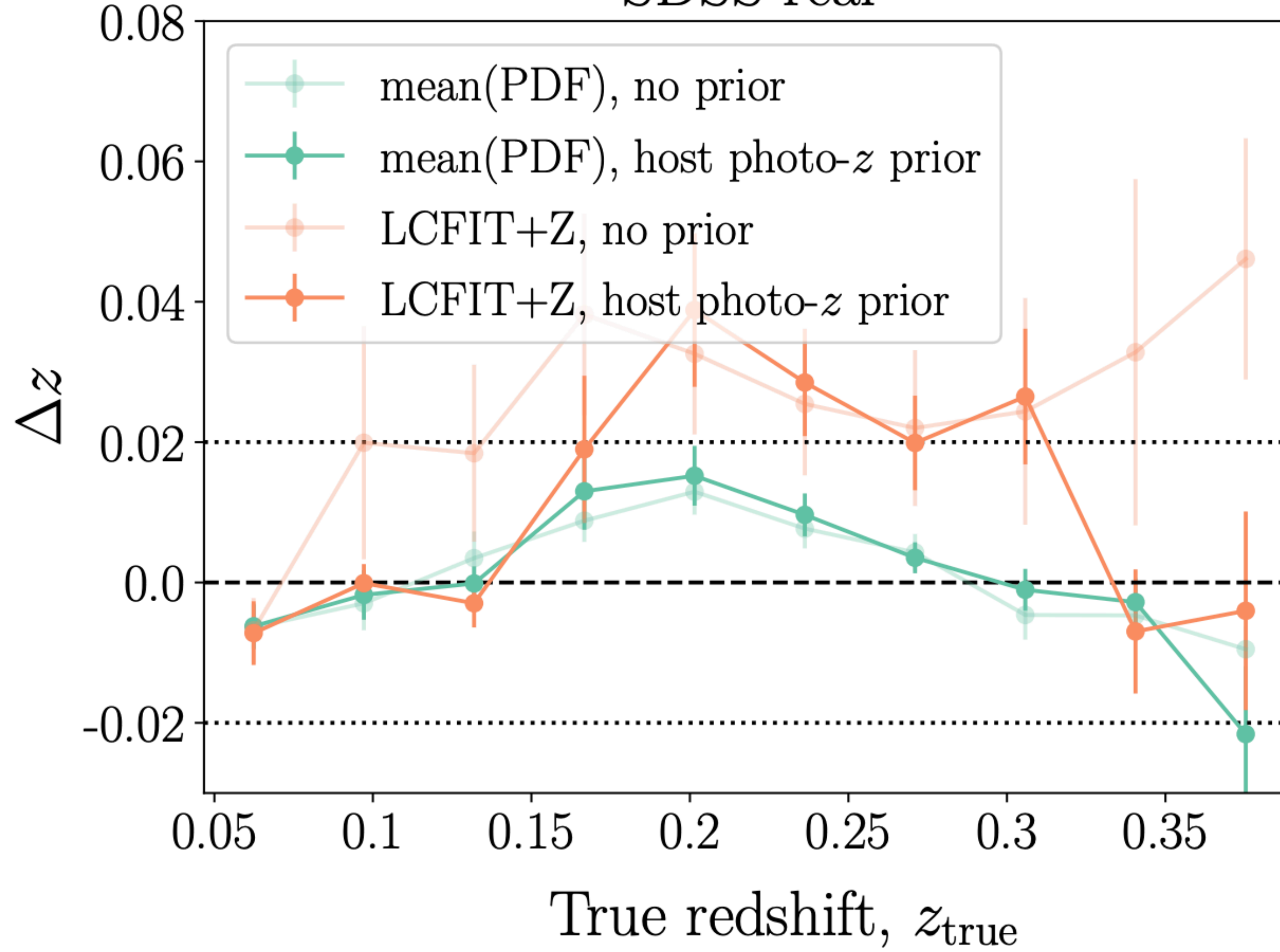
(Stain Color Jitter)



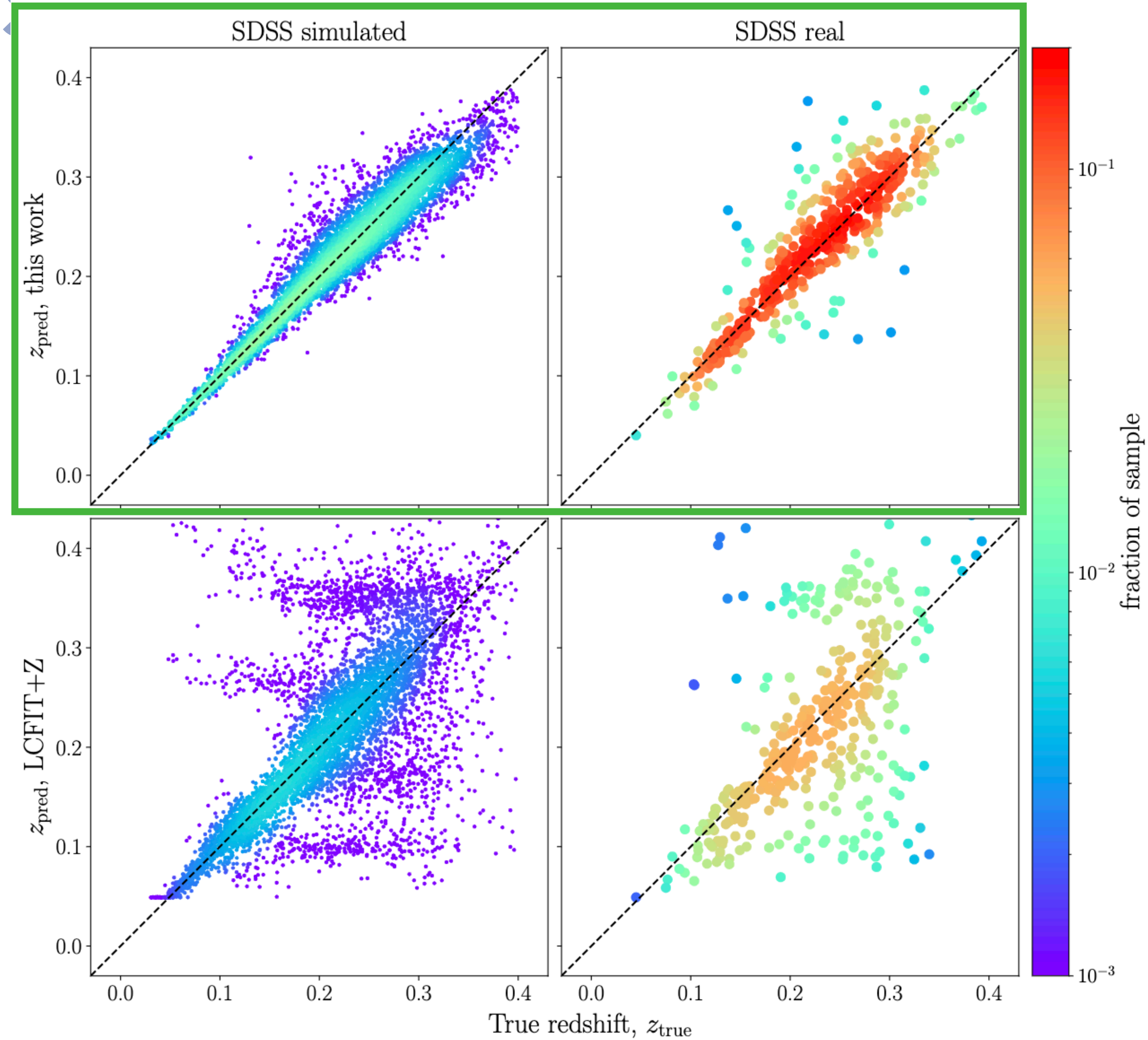
Discretized PDF



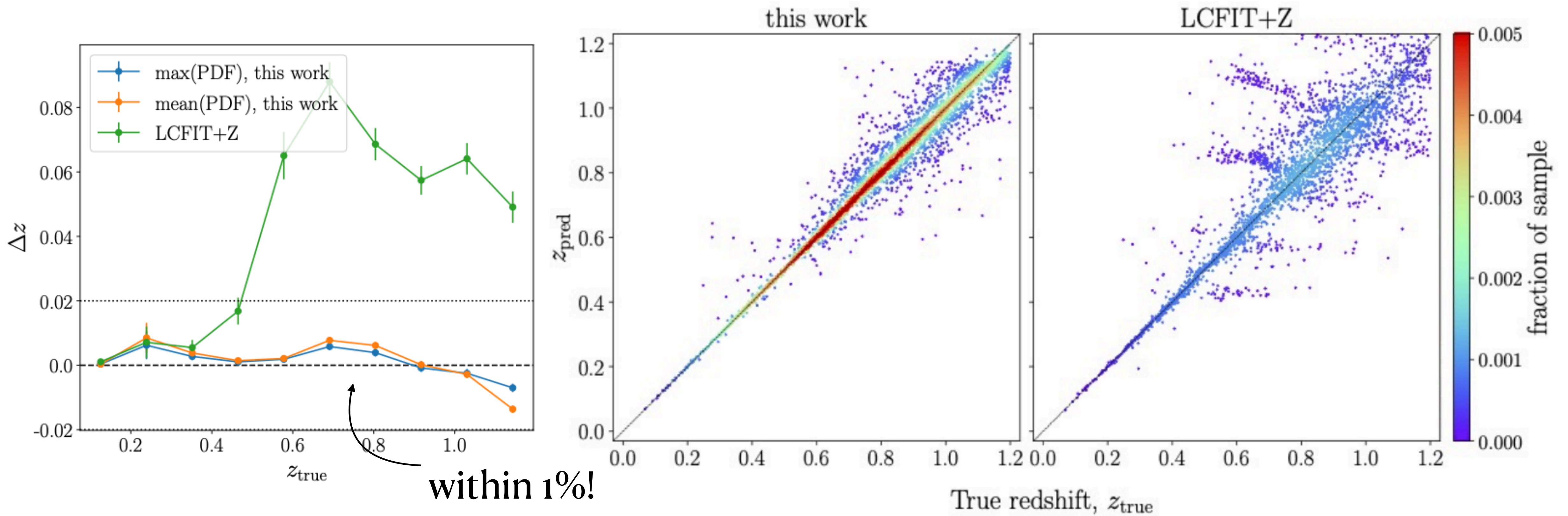
SDSS real



Tested on SDSS simulations & real data



Tested on LSST simulations



Survey-Agnostic Performance

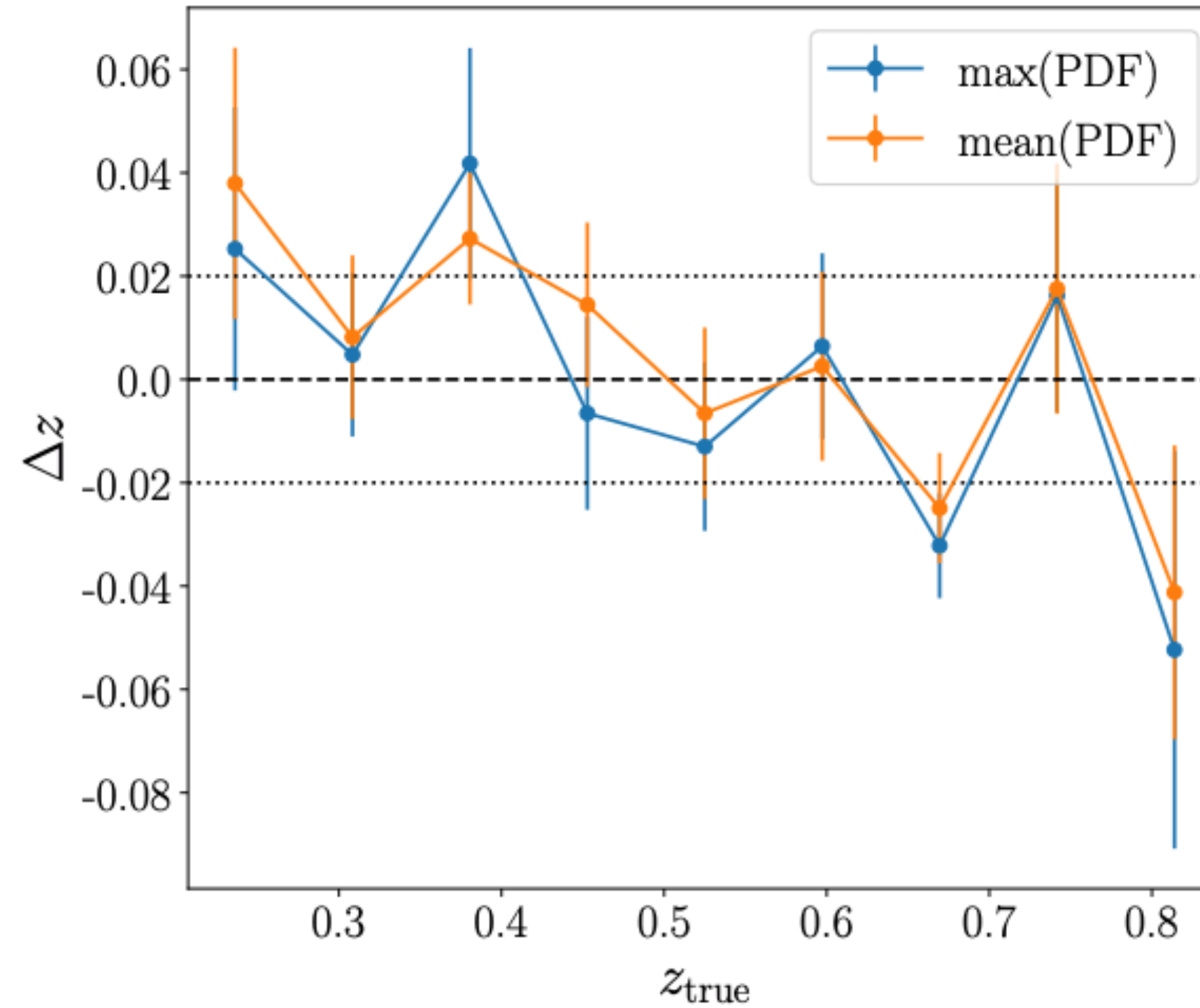
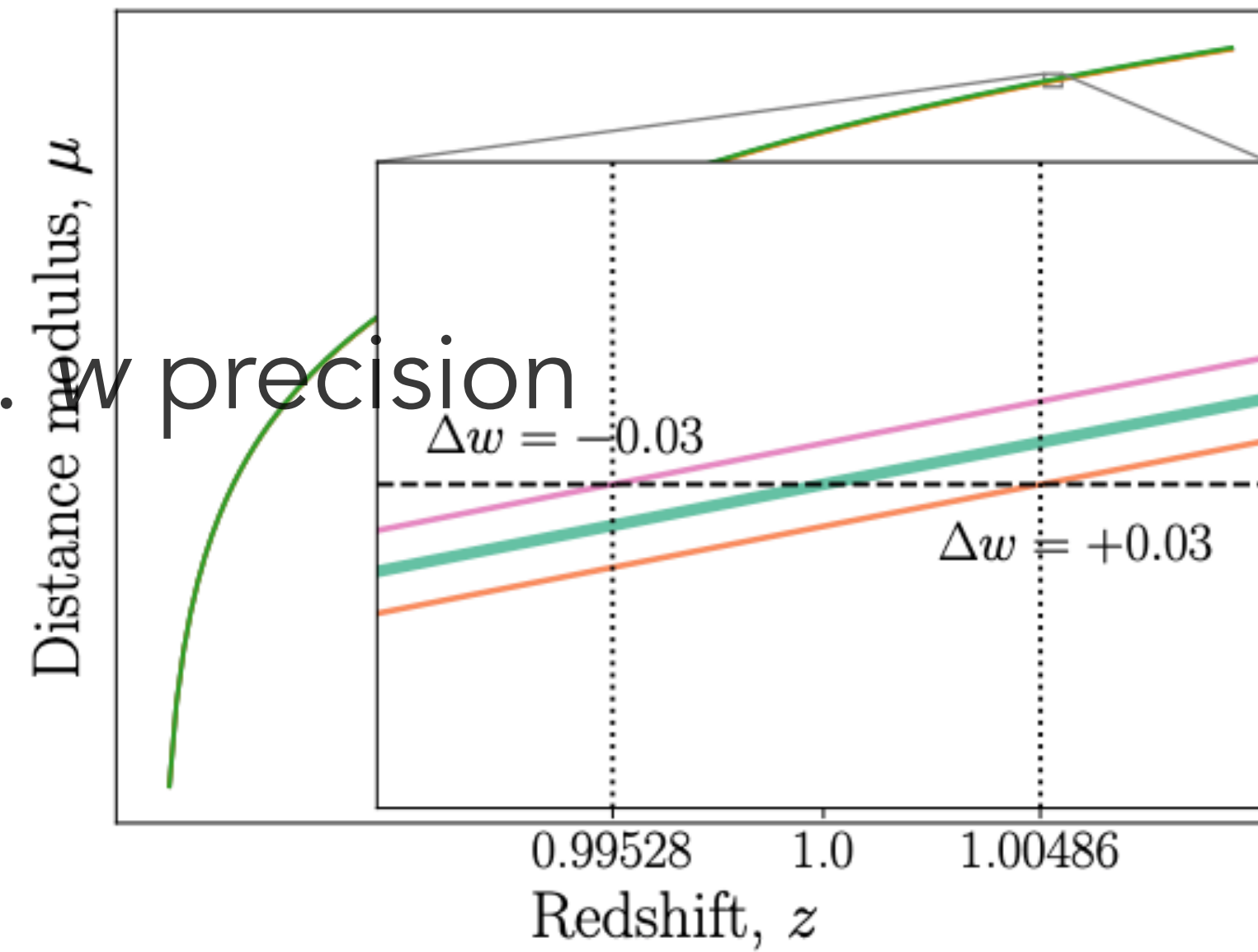


Figure 14. Mean binned residuals, $\Delta z \equiv \frac{z_{\text{pred}} - z_{\text{true}}}{1 + z_{\text{true}}}$, as a function of true redshift, z_{true} , for the DES3YR SNe Ia sample produced by a model trained on the PLAsTiCC dataset. The max(PDF) and mean(PDF) methods of obtaining point estimates from Photo-zSNthesis PDFs are described in §4.1.1.

Photo-z's for Cosmology

Rough estimate of redshift precision vs. Δw precision



shows we can almost constrain $\Delta w = \pm 0.1$

