Towards Precision Photometric Supernova Cosmology with Machine Learning

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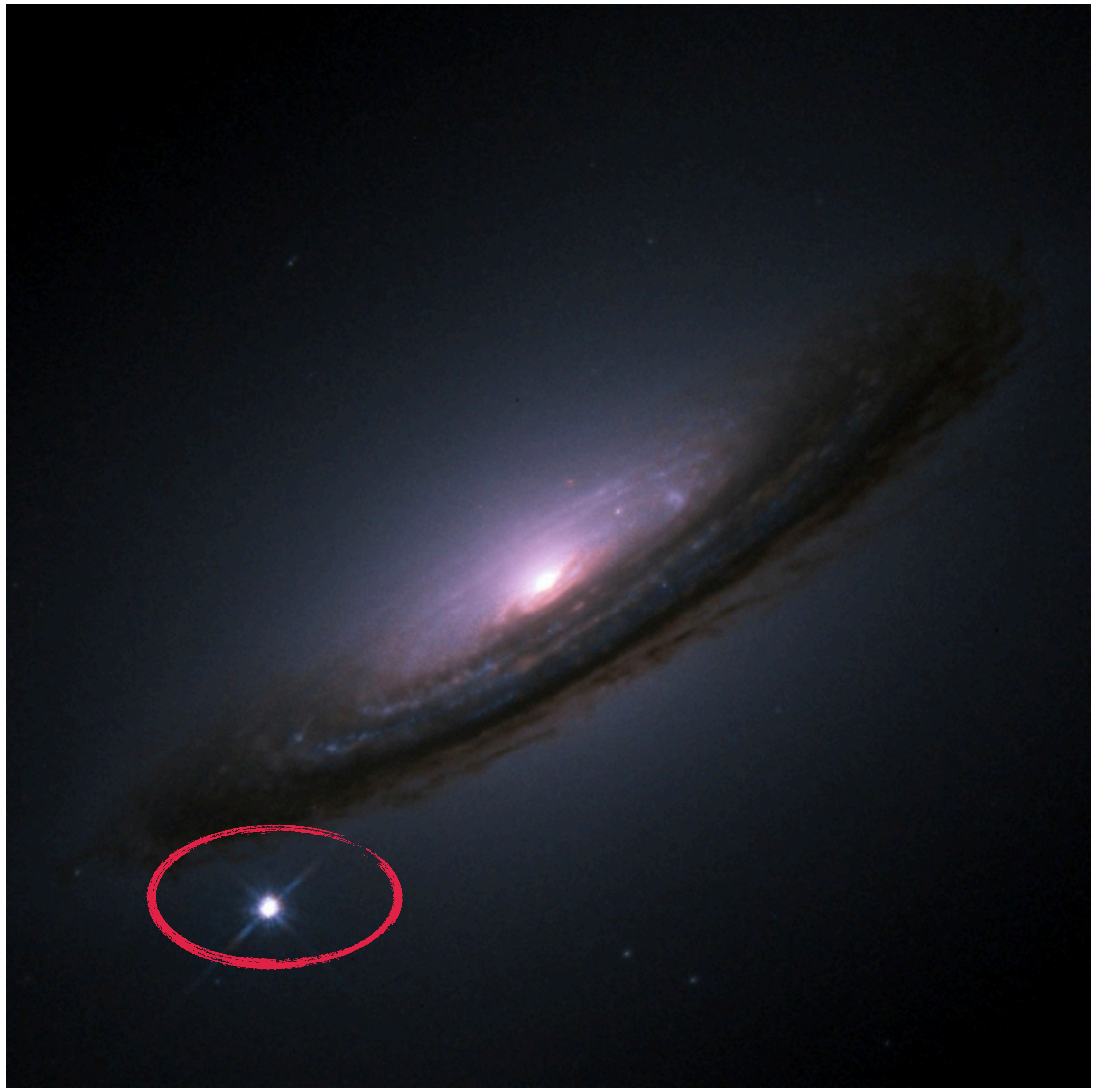
Type Ia supernovae are standard(izable) candles

- *standard(izable) candles:* events that (can be systematically corrected to) occur with the same luminosity every time

- measure brightness ⟶ know distance!

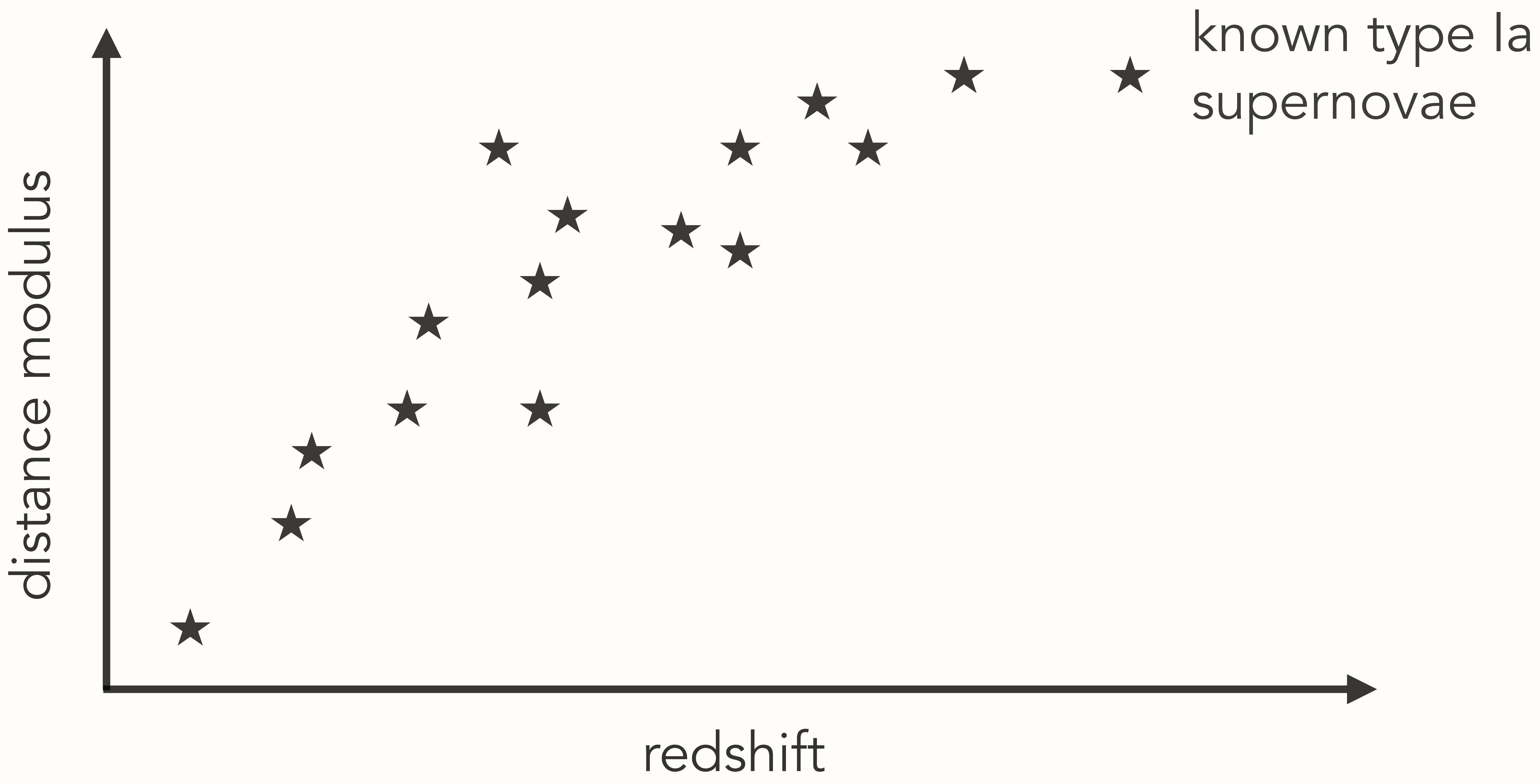
Type Ia supernovae are standard(izable) candles

- *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 $z > 1$)

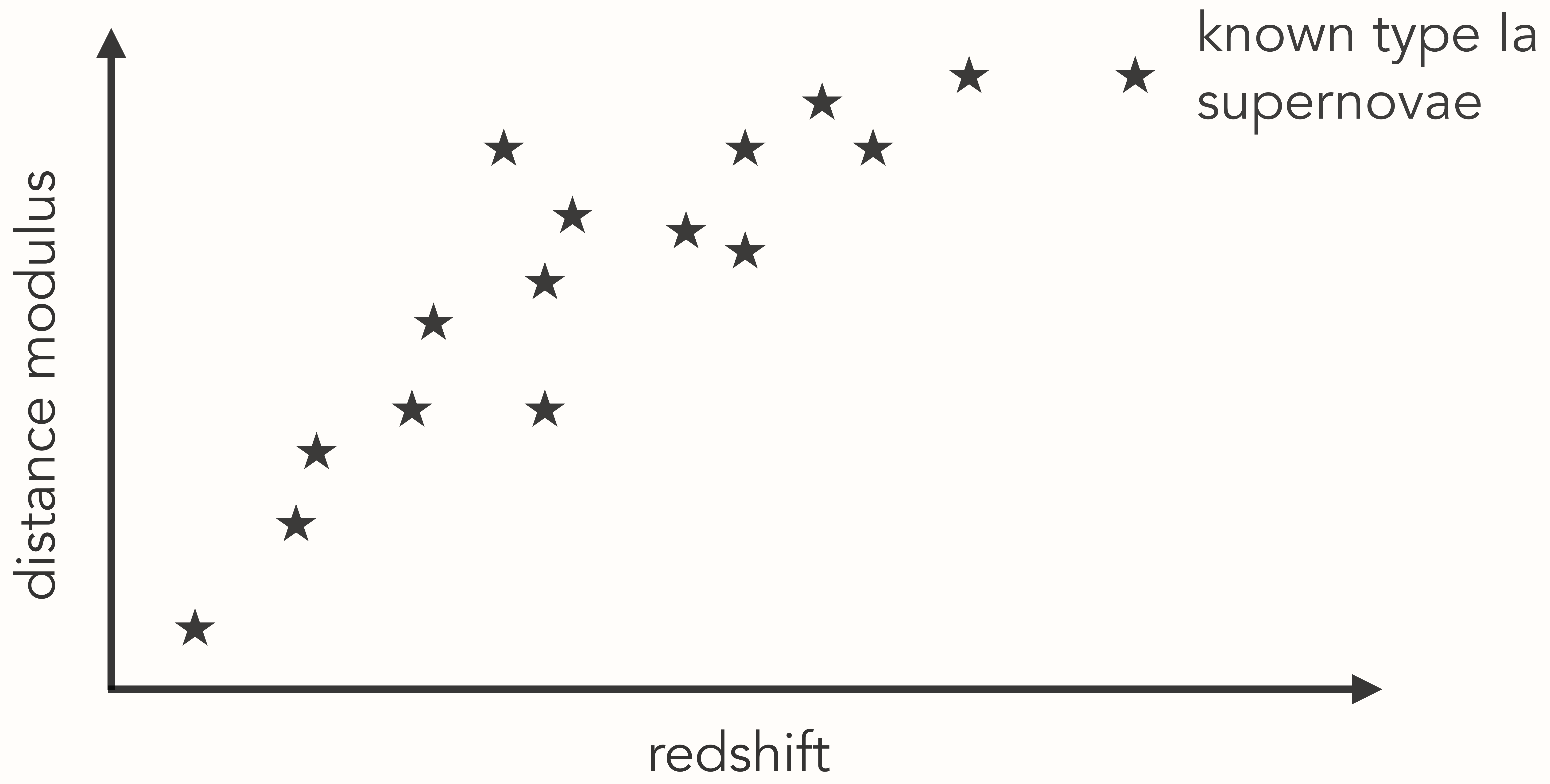


The Hubble Diagram

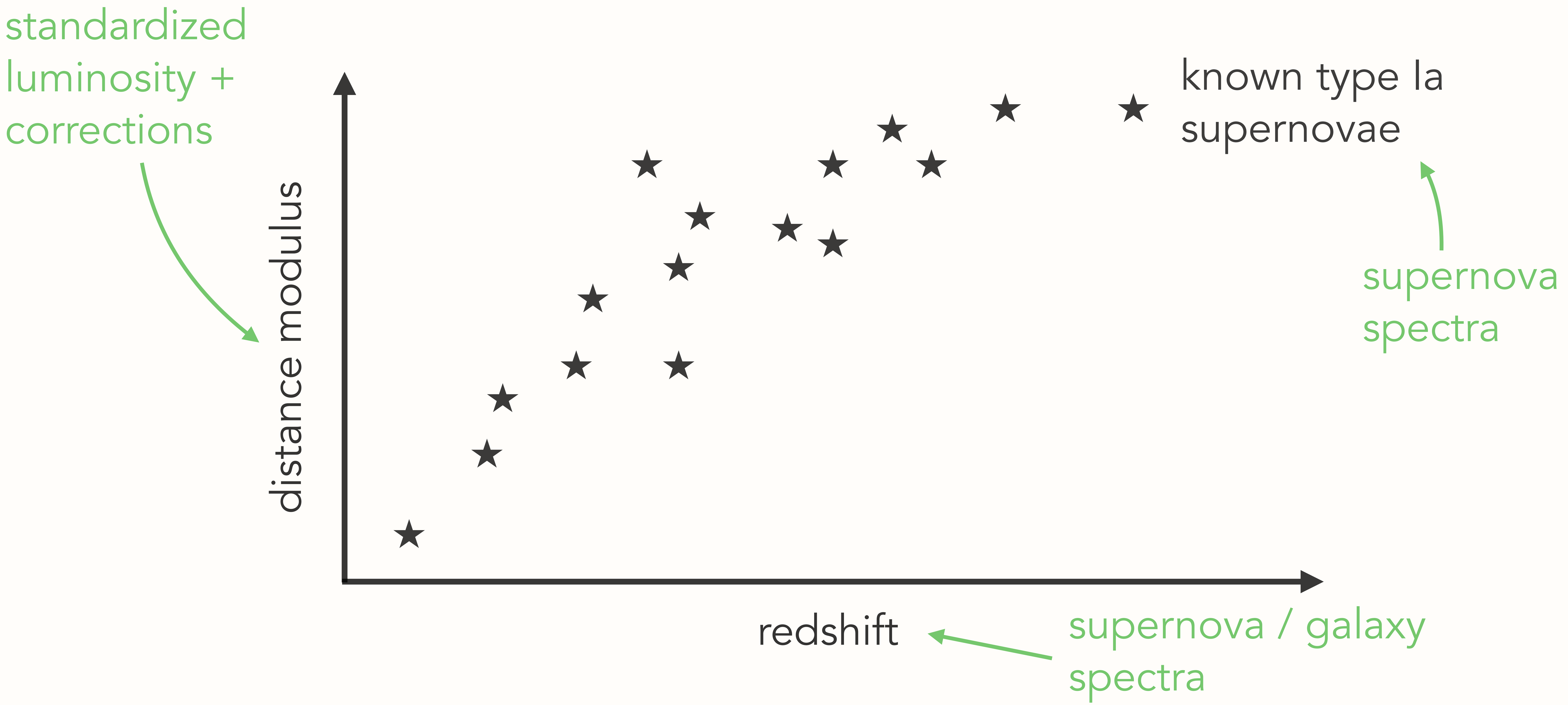
Standard candles can tell us about cosmology!



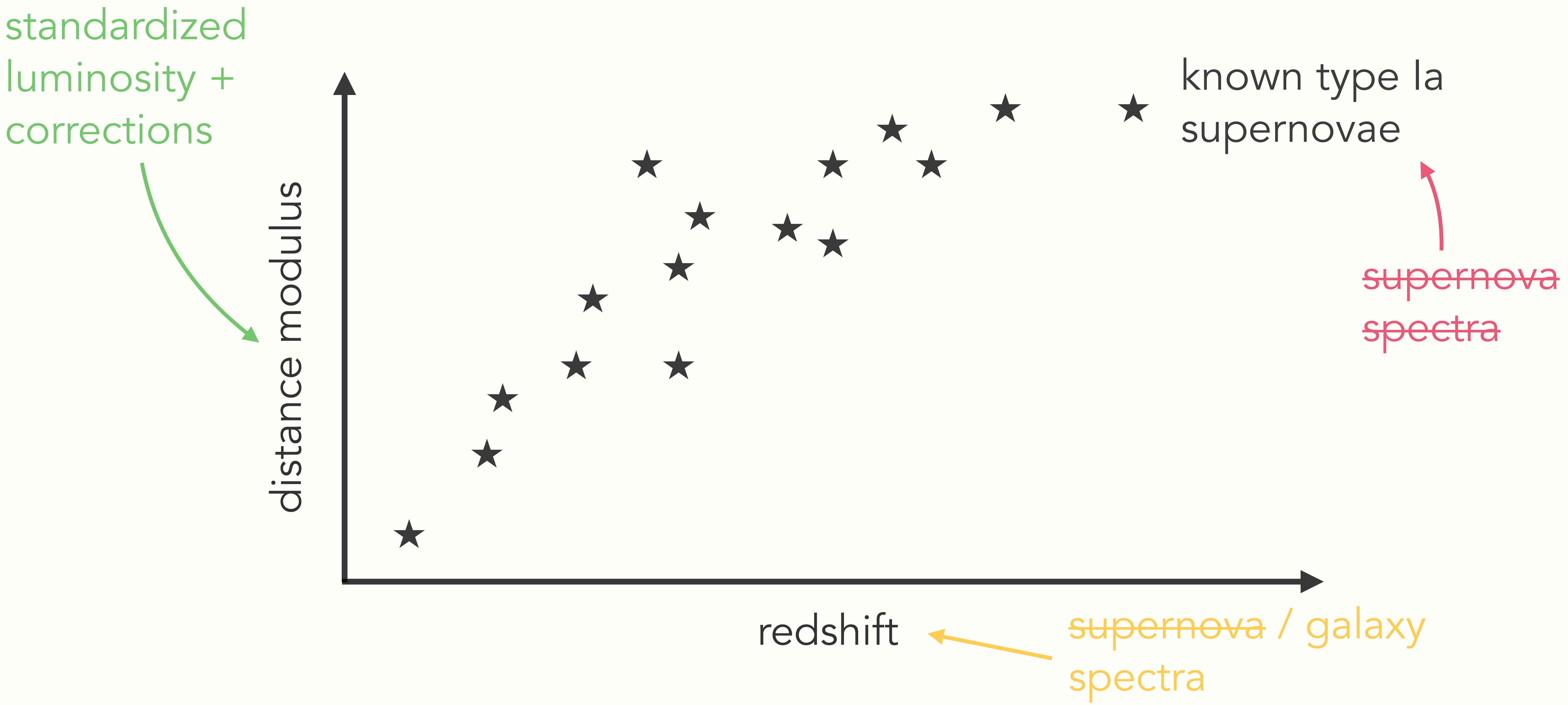
How do we know these quantities?

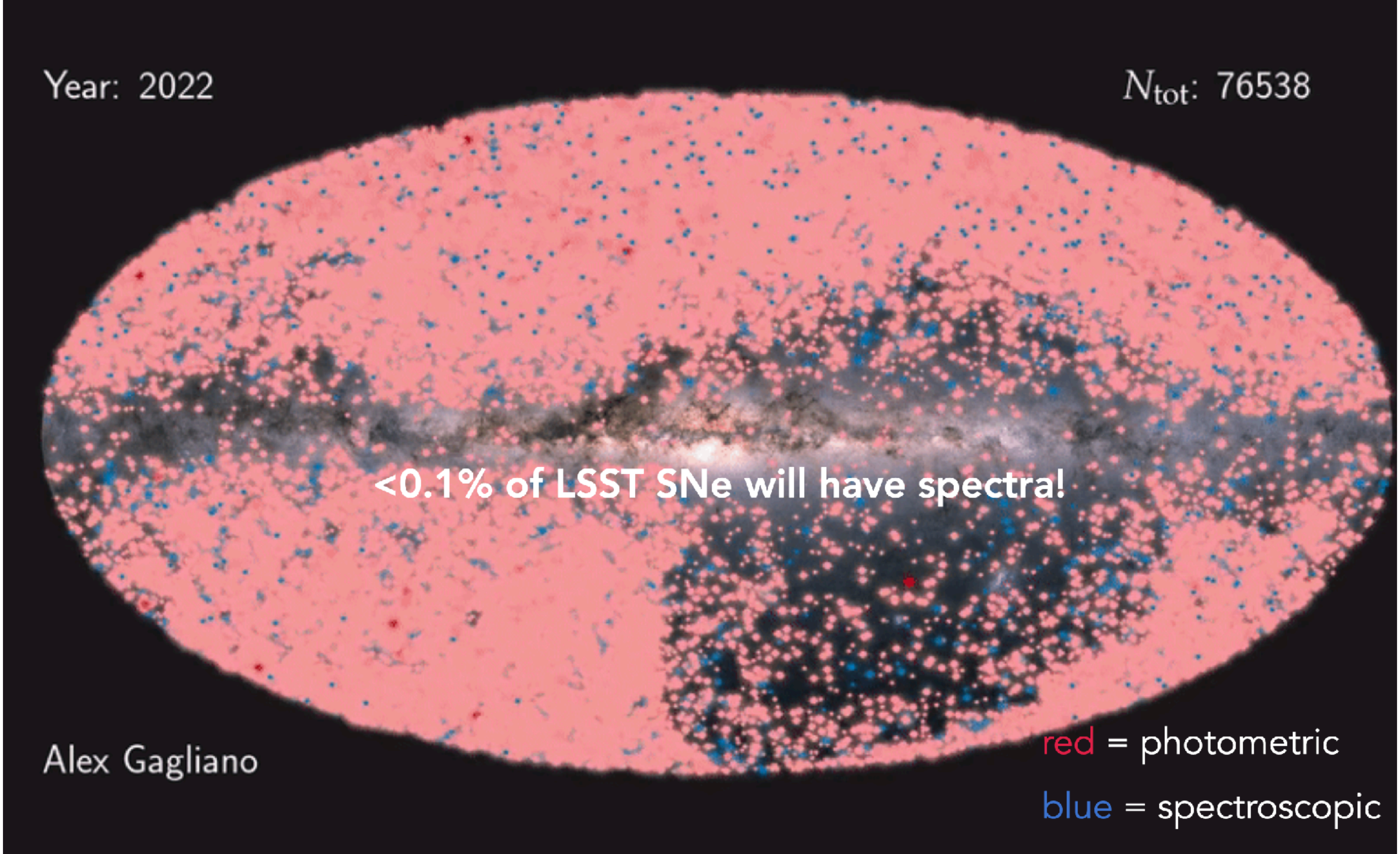


How do we know these quantities?



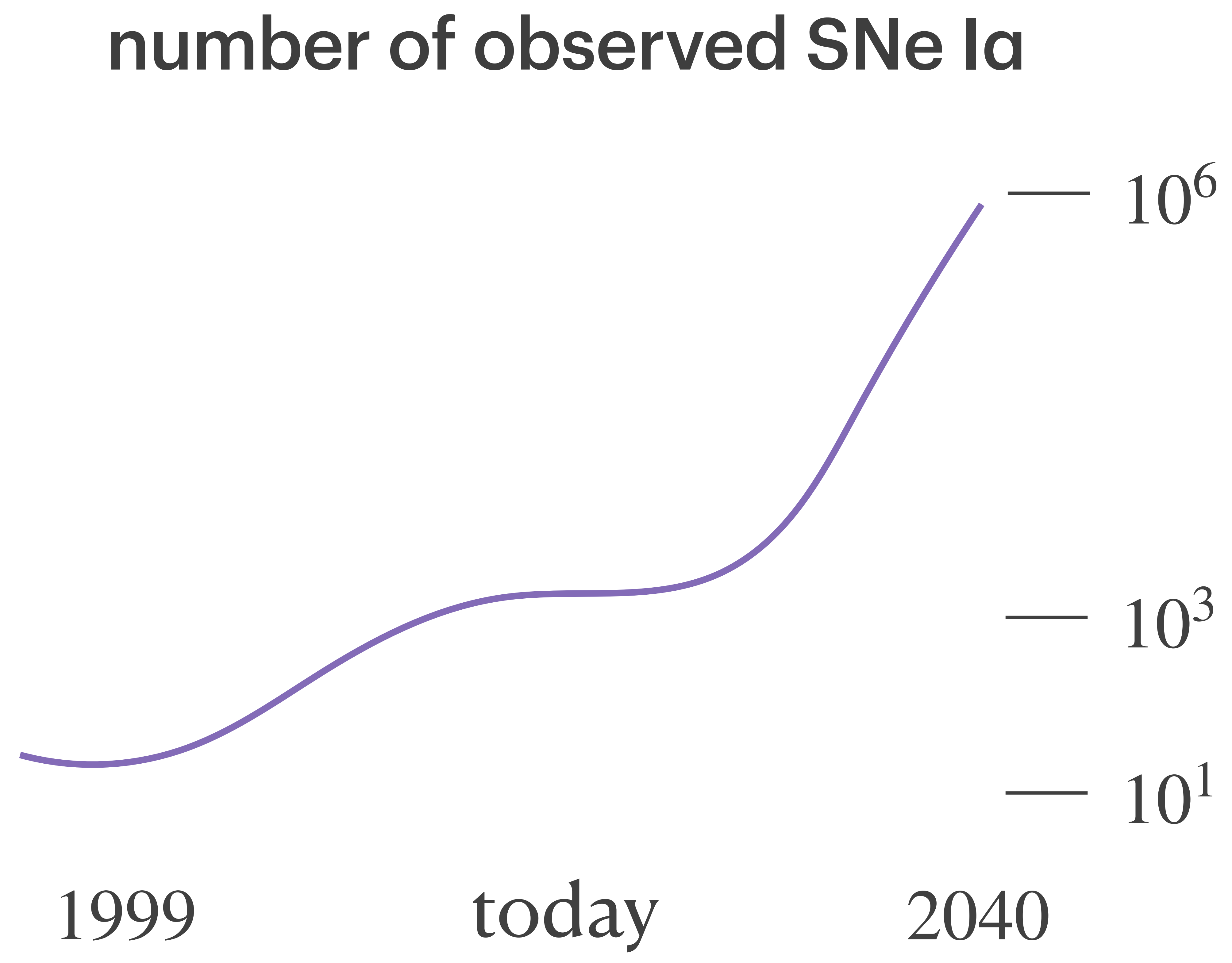
How do we know these quantities in the Rubin era?




Year: 2022
N_{tot}: 76538
<0.1% of LSST SNe will have spectra!
Alex Gagliano
red = photometric
blue = spectroscopic

Cosmology in the Rubin era cannot depend on spectra

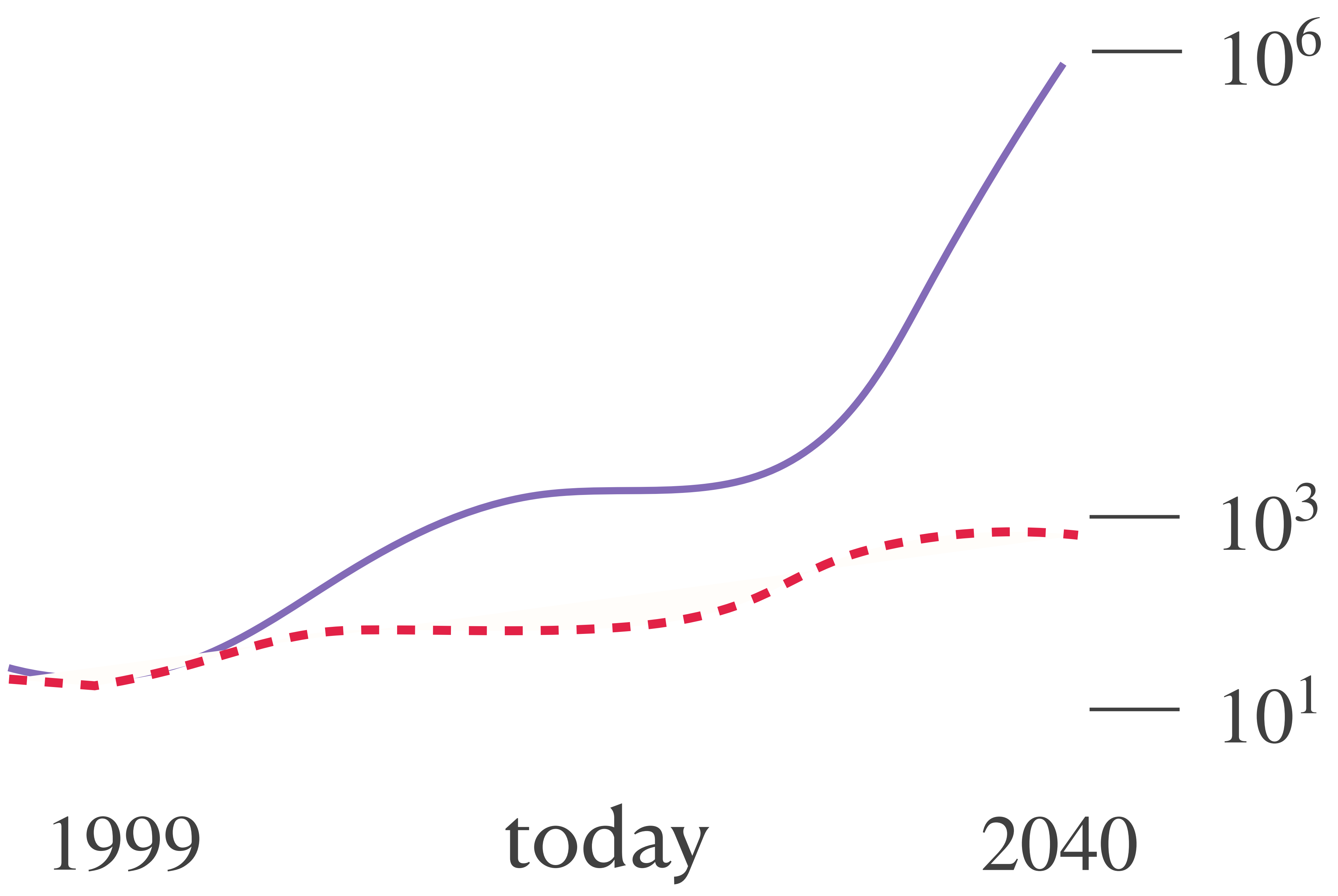
- Number of photometrically observed SNe Ia will skyrocket in the Rubin era



Cosmology in the Rubin era cannot depend on spectra

- 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)

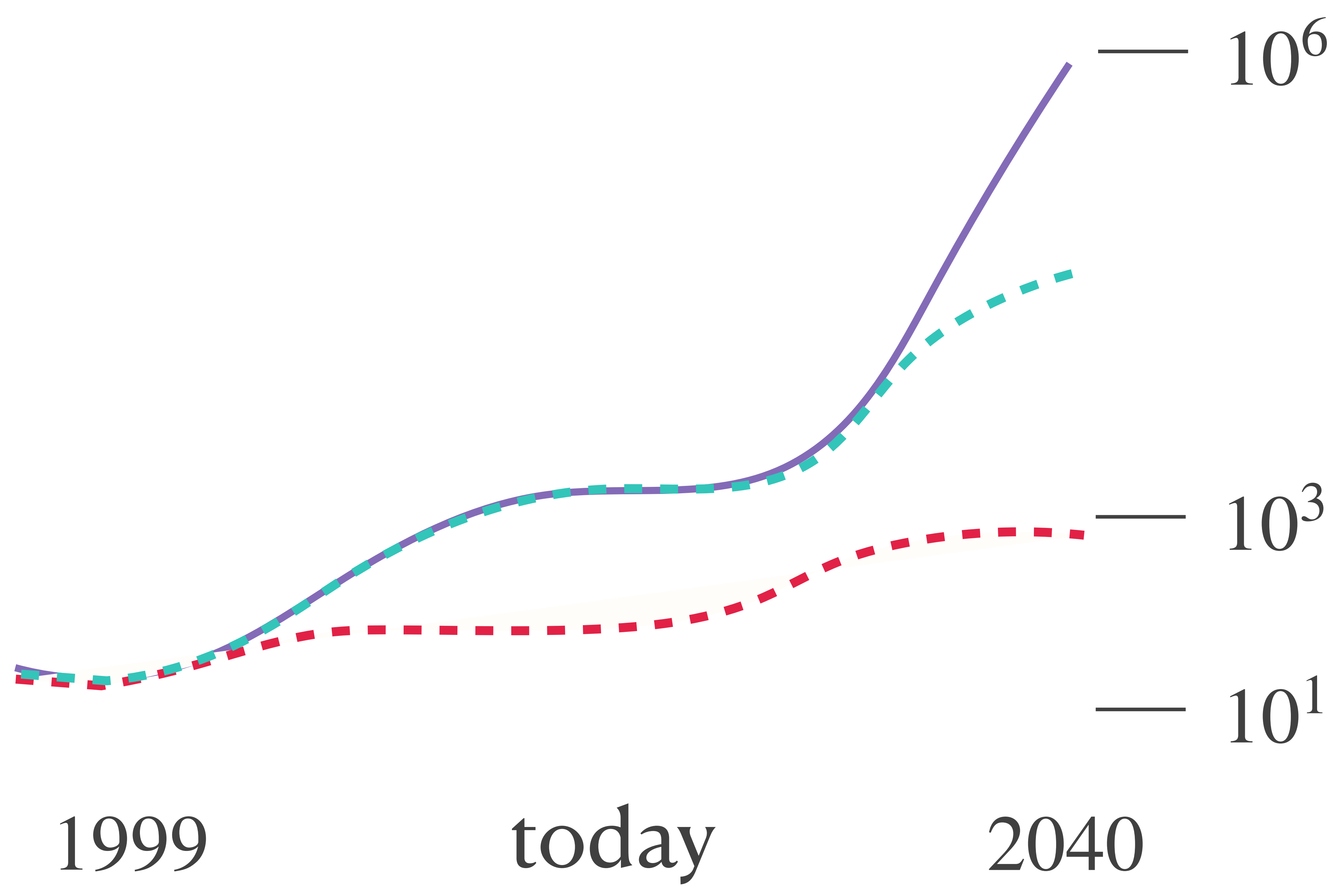
number of observed SNe Ia



Cosmology in the Rubin era cannot depend on spectra

- 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)
  - SN host galaxies with spectra make up 100% of the DES5YR sample (**HQ**+23), but will not scale to Rubin data volumes

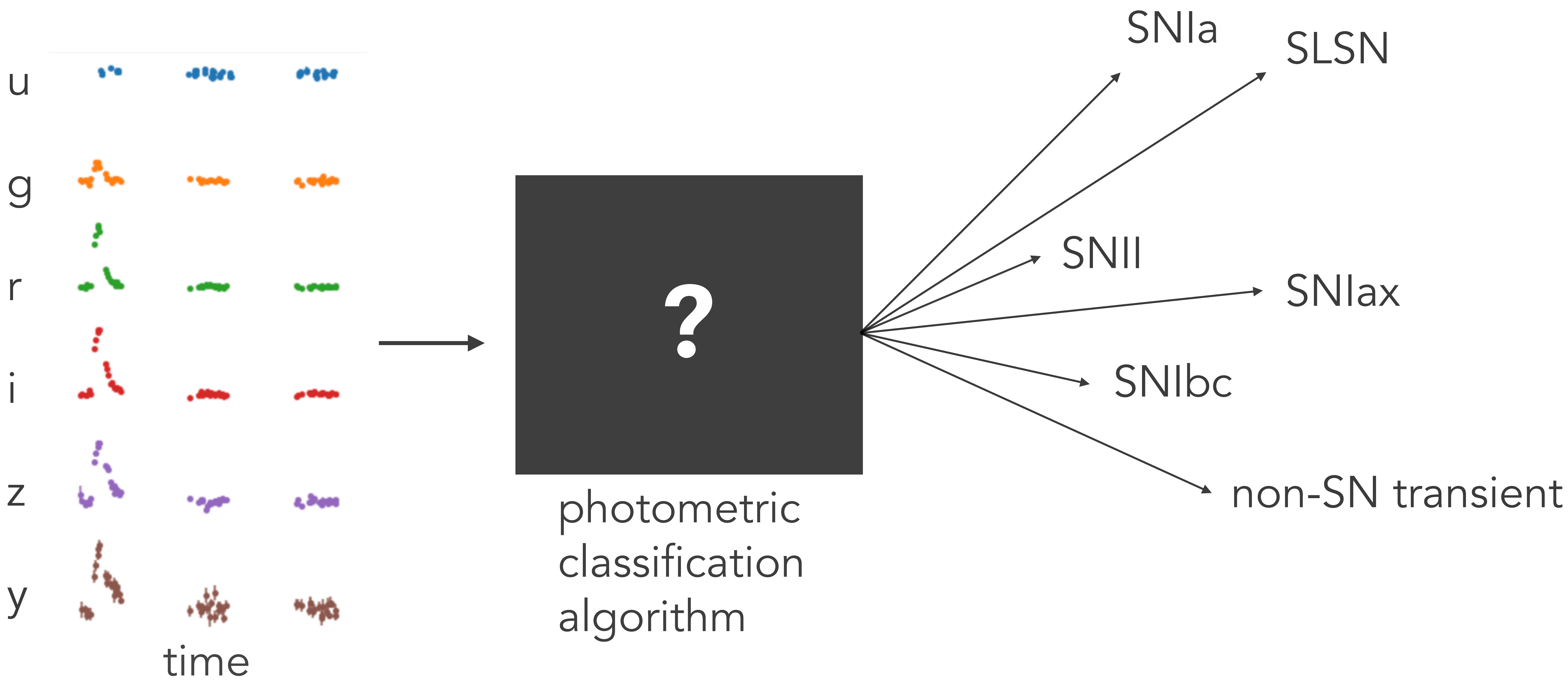
number of observed SNe Ia



Cosmology in the Rubin era will depend on photometry

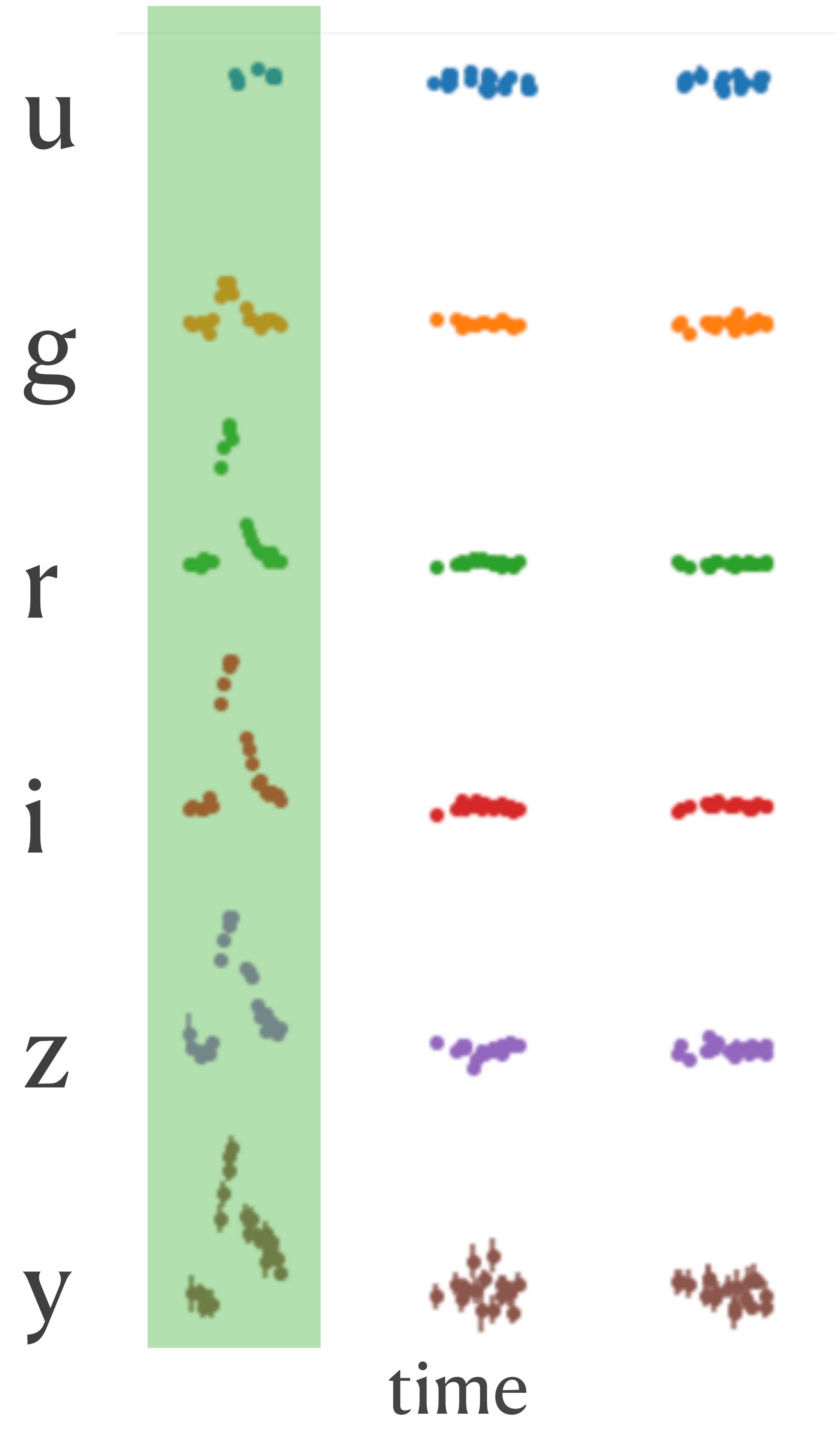
- Number of photometrically observed SNe Ia will skyrocket in the Rubin era
    - SNe Ia with spectra already make up only <10% of current sample (5-year Dark Energy Survey, DES5YR) → **photometric classification**
    - SN host galaxies with spectra make up 100% of the DES5YR sample (**HQ**+23), but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

SN Photometric Classification



SCONE

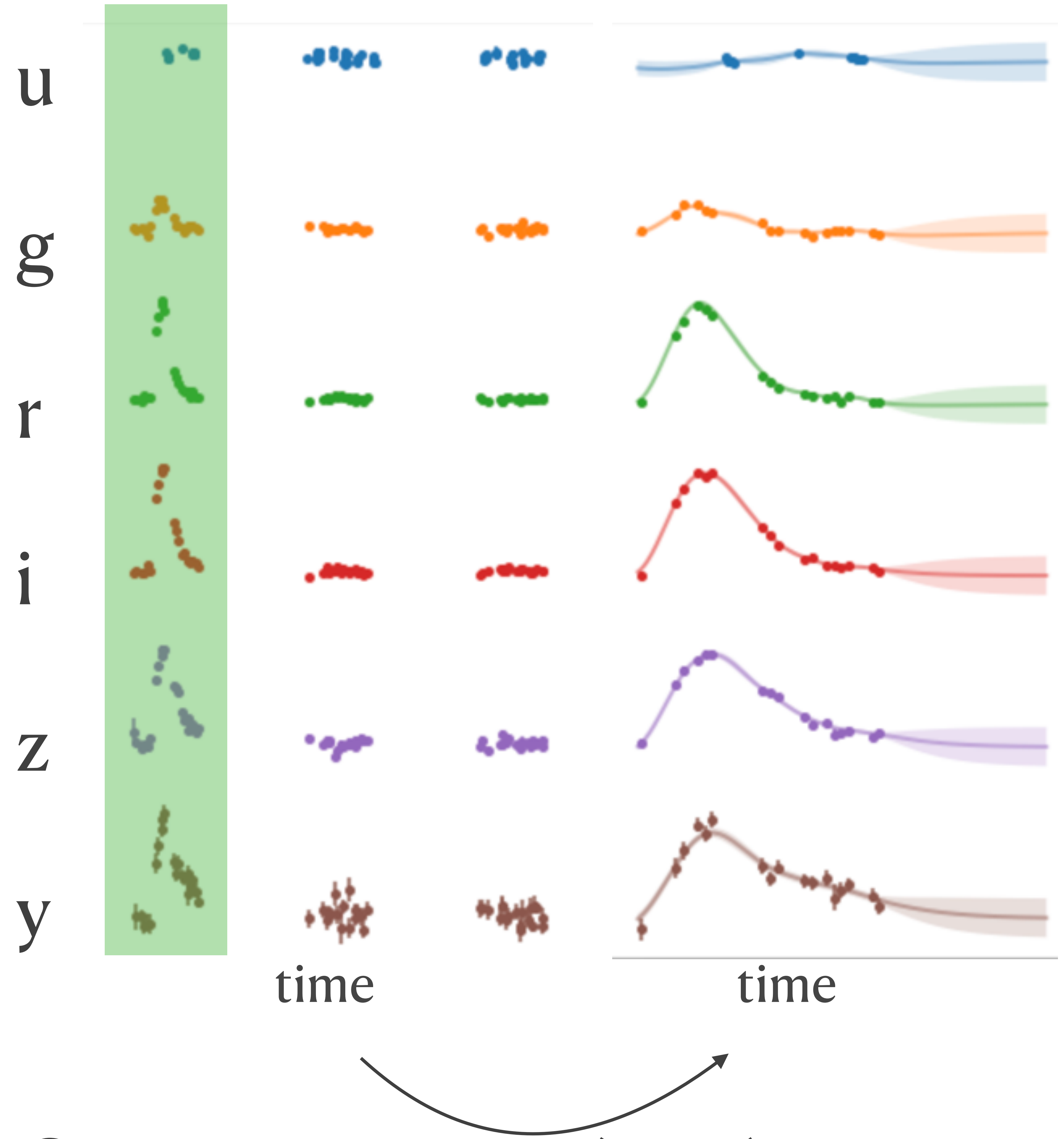
Convolutional Neural Network for Supernova Classification



HQ et al., AJ, 2021 (arXiv: 2106.04370)

SCONE

Convolutional Neural Network for Supernova Classification

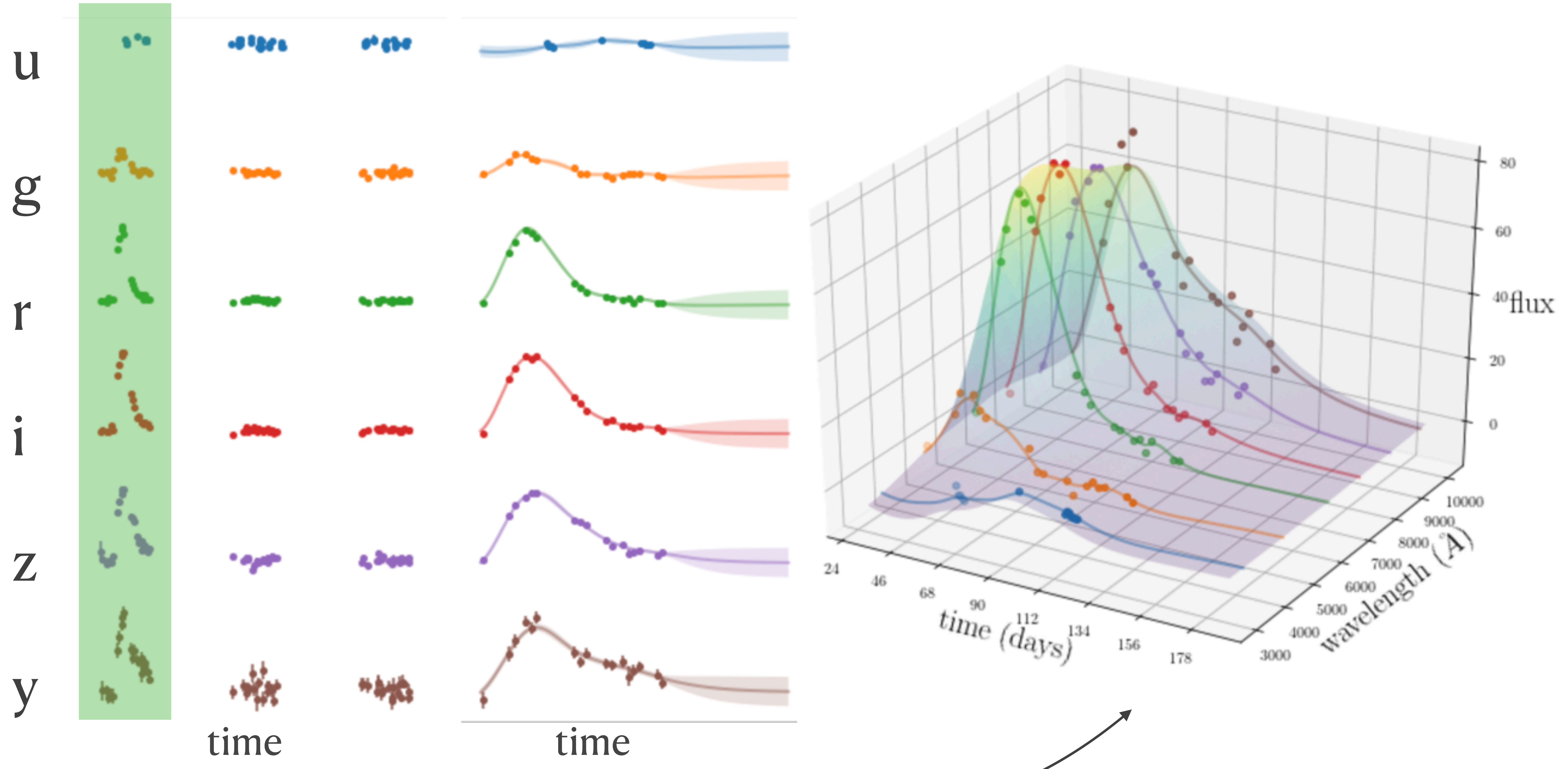


Gaussian process (time)

HQ et al., AJ, 2021 (arXiv: 2106.04370)

SCONE

Convolutional Neural Network for Supernova Classification



Gaussian process (time)

Gaussian process (wavelength)

HQ et al., AJ, 2021 (arXiv: 2106.04370)

SCONE

Convolutional Neural Network for Supernova Classification

Gaussian process (time)

Gaussian process (wavelength)

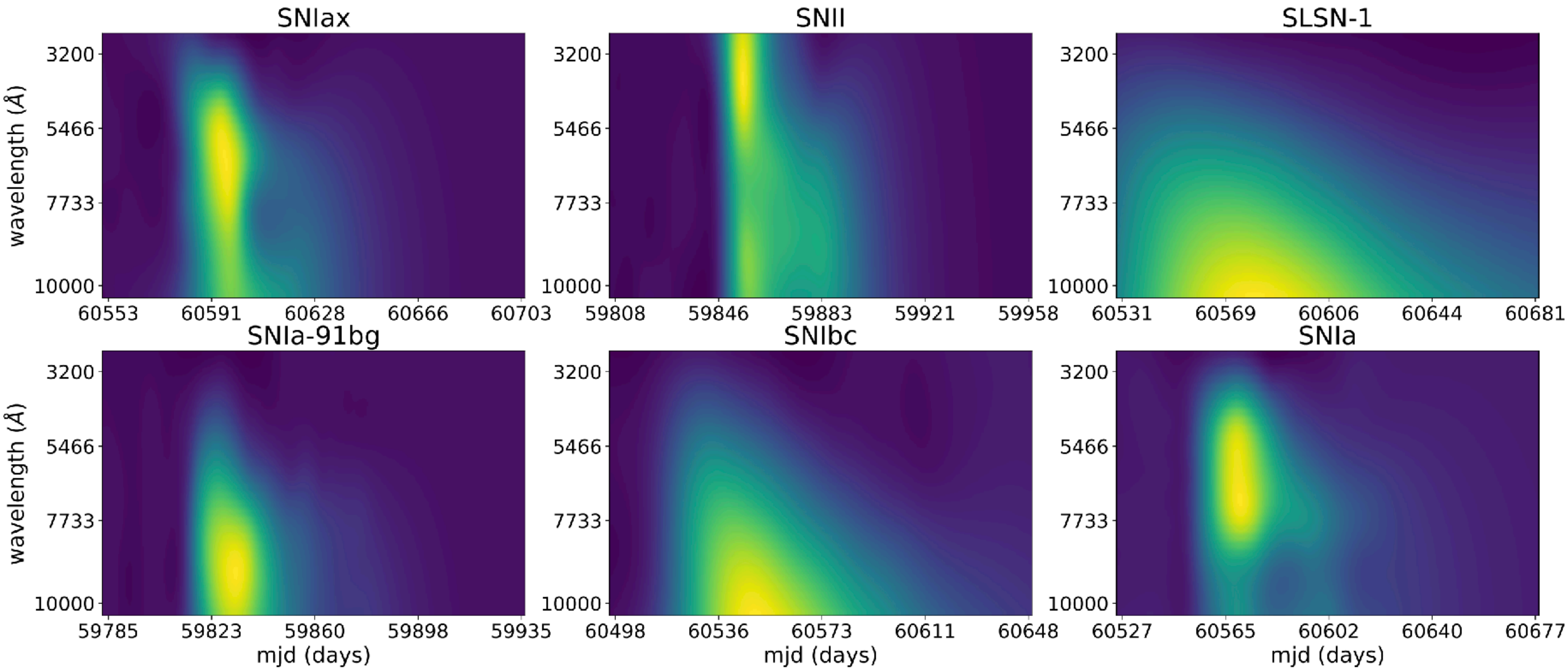
color by flux

HQ et al., AJ, 2021 (arXiv: 2106.04370)

SCONE

Convolutional Neural Network for Supernova Classification

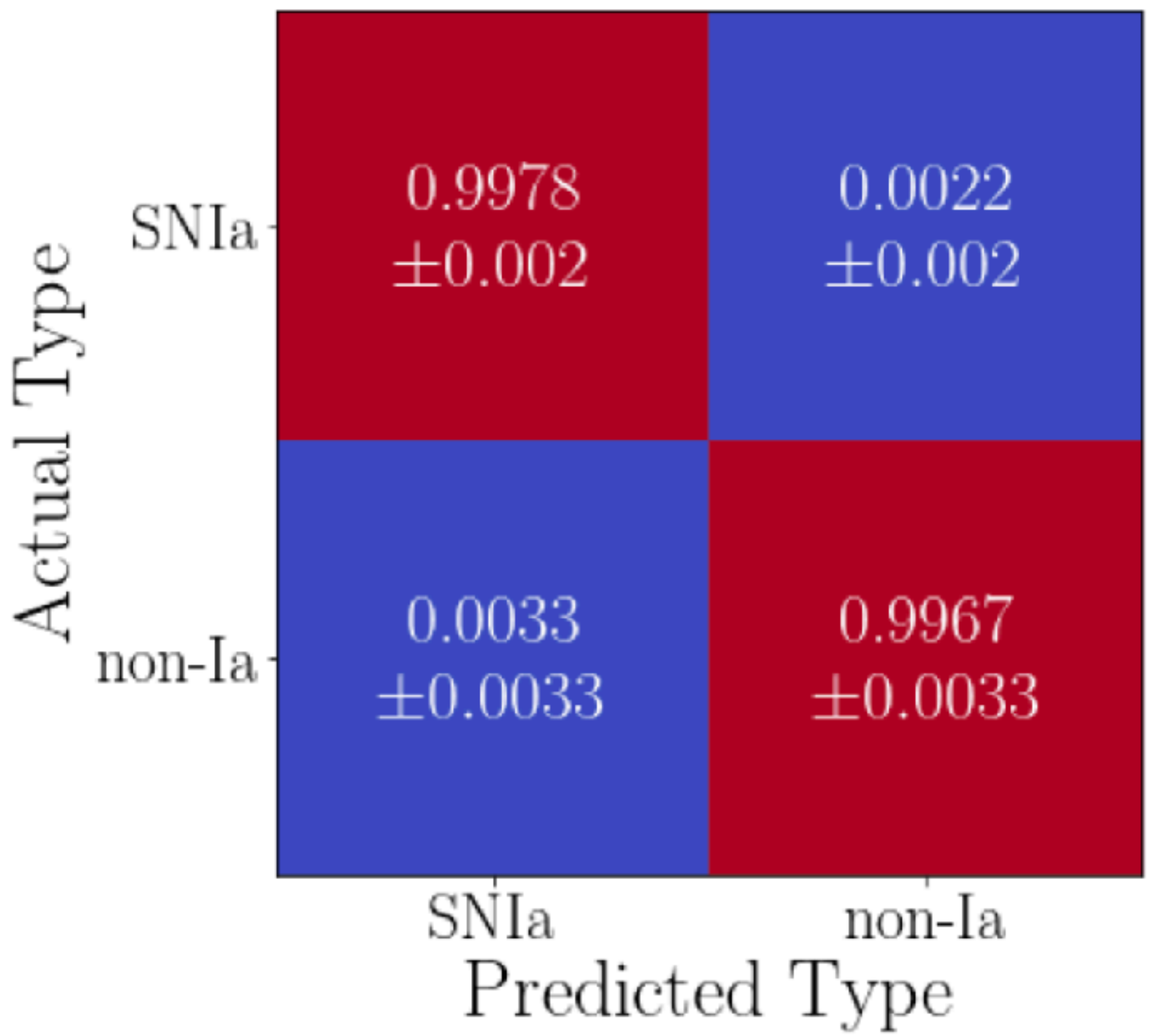
HQ et al., AJ, 2021 (arXiv: 2106.04370)



HQ et al., AJ, 2021 (arXiv: 2106.04370)

SCONE performs well on simulations + real data

SN Ia vs. non-Ia classification



- **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

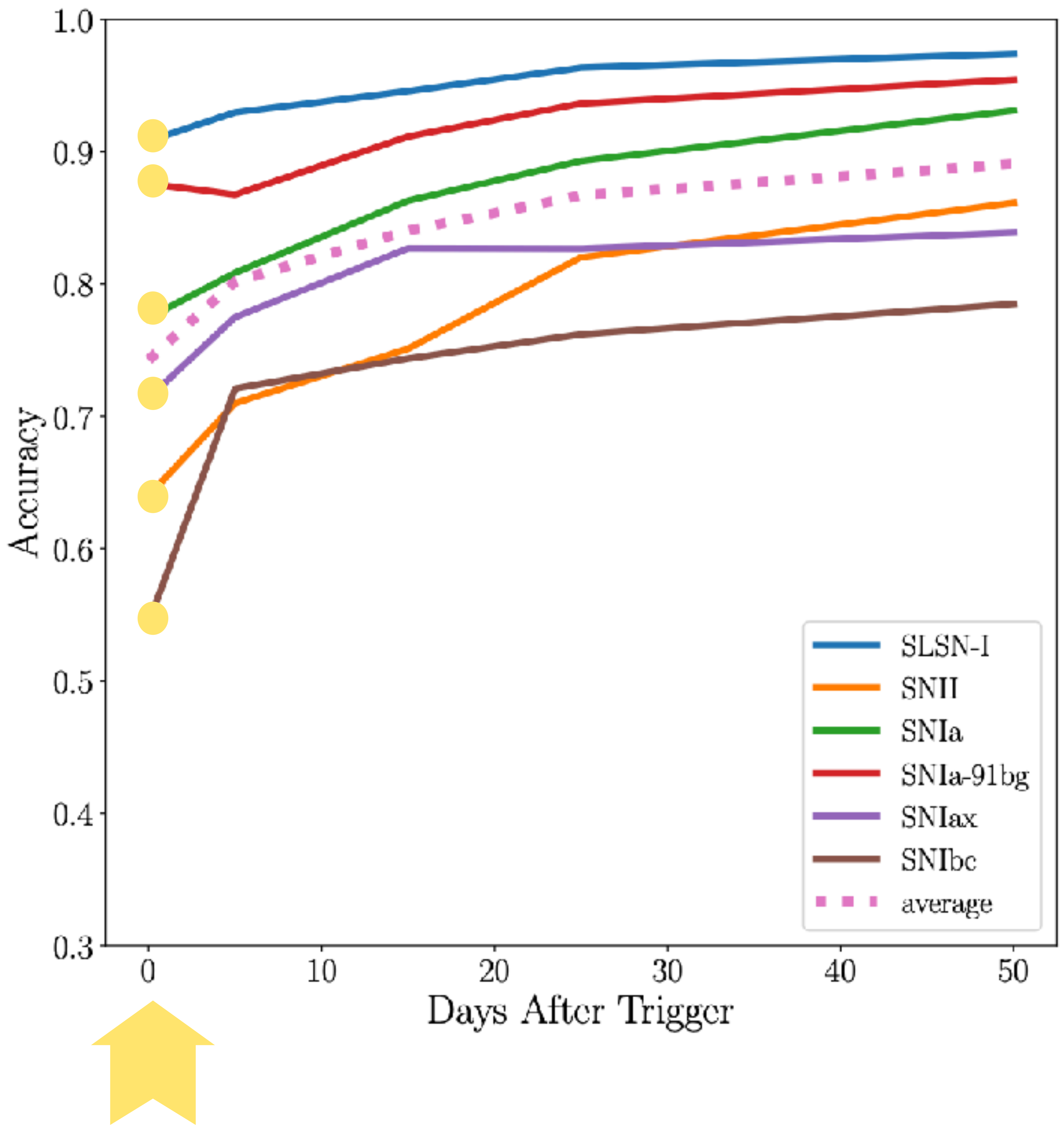
HQ et al., AJ, 2021 (arXiv: 2106.04370)

SCONE for Early-Time Classification

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

HQ et al., AJ, 2022 (arXiv:2111.05539)

SCONE for Early-Time Classification



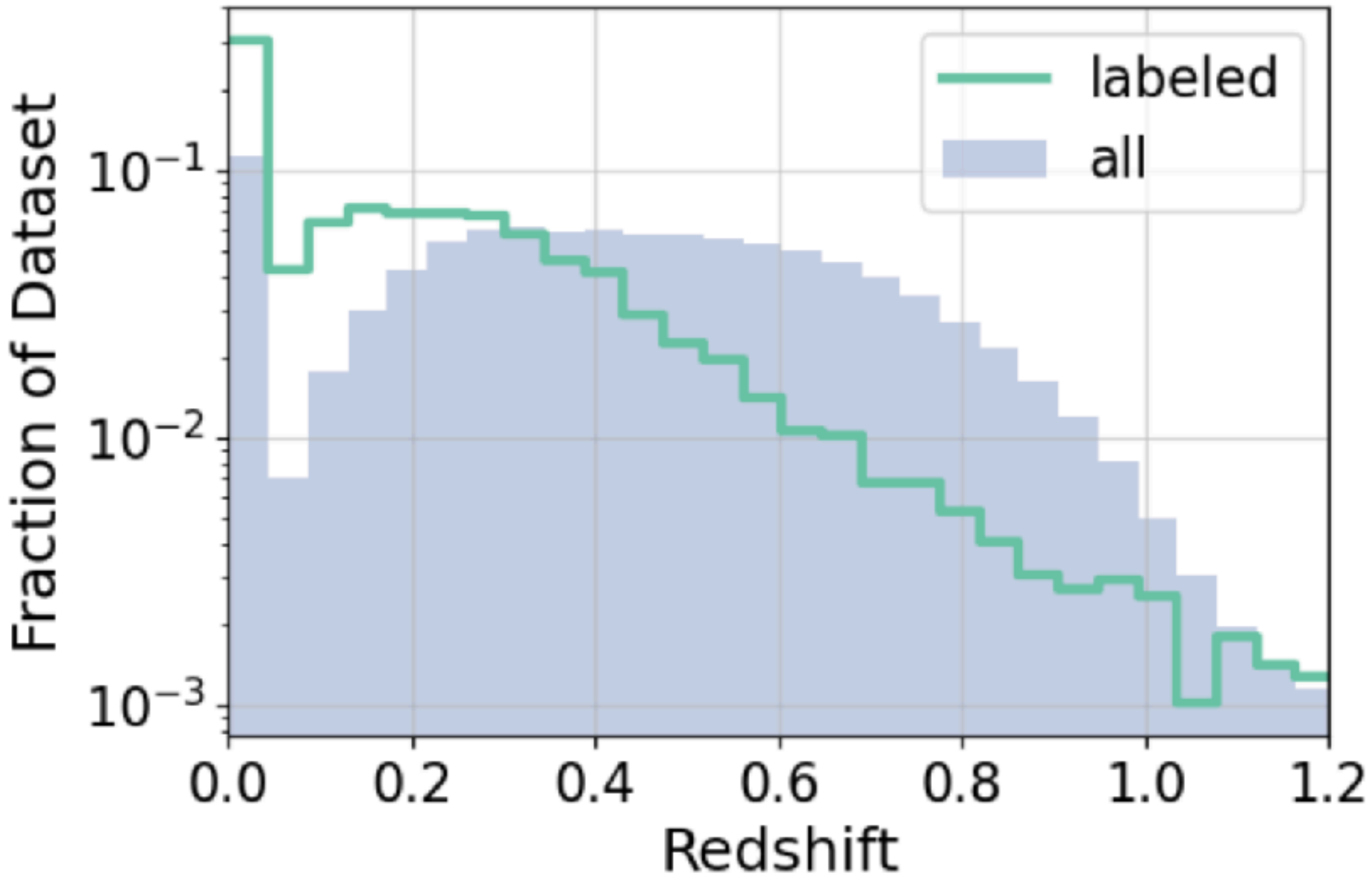
75% average accuracy (with redshift) on the night of trigger

HQ et al., AJ, 2022 (arXiv:2111.05539)

Training a model with real data

Task: PLAsTiCC classification (14 transient/variable types)

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



HQ & S. M. Xie, ICML 2024 (arXiv:2402.03325)

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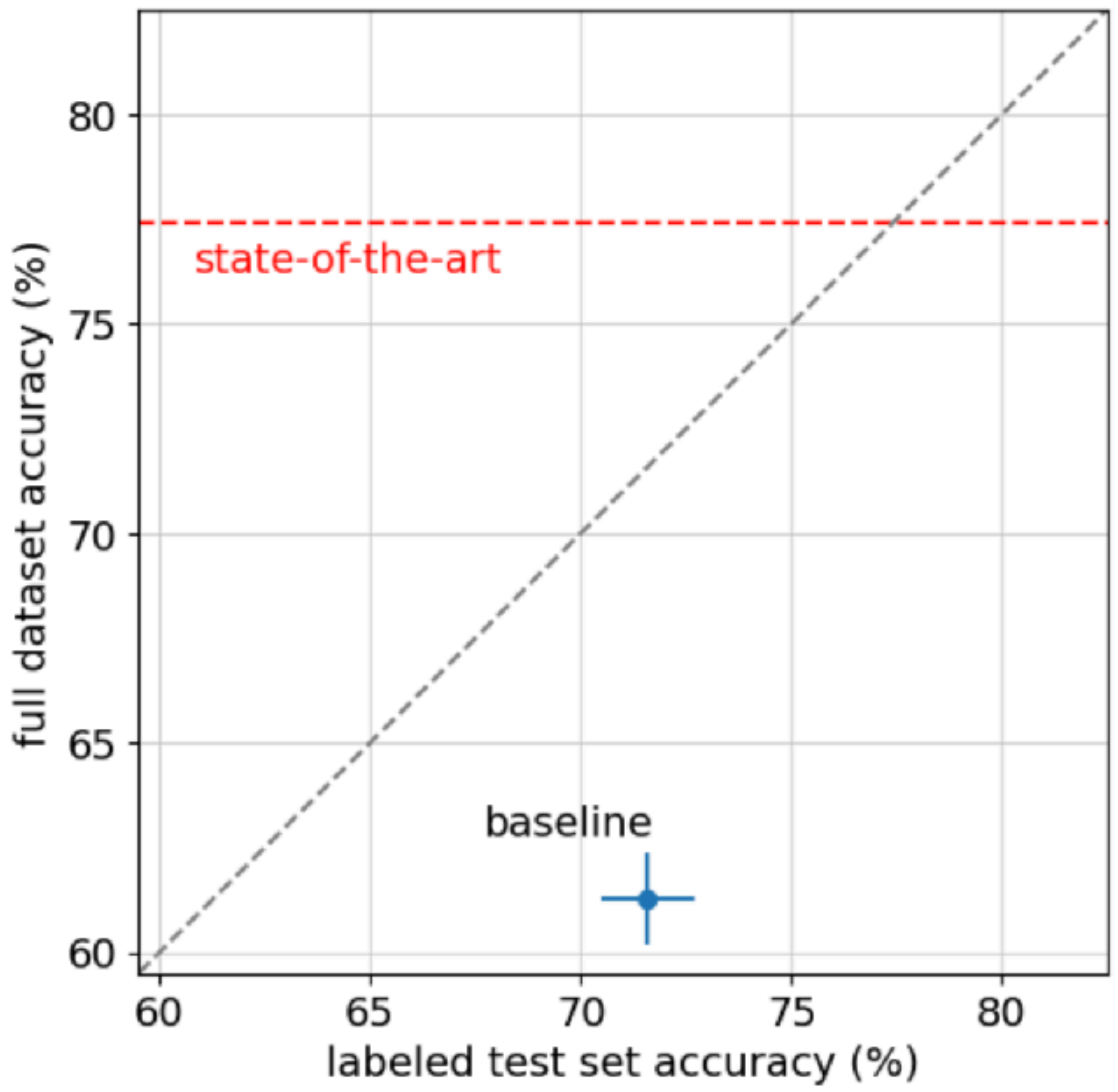
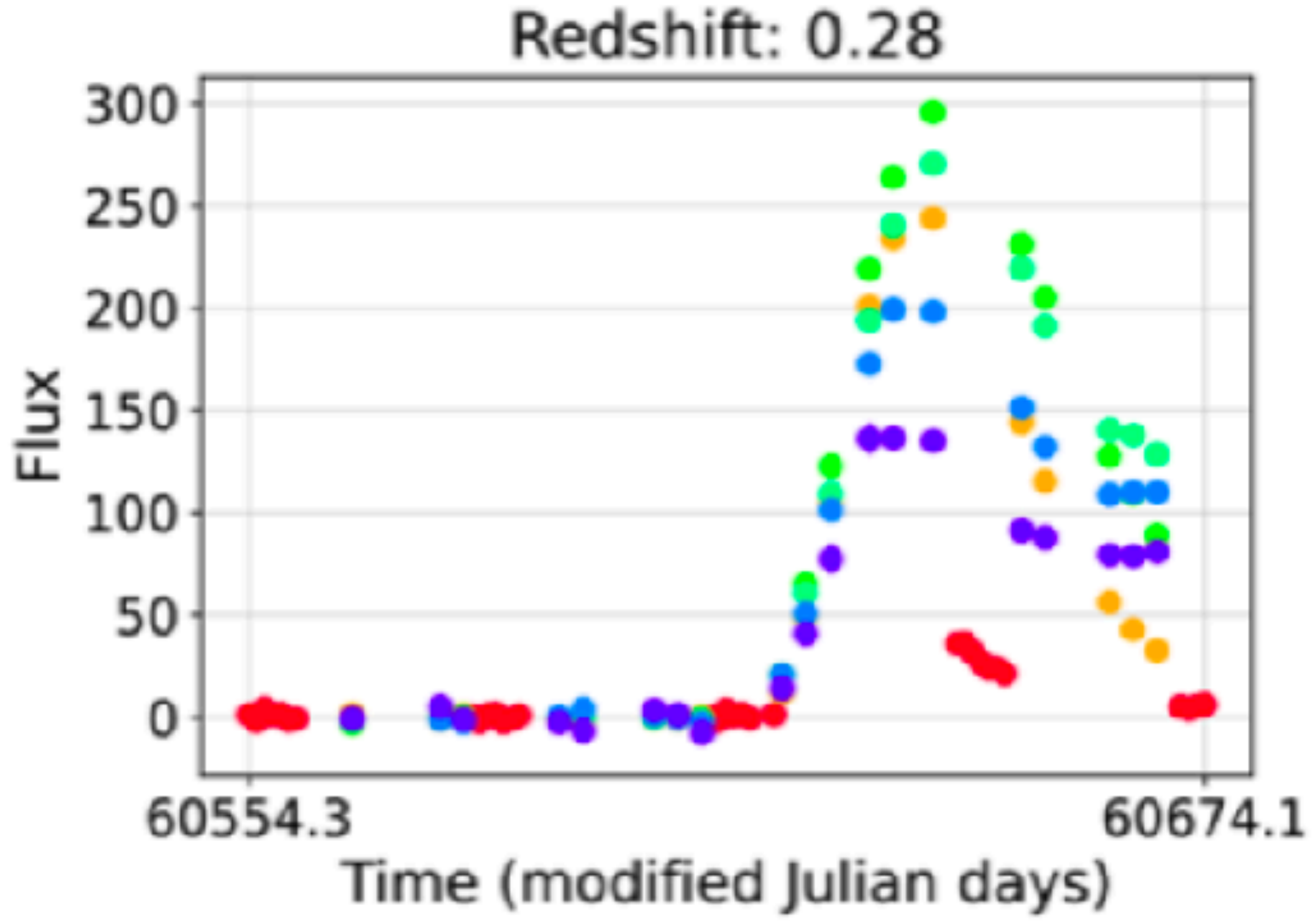


HQ & S. M. Xie, ICML 2024 (arXiv:2402.03325)

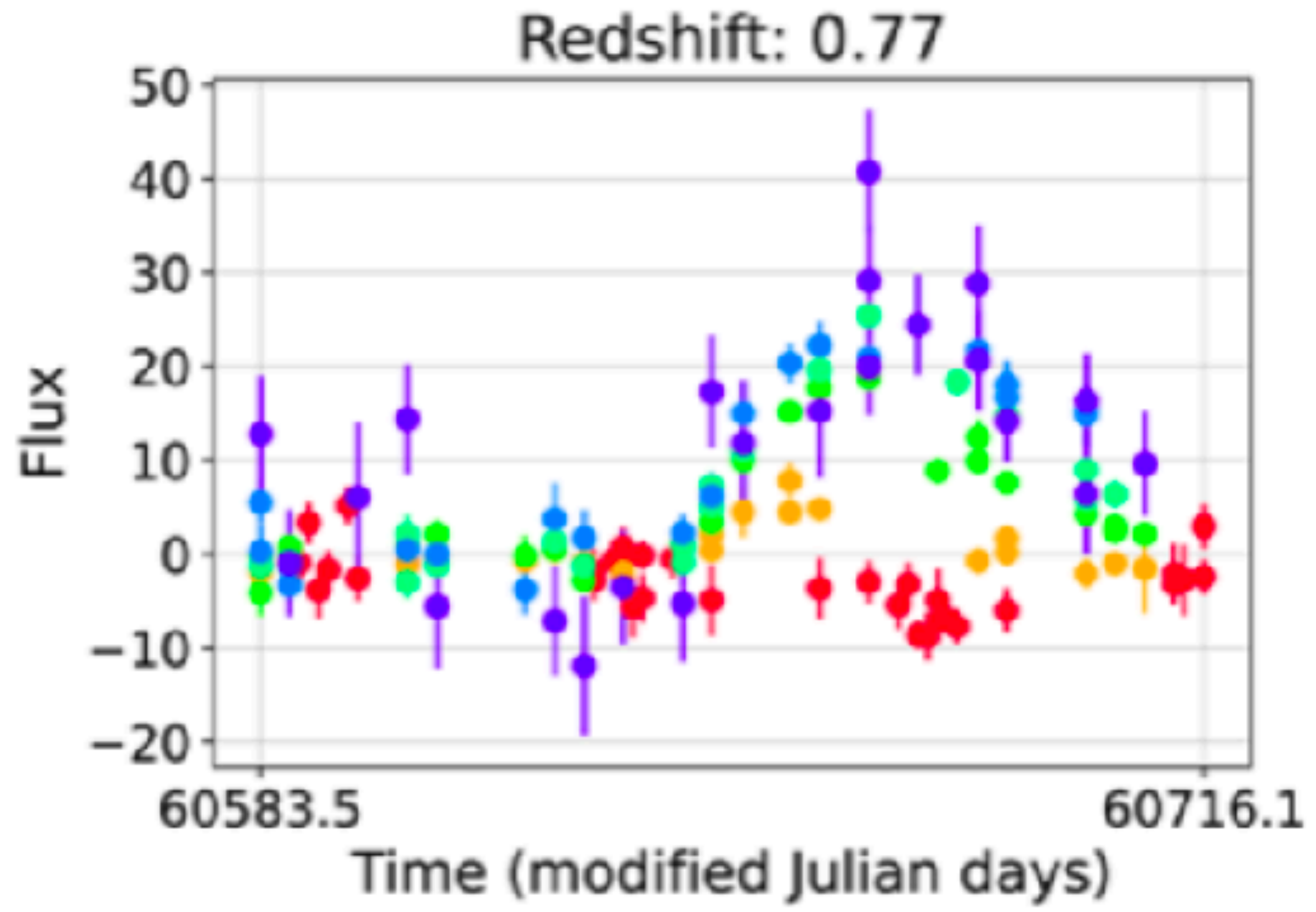
Training a model with real data

Augment lightcurves from spectroscopic data to resemble full dataset

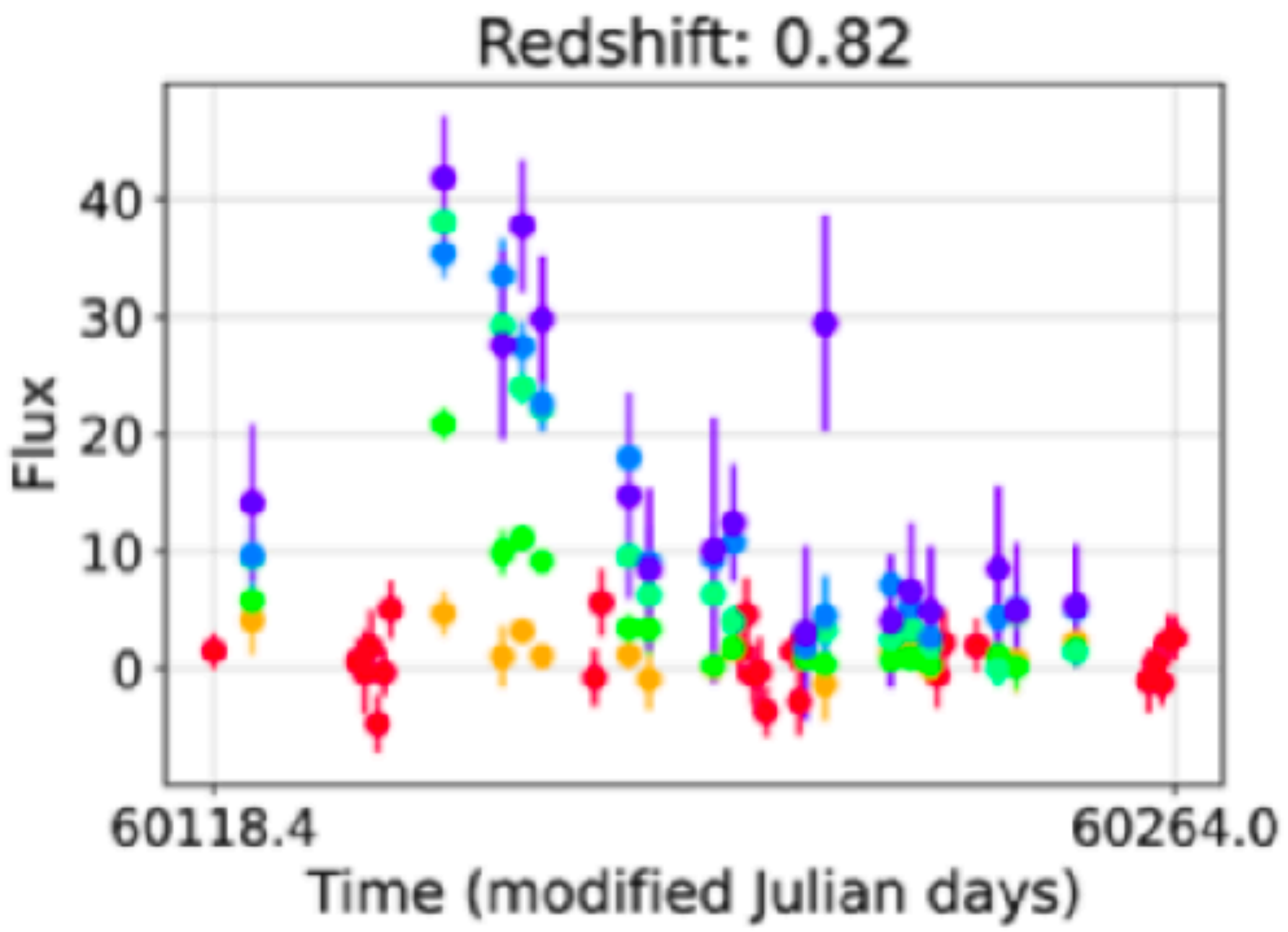
from spectroscopic data



redshifting augmentation



from full dataset



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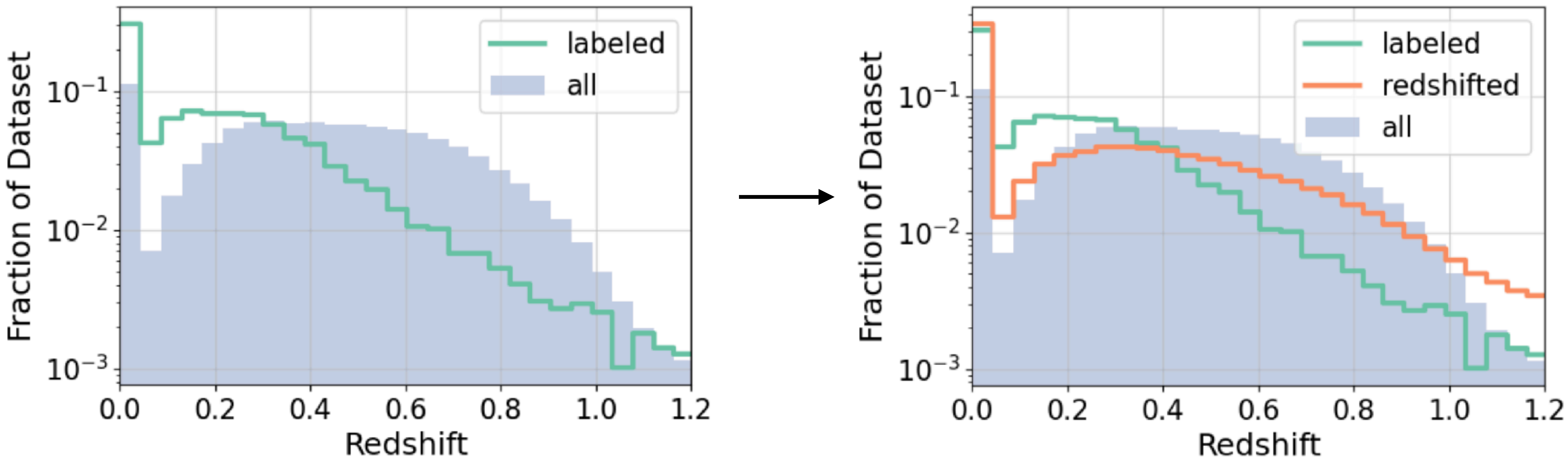
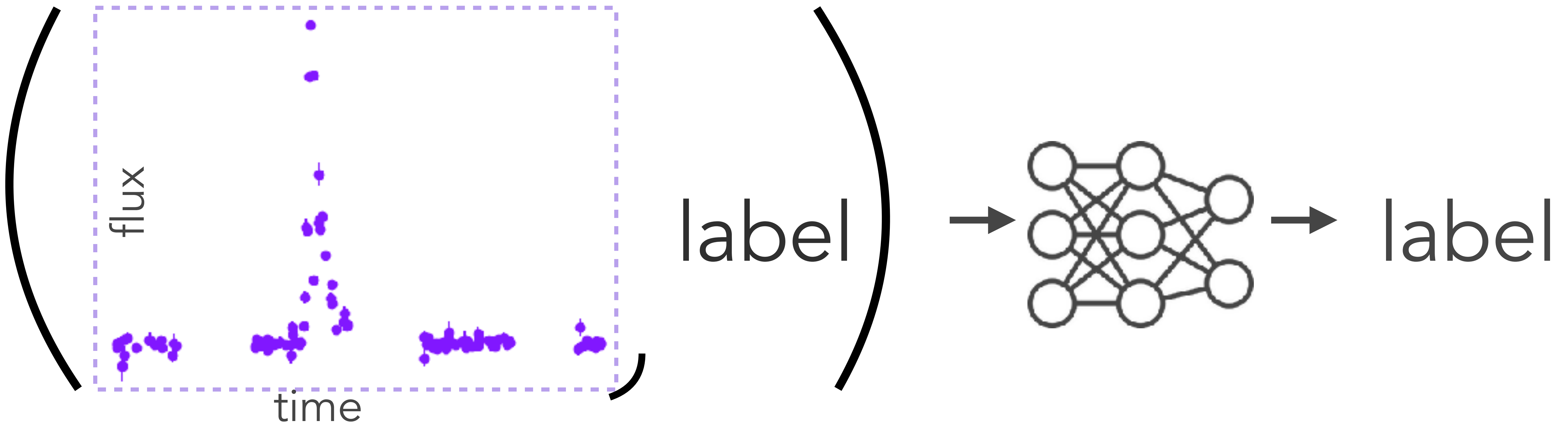


HQ & S. M. Xie, ICML 2024 (arXiv:2402.03325)

Training a model with real data

train w/
redshifted
labeled data



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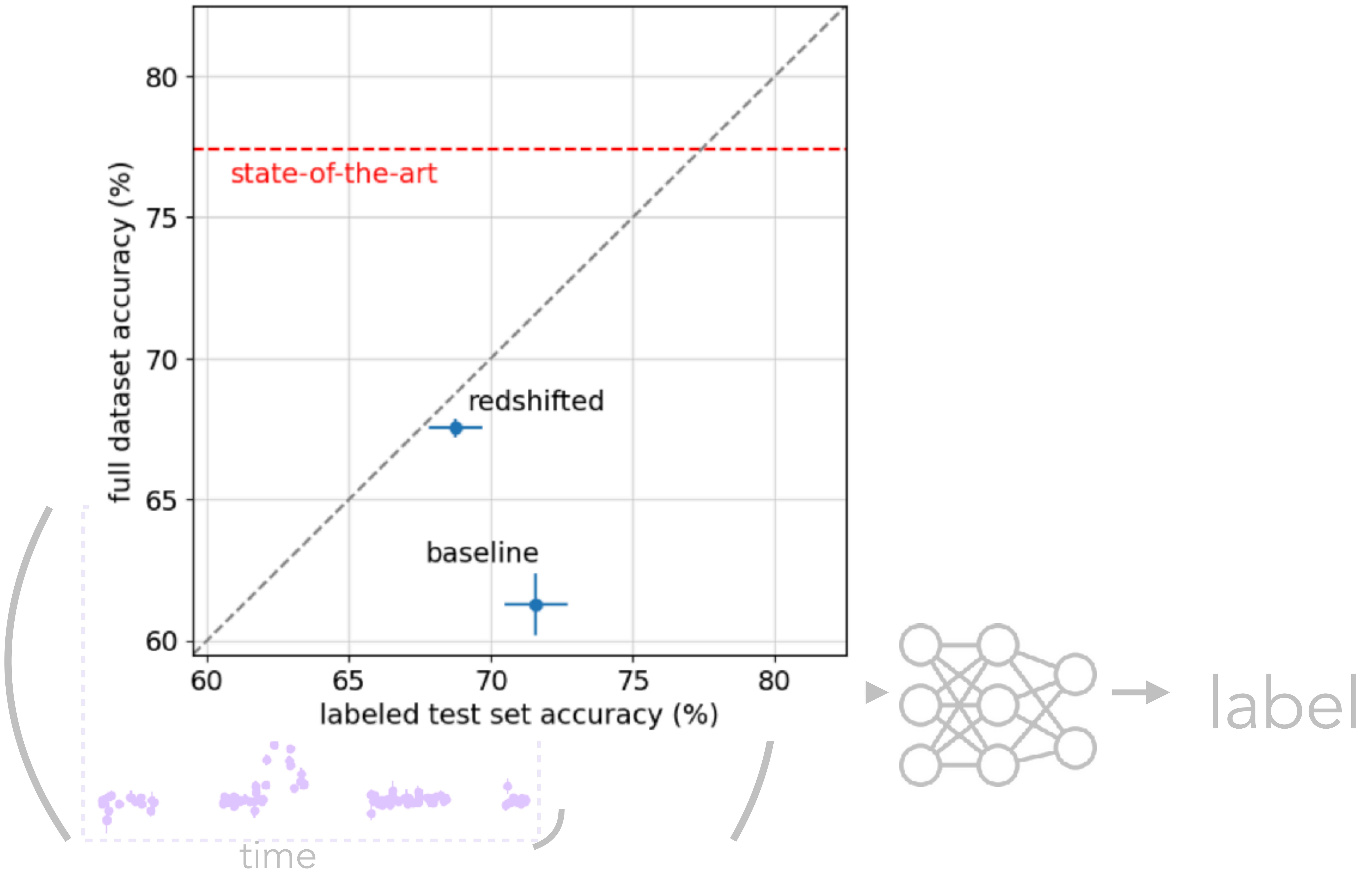
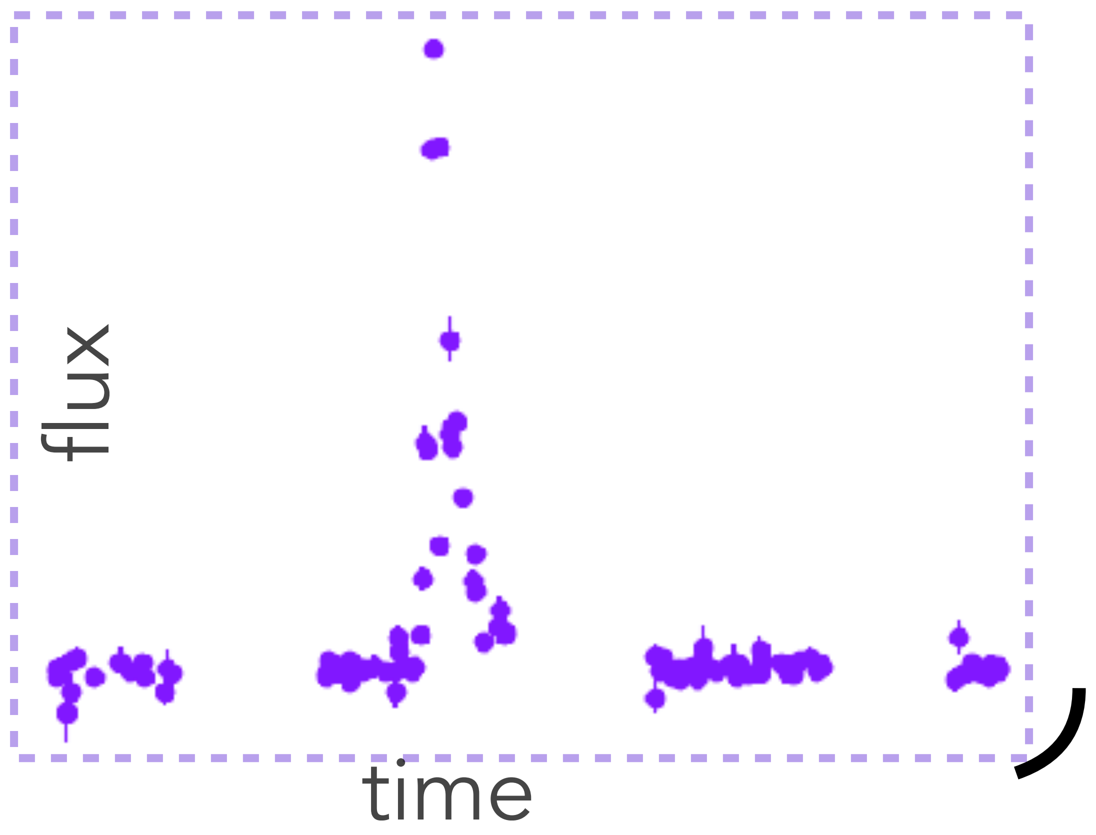


HQ & S. M. Xie, ICML 2024 (arXiv:2402.03325)

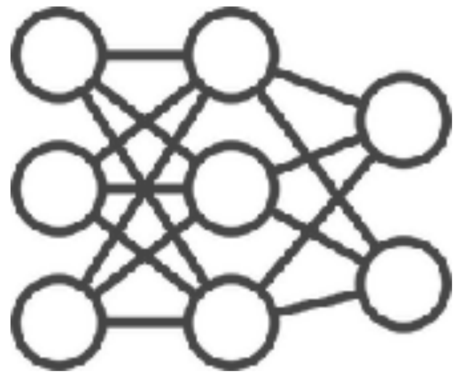
Training a model with real data

this was 0.1%…
what about the other 99.9%?

train w/ redshifted labeled data



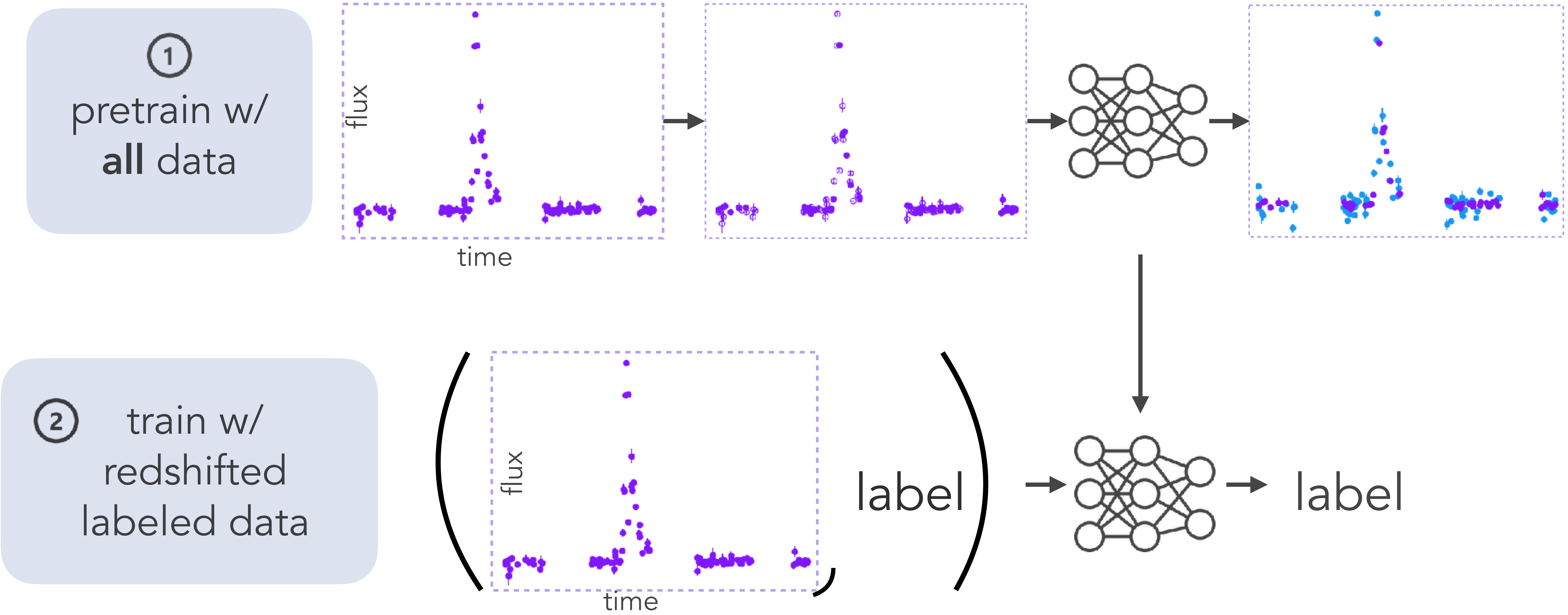
label



label

HQ & S. M. Xie, ICML 2024 (arXiv:2402.03325)

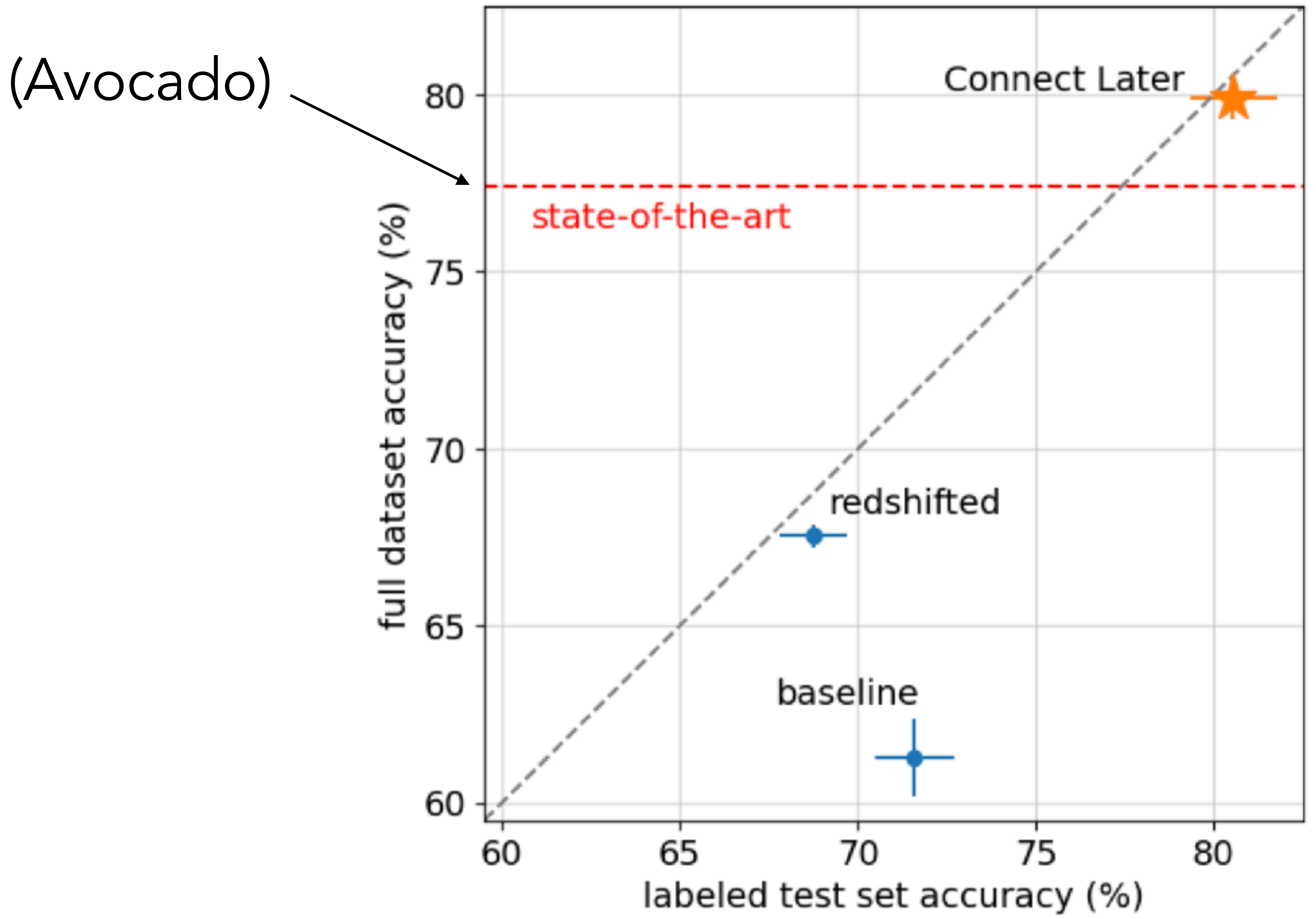
Connect Later: Incorporates Labeled + Unlabeled Data



HQ & S. M. Xie, ICML 2024 (arXiv:2402.03325)

Connect Later outperforms all variants for

Task: PLAsTiCC classification (14 transient/variable types)



HQ & S. M. Xie, ICML 2024 (arXiv:2402.03325)

Photometric Redshift Estimation

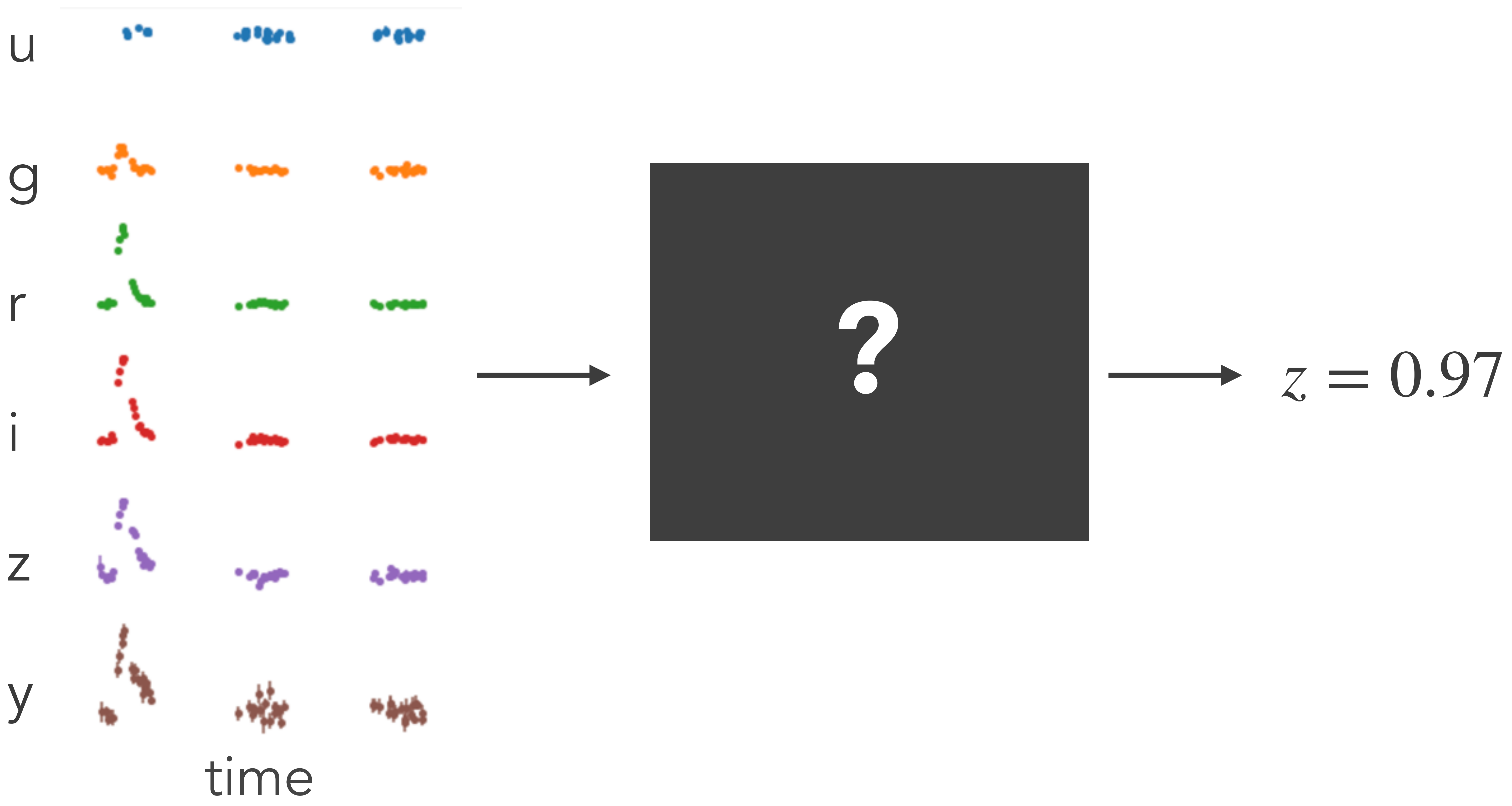
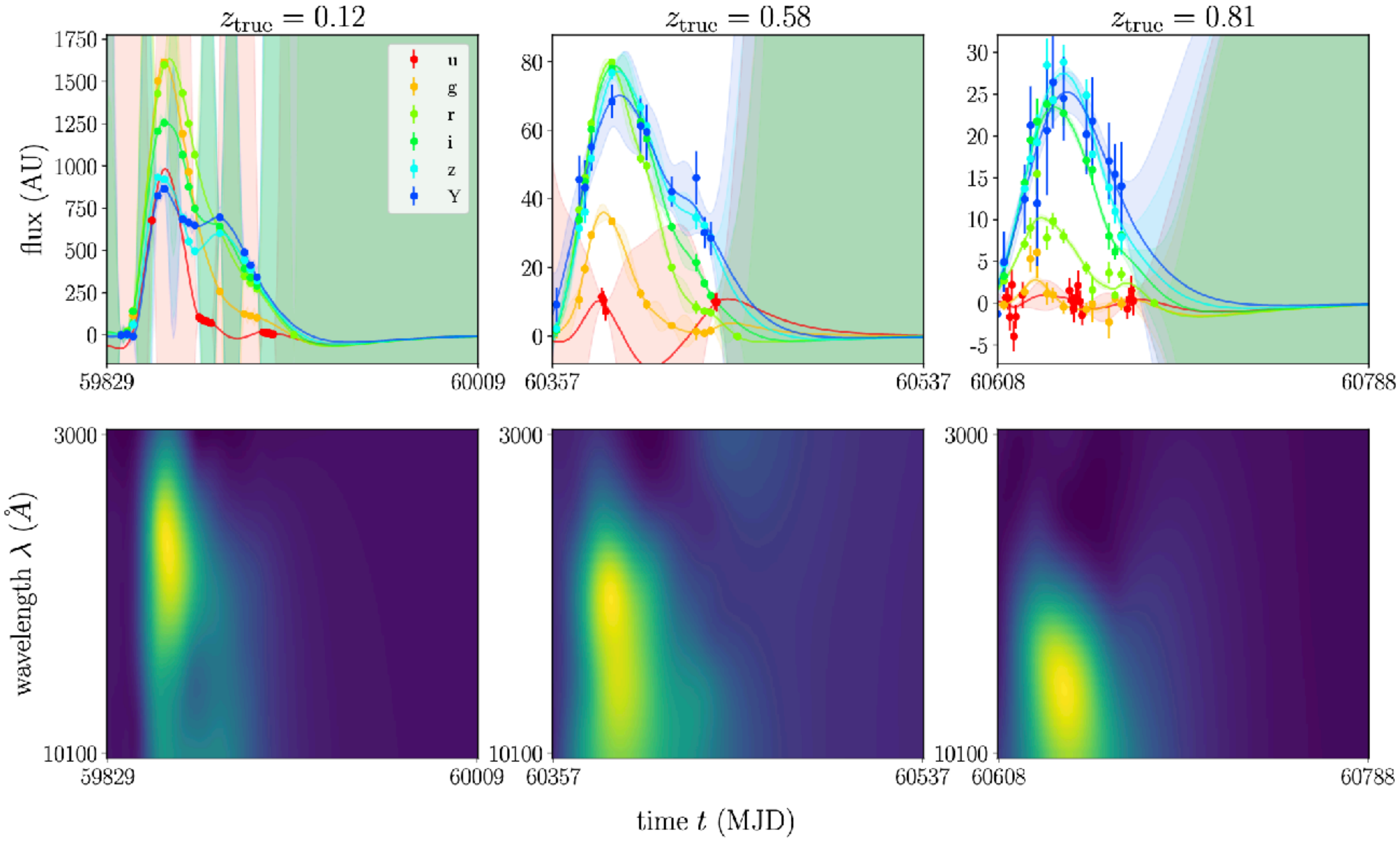
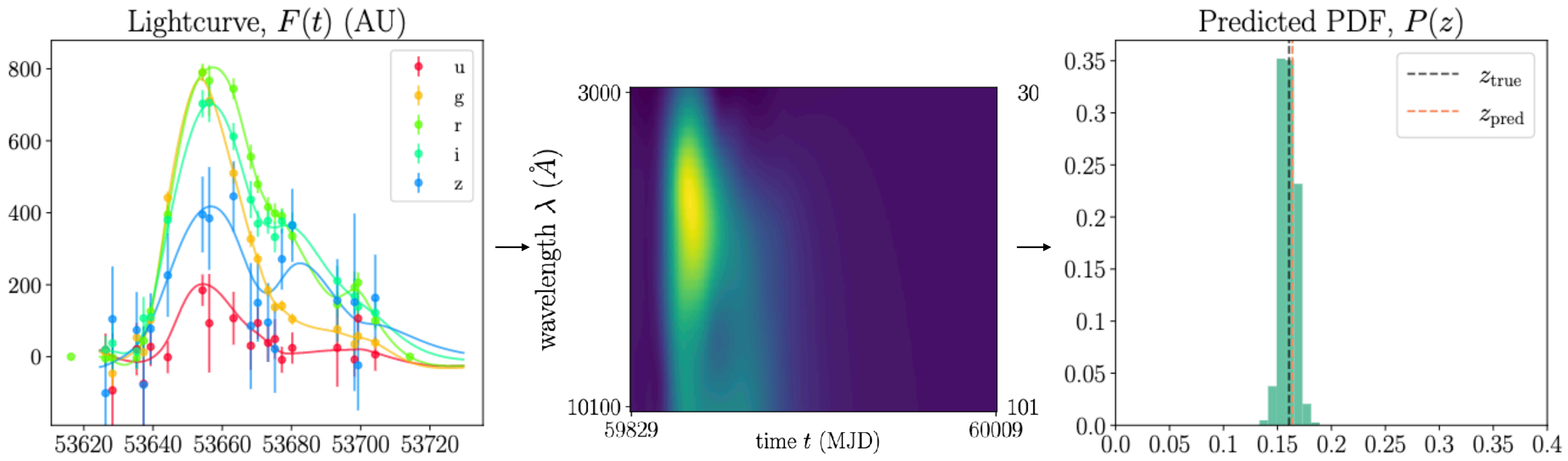


Image Representation Makes Redshift Visible



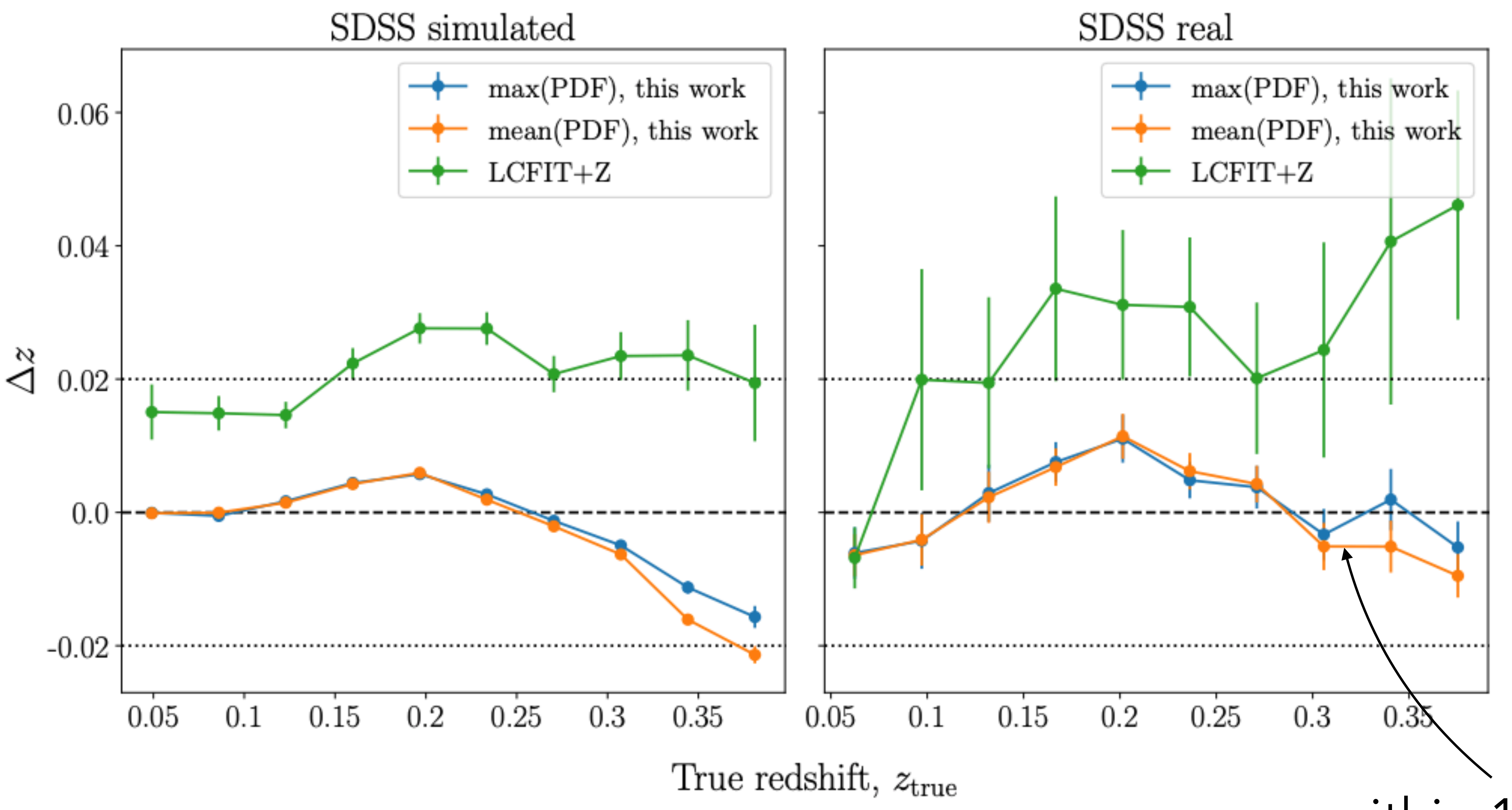
HQ & M. Sako, AJ, 2023 (arXiv:2305.11869)

Photo-zSNthesis: Converting SN Ia Lightcurves to Redshift PDFs



HQ & M. Sako, ApJ, 2023 (arXiv:2305.11869)

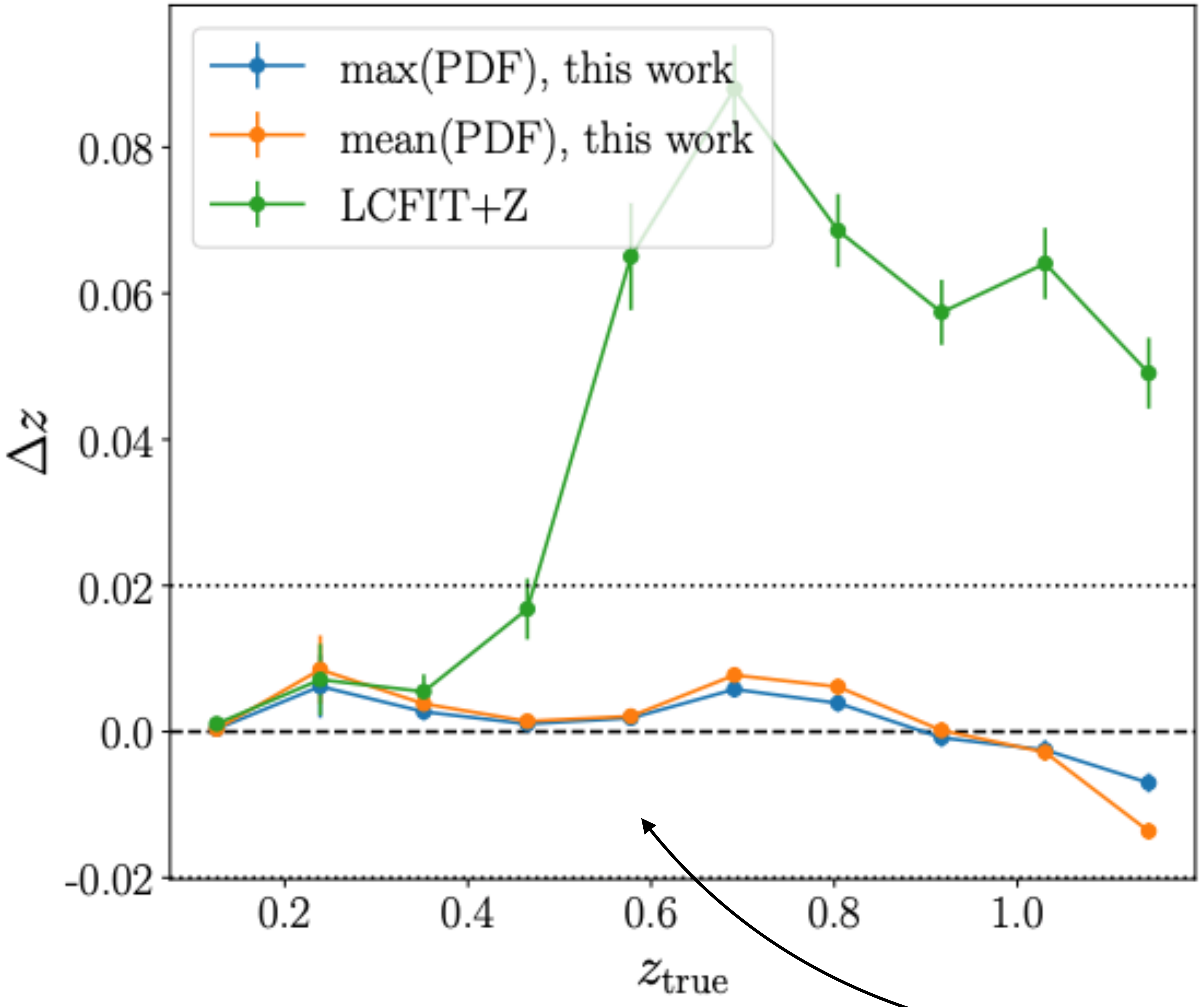
Tested on SDSS simulations + real data



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

HQ & M. Sako, ApJ, 2023 (arXiv:2305.11869)

Tested on LSST simulations



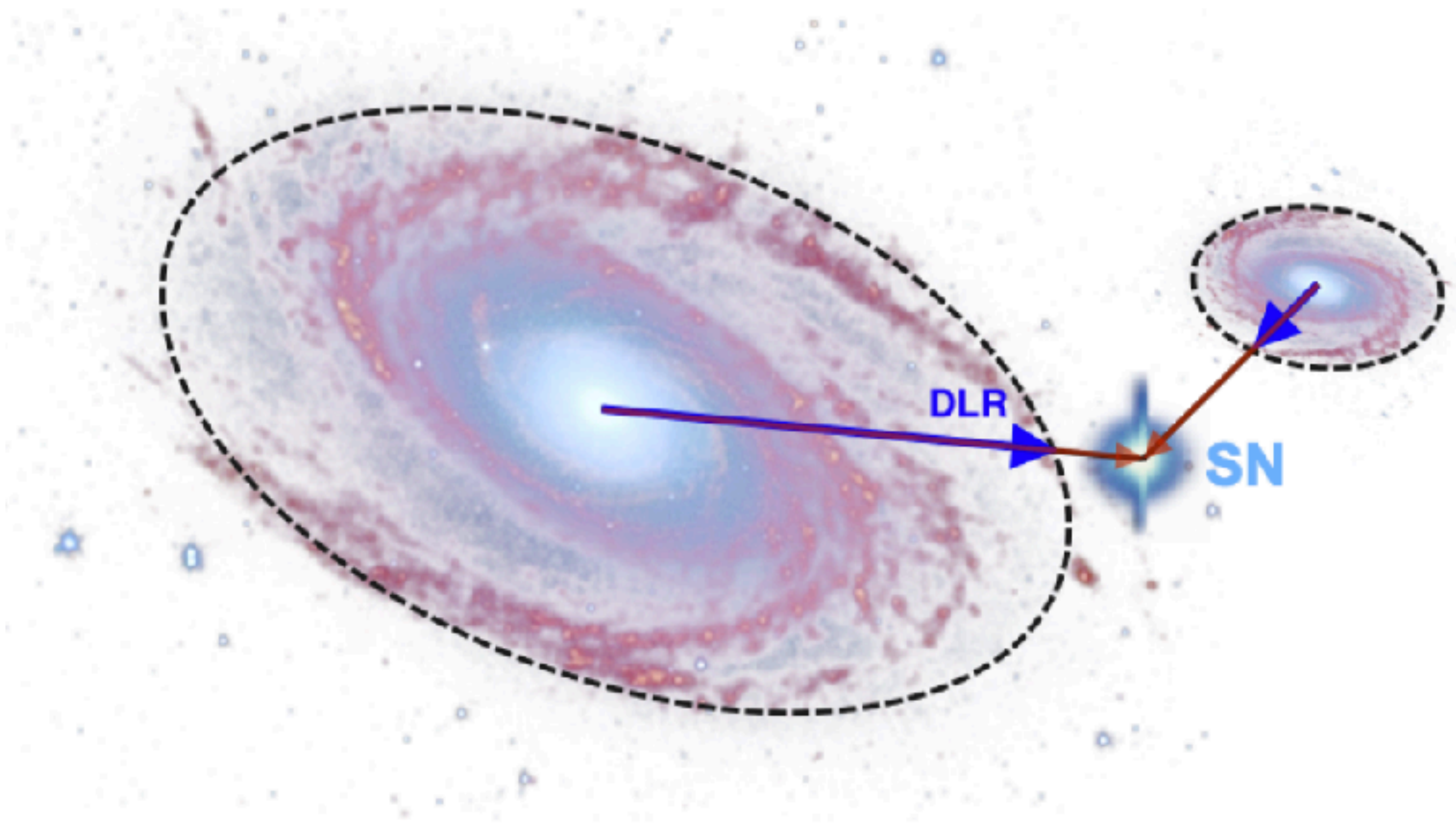
within 1%!

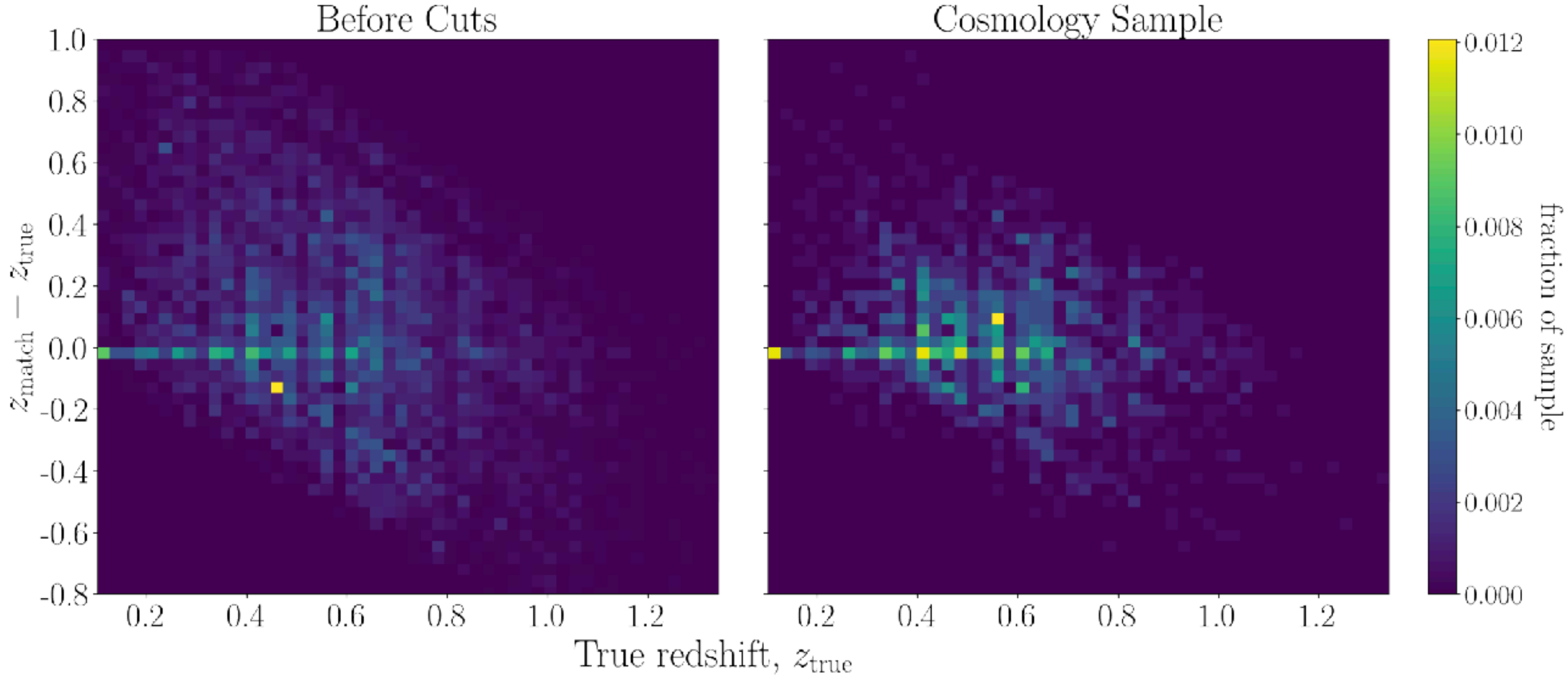
HQ & M. Sako, ApJ, 2023 (arXiv:2305.11869)

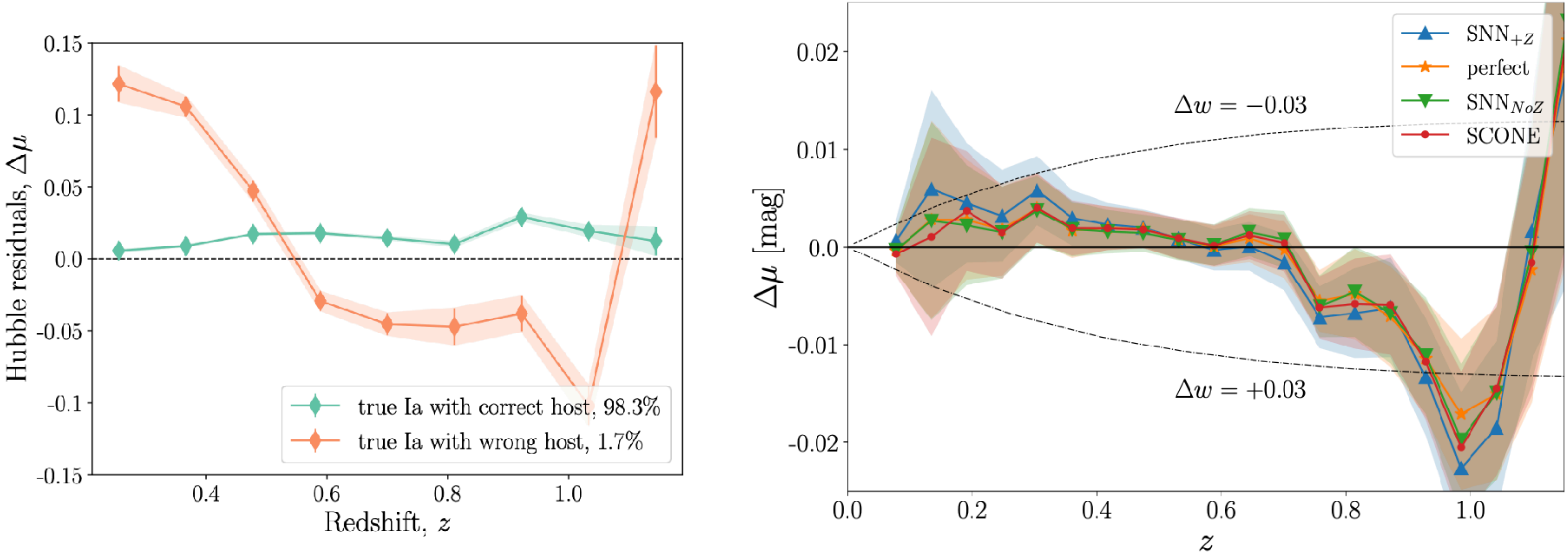
Summary

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

Appendix

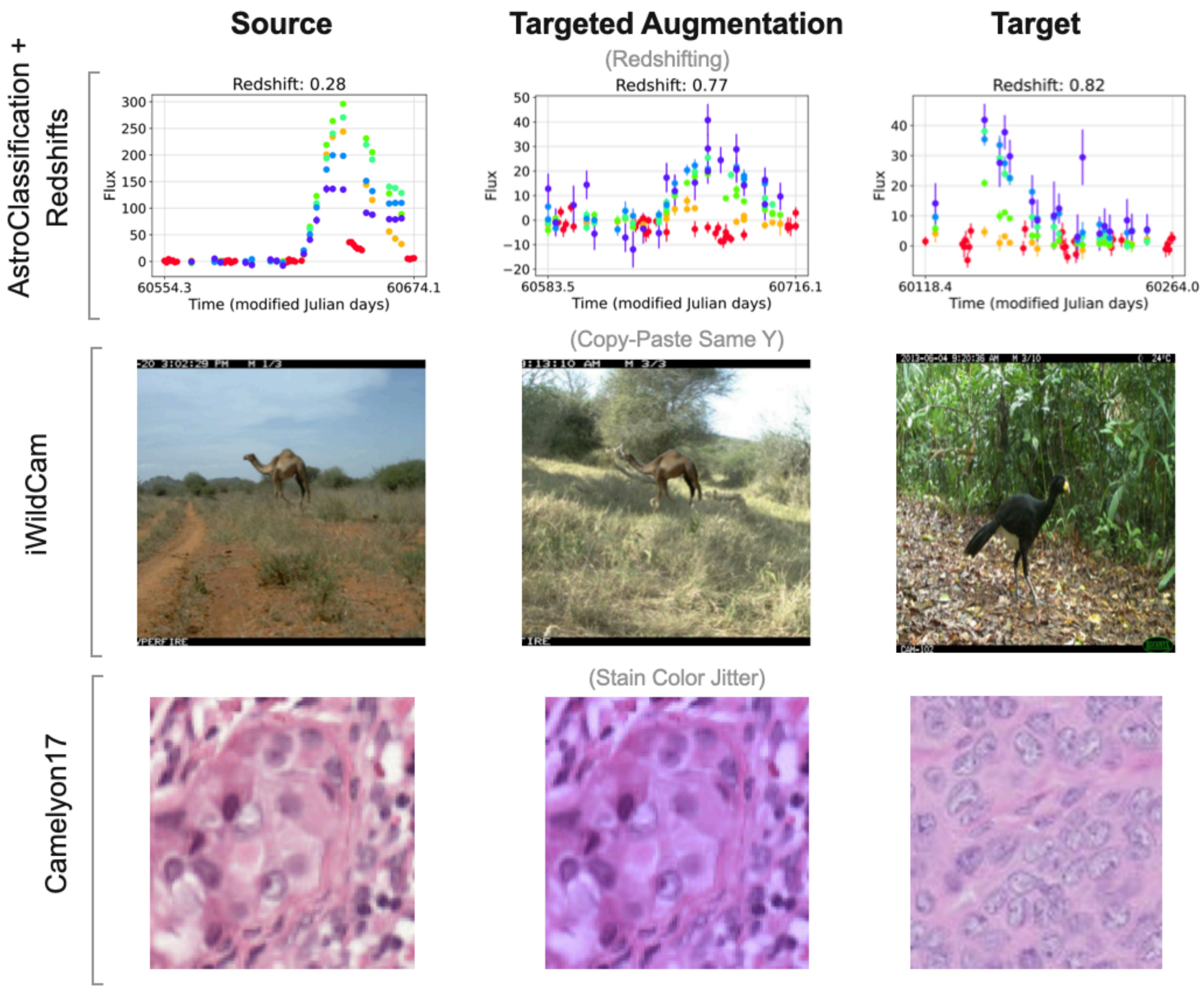

DLR
SN


Before Cuts
Cosmology Sample
$z_{\rm match} - z_{\rm true}$
True redshift, $z_{\rm true}$
fraction of sample
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
0.2
0.4
0.6
0.8
1.0
1.2
0.012
0.010
0.008
0.006
0.004
0.002
0.000

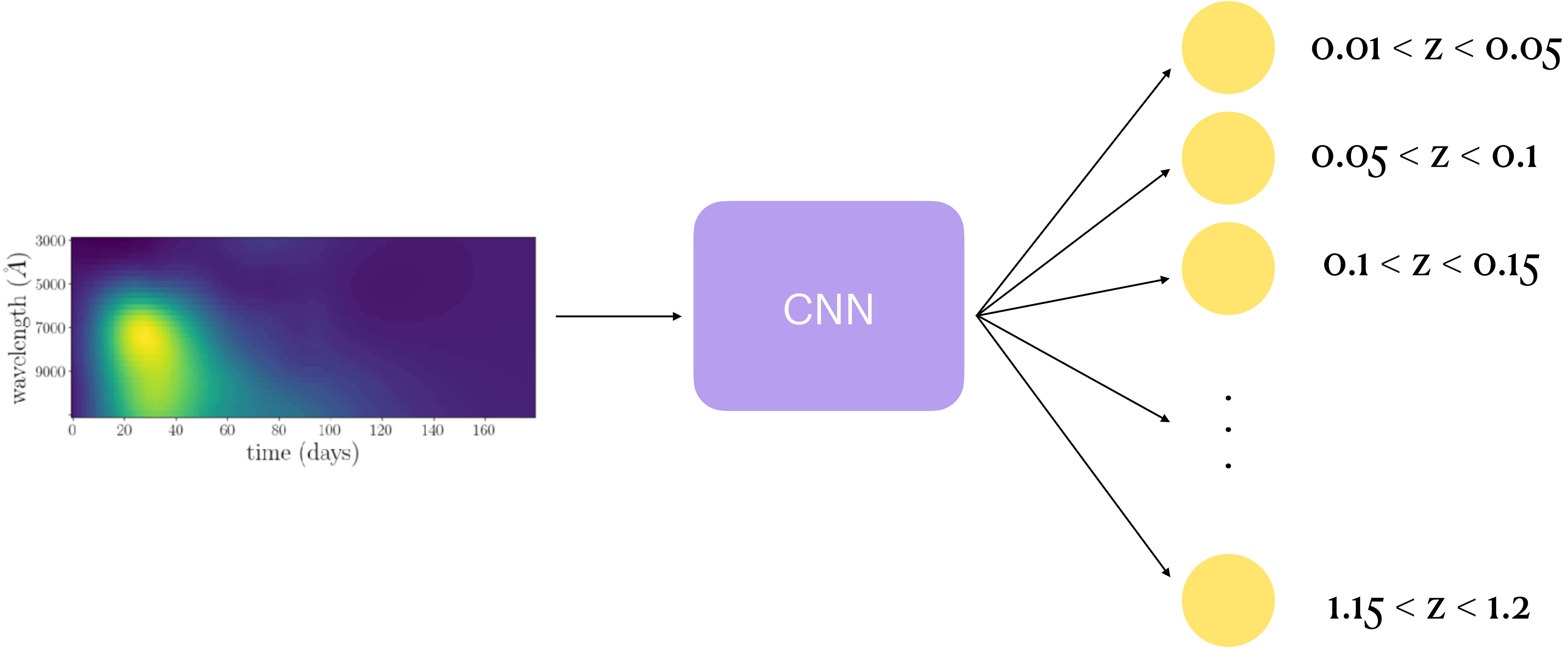

0.15
0.1
0.05
0.0
-0.05
-0.1
-0.15
Hubble residuals, $\Delta\mu$
0.4
0.6
0.8
1.0
Redshift, z
true Ia with correct host, 98.3%
true Ia with wrong host, 1.7%
0.02
0.01
0.0
-0.01
-0.02
$\Delta\mu$ [mag]
0.0
0.2
0.4
0.6
0.8
1.0
z
$\Delta w = -0.03$
$\Delta w = +0.03$
SNN$_{+Z}$
perfect
SNN$_{NoZ}$
SCONE

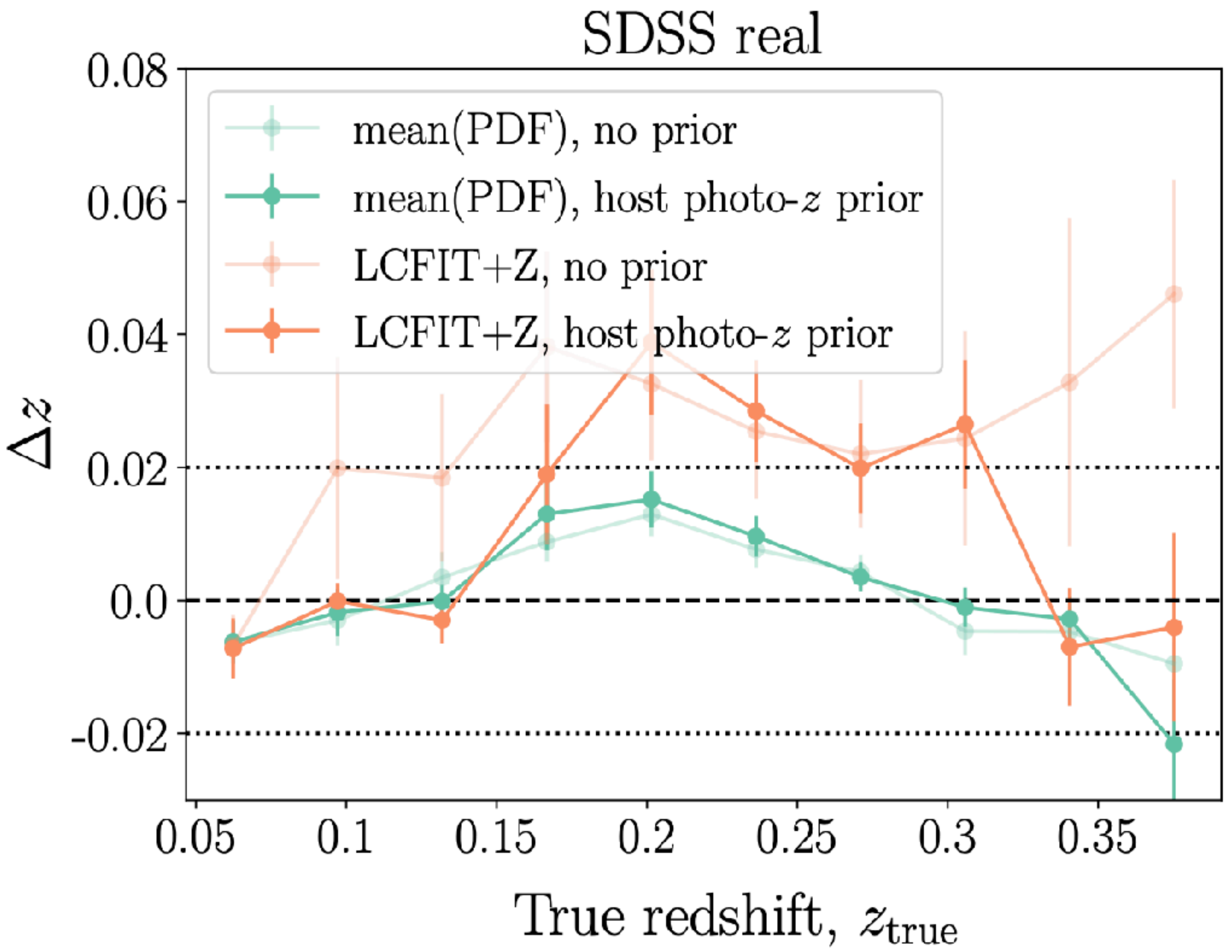
Why pretraining?

- 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)


Source
Targeted Augmentation
Target
AstroClassification + Redshifts
(Redshifting)
Redshift: 0.28
Redshift: 0.77
Redshift: 0.82
Flux
Time (modified Julian days)
60554.3
60674.1
60583.5
60716.1
60118.4
60264.0
iWildCam
(Copy-Paste Same Y)
Camelyon17
(Stain Color Jitter)

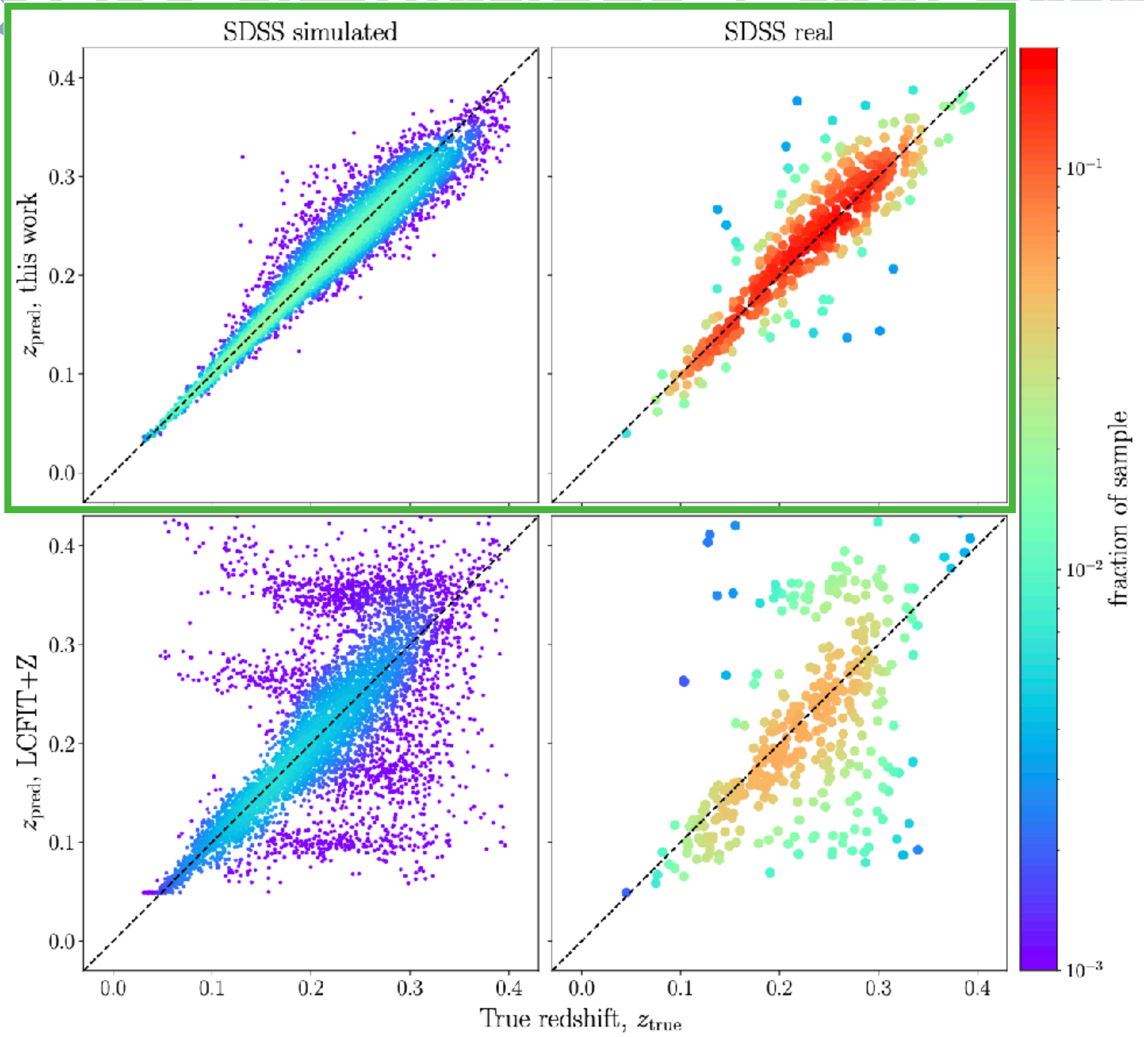
Discretized PDF





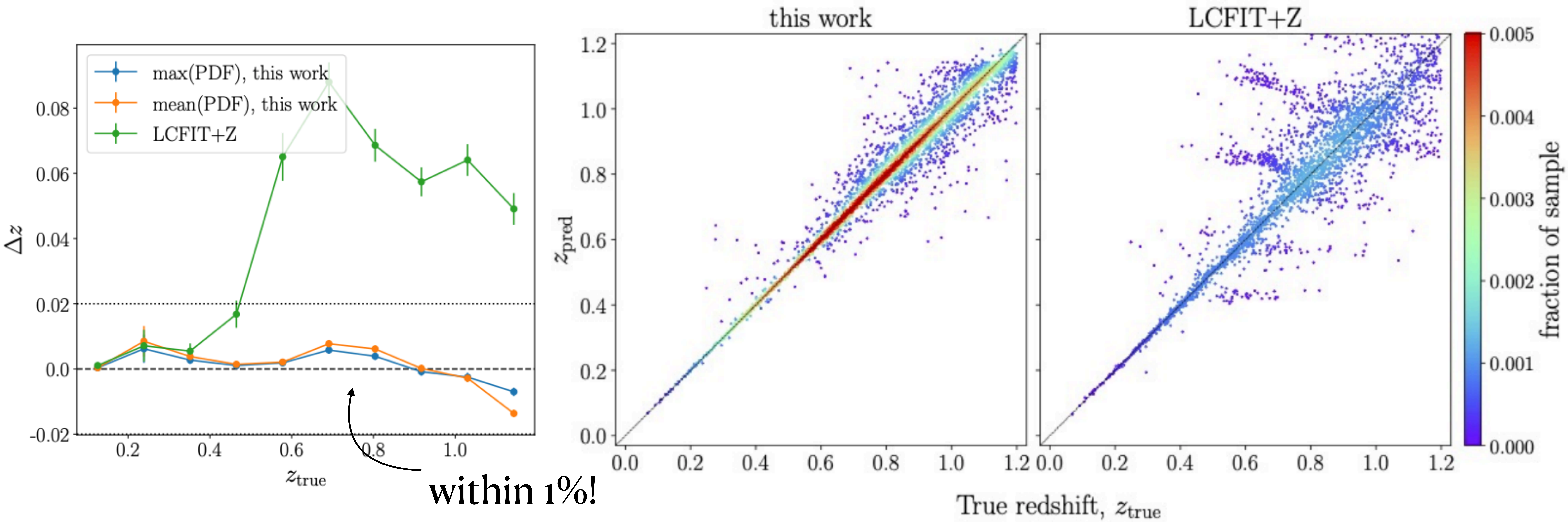
SDSS real
0.08
0.06
0.04
0.02
0.0
-0.02
Δz
mean(PDF), no prior
mean(PDF), host photo-z prior
LCFIT+Z, no prior
LCFIT+Z, host photo-z prior
0.05
0.1
0.15
0.2
0.25
0.3
0.35
True redshift, $z_{\rm true}$

Tested on SDSS simulations + real data



HQ & M. Sako, ApJ, 2023 (arXiv:2305.11869)

Tested on LSST simulations



within 1%!

HQ & M. Sako, ApJ, 2023 (arXiv:2305.11869)

Survey-Agnostic Performance

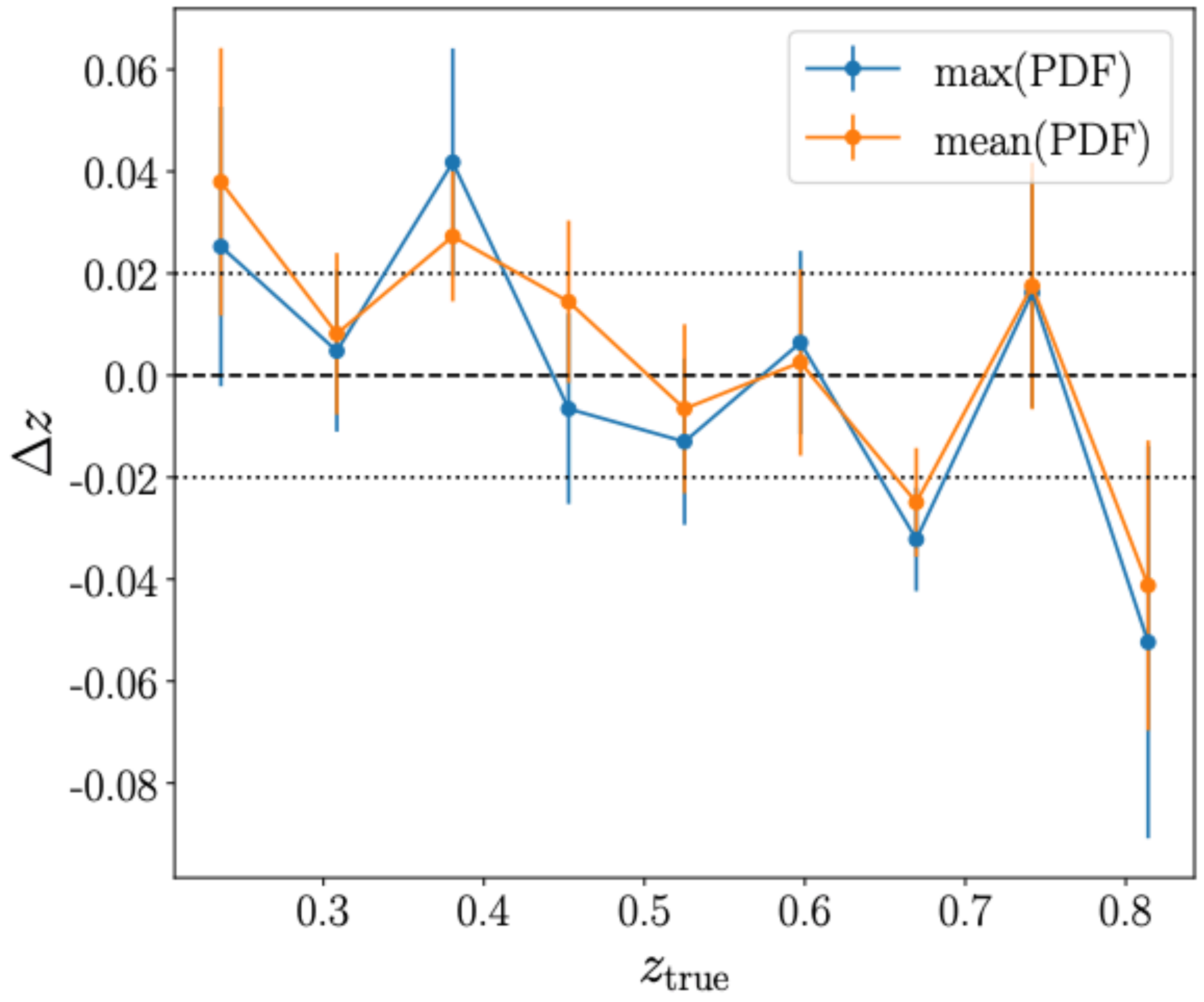
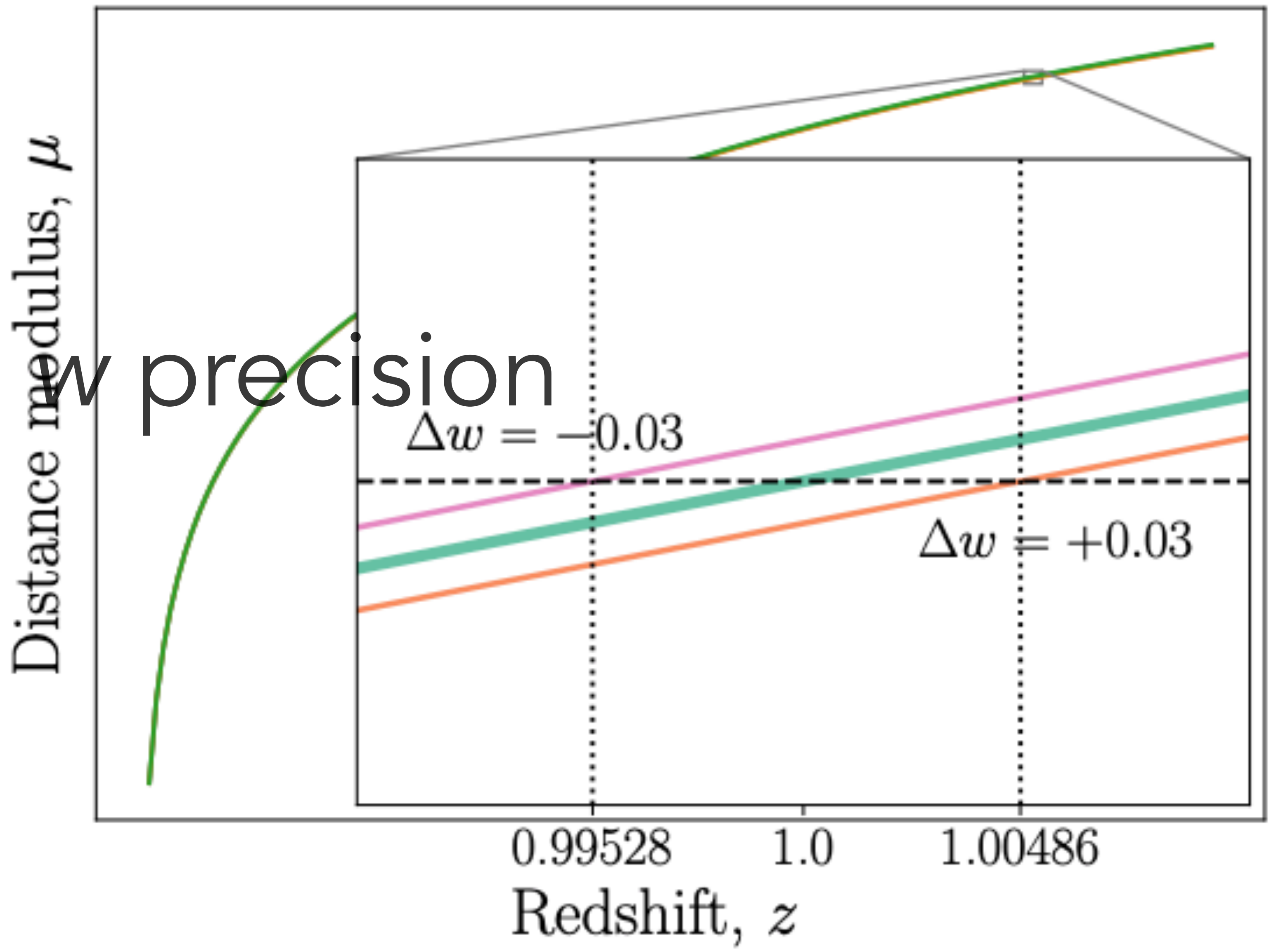


Figure 14. Mean binned residuals, $\Delta z \equiv \frac{z_{\mathrm{pred}} - z_{\mathrm{true}}}{1+z_{\mathrm{true}}}$, as a function of true redshift, z_{true}, for the DES3YR SNe Ia sample produced by a model trained on the PLAsTiCC dataset. The max(PDF) and mean(PDF) methods of obtaining point estimates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

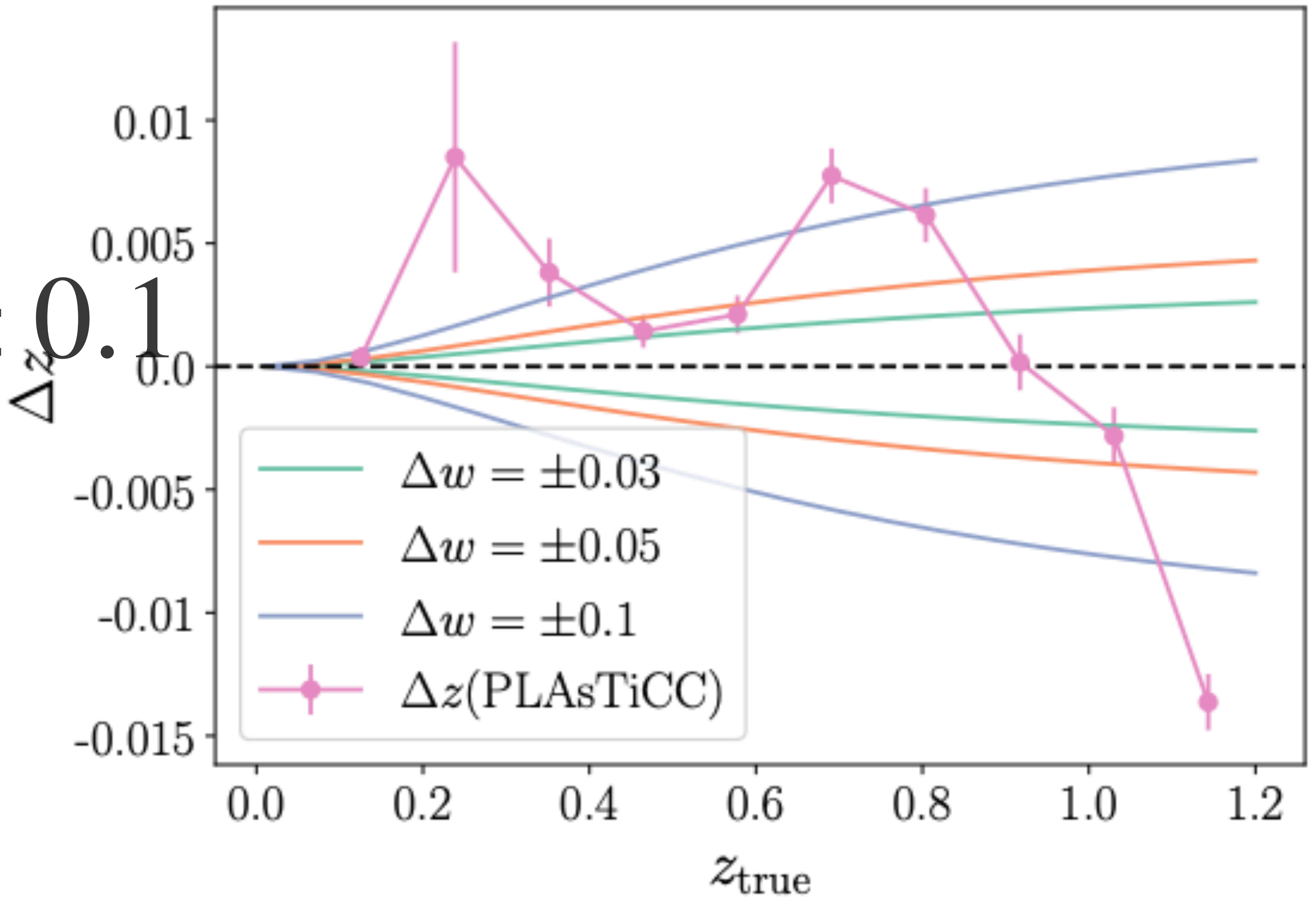
HQ & M. Sako, AJ, 2023 (arXiv:2305.11869)

Photo-z's for Cosmology

Rough estimate of redshift precision vs. w precision



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



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