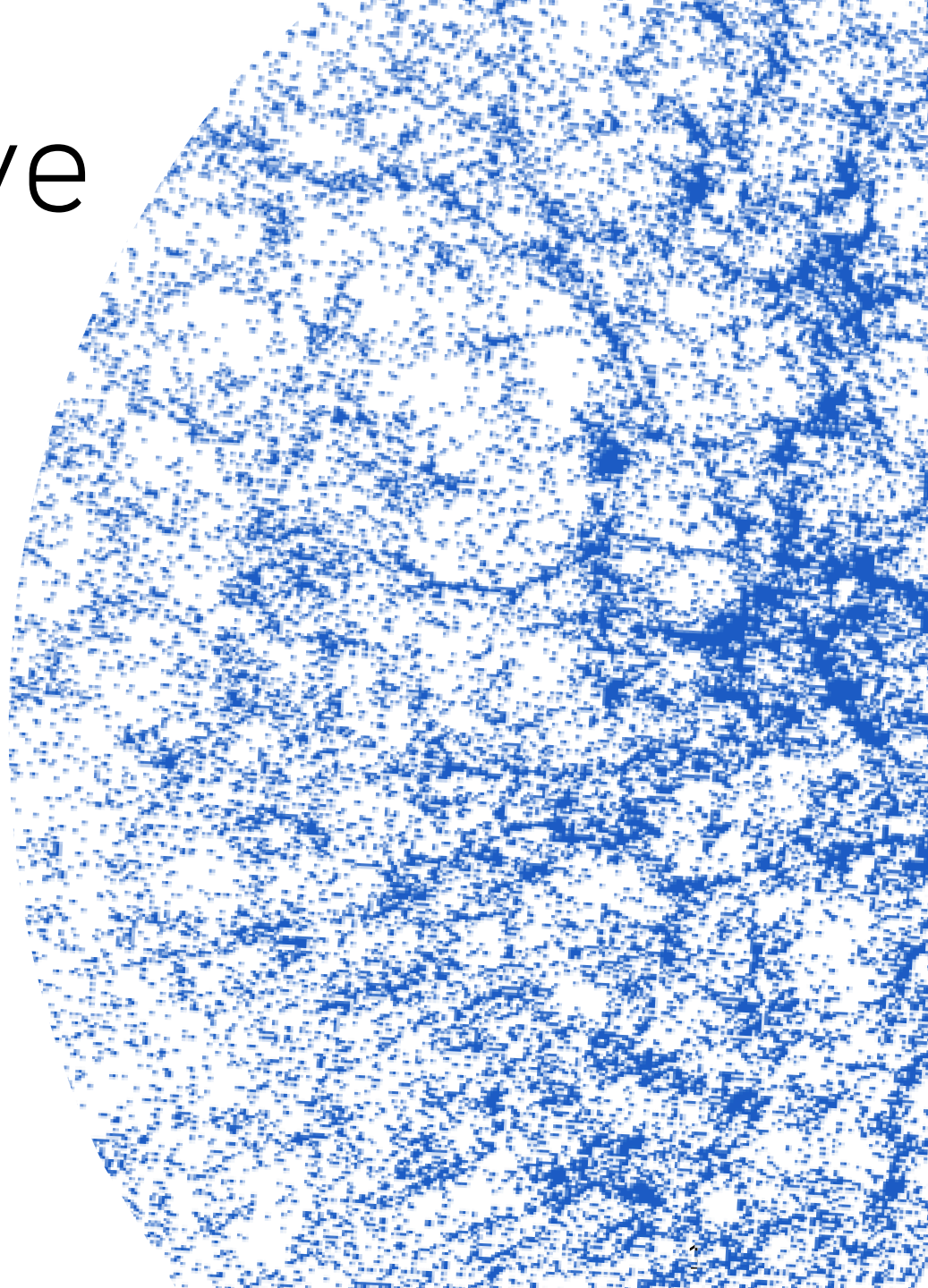
Calibrated Predictive Distributions for Photometric Redshifts



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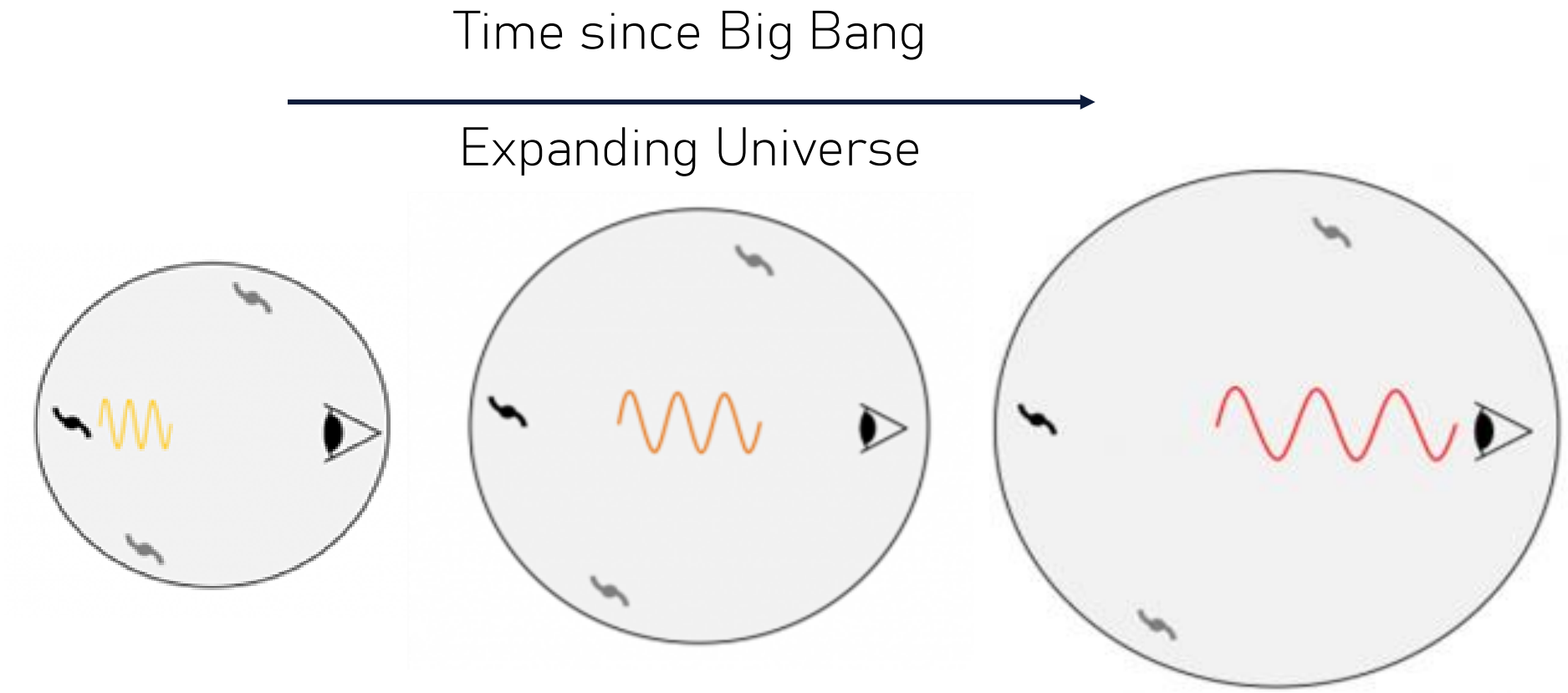
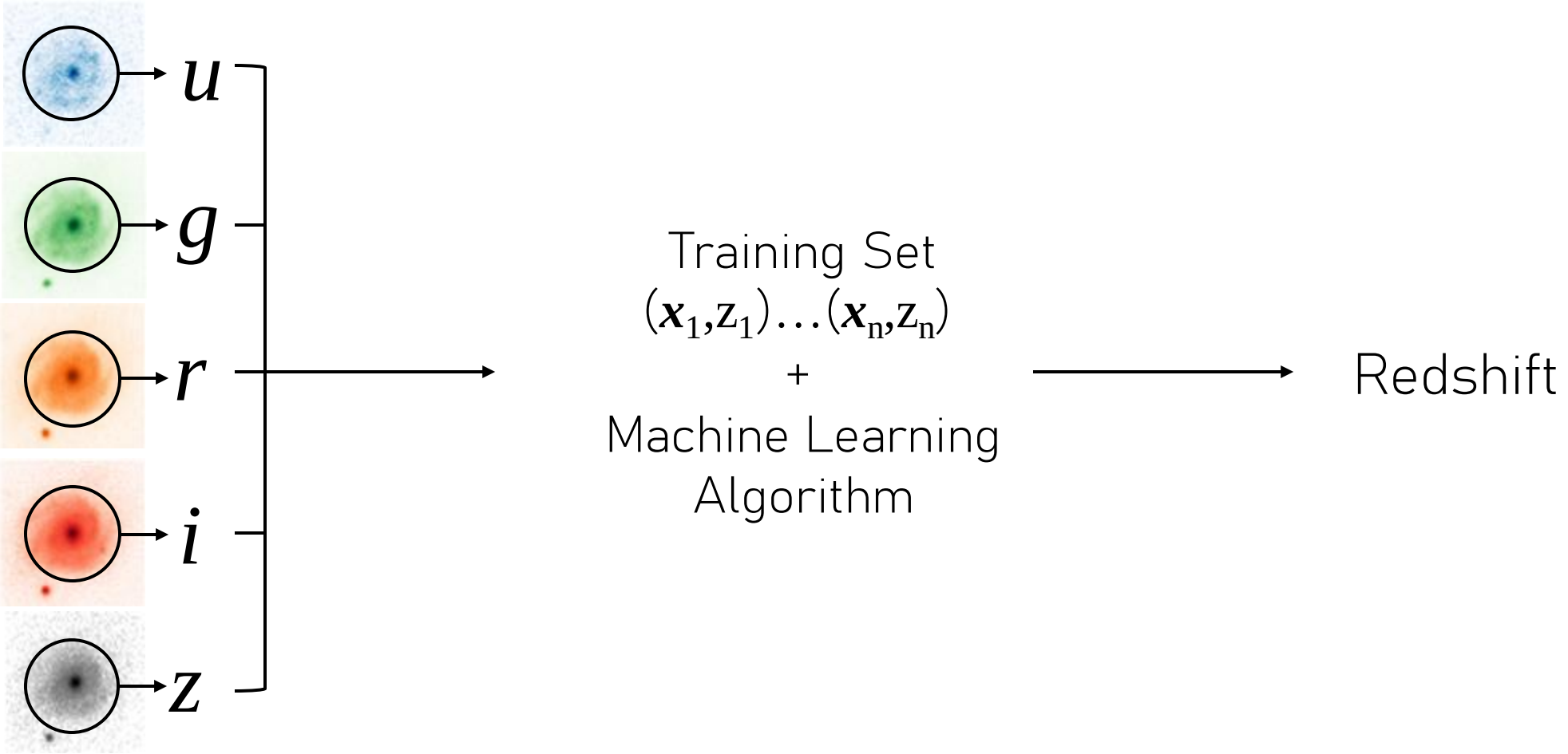
Redshift is a proxy for galaxy distances



Knowing redshifts of objects is the first step for all extragalactic studies but measuring it directly **is incredibly resource intensive**

Image courtesy: Sloan Digital Sky Survey

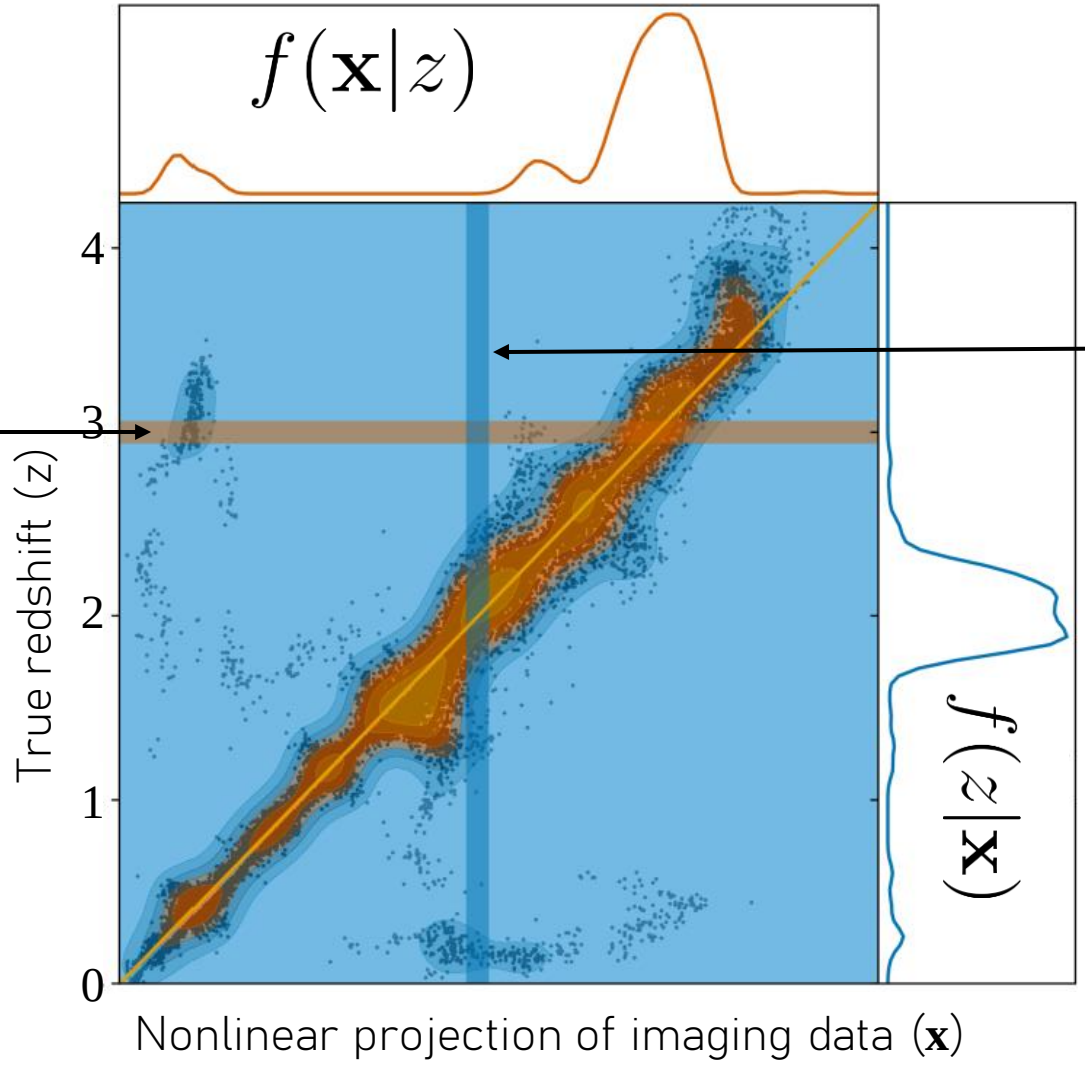
Photometric Redshifts (photo-z)



Magnitudes, Colors, etc.

Why Predict Entire Distribution $\widehat{f}(z|\mathbf{x})$?

Galaxies with very different imaging data can have similar redshifts



Galaxies with similar imaging data can have very different redshifts

Imaging data has incomplete and noisy information about redshift

Adapted from Malz & Hogg, 2020

Calibrated Predictive Distributions

Fraction of times the true value falls within the limits $\mathbf{y}_1$ and $\mathbf{y}_2$

=

The integral of the PDF between these limits (PIT)

for any arbitrary subset of the test data

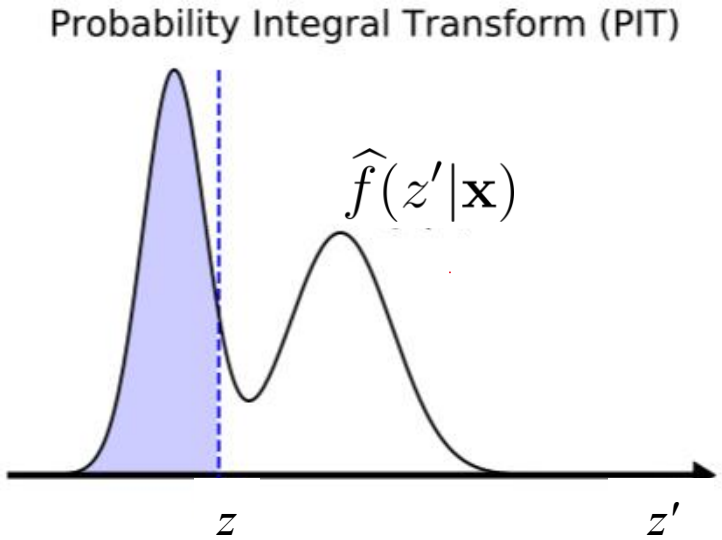
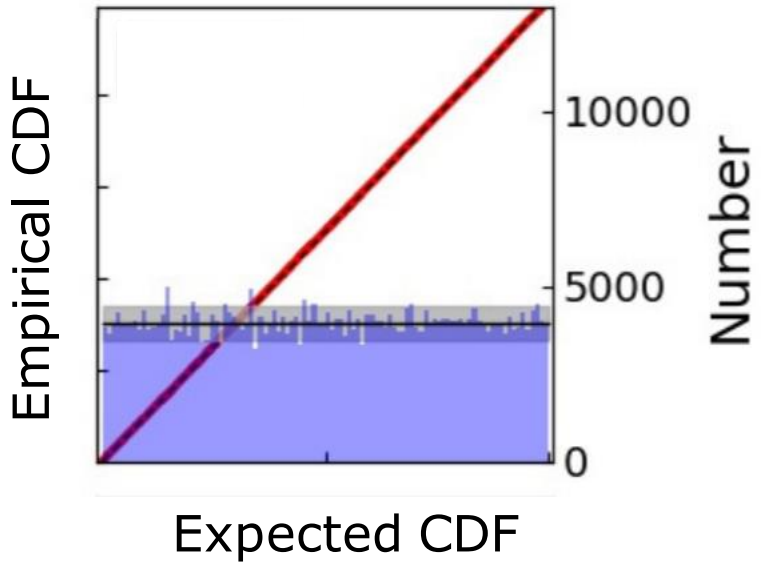
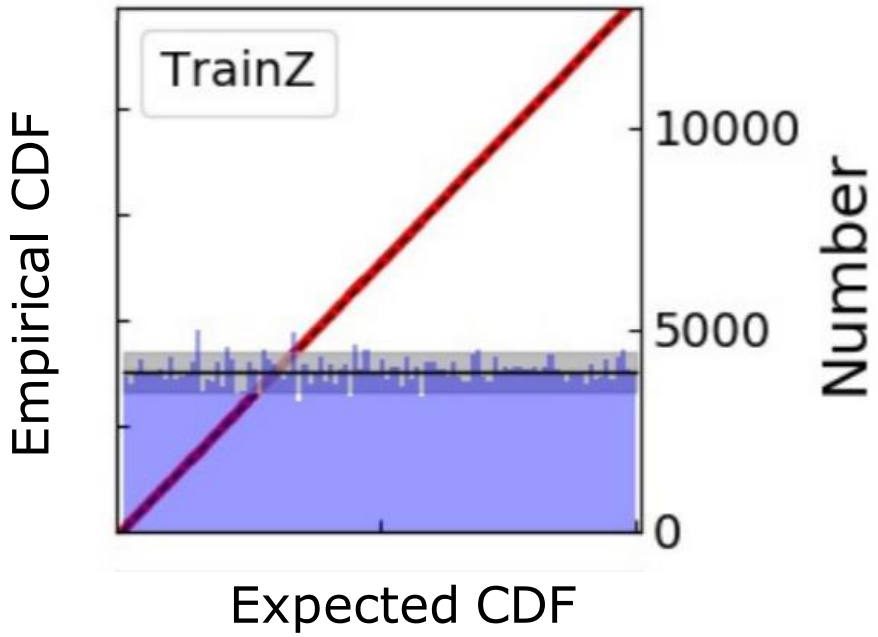


Image credit: Zhao+2021 & Schmidt+2020



Current Methods only Achieve Global Calibration

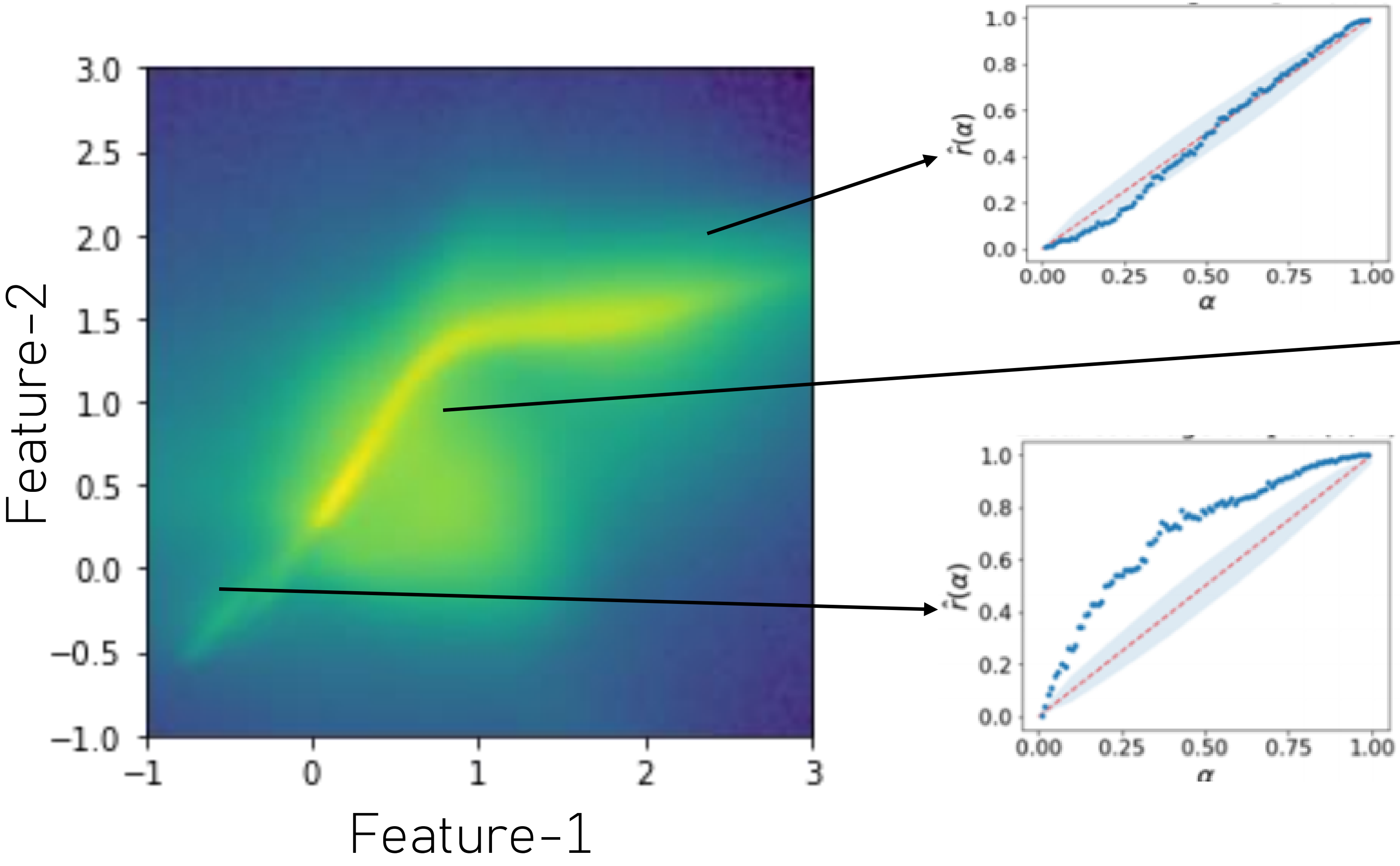
Evaluate PIT Distribution for the **test set as a whole**

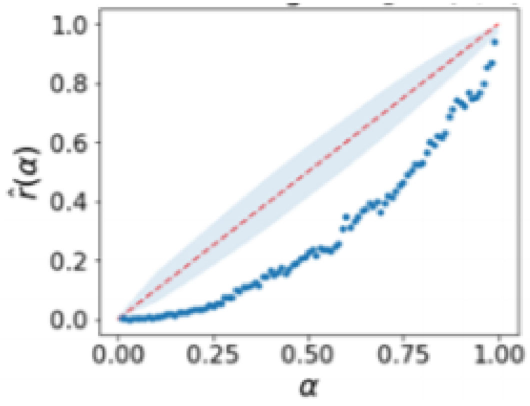


e.g., The uninformative TrainZ distribution from Schmidt, Malz et al. 2020.

Many methods achieve marginal coverage but so does an uninformative prediction like the marginal distribution of the training set.

Global Calibration can be achieved while being **always wrong!**





Local Calibration

is what we want!

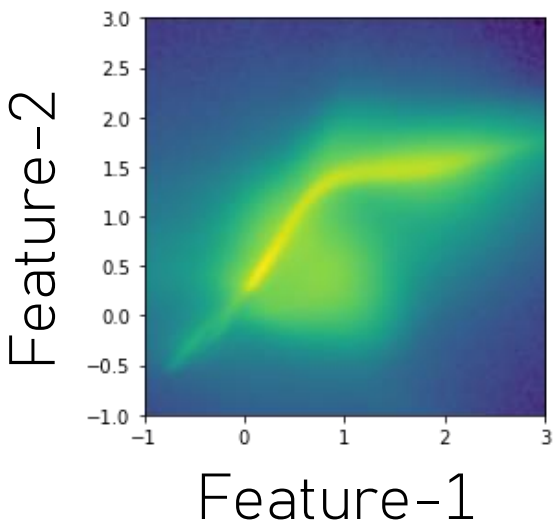
Requirements for Astronomy Experiments

Legacy Survey of Space and Time

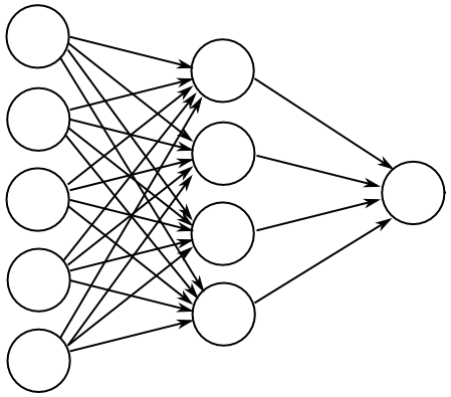
Moments of the photometric redshift predictive distributions should be within 0.2% of the truth to meet LSST goals

Image courtesy: Vera Rubin Observatory

Estimating Local (Conditional) PIT



Inputs



Train

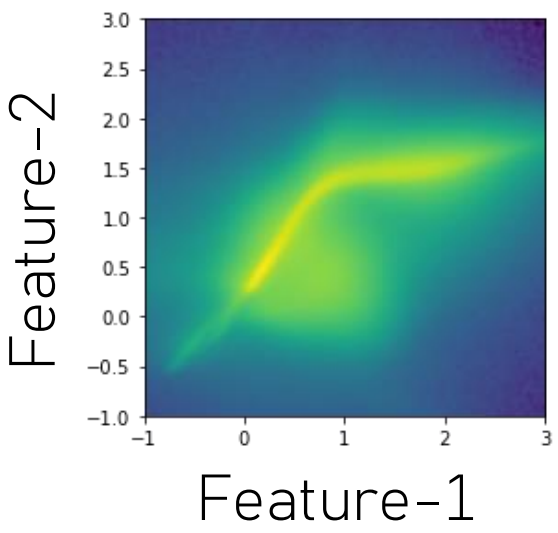
$$\begin{cases} \mathbf{1} & \text{if } \mathrm{PIT}(z'; \mathbf{x}) \leq \gamma \\ \mathbf{0} & \text{Otherwise} \end{cases}$$

Calibration Data + coverage probability (γ)

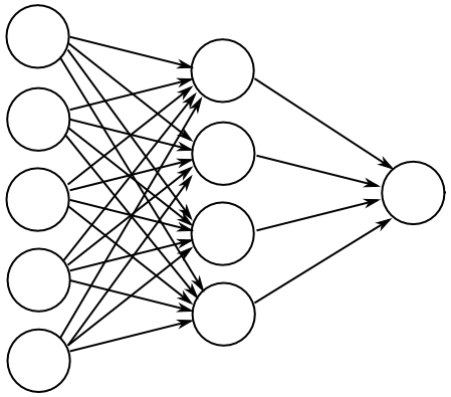
Your favorite regression method

Labels (based on initial PDFs)

Estimating Local (Conditional) PIT



Inputs



Train

$$\mathbb{P}\left(\mathrm{PIT}(z;\mathbf{x}) \leq \gamma \mid \mathbf{x}\right)$$

Calibration Data + coverage probability (γ)

Your favorite regression method

Labels (based on initial PDFs)

Calibration using Local PIT (Cal-PIT)

$$\widetilde{F}(z|\mathbf{x}) := \hat{r}^{\hat{f}}\left(\hat{F}(z|\mathbf{x}); \mathbf{x}\right)$$

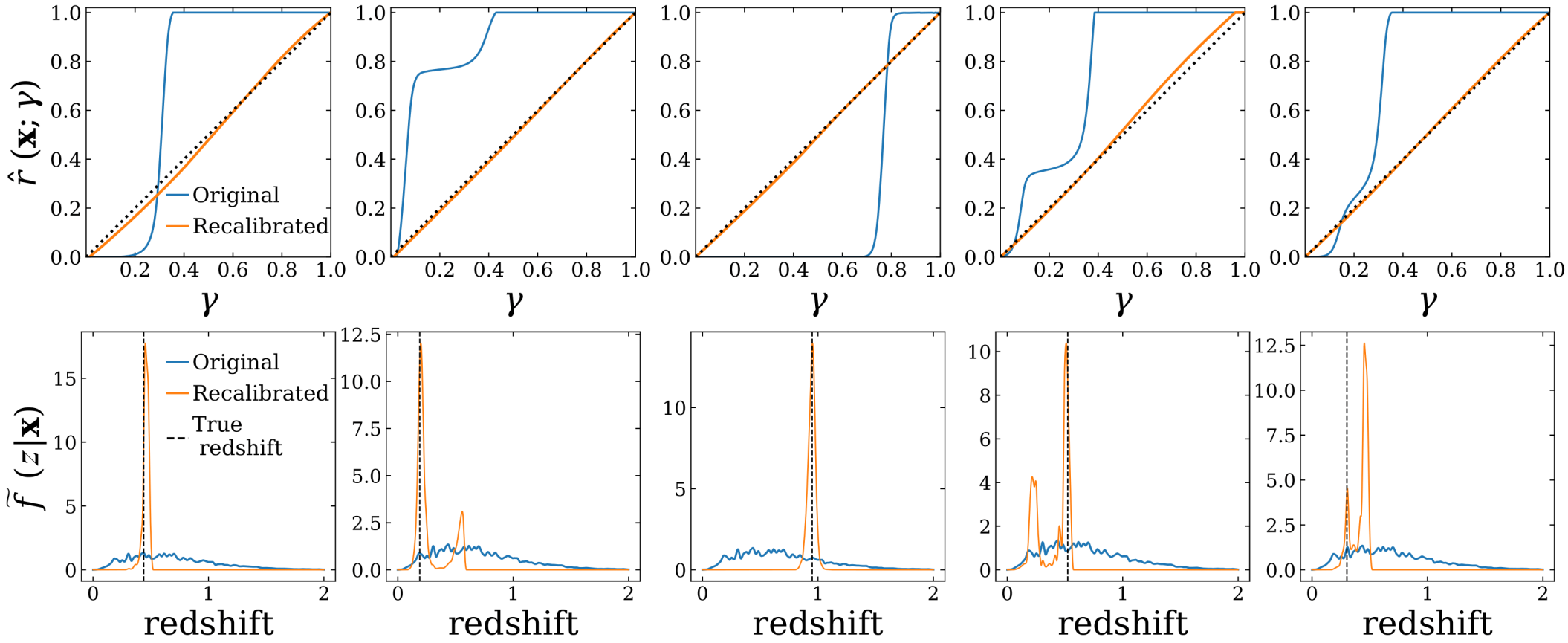
New distribution (calibrated by construction)

Learnt regression function

Old distribution (uncalibrated)

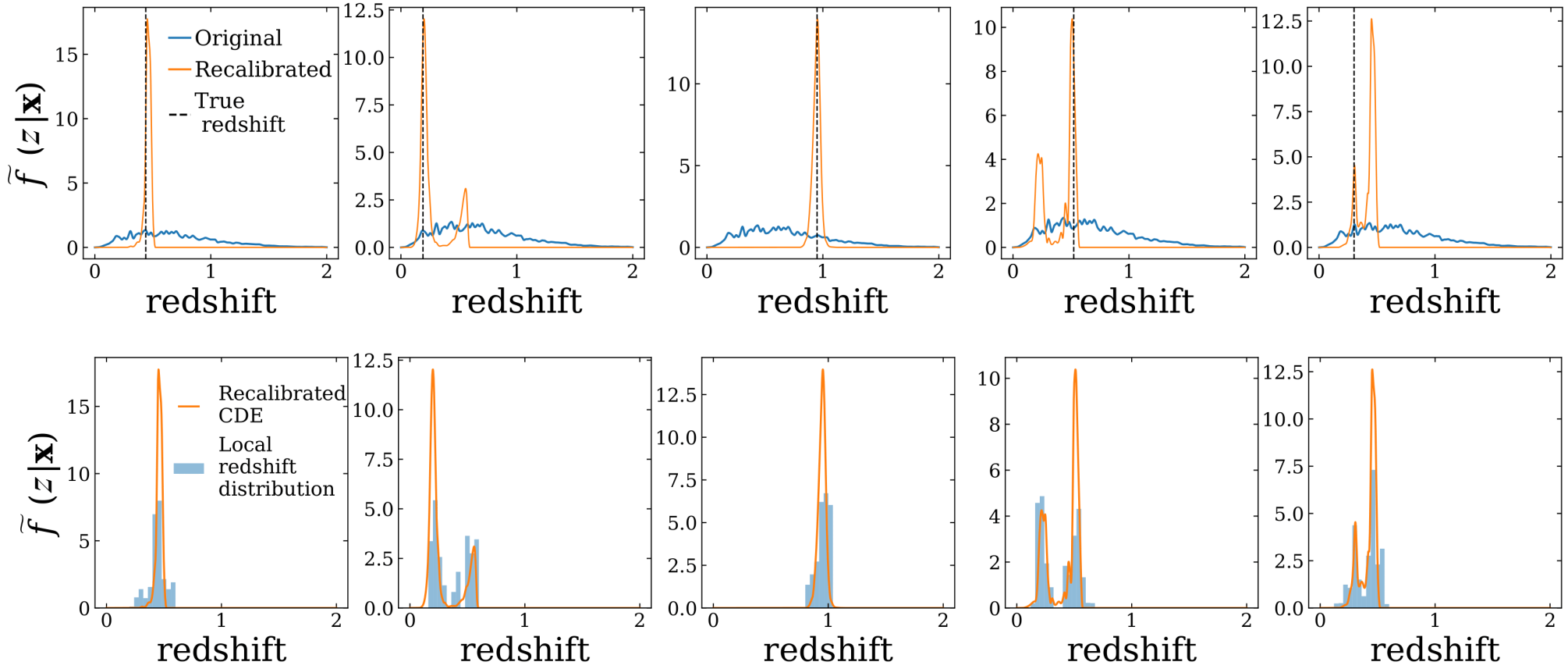
Photometric Redshift Predictive Distributions

We start with the marginal distribution $f(y)$ as our initial guess



Post re-calibration, performance is better on metrics of conditional coverage

Photometric Redshift Predictive Distributions



Bimodality can be recovered even if the initial guess was unimodal

Summary

- Predictive distributions are more useful for physical sciences than point estimates and intervals.

- We can produce predictive distributions with correct conditional coverage with calibration using local PIT (Cal-PIT).

- The method is general purpose and non-parametric.

Ref: **Dey, Zhao et al. 2022** (arXiv:2205.14568)

Thanks for your attention!
Have questions, comments or want to collaborate?
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