Optimizing Roman Photometric Redshifts for HLIS

Brett Andrews

In collaboration with:

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- **Ashod Khederlarian**
- **Yoki Salcedo**
- **Marcos Tamargo-Arizmendi**
- **Emma Moran** (Pitt undergrad applying to grad school in Fall)
- **TQ Zhang**
- **Jeff Newman**
- **Biprateep Dey** (UToronto/CITA)
- **Chun-Hao To** (UChicago)

Roman Virtual Lecture Series

9.25.2025

University of Pittsburgh

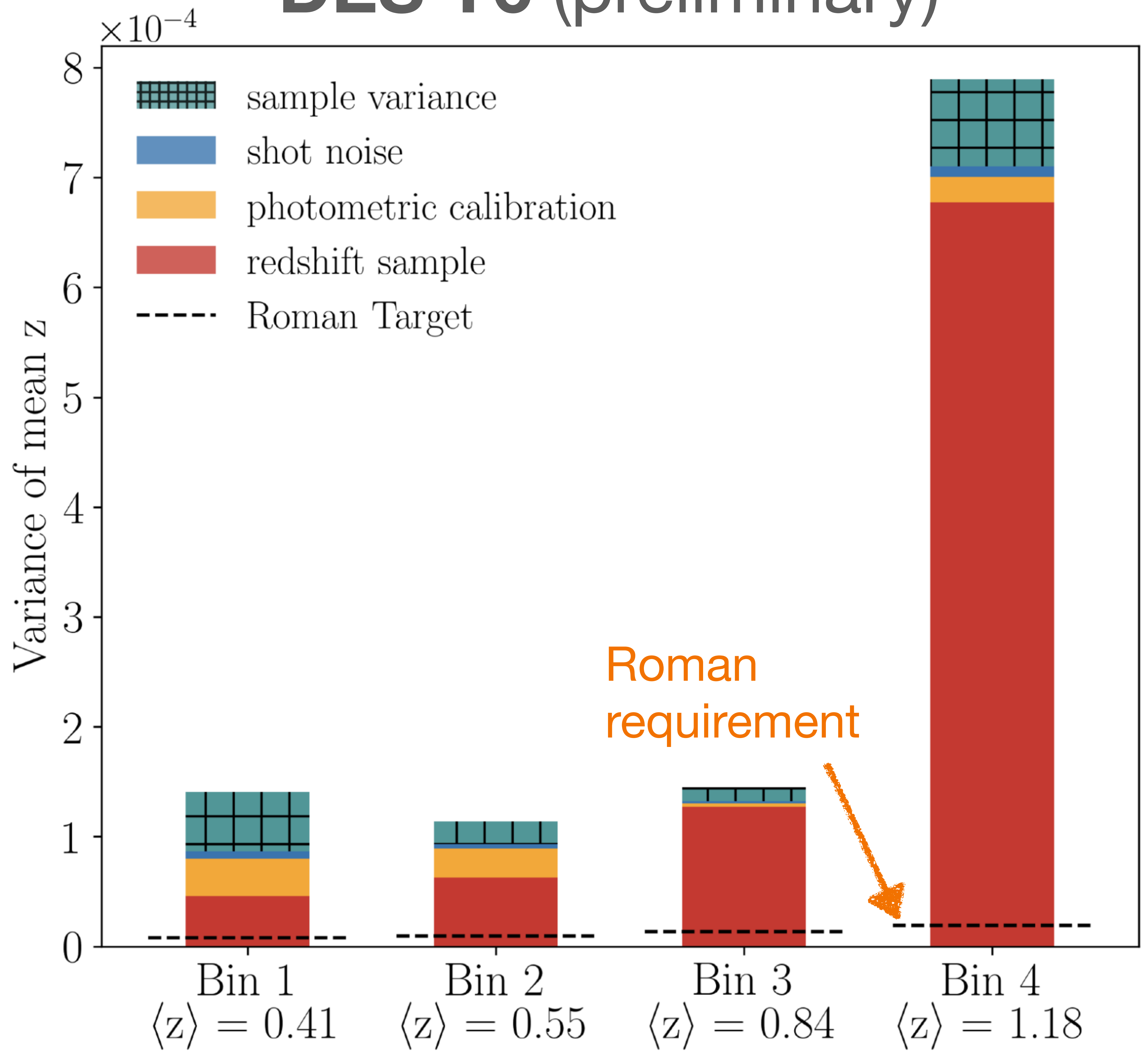
HLIS

NSF

NASA

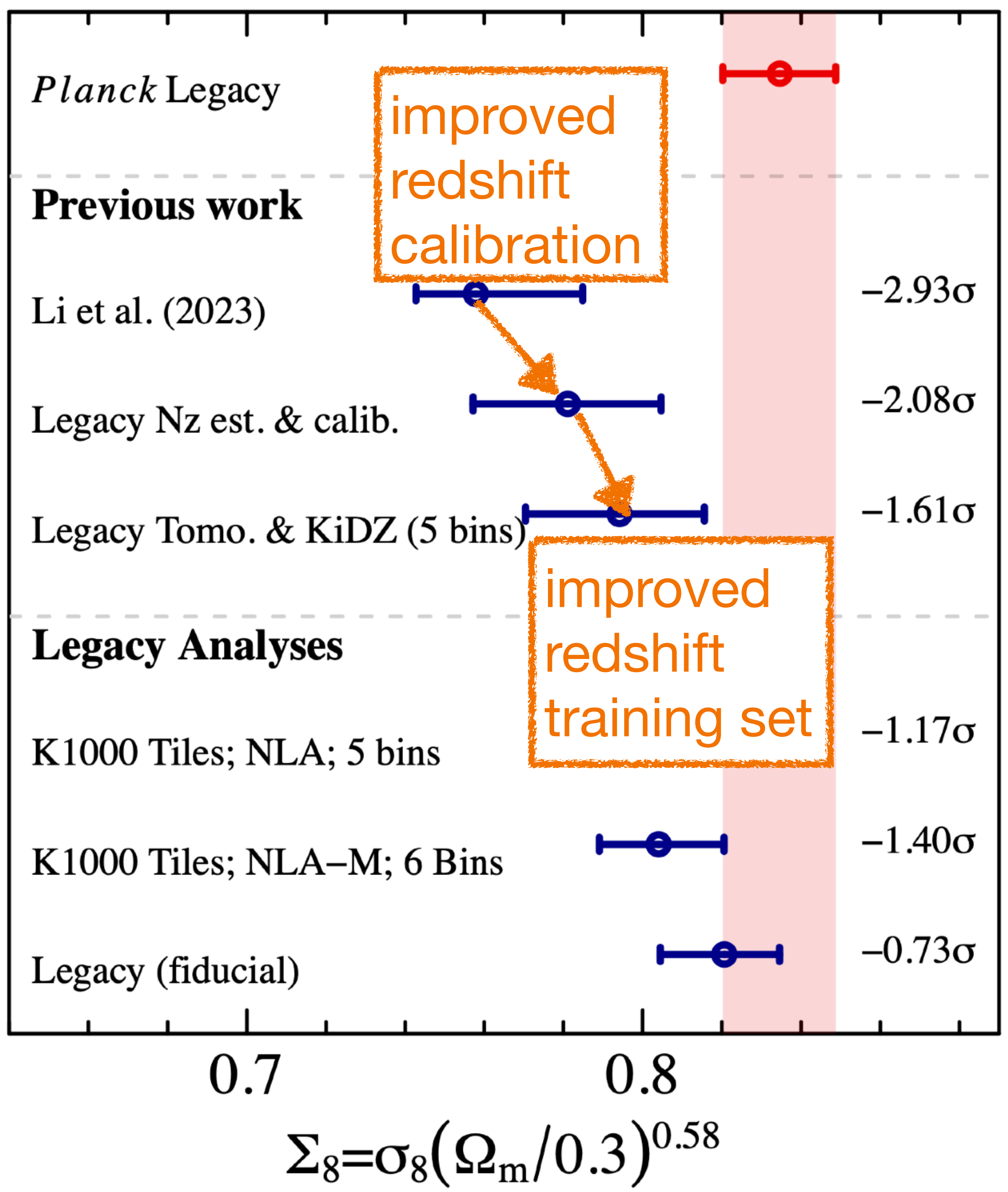
Roman Cosmic Shear Analyses: Strict Photo-z Calibration Requirements

DES Y6 (preliminary)



Boyan Yin et al. (in prep.)

KiDS-Legacy



Wright et al. (2025)

Outline

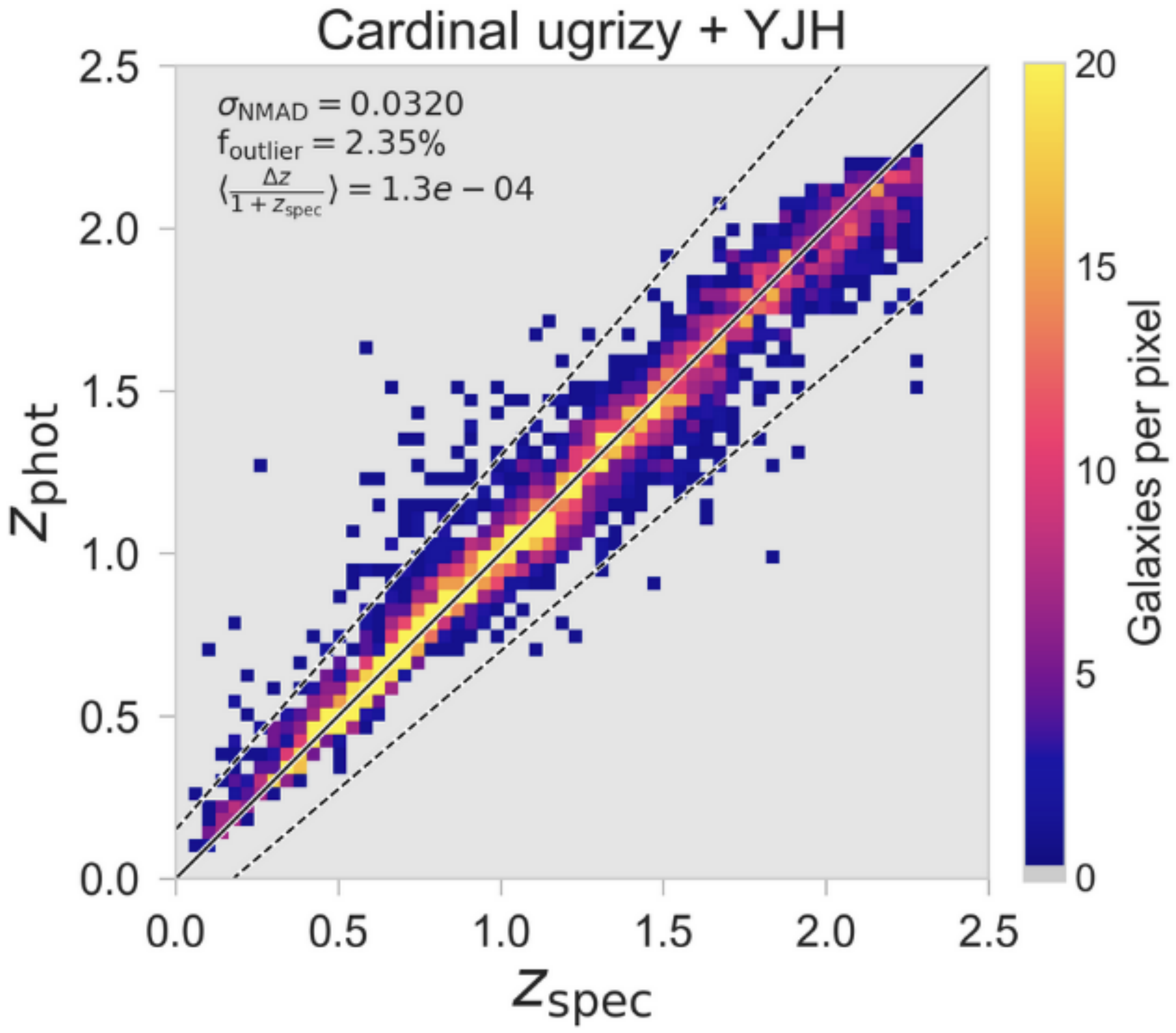
1. Optimizing survey design
2. Improving spec-z training sets
3. Calibrating with cross-correlations
4. Using deep learning for image-based photo-z's

HLIS Survey Design: Photo-z Forecasts

- **Random Forest** (decision-tree-based ML method)
  - photometry: LSST *ugrizy* (Y4 depth) + Roman bands ($H < 24.5$)
  - spec-z's: representative training set w/ 20k objects *(strong assumption!)*

- Simulated and Observational Data:
  - **Cardinal** simulation (Chun-Hao To et al. 2024)
  - **OpenUniverse2024** simulation (OpenUniverse et al. 2025)
  - **COSMOS2020** catalog (Weaver et al. 2022)
  - caveats: none perfect but provide sense of range of outcomes

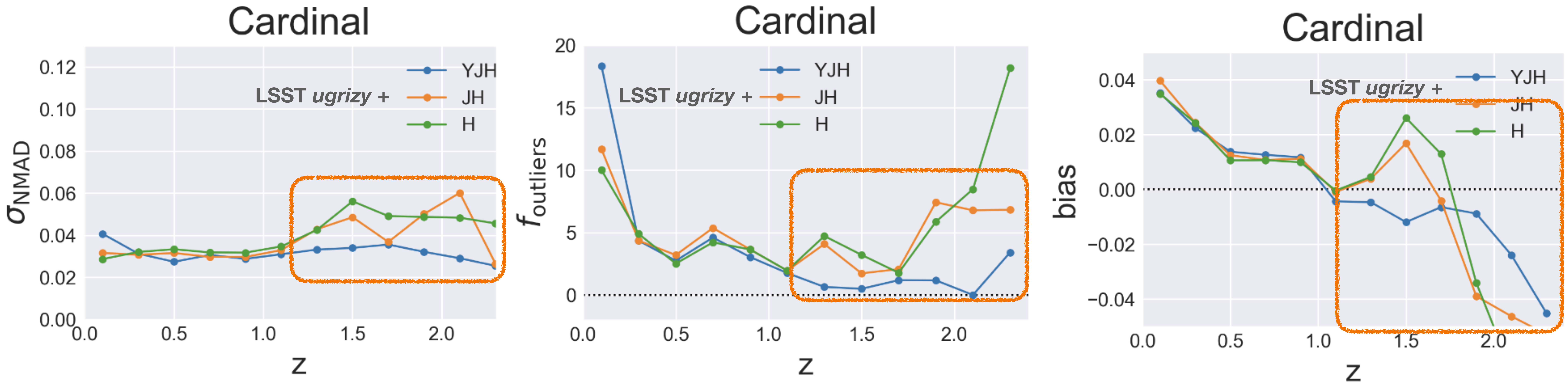
HLIS Medium Tier: YJH-only (drop F184)



- Design Reference Mission:
  - Y, J, H, and F184 imaging (2000 deg^2)

- HLIS Cosmology PIT and ROTAC Recommendation:
  - **YJH Medium Tier** (2400 deg^2)
    - F184 mostly helpful at z > 3 (beyond lensing sample)

HLIS Wide Tier: H-only



HLIS Cosmology PIT and ROTAC Recommendation:

- **H-only Wide Tier** (2700 deg^2)
  - 2x increase in area (vs. JH) with only slightly worse photo-z point estimates
  - *Will require highly complete spec-z training set*

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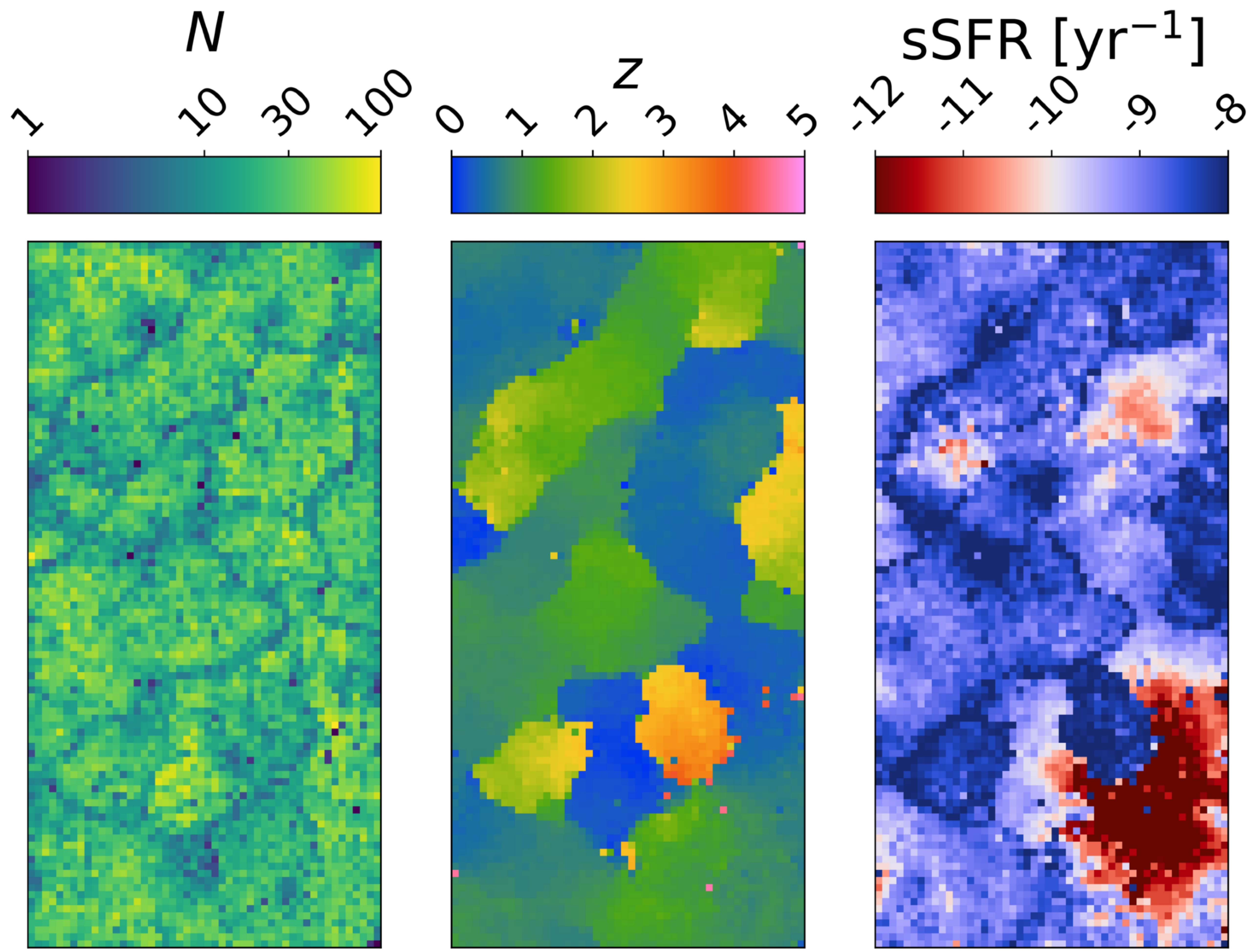
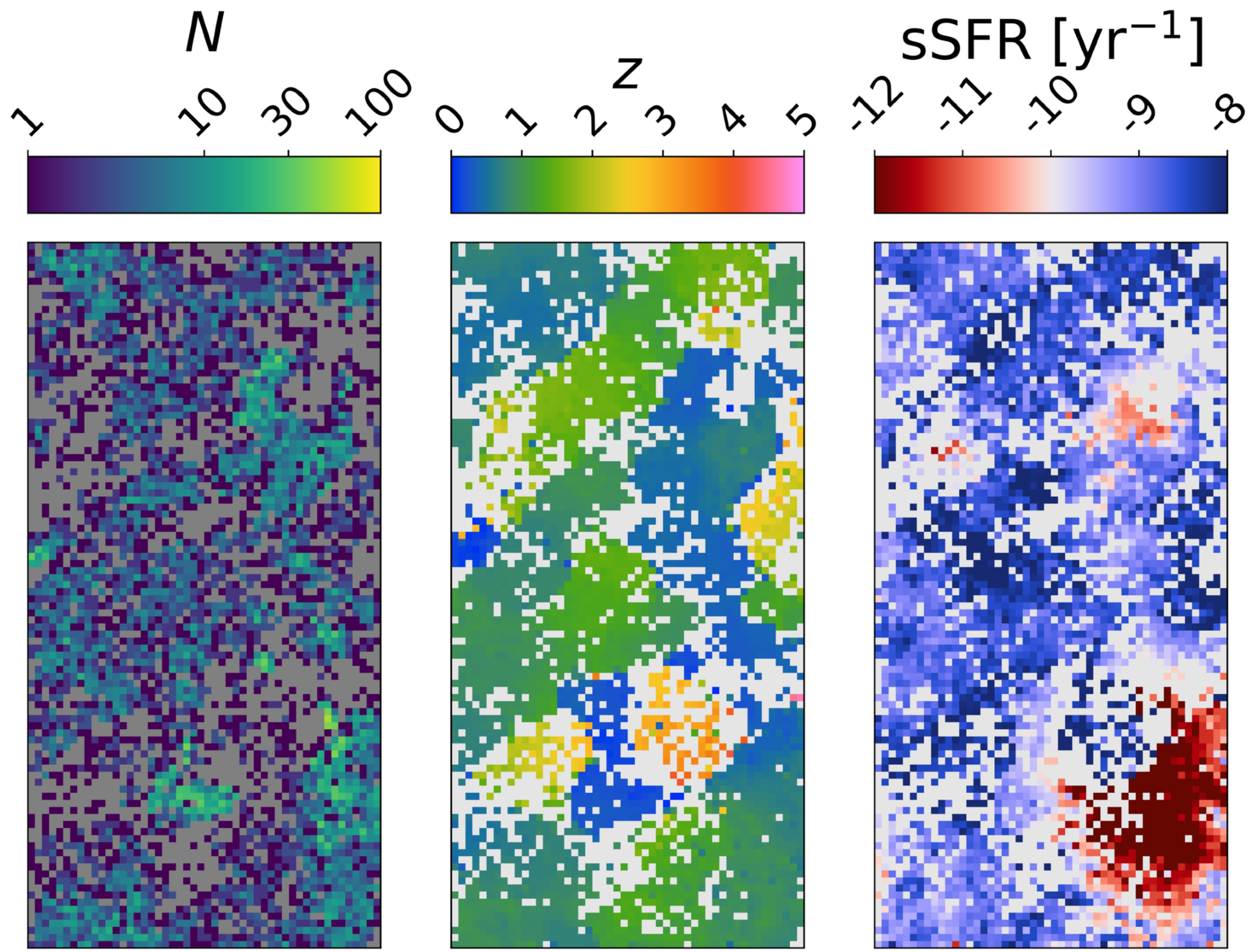
Spectroscopic Incompleteness: Key Photo-z Calibration Challenge



Photometric Objects
LePHARE many-band $\boldsymbol{z_{phot}}$
COSMOS2020 *u*grizyJH* + LePHARE sSFR
Finian Ashmead, Newman, **BHA**, et al. (in prep.)

Spectroscopic Incompleteness: Key Photo-z Calibration Challenge



Spectroscopic Objects

z_{spec} (confidence > 95%) from Khostovan et al. (2025)

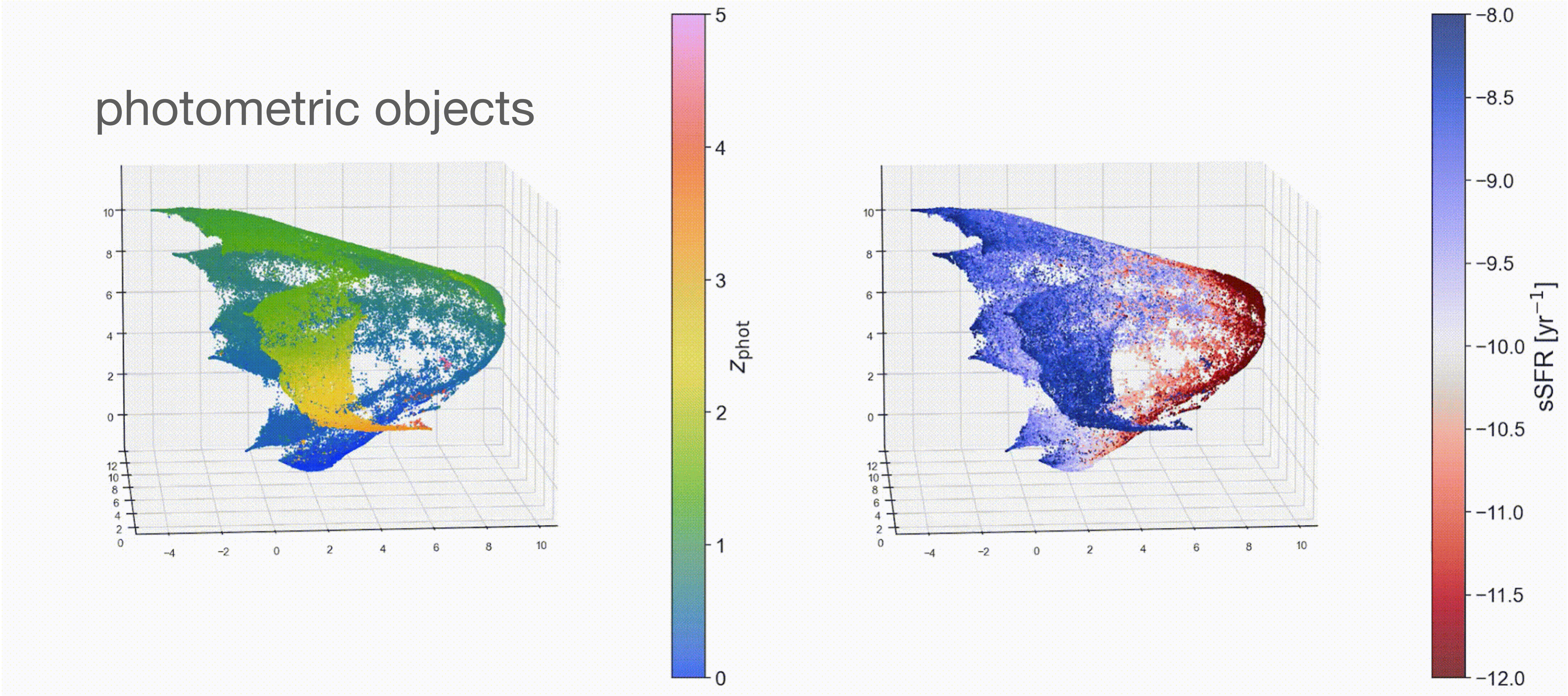
COSMOS2020 *u*grizyJH* + LePHARE sSFR

Finian Ashmead, Newman, **BHA**, et al. (in prep.)

Creating a Representative Spec-z Training Set

- **UMAP** as a SOM-alternative for dimensionality reduction of $u^{*}grizyJH$ color space

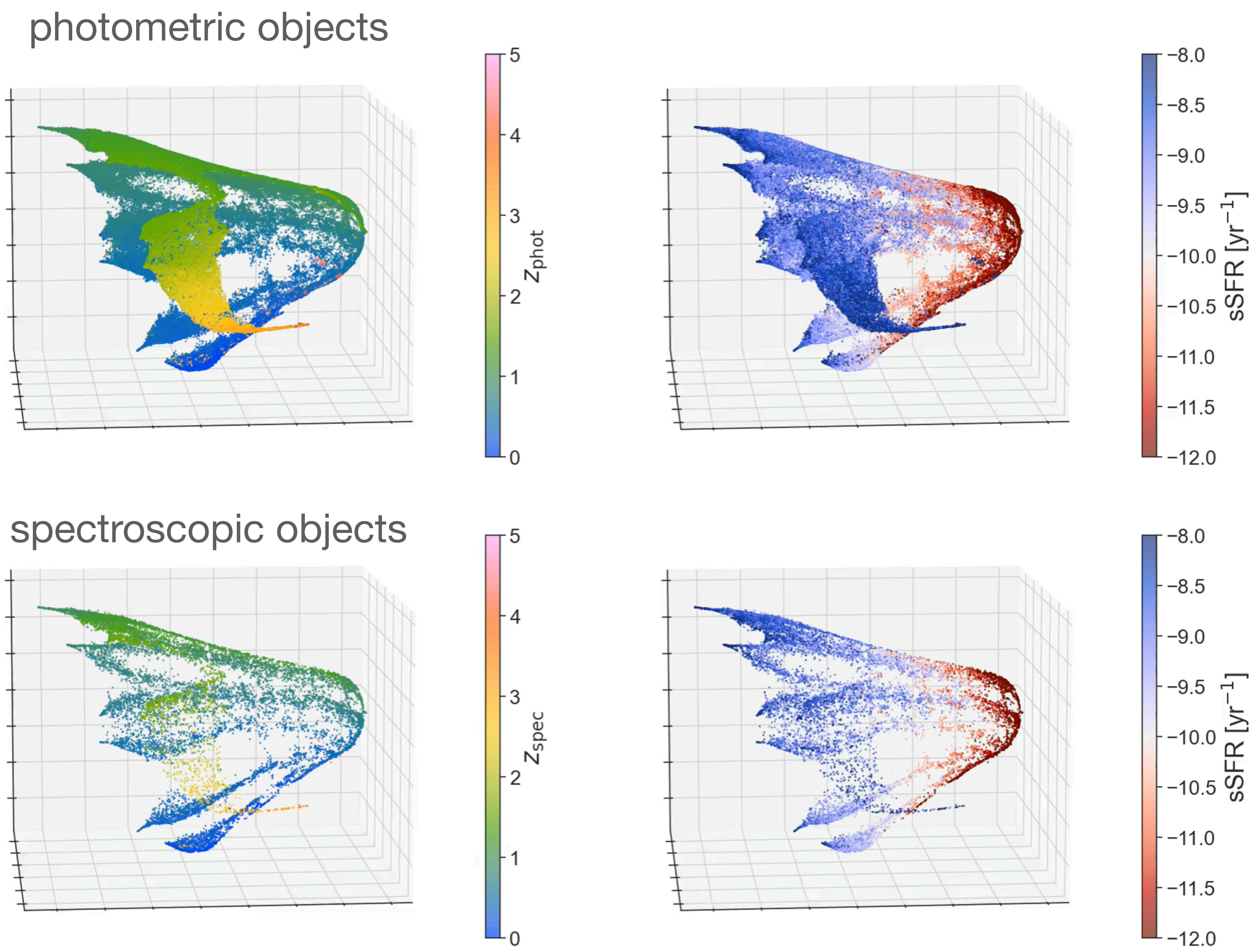
- Produces thin (almost 2-D) manifold that is monotonic in redshift and specific SFR



Finian Ashmead, Newman, **BHA**, et al. (in prep.)

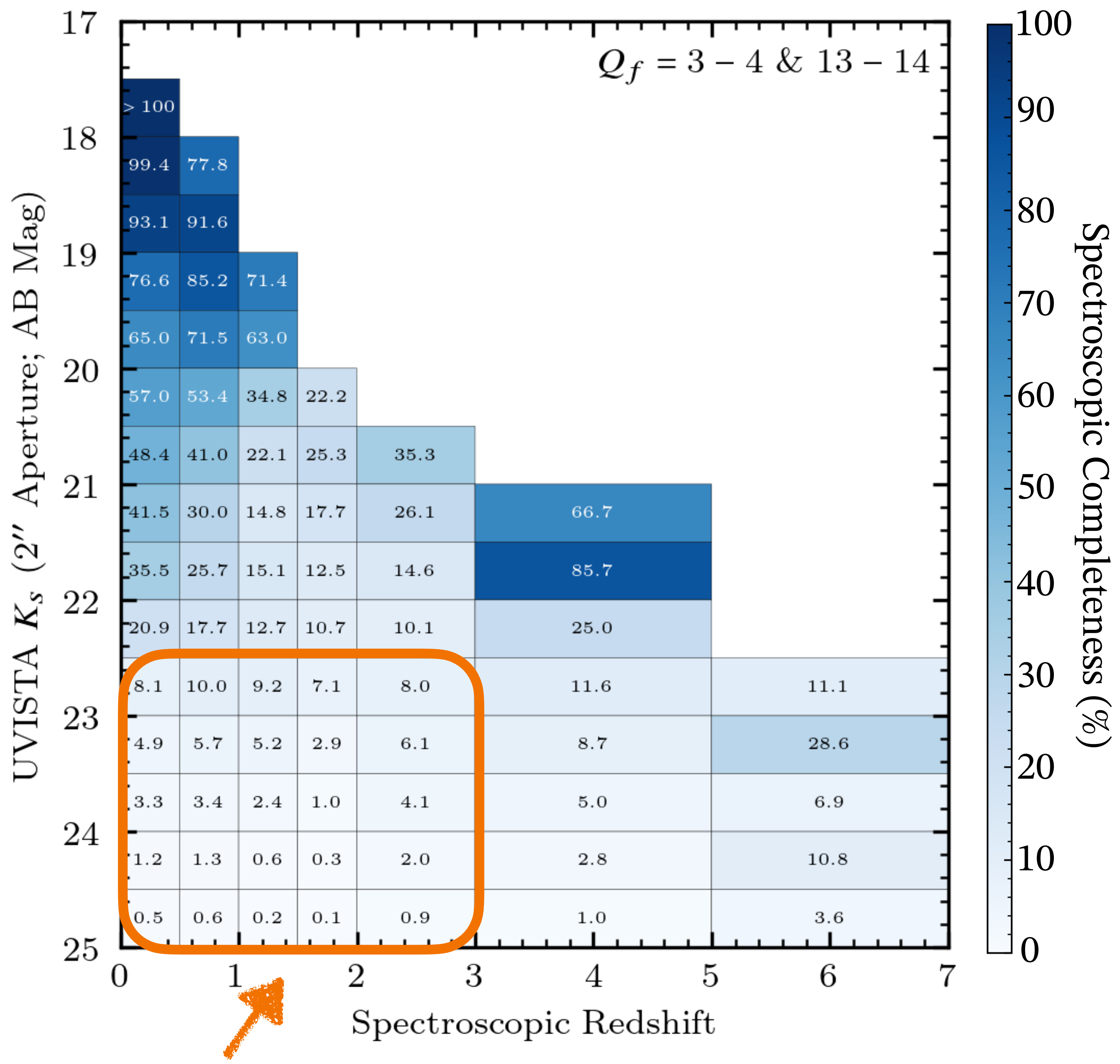
Creating a Representative Spec-z Training Set

- **UMAP** as a SOM-alternative for dimensionality reduction of *u*grizyJH* color space
- Produces thin (almost 2-D) manifold that is monotonic in redshift and specific SFR
- Non-representative spec-z datasets sparsely populate the manifold, but in a physically-meaningful and well-behaved way!
- Next step: re-weighting and interpolating spec-z datasets ➔ e.g., as input for SOMPZ



Finian Ashmead, Newman, **BHA**, et al. (in prep.)

Need Deep NIR-selected Spec-z Training Sets



<10% completeness

Khostovan et al. (2025)

- Existing spec-z datasets sparsely cover color–magnitude–redshift space, especially at faint NIR magnitudes and z > 1

Subaru-PFS/Roman (SuPR) Deep Survey

- Want **spec-z's down to H_{AB} ~ 24.5** (depth of weak lensing sample) with representative colors
- Requested **50 dark nights**
- 5-15 pointings w/ **60-20 hour exposure** times for **10k-30k objects**
- **COSMOS and XMM-LSS** fields (HLIS and LSST equatorial deep fields)

DESI Deep Survey

- complements SuPR Deep Survey at z < 1.6 (**Biprateep Dey** et al. (inc. **BHA**) in prep.)

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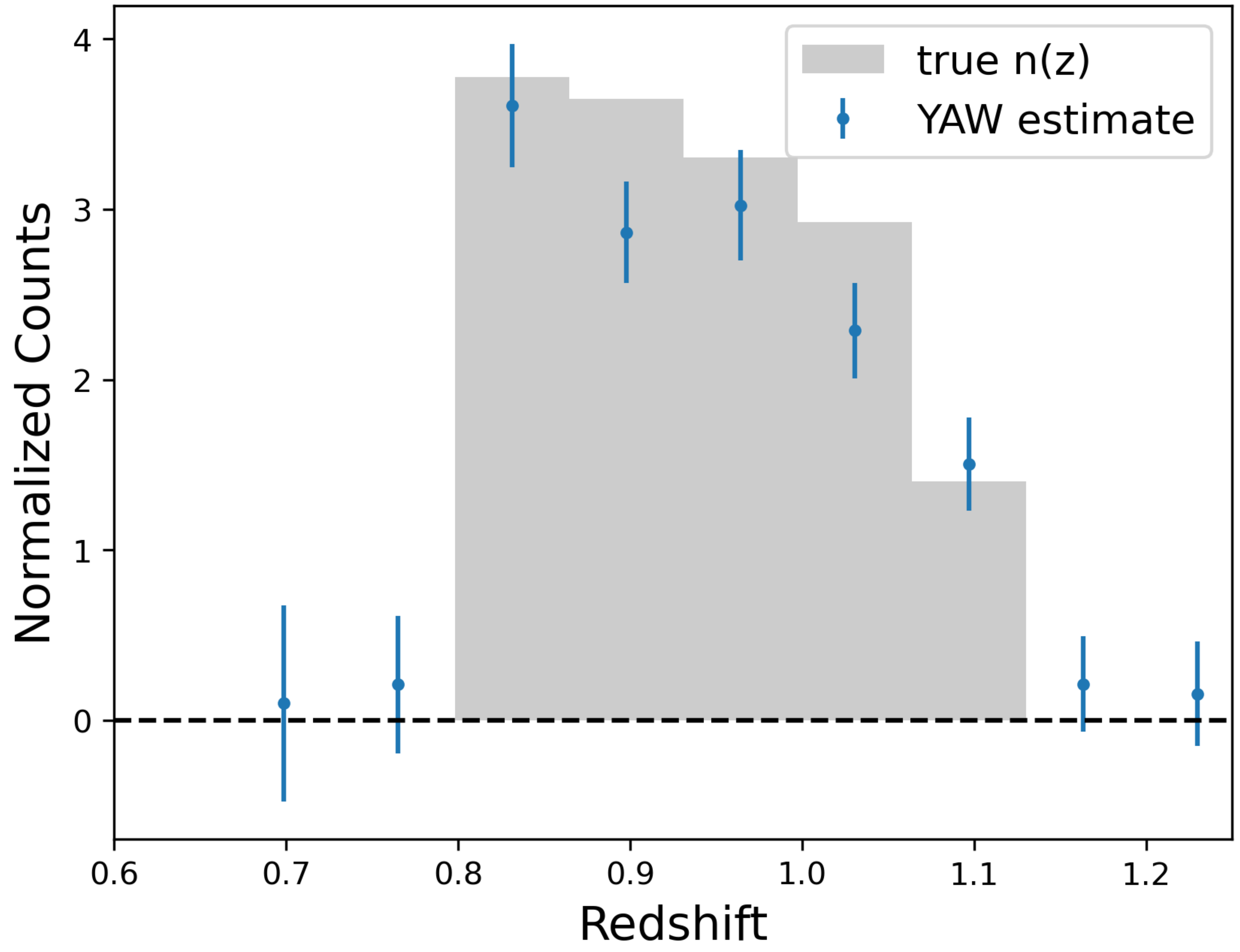
Calibrating Redshift Distributions with Cross-Correlations

- Provides an independent cross-check on photo-z distributions
- Cross-correlate with DESI and (hopefully) Roman HLSS grism samples
- Currently testing and validating clustering-z code (RAIL YAW) with mock DESI catalogs from simulations



Yoki Salcedo, Newman, et al. (inc. **BHA**) (in prep.)

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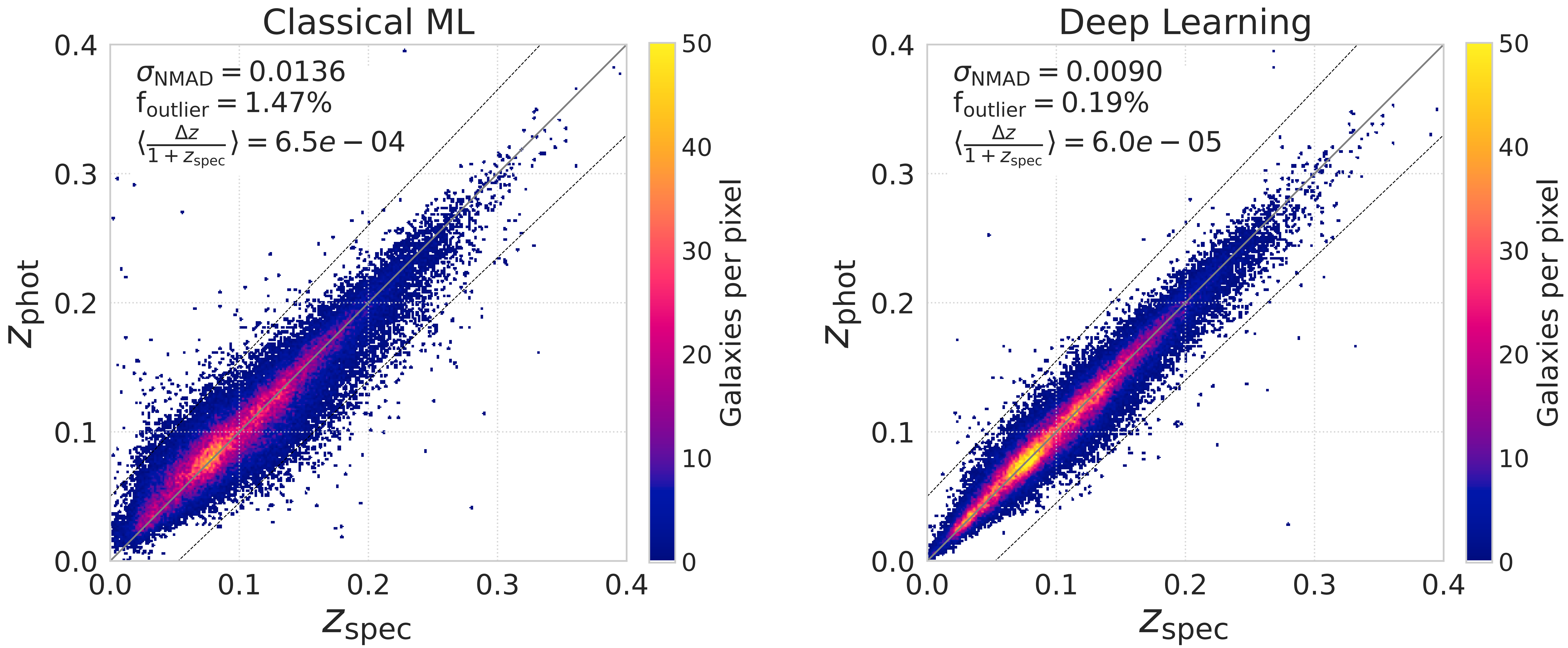
SDSS Main Galaxy Sample

Deep learning models produce best photo-z's regardless of metric.



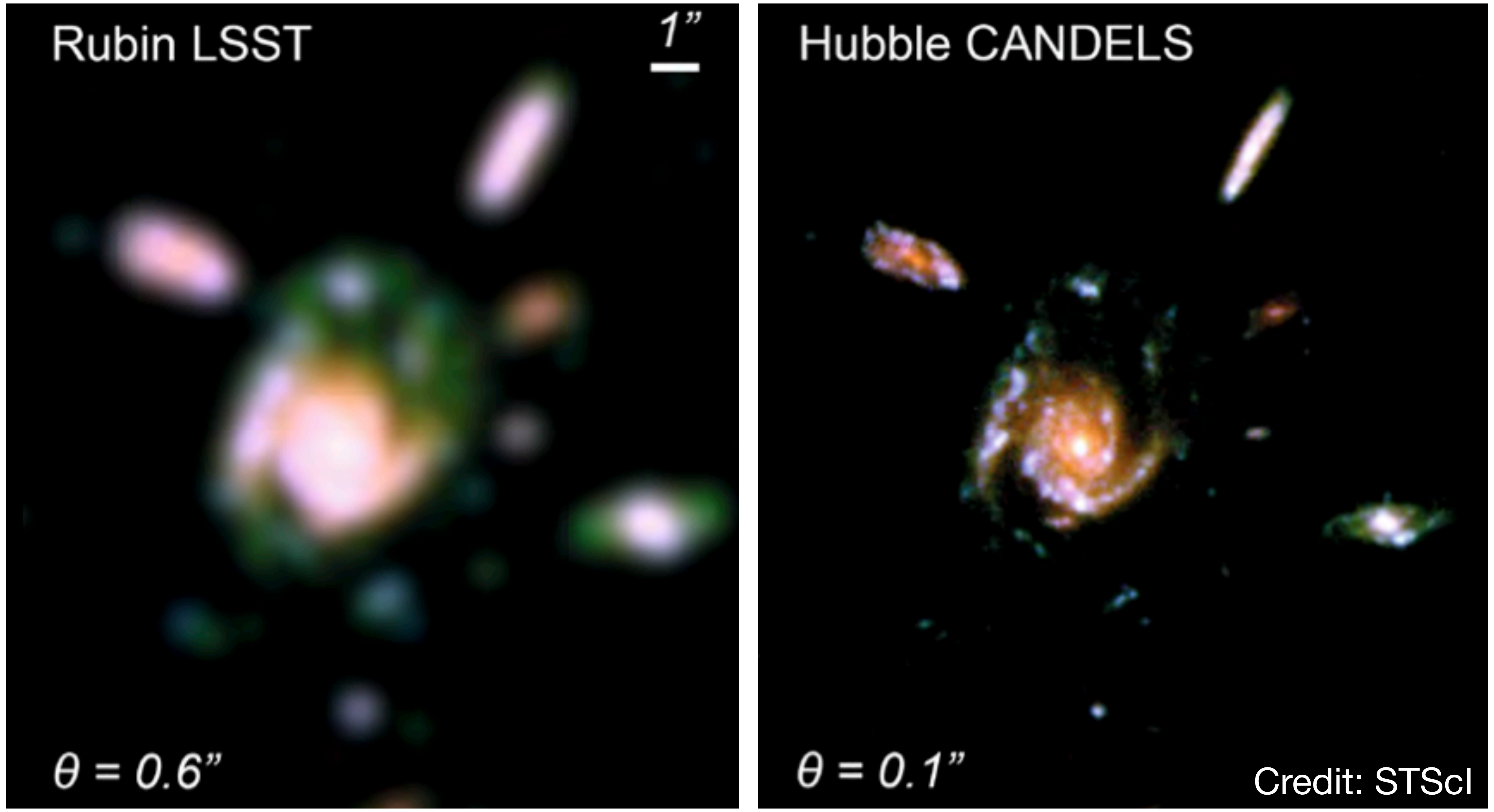
photometry-based

image-based

Emma Moran, BHA, Newman, & Dey (2025) ➔ [arxiv:2507.06299]

Dey, **BHA**, Newman, et al. (2022)

Challenges at High-z



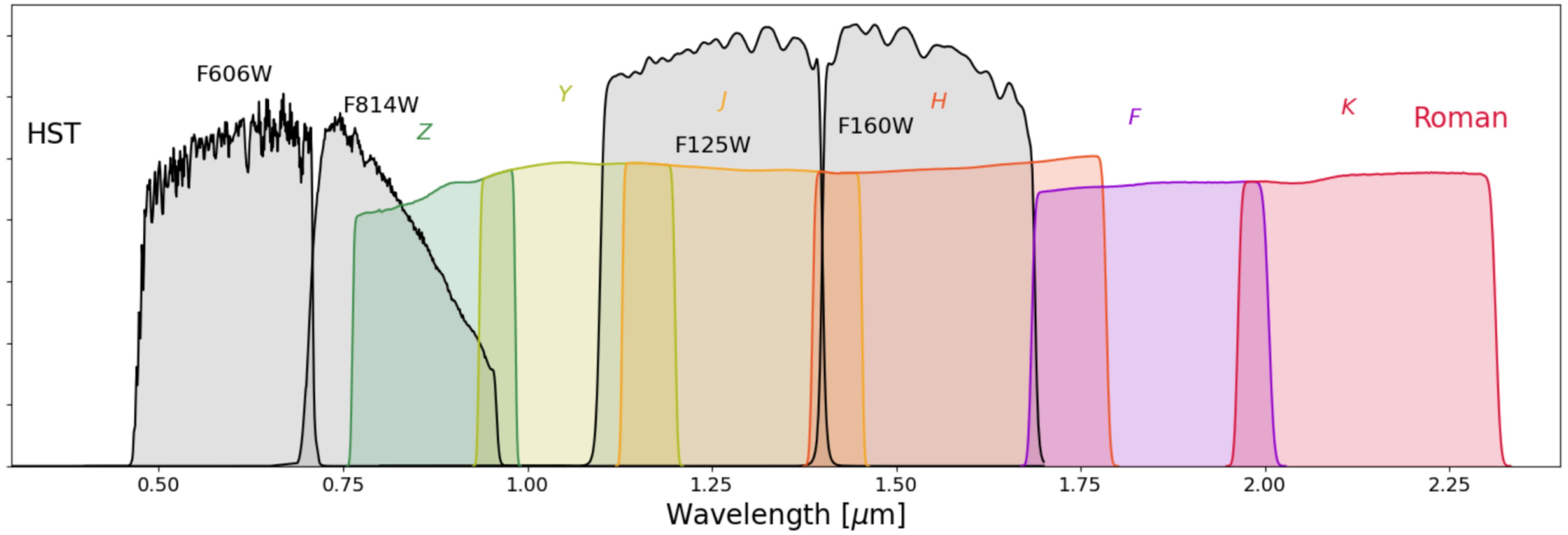
- spatial resolution
- wavelength coverage: want to span 4000 A break
  - LSST *ugrizy* z ~ 1.3 ➔ Roman YJH extends out to z ~ 2.5
- small and incomplete spec-z training sets (esp. at deep NIR mags)

Deep Learning Photo-z's with Roman

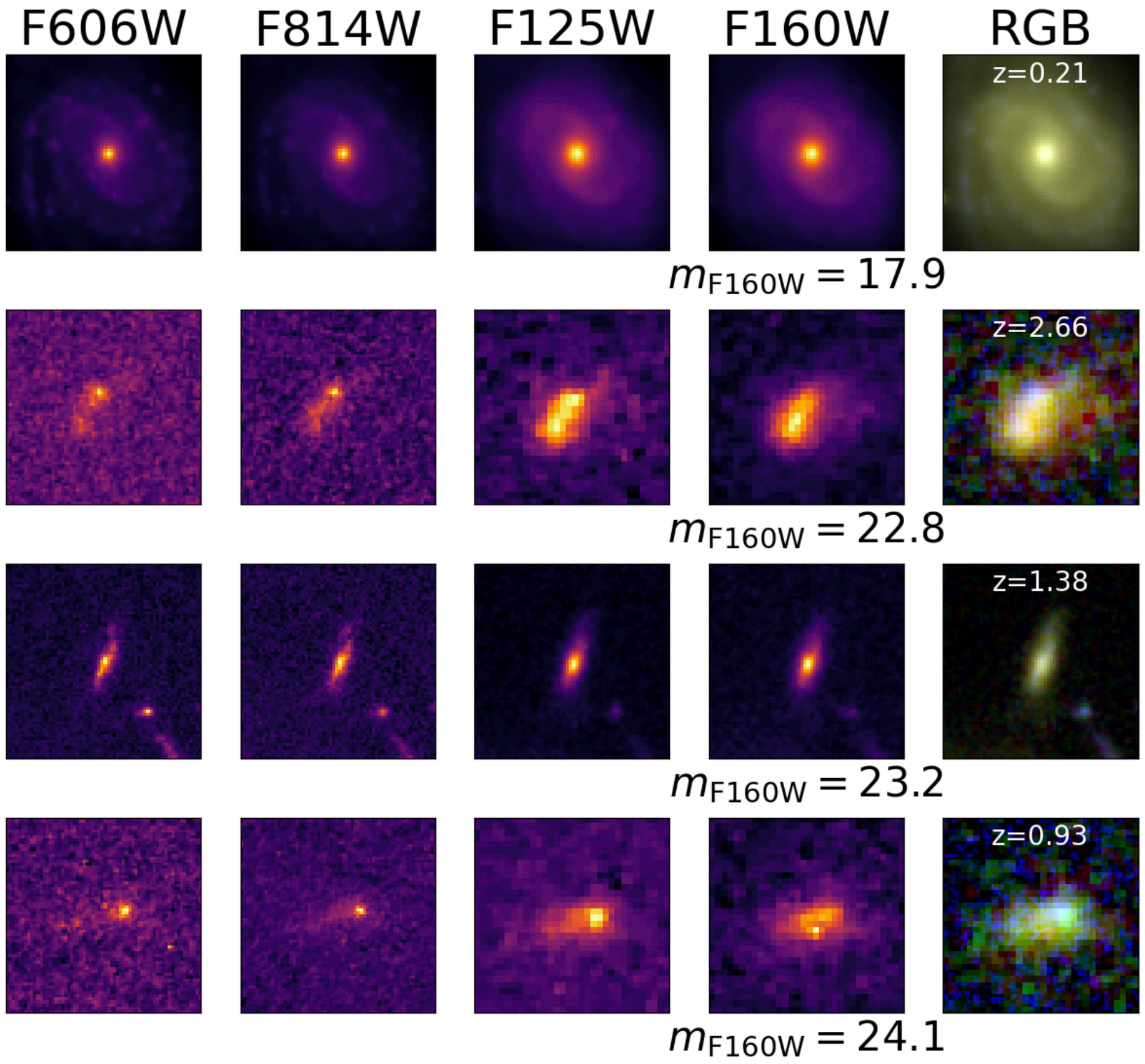
Major open questions:

- Deep learning vs. SED template-fitting or classical ML photo-z methods
- Can deep learning models leverage galaxy images without measured redshifts?
- Foundation model approach vs. a redshift-focused model
- Scaling with brightness?
- Scaling with training set size?

HST CANDELS: Key Roman Precursor Dataset



- Roman-like resolution in NIR
- 100k galaxy images
- 20k galaxies w/ redshifts (spec-z's, grism-z's, many-band photo-z's)



Ashod Khederlarian, **BHA**, Newman, et al. (in prep.)

Optimal Deep Learning Approach?

- **fully-supervised**
  - only trains on images of the 20k objects with redshifts
- **self-supervised** (foundation model approach)
  - sequential training: train network on 100k images then fine-tune weights with 20k redshifts
- **semi-supervised**
  - simultaneous training of 100k images and 20k redshifts

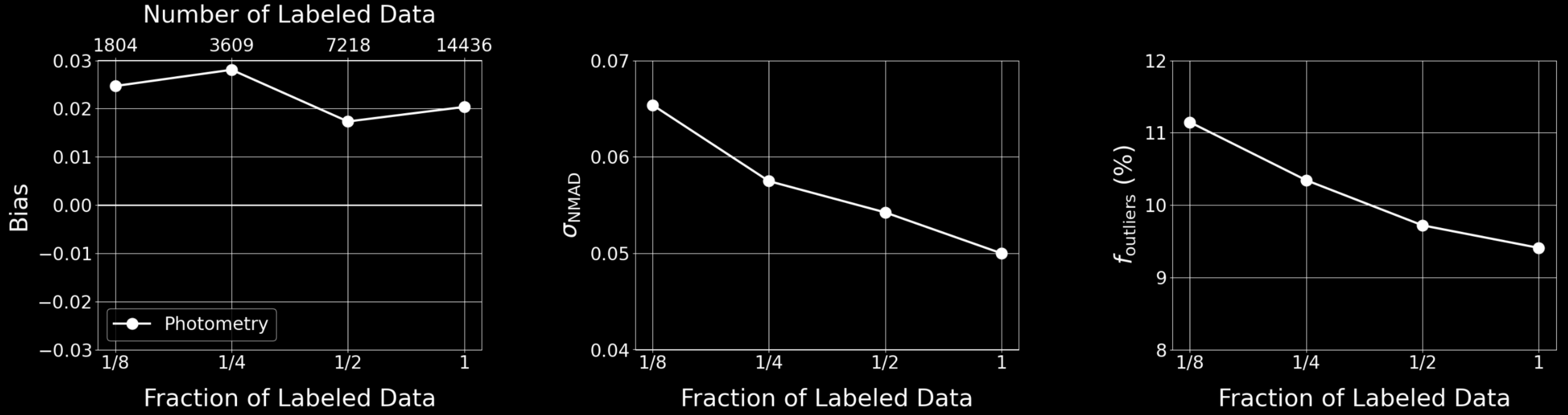
Photometry-only performance

$$\Delta z = \frac{z_{\mathrm{pred}} - z_{\mathrm{true}}}{1 + z_{\mathrm{true}}}$$

bias $= \langle \Delta z \rangle$

$\sigma_{\mathrm{NMAD}} = 1.48 \times \mathrm{median}[\Delta z - \mathrm{median}(\Delta z)]$

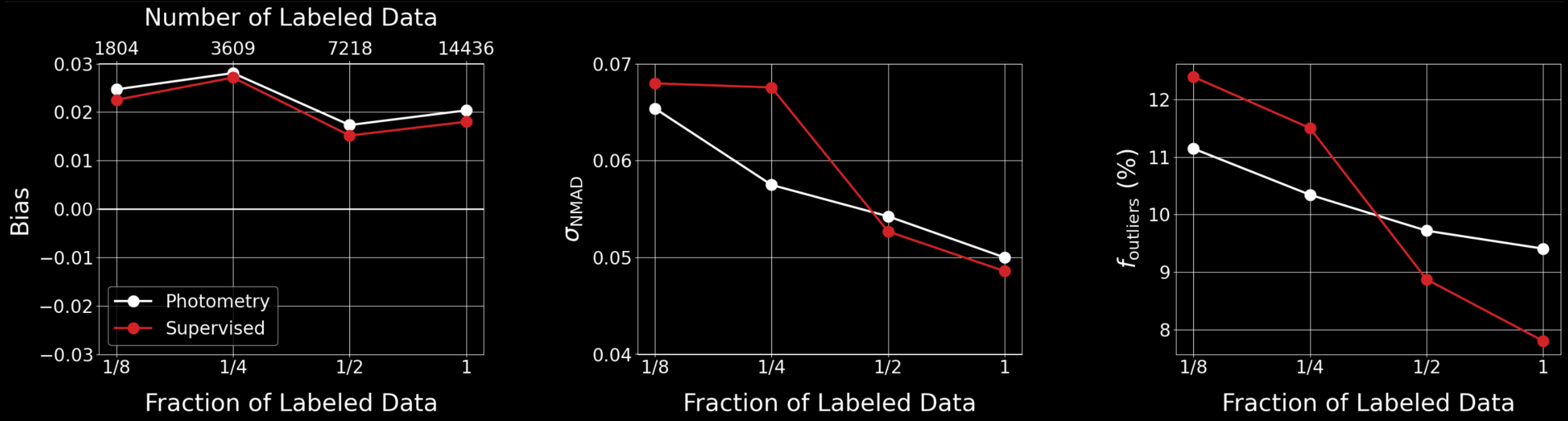
fraction of $\Delta z > 0.15$



slide courtesy of **Ashod Khederlarian**

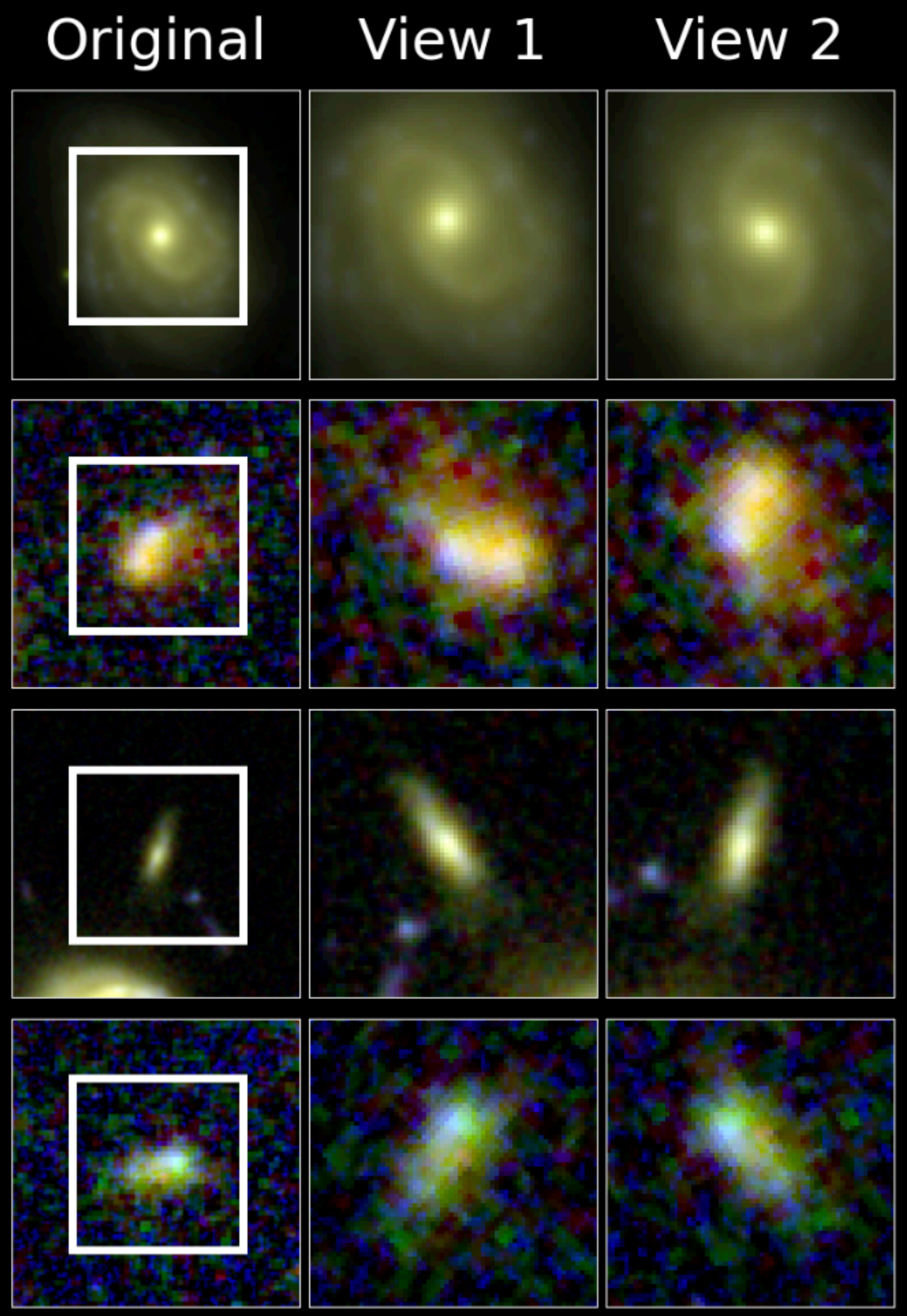
Fully-supervised CNN

Uses only the ~20k galaxies with redshifts

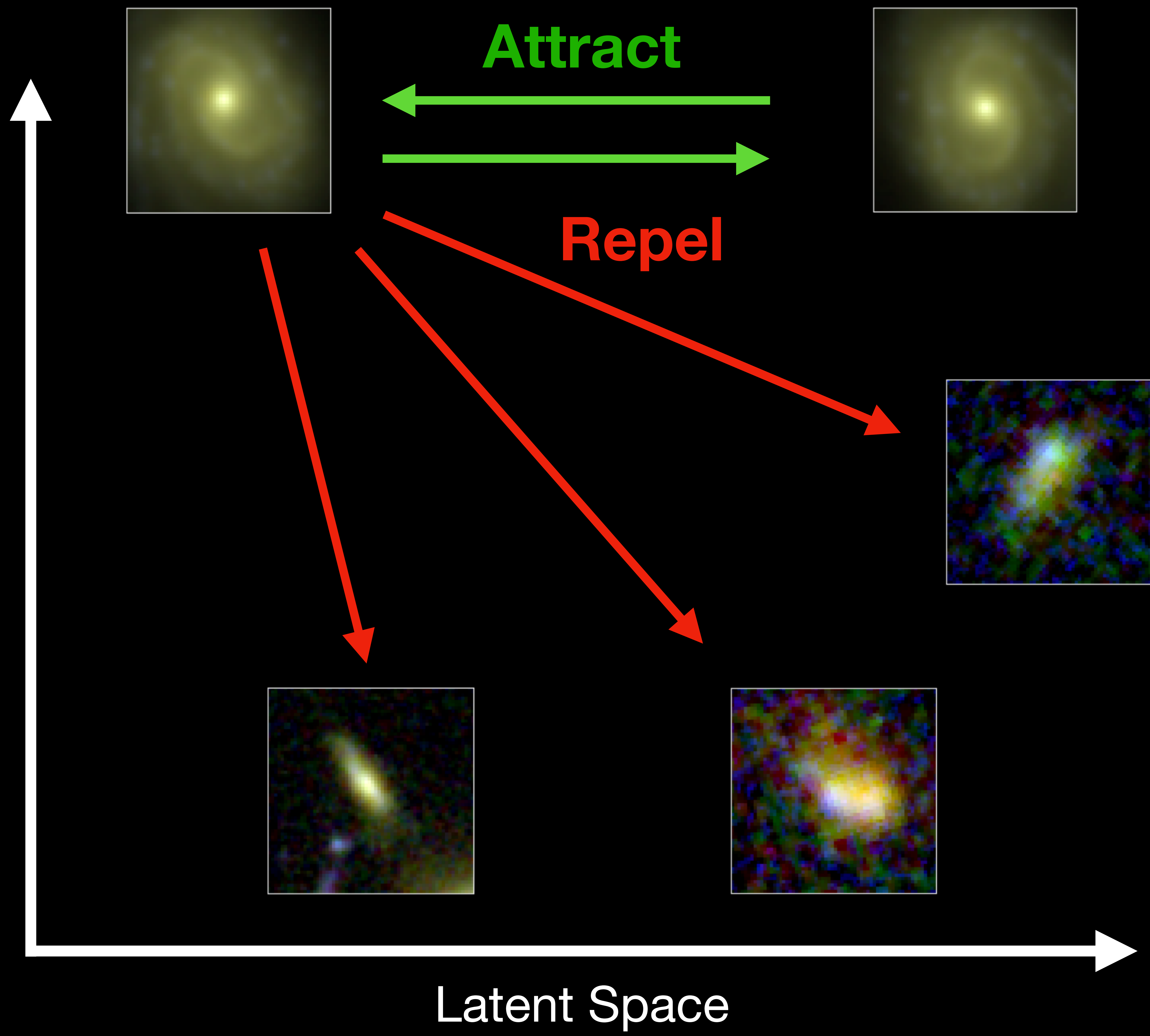


slide adapted from **Ashod Khederlarian**

Contrastive Learning: Leveraging Galaxies w/o Redshifts

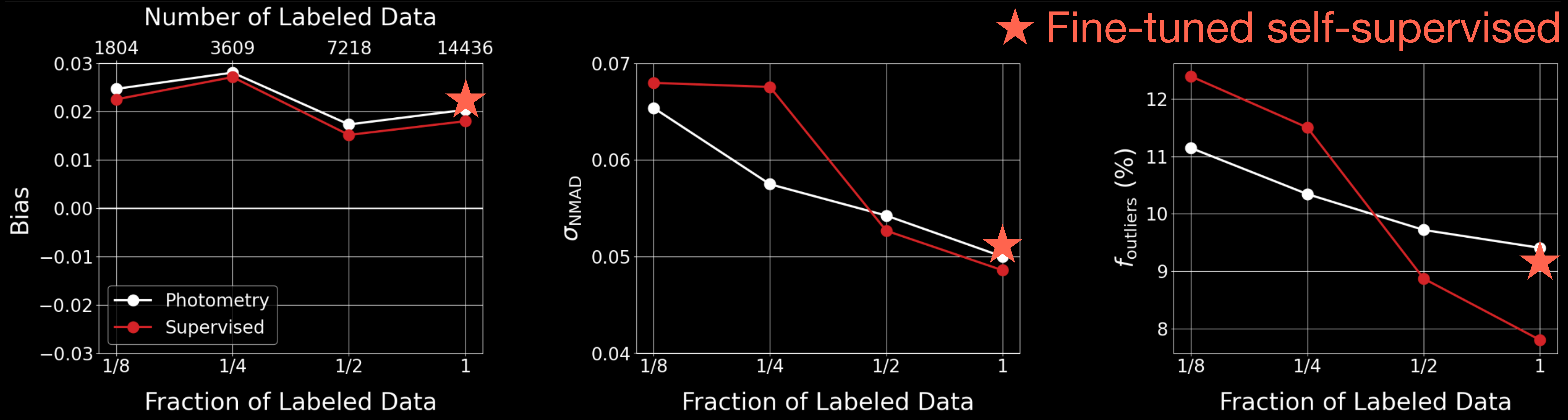


MoCo from He et al. (2020)



slide adapted from **Ashod Khederlarian**

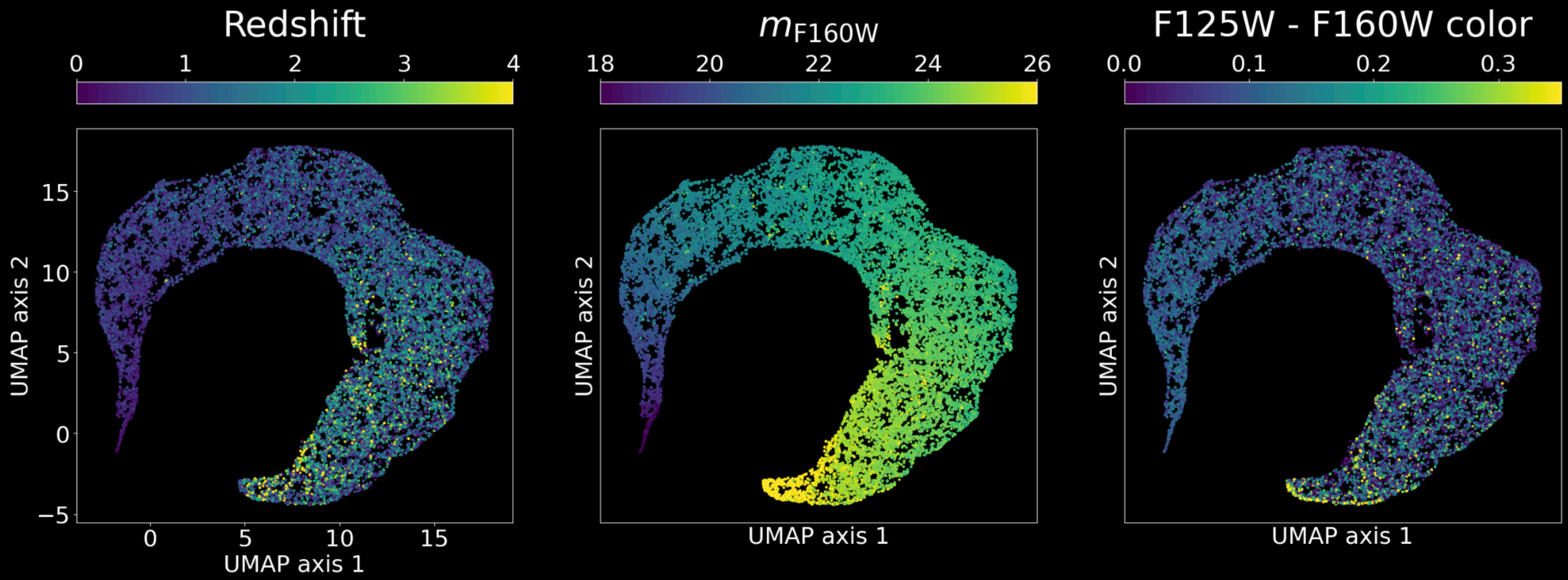
Self-supervised approach (fine-tuned for redshift estimation)



While this approach worked well for SDSS, it does **NOT** meaningfully outperform photometry-only for CANDELS

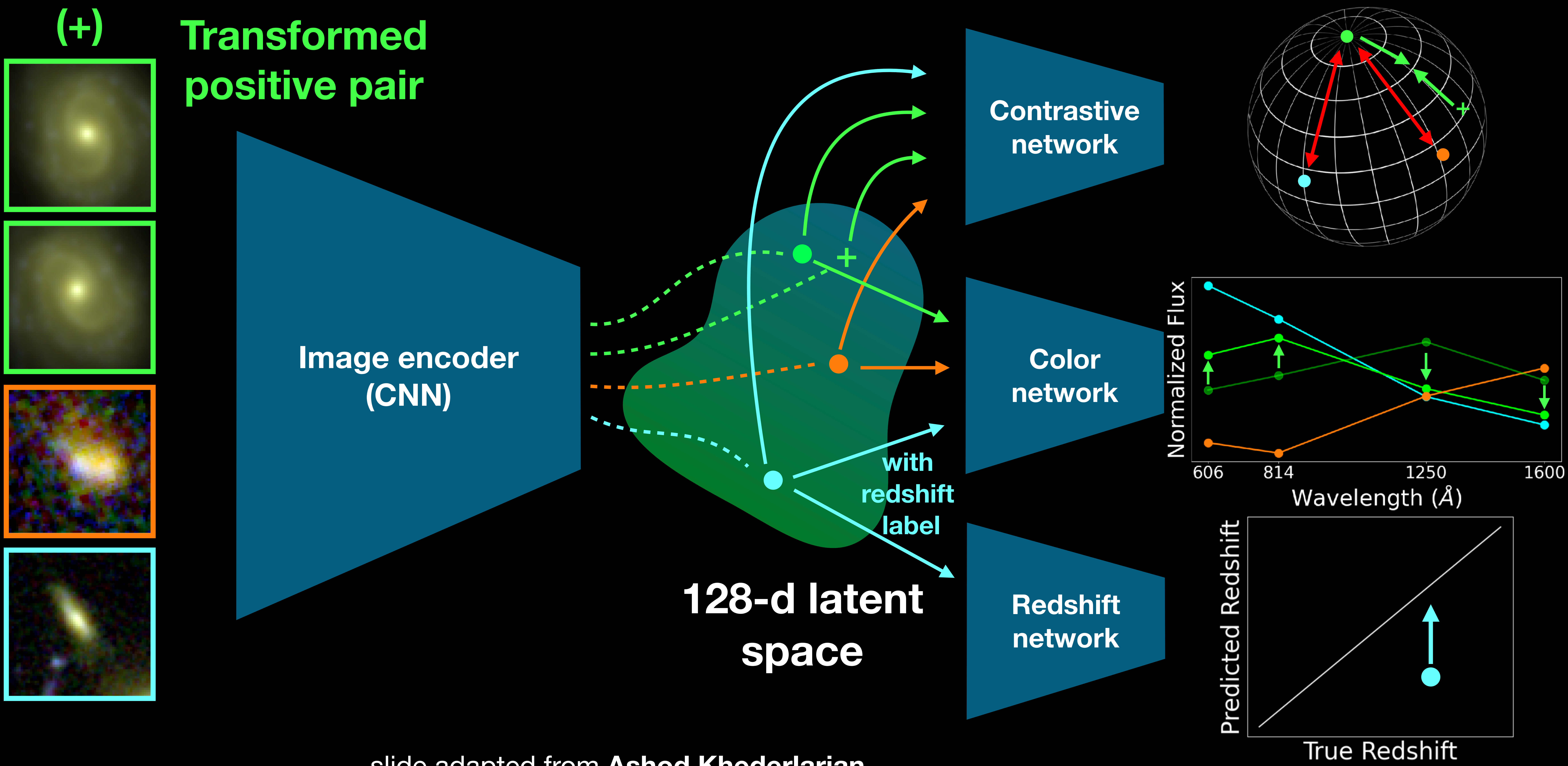
slide adapted from **Ashod Khederlarian**

Self-supervised Latent Space



slide adapted from **Ashod Khederlarian**

Aligning the Semi-supervised Latent Space



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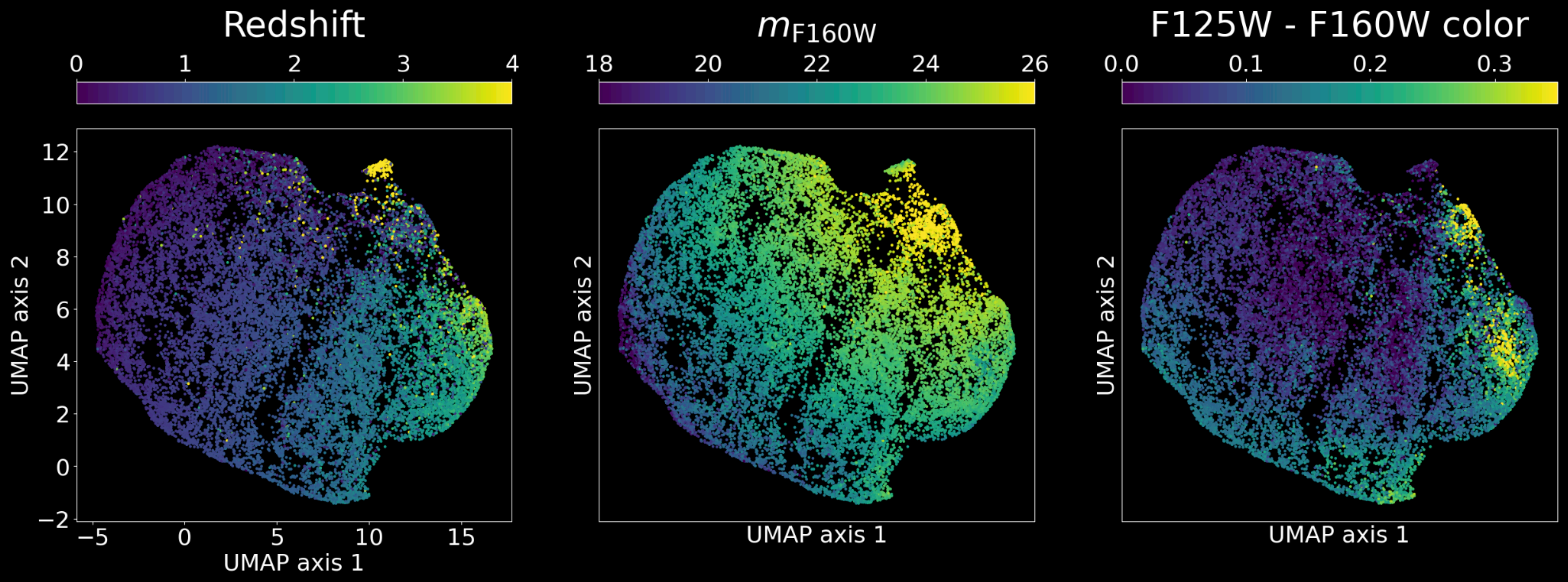
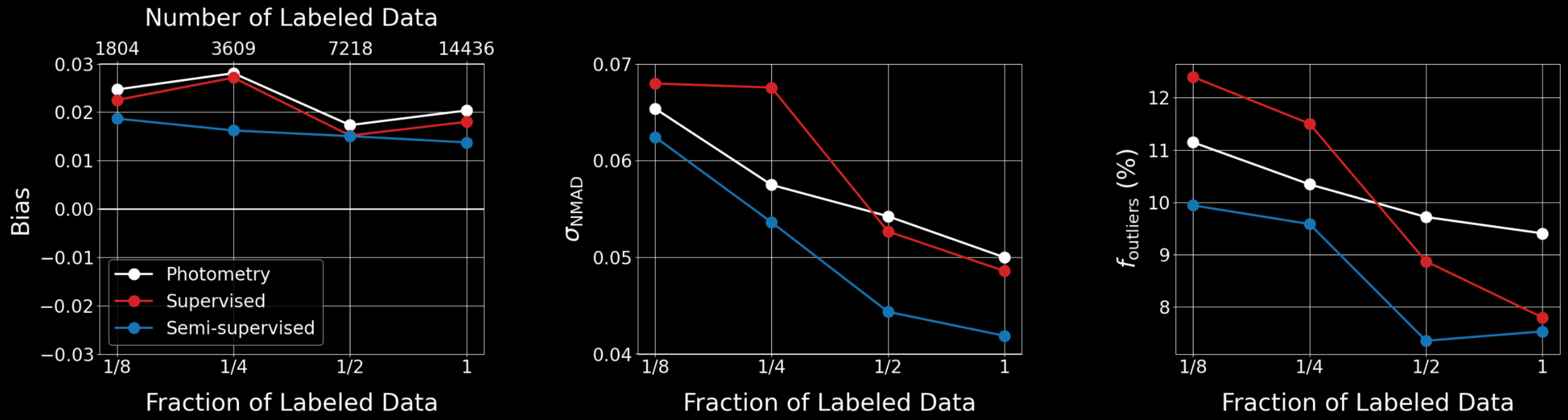
Semi-supervised Latent Space



slide adapted from **Ashod Khederlarian**

Semi-supervised Approach:

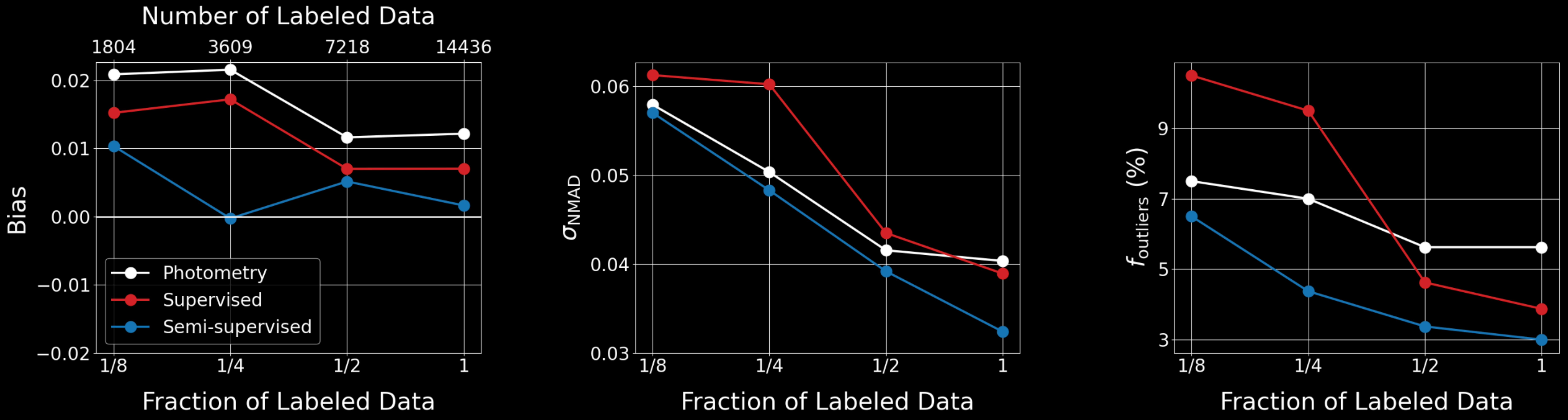
Best Performance for ALL Redshift Training Set Sizes



slide adapted from **Ashod Khederlarian**

Semi-supervised Approach:

Best Performance for ALL Redshift Training Set Sizes → esp. for bright (H < 22) galaxies



slide adapted from **Ashod Khederlarian**

Summary

- Photo-z forecasts influential in HLIS survey design, esp. **H-only wide tier**

- Spec-z training sets suffer from incomplete coverage across color-mag-redshift space
  - UMAP as a SOM-alternative to optimally leverage spec-z datasets (**Finian Ashmead** et al. in prep.)
  - Need new deep NIR-selected spec-z training sets: **Subaru-PFS/Roman (SuPR) Deep Survey**

- Cross-correlations will provide a key independent cross-check on redshift distributions (**Yoki Salcedo** et al. in prep.)

- Deep learning improve photo-z's for Roman-like images (**Ashod Khederlarian** et al. in prep.)