Photometric Redshifts for Next Generation Imaging Surveys

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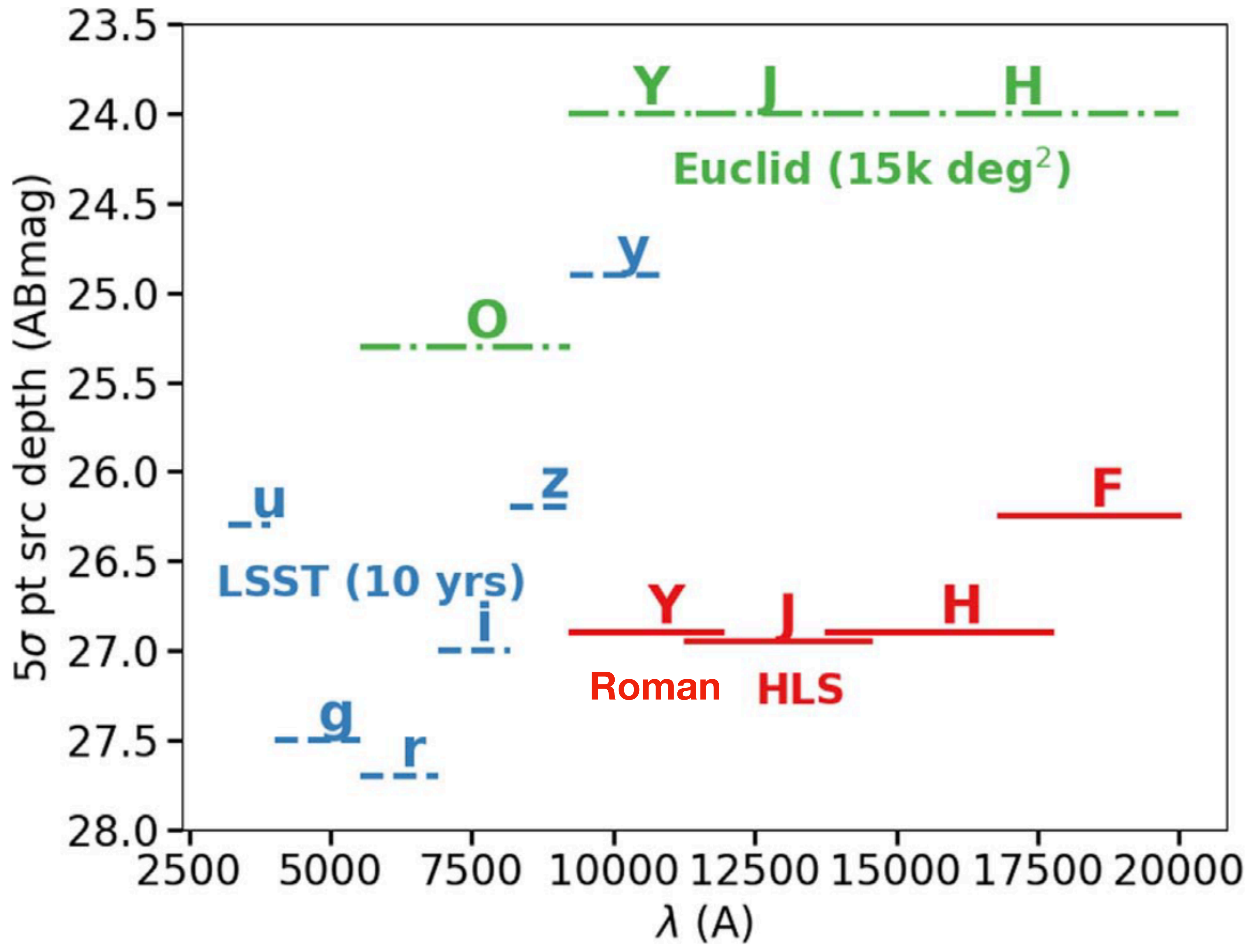
Roman + LSST Science Relies on Photo-z's

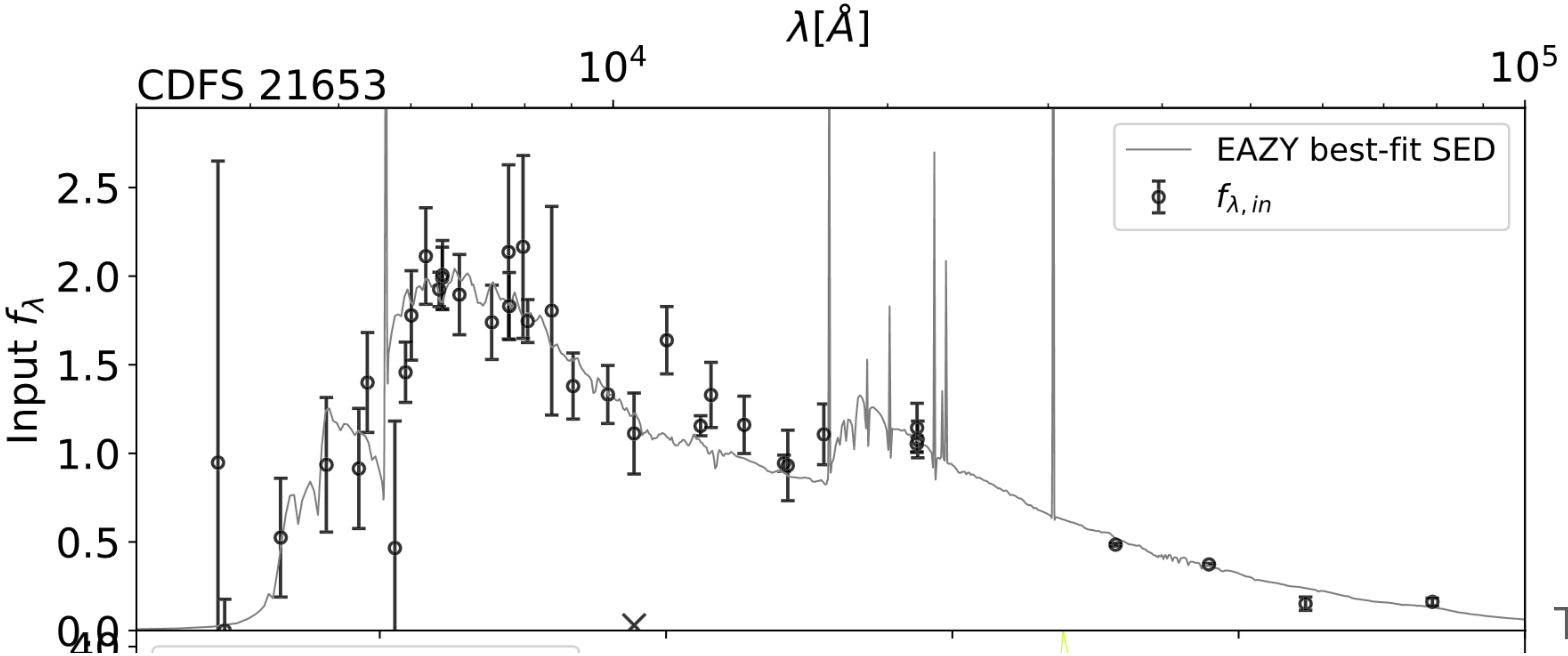
- Wide range of cosmology and galaxy evolution science cases require measuring galaxy redshifts (e.g., large-scale structure, galaxy clusters, weak lensing, galaxy luminosity function).

- Getting spectroscopic redshifts (spec-z's) for all galaxies down to the full depth of Roman and LSST imaging is completely infeasible → ***need photometric redshifts (photo-z's)***.



Tee et al. (2023)

Traditional Photo-z Methods



Tanigawa et al. (2024)

SED template-fitting

- Redshift SED templates (or combinations) to find best match to the observed SED.

Classic Machine Learning

- Train model to learn mapping from observed SEDs to redshift.

Can deep learning outperform traditional photo-z methods for Roman?

OPPORTUNITIES

- ***O*(10^9) well-resolved images** (~kpc at z=3) in bands that **span the 4000 Å break out to z ~ 3**.
- Deep learning can **extract additional redshift information from the pixels** directly.
- **Galaxy morphology evolves strongly from z = 0 → 3**, so deep learning may help distinguish between degenerate redshift solutions.

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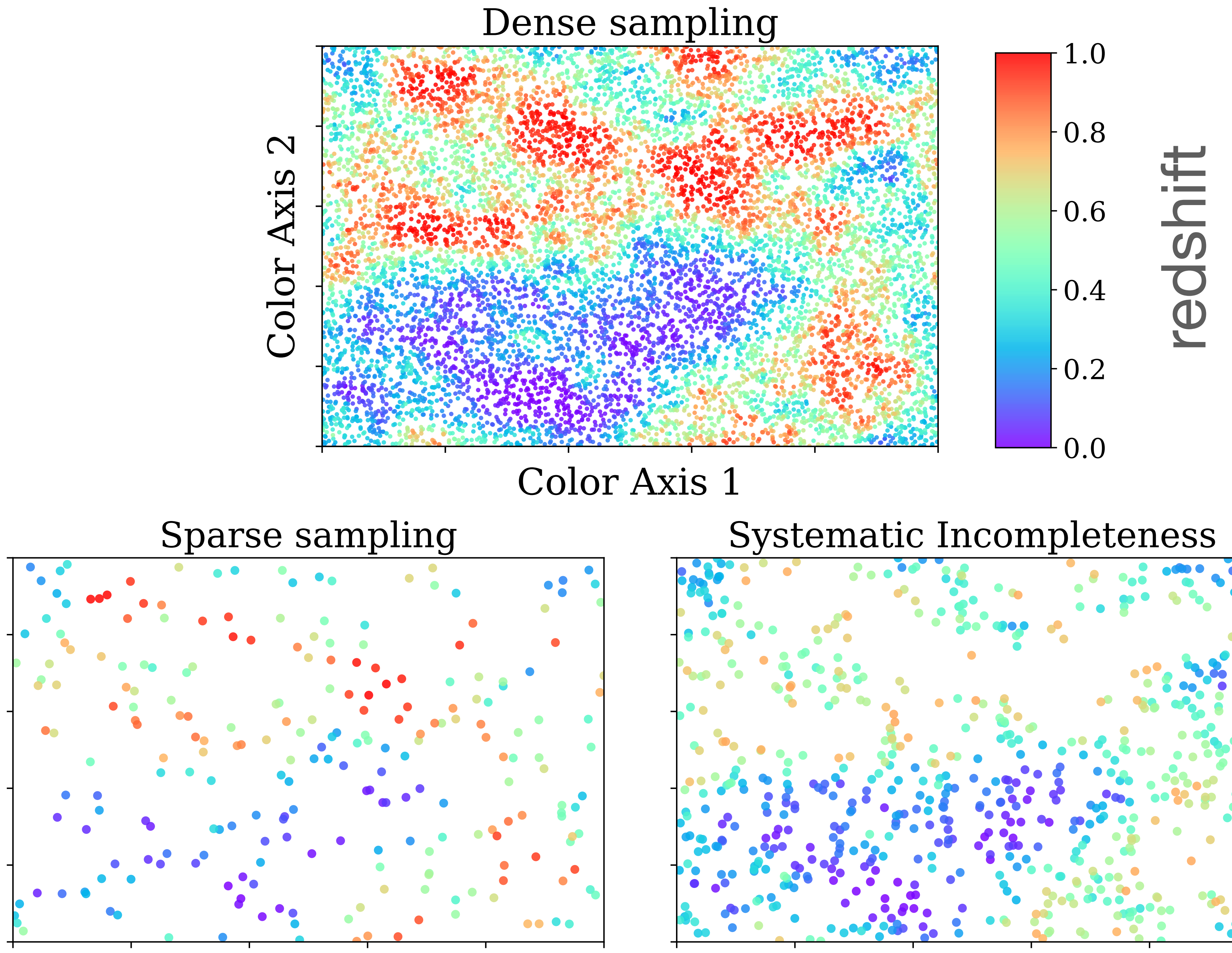
Challenges



Newman & Gruen (2022)

- Existing spec-z training sets **sparsely sample** and **do NOT span** the color-redshift space of photometric objects.

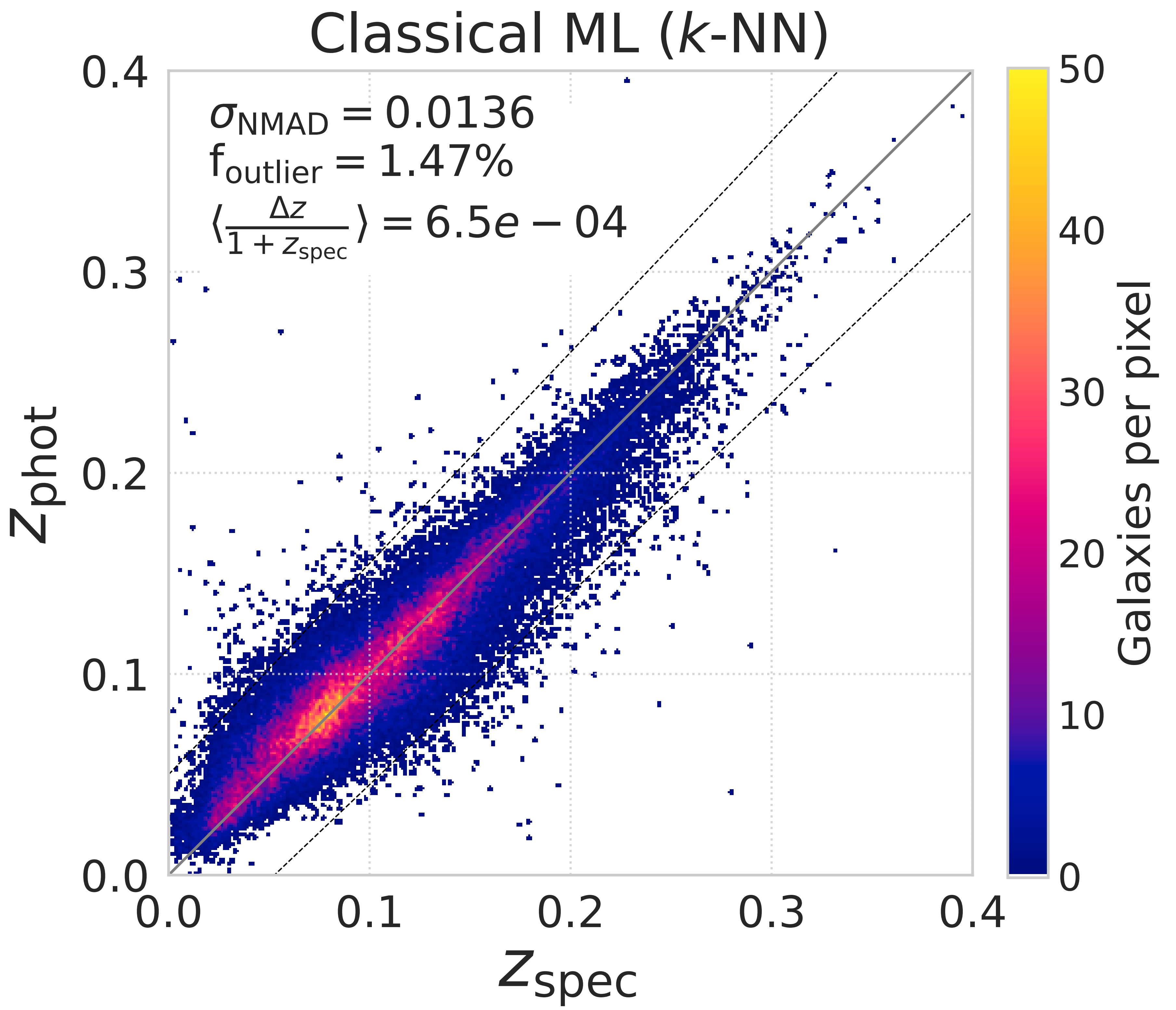
Deep Learning Produces State-of-the-art Photo-z's at Low-z

SPECTROSCOPIC TARGET SELECTION IN THE SLOAN DIGITAL SKY SURVEY: THE MAIN GALAXY SAMPLE

Michael A. Strauss,[1] David H. Weinberg,[2,3] Robert H. Lupton,[1] Vijay K. Narayanan,[1] James Annis,[4] Mariangela Bernardi,[5] Michael Blanton,[4] Scott Burles,[5] A. J. Connolly,[6] Julianne Dalcanton,[7] Mamoru Doi,[8,9] Daniel Eisenstein,[5,10,11] Joshua A. Frieman,[4,5] Masataka Fukugita,[3,12] James E. Gunn,[1] Željko Ivezić,[1] Stephen Kent,[4] Rita S. J. Kim,[1,13] G. R. Knapp,[1] Richard G. Kron,[4,5] Jeffrey A. Munn,[14] Heidi Jo Newberg,[4,15] R. C. Nichol,[16] Sadanori Okamura,[9,17] Thomas R. Quinn,[7] Michael W. Richmond,[18] David J. Schlegel,[1] Kazuhiro Shimasaku,[9,17] Mark SubbaRao,[5] Alexander S. Szalay,[13] Dan Vanden Berk,[4] Michael S. Vogeley,[19] Brian Yanny,[4] Naoki Yasuda,[20] Donald G. York,[5] and Idit Zehavi[4,5]

Received 2002 February 4; accepted 2002 June 13

- SDSS Main Galaxy Sample
  - ***O*(500k)** *ugriz* + spec-z's
  - Complete coverage of color—redshift space



data from Beck et al. (2016)

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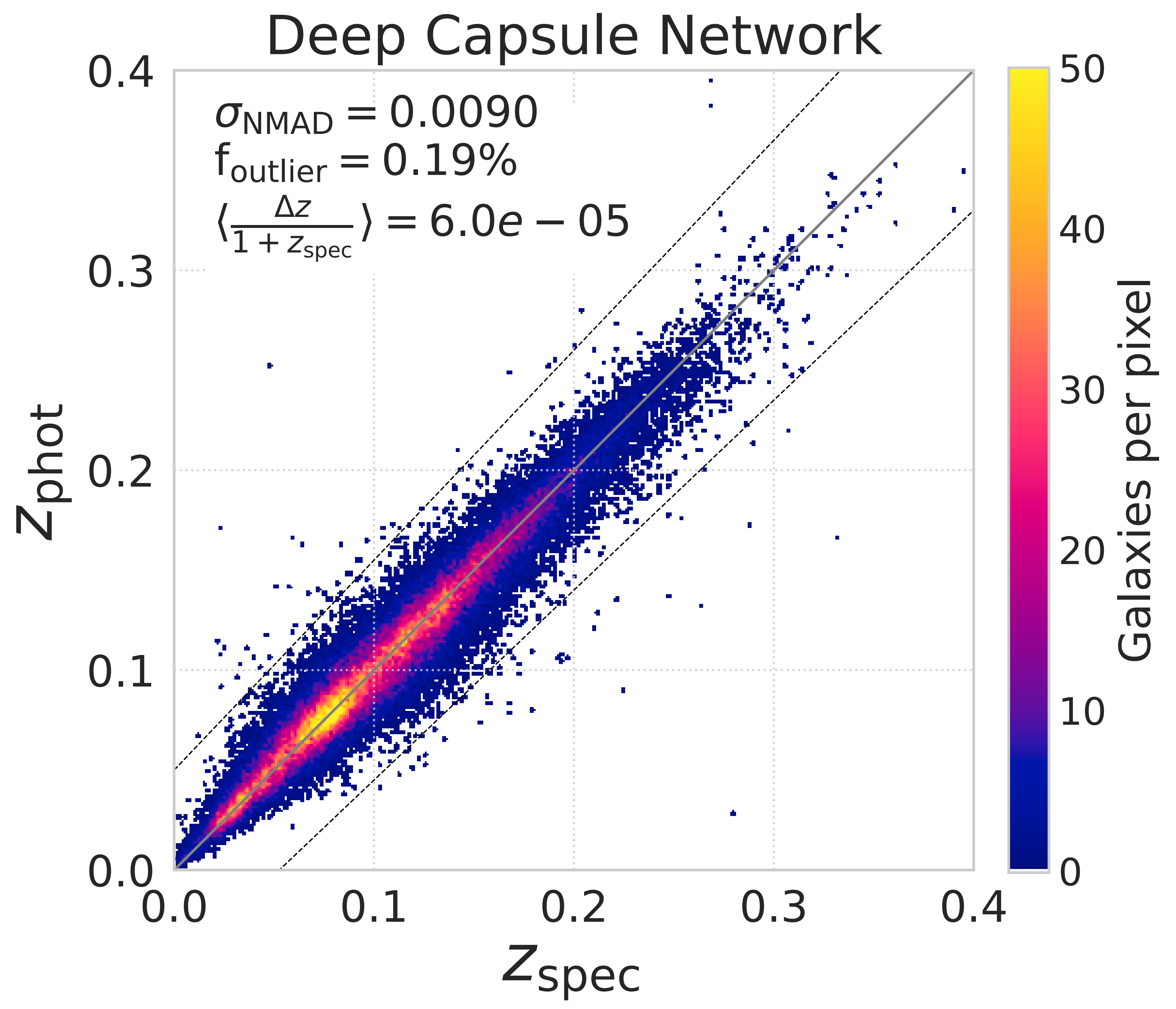

B. Dey, **Andrews**, Newman, et al. (2022)

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  - ***O*(500k)** *ugriz* + spec-z's
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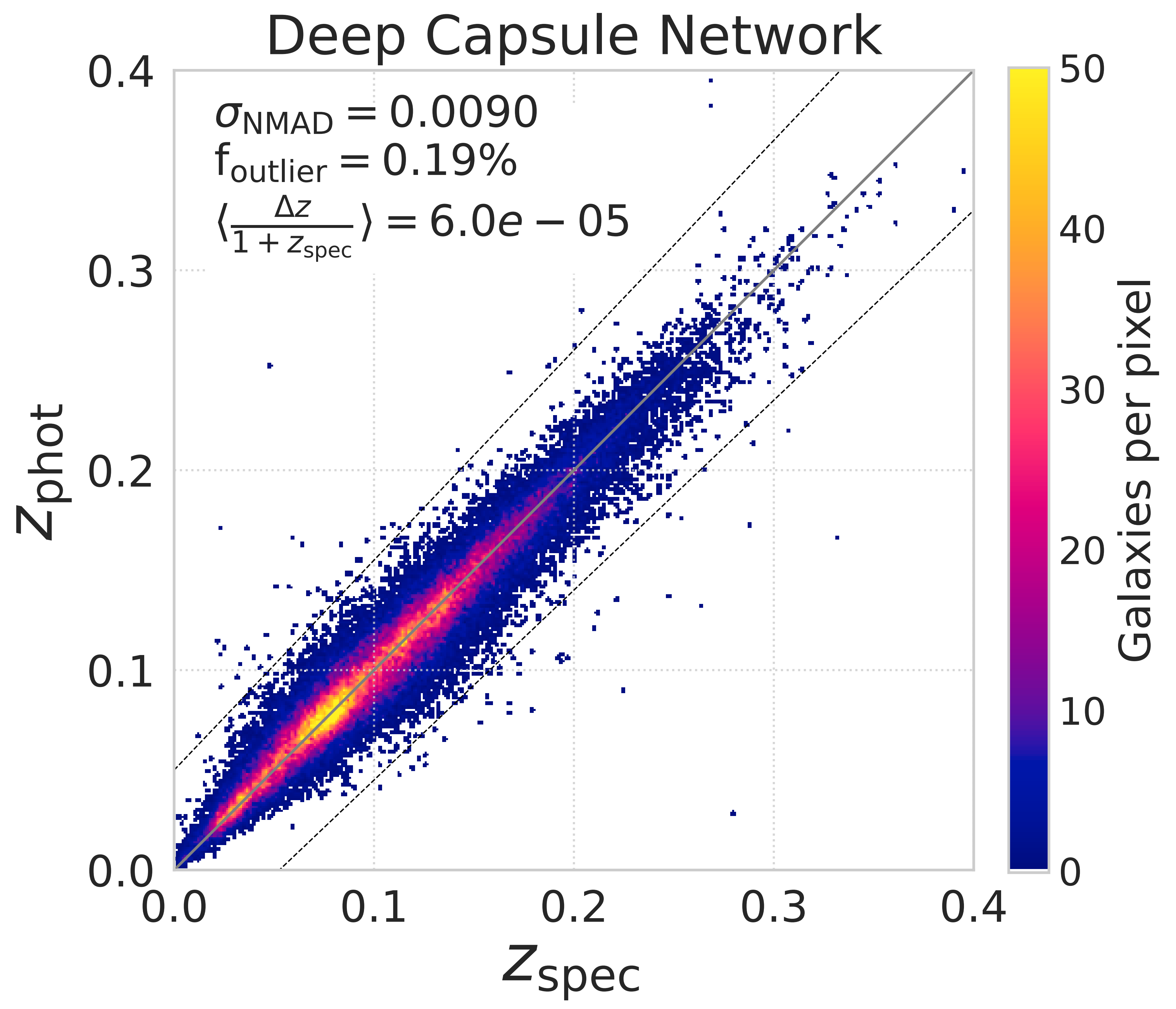
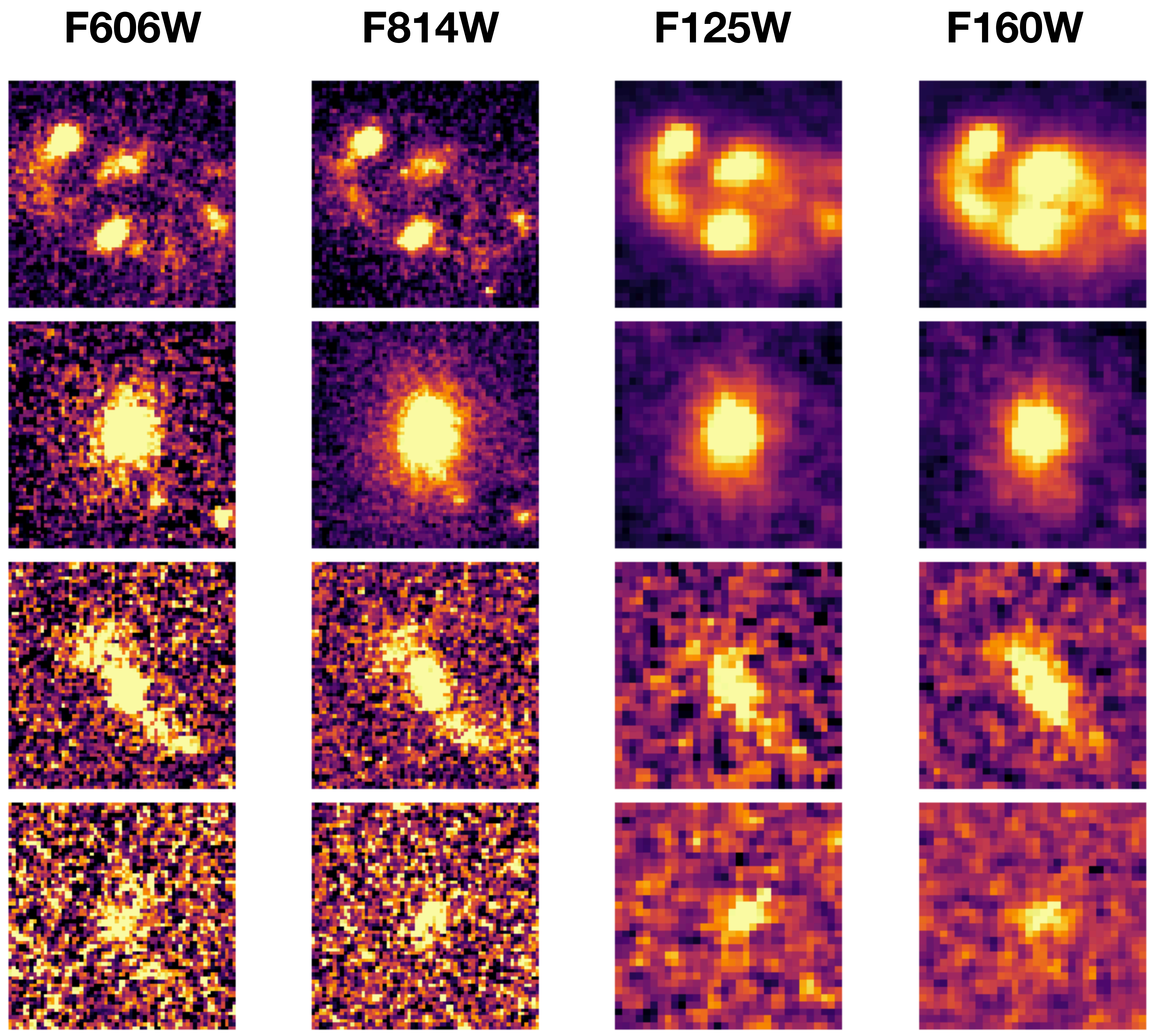
- **Generic result**: multiple deep learning methods produce similarly excellent results.



B. Dey, **Andrews**, Newman, et al. (2022)

Roman Prototype Data Set: HST CANDELS

- ***O*(100k)** 4 band HST imaging out to H-band (1.6 microns)
- ***O*(20k)** training redshifts:
  - *Much smaller than SDSS MGS*
  - spec-z's and grism-z's
    - **biased in color—redshift space**
  - COSMOS2020 many (~30) band photo-z's
    - **good but not perfect**



CANDELS Deep Learning Photo-z's

Separate Image Compression and Redshift Prediction Tasks

Image Compression: Self-supervised Contrastive Learning

- Leverage all available images to train network, not just objects with known redshifts → key for Roman.
- Use neural network to compress CANDELS HST images into a low-D morphological encoding.

Redshift Regression

- Combine morphological encodings with ground-based LSST-like *ugrizy* photometry to train a (simple) redshift regression network.

Preliminary Results

- Despite insufficient quantity and representativeness of training data, we achieve a **small but statistically significant improvement in photo-z's**. (**Ashod Khederlarian**)

Optimism for Roman Deep Learning Photo-z's

Deep Learning Approach

- Still more room for deep learning methodological improvements (e.g., new model architectures, training strategies, data augmentation)

Imaging

- Roman will have ***10,000x* more objects** than CANDELS.

Ongoing Efforts to Improve Spectroscopic Training Sets

- Developing statistical methods to better leverage limited spectroscopic data (**Finian Ashmead**)
- DESI is 4x more efficient for deep spectroscopy than forecasts expected (**Biprateep Dey**)