Photometric Redshifts for Next Generation Surveys (like Rubin LSST!)

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Achieving the full potential of next-generation surveys like LSST via photometric redshifts presents many challenges...

- **Rubin LSST will rely on photometric redshifts for almost all extragalactic analyses**
  - **AGN, cosmology, galaxies, strong lensing, identification of transient hosts...**
- **In a recent *Annual Reviews* article, Daniel Gruen and I describe key challenges for photo-*z*'s *for* Rubin LSST and other future surveys (Links:** https://www.annualreviews.org/doi/abs/10.1146/annurev-astro-032122-014611 **or** https://arxiv.org/abs/2206.13633)

Photometric Redshifts for Next-Generation Surveys

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Keywords

galaxies, galaxy evolution, cosmology, machine learning, probability

Abstract

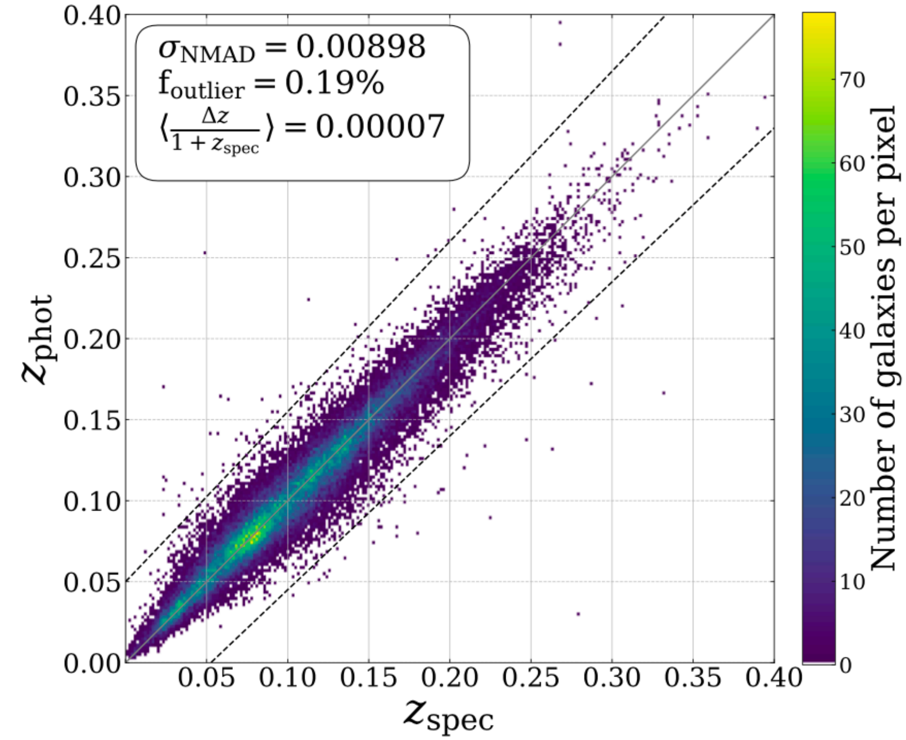
Photometric redshifts are essential in studies of both galaxy evolution and cosmology, as they enable analyses of objects too numerous or faint for spectroscopy. The Rubin Observatory, Euclid, and Roman Space Telescope will soon provide a new generation of imaging surveys with unprecedented area coverage, wavelength range, and depth. To take full advantage of these datasets, further progress in photometric redshift methods is needed. In this review, we focus on the greatest common challenges and prospects for improvement in applications of photo-z's to the next generation of surveys:

- Gains in *performance* – i.e., the precision of redshift estimates for individual galaxies – could greatly enhance studies of galaxy evolution and some probes of cosmology.
- Improvements in *characterization* – i.e., the accurate recovery of redshift *distributions* of galaxies in the presence of uncertainty on individual redshifts – are urgently needed for cosmological measurements with next-generation surveys.
- To achieve both of these goals, improvements in the scope and treatment of the samples of spectroscopic redshifts which make high-fidelity photo-z's possible will also be needed.

For the full potential of the next generation of surveys to be reached, the characterization of redshift distributions will need to improve by roughly an order of magnitude compared to the current state of the art, requiring progress on a wide variety of fronts. We conclude by presenting a speculative evaluation of how photometric redshift methods and the collection of the necessary spectroscopic samples may improve by the time near-future surveys are completed.

In what ways do we want to improve photo-z's for Rubin LSST?

- Our review article focuses on ways we need to improve both the performance of photo-z algorithms and the characterization of redshift distributions
- The performance of an algorithm is how well we can predict the redshifts and other properties of individual objects
  - NMAD, catastrophic outlier rate, etc. are measures of performance
  - Photo-z performance will affect Rubin galaxy science in many ways -- see my talk in the Galaxies session!



In what ways do we want to improve photo-z's for Rubin LSST?

- The characterization of redshift distributions is how well we know the distribution of redshifts for any sample of interest
  - E.g.: the mean, variance, etc. of the redshift distribution of objects placed in a bin for analysis
  - Uncertainties in the moments of *z* distributions must be <0.1% to not dominate over random errors in Rubin cosmology analyses

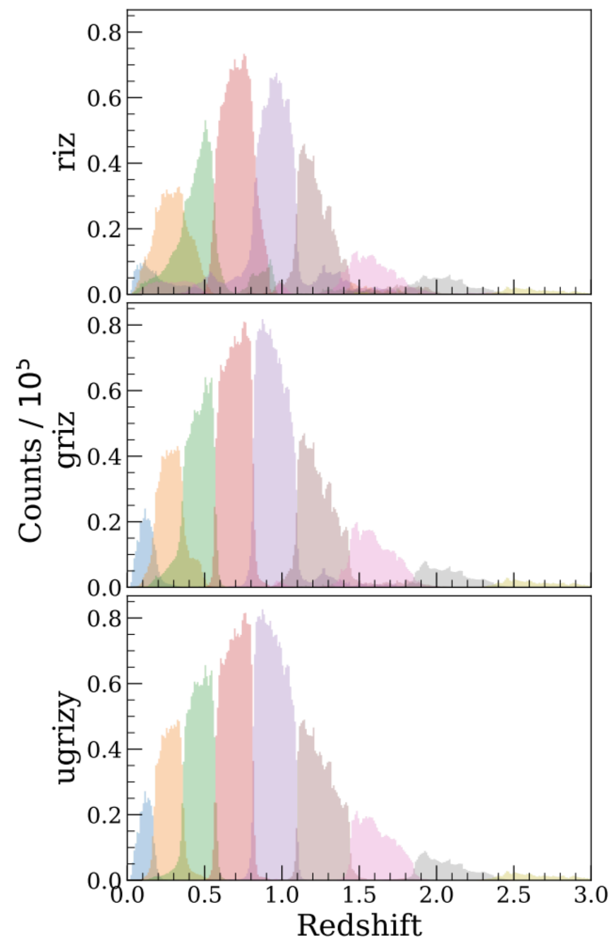
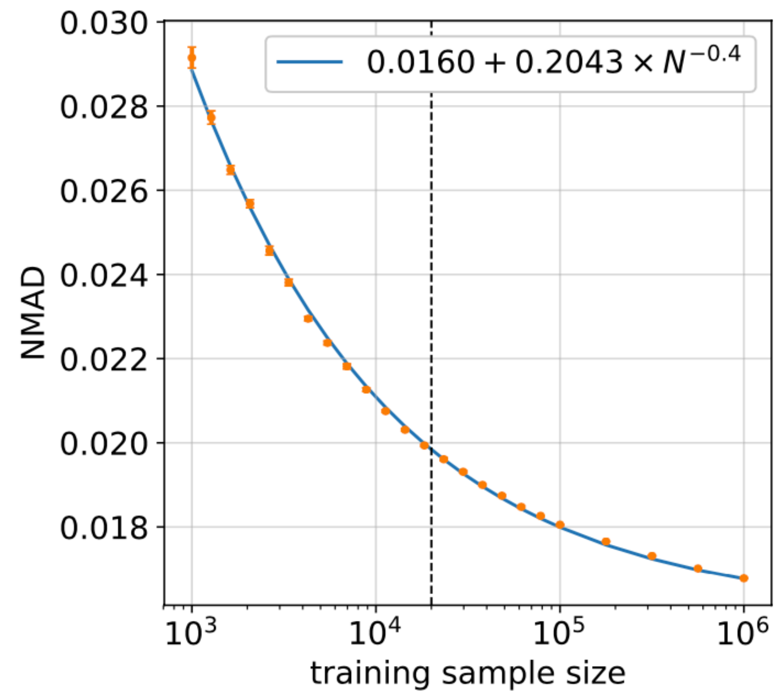


Figure: Zuntz et al. 2022

Better spectroscopic datasets can greatly improve the science yield of LSST

- For machine learning-based methods, we use objects with secure redshift measurements from spectroscopy to train algorithms
- For template-based methods, they are used to refine models of galaxy spectral energy distributions
- A baseline spectroscopic training set for Rubin LSST would consist of deep spectroscopy of >20,000 objects over a broad sky area with spectra spanning the full optical window
- Support for such activities was recommended in the Snowmass Cosmic Frontier report
  - See the Snowmass CF4 and CF6 reports and the white paper Enabling Flagship Dark Energy Experiments to Reach their Full Potential (Blazek et al.)



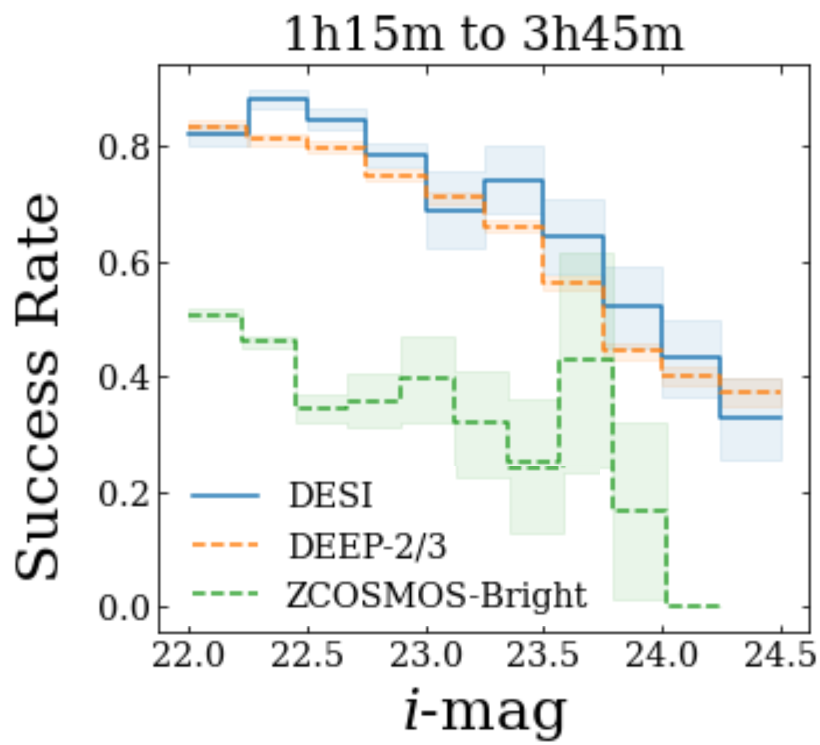
Newman et al. 2019

The DESI instrument could be an efficient option for obtaining this data

- In test spectroscopy with DESI, we obtained a redshift measurement success rate in 1.5 hours median exposure time to similar to what is achieved in 1 hour with DEIMOS at the Keck Observatory (Dey et al. 2023, in prep.; see his talk in the session tomorrow!)

- Implies that DESI could complete a baseline photo-*z* training survey to LSST Year 1 depth in 20-30 dark nights

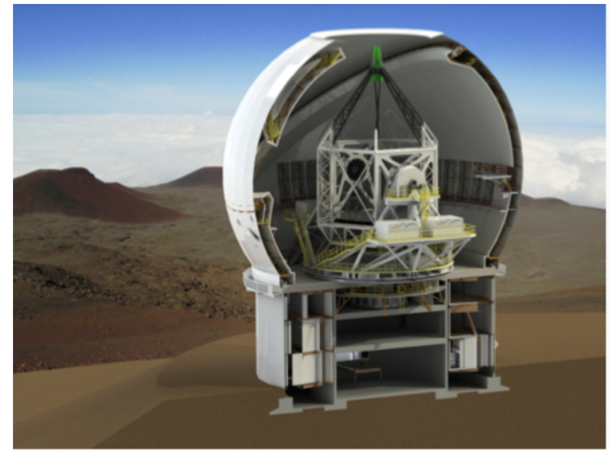
  - 200-300 nights to full Year 10 depth

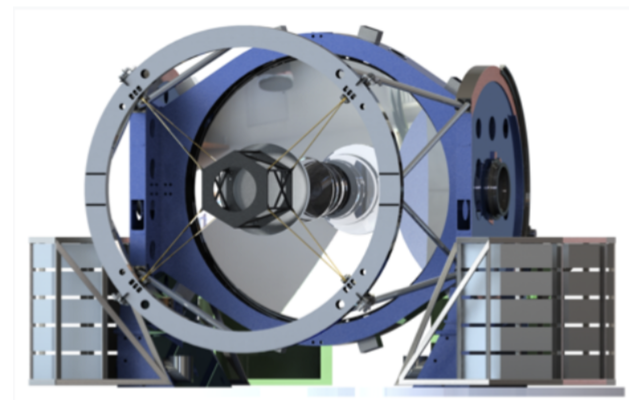


Dey et al. 2023, in prep.

A Stage V Spectroscopic Facility would be ideal for obtaining full-depth LSST training sets

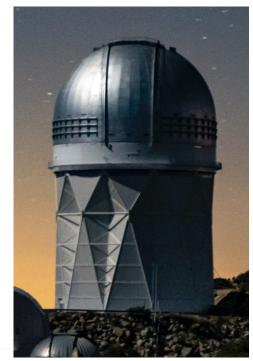
- "Spec-S5": a high priority from the Snowmass Cosmic Frontier report
- Example concepts: MegaMapper, the Maunakea Spectroscopic Explorer, ESO Wide-field Spectroscopic Telescope (WST)
  - 6.5-12m telescope, 1.5-7.5 sq. deg. field of view, 20k-50k fiber positioners
- Would be able to explore dark matter, dark energy, cosmic inflation, and Milky Way structure, all simultaneously
- Rubin LSST data would play a key role in target selection
- Scaling from DESI, could obtain baseline LSST photo-z training sample to full survey depth in 20-60 nights!

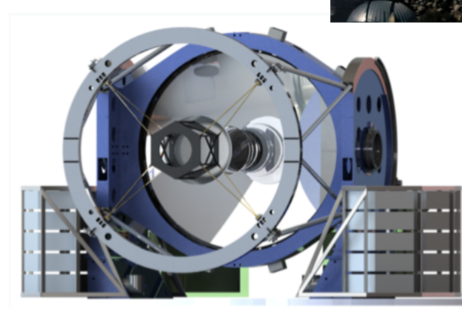


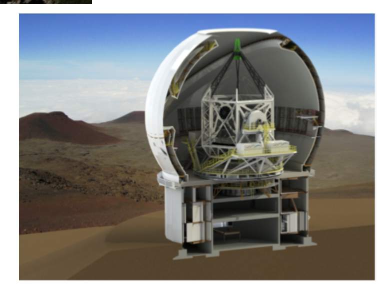


Conclusions

- **Rubin Observatory LSST will provide a dataset of unprecedented constraining power...**
  - **but extracting full value from that data will require both improved methods and better spectroscopic training sets**
- **A DESI-2 program and Spec-S5 could play key roles in enabling these improvements**
- **For lots more details, see our ARAA article!**
  - **Journal version:** https://www.annualreviews.org/doi/abs/10.1146/annurev-astro-032122-014611
  - **ArXiv version (with some formatting advantages):** https://arxiv.org/abs/2206.13633







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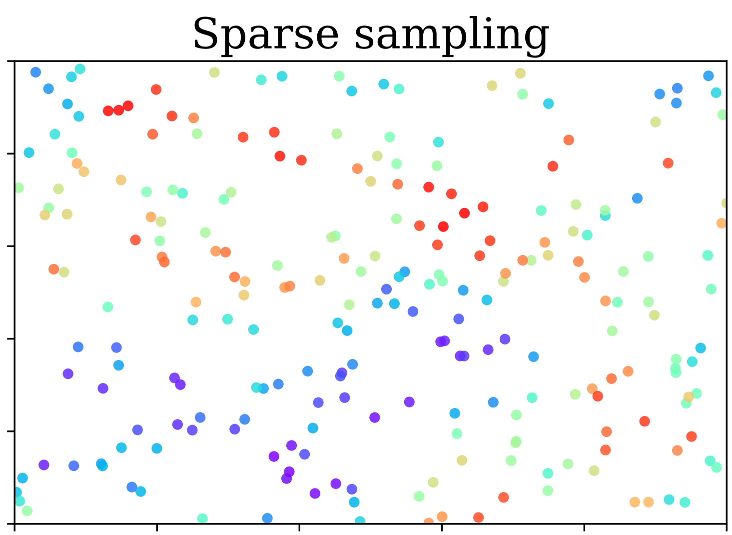
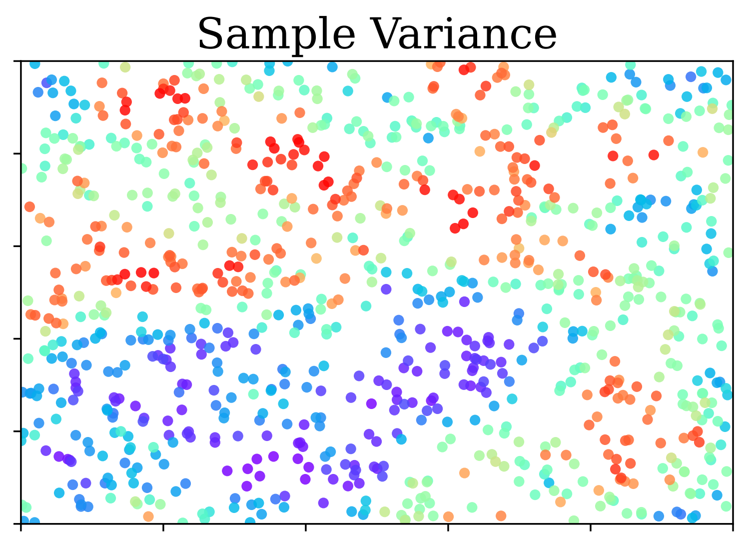
Real-world datasets fall short of this ideal in many ways:

- **Spectroscopic samples of faint galaxies tend to be small: sparsely sample the underlying distribution**
- **When spectroscopy is obtained over small areas of sky, density fluctuations in the universe cause some redshifts to be over- or under-sampled**

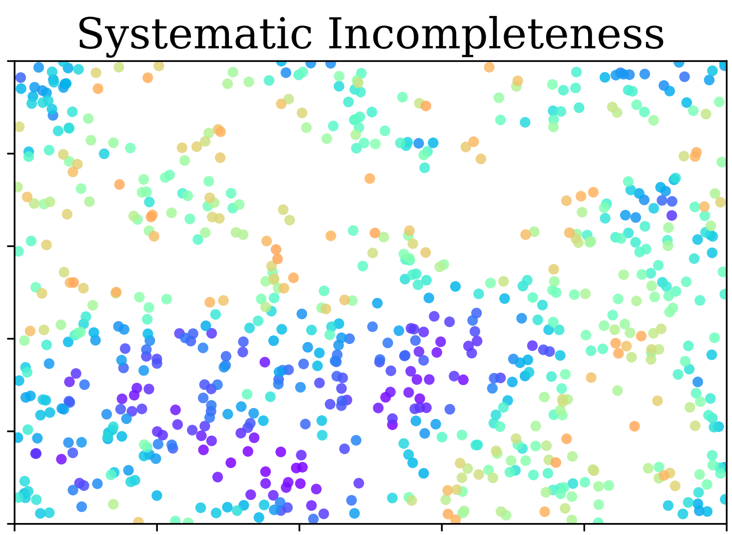


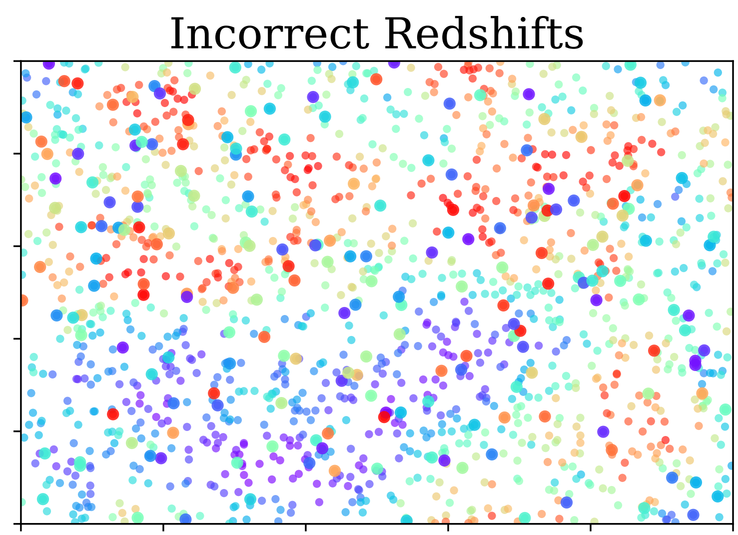


Figures: Newman & Gruen 2022

Real-world datasets fall short of this ideal in many ways:

- Some populations of galaxies are difficult to measure redshifts for, and end up missing from the spectroscopic samples
  - Fail 10-40% of the time
- 0.5-5 percent of the time (depending on sample), spectroscopic redshift estimates are badly incorrect
  - Leads to mis-training or inaccurate characterization

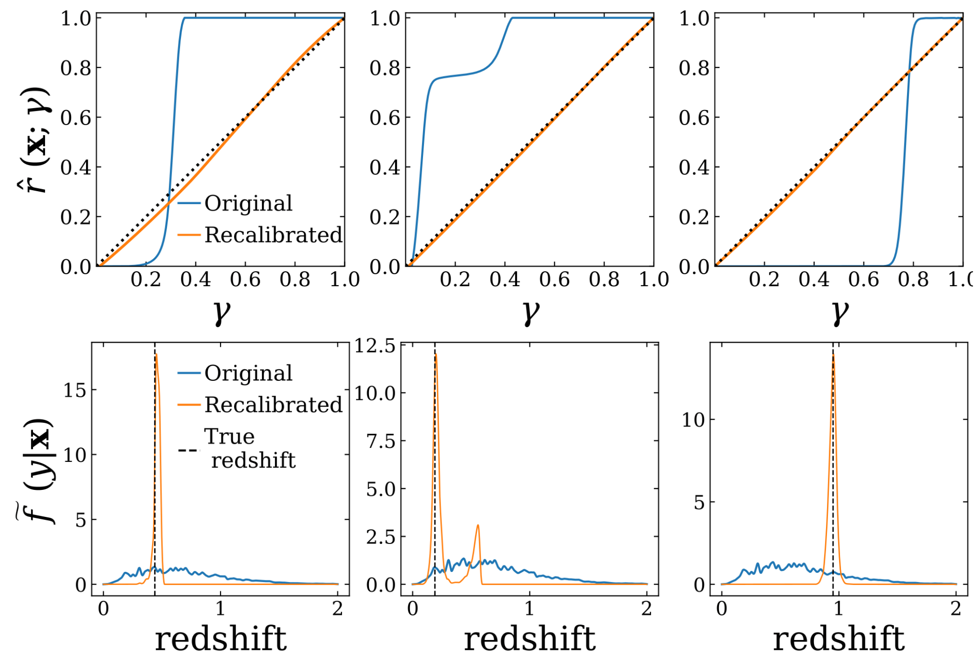




Figures: Newman & Gruen 2022

Better methods, and better datasets, will be needed to make optimal use of Rubin Observatory data

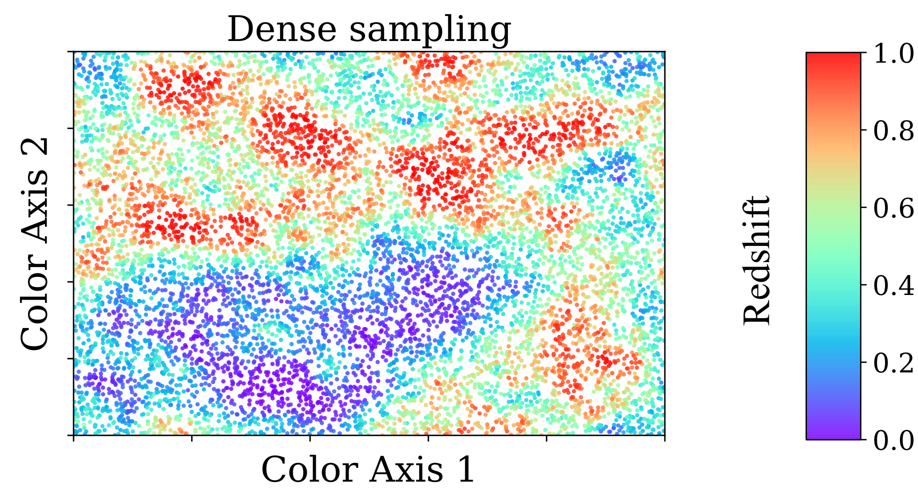
- **An example of challenges we are working on: how to get well-calibrated probability distributions for the redshift of an object?**
  - **Result: the Cal-PIT algorithm (Dey, JN et al. 2021; Dey, Zhao, JN et al. 2022)**
  - **Basic idea: recalibrate PDFs so that the fraction of times the true value falls within the limits y_1 and y_2 = the integral of the PDF between these limits (PIT)**
    - **Recalibrates via regression as a function of position in parameter space: local, not global, correction**
  - **Such methods can be useful for ML-based inference across many fields**



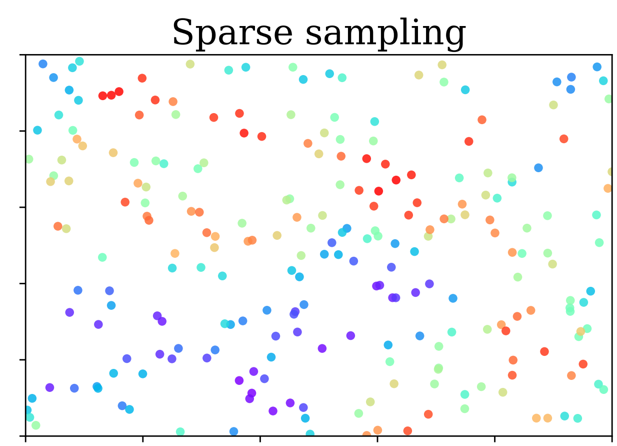
- **After recalibration, *P-P* plot approaches diagonal (ideal) and PIT distribution becomes flat (as for a true PDF)**

Some of the ways that real-world spectroscopic datasets fall short of the ideal: 1) sparse sampling

- **Ideal case: we obtain redshifts for objects densely and evenly sampling the distribution of galaxies in SED space**
  - **Here, a toy model: e.g., what you would get dimensionality-reducing SED space to 2D**
  - **Can easily determine redshift at any point from redshifts of objects in the local neighborhood**

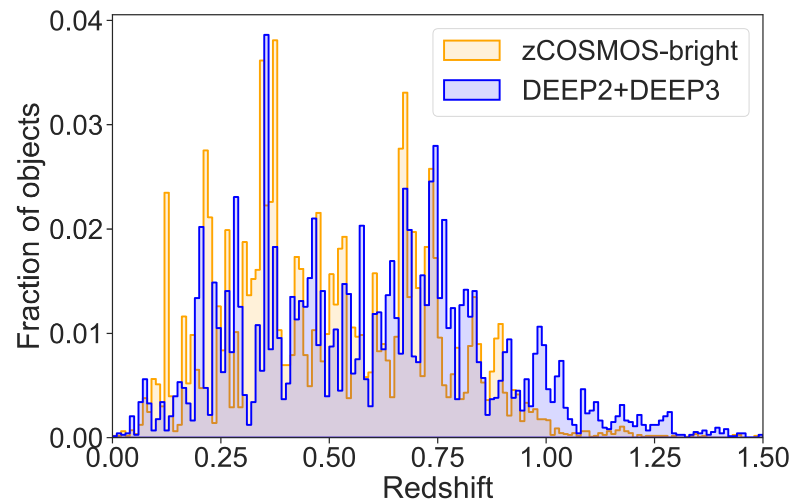


- **Real world: if we want spectroscopy of faint galaxies, sample sizes will be small and will only sparsely cover SED space**
  - **The objects with spectroscopy in the same neighborhood may not be all that close...**

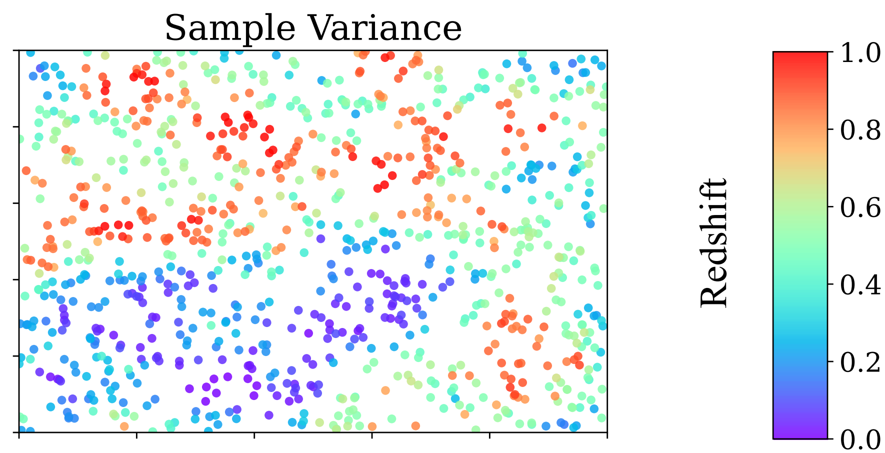


Some of the ways that real-world spectroscopic datasets fall short of the ideal: 2) sample / cosmic variance

- **Ideal case: the redshifts in your spectroscopic training set have a redshift distribution matching the overall average across the sky**

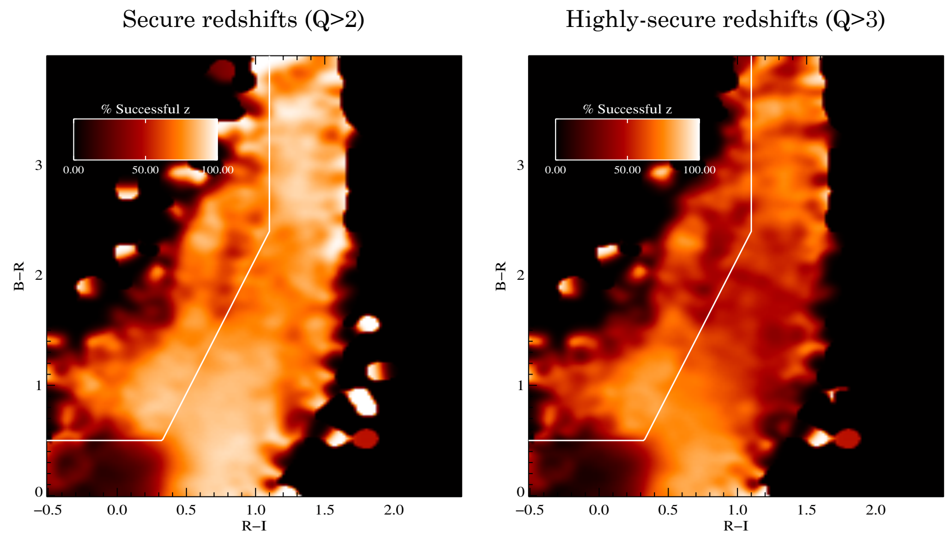


- **Real world: Deep training sets are obtained over only small areas of sky**
  - **The selected regions will be overdense or underdense at some redshifts due to large-scale structure**
  - **This can easily imprint on redshift distributions across the sky with ML methods**

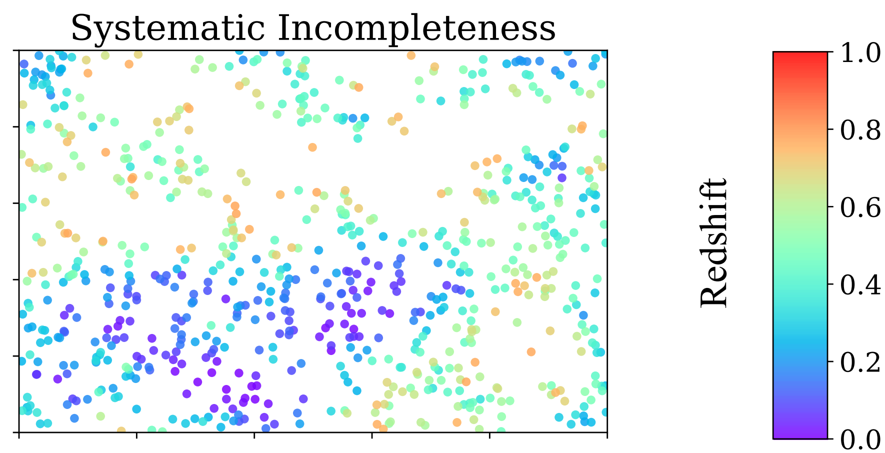


Some of the ways that real-world spectroscopic datasets fall short of the ideal: 3) systematic incompleteness

- **Ideal case: every galaxy you target for spectroscopy provides a secure measurement of its redshift**



- **Real world: When we target faint samples, we fail to measure the redshift ~30% or more of the time**
  - **The objects we do get redshifts for are systematically different in properties (including redshift) than the things we succeed for**



Some of the ways that real-world spectroscopic datasets fall short of the ideal: 4) incorrect redshifts

- **Ideal case: every time you measure the redshift spectroscopically you get the correct *z***

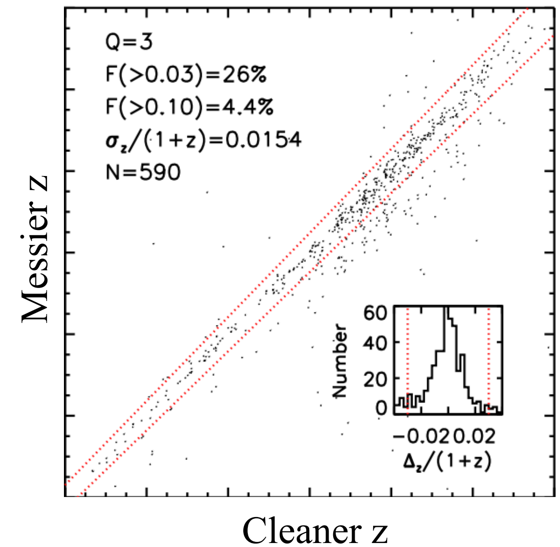
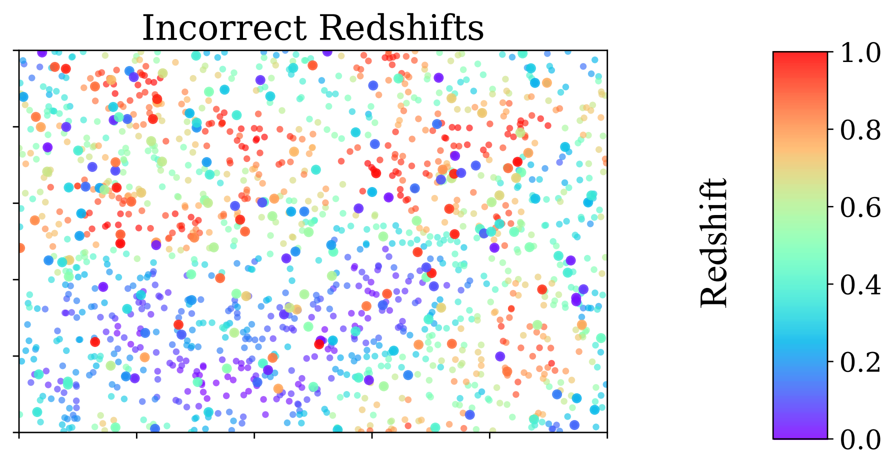


Figure: Coil et al. 2010

- **Real world: Depending upon the sample, 0.5%-10% of redshift measurements will be incorrect**
  - **E.g.: misidentified a single emission line, or mistook sky subtraction residuals for lines**
  - **Need robust ML methods for photometric redshifts**



Some of the ways that real-world spectroscopic datasets fall short of the ideal: 5) color selections

- **Ideal case: you can just use redshifts from pre-existing spectroscopic surveys and don't need to obtain any new measurements**

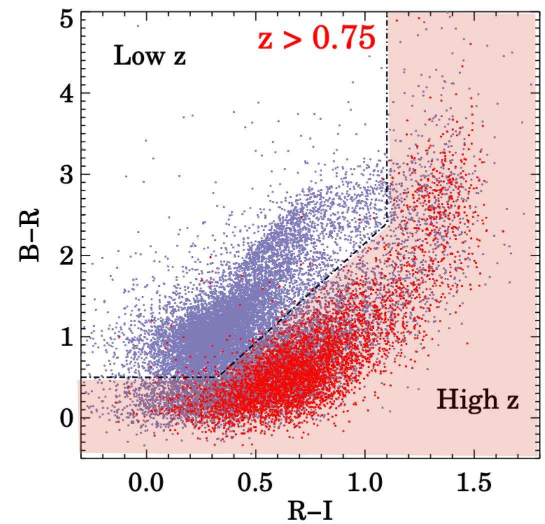
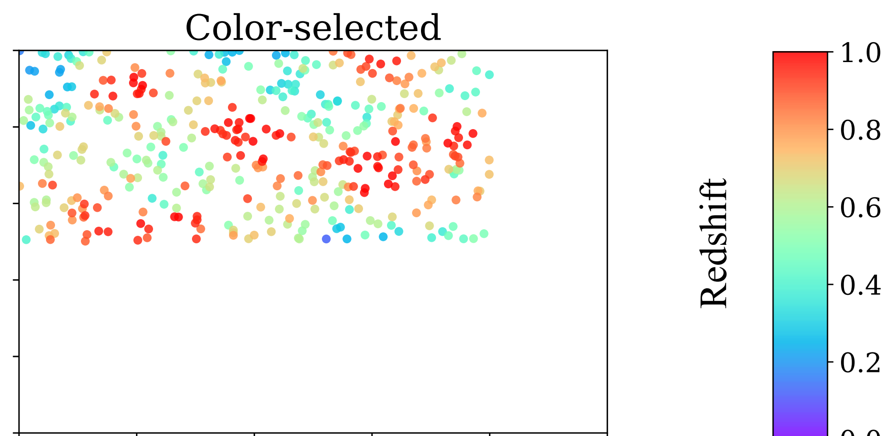


Figure: Newman et al. 2013

- **Real world: Most large high-*z* surveys rely on color cuts to target a limited redshift range of interest**
- **Heterogeneous coverage of color space is a major problem in photo-z training and calibration**



Some of the ways that real-world spectroscopic datasets fall short of the ideal: 6) difficulties training at very low *z*

- **Ideal case: Training samples provide good coverage across all possible redshifts**

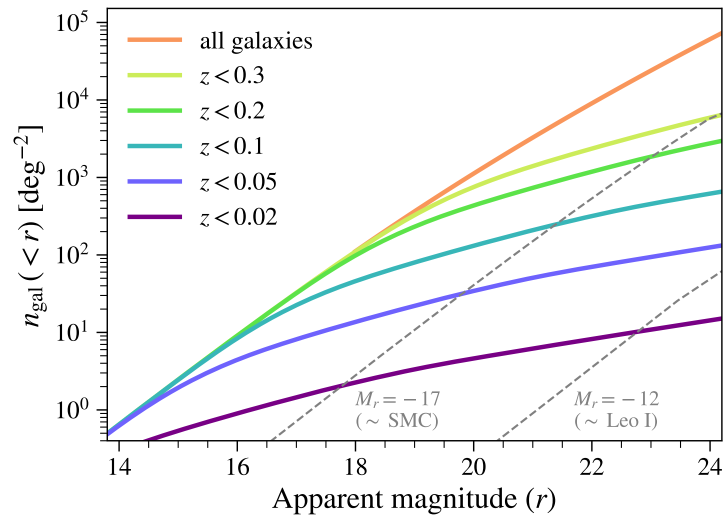
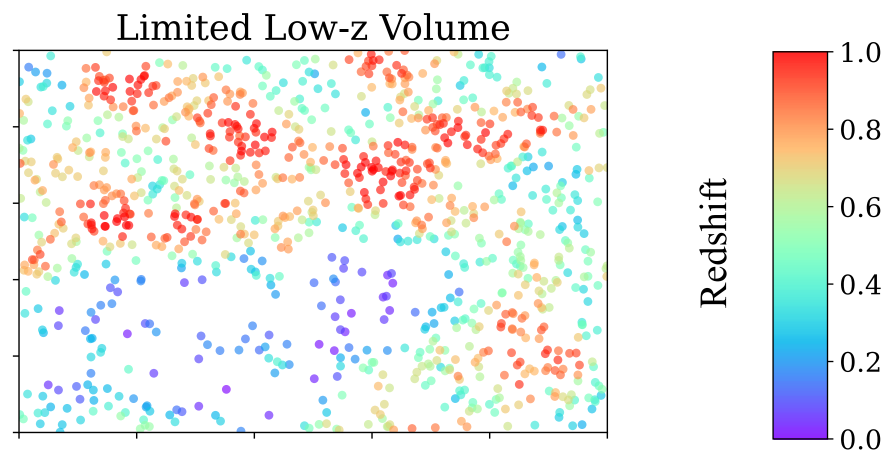


Figure: MSE team / Yao-Yuan Mao

- **Real world: The universe has little volume at low redshifts so low-z galaxies are rare in magnitude-limited samples**
- **Since they are poorly represented in training sets photo-*z* algorithms tend to disfavor low z solutions**



Do template-based photo-z's solve these problems by being less dependent on training sets?

- Nope...
- Kodra et al. 2022 tested many template-based methods applied to CANDELS data
- Methods that all agree well with spec-z's where we have them predict very different redshift distributions vs. magnitude, from the same data

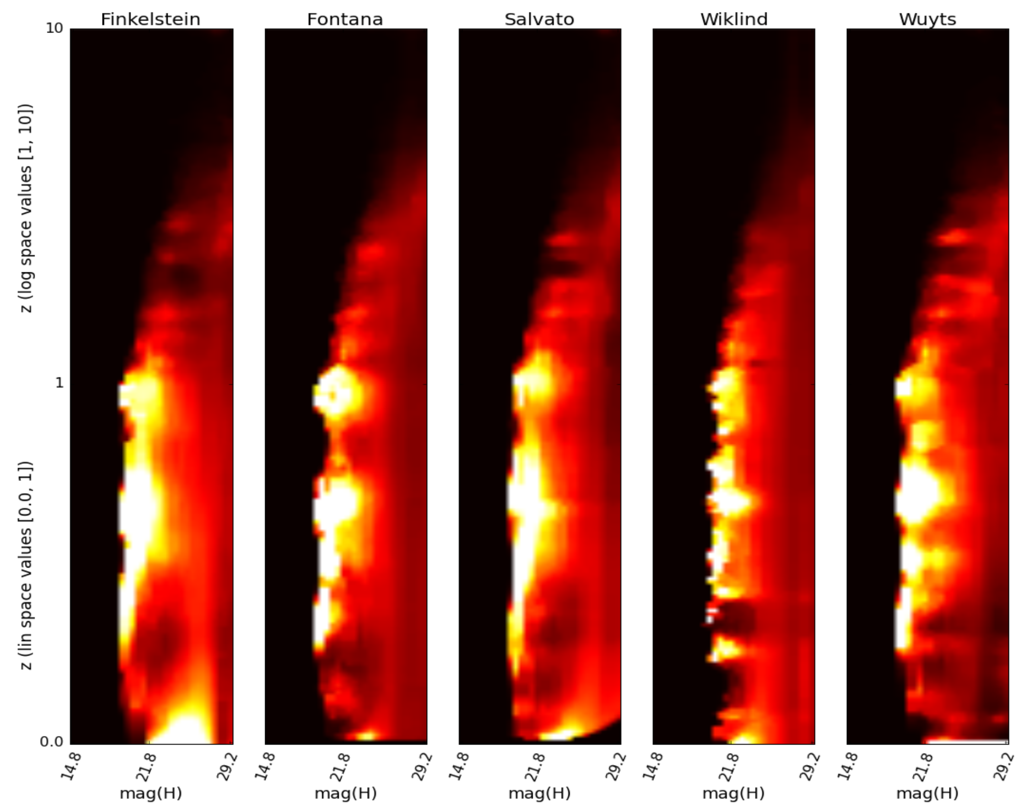
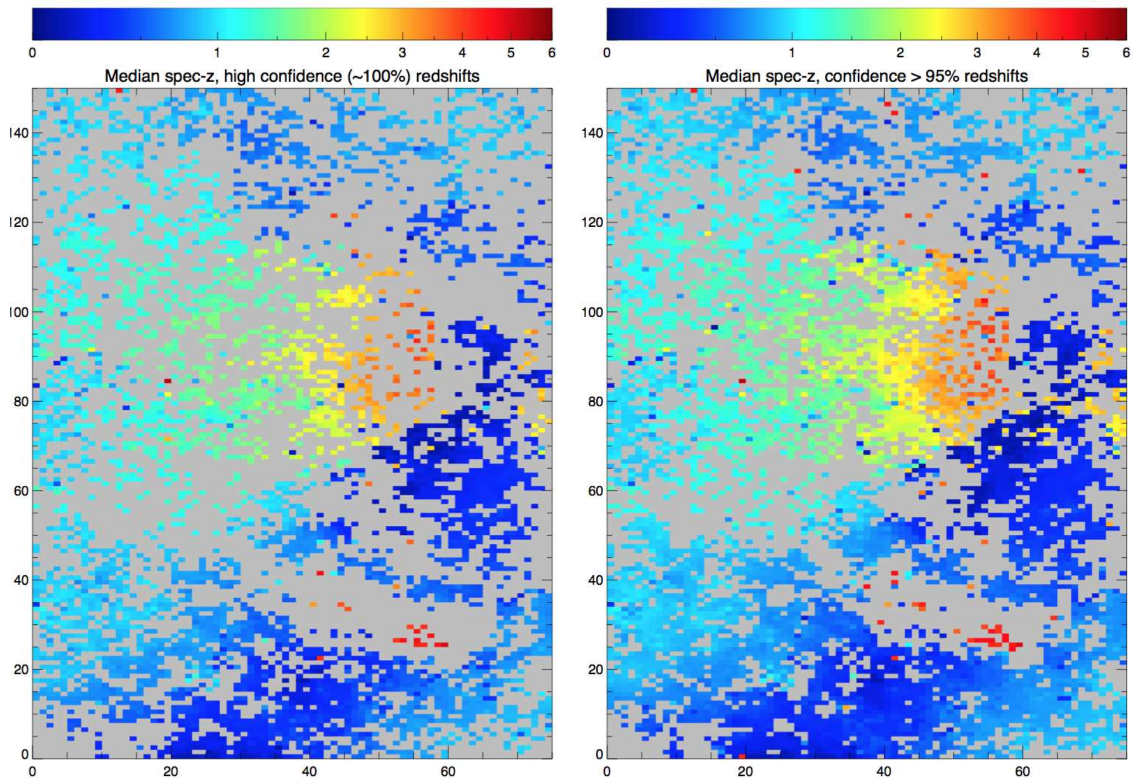


Figure: Kodra et al. 2023

If we restrict to the most-secure redshifts, much more of color space is untrained by current samples

- **Grey regions: cells in self-organized maps of galaxy color space that are not constrained by spectroscopic redshifts**



cells with <1% failure rate z's   with <5% failure rate z's

Masters et al. 2015