Mitigating 3x2pt Systematics

Augmented Photo-z Training Samples and Optimal Tomographic Binning

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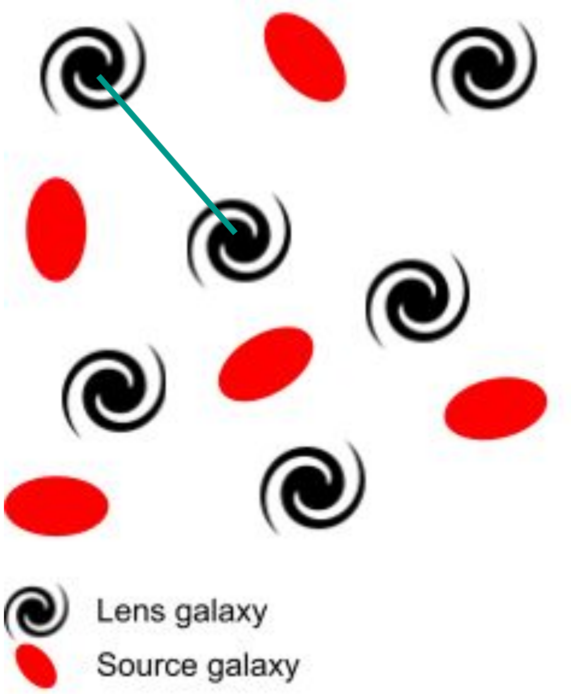
Cosmo21 May 2024

Read the papers!

Moskowitz et al. 2024

Moskowitz et al. 2023

3x2pt Method

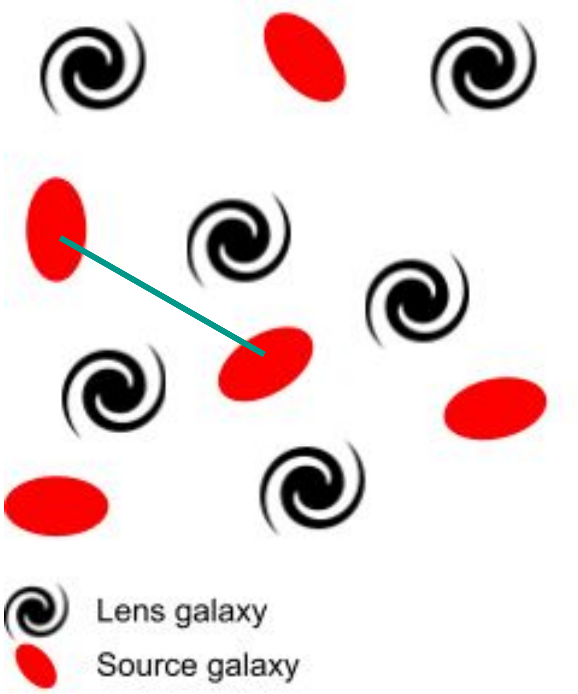


Set of 3 2pt correlations: clustering, cosmic shear, galaxy-galaxy lensing

In practice: bin galaxies tomographically, and compute correlations within and between bins

Since we bin by redshift, there are systematics related to redshift estimation

3x2pt Method



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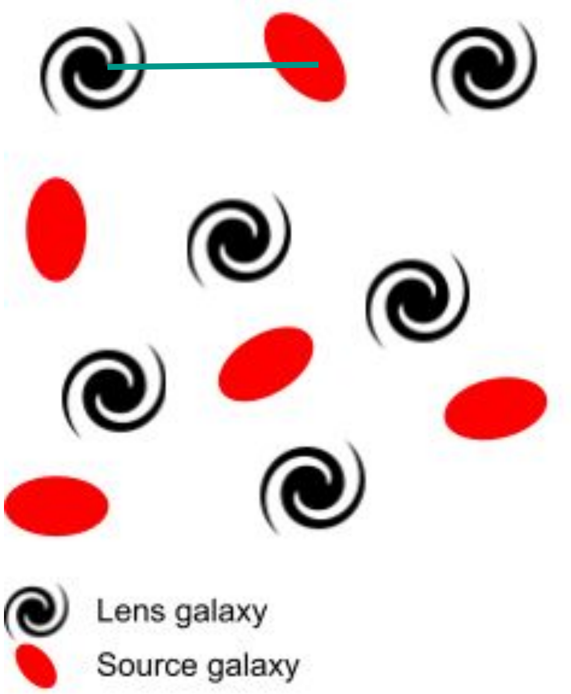

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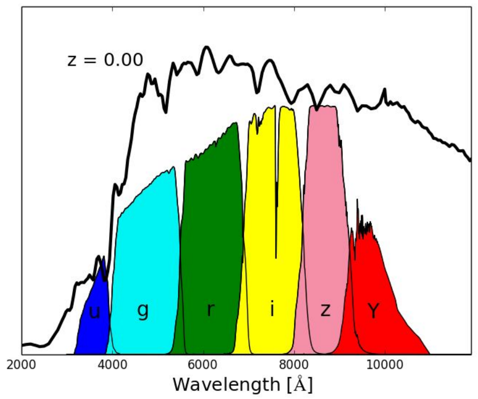
Augmented Photo-z Training Samples

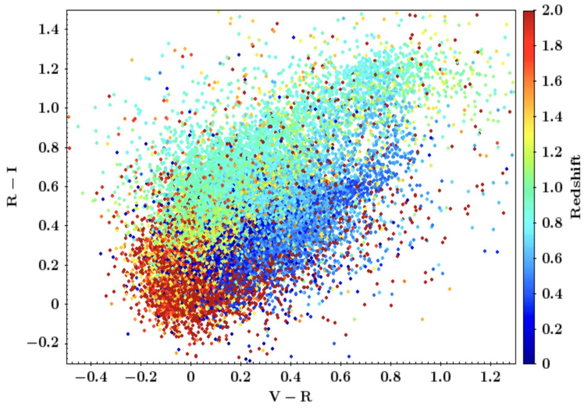
Moskowitz et al. 2024

What are photo-z's and why do we need them?

- LSST will see so many galaxies, it's infeasible to measure spectroscopic redshifts for all of them
- There is an intrinsic relationship between redshift and a galaxy's photometry
- This relationship can be modelled using ML techniques if you have a training set with spectroscopic redshifts



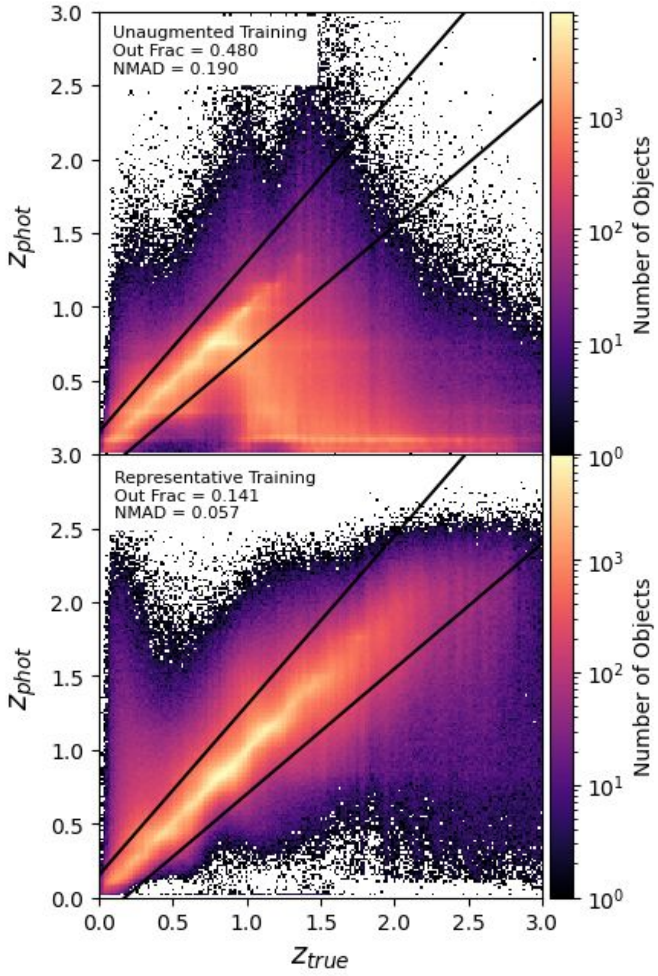
Carlos Cunha



Will Hartley

What makes photo-z's difficult?

- Spectroscopic redshifts are easier to obtain for brighter, redder objects→tend to be lower redshift than expected LSST data
- LSST will go much deeper than existing spectroscopic samples, including DESI
- Training samples for LSST photo-z's will be non-representative!
    - Leads to poor photo-z estimation for galaxies with features not represented in the training sample



Moskowitz et al. 2024

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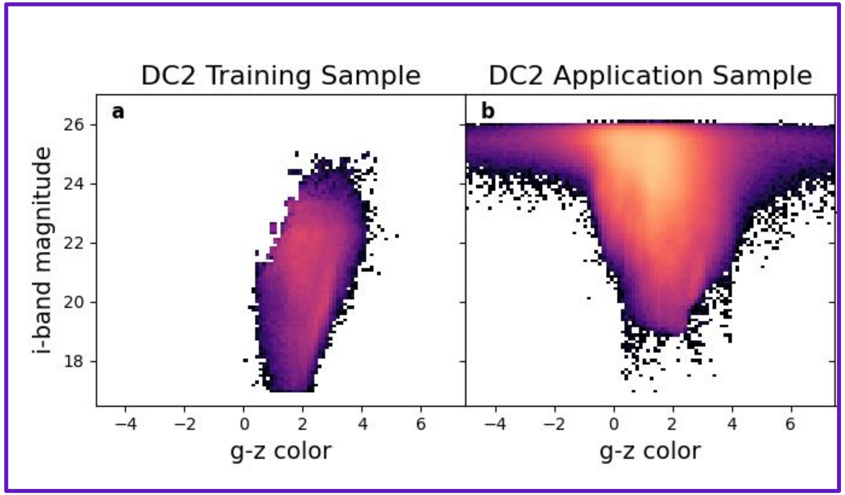
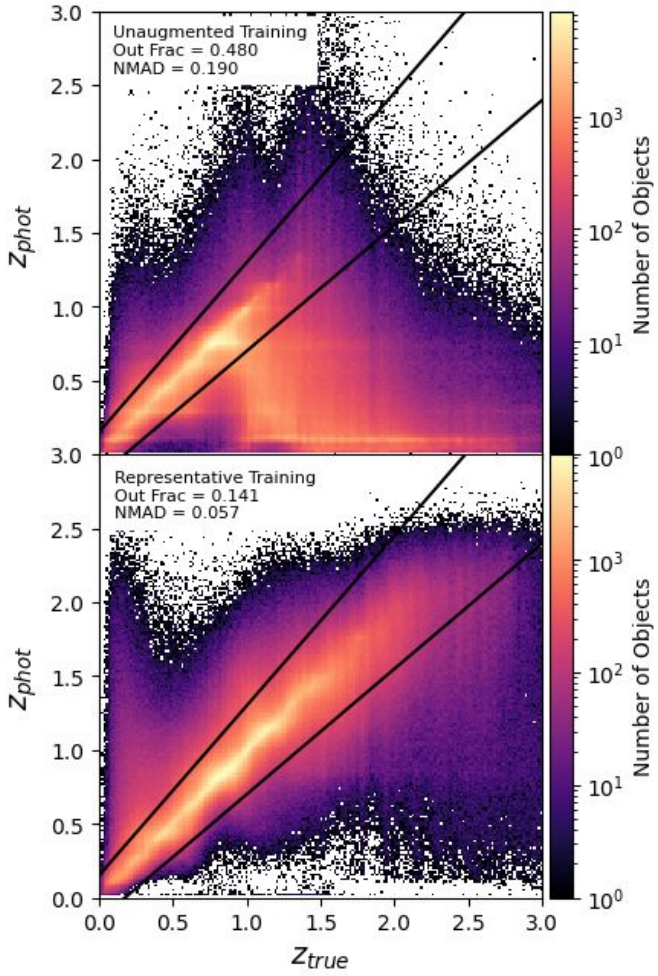




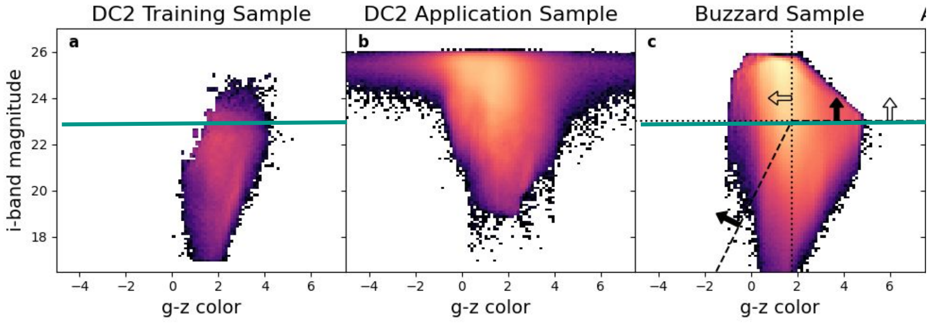
Used the DC2 simulation to create a training sample that looks like current spectroscopic samples and estimated photo-z's using FlexZBoost

Moskowitz et al. 2024

Augmentation

Can we add simulated galaxies to the training sample to improve photo-z quality?

- Select 10,000 Buzzard galaxies with features that are unrepresented in DC2 training sample
  - $\boxed{i\text{-mag} > 23}$
  - (g-z) color < 1.75
  - $z_{true} > 1.0$



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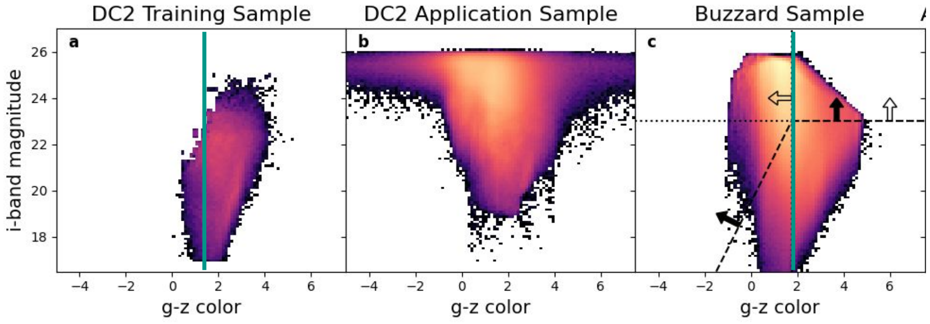

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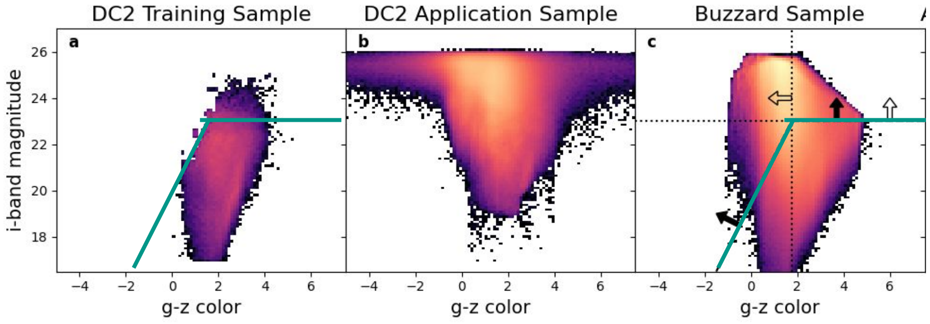
Combination matched to DC2 training sample boundaries



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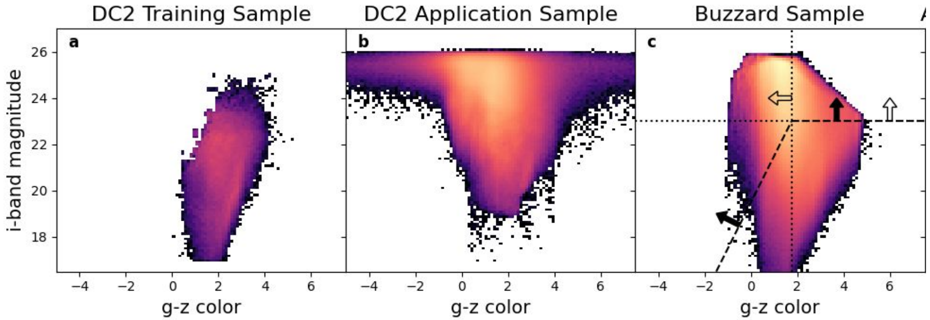
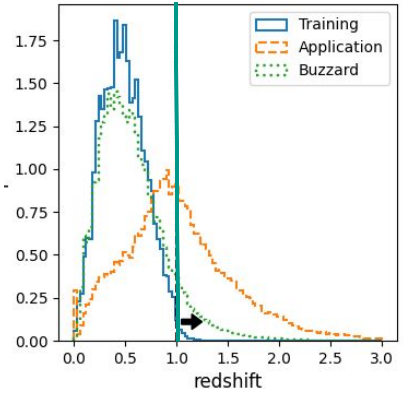
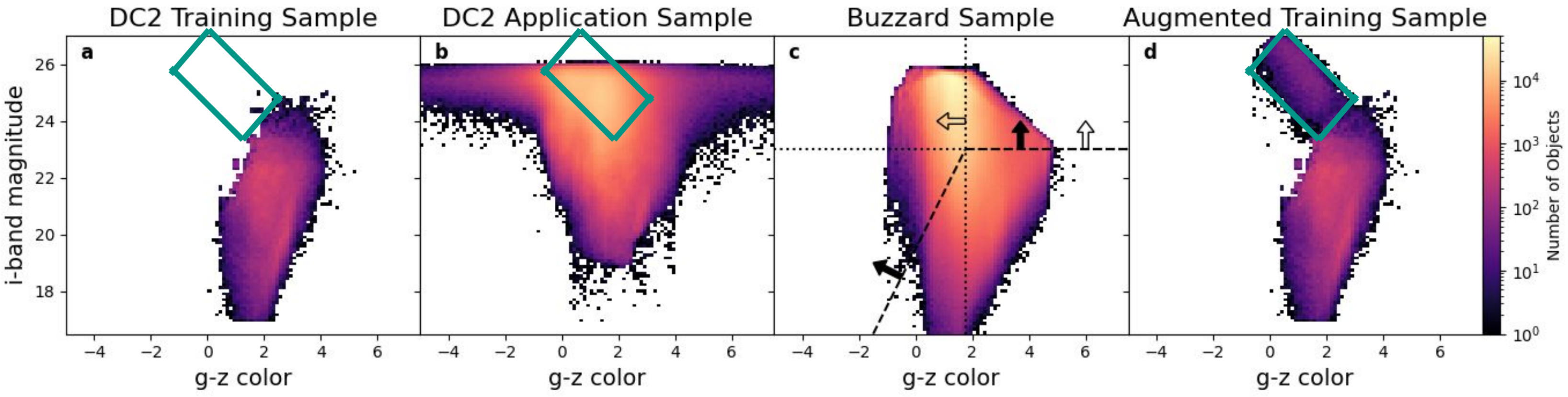
Combination matched to DC2 training sample boundaries





Simulation Post-Processing

- Buzzard was chosen for augmentation specifically because it uses different methods to create SEDs for galaxies than DC2→different color-redshift relation
- Shifting the Buzzard magnitudes so the median magnitude in each band matches the median of the DC2 application sample (simulating real data)
  - Produces best case augmented training sample



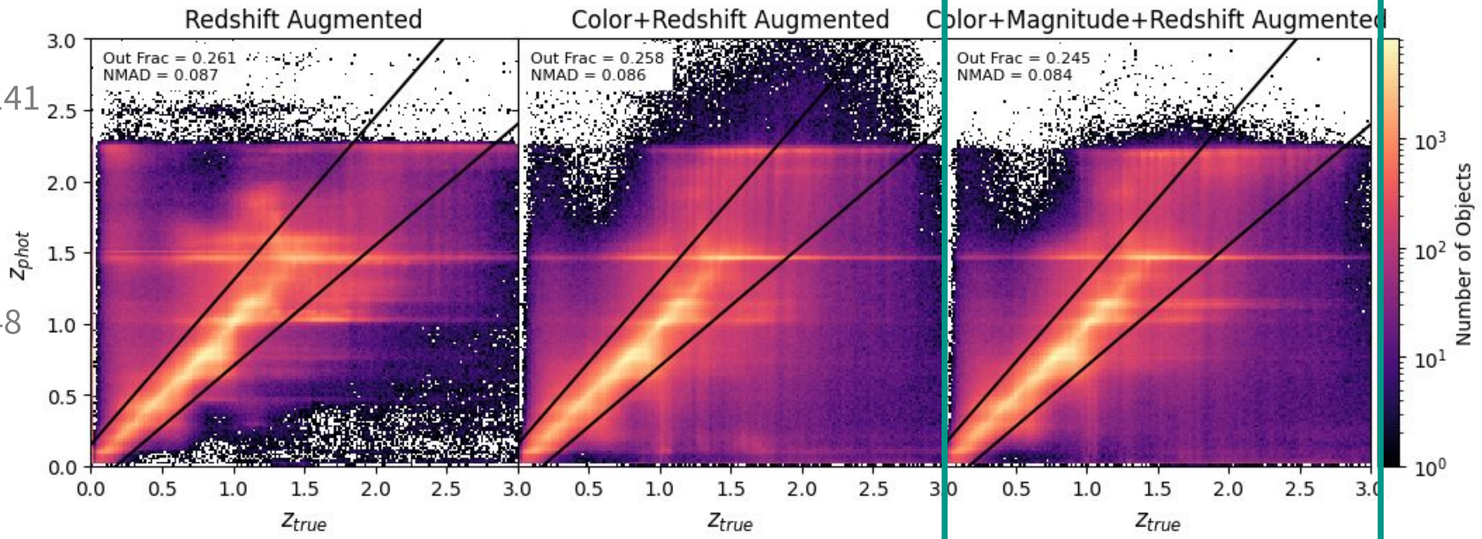
Moskowitz et al. 2024

Does Augmentation Work?

Single Feature | Double Feature | Triple Feature

<u>Representative:</u>
Outlier fraction: 0.141
NMAD: 0.057

<u>Unaugmented:</u>
Outlier fraction: 0.48
NMAD: 0.19



% improvement	46% (outlier frac) 54% (NMAD)	46% (outlier frac) 56% (NMAD)	49% (outlier frac) 56% (NMAD)
% recovery	65% (outlier frac) 77% (NMAD)	65% (outlier frac) 78% (NMAD)	69% (outlier frac) 80% (NMAD)

Moskowitz et al. 2024

Optimized Tomographic Binning

Moskowitz et al. 2023

Why binning?

- Even with our improved photo-z estimates, they're still not precise enough for 3D correlation functions→instead we bin by redshift and do 2D angular correlations within each bin
- Bins are often chosen to be equally spaced in redshift (equal Δz) or with an equal number of galaxies in each bin
  - Can also space equally in comoving distance ($\Delta\chi$)
- But there are an infinite number of choices to make→**is there a better choice to maximize the 3x2pt information we get out?**
- LSST will also be past the shot noise limit, **can we remove some galaxies to further improve the 3x2pt results?**

Optimizing the Bin Edges

Introduce the binning equation parameterized by α and β

$$\mathcal{M} = \int_0^{z_{max}} \left(\frac{dN}{dz}\right)^{\alpha} \left(\frac{d\chi}{dz}\right)^{\beta} dz$$

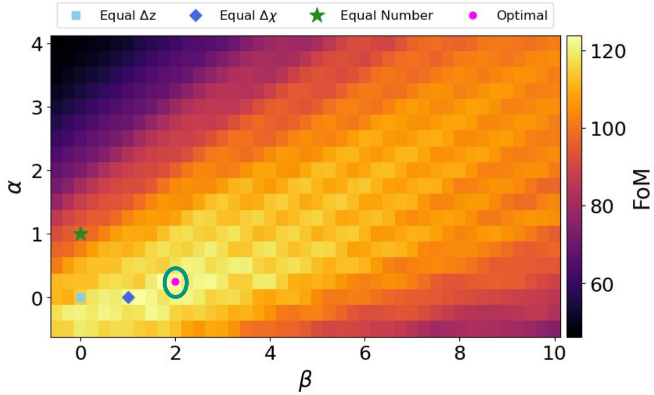
Divide M evenly into the number of bins, then interpolate back to redshift

For (α, β) = (0,0): M = z_{max}, recover equal Δz bins

For (α, β) = (1,0): M = $N_{gal,tot}$, recover equal number bins

For (α, β) = (0,1): M = χ_{max}, recover equal Δχ bins

Calculate DETF figure of merit for each choice of (α, β) → maximize the FOM to optimize the bin edges



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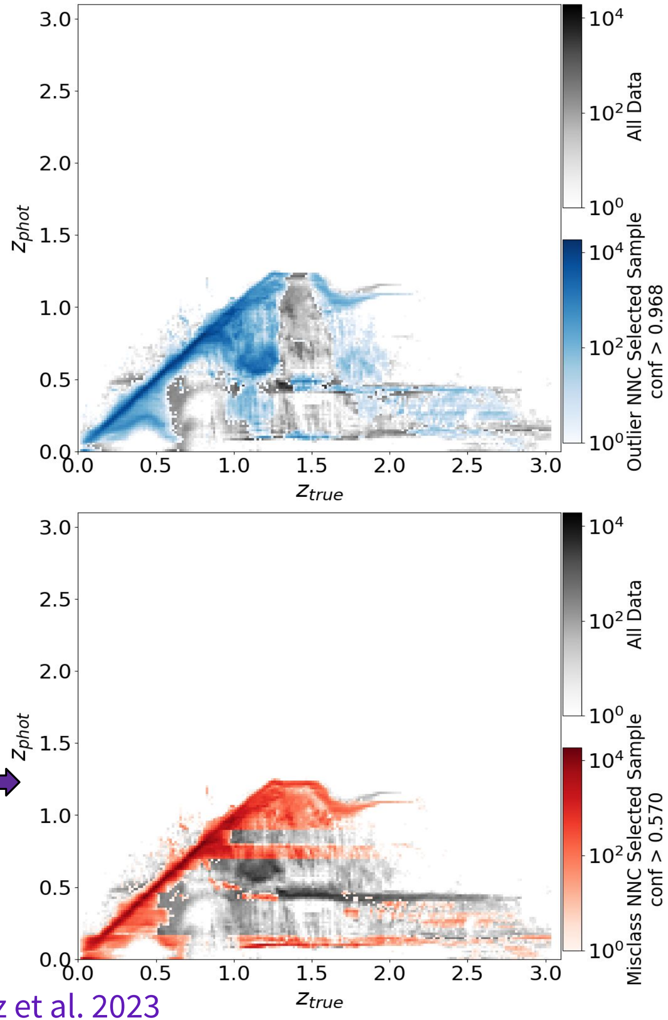
Find (α, β) = (0.25, 2.0) produces highest FOM for the cosmoDC2 simulation

Photo-z Post Processing: Neural Network Classifiers

- LSST won’t be shot noise limited→can potentially improve binning further by removing galaxies with bad photo-z estimates
- Train two NNCs to estimate which galaxies are likely to have “bad” photo-z’s:
  - Photo-z estimate is an outlier compared to the true redshift (outlier NNC; Broussard & Gawiser 2021)
  - Photo-z estimate is far enough away from the true redshift to be sorted into a different bin than it otherwise would be (misclassification NNC; Moskowitz et al. 2023)
  - Find the amount of galaxies to remove that maximizes FOM



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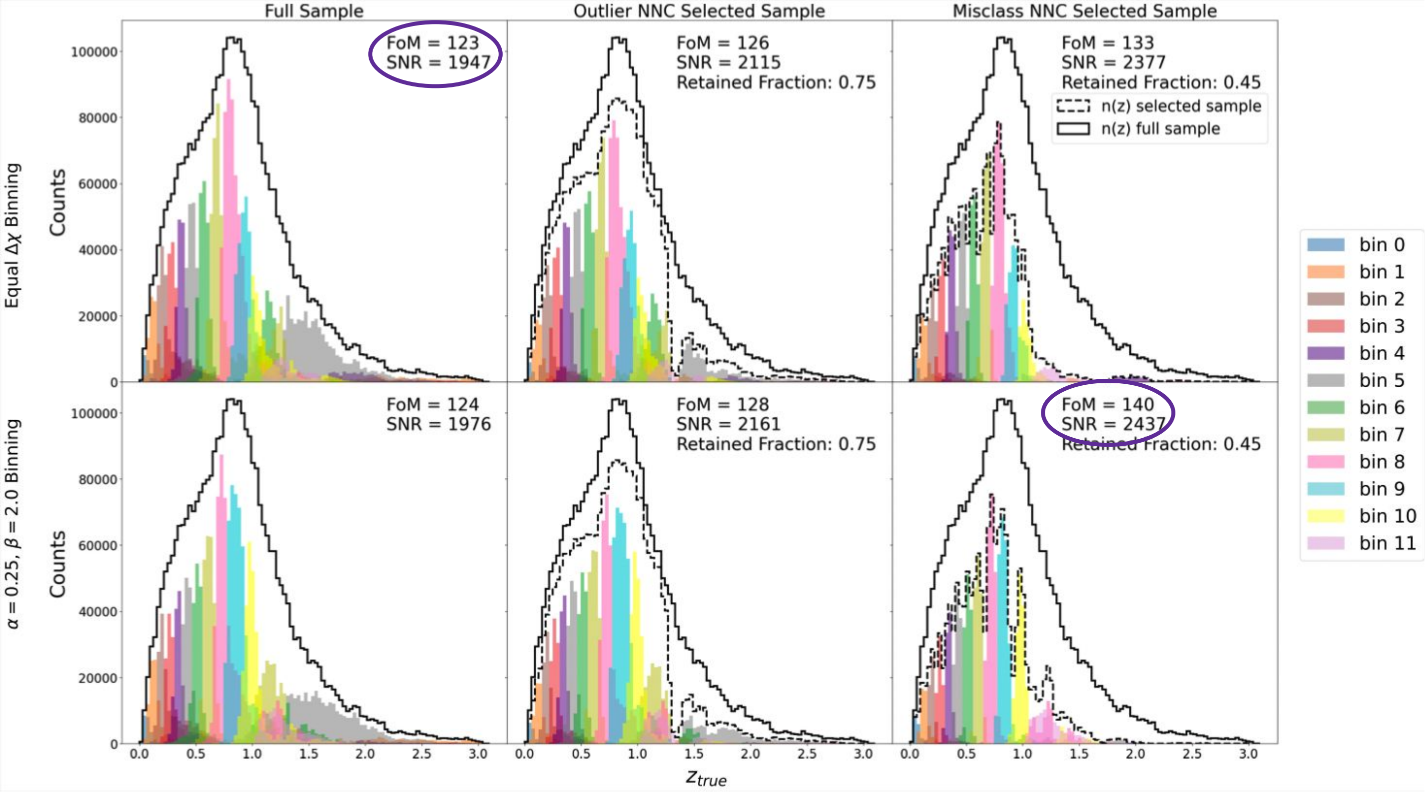
The Optimized Binning Choice

The optimized binning prefers narrower low-z bins and wider high-z bins



Improve the FoM by ~13%, equivalent to ~1 extra year of observing

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Conclusions and Future Work

- LSST will rely on non-representative training samples for photo-z estimation
- Training sample augmentation can reduce the outlier fraction of photo-z estimates by as much as **50%** when working with realistically non-representative training samples
  - More sophisticated augmentation procedures and simulations with higher redshift ranges could improve this even more
- The combination of optimized tomographic bin edges and NNC sample selection can improve the DETF FOM by **~13%**, **equivalent to an extra year of LSST**
- Conducting a full cosmological parameter estimation with these analysis choices will show if they can reduce bias from incorrect n(z) estimates