# **Optimizing Roman Photometric** Redshifts

### **Brett Andrews**

In collaboration with: **Jeff Newman TQ Zhang Biprateep Dey (U. Toronto/CITA)** 



**Finian Ashmead** On behalf of:



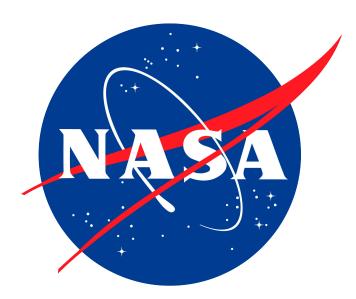




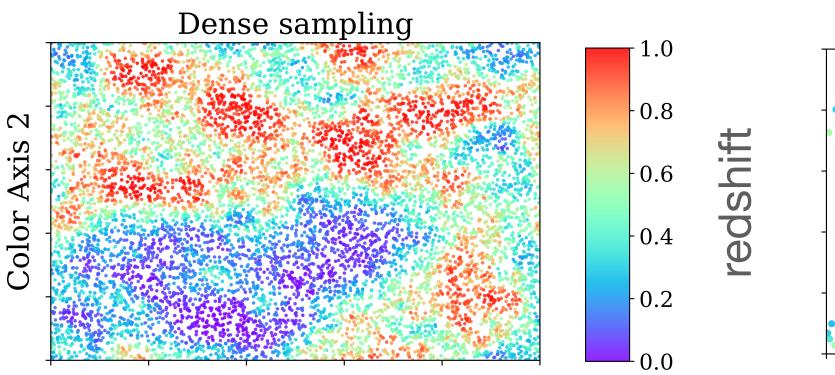
**Ashod Khederlarian** 

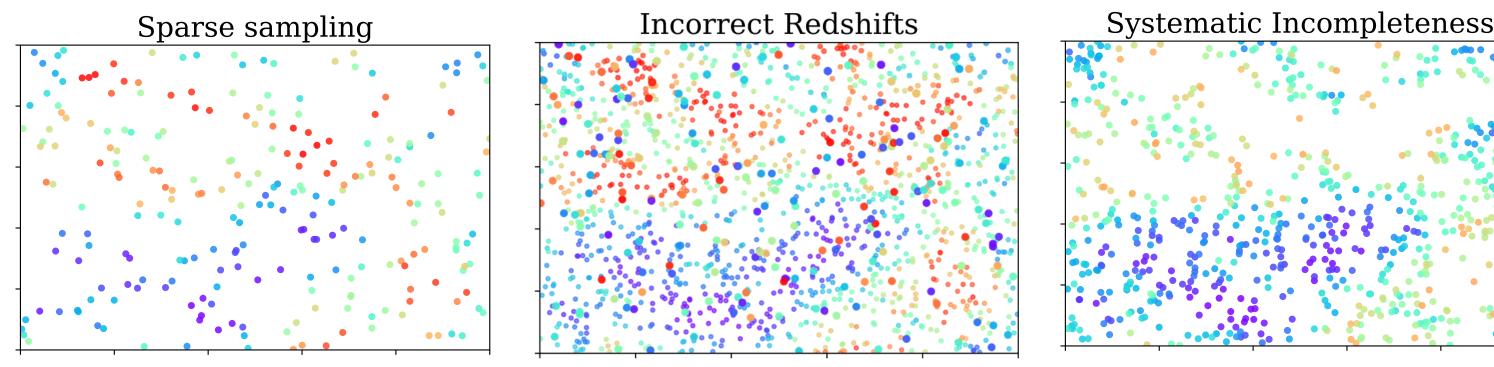
#### **Yoki Salcedo**

#### **Roman HLIS Cosmology PIT** 10.8.2024



## **Photo-z Calibration Challenges**





Color Axis 1

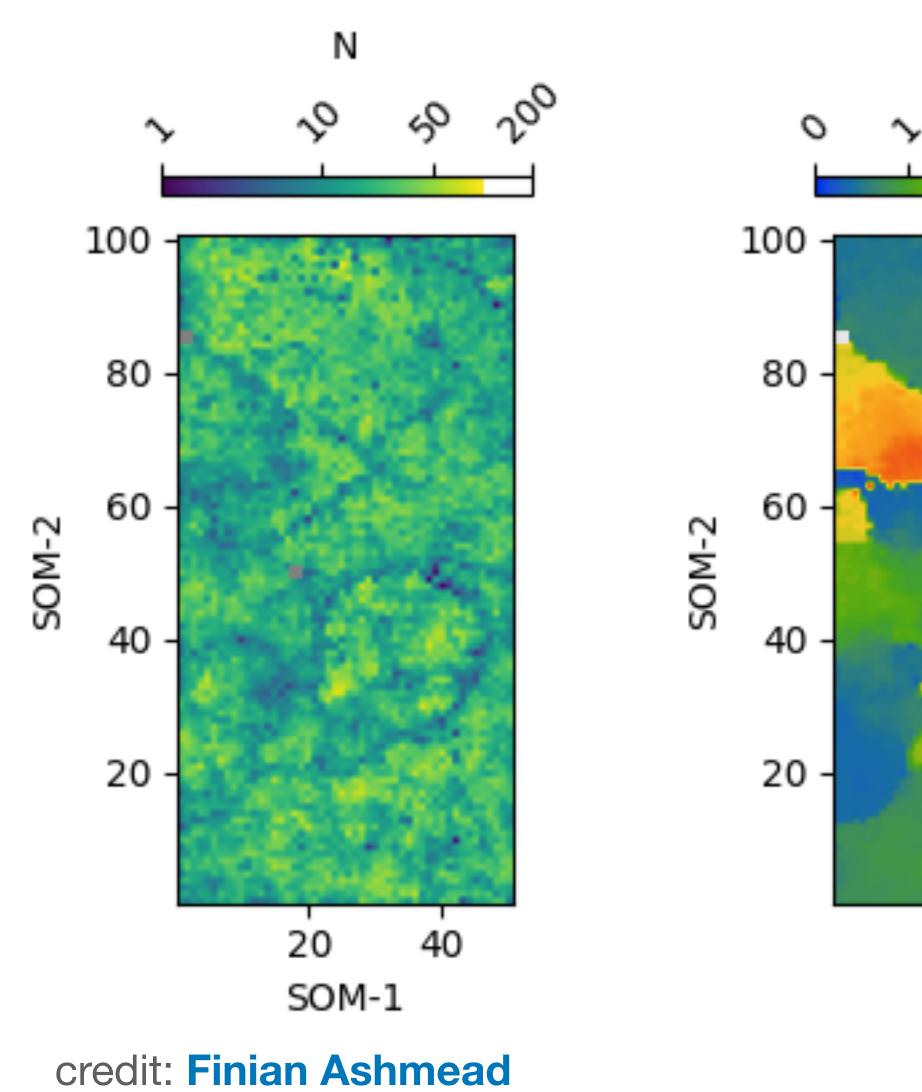
#### Newman & Gruen (2022)

- - sparse sampling
  - incorrect redshifts
  - systematic incompleteness

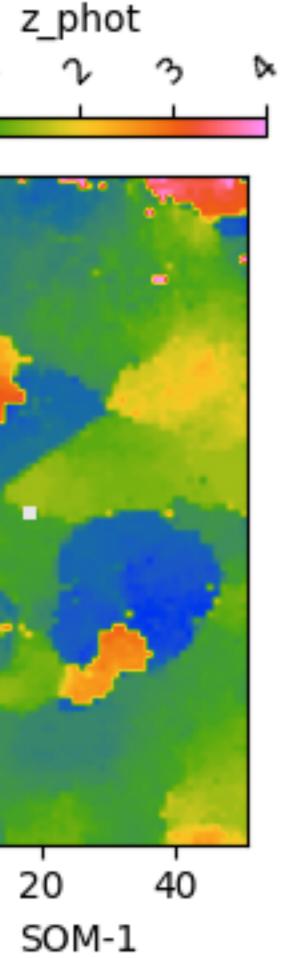
 Compared to photometric objects in color-redshift space, existing spec-z training sets suffer from

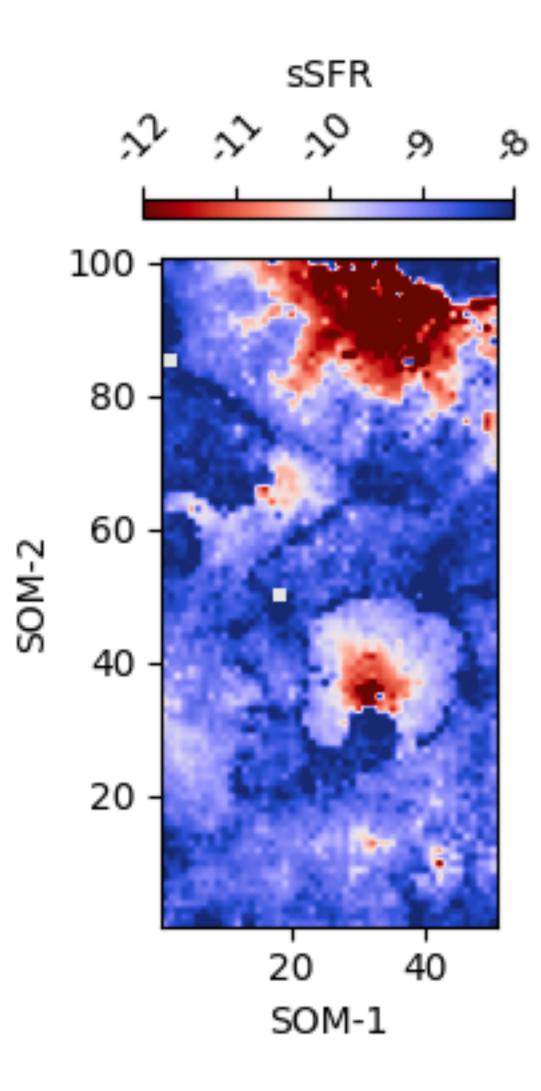


## SOM: sharp boundaries and discrete binning hinder interpolation

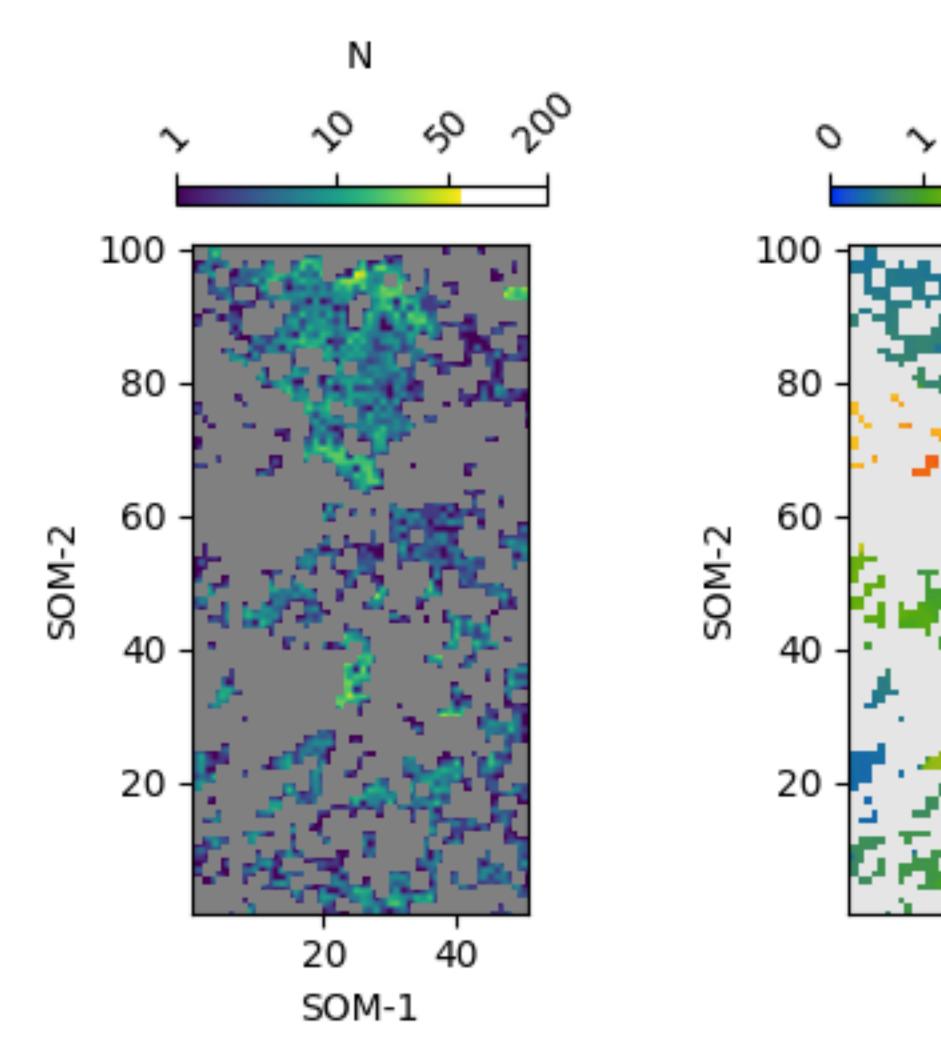


*u\*grizyJHKs* data from Weaver et al. (2022)



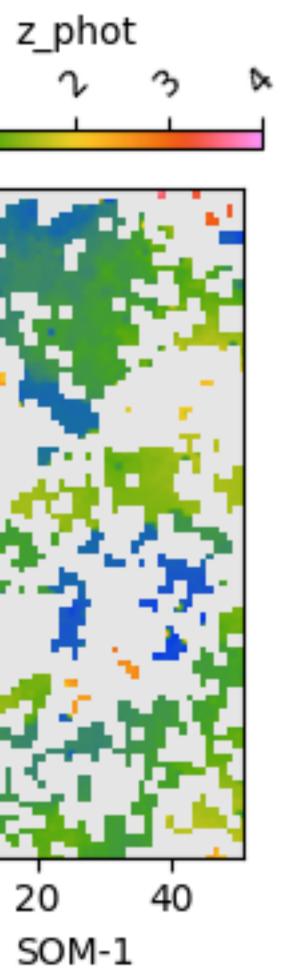


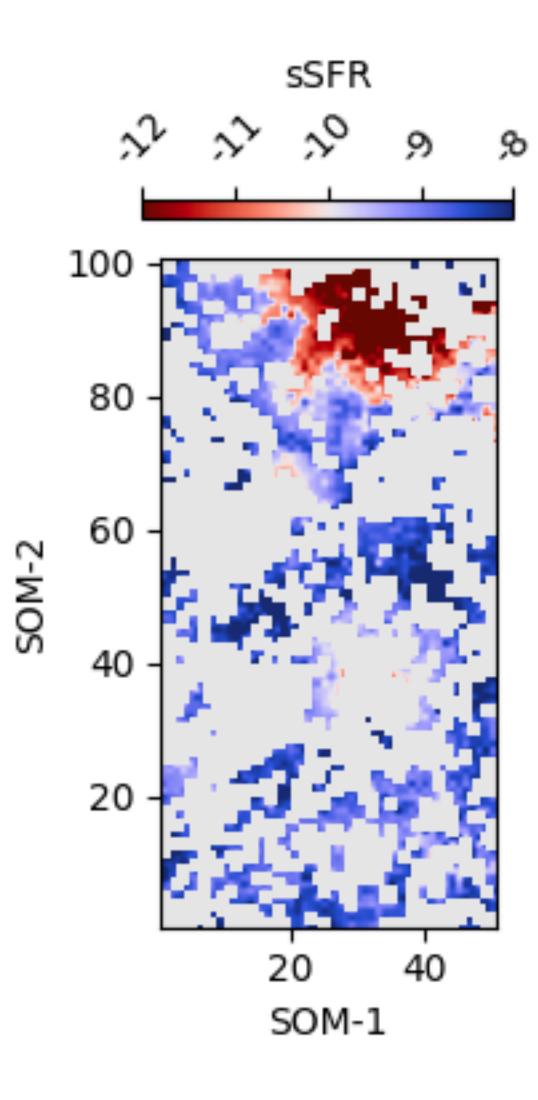
### Spec-z's sparsely populate color-space and are systematically incomplete.



#### credit: Finian Ashmead

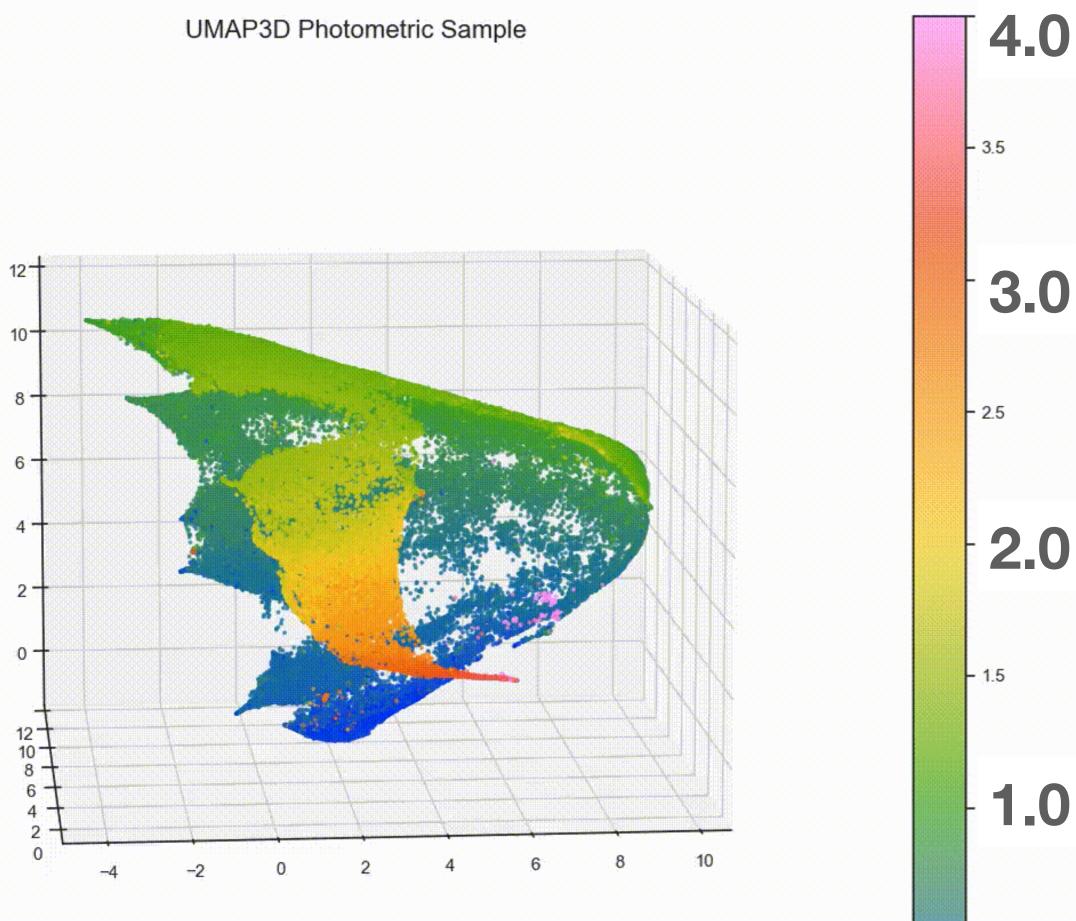
*u\*grizyJHKs* data from Weaver et al. (2022) spec-z's (confidence > 95%) from Khostovan et al. (in prep.)





## Roman WFS (PI: Newman): Optimizing Spec-z Training Sets w/ UMAP

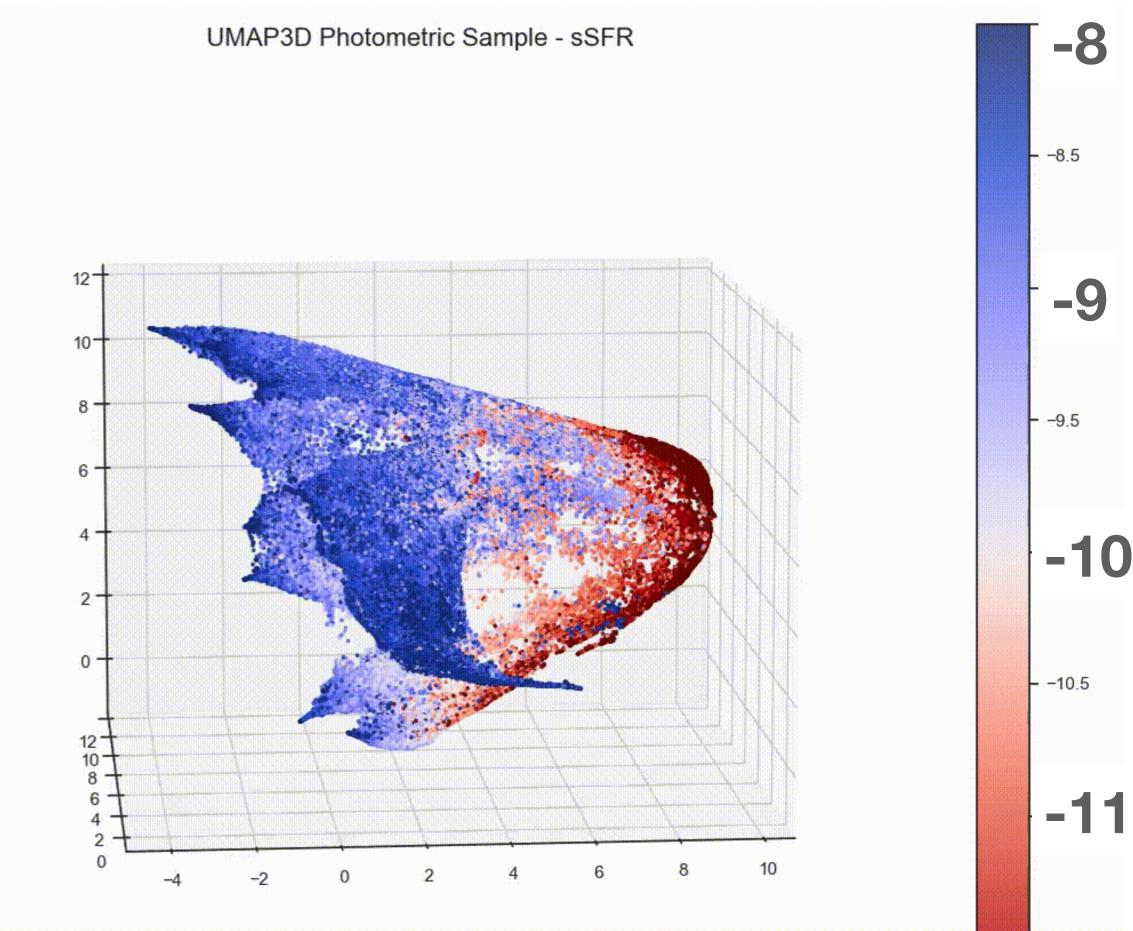
#### Photo-z



- 0.5

0

log(sSFR)

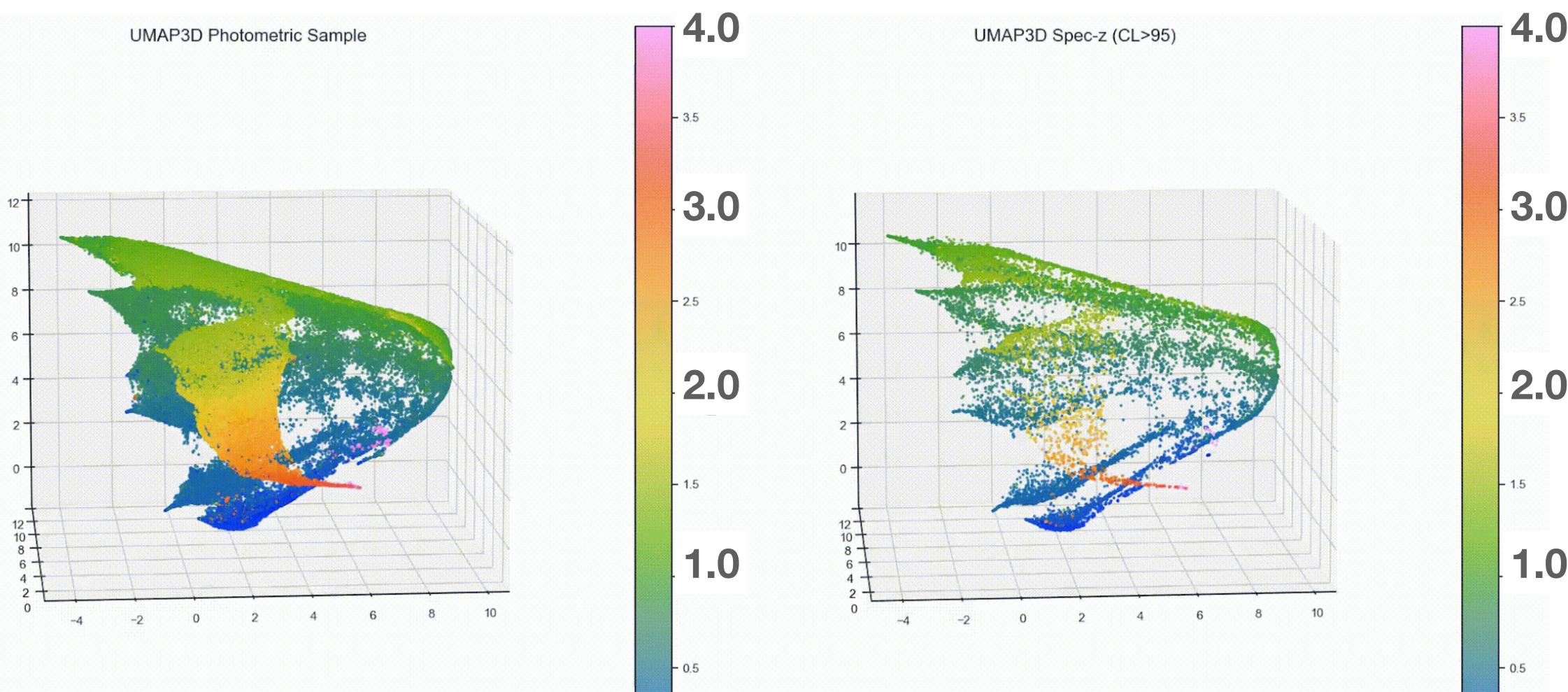


credit: Finian Ashmead



- -11.5

## UMAP Color Manifold Enables Interpolation Photo-z



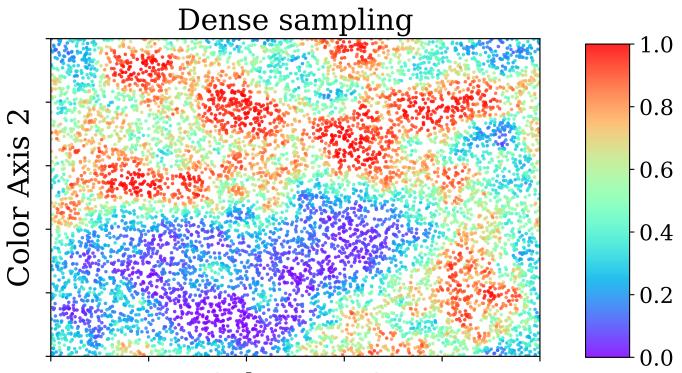
0

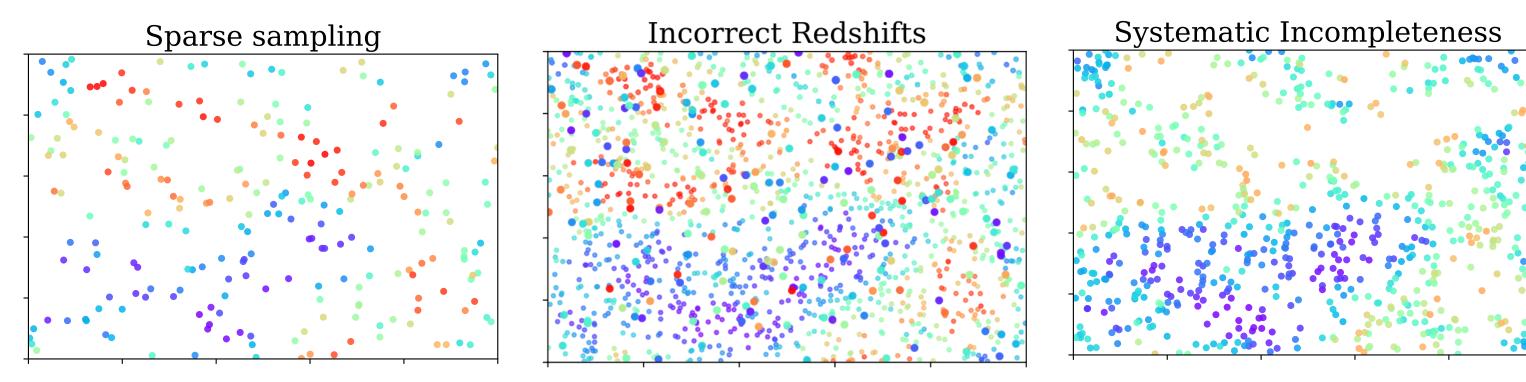
credit: Finian Ashmead

0

## **Photo-z Calibration Challenges**

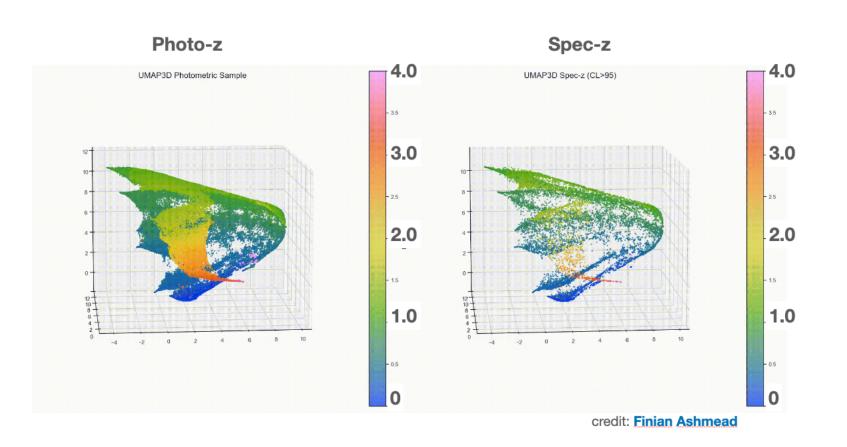
redshift





Color Axis 1

Newman & Gruen (2022)



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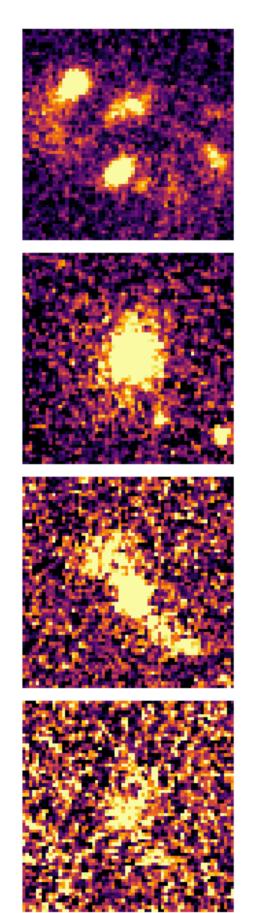
sparse sampling  $\rightarrow$  interpolation



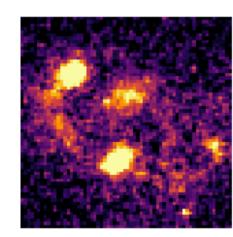
## Roman WFS (PI: Andrews): Image-based Deep Learning Photo-z's

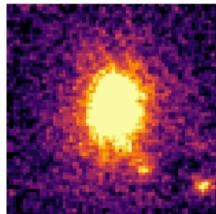
- Goal: leverage Roman's spatiallyresolved color information for better photo-z's.
- Prototyping on O(100k) 4 band HST CANDELS imaging out to H-band with O(20k) training redshifts.
- Currently achieving similar performance to classical ML methods and still room for algorithmic improvement.
- We expect our approach to scale much better than other methods given the massive size of the Roman dataset.

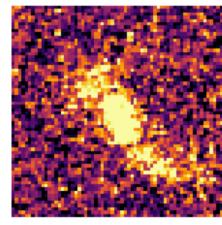
**F606W** 

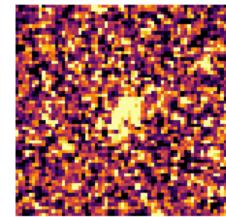


**F814W** 

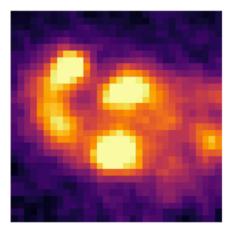


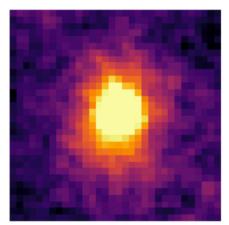


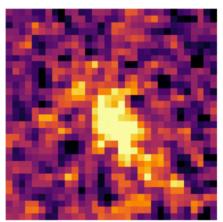


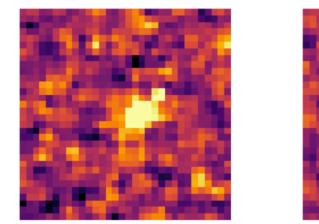


**F125W** 

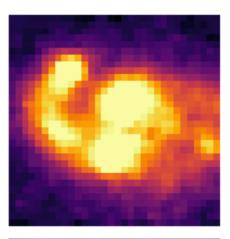


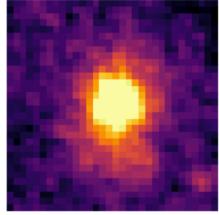


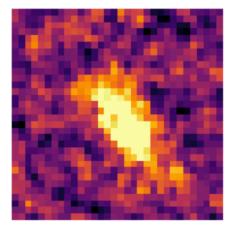


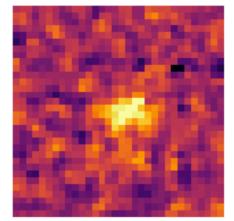


**F160W** 









#### credit: Ashod Khederlarian

### Clustering between photometric and spectroscopic samples can calibrate redshift distributions.

0.5

0.4

0.3

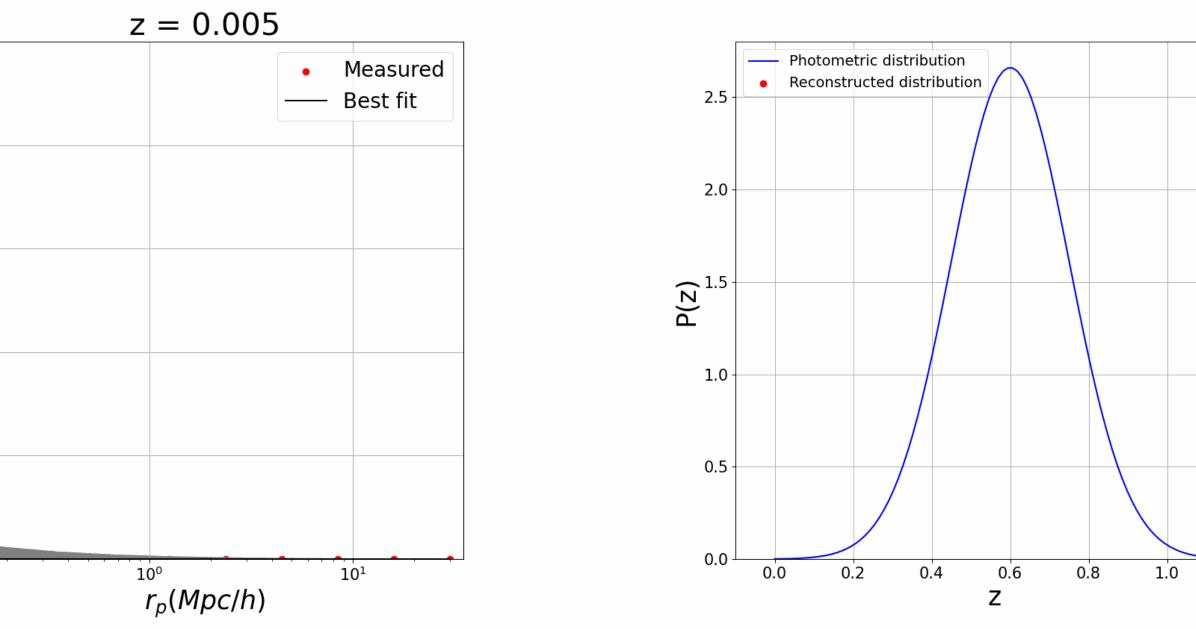
0.2

0.1

0.0 10<sup>-1</sup>

ω<sub>sp</sub>

- Yoki Salcedo (Pitt) will work on adapting and testing RAIL framework for clustering redshifts (RAIL version of yetanother-wizz) for Roman.
- Clustering redshifts can test or improve calibration of redshift distributions.
- Also worked on DESI-2 target selection; DESI and DESI-2 will provide key samples for crosscorrelation



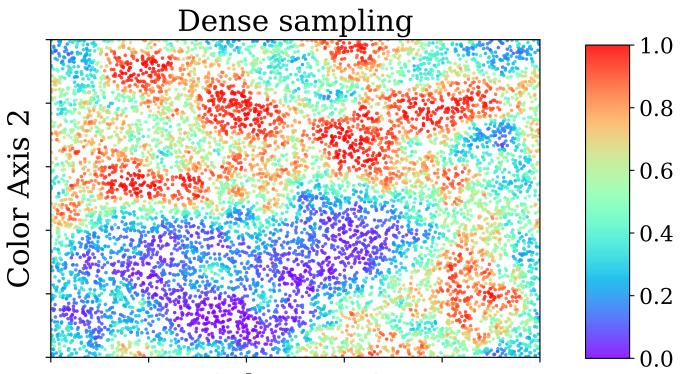
credit: Yoki Salcedo

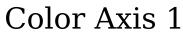




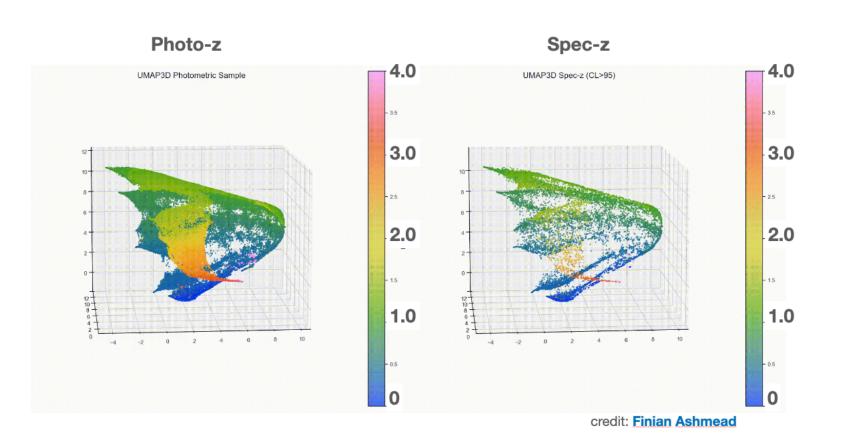
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redshift

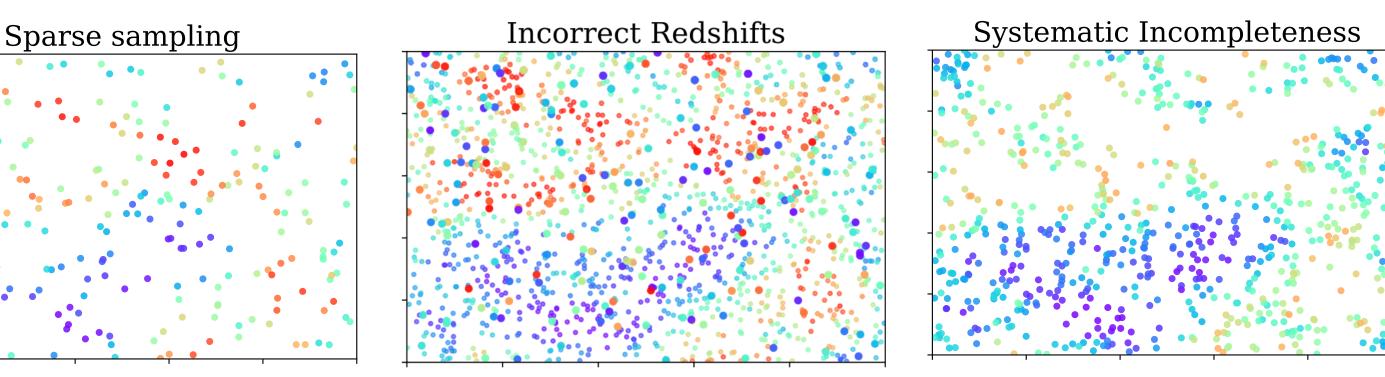




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