

Decoding the Cosmos

Hiranya V. Peiris

***Former Hubble/Fermi/KICP Fellow
2004-2007***



European Research Council
Established by the European Commission



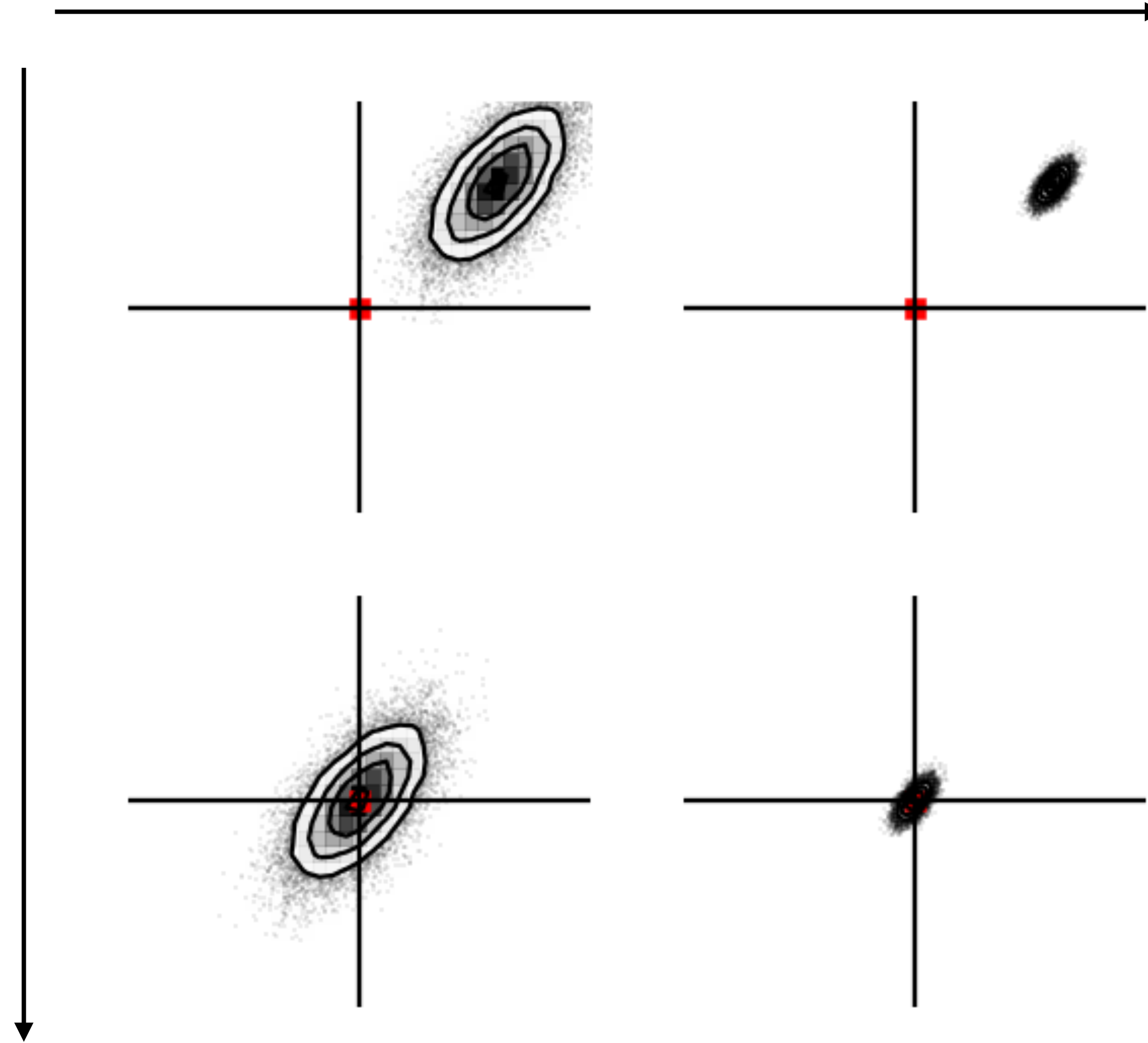
UNIVERSITY OF
CAMBRIDGE



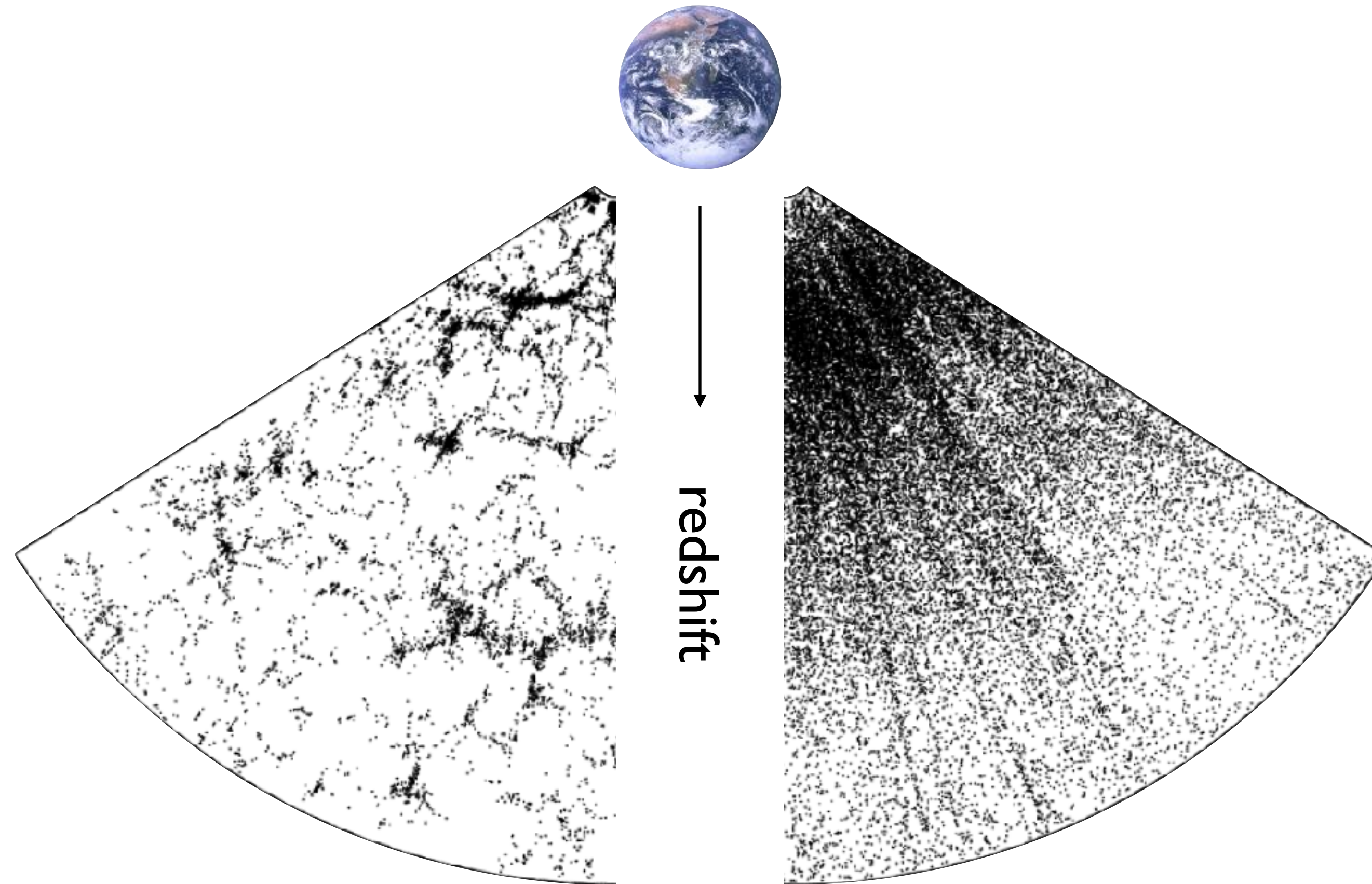
UK Research
and Innovation

precision

accuracy



Observational frontier with galaxy surveys



Spectroscopic
DESI (ground)

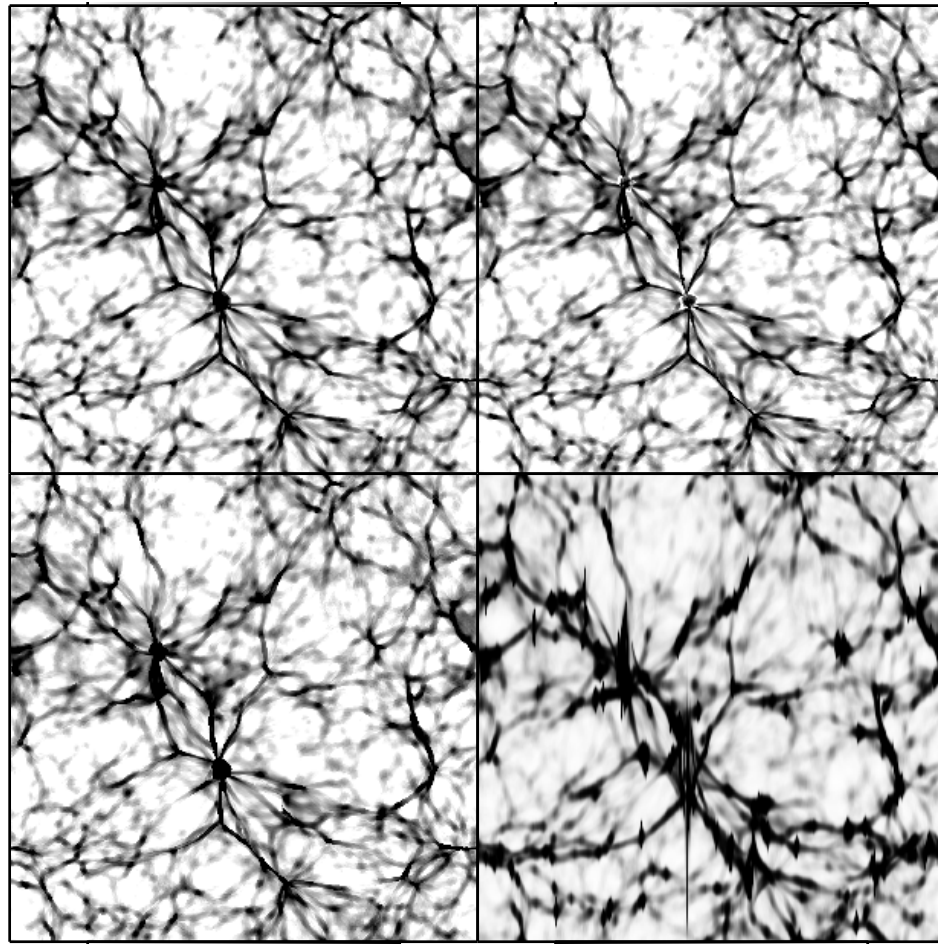
Photometric
LSST (ground), Euclid (space), Roman (space)



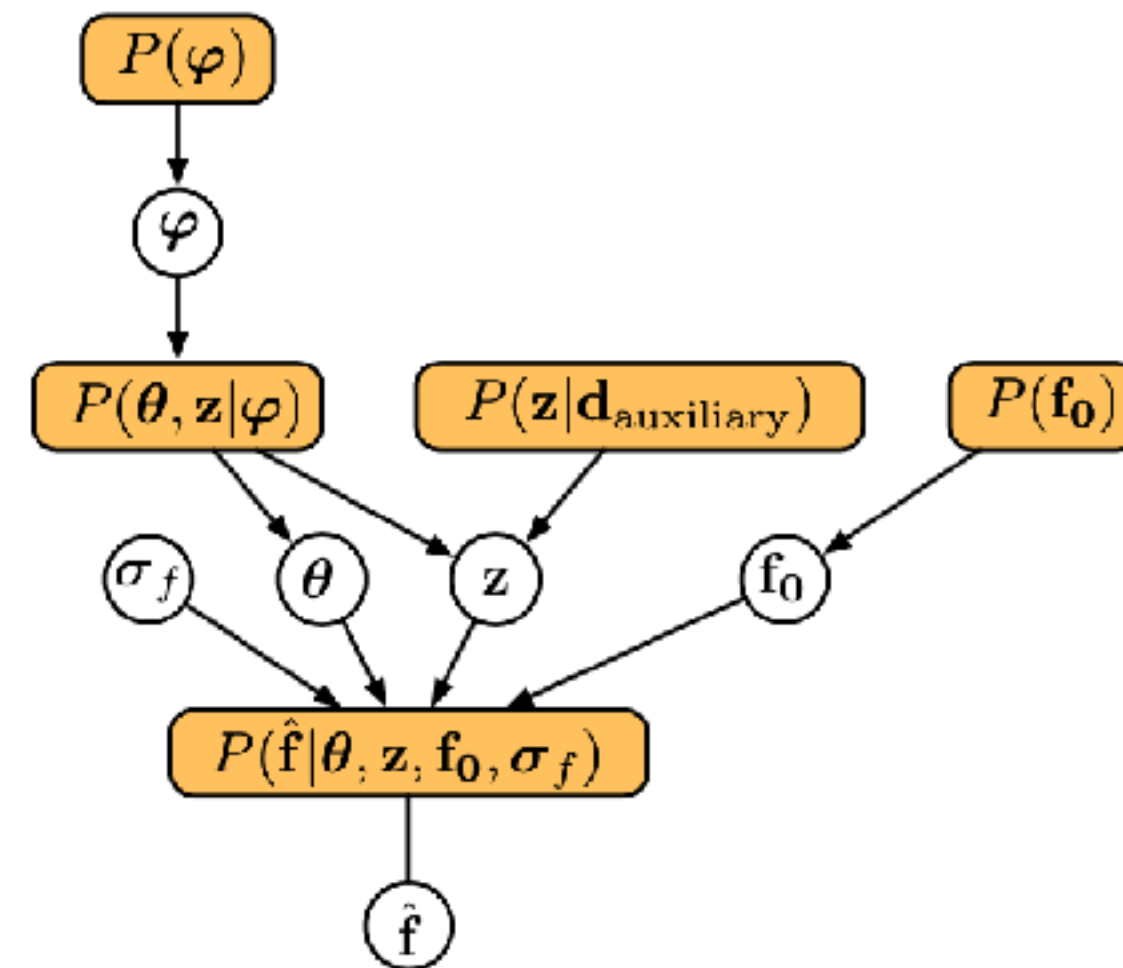
CREDIT: RUBIN OBSERVATORY



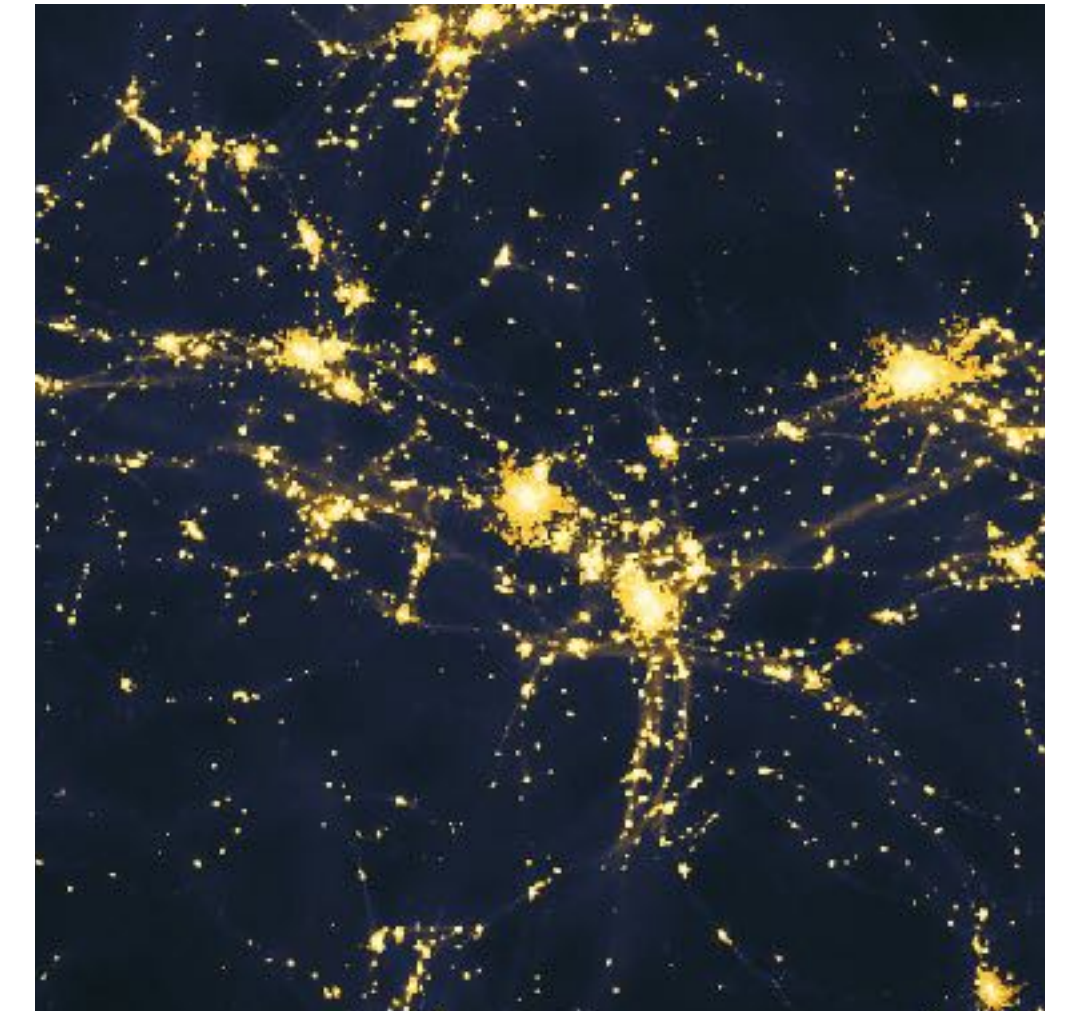
Solving cosmological modelling challenges with machine learning



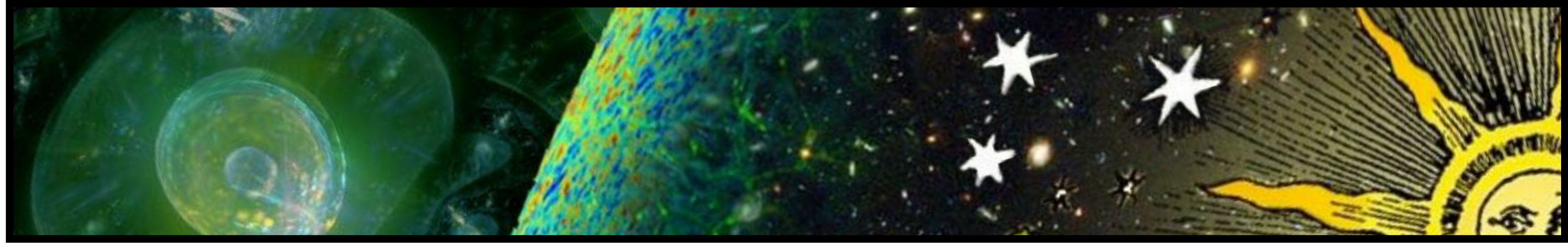
Emulation:
ML-accelerated forward-modelling of observations



Simulation-based inference:
high dimensional cosmological inference with ML-accelerated parts



Explainable AI:
machine-assisted knowledge extraction



Simulation-based inference with ML-accelerated components



Justin Alsing
(OKC/Stockholm)



Stephen Thorp
(OKC/Stockholm)



Sinan Deger
(IoA/KICCC/Cambridge)



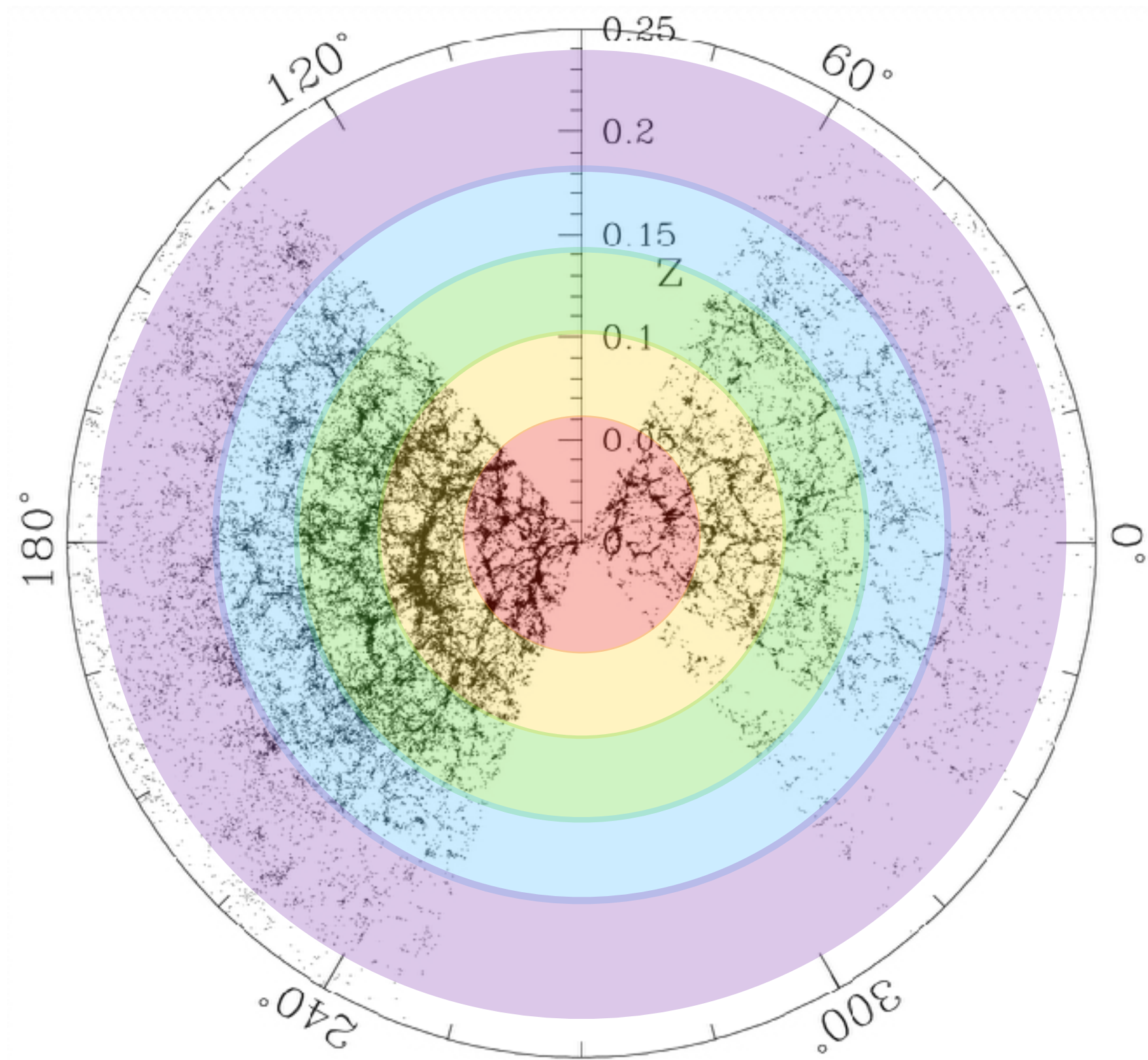
Boris Leistedt
(Imperial College London)



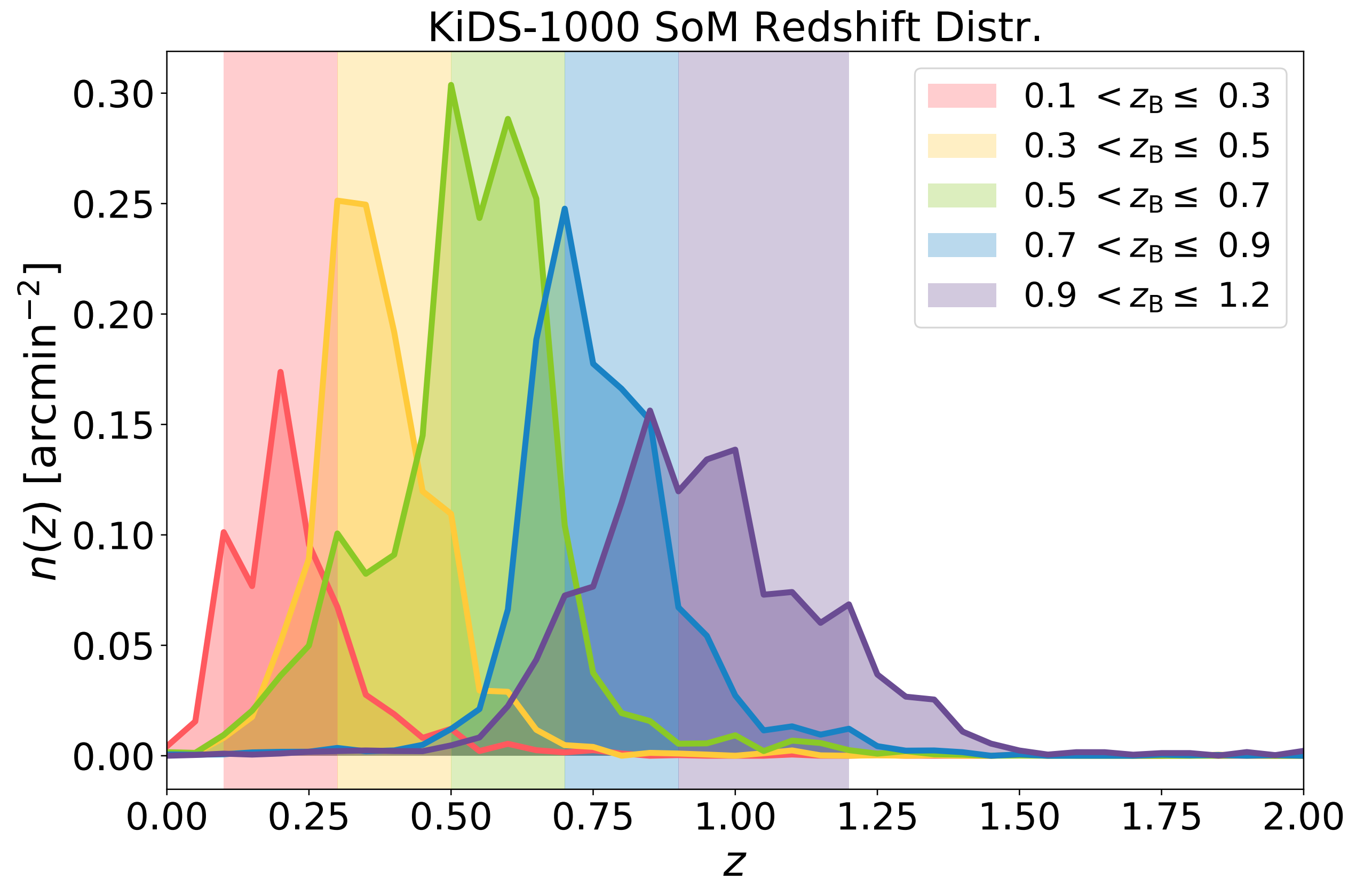
Arthur Loureiro
(OKC/Stockholm)

With: Joel Leja, Daniel Mortlock

Photometric catalogues require redshift estimation



Blanton et al. (2003)

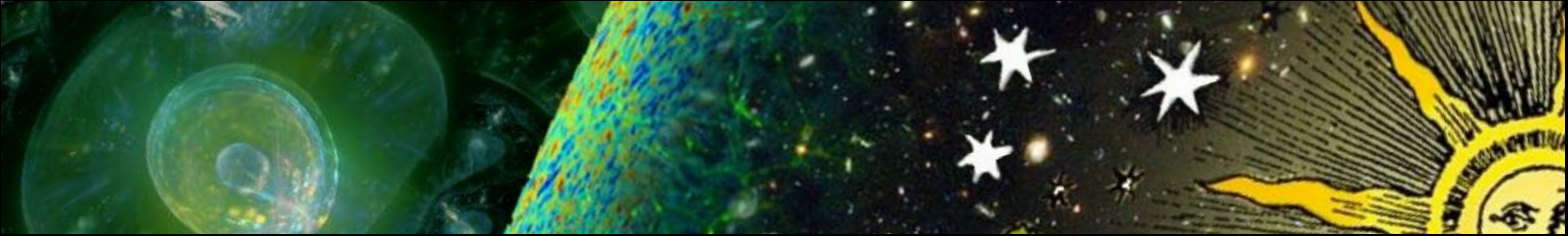


Loureiro et al. (2023)

The background of the slide is a vast field of galaxies, known as the Hubble Ultra Deep Field. It shows a dense collection of galaxies in various colors (yellow, orange, red, blue, purple) and shapes (spiral, elliptical, irregular), scattered across a dark cosmic background. The galaxies are of various sizes and orientations, creating a complex and rich visual texture.

Key idea: learn joint distribution of galaxy properties over cosmic history

Machine learning models can accurately describe this complicated web of interdependencies



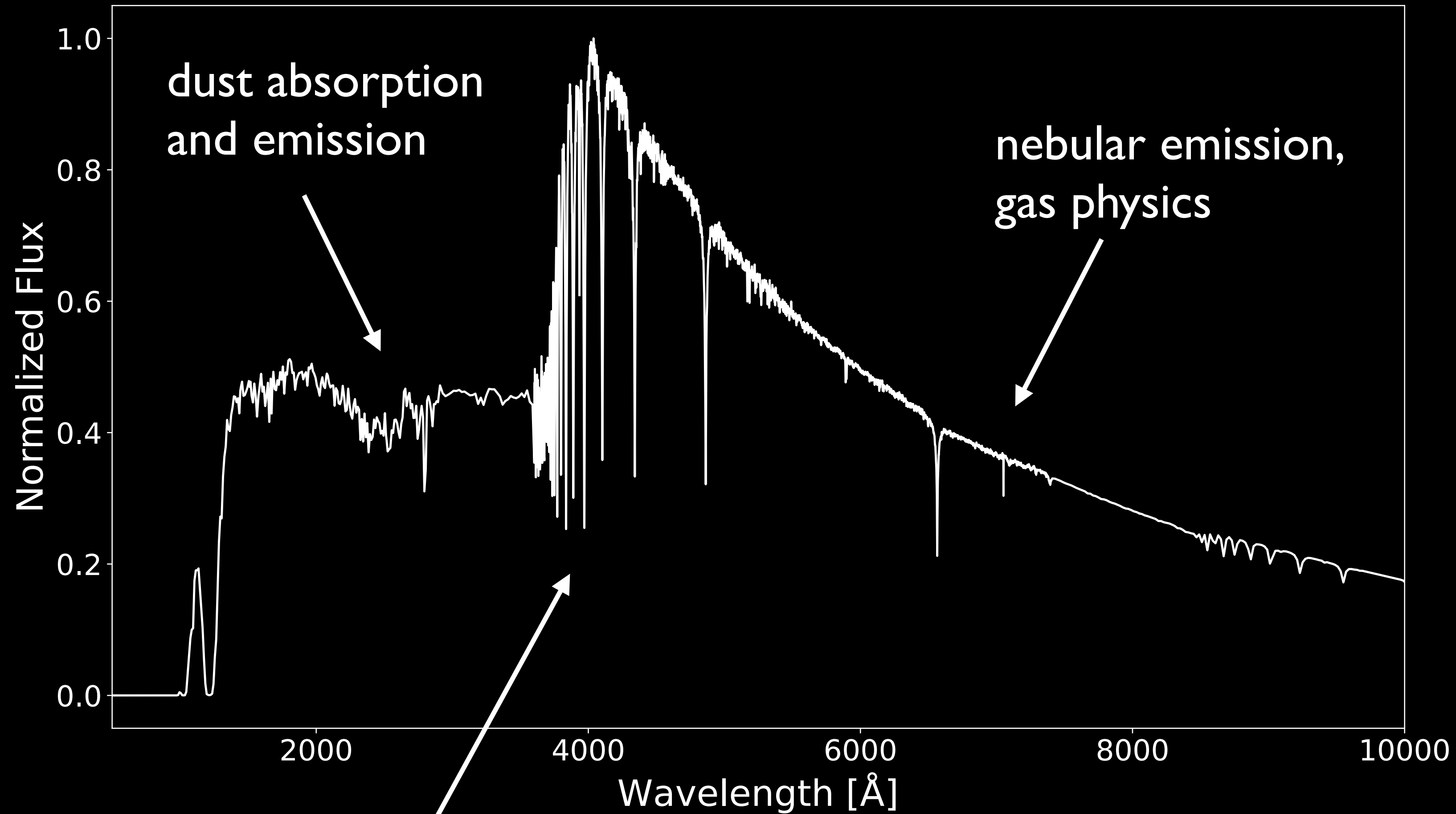
***To decode the cosmos,
we need to understand galaxies***

Recipe for making galaxy spectra and colours

- mass
- star formation history
- dust
- gas
- metallicity
- active galactic nuclei
- redshift
- ...

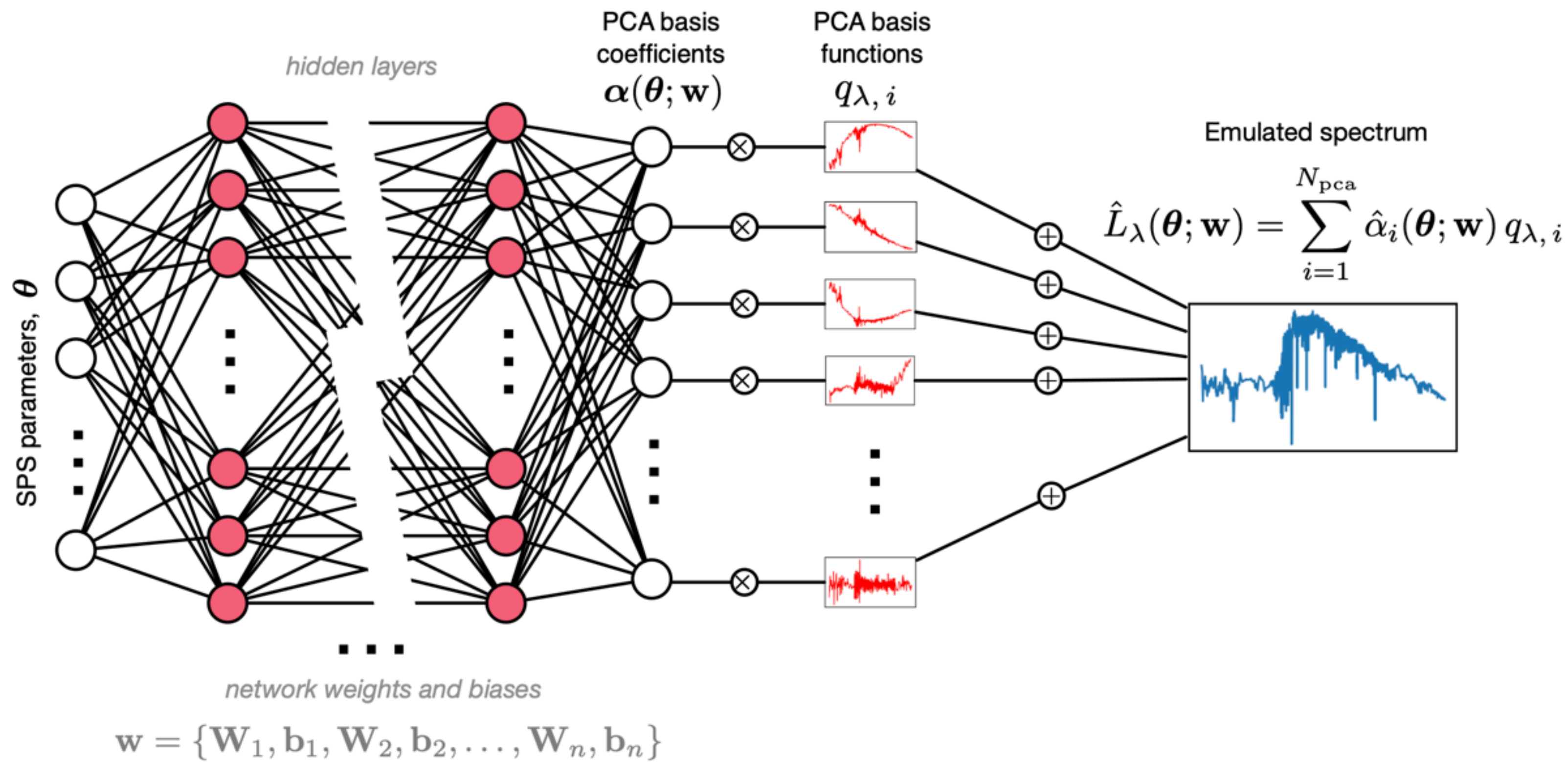


Model galaxy spectra using stellar population synthesis

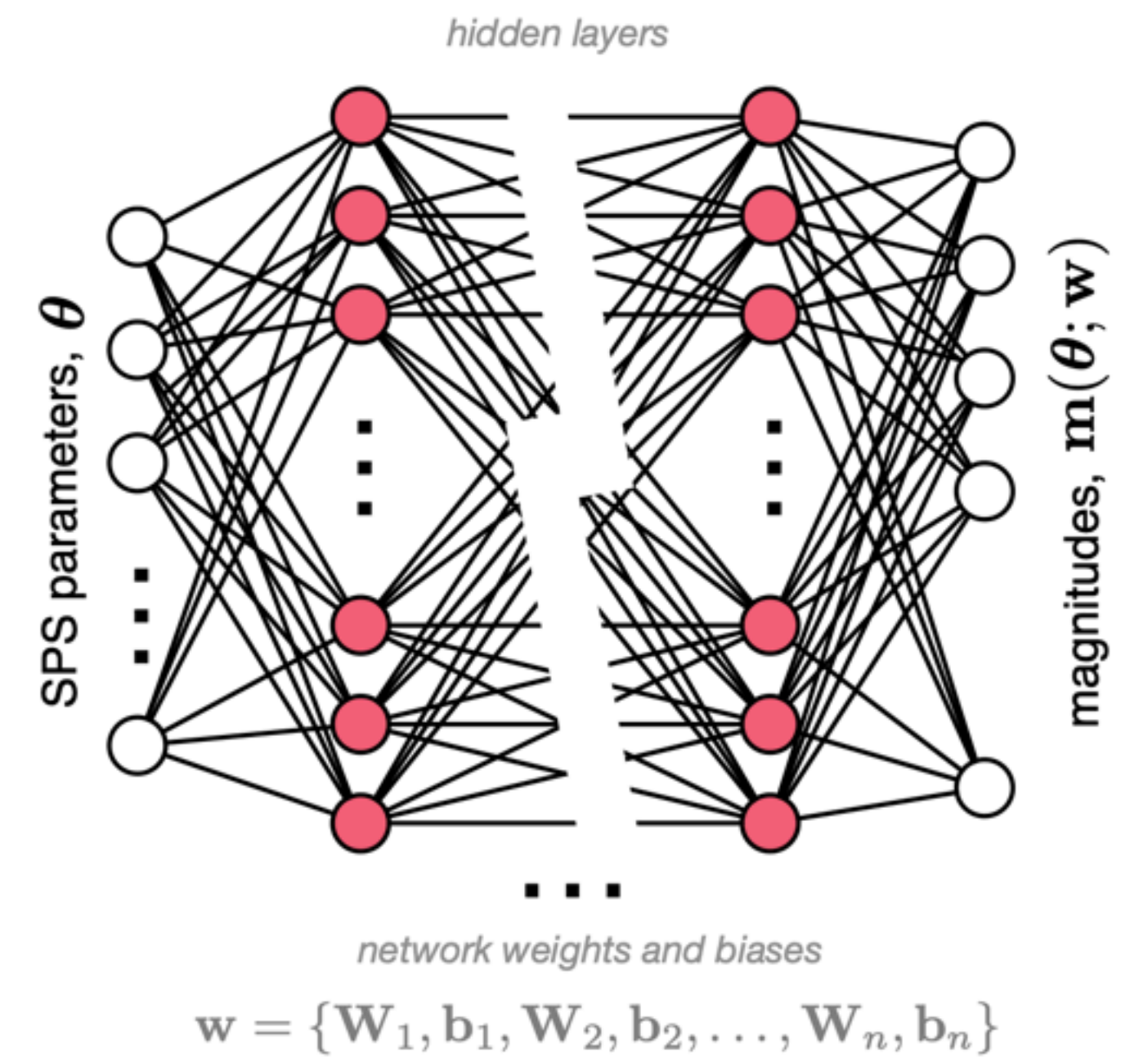


add up light from all the stars (at their ages and metallicities)

Speeding things up with neural emulators



Emulating spectra

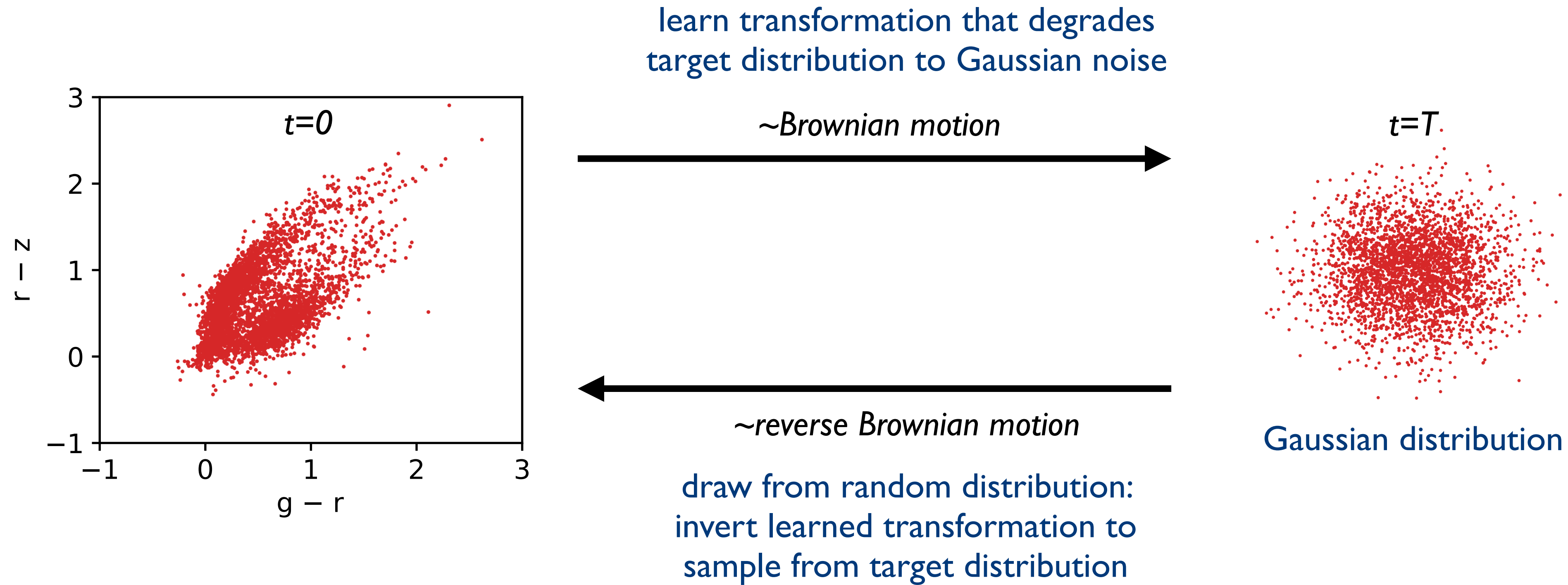


Emulating photometry

16-parameter SPS model | sub-percent accuracy | factors x 10⁴ speed-up | differentiable

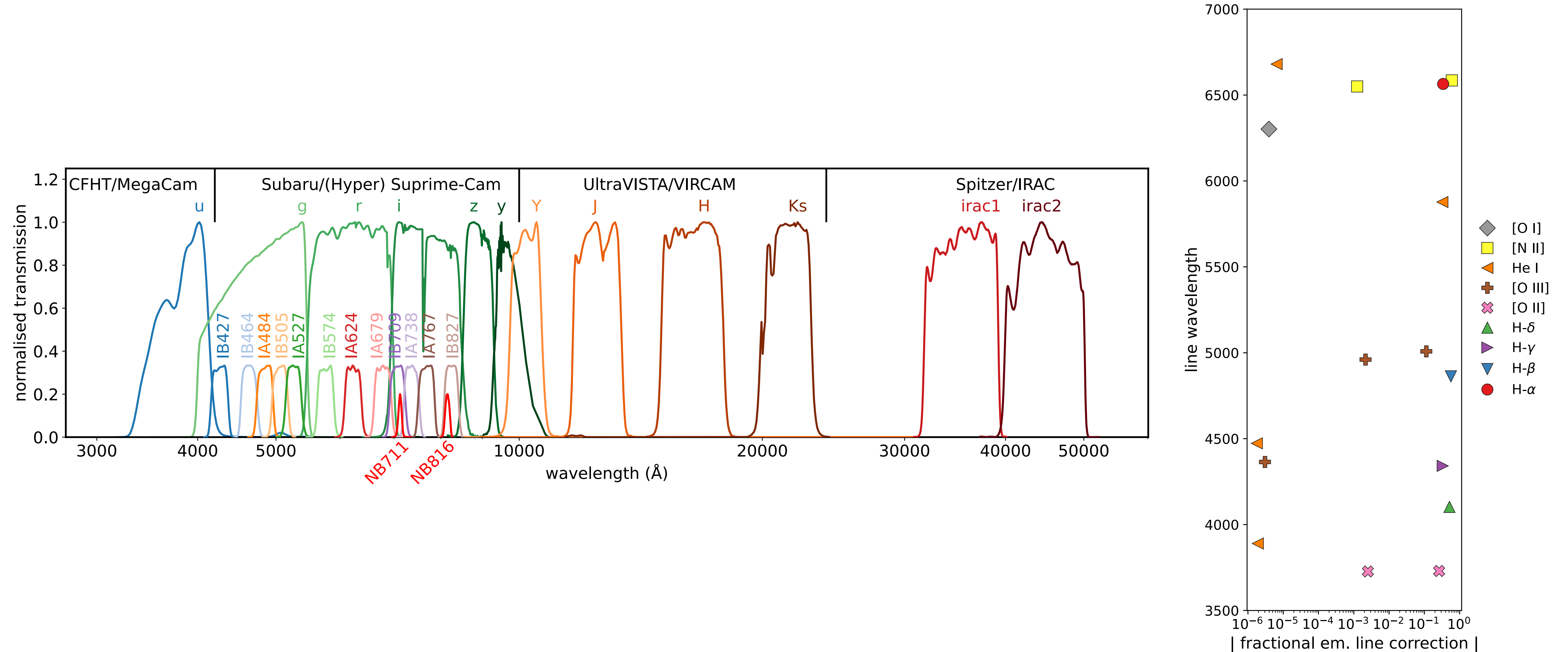
ALSING, PEIRIS, LEJA, HAHN, TOJEIRO, MORTLOCK, LEISTEDT, JOHNSON, CONROY (APJS, 2020)

Flexible neural models for distribution of galaxy properties



score-based diffusion model

Pop-Cosmos: galaxy population model calibrated with COSMOS2020

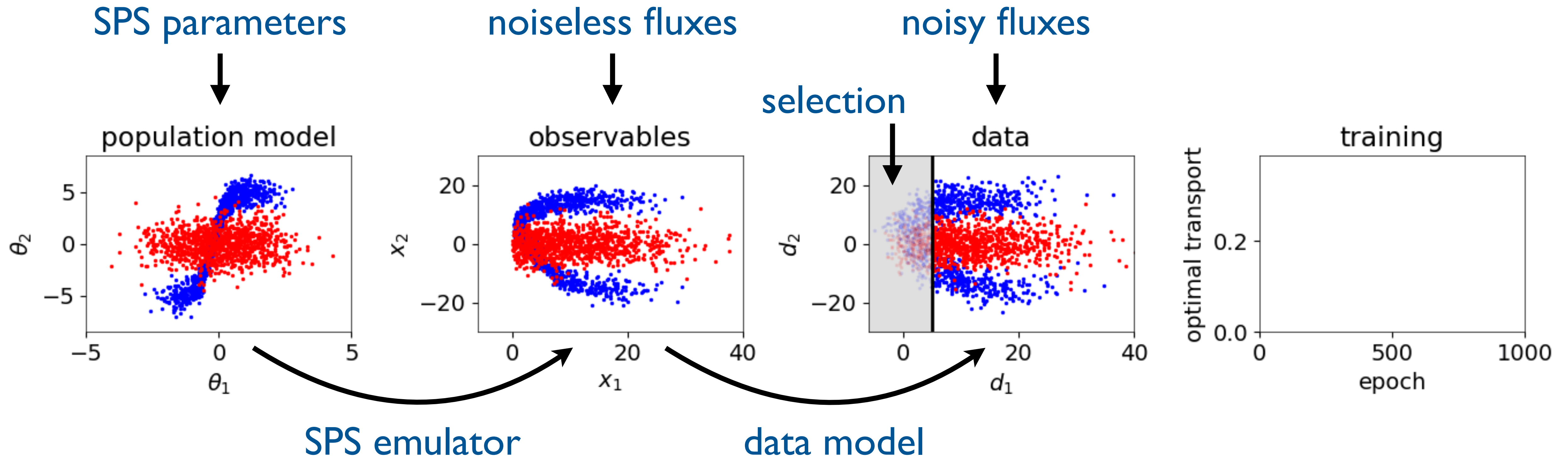


~140,000 galaxies | 26 bands near-UV to mid-IR | deep $z < 4$ | simple selection $r < 25$

Zero-point calibration | emission line corrections | Student-t uncertainty model

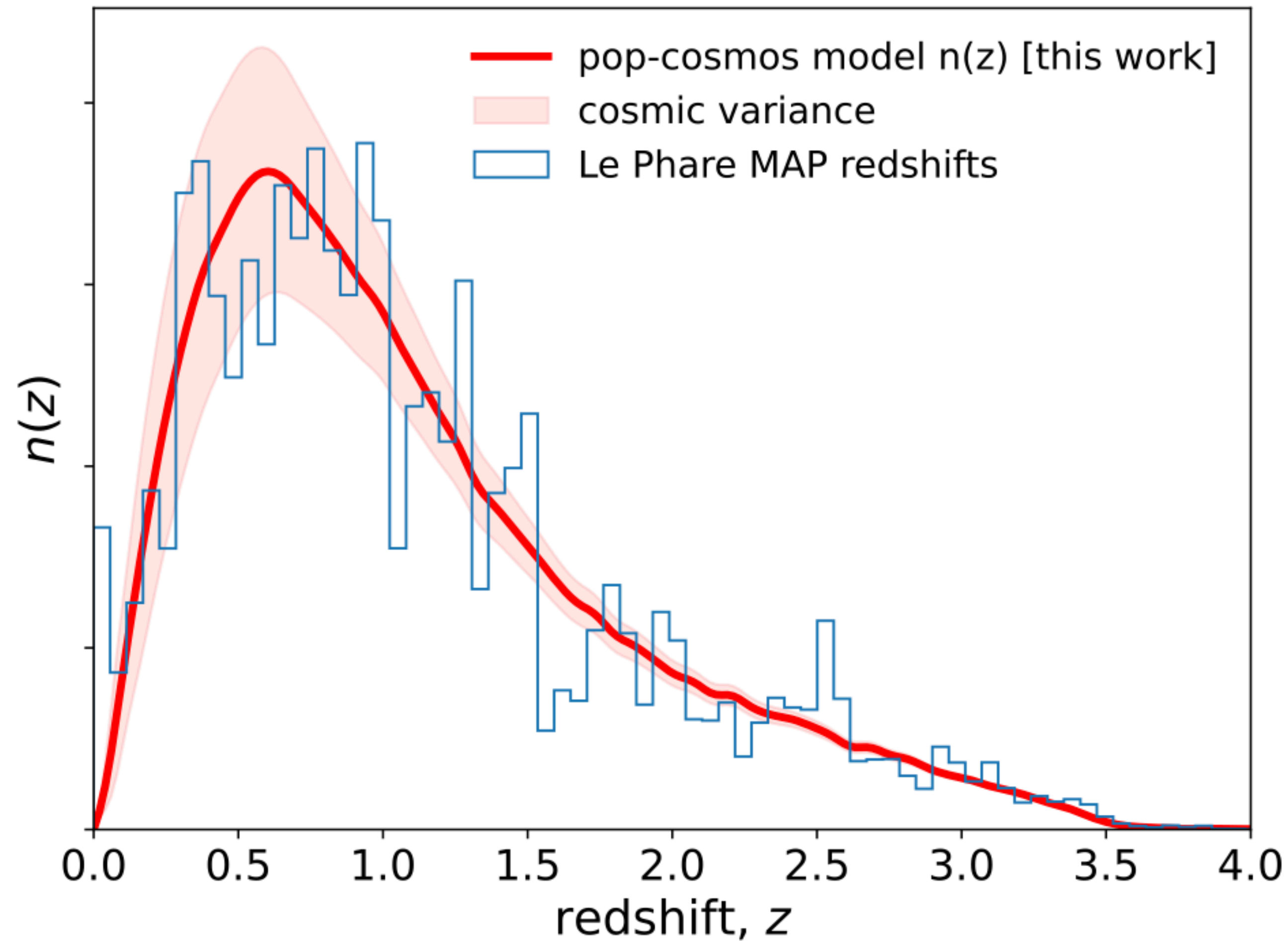
WEAVER ET AL (2021), ALSING ET AL (2022, APJS), LEISTEDT ET AL. (2022, APJS), ALSING ET AL (ARXIV:2402.00935)

Learning the galaxy population model



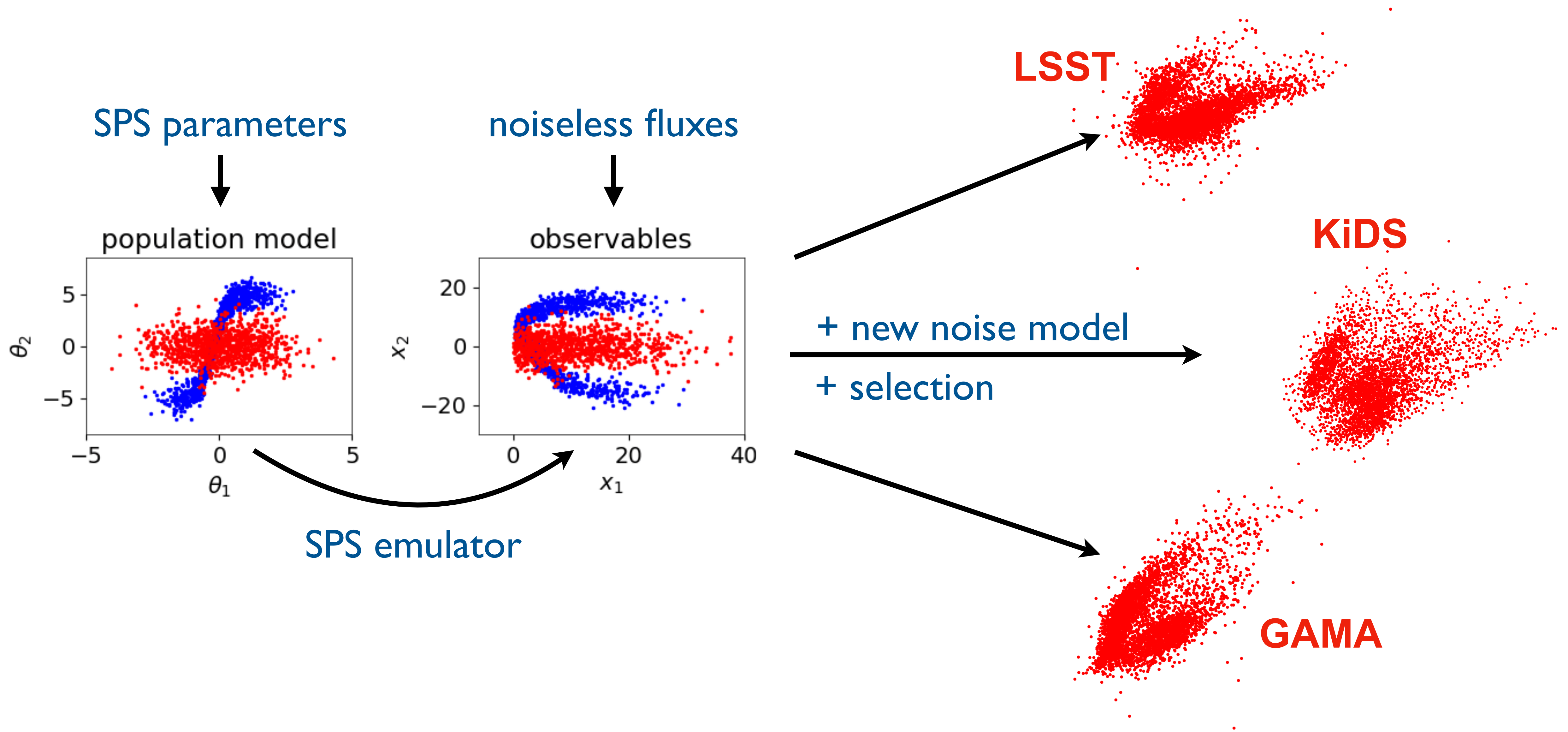
Pop-Cosmos: a generative model for galaxy surveys

Pop-Cosmos prediction for COSMOS2020 redshift distribution

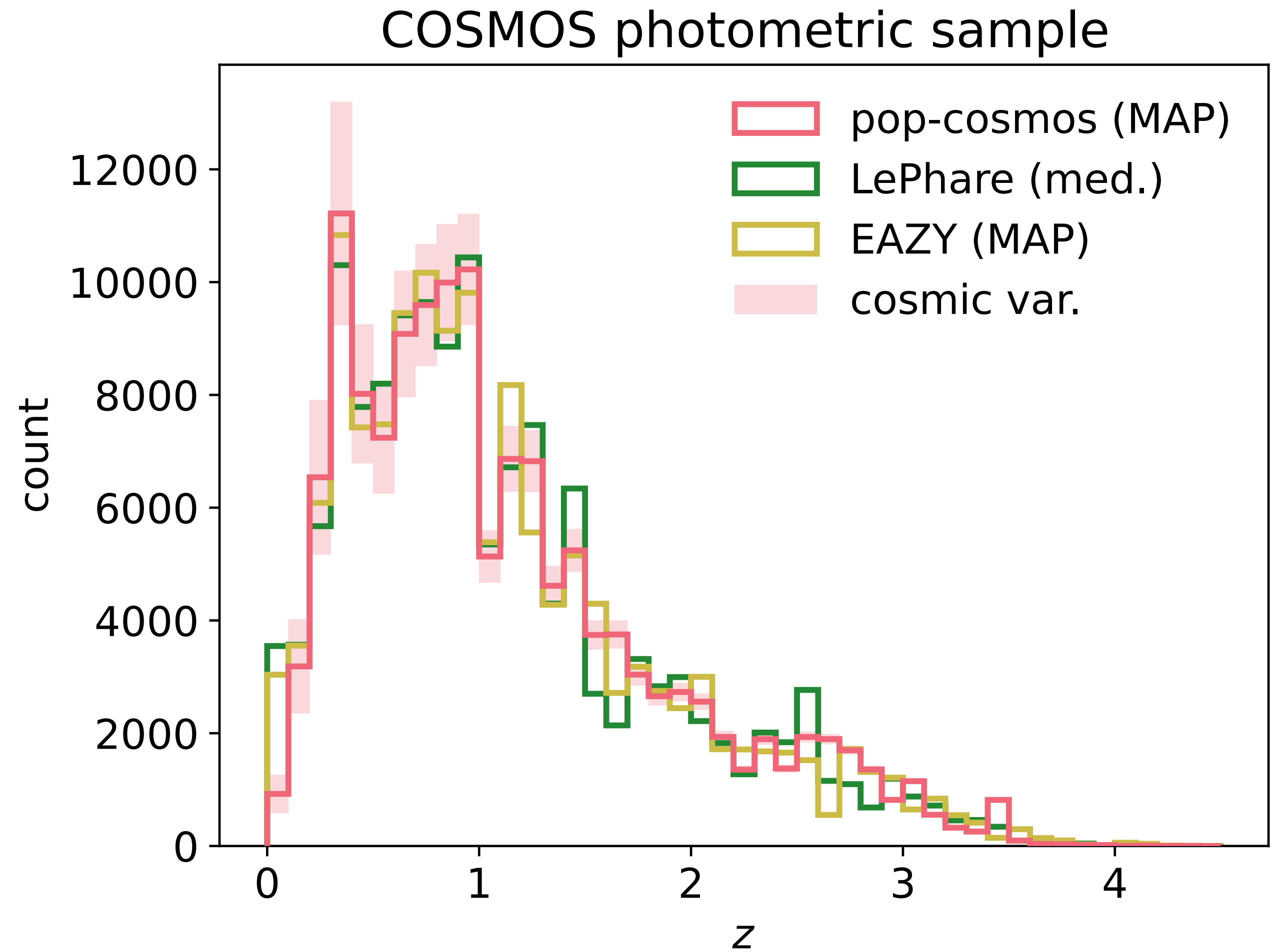
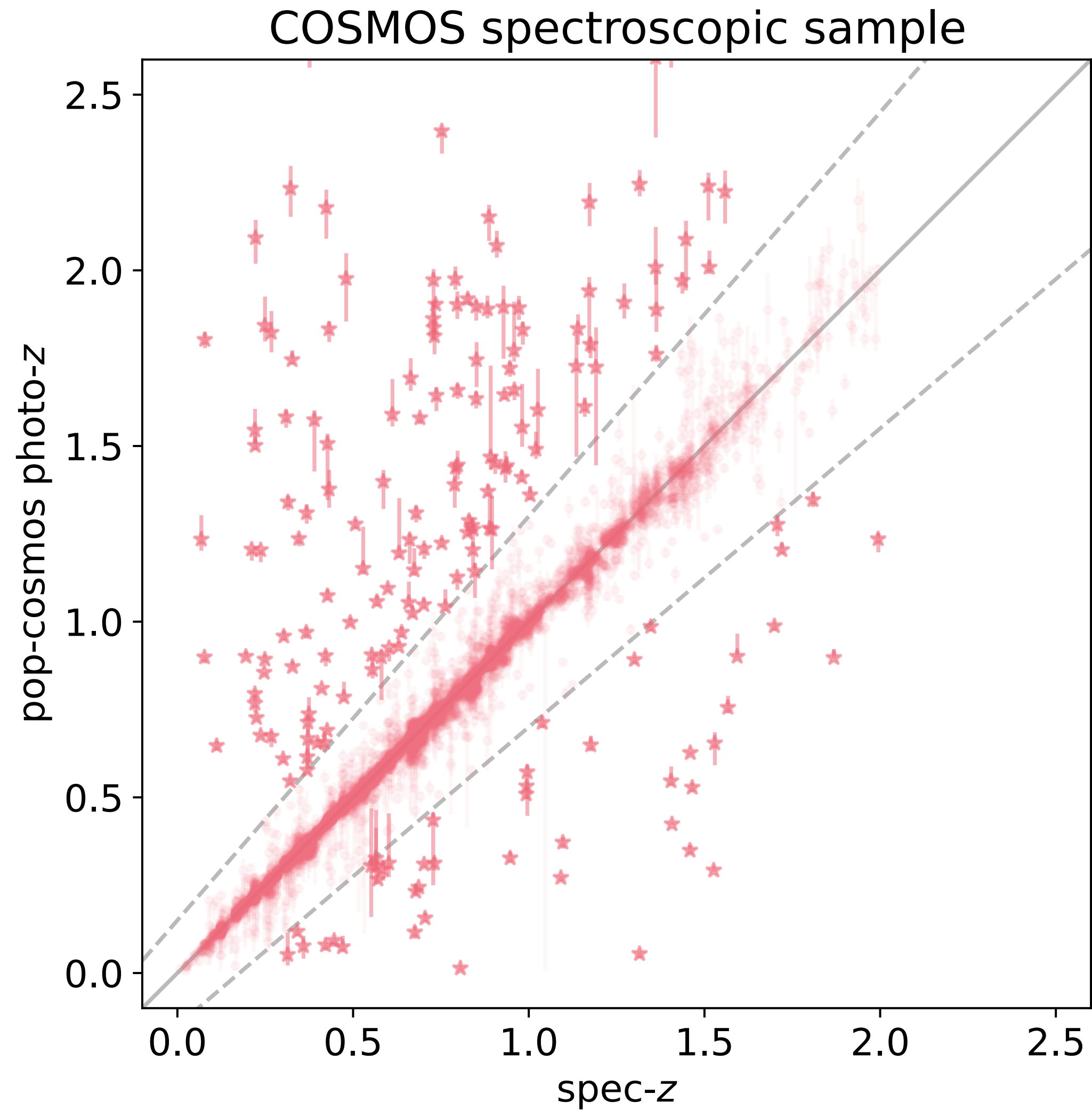


- *First time full joint density of galaxy properties has been estimated from large galaxy catalogue*
- *Can predict properties (incl. redshift distribution) of any catalogue of comparable / shallower depth*
- *Bonus: information on full galaxy population over cosmic time*

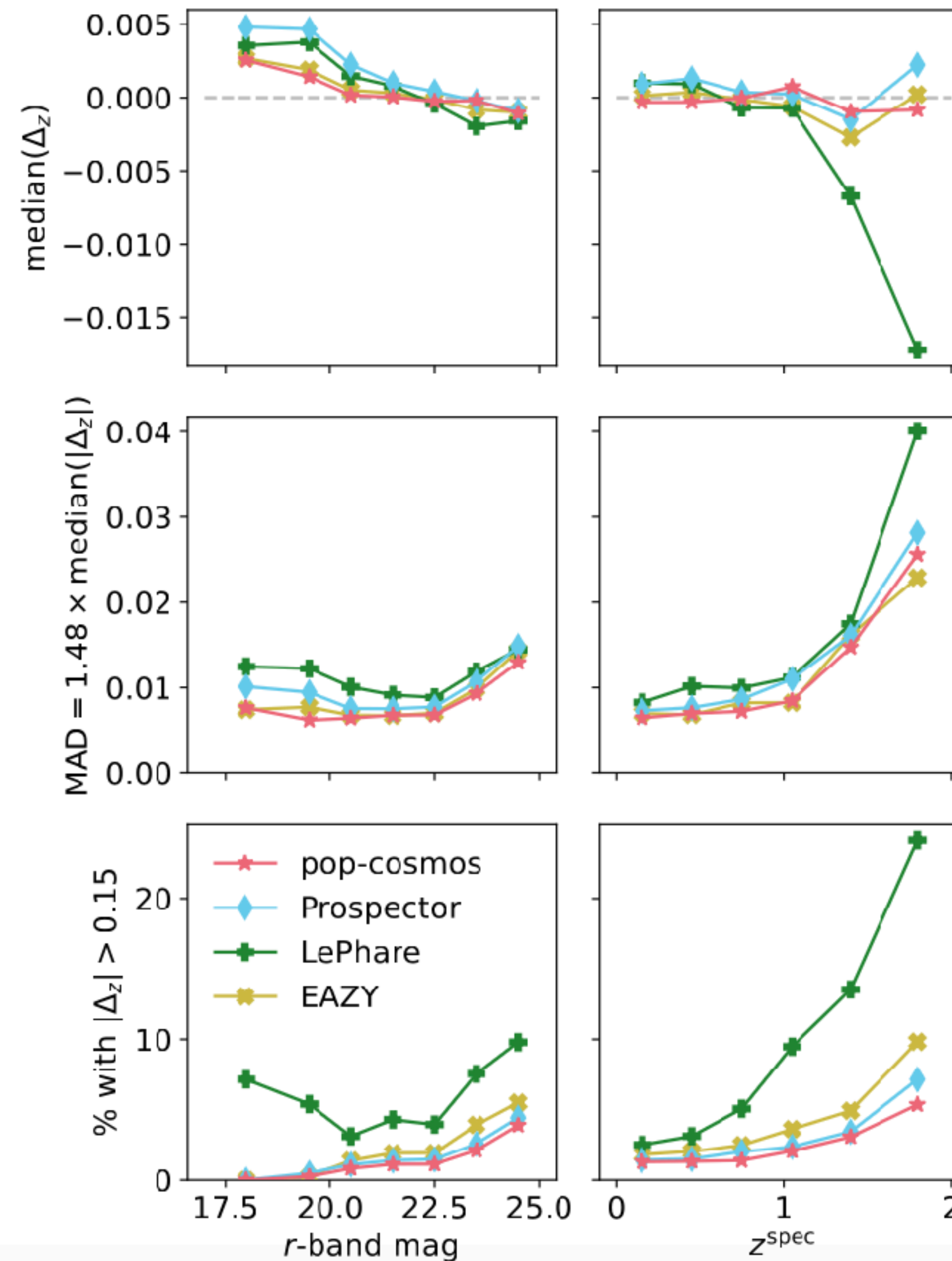
Forward-modelling other catalogues



Pop-Cosmos as a prior for galaxy photo-z inference



Quality of individual redshifts

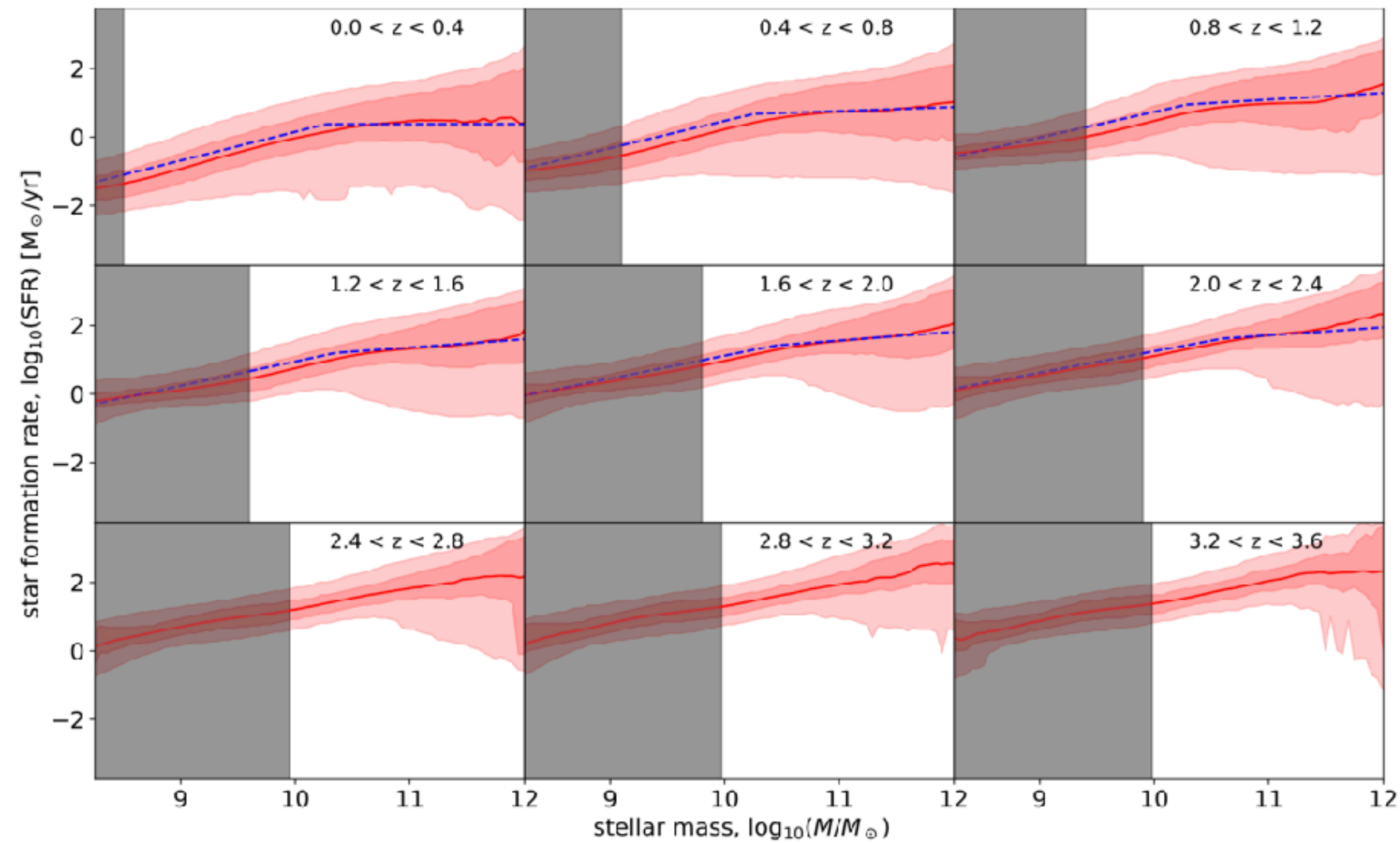


less biased

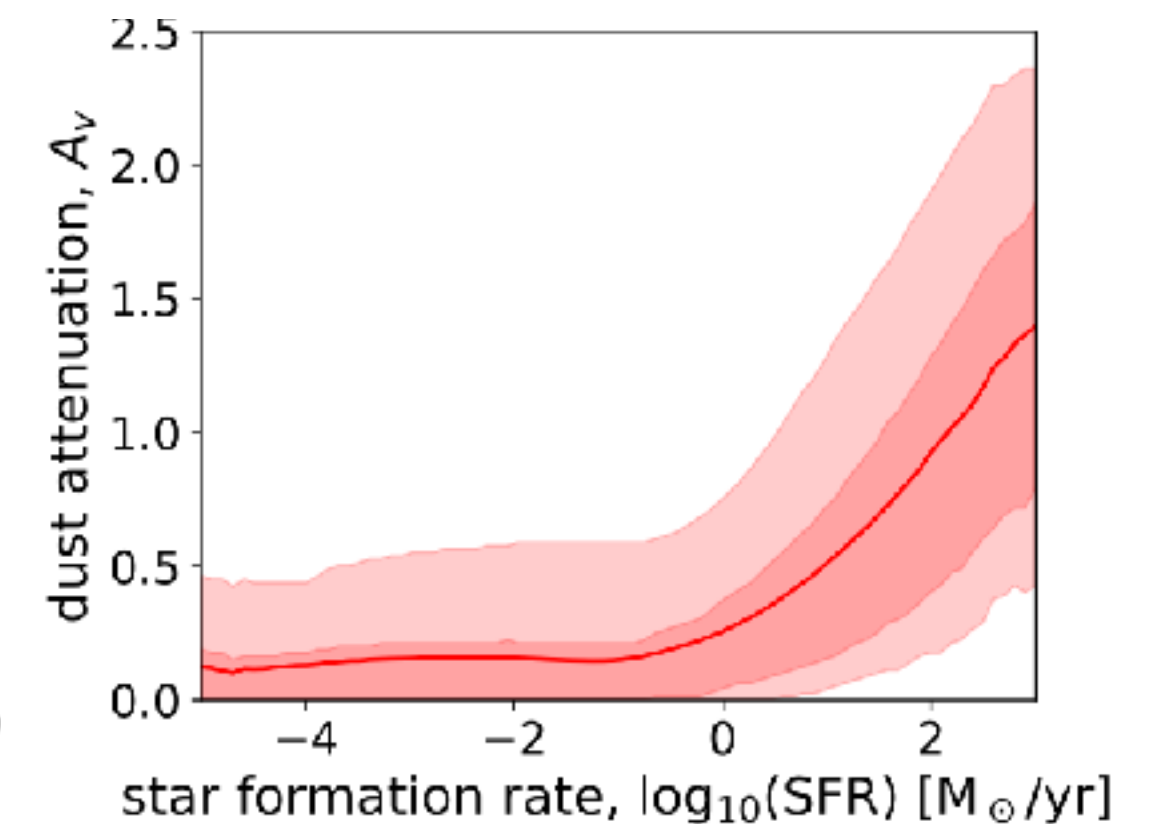
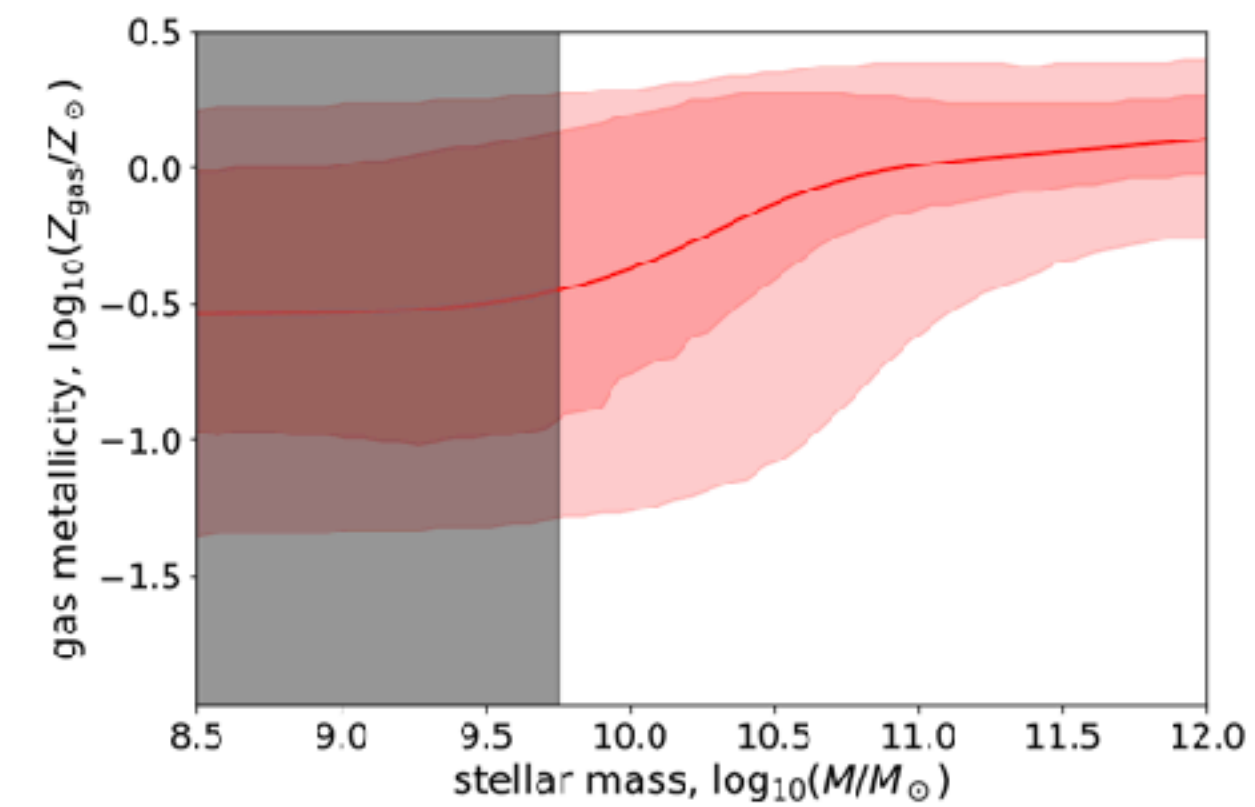
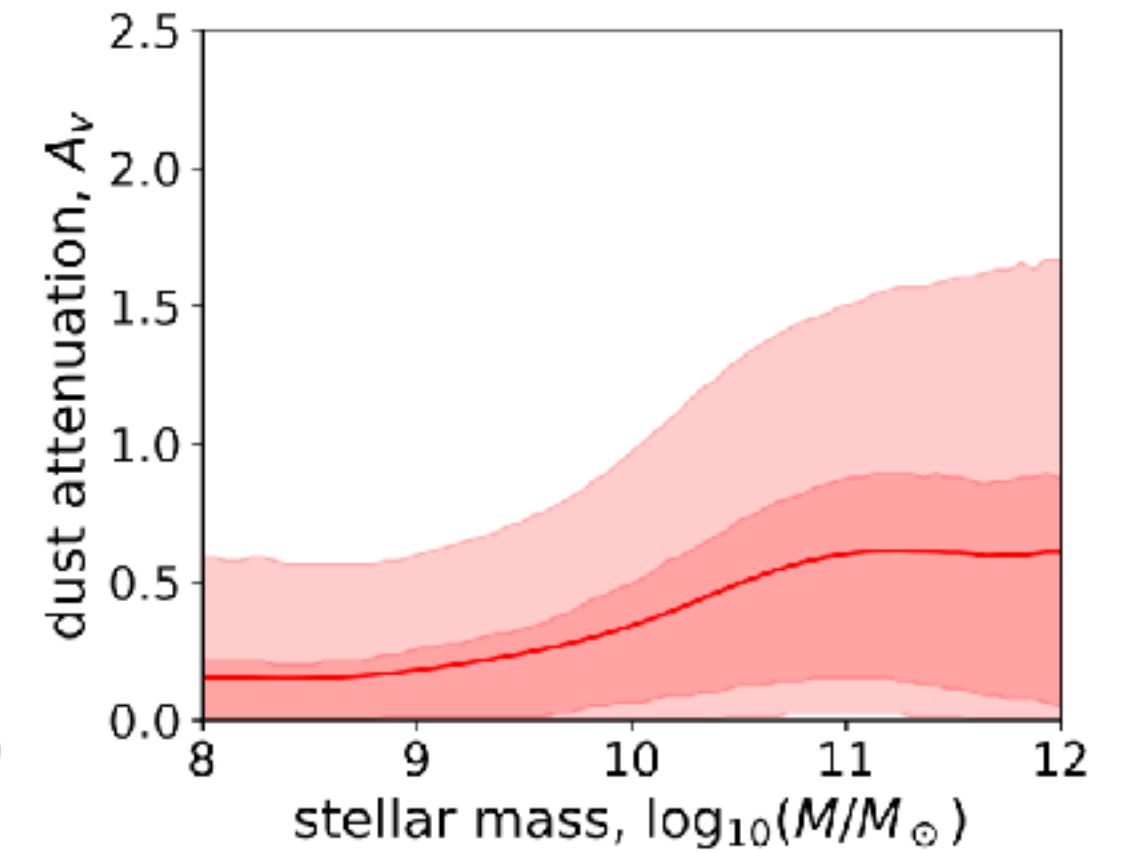
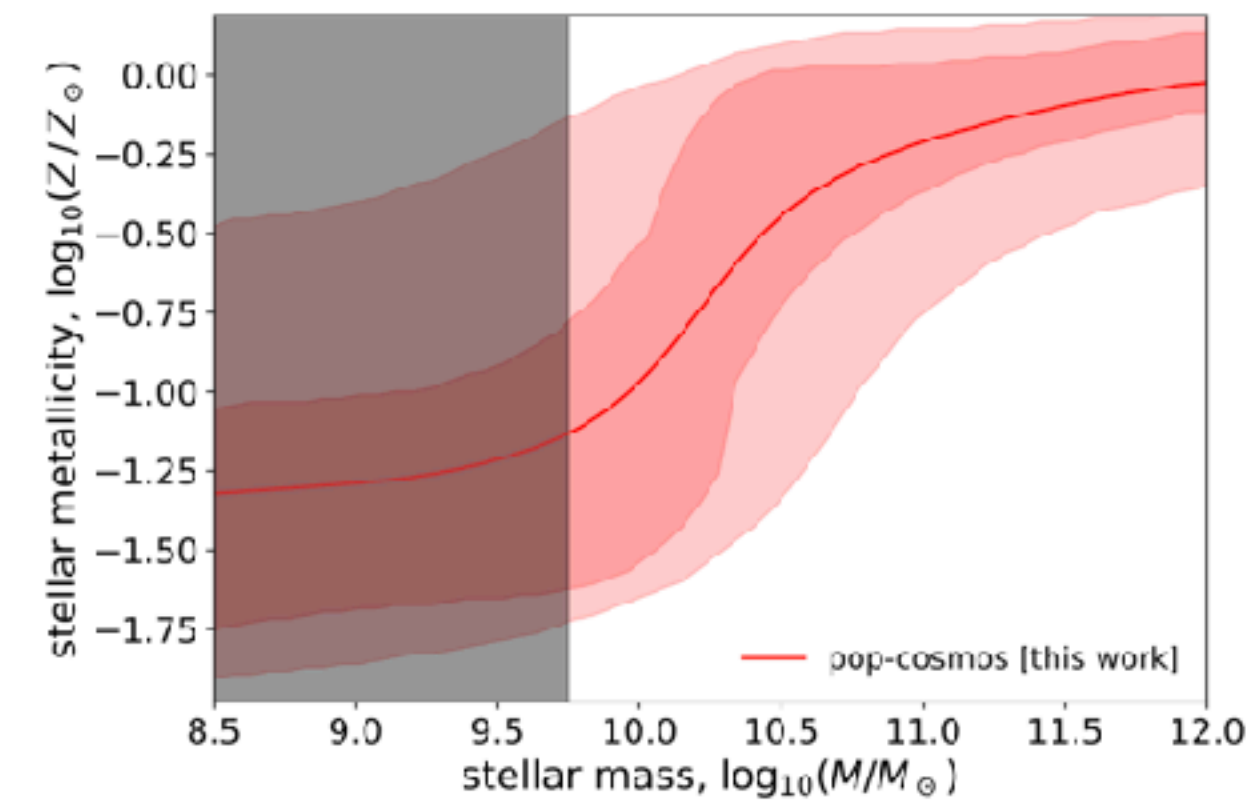
smaller errors

fewer outliers

Bonus: information on full galaxy population over cosmic time

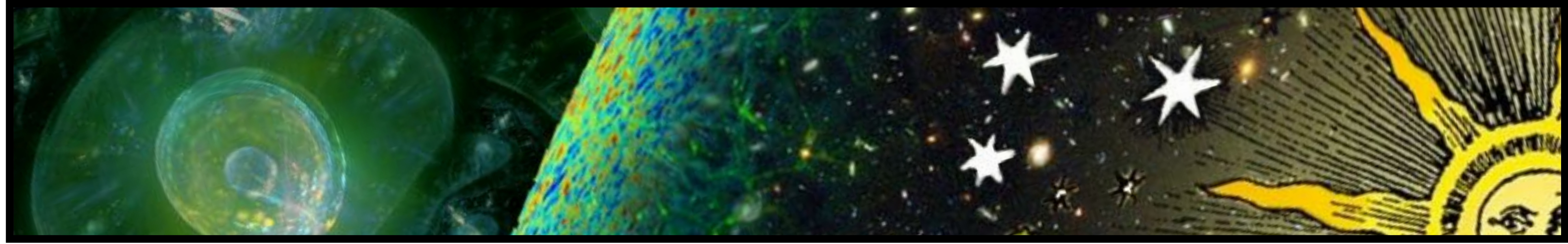


star forming sequence



metallicity

dust



Knowledge extraction using deep learning



Luisa Lucie-Smith
(MPA/Garching)



Andrew Pontzen
(UCL)



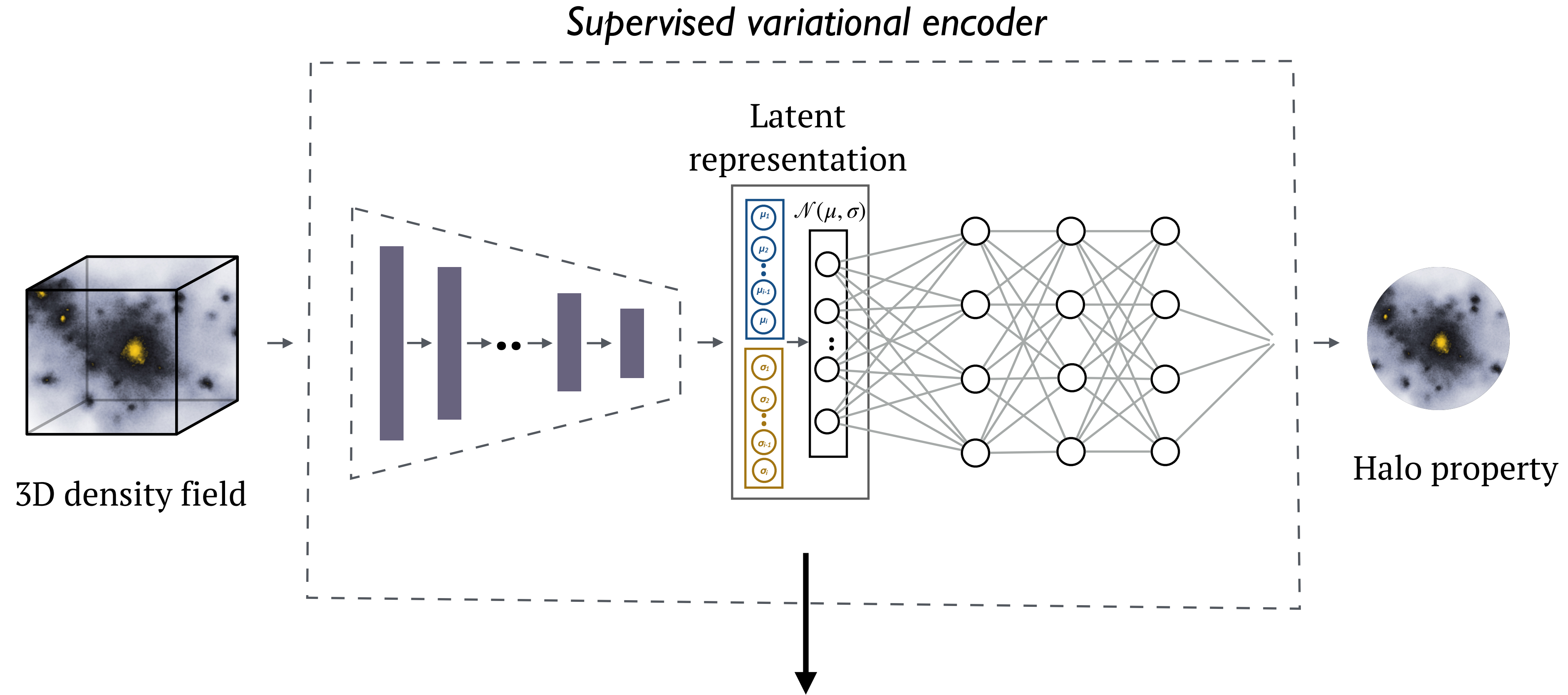
Lillian Guo
(UCL)



Davide Piras
(Geneva)

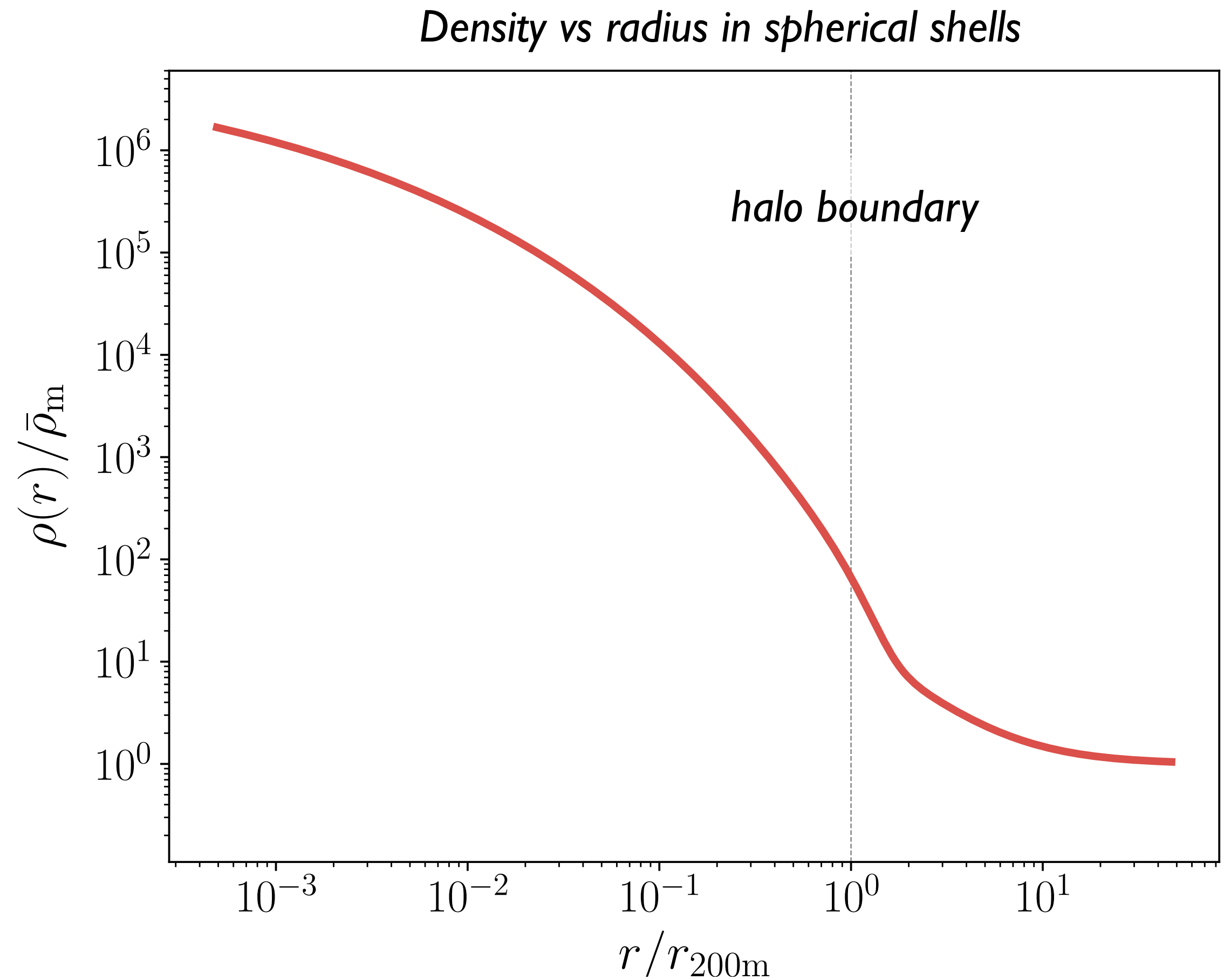
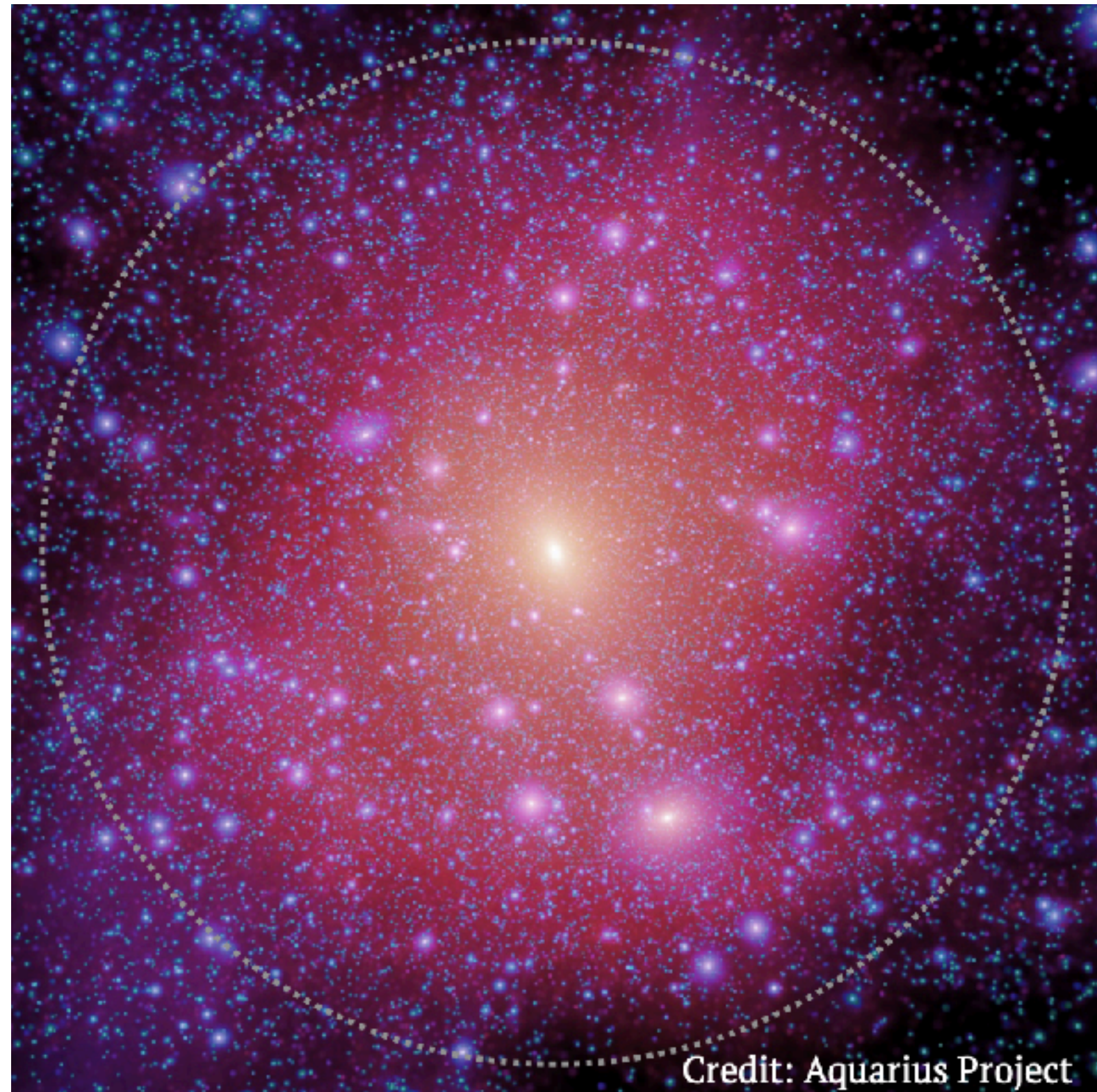
With: Brian Nord, Jeyan Thiyagalingam

Frameworks for knowledge extraction using AI



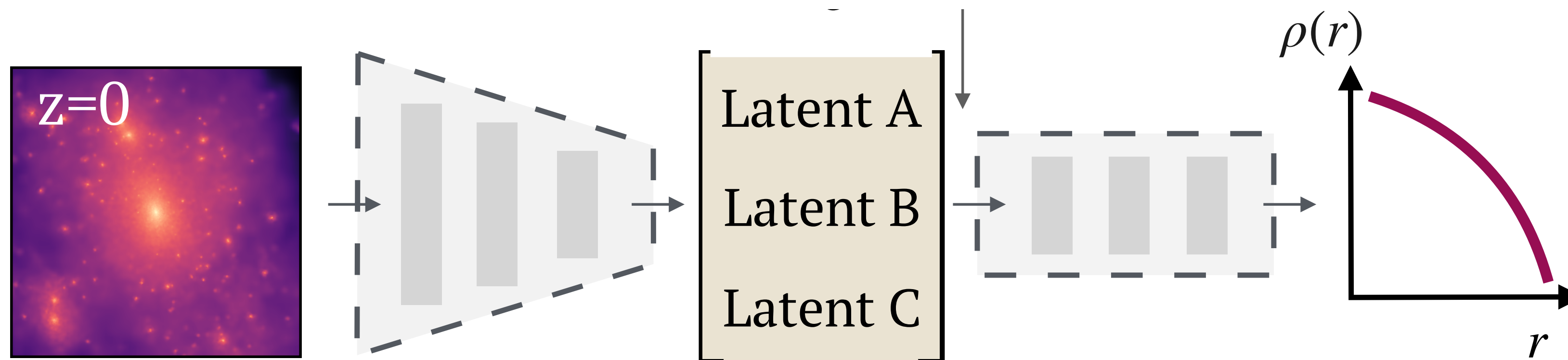
Model compression to enable “explainable” AI

Dark matter halo density profiles

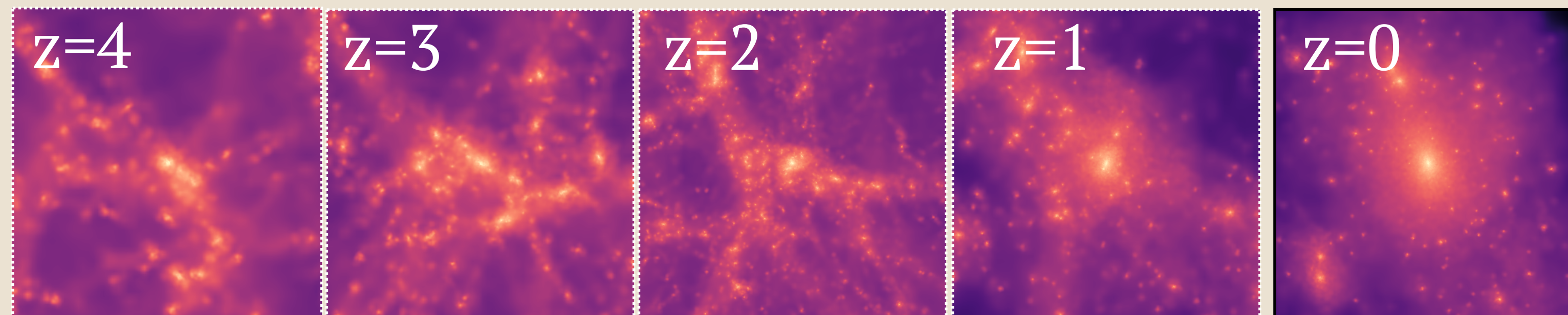


Key ingredient in cosmological analyses and beyond
(e.g. dark matter detection)

What physics is encoded in the dark matter halo profile?



Mutual information between latents and halo assembly history



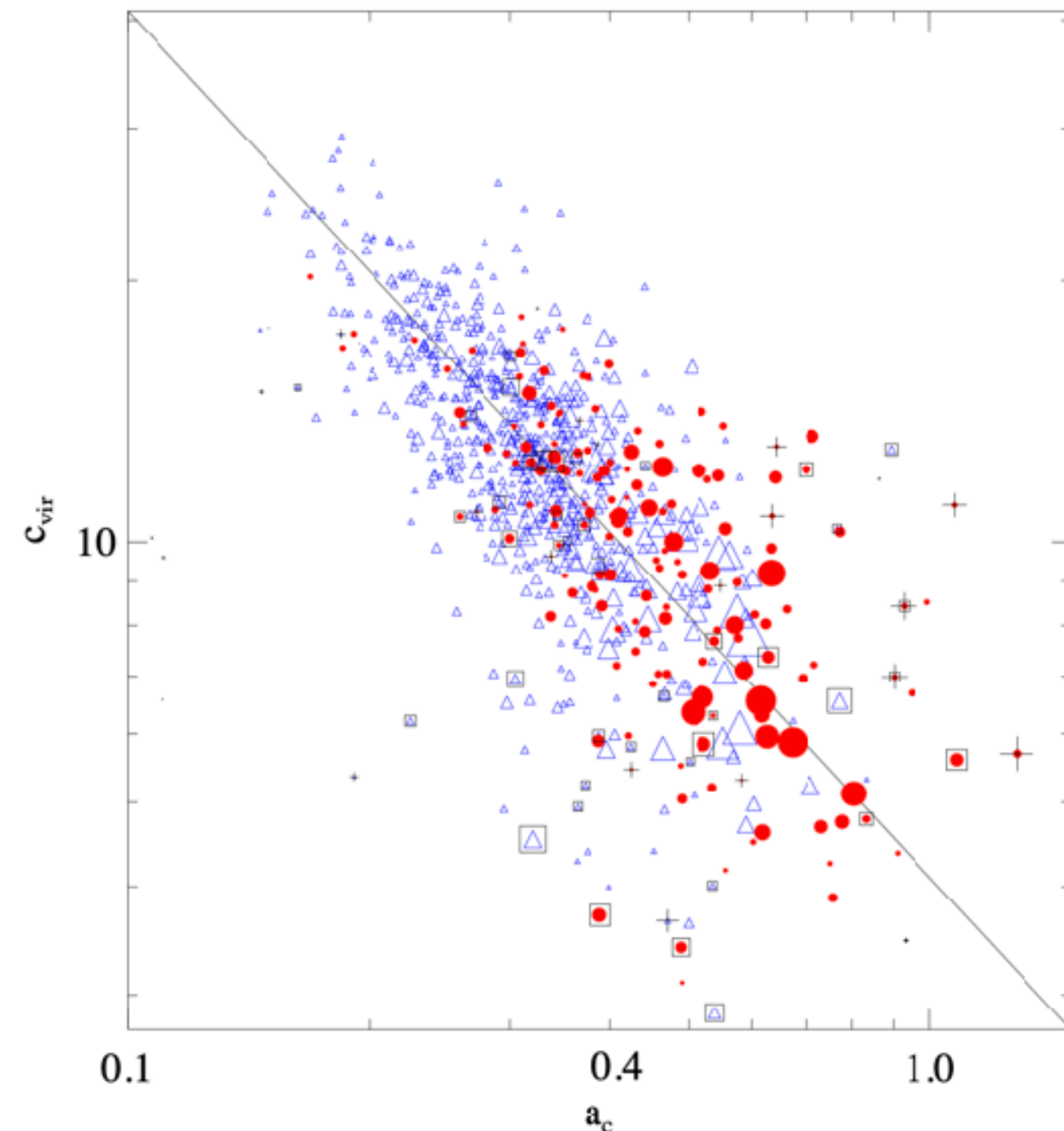
Cosmological simulation

Network **not given assembly history of halos during training.**

The learnt degrees of freedom nevertheless **relate to halos' mass accretion history in specific, interpretable ways.**

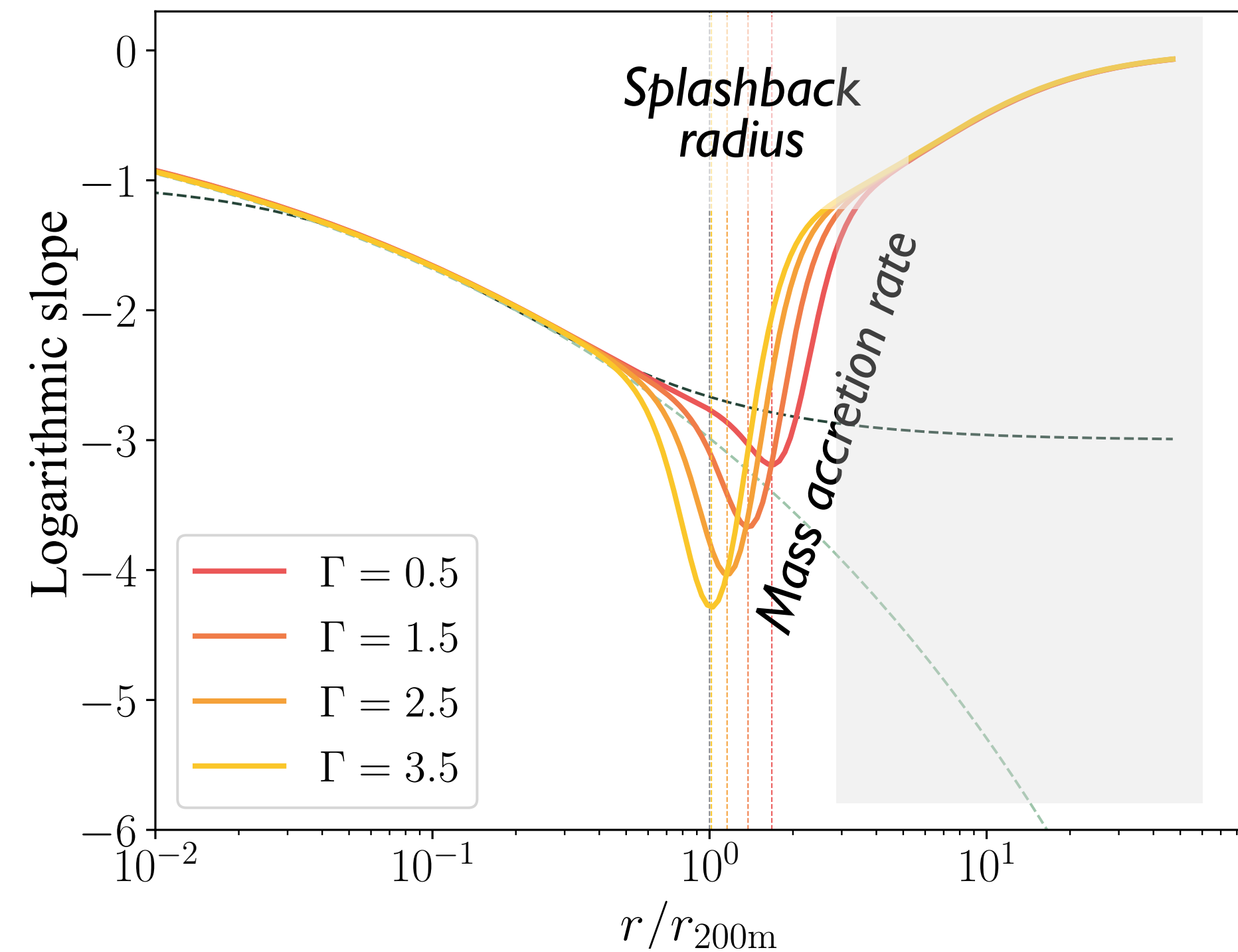
Seeing halo properties in terms of their full evolution histories

IVE recovers known relation between **inner profile** and **early assembly history**



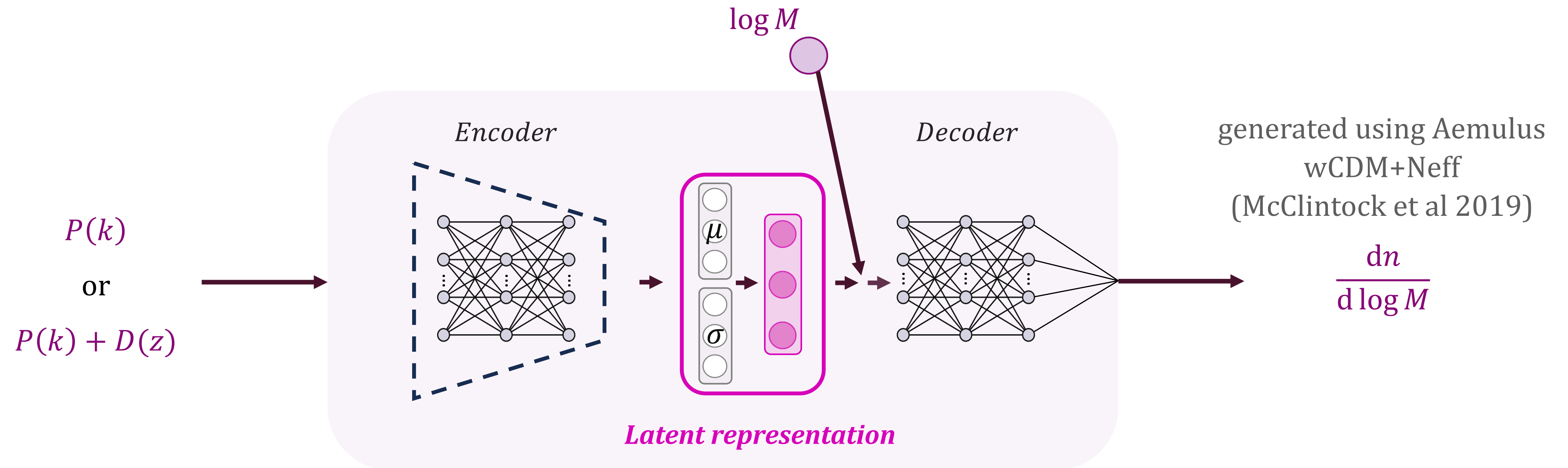
Halo concentration versus formation epoch
(e.g. Wechsler et al 2002)

IVE discovers that **outer profile** depends on **single dof** related to **most recent accretion rate**



Relation to splashback radius
(e.g. Diemer 2020)

Understanding non-universality in halo mass function

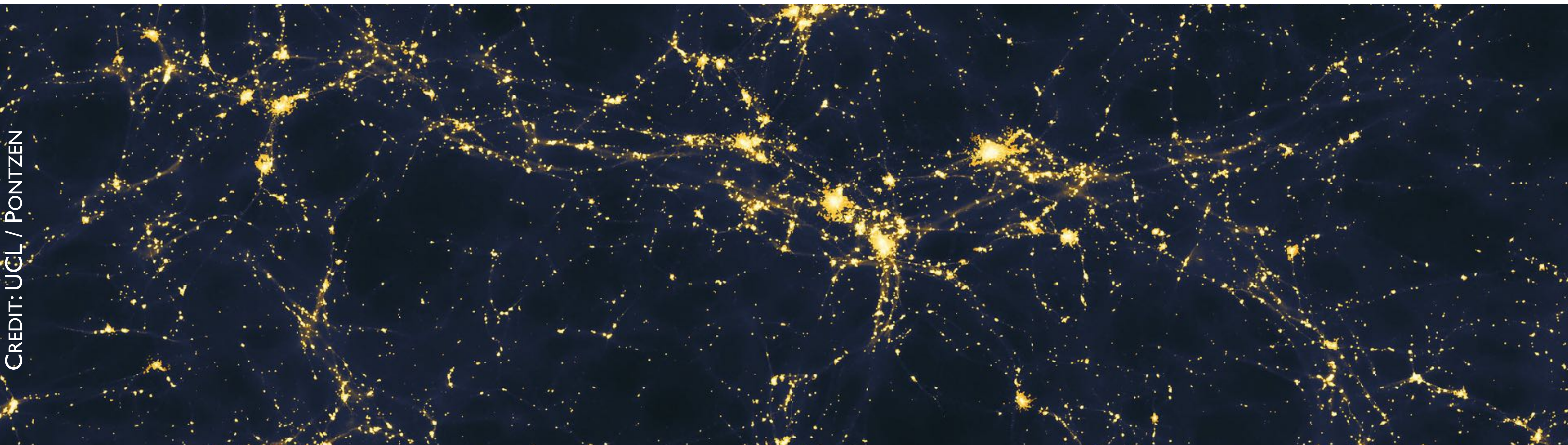


- How many independent degrees of freedom are needed to describe the HMF to percent-accuracy?
- Can we isolate and quantify universal and non-universal information in the HMF?

Previous work suggests linear growth related to non-universality
(Ondaro-Mallea et al 2021; Euclid collaboration et al. 2023)

***“More is different”*: emergent phenomena in cosmology**

- Modern machine learning methods can help us **embrace the complexity** and assist us in **gaining new insight**.

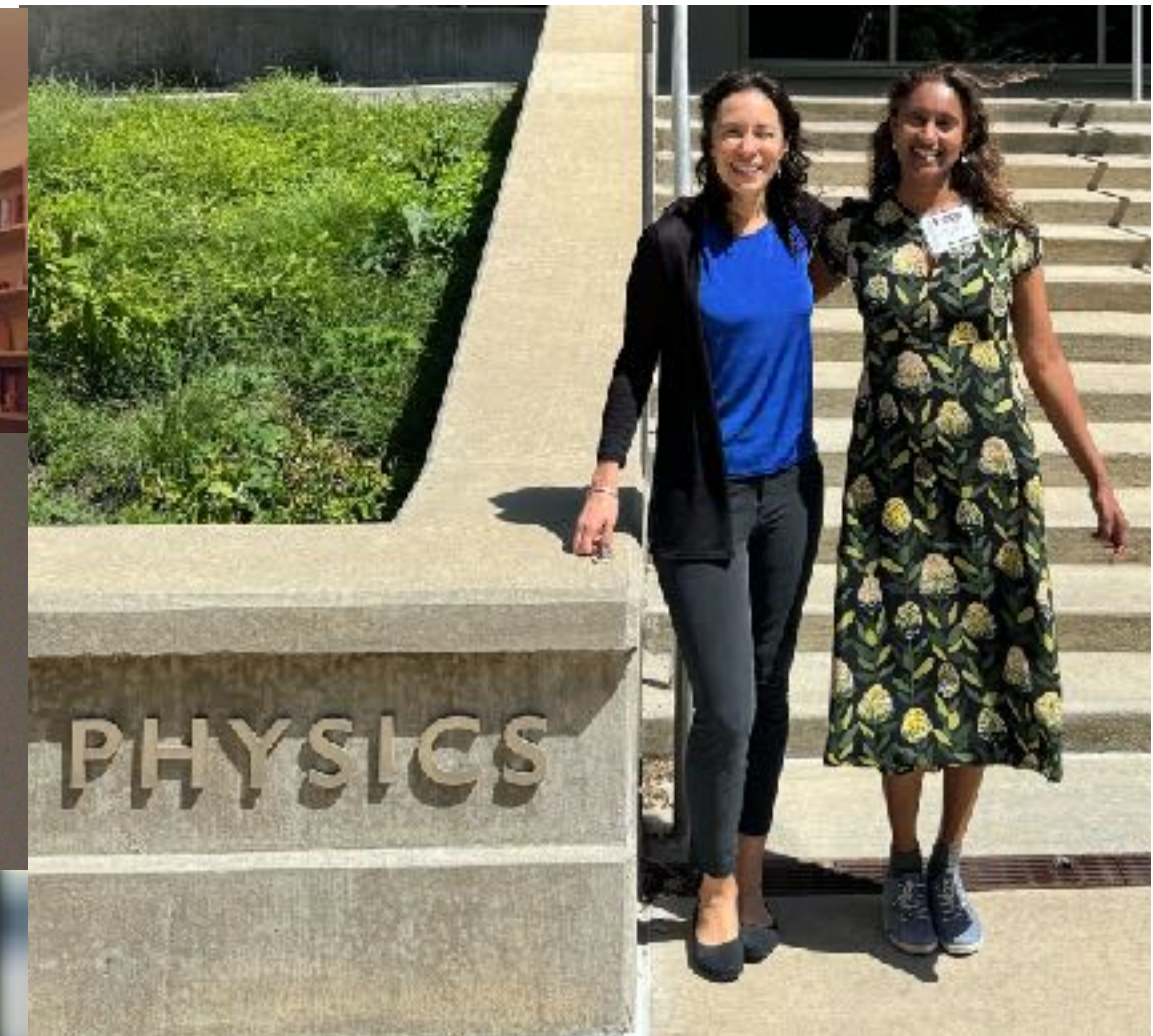


What I found at KICP 2004—2007

It's all about the people



Inspiring faculty



Inspiring students

Inspiring peers

Successful environment for enabling interdisciplinary research

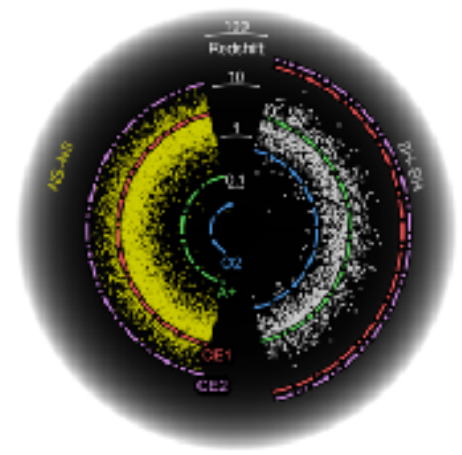
Laying down the tracks as the train of data-driven cosmology got going.

My current research snapshot



COSMICEXPLORER: Exploring the Cosmos with the Vera Rubin Observatory

ERC Advanced Grant project focusing on Data-intensive (static and transient) cosmology with Rubin data (with a strong focus on explainable AI methods)



Fundamental physics from populations of compact object mergers

Leveraging ML methods and simulation-based inference to accelerate and enable population studies with next generation gravitational wave facilities.



Detecting Axion Dark Matter in the Sky and in the Lab

Exploring axion dark matter hypothesis through its cosmological signatures + searching for QCD axion in the lab via tunable plasmon haloscopes (founding member of ALPHA Collaboration)



Cosmology x Quantum

Emulating early universe physics within an analogue quantum simulator in the laboratory (collaboration with Cambridge Physics / Hazibabic BEC Lab)



Happy 20th birthday and congratulations KICP!

From your friends at KICC.