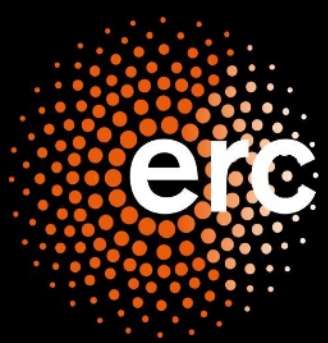


# *pop-cosmos*

*investigating the explainability of a high-dimensional,  
data-driven generative model in cosmology*

*Hiranya V. Peiris*



European Research Council  
Established by the European Commission



UNIVERSITY OF  
CAMBRIDGE

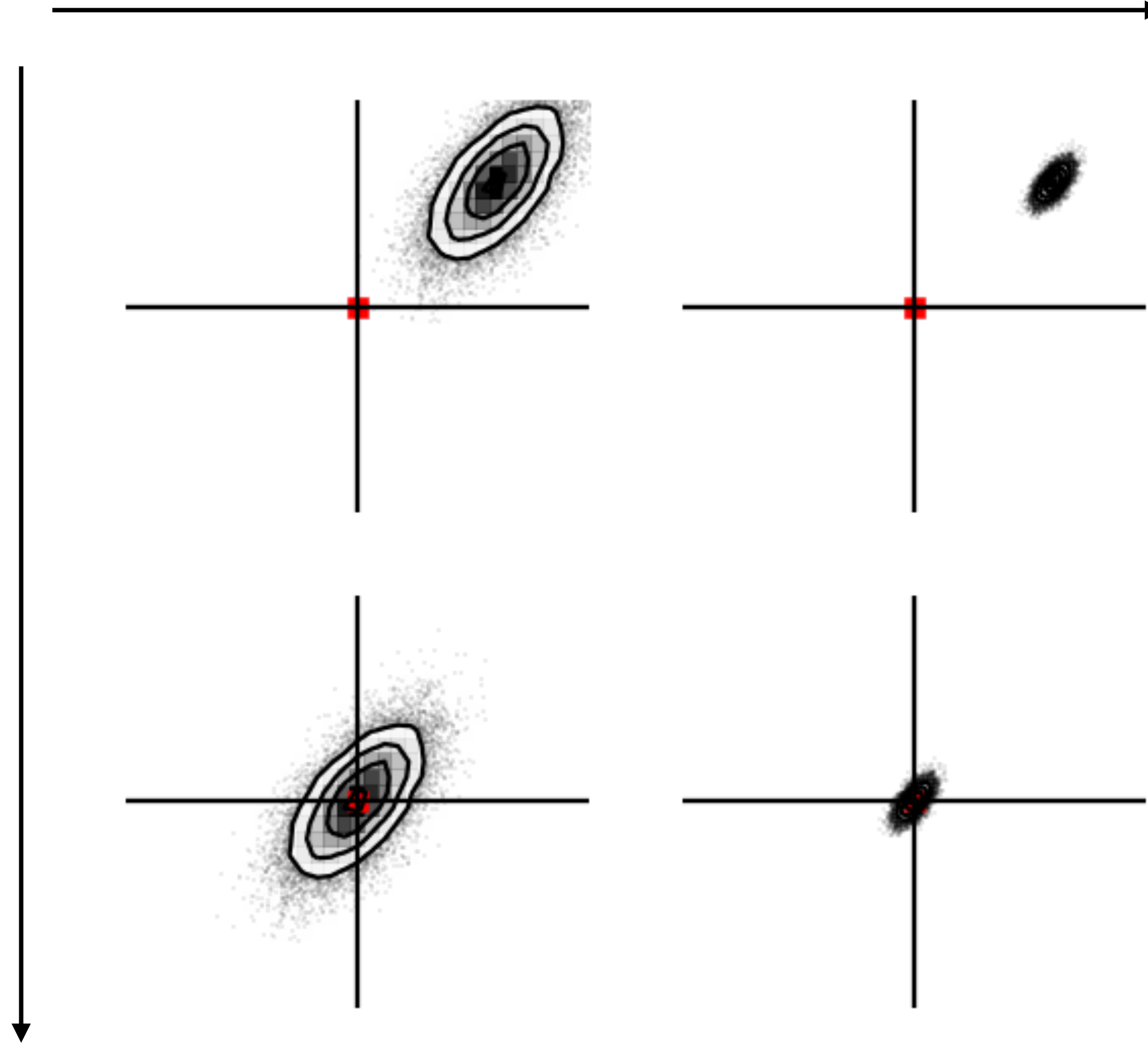


UK Research  
and Innovation



*precision*

*accuracy*





# Characteristics of (good) physical models

- Follow from explicitly enumerable set of assumptions and physical principles
- Leads to mathematical models that can be solved (analytically/numerically) to yield useful **predictions** (deterministically/probabilistically).
- **Explainable** (rooted in cause-effect relationships grounded in domain knowledge.)
- **Generalises** beyond initial domain to explain wider range of phenomena.
- **Compresses** information: explains wide range of phenomena from minimal set of ingredients (~Occam's razor.)
- **Domain of validity** can be quantified explicitly.



# ***My definitions***

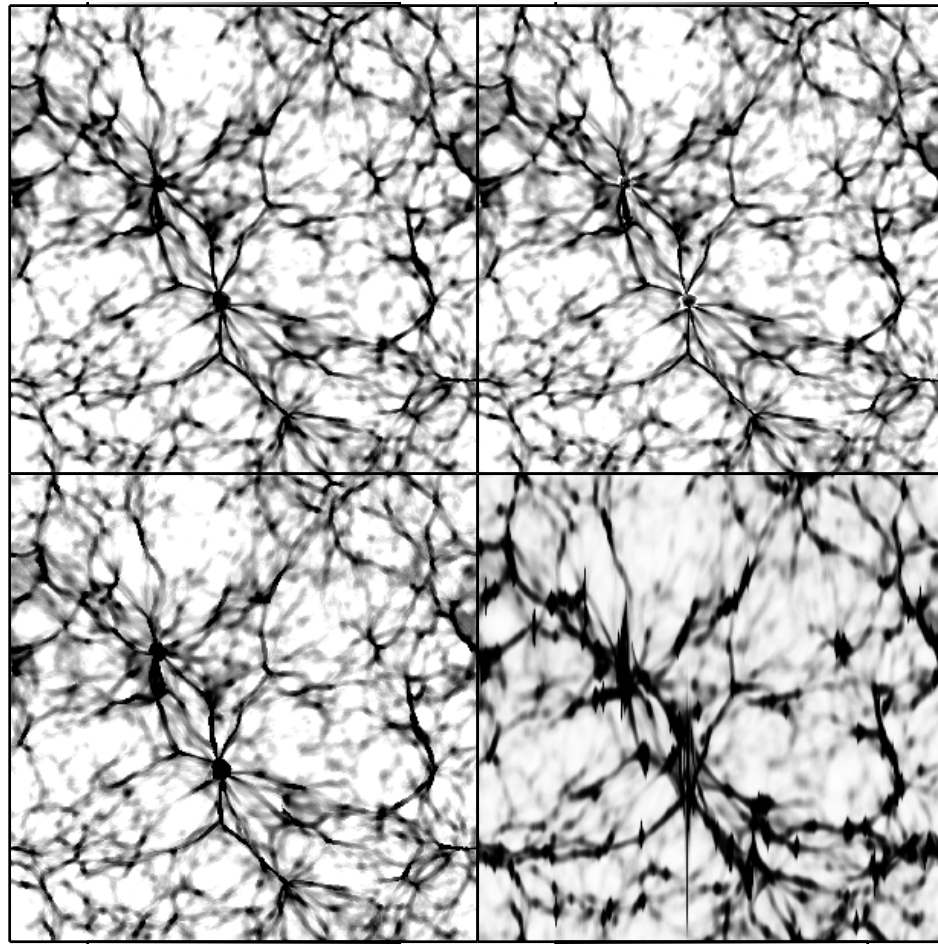
**(i) interpretability:** *account for why ML system reaches particular decision or prediction;*

**(ii) explainability:** *map this account onto existing knowledge in relevant science domain.*

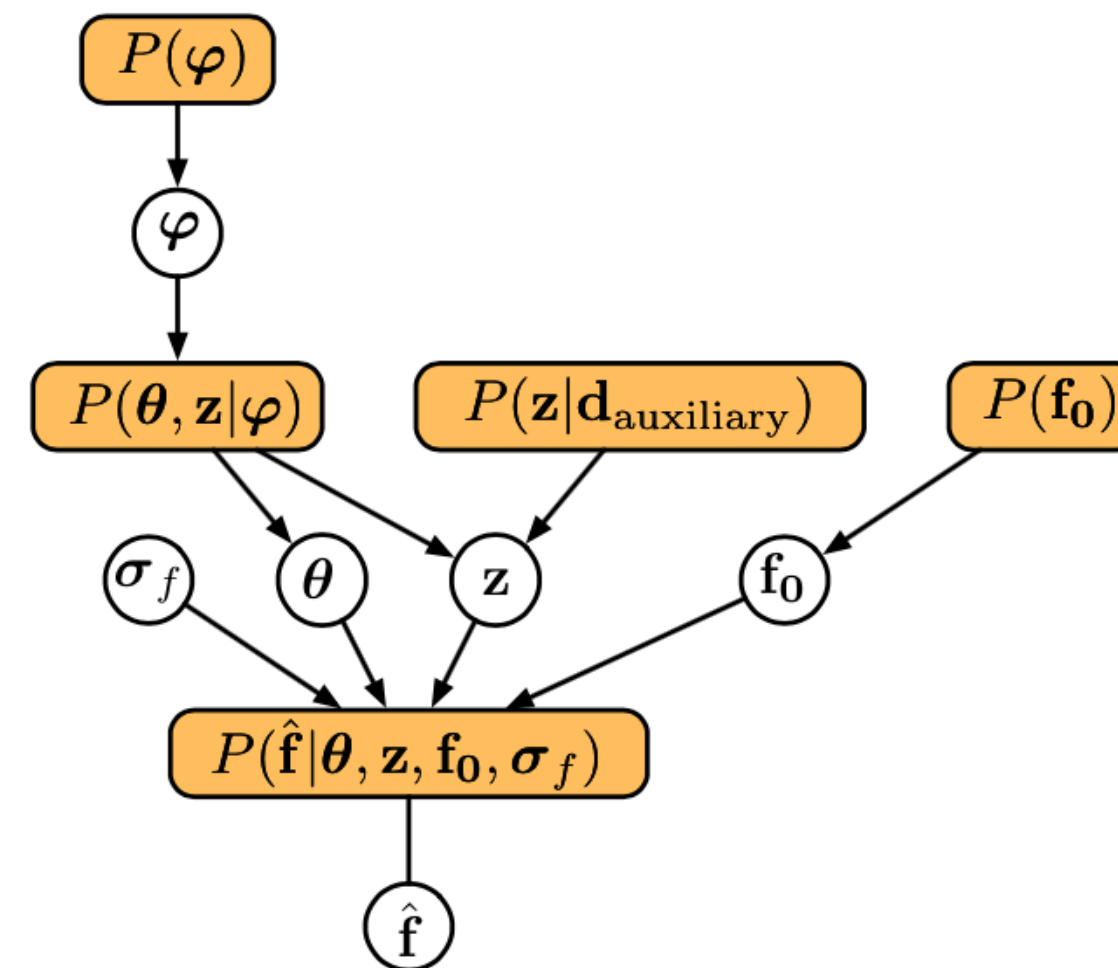
- *Currently challenging because of “black box” nature of ML architectures.*
- *Many physical models satisfy my list of characteristics only partially, e.g. systems exhibiting emergent phenomena, chaotic systems.*



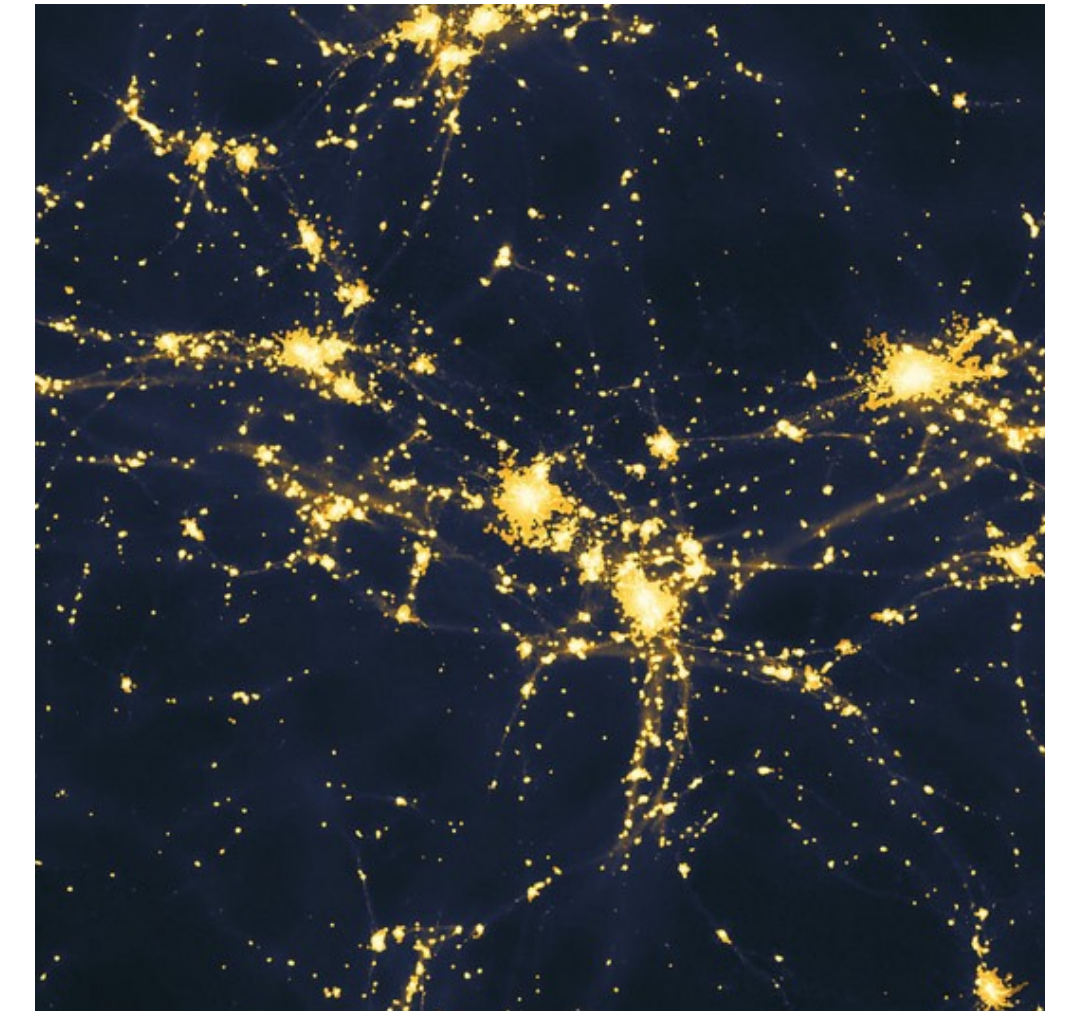
# Solving cosmological modelling challenges with machine learning



**Emulation:**  
*ML-accelerated forward-modelling of observables*



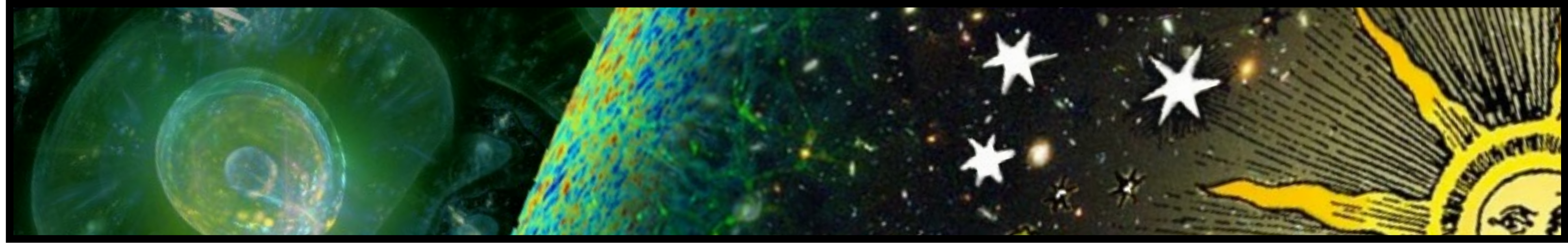
**Simulation-based optimisation:**  
*data-driven calibration of high-dimensional generative models*



**Explainable AI:**  
*machine-assisted knowledge extraction*

See [Luisa Lucie-Smith talk](#)





## *pop-cosmos team*



Justin Alsing



Stephen Thorp



Sinan Deger



Boris Leistedt



Arthur Loureiro



Daniel Mortlock



Joel Leja

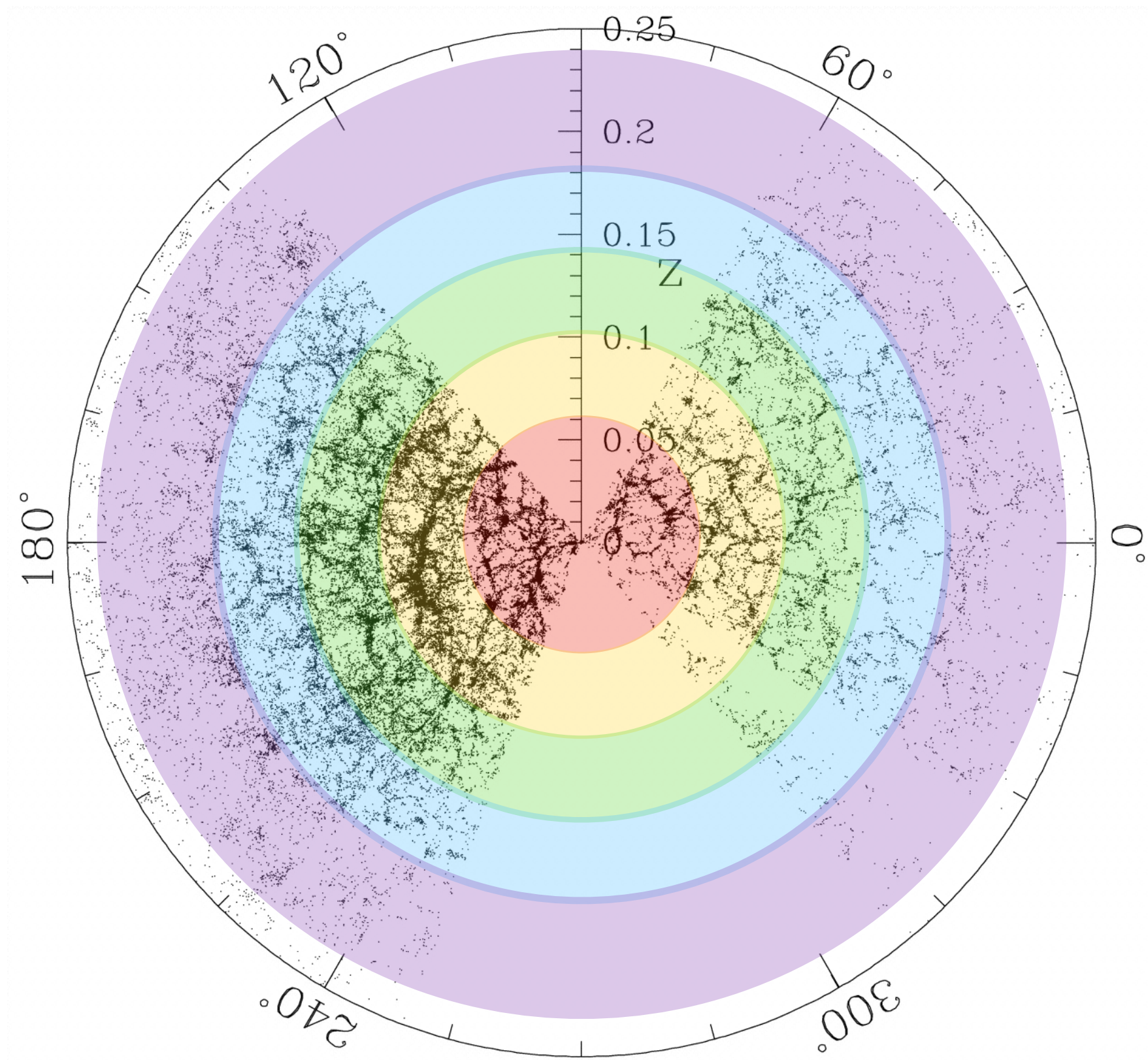


Hiranya Peiris

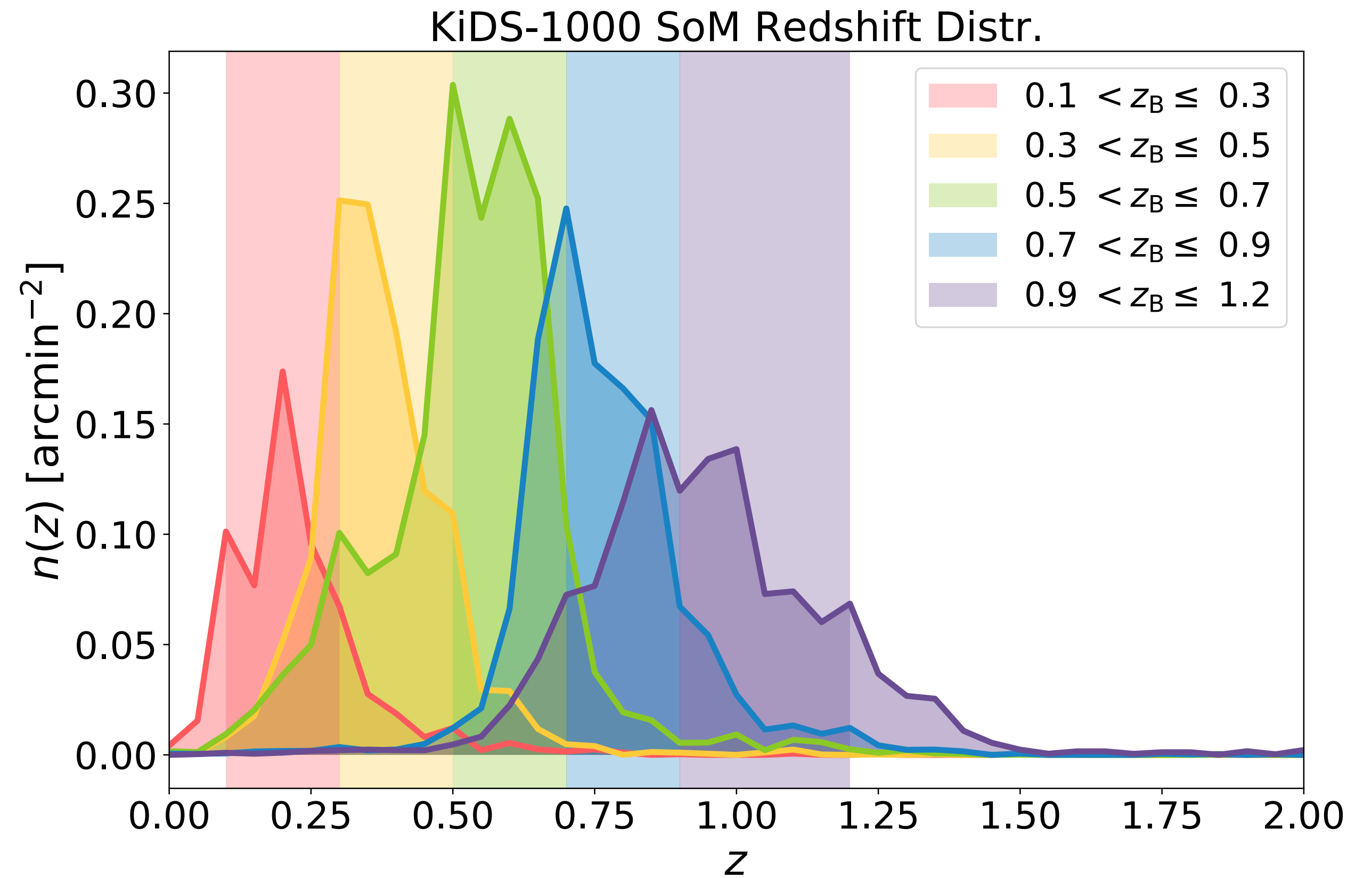




# Photometric catalogues require redshift estimation



Blanton et al. (2003)



Loureiro et al. (2023)



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

***Machine learning models can accurately describe this complicated web of interdependencies***

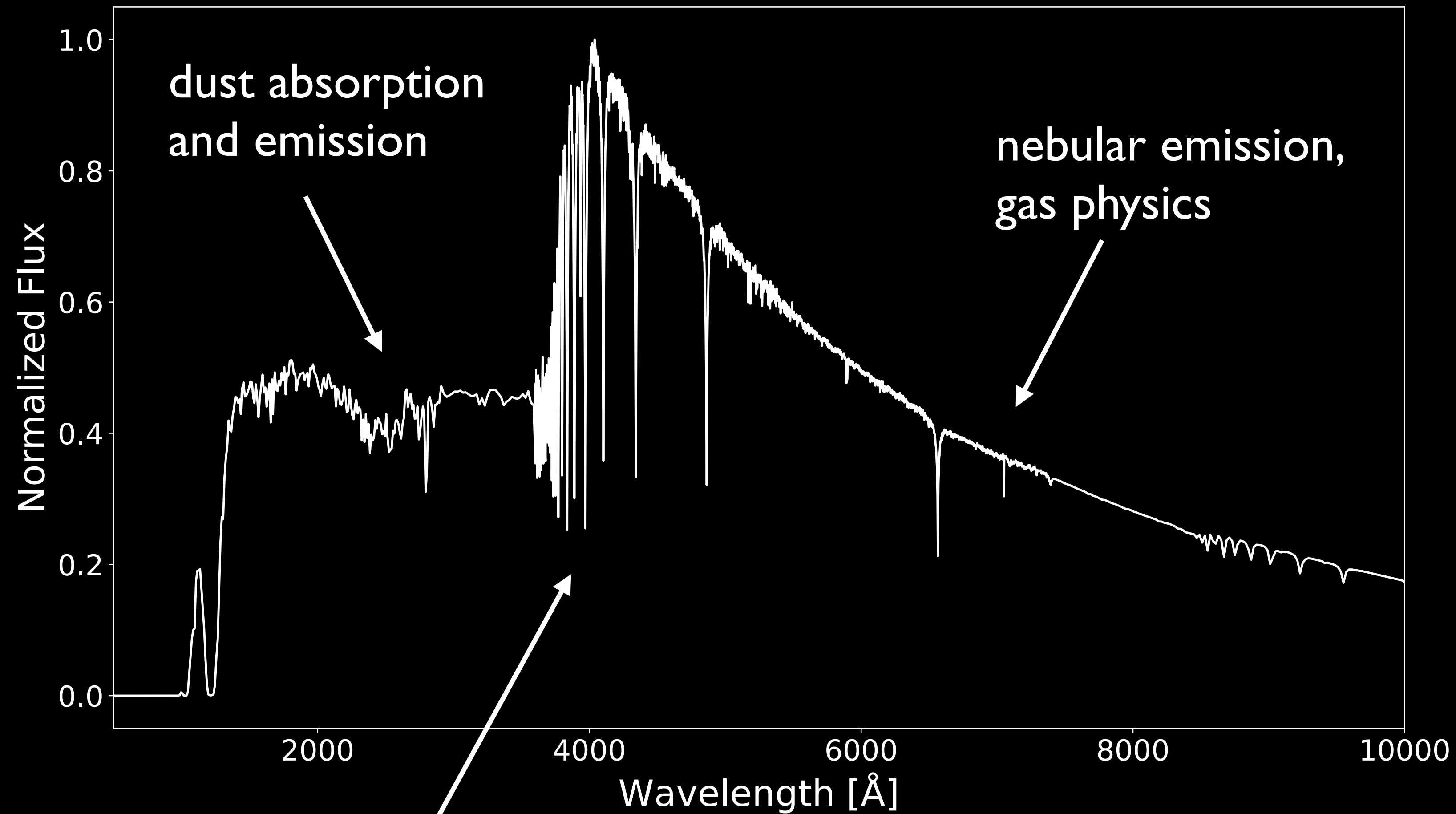


# Recipe for making galaxy spectra and colours

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



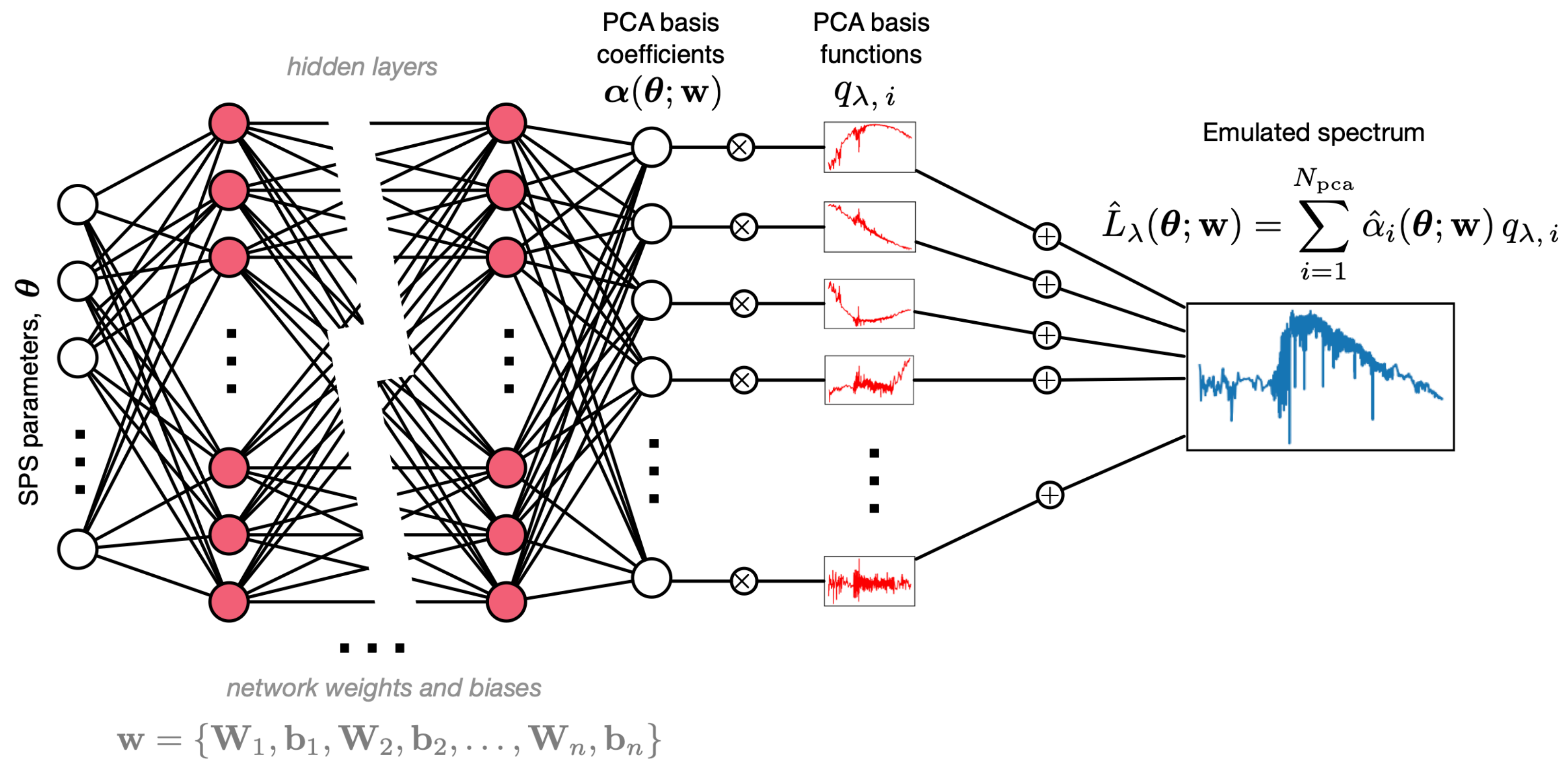
# Model galaxy spectra using stellar population synthesis



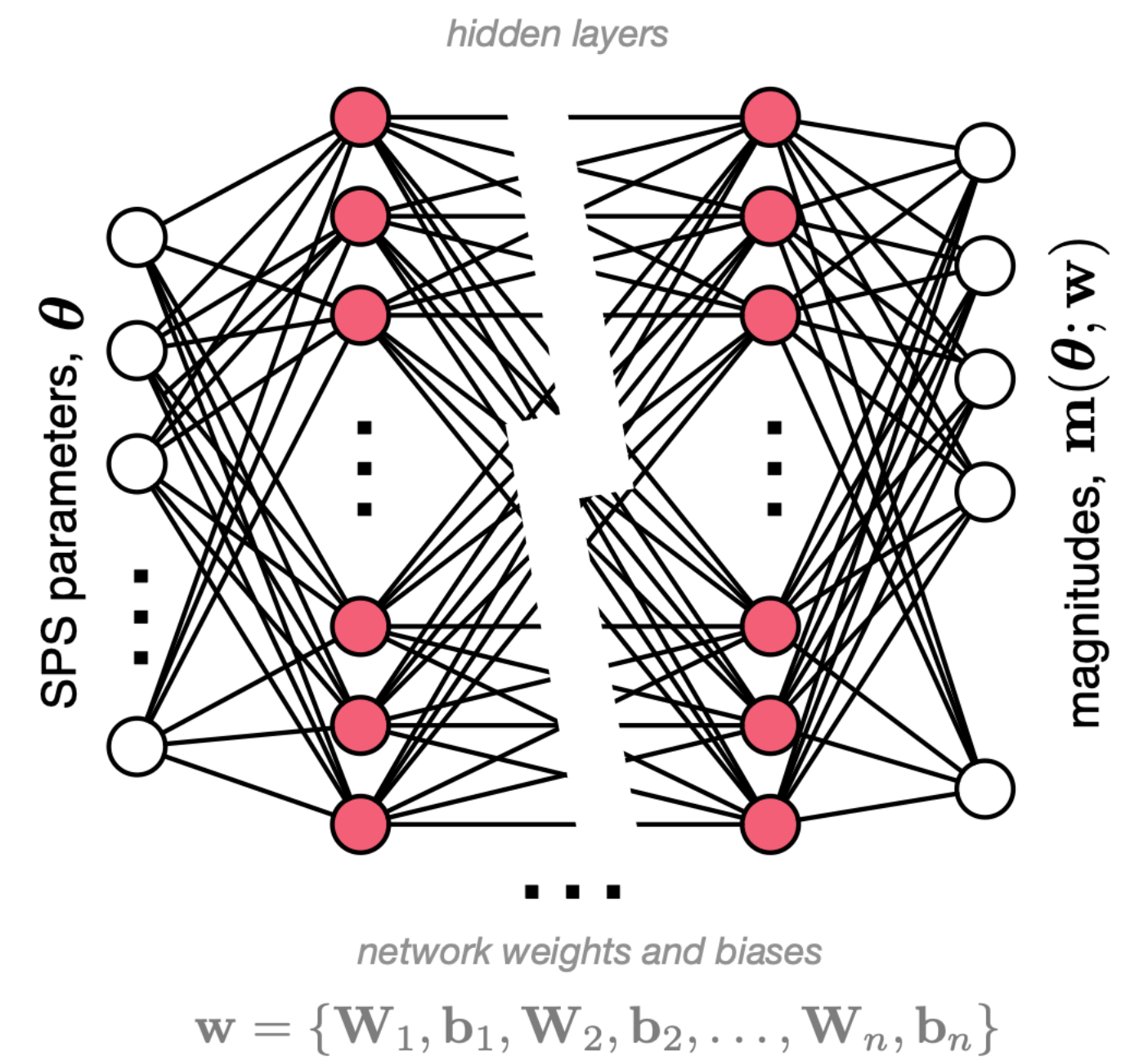
add up light from all the stars (at their ages and metallicities)



# Speeding things up with neural emulators



**Emulating spectra**

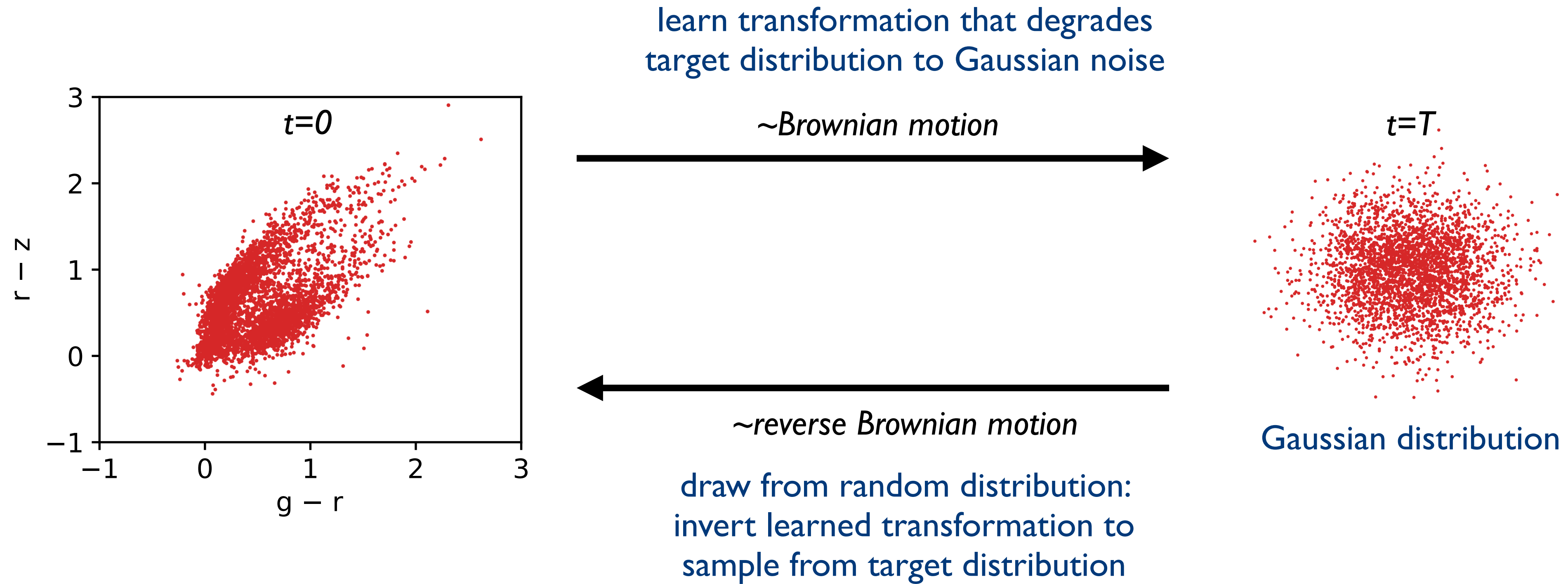


**Emulating photometry**

**16-parameter SPS model | sub-percent accuracy | factors x 10<sup>4</sup> speed-up | differentiable**

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

# Flexible neural models for distribution of galaxy properties



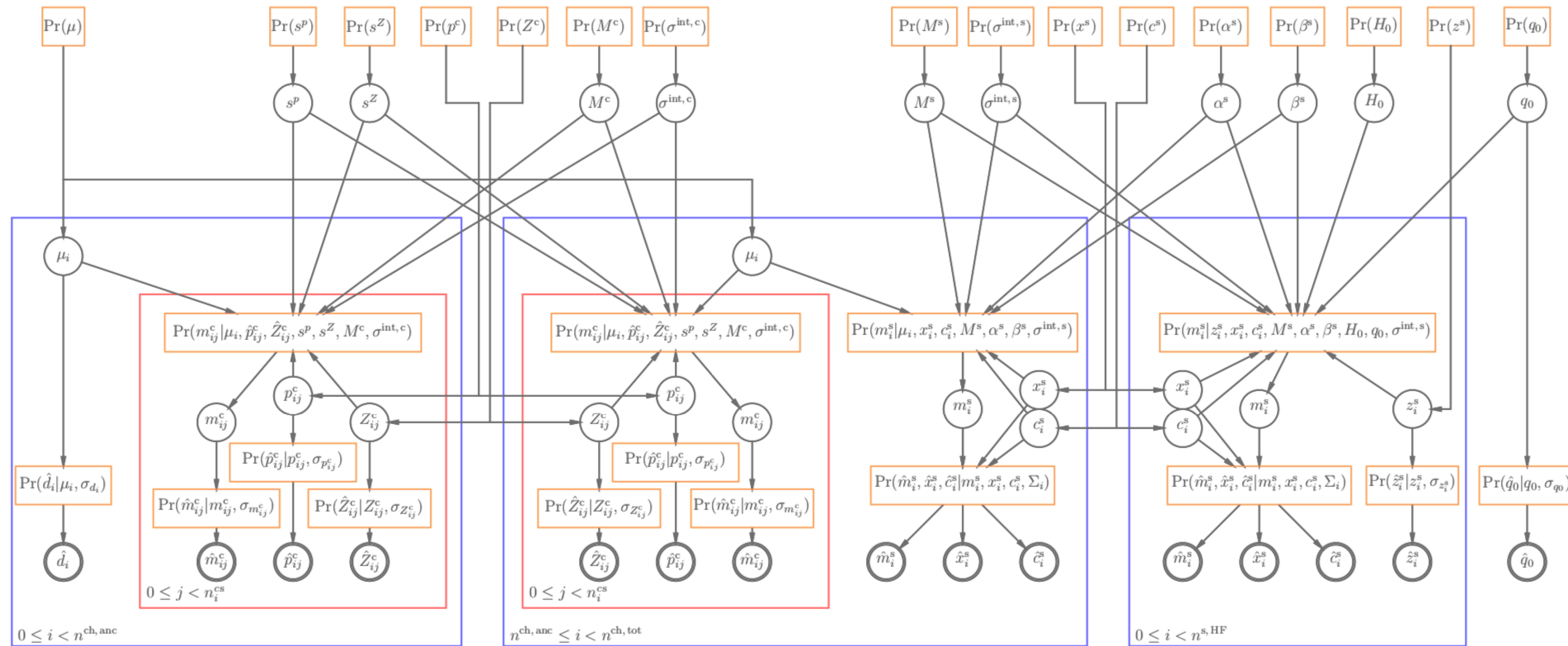
**score-based diffusion model**







# Solving explicit parametric BHM intractable even in principle

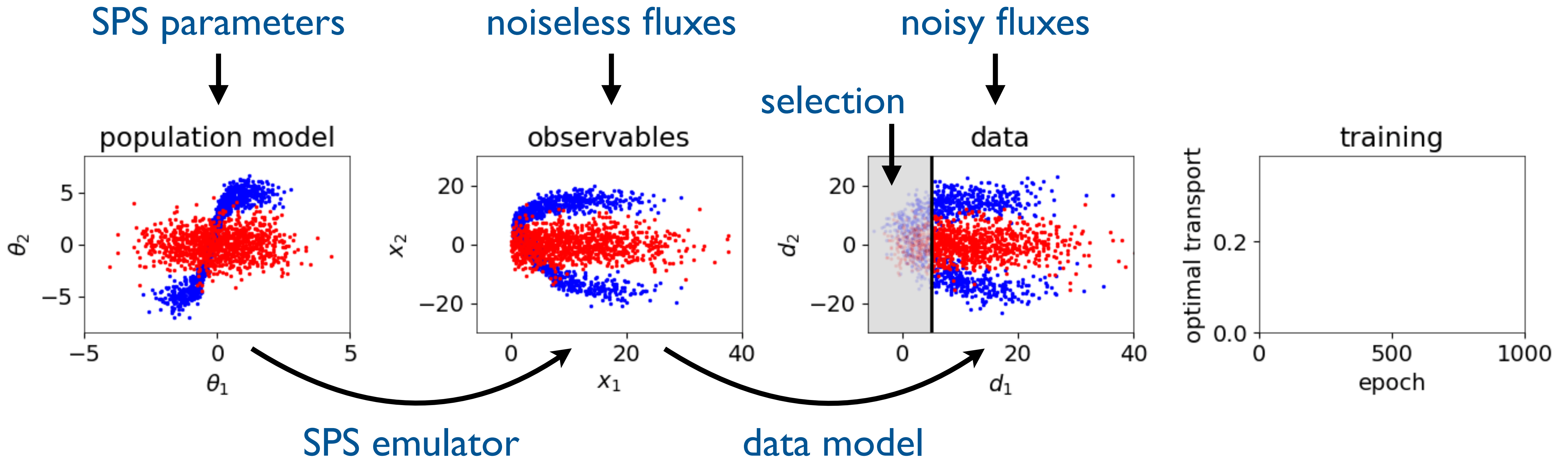


**forward model of dataset = selection x data model x population model**

*intractable*

*no good parametric model*

# Learning the galaxy population model

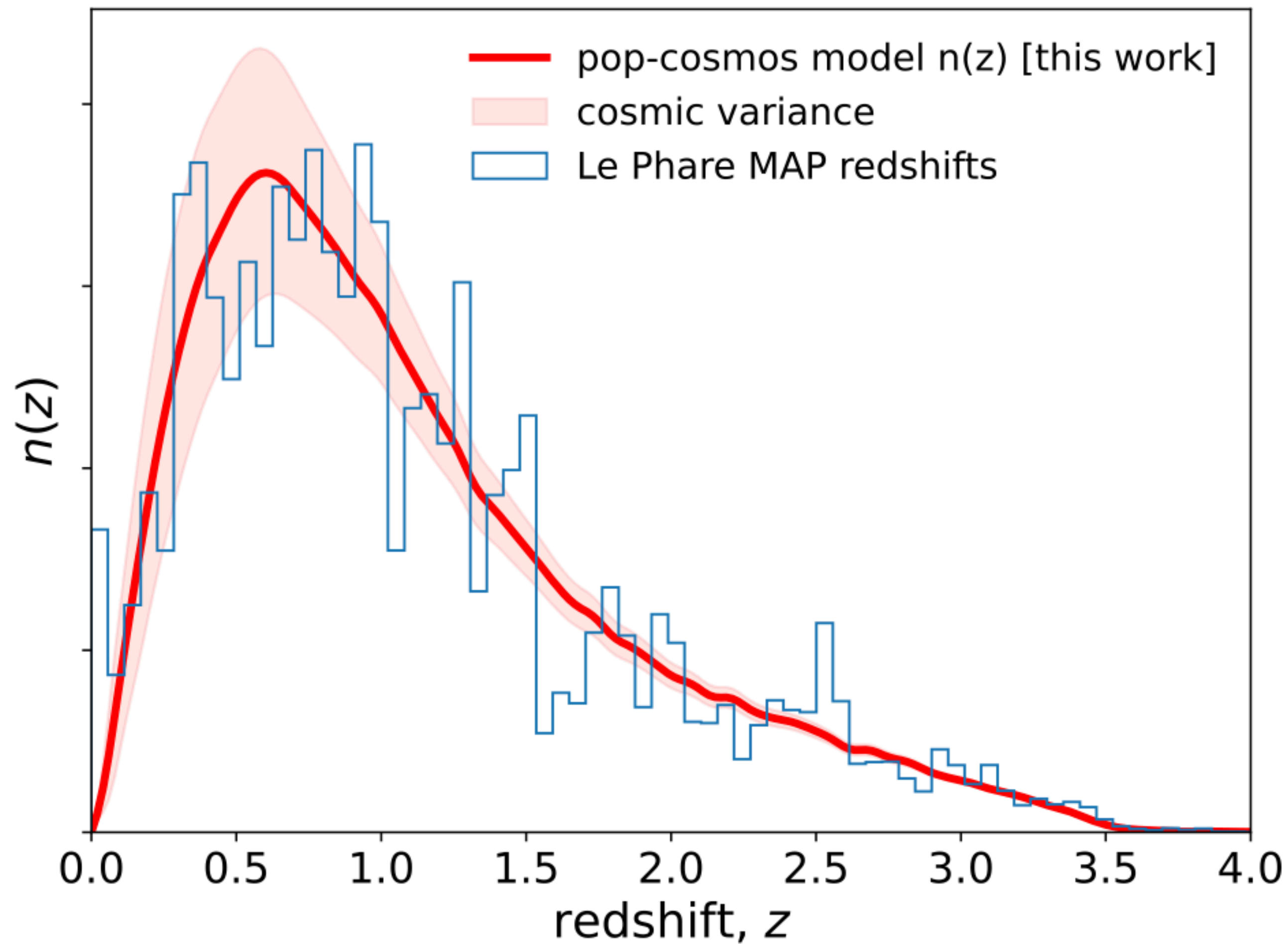


**Equivalent to data-driven calibration of population prior in hierarchical Bayes**



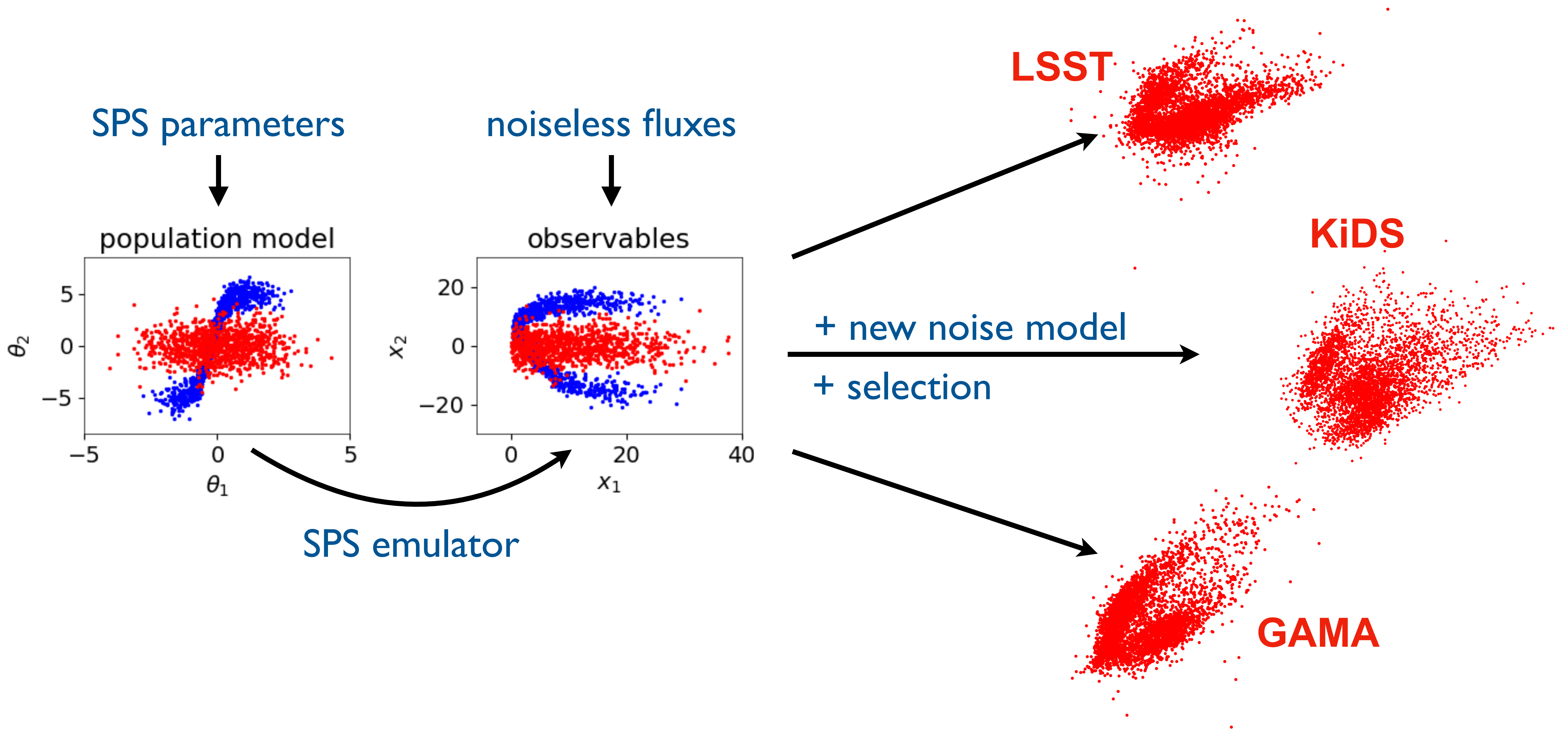
# Pop-Cosmos: a generative model for galaxy surveys

Pop-Cosmos prediction for COSMOS2020 redshift distribution



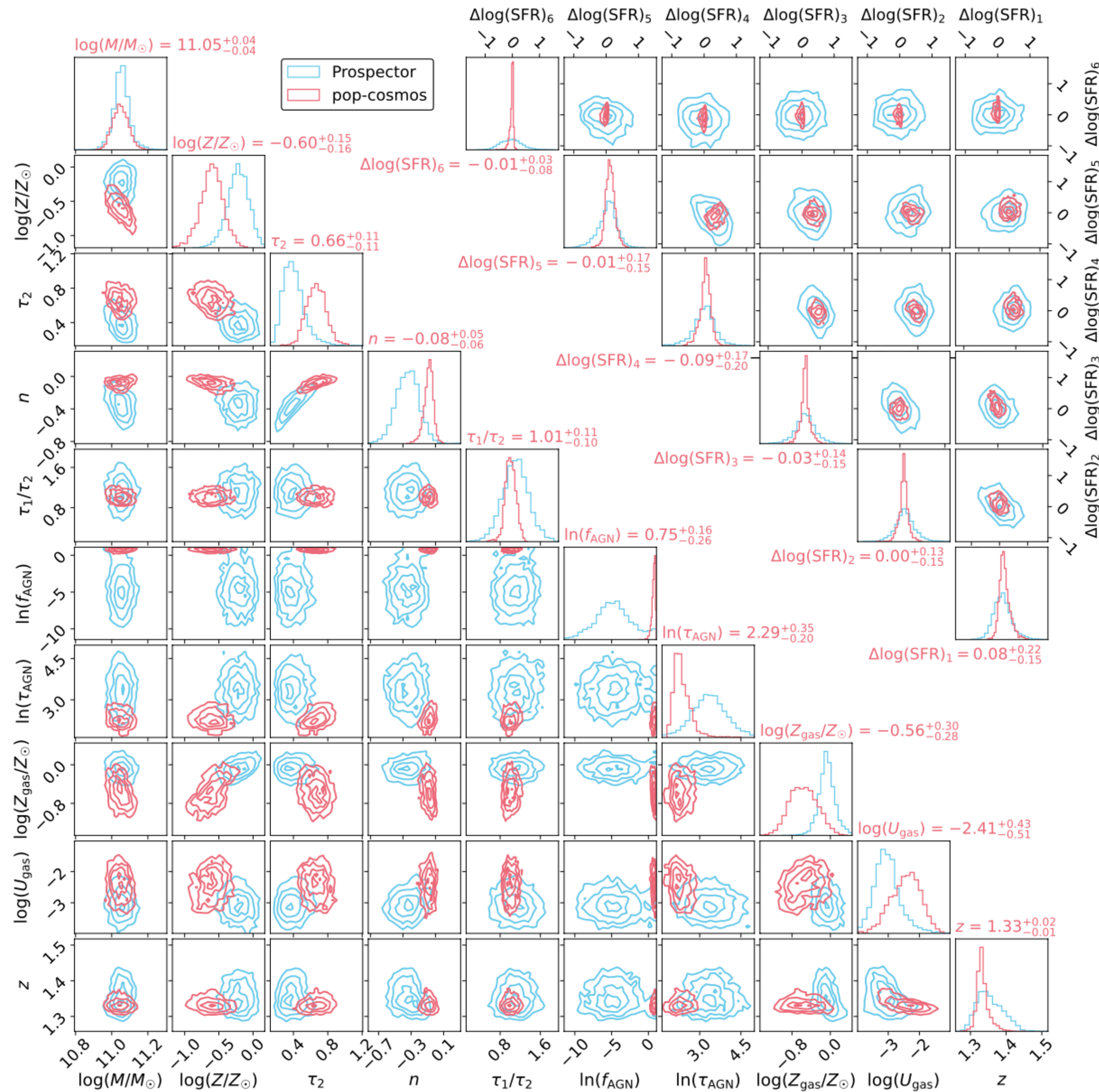
- *First time full joint density of galaxy properties has been estimated from large galaxy catalogue*
- *Can predict properties (incl. redshift distribution) of any catalogue of comparable / shallower depth*
- *Bonus: information on full galaxy population over cosmic time*

# Forward-modelling other catalogues





# Full Bayesian SED fitting of large photometric catalogues

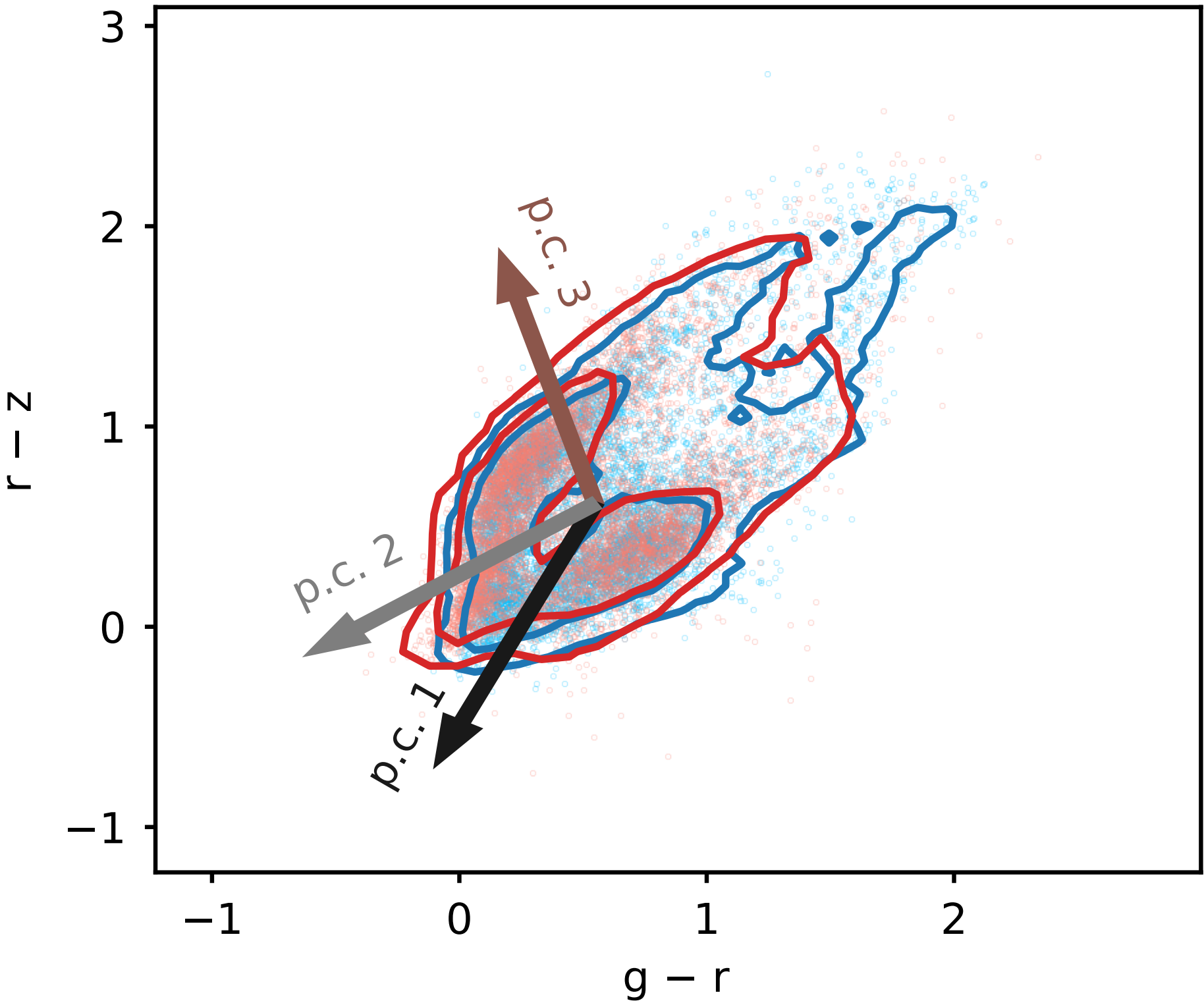


**15 GPU-sec / galaxy under pop-cosmos prior |  
0.6 GPU-sec / galaxy under Prospector prior.**

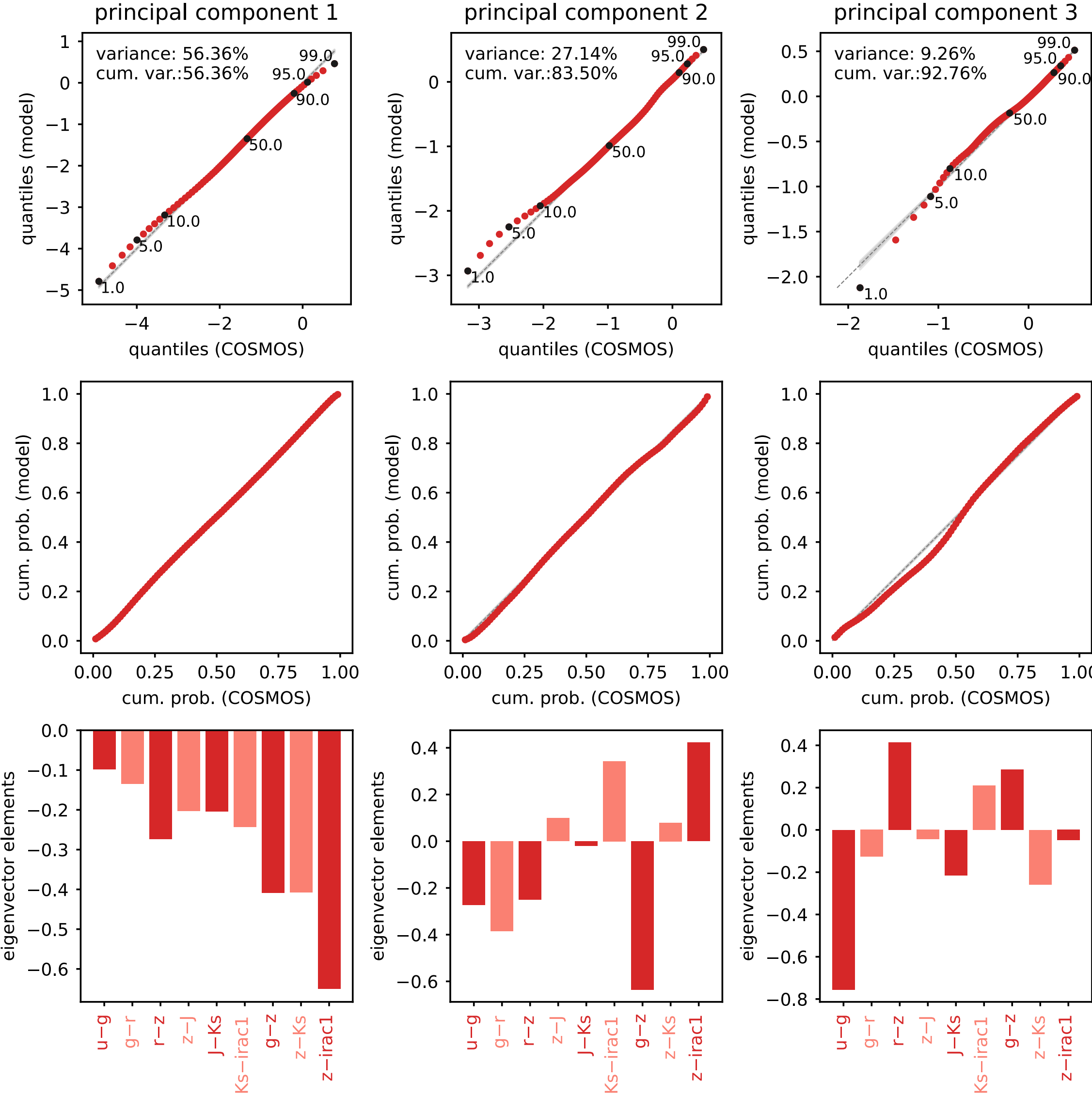
<https://zenodo.org/records/13627489>

- Demonstration analysis of  $\sim 300,000$  COSMOS2020 galaxies — 3 x larger than previously possible under full SPS prior, with modest GPU requirements.
- Comparison: FSPS under Prospector  
25 CPU-hrs / galaxy

# Data-space validation of high-dimensional generative model

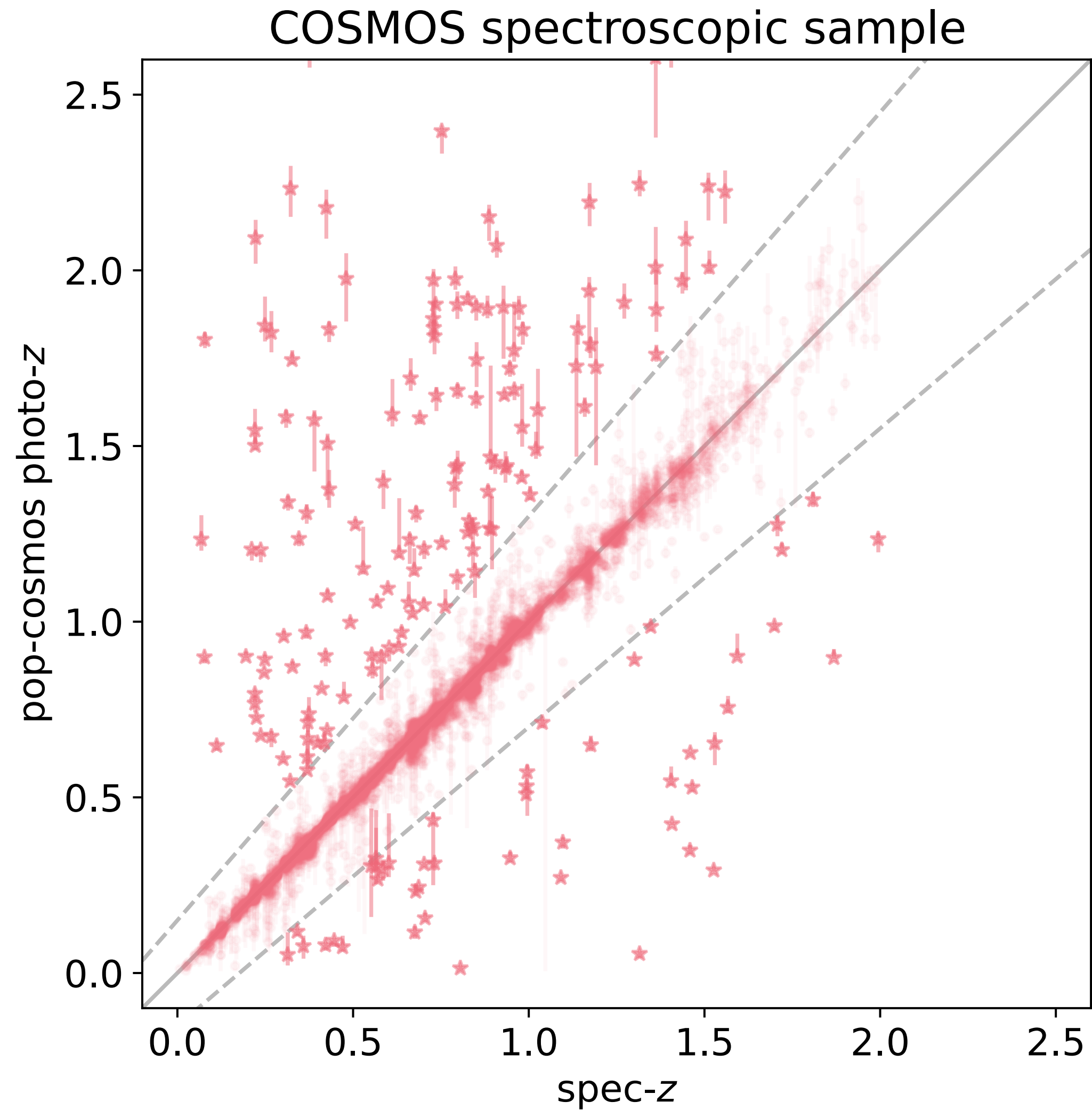


**Validated using magnitude marginals, densities in colour pairs, and PP and QQ plots in PCA projections**

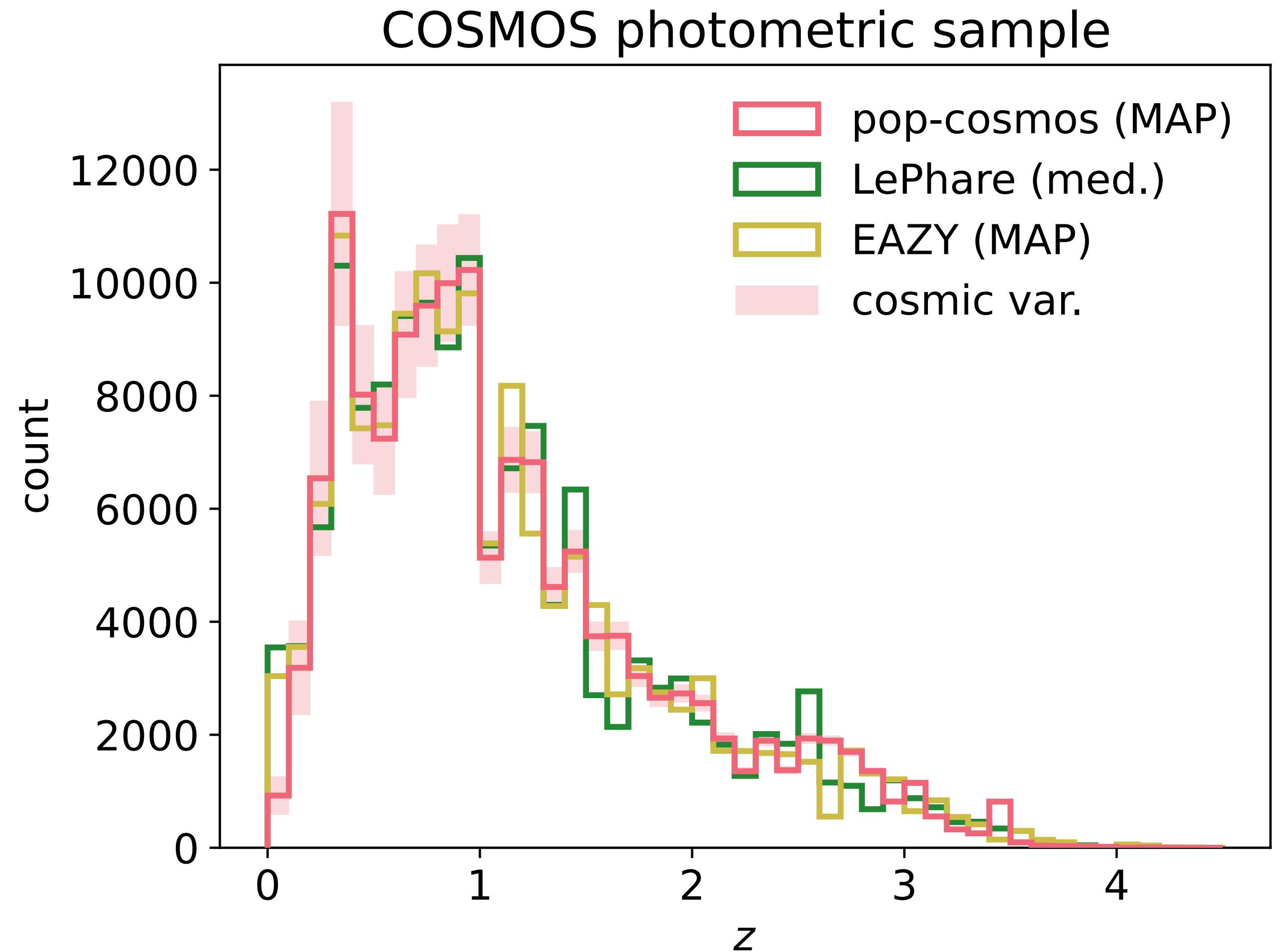




# ***Pop-Cosmos as a prior for galaxy photo-z inference***



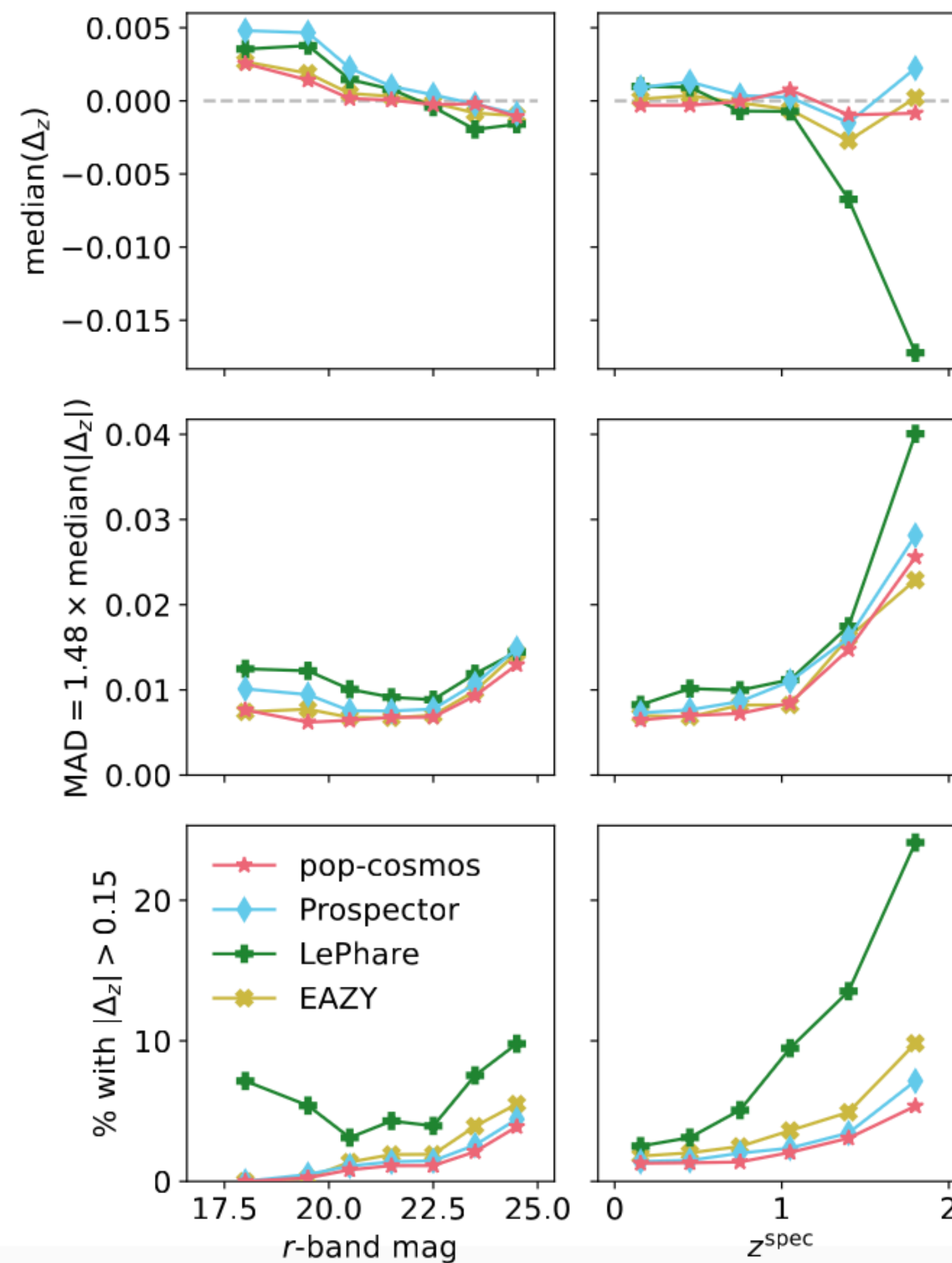
***Validate where “ground truth” known***



***Validate against state-of-the-art***



# Quality of individual redshifts



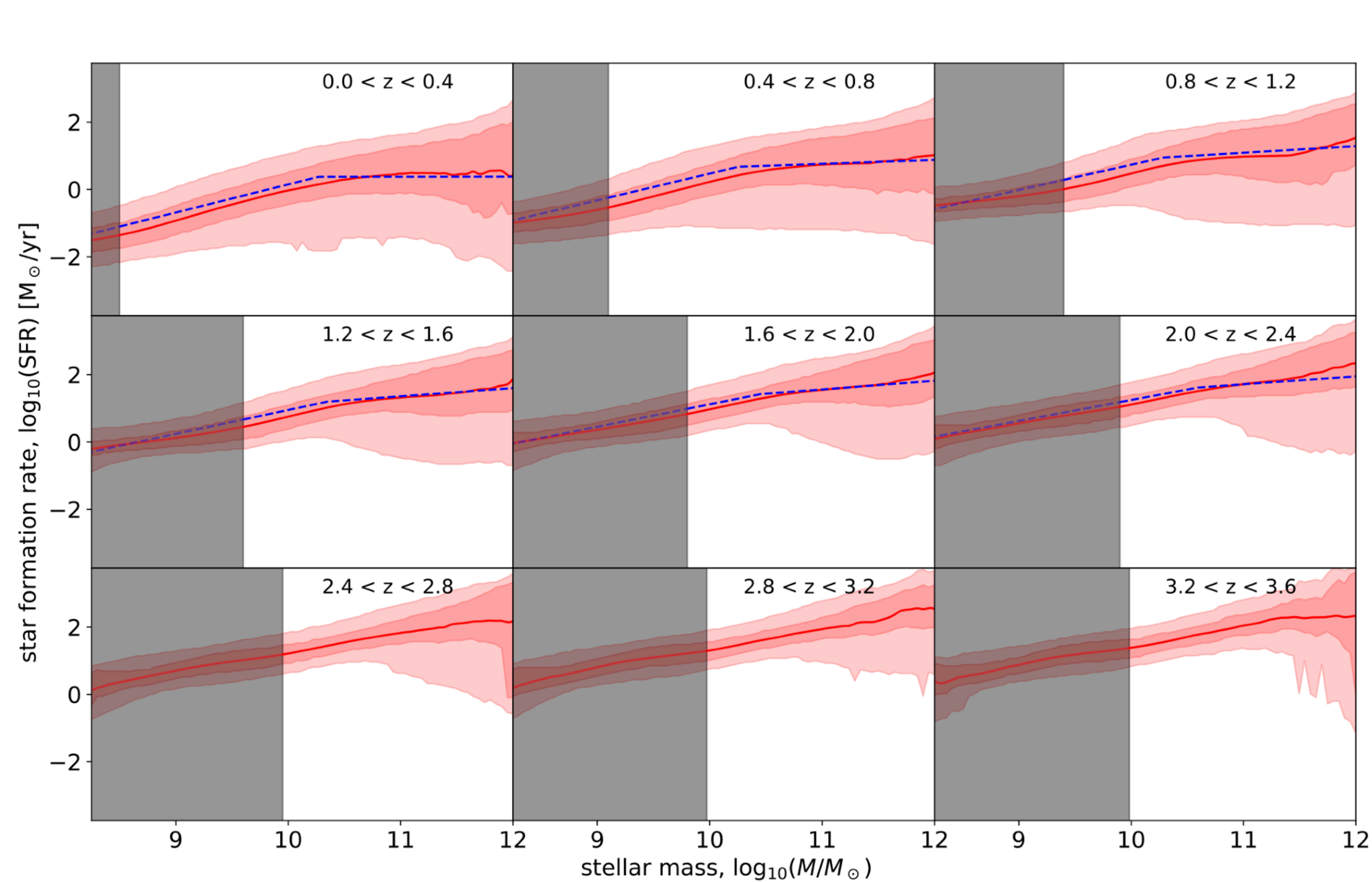
*less biased*

*smaller errors*

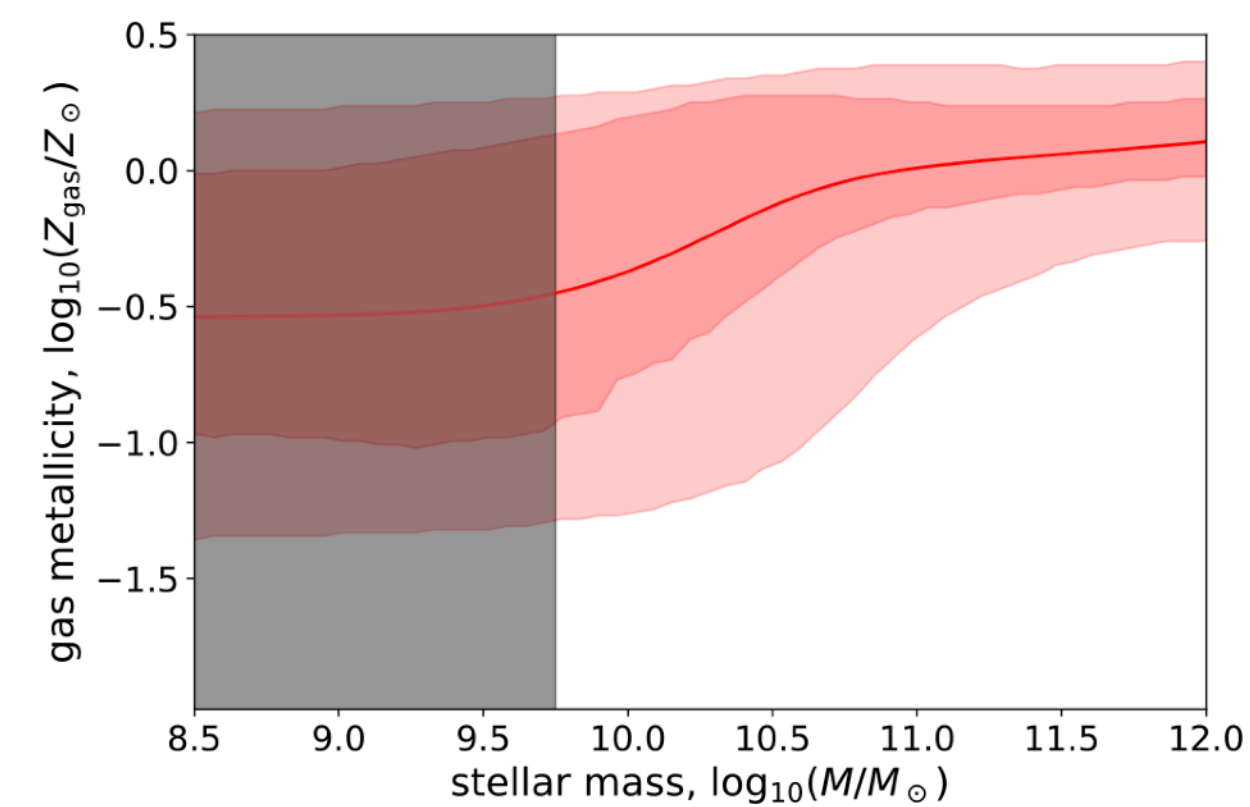
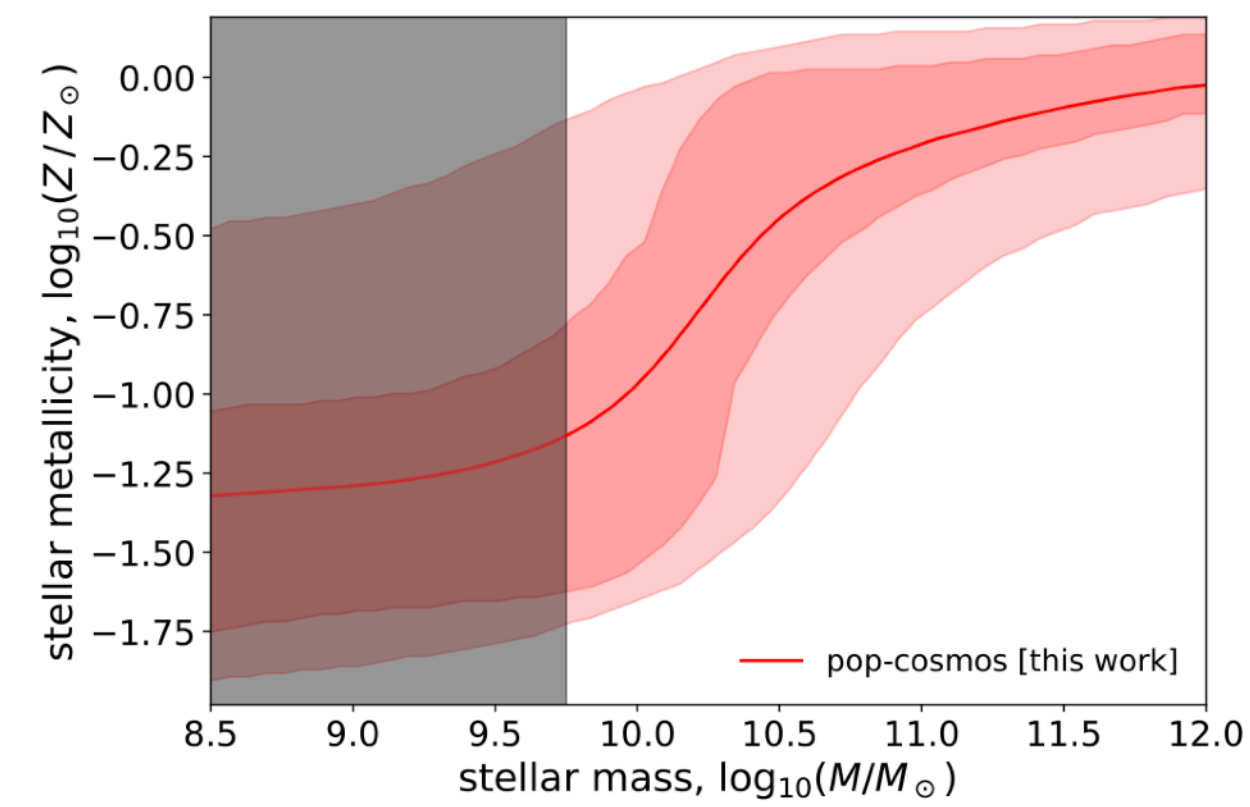
*fewer outliers*

**Validate with standard domain-specific metrics**

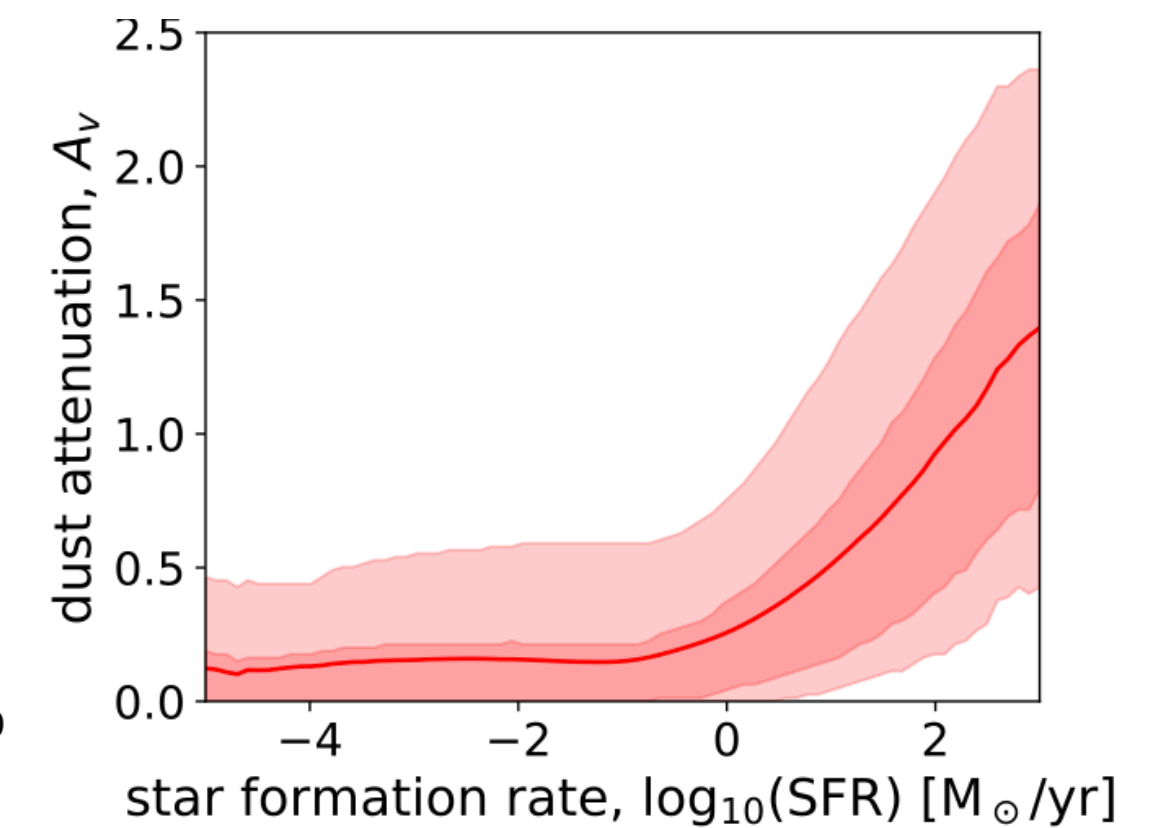
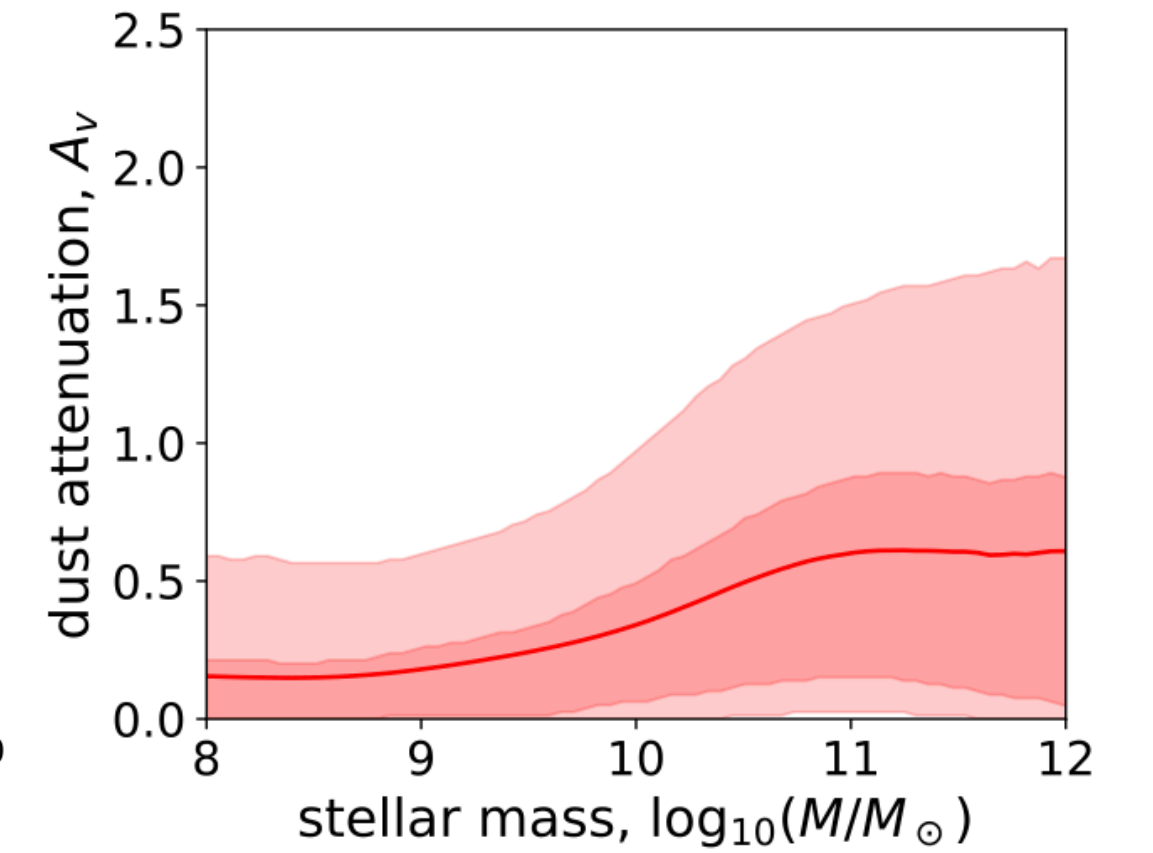
# Bonus: information on full galaxy population over cosmic time



*star forming sequence*



*metallicity*

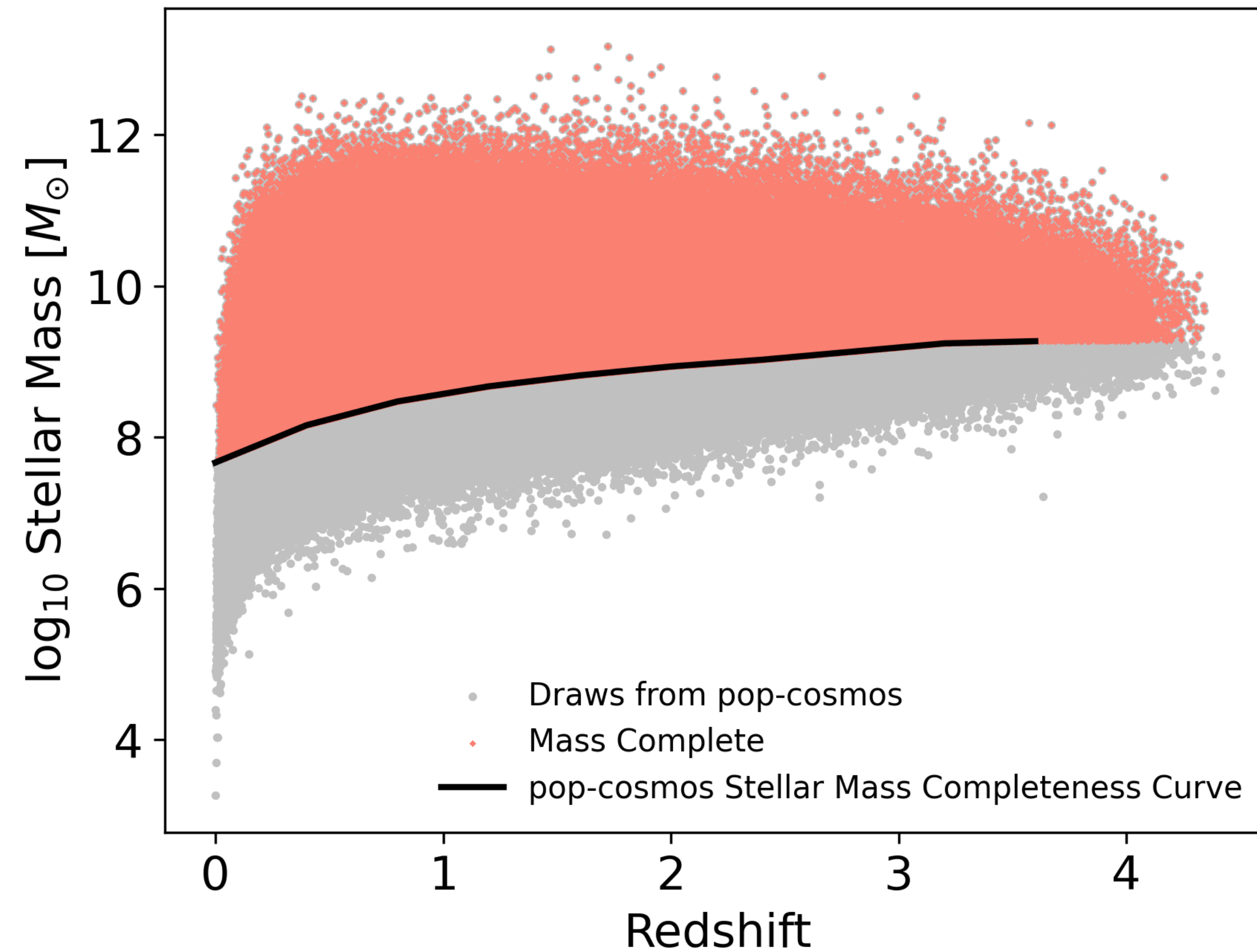


*dust*

**Validate against domain knowledge for key population properties in lower-dimensional projections**

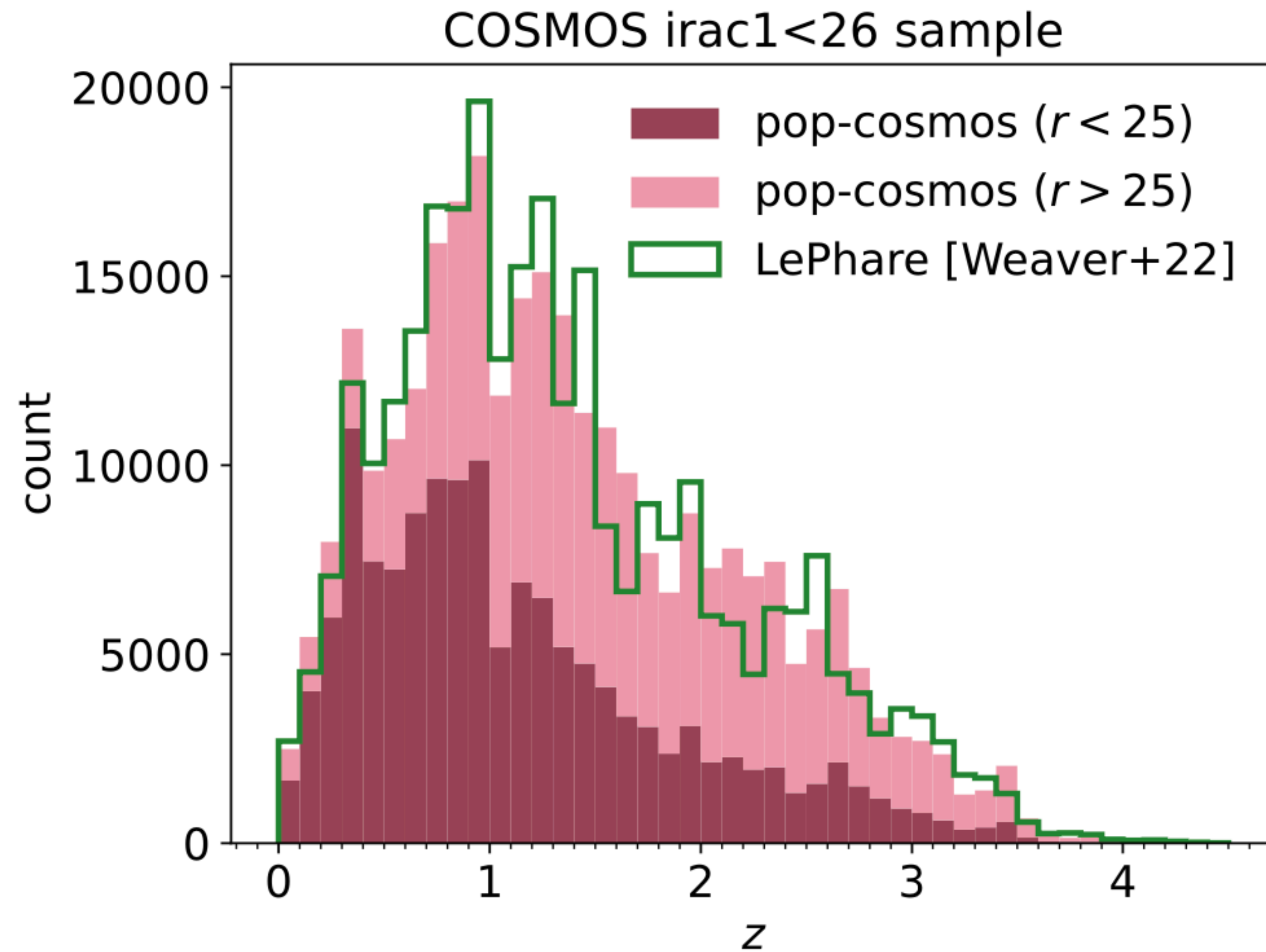


# Mass-completeness of pop-cosmos



**Establish explicit domain of validity for pop-cosmos so we know when we are extrapolating**

# ***Extrapolation to redshifts of IRAC1 < 26 galaxies***

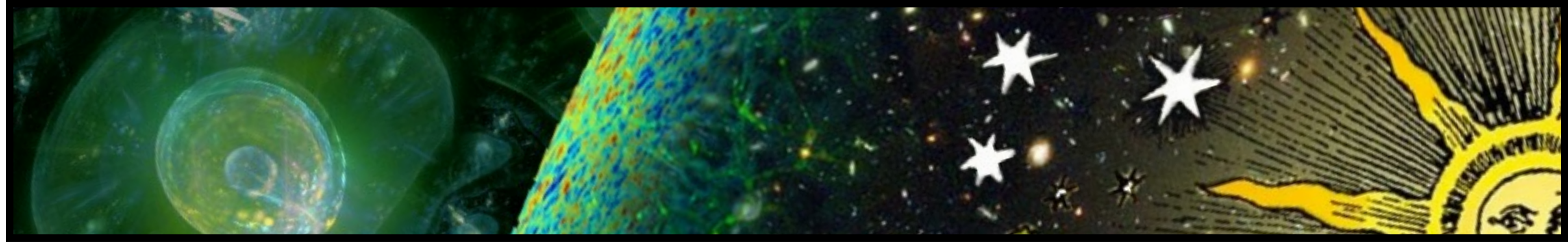


***Test generalisation of model to deeper selection of COSMOS2020 galaxies***



# Characteristics of pop-cosmos generative model

- ✓ Follow from explicitly enumerable set of assumptions and physical principles
- ✓ Leads to mathematical models that can be solved (analytically/numerically) to yield useful **predictions** (deterministically/probabilistically).
- ✓ **Explainable** (rooted in cause-effect relationships grounded in domain knowledge.)
- ✓ **Generalises** beyond initial domain to explain wider range of phenomena.
- ✓ **Compresses** information: explains wide range of phenomena from minimal set of ingredients (~Occam's razor.)
- ✓ **Domain of validity** can be quantified explicitly.



***For more details***





