Constraining the X-ray heating and ionization of the IGM with

SIMULATION-BASED INFERENCE

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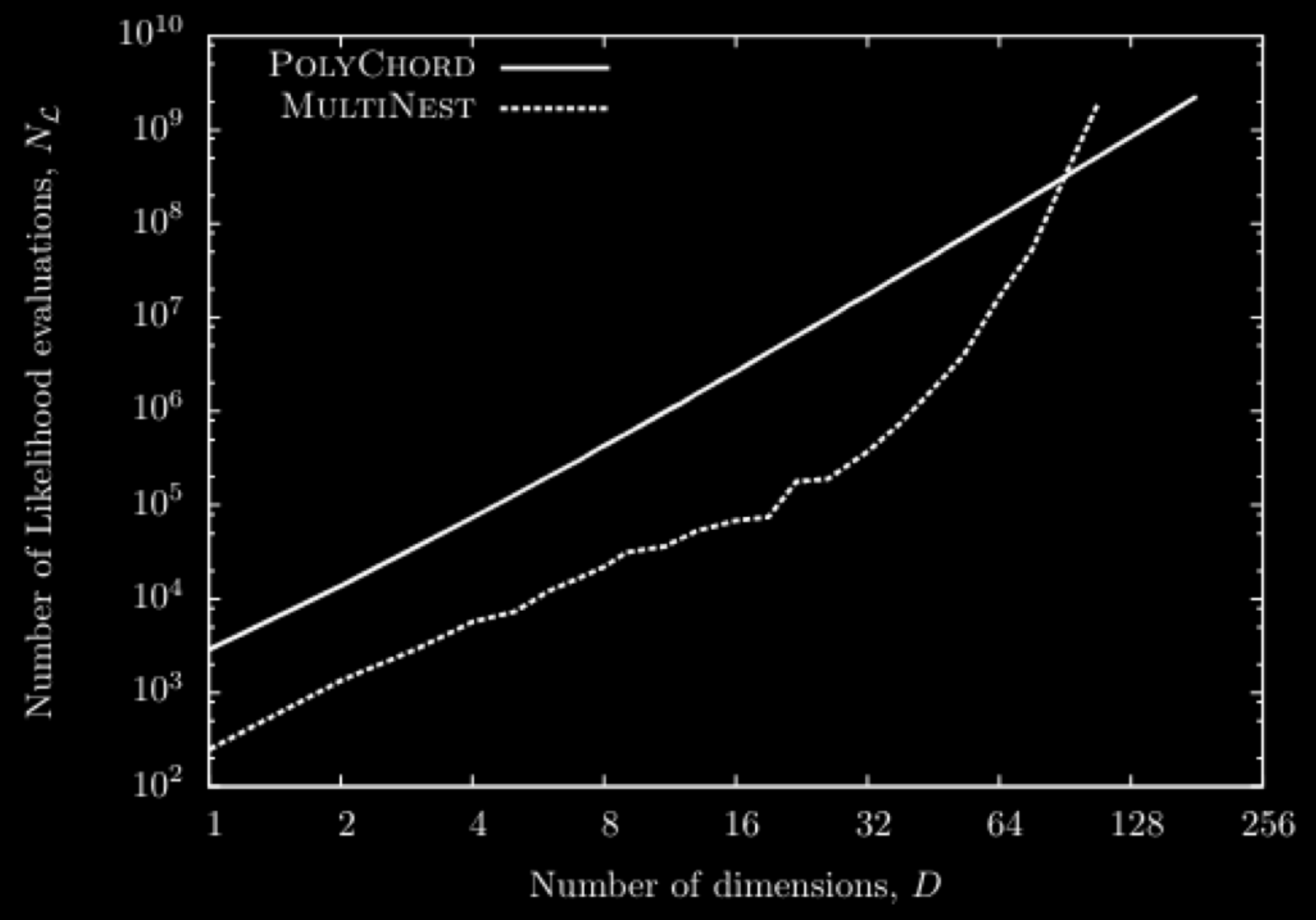
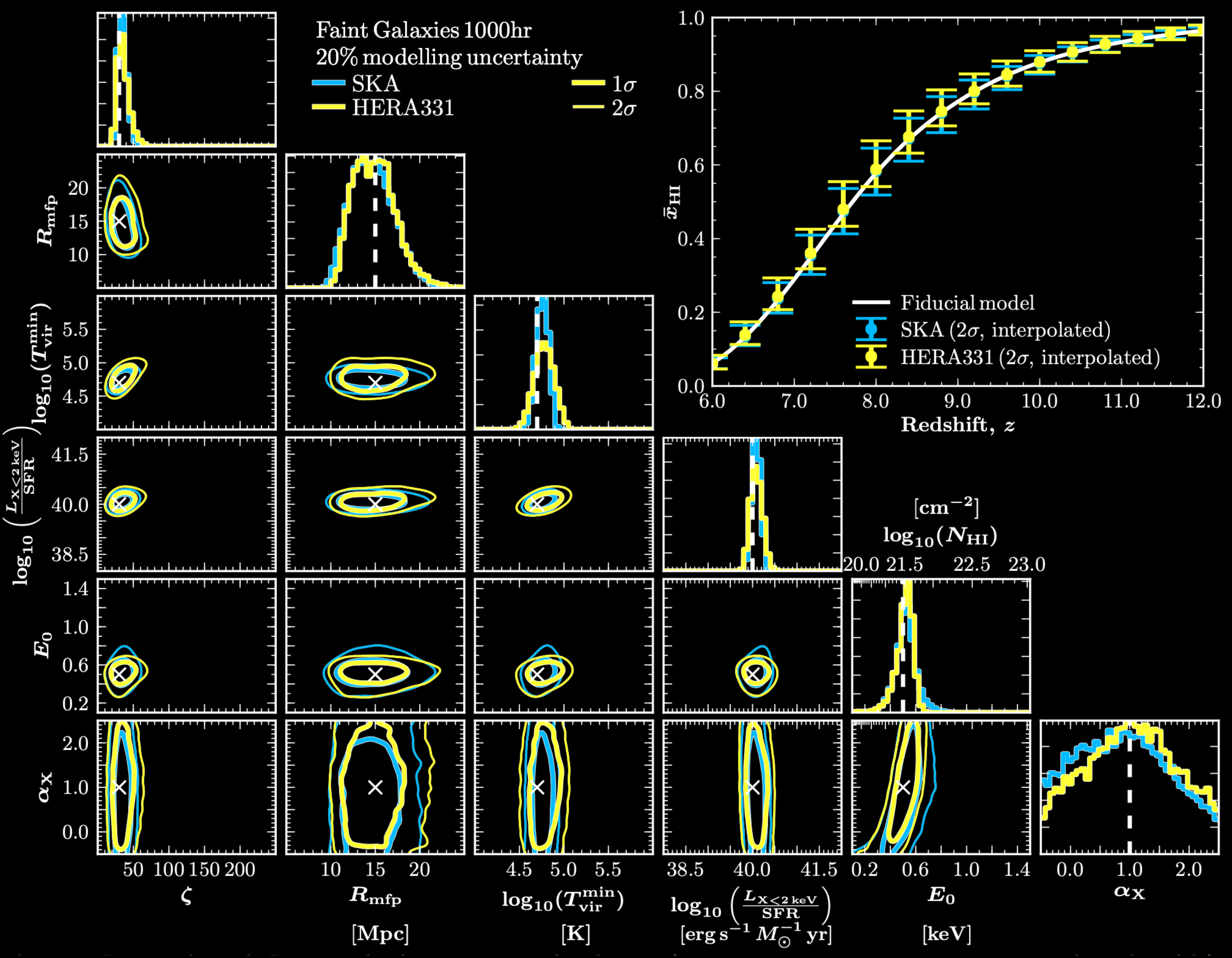
Motivation

- CD and EoR host invaluable information about the cosmology and astrophysics of the early universe.
- Interferometric observations of the 21-cm line → Parameter inference

- Modeling the evolution of these epochs is challenging.
- Difficult to perform statistical analysis using the conventional MCMC methods.



Handley et al. (2019)



Greig et al. (2017)

A step towards evading these issues

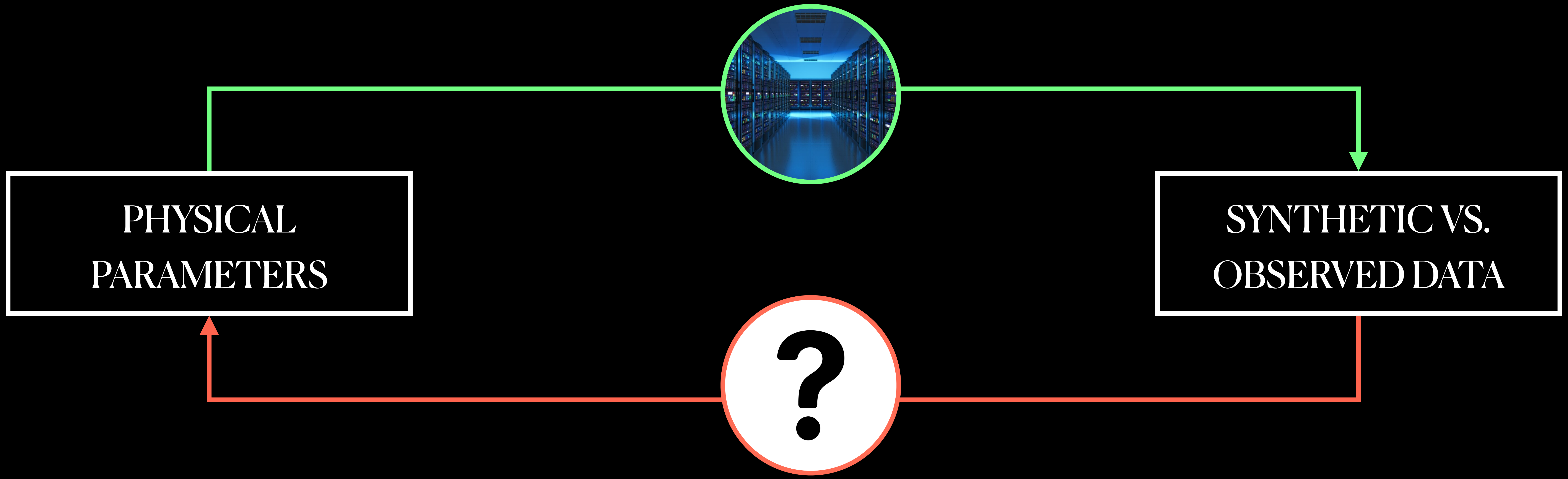
- Likelihood free inference through deep learning

How to learn from data?

Solving the inverse problem

Physics and instrument simulators

➡ Probability of observed data given a model



Inverse problem

➡ Probability of a physical model given observed data

Bayes' Theorem

$$p(\theta|x) = \frac{p(x|\theta)}{p(x)}\, p(\theta)\,,$$

Posterior: $p(\theta|x)$

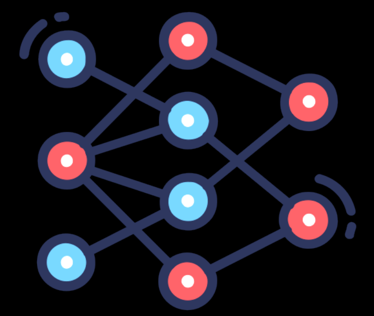
Likelihood: $p(x|\theta)$

Evidence: $p(x)$

Prior: $p(\theta)$

Methods

$\int dV$ CLASSICAL LIKELIHOOD-BASED INFERENCE



AI BASED SIMULATION BASED INFERENCE

Sometimes the problem is intractable

$$p(\theta|x) = \frac{\int d^N\eta\, p(x|\theta,\eta)\, p(\eta,\theta)}{p(x)}$$

Evaluating posteriors for parameters of interest commonly requires integrating over all parameters that are not of interest.

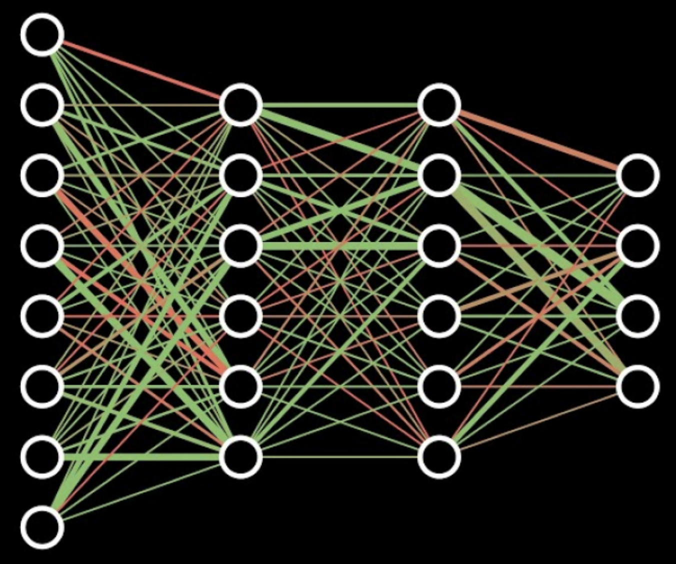
Simulation-Based Inference

Neural Ratio Estimation (NRE)

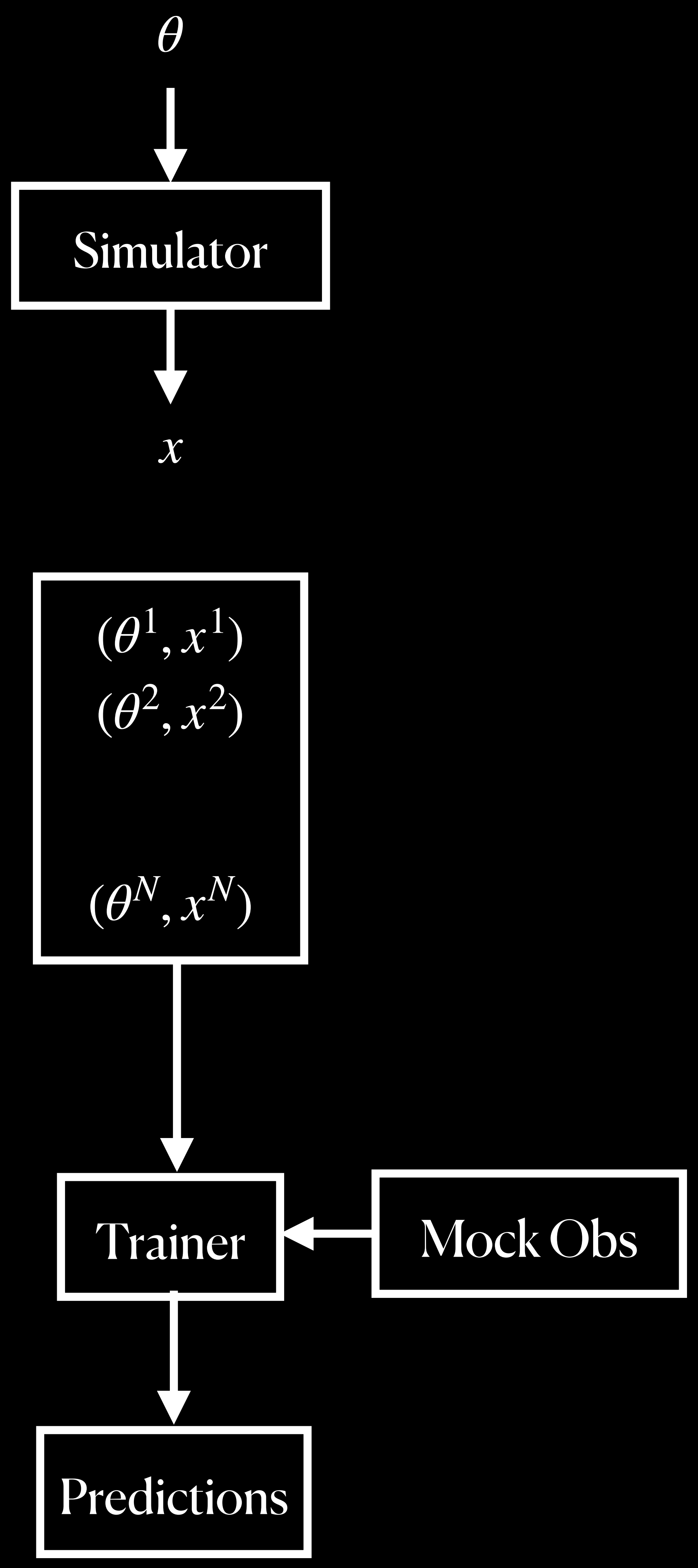
- Likelihood-to-evidence ratio: $$r(x,\theta) = \frac{p(x\,|\,\theta)}{p(x)} = \frac{p(\theta\,|\,x)}{p(\theta)} = \frac{p(x,\theta)}{p(x)\,p(\theta)}$$

- Generate sample-parameter pairs from the simulator $\{(x^1,\theta^1),(x^2,\theta^2),\ \ldots\}$

- Train a neural network to approximate this ratio



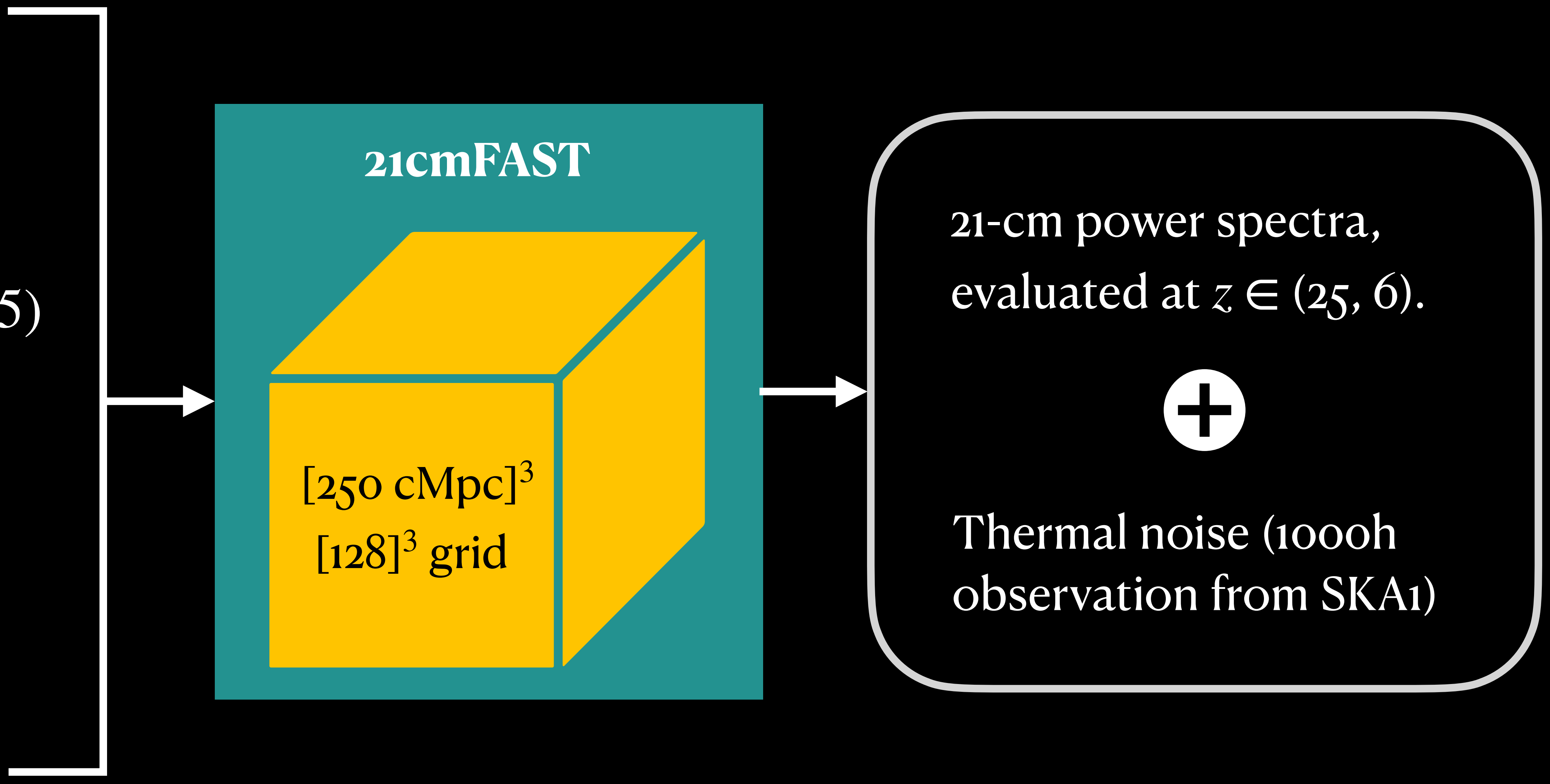
Implementation of NRE using swyft (https://github.com/undark-lab/swyft)

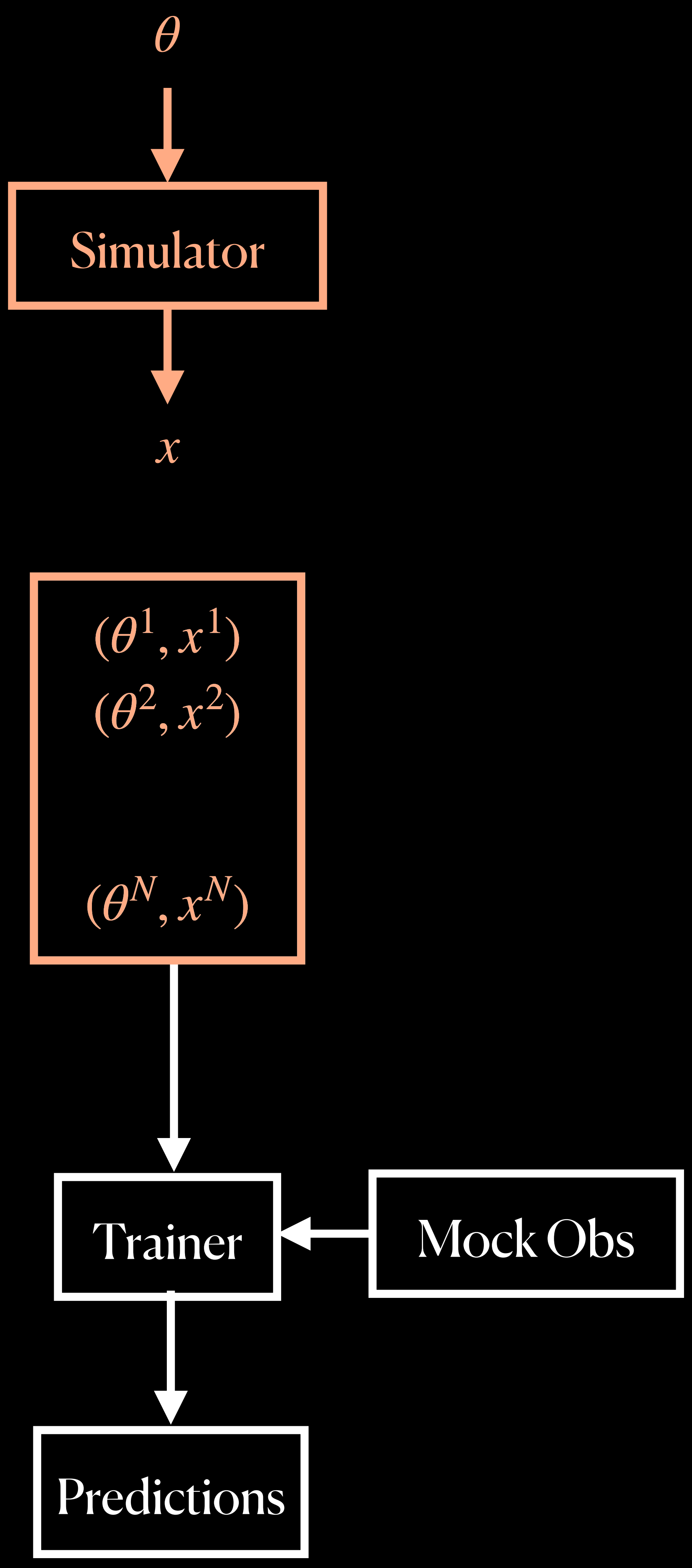


Generative model for the 21-cm signal

We use the publicly available semi-numerical formalism, 21cmFAST

1. Ionizing efficiency: $\zeta \in (10, 100)$
2. Minimum virial temperature of haloes: $T_{\rm vir}^{\rm min} \in (10^4, 10^6)$
3. Mean free path of ionizing photons: $R_{\rm mfp} \in (5, 25)$
4. Integrated soft-band luminosity: $\log_{10}(L_{\rm X}) \in (38, 42)$
5. X-ray energy threshold for self-absorption: $E_0 \in (0.1, 1.5)$ keV
6. X-ray spectral index: $\alpha_{\rm X} \in (-0.5, 2.5)$

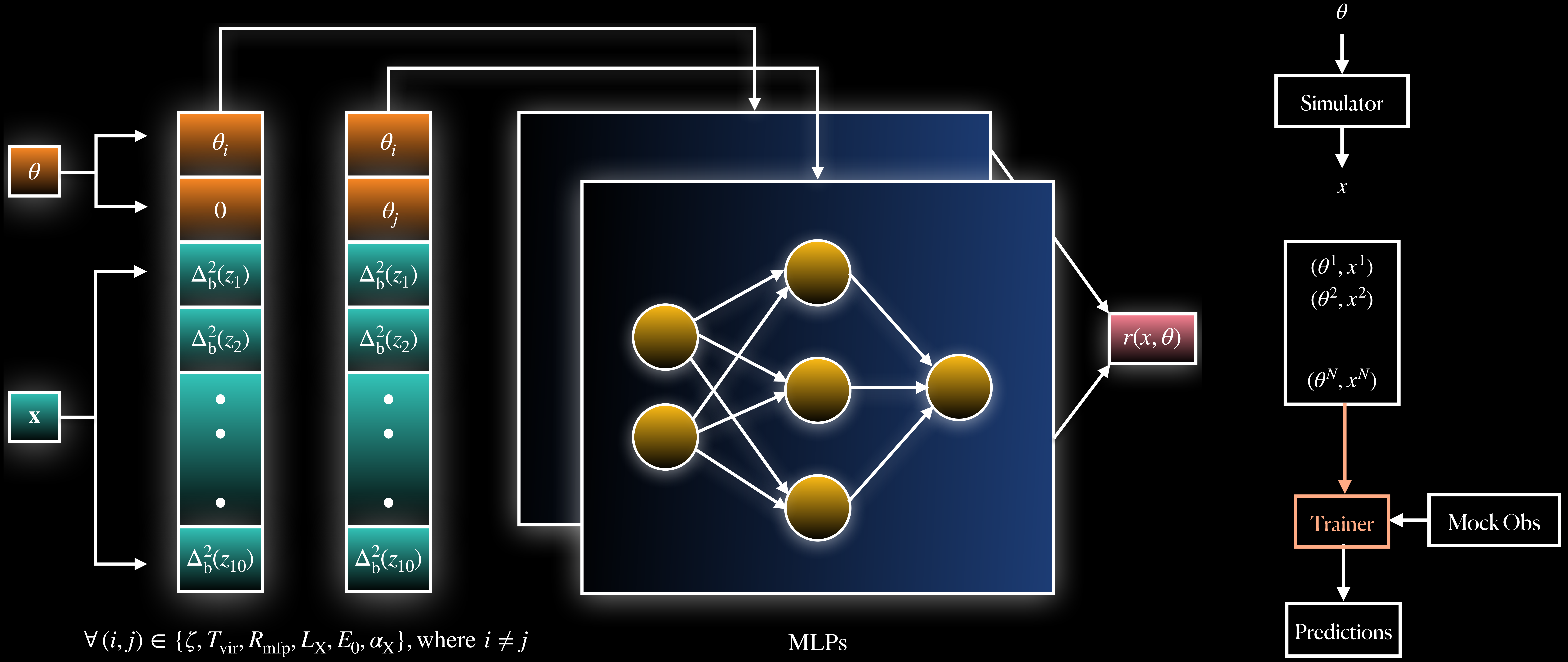




Training Data

- Composed of 20,000 power spectra samples.
- We use 80% of the samples for training, 10% for validation, and 10% for the test dataset.

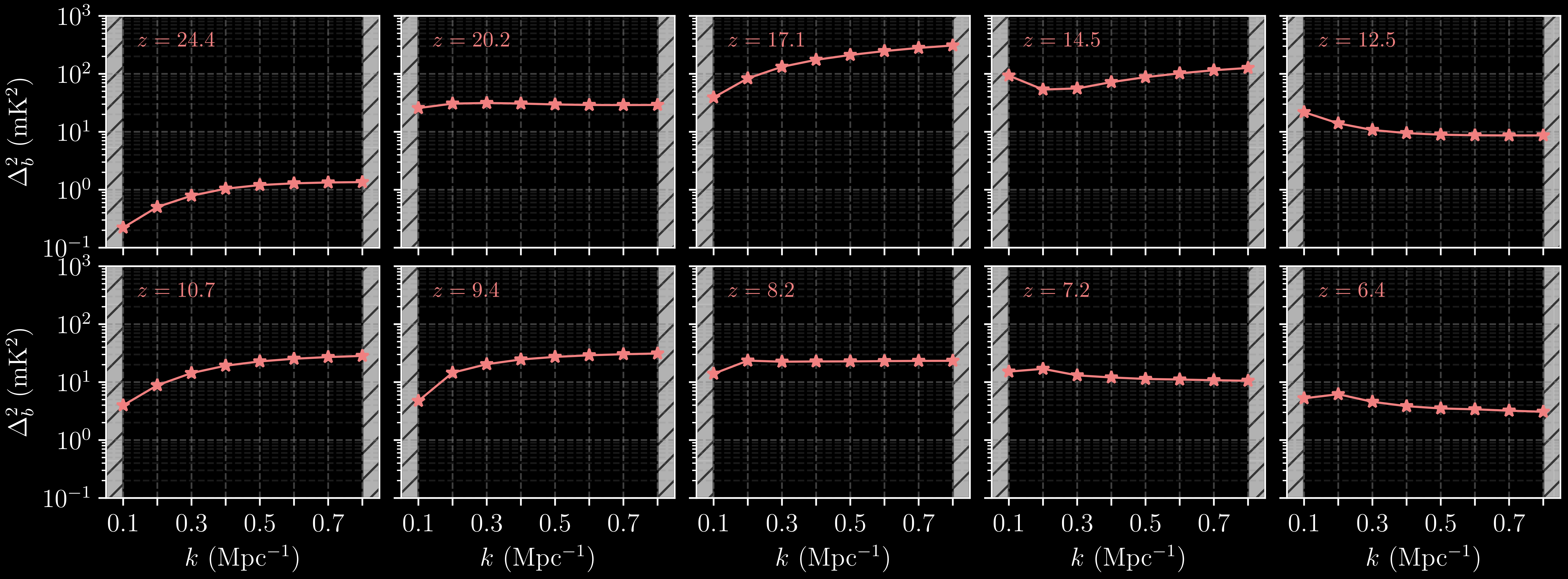
Neural Ratio Estimator

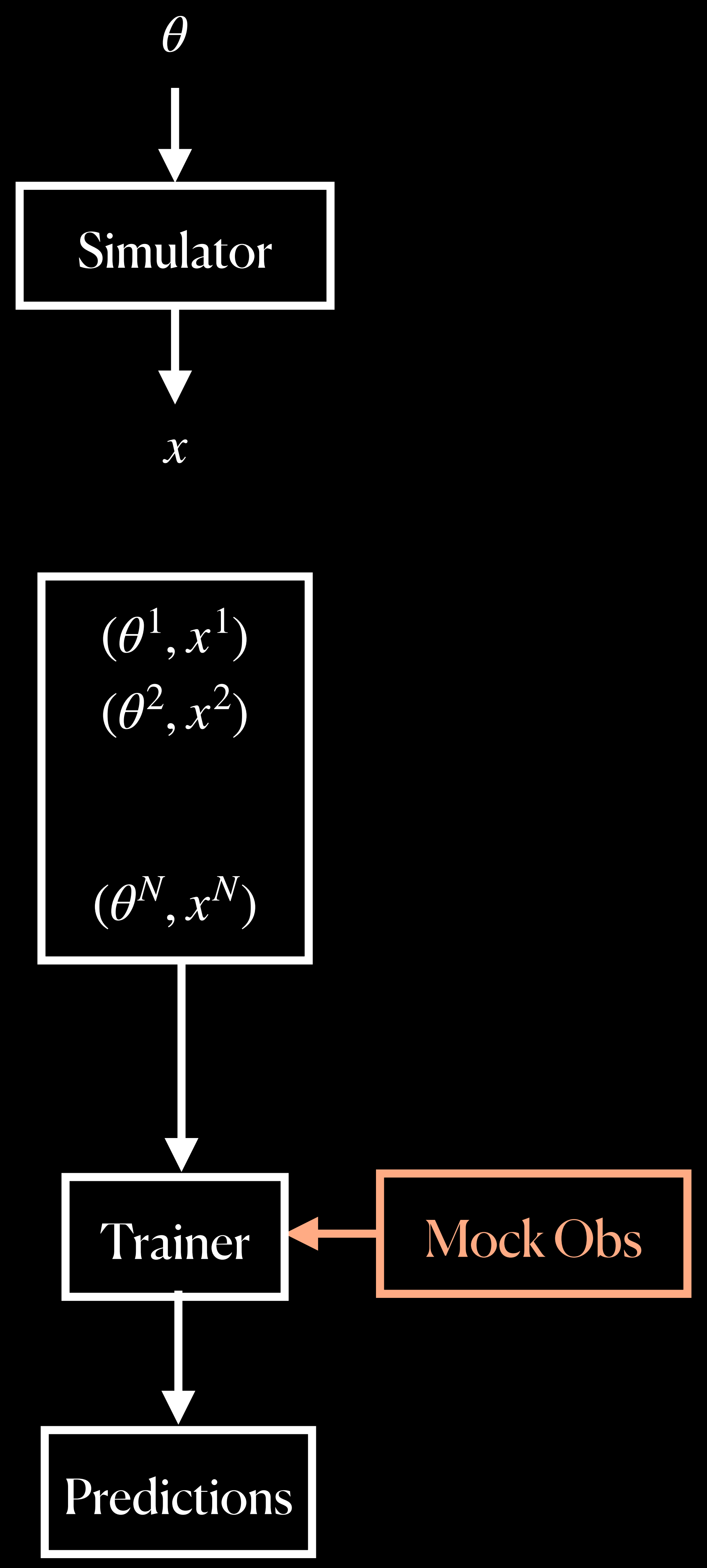


Simulated Mock Observation

FAINT GALAXIES Model

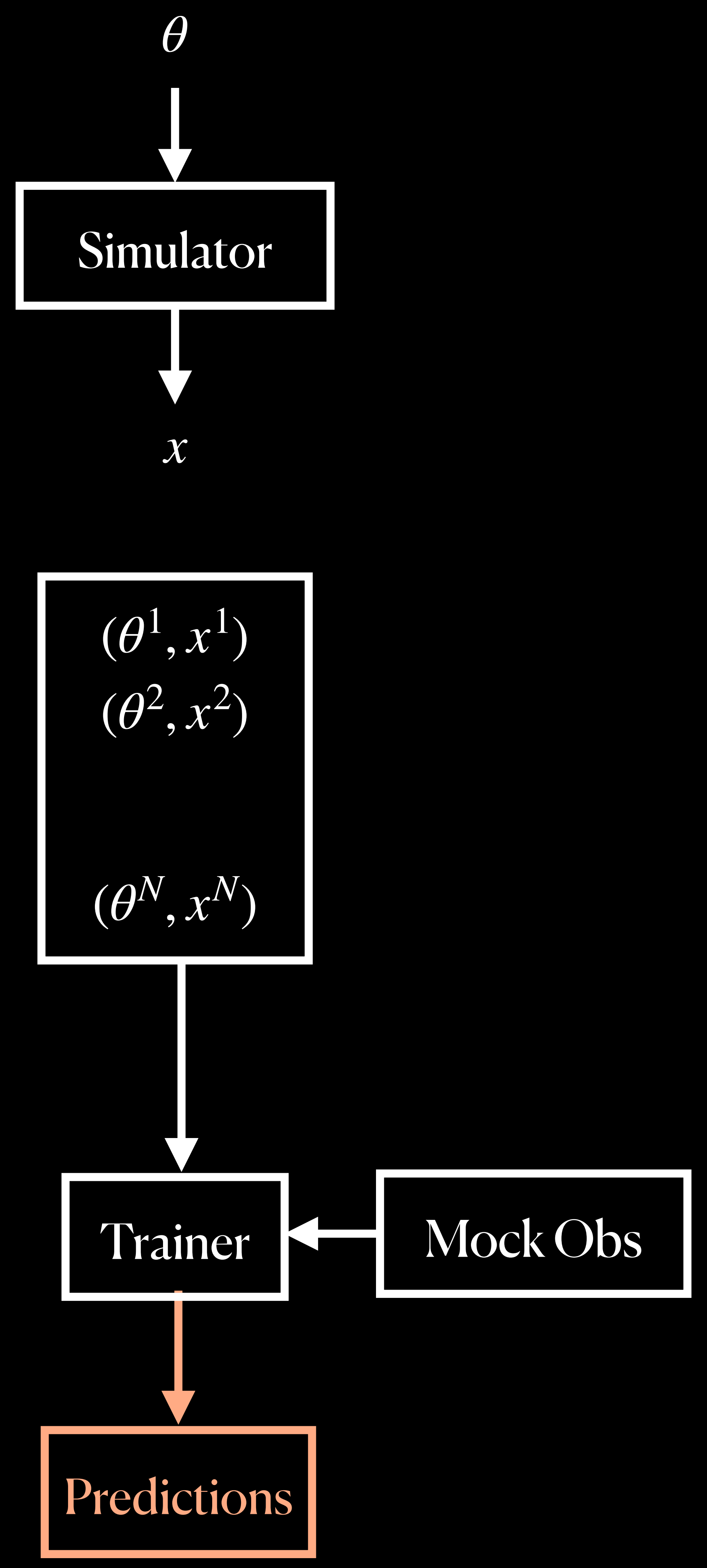
$$\{\zeta,\ \log_{10}(T_{\rm vir}^{\rm min}), R_{\rm mfp},\ \log_{10}(L_{\rm X}), E_0, \alpha_{\rm X}\} = \{30, 4.70, 15, 40.5, 0.5, 1\}$$





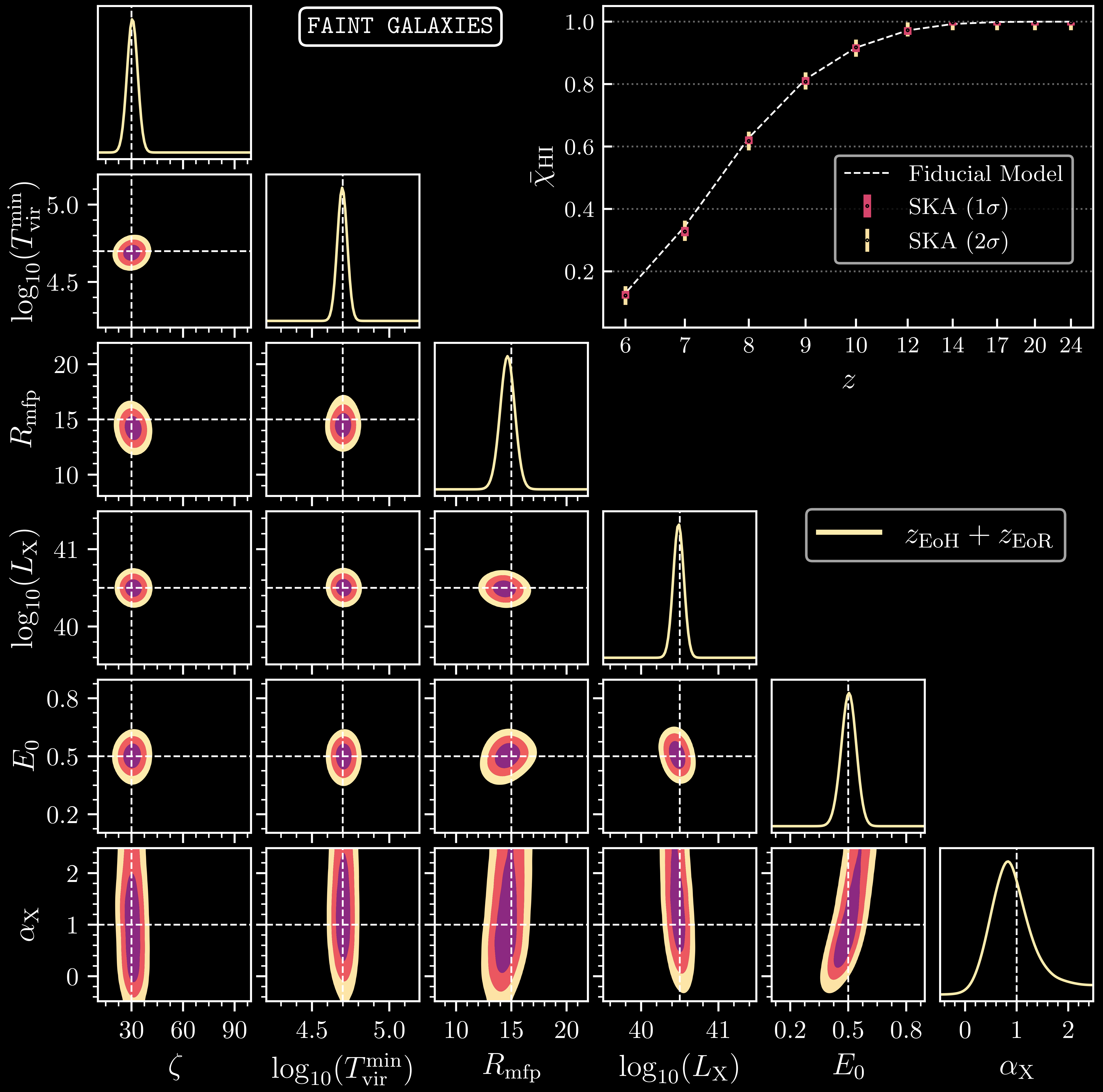
- We restrict our analysis to the k-modes in the range $k \in (0.1, 0.8)$ Mpc^{-1}.

Predictions



Recovered 1D and 2D marginal posteriors

	Inferred	True
ζ	$30.25^{+2.70}_{-1.80}$	30
$\log_{10}(T_{\rm vir}^{\rm min})$	$4.70^{+0.03}_{-0.02}$	4.70
$R_{\rm mfp}$	$14.65^{+0.56}_{-0.56}$	15
$\log_{10}(L_{\rm X})$	$40.49^{+0.04}_{-0.06}$	40.5
E_0	$0.50^{+0.03}_{-0.03}$	0.50
$\alpha_{\rm X}$	$0.84^{+0.39}_{-0.39}$	1.0



Sensitivity of model parameters during EoH and EoR

Divide the entire redshift range into two bins

$$z = \{24.4, 20.2, 17.1, 14.5, 12.5, 10.7, 9.4, 8.2, 7.2, 6.4\}$$

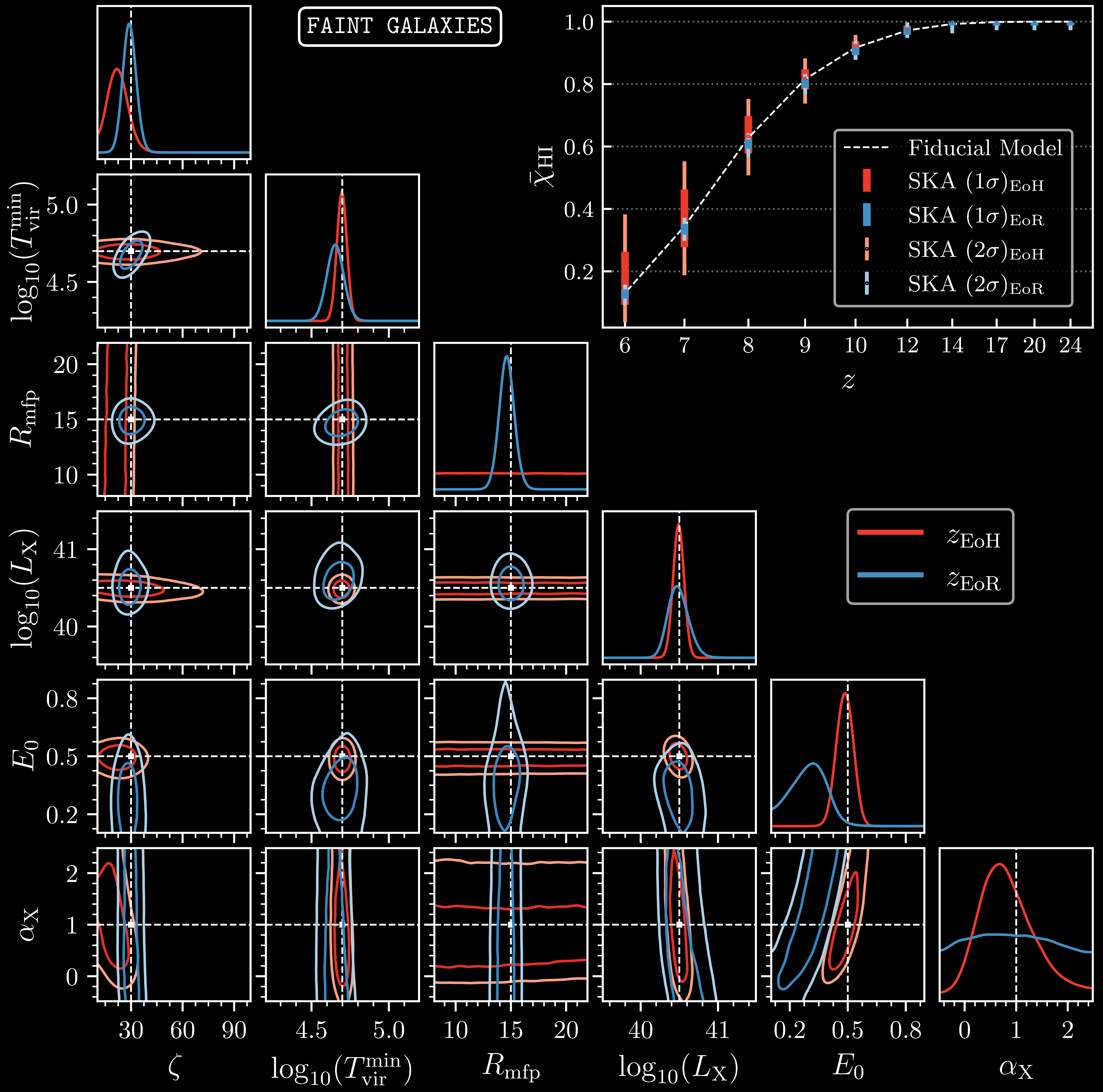
$z_{\mathrm{EoH}} \rightarrow p(\theta \mid x_{z_{\mathrm{EoH}}})$

$z_{\mathrm{EoR}} \rightarrow p(\theta \mid x_{z_{\mathrm{EoR}}})$

- This analysis does not require any extra 21-cm power spectra simulations.
- Re-use the simulations with a minimal change in the network architecture

Recovered posteriors from z_{EoH} and z_{EoR}

	z_{EoH}	z_{EoR}	True
ζ	$22.15^{+5.40}_{-5.40}$	$29.35^{+2.70}_{-3.60}$	30
$\log_{10}(T_{\mathrm{vir}}^{\mathrm{min}})$	$4.70^{+0.03}_{-0.02}$	$4.66^{+0.04}_{-0.05}$	4.70
R_{mfp}	–	$14.65^{+0.56}_{-0.56}$	15
$\log_{10}(L_{\mathrm{X}})$	$40.49^{+0.06}_{-0.06}$	$40.47^{+0.12}_{-0.12}$	40.5
E_0	$0.49^{+0.03}_{-0.04}$	$0.32^{+0.07}_{-0.10}$	0.50
α_{X}	$0.68^{+0.51}_{-0.45}$	–	1.0



Summary

- Performed the Simulation-Based Inference (SBI) through Marginal Neural Ratio Estimation.
- Constrain the astrophysical parameters which govern the heating and reionization of the IGM.
- Re-use the simulations and utilize the same training dataset for various applications: More efficient

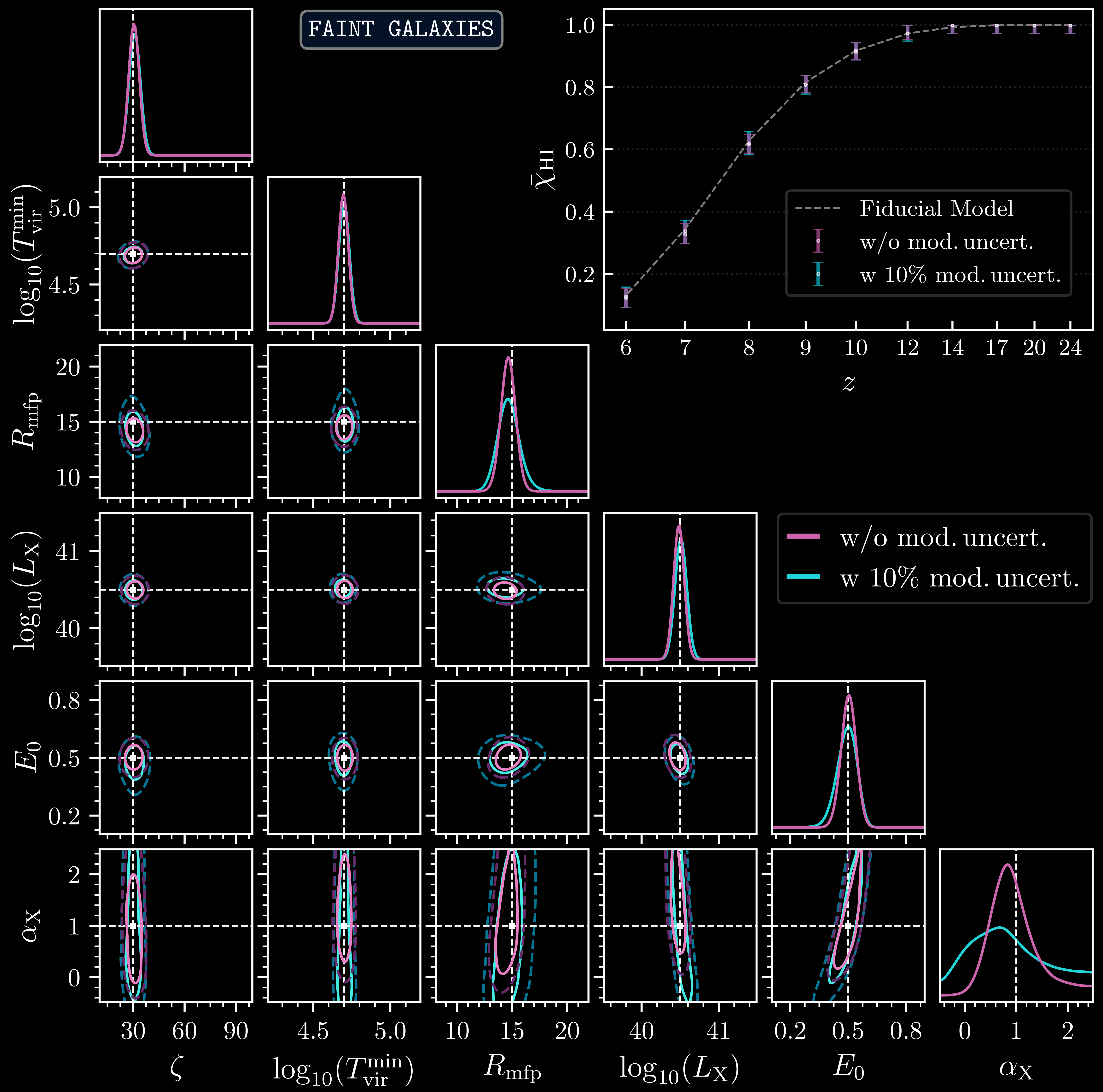
Repository https://github.com/anchal-009/swyft_21cmPk

Next steps

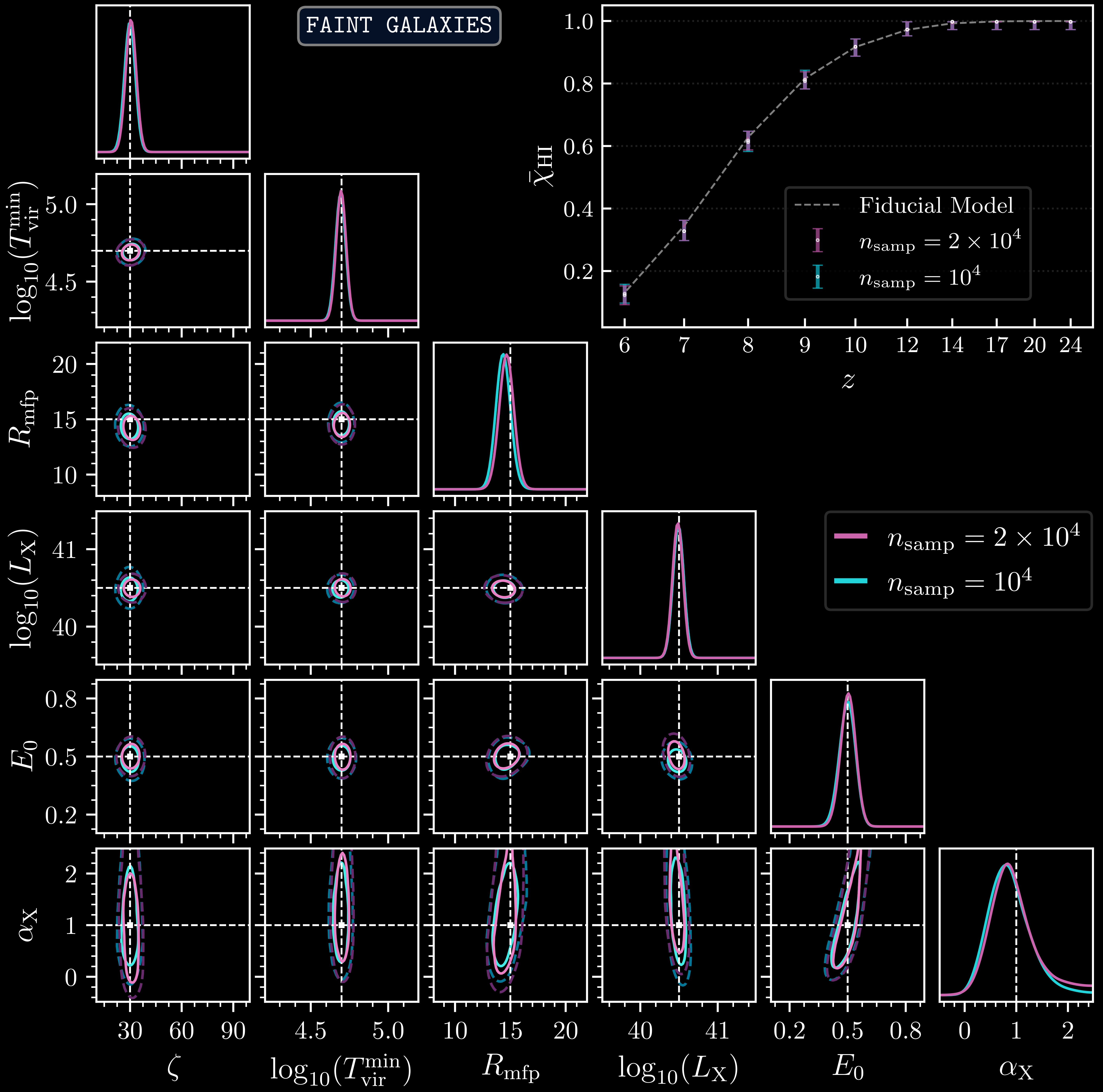
- Higher order information: 21-cm bispectrum
- Morphology of ionized regions
- CNN on the 21-cm tomographic images

BACKUP SLIDES

Impact of including modeling uncertainty



Impact of size of the training data



Coverage of the trained network