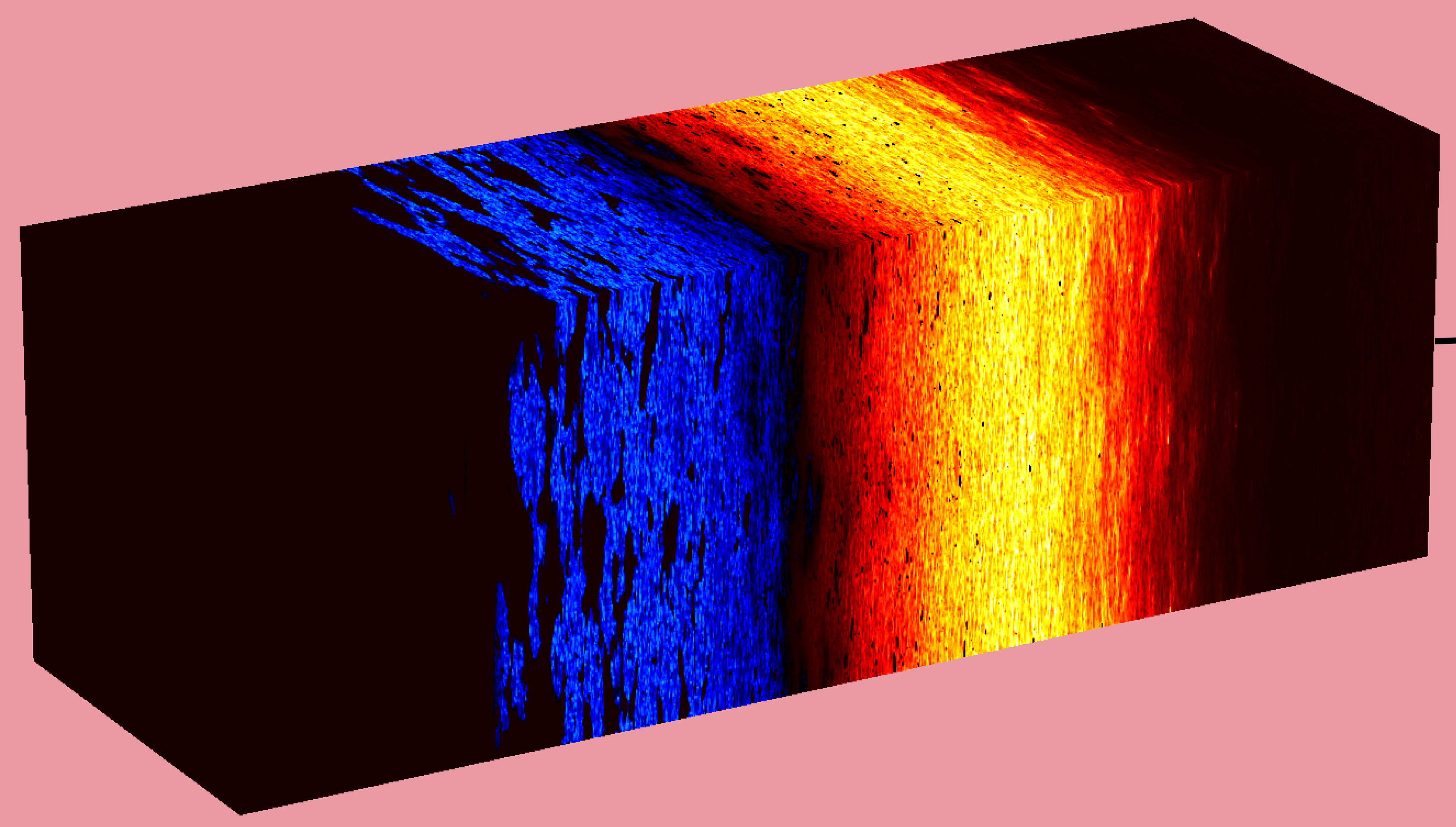
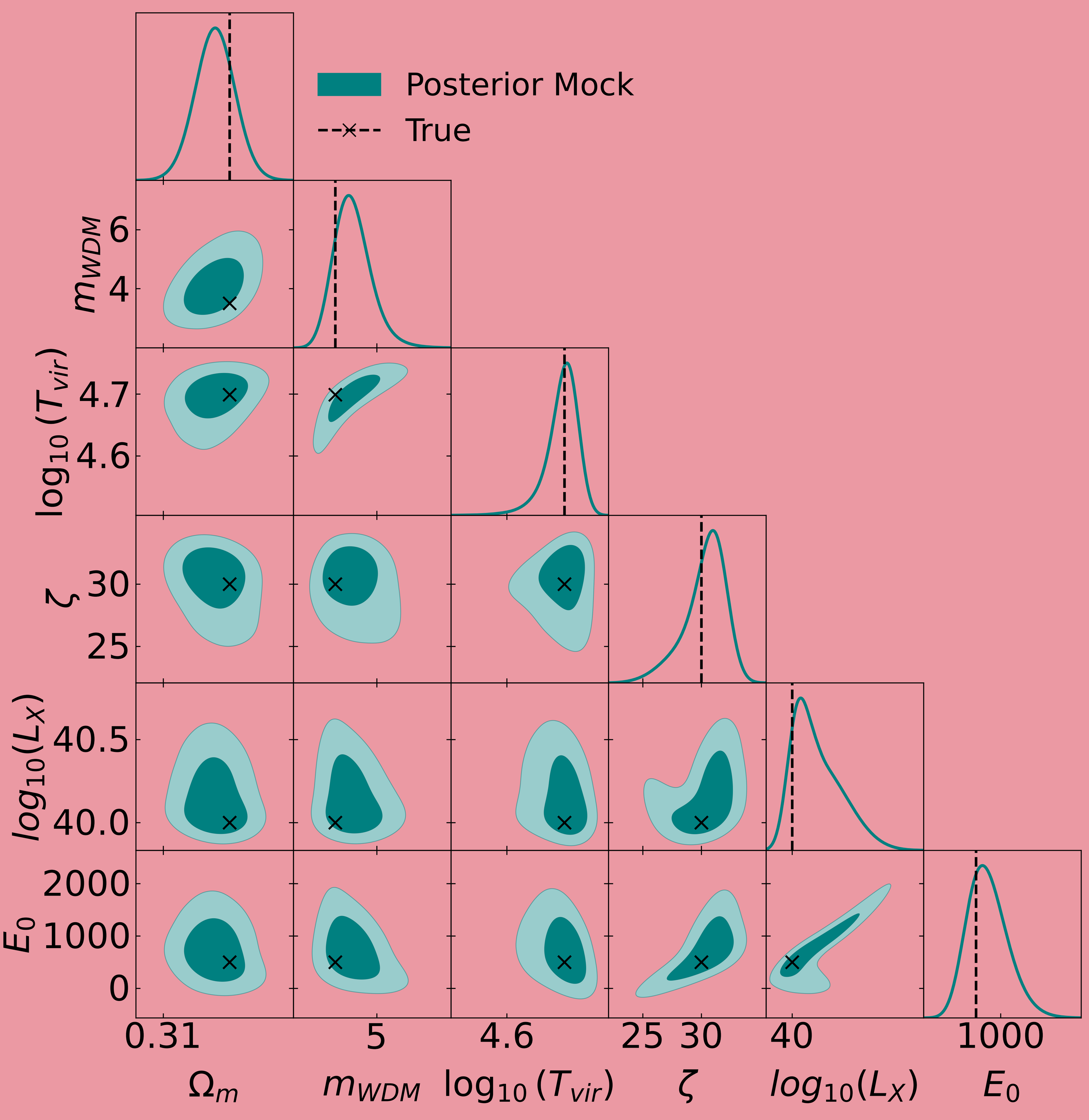
Simulation-based inference with flows is an **optimal** framework for **fast** parameter estimation from the **21cm** light cone.



BayesFlow



Optimal, fast, and robust inference of reionization-era cosmology with the 21cmPIE-INN

Benedikt Schosser[1,2], Caroline Heneka[2], Tilman Plehn[2,3]

Machine Learning for 21cm Physics

- 21cm physics: Unique insight into **Cosmic Dawn** and **Epoch of Reionization**. Enables large-scale structure mapping through experiments like LOFAR and future SKA. Intensity mapping will allow the investigation of fundamental physics.
- Need for ML: Traditional methods (e.g. MCMC) struggle with **volume** and **complexity** of the data. Non-Gaussian information is lost in a power spectrum analysis.

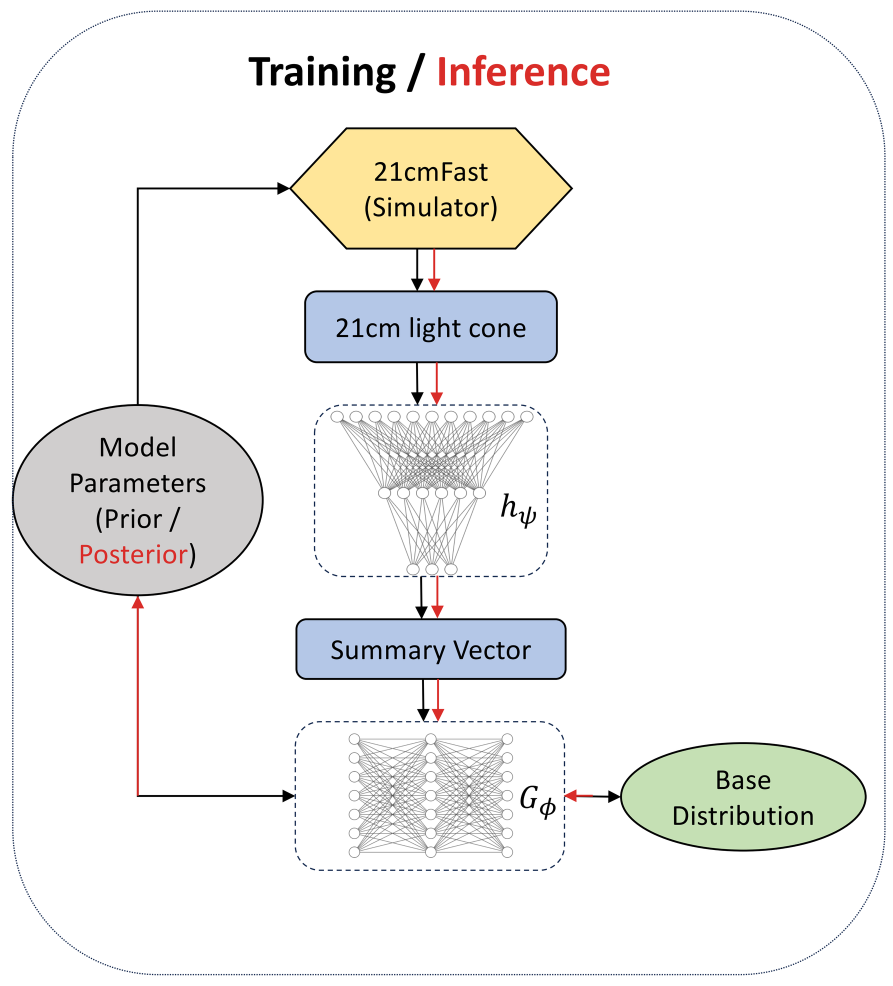
Dataset

- 6d parameter set: Ω_m, m_WDM, T_vir, ζ, L_X, E_0
- Redshift: $z = 5 \ldots 35$
- Total of 5000 simulated light cones

Setup

Combination of summary network h_ψ (3D-CNN) and inference network G_ϕ (cINN).

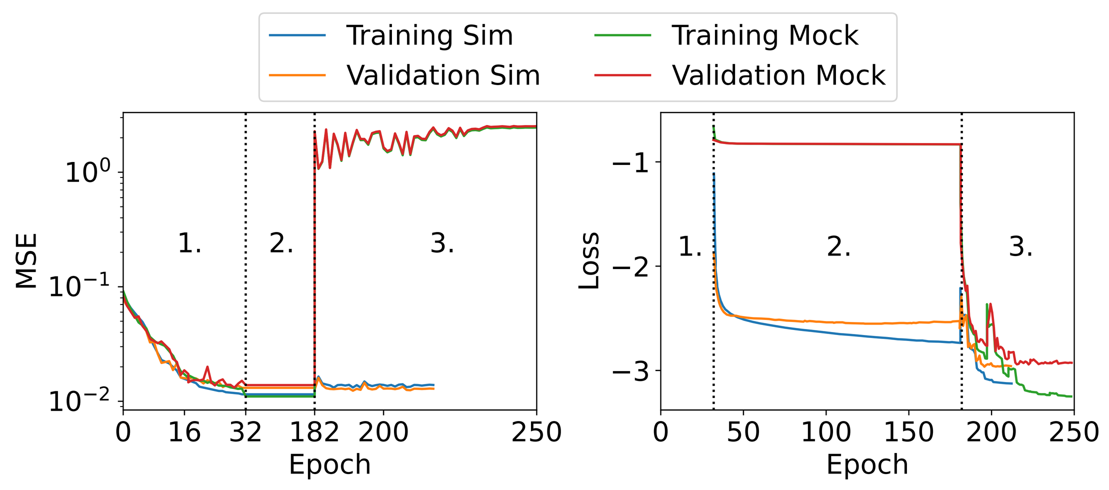
$$\mathcal{L} = D_\mathrm{KL}[p(\theta|x), p_{\psi,\phi}(\theta|x)]$$
$$= -\left\langle \frac{|\overline{G}_\phi(\theta|h_\psi(x))|^2}{2} + \log\left|\frac{\partial \overline{G}_\phi(\theta|h_\psi(x))}{\partial\theta}\right|\right\rangle_{p(\theta|x)}$$



Training

3-stage training to find the optimal representation

1. Pretrain summary network
2. Pretrain inference network
3. Combined training for optimal convergence



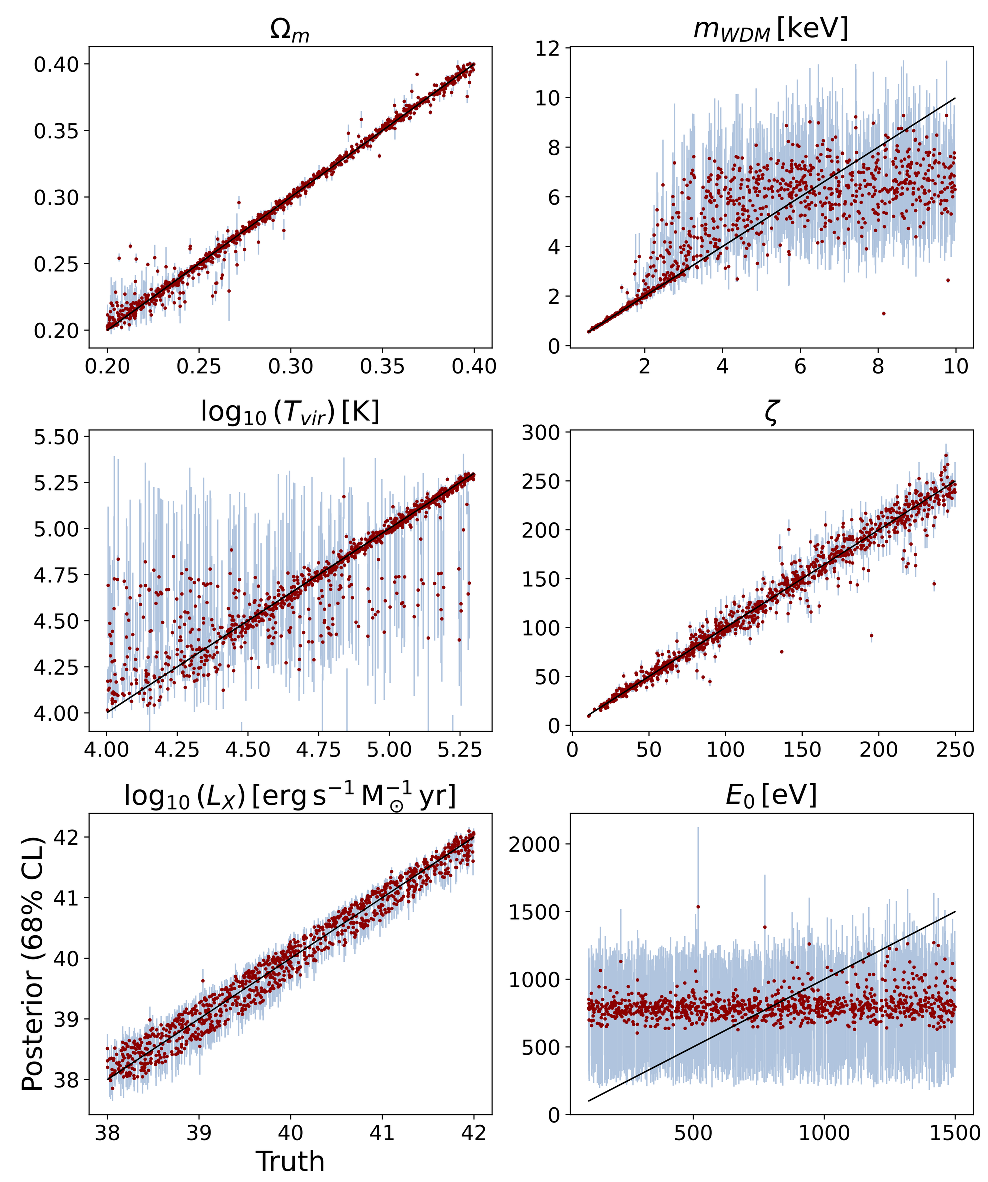
Validation Methods

Use multiple checks to confirm correct approximation of unknown posterior:

- Statistical recovery of the truth
- Calibration error
- Simulation-based calibration

Correct Parameter Recovery

The posterior of simulated data statistically recovers the true value.



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[1] B. Schosser et al., arXiv:2401.04174, (This work).
[2] A. Mesinger et al., arXiv:1003.3878,(21cmFAST, Simulation).
[3] S. T. Radev et al., arXiv:2003.06281.(BayesFlow, Inference)

Link to the full paper

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