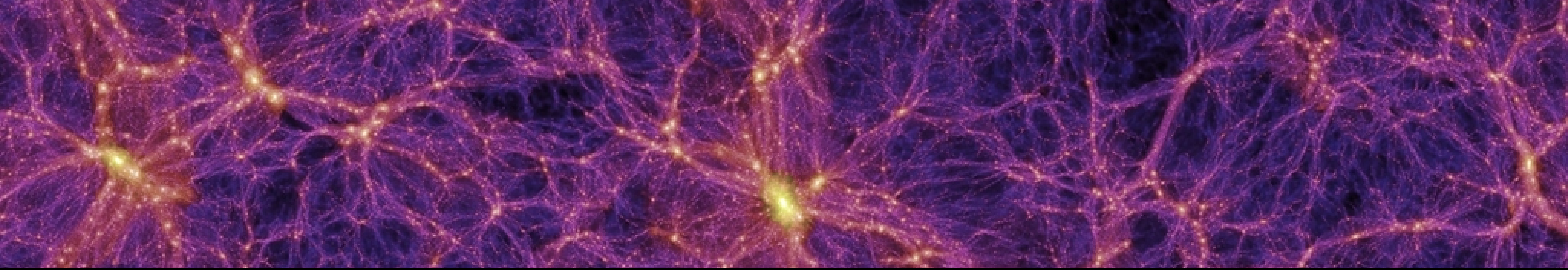


EFTofLSS meets simulation-based inference: σ_8 from biased tracers

Beatriz Tucci
In collaboration with: Fabian Schmidt

Based on arXiv:2310.03741

LEFTfield

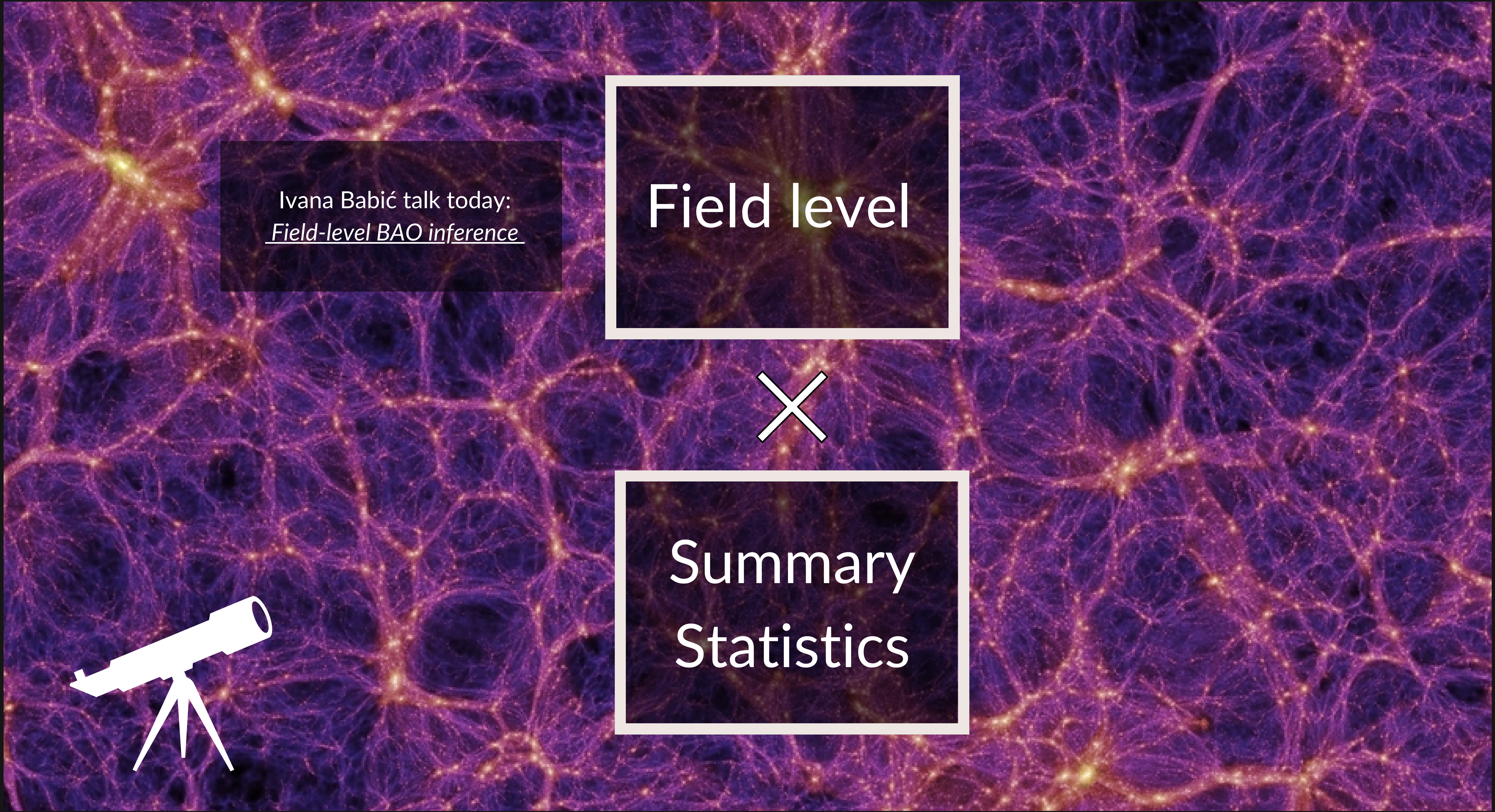
MAX-PLANCK-INSTITUT FÜR ASTROPHYSIK

Ivana Babić talk today:
Field-level BAO inference

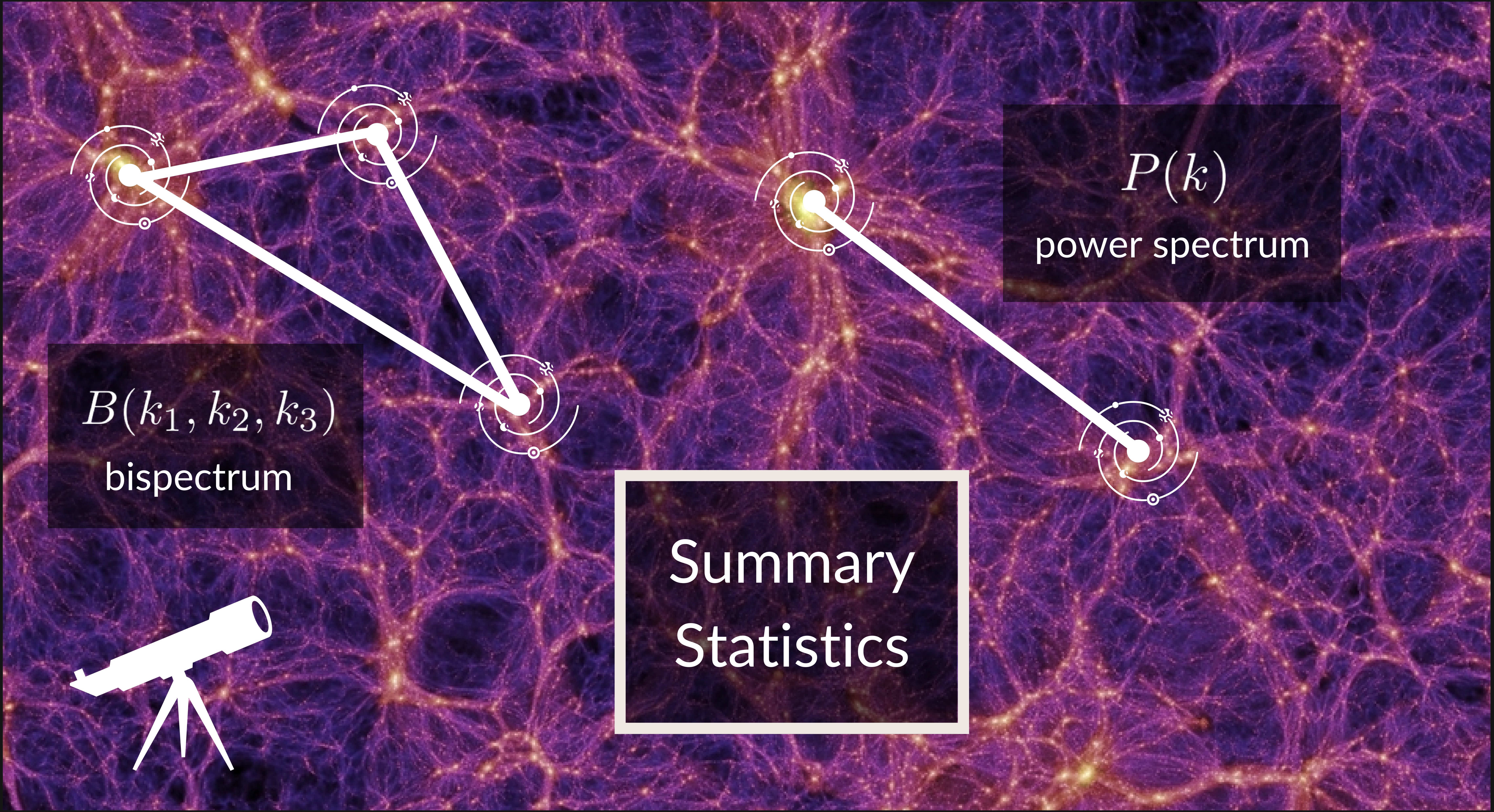
Field level

×

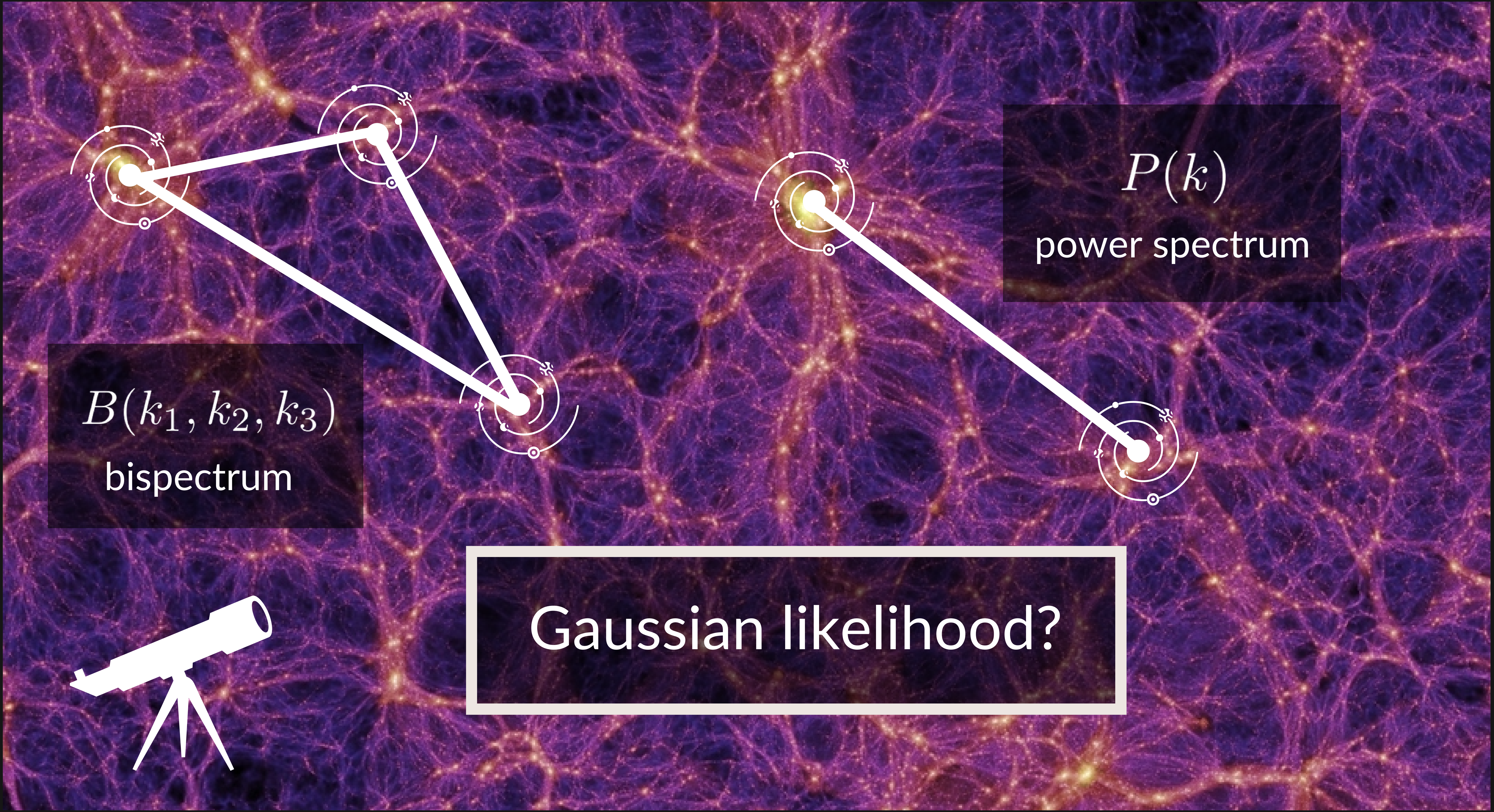
Summary Statistics



The Millennium Simulation Project



The Millennium Simulation Project



The Millennium Simulation Project

Standard inference in cosmology

Parameters posterior

Likelihood

Prior over the parameters

$$p(\boldsymbol{\theta}|\boldsymbol{x}) \propto \mathcal{L}(\boldsymbol{x}|\boldsymbol{\theta})\mathcal{P}(\boldsymbol{\theta})$$

Standard inference in cosmology

Parameters posterior

Likelihood

Prior over the parameters

$$p(\boldsymbol{\theta}|\boldsymbol{x}) \propto \mathcal{L}(\boldsymbol{x}|\boldsymbol{\theta})\mathcal{P}(\boldsymbol{\theta})$$

Possible problems:

- Need of analytical approximations
- Cumbersome covariance estimations
- Binning effects

Simulation-based inference

Parameters posterior

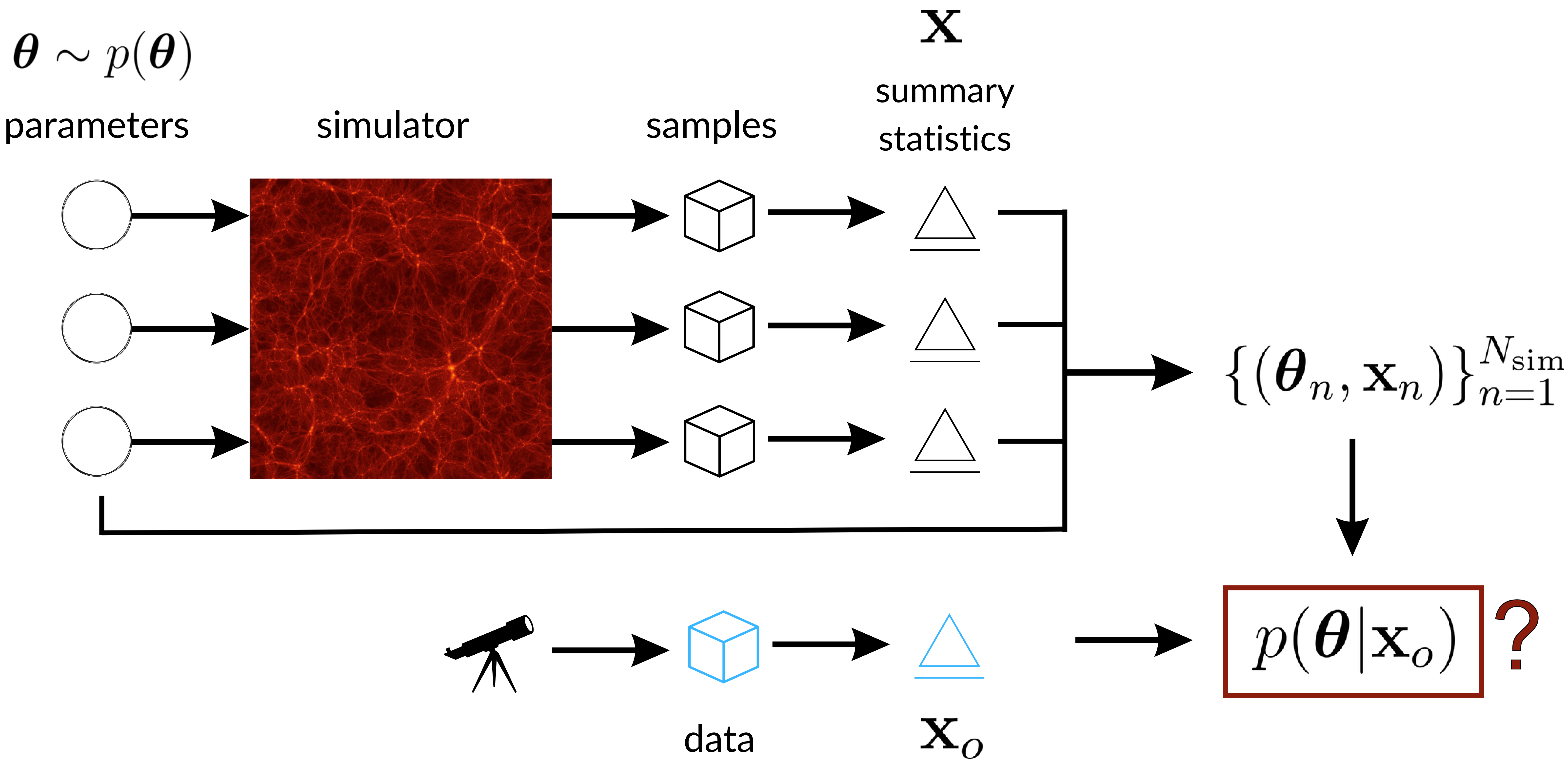
Likelihood

Prior over the parameters

$$p(\boldsymbol{\theta}|\boldsymbol{x}) \propto \mathcal{L}(\boldsymbol{x}|\boldsymbol{\theta})\mathcal{P}(\boldsymbol{\theta})$$

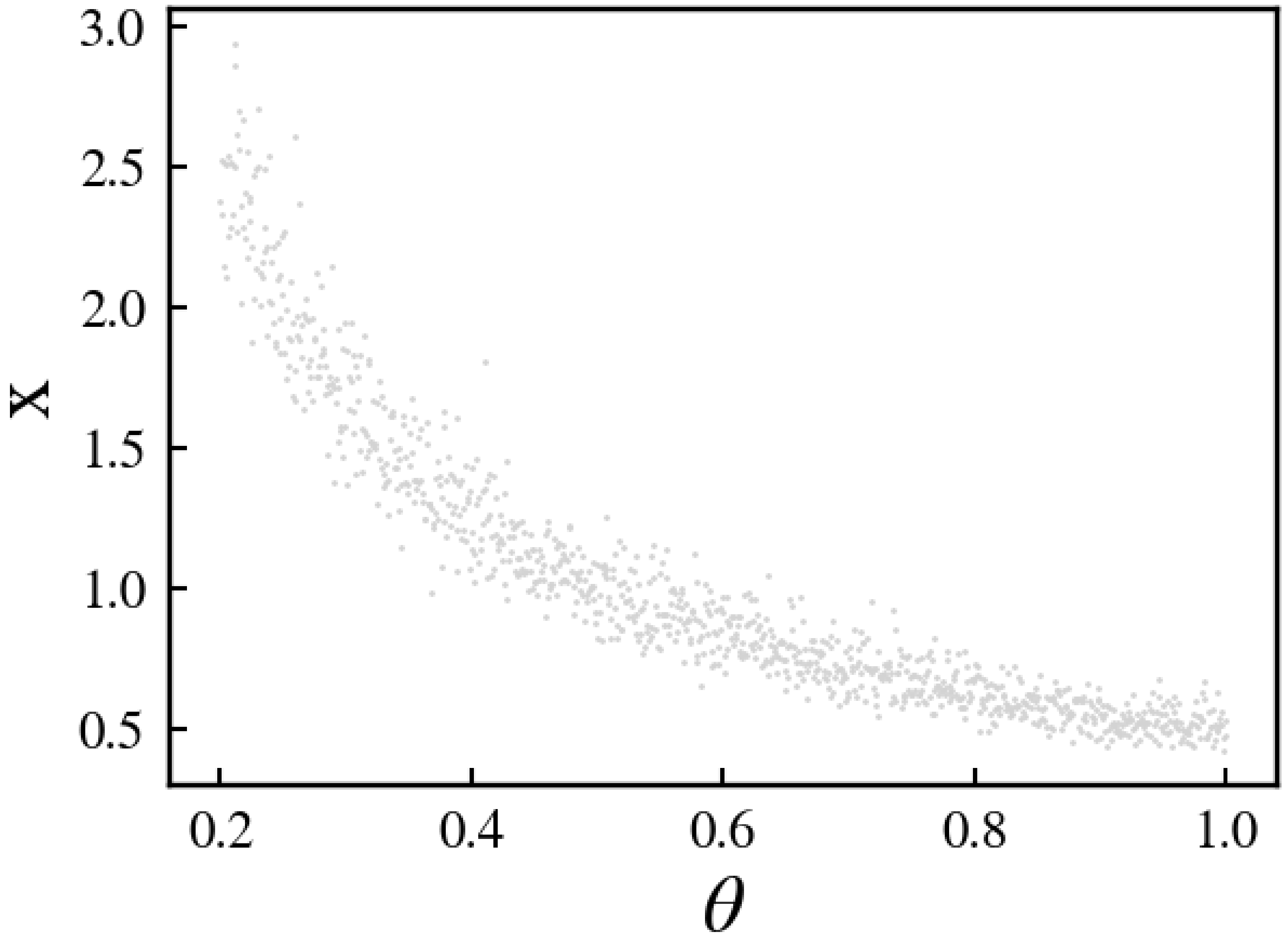
$$\boldsymbol{x} \sim \text{simulator}(\boldsymbol{\theta})$$

Simulation-based inference



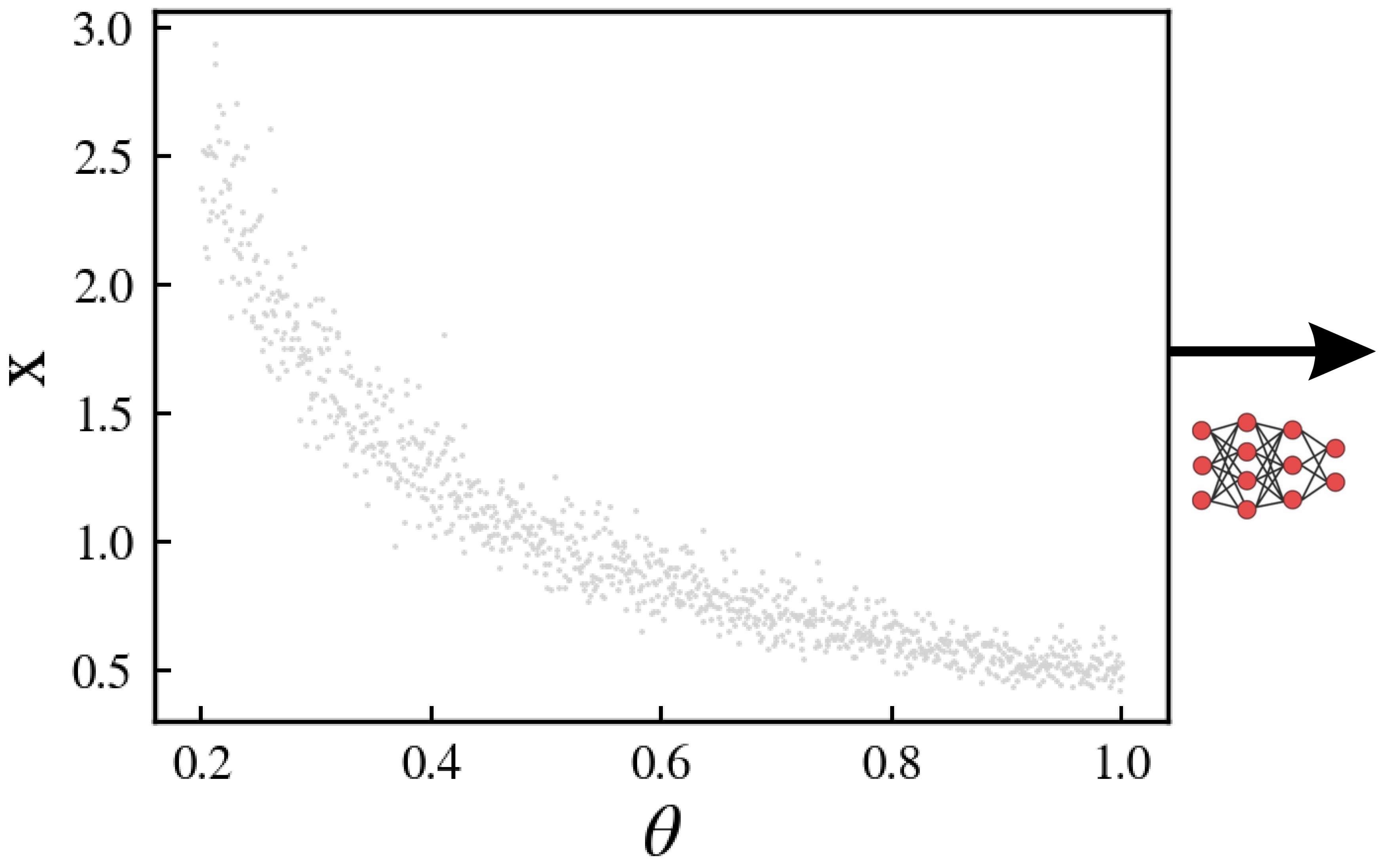
Simulation-based inference

$$\{(\boldsymbol{\theta}_n, \mathbf{x}_n)\}_{n=1}^{N_{\text{sim}}}$$

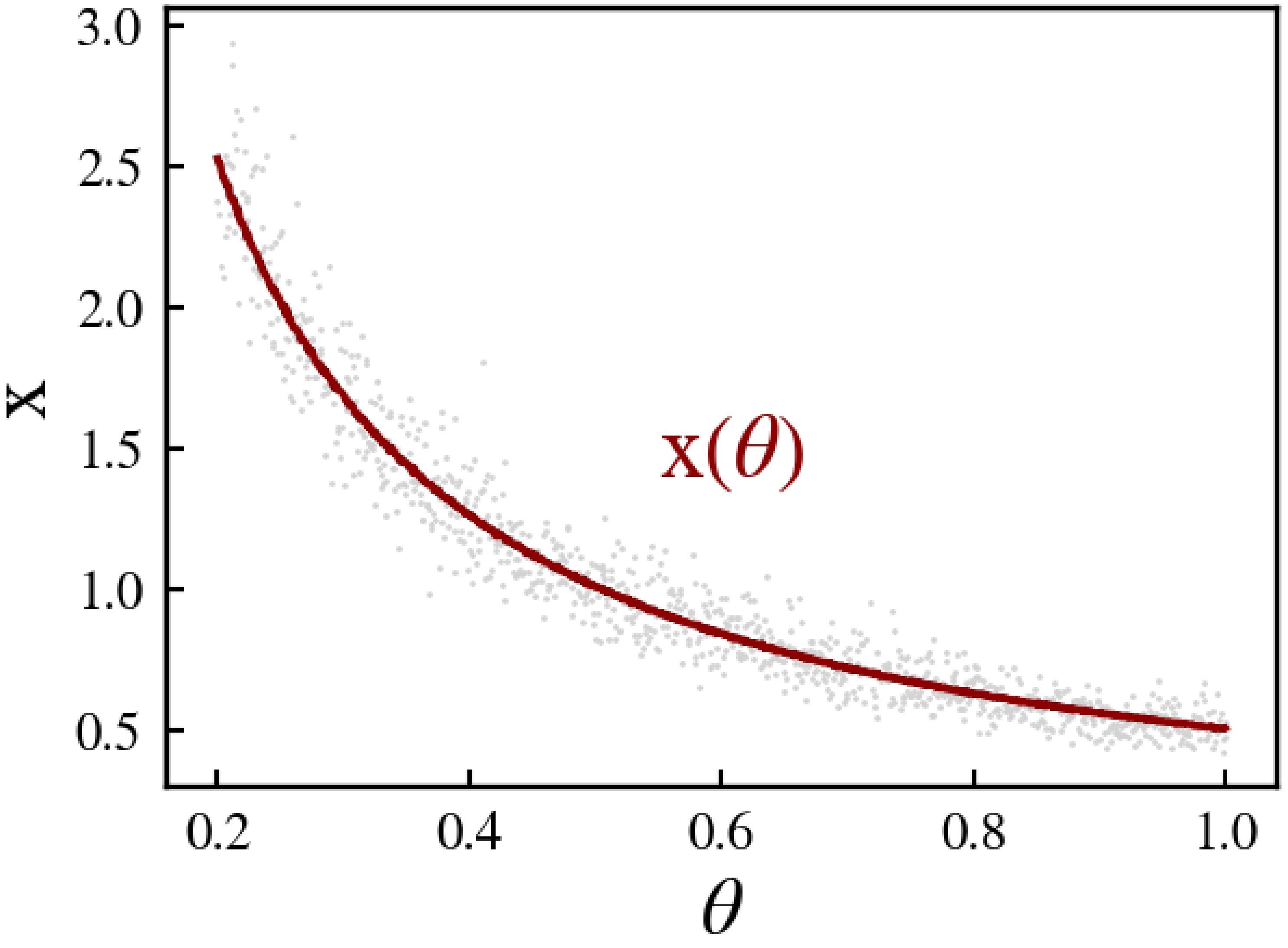


Simulation-based inference

$$\{(\boldsymbol{\theta}_n, \mathbf{x}_n)\}_{n=1}^{N_{\mathrm{sim}}}$$



Summary statistics emulators

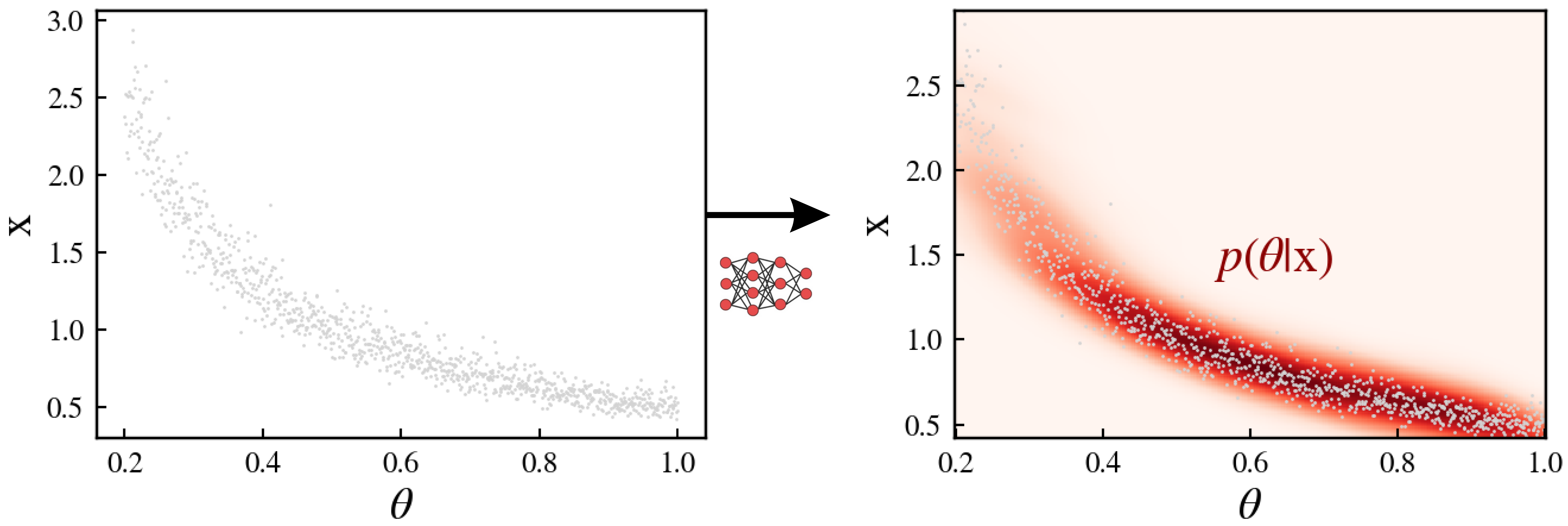


This is not what we are doing!

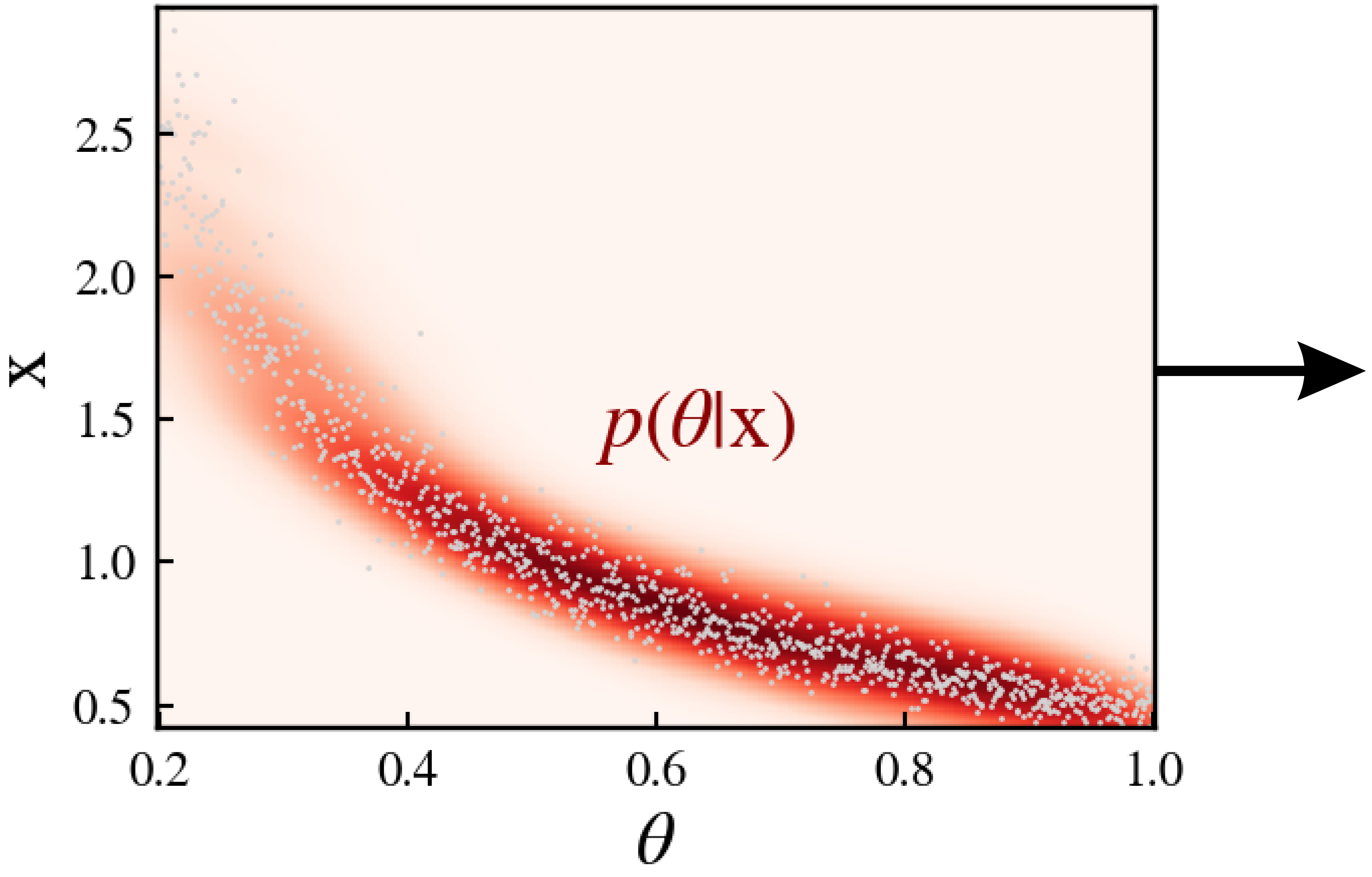
Simulation-based inference

$$\{(\boldsymbol{\theta}_n, \mathbf{x}_n)\}_{n=1}^{N_{\text{sim}}}$$

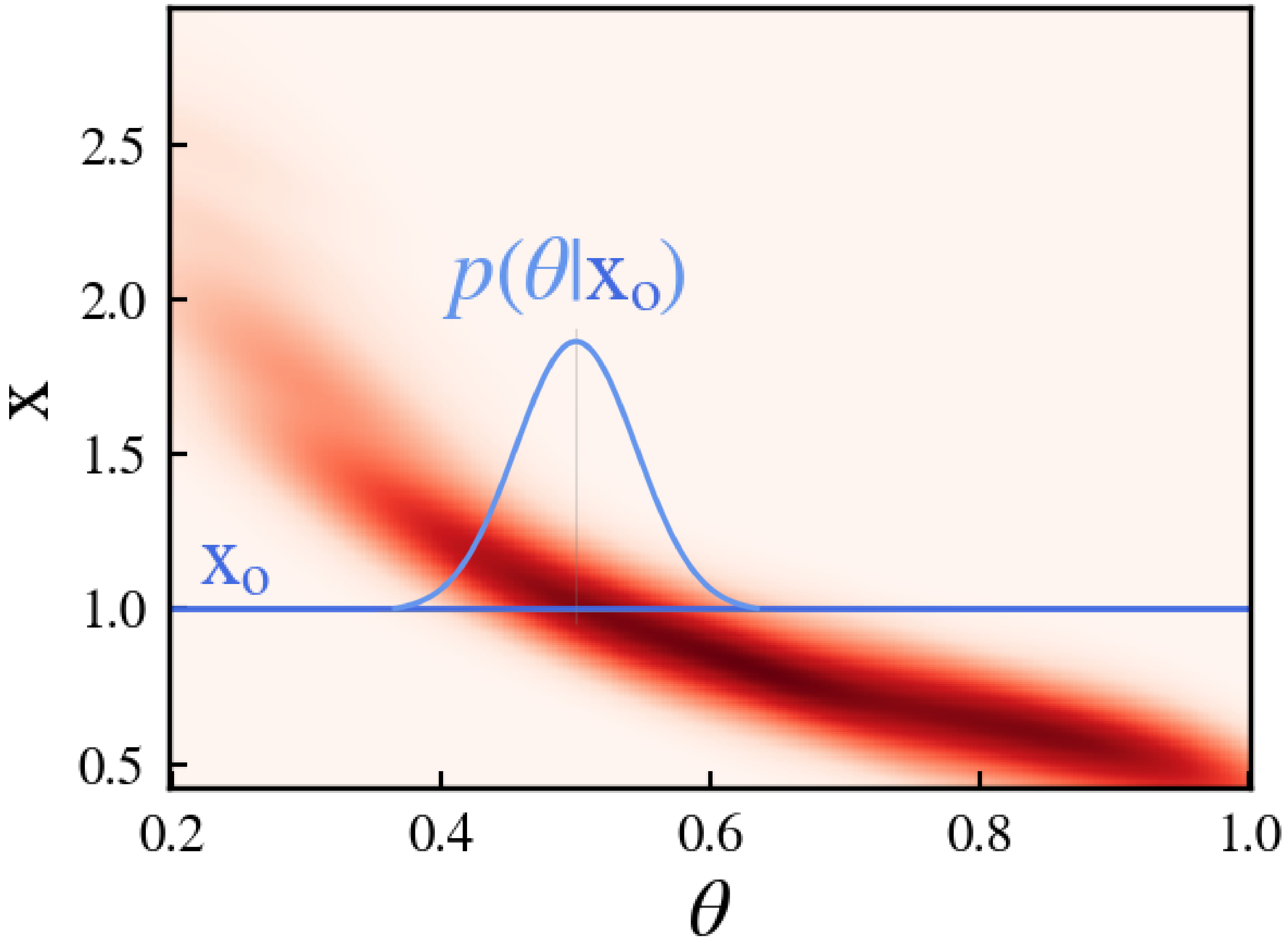
Neural Posterior Estimation (NPE)



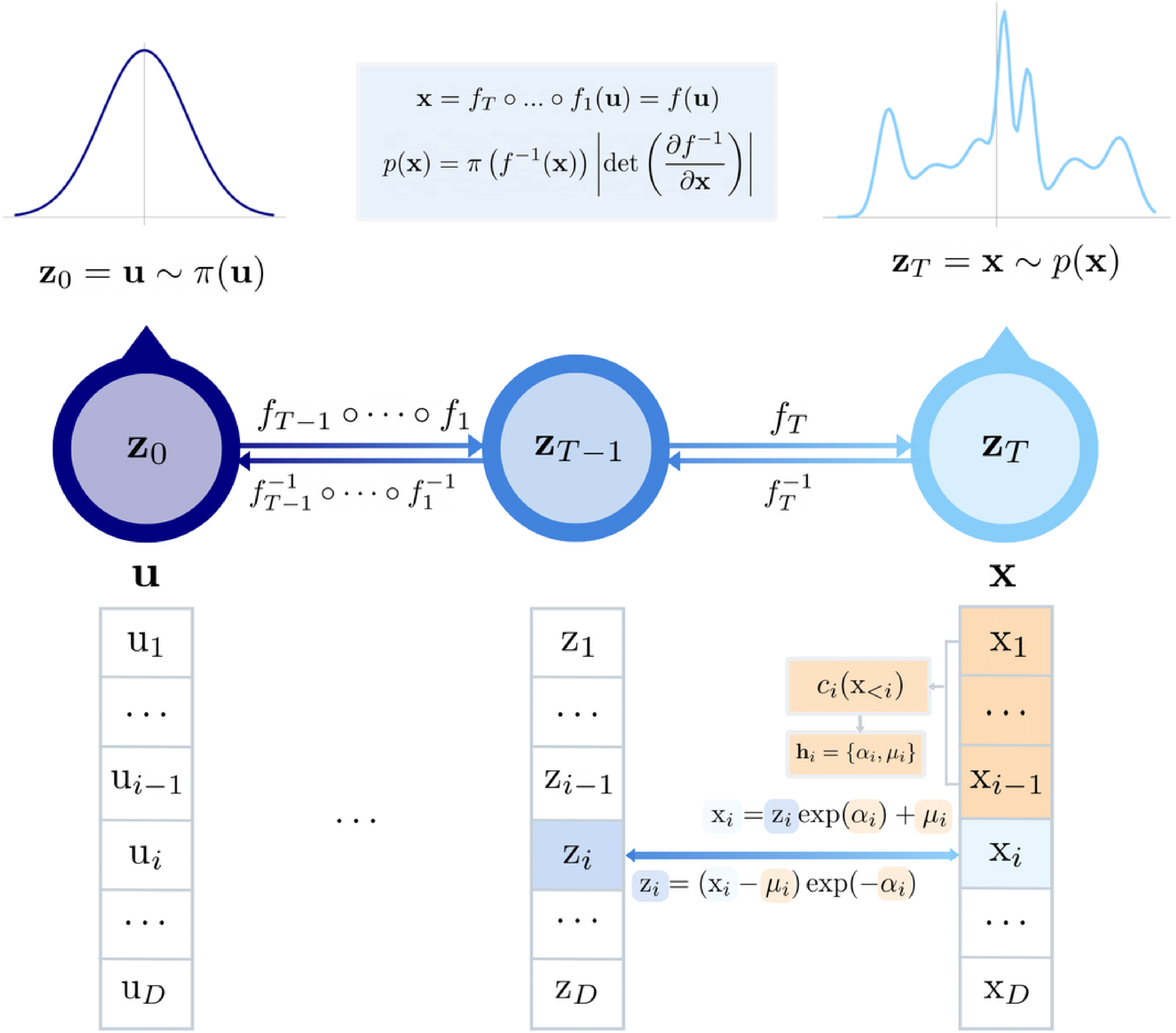
Simulation-based inference



Posterior



Normalizing Flows

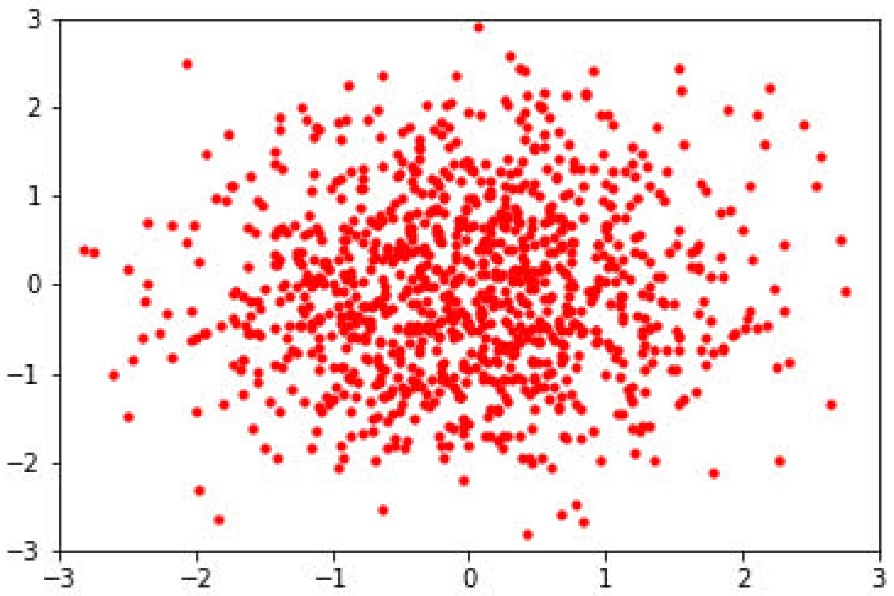


Tucci, Schmidt (2023)

Neural Density Estimators (NDEs):

- Neural Posterior Estimation (NPE)
- Neural Likelihood Estimation (NLE)

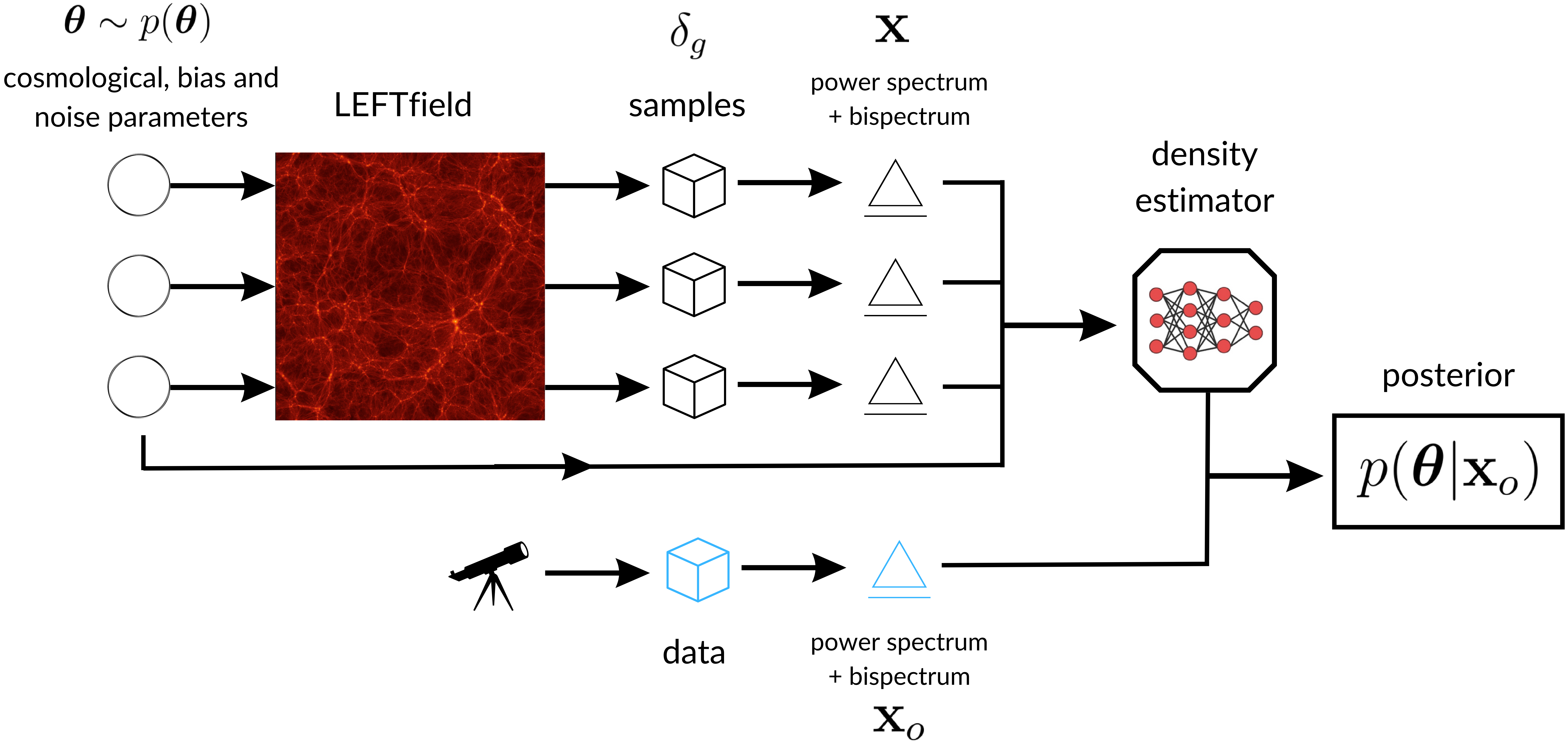
sbi: A toolkit for simulation-based inference
Tejero-Cantero et al. (2020)



Credits: Miles Cranmer

Learns an invertible dynamical model for samples of the distribution

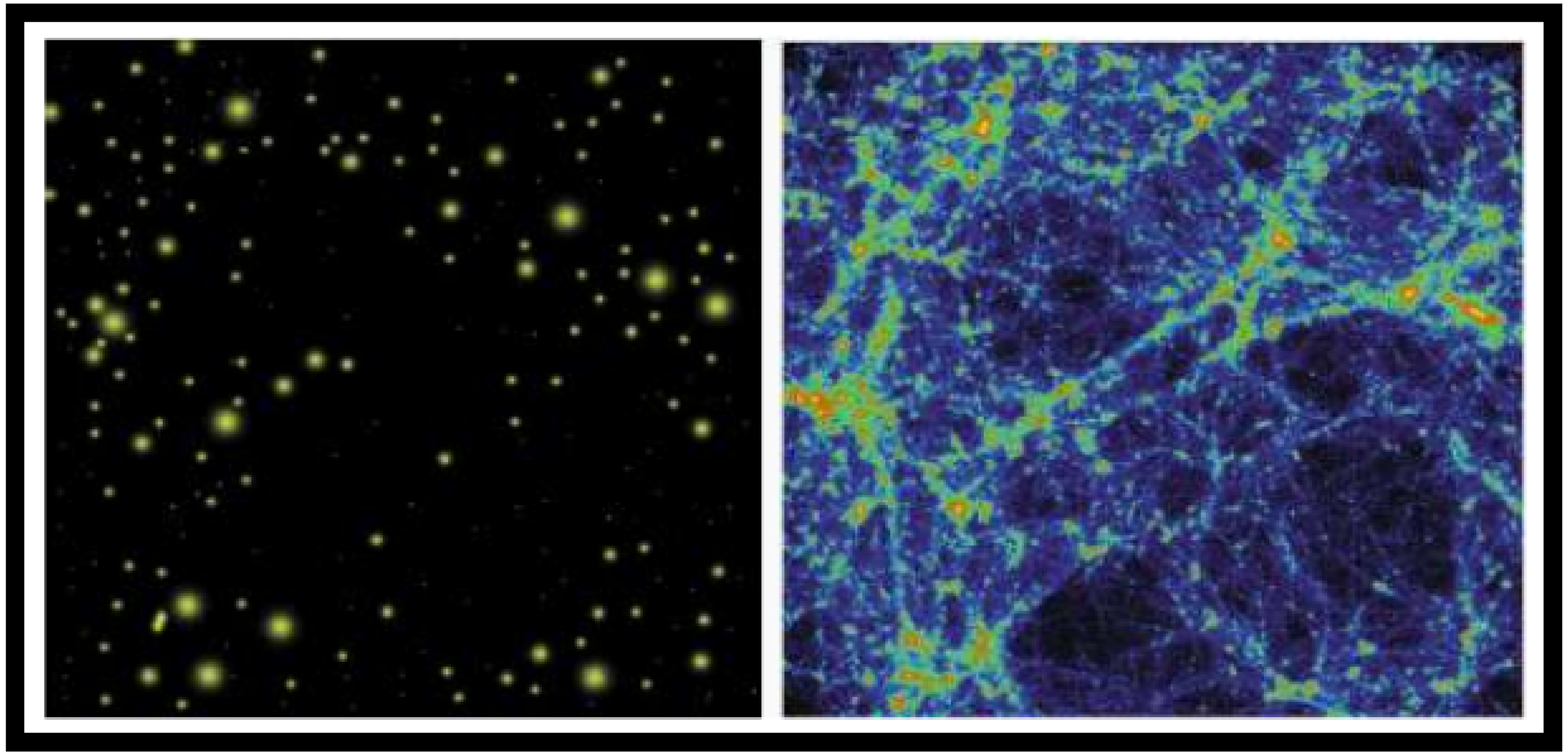
Simulation-based inference



The bias expansion

Cooray & Sheth (2002)

Cosmological tracers



Matter distribution

$$\delta_g(\mathbf{x},\tau) = \sum_{\mathcal{O}} b_{\mathcal{O}}(\tau)\mathcal{O}(\mathbf{x},\tau) + \varepsilon(\mathbf{x},\tau) + \sum_{\mathcal{O}} \varepsilon_{\mathcal{O}}(\mathbf{x},\tau)\mathcal{O}(\mathbf{x},\tau)$$

For a review, see:
Desjacques, Jeong & Schmidt (2016)

Forward model

$$\alpha \equiv \sigma_8/\sigma_8^{\rm fid} \qquad \hat{s}(\boldsymbol{x}) \sim \mathcal{N}(0,1)$$

$$\boxed{\delta_\Lambda^{(1)}(\boldsymbol{k},z) = W_\Lambda(k)\sqrt{\alpha^2 P_L(k,z)}\,\hat{s}(\boldsymbol{k})}$$

An n-th order Lagrangian Forward Model for Large-Scale Structure
Fabian Schmidt (2021)

Forward model

$\alpha \equiv \sigma_8/\sigma_8^{\mathrm{fid}}$ $\hat{s}(\boldsymbol{x}) \sim \mathcal{N}(0,1)$

$$\delta_\Lambda^{(1)}(\boldsymbol{k},z) = W_\Lambda(k)\sqrt{\alpha^2 P_L(k,z)}\,\hat{s}(\boldsymbol{k})$$

$1+\delta(\boldsymbol{x},\tau) = |\mathbf{1}+\boldsymbol{M}(\boldsymbol{q},\tau)|^{-1}$ $M_{ij} \equiv \partial_i s_j$

$$\mathrm{tr}[\boldsymbol{M}_\Lambda^{(1)}] = -\delta_\Lambda^{(1)}$$

LPT recursion relations

$$\boldsymbol{s}^{(n)}$$

Lagrangian Bias Operators

1^{st}	$\mathrm{tr}[\boldsymbol{M}_\Lambda^{(1)}]$
2^{nd}	$\mathrm{tr}[\boldsymbol{M}_\Lambda^{(1)}\boldsymbol{M}_\Lambda^{(1)}]$, $(\mathrm{tr}[\boldsymbol{M}_\Lambda^{(1)}])^2$

$$\delta_{g,\mathrm{det}}^L(\mathbf{q},\tau) = \sum_{\mathcal{O}^L} b_{\mathcal{O}^L}(\tau)\mathcal{O}^L(\mathbf{q},\tau)$$

An n-th order Lagrangian Forward Model for Large-Scale Structure
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Forward model

$\alpha \equiv \sigma_8/\sigma_8^{\rm fid}$ $\quad$ $\hat{s}(\boldsymbol{x}) \sim \mathcal{N}(0,1)$

$$\delta_\Lambda^{(1)}(\boldsymbol{k}, z) = W_\Lambda(k)\sqrt{\alpha^2 P_L(k,z)}\,\hat{s}(\boldsymbol{k})$$

$1 + \delta(\boldsymbol{x},\tau) = |\mathbf{1} + \boldsymbol{M}(\boldsymbol{q},\tau)|^{-1}$ $\quad$ $M_{ij} \equiv \partial_i s_j$

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LPT recursion relations

$$\boldsymbol{s}^{(n)}$$

$$\delta_{g,\rm det}^L(\mathbf{q},\tau) = \sum_{\mathcal{O}^L} b_{\mathcal{O}^L}(\tau)\mathcal{O}^L(\mathbf{q},\tau)$$

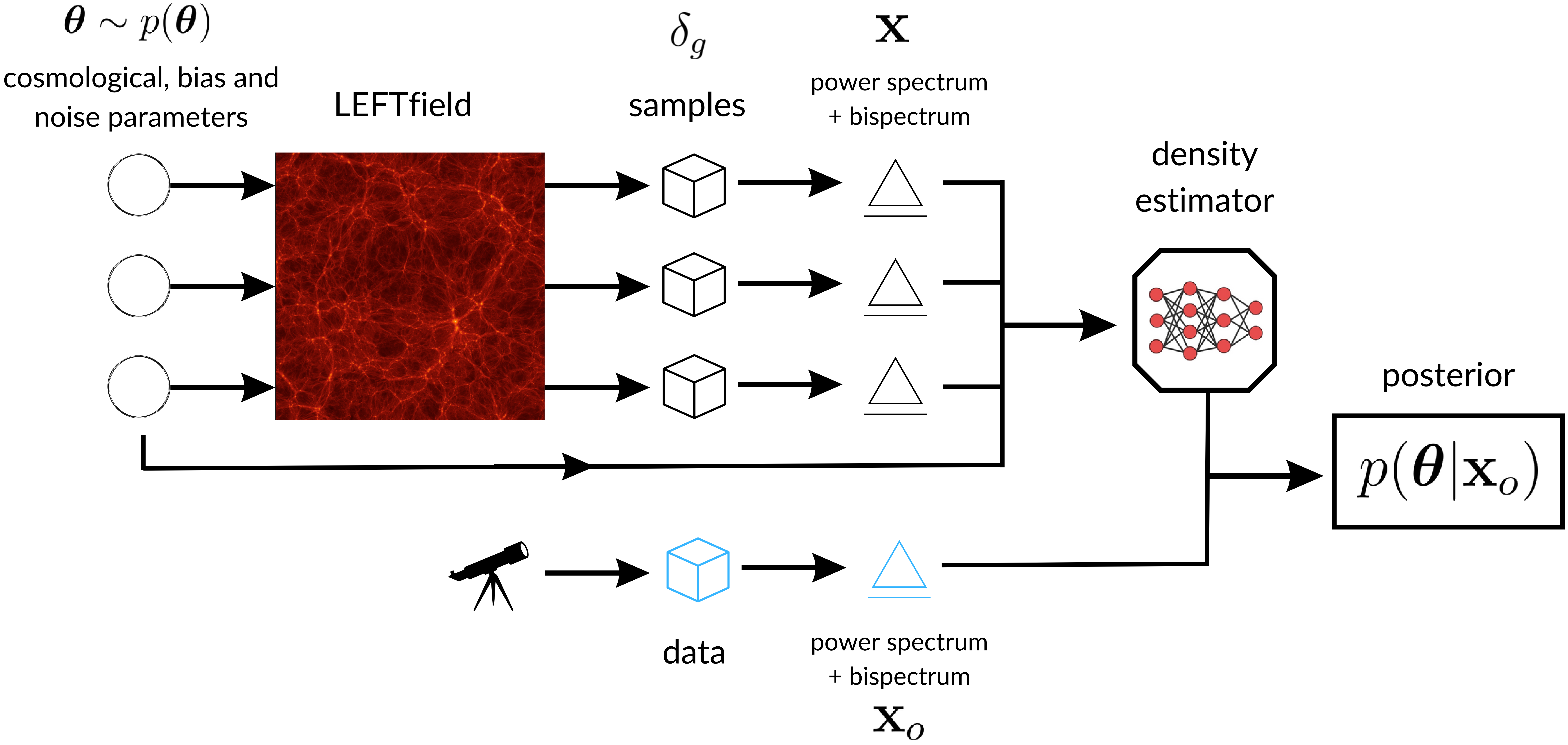
$\boldsymbol{x}(\boldsymbol{q},\tau) = \boldsymbol{q} + \boldsymbol{s}(\boldsymbol{q},\tau)$

$\varepsilon \sim \mathcal{N}(0, P_\varepsilon)$

$$\delta_g(\boldsymbol{x},\tau) = \delta_{g,\rm det}(\boldsymbol{x},\tau) + \varepsilon(\boldsymbol{x},\tau) + c_{\varepsilon\delta}(\tau)\varepsilon(\boldsymbol{x},\tau)\delta(\boldsymbol{x},\tau) + c_{\varepsilon^2}(\tau)\varepsilon^2(\boldsymbol{x},\tau)$$

An n-th order Lagrangian Forward Model for Large-Scale Structure
Fabian Schmidt (2021)

Simulation-based inference



Our main goals

Considering an Euclid-like mock survey, we want to answer:

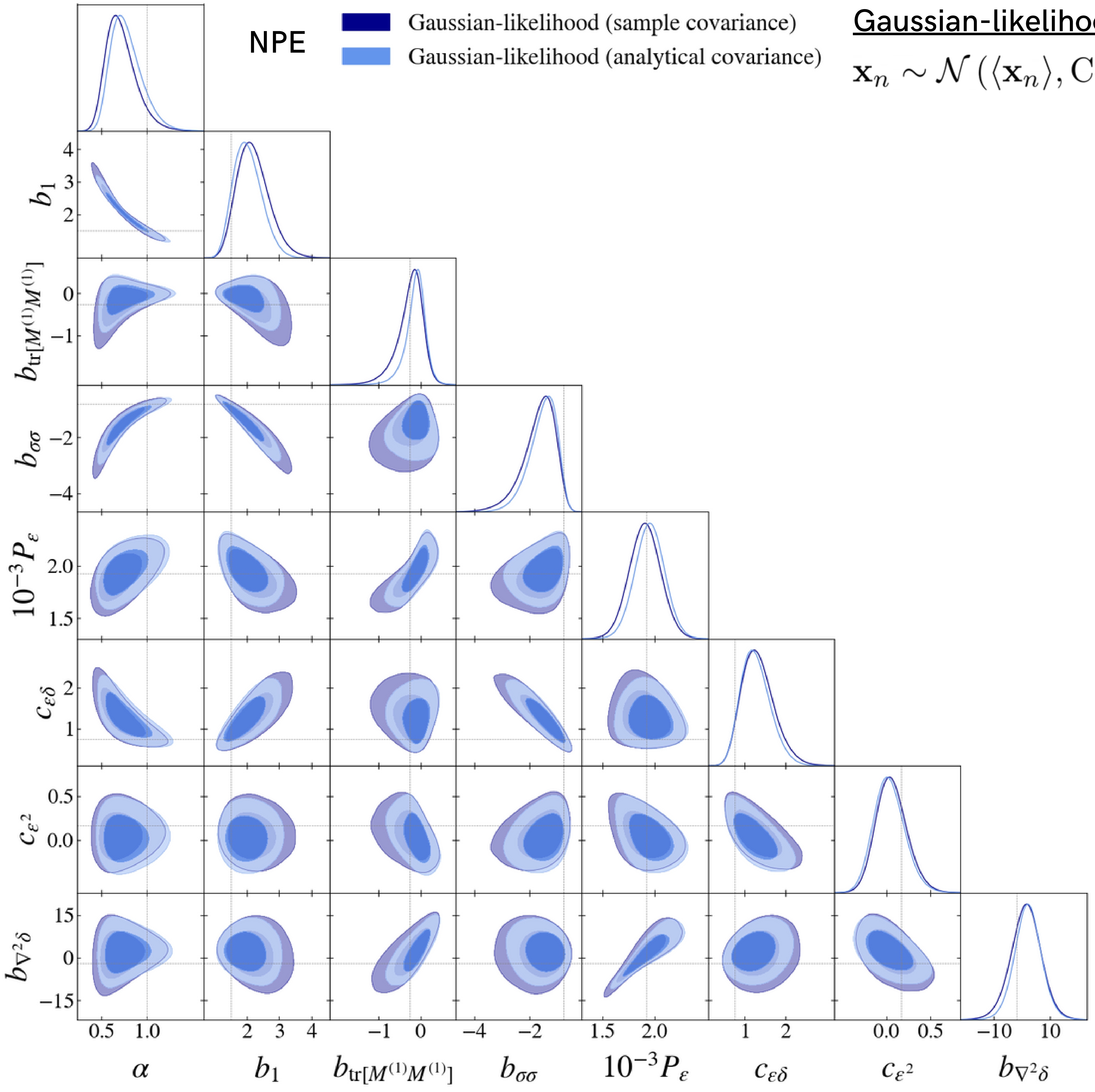
- *Does the non-Gaussianity of the power-spectrum and bispectrum distributions at low-k affect cosmological inference?*
- *How many simulations are needed for posterior estimation?*

Cosmological inference | Euclid configuration

$N_{\rm sim} = 10^5$

$k_{\max} = \Lambda = 0.1 h\mathrm{Mpc}^{-1}$

$D = N_{\rm bin} + N_{\rm tri} = 33$



Gaussian-likelihood

$\mathbf{x}_n \sim \mathcal{N}(\langle \mathbf{x}_n \rangle, \mathrm{Cov}[\mathbf{x}_o])$

$\alpha \equiv \sigma_8/\sigma_8^{\rm fid}$

Cosmological inference | Euclid configuration

$$N_{\rm sim} = 10^5$$
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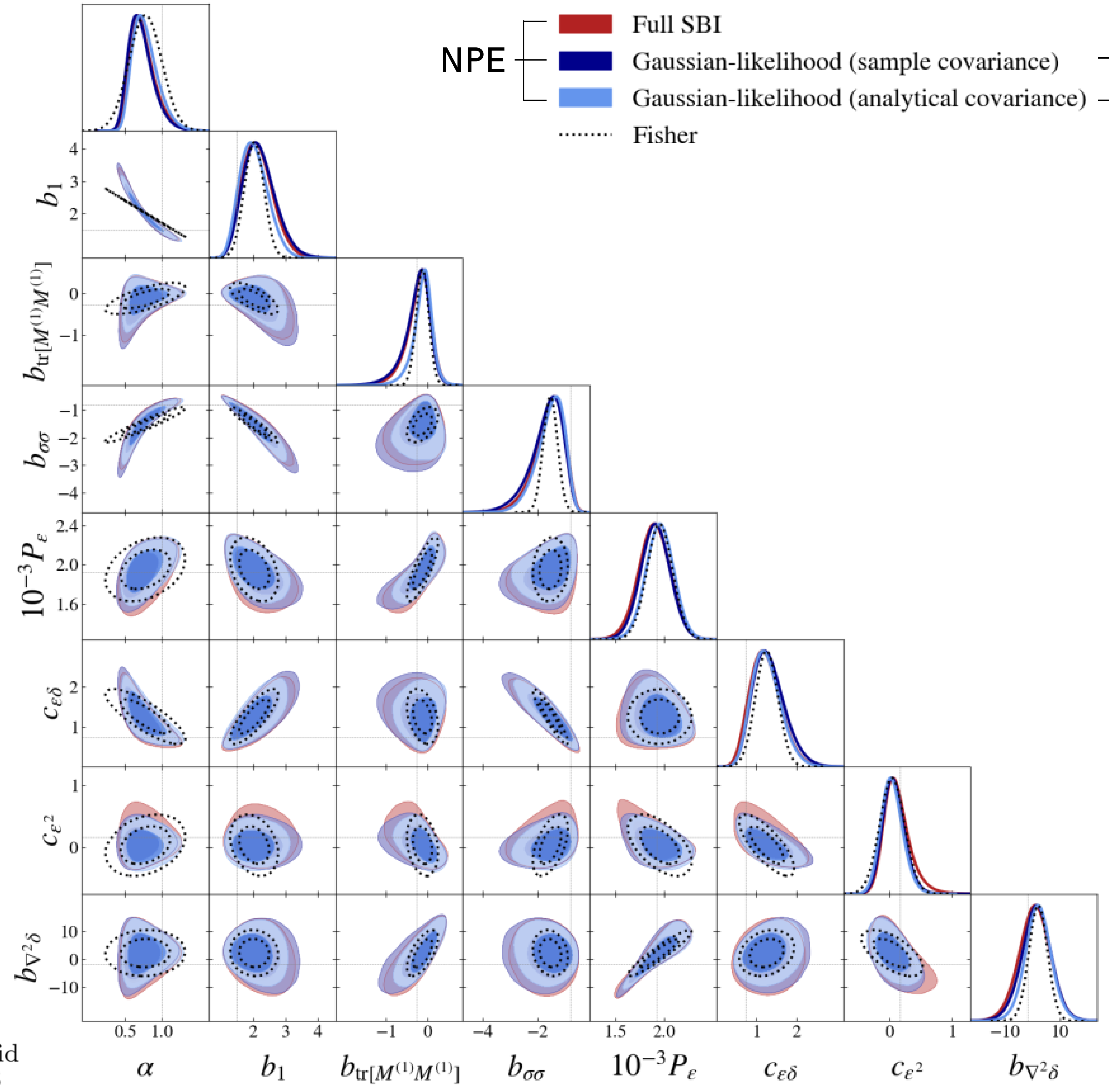


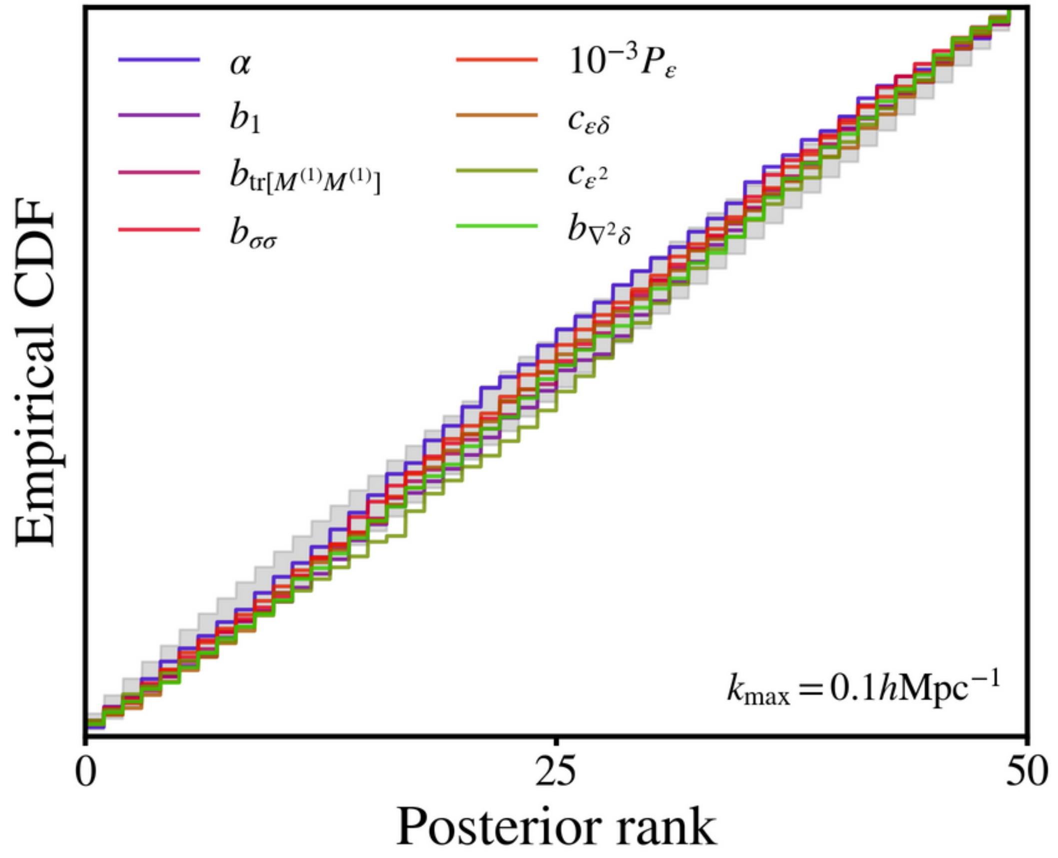
Gaussian-likelihood

$$\mathbf{x}_n \sim \mathcal{N}\left(\langle \mathbf{x}_n \rangle, \mathrm{Cov}[\mathbf{x}_o]\right)$$

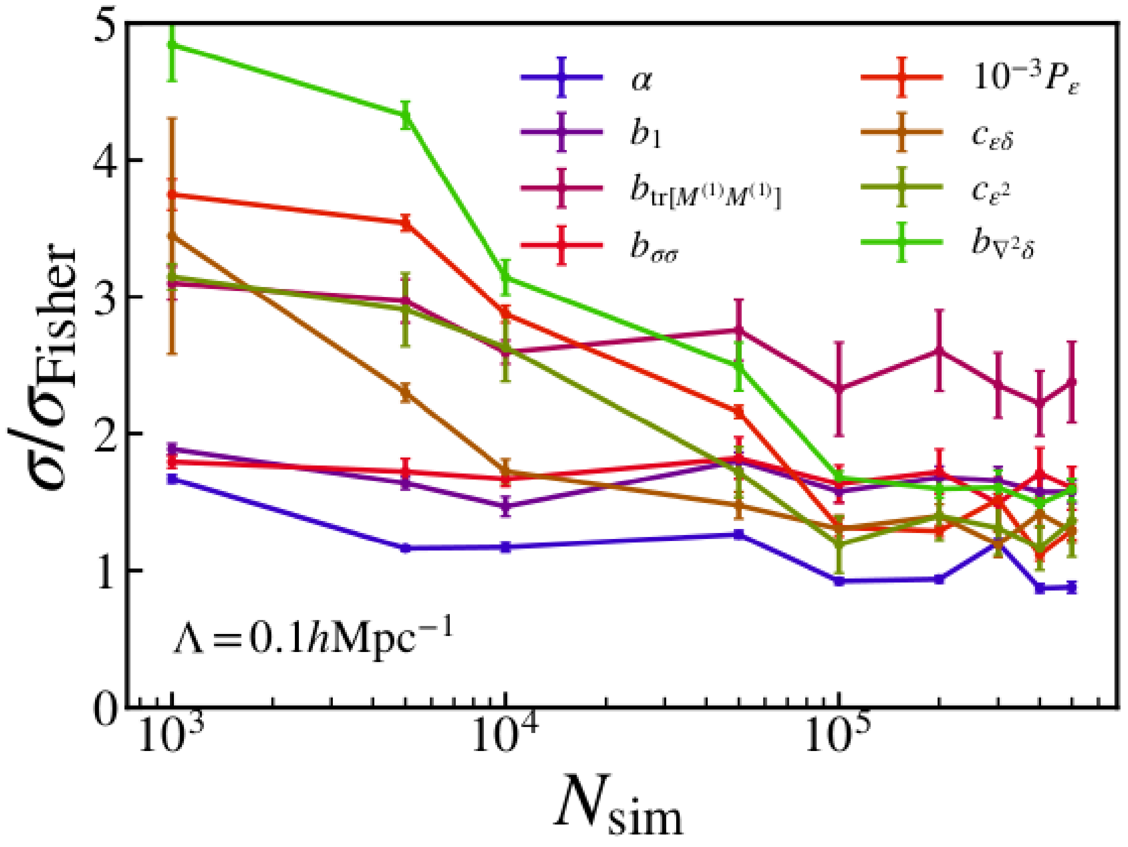
$$\alpha \equiv \sigma_8/\sigma_8^{\rm fid}$$

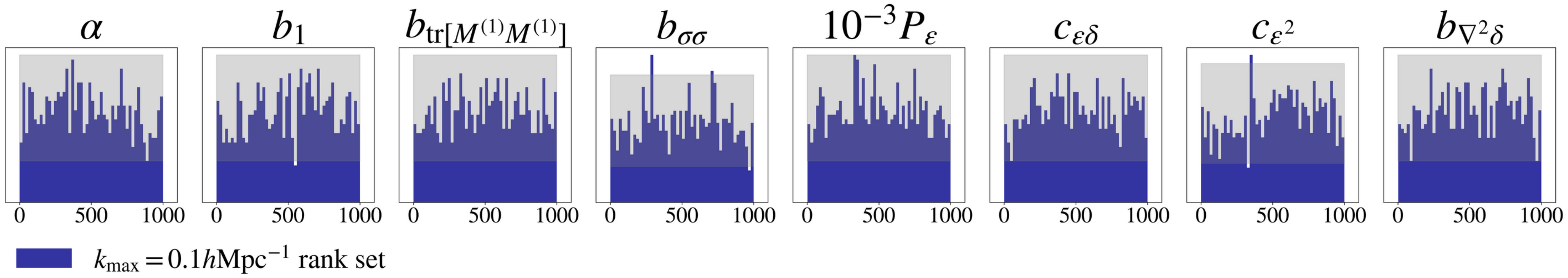
Posterior diagnostics

Simulation-based calibration



Convergence





Conclusion & Next Steps

- Simulation-based inference has proven to be a powerful tool for galaxy clustering analysis and offers several advantages over the likelihood-based approach;

- In the future, we plan to sample more cosmological parameters, add more summary statistics and improve observational aspects of the forward model (masks, systematic effects, etc);

- Comparison of field-level inference with HMC and SBI with summary statistics (P+B).

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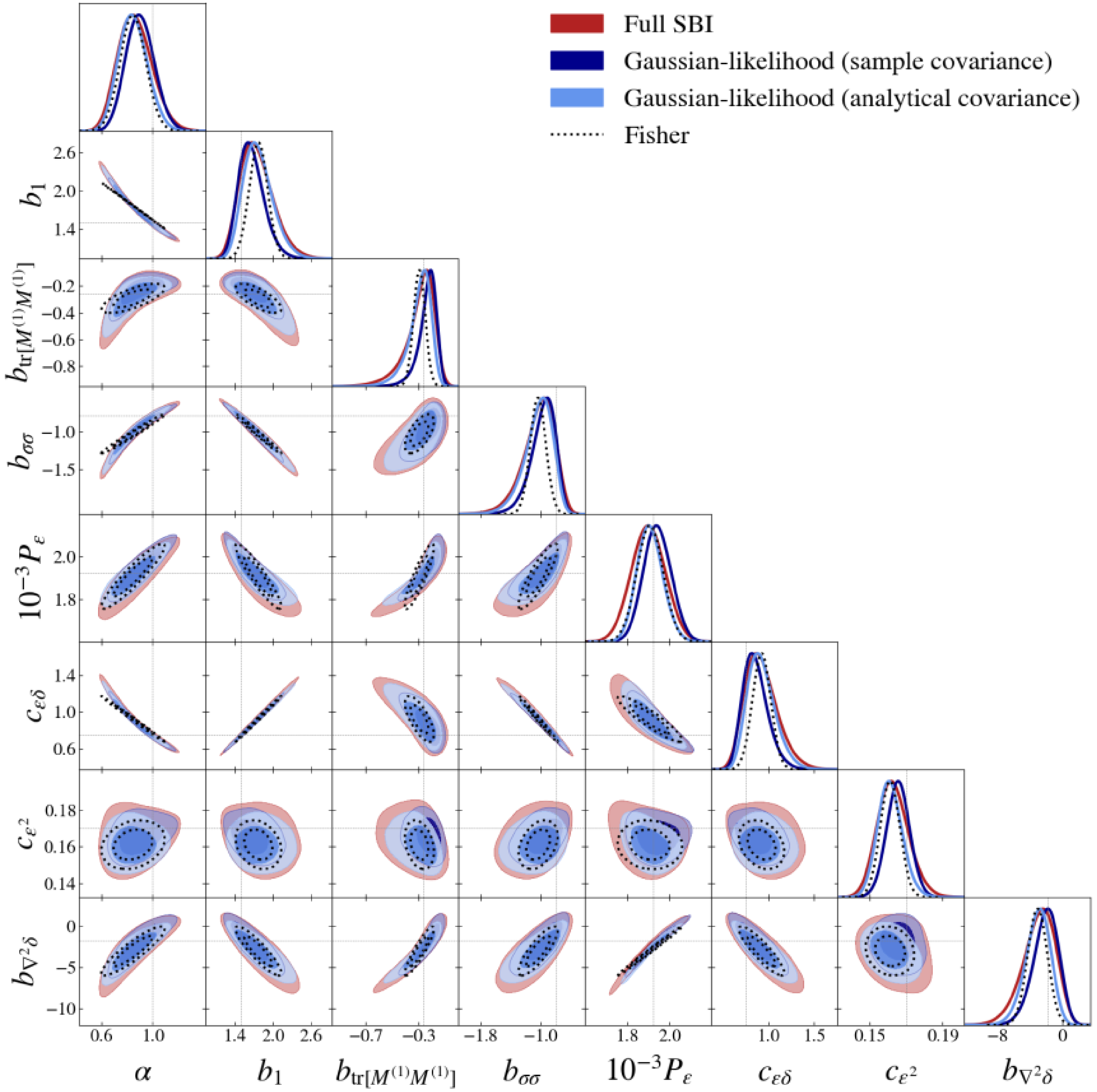
Cosmological inference | Euclid configuration

Tucci, Schmidt (in prep.)

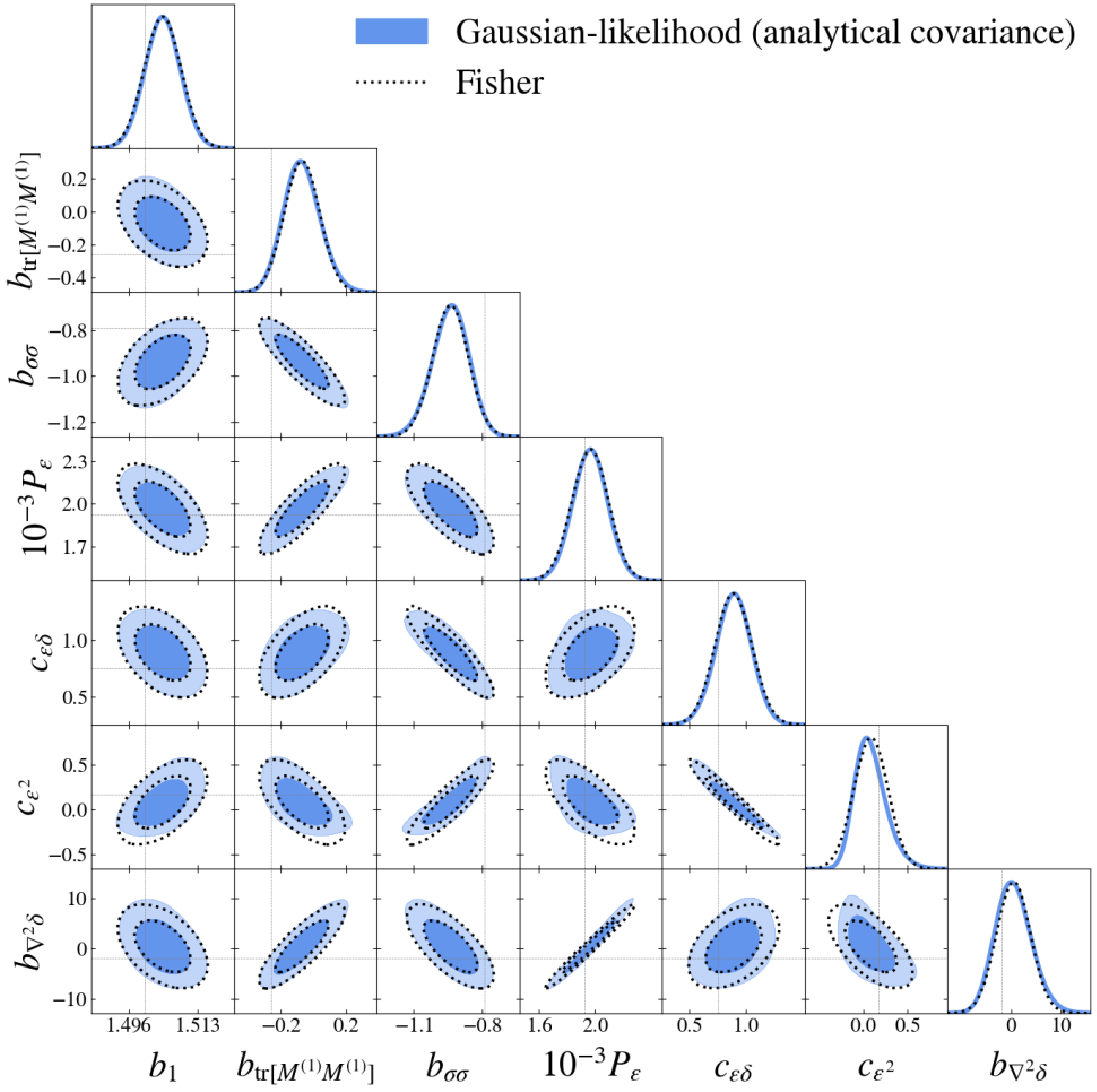
$N_{\rm sim} = 10^5$

$k_{\rm max} = \Lambda = 0.2 h{\rm Mpc}^{-1}$

$D = 49$



Euclid | Gaussian-likelihood

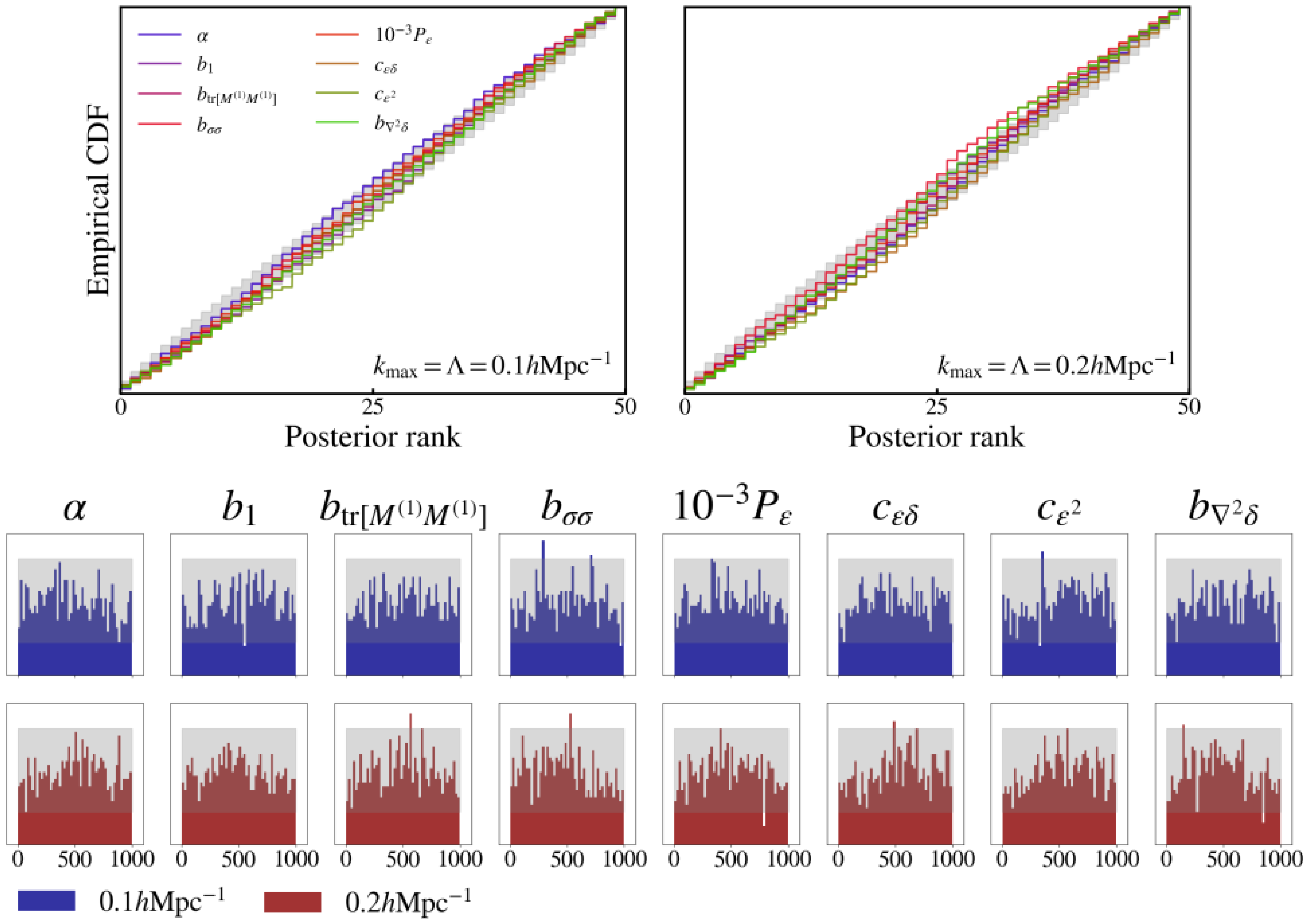


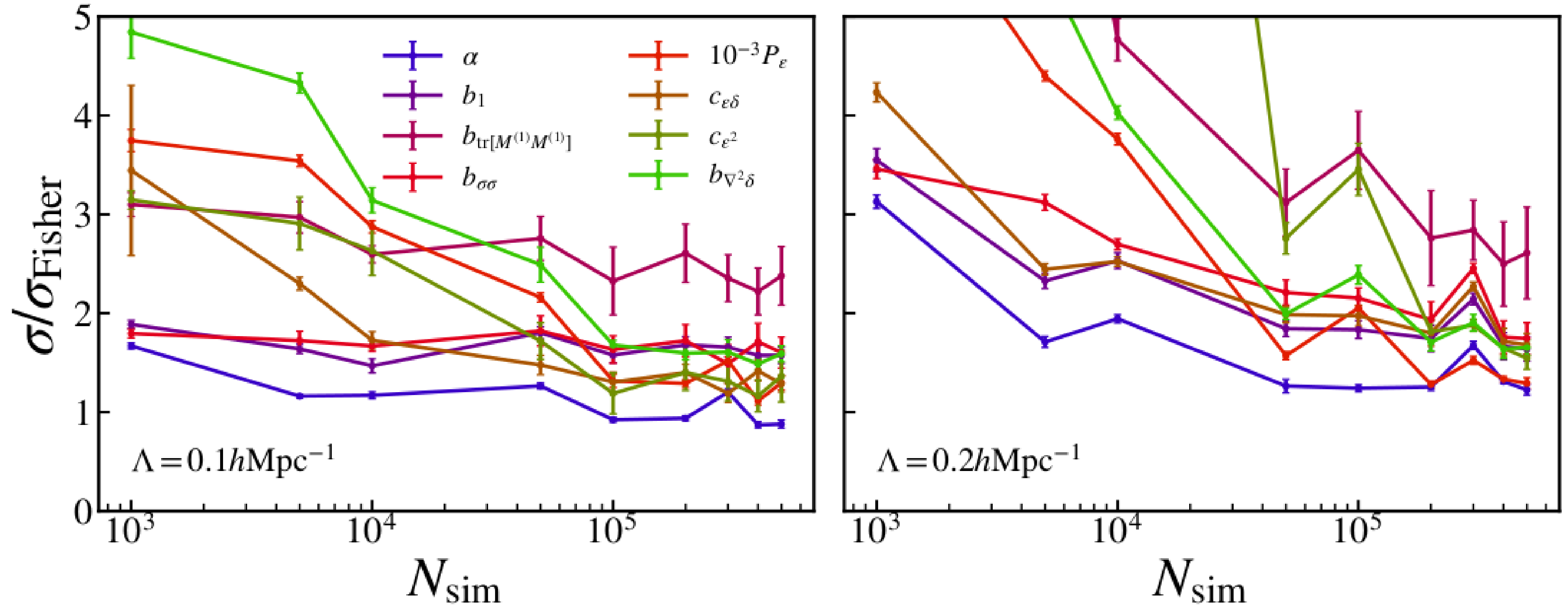
$$\mathbf{x}_n \sim \mathcal{N}\left(\langle \mathbf{x}_n \rangle, \mathrm{Cov}[\mathbf{x}_o]\right)$$

$$N_{\mathrm{sim}} = 10^5$$

$$k_{\mathrm{max}} = \Lambda = 0.1 h\mathrm{Mpc}^{-1}$$

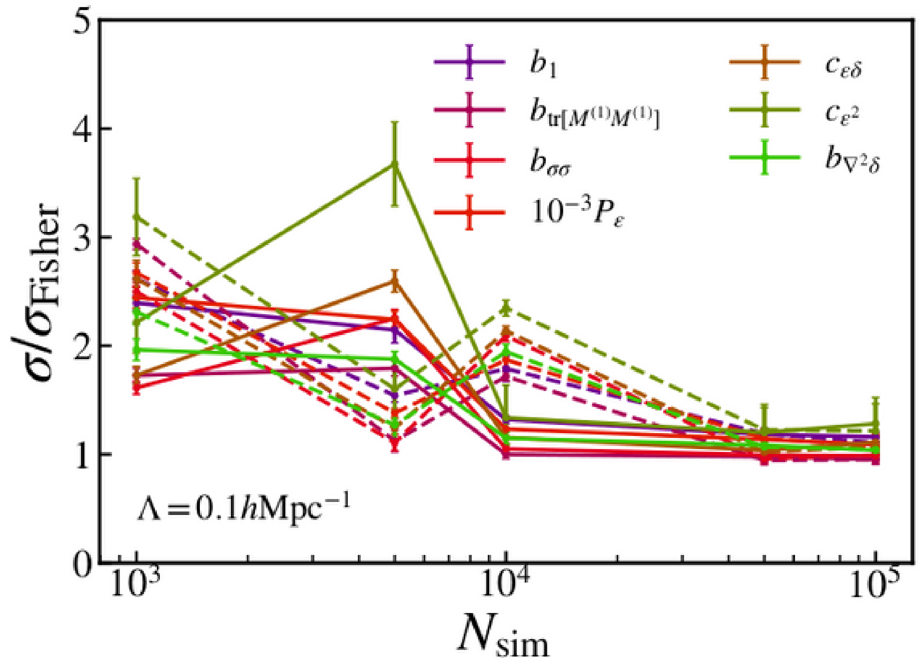
Posterior diagnostics

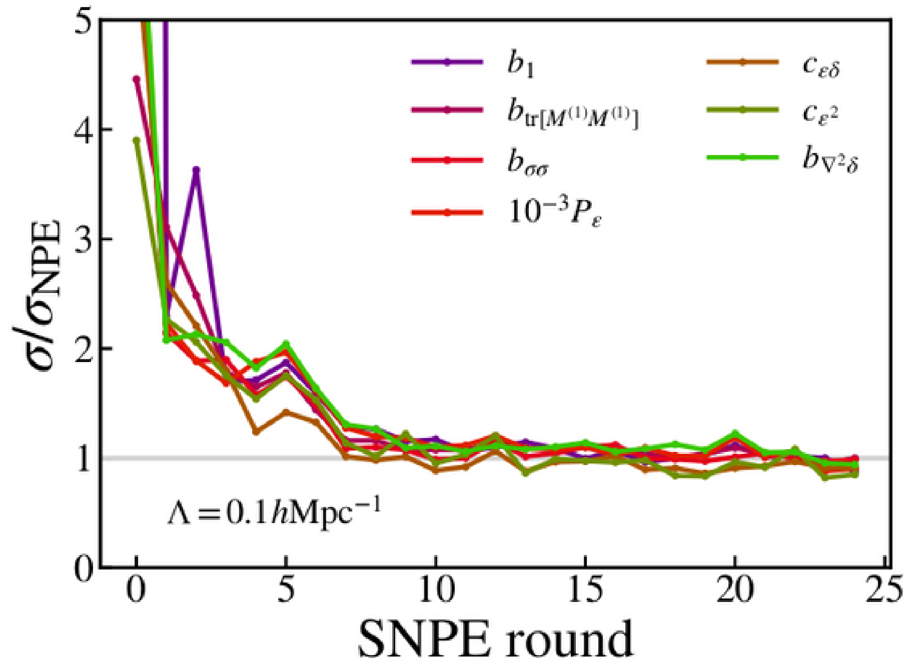


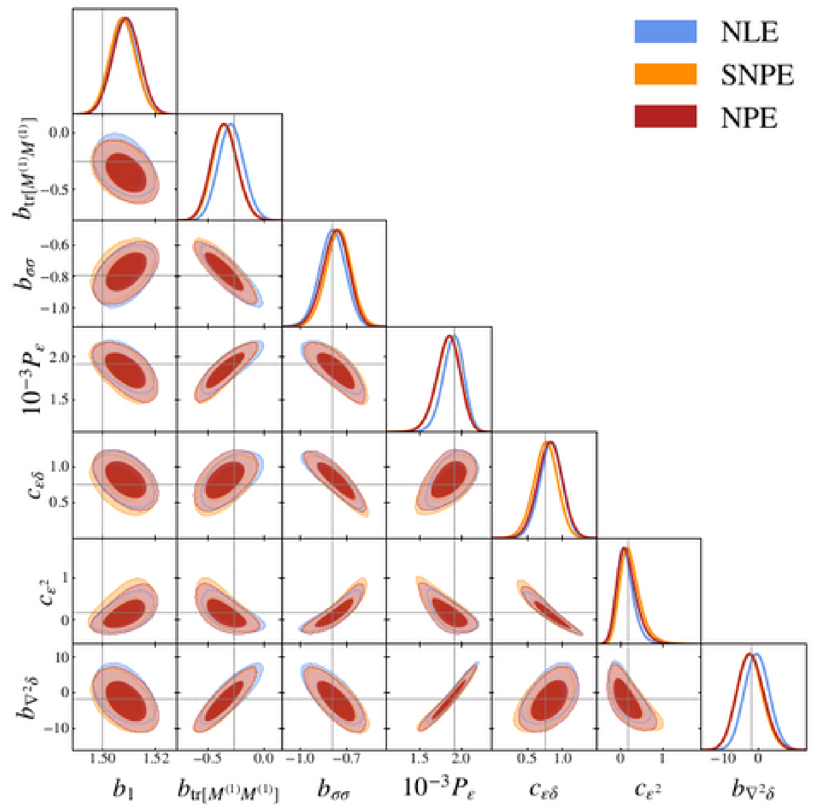


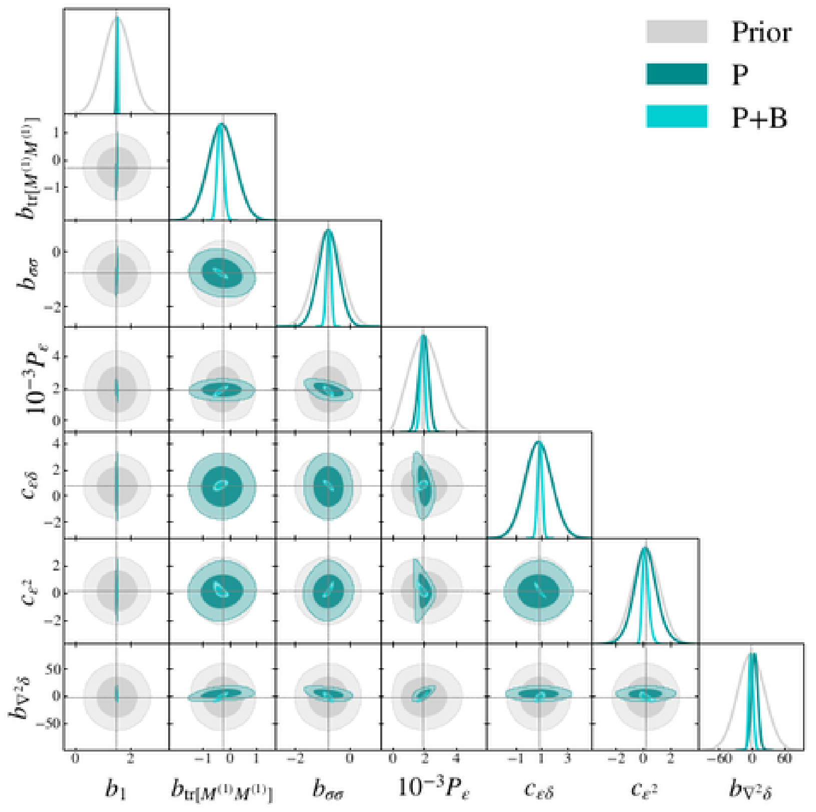
Inference tests

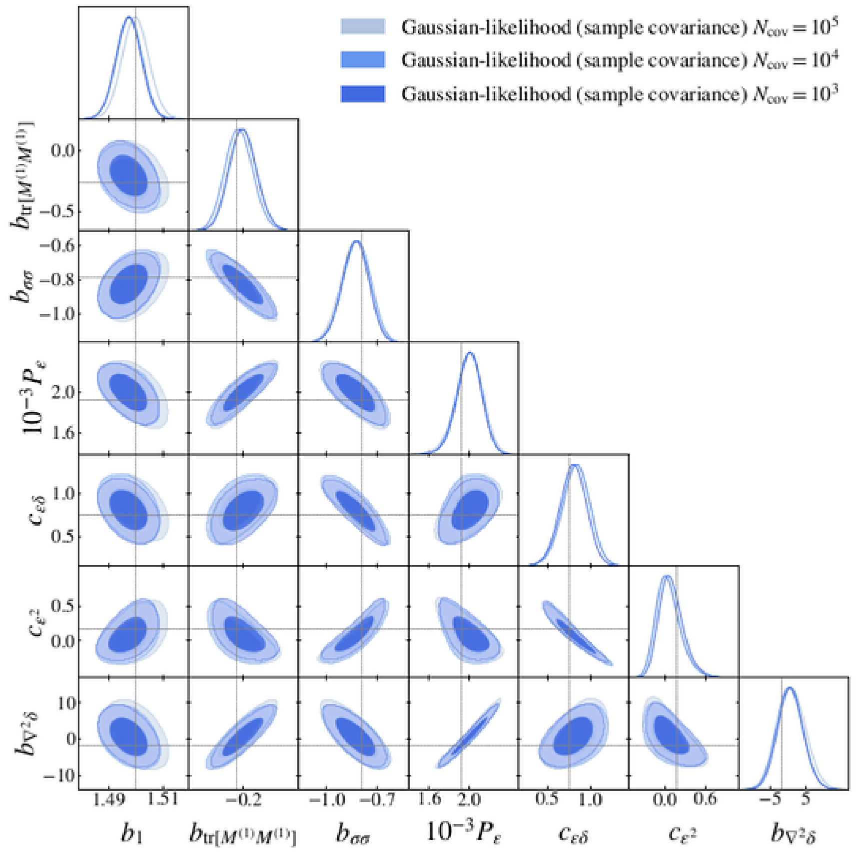
PB normalization

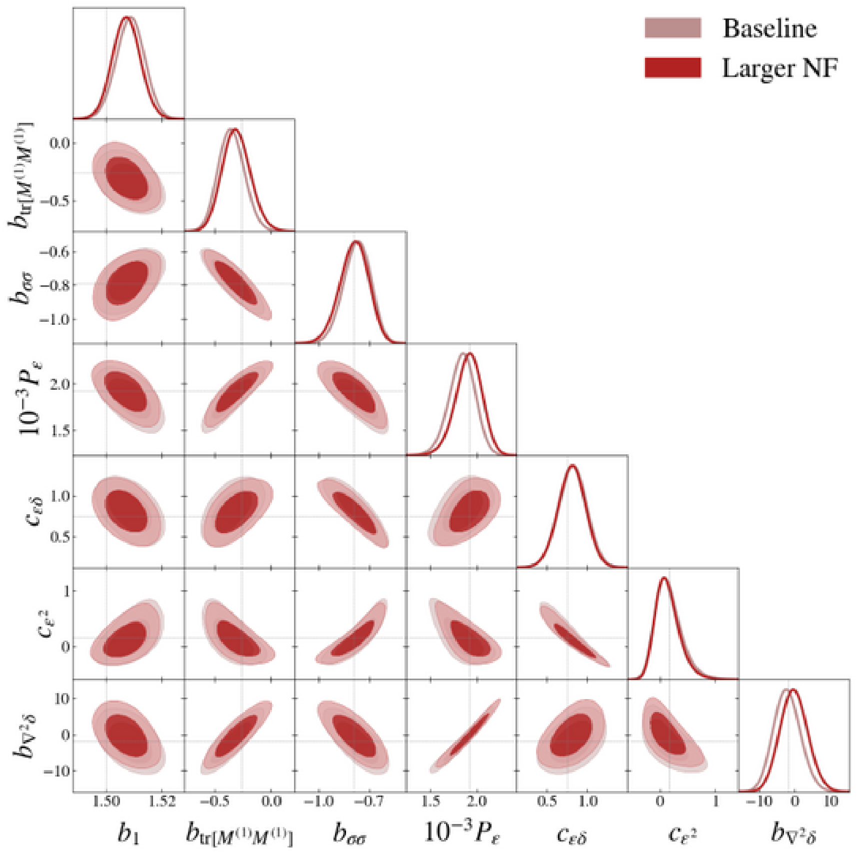






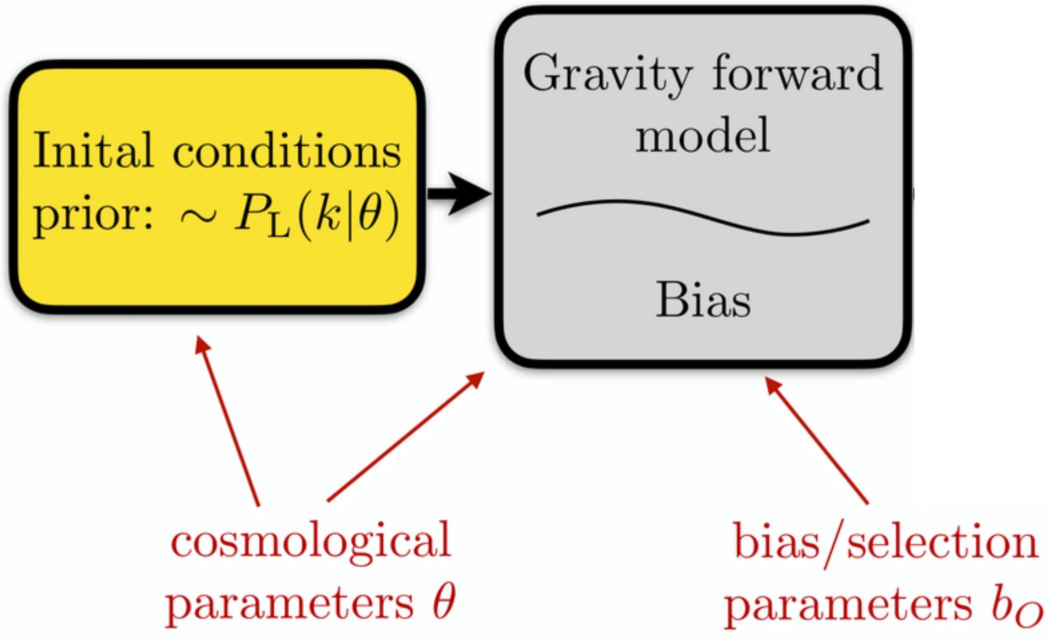






LEFTfield | forward model

EFTofLSS based approach



An n-th order Lagrangian Forward Model for Large-Scale Structure
Fabian Schmidt (2021)

$$\varepsilon \sim \mathcal{N}(0, \sigma_\varepsilon)$$

Perturbation Theory

$$\langle \delta_g(k_1)\delta_g(k_2)\delta_g(k_3)\rangle'^{\rm LO}_{\rm stoch} = B_\varepsilon + 2b_1 P_{\varepsilon\varepsilon_\delta}(P_{\rm m}(k_1) + 2\ \text{perm.})$$

Forward Model

$$\langle \delta_g(k_1)\delta_g(k_2)\delta_g(k_3)\rangle'^{\rm LO}_{\rm stoch} = 6c_\varepsilon^{\rm NG} P_\varepsilon^2 + 2b_1 P_\varepsilon \sigma_{\varepsilon\delta}(P_{\rm m}(k_1) + 2\ \text{perm.})$$

$$\delta_g(\mathbf{x},\tau) = \delta_{g,\rm det}(\mathbf{x},\tau) + \varepsilon(\mathbf{x},\tau) + \sigma_{\varepsilon\delta}(\tau)\varepsilon(\mathbf{x},\tau)\delta(\mathbf{x},\tau) + c_\varepsilon^{\rm NG}(\tau)\varepsilon^2(\mathbf{x},\tau)$$