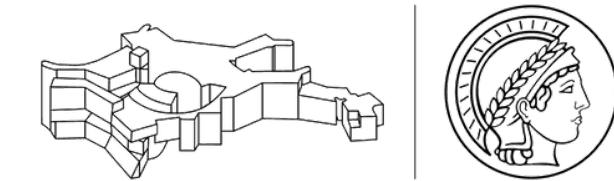


# EFTofLSS meets simulation-based inference: $\sigma_8$ from biased tracers

*LEFT*field

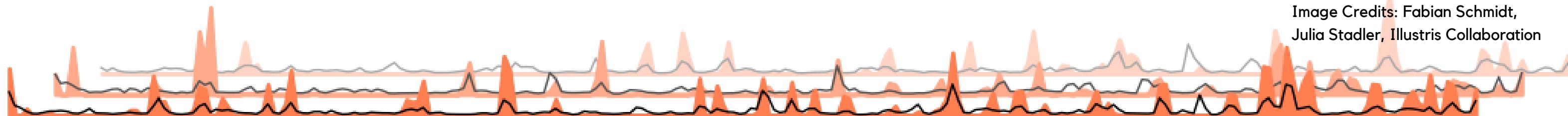


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Beatriz Tucci

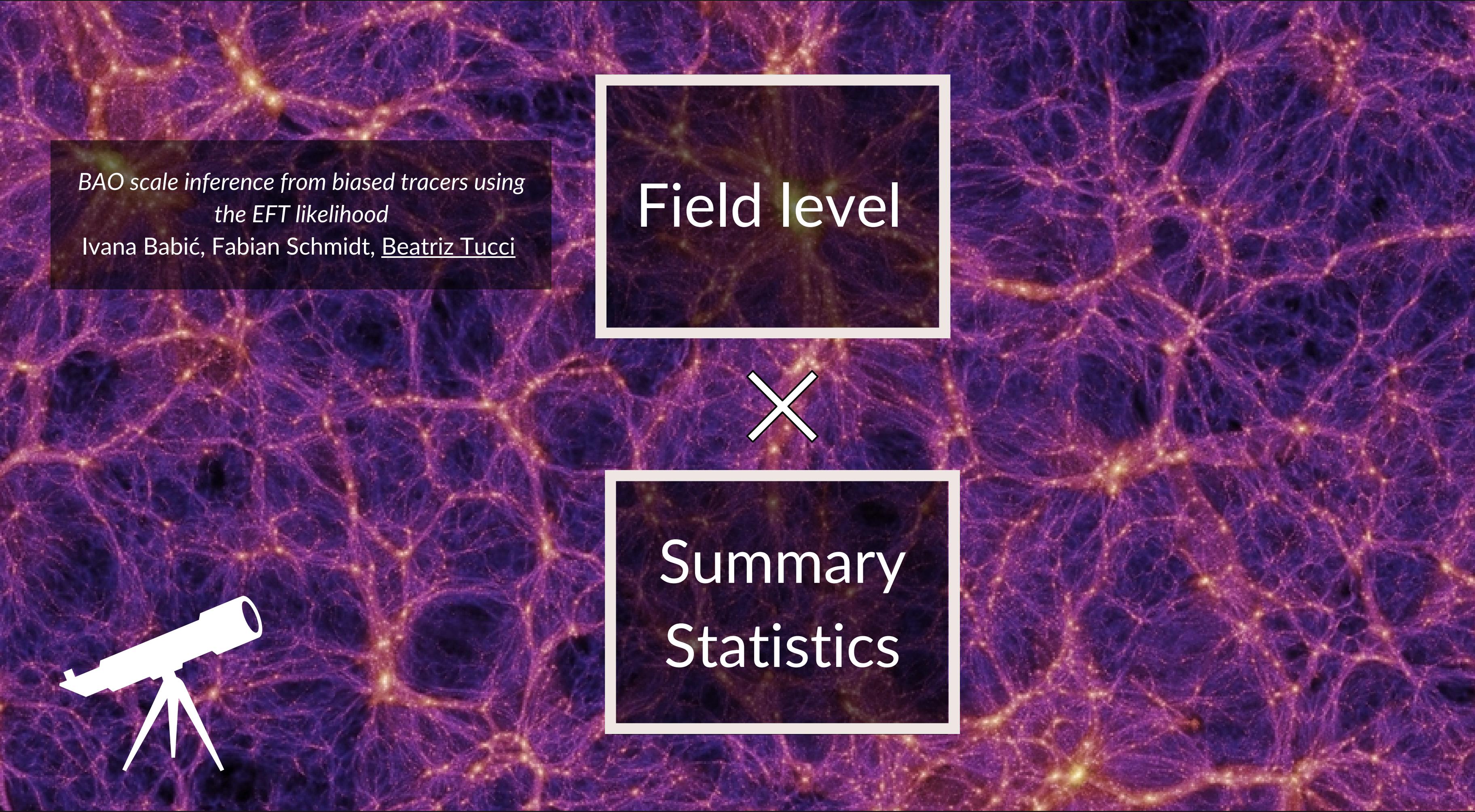
| PhD Student at MPA  
Supervisor: Fabian Schmidt

Image Credits: Fabian Schmidt,  
Julia Stadler, Illustris Collaboration





*How can we extract cosmological  
information from the large-scale  
distribution of galaxies in the sky?*



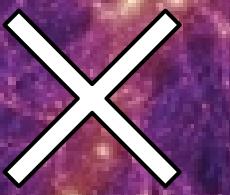
A background image showing a simulation of the large-scale distribution of galaxies or matter in the universe. The image is dominated by a dark purple color, with numerous thin, glowing orange and yellow filaments representing the filamentary structures of the cosmic web. Small, bright orange and yellow points represent individual galaxies or tracers.

*BAO scale inference from biased tracers using  
the EFT likelihood*

Ivana Babić, Fabian Schmidt, Beatriz Tucci

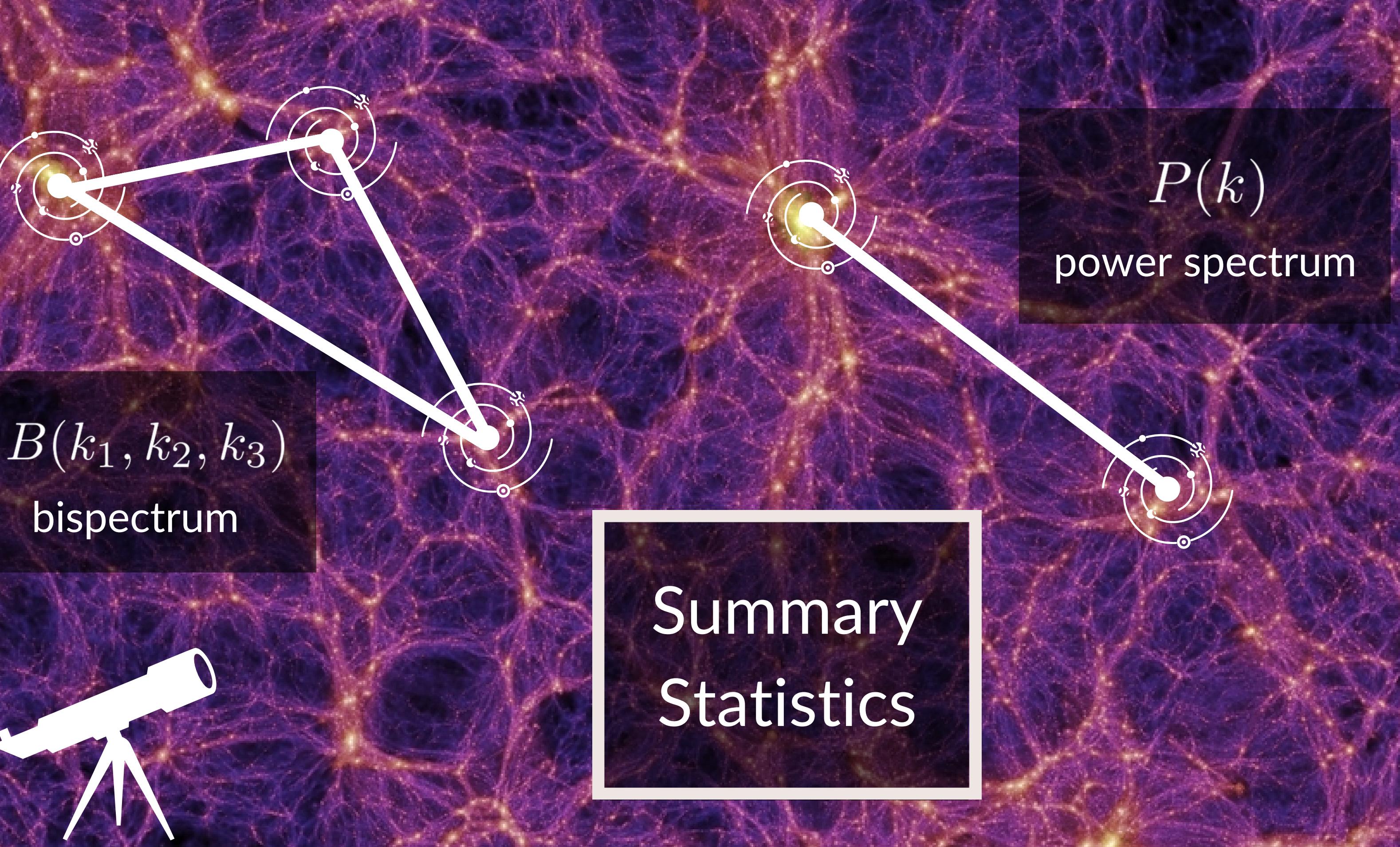


Field level



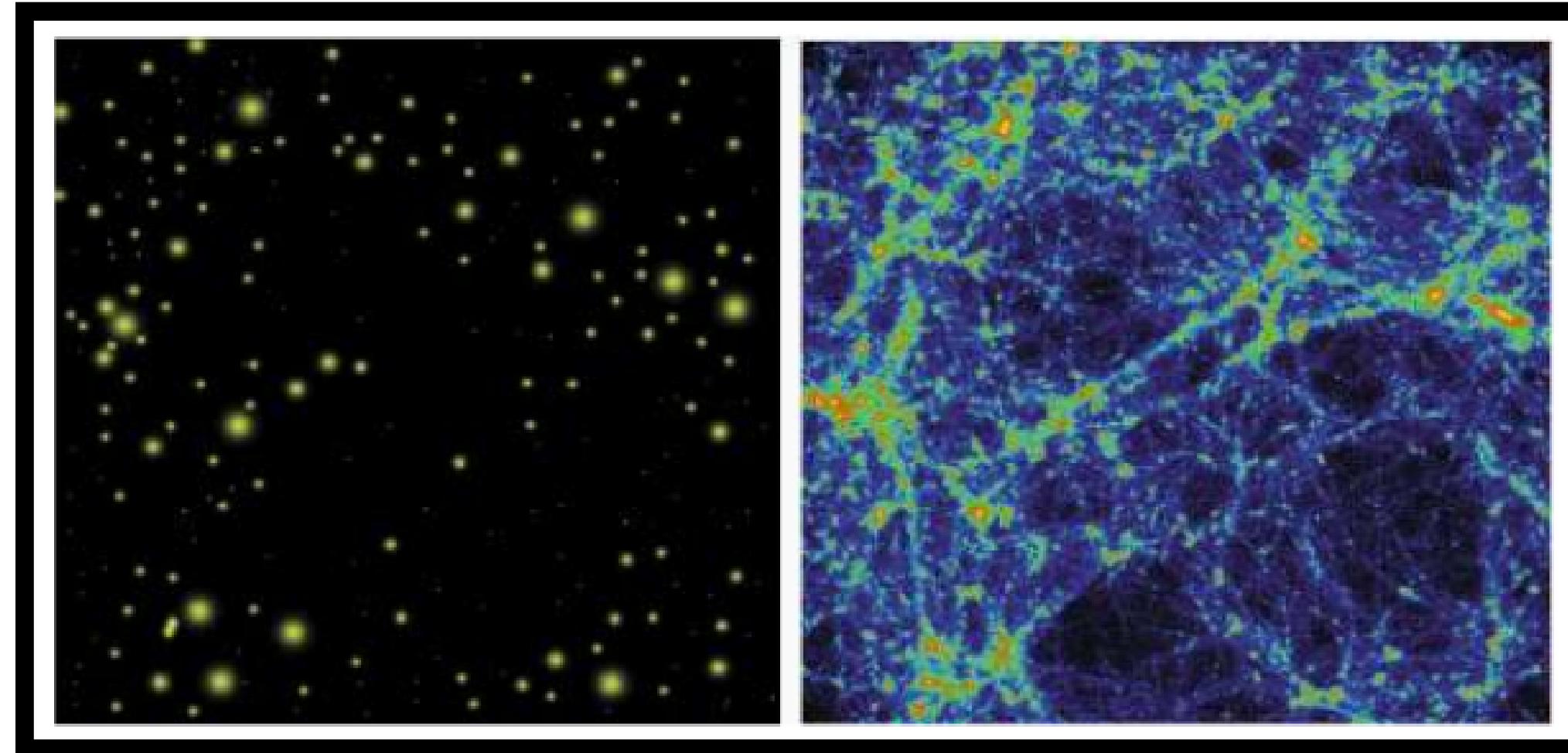
Summary  
Statistics





# The bias expansion

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)

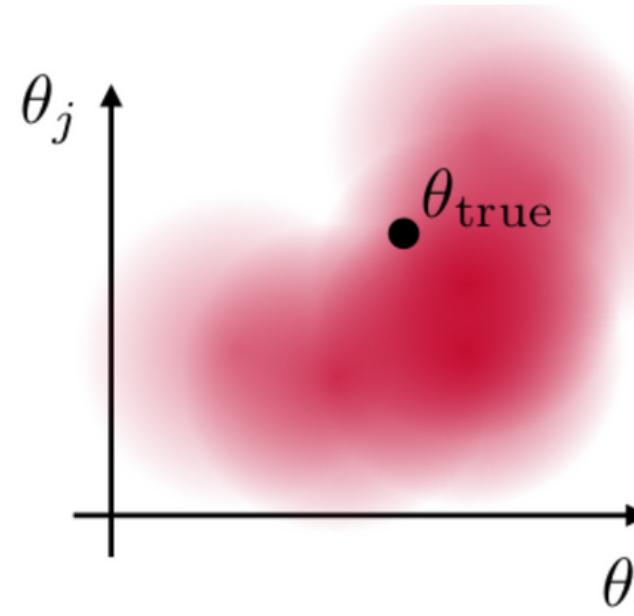
# Standard inference in cosmology

Parameters  
posterior

Likelihood

Prior over the  
parameters

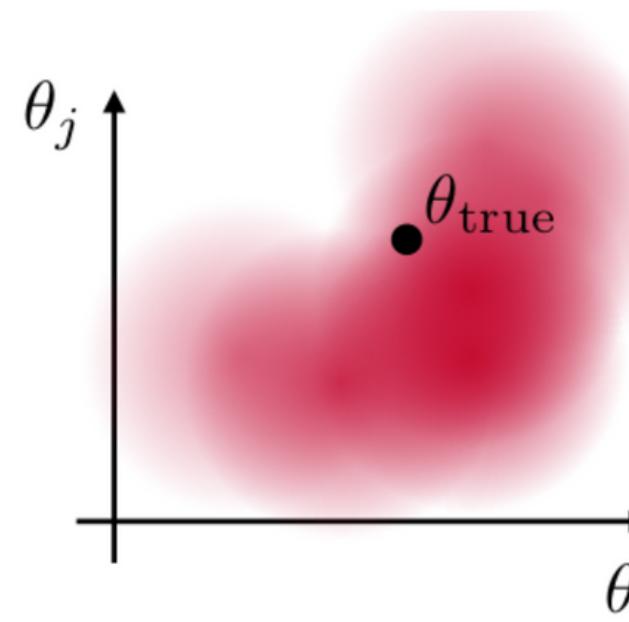
$$p(\theta|x) \propto \mathcal{L}(x|\theta)\mathcal{P}(\theta)$$



# Standard inference in cosmology

Parameters  
posterior

$$p(\theta|x) \propto \text{Likelihood} \quad \text{Prior over the parameters}$$
$$\mathcal{L}(x|\theta)\mathcal{P}(\theta)$$



## PROBLEMS:

- Analytical approximations (when available)
- Cumbersome covariance estimations

Superconfident posteriors!  
(Underestimation of errors)

# Simulation-based inference

Parameters  
posterior

Prior over the  
parameters

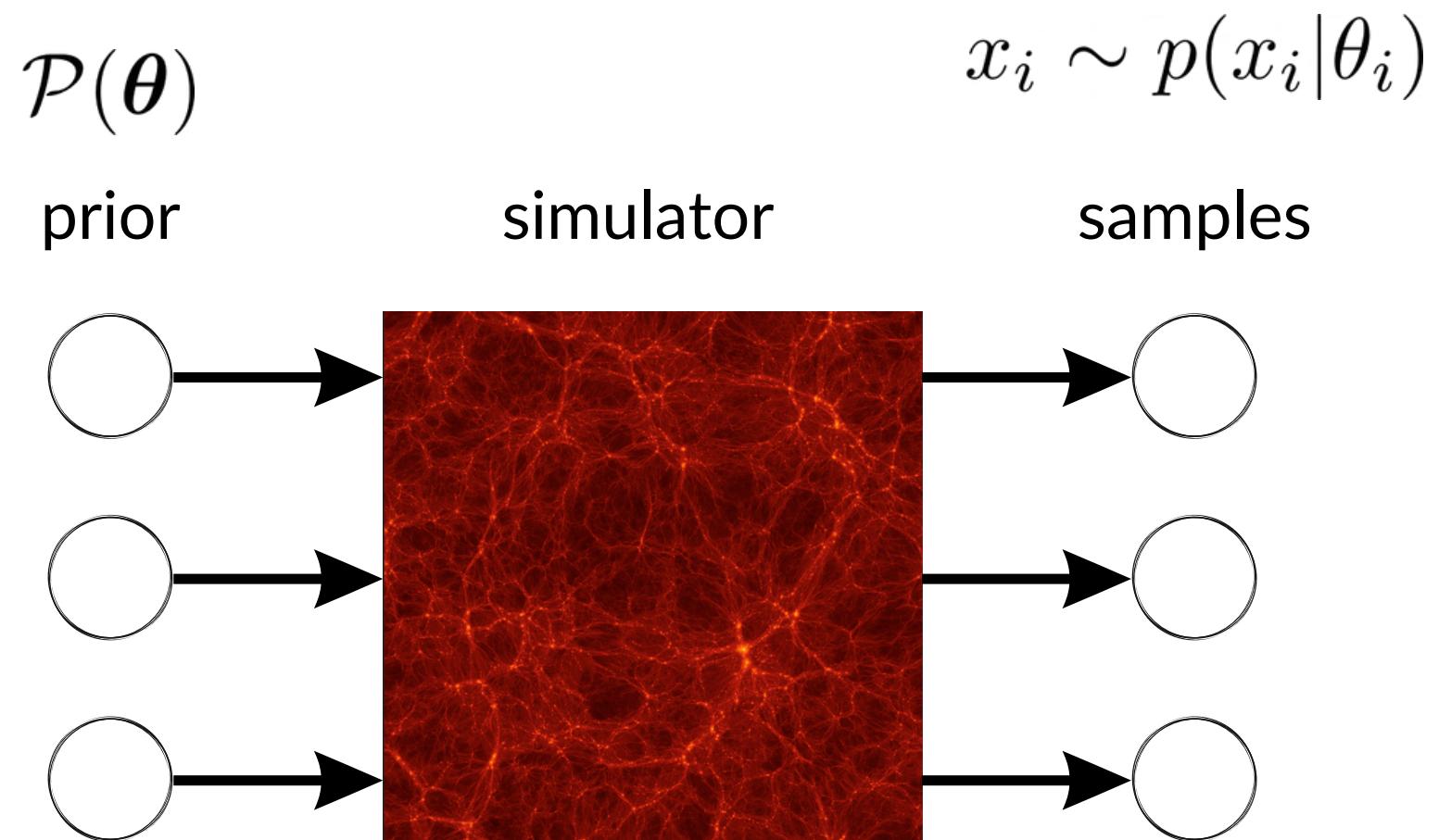
$$p(\theta|x) \propto \cancel{\mathcal{L}(x|\theta)} \mathcal{P}(\theta)$$

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

# Simulation-based inference

# TWO INGREDIENTS:

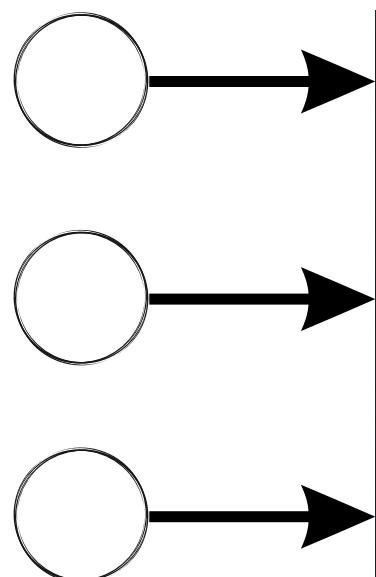
- A simulator that can generate samples
  - A prior over the parameters



# Simulation-based inference

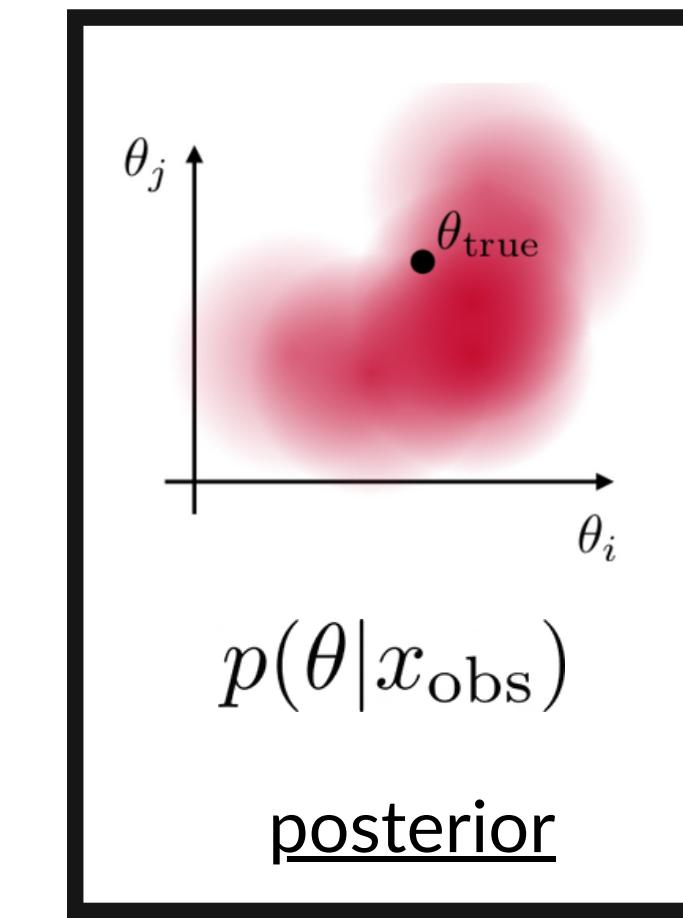
$$\mathcal{P}(\theta)$$

prior



$$x_i \sim p(x_i | \theta_i)$$

samples



$$x_{\text{obs}} \sim p(x_{\text{obs}} | \theta_{\text{true}})$$

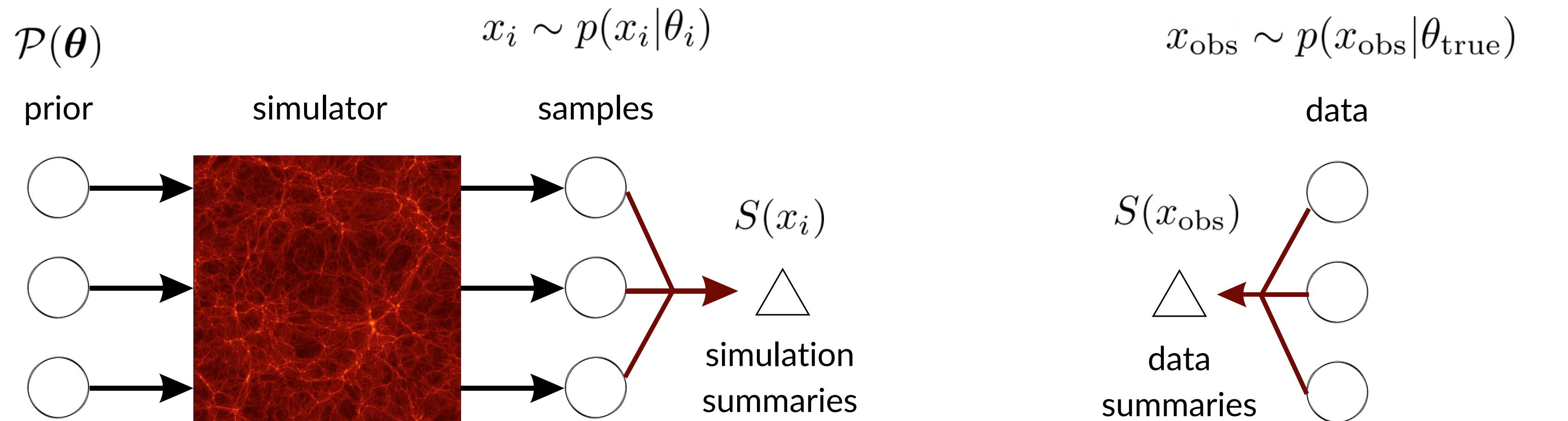
data



?

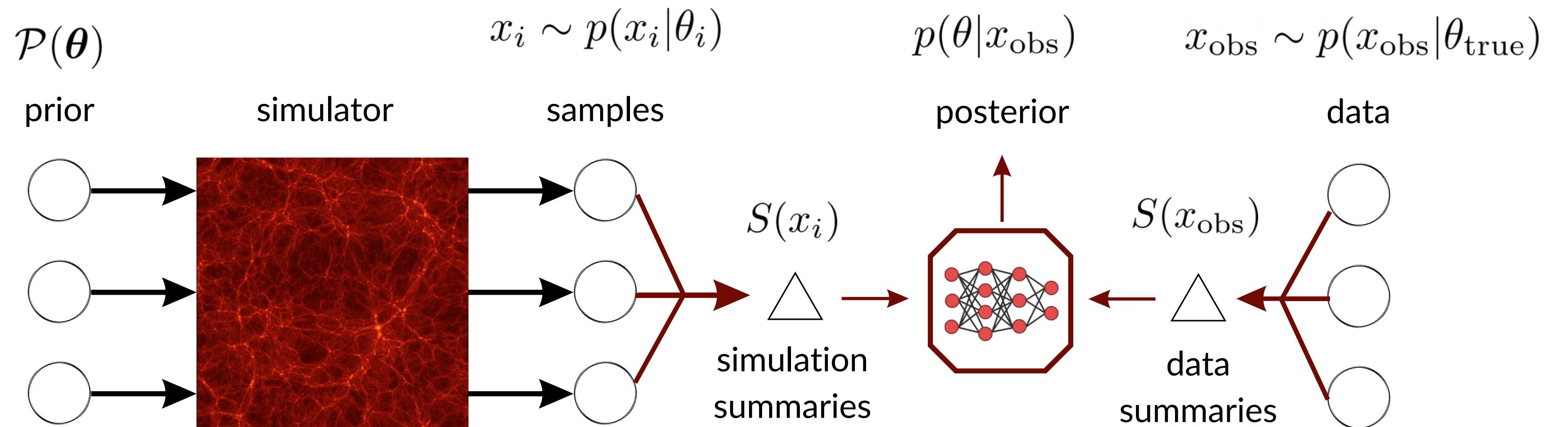
=

# Simulation-based inference



# Neural Density Estimators

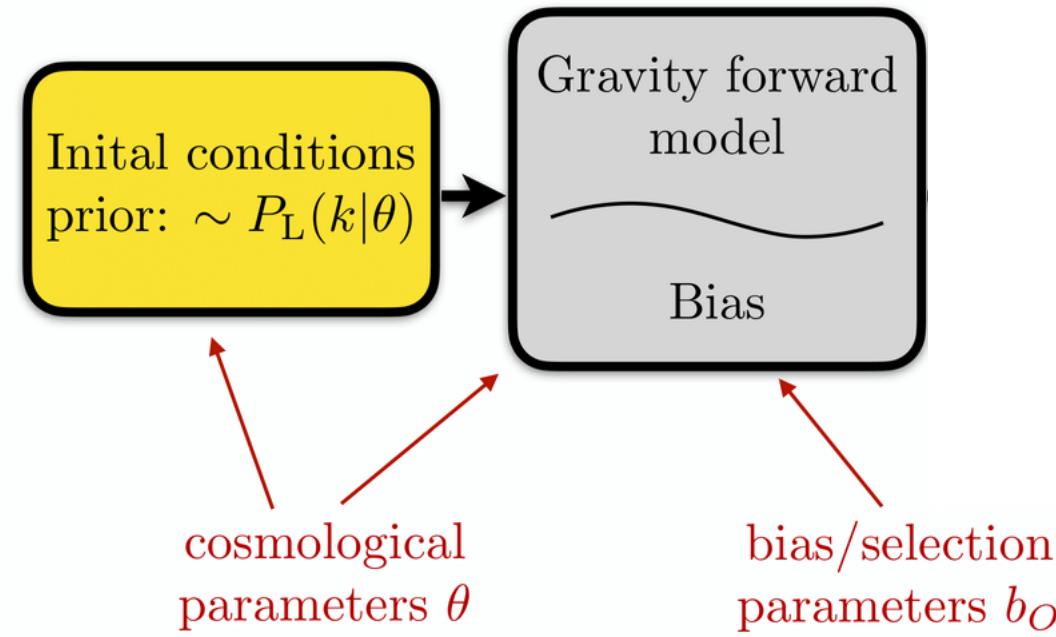
*sbi: A toolkit for simulation-based inference*  
Tejero-Cantero et al. (2020)



# LEFTfield | forward model



## EFTofLSS based approach



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

## Lagrangian Perturbation Theory

$$\begin{aligned}
 \mathbf{x}(\tau) &= \mathbf{q} + \mathbf{s}(\mathbf{x}, \tau) \\
 M_{ij}^{(n)} &= \partial_i s_j^{(n)} \\
 &\downarrow \\
 \text{Lagrangian Bias Operators} \\
 \delta_{g,\text{det}}^L(\mathbf{q}, \tau) &= \sum_{\mathcal{O}^L} b_{\mathcal{O}^L}(\tau) \mathcal{O}^L(\mathbf{q}, \tau) \\
 &\downarrow \text{displacement (CIC)} \\
 \delta_g(\mathbf{x}, \tau) &= \delta_{g,\text{det}}(\mathbf{x}, \tau) + \varepsilon(\mathbf{x}, \tau) + \sigma_{\varepsilon\delta}(\tau) \varepsilon(\mathbf{x}, \tau) \delta(\mathbf{x}, \tau) + c_\varepsilon^{\text{NG}}(\tau) \varepsilon^2(\mathbf{x}, \tau)
 \end{aligned}$$

Below the equations, there are two columns of text:

- 1<sup>st</sup>       $\text{tr}[M^{(1)}]$
- 2<sup>nd</sup>       $\text{tr}[(M^{(1)})^2], (\text{tr}[M^{(1)}])^2$

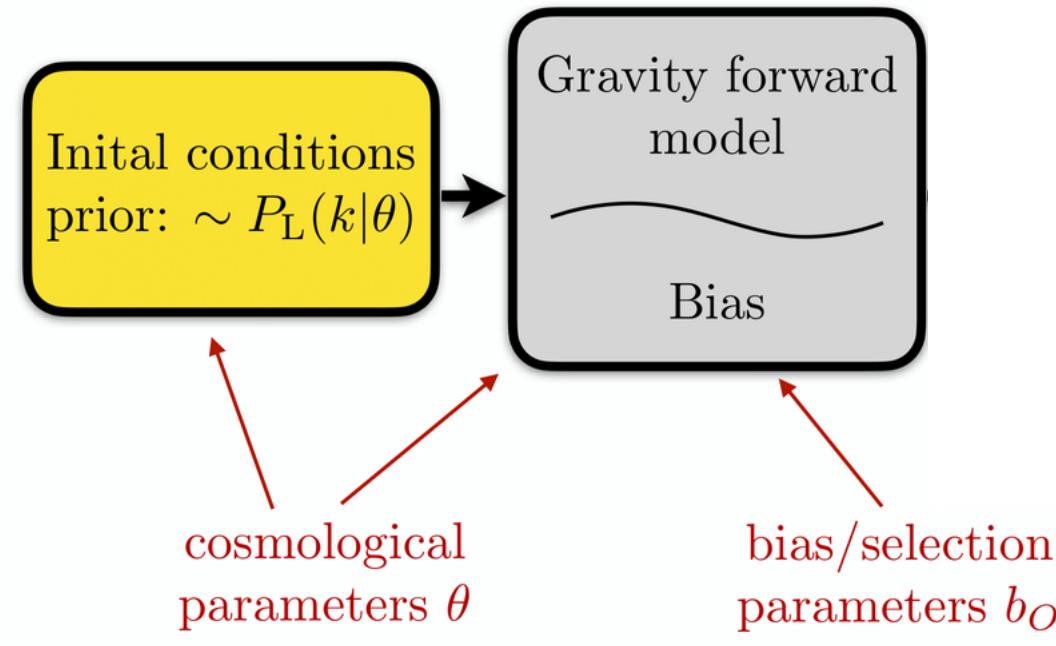
$$\delta_g(\mathbf{x}, \tau) = \delta_{g,\text{det}}(\mathbf{x}, \tau) + \varepsilon(\mathbf{x}, \tau) + \sigma_{\varepsilon\delta}(\tau) \varepsilon(\mathbf{x}, \tau) \delta(\mathbf{x}, \tau) + c_\varepsilon^{\text{NG}}(\tau) \varepsilon^2(\mathbf{x}, \tau)$$

# LEFTfield | forward model



EFTofLSS based approach

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



Perturbation Theory

$$\langle \delta_g(k_1) \delta_g(k_2) \delta_g(k_3) \rangle_{\text{stoch}}^{\prime \text{LO}} = B_\varepsilon + 2b_1 P_{\varepsilon \varepsilon \delta} (P_m(k_1) + 2 \text{ perm.})$$

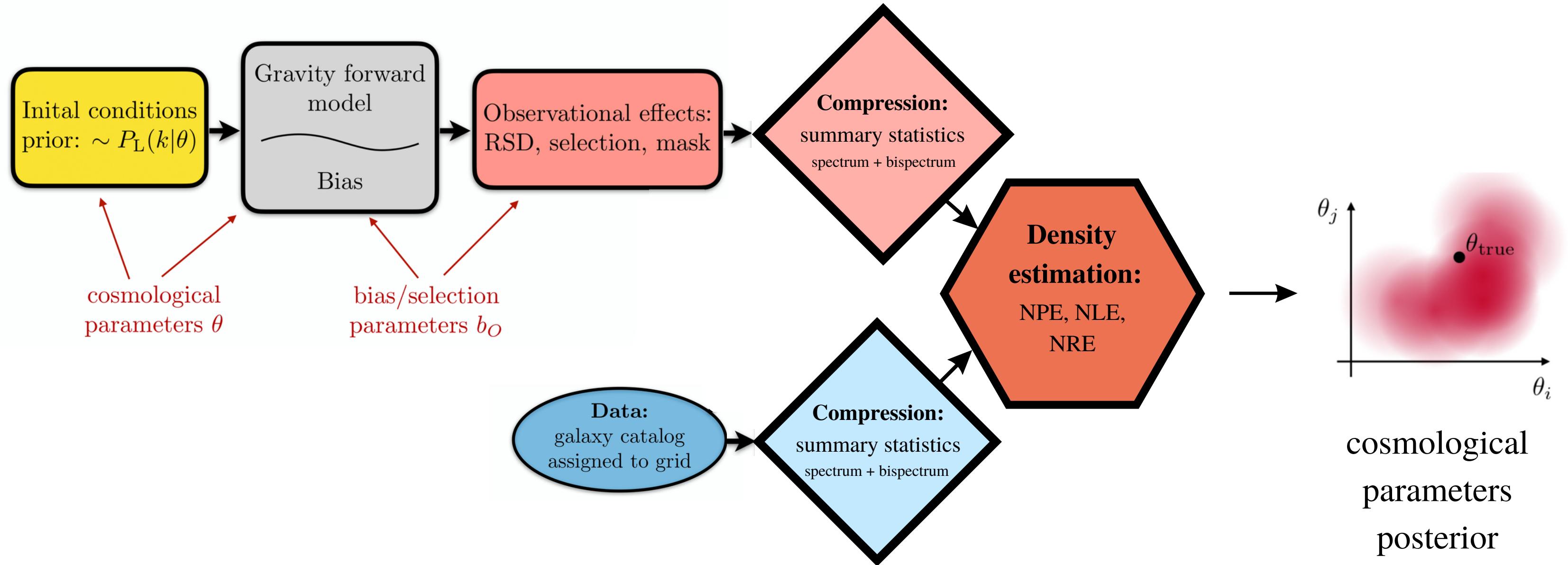
Forward Model

$$\langle \delta_g(k_1) \delta_g(k_2) \delta_g(k_3) \rangle_{\text{stoch}}^{\prime \text{LO}} = 6c_\varepsilon^{\text{NG}} P_\varepsilon^2 + 2b_1 P_\varepsilon \sigma_{\varepsilon \delta} (P_m(k_1) + 2 \text{ perm.})$$

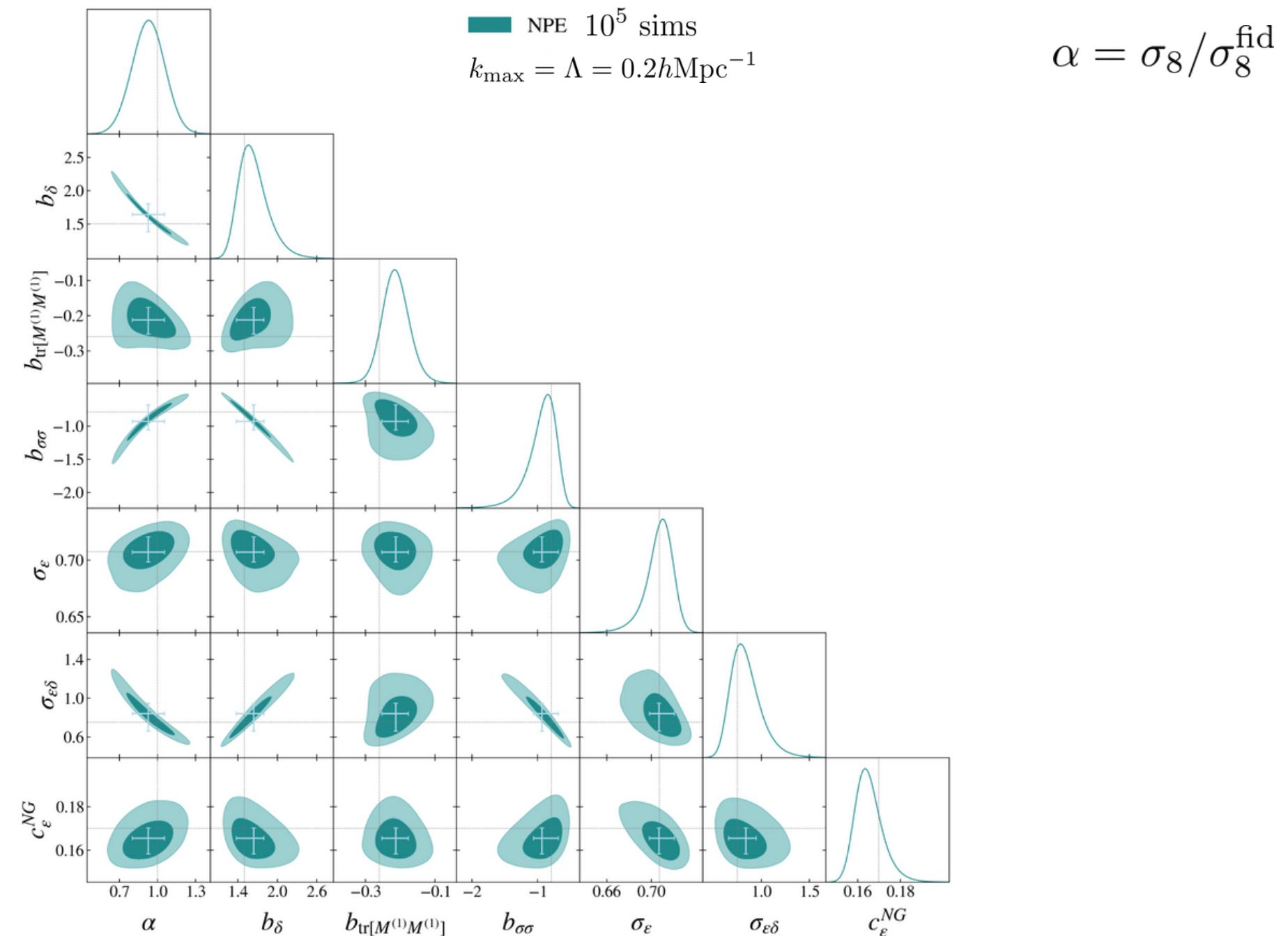
An  $n$ -th order Lagrangian Forward Model for Large-Scale Structure  
Fabian Schmidt (2021)

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

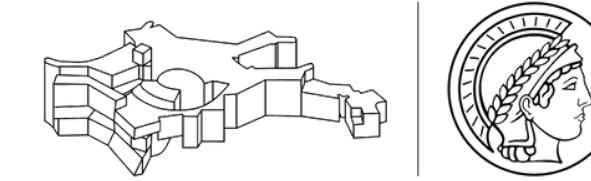
# LEFTI | LEFTfield & LFI



# Euclid | 2LPT, 2nd order bias expansion



PRELIMINARY!



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Thank you!

A large, horizontal rectangular image at the bottom of the slide shows a detailed astronomical observation of a nebula or galaxy core. The image is dominated by warm orange and yellow hues, with intricate patterns of gas and dust visible against a darker background.

Beatrix Tucci | PhD Student at MPA  
Supervisor: Fabian Schmidt