From Cosmic Shear to Subhalo Detection:

Leveraging Simulation-Based Inference for Precision Cosmology

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08/11/2024 - FLAT Talk

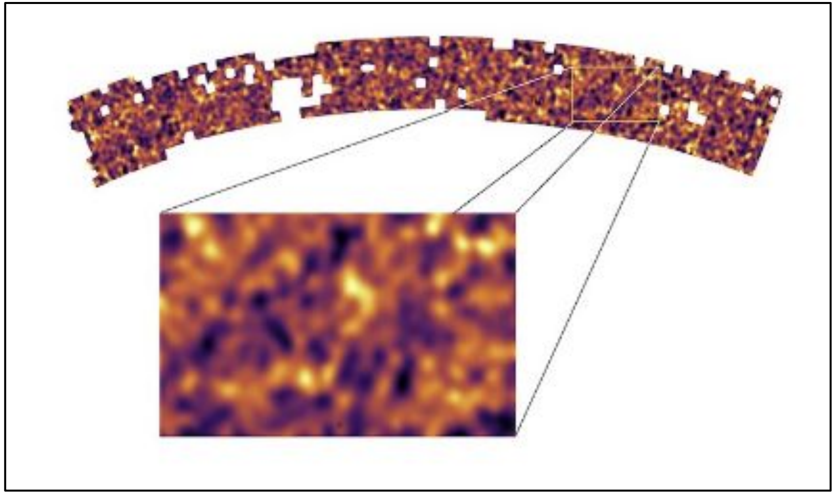
Kilo-Degree Survey

Institute for Computational Cosmology

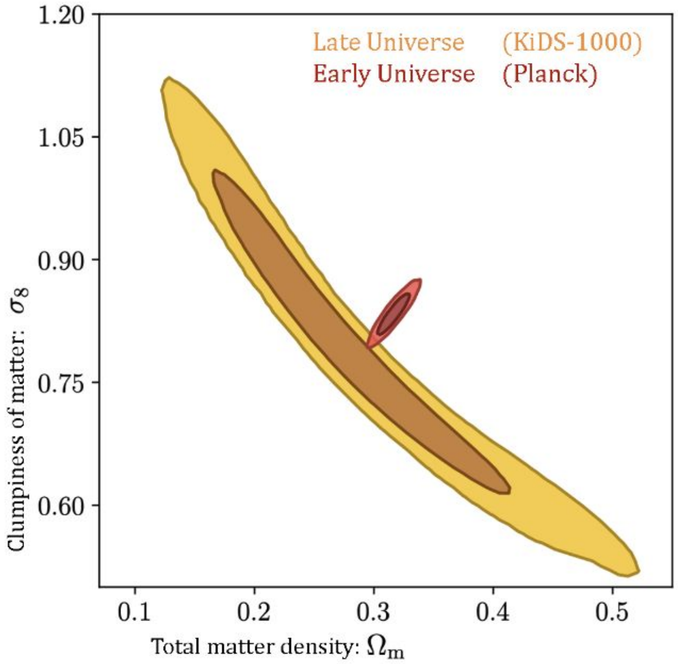
Durham Centre for Extragalactic Astronomy

Durham University

Cosmological Inference



Observable



Posterior given a model

Simulation-Based Inference (SBI)

a.k.a. Likelihood-free inference or implicit likelihood inference

Likelihood

Posterior

Prior

Joint probability

$$P(\boldsymbol{\theta}|\boldsymbol{d}) = \frac{P(\boldsymbol{d}|\boldsymbol{\theta}) \cdot P(\boldsymbol{\theta})}{P(\boldsymbol{d})} \propto P(\boldsymbol{\theta}, \boldsymbol{d}) \cdot P(\boldsymbol{\theta})$$

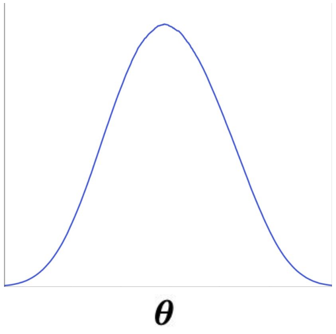
$\boldsymbol{\theta}$: Model parameters

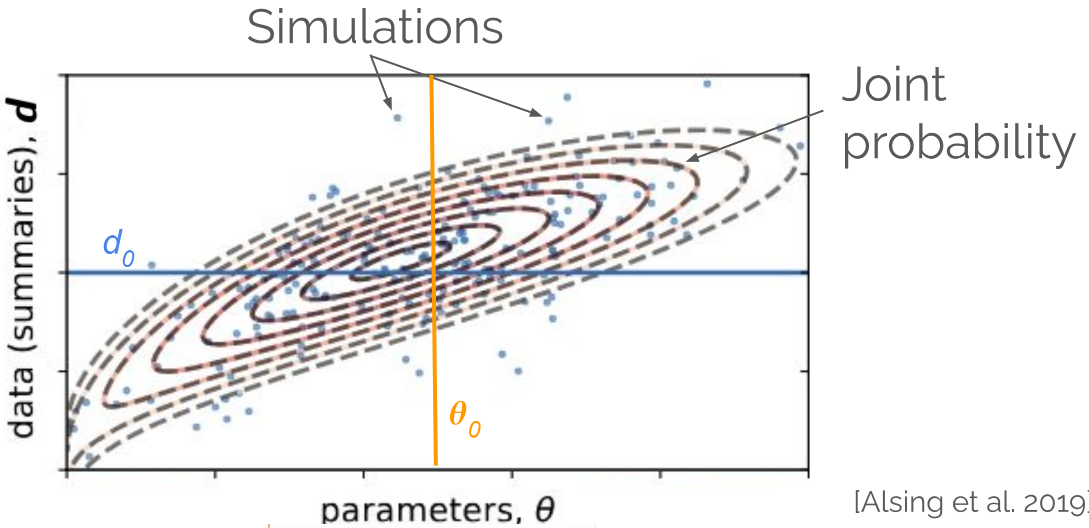
$\boldsymbol{d}$: Data

Simulation-Based Inference (SBI)

Posterior

$P(\boldsymbol{\theta}|\boldsymbol{d}_0)$

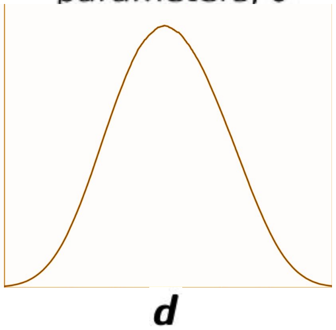




[Alsing et al. 2019]

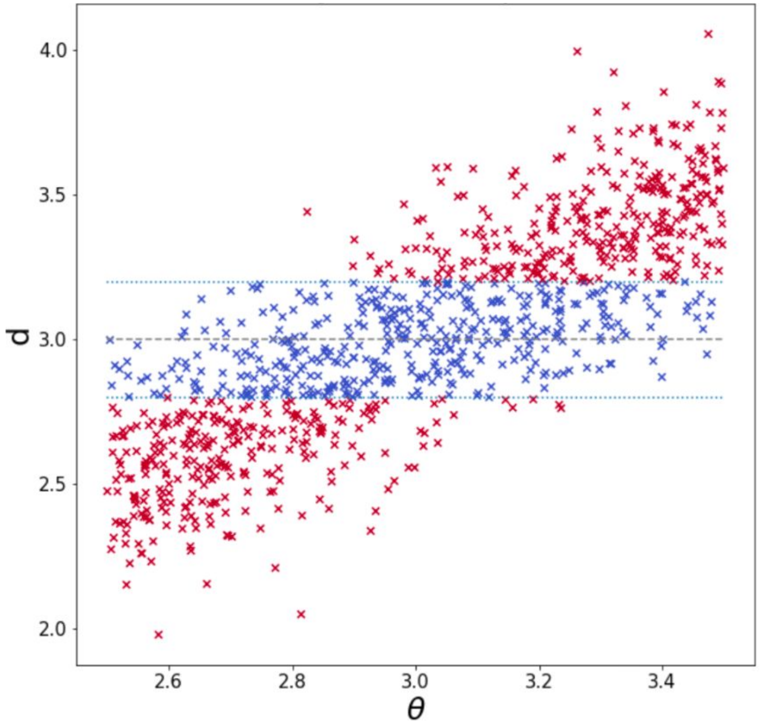
Likelihood

$P(\boldsymbol{d}|\boldsymbol{\theta}_0)$

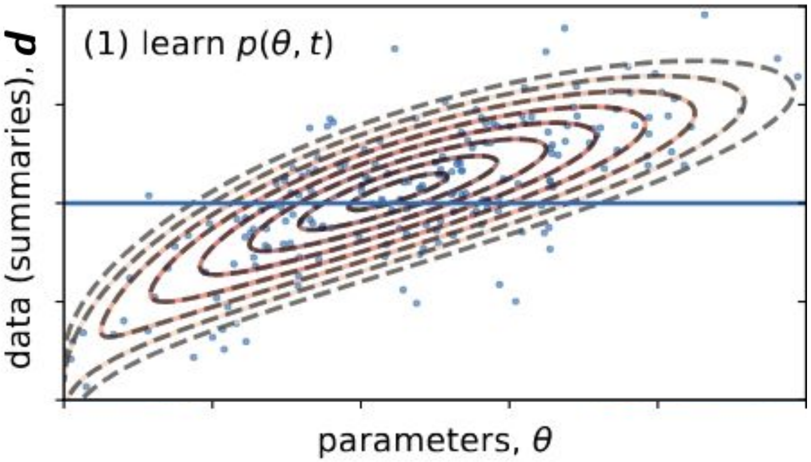


Density Estimation

Approximate Bayesian Computation



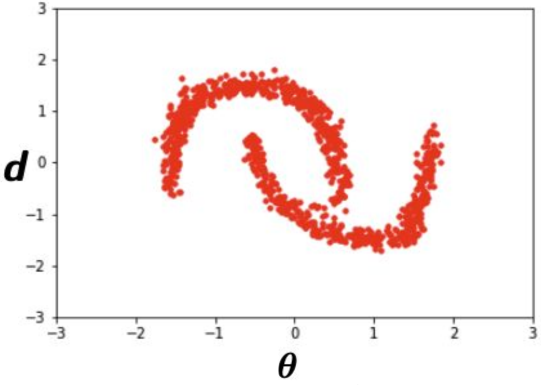
Neural Density Estimation



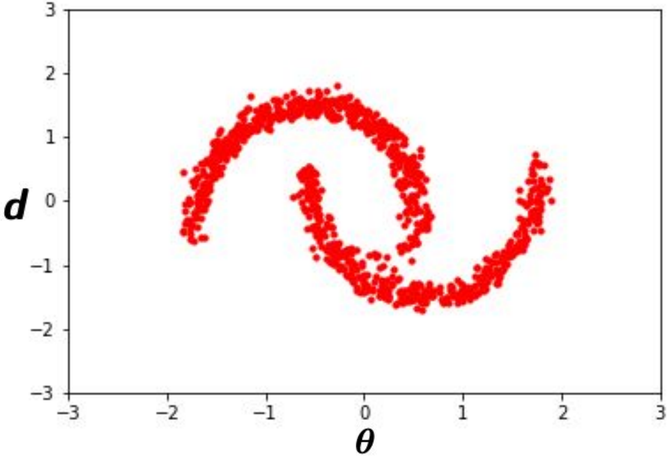
Neural Density Estimation

e.g. Normalising flows

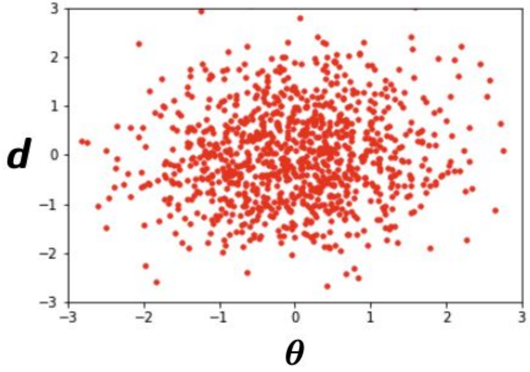
$P(\boldsymbol{\theta}, \boldsymbol{d})$
from simulations



Learn transformations to



Gaussian distribution

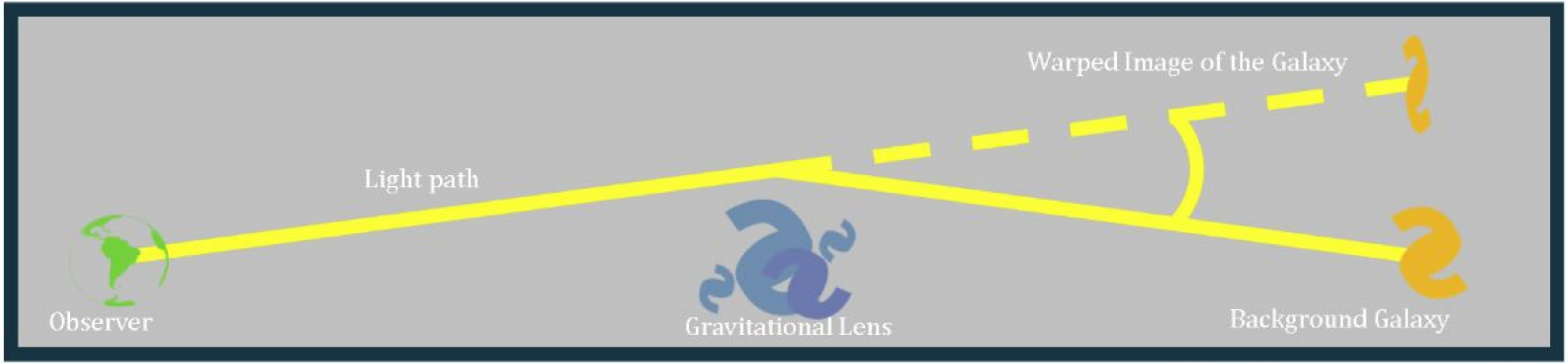


Credit: Eric Jang

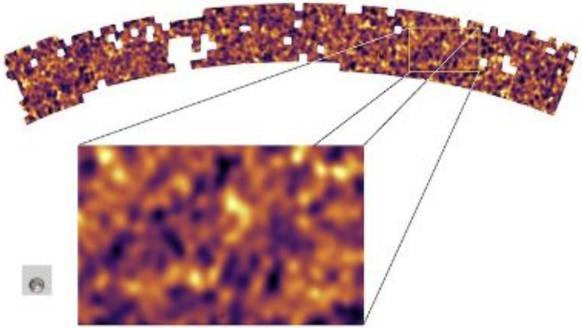
Invertible

Cosmic Shear
& Large-Scale Structure

Weak Gravitational Lensing



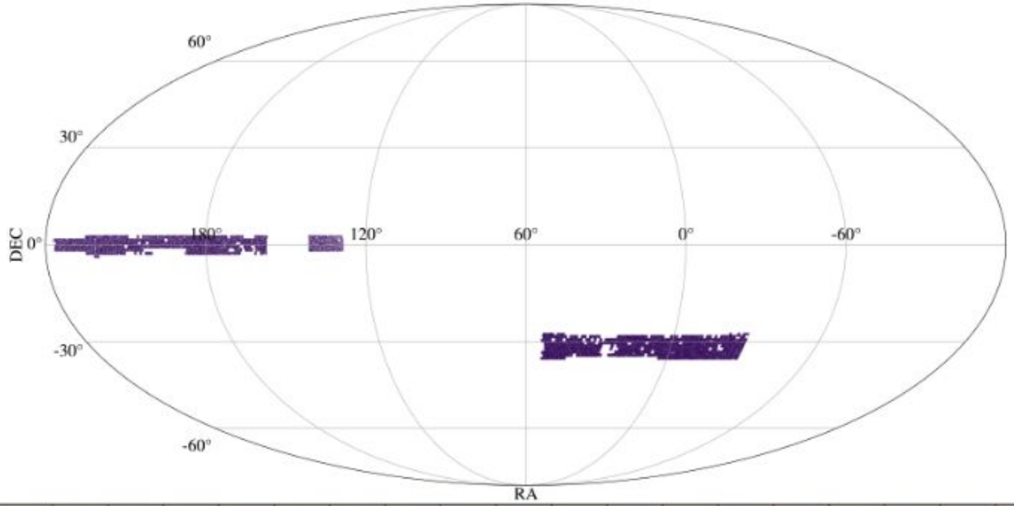
Cosmic shear:

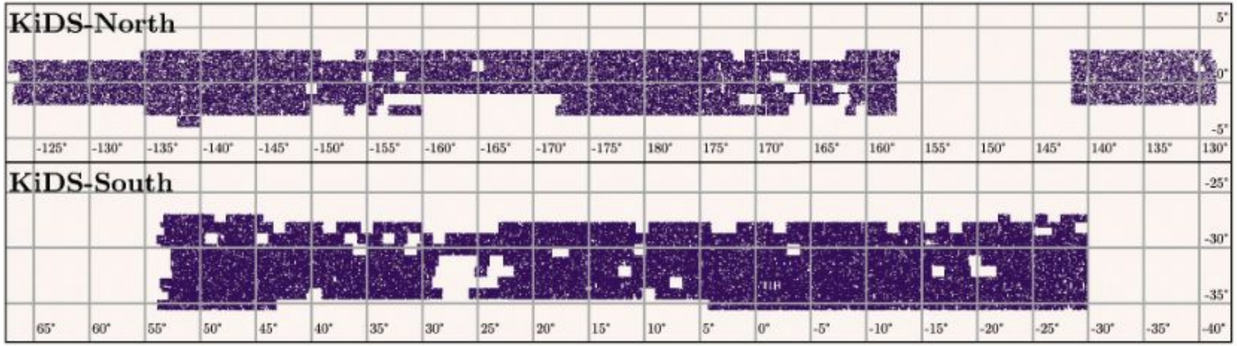


Foreground matter field

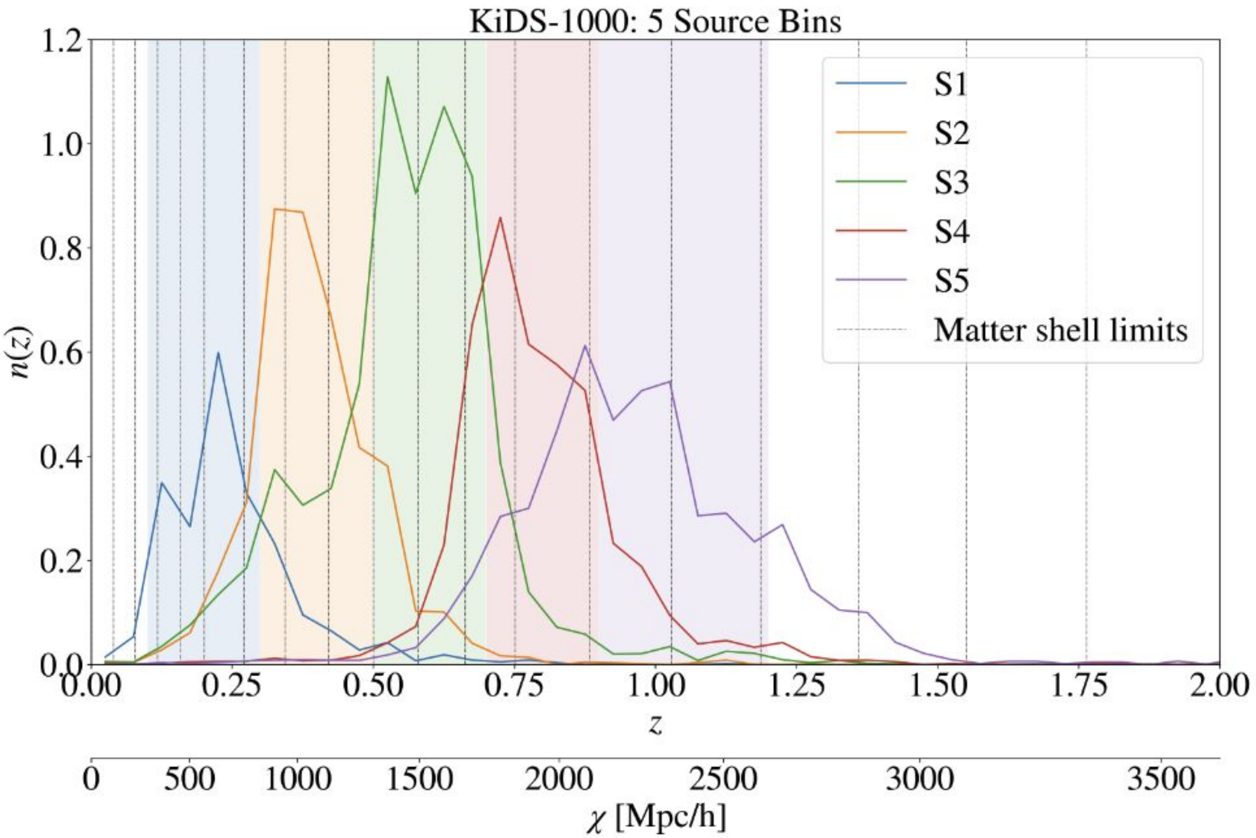
Distant galaxy population

Kilo-Degree Survey: KiDS-1000

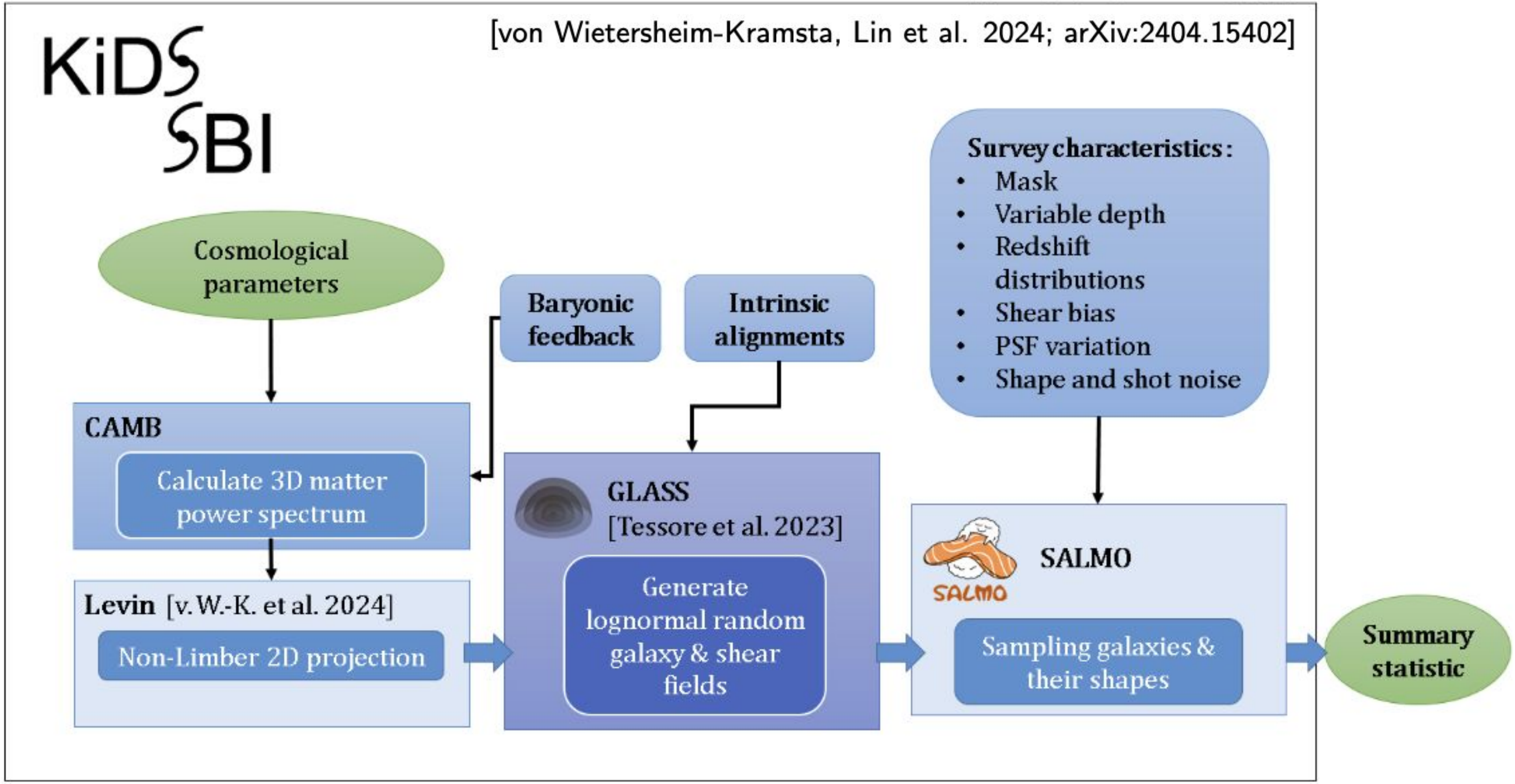




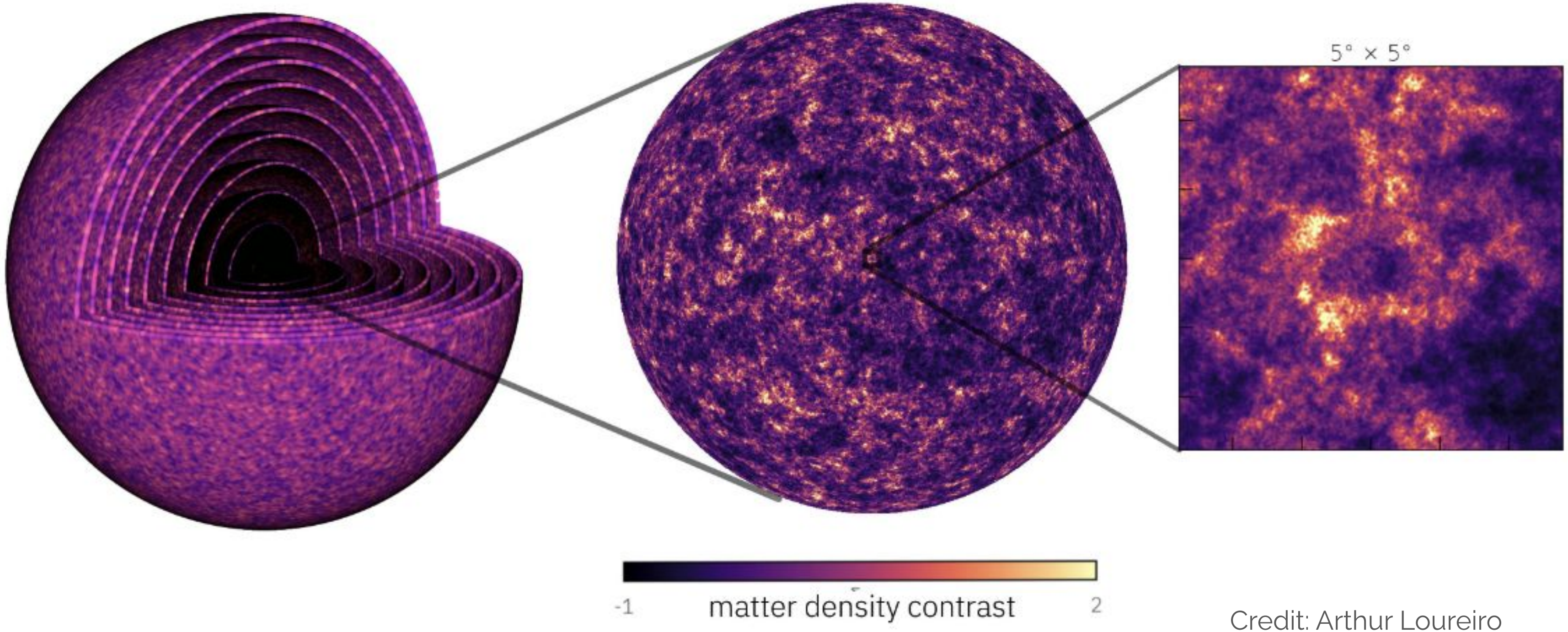
KiDS-1000 Galaxy Population



Forward Simulations

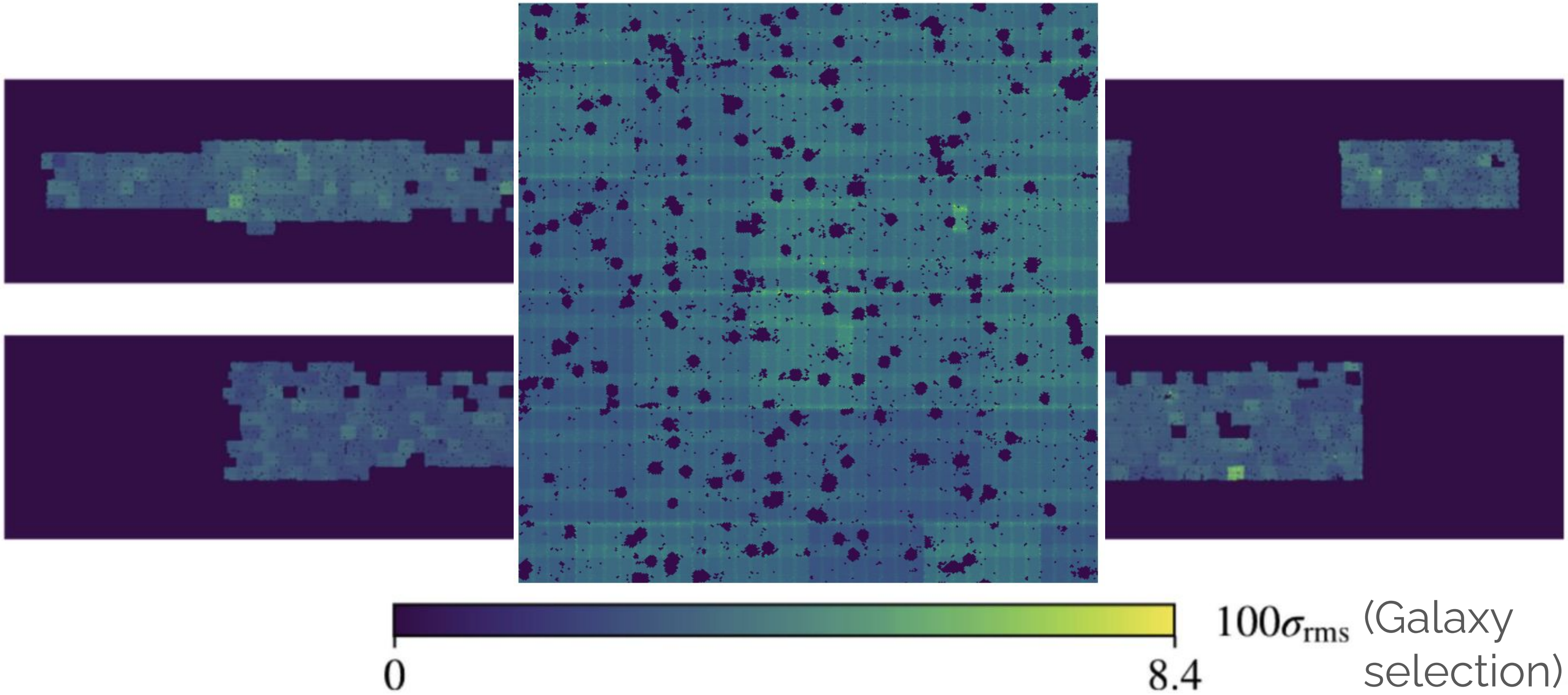


Simulating the Matter Field



Credit: Arthur Loureiro

Adding Realism: Variable Depth

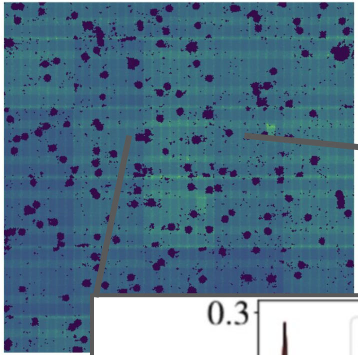


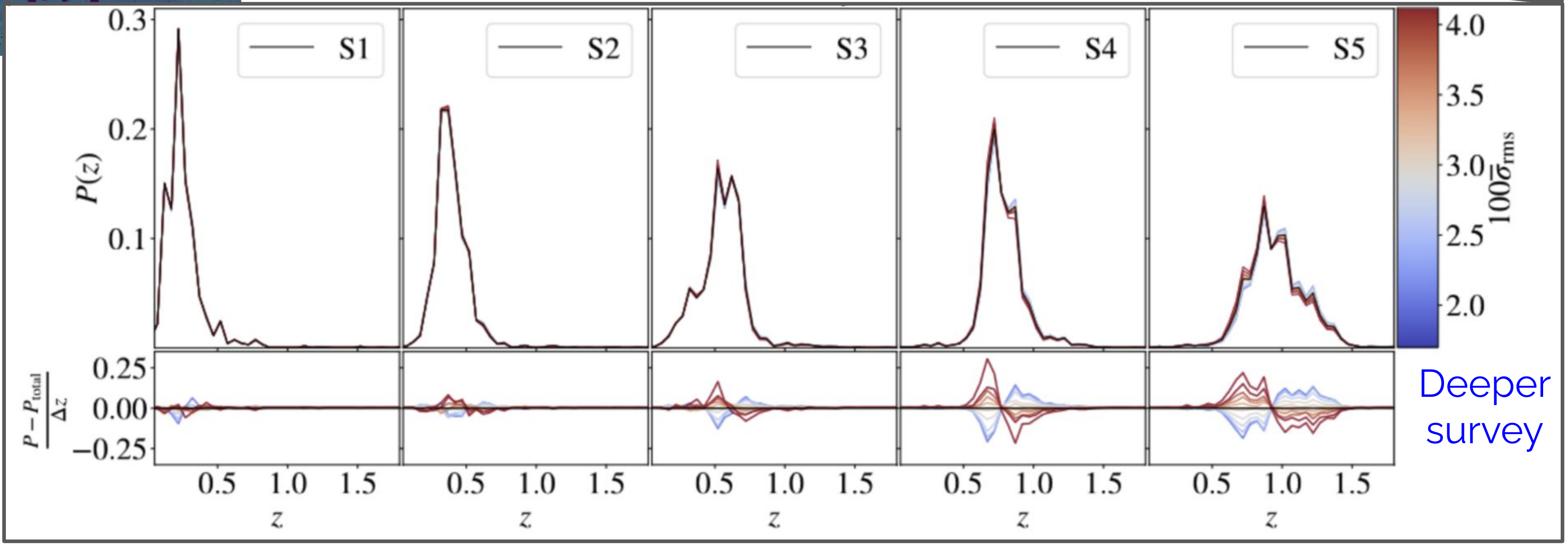
(Galaxy selection)

Deeper survey

Less deep survey

Adding Realism: Variable Depth

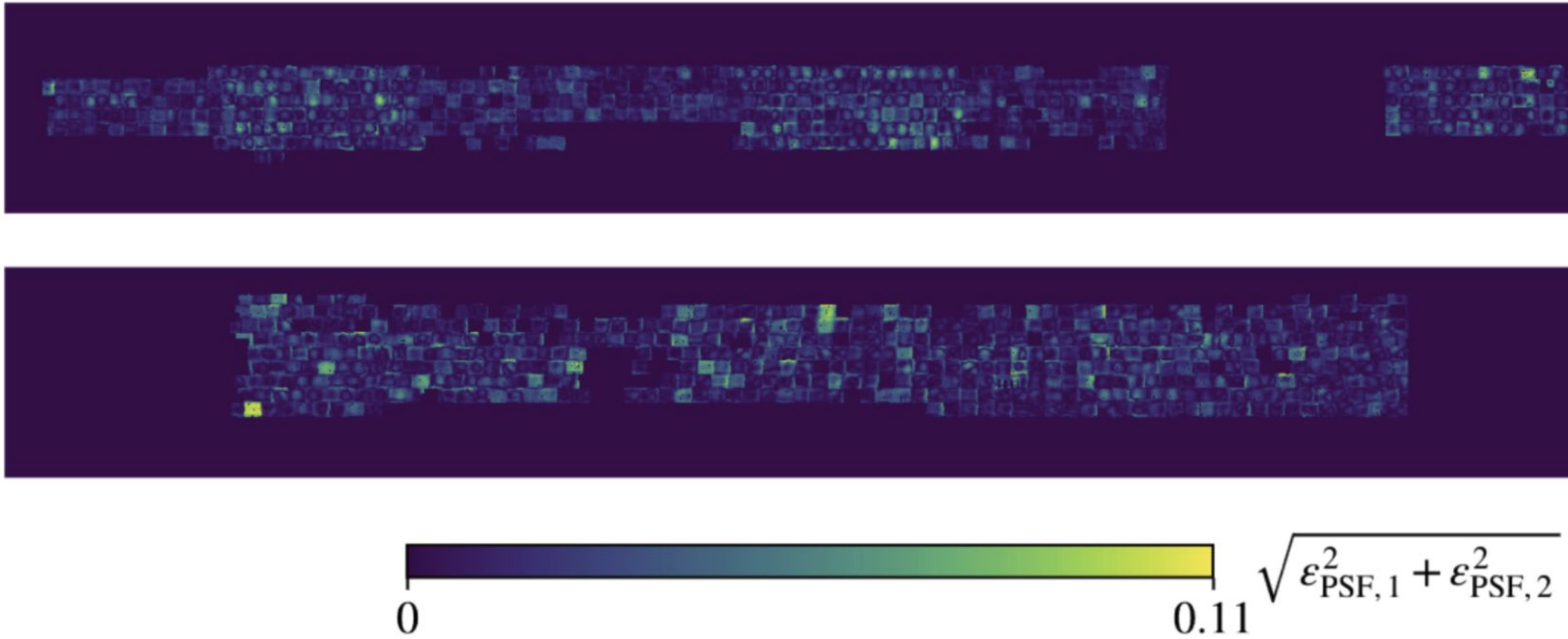




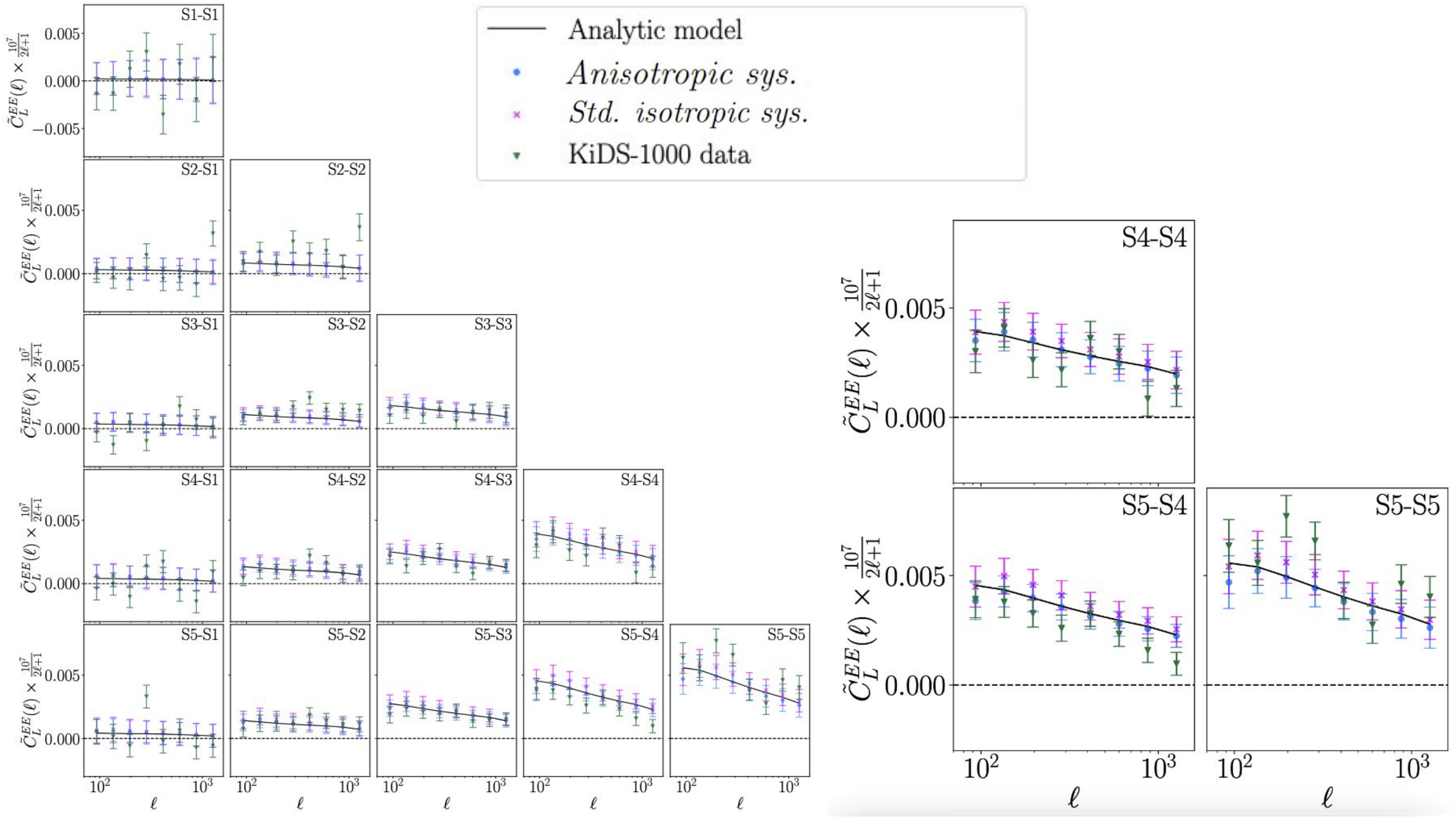
Less deep survey

Deeper survey

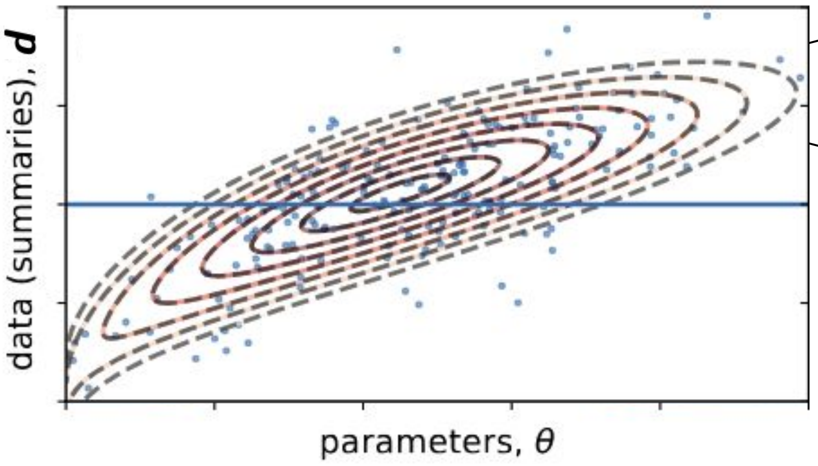
Adding Realism: PSF Shape Variations



Cosmic Shear Measurement



SBI: Neural Likelihood Estimation



Varying 32 parameters

18,000 simulations

Ensemble of 5 NDEs

6 x MAFs

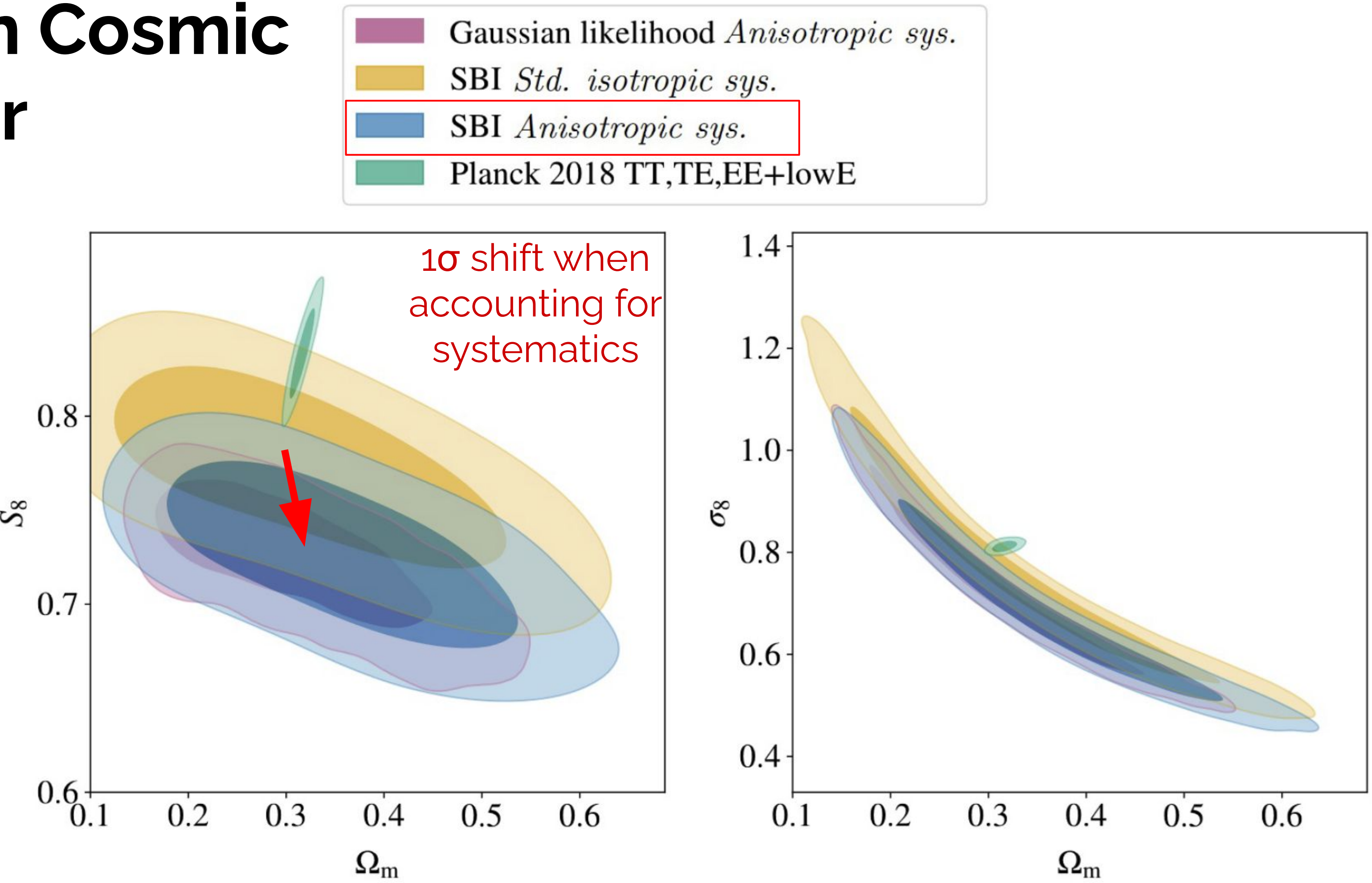
5 x MADEs

2 hidden layers
50 neurons each

→ 6 x 5 x |**d**| multivariate Gaussians,
P(**d**|$\boldsymbol{\theta}$, **w**)

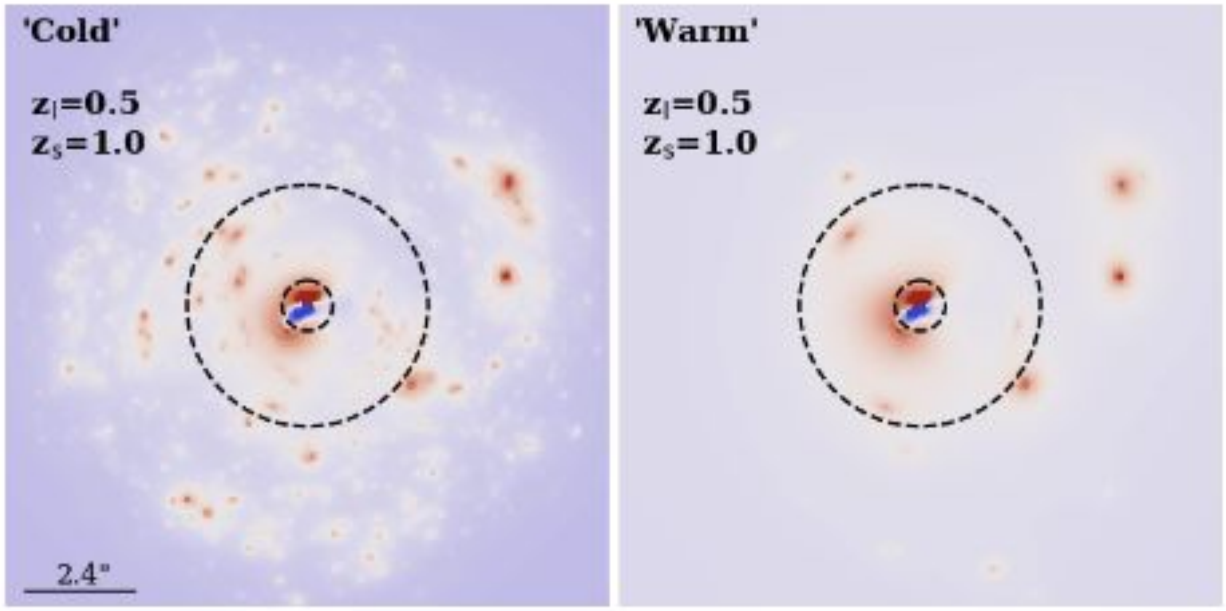
SBI in Cosmic Shear

Weak lensing parameter for “clumpiness”



Strong Gravitational Lensing & Substructure

Search for Substructure



[He et al. 2022]

Forward Simulations

(Same as used in He et al. 2022)

Source:

Elliptical Core-Sersic

z = 1

Lens:

Power law mass

z = 0.5

No external shear

Subhalos:

Truncated NFW mass

M_{hf} = 10^7

$n_{subhaloes}$ ∈ [0, 30]

All other parameters fixed

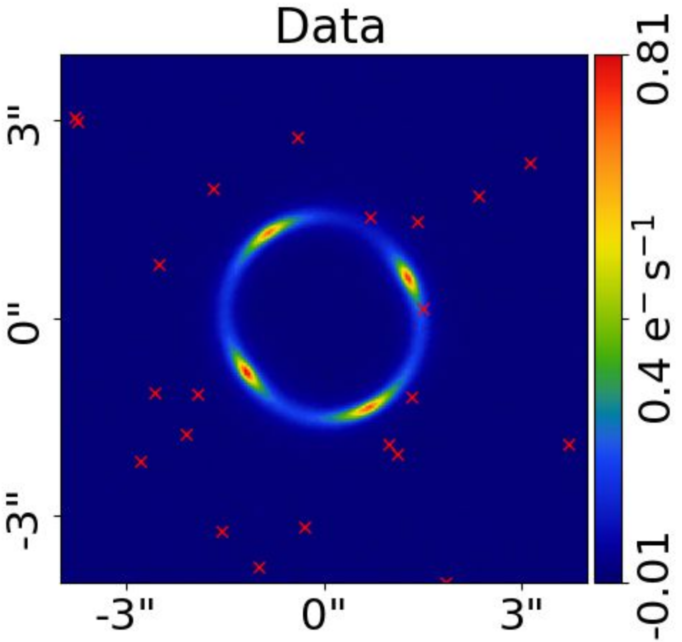
Exposure = 8000s

Sky background = 0.1

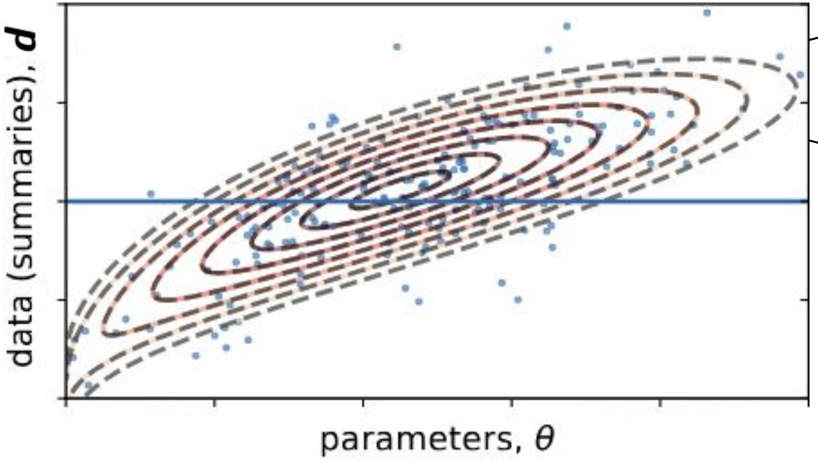
Pixel scale = 0.05”

σ_{PSF} = 0.05”

Poisson noise



SBI: Neural Posterior Estimation



Varying 1 parameter: $\mathbf{n}_{\mathbf{subhaloes}}$

1,000 simulations

Ensemble of 2 NDEs

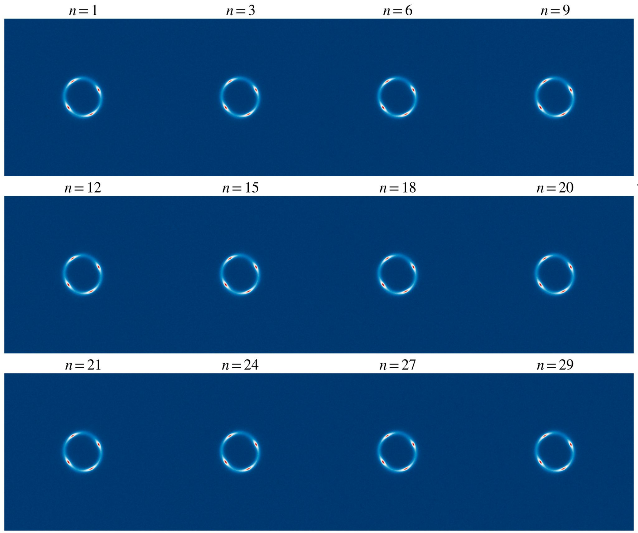
2 x MAFs

5 x MADEs

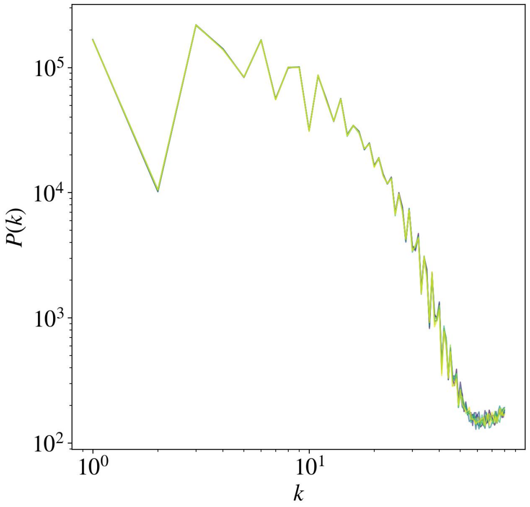
2 hidden layers
50 neurons each

→ 2 x 5 x |**d**| multivariate Gaussians, P($\boldsymbol{\theta}$|**d**, **w**)

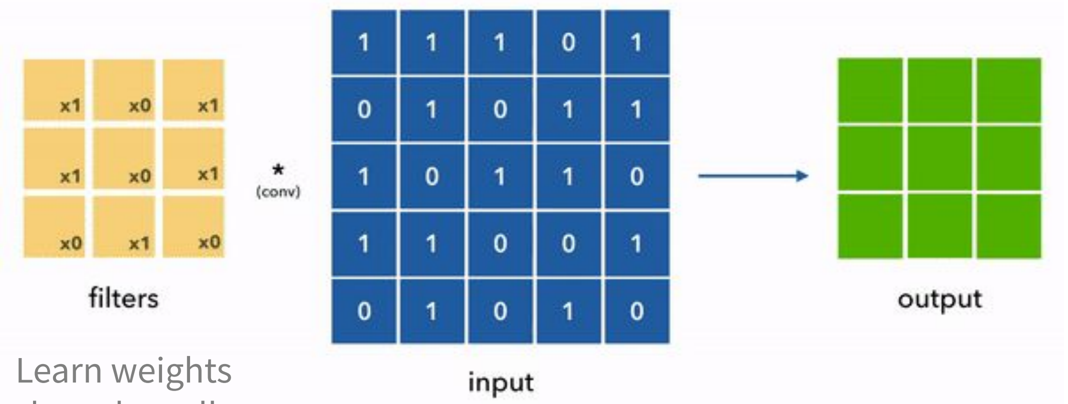
Data Compression



1. **Image Power Spectra**



2. **CNN**



Learn weights based on all simulated images

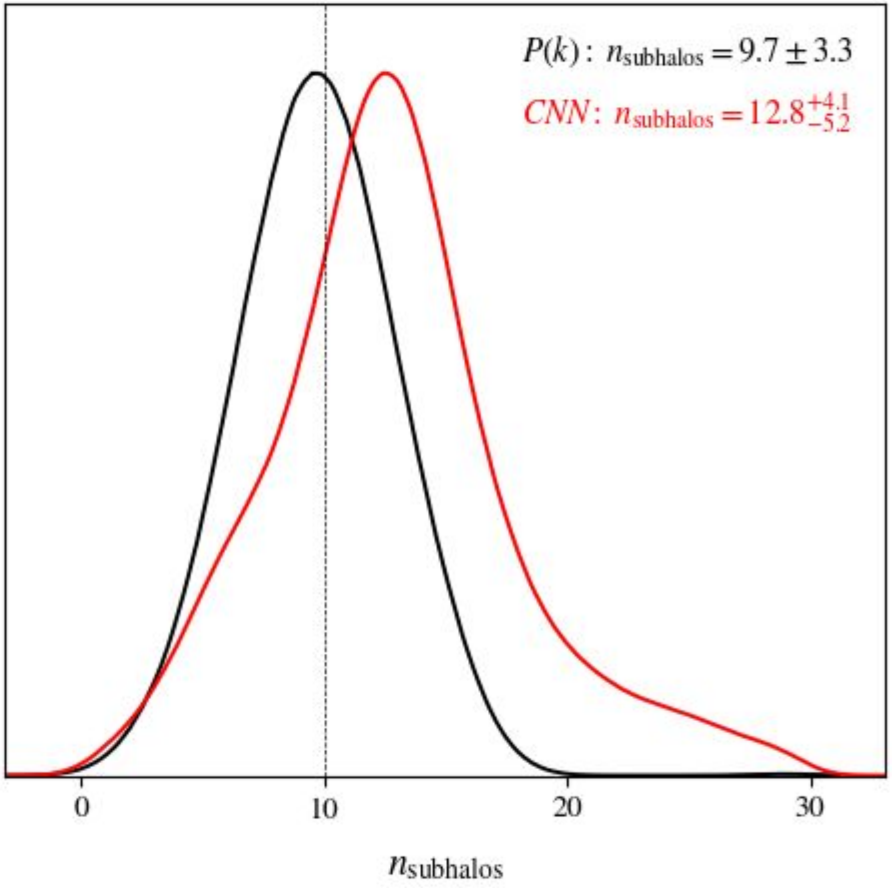
Convolutional layer

SBI for Substructure Search

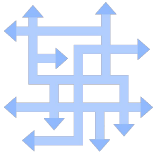
Truth: $n_{subhalos}$ = *10*

Measuring P(k) from a noisy image

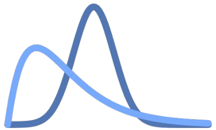
Measuring CNN from a noisy image ($\mathbb{R}^{10}$)



Conclusions



SBI allows for an **arbitrarily complex** model



SBI gives an **implicit likelihood** function
(can be non-Gaussian)

$d_0, d_1, d_2 \ldots$

SBI can be **amortisable**
(all model evaluations can be data-independent)