Simulation-Based Inference for Large-Scale Structure

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mwiet.github.io

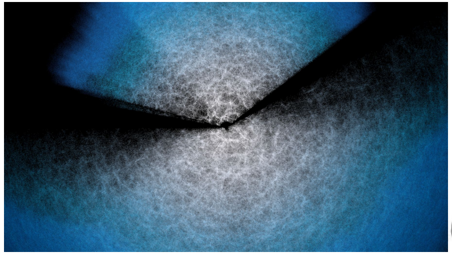
DESI Summer Collaboration Meeting - Durham University - 16th July 2026

Durham Centre for Extragalactic Astronomy

Institute for Computational Cosmology

Durham University

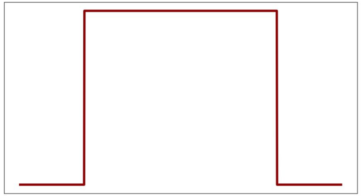
Cosmological Parameter Inference



$\boldsymbol{d}$

Data

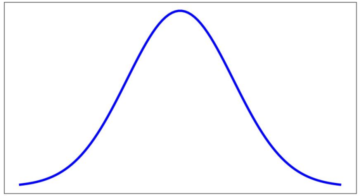
$P(\theta)$



$\boldsymbol{\theta}$

Prior

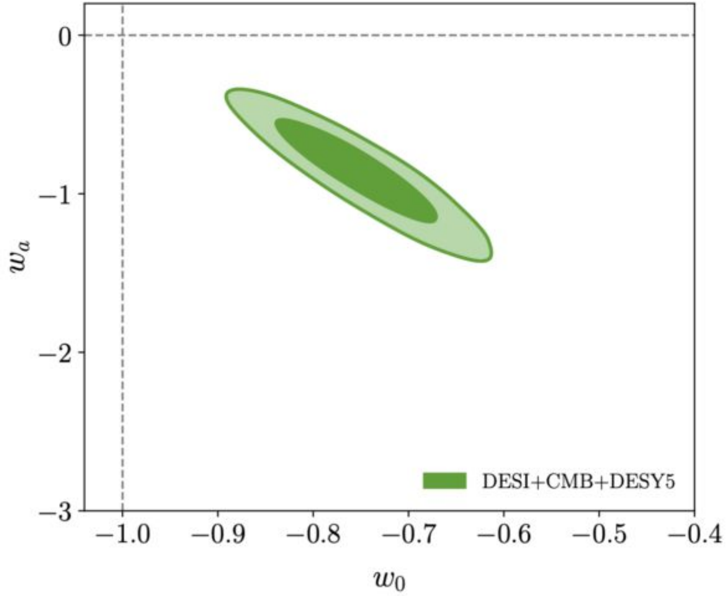
$P(\boldsymbol{d}|\boldsymbol{\theta})$



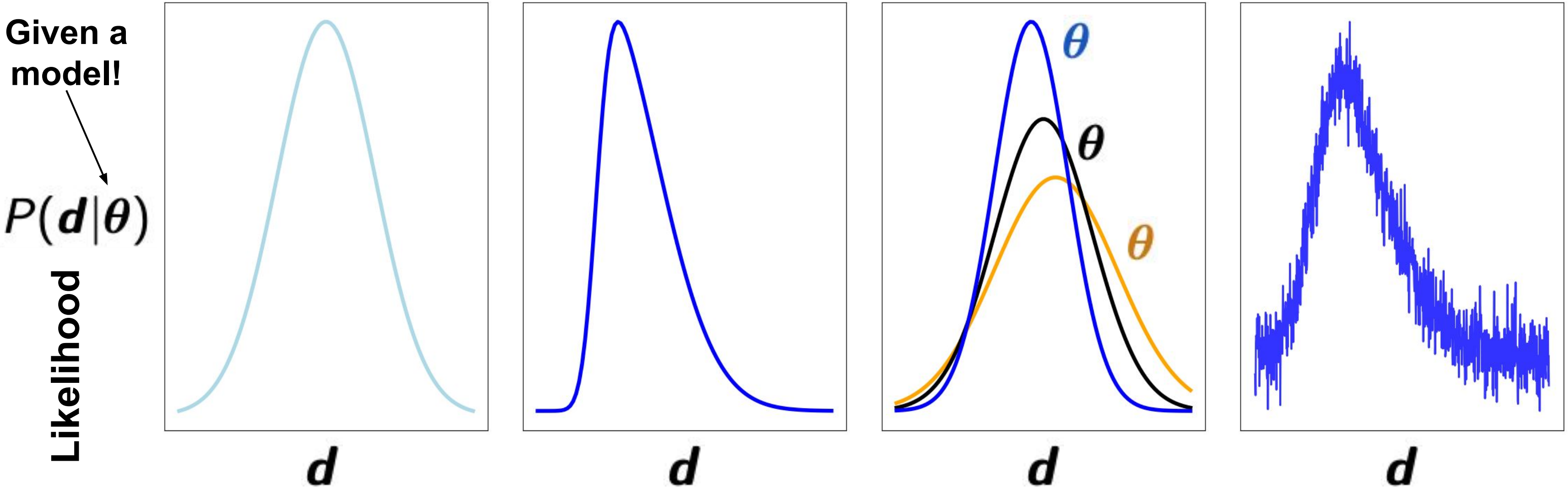
$\boldsymbol{d}$

Likelihood

$P(\boldsymbol{\theta}|\boldsymbol{d})$: Posterior



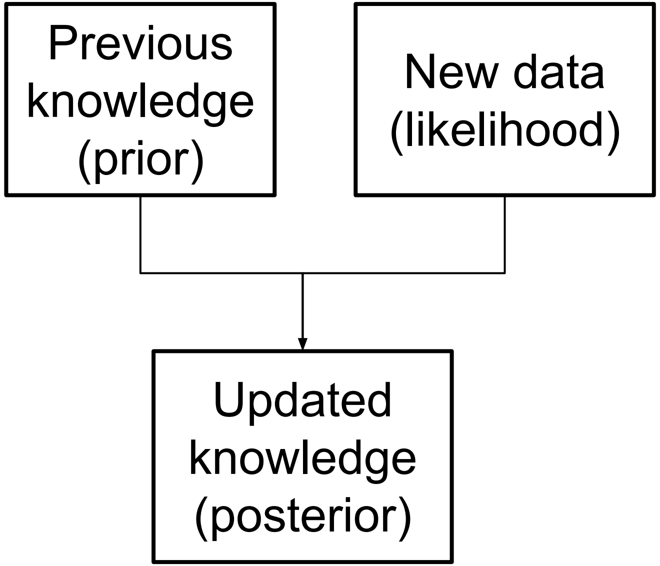
SBI as a Solution to Likelihood Misspecification



Analytic	Biased	Signal-dependent uncertainty	Intractable
e.g. $P(d\,|\,\theta) \propto e^{-(d-\mu)^2}$	e.g. Instrumental systematics	e.g. Cosmic variance	e.g. Non-trivial selection functions

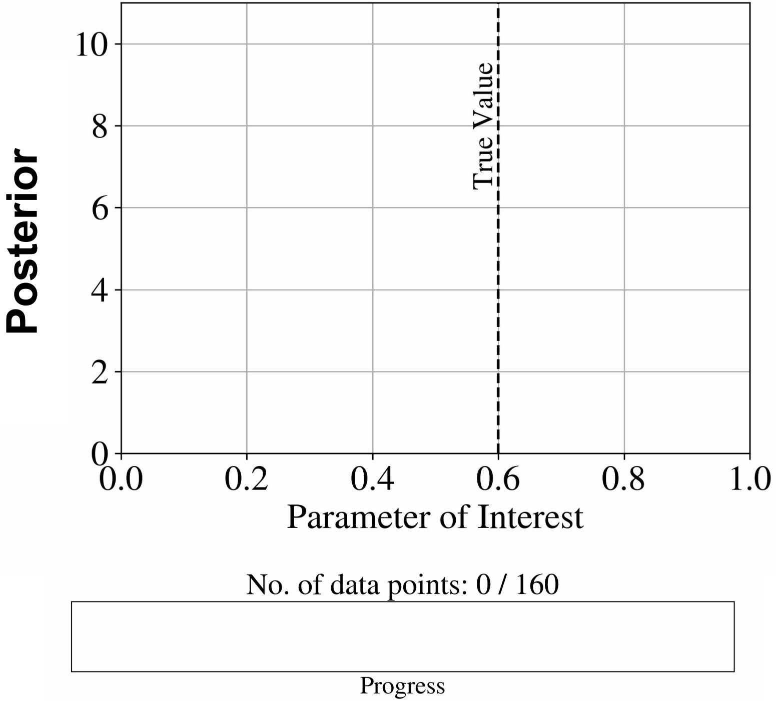
SBI as a Solution to Likelihood Misspecification

Bayesian Inference



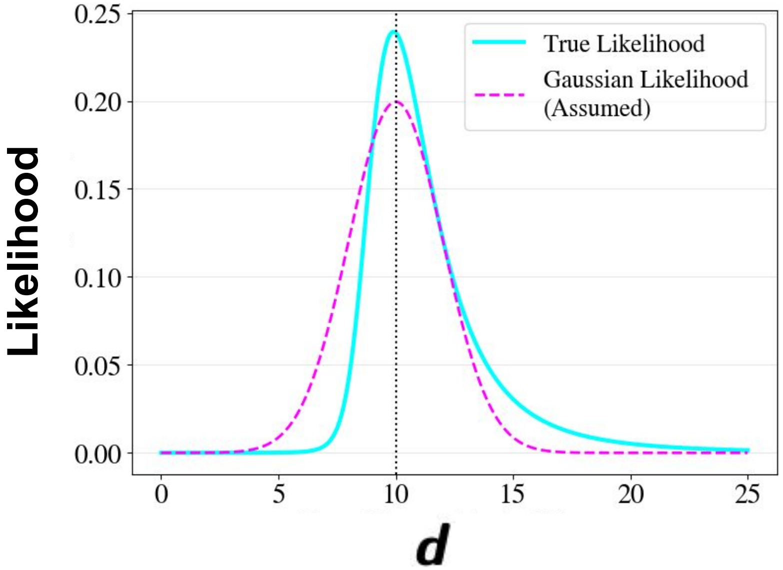
1-dimensional Gaussian likelihood:

Looping prior → posterior



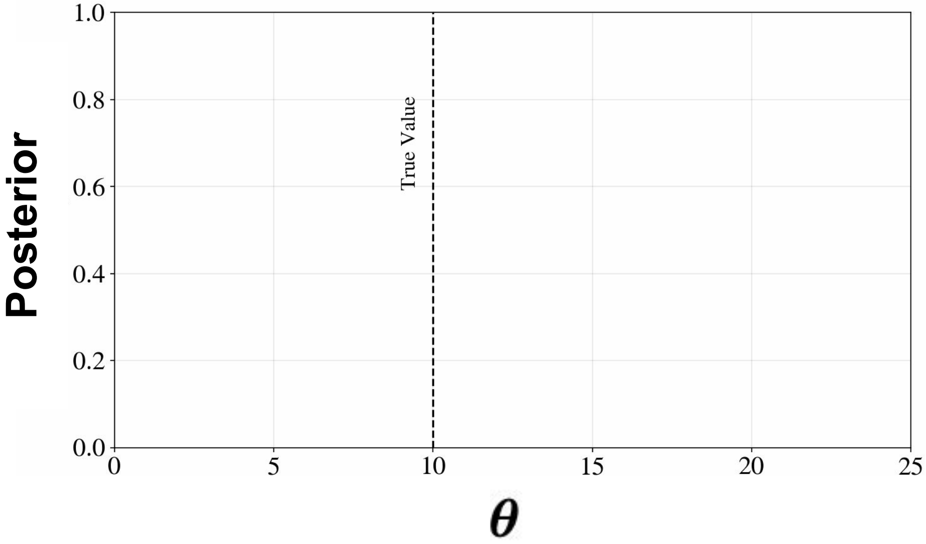
SBI as a Solution to Likelihood Misspecification

Likelihood Misspecification



1-dimensional misspecified likelihood:

Looping prior → posterior



SBI as a Solution to Likelihood Misspecification

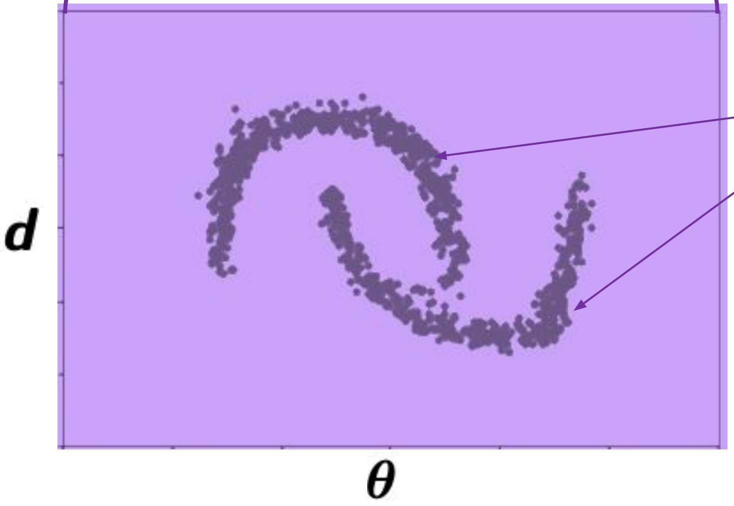
Posterior **Likelihood** Prior **Joint probability**

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

$\boldsymbol{\theta}$: Model parameters

$\boldsymbol{d}$: Data

Simulation-based or **likelihood-free** or **implicit likelihood inference**

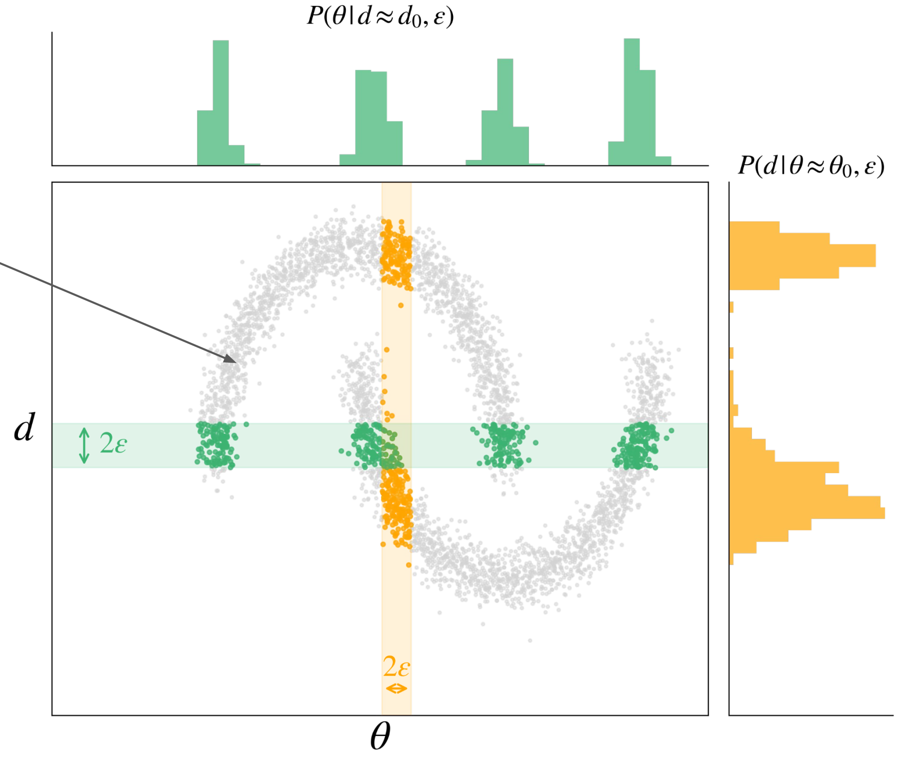


Populate with **simulations** given a model

SBI as a Solution to Likelihood Misspecification

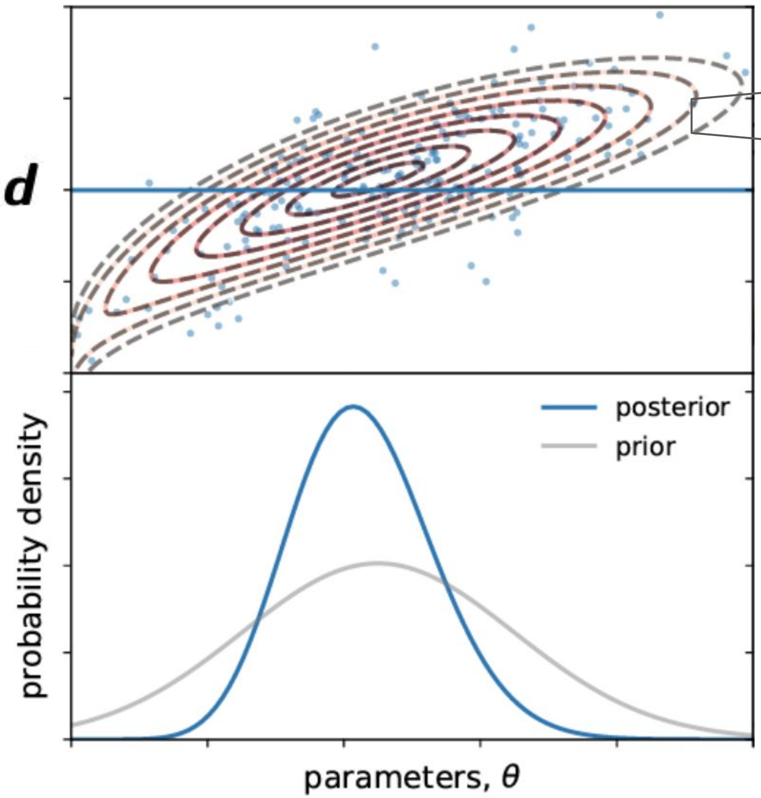
Naively one could get the likelihood from clipping p(d,θ), i.e. ABC:

Loses information from excluded simulations

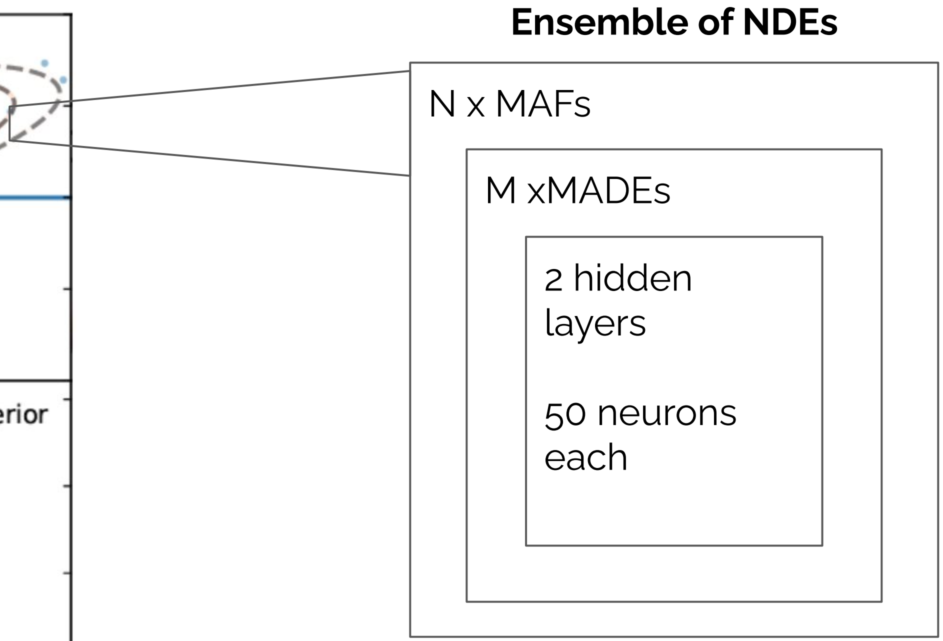


+
Can be inaccurate
Scales poorly in high dimensions

SBI as a Solution to Likelihood Misspecification



Alsing et al. (2019), MNRAS, 488(3), 4440-4458.



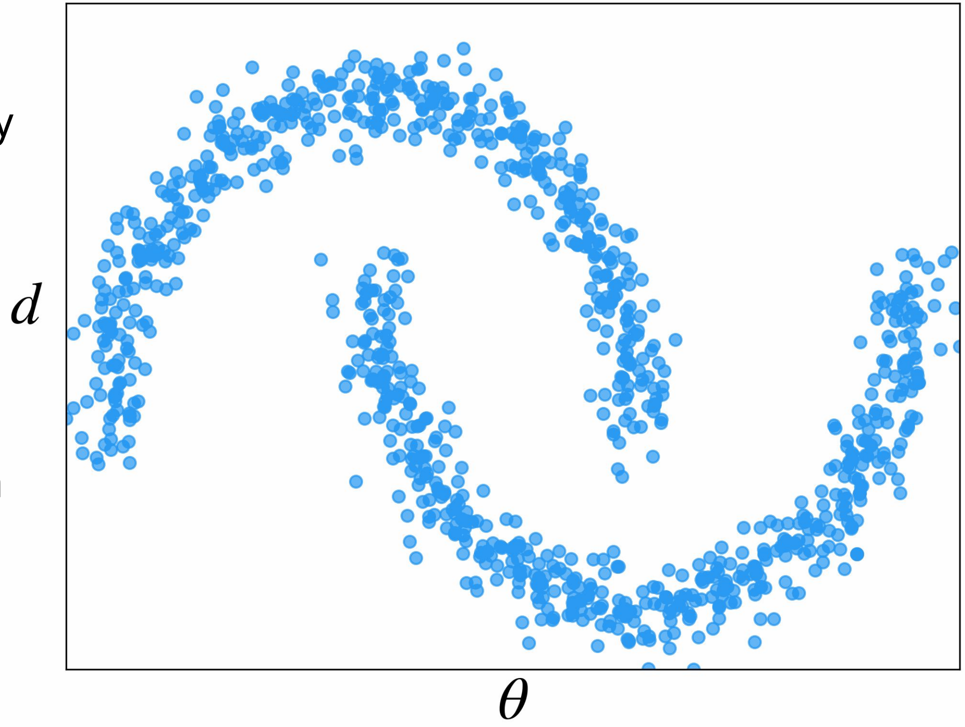
→ N x M x |***d***| multivariate Gaussians, P(***d***|***θ***, **w**)

SBI as a Solution to Likelihood Misspecification

Network learns the transformation between an arbitrary multivariate distribution and a multivariate Gaussian

→ Sample Gaussian

→ Apply inverse transformation



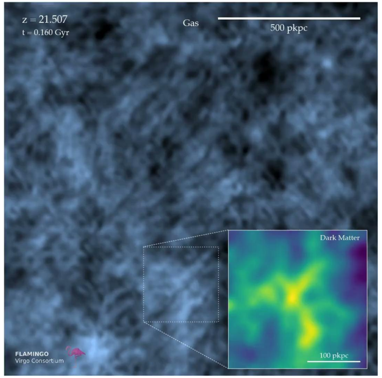
Uses all available simulations

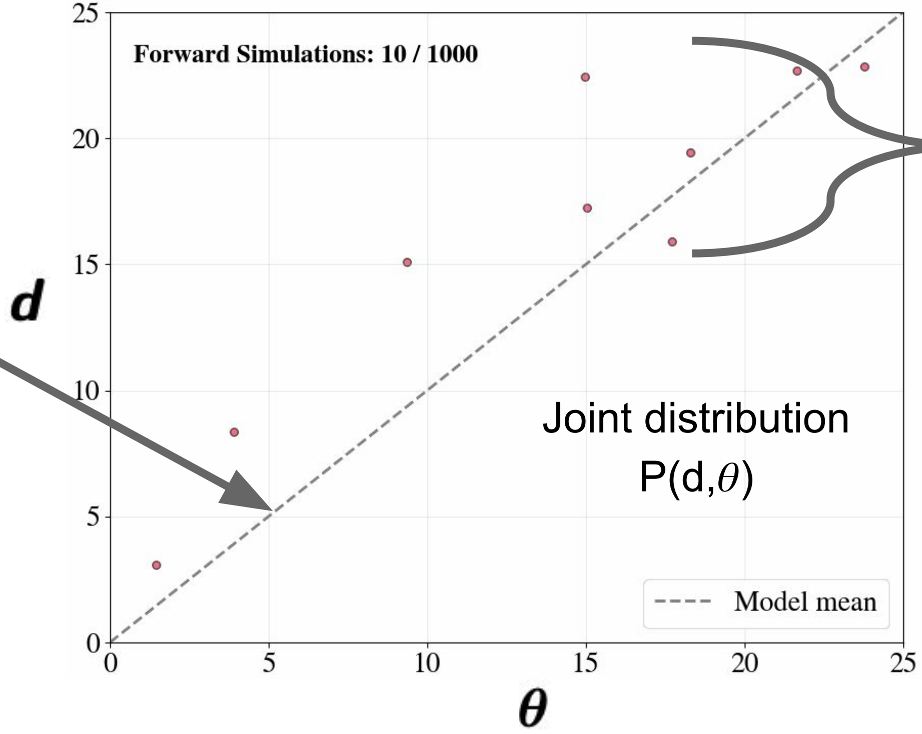
Scales well into higher dimensions

Forward Modelling for SBI

Skewed Gaussian example

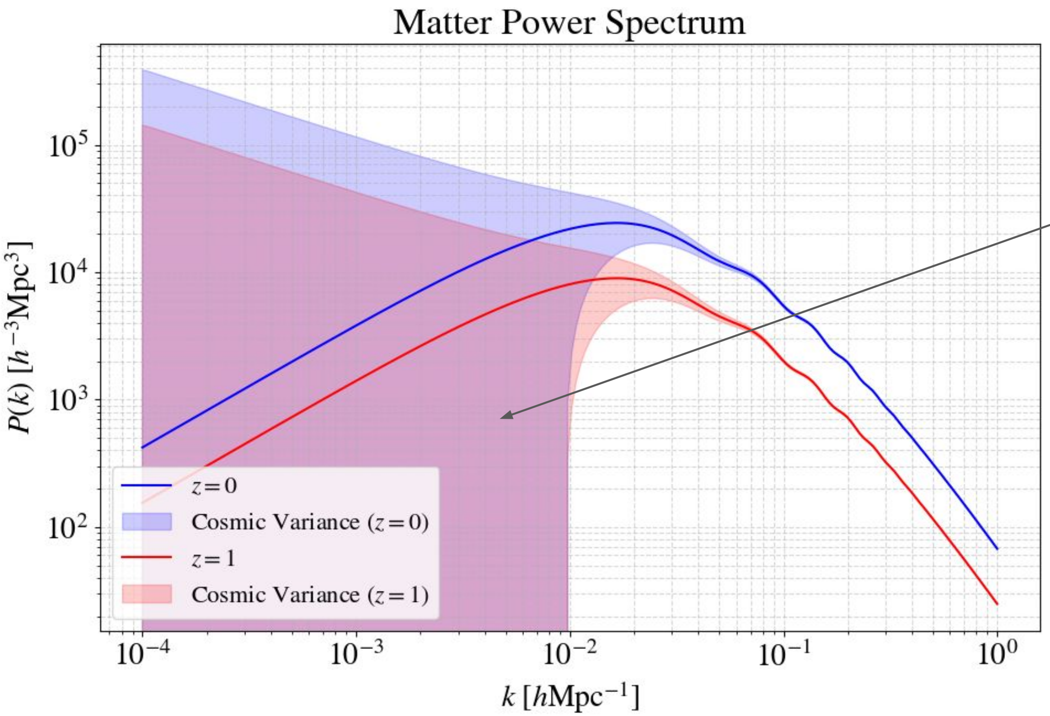
Mean signal





Data model
(noise+systematics)

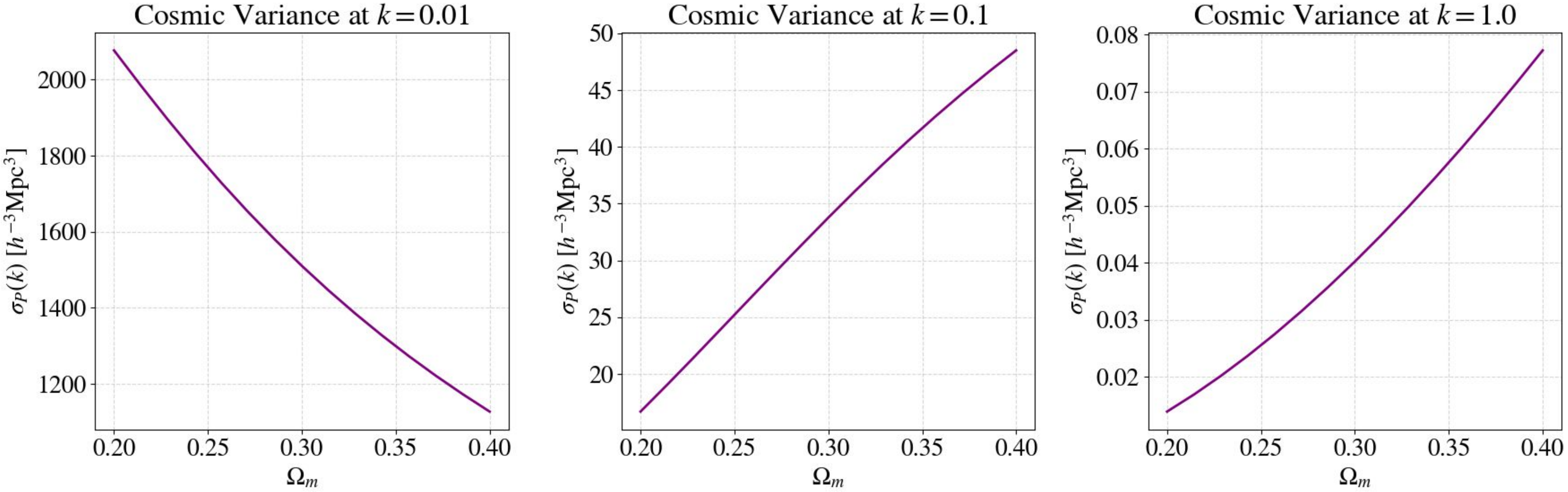
Example of Likelihood Misspecification in LSS



Cosmic variance ∝ *P(k)*

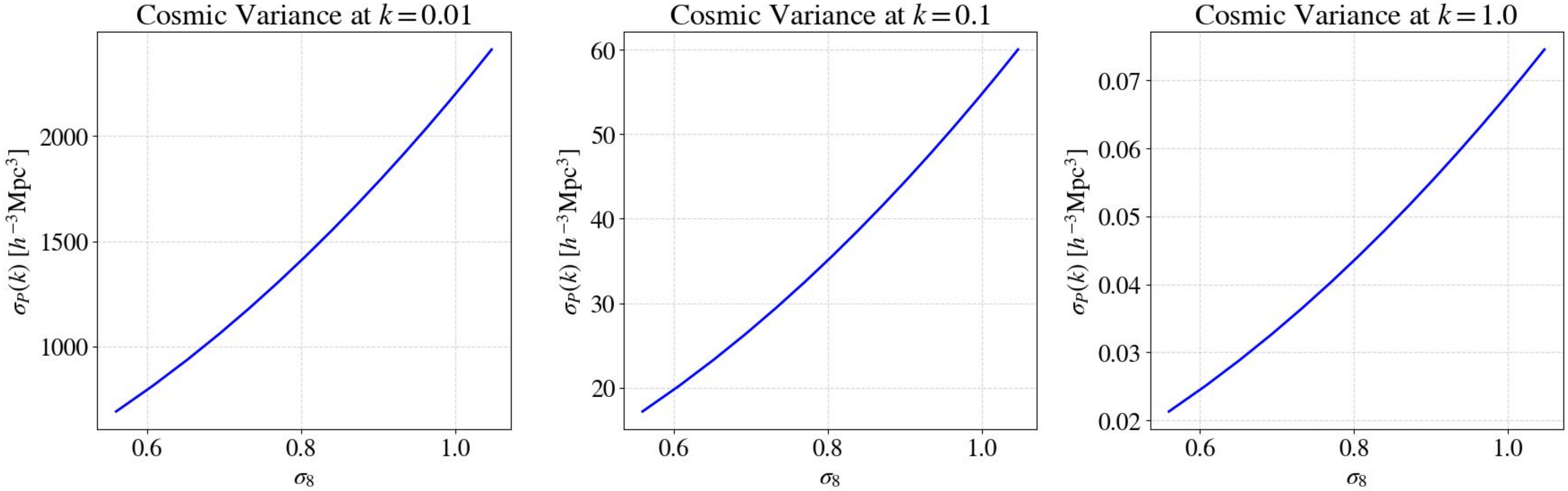
Example of Likelihood Misspecification in LSS

Assuming a survey volume of 9 (Gpc/h)^3 and fixing all parameters at Planck 2018



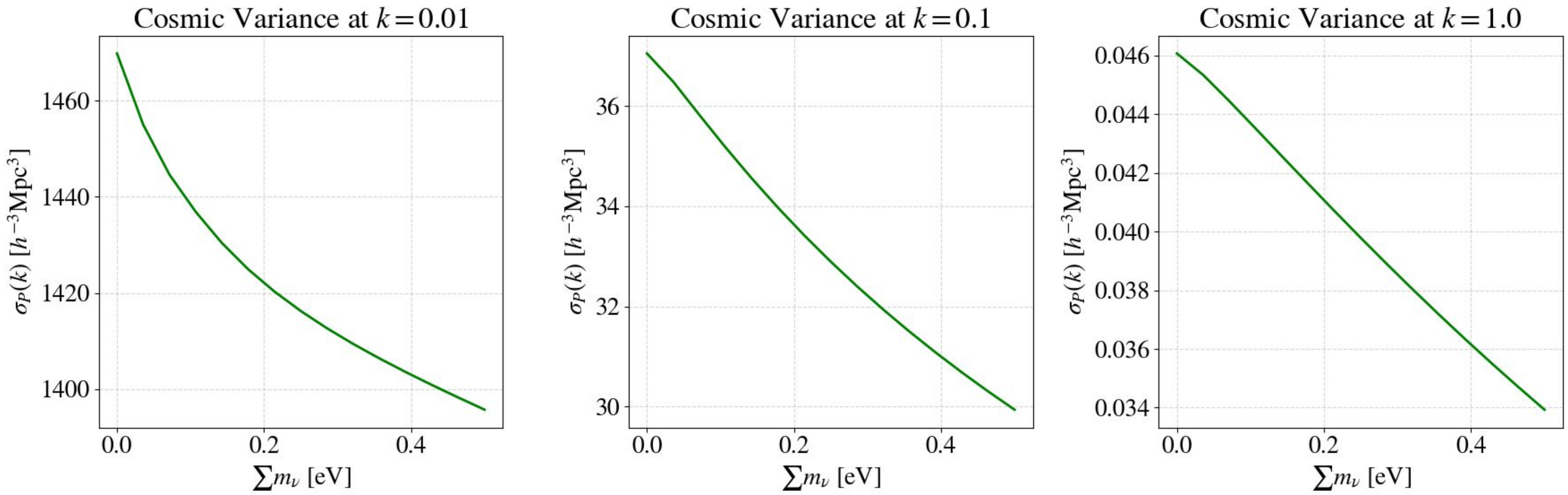
Example of Likelihood Misspecification in LSS

Assuming a survey volume of 9 $(\mathrm{Gpc}/h)^3$ and fixing all parameters at Planck 2018
Varying A_S:

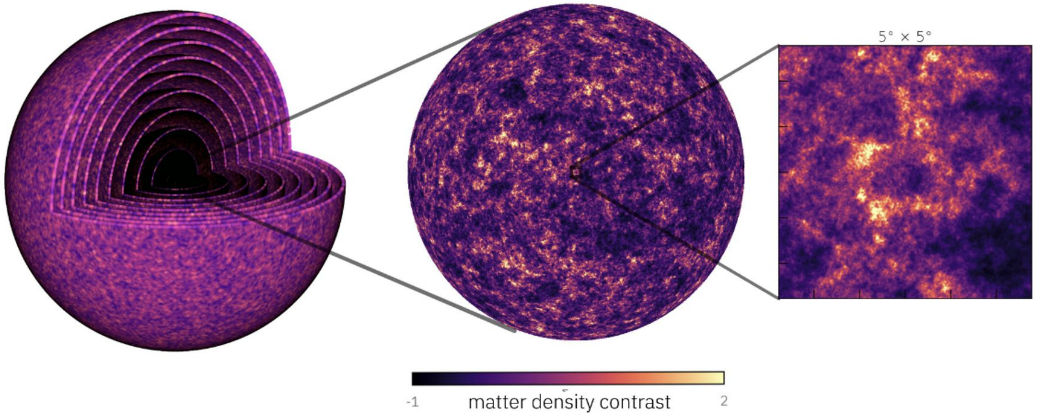


Example of Likelihood Misspecification in LSS

Assuming a survey volume of 9 $(\mathrm{Gpc}/h)^3$ and fixing all parameters at Planck 2018

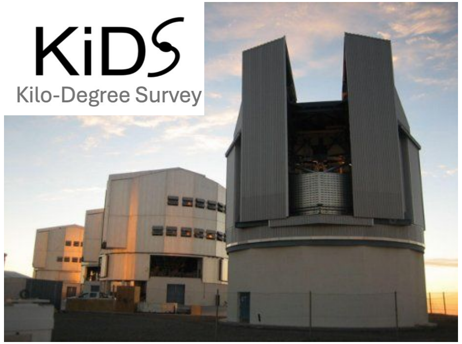


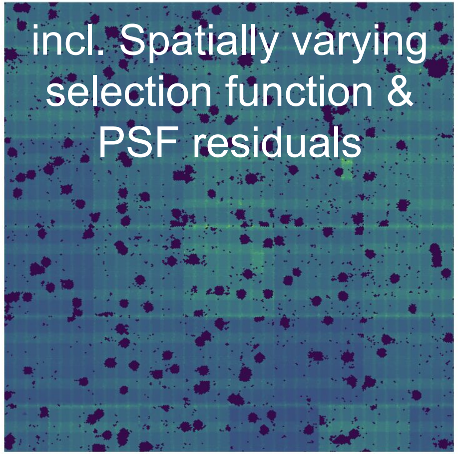
SBI in LSS: Kilo-Degree Survey



GLASS: Convergence and galaxy field forward simulations (Tessore et al. 2023)

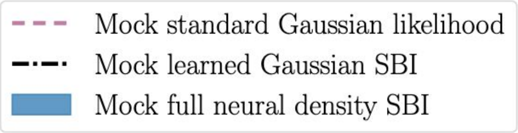
\+ Kilo-Degree Survey data model

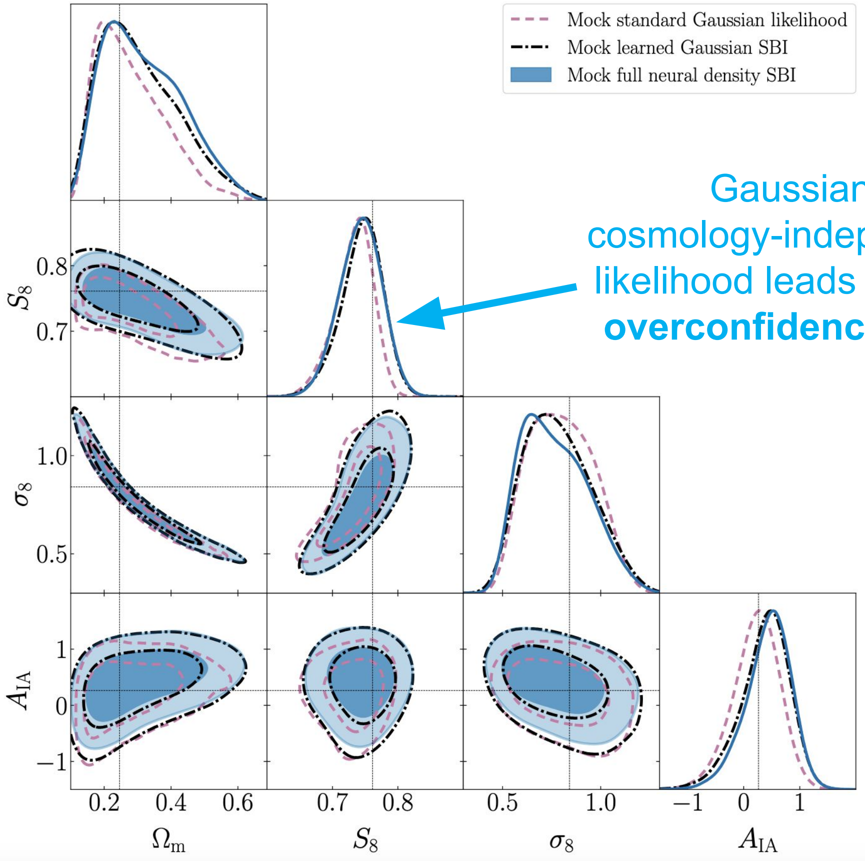




von Wietersheim-Kramsta, Lin et al. 2024

SBI in LSS: Kilo-Degree Survey



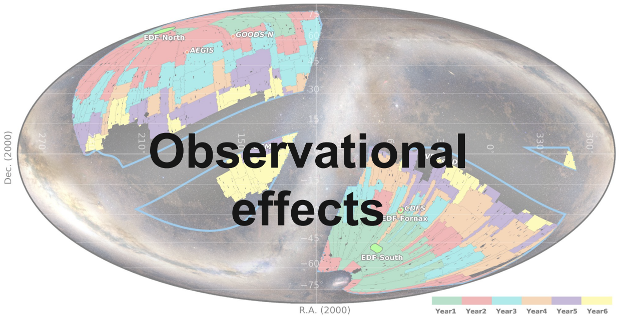


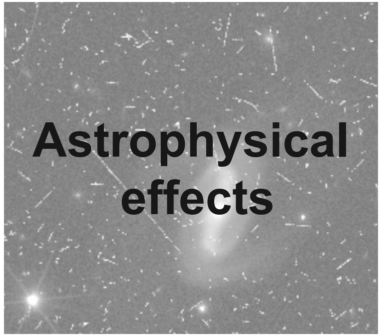
Gaussian cosmology-independent likelihood leads to 10% **overconfidence** in S_8

von Wietersheim-Kramsta, Lin et al. (2024)
Lin, von Wietersheim-Kramsta et al. (2022)

SBI in LSS: Systematics

Modelled at field level:





PSF Variations

Shear Measurement Bias

Spatial variability in selection

Redshift uncertainty + variations

Survey mask

Shape & shot noise

All correlated across 5 tomographic bins!

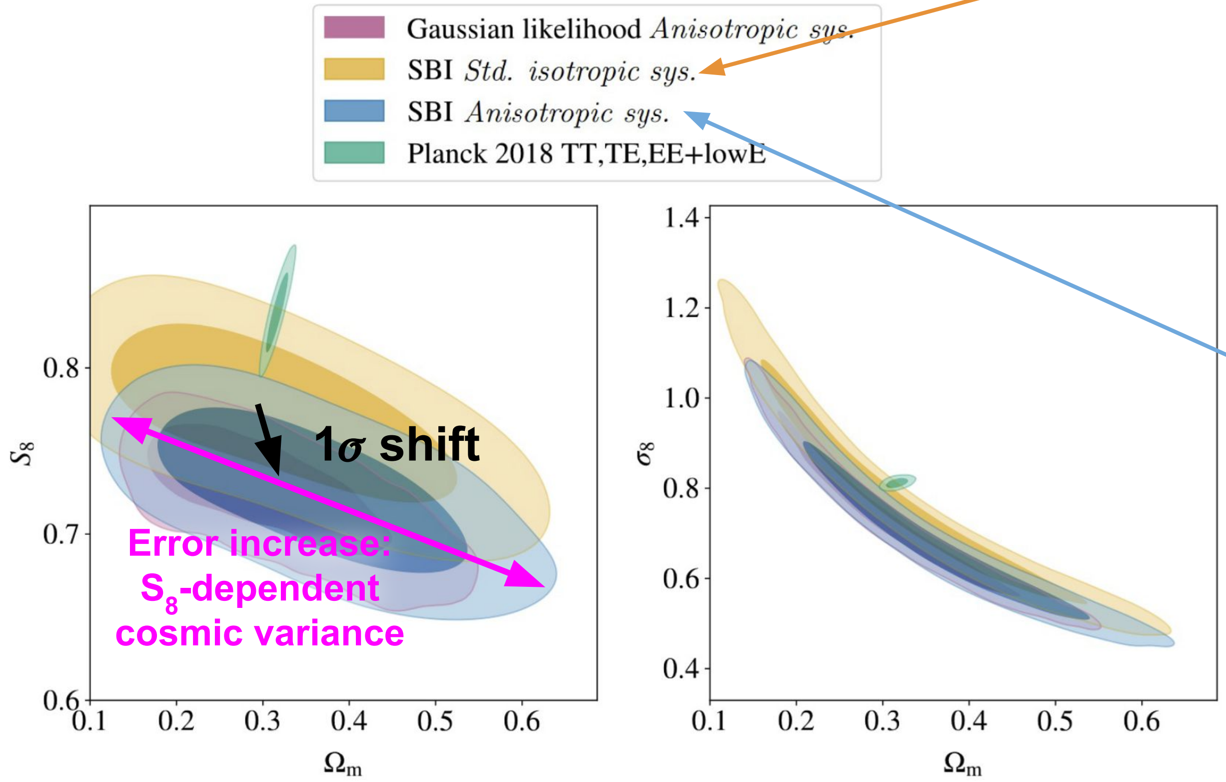
Source clustering

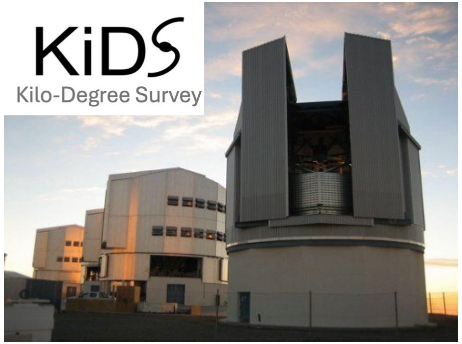
NLA intrinsic alignments

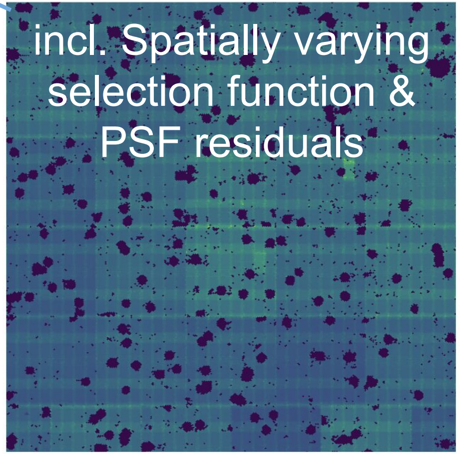
Baryon feedback (*2-point level*)

SBI in LSS: Kilo-Degree Survey

+ Kilo-Degree Survey data model



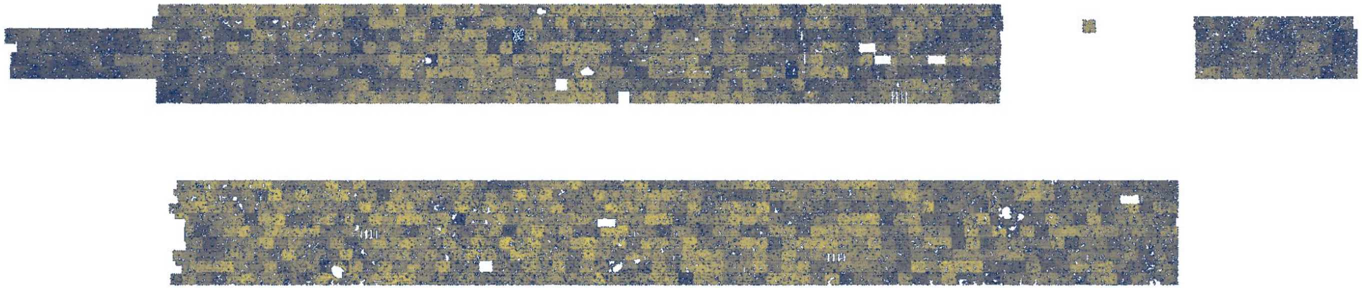




von Wietersheim-Kramsta, Lin et al. 2024

SBI in LSS: KiDS-Legacy

KiDS
Kilo-Degree Survey



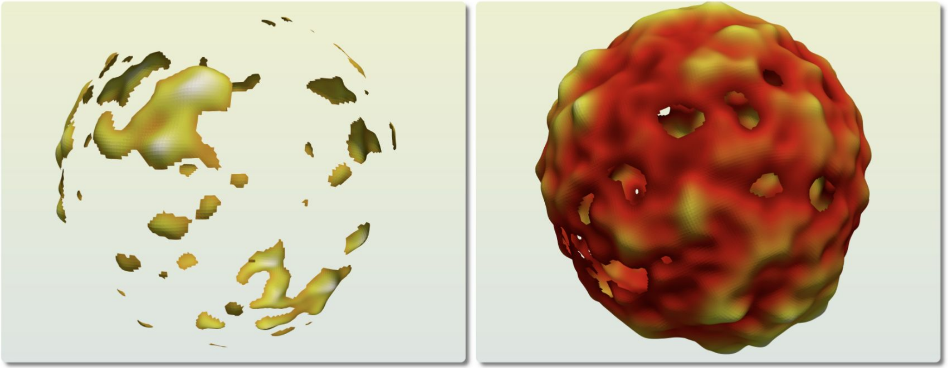
+ extra 350 deg^2
+ 1 extra i-band pass
+ 1 tomographic bin
+ new images sims for calib.
+ new redshift calibration

+ new baryon feedback model
+ new mass-dependent IAs model
+ new var. depth tracer & models
+ more cosmologies

Coming soon…

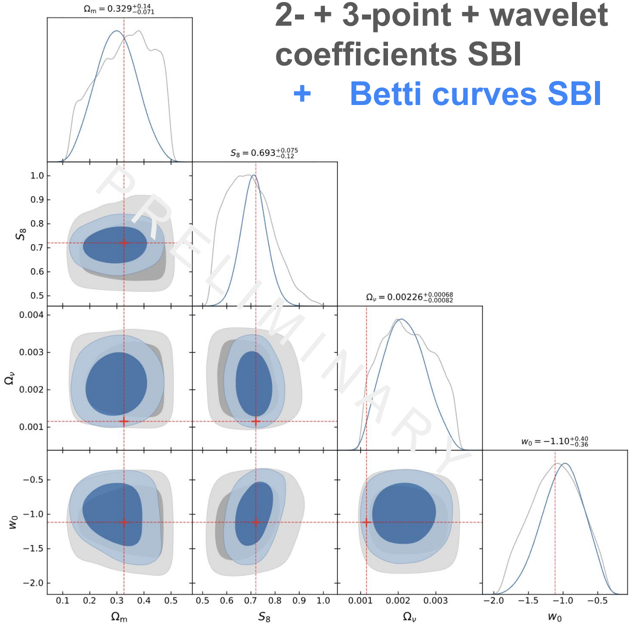
Lin, von Wietersheim-Kramsta et al. in prep.

SBI in LSS: *Euclid* topological measures



Low threshold High threshold

TOPOS2 (Pranav 2021)
used in SBI for DES Y3 (Prat et al. 2025)



2- + 3-point + wavelet coefficients SBI

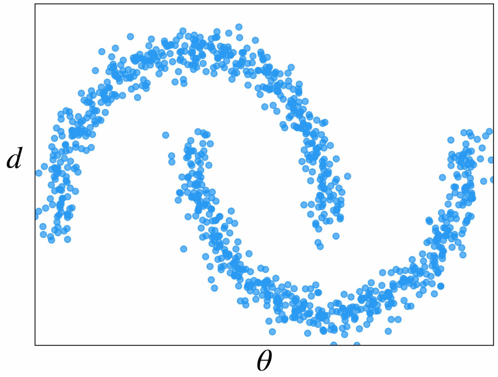
+ Betti curves SBI

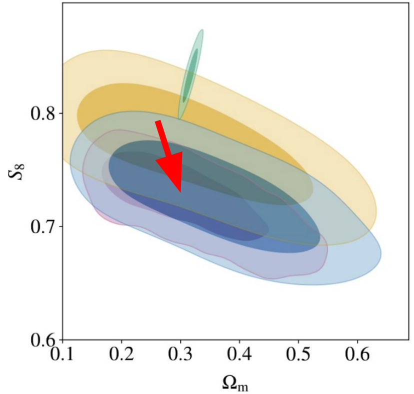
Conclusions

- SBI can:
  - Make intractable likelihoods tractable
  - Avoid likelihood misspecification
  - Simplify probe combination

- Lesson from the Kilo-Degree Survey:
  - **Ignoring cosmology-dependent noise → Overconfidence**
  - **Complex correlated systematics** matter
  - **Field-level forward modelling + SBI** incorporates them

- Consideration from Stage IV:
  - **Increased sensitivity** to increasingly complex systematics





von Wietersheim-Kramsta, Lin et al. (2024)

Thank you!