Towards a Simulation-Based Analysis of KiDS-1000 Weak Gravitational Lensing

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Likelihood-Free in Paris, 22/04/2022

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& the KiDS team

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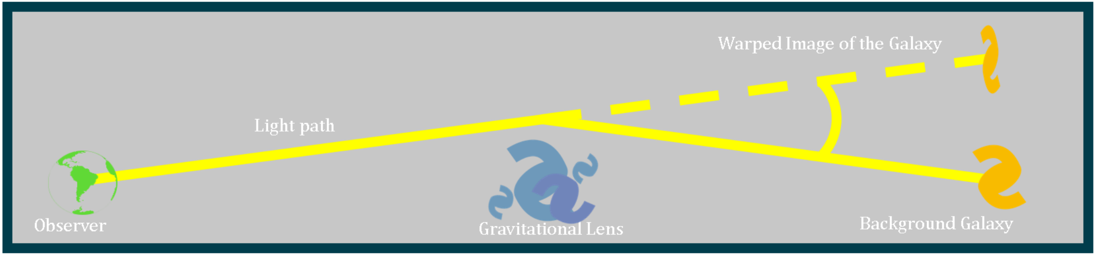
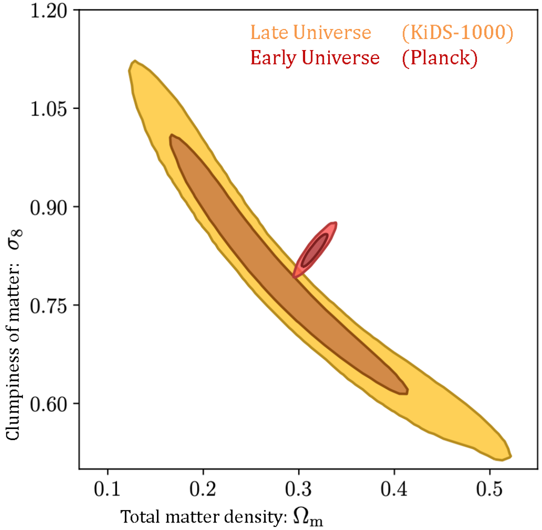
GERMAN CENTRE FOR COSMOLOGICAL LENSING

Gravitational Lensing



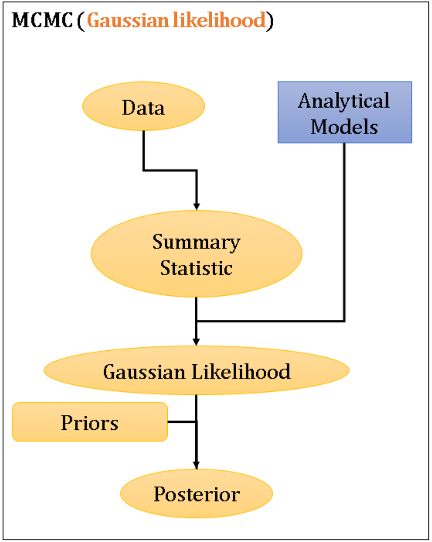
Kilo-Degree Survey

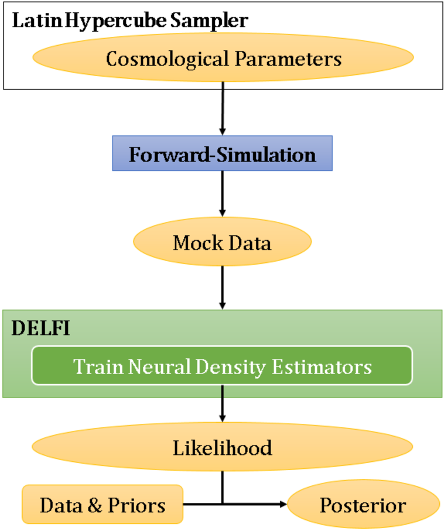


Goals of the Analysis

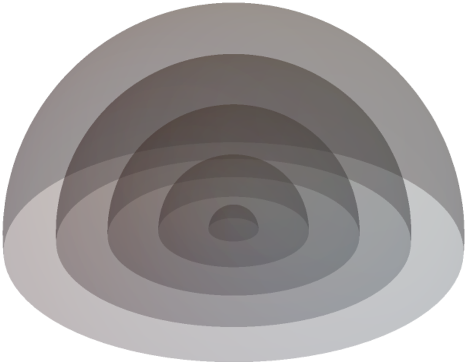
- Re-analyse KiDS-1000 weak gravitational lensing data
- Consider new observational systematic effects
- Proof of working SBI methodology on real data
- Show that SBI could be the **new standard** analysis method for galaxy surveys

Conventional vs. SBI Analysis



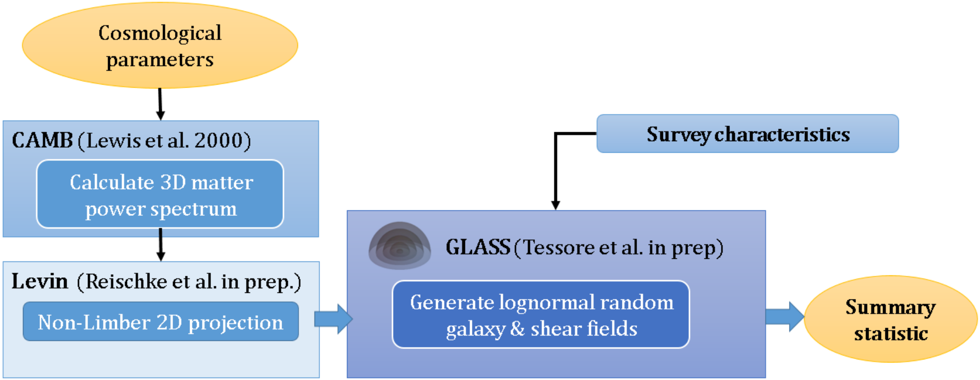


GLASS: Generator for Large Scale Structure

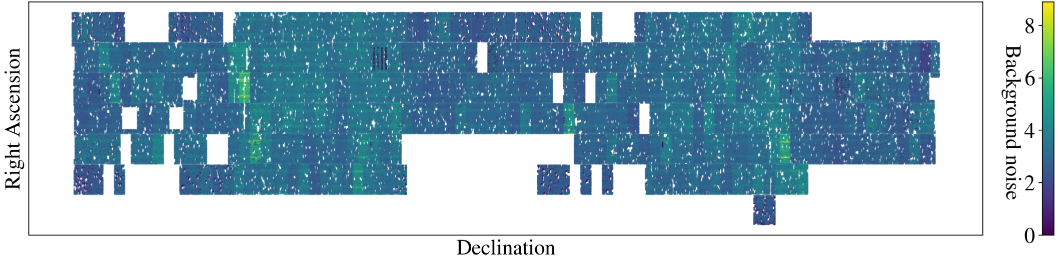


[Tessore et al. in prep] - `github.com/glass-dev/glass`

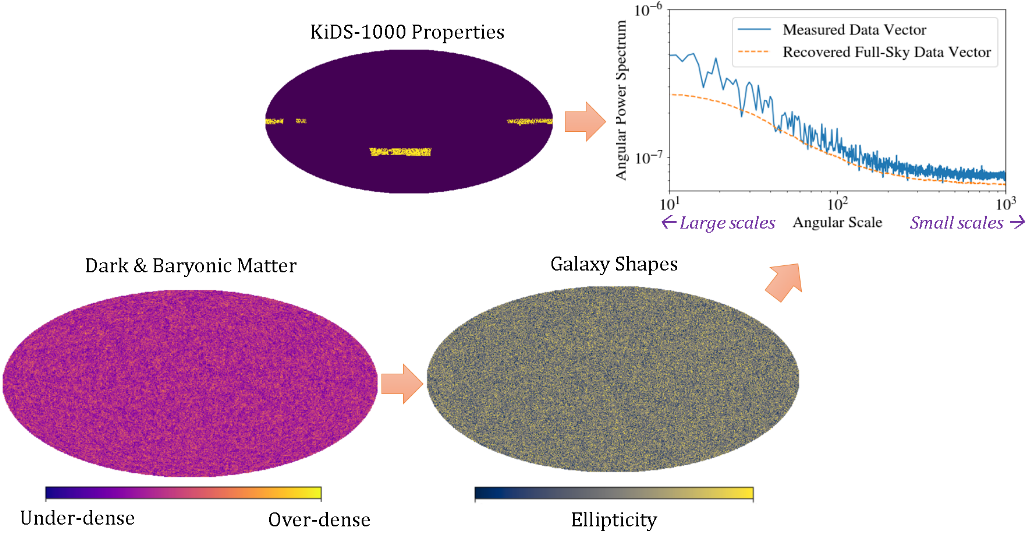
Forward-Simulation Pipeline



New Systematics: Variable Depths

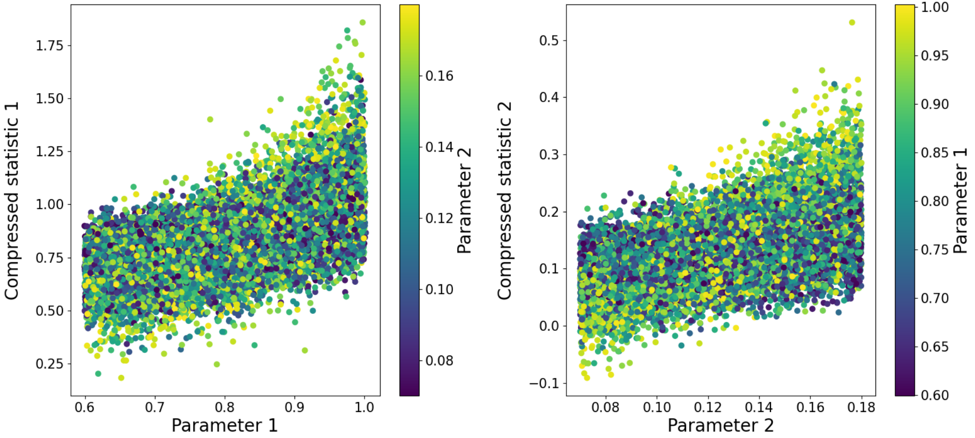


Pipeline Results



Score Compression

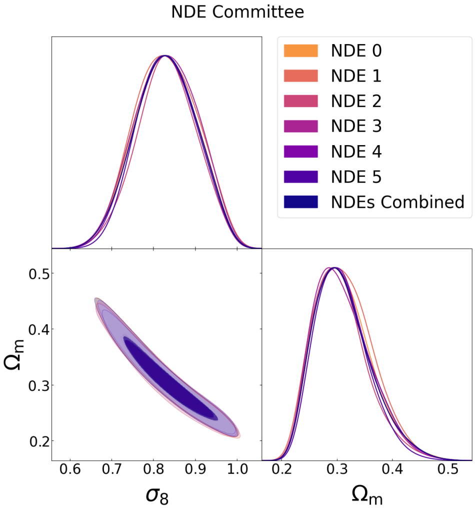
Linearly score compressed data vs. parameters



[Alsing et al. 2018]

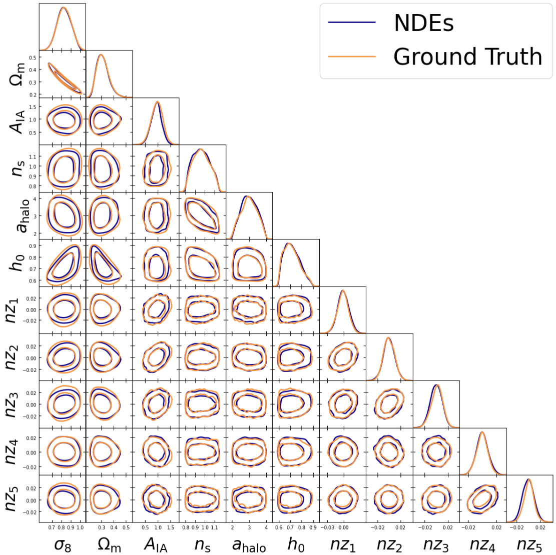
$$\mathbf{t} = \mathbf{M}(\mathbf{d})$$

PyDELFI

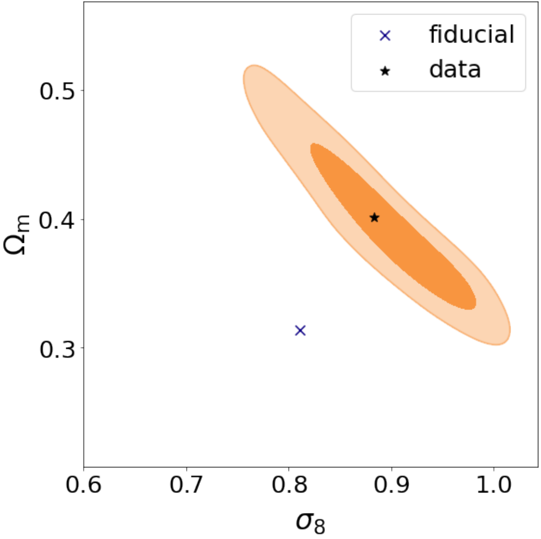


[Alsing et al. 2019]

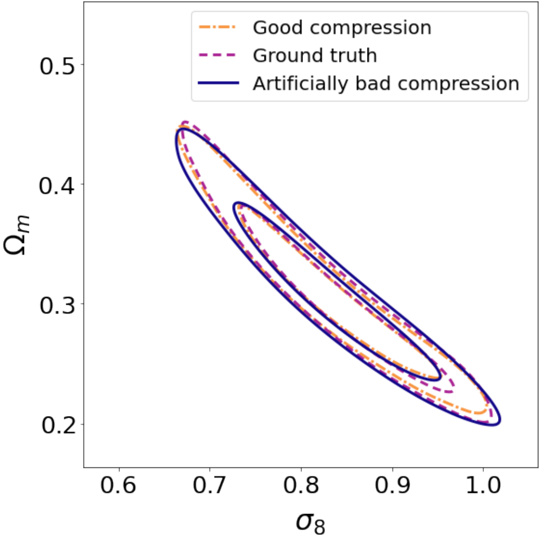
Posterior Contour Comparison



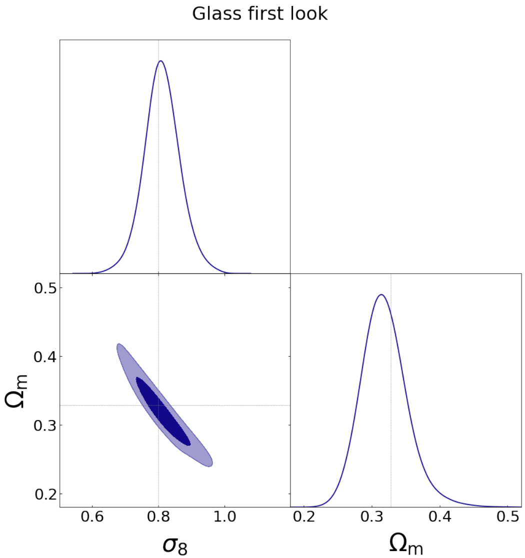
Sensitivity to Fiducial Cosmology



Sensitivity to Compression



Full SBI with mock data using GLASS



What has been achieved?

- Dropped the Gaussian likelihood assumption
- Introduced new systematic effects
- Tested the full pipeline

Next Steps

- More systematic effects (e.g. intrinsic alignments)
- Re-analyse KiDS-1000
- Expand analysis: add galaxy position information
- Apply to next-generation surveys

Questions?

Want to get in touch?

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References

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Massive optimal data compression and density estimation for scalable, likelihood-free inference in cosmology
Monthly Notices of the Royal Astronomical Society Volume 477, Issue 3, July 2018, Pages 2874–2885.

Appendices A - Pipeline Setup

- Shear-shear weak lensing from KiDS-1000 using $\xi_\pm$ 2-point correlation functions
- Latin hypercube of cosmology values as simulation input

Parameter	Prior Range	Data	Fiducial
σ_8	[0.6, 1.0]	0.8	0.811
ω_{b}	[0.019, 0.026]	0.0230	0.0224
ω_{c}	[0.07, 0.18]	0.120	0.120
n_{s}	[0.8, 1.15]	0.960	0.965
h_0	[0.6, 0.9]	0.674	0.674
a_{bary}	[2.0, 4.0]	3.10	3.13
A_{IA}	[-6.0, 6.0]	0.960	0.974
δ_z	$\mathcal{N}(\mu, C)$	0.0	0.0

Table: KiDS-1000 varied parameters and priors.

Appendices B - Compression and DELFI

- A stack of NDEs are used in DELFI

$$p(\mathbf{t}|\theta; \mathbf{w}) = \prod_{\alpha=1}^{N_{\mathrm{NDEs}}} \beta_\alpha p_\alpha(\mathbf{t}|\theta; \mathbf{w}), \tag{1}$$

- A mixture of Gaussian Mixture Density Networks (MDNs) and Masked Autoregressive Flows (MAFs) are employed in this ensemble
- Further massive compression from summary statistics to reduce dimensionality via score compression

$$\mathcal{L} = \mathcal{L}_* + \delta\boldsymbol{\theta}^T \nabla \mathcal{L}_* - \frac{1}{2}\delta\boldsymbol{\theta}^T \mathbf{J}_* \delta\boldsymbol{\theta}, \tag{2}$$

$$\boldsymbol{t} = \nabla\boldsymbol{\mu}^T \boldsymbol{C}^{-1}(\boldsymbol{d} - \boldsymbol{\mu}), \tag{3}$$

- Remap this to a MLE estimate via the Fisher matrix

$$\hat{\theta} = \theta_* + \boldsymbol{F}_*^{-1} \nabla \mathcal{L}_* = \theta_* + \boldsymbol{F}_*^{-1} \boldsymbol{t}_*, \tag{4}$$