Simulation-Based Inference of KiDS-1000 Cosmic Shear

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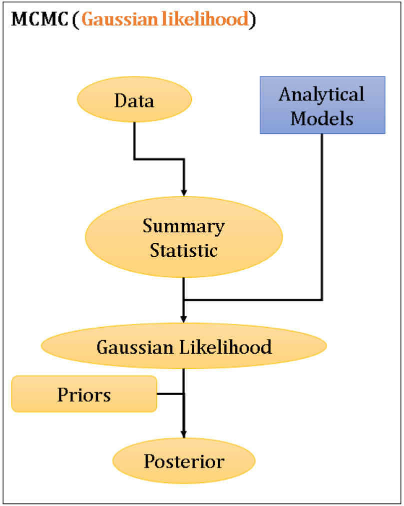
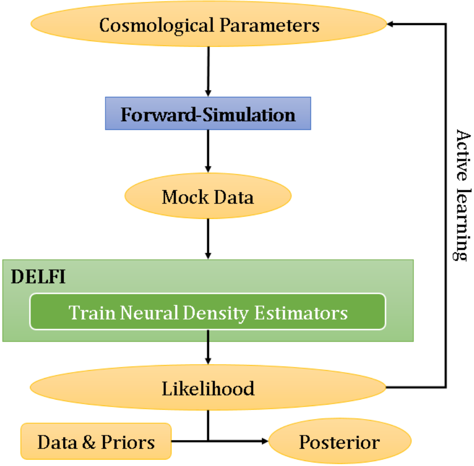
KiDS

Conventional vs. SBI Analysis

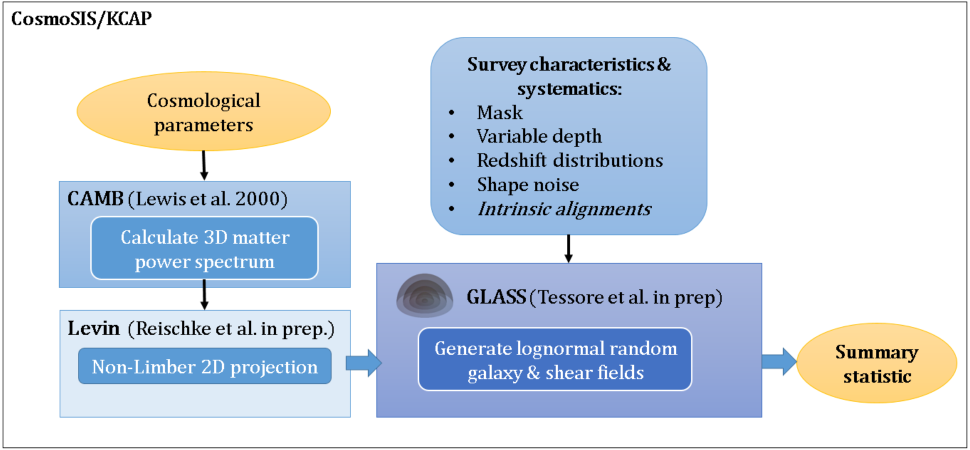




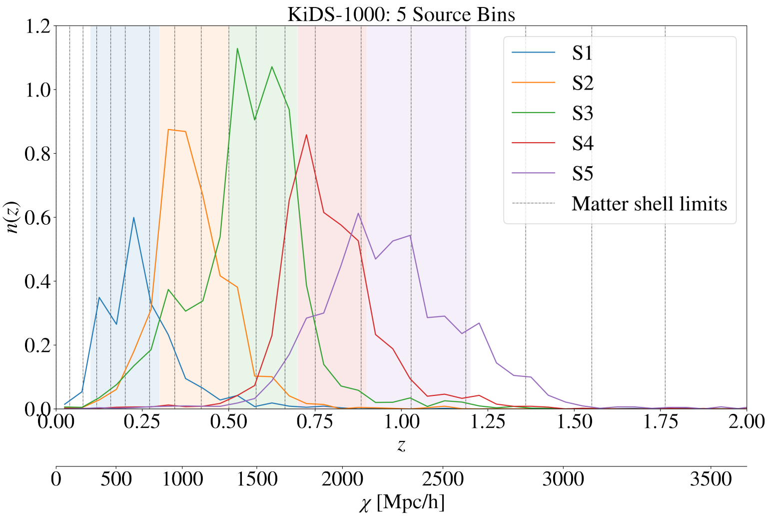
Goals of the Analysis

- Re-analyse KiDS-1000 cosmic shear without assuming a Gaussian likelihood
- Consider new observational systematic effects to propagate to the likelihood
- Proof of working SBI methodology on real data

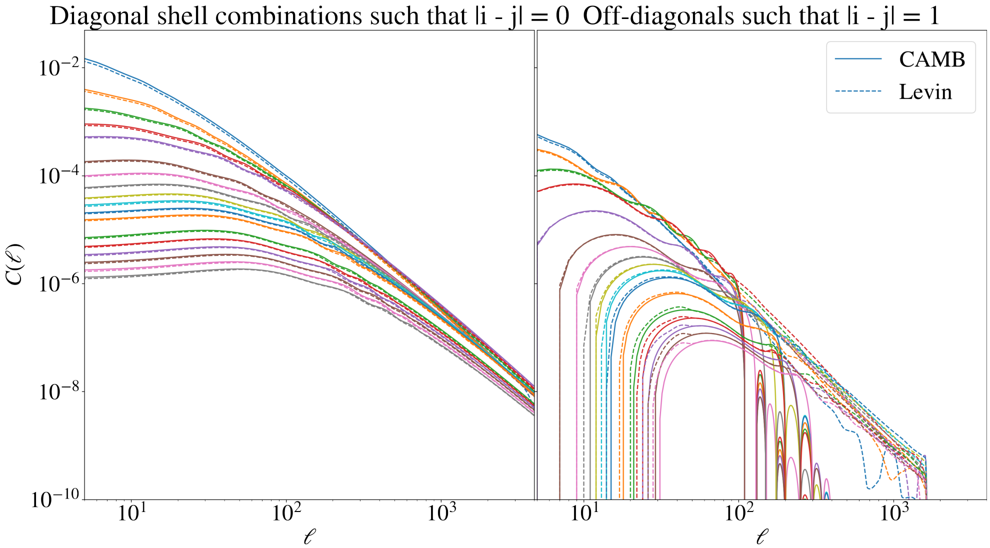
Forward-Simulation Pipeline



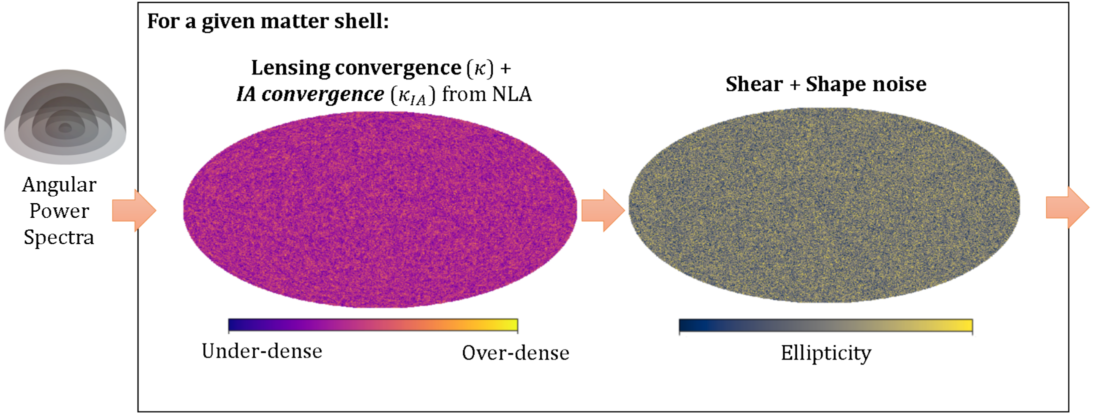
Split Redshift Space into Shells



Levin: Non-Limber 2D Projection



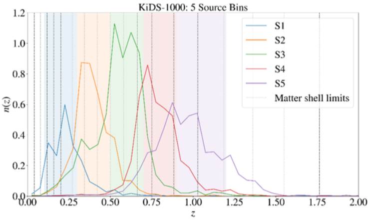
GLASS: Generator for Large Scale Structure



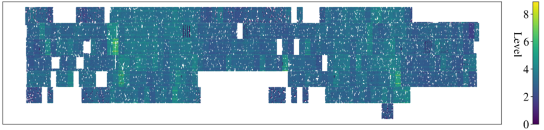
GLASS: Survey Characteristics

Sample galaxies according to

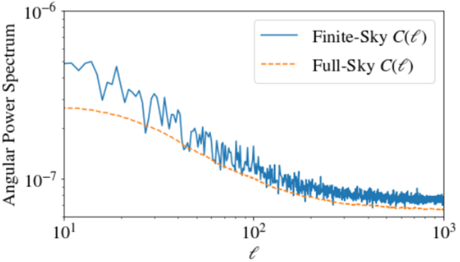
1.



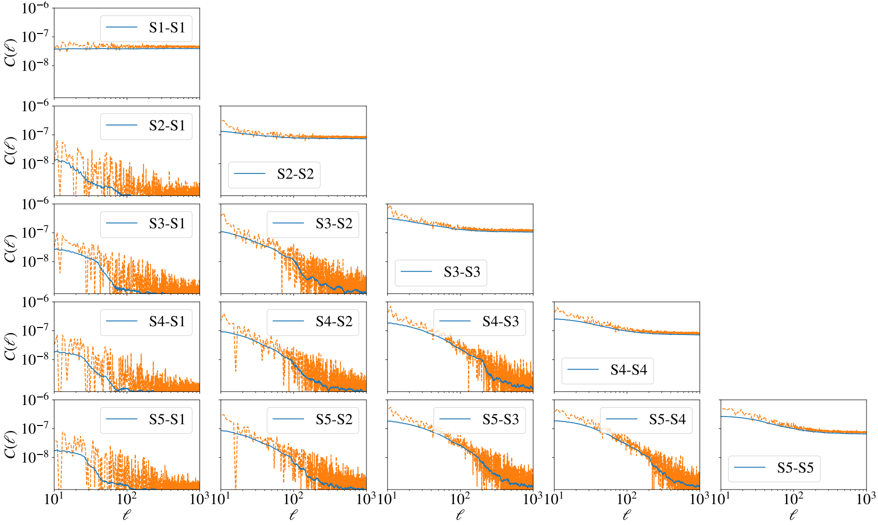
2. Mask and spatial variability



Get our summary statistic

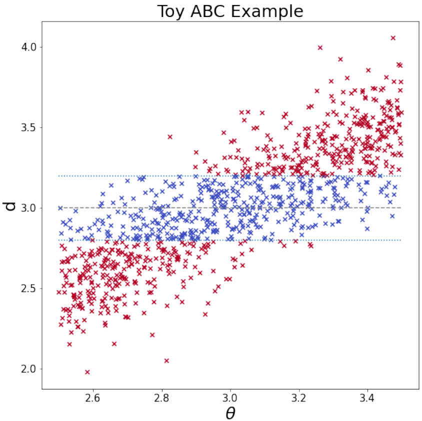


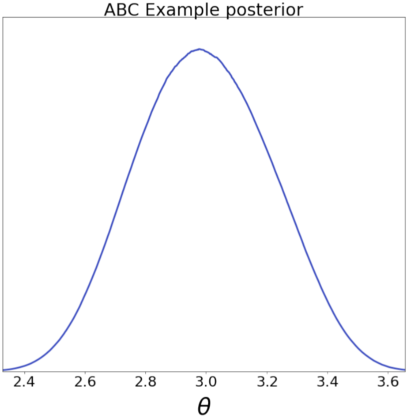
Pipeline Results



SBI - Approximate Bayesian Computation

$$P(\boldsymbol{\theta}|\boldsymbol{d}) = \frac{P(\boldsymbol{d}|\boldsymbol{\theta}) \cdot P(\boldsymbol{\theta})}{P(\boldsymbol{d})} \tag{1}$$





SBI - Density Estimation

$$P(\boldsymbol{\theta}|\boldsymbol{d}) = \frac{P(\boldsymbol{d}|\boldsymbol{\theta}) \cdot P(\boldsymbol{\theta})}{P(\boldsymbol{d})} \tag{2}$$

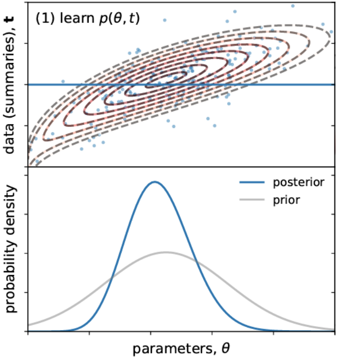
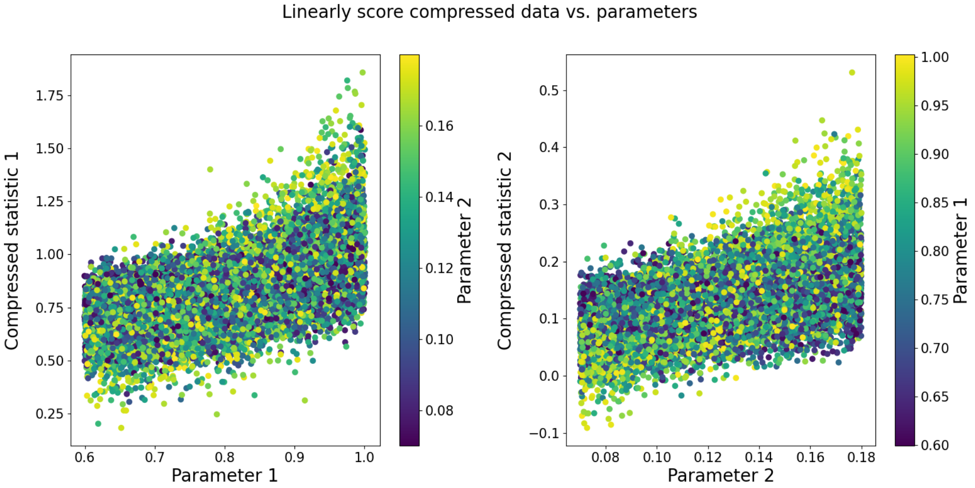


Figure: [Alsing et al. 2019]

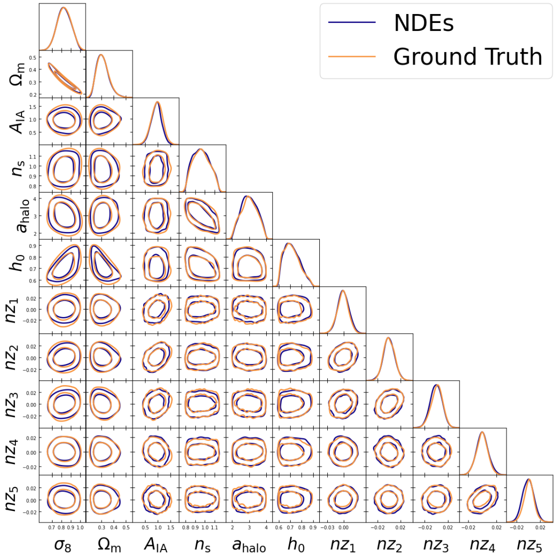
Score Compression



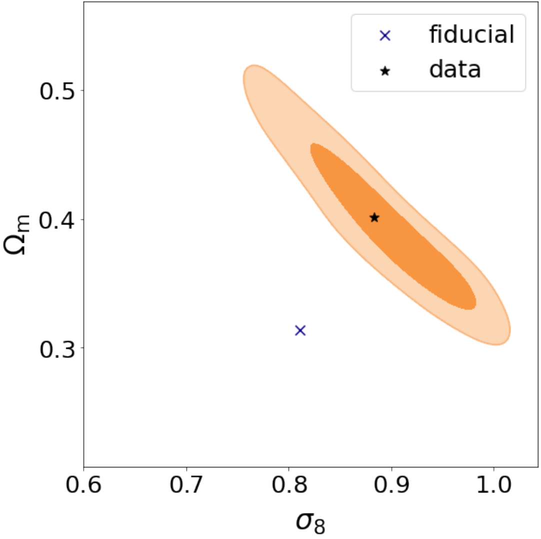
[Alsing et al. 2018]

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

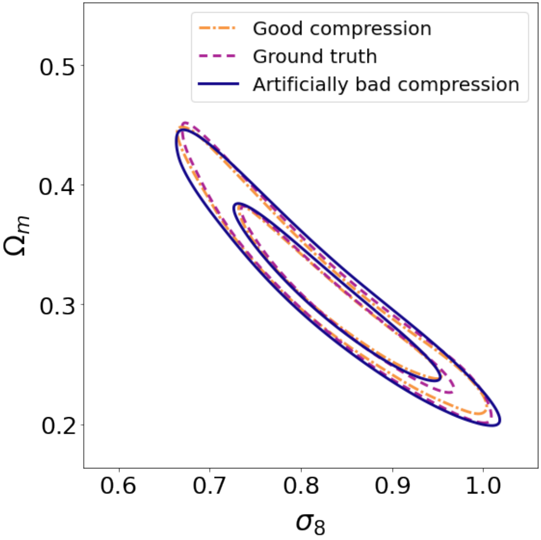
Posterior Contour Comparison



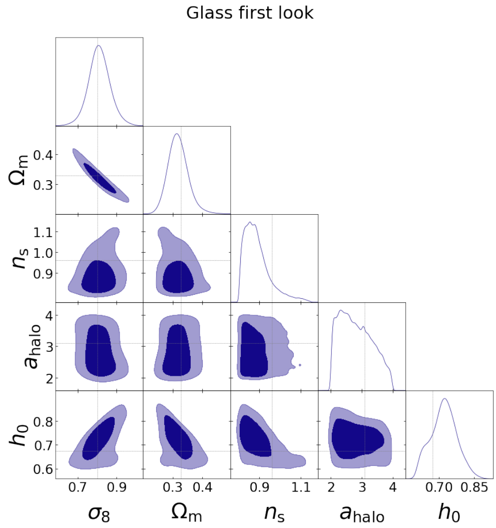
Sensitivity to Fiducial Cosmology



Sensitivity to Compression



Initial SBI with mock data using GLASS



Next Steps

- More systematic effects (e.g. intrinsic alignments)
- Re-analyse KiDS-1000
- Long-term: apply to KiDS-Legacy
- Long-(long)-term: do a full 3x2pt analysis

Questions?

References

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Improving lognormal models for cosmological fields
MNRAS Volume 459, Issue 4, 11 July 2016, Pages 3693–3710.

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Likelihood-free inference with neural compression of DES SV weak lensing map statistics
MNRAS Volume 501, Issue 1, February 2021, Pages 954–969.

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David Levin (1994)
Fast integration of rapidly oscillatory functions
JCAM Volume 67, Issue 1, 20 February 1996, Pages 95-101.

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Justin Alsing et al. (2019)
Fast likelihood-free cosmology with neural density estimators and active learning
Monthly Notices of the Royal Astronomical Society Volume 488, Issue 3, September 2019, Pages 4440-4458.

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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

$$p(\mathbf{t}|\theta;\mathbf{w}) = \prod_{\alpha=1}^{N_{\mathrm{NDEs}}} \beta_\alpha p_\alpha(\mathbf{t}|\theta;\mathbf{w}), \tag{3}$$

- 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

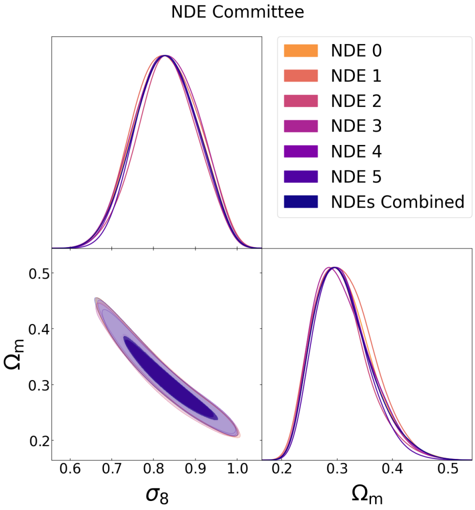
$$\mathcal{L} = \mathcal{L}_* + \delta\boldsymbol{\theta}^T\nabla\mathcal{L}_* - \frac{1}{2}\delta\boldsymbol{\theta}^T\mathbf{J}_*\delta\boldsymbol{\theta}, \tag{4}$$

$$\boldsymbol{t} = \nabla\boldsymbol{\mu}^T\boldsymbol{C}^{-1}(\boldsymbol{d}-\boldsymbol{\mu}), \tag{5}$$

- Remap this to a MLE estimate via the Fisher matrix

$$\hat{\theta} = \theta_* + \boldsymbol{F}_*^{-1}\nabla\mathcal{L}_* = \theta_* + \boldsymbol{F}_*^{-1}\boldsymbol{t}_*, \tag{6}$$

Appendices C - PyDELFI



[Alsing et al. 2019]