

Multi-Probe Large-Scale Structure Cosmology with Simulation-Based Inference and Deep Learning

05 June 2025 Swiss Cosmology Days 2025, ETH Zürich

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Motivation

Non-Gaussian statistics is a powerful probe of LSS (<u>Ajani et</u> <u>al. 2020, Kratochvil et al. 2012,...</u>)

- Theoretical modeling is very challenging, extracting from simulations much less so
 - but one needs a solid simulation base
 - CosmoGrid simulation suite (Kacprzak et al. 2022a)



Ajani et al. 2020, stage IV-like, weak lensing

DES: Gatti et al. 2024, DES Y3, weak lensing











Non-Gaussian information can also be extracted using Deep Learning, aiming for minimal information loss



Combine different probes to get more information



Jeffrey et al. 2024, DES Y3, weak lensing





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Jeffrey et al. 2024, DES Y3, weak lensing

Kacprzak et al. 2022b, stage III-like, weak lensing+galaxy clustering











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Kacprzak et al. 2022b, stage III-like, weak lensing+galaxy clustering







CosmoGrid

The COSMOGRIDV1 dataset consists of a total of 20128 simulations divided into three main parts:

- grid: a set of 2500 cosmologies, each with 7 simulations from unique initial conditions (a total of 17500 N-body runs),
- fiducial: simulations and the fiducial cosmology and its $\pm \Delta$ derivatives, with 200 unique initial conditions (2600 runs),
- **benchmark**: simulation benchmarks used for systematics testing of features chosen for parameter inference (28 runs).



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Forward model







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Forward model







Pipeline

Synthetic DES Y3 data



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Inference & constraints





Pipeline



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Towards real data

Validation:

- 1. Internal data (consistency): cosmology from CosmoGrid
 - \rightarrow no model mismatch
- 2. Mock DESY3-like data: cosmology from external simulations
 - a. Buzzard (multiple realizations, De Rose et <u>al. 2019</u>)
 - b. Cardinal (<u>To et al. 2023</u>)
 - c. MICE (Fosalba et al. 2013)
- 3. tests of other systematics (source clustering, resolution,...)



DES Collaboration: MacCrann et al. 2018



Smoother maps = less small-scale information

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Towards real data

single-probe vs. probe combination



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2-pt vs. deep learning (probe combination)



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Conclusion

- Simulation-based inference of Cosmology
 - CosmoGridV1 N-body suite
 - Forward modeling of DES Y3 mocks
 - No likelihood assumption
- From multi-probe maps
 - Weak lensing
 - Galaxy clustering
- Non-Gaussian information
 - Peaks
 - Learned summary statistics
- Using deep learning
 - Learned summary statistics
 - Likelihood as normalizing flow

