Forecasting the power of Higher Order Weak Lensing Statistics with automatically differentiable simulations

Denise Lanzieri[1], François Lanusse[1], Jean-Luc Starck[1], Chirag Modi[2], Ben Horowitz[3], Joachim Harnois-Déraps[4]

CosmoStat

1. Université Paris Cité, Université Paris-Saclay, CEA, CNRS, AIM, F-91191, Gif-sur-Yvette, France
2. Center for Computational Astrophysics, Flatiron Institute, 162 5th Ave, New York, NY 10010, USA
3. Department of Astrophysical Sciences, Princeton University, Princeton, NJ 08544, USA
4. School of Mathematics, Statistics and Physics, Newcastle University, NE1 7RU, Newcastle-upon-Tyne, UK

LSST DESC Dark Energy Science Collaboration

Introduction

- The next generation of weak lensing surveys (LSST, Euclid, WFIRST) will provide large volumes of high quality data with unprecedented statistical power and great potential for new discoveries.
- Existing analysis methods based on the two-point summary statistics are reaching their limits at every step of the science analysis.
- Several alternative inference techniques have been proposed, but most of them require the computation of the gradient of the likelihood.
- The goal of this work is to develop tools for building automatically differentiable lensing simulations.
- In this first application, we use this new methodology to investigate the relative constraining power of various map-based higher order weak lensing statistics.

Need for automatic differentiation

- The two-point function analyses overlook the non-Gaussian information contained in the mode coupling and in the phase correlation:
  - Alternative measurement techniques proposed to access the non-Gaussian information lack of an analytical models to describe the observed signals.
- Methods like Hierarchical Bayesian Inference e.g. BORG, need derivatives of the likelihood.
- Simulation-Based Inference techniques can greatly benefit from differentiable simulation [1] [2].

How do we simulate the Universe in a differentiable way?

- We build a set of N-body simulation based on the FlowPM code [3], a fast particle-mesh solver.
- We build a weak gravitational lensing package by implementing ray-tracing and simulating lensing lightcones in the Tensorflow framework.
- The model provides derivatives with respect to cosmological and nuisance parameters through automatic differentiation.

Hybrid Physical-Neural ODE

- Flow N-body PM simulation:
  - Fast (don't solve the full N-body problem).
  - Not able to resolve structures with scales smaller than the mesh resolution.
  - We use a minimally-parametric neural network component modeling a residual effective force compensating for the PM approximations [4].

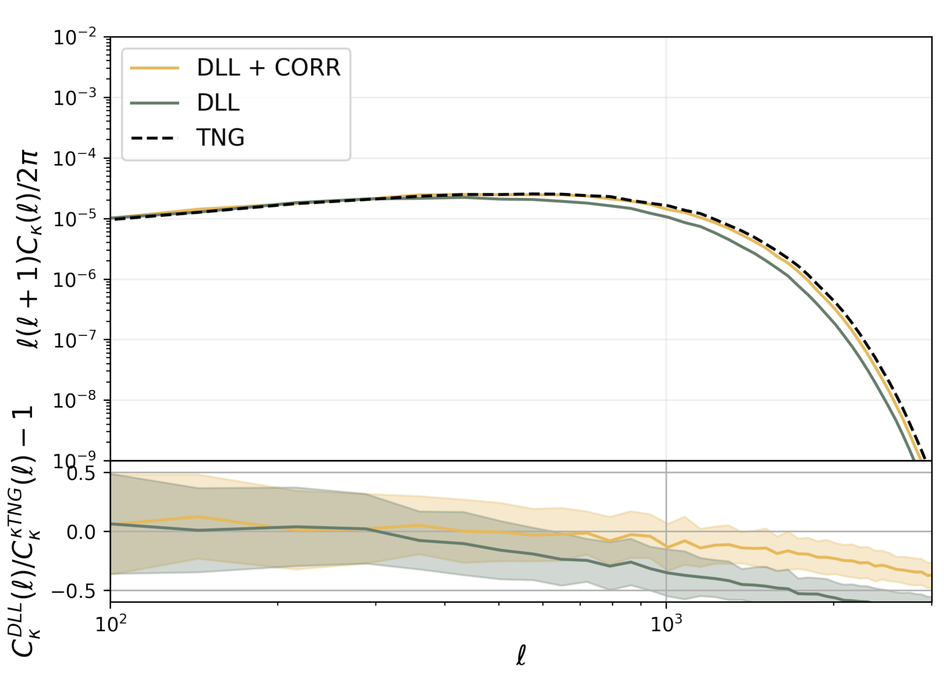

Figure: Top panel: Convergence power spectra of high resolution κTNG simulation and our Differentiable Lensing Lightcone (DLL) simulations before (grey line) and after (gold line) using the correction models. Bottom panel: Fractional convergence power spectra of κTNG simulation and DLL simulations before and after using the correction model. The neural network enhanced simulation tracks the reference power spectrum (black dashed line), recovering most of the missing information.

Higher Order Weak Lensing Statistic

- To extract the cosmological information from the simulated κmaps, we use two analysis statistics:

1. The Starlet Peak counts, defined as the local maxima in the convergence map convolved with a starlet filter $\mathcal{W}(\theta_{\text{ker}})$:

$$\text{Peaks} = (\kappa * \mathcal{W})(\theta_{\text{ker}}). \tag{1}$$

2. The Starlet l_1-norm, defined as the sum of the absolute values of the Starlet coefficients of the weak lensing map in a given bin i:

$$l_1^{j,i} = \sum_{u=1}^{\text{coef}(\mathcal{S}_{j,i})} |\mathcal{S}_{j,i}[u]| = ||\mathcal{S}_{j,i}||_1 \tag{2}$$

From simulation to cosmological and nuisance constraints

- We build the Fisher matrix to forecast error from a given experimental set up and quantify how much information we can extract from it.

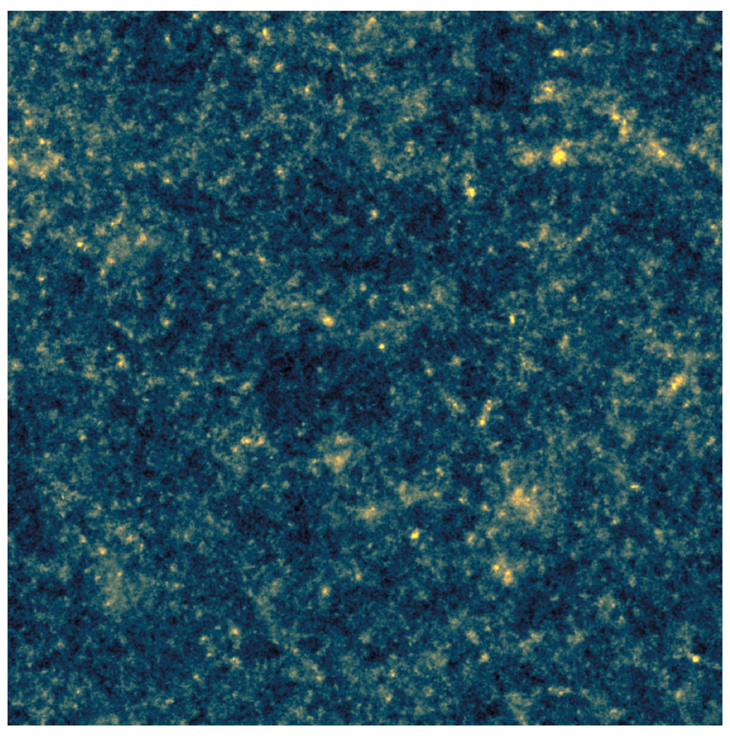

Figure: Simulated convergence map at z=1.0, based on a 3D simulation of side length 205 Mpc/h and 128 particles. The 2D lensing map has an angular extent of 5°.

- Since the mock maps are entirely differentiable, we compute the derivative with respect to cosmological and intrinsic alignment A_{IA} nuisance parameters **simultaneously** and **without additional computational cost**.

Automatic Differentiation in Tensorflow

- Analytic derivatives of arbitrary expressions can be obtained by the chain rule.
- TensorFlow remembers what operations happen in what order during the forward pass and traverses this list of operations in reverse order to compute gradients.

First application: Fisher forecasts

- We apply our framework to reproduce the analysis choices of the LSST Y1 data [5].
- We simulate weak lensing convergence maps for a single source redshift z=1 and angular extend of 5°, based on a 3D simulation with 128 particles in a box of side length 205 Mpc/h.
- We use Fisher matrix to estimate the information content extracted with a given statistic for more cosmological parameters simultaneously.
- In the following figure, we show an application of our tool. We perform the comparison between two statistics of order higher than second: peak counts and $l_1$norm of the same Starlet transform scale, illustrating the increased information content of the l1norm statistic.

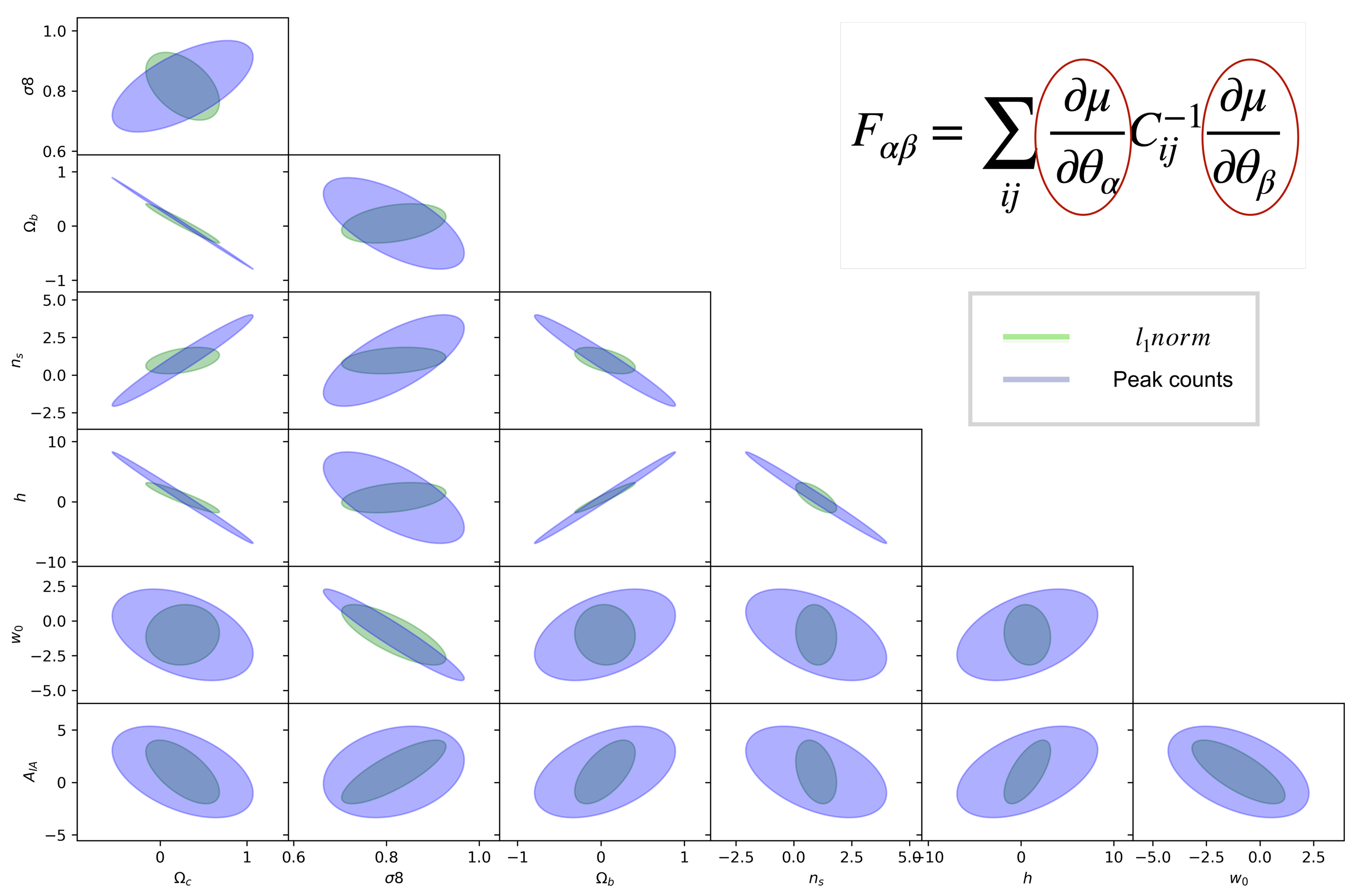

Figure: Fisher constraints from Starlet peak counts compared to constraints from the l1-norm, both computed on a noisy maps filtered with a single-scale starlet kernel at 4.7 arcmin.

References

[1] T. L. Makinen, T. Charnock, J. Alsing, and B. D. Wandelt, "Lossless, scalable implicit likelihood inference for cosmological fields", *Journal of Cosmology and Astroparticle Physics*, vol. 2021, no. 11, p. 049, 2021.

[2] J. Zeghal, F. Lanusse, A. Boucaud, *et al.*, "Neural posterior estimation with differentiable simulators", *arXiv preprint arXiv:2207.05636*, 2022.

[3] C. Modi, F. Lanusse, and U. Seljak, "Flowpm: Distributed tensorflow implementation of the fastpm cosmological n-body solver", *arXiv preprint arXiv:2010.11847*, 2020.

[4] D. Lanzieri, F. Lanusse, and J.-L. Starck, "Hybrid physical-neural odes for fast n-body simulations", *arXiv preprint arXiv:2207.05509*, 2022.

[5] R. Mandelbaum, T. Eifler, R. Hložek, *et al.*, "The lsst dark energy science collaboration (desc) science requirements document", *arXiv preprint arXiv:1809.01669*, 2018.

denise.lanzieri@cea.fr