Likelihood-free Inference with Non-Gaussian statistics of weak lensing observables & DES Y3 data

Marco Gatti (UPenn)

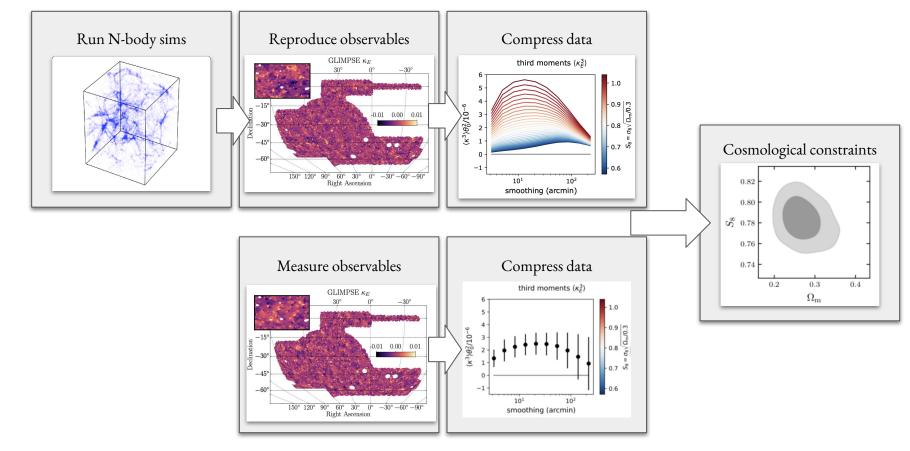
with N. Jeffrey, L. Whiteway, B.Jain ++ (DES collaboration)



ML-IAP/CCA-2023



Simulation-based Inference with Non-Gaussian statistics



data

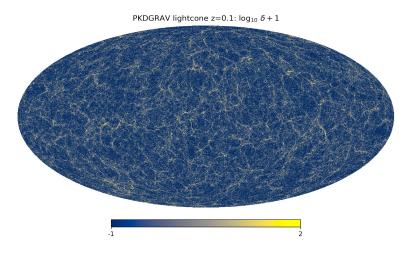
Dirac-simulations

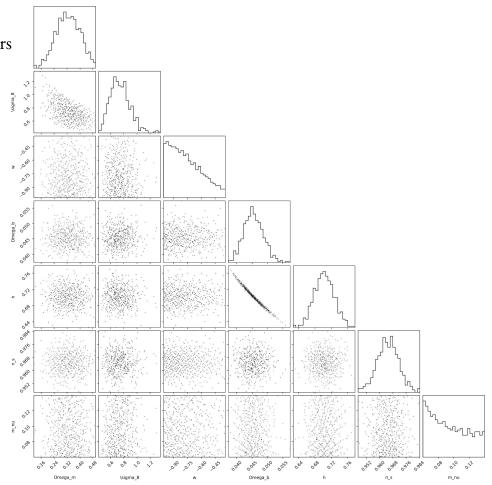
-750 full-sky N-body simulations, 7 cosmological parameters (wCDM), run with PKDRAV3

- 50k GPU hours to run sims, ~ few TB of storage for the mocks. ~500kCPU hours to make mocks and measure statistics

- density field, convergence & shear maps in ~70 redshifts between z=0 and z =49

- Resolution: ~1.6 arcminutes (ell~4000)





Reproduce observables

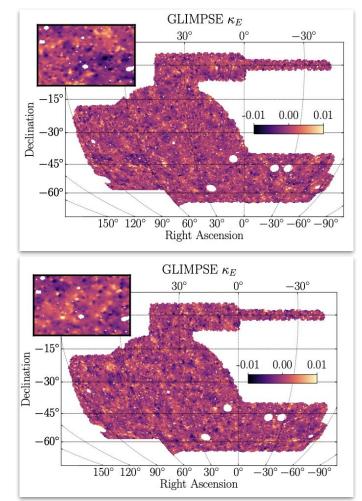
Our weak lensing mocks include:

- Tomography (4 bins)
- Realistic shape noise
- Source clustering
- Photo-z uncertainties
- Shear bias
- Intrinsic alignment (NLA+bias)

We marginalise over all the relevant nuisance parameters describing observational & astrophysical systematics during the inference



data



Probes considered (and possibly combined):

Gatti et al, 2310.17557

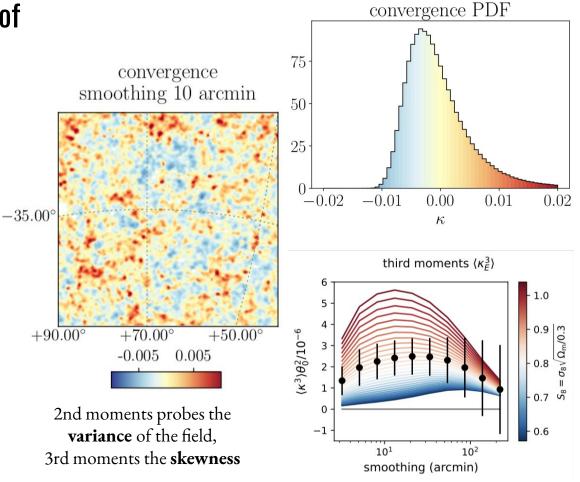
Jeffrey et al, in prep.

Prat et al, in prep.

- 2nd & 3rd moments
- Wavelet-based: Wavelet Phase Harmonics (WPH)
- Scattering Transform (ST)
- Power spectraPeaks
- Teaks - CNN
- Persistent homology
- Betti numbers

Probes considered (and possibly combined):

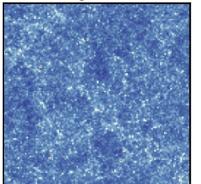
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- Peaks
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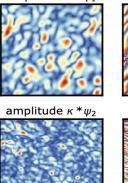
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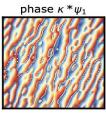
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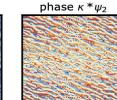
convergence field κ

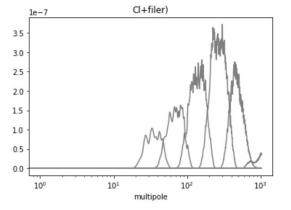


amplitude $\kappa * \psi_1$









Smoothed maps well localised in real space and Fourier space

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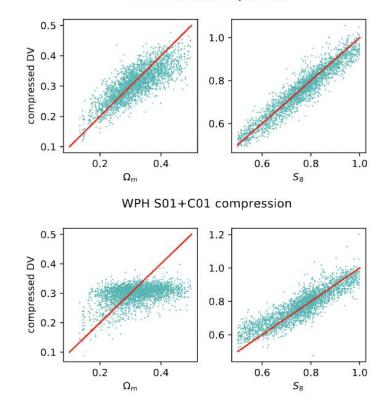
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Input field I_0 Coefficients: $S_0 \equiv \langle I_0 \rangle$ Fields $I_1 \equiv \left| I_0 \star \psi_1 \right|$ Coefficients: $S_1 \equiv \langle I_1 \rangle$ $i_1 = 0$ $i_1 = 0, i_2 =$ Fields $I_2 \equiv |I_0 \star \psi_1| \star \psi_2|$ Coefficients: $S_2 \equiv \langle I_2 \rangle$ $1=0, i_2=4$ 0.67 1.93 3.14 Cheng+21 $j_1=0, j_2=6$ $j_1=2, j_2=6$ $j_1 = 4, j_2 = 6$

Data compression : neural compression

Table 3. Neural Network Layers and number of parameters

Layer (type)	output shape	number of parameters	
Dense	900	900*(length DV+1)	
LeakyReLU	900	0	
Dense	800	720800	
LeakyReLU	800	0	
Dense	100	80100	
ReLU	100	0	
Dense	100	10100	
ReLU	100	0	
Dense	1	101	



2nd moments compression

Likelihood inference with neural density estimators (NDE)

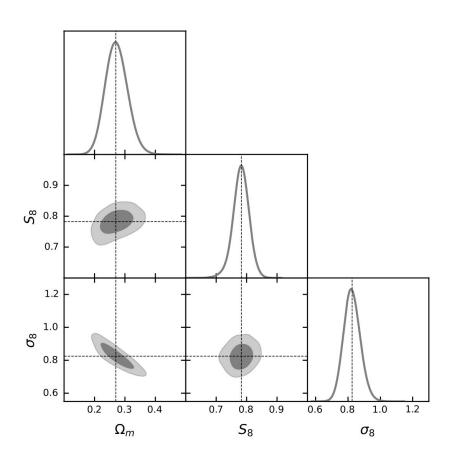
Simulation-based inference allows us to infer unknown cosmological parameters by directly comparing observed data with forward-simulated mock data.

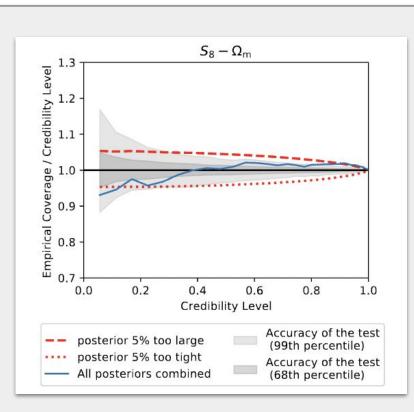
1 - draw simulated data vectors with noise {d_i,theta_i}

2 - use neural density estimators to estimate p(d|theta)

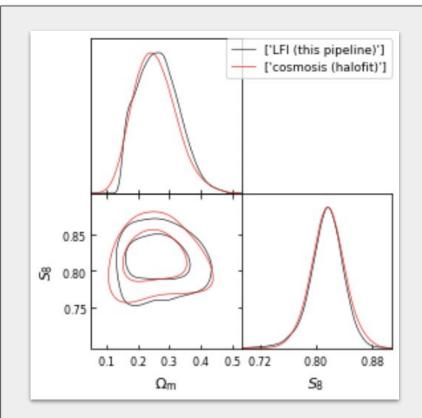
3 - use your observed data d_o to get the likelihood $L = p(d_o|theta)$

LFI requires significantly less simulations than the emulator approach! (~20 times less)





Check 1: is the posterior size correct?



Check 2: simulation based analysis of power spectra (LFI) vs standard Gaussian Likelihood + theory modeling

Summary Statistic(s)	$\sigma(S_8)$ [x100]	$\sigma(\Omega_{ m m})$ [x100]	$FoM(S_8, \Omega_m)$
2nd moments	2.7	3.4	904
2nd+3rd moments	2.6(+ 3%)	3.4(0%)	1035(+15%)
2nd moments + ST	2.7(+ 2%)	3.0(+12%)	1245(+38%)
2nd moments + WPH	2.4(+11%)	2.9(+15%)	1385(+53%)
2nd+3rd moments+ST+WPH	2.1(+21%)	2.9(+14%)	1733(+92%)

Validation with independent sims

