Quasi-maximum likelihood estimation of Primordial Non-Gaussianity



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On behalf of Gabriel Jung

In collaboration with: Michele Liguori, William Courlton, Benjamin Wandelt, Marco Baldi, Paco Villaescusa-Navarro, Licia Verde arxiv: Jung et al 2022 (2206.01624) Coulton et al 2022 (2206.01619)

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Non Gaussianity

Bispectrum:
$$\langle \delta(k_1) \delta(k_2) \delta(k_3) \rangle = (2\pi)^3 \delta_D(k_1 + k_2 + k_3) B_{\delta}(k_1, k_2, k_3)$$

Primordial non-Gaussianity:

- Different shapes related to different models of inflation
 ⇒ Local, equilateral, orthogonal
- Parametrized by their **amplitude parameter** $f_{\rm NL}$

Matter bispectrum

- Large non-Gaussian signal due to gravitational evolution
- Analytical predictions are hard to make, perturbation theory only works on large scales (k_{max} ~ 0.2h/Mpc at 1-loop)

 \Rightarrow To probe nonlinear scales, simulation-based inference is the solution!

Pipeline



Data \implies **Summary** statistics



$$\hat{P}(k_i) = \frac{1}{VN_i} \sum_{\mathbf{k} \in \Delta_i} \delta(\mathbf{k}) \delta^*(\mathbf{k})$$

• Bispectrum modes

$$w(k_1, k_2, k_3) \mathbf{B}(k_1, k_2, k_3) = \sum_{n=1}^{N} \beta_n Q_n(k_1, k_2, k_3)$$

2

0

-2

-4

Separable modal basis: $Q_n(k_1, k_2, k_3) = q_r(k_1)q_s(k_2)q_t(k_3) + \text{perms}$, with $n \equiv \{r, s, t\}$

Only ~100 well chosen modes to describe the bispectrum up to $k_{\text{max}} = 0.5h/\text{Mpc}$

Method originally developed for CMB

- Fergusson, Liguori & Shellard (0912.3411)
- Planck NG (1905.05697)

Later implemented in the LSS context

- Schmittfull, Regan & Shellard (1207.5678)
- Hung, Fergusson & Shellard (1902.01830)
- Byun, Oddo, Porciani & Sefusatti (2010.09579)



Figure 6.2 – The first eight orthogonal one dimensional polynomials $q_n(x)$ defined on the tetrahedral. They are well defined and well behaved within the boundaries of the domain.

Summary statistics —> Compressed statistics

• Compression to the score function (J. Alsing, B. Wandelt ; 1712.00012):



- 1. Assume an approximate form for the likelihood of the summary statistics [compression equivalent to MOPED astro-ph/9911102 (A. Heavens, R. Jimenez & O. Lahav)]
- 2. Define the compressed statistics **t** to be the **score-function** the parameter gradient of the log-likelihood evaluated at some fiducial parameter set θ_* .

$$\mathbf{t} =
abla_{oldsymbol{ heta}} oldsymbol{\mu}_*^{\mathrm{T}} \mathbf{C}_*^{-1} (\mathbf{d} - oldsymbol{\mu}_*)$$

Summary statistics —> Compressed statistics

$$\mathbf{t} = \nabla_{\boldsymbol{\theta}} \boldsymbol{\mu}_*^{\mathrm{T}} \mathbf{C}_*^{-1} (\mathbf{d} - \boldsymbol{\mu}_*)$$

- **µ** and **C** are the mean and the covariance of **d**, evaluated at the fiducial cosmology from simulations.
- The **derivative** is computed from simulations with a step $\Delta \theta$ away from fiducial θ_{fid}

$$\frac{\partial \mathbf{d}_n}{\partial \theta} \simeq \frac{\mathbf{d}_n(\theta_{\mathrm{fid}} + \Delta \theta) - \mathbf{d}_n(\theta_{\mathrm{fid}} - \Delta \theta)}{2\Delta \theta}$$

- 1. This compression results in just n numbers, i.e. the number of parameters we aim to infer from data.
- 2. Compression to the score is **optimal** in the sense that it saturates the information inequality.
- 3. Covariance does not depend on parameters θ (score-function is equivalent to MOPED).
- 4. By construction the covariance of **t** is $\mathbf{F} = \nabla_{\theta} \boldsymbol{\mu}^{\mathrm{T}} \mathbf{C}^{-1} \nabla_{\theta}^{\mathrm{T}} \boldsymbol{\mu}$. computed at fiducial point $\boldsymbol{\theta}_{\mathrm{fid}}$

The quasi-ML estimator of θ is thus:

$$\hat{oldsymbol{ heta}} = oldsymbol{ heta}_* + \mathbf{F}_*^{-1} \mathbf{t}$$

Data: N-body simulations

• Quijote simulations ($f_{\rm NL} = 0$)

https://quijote-simulations.readthedocs.io (F. Villaescusa-Navarro)

Large suite (~44000) of N-body simulations with 512³ particles and a size of 1 Gpc/h

- \Rightarrow 8000 simulations at fiducial cosmology to estimate covariances
- \Rightarrow Sets of 500 simulations for numerical derivatives (σ_8 , Ω_m , Ω_b , h, n_s)

• Non-Gaussian Quijote-like ($f_{\rm NL} = \pm 100$)

⇒ Sets of 500 simulations for three primordial shapes: local, equilateral and orthogonal ⇒ Numerical derivatives ($f_{\rm NL}^{\rm local}$, $f_{\rm NL}^{\rm equil}$, $f_{\rm NL}^{\rm ortho}$)

Table 1. The cosmological parameters and PNG amplitudes of the QUIJOTE andQUIJOTE-PNG simulations.

	σ_8	Ω_m	Ω_b	n_s	h	$f_{ m NL}^{ m local}$	$f_{ m NL}^{ m equil}$	$f_{ m NL}^{ m ortho}$
Fiducial	0.834	0.3175	0.049	0.9624	0.6711	0	0	0
Steps	± 0.015	± 0.01	± 0.002	± 0.02	± 0.02	± 100	± 100	± 100

Quijote-PNG: Power spectrum



Quijote-PNG: Bispectrum ratio NG/G





Figure 6. Joint constraints on cosmological parameters and PNG from the power spectrum and the modal bispectrum for different k_{\max} at z = 1.



Coulton et al 2022 (2206.01619)



- Nonlinear regime ($k_{max} = 0.5h/Mpc$ here) improves the constraints significantly
- Combining power spectrum and bispectrum also improves the constraints by a factor ~2, even if the power spectrum constraining power is very small

Table 2. Joint constraints on cosmological parameters and PNG from the power spectrum and the modal bispectrum at z = 1, for different k_{max} . We analyzed 8000 QUIJOTE N-body simulations of 1 $(\text{Gpc}/h)^3$ volume at fiducial cosmology, and sets of 500 N-body simulations with one adjusted parameter.

Independent
constraints:

	k_{\max}	σ_8	Ω_m	Ω_b	n_s	h	$f_{ m NL}^{ m local}$	$f_{ m NL}^{ m equil}$	$f_{ m NL}^{ m ortho}$
	$(h{ m Mpc}^{-1})$	0.834	0.3175	0.049	0.9624	0.6711	0	0	0
P(k)	0.07	± 0.17	± 0.32	± 0.32	± 3.9	± 4.4			
	0.2	± 0.012	± 0.039	± 0.018	± 0.24	± 0.24			
	0.5	± 0.0045	± 0.011	± 0.0062	± 0.042	± 0.062			
β_n	0.07	± 0.59	± 0.95	$\pm 1.$	± 12	± 14			
	0.2	± 0.014	± 0.051	± 0.023	± 0.32	± 0.31			
	0.5	± 0.0063	± 0.016	± 0.006	± 0.066	± 0.071			
$P(k) + \beta_n$	0.07	± 0.17	± 0.31	± 0.31	± 3.7	± 4.2			
	0.2	± 0.011	± 0.035	± 0.015	± 0.21	± 0.21			
	0.5	± 0.0038	± 0.0091	± 0.0048	± 0.031	± 0.048			
P(k)	0.07	± 0.55	± 0.41	± 0.36	± 4.5	± 4.9	± 200000	± 500000	± 180000
	0.2	± 0.13	± 0.07	± 0.031	± 0.49	± 0.39	± 31000	± 85000	± 36000
	0.5	± 0.069	± 0.035	± 0.013	± 0.24	± 0.18	± 9600	± 29000	± 11000
β_n	0.07	± 1.1	± 1.3	± 1.4	± 18	± 20	± 670	± 2300	± 1500
	0.2	± 0.016	± 0.059	± 0.027	± 0.37	± 0.36	± 91	± 390	± 300
	0.5	± 0.0068	± 0.018	± 0.0064	± 0.078	± 0.079	± 39	± 150	± 110
$P(k) + \beta_n$	0.07	± 0.17	± 0.31	± 0.31	± 3.7	± 4.2	± 350	± 930	± 610
	0.2	± 0.011	± 0.035	± 0.015	± 0.21	± 0.21	± 52	± 170	± 120
	0.5	± 0.0038	± 0.0093	± 0.0048	± 0.033	± 0.048	± 22	± 94	± 58

$f_{\rm NL}^{\rm local}$	$f_{ m NL}^{ m equil}$	$f_{\rm NL}^{ m ortho}$
± 16	± 77	± 40

Quijote-PNG: modal bispectrum convergence



Quasi-optimality of the estimator



Summary

Conclusions:

- We prove the capability of our approach to optimally extract PNG information on non-linear scales beyond the perturbative regime!!
- The overall estimation procedure is unbiased and fast.
- The Gaussian likelihood assumption only leads to sub-optimality. This can be improved with neural networks.
- The dark matter power spectrum itself contains negligible PNG information, as expected, including it as an ancillary statistic increases the PNG information content extracted from the bispectrum by a factor of order 2.

Future work:

- Extend the pipeline to include: biased tracers (dark matter halos and galaxies).
- This has already been done in Coulton et al 2022 (arXiv:2206.15450), while the accompanying paper with modal estimator and score function is coming soon (Jung et al 2022, in prep.)
- The halo PNG Quijote catalogues are public now (https://quijote-simulations.readthedocs.io)!!
- Account for redshift space and incomplete sky-coverage