Robust Neural-Network enhanced approach for estimating f_{NL}^{loc}

Cosmology From Home 2022

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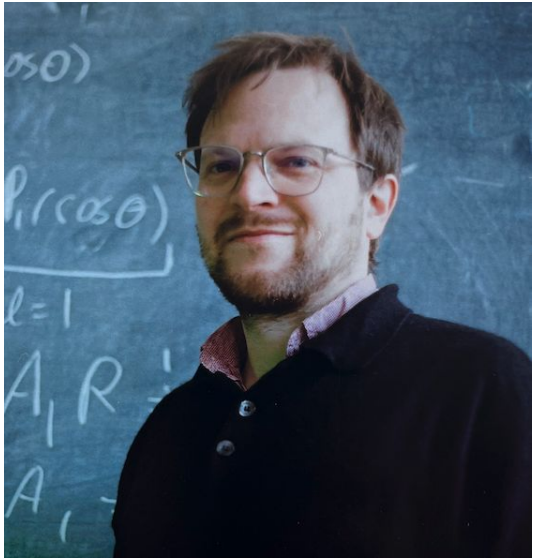
Based on **arxiv:2205.12964** and in collaboration with



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Quick intro to Local PNG

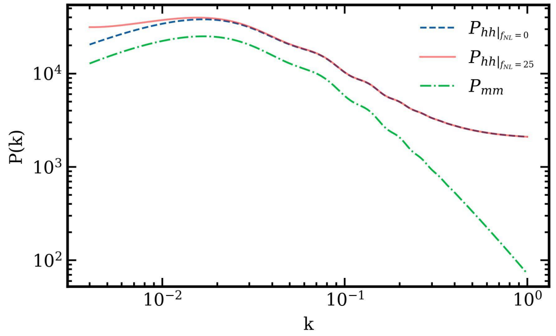
A local non-linear correction to the primordial potential

$$\Phi_{NG}(\mathbf{x}) = \Phi_G(\mathbf{x}) + f_{NL}(\Phi_G(\mathbf{x})^2 - \langle \Phi_G^2 \rangle)$$

In CMB, this induces a clean squeezed bispectrum,

$$f_{NL}^{est} = 0.8 \pm 5.0$$ (Planck constraints, near information limit)

In LSS, this induces **scale-dependent bias in the clustering of tracers**



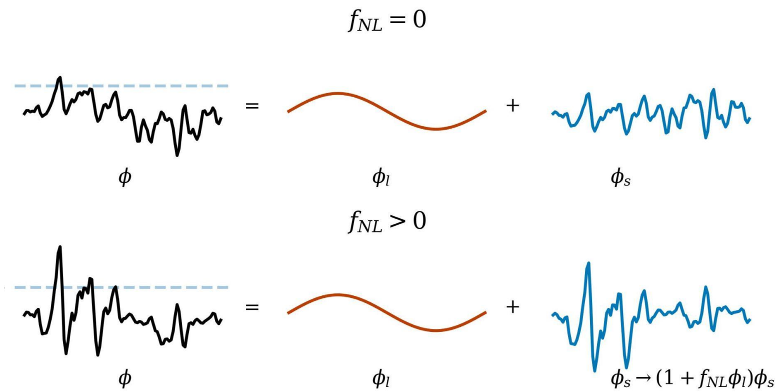
$$P_{hh}(k_L) = \left(b_G + \frac{b_{NG} f_{NL}}{k_L^2} \right)^2 P_{mm}(k_L)$$

$$f_{NL}^{est} = -12 \pm 21$$ (Eva-Maria Mueller et. al. 2021 BOSS dataset)

A highly motivated target is $\sigma(f_{NL}) \sim 1$

Scale dependent bias:

Long-Short decomposition:



$$\Phi_G = \Phi_l + \Phi_s$$

$$\Phi_{NG}(\mathbf{x}) = \Phi_G(\mathbf{x}) + f_{NL}(\Phi_G(\mathbf{x})^2 - \langle \Phi_G^2 \rangle)$$

$$\Phi_{NG}(\mathbf{x}) = \underbrace{\Phi_l(\mathbf{x}) + f_{NL}\left(\Phi_l(\mathbf{x})^2 - \langle \Phi_l^2 \rangle\right)}_{\text{long}} + \underbrace{(1 + 2f_{NL}\Phi_l(\mathbf{x}))\Phi_s(\mathbf{x}) + f_{NL}(\Phi_s(\mathbf{x})^2 - \langle \Phi_s^2 \rangle)}_{\text{short}}$$

$$\sigma_8^{loc}(\mathbf{x}) = (1 + 2f_{NL}\Phi_l(\mathbf{x}))\bar{\sigma}_8$$

b_h^G = constant is response of halo abundance to long-wavelength perturbation $\delta_m(k_L)$

for $f_{NL} \neq 0$, halo abundance on large-scale acquires additional dependence on Φ_l mediated by σ_8^{loc} leading to an additional bias term proportional to $\Phi_l = \delta_l / k^2$

$$\delta_h(\mathbf{k_L}) = b_h(\mathbf{k_L})\delta_m(\mathbf{k_L}) + N_{hh} \qquad b_h(k) = b_h^G + b_h^{NG}\frac{f_{NL}}{\alpha(k,z)} \qquad \alpha(k,z) \propto k^2$$

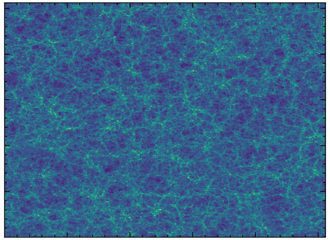
Our Idea:

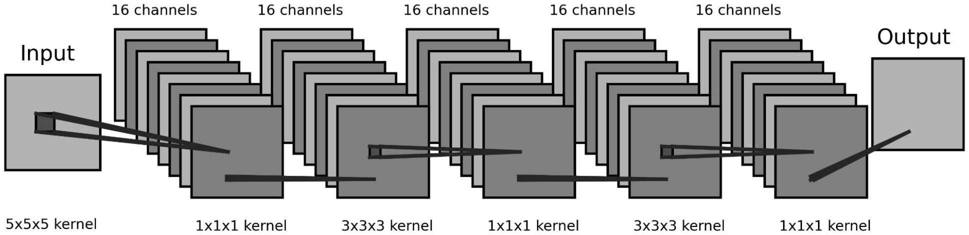
- In principle, one would be able to constrain f_{NL} with a low noise estimate of local σ_8
- CNNs give very strong constraints on parameters like σ_8 and can potentially tap into the higher order information encoded in the density field.

We design a NN with small receptive field to learn π field which locally estimates σ_8

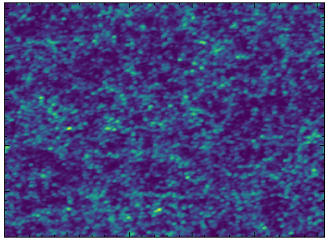
$$\mathcal{L} = \left[\left(\frac{1}{N_{\text{voxels}}} \sum_{\text{voxels } \mathbf{x}} \pi(\mathbf{x}) \right) - \sigma_{\mathbf{8}}^{\text{true}} \right]^{\mathbf{2}}$$

δ_m





π



We use Quijote simulations with fixed cosmology and with $\sigma_8 \in \{0.819, 0.849\}$ for training.

Interpretation and Validation

The bias model for π similar to that of δ_h

$$\pi(\mathbf{k_L}) = b_\pi(k_L)\delta_m(\mathbf{k}_L) + N_{\pi\pi}$$

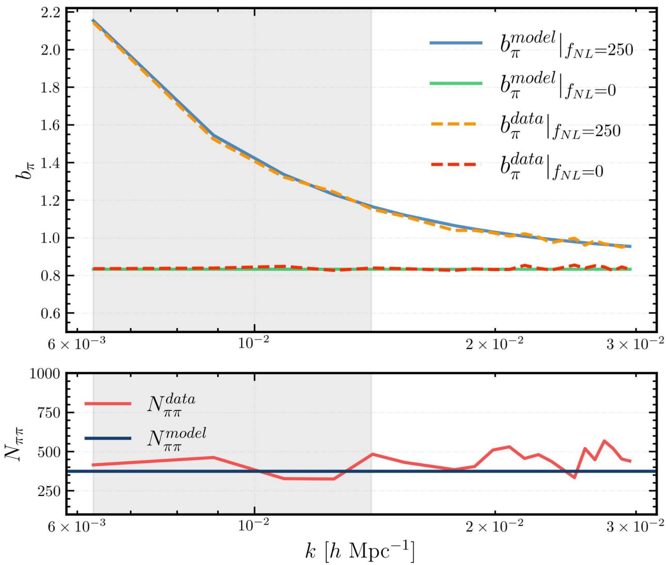
With

$$b_\pi(k) = b_\pi^G + b_\pi^{NG}\frac{f_{NL}}{\alpha(k,z)}$$

We evaluate this on **“unseen, non-gaussian”** sims

- Recover $1/k^2$ scaling, constant noise for $k \to 0$
- Find 100% correlation with matter field

Robust $1/k^2$ scale dependence, can’t be faked!



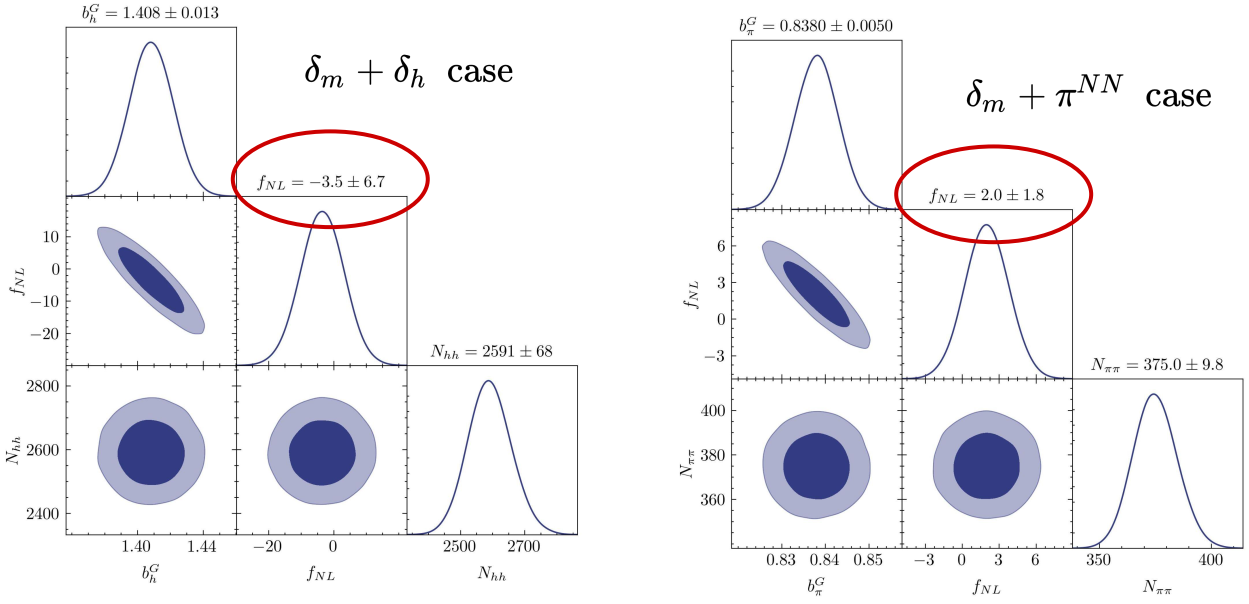
It’s more interpretable than a "black box" approach. We can do several field level null-tests; cross-correlate with noise maps. Also with other cosmological fields.

Likelihood analysis: $f_{NL} = 0$ universe

$$\mathcal{L}(\Theta|\mathcal{D}) \propto \prod_k \frac{1}{\sqrt{\mathrm{Det}\,C(k)}} \exp\left(-\frac{\mathcal{D}(k)^\dagger C(k)^{-1} \mathcal{D}(k)}{2V}\right)$$

where

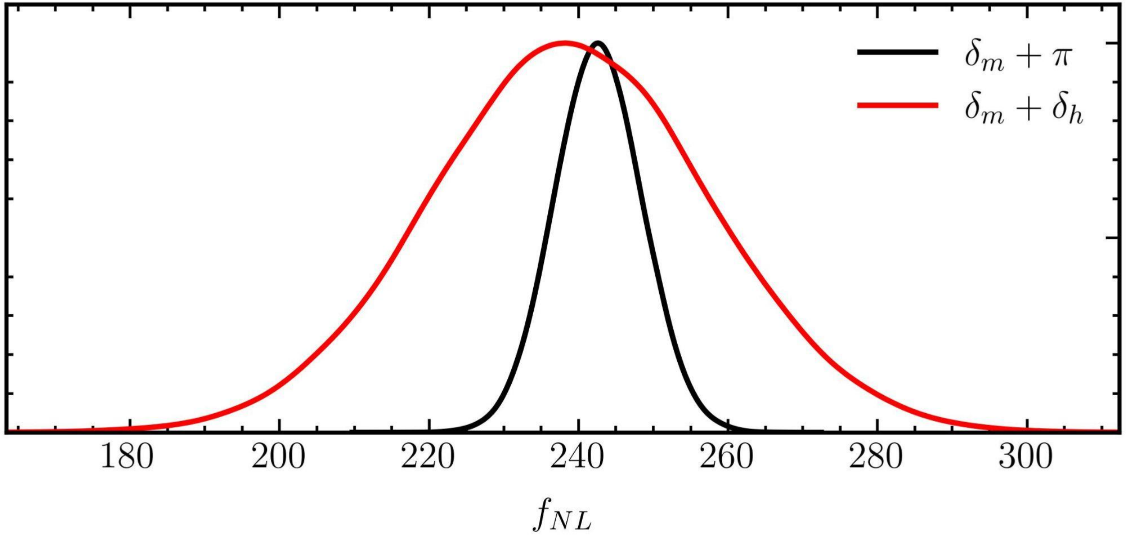
$$N_{sim} = 100$$
$$\mathcal{D} = [\delta_m(k), \pi(k)]$$
$$k_{max} = 0.014\ \mathrm{Mpc}^{-1}$$
$$M_{min} \approx 10^{13} M_\odot$$



Factor of 3.5 improvement with π field for a halo catalogue with $M_{min} \approx 10^{13} M_\odot$

Likelihood analysis: $f_{NL} = 250$ case

Result from analysis of 10 simulations with $f_{NL} = 250$



Unbiased estimate of f_{NL} with a factor of 3.5 improvement on error bar!

Summary

We propose a **robust and interpretable** CNN based approach for constraining f_{NL}

- Robust to small-scale baryonic/galaxy formation uncertainties via the $1/k^2$ large-scale bias dependence.
- Unlike fully “black-box” CNN approaches, our formalism is interpretable.

We get a factor of **>3.5** improvement on $\sigma(f_{NL})$ in comparison to a traditional matter + halo-based analysis. Note however that the CNN gets to see the matter distribution which is unobservable.

The application to halo catalogs is work in progress.