Probing primordial non-Gaussianity by reconstructing the initial conditions with machine learning

Xinyi Chen
Yale University

w/ Nikhil Padmanabhan,
Daniel Eisenstein

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Image: D. Schlegel

Status of LSS on constraining local PNG

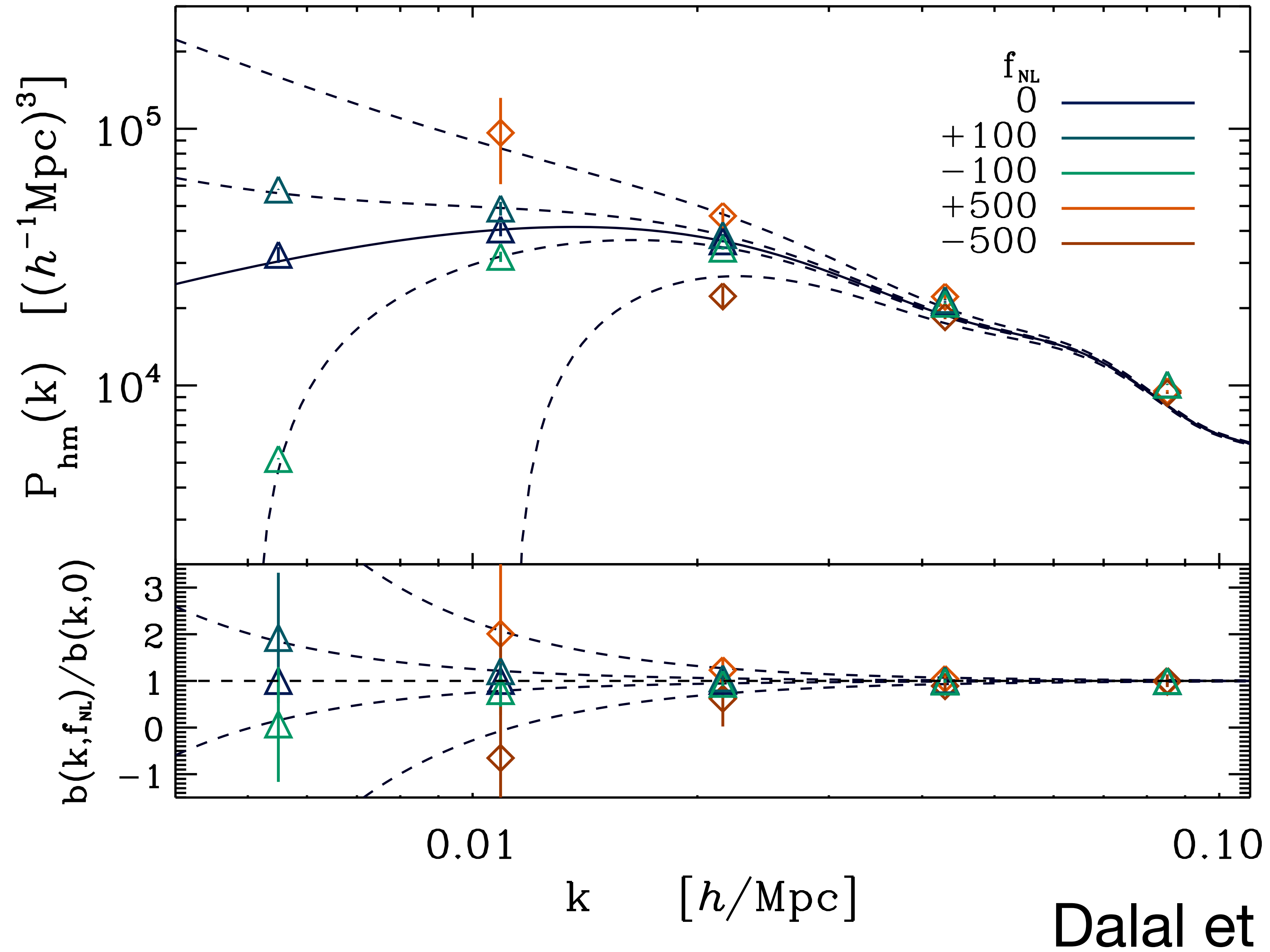
Primordial potential with local type $f_{\rm NL}$:

$$\Phi(\boldsymbol{x}) = \phi_G(\boldsymbol{x}) + f_{\rm NL}\{\phi_G^2(\boldsymbol{x}) - \langle \phi_G^2(\boldsymbol{x})\rangle\} + \dots$$

Gaussian potential

Sensitivity goal: $\sigma(f_{\rm NL}) < 1$

- Current best: -12±21 (eBOSS DR16 QSO, Mueller et al. 2022)
- Usual technique: scale-dependent bias on galaxy power spectrum
  - Systematics
  - **Cosmic variance** on large scales
  - Forecast DESI $\sigma(f_{\rm NL}) \sim 10$ (Sailer et al. 2021)
- **Adding Bispectrum -> tighter constraints**
  - e.g. a factor of ~2-4 Pk -> Pk+Bk (*SPHEREx*, Dore et al. 2014, Heinrich, Dore & Krause 2023)
  - **Large bispectrum from gravity** → Reconstruction
  - **Large data vectors** → Near-optimal 2-pt bispectrum estimator



Dalal et al. 2008

$$\Delta b \propto \frac{f_{\rm NL}}{k^2 T(k)}$$

Transfer function

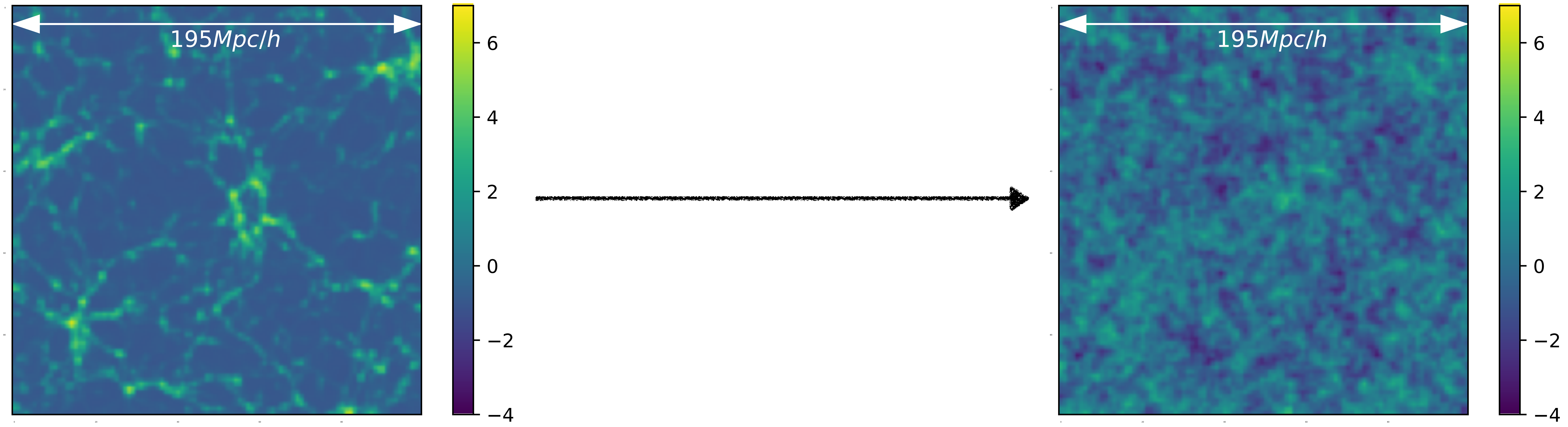
New approach to constraining PNG

- Reconstructing the density field
- Computing and fitting a near-optimal 2-pt bispectrum estimator

New approach to constraining PNG

- **Reconstructing the density field**
- Computing and fitting a near-optimal 2-pt bispectrum estimator

Reconstruction of the initial conditions: reverse a late-time density field back to initial density field

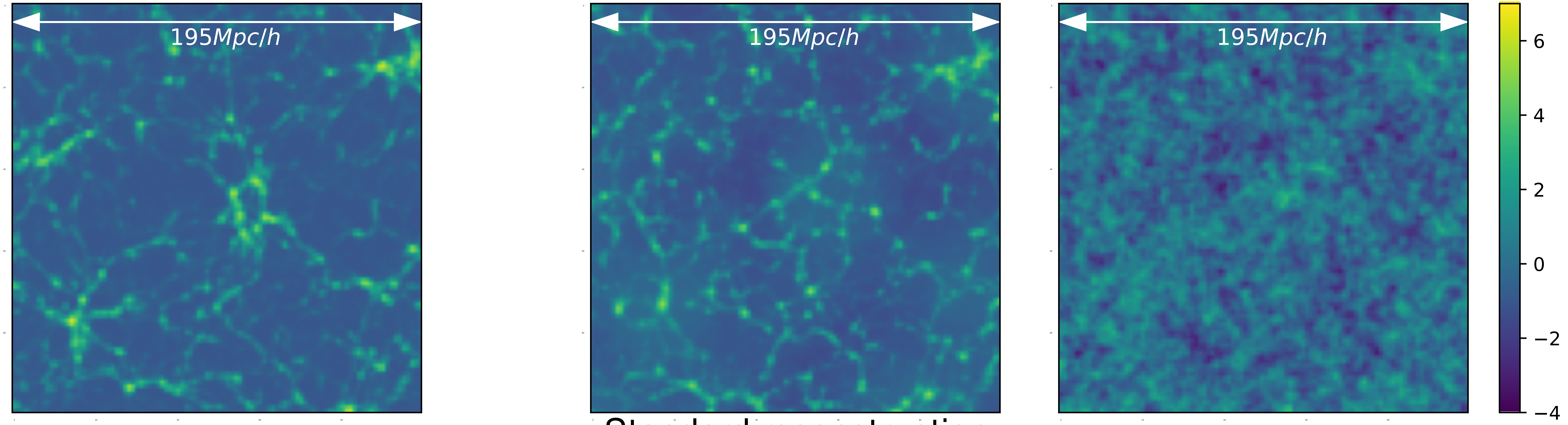


Late-time

Initial

Matter density fields at high resolution (1024^3 particles in 1 Gpc/h box) at z=0, on a 512^3 grid, using Quijote simulations (Villaescusa-Navarro et al. 2020)

Density field reconstructed by the standard reconstruction algorithm still nonlinear



Late-time

Standard reconstruction (Eisenstein et al. 2007)

Initial

Matter density fields at high resolution (1024^3 particles in 1 Gpc/h box) at z=0, on a 512^3 grid, using Quijote simulations (Villaescusa-Navarro et al. 2020)

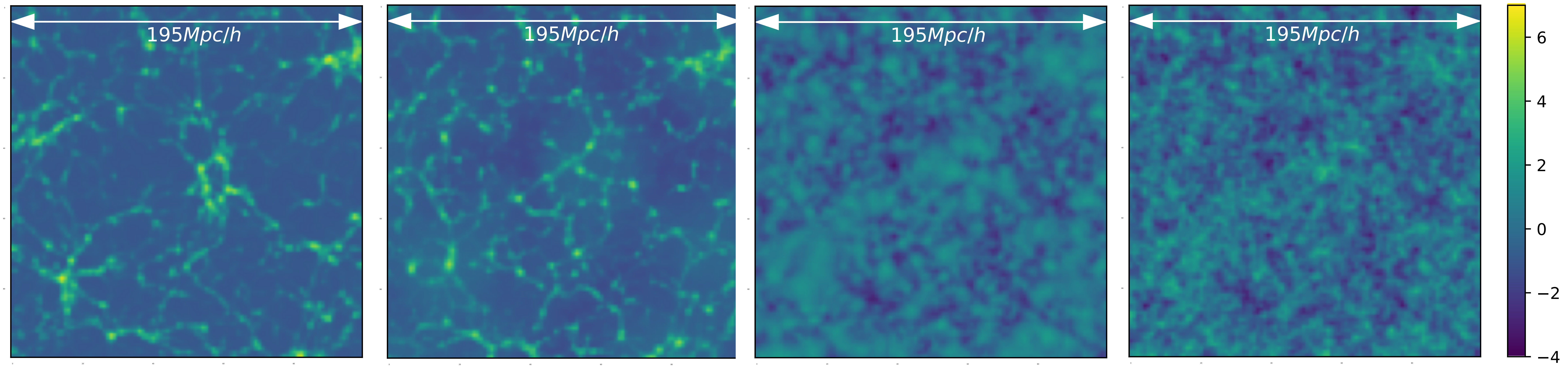
A new reconstruction method

A hybrid method that combines convolutional neural network (CNN) with a traditional algorithm based on perturbation theory (**Chen** et al. 2023, Shallue & Eisenstein 2023)

Matter density fields at high resolution (1024^3 particles in 1 Gpc/h box) at z=0, on a 512^3 grid, using Quijote simulations (Villaescusa-Navarro et al. 2020)

Large-scales use perturbation theory, small-scales use CNN

- First step: traditional algorithm
- Second step: train CNN with reconstructed density fields
- CNN is relatively local, but perturbation theory provides good approximation on large scales. **So traditional algorithm for large scales, CNN for smaller scales.**



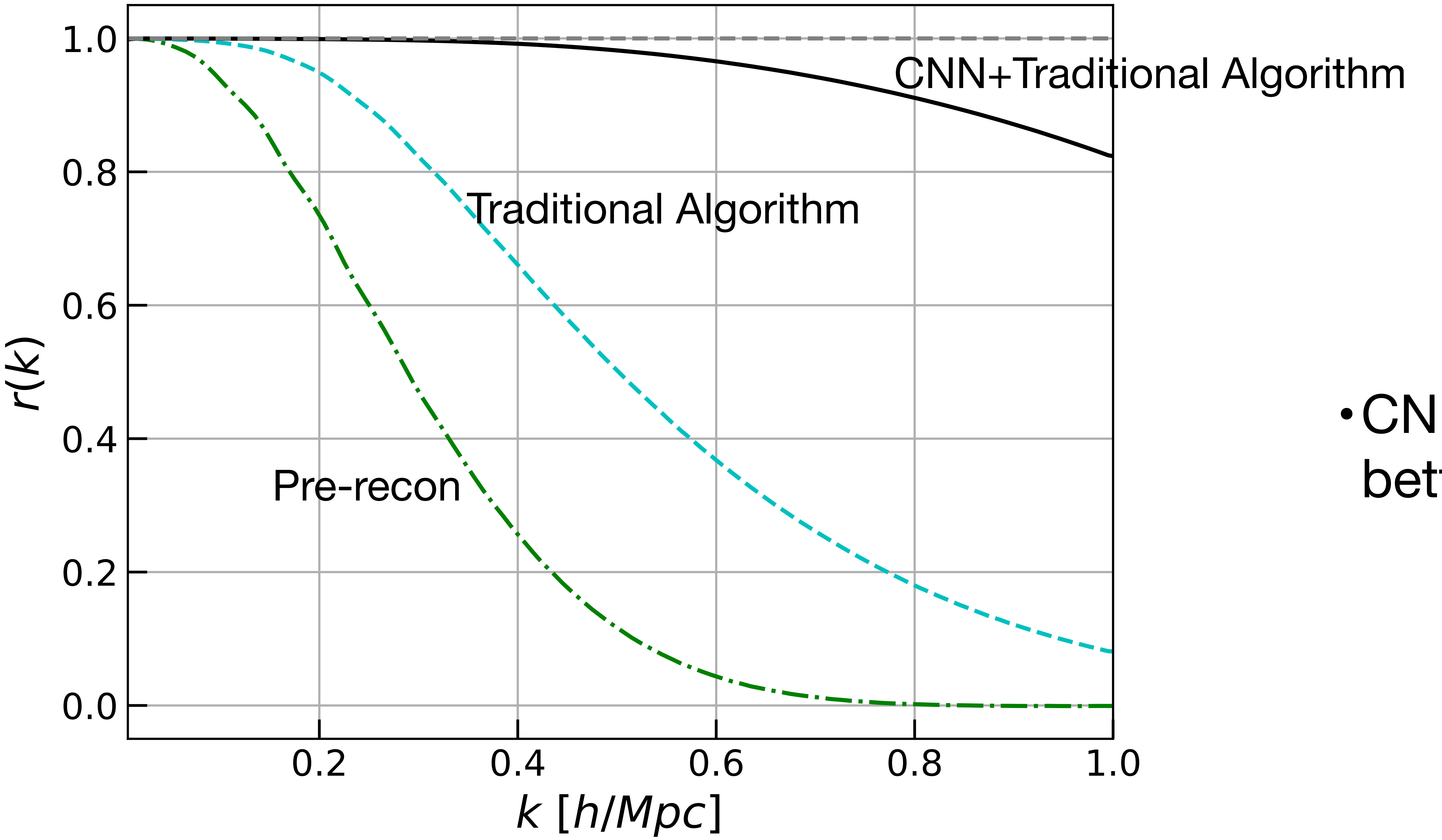
Late-time

Standard recon

CNN trained w/ standard recon field

Initial

CNN improves cross-correlation



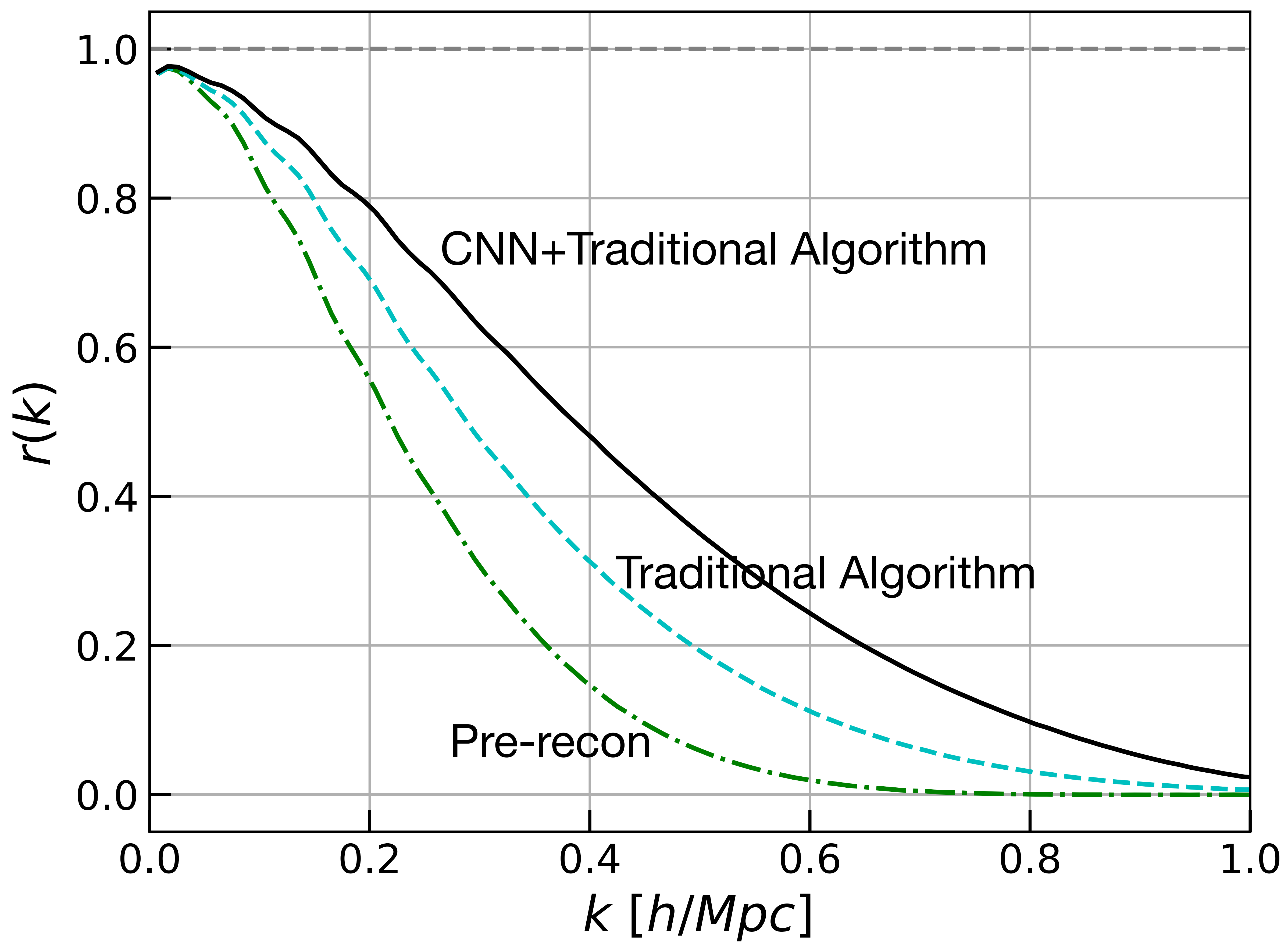
$$r(k) = \frac{\langle \delta^*(\boldsymbol{k})\delta_{\rm ini}(\boldsymbol{k})\rangle}{\sqrt{\langle \delta^2(\boldsymbol{k})\rangle\langle \delta^2_{\rm ini}(\boldsymbol{k})\rangle}}$$

- CNN+Algorithm performs significantly better

Real space matter field z=1, using Quijote simulations (Villaescusa-Navarro et al. 2020)

Reconstruction algorithm used: Hada & Eisenstein 2018 (HE18)

Hybrid recon boosts traditional algorithms in halo fields too



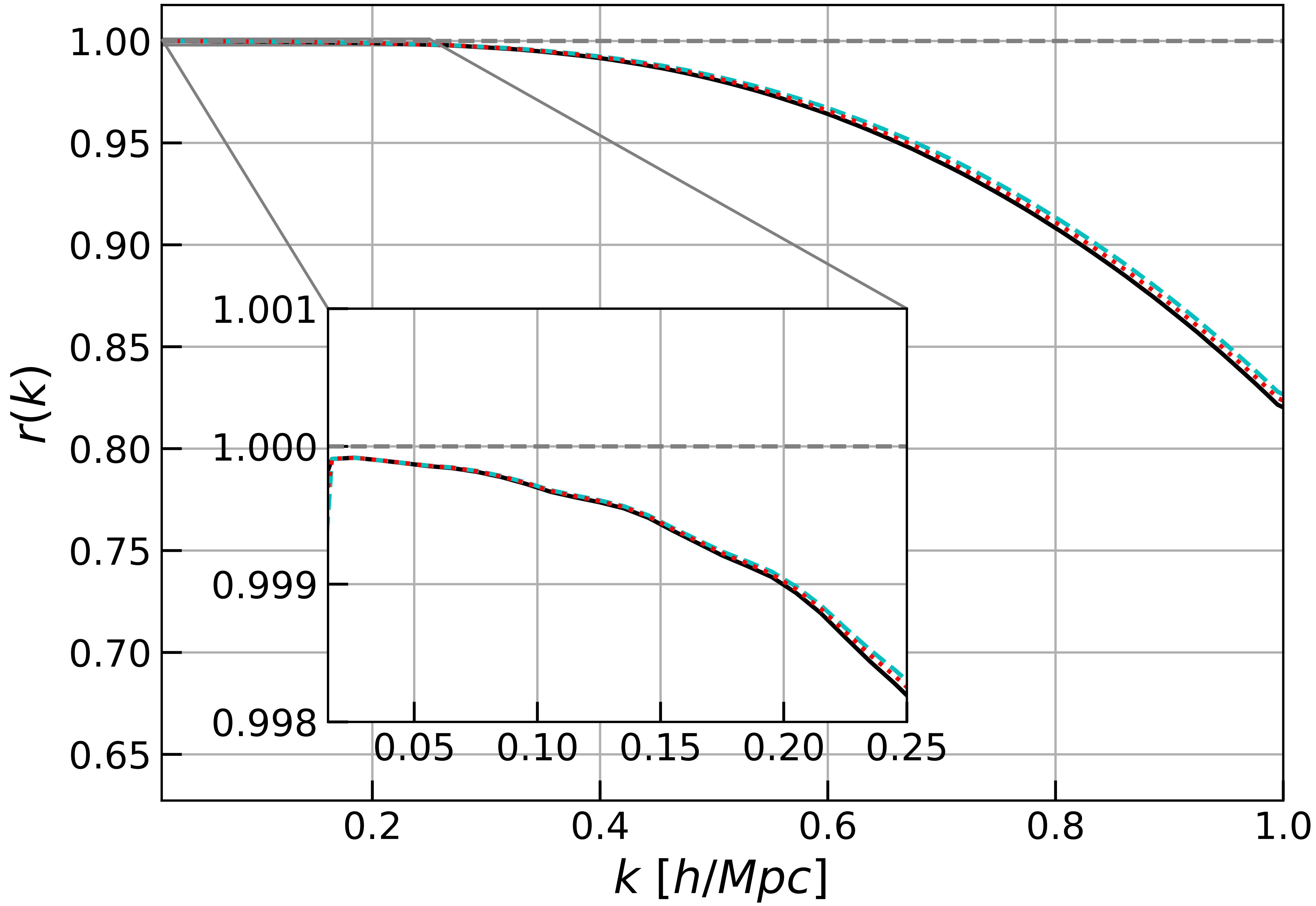
z=1

$\bar{n} = 2.0 \times 10^{-4} h^3 \mathrm{Mpc}^{-3}$
$b = 2.9$
$b^2\bar{n} = 1.7 \times 10^{-3} h^3 \mathrm{Mpc}^{-3}$

Similar to DESI Y1 LRG:
$b^2\bar{n} \sim 1.4 \times 10^{-3} h^3 \mathrm{Mpc}^{-3}$

Reconstruction algorithm used: Hada & Eisenstein 2018 (HE18)

Model trained with no PNG works for PNG



$$r(k) = \frac{\langle \delta^*(\boldsymbol{k})\delta_{\rm ini}(\boldsymbol{k})\rangle}{\sqrt{\langle \delta^2(\boldsymbol{k})\rangle\langle \delta^2_{\rm ini}(\boldsymbol{k})\rangle}}$$

CNN+Algorithm

- $f_{\rm NL} = +100$
- $f_{\rm NL} = 0$
- $f_{\rm NL} = -100$

Real space matter field z=1, using Quijote-PNG simulations (Coulton et al. 2022)

Reconstruction algorithm used: Hada & Eisenstein 2018

New approach to constraining PNG

- Reconstructing the density field
- **Computing and fitting a near-optimal 2-pt bispectrum estimator**

Cross-power estimator

Primordial potential with local type $f_{\rm NL}$:

$$\Phi(\boldsymbol{x}) = \phi_G(\boldsymbol{x}) + f_{\rm NL}\{\phi_G^2(\boldsymbol{x}) - \langle\phi_G^2(\boldsymbol{x})\rangle\} + \ldots$$

Gaussian potential

$$\langle \Phi^2 \delta \rangle$$

Reconstructed/Linear

Primordial potential $\quad \Phi(\boldsymbol{k}) = \dfrac{\delta(\boldsymbol{k})}{M_\Phi(k)}$

Transfer function

$$M_\Phi(k) = \frac{2}{3}\frac{k^2 T(k)}{\Omega_{\rm m,0} H_0^2}$$

$$\Phi^2(\boldsymbol{k}) = \int {\rm d}\boldsymbol{x} e^{-i\boldsymbol{k}\cdot\boldsymbol{x}}\Phi^2(\boldsymbol{x}) = \frac{1}{(2\pi)^3}\int {\rm d}\boldsymbol{k}_1 \Phi(\boldsymbol{k}_1)\Phi(\boldsymbol{k}-\boldsymbol{k}_1)$$

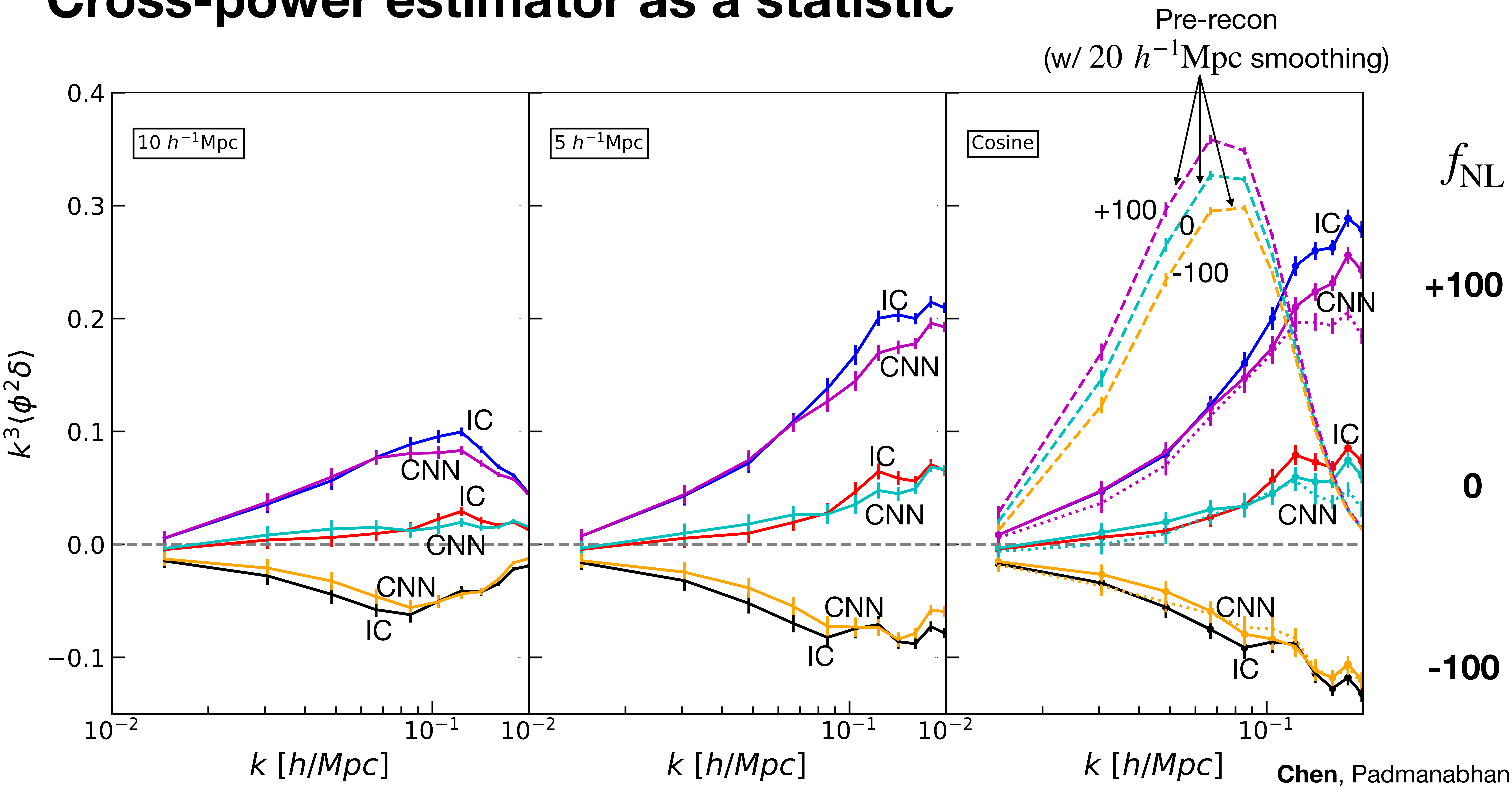
$$\langle \Phi^2(\boldsymbol{k})\delta(-\boldsymbol{k})\rangle = \frac{1}{(2\pi)^3}\int {\rm d}\boldsymbol{k}_1 M_\Phi(k)\boxed{\langle \Phi(\boldsymbol{k})\Phi(\boldsymbol{k}-\boldsymbol{k}_1)\Phi(-\boldsymbol{k})\rangle}$$

Primordial bispectrum

Integral of bispectrum, but has access to higher k than bispectrum

Near optimal by maximum likelihood estimation, first proposed by Schmittfull, Baldauf & Seljak 2015

Cross-power estimator as a statistic



Chen, Padmanabhan & Eisenstein (in prep.)

Cosine filter between k=0.2-0.25 h/Mpc

Real space matter field z=1

Fisher error $\sigma(f_{\rm NL})$ for cross-power with matter density field of 1 Gpc/h volume

$k_{\rm max}$	Smoothing	IC	CNN+HE18 $z=1$	NL $z=1$
$0.1\ h/\mathrm{Mpc}$	$10\ h^{-1}$ Mpc	52.7	57.2	76.2
	$5\ h^{-1}$ Mpc	48.0	52.4	
	Cosine	46.4	50.7	
$0.2\ h/\mathrm{Mpc}$	Cosine	15.8	17.4	54.5

3x

(Smoothed at $20\ h^{-1}$Mpc)

For eBOSS QSO survey volume (2.9 Gpc/h): $\sigma(f_{\rm NL}) \sim 4$

- Cross-power accesses higher k, thus more information than bispectrum when compared at the same $k_{\rm max}$, need smoothing
- Single parameter forecast: CNN+HE18 $\sigma(f_{\rm NL})$~50, pre-recon $\sigma(f_{\rm NL})$~76 ($k_{\rm max} = 0.1\ h/\mathrm{Mpc}$) — ~1.5x improvement
- Reconstruction allows higher $k_{\rm max}$
- Optimistic without including other bias terms (square, shift, tidal) -> can compute similar cross-power estimators

Summary

- Reconstruction with CNN+Algorithm removes most gravitational nonlinearity and strengthens the primordial signal
- Cross-power estimator easy to compute and promising to estimate $f_{\rm NL}$
- Application of reconstruction on cross-power estimator gives low $\sigma(f_{\rm NL})$ although slightly biased mean

Ongoing work

- Including quadratic gravitational bias terms in the model (estimate each bias term — square, shift, tidal — with bispectrum estimator)
- Developing probabilistic ML model to do better reconstruction for high shot noise biased tracer (also w/ Carolina Cuesta-Lazaro)
- Applying to non-local types of PNG, extending cross-power estimator (can be more helpful there because equilateral and orthogonal can’t rely on scale-dependent bias)
- Constraining primordial features with DESI data with hybrid reconstruction (also w/ Xingang Chen)

In relation to future surveys…

Still a lot to be done
For now —

- Reconstruction will benefit from higher-number density
- Reconstruction allows us to use higher k modes, so large volume less important, but not so if we want to combine with scale-dependent bias approach

Xinyi Chen
xinyi.chen@yale.edu