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

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CCAPP Symposium, 09/18/25

Image: D. Schlegel

Planck, ACT, Simons Observatory, …

SIMONS OBSERVATORY

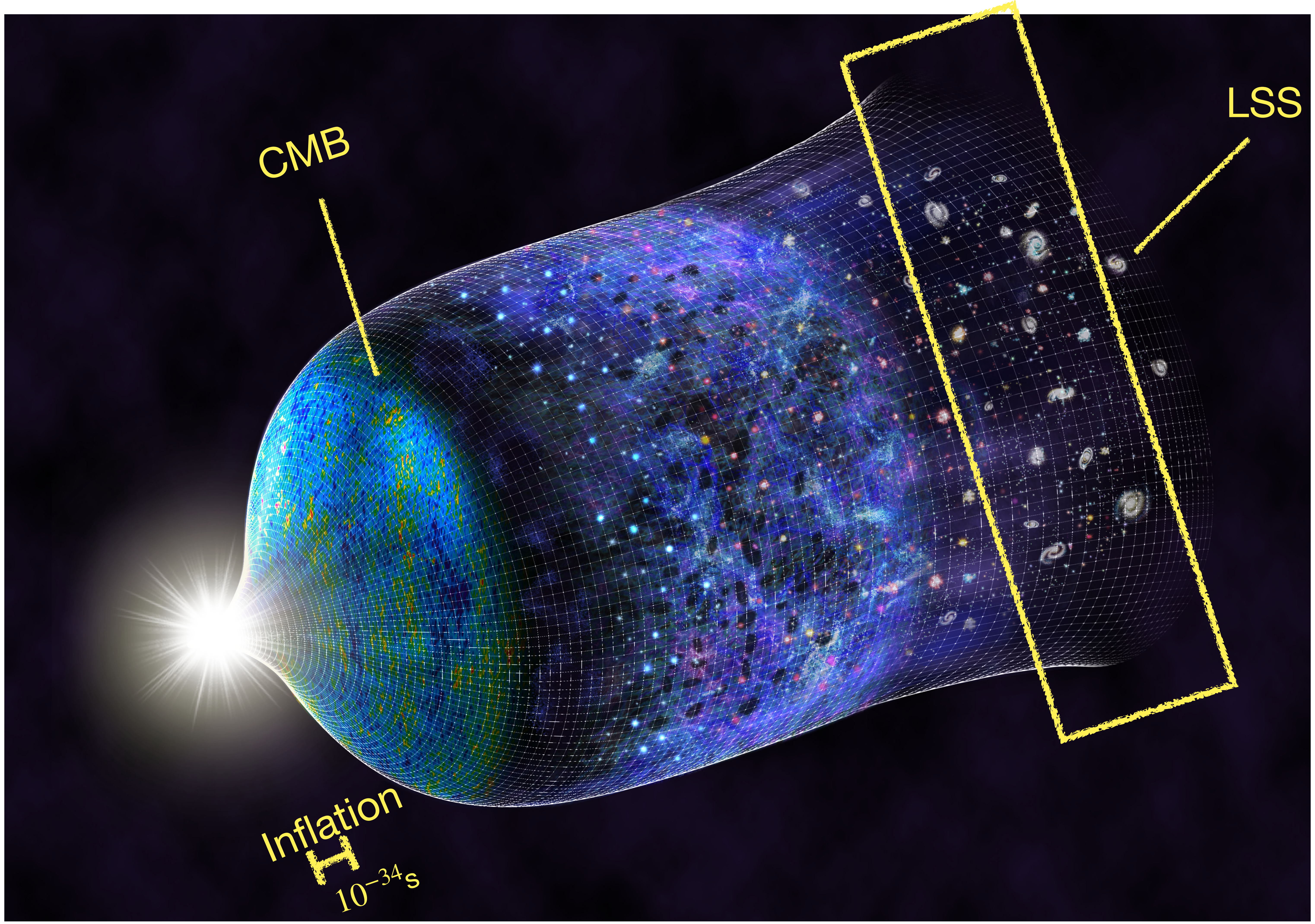


Image: Nicolle R. Fuller, National Science Foundation

DESI, *Euclid*, *Roman*, …

DARK ENERGY SPECTROSCOPIC INSTRUMENT

NANCY GRACE ROMAN SPACE TELESCOPE

Understand the mechanism behind inflation

- Inflation seeded the **density fluctuations** that we can observe today
- **Primordial non-Gaussianities (PNG)**:
  - Deviations from the initial Gaussian density fluctuations. Consequence of many inflation models
  - Robust probe of dynamics during inflation
- Multiple types: different types of inflationary physics give rise to **higher-point correlations** peaked at different configurations —e.g. local, equilateral, orthogonal
- The size of PNG — $f_{\rm NL}$

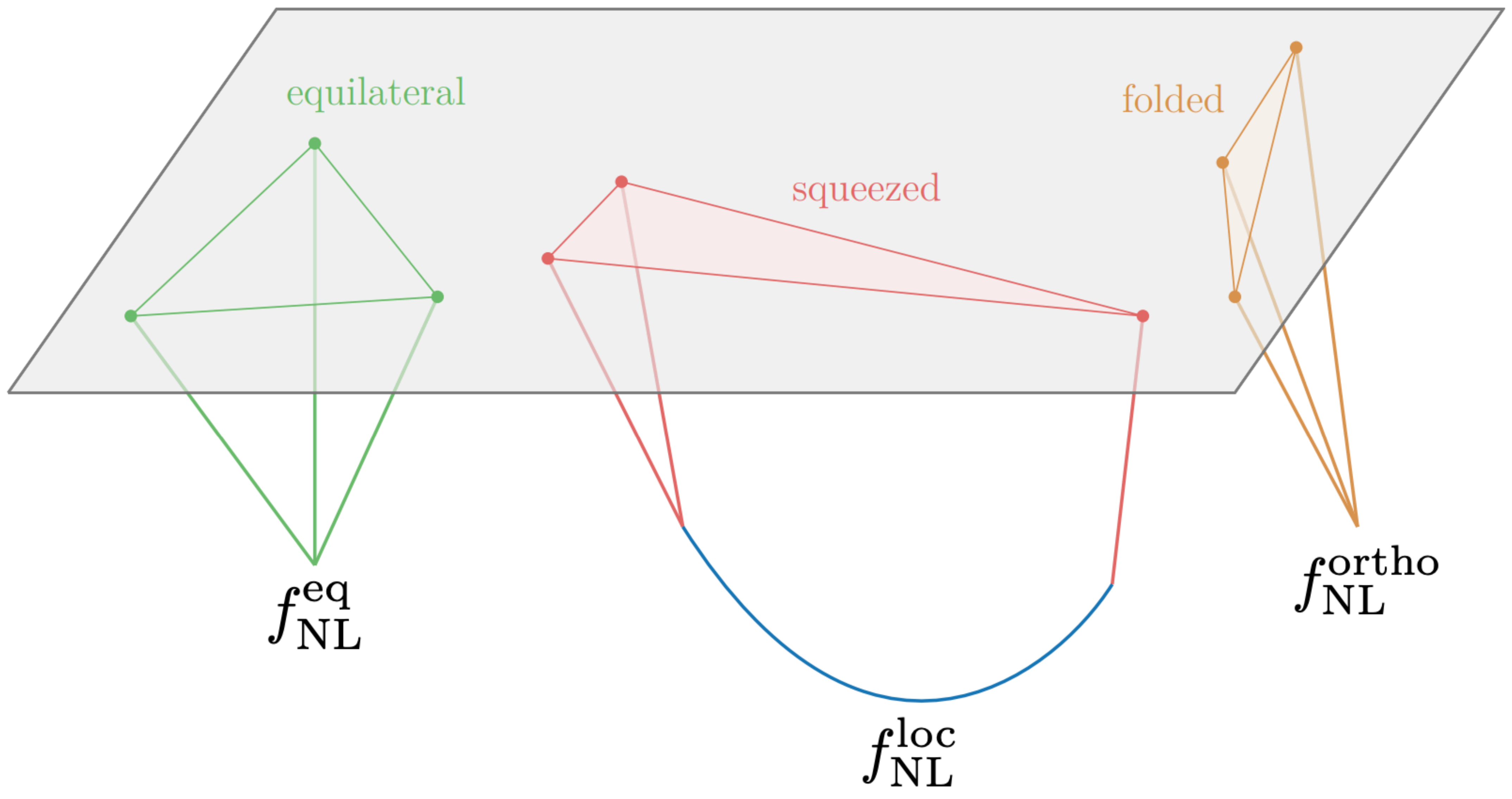


Image: A. Joyce

Local type $f_{\rm NL}^{\rm loc}$

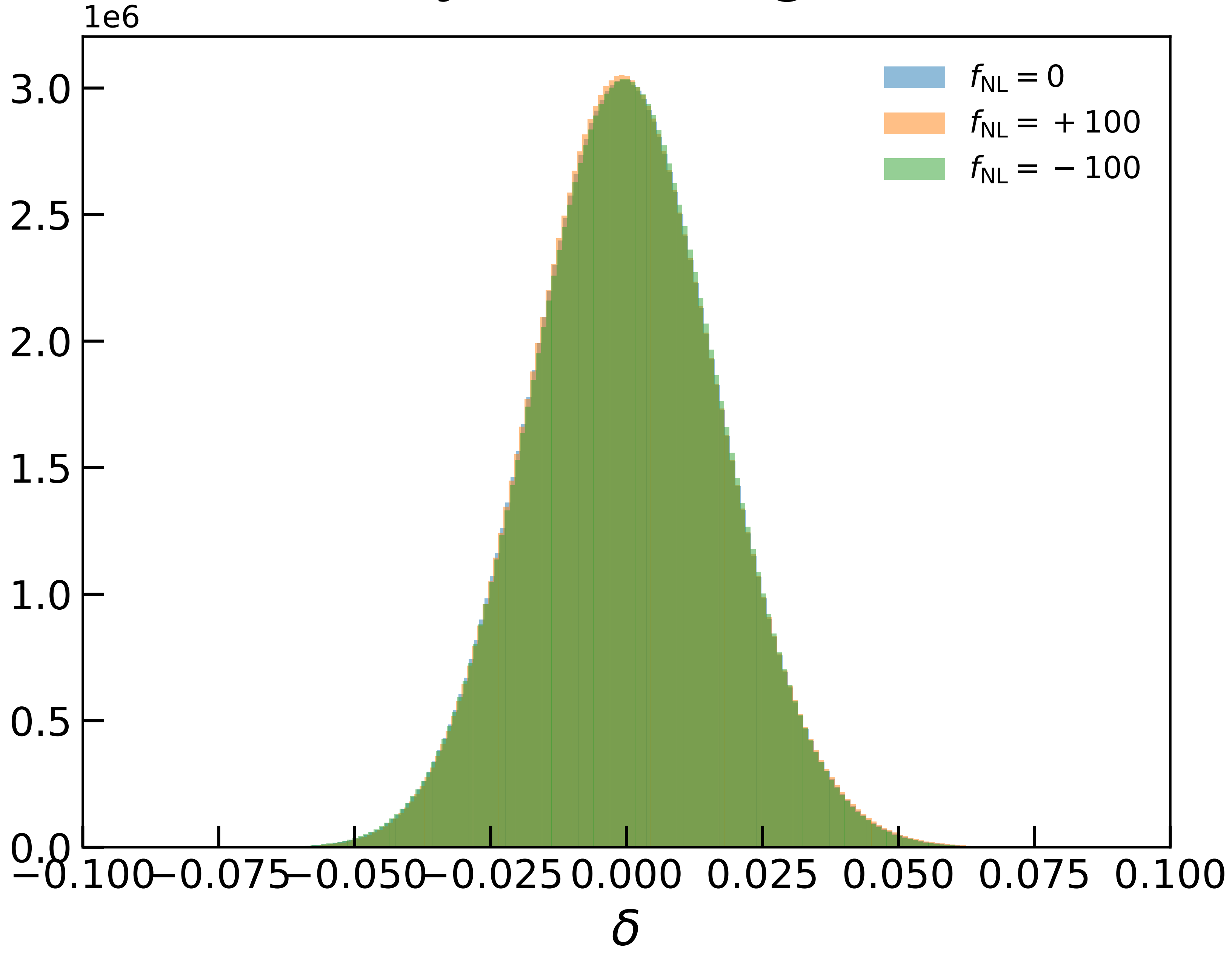
$$\Phi(\boldsymbol{x}) = \phi_G(\boldsymbol{x}) + f_{\rm NL}^{\rm loc}\{\phi_G^2(\boldsymbol{x}) - \langle\phi_G^2(\boldsymbol{x})\rangle\} + \ldots$$

Primordial potential   Gaussian field

- Sensitive probe of **multi-field models**
- Multi-field: $|f_{\rm NL}^{\rm loc}| > 1$, single field $|f_{\rm NL}^{\rm loc}| < 0.01$

A sensitivity of $|f_{\rm NL}^{\rm loc}| < 1$: $\sigma(f_{\rm NL}^{\rm loc}) < 1$

Very small signal

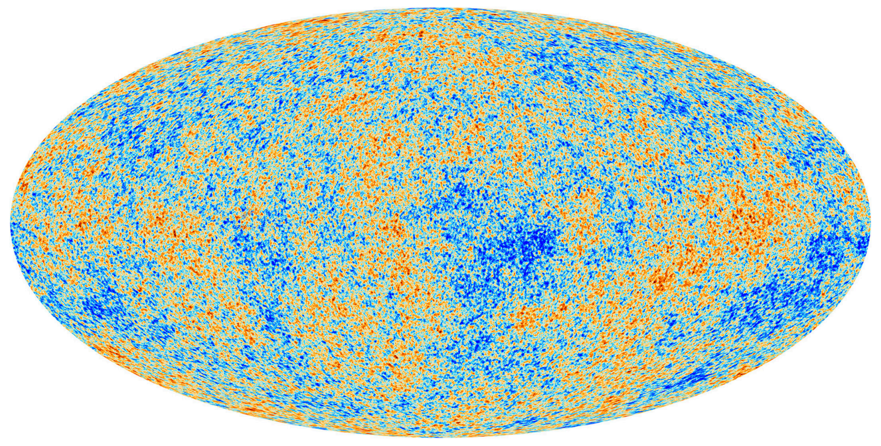


Matter density field at z=127 using Quijote simulations (Villaescusa-Navarro et al. 2020)

Equilateral type $f_{\rm NL}^{\rm eq}$

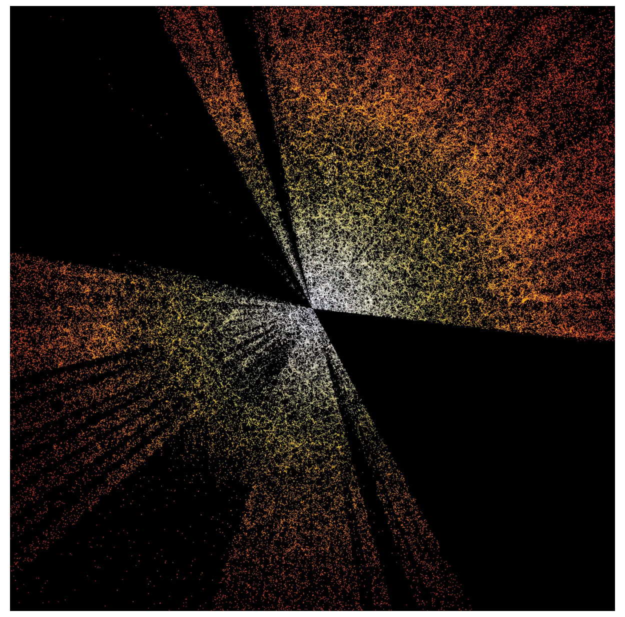
- A probe of the self-coupling of the inflaton and its strong-coupling scale
- Theoretical threshold: $f_{\rm NL}^{\rm eq} \sim 1$: $\sigma(f_{\rm NL}^{\rm eq}) < 1$
- Hard to measure: signal more contaminated by gravitational nonlinearity

Status of measurement with CMB

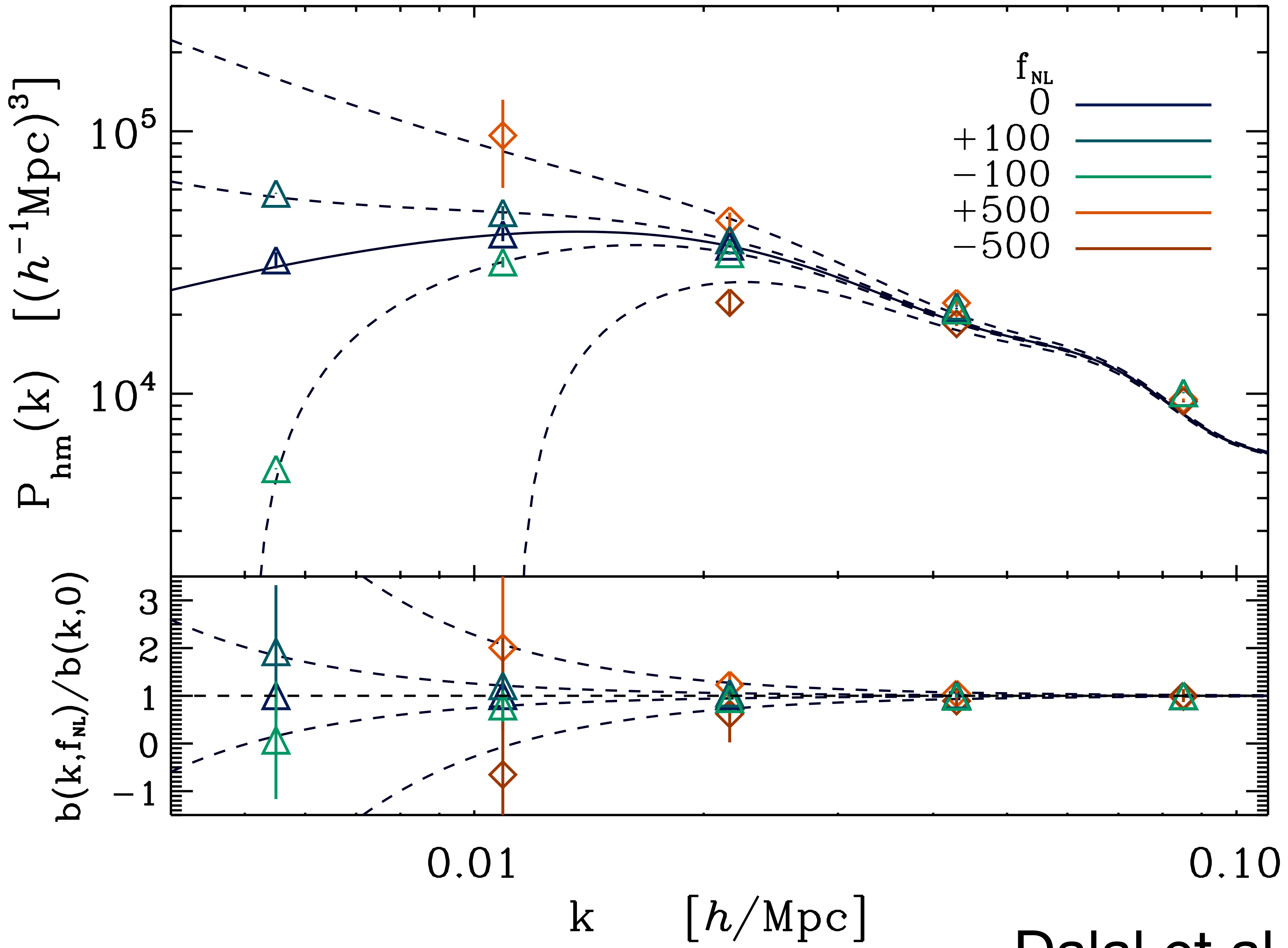


- Current best:
  - $f_{\rm NL}^{\rm loc}$ = 0.9±5.1 (*Planck* Collaboration 2020)
  - $f_{\rm NL}^{\rm eq}$ = -26±47 (*Planck* Collaboration 2020)
- Limited by **2D** nature
- Only a factor of 2 improvement in future

Status of measurement with LSS



- Current best:
  - $f_{\mathrm{NL}}^{\mathrm{loc}}$ = -3.6±9.0 (DESI DR1 QSO+LRG P(k) only, Chaussidon et al. 2024)
  - $f_{\mathrm{NL}}^{\mathrm{eq}}$ = 260±300 / 207±292 (BOSS, Cabass et al. 2022, D'Amico et al. 2022)
- Many **more modes from 3D**
- Local type measurable in two-point statistics: scale-dependent bias on galaxy power spectrum
  - Systematics
  - **Cosmic variance** on large scales

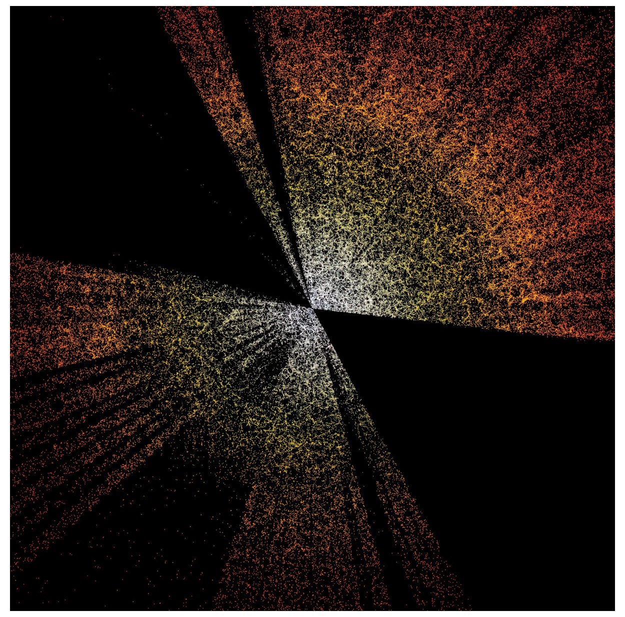


Dalal et al. 2008

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

Transfer function

Status of measurement with LSS



Bispectrum comes to rescue

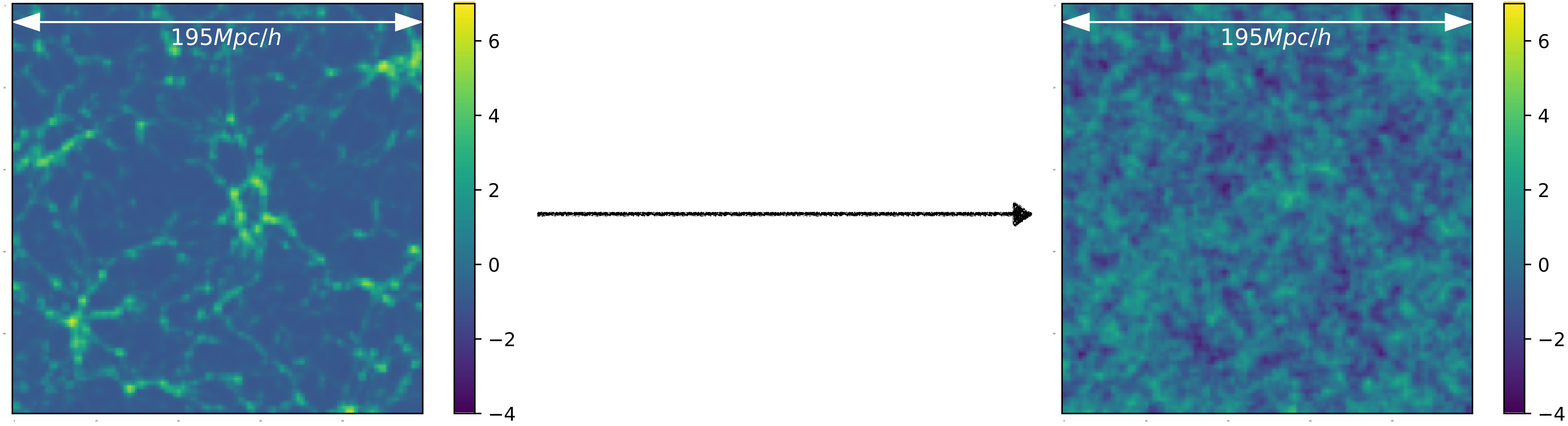
- Adding bispectrum for local -> tighter constraints
  - e.g. a factor of ~3 Pk -> Bk, a factor of ~4 Pk -> Pk+Bk (*SPHEREx*, Dore et al. 2014)
- All other types need bispectrum
- Large bispectrum from gravity → Reconstruction
- Large data vectors

→ Near-optimal 2-pt bispectrum estimator

New approach to constraining PNG

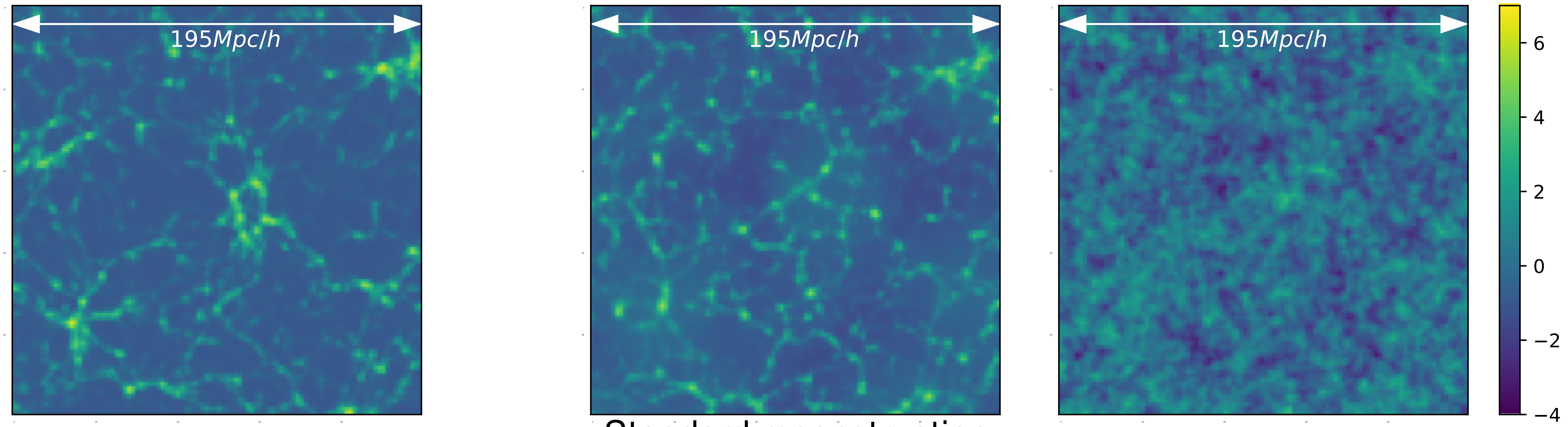
- Reconstructing the density field
- Computing and fitting a near-optimal 2-pt bispectrum estimator

Reconstruction of the initial conditions



Normalized matter density fields at z=0, using Quijote simulations (Villaescusa-Navarro et al. 2020)

Density field reconstructed by the standard reconstruction algorithm still nonlinear



Late-time

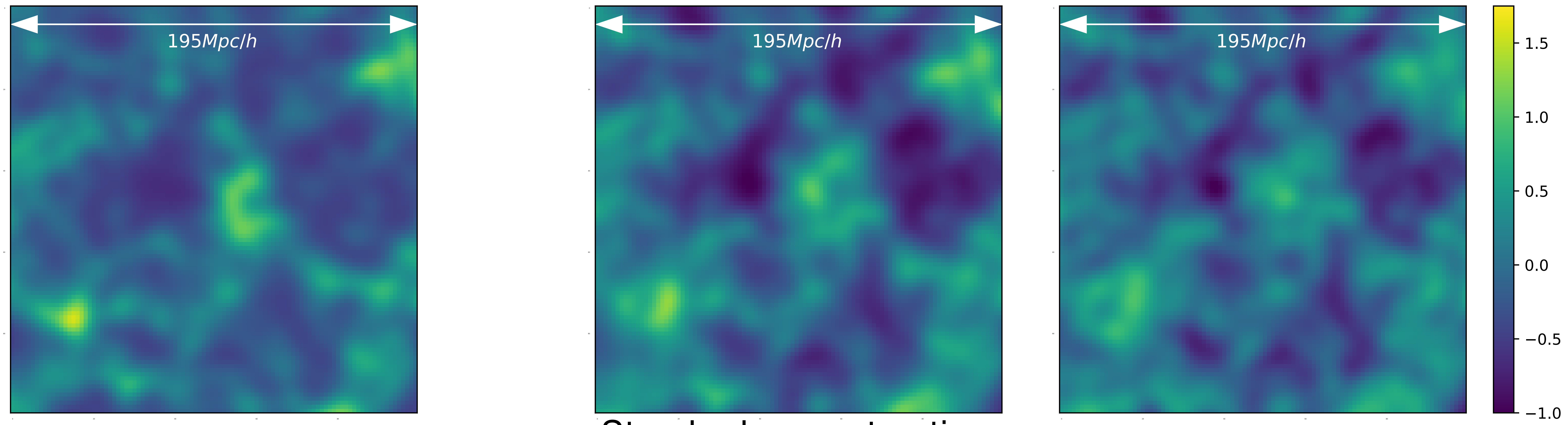
Standard reconstruction (Eisenstein et al. 2007)

Initial

Normalized matter density fields at z=0, using Quijote simulations (Villaescusa-Navarro et al. 2020)

Density field reconstructed by the standard reconstruction algorithm still nonlinear

Smoothed at 5 Mpc/h



Late-time

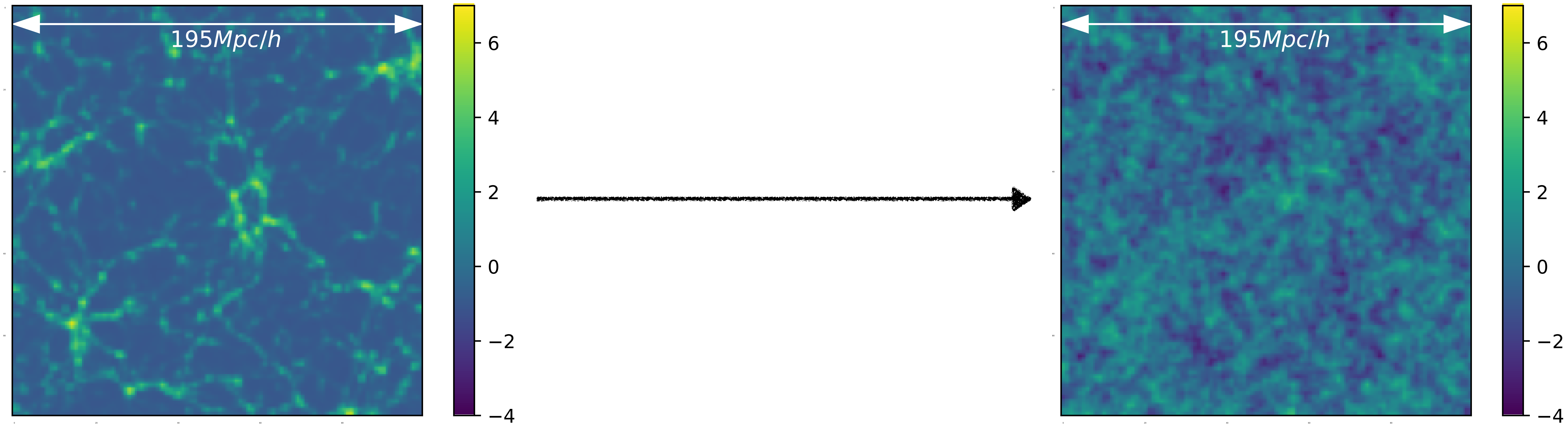
Standard reconstruction (Eisenstein et al. 2007)

Initial

Normalized matter density fields at z=0, using Quijote simulations (Villaescusa-Navarro et al. 2020)

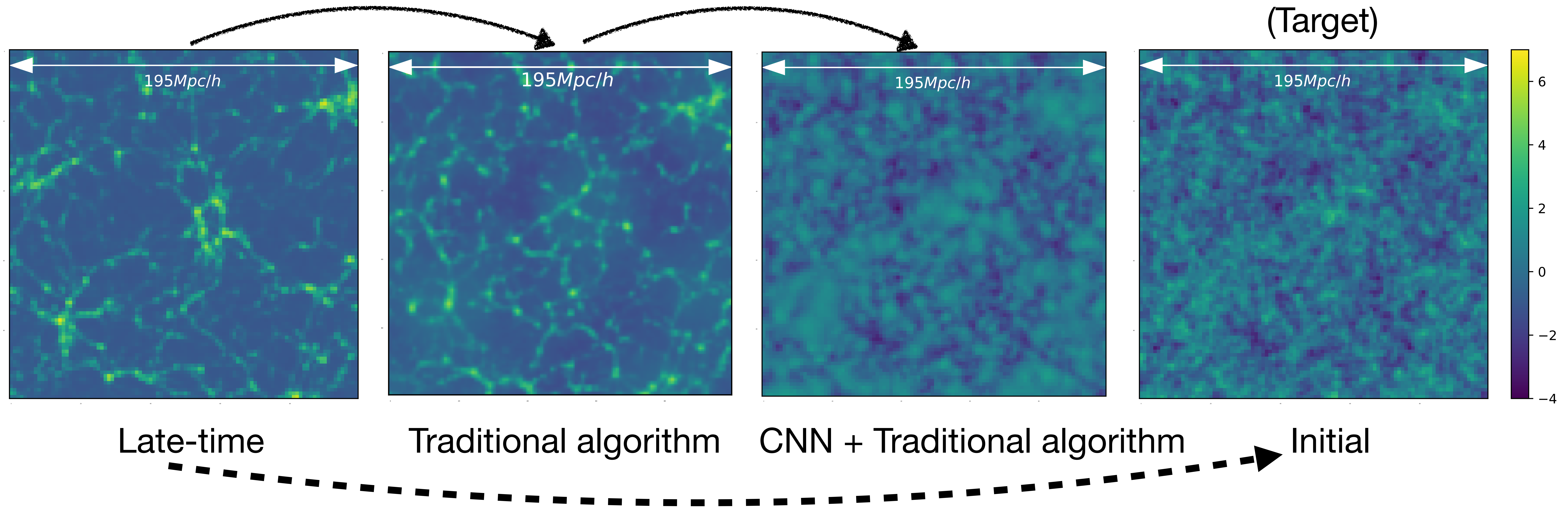
A new reconstruction method

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



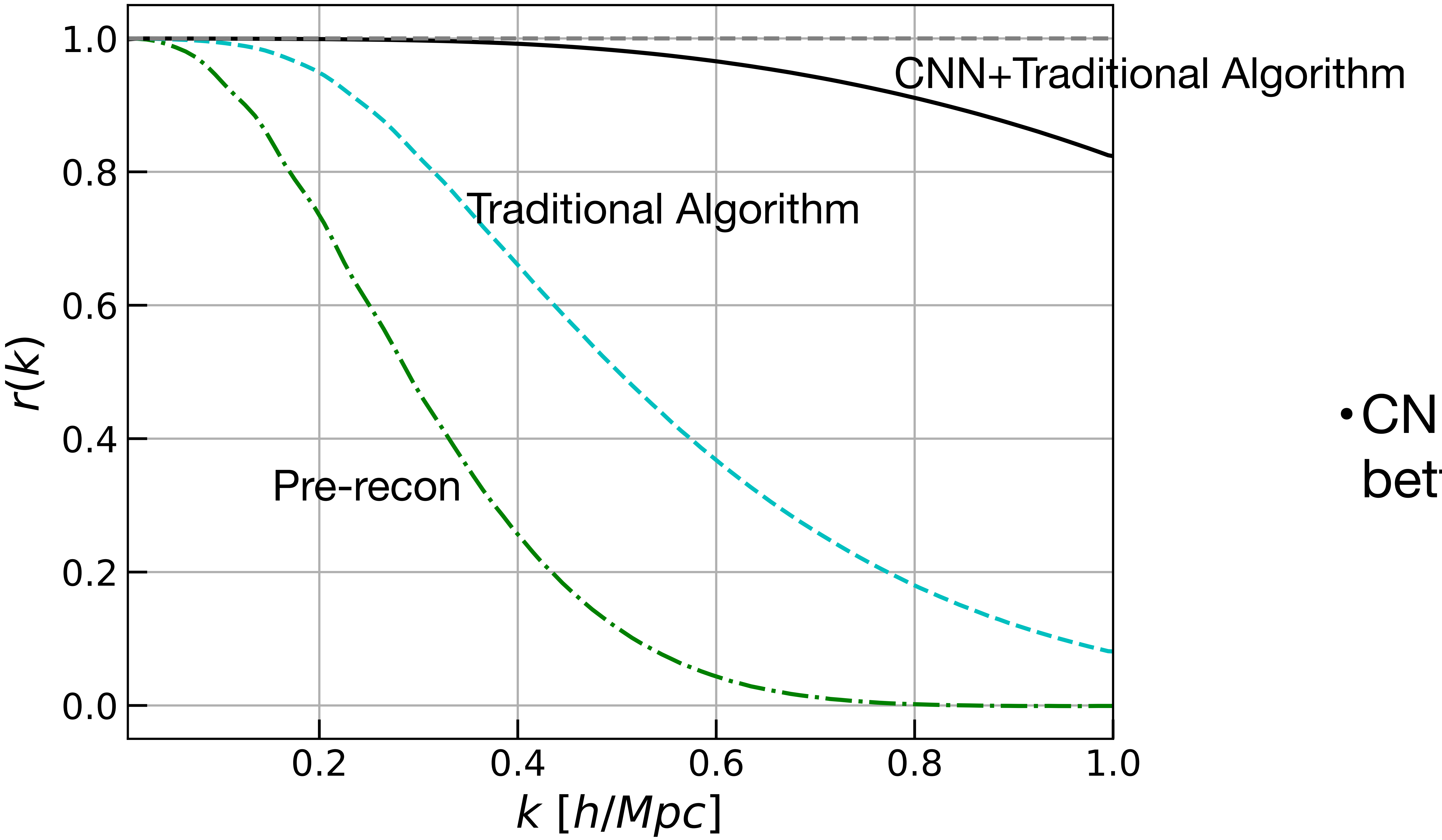
Large-scales use perturbation theory, small-scales use CNN

- 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.**



Normalized matter density fields at z=0, using Quijote simulations (Villaescusa-Navarro et al. 2020)

CNN improves cross-correlation in matter field



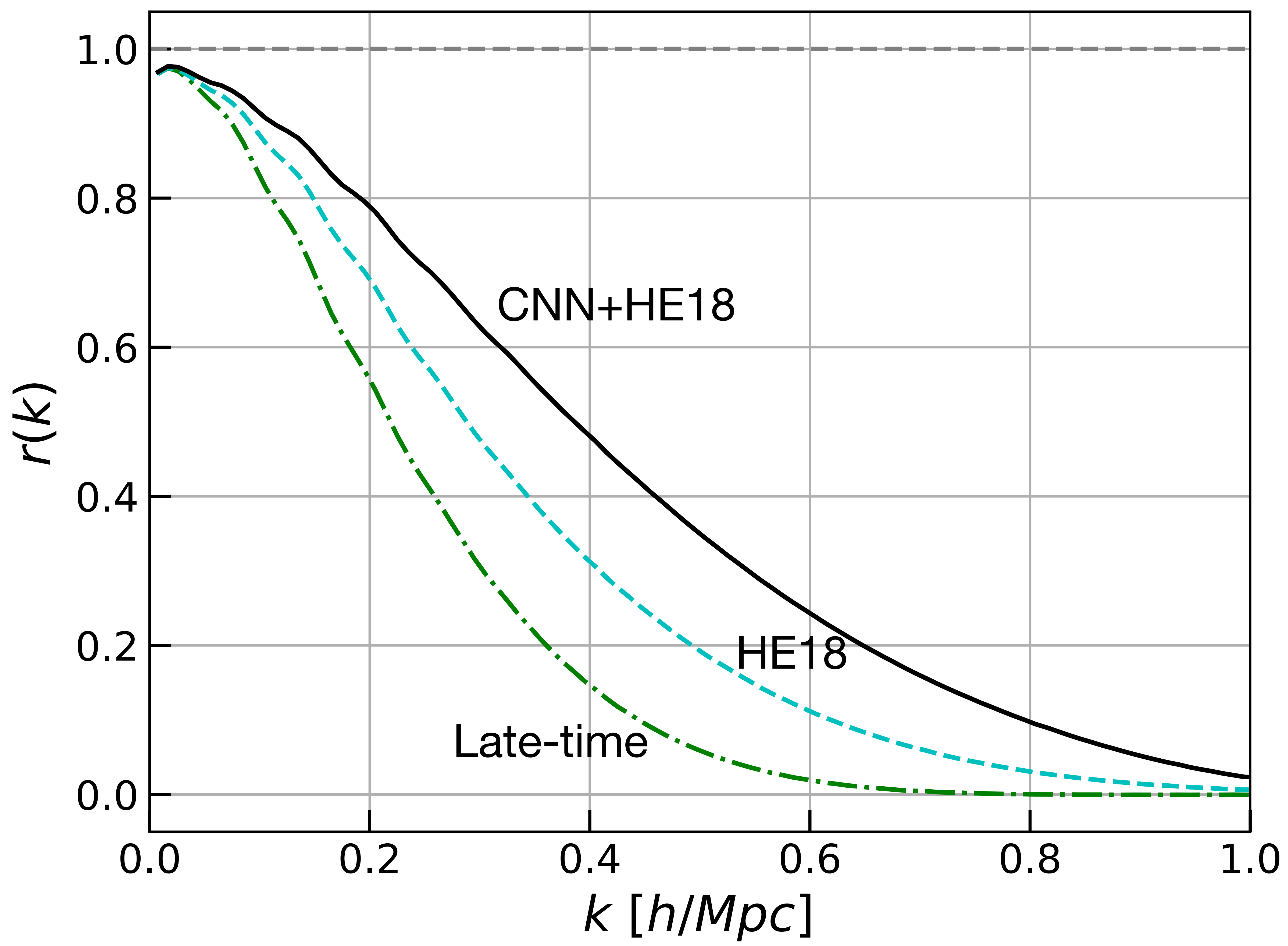
$$r(k) = \frac{\langle \delta^*(\boldsymbol{k})\delta_{\mathrm{ini}}(\boldsymbol{k})\rangle}{\sqrt{\langle \delta^2(\boldsymbol{k})\rangle\langle \delta_{\mathrm{ini}}^2(\boldsymbol{k})\rangle}}$$

- 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

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

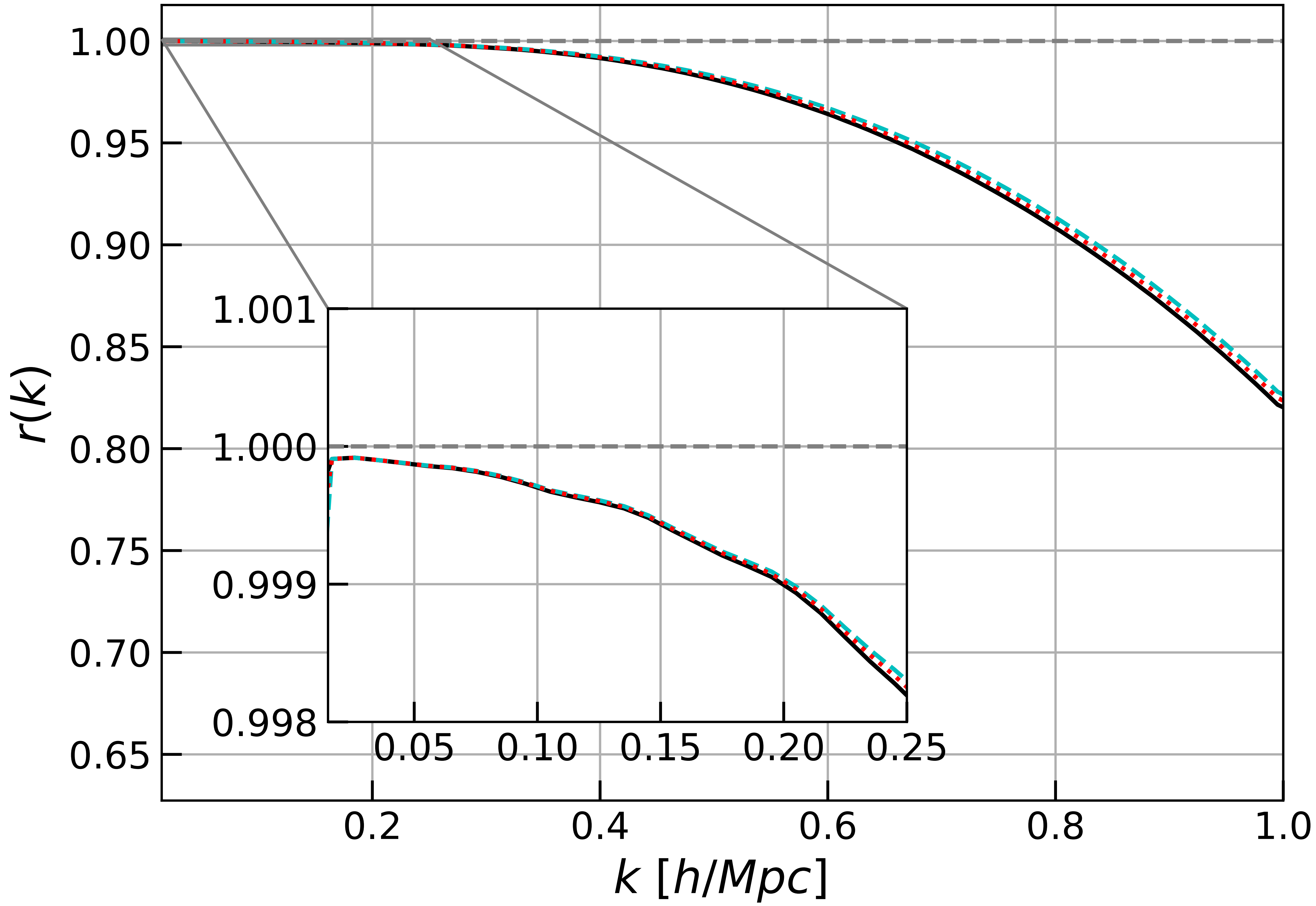
Similar to DESI Y1 LRG:
$b^2\bar{n} \sim 1.4 \times 10^{-3} h^3 \mathrm{Mpc}^{-3}$

Reconstruction algorithm used: Hada & Eisenstein 2018 (HE18)

Now adding PNG…

Three categories of sims: $f_{\mathrm{NL}} = 0, f_{\mathrm{NL}} = +100, f_{\mathrm{NL}} = -100$, matter density fields

Model trained with no PNG works for PNG



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

CNN+Algorithm

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

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

Reconstruction algorithm used: Hada & Eisenstein 2018

Cross-power estimator for local type

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

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

Gaussian potential

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

Reconstructed/Linear

Primordial potential

$$\Phi(\boldsymbol{k}) = \frac{\delta(\boldsymbol{k})}{M_\Phi(k)}$$

Transfer function

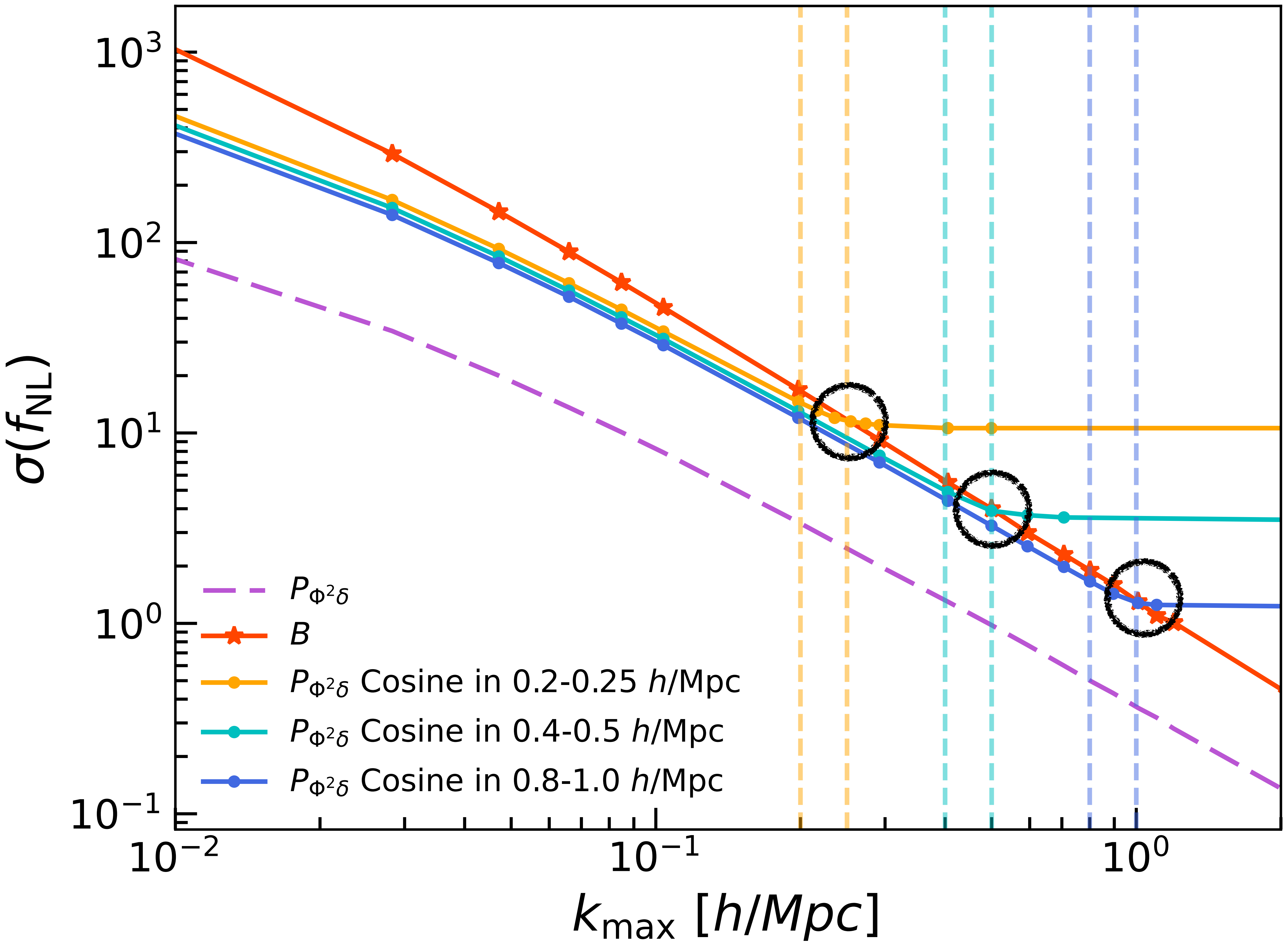
$$M_\Phi(k) = \frac{2}{3}\frac{k^2T(k)}{\Omega_{\rm m,0}H_0^2}$$

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

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

Primordial bispectrum

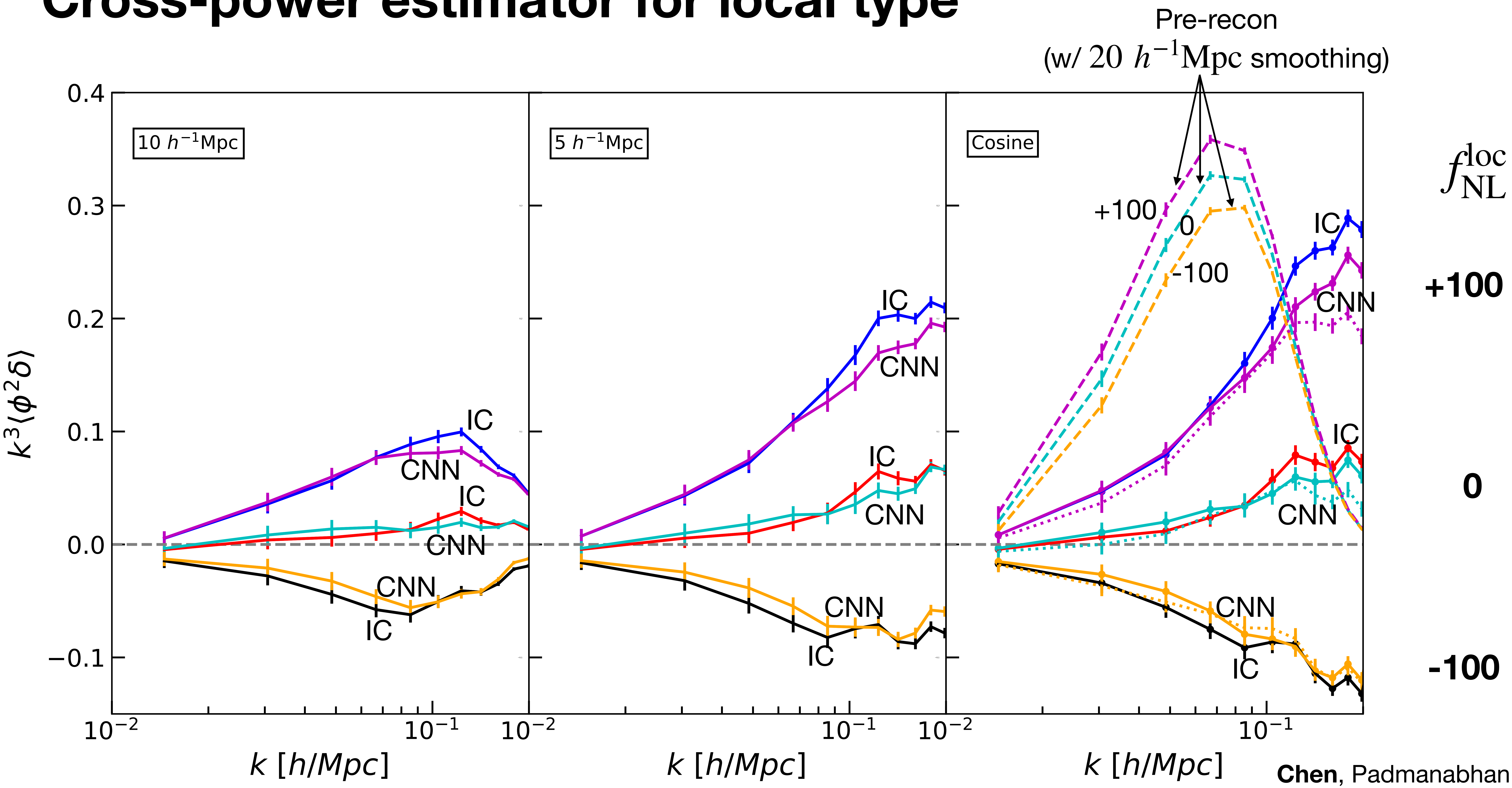
Optimality specifically for $\langle \Phi^2 \delta \rangle$



- Analytical calculation for a linear field
- When setting the integration limit as well as evaluating at a k the same as the bispectrum $k_{\max}$, $\langle \Phi^2 \delta \rangle$ have same information as the bispectrum

Chen, Padmanabhan & Eisenstein 2025

Cross-power estimator for local type



Chen, Padmanabhan & Eisenstein
2025

Cosine filter between
k=0.2-0.25 h/Mpc

Real space matter field z=1

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

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

1.5x

3x

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

Chen, Padmanabhan & Eisenstein 2025

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

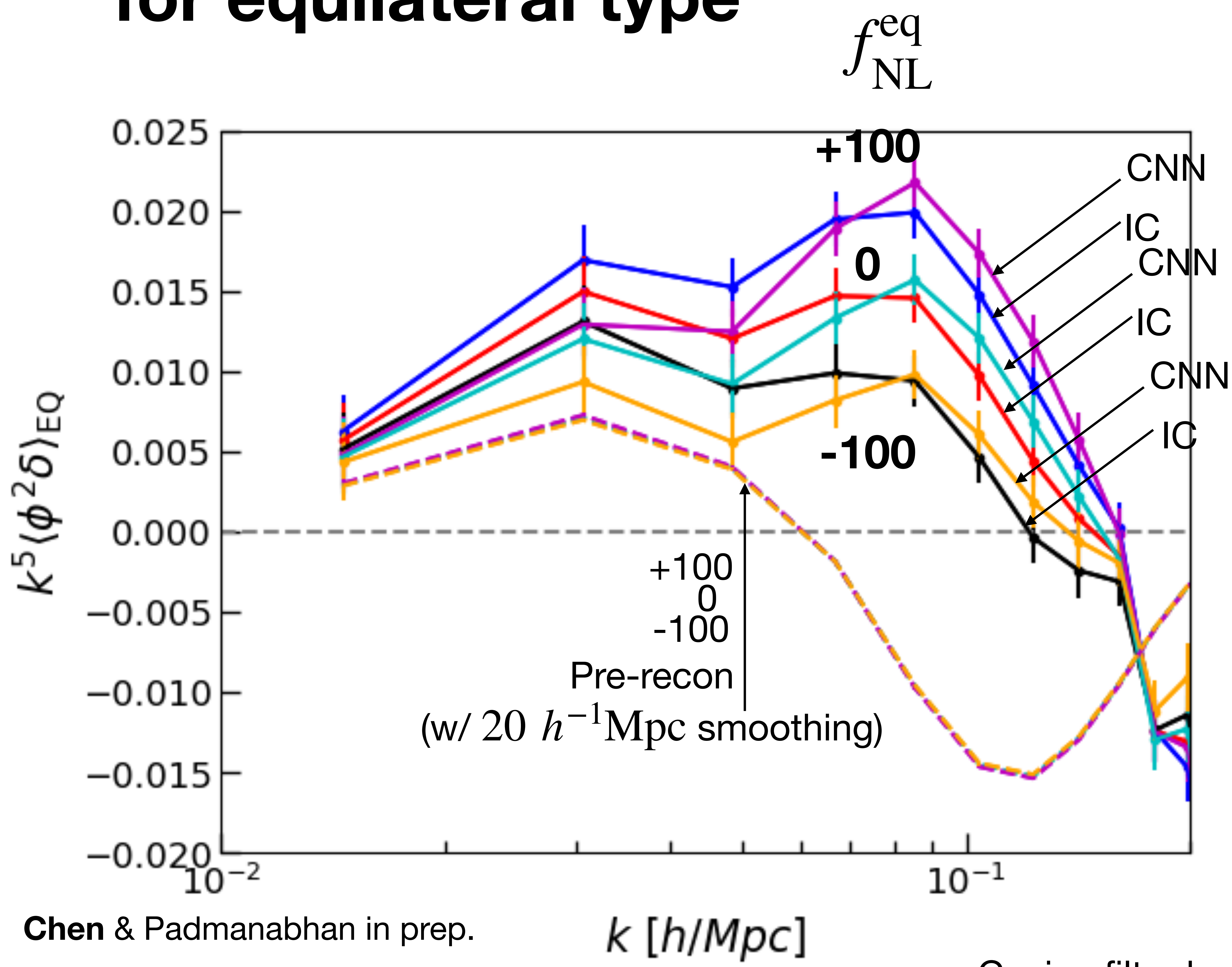
- Single parameter forecast: CNN+HE18 $\sigma(f_{\rm NL}^{\rm loc})$~50, pre-recon $\sigma(f_{\rm NL}^{\rm loc})$~76 ($k_{\rm max} = 0.1\ h/{\rm Mpc}$, z=1) — ~1.5x improvement
- Hybrid reconstruction allows higher $k_{\rm max}$ -> **getting larger volume is less necessary**
- Optimistic without including gravitational bias terms (squared, shift, tidal) -> can compute similar cross-power estimators

Cross-power estimator for equilateral type

$\langle \Phi^2 \delta \rangle_{\mathrm{EQ}}$ = sum of a few terms which are powers of P_Φ weighted Φ, squared, cross-correlated with powers of P_Φ weighted δ

$$\langle \mathrm{FFT} \left(\mathrm{IFFT} \left[\frac{\tilde{\Phi}(k)}{P_\Phi^n} \right] \right)^2 \frac{\tilde{\delta}(k)}{P_\Phi^m} \rangle$$

Cross-power estimator for equilateral type



Chen & Padmanabhan in prep.

Real space matter field z=1

Cosine filter between k=0.2-0.25 h/Mpc

- Smaller signal, large noise in equilateral type
- Differences still more distinguishable after reconstruction
- Bias also exists, needs careful calibration

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

$k_{\rm max}\ h/{\rm Mpc}$	Smoothing	IC	CNN+HE18	NL z=1
0.1	Cosine	151	134	698
0.2	Cosine	118	108	279

5x

1.2x

Chen & Padmanabhan in prep.

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

For DESI QSO survey volume (~2.9 Gpc/h): $\sigma(f_{\rm NL}^{\rm eq}) \sim 22$

- Single parameter forecast: CNN+HE18 $\sigma(f_{\rm NL}^{\rm eq})$~698, pre-recon $\sigma(f_{\rm NL}^{\rm eq})$~134 ($k_{\rm max} = 0.1\ h/{\rm Mpc}$, z=1) — ~5x improvement
- Optimistic without including gravitational bias terms

Summary

- Hybrid reconstruction removes most gravitational nonlinearity and strengthens the primordial signals
- Cross-power estimator is easy to compute and contains the same information of f_{NL} as the bispectrum
- Application of reconstruction on cross-power estimator gives lower $\sigma(f_{\mathrm{NL}})$ although slightly biased mean

Ongoing work and outlook

- Including quadratic gravitational bias terms in the model (estimate each bias term —growth, shift, tidal — with its own cross-power)
- Calibrating the bias in the measurement
- Applying to real data: high shot noise biased tracer

Thank you!😀