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

Xinyi Chen
Yale University

w/ Nikhil Padmanabhan, Daniel Eisenstein, Fangzhou (Albert) Zhu, and Sasha Gaines

DESI Lunch 10/11/23

Image: D. Schlegel

Planck, ACT, Simons Observatory, CMB-S4, …

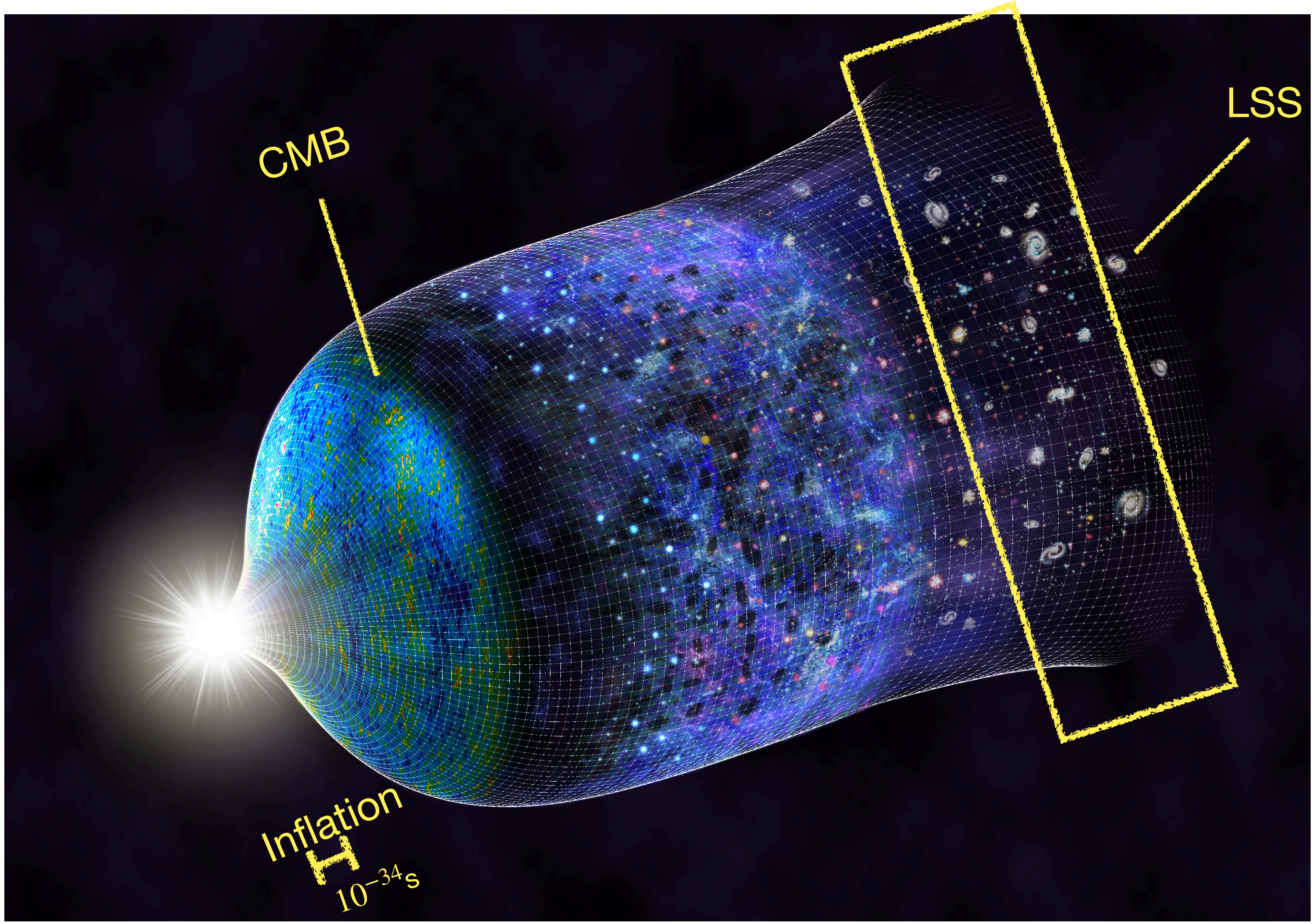


Image: Nicolle R. Fuller, National Science Foundation

DESI, *Euclid*, *Roman*, …

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
- f_{NL}: local, equilateral, orthogonal

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

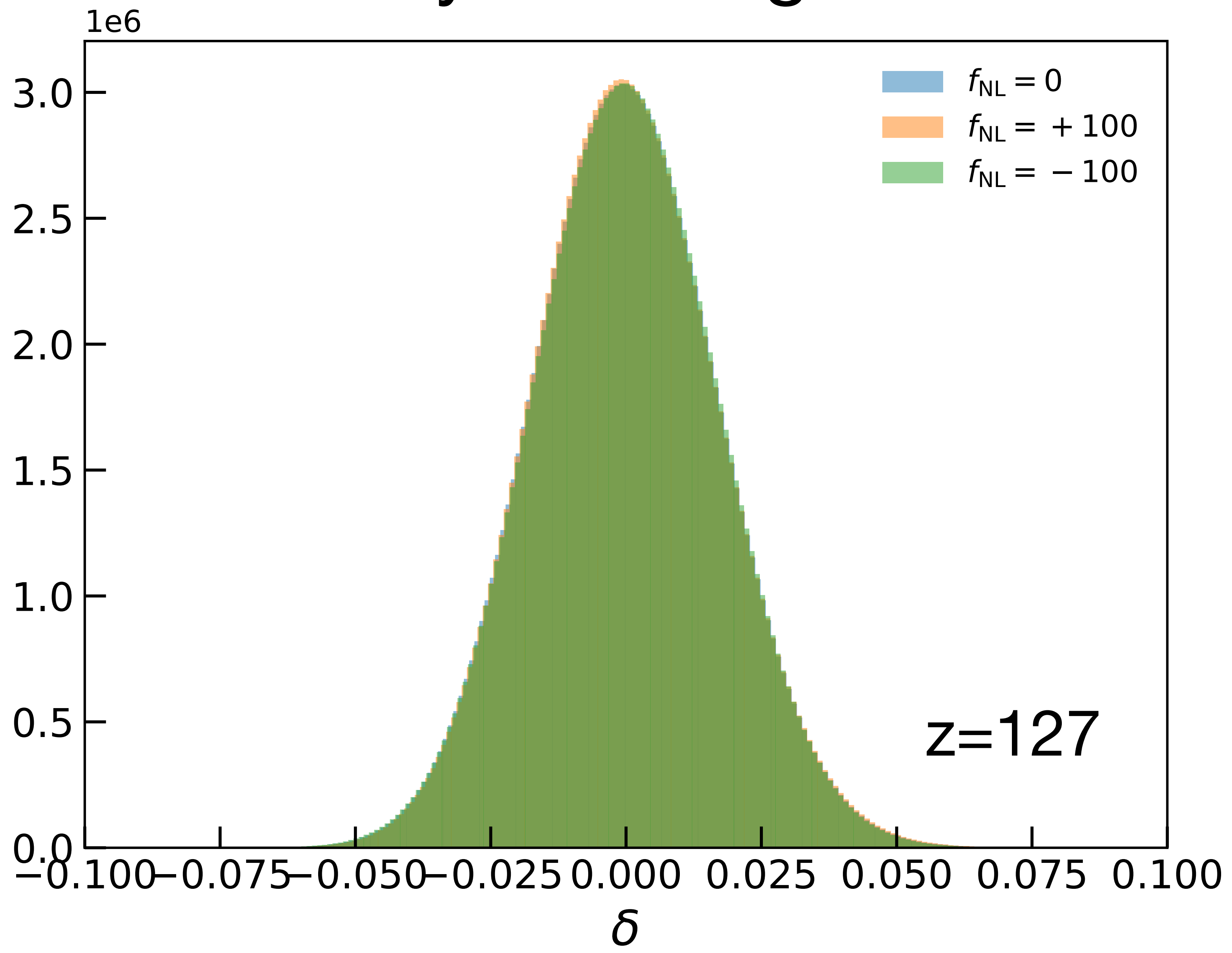
$$\Phi(\boldsymbol{x}) = \phi(\boldsymbol{x}) + f_{\rm NL}^{\rm loc}\{\phi^2(\boldsymbol{x}) - \langle\phi^2(\boldsymbol{x})\rangle\} + \ldots$$

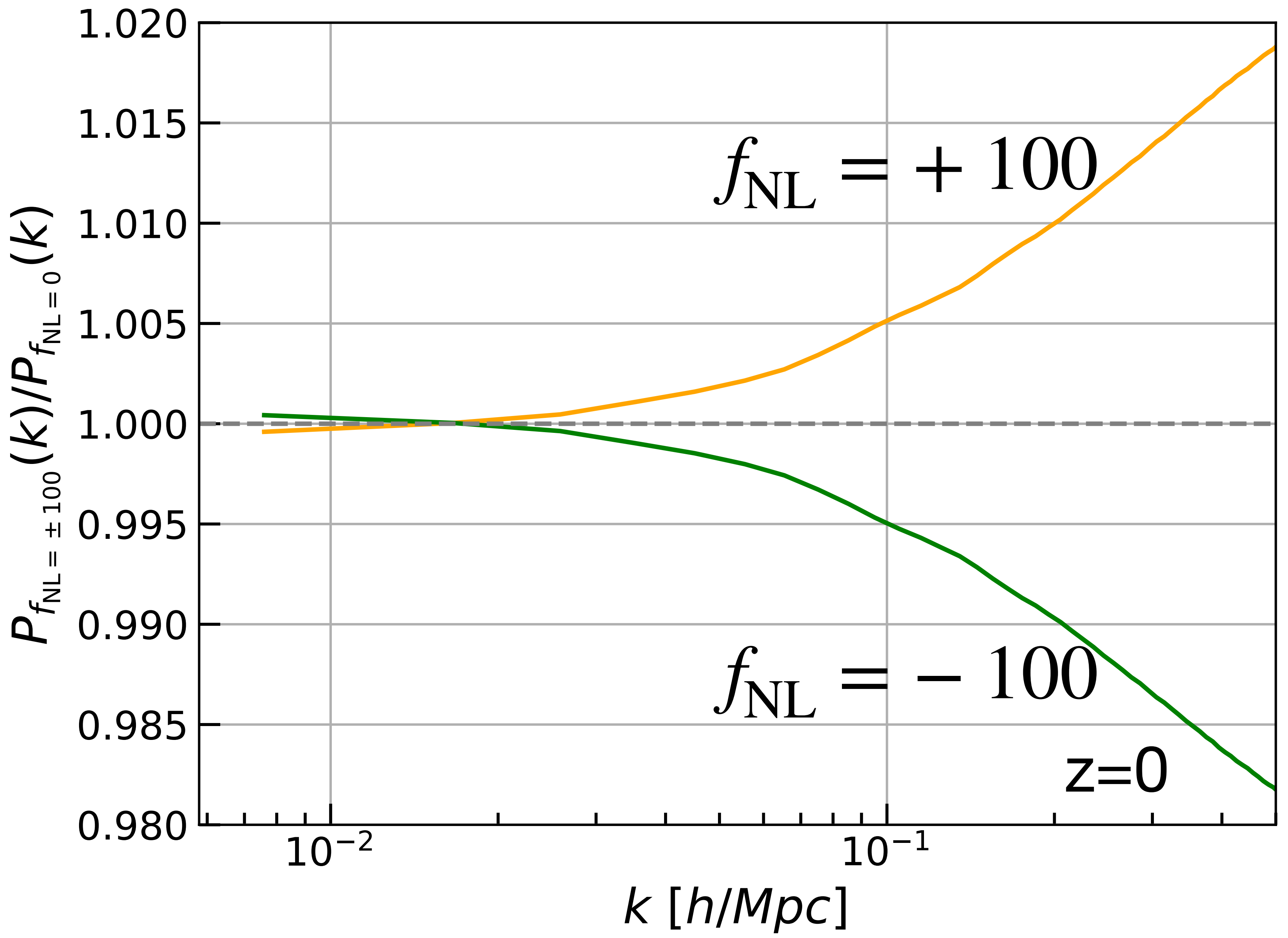
Primordial potential Gaussian field

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

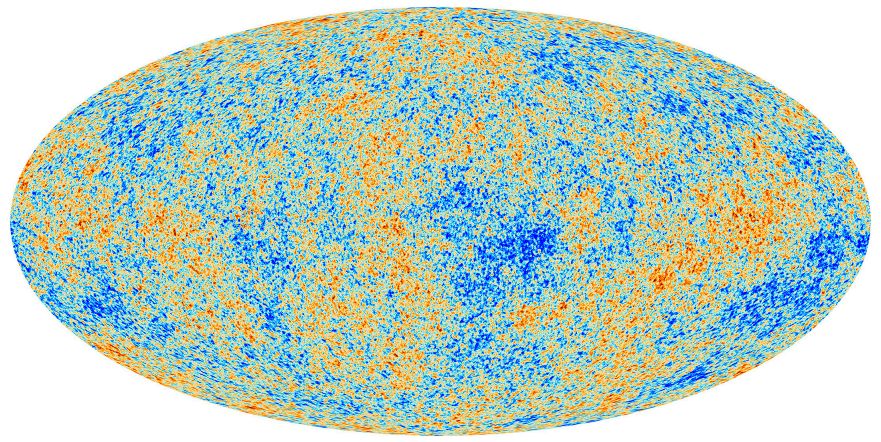
Very small signal





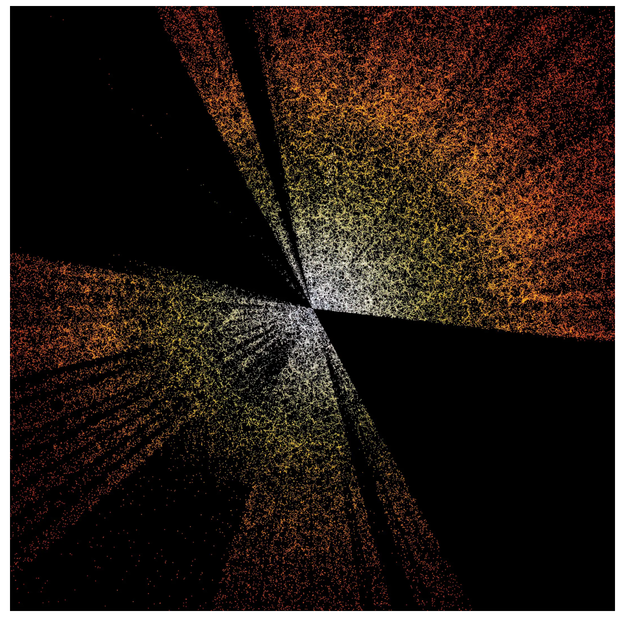
Matter density field

Status of CMB

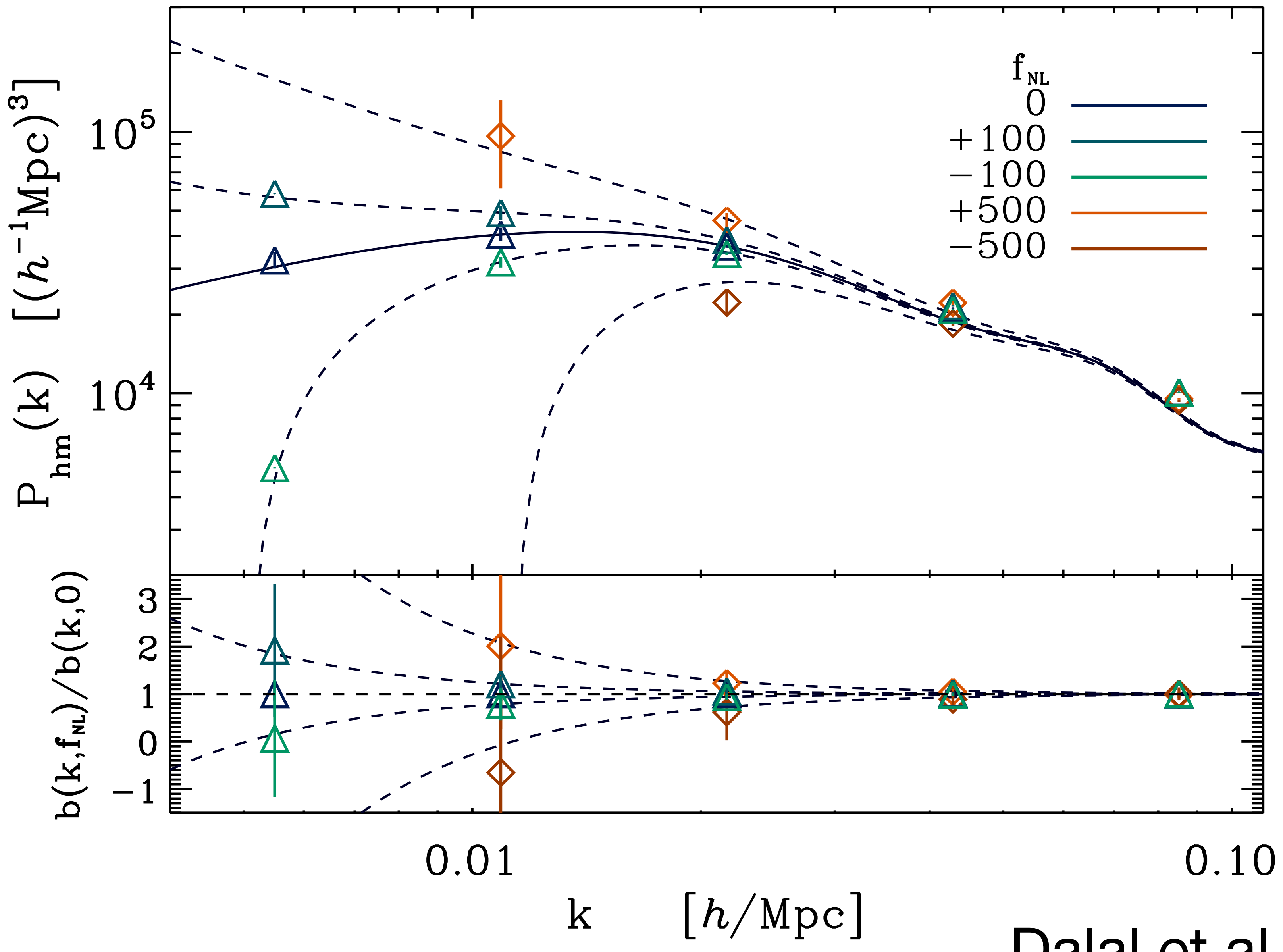


- Current best: 0.9±5.1 (Planck Collaboration 2020)
- Limited by **2D** nature
- Only a factor of 2 improvement in future
- CMB secondary probes x LSS

Status of LSS



- Current best: -12±21 (eBOSS DR16 QSO, Mueller et al. 2022)
- Many **more modes from 3D**
- Scale-dependent bias of 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**
  - A factor of ~3 Pk -> Bk, ~4 Pk -> Pk+Bk (e.g., Dore et al. 2014)
  - **Large data vectors**
  - **Large bispectrum from gravity**



Dalal et al. 2008

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

Transfer function

- Near-optimal bispectrum estimator
- Field level fits

Reconstruction

New approach to constrain PNG

- Reconstructing the density field
- Fitting templates at field level
- Computing and fitting a near-optimal bispectrum estimator

New approach to constrain PNG

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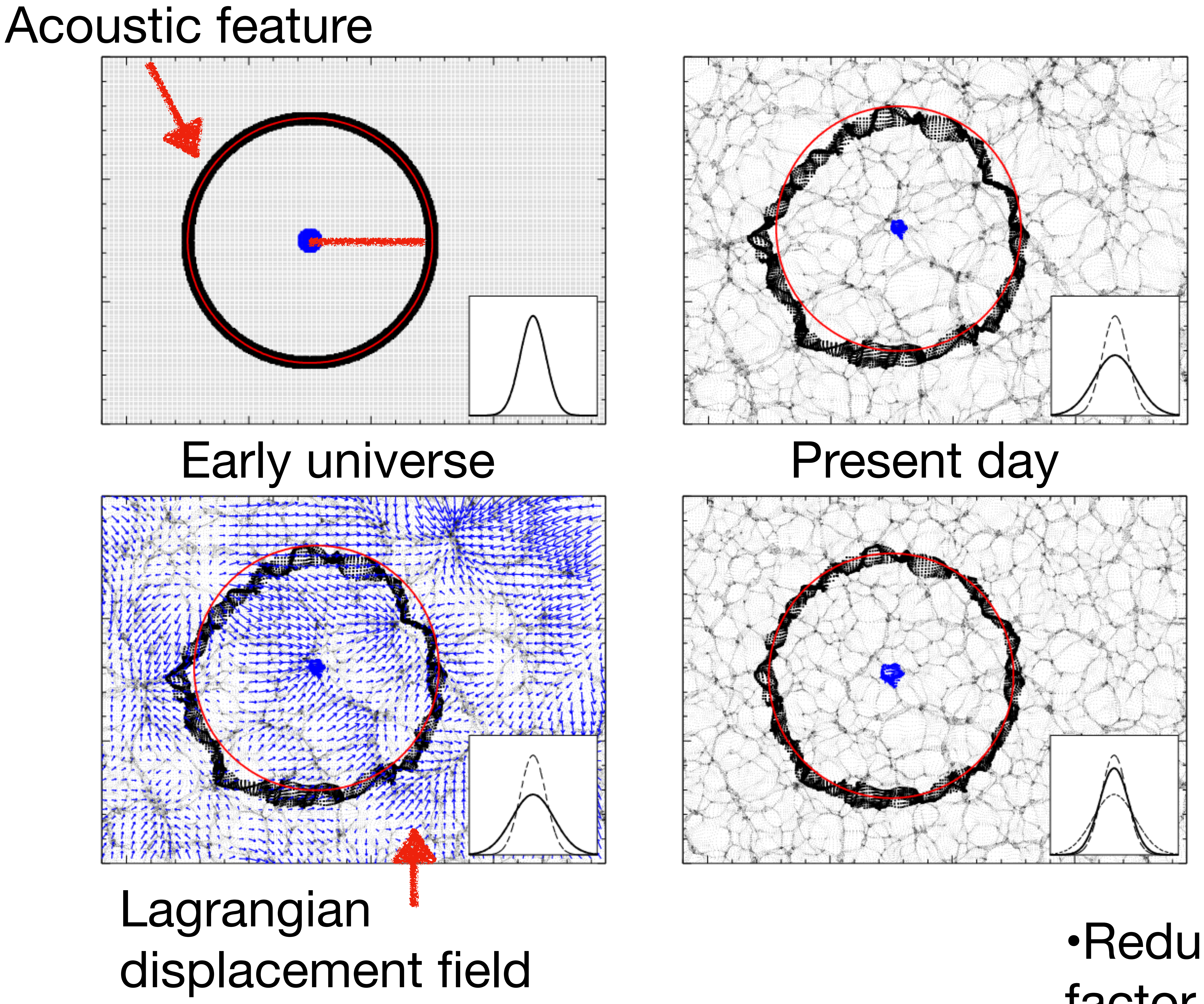
Reconstruction of the initial conditions: reverse a late-time density field back to initial density field



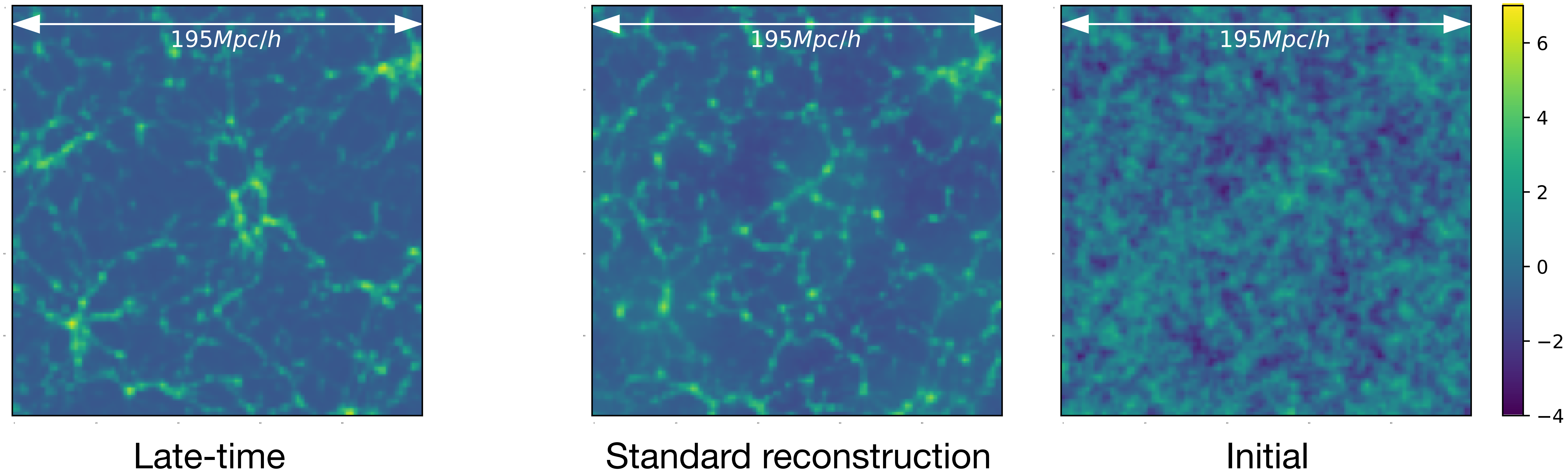
Padmanabhan et al. 2012

Idea behind standard reconstruction (Eisenstein et al. 2007)

- The initial density field in the early universe is very smooth
- As the universe evolves, the black points spread out which broadens the acoustic feature
- Estimate the displacement field and move the particles back to their initial positions.

- Reduces the distance error in BAO analysis by a factor of ~2

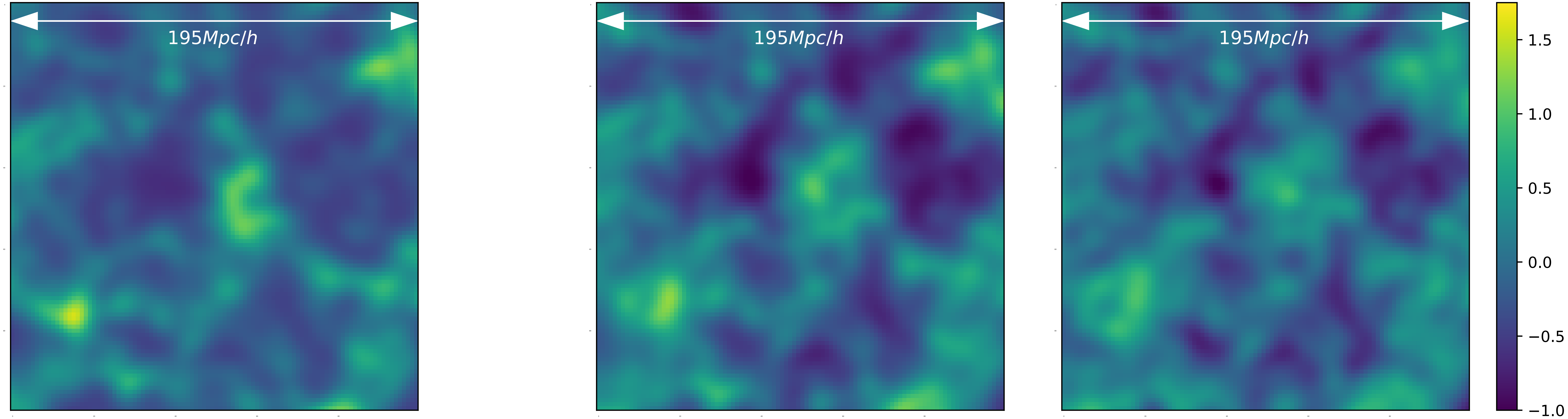
Density field reconstructed by the standard reconstruction algorithm still nonlinear



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

Smoothed at 5 Mpc/h



Late-time | Standard reconstruction | 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)

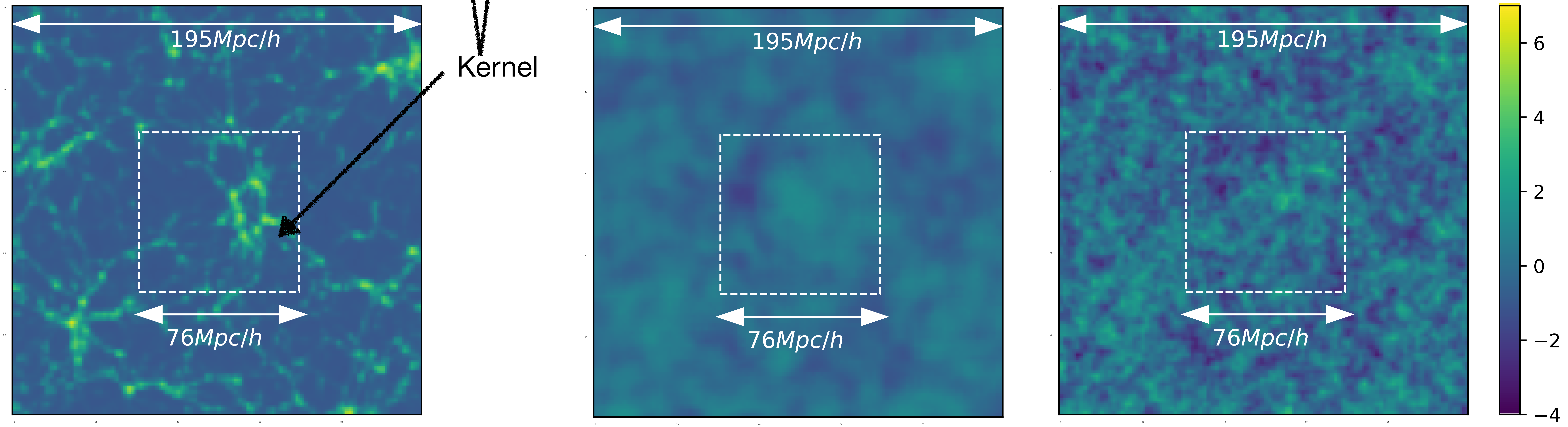
A new reconstruction method

A hybrid method that combines convolutional neural network (CNN) with traditional algorithm based on perturbation theory

Density field by CNN trained with late-time density field

- Considers neighbor points by grouping them in a batch
- Trains with 8 simulations, normalized field, with initial density field the target

Extract information from this volume to determine the reconstructed density at the center



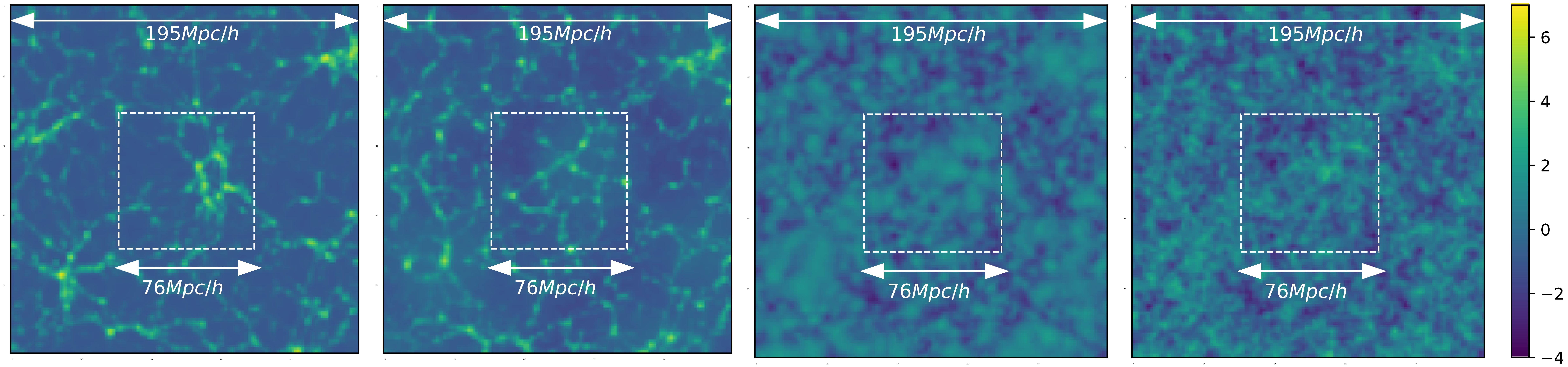
Late-time

CNN trained w/ late-time field

Initial

Training with *reconstructed* density field significantly improves performance

CNN is relatively local. Algorithm provides good approximation on large scale (Zel'dovich approximation is only valid for large scales). CNN then reconstructs further on smaller scales.



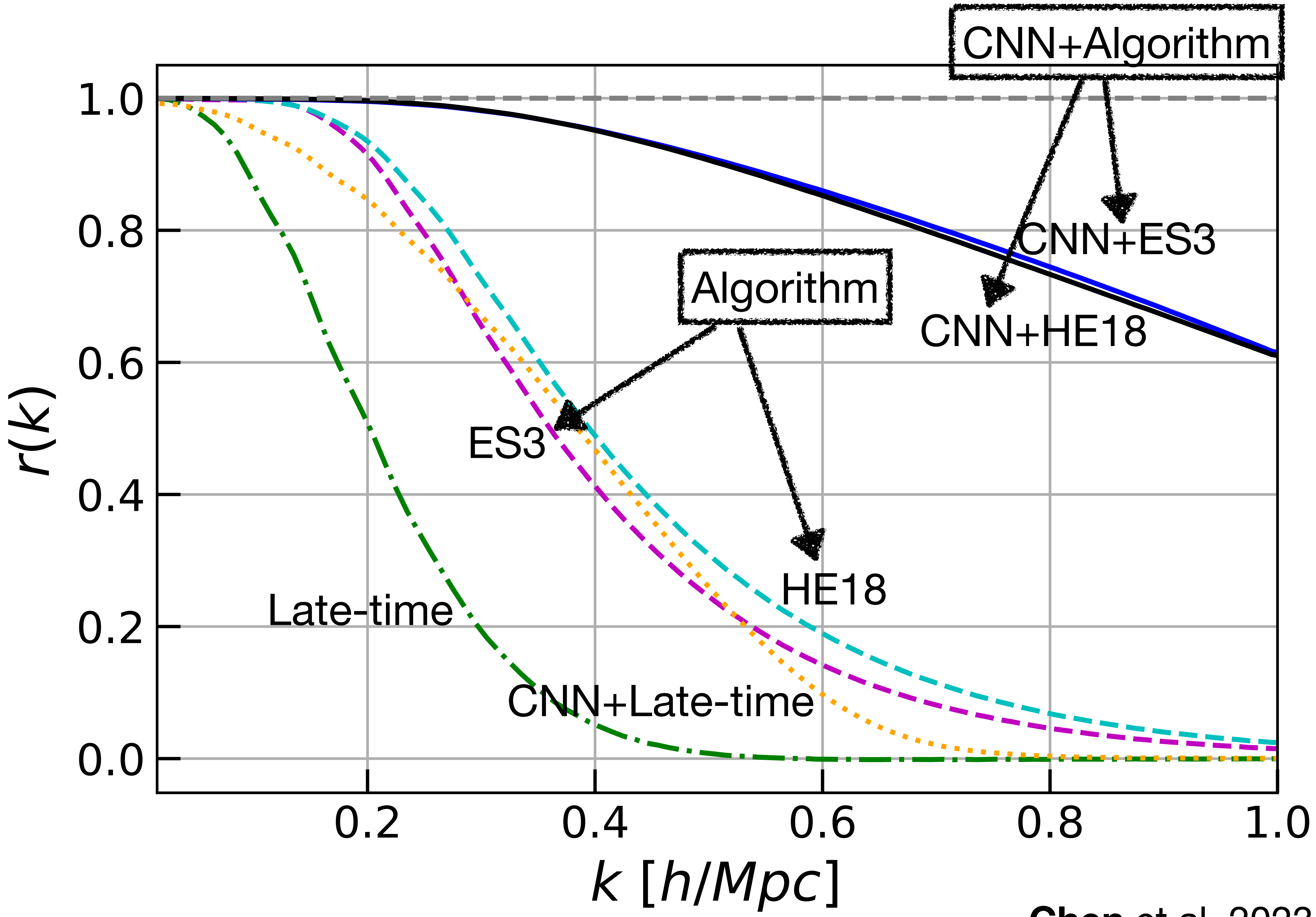
Late-time

Standard recon

CNN trained w/ standard recon field

Initial

CNN improves cross-correlation



Chen et al. 2023

Real space

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

- CNN+Algorithm performs significantly better than algorithms alone and CNN+Late-time density field
- CNN+ES3 and CNN+HE18 are similar

Two reconstruction algorithms:

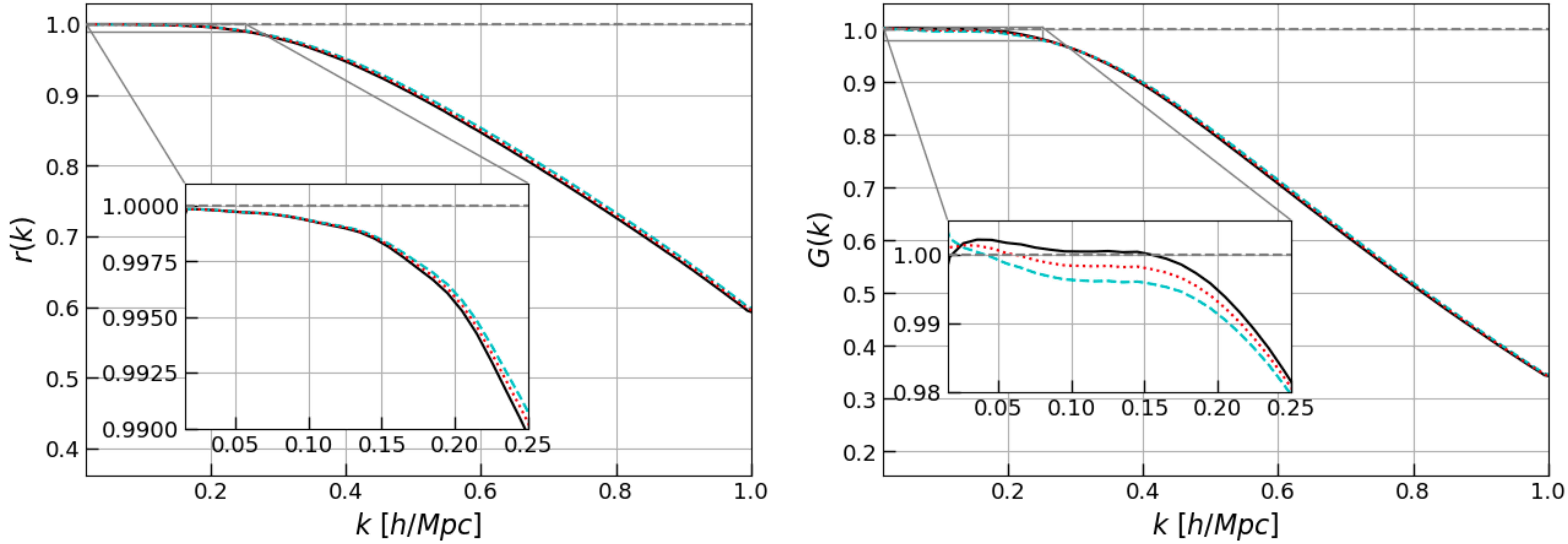
- Eisenstein et al. 2007, **ES3**, i.e., standard
- Hada & Eisenstein 2018, **HE18**

Now adding PNG…

Three categories of sims: $f_{\rm NL} = 0, f_{\rm NL} = +100, f_{\rm NL} = -100$

Model trained with no PNG works for PNG

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



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

— $f_{\rm NL} = +100$

⋯ $f_{\rm NL} = 0$

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

CNN+HE18

New approach to constrain PNG

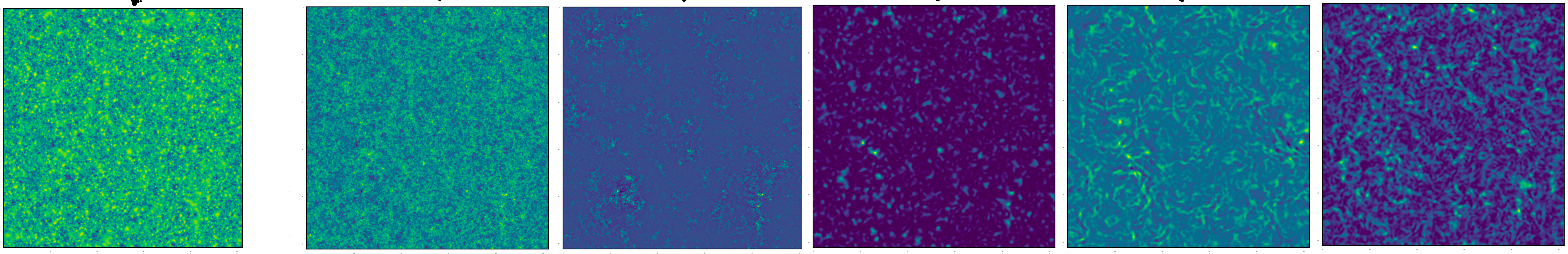
- Reconstructing the density field
- **Fitting templates at field level**
- Computing and fitting a near-optimal bispectrum estimator

Templates for fitting $f_{\rm NL}$

- δ_G=No PNG IC
- $\delta_{f_{\rm NL}} = \phi_G^2(k) M_\phi(k)$
- δ^2,δ_{∇^2},δ_{s^2} all computed using δ_G

Gaussian Growth Shift Tidal

$$\delta_{\rm CNN} = b_G \delta_G + f_{\rm NL} \delta_{f_{\rm NL}} + b_2 \delta^2 + b_{\nabla^2} \delta_{\nabla^2} + b_{s^2} \delta_{s^2} + \ldots$$



Small error but fits are slightly biased

- Errors in 1 Gpc volume, std of 90 sims
- With 5 Mpc/h smoothing for the quadratic fields
- k cut at 0.1 h/Mpc

z=0

CNN	b_G	$f_{\rm NL}$	b_2	b_{∇^2}	b_{s^2}
$f_{\rm NL}=0$	0.9995±0.0007	-15.2±4.7	0.006±0.001	-0.014±0.001	0.014±0.001
$f_{\rm NL}=+100$	1.0011±0.0007	77.5±4.8	0.005±0.001	-0.015±0.001	0.014±0.001
$f_{\rm NL}=-100$	0.9980±0.0007	-107.4±4.6	0.007±0.001	-0.014±0.001	0.013±0.001

Chen, Padmanabhan & Eisenstein in prep.

Accounting for the shift in the mean at $f_{\rm NL}=0$:

$f_{\rm NL}=100$: ~92

$f_{\rm NL}=-100$: ~-92

For >2 Gpc survey volume (e.g. DESI):

$\sigma(f_{\rm NL})\sim 2$

Small error but fits are slightly biased

- Errors in 1 Gpc volume, std of 90 sims
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z=0

CNN	b_G	$f_{\rm NL}$	b_2	b_{∇^2}	b_{s^2}
$f_{\rm NL}=0$	0.9995±0.0007	-15.2±4.7	0.006±0.001	-0.014±0.001	0.014±0.001
$f_{\rm NL}=+100$	1.0011±0.0007	77.5±4.8	0.005±0.001	-0.015±0.001	0.014±0.001
$f_{\rm NL}=-100$	0.9980±0.0007	-107.4±4.6	0.007±0.001	-0.014±0.001	0.013±0.001

Chen, Padmanabhan & Eisenstein in prep.

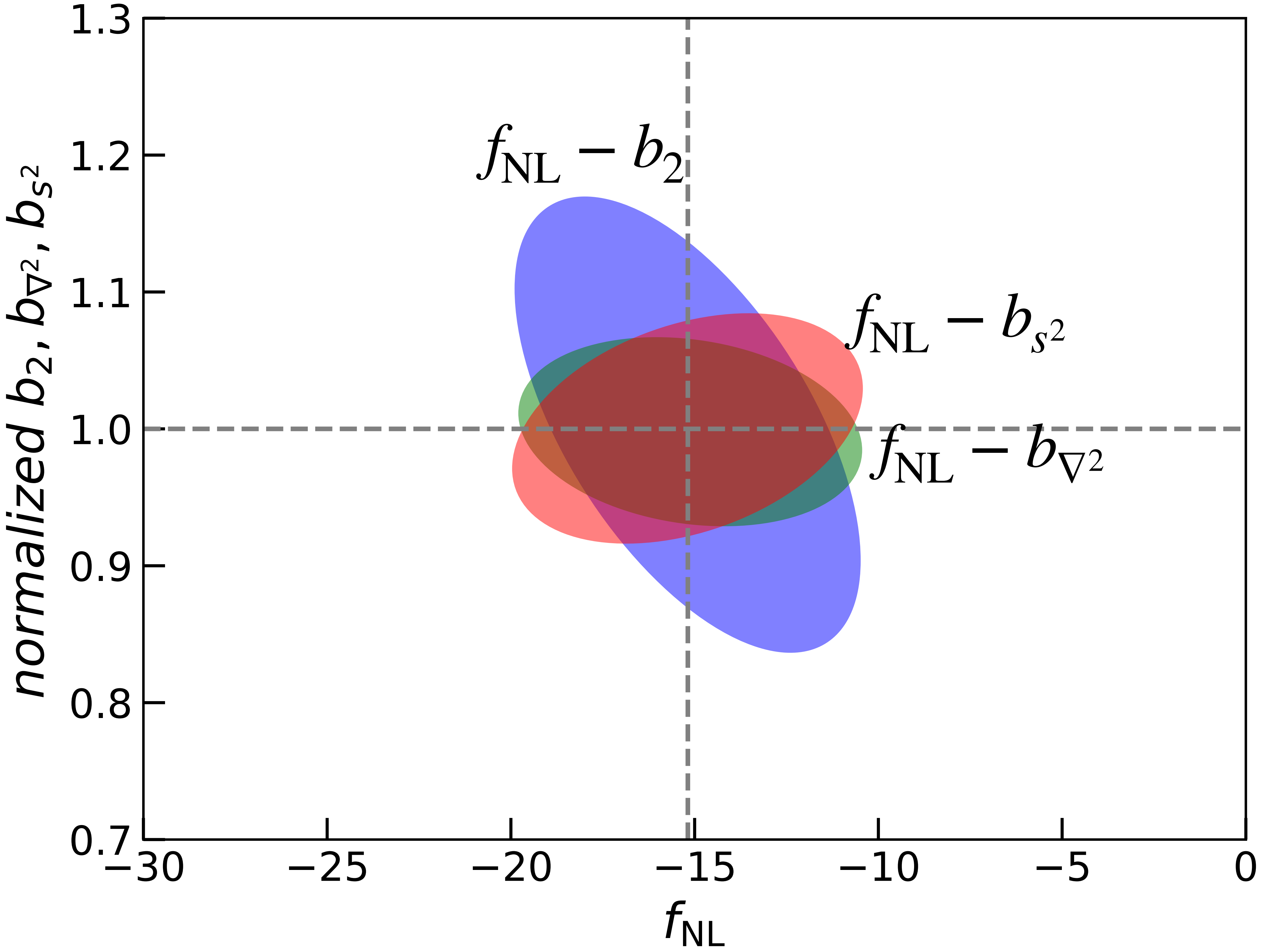
- k cut at 0.05 h/Mpc

Nonlinear	b_2	b_{∇^2}	b_{s^2}
$f_{\rm NL}=0$	0.825±0.006	-1.018±0.008	0.188±0.005
$f_{\rm NL}=+100$	0.825±0.007	-1.018±0.010	0.188±0.005
$f_{\rm NL}=-100$	0.825±0.006	-1.018±0.007	0.188±0.005

From F2 kernel: $b_2=\dfrac{17}{21}\sim 0.81$ $\quad b_{\nabla^2}=-1$ $\quad b_{s^2}=\dfrac{4}{21}\sim 0.19$

Strong degeneracy between $f_{\rm NL}$ and b_2

1-σ covariance ellipse



$f_{\rm NL} = 0$

Cross-correlation coefficient between

$f_{\rm NL} - b_2$: ~-0.6

$f_{\rm NL} - b_{\nabla^2}$: ~-0.2

$f_{\rm NL} - b_{s^2}$: ~0.4

New approach to constrain PNG

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

Near optimal bispectrum estimator

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

Primordial potential

Reconstructed/Linear

Transfer function

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

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

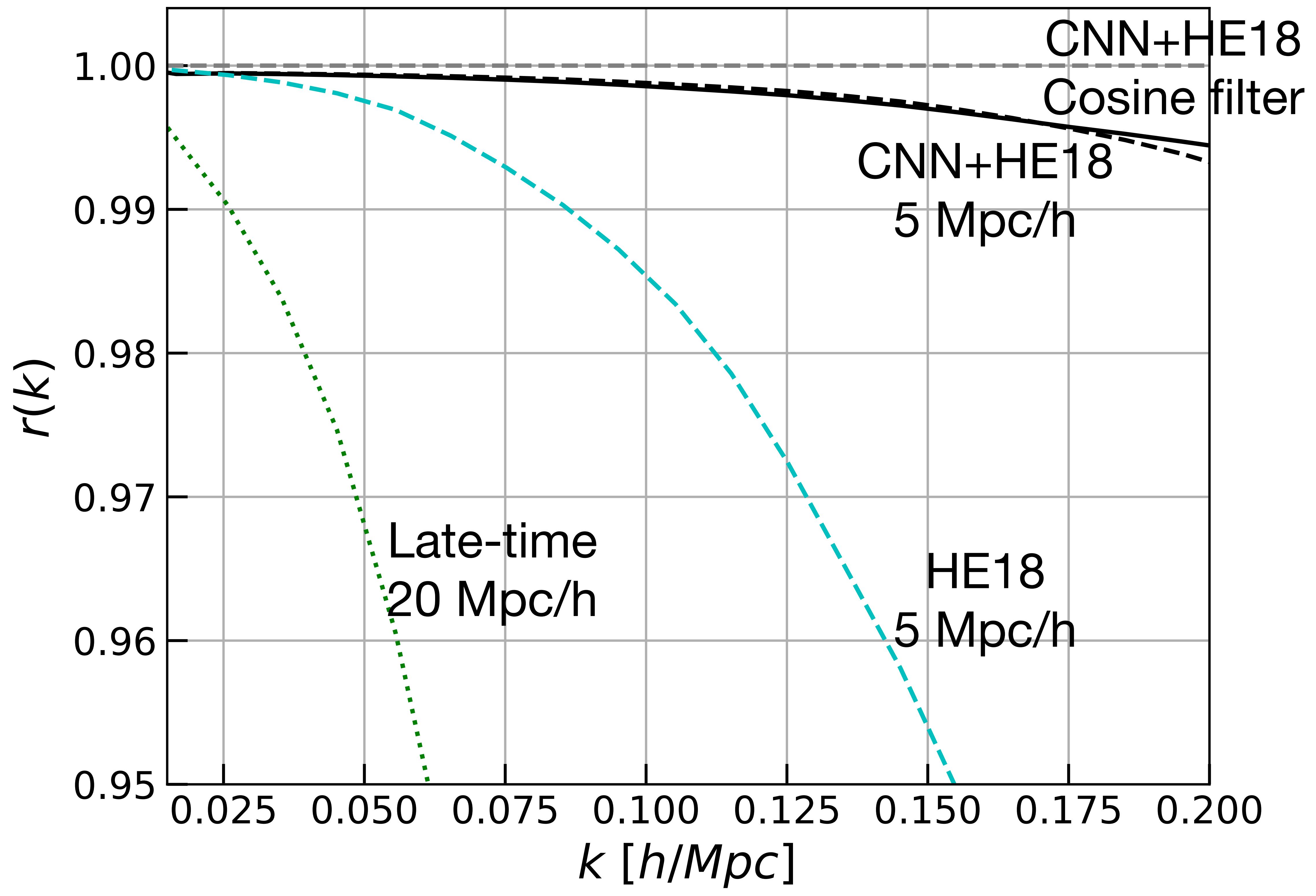
$$\langle \Phi^2(\boldsymbol{k})\delta(-\boldsymbol{k})\rangle = \frac{1}{(2\pi)^3} \int \mathrm{d}\boldsymbol{k}_1 M_\Phi(-\boldsymbol{k}) \underbrace{\boxed{\langle \Phi(\boldsymbol{k})\Phi(\boldsymbol{k}-\boldsymbol{k}_1)\Phi(-\boldsymbol{k})\rangle}}_{\text{Primordial bispectrum}}$$

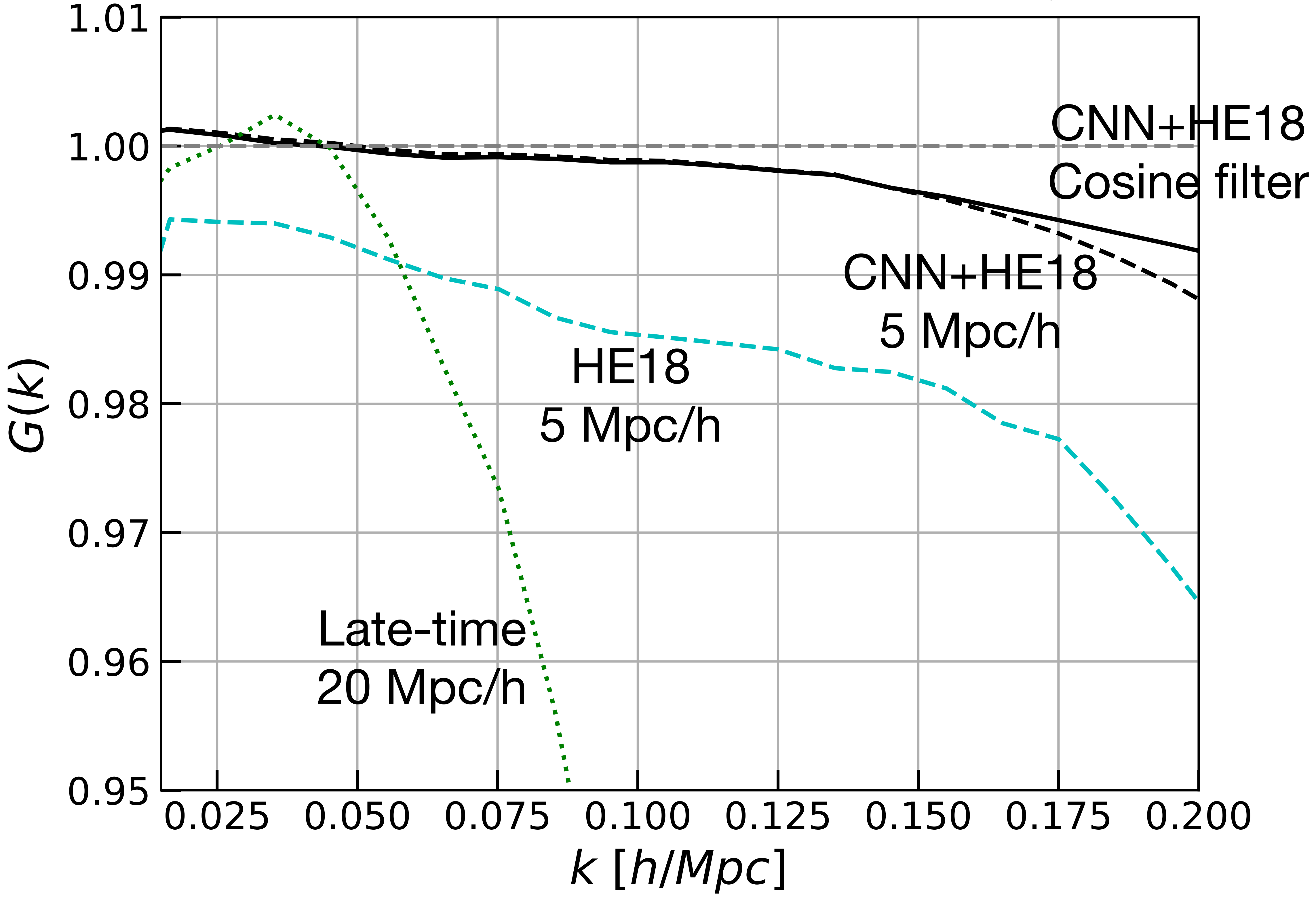
Integral of bispectrum

Why near optimal? Maximum likelihood estimation by Schmittfull, Baldauf & Seljak 2015

Reconstructed Φ^2 field cross-correlation close to IC too

$$G(k) = \frac{\langle \Phi^{2\,*}(\boldsymbol{k}) \Phi^2_{\mathrm{ini}}(\boldsymbol{k}) \rangle}{\langle \left(\Phi^2_{\mathrm{ini}}(\boldsymbol{k}) \right)^2 \rangle}$$

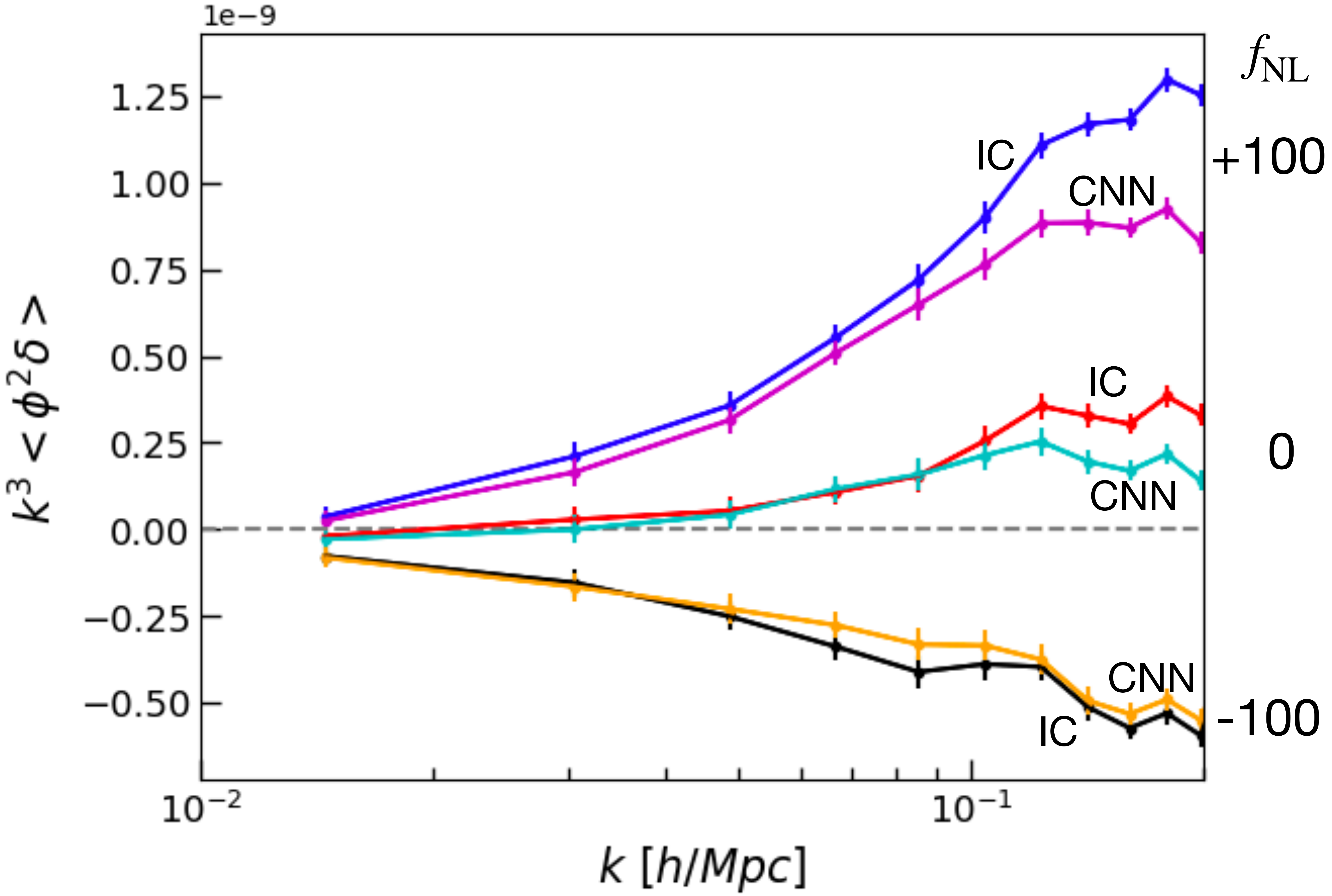




Cosine filter: between k in 0.2-0.25 h/Mpc

$$r(k) = \frac{\langle \Phi^{2\,*}(\boldsymbol{k}) \Phi^2_{\mathrm{ini}}(\boldsymbol{k}) \rangle}{\sqrt{\langle \left(\Phi^2(\boldsymbol{k}) \right)^2 \rangle \langle \left(\Phi^2_{\mathrm{ini}}(\boldsymbol{k}) \right)^2 \rangle}}$$

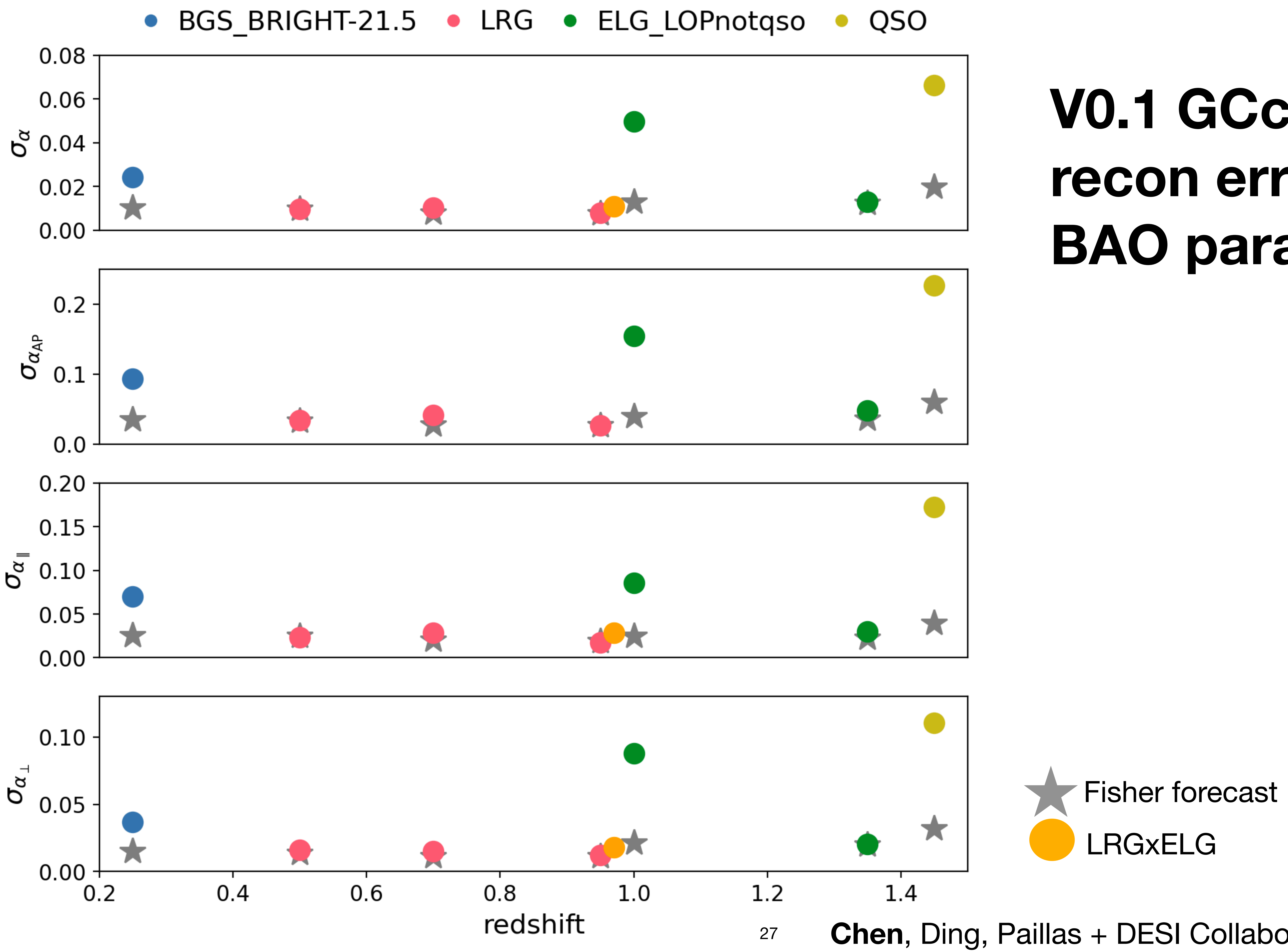
Near optimal bispectrum estimator as a statistic



with cosine filter between
k=0.2-0.25 h/Mpc

- Biased, consistent with template fits
- Trying to understand and minimize the bias
- Forecast with a model based on perturbation theory at tree level w/o b_2 gives $\sigma(f_{\rm NL})$~1.5. Need to fit together due to high degeneracy. Error will be larger.

V0.1 GCcomb post-recon errors of the BAO parameters



Chen, Ding, Paillas + DESI Collaboration in prep.

Summary

- Reconstruction with CNN+algorithm shows promising constraining power for PNG
- Template fits are biased but errors are lower
- Bispectrum estimator consistent with template fitting

- Minimizing the bias ongoing
- Plan:
  - Fitting templates in reality: fitting coefficients together with δ_G, forward model
  - Estimate each template term with bispectrum estimator
  - High shot noise biased tracer

Thank you! 😀