DarkAI: Reconstructing the large-scale density field of dark matter using AI

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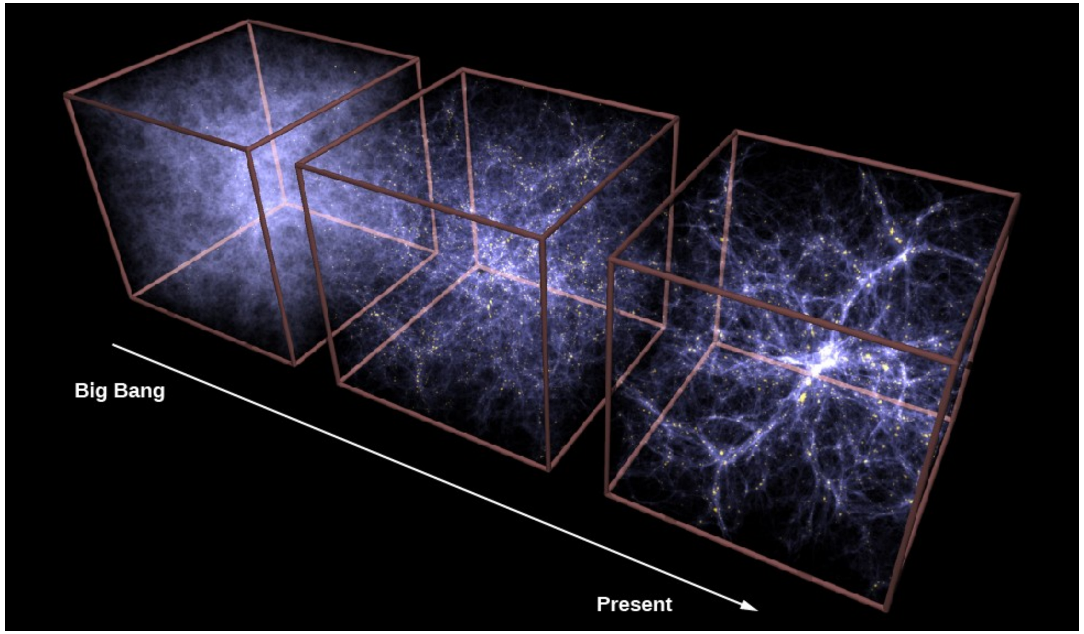
Reconstructing the mass distribution of the Universe

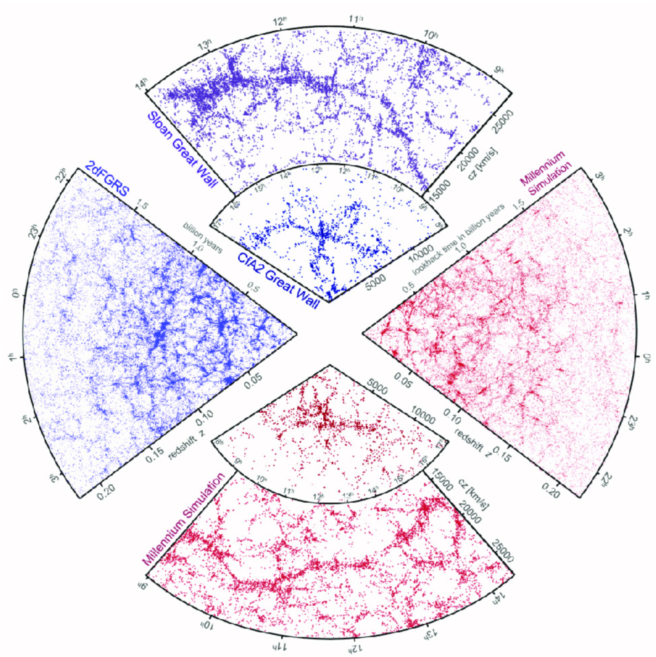
Well-understood

Initial conditions — Dark matter distribution — Dark matter halo — Galaxy distribution

Nbody simulations



Mock galaxy survey



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Opportunity to reconstruct the underlying cosmic density field

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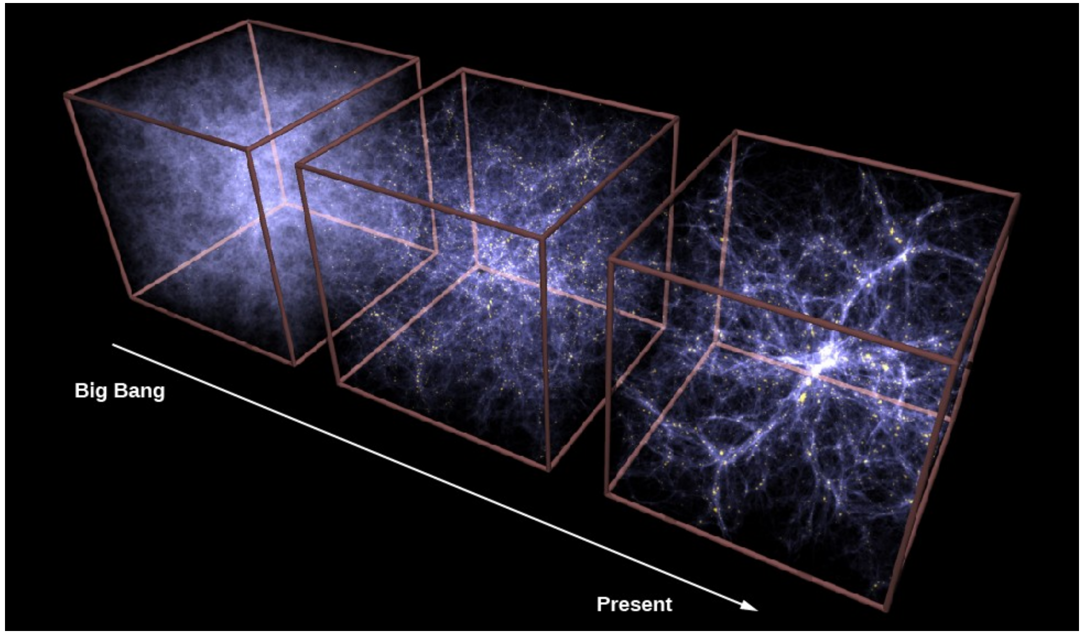

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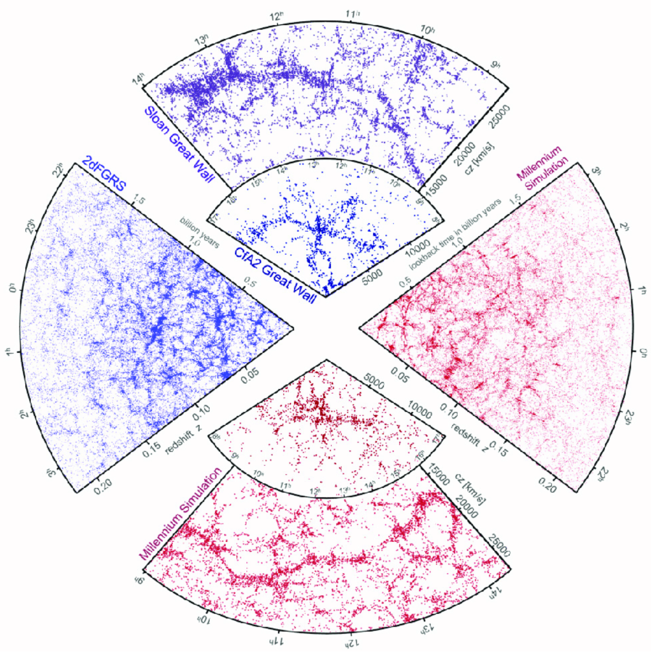
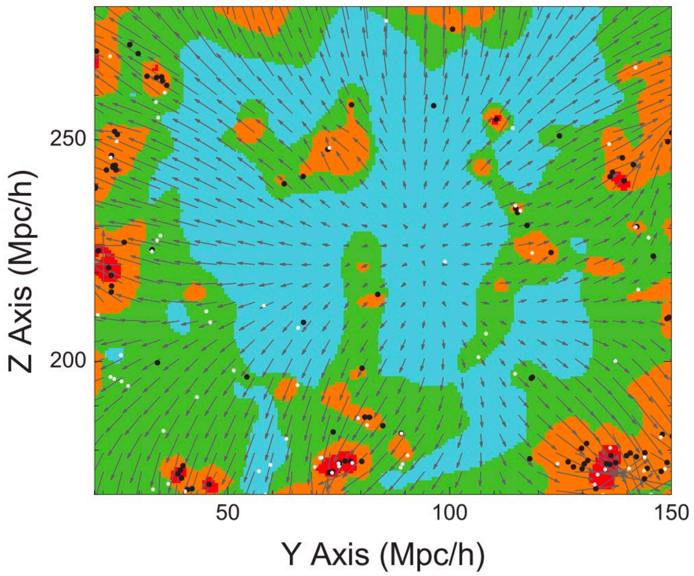


Reconstructing the mass distribution of the Universe can provide us

- Velocity & Tidal field (Wang et al. 2012)



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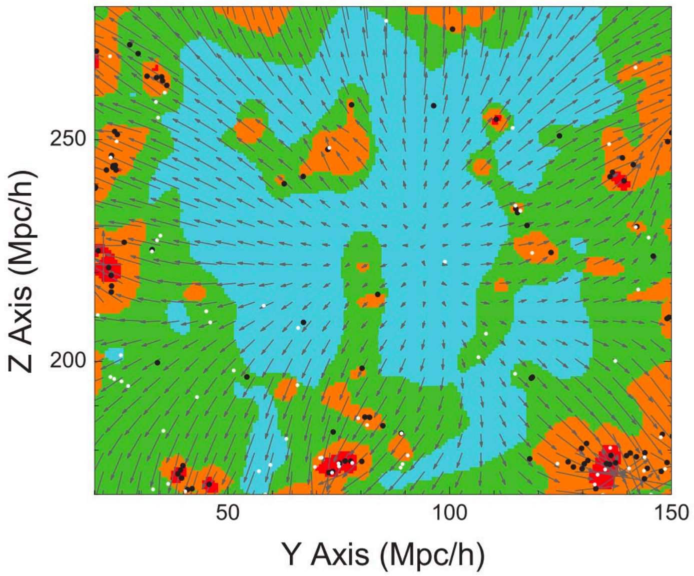

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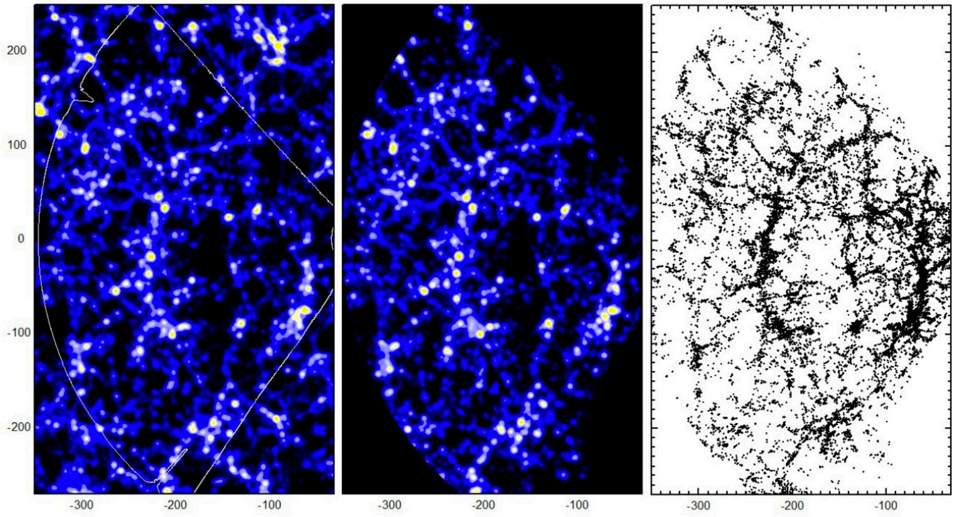

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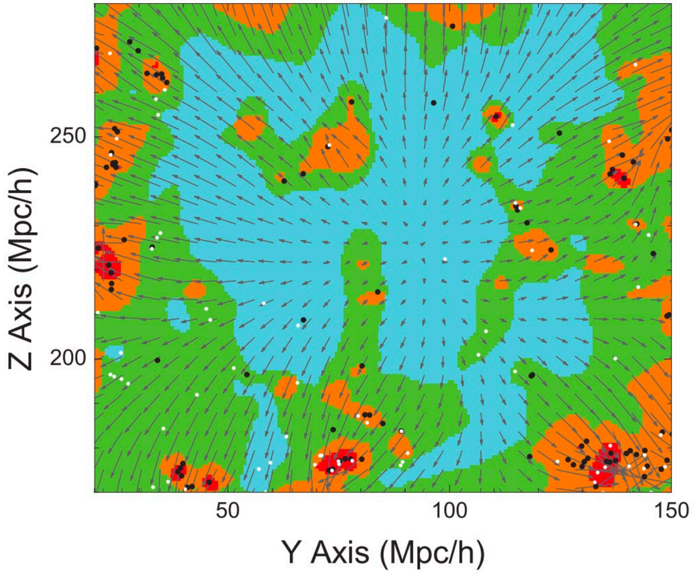

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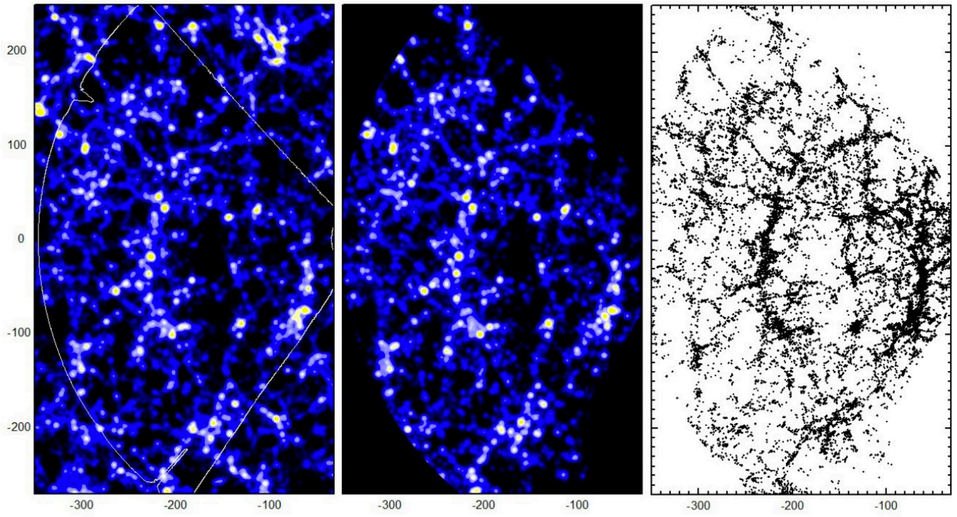
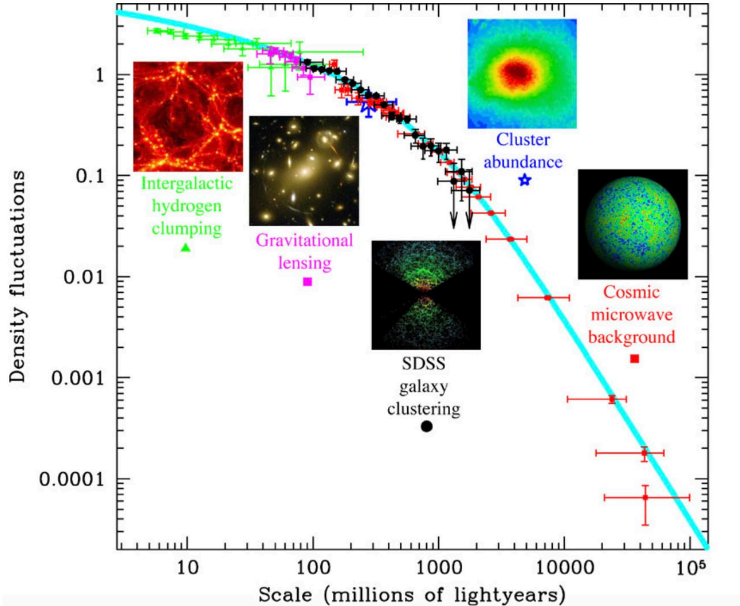


- Real-space dark matter power spectrum (Tegmark et al. 2004)



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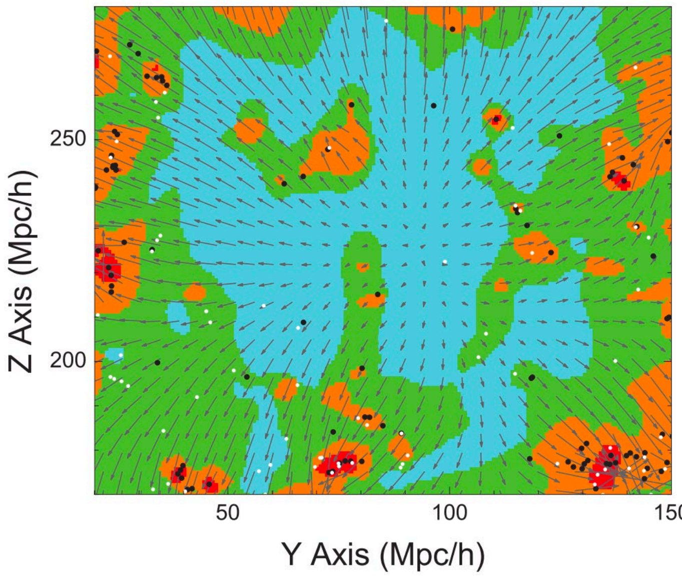

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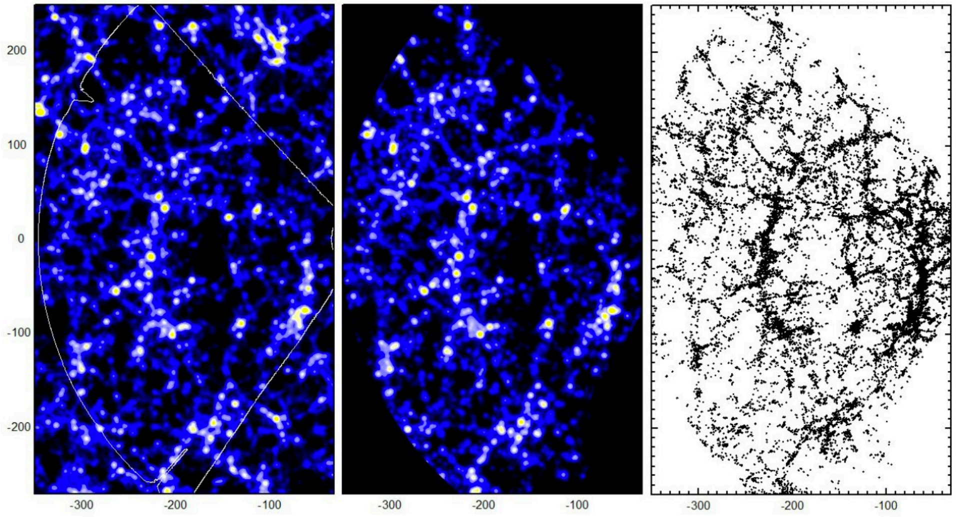
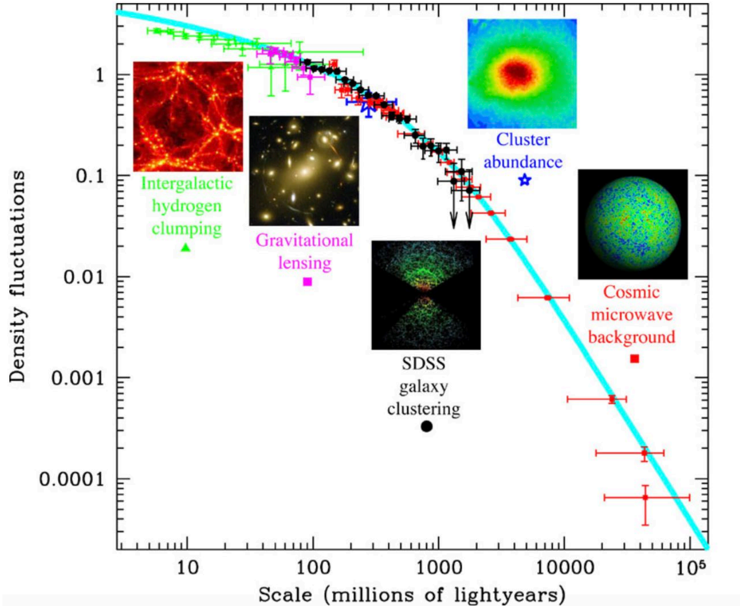


Galaxy formation

- Real-space dark matter power spectrum (Tegmark et al. 2004)



Cosmology

The challenge in reconstructing the density field

1) Galaxies bias:

- Biased tracers of the underlying mass distribution
- Exact form of the bias is complicated.
- Linear bias form used to reconstructing velocity field
- Linear bias: only valid for small density fluctuations

  motivated more by simplicity than by physical principles

$$\boldsymbol{v}(\boldsymbol{k}) = H\, a\, f(\Omega)\, \frac{i\boldsymbol{k}}{k^2}\, \frac{\delta_{\rm h}(\boldsymbol{k})}{b_{\rm hm}}.$$

$$\delta_h(\boldsymbol{x}) = b_1\delta(\boldsymbol{x}) + \frac{1}{2}b_2[\delta(\boldsymbol{x})^2 - \sigma_2] + \frac{1}{2}b_{s2}[s(\boldsymbol{x})^2 - \langle s^2\rangle] + \text{higher order terms}\,.$$

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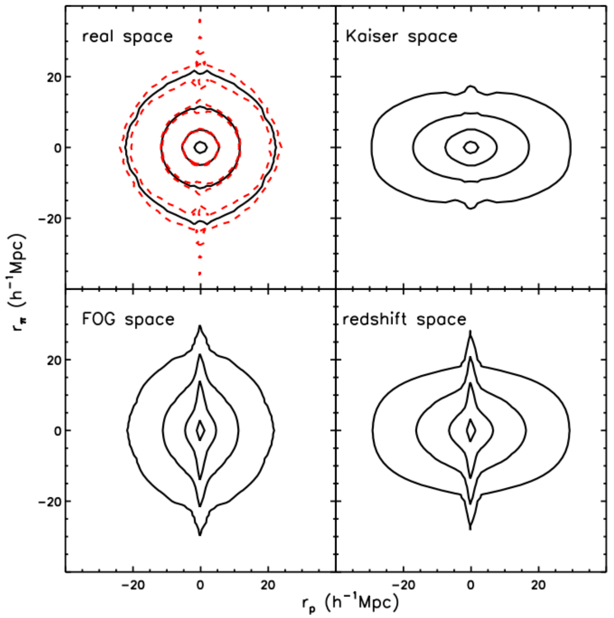
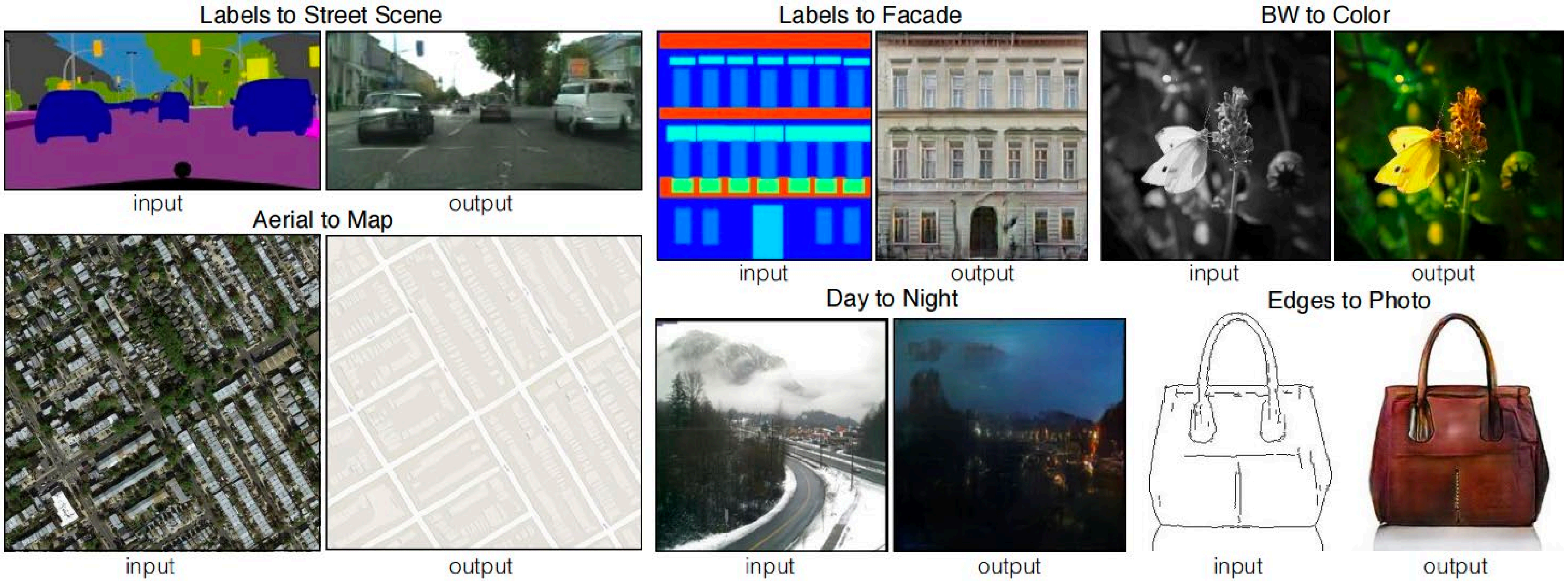
2) Redshift space distortions

- Kaiser effect and FOG effect
- Causing modeling the bias parameters more complicated
- Iteration to make the RSD correction
- Linear theory limited in the high-density regions



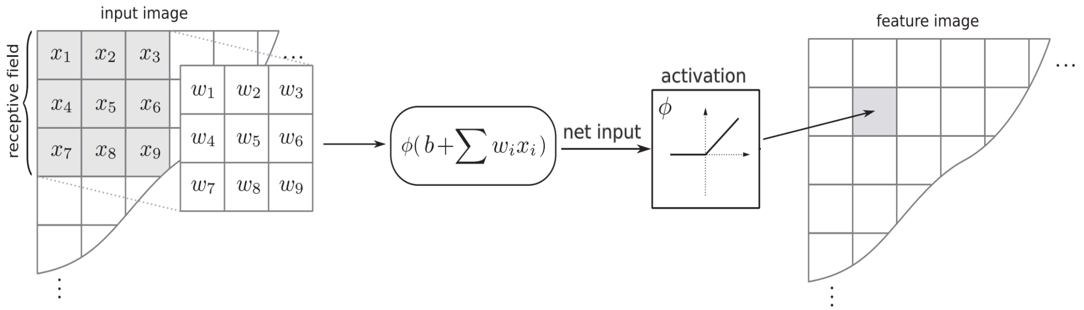
Deeping learning method: UNet model

- Provides a general model for image-to-image translation
- Apply to a wide variety of image generation tasks, including translating photography from day to night and product sketches to photographs

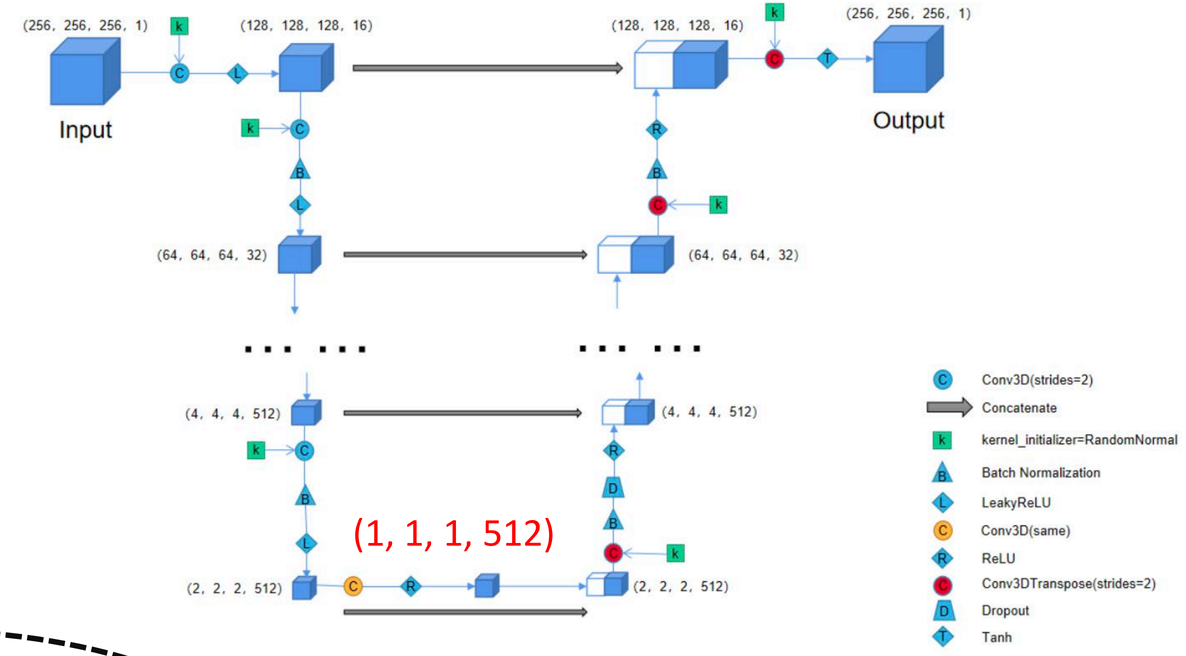


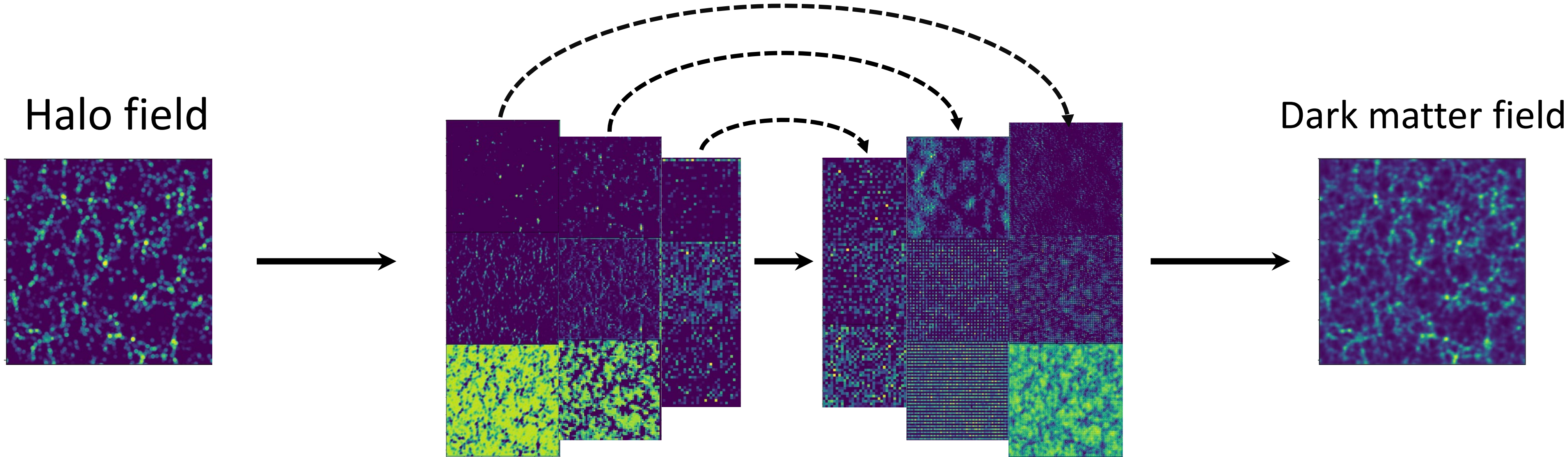
Deeping learning method: UNet model

Convolutional neural network (CNN) :



Encoder-decoder with skip connections:





Generating training and testing data

1) Evolute the particles:

- cola_halo code: COmoving Lagrangian Acceleration (COLA) fast simulation
- Generate 30 simulations: 15 training, 5 validation, and 10 testing samples
- Planck2018 cosmology, $\Omega_m = 0.3111$, $\Omega_\Lambda = 0.6889$, $h = 0.6766$, $\sigma_8 = 0.812$.
- 512^3 particles, 500Mpc/h
- Add RSD along the z-axis for halos. Keep real space for dark matter.

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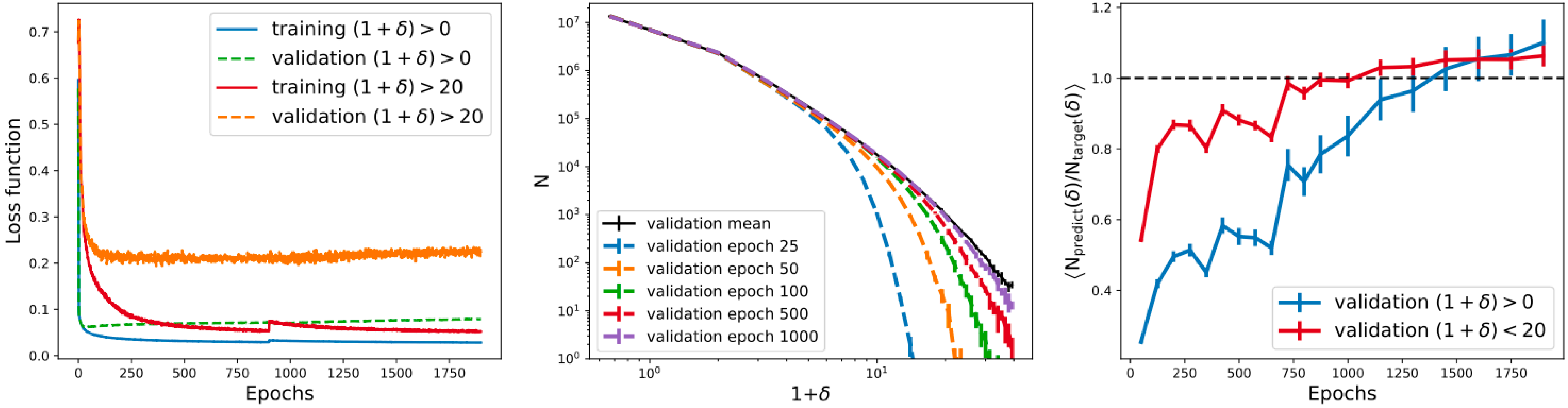
2) Construct the density fields:

- CIC scheme, 256^3 voxels,Top-hat smoothing with $R_s = 5\ h^{-1}$Mpc
- Halo mass weighting
- Rescaled the overdensity values to lie in the interval [−1, 1]

$$s(x) = 2x/(x + a) - 1, \quad a=5$$

Training process

- Run 1000 epochs: check both training and validating samples
- The differences between the prediction and the target keep less until epoch around epoch 600
- The performance would not be improved after epoch 600
- Save best model during epoch 700-1000 based on validate samples



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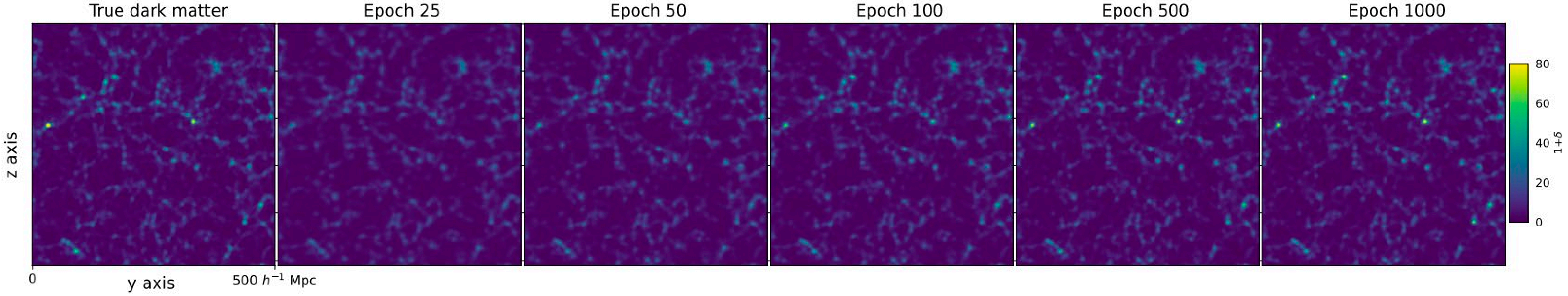


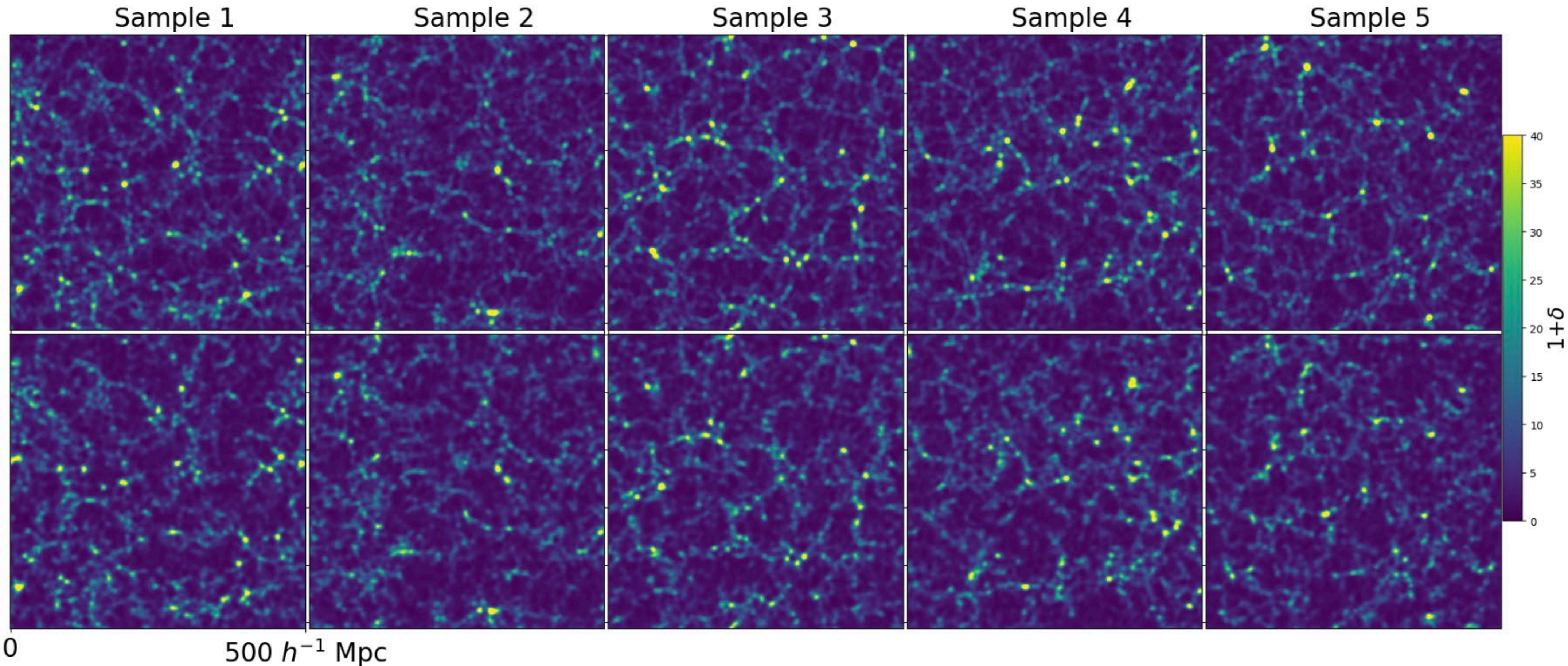
Testing: COLA samples

1) Comparisons of the projected density

- 5 samples randomly selected from the 10 COLA test samples in a slice of 500 × 500 × 9.76 h^{-1}Mpc
- The reconstruction exhibit recognizable, large-scale structures including clusters, filaments, and voids
- The reconstruction is generally very successful over the different scales
- Differ slightly from the target at regions around clusters.

Truths

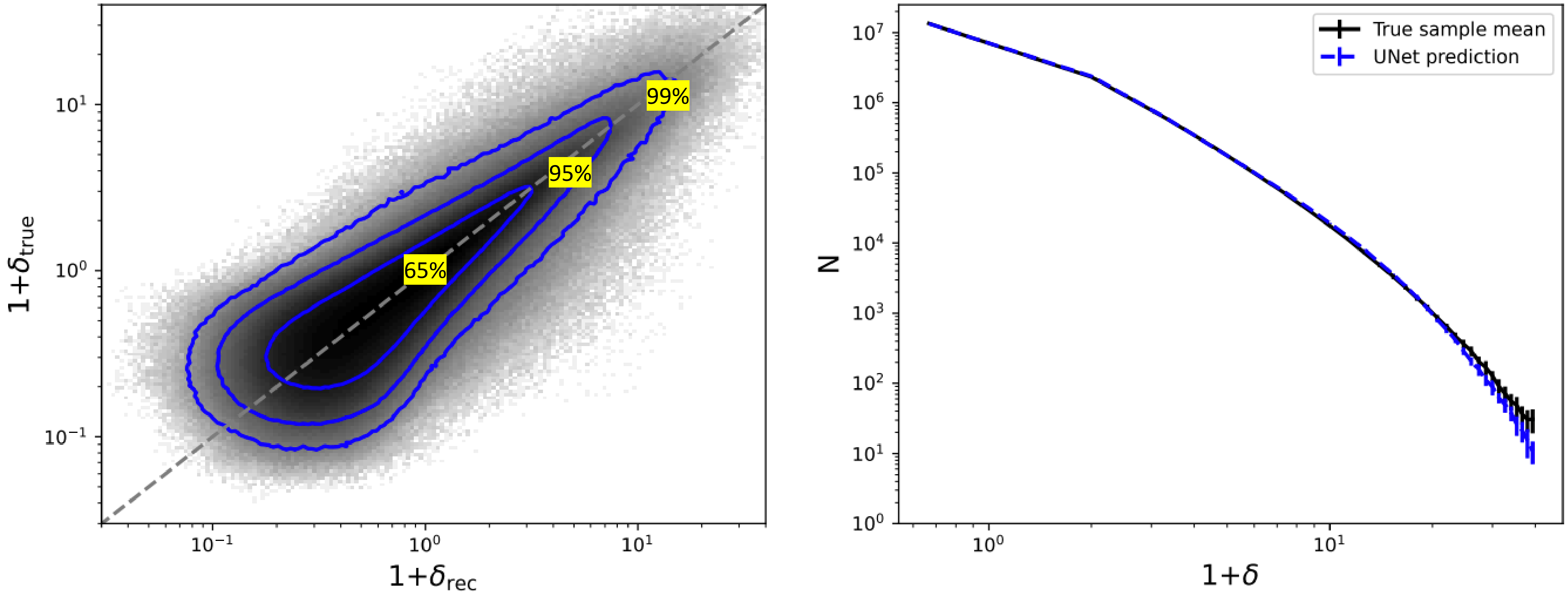
UNet predictions



Testing: COLA samples

2) Density-density relation (left panel) and histogram distribution (right panel)

- No significant bias between δ_{rec} and δ_{true}
- 99.98% grids keeps accuracy $\Delta\delta/\delta < 5\%$
- Reason: small number of massive halos in currect trainng volume



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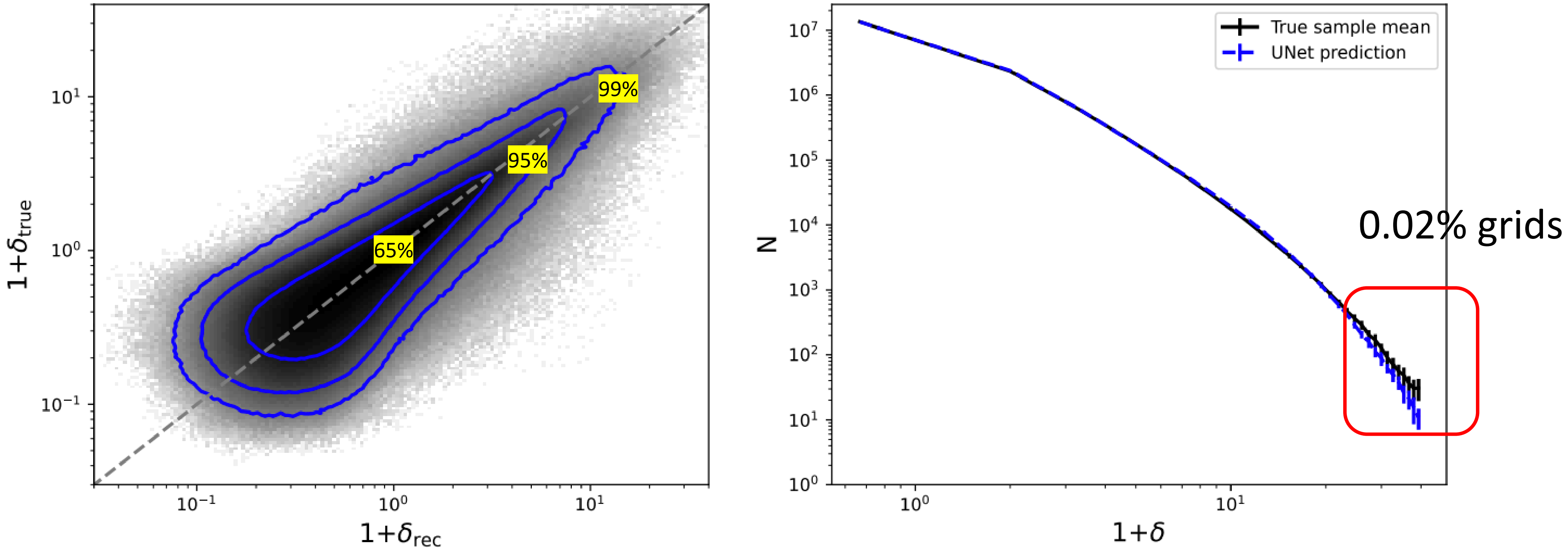


Testing: COLA samples

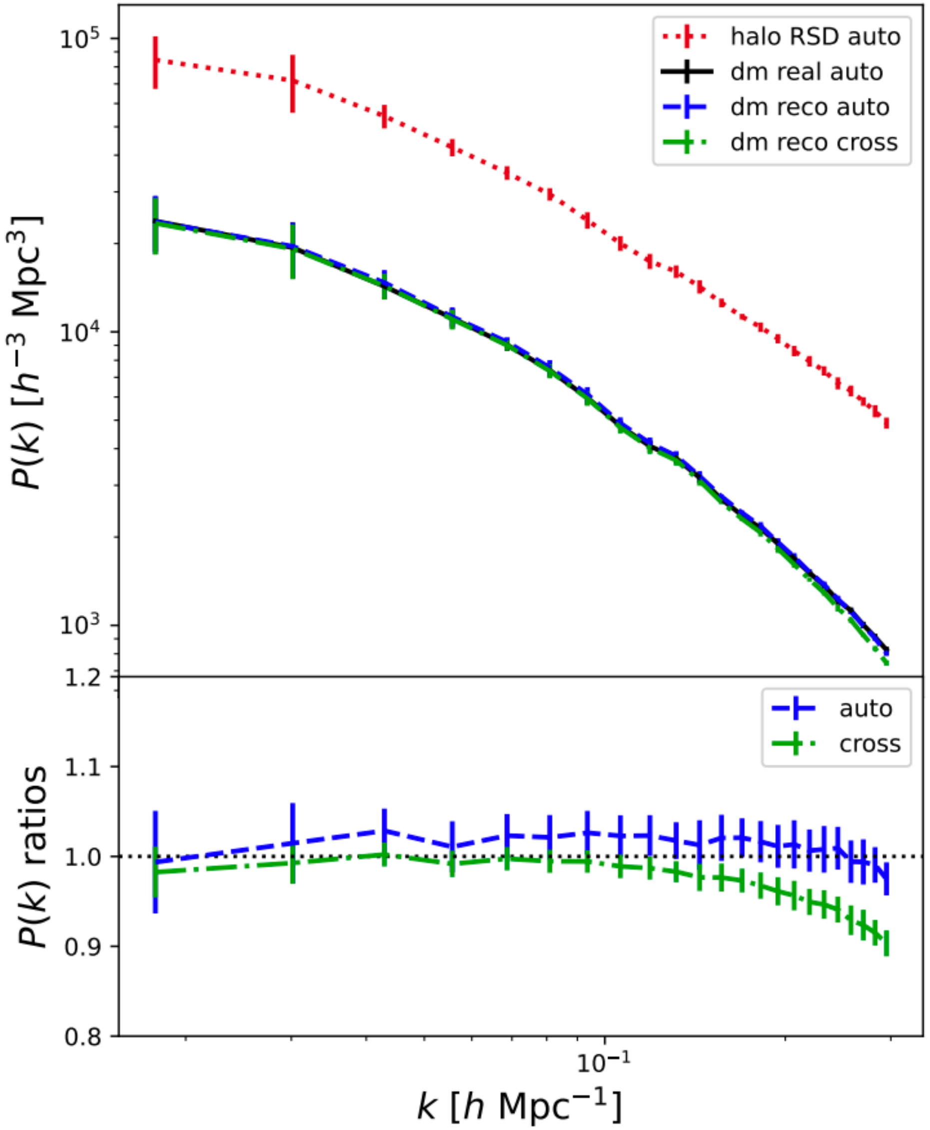
3) Monopole power spectrum

- Cross-correlation:

P(k) ratios is 0.99 $\pm$ 0.01, k < 0.1 h Mpc^{-1}

1% reduction at k = 0.1 h Mpc^{-1}

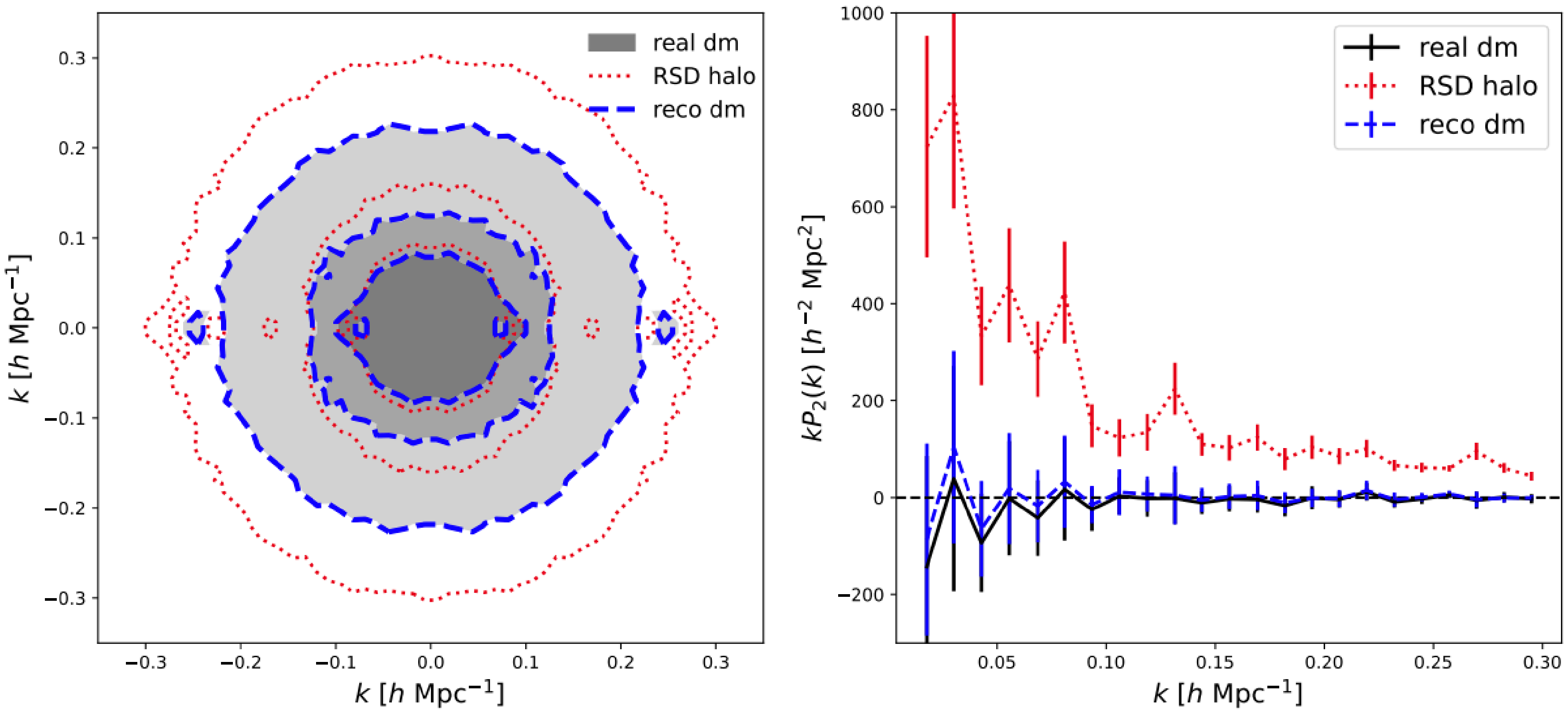
10% reduction at k = 0.3h Mpc^{-1}



Testing: COLA samples

4) 2D power spectrum

- UNet-reconstructed $P\,(k_{\perp}, k_{\parallel})$ is clearly more isotropic and perfectly round.
- Quadrupole $P_2\,(k)$ is very close to zero.
- The correction for the RSDs is overall very successful.

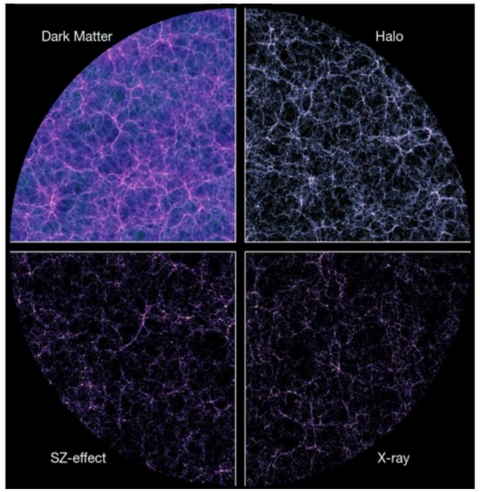


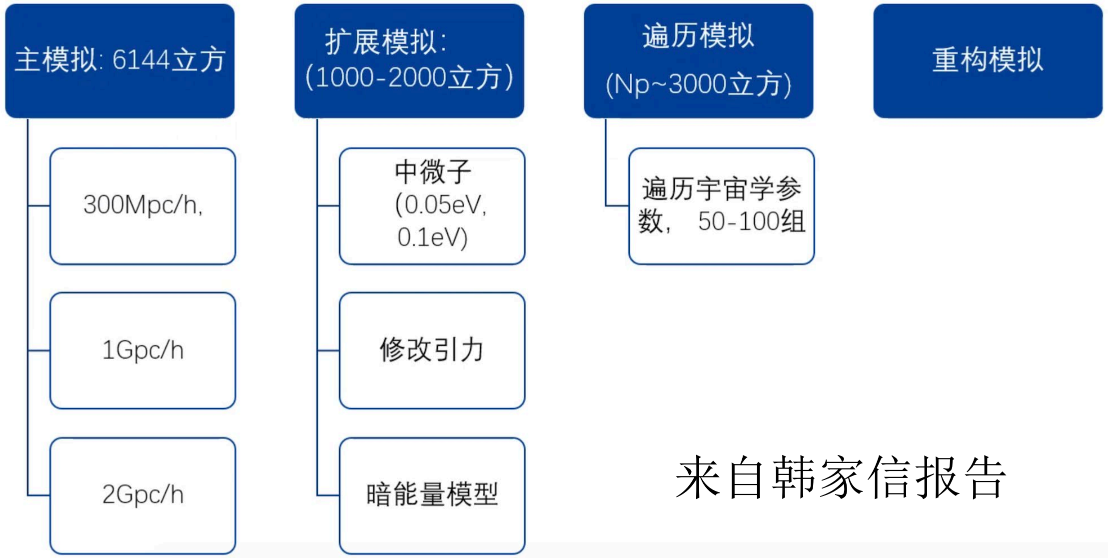
Application to Jiutian

Simulation for CSST

- 标准宇宙学模型 （Planck2018）
- 分层互补，匹配分辨率和尺度需求
- 6144^3 粒子，纯暗物质
- 已完成1Gpc/h
  - L-GADGET3 (李明)
  - 1万核，28天（14天模拟+14天后处理）
  ~700万核时，22TB+内存
  - 6.8TB/snapshot， 共900TB+
  (Millennium: 2160^3, 500Mpc/h, mp=8x10^8, 34万核时， 25TB数据)
  - 完成初步测试和半解析星系建模

边长(Mpc/h)	粒子质量($M_\odot$/h)
300	10^7
1000	3.6×10^8
2000	2.8×10^9





来自韩家信报告

Application to Jiutian

主模拟：九天

盒子大小：1000Mpc/h

粒子数：6144^3

计算：1万核，28天

内存：22TB+

存储：900TB+

Application to Jiutian

训练数据：COLA
盒子大小：500Mpc/h
粒子数：512^3
计算：28核，0.5小时
内存：<3GB
存储：10GB

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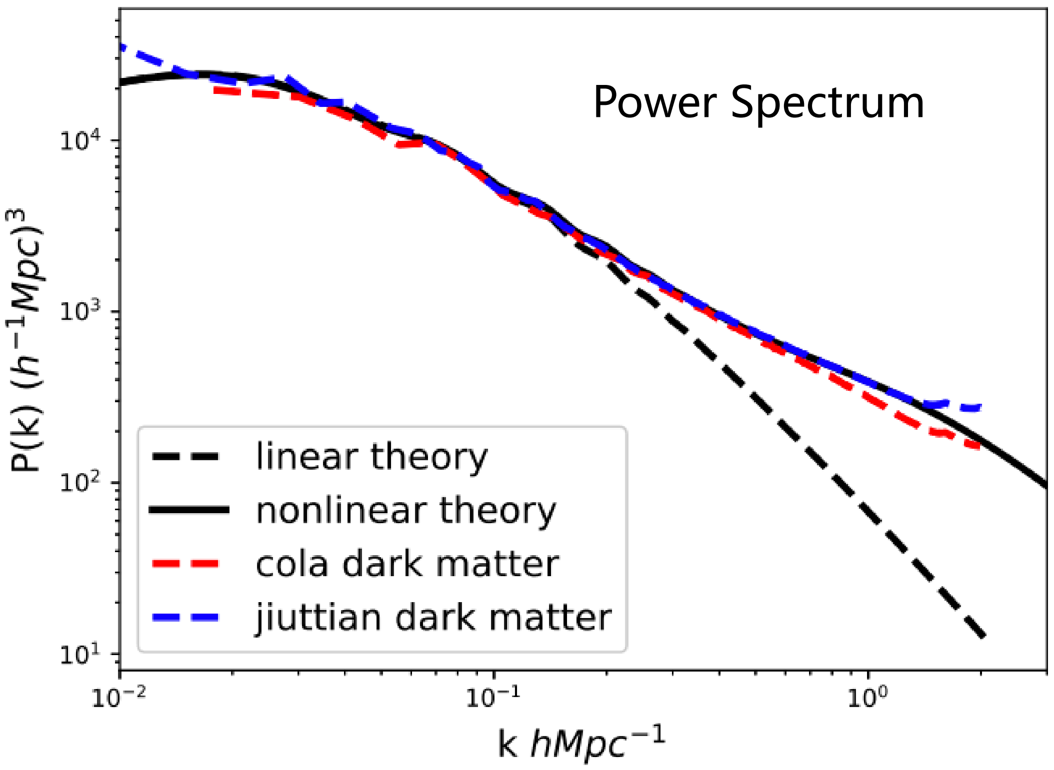

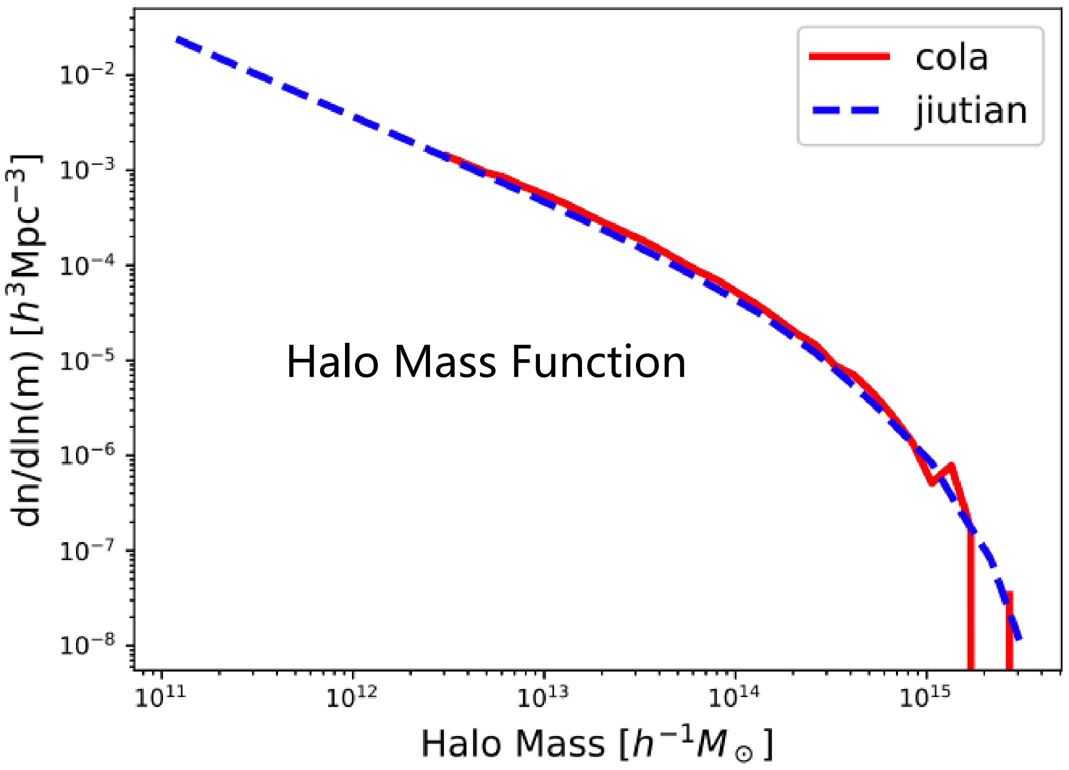

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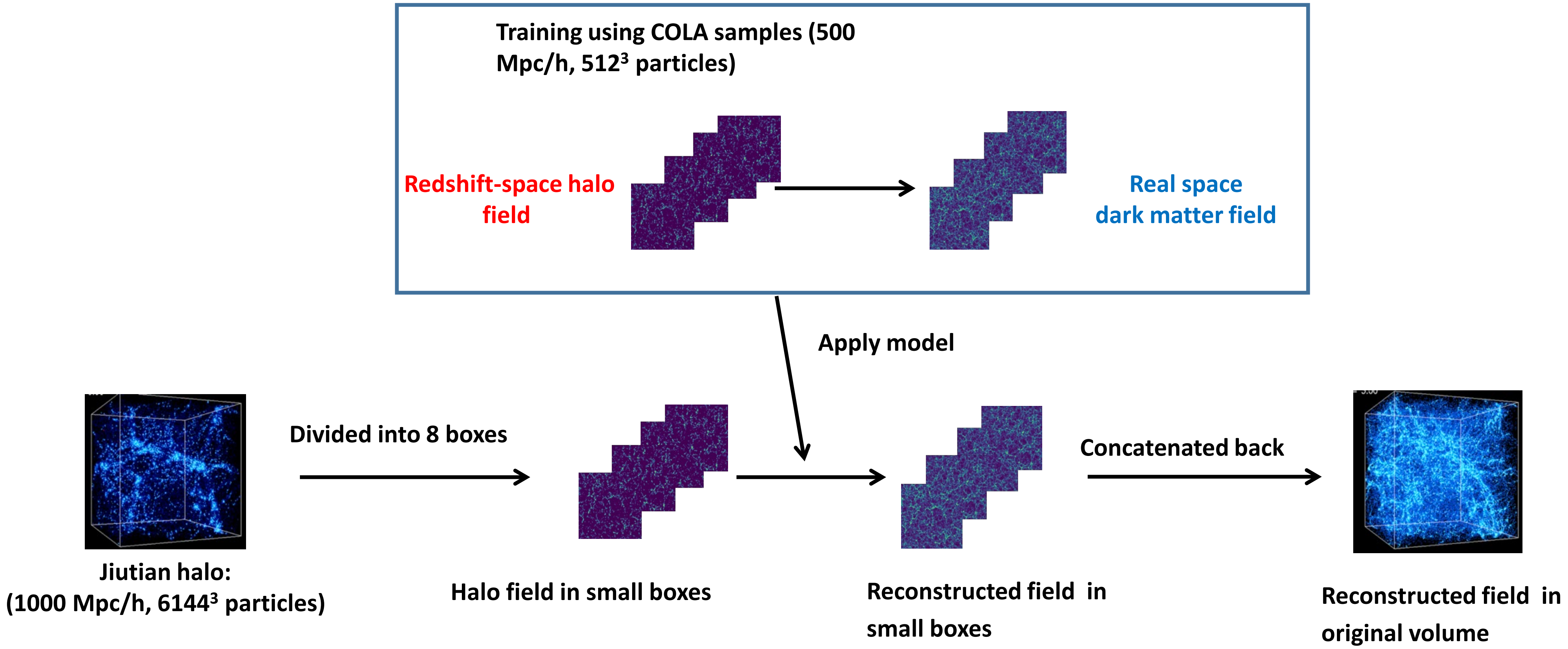
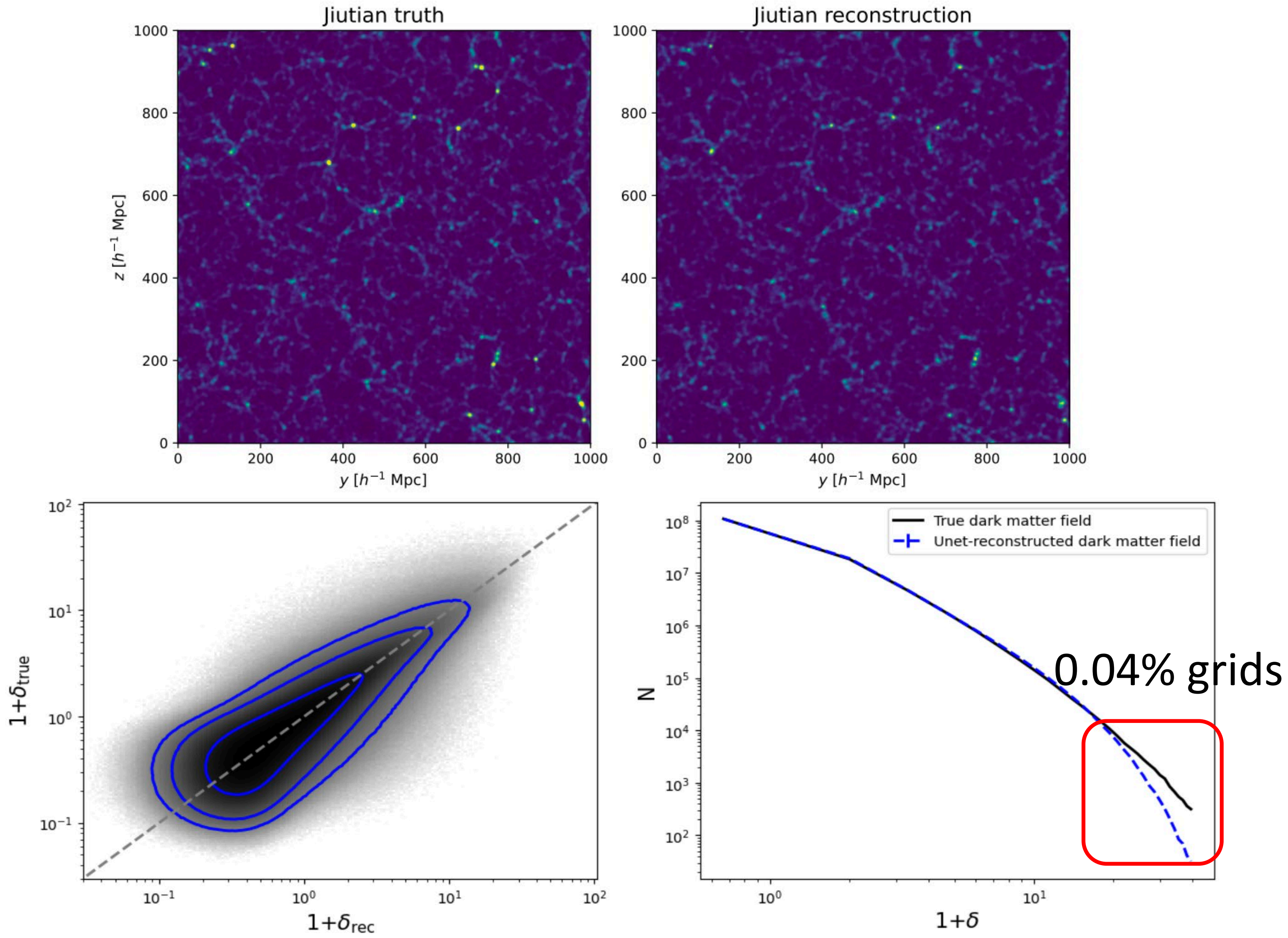


Results: Jiutian simulation

- Reconstructing dark matter density field based on UNet



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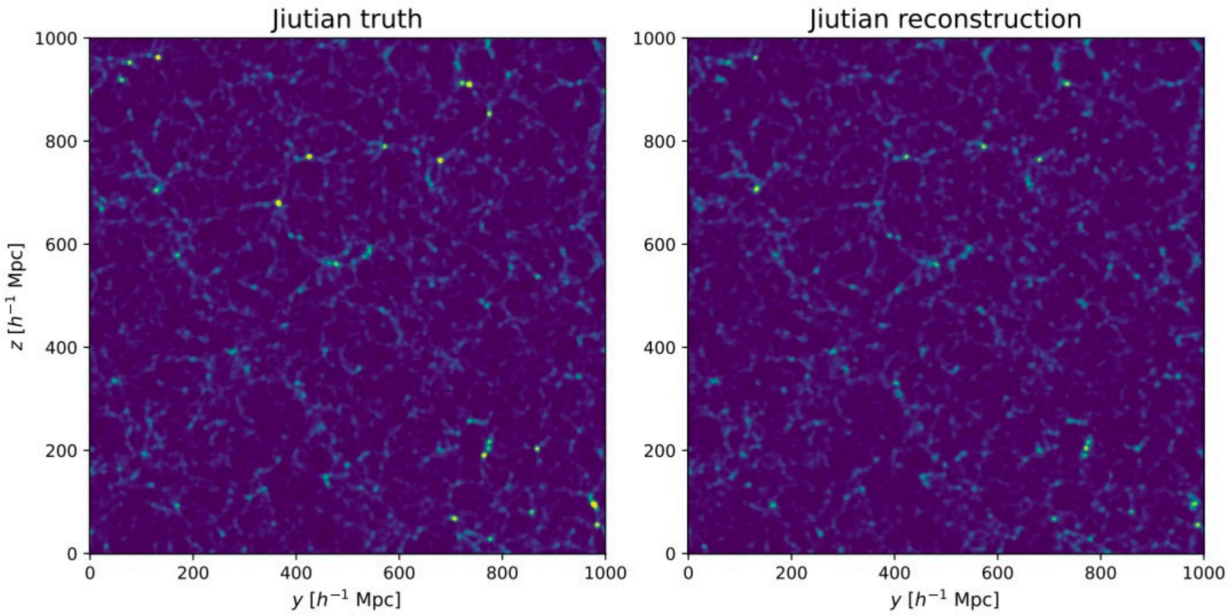
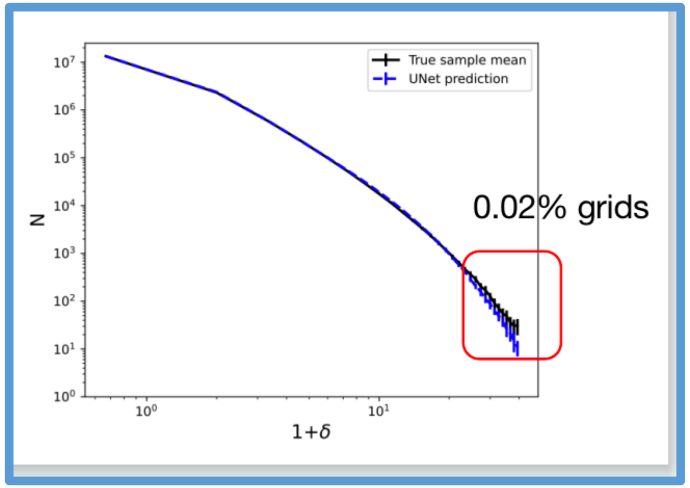
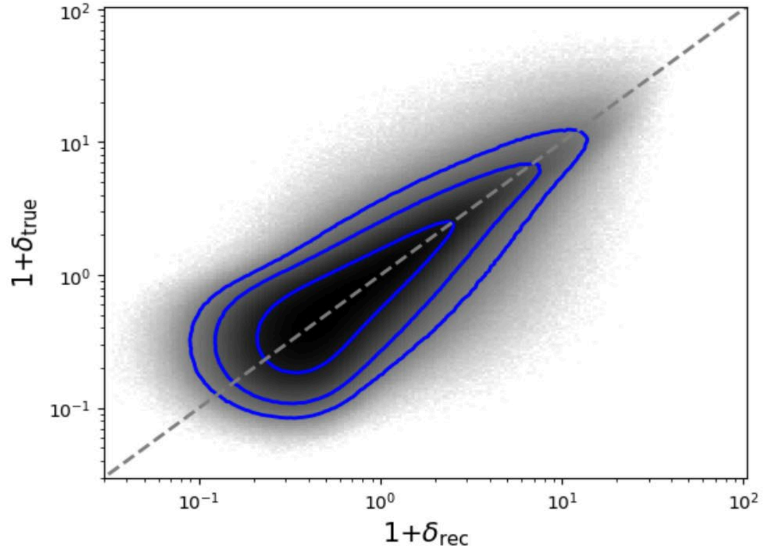
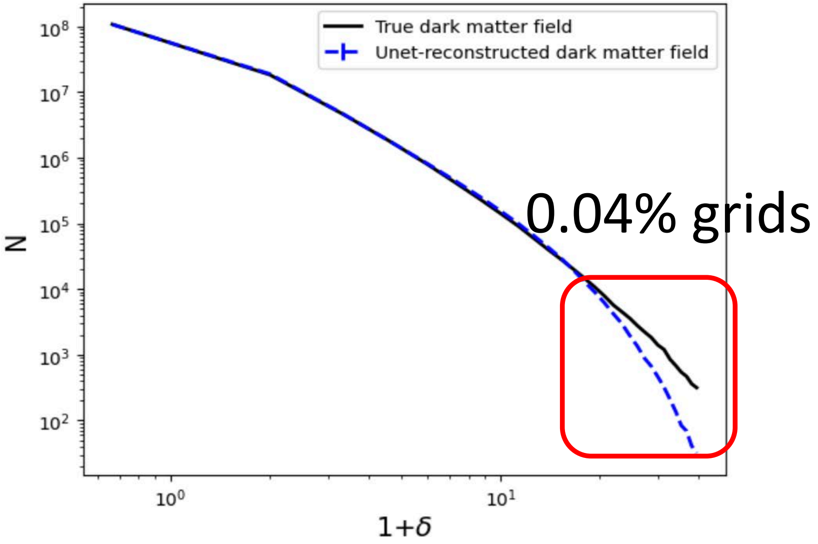


COLA







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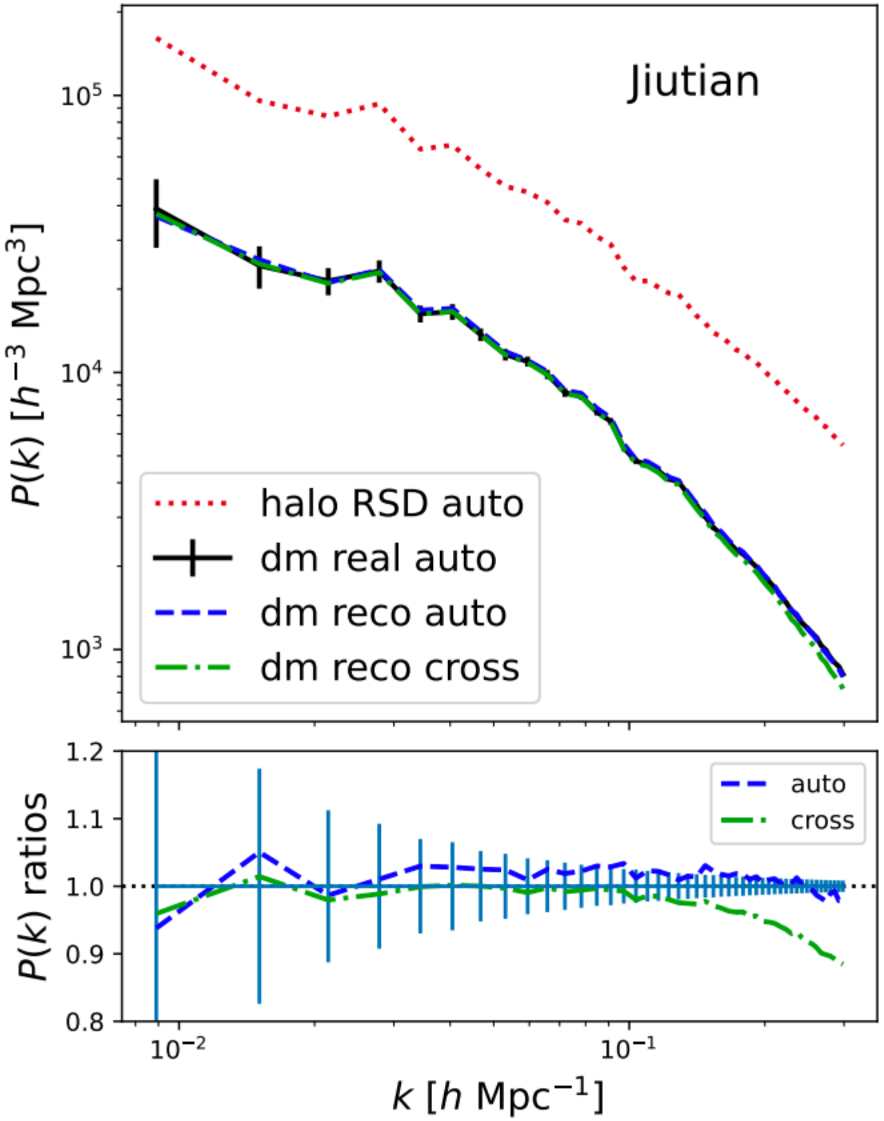

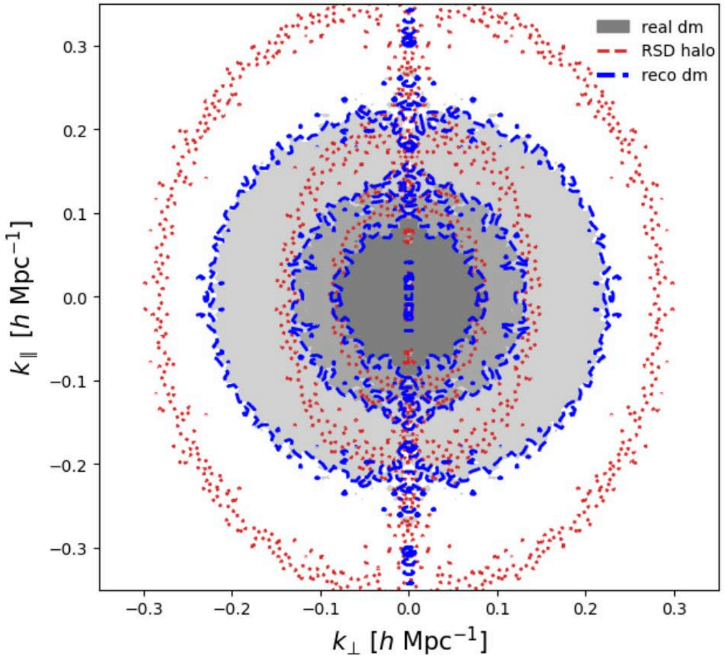

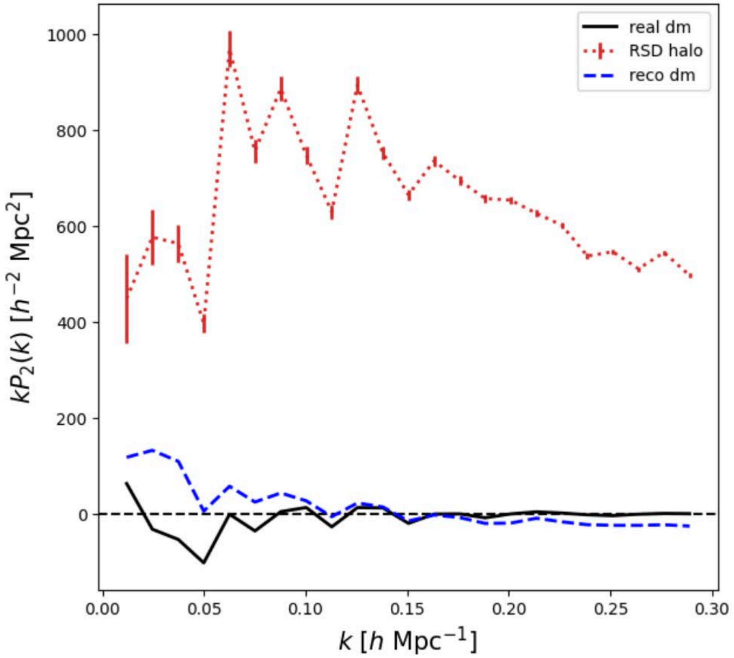

The real-space P(k) is also recovered accurately, with only small reduction of the cross-correlation power spectrum at 1% and 10% levels at k = 0.1 and 0.3 h Mpc^{-1}, respectively.

Application to ELUCID simulation

Check the impact of cosmology

- COLA and Jiutian simulations :

  Planck2018 cosmology

  $\Omega_m = 0.3111$, $\Omega_\Lambda = 0.6889$, $h = 0.6766$, $\Omega_b = 0.049$, $\sigma_8 = 0.817$.

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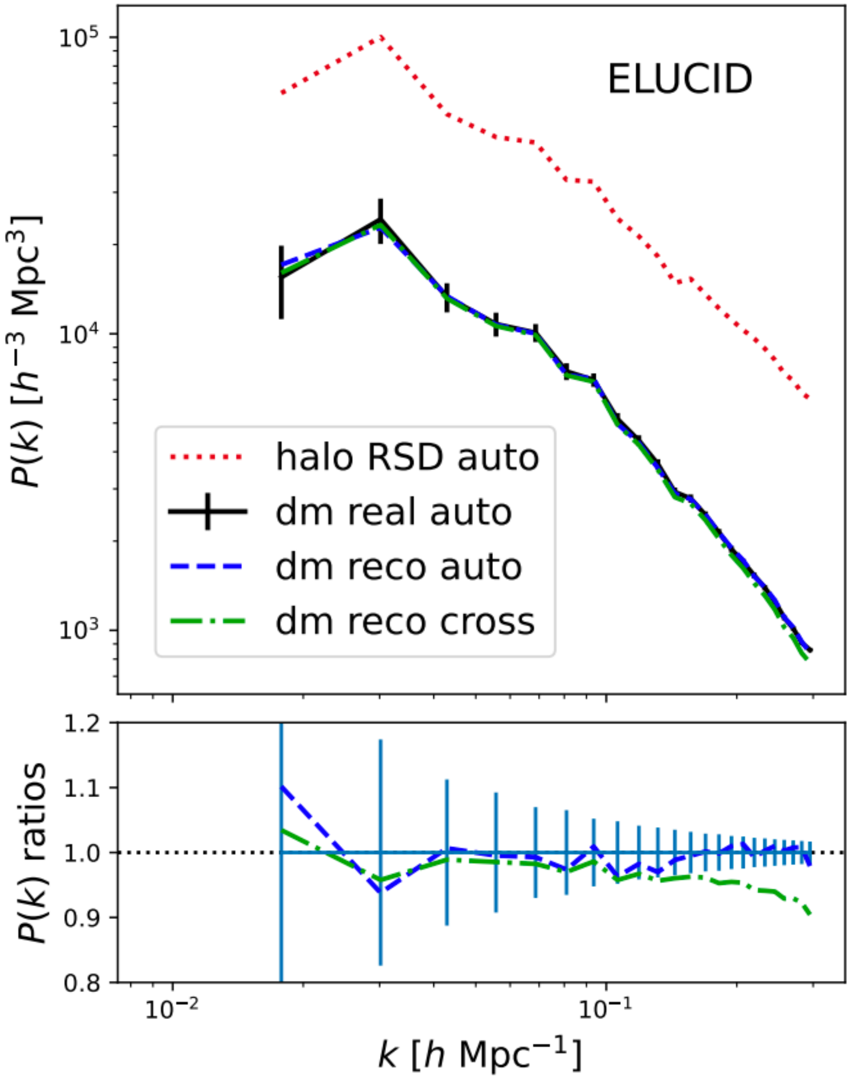
- ELUCID simulation (500Mpc/h, 3072^3 particles):

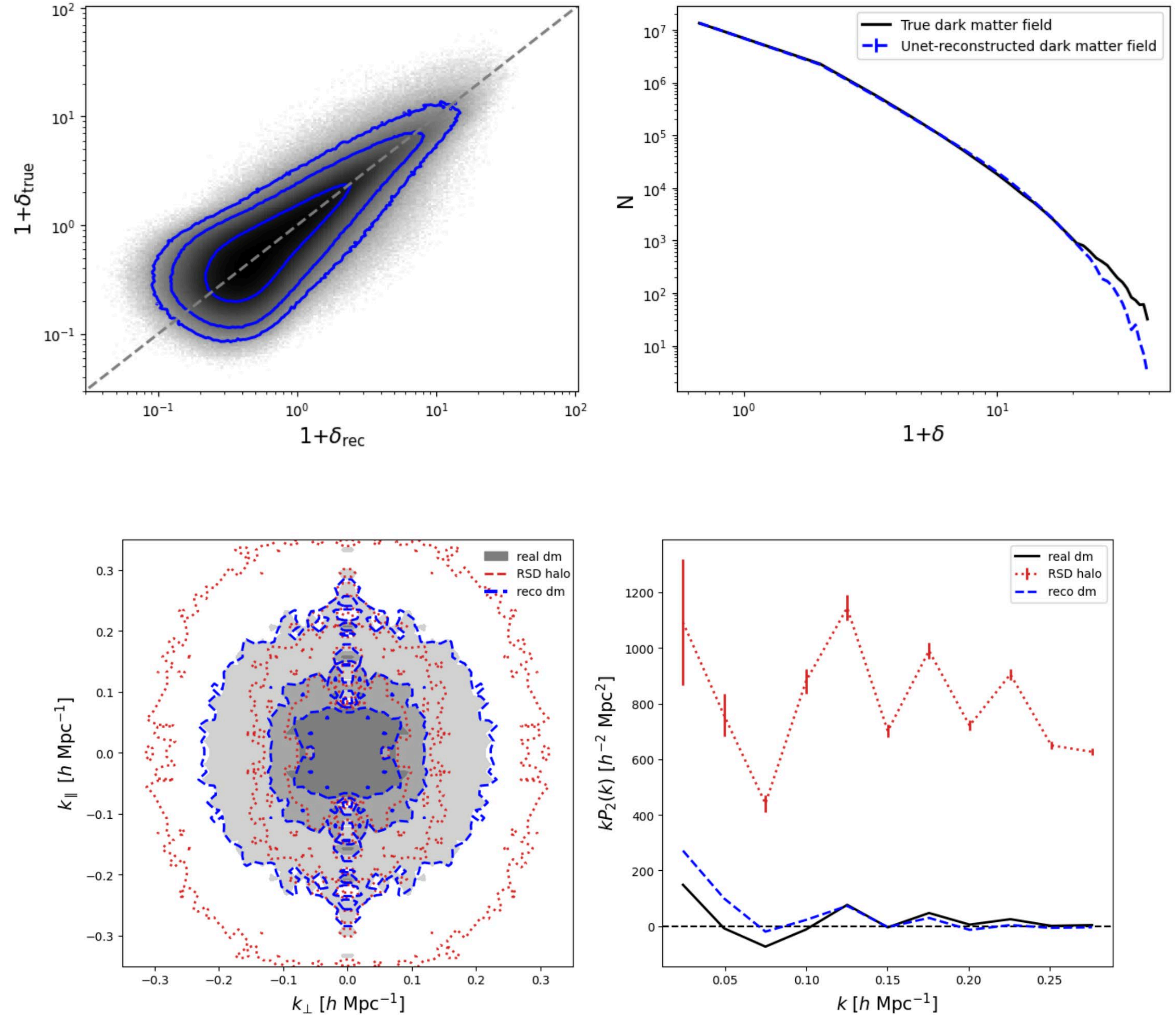
  WMAP5 cosmology

  $\Omega_m = 0.258$, $\Omega_\Lambda = 0.742$, $\Omega_b = 0.044$, h = 0.72, $\sigma_8 = 0.80$

Results: ELUCID simulation

- No large distinction of the results between the WMAP5 and Planck18 cosmology





Testing: velocity field reconstruction

- Reconstruct velocity field

VS.

Halo density field $\delta_h(k)$ with a bias b_{hm}

$$\boldsymbol{v}(\boldsymbol{k}) = H\ a\, f(\Omega)\, \frac{i\boldsymbol{k}}{k^2}\, \frac{\delta_{\rm h}(\boldsymbol{k})}{b_{\rm hm}}$$

(Wang et al 2012, Shi et al 2016)

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UNet-reconstructed δ(k)

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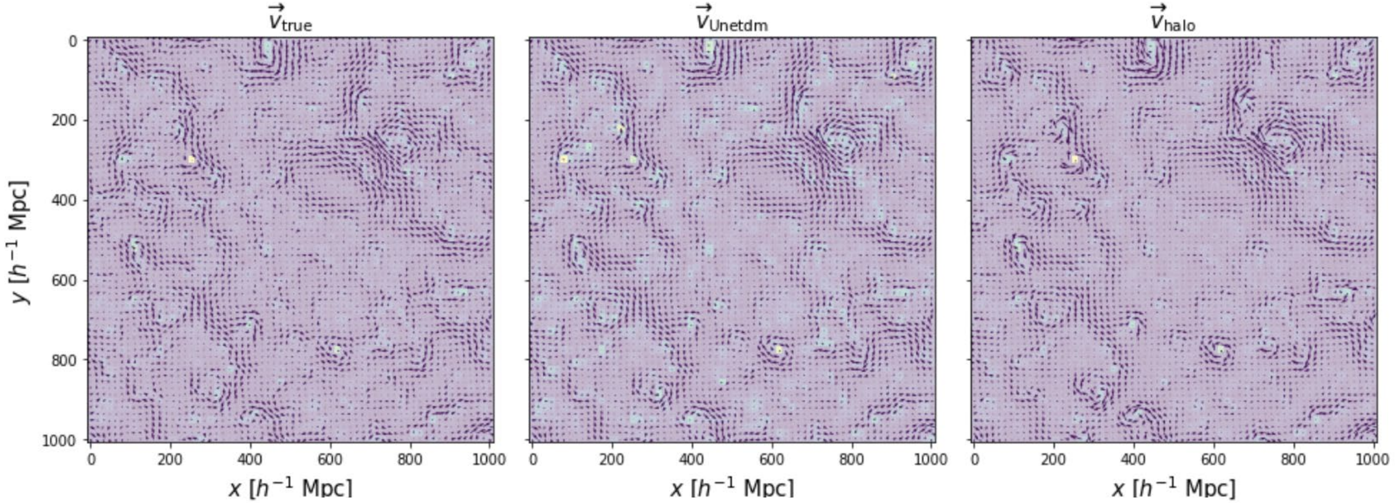
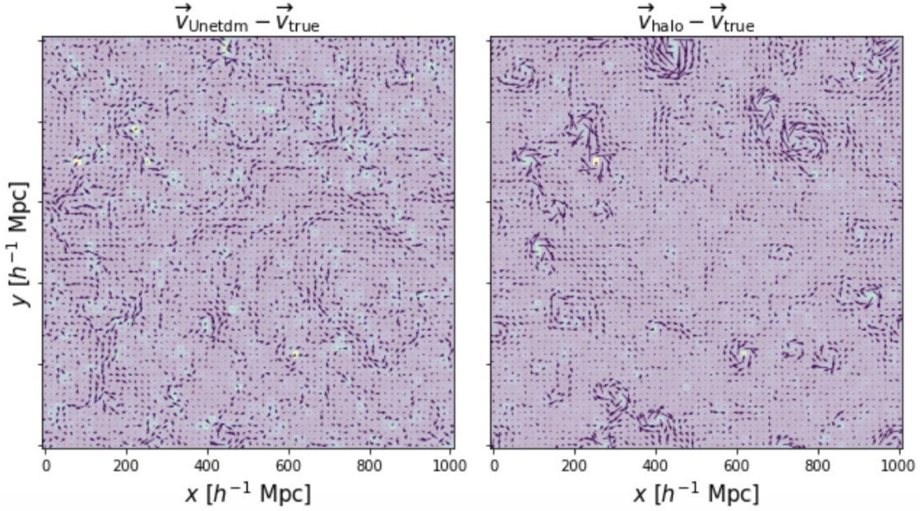
Velocity field



Velocity difference field



UNet dark matter

Halo-based with linear bias

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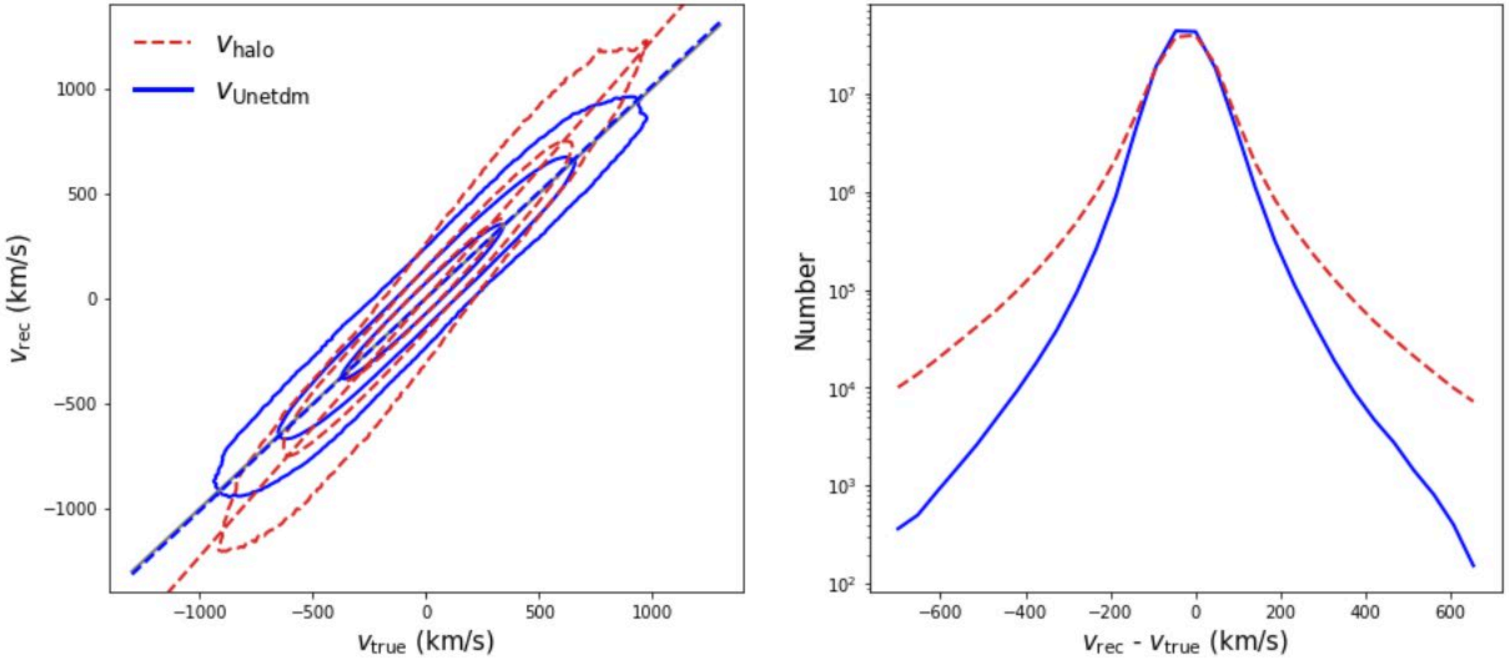
	Slope	Scatter
Halo :	1.15	78.2 km/s
UNet :	1.01	57.0 km/s

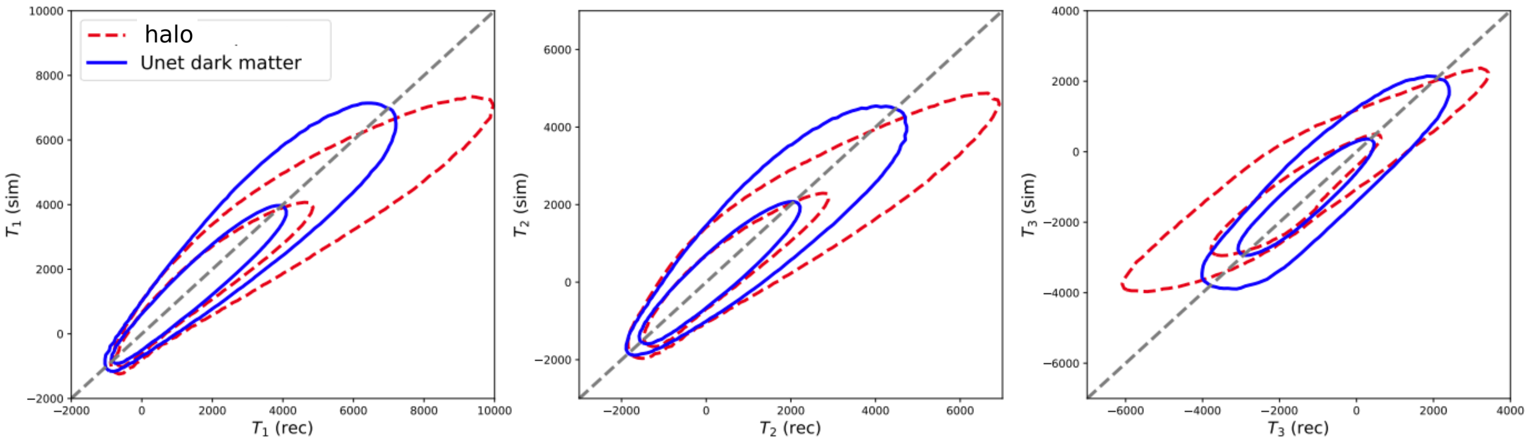
- Unbiased relation
- 21.1% scatter errror reduction



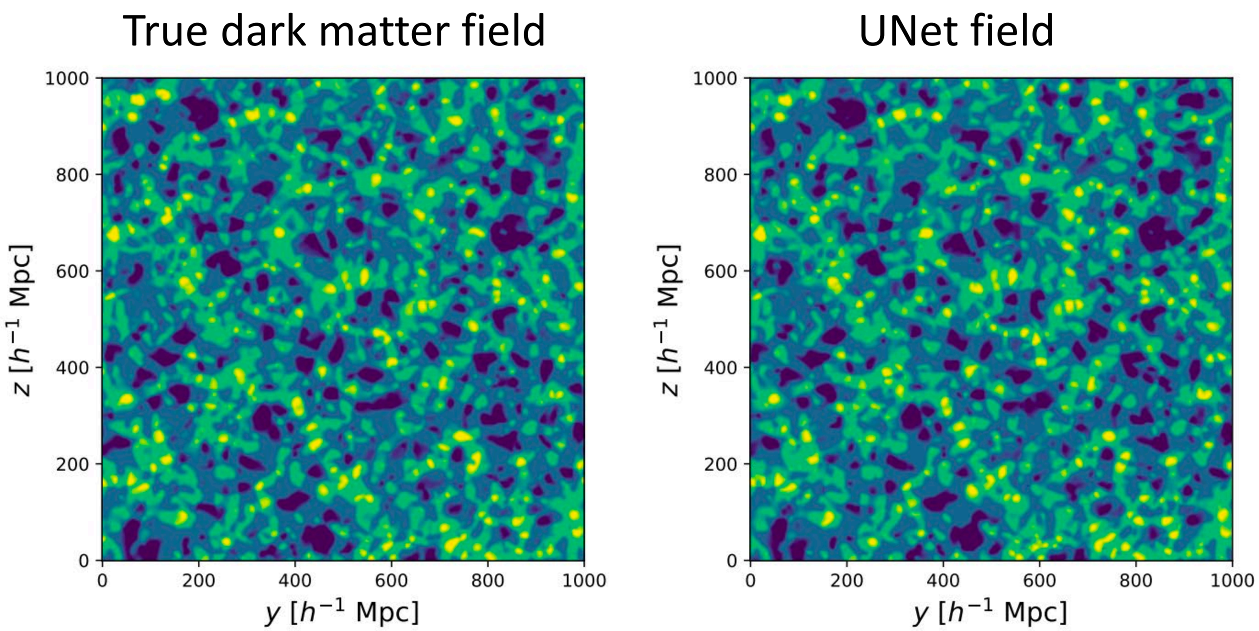
The three contours encompass 67%, 95%, and 99% of the grid cells

Testing: tidal field reconstruction

- Reconstruct tidal field:



- Classification of the large-scale structure:



- cluster : yellow
- filament: yellow-green
- sheet: green
- void: black

Summary & Conlusions

1) Method: Reconstruct the cosmic density field from the redshift-space halo feild based on Unet

2) Testing:

- Three simulations: COLA, Jiutian and ELUCID
- Statistics: projected density, density-density relation, historgram, 1D & 2D P(k)
- Fields: denstiy, velocity and tidal fields

3) Conlusions:

- Accurate reconstruction with only 1% and 10% reduction of the cross P(k) at k = 0.1 and 0.3 h Mpc^{-1}
- RSD corrected successfully
- Low-resolution-COLA-trained network generalizes to the typical high-resolution N-body simulation
- UNet-based field outperforms the traditional method in accurately recovering the velocity & tidal field

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