Field-Level Emulation with Neural Networks

Drew Jamieson
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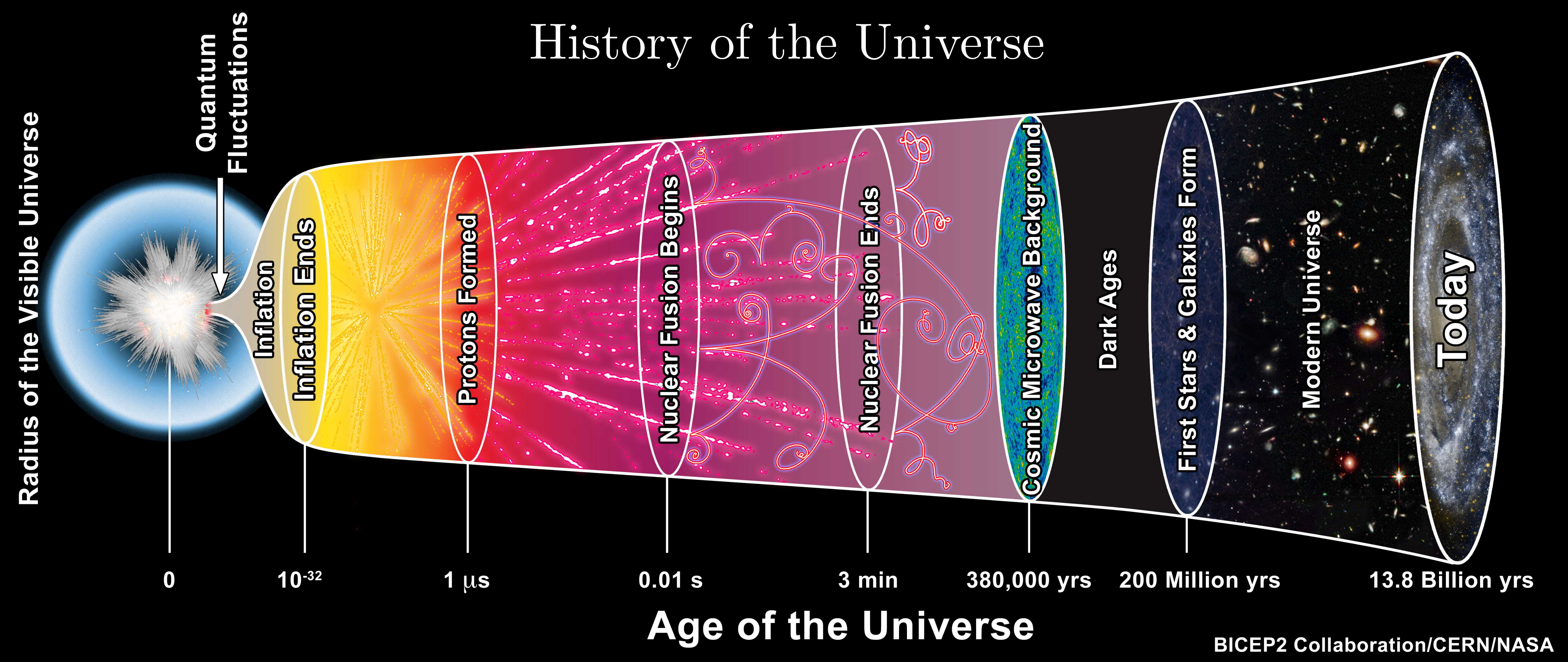
MAX-PLANCK-INSTITUT FÜR ASTROPHYSIK

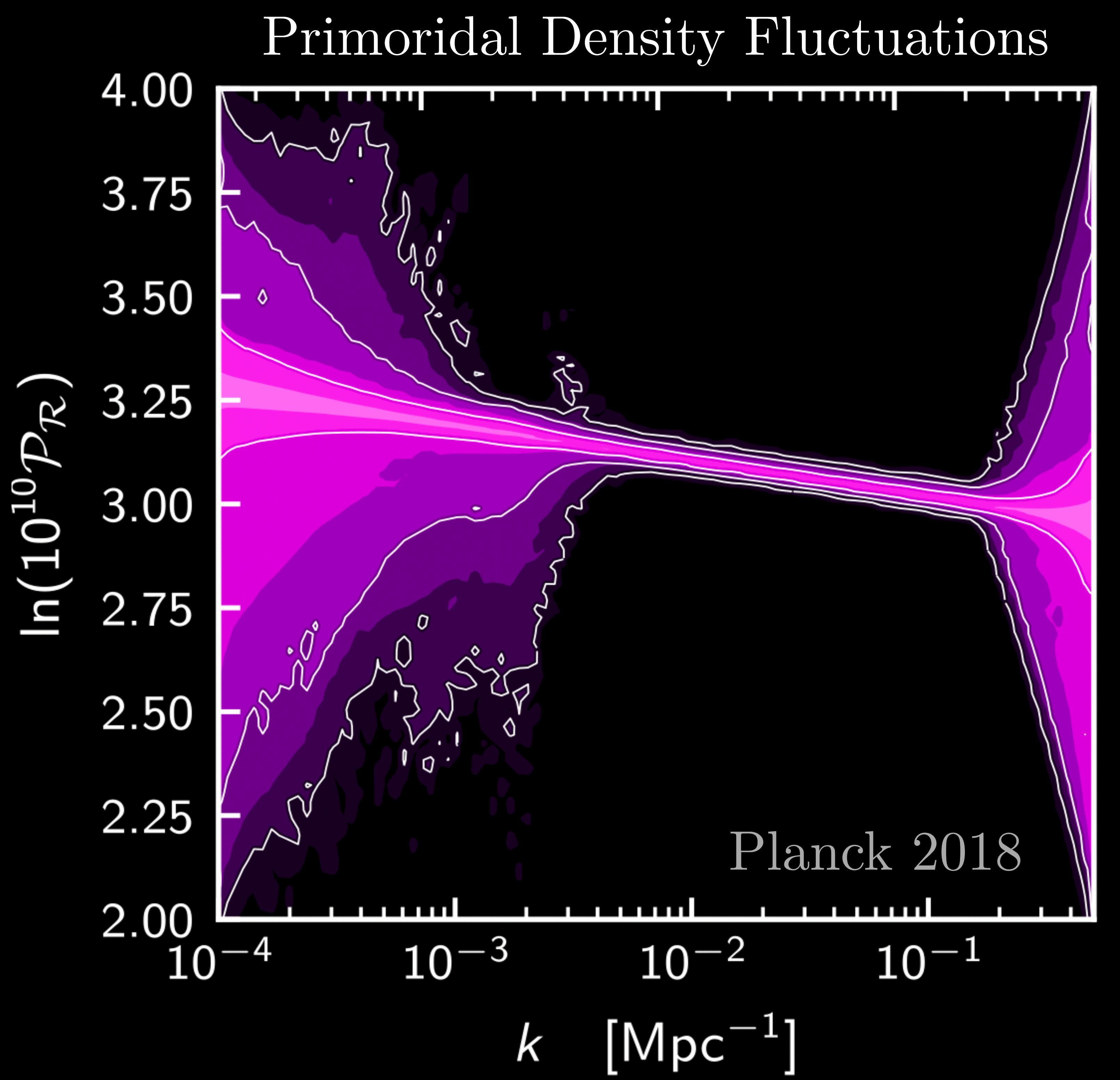
arXiv:2206.04594
arXiv:2206.04573
arXiv:2303.13056
arXiv:2307.09134
arXiv:2312.09271
arXiv:2408.07699
arXiv:2408.07699
arXiv:2502.13242

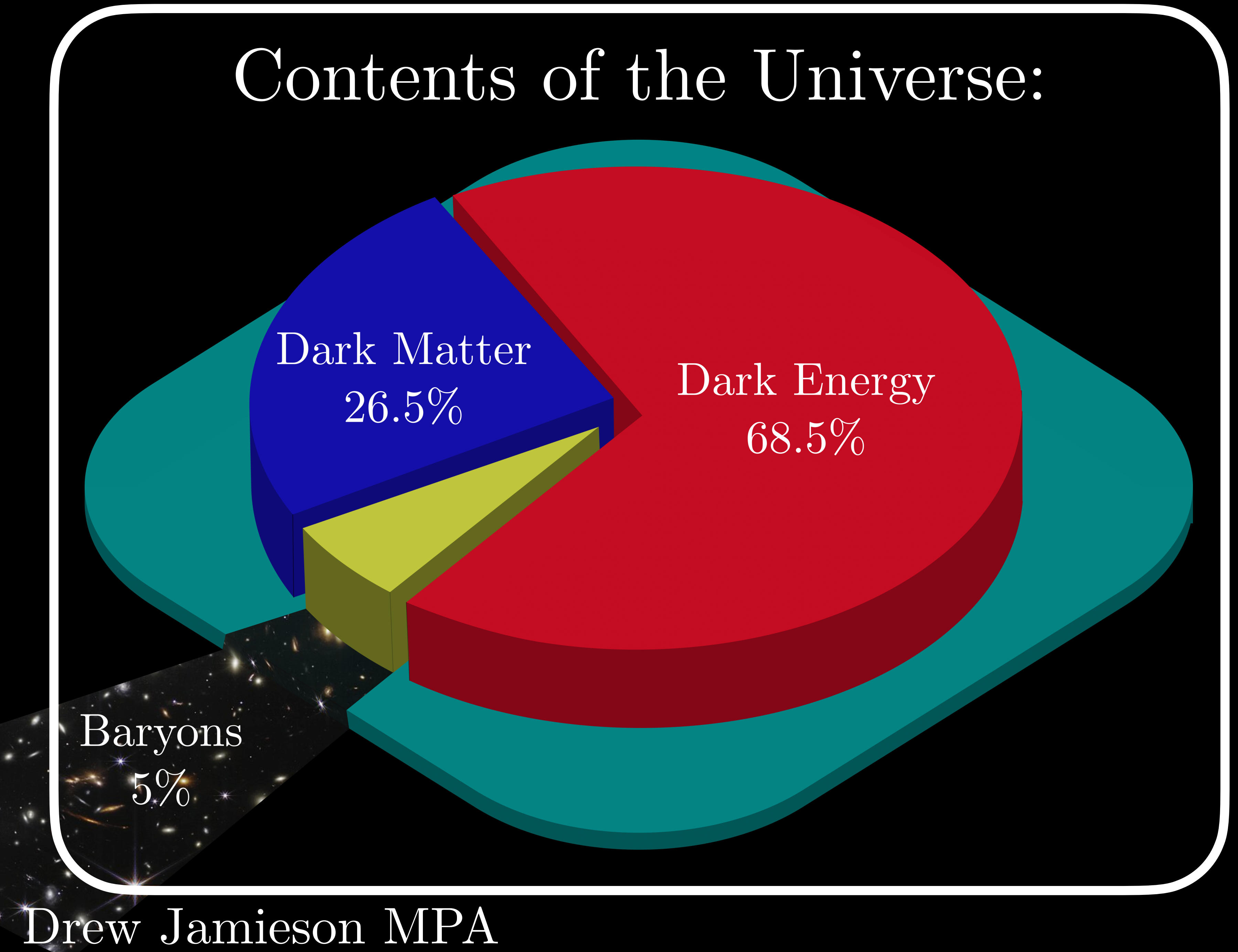
<u>Collaborators</u>

Peng Cheng Laboratory:	Yin Li
Flatiron Institute:	Shirley Ho, David Spergel, Francisco Villaescusa-Navarro, Renan Alves de Oliveira, Siyu He
Carnegie Mellon:	Aarti Singh, Vaibhav Jindal, Albert Liang
Stockholm University:	Ludvig Doeser, Jens Jasche
University of Edinburgh:	Marcos Pellejero
DIPC:	Raúl Angulo

Map2Map with style parameters:
https://github.com/eelregit/map2map
https://github.com/dsjamieson/map2map_emu



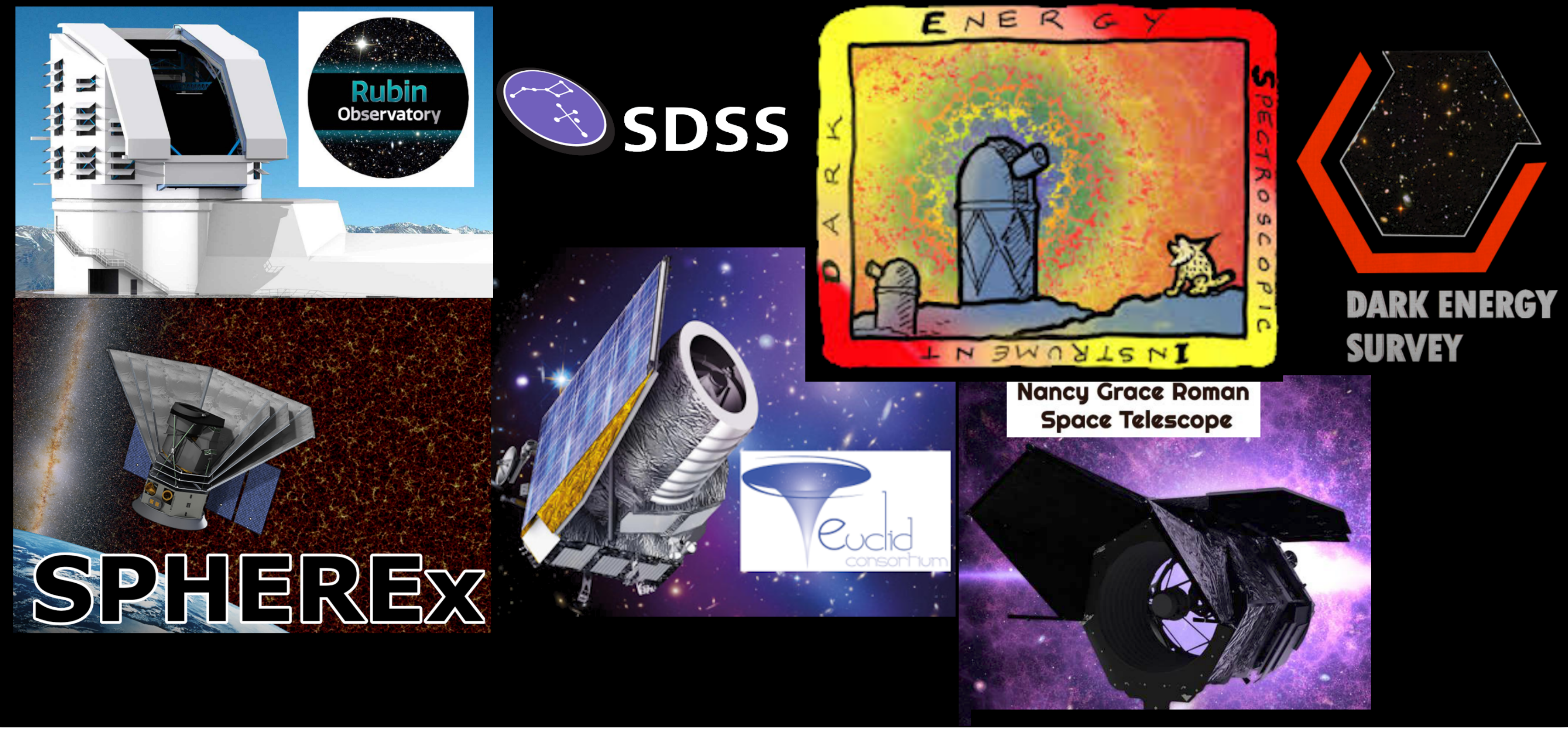




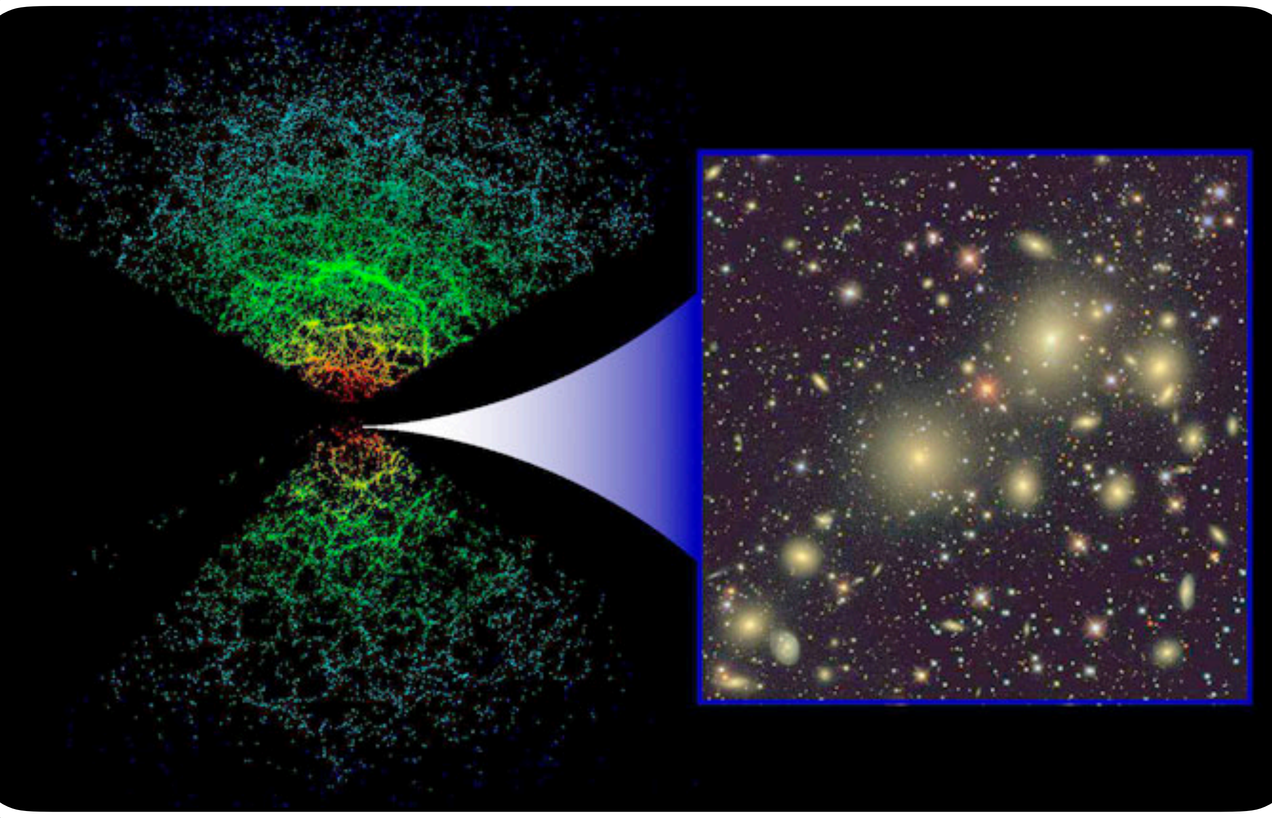
- Most of the energy density and matter not understood
- Initial conditions consistent with Gaussian statistics
- Slightly red-tilted power spectrum: inflation?
- To learn more about the early universe we need
  - Primordial non-Gaussianity
  - Primordial gravitational waves

Modern cosmological surveys and inference

Surveys

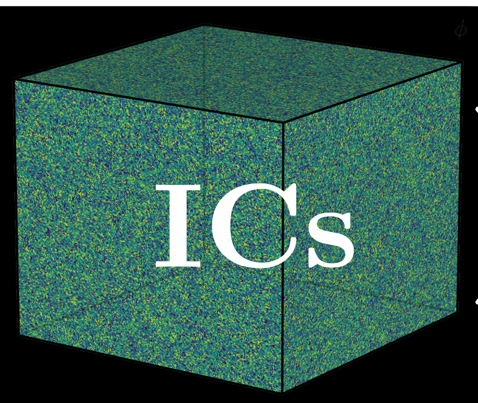


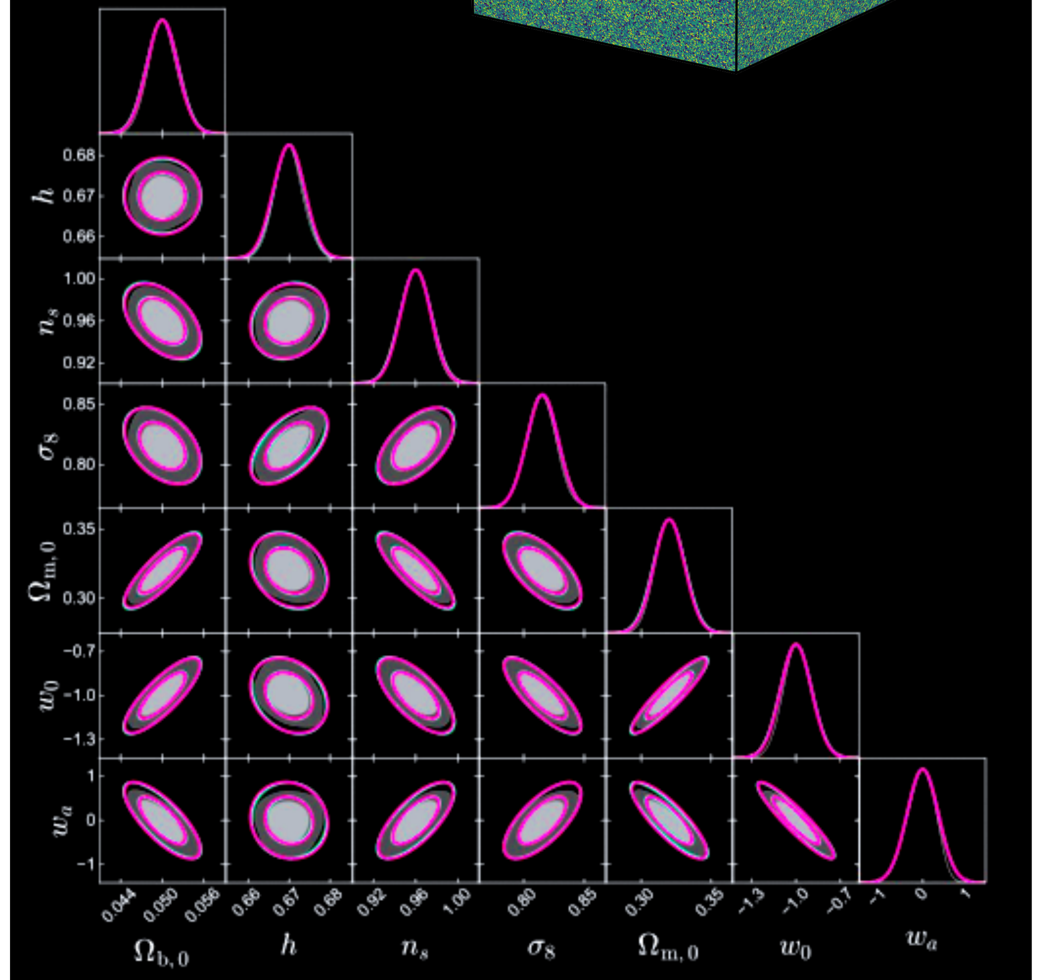
Data



Comparison & Inference

$\mathscr{P}($ ICs $)$





Parameters

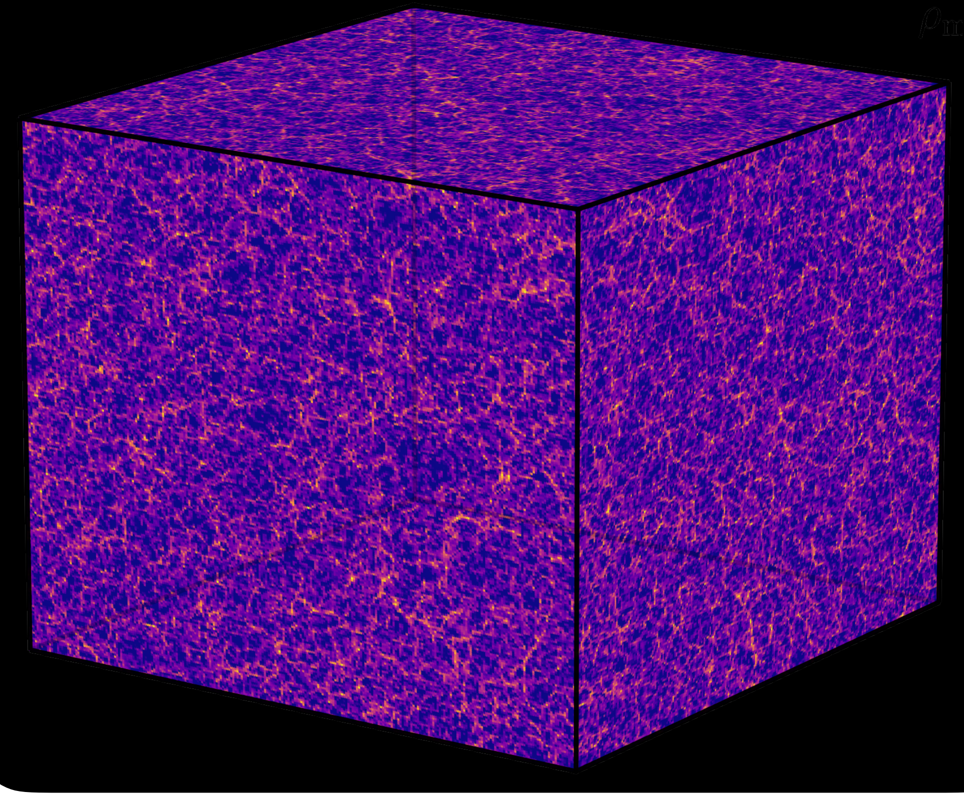
Constraints

ΛCDM + extensions

$f_{\rm NL}$ Ω_K

M_ν $w_0 + w_1 a$

Model



Forward-model prediction

Predicting the large-scale structure

$z = 20.00$

Villaescusa-Navarro

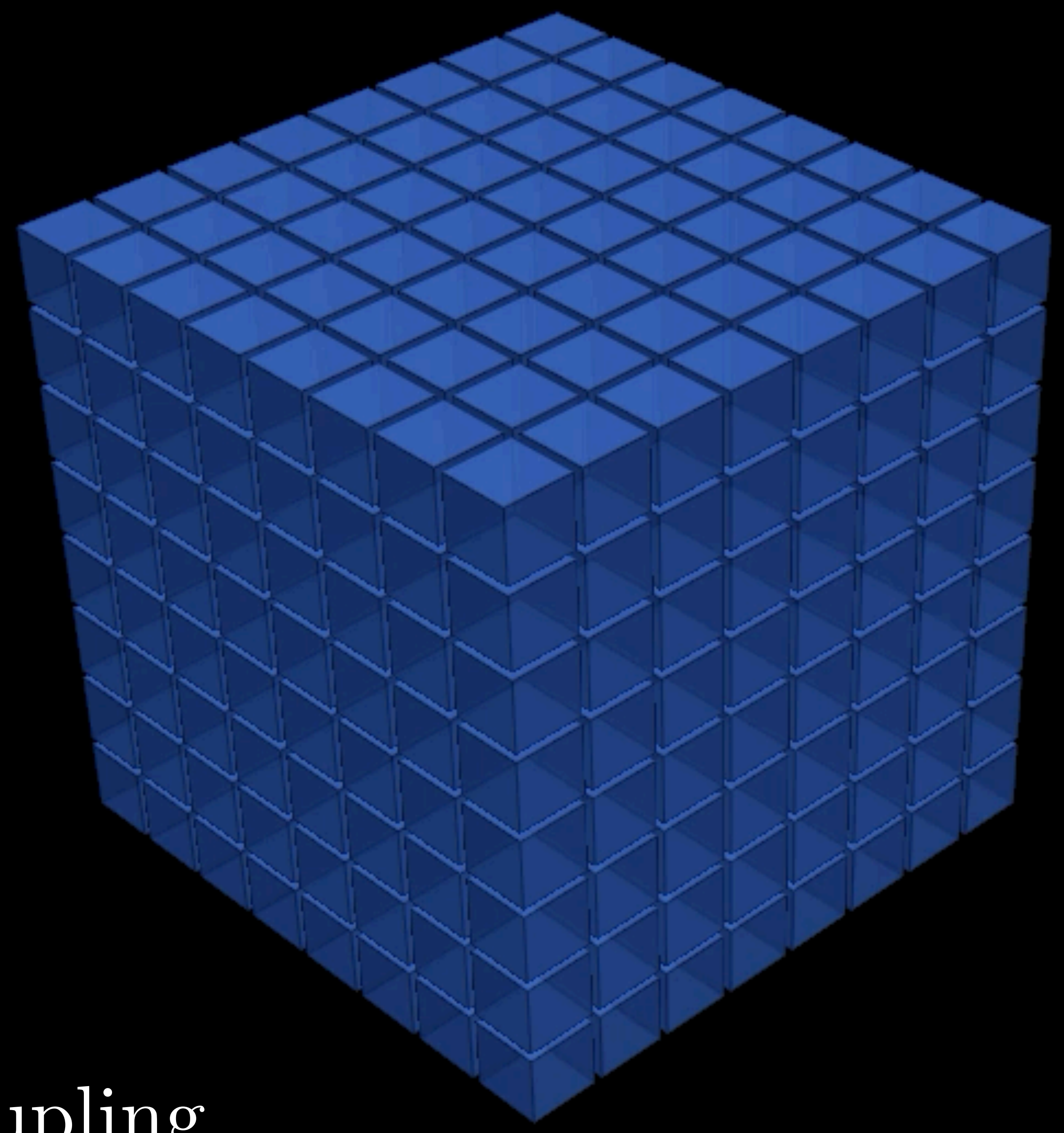
N-Body Simulations

- Newtonian gravity in an expanding universe
- Evolve $10^5 - 10^6$ N-body *particles*
- Integrate $\sim 10^3$ time steps
- Costs $\sim 10^3$ CPU hours
- Difficult to accelerate with GPUs

Can be very accurate, but too expensive to use directly for inference

Accelerating Our Predictions With Machine Learning

- Initial data on 3D grid: just like 3D image processing

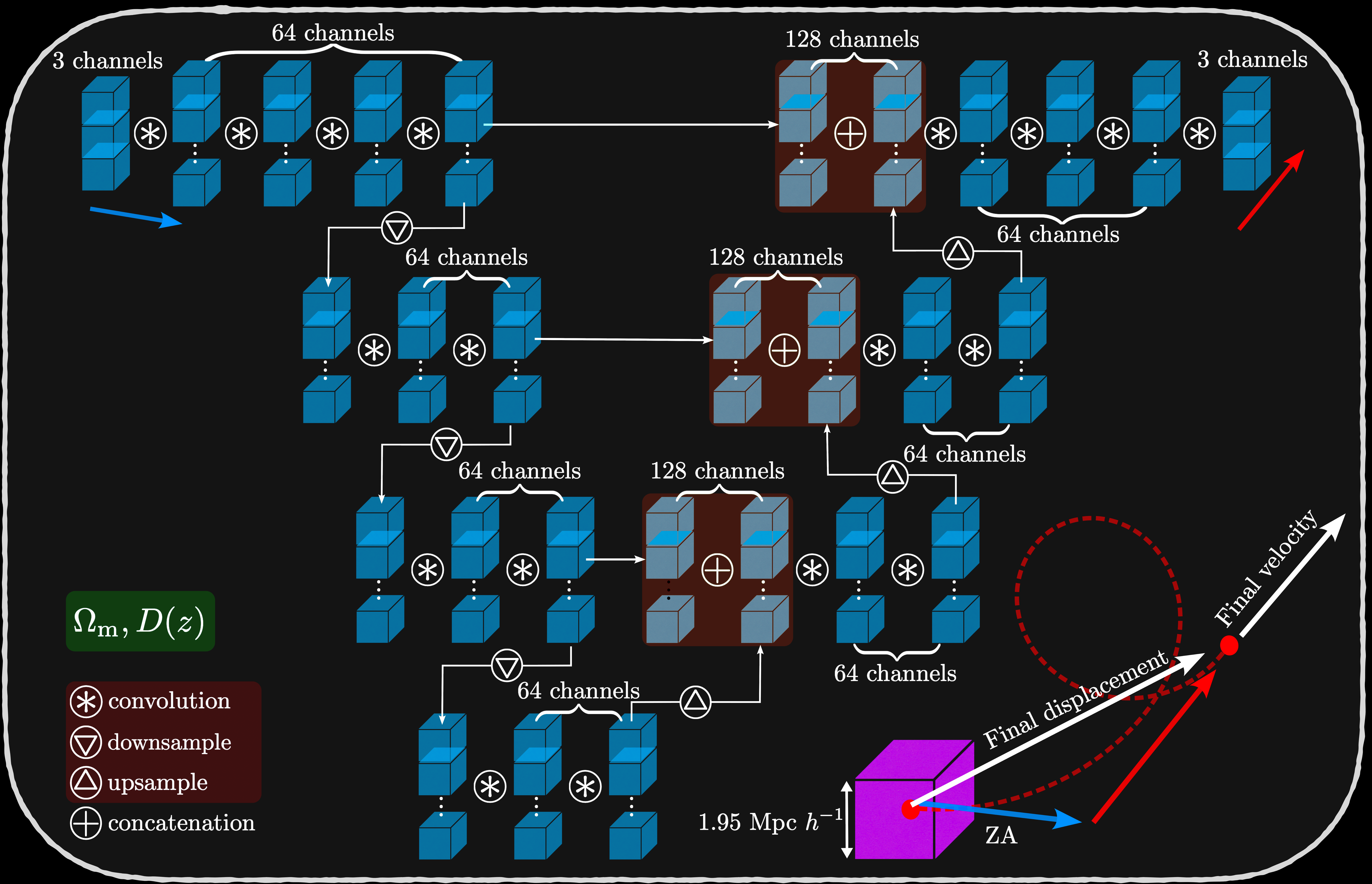


- Map from early to late times is deterministic
- Convolutions, up/down sampling probes different scales
- Mixing information from different scale: nonlinear mode coupling
- Finite receptive field: preserves large scales

Map2Map

- U-Net/V-Net design
- 4 convolutional layers
- Receptive field: 190 Mpc/h
- Preserves ZA on large scales
- Input ZA field at z=0
- Output nonlinear field at redshift z

Map2Map: https://github.com/eelregit/map2map



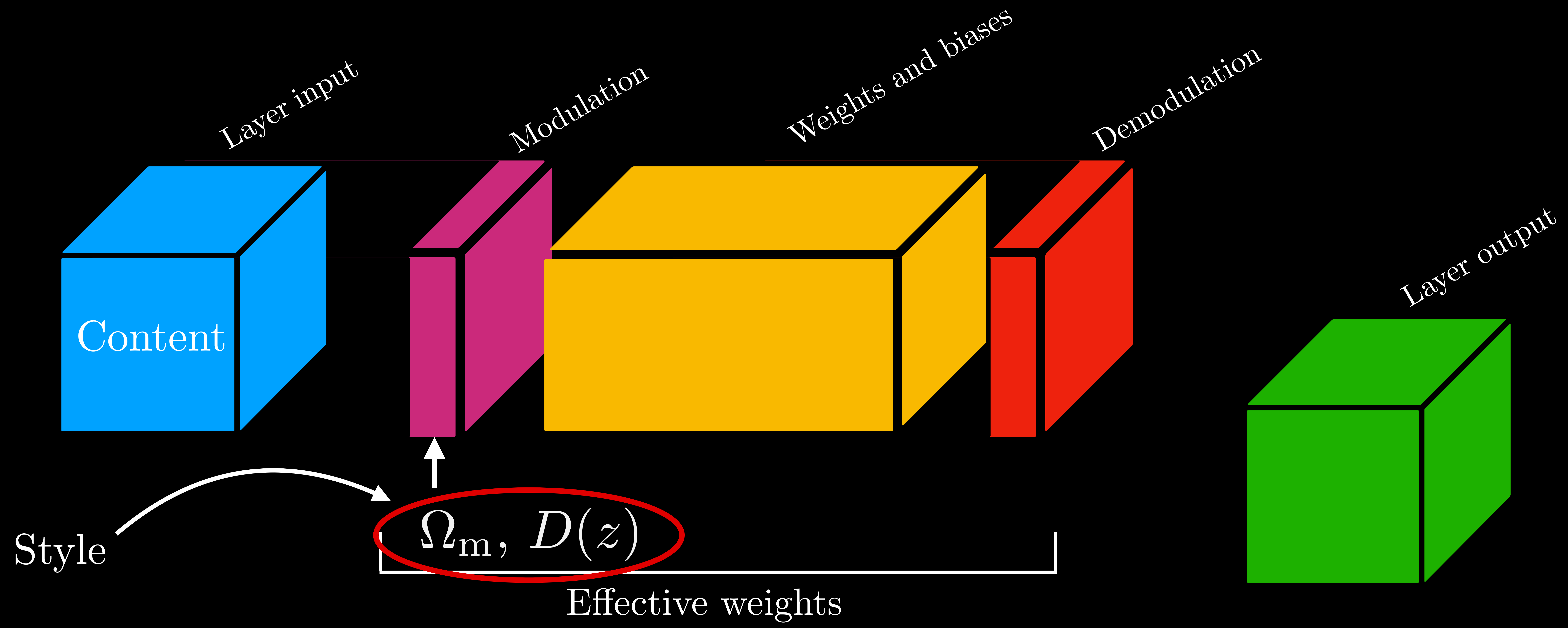
Style vs. content

Gatys, Ecker, Bethge arXiv:1508:06576
Karras, Laine, Aittala, Hellsten, Lehtinen, Aila arXiv:1912.04958

Content | Style | Results

Cosmology dependence

StyleGAN2: http://arxiv.org/abs/1912.04958



- Based on StyleGAN2: https://github.com/NVlabs/stylegan2
- $\Omega_{\rm m}$ is a style parameter input for every convolutional operation
- Model learns to interpolate predictions of LSS for different cosmologies

arXiv > astro-ph > arXiv:2408.07699

Astrophysics > Cosmology and Nongalactic Astrophysics

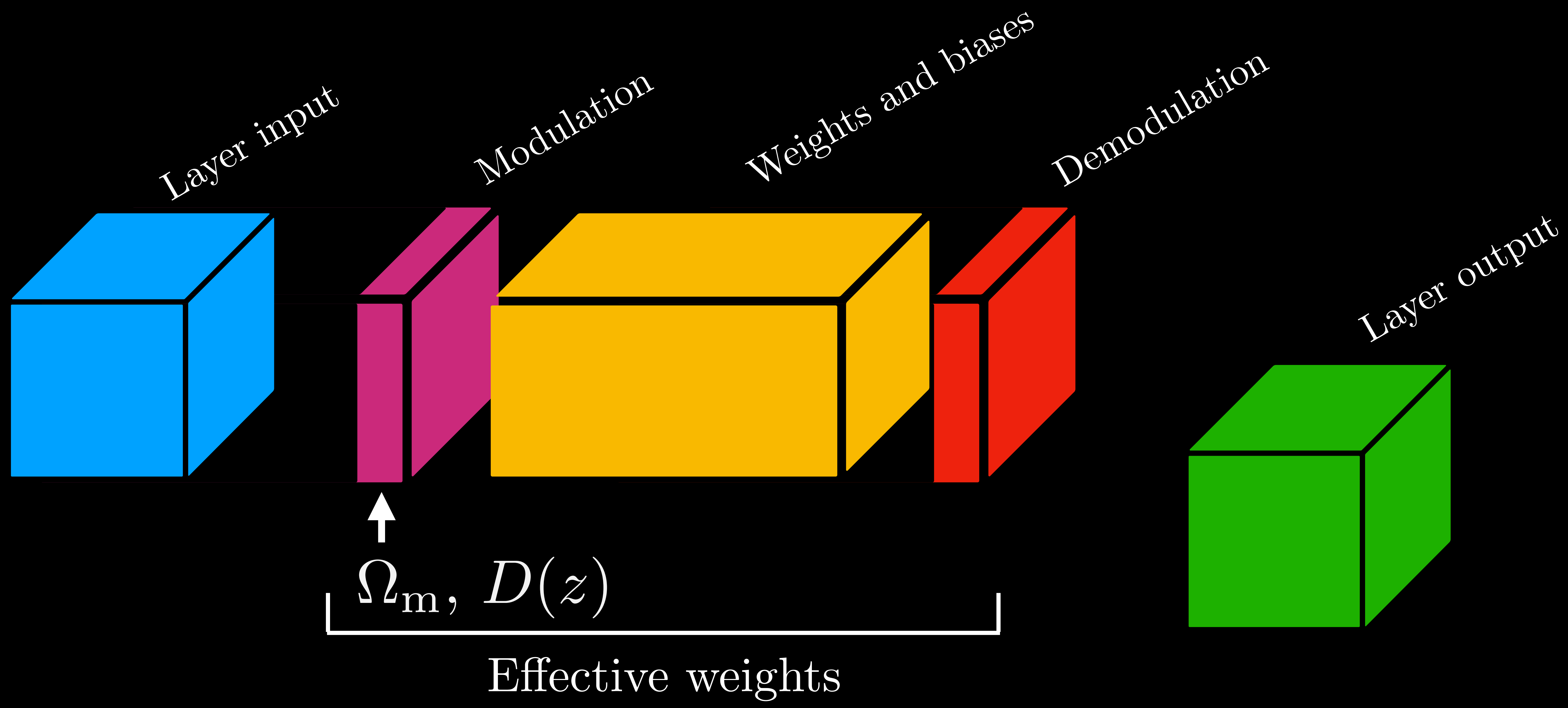
[Submitted on 14 Aug 2024]

Field-level Emulation of Cosmic Structure Formation with Cosmology and Redshift Dependence

Drew Jamieson, Yin Li, Francisco Villaescusa-Navarro, Shirley Ho, David N. Spergel

Do not need a velocity model!

$$\boxed{\vec{v} = \dot{\vec{x}} = \frac{\partial \vec{x}}{\partial D}\frac{\mathrm{d}D}{\mathrm{d}t}}$$



Evaluate velocities during training

arXiv > astro-ph > arXiv:2408.07699

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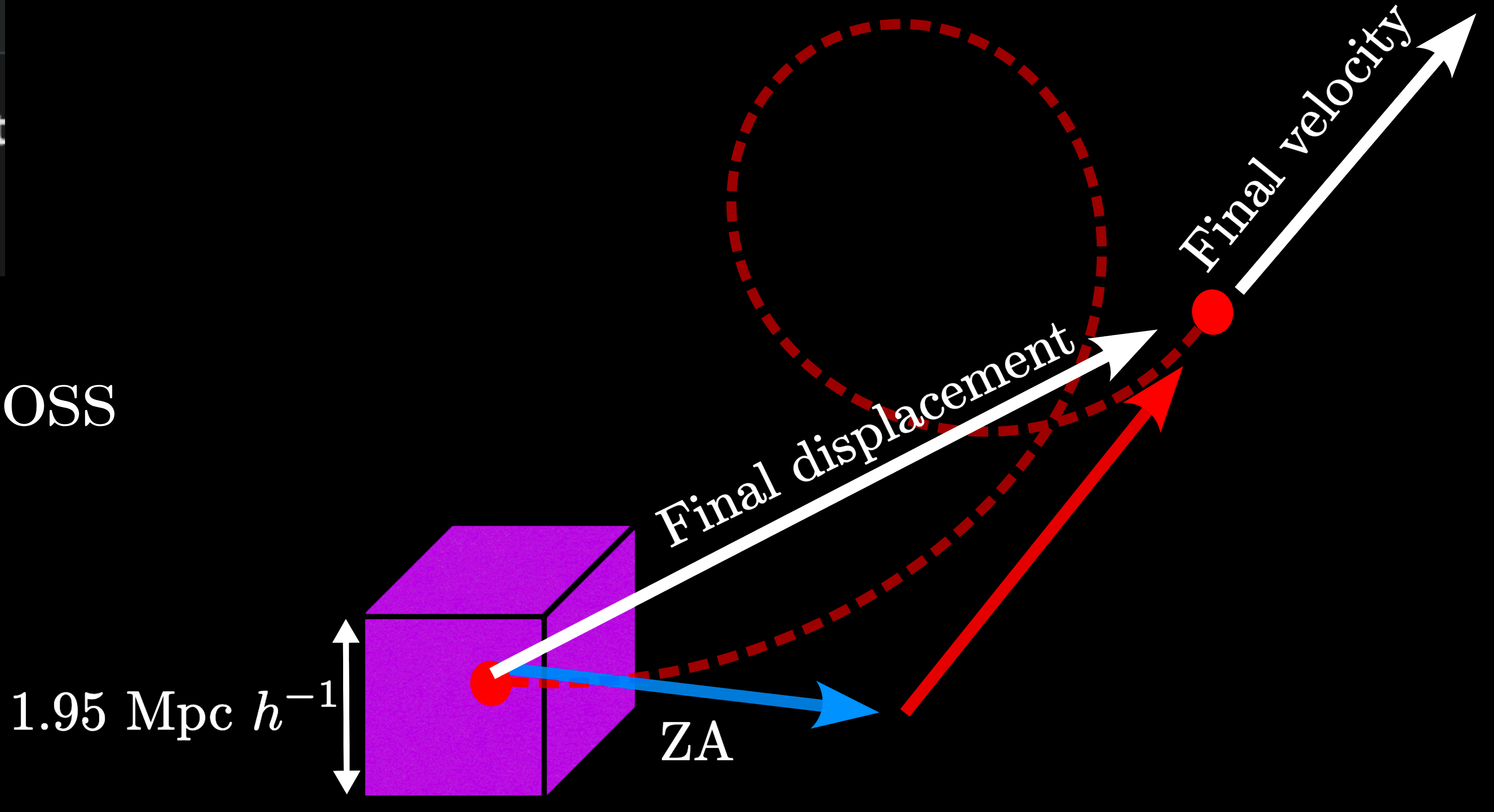
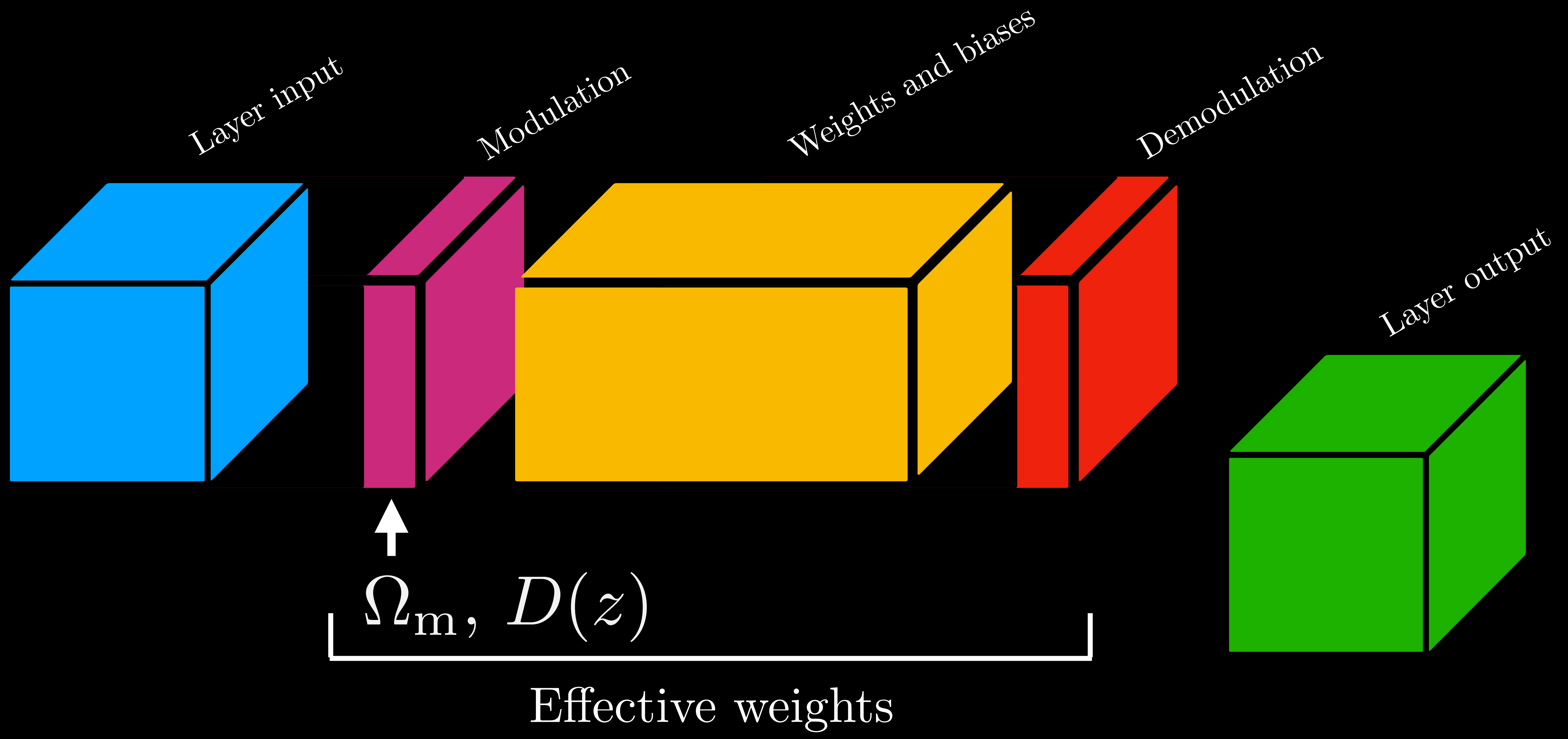
Evaluate velocities during training and add to loss



$$\begin{aligned}\text{Loss} = &\ 3\log\left(\sum(\text{displacement error})^2\right)\\ &+\log\left(\sum(\text{density error})^2\right)\\ &+3\log\left(\sum(\text{velocity error})^2\right)\\ &+\log\left(\sum(\text{momentum error})^2\right)\end{aligned}$$



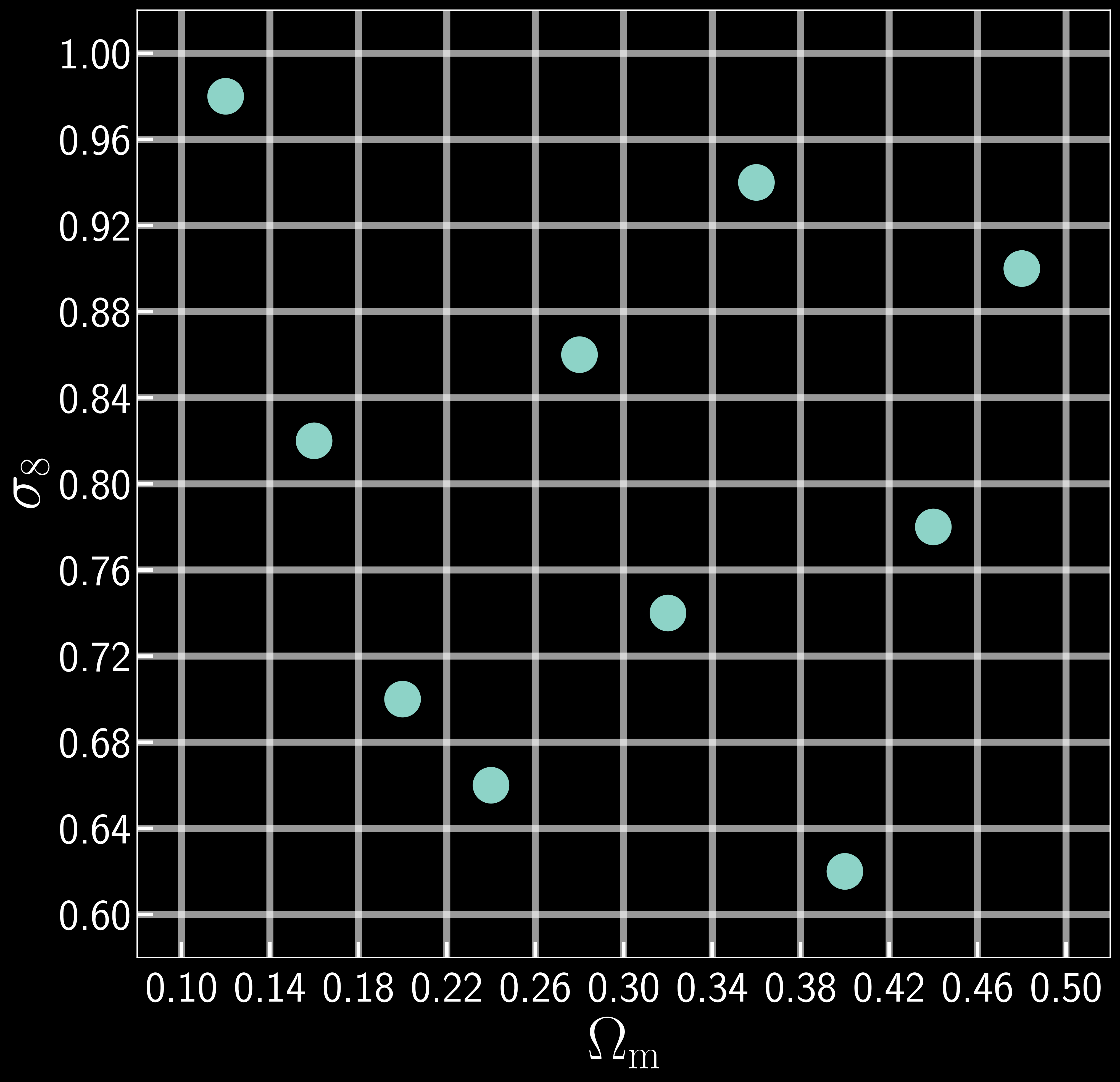
Train on full 6D N-body phase space

Training Data: Quijote Latin Hypercube

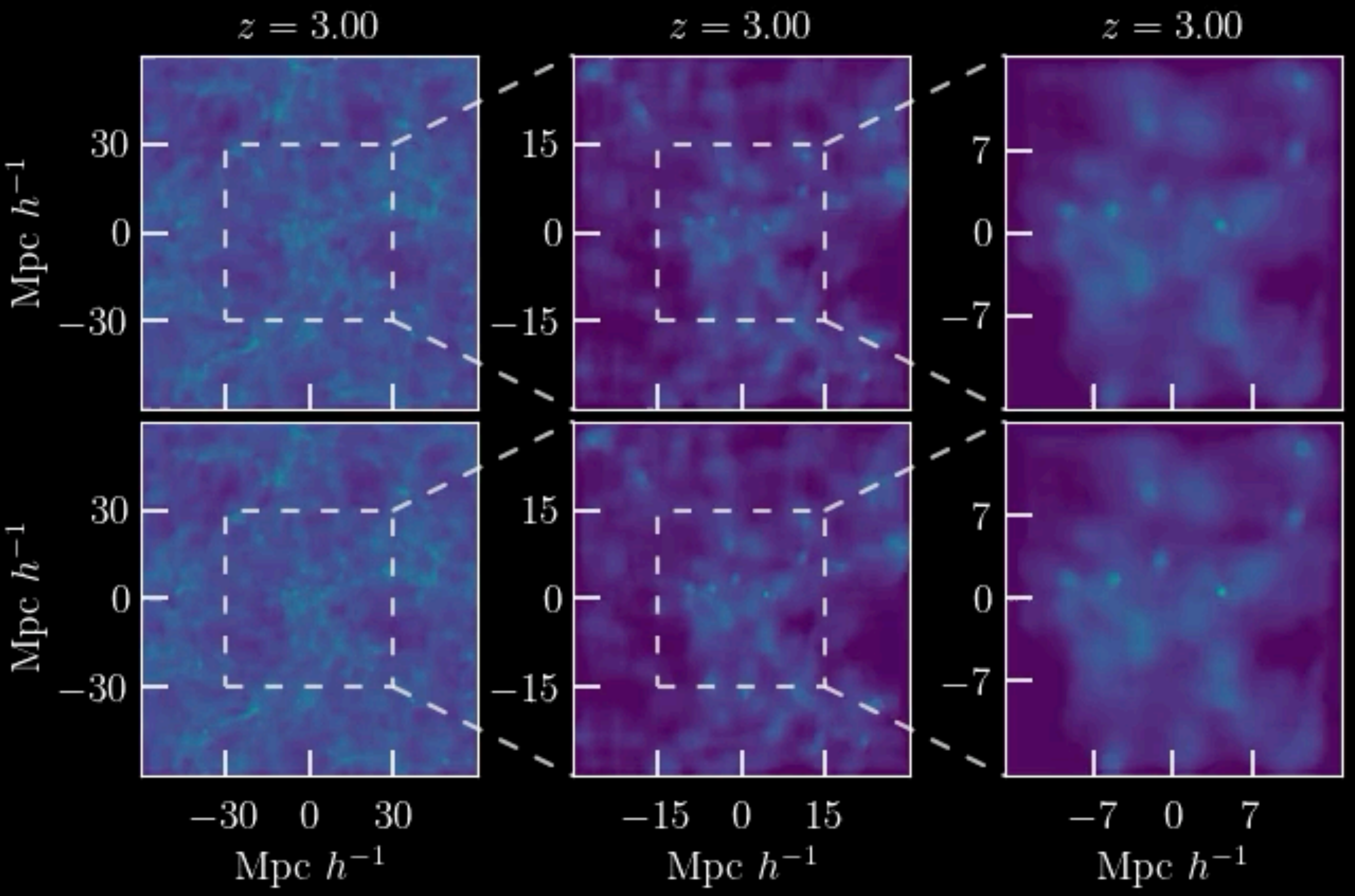
Villaescusa-Navarro et al. arXiv:1909:05273

- 2000 simulations
- 512^3 particles 1 Gpc/h box
- Latin hypercube sample of 5 parameters

Ω_m	$0.1 - 0.5$
Ω_b	$0.03 - 0.07$
h	$0.5 - 0.9$
n_s	$0.8 - 1.2$
σ_8	$0.6 - 1.0$



Cosmology and time dependence



Emulator

- Processes 256^3 box in 0.5 s
- $\sim 20000\times$ faster than N-body
- Parallelize crops across GPU
- Excellent multi-GPU scaling
- Larger volumes trivial
- GPU memory bound
- Higher resolution not trivial

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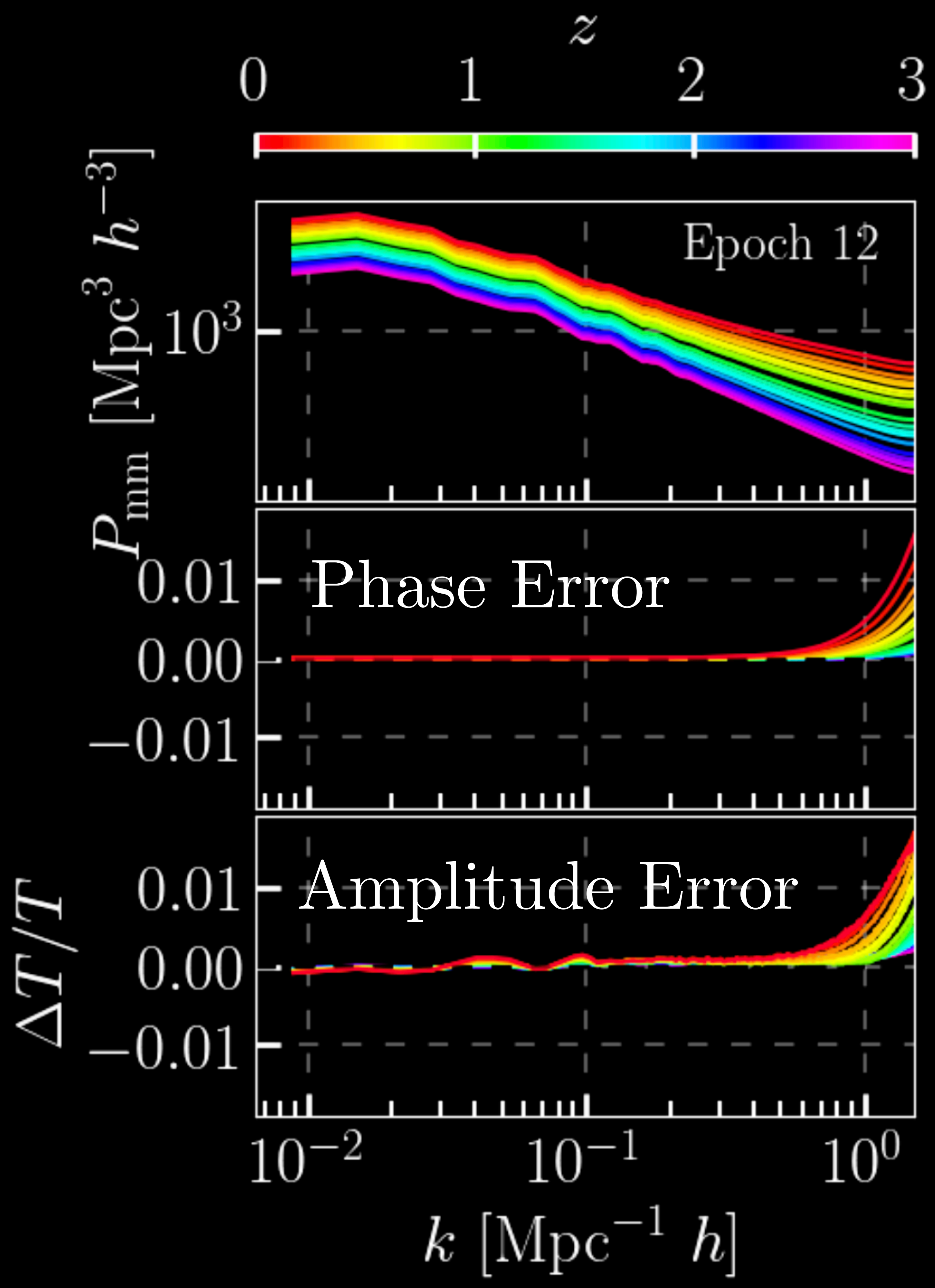
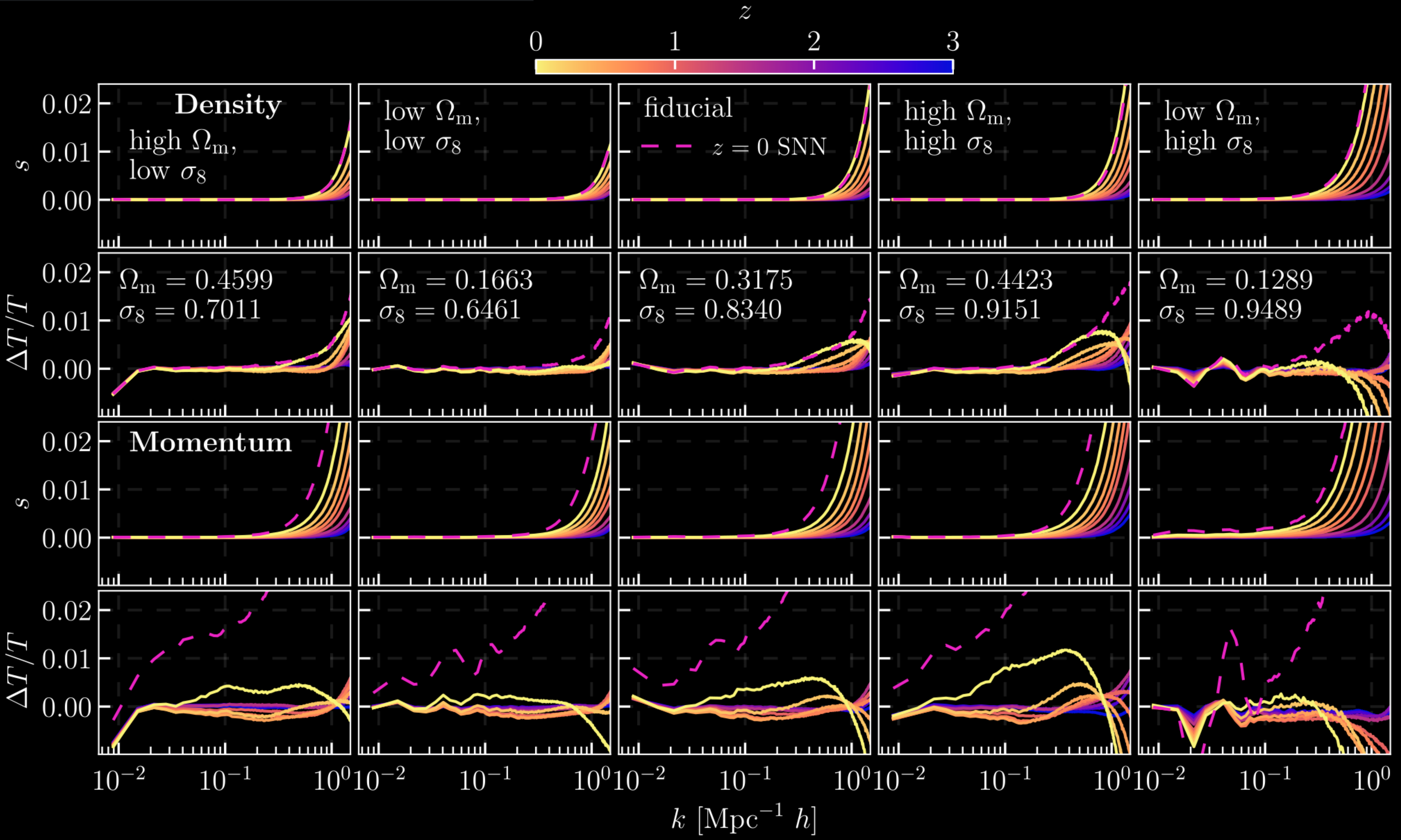




arXiv > astro-ph > arXiv:2206.04594

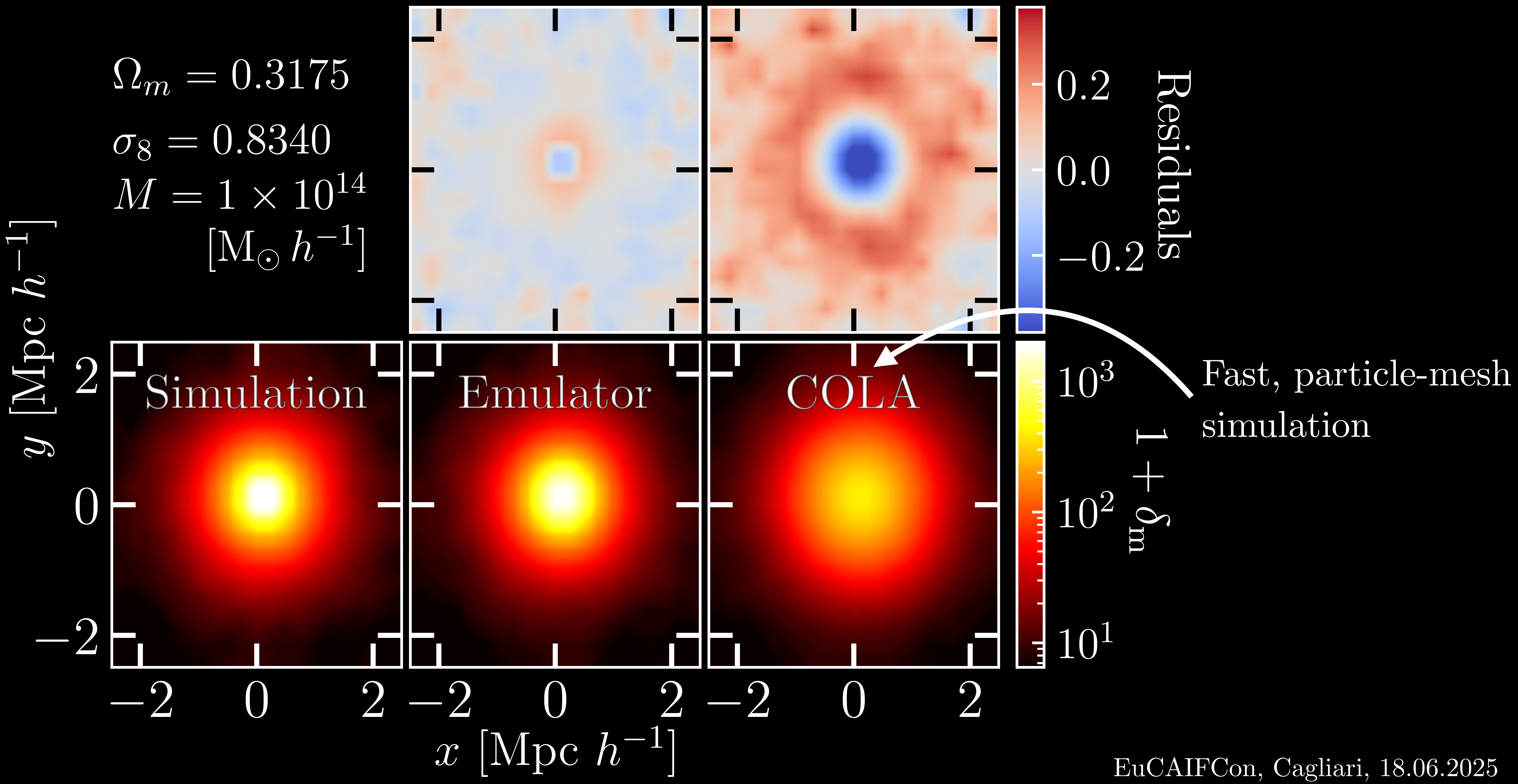
Astrophysics > Cosmology and Nongalactic Astrophysics

[Submitted on 9 Jun 2022 (v1), last revised 14 Jun 2022 (this version, v2)]

Field Level Neural Network Emulator for Cosmological N-body Simulations

Drew Jamieson, Yin Li, Renan Alves de Oliveira, Francisco Villaescusa-Navarro, Shirley Ho, David N. Spergel

Halos and Small-scale Errors



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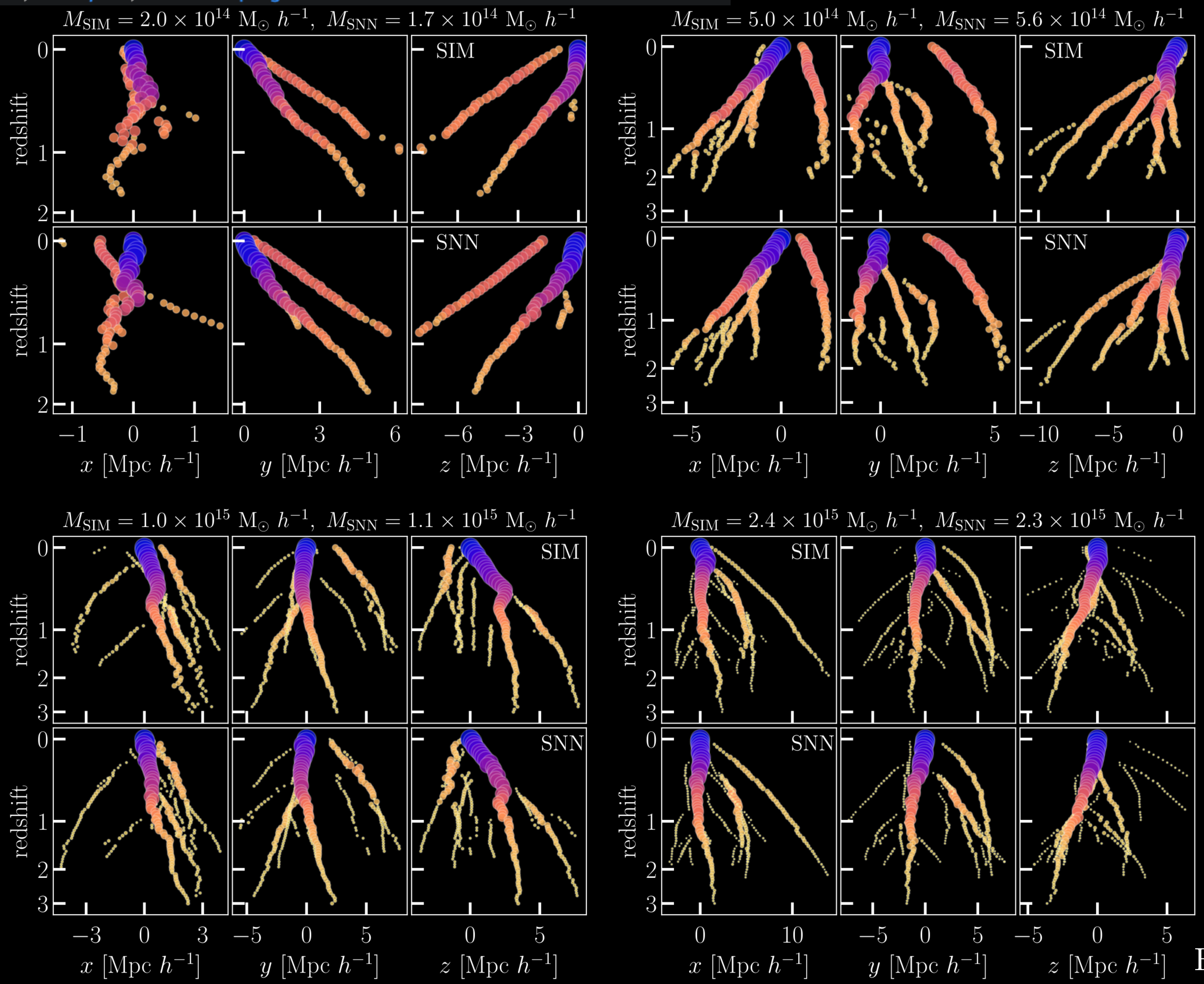
Field-level Emulation of Cosmic Structure Formation with Cosmology and Redshift Dependence

Drew Jamieson, Yin Li, Francisco Villaescusa-Navarro, Shirley Ho, David N. Spergel

Emulated Halo Merger Trees



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[Submitted on 14 Aug 2024]

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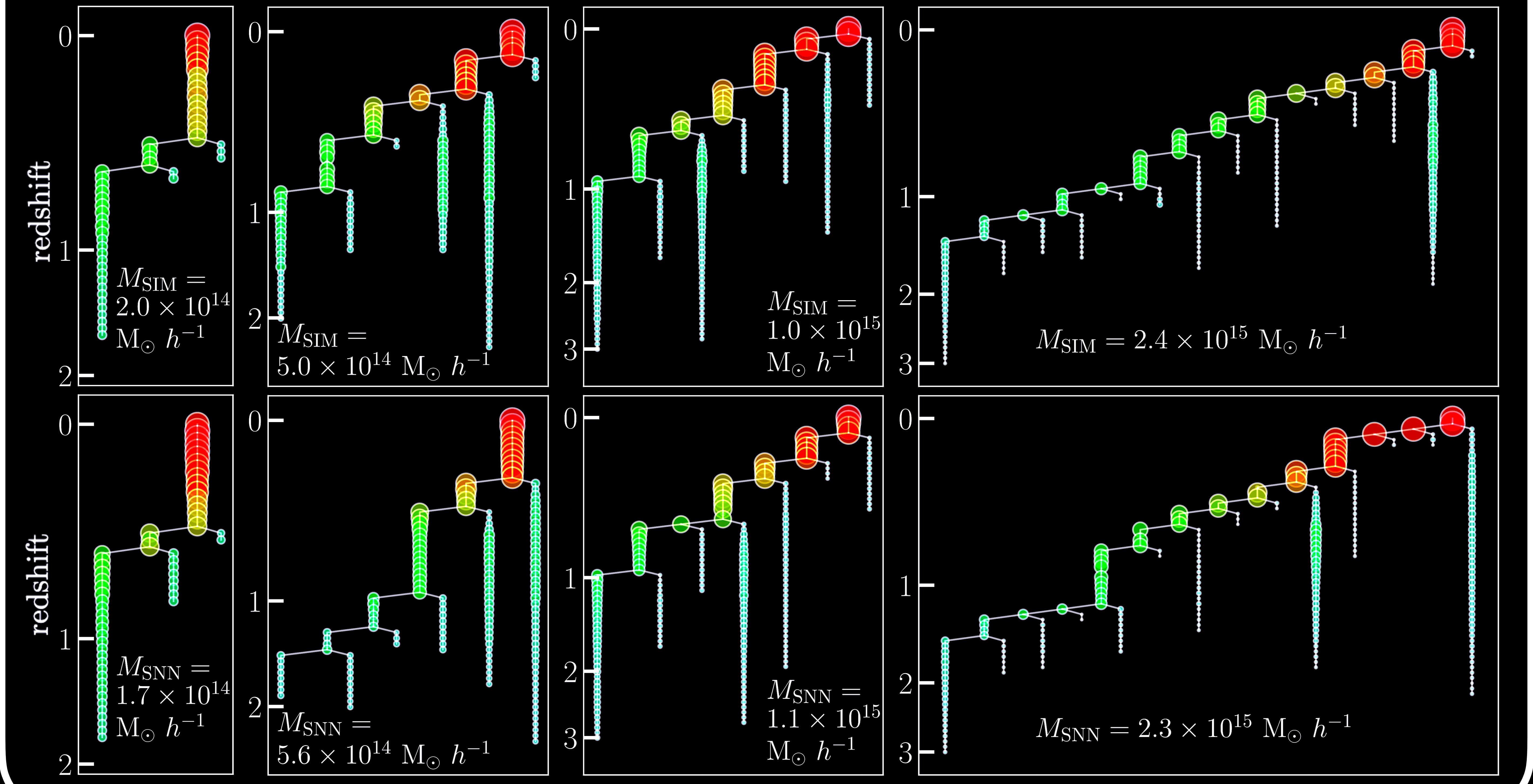
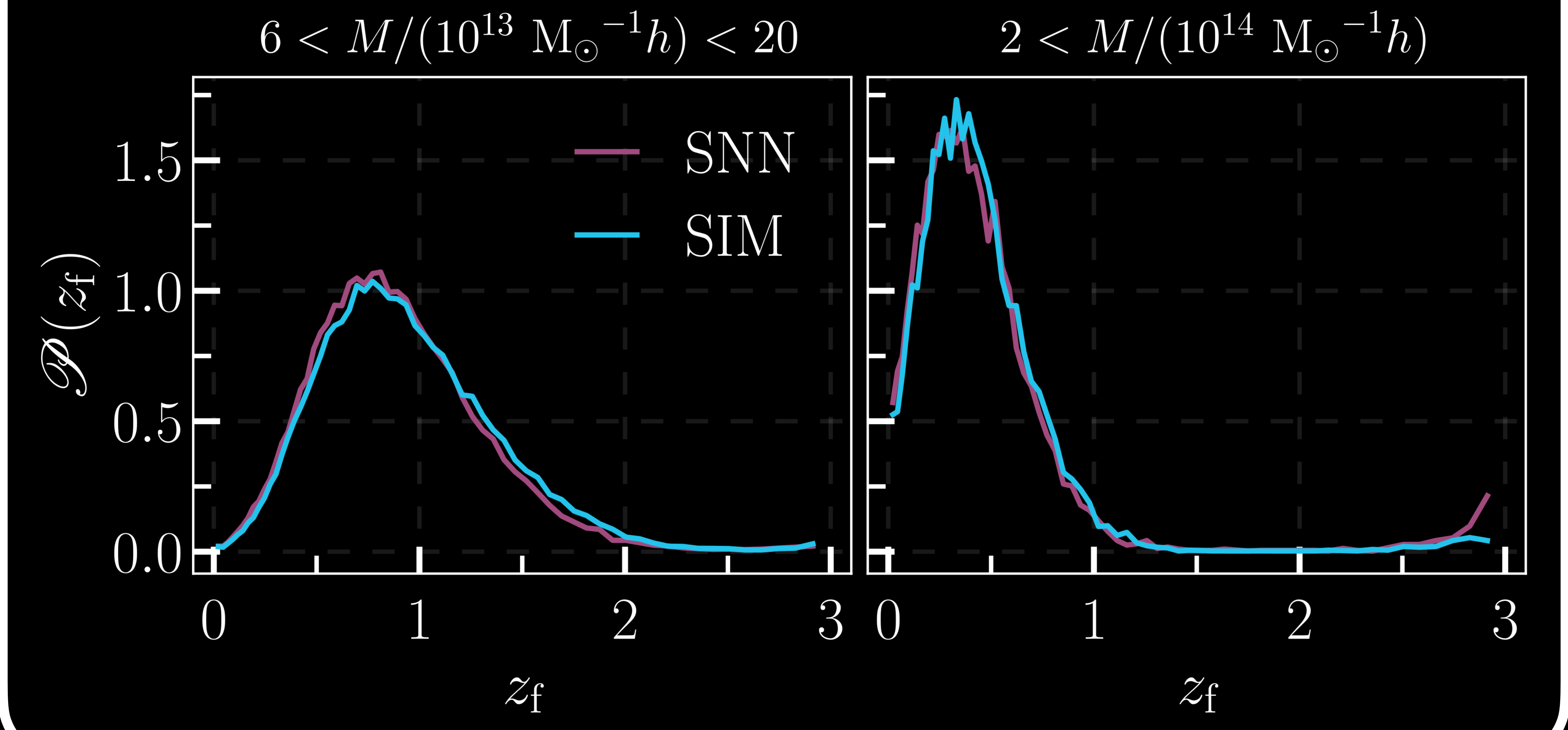
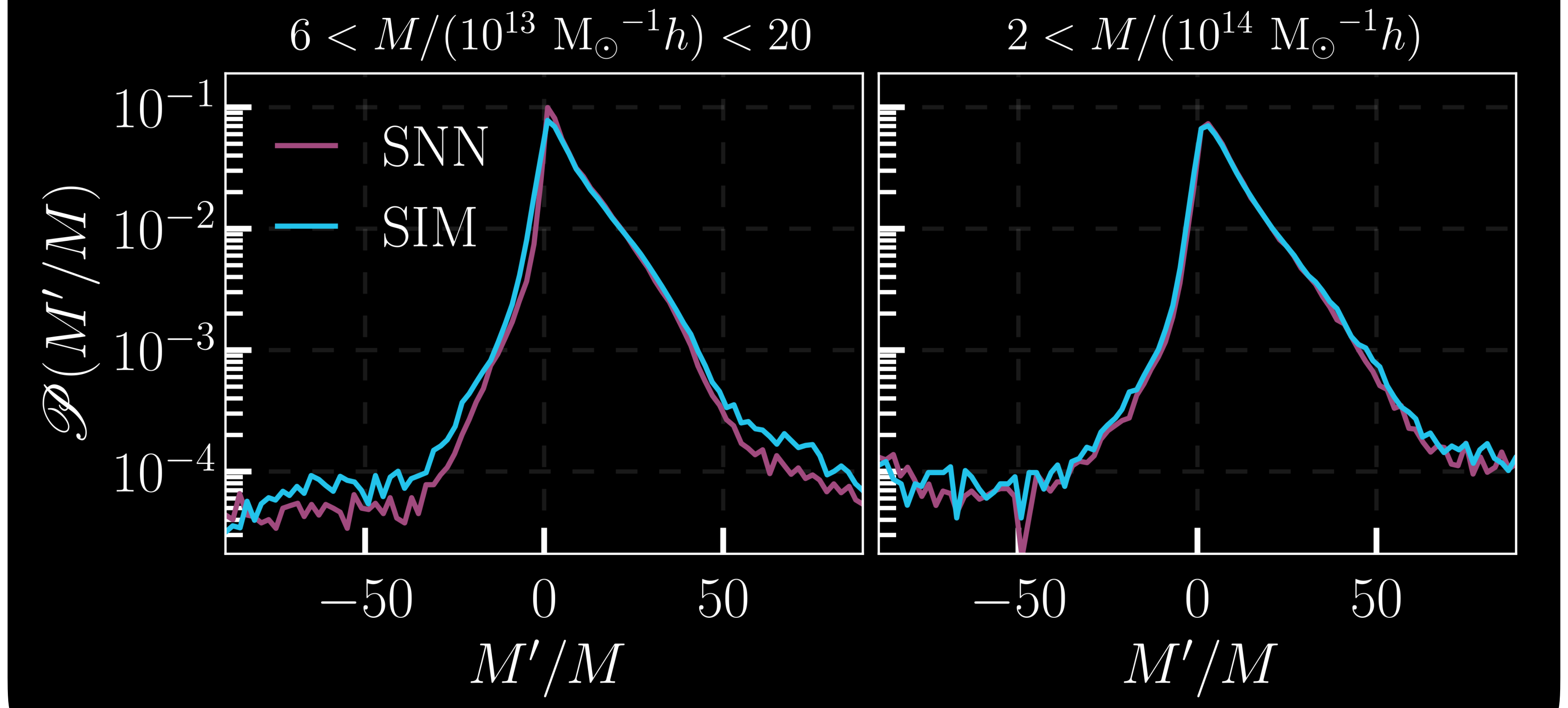
Individual Merger Trees



Formation Redshift



Mass Accretion



arXiv > astro-ph > arXiv:2502.13242

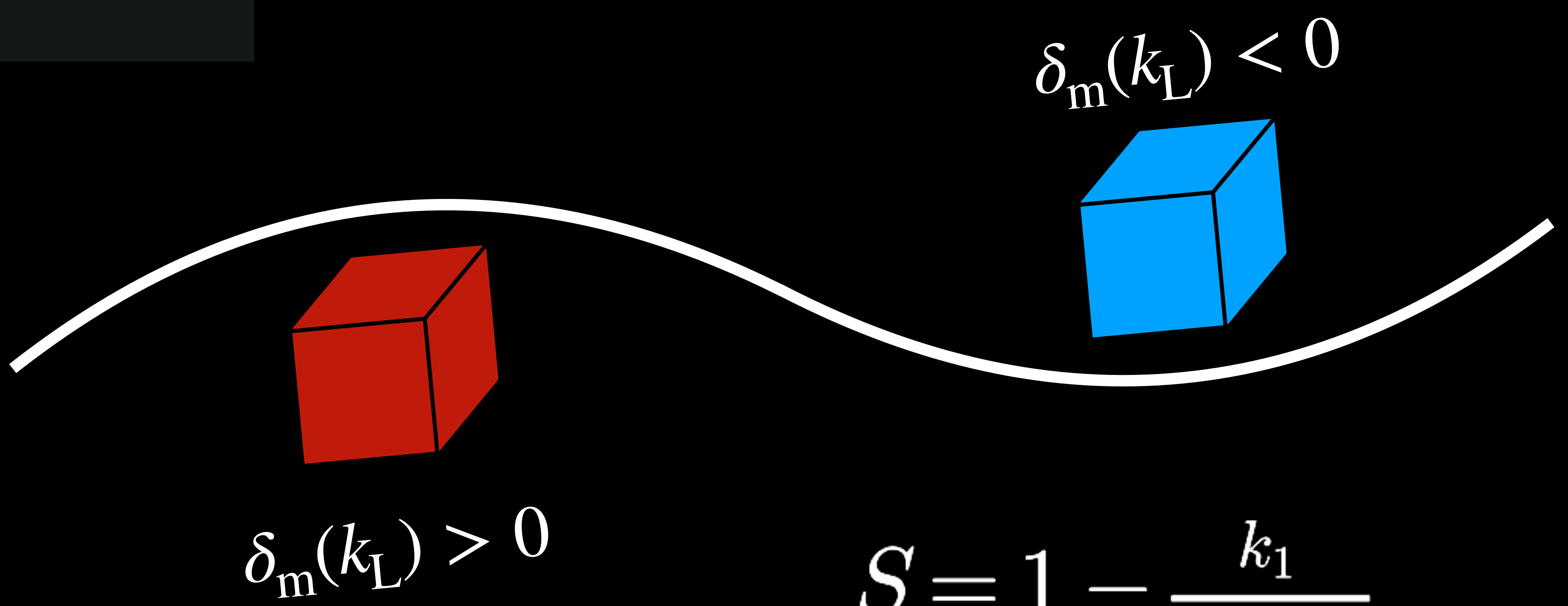
Astrophysics > Cosmology and Nongalactic Astrophysics

[Submitted on 18 Feb 2025]

Learning the Universe: $3\ h^{-1}$ Gpc Tests of a Field Level N-body Simulation Emulator

Matthew T. Scoggins, Matthew Ho, Francisco Villaescusa-Navarro, Drew Jamieson, Ludvig Doeser, Greg L. Bryan

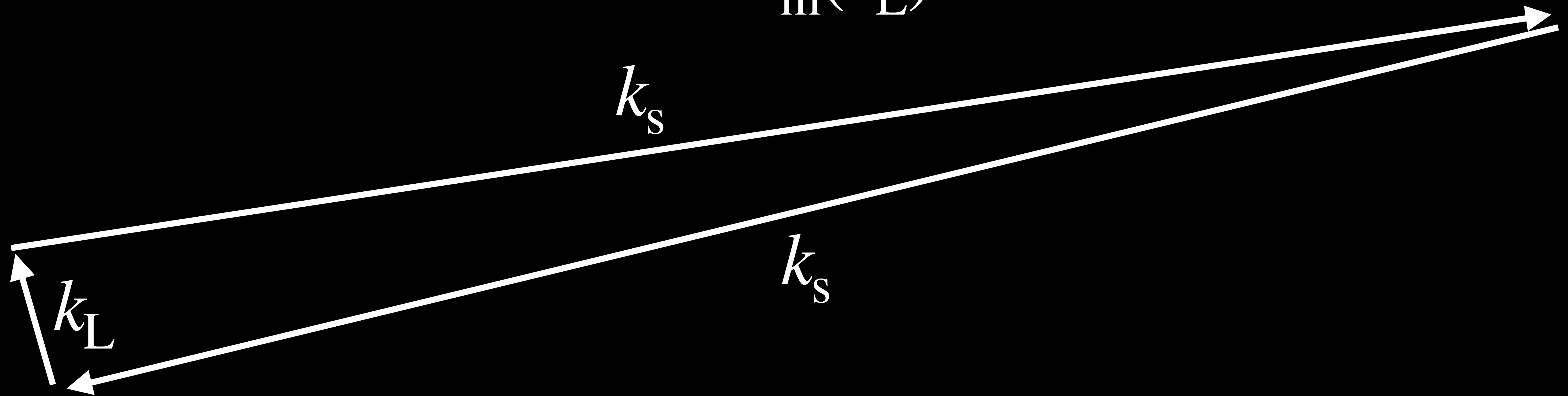
Modes larger than the receptive field



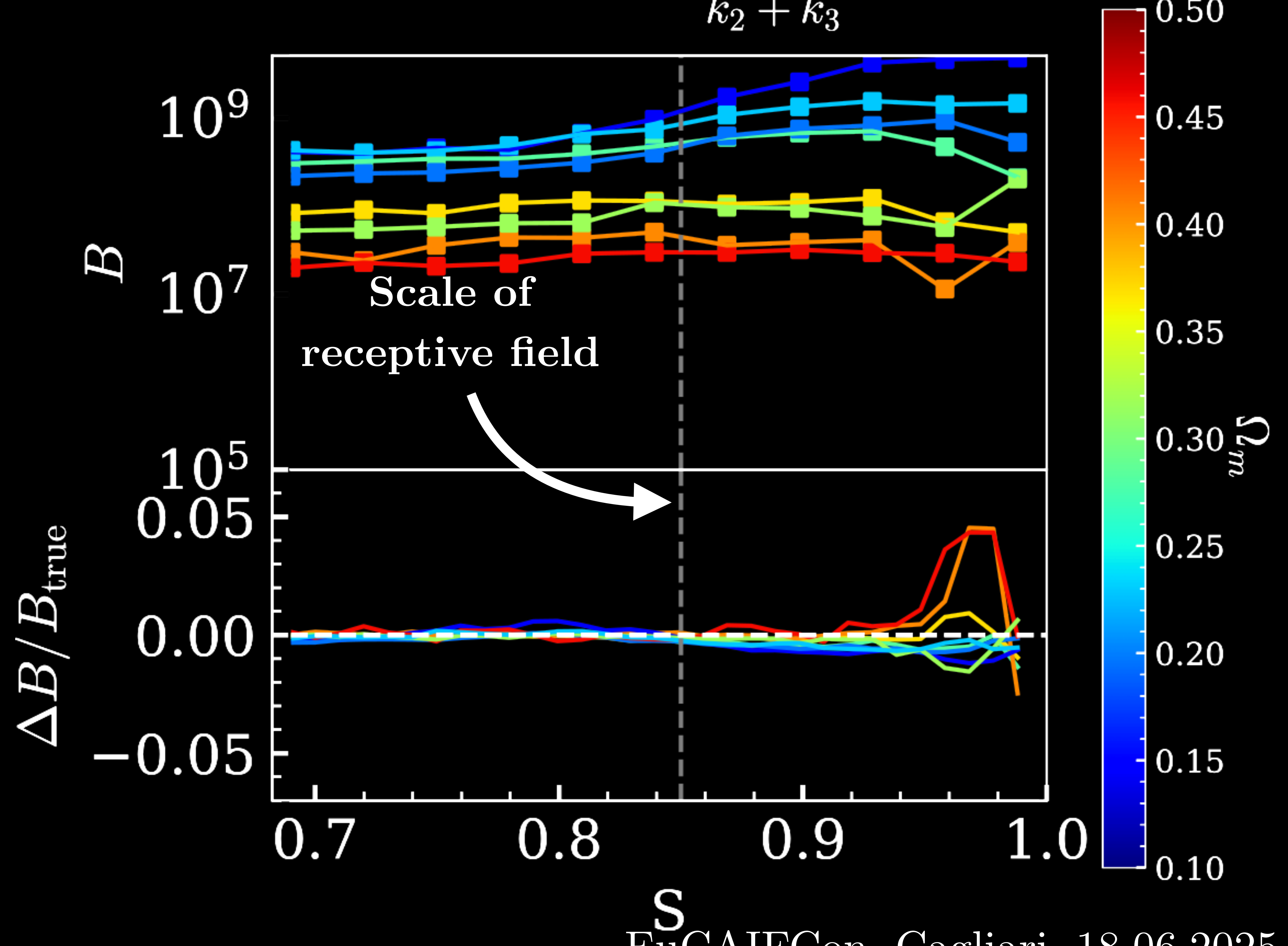
Large volume simulatons: $L_{\rm box} = 3$ Gpc/h

Squeezed bispectrum configurations:

$$\langle \delta_m(k_L)\delta_m(k_s)\delta_m(k_s)\rangle \propto \frac{\partial P_{mm}(k_s)}{\partial \delta_m(k_L)} \qquad k_L \ll k_s$$



$$S = 1 - \frac{k_1}{k_2 + k_3}$$



Emulator captures the effects of large-scale modes!

$$\boxed{\text{Is it learning physics?}}$$

arXiv > astro-ph > arXiv:2206.04573

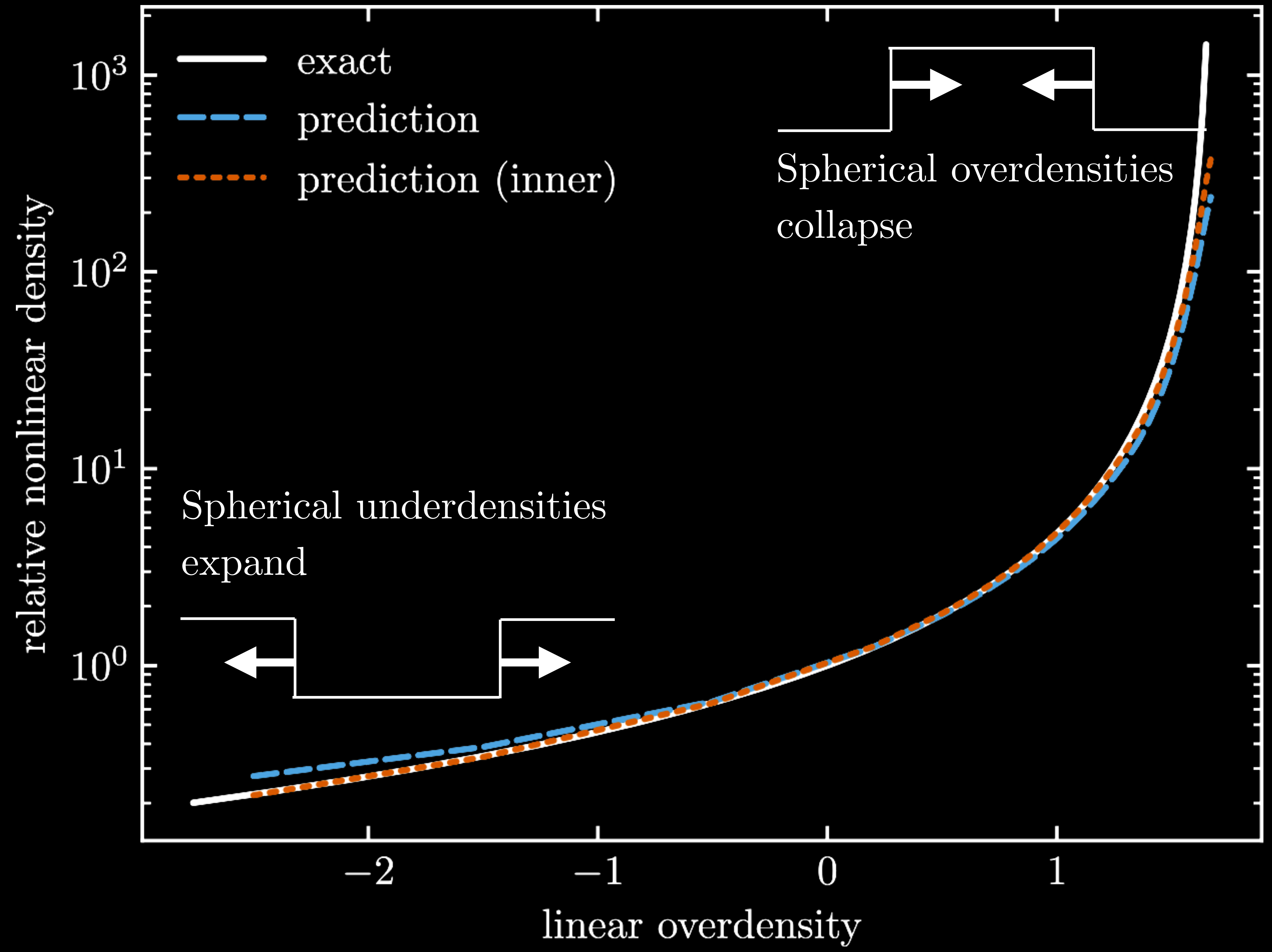
Astrophysics > Cosmology and Nongalactic Astrophysics

[Submitted on 9 Jun 2022 (v1), last revised 14 Jun 2022 (this version, v2)]

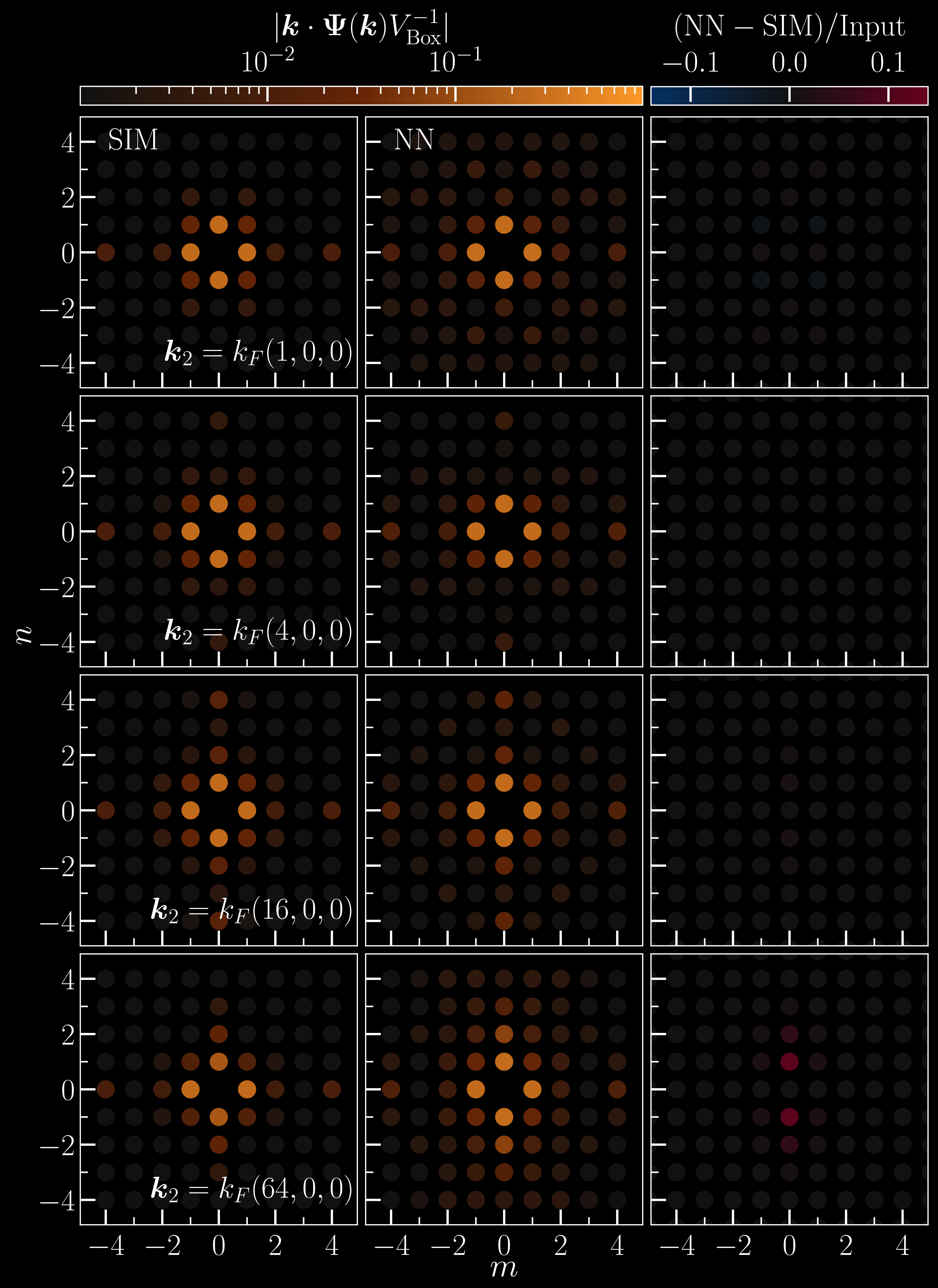
Simple lessons from complex learning: what a neural network model learns about cosmic structure formation

Drew Jamieson, Yin Li, Siyu He, Francisco Villaescusa-Navarro, Shirley Ho, Renan Alves de Oliveira, David N. Spergel

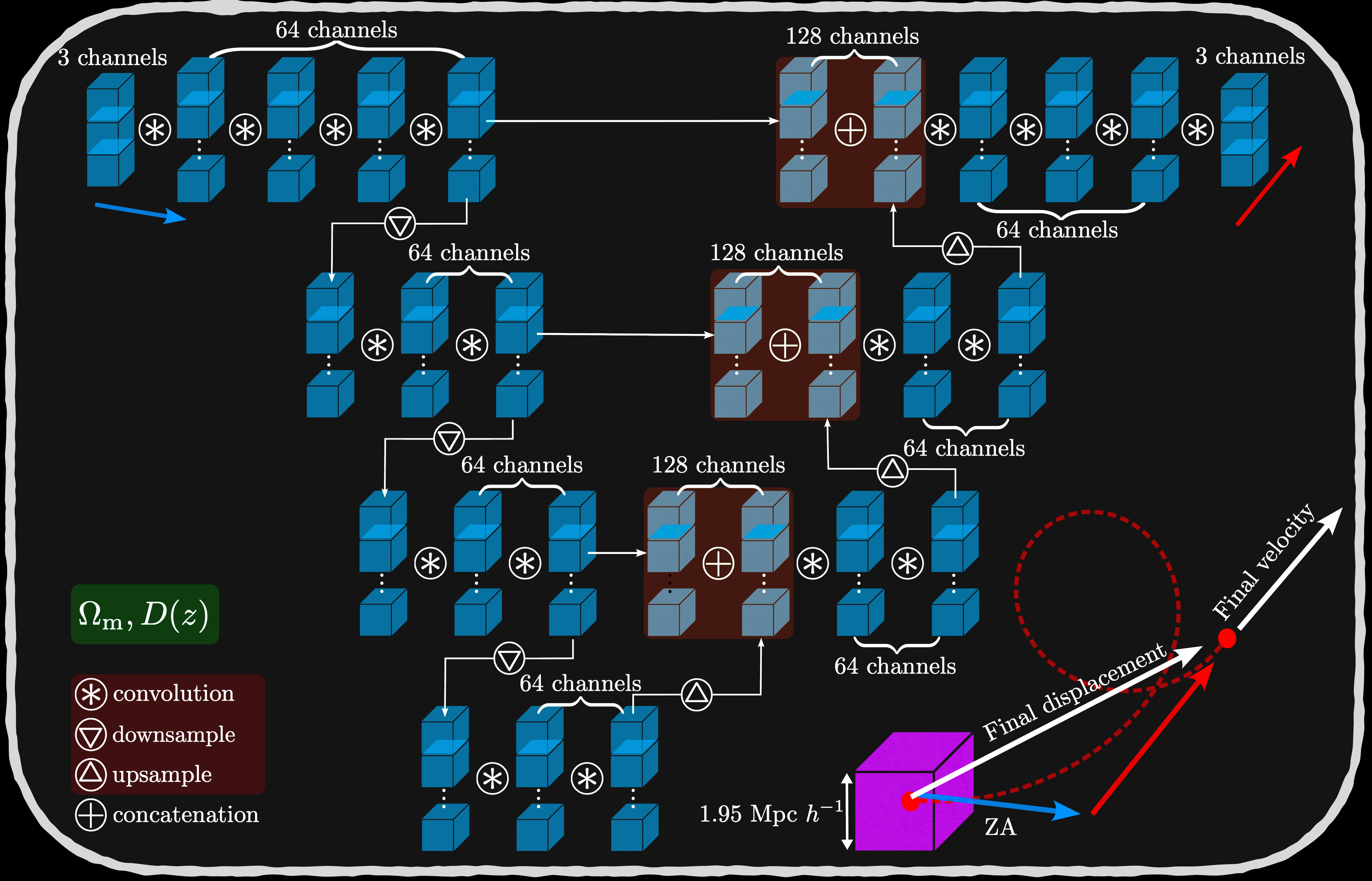
Spherical evolution



Mode coupling



Applications



Inferring initial conditions

arXiv:2312.09271

Modelling the galaxy field

arXiv:2307.09134

High-order N-point statistics

Coming soon

Mocks for modern surveys

Coming soonish

arXiv > astro-ph > arXiv:2312.09271

Astrophysics > Cosmology and Nongalactic Astrophysics

[Submitted on 14 Dec 2023]

Bayesian Inference of Initial Conditions from Non-Linear Cosmic Structures using Field-Level Emulators

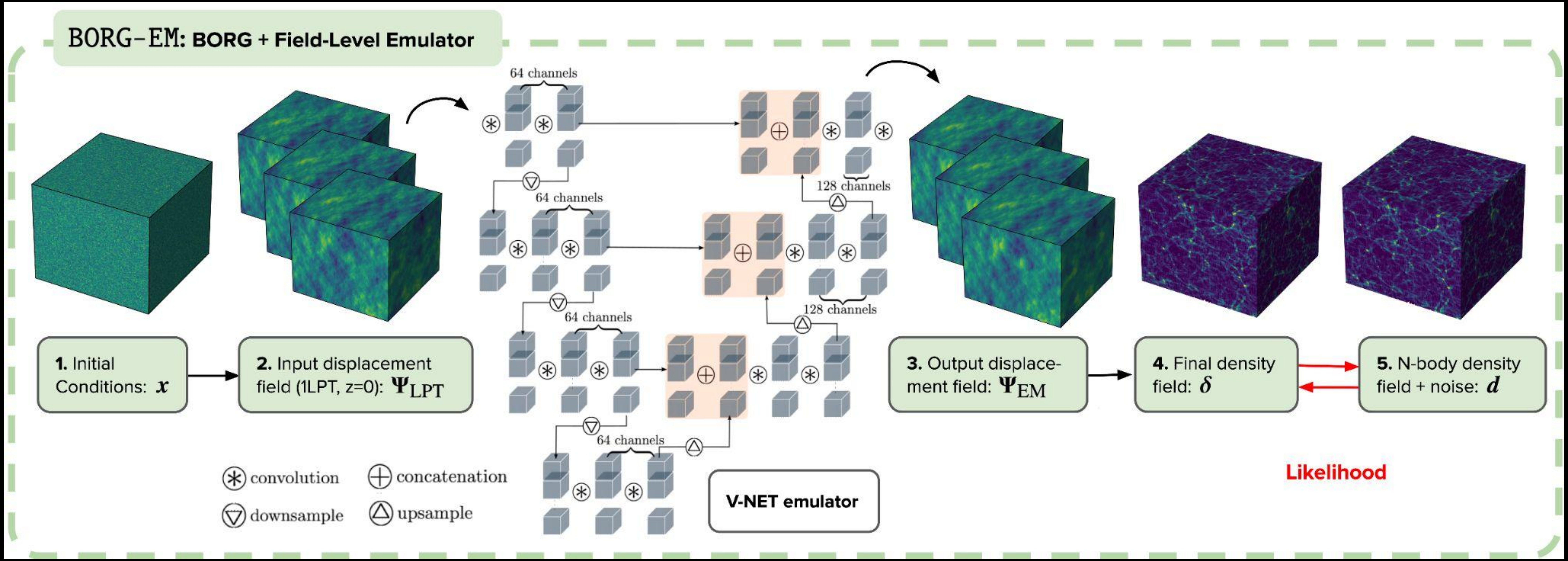
Ludvig Doeser, Drew Jamieson, Stephen Stopyra, Guilhem Lavaux, Florent Leclercq, Jens Jasche

BORG

Jasche, Wandelt arXiv:1203.3639

Ludvig Doeser, Stockholm

Can it infer initial conditions?



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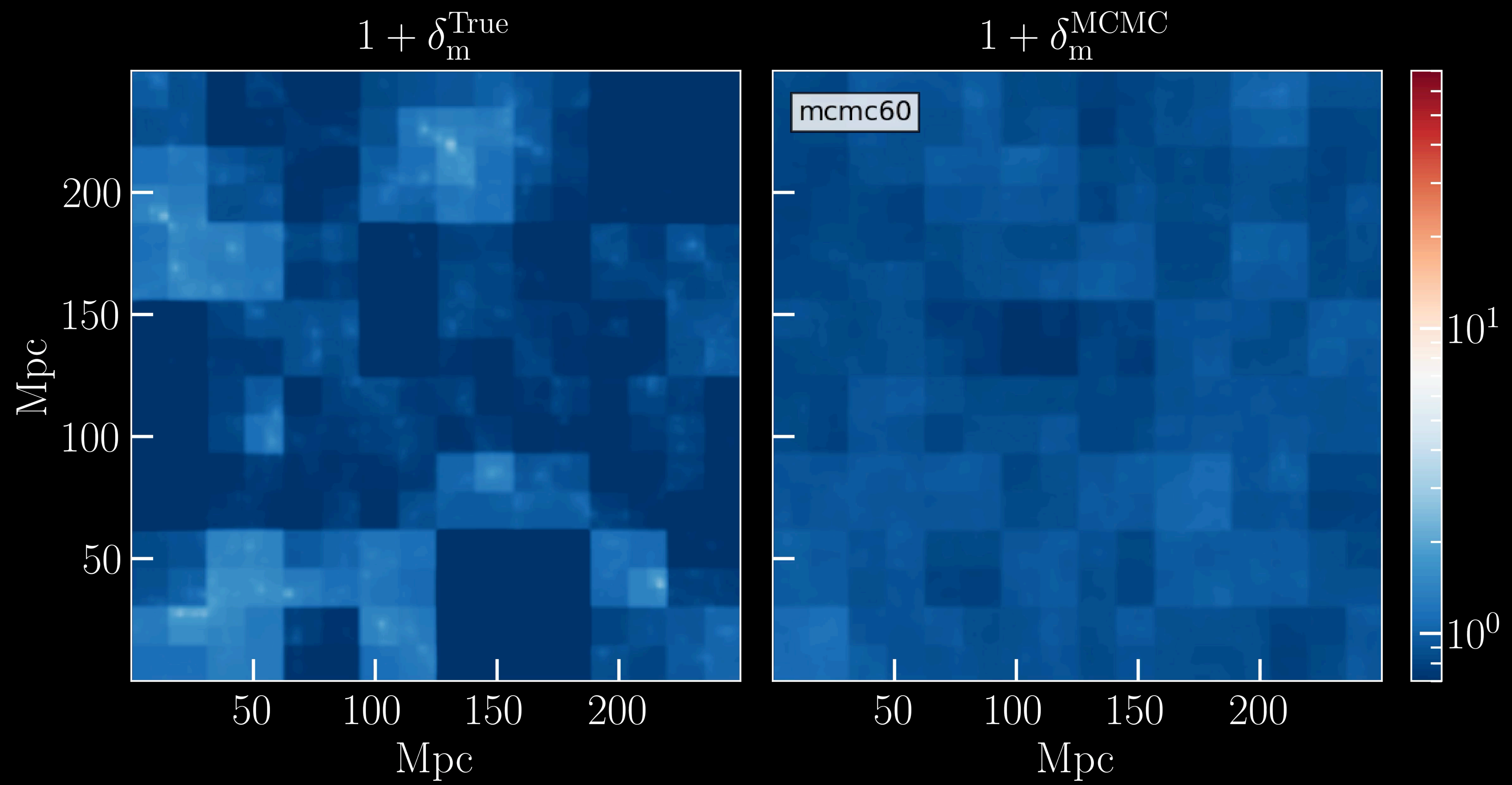
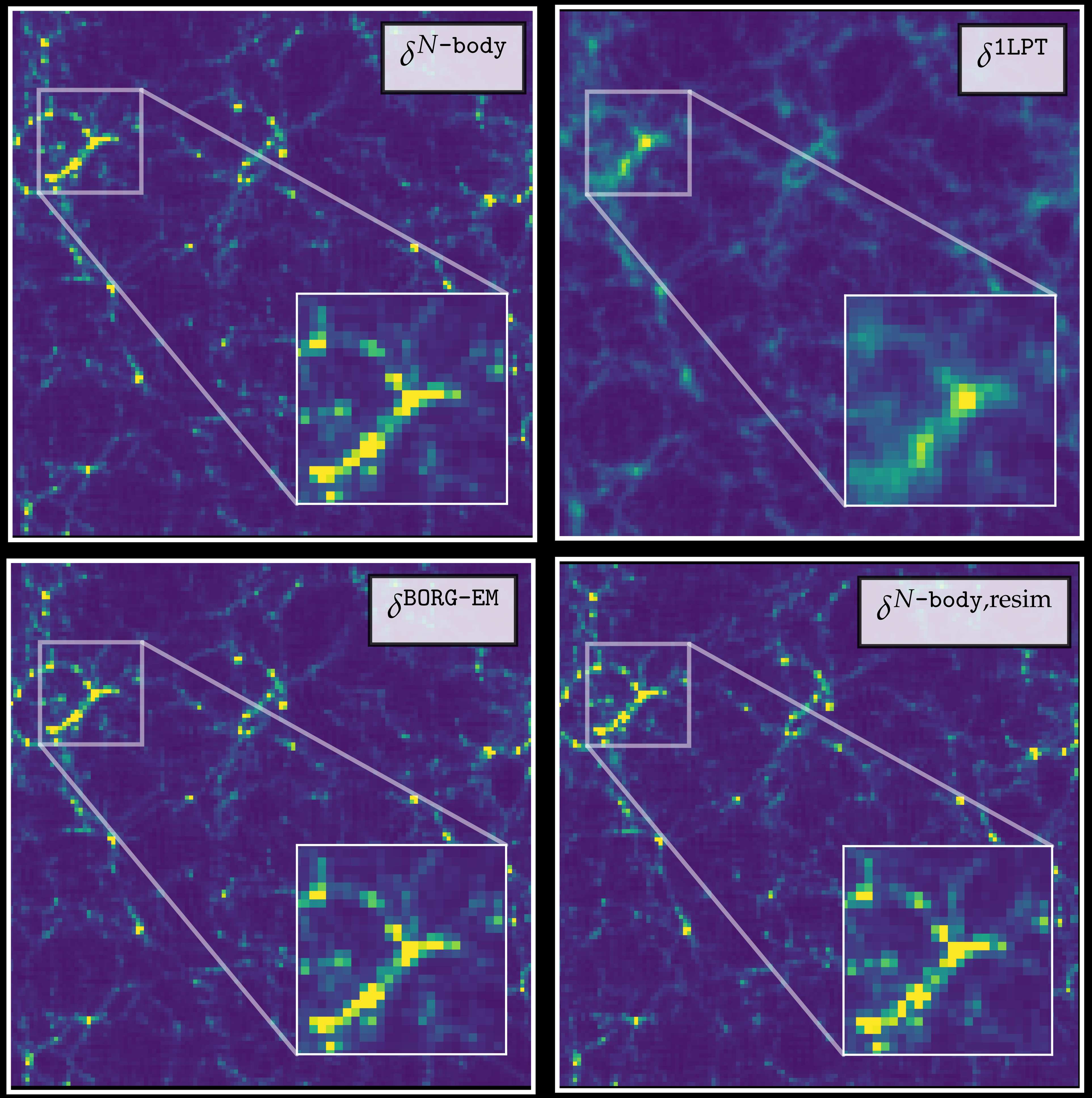


- HMC sampling of 128^3 parameters
- Infere poserior on initial conditions
- Sampling from posterior and resimulating generates consistent late-time LSS

Ludvig Doeser, Stockholm

BORG

Jasche, Wandelt arXiv:1203.3639



Some Relevant Work By Others

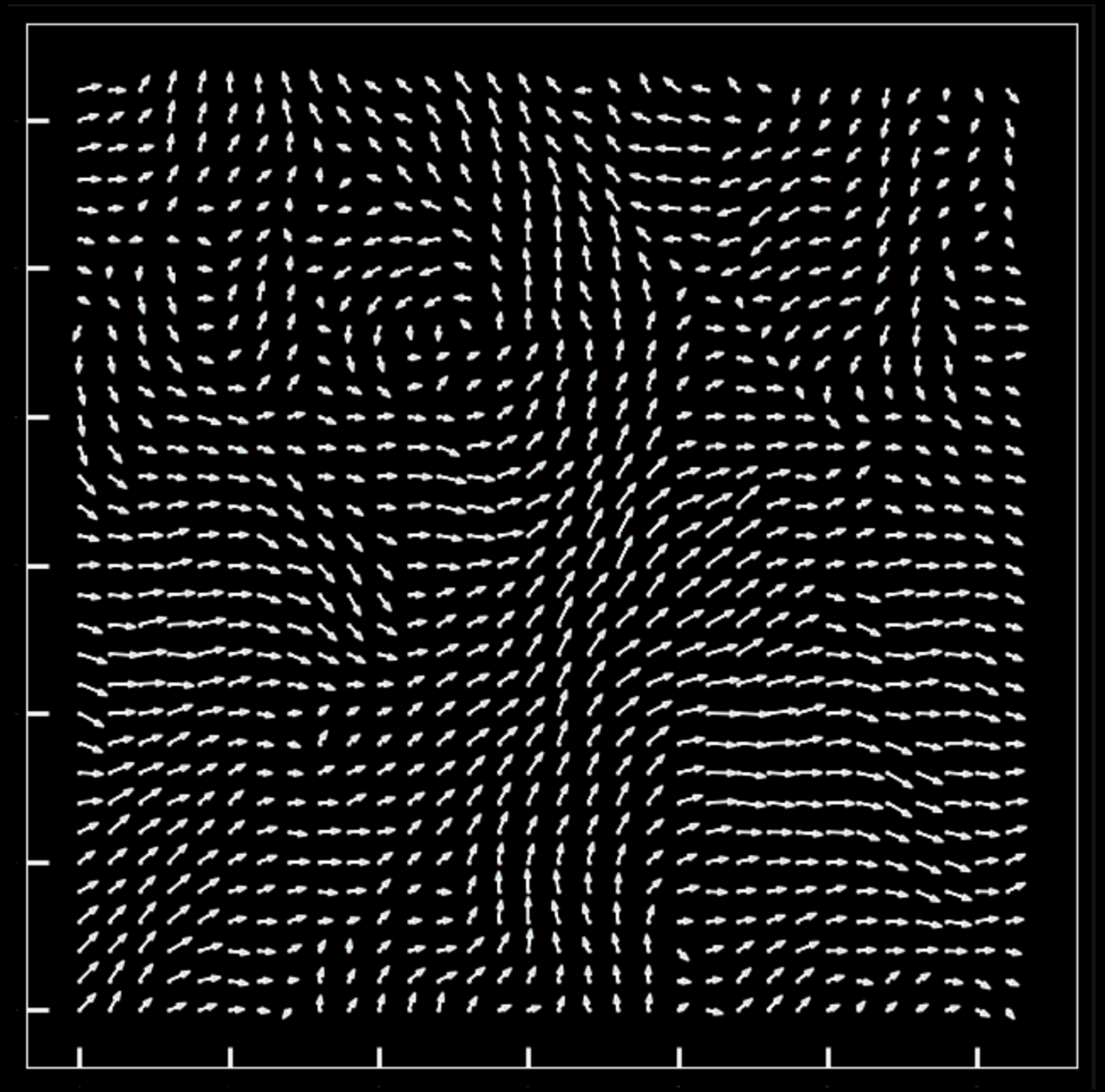
- Fast simulation error correction in post (NECOLA)
  Neerav Kaushal *et al.* arXiv:2111.02441

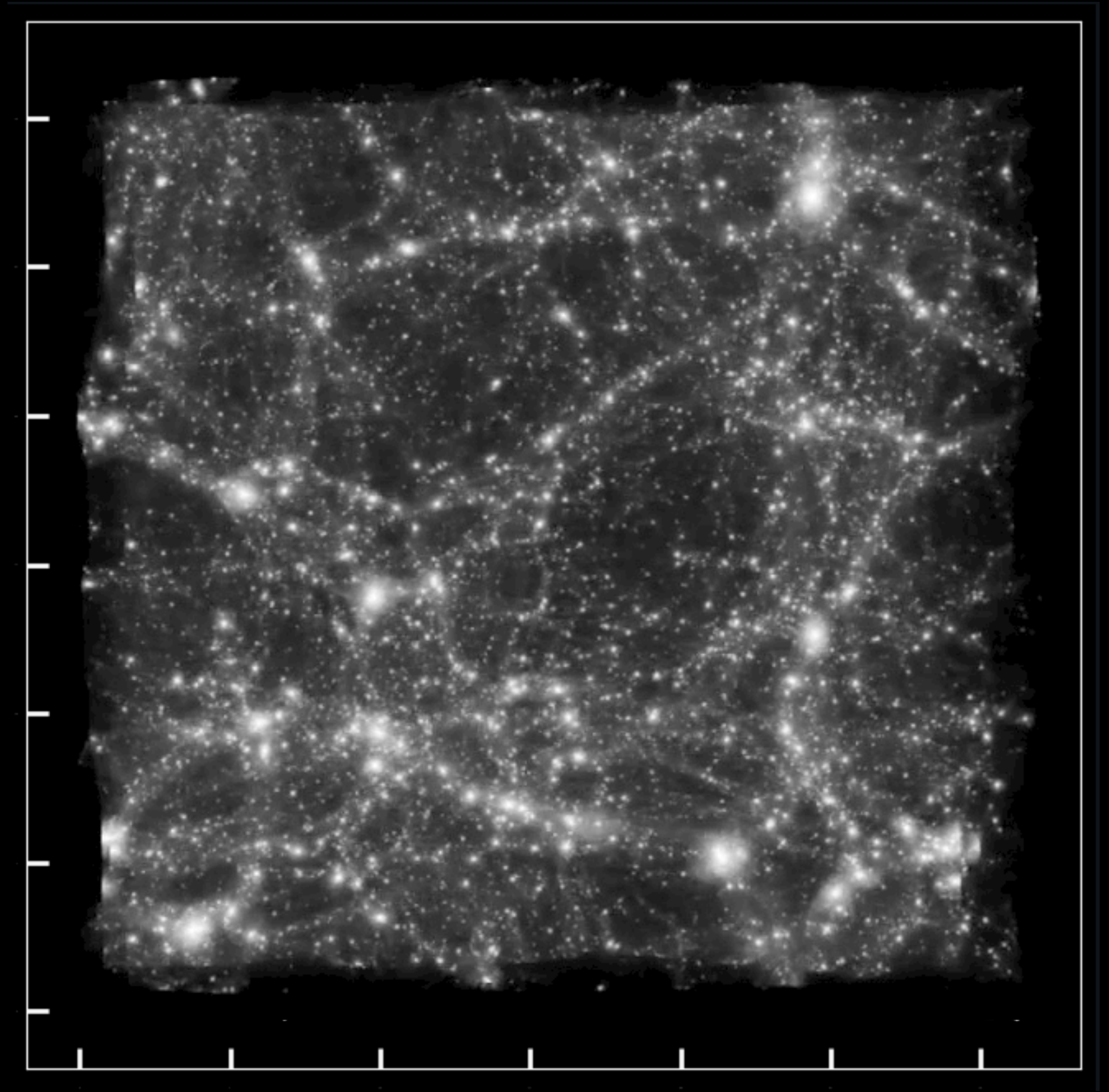
- Fast simulation error correction on-the-fly COCA
  Deaglan J. Bartlett *et al.* arXiv:2409.02154

- Modified gravity field-level emulator
  Daniela Saadeh, Kazuya Koyama, Xan Morice-Atkinson arXiv:2406.03374

- Fast, differentiable simulations (PMWD)
  Yin Li *et al.* (including me arXiv:2211.09958

- Super-resolution generative upsampling with Map2Map
  Xiaowen Zhang *et al.* arXiv:2305.12222





Conclusion:

https://github.com/eelregit/map2map

https://github.com/dsjamieson/map2map_emu

- Emulator is fast and accurate in the nonlinear regime
- Differentiable, can sample over cosmology and ICs
- Models the phase space of N-body at the field level
- Models the redshift dependence of structure formation

arXiv:2206.04594 arXiv:2307.09134

arXiv:2206.04573 arXiv:2312.09271

arXiv:2303.13056 arXiv:2408.07699

arXiv:2502.13242

Outlook

- Additional parameters: $\Omega_K, M_\nu, w(z), \ldots$
- Super-resolution?
- Baryons?
- Lightcones?

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