From lognormal fields to realistic simulations

Davide Piras (d.piras@ucl.ac.uk), Benjamin Joachimi, Francisco Villaescusa-Navarro

UCL

UCL CDT DIS

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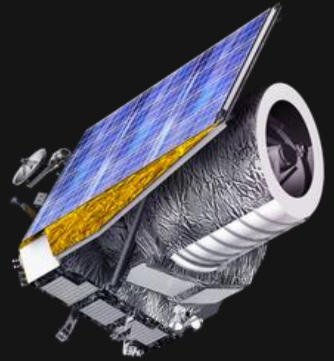
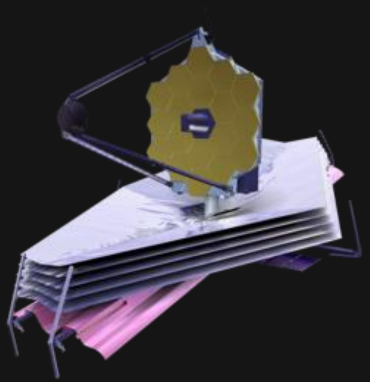
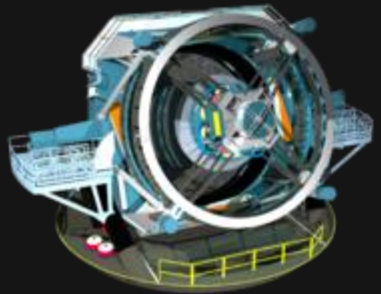
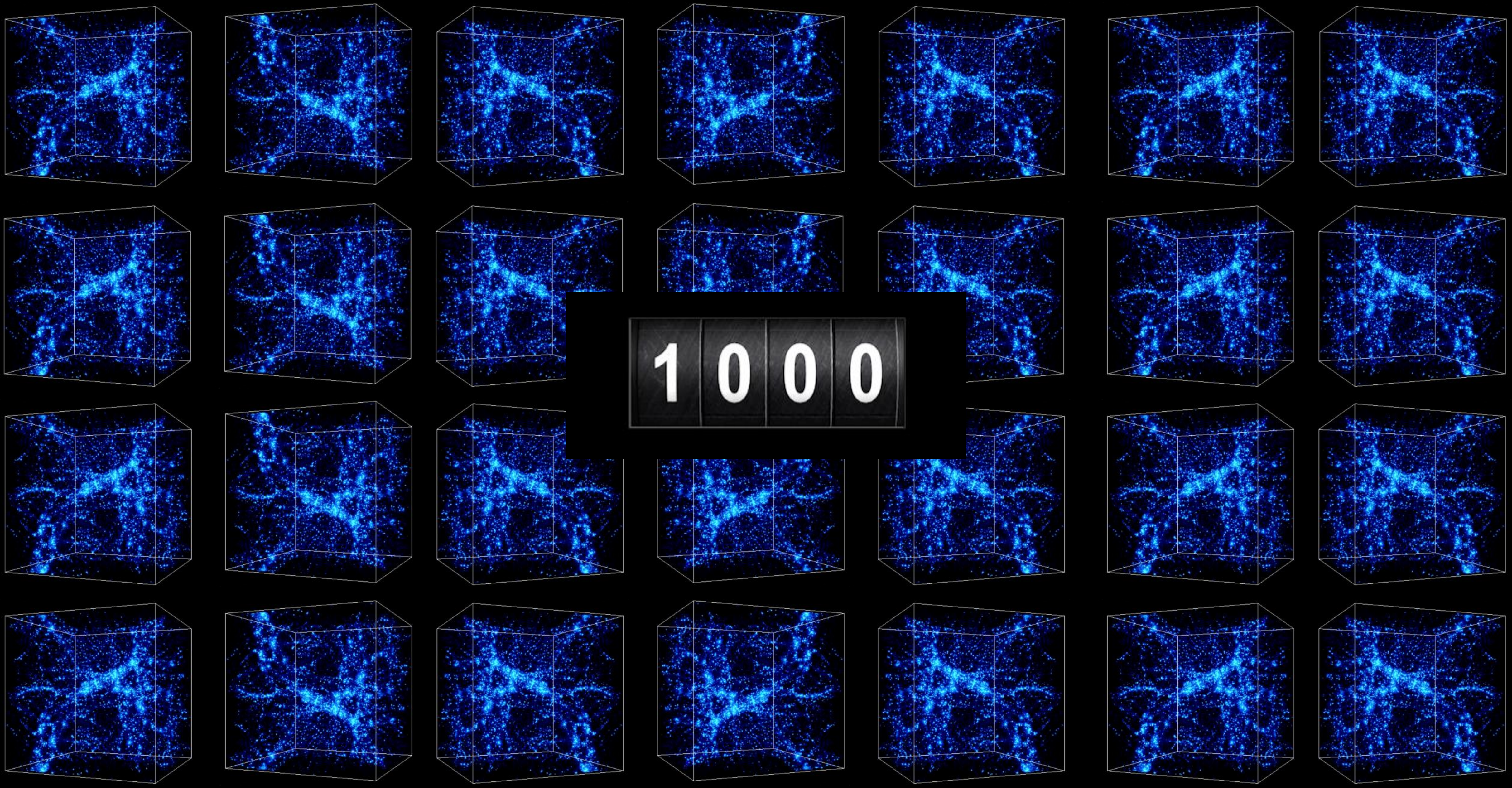
2017

$\varepsilon \rightarrow 0$





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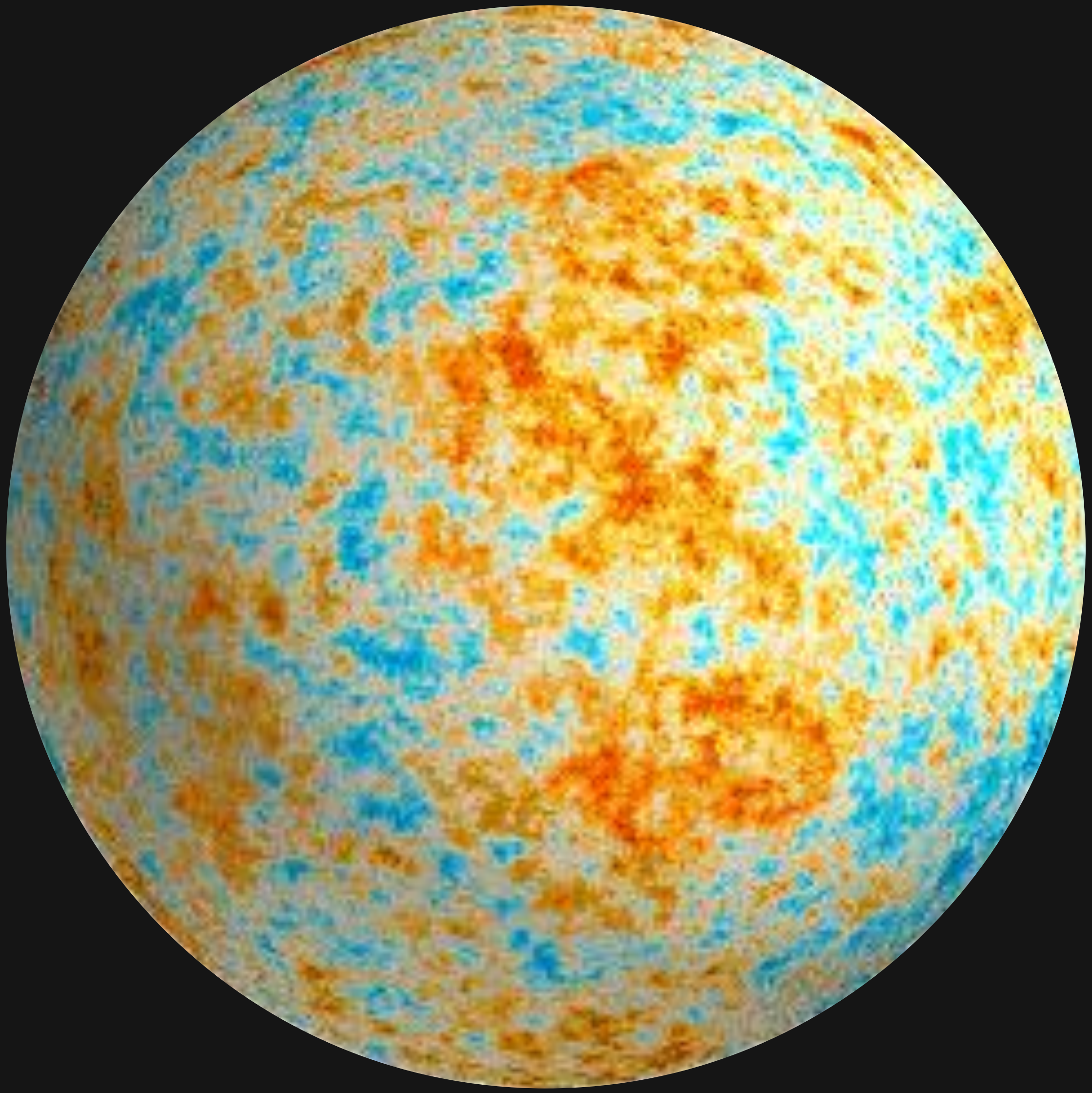
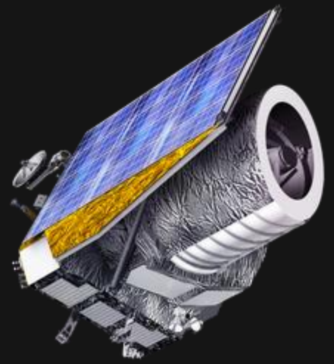


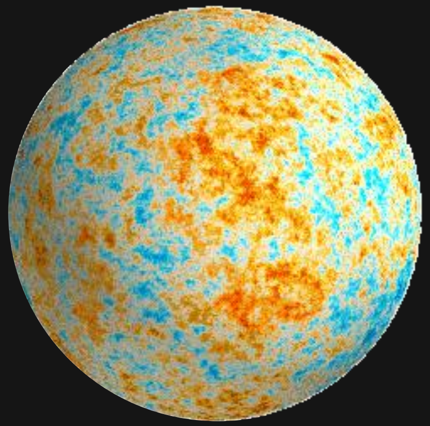
Random field maps on the sphere

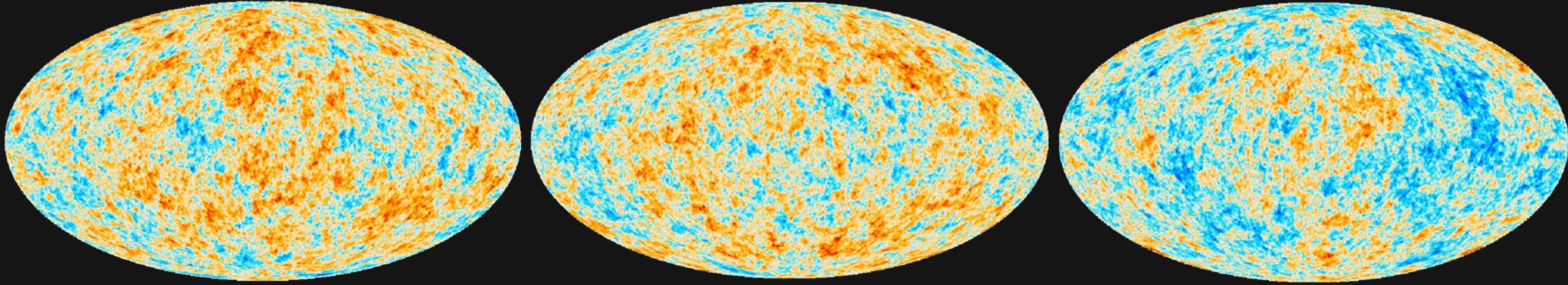
2017

2019

$\varepsilon \rightarrow 0$

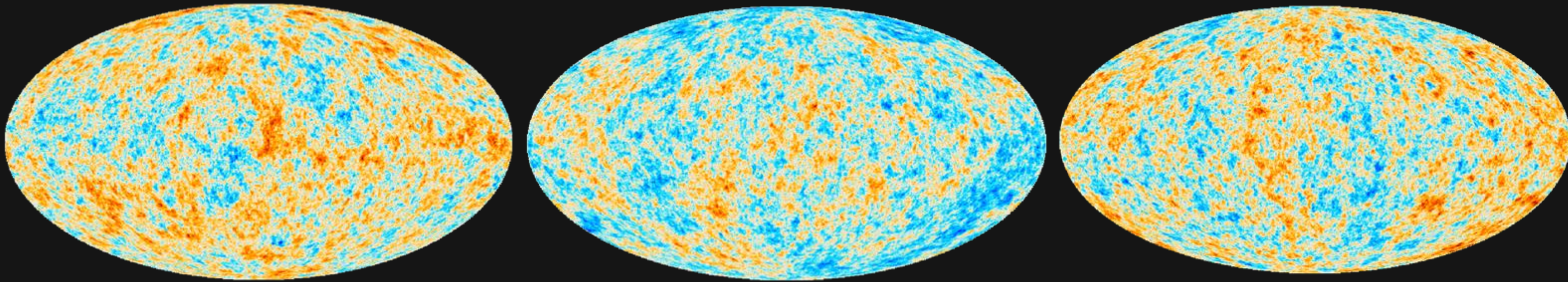






Original

Generated



2017

2019

2020

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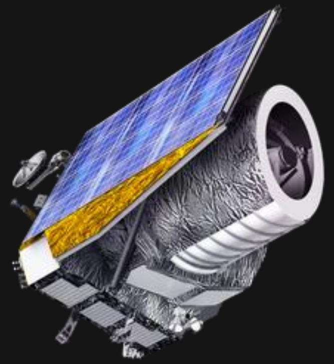
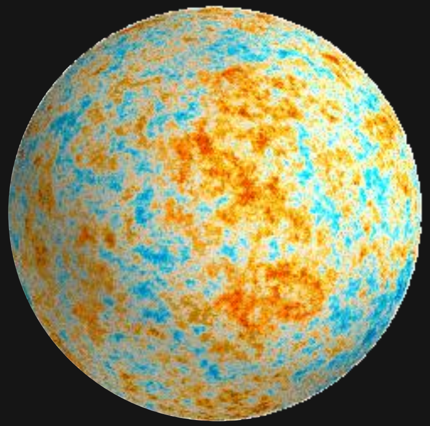
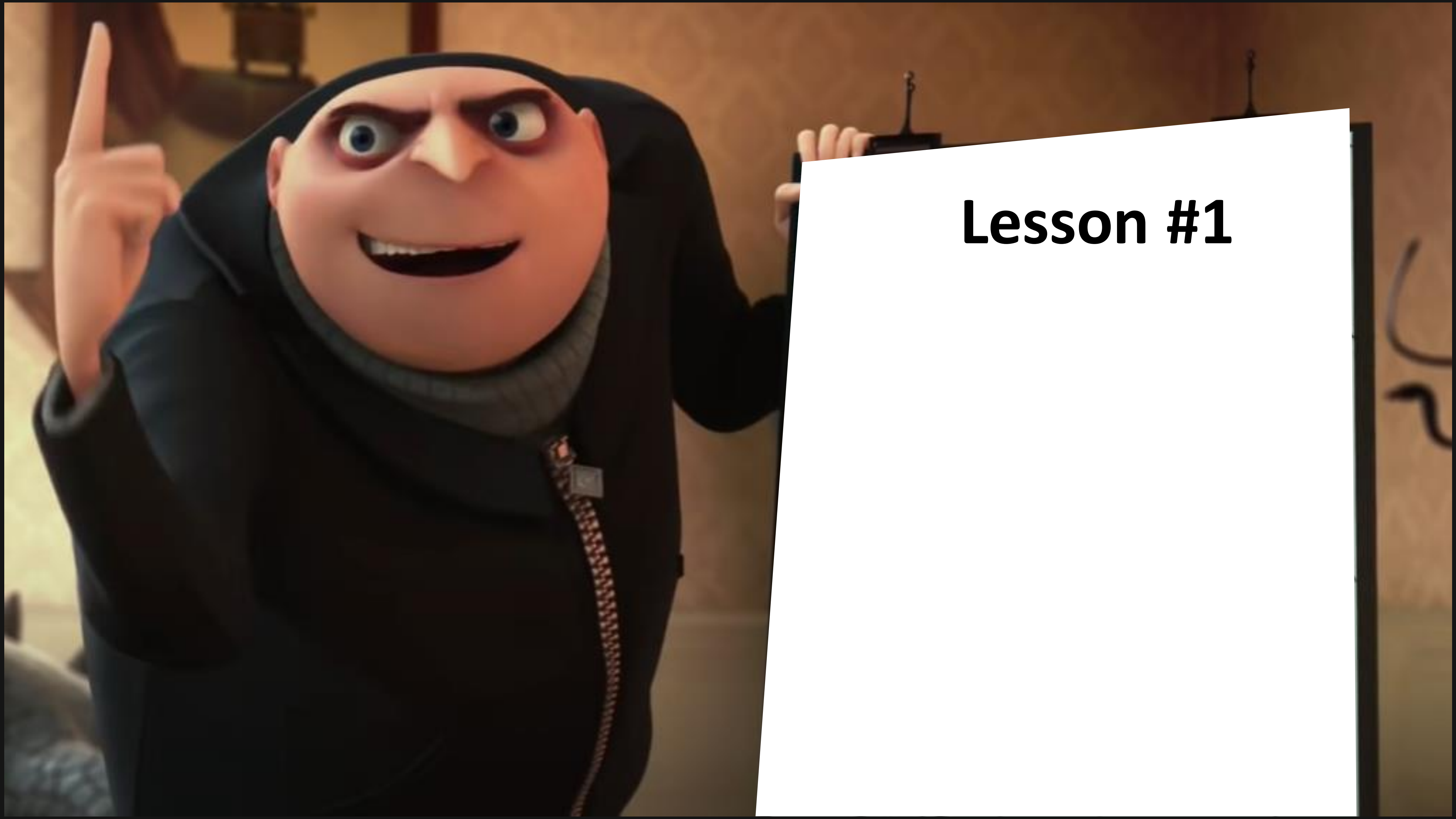
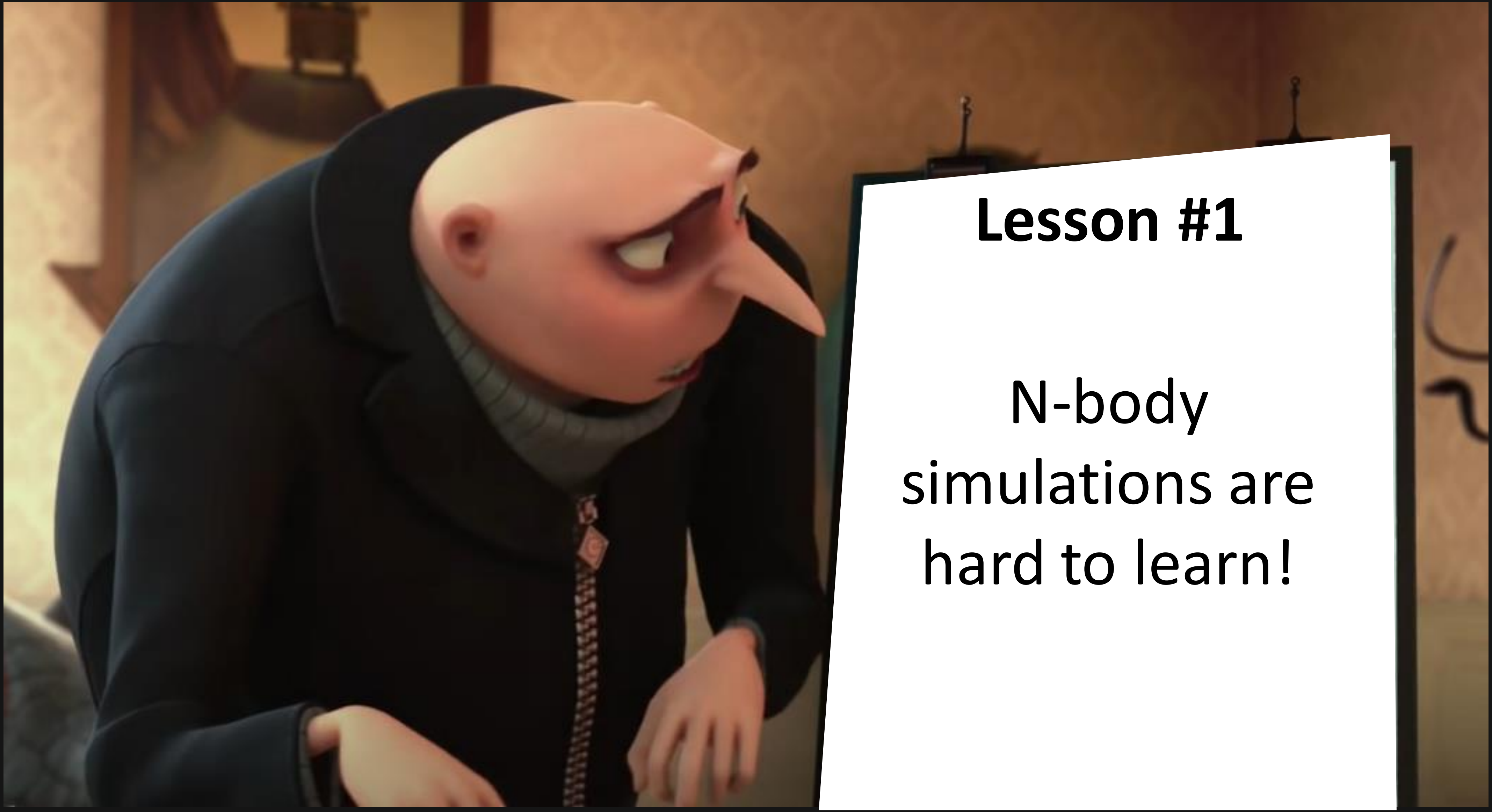





Lesson #1

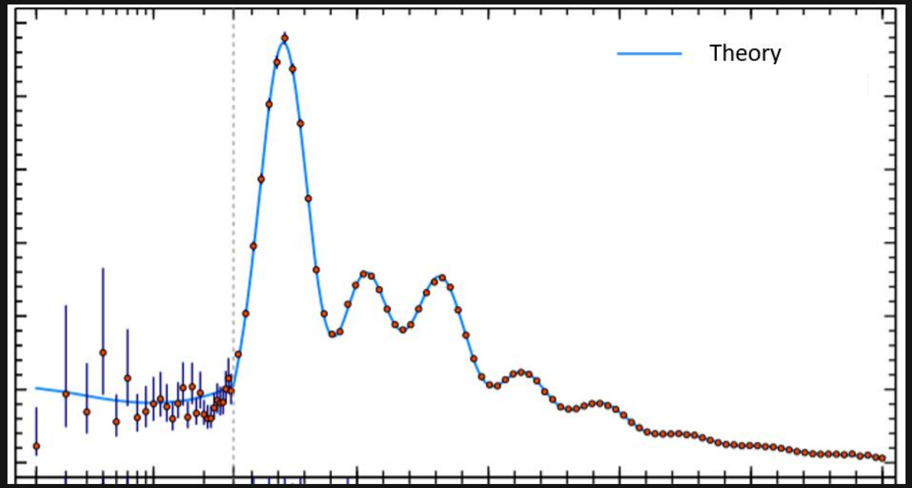

Lesson #1
N-body simulations are hard to learn!

CosmoPower: flexible emulation of cosmological power spectra

16:40

CosmoPower: flexible emulation of cosmological power spectra

- Create labelled training data

(

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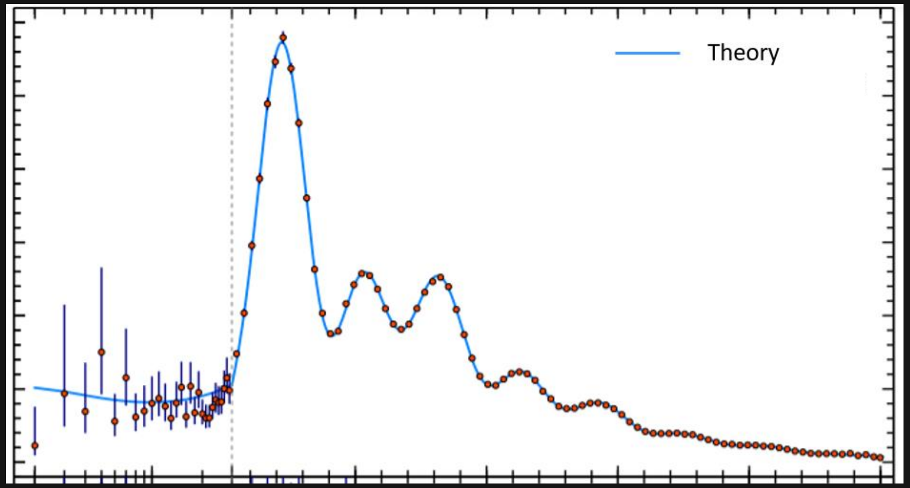
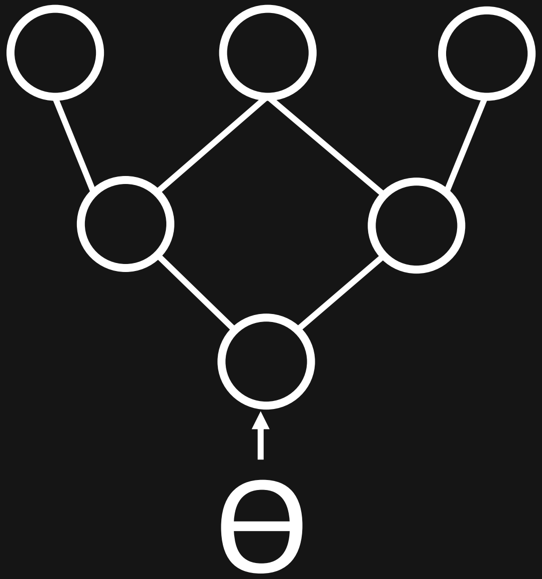
CosmoPower: flexible emulation of cosmological power spectra

- Create labelled training data

- Train ML model





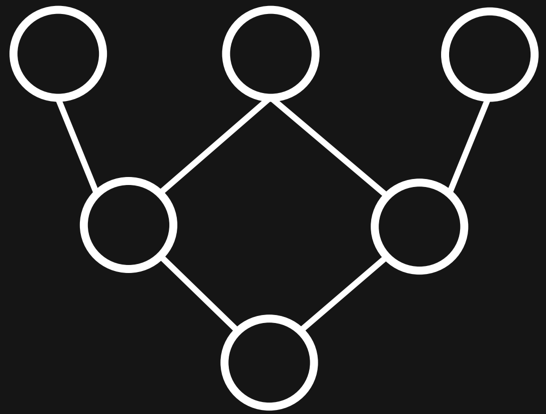
16:40

CosmoPower: flexible emulation of cosmological power spectra

- Create labelled training data

- Train ML model

- Plug trained model into posterior sampler



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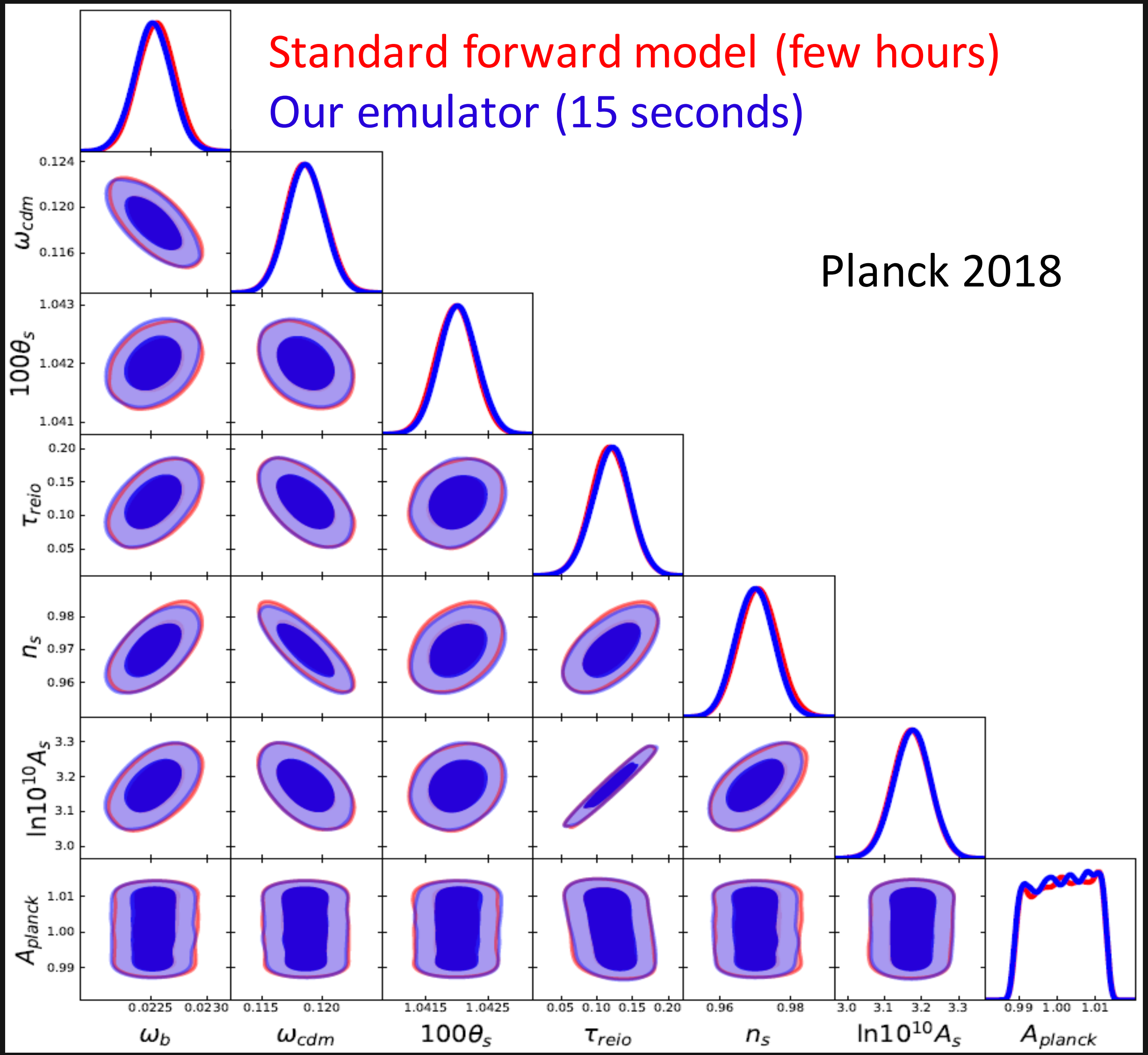
CosmoPower: flexible emulation of cosmological power spectra



A. Spurio Mancini, **D. Piras**, J. Alsing, B. Joachimi, M. Hobson, *CosmoPower: emulating cosmological power spectra for accelerated Bayesian inference from next-generation surveys*, 2021, submitted to MNRAS

16:40

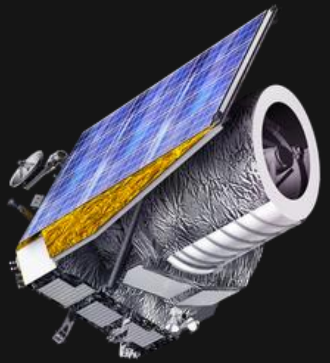
2017

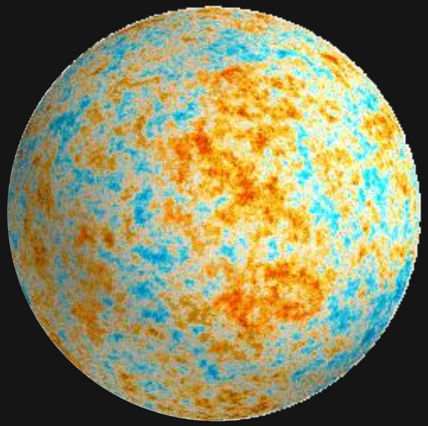
2019

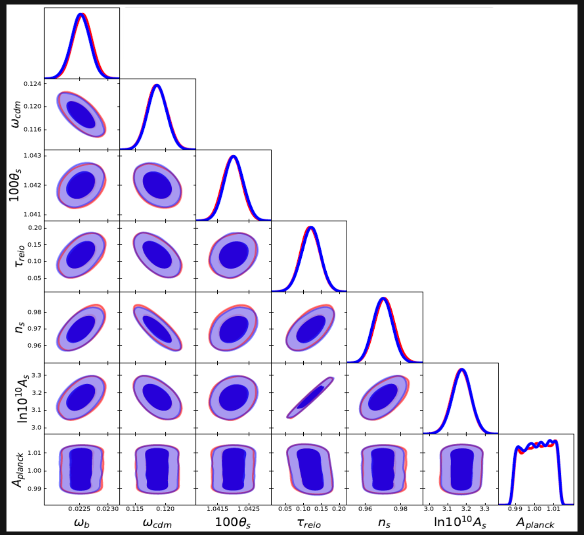
2020

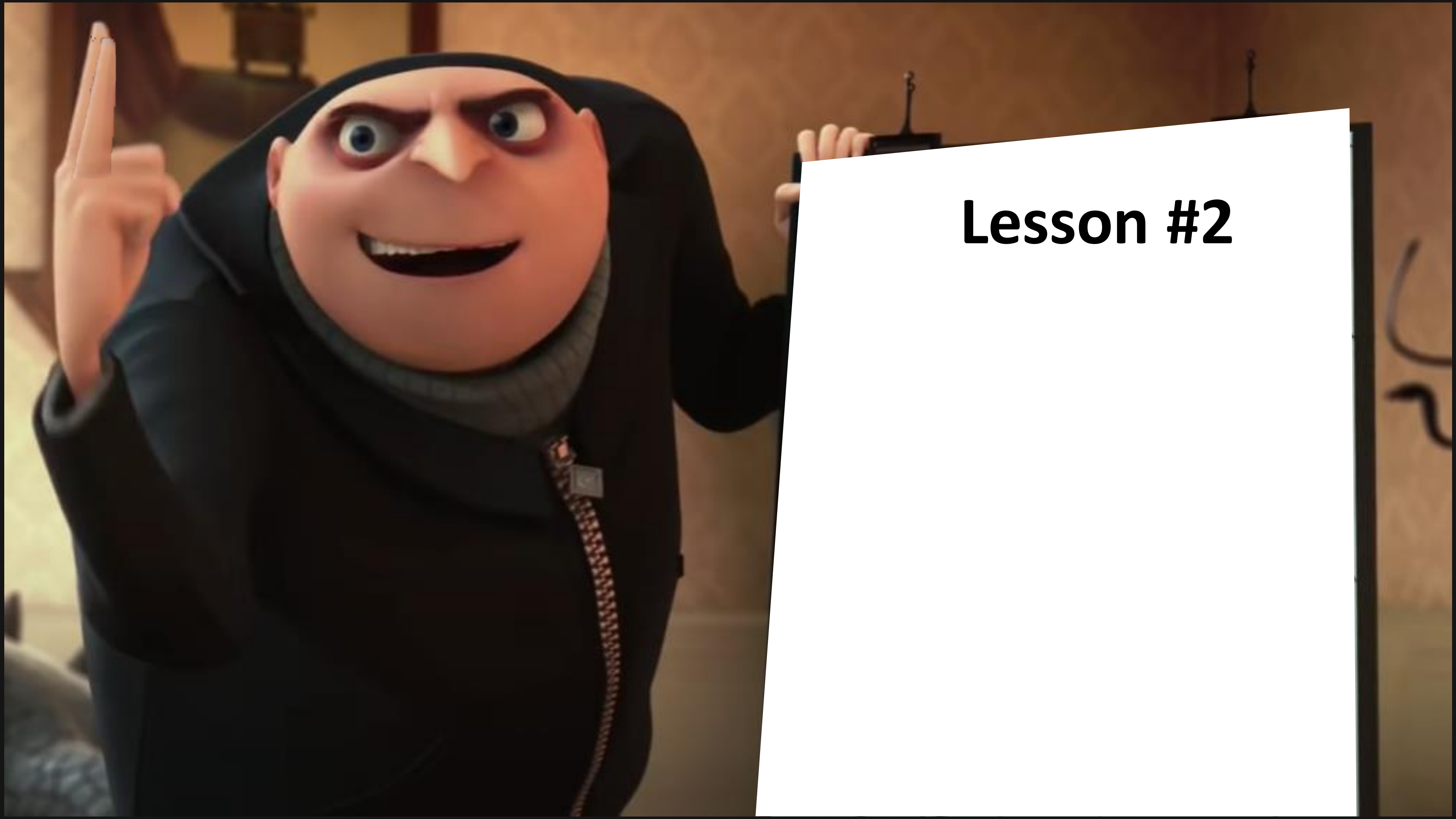
2021

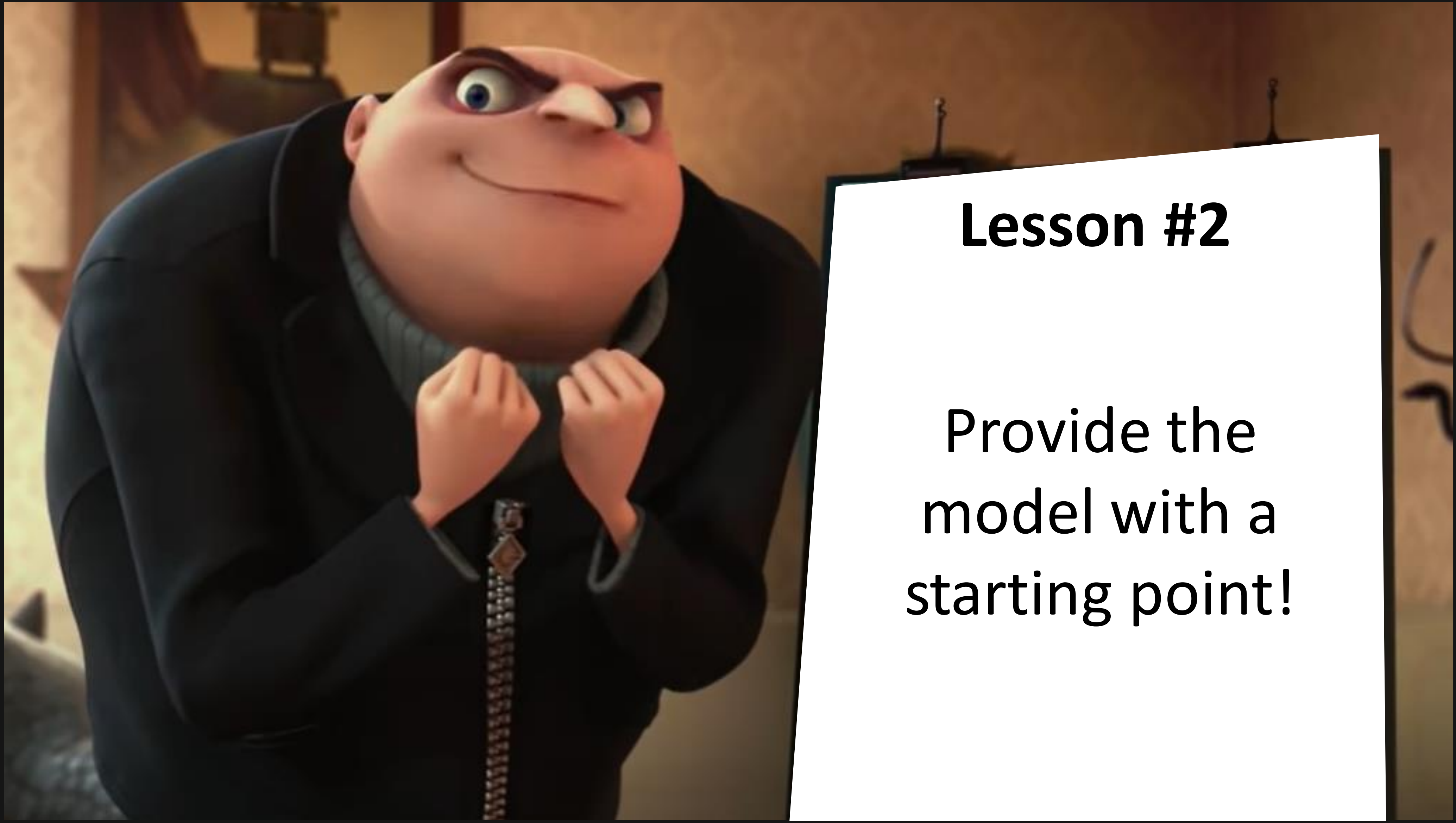
$\varepsilon \rightarrow 0$





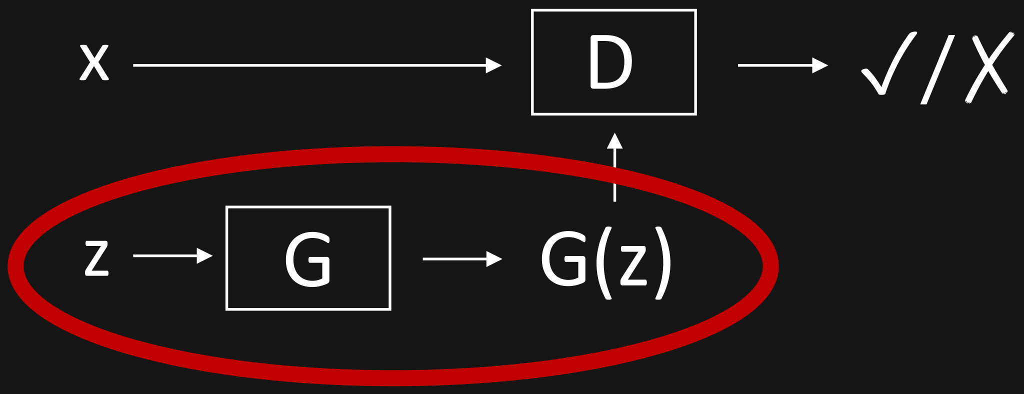



Lesson #2


Lesson #2
Provide the model with a starting point!

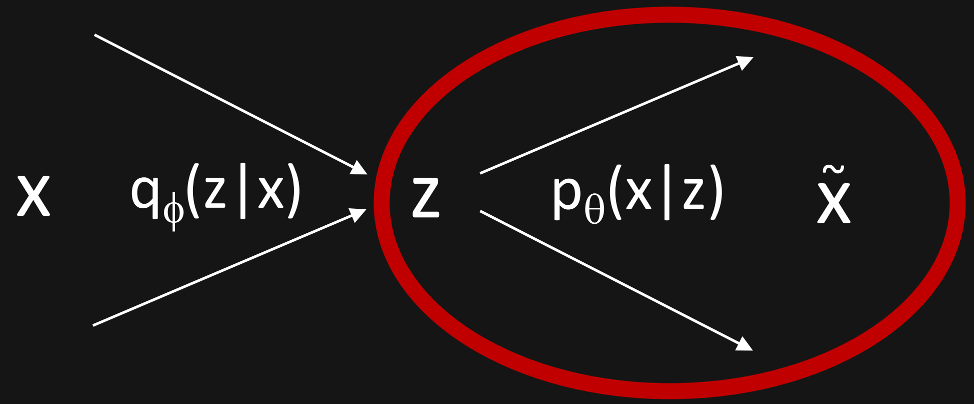
GAN

Generative **A**dversarial **N**etwork



VAE

Variational **A**uto**E**ncoder



What information can we provide?

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- Many fast approximations of N-body simulations exist

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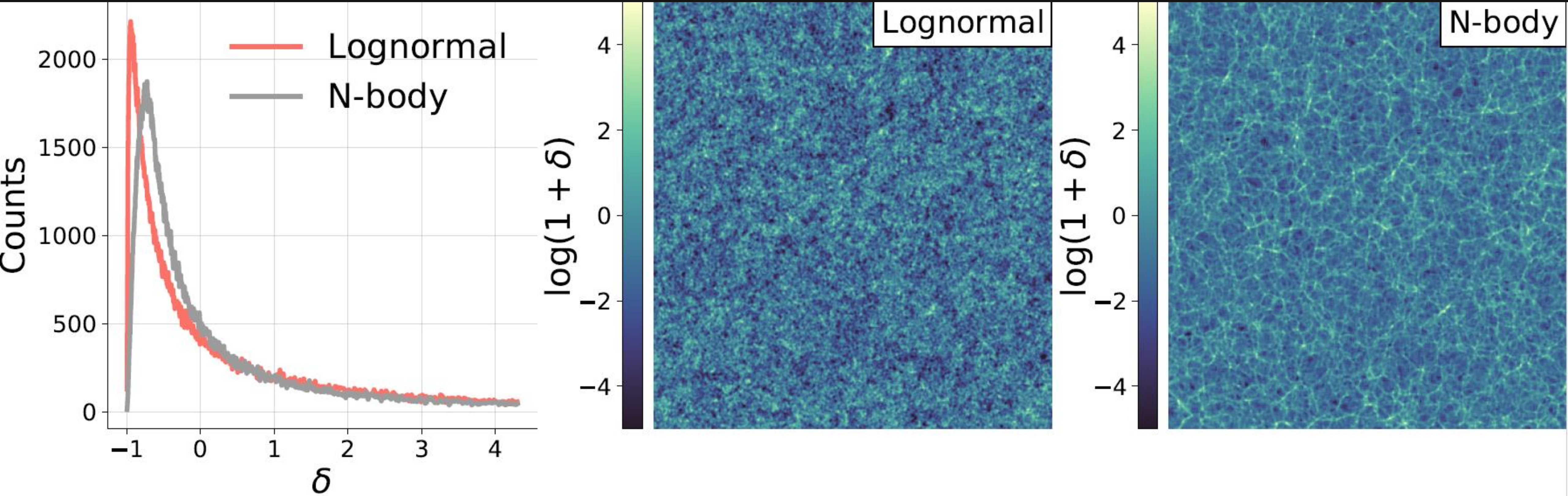
- They trade accuracy with speed

What information can we provide?

- Many fast approximations of N-body simulations exist
- They trade accuracy with speed
- Lognormal fields are decent, and extremely cheap

From lognormal to N-body



D. Piras, B. Joachimi, F. Villaescusa-Navarro, *Fast and realistic large-scale structure from machine-learning-augmented random field simulations*, in preparation

How to create the dataset?

How to create the dataset?

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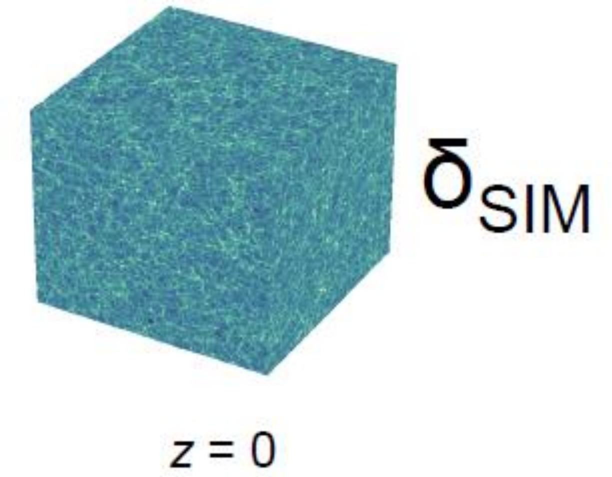
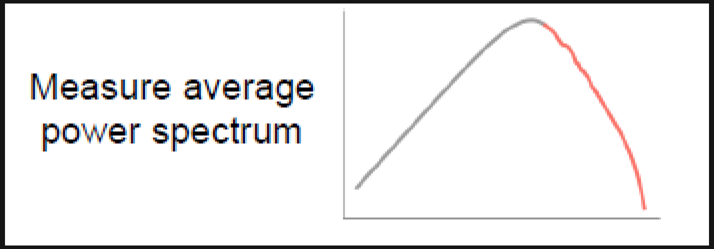
- Start from the Quijote simulations

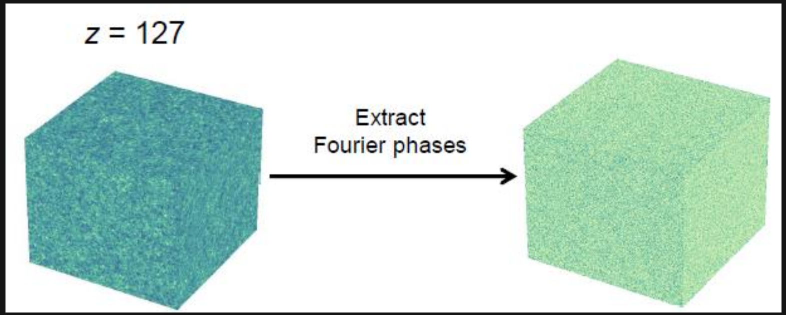


How to create the dataset?

- Start from the Quijote simulations

- Need 2 ingredients: Fourier amplitudes and phases





How to create the dataset?

- Start from the Quijote simulations
- Need 2 ingredients: Fourier amplitudes and phases
- The lognormal field is highly correlated with the N-body

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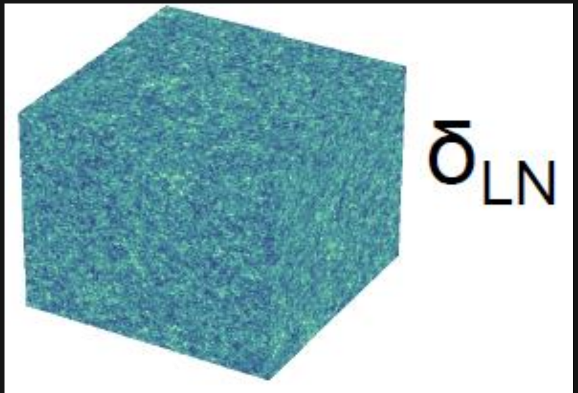
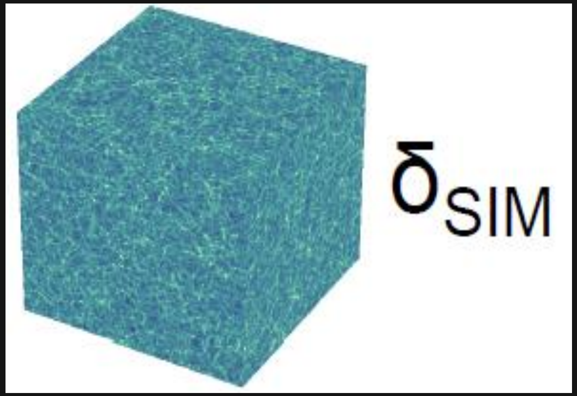
- The lognormal field is highly correlated with the N-body





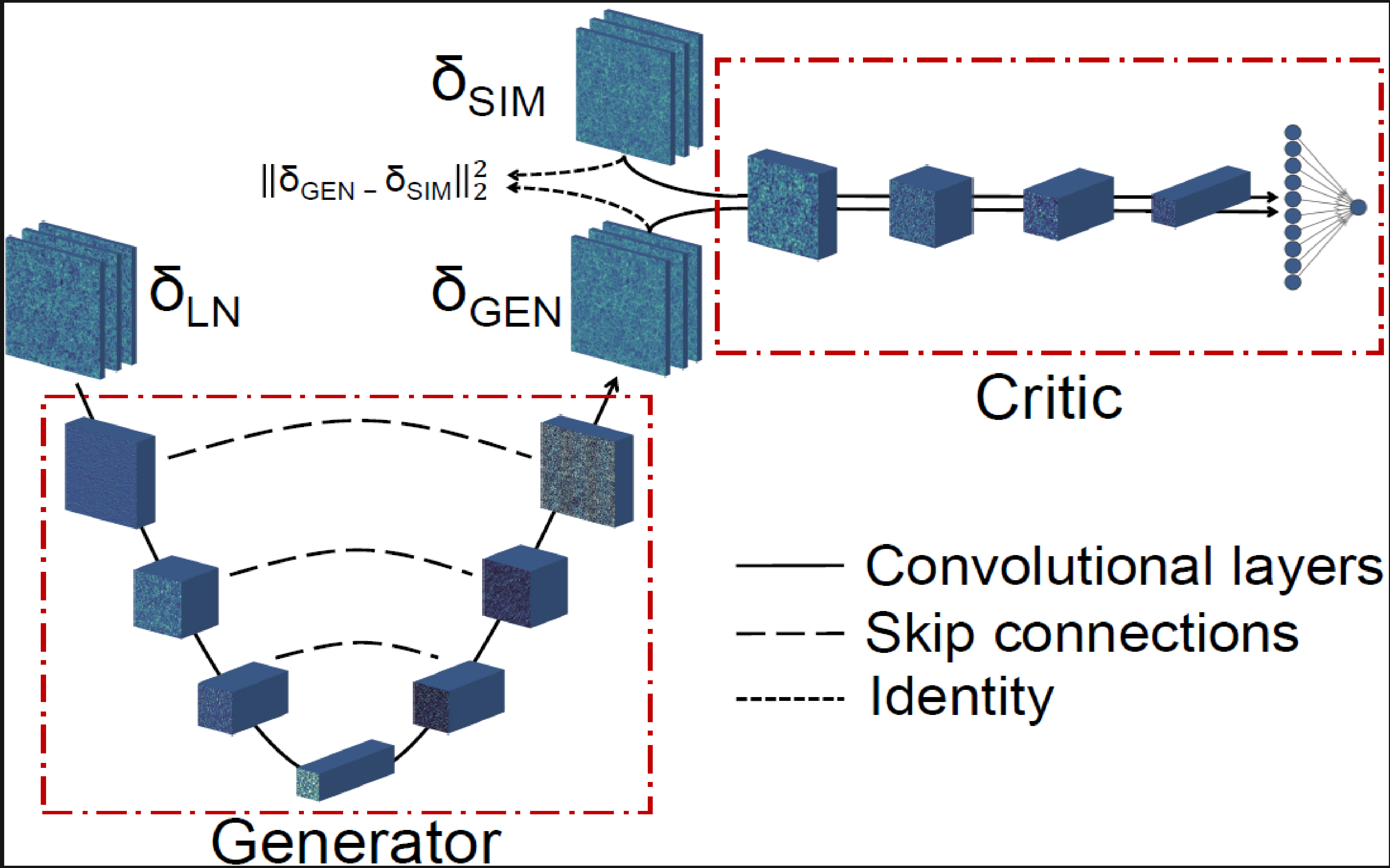
- Same power spectrum by construction

- We find correlation between the position of the peaks and voids

- We consider 2-D slices of the density fields (512x512)

The model

Wasserstein GAN with gradient penalty



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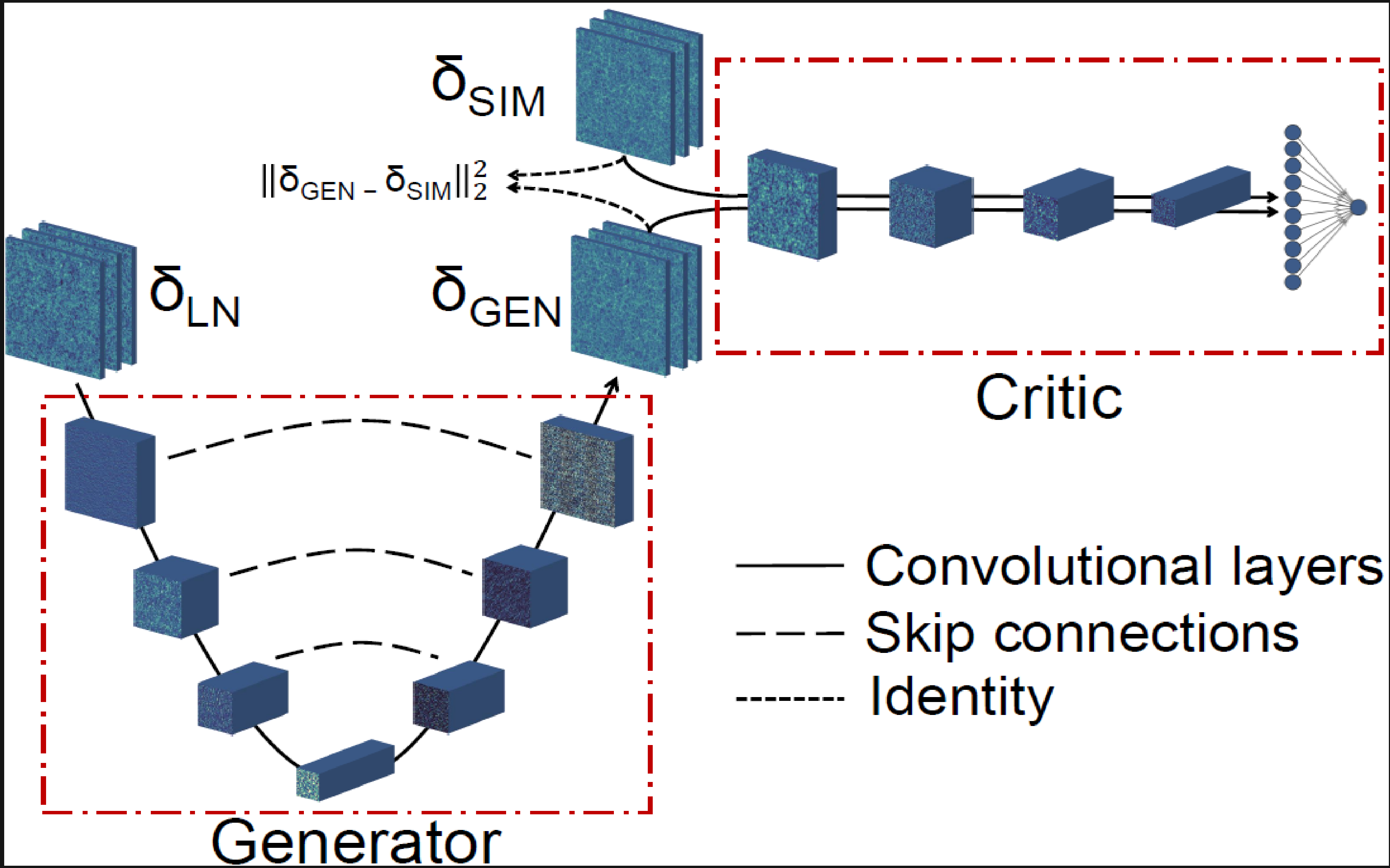
The model

Wasserstein GAN with gradient penalty

Generator is U-net



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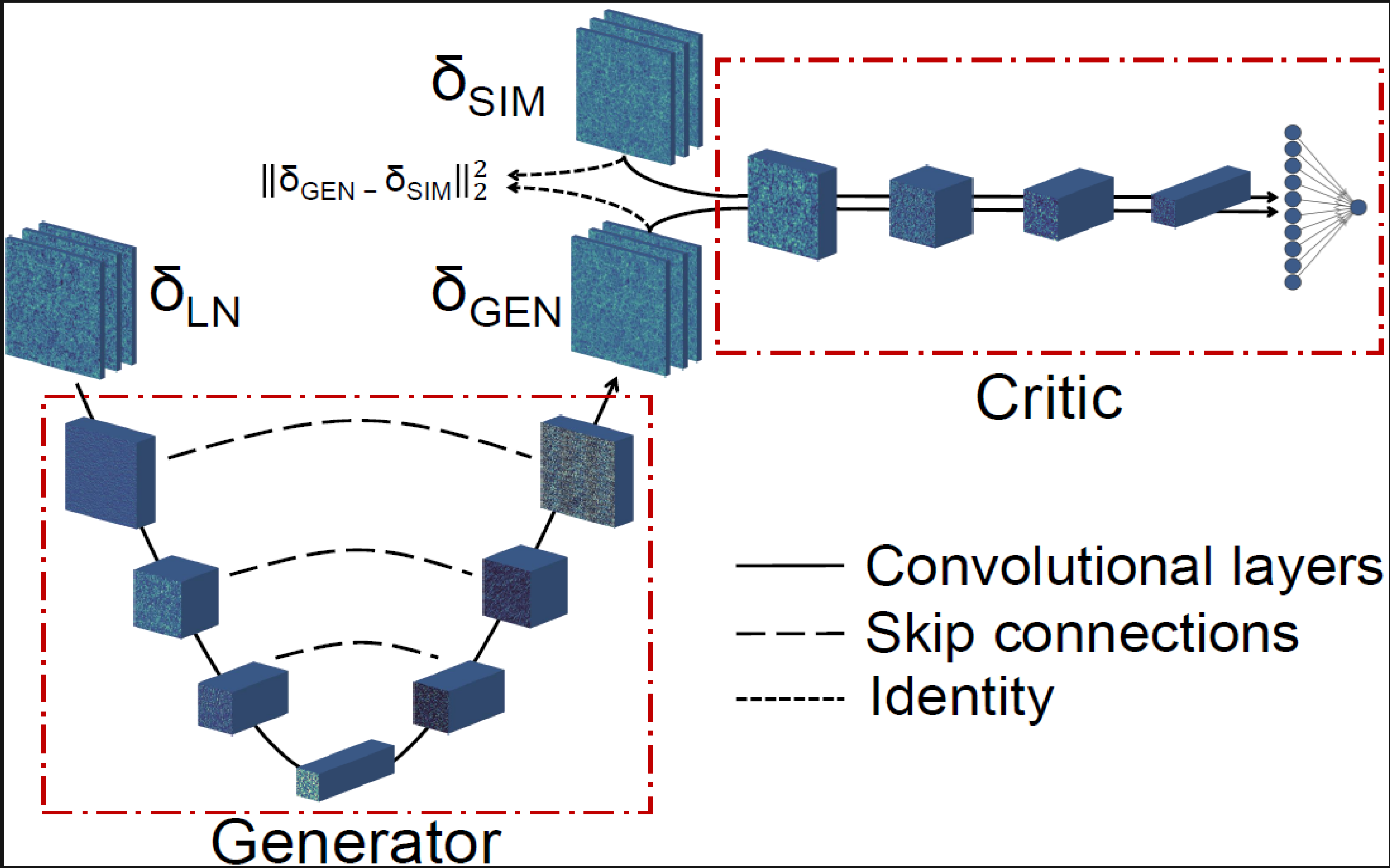
The model

Wasserstein GAN with gradient penalty

Generator is U-net

Add L2 penalisation term



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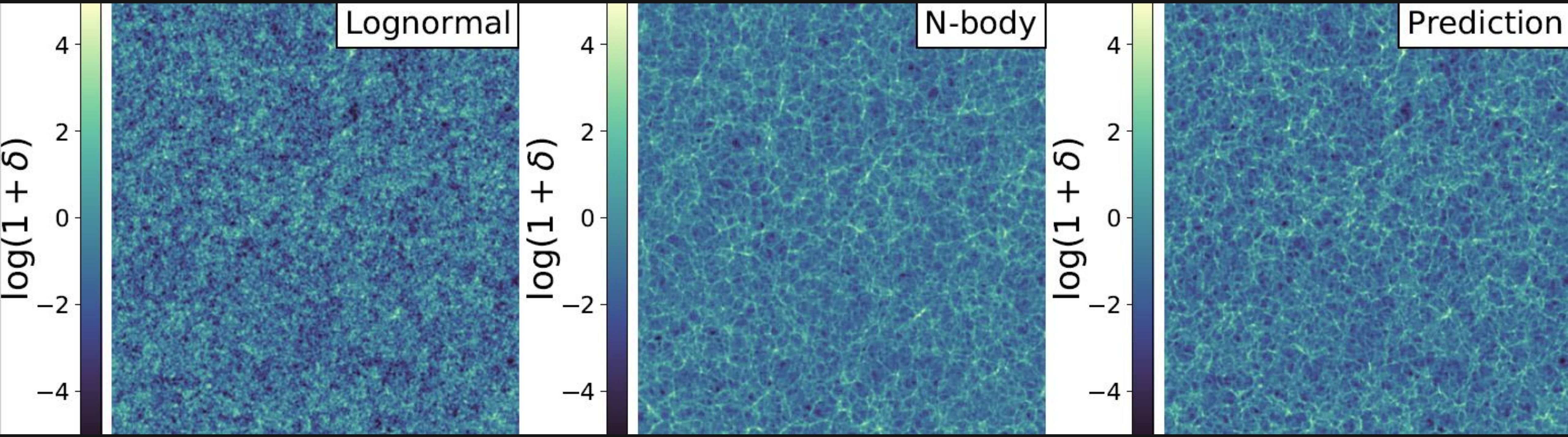
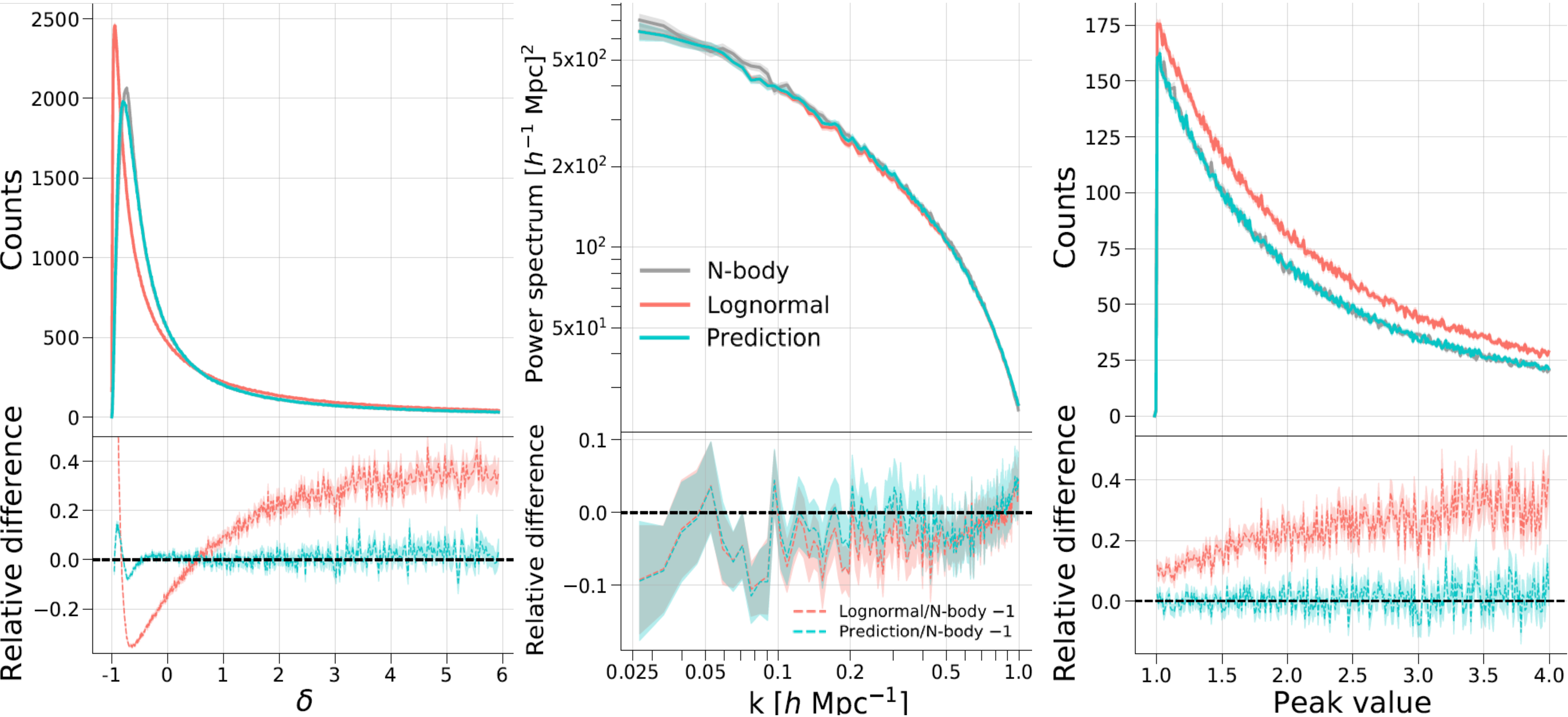
Results



Density Power spectrum Peak counts

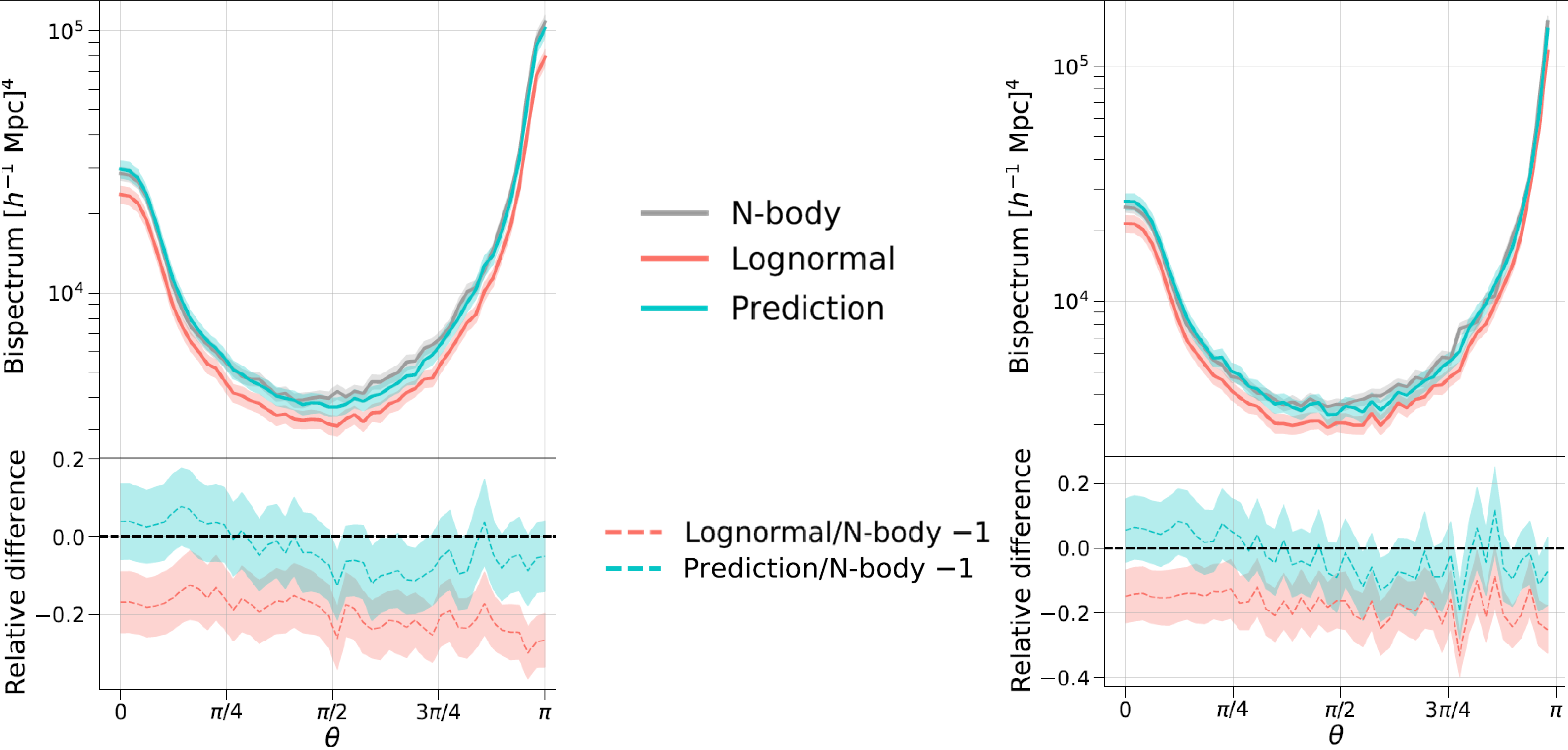


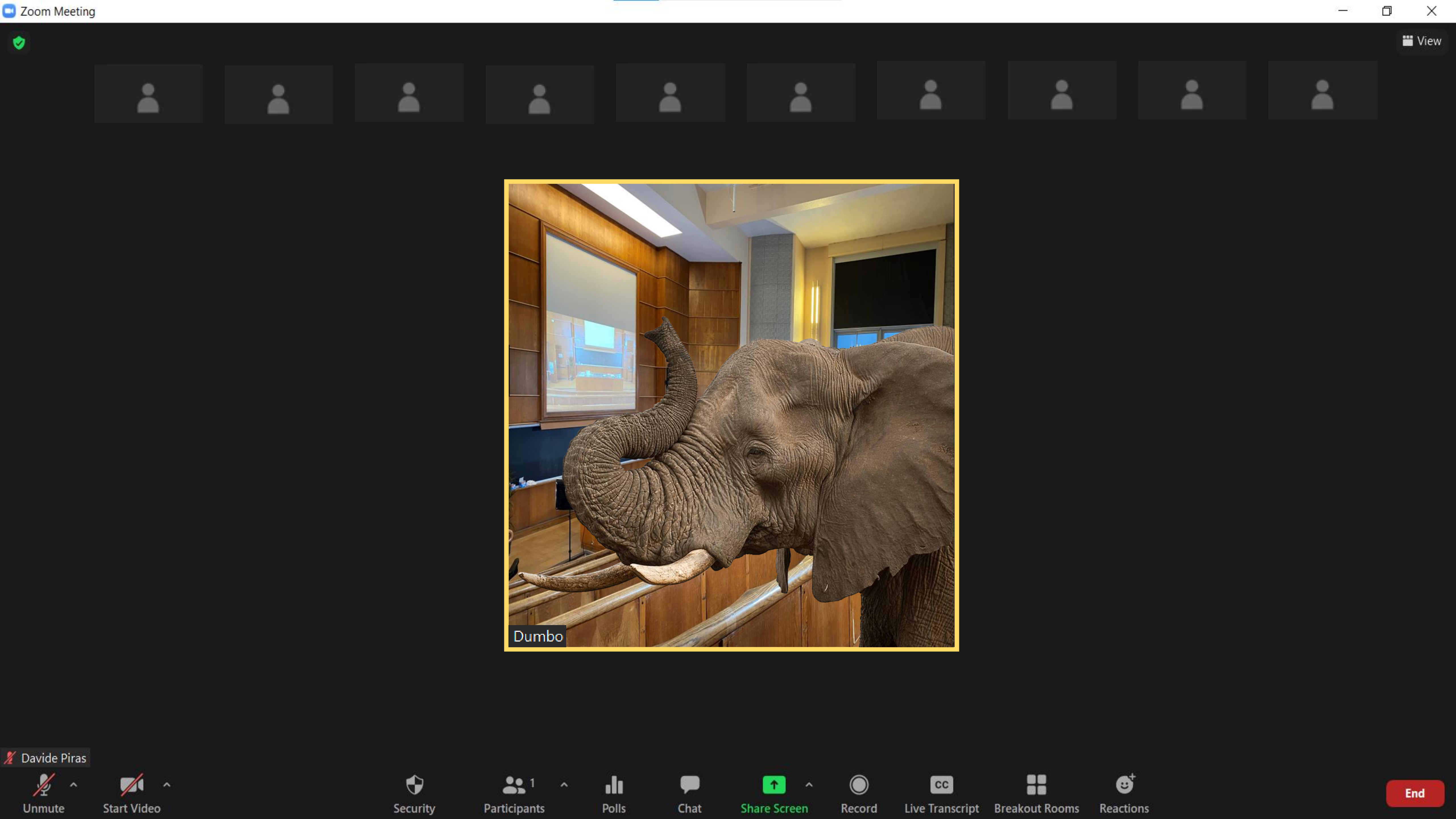
Bispectrum

(k_1=0.4 h Mpc^{-1}, k_2=0.6 h Mpc^{-1})

Bispectrum

(k_1=0.5 h Mpc^{-1}, k_2=0.5 h Mpc^{-1})




Zoom Meeting
View
Dumbo
Davide Piras
Unmute
Start Video
Security
Participants
1
Polls
Chat
Share Screen
Record
CC
Live Transcript
Breakout Rooms
Reactions
End

The elephants in the room

- We need to make model conditional on redshift and cosmological parameters

The elephants in the room

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- We need to apply this model on the sphere

The elephants in the room

- We need to make model conditional on redshift and cosmological parameters
- We need to apply this model on the sphere
- Work in progress!

Conclusions

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- We trained a model that maps lognormal fields to more realistic simulations

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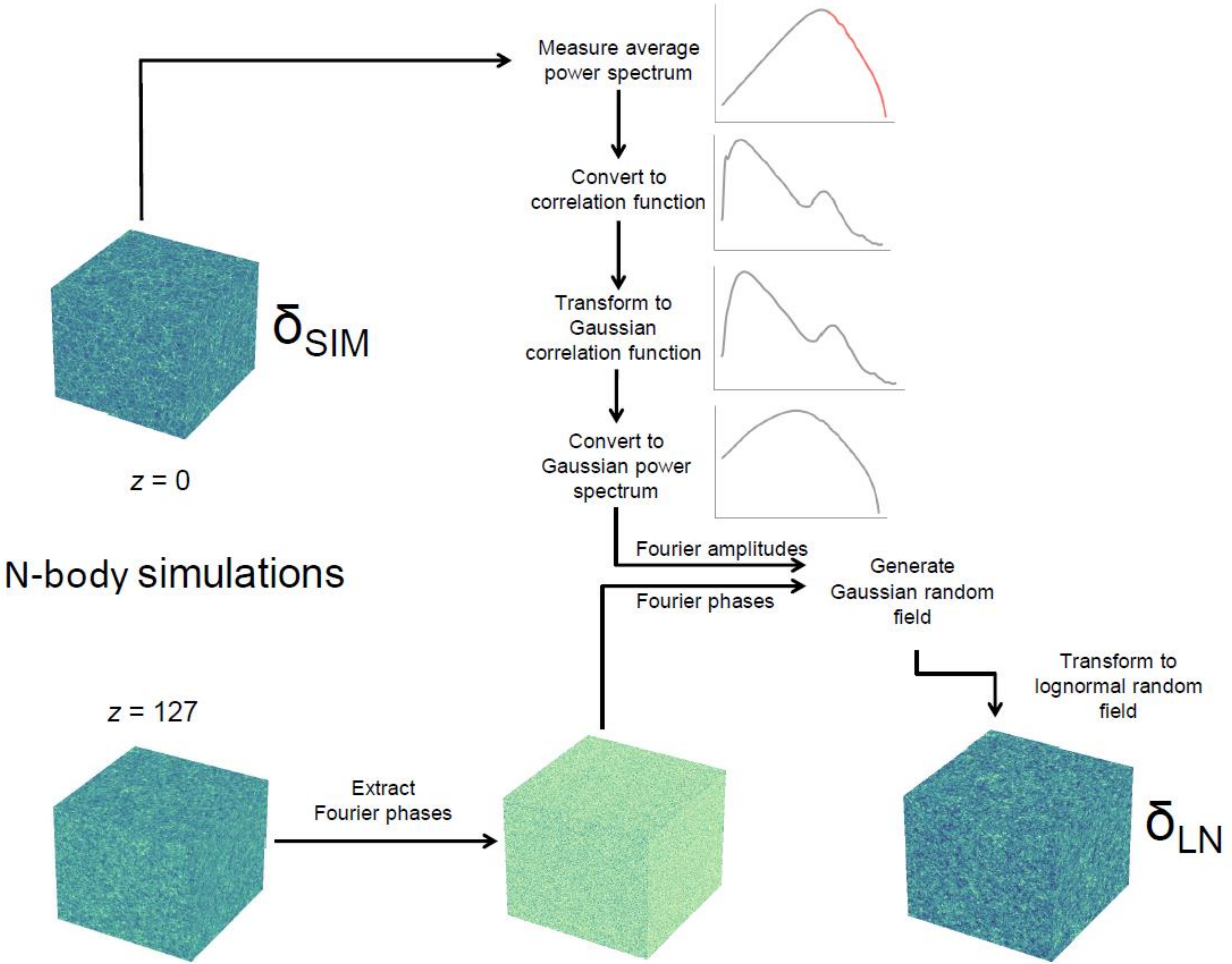
Thank you.
d.piras@ucl.ac.uk

Extra slides



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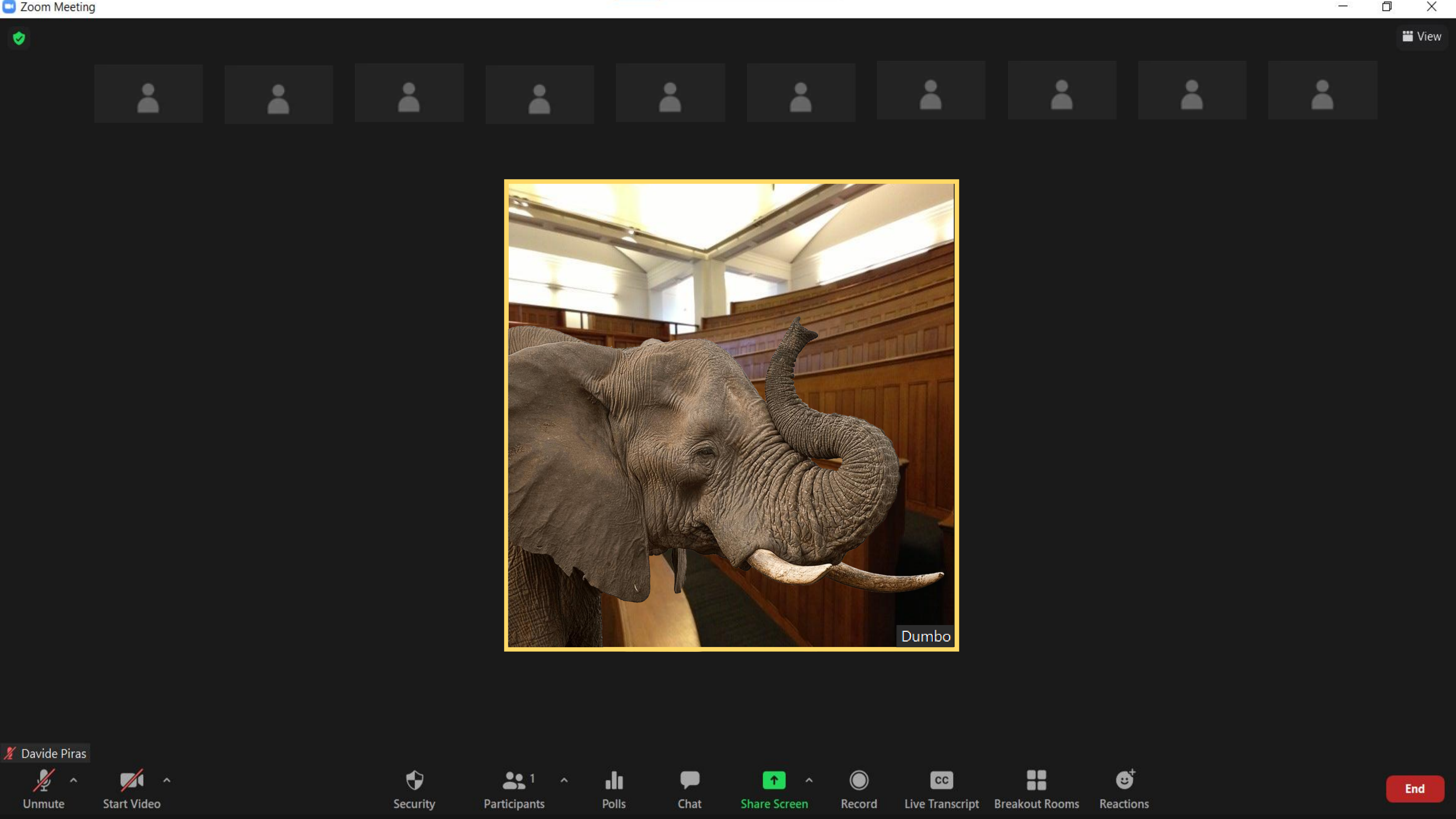
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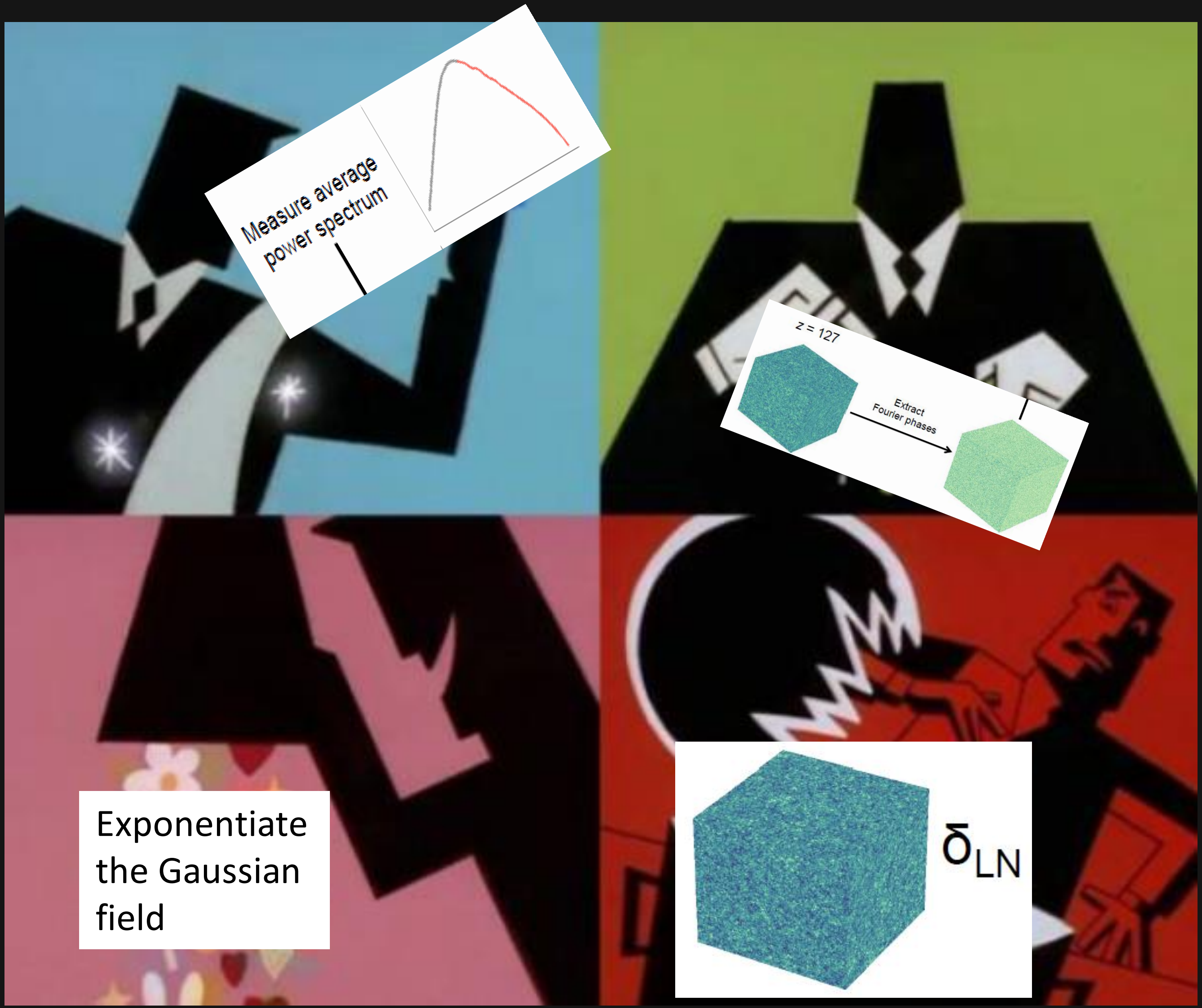
Memes


>10^3 SIMULATIONS
Flagship mock galaxy catalog
FLAGSHIP SIMULATION
EUCLID


Measure average power spectrum
z = 127
Extract Fourier phases
Exponentiate the Gaussian field
δLN