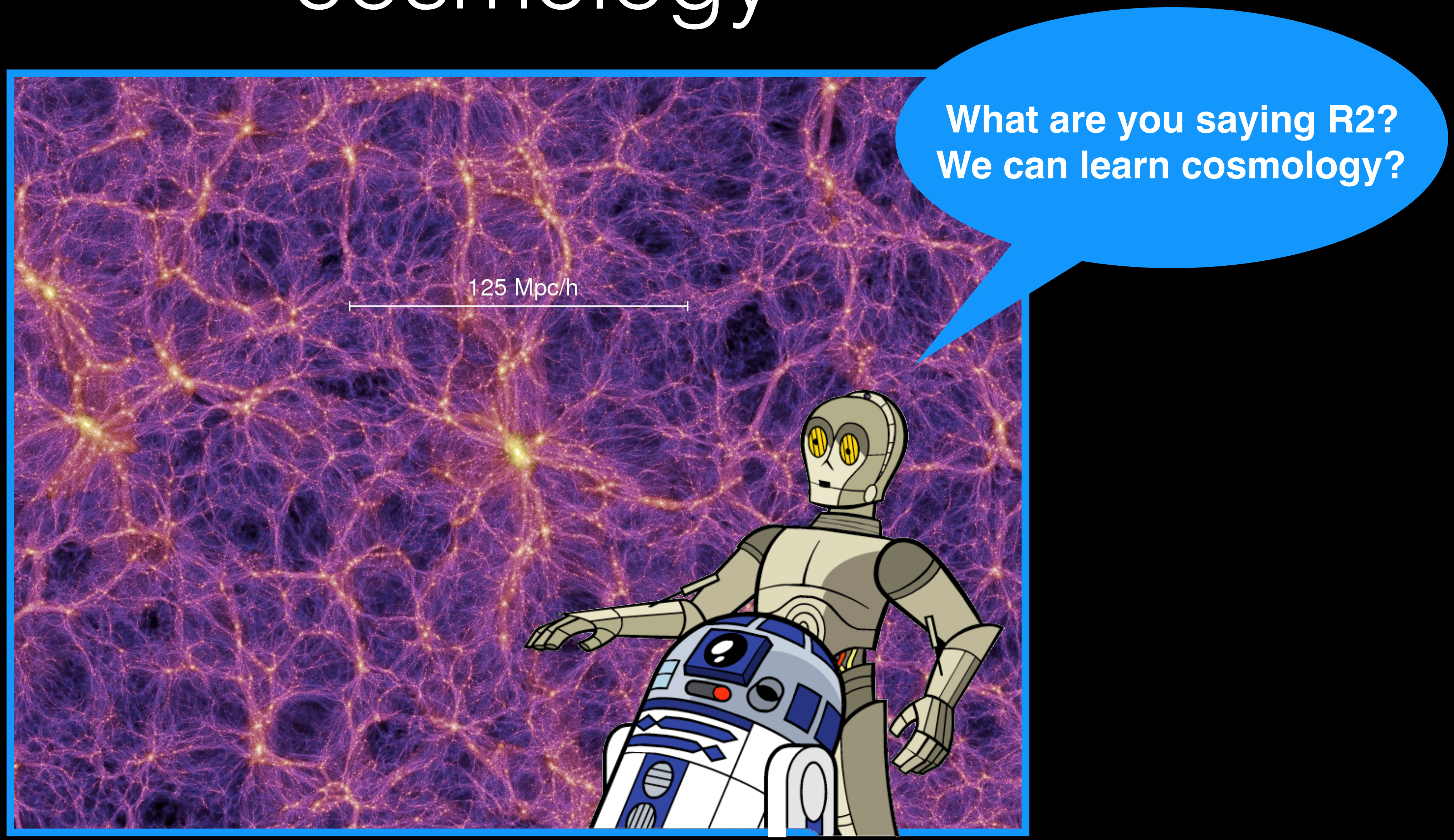
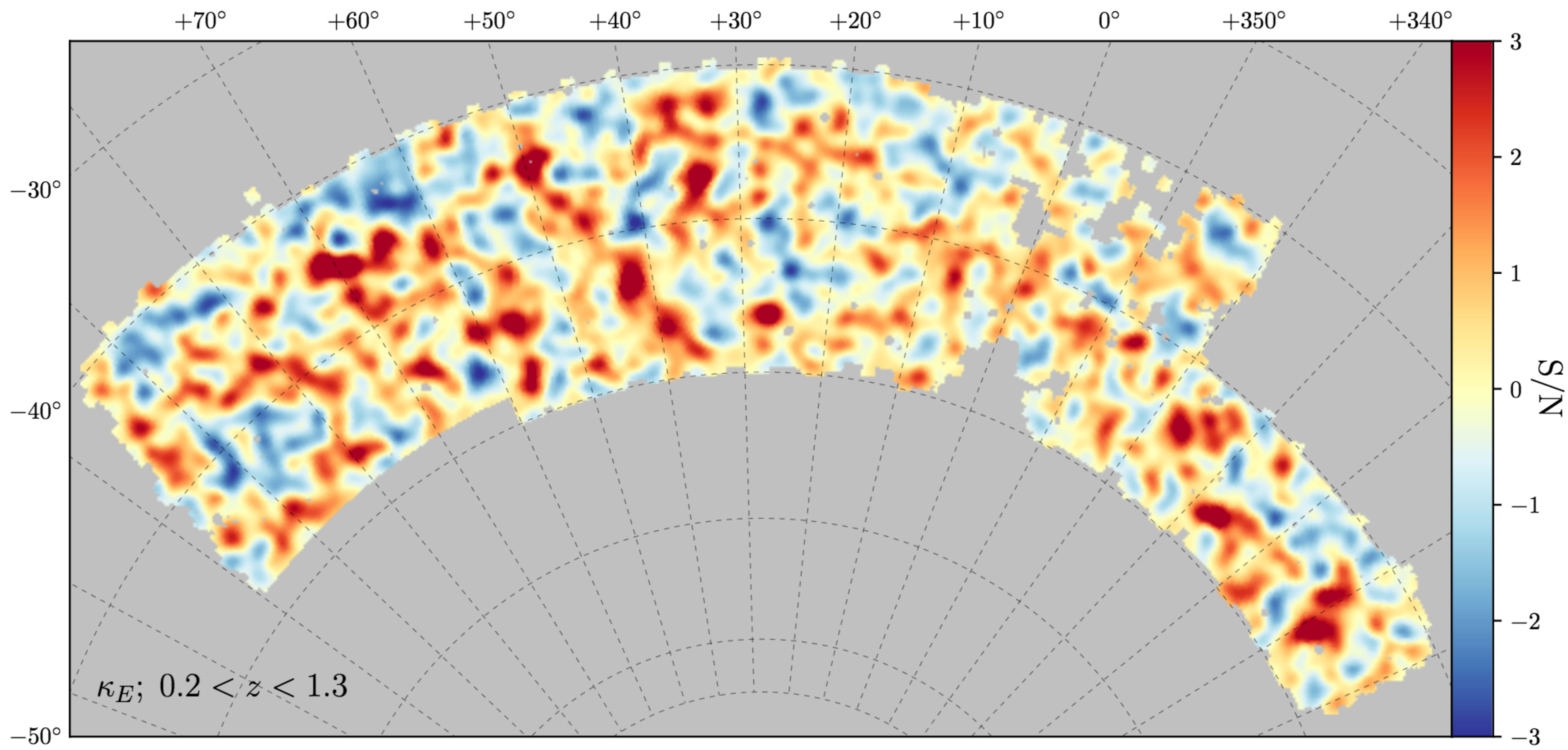
Artificial Intelligence methods for cosmology



Tomasz Kacprzak (ETH Zurich),
Janis Fluri (ETH Cosmology), Aurelien Lucchi (ETH Computer Science),
Nathanaël Perraudin (Swiss Data Science Center)

8th KIAS workshop on Cosmology and Structure Formation, 9 Nov 2018

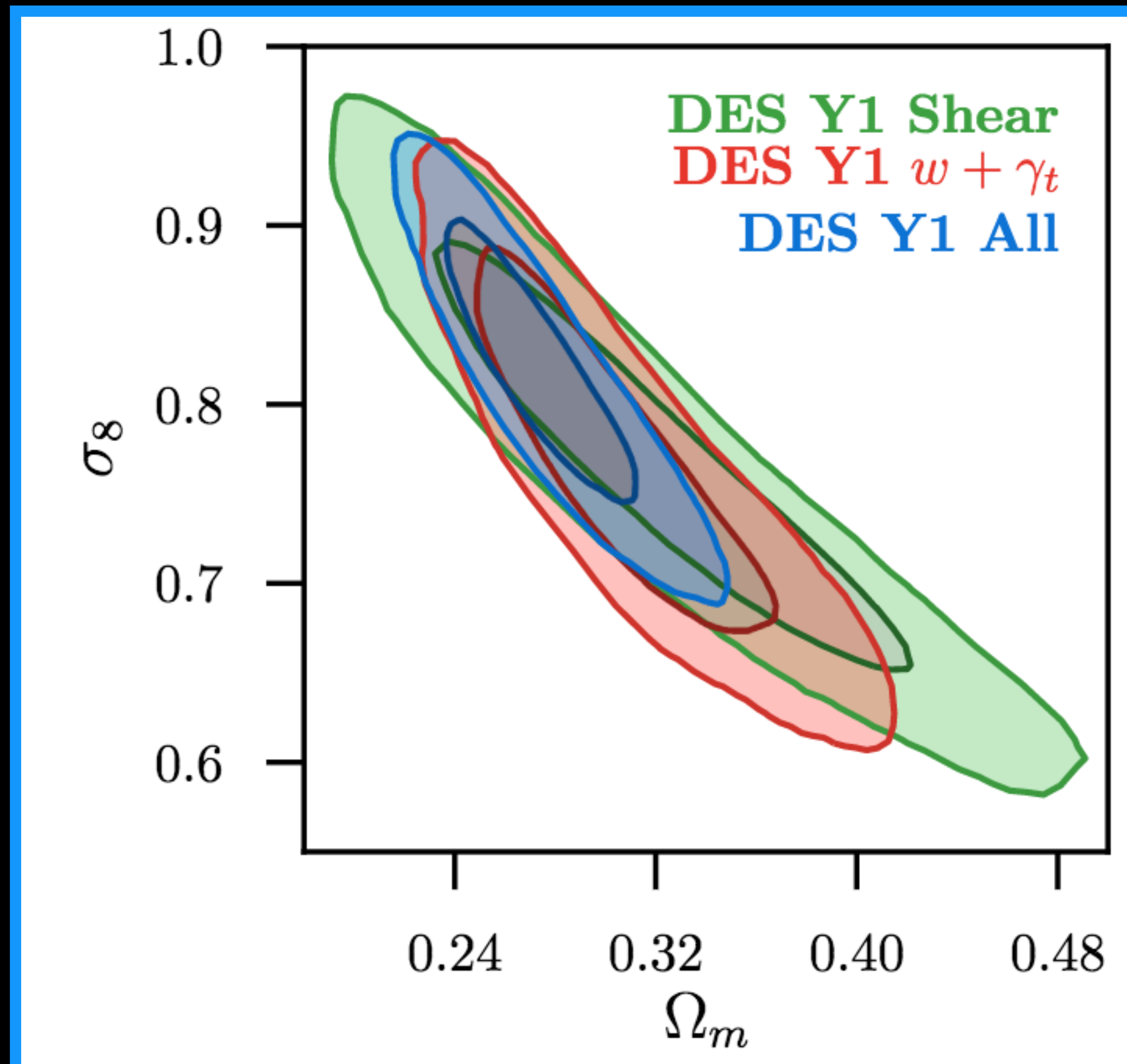
Using mass maps of the universe to constrain cosmological parameters



Chang + DES Collaboration 2017 1708.01535

Cosmological parameters

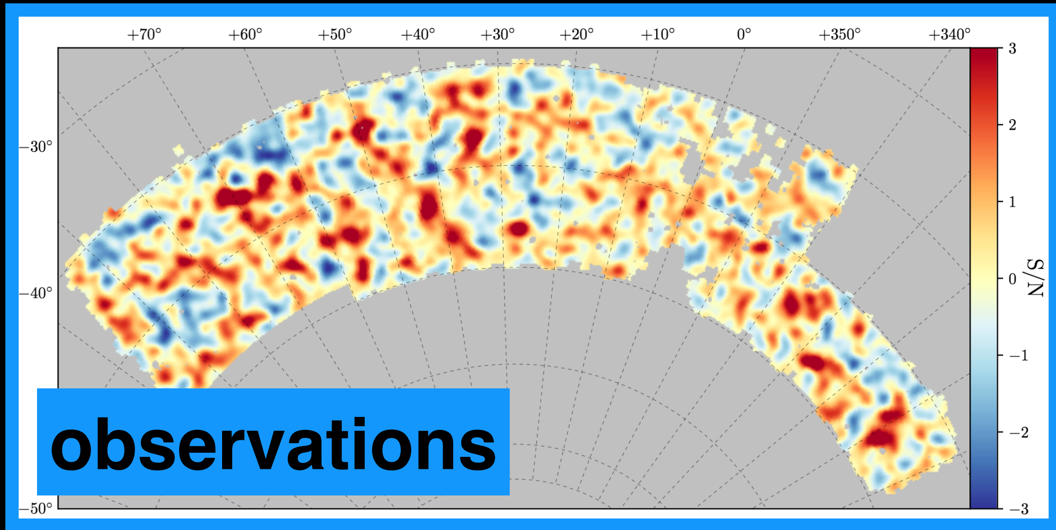
amplitude of matter fluctuations



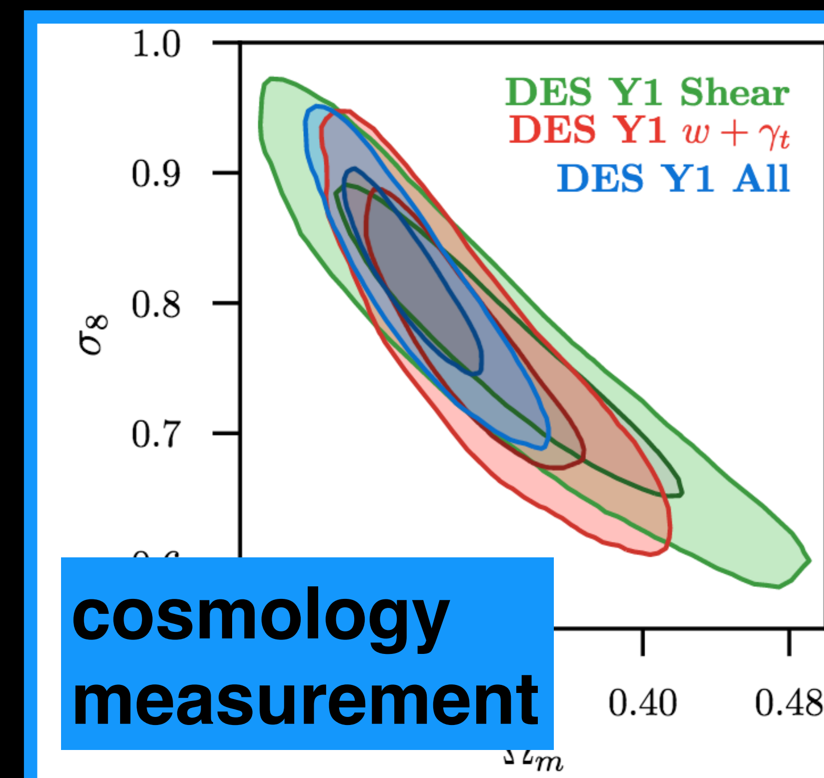
matter density

DES Collaboration 2017 1708.01530

Traditional inference



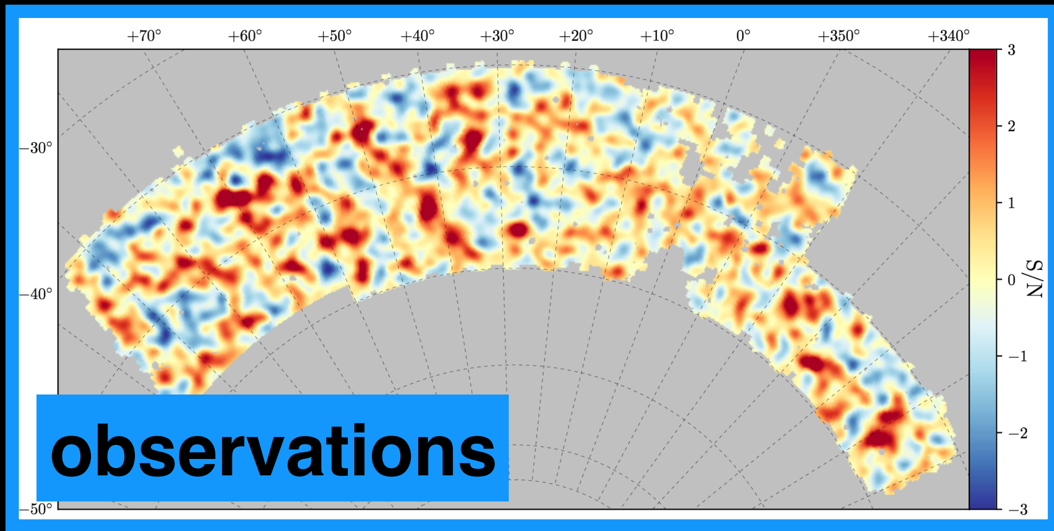
comparison method?

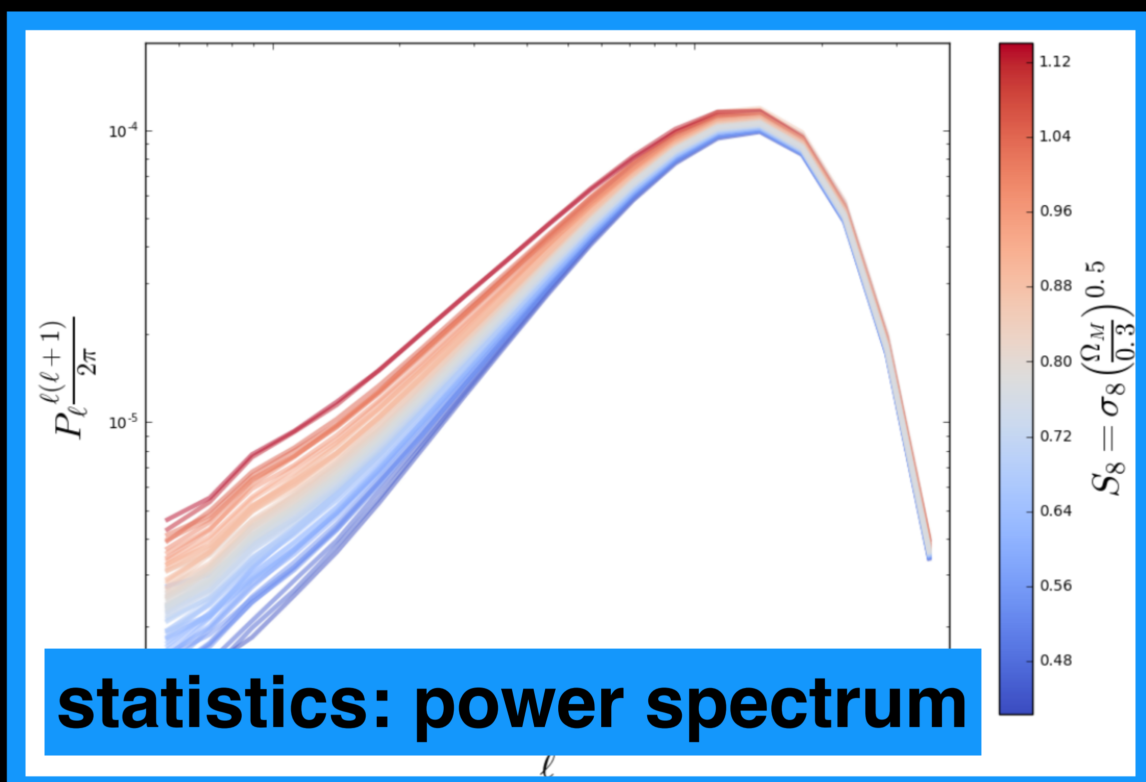


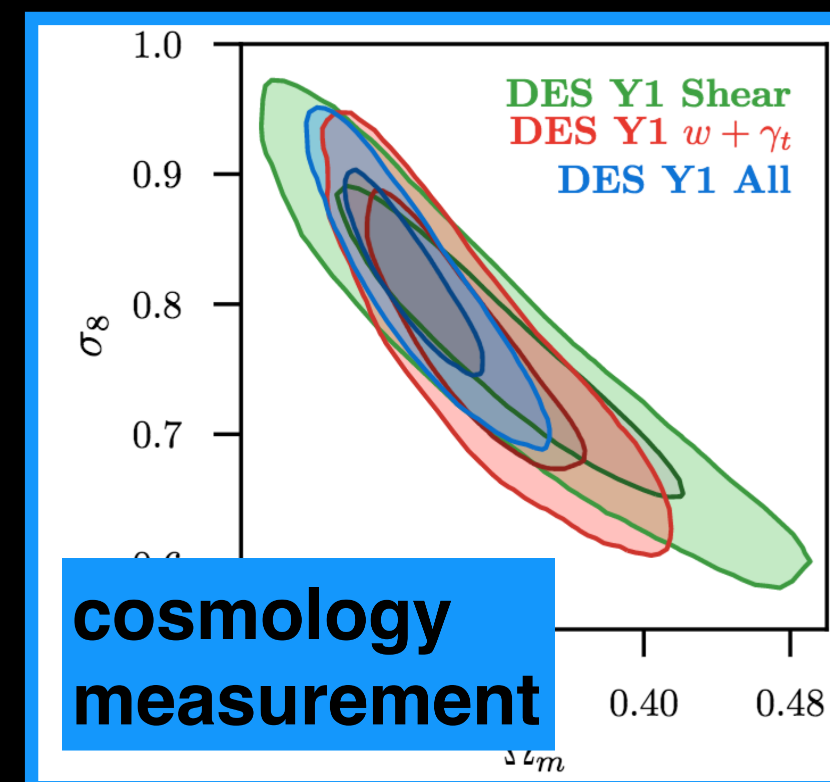
$$\Omega_m \quad \sigma_8 \quad H_0 \quad \ldots$$

theory prediction

Traditional inference







$$C_l = \frac{9}{16}\left(\frac{H_0}{c}\right)^4 \Omega_m^2 \int_0^{\chi_h} d\chi \left[\frac{g(\chi)}{ar(\chi)}\right]^2 P\left(\frac{l}{r}, \chi\right),$$

theory prediction: analytical

Advanced statistics

Three-point functions

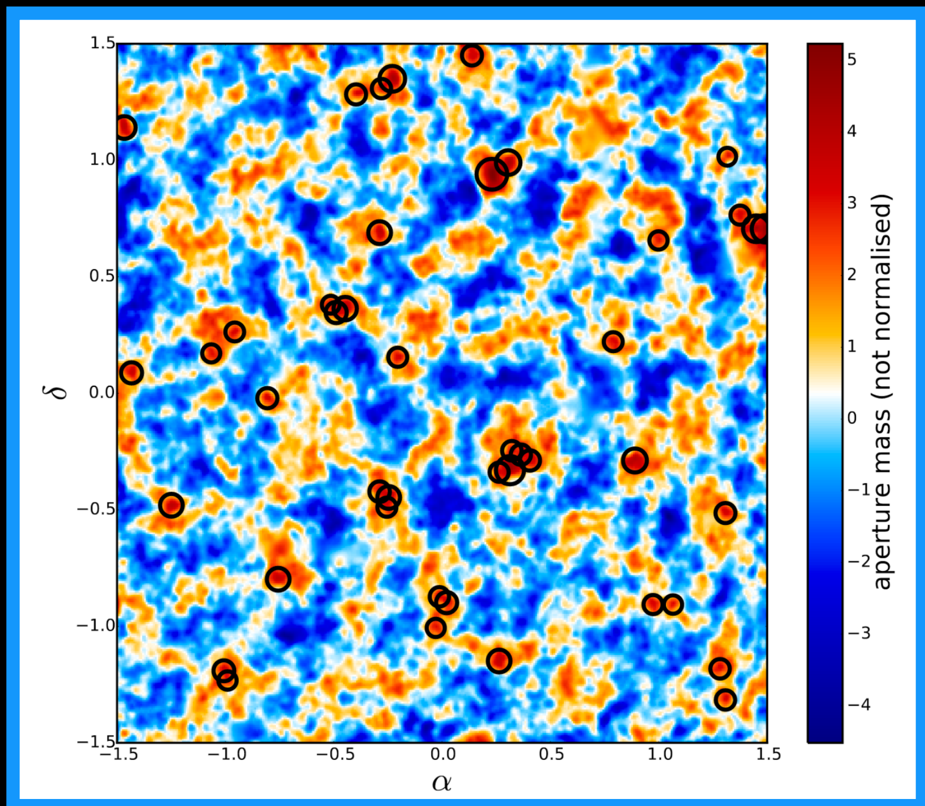
Higher-order moments of convergence

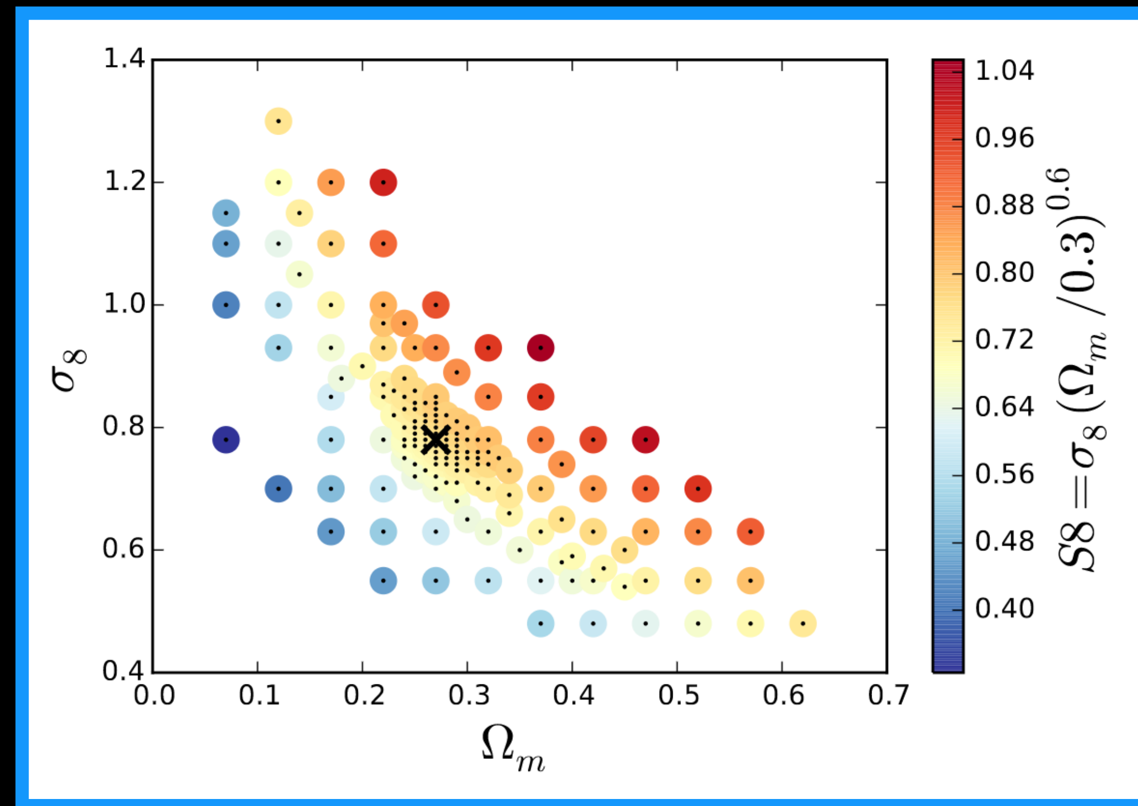
Full convergence distribution

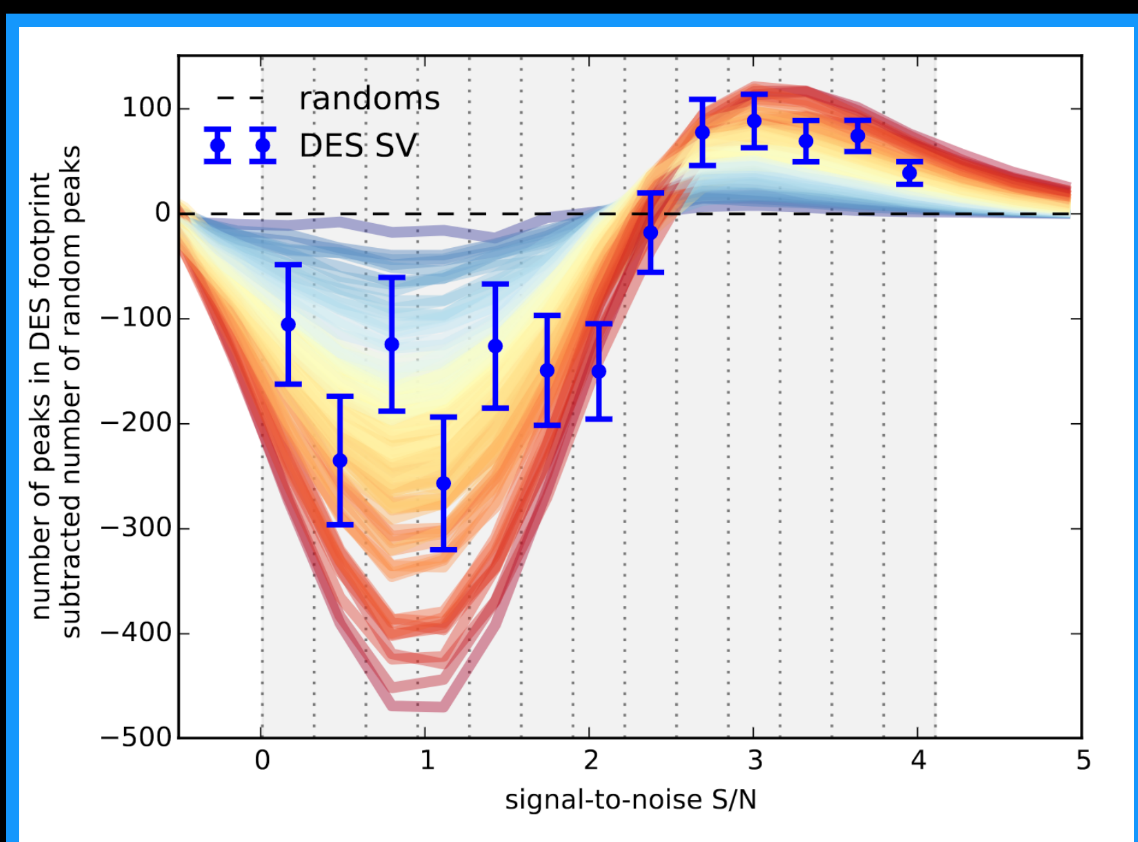
Minkowski functionals

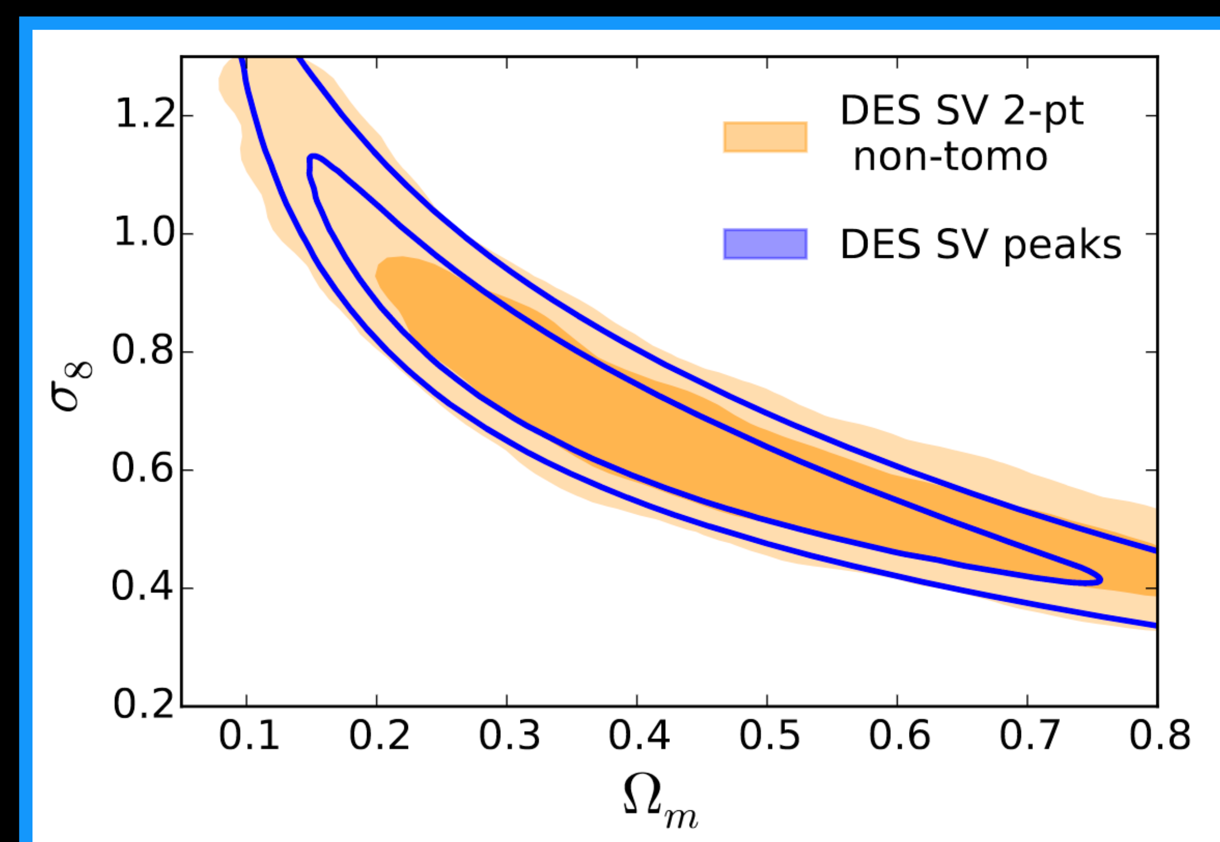
Peak statistics

Cosmology with peak statistics









TK+DES Collaboration, 2016, 1603.05040

Advanced statistics

Three-point functions

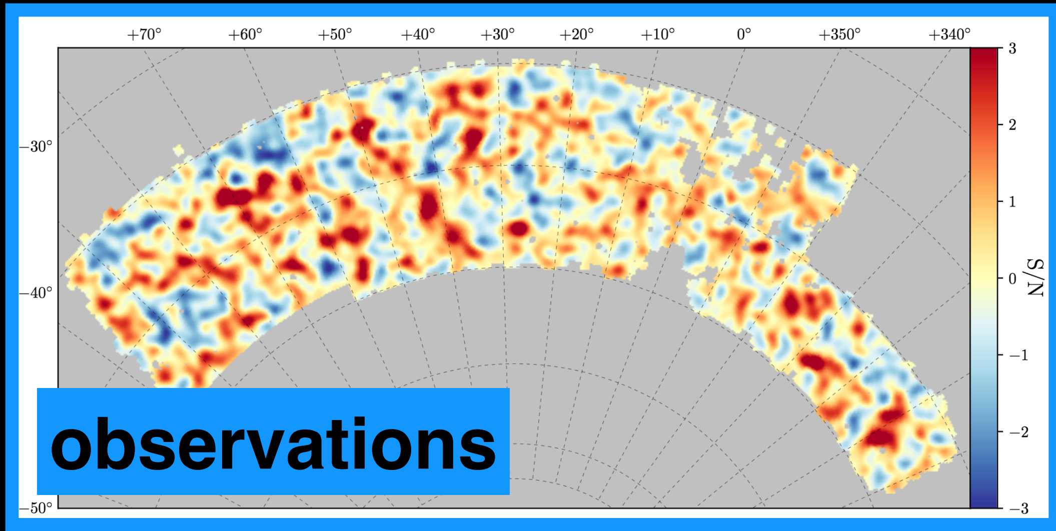
Higher-order moments of convergence

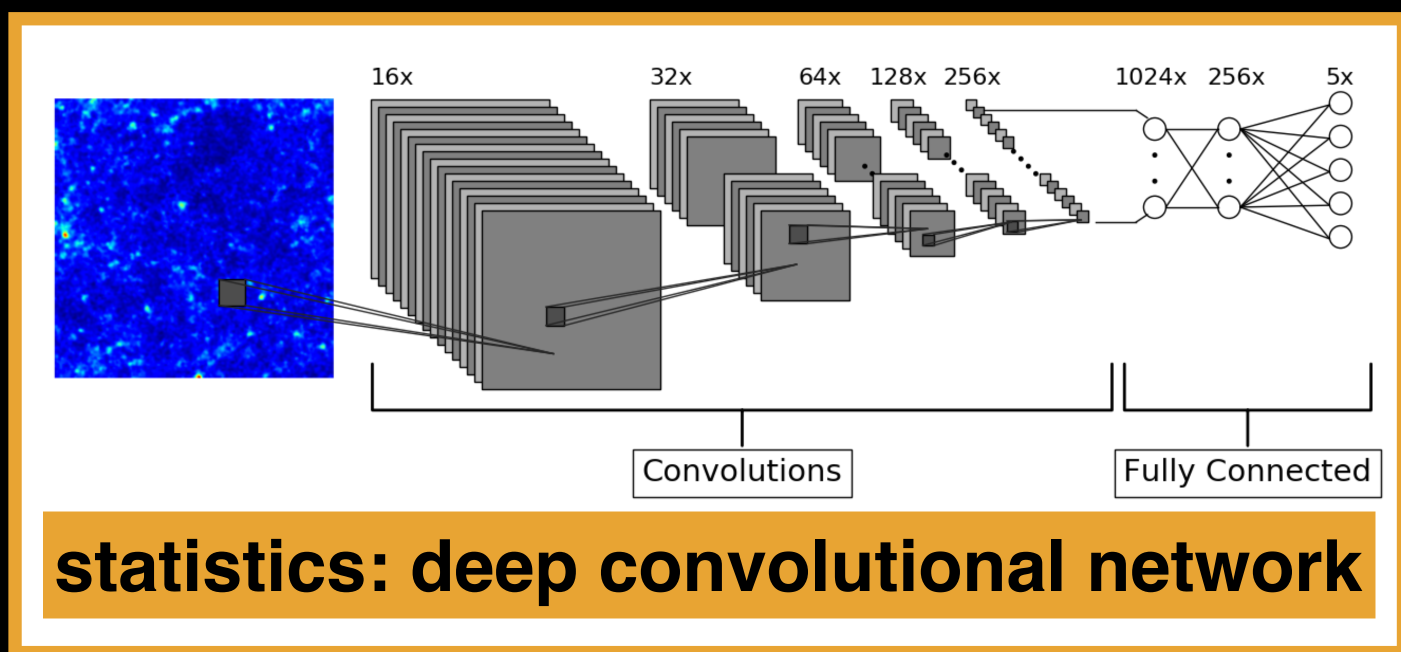
Full convergence distribution

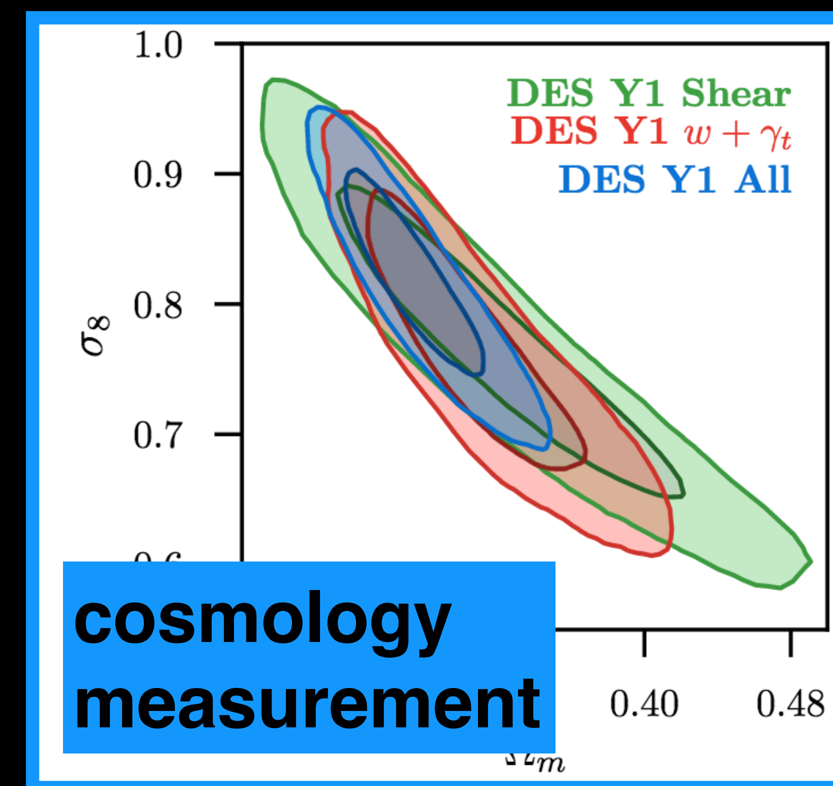
Minkowski functionals

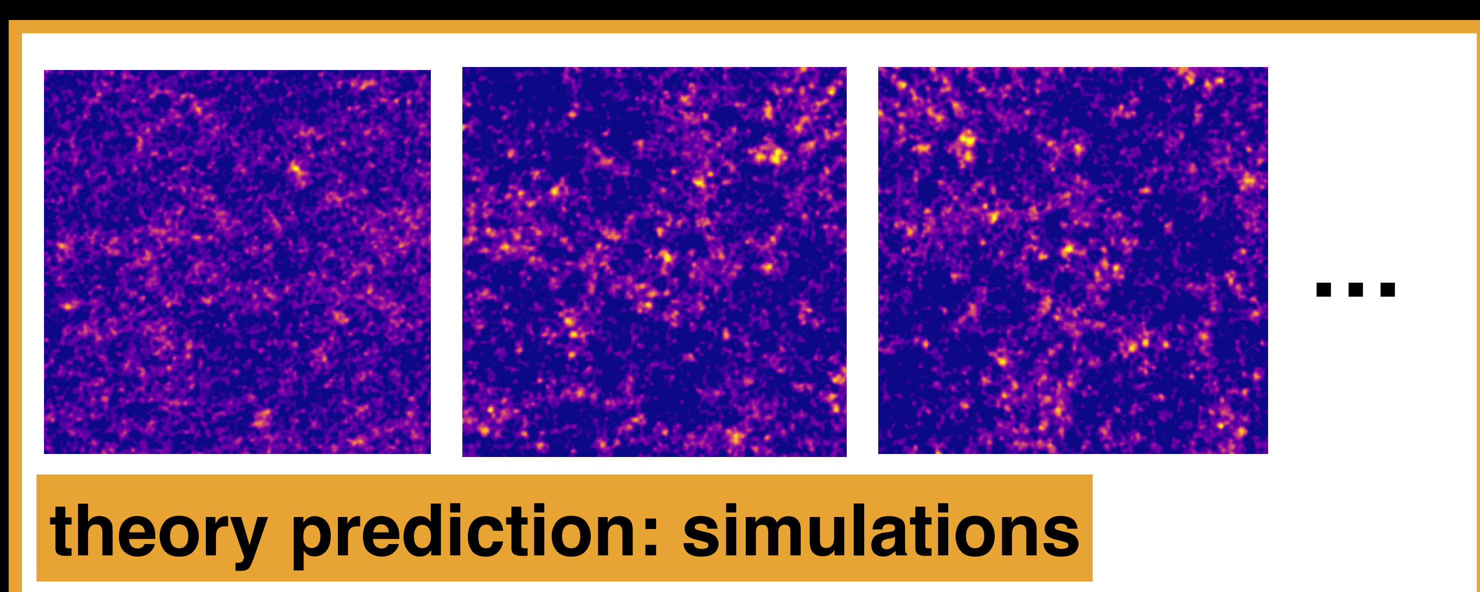
Peak statistics

Inference with Deep Learning

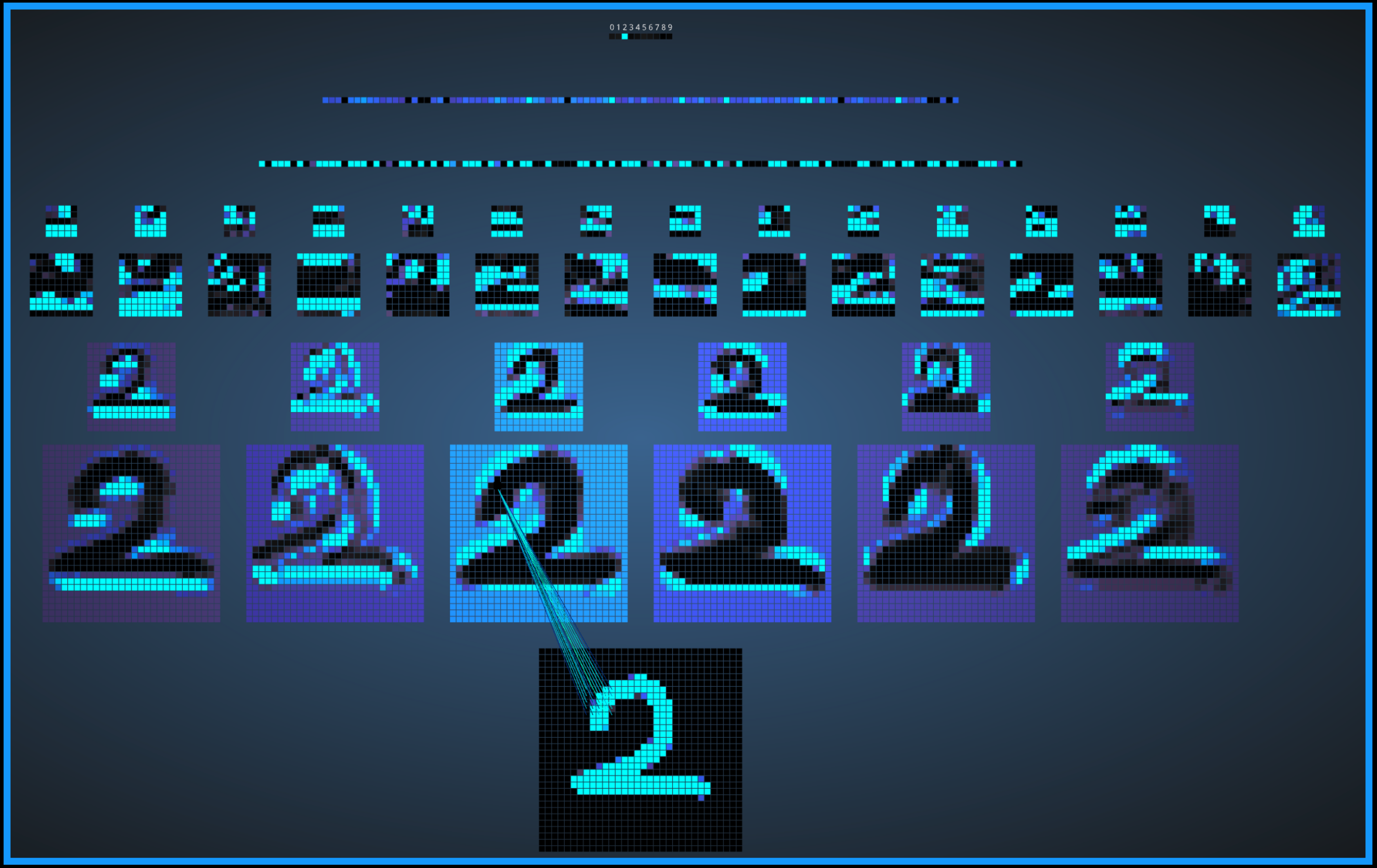






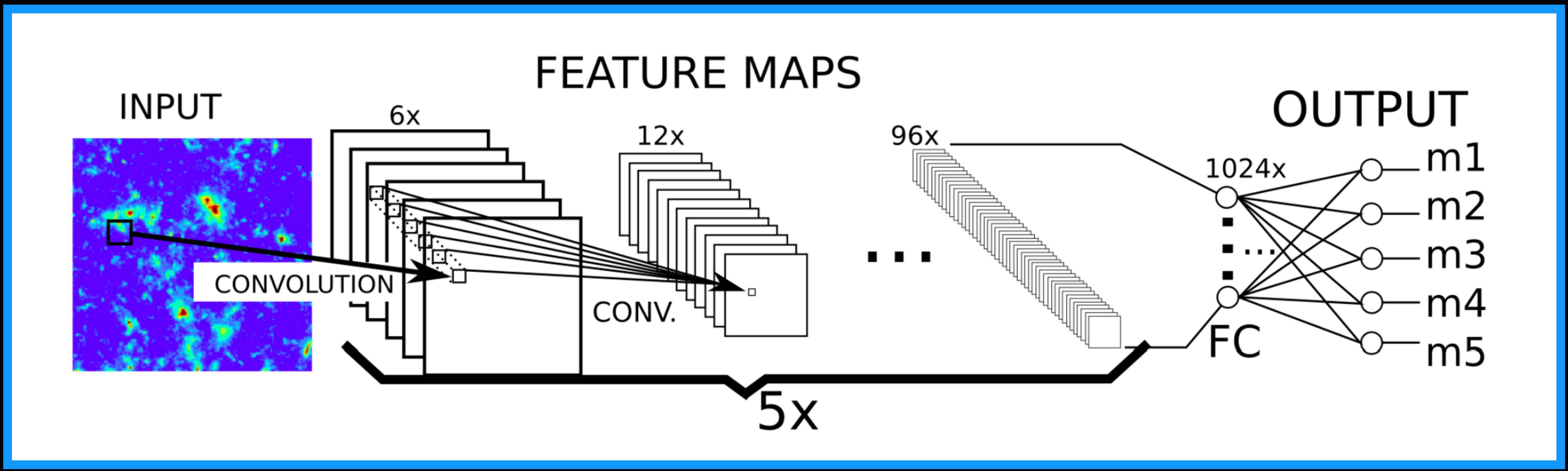


Simple Convolutional Neural Network demo



http://scs.ryerson.ca/~aharley/vis/conv/flat.html

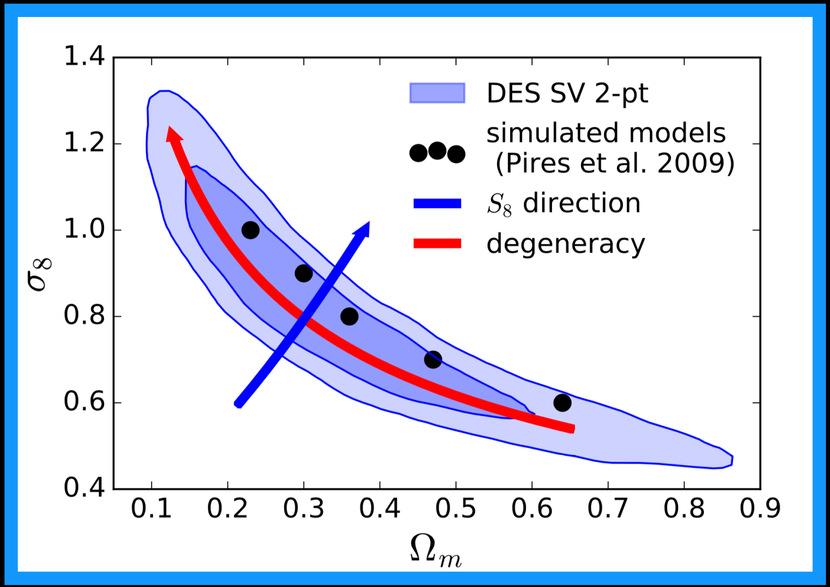
Cosmological model discrimination

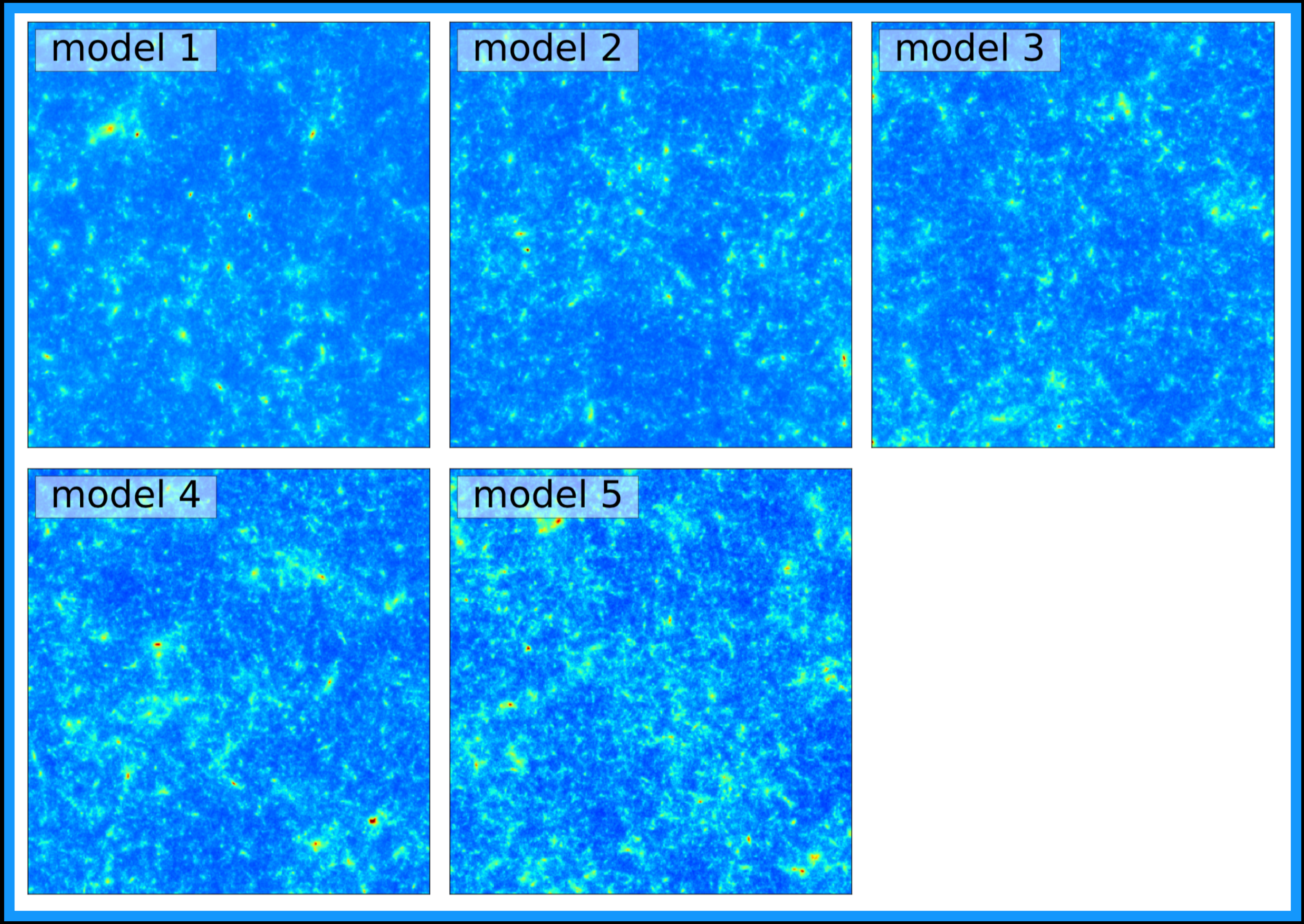


Deep network with 10 million trainable parameters

Schmelze, TK, et al., 2017 1707.05167

Cosmological model discrimination

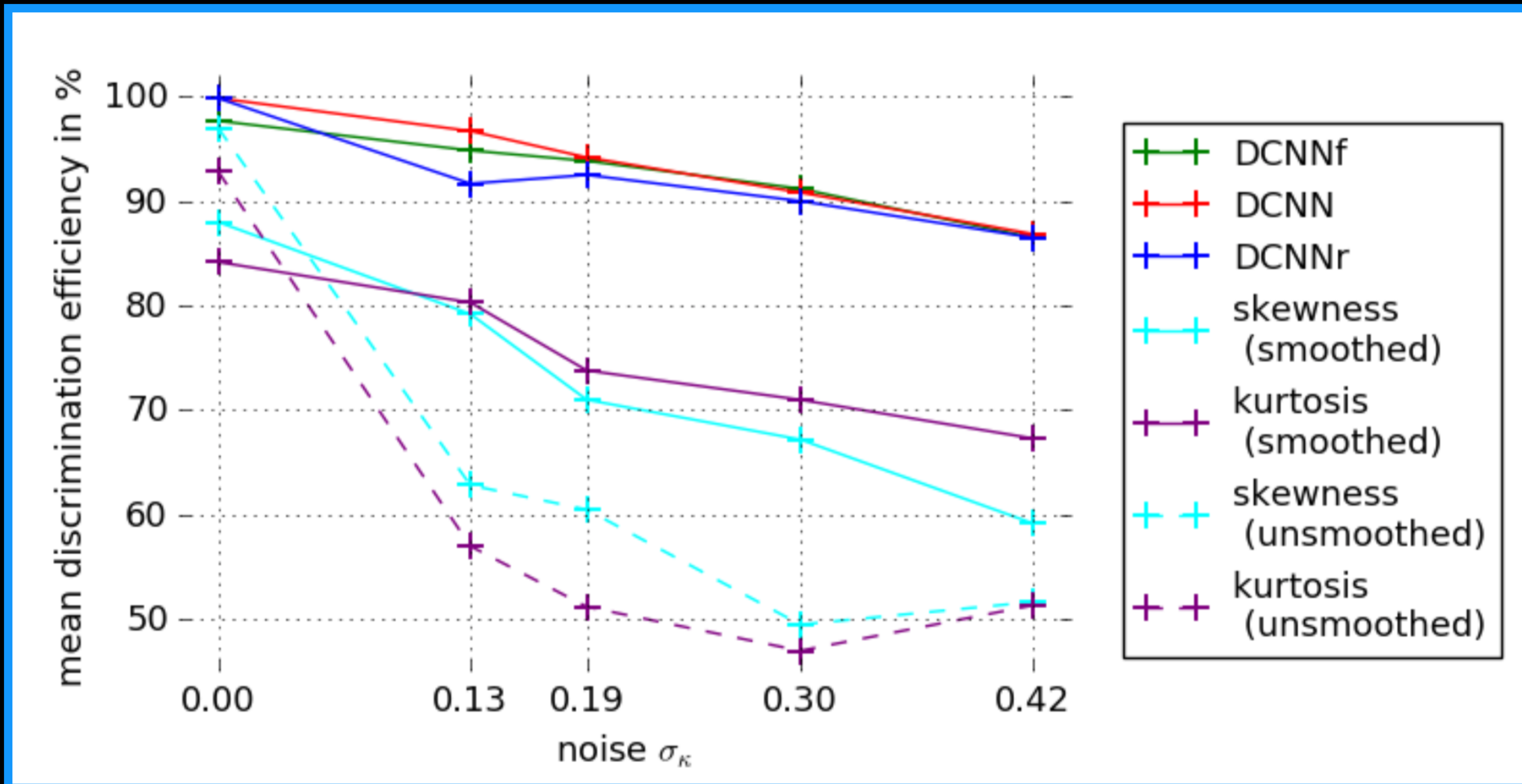




Using five cosmological models
with almost the same power spectra

Schmelze, TK, et al., 2017 1707.05167

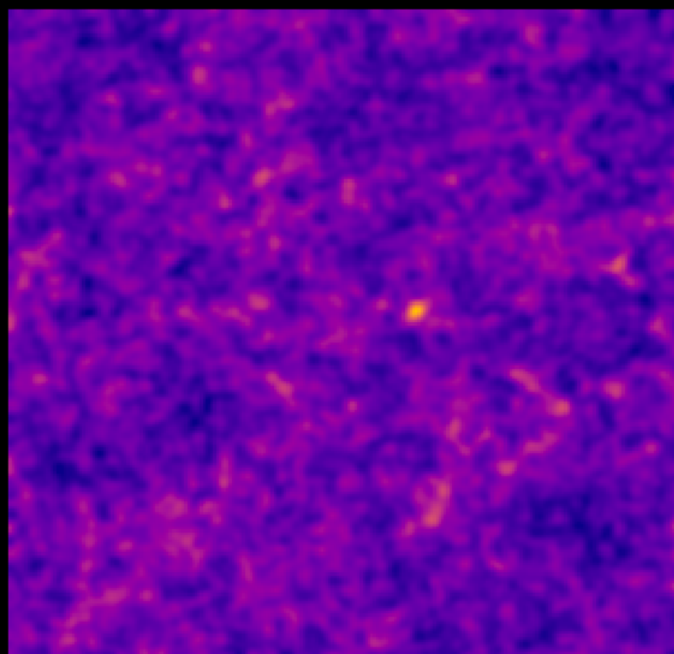
Cosmological model discrimination



DCNN performs better
and maintains decent accuracy for high noise levels

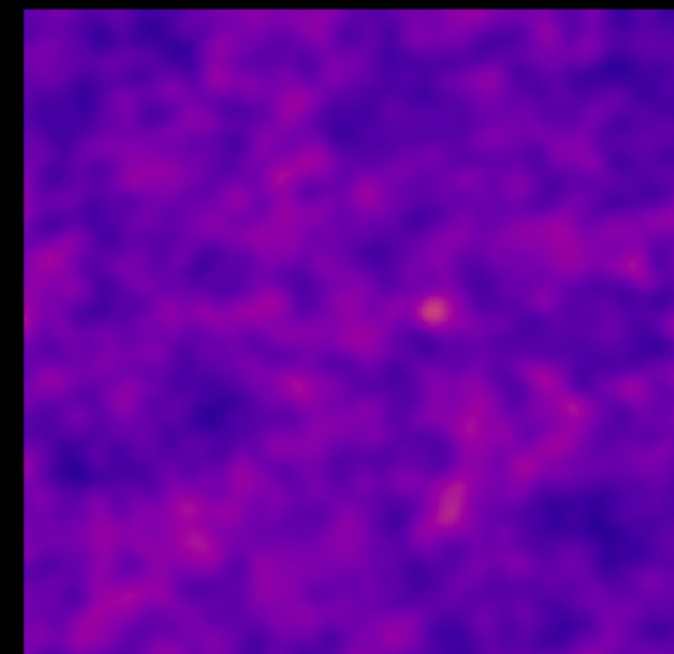
Schmelze, TK, et al., 2017 1707.05167

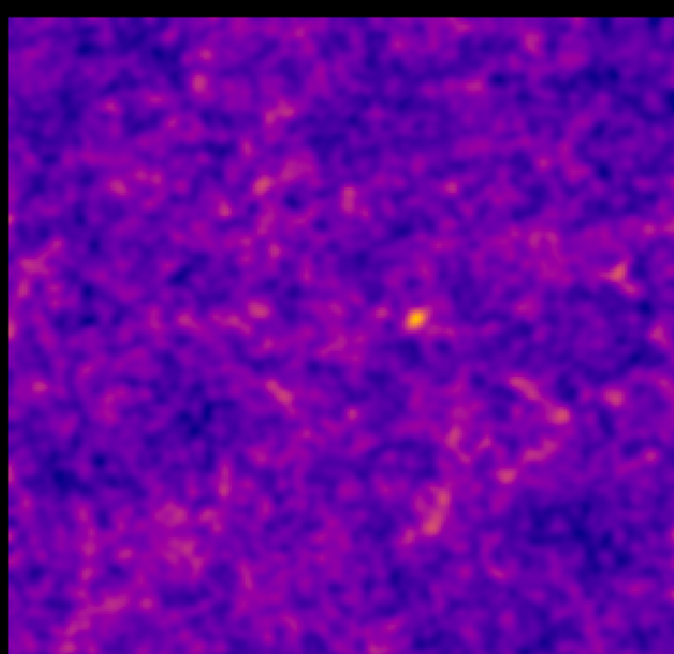
What is the advantage of deep learning for current and upcoming data?



add smoothing →

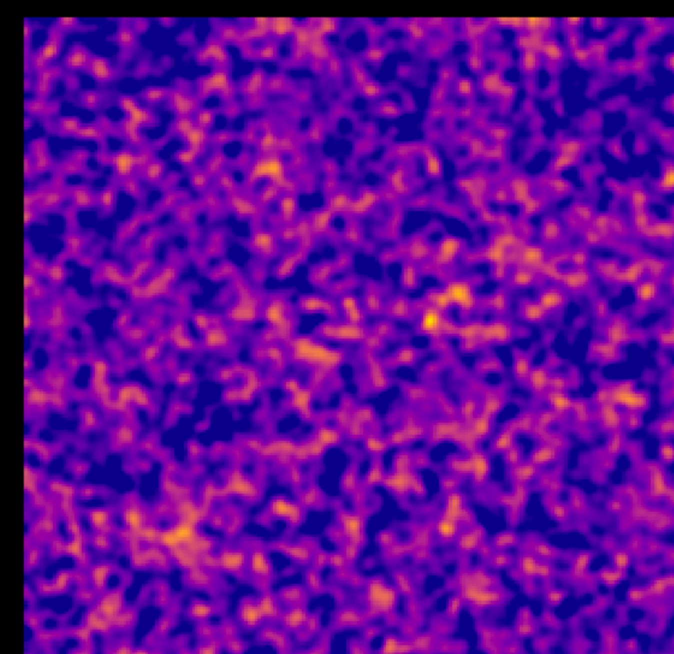
quality of simulations





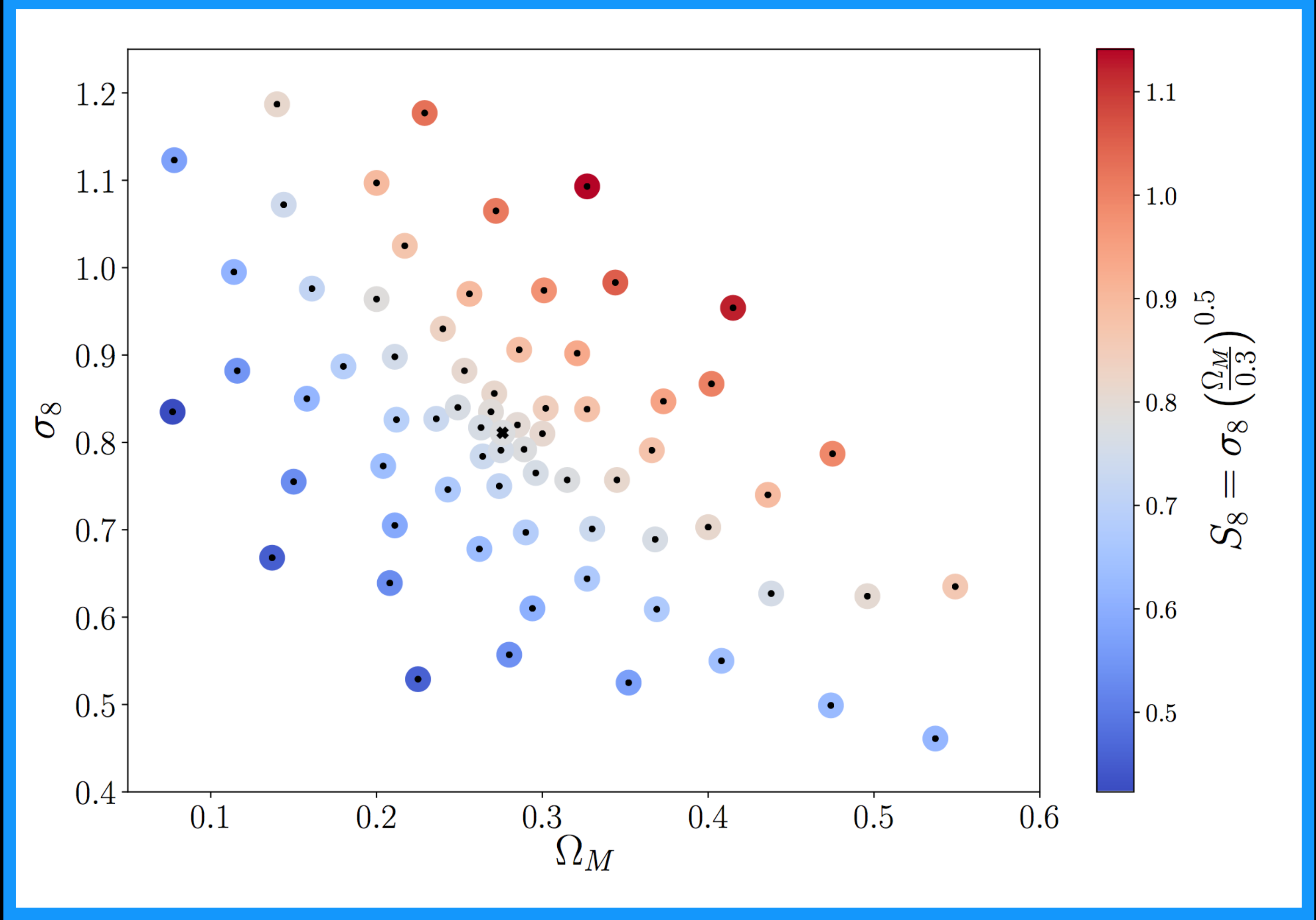
add noise →

quality of observations



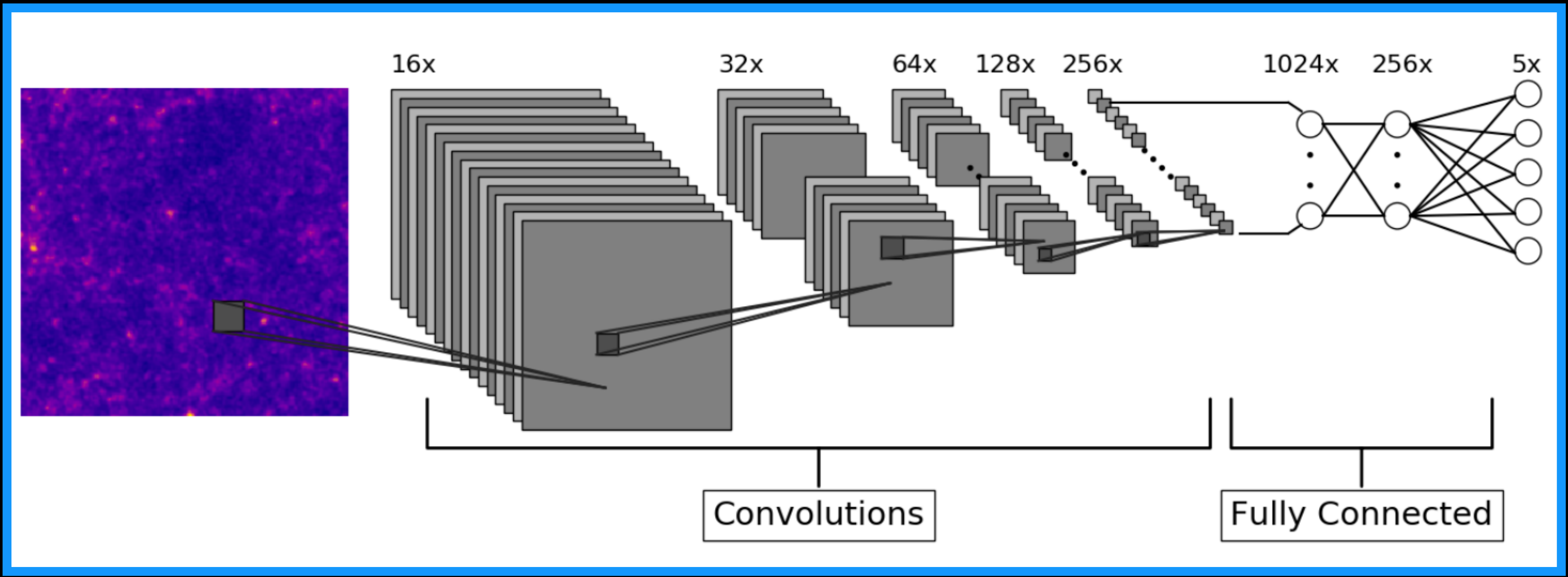
Simulation grid

- 4 full sky convergence maps per cosmology
- 3072 flat, 10 x 10 deg maps per cosmology
- 256 x 256 pixels per map
- cosmological parameters: Ω_m σ_8, others fixed
- using L-Picola for simulations



Fluri, TK, et al. 1807.08732

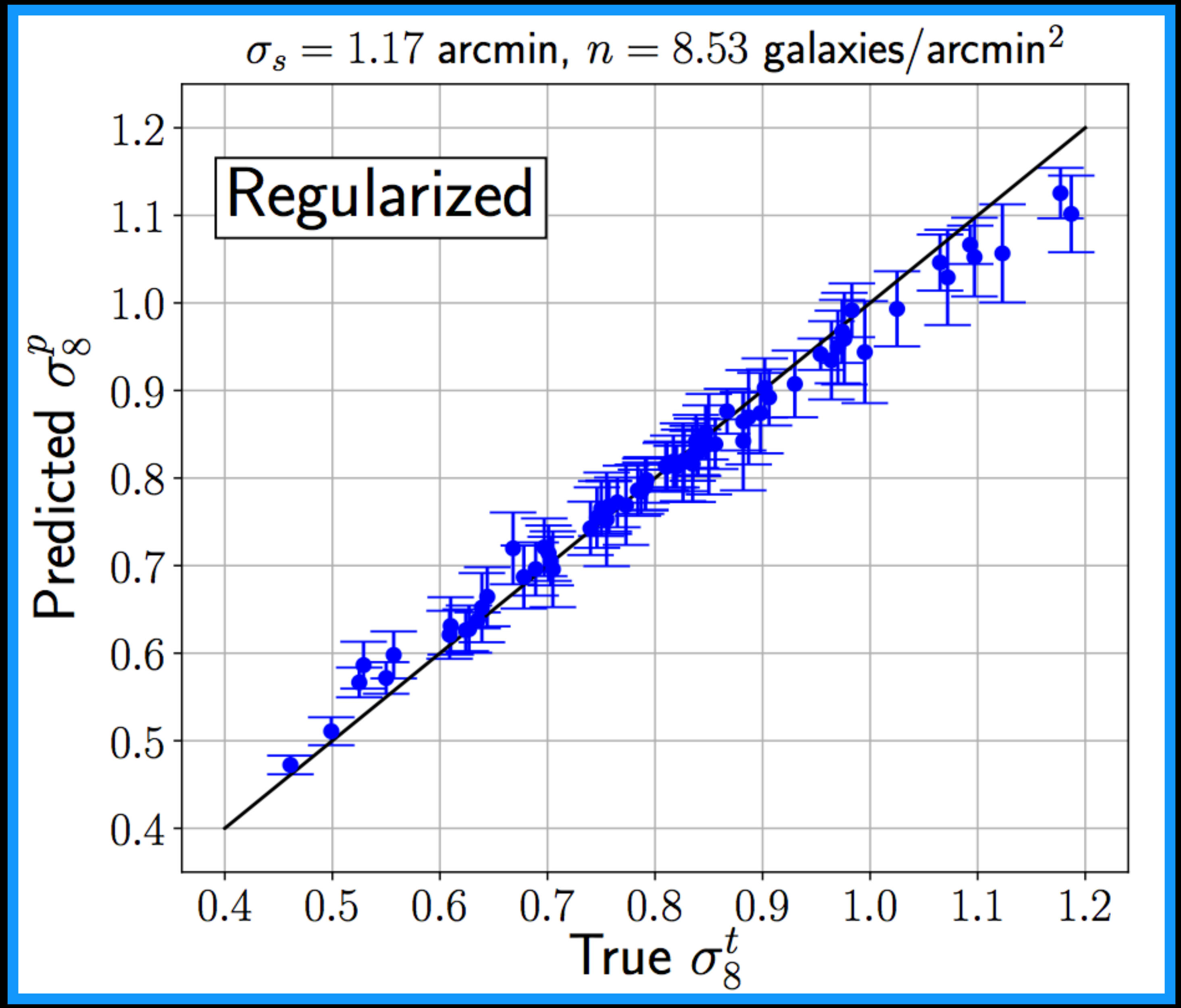
Deep Convolutional Neural Network



Using likelihood loss to predict the covariance of parameters

Fluri, TK, et al. 1807.08732

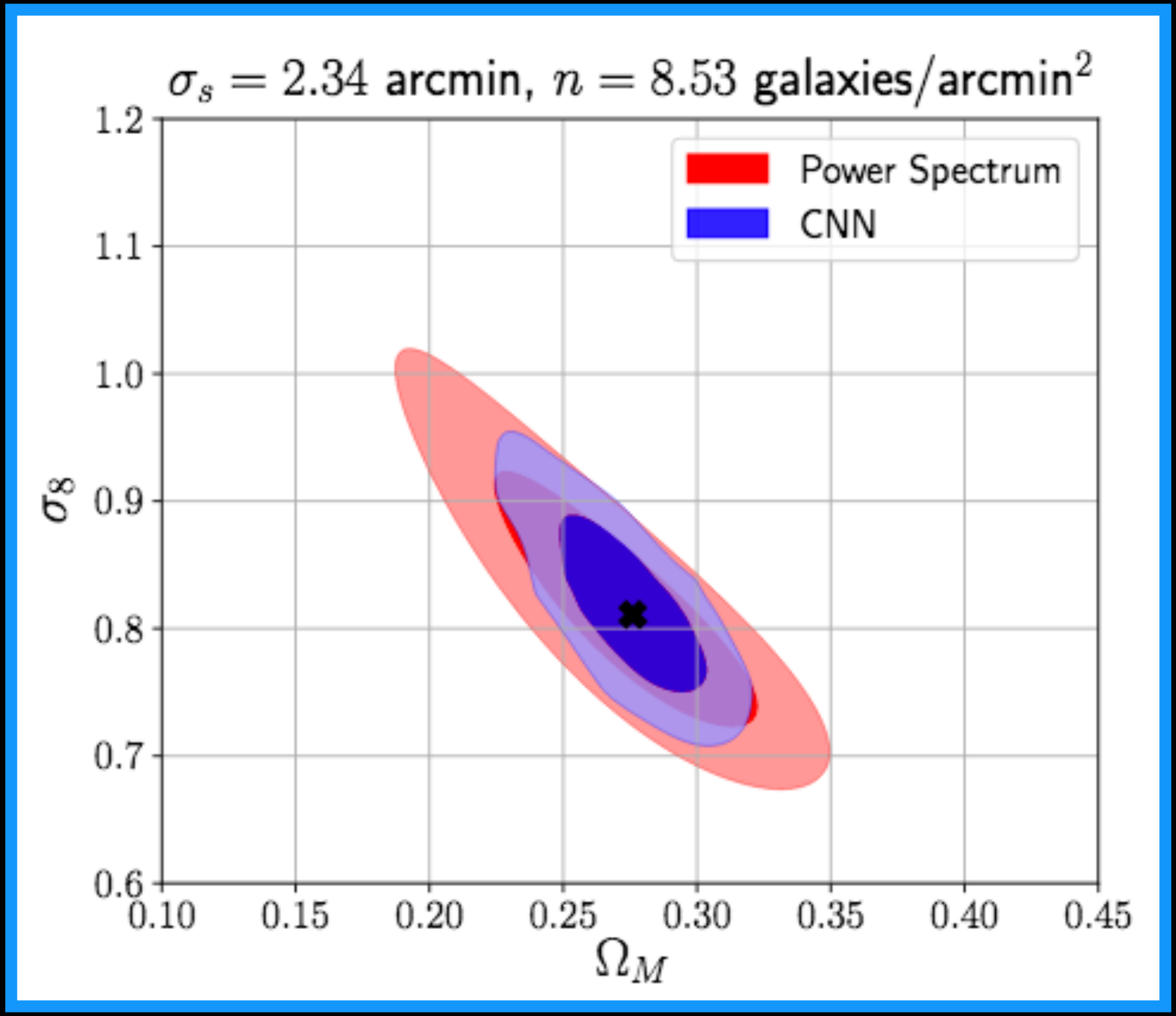
Deep Convolutional Neural Network



Creating likelihood from simulations, using 400 deg^2

Fluri, TK, et al. 1807.08732

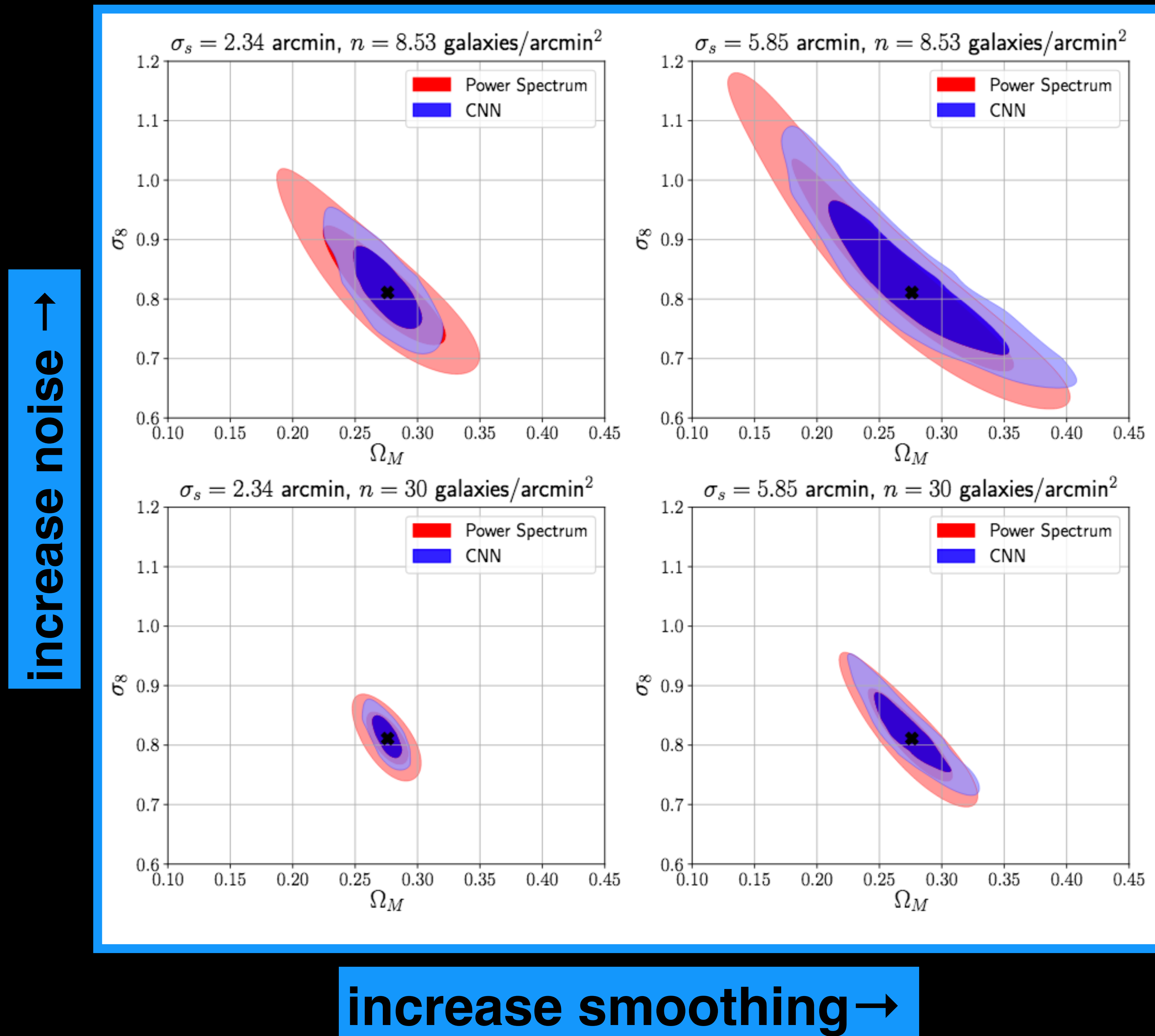
Deep learning captures more information



40% increase in constraining power over the power spectrum

Fluri, TK, et al. 1807.08732

Deep learning captures more information

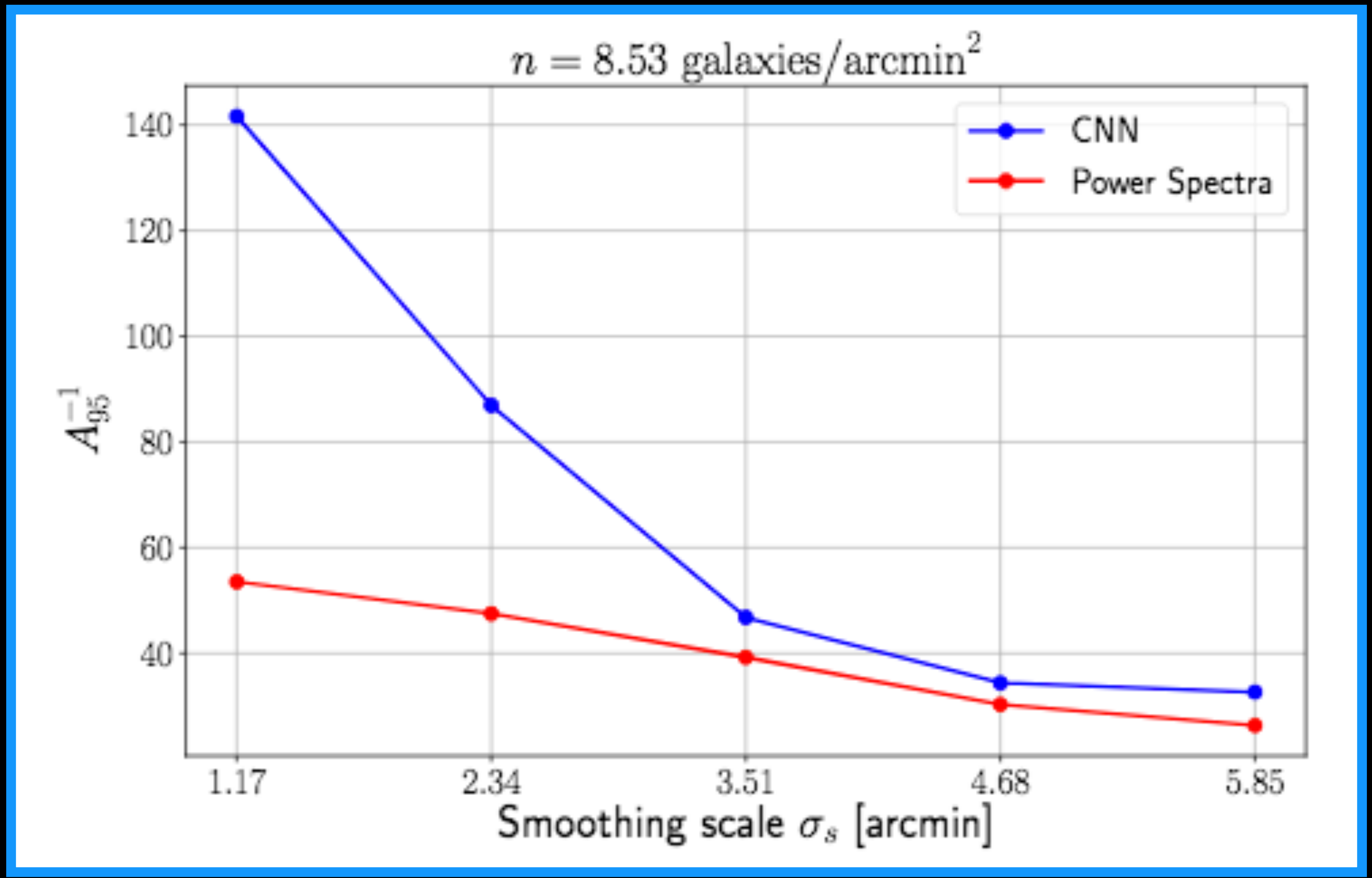


Gain in constraining power depends on noise level and smoothing scale

Fluri, TK, et al. 1807.08732

Deep learning captures more information

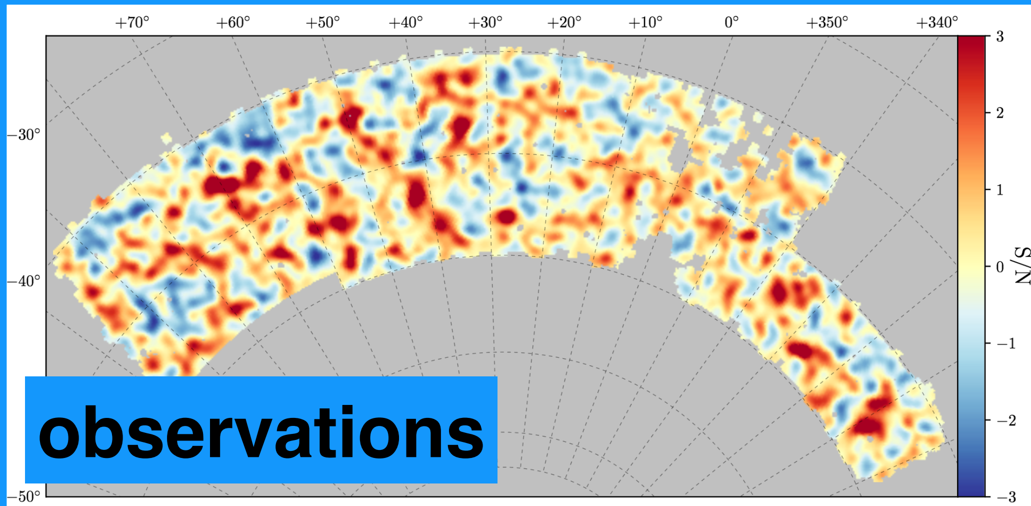
(better) ← contour area → (worse)



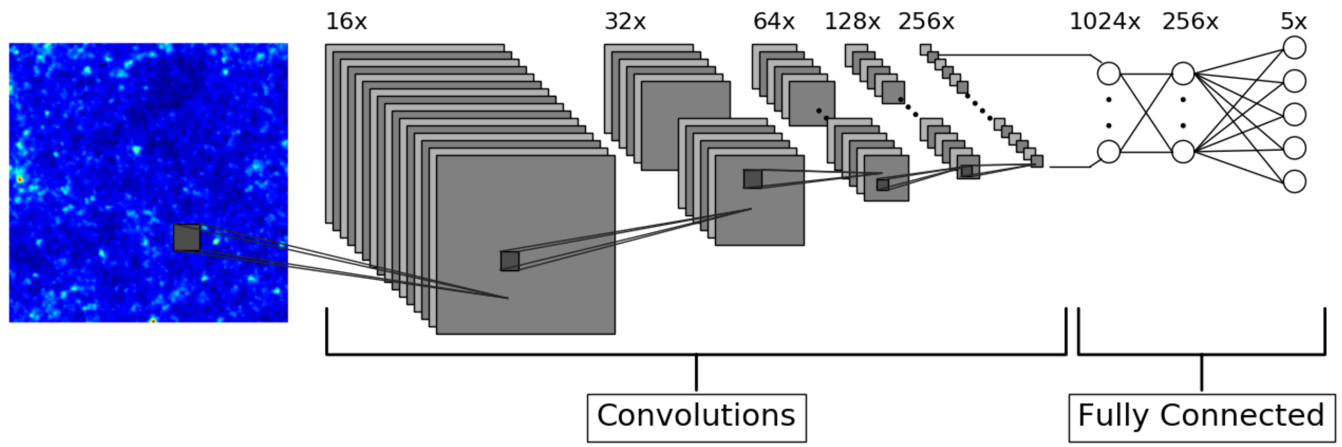
← smoothing scale →

Fluri, TK, et al. 1807.08732

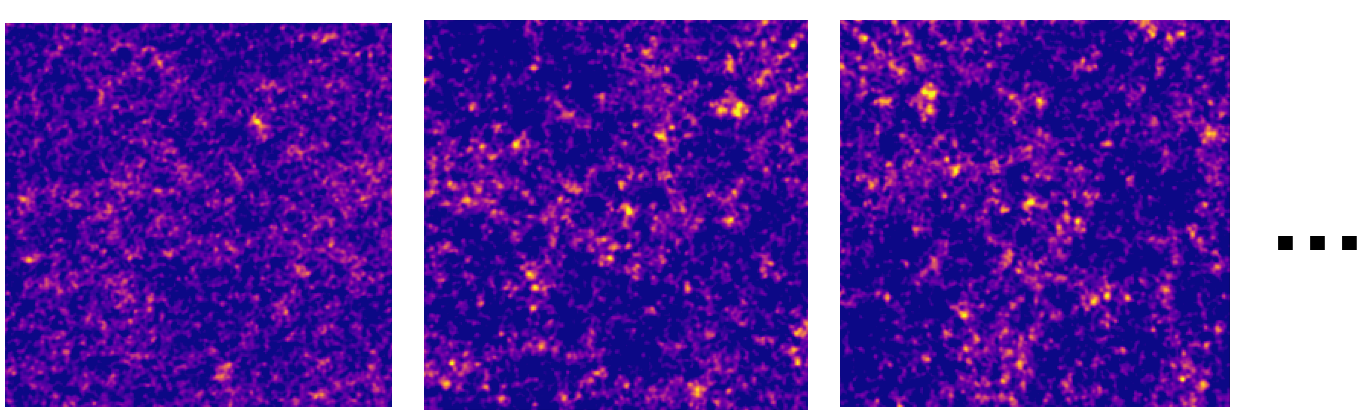
Inference with Deep Learning



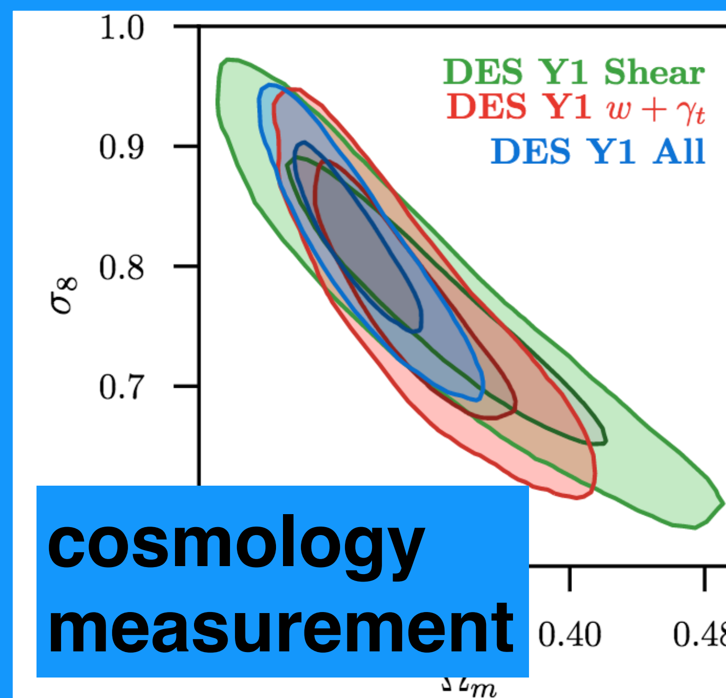
observations



statistics: deep convolutional network



theory prediction: simulations

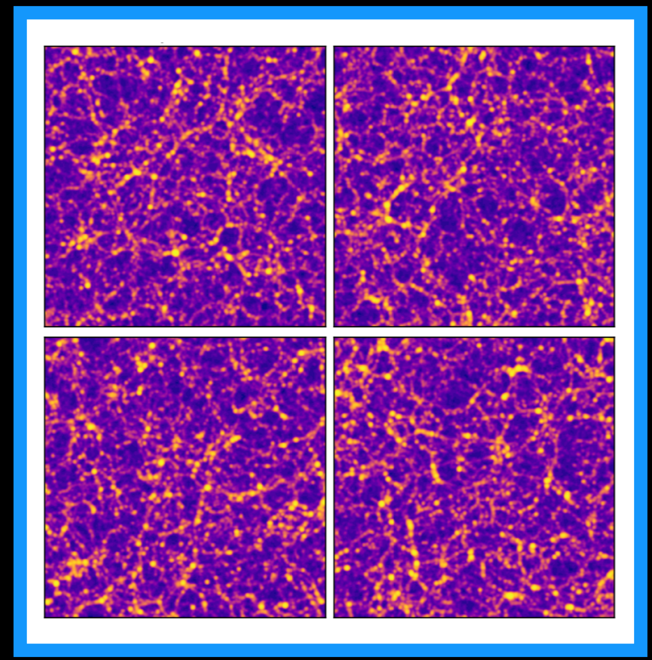


cosmology measurement

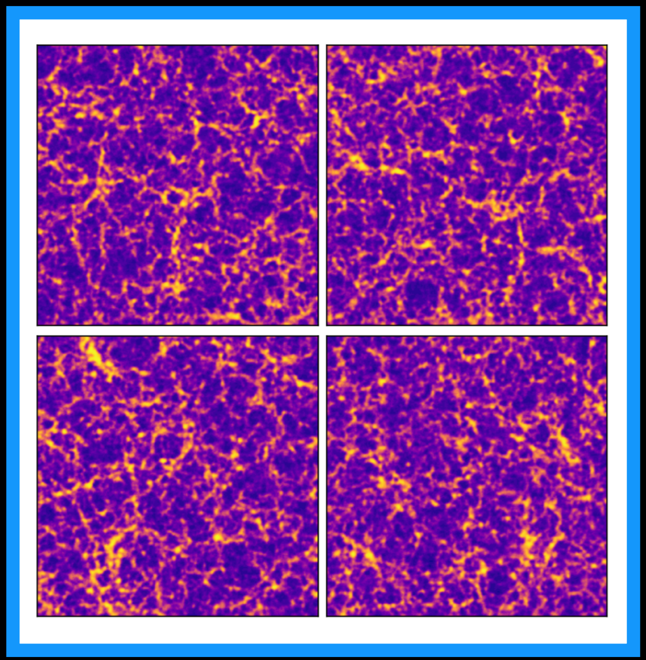
What's next?

- Generative Adversarial Networks (GAN) for generating N-body -like data (Rodrigues, TK, et al. 2018, 1801.09070)

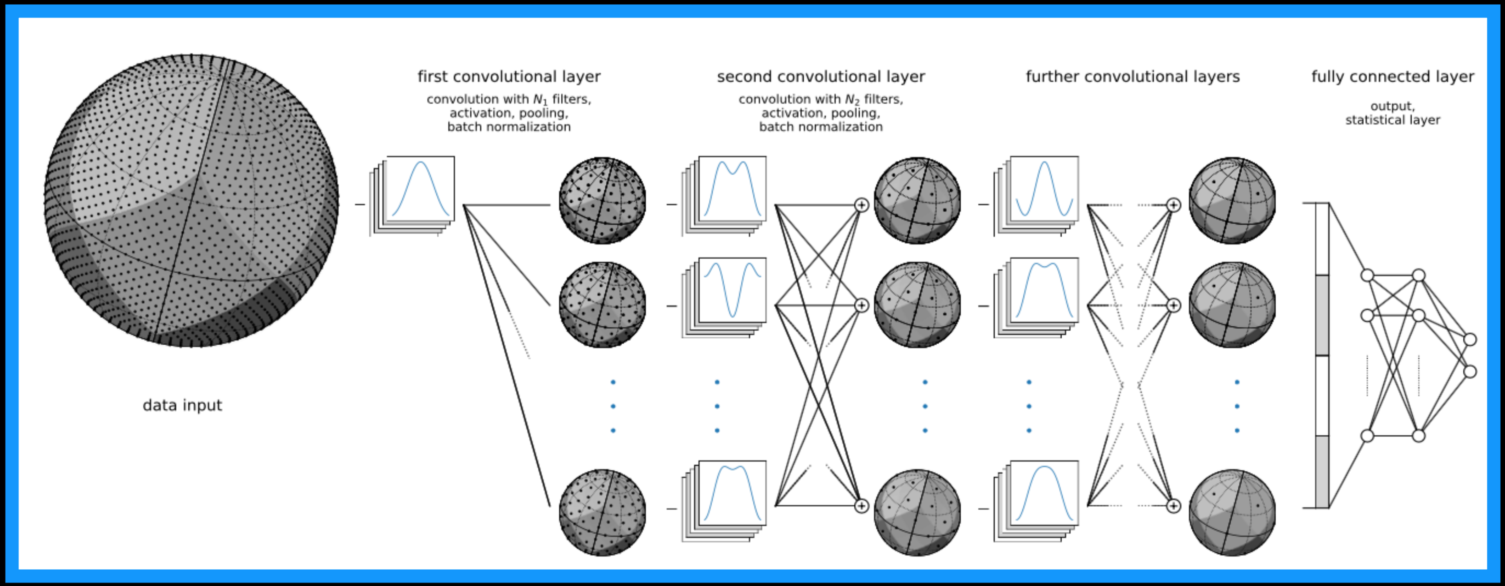
N-body



GAN

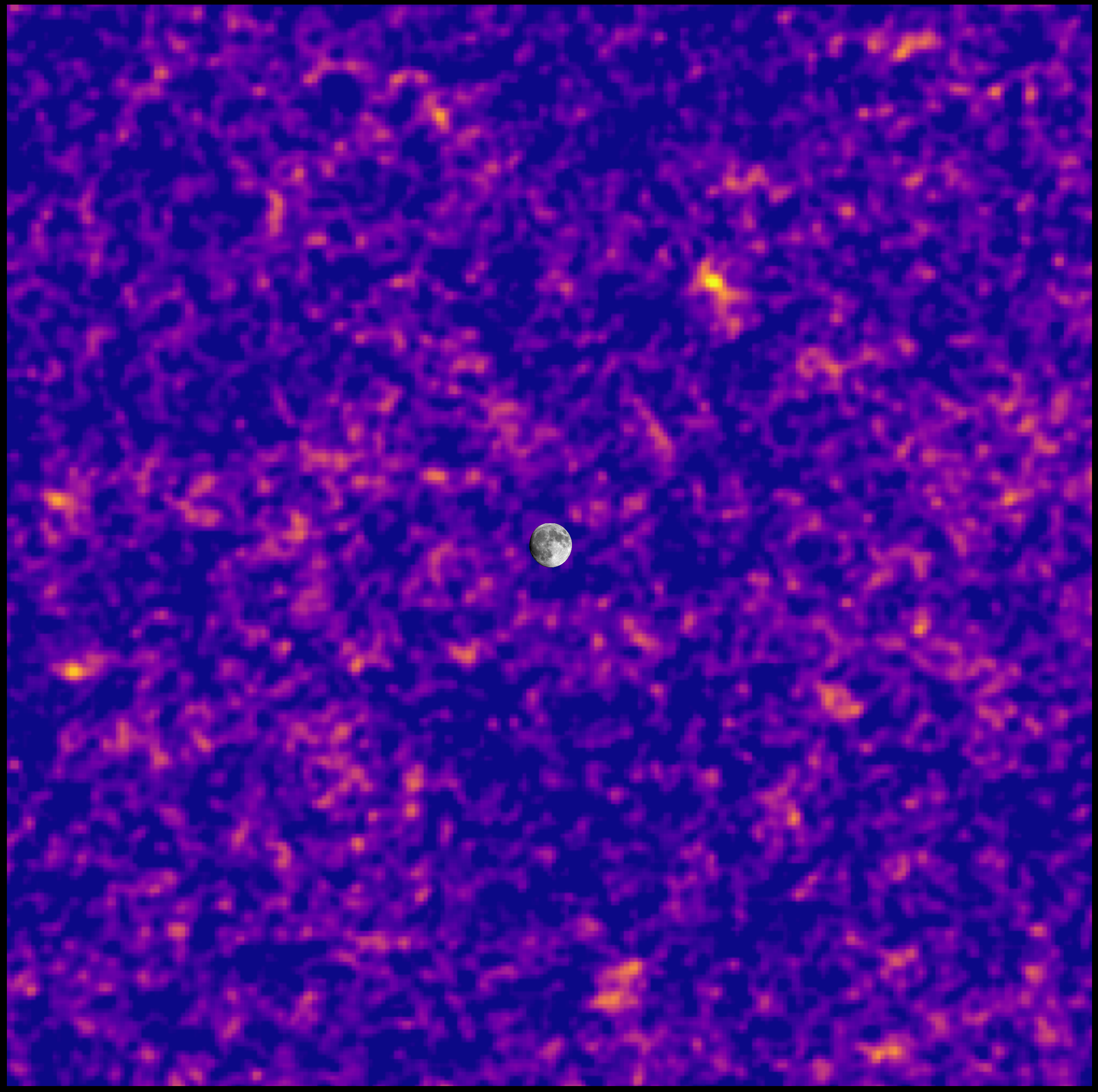


- CNNs on the sphere (Perraudin, TK, et al. 2018 1810.12186)

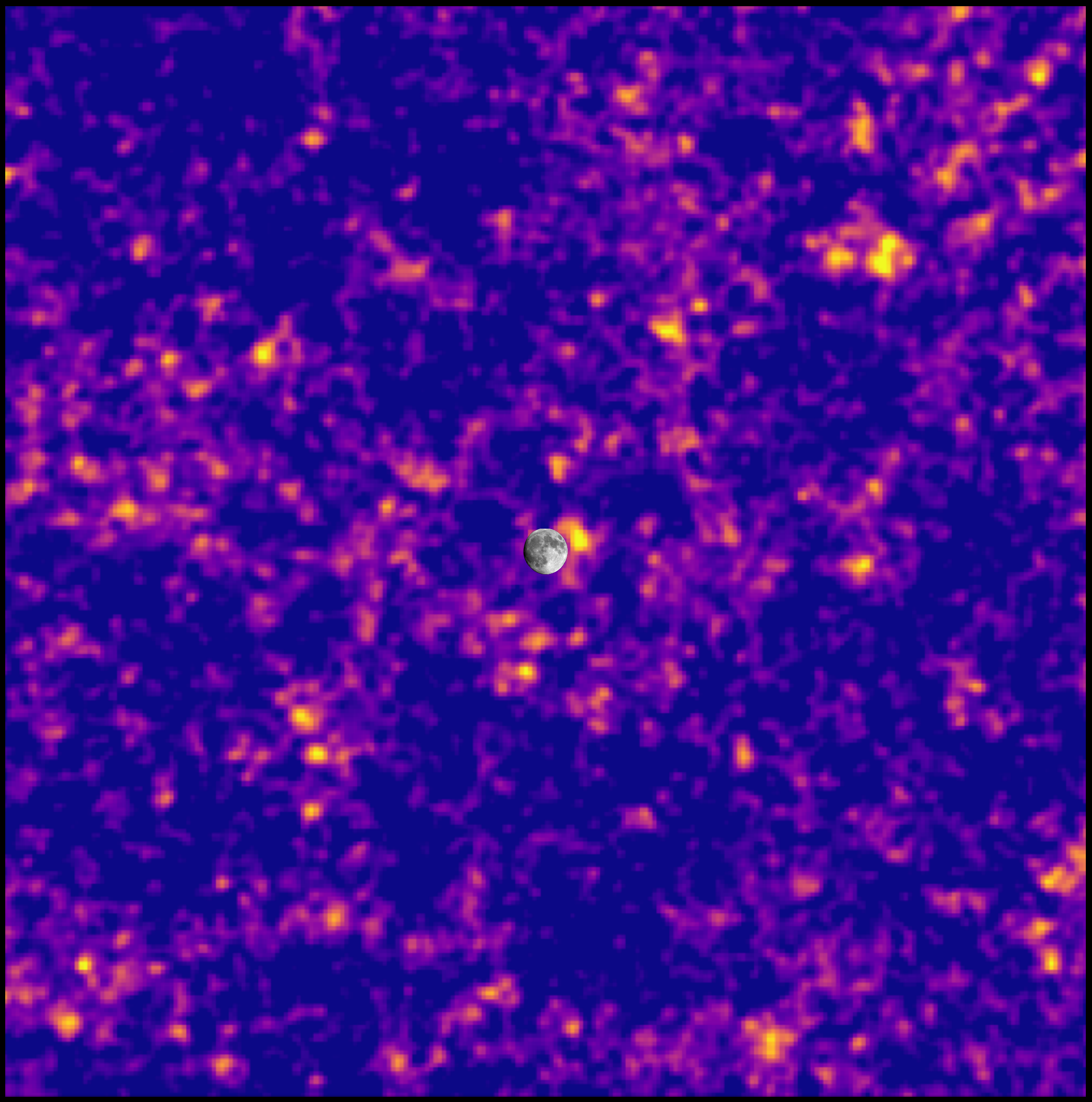


- Workshop: **Artificial Intelligence methods in Cosmology, 9-12 June 2019** sites.google.com/site/aicosmo2019

Large scale structure carries information about the cosmological model

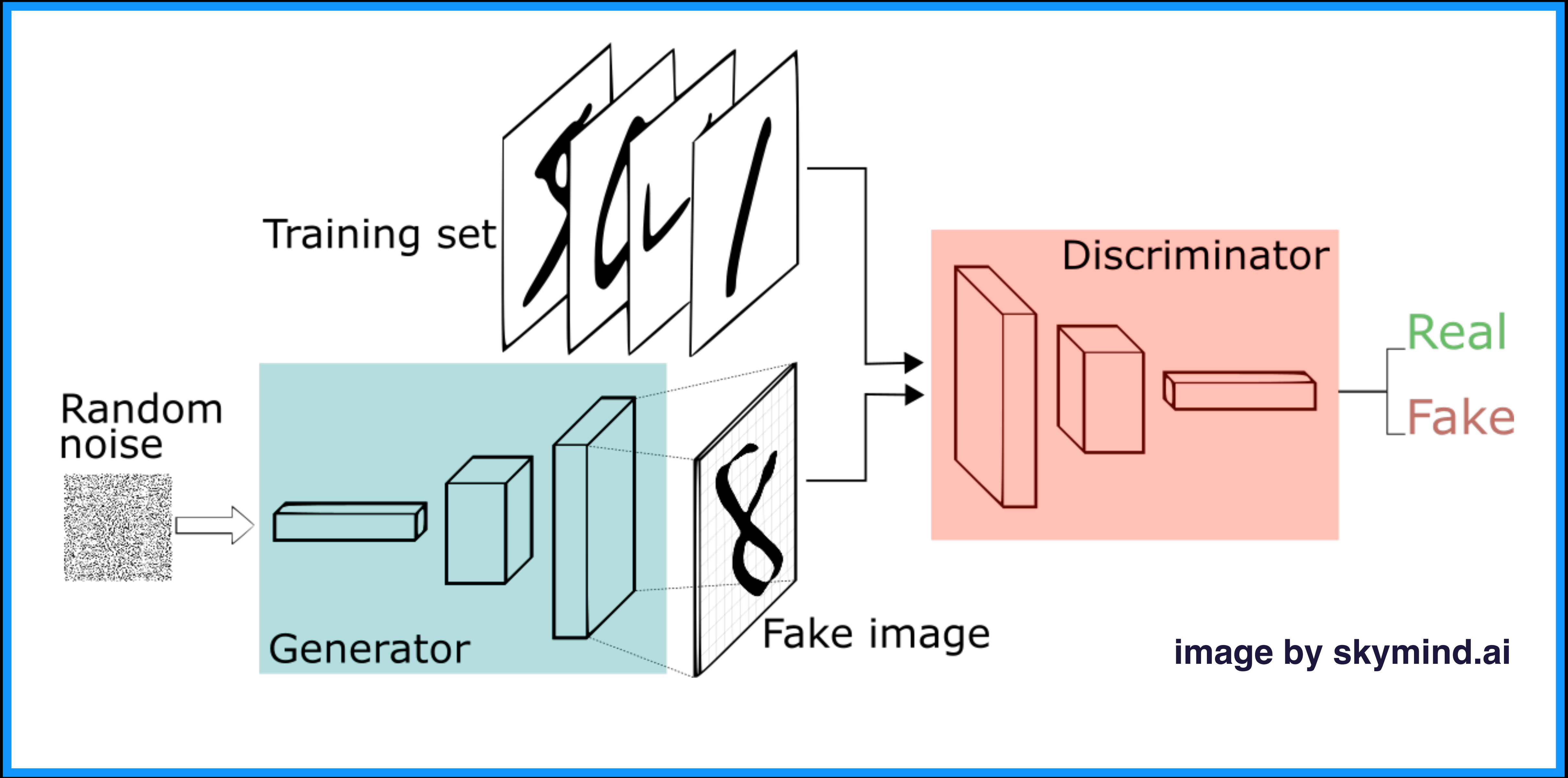


low σ_8 low Ω_m



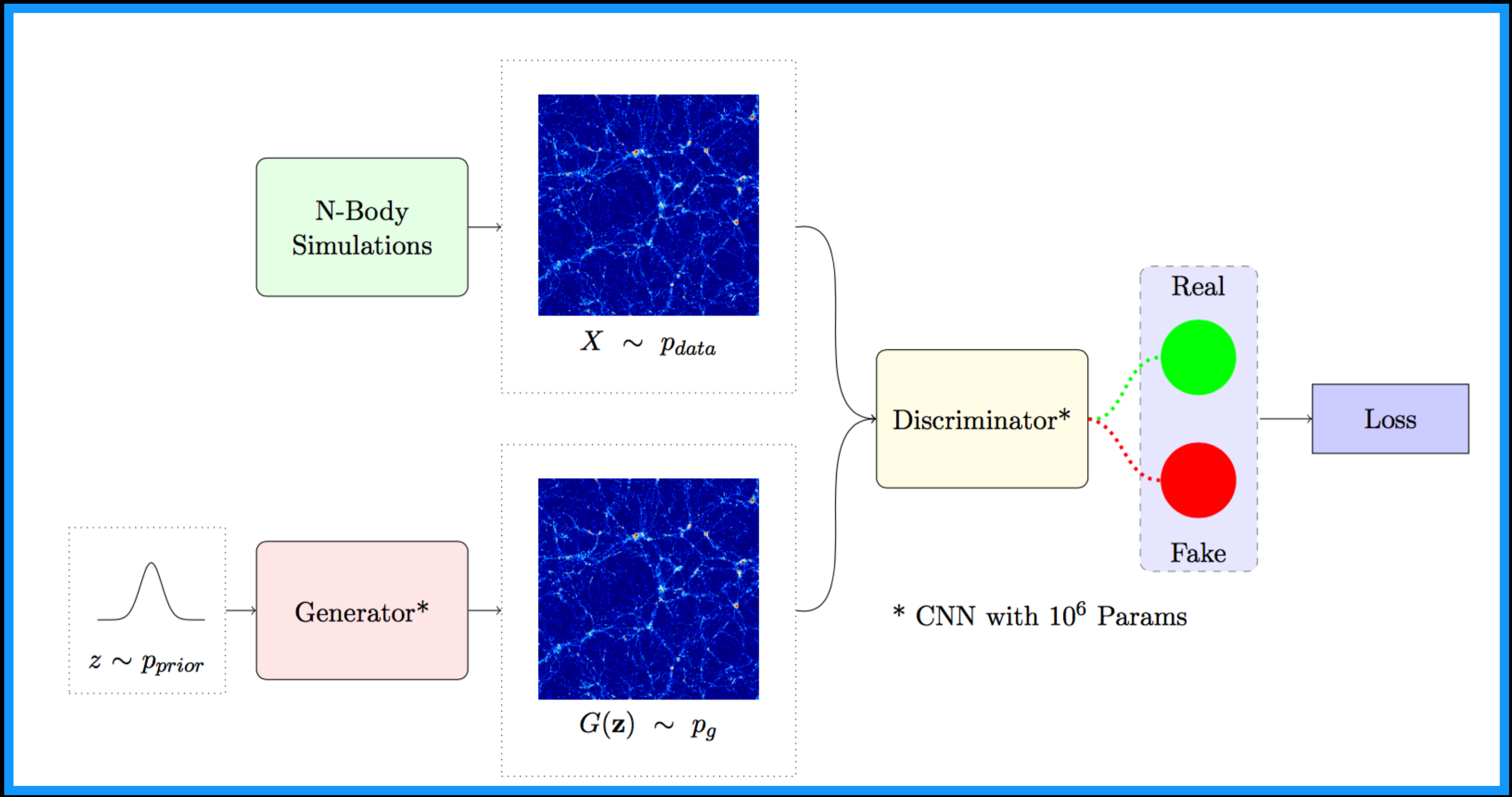
high σ_8 high Ω_m

Generative Adversarial Networks



GANs learn the distribution underlying the data and simulate new instances very fast

Fast simulations of the cosmic web using Generative Adversarial Networks

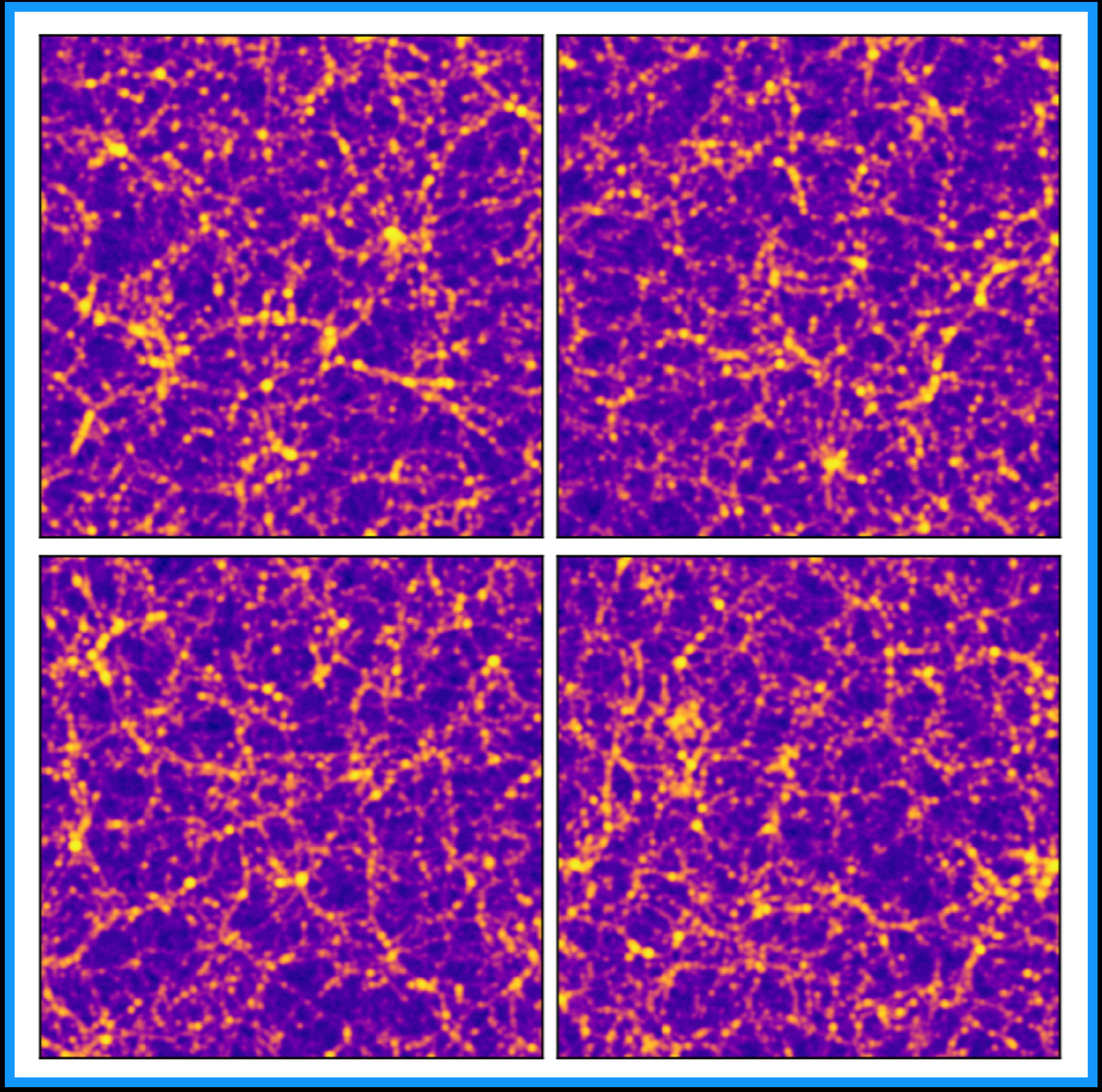


Train on existing simulations
Generate new cosmic web in a fraction of a second on a laptop

image by AL and Andres Rodrigues

N-body cutouts

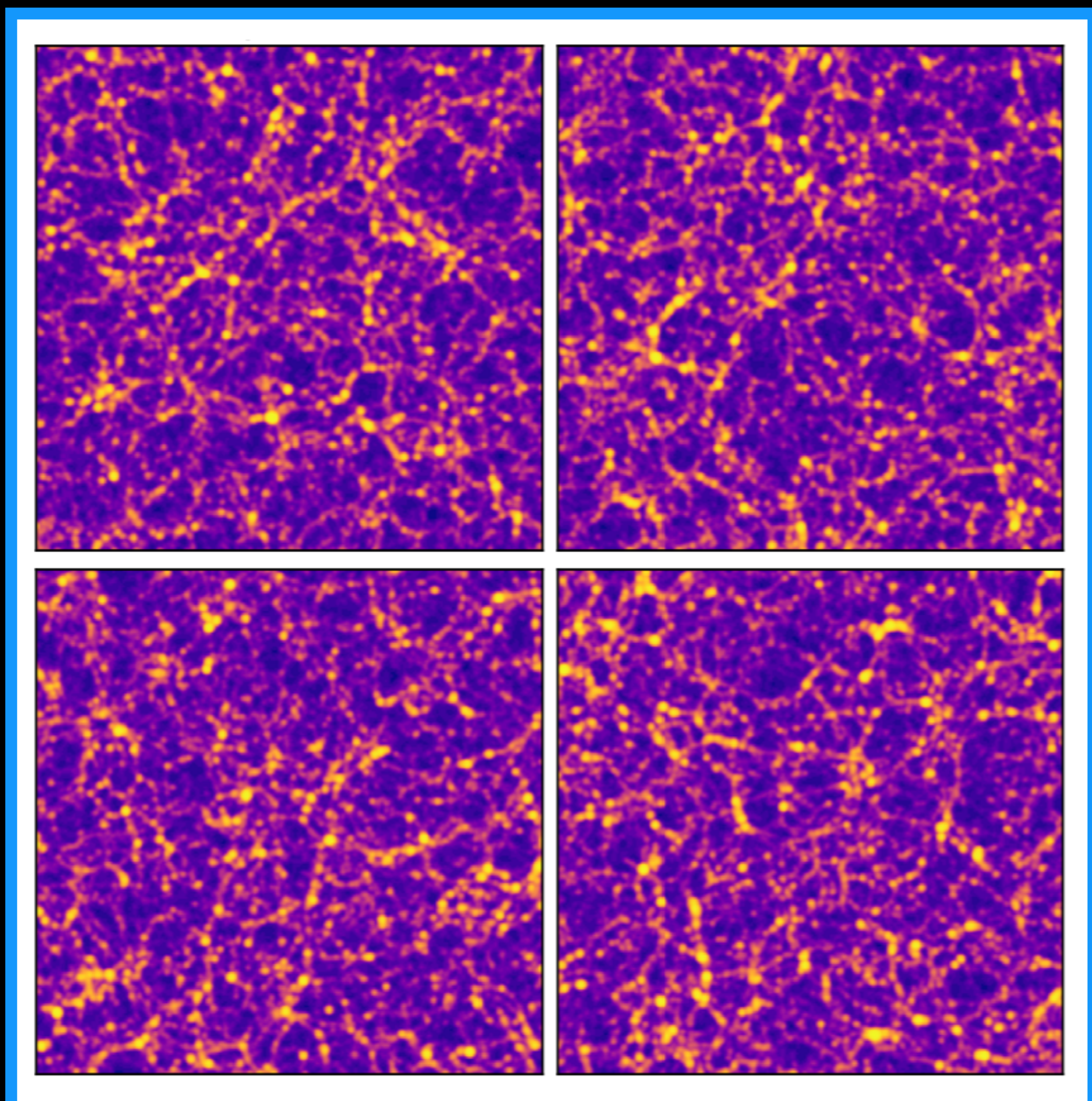
size: 500 Mpc, applied transformation similar to logarithm



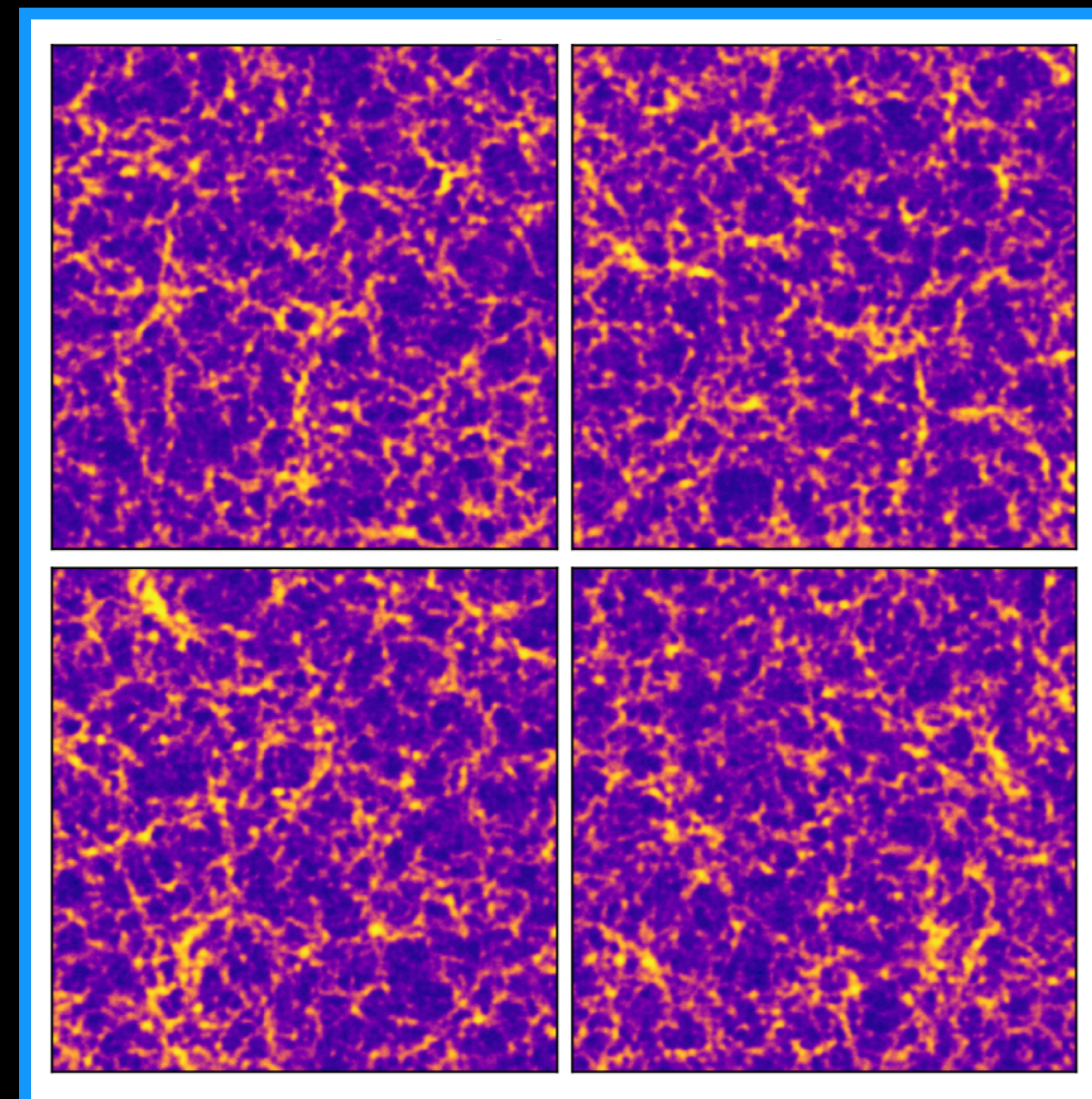
Rodrigues, TK, et al. 1801.09070

N-body vs GAN

N-body



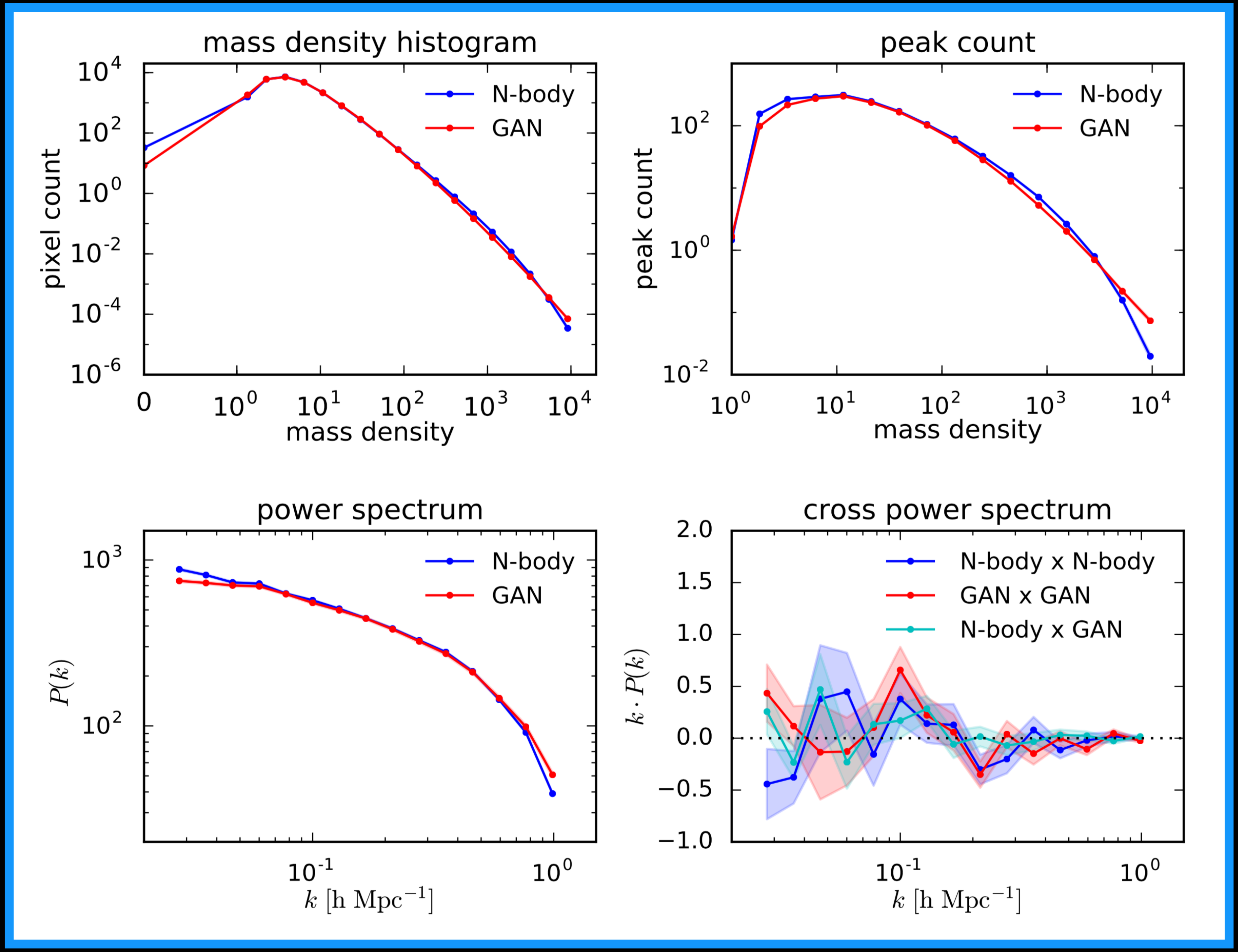
GAN



Rodrigues, TK, et al. 1801.09070

N-body vs GAN: statistics comparison

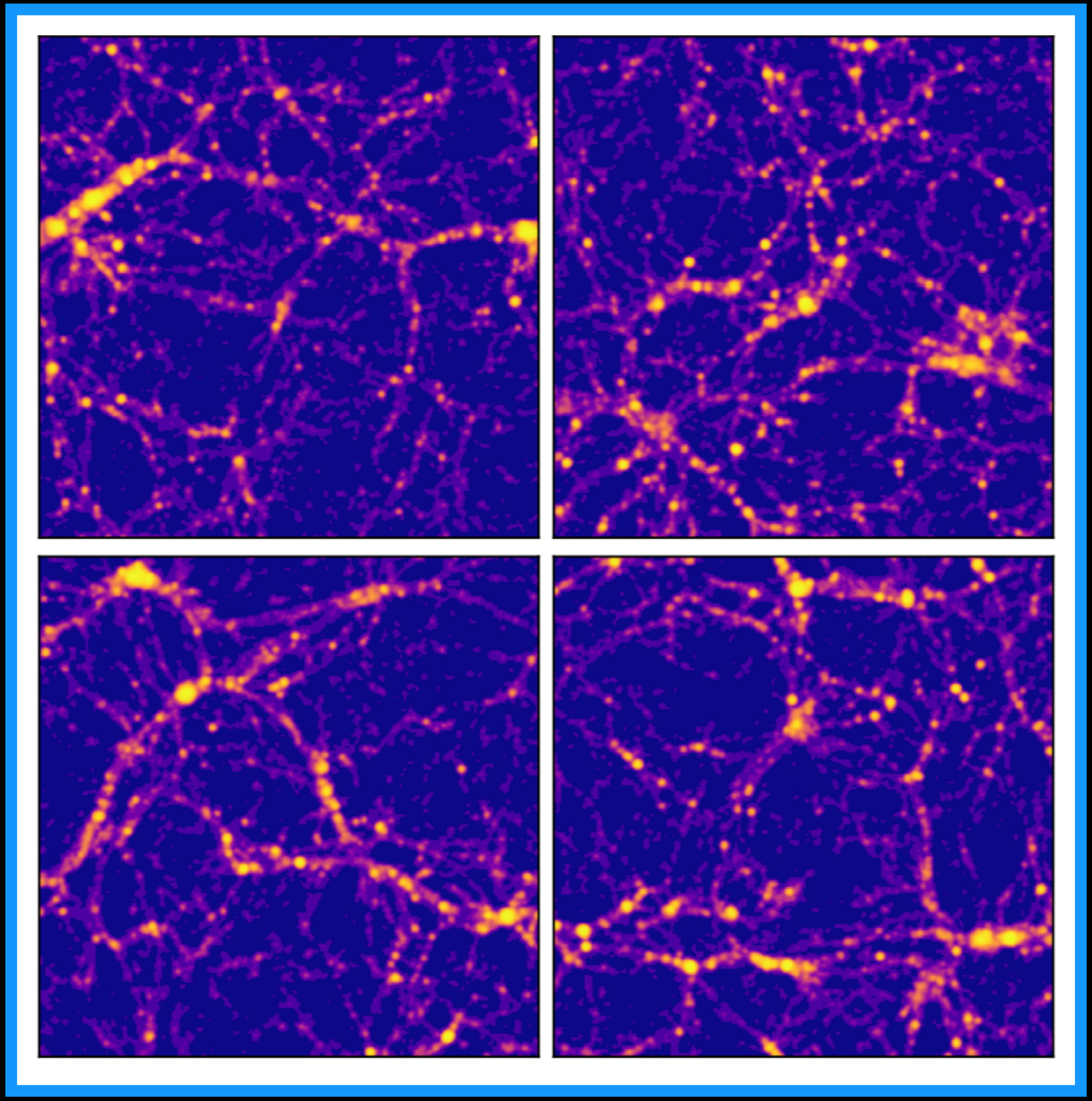
500 Mpc slices



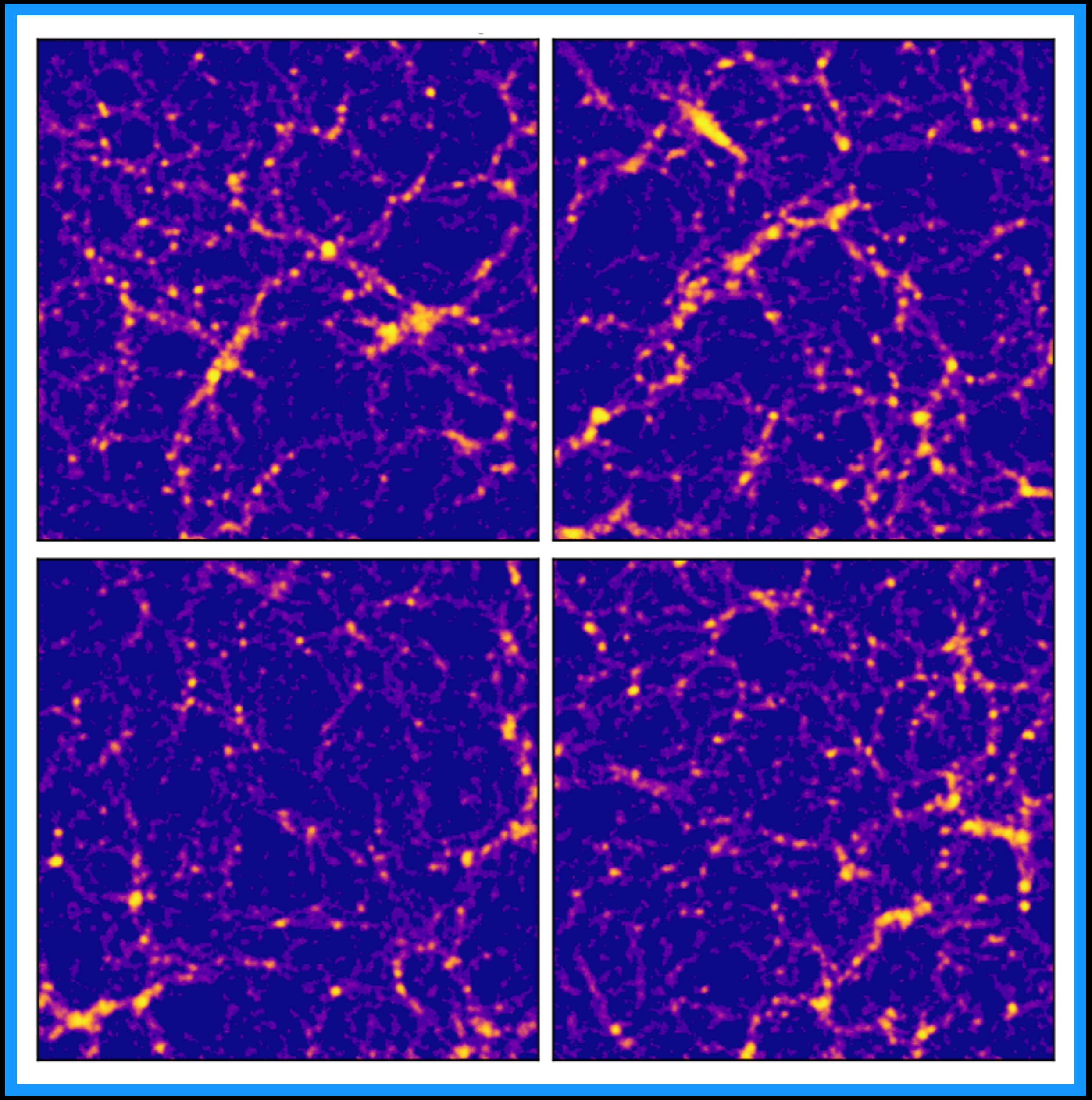
Rodrigues, TK, et al. 1801.09070

100 Mpc cutouts

N-body



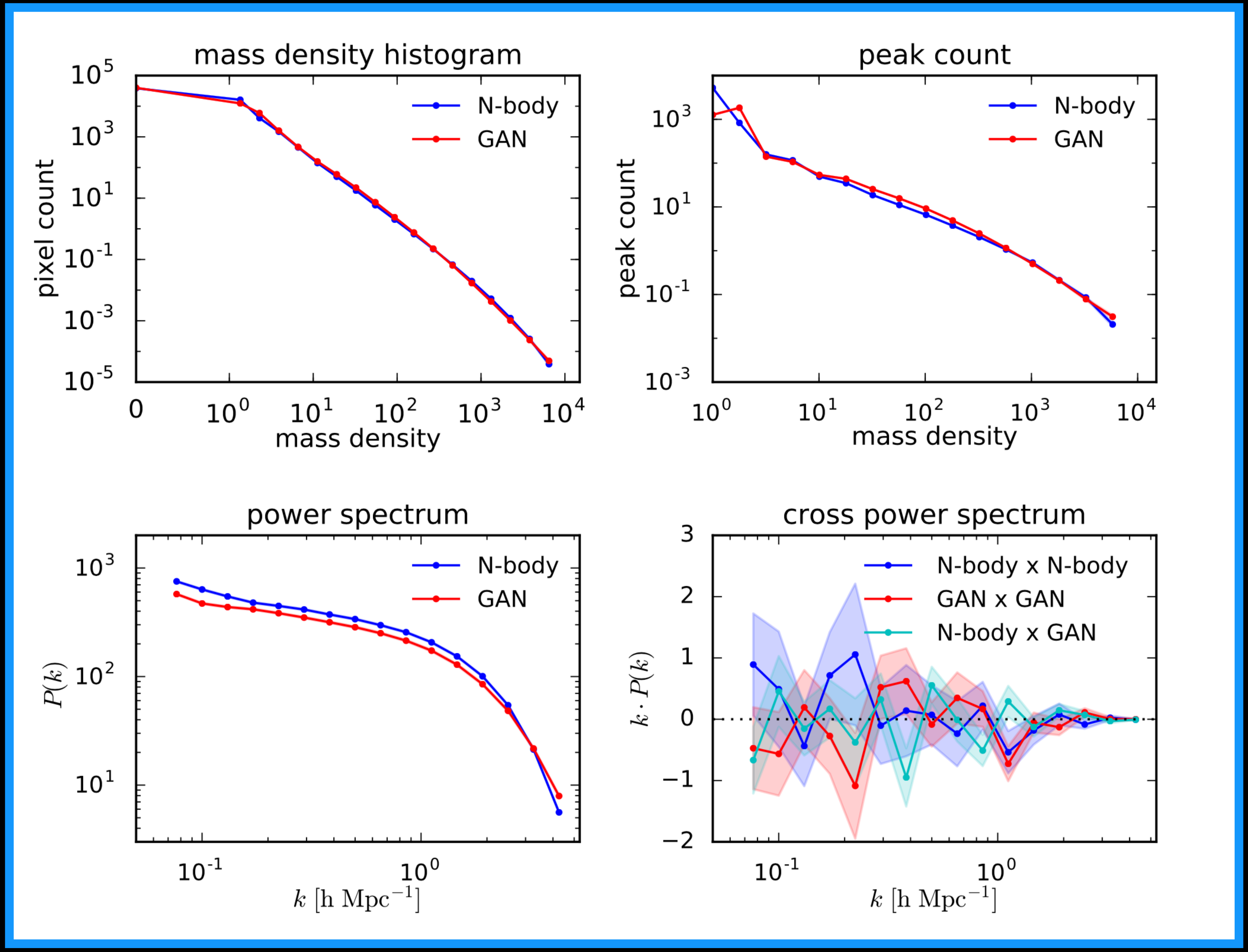
GAN



Rodrigues, TK, et al. 1801.09070

N-body vs GAN: statistics comparison

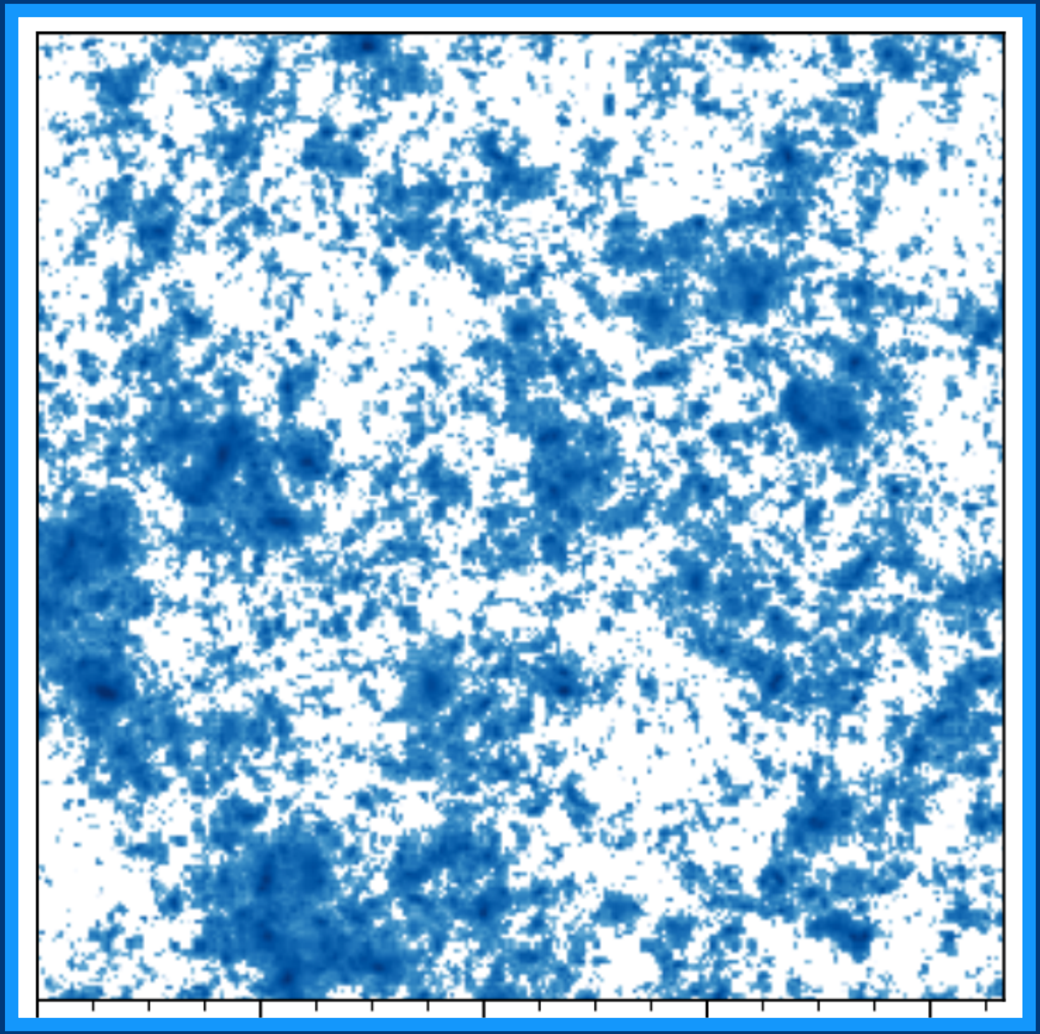
100 Mpc slices

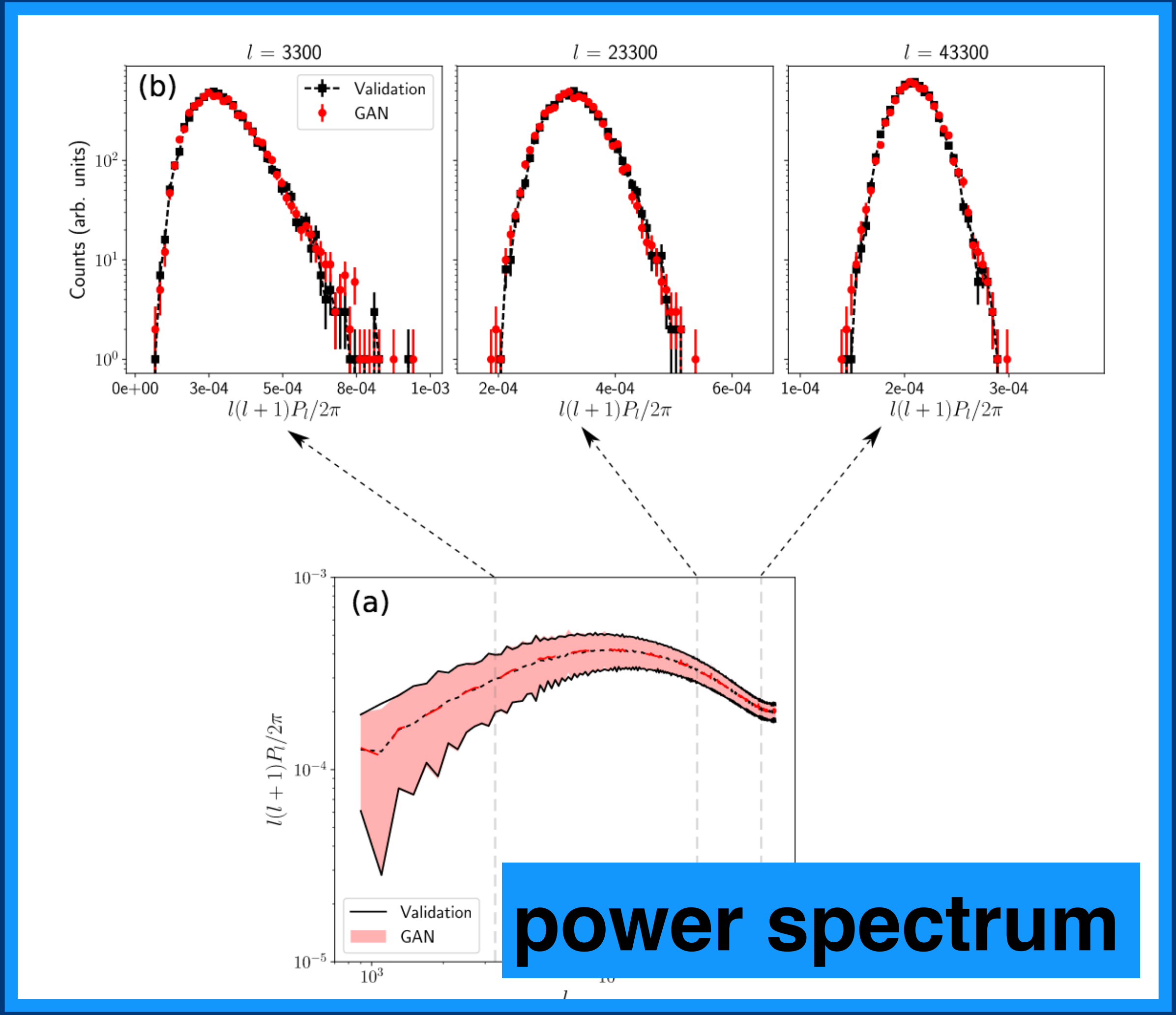


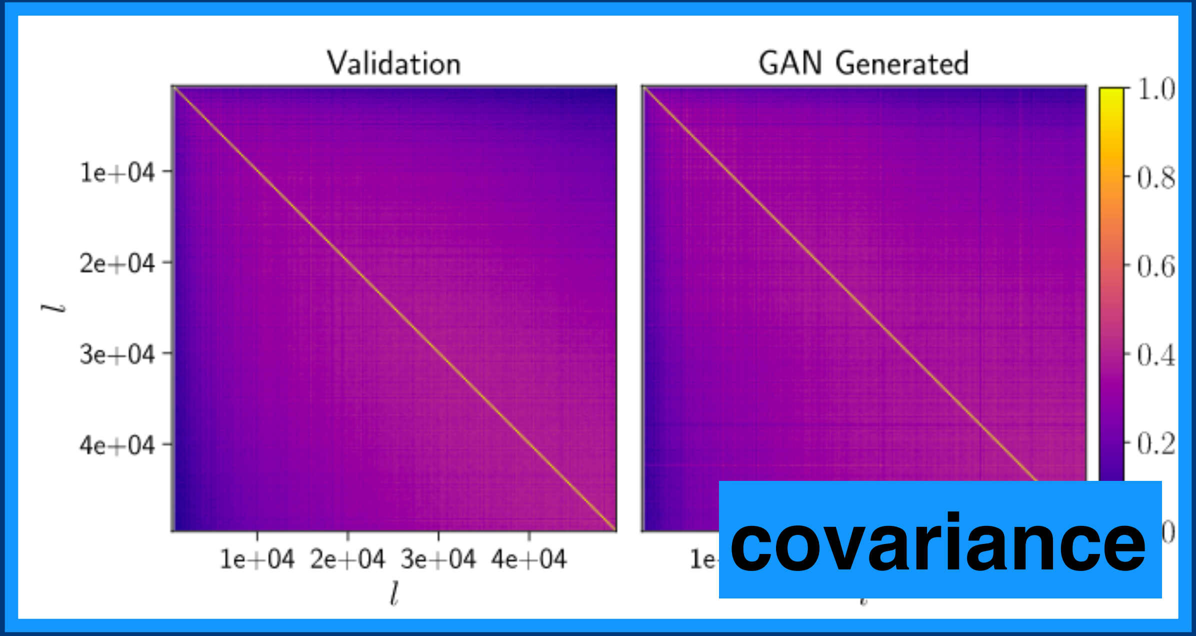
Rodrigues, TK, et al. 1801.09070

Convergence maps generation

Mustafa et al. 2017 1706.02390

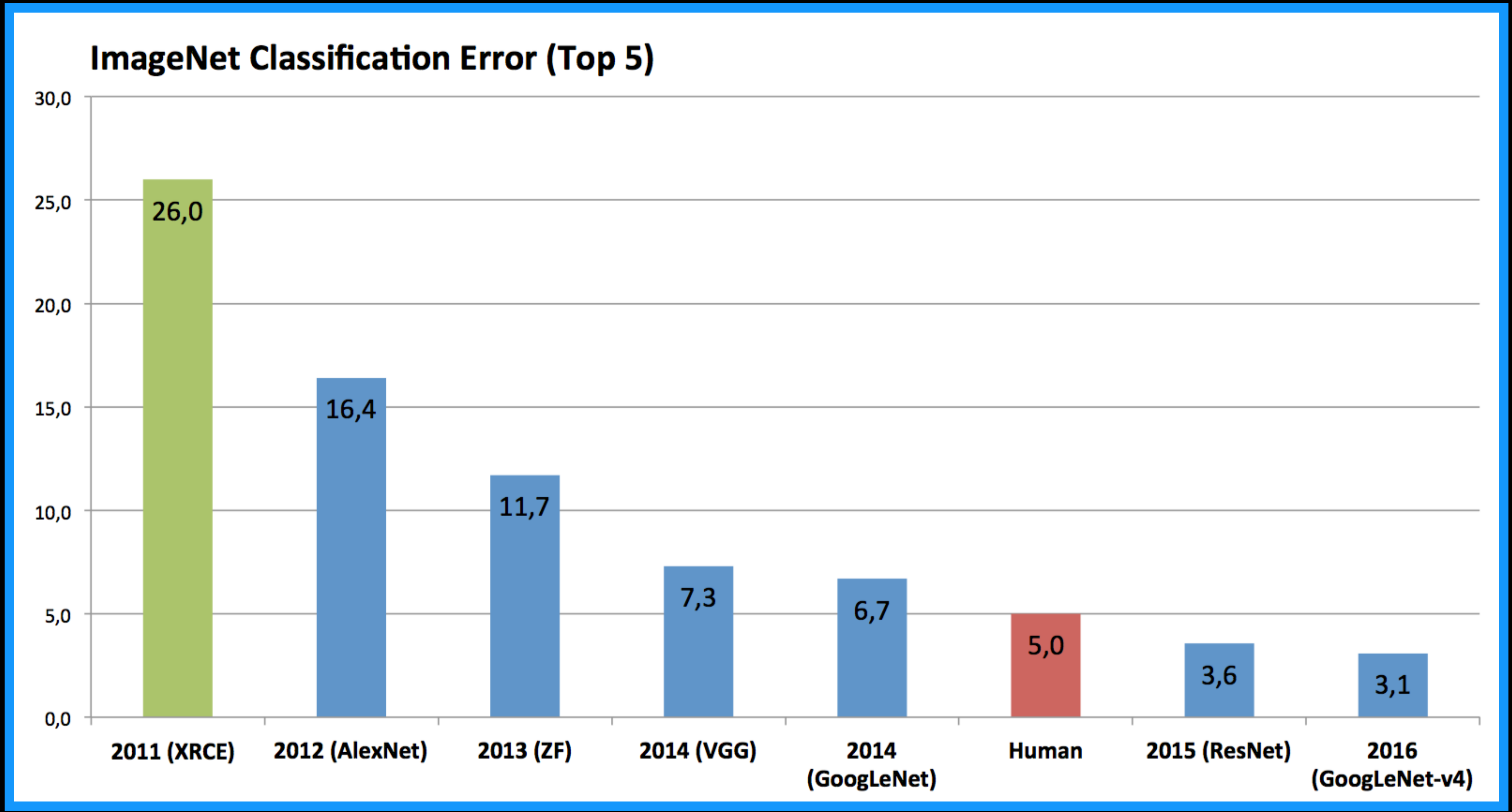






- Generating convergence maps directly is easier
- Very good agreement in statistics

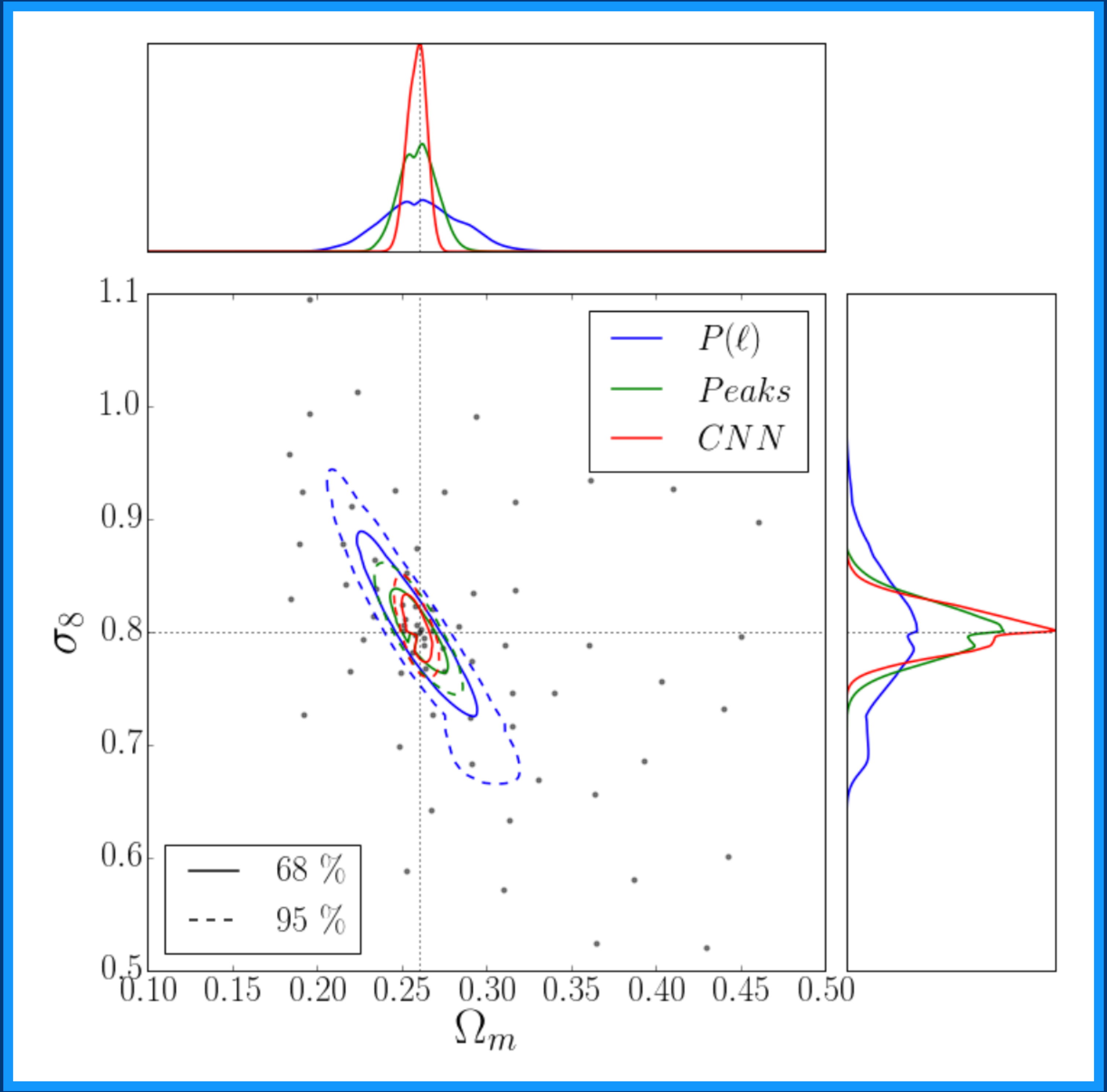
Deep Learning on ImageNet



ImageNet, Russakovsky 2014, 1409.0575
Von Zitzewitz 2017

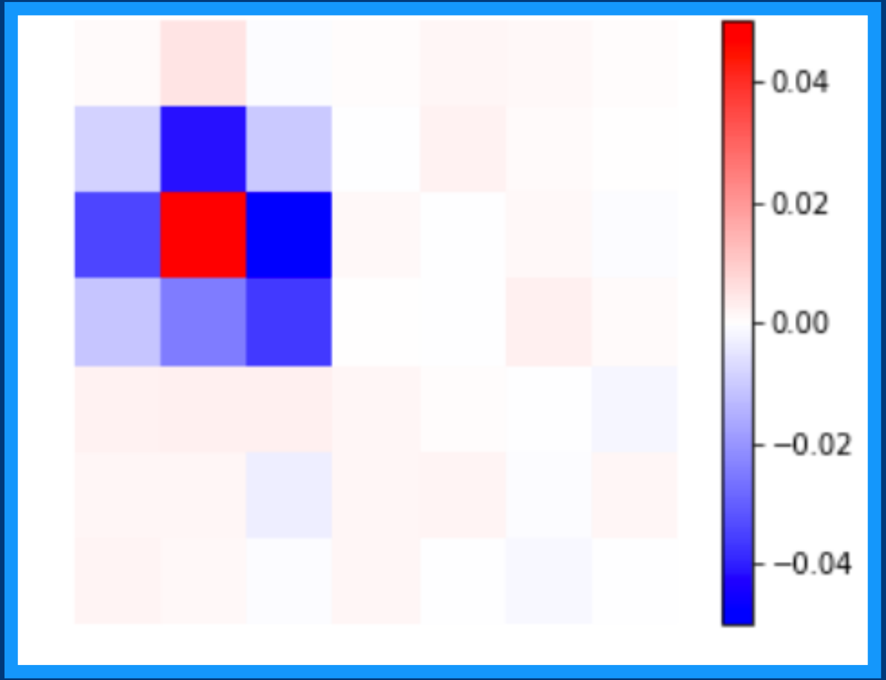
So it works, what now?

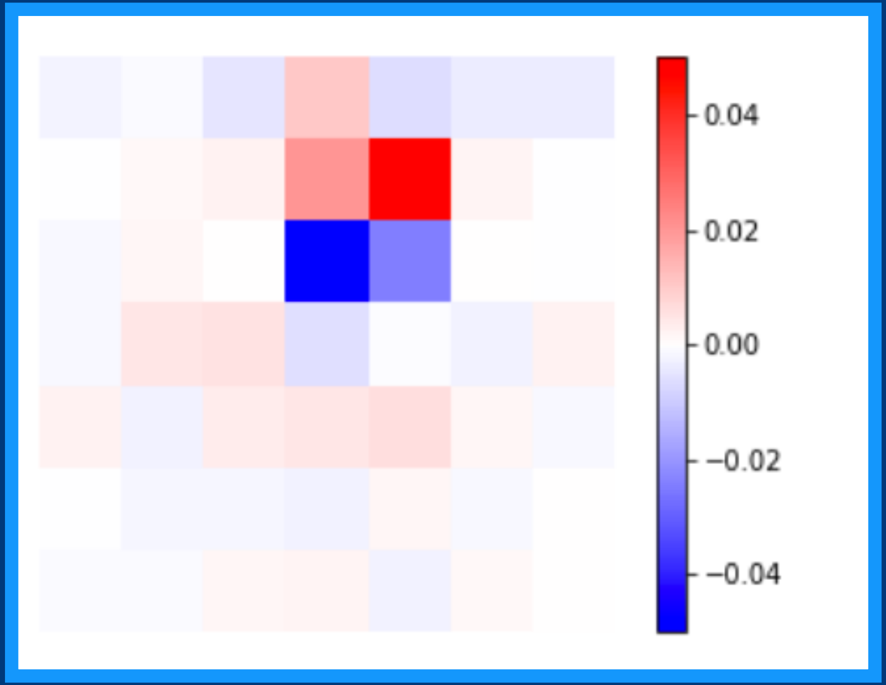
probabilistic inference scheme



Gupta et al. 1802.01212

Opening the “Black Box”





peek height

peek steepness

“Learning from deep learning”
investigating filters learned by the network

Ribli et al. 2018 1806.05995

Applications to natural images

Figure 5: 1024 × 1024 images generated using the CELEBA-HQ dataset. See Appendix F for a larger set of results, and the accompanying video for latent space interpolations.

"Progressive Growing of GANs for Improved Quality, Stability, and Variation"
Kerras at al. 2017 1710.10196