AI analyses dark matter maps:

improving the precision of cosmological measurements with CNNs

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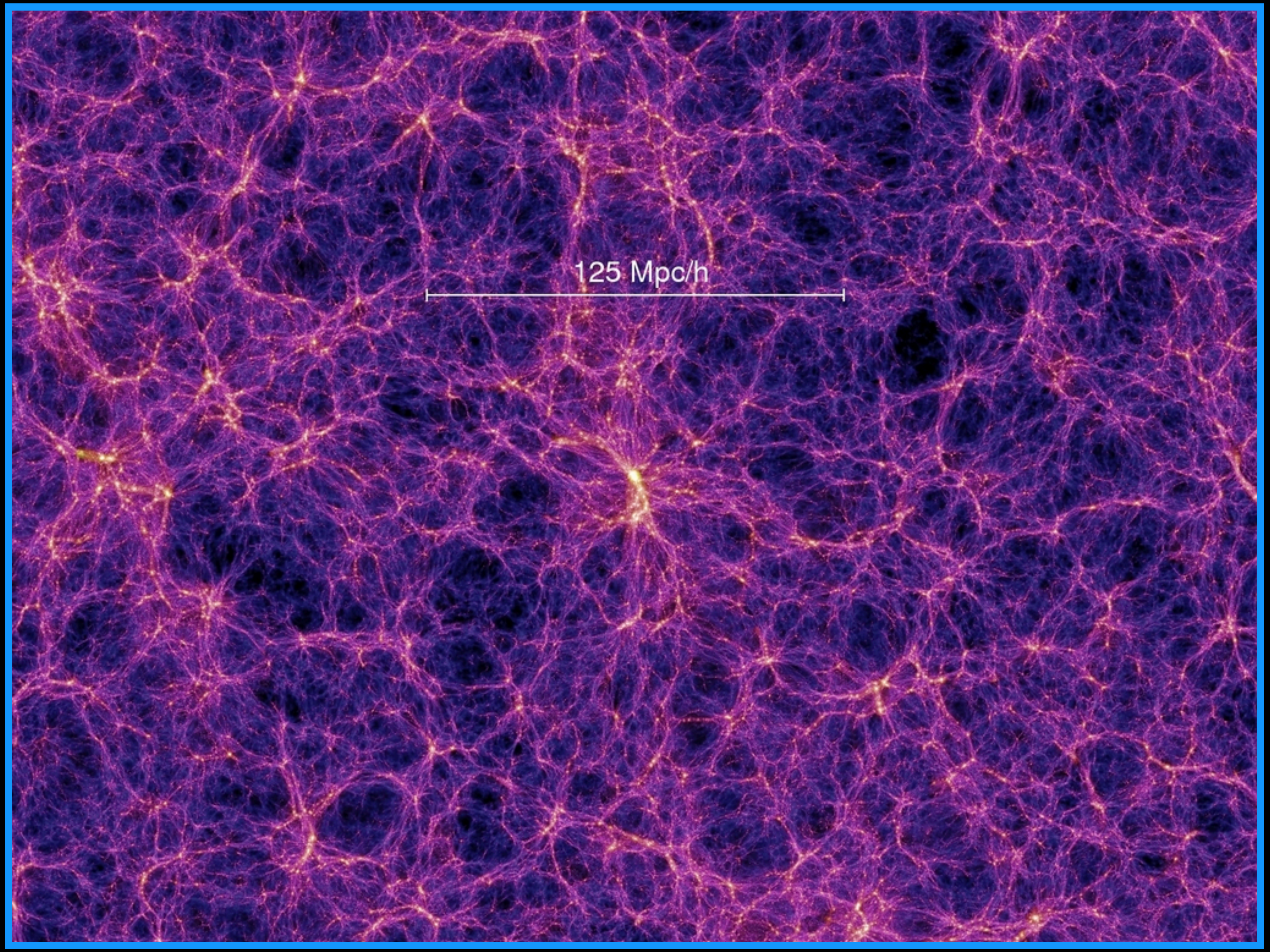
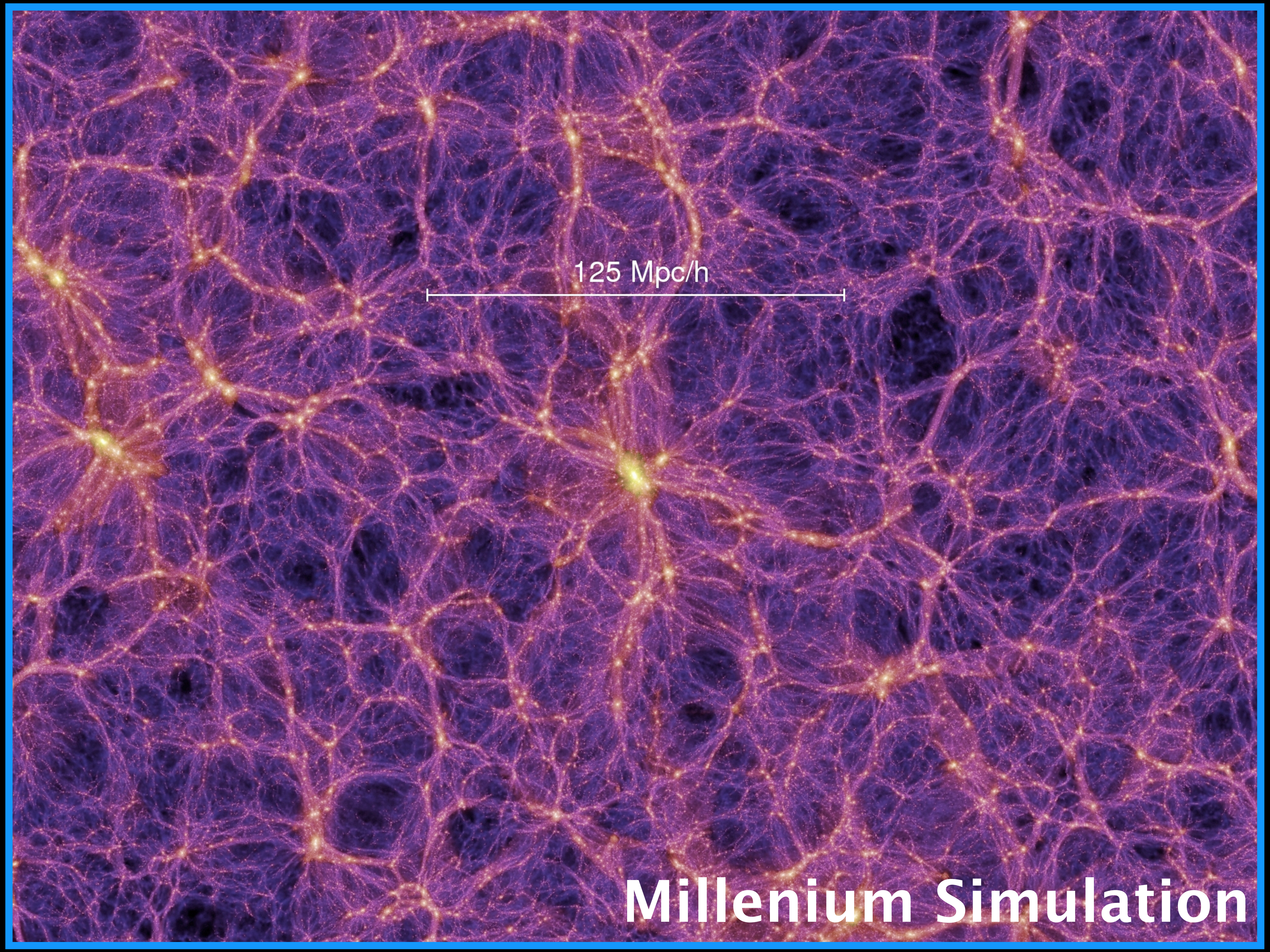
Distribution of dark matter in the universe



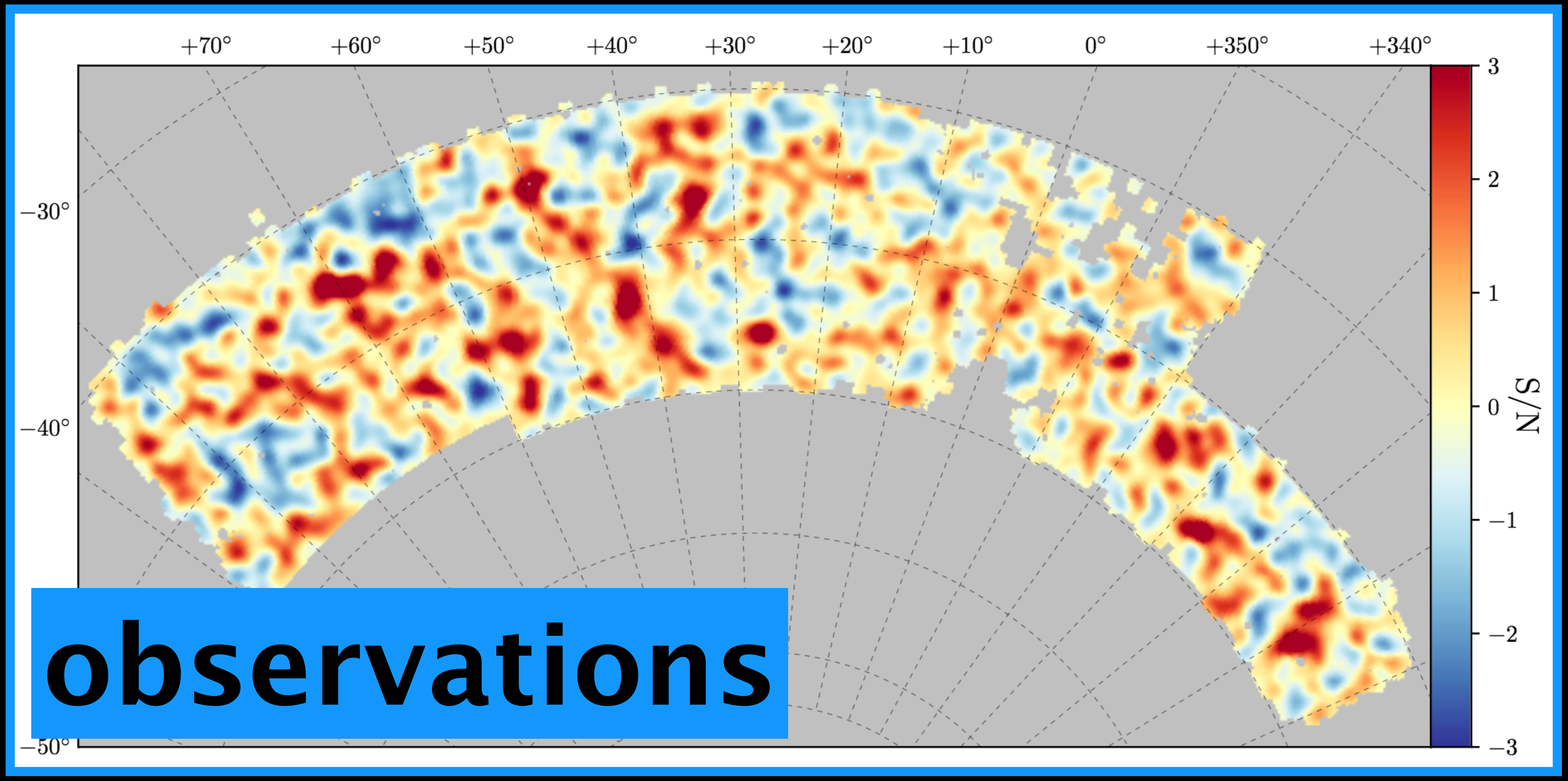
4.7 billion years after the big bang



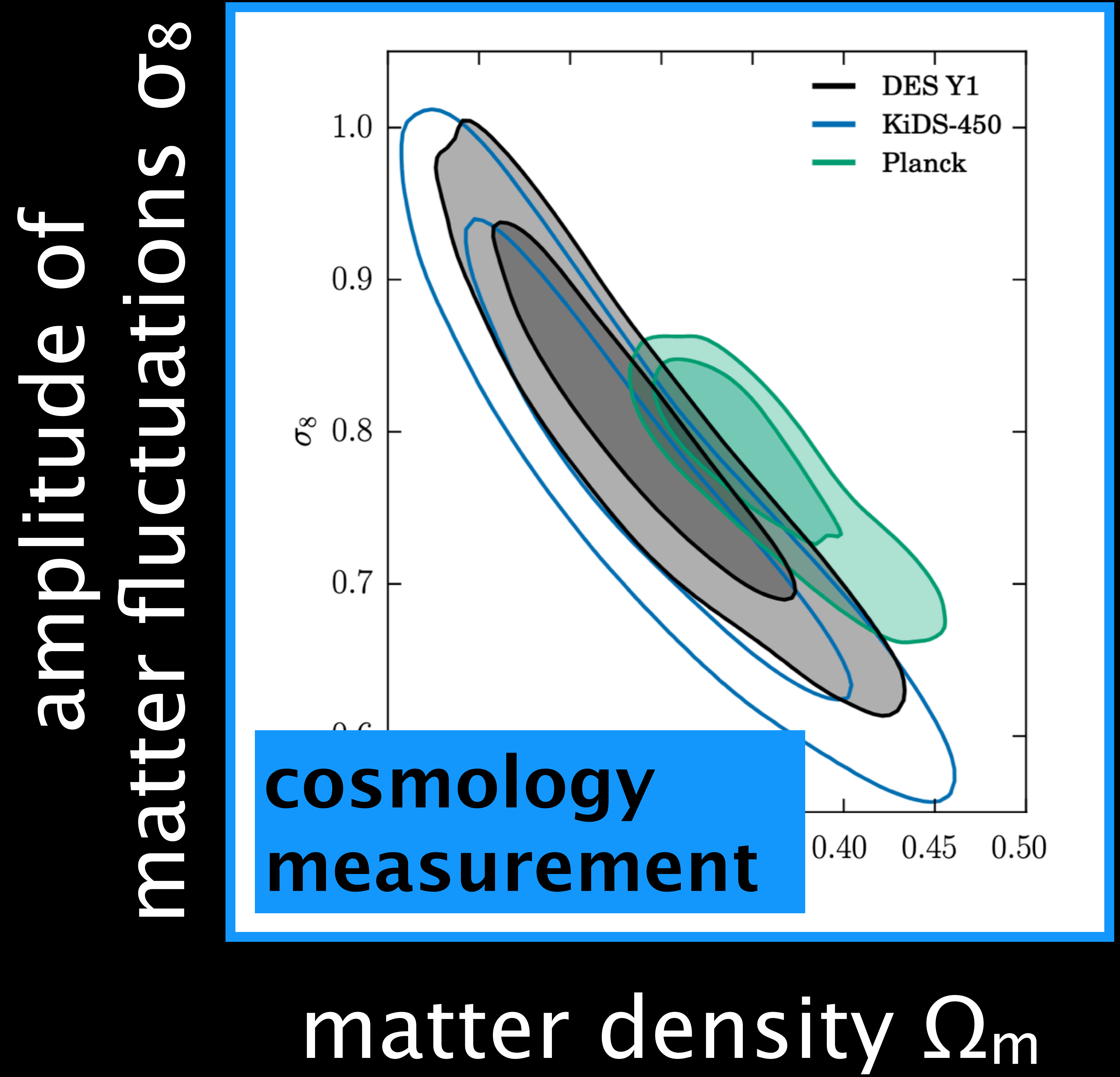
today, 13.6 billion years

Dark matter distribution can teach us about the laws of physics: gravity, dark energy, dark matter

Cosmological parameter inference

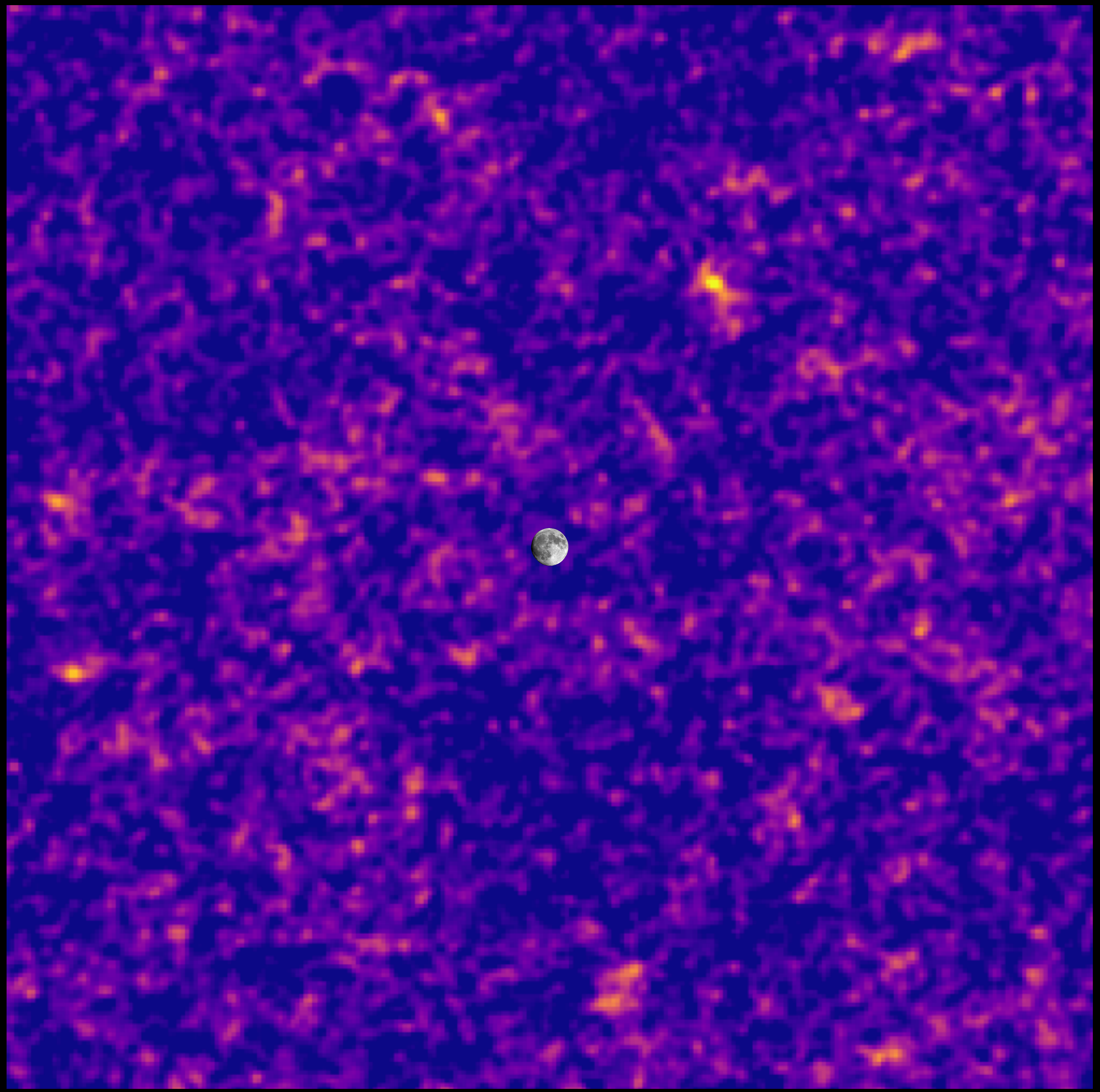


DES Collaboration (+TK) 2017 1708.01535

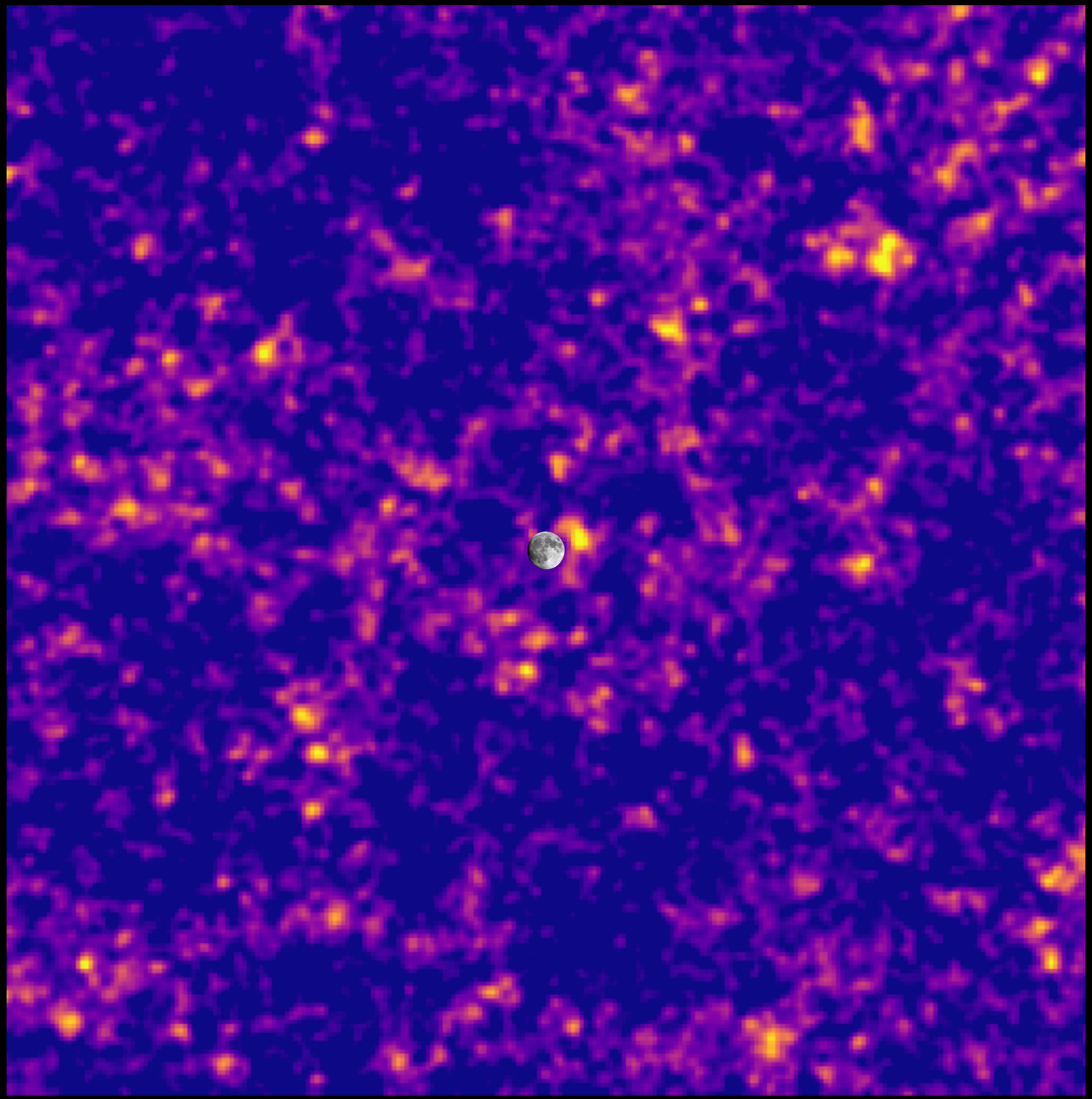


DES Collaboration (+TK) 2017 1708.01530

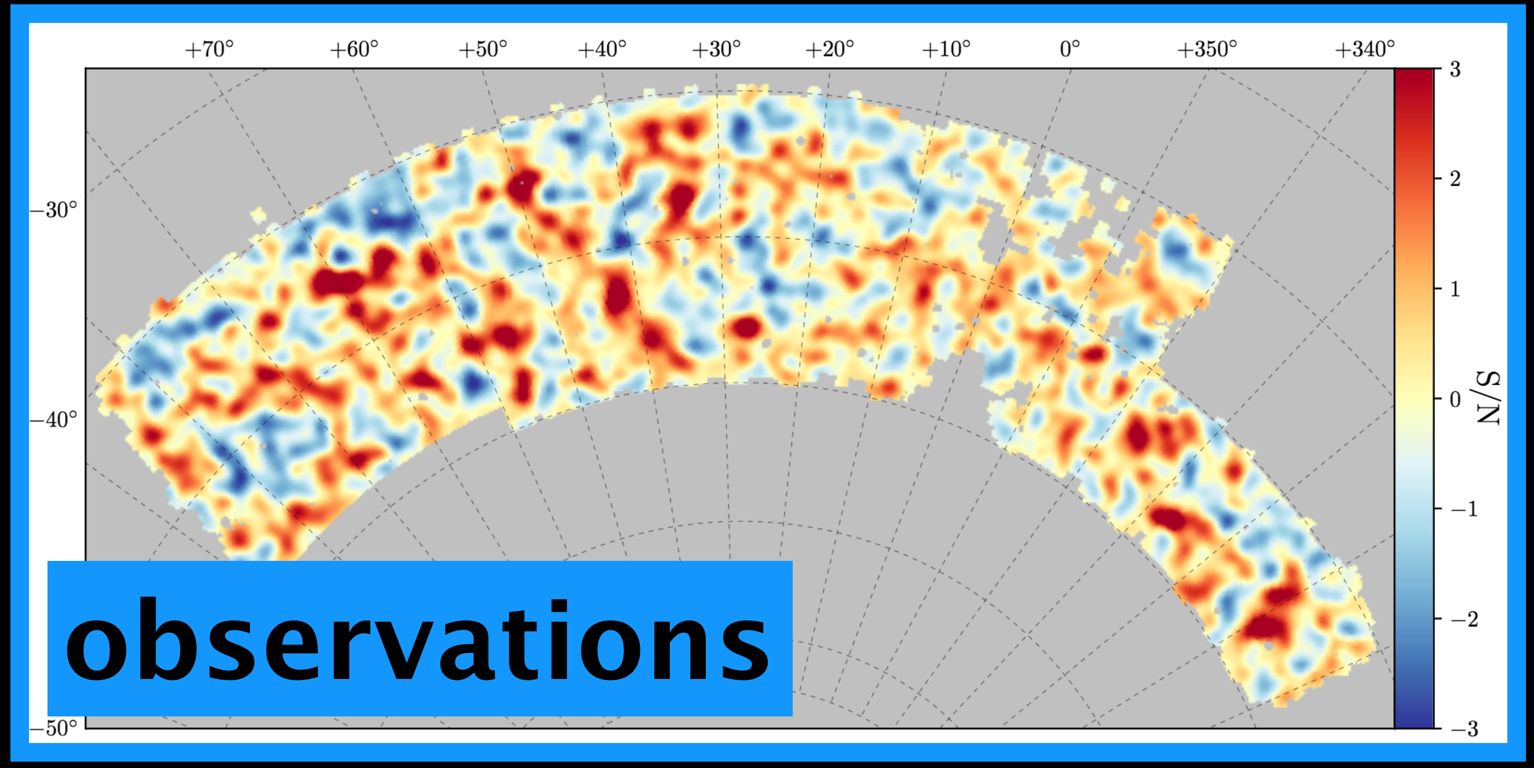
Dark matter distribution carries non-Gaussian information about the cosmological model



low σ_8 low Ω_m



high σ_8 high Ω_m



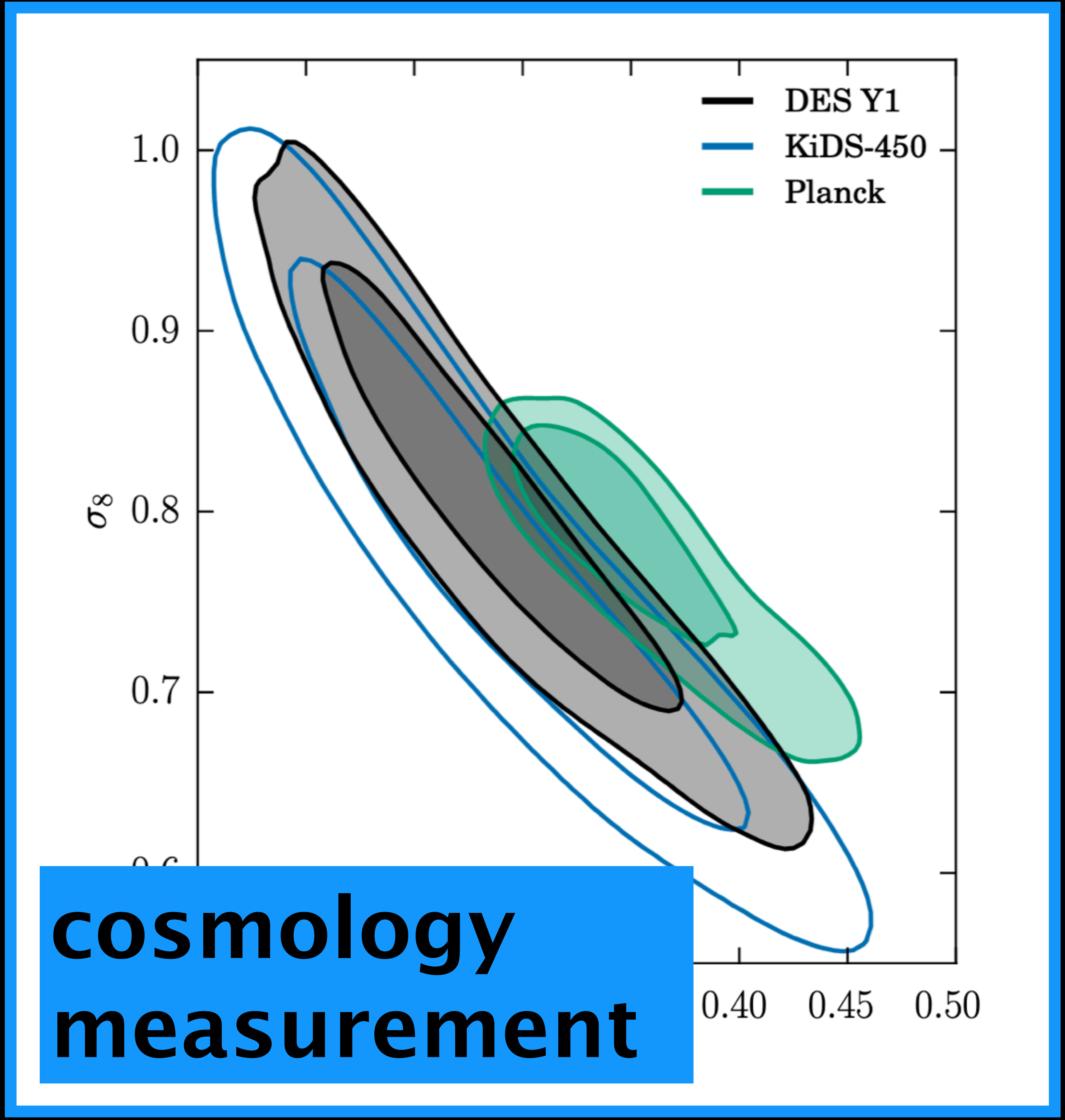
observations

comparison method?

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

theory prediction

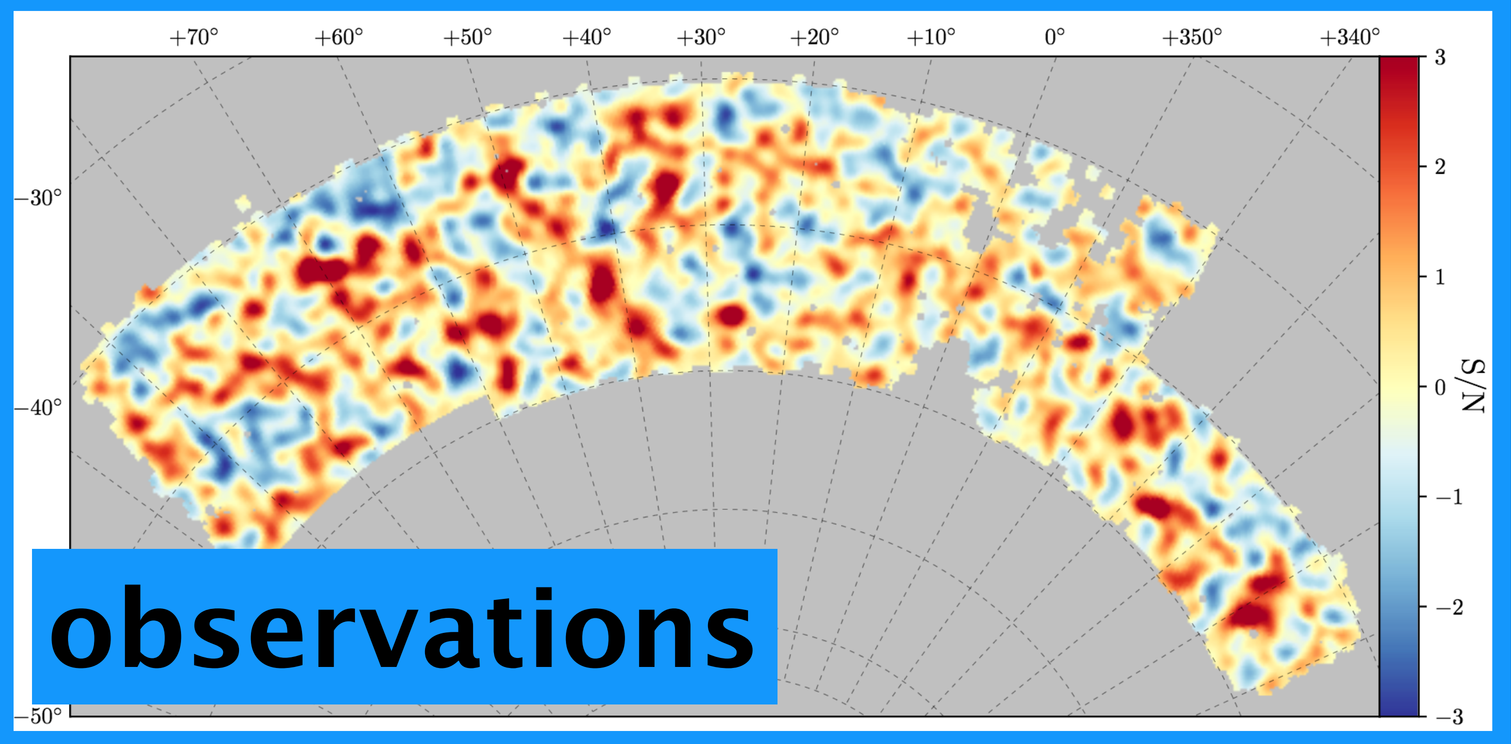
σ8

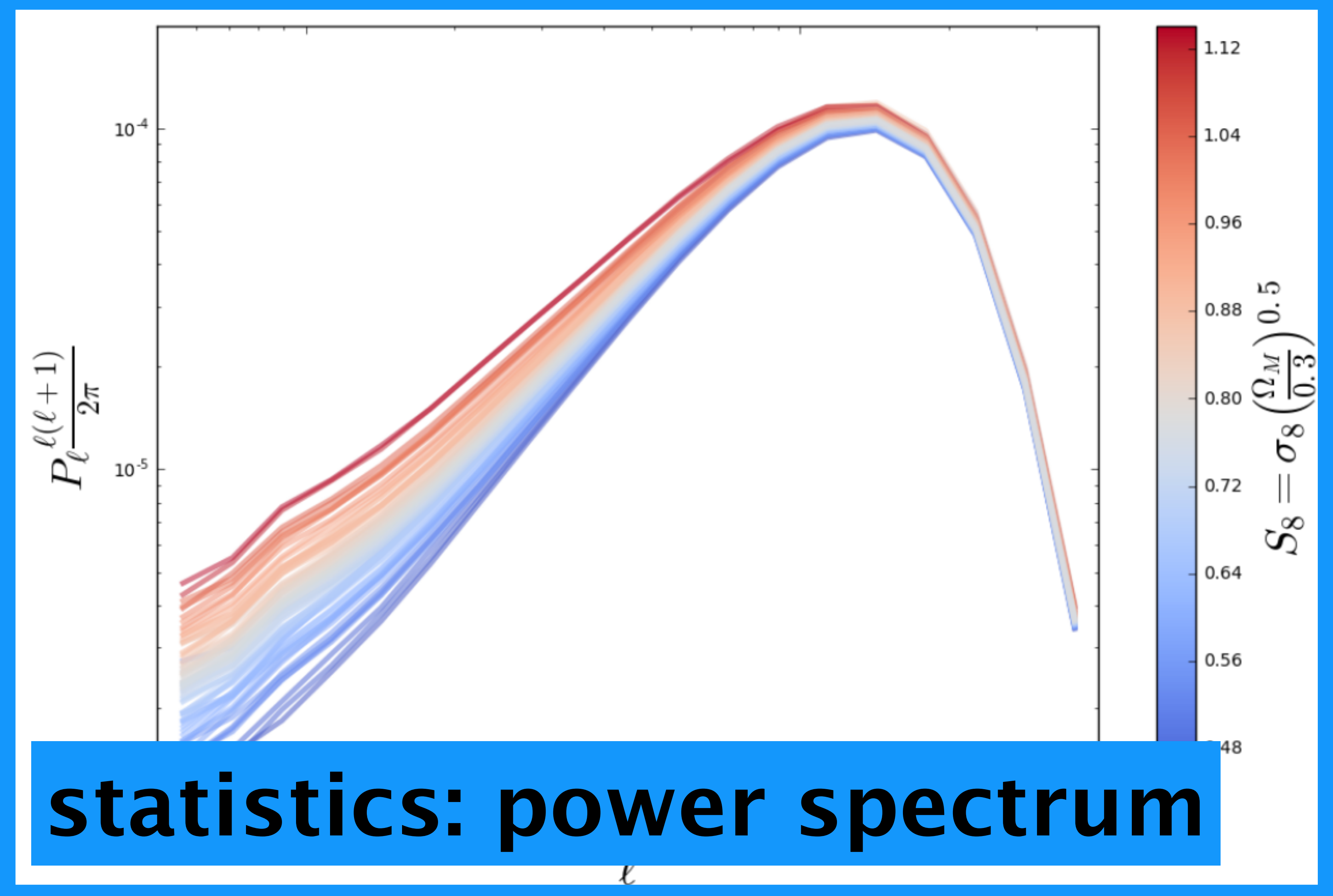


cosmology measurement

Ωm

Traditional inference

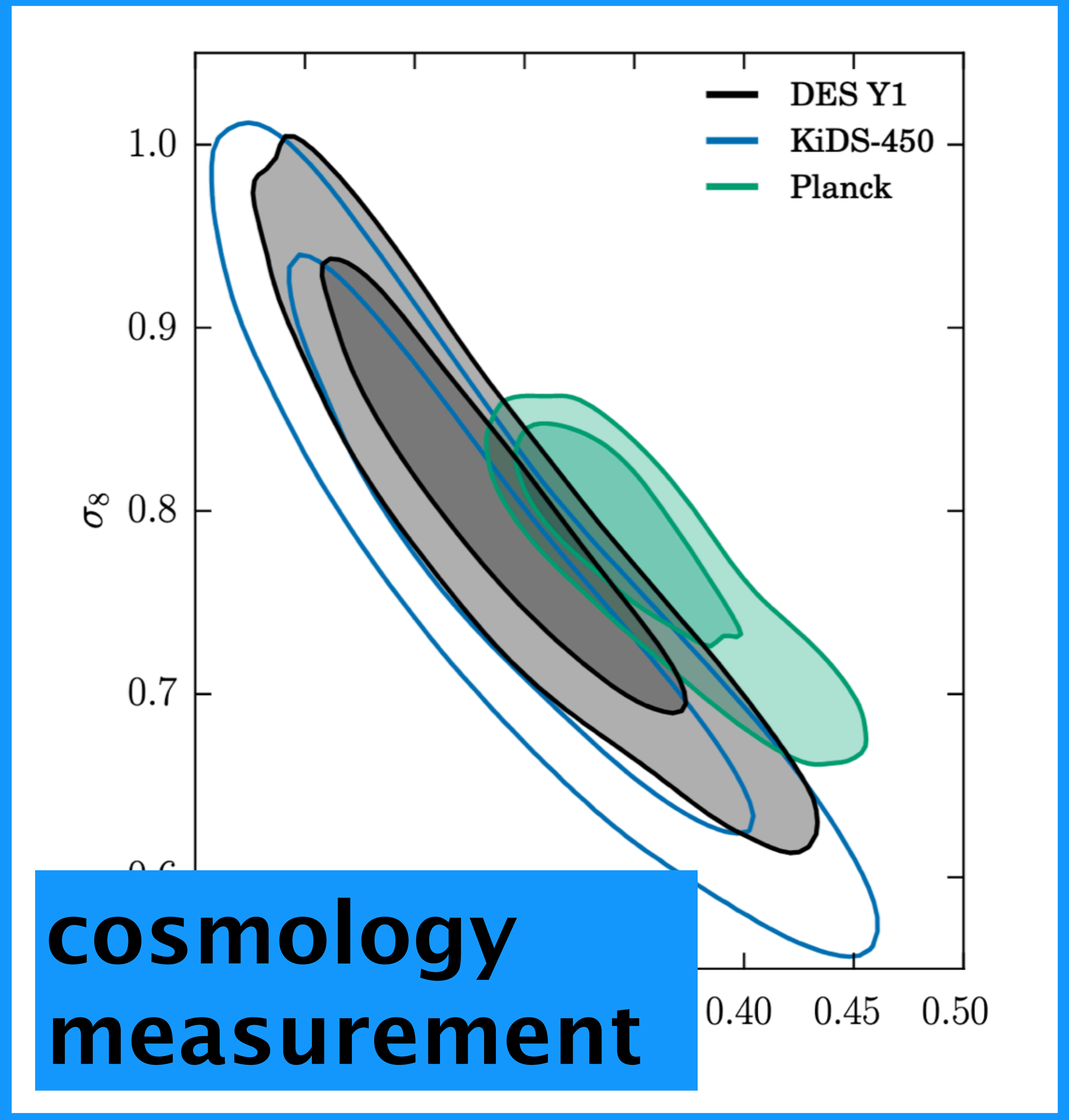




$$C_l = \frac{9}{16}\left(\frac{H_0}{c}\right)^4 \Omega_m^2 \int_0^{\chi_h} d\chi \left[\frac{g(\chi)}{ar(\chi)}\right]^2 P\left(\frac{l}{r},\chi\right),$$

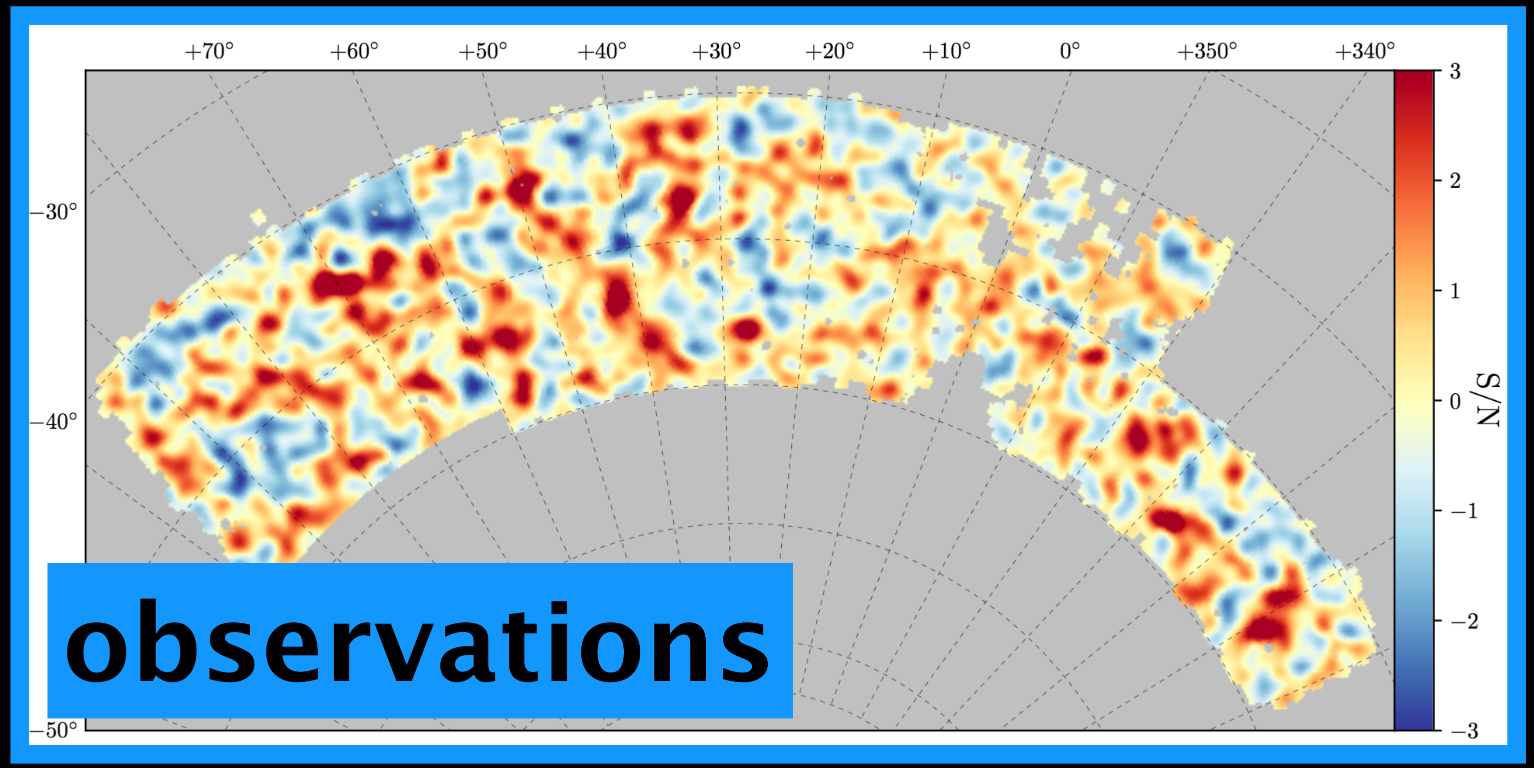
theory prediction: analytical

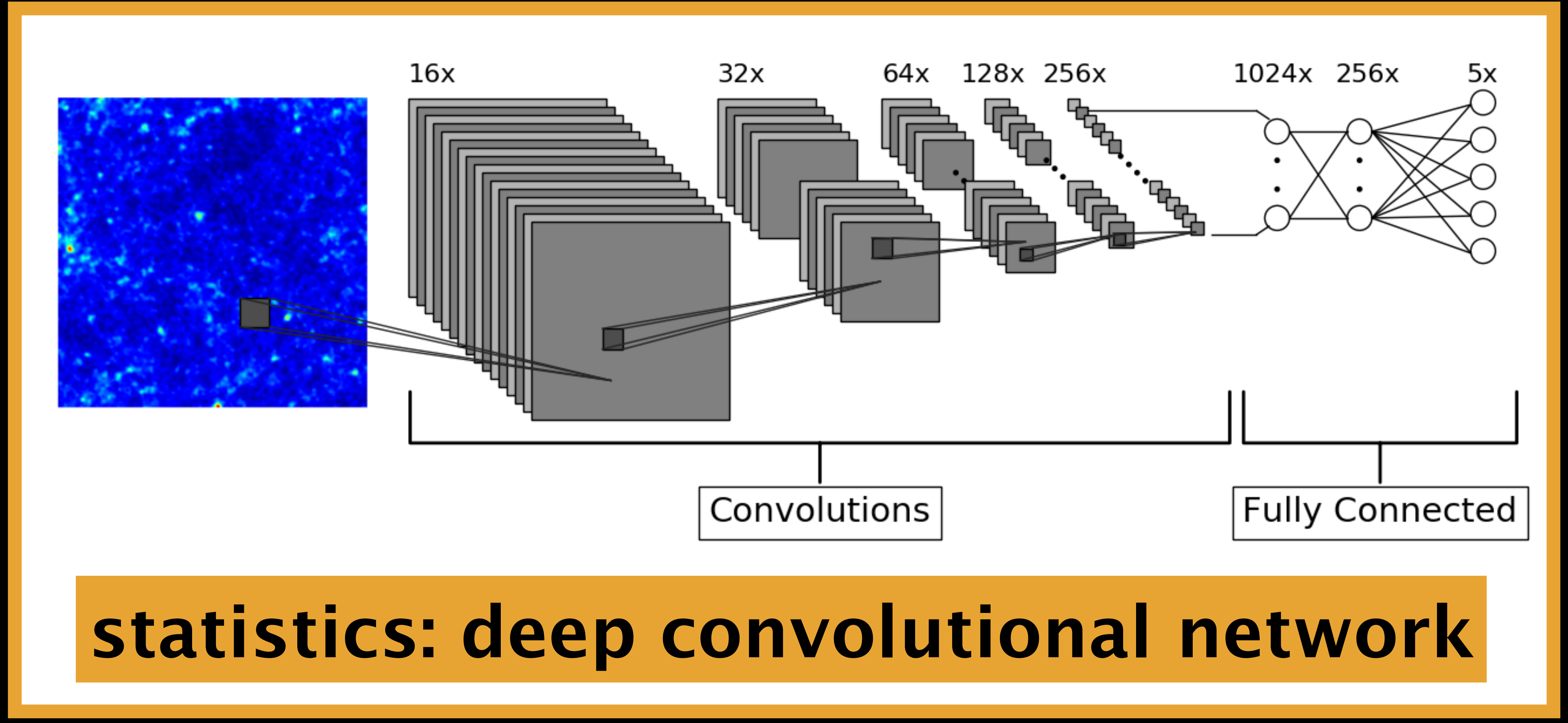
σ_8

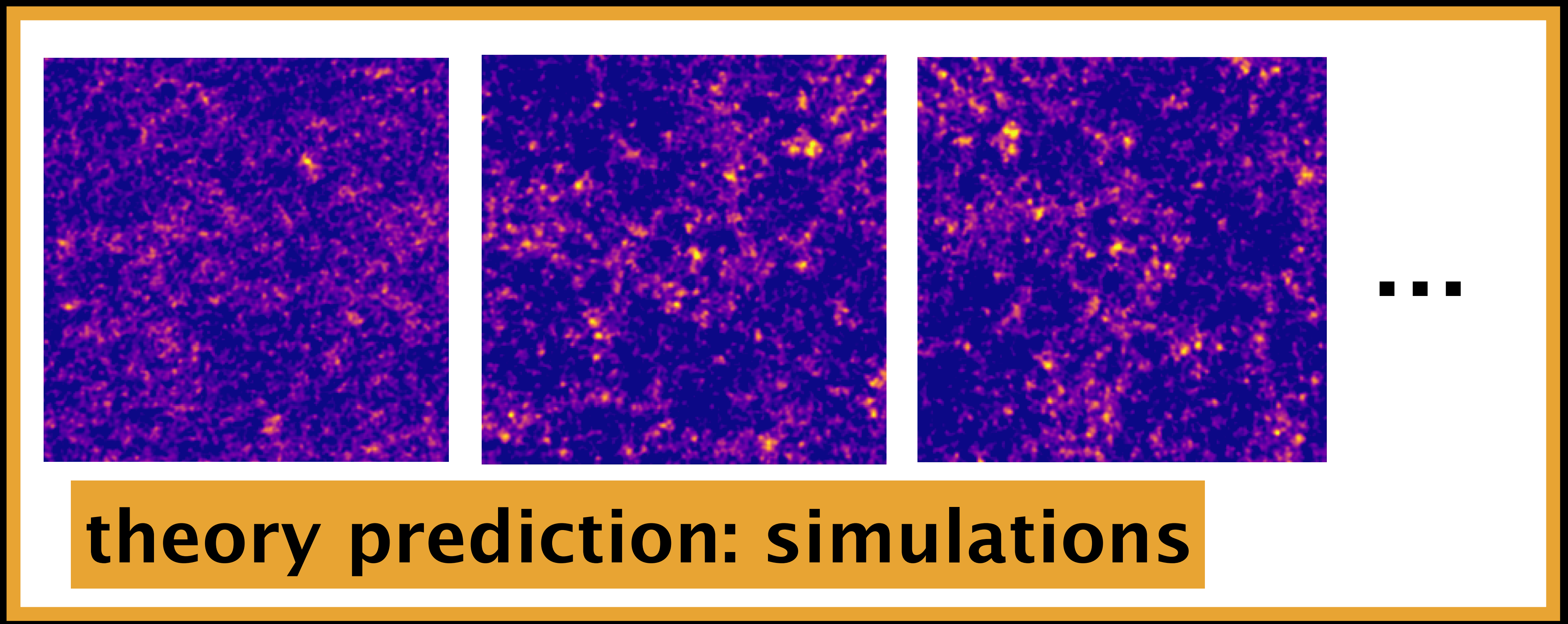


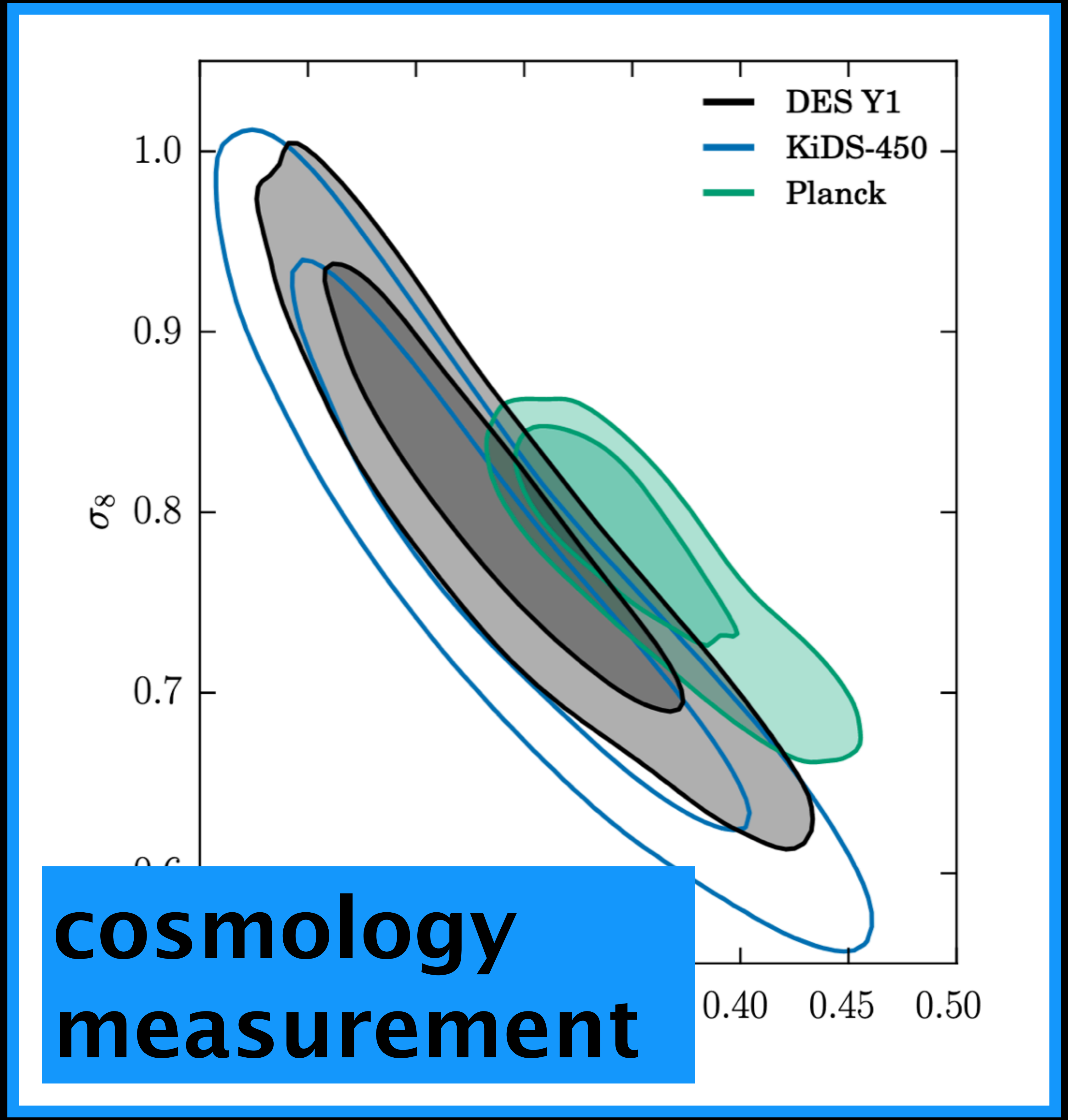
Ω_m

Inference with Deep Learning





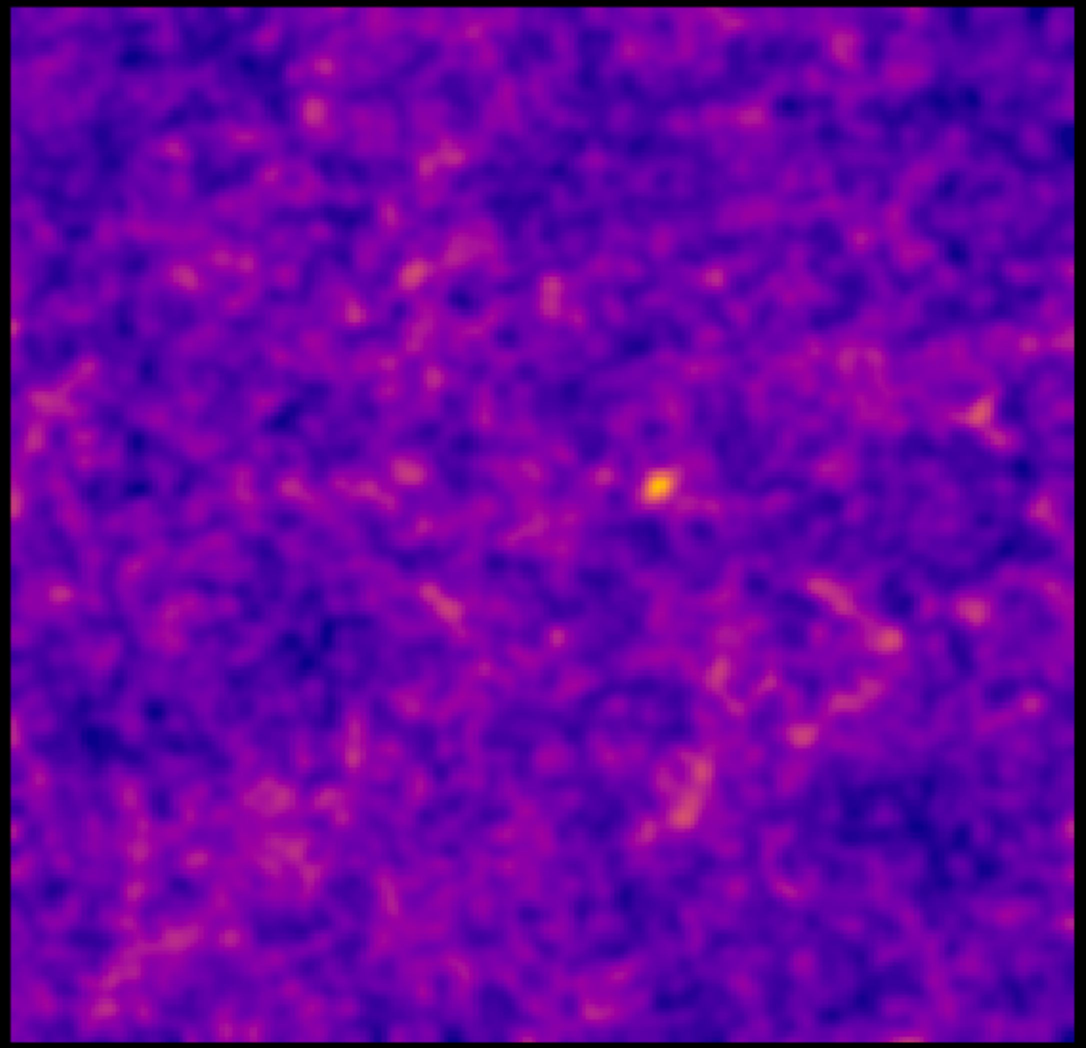




σ_8

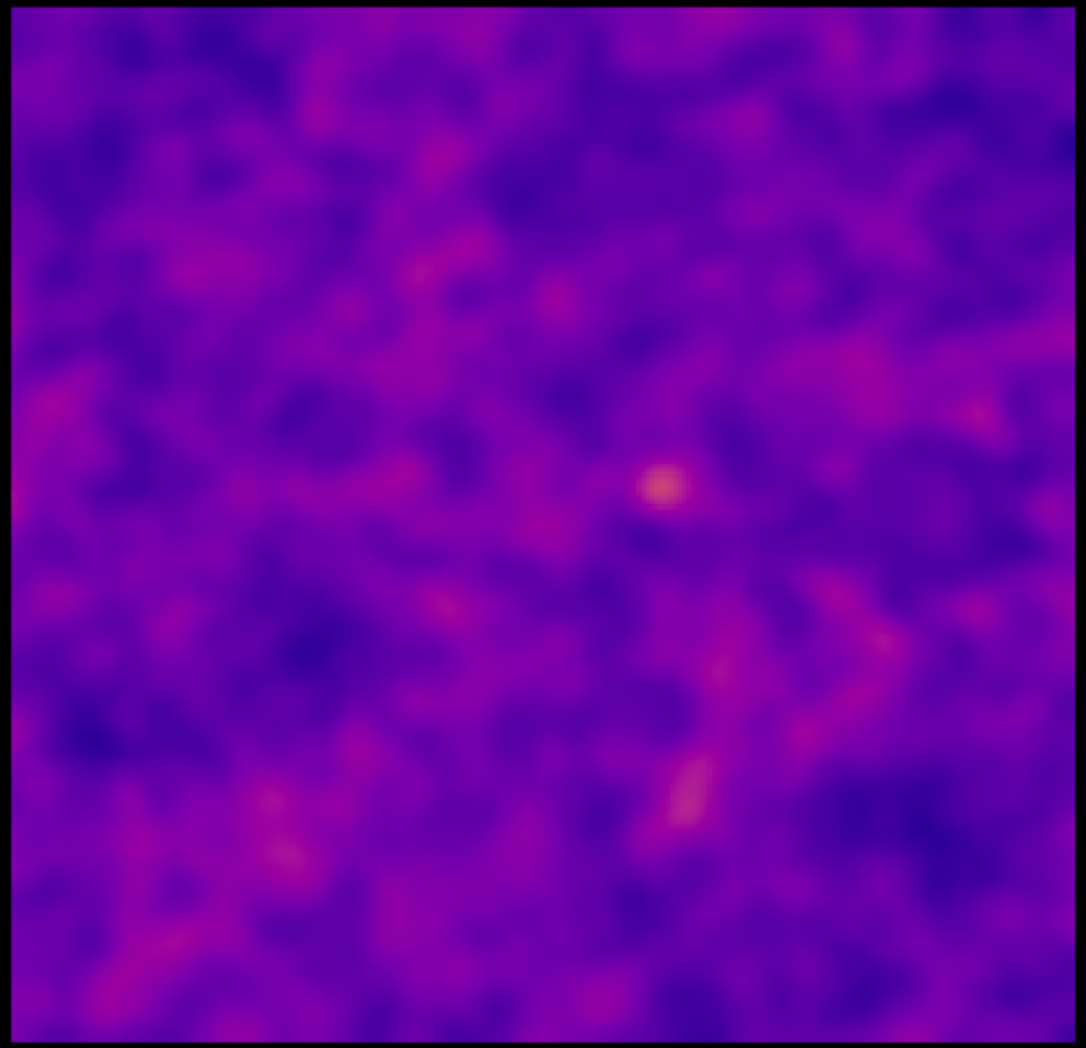
Ω_m

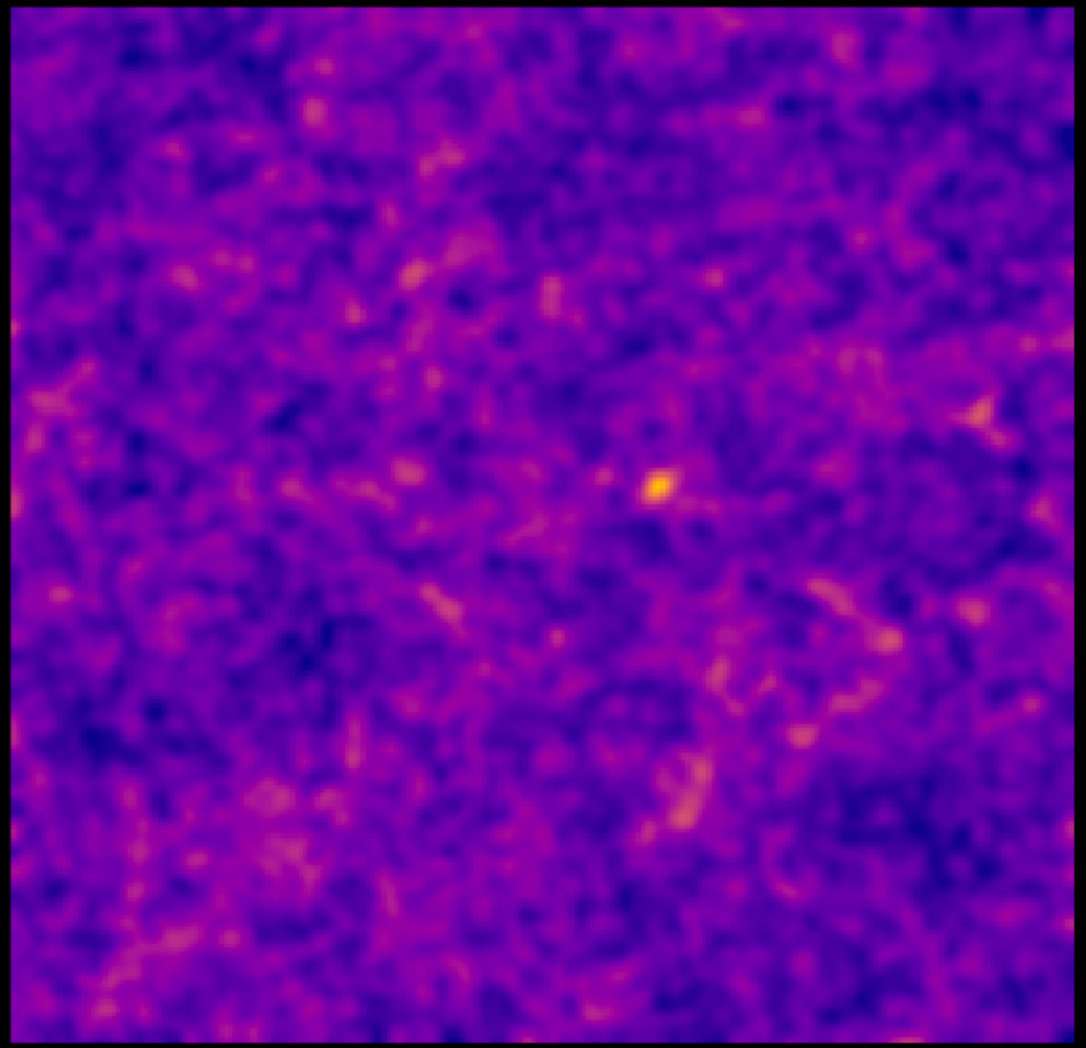
What is the advantage of deep learning for current and upcoming data?



add smoothing→

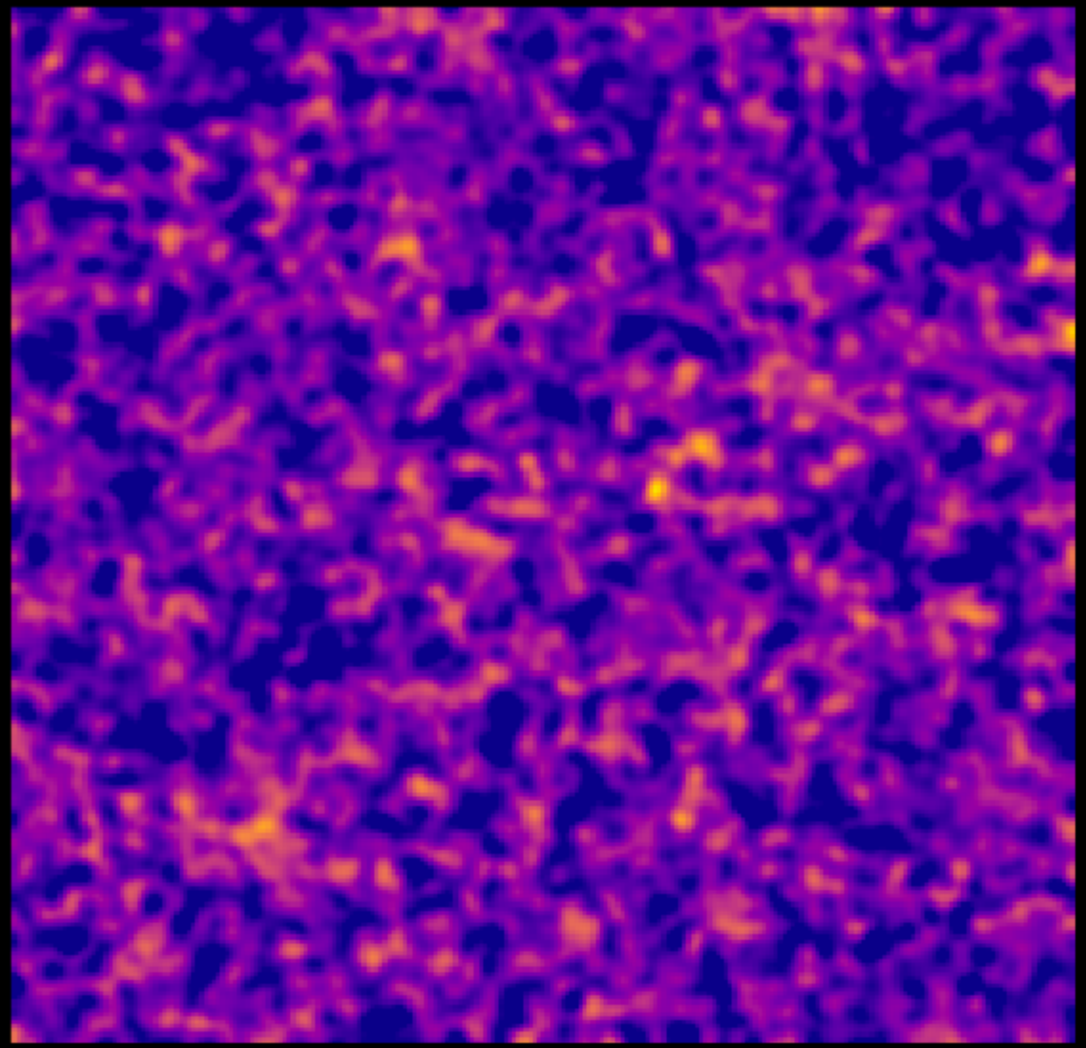
quality of simulations



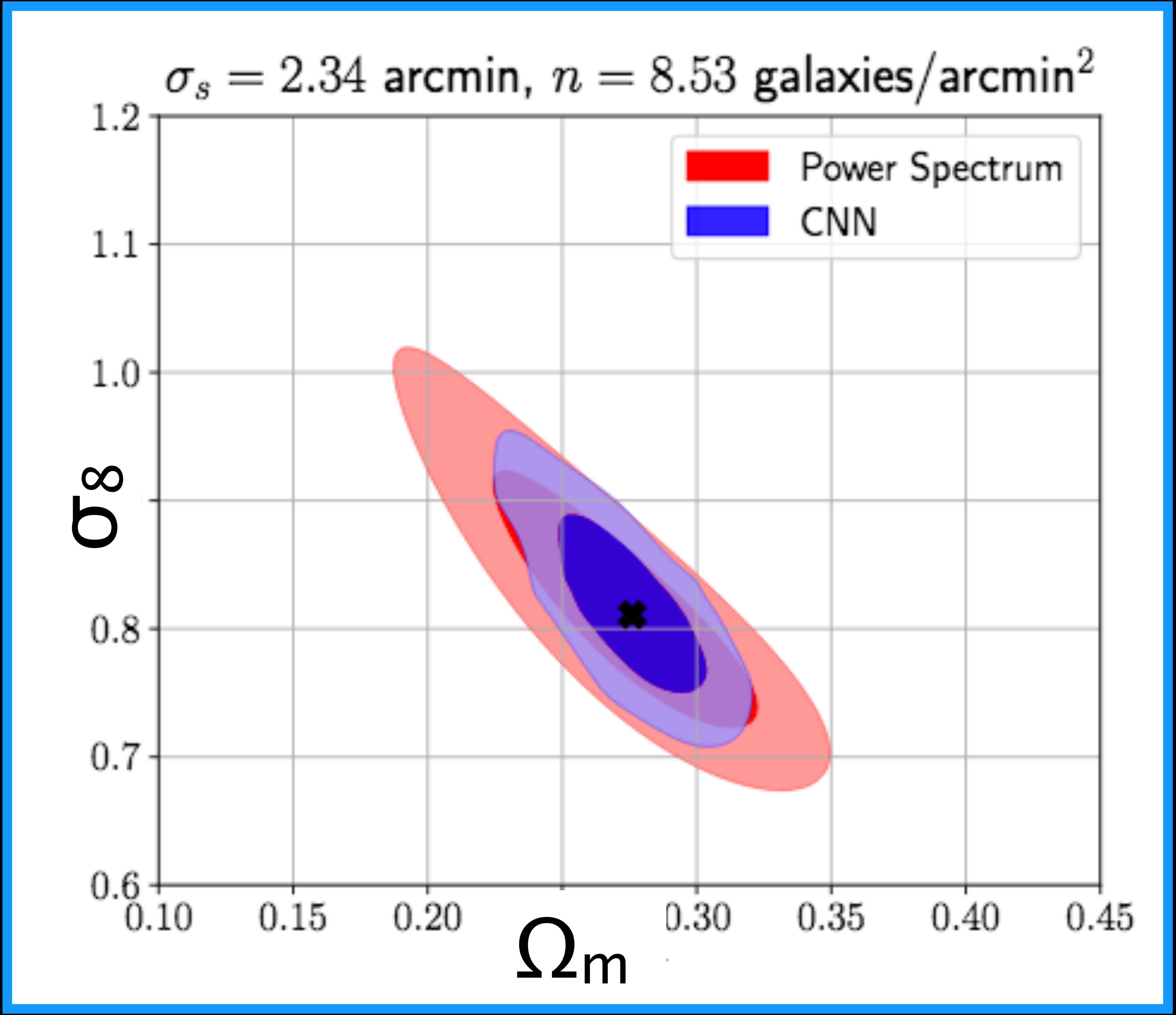


add noise →

quality of observations



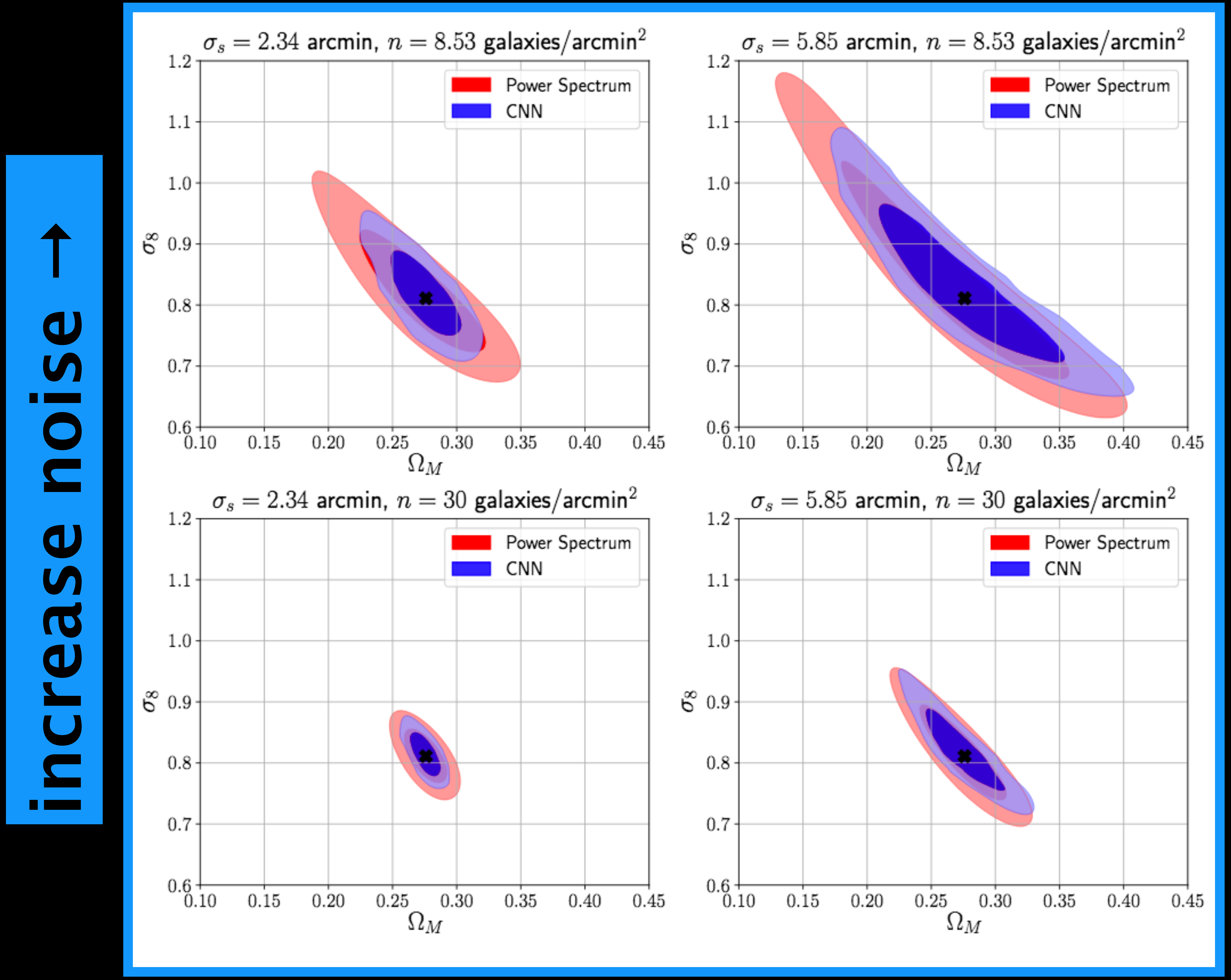
Deep learning captures more information



40% increase in constraining power!

Fluri, TK, et al. 1807.08732

Deep learning captures more information



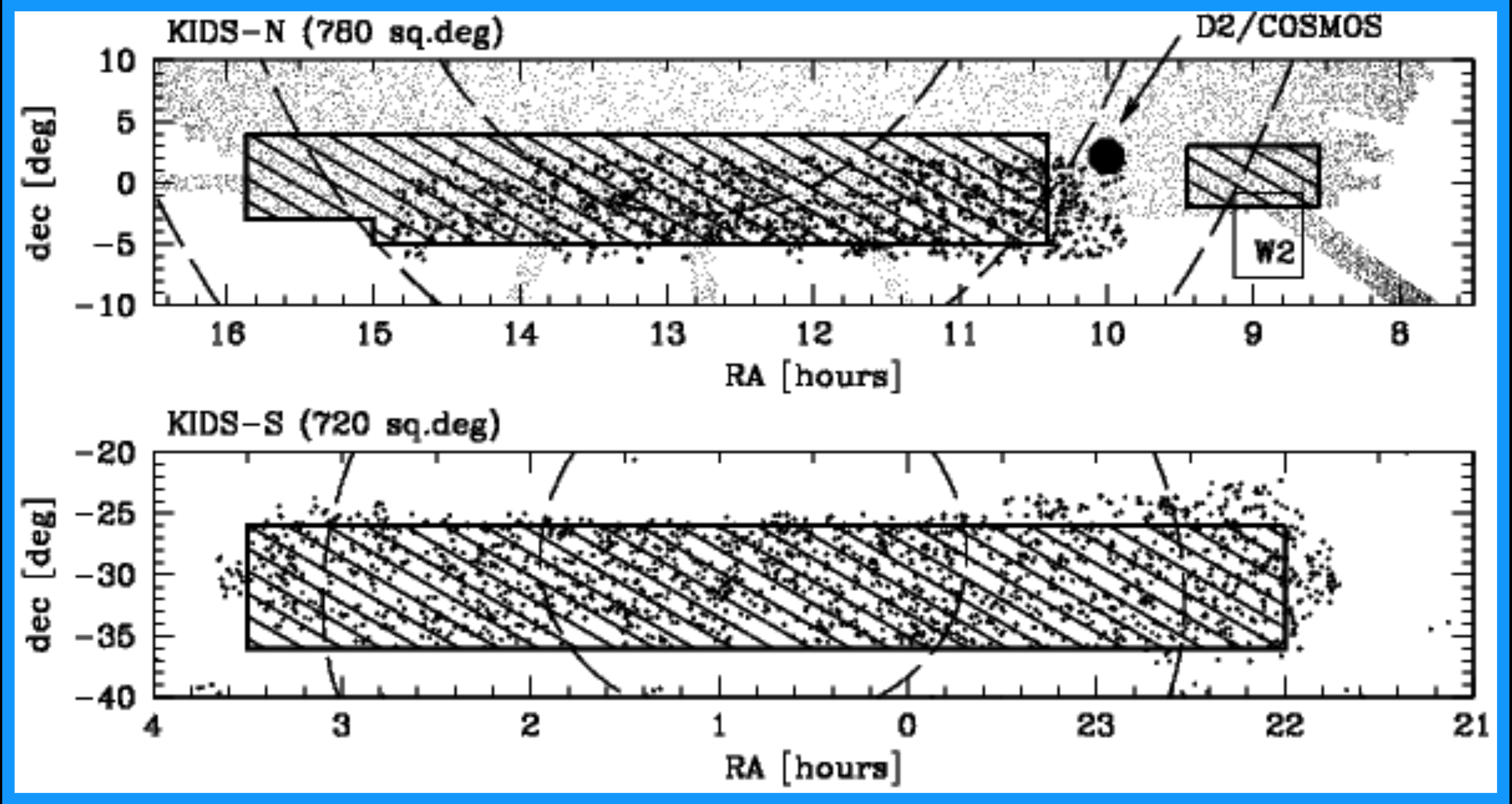
increase smoothing→

Gain in constraining power depends on noise level and smoothing scale

Fluri, TK, et al. 1807.08732

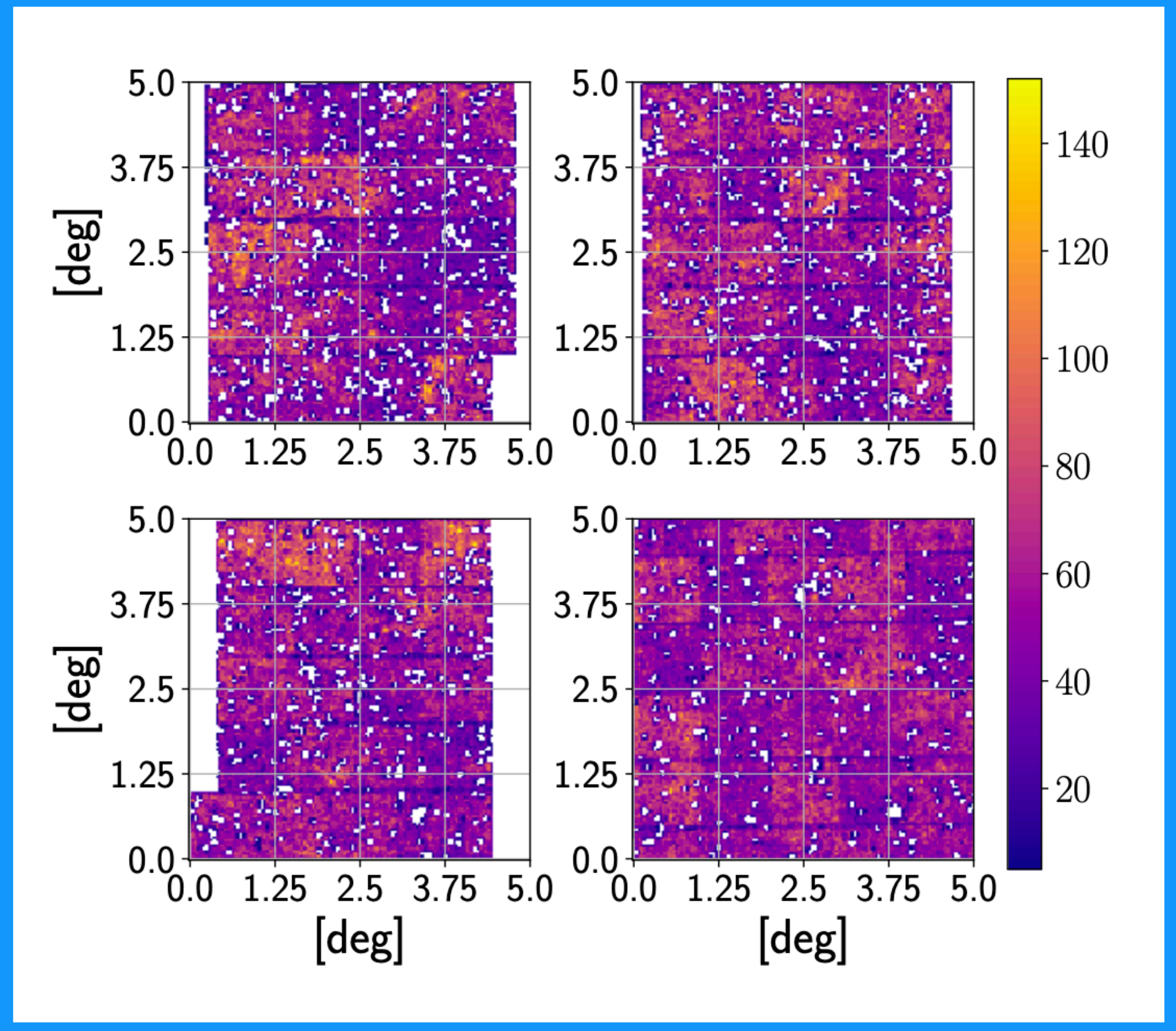
Analysis of KiDS-450 with deep learning

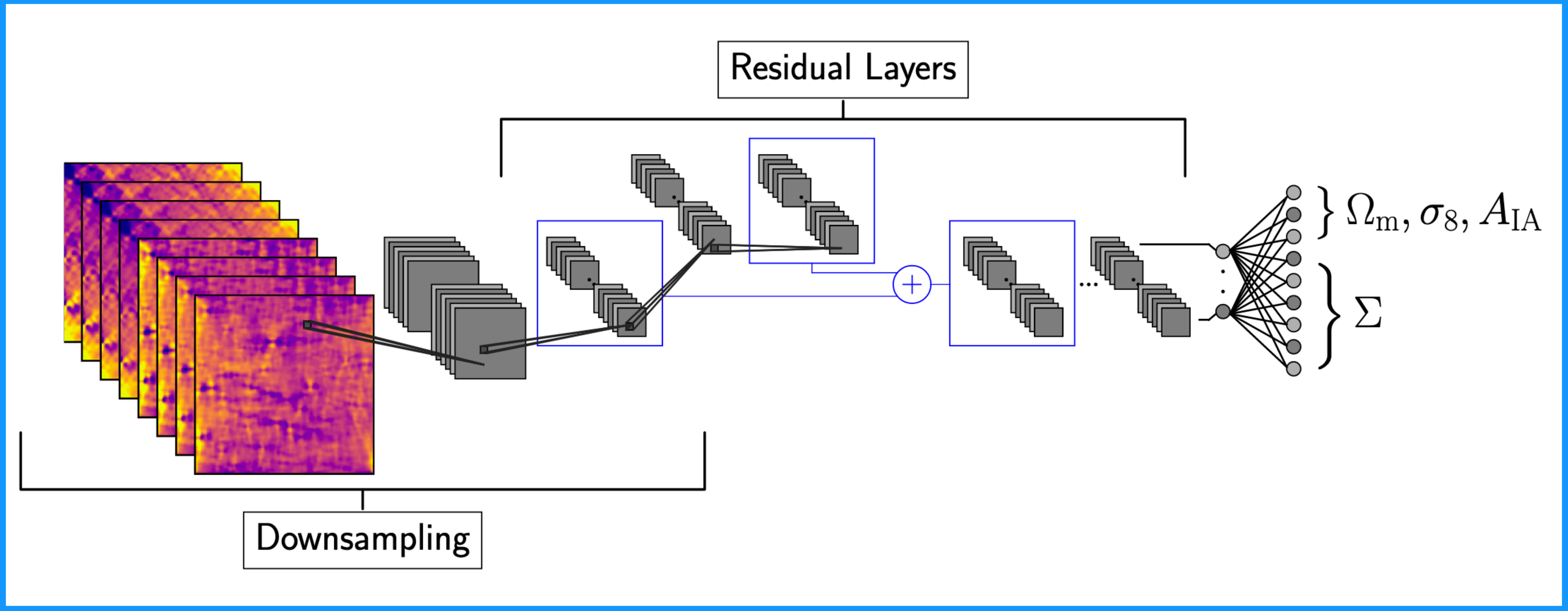
- Kilo-Degree Survey intermediate data set
- Using weak gravitational lensing to create the dark matter maps
- Low-noise dataset
- Taken by VLT Survey Telescope using OmegaCAM



kids.strw.leidenuniv.nl

Analysis of KiDS-450 with deep learning





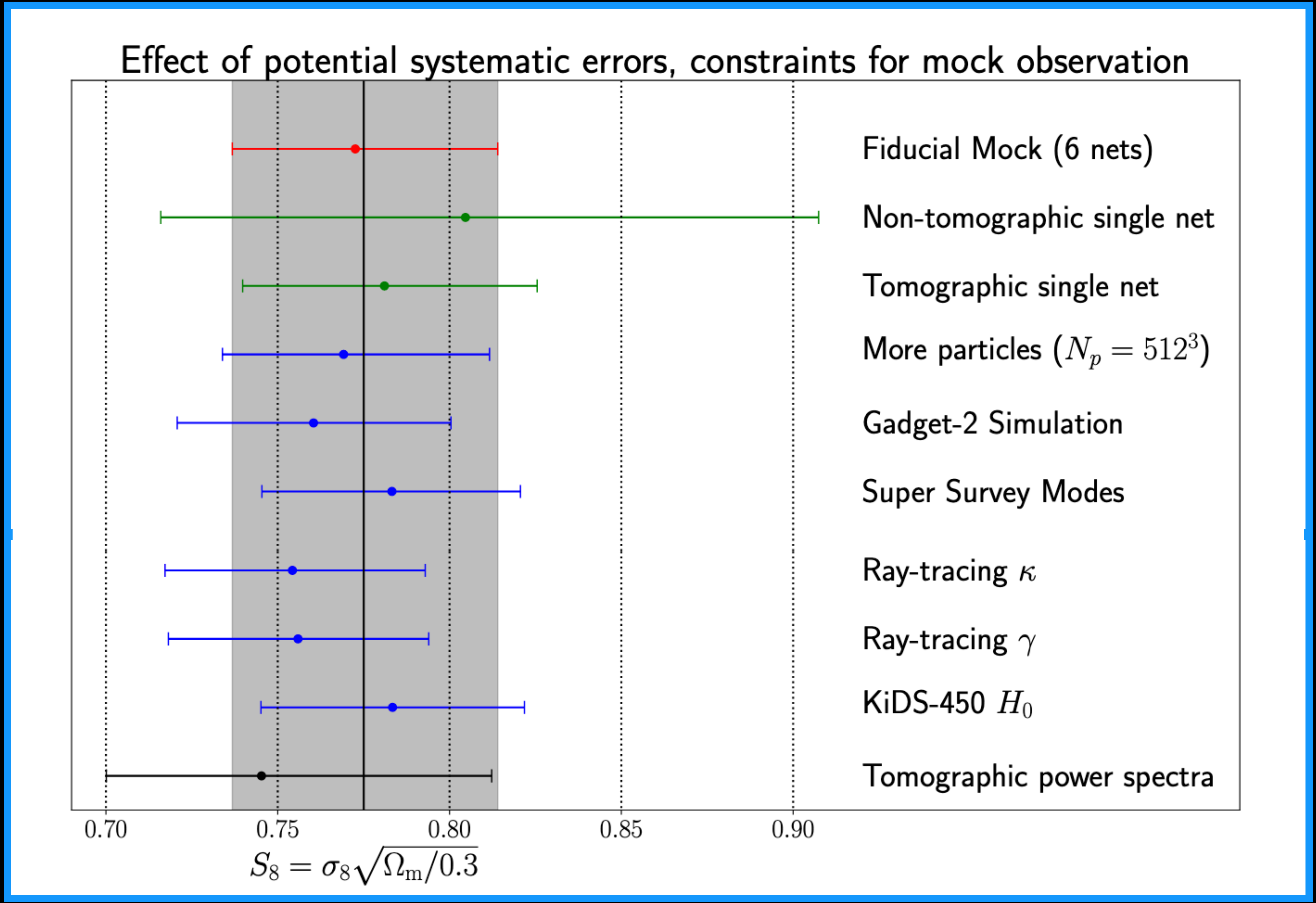
**data:
20 x 4
tomographic mass
maps**

network: 3 parameter output

likelihood analysis

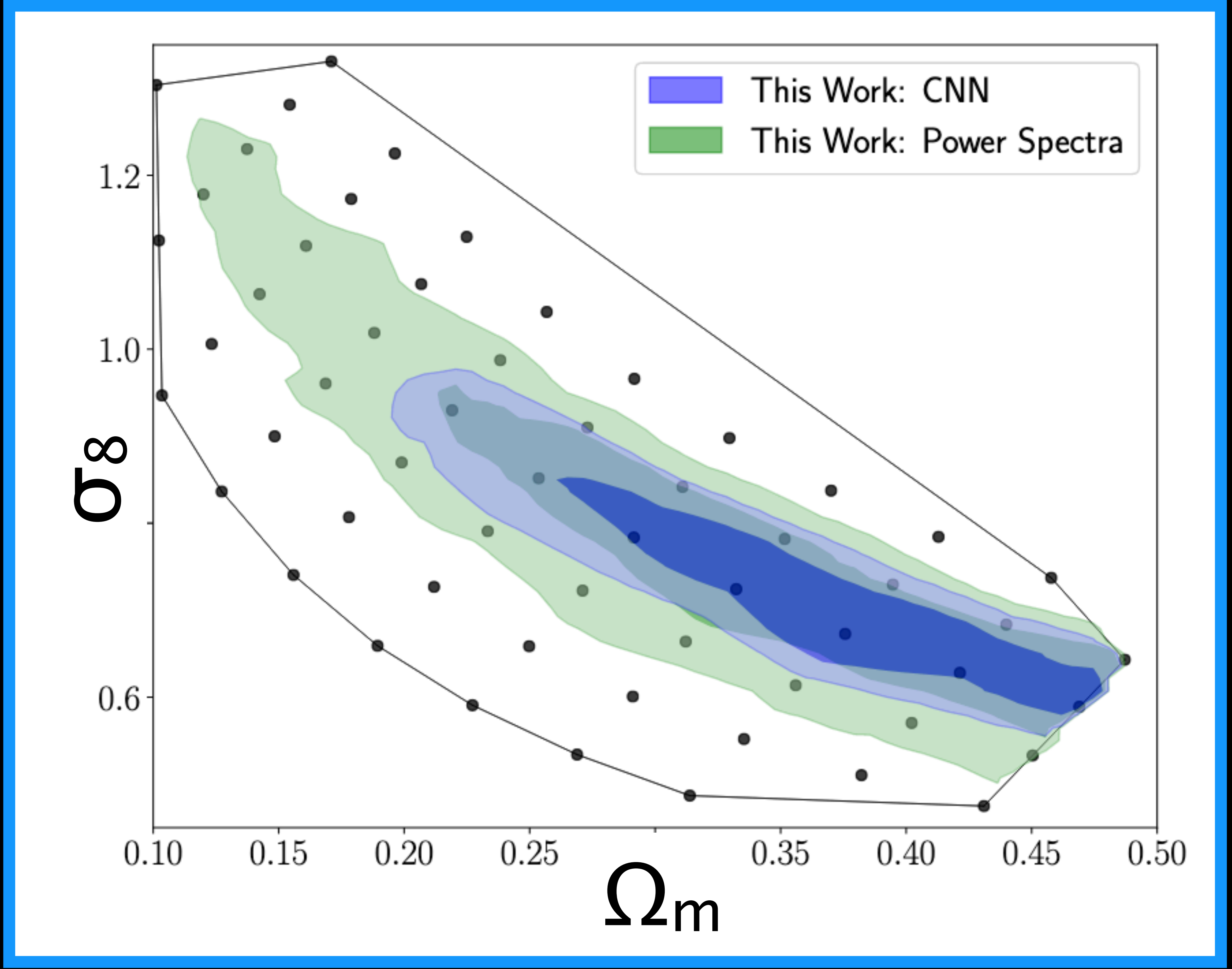
Fluri, TK, et al. 1906.03156

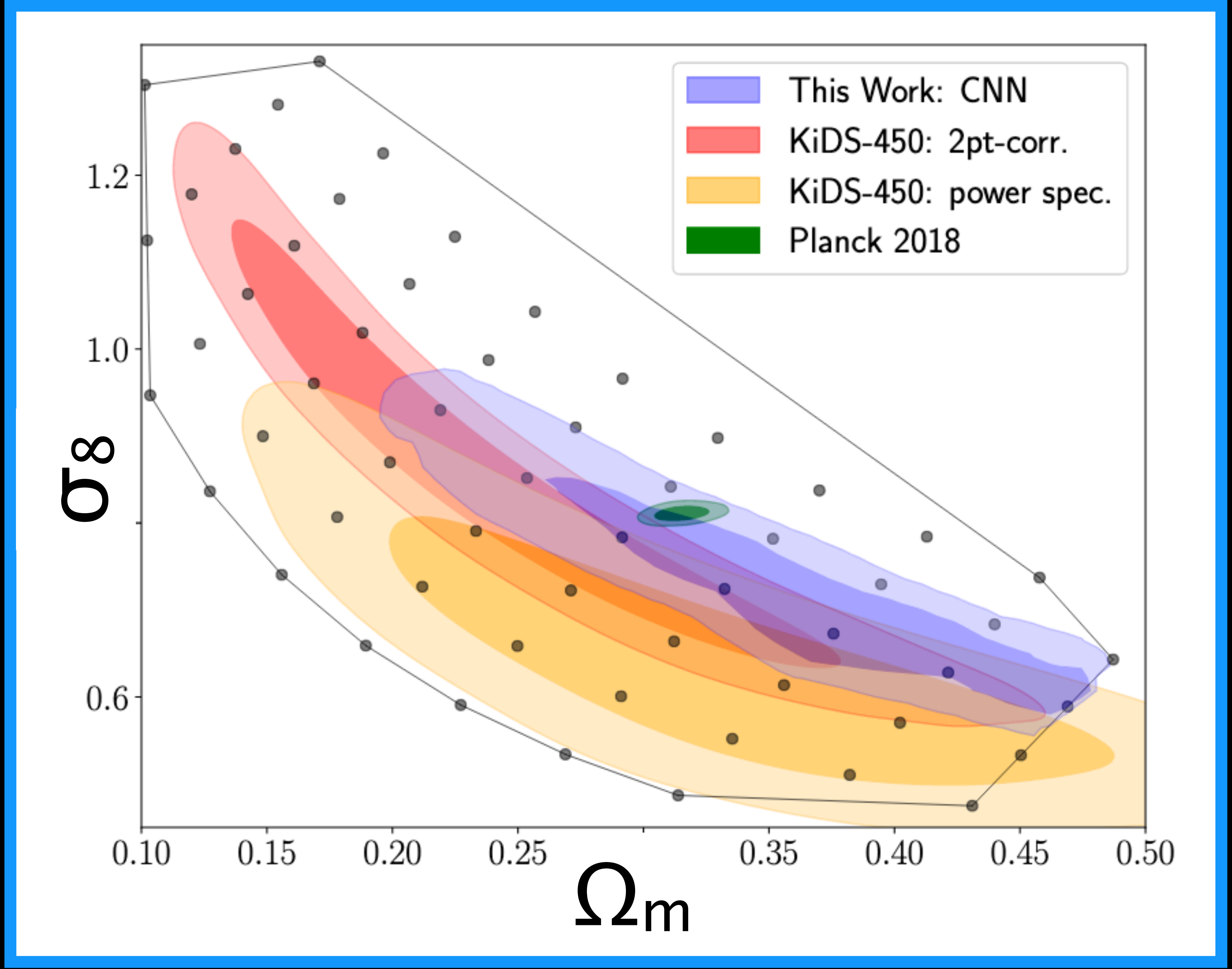
KiDS-450: robustness to simulation details



Fluri, TK, et al. 1906.03156

Analysis of KiDS-450 with deep learning





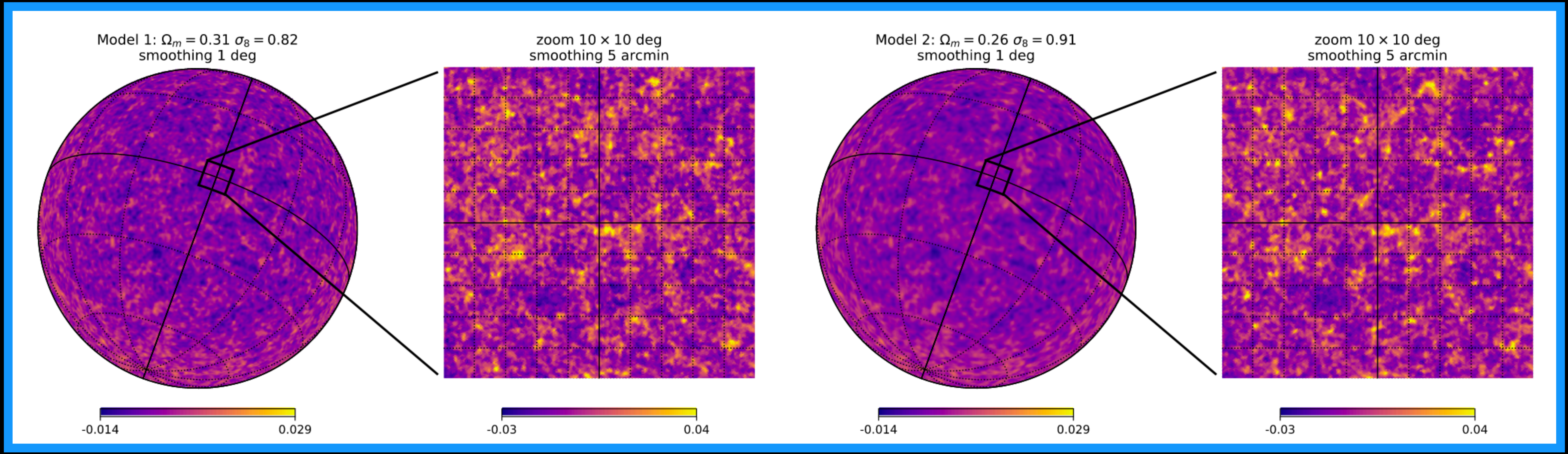
$S_8 = \sigma_8(\Omega_m/0.3)^{0.5} = 0.777 +/- 0.037$

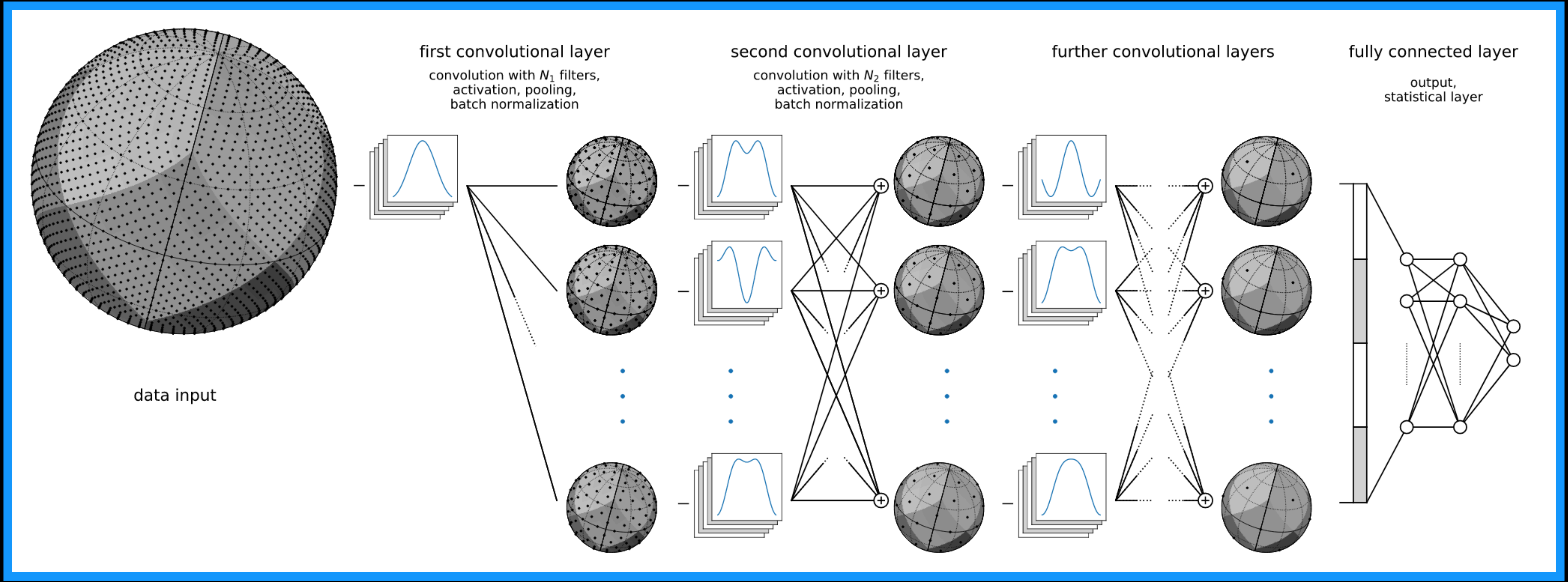
30% increase of constraining power compared to equivalent analysis with the power spectra

blinding strategy used in the analysis

Fluri, TK, et al. 1906.03156

Deep learning on the sphere: a tool for wide area surveys

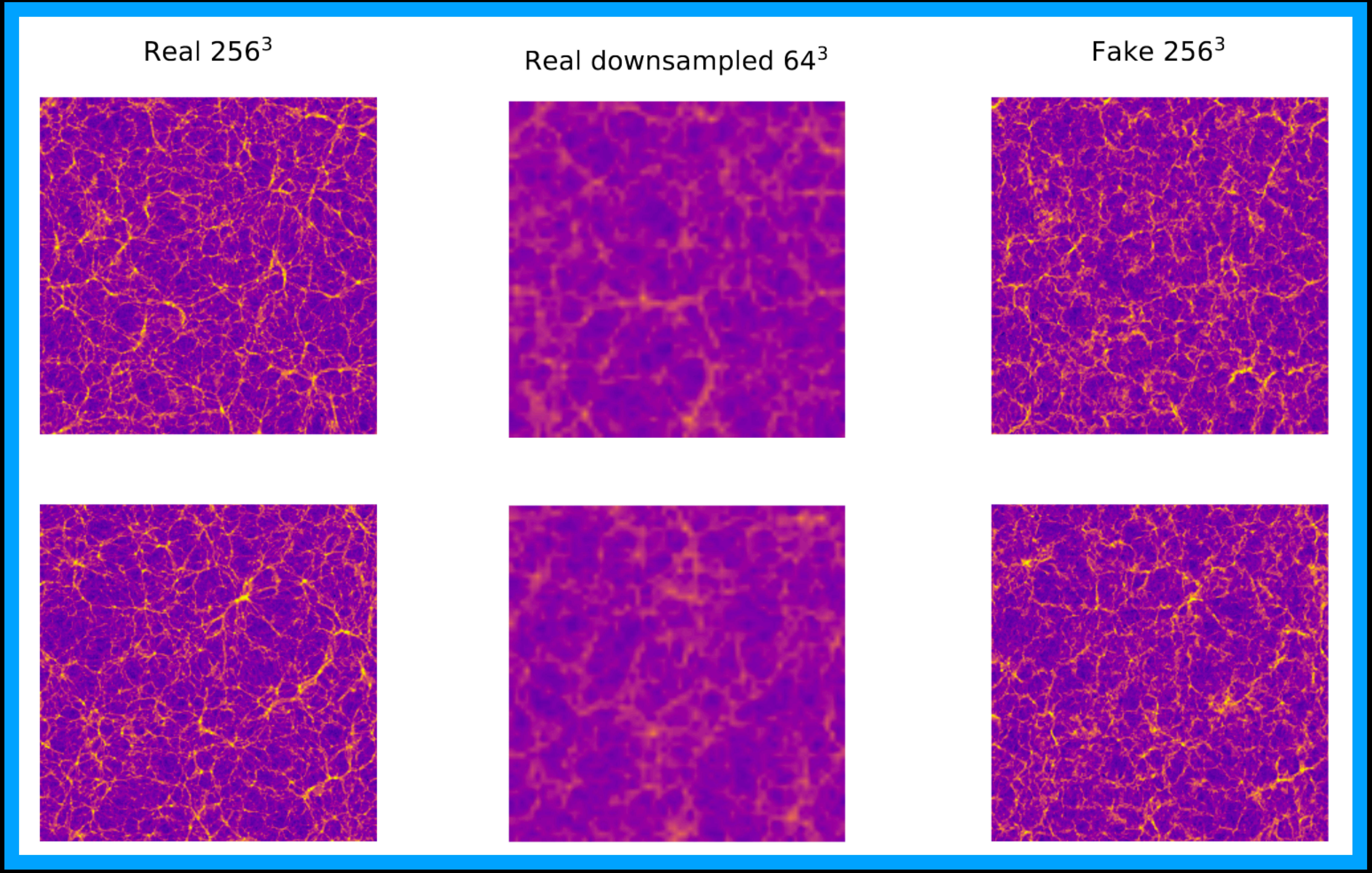




github.com/SwissDataScienceCenter/DeepSphere

Perraudin, TK, et al. 1810.12186

Experimenting with GANs for N-body simulations



256^3 voxel cubes
Sequential Patch-GAN approach for upsampling
Challenge: data and codes available → beat our score!

github.com/nperraud/3DcosmoGAN

Perraudin, TK, et al. 1908.05519

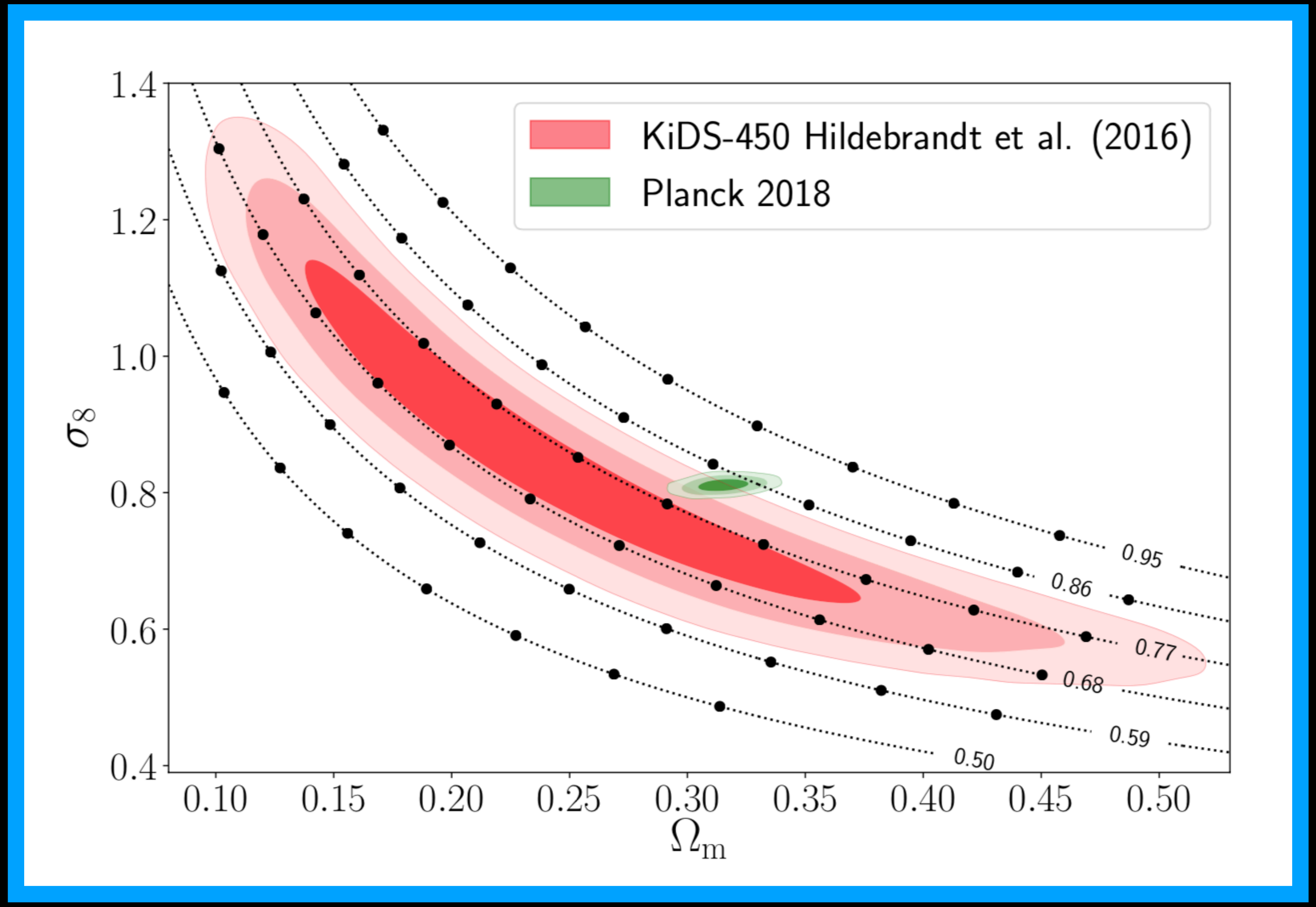
Summary

- Deep learning can improve the information gain from existing, non-linear cosmological data
- Moving towards simulation-based inference
- Currently limited by theory modelling and simulations

Extra slides

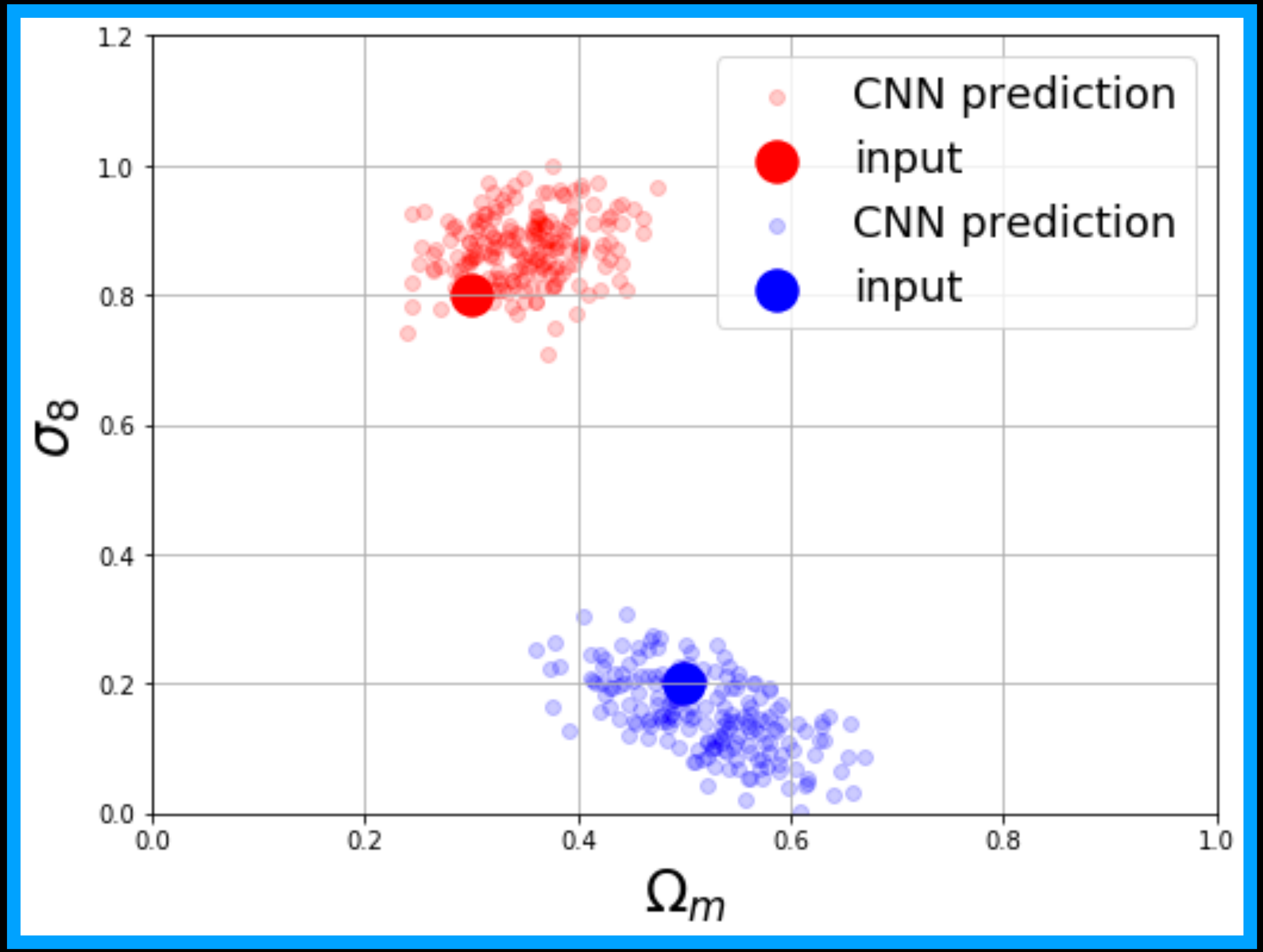
Simulations

- Very heavy simulation load
- PkdGrav3 on GPUs
- 90% of time for simulations, 10% for CNN training
- 57 cosmologies x 12 N-body simulations, convergence and IA map creation
- Inclusion of effects: baryons, advanced intrinsic alignment models



Likelihood modelling

- CNN is a feature extractor
- we create likelihood of features given true value
- we model the likelihood as a Gaussian with mean and covariance varying as a function of cosmological parameters
- we calculate the posterior with a prior across the spaces spanned by the training set



Training details

- ResNets with 10, 15 and 25 layers
- On the fly noise addition
- Likelihood loss used in training

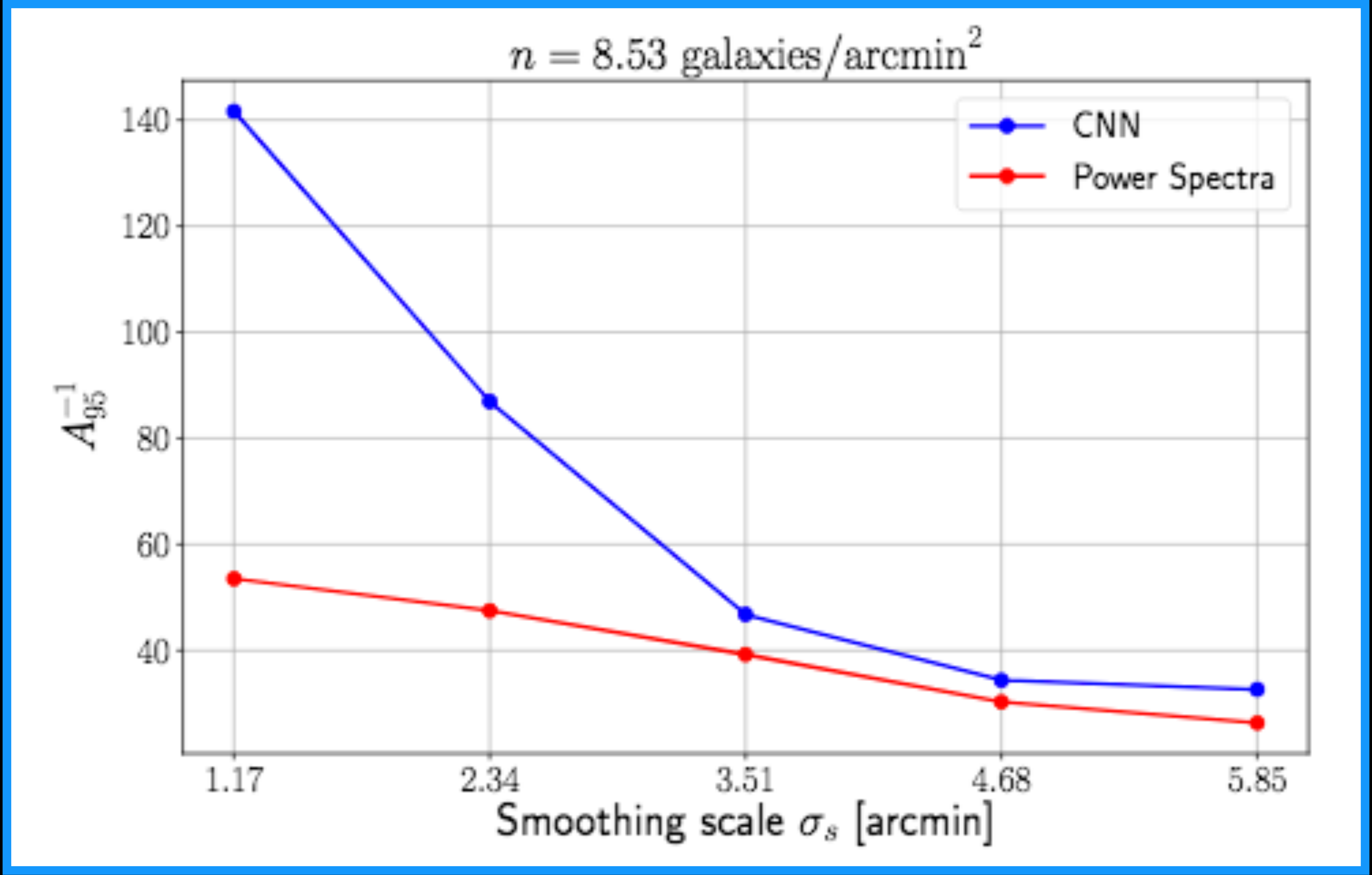
$$L = \frac{1}{2}\left(\ln\left(|\Sigma|\right) + \left(\theta_p - \theta_t\right)^T \Sigma^{-1} \left(\theta_p - \theta_t\right)\right),$$

Σ **prediction of covariance matrix learned by the network (6 parameters)**

θ_p **predicted parameters (3)**

θ_t **target parameter (3)**

Deep learning captures more information



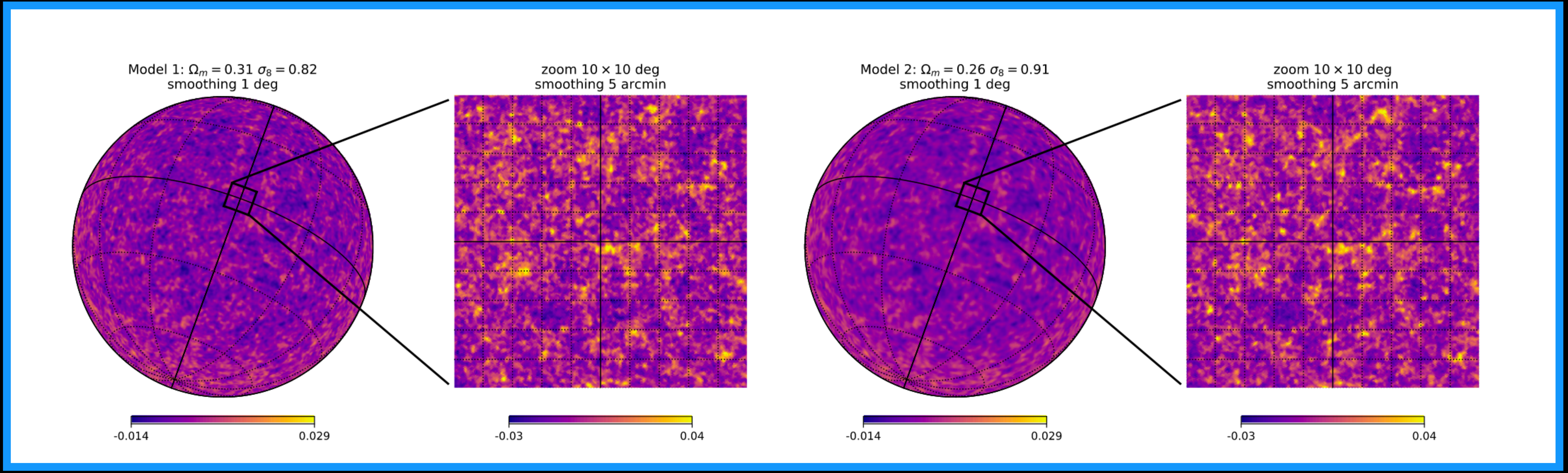
← worse inverse contour area better →

← smoothing scale →

Fluri, TK, et al. 1807.08732

Deep learning on the sphere

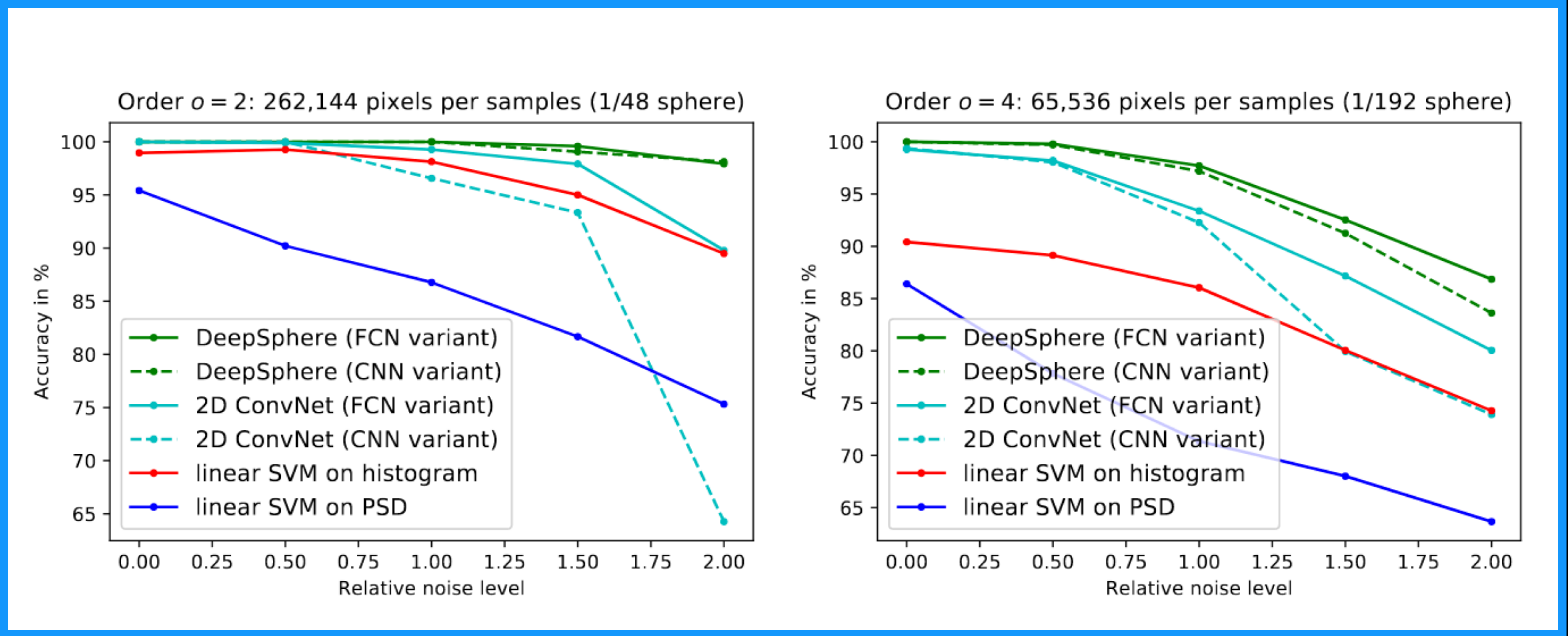
σ_8=0.82, Ω_m=0.31 | **σ_8=0.91, Ω_m=0.26**



two models with the same power spectrum

Perraudin, TK, et al. 1810.12186

Deep learning on the sphere



DeepSphere maintains advantage over baselines
for higher noise levels

github.com/SwissDataScienceCenter/DeepSphere

Perraudin, TK, et al. 1810.12186