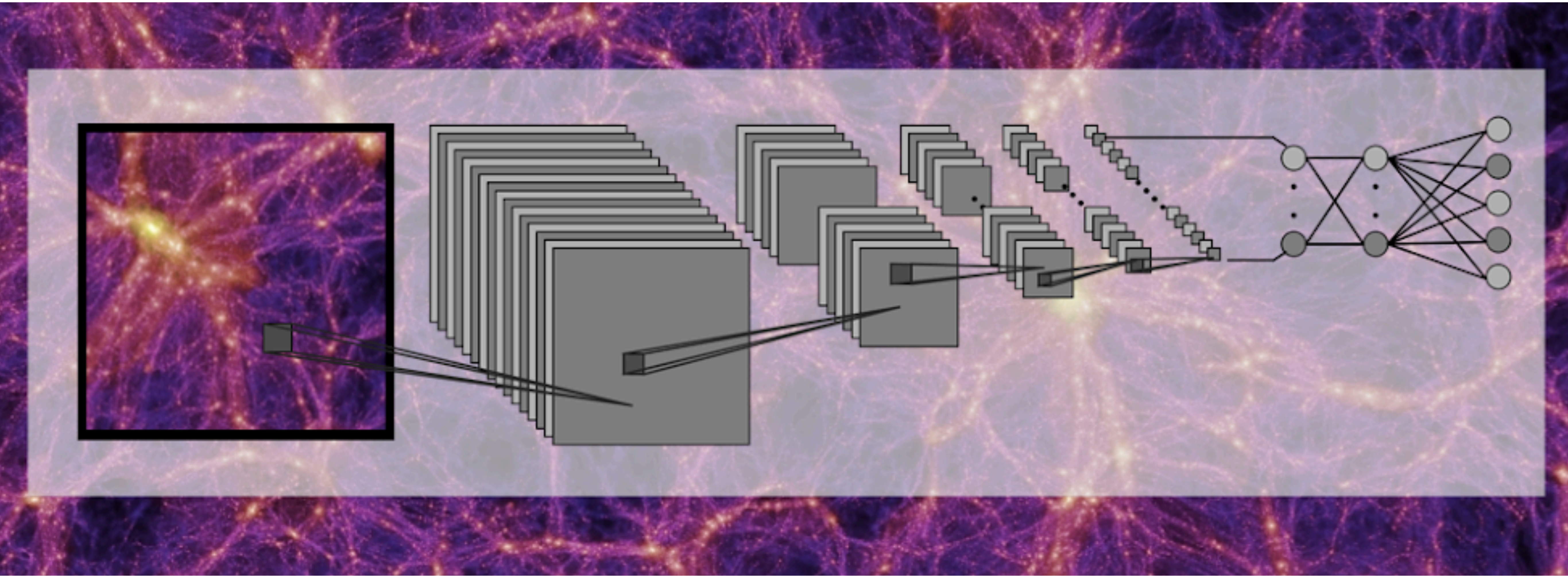
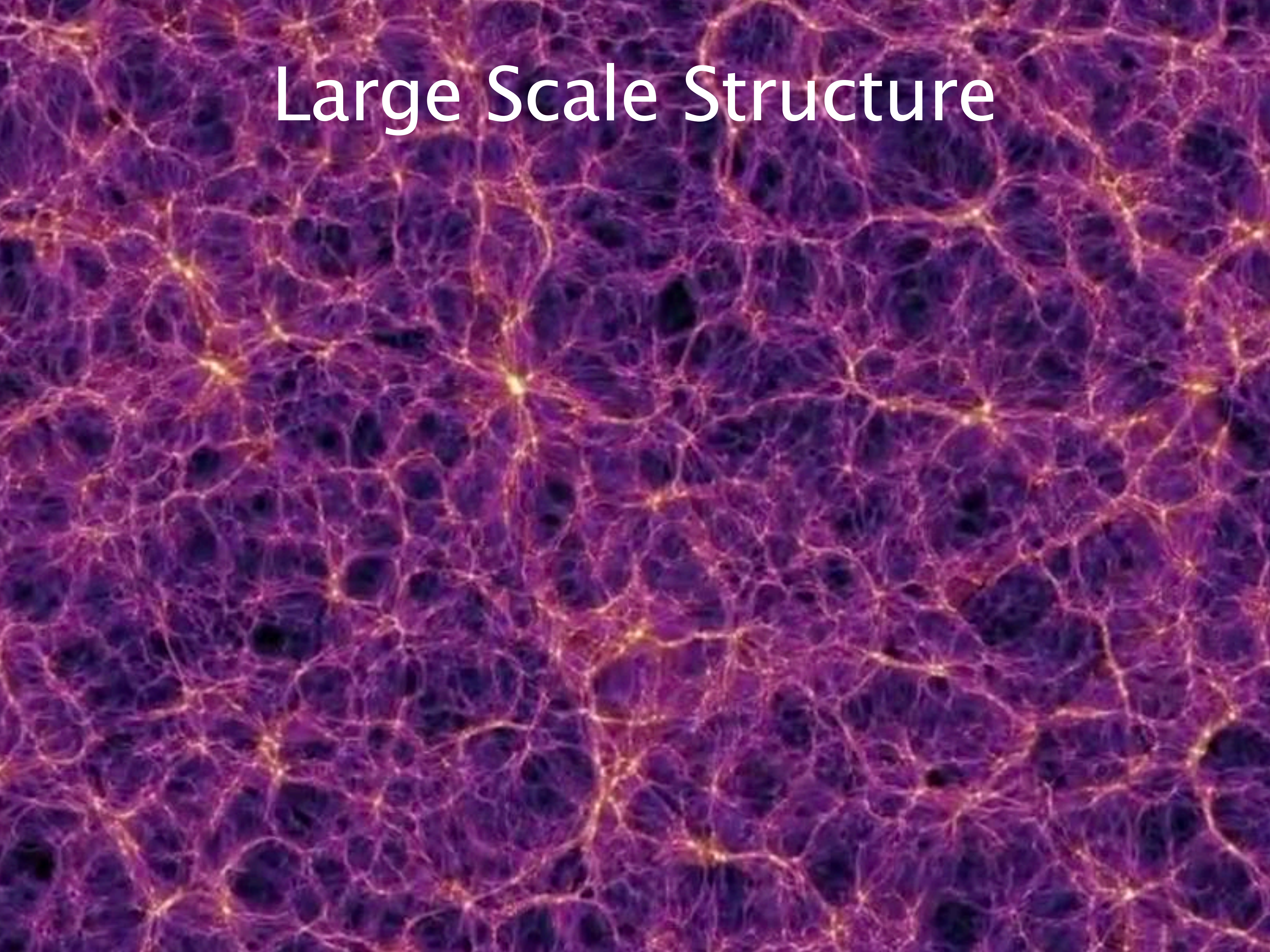
Cosmology from Large Scale Structure with Artificial Intelligence



Tomasz Kacprzak (ETH Zurich)
Janis Fluri, Aurelien Lucchi (ETH-CS), Nathanael Perraudin (ETH-SDSC)

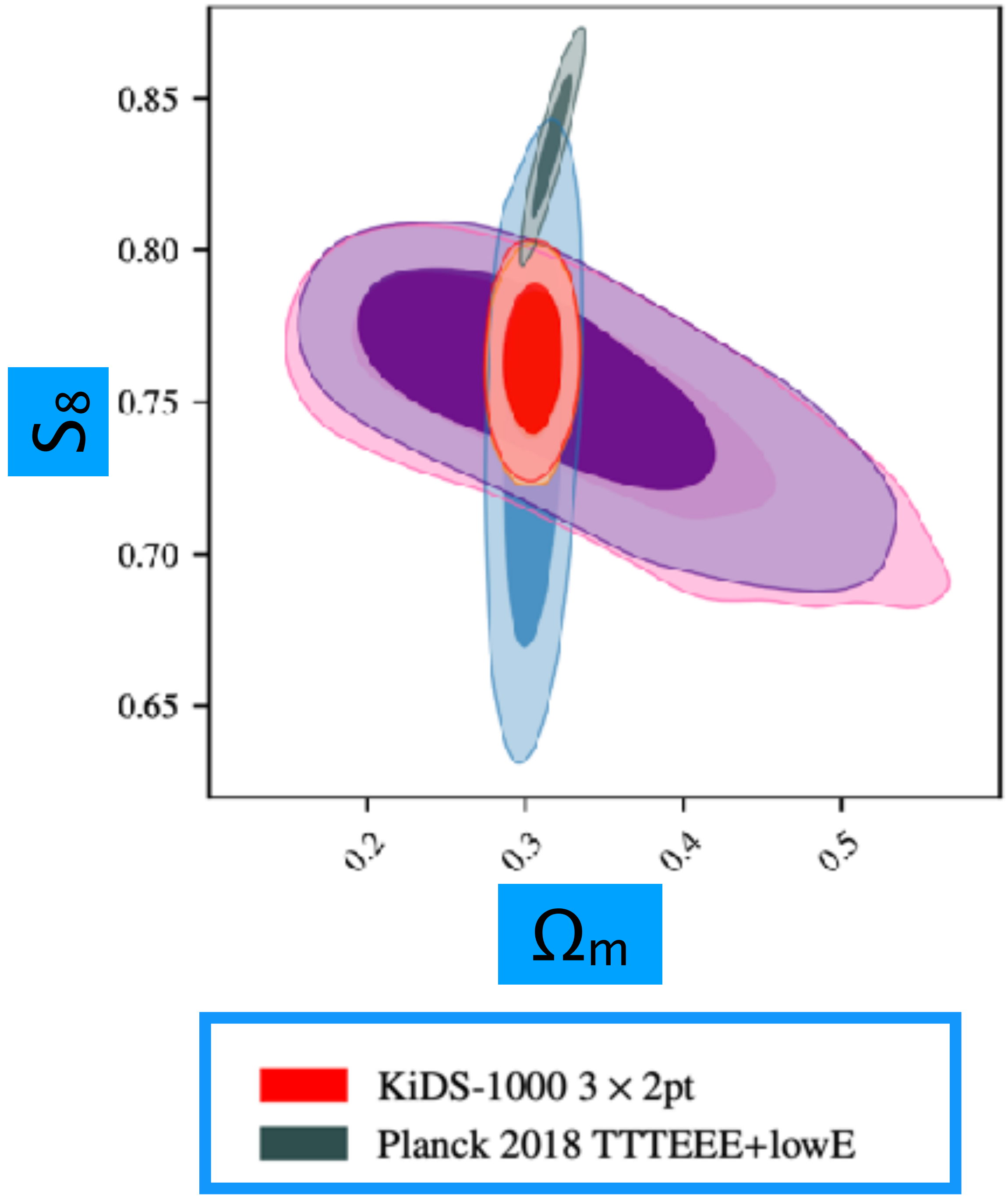
GCCL Seminar, 30 October 2020

Large Scale Structure



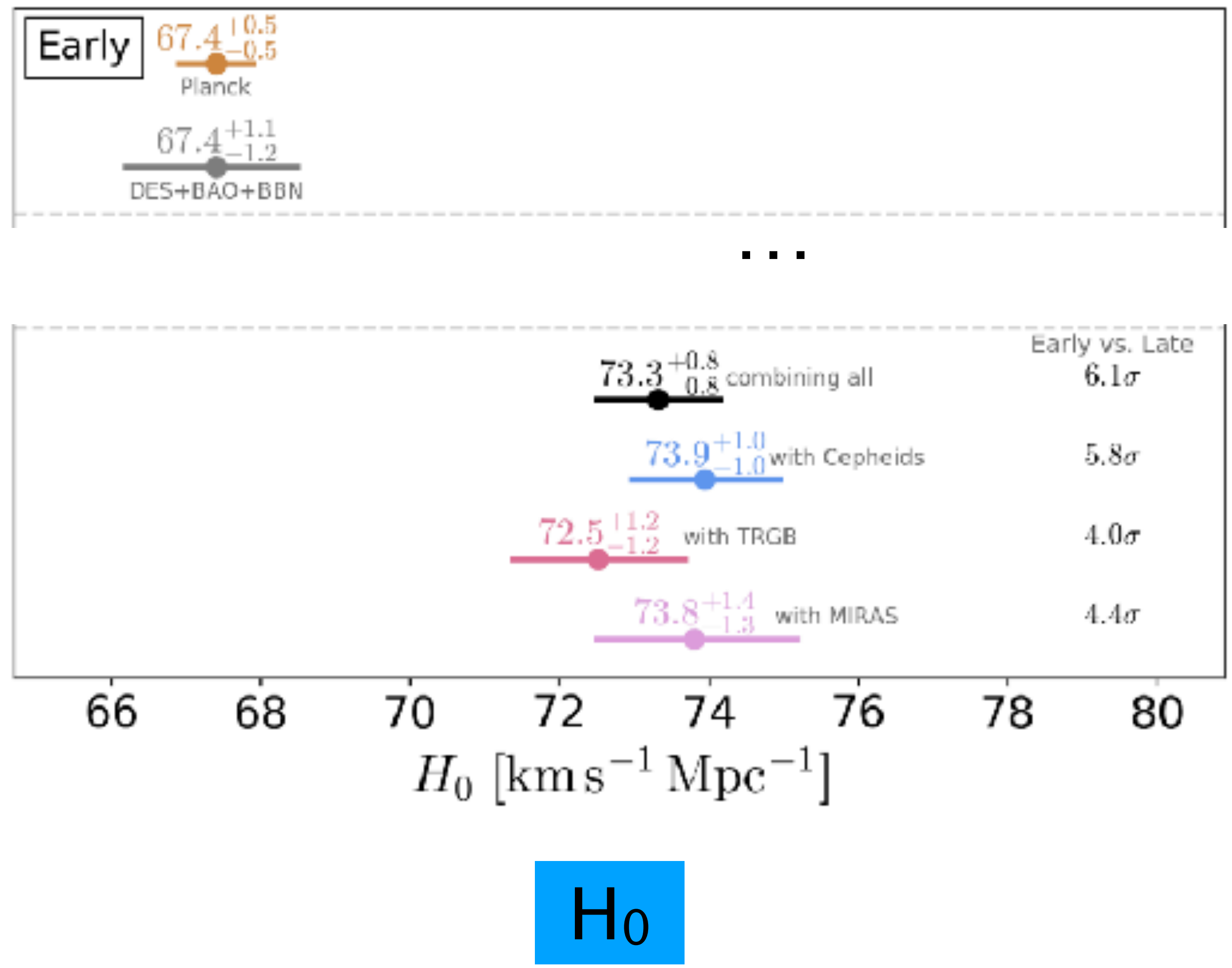
Tensions between early and late universe

3σ tension on S_8



Heymans et al. 2020, 2007.15632

4-5σ tension on H_0

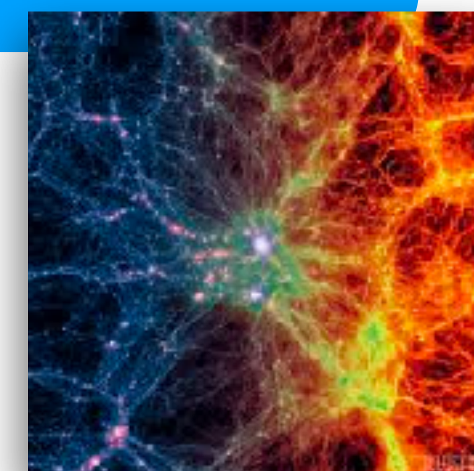


Verde et al. 2019, 1907.10625

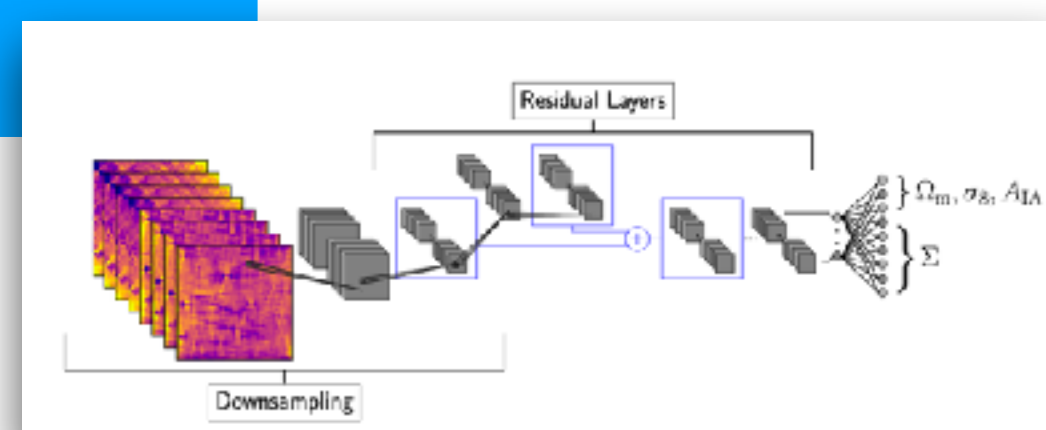
Sources of cosmological information

More data

Smaller scales



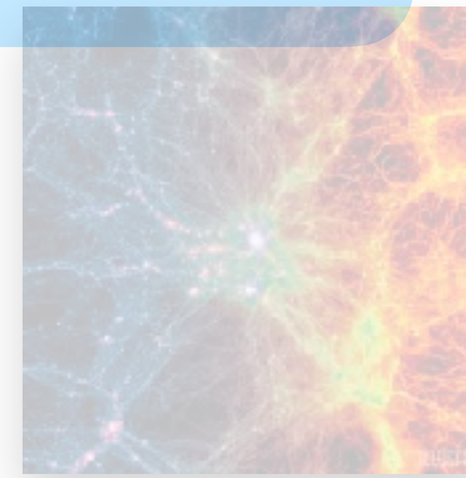
Improved analysis methods



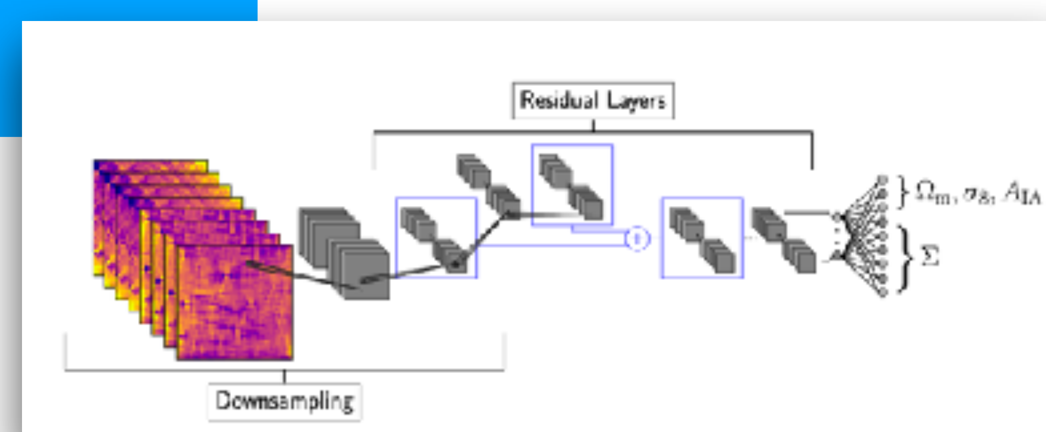
Sources of cosmological information

More data

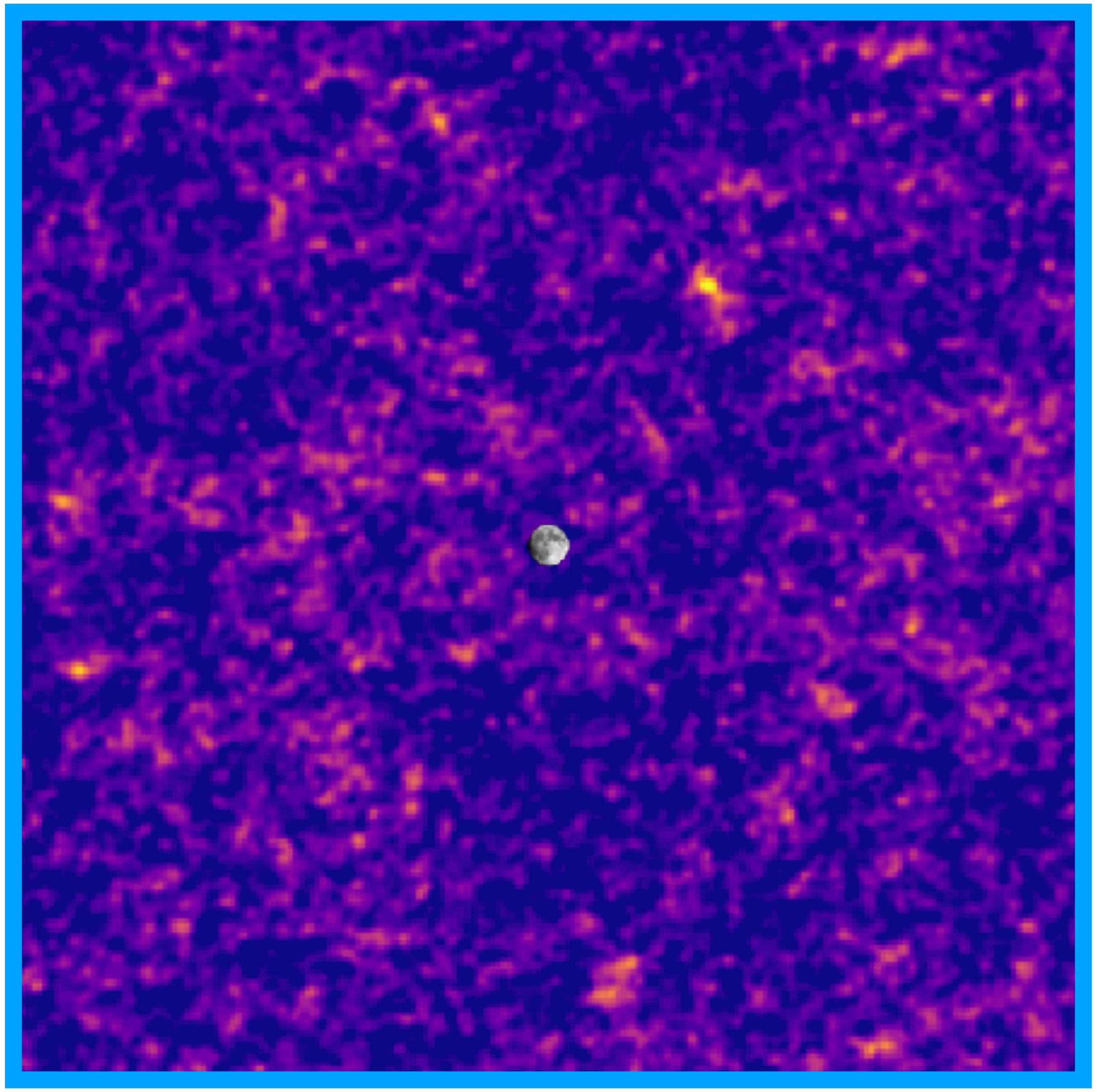
Smaller scales



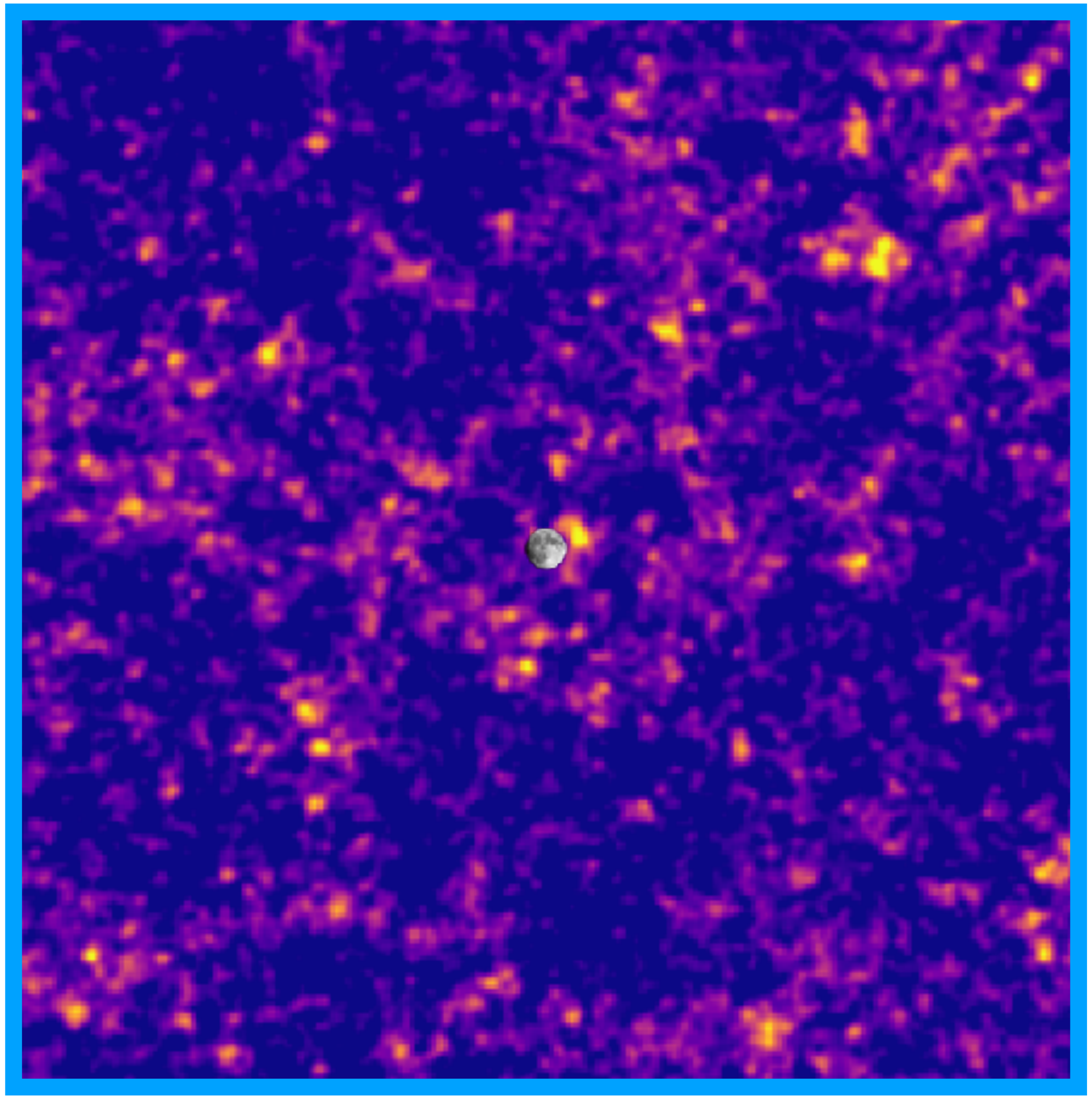
Improved analysis methods



LSS tracer: mass maps



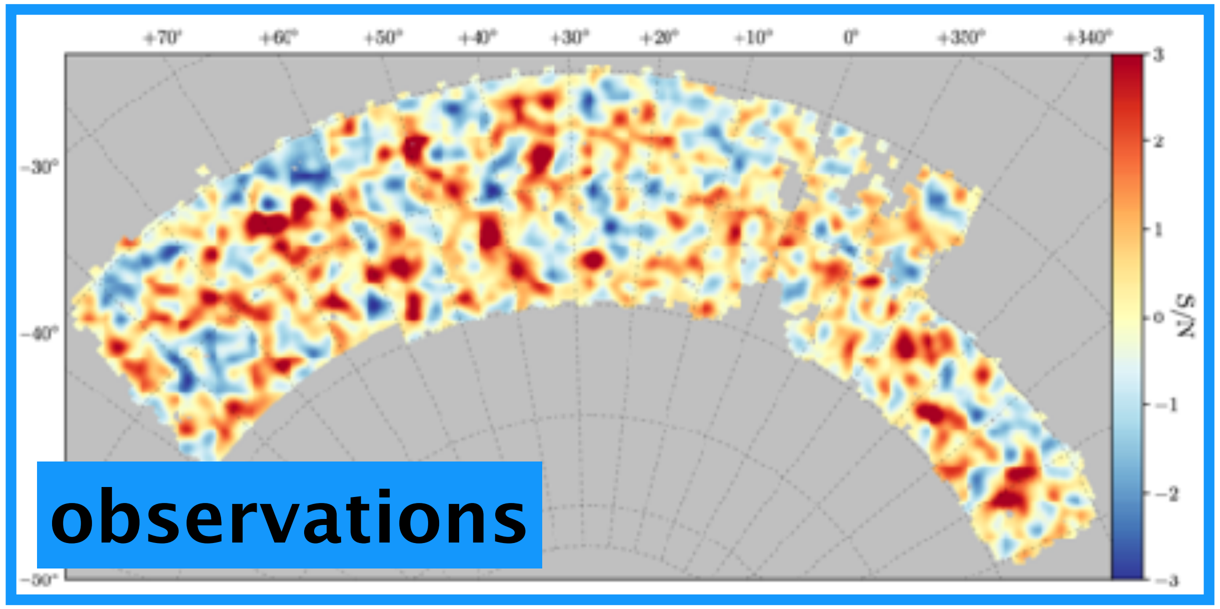
low σ_8 low Ω_m

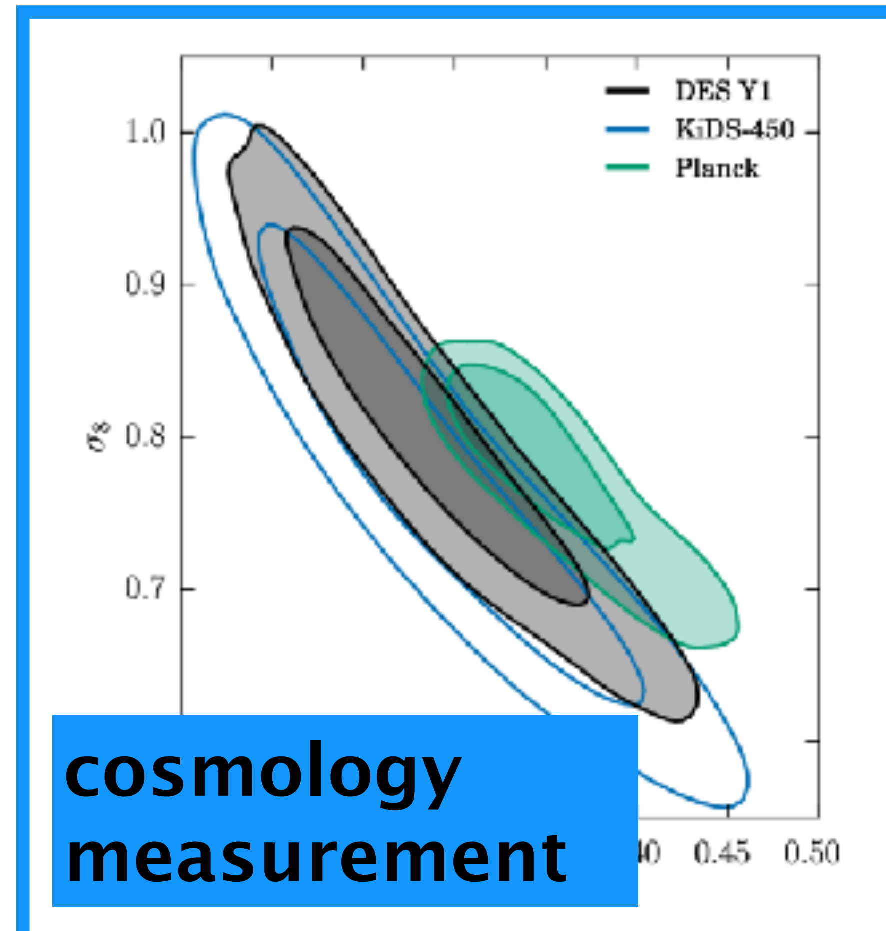


high σ_8 high Ω_m

Cosmological parameter inference

Chang et al. (+TK) 2017 1708.01535



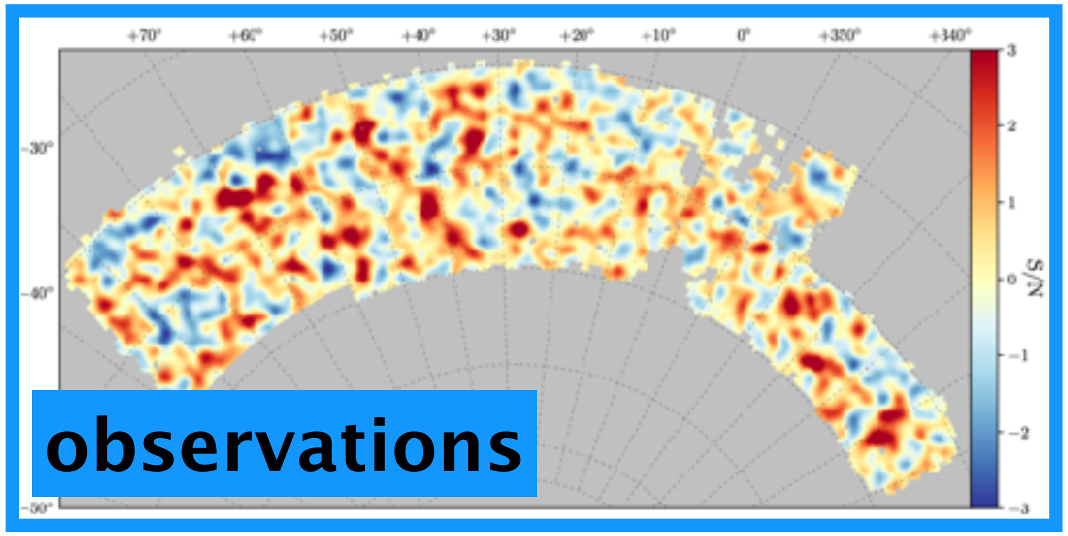


amplitude of matter fluctuations σ_8

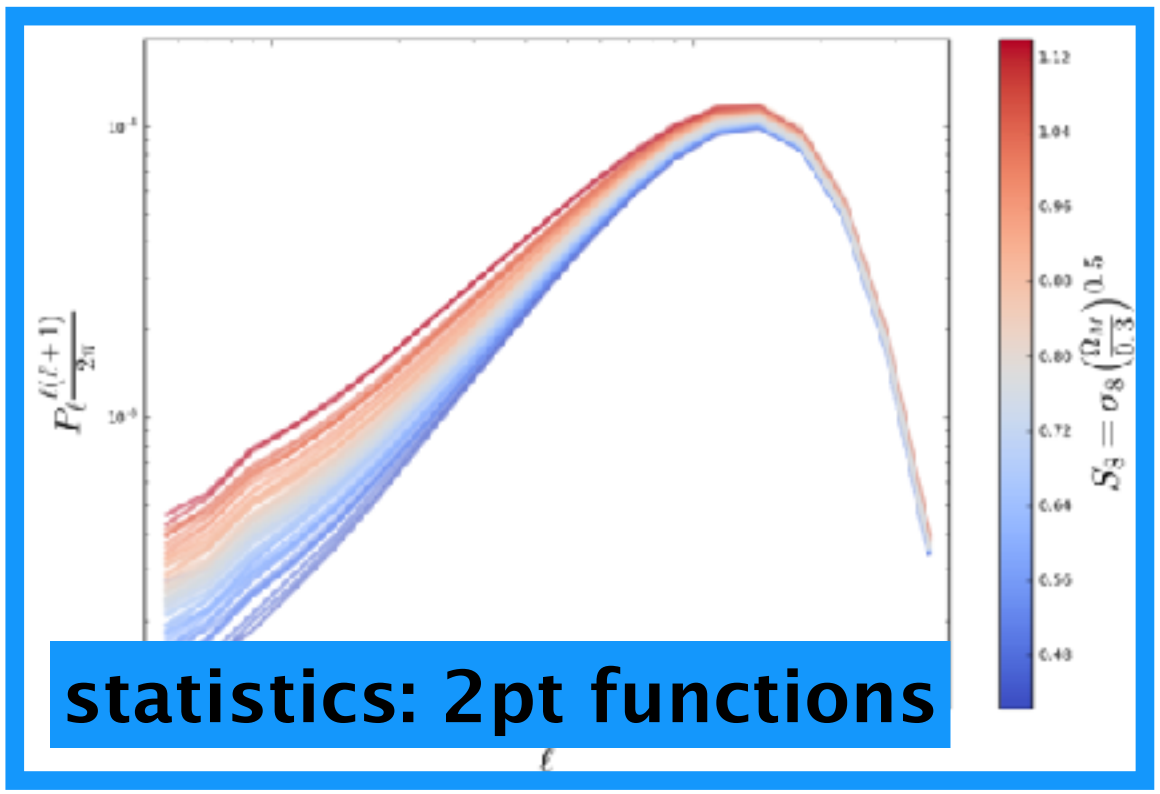
matter density Ω_m

DES Collaboration (+TK) 2017 1708.01530

Traditional inference



observations

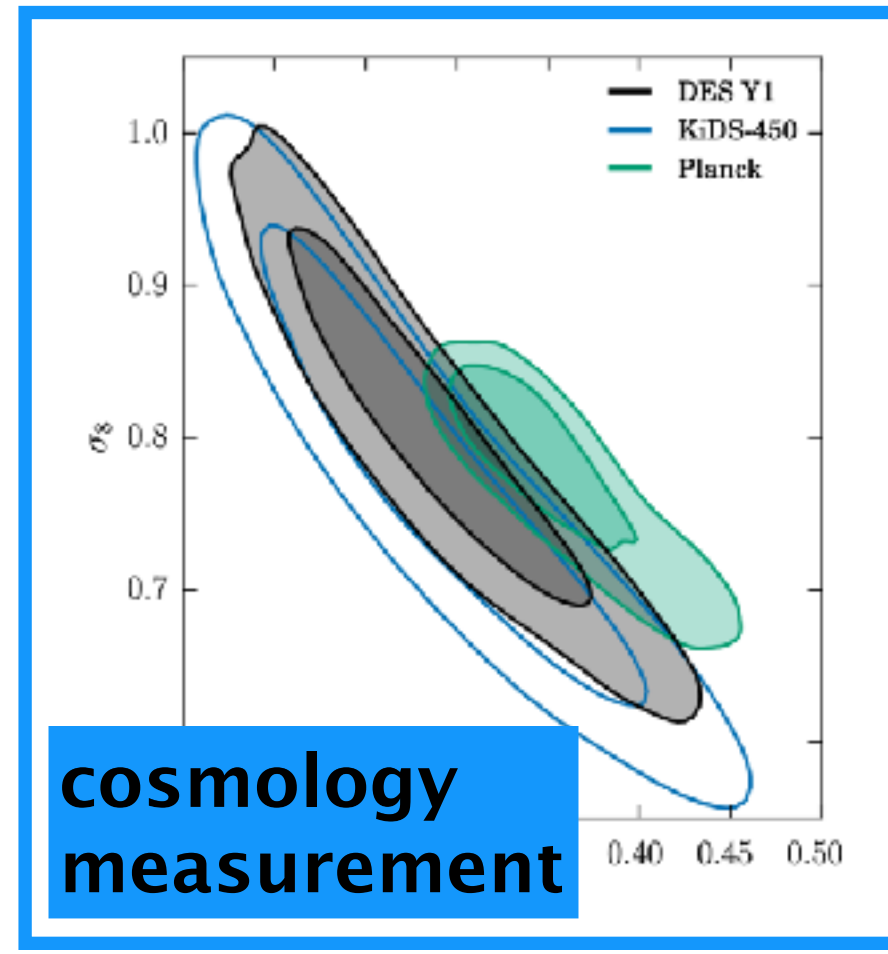


statistics: 2pt functions

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

theory prediction: analytical

σ_8



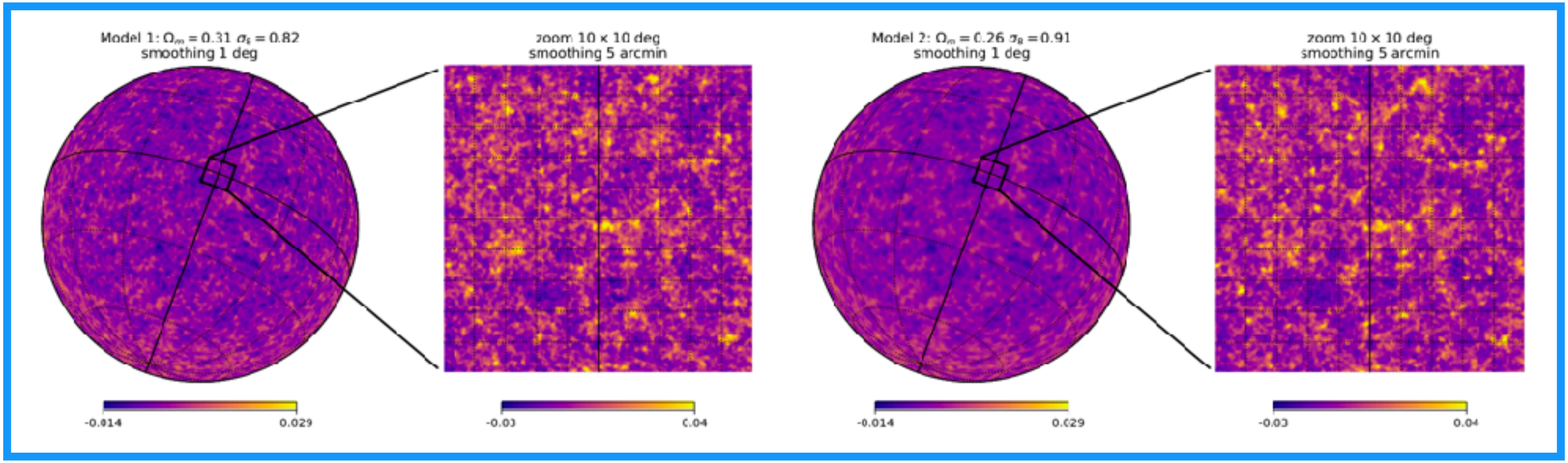
cosmology measurement

Ω_m

Degeneracy between Ω_m and σ_8

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

Non-Gaussian statistics

Three-point functions

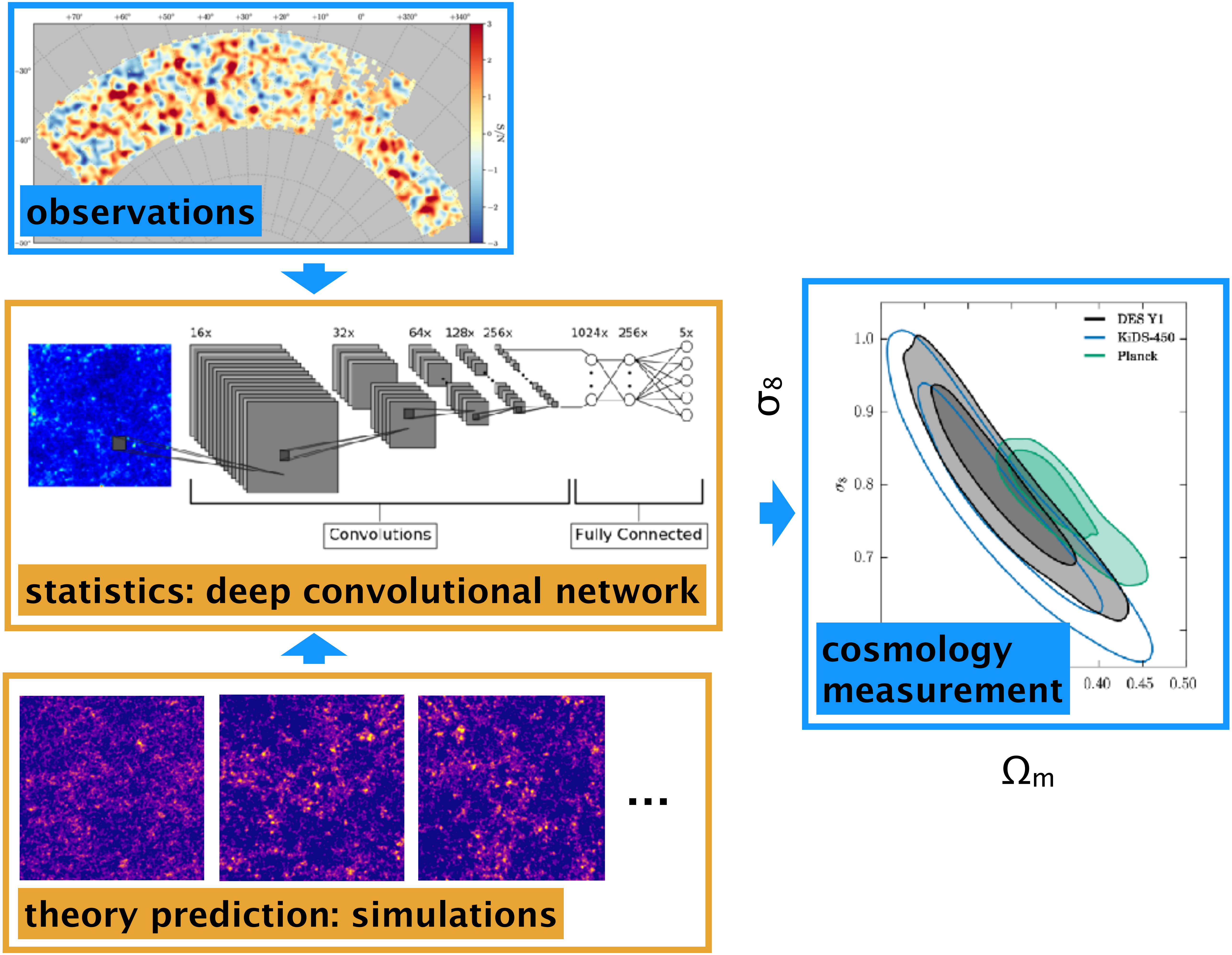
Higher-order moments of convergence

Full convergence distribution

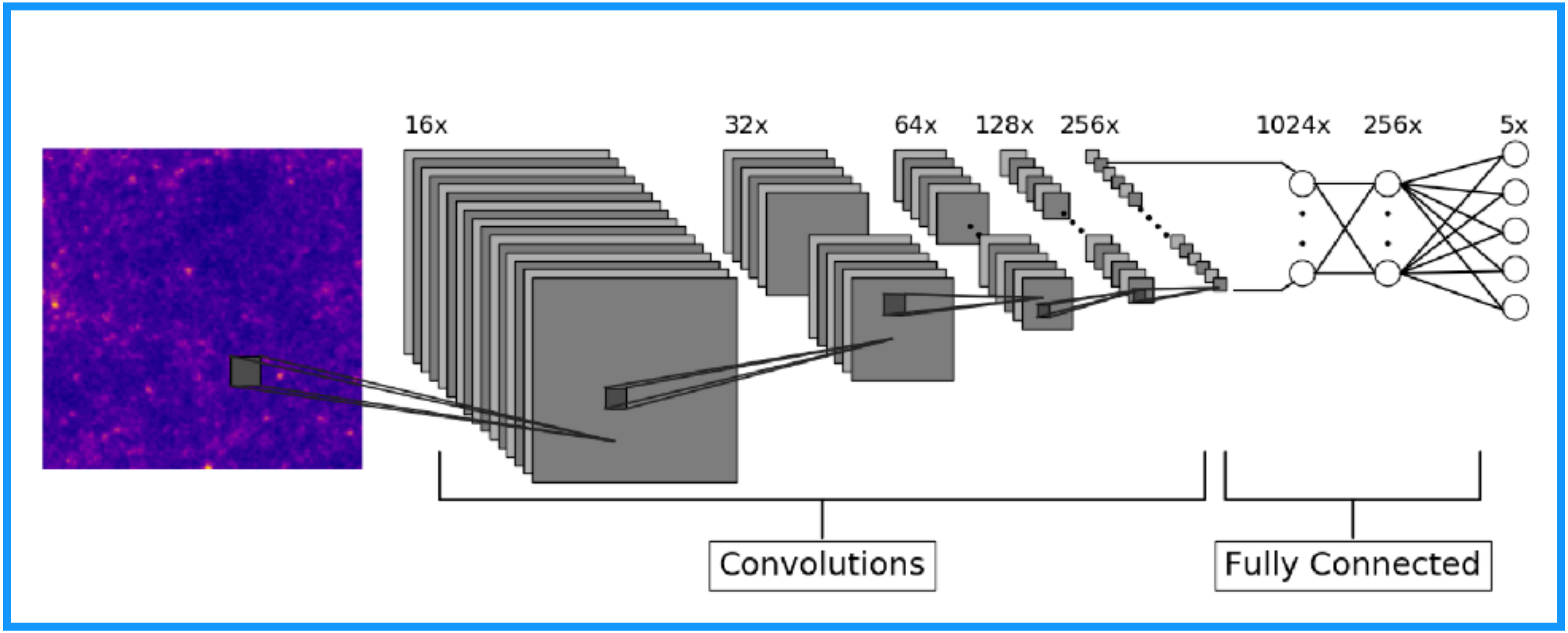
Minkowski functionals

Peak statistics

Deep neural networks


observations
16x
32x
64x
128x
256x
1024x
256x
5x
Convolutions
Fully Connected
statistics: deep convolutional network
theory prediction: simulations
...
σ8
DES Y1
KiDS-450
Planck
1.0
0.9
0.8
0.7
0.40
0.45
0.50
cosmology
measurement
Ωm

Deep learning analysis of mass maps



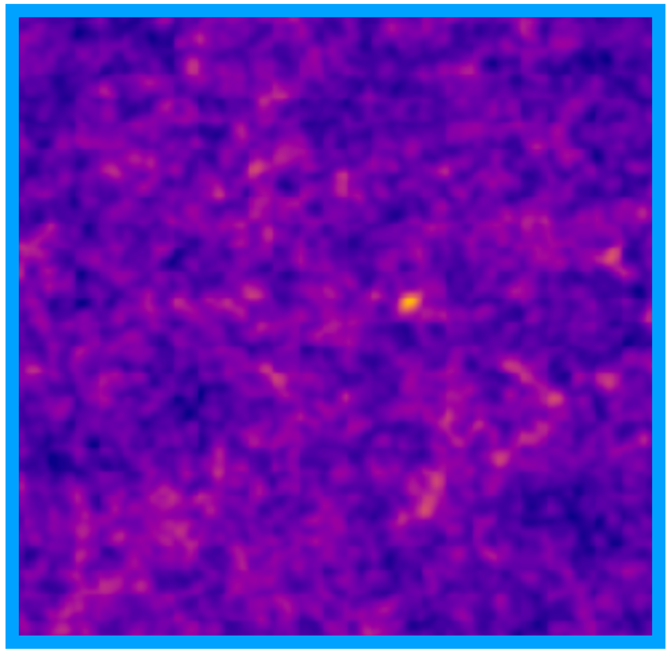
5 convolutional layers, 2 fully connected layers

10 deg^2 convergence maps

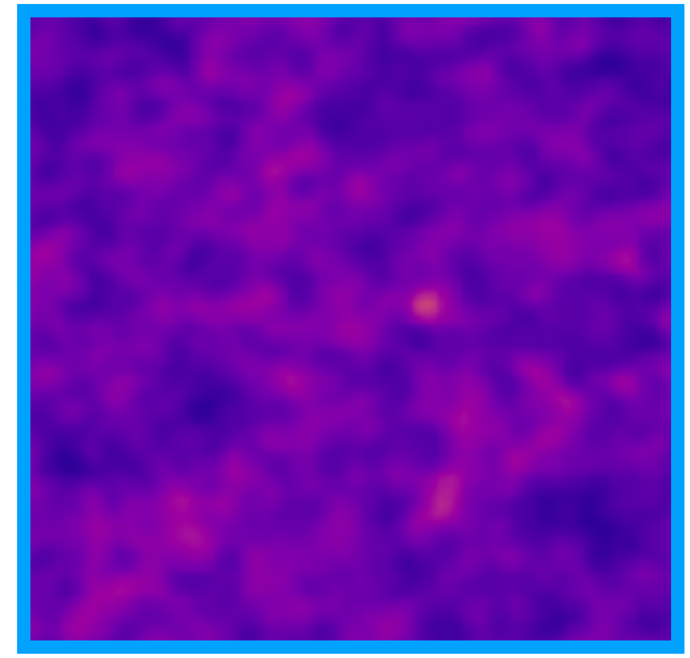
Forecast using simulated data

Fluri, TK, et al. 1807.08732

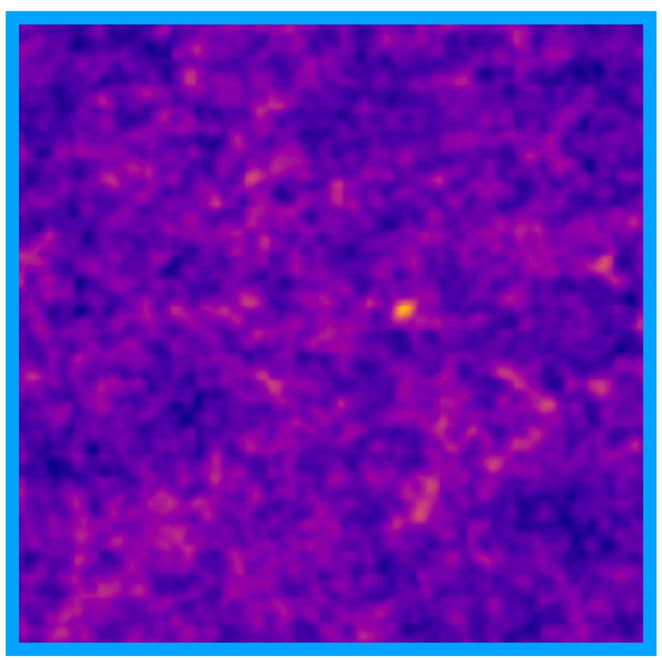
What is the advantage of deep learning for current and upcoming data?



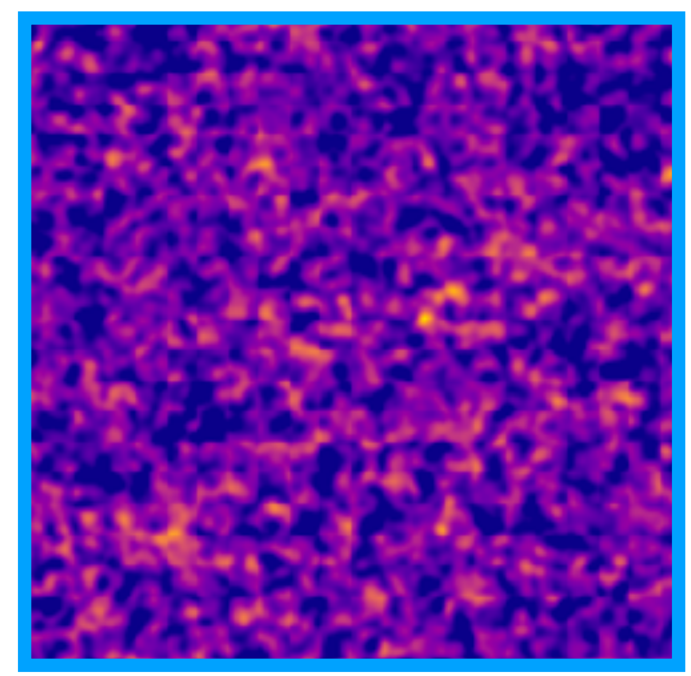
add smoothing →



quality of simulations

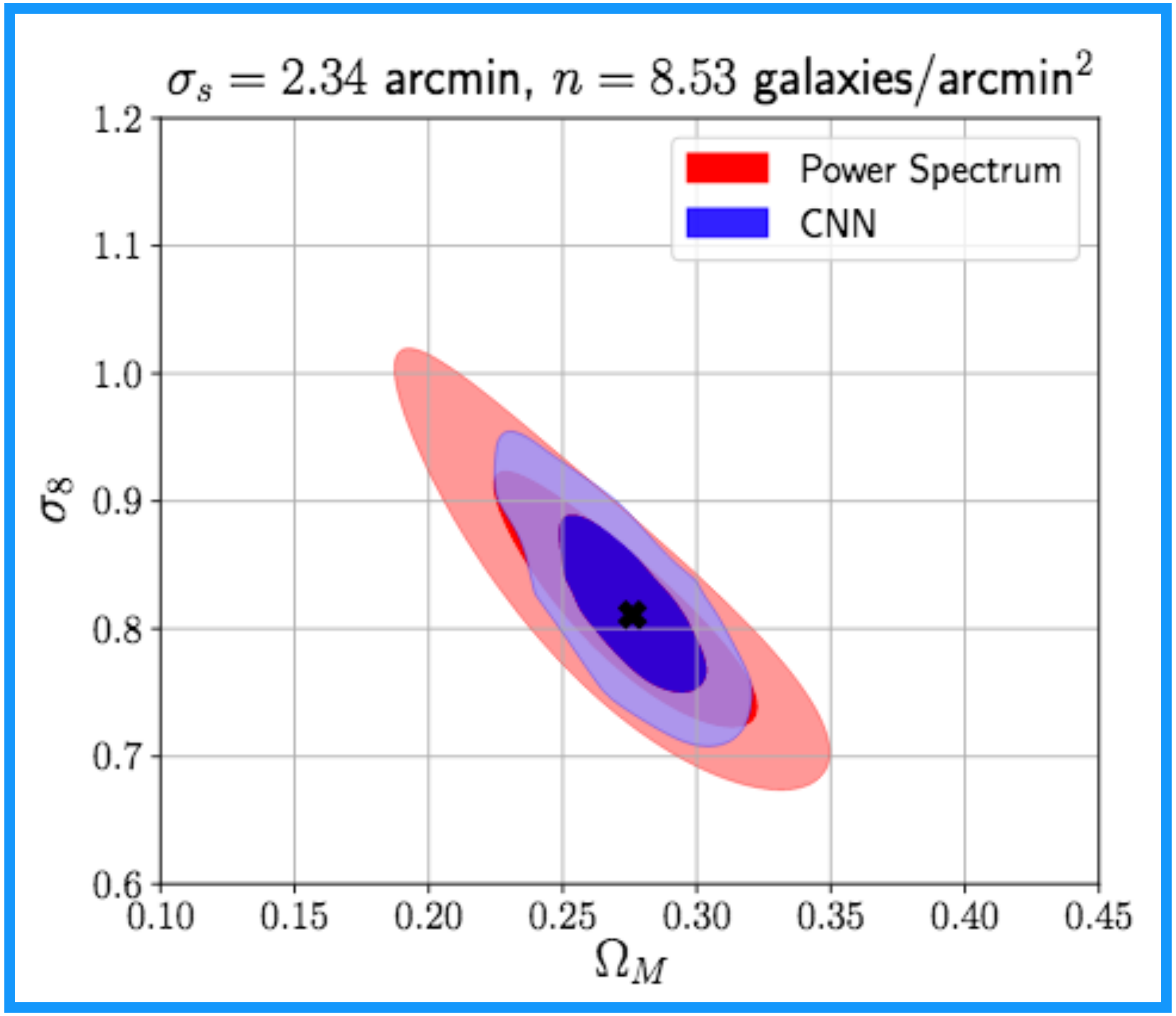


add noise →



quality of observations

Deep learning captures more information

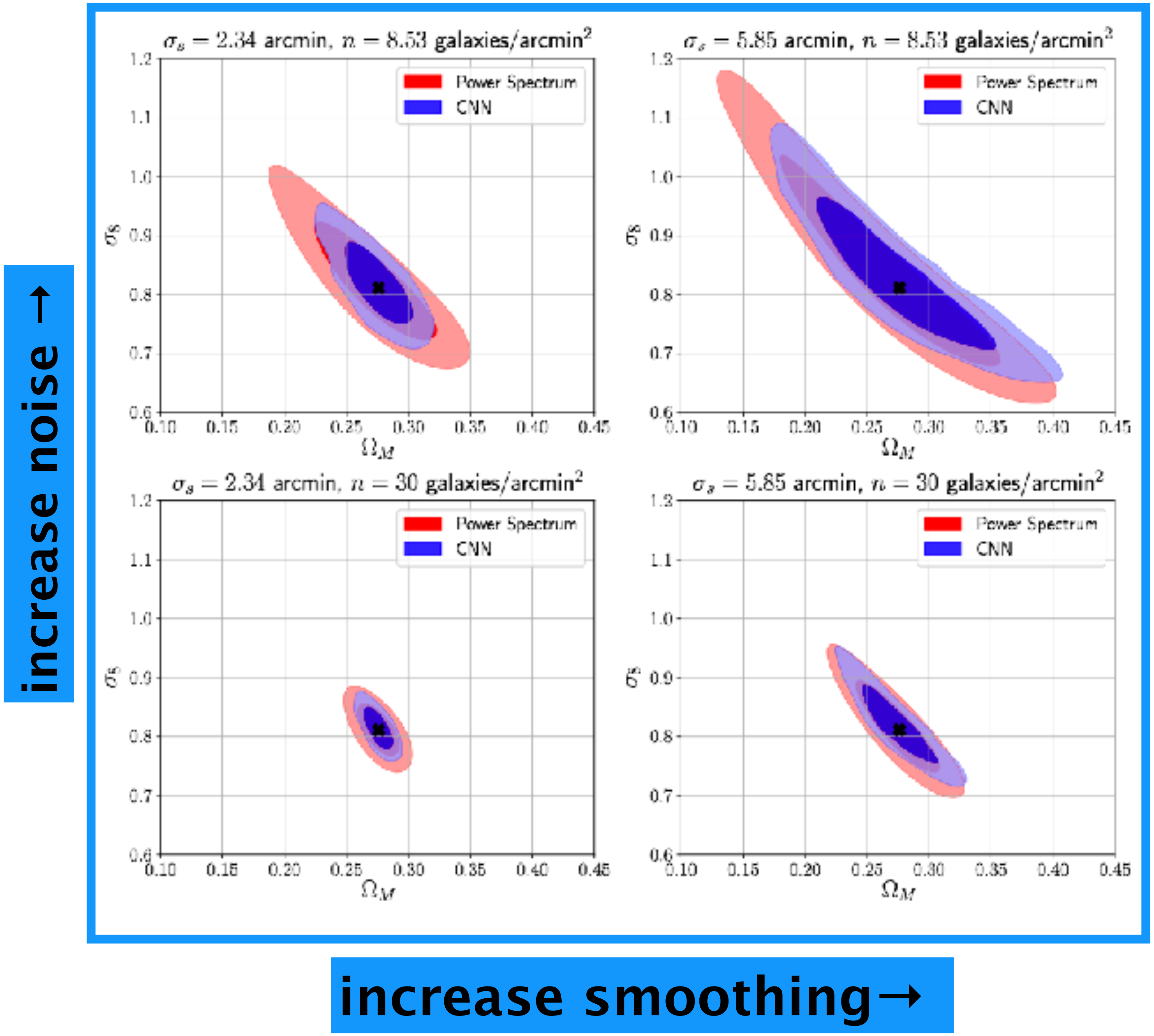


40% increase in constraining power!

Forecast using simulated data for Stage 2-like data

Fluri, TK, et al. 1807.08732

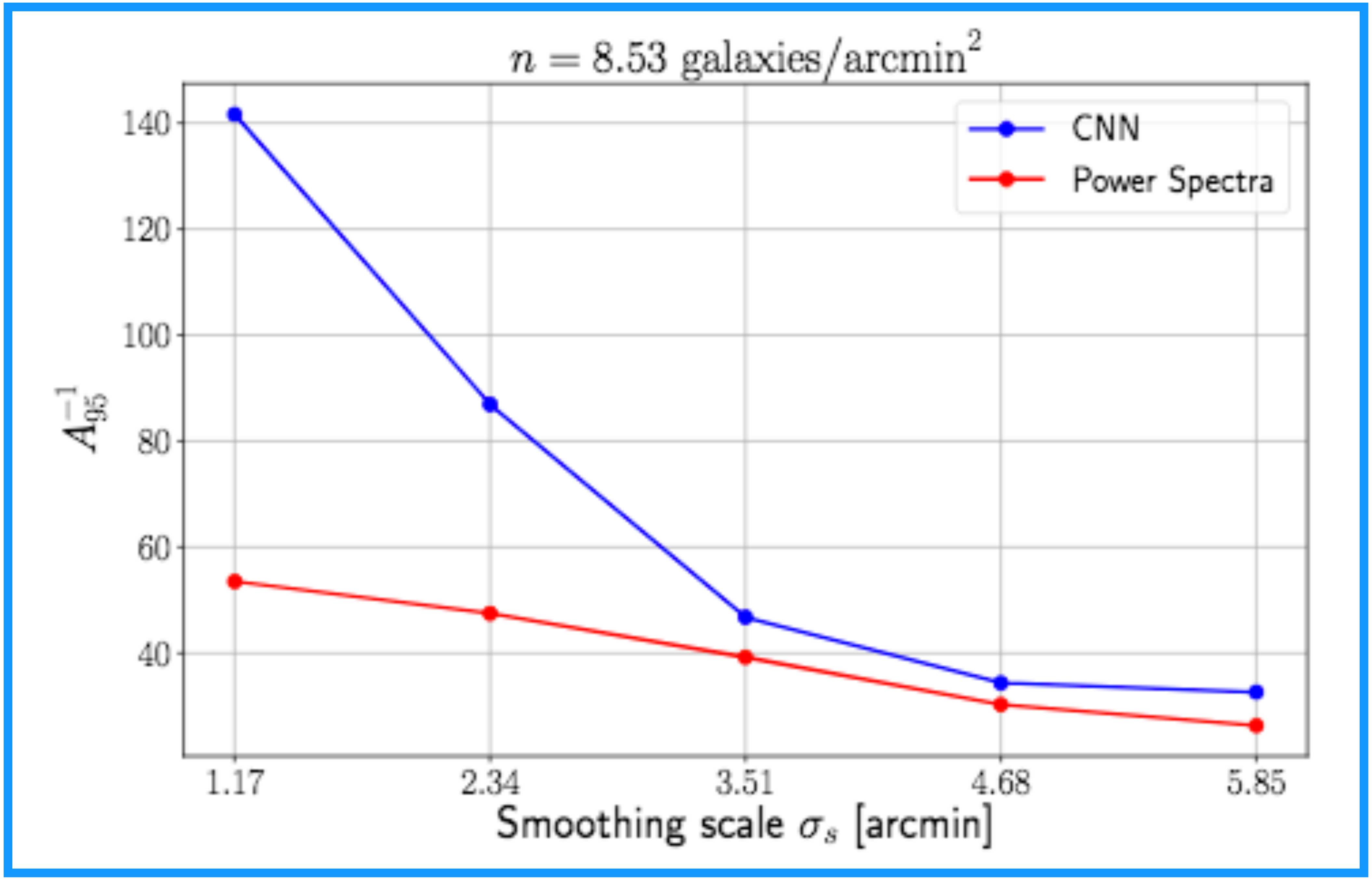
Deep learning captures more information



Gain in constraining power depends on noise level and smoothing scale

Fluri, TK, et al. 1807.08732

Deep learning captures more information



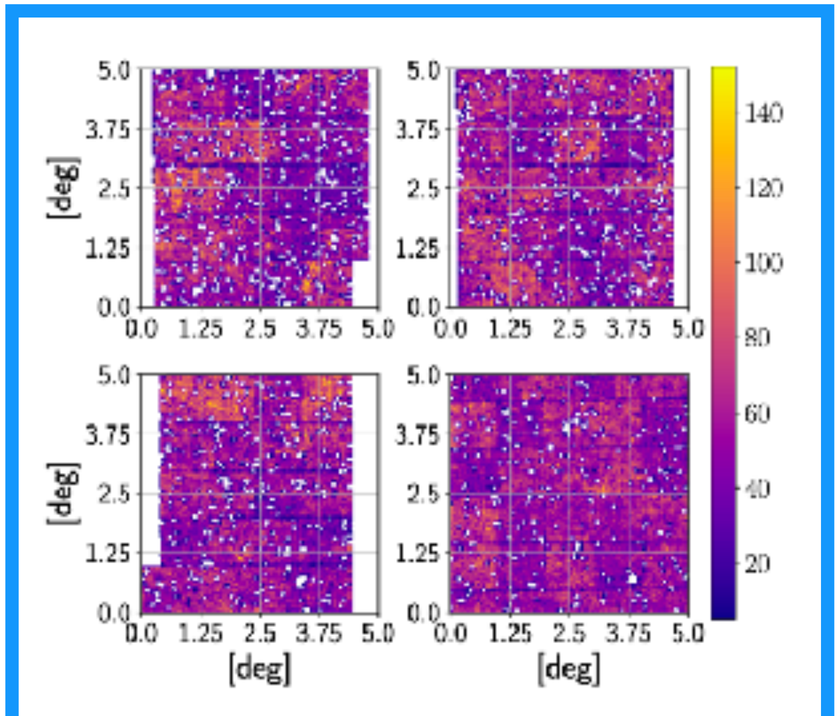
inverse contour area

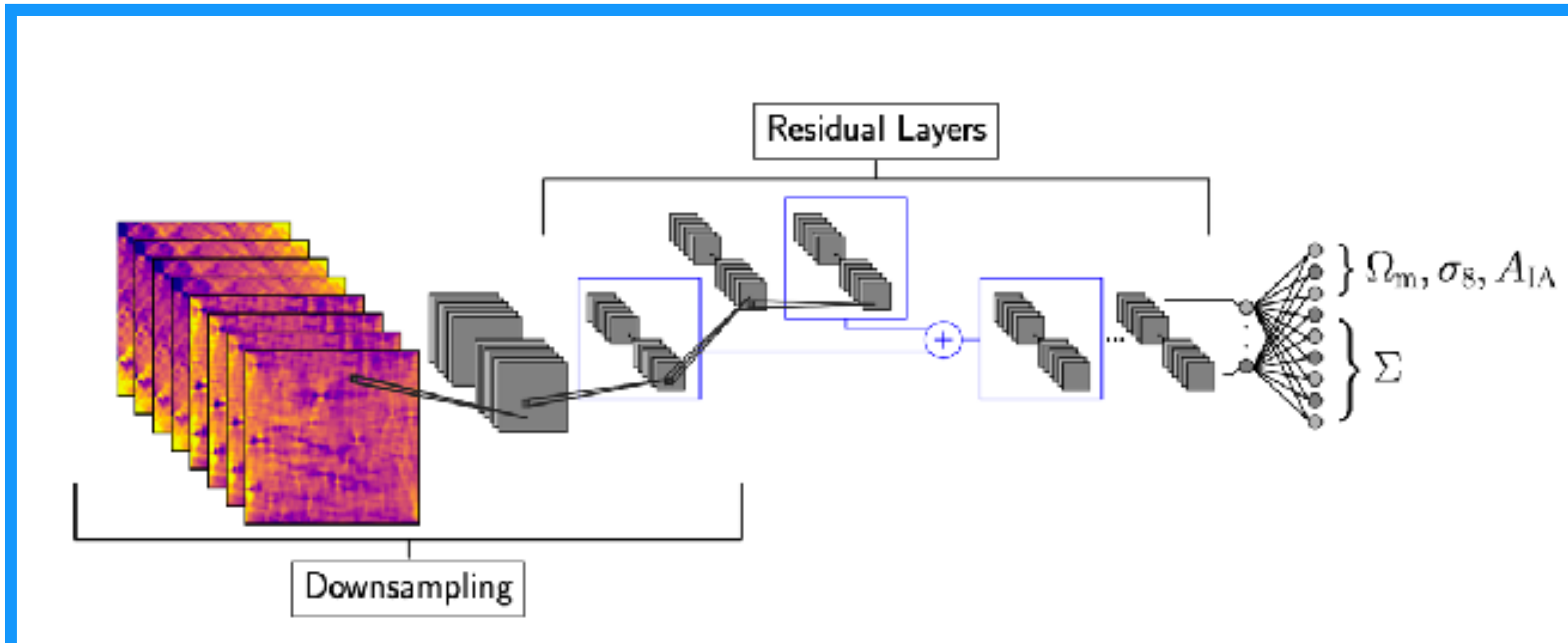
← worse better →

← smoothing scale →

Fluri, TK, et al. 1807.08732

Analysis of KiDS-450 with deep learning





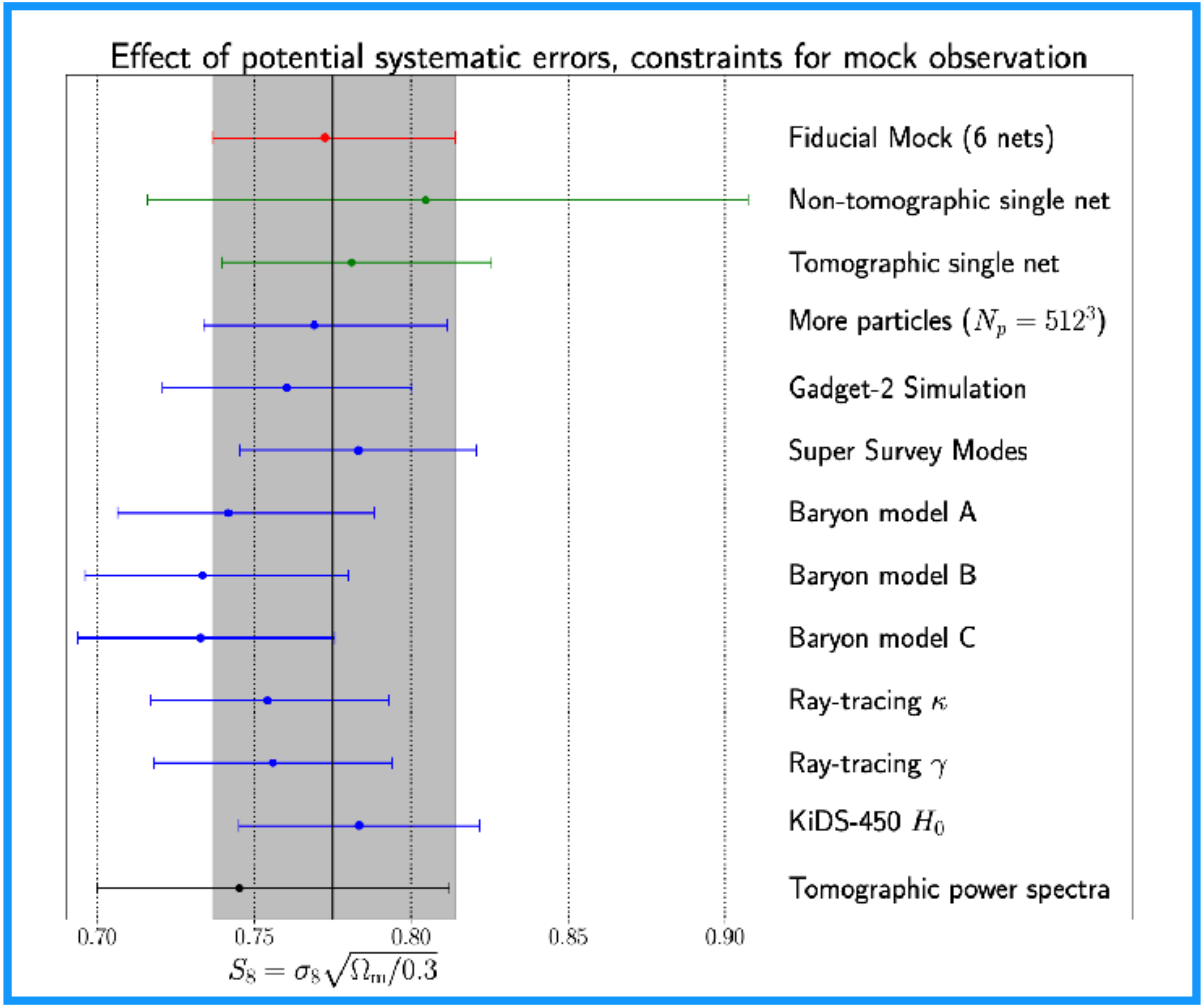
data:
20 x 4
tomographic
shear maps

network: 3 parameter output

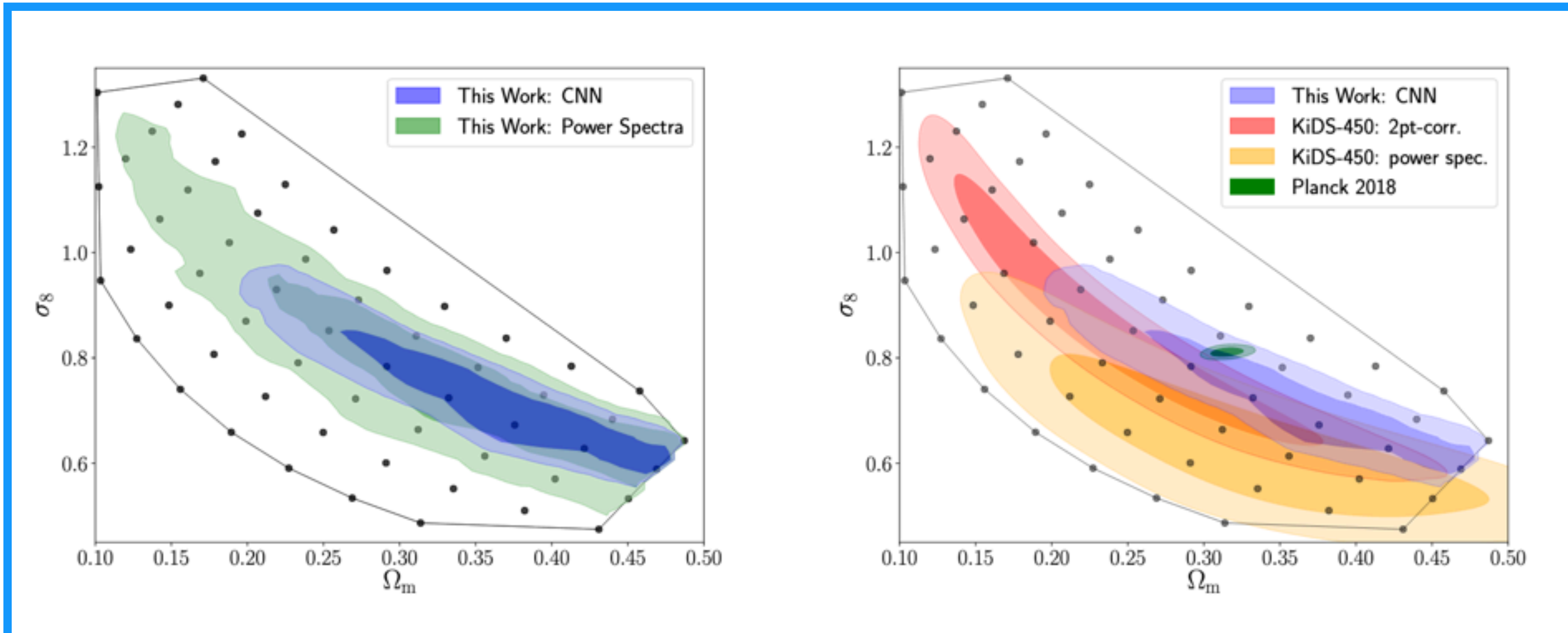
likelihood analysis

Fluri, TK, et al. 1906.03156

KiDS-450: robustness to simulation details



Analysis of KiDS-450 with deep learning



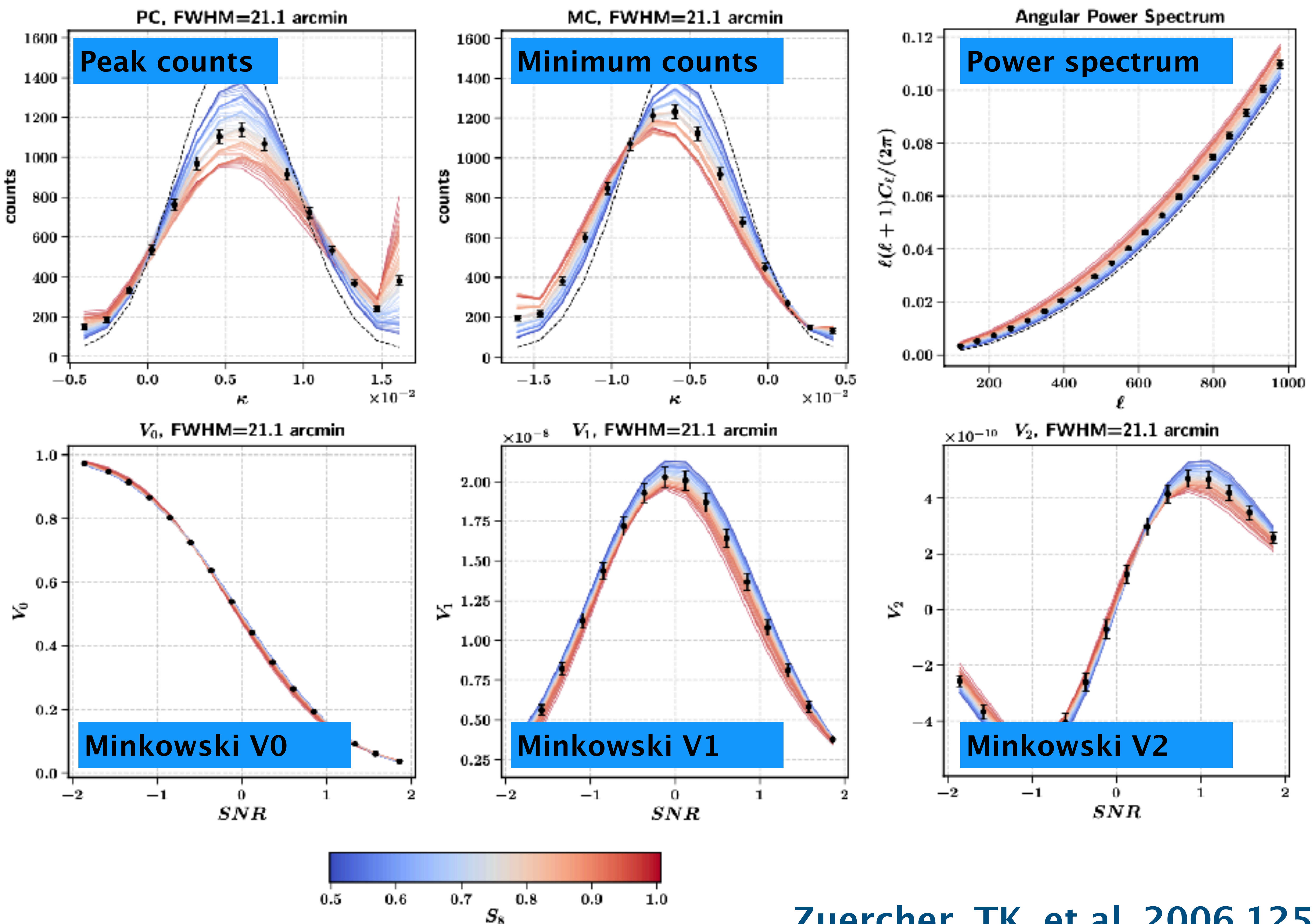
$S_8 = \sigma_8(\Omega_m/0.3)^{0.5} = 0.777 +/- 0.037$
$A_{IA} = 1.398 +/- 0.774$

Gaussian smoothing with σ=2.34 arcmin

Blinded analysis

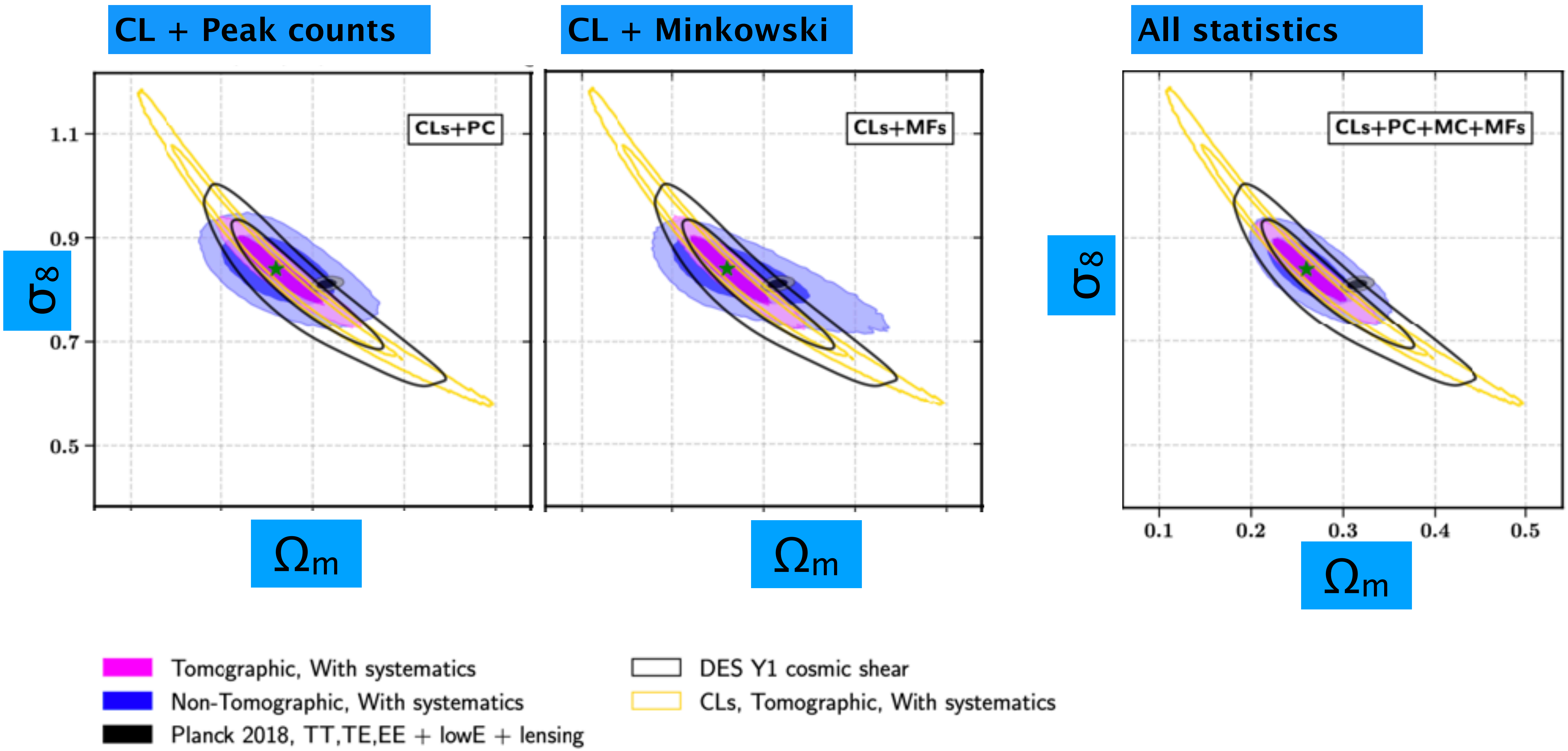
Fluri, TK, et al. 1906.03156

Hand-designed statistics



Zuercher, TK, et al. 2006.12506

Hand-picked statistics: forecast for Stage 3 surveys

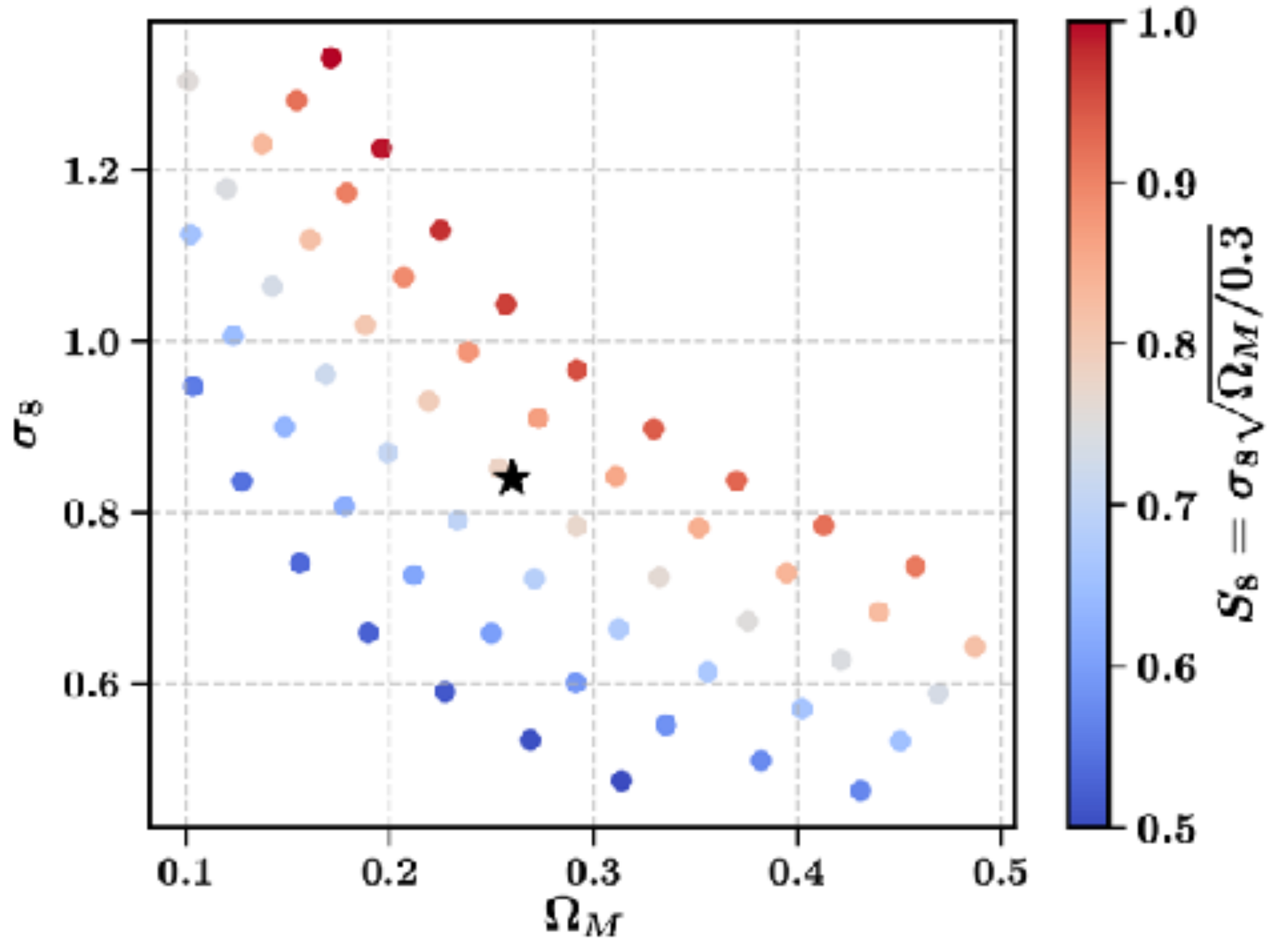


- Using only large and intermediate scales
- Gaussian smoothing with FWHM=21 arcmin
- Starting to constrain Ω_m

Zuercher, TK, et al. 2006.12506

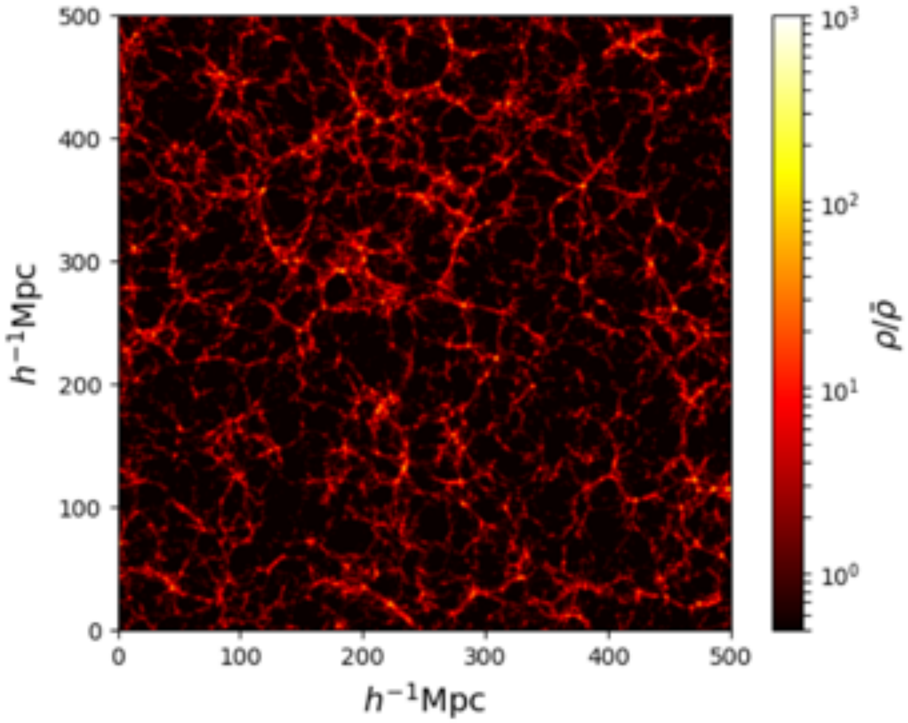
Large simulation grids

- Full sky convergence maps
- Ω_{m}, σ_{8}, A_{IA} + systematics
- PkdGrav3
- 900 Mpc/h, 768^{3} particles
- 14 replications in each dimension up to z=3
- 87 shells per simulation



Zuercher, TK, et al. 2006.12506

Quichote simulations



Name	Ω_m	Ω_b	h	n_s	σ_8	M_ν(eV)	w	realizations	simulations	ICs	$N_c^{1/3}$	$N_\nu^{1/3}$
Fid	0.3175	0.049	0.6711	0.9624	0.834	0	-1	15000 500 500 1000 100	standard standard paired fixed standard standard	2LPT Zeldovich 2LPT 2LPT 2LPT	512 512 512 256 1024	0 0 0 0 0
Ω_m^+	0.3275	0.049	0.6711	0.9624	0.834	0	-1	500 500	standard paired fixed	2LPT	512	0
Ω_m^-	0.3075	0.049	0.6711	0.9624	0.834	0	-1	500 500	standard paired fixed	2LPT	512	0
Ω_b^{++}	0.3175	0.051	0.6711	0.9624	0.834	0	-1	500 500	standard paired fixed	2LPT	512	0
Ω_b^+	0.3175	0.050	0.6711	0.9624	0.834	0	-1	500	paired fixed	2LPT	512	0
Ω_b^-	0.3175	0.048	0.6711	0.9624	0.834	0	-1	500	paired fixed	2LPT	512	0
Ω_b^{--}	0.3175	0.047	0.6711	0.9624	0.834	0	-1	500 500	standard paired fixed	2LPT	512	0
h^+	0.3175	0.049	0.6911	0.9624	0.834	0	-1	500 500	standard paired fixed	2LPT	512	0
h^-	0.3175	0.049	0.6511	0.9624	0.834	0	-1	500 500	standard paired fixed	2LPT	512	0
n_s^+	0.3175	0.049	0.6711	0.9824	0.834	0	-1	500 500	standard paired fixed	2LPT	512	0
n_s^+	0.3175	0.049	0.6711	0.9424	0.834	0	-1	500 500	standard paired fixed	2LPT	512	0
σ_8^+	0.3175	0.049	0.6711	0.9624	0.849	0	-1	500 500	standard paired fixed	2LPT	512	0
σ_8^-	0.3175	0.049	0.6711	0.9624	0.819	0	-1	500 500	standard paired fixed	2LPT	512	0
M_ν^{+++}	0.3175	0.049	0.6711	0.9624	0.834	0.4	-1	500 500	standard paired fixed	Zeldovich	512	512
M_ν^{++}	0.3175	0.049	0.6711	0.9624	0.834	0.2	-1	500 500	standard paired fixed	Zeldovich	512	512
M_ν^+	0.3175	0.049	0.6711	0.9624	0.834	0.1	-1	500 500	standard paired fixed	Zeldovich	512	512
w^+	0.3175	0.049	0.6711	0.9624	0.834	0	-1.05	500	standard	Zeldovich	512	0
w^-	0.3175	0.049	0.6711	0.9624	0.834	0	-0.95	500	standard	Zeldovich	512	0
LH	[0.1 , 0.5]	[0.03 , 0.07]	[0.5 , 0.9]	[0.8 , 1.2]	[0.6 , 1.0]	0	-1	2000 2000 2000	standard fixed standard	2LPT	512 512 1024	0
LHνw	[0.1 , 0.5]	[0.03 , 0.07]	[0.5 , 0.9]	[0.8 , 1.2]	[0.6 , 1.0]	[0 , 1]	[-1.3 , -0.7]	5000	standard	Zeldovich	512	512
total	-	-	-	-	-	-	-	43100	-	-	-	-
	-	-	-	-	-	-	-	-	-	-	19696	10240

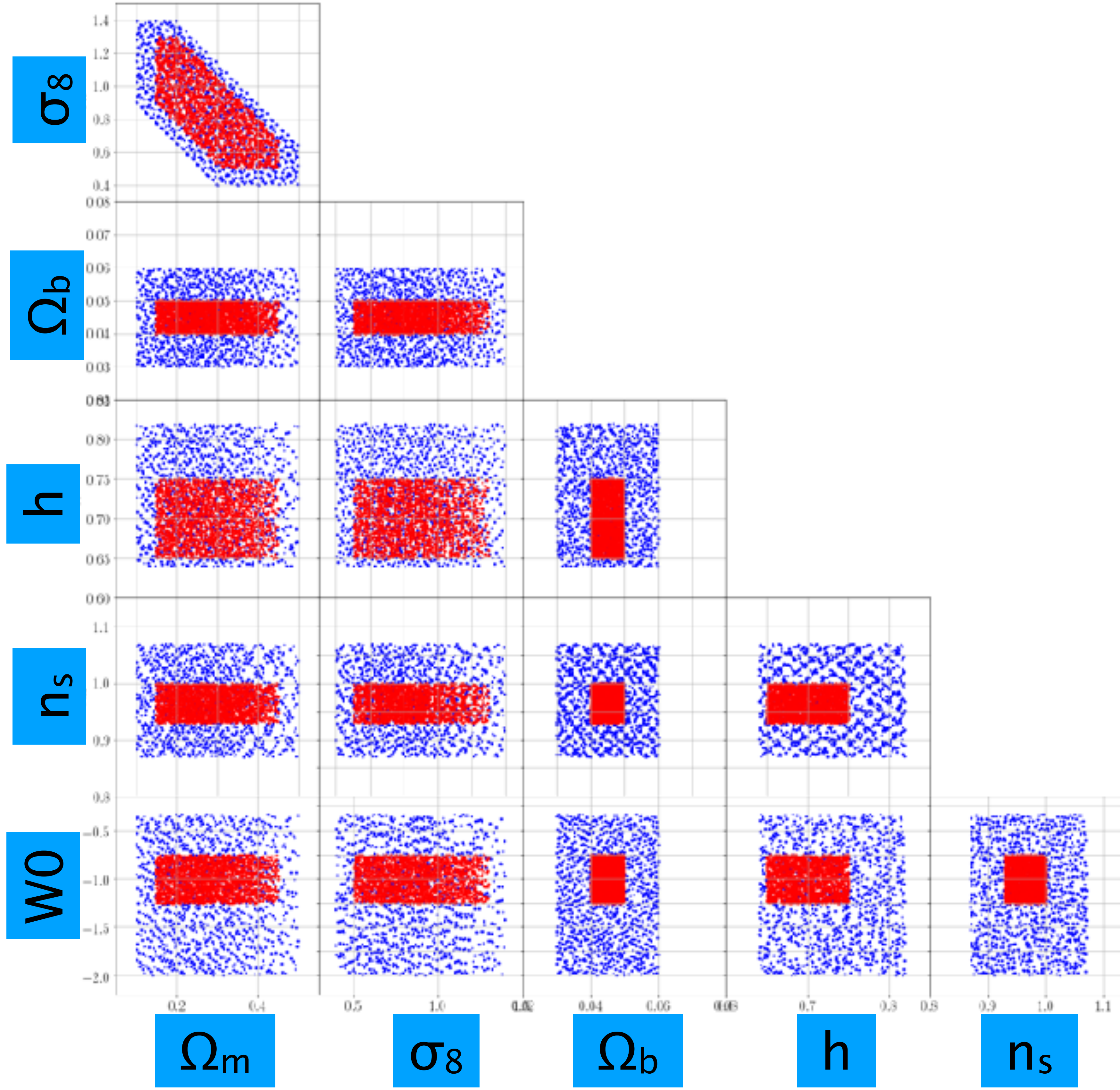
- 1 Gpc/h boxes
- 512^3 particles
- Snapshots at z=0, 0.5, 1, 2, 3
- public data
- 7000 cosmological models

Villaescusa-Navarro et al. 2019, 1909.05273

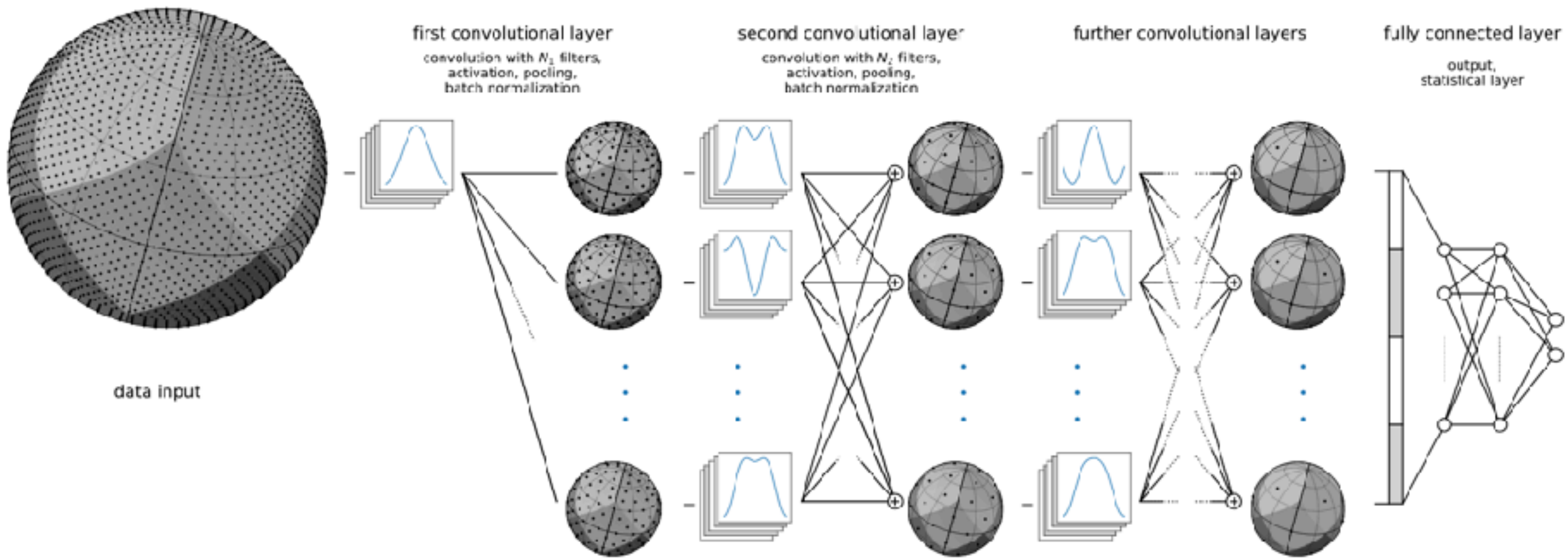
CSCS production project: "Measuring Dark Energy with Deep Learning"

TK, Janis Fluri, Joachim Stadel, Aurel Schneider

- 1500 Mpc/h,
- 1024^3 particles
- 25000 independent simulations
- 5 cosmological parameters
- Baryonic feedback+intrinsic alignment
- 100 maps per sim
- Halo catalogs
- 0.7m GPU node hours
- 400 TB light cone output



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



github.com/SwissDataScienceCenter/DeepSphere

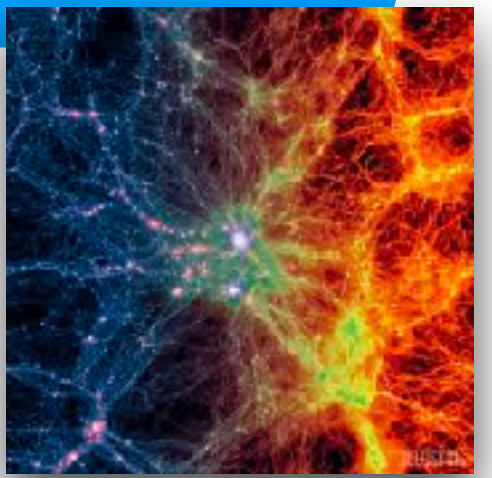
- Various CNN architectures on the sphere with Healpix sampling
- Using graph representation, useful for analysis of data on part of the sphere
- Tensorflow interface

Perraudin, TK, et al. 1810.12186

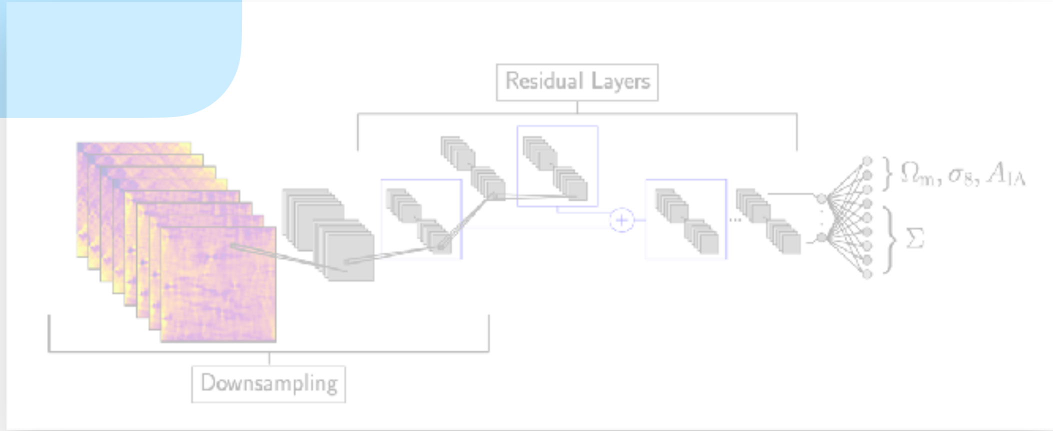
Sources of cosmological information

More data

Smaller scales

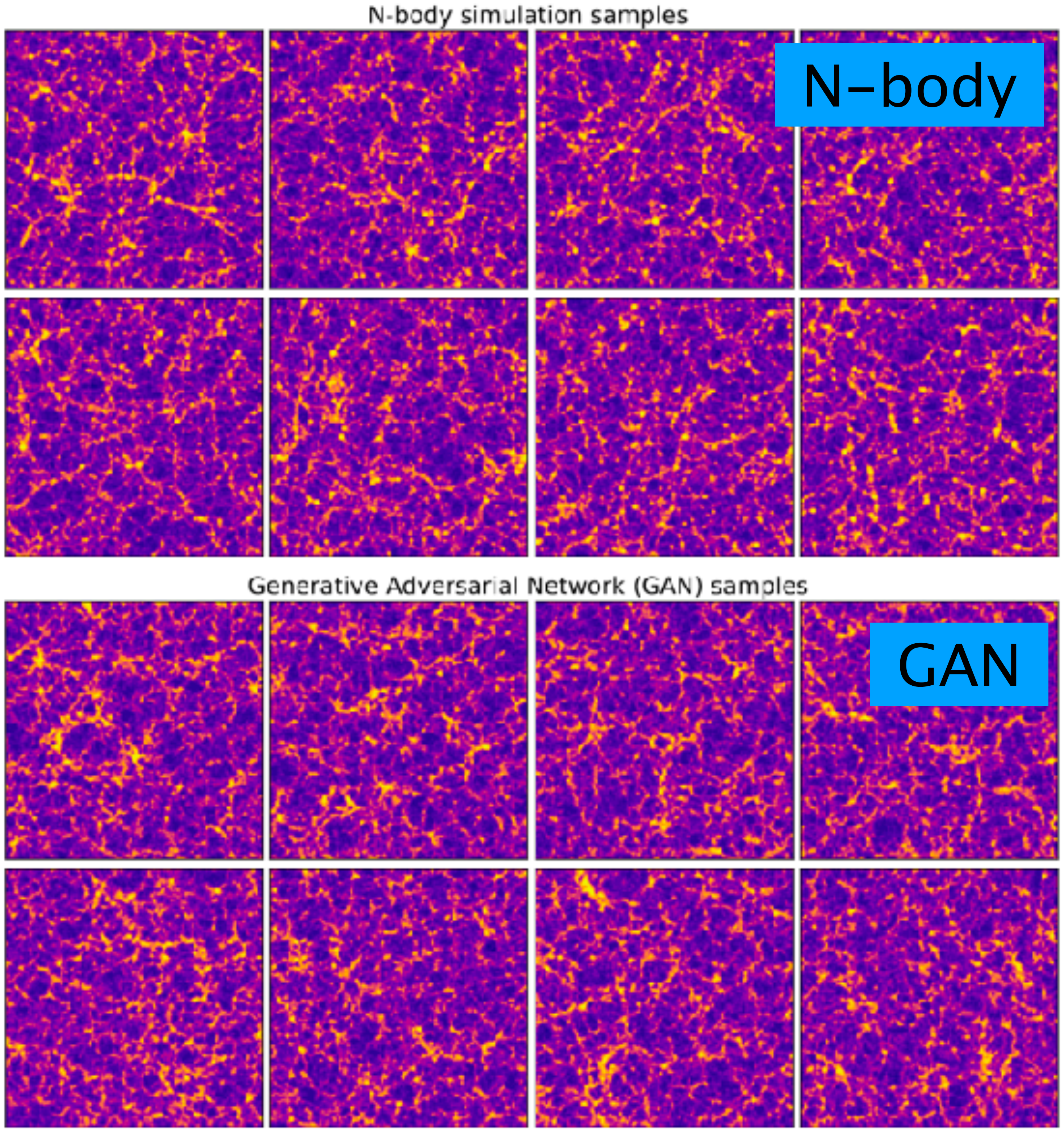


Improved analysis methods



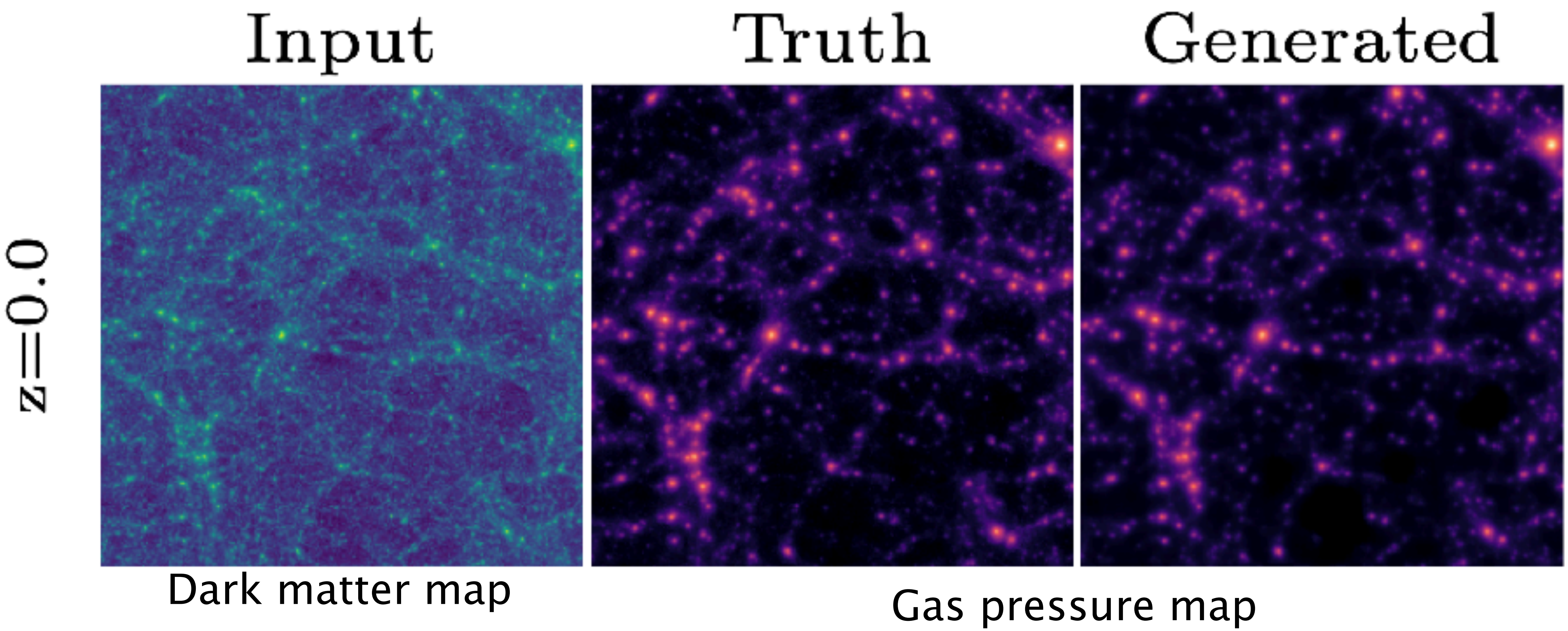
Simulations with generative models

- Training on 2D images of N-body simulations of cosmic web
- Generative model samples new realisations
- New realisations are statistically consistent with training set
- Good agreement on summary statistics



Rodriguez, TK, et al. 2018, 1801.09070

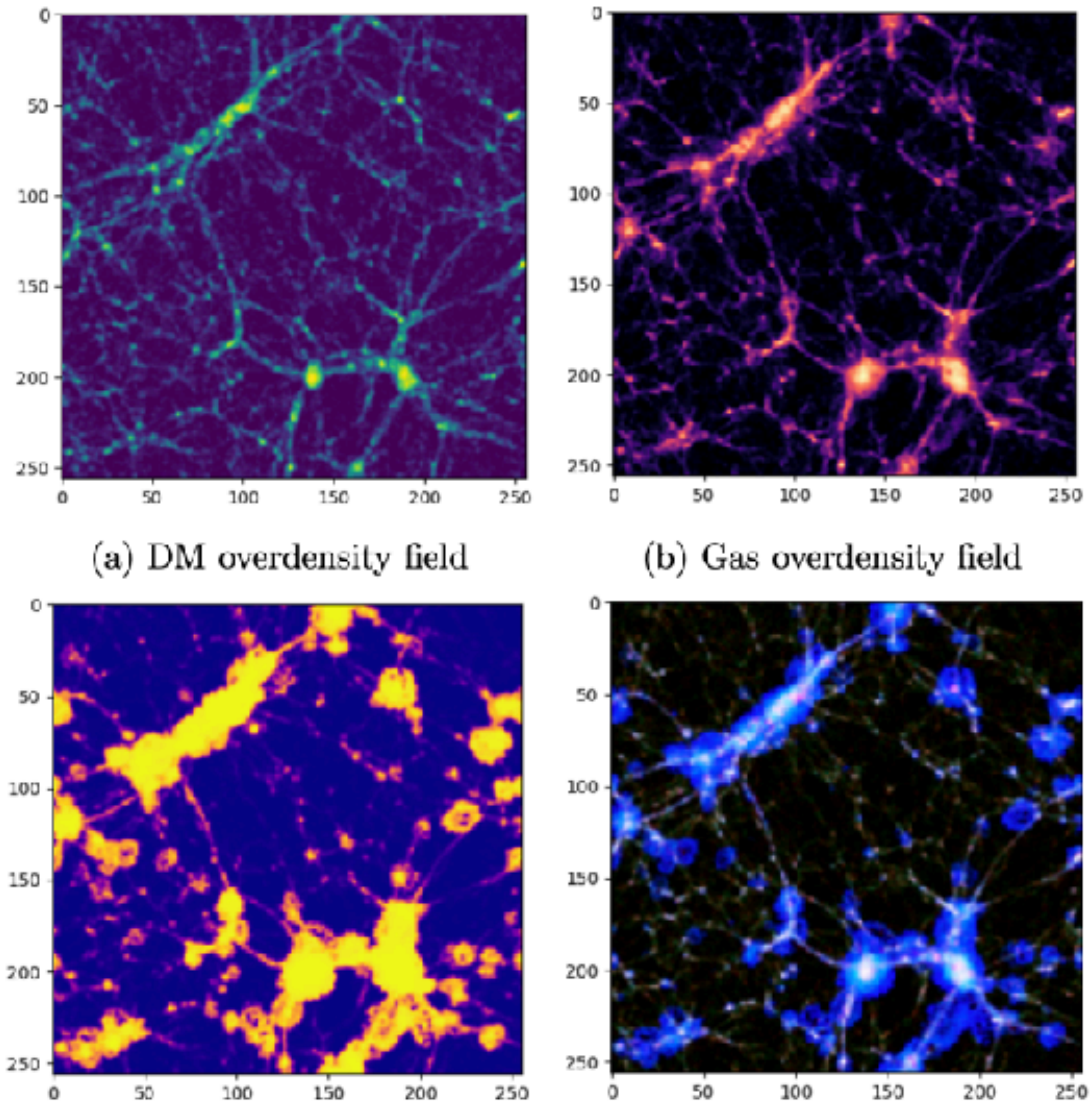
"Painting with baryons: augmenting N-body simulations with gas using deep generative models"



- Using BAHAMAS simulations to create gas pressure maps for corresponding dark matter maps
- Using GAN and VAE

Troester et al. 2019, 1903.12173

"Towards Universal Cosmological Emulators with Generative Adversarial Networks"



(a) DM overdensity field

(b) Gas overdensity field

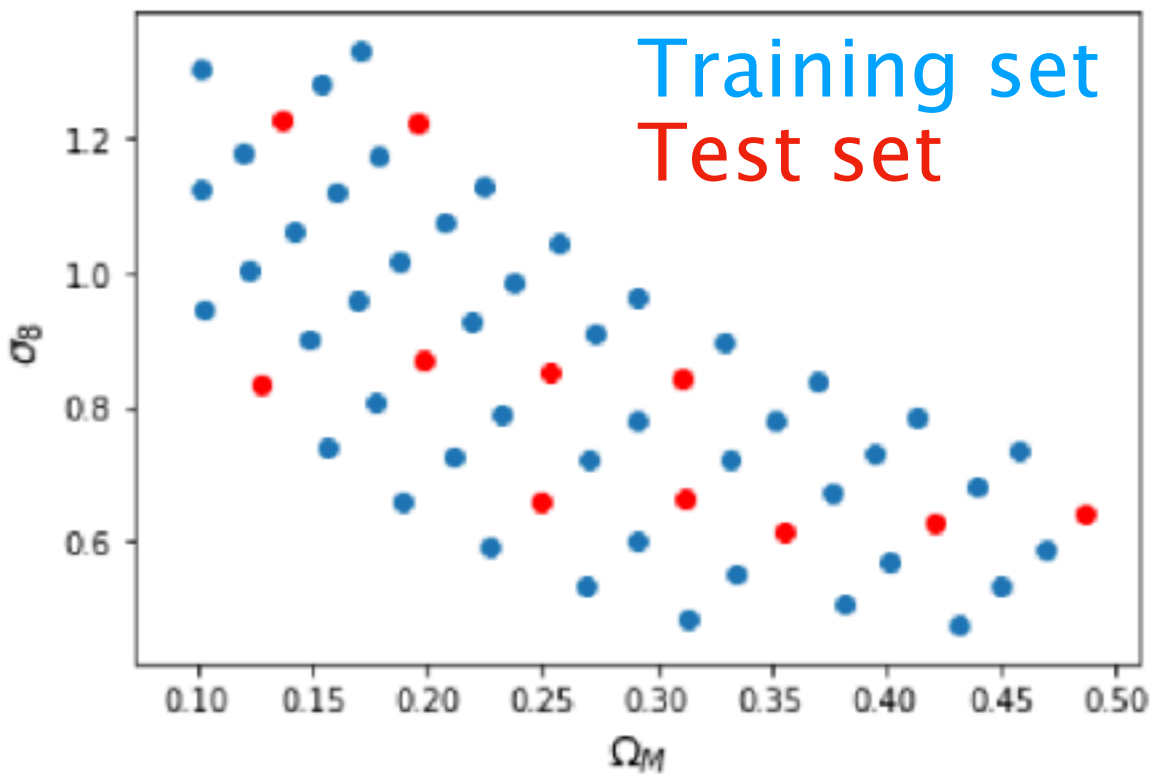
(c) Internal energy field

(d) All components combined

Figure 3: Samples from the Illustris simulation dataset used to train the GAN algorithm: 2-D slices of the different simulation components.

Tamosiunas et al. 2020, 2004.10223

"Emulation of cosmological mass maps with conditional generative adversarial networks”



- Interpolation to unseen cosmological parameters
- The emulator captures both the signal and it’s variability

Perraudin, TK, et al. 2020, 2004.08139

"Emulation of cosmological mass maps with conditional generative adversarial networks"

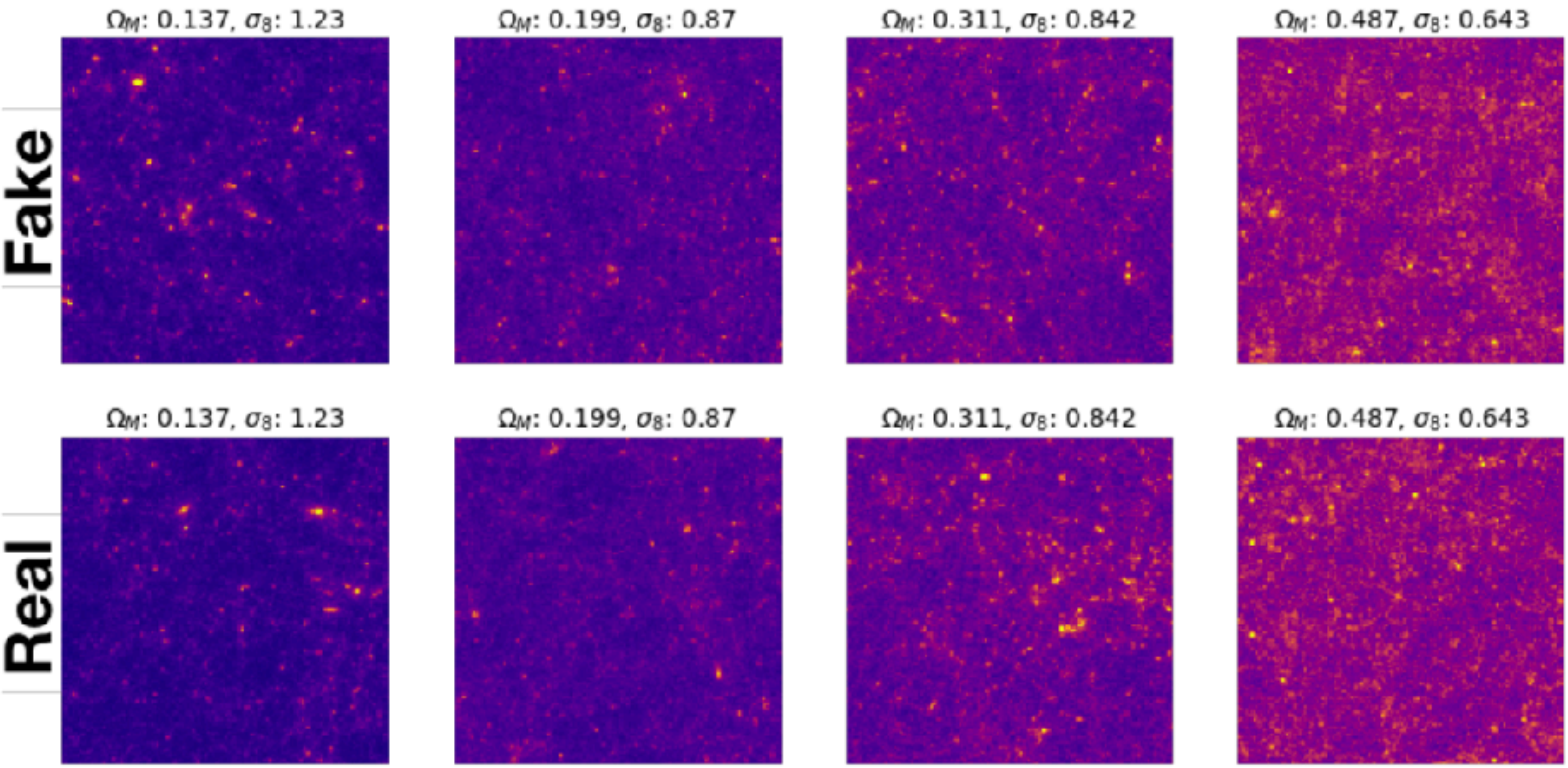
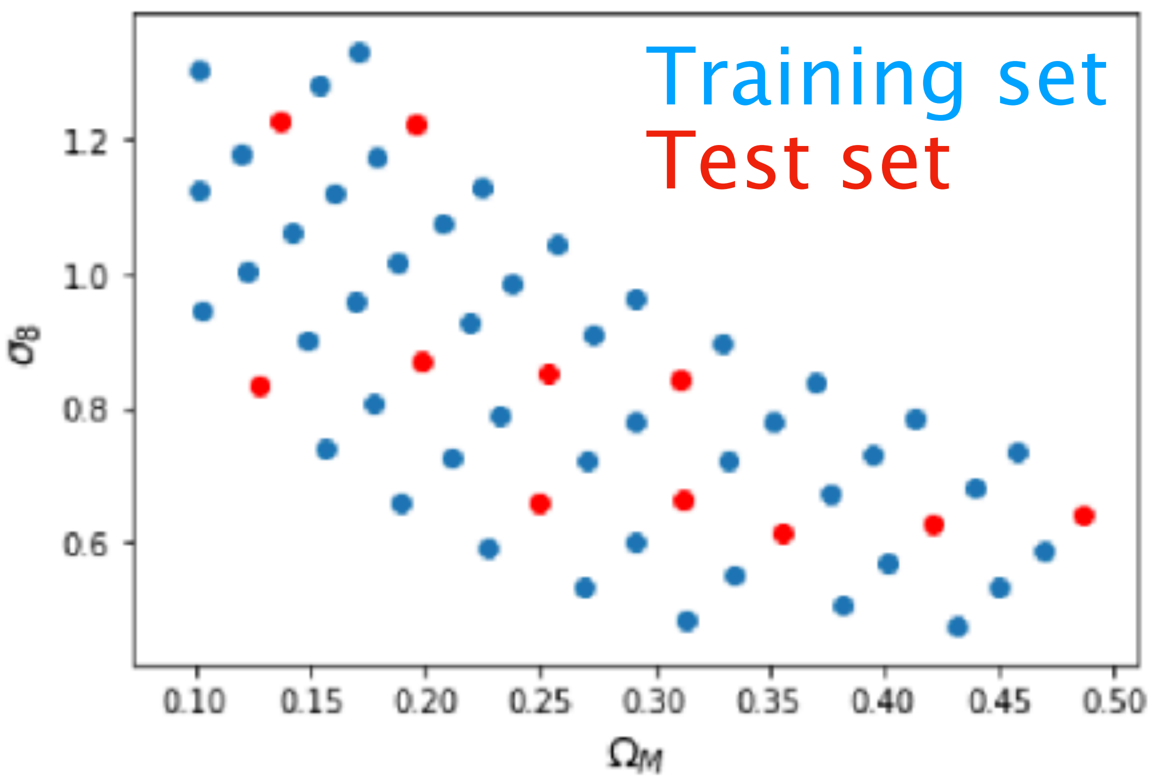


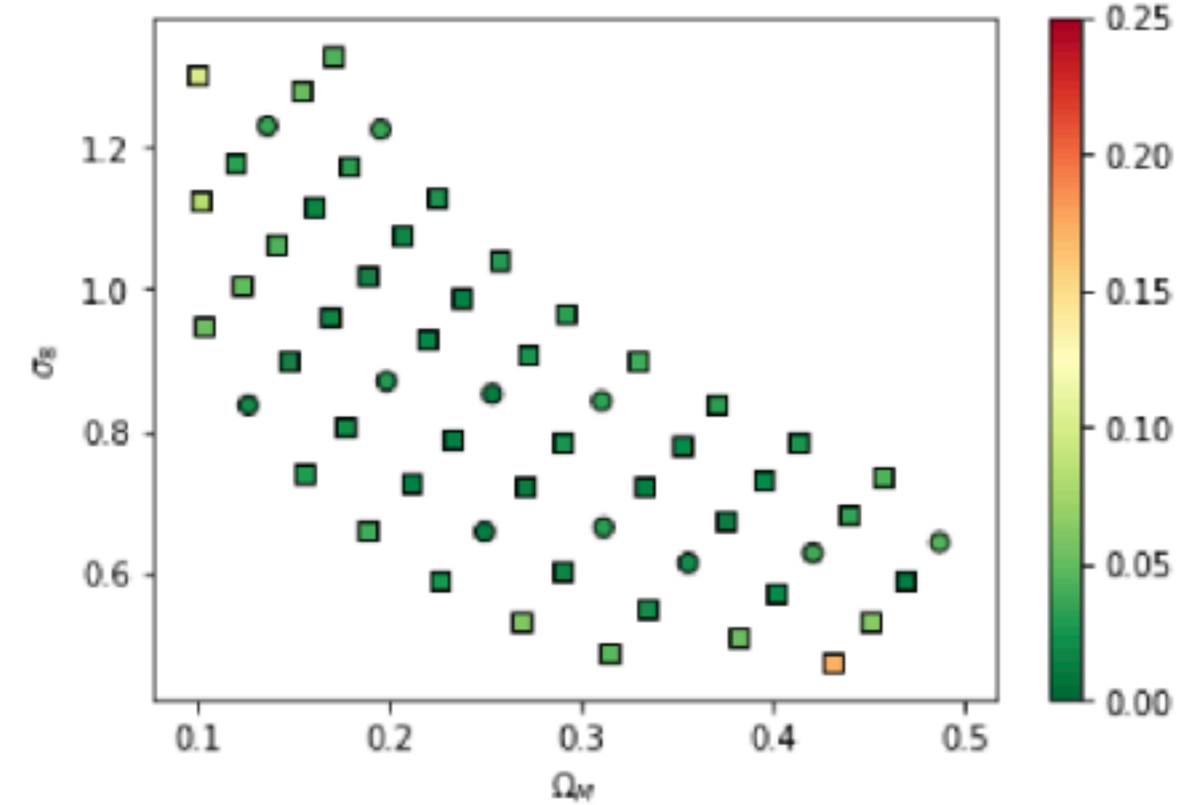
Figure 2: GAN generated images and real images for four combinations of cosmological parameters.

Perraudin, TK, et al. 2020, 2004.08139

"Emulation of cosmological mass maps with conditional generative adversarial networks"



Mean fractional error on power spectrum



- Very good match of summary statistics

Perraudin, TK, et al. 2020, 2004.08139

Deep learning for cosmological simulations: a growing field

- ★ **Super-resolution emulator of cosmological simulations using deep physical models**
  Ramanah et al. (2020), 2001.05519

- ★ **CosmoGAN: creating high-fidelity weak lensing convergence maps using Generative Adversarial Networks**
  Mustafa et al. (2017), 1706.02390

- ★ **Learning neutrino effects in Cosmology with Convolutional Neural Networks**
  Giusarma et al. (2019) 1910.04255

- ★ **Learning to Predict the Cosmological Structure Formation**
  He et al. (2019), 1811.06533

- ★ **Cosmological N-body simulations: a challenge for scalable generative models**
  Perraudin, TK, et al. (2019), 1908.05519

- ★ **HIGAN: Cosmic Neutral Hydrogen with Generative Adversarial Networks**
  Zamudio-Fernandez et al. (2019), 1904.12846

- ★ **A black box for dark sector physics: Predicting dark matter annihilation feedback with conditional GANs**
  List, Bhat, Lewis (2019), 1910.00291

- ★ **The Quijote simulations.**
  Francisco Villaescusa-Navarro et al. (2020), 1909.05273

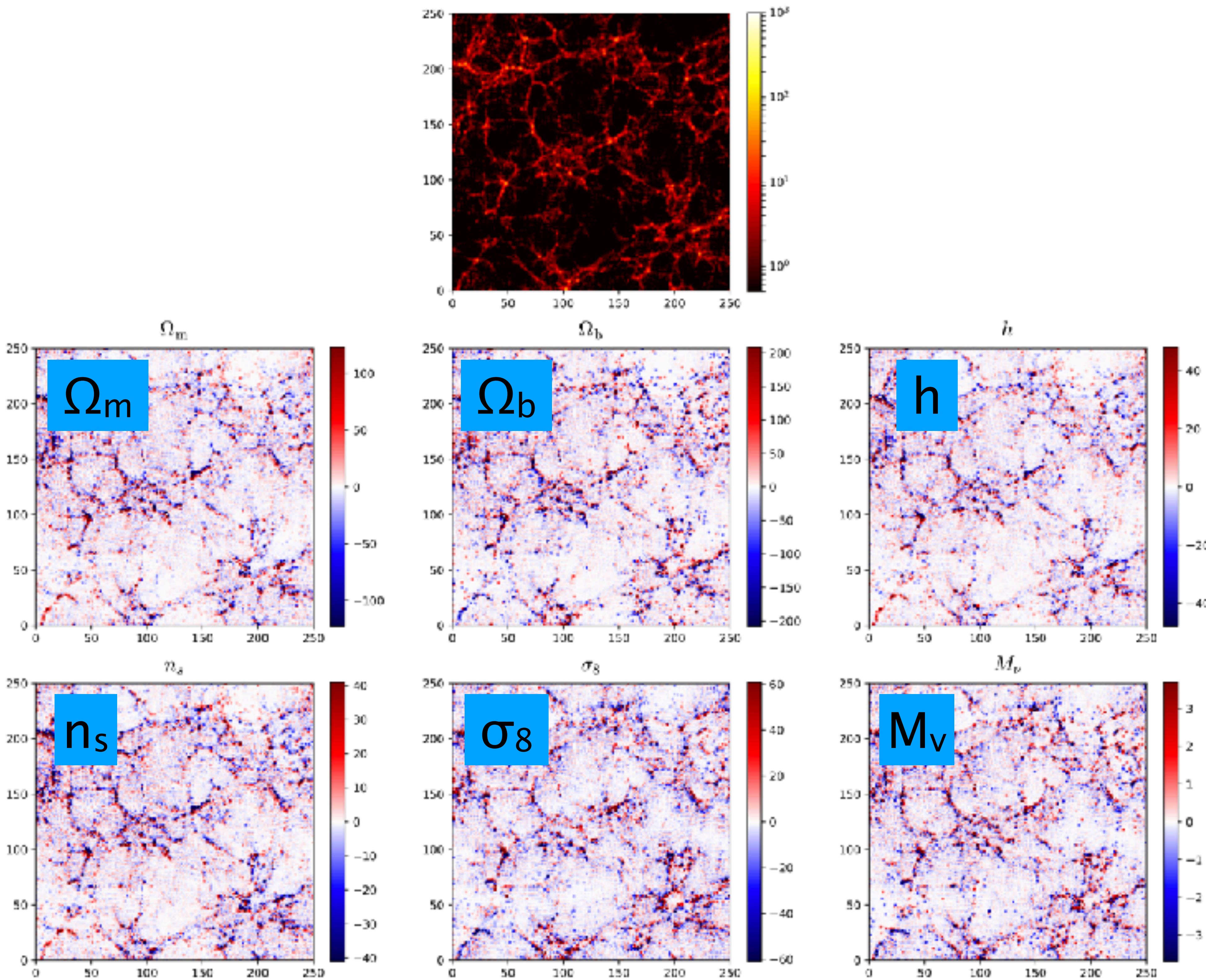
- ★ **The CAMELS project: Cosmology and Astrophysics with MachinE Learning Simulations**
  Francisco Villaescusa-Navarro et al. (2020), 2010.00619

The way forward

- Moving towards **Computational Cosmology**
- Building **multi-probe cosmological simulations** for practical parameter measurement
- Reaching information floor of cosmological datasets with Artificial intelligence - based parameter inference
- Cosmological constraints using large-scale simulation grids
- Building large simulations in a collaborative way, publishing data sets to the community
- Using AI to build simulations including more realistic physical effects
- Capitalising on **latest advances in AI i**n practical cosmological measurements

Additional slides

LSS carries information about cosmological parameters



Villaescusa-Navarro et al. 2019, 1909.05273