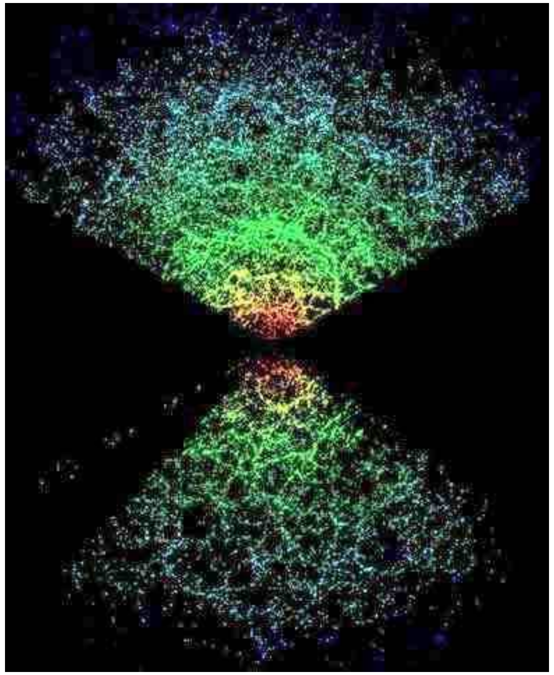







Cosmic Large-Scale Structure

Deep Learning



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Sep, 2019 @ BNU

Motivation

Complicated system!

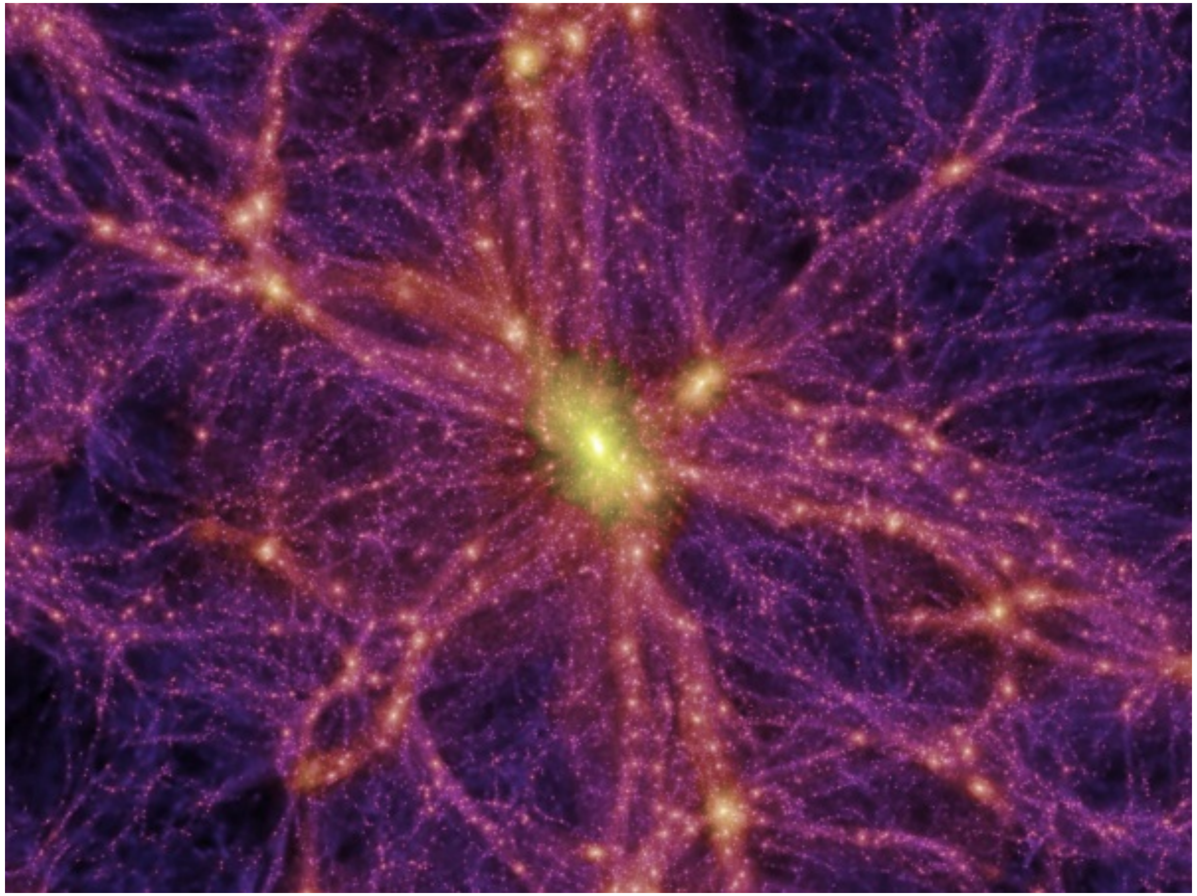
Analytically difficult!

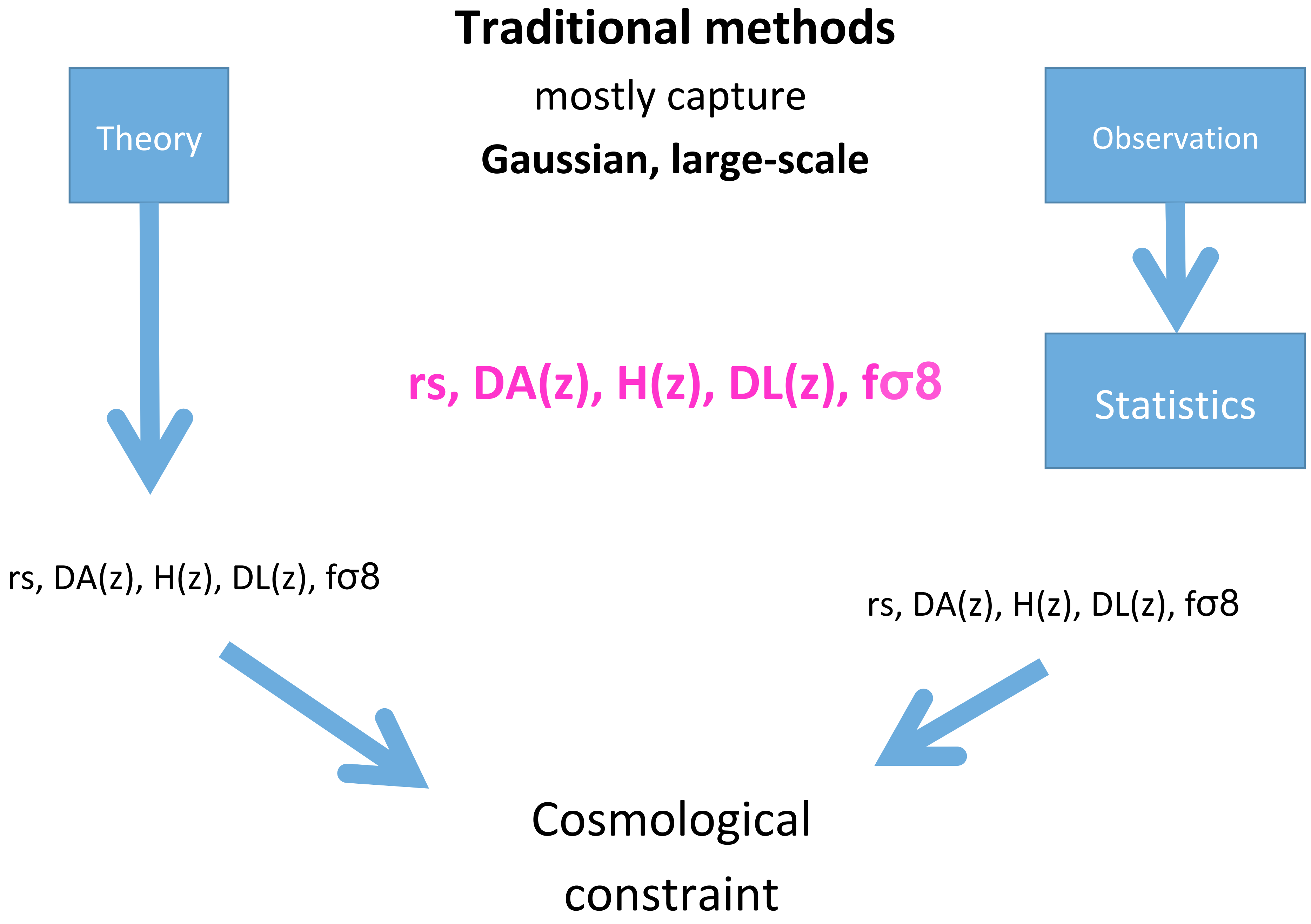
Theoretically difficut!

Statistically difficult!

...

Too complicated,
too difficult!




Traditional methods
mostly capture
Gaussian, large-scale
Theory
Observation
Statistics
rs, DA(z), H(z), DL(z), fσ8
rs, DA(z), H(z), DL(z), fσ8
rs, DA(z), H(z), DL(z), fσ8
Cosmological
constraint

Machine Learning

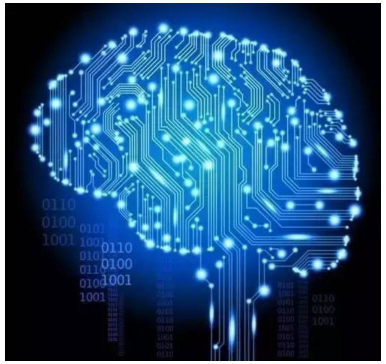
(Hopefully) can cover non-Gaussian, non-linear, small-scale

Theory

Mocks

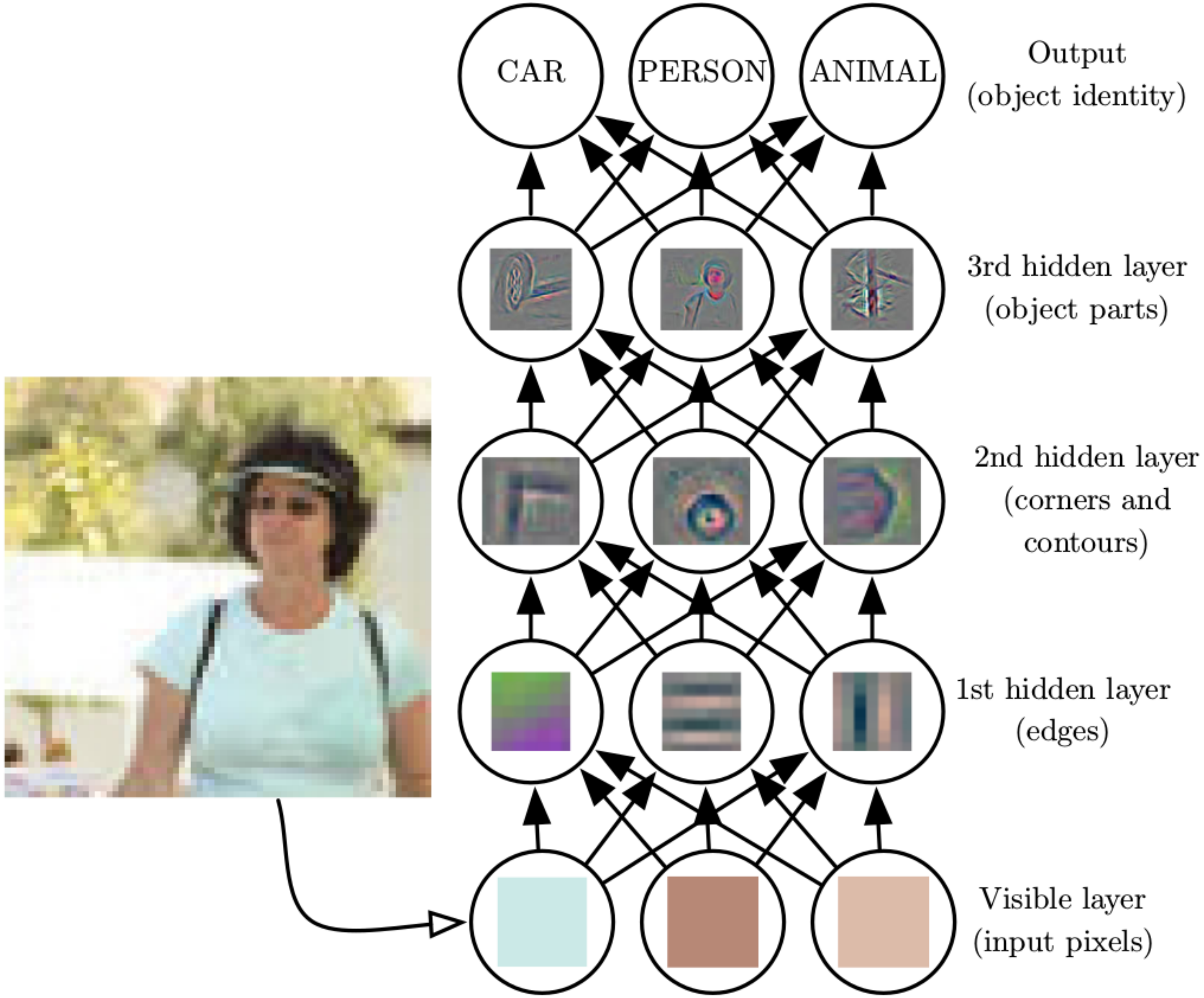
Observation

Machine Learning



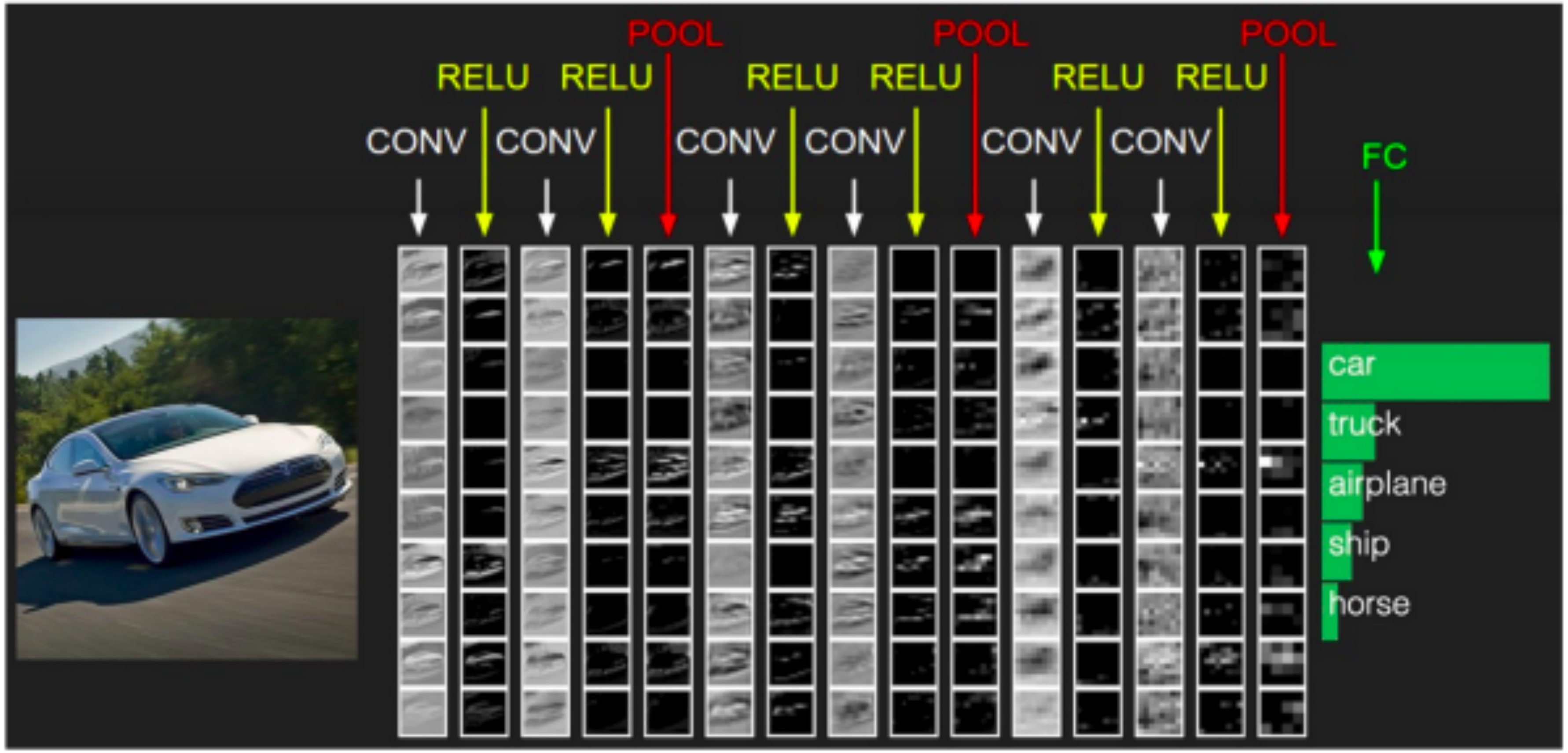
Cosmological constraint

Deep Learning



- Inputs are just pixels
- Based on that, more sophisticated features constructed. See hidden layers.
- E.g., first layer identifies edges based on brightness contrast; second layer identifies angles and boundaries based on edges; third layer groups together angles and boundaries and can identify some objects

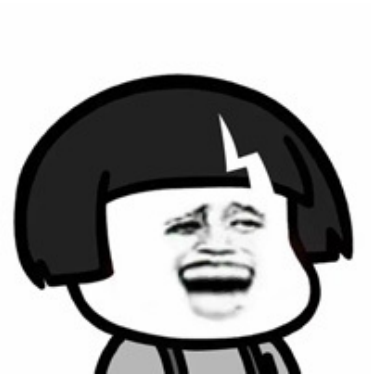
Convolutional Neural Network (CNN)



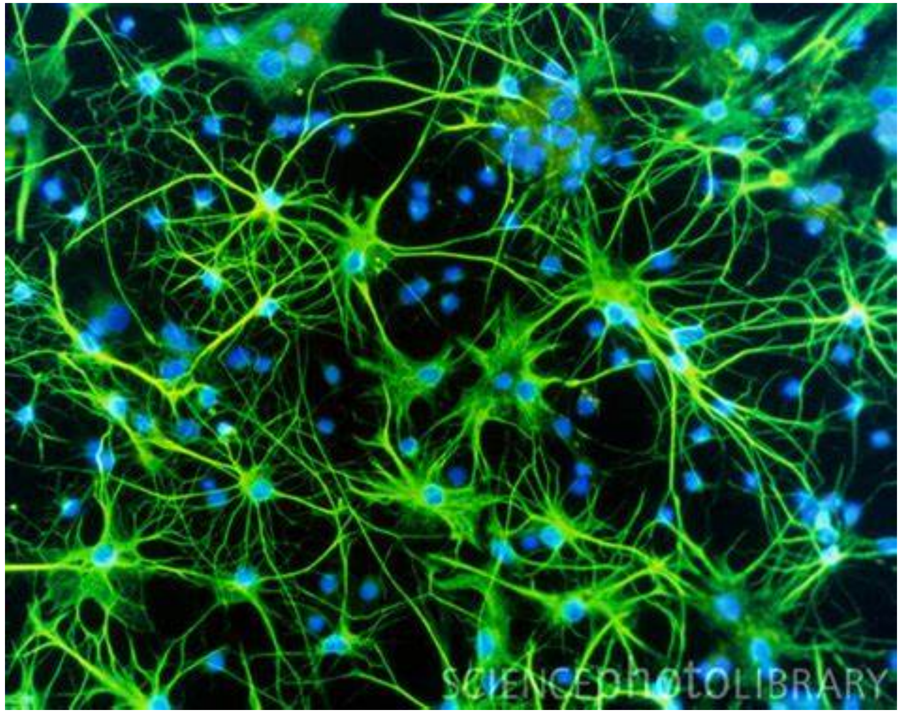
Automatical extraction of various features

Connectionism (联结主义)

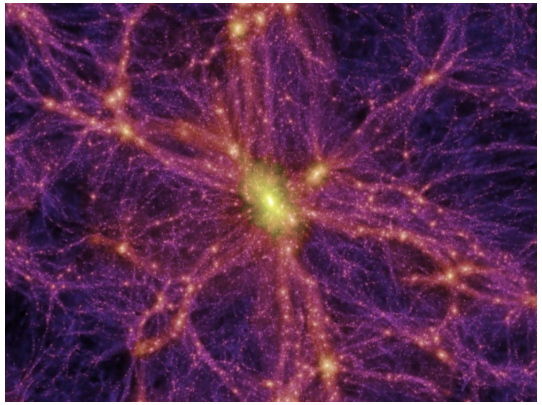
- When connecting together a large number of simple units, the system becoms intellegent.
- Example: Human's Brain

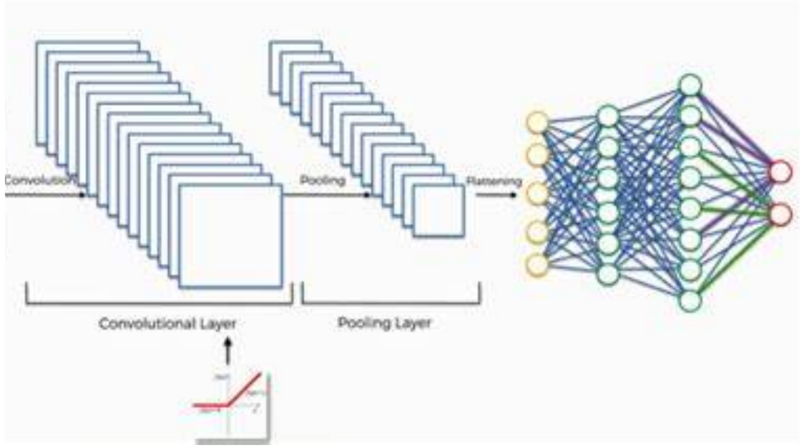


Your brain is just a collection of naieveness



Parameter Regression





Cosmological Parameters

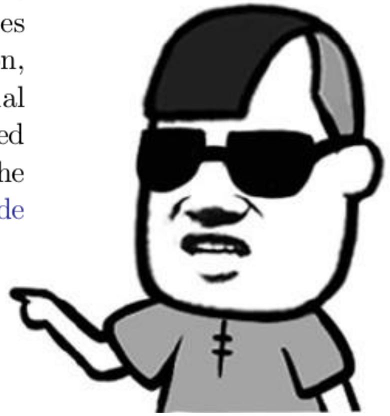
Build-up a neural system recognizing the Universe!

Pan et al., arXiv:1908.10590

COSMOLOGICAL PARAMETER ESTIMATION FROM LARGE-SCALE STRUCTURE DEEP LEARNING

Shuyang Pan, Miaoxin Liu,[1] Jaime Forero-Romero,[2] Cristiano G. Sabiu,[3] Zhigang Li,[4] Haitao Miao,[1] and Xiao-Dong Li [*1]

We propose a light-weight deep convolutional neural network to estimate the cosmological parameters from simulated 3-dimensional dark matter distributions with high accuracy. The training set is based on 465 realizations of a cubic box size of 256 h^{-1} Mpc on a side, sampled with 128^3 particles interpolated over a cubic grid of 128^3 voxels. These volumes have cosmological parameters varying within the flat ΛCDM parameter space of $0.16 \leq \Omega_m \leq 0.46$ and $2.0 \leq 10^9 A_s \leq 2.3$. The neural network takes as an input cubes with 32^3 voxels and has three convolution layers, three dense layers, together with some batch normalization and pooling layers. We test the error-tolerance abilities of the neural network, including the robustness against smoothing, masking, random noise, global variation, rotation, reflection and simulation resolution. In the final predictions from the network we find a 2.5% bias on the primordial amplitude σ_8 that can not easily be resolved by continued training. We correct this bias to obtain unprecedented accuracy in the cosmological parameter estimation with statistical uncertainties of $\delta\Omega_m$=0.0015 and $\delta\sigma_8$=0.0029. The uncertainty on Ω_m is 6 (and 4) times smaller than the Planck (and Planck+external) constraints presented in Ade et al. (2016).



Related work: Ravanbakhsh et al. 2017, Mathuriya et al. 2018

First two authors are first-year under-graduates

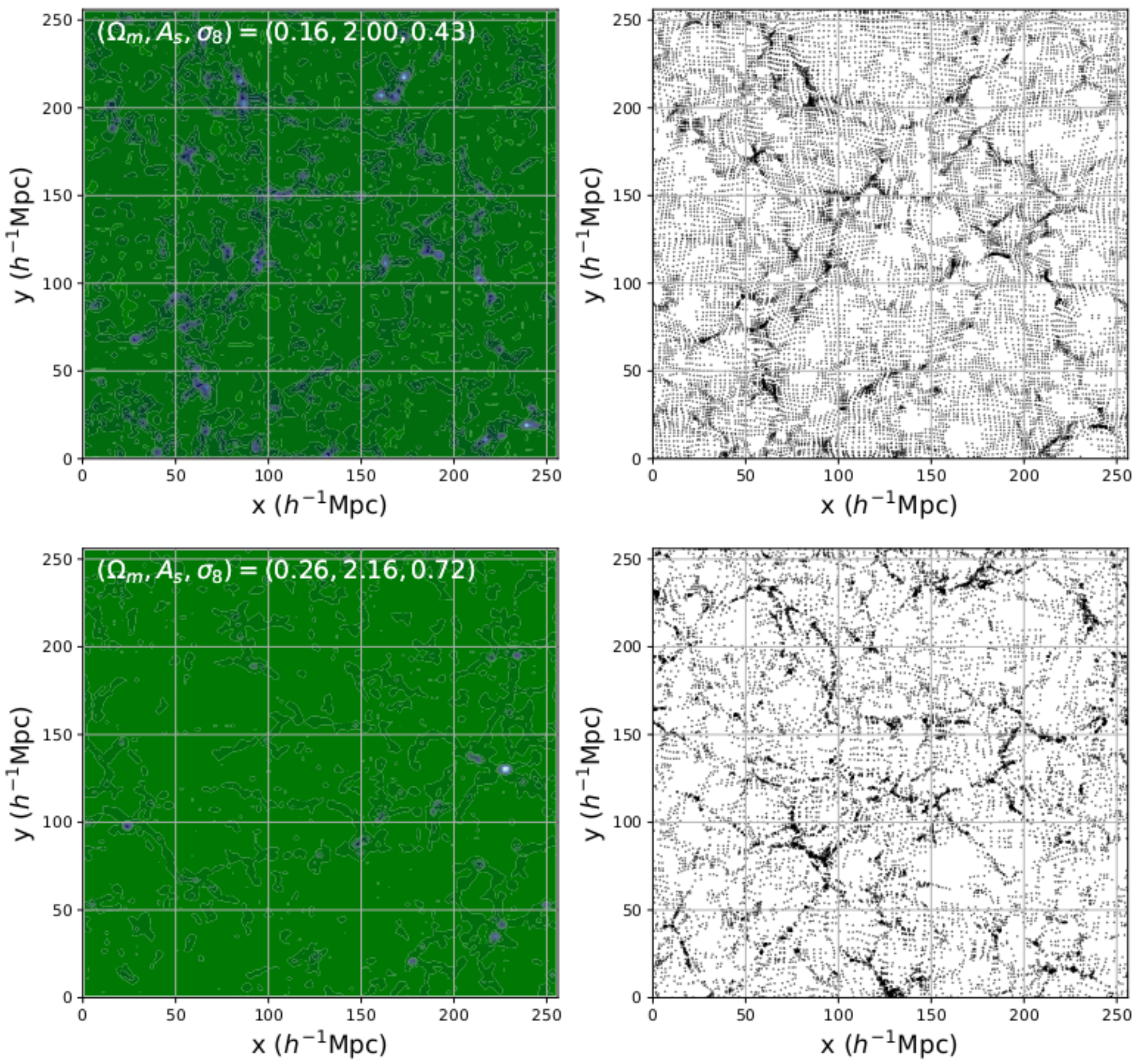
Training Set

COLA simulation, ~500 cosmologies

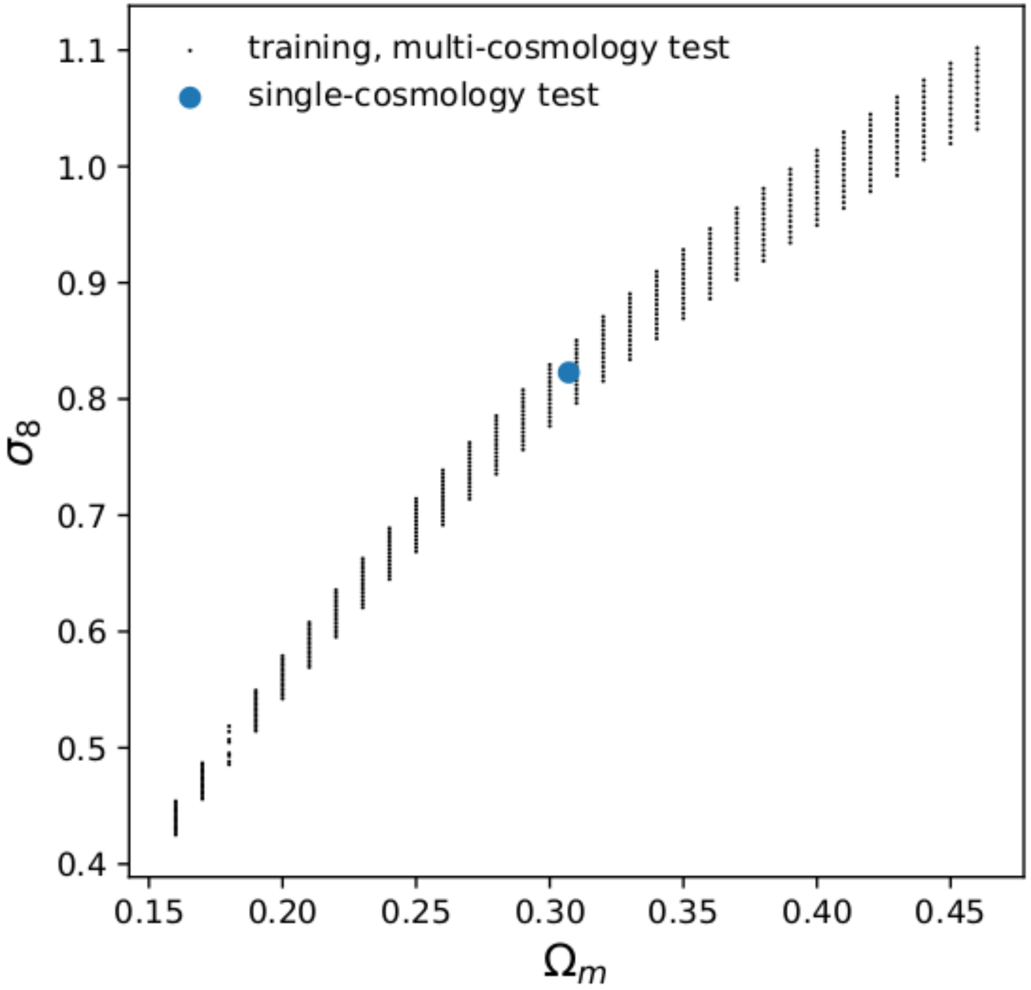
•$0.16 \leq \Omega_m \leq 0.46$, step size 0.01

•$2.0 \leq 10^9 A_s \leq 2.3$, step size 0.02

•128^3 particles, $(256\ h^{-1}\ \mathrm{Mpc})^3$ box,

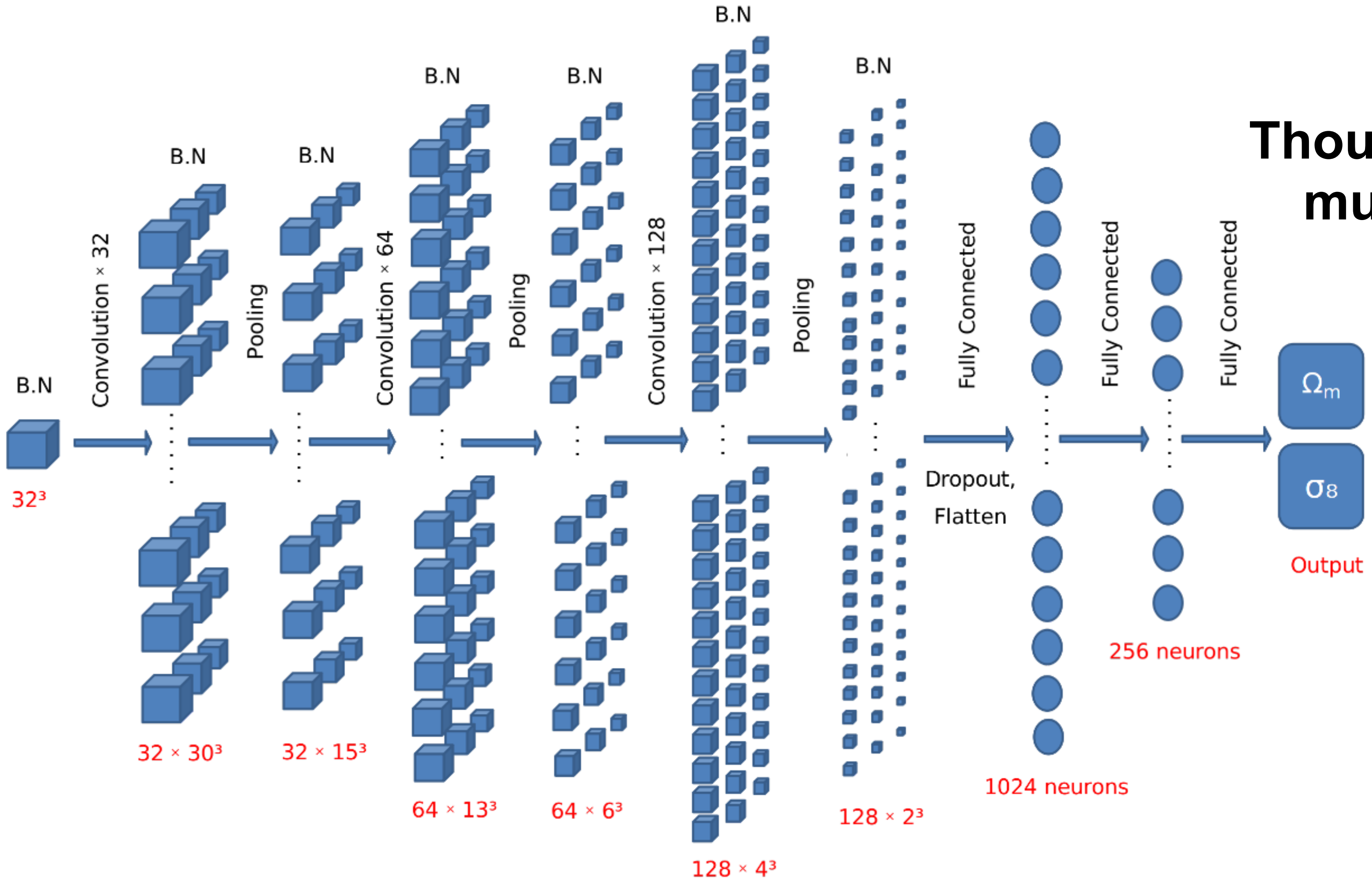


Distribution in Ω_m-σ_8 space



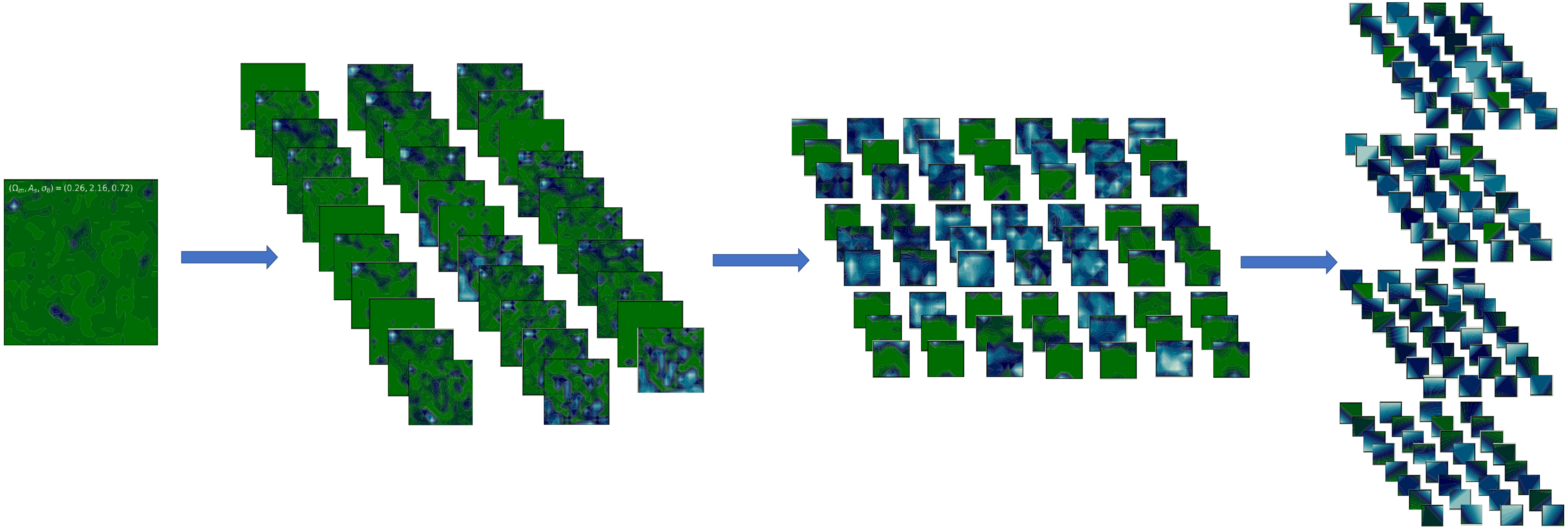
From Ω_m-A_s to Ω_m-σ_8 a degeneracy happens

Our Architecture



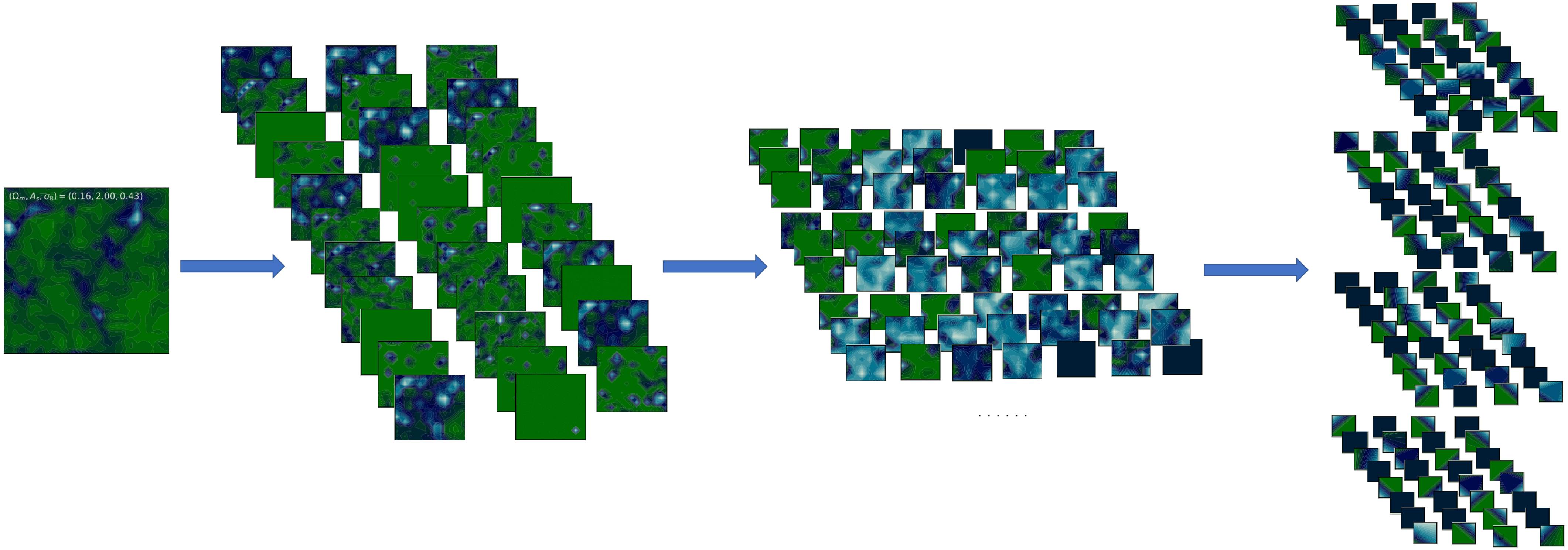
Thousands of neurons, much simpler than our head

LSS feature extraction



$(\Omega_m\text{-}\sigma_8)$ = 0.26, 0.72

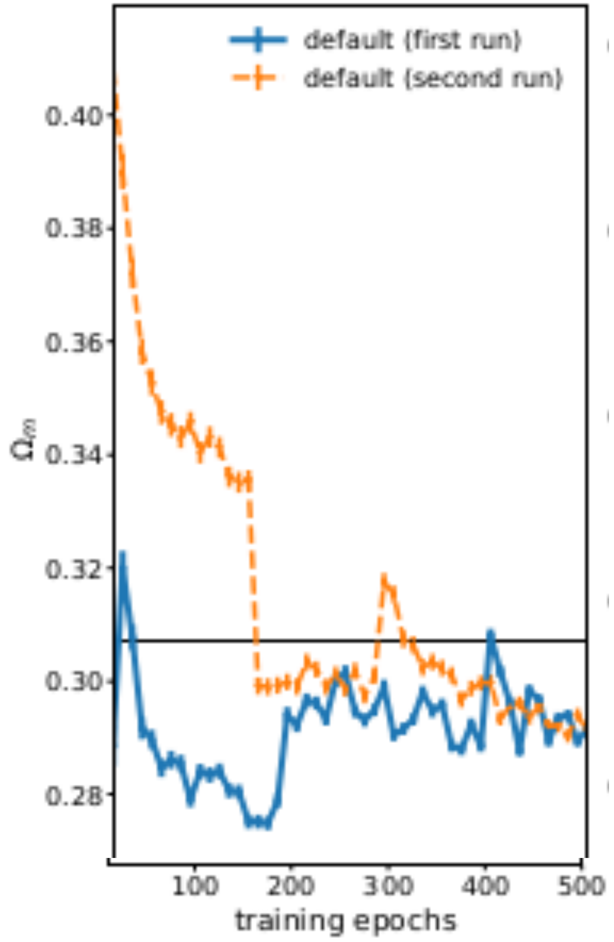
LSS feature extraction

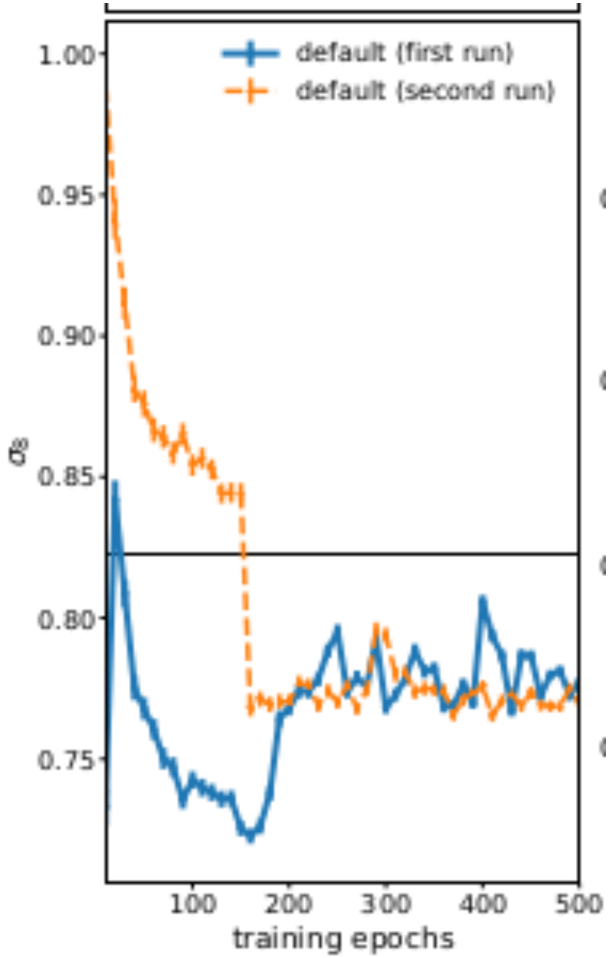


$(\Omega_m\text{-}\sigma_8) = 0.16,\ 0.43$

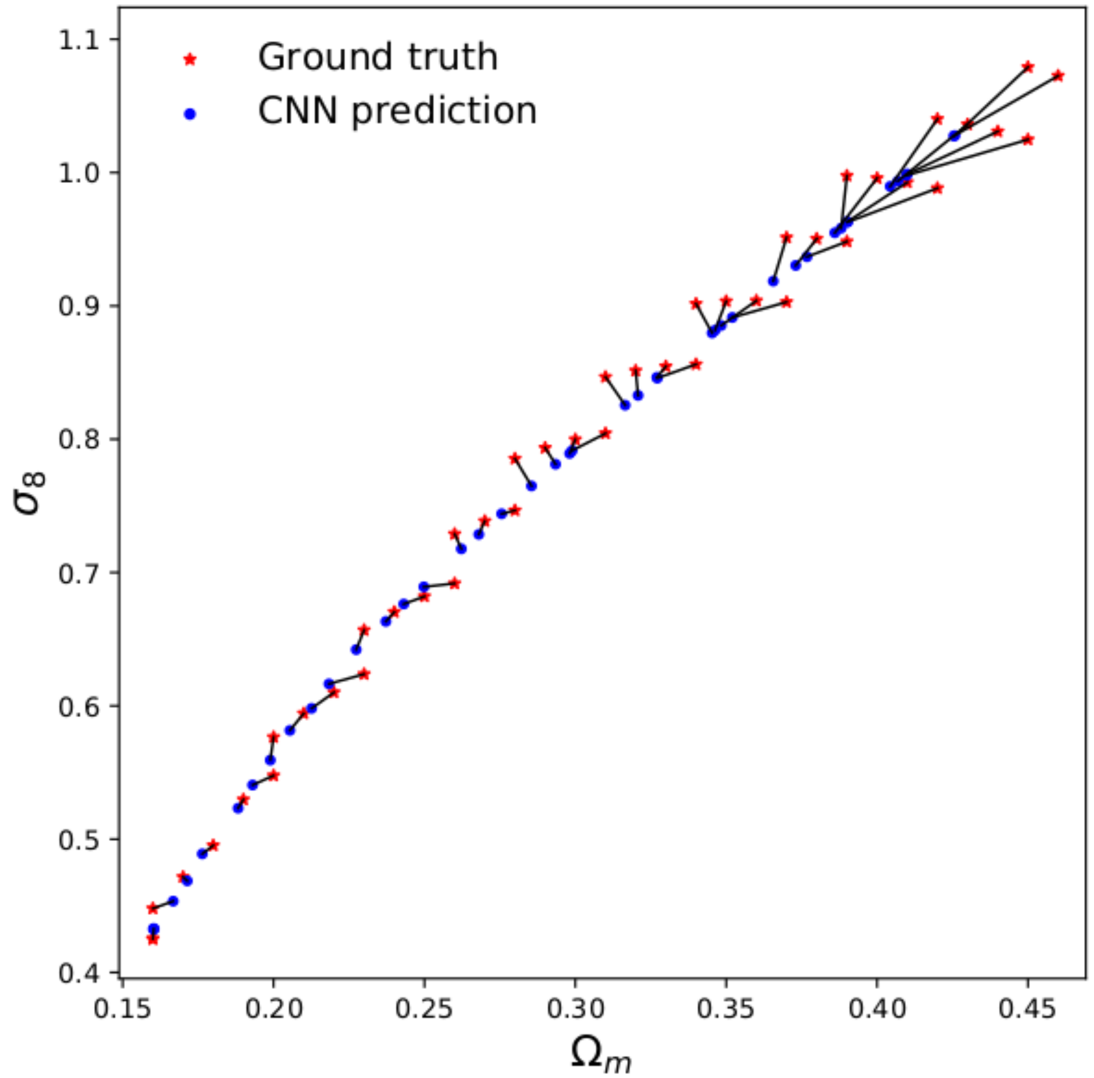
Training (converge after 200 epochs)

Understanding the Universe in ~1 week



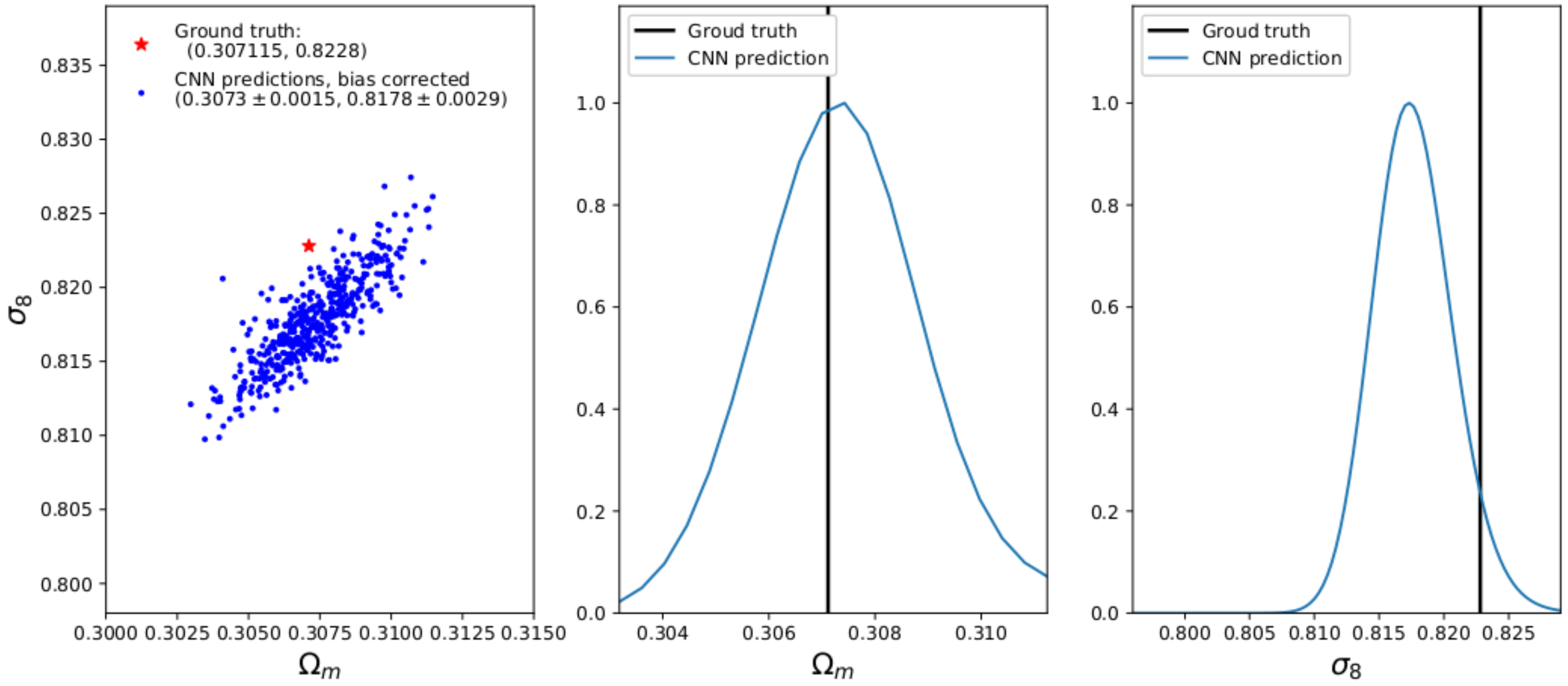


Controlling Bais



We add a regression after the neural networks to learn the noise and correct it

Single-cosmology Test



Unprecedented Precision

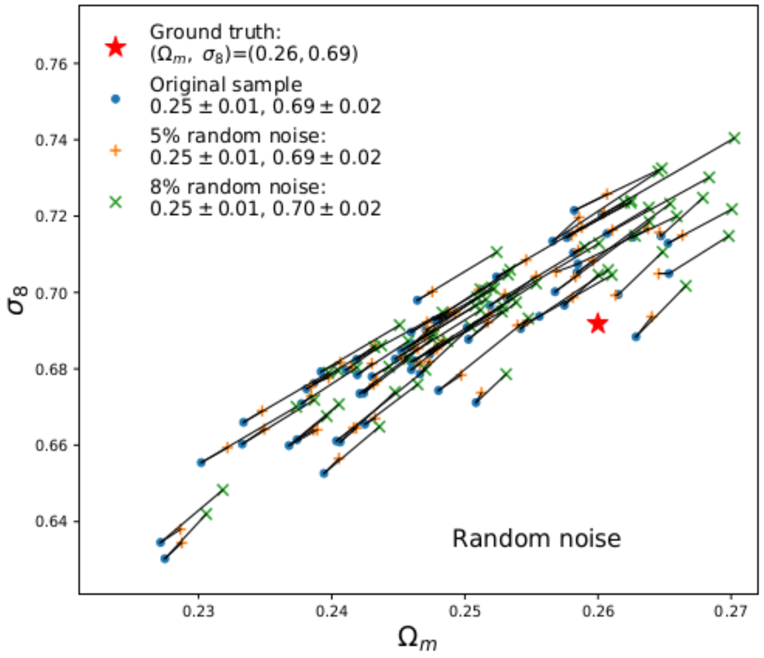
Just using a $(256\ \mathrm{Mpc}/h)^3$ sample, the CNN achievers

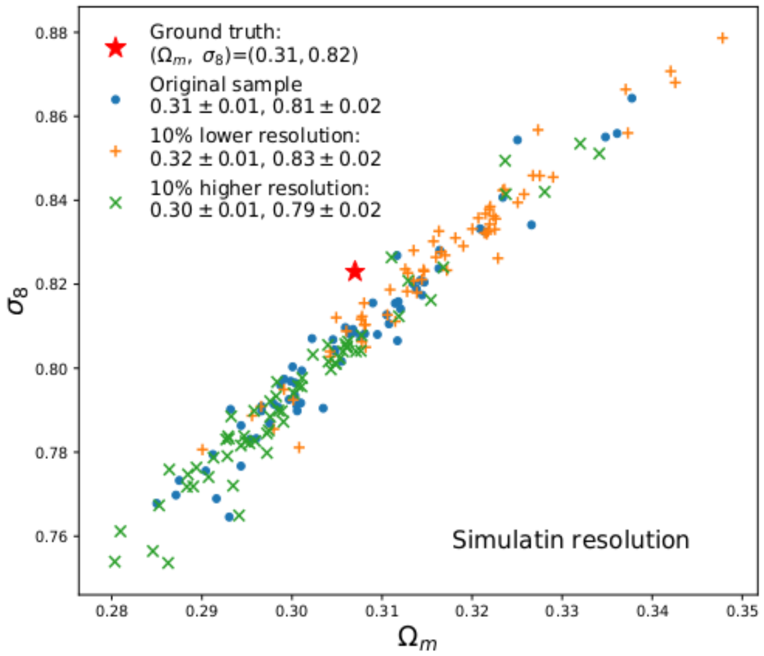
$$\delta\Omega_m = 0.0015,\quad \delta\sigma_8 = 0.0029$$

Uncertainty of Ω_m **6 (and 4) times smaller** than the Planck (and Planck+external) constraints

Machine outperforms any man-designed statistics

Robustness Tests

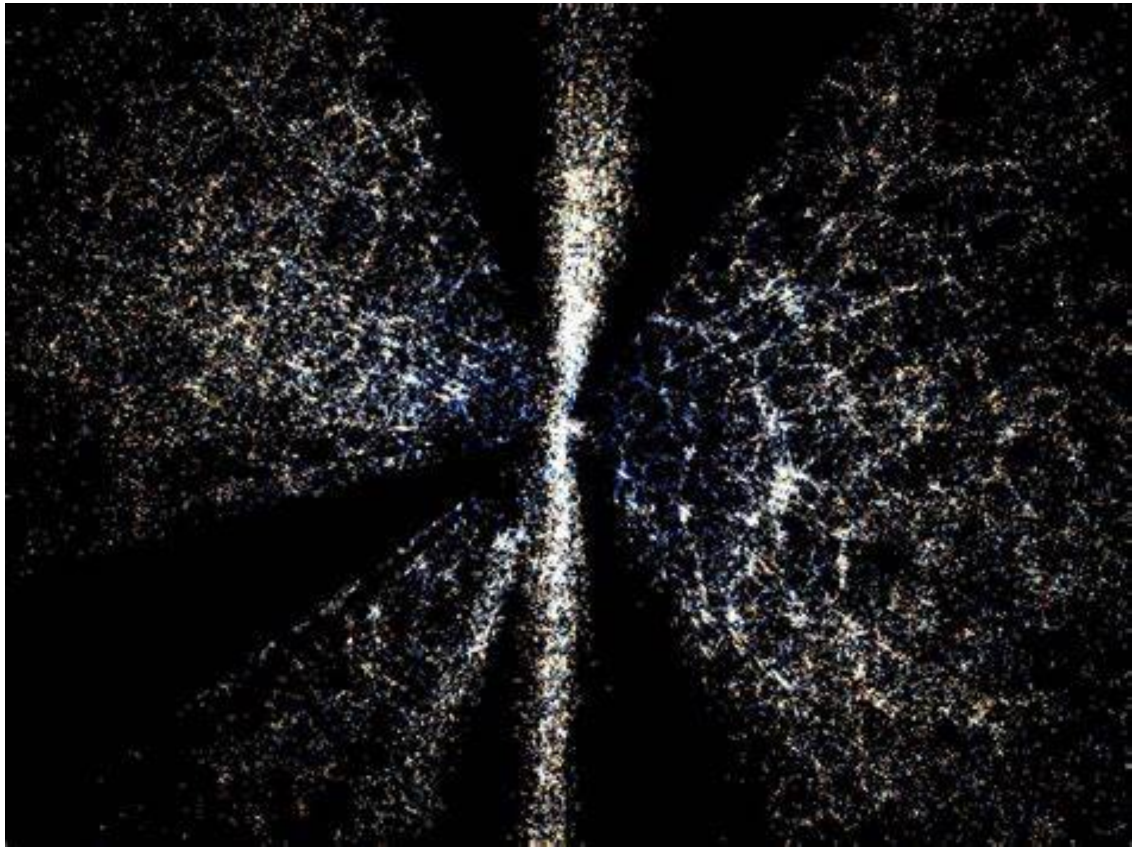




Robustness tests on samples having 32^3 voxels.
A 3% smoothing or 10% global variation leads to considerable change in the predicted results (~ 2σ shift in central values, ~ 100% enlarged errors).
1% smoothing, 5% global variation, and 10% change in the simulation’s resolution mildly affect the prediction (~ 1σ shift in central values, errors unchanged).
Other cases, including the 1 or 4 3 voxels removal, 5% or 8% random noise addition, rotation and relfection, does not affect the results at all.

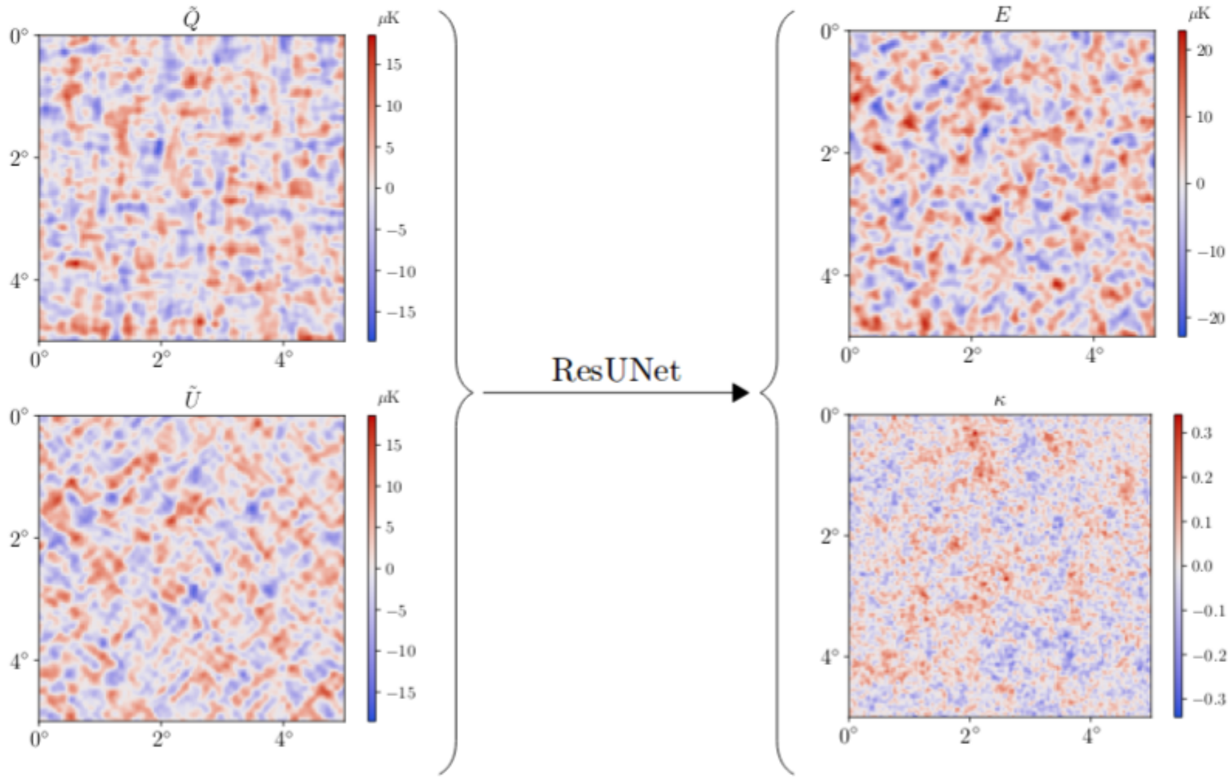
Next Step

ML on multi-cosmology SDSS mock surveys



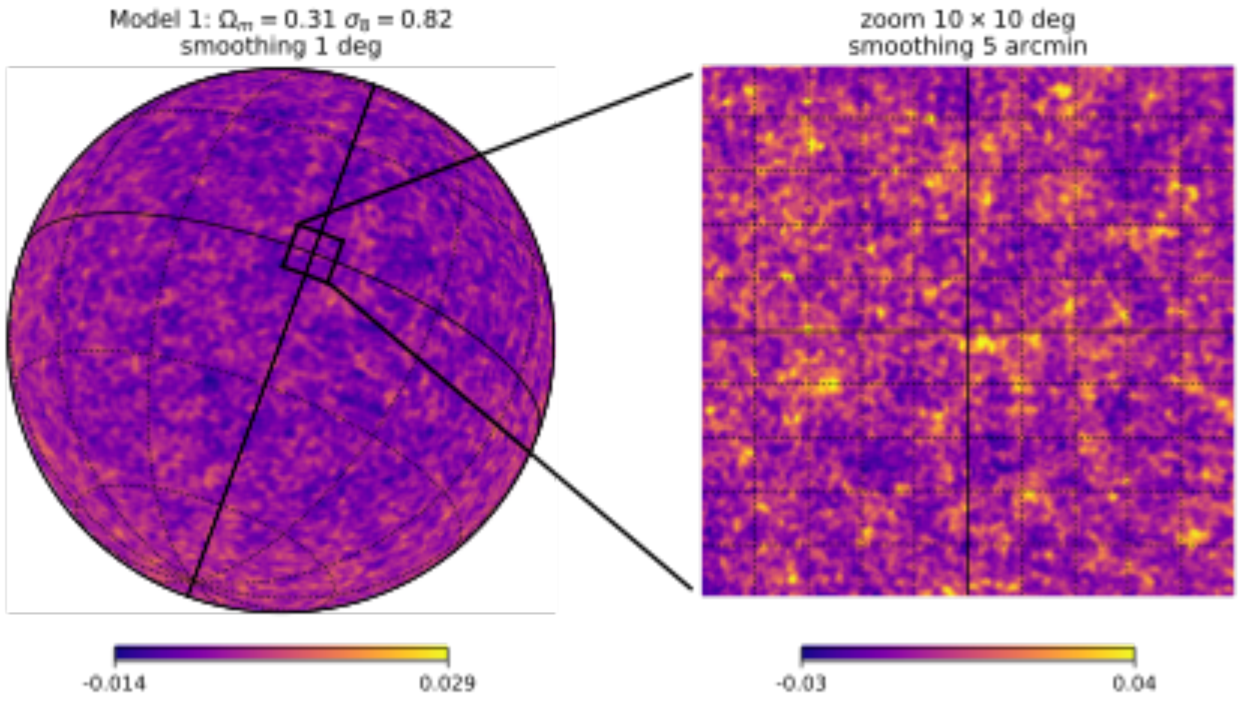
CMB related works

Lensing Reconstruction (Caldeira et al., 1810.01483)



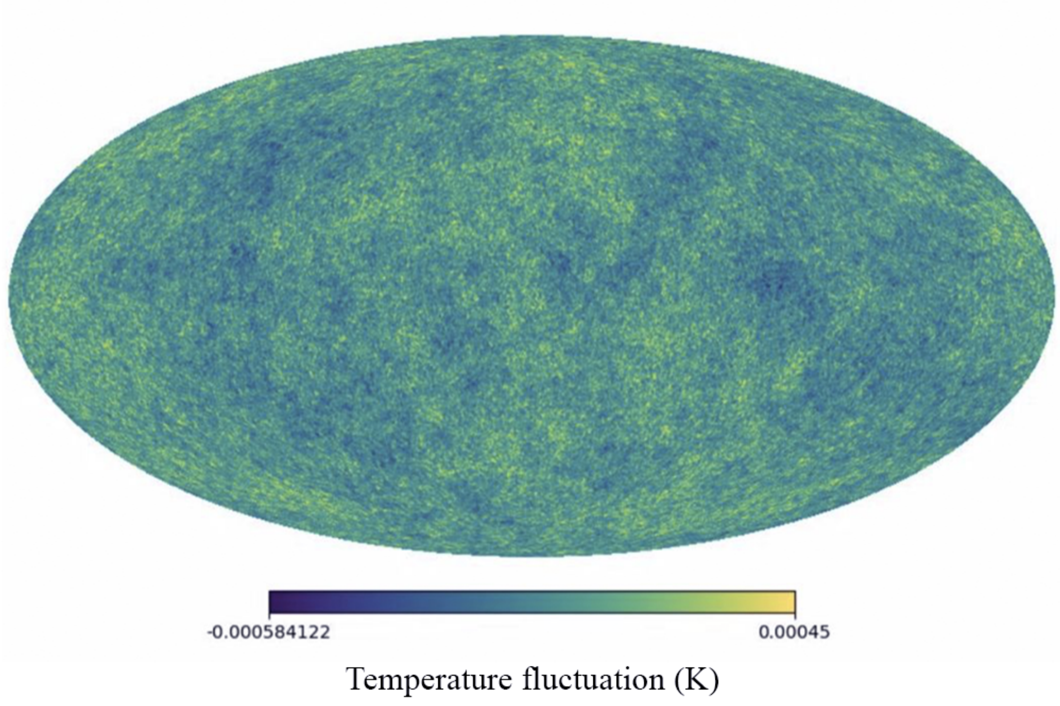
CMB related works

CNN on sphere (Perraudin et al. 1810.12186)



CMB related works

Fast simulation (Mishra et al. 1908.04682)



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