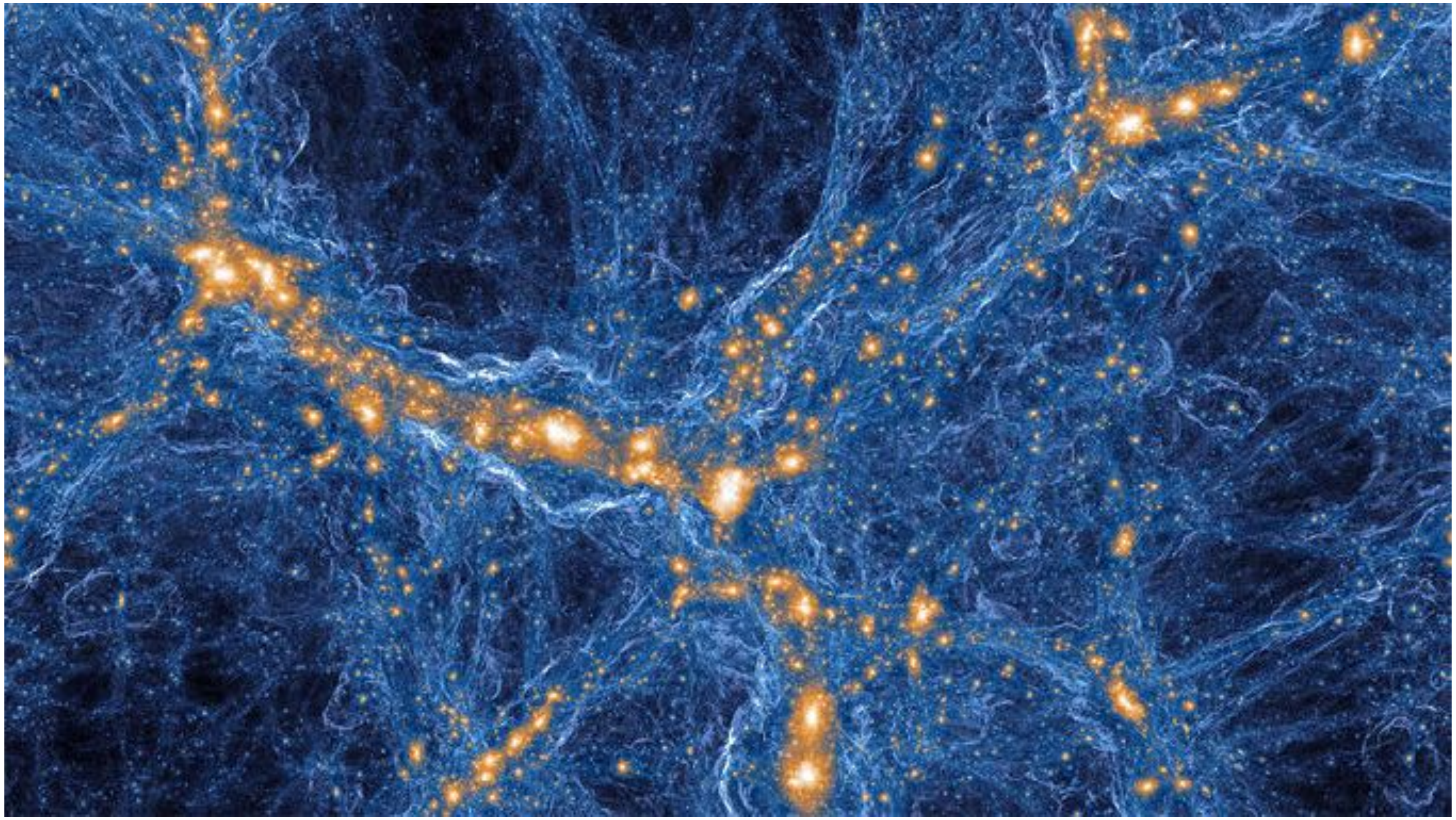
A Deep Learning approach to Large Scale Structure Cosmology

Cristiano Sabiu (University of Seoul)
Collaborators: Kenji Kadota, Jacobo Asorey, Seyeon Hwang, Sumi Kim, Inkyu Park



From Galaxies to Cosmology with Deep Spectroscopic Surveys
Marseille 2022/07/06

Contents

Background

* The goal of modern cosmology is to **understand the physics** that governs our Universe on the largest scales

* Figure out the **constituents of the Universe**

$$R_{\mu\nu} - \frac{1}{2}g_{\mu\nu}R - \Lambda g_{\mu\nu} = 8\pi G T_{\mu\nu}$$

The game we play…

1) We start with Einstein's GR
2) Plug in a homogeneous/isotropic metric
3) Plug in energy/matter components
4) Obtain evolution equations for:
   - **Expansion of the Universe**
   - **Growth of density perturbations**

Background

* What causes cosmic acceleration?
  - Vacuum energy or Scalar field(s)?
  - Or something more strange*?!
    * (if that's not strange enough)

* What is Dark Matter?
  - Is it Self-interacting?
  - Is it Decaying?

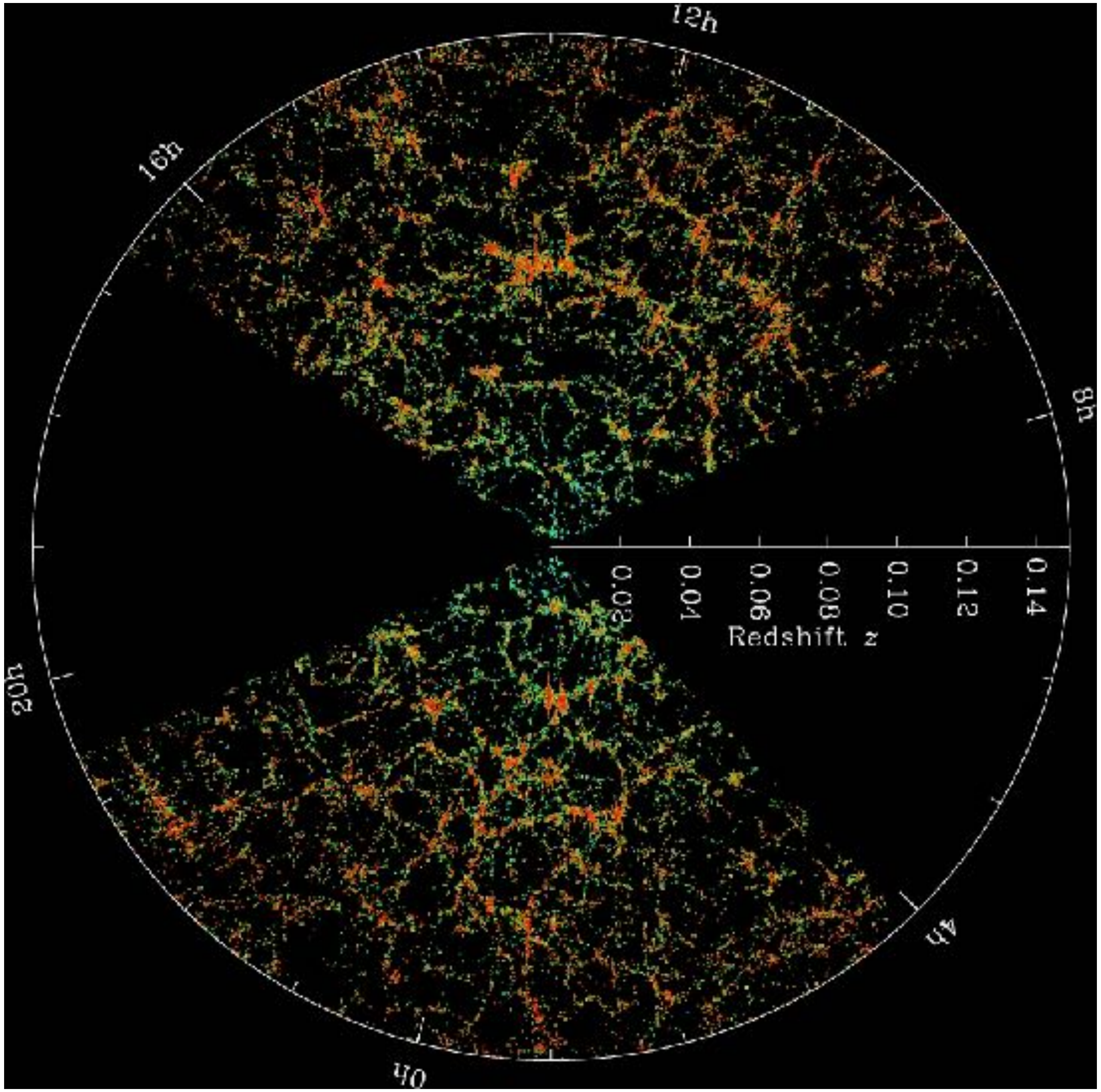
Each of the above possibilities could effect
- Universe expansion
- Clustering of matter

Background

We can now map large volumes of the Universe in 3D using galaxies as tracers of the underlying matter potential

But then what do we do with all these galaxy positions?

SDSS

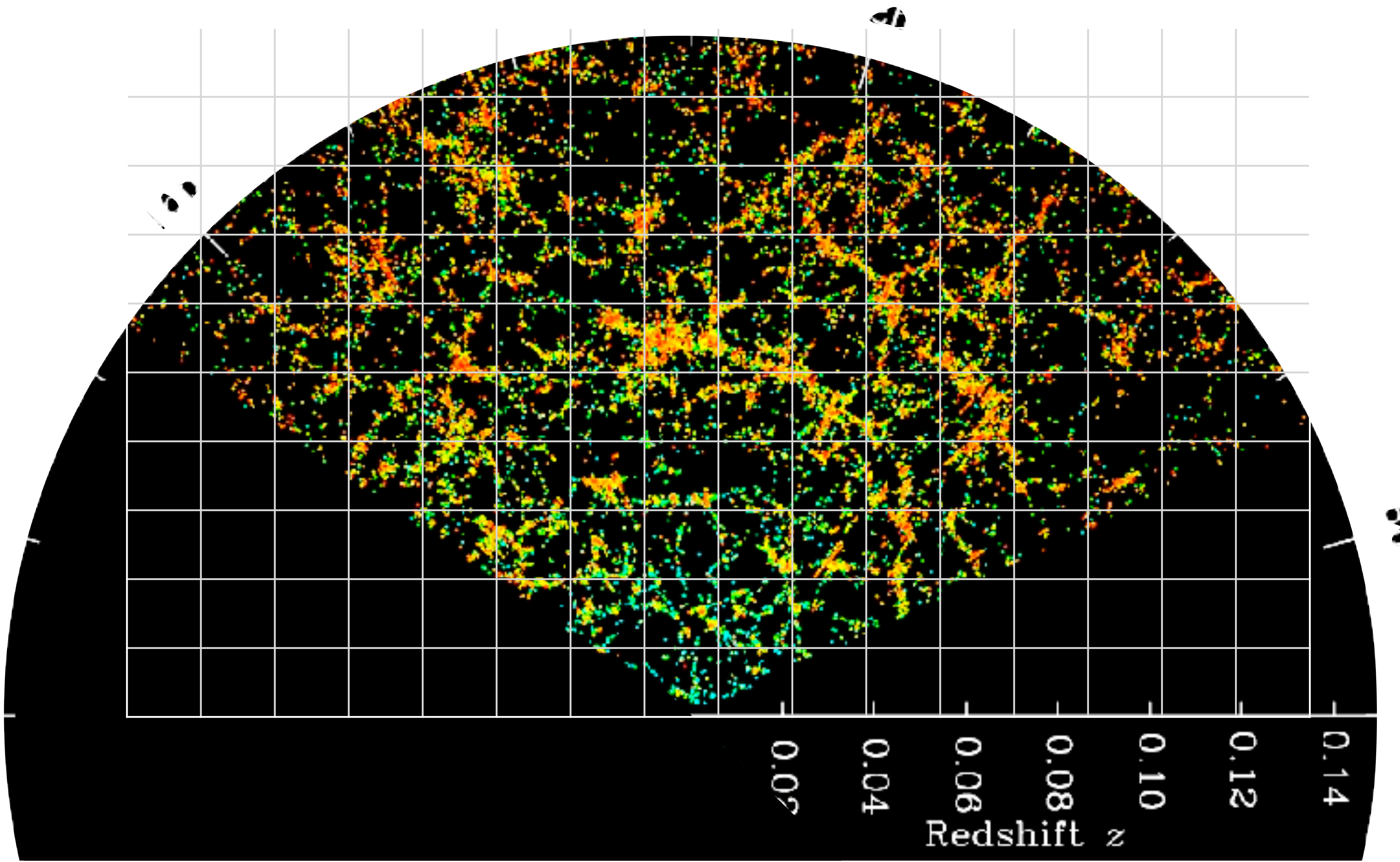


Background

Count galaxies in cells and compute power spectra, P(k)

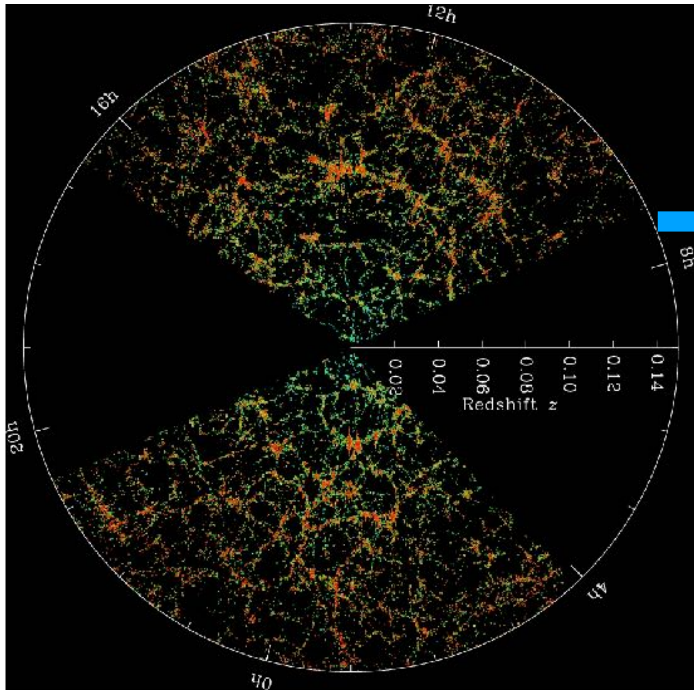
Or count pairs and compute correlation functions:

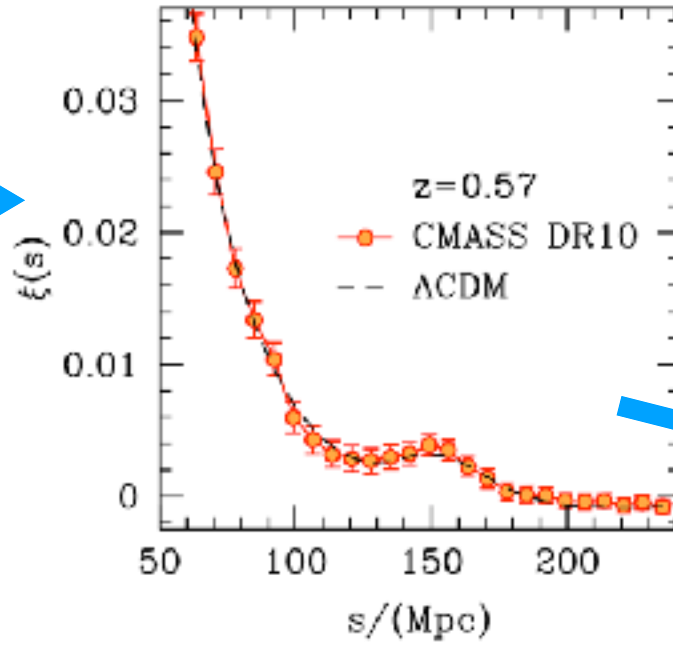
$$\xi(r) = \langle \delta(x)\delta(x+r) \rangle_x$$



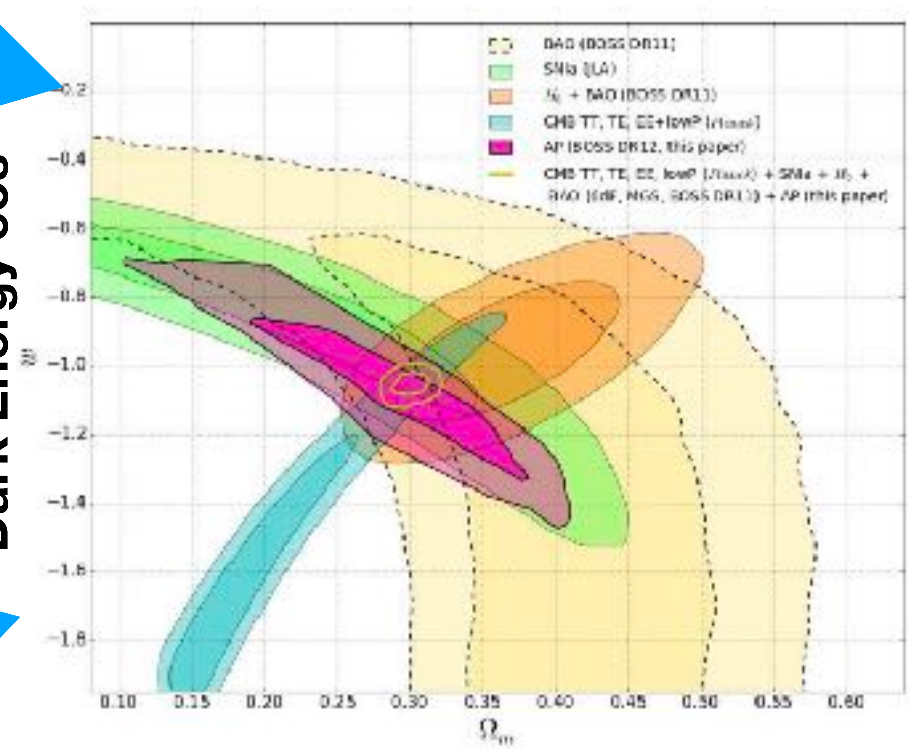
SDSS

Galaxy Clustering



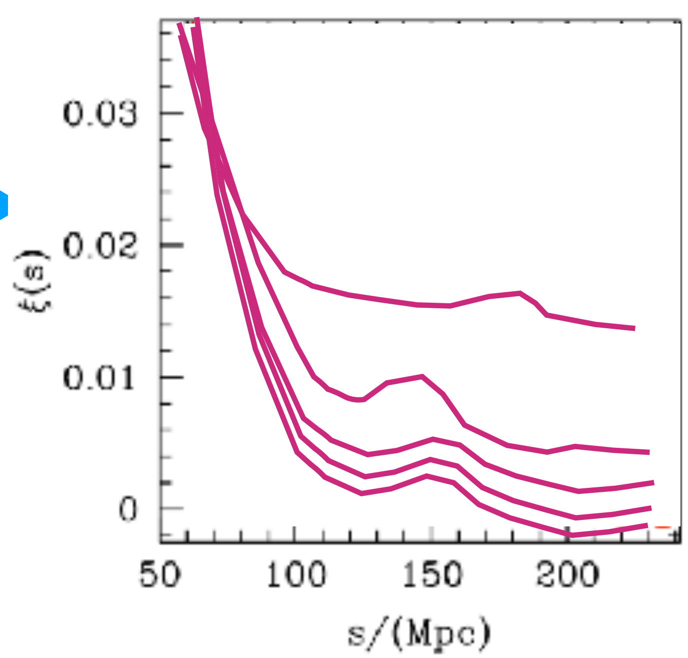


Dark Energy eos

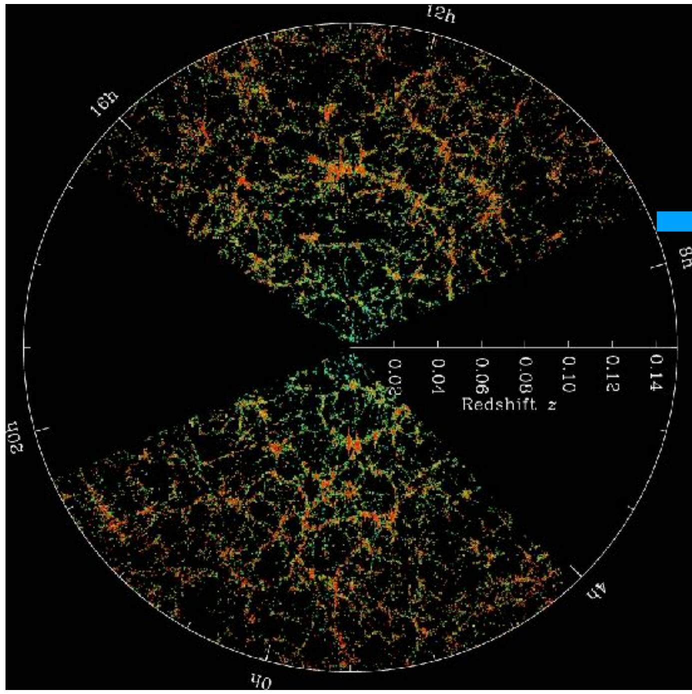


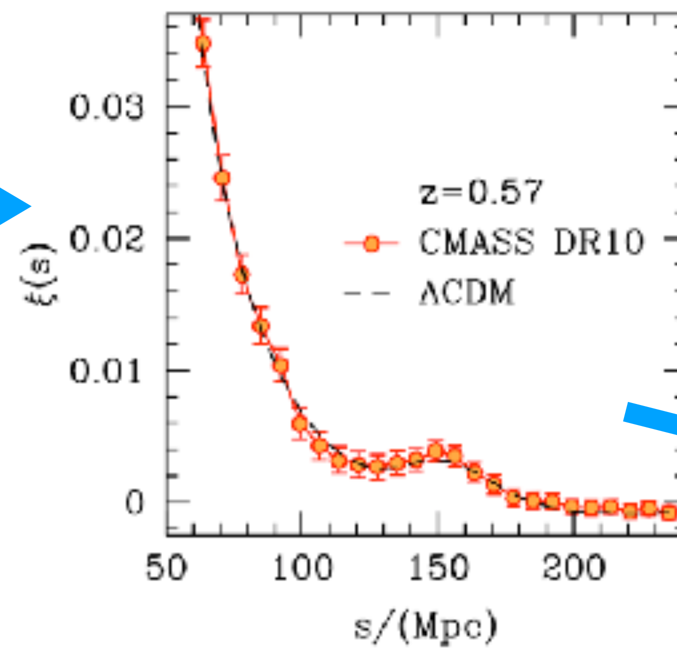
Matter Fraction

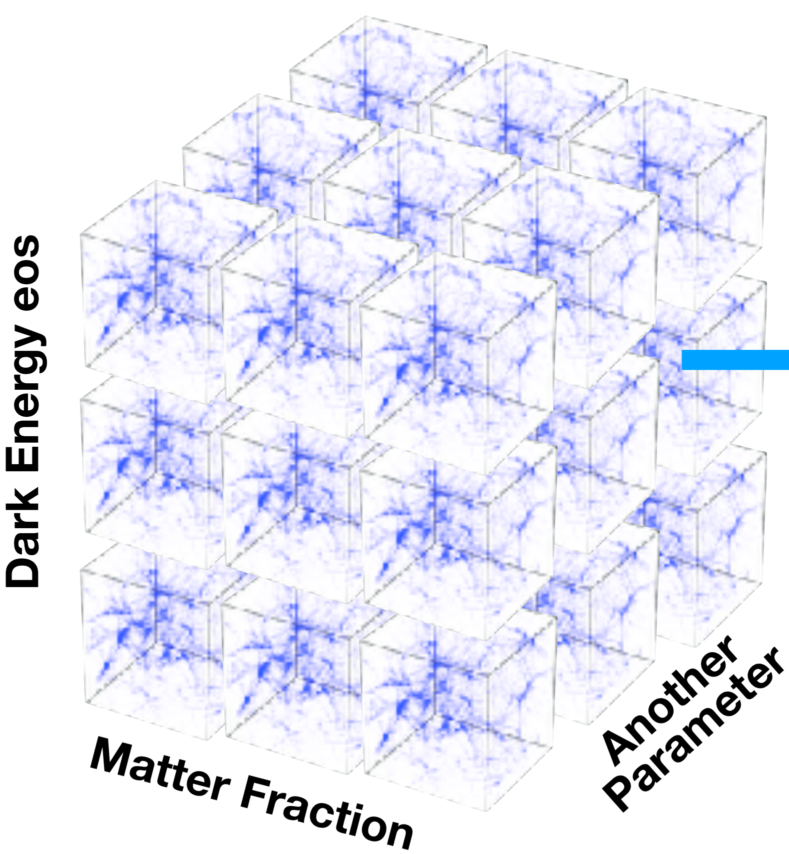
Linear Power Spectrum
+ Fitting formulae
Or Perturbation Theory
Or Emulator

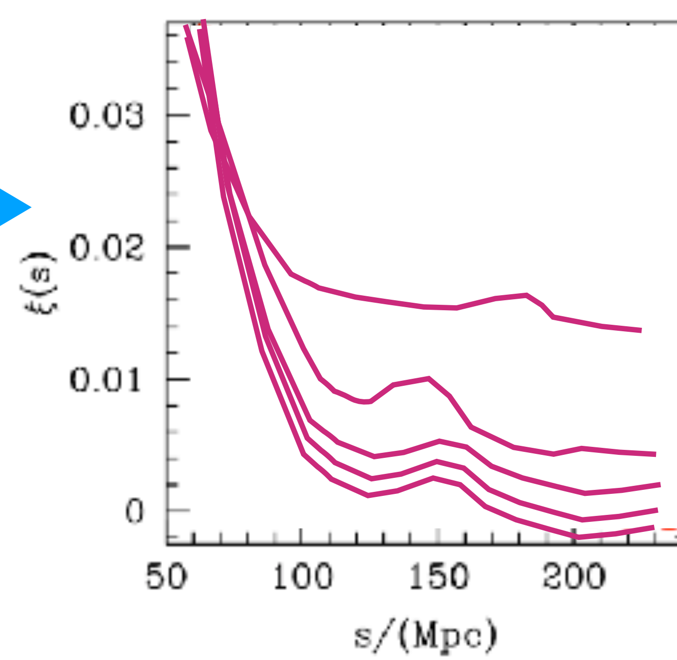


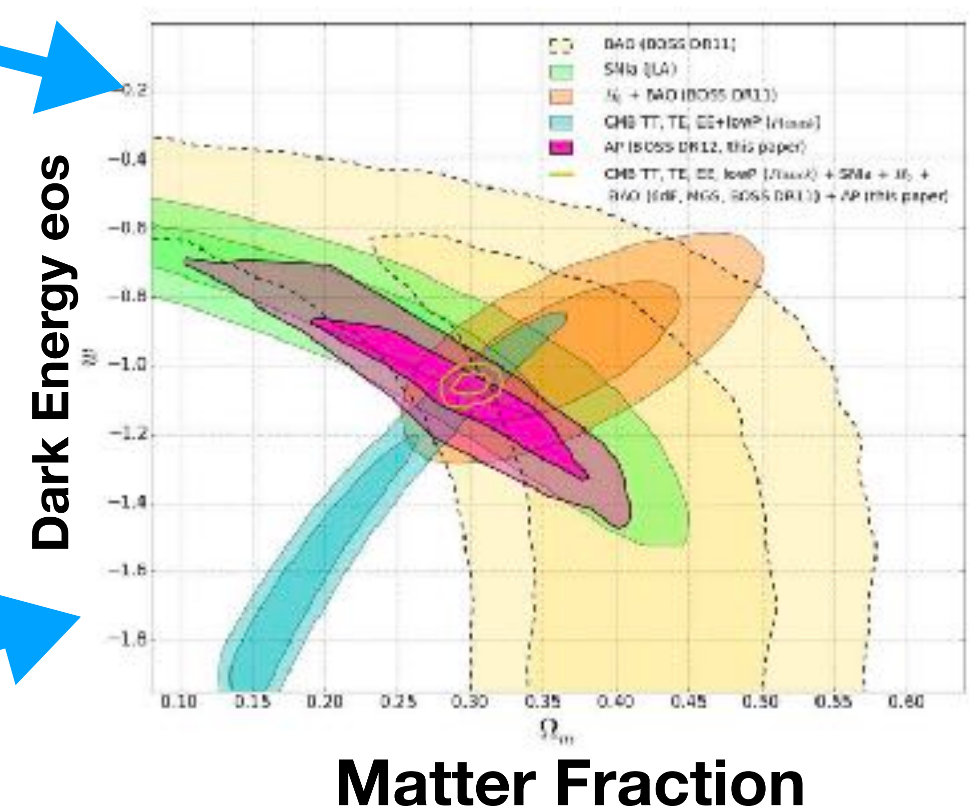
Galaxy Clustering











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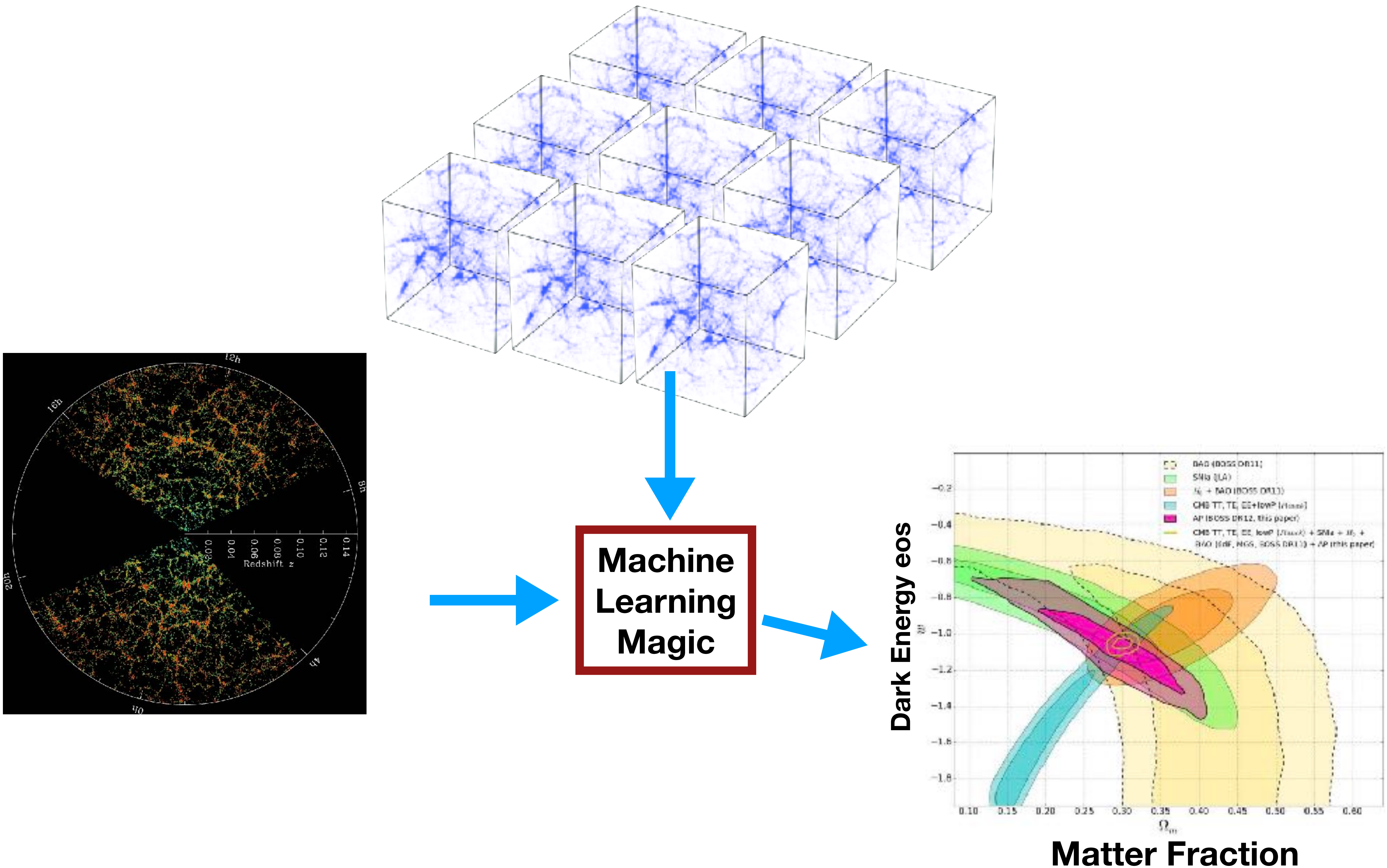
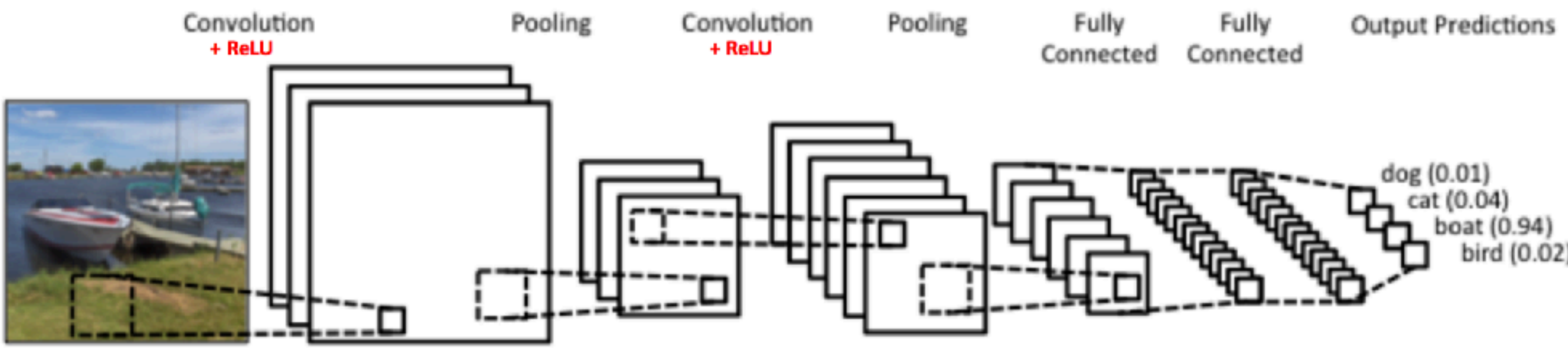


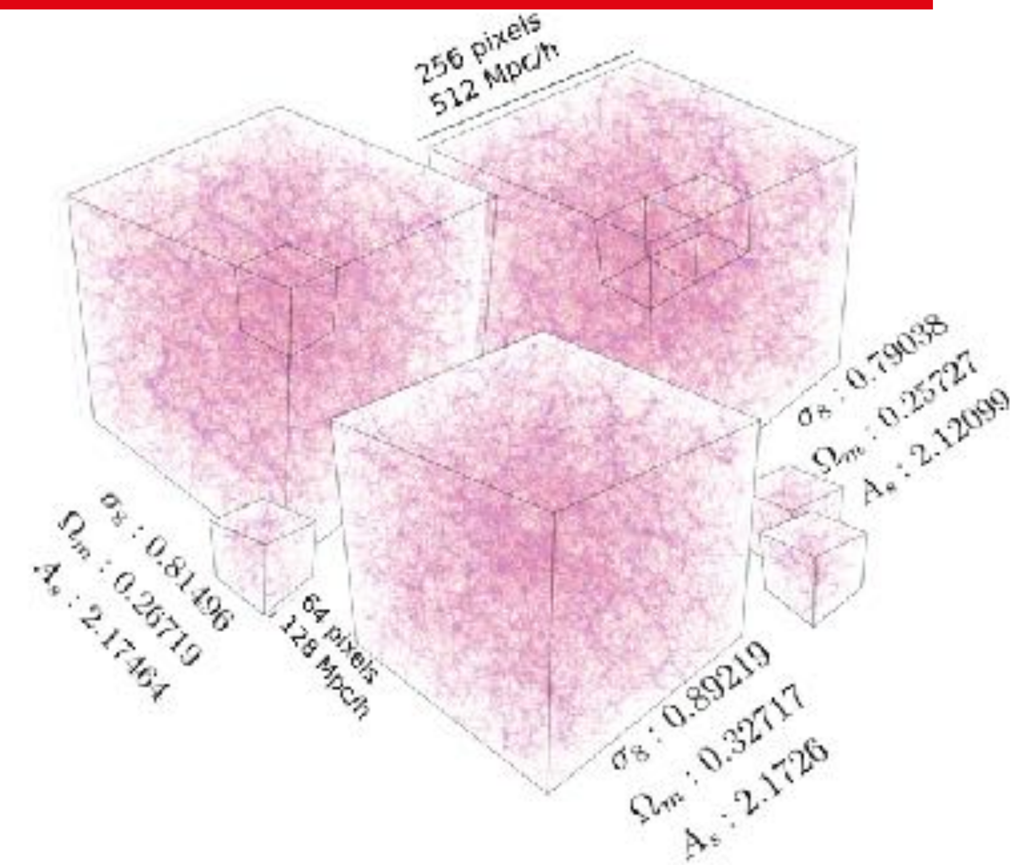
Convolutional Neural Networks

A convolutional neural network for image classification



Deep Learning the Large Scale Structure

Ravanbakhsh et al. (2017), Mathuriya et al. (2018) showed that <u>convolutional neural networks</u> can be trained to predict cosmological parameters from the visual shape of the large scale structure, i.e. the filaments, clusters and voids of the cosmic density field.

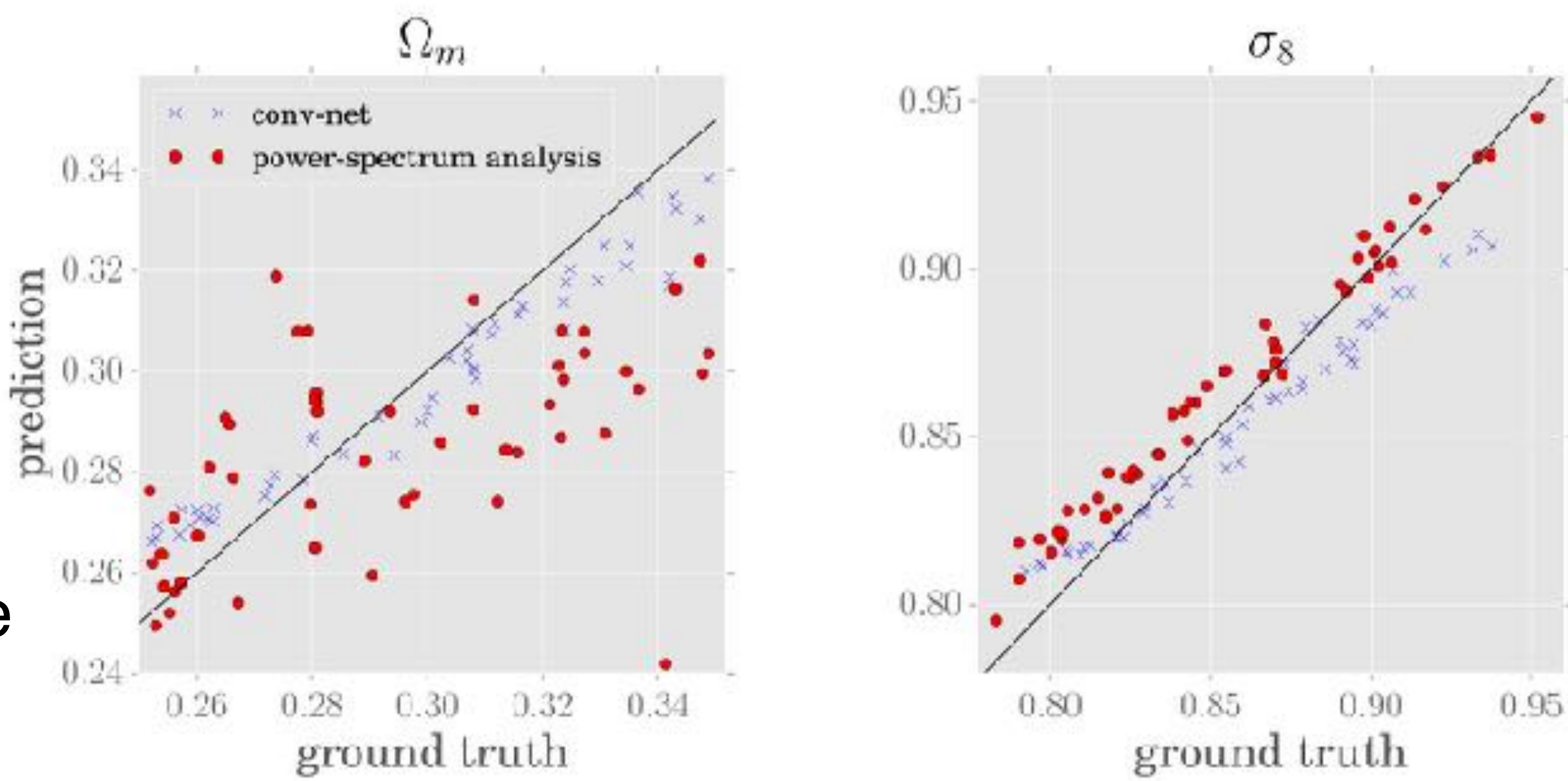


500 COmoving Lagrangian Acceleration(COLA) simulations

512Mpc box with 512^3 dark matter particles

Output at z=0

First work showing that a connection can be built from the density field directly to the parameters



Deep Learning the Large Scale Structure

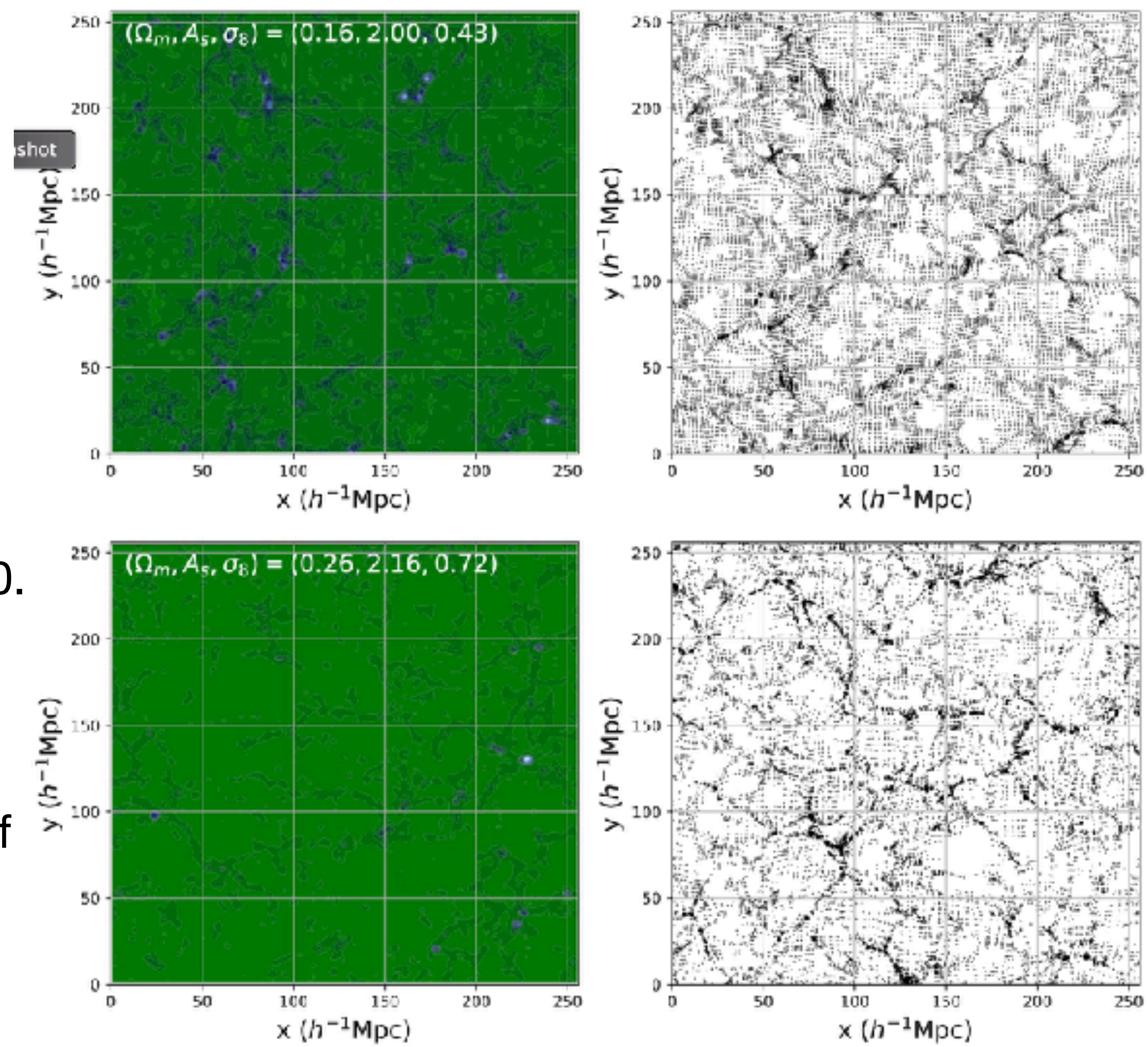
In a grid of 31x15 parameter combinations

$$0.16 < \Omega_M < 0.46$$
$$0.4 < \sigma_8 < 1.1$$

We run COLA DM simulations with with 128^3 particles, in a 256 Mpc box, using timesteps 40 output at z=0.

We grid the data onto 2Mpc voxels.

The input of the whole network is a 32^3-voxel (i.e. (64Mpc)3) subcube of the density field.

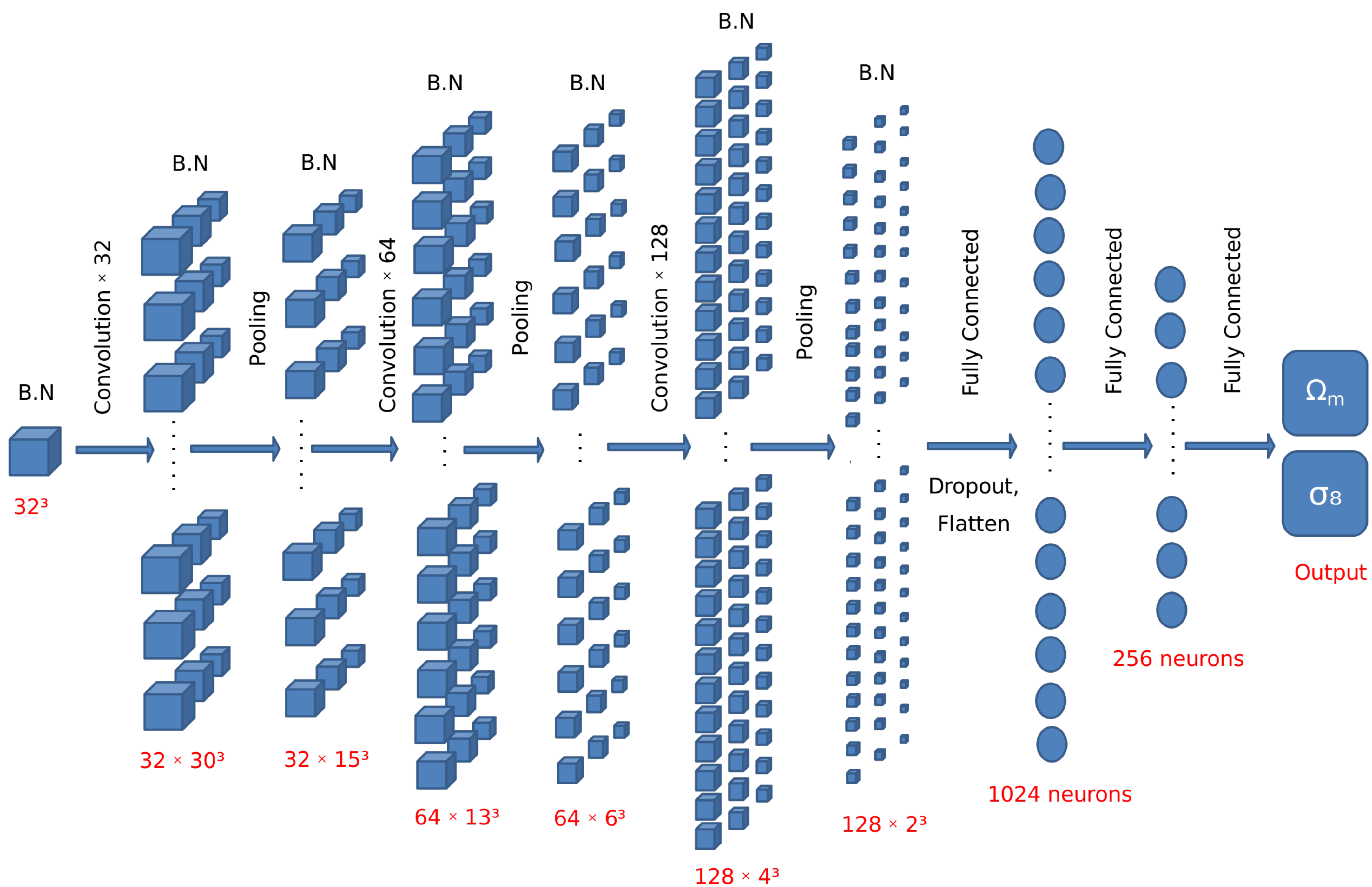


arXiv:1908.10590

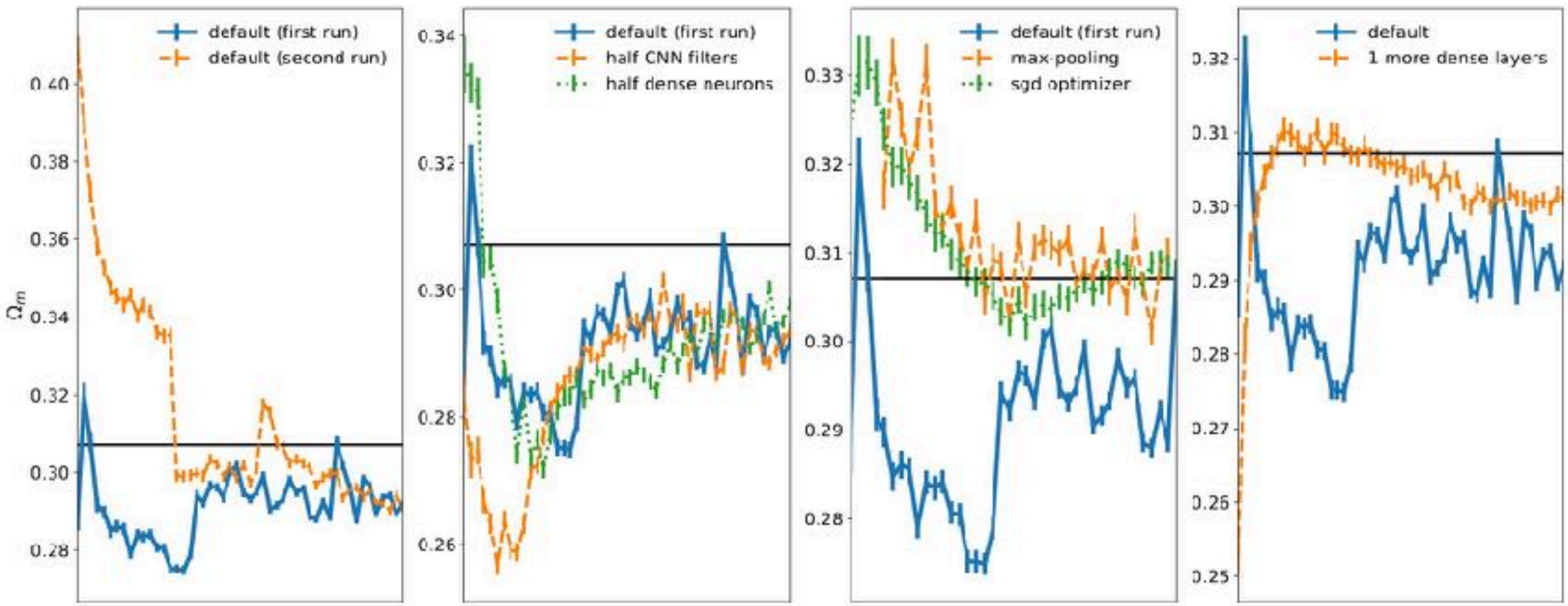
Pan, Liu, Forero-Romero, Sabiu, Li, Miao, (led by) Xiao-Dong Li

Deep Learning the Large Scale Structure

Default Architecture



Deep Learning the Large Scale Structure



Learning Curves

Varying:
- **# of CNN filters**
- **# of dense neurons**
- **# of neuron layers**
- **Optimiser**
- **Pooling type**

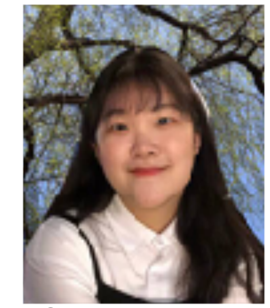
Clear advantage in max-pooling over the average pooling

Clear advantage of the sgd optimiser over the default 'Adam' optimiser.

Adding an extra dense layer improves convergence

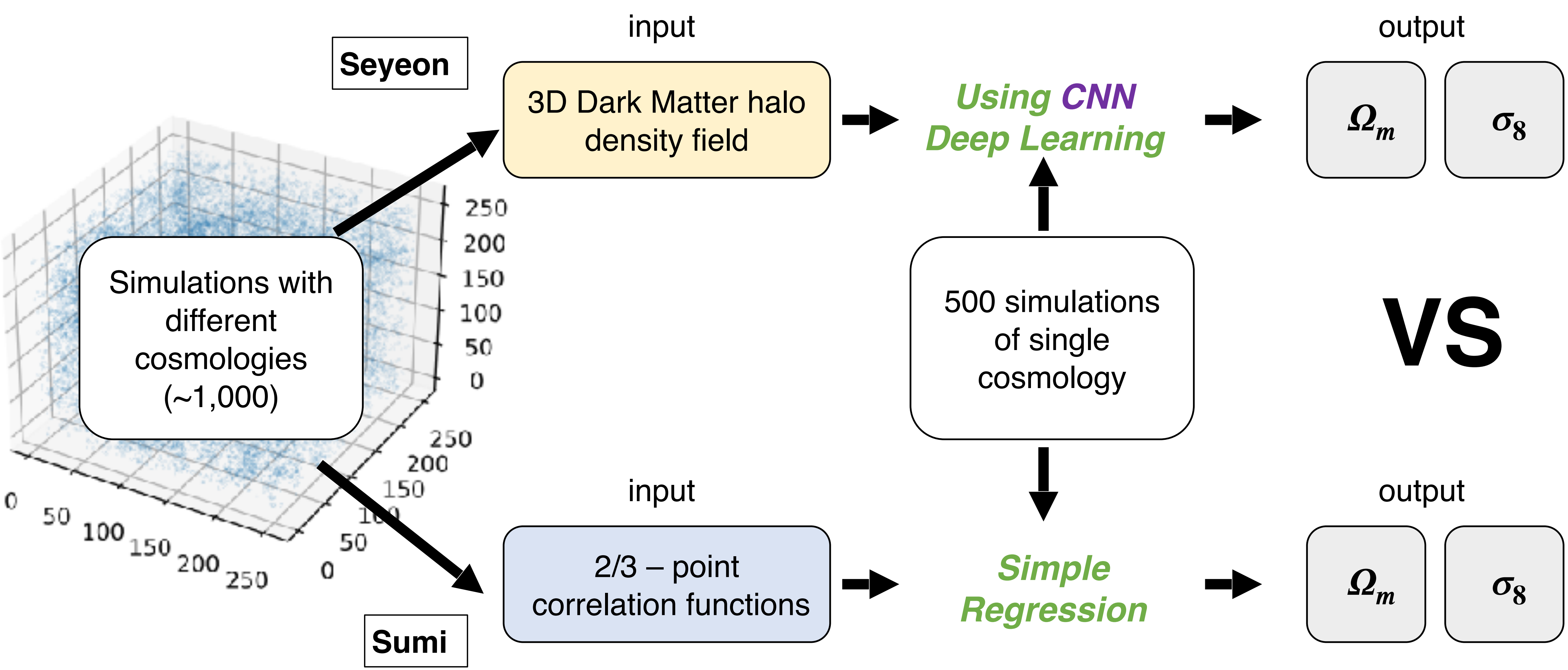
Information Content: Deep Learning vs Correlation Functions

CLML (Cosmology with Large scale structure using Machine Learning)



Seyeon Hwang

Sumi Kim



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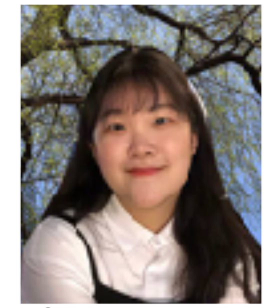
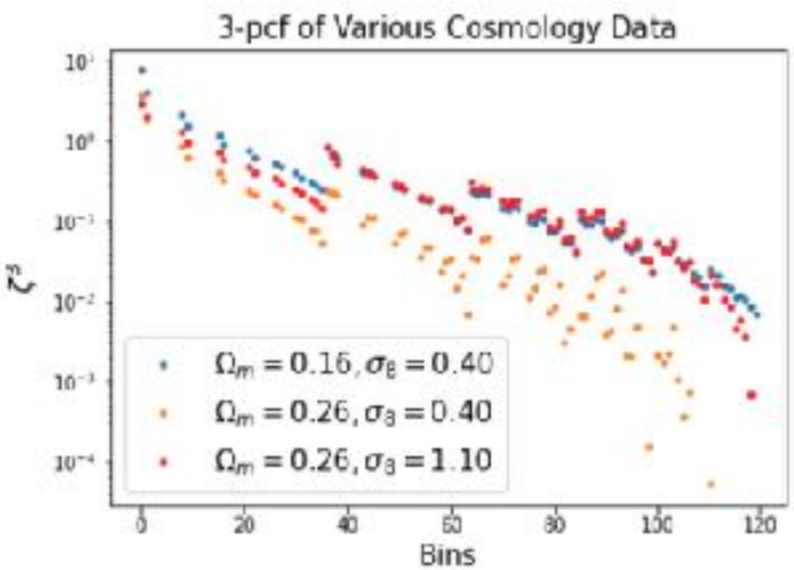
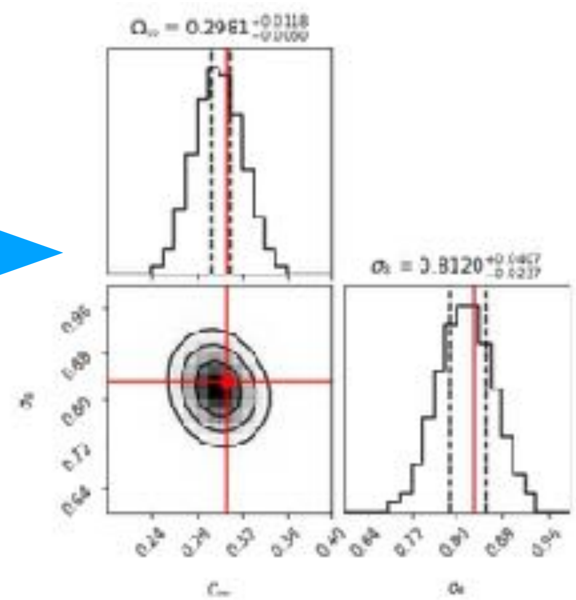
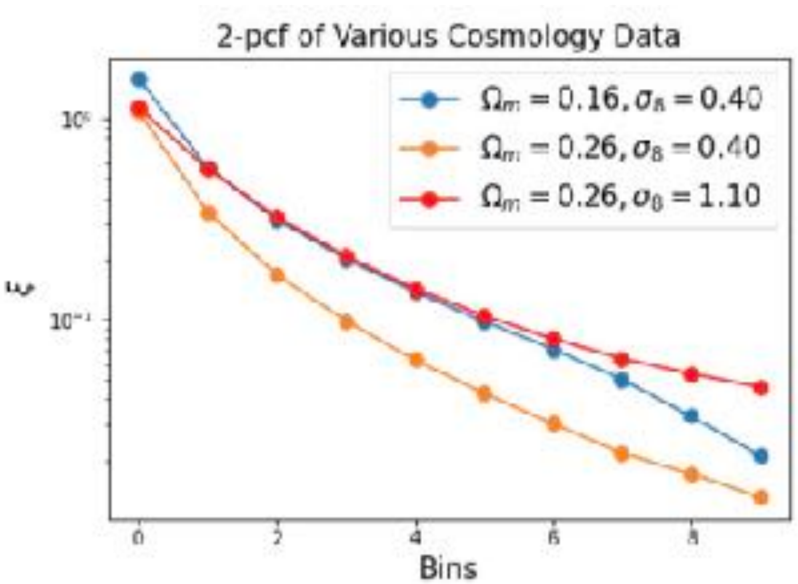

Seyeon Hwang

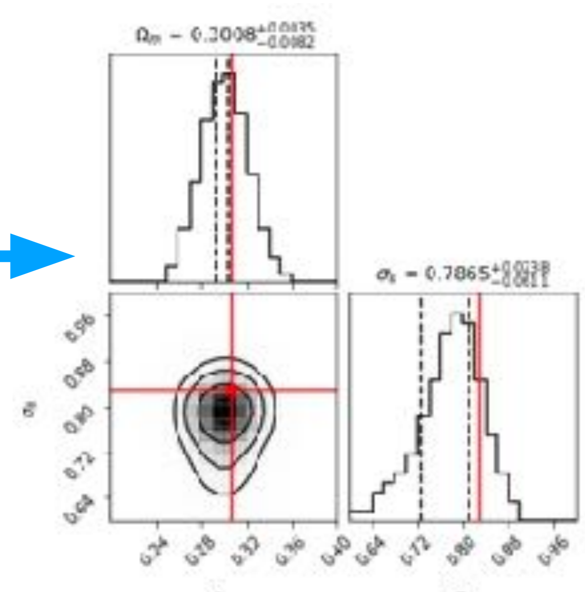

Sumi Kim

- N-point correlation Information

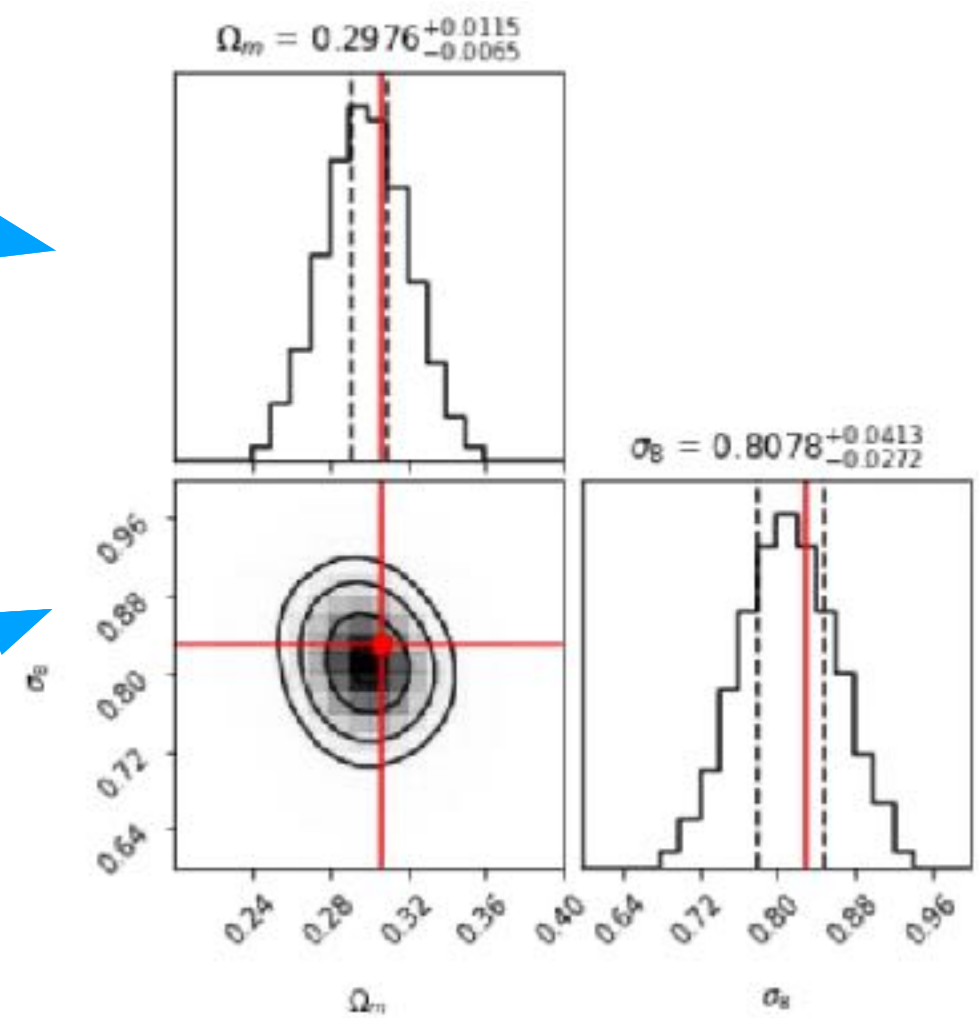




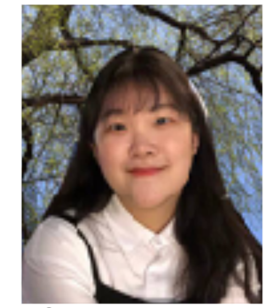




Combined 2- & 3-point information



Information Content: Deep Learning vs Correlation Functions



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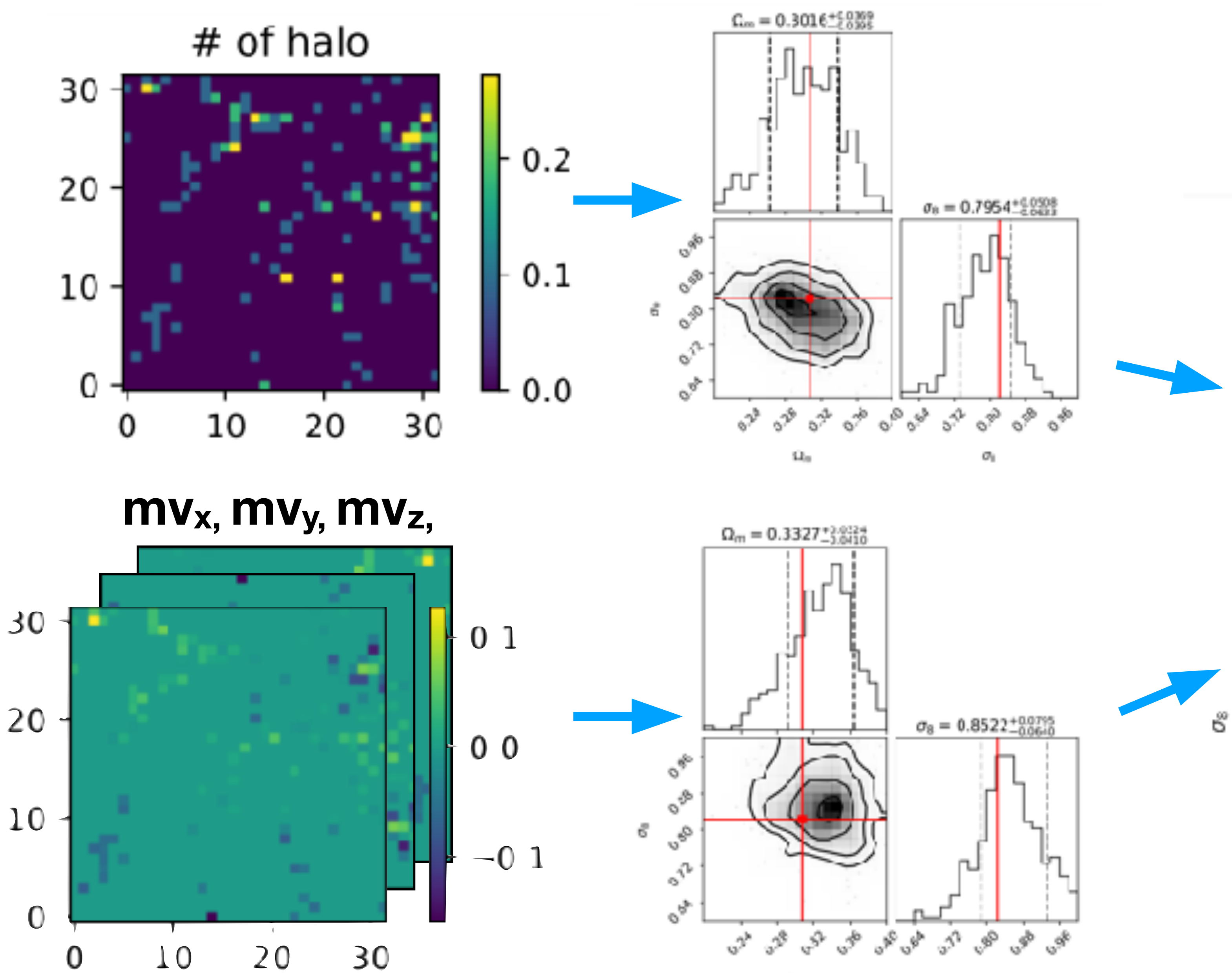
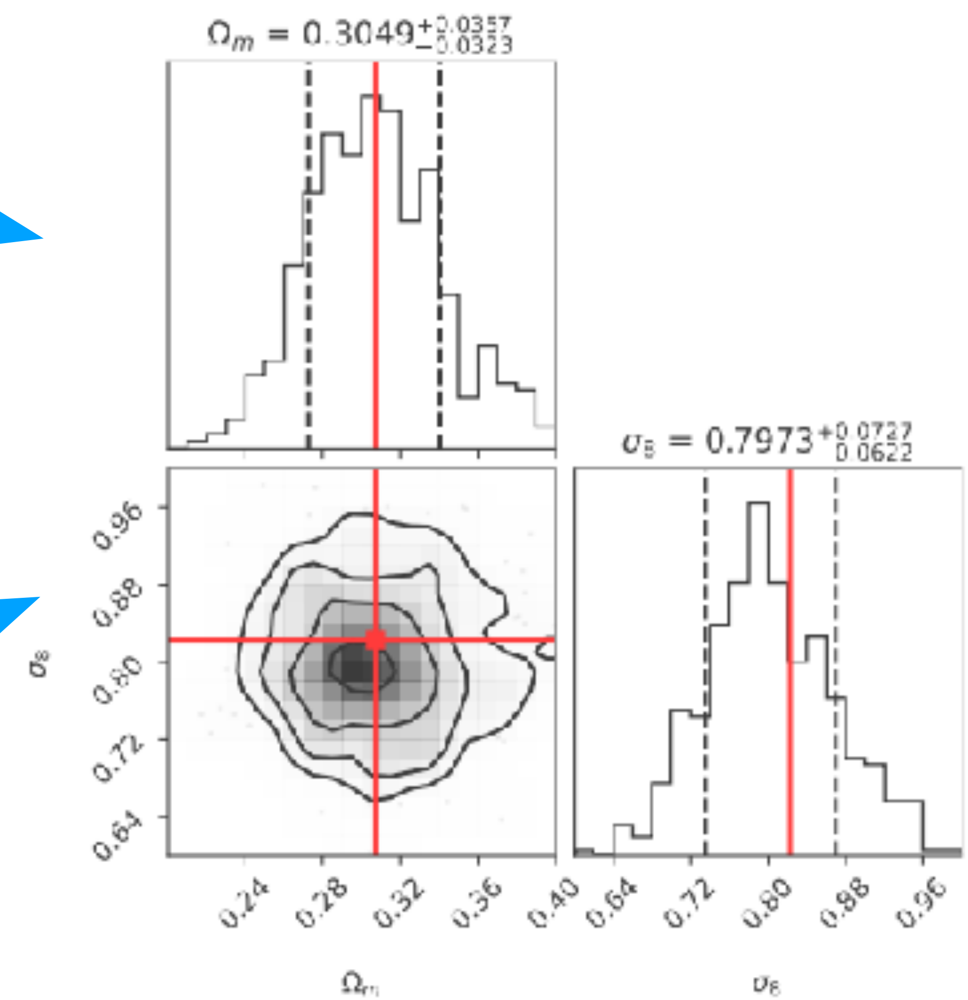
CLML (Cosmology with Large scale structure using Machine Learning)

- Deep Learning Information

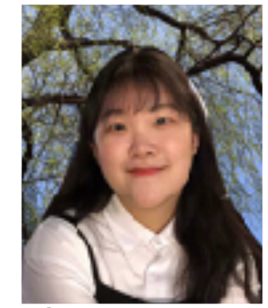


Combined Mass & Velocity



Information Content: Deep Learning vs Correlation Functions

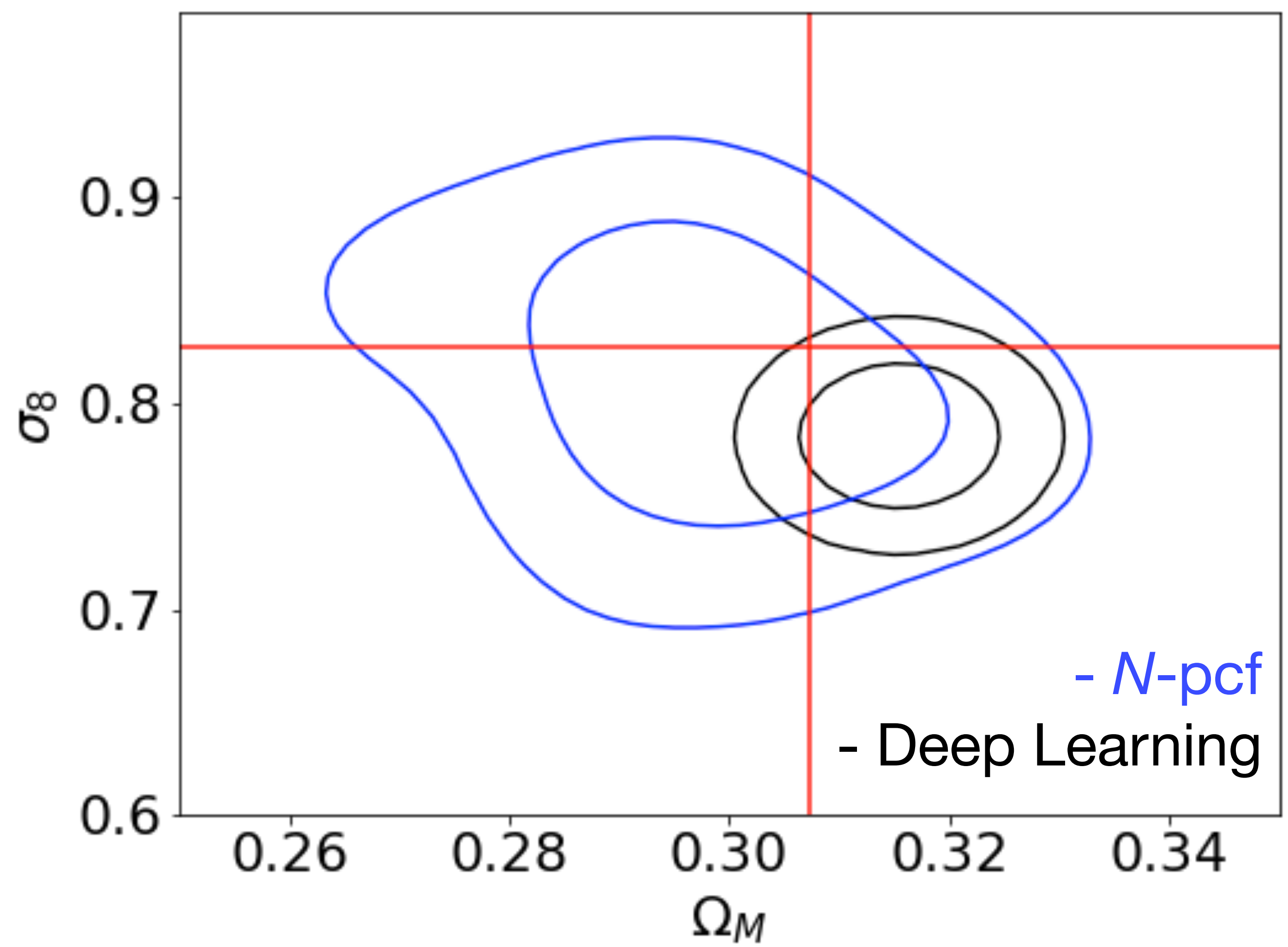
CLML (Cosmology with Large scale structure using Machine Learning)


Seyeon Hwang


Sumi Kim

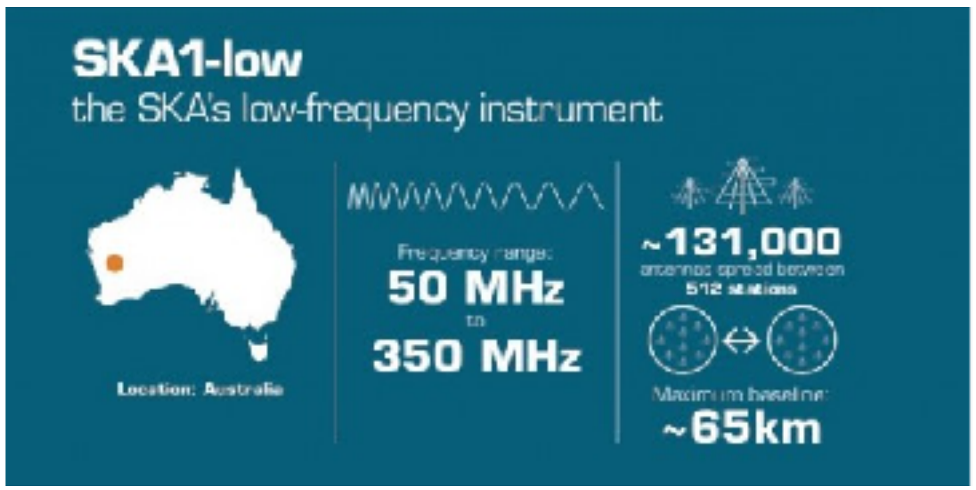
*** **Preliminary Result** ***

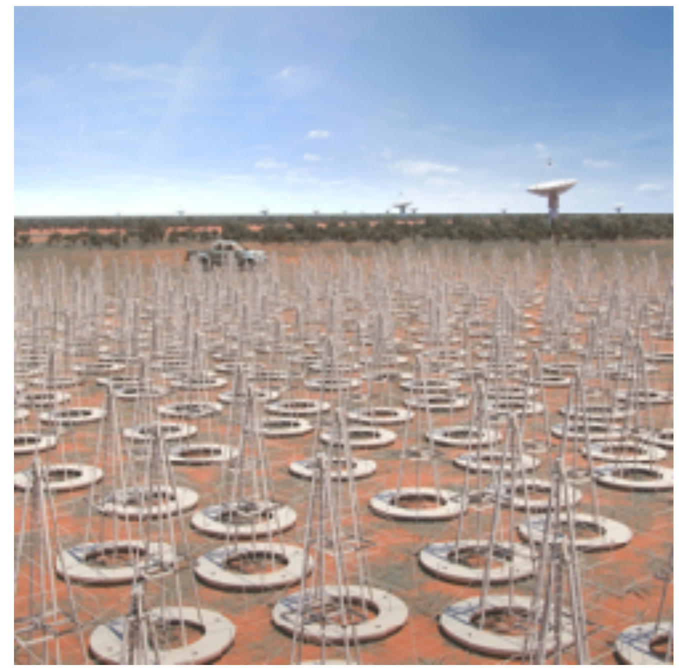
- Using 500 simulations of a single cosmology, we test the accuracy and precision of both methods
- CNN seems to be more constraining (higher information).
- CNN has a moderate bias compared to Npcf. However biases can be modelled and corrected.
- Exact *N*-pcf calculated using the GRAMSCI code https://arxiv.org/abs/1901.00296



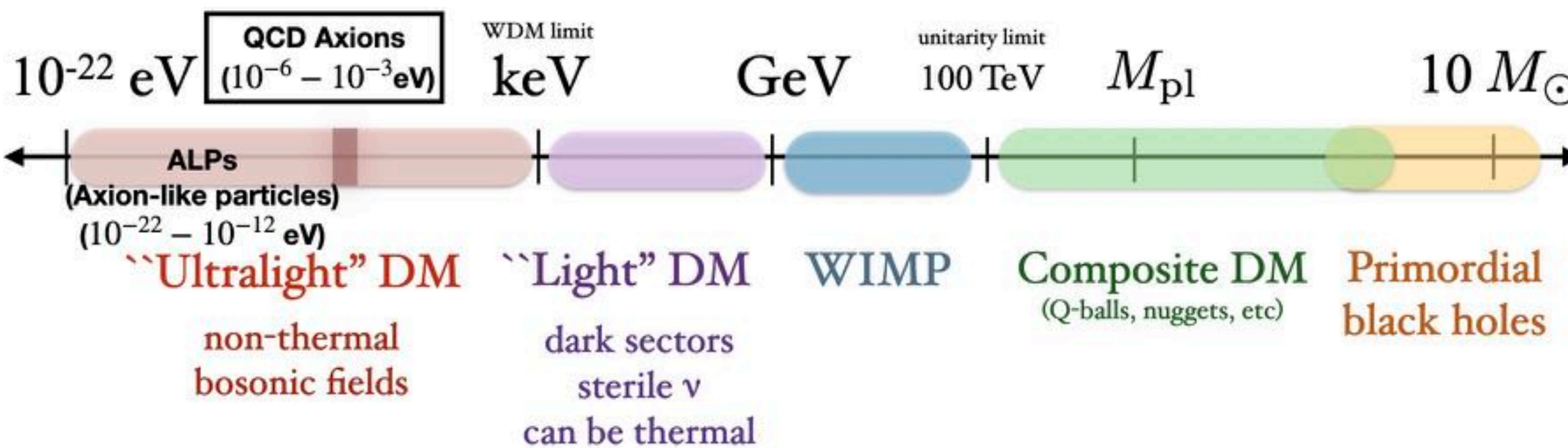
Deep Learning the 21cm Intensity Field

Future Radio surveys like SKA will map significant volumes of the high redshift Universe.



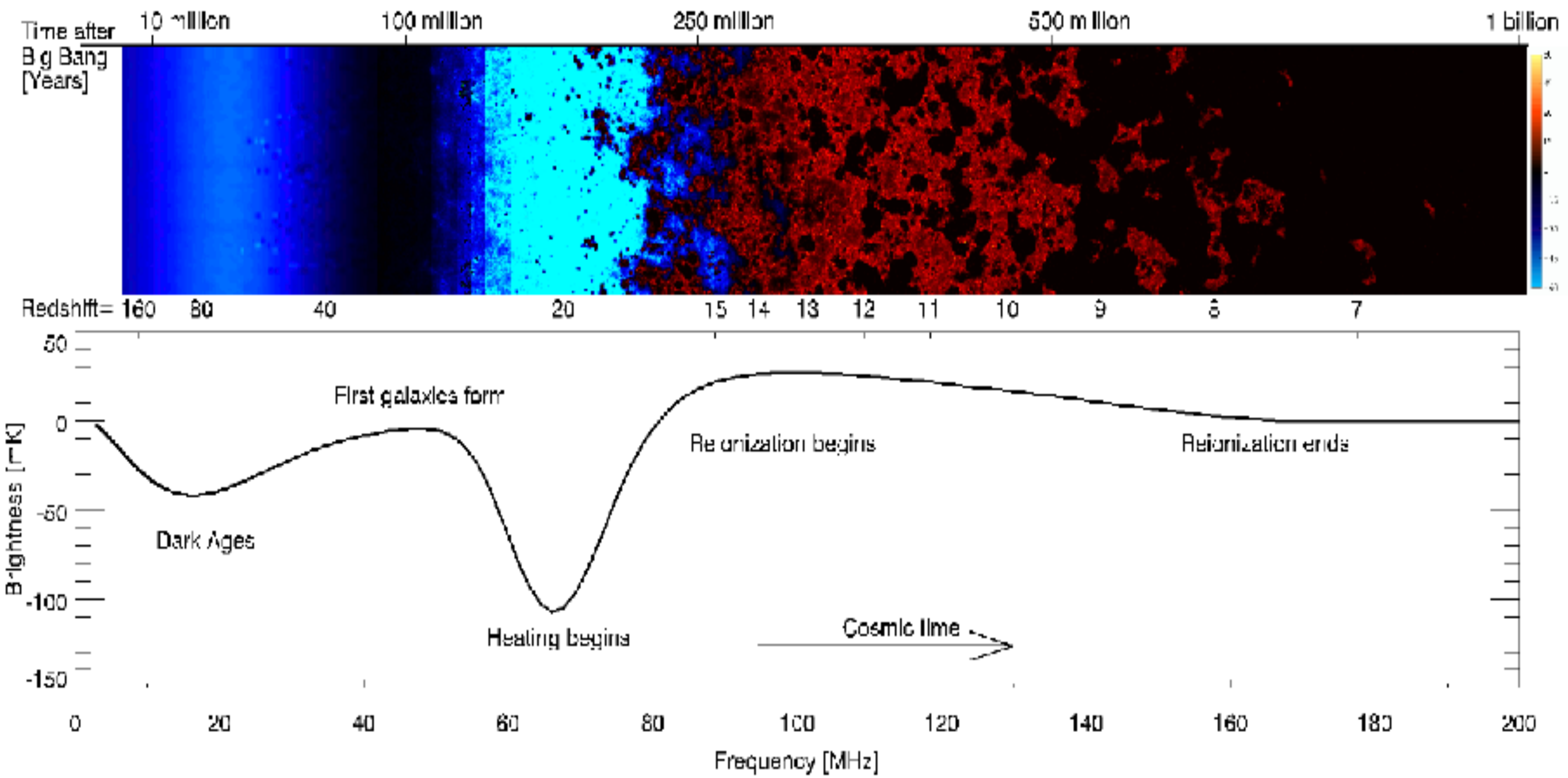


What can we earn about the nature of Dark Matter?

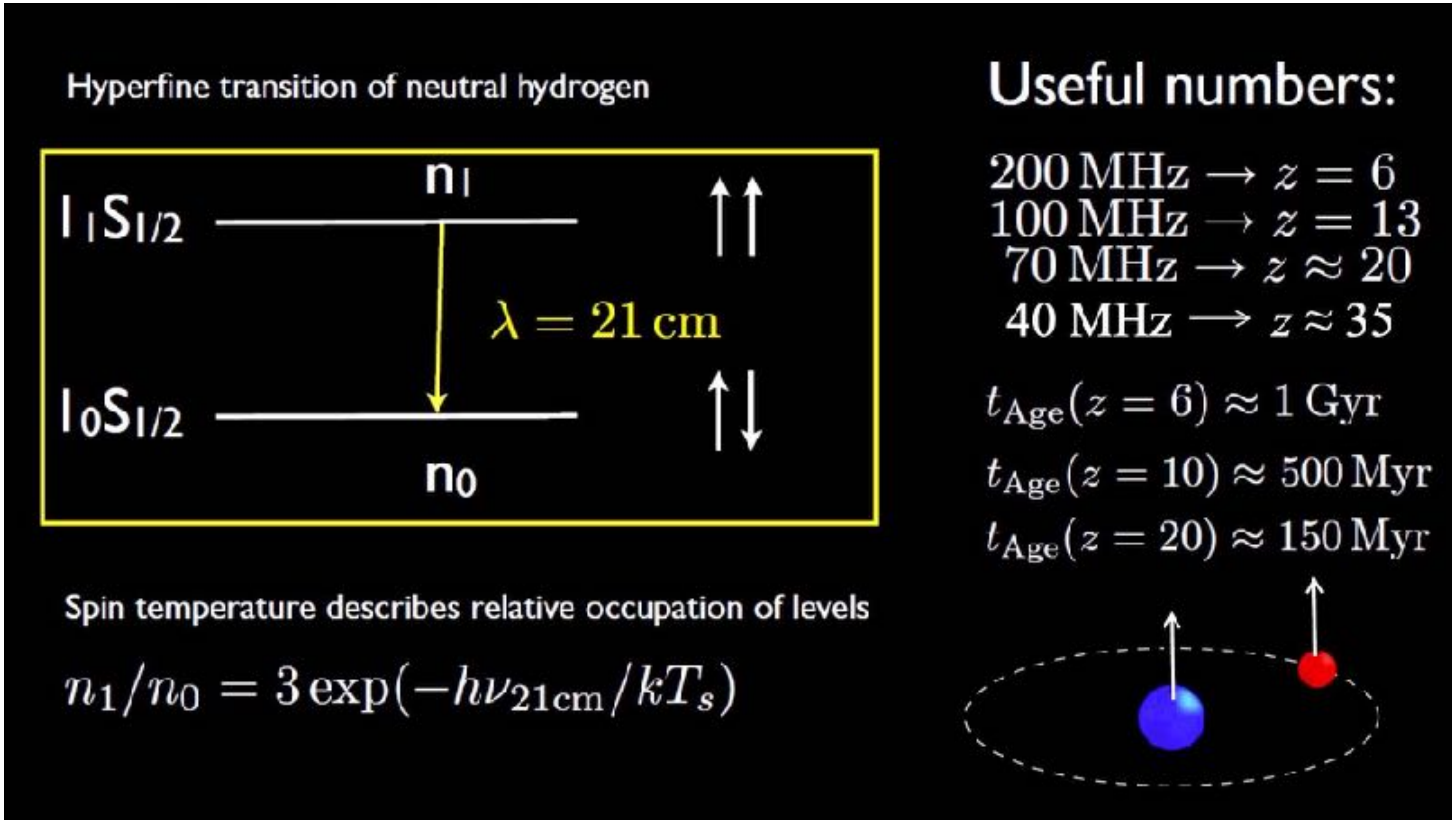


21cm Intensity Mapping

Cosmic Reionization History



21cm Intensity Mapping



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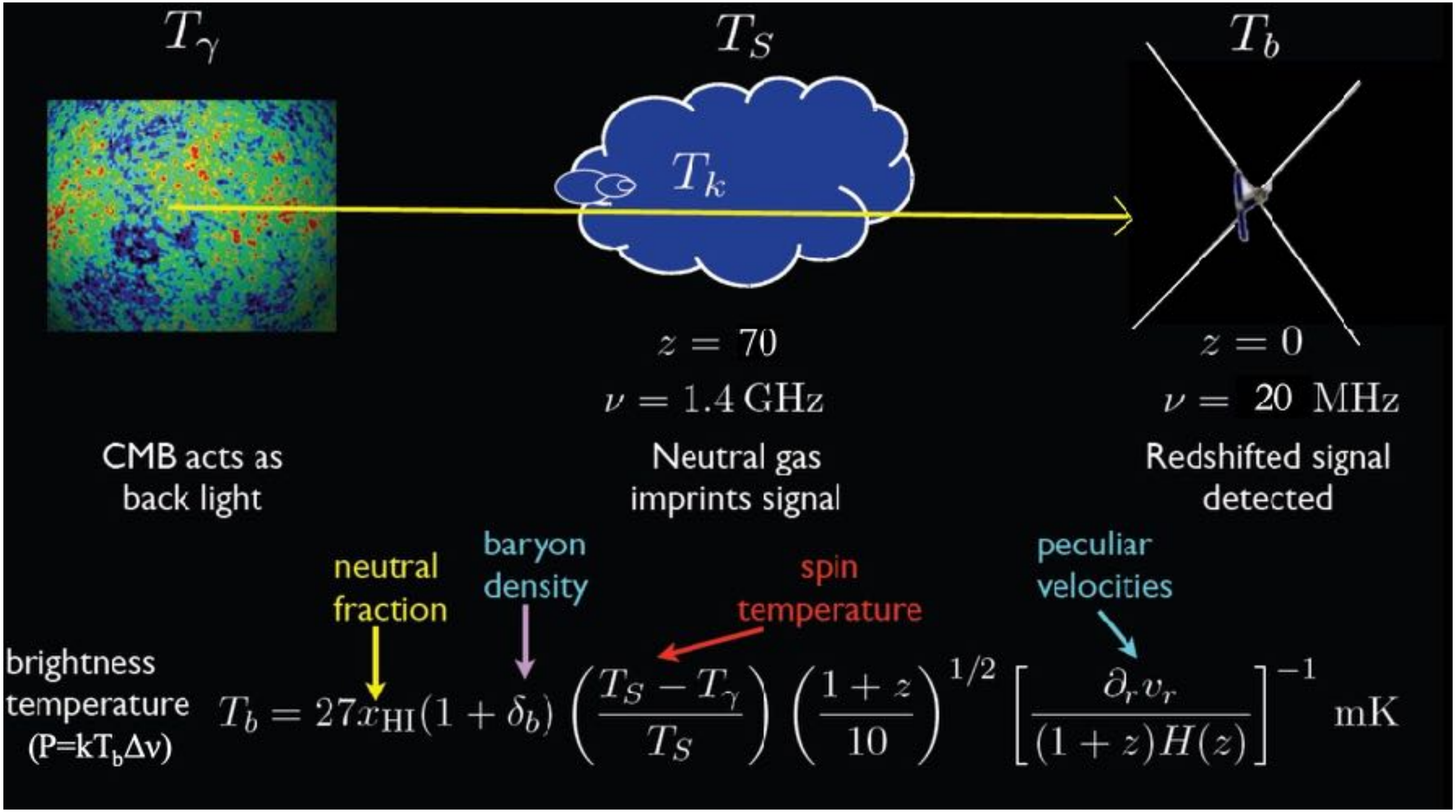
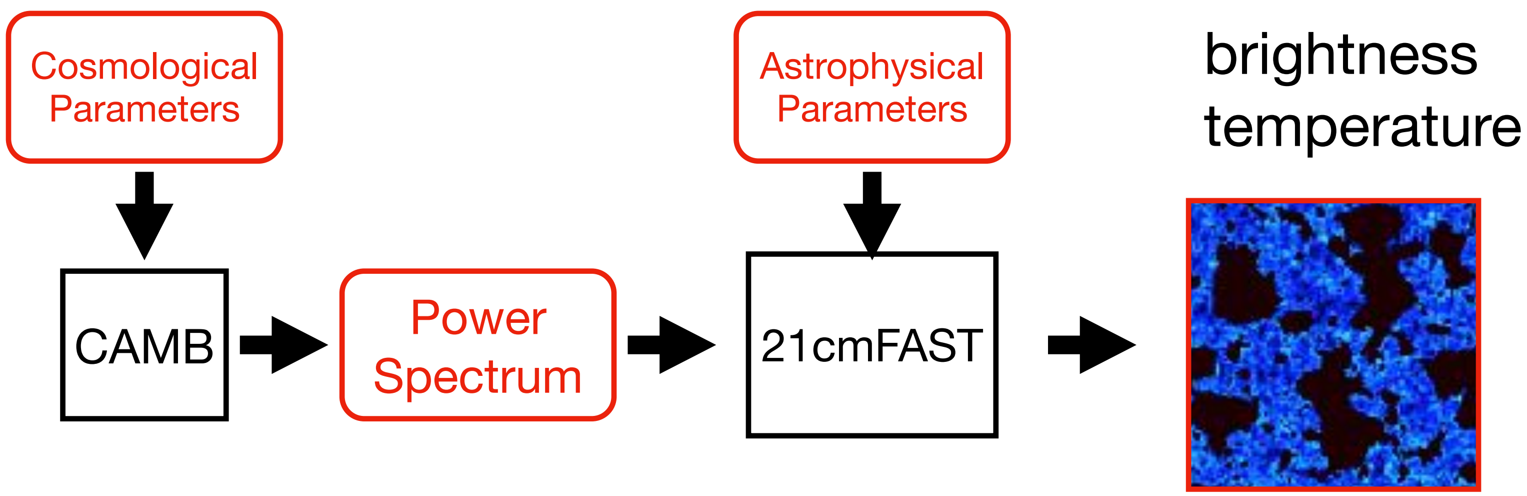


21cm Intensity Mapping

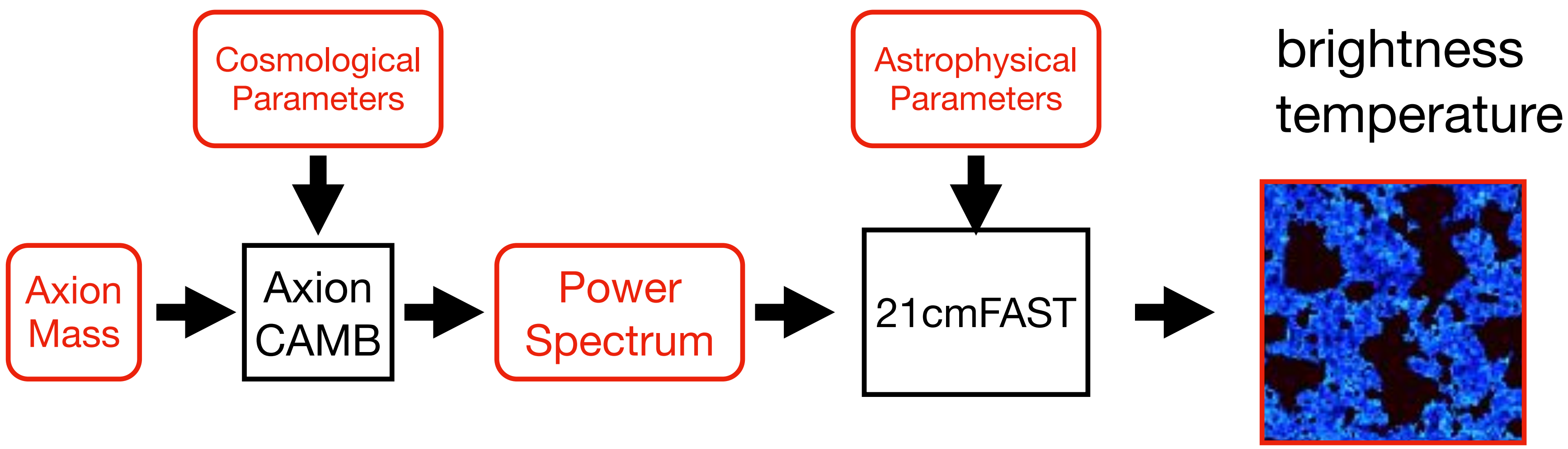
Pipeline



Mesinger & Furlanetto 2007
Mesinger et al. 2011

21cm Intensity Mapping

Pipeline



Hlozek et al. 2015

Mesinger & Furlanetto 2007
Mesinger et al. 2011

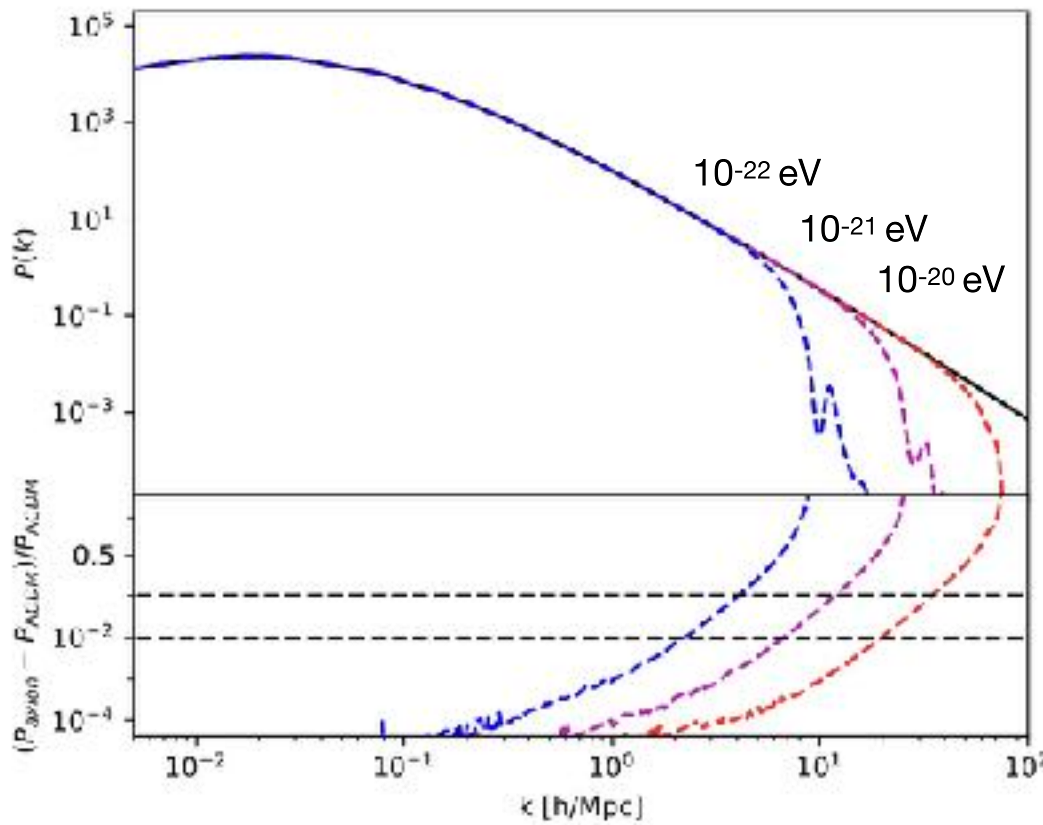
21cm Intensity Mapping

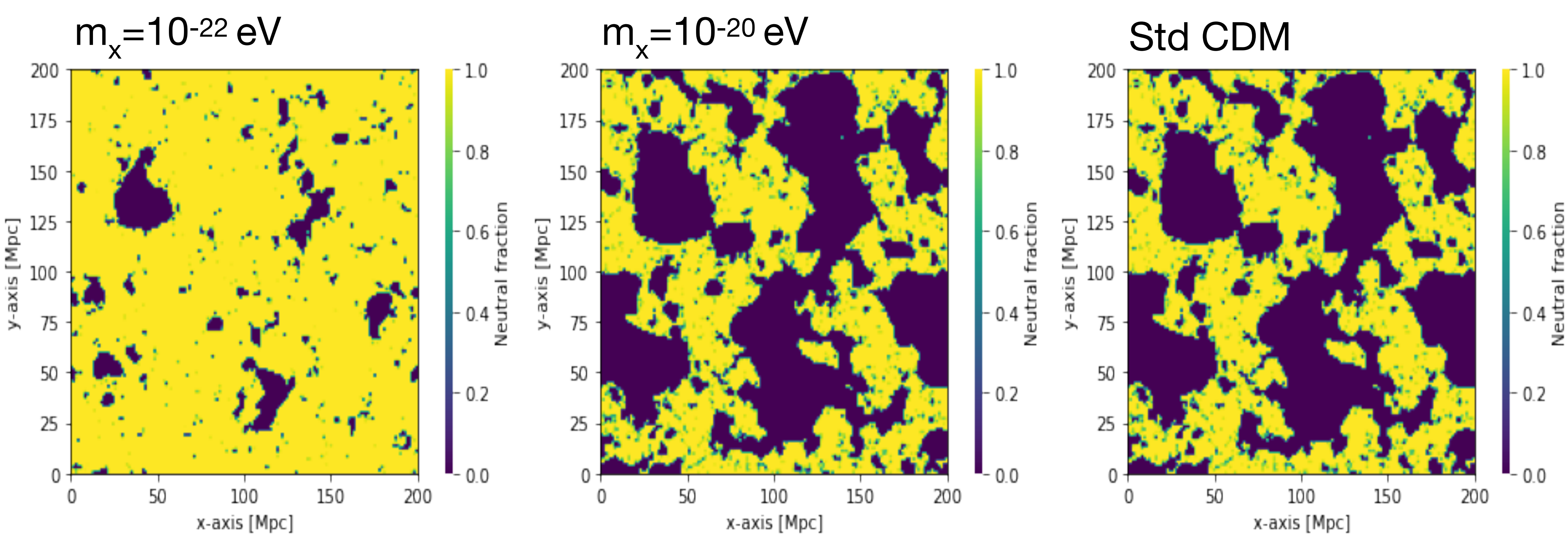
Varying Axion Mass

★The linear power spectrum has a suppression of power at progressively lower k for decreasing axion masses

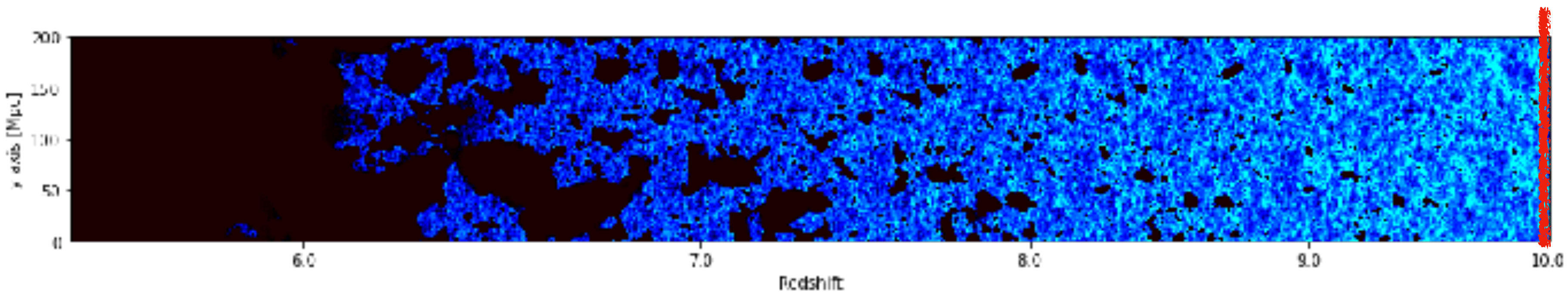
★This has a significant effect on the collapse fraction of gas

★Delays the onset of reionization compared to Std CDM

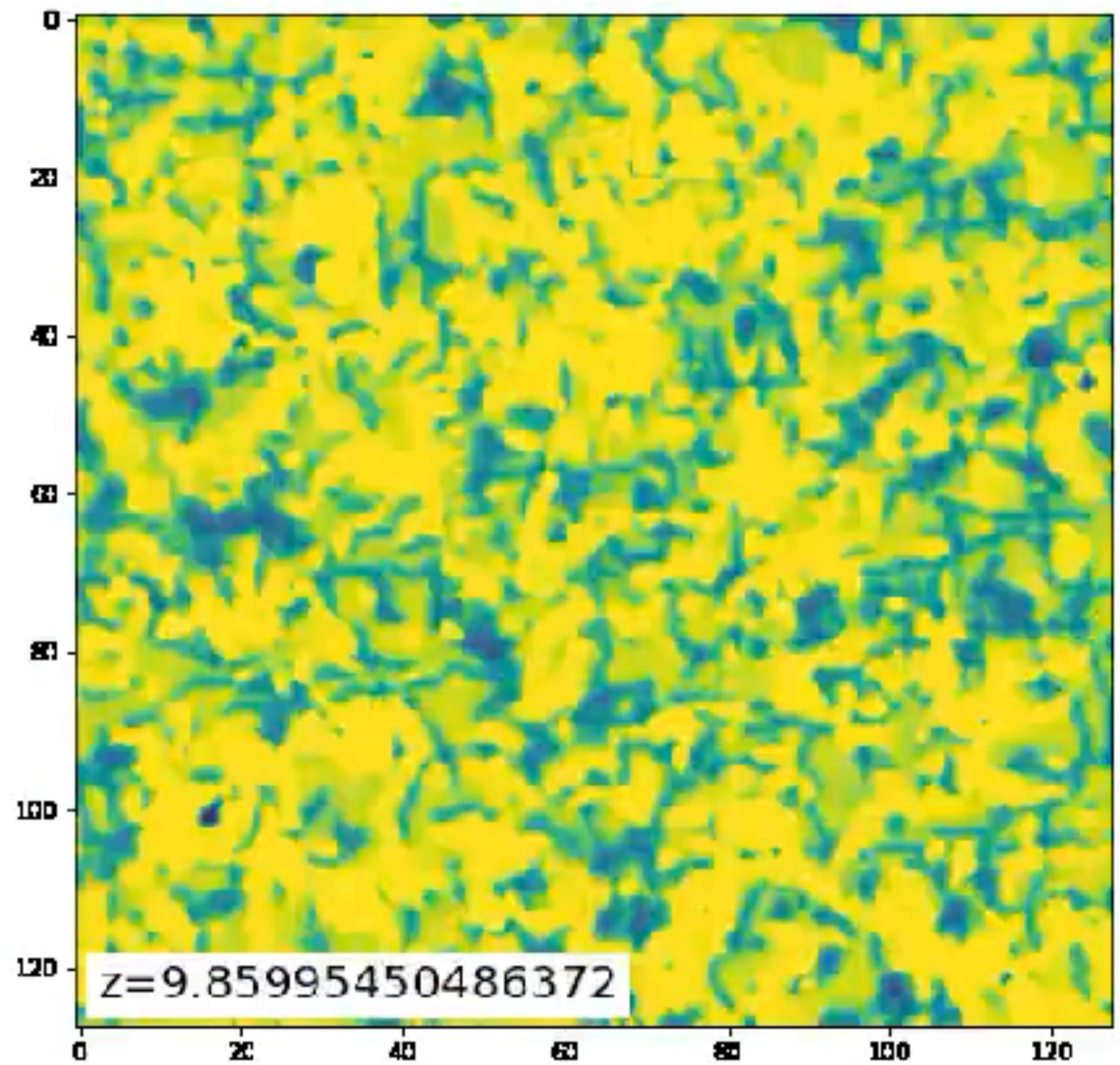




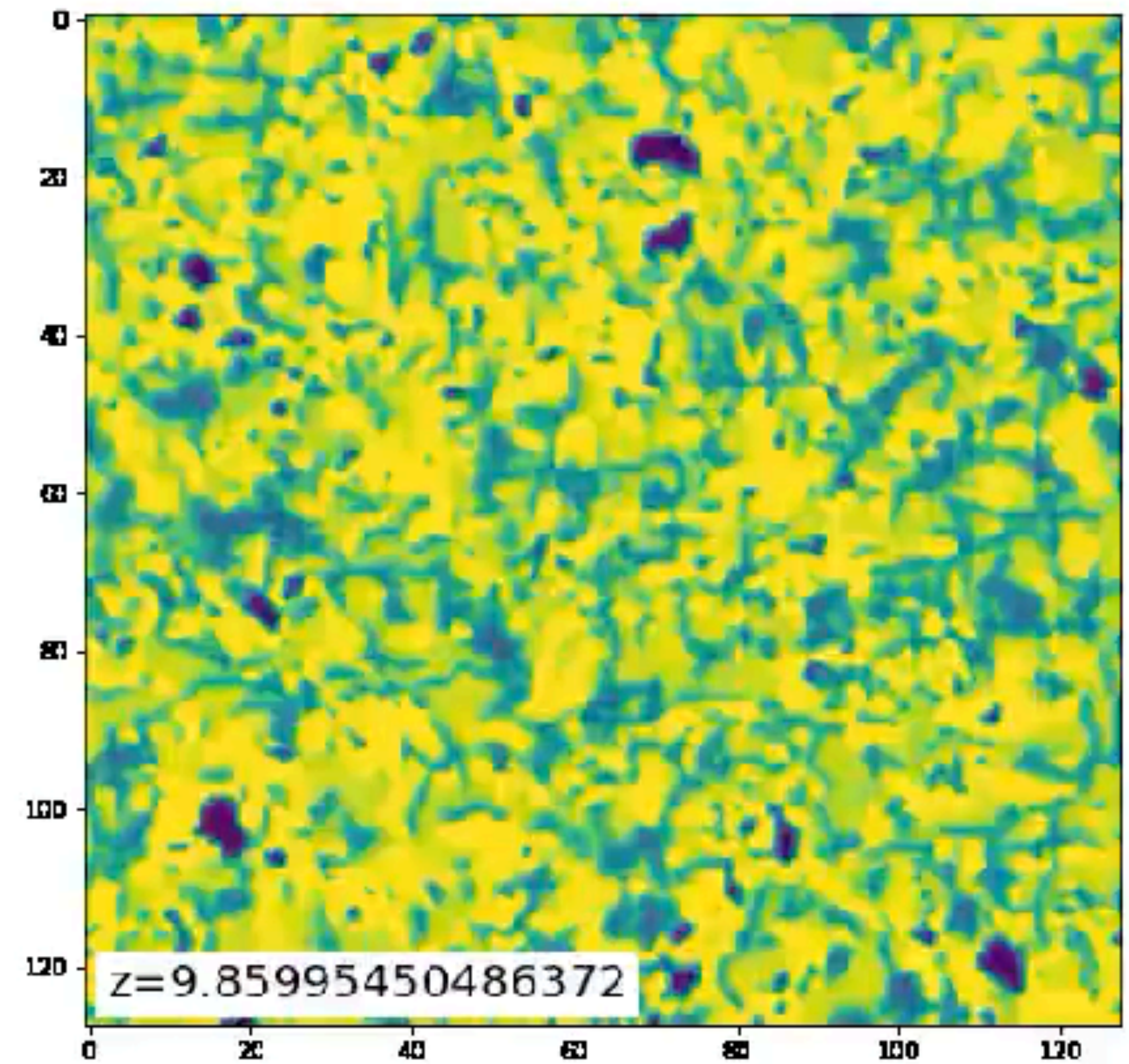
Redshift Evolution of the neutral fraction



$m_x = 10^{-22}$ eV



Std CDM



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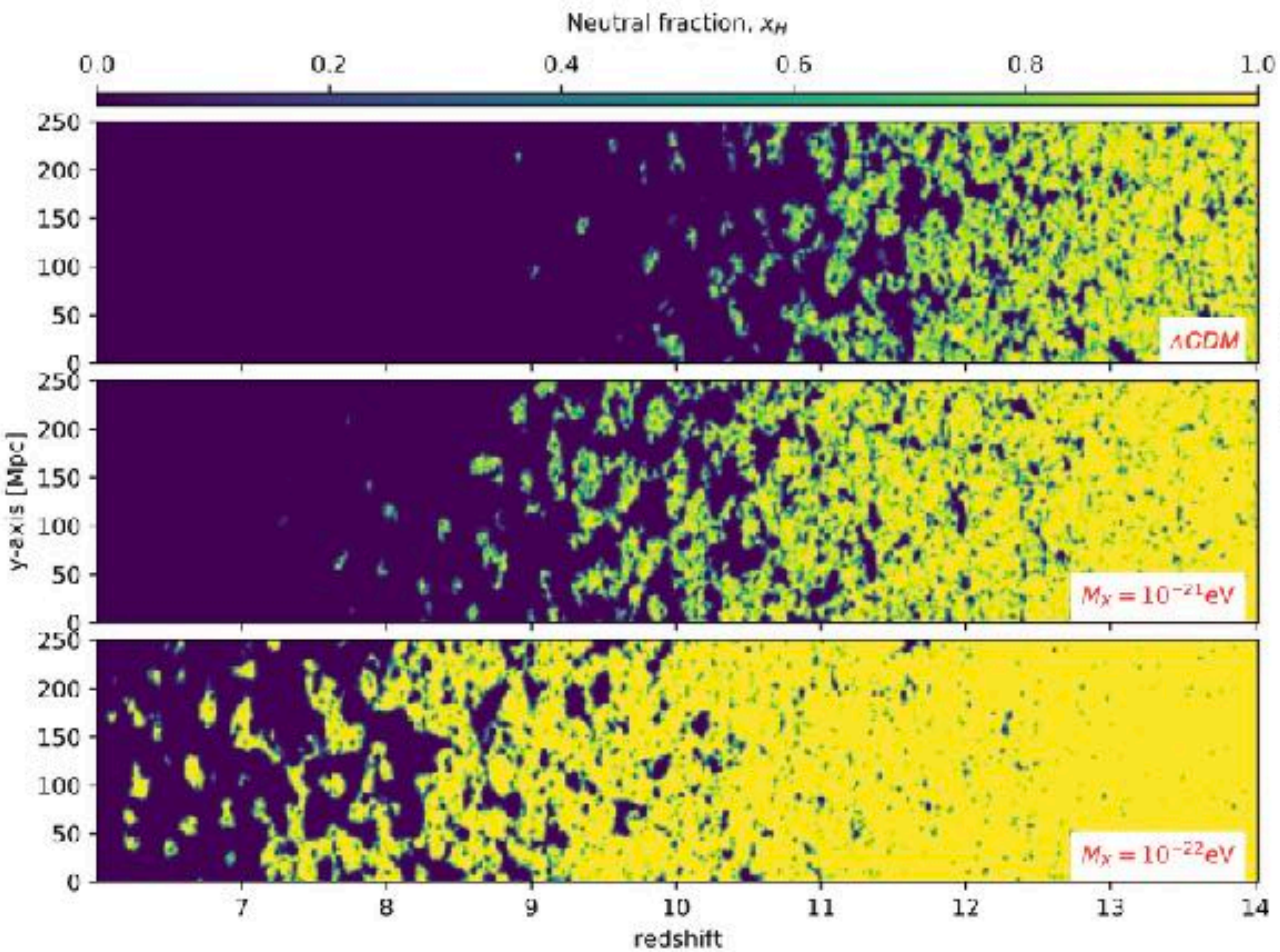
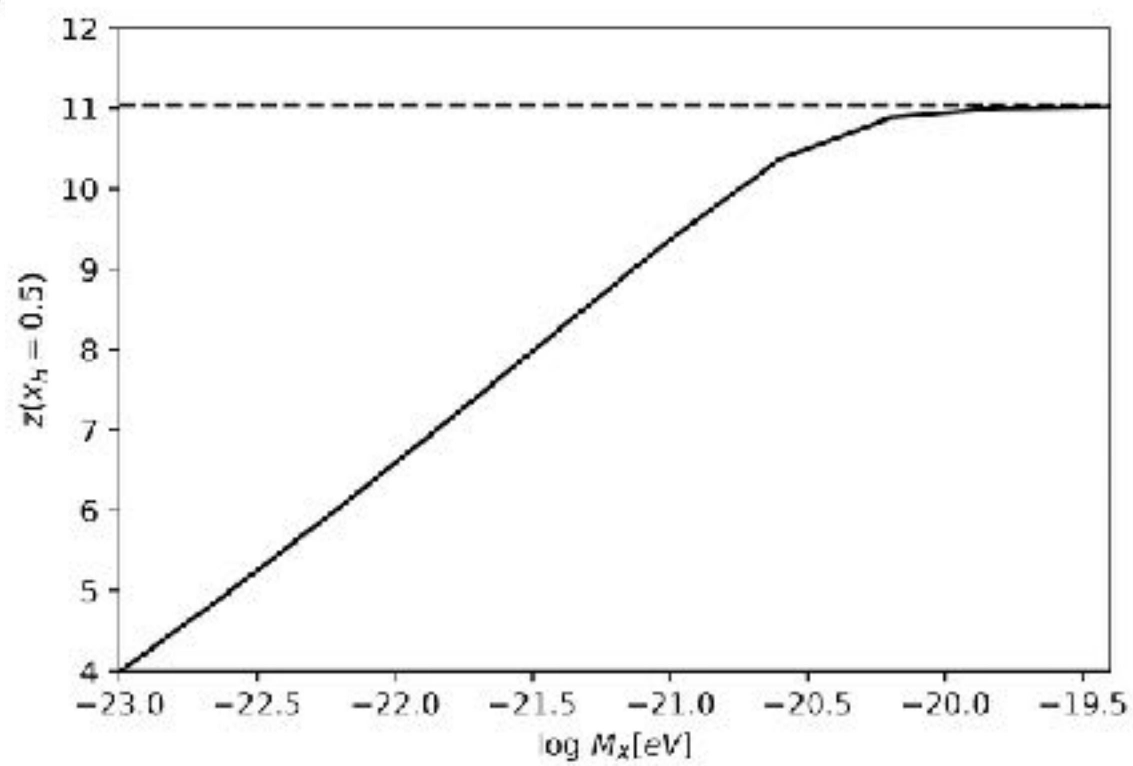
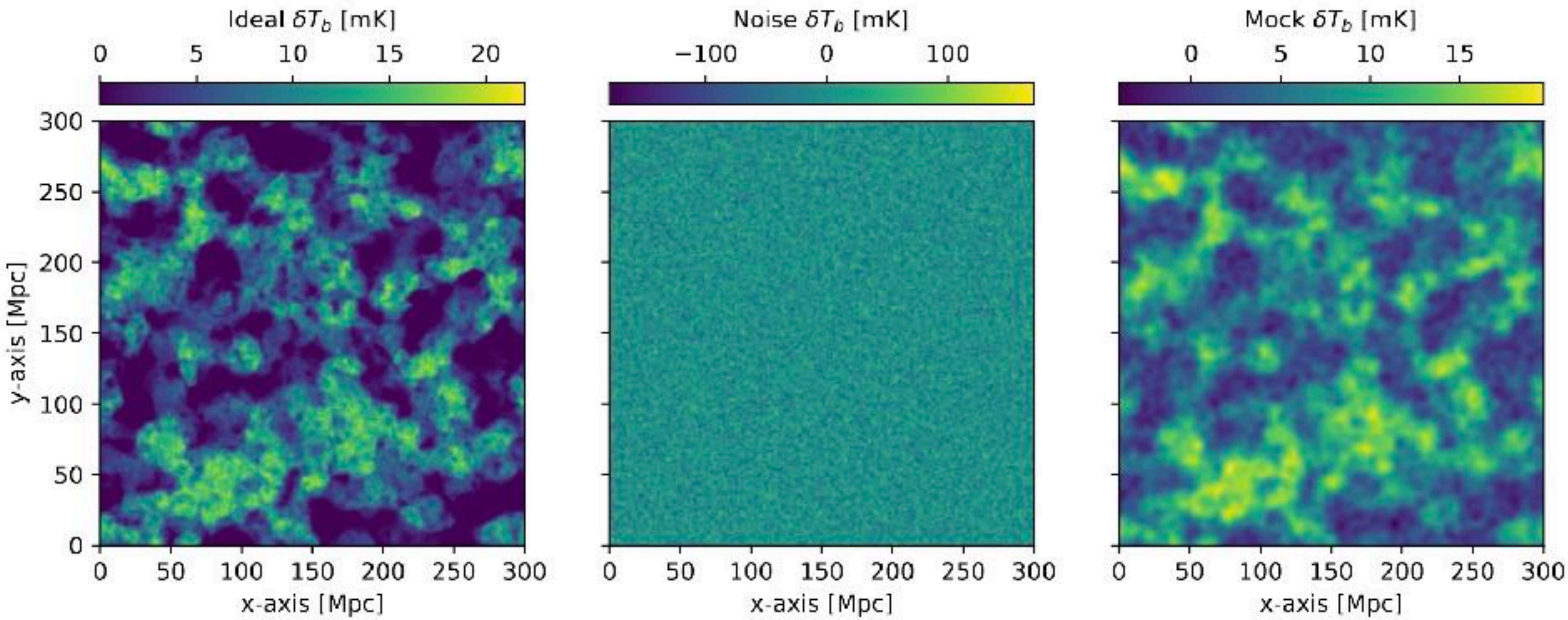




★We can look at the redshift when the universe if half ionised as a function of axion mass

21cm Intensity Mapping

Towards Realistic Images: Noise and Telescope Resolution



Noiseless, Ideal simulation

$$\sigma_{noise} = T_{sys}\sqrt{\frac{4\pi f_{sky}}{\Omega_{beam} N_{dish} t_{int} \Delta\nu}}.$$

N$_{\text{dish}}$ =is the number of antenna, $\Delta\nu = 1$MHz is the frequency bandwidth, $f_{sky} = 0.02$ is the fraction fo sky observed, $t_{int} = 1{,}000$h is the integration time, and $T_{sys} = T_{rx} + T_{gal}$ the system temperature is composed of $T_{rx} = 0.1T_{gal} + 40K$ and $T_{gal} = 25\left(\frac{\nu}{408MHz}\right)^{-2.75}$

Radio telescopes have an angular resolution $\Delta\theta \sim \frac{\lambda}{B}$, where B is the baseline which we adopt as 500m for the core antennas of the SKA1-Low design, and since $\lambda = \lambda_{21}(1+z)$, the resolution acquires a mild redshift dependence.

21cm Intensity Mapping

Data structure

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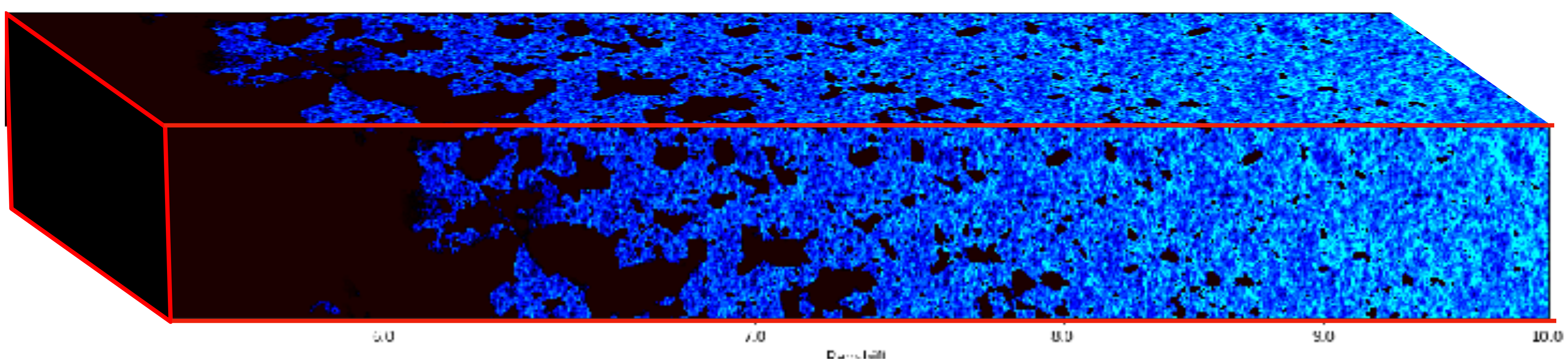
128 l

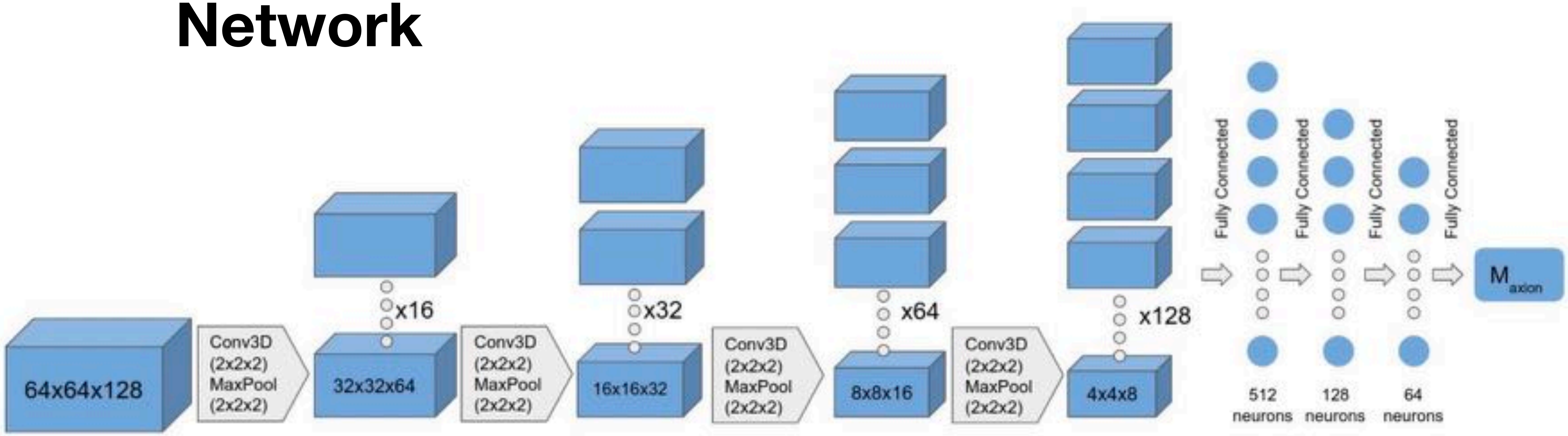


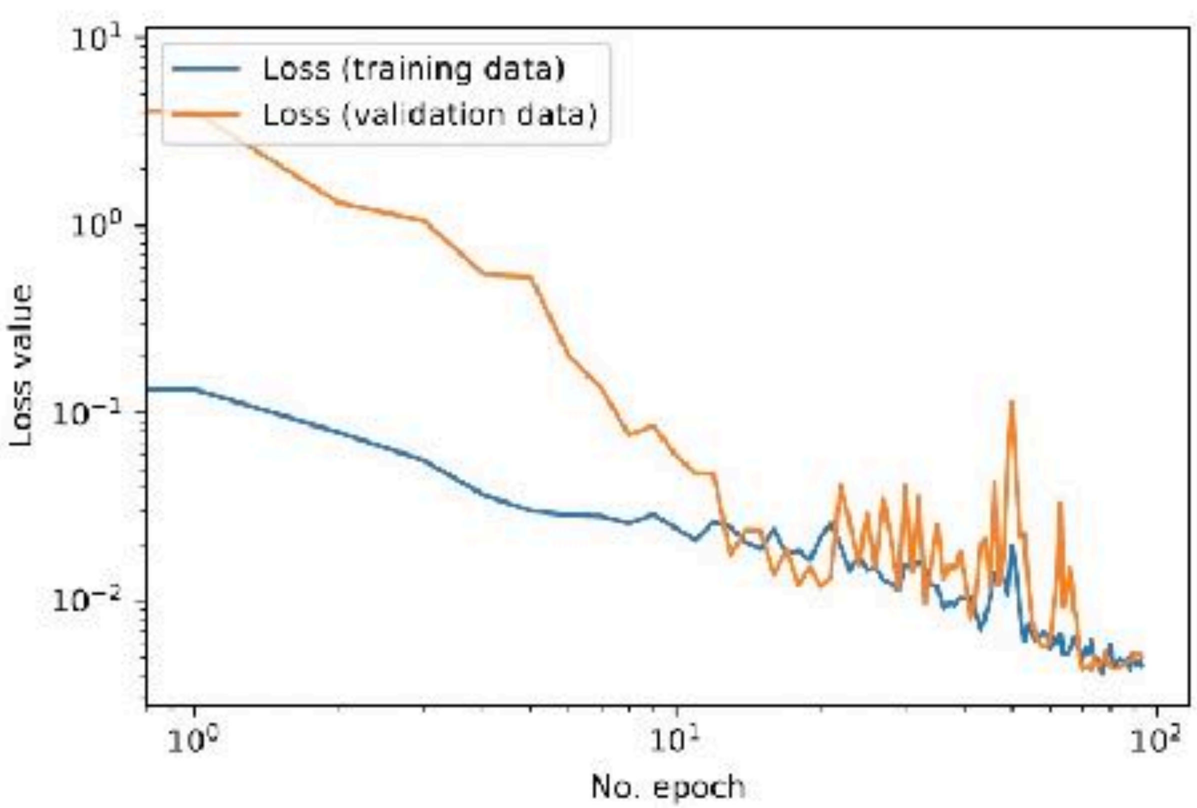
128 Mpc

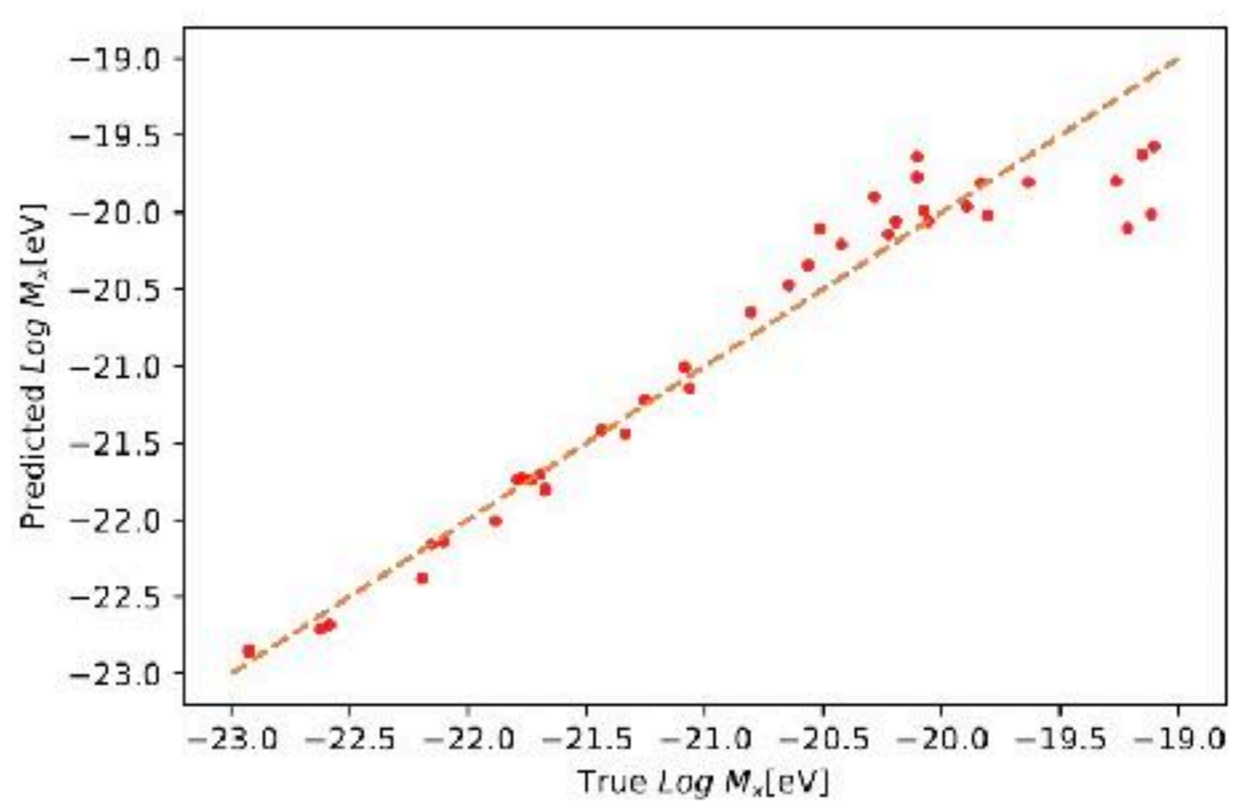
64 x 64 x 128 cells of 21cm Brightness temperature
Spanning 2 spatial dimensions and 1 redshift/frequency

21cm Intensity Mapping

3D Convolutional Neural Network







21cm Intensity Mapping

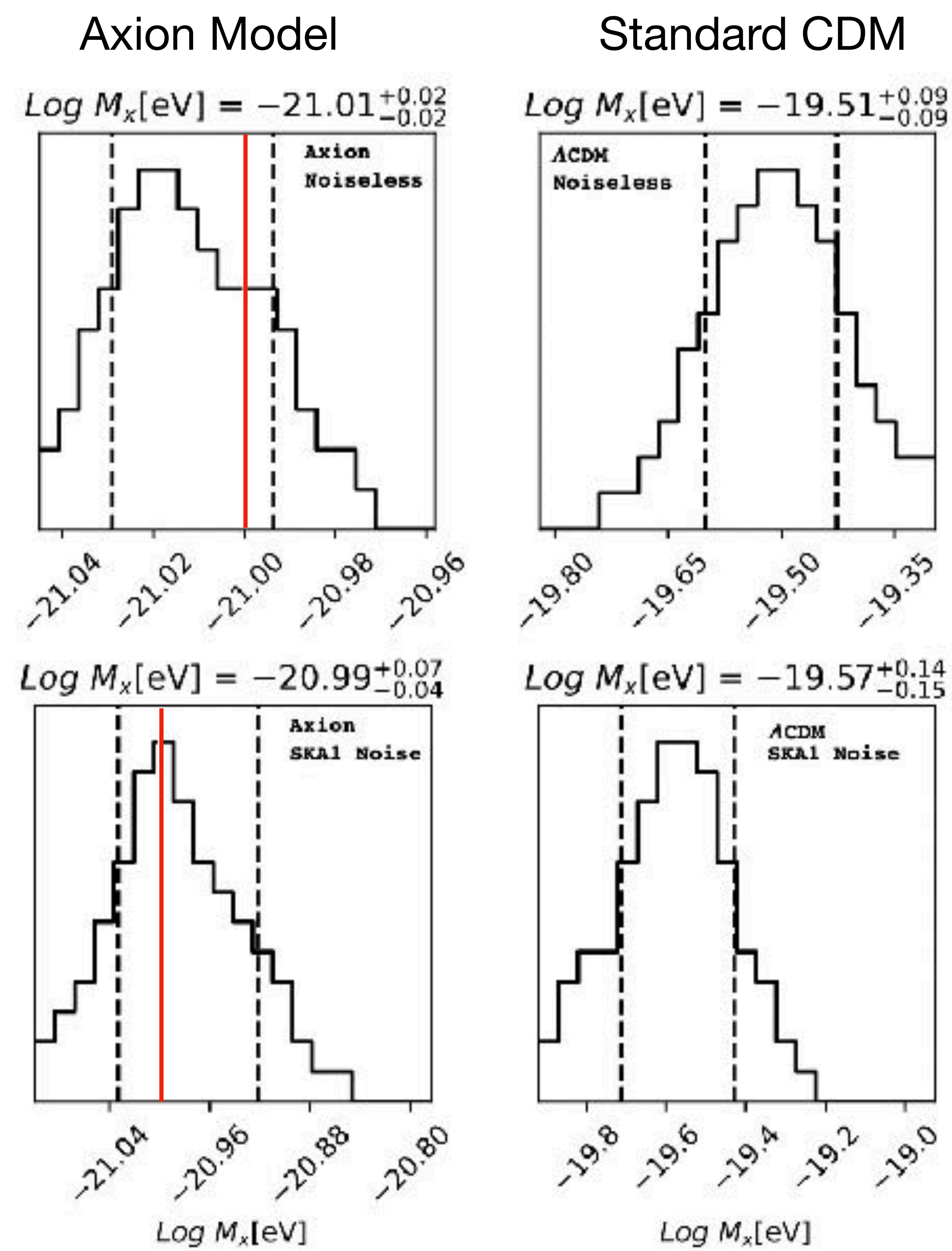
3D Convolutional Neural Network

We trained two CNN networks:
1) on the ideal noiseless sims
2) on the realistic SKA1 noise sims

We now probe those two trained networks.

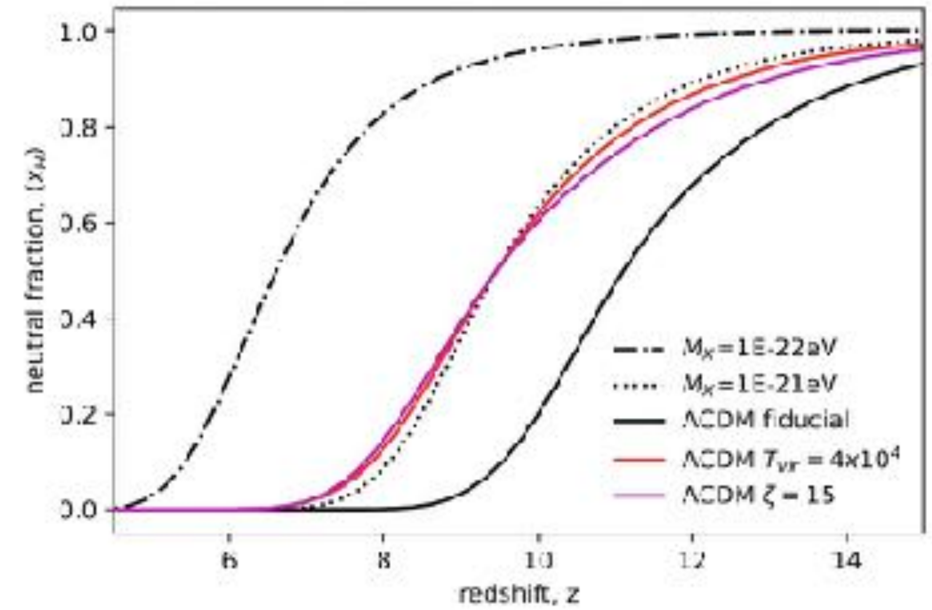
We create 200 mock observations each for the standard DM and an ultra light axion dark matter of fixed mass logM=-21

We analyses each in the ideal no noise case and for realistic SKA1-Low noise



21cm Intensity Mapping

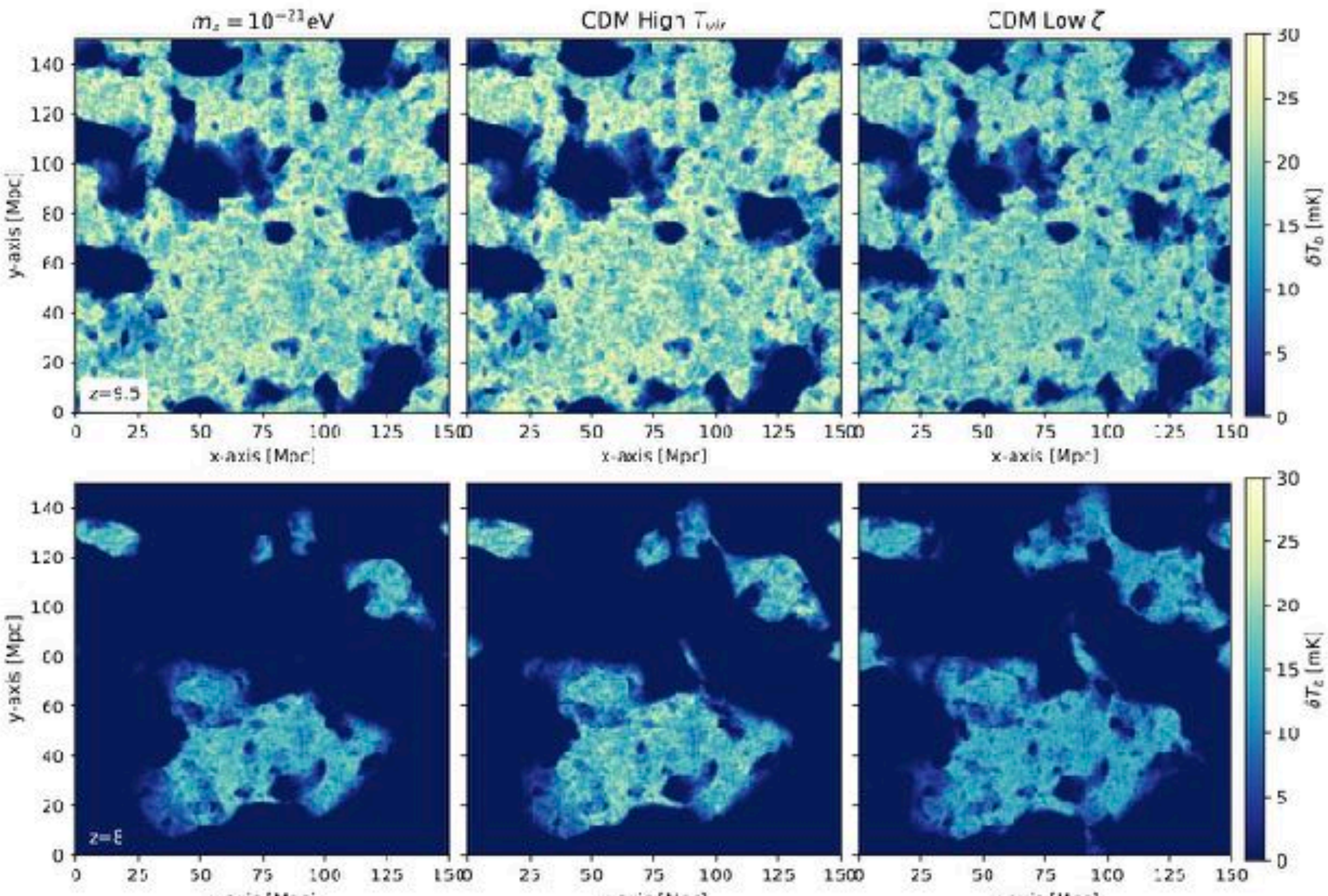
Breaking Degeneracy between Axion Mass and Astrophysical parameters

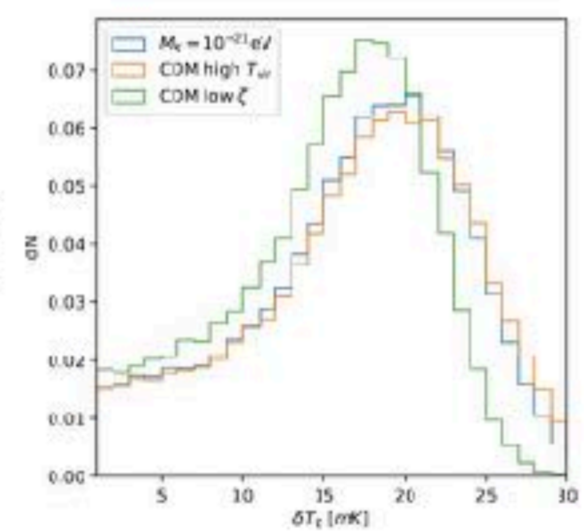


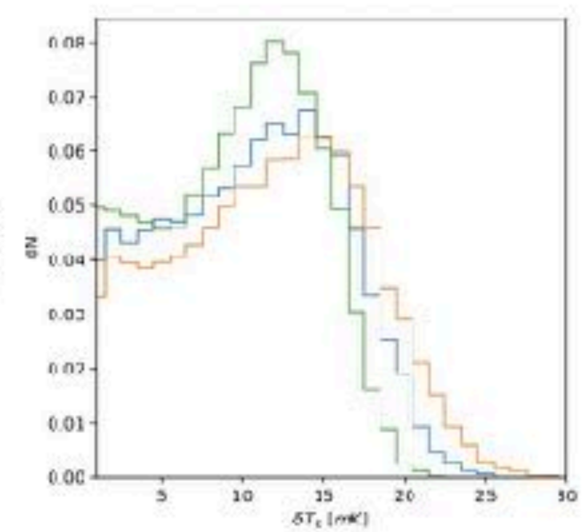
Fid astro params
Axion

High Tvir
Std CDM

Low efficiency
Std CDM

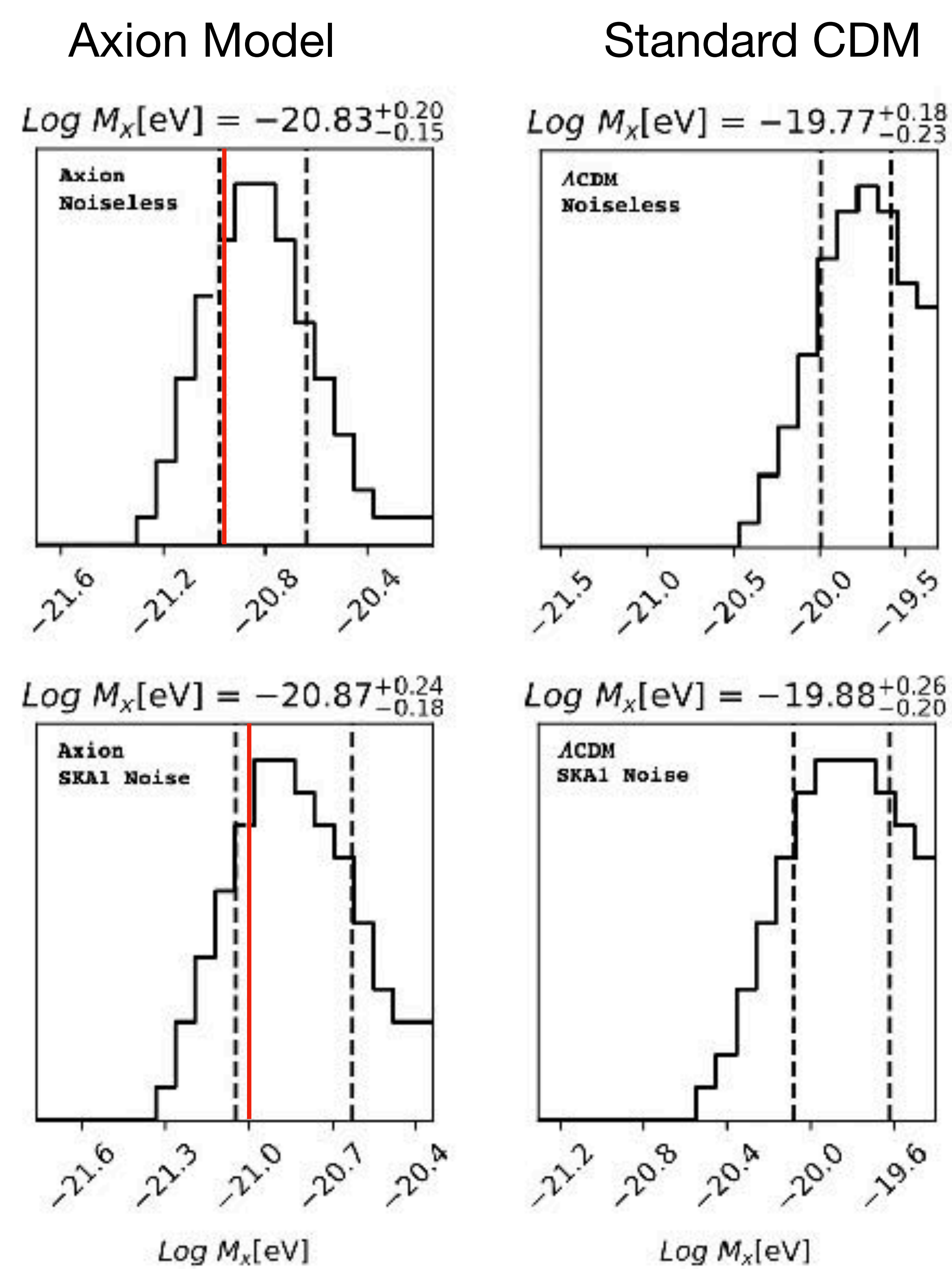






Results & Conclusions

- ★ We made realistic SKA-1 LOW images of the 21cm signal in an axion DM scenario.
- ★ We applied a machine learning approach using convolutional neural networks and found that the trained network could constrain the axion particle mass
- ★ Astrophysical Parameters can mimic the axion signature - but not exactly
- ★ Marginalising over a wide range of nuance parameters we were able to constrain the **axion mass to ~20%** using a modest SKA1-Low design while assuming a fiducial Planck 2015 cosmology.
- ★ The axion can be detected with SKA at if the axion is $\underline{M_X < 1.86 \times 10^{-20}\mathrm{eV}}$ although this can decrease to $\underline{M_X < 5.25 \times 10^{-21}\mathrm{eV}}$ if we relax our assumptions



Take your own message home

but here are some suggestions…

- ★ **Spectroscopic surveys** have provided us with a exquisite measurements of the **expansion history** and **growth of structure** in the universe allowing us to <u>constrain models</u>…

- ★ **Deep Learning** may allow us to extract more <u>cosmological information</u> than standard techniques

- ★ Adopting a fully **forward modelling** approach to cosmology (required by most ML) may shed light on some important issues, e.g. <u>parameter tensions</u>, <u>error/covariance under-estimation</u>, etc

Thank You