Applying Deep Neural Network to dark matter halo catalogues to constrain the dark energy equation-of-state parameters

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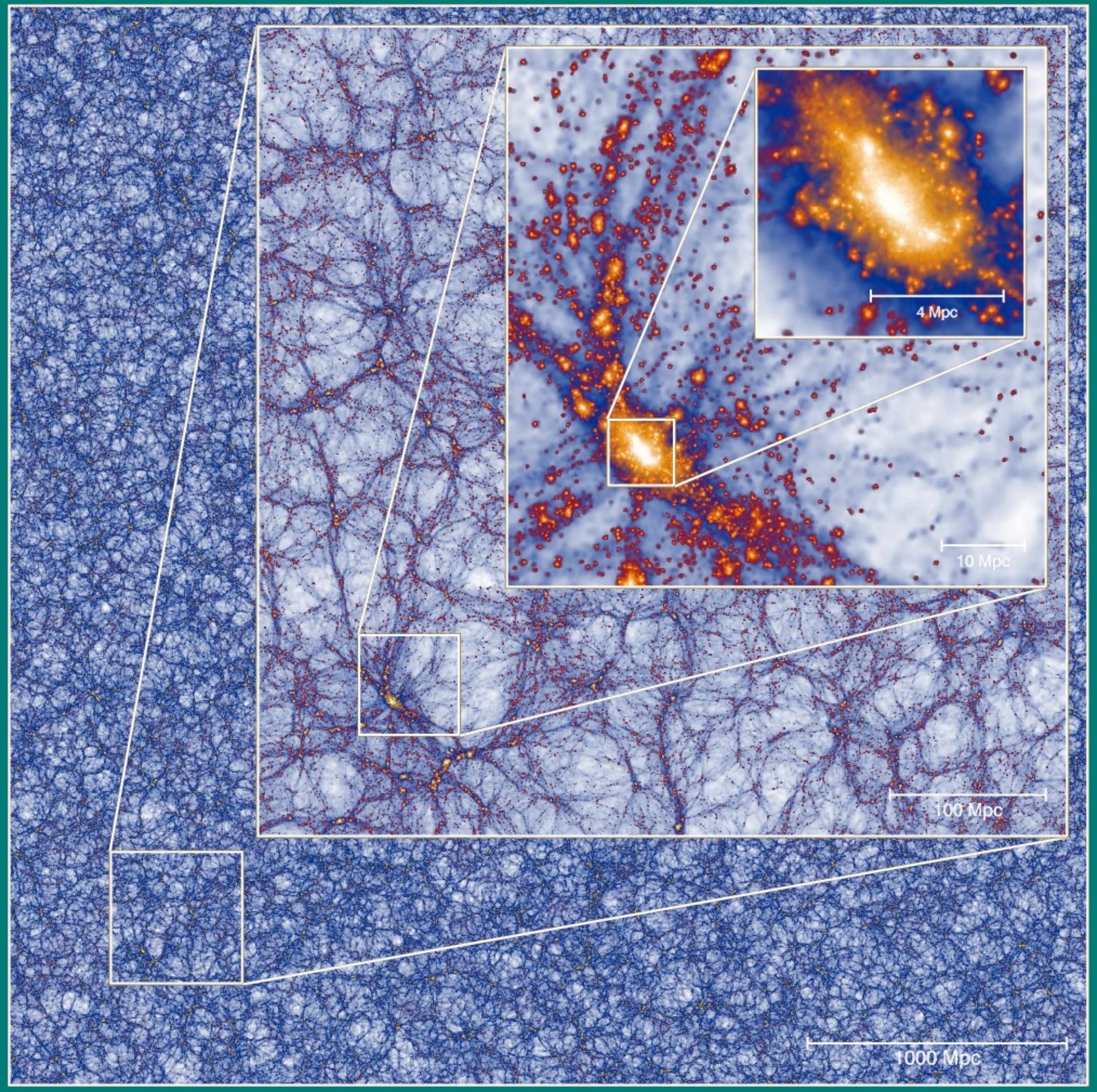
Project Motivation

- There are plenty of Dark Energy models, which have to be explored.
- Standard cosmological analyses based on abundances, two-point and higher-order statistics have been widely used up
- These statistics can only exploit a sub-set of the whole information content available

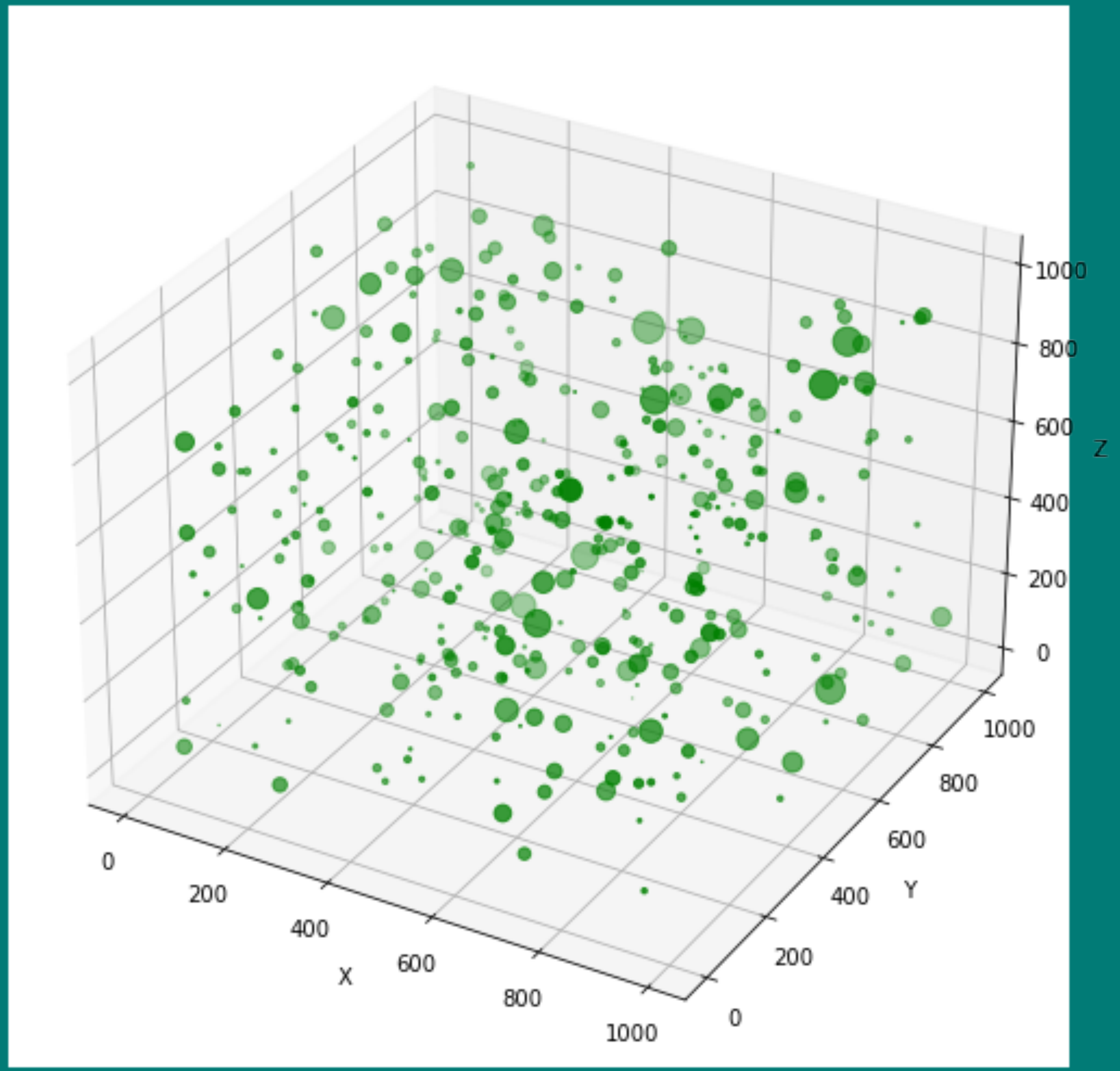


MIlenium XXL, A.Smith et al 2017

Idea

- Using directly the cosmic web information
- Using only Coordinates, mass as what we will observe in reality
- We propose the application of the DNN in distinguishing different cosmological models by training the network on diverse mock dark matter halo and galaxy catalogs.

Coordinates of 400 Halos at Om=0.2



Project Set up

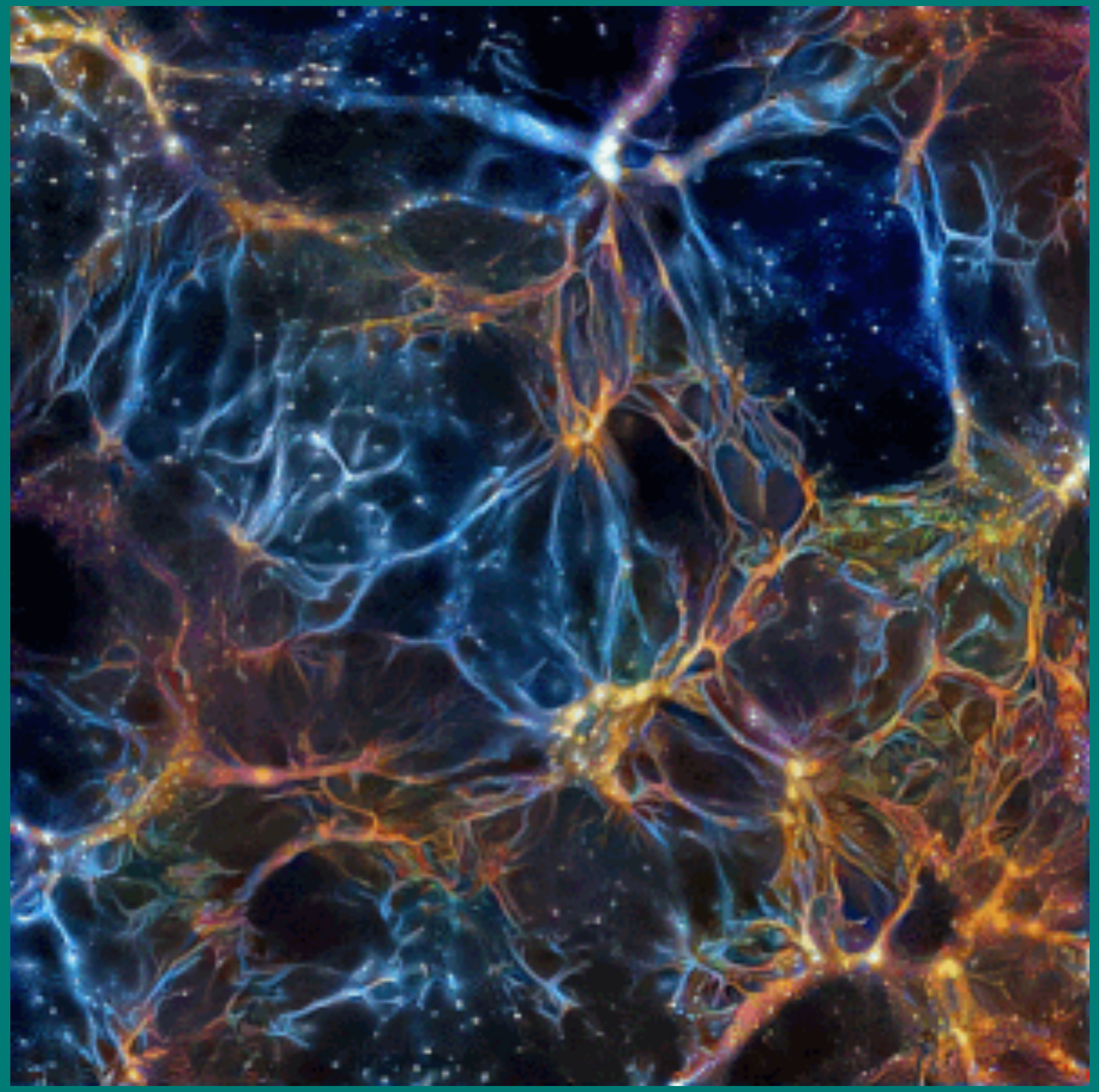
Simulation Data set

- Pinocchio simulations
- Quijote simulations

Pinocchio, arXiv:1610.07624, Rizzo et al 2017

Neural Network Architecture

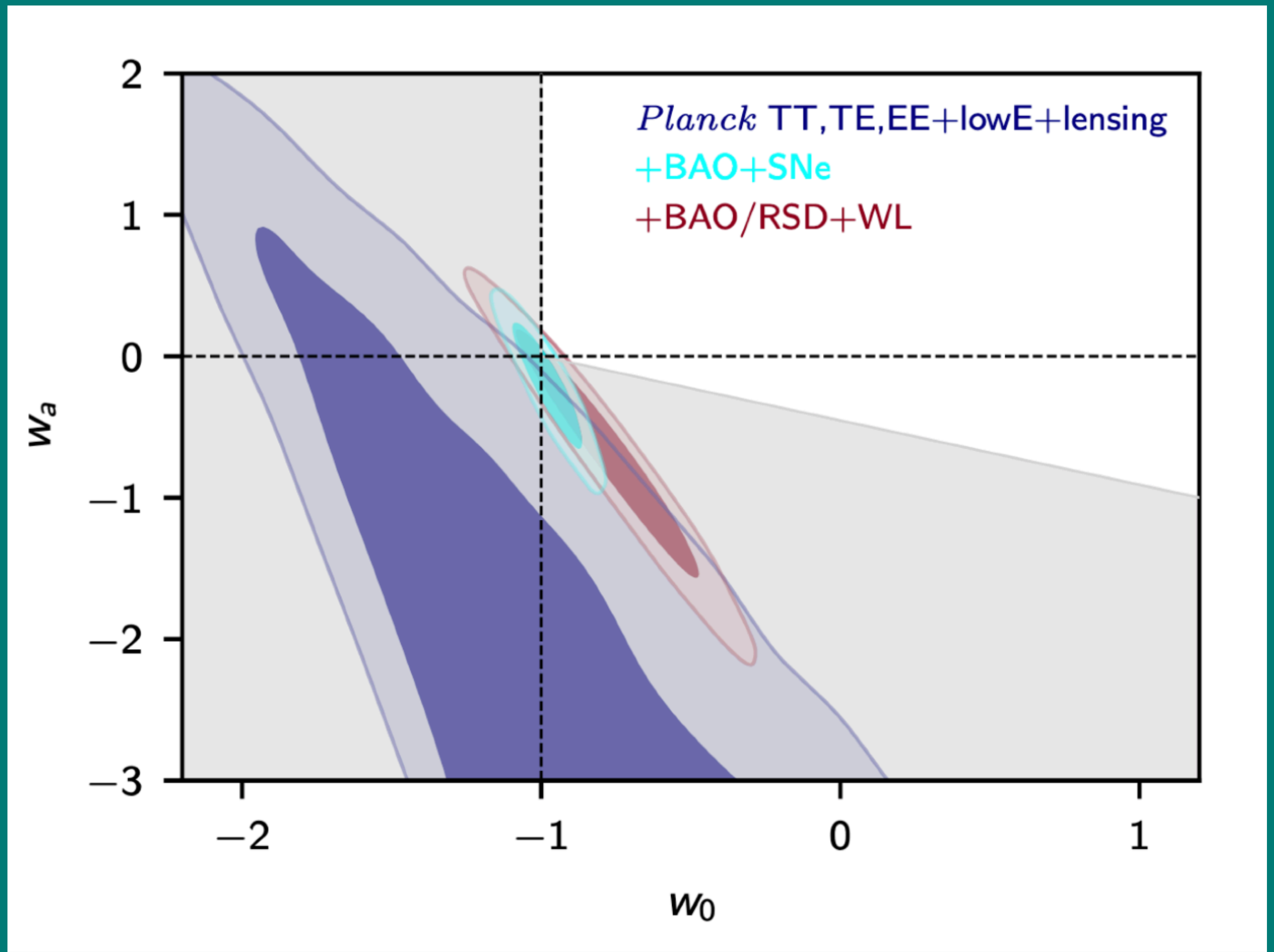
- Sequential model
- Regression problem
- Implemented in Keras and TensorFlow



Quijote, arXiv:1909.05273 FVN et al 2020

The Parameter space

- To check the pipeline first we started with Ω_m= [0.3, 0.5, 0.7, 0.9], simulated by Pinocchio
- Then more realistic values of Ω_m= [0.3075, 0.3175, 0.3275] both with Pinocchio and Quijote simulation
- Moving to DE models we have started with w_0= [-1.05, -1.00, -0.95]
- 9 different sets of DE model with the combination of various w_0= [-1.1, -1.0, -0.9] and w_a= [-0.5, 0, 0.5] with Pinocchio code



Planck Collaboration 2018: Cosmological parameters

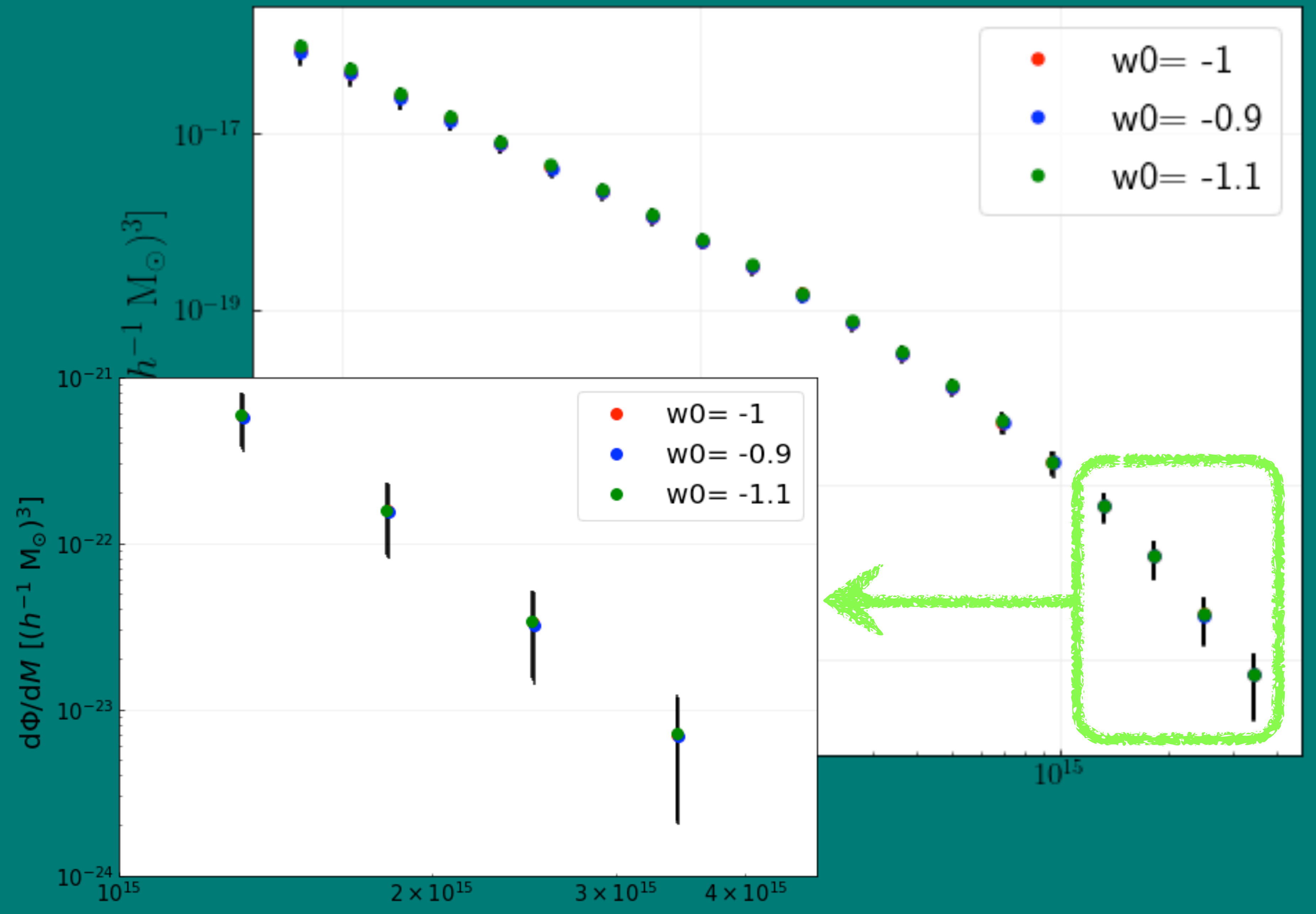
Preliminary Results

- For the tests with different Ω_m, in both cases, the NN is able to predict the value of Ω_m correctly on the test set with less than 0.02% error.

- The NN prediction for three different values of w_0= [-1.05, -1.00, -0.95] of Quijote simulation when the fiducial value is close to w_0= -1.00, has less than 0.04% error.

Challenges

- Sparsity in the data
- Intrinsic randomness in the dataset coordinates which can be interpreted as noise for the NN
- Indistinguishability of DE model at level of dark matter halo catalogue

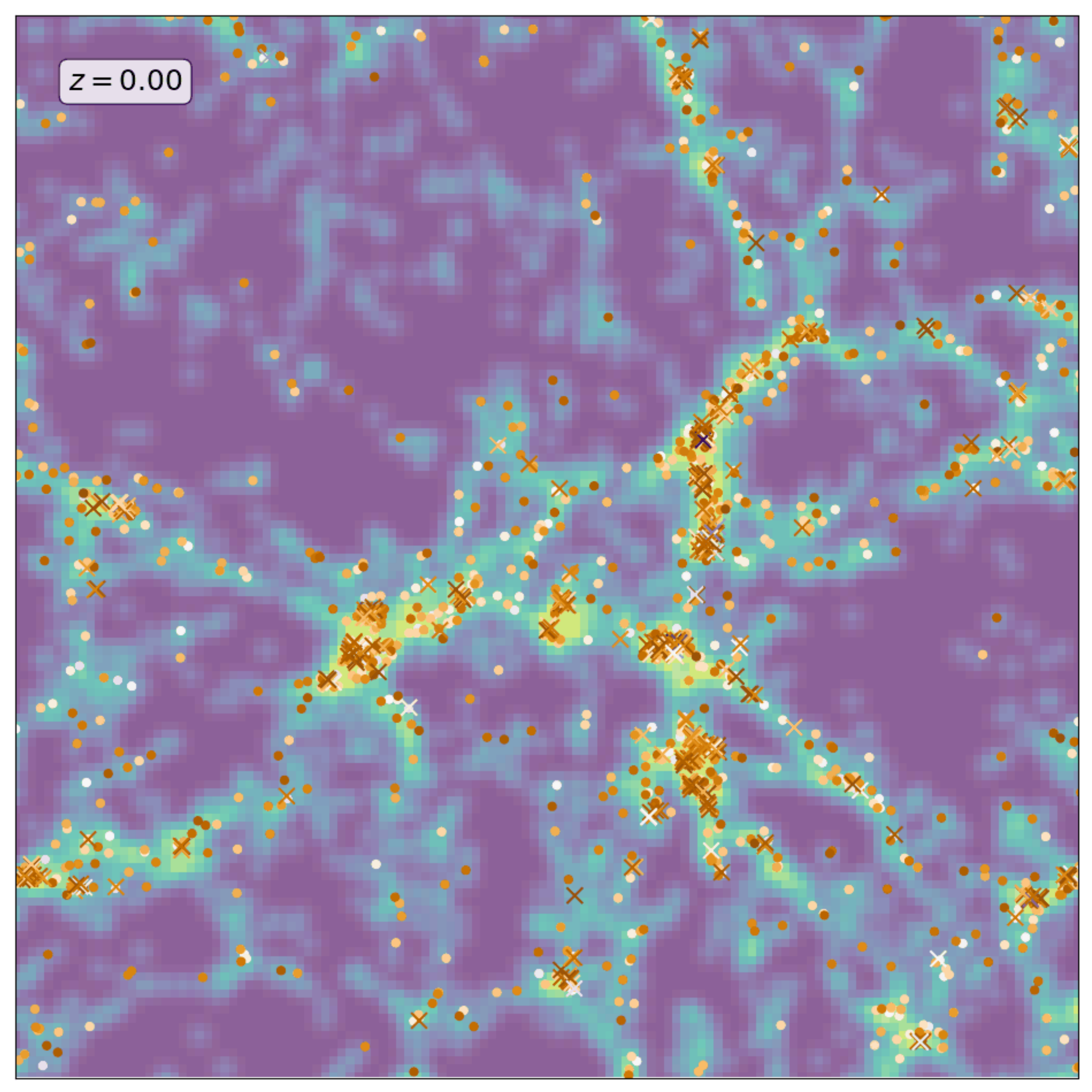


Mass Function for different DE models

Plotted by CosmoBolognaLib
https://github.com/federicomarulli/CosmoBolognaLib

Future Prospect

- Applying subhalo abundance matching (SHAM) and/or halo occupation distribution (HOD) techniques to populate the dark matter catalogues with galaxies and galaxy clusters.
- We plan to compare the cosmological constraints from the neural network and standard probes, such as the two-point and three-point correlation functions of galaxy and galaxy clusters.
- Application of the tools on larger mock catalogues should be tested, in order to provide forecasts for next-generation galaxy redshift surveys, such as Euclid and LSST.



https://https://github.com/TommasoRonconi/scampy