



Motivation

✓ NN can <u>indeed</u> learn from fast approximation methods the evolution of dark matter particles outperforming analytical methods.

Goal

 \checkmark Improvement of this methodology by using high resolution and full N-body simulations for universes with different cosmological parameters.

Types of cosmological simulations

✓ N-body

- Brute force method;
- Computationally expensive.

Linear Theory

- <u>ZA, 2LPT;</u>
- Ideal for large-scales, small matter density.

✓ Fast

Approximations

- Resolves well smallscale issues;
- COLA, L-PICOLA.

✓ Neural Networks

- Outperform Linear Theory and Fast Approximations;
- Need a dataset for training.





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Fig. 1: Slice density δ distribution of dark matter particles in a box of 1 Gpc.

Fast and Accurate Non-Linear Predictions of Universes with Deep Learning

Renan Alves de Oliveira^{1, 2, ⊠}, Yin Li², Francisco Villaescusa-Navarro², Shirley Ho², David N. Spergel² ¹ PPGCosmo, Universidade Federal do Espírito Santo, Vitória, ES, Brazil ² Center for Computational Astrophysics, Flatiron Institute, New York, NY, USA



Metrics Used

• Power Spectrum P of Ψ and δ ; \checkmark Transfer function: (1)

$$T(k) = \sqrt{\frac{P_{pred}(R)}{P_{true}(k)}}$$

Cross-Correlation:

$$r(k) = \frac{P_{pred \times true}(k)}{\sqrt{P_{pred}(k)P_{true}(k)}}$$



with N-body sims.



Fig. 4: Accuracy comparison between predictions by the fast approximator (blue dot-dashed) and our NN (green dashed) for universes with different cosmological parameters used in training.

References in hyperlinks | fisica.renan@gmail.com



Results

Fiducial Universes

Fig. 3: Metrics for NN and fast approximator model compared

Other Universes

✓ Tested on 2000 types of universes