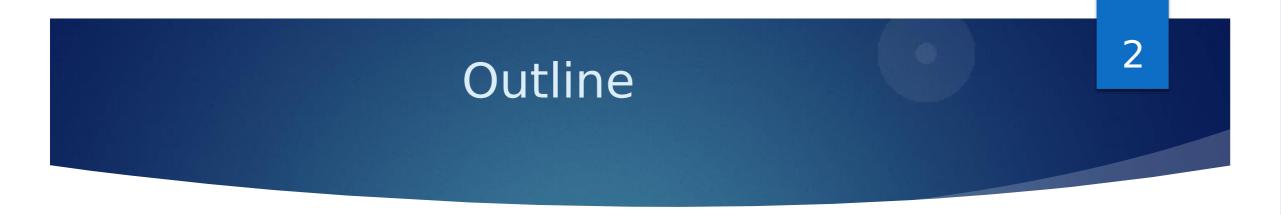
Dark Energy imprints on non linear dynamics of dark matter Using Artificial Intelligence

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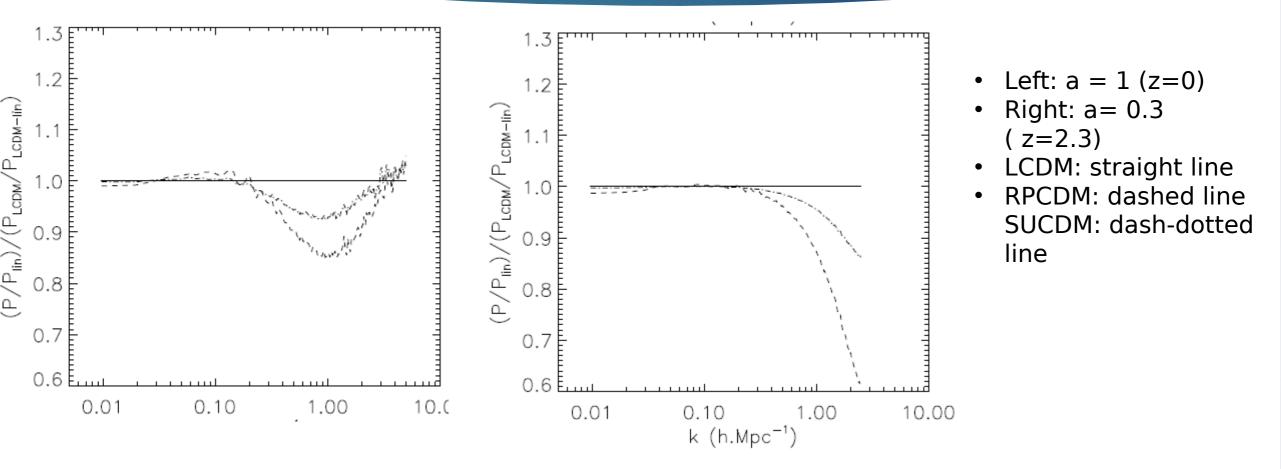
- The aim is to study the signature of dark energy on the formation of the large structures of the Universe.
- Dependency between cosmology and linear dynamics of DM collapse is very well understood, but it has its limitations when it comes to the effect of dark energy
- The main task will thus be to study the influence on dark energy (i.e. cosmological model) on non-linear dynamics and how properties of NDL inform us on the nature of DE.
- Neural Networks, which are widely used in various fields, produced many promising results, and we will test their ability to reproduce non-linear dynamics

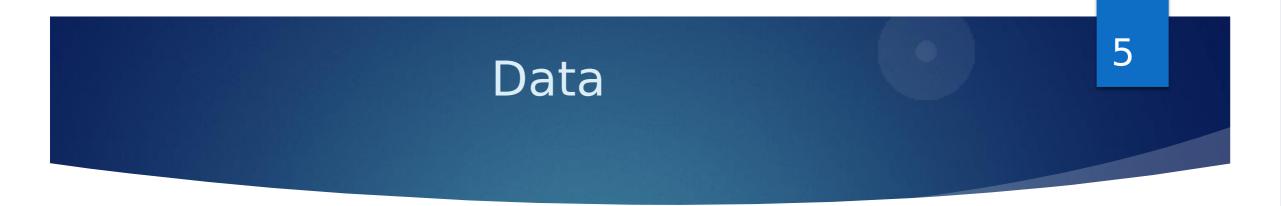
Dark Energy- non linear dynamics Correlation

- We would like to study the latter phenomenon in more detail and thus quantify according to the different cosmological parameters and the nature of gravitation the differences observed on the nonlinear growth of matter fluctuations.
- This would offer a method to distinguish between cosmological models.
- Using high resolution N-Body simulations, it has been shown (e.g. *cf Alimi et.al arxiv:0903.5490*) that working with quintessence models, disperancies appear in the nonlinear regime with respect to ACDM model
- The considered Quintessence models are the ones characterized by Ratra-Peebles (RPCDM) and SUGRA potentials (SULCDM)
- This was done by comptuting the ratio:

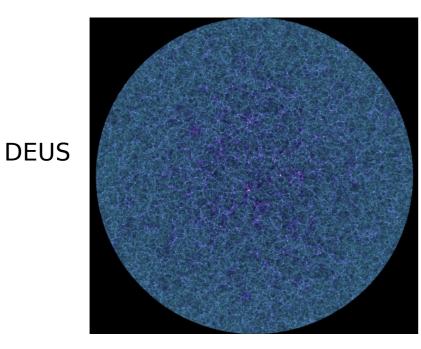
$$R_{\text{QCDM}} = \frac{P_{nl}^{\text{QCDM}}(k)}{P_{nl}^{\text{ACDM}}(k)} \frac{P_{lin}^{\text{ACDM}}(k)}{P_{lin}^{\text{QCDM}}(k)},$$

Dark Energy- non linear dynamics Correlation





We will use the extensive set of large structure formation simulations carried out in the DEUS project and recently in the Quijote project



Quijote

Deep Learning in cosmology

- Few previous works claim that it is possible to build a neural network capable of reproducing the non linear of a field of cosmic matter, namely, D3M (*cf. He et.al arXiv:1811.06533v2*) and 3DCosmoGAN (*cf. Perraudin et.al arXiv:1908.05519*).
- Generated cosmic fields, are compared to the cosmic fields resulting from a "true" simulation that is supposed to correctly follow the non-linear dynamics.

Deep Learning in Cosmology D3M

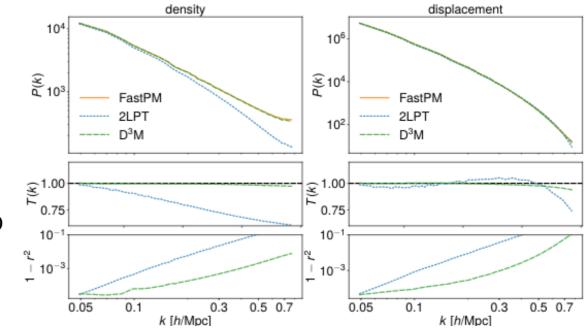
- D3M is a Convolutional Neural Network with a U-net architecture
- The training set consisted of 10,000 pairs of cosmic matter fields (density or displacement fields) respectively at very large z (initial conditions) and at z=0 (non-linearly evolved field in the final state), they belong to cosmology with $\{\Omega_M, A_s\} = \{0,3089,2.192 \times 10^{-9} \stackrel{\text{\tiny def}}{=} A_0\}$
- Generated cosmic fields, are compared to the cosmic fields resulting from a a simulation using a Particle-Mesh code (FASTPM).
- This comparison is made using different "metrics" point wise comparison, 2-Point-Correlation-Functions (i.e. power spectrum P(k)), or 3PCF (i.e. bispectra).

Deep Learning in Cosmology D3M

$$[\Omega_M, A_s] = \{0, 3089, 2.192 \times 10^{-9} \stackrel{\text{def}}{=} A_0\}$$

		T(k)	r(k)	T(k)	r(k)	
	pointwise	$k = 0.11 \mathrm{h/Mpc}$	k = 0.11 h/Mpc	k = 0.51 h/Mpc	k = 0.51 h/Mpc	SPCF
test phase						
2 LPT Density	NA	0.96	1.00	073	0.94	0.0782
D ³ M Density	NA	1.00	1.00	0.99	1.00	0.0079
2 LPT Displacement	0.093	0.96	1.00	1.04	0.89	NA
D ³ M Displacement	0.028	1.00	1.00	0.99	1.00	NA

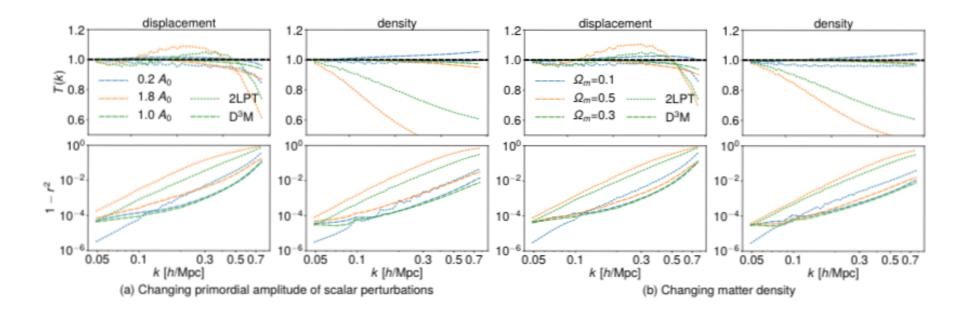
We should focus on hight values of k to better follow NLD



Deep Learning in Cosmology D3M

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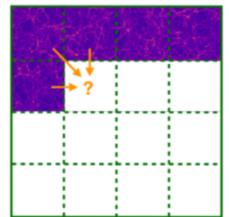
Generating different cosmologies

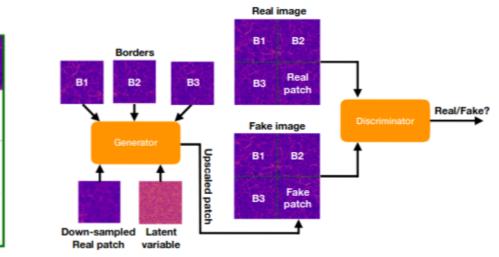


- 3DCosmoGAN is scalable GAN approach to generate N-Body 3D cubes
- The training set is based on density representation (rather than particle positions)
- This comparison is made using a mass histogram, peak histogram and power spectrum.
- The method consists of 2 main steps:
 - Patch-by-patch approach
 - Multi-scale approach

The method consists of 2 main approaches:

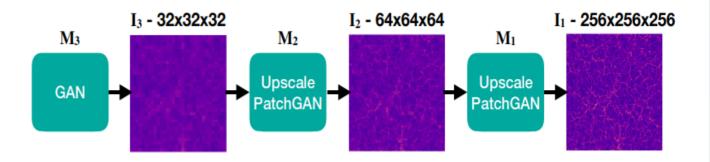
- Patch-by-patch approach
 - It produces the image patch by patch (e.g. a 64³ image is obtained by generating 8*32³ patches)
 - During the generation phase, each patch is modeled as a function of neighboring patches.
- Multi-scale approach



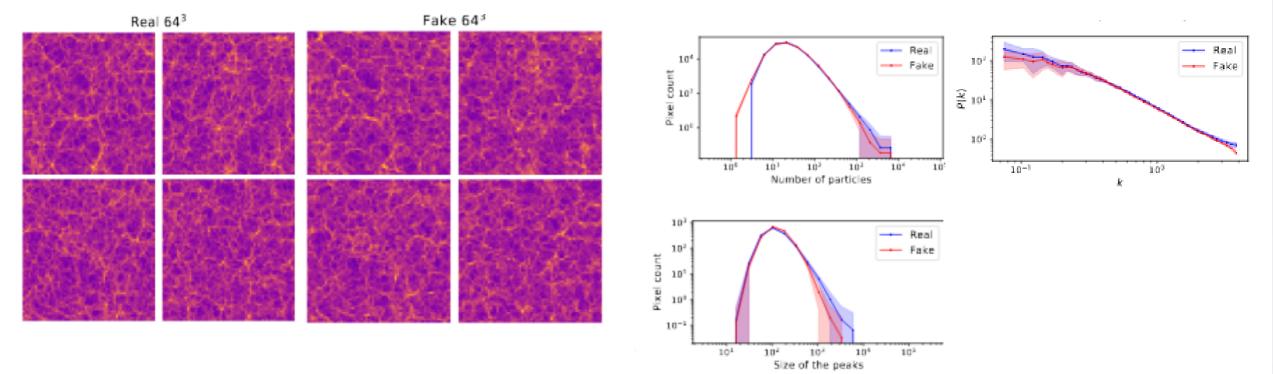


The method consists of 2 main steps:

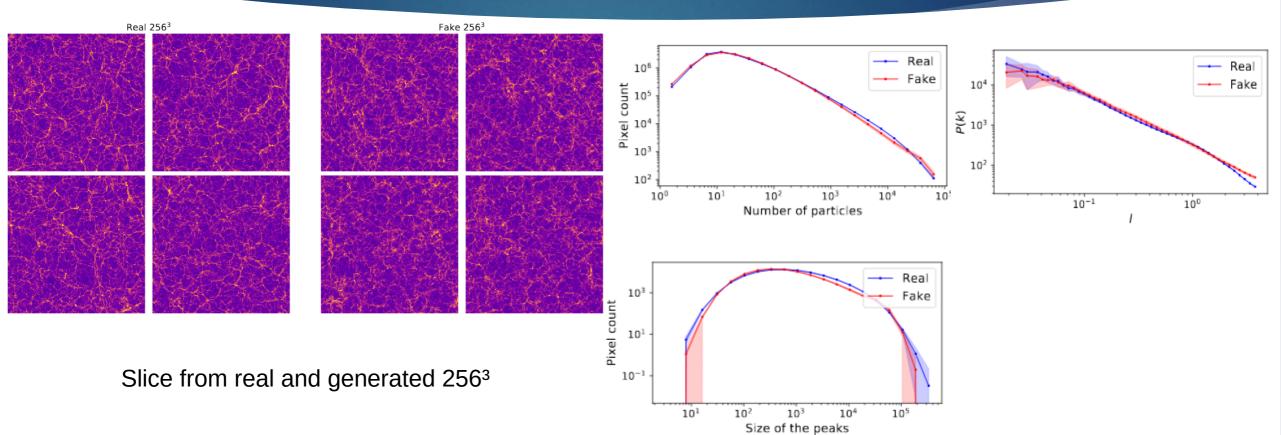
- Patch-by-patch approach
- Multi-scale approach
 - Using multiple intermediary GANs, each learning features at different scale.
 - This procedure allows to handle high data volume and capture global feature, since in the patch-by-patch approach, the discriminator and generator have only access to a limited part of image.



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Slice from real and generated 64³



Test of the influence of the N-body algorithm to deal with non-linear dynamics

- Testing the effects of the algorithms (e.g. AMR or a Treecode) and resolution on the performance of the results.
- Comparing the efficiency of particle-based and voxel-based representations.
- This will give a us a better idea on how powerful D3M/3DCosmoGAN really are in reproducing non-linear dynamics
- Testing the effect of the cosmology on non-linear dynamics
- Testing the ability of Deep Learning to reproduce non-linear dynamics



Test of the influence of the N-body algorithm to deal with non-linear dynamics

Testing the effect of the cosmology on non-linear dynamics

- Using simulations with different cosmologies.
- Computing metrics that allow to better quantify disperancy between cosmologies due to non-linear dynamics (e.g. observables related to skeletons and specifically singularities), which will inform us on the dependance of singularities on cosmology.
- Testing the ability of Deep Learning to reproduce non-linear dynamics

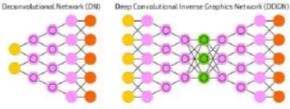
- Test of the influence of the N-body algorithm to deal with non-linear dynamics
- Testing the effect of the cosmology on non-linear dynamics
- Testing the ability of Deep Learning to reproduce non-linear dynamics
 - Extending 3DCosmoGAN to higher resolutions than 256³ (i.e. adding new intermediary GANs)
 - Trying new types of Deep Learning algorithms
 - Reinforcment learning
 - Unsupervised learning



A mostly complete chart of **Neural Networks** O Backfed Input Cell Deep Feed Forward (DFF) ©2016 Fjedor van Veen - asimovinstitute.org Input Cell Noisy Input Cell Feed Forward (FF) Radial Basis Network (RBF) Perceptron (P) Hidden Cell. Probablistic Hidden Cell Spiking Hidden Cell Recurrent Neural Network (RNN) Long / Short Term Memory (LSTM) Gated Recurrent Unit (GRU) Output Cell Match Input Output Cell Recurrent Cell Memory Cell. Auto Encoder (AE) Variational AE (VAE) Denoising AE (DAE) Sparse AE (SAE) Different Memory Cell Kernel Convolution or Pool Markev Chain (MC) Hopfield Network (HN) Boltzmann Machine (BM) Restricted BM (RBM) Deep Belief Network (DBN)

Deep Convolutional Network (DCN)



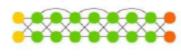


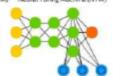
Generative Adversarial Network (GAN) Liquid State Machine (LSM) Extreme Learning Machine (ELM) Echo State Network (ESN)















Thank You !