

Cosmological properties of the cosmic web

Majd Shalak, Jean-Michel Alimi

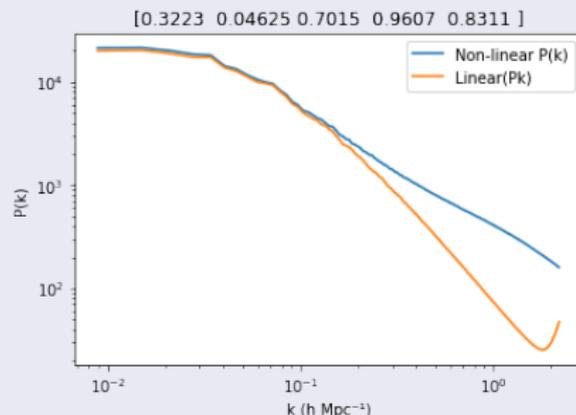
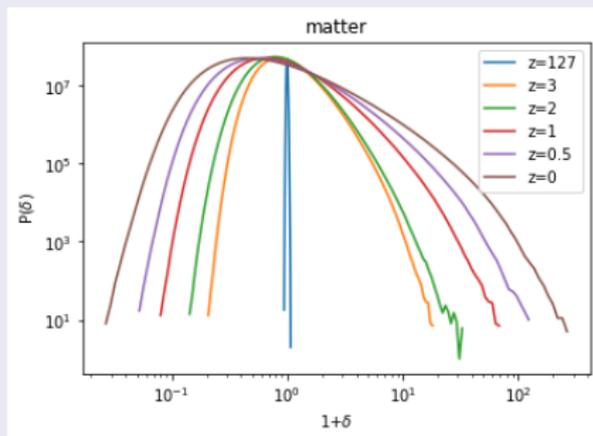
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Non-linear dynamics

- The phenomenon of structure formation is the result of a complex physical process, which depends on the cosmology, and on the gravitational dynamics, strongly non-linear.
- The aim is to study the influence of the cosmological model on the non-linear dynamics of structure formation and to study how the properties of non-linear dynamics inform us about cosmology (e.g. nature of Dark Energy)
- To sound the non-linearities and non-gaussianities in the matter field we compute:
 - Power spectrum $P(k)$
 - Probability density function $P(\delta)$ and its moments

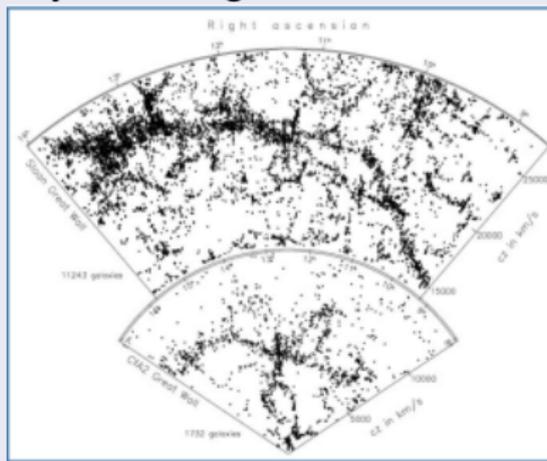
Non-linear dynamics



- Left: Evolution of the PDF calculated with the redshift, the distribution becomes more and more non-Gaussian
- Right: Comparison between linear and nonlinear $P(k)$.

Introduction

We introduce the cosmic web measurement to better understand the nonlinear dynamics of the cosmic field from the properties of the cosmic web categories: voids, walls, filaments, nodes, which is the result of gravitational instability that drags the matter to cluster in such a way.



TWEB Algorithm

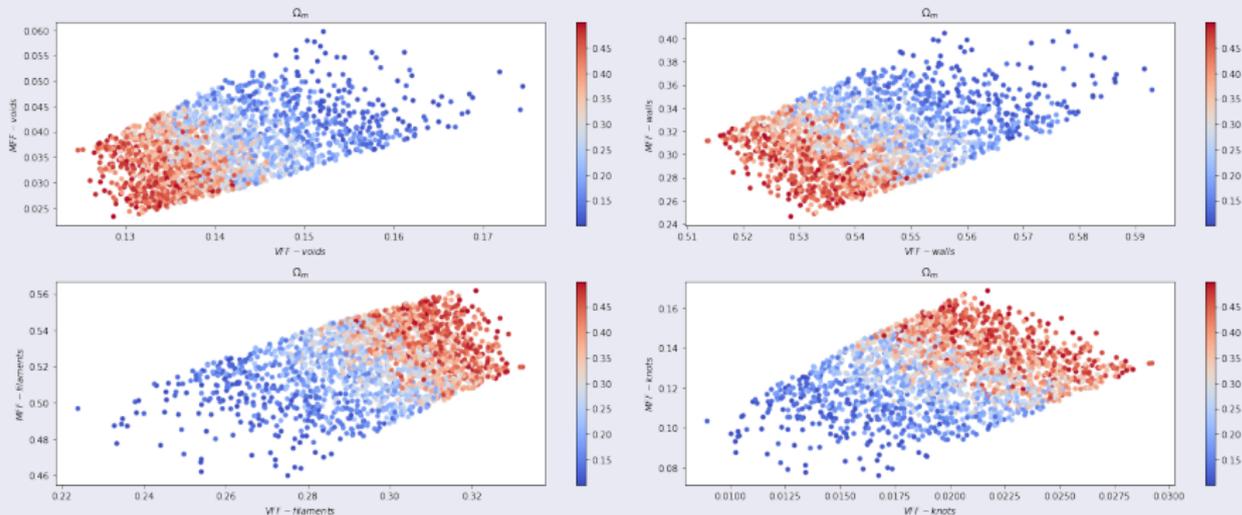
- Our definition of the cosmic web is based on the local dimensionality of the collapse.
- To quantify this latter, we compute the tidal field, and dimensionality of the collapse is equal to the number of positive eigenvalues
- Thus, a point is part of a knot, filament or wall if it has respectively 3, 2 or 1 positive eigenvalue, if it has no positive eigenvalue, it is part of a void.
- To perform these calculations, we need to interpolate and smooth the density field, we employ the Cloud-In-Cell (CIC) interpolation scheme, on a regular grid consisted of 1024^3 cells, and a gaussian smoothing filter with a $2h^{-1}Mpc$ radius.
- These calculations are done by using 2000 different Λ CDM model of the Quijote suite of N-Body simulations

Observables

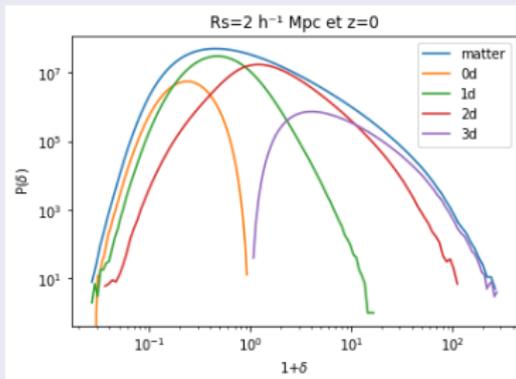
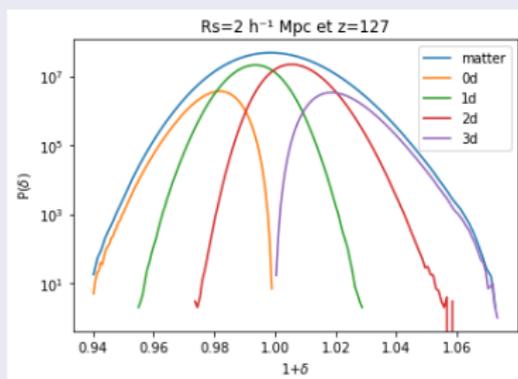
- After classifying every single point to a specific category, several observables can be computed for each category:
 - Volume filling fraction VFF , proportion of volume occupied by the category.
 - Mass filling fraction, MFF , proportion of mass occupied by the category.
 - Probability density function(PDF) and its moments:
 - $\sigma = \sqrt{\langle (\delta - \bar{\delta})^2 \rangle}$
 - Skewness: $S = \sqrt{\langle (\delta - \bar{\delta})^3 \rangle} / \sigma^3$
 - Kurtosis: $S_4 = \sqrt{\langle (\delta - \bar{\delta})^4 \rangle} / \sigma^4 - 3$
 - Power spectrum

Mass and Volume filling fractions

They quantify the proportion of mass and volume occupied by each category

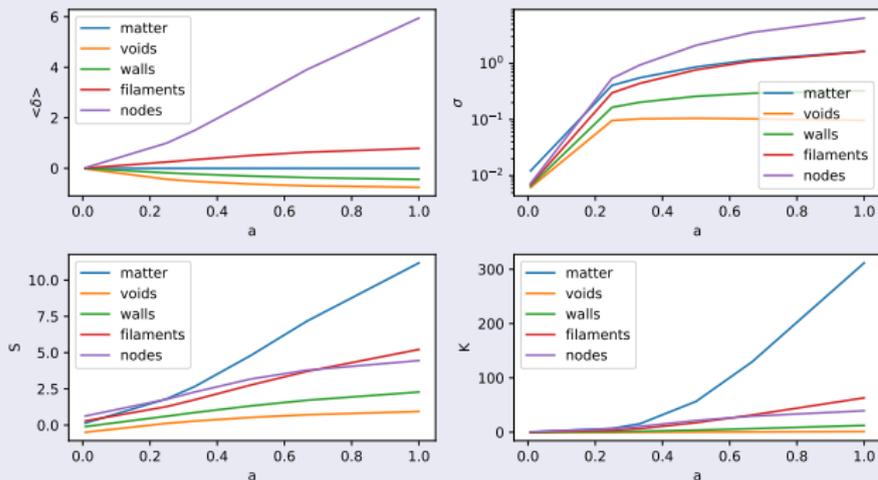


PDF



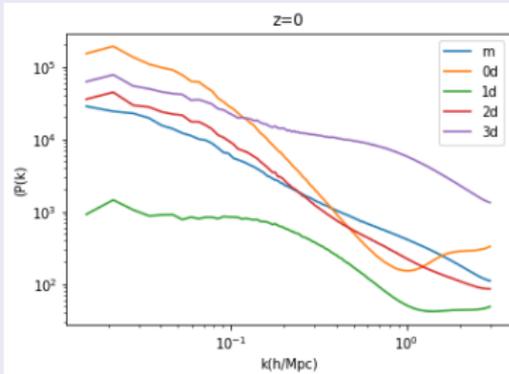
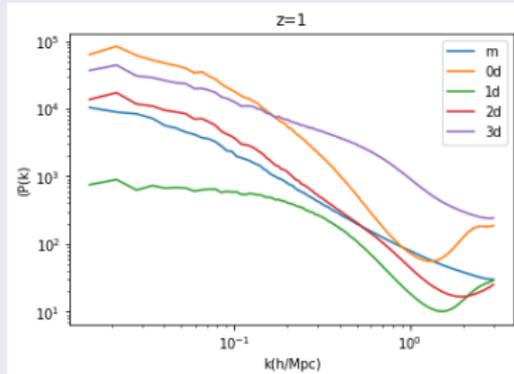
- The PDFs show that the cosmic web categories don't follow a gaussian distribution at initial conditions, unlike the matter which has an almost perfect gaussian distribution at early times.
- At late times (z=0), each category evolve differently from the other, all while being non-gaussian.

PDF moments



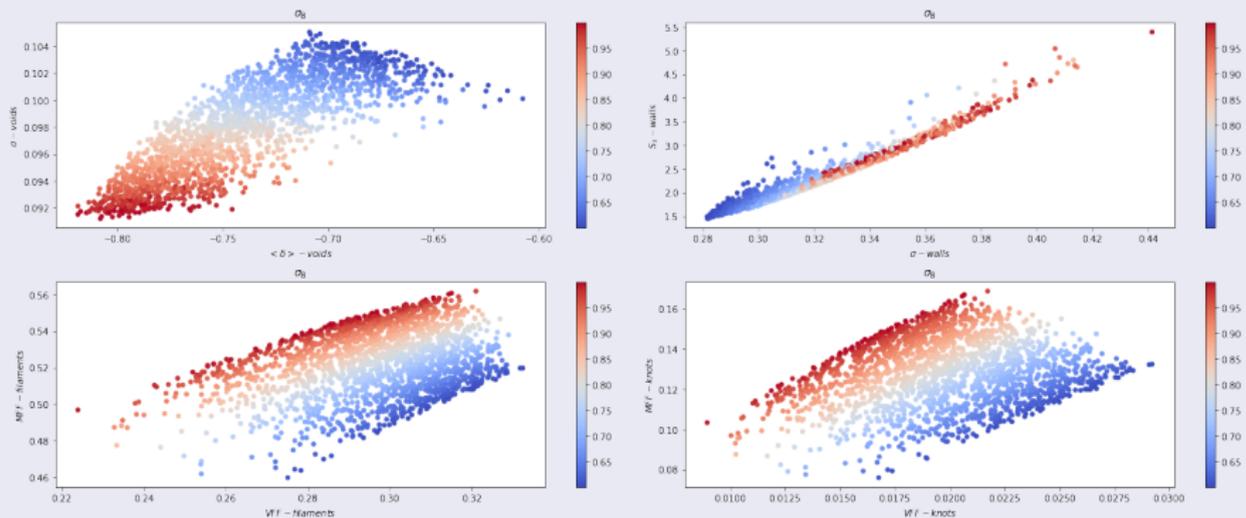
- $S = \sqrt{\langle (\delta - \bar{\delta})^3 \rangle} / \sigma^3$, $K = \sqrt{\langle (\delta - \bar{\delta})^4 \rangle} / \sigma^4 - 3$
- They sound the non-gaussianities in each field.
- Categories already have larger skewness than the matter (at $z=127$), so their initial distributions are non-gaussians, unlike the matter field.

Power spectrum



- The calculation of power spectra shows that the categories have a power spectrum different from that of matter, at all scales.

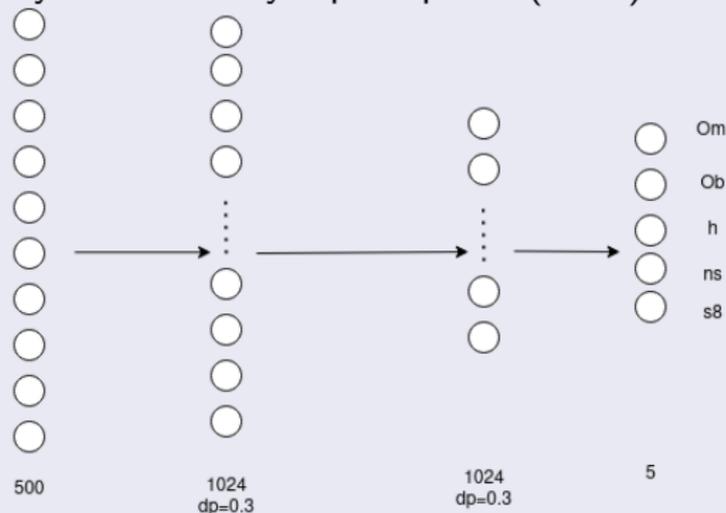
Cosmological dependence of the CW



- Looking at the scalar observables, we conclude that they indeed **depend** on cosmological parameters.
- This motivated us to perform cosmological parameters inference using cosmic web properties

MLP

To perform cosmological parameters inference we employ neural networks techniques, namely the multi layer perceptron (MLP) method



It is consisted of a series of fully connected layers (an input layer, an output layer, and between them a number of hidden layers)

Neural Networks

- Each layer is consisted of a given number of neurons, and each 2 consecutive layers are connected via a weight matrix, followed by a non-linear activation function.
- After randomly initialising the weights, the input vector is passed through the network layer, and after each iteration, the weights are updated in order to optimize the **loss function**

$$\mathbb{L}(y_{true}, y_{pred}) = \frac{1}{N_{sim}} (y_{pred} - y_{true})^2$$

- 1800 simulations are used for training

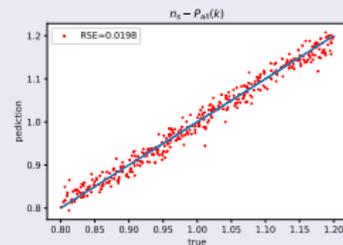
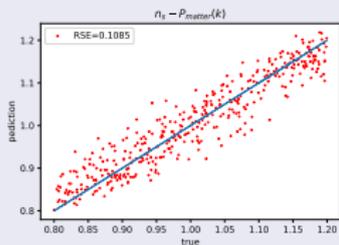
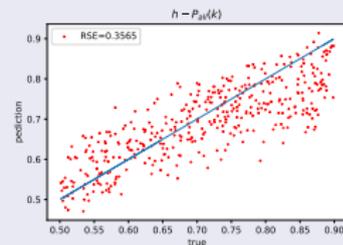
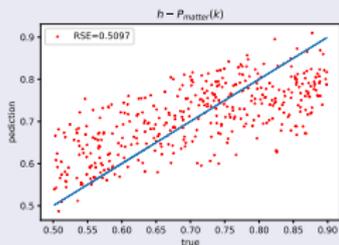
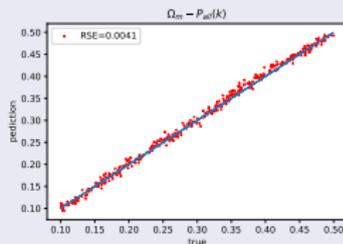
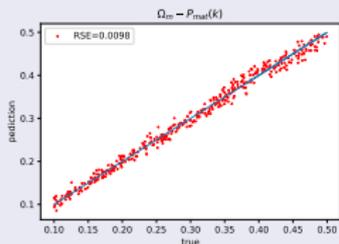
Inference

We test our network with 200 simulations with cosmologies totally different from the ones it had trained on, to evaluate the result, for each parameter, we can do it :

- Visually, by plotting predicted vs true value scatter plot, the less scattered around the identity line, the better the performance is.
- Quantitatively by Computing the Relative Squared Error

$$RSE = \frac{\sum_{i=1}^{n_{test}} (y_{pred}^i - y_{true}^i)^2}{\sum_{i=1}^{n_{test}} (y_{true}^i - \langle y_{true} \rangle)^2}$$

Results



Results

Observable	RSE_{Ω_m}	RSE_{Ω_b}	RSE_h	RSE_{n_s}	RSE_{σ_8}
$P(k)$ - matter	0.0098	0.4507	0.5097	0.1085	0.0022
$P(k)$ - 0d	0.0405	0.4003	0.4322	0.0388	0.0034
$P(k)$ - 1d	0.0802	0.9419	0.8534	0.0340	0.0027
$P(k)$ - 2d	0.0105	0.3760	0.3975	0.0569	0.0018
$P(k)$ - 3d	0.0047	0.5115	0.5379	0.1555	0.0055
$P(k)$ - all fields	0.0041	0.6317	0.3565	0.0198	0.0016

- Best inference is when we include all the categories
- Each parameter is better predicted by a particular category.
 - Low dimensionality categories better predict n_s
 - Filaments are sensitive to Ω_b
 - Knots (i.e. clusters) are sensitive to Ω_m

Conclusion

- Cosmic web provides a finer sound of non-linear dynamics
- Geometrical as well as dynamic properties of the cosmic web depend on cosmological parameters.
- Including cosmic web in cosmological parameters inference provides better constraints than with only the whole matter field.
- Different categories give different inference accuracy, and each parameter is better predicted by a particular category.