

Bayesian large-scale structure inference and cosmic web analysis

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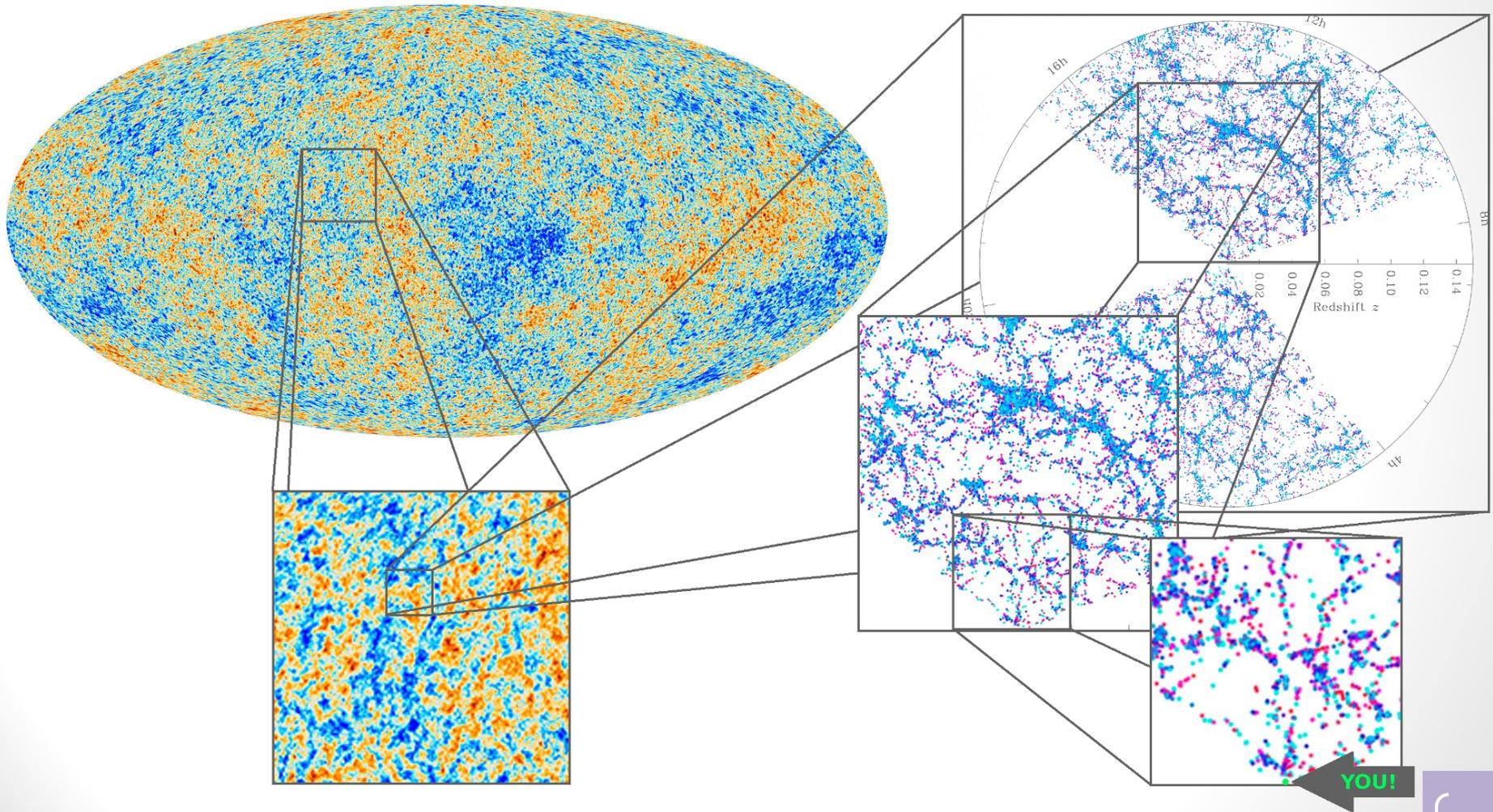


In collaboration with:

Nico Hamaus (LMU), Jens Jasche (ExC Universe, Garching), Guilhem Lavaux (IAP),
Emilio Romano-Díaz (U. Bonn), Paul M. Sutter (Trieste/Ohio State U.),
Benjamin Wandelt (IAP/U. Illinois)

The big picture: the Universe is highly structured

You are here. Make the best of it...



Planck collaboration (2013)

M. Blanton and the Sloan Digital Sky Survey (2010-2013)

How did structure appear in the Universe?

A joint problem!

- How did the Universe begin?
 - What are the statistical properties of the initial conditions?
- How did the large-scale structure take shape?
 - What is the physics of dark matter and dark energy?

We have theoretical and computer models...

- Initial conditions:
a Gaussian random field



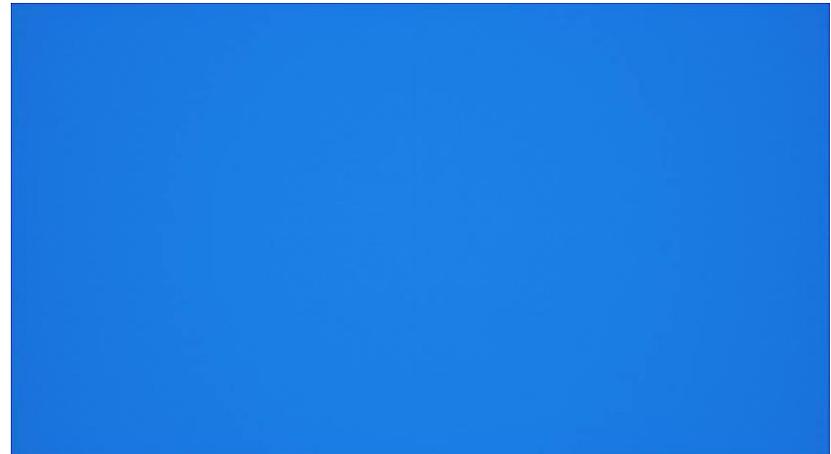
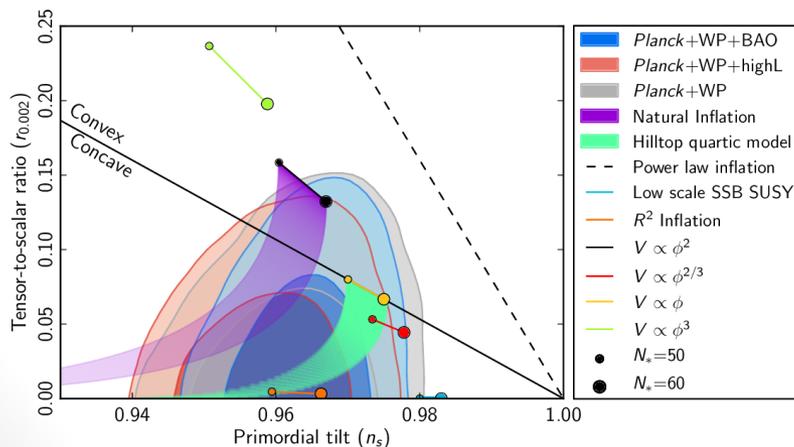
- Structure formation:
numerical solution of the Vlasov-Poisson system for dark matter dynamics

$$\mathcal{P}(\delta^i | S) = \frac{1}{\sqrt{|2\pi S|}} \exp\left(-\frac{1}{2} \sum_{x,x'} \delta_x^i S_{xx'}^{-1} \delta_{x'}^i\right)$$

Everything seems consistent with the simplest inflationary scenario, as tested by Planck.

$$\frac{\partial f}{\partial \tau} + \frac{\mathbf{p}}{ma} \cdot \nabla f - ma \nabla \Phi \cdot \frac{\partial f}{\partial \mathbf{p}} = 0$$

$$\Delta \Phi = 4\pi G a^2 \bar{\rho} \delta$$



But some questions remain

1. How do we **test** these frameworks?
 - Usually the two problems of initial conditions and structure formation are addressed in isolation.
 - Ideally, galaxy surveys should be analyzed in terms of the joint constraints that they place on these two questions.

2. How did this happen in **our** Universe?

1. How do we test our models?



J. Cham – PhD comics

Redshift range	Volume (Gpc ³)	k_{\max} (Mpc/h) ⁻¹	N_{modes}
0-1	50	0.15	10 ⁷
1-2	140	0.5	5x10 ⁸
2-3	160	1.3	10 ¹⁰

M. Zaldarriaga

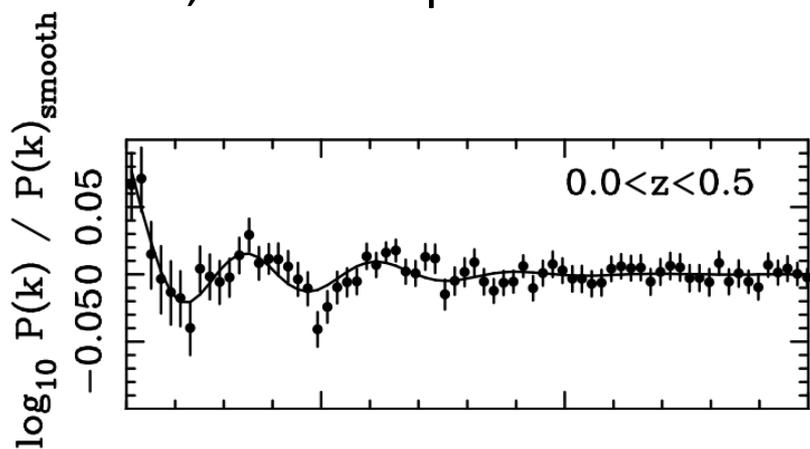
- Precise tests require many modes.
- In 3D galaxy surveys, the number of modes usable scales as k_{\max}^3 .
- The challenge: non-linear evolution at **small scales** and **late times**.
- The strategy:
 - Pushing down the smallest scale usable for cosmological analysis
 - Inferring the initial conditions from galaxy positions



In other words: go beyond the **linear** and **static** analysis of the LSS.

2. How did this happen in our Universe?

- This means that we cannot do, for example:



Percival *et al.* 2010, arXiv:0907.1660

- Standard analyses: reduce the data to some statistics, then fit some model parameters

- We have to do a **joint analysis** of all aspects, including **density reconstruction**
 - Provides powerful constraints
 - Propagates uncertainties between all parts of the analysis
 - Avoids using the data twice
- It is a process known as **data assimilation**

Can we just **fit the entire survey?**

Why Bayesian inference?

- What do we need to fit the entire survey?

Inference of signals = ill-posed problem

- Incomplete observations: finite resolution, survey geometry, selection effects
- Noise, biases, systematic effects
- Cosmic variance

➡ No unique recovery is possible!



“What is the formation history of the Universe?”



“What is the probability distribution of possible formation histories (signals) compatible with the observations?”

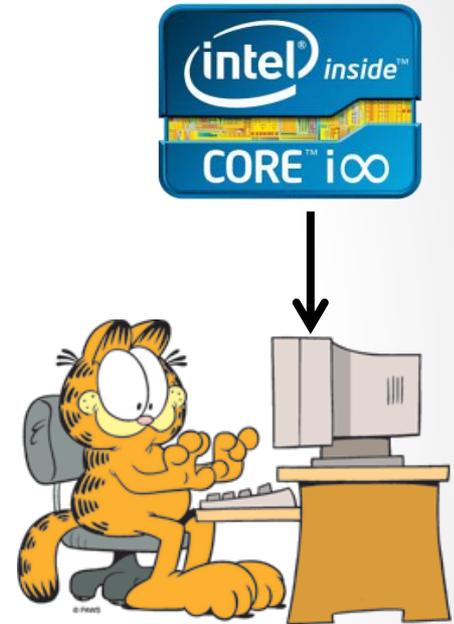
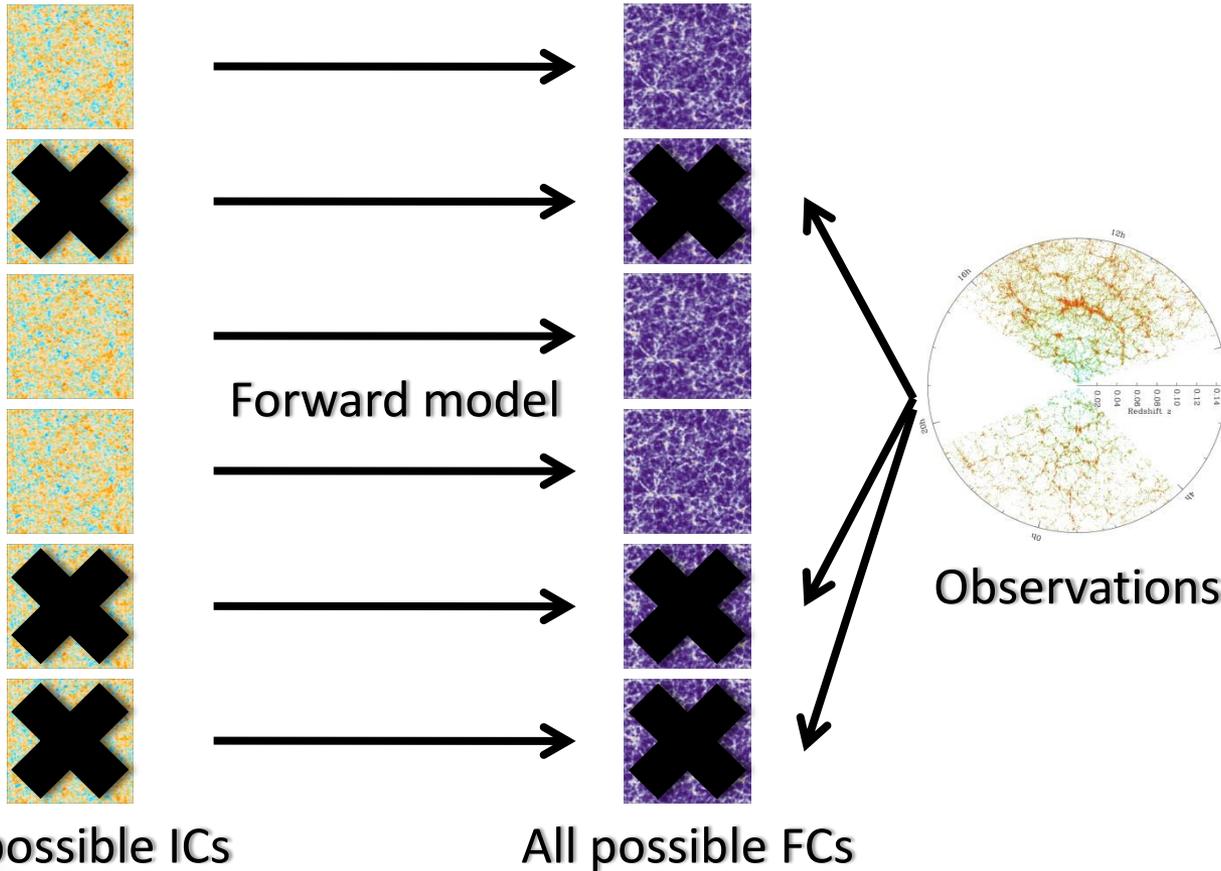
Bayes' theorem: $\mathcal{P}(s|d)\mathcal{P}(d) = \mathcal{P}(d|s)\mathcal{P}(s)$

- Cox-Jaynes theorem: Any system to manipulate “*plausibilities*”, consistent with Cox’s desiderata, is isomorphic to **(Bayesian) probability theory**

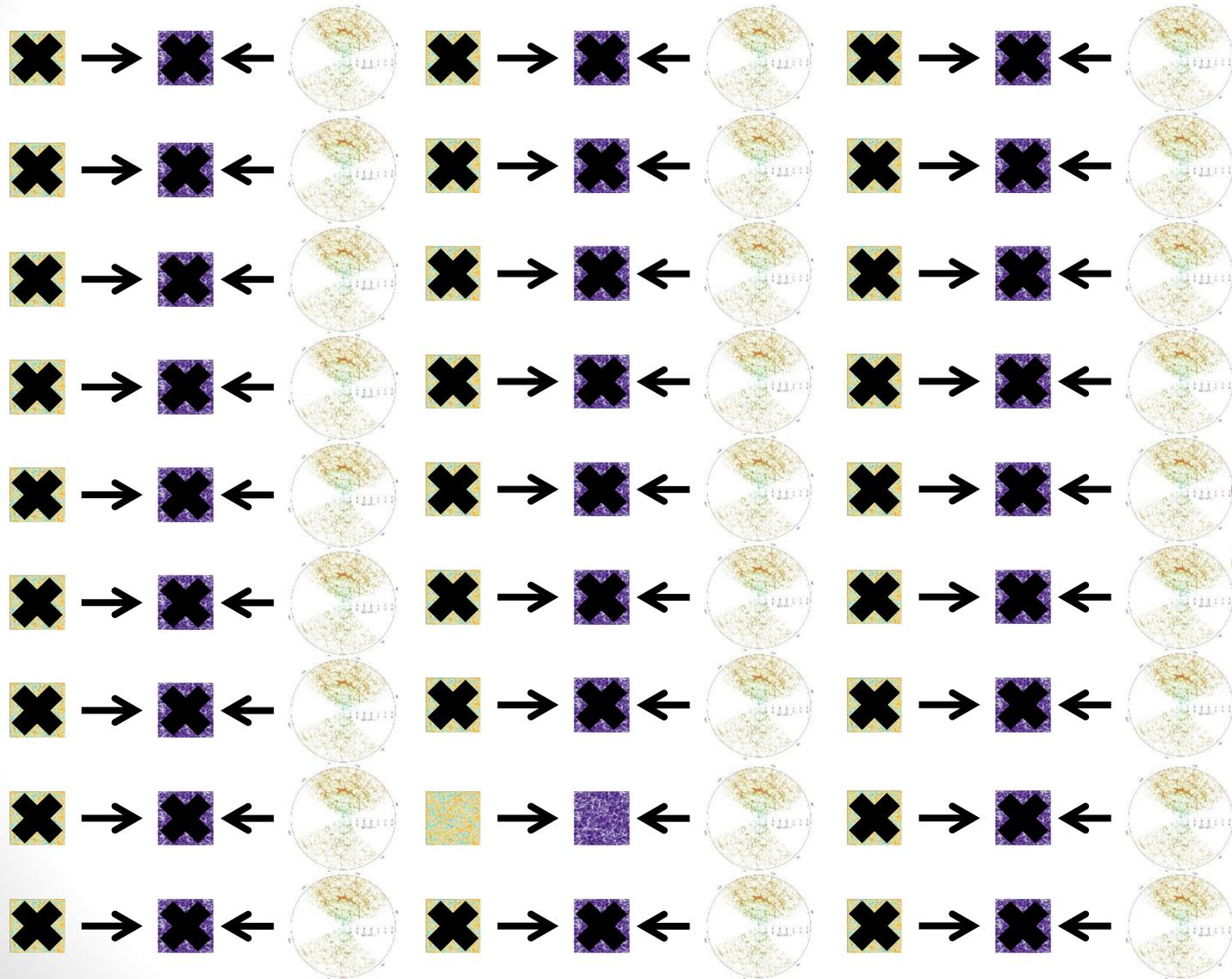
➡ How to do that?

Bayesian forward modeling: the ideal scenario

Forward model = N-body simulation + Halo occupation +
Galaxy formation + Feedback + ...



Bayesian forward modeling: the ideal scenario



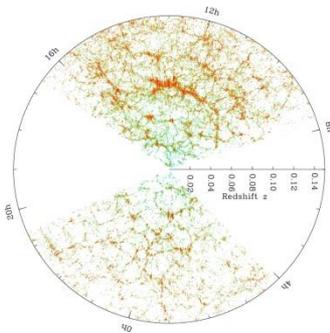
$d \approx 10^7$

BORG: *Bayesian Origin Reconstruction from Galaxies*



What makes the problem tractable:

- **Sampler:** Hamiltonian Markov Chain Monte Carlo method
- **Data model:** Gaussian prior – Second-order Lagrangian perturbation theory (2LPT) – Poisson likelihood
(and also: luminosity-dependent galaxy bias, automatic noise level calibration)



Observations

(galaxy catalog + meta-data: selection functions, completeness...)



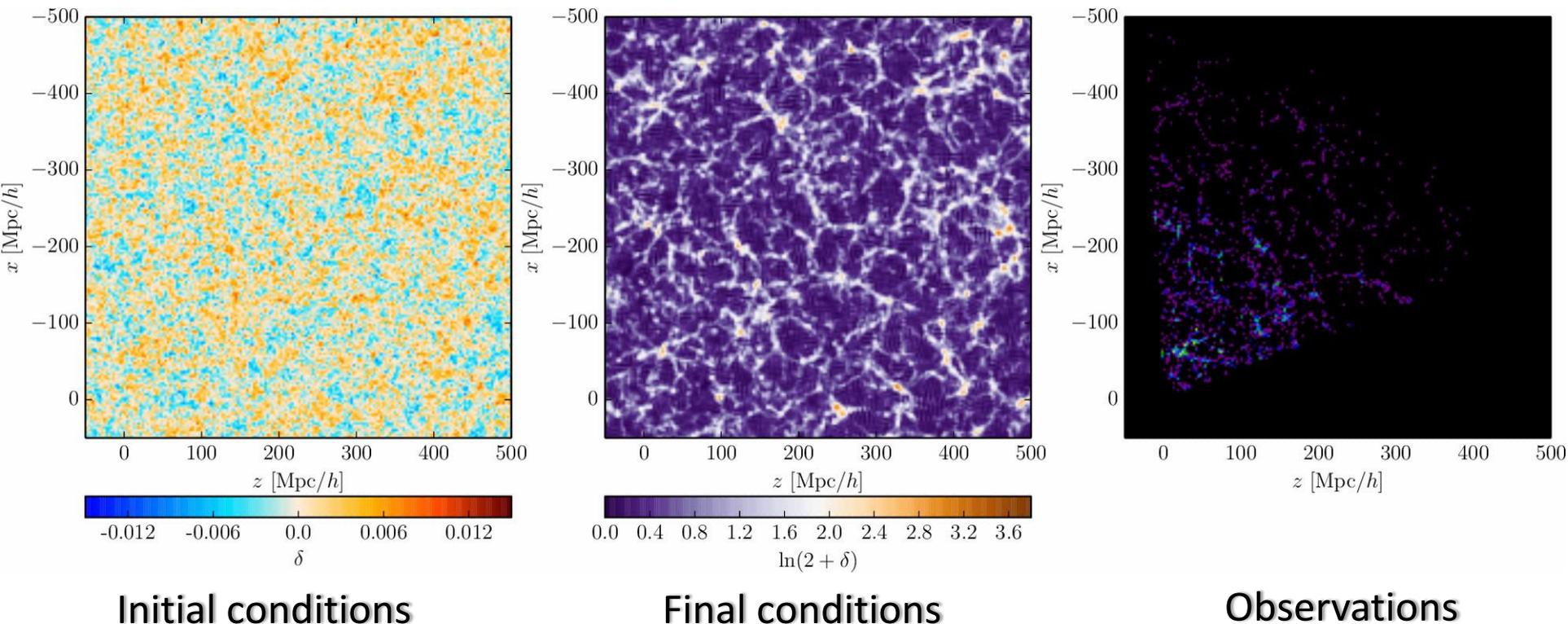
Samples of possible 4D states

Jasche & Wandelt 2013, [arXiv:1203.3639](https://arxiv.org/abs/1203.3639)

Jasche, FL & Wandelt 2015, [arXiv:1409.6308](https://arxiv.org/abs/1409.6308)

CHRONO-COSMOGRAPHY

BORG at work: SDSS chrono-cosmography

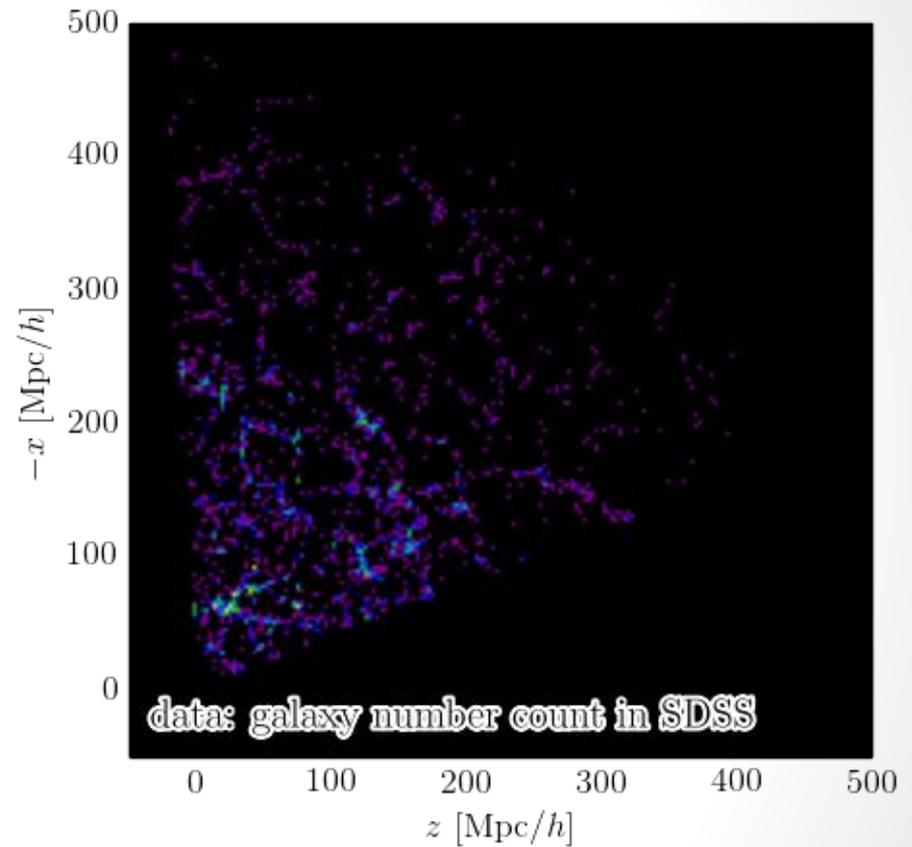
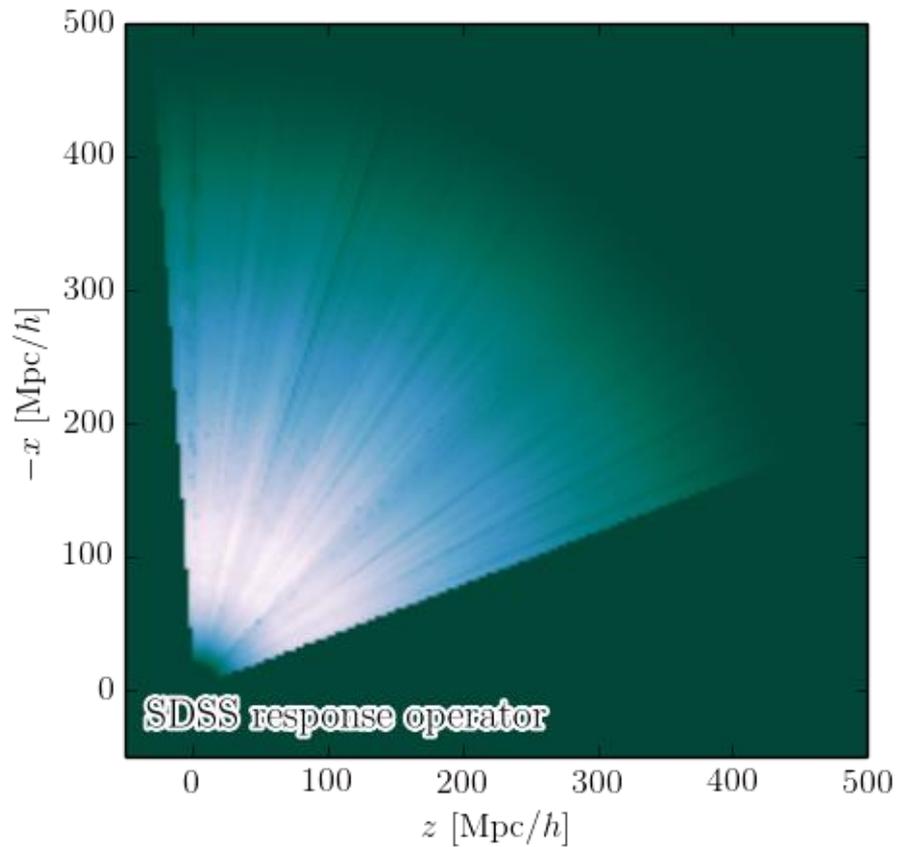


The BORG SDSS run:

334,074 galaxies, \approx 17 millions parameters, 12,000 samples, 3 TB, 10 months on 32 cores

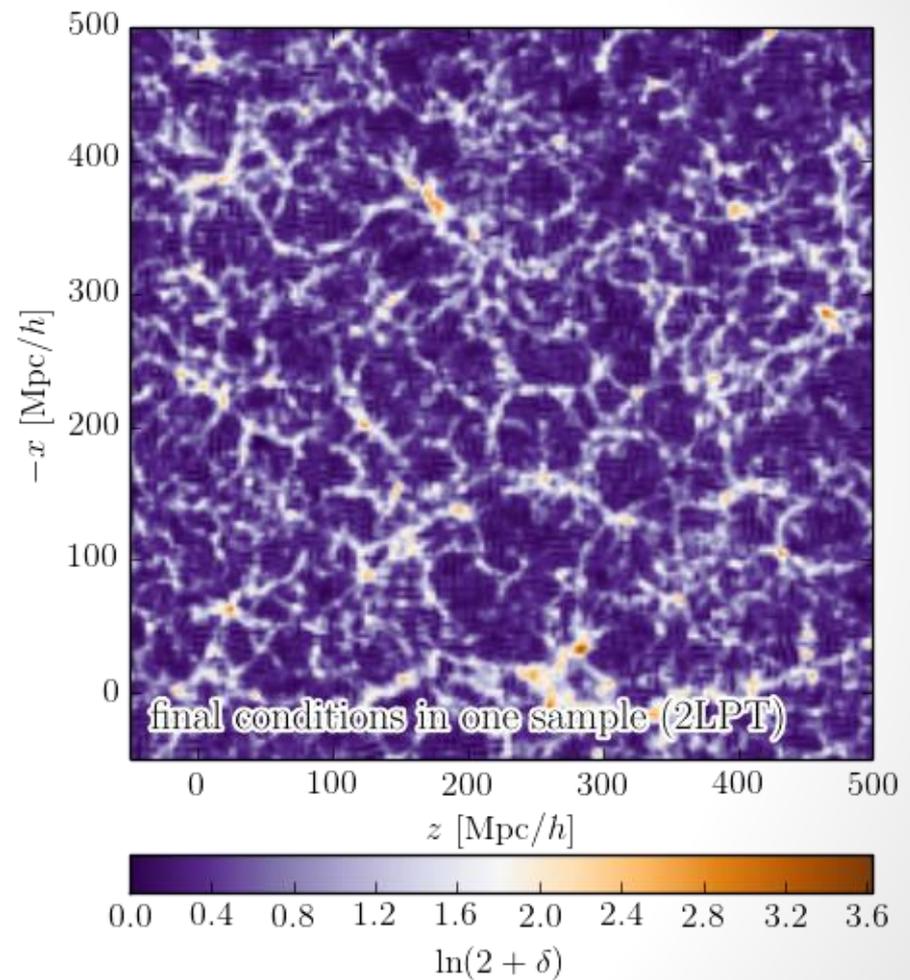
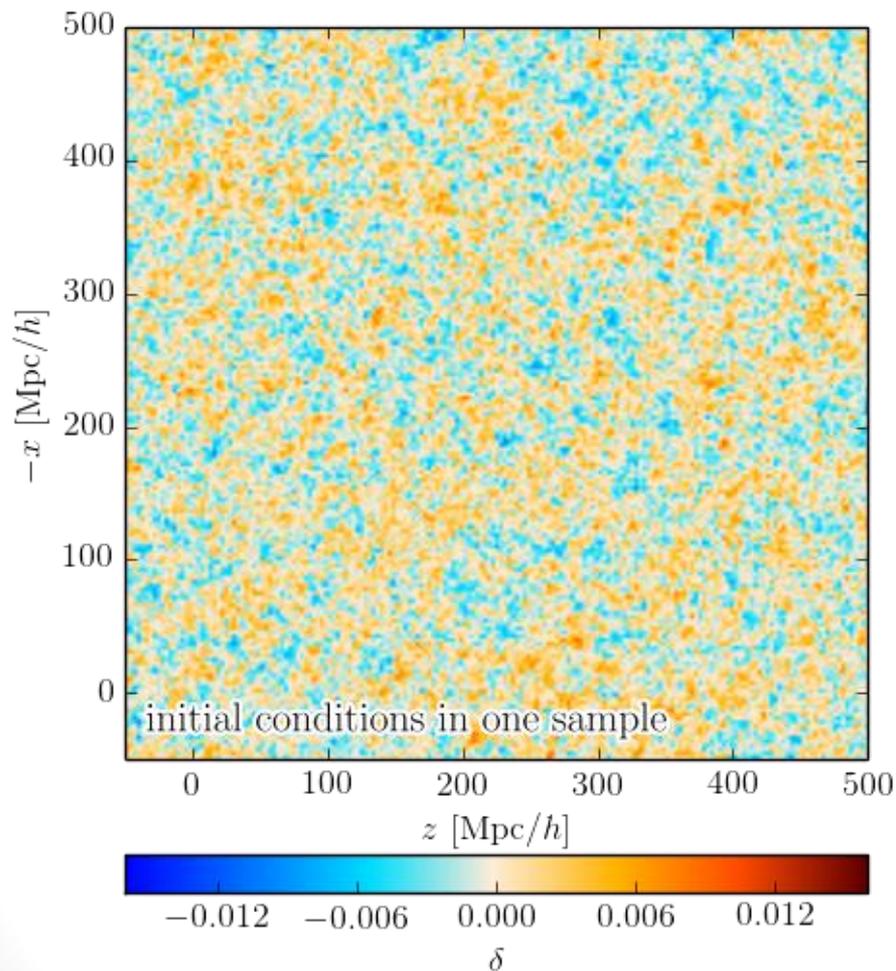
Jasche, FL & Wandelt 2015, arXiv:1409.6308

Bayesian chrono-cosmography from SDSS DR7



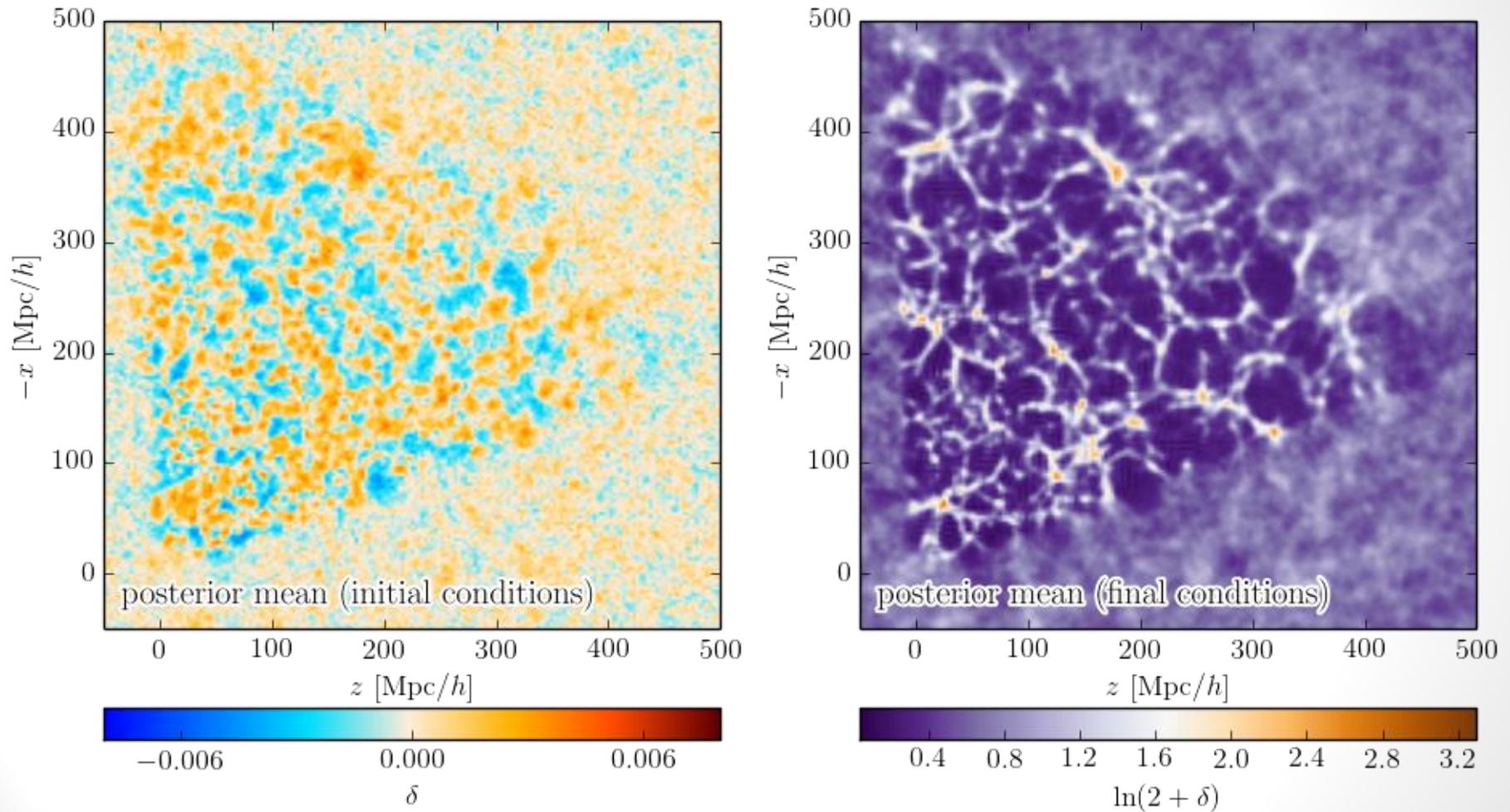
Data

Bayesian chrono-cosmography from SDSS DR7



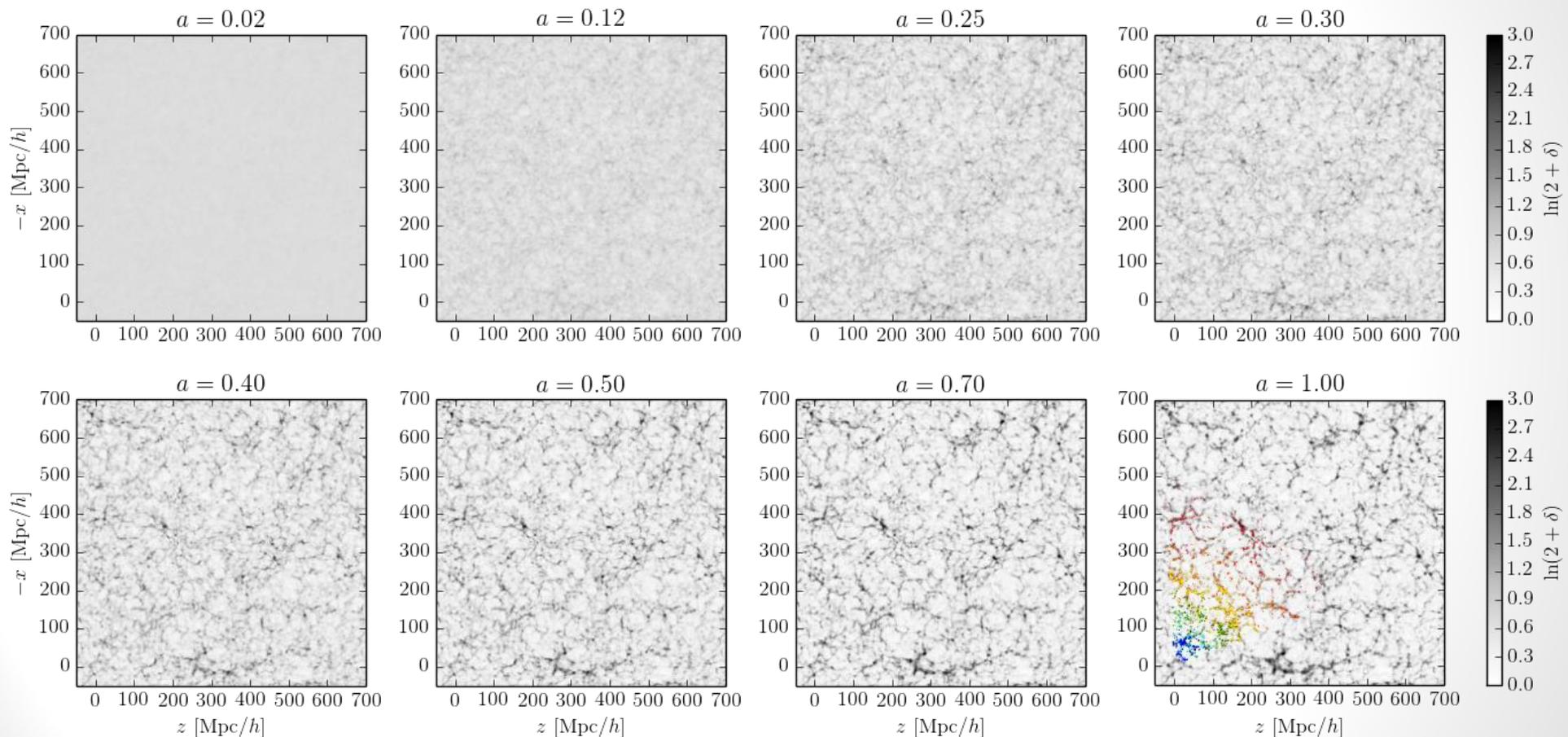
One sample

Bayesian chrono-cosmography from SDSS DR7

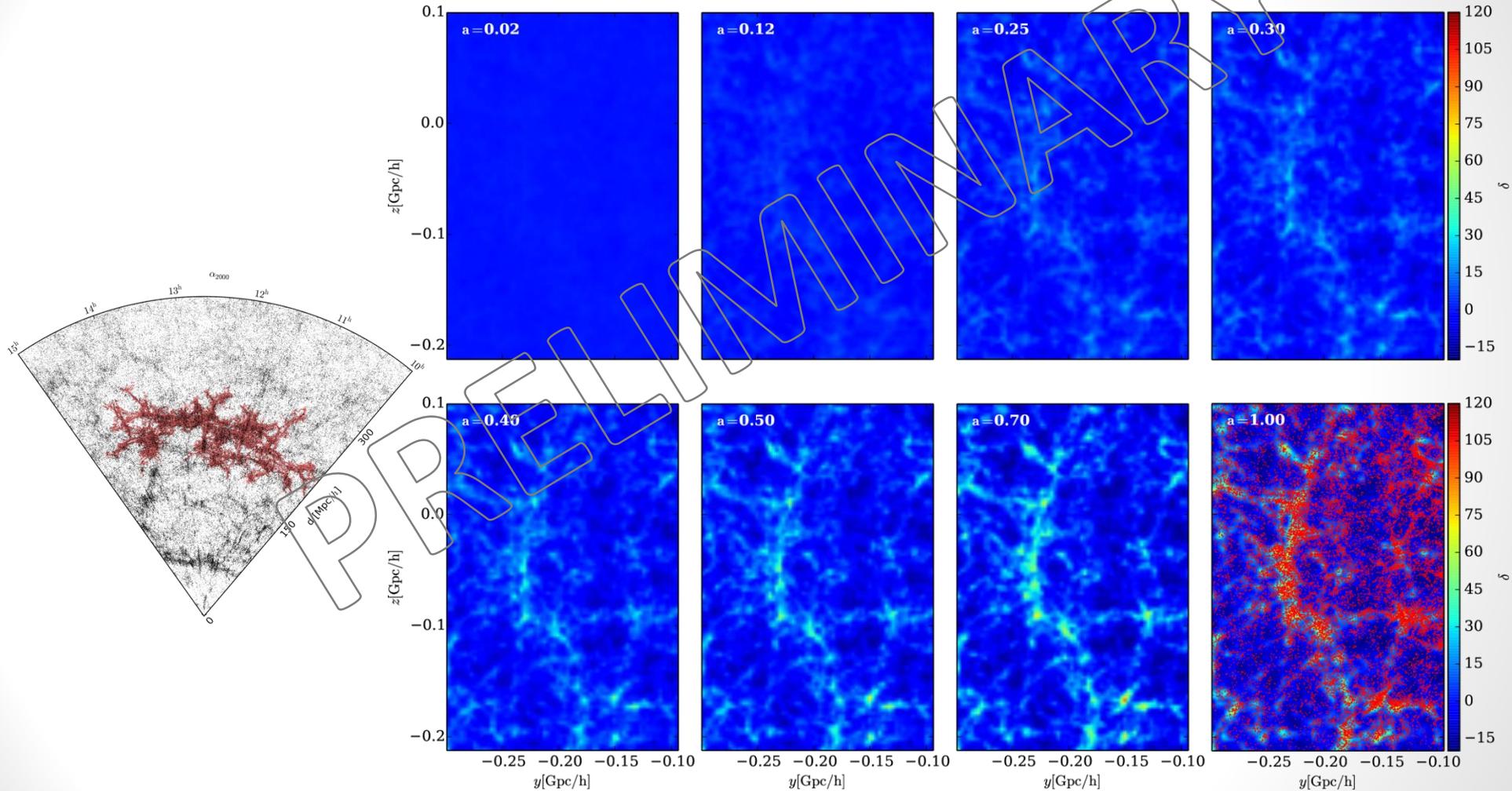


Posterior mean

Evolution of cosmic structure

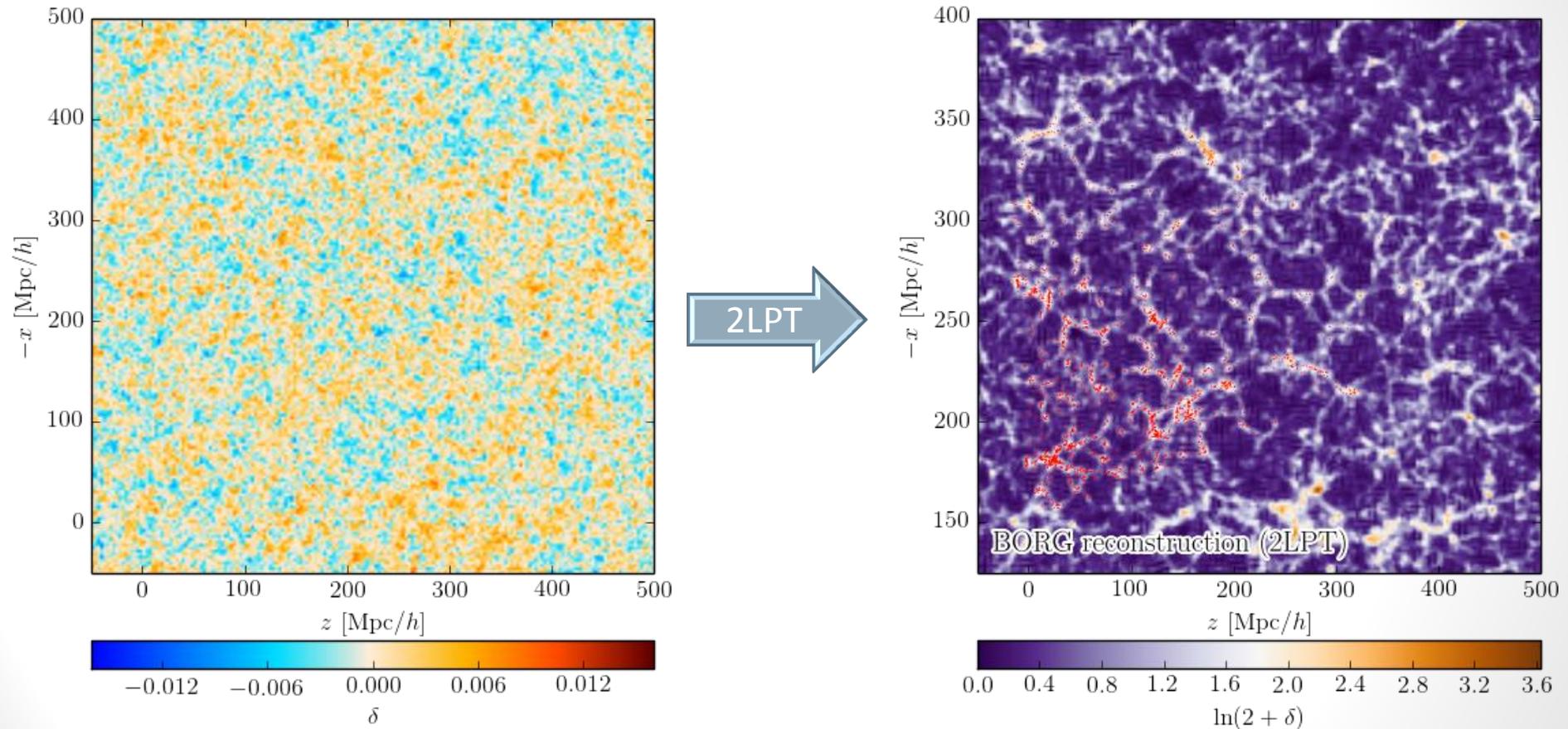


The formation history of the Sloan Great Wall

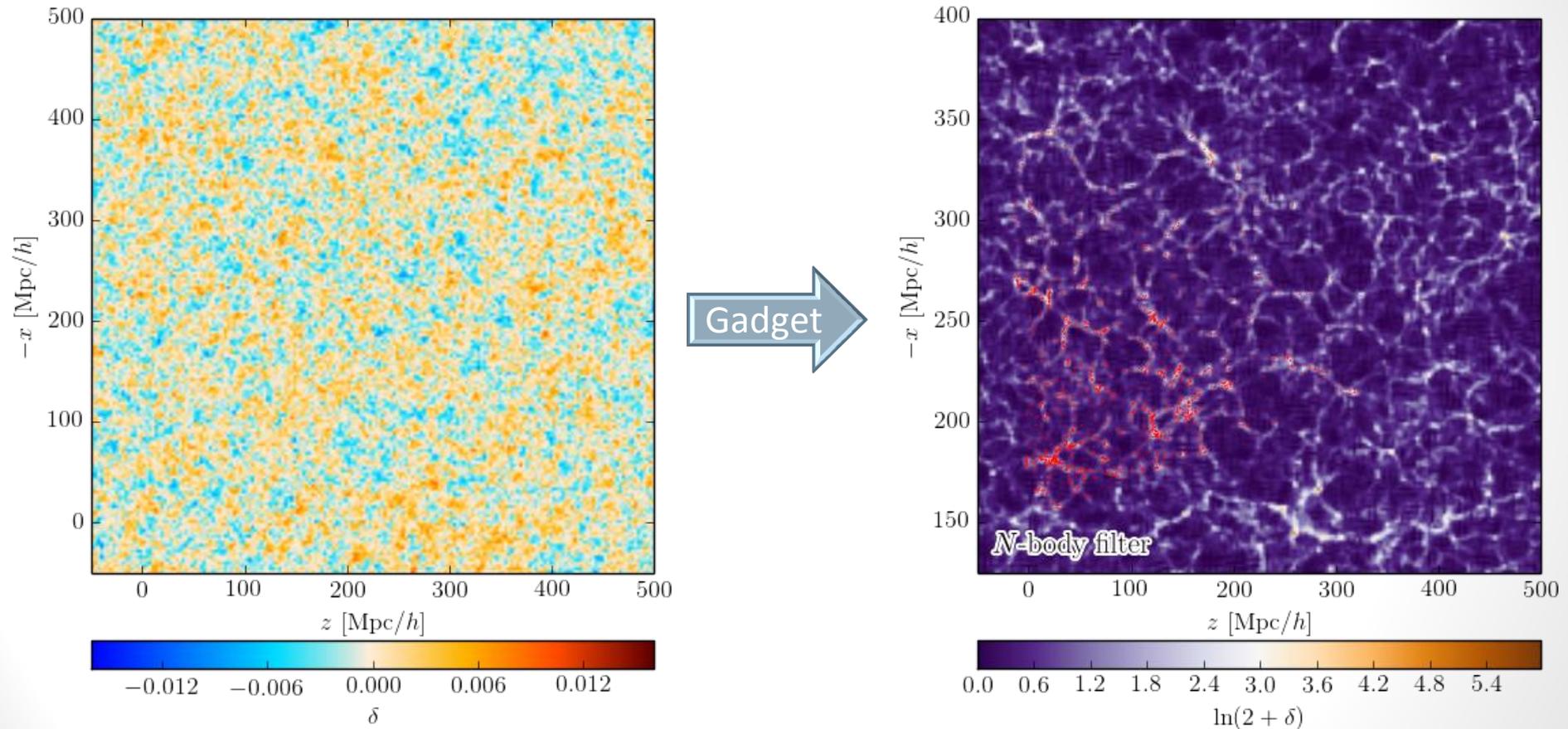


THE NON-LINEAR REGIME OF STRUCTURE FORMATION

Non-linear filtering via constrained simulations



Non-linear filtering via constrained simulations



COLA: *CO*moving Lagrangian Acceleration

- Write the displacement vector as: $\mathbf{s} = \mathbf{s}_{\text{LPT}} + \mathbf{s}_{\text{MC}}$

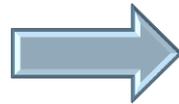
Tassev & Zaldarriaga 2012, arXiv:1203.5785

- Time-stepping (omitted constants and Hubble expansion):

Standard:

$$\partial_\tau^2 \mathbf{s} = -\nabla \Phi$$

2LPT
~ 3 timesteps

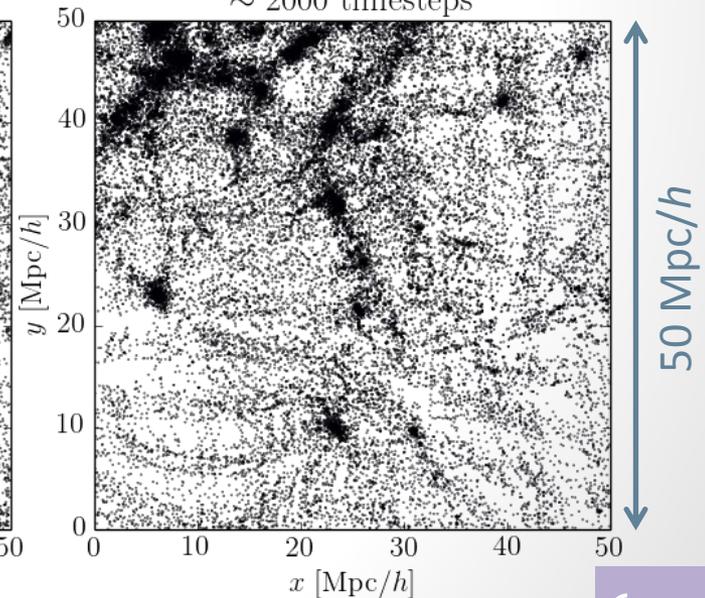
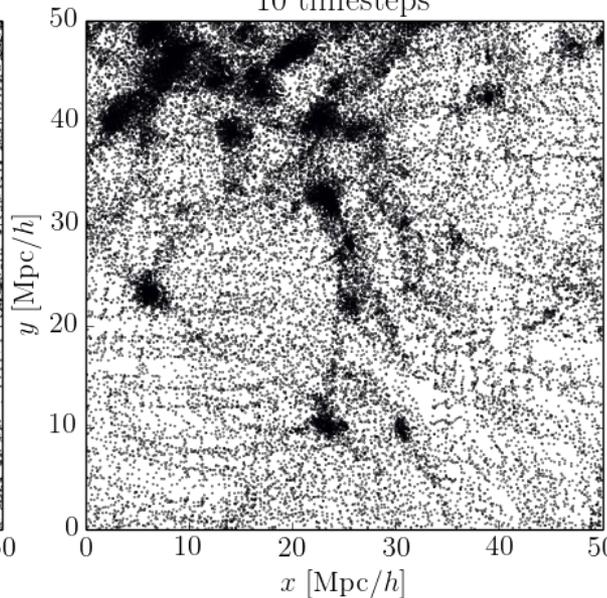
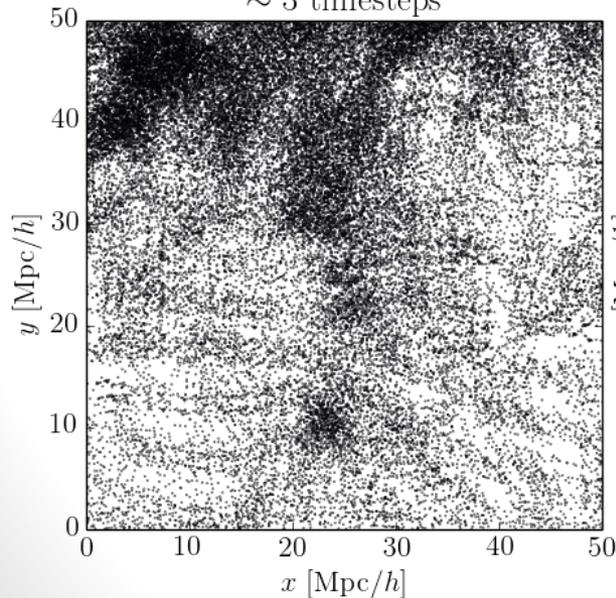


Modified:

$$\partial_\tau^2 \mathbf{s}_{\text{MC}} = \partial_\tau^2 (\mathbf{s} - \mathbf{s}_{\text{LPT}}) = -\nabla \Phi - \partial_\tau^2 \mathbf{s}_{\text{LPT}}$$

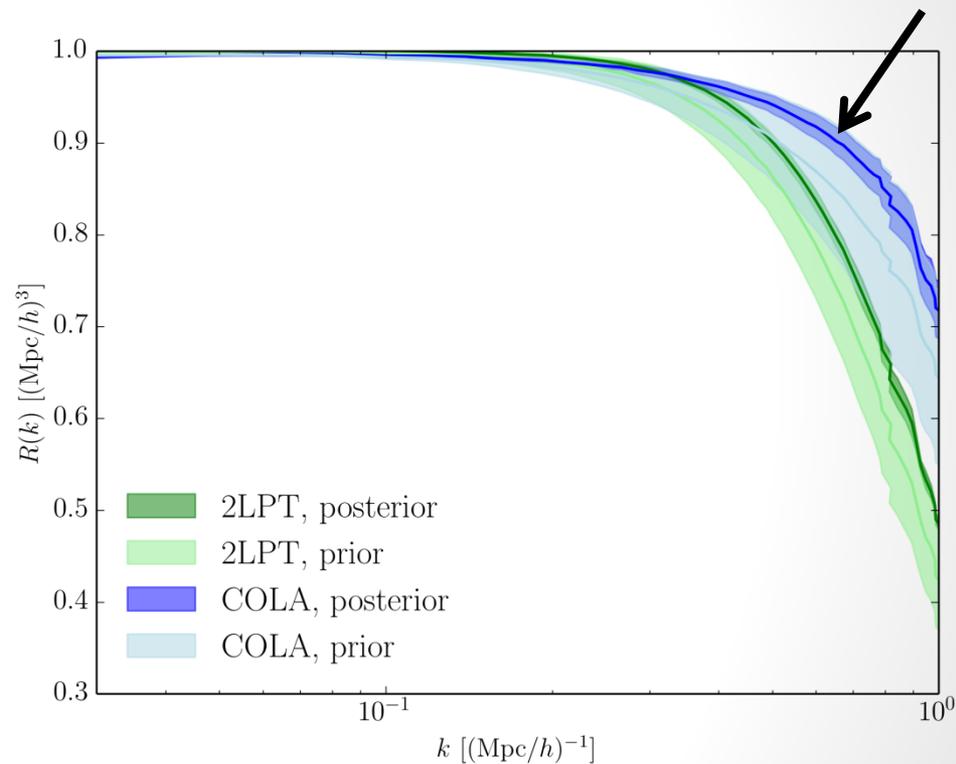
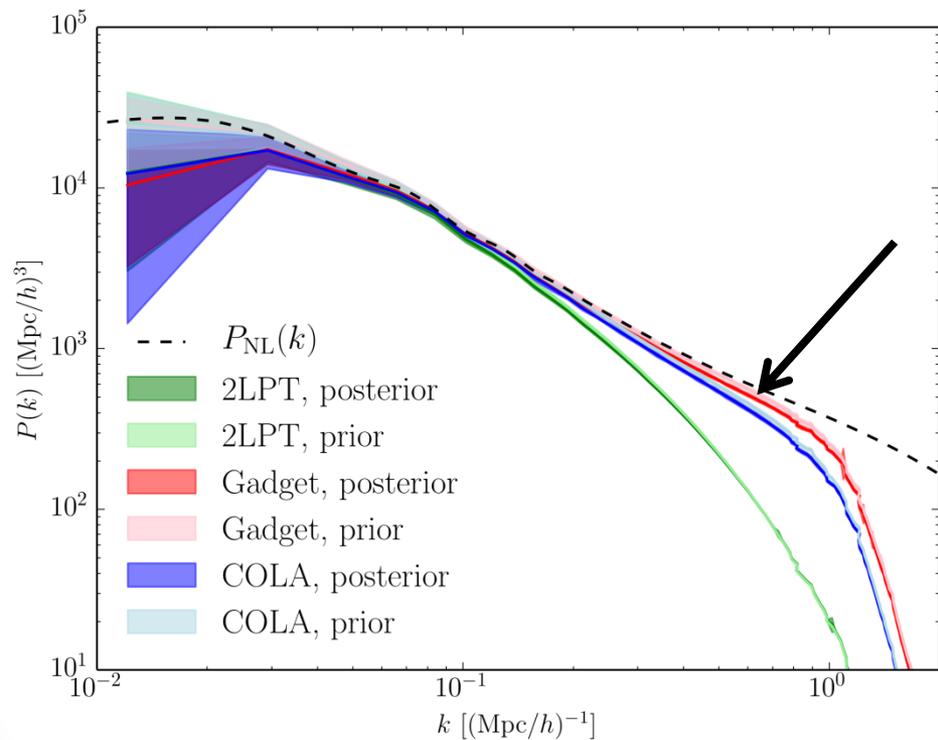
COLA
10 timesteps

GADGET
~ 2000 timesteps



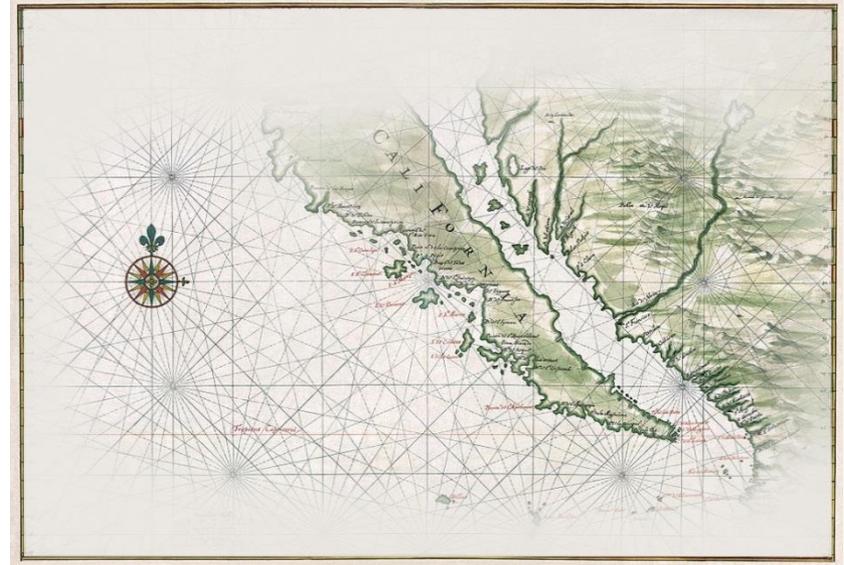
Tassev, Zaldarriaga & Eisenstein 2013, arXiv:1301.0322

Non-linear filtering improves the fit

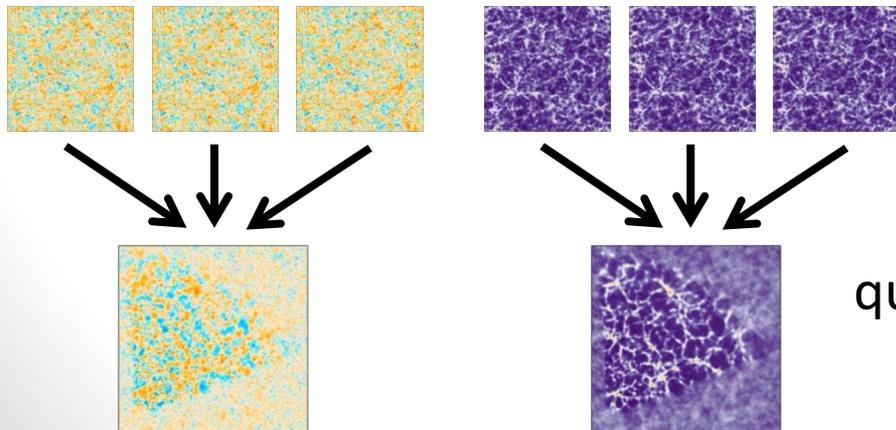


HOW IS THE COSMIC WEB WOVEN?

Uncertainty quantification



Uncertainty quantification is crucial!



Can we **propagate** uncertainty quantification to **cosmic web analysis**?

Cosmic web classification procedures

void, sheet, filament, cluster?

- The **T-web**:

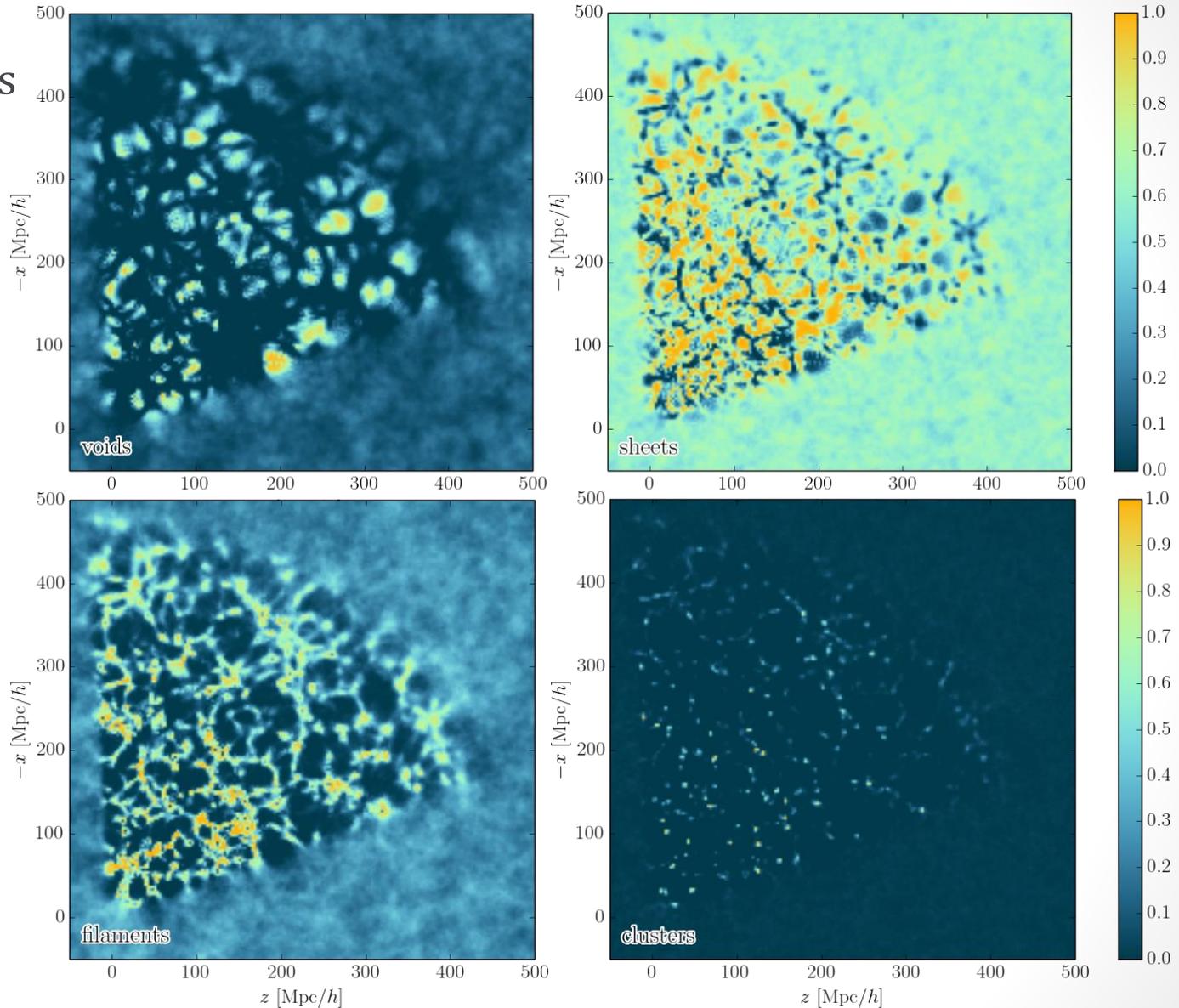
uses the sign of μ_1, μ_2, μ_3 : eigenvalues of the tidal field tensor,

Hessian of the gravitational potential: $T_{ij}(\mathbf{x}) = \partial_i \partial_j \Phi(\mathbf{x})$

Hahn et al. 2007, arXiv:astro-ph/0610280

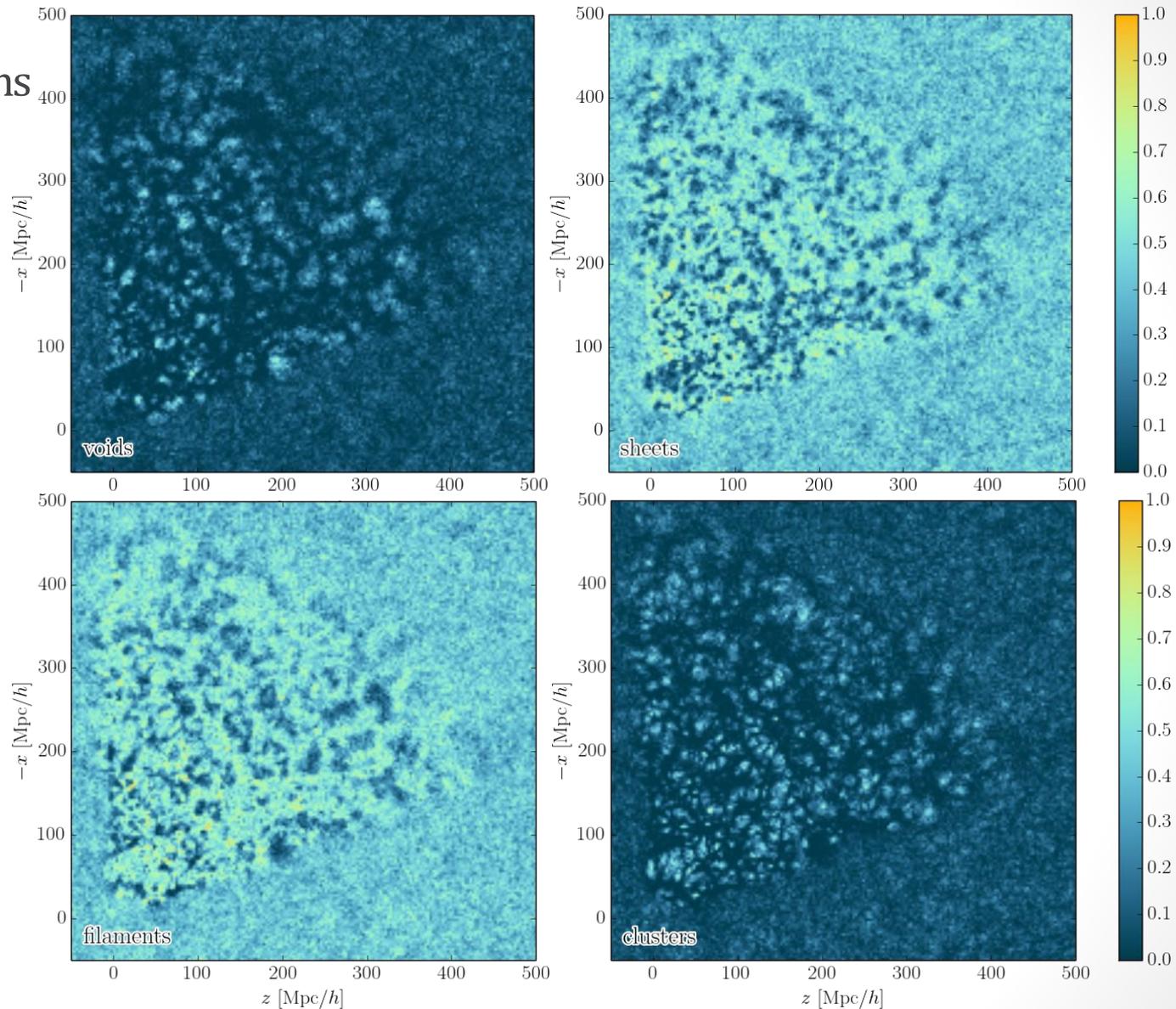
T-web structures inferred by BORG

Final conditions



T-web structures inferred by BORG

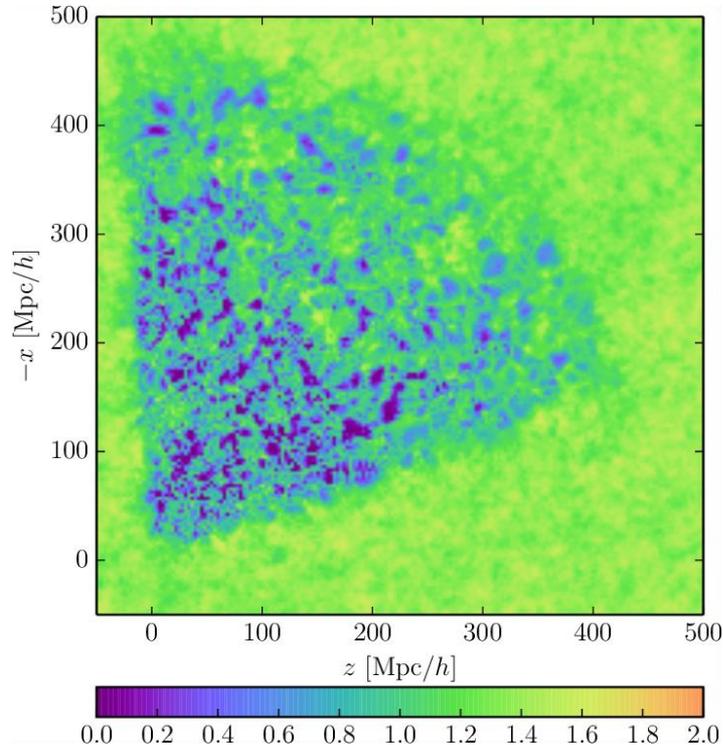
Initial conditions



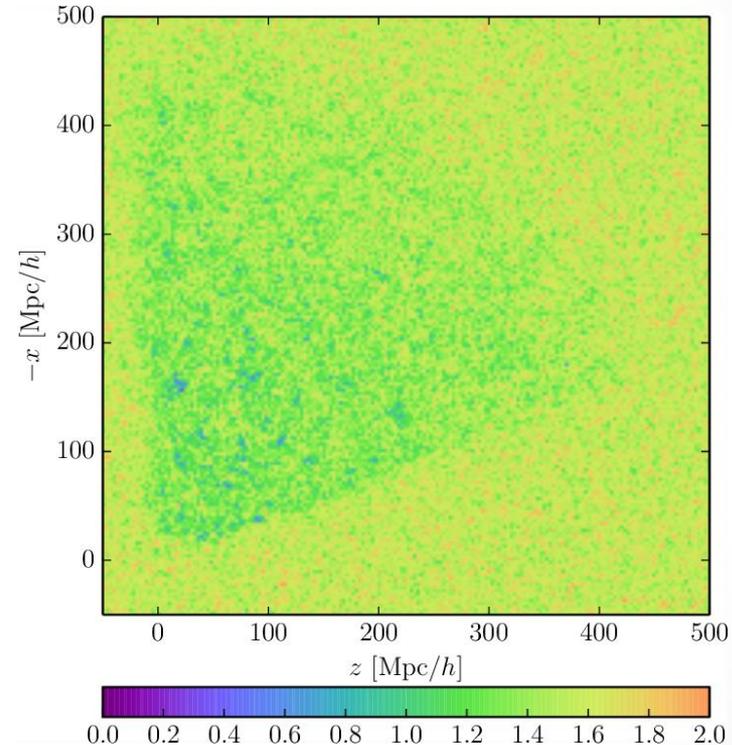
Entropy of the structure types posterior

$$H [\mathcal{P}(T(\vec{x}_k)|d)] \equiv - \sum_{i=0}^3 \mathcal{P}(T_i(\vec{x}_k)|d) \log_2(\mathcal{P}(T_i(\vec{x}_k)|d)) \quad \text{in shannons (Sh)}$$

Final conditions



Initial conditions



(more to come on the connection between **cosmic web analysis**
and **information theory**)

A decision rule for structure classification

- Space of “input features”:

$\{T_0 = \text{void}, T_1 = \text{sheet}, T_2 = \text{filament}, T_3 = \text{cluster}\}$

- Space of “actions”:

$\{a_0 = \text{“decide void”}, a_1 = \text{“decide sheet”}, a_2 = \text{“decide filament”}, a_3 = \text{“decide cluster”}, a_{-1} = \text{“do not decide”}\}$

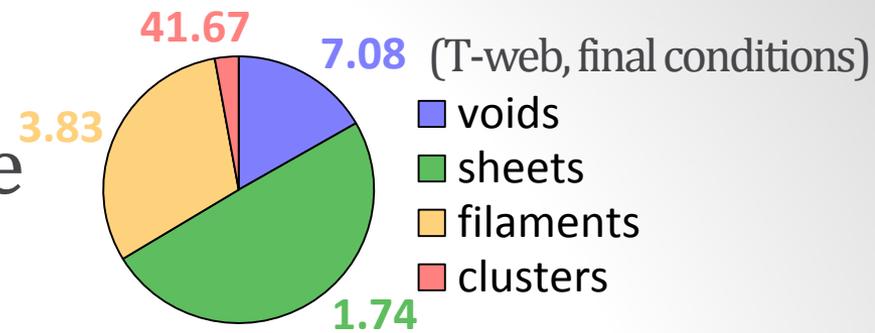
➡ A problem of **Bayesian decision theory**:

one should take the action which maximizes the utility

$$U(a_j(\vec{x}_k)|d) = \sum_{i=0}^3 G(a_j|T_i) \mathcal{P}(T_i(\vec{x}_k)|d)$$

- How to write down the gain functions?

Gambling with the Universe



- One proposal:

$$G(a_j | T_i) = \begin{cases} \frac{1}{\mathcal{P}(T_i)} - \alpha & \text{if } j \in \llbracket 0, 3 \rrbracket \text{ and } i = j & \text{“Winning”} \\ -\alpha & \text{if } j \in \llbracket 0, 3 \rrbracket \text{ and } i \neq j & \text{“Loosing”} \\ 0 & \text{if } j = -1. & \text{“Not playing”} \end{cases}$$

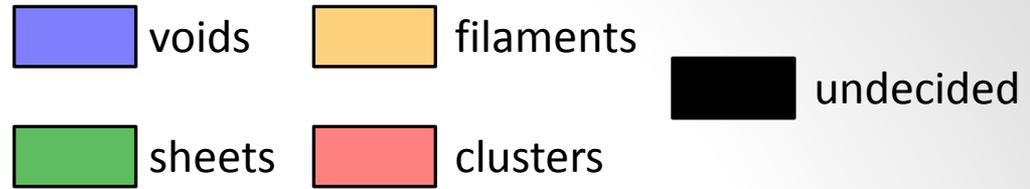
- Without data, the expected utility is

$$U(a_j) = 1 - \alpha \quad \text{if } j \neq -1 \quad \text{“Playing the game”}$$

$$U(a_{-1}) = 0 \quad \text{“Not playing the game”}$$

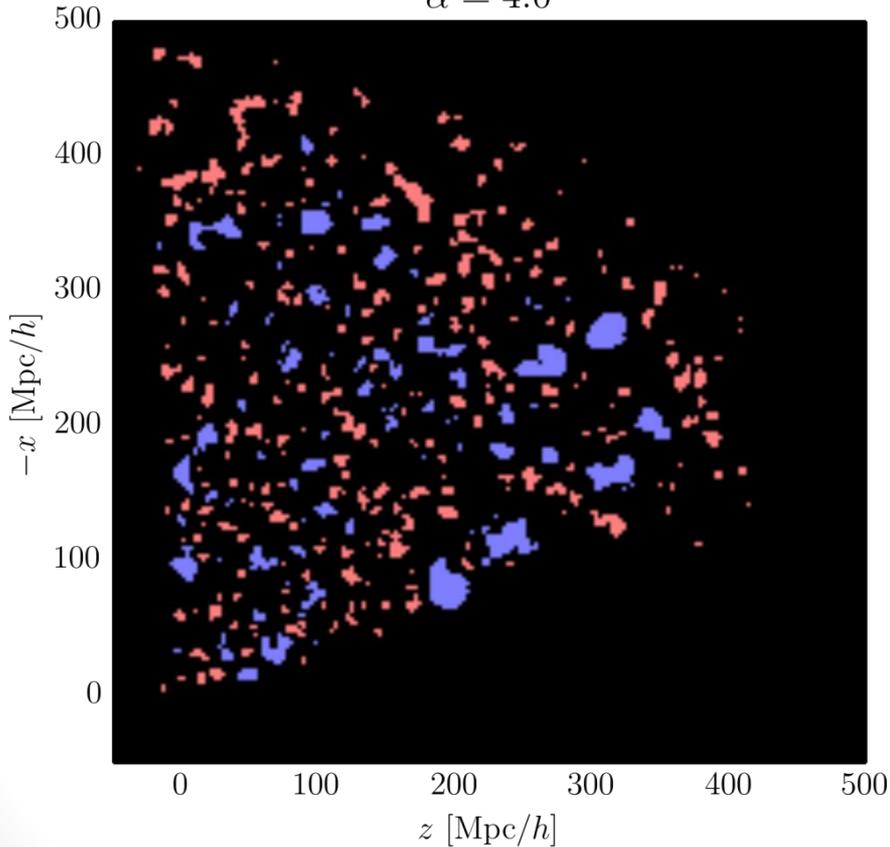
- With $\alpha = 1$, it's a *fair game* \Rightarrow always play \Rightarrow “speculative map” of the LSS
- Values $\alpha > 1$ represent an *aversion for risk* \Rightarrow increasingly “conservative maps” of the LSS

Playing the game...



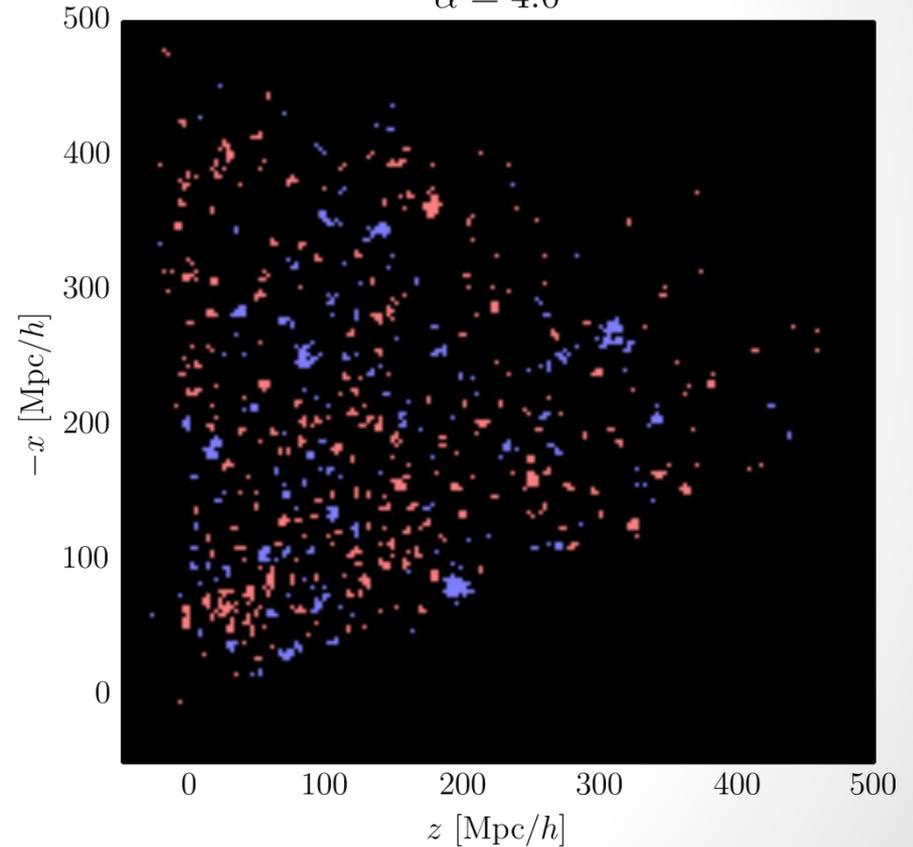
Final conditions

$\alpha = 4.0$



Initial conditions

$\alpha = 4.0$



Inference of the dark matter phase-space sheet

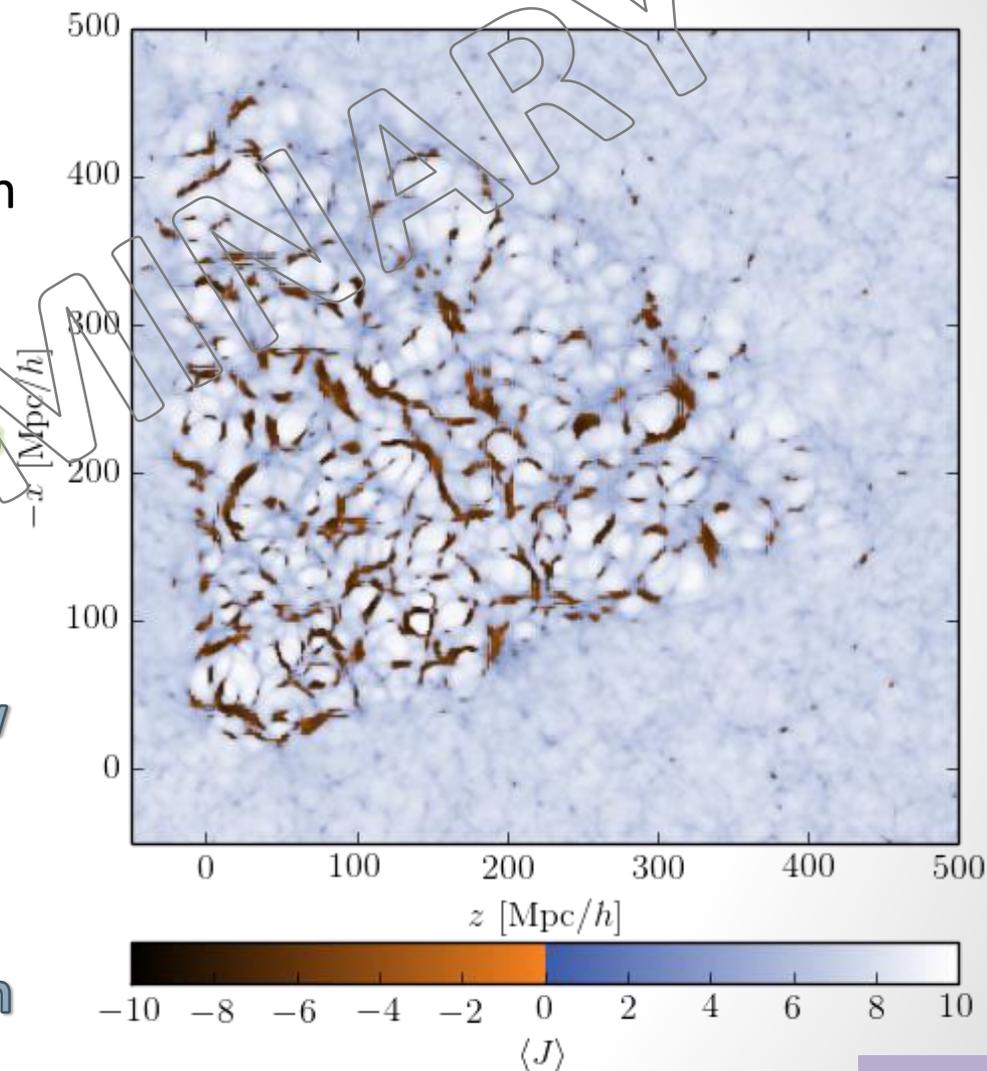
- The dark matter phase-space sheet has been studied so far in simulations

e.g. Neyrinck 2012, arXiv:1202.3364

Abel, Hahn & Kaehler 2012, arXiv:1111.3944

Shandarin, Habib & Heitmann 2012, arXiv:1111.2366

- BORG infers **Lagrangian dynamics** in real data
- This is opening the way to **new confrontations** between data and theory
- Identified structures have a direct **physical interpretation**



Cosmic web classification procedures

void, sheet, filament, cluster?

- The **T-web**:

uses the sign of μ_1, μ_2, μ_3 : eigenvalues of the tidal field tensor, Hessian of the gravitational potential: $T_{ij}(\mathbf{x}) = \partial_i \partial_j \Phi(\mathbf{x})$

Hahn *et al.* 2007, arXiv:astro-ph/0610280

- **DIVA**:

uses the sign of $\lambda_1, \lambda_2, \lambda_3$: eigenvalues of the shear of the Lagrangian displacement field: $R_{\ell m}(\mathbf{q}) = \partial_m \Psi_\ell(\mathbf{q})$

Lavaux & Wandelt 2010, arXiv:0906.4101

- **ORIGAMI** :

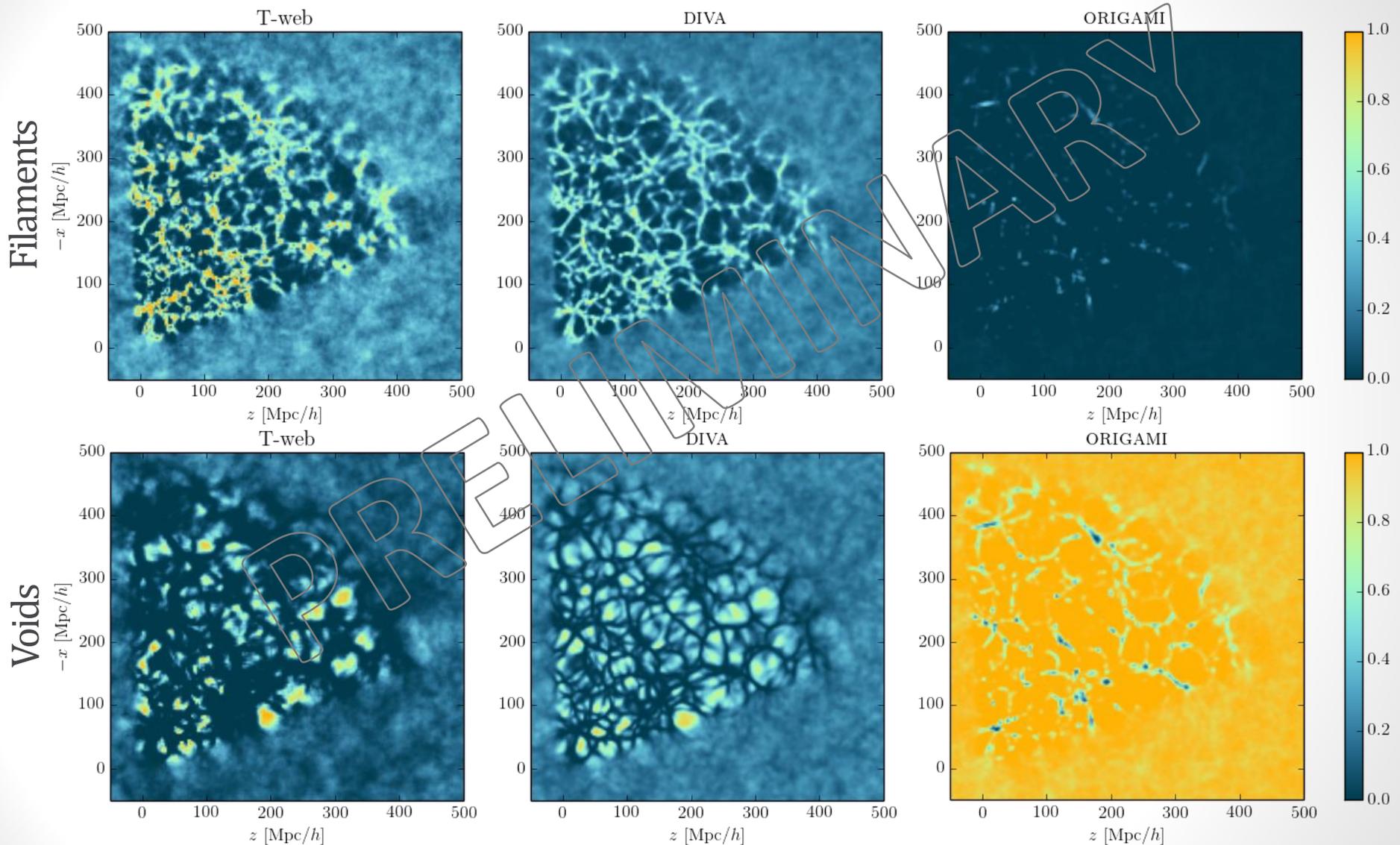
uses the dark matter “phase-space sheet” (number of orthogonal axes along which there is shell-crossing)

Falck, Neyrinck & Szalay 2012, arXiv:1201.2353

Lagrangian
classifiers

now usable
in real data!

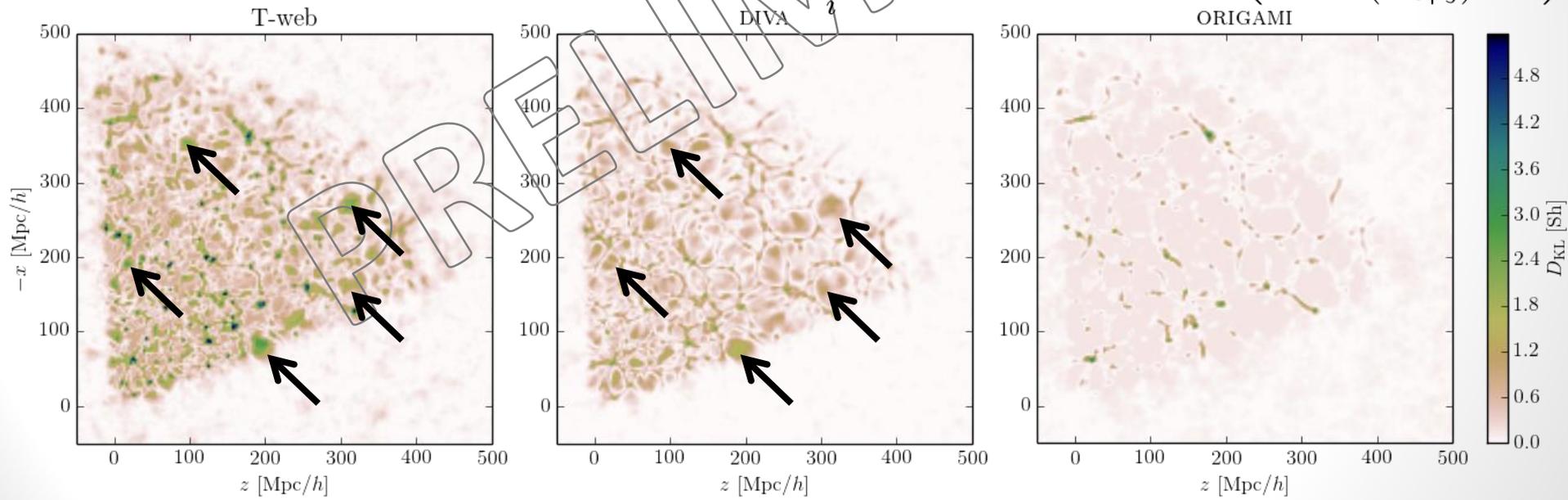
Comparing classifiers



How much did the data surprise us?

- One possible criterion, in analogy with Bayesian experimental design: **maximize the expected information gain**, $U(\xi)$ (in Sh)

$$U(d, \xi) \equiv D_{\text{KL}}(\mathcal{P}(T(\vec{x}_k)|d, \xi) || \mathcal{P}(T|\xi)) \equiv \sum_i \mathcal{P}(T_i(\vec{x}_k)|d, \xi) \log_2 \left(\frac{\mathcal{P}(T_i(\vec{x}_k)|d, \xi)}{\mathcal{P}(T_i|\xi)} \right)$$



Cosmic voids carry large **information gain**

HINTS FROM THE DARK

Dark matter voids: pipeline

Why BORG?

Sparsity & Bias

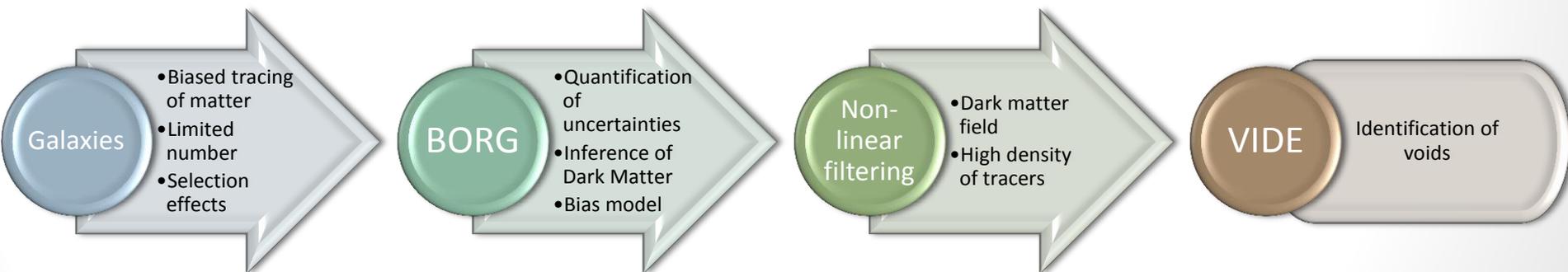
Sutter *et al.* 2013, arXiv:1309.5087

Sutter *et al.* 2013, arXiv:1311.3301

How?

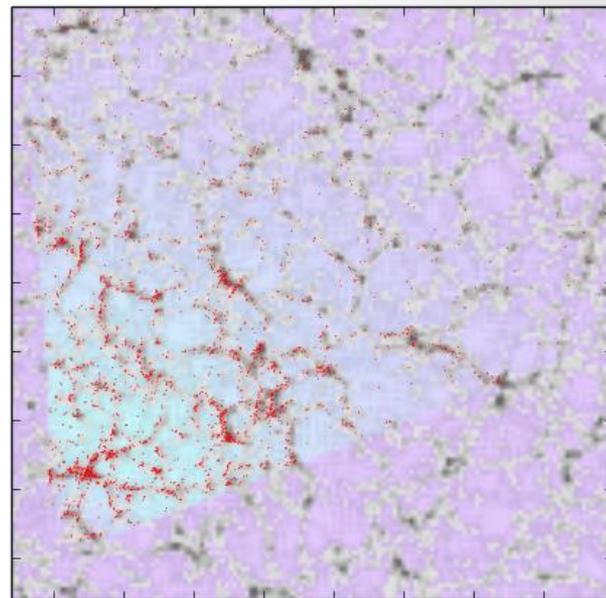
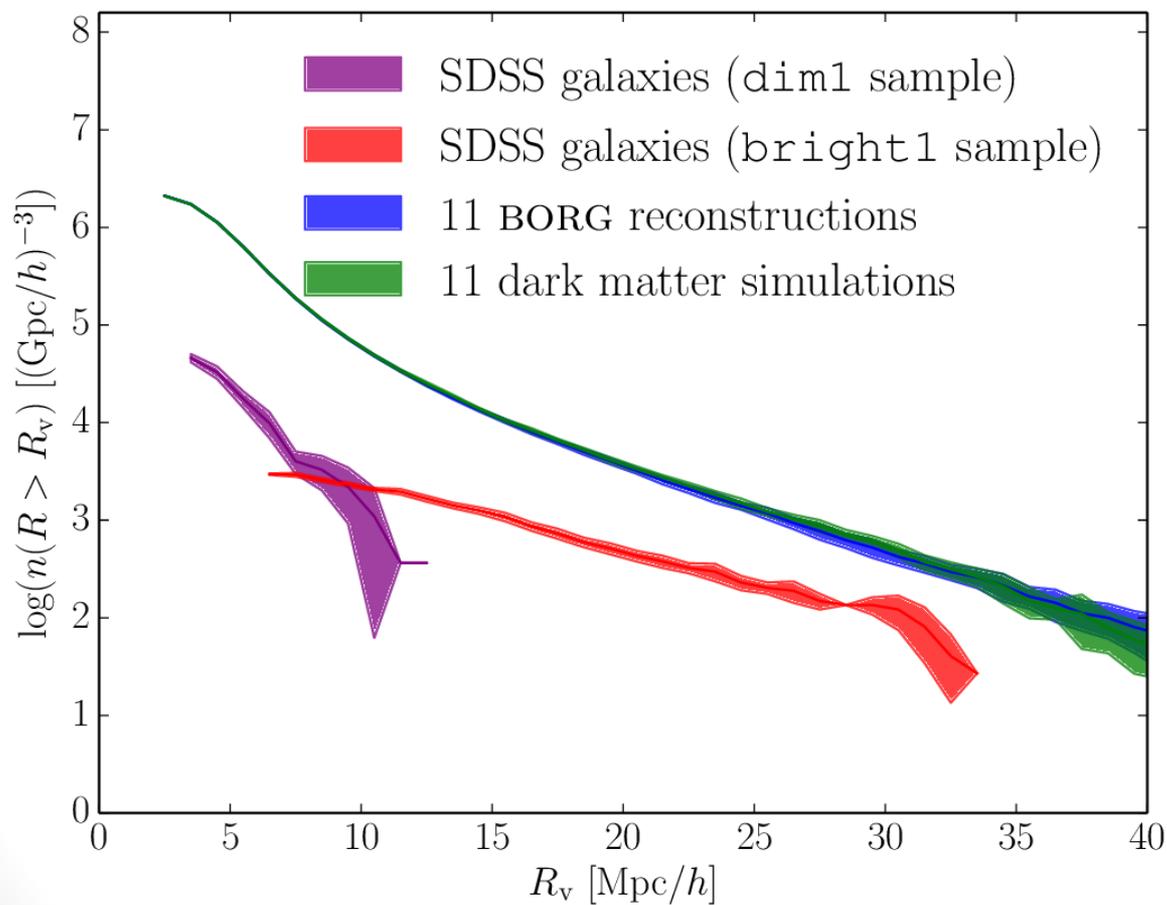
VIDE toolkit: Sutter *et al.* 2015, arXiv:1406.1191
www.cosmicvoids.net

based on ZOBOV: Neyrinck 2007, arXiv:0712.3049



BORG unveils many more voids

Void number function

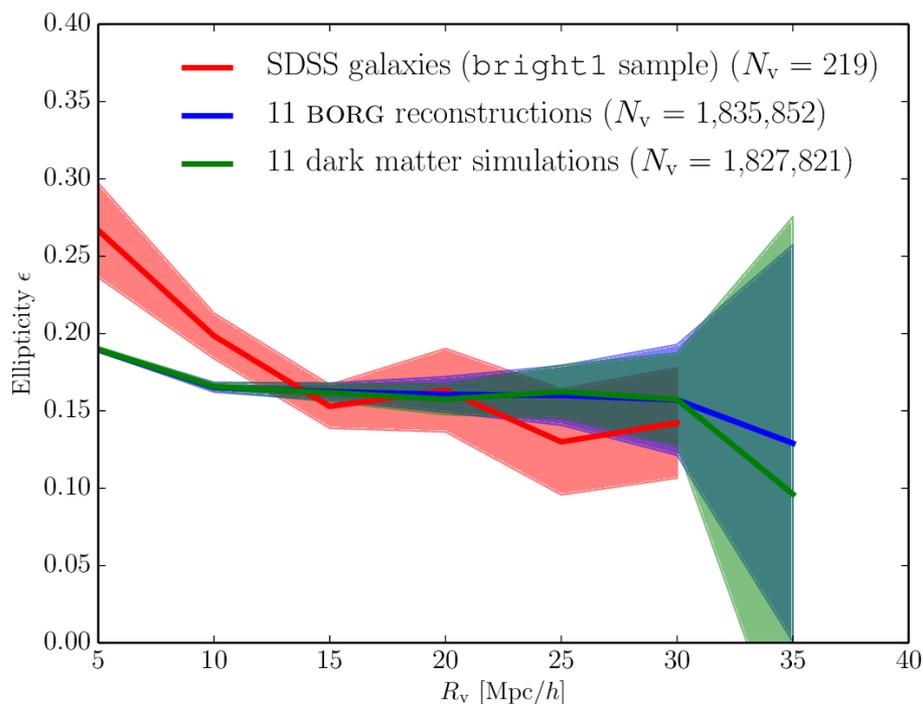


Voids in constrained regions only

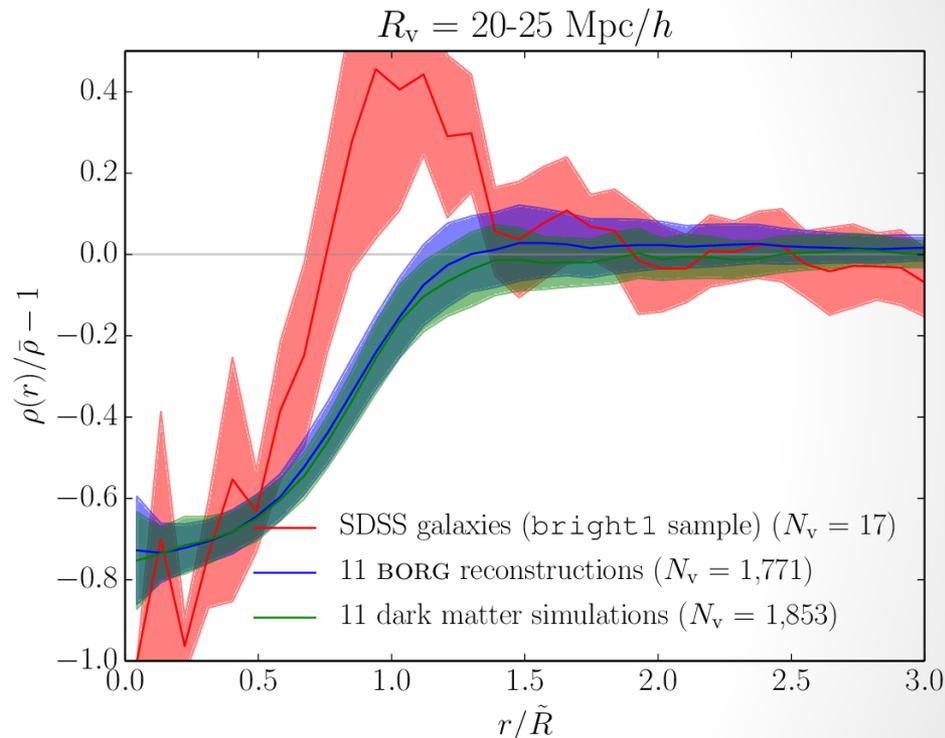
Voids are **Poisson-dominated** objects:
10x more voids require 100x more galaxies!

Reduction of statistical uncertainty in voids catalogs

Ellipticity distribution



Radial density profile

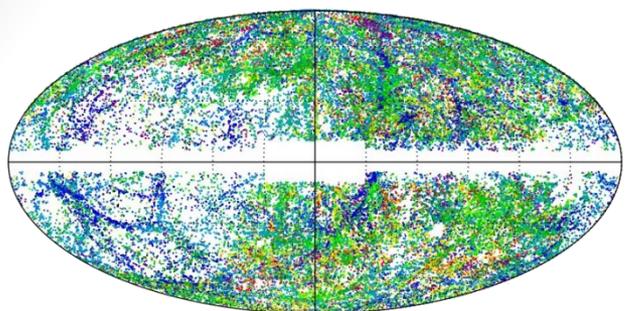


All catalogs are publicly available at www.cosmicvoids.net for follow-up projects.

For example, these voids should have an **effect on CMB photons...**

HOW TO DETECT SECONDARY EFFECTS IN THE COSMIC MICROWAVE BACKGROUND?

Producing LSS-CMB observables



2M++ catalog

Lavaux & Hudson 2011, arXiv:1105.6107

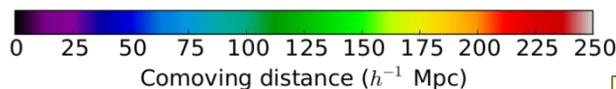
Initial conditions from BORG

Lavaux & Jasche 2015, arXiv:1509.05040



Filtering with COLA

Tassev, Zaldarriaga & Eisenstein, arXiv:1301.0322



Non-linear dynamics



Gravitational potential
↓
Integrated Sachs-Wolfe (iSW) and Rees-Sciama (RS) effects

Momentum field
↓
kinetic Sunyaev-Zel'dovich (kSZ) effect

Gas profiles in clusters
↓
thermal Sunyaev-Zel'dovich (tSZ) effect

Raytracing algorithm

Cai *et al.* 2010, arXiv:1003.0974

kSZ/tSZ model

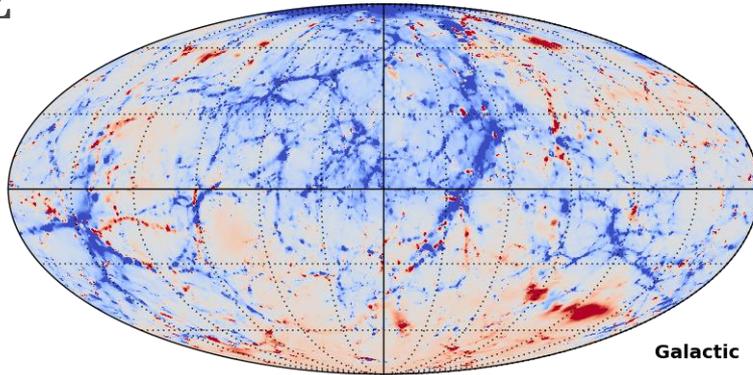
Lavaux, Afshordi & Hudson 2012, arXiv:1207.1721



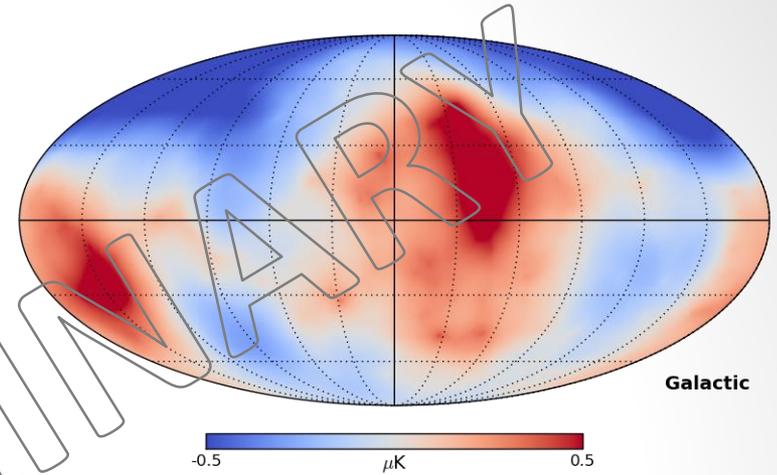
Better modeling yields higher Signal/Noise ratio

Templates for secondary effects in the CMB

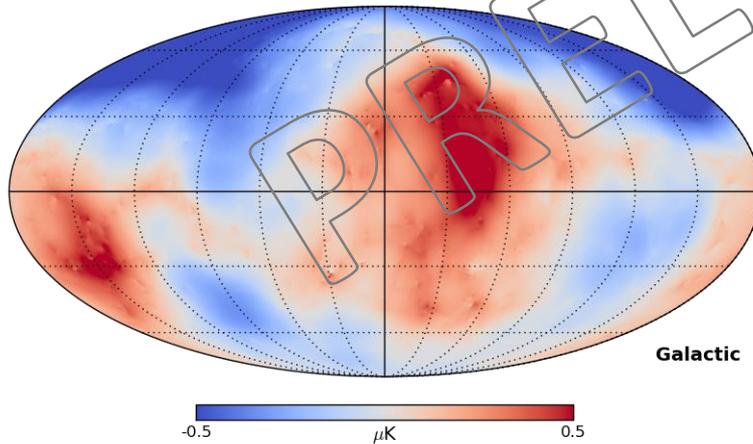
kSZ



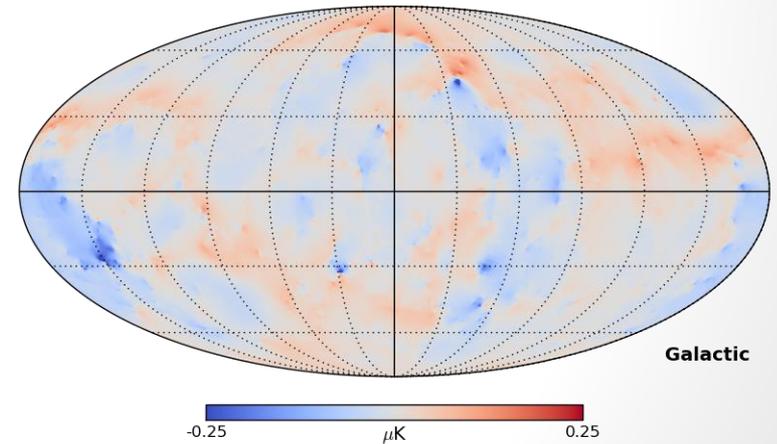
iSW



iSWRS



Only non-linear effects (iSWRS – iSW)



- Simulations in **one** BORG sample, raytraced from 0 to 100 Mpc/h
- The full posterior is available for Hierarchical Bayesian analysis

with G. Lavaux, J. Jasche, B. Wandelt

Summary & concluding thoughts

- A new method for principled analysis of galaxy surveys: **Bayesian large-scale structure inference**
 - Uncertainty quantification (noise, survey geometry, selection effects and biases)
 - Non-linear and non-Gaussian inference, with improving techniques
- Application to data: four-dimensional **chrono-cosmography**
 - Simultaneous analysis of the morphology and formation history of the large-scale structure
 - Physical reconstruction of the initial conditions
 - Characterization of the dynamic cosmic web underlying galaxies
 - Inference of cosmic voids at the level of the dark matter field
 - Cross-correlation of galaxy surveys and CMB data through kSZ/iSW/RS effects