

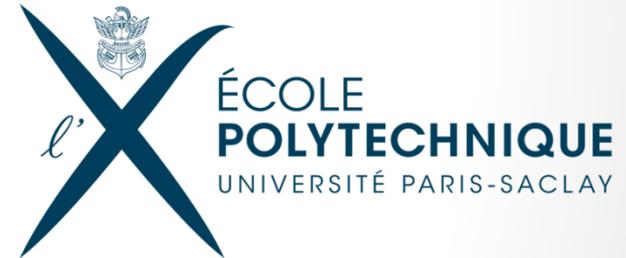
Bayesian large-scale structure inference and cosmic web analysis

Florent Leclercq

Institut d'Astrophysique de Paris
Institut Lagrange de Paris
École polytechnique ParisTech



March 2nd, 2015



In collaboration with:

Héctor Gil-Marín (U. Portsmouth), Nico Hamaus (IAP), Jens Jasche (Excellence Cluster Universe Garching),
Alice Pisani (LAM/IAP), Emilio Romano-Díaz (U. Bonn), Paul M. Sutter (Trieste/IAP/Ohio State U.),
Benjamin Wandelt (IAP/U. Illinois), Matías Zaldarriaga (IAS Princeton)

How did structure appear in the Universe?

A joint problem!

- **How did the Universe begin?**
 - What are the statistical properties of the initial conditions?
- Usually these problems are addressed in isolation.
- This talk:
 - A case for physical inference of four-dimensional dynamic states
 - A description of methodology and progress towards enriching the standard for analysis of galaxy surveys
 - A round trip: from theory to data, from data to theory
- **How did the large-scale structure take shape?**
 - What is the physics of dark matter and dark energy?

Outline

1. Bayesian Inference
2. Chrono-Cosmography
3. The Non-Linear Regime of Structure Formation
4. Cosmic Web Classification

1. BAYESIAN INFERENCE

- Data assimilation with BORG
- The BORG SDSS run

J. Jasche, B. Wandelt, arXiv:1203.3639.

Bayesian physical reconstruction of initial conditions from large scale structure surveys

J. Jasche, B. Wandelt, arXiv:1306.1821.

Methods for Bayesian power spectrum inference with galaxy surveys

J. Jasche, F. Leclercq, B. Wandelt, arXiv:1409.6308.

Past and present cosmic structure in the SDSS DR7 main sample

Why Bayesian inference?

- Why do we need Bayesian inference?

Inference of signals = ill-posed problem

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



➡ No unique recovery is possible!

“What is the formation history of the Universe?”

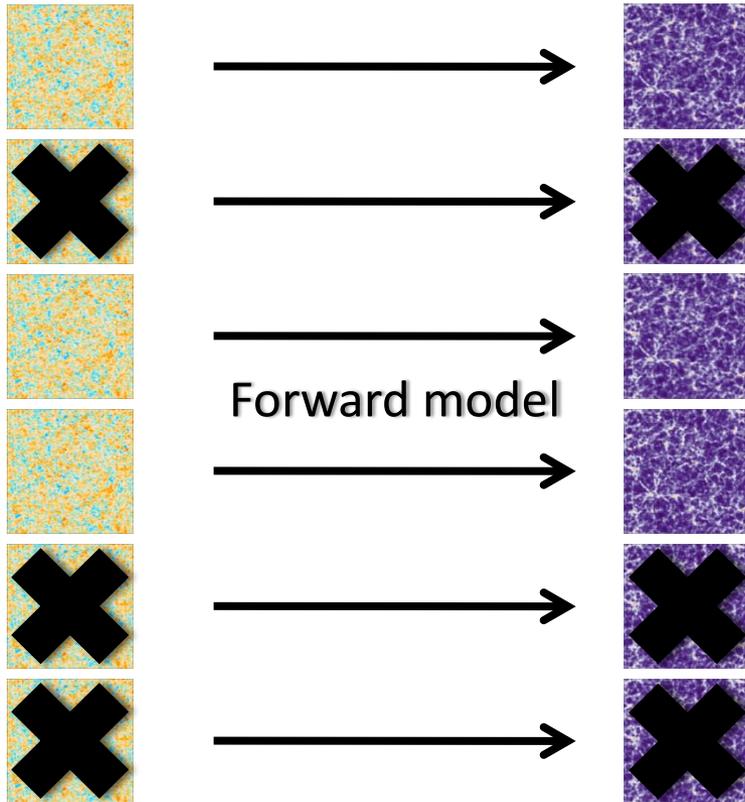


“What is the probability distribution of possible formation histories (signals) compatible with the observations?”

$$p(s|d)p(d) = p(d|s)p(s)$$

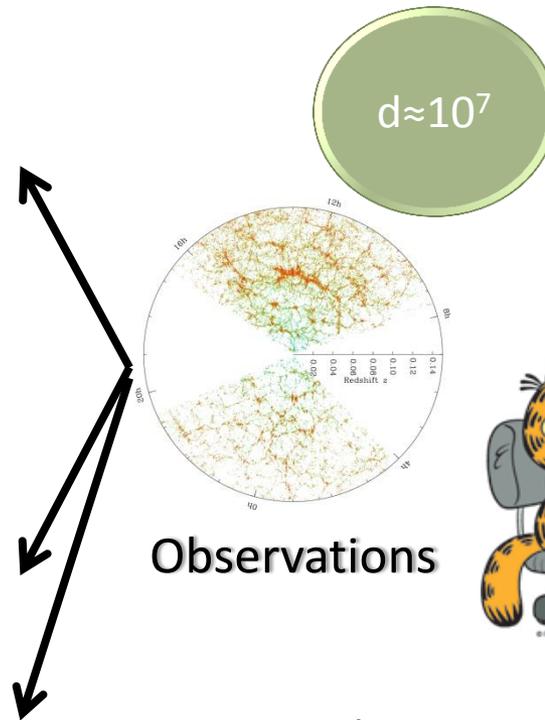
Bayesian forward modeling: the ideal scenario

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

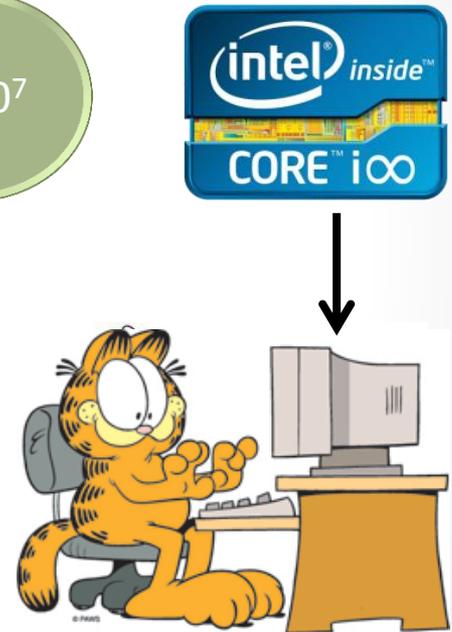


All possible ICs

All possible FCs



Observations

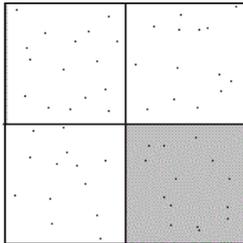


We need a *very, very, very*
big computer!

(Parameter) Space: the final frontier



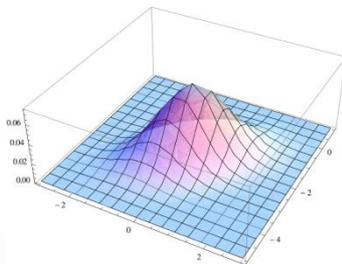
- The “curse of dimensionality” Bellman 1961



dimension	fraction of particles in quadrant of hypercube
1	$2^{-1} = 0.5$
10	$2^{-10} = 9.7 \times 10^{-4}$
100	$2^{-100} = 7.8 \times 10^{-31}$
1000	$2^{-1000} = 9.3 \times 10^{-302}$

Adding extra dimensions...

- Exponential increase of the **number of particles needed** for uniform sampling
- Exponential increase of **sparsity** given a fixed amount of particles
- High-dimensional probability distribution functions



Traditional sampling methods **will fail**
but **gradients** carry capital information

Hamiltonian Monte Carlo

- Use classical mechanics to solve statistical problems!

- The potential: $\psi(\mathbf{x}) \equiv -\ln(\mathcal{P}(\mathbf{x}))$

- The Hamiltonian: $H \equiv \frac{1}{2} \mathbf{p}^T \mathbf{M}^{-1} \mathbf{p} + \psi(\mathbf{x})$

$$(\mathbf{x}, \mathbf{p}) \quad \Rightarrow \quad \left\{ \begin{array}{l} \frac{d\mathbf{x}}{dt} = \frac{\partial H}{\partial \mathbf{p}} = \mathbf{M}^{-1} \mathbf{p} \\ \frac{d\mathbf{p}}{dt} = -\frac{\partial H}{\partial \mathbf{x}} = -\frac{\partial \psi(\mathbf{x})}{\partial \mathbf{x}} \end{array} \right. \quad \Rightarrow \quad (\mathbf{x}', \mathbf{p}')$$

$$a(\mathbf{x}', \mathbf{x}) = e^{-(H' - H)} = 1$$

gradients

acceptance ratio unity

- HMC **beats the curse of dimensionality** by:

- Exploiting gradients
- Using conservation of Hamiltonian

Duane *et al.* 1987

The LSS data model

- Gaussian prior for the initial density field: $\mathcal{P}(\delta^i|S) = \frac{\exp\left(\frac{1}{2} \sum_{kk'} \hat{\delta}_k^i S_{kk'}^{-1} \hat{\delta}_{k'}^i\right)}{|2\pi S|}$
- Poisson likelihood: $\mathcal{P}(N^\ell|\delta^i) = \prod_x \frac{\exp(-\lambda_x^\ell(\delta^i)) (\lambda_x^\ell(\delta^i))^{N_x^\ell}}{N_x^\ell!}$

Poisson “intensity field”: $\lambda_x^\ell(\delta^i) = R_x^\ell \bar{N}^\ell (1 + \delta_{x,g}^\ell) = R_x^\ell \bar{N}^\ell \beta^\ell (1 + \delta_{\text{NL}}[\delta^i]_x)^{\alpha^\ell}$

$$\tilde{N}^\ell \equiv \bar{N}^\ell \beta^\ell$$

- The posterior distribution:

$$\mathcal{P}(\delta^i | \{N^\ell\}, S) = \frac{\exp\left(\frac{1}{2} \sum_{kk'} \hat{\delta}_k^i S_{kk'}^{-1} \hat{\delta}_{k'}^i\right)}{|2\pi S|} \times \prod_{x,\ell} \frac{\exp\left(-R_x^\ell \tilde{N}^\ell (1 + \delta_{\text{NL}}[\delta^i]_x)^{\alpha^\ell}\right) \left(R_x^\ell \tilde{N}^\ell (1 + \delta_{\text{NL}}[\delta^i]_x)^{\alpha^\ell}\right)^{N_x^\ell}}{N_x^\ell!}$$

↑ NGP-binned data ← Covariance matrix ↑ Survey response operator (mask, radial selection) ← Noise level ← Structure formation model (2LPT+CiC) ← Bias parameters

Jasche & Wandelt 2013, arXiv:1203.3639

Jasche & Wandelt 2013, arXiv:1306.1821

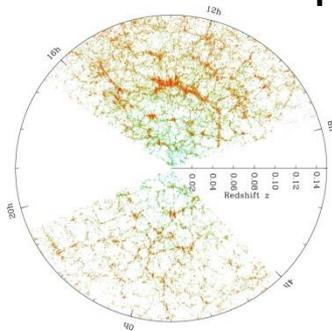
Jasche, FL & Wandelt 2014, arXiv:1409.6308

BORG: *Bayesian Origin Reconstruction from Galaxies*

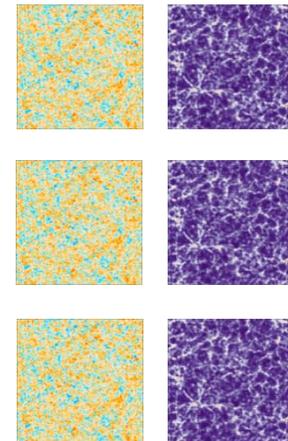
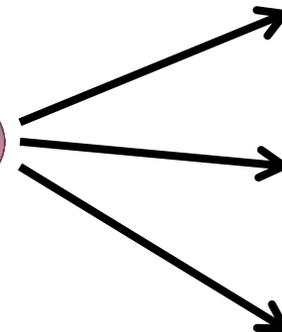


What makes the problem tractable:

- **Sampler**: Hamiltonian Markov Chain Monte Carlo method
- **Physical model**: Gaussian prior – Second-order Lagrangian perturbation theory (2LPT) – Poisson likelihood



Observations



Samples of possible 4D states

see also:

Kitaura 2013, arXiv:1203.4184

Wang, Mo, Yang & van den Bosch 2013, arXiv:1301.1348

The BORG SDSS run

- 463,230 galaxies from the NYU-VAGC based on SDSS DR7
- Comoving cubic box of side length 750 Mpc/h, with periodic boundary conditions
- 256^3 grid, resolution 3 Mpc/h  ≈ 17 millions parameters
- 12,000 samples, four-dimensional maps
- ≈ 3 TB disk space
- 10 months wallclock time on 16-32 cores

Jasche, FL & Wandelt 2014, arXiv:1409.6308

2. CHRONO-COSMOGRAPHY

- Past and present cosmic structure in the Sloan volume
- The Sloan Great Wall

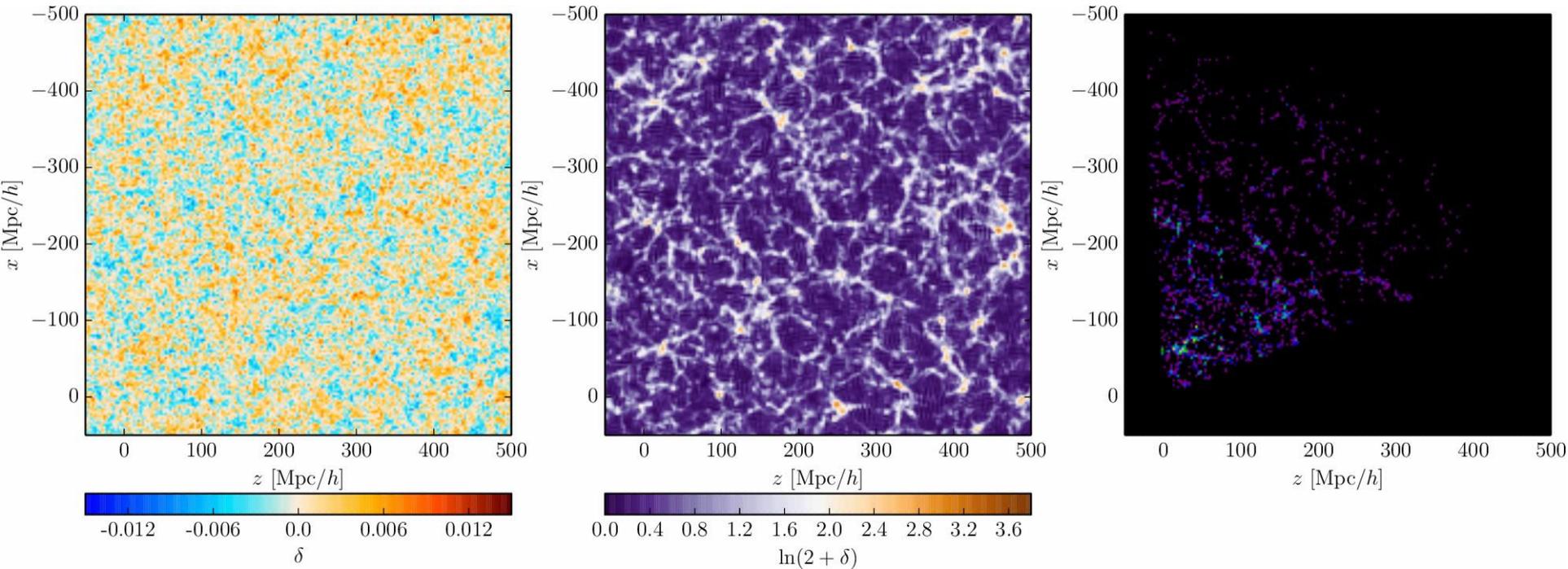
J. Jasche, F. Leclercq, B. Wandelt, arXiv:1409.6308.

Past and present cosmic structure in the SDSS DR7 main sample

J. Jasche, E. Romano-Díaz, F. Leclercq, B. Wandelt, in prep.

The Sloan Great Wall through Bayesian eyes

BORG at work – chronocosmography



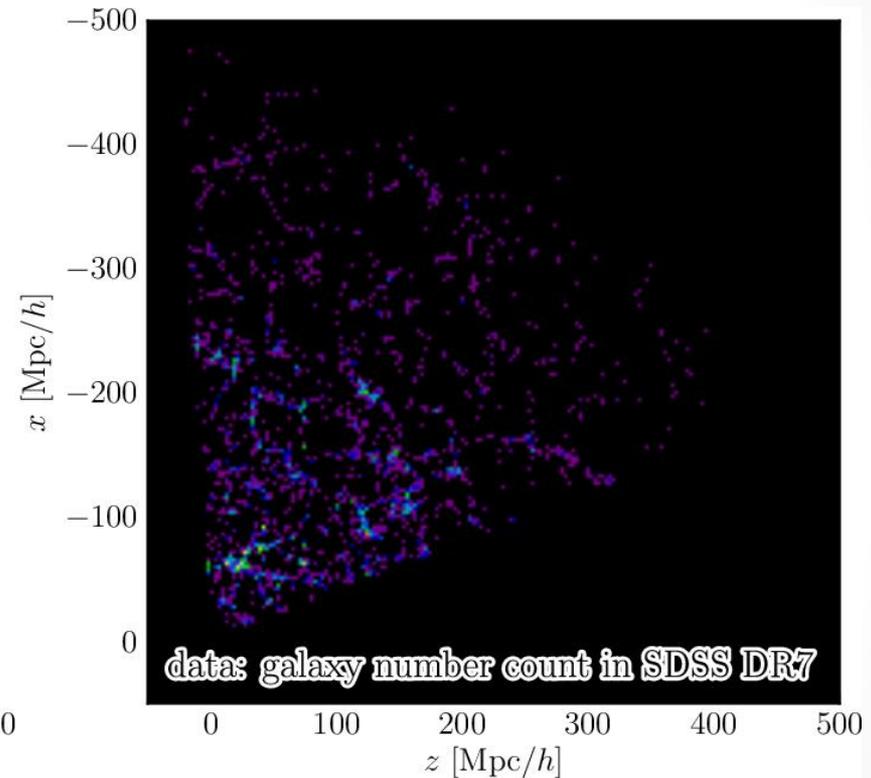
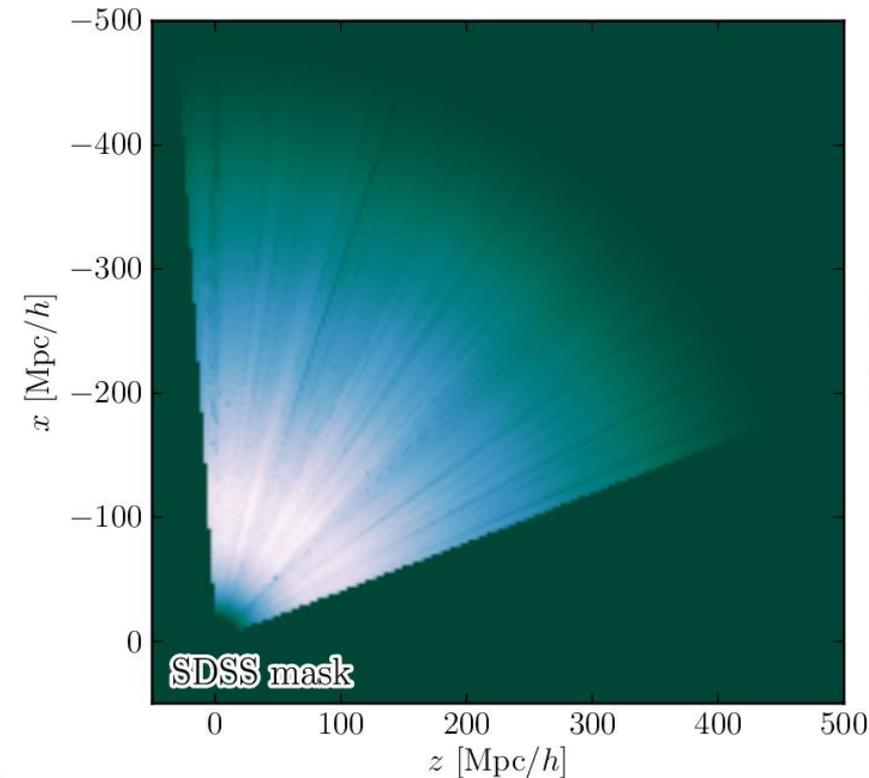
Initial conditions

Final conditions

Observations

Jasche, FL & Wandelt 2014, arXiv:1409.6308

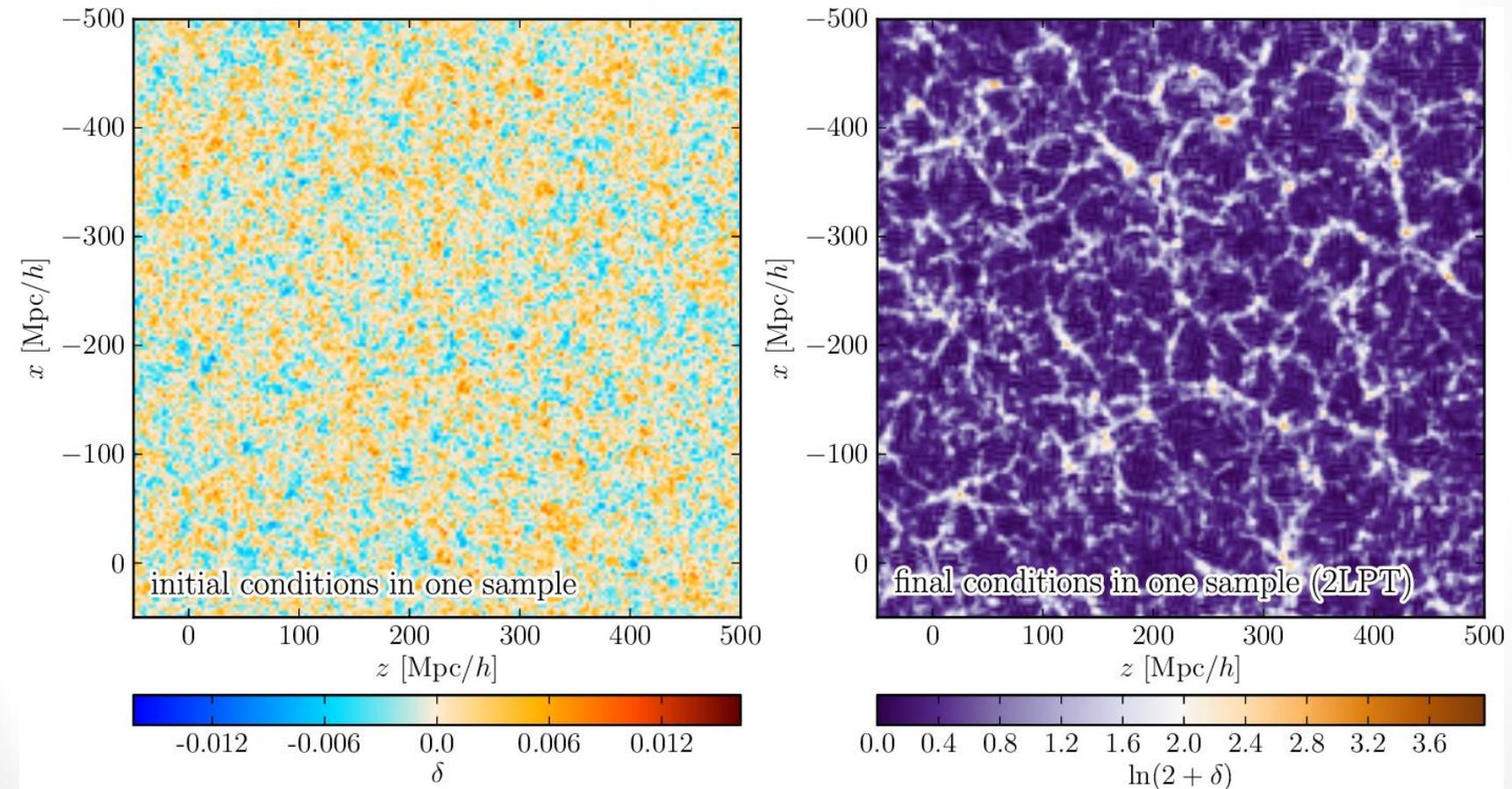
Bayesian chronocosmography from SDSS DR7



Jasche, FL & Wandelt 2014, arXiv:1409.6308

Data

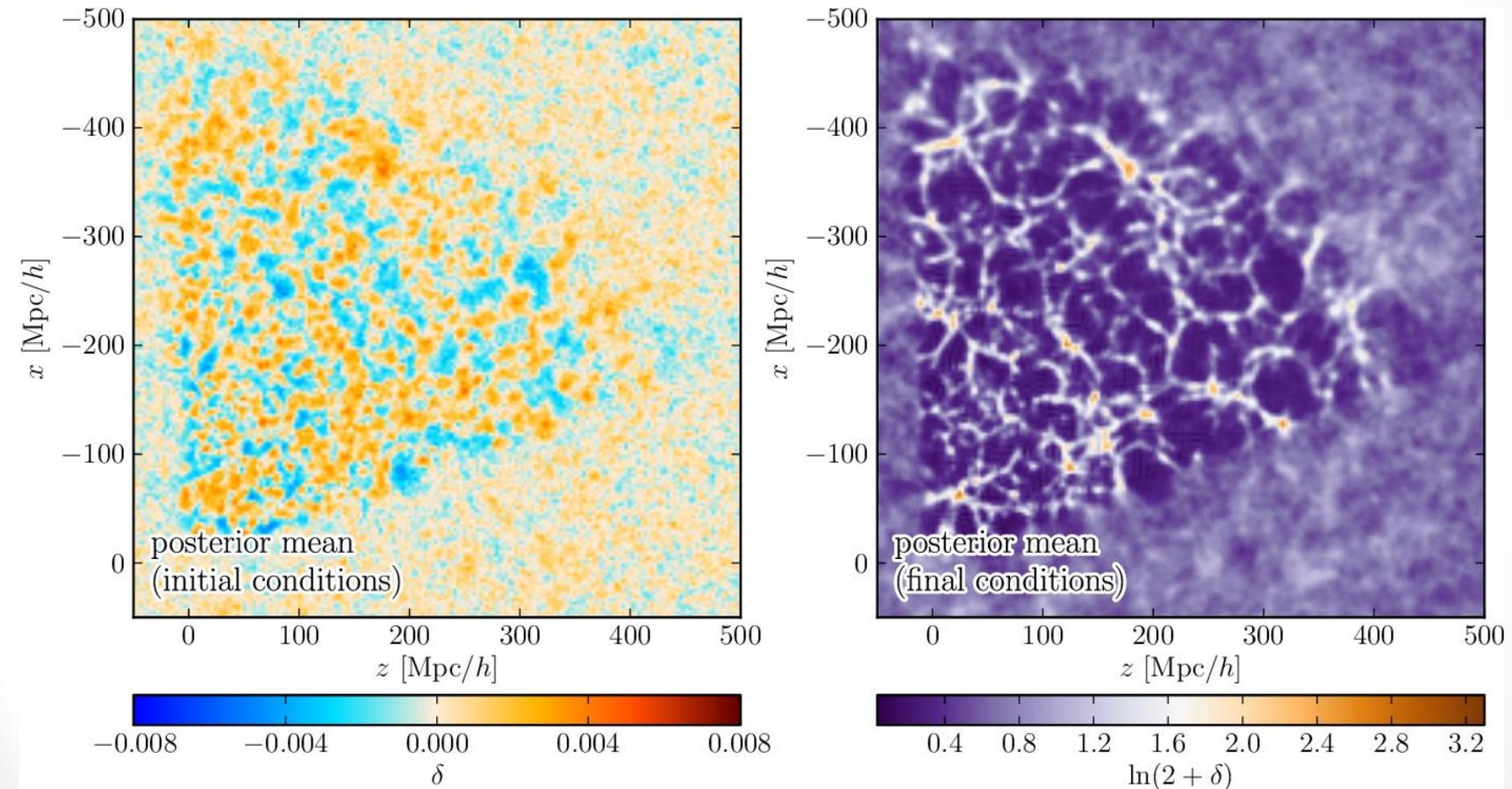
Bayesian chronocosmography from SDSS DR7



Jasche, FL & Wandelt 2014, arXiv:1409.6308

One sample

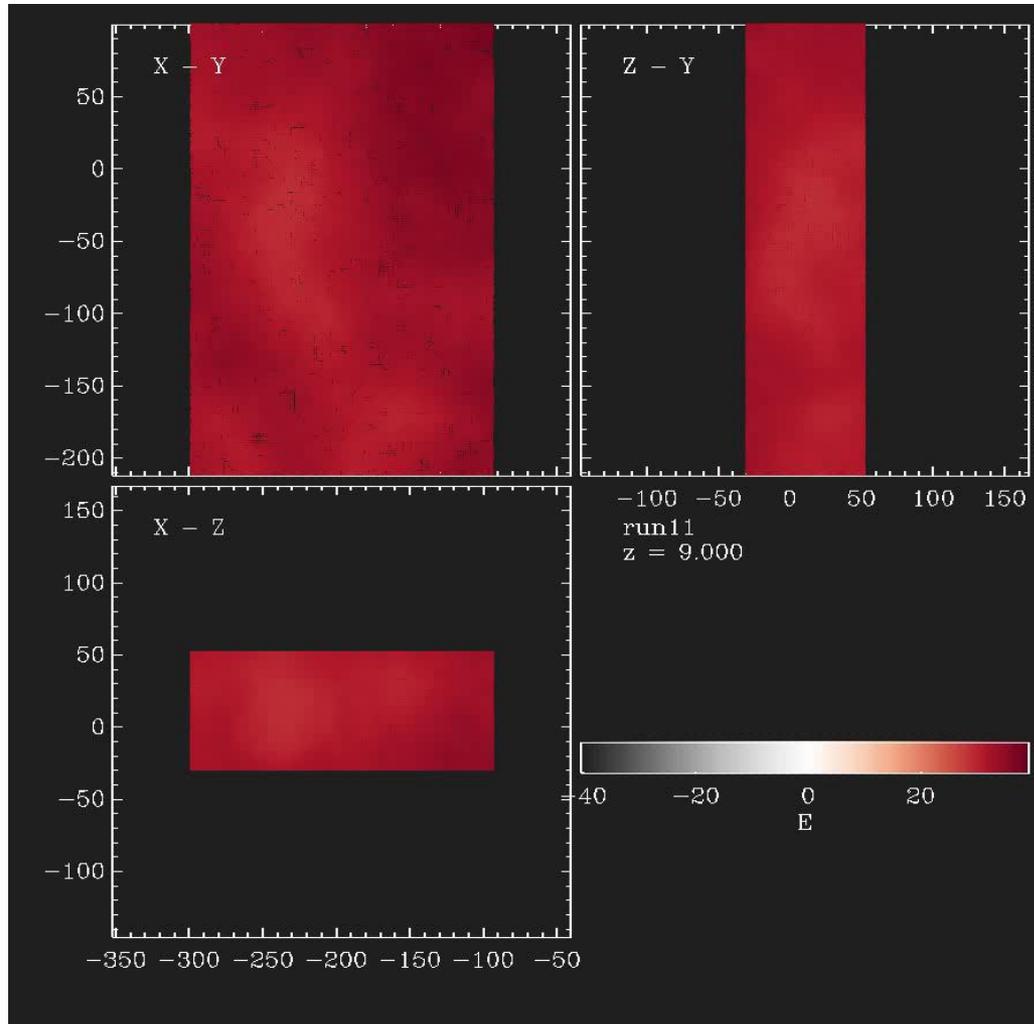
Bayesian chronocosmography from SDSS DR7



Jasche, FL & Wandelt 2014, arXiv:1409.6308

Posterior mean

The Sloan Great Wall through Bayesian eyes



The Sloan Great Wall:

Gott *et al.* 2005, arXiv:astro-ph/0310571

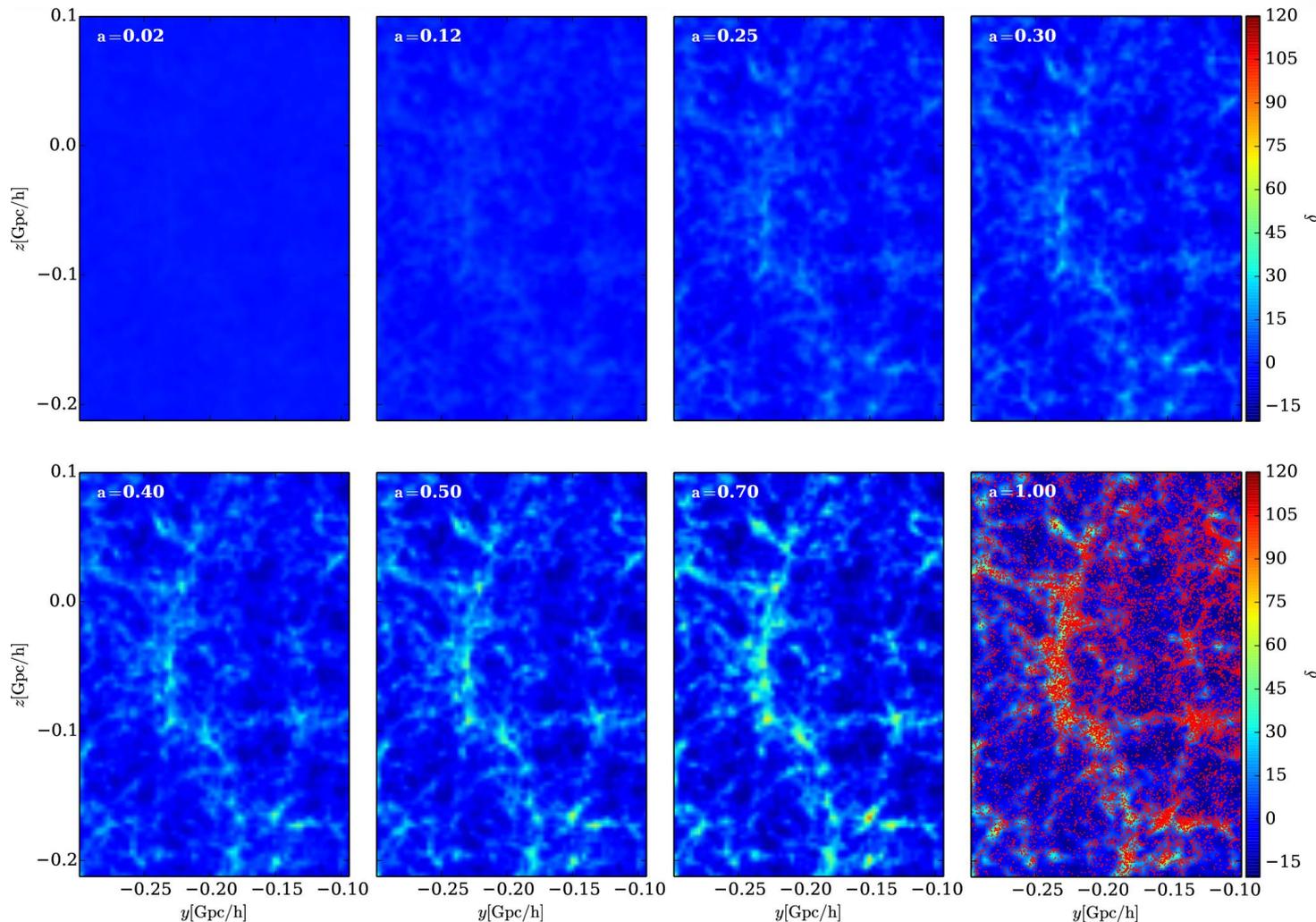
Nichol *et al.* 2006, arXiv:astro-ph/0602548

Einasto *et al.* 2010, arXiv:1007.4492

Einasto *et al.* 2011, arXiv:1105.1632

Jasche, Romano-Díaz, FL & Wandelt 2015, in prep.

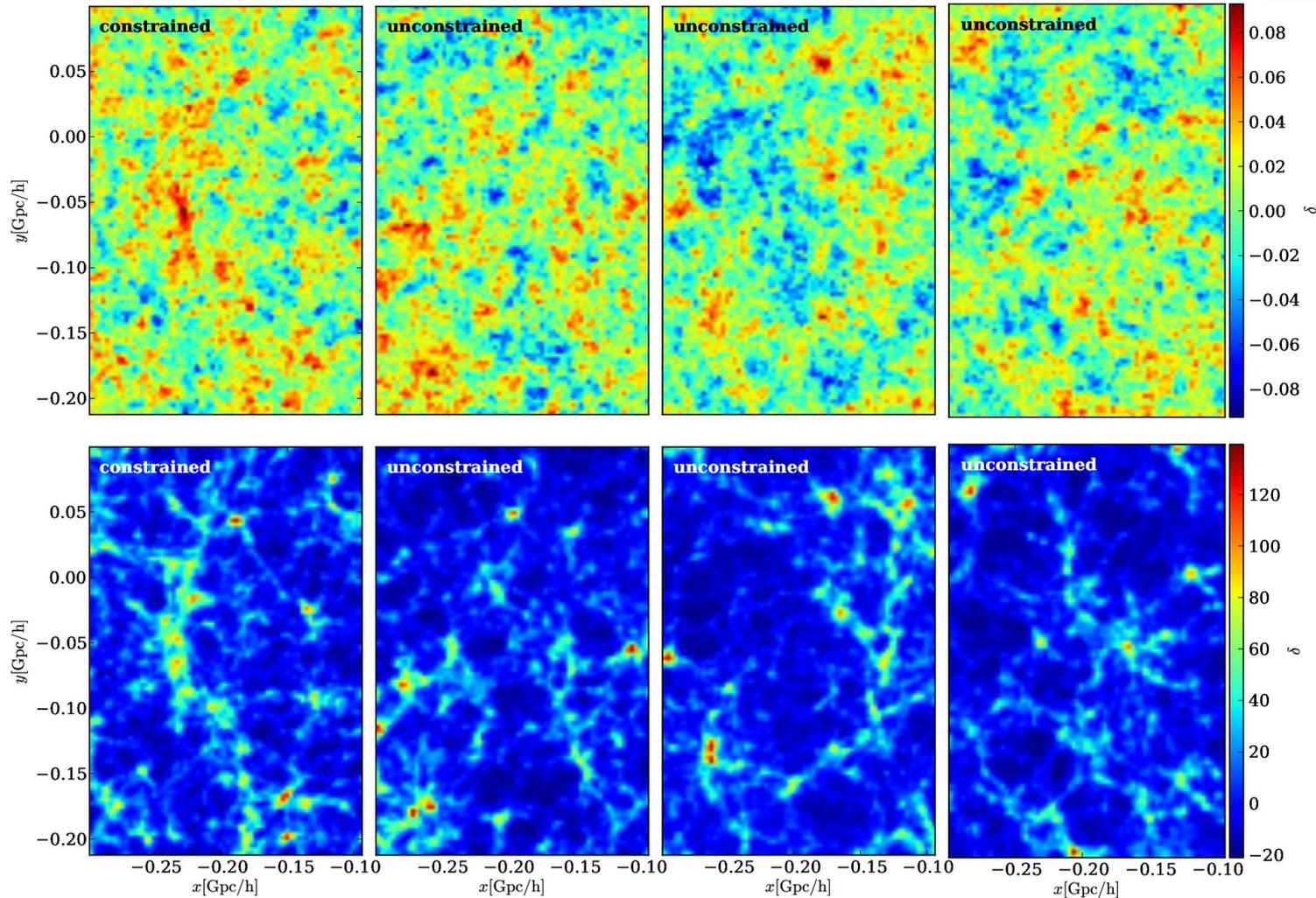
The formation history of the SGW



Jasche, Romano-Díaz, FL & Wandelt 2015, in prep.

Is the SGW special in Λ CDM?

Sylos Labini *et al.* 2009, arXiv:0909.0132



Jasche, Romano-Díaz, FL & Wandelt 2015, in prep.

3. THE NON-LINEAR REGIME OF STRUCTURE FORMATION

- Non-linear filtering of BORG results
- Remapping Lagrangian Perturbation Theory
- The COLA method

F. Leclercq, J. Jasche, P. M. Sutter, N. Hamaus, B. Wandelt, arXiv:1410.0355.
Dark matter voids in the SDSS galaxy survey

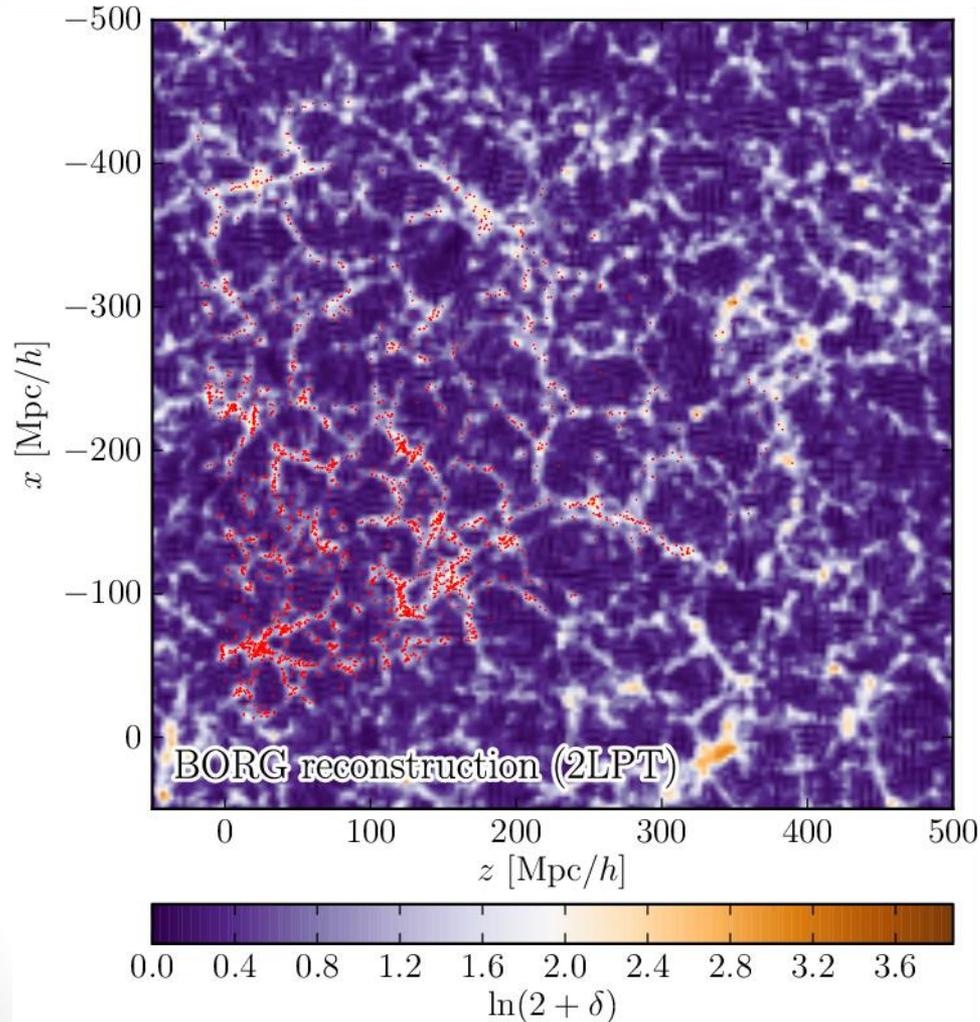
F. Leclercq, J. Jasche, H. Gil-Marín, B. Wandelt, arXiv:1305.4642.

One-point remapping of Lagrangian perturbation theory in the mildly non-linear regime of cosmic structure formation

S. Tassev, M. Zaldarriaga, D. Eisenstein, arXiv:1301.0322.
Solving Large Scale Structure in Ten Easy Steps with COLA

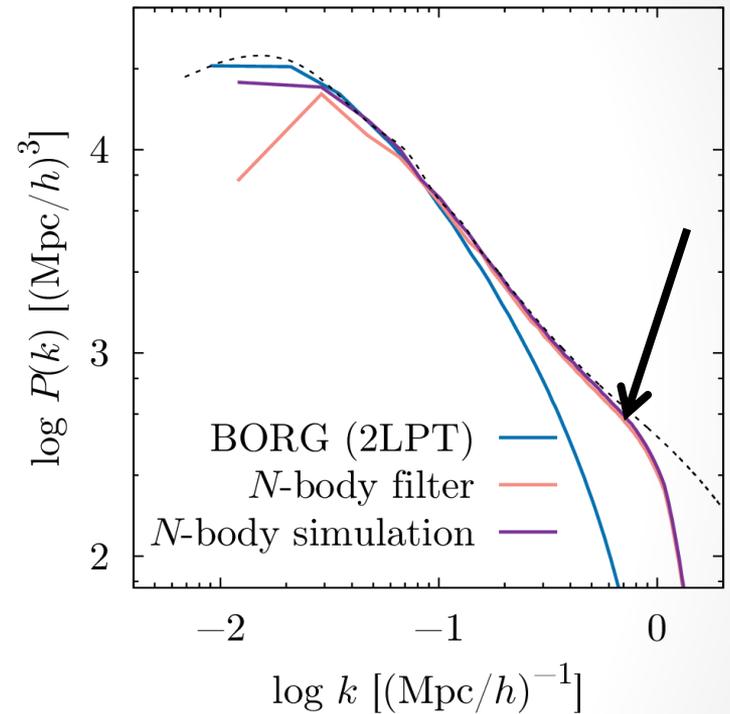
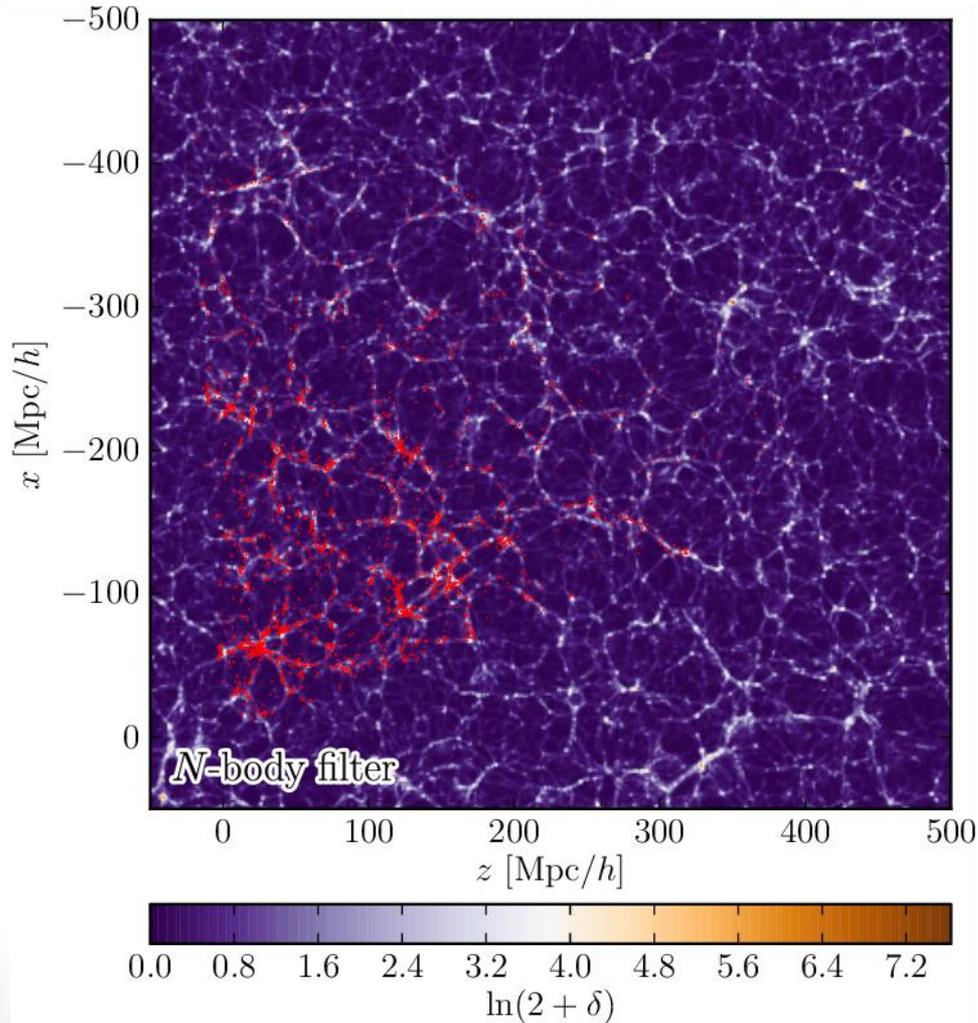
S. Tassev, D. Eisenstein, B. Wandelt, M. Zaldarriaga, in prep. + F. Leclercq, B. Wandelt, *et al.*, in prep.
sCOLA: The N-body COLA method extended to the Spatial Domain

Non-linear filtering



FL, Jasche, Sutter, Hamaus & Wandelt 2014, arXiv:1410.0355

Non-linear filtering

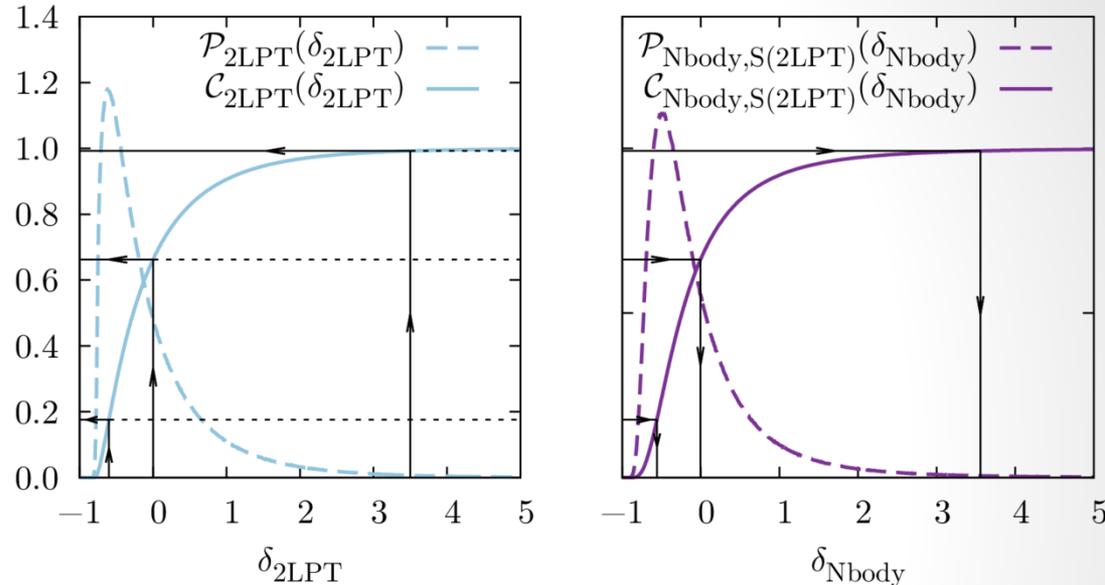


FL, Jasche, Sutter, Hamaus & Wandelt 2014, arXiv:1410.0355

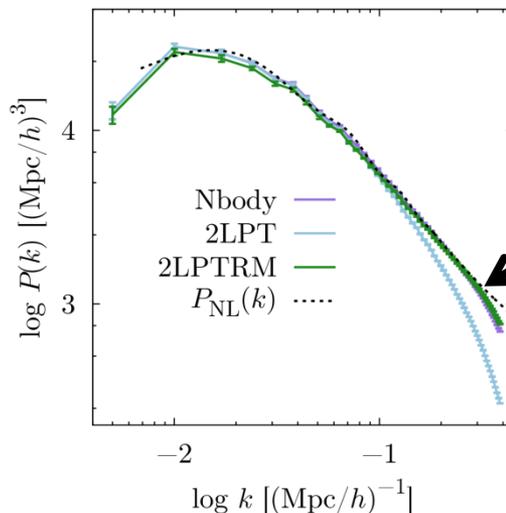
Remapping 2LPT in the mildly non-linear regime

FL, Jasche, Gil-Marín & Wandelt 2013, arXiv:1305.4642

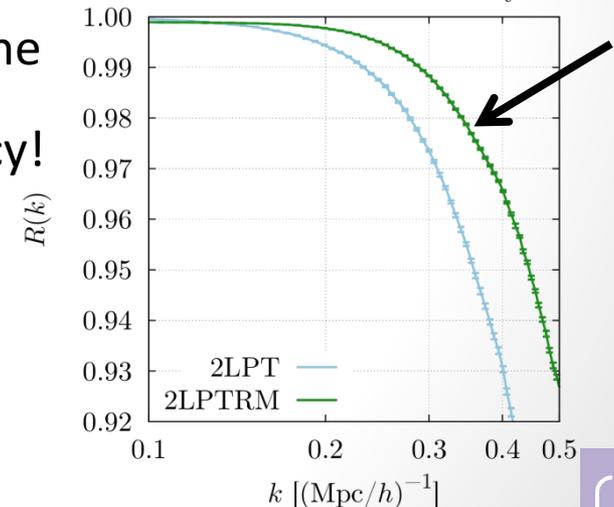
- Replacing the one-point distribution of 2LPT by one which accounts for the full non-linear system...



- ...also improves the higher-order correlators...



• ...and the phase accuracy!



COLA: *CO*moving Lagrangian Acceleration

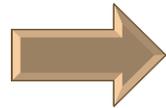
- Write the displacement vector as: $\mathbf{s} = \mathbf{s}_{\text{LPT}} + \mathbf{s}_{\text{MC}}$

Tassev & Zaldarriaga 2012, arXiv:1203.5785

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

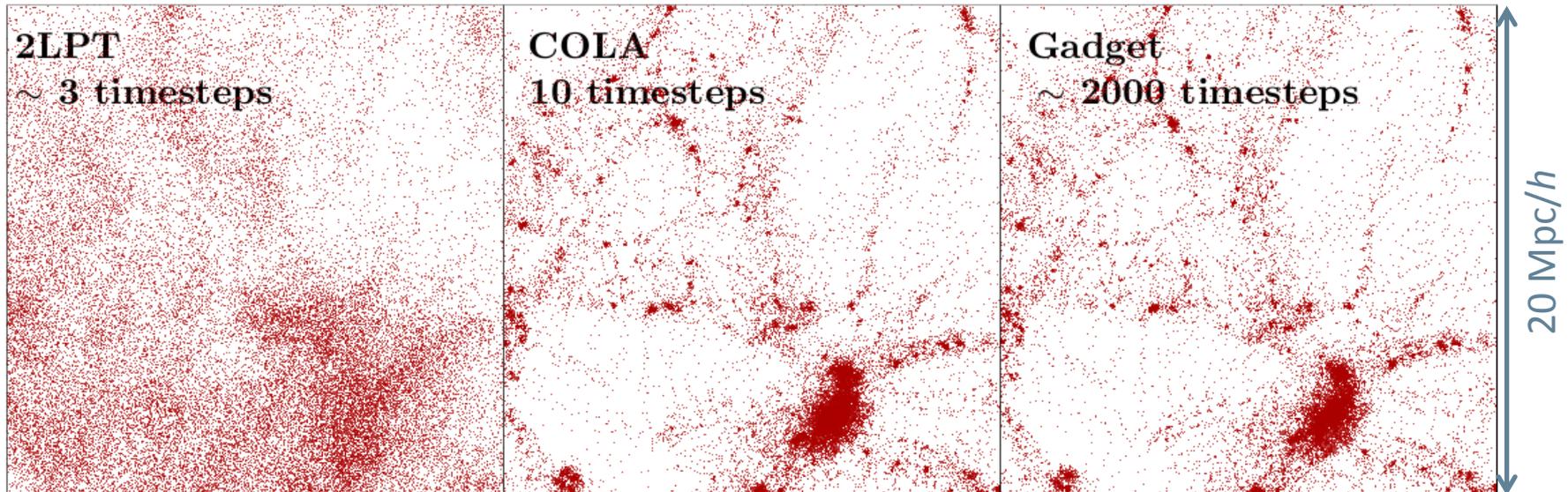
Standard:

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



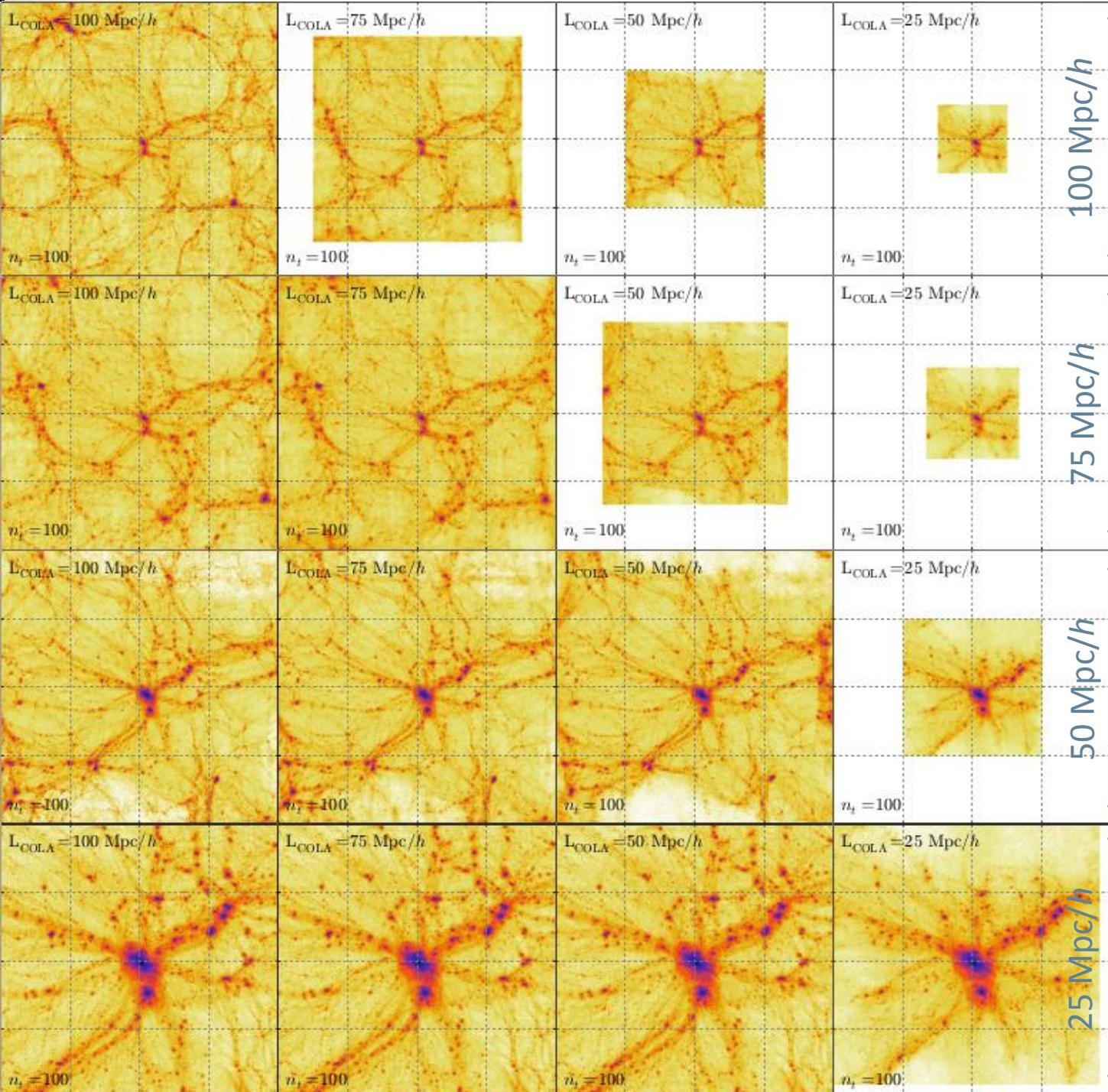
Modified:

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



Original COLA “in time”

Tassev, Zaldarriaga & Eisenstein 2013, arXiv:1301.0322



Extending COLA

New COLA “in space”

$$n_t = 100$$

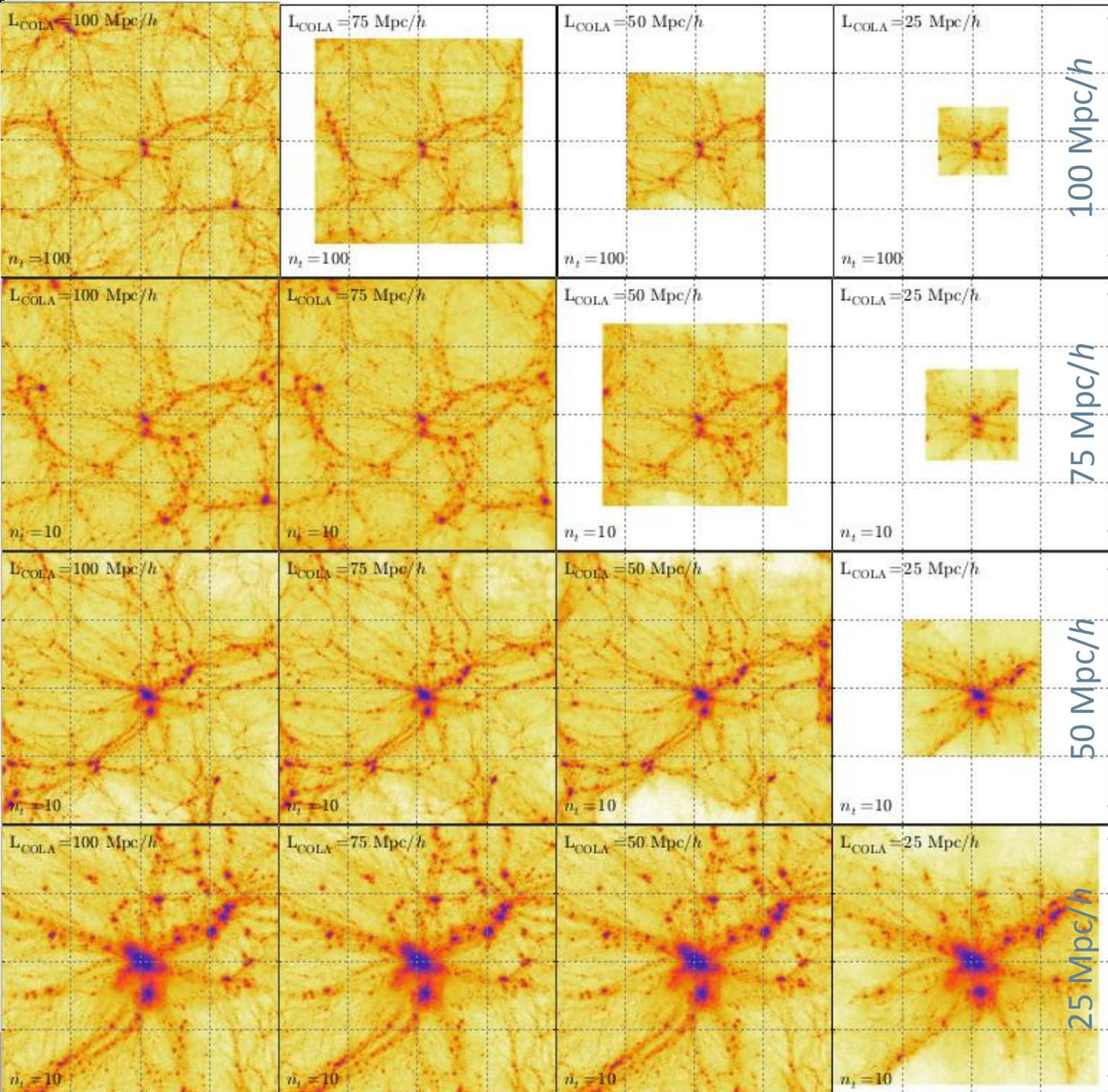
100 Mpc/h

75 Mpc/h

50 Mpc/h

25 Mpc/h

Tassev, Eisenstein,
Wandelt & Zaldarriaga,
in prep.
+ FL, Wandelt, *et al.*, in prep.



Extending COLA

New COLA “in space and time”
 $n_t = 10$

Tassev, Eisenstein,
 Wandelt & Zaldarriaga,
 in prep.
 + FL, Wandelt, *et al.*, in prep.

4. COSMIC WEB CLASSIFICATION

- Dark matter voids in the SDSS
- Tidal shear analysis in the SDSS, dynamic structure type classification
- Cosmic-web classification and Bayesian decision theory

F. Leclercq, J. Jasche, P. M. Sutter, N. Hamaus, B. Wandelt, arXiv:1410.0355.

Dark matter voids in the SDSS galaxy survey

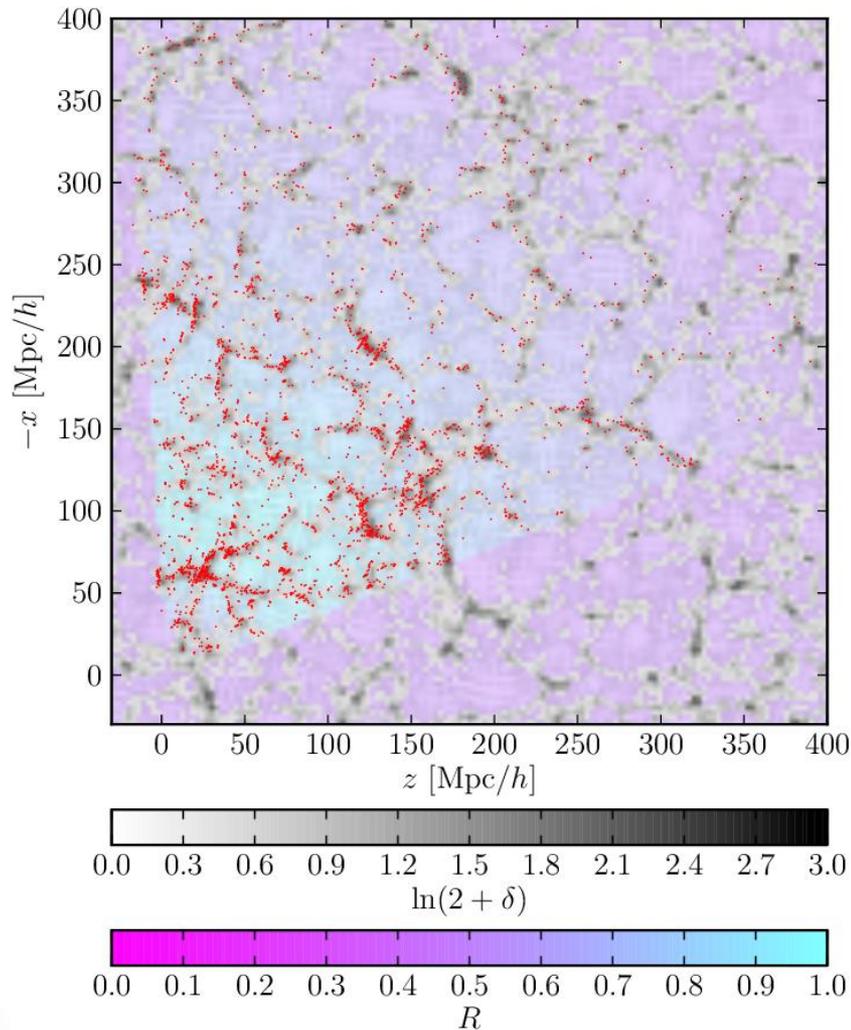
F. Leclercq, J. Jasche, B. Wandelt, arXiv:1502.02690.

Bayesian analysis of the dynamic cosmic web in the SDSS galaxy survey

F. Leclercq, J. Jasche, B. Wandelt, in prep.

Cosmic web-type classification using decision theory

Dark matter voids in the SDSS



- Why?

Sparsity & Bias

Sutter *et al.* 2013, arXiv:1309.5087

Sutter *et al.* 2013, arXiv:1311.3301

- How?

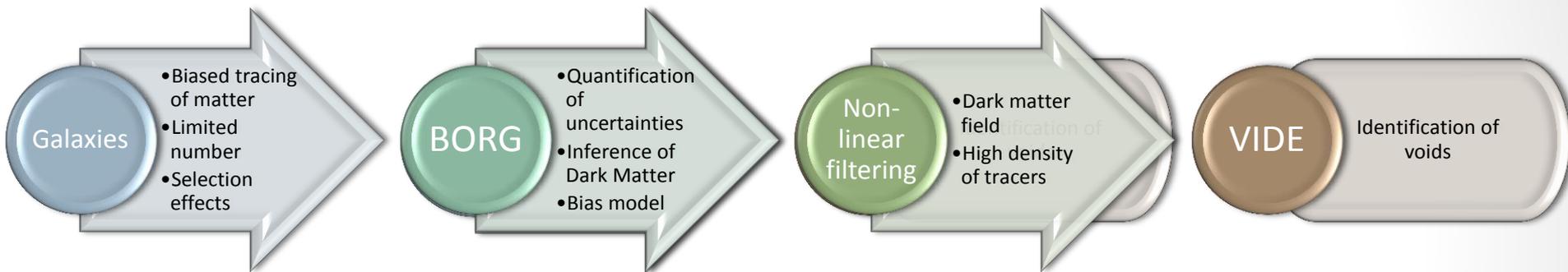
VIDE toolkit: Sutter *et al.* 2014, arXiv:1406.1191

www.cosmicvoids.net

based on ZOBOV: Neyrinck 2007, arXiv:0712.3049

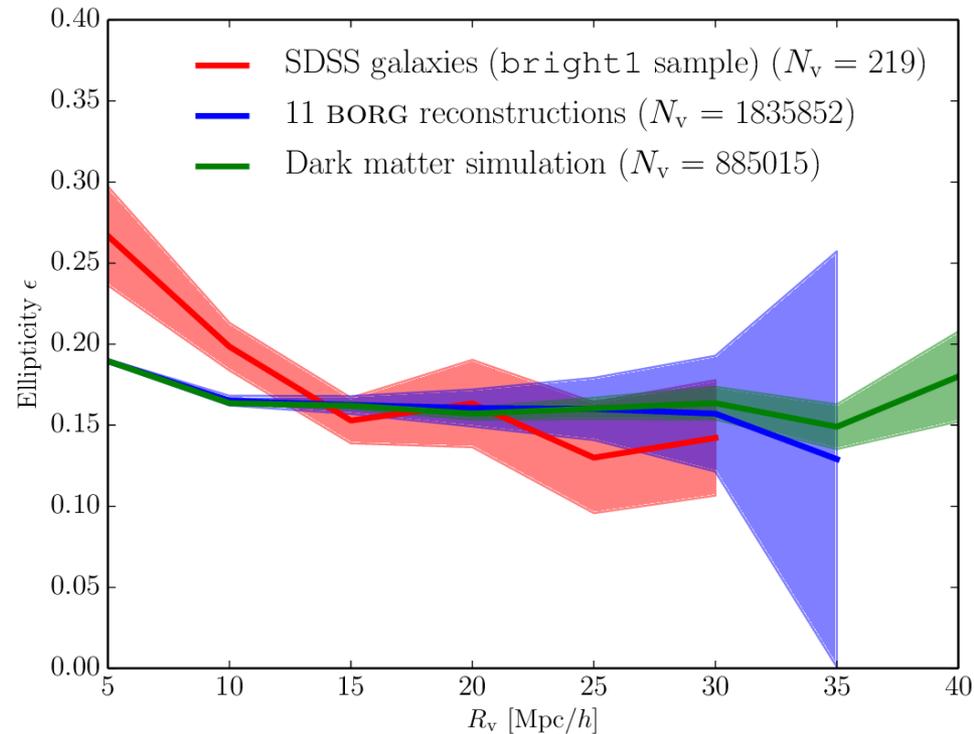
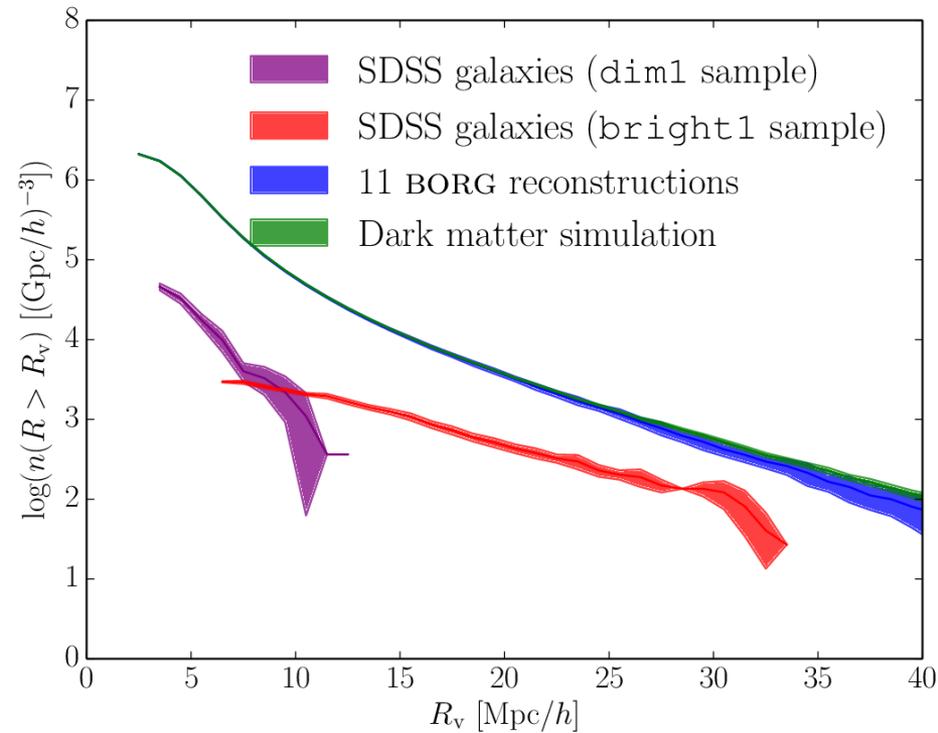
FL, Jasche, Sutter, Hamaus & Wandelt 2014, arXiv:1410.0355

Dark matter voids: pipeline



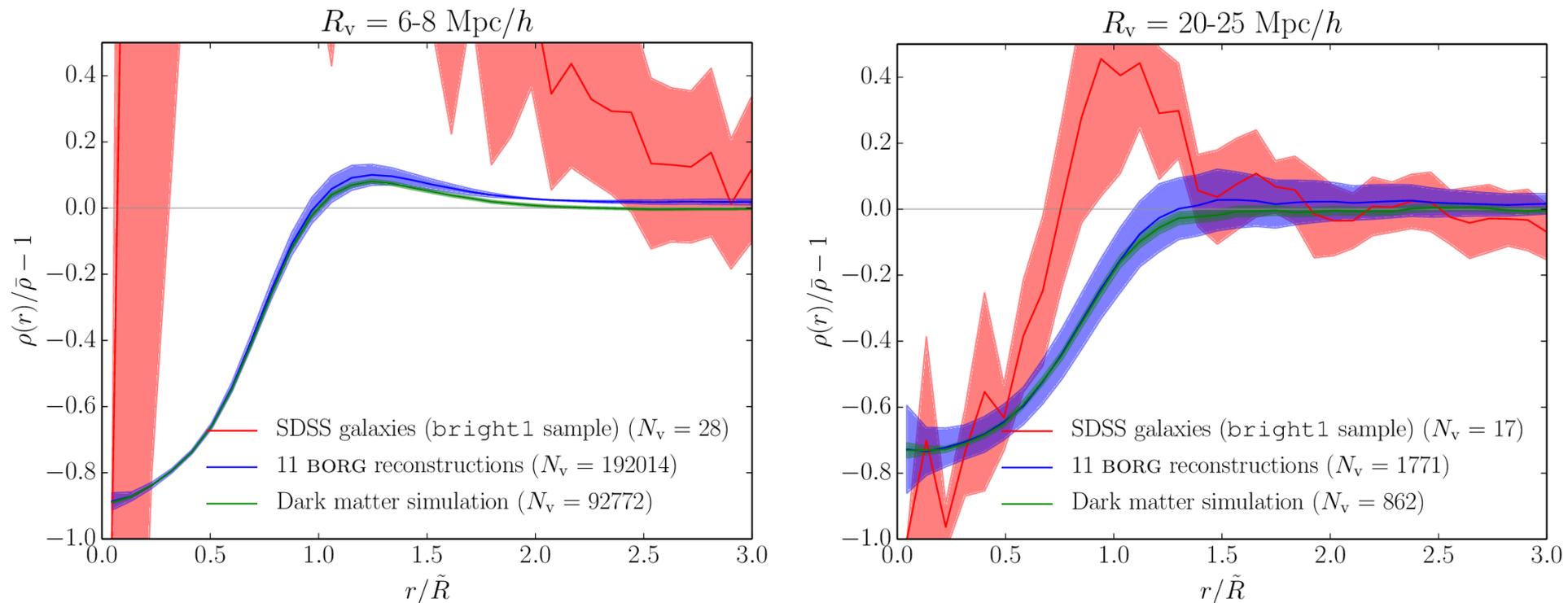
FL, Jasche, Sutter, Hamaus & Wandelt 2014, arXiv:1410.0355

Dark matter void properties



FL, Jasche, Sutter, Hamaus & Wandelt 2014, arXiv:1410.0355

Dark matter void properties



All catalogs will be made publicly available at

www.cosmicvoids.net

FL, Jasche, Sutter, Hamaus & Wandelt 2014, arXiv:1410.0355

Tidal shear analysis

- $\lambda_1, \lambda_2, \lambda_3$: eigenvalues of the tidal field tensor, the Hessian of the gravitational potential: $T_{ij} = \partial_i \partial_j \Phi$ $\lambda_1 + \lambda_2 + \lambda_3 = \delta$
 - Voids: $\lambda_1, \lambda_2, \lambda_3 < 0$
 - Sheets: $\lambda_1 > 0$ and $\lambda_2, \lambda_3 < 0$
 - Filaments: $\lambda_1, \lambda_2 > 0$ and $\lambda_3 < 0$
 - Clusters: $\lambda_1, \lambda_2, \lambda_3 > 0$

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

see also:

- Extensions:

Forero-Romero *et al.* 2008, arXiv:0809.4135

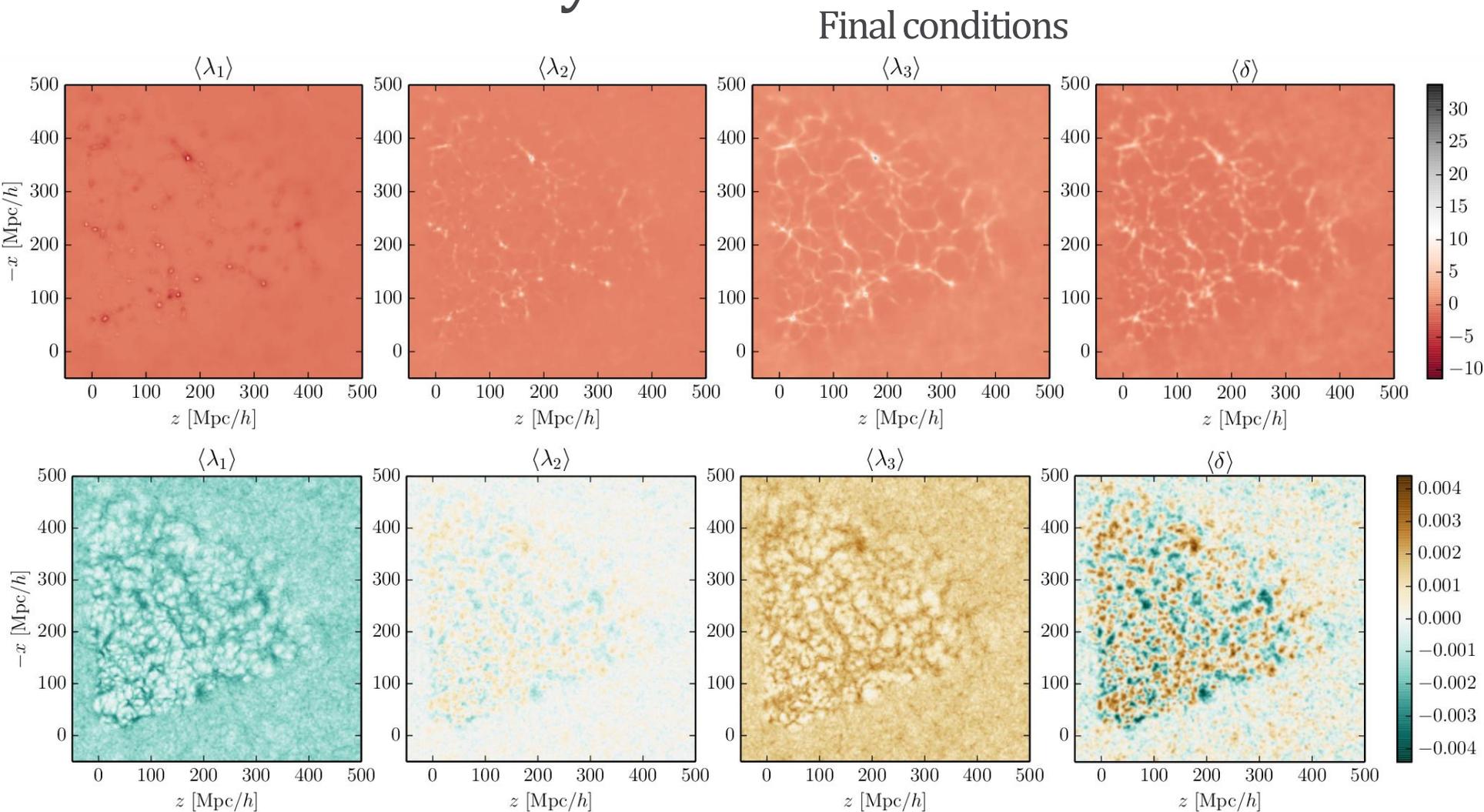
Hoffman *et al.* 2012, arXiv:1201.3367

- Similar web classifiers:

DIVA, Lavaux & Wandelt 2010, arXiv:0906.4101

ORIGAMI, Falck, Neyrinck & Szalay 2012, arXiv:1201.2353

Tidal shear analysis

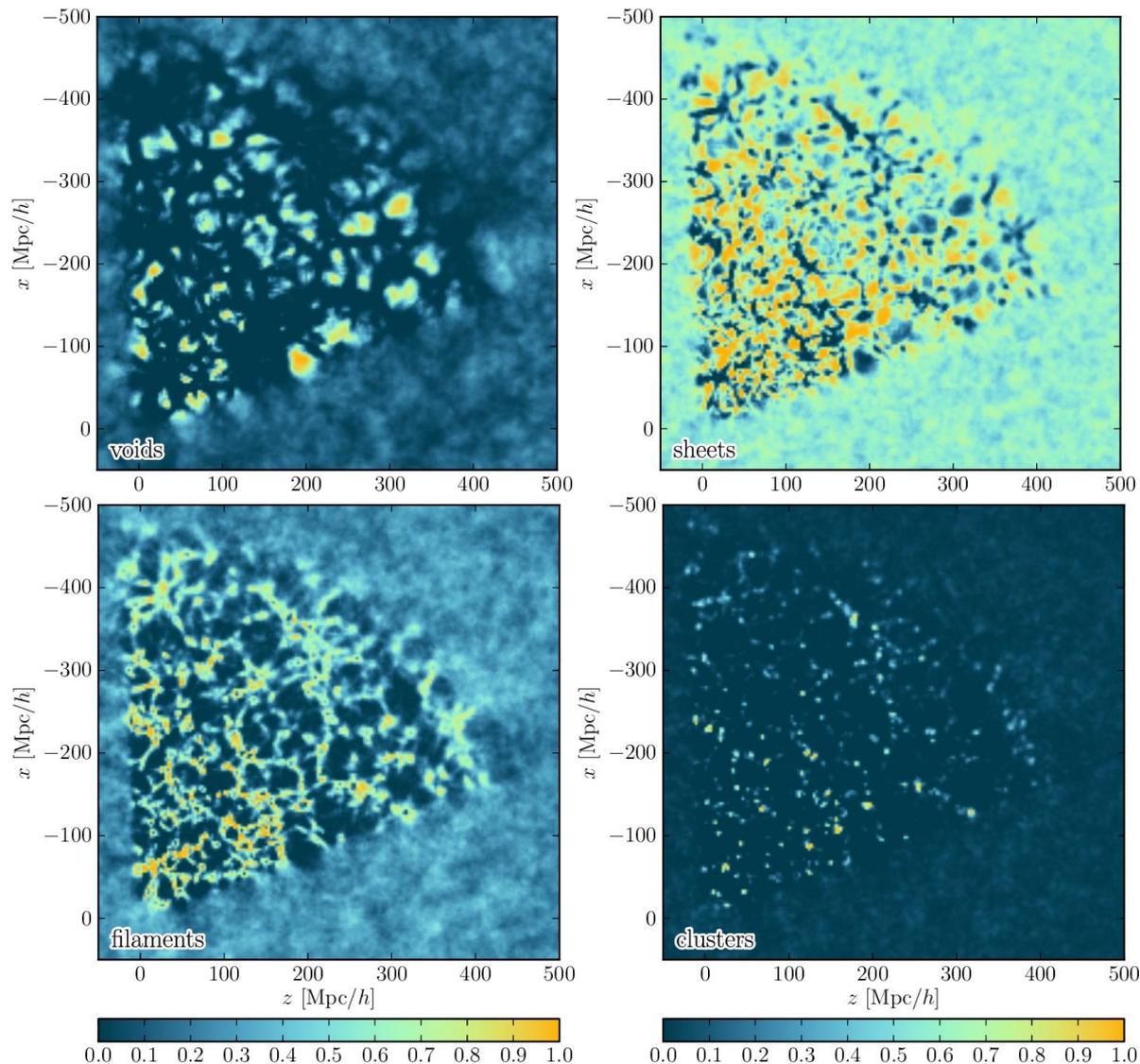


FL, Jasche & Wandelt 2015, arXiv:1502.02690

Initial conditions

Dynamic structures inferred by BORG

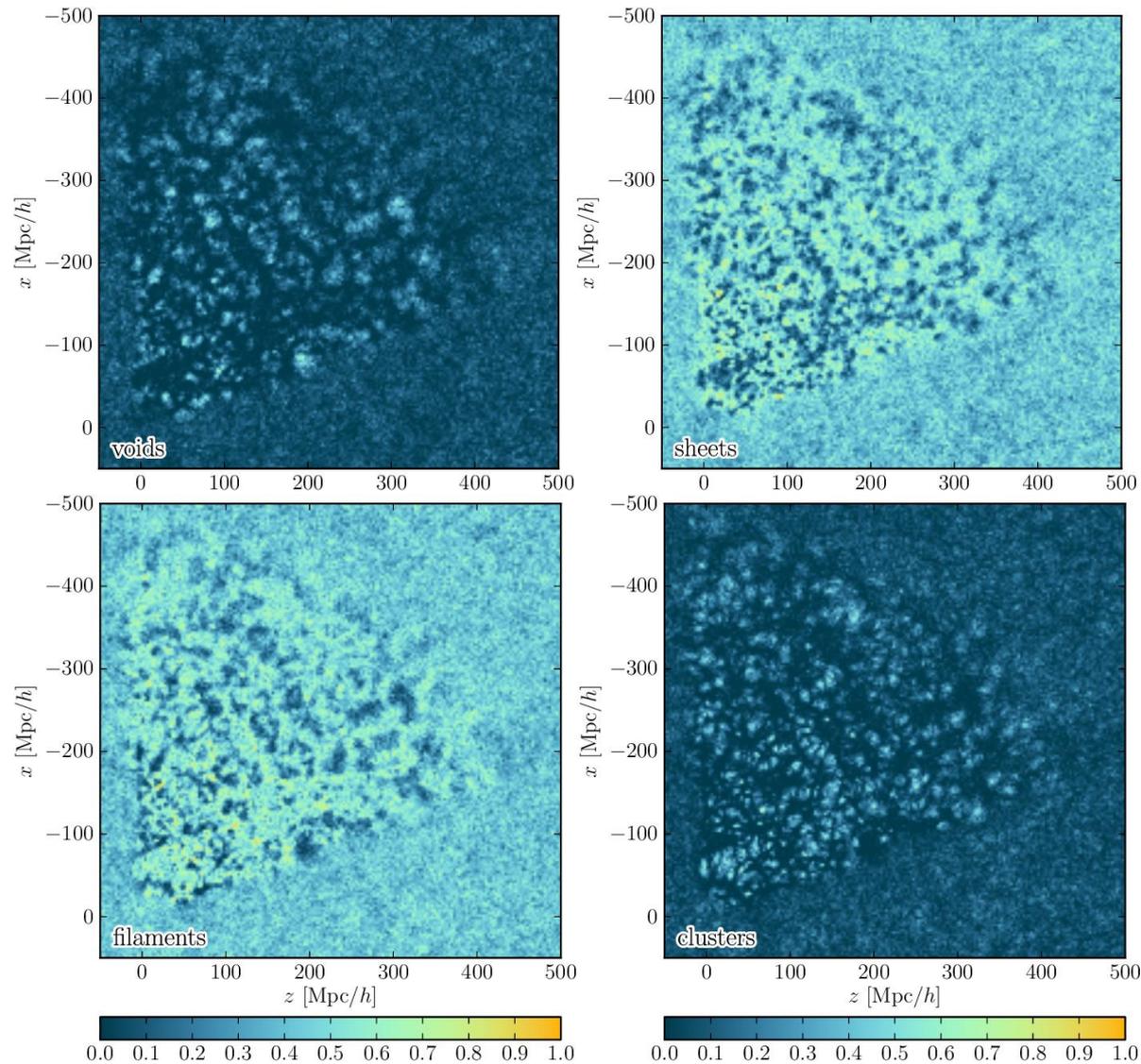
Final conditions



FL, Jasche & Wandelt 2015, arXiv:1502.02690

Dynamic structures inferred by BORG

Initial conditions

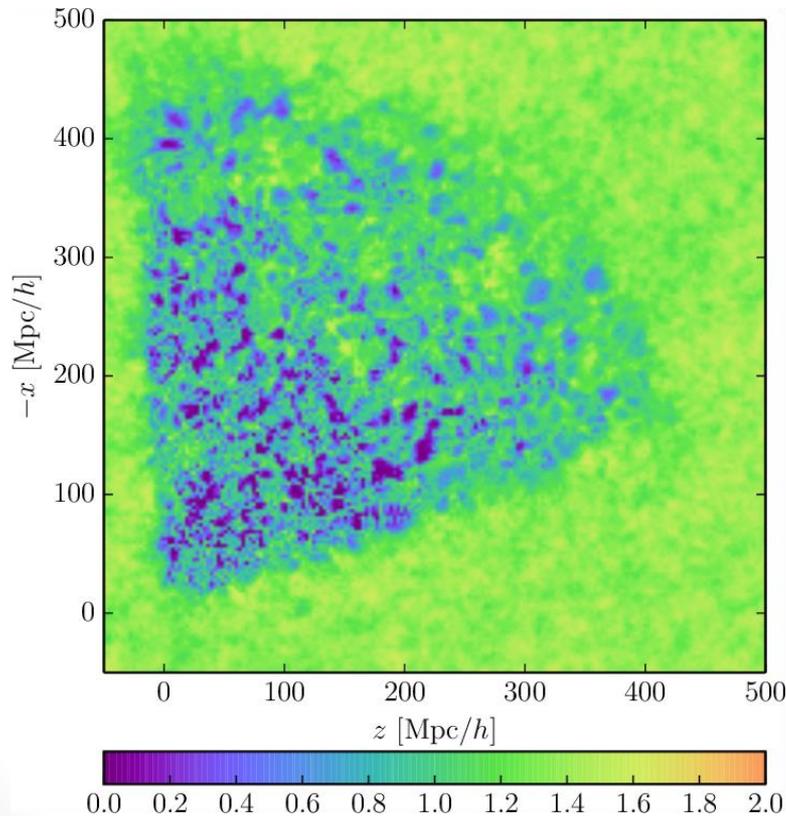


FL, Jasche & Wandelt 2015, arXiv:1502.02690

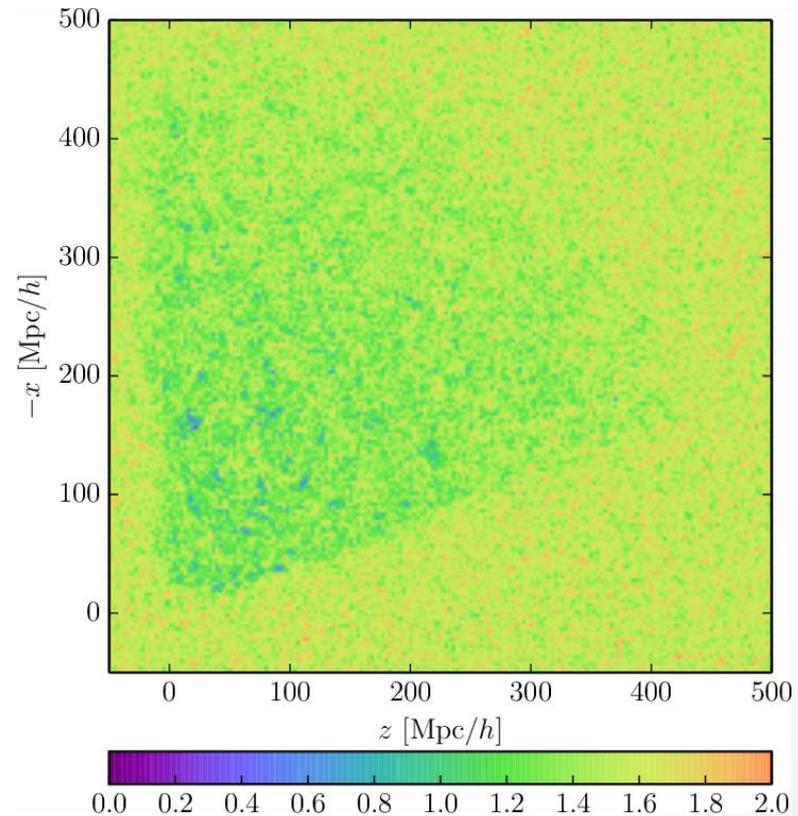
Entropy of the structure types pdf

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

Final conditions



Initial conditions

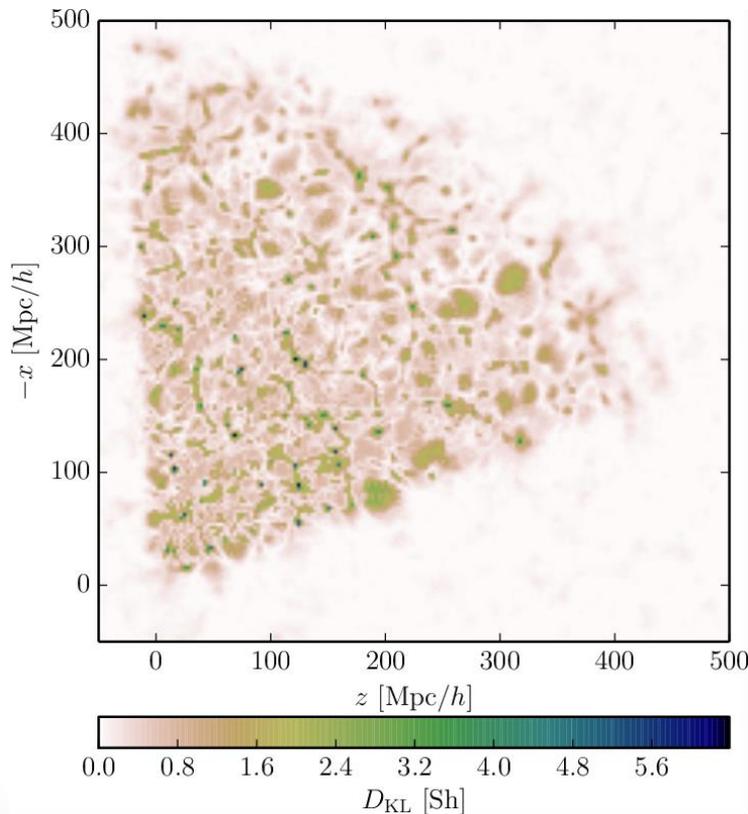


FL, Jasche & Wandelt 2015, arXiv:1502.02690

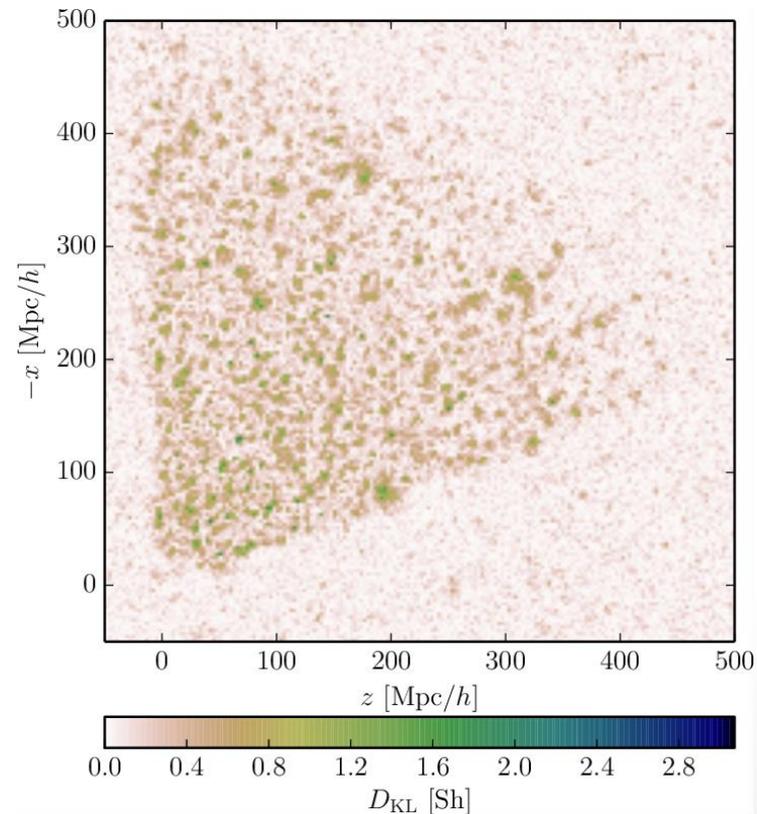
Kullback-Leibler divergence posterior/prior

$$D_{\text{KL}}(\mathcal{P}(\mathbf{T}(\vec{x}_k)|d)||\mathcal{P}(\mathbf{T})) \equiv \sum_i \mathcal{P}(\mathbf{T}_i(\vec{x}_k)|d) \log_2 \left(\frac{\mathcal{P}(\mathbf{T}_i(\vec{x}_k)|d)}{\mathcal{P}(\mathbf{T}_i)} \right) \quad \text{in Sh}$$

Final conditions



Initial conditions



FL, Jasche & Wandelt 2015, arXiv:1502.02690

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:

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

- Without data, the expected utility is

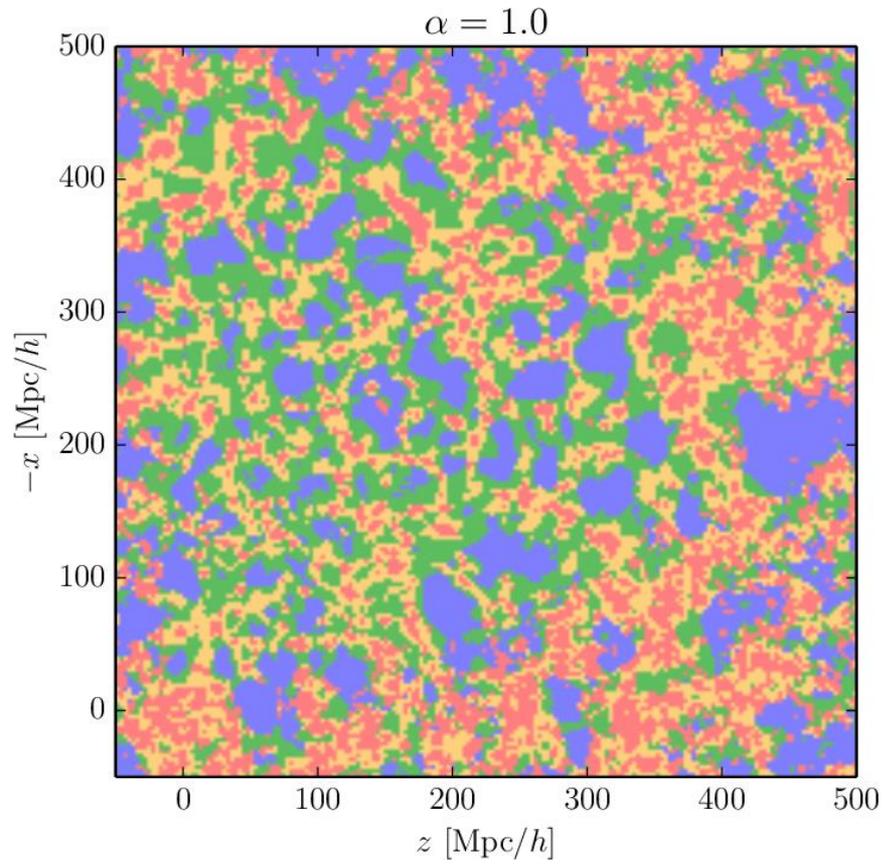
$$U(a_j) = 1 - \alpha \quad \text{if } j \neq -1 \quad \text{“Playing the game”}$$

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

- 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...

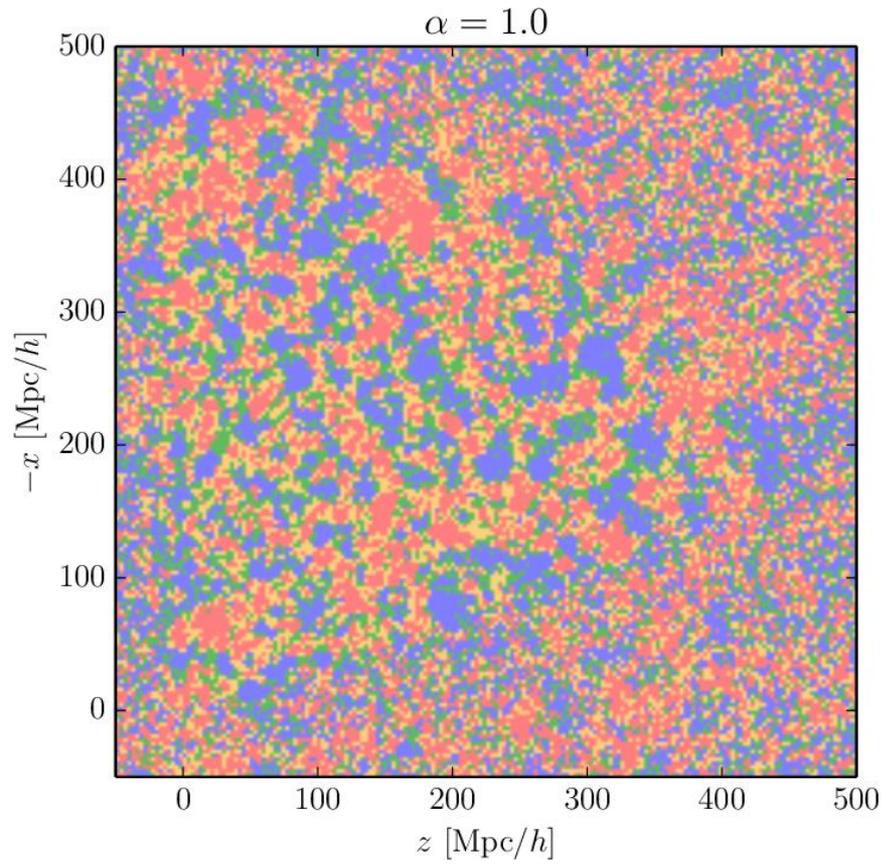
Final conditions



FL, Jasche & Wandelt, in prep.

Playing the game...

Initial conditions



FL, Jasche & Wandelt, in prep.

Summary & Conclusions

- Bayesian large-scale structure inference in 10 millions dimensions is possible!
 - Uncertainty quantification (noise, survey geometry, selection effects and biases)
 - Non-linear and non-Gaussian inference with improving techniques
- Application to data: four-dimensional **chronocosmography**
 - Simultaneous analysis of the morphology and formation history of the large-scale structure
 - Physical reconstruction of the initial conditions
 - Inference of cosmic voids at the level of the dark matter distribution
 - Characterization of the dynamic cosmic web underlying galaxies

Mapping the Universe: epilogue?

