Cosmology beyond BAO: voids, dark energy and the cosmic web

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with many thanks to F. Leclercq, N. Hamaus, G. Lavaux, J. Jasche, A. Pisani, P. Sutter

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Large Scale Structure



The goals of Large Scale Structure analysis

- How did the universe begin?
 - Nature of primordial perturbations
- What does it contain?
 - Dark matter
 - Dark energy
 - Baryonic physics
- How did it evolve
 - Expansion history
 - Growth of structure

The large scale structure challenge

- Problem: to access the small scales need to deal with non-linearity and bias
- Possible approaches:
 - Avoid: Observe at high redshift before density contrast became non-linear
 - Attack: Full, physical & statistical forward model of the survey
 - Adapt: Focus on less complicated parts of the Universe, e.g. those that retain more memory of the initial conditions: cosmic voids

How do we summarize this? In terms of the soap or the bubbles?



Redshift space

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Why cosmic voids?

- Biggest "objects" in the Universe fill most of the volume!
- Simpler dynamics and evolution than high density regions (see *Horizon AGN*)
- Easier to link luminous objects to underlying dark matter
- The first regions in the universe that are dominated by dark energy
- Neutrino signatures in profile?
- If acceleration of the universe is caused by modified gravity it should act most strongly in voids
- A free, additional observational probe in current and future surveys: ~10⁵ voids in Euclid!

Several active groups and a rapidly growing body of work



Classical cosmography with voids

- Can be used to define cosmological tests:
 - Alcock-Paczynski (Lavaux & Wandelt 2010, Hamaus et al., arXiv:1602.01784)
 - New "static ruler" (Hamaus et al., arxiv:1307.2571)





Alcock-Paczynski test

Perform *Alcock-Paczynski test* to constrain cosmological parameters:

Angular separation $\delta r_{\perp} = D_A(z) \, \delta \Theta$ Radial separation $\delta r_{\parallel} = cH^{-1}(z) \delta z$ $\delta \mathbf{r} = (\mathbf{c}/\mathbf{H})\delta \mathbf{z}$ $\delta \mathbf{r} = \mathbf{D}_{\mathbf{A}} \delta \Theta$ Observer

ANGULAR DIAMETER DISTANCE & HUBBLE RATE

$$D_A(z) = c \int_0^z H^{-1}(z') \, \mathrm{d} z' ~,~~ H(z) = H_0 \sqrt{\Omega_\mathrm{m} (1+z)^3 + \Omega_\Lambda}$$

Any deviation from the fiducial cosmology causes geometric distortions. \Rightarrow Determine ellipticity ε via

$$arepsilon = rac{\delta r_{\parallel}}{\delta r_{\perp}} = rac{D_A^{
m true}(z)H^{
m true}(z)}{D_A^{
m fid}(z)H^{
m fid}(z)}$$

Matter, galaxies, voids in simulation



A universal profile for voids



Hamaus, Sutter & Wandelt PRL 2014, arxiv:1403.5499

The profile fits DM voids, halo voids, "galaxy" voids $R_{eff} = 10-15 h^{-1} Mpc$



Sutter et al., arxiv:1309.5087; Hamaus, Sutter & Wandelt, arxiv:1403.5499

Void ρ and v profile

Estimate density and velocity profile by "stacking" tracer particles around void centers

$$\rho_{\mathrm{v}}(\mathbf{r}) = \frac{3}{4\pi} \sum_{i} \frac{m_i(\mathbf{r}_i)}{(\mathbf{r} + \delta \mathbf{r})^3 - (\mathbf{r} - \delta \mathbf{r})^3}$$

EMPIRICAL BEST-FIT MODEL (4 PARAMETERS)

$$\frac{\rho_{\rm v}(r)}{\bar{\rho}} - 1 = \delta_c \frac{1 - (r/r_{\rm s})^{\alpha}}{1 + (r/r_{\rm v})^{\beta}} , \qquad r_{\rm v} \equiv (3V_{\rm v}/4\pi)^{1/3}$$

$$v_{v}(r) = \frac{1}{N(r)} \sum_{i} v_{i}(r_{i}) \cdot \frac{r_{i}}{r_{i}}$$

MASS CONSERVATION TO LINEAR ORDER

$$v_{\mathrm{v}}(r) = -rac{1}{3}rac{f(z)H(z)}{1+z}r\Delta_{\mathrm{v}}(r) \ , \quad \Delta_{\mathrm{v}}(r) \equiv rac{3}{r^3}\int_0^r \left(rac{
ho_{\mathrm{v}}(s)}{ar
ho} - 1
ight)s^2\mathrm{d}s$$

In General Relativity: $f(z) = \Omega_{\rm m}^{0.55}(z)$

An astonishing result: *density profile fit* + *linear theory* predicts velocity profile!



Simple dynamics: easy to model in redshift space!

Hamaus, Sutter & Wandelt PRL 2014, arxiv:1403.5499

Void profiles in redshift space

Void-galaxy cross-correlation function in redshift space:

$$1 + \tilde{\xi}_{\mathrm{vg}}(\tilde{\mathbf{r}}) = \int \mathcal{P}\left(\mathbf{v}, \mathbf{r}\right) \left[1 + \xi_{\mathrm{vg}}(\mathbf{r})\right] \, \mathrm{d}^{3}\mathbf{v} = \int_{-\infty}^{\infty} \mathcal{P}\left(\mathbf{v}_{\parallel}, \mathbf{r}\right) \frac{\rho_{\mathrm{v}}(\mathbf{r})}{\bar{\rho}} \, \mathrm{d}\mathbf{v}_{\parallel}$$

Assume a Gaussian pairwise velocity distribution with mean $v_v(r)\frac{r_{\parallel}}{r}$

$$\mathcal{P}\left(\mathbf{v}_{\parallel},\mathbf{r}\right) = \frac{1}{\sqrt{2\pi}\sigma_{v}(\mathbf{r})} \exp\left[-\frac{\left(\mathbf{v}_{\parallel}-\mathbf{v}_{v}(\mathbf{r})\frac{r_{\parallel}}{r}\right)^{2}}{2\sigma_{v}^{2}(\mathbf{r})}\right]$$

and with velocity dispersion

$$\sigma_{v}^{2}(\mathbf{r}) = \sigma_{\parallel}^{2}(\mathbf{r})\frac{r_{\parallel}^{2}}{r^{2}} + \sigma_{\perp}^{2}(\mathbf{r})(1-\frac{r_{\parallel}^{2}}{r^{2}})$$

Assume:

$$\sigma_{\parallel,\perp}(r) \equiv \sigma_{\nu} = \text{const.}$$



Joint measurement of growth f/b and on *Alcock-Paczynski* parameter ε

Using BOSS data. AP measuremet is 4 times tighter than RSD from SDSS DR12 galaxy clustering analysis!

(Gil-Marin *et al.* arXiv:1509.06386)



Preliminary Euclid forecasts => 30 times higher Figure of merit than standard BAO

Hamaus et al. arXiv:1602.01784

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Joint constraint on growth f/b and on matter density



Hamaus et al. arXiv:1602.01784

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Bright future for cosmic voids

- Voids are not empty! Substructure in voids
 - Probes nature of dark matter
 - Contains information about small-scale primordial spectrum frozen in
 - Gives additional dynamical information, if clumps contain neutral gas

Galaxy and Mass Assembly (GAMA): Fine filaments of galaxies detected within voids

and Daladhan 2 David Olandilla 2 Mehme⁻⁻⁻⁻⁻⁻⁻ C ABSTRACT Simon Based on data from the Galaxy and Mass Assembly (GAMA) survey, we report on the Benne discovery of structures that we refer to as 'tendrils' of galaxies: coherent, thin chains of galaxies that are rooted in filaments and terminate in neighbouring filaments or Maritza voids. On average, tendrils contain 6 galaxies and span 10 h^{-1} Mpc. We use the so-Kevin l called line correlation function to prove that tendrils represent real structures rather than accidental alignments. We show that voids found in the SDSS-DR7 survey that overlap with GAMA regions contain a large number of galaxies, primarily belonging to tendrils. This implies that void sizes are strongly dependent on the number density and sensitivity limits of a survey. We caution that galaxies in low density regions, that may be defined as 'void galaxies,' will have local galaxy number densities that depend on such observational limits and are likely higher than can be directly measured.



Bright future for cosmic voids

- Voids as a cosmic tracer
 - Void centers have sub-Poissonian statistics
 - Low noise tracer of large scale structure
 - E.g. BAO with voids (Liang et al 2015)
- Gravitational Lensing from voids
 - First measurement Melchior et al. 2013 (SDSS)
 - Latest: Sánchez et al. 2016 (DES SV)

Counting voids to probe dark energy



Pisani Sutter, Hamaus, Alizadeh, Biswas, Wandelt, Hirata arXiv: 1503.07690

Fisher forecast of void abundance constraints from Euclid



Pisani Sutter, Hamaus, Alizadeh, Biswas, Wandelt, Hirata arXiv: 1503.07690



The BORG SDSS run

- 334,074 galaxies from the NYU-VAGC based on SDSS DR7
- Comoving cubic box of side length 750 Mpc/h, with periodic boundary conditions
- 256³ grid, resolution 3 Mpc/h interval and the second second
- 12,000 samples, four-dimensional maps
- **3** TB disk space
- 10 months wallclock time on 16-32 cores

Jasche, Leclercq, BDW 2015

Bayesian chronocosmography from SDSS



How did we get that?



BORG: Bayesian Origin Reconstruction from Galaxies

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



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
 - Identified structures have a direct physical interpretation



FL, Jasche, Lavaux & Wandelt 2016, arXiv:1601.00093

Exploiting Lagrangian space dynamic analysis



Hahn, Abel & Khaeler, arXiv:1210.6652

Consistent histories of cosmic structure evolution



Dynamical velocities



How do we find beyond-BAO Large Scale Structure statistics that inform us about cosmology?

 Example: what can the mildly non-linear regime (the *cosmic web*) teach us about dark energy?

Physical cosmic web classification

• The **T-web**:

void, sheet, filament, cluster?

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

and many others...

Lagrangian classifiers

now usable in real data!

Comparing classifiers



FL, Jasche, Lavaux & Wandelt 2016, arXiv:1601.00093

What is the information content of these maps?

Shannon entropy



How much did the data surprise us?

information gain a.k.a. relative entropy or Kullback-Leibler divergence posterior/prior

$$D_{\mathrm{KL}}\left[\mathcal{P}(\overline{q})(\vec{x}_{k}, \underline{M}) \not p_{i} \mathcal{P}(\overline{q}_{2}) \left(\underbrace{\frac{p_{i}}{\underline{q}_{i}}}_{i} \underbrace{\mathcal{P}}(\mathrm{T}_{i}(\vec{x}_{k}) | d) \log_{2} \left(\frac{\mathcal{P}(\mathrm{T}_{i}(\vec{x}_{k}) | d)}{\mathcal{P}(\mathrm{T}_{i})} \right) \quad \text{ in Sh}$$



(more about the Kullback-Leibler divergence later)

FL, Jasche & Wandelt 2015, arXiv:1502.02690

How similar are different classifications?

Jensen-Shannon divergence

$$D_{\rm JS}[\mathcal{P}:\mathcal{Q}] \equiv \frac{1}{2} D_{\rm KL} \left[\mathcal{P} || \frac{\mathcal{P} + \mathcal{Q}}{2} \right] + \frac{1}{2} D_{\rm KL} \left[\mathcal{Q} || \frac{\mathcal{P} + \mathcal{Q}}{2} \right] \quad \text{in Sh,}$$
 between 0 and 1



(more about the Jensen-Shannon divergence later)

FL, Lavaux, Jasche & Wandelt 2016, arXiv:1606:06758.

Which is the best classifier?

- Decision theory: a framework to classify structures in the presence of uncertainty.
 Can we extend the decision problem to the space of classifiers?
- Idea: maximize a utility function

 $U(\xi) = \langle U(d, \mathbf{T}, \xi) \rangle_{\mathcal{P}(d, \mathbf{T}|\xi)}$

An important notion: the mutual information between two random variables

$$I[X:Y] \equiv D_{\mathrm{KL}}[\mathcal{P}(x,y)||\mathcal{P}(x)\mathcal{P}(y)]$$

$$= \sum_{x \in \mathcal{X}, y \in \mathcal{Y}} \mathcal{P}(x, y) \log_2 \left(\frac{\mathcal{P}(x, y)}{\mathcal{P}(x) \mathcal{P}(y)} \right)$$

• Property:
$$I[X:Y] = \langle D_{\mathrm{KL}}[\mathcal{P}(x|y)||\mathcal{P}(x)] \rangle_{\mathcal{P}(Y)}$$

Mutual information is the expected information gain about X due to observing Y

Utility for model selection: example: dark energy equation of state

• Example: Let us consider three dark energy models with w = -0.9, w = -1, w = -1.1. Which classifier separates them hest?

Which classifier separates them best?

 The Jensen-Shannon divergence between posterior predictive distributions can be used as an approximate predictor for the change in the Bayes factor

Vanlier et al. 2014, BMC Syst Biol 8, 20 (2014)

• In analogy: $U_2(d,\xi)(\vec{x}_k) = D_{\mathrm{JS}}\left[\mathcal{P}(\mathrm{T}(\vec{x}_k)|d,\mathcal{M}_1):\mathcal{P}(\mathrm{T}(\vec{x}_k)|d,\mathcal{M}_2)|\xi\right]$

$$\mathcal{U}_{2}(\xi) = I \left[\mathcal{M}: \mathcal{R}(d) | \xi \right]$$

model classifier mixture distribution
$$\mathcal{R}(d) \equiv \frac{\mathcal{P}(\mathrm{T}(\vec{x}_{k}) | d, \mathcal{M}_{1}) + \mathcal{P}(\mathrm{T}(\vec{x}_{k}) | d, \mathcal{M}_{2})}{2}$$

FL, Lavaux, Jasche & Wandelt 2016, arXiv:1606:06758.

Information about DE equation of state in web type classification



Recent progress

- Lavaux and Jasche (in prep.)
- Now includes redshift space distortions
- ~10 times faster sampling
- Example:
 - 2M++ catalog (67, 224 galaxies from the (based on 2MRS, 6dF and SDSS-DR7))
 - Comoving cubic box of 677.7 Mpc/h
 - 256^3 grid, resolution 2.64 Mpc/h => 17 million parameters
 - 3 bias parameters and mean galaxy density sampled, each per subcatalog
 - 4 luminosity bins



Conclusions

- Voids are a promising new line of attack for large scale structure inference for
 - Precision cosmology
 - Tests of gravity
- A new era of principled analysis of the observable structure, the dynamics and initial conditions of the Universe
- Information theory provides a framework for quantifying the most informative observations and data summaries beyond the power spectrum

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Parameters in the void-profile



Controlling z-systematics



Pisani et al., arXiv: 1506.07982