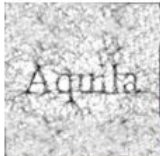


Field Level Inference of Voids and Galaxy Clusters

Guilhem Lavaux (IAP)

collab.: S. Stopyra, H. Peiris, A. Pontzen, J. Jasche
based upon [2304.09193](#) & [2107.06903](#)



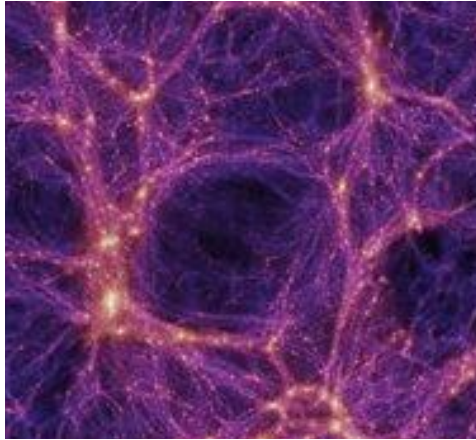
Motivation / Objective

- Cosmology w/ Large scale structures
- Galaxy cluster masses from full surveys
- Void definition as anti-halos

- Automating research
- Quality of inference through
 - posterior predictive tests
 - accuracy tests w/ N-body

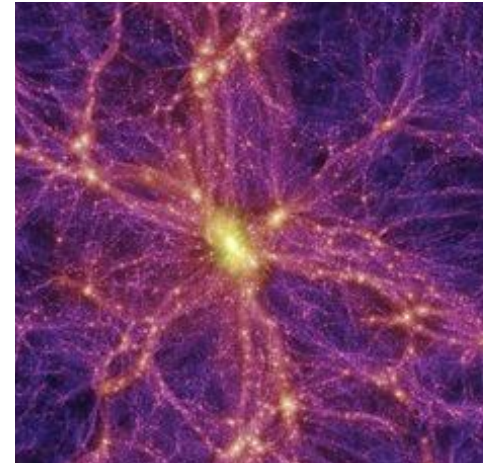


Voids



- Linear on scales $> 5 \text{ Mpc}/h$
- Shapes can probe cosmology (Alcock-Paczynski test)
- Density-profile can be used to probe modified gravity/neutrinos

Clusters



- Non-linear after collapse
- Abundance/mass can probe cosmological parameters (halo mass function).
- Can probe small-scales.

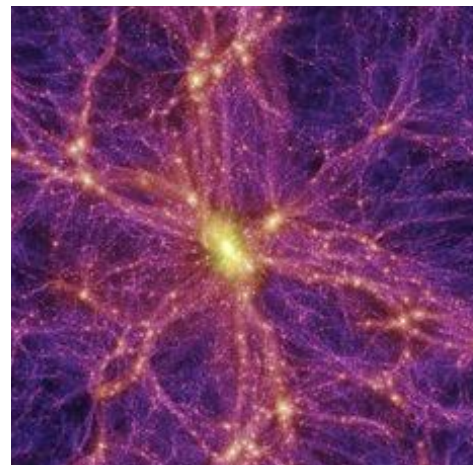


Voids



- Apply void finders to galaxy distribution
(variety of methods/definition)
- Abundance hard to model
(recent progress on this).

Clusters



- Estimate masses via proxies
(velocity dispersion, X-ray emission, SZ-effect, weak-lensing).
- Often disagreements, even on nearby clusters.

Common theme: hard to get at dark matter distribution directly. Can we infer it?



Achieving complete characterization of cosmic structure

'What I cannot create, I do not understand.'

Richard P. Feynman, 1988

Bayesian Physical forward modeling

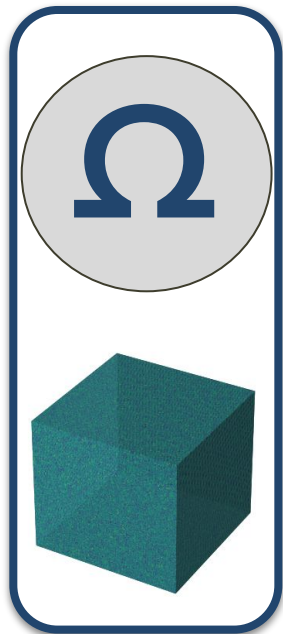
- **Field-level inference**
 - Beyond summary statistics
 - Beyond random realizations
- **Non-linear and dynamical inference**
 - Beyond linear structure growth
 - Redshift Distortions
 - Light-Cone effects
- **Causal inference**
 - Beyond associative analyses





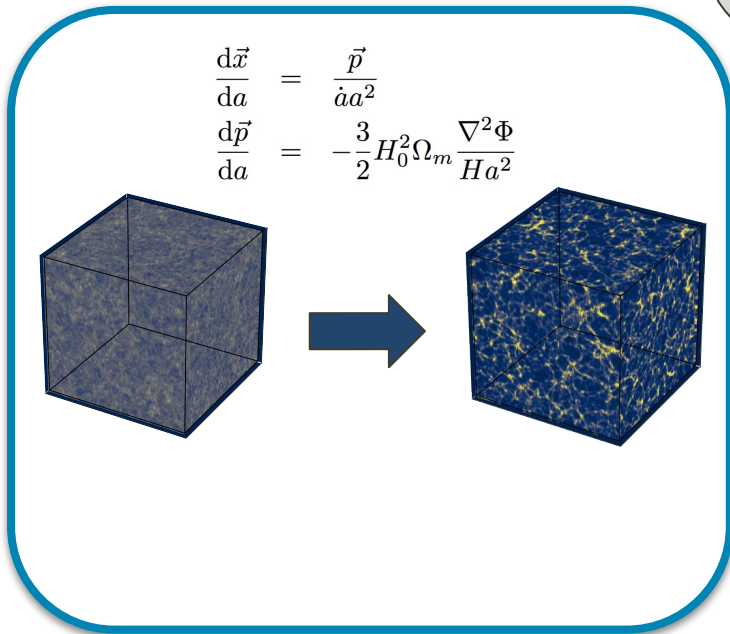
Bayesian Forward modeling cosmic structure surveys with BORG

Prior Model



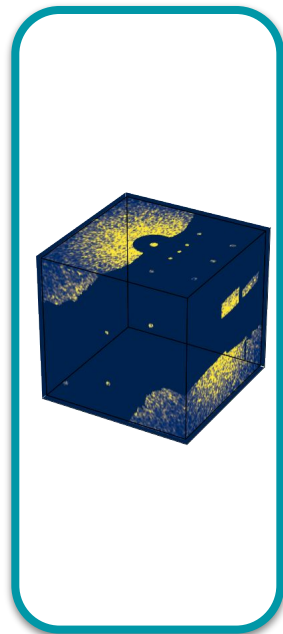
$$\pi(\mathbf{x}, \Omega)$$

Structure Formation Model



$$\pi(\rho_{\mathbf{m}}|\mathbf{x}, \Omega)$$

Data model

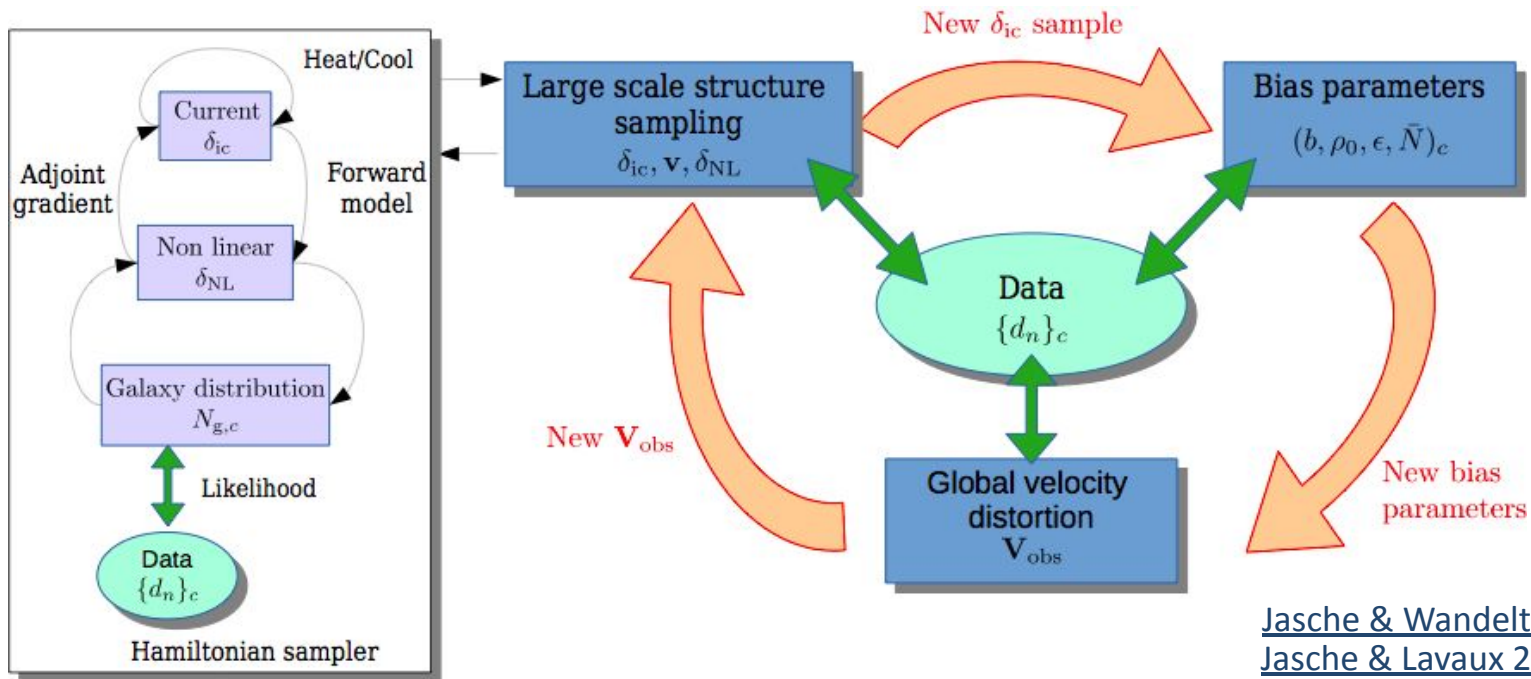


$$\pi(\mathbf{N}_{\mathbf{g}}|\rho_{\mathbf{m}}, \alpha, \Omega)$$



BORG: A large scale MCMC framework

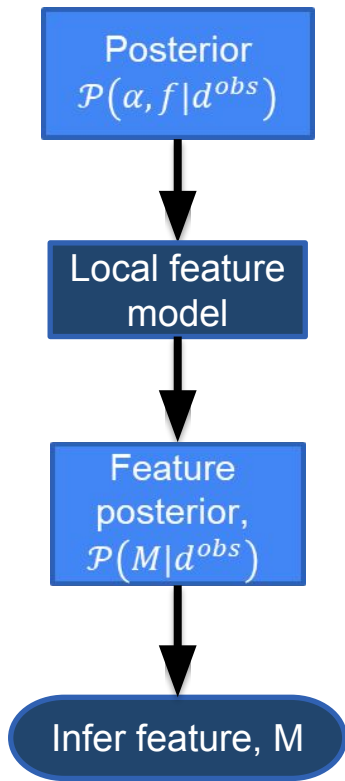
- BORG's MCMC framework allows building flexible data models
 - Hierarchical Bayes and block sampling
 - Efficient **Hamiltonian Monte Carlo (HMC)** technique
 - **Fully differentiable physics forward model**



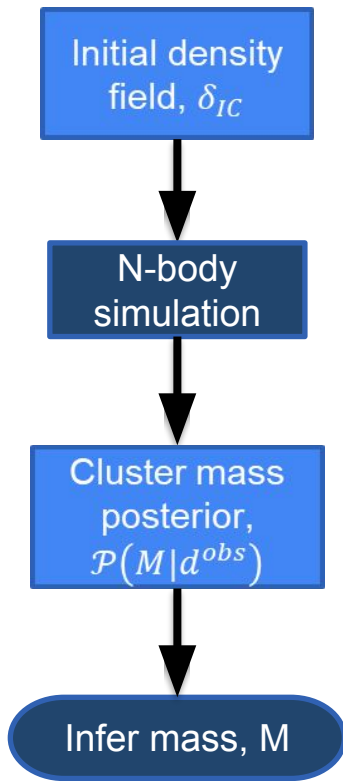


After the inference: Posterior resimulation

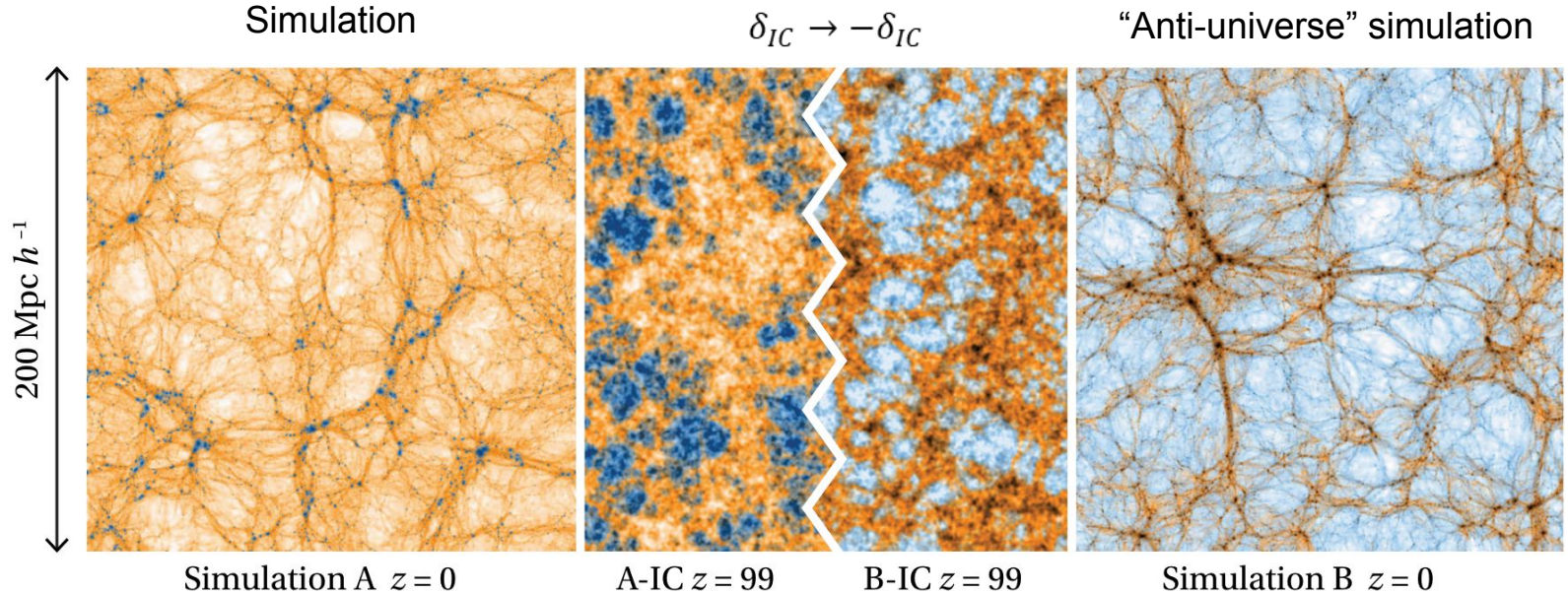
Generic Feature extraction:



Example – Cluster Mass



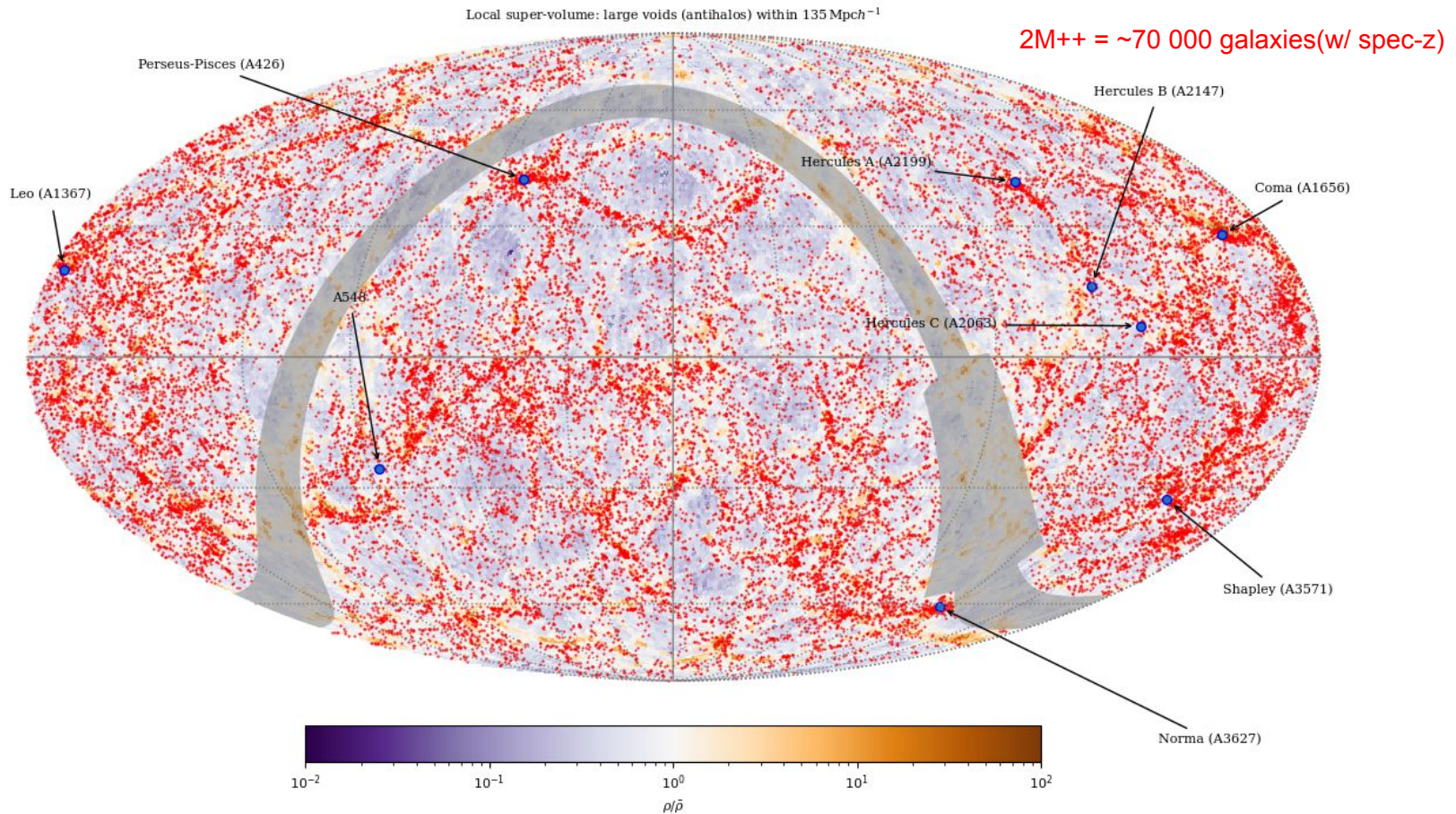
- Can also infer local features in data.
- Need **NOT** be the same model used for field inference.
- E.g., information on cluster masses held in initial density over a large Lagrangian patch.
- But need a full N-body simulation to extract it.



- Can also use posterior resimulations to study voids.
- Model voids as **Anti-halos**[1]: voids = halos from an “anti-universe” simulation.
- Mass function well-defined. Clear connection to initial conditions.
- Cover up to 25 Mpc/h radius regime of voids.
- May only be done if you **HAVE** initial conditions, provided by Field Level Inference

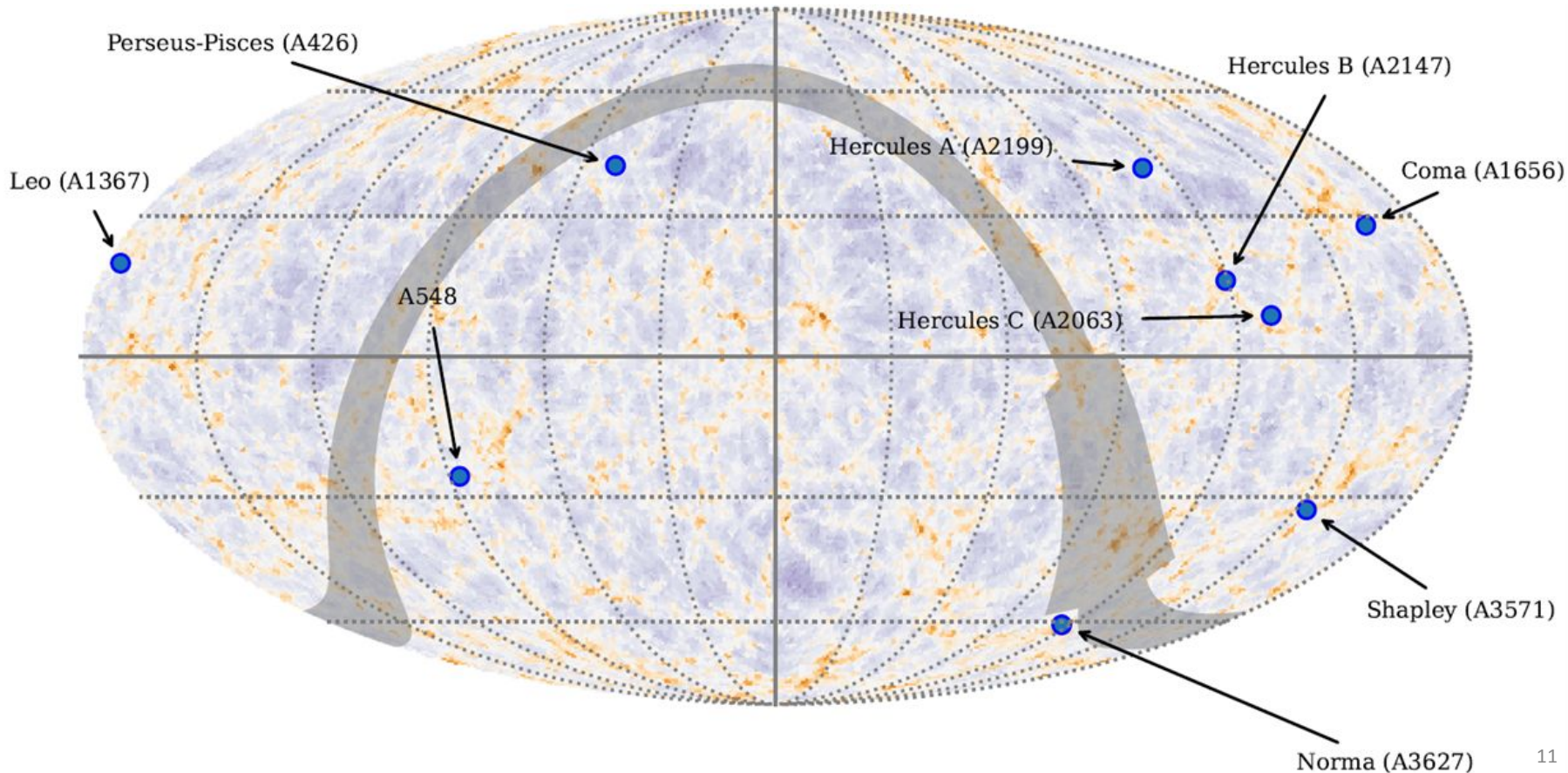


Field Level Inference with BORG: the case of 2M++, a new inference run



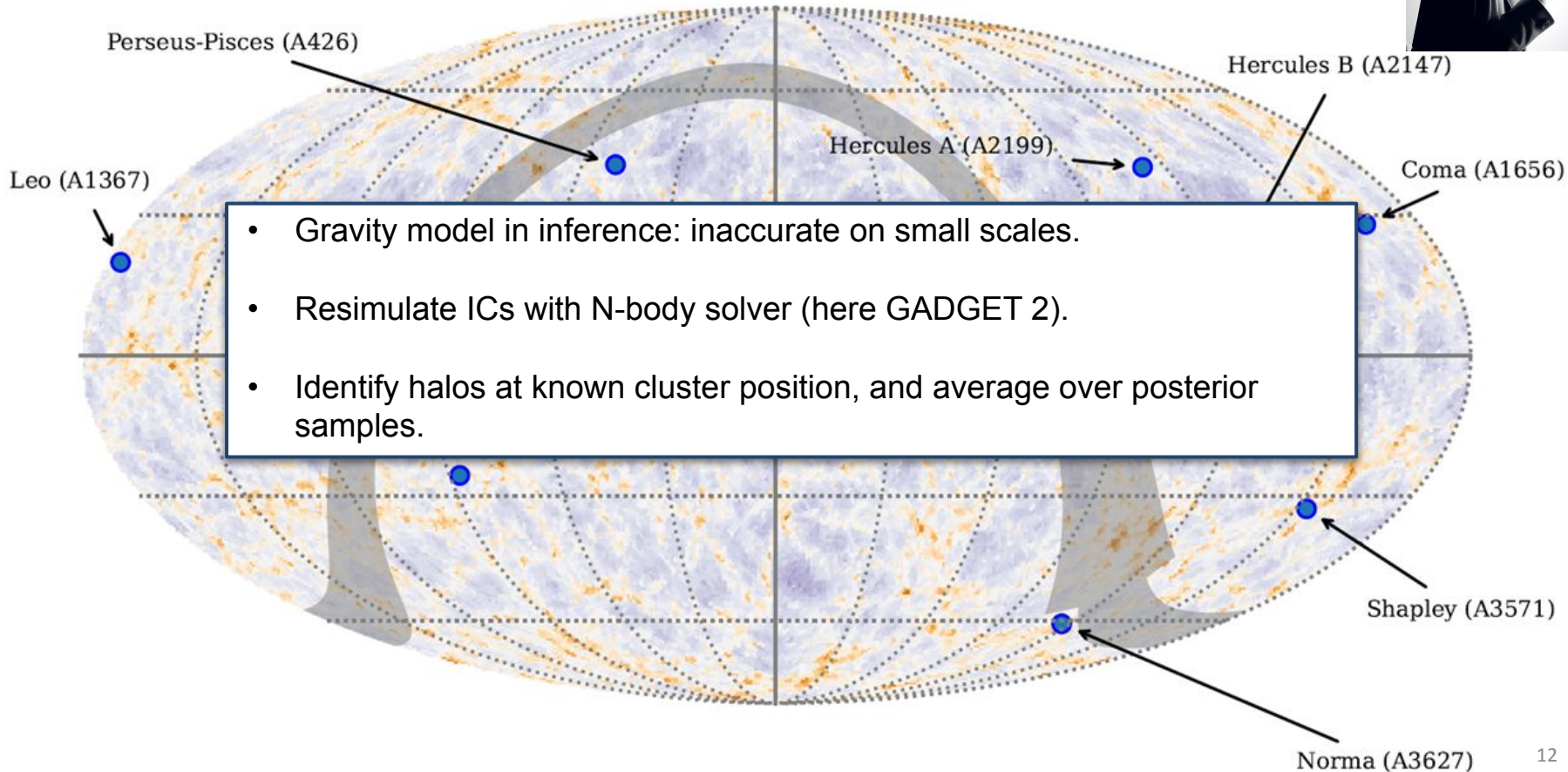


Some galaxy clusters of interest to check masses





Two features of interest: 1/ accuracy of the N-body solver

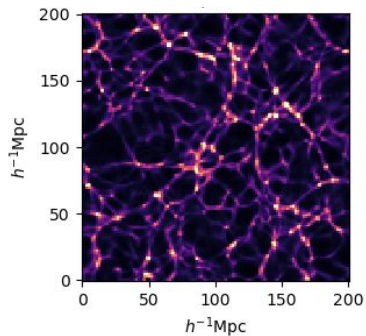




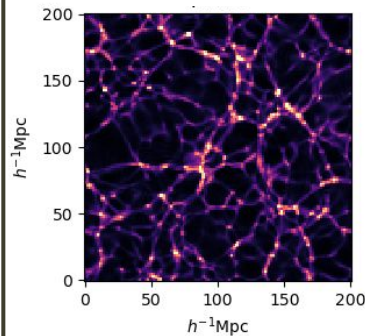
Two features of interest: 1/ accuracy of the N-body solver



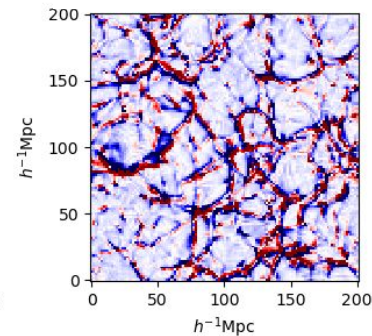
Reference PM 100 timesteps



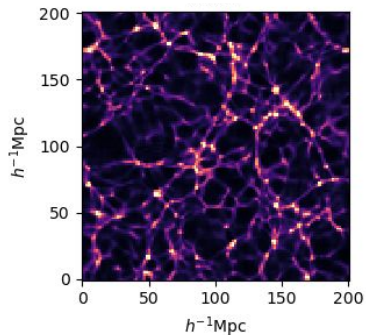
PM 10 timesteps



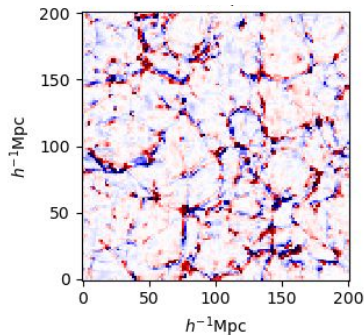
Difference to PM100



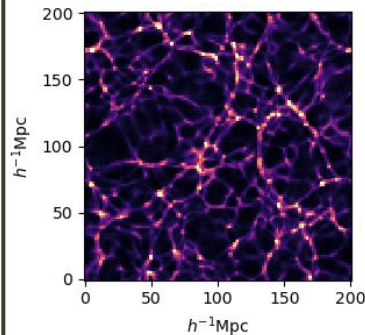
t-COLA 10 timesteps



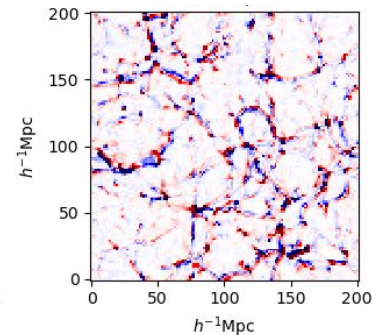
Difference to PM100



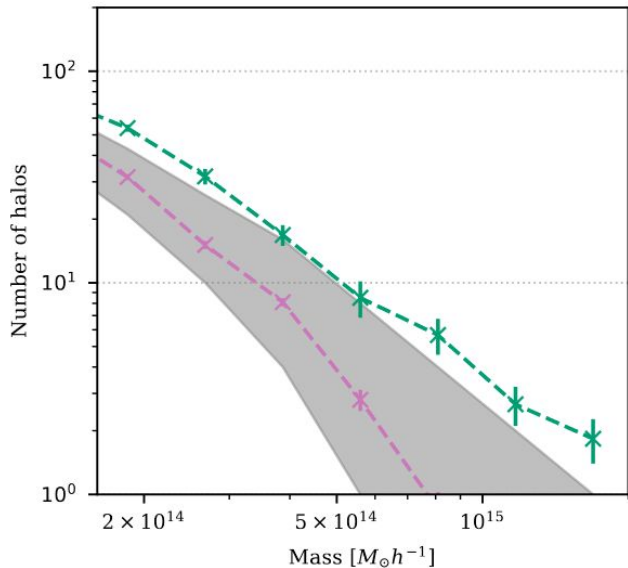
t-COLA 20 timesteps



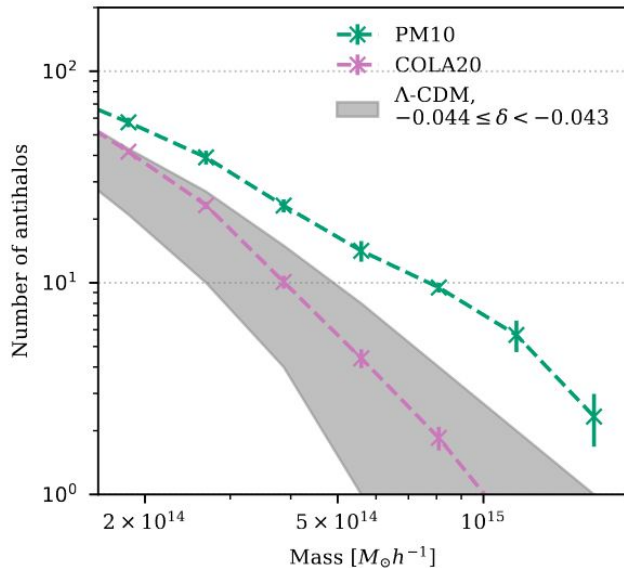
Difference to PM100



Halos



Antihalos



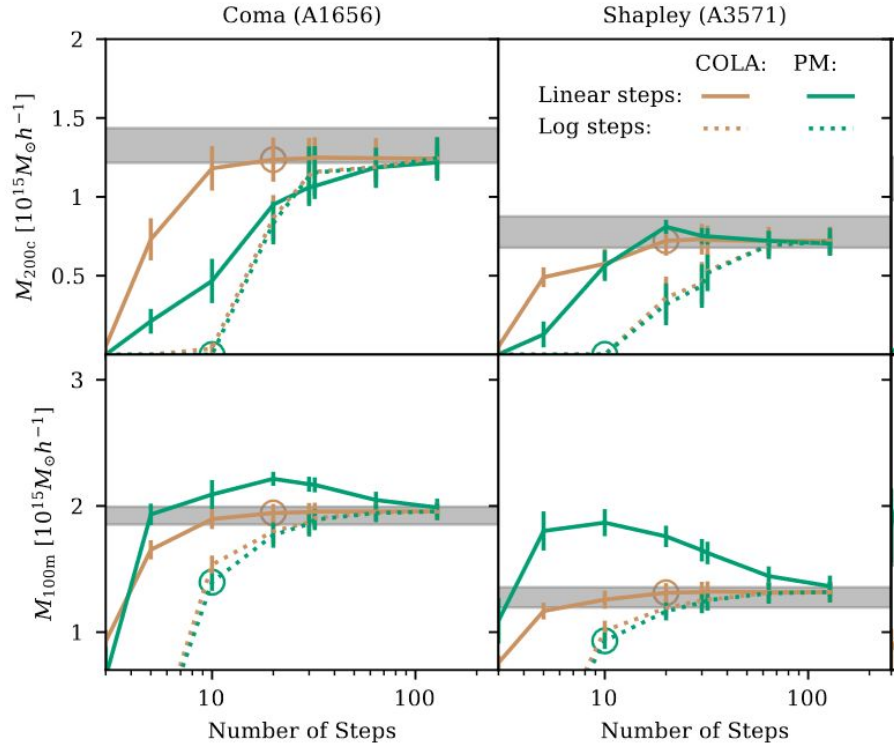
However, inference model accuracy matters.

E.g., 10-step particle mesh underestimates core density at 10^{15} Msol/h.

BORG compensates by inferring higher initial density.

Leads to overestimate masses!

Accuracy requirements



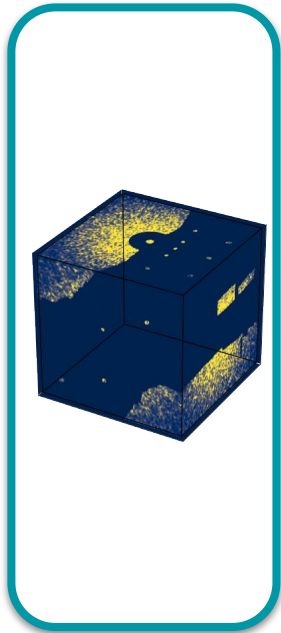
- Must choose models that are compatible at the virial radius scale.
- Investigated COLA/PM models with different time-step resolutions.
- COLA with 20 linearly-spaced steps could reproduce masses for most massive clusters.
- Insufficient for constraining $\sim 10^{14} M_{\odot}/h$ clusters, but mass functions are correct.



Two features of interest: 2/ resilience to systematics



Data model



$$\mathbf{N}_g = \mathbf{A} \odot \lambda_g$$

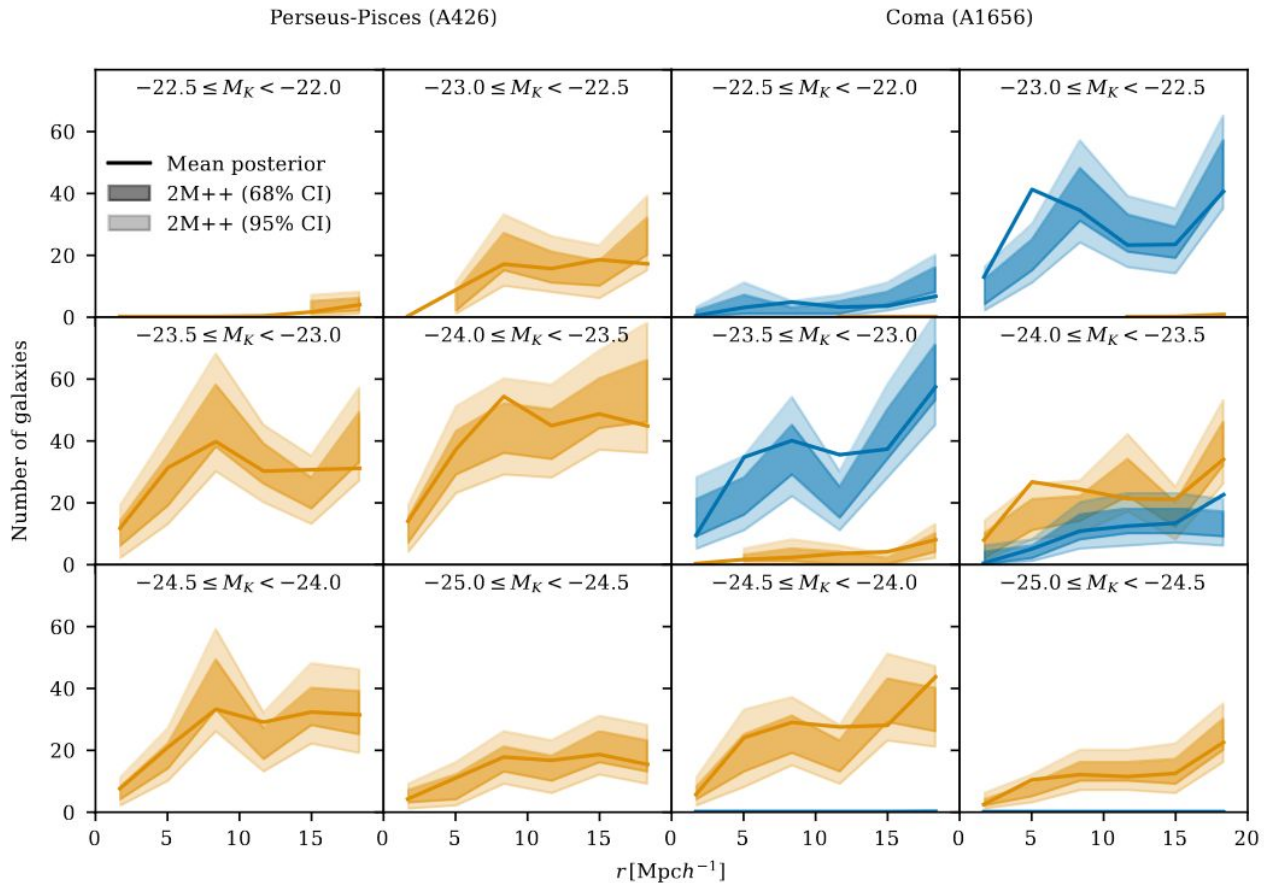
\mathbf{A} = foreground map, (+ Jeffreys prior)

λ = output of galaxy bias model

$$\pi(\mathbf{N}_g | \rho_m, \alpha, \Omega)$$

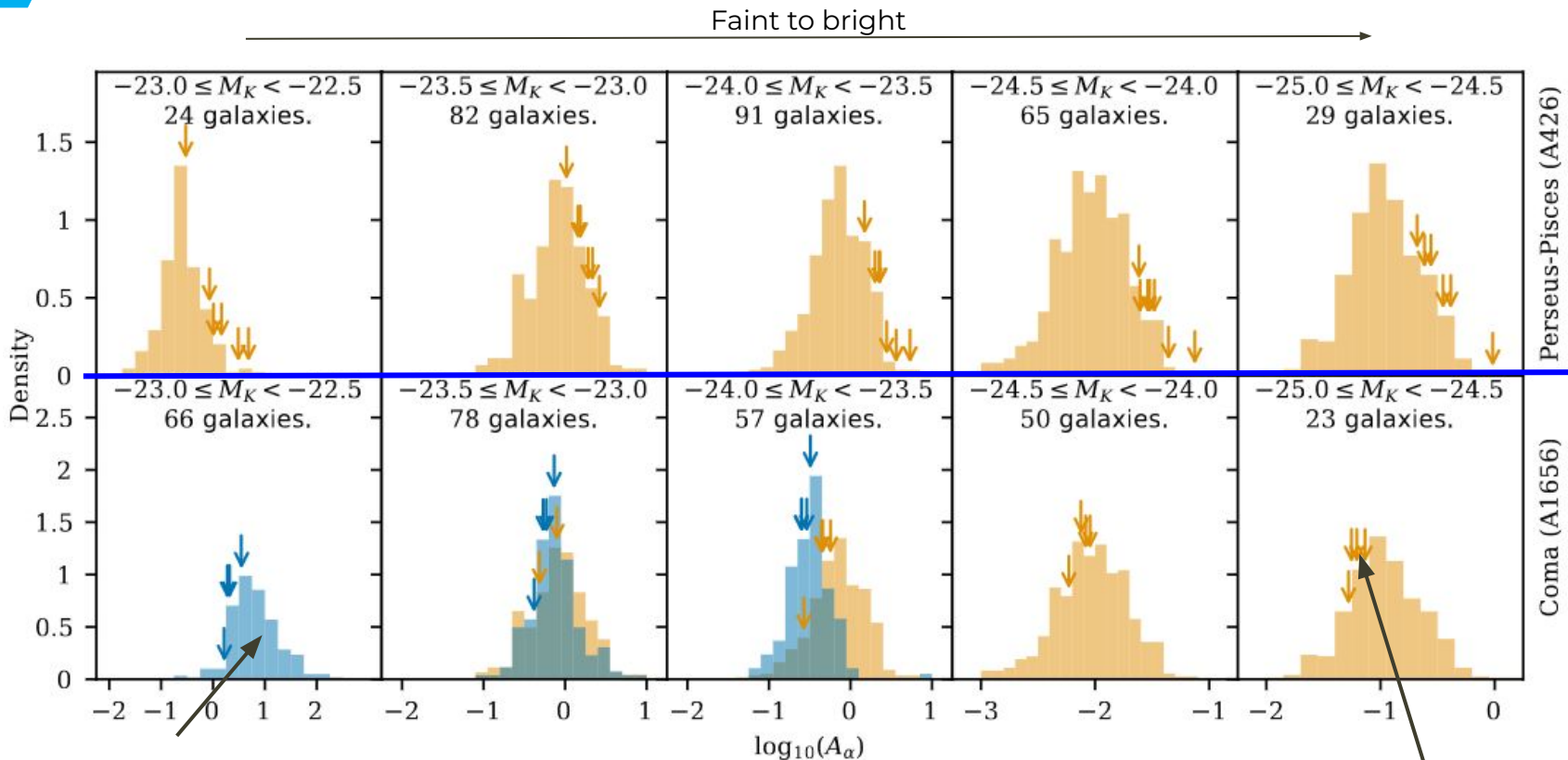


Posterior predictive tests: galaxy abundances





Posterior predictive tests: amplitude of systematic pixels

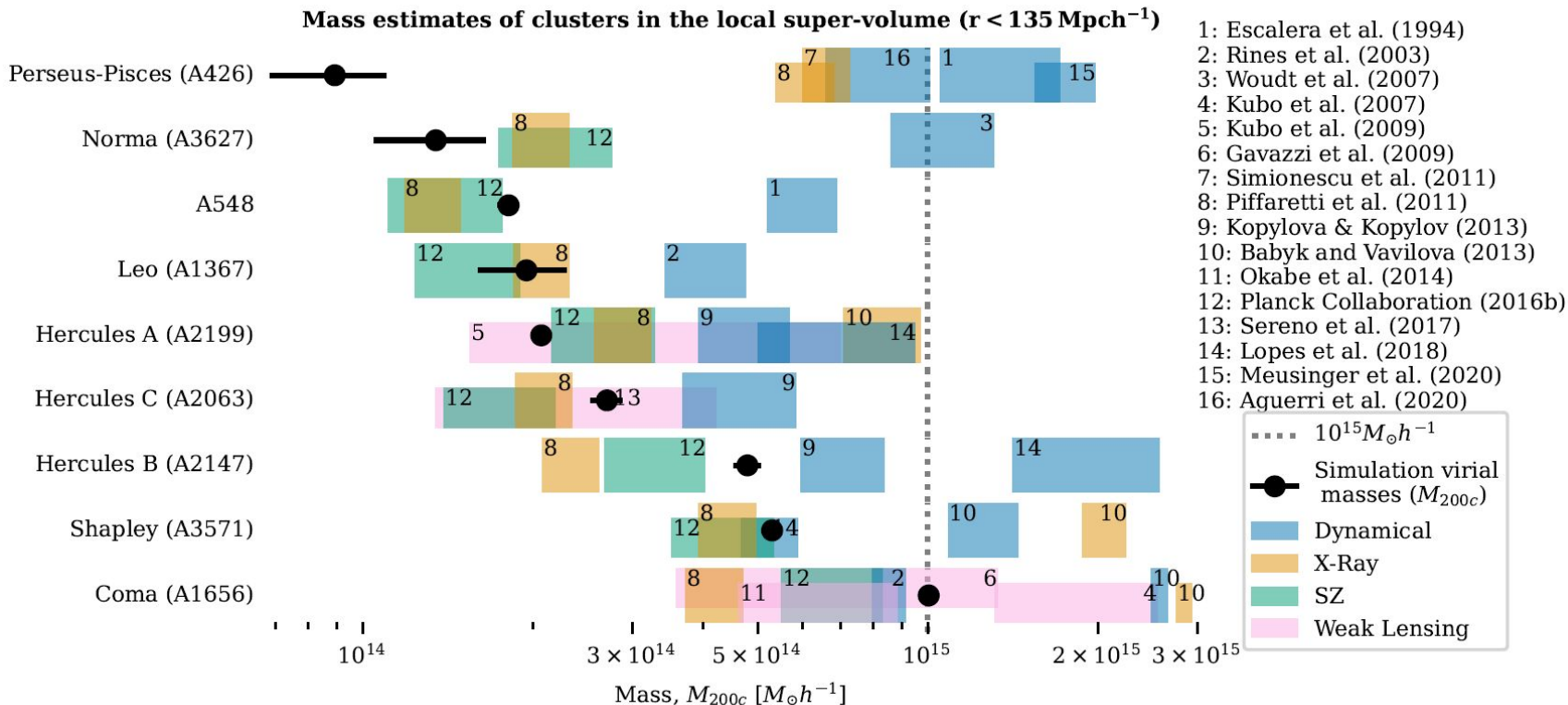


Amplitude **over full sky** at the distance of the **object**

Amplitude at the *location* of the **object**

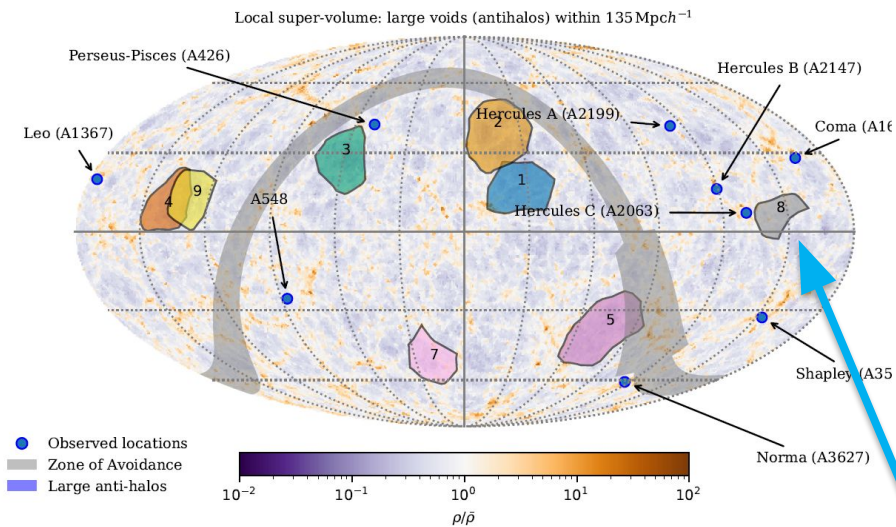


Mass Estimates with BORG Posterior Resimulation

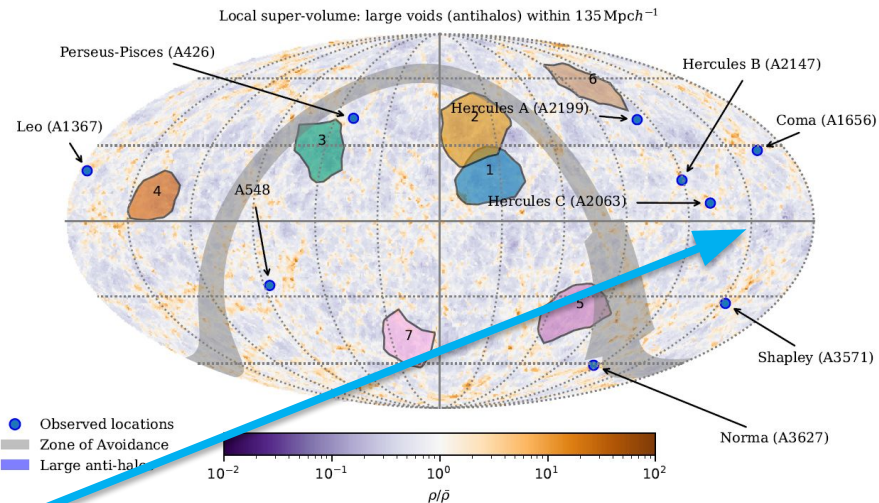


- N samples from posterior. N anti-halo catalogues. How to combine them?
- What is the 'same' void in different MCMC samples?
- How do we know if an anti-halo is reliably constrained?

MCMC Sample 8500

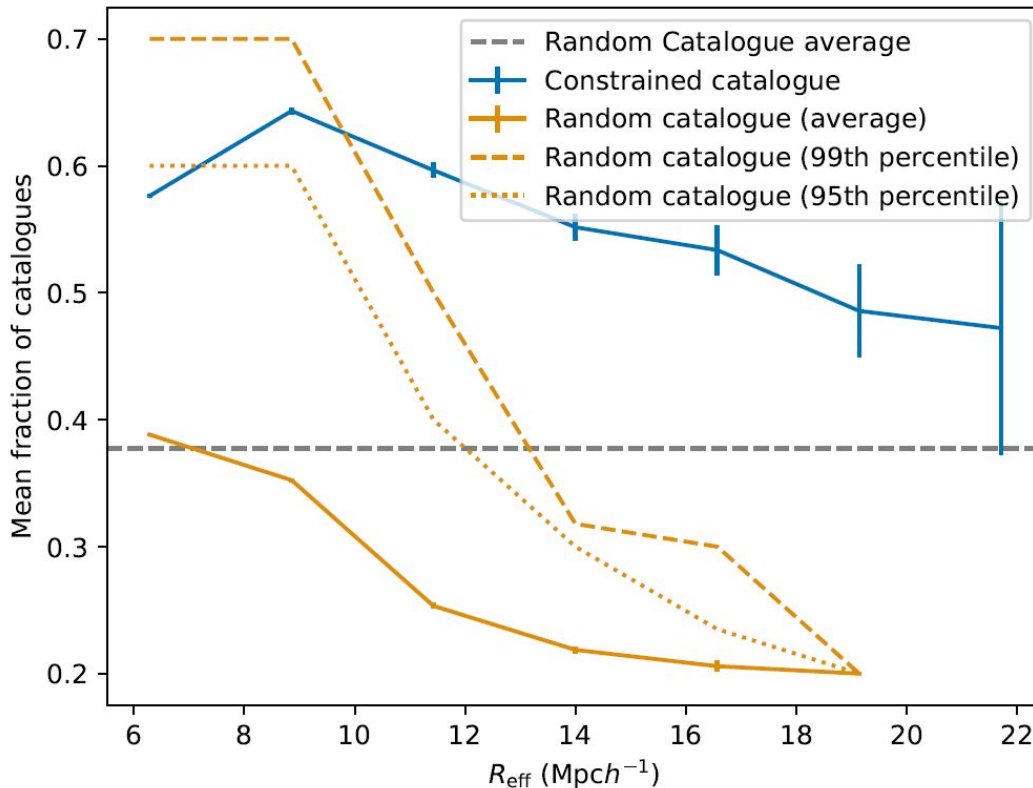


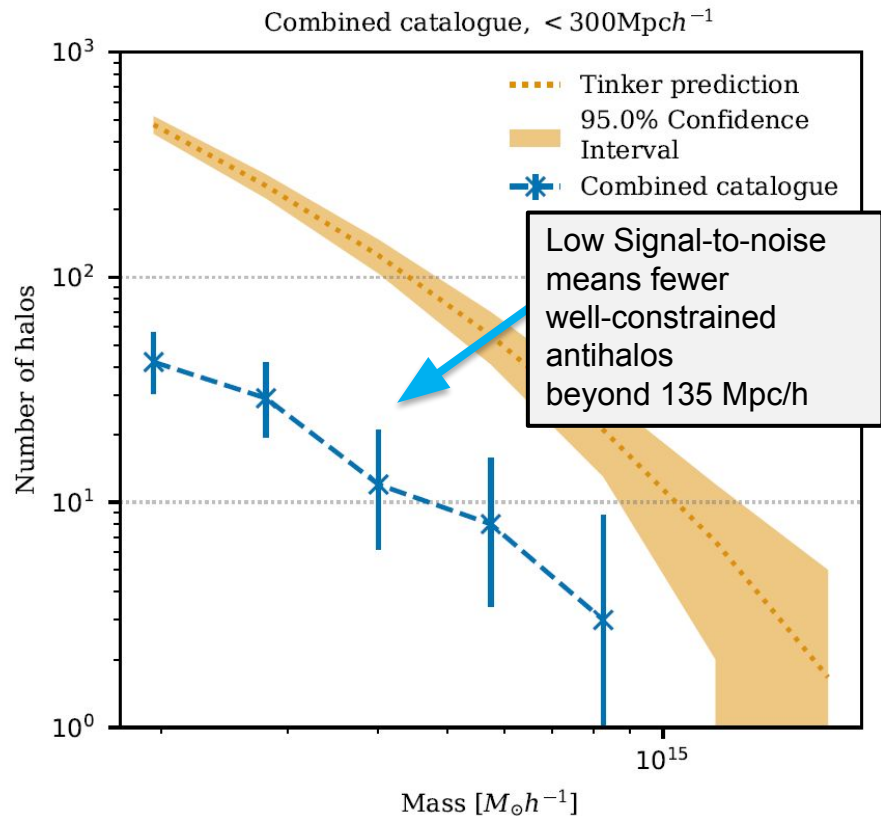
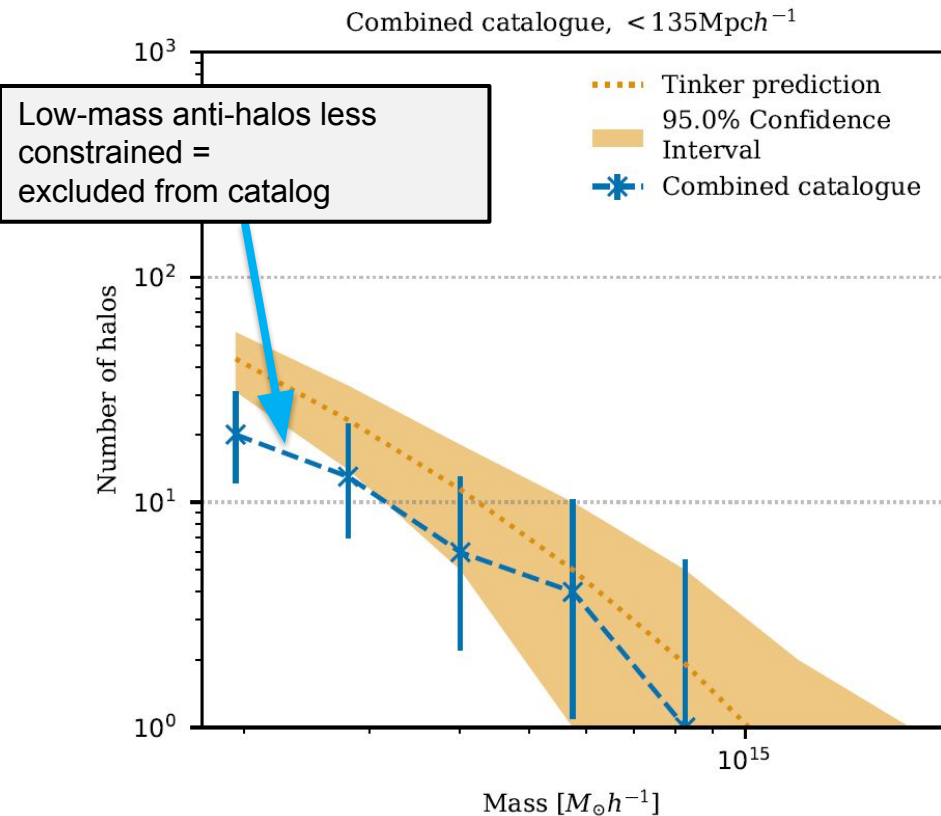
MCMC Sample 8800



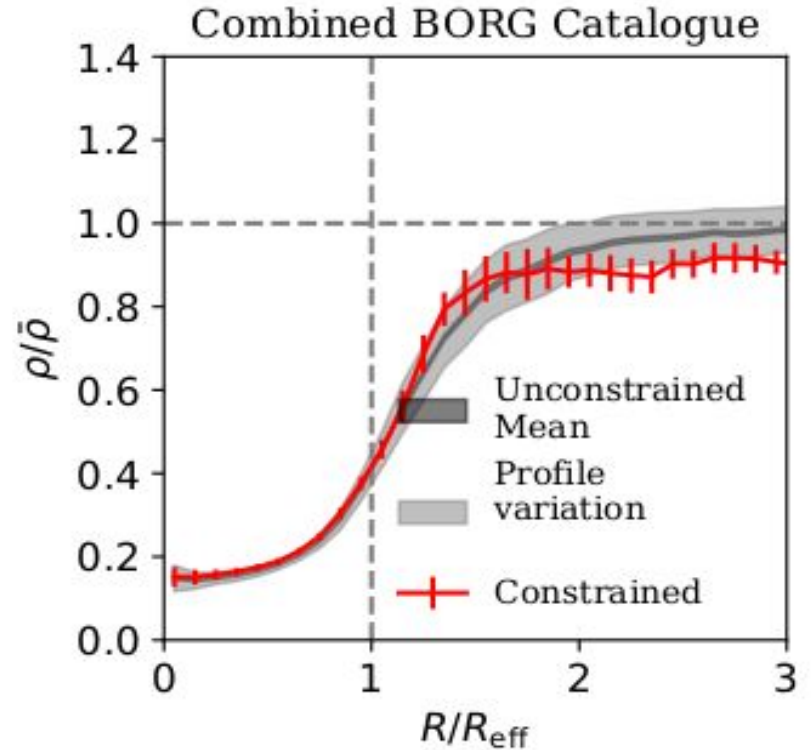
Inconsistent appearance between MCMC samples indicates less-constrained anti-halos.

- Cut void from all catalogues with low signal-to-noise (SNR).
- Match remaining voids on distance (<1 void radii), and size.
- Exclude ambiguous matches.
- Retain voids appearing in high fraction of samples.





- Test physics using mean void profile
- Slightly low profile observed, but within variance of similar regions in simulations.
- Modified gravity may change void evolution.
- Massive neutrini also affect void size-distribution.



Conclusions

- Estimated masses of the largest clusters w/ resimulation of BORG initial conditions.
- Method for combining catalogues from different MCMC samples into one catalogue.
- Agreement with X-ray/SZ data.
- Abundance consistent with Lambda-CDM.
- Removes voids with low signal-to-noise and retains high-confidence voids.
- Void profiles compatible with Λ -CDM

