CosmicAtlas

Cosmological Catalogs for Large Scale Structure

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Mock Innsbrück: the connection between galaxies and dark matter haloes

Main goal

To generate **galaxy mock catalogs** for forth-coming galaxy redshift surveys (DESI, Euclid, JPAS, LSST)
`Challenge:` large Cosmological Volumes with high-mass resolution

State of the Art

***N*-body simulations:**

- ⋆ Pure DM. **FlagShip**
- ⋆ Hydro-sims

Predictive methods:

- ⋆ **ICE-COLA** Izard et al. 2016
- ⋆ PM (FastPM) Izard et al. 2016
- ⋆ **PINNOCHIO** Monaco 2016, Minauri et al. 2016
- ⋆ **Peak-PATCH** Bond, Myers 1996

Calibrated methods

- ⋆ **PATCHY** Kitaura et. al 2015
- ⋆ **Halo-GEN** Avila et al. 2015
- ⋆ Log-normal Agrawal et al. 2017

Machine Learning appraoches

e.g. Blot et al. arXiv:1806.09497, Lippich et al. arXiv:1806.09477, Colavincenzo et al. arXiv:1806.09499

A new calibrated method

- *Bias Assignment Method* (BAM) (Balaguera, Kitaura et al., 2018, 2019; Pellejero, Balaguera, Kitaura, et al 2020)
- Relies on the idea of *mapping* the halo distribution onto a dark matter density using a non-parametric halo-bias
- Halo-bias calibrated to the 2-pt statistics of a reference.

Developers

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Collaborators

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Ariel Sánchez (MPE)
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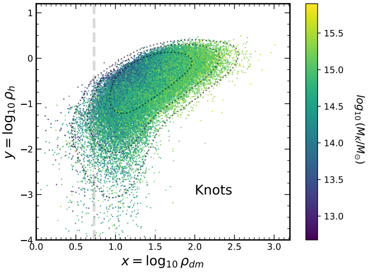
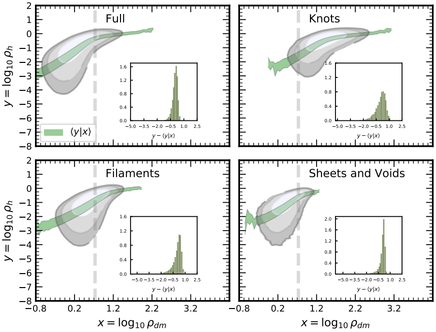
CosmicAtlas: The BAM approach

- **BAM** is designed to (iteratively) **learn** the statistical halo properties from a reference N-body simulation. Main ingredient is the **halo bias**, $\mathcal{B} = \mathcal{B}(N_h|\Theta_{\rm dm})$ including **stochastic** and **deterministic** dependencies on the dark matter distribution ($\Theta_{\rm dm}$) such as
  - **non-linear local** DM
  - **long-range non-local** DM: *tidal field, shear tensor*
  - **short-range non-local** DM: *mass of percolated collapsing regions*

Halo-bias in different cosmic-web types

Mass of connected collapsing regions





Balaguera, Kitaura et al. arXiv:1806.05870

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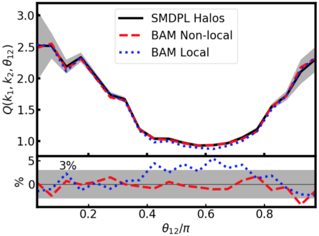
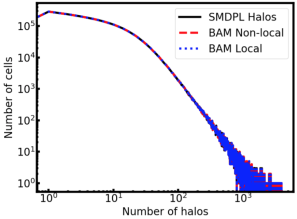
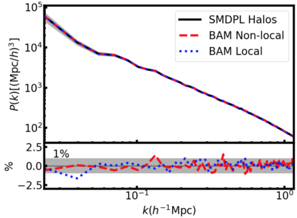


Small MultiDark Planck Simulation:
400 $Mpch^{-1}$ cube with 3840^3 particles.
Halo-Mass resolution $2\times10^8 M_\odot h^{-1}$
BAM:160^3 particles!





Pellejero, Balaguera, Kitaura et al. arXiv:1910.13164

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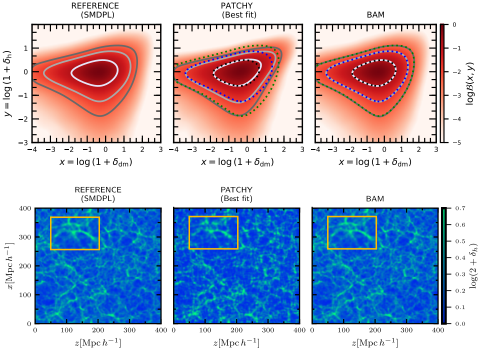
Small MultiDark Planck Simulation: Patchy vs BAM



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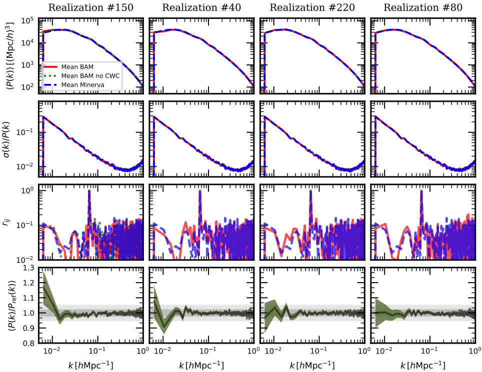
- **BAM** has been proven to be in capacity to construct ensemble of mock catalogs

Reference: Minerva Simulation Grieb et al. 2012



Balaguera, Kitaura et al., arXiv:1906.06109

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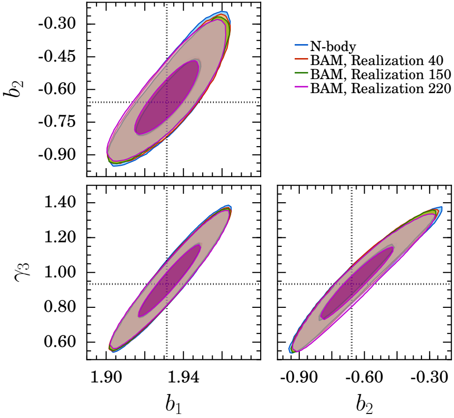
- Covariance matrices with $\sim 2\%$ accuracy in error parameters of model $P(k)$ (real space).

Error parameters from covariance matrix: BAM vs Minerva simulations



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How it works

Calibration

Input: Reference halo catalog and its IC (down-sampled) to learn bias.
Outputs: Halo bias, BAM kernel, Scaling Relations.

Sampling on new IC

Apply Bias and Kernel to new DM evolved from a new IC

Assign properties of DM tracers. Extrapolate to larger volumes

Calibration: iterative procedure

DM density field convolved with BAM kernel (first iteration: $\mathcal{K}(\mathbf{k}) = \delta^3(\mathbf{k})$)

$$\tilde{\delta}^{i}_{\alpha\mathrm{dm}}(\mathbf{r}) \equiv \mathcal{K}_i^{(\alpha-1)} \otimes \delta^{i}_{\mathrm{dm}}(\mathbf{r})$$

Measure the dark matter properties (local and non-local)

$$\Theta_{\mathrm{dm}} \equiv \{\delta_{\mathrm{dm}}, T-\mathrm{CWC}, M_{\mathrm{KNOTS}}, V-\mathrm{CWC}\},$$

Halo-bias: distribution of number counts conditional to DM-properties

$$\mathcal{B}(N_{\mathrm{h}}|\Theta_{\mathrm{dm}}) = \frac{\sum_{i=1}^{N_{\mathrm{cells}}} \mathbf{1}_{N_h}(N_{\mathrm{h}}(\mathbf{r}_i)) \prod_{\kappa=1}^{\mathcal{N}_{\mathrm{p}}} \mathbf{1}_{\gamma_\kappa}(\{\Theta_{\mathrm{dm}}(\mathbf{r}_i)\}_\kappa)}{\sum_{i=1}^{N_{\mathrm{cells}}} \prod_{\kappa=1}^{\mathcal{N}_{\mathrm{p}}} \mathbf{1}_{\gamma_\kappa}(\{\Theta_{\mathrm{dm}}(\mathbf{r}_i)\}_\kappa)},$$

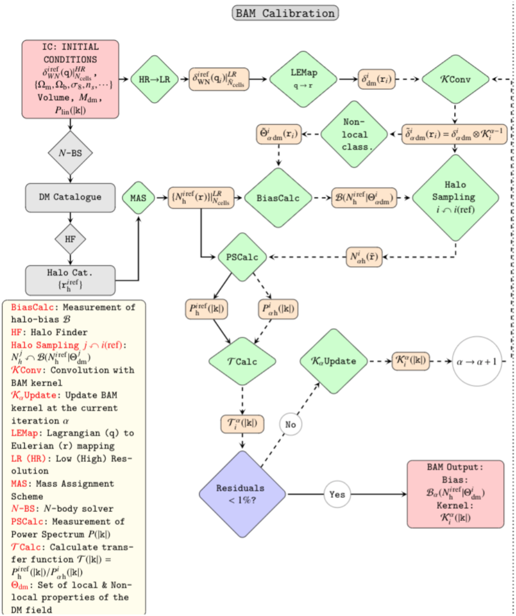
Sampling number counts

$$\{N^{i}_{\alpha\mathrm{h}}(\mathbf{r})\} \curvearrowleft \mathcal{B}\left(N_{\mathrm{h}}^{i\,\mathrm{ref}} \mid \Theta^{i}_{\mathrm{dm}} = \Theta^{i}_{\alpha\mathrm{dm}}(\mathbf{r})\right),$$

Transfer function and Metropolis-Hasting (MH) selection criteria for kernel $\mathcal{K}$ at each wavenumber k

$$\mathcal{T}_i^{\alpha}(k) \equiv \frac{P_{\mathrm{h}}^{i\,\mathrm{ref}}(k)}{P^{\alpha}_{i\,\mathrm{h}}(k)}, \qquad \omega_i^{(\alpha)}(k) \equiv \begin{cases} \mathcal{T}_i^{\alpha}(k) & \text{if } MH = 1 \\ 1 & \text{if } MH = 0, \end{cases} \qquad \mathcal{K}_i^{(\alpha)}(k) = \prod_{\ell=1}^{\ell=\alpha} \omega_i^{(\ell)}(k)$$

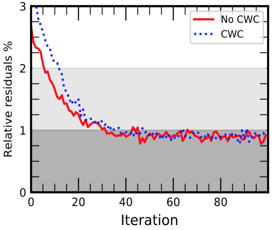
BAM's flow chart: calibration procedure



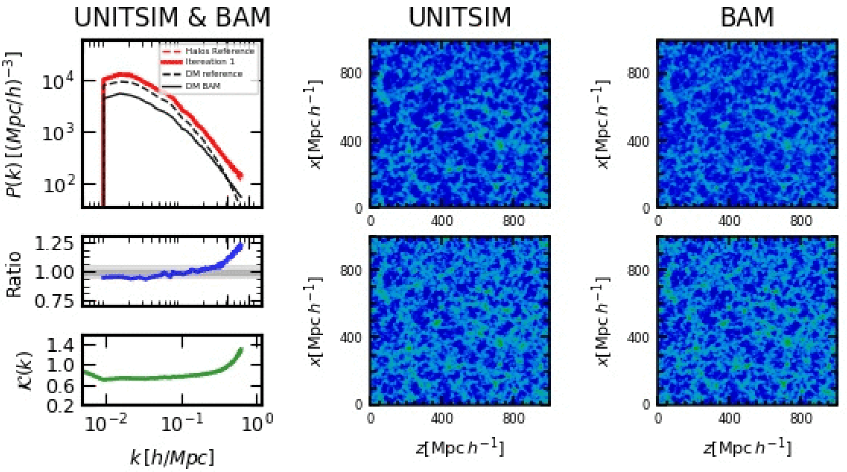
Convergence criteria based on power spectra

$$\mathrm{Res} = \frac{100}{N_\mathrm{F}} \sum_j \left| \frac{P^{i\,\mathrm{ref}}_\mathrm{h}(k_j)}{P^{\alpha}_{i\,\mathrm{h}}(k_j)} - 1 \right| \leq 1\%$$

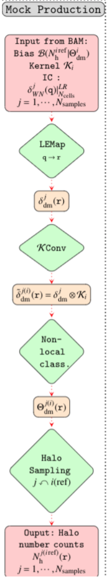
achieved in $\sim$ 50 iterations



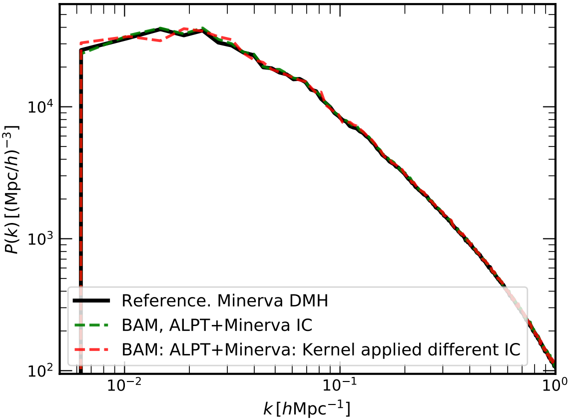
Calibration with the UNIT simulation



Generation of new mock



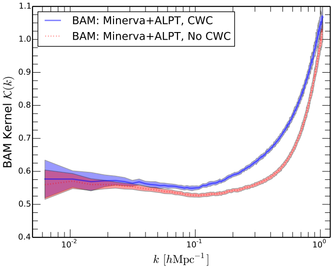
Apply bias and Kernel onto a new IC evolved with an approximated method:



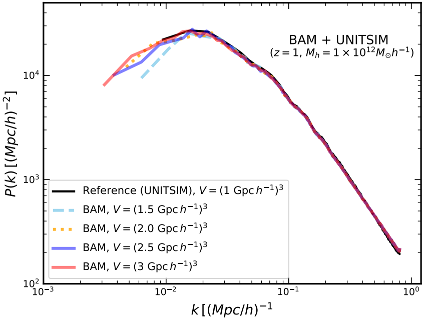
BAM towards larger volumes

Extrapolation of the kernel to smaller wave-numbers allows to generate larger volumes

Shape of the BAM Kernel (from the Minerva sims.). Constant on large scales



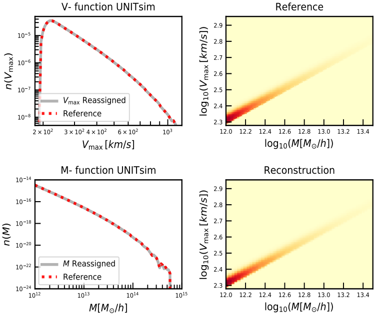
Extrapolation to larger volumes (example with the UNITsim)
Balaguera, Kitaura et al., in prep



Ideally, BAM can use one pair-fixed amplitude simulation (e.g. the UNITsim) (Angulo & Ponzen 2016, Chuang et al 2016, Villaescusa-Navarro et al. 2018) to reduce cosmic variance and obtain smooth kernels on large scales.

Halo properties

Reconstruction of $V_{\rm max}$ and Halo-mass



Use $V_{\rm max}$ as main mass-proxy (Cheng Z. et al. 2016; Zehavi et al. 2019)

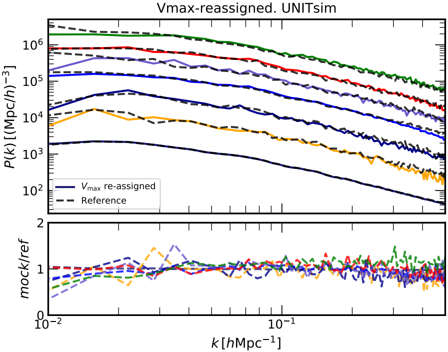
$$V_{\rm max} \curvearrowleft \mathcal{P}(V_{\rm max}|\Theta_{\rm dm})$$

Other properties can be assigned from reference scaling relation

$$M \curvearrowleft \mathcal{P}(M|V_{\rm max},\Theta_{\rm dm})$$

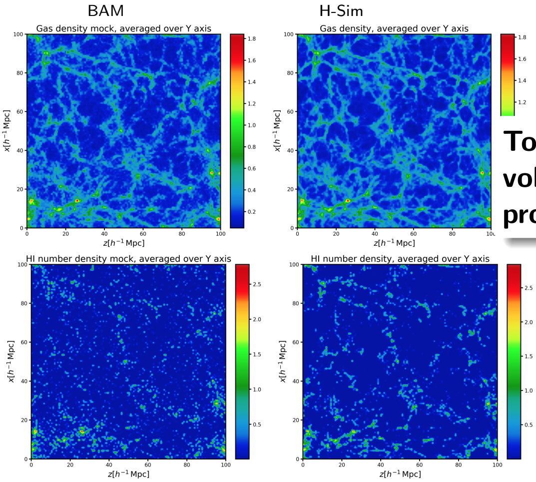
$$R_s \curvearrowleft \mathcal{P}(R_s|M,V_{\rm max},\Theta_{\rm dm})\cdots$$

Clustering in bins of $V_{\rm max}$



Balaguera, Kitaura et al., in prep

BAM applied to hydro-simulations



Towards cosmological volumes with gas properties

- ⋆ Mock catalogs with gas-properties by learning from hydro-simulations and extrapolating to larger volumes.
- ⋆ Example Hydro-simulations with (SPH) code, (GADGET3-OSAKA) (Shimizu et al. 2019, Aoyama et al. 2018)
- ⋆ BAM replicates Gas temperature, HI-density

Simulation provided by K. Nagamine (Osaka Univ).
Kitaura, Sánchez, Nagamine, Balaguera, in prep

Summary

Why BAM for mocks?

- BAM captures (almost) all properties of halo-bias.
- Speed: few ($\sim 50 - 80$) iterations for calibration. For 500^3 (160^3) mesh, iteration takes ~ 30 (~ 5) secs (8 cores).
- Calibration does not depend on the accuracy of the approximated gravity solver with respect to $N-$body DM clustering.
- Accurate covariance matrices for clustering of dark matter haloes. Pushing towards the same precision for galaxies.