Mon. Not. R. Astron. Soc. **000**, 1–3 (2015) Printed 12 March 2015 (MN LATEX style file v2.2)

Galaxy-dark matter offsets in galaxy clusters and groups of the Illustris simulation

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arXiv

ABSTRACT
Being able to find the center of the dark matter component of a galaxy cluster or group enables correct stacking and mass estimation if any parametric halo profile is employed.

Key words: galaxy clusters, dark matter, something else

1 INTRODUCTION

Galaxies that belongs to a galaxy cluster or group are stochastic samples of the underlying dark matter mass density.

We look for summary statistic that would have the least biased estimate of the dark matter density peak. For stacking the different sets of data, find a good proxy for the dark matter density peak is important for the peak not to be smoothed out.

2 DATA

2.1 Test data from Gaussian mixture(s)

In order to examine the performance of commonly used point-estimates of the distribution of the galaxy data, we test them on Gaussian mixtures with known mean and variance.
Fig 1. one Normal mixture
Fig 2. one big normal mixture and one smaller normal mixture
Fig 3. bridged normal mixtures

We provide all the code and data of these test in our Bitbucket repository for comparison purposes for point estimator not listed.

2.2 Data from the Illustris simulation

2.2.1 Properties of the galaxy clusters / groups

Most important properties of the galaxy clusters that we examine in this study include, colors, magnitude, richness, concentration and non-relaxedness. We define and examined these properties one by one. Fig 4. Relaxedness Fig 5.

Richness characterizes the number of galaxies in a given cluster. We provide several definitions of non-relaxedness to characterize whether the clusters underwent any recent merger activities. These definitions of non-relaxedness. The Shapiro-Wilk statistic can characterize the deviation from normality with the highest statistical power ().

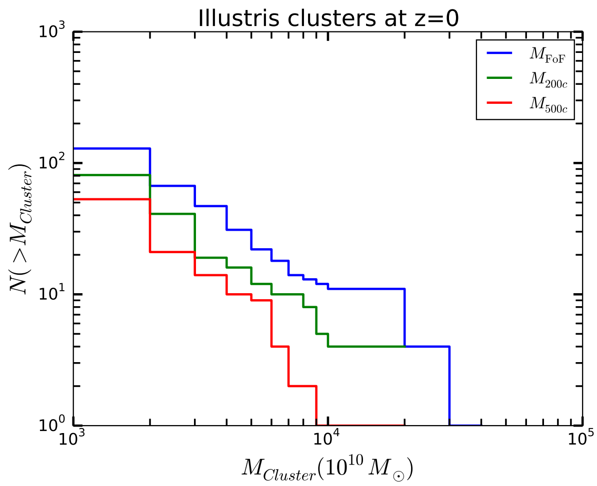

Figure 1.

2.2.2 Volume Selection

1. Rockstar halo finder 2. Light cone 3. spatial projections

2.2.3 Galaxy Selection

2.2.4 Galaxy weights

2.2.5 Data with and without noise

1. Mass-richness diagram - with different cuts

3 METHODS

3.1 Galaxy Centers

3.1.1 Unweighted and weighted centroids

We follow the usual definition of spatial centroid as

$$\vec{x} = \frac{1}{n}\sum_i \vec{x}_i. \tag{1}$$

While the weighted centroids are just:

$$\vec{x}_w = \frac{\sum_i w_i \vec{x}_i}{\sum_i w_i}, \tag{2}$$

for each spatial dimension and the weights w_i for the $i-th$ galaxy is described in section. Centroids and weighted centroids can be biased by merging activities yet do not provide explicit evidence for ongoing merger or accretion.

3.1.2 Cross-validated Kernel Density Estimation (KDE) and the peak finder

We employed a KDE algorithm to infer a smooth density distribution of the galaxies while using smoothed cross-validation to obtain the optimal smoothing bandwidth matrices (H). Specifically, we made use of the KDE function in the statistical package ks (Duong) in the R statistical computing environment (R Core Team 2014). Cross validation eliminates free parameters in the KDE and minimizes the asymptotic mean-integrated squared error (AMISE) for a best fit to the data. After obtaining the KDE estimate, we employed a finite differencing algorithm to find the local maxima. We sorted the local maxima according to the KDE density at the maxima locations and identified the dominant peak.

3.1.3 Shrinking aperture

Another method that is popular among astronomers for summarizing a spatial distribution include what we call a shrinking aperture method. This method is dependent on the initial location of the aperture.

Data: subhalo that satisfy cuts as a galaxy

```
initial˙center = mean(data_array)
dist_array = euclidean˙dist(initial˙center, data˙array)
apert = get_90th_percentile(dist_array)
while (newCenterDist - oldCenterDist) / oldCenterDist ≥ 2e-2 do
    new data array = old data array within apert
    newCenter = mean value of new data along each spatial dimension
end
```

Algorithm 1: Shrinking aperture algorithm

3.1.4 Brightest Cluster Galaxies (BCG)

From the provided

3.2 DM Centers

3.3 Finding offsets

We computed the projected offsets between the galaxy density peaks inferred from the cross-validated KDE and the dark matter density peak. (TBD) The viewing angles of the projections are defined by an elevation angle ξ and an azimuthal angle ϕ. We sample at 5 evenly spaced values of ξ where $0 \leq \xi \leq \pi/2$ and 10 evenly spaced values of ϕ where $0 \leq \phi \leq \pi$, to give 50 samples for each cluster with mass $> 10^{14} M_\odot$.

This method gives us samples of the joint distribution:

$$P(\Delta\eta, \phi, \xi, h_{mer}, \psi_g, \psi_D, I_g, I_D | \theta, \sigma_{CDM}). \tag{3}$$

Binning the samples based on $\Delta\eta$ and h_{mer} only gives us the marginal distribution:

$$P(\Delta\eta, h_{mer} | \theta, \sigma_{CDM}), \tag{4}$$

that we have far too few samples of ...

4 RESULTS

4.1 Benchmark results from Gaussian mixtures

(We expect some of the existing point-estimates are quite crappy e.g. the shrinking aperture method, and will not use them for the Illustris data)

4.2 Galaxy-DM Offset in Illustris

4.2.1 Projected offsets

4.2.2 Correlations between the offsets and properties of the cluster / groups

5 DISCUSSION

5.1 Comparison to other simulations

5.2 Comparison to other observational studies

5.3 Galaxy-DM Offset in Merging Galaxy Clusters

6 ACKNOWLEDGEMENTS

APPENDIX A: KDE

This paper has been typeset from a TEX/ LATEX file prepared by the author.