MAXIMUM LIKELIHOOD DEPROJECTION OF CLJ1226.9 WITH NIKA

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ABSTRACT

We explore the ability to deproject SZ maps into non parametric pressure profiles. Keywords: galaxy clusters: individual: CLJ1226.9+3352

1. INTRODUCTION

2. MAXIMUM LIKELIHOOD DEPROJECTION TECHNIQUE WITH NIKA

2.1. Overview

Deproction by maximum likelihood is simply a fitting routine which models a cluster with N individual pressure bins. That is, the pressure bins (spherical shells) are integrated along the line of sight, converted to a Compton y map, on the sky. This map is then convolved with the instrument's beam and transfer function.

We start with NIKA data, as it has the strongest map significance (and overall detection significance) to get a sense of how our technique performs. In Figure 3, we have fit our (projected) pressure shells to a virtual map (a model from a previous study, plus noise).

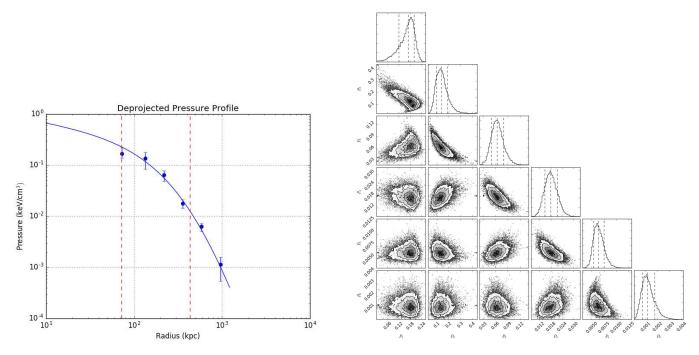


Figure 1. Our maximum likelihood fits to NIKA virtual data. We used 6 bins, 2500 steps, 250 of which were burn in. 30 walkers were used. No mean level was fit. The error bars on the second bin appears much large than it should be. However, it could also be that the error bar on the first bin is artificially small.

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Two problems which we are currently trying to resolve are:

- 1. Error bars don't appear accurate to be accurate.
- 2. Profile fits at large radii in NIKA (and Bolocam) had, at some point, been too large.

Some potential issues to be (double) checked:

- 1. Is the point source being subtracted
 - Yes, as a simple Gaussian.
- 2. Do we need to account for a mean level?
 - Maybe, but I think the below analysis says this is not the "right" way to do it.

What's left to be considered are:

- 1. Using Planck constraints
 - I think this is the best approach.
- 2. Restricting the outer profile but some other prior (going to "zero" at some radius).
 - I don't like it, and I don't think it'd work, but it is a last resort.

2.2. Mean Level

Similar to Czakon et al. (2015), we wish to account for a mean level (signal offset) in the MUSTANG maps. We do not wish to fit for a mean level simultaneously as a bulk component given the degeneracies. Therefore, to determine the mean level independent of the other components, we create a MUSTANG noise map and calculate the mean within the inner arcminute for each cluster. This mean is then subtracted before the other components are fit.

2.2.1. Point Sources

For MUSTANG, point sources are treated in the same manner as in Romero et al. (2015). A point source is identified by NIKA (Adam et al. 2015) in CLJ1226, which is posited to be a submillimeter galaxy (SMG) behind the cluster. We fix the point source amplitude in the NIKA map to that found in Adam et al. (2015). As of November 2016, the point source subtraction and beam convolutions are performed with a simple (single) Gaussian. However, we look to use a more accurate beam (probably a double Gaussian).

For the Bolocam image

2.2.2. Centroid

The default centroids used when gridding our bulk ICM component are the ACCEPT centroids. Given the offsets between ACCEPT and Bolocam centroids (Table ??), we perform a second set of fits where we grid the bulk ICM component using the Bolocam centroids. The ACCEPT centroid are taken to be the X-ray peaks unless their centroiding algorithm produced a centroid more than 70 kpc from the X-ray peak, in which case they adopt that centroid (Cavagnolo et al. 2008).

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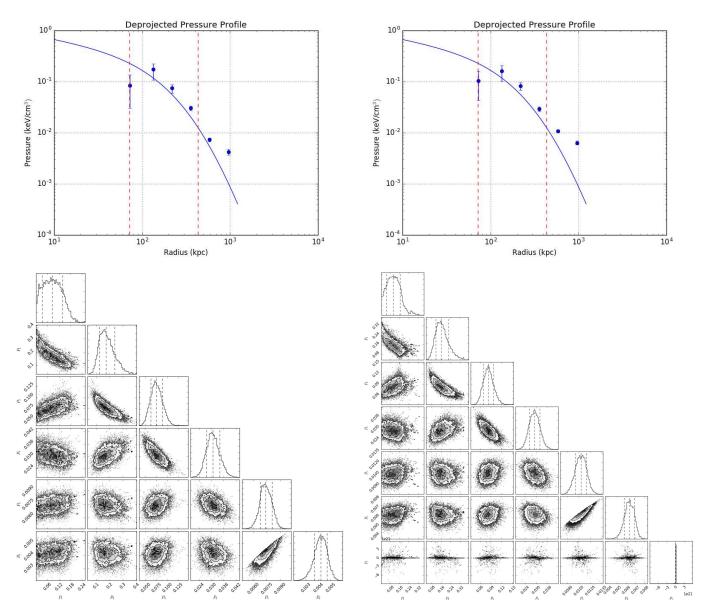


Figure 2. Deprojected results when fitting to real NIKA data. Here we used 6 bins, 2000-3000 steps, 250-500 of which were burn-in steps, and 30 walkers. The left panels show results to NIKA (real) data with no mean level subtraction. The right panels show the same results, but with a fitted mean level.

2.3. Extra Confusion

Ah, but why do the fits change so much on the virtual data when I try to fit a mean level??? This should suggest that the problem is with the fitting algorithm somehow. But...how? And why (as evidenced in Section 2.4) is it such a problem for NIKA as compared to MUSTANG or Bolocam?

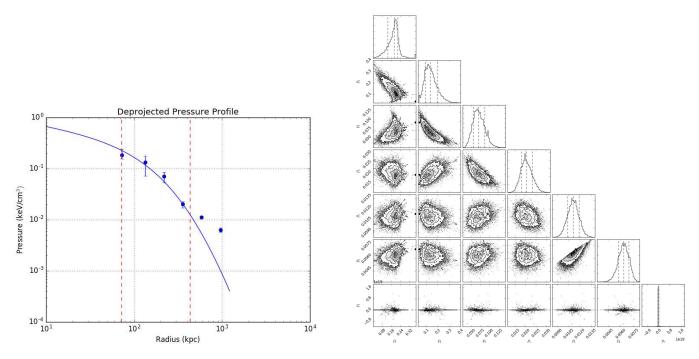


Figure 3. Deprojected results when fitting to virtual NIKA data. Here we used 6 bins, 2400 steps, 400 of which were burn-in steps, and 30 walkers. This shows the same symptoms as the real data!!! That was unexpected! But then, this strongly points to an issue in the algorithm over an issue in the real data.

$2.4.\ Fits\ with\ MUSTANG\ and\ Bolocam$

2.4.1. MUSTANG

In Figure 4, it is clear that trying to fit for a mean level with MUSTANG data is not appropriate, at least not without any other constraints. The (real) MUSTANG map already has the point source subtracted and the mean level subtracted (see Romero+ 2016 for how the mean level is calculated.)

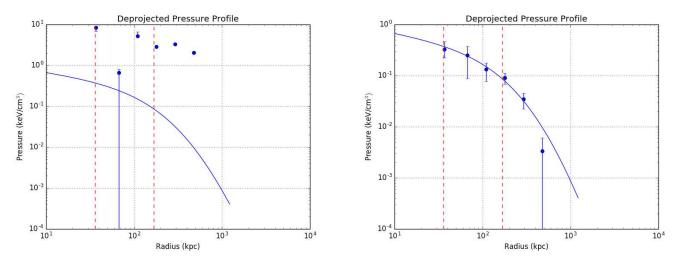


Figure 4. Deprojected MUSTANG results when fit to virtual data. Here we used 6 bins, 2400 steps, 400 of which were burn in, and 30 walkers. The left hand panel shows the deprojected pressure profiles when a mean level is also fit. The right hand side shows the fits without fitting for a mean level.

2.4.2. Bolocam

In Figure 5, we find that fittin for a gmean level with Bolocam data does not appear to be problematic. However, the (real) Bolocam map already has the mean level subtracted (Czakon et al. 2015).

3. AUGMENTED OUTPUTS

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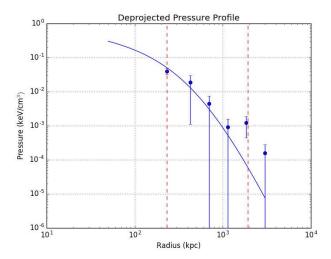


Figure 5. Deprojected Bolocam results when fit to virtual data. Here we used 6 bins, 2400 steps, 400 of which were burn in, and 30 walkers. The left hand panel shows the deprojected pressure profiles when a mean level is also fit. The right hand side shows the fits without fitting for a mean level.

 $\begin{array}{ccccc} 1. & -0.68 & 0.35 & 0.33 \\ -0.68 & 1. & -0.53 & -0.48 \\ 0.35 & -0.53 & 1. & 0.94 \\ 0.33 & -0.48 & 0.94 & 1. \end{array}$

4. COVARIANCE

5. CONCLUSIONS

We developed an algorithm. It requires a lot of testing. It behaves unexepectedly.

REFERENCES

Cavagnolo, K. W., Donahue, M., Voit, G. M., & Sun, M. 2008, ApJ, 682, 821
Czakon, N. G., Sayers, J., Mantz, A., et al. 2015, ApJ, 806, 18
Romero, C., Mason, B. S., Sayers, J., et al. 2015, ArXiv e-prints

Adam, R., Comis, B., Macías-Pérez, J.-F., et al. 2015, A&A, 576, A12