

JoXSZ – Joint X-SZ fitter for galaxy clusters

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Abstract. High-resolution observations of the thermal Sunyaev-Zeldovich (SZ) effect and of the X-ray emission of galaxy clusters are becoming more and more widespread, offering us an unique asset to the study of the thermodynamic properties of the intracluster medium. We present JoXSZ, a Bayesian forward-modelling Python code designed to jointly fit the SZ data and the three dimensional X-ray data cube. JoXSZ is able to derive the thermodynamic profiles of galaxy clusters for the first time making full and consistent use of all the information contained in the observations. JoXSZ will be publicly available on GitHub in the near future.

1. Introduction

Galaxy clusters are the largest and most massive gravitationally bound objects in the Universe, and thus they offer a unique tracer of cosmic evolution. The thermodynamic properties of a galaxy cluster can be gathered from observation in the optical band, the X-ray band or microwaves. While clusters have been extensively studied using X-ray observations since the end of the 70's, radio measurements via the Sunyaev-Zeldovich (SZ) effect became widespread in the last decade (e.g., Birkinshaw & Lancaster 2005; Mroczkowski et al. 2009; Korngut et al. 2011; Sayers et al. 2013; Adam et al. 2015; Romero et al. 2017).

SZ and X-ray observations both encode information about the intracluster medium. Our aim is to provide the first, to the best of our knowledge, publicly available code for jointly fitting the pressure profile of galaxy clusters. JoXSZ, as we named it, is built upon the SZ data fitting pipeline described in PreProFit (Castagna & Andreon 2019, source code available on GitHub at <https://github.com/fcastagna/preprofit>) and an up-dated version of the X-ray data cube fitter MBProj2, originally developed by Sanders et al. (2018). A special attention has been given to highly time-consuming operations, since a joint fit is notoriously slow (e.g., Ruppin et al. 2019).

2. Program flow

As outlined in Fig. 1, the modeling behind JoXSZ relies on the parametrization of three quantities: the pressure profile, described by the generalized Navarro, Frenk & White (gNFW) model (Nagai et al. 2007), the electronic density profile, represented by a modified β -model (Vikhlinin et al. 2006), and the metallicity profile, which is assumed to be flat but let free to vary.

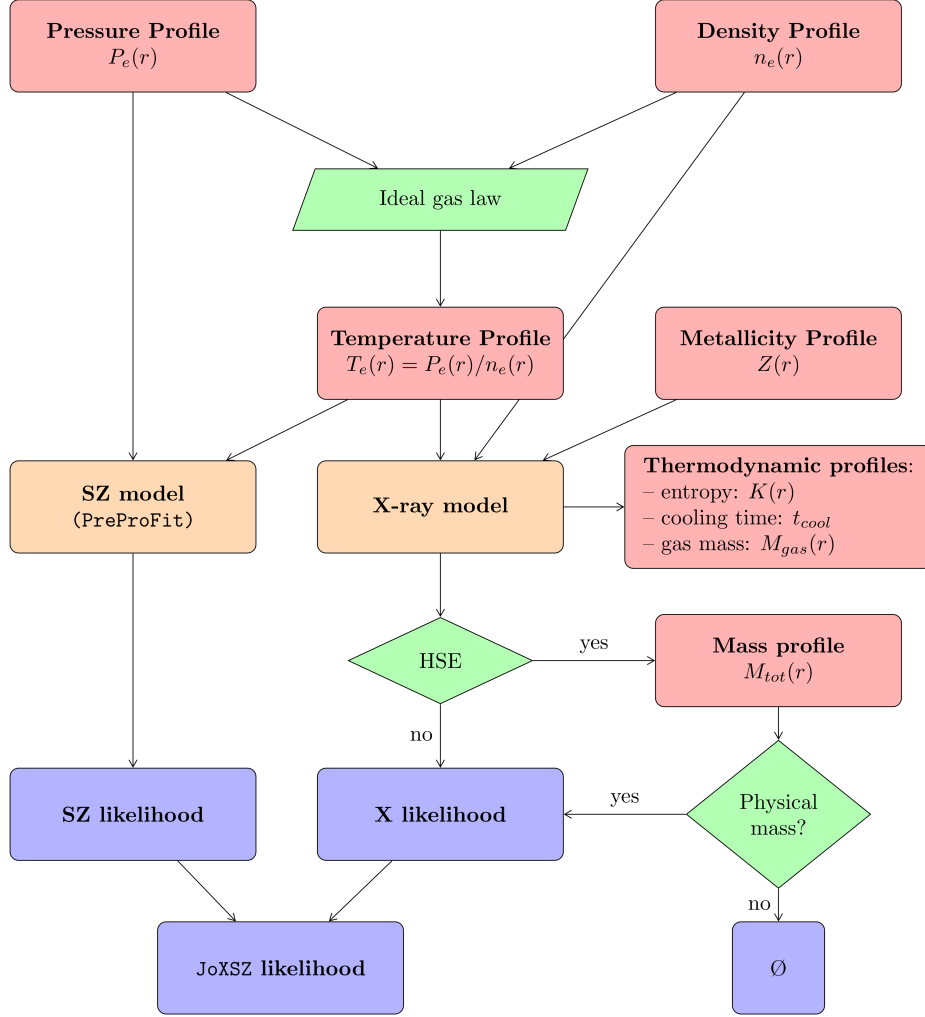


Figure 1. Flow chart of JoXSZ. Figure adapted from Castagna & Andreon in preparation.

The modelization on SZ data, conducted with `PreProFit`, predominantly involves the pressure profile, though the temperature also takes a part. As outlined in Fig. 2, `PreProFit` projects the three-dimensional pressure profile into a two-dimensional map through the forward Abel transform, then convolves the map with the instrumental beam and the transfer function. Finally, the surface brightness profile is derived through opportune temperature-dependent conversion factors, and the fit to the data is measured by way of the likelihood function of the model.

The modelization on X-ray data, conducted with an up-dated version of `MBProj2`, takes into account the metallicity profile, the density profile and the temperature profile derived as the ratio between pressure and density assuming the ideal gas law. `MBProj2` fits surface brightness profiles in multiple X-ray energy bands and automatically computes thermodynamic profiles such as entropy, cooling time and gas mass. Optionally,

our up-dated version of MBProj2 derives the total mass profile under the assumption of hydrostatic equilibrium adopting a positive prior on mass at all radii.

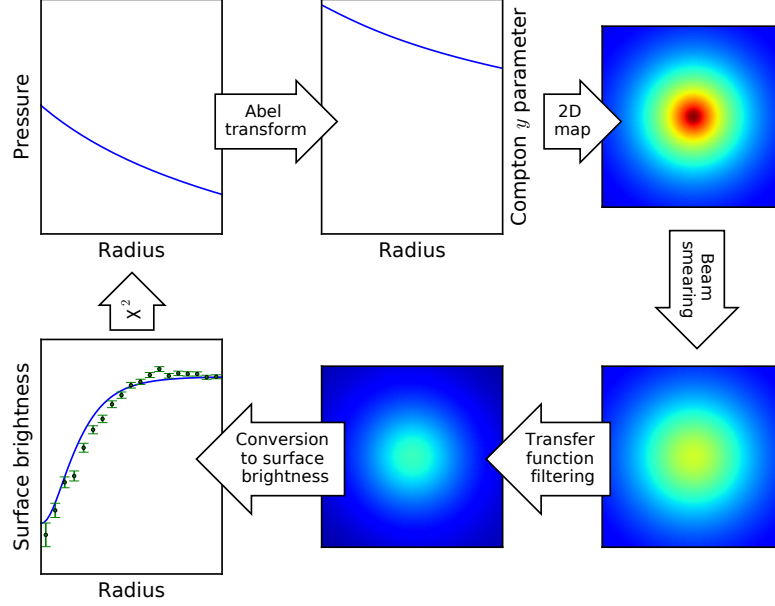


Figure 2. Block diagram describing the program flow of PreProFit. Figure taken from Castagna & Andreon (2019).

3. Functionalities and requirements

JoXSZ relies on a Bayesian forward-modelling approach. The posterior is sampled with *emcee* (Foreman-Mackey et al. 2013) using an affine-invariant ensemble sampler (Goodman & Weare 2010). A large number of parameters are involved, allowing us to fit extremely flexible profiles to the intracluster medium: the gNFW pressure profile has 5 parameters, the Vikhlinin density profile has 7, to which one should add the metallicity Z , the temperature ratio T_{SZ}/T_X and a backscale parameter which controls the scaling of the background. As a result, up to 15 parameters can be fitted. Users can specify the list of parameters to fit and is free to select their prior distributions. The number of random walkers, the number of iterations, the burn-in period extent, and the starting values of the chains can be set by the user as well.

Multi-threading computation is supported by JoXSZ and is strongly encouraged to minimize the time of execution. The SZ model requires the largest amount of execution time (94%): within the SZ section of the program, Abel transform requires 33% of the CPU time, two-dimensional image interpolation 18%, beam smearing 24%, transfer function filtering 23%, and other minor operations account for the remaining 2%.

Qualitative and quantitative diagnostics are both provided by JoXSZ to evaluate the convergence of the chains to the stationary distribution. The acceptance fraction

is reported in the program output, as well as the traceplot and the cornerplot are automatically displayed, informing the user of the parameter evolution across iterations and of the joint posterior distribution, respectively. Users can also visualize the surface brightness profile for the best-fitting values and compare it to the observed data.

JoXSZ has been developed and tested with Python 3.6. The following libraries are required to build: *mbproj2*, *PyAbel*, *numpy*, *scipy*, *astropy*, *emcee*, *six*, *matplotlib*, *corner*. JoXSZ is planned to be publicly released on GitHub(<https://github.com/fcastagna>) at the time of acceptance of the fully referred paper.

4. Conclusion

We have presented JoXSZ, the first publicly available code to perform a joint fit of galaxy clusters on both SZ and X-ray data. JoXSZ is meant to automate and generalize the whole data analysis process in a consistent and easy-to-use software pipeline. It is extensively documented and since it allows the analysis of data coming from different sources, it can be useful to a wide community. JoXSZ adopts a flexible parametrization of pressure, electron density, temperature and metallicity of the cluster, and efficiently fits these quantities following a Bayesian forward-modelling approach. Users are free to set up the program in accordance with their needs and requirements: among other things, to decide how many and which parameters to fit, or which prior to adopt for the free parameters.

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