PANCO2
The second Pipeline for the Analysis of NIKA2 Cluster Observations

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Introduction

- Cluster physics & cosmology need ICM pressure profile measurements
  - High-resolution SZ observations (see talk by L. Perotto)

- NIKA2 LPSZ: 50 clusters to measure pressure profile at high-z with high resolution SZ
  - Need fast and accurate individual pressure profile evaluations

- This work: a new Python software to measure ICM pressure distribution
  - Using bayesian MCMC to fit a pressure profile on an SZ map
  - **Forward modeling approach** that takes into account mm data features
  - **Flexible user inputs:** radial binning, parameter priors, choice of center, …
  - Optimized: uses efficient Python numerical computation libraries, MCMC multithreading

- So far tested on simulations and working on NIKA2 data (see talks by E. Artis, M. Muñoz)
  - Generalization to any instrument in progress
Algorithm

Validation on simulated input & results showcase

Validation on MUSIC hydrodynamical simulations

Conclusions & perspectives
Algorithm flowchart

**Inputs**
- Priors
- Cluster info (z, Y)
- P(r) model

**NIKA2 pipeline outputs**
- Transfer function
- NIKA2 map, noise covariance

**External data (optional)**
- Point source information
- X-ray density profile

**MCMC adjustment**
- NIKAZ map model
- Likelihood P(D | \(\theta\))
- Posterior distribution P(\(\theta | D\))
- MCMC sampling

**Outputs**
- Markov chains: posterior sampled in parameter space
- Pressure profile confidence intervals
- (T, K, M) profiles confidence intervals
- (R500, Y500, M500) confidence intervals
ICM pressure modeling

- Pressure distribution modeled by a pressure profile \( P(r) \)
- Two models implemented:
  - **gNFW:** \( P(r) = P_0 \left( \frac{r}{r_p} \right)^{-c} \left[ 1 + \left( \frac{r}{r_p} \right)^a \right]^{\frac{c-h}{a}} \)
    
    Normalisation \( P_0 \), two slopes \((b, c)\), transition radius \( r_p \) and sharpness \( a \)
  
  - **Binned:** \( P(R_i < r < R_{i+1}) = P_i \left( \frac{r}{R_i} \right)^{-\alpha_i} \)
    
    For \( n \) bins, \( n \) pressure \( P_i \) at radii \( R_i \), and \( \alpha_i = -\log(P_{i+1}/P_i) / \log(R_{i+1}/R_i) \)
    
    Inner and outer slopes (outside bins) are extrapolated
ICM pressure modeling

○ Pressure distribution modeled by a pressure profile $P(r)$

○ Two models implemented:

  • **gNFW:** $P(r) = P_0 (r/r_p)^{-c} \left[1 + (r/r_p)^a\right]^{\frac{c-b}{a}}$
    
    Normalisation $P_0$, two slopes $(b, c)$, transition radius $r_p$ and sharpness $a$

  • **Binned:** $P(R_i < r < R_{i+1}) = P_i (r/R_i)^{-\alpha_i}$
    
    For $n$ bins, $n$ pressure $P_i$ at radii $R_i$, and $\alpha_i = -\frac{\log(P_{i+1}/P_i)}{\log(R_{i+1}/R_i)}$
    
    Inner and outer slopes (outside bins) are extrapolated

○ Advantages and drawbacks:

  **gNFW**

  • widely used
    → easy to compare with literature

  • smooth
    → easy to differentiate and extrapolate

  • restricted shape
    → cannot identify features

  • strongly correlated parameters
    → slow MCMC

  **Binned**

  • less restricted shape
    → can identify features

  • lower parameter correlations
    → faster MCMC

  • not smooth
    → trickier to differentiate and extrapolate

Best model depends on analysis goals
SZ signal modeling

- Pressure profile integrated along the line of sight
  Numerical integration for gNFW, analytical for binned

→ Compton parameter $y$ map
SZ signal modeling

- Pressure profile integrated along the line of sight
  
  \[ \text{Numerical integration for gNFW, analytical for binned} \]

  \[\rightarrow \text{Compton parameter } y \text{ map}\]

- Convolved by the NIKA2 beam (PSF smearing) and transfer function (pipeline filtering)

  \[\rightarrow \text{Filtered (data-like) } y \text{ map}\]
SZ signal modeling

- Pressure profile integrated along the line of sight
  *Numerical integration for gNFW, analytical for binned*
  
  → Compton parameter $y$ map

- Convolved by the **NIKA2 beam** (PSF smearing) and **transfer function** (pipeline filtering)
  
  → Filtered (data-like) $y$ map

- Conversion to surface brightness units
  *Coefficient taken in input, treated as nuisance parameter*
  
  → Filtered, calibrated SZ map
SZ signal modeling

- Pressure profile integrated along the line of sight
  *Numerical integration for gNFW, analytical for binned*

  \[ \rightarrow \text{Compton parameter } y \text{ map} \]

- Convolved by the **NIKA2 beam** (PSF smearing) and **transfer function** (pipeline filtering)

  \[ \rightarrow \text{Filtered (data-like) } y \text{ map} \]

- Conversion to surface brightness units
  *Coefficient taken in input, treated as nuisance parameter*

  \[ \rightarrow \text{Filtered, calibrated SZ map} \]

- (Optional) Point source contamination: point sources with variable fluxes can be part of the model
  *Treated as nuisance parameters; see Keruzore+20*
SZ signal modeling

- Pressure profile integrated along the line of sight
  *Numerical integration for gNFW, analytical for binned*
  \[ \rightarrow \text{Compton parameter } \gamma \text{ map} \]

- Convolved by the **NIKA2 beam** (PSF smearing)
  and **transfer function** (pipeline filtering)
  \[ \rightarrow \text{Filtered (data-like) } \gamma \text{ map} \]

- Conversion to surface brightness units
  *Coefficient taken in input, treated as nuisance parameter*
  \[ \rightarrow \text{Filtered, calibrated SZ map} \]

- (Optional) Point source contamination: point sources with variable fluxes can be part of the model
  *Treated as nuisance parameters; see Keruzore+20*

- Summary — Parameters of the model:
  - Pressure profile parameters
  - Conversion coefficient
  - (optional) Point source fluxes
  - (optional) Map zero level
Model fitting

- Model map from previous slide $M(\vartheta)$ fitted on the data with likelihood function:

$$-2 \log L(\vartheta) = \sum_{\text{pixels}} \left( \frac{D_{\text{NIKA2}} - M(\vartheta)}{\sigma_{\text{NIKA2}}} \right)^2 + \left( \frac{Y^\text{input}_\Delta - Y_\Delta(\vartheta)}{\delta Y^\text{input}_\Delta} \right)^2$$

*Comparison between NIKA2 map $D$ and model map $M(\vartheta)$ (with noise rms map $\sigma$)*

*Constraint on integrated SZ signal from input survey (Planck, ACT)*

$$Y_\Delta(\vartheta) \propto \int_0^{R_\Delta} P_s(r; \vartheta) r^2 dr$$

- A noise covariance matrix can also be included for correlated noise
- Priors on parameters defined by the user $\rightarrow$ posterior distribution
- MCMC sampling of the posterior distribution
  - Convergence check based on Gelman-Rubin and autocorrelation
  - User-defined analysis parameters: # of chains, burn-in length, convergence check parameters
- Once convergence is reached:
  - remove the chains considered unconverged by the convergence check
  - (optional) thinning: keep one point every autocorrelation length

$\rightarrow$ Final chains
Algorithm

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Conclusions & perspectives
Results on simulated input

- Test — run the fit:
  - Of a simulated cluster map
  - With white noise, realistic filtering
  - With constraints on $Y_{500}$
  - With a binned pressure profile
  - Combined with X-ray density profile

- Convergence reached in <10 minutes with 30 chains running on 30 threads

- Example will be included in the public release
Results: Data, model, residuals

Data

Best-fit model

Residuals

Data — Best-fit model

Residuals compatible with noise

Surface brightness [mJy/beam]
Results: Markov chains

$P_0 \ldots P_n$: pressure at radial bins;

Calib: Conversion coefficient;

Zero: map zero level

Chains visually converged
Results: parameter distributions

$P_0 \ldots P_n$: pressure at radial bins;

Calib: Conversion coefficient;

Zero: map zero level
Pressure profile interpolations

- For binned profiles, we need to interpolate the pressure profile between the radial bins.
- Interpolation scheme:
  - Perform interpolation on each pressure profile in the Markov chains
  - Use each profile to estimate quantities of interest (mass, temperature, etc)
  - Infer confidence intervals
- Power-law interpolation gives bumpy profiles, which leads to discontinuities in the mass profiles since $M_{\text{HSE}}(r) \propto \frac{dP}{dr}$
Pressure profile interpolations

- For binned profiles, we need to interpolate the pressure profile between the radial bins.

- Interpolation scheme:
  - Perform interpolation on each pressure profile in the Markov chains
  - Use each profile to estimate quantities of interest (mass, temperature, etc)
  - Infer confidence intervals

- Power-law interpolation gives bumpy profiles, which leads to discontinuities in the mass profiles since $M^{\text{HSE}}(r) \propto \frac{dP}{dr}$

- 3 interpolation methods implemented:
  - Power-law interpolation (linear in log-log) → bumpy profile
  - Spline interpolation (in log-log) → smooth but can give weird extrapolation
  - gNFW fit on each MCMC sample → smooth and “physics motivated”

Best method depends on analysis goals
**Results: pressure profile**

**Pressure profile**

- **NIKA2 binned**
- **NIKA2 power law interp.**
- **Input profile**

**If binned, correlation matrix of the pressure bins**

**Recovered pressure profile in excellent agreement with the true input profile**
Results: Entropy, temperature, mass

If available X-ray density:

X-ray + SZ profiles combination for further thermodynamical properties:

- Temperature $kT_e = P_e / n_e$
- Entropy $K_e = P_e n_e^{-5/3}$
- HSE mass $M^{HSE}(r) = -\frac{1}{G\mu m_p} \frac{r^2}{n_e} \frac{dP_e}{dr}$
Results: integrated quantities

If available X-ray density:

1. Compute overdensity profiles $\delta(r)$ from each mass profile from MCMC chains

2. Solve each profile for $\delta(r) = 500$
   $\rightarrow R_{500}$ value for each MCMC sample
   $\rightarrow$ probability distribution for $R_{500}$

3. For each sample, compute $M(< R_{500}), Y(< R_{500})$
   $\rightarrow M_{500}, Y_{500}$ values for each MCMC sample
   $\rightarrow$ probability distribution for $M_{500}, Y_{500}$
Outline

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**Scope**

- **Goal:** testing on “real life” clusters
- **Data used:** simulated NIKA2 observations of clusters from hydrodynamical simulations
  - Clusters from the MUSIC simulation (Sembolini+13)
  - 32 clusters forming a sample similar to the NIKA2 LPSZ
  - Maps from Ruppin+19: include cluster SZ signal, PSF filtering, transfer function filtering, correlated noise
- **PANCO2 analysis:** fit the pressure profile of the ICM
  - Binned pressure profile
  - From the center of the map (some clusters are off-centered)
  - Taking into account noise covariance matrix
Results examples: $z = 0.54$

Recovered profiles in agreement with true profiles
Results examples: $z = 0.82$

Recovered profiles in agreement with true profiles
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Summary

- **A new software** to fit pressure profiles on SZ maps
  - Takes into account mm data features through forward-modeling
  - Fit done using bayesian MCMC for inference on ICM physical properties
  - Highly customizable analyses
  - Very efficient: most simple analysis ~10 minutes

- **Validated** on simulations
  - Excellent agreement between truth and results for simple simulations
  - Same for complex hydrodynamical simulations

- **Official pipeline** for the NIKA2 SZ Large Program
  - Routinely used for LPSZ analyses
  - Efficient enough for cluster sample analyses

- **Public release**: stay tuned!
  - Generalization to any other instrument in progress
  - Will come with extensive documentation and an accompanying paper

*Many thanks to all beta-testers for their reports and the resulting improvements*