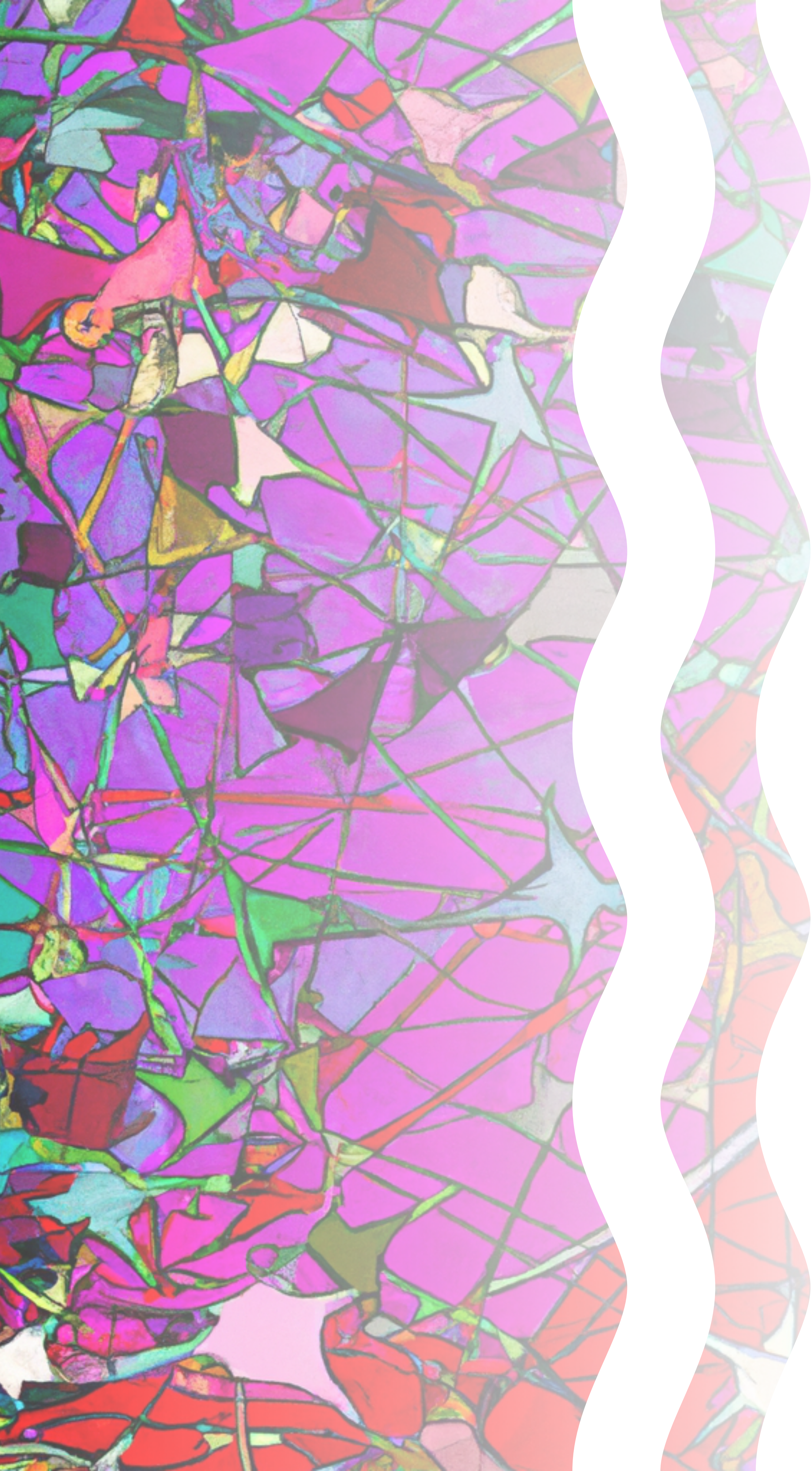


picasso

Painting intra-cluster gas on gravity-only simulations

Model and first data products

Florian Kéruzoré

Argonne National Laboratory

mmUniverse 2025 — June 26th, 2025

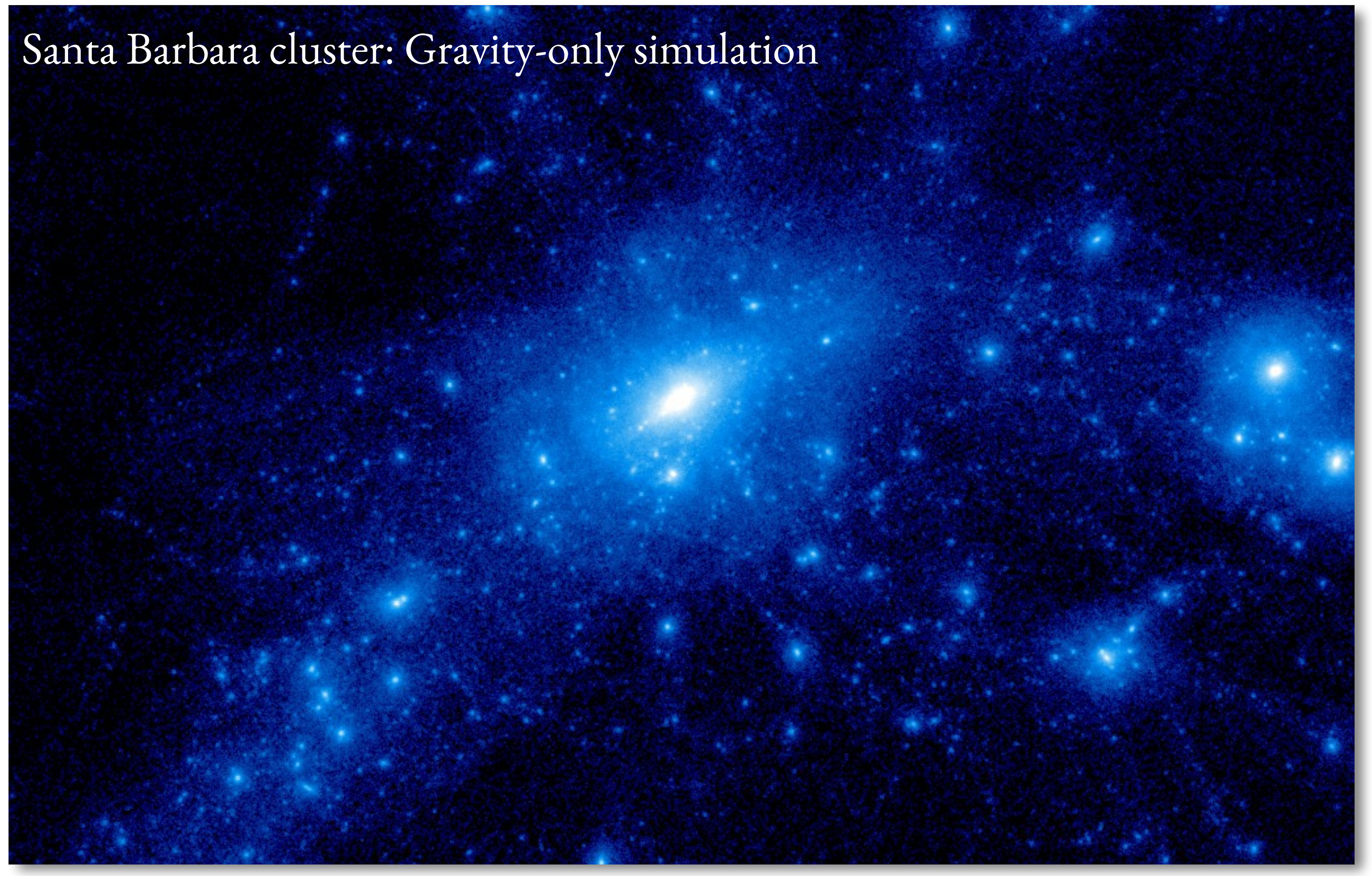
Argonne NATIONAL LABORATORY

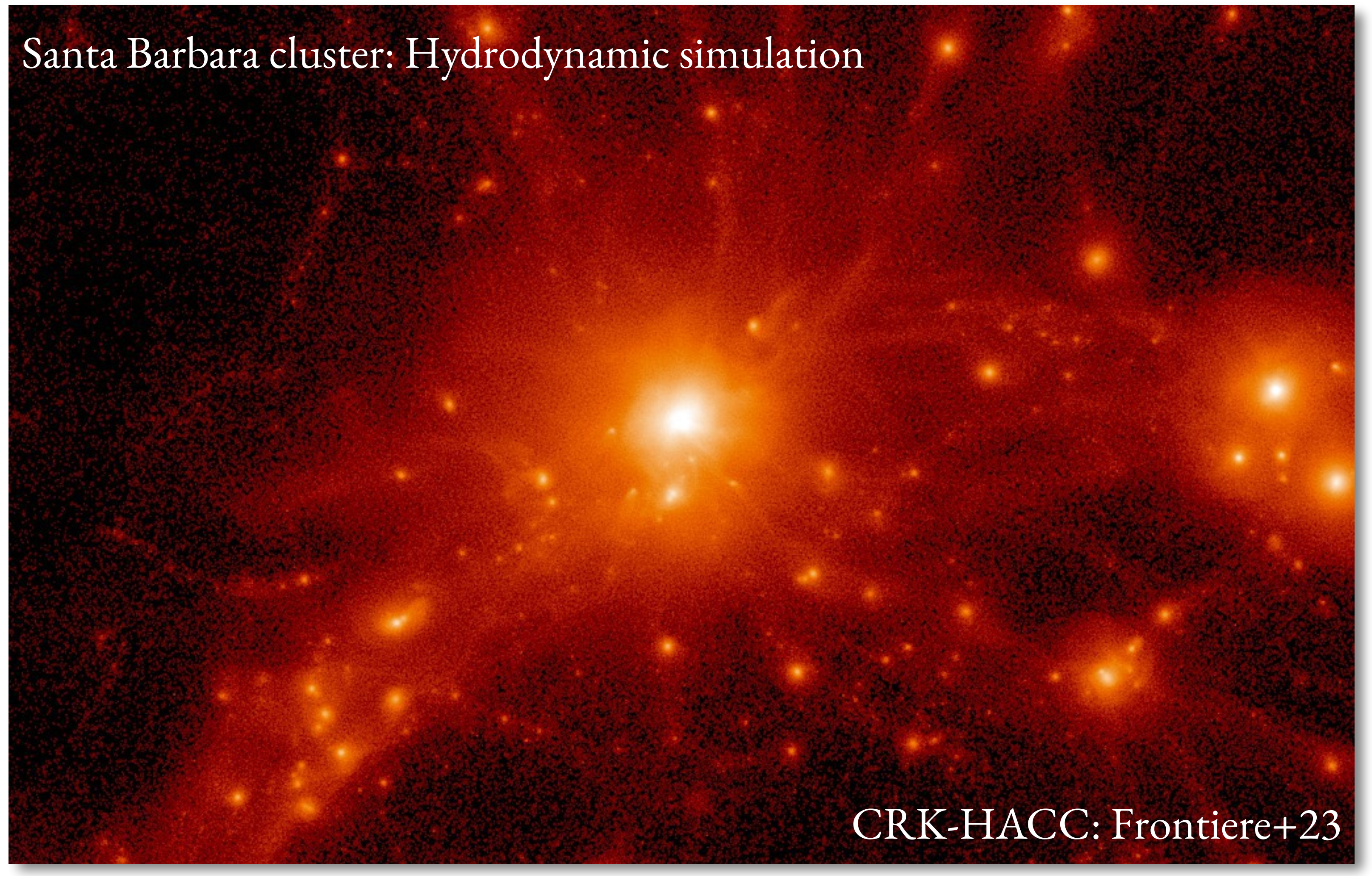
Context

- **tSZ-selected cluster samples = powerful cosmological probe**
  See previous 24 cluster talks

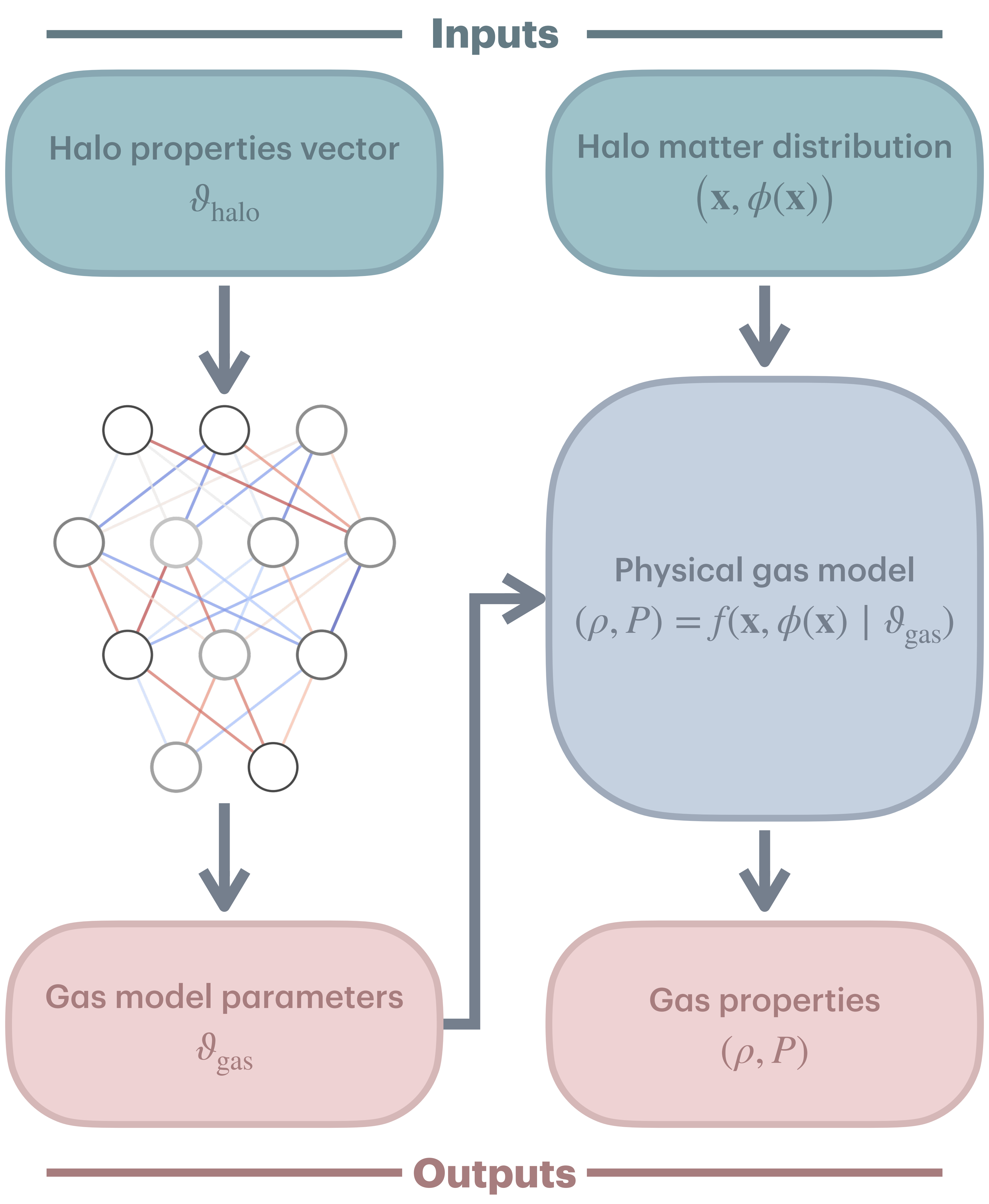
- **Synthetic datasets needed for cluster cosmology**
  See previous 6 simulation talks
  - Using cosmological simulations
  - Two categories:
    - **Hydrodynamic** (include baryonic physics, but slow and uncertain)
    - **Gravity-only / G-O** (fast, but no baryons)

- **Need post-processing to "paint" observables on G-O**
  - In particular intracluster gas for SZ effects @ mm wavelengths



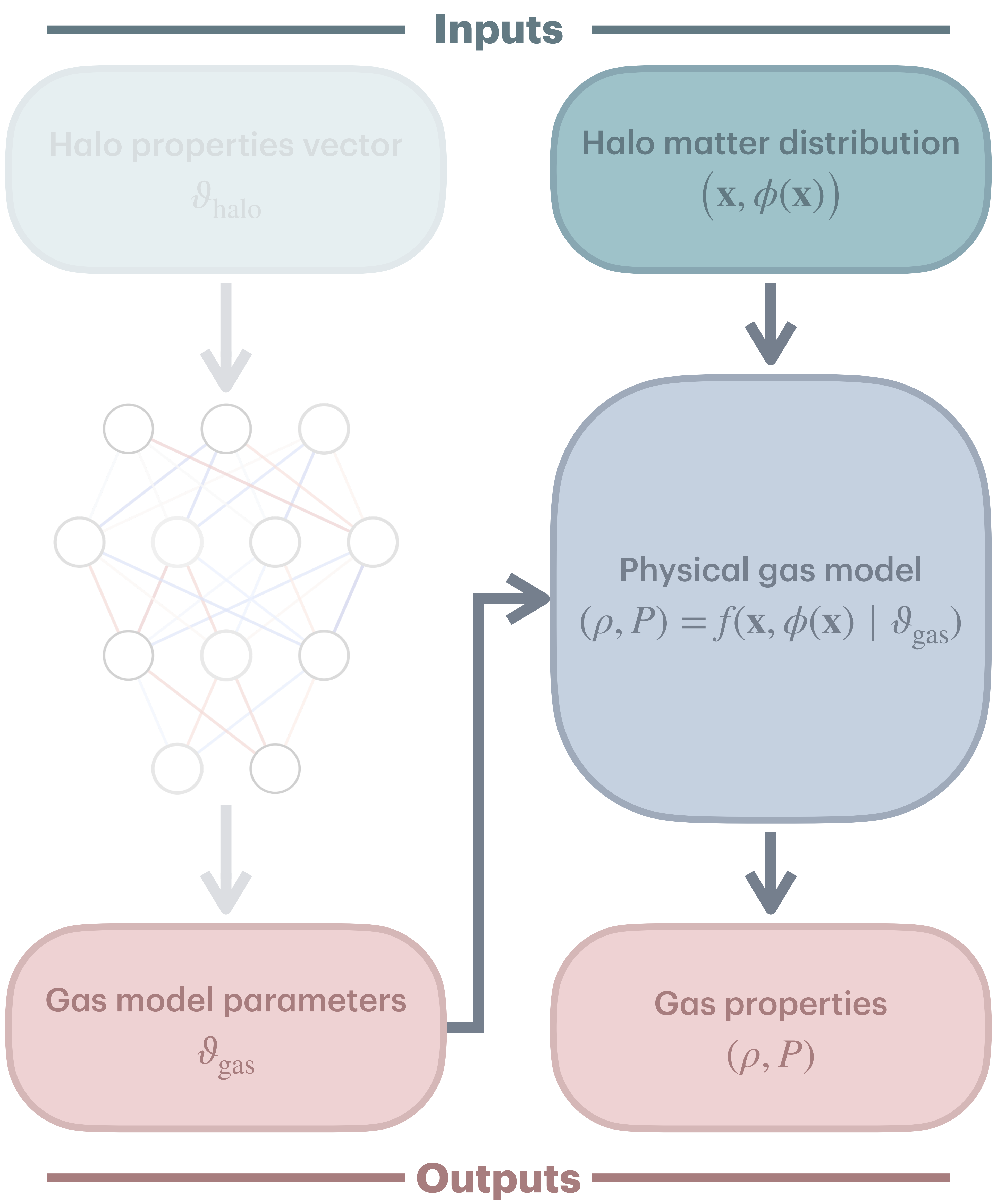


The picasso gas model



- **ML-powered model to “paint” gas on gravity-only halos**
- **Combines:**
  - A parametric gas model: *thermodynamics = f(potential | parameters)*
  - A neural network predicting model parameters

The picasso gas model



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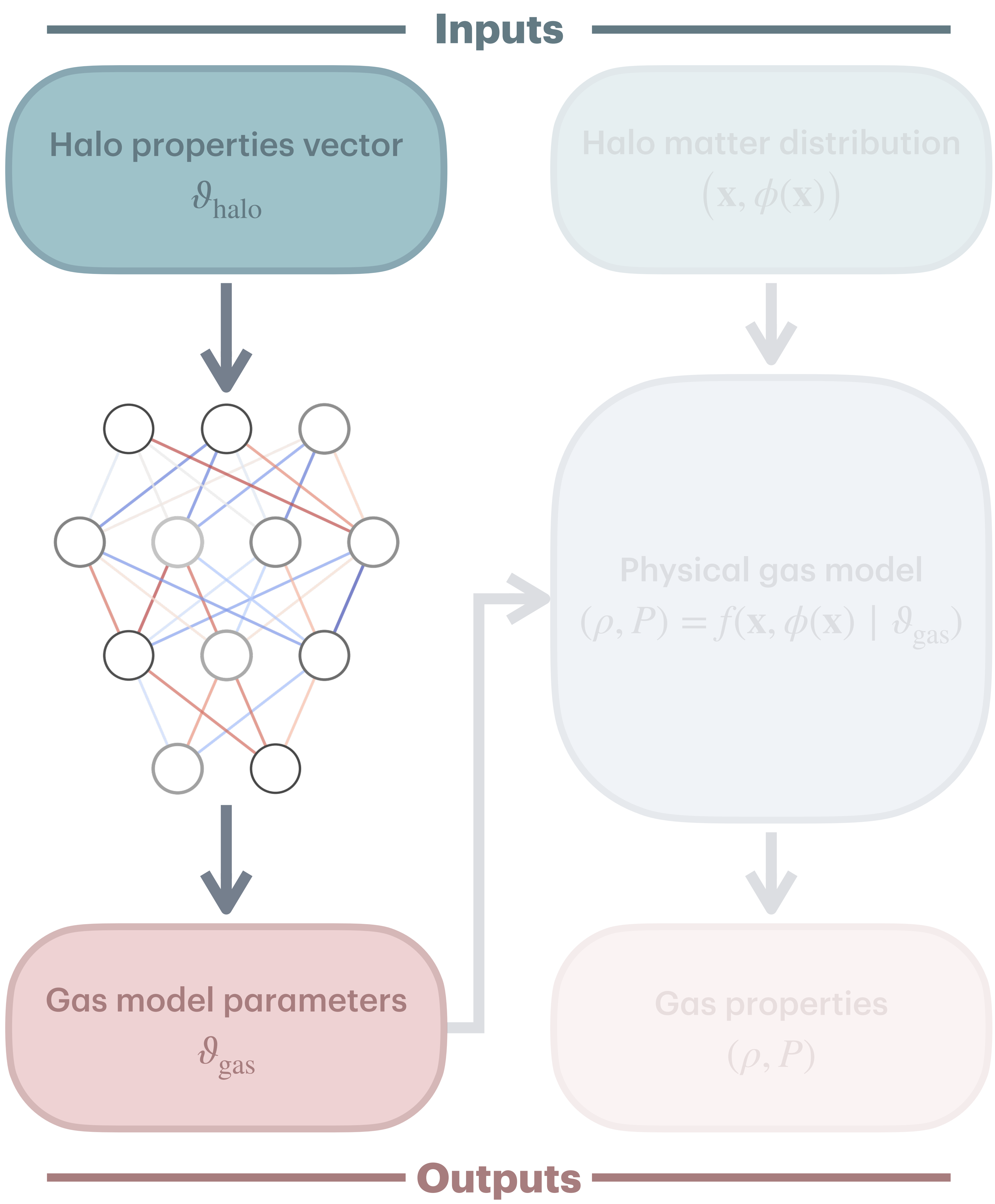

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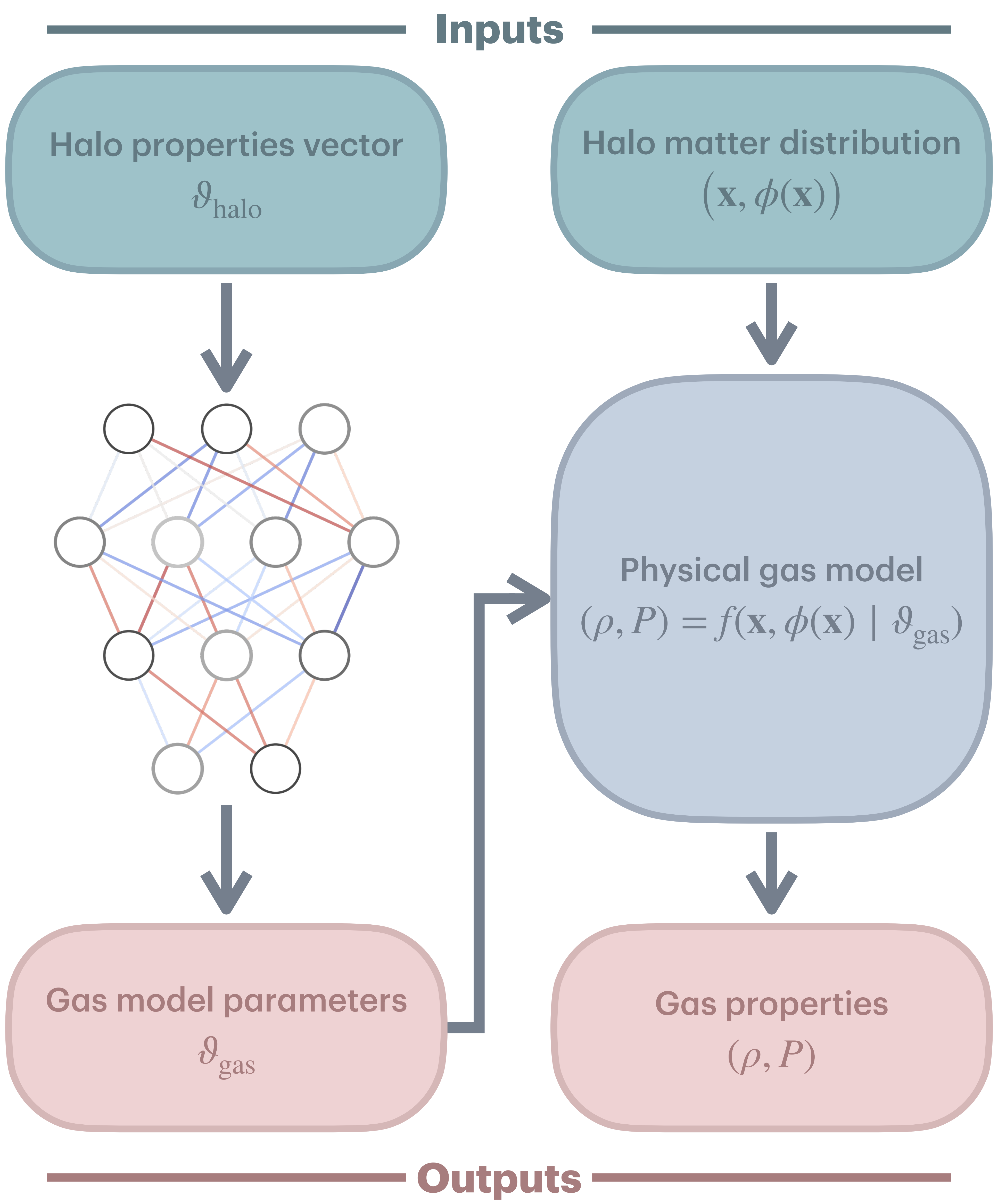
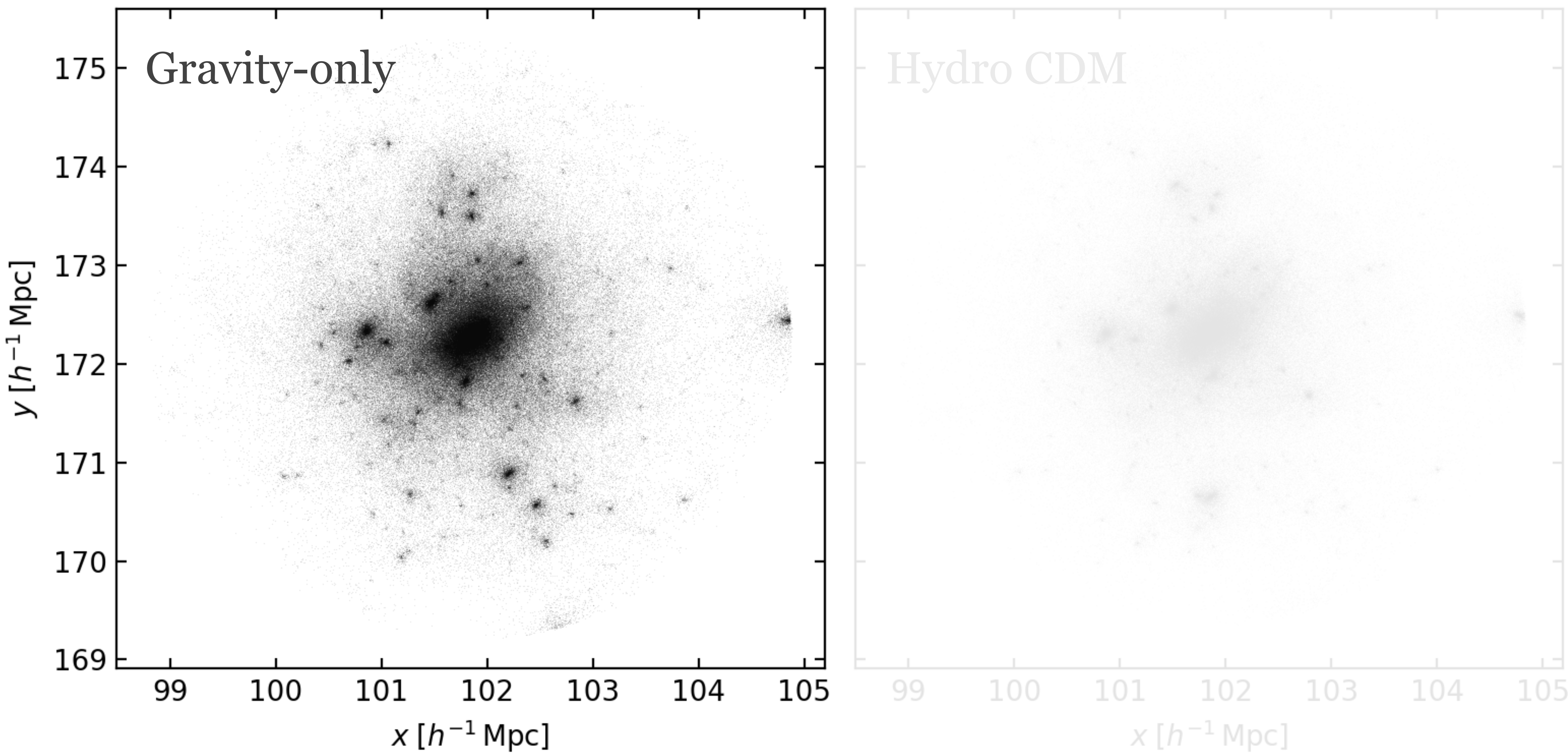


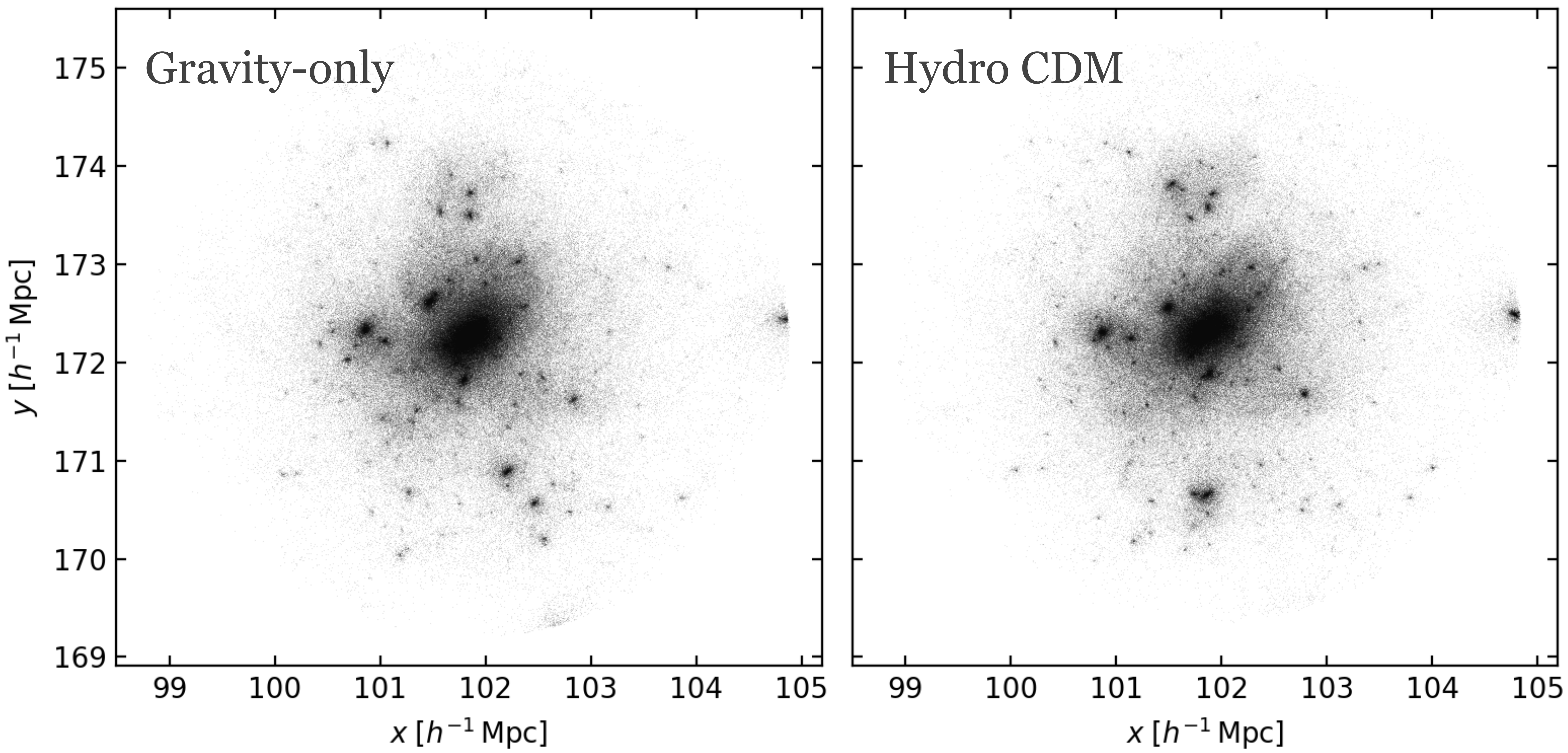
- **ML-powered model to "paint" gas on gravity-only halos**
- **Combines:**
  - A parametric gas model: *thermodynamics* = *f(potential* | *parameters)*
  - A neural network predicting model parameters
- Trained on **pairs of gravity-only / hydrodynamic simulations**
- **Fast, GPU-accelerated, differentiable (JAX)**
- **Publicly available & documented**

Model training: Simulation pairs



- **Training simulation:**
  - $576\ \mathrm{Mpc}/h,\ \gtrsim 10^{10}$ particles
  - Baryon mass resolution: $2 \times 10^{8}\ M_{\odot}/h$
- **Two runs from same initial conditions:**
  - Gravity-only
  - Hydrodynamic
- **Same initial conditions → Same halos!**
- **Target data: Gas properties of hydro halos**
  - For each G-O halo, find hydro counterpart
  - Target = counterpart gas properties

Model training: Simulation pairs



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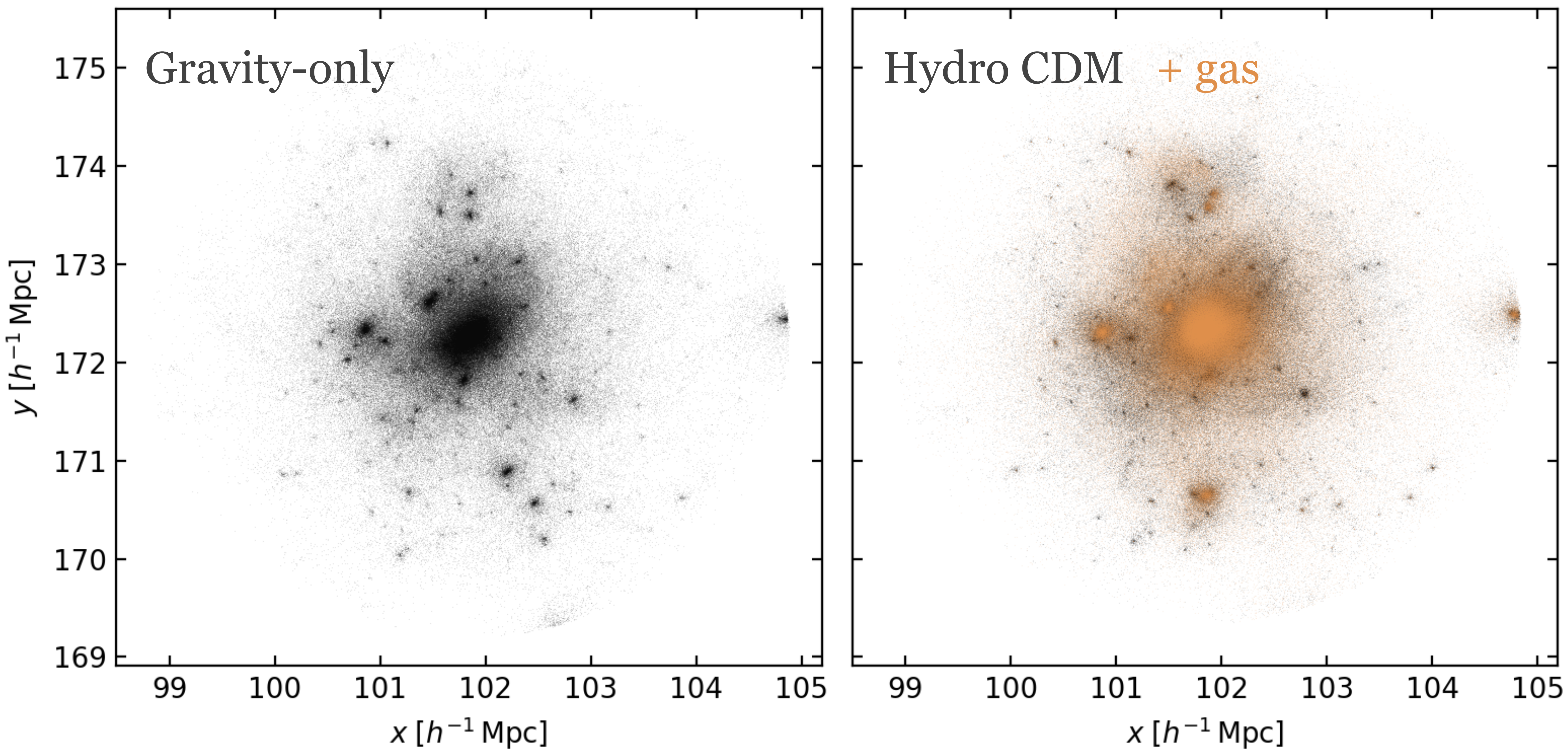

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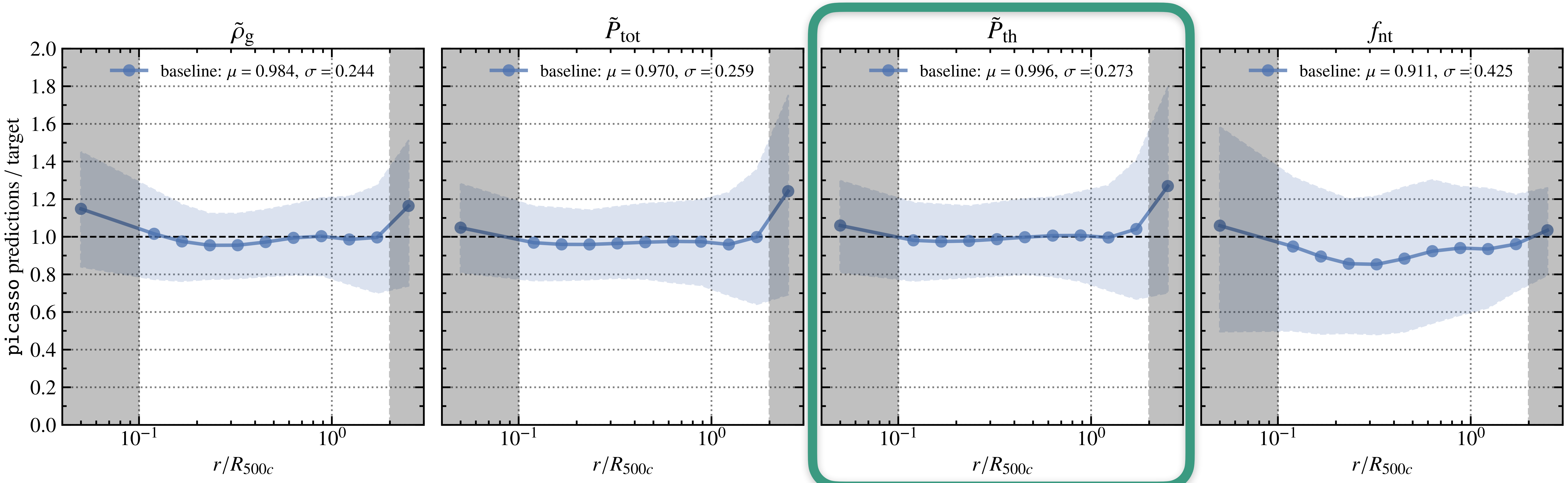
Baseline model results

- **Baseline model: Full input vector**
  All halo properties used to make predictions

- **Results:** for the training range ($r \in [0.1, 2] \times R_{500c}$),
  - **Few-% accuracy** on main property of interest ($P_{\rm th}$)
  - **~20% scatter** similar to "pasting" methods (FK+23)

Symbol	Meaning
$\log_{10}(M_{200c}/10^{14}\,h^{-1}M_\odot)$	(log-scaled) Halo mass
c_{200c}	Halo concentration
$\Delta x/R_{200c}$	Normalized offset between center of mass and potential peak
$c_{\rm acc.}/c_{200c}$	Ratio between accumulated mass and NFW fit concentrations
$c_{\rm peak}/c_{200c}$	Ratio between differential mass profile peak and NFW fit concentrations
e	Halo ellipticity, eq. (13)
p	Halo prolaticity, eq. (13)
$a_{\rm lmm}$	Scale factor of last major merger
a_{25}	Scale factor at which $M = 0.25 \times M_{z=0}$
a_{50}	Scale factor at which $M = 0.50 \times M_{z=0}$
a_{75}	Scale factor at which $M = 0.75 \times M_{z=0}$
$\dot{M}$	Mass accretion rate between last two redshift snapshots

Thermal pressure

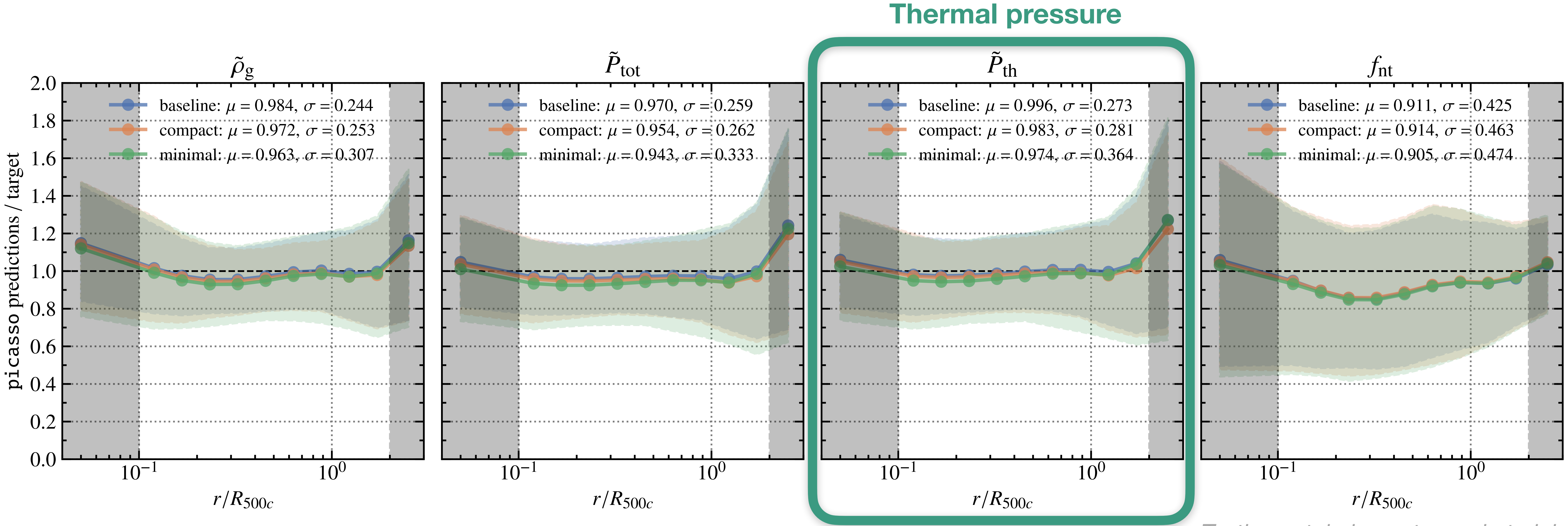


Testing set: halos not seen in training

Compact / minimal model results

- **Compact & Minimal models: Smaller input vectors**
  - **Compact:** No mass assembly history
  - **Minimal:** (M_{200c}, c_{200c}) only
- **Results:**
  - **Compact:** same bias / almost same scatter
  - **Minimal:** almost same bias / larger scatter
  - → Promising: can be used from limited inputs

Symbol	Compact?	Minimal?
$\log_{10}(M_{200c}/10^{14}\,h^{-1}M_\odot)$	✓	✓
c_{200c}	✓	✓
$\Delta x/R_{200c}$	✓	×
$c_{\rm acc.}/c_{200c}$	✓	×
$c_{\rm peak}/c_{200c}$	✓	×
e	✓	×
p	✓	×
$a_{\rm lmm}$	×	×
a_{25}	×	×
a_{50}	×	×
a_{75}	×	×
$\dot{M}$	×	×



Testing set: halos not seen in training

Computational performance assessment

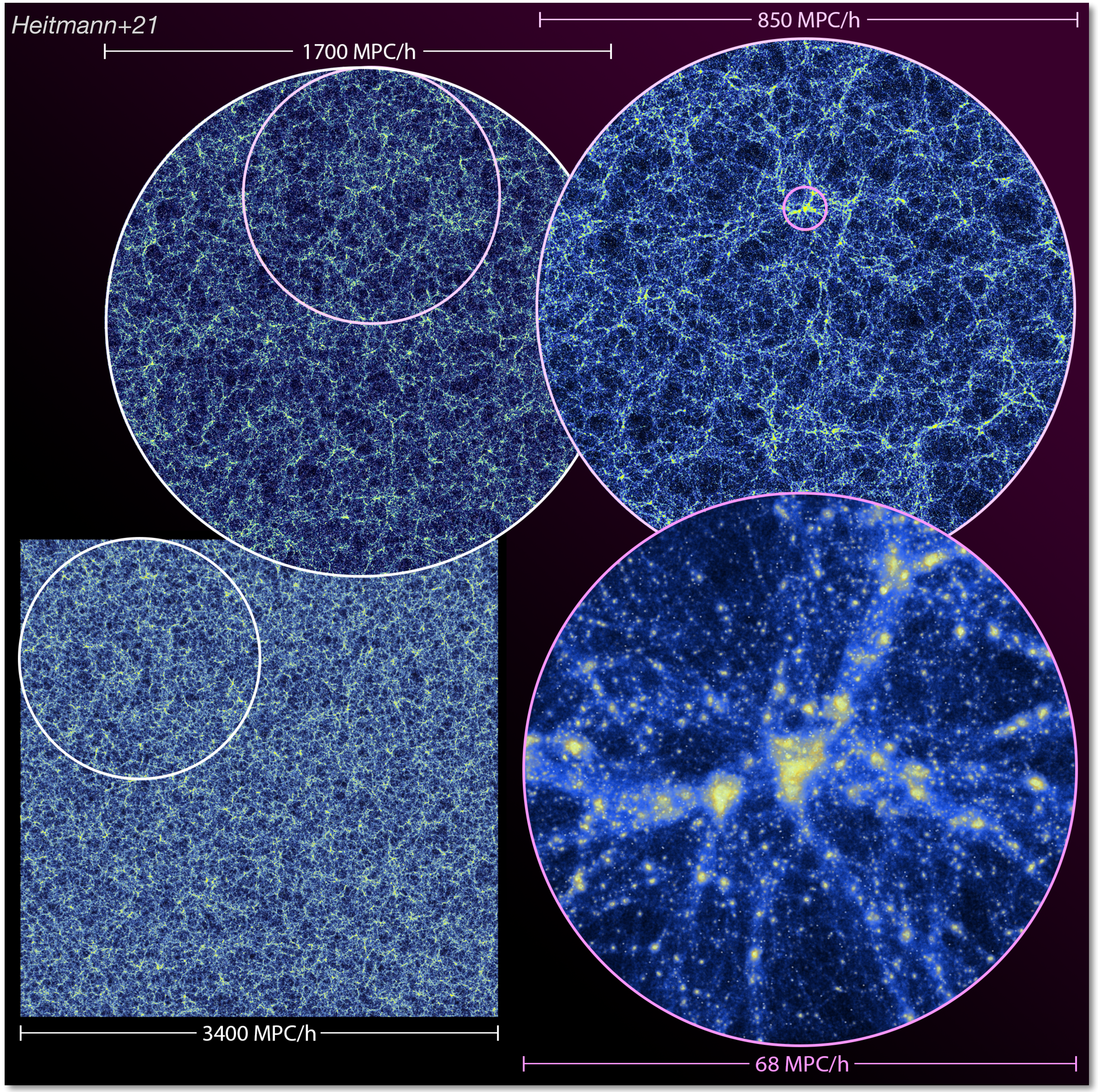
Comparing two painting algorithms on the same problem: painting on potential distribution 3D grid (64^3 cells)

- **"Baryon pasting"** *(As implemented in FK+23)*
  - Fully analytical prescription
  - Gas density + thermal pressure
  - CPU-only
  - Few %-level accuracy, 20% precision
  - Prediction time: 711 ms/halo
- **`picasso`**
  - Parametric model + ML
  - Gas density + pressure + non-therm. pressure
  - CPU+GPU
  - Few %-level accuracy, 20% precision
  - Prediction time: **61 µs/halo**

picasso: Same accuracy and precision, 10^4x faster

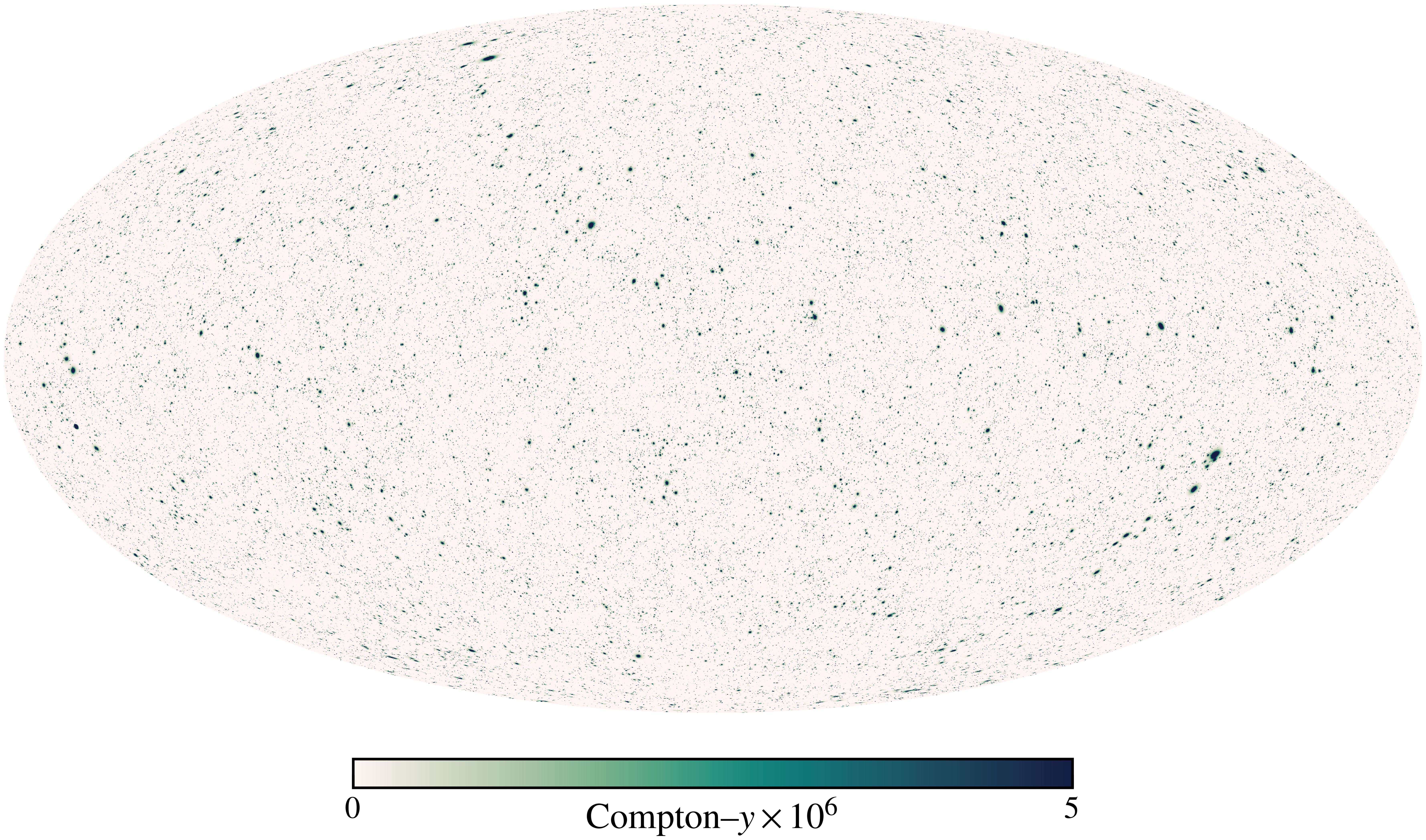
→ Painting on 1,000,000 halos: 20 h → 1 min

Application: picasso-TLJ



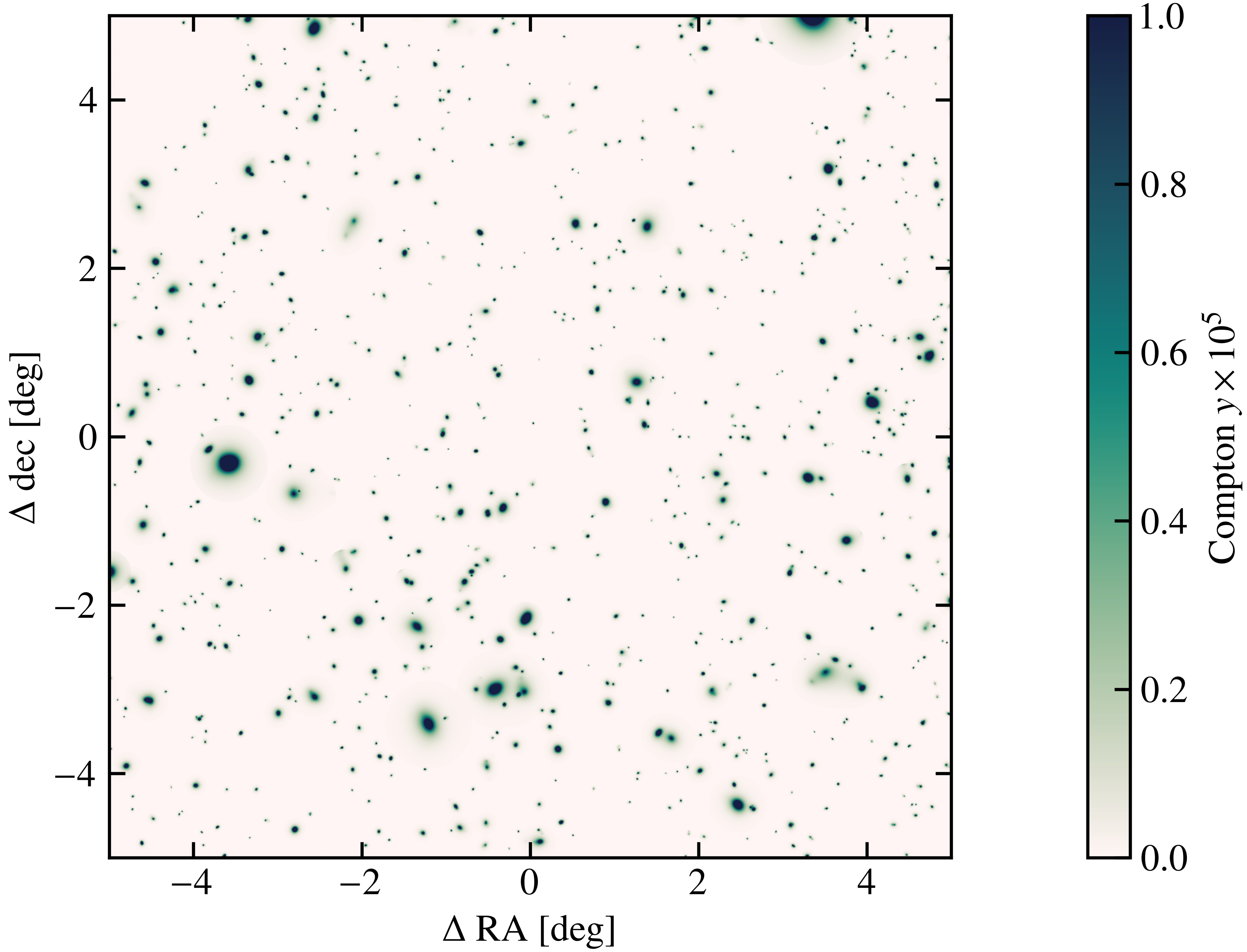
- **The Last Journey simulation (Heitmann+21):**
  - $(3.4\ \mathrm{Gpc}/h)^3$
  - $\gtrsim 10^{12}$ particles ($m \sim 3 \times 10^9\ M_\odot/h$)
  - *Planck* 2018 cosmology
- **Lightcone:**
  - Full lightcone without repetitions up to $z = 2$
  - Full particle output for $M_{200c} > 10^{13}\ M_\odot/h$

picasso-TLJ: tSZ map



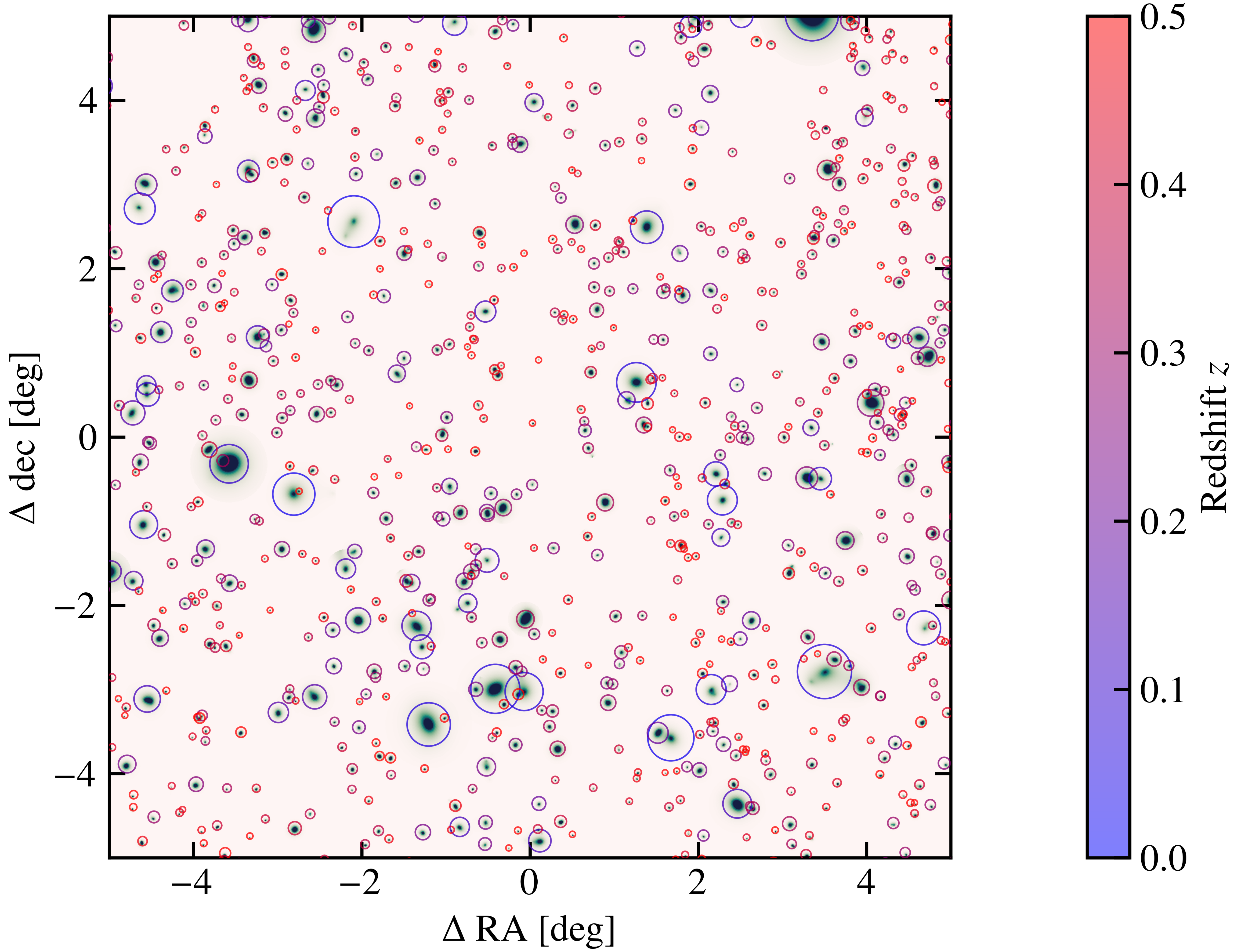
Full-sky (z < 0.5)

picasso-TLJ: tSZ map



Zoom on 100 deg²

picasso-TLJ: tSZ map



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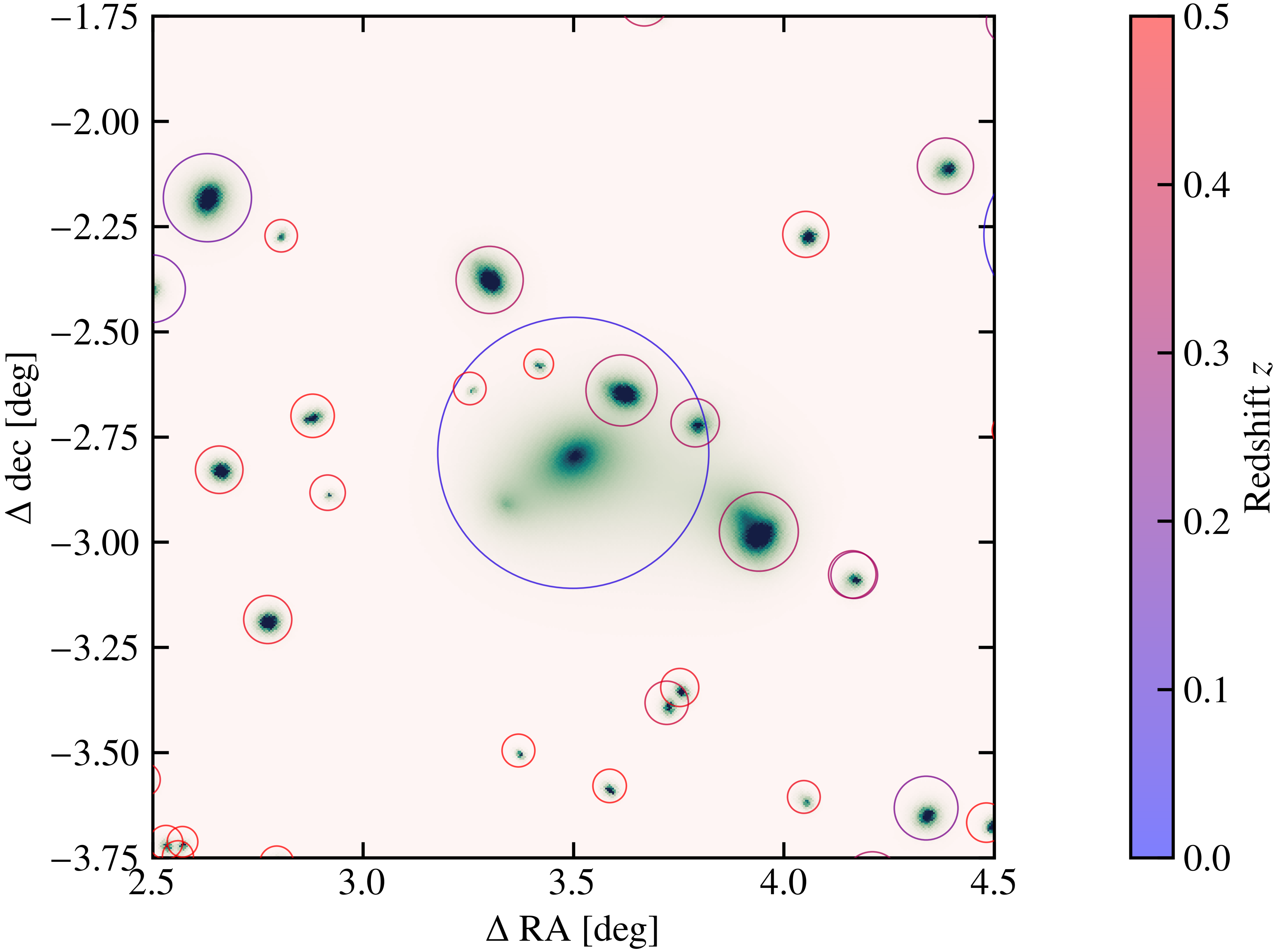
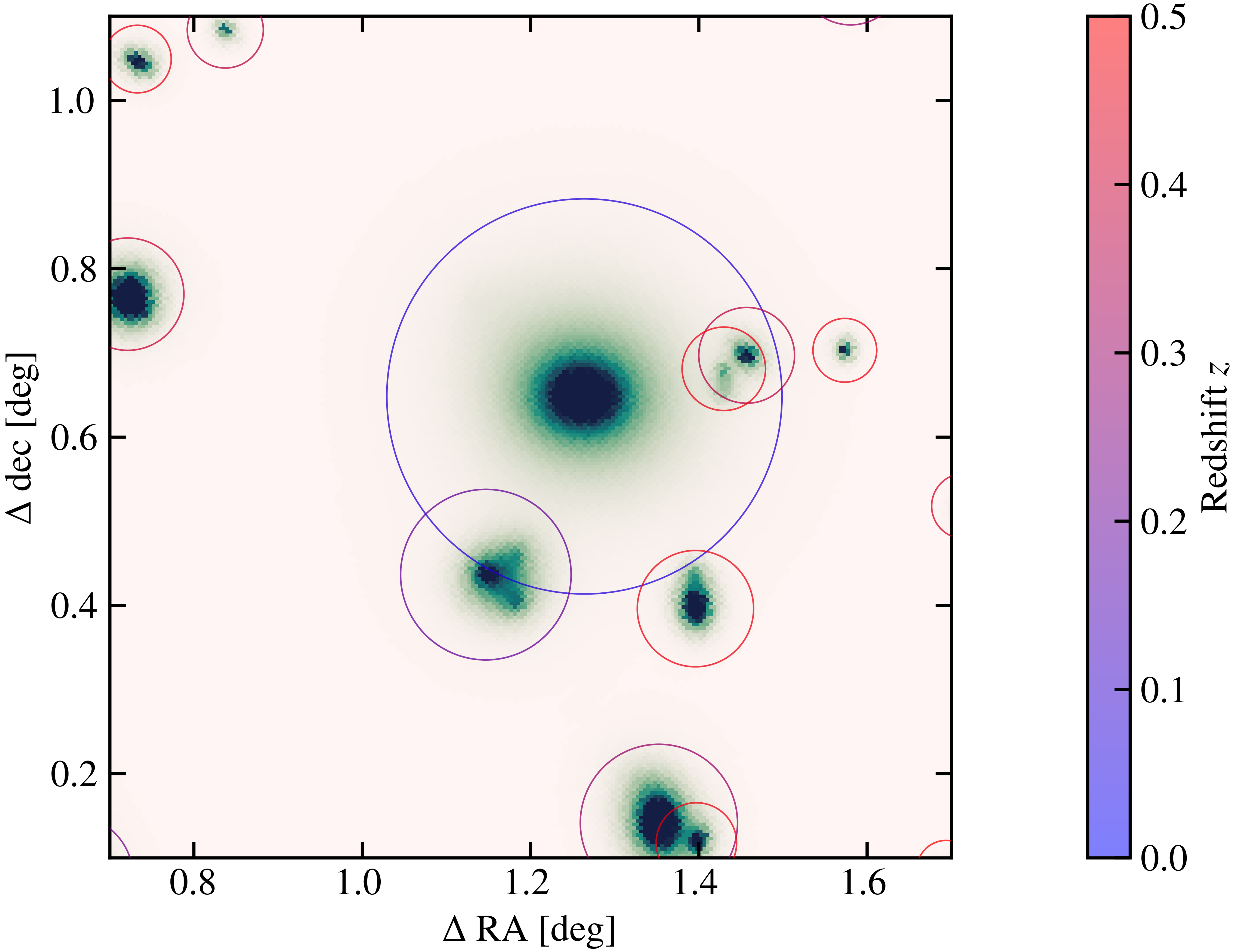
picasso-TLJ: tSZ map



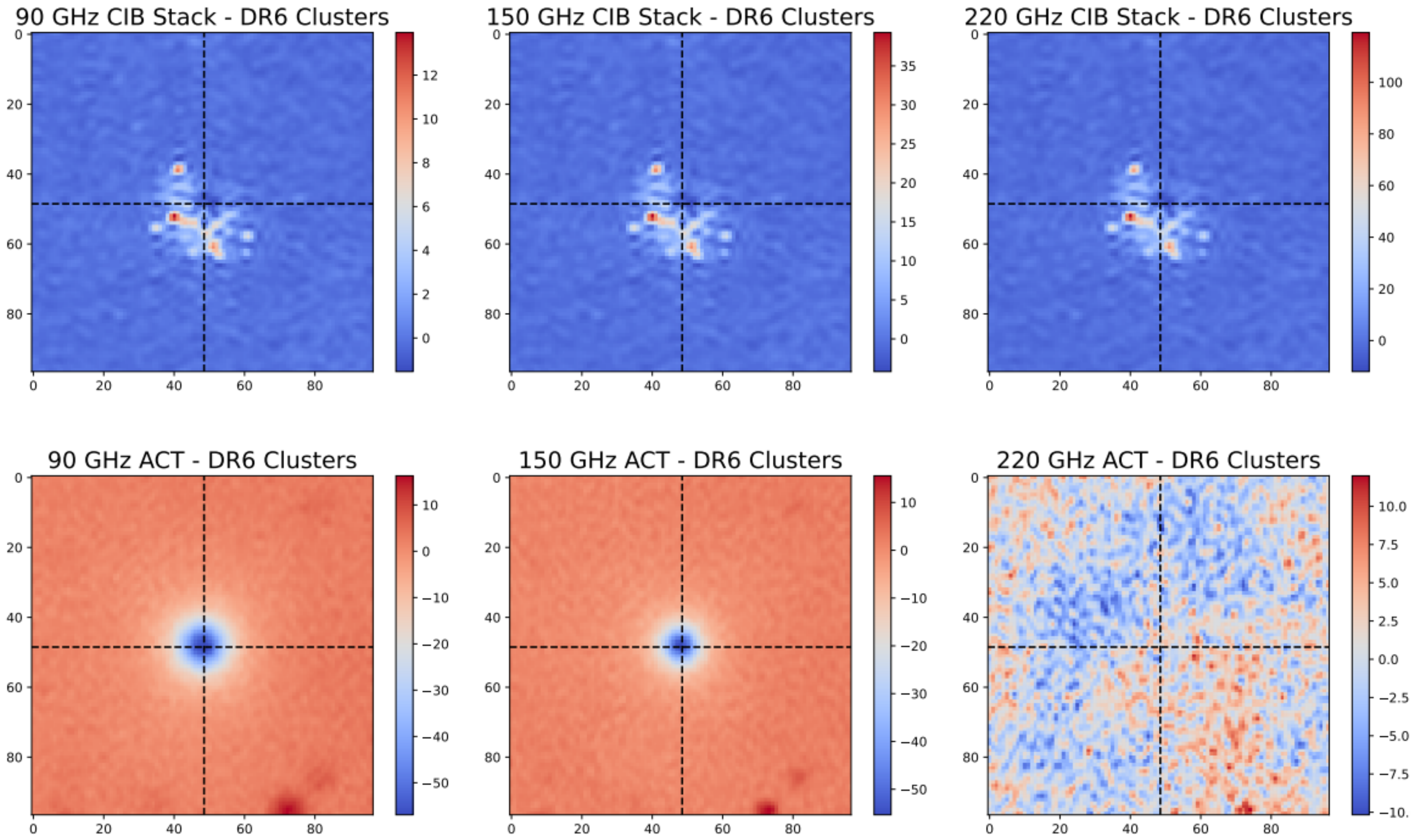
Zoom on 4 deg²

picasso-TLJ: tSZ map



Zoom on 1 deg²

Beyond tSZ: Cosmic infrared background



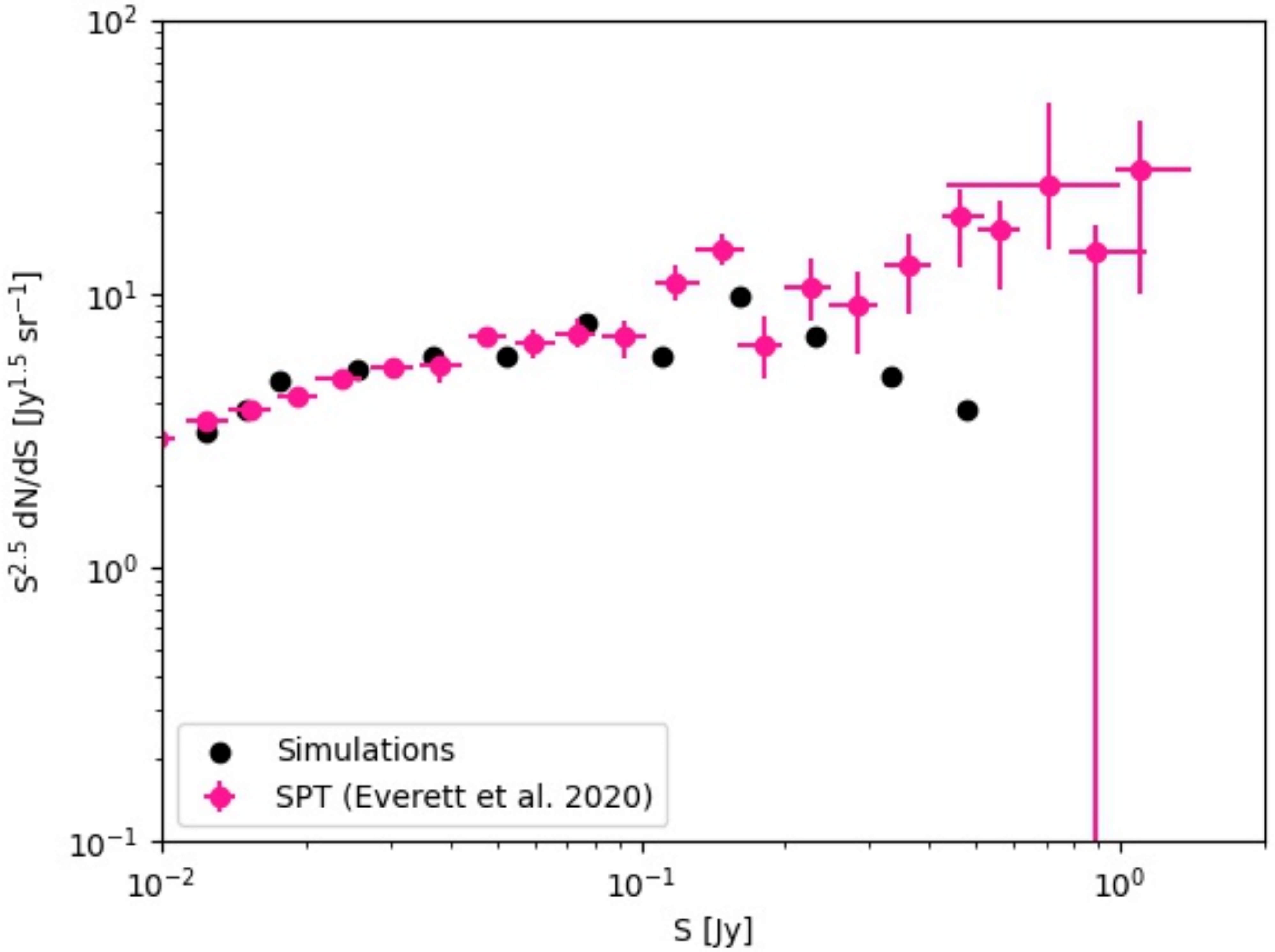

Maya Mallaby-Kay


Giulia Campitiello

- **CIB:** diffuse far-IR radiation from dusty star forming galaxies
- Faint signal in CMB maps that can **contaminate SZ measurements** and Compton-y maps.
- Incorrect tSZ measurements due to CIB contamination could lead us to **incorrect estimates for the temperature and density of halos.**

→ **Impact of CIB on SZ detection studies**

Beyond tSZ: Radio sources

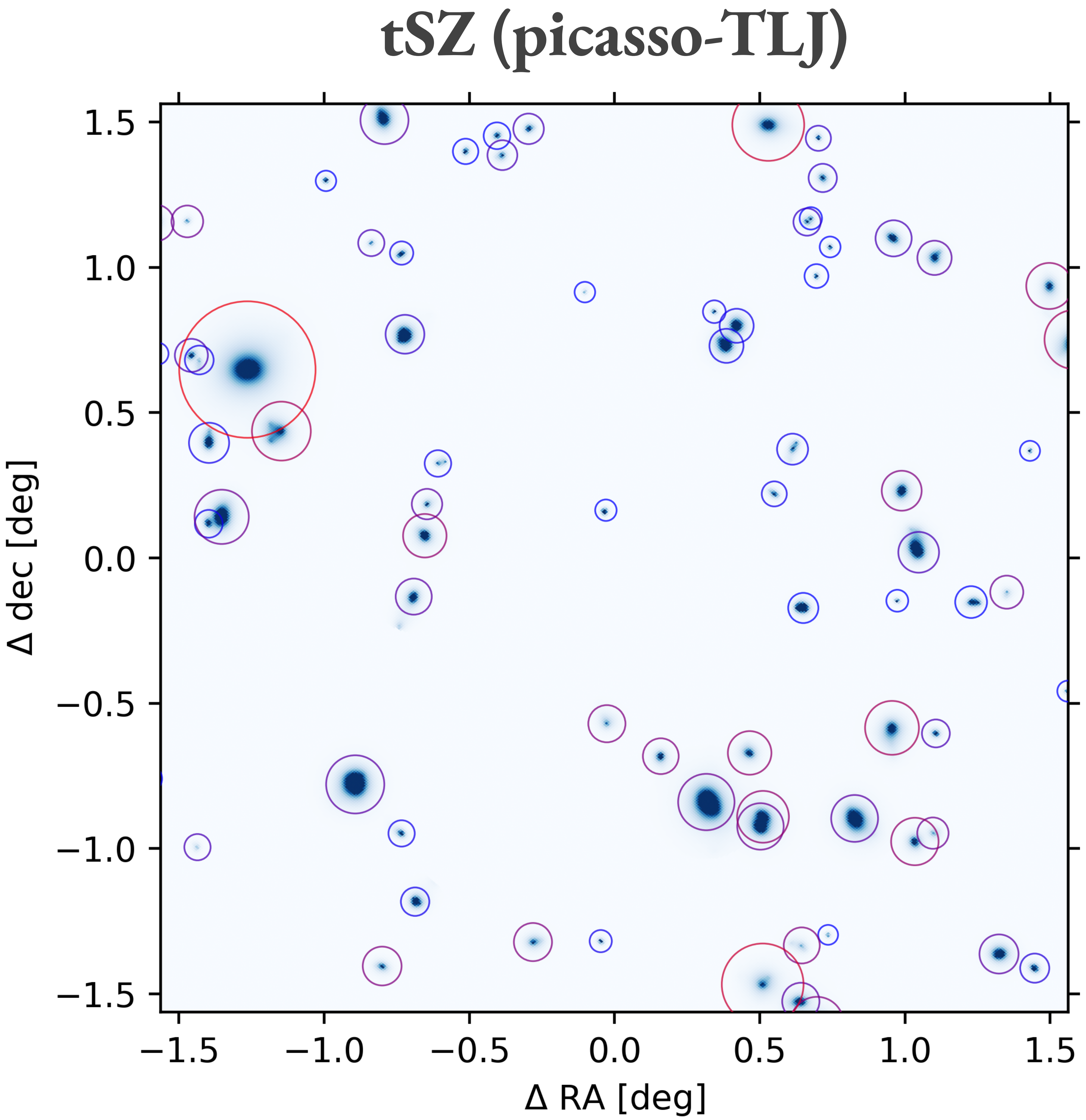


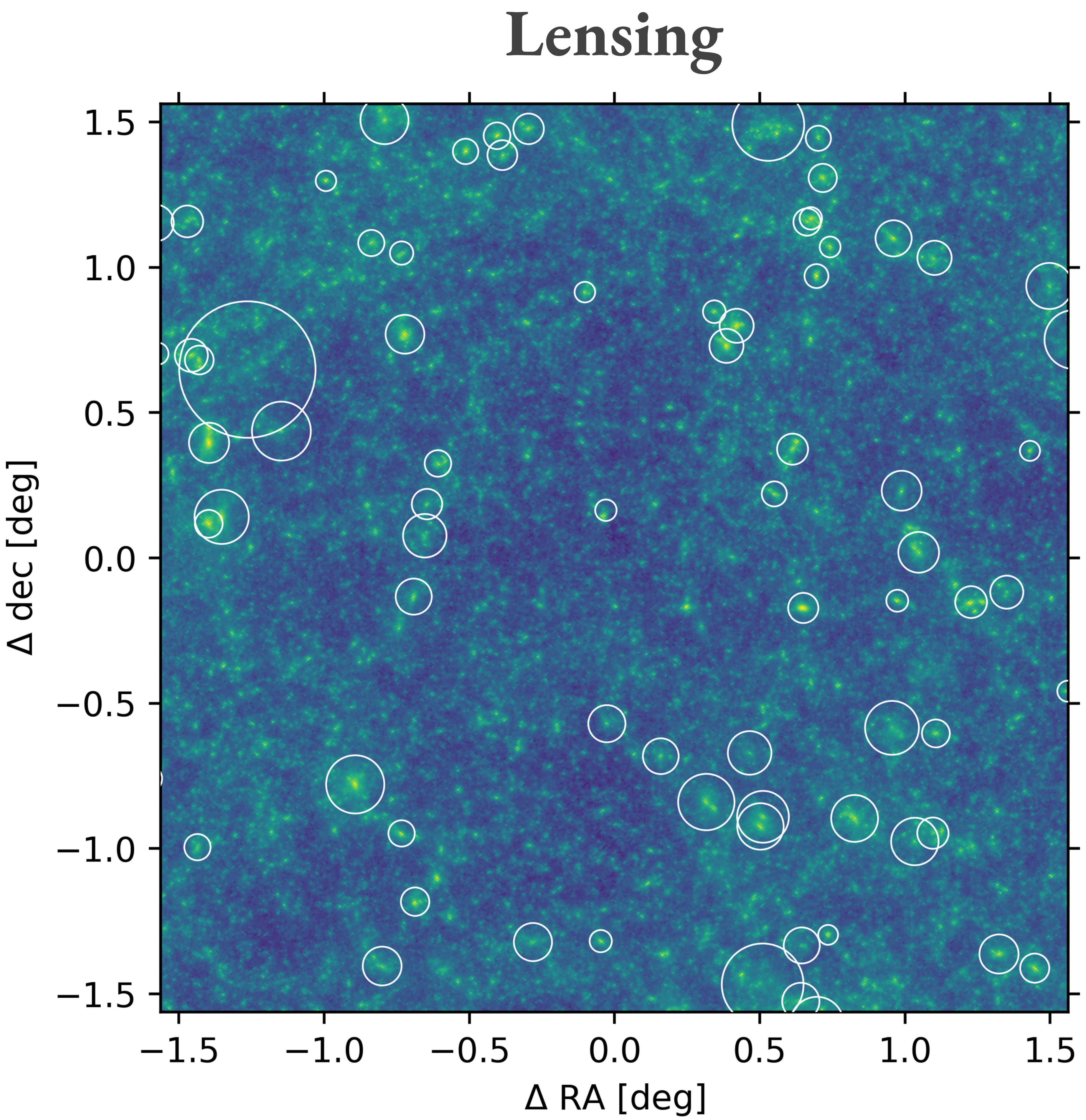
Giulia Campitiello

- **Radio galaxies hosted in cluster halos can contaminate cluster detections.**
- **Model their contribution** using the luminosity functions from Massardi et al. 2010
  - Separately describe flat- and steep-spectrum sources, to predict their abundance.
- Convert the 1.4 GHz luminosities into fluxes at **SPT frequencies.**

→ Impact of radio sources on SZ detection studies

Beyond tSZ: Last Journey lensing maps





Patricia Larsen

→ tSZ x lensing studies

Conclusions

- **New physics-informed, AI/ML-powered gas model**
  - **Fast, GPU-enabled, differentiable**
  - **Flexible:** trained model can be used on a variety of inputs
- **Accurate / precise predictions** of intracluster gas thermodynamics
- **Model availability:**
  - Available on GitHub, including trained models
  - Documentation available online, including tutorials

- **Application:**
  - **tSZ-painting** the Last Journey simulation
  - **Halo-particle-based tSZ** on full lightcone
  - **Parallel efforts** to include other mm-wave x-gal components
  - **Calibration of SPT-3G cluster cosmology:**
    - Cluster detection (see talks by L. Bleem, K. Kornoelje)
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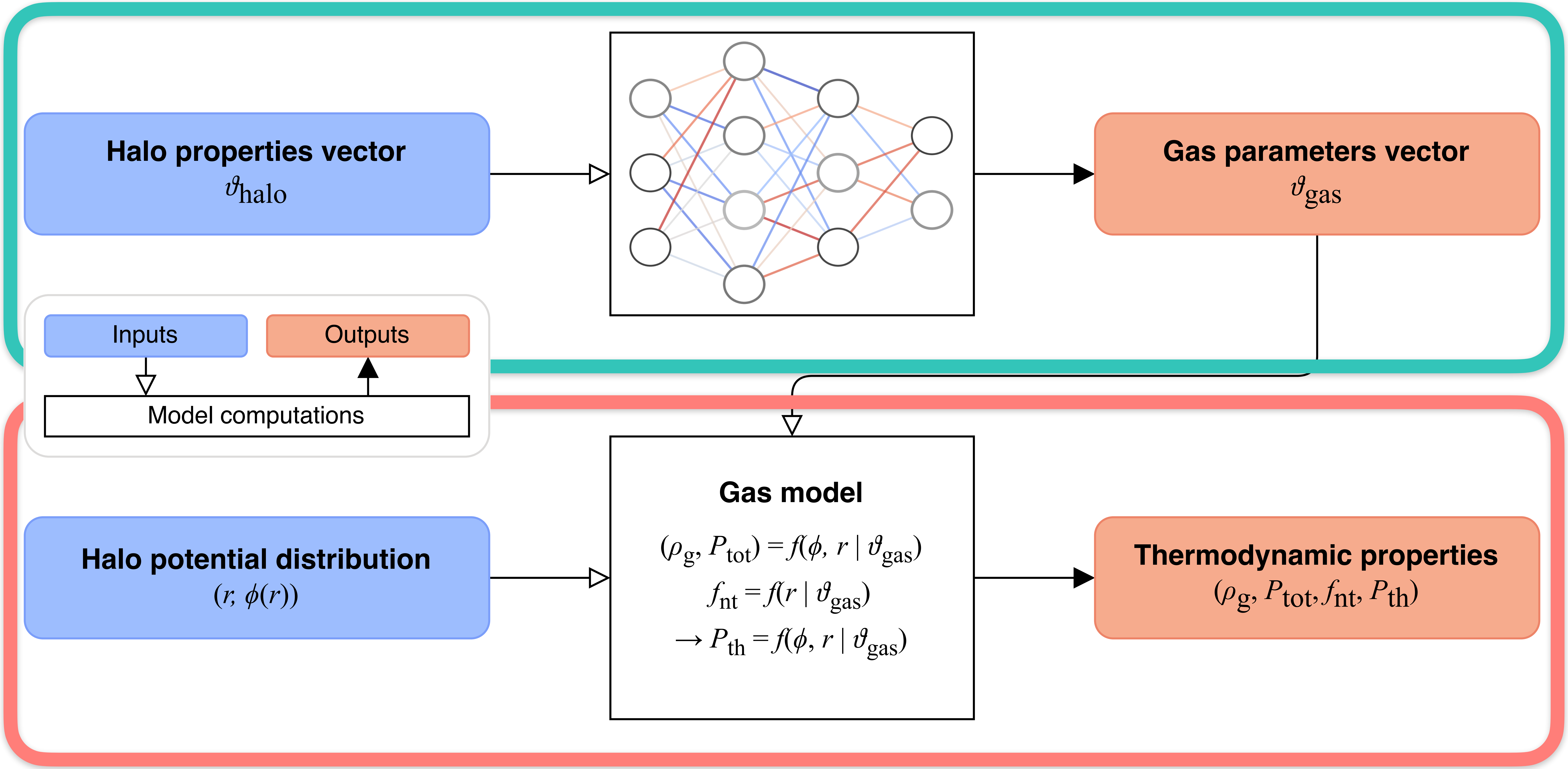
- **Paper:** Kéruzoré et al. (2024), OJAp 7, arXiv:2408.17445
- **picasso Github:** fkeruzore/picasso
- **picasso documentation:** picasso-cosmo.readthedocs.io

Thank you!

Backup

The picasso model workflow

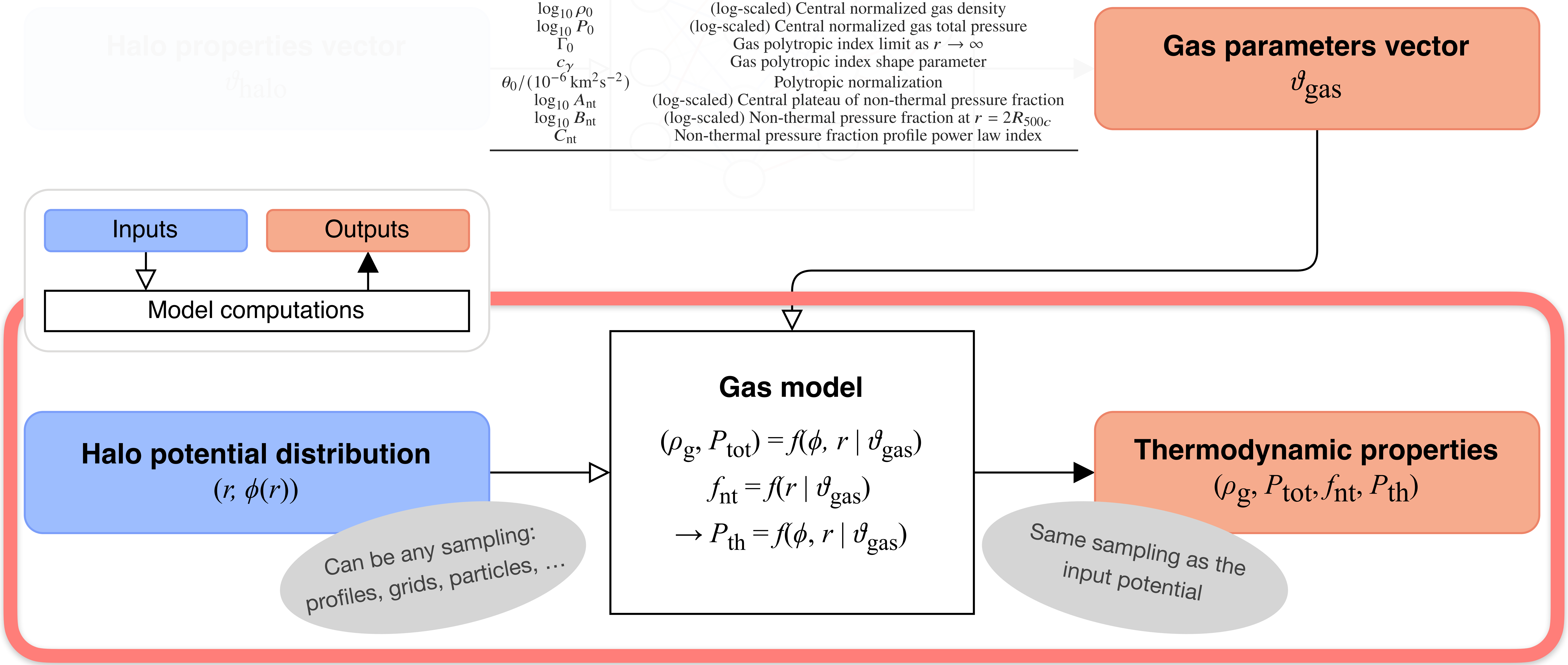
Combines a parametric gas model with ML predicting model parameters



The picasso model workflow: Parametric gas model

Gas density: $\rho(\phi) = \rho_0 \theta^{\Gamma/(\Gamma-1)}(\phi)$; **Total pressure:** $P(\phi) = P_0 \theta^{1/(\Gamma-1)}(\phi)$; **Non-thermal pressure fraction:** $f_{\rm nt}(r) = A_{\rm nt} + (B_{\rm nt} - A_{\rm nt})\left(r/R_{200m}\right)^{C_{\rm nt}}$

Symbol	Meaning
$\log_{10} \rho_0$	(log-scaled) Central normalized gas density
$\log_{10} P_0$	(log-scaled) Central normalized gas total pressure
Γ_0	Gas polytropic index limit as $r \to \infty$
c_γ	Gas polytropic index shape parameter
$\theta_0 / (10^{-6}\,{\rm km^2 s^{-2}})$	Polytropic normalization
$\log_{10} A_{\rm nt}$	(log-scaled) Central plateau of non-thermal pressure fraction
$\log_{10} B_{\rm nt}$	(log-scaled) Non-thermal pressure fraction at $r = 2R_{500c}$
$C_{\rm nt}$	Non-thermal pressure fraction profile power law index



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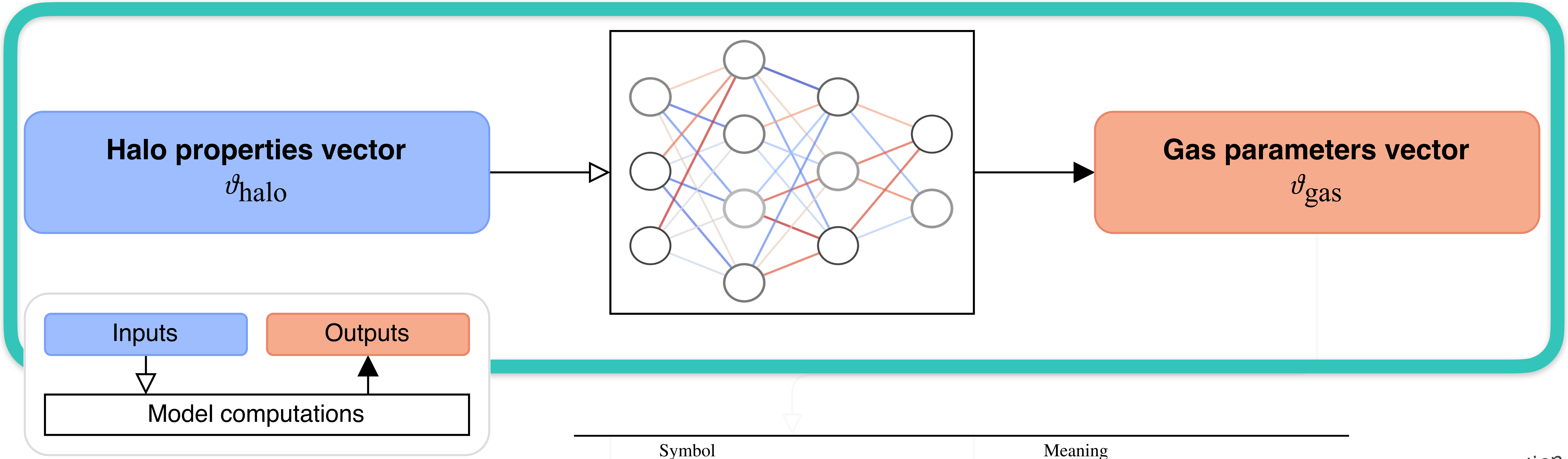
→ **Model with 8 parameters,** $\vartheta_{\rm gas}$

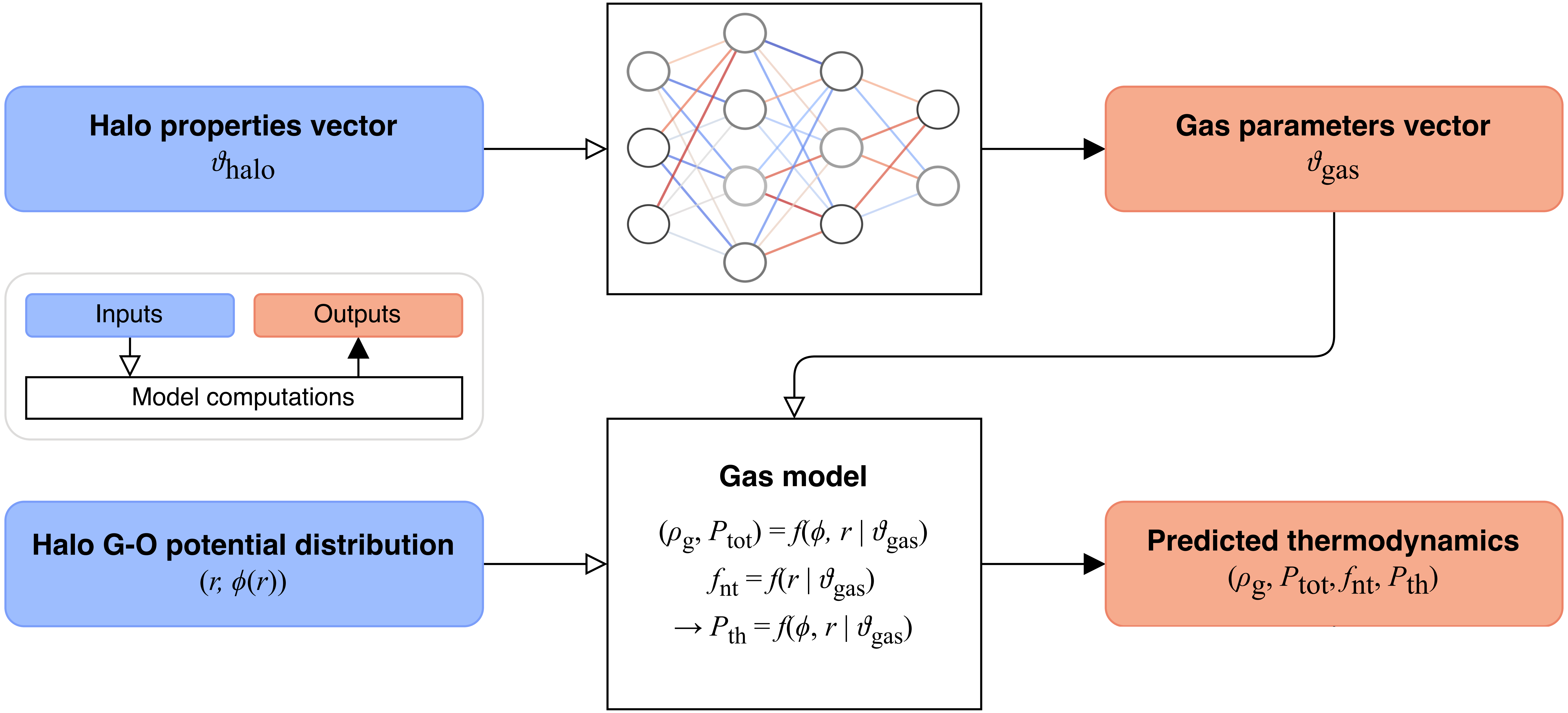
The picasso model workflow: ML predictor



- **Parameters $\vartheta_{\rm gas}$ predicted:**
  - Per halo
  - By a neural network
  - Inputs = halo properties

Symbol	Meaning	
$\log_{10}(M_{200c}/10^{14}\,h^{-1}M_\odot)$ c_{200c}	(log-scaled) Halo mass Halo concentration	Mass / concentration
$\Delta x/R_{200c}$ $c_{\rm acc.}/c_{200c}$ $c_{\rm peak}/c_{200c}$	Normalized offset between center of mass and potential peak Ratio between accumulated mass and NFW fit concentrations Ratio between differential mass profile peak and NFW fit concentrations	Disturbance state
e p	Halo ellipticity, eq. (13) Halo prolaticity, eq. (13)	Morphology
$a_{\rm lmm}$ a_{25} a_{50} a_{75} $\dot{M}$	Scale factor of last major merger Scale factor at which $M = 0.25 \times M_{z=0}$ Scale factor at which $M = 0.50 \times M_{z=0}$ Scale factor at which $M = 0.75 \times M_{z=0}$ Mass accretion rate between last two redshift snapshots	Mass assembly history

Model training: Workflow



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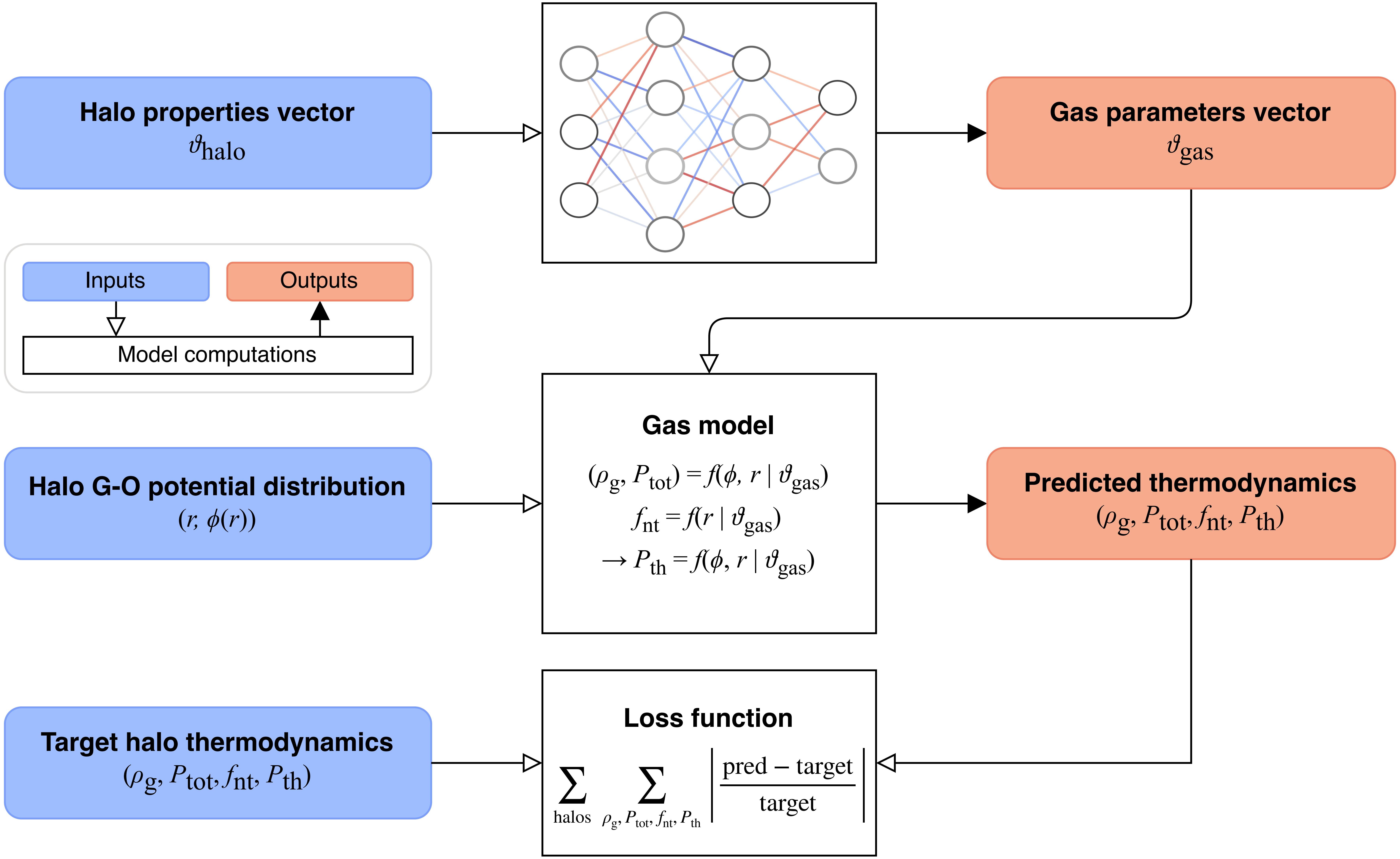

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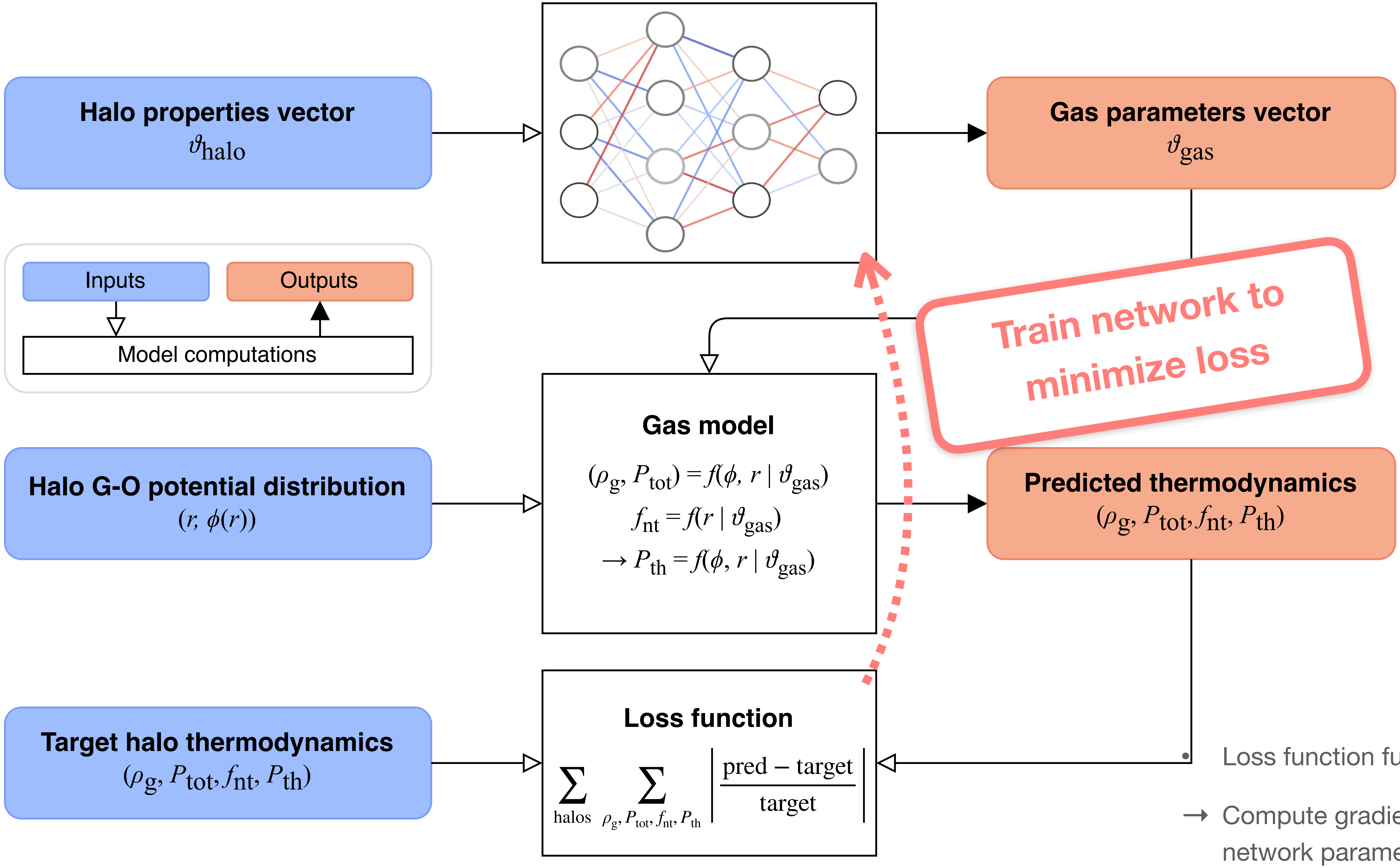
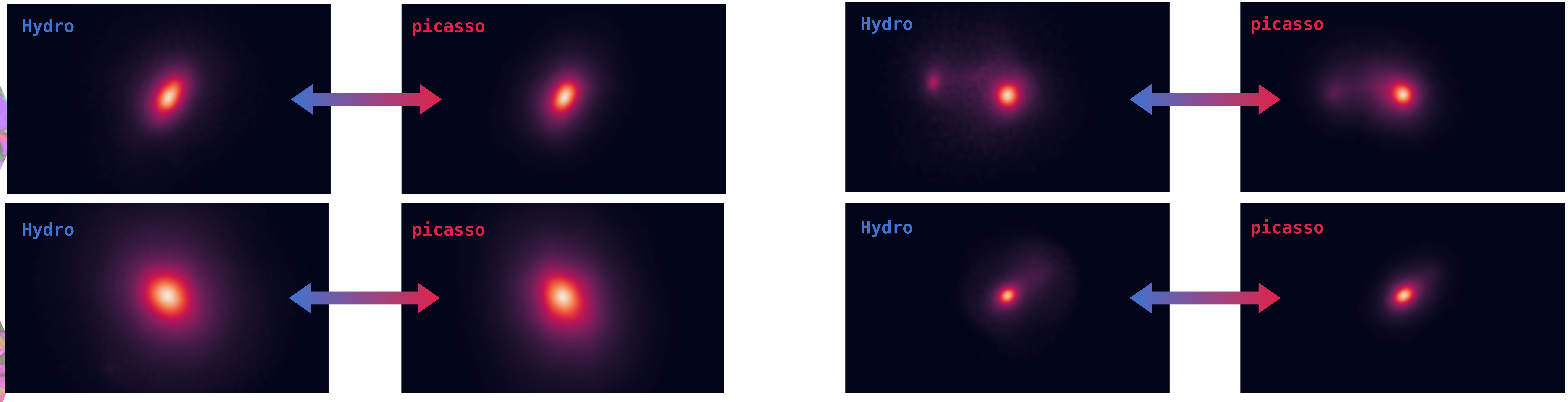


Loss function fully differentiable

→ Compute gradients w.r.t. neural network parameters, and optimize

picasso is not a spherical model!

- **We train using profiles, but learn the mapping between G-O halo potential and gas properties**
- **Once trained,** picasso can predict gas properties for any potential distribution: profiles, particles, 3D grids, …
- **tSZ maps comparison:**
  - From gas particles in **hydrodynamic simulation** vs. from **G-O simulation particles with trained picasso**
  - Amplitude and shape of the tSZ signal well reproduced, including some subhalo structure

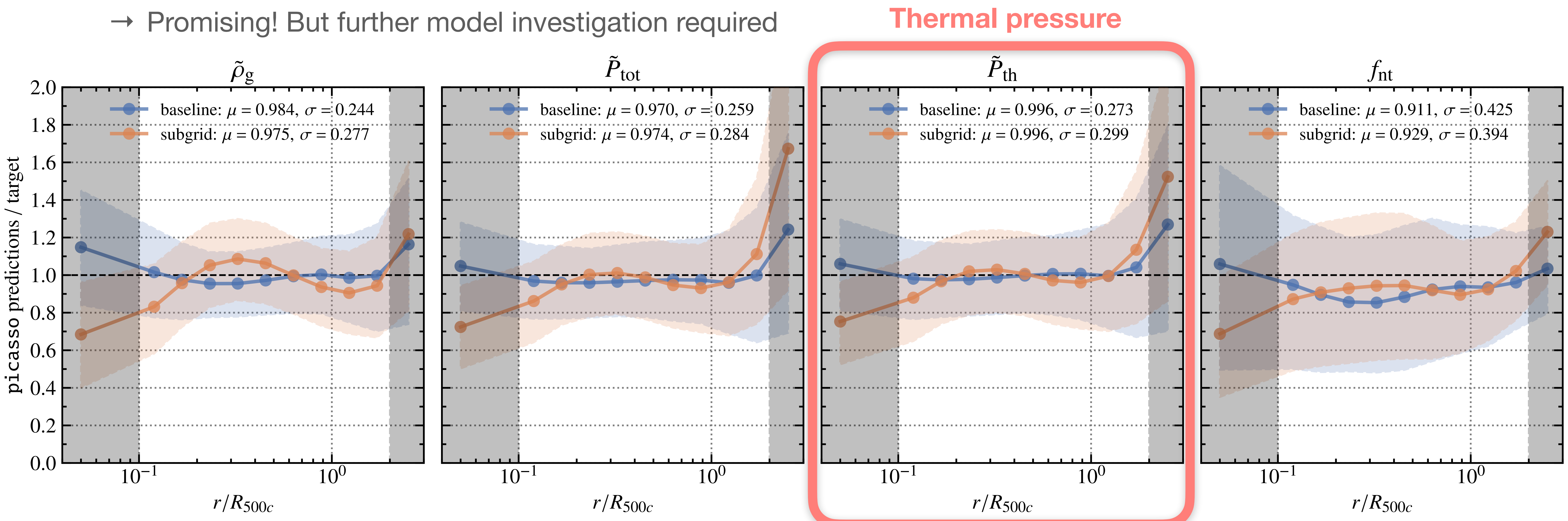


Subgrid model results

- **Subgrid model:**
  - Train on **full-physics hydrodynamic simulation**
    - Sub-resolution baryonic physics affect large scale matter distribution & cluster properties
    - Empirically modelled, including AGN & SN feedback, cooling, star formation, winds
  - Full (baseline) input vector

- **Results:**
  - Bias slightly worse and not constant with radius (still few-% at $r > 0.2 R_{500c}$)
  - Scatter slightly degraded

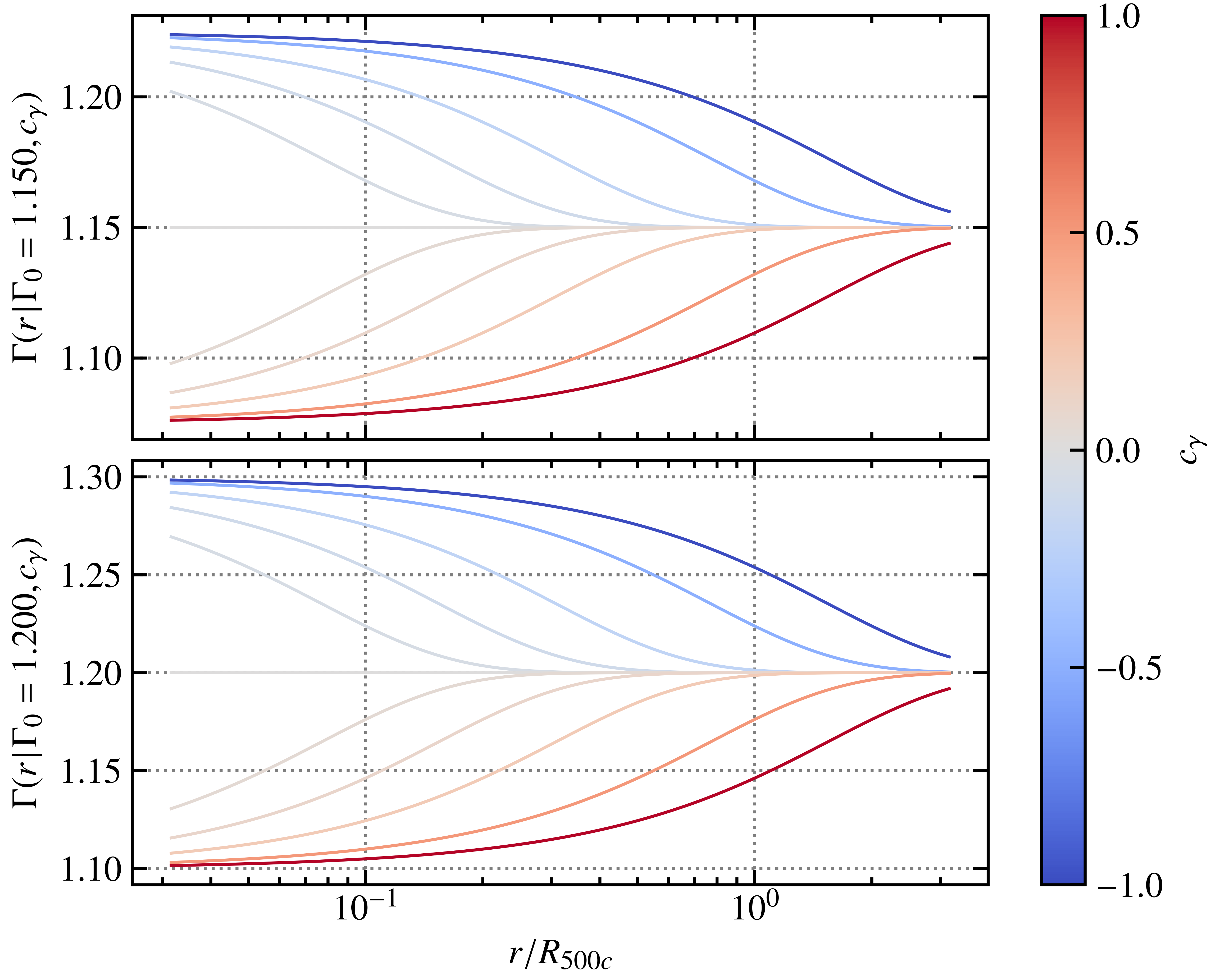
→ Promising! But further model investigation required



Testing set: halos not seen in training

Fixed vs. radius-varying polytropic index

- Models presented before fixed $c_\gamma = 0 \;\Rightarrow \Gamma(r) = \Gamma_0$
- Allowing $c_\gamma \neq 0$ does not change results significantly



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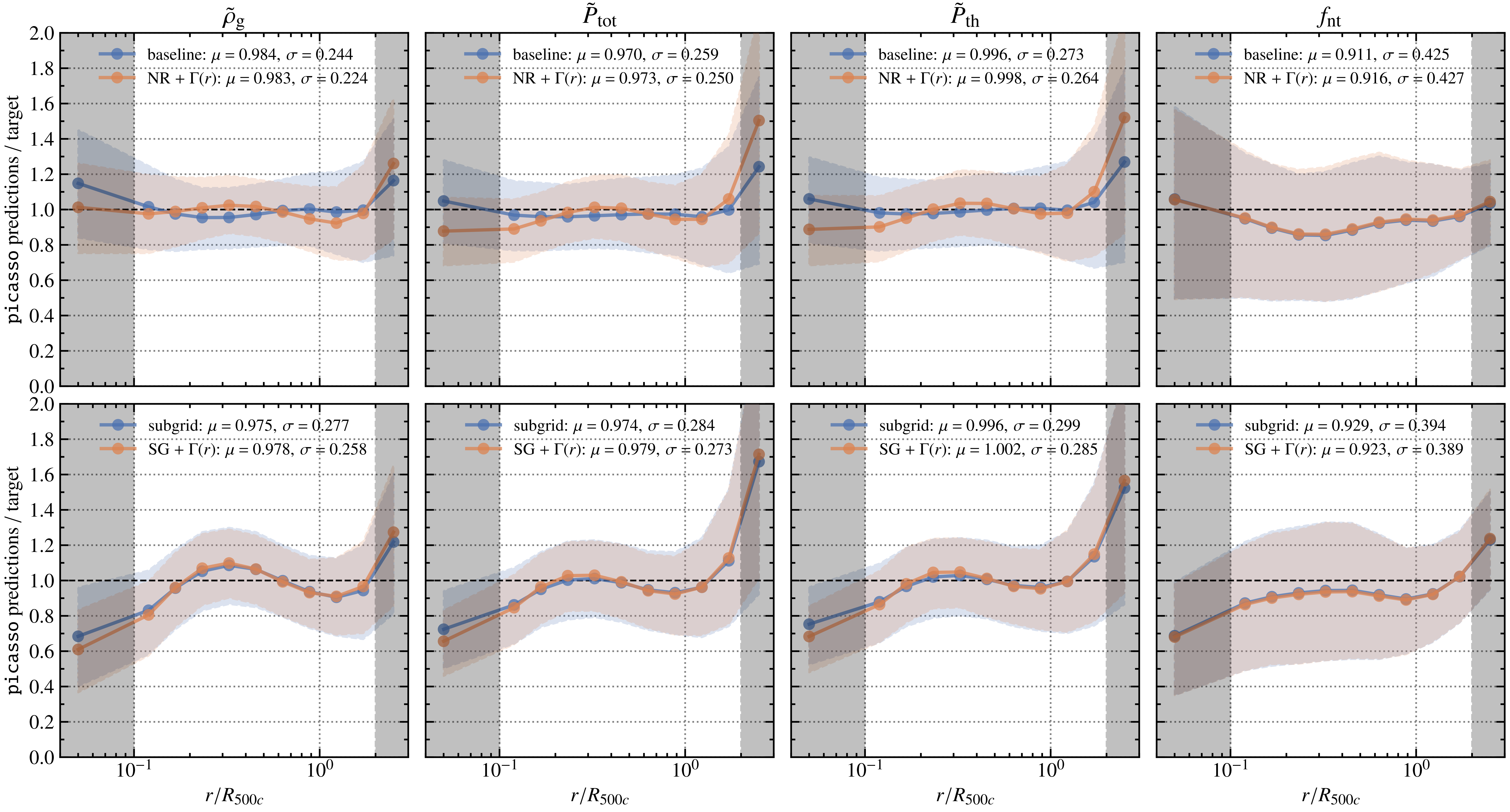

z>0

- Use model trained at $z = 0$ to predict properties at $z = 0.5$