An Observationally Driven Approach for Probing the Circum-Galactic Medium with Neural Networks

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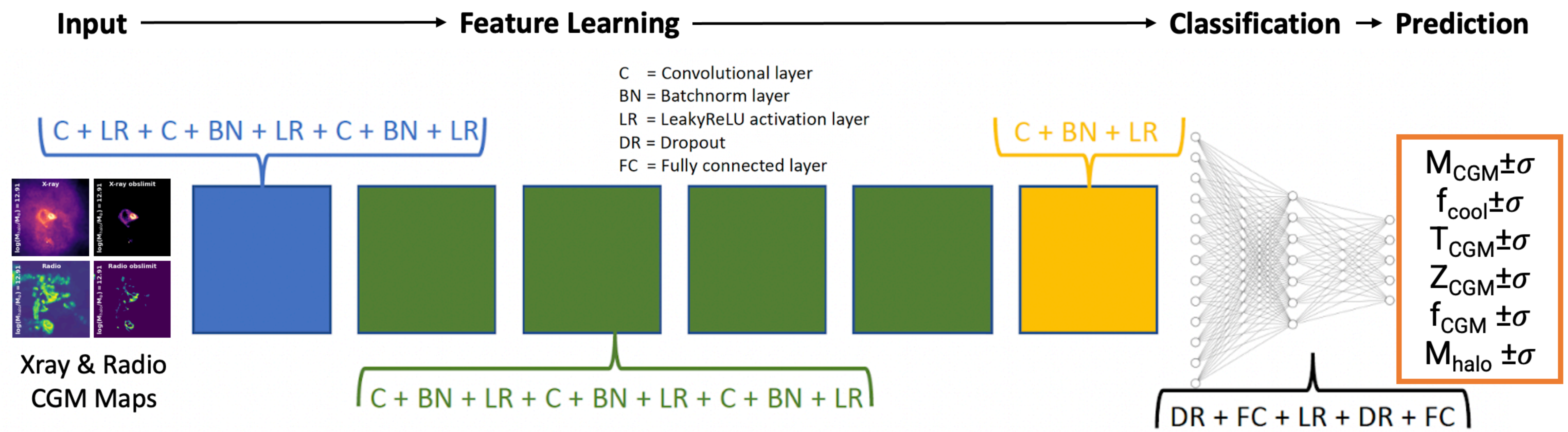
Abstract

We apply a convolutional neural network to perform an inference analysis for 6 selected properties, or parameters, of the circum-galactic medium (CGM), including M_{halo}, f_{cgm}, log(T), M_{CGM}, f_{cool}, and log(Z). The network both uses parameter values from the **CAMELS (Cosmology and Astrophysics with MachinE Learning Simulations)** version of the hydrodynamic simulation, IllustrisTNG (CV set), with a dual-field focus with HI (Radio) for gas ~10^4K and Soft X-Ray for gas ~10^6-$10^{7.5}$ K. X-Ray and Radio are tested both as individual fields, and then together as a "multifield". This combination of fields is chosen due to its close relation to the observable hot and cold gas, within individual galaxies, groups, and clusters. The results of this study show that X-Ray is not a robust enough probe to extend to lower masses. Therefore, we must employ the "multifield" approach as a solution, and use Radio as the secondary field in conjunction with X-Ray for improved results and inferencing power. We hope to extend this analysis to additional simulations, like SIMBA and Astrid, for cross-simulation inferencing analysis.

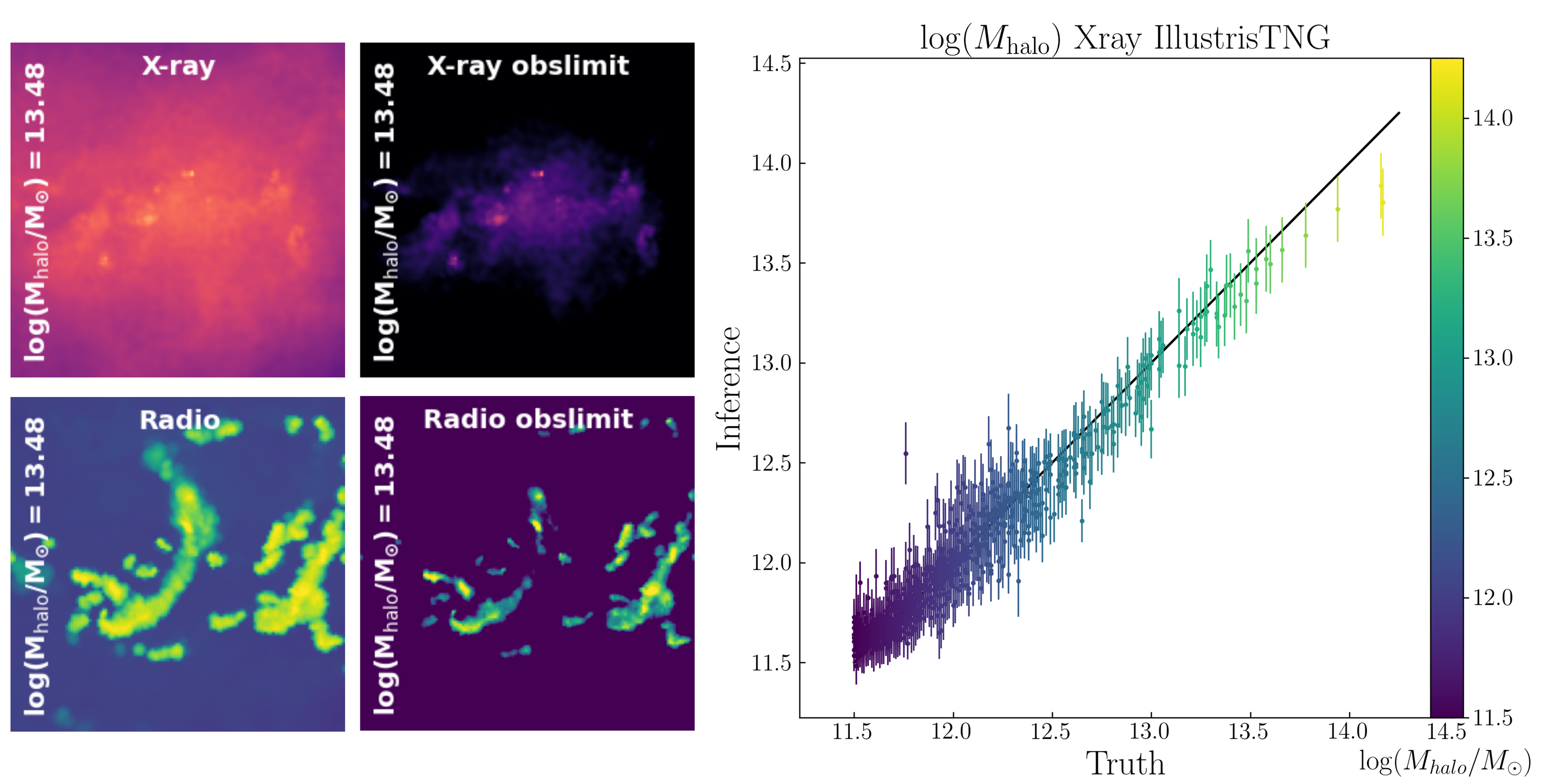
Convolutional Neural Network Structure



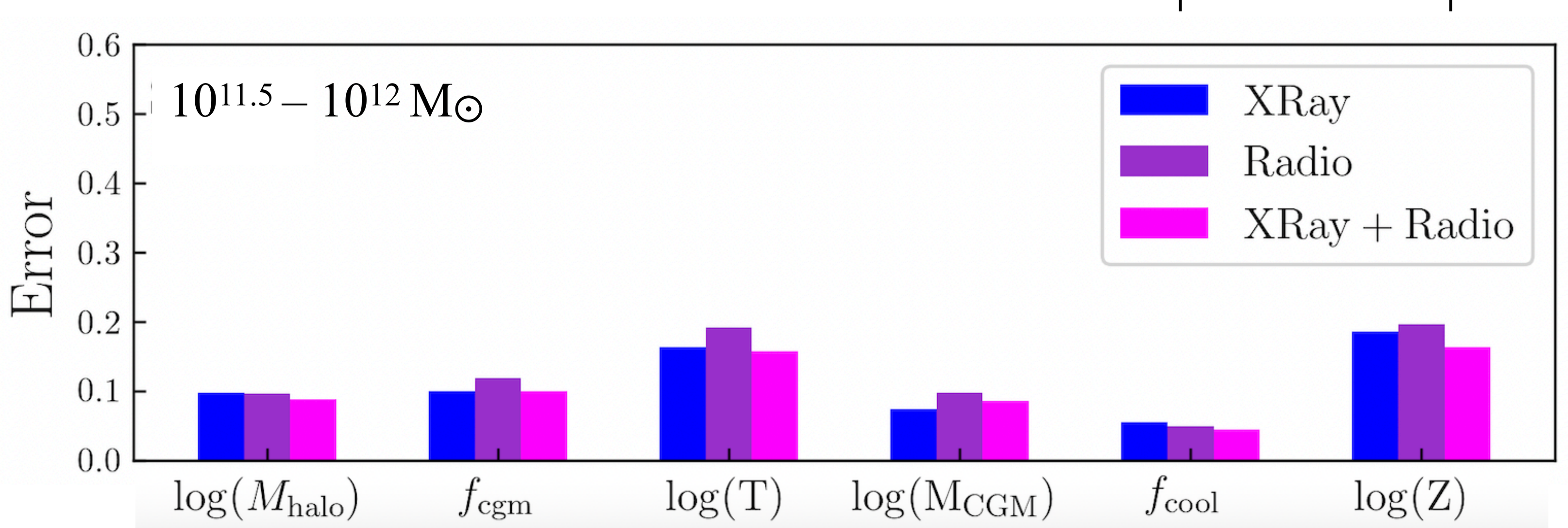
The network[2] is based on the CAMELS Multifield Dataset (CMD)[1] network used for astrophysical feedback and cosmological parameters.

CGM Inference with X-Ray + Radio

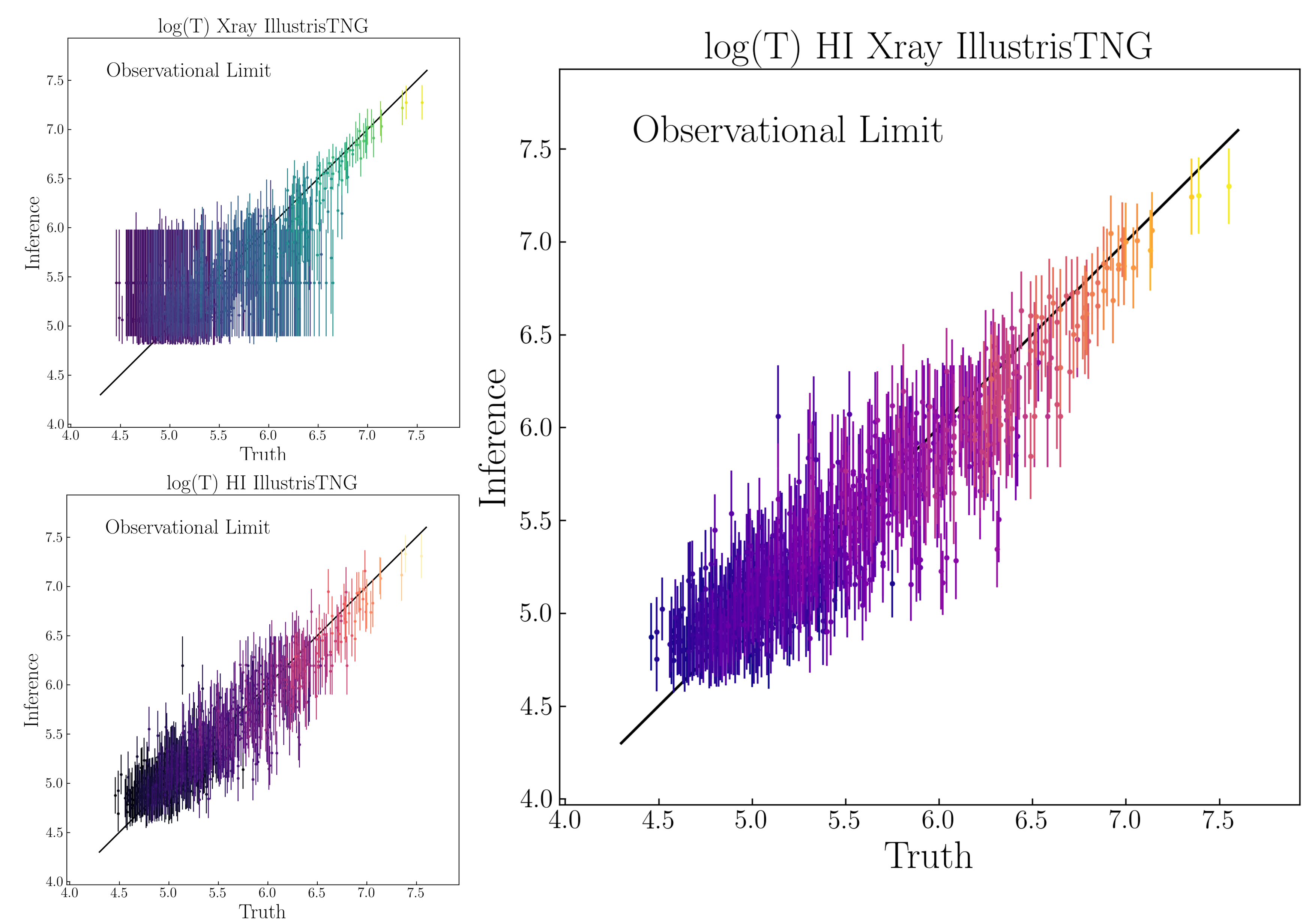
X-Ray map input ($M_{halo}=10^{13.11}$), and Truth-Inference plot output.



Error by Halo Type (Sub-L* mass) with observational limits. The error is the distance from the black line in the Inference plot to the points.



Observational Limit Results



Machine Learning can infer the temperature of the CGM. Our CNN algorithm is poorly constrained with Xray only or HI (radio) only, but in combination the errors are significantly better.

Lessons & Future Work

Two fields are better than one! We see the strengths of combining two fields, specifically with Radio in the observational limits of X-Ray (eROSITA observational depth) and Radio (radio survey Radio column density limit).

In the future, we plan to include:

1. **CAMELS-SIMBA and Astrid:** for additional information about possible constraints and the accuracy of each model compared to multi-wavelength observational data.
2. **Additional fields:** including kSZ, tSZ, FRBs, and weak lensing.
3. **Realistic Noise:** including background/foreground, to make the network comparable to observational surveys.

References

1. Villaescusa-Navarro, F., et al., 2021a, Multifield Cosmology with Artificial Intelligence, ApJ
2. Villaescusa-Navarro, F., et al., 2021b, The CAMELS Multifield Dataset: Learning the Universe's Fundamental Parameters with Artificial Intelligence, ApJ

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