Exploring the Nature of Dark Matter with Cosmological Simulations and Machine Learning

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Motivation

The standard paradigm for Dark Matter (DM), ΛCDM, successfully describe large-scale structure, but is met with small scale problems. One alternative is the Self-Interacting Dark Matter (SIDM) model, which introduces DM-DM interactions that modify structure formation at small scale but still preserves the succes at large scale from ΛCDM [1]. Exploring the DM-models with Machine Learning can provide an opportunity to characterize subtle patterns helping to constrain DM-models and infer DM Particle Physics from observation[2].

Simulation framework

The simulations are executed using the AREPO-code [3], and the MUSIC-code [4] to generate initial conditions.

The SIDM is velocity dependent following the cross-section for a resonant SIDM light mediator model[5].

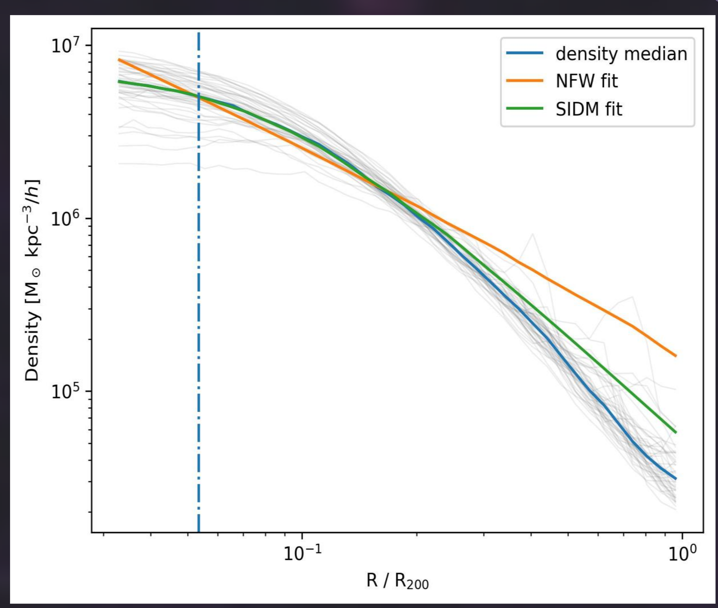
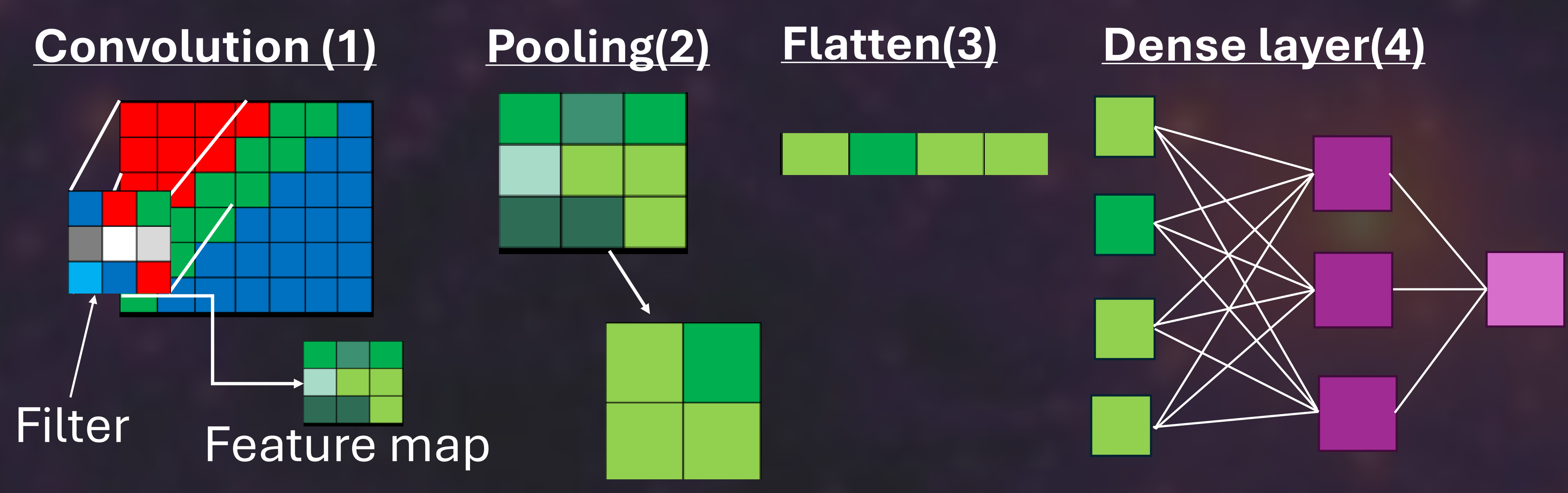


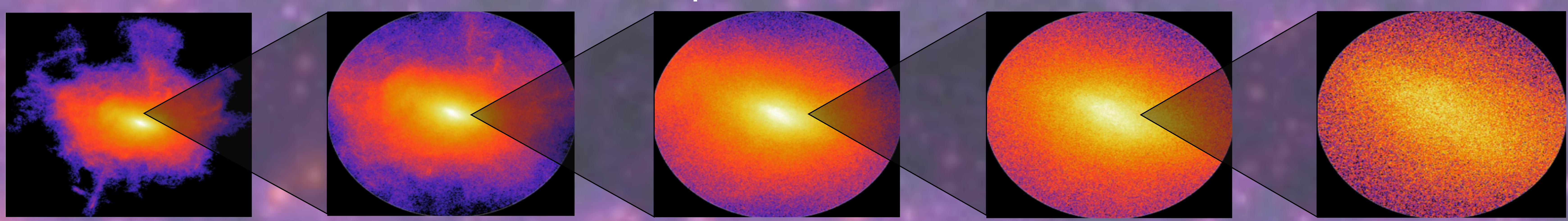
Fig 1:Stacked density profiles from SIDM-simulations all scaled by their respective virial radii approximated to be R200. The vertical dot-dashed line indicating the trust radius.

Convolutional Neural Network (CNN)



(1) Input is being evaluated by a filter extracting local patterns in a map. (2) Downsamples feature map. (3) Converts map into 1D-array. (4) Array act as input for dense layers followed by hidden layers (Multi-layer perceptron). [6]

Input for CNN



Full subhalo — *Cropped to R200* — *Cropped to 0.5R200* — *Cropped to 0.25R200* — *Cropped to 0.1R200*

Results

A single CNN architecture was trained on subhalo crops from two simulation sizes with varying particle counts, classifying them as CDM(0) or SIDM(1).

Cropping subhalos enhances the inner halo, where SIDM and DM differ most. Starting from R200 which defines a bound halo.

Simulation	Accuracy
0.5R200 crop (128^3)	83.6%
0.25R200 crop (128^3)	87.1%
0.1R200 crop (128^3)	86.6%
0.5R200 crop (512^3)	99.3%
0.25R200 crop (512^3)	100%
0.1R200 crop (512^3)	100%

Table 1: Model performance on test data. The test set was pre-sorted, using the same cropping and simulation size.

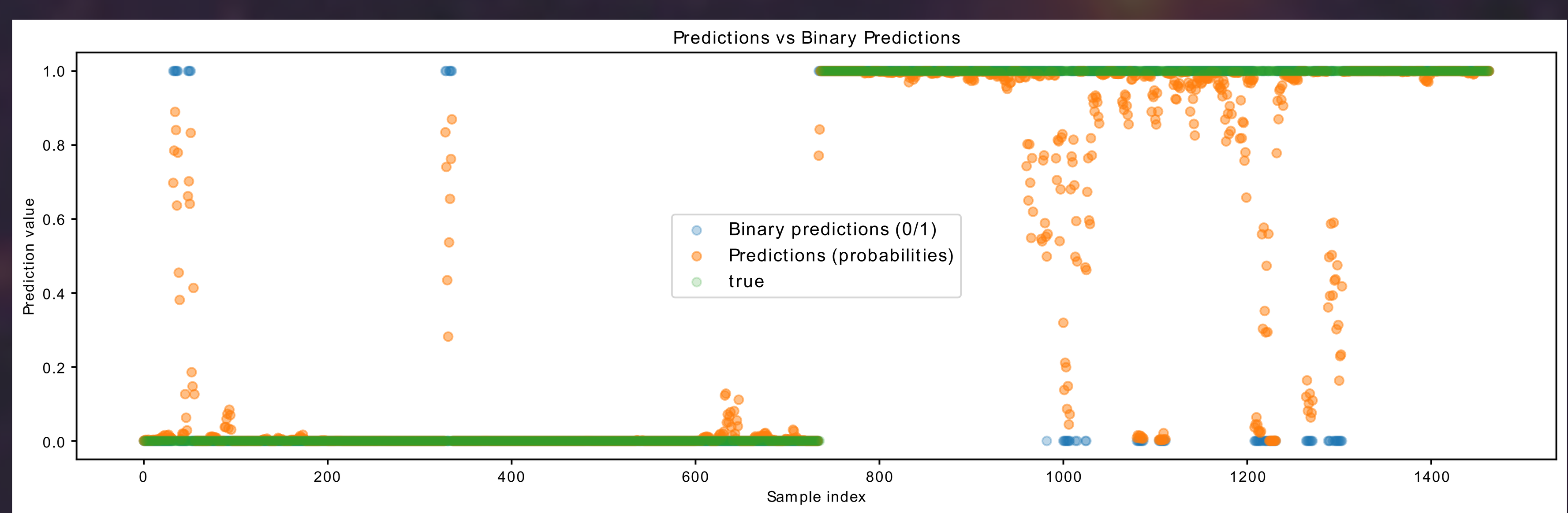


Fig 2: Applied to the 0.25R200 (512^3) dataset, the model trained with 0.1R200(512^3) achieves 94.06% accuracy with increased uncertainty, as shown in the figure. Alignment between predicted probabilities and binary classifications in the 0.1R200 (512^3) reference model indicates 100% certainty in its predictions. This gives an insight on the certainty of the predictions since every prediction >0.5 is categorized as 1, and <0.5 as 0.

Conclusion

- SIDM offers a potential solution to small-scale problems.
- Generate simulations for CDM and SIDM using AREPO.
- A CNN can succesfully identify the difference between the two models, when being trained on the innermost region.

References:

[1] Spergel, D. N., & Steinhardt, P. J. (2000). *Observational evidence for self-interacting cold dark matter*. Physical Review Letters, 84(17), 3760–3763.
[2] Rose, J. C. et al., 2026, *Introducing the DREAMS Project: DaRk mattEr and Astrophysics with Machine learning and Simulations*, Flatiron Institute
[3] Weinberger, R., Springel, V., Pakmor, R., et al. (2020). *The AREPO public code release*. The Astrophysical Journal Supplement Series, 248(2), 32. https://doi.org/10.3847/1538-4365/ab96d4
[4] Vogelsberger et al. (2016). *ETHOS and small-scale structure problems in CDM* — Monthly Notices of the Royal Astronomical Society (MNRAS)
[5] Tulin, S., & Yu, H.-B. (2018). Dark matter self-interactions and small-scale structure. *Physics Reports*, 730, 1–57. https://doi.org/10.1016/j.physrep.2017.11.004
[6] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," *Advances in Neural Information Processing Systems (NeurIPS)*, 2012.

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