Deep Learning Generative Models to Infer Mass Maps from SZ, X-ray and Galaxy Members Observations in Galaxy Clusters.

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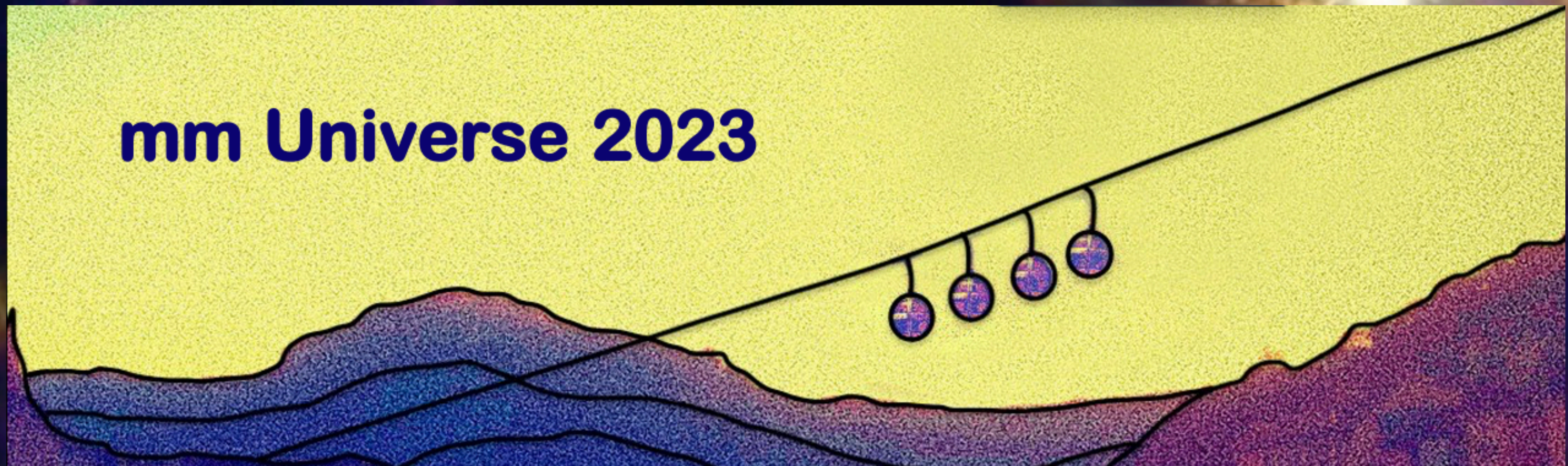


Motivation

- In de Andres et al 2022, we have predicted the mass of galaxy clusters from SZ observations using deep learning, particularly for the Planck PSZ2 catalog.

- We want to generalise this approach to infer projected mass density maps from an observation, e.g. from tSZ we aim at inferring the mass map in 2D.

- Weak lensing traces projected mass density, but WL surveys are scarce (tens of clusters) compared to Compton-y and X-ray whose surveys observe hundreds or thousands of galaxy clusters.

Final goal: Simulation based inference

De Andres et al 2022

nature > nature astronomy > articles > article

Article | Published: 17 October 2022

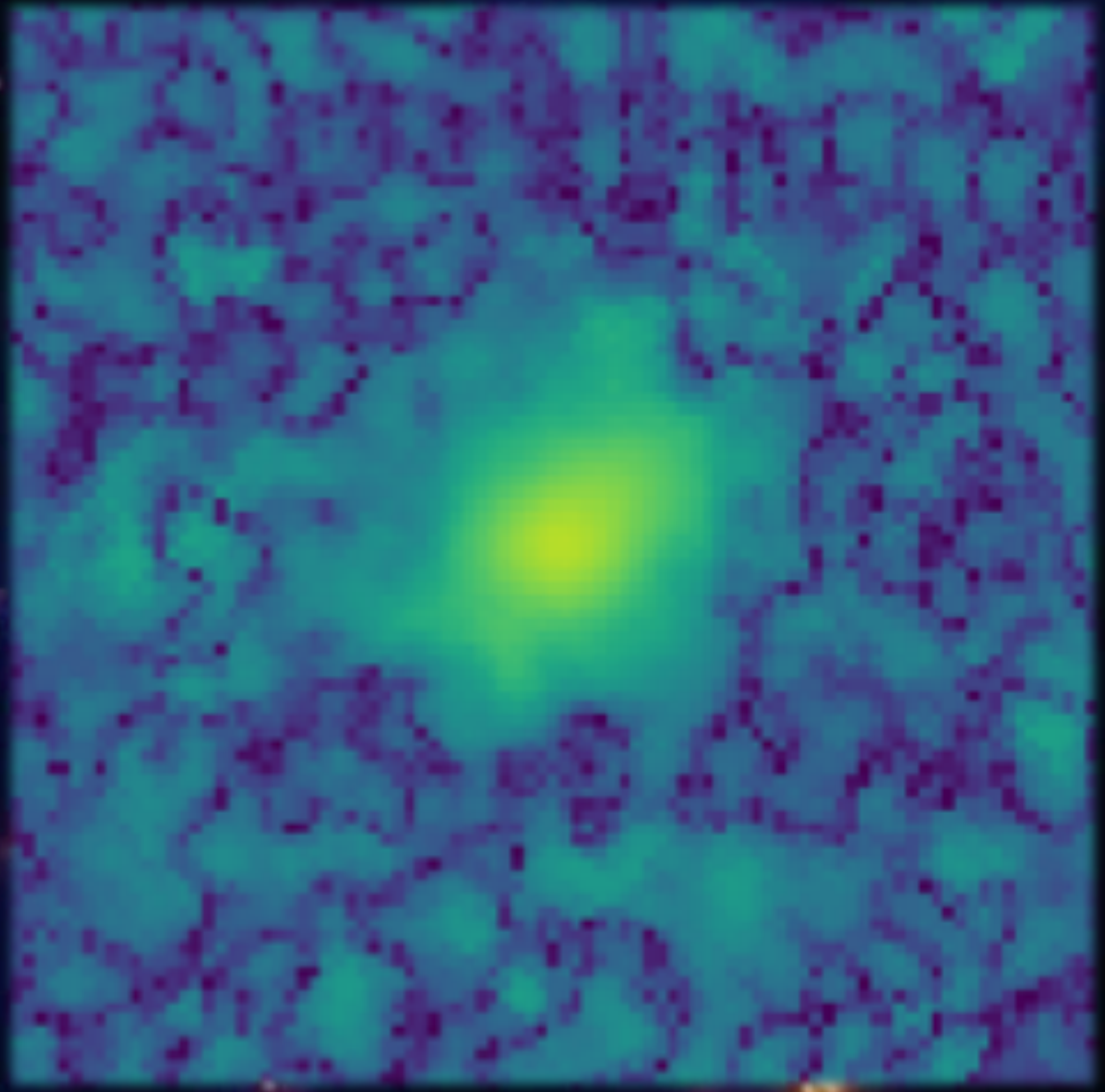
A deep learning approach to infer galaxy cluster masses from Planck Compton-y parameter maps

Daniel de Andres, Weiguang Cui, Florian Ruppin, Marco De Petris, Gustavo Yepes, Giulia Gianfagna, Ichraf Lahouli, Gianmarco Aversano, Romain Dupuis, Mahmoud Jarraya & Jesús Veg
Ferrero

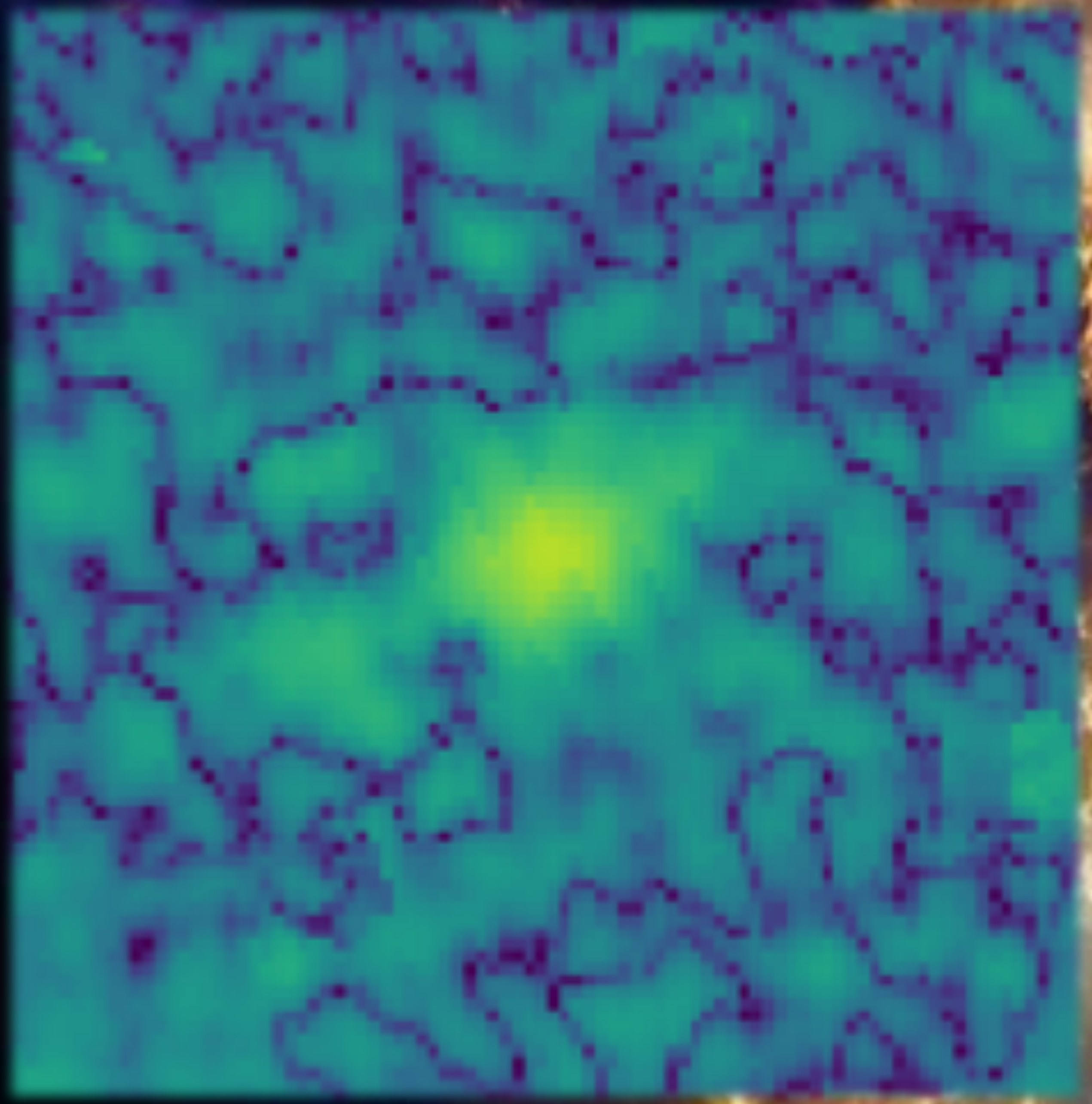
Nature Astronomy **6**, 1325–1331 (2022) | Cite this article

Training on simulated data from cosmological simulations to predict properties of real surveys

Simulation of a Compton-y observation



Real Compton-y Planck observation



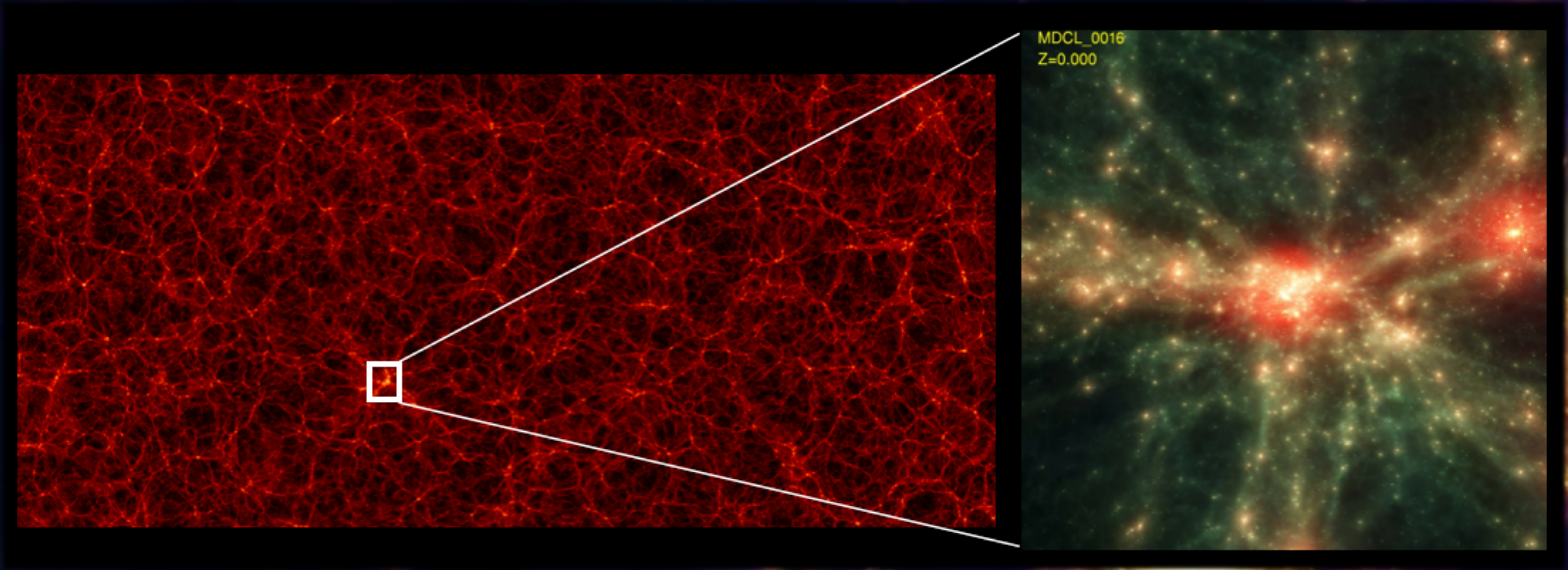
Outline

- Cosmological simulations: The Three Hundred Project.
- Mock dataset of images: SZ, Xray and stars.
- Deep learning model and results on the inference of mass maps.

- **Machine Learning group:** Daniel de Andrés, Weiguang Cui, Gustavo Yepes, Marco De Petris, Florian Ruppin, Federico De Luca, Giulia Gianfagna, Jesús Vega Ferrero, Alejandro Jiménez (+EURANOVA people: Gianmarco Aversano).

The Three Hundred Project

A set of **Cosmological hydrodynamical simulations**: Zoom-in simulations of $15/h$ Mpc radius around the 324 most massive clusters of the full $1/h$ Gpc MultiDark N-Body simulation.

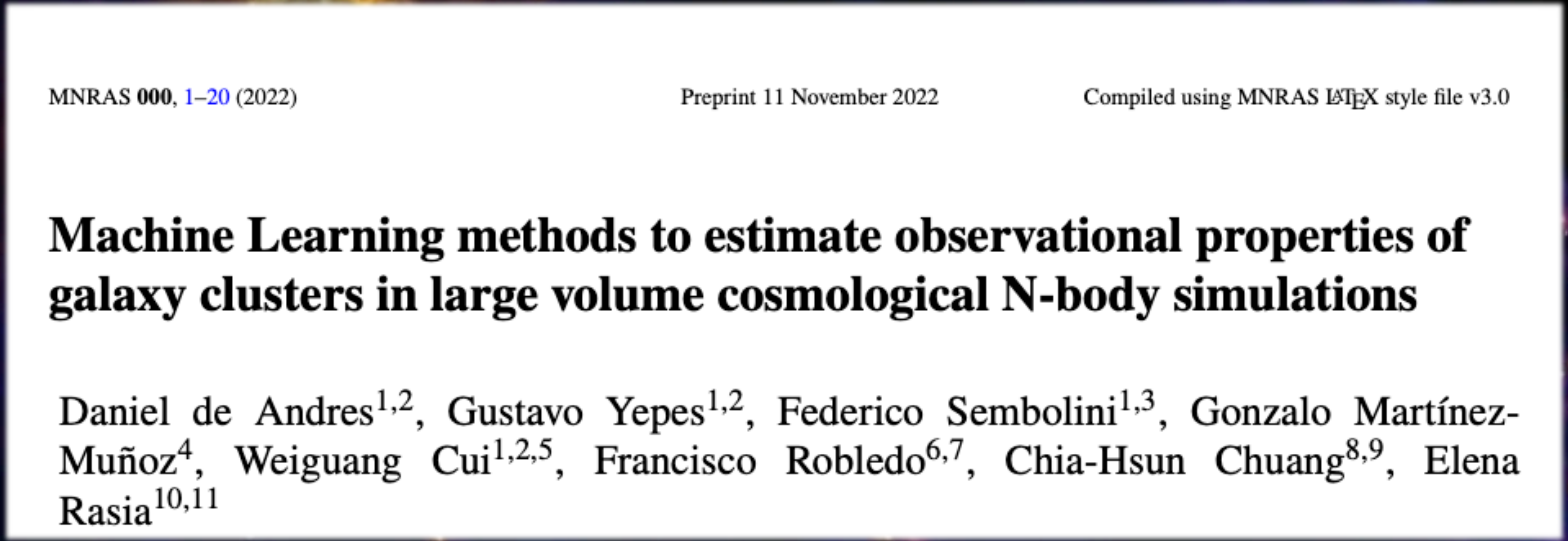


The Three Hundred Project

- A set of Cosmological hydrodynamical simulations: Zoom-in simulations of $15/h$ Mpc radius around the 324 most massive clusters of the full $1/h$ Gpc MultiDark N-Body simulation.

- DATA SAMPLE: 3 different versions of the same 324 simulations with different physics: GADGET-MUSIC (SN feedback, stellar winds), GADGET-X (+AGN Feedback), GIZMO-SIBMA (+stronger AGN Dave's model).

- Mock observations: X-ray (XMM, Athena), t-SZ, CCD (SDSS bands), lensing maps. Participate in Check-Mate and NIKA2 LPSZ as simulation providers.


MNRAS 000, 1–20 (2022) Preprint 11 November 2022 Compiled using MNRAS LaTeX style file v3.0

Machine Learning methods to estimate observational properties of galaxy clusters in large volume cosmological N-body simulations

Daniel de Andres[1,2], Gustavo Yepes[1,2], Federico Sembolini[1,3], Gonzalo Martínez-Muñoz[4], Weiguang Cui[1,2,5], Francisco Robledo[6,7], Chia-Hsun Chuang[8,9], Elena Rasia[10,11]

A first use of ML applied to The300

MNRAS 000, 1–20 (2022) Preprint 11 November 2022 Compiled using MNRAS LaTeX style file v3.0

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ML models

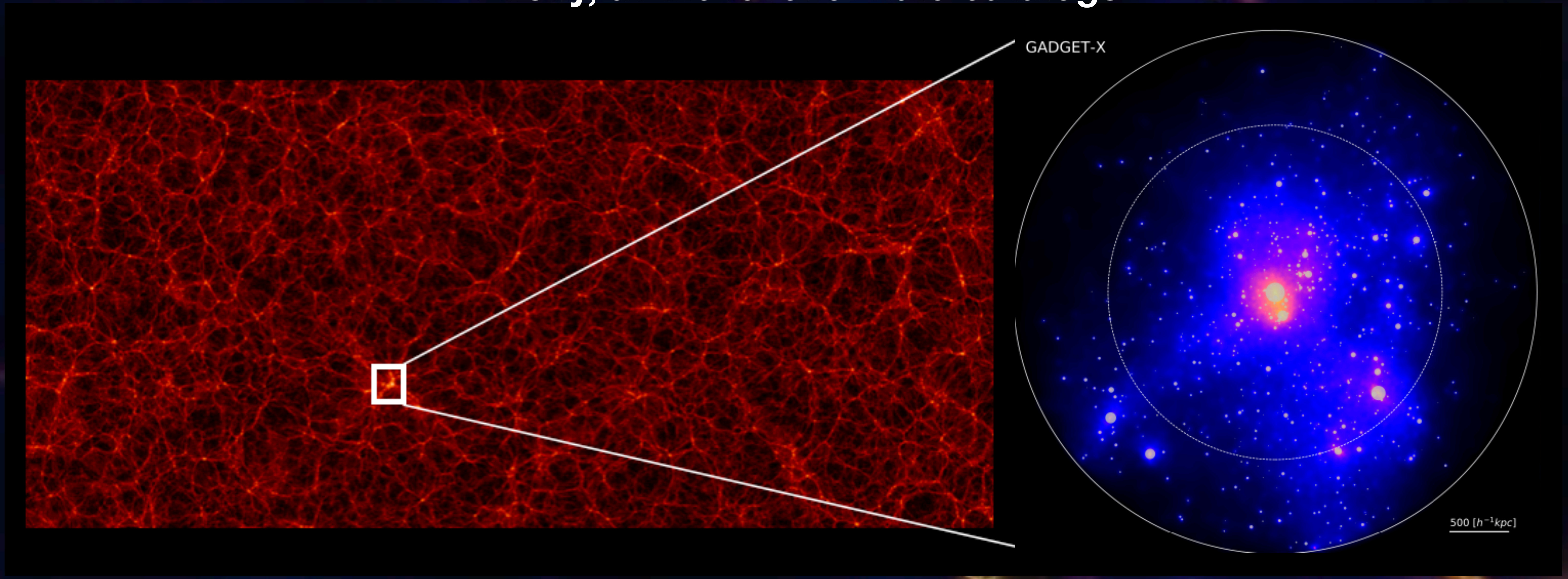
- XGBoost
- Neural nets
- NGBoost

The300 halos + ICM properties

Big N-body simulation halo catalogs

Predictions of ICM properties in Big N-body simulations: Ysz, Yx, Tx, Mgas, Mstar.

Firstly, at the level of halo catalogs



Deep learning applications on The300

nature > nature astronomy > articles > article

Article | Published: 17 October 2022

A deep learning approach to infer galaxy cluster masses from Planck Compton-*y* parameter maps

Daniel de Andres, Weiguang Cui, Florian Ruppin, Marco De Petris, Gustavo Yepes, Giulia Gianfagna, Ichraf Lahouli, Gianmarco Aversano, Romain Dupuis, Mahmoud Jarraya & Jesús Veg Ferrero

Nature Astronomy **6**, 1325–1331 (2022) | Cite this article

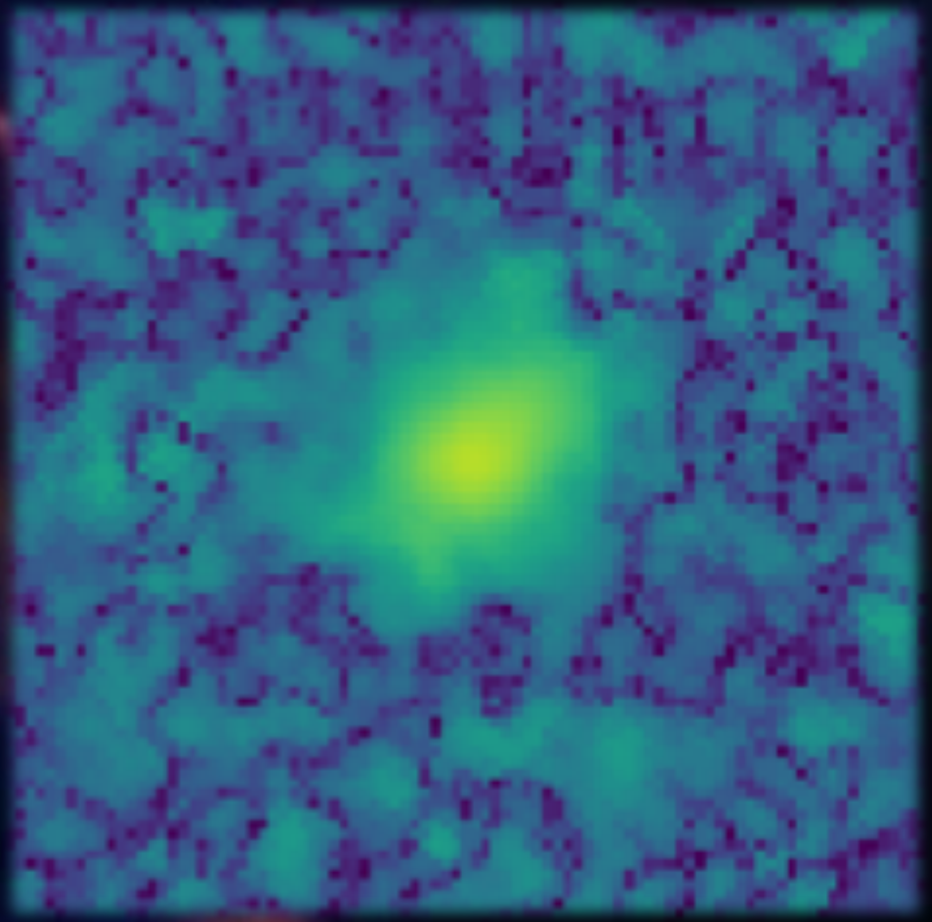
JOURNAL ARTICLE

See A.Ferragamo's talk tomorrow

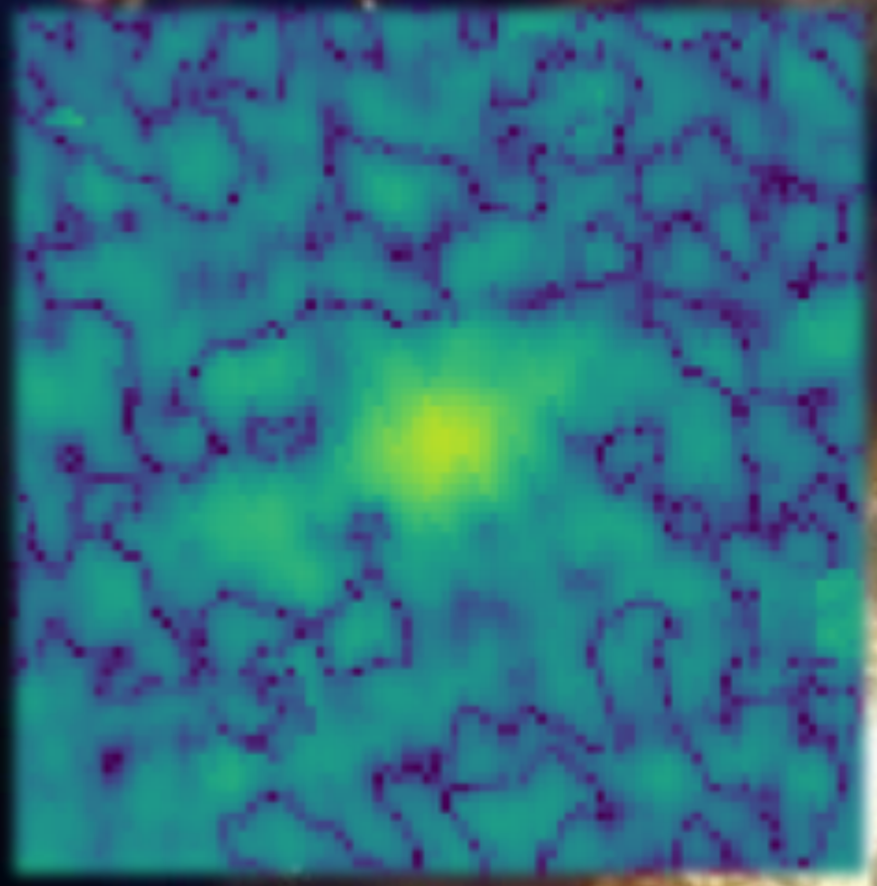
THE THREE HUNDRED project: a machine learning method to infer clusters of galaxy mass radial profiles from mock Sunyaev–Zel'dovich maps

A Ferragamo, D de Andres, A Sbriglio, W Cui, M De Petris, G Yepes, R Dupuis, M Jarraya, I Lahouli, F De Luca ... Show more

Simulation of a Galaxy Clusters observation



Real Compton-y Planck observation



Deep Learning Generative Models to Infer Mass Maps

Mock data images

Mock data images

“Theoretical dataset” free from contamination/noise and no telescope’s impact:

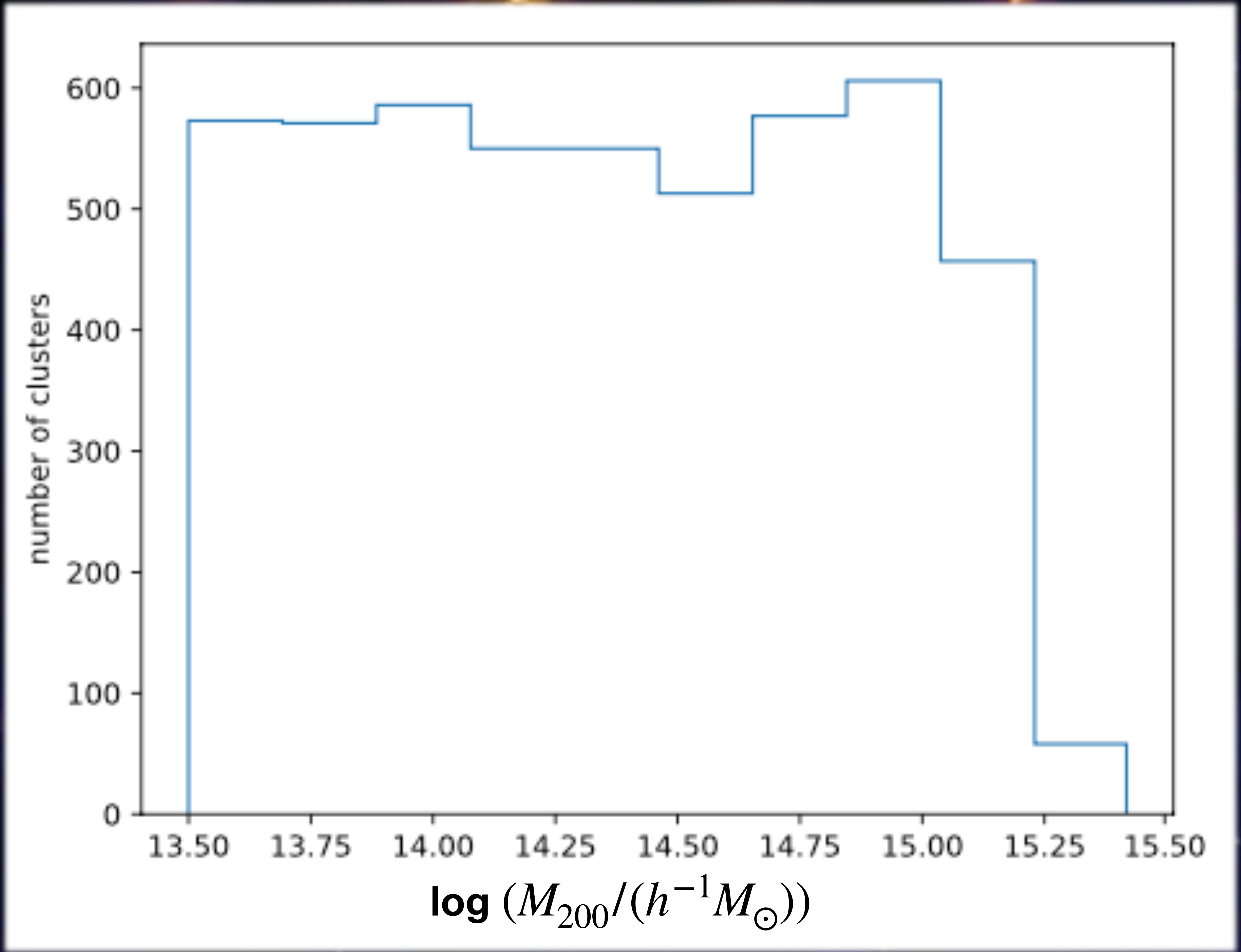
- **Compton-y parameter maps** PYMSZ, https://github.com/weiguangcui/pymsz

- **Bolometric X-ray surface brightness** estimated by emulating the X-ray energies by thermal bremsstrahlung in the hot intra-cluster medium using a wrapper of AtomDB https://atomdb.readthedocs.io/en/master/ , https://github.com/rennehan/xraylum

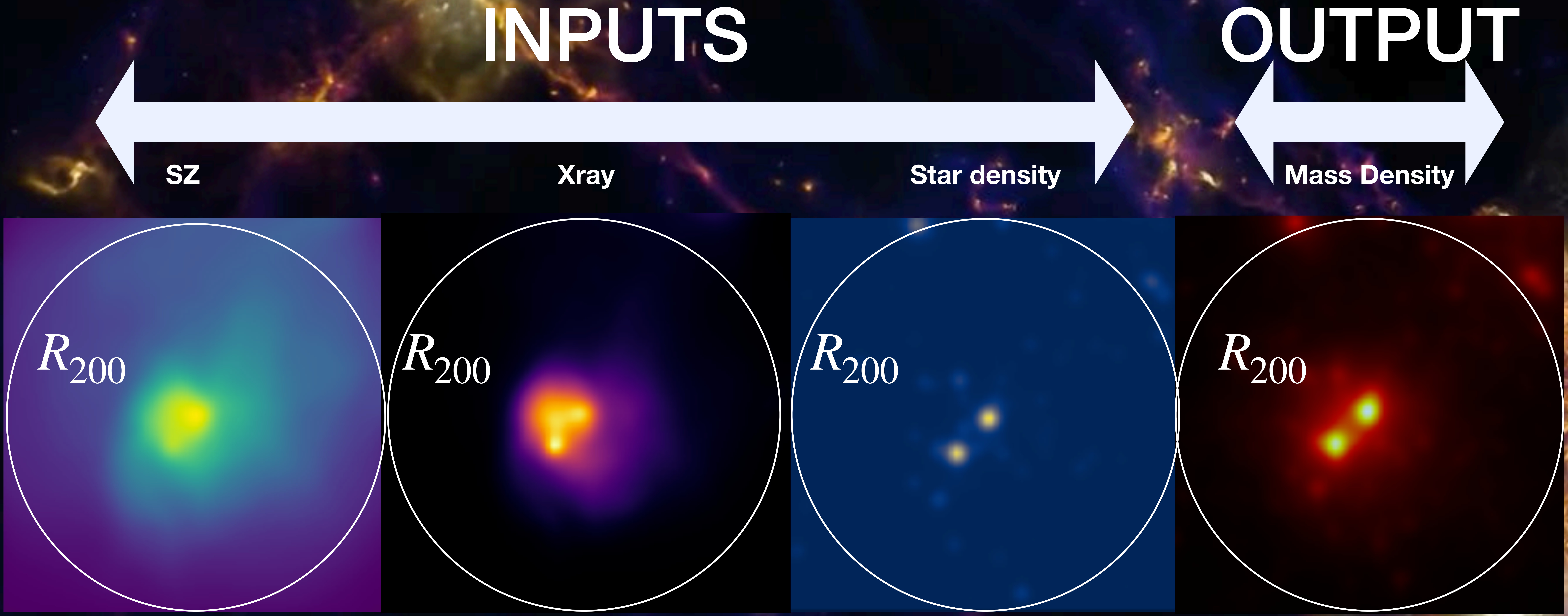
- **star density maps** are generated by projecting the sum of the masses of the star particles in the observer’s line of sight. That value is divided by the surface area of a pixel.

- **mass density maps** are generated by projecting the sum of the masses of all the particles, i.e., gas, star, dark matter and black holes particles in the observer’s line of sight

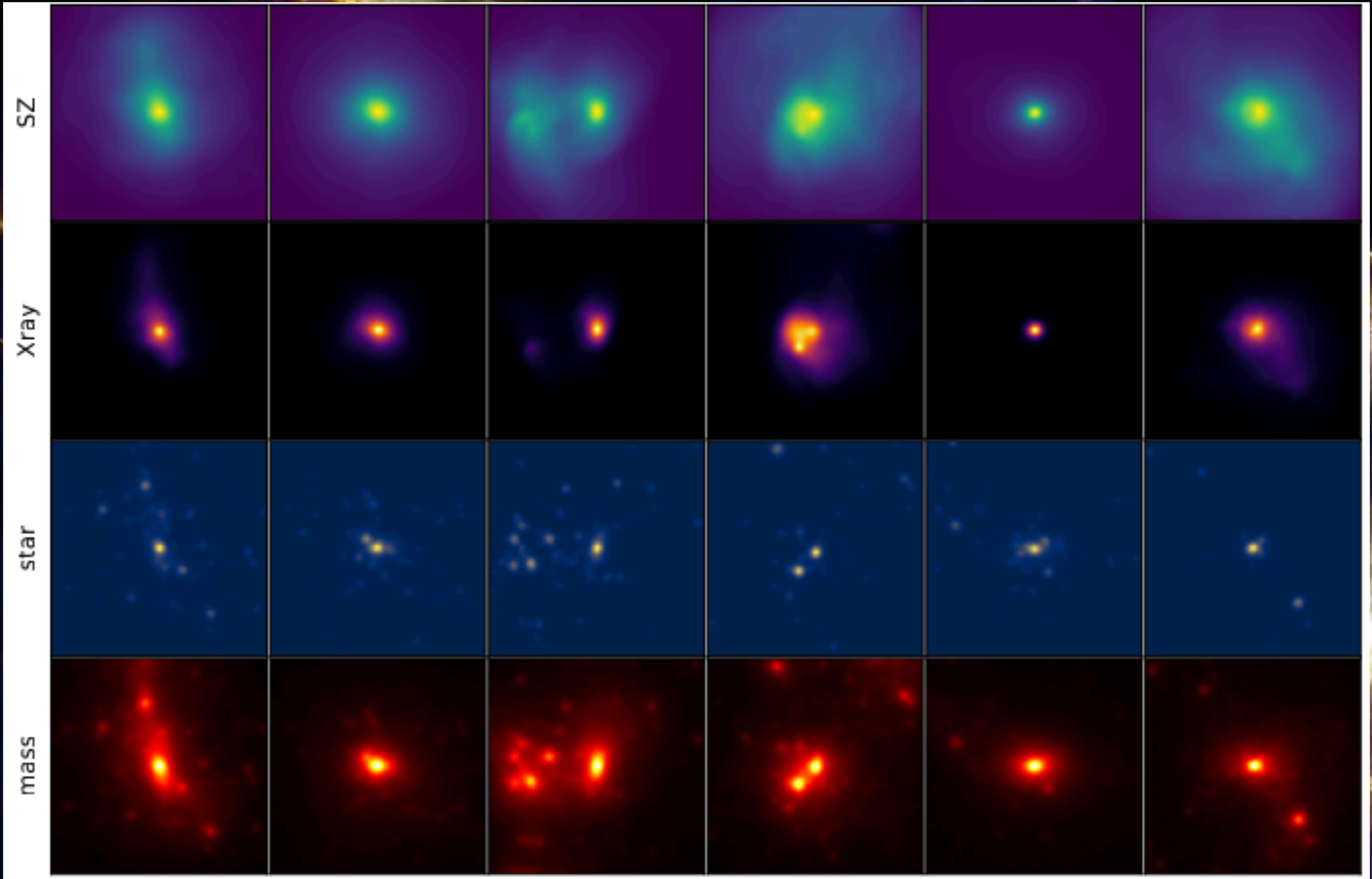
DATASET



- Only halos with $M_{200} > 10^{13.5} h^{-1} M_{\odot}$ are considered following a flat distribution in mass at redshift z~0.
- 29 l.o.s. projections and 5040 different halos and thus, ~**146 000 mock** images to train deep learning models.
- Density maps are sized such that the number of pixels is a function of R_{200} $2R_{200} = N_{pix}$= 80 .
- Maps are Gaussian-smoothed with a beam FWHM of ~$0.01 R_{200}$.



The statistical inference problem is stated as follows: How much information is available on the input maps to reconstruct the output mass density map?


SZ
Xray
star
mass

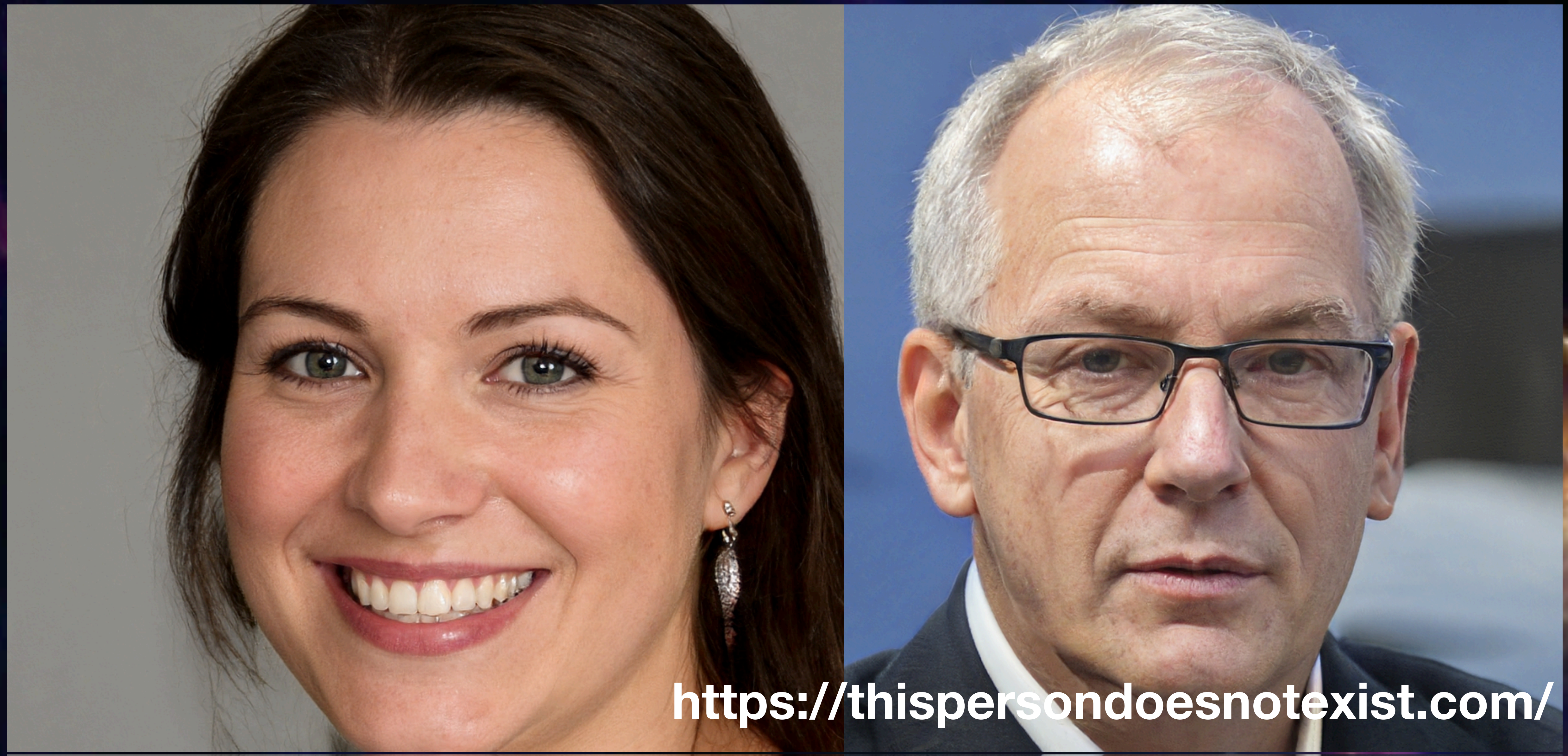
Deep learning generative models and results

Deep Learning is performing very well in other fields….

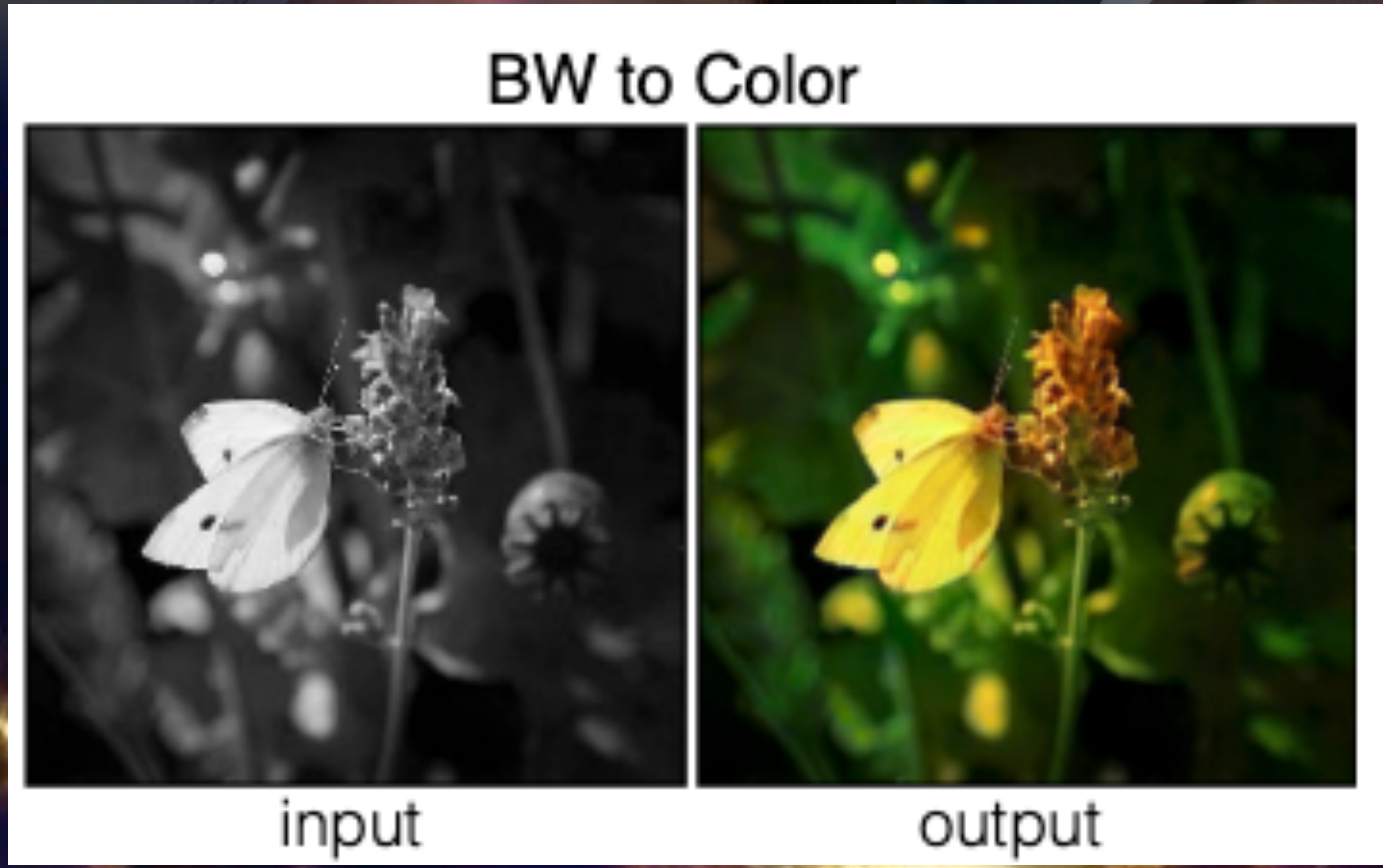
Image translation

Phillip Isola et al 2018

These people do not exist



https://thispersondoesnotexist.com/



Our model

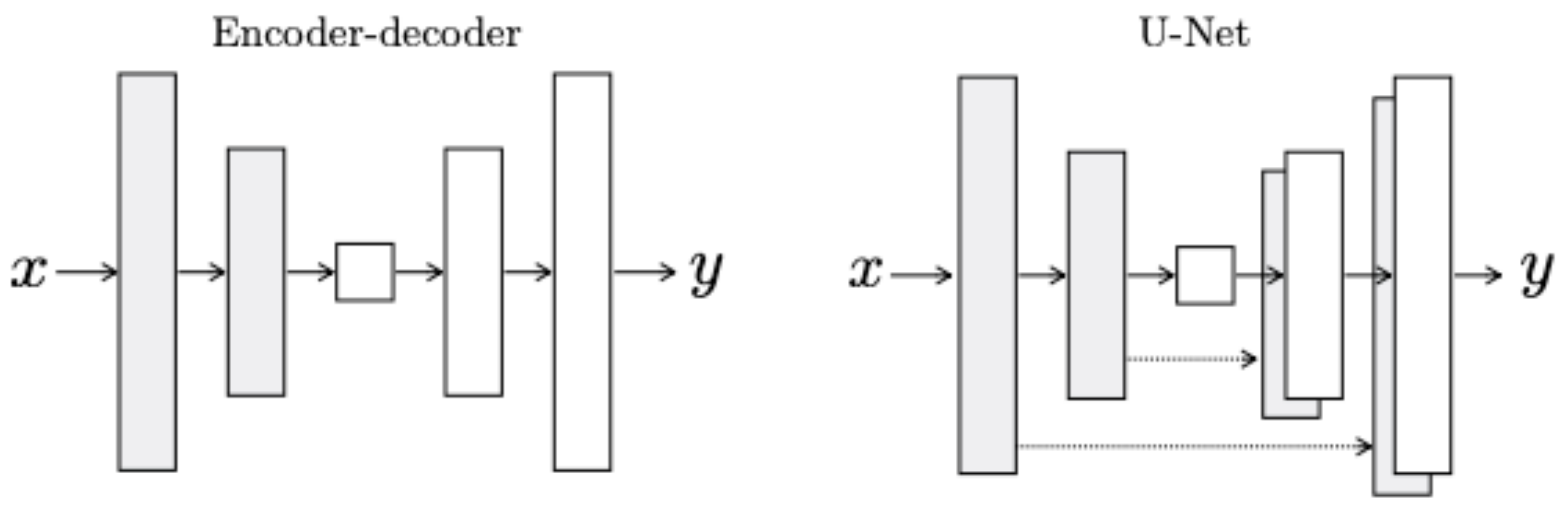


Figure 3: Two choices for the architecture of the generator. The "U-Net" [50] is an encoder-decoder with skip connections between mirrored layers in the encoder and decoder stacks.

Phillip Isola et al 2018

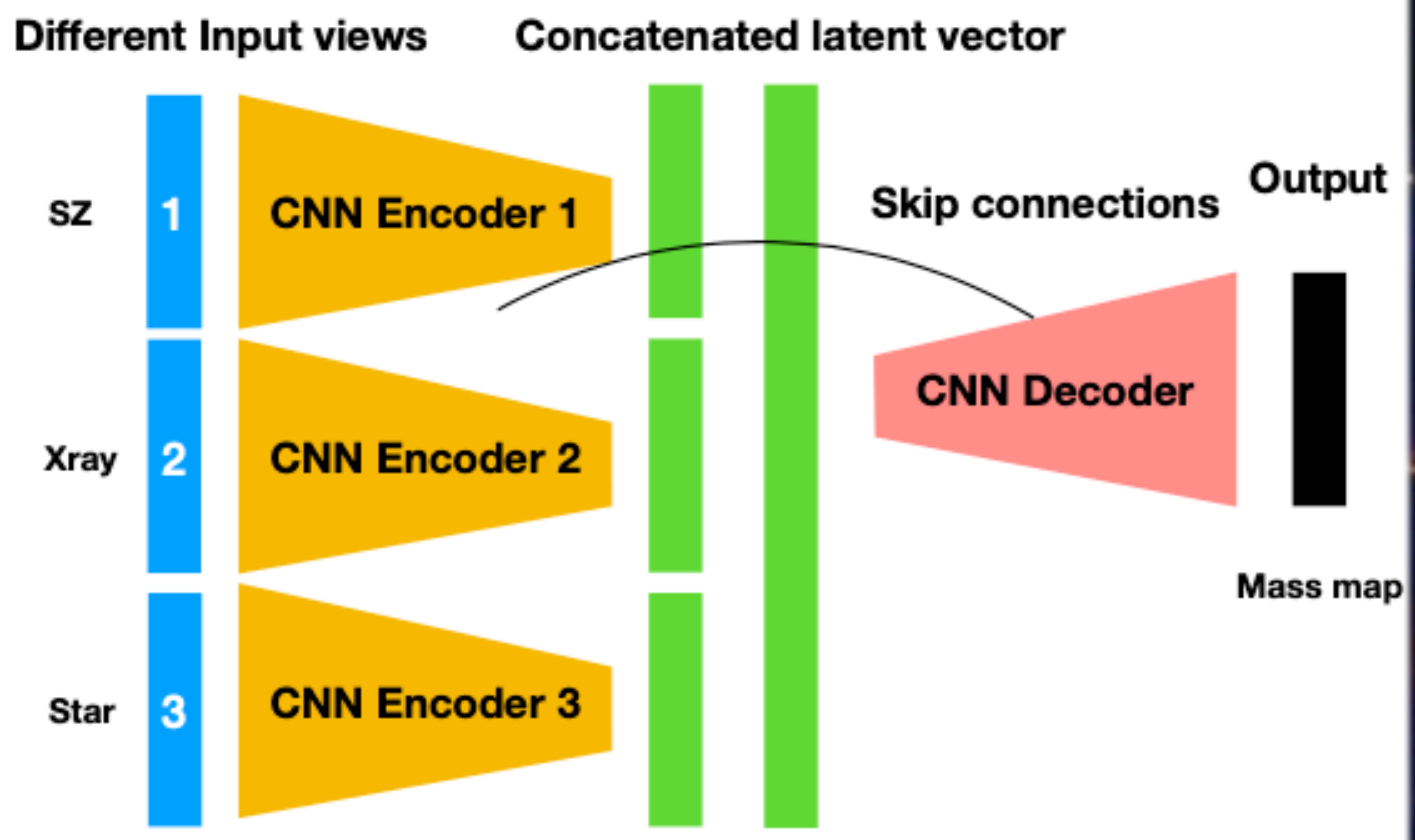
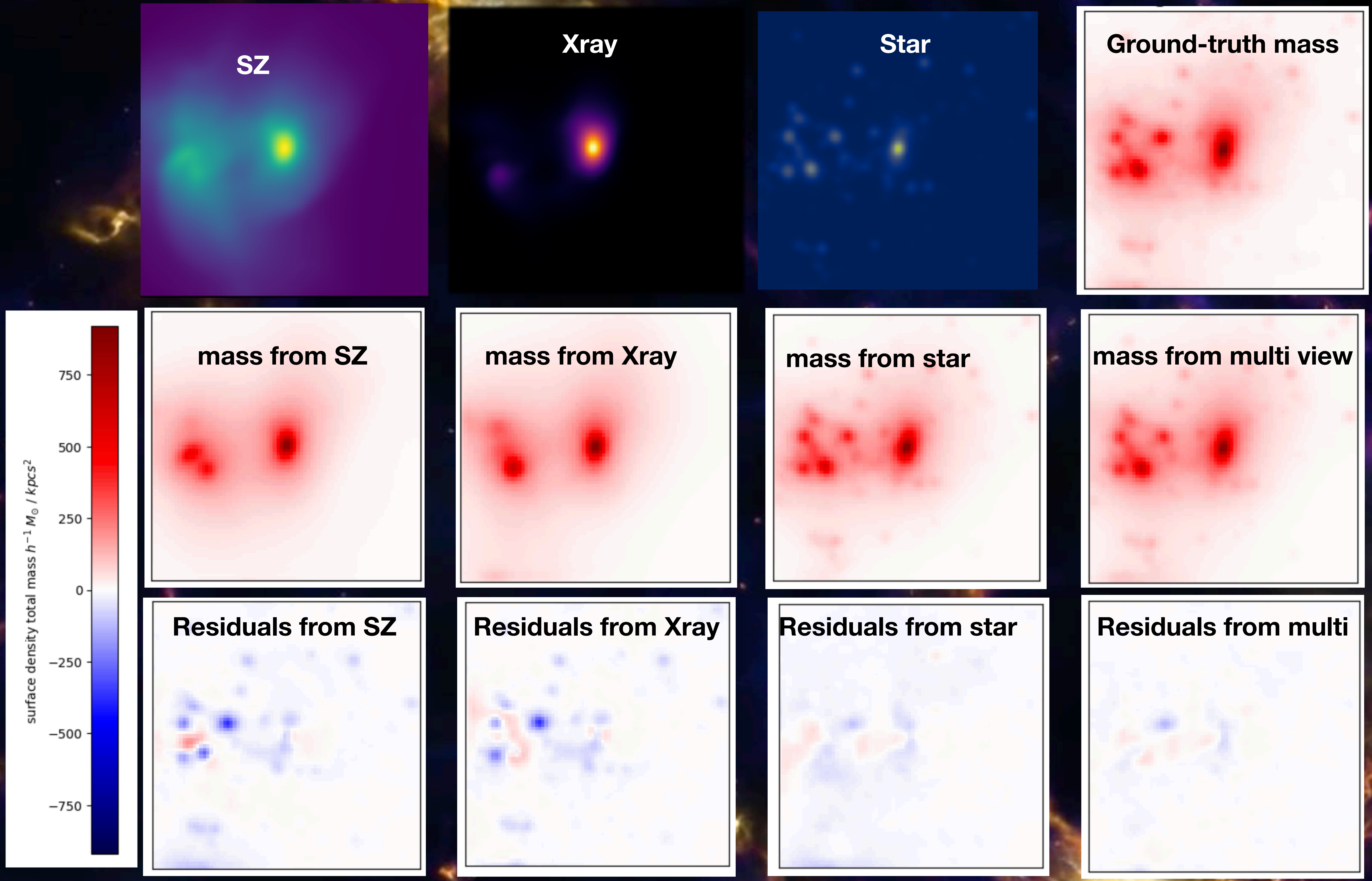


Figure 4. Multi-view approach

De Andrés et al 2023 in prep.

- One of the main advantages of this model is that it can make use of several input views to reconstruct the output density mass map.

- We train separately 4 UNETS varying the input view: SZ, Xray, star and multi view.


SZ
Xray
Star
Ground-truth mass
mass from SZ
mass from Xray
mass from star
mass from multi view
Residuals from SZ
Residuals from Xray
Residuals from star
Residuals from multi
surface density total mass $h^{-1} M_\odot$ / $kpcs^2$
750
500
250
0
−250
−500
−750

To do list

- Convolve our maps with the telescope's impact, add particle/instrumental and astrophysical background events.
- Train the model with data whose redshift and mass distributions match the surveys of interest: eRosita, XMM, NIKA.
- Marginalise over different baryon physics simulations.

Take home message

- Deep learning models can be used for generating the 2D mass density distribution from observational SZ, X-ray, star data.

- This method has been tested with ‘theoretical’ simulated mock data.

- The objective is performing simulation based inference -> we can use our models to generate 2D mass density maps of NIKA2, SPT, eRosita, SDSS.

- The model architecture is flexible so that different luminosity bands can be combined. This application can be used for different photometric surveys.

Thanks

questions?

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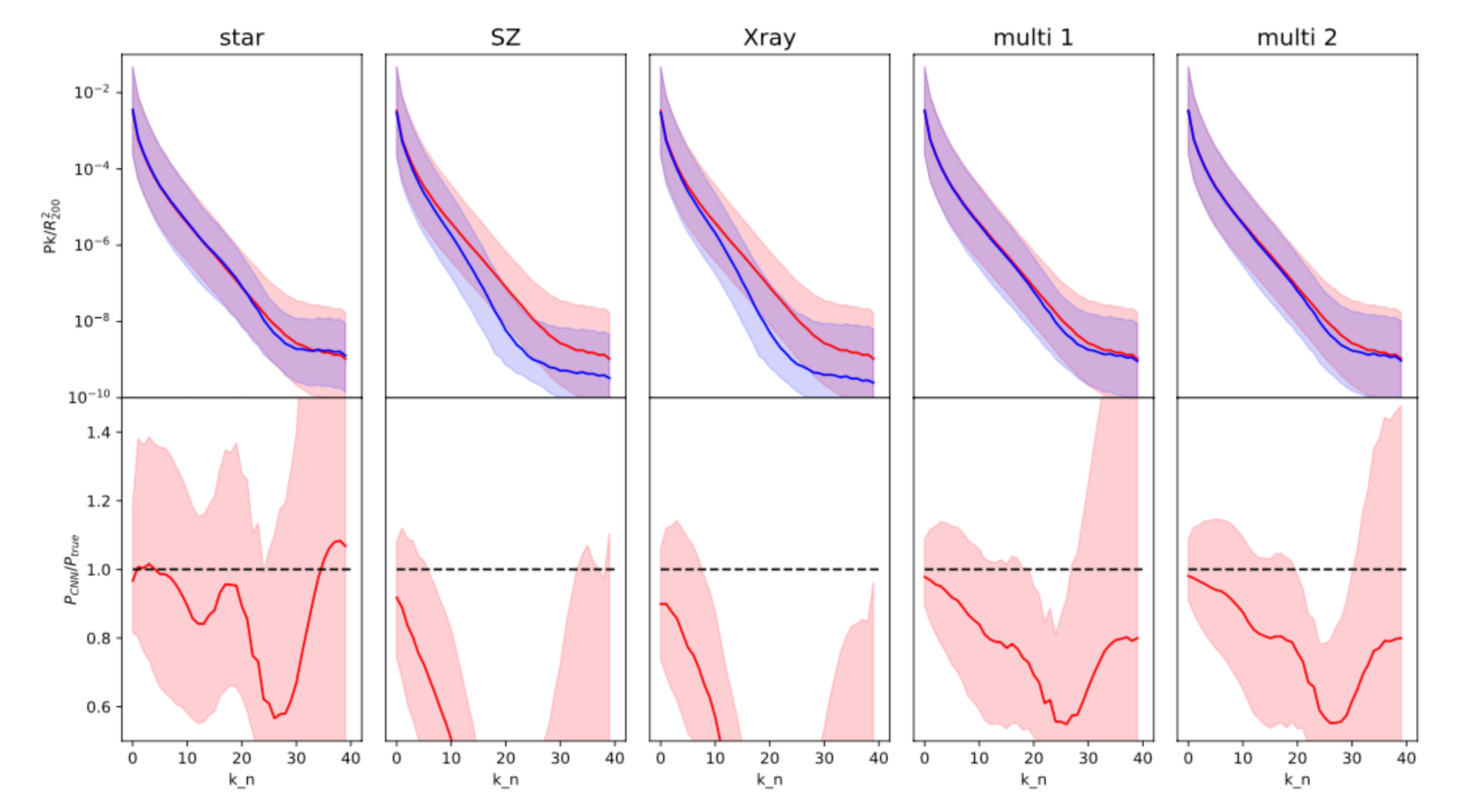
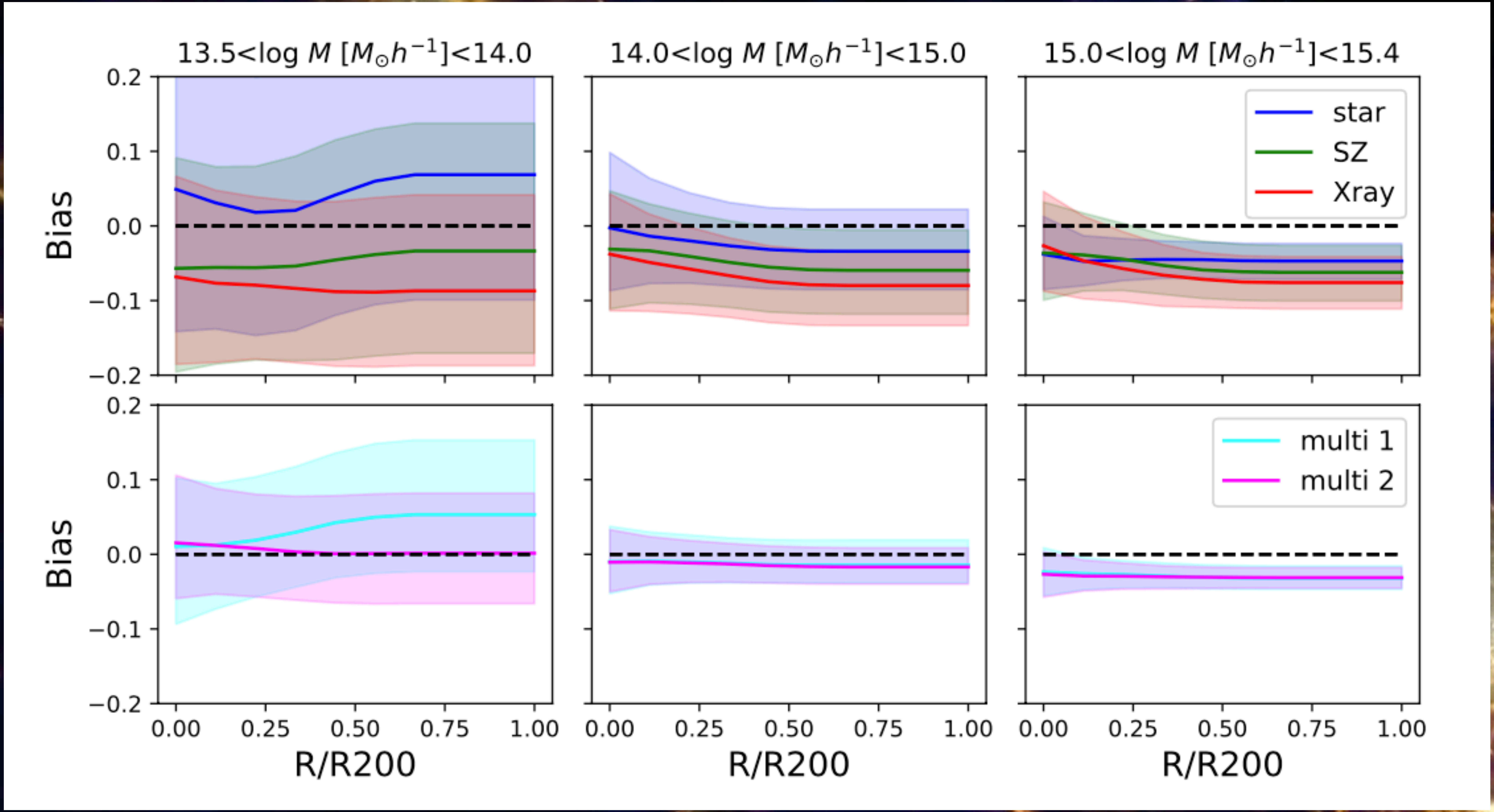
Just-in-case slides


probability density
star, $-0.04^{+0.12}_{-0.11}$
SZ, $-0.05^{+0.17}_{-0.22}$
X-ray, $-0.06^{+0.16}_{-0.21}$
multiview 1, $-0.02^{+0.09}_{-0.09}$
multiview 2, $-0.02^{+0.09}_{-0.08}$
$(Pred_{ij} - True_{ij})/True_{ij}$ inside the whole map
star, $-0.03^{+0.12}_{-0.10}$
SZ, $-0.02^{+0.16}_{-0.17}$
X-ray, $-0.04^{+0.15}_{-0.17}$
multiview 1, $-0.01^{+0.08}_{-0.08}$
multiview 2, $-0.01^{+0.08}_{-0.08}$
$(Pred_{ij} - True_{ij})/True_{ij}$ inside R_{500}
star, $-0.02^{+0.12}_{-0.10}$
SZ, $-0.01^{+0.13}_{-0.14}$
X-ray, $-0.03^{+0.14}_{-0.14}$
multiview 1, $-0.01^{+0.08}_{-0.07}$
multiview 2, $-0.01^{+0.08}_{-0.07}$
$(Pred_{ij} - True_{ij})/True_{ij}$ inside $R_{500}/2$


star
SZ
Xray
multi 1
multi 2
Pk/R_{200}^2
10^{-2}
10^{-4}
10^{-6}
10^{-8}
10^{-10}
P_{CNN}/P_{true}
1.4
1.2
1.0
0.8
0.6
0
10
20
30
40
k_n


13.5<log M [M⊙h⁻¹]<14.0
14.0<log M [M⊙h⁻¹]<15.0
15.0<log M [M⊙h⁻¹]<15.4
Bias
Bias
star
SZ
Xray
multi 1
multi 2
0.2
0.1
0.0
−0.1
−0.2
0.00
0.25
0.50
0.75
1.00
R/R200
R/R200
R/R200