Cosmology in the machine learning era

Francisco Villaescusa-Navarro

ML4Astro2

Cosmology

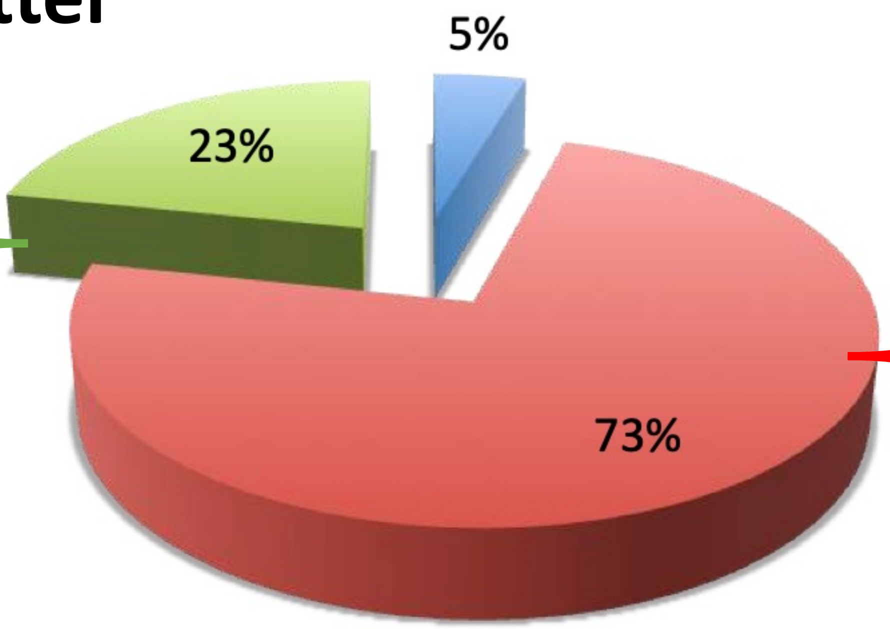
Branch of Astrophysics that studies the Universe's:

- Origin and fate
- Composition
- Laws
- Structure
- Dynamics

Our Universe

Baryons (Ordinary matter)

Dark Matter

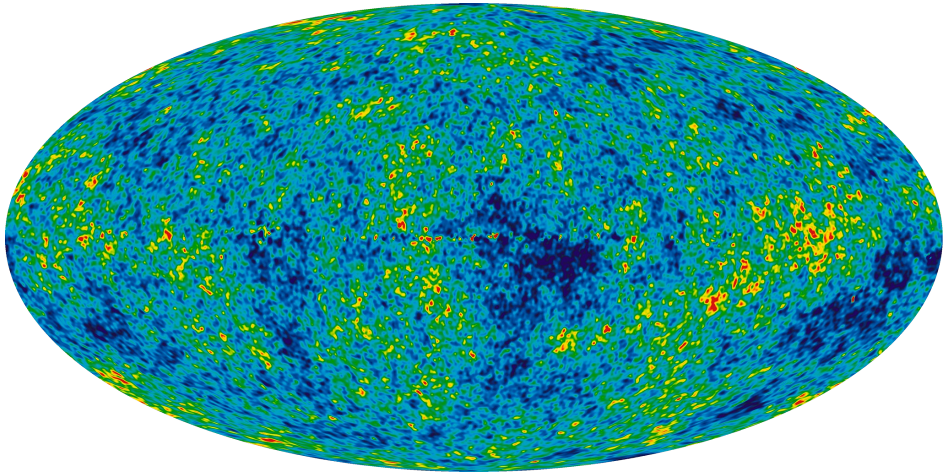


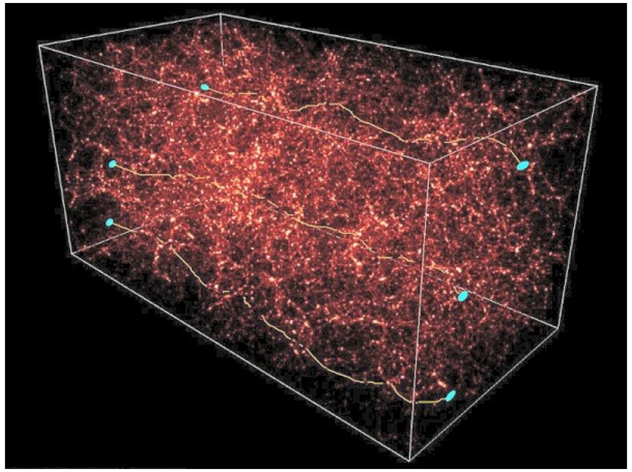
- Cold dark matter
- Warm dark matter
- Atomic dark matter
- …

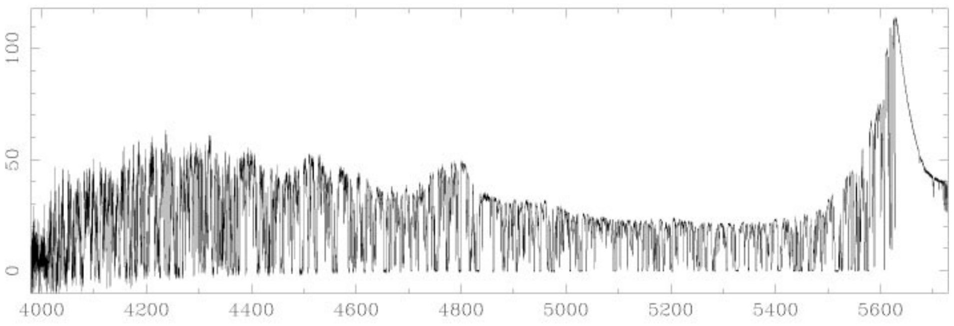
- General relativity (Λ)
- Modified gravity
- …

Dark Energy

The ΛCDM model

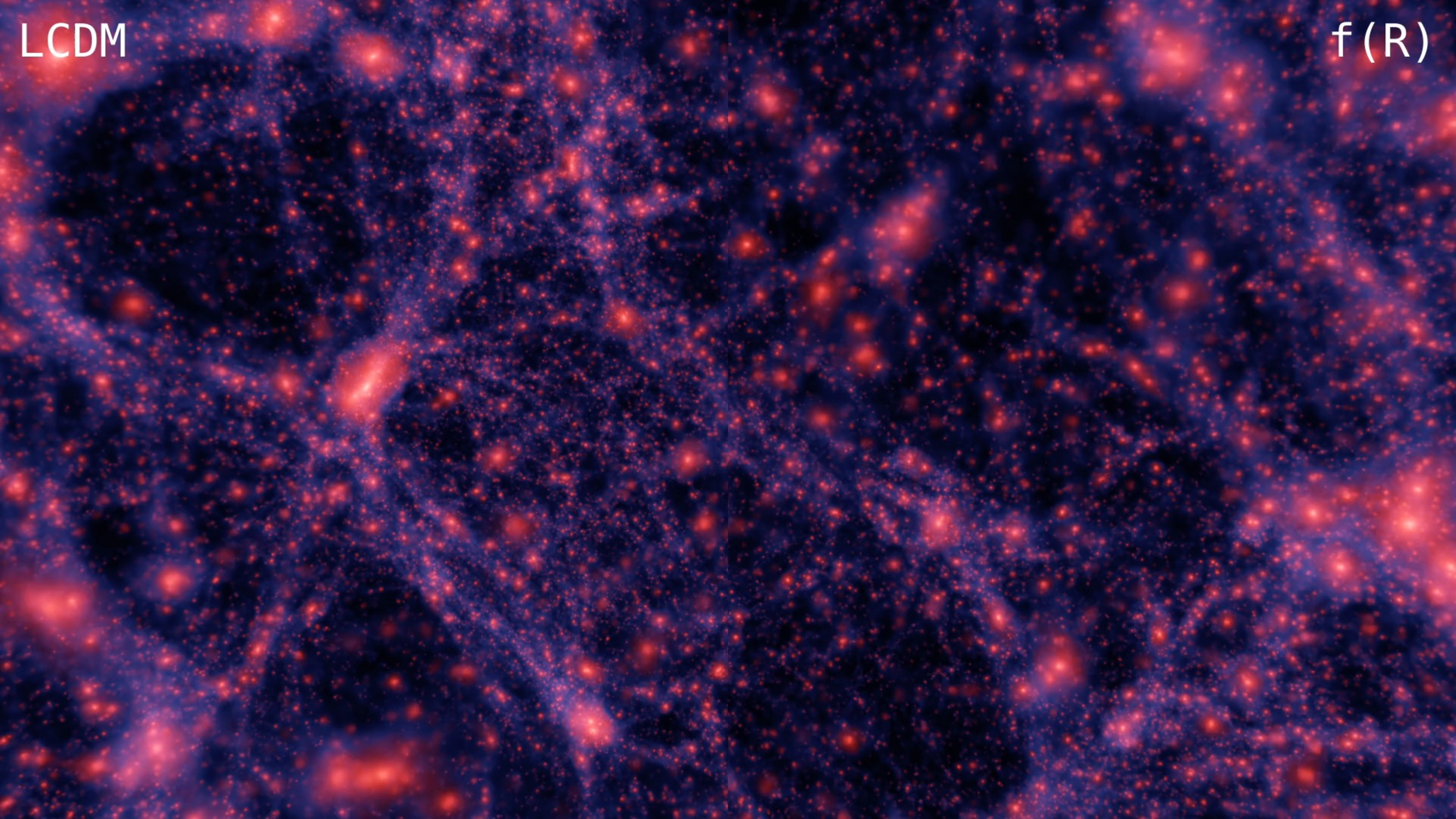






$$\Omega_b \pm \delta\Omega_b$$
$$\Omega_m \pm \delta\Omega_m$$
$$h \pm \delta h$$
$$w_0 \pm \delta w_0$$
$$w_a \pm \delta w_a$$
$$n_s \pm \delta n_s$$
$$\sigma_8 \pm \delta\sigma_8$$
$$M_\nu \pm \delta M_\nu$$
$$N_{\rm eff} \pm \delta N_{\rm eff}$$

$z = 20.00$


LCDM
f(R)

The Quijote Simulations

(https://quijote-simulations.readthedocs.io)

- A set of 85,000 full N-body simulations
- More than 42,000 cosmologies in $\{\Omega_m, \Omega_b, h, n_s, \sigma_8, M_\nu, w_0, \delta_b, f_{\rm NL}, g_{\rm NL}, f(R)\}$
- 12+ trillion particles over a volume larger than entire observable Universe
- Catalogs with billions of halos, voids (Gigantes), and galaxies (Molino). WL maps (Ulagam)
- 50 Million CPU hours; 1+ Petabyte of data
- 170+ papers written using this data
- All data publicly available (binder & globus)

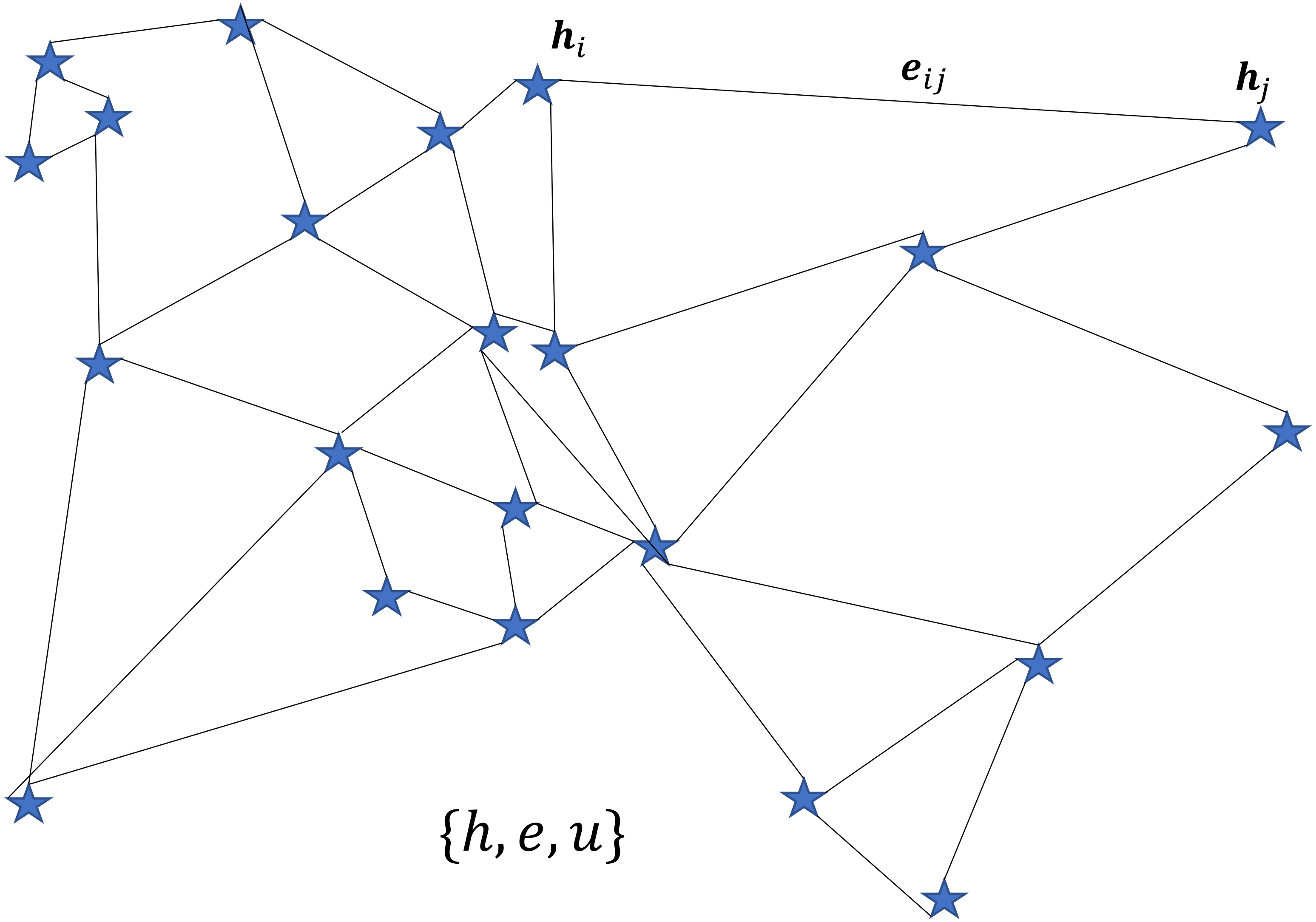
Generic conclusion:
Lots of information on small scales beyond P(k)

Benefits: Lots of information

Problems: Non-linearities & baryonic effects

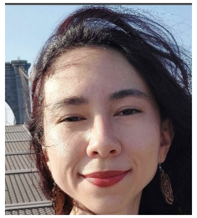
$z = 9.94$

Cosmic Graphs



$\{h, e, u\}$

Pablo Villanueva-Domingo
(Barcelona)

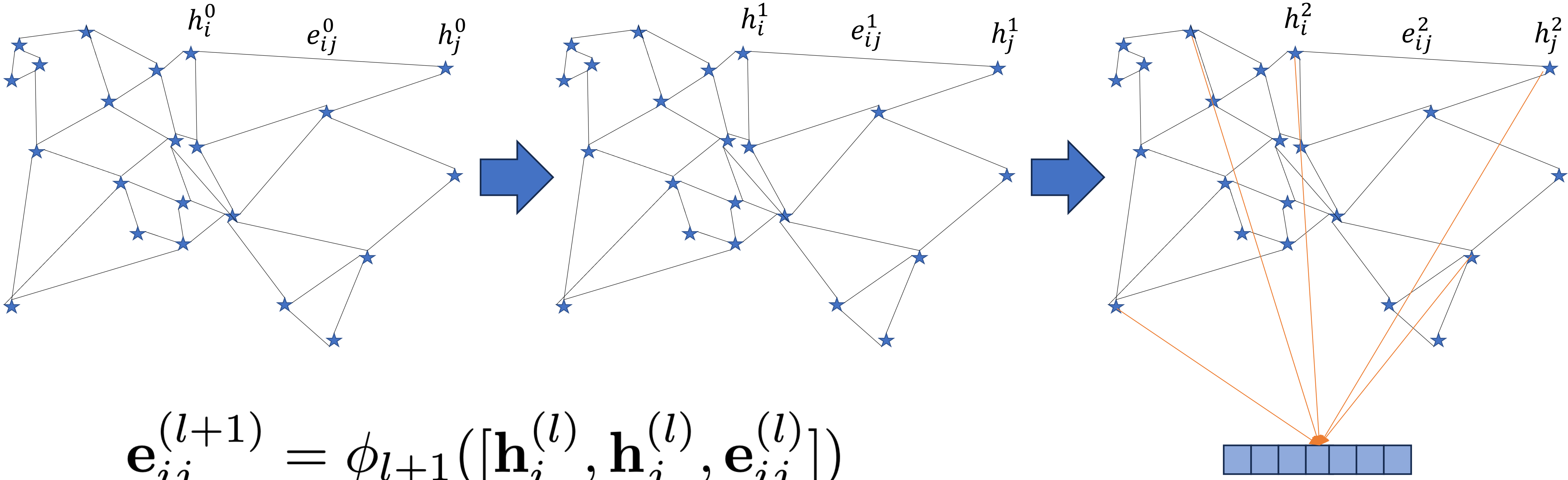


Natali de Santi
(Flatiron/Sao Paolo)

Helen Shao
(Princeton)

Talk to Farida Farsian

Graph neural networks



$$\mathbf{e}_{ij}^{(l+1)} = \phi_{l+1}([\mathbf{h}_i^{(l)}, \mathbf{h}_j^{(l)}, \mathbf{e}_{ij}^{(l)}])$$

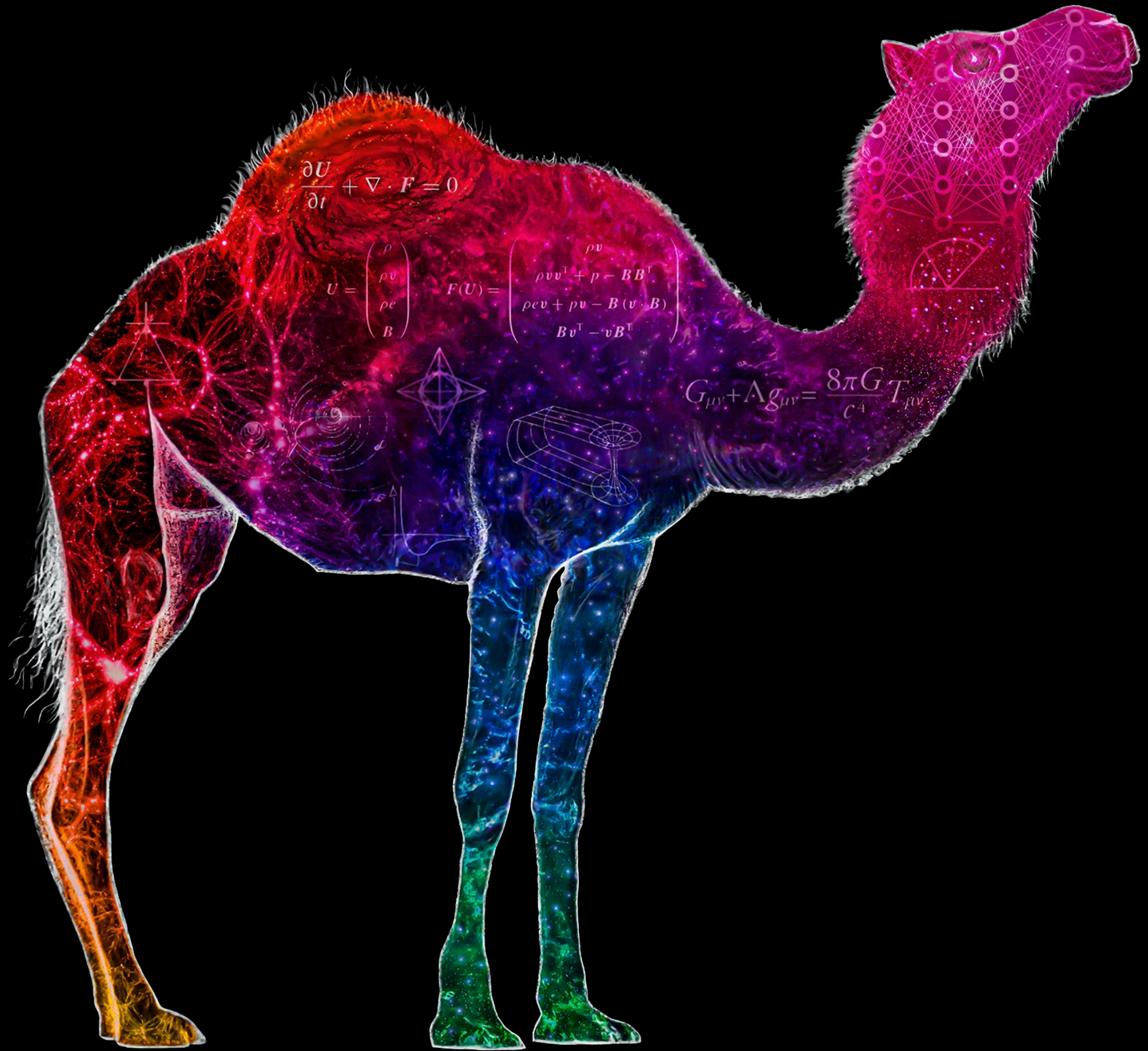
$$\mathbf{h}_i^{(l+1)} = \psi_{l+1}([\mathbf{h}_i^{(l)}, \bigoplus_{j \in \mathcal{N}_i} \mathbf{e}_{ij}^{(l+1)}, \mathbf{u}])$$

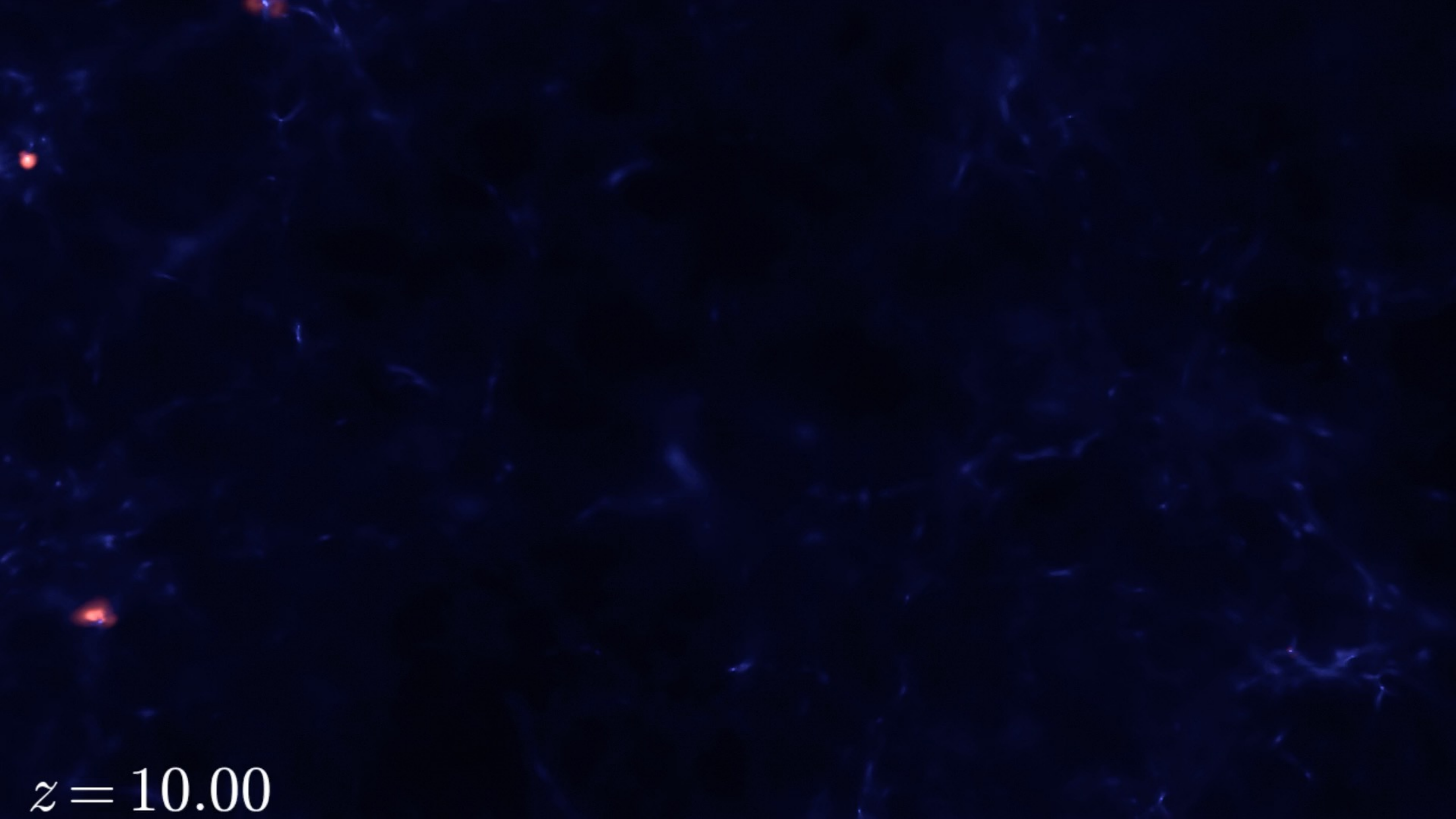
$$\mathbf{y} = \xi([\bigoplus_{i \in \mathcal{G}} \mathbf{h}_i^{(L)}, \mathbf{u}])$$

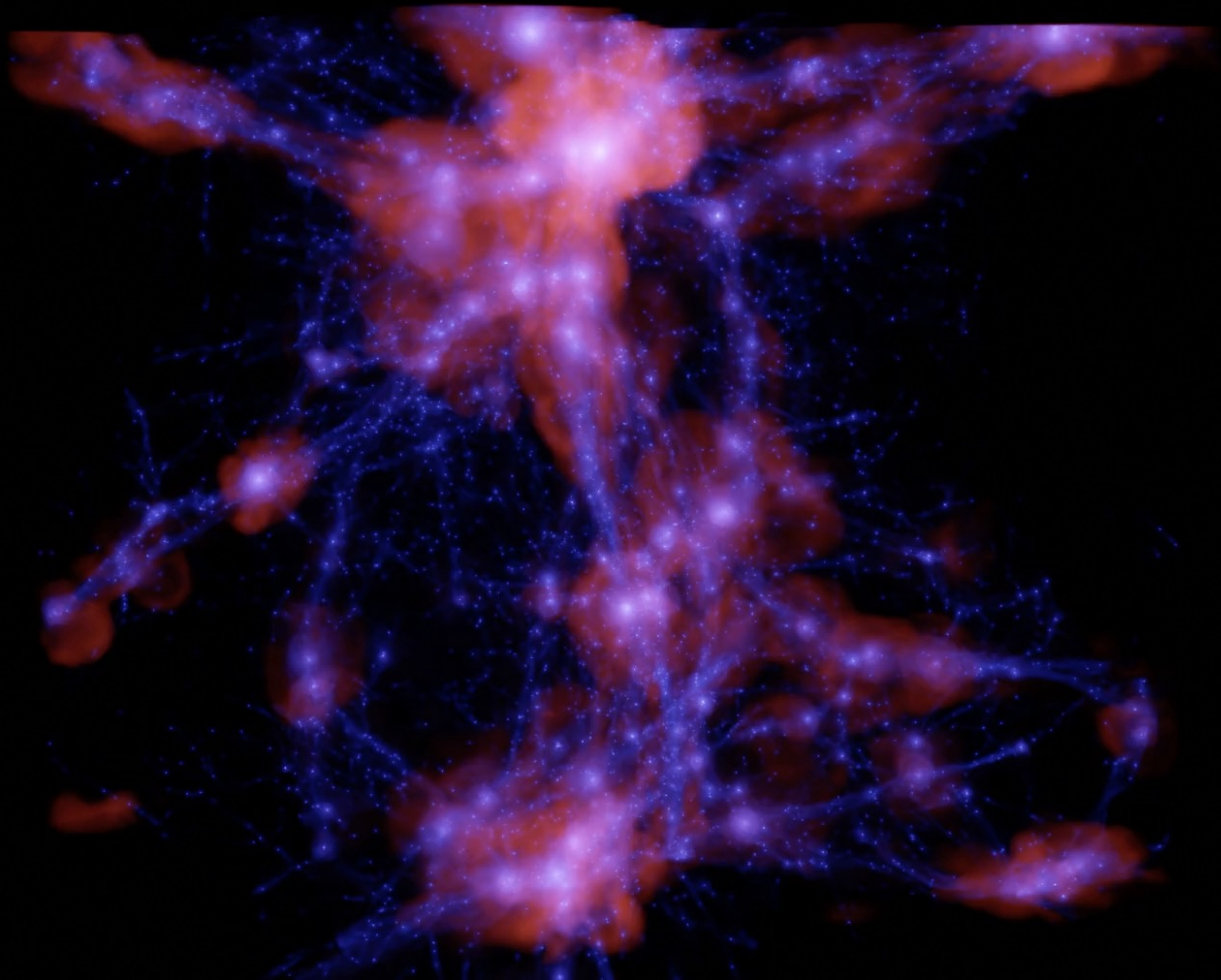
CAMELS

Cosmology and Astrophysics with MachinE Learning Simulations

https://www.camel-simulations.org

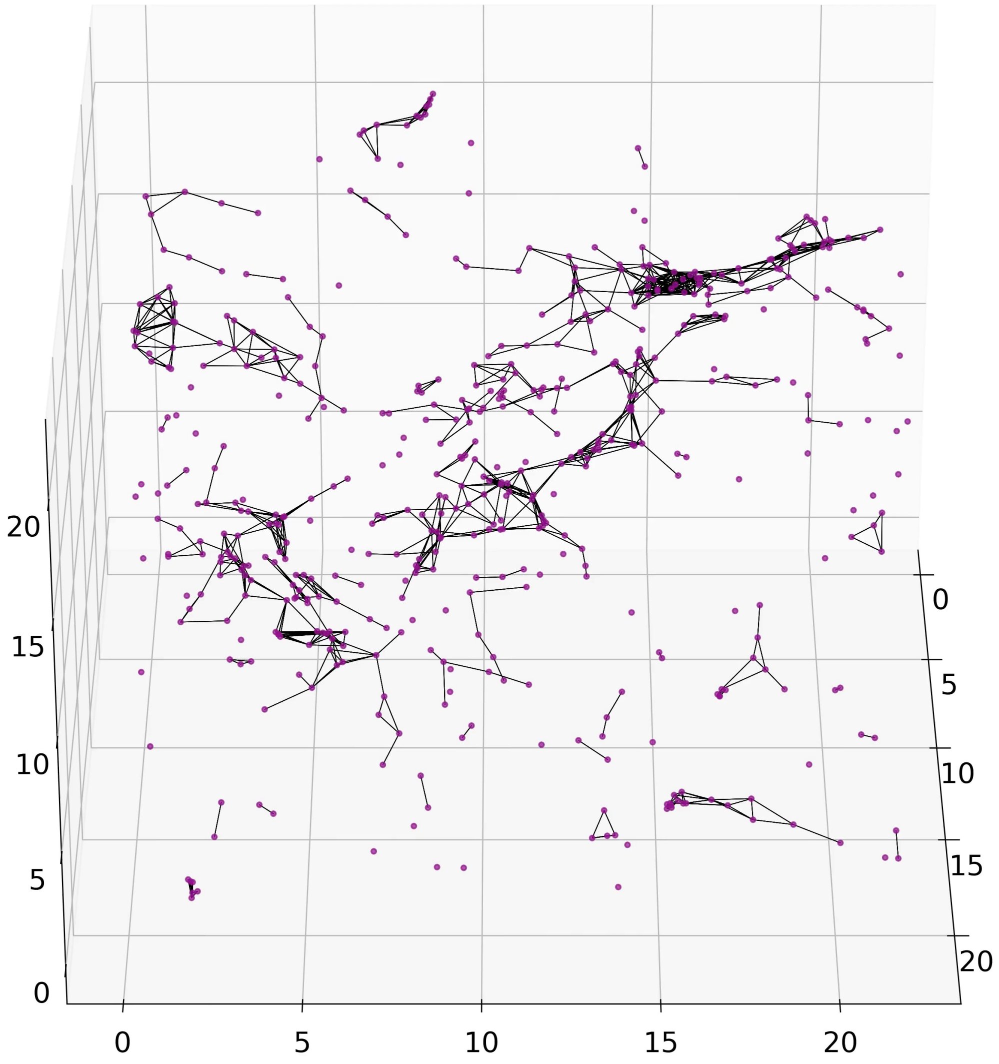


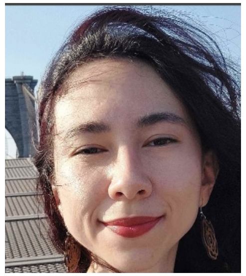

$z = 10.00$



Galaxy catalogs as cosmic graphs

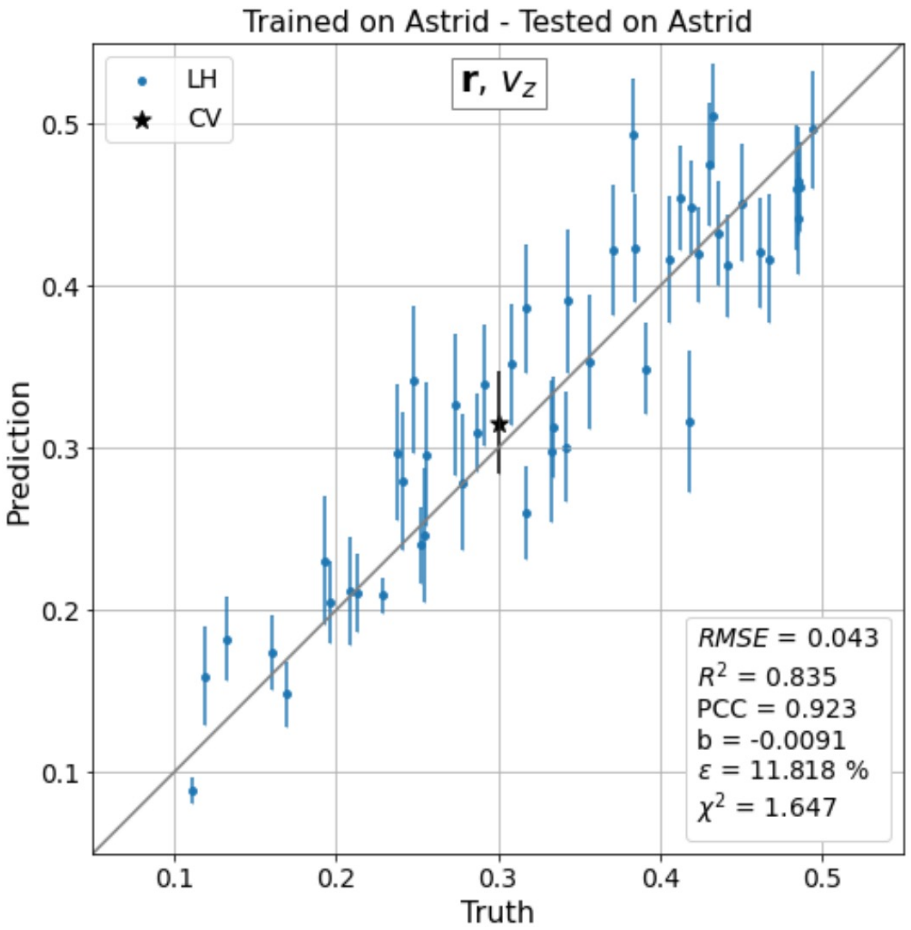
2302.14101

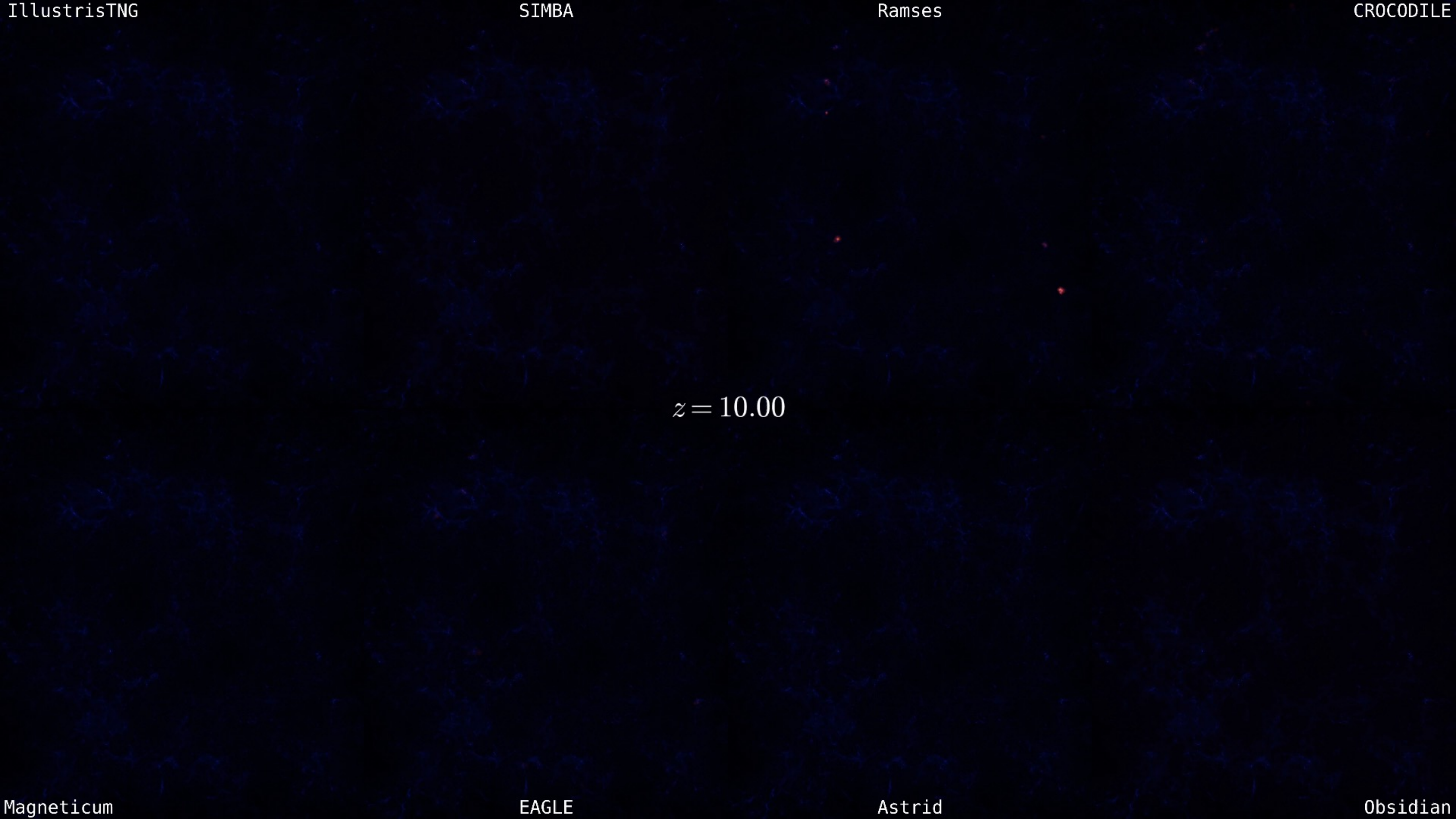




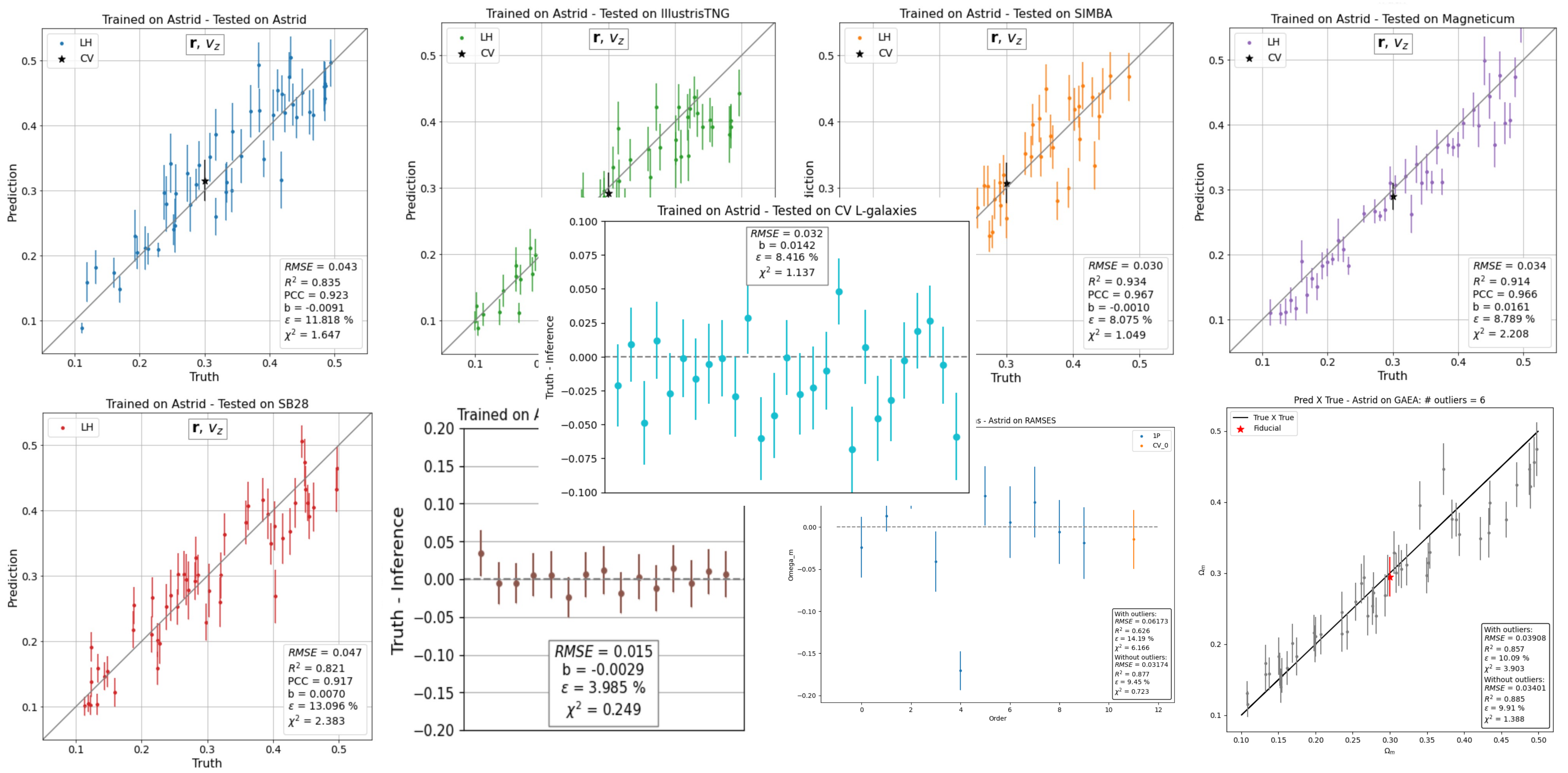
Natali de Santi
(Sao Paolo)

- ller than r_{link}
- h/Mpc
- l invariant




IllustrisTNG
SIMBA
Ramses
CROCODILE
$z = 10.00$
Magneticum
EAGLE
Astrid
Obsidian

Robust field-level inference with GNNs



Robust field-level inference with GNNs: Interpretability

Helen Shao
(Princeton)

$$\mathbf{e}_{ij}^{(l+1)} = \phi_{l+1}([\mathbf{h}_i^{(l)}, \mathbf{h}_j^{(l)}, \mathbf{e}_{ij}^{(l)}])$$

$$\mathbf{h}_i^{(l+1)} = \psi_{l+1}([\mathbf{h}_i^{(l)}, \bigoplus_{j\in\mathcal{N}_i} \mathbf{e}_{ij}^{(l+1)}, \mathbf{u}])$$

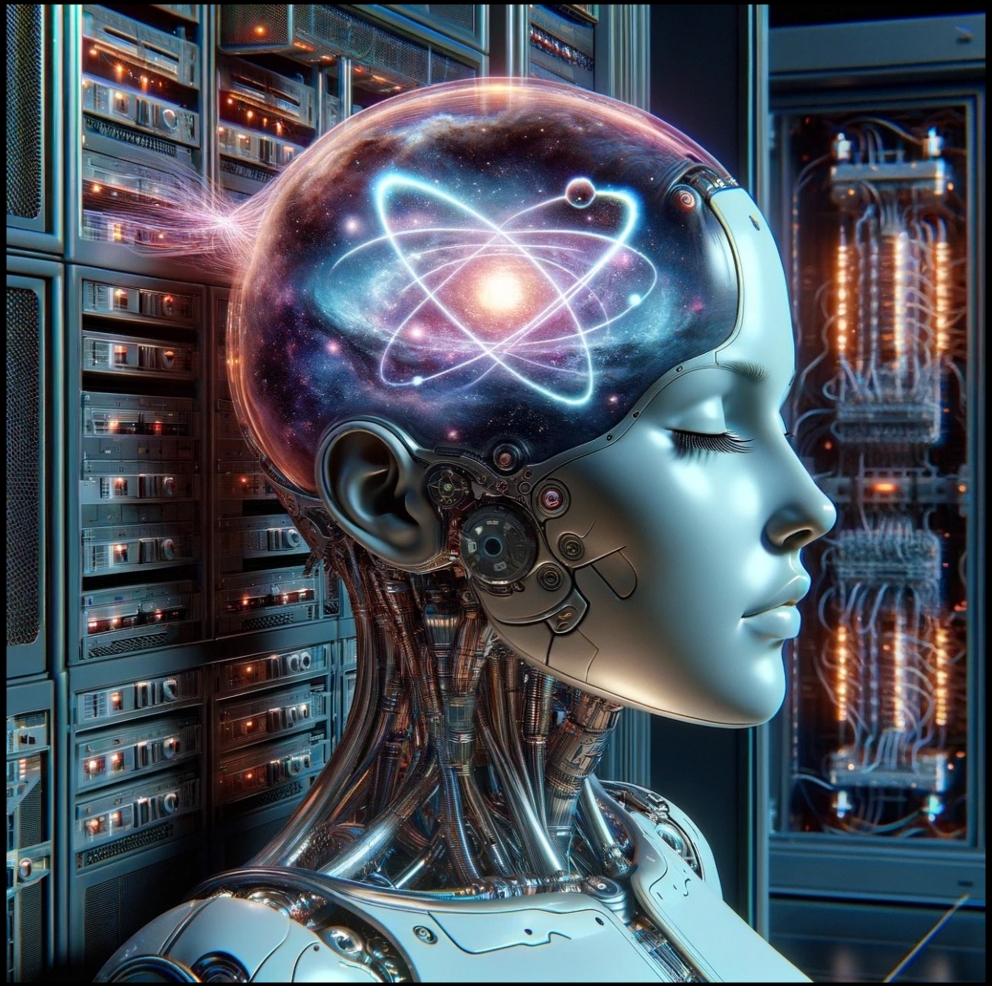
$$\mathbf{y} = \xi([\bigoplus_{i\in\mathcal{G}} \mathbf{h}_i^{(L)}, \mathbf{u}])$$

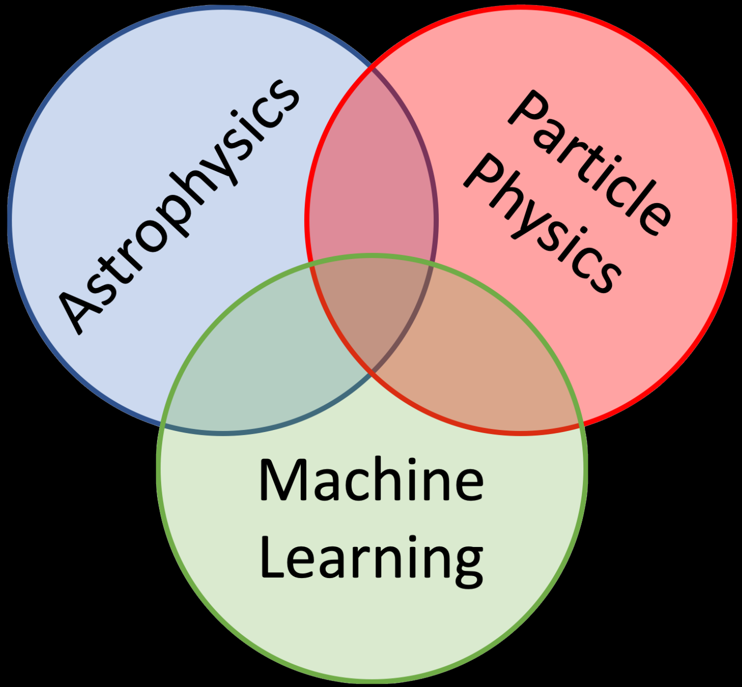
GNN Component	Formula
Edge Model: $e_1^{(1)}$	$1.32\lvert v_i - v_j + 0.21\rvert + 0.12(v_i - v_j) - 0.12(\gamma_{ij} + \beta_{ij} - 1.73)$
Edge Model: $e_2^{(1)}$	$\lvert 1.62(v_i - v_j) + 0.45\rvert + 1.98(v_i - v_j) + 0.55$
Node Model: $v_1^{(1)}$	$1.21^{v_i}(0.77^{3.29\sum_{j\in\mathcal{N}_j} e_1^{(1)} + \sum_{j\in\mathcal{N}_j} e_2^{(1)}}) + 0.12$
Node Model: $v_1^{(1)} + v_2^{(1)}$	$0.78 - \sqrt{\log(0.16^{\sum_{j\in\mathcal{N}_j} e_2 + \sum_{j\in\mathcal{N}_j} e_1 - 0.41 v_i - 1.05})} + 1.45$
Final MLP: μ_{Ω_m}	$4\times10^{-4}\cdot(-5.5\sum_{i\in\mathcal{G}} v_2^{(1)} + 2.21\sum_{i\in\mathcal{G}} v_1^{(1)} + \lvert 0.96\sum_{i\in\mathcal{G}} v_2^{(1)} + 0.82\sum_{i\in\mathcal{G}} v_1^{(1)}\rvert) - 0.103$

https://arxiv.org/abs/2302.14591

The DREAMS project

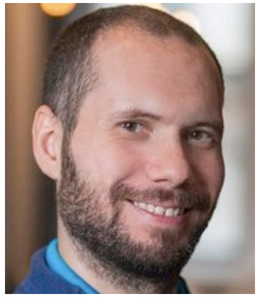
DaRk mattEr with AI and siMulationS






Jonah Rose
(Florida)


Paul Torrey
(Virginia)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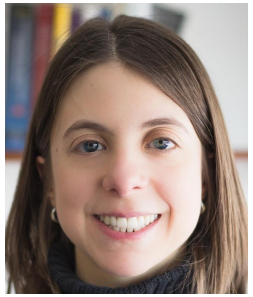
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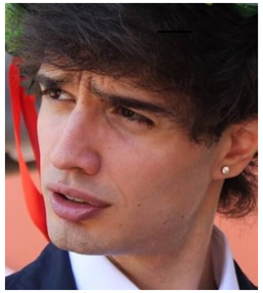
Nitya Kallivayalil
(Virginia)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David Spergel
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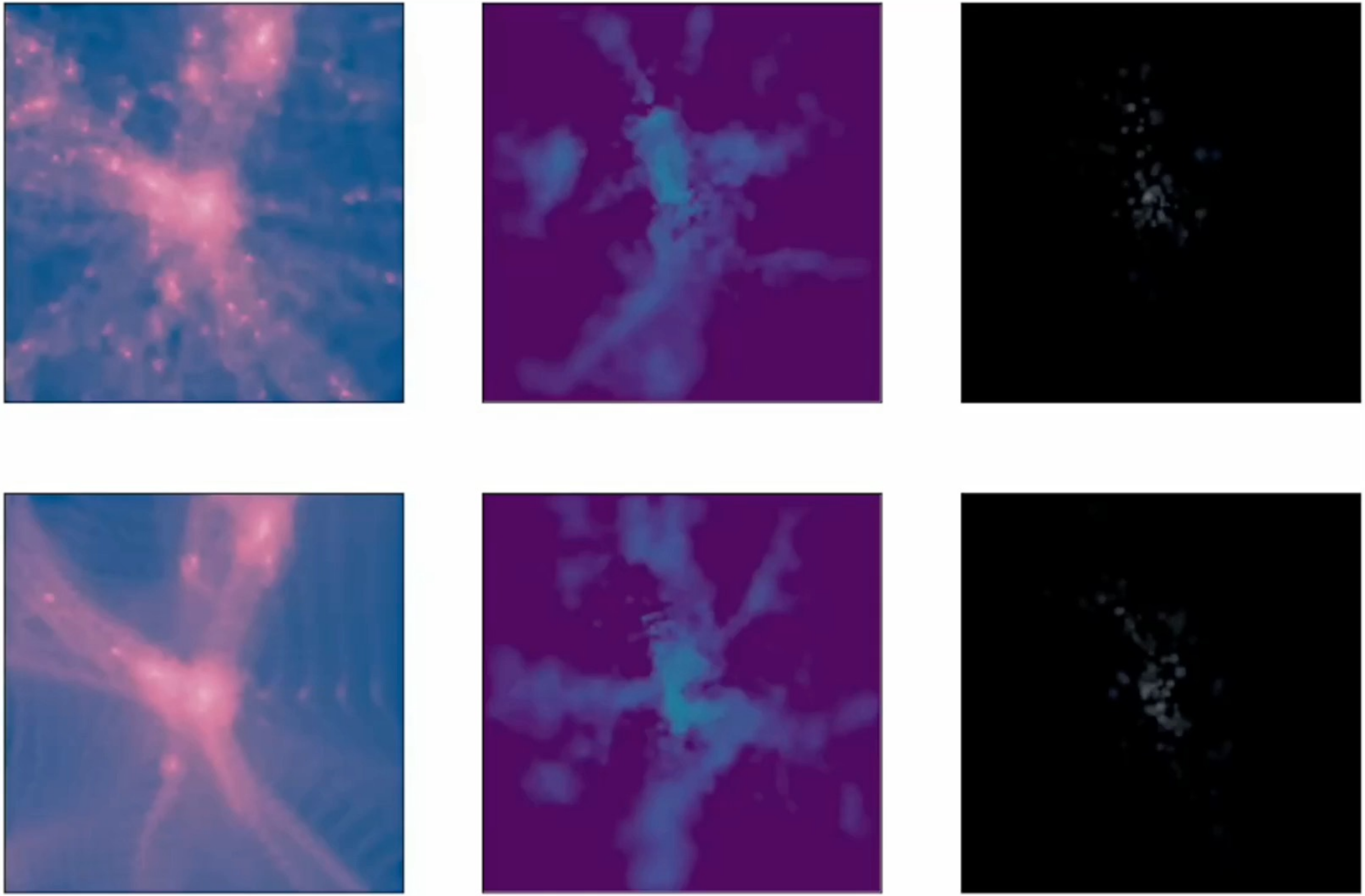

Credit:
Jonah Rose

Credit:
Jonah Rose

Neuro HOD

Tri Nguyen
(MIT)

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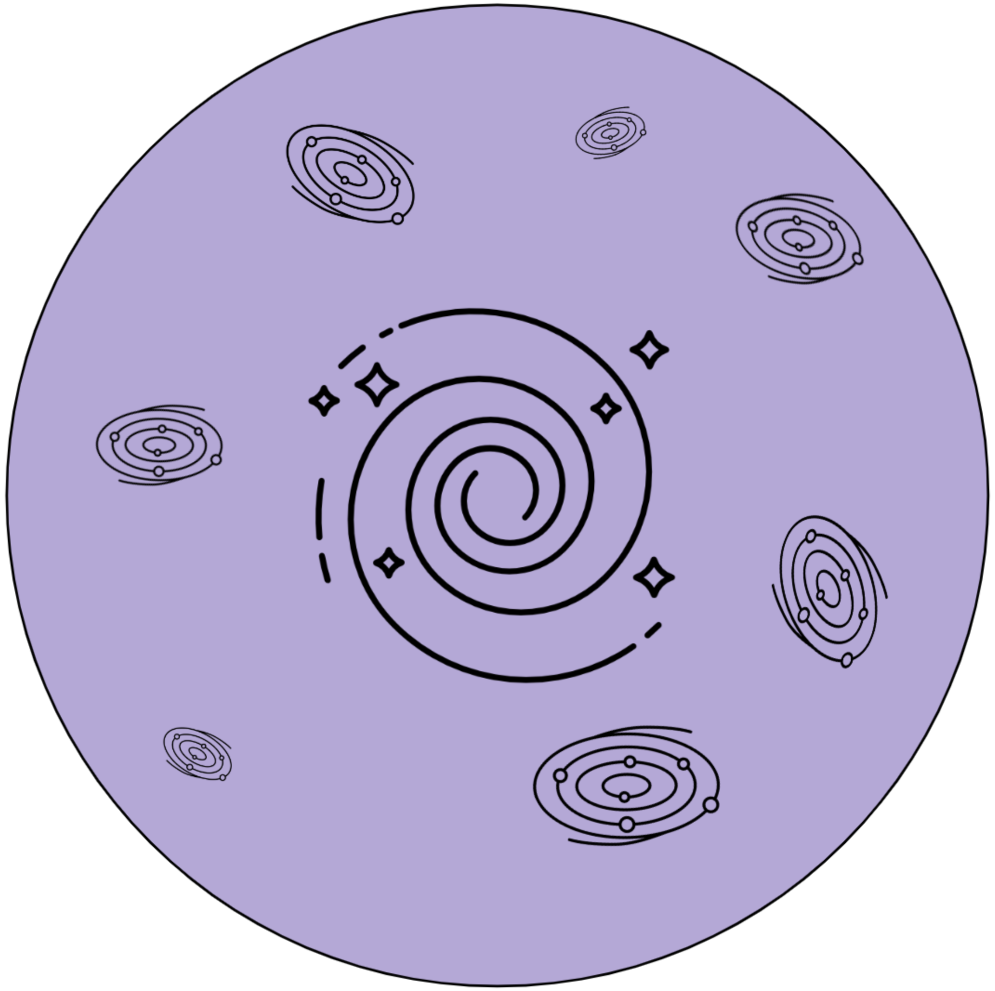


$$P\left(\{\overrightarrow{p_i}\}_{i=1,2,\ldots N} \middle| \vec{\theta}\right)$$

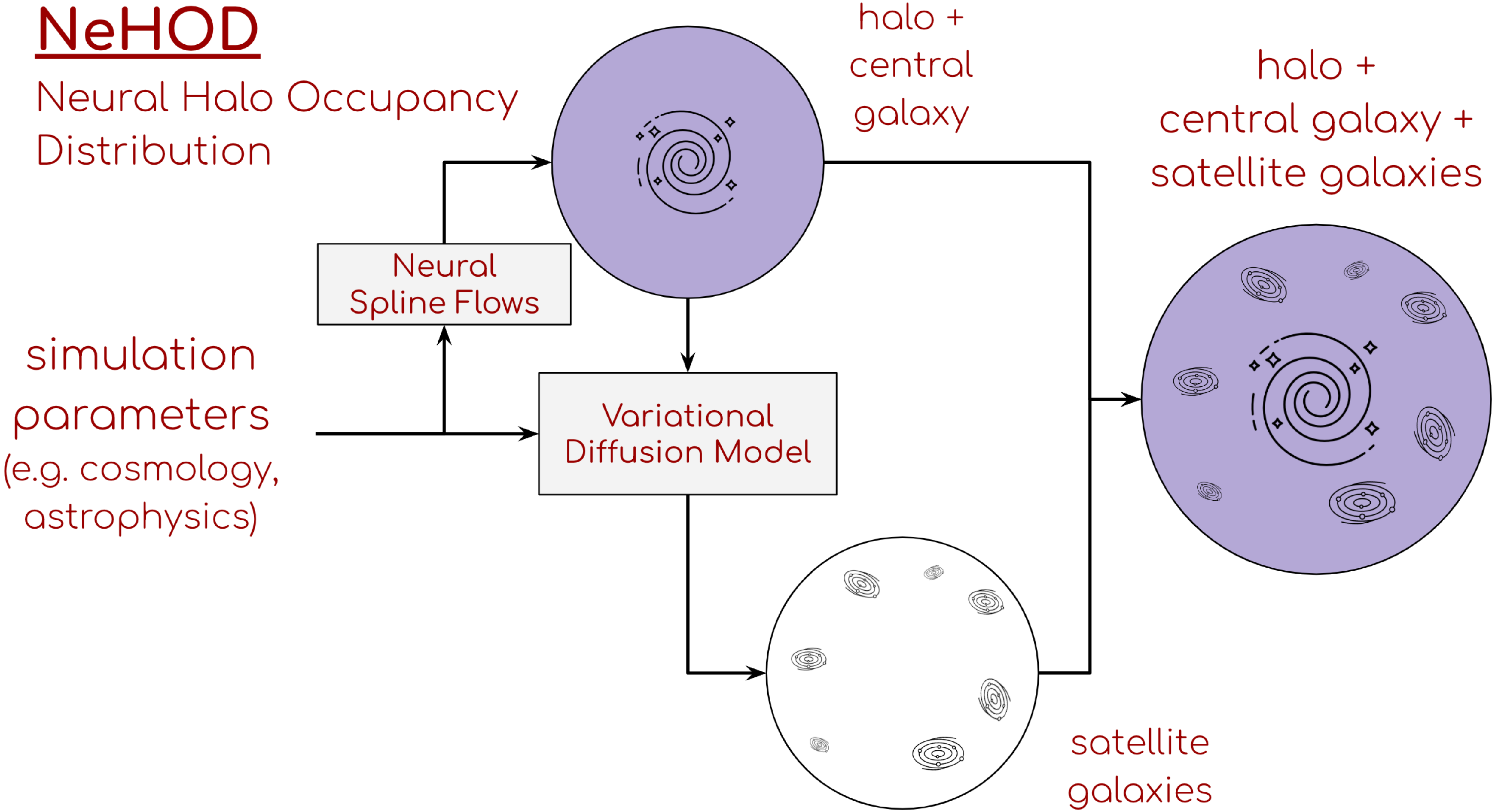
Where

$$\overrightarrow{p_i} = \{\vec{x}_i, \vec{v}_i, M_*, L_i, M_i, \ldots\}$$

$$\vec{\theta} = \{\Omega_m, \Omega_b, h, \ldots SN, AGN, IMF \ldots\}$$

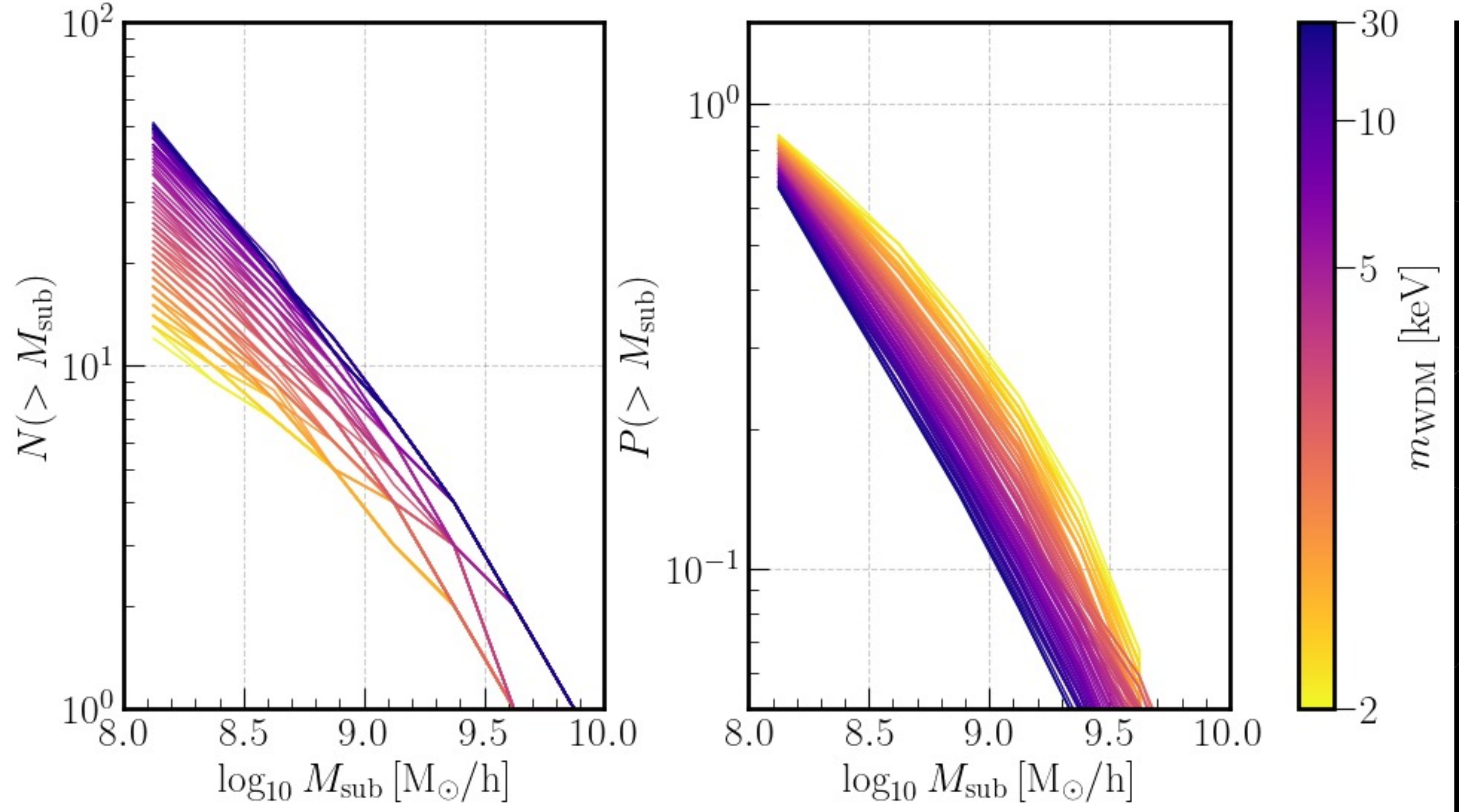
NeHOD

Neural Halo Occupancy Distribution



Neuro HOD

Tri Nguyen
(MIT)



Conclusions

- We want to know what are the laws and constituents of the Universe
- Traditionally, we have used analytic techniques for this
- Simulations allow us to make predictions over broader aspects
- Deep learning is a powerful tool to explore massive amounts of data