Inferring galactic dark matter density maps from survey images* with diffusion models

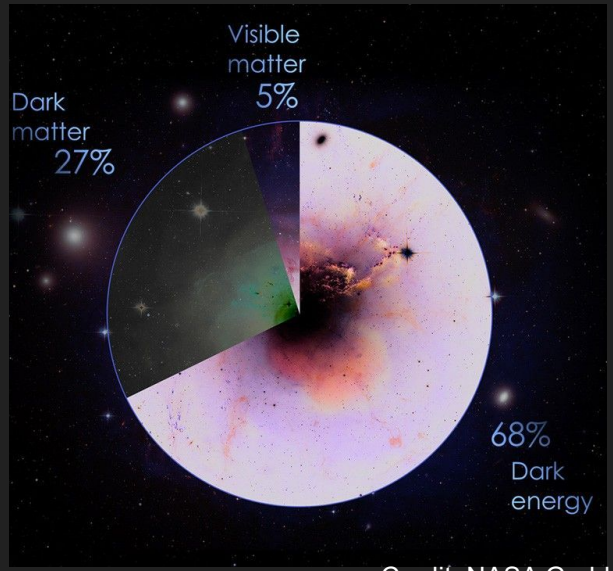
Xiaowei Ou (UVA)
GECO and CosmicAI Fellow

Collaborators: Lina Necib, Carol Cuesta-Lazaro, Paul Torrey, and more

Credit: ESA/Gaia/DPAC

What, Why, and How

An invisible substance with Weak/No interaction with normal matter



Credit: NASA Goddard

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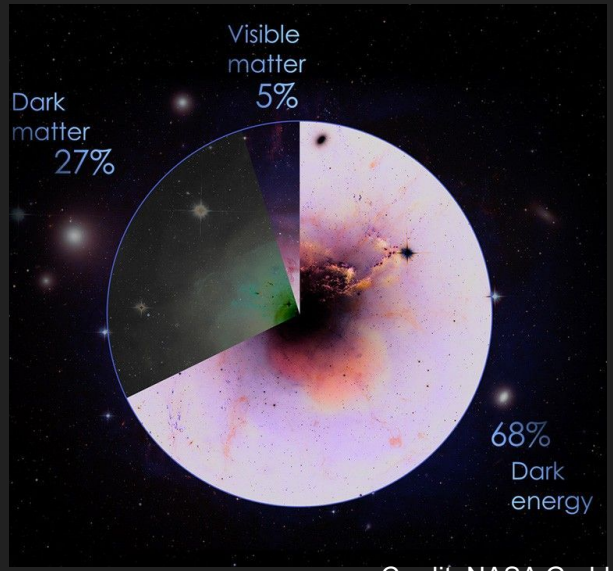
Besides through gravity…



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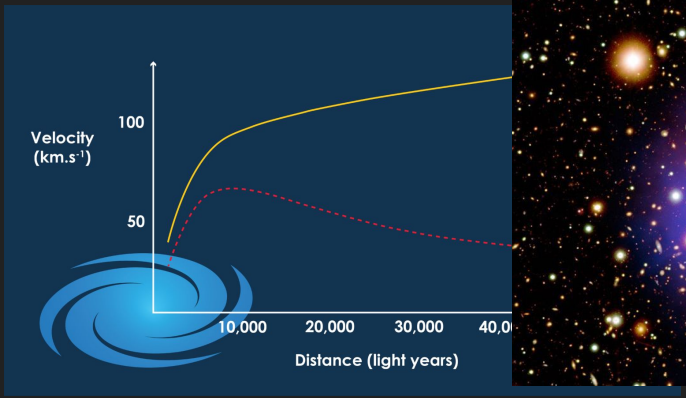
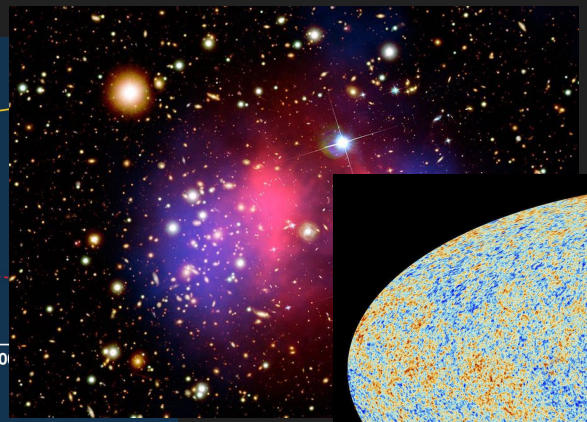
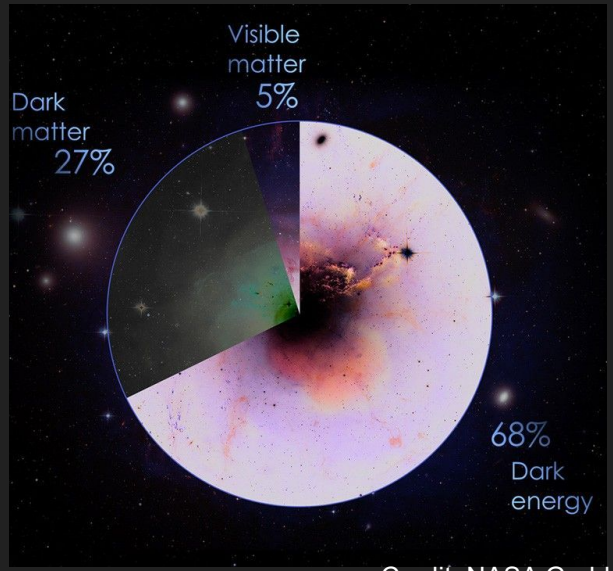




Credit: Euclid Consortium



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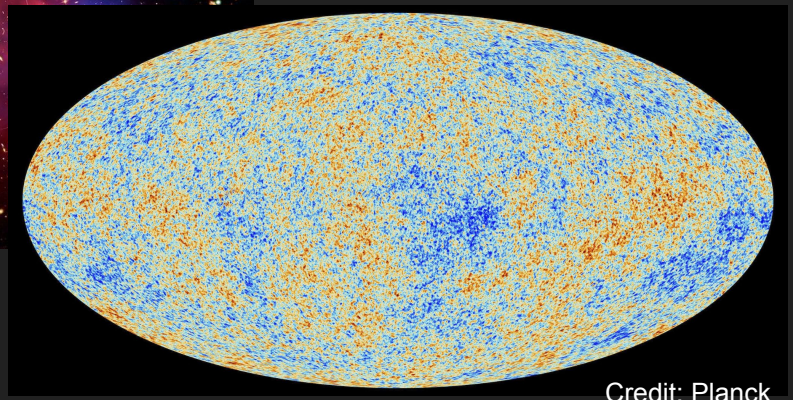

Credit: Planck

What, Why, and How

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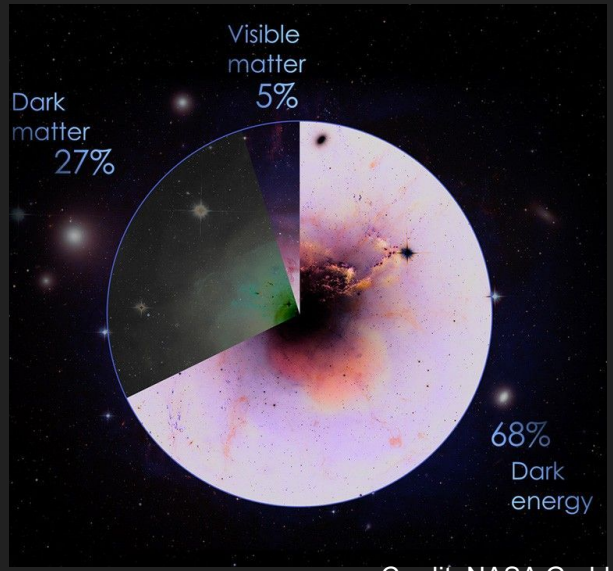

Credit: NASA Goddard

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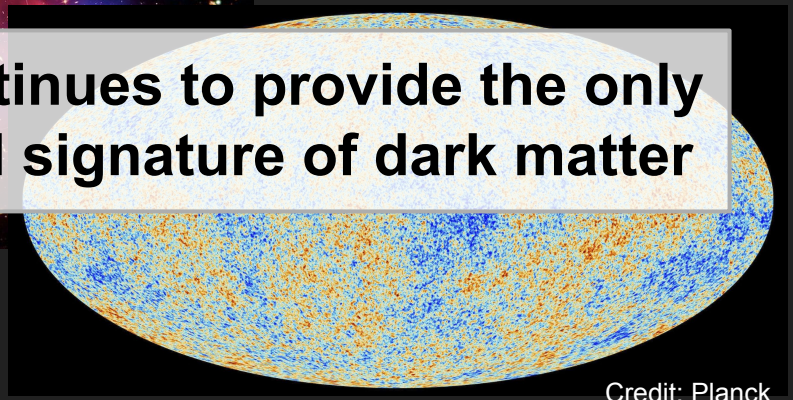
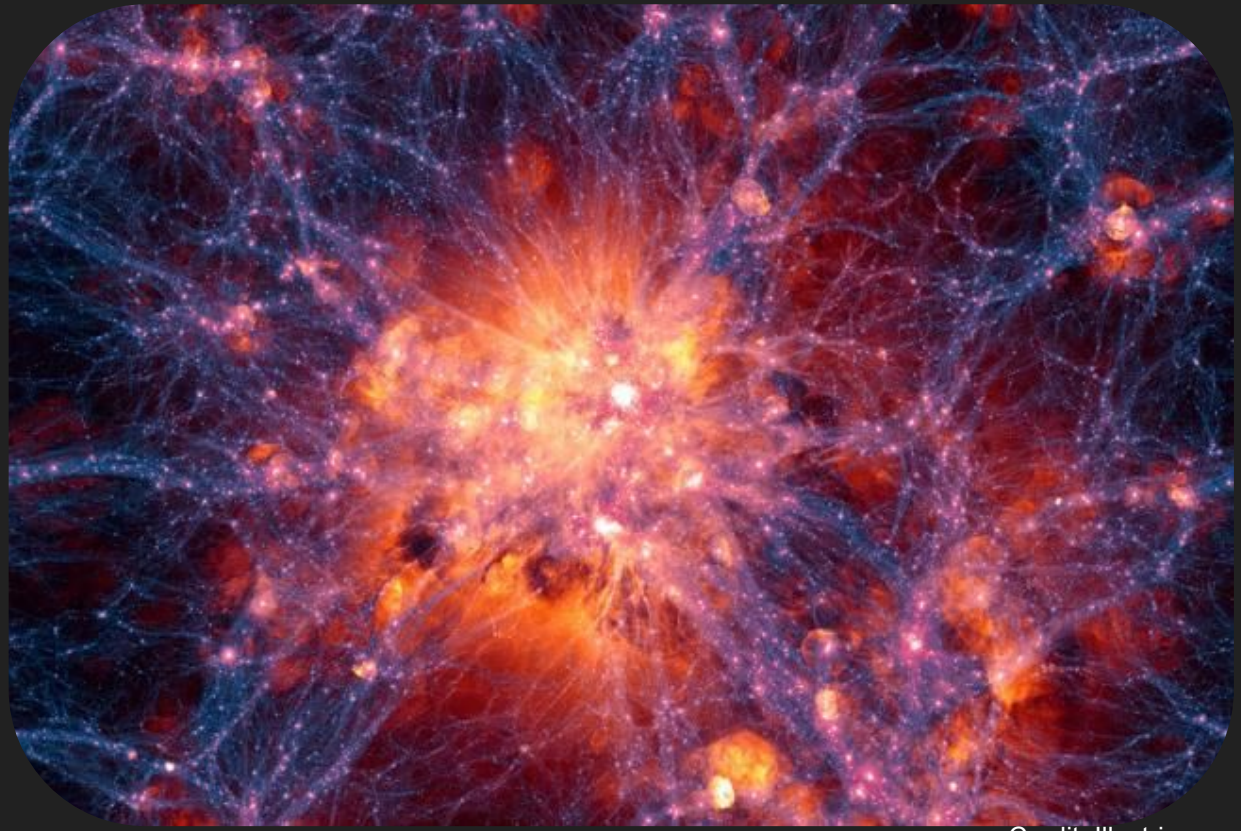
Astrophysics continues to provide the only positive empirical signature of dark matter



Credit: Planck

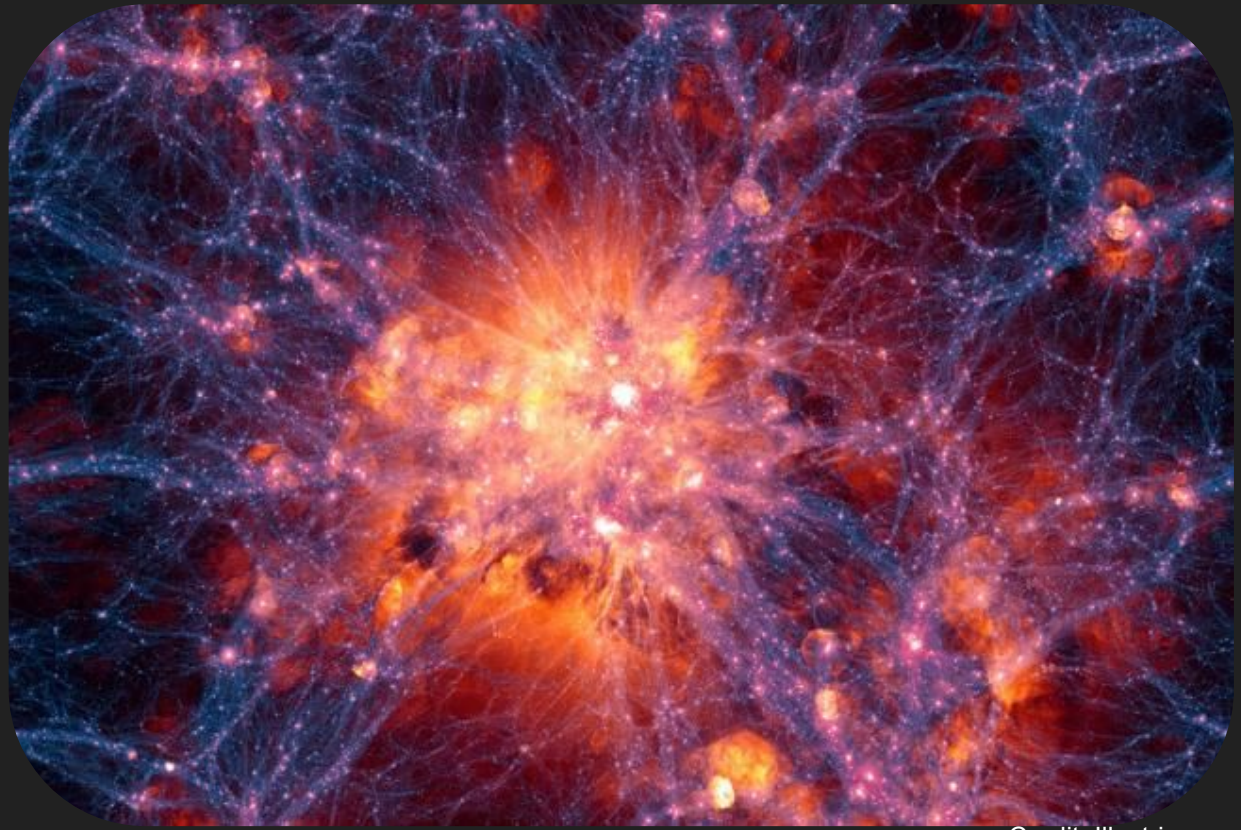
What, **Why**, and How



Credit: Illustris

Dark matter serves as the scaffolding for galaxy formation.

What, **Why**, and How



Credit: Illustris

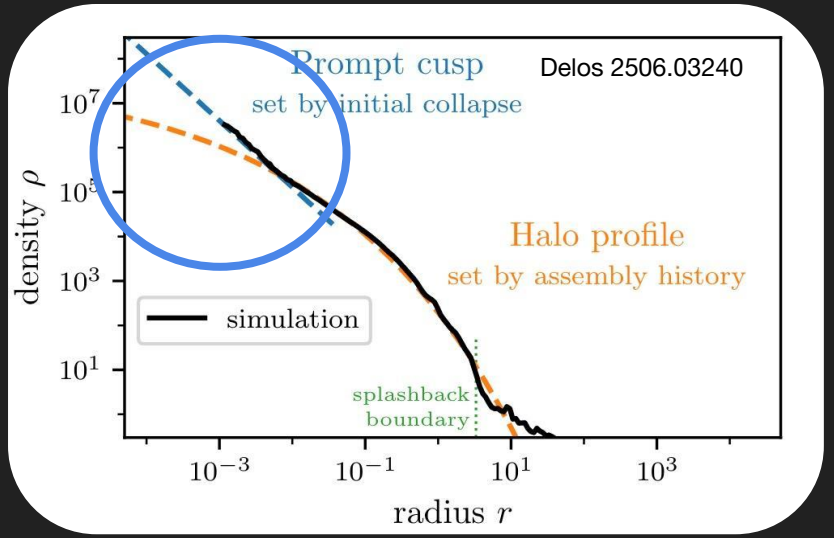
Dark matter serves as the scaffolding for galaxy formation.

Yet we have almost no clue about its fundamental particle nature!

What, Why, and **How**: **Distribution!**

Small-scale behavior as a Probe of DM

Map dark matter distribution in galaxies

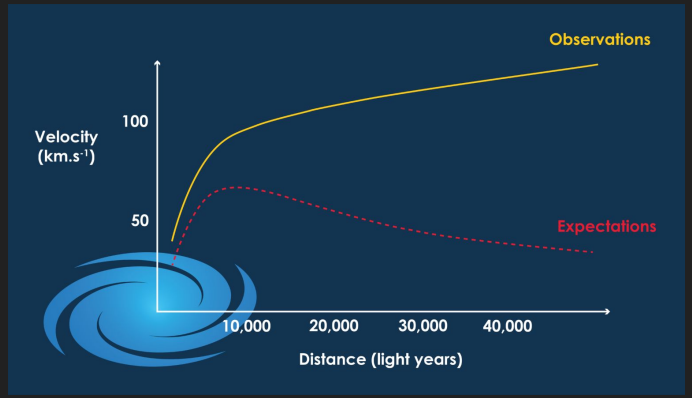


Density Profiles:

- **CDM cusps**
- **SIDM cores and super-cusps**
- **Fuzzy DM soliton cores**

What, Why, and **How**: **Distribution!**

Mapping dark matter in galaxies is not easy…



Credit: Euclid Consortium

Credit: NASA

Expensive observation / model-dependent assumptions

What we have: deep, wide, multi-band imaging for galaxies

Credit: ESA/Euclid

Unresolved star lights comes in pixelated images

Kinematic informations are very limited

Still encodes valuable information

What can we (plausibly) infer from just 2D images?

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Integrated starlight

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Stellar mass distribution

Integrated starlight

Credit: ESA/Euclid

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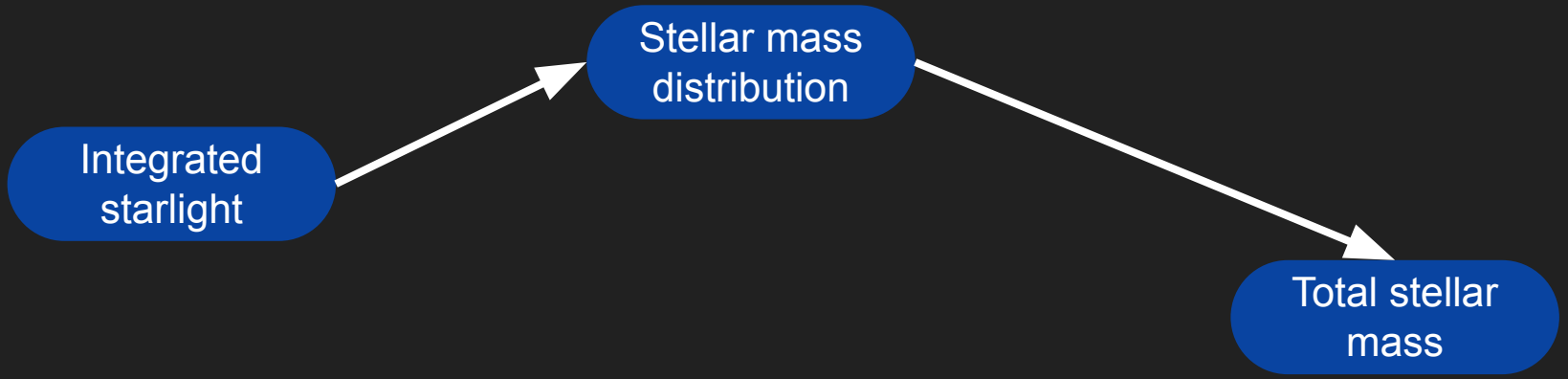
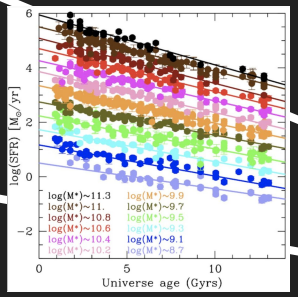


What can we (plausibly) infer from just 2D images?

Integrated starlight

Stellar mass distribution

Star formation history



Total stellar mass

Credit: Popesso et al. (2023)

What can we (plausibly) infer from just 2D images?

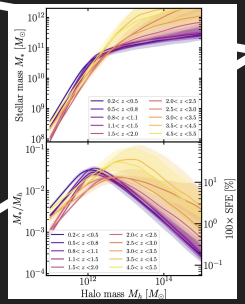
Integrated starlight

Stellar mass distribution

Star formation history

Total stellar mass

Total dark matter halo mass



Credit: Shuntov et al. (2022)

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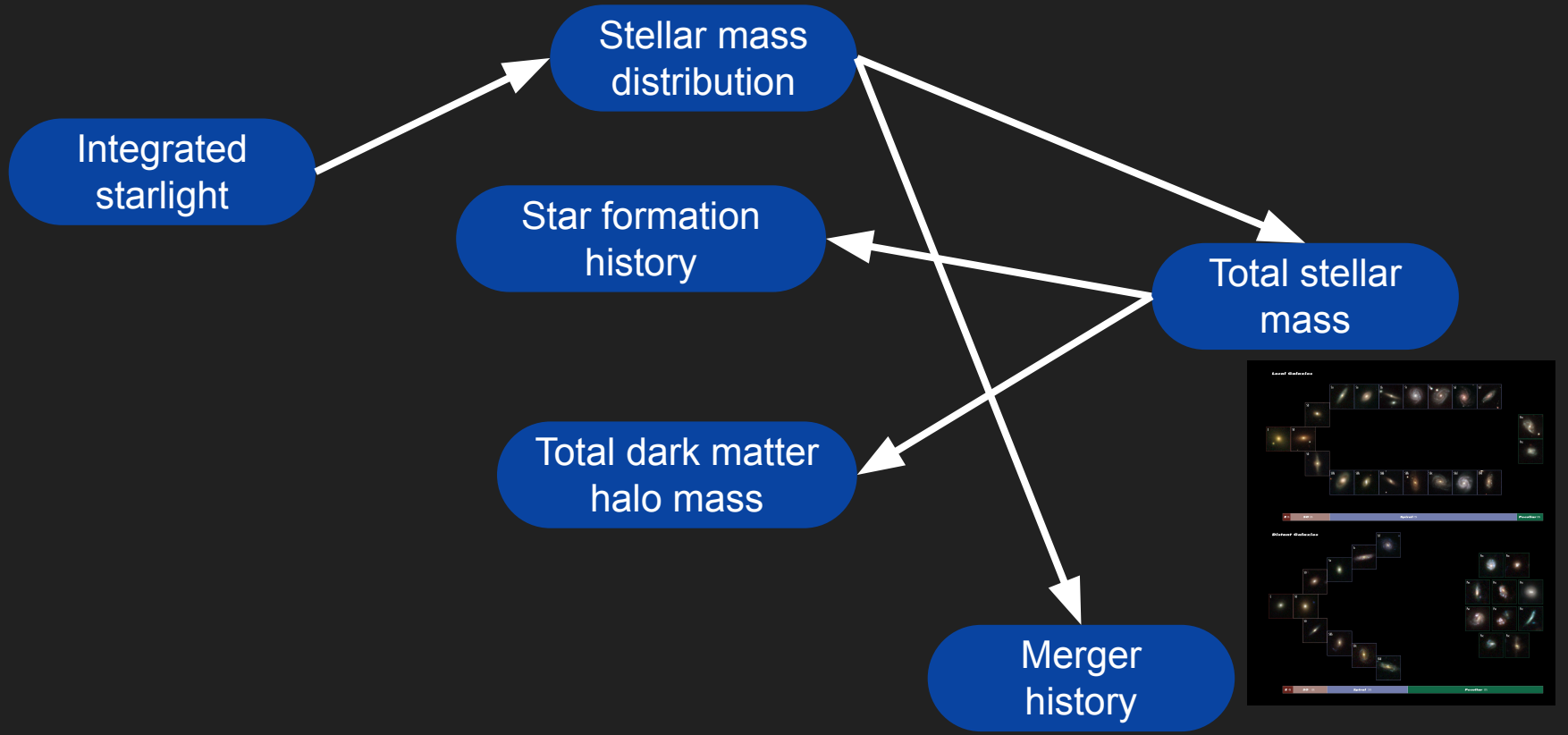

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Credit: ESA/Hubble

What can we (plausibly) infer from just 2D images?

Stellar mass distribution

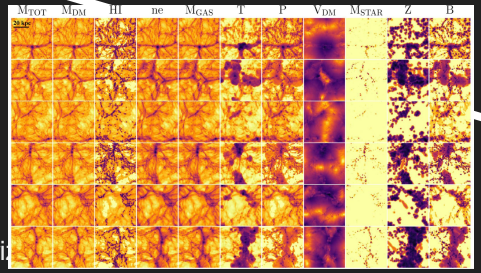
Integrated starlight

Star formation history

Total stellar mass

Dark matter distribution

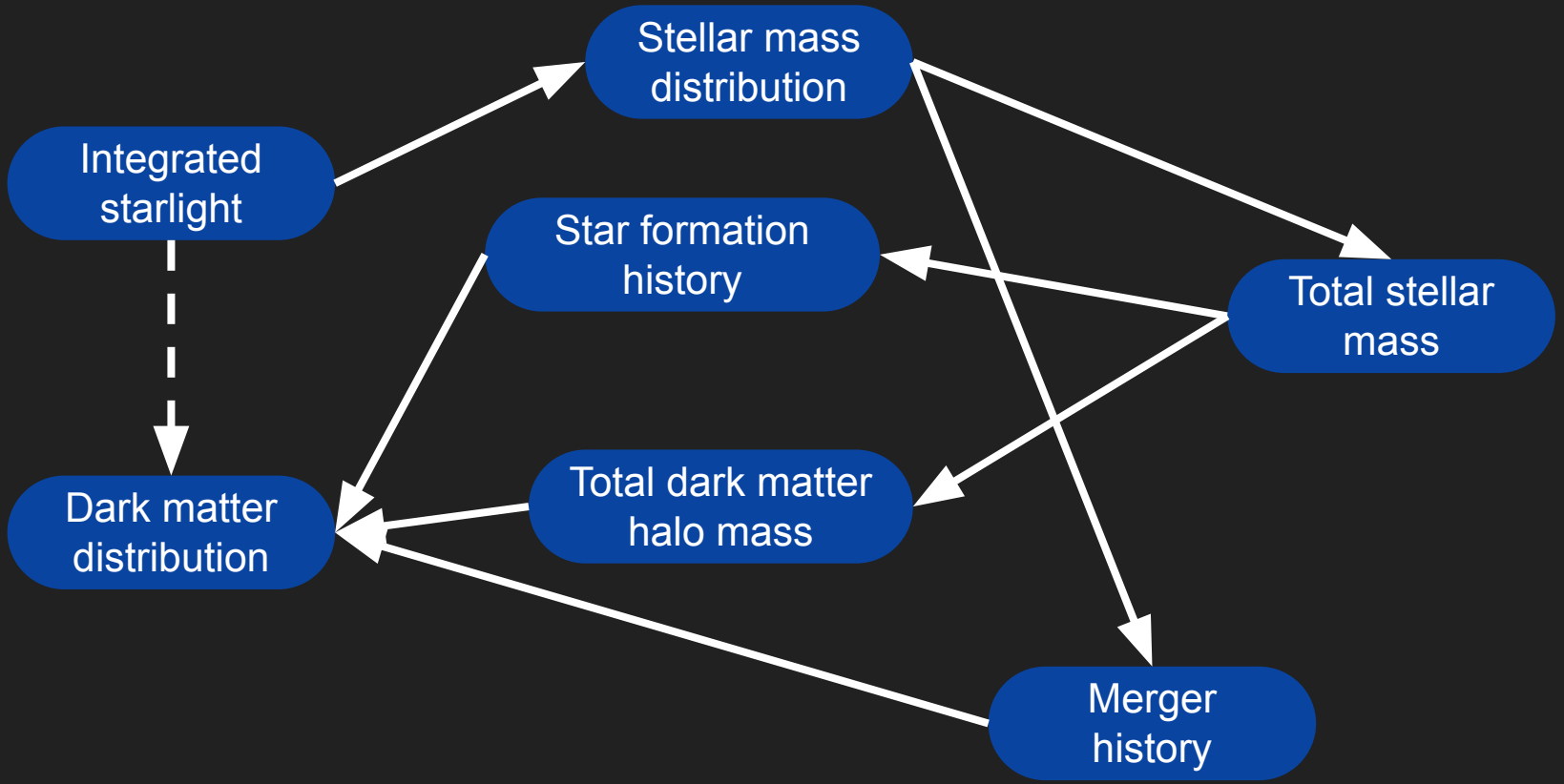
Total dark matter halo mass



Merger history

Credit: DREAMS

What can we (plausibly) infer from just 2D images?



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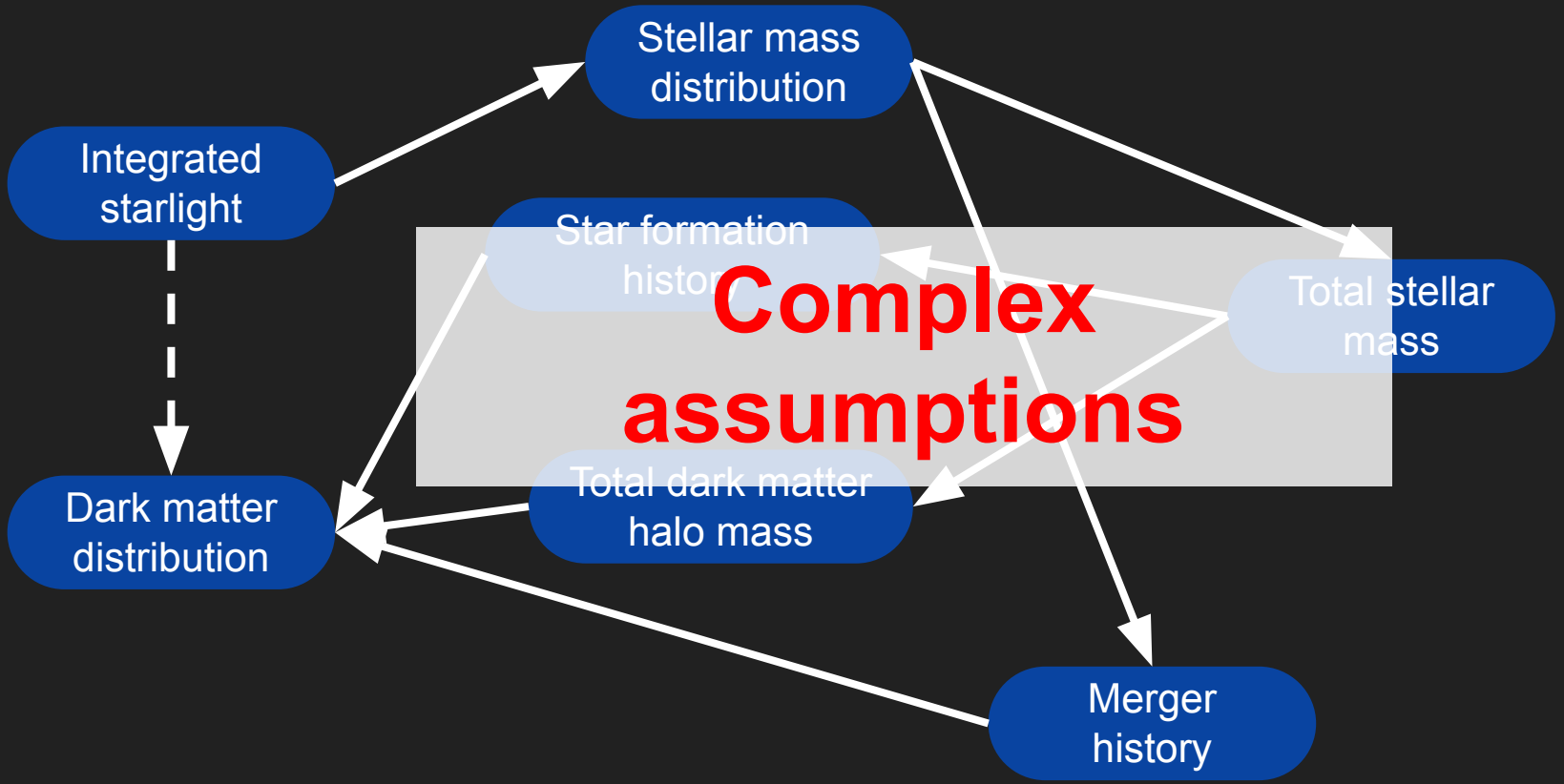

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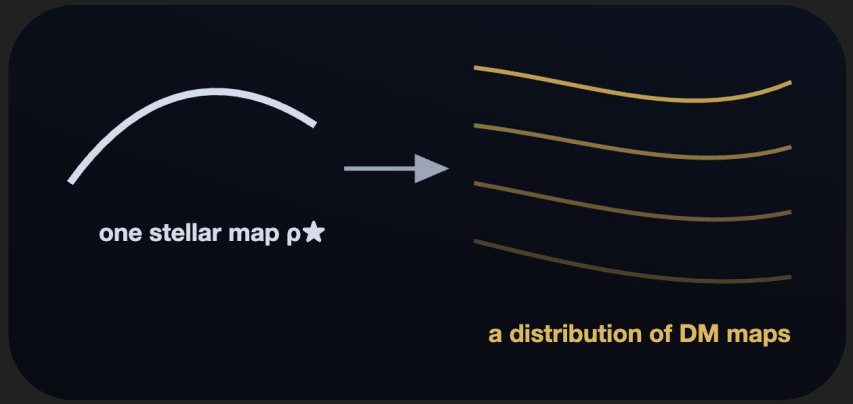
Can we map dark-matter density directly from stellar density?



The mapping is not deterministic!

Same stellar density → different DM density, set by assembly & feedback history, dark matter physics, etc.

To learn a bridge between two physical fields — we need a model that factors in these uncertainties

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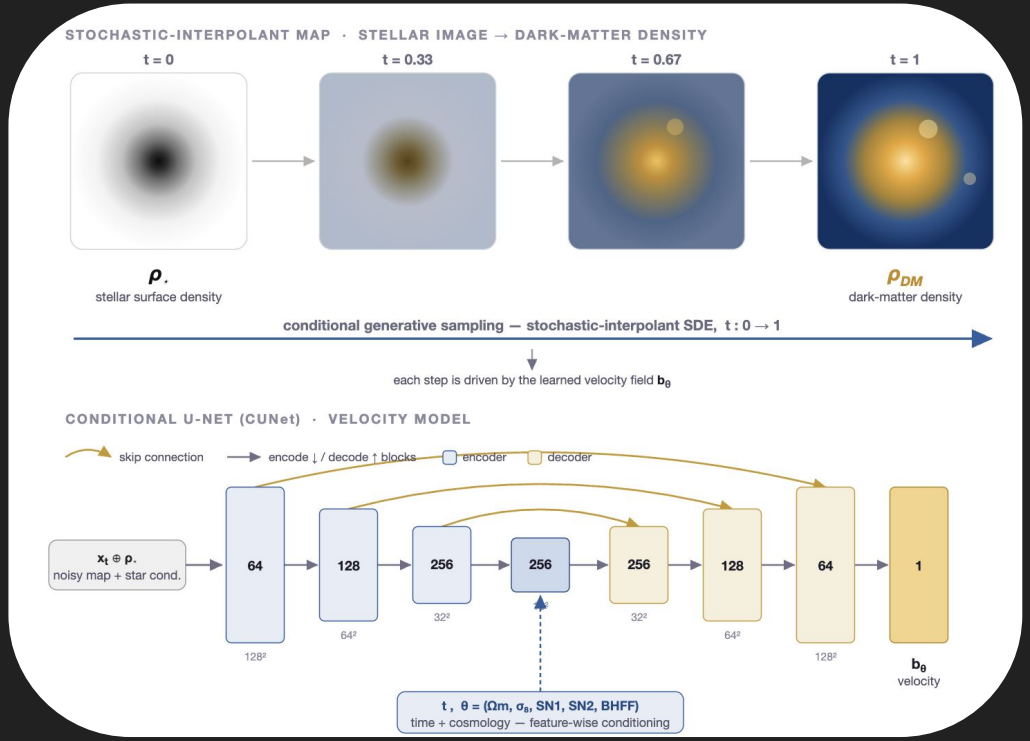
BaryonBridge*: stochastic interpolant



Learn the velocity field

Stochastic process sample ensemble of valid target maps

Flexible input maps/features for future surveys

Trained with the DREAMS simulation

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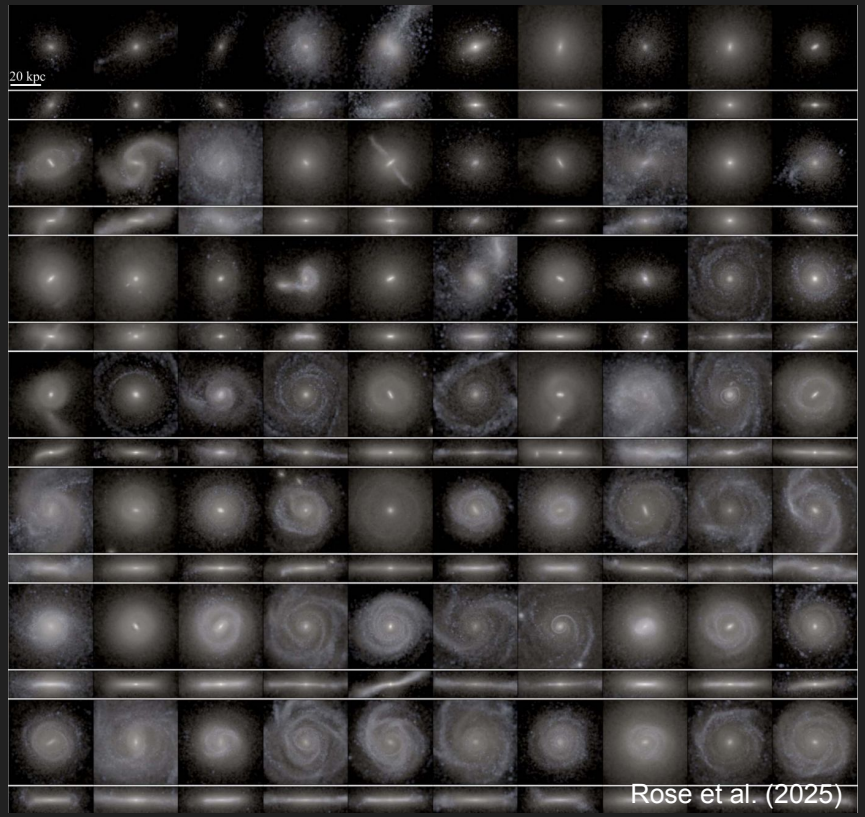
*: Cuesta-Lazaro et al. (2024), Horowitz et al. (2025)

Utilizing DREAMS simulation suite as the training data



Rose et al. (2025)

Combine astrophysics with particle physics through machine learning

Thousands of simulations with:

- Different **mass regimes**: Milky Way-mass to dwarf galaxies*
- Different **dark matter models**: CDM, WDM, SIDM…
- Varying **galaxy formation models**: IllustrisTNG, FIRE*, RAMSES…
- Different **simulation codes**: AREPO*, GIZMO…

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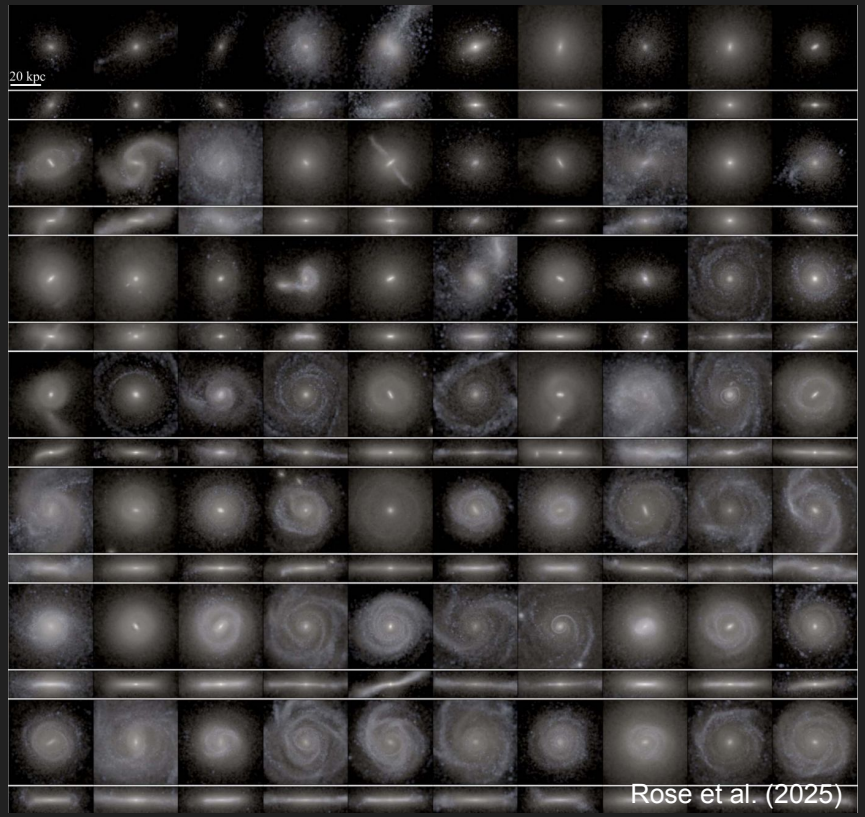

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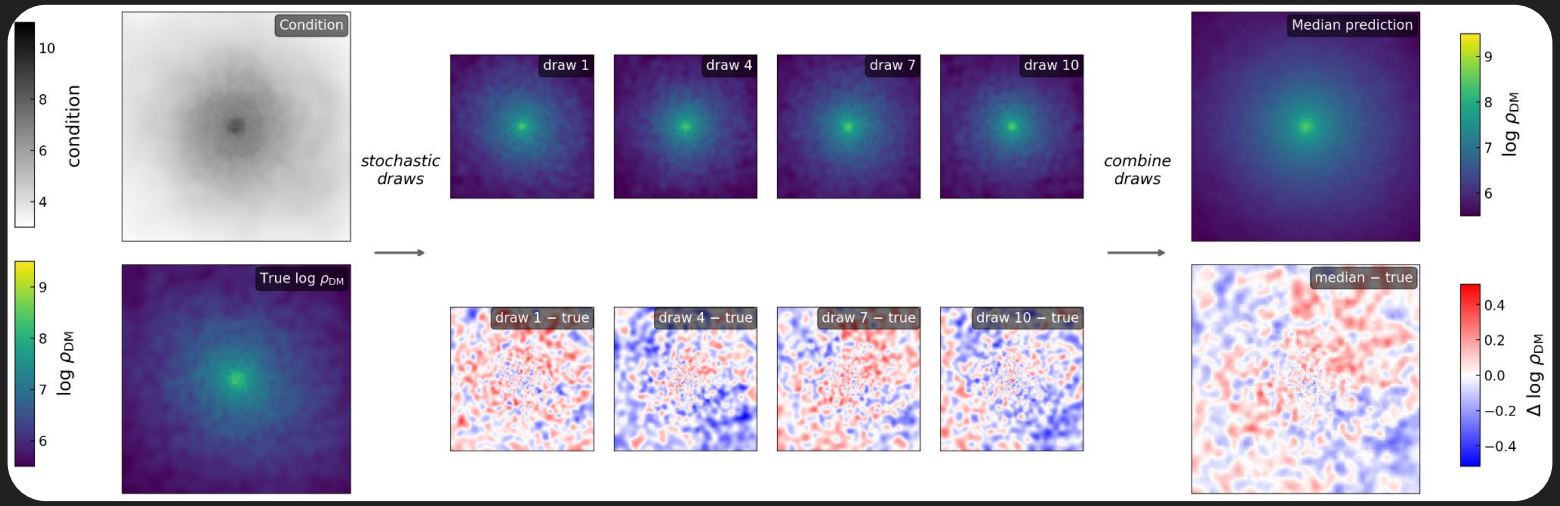
It works —



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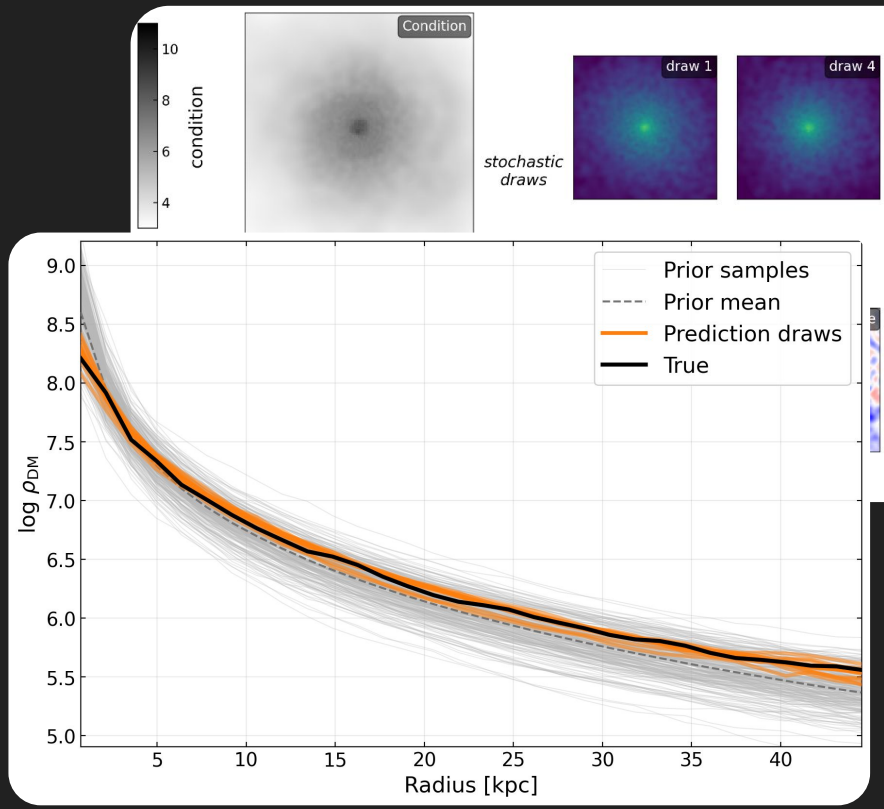
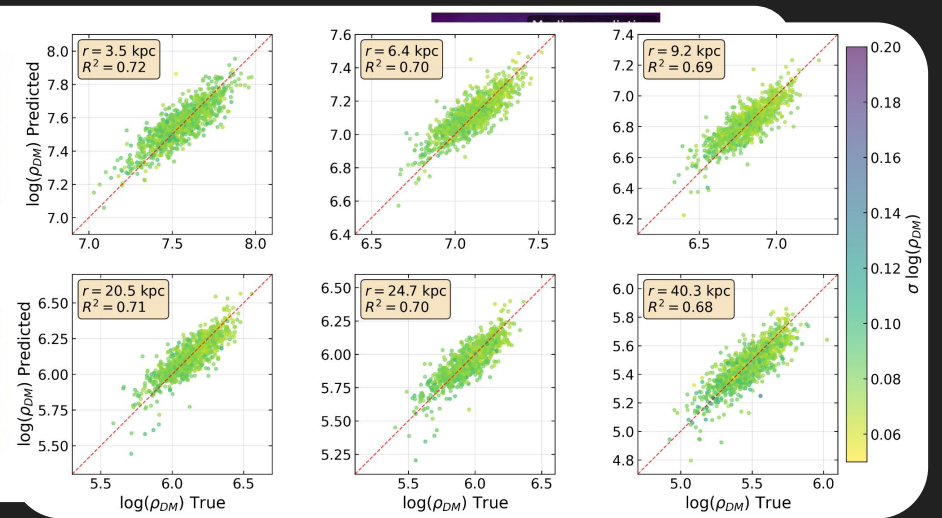
It works — with reasonable performance





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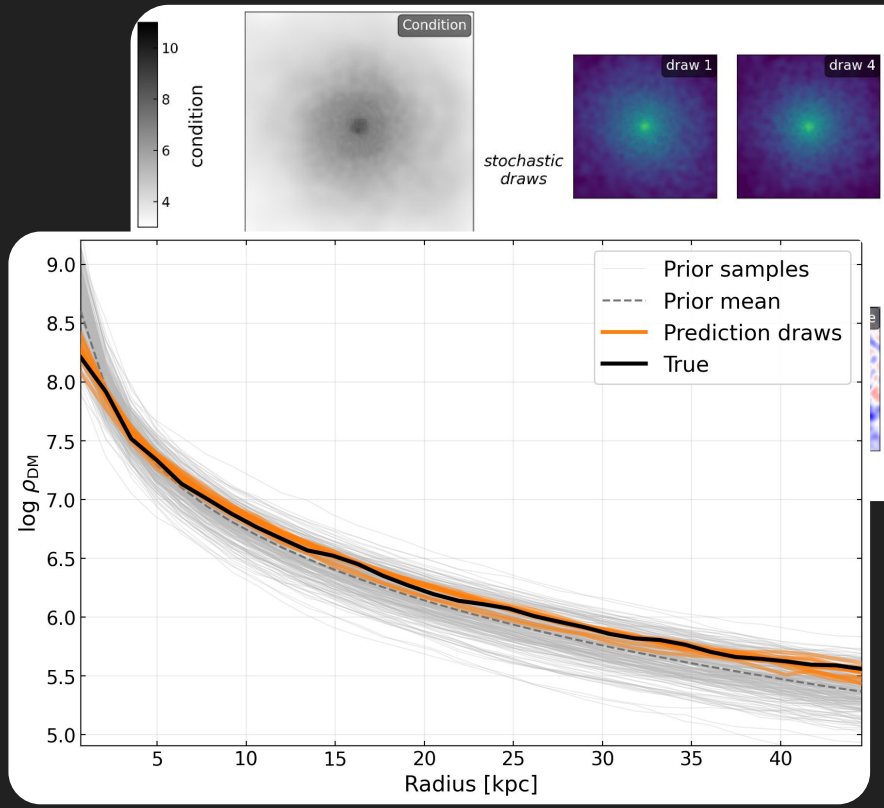

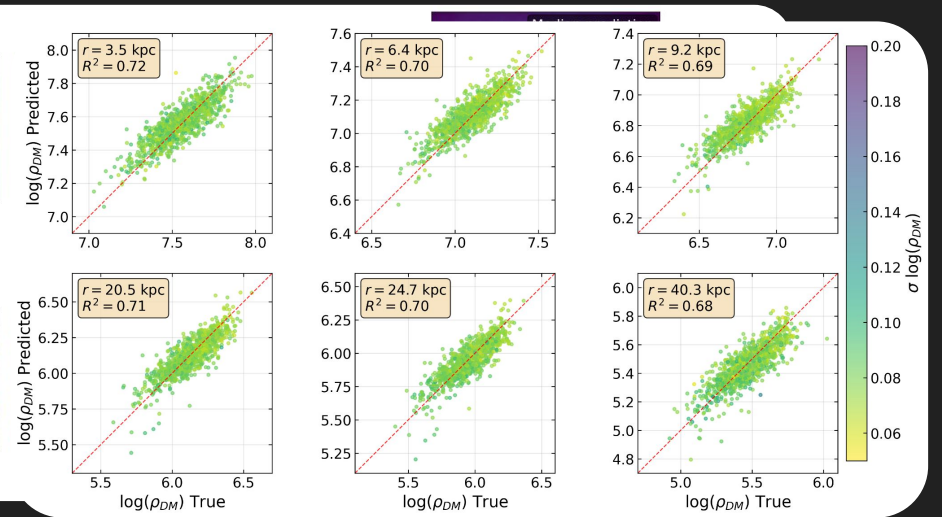

~0.1 dex accuracy < prior ≈ **0.5 dex**

with/without explicit simulation parameter conditioning

→ model uses stellar structure, not just the mean halo.

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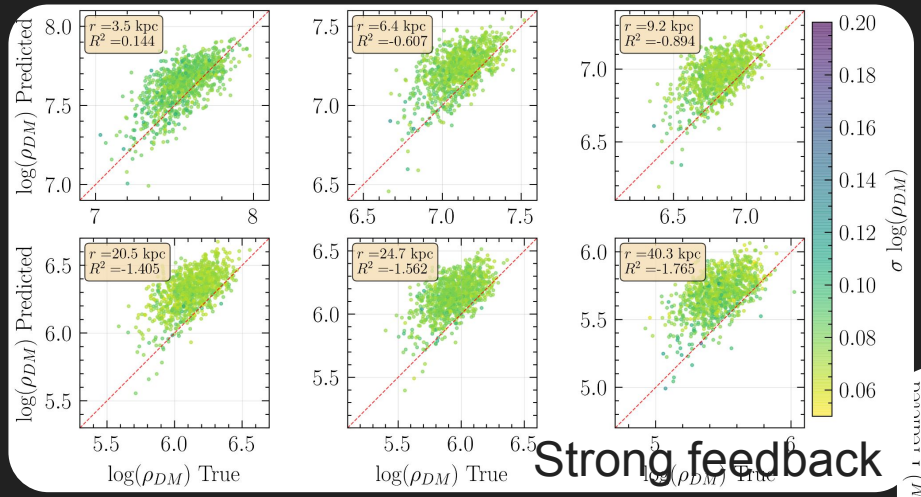
Simulation parameter conditioning –

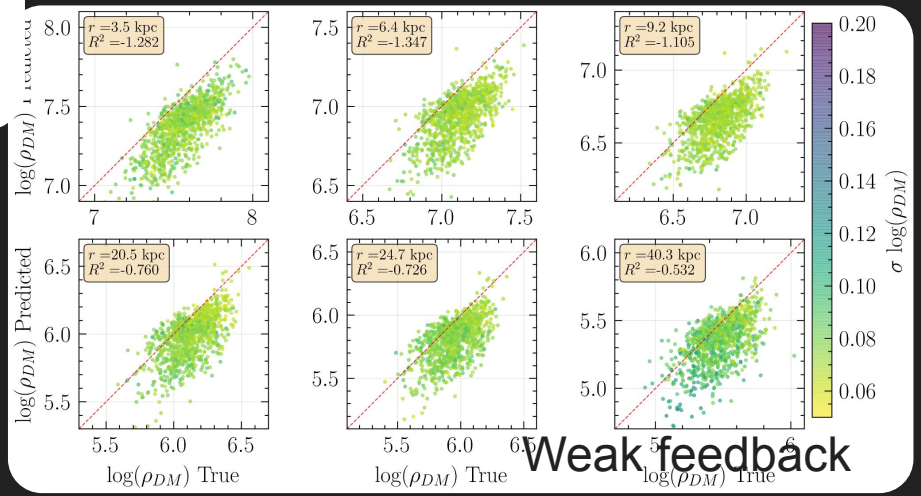
How sensitive is the model to the conditions?

Simulation parameter conditioning – reasonable



How sensitive is the model to the conditions?

Strong(weak) supernova feedback results in over(under)-estimated prediction



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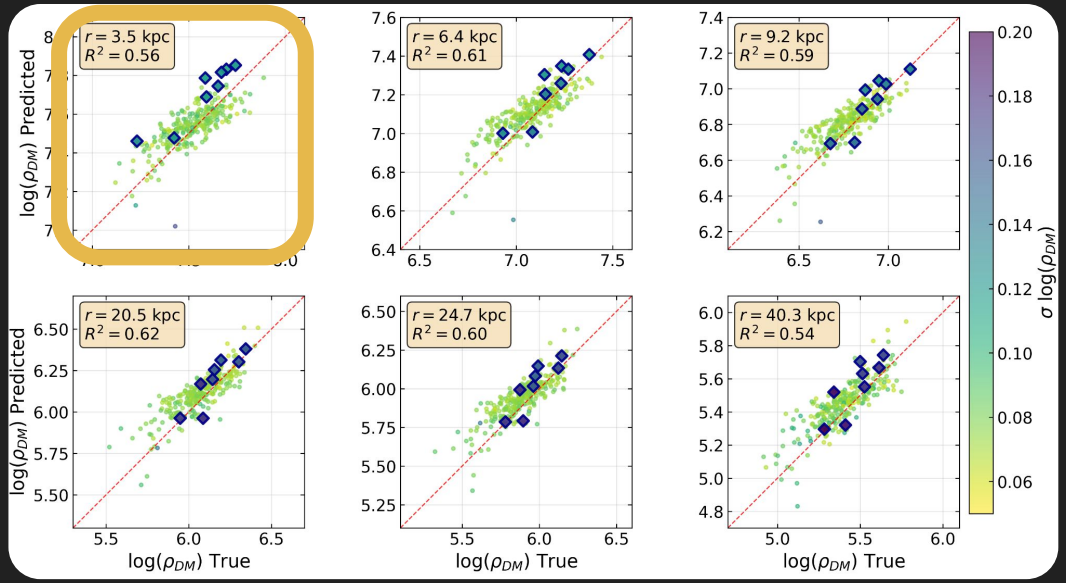
Out-of-domain tests with IllustrisTNG50 and FIRE



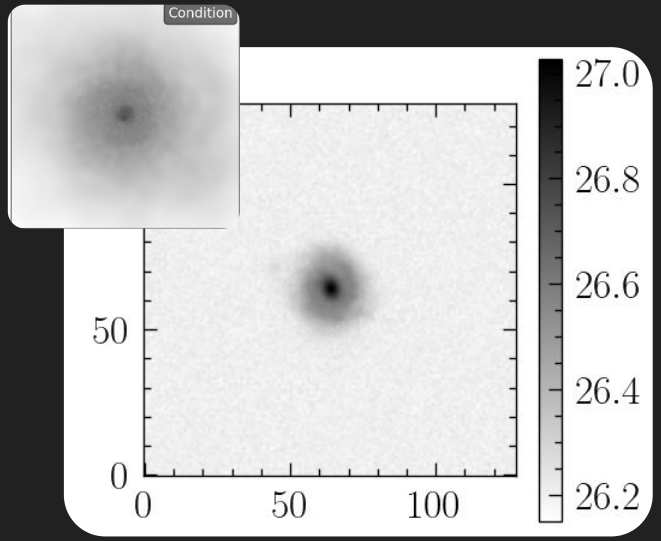
Inner r ≲ 5 kpc: over-predicts cored centers for FIRE (🔷)

Bursty FIRE feedback lies outside the training suite DREAMS TNG-like range

Marks where **stellar map alone is insufficient**

The diffusion model demonstrates learnable mapping between 2D star map to underlying dark matter map… what's next?

Realistic images*



Beyond Milky Way-mass, CDM, TNG-like astrophysics…

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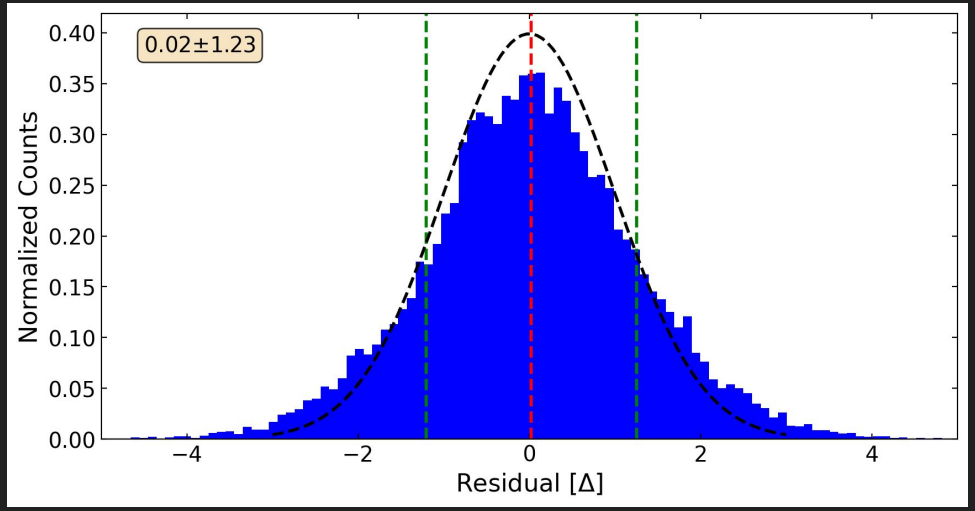
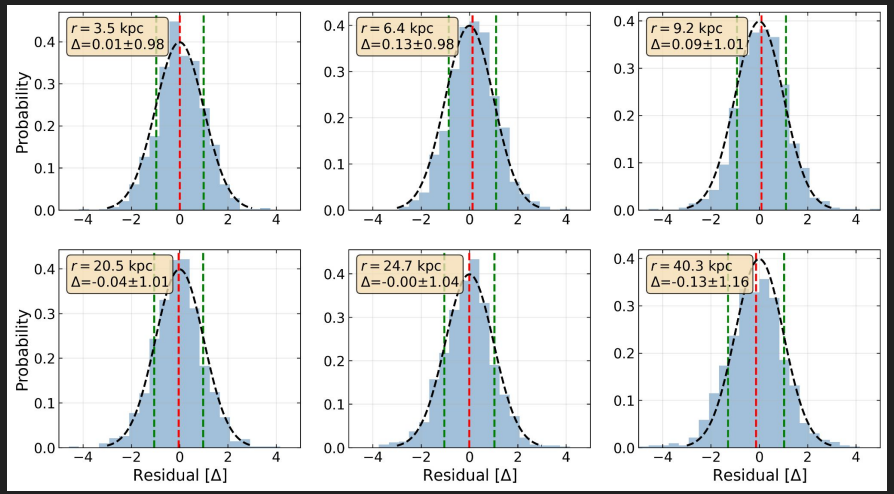
Backup





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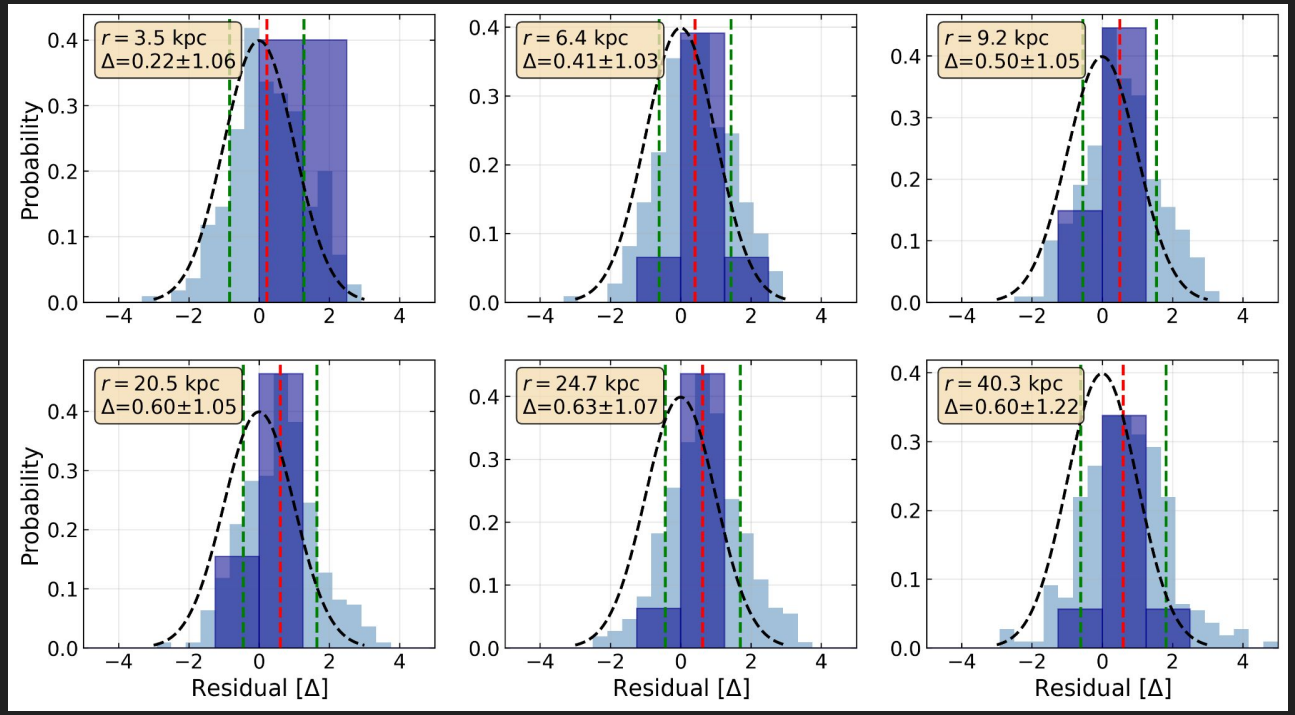
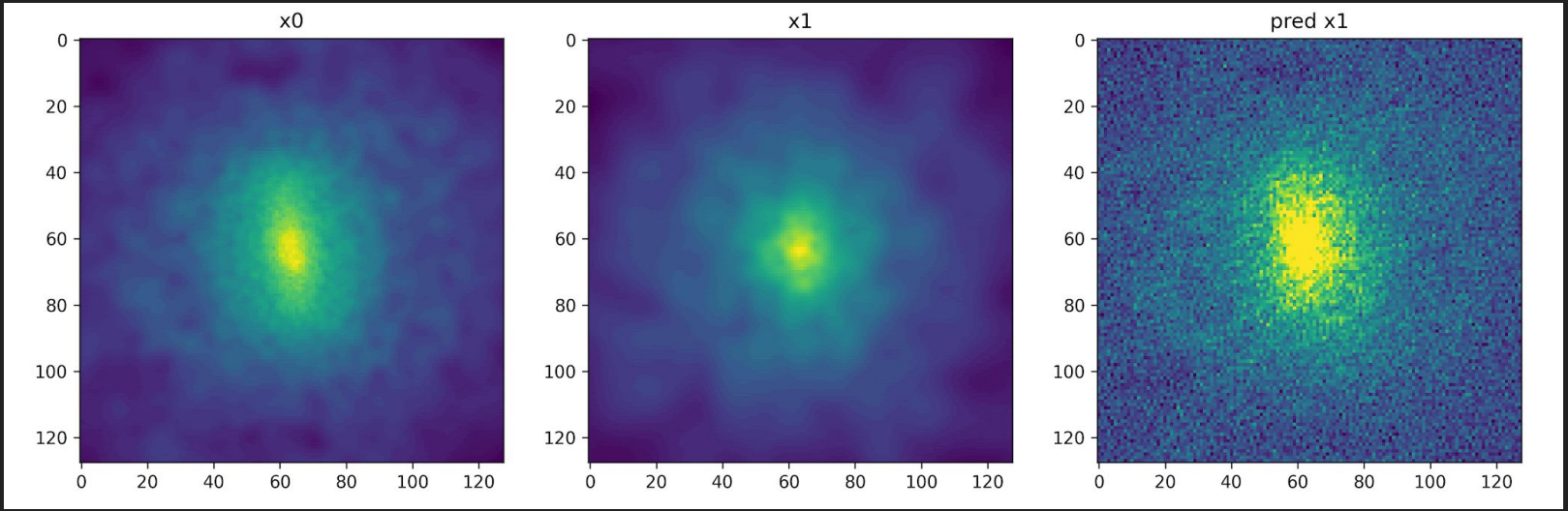

r = 3.5 kpc
Δ=0.22±1.06
r = 6.4 kpc
Δ=0.41±1.03
r = 9.2 kpc
Δ=0.50±1.05
r = 20.5 kpc
Δ=0.60±1.05
r = 24.7 kpc
Δ=0.63±1.07
r = 40.3 kpc
Δ=0.60±1.22
Probability
Residual [Δ]

Actual training process for an example galaxy



Input stellar density field **True dark matter density** **Predicted dark matter density**