Generative AI for hydrodynamical simulations: 2D, 3D, or 6D galaxy models?

SKA research at
Zurich University of Applied Sciences (ZHAW)

Centre for Artificial Intelligence (CAI)
Institute for Business Information Technology (IWI)

June 10, 2024

Philipp Denzel, Frank-Peter Schilling, Elena Gavagnin

Slides On My Website

https://phdenzel.github.io/

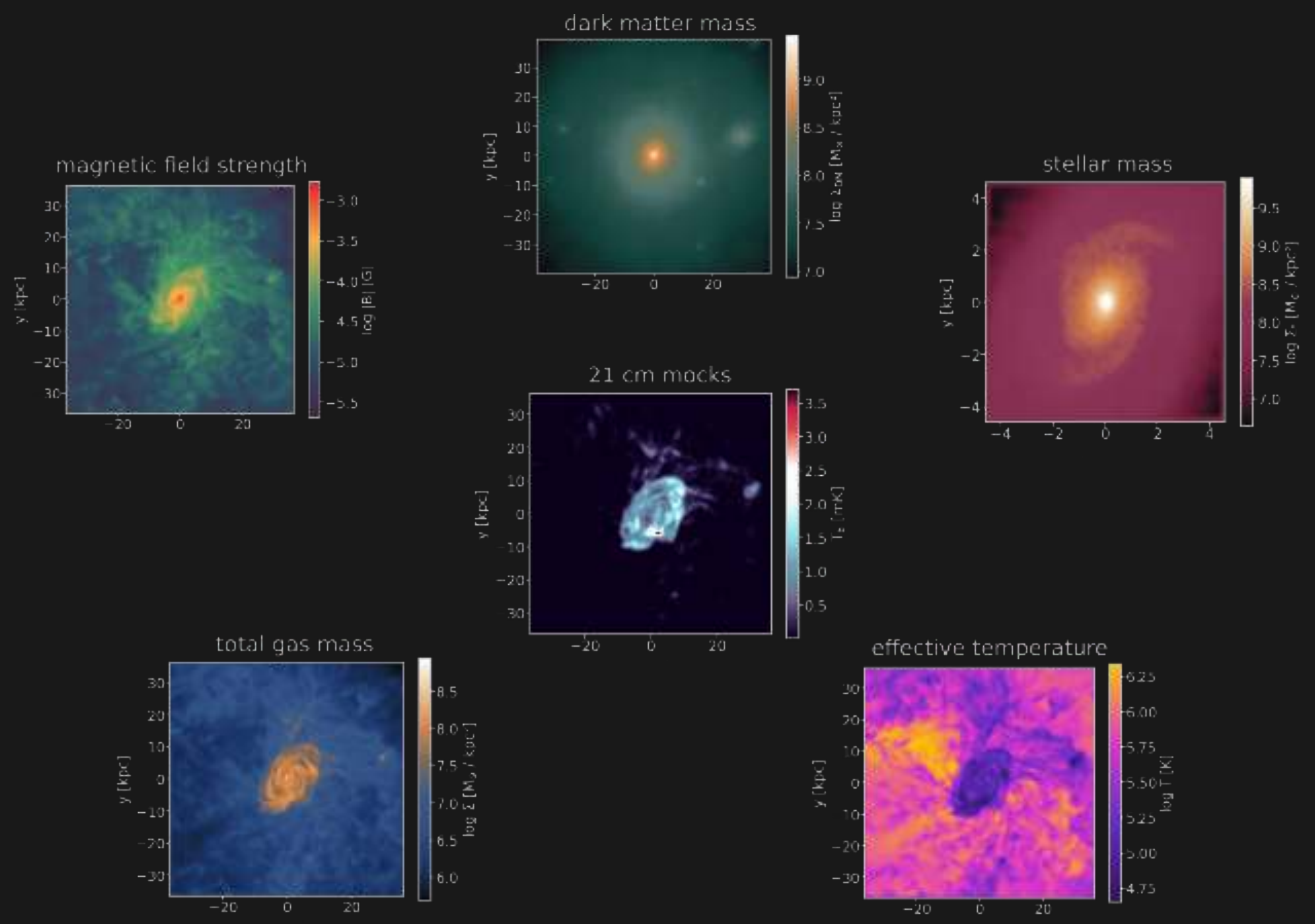
Outlook

- 2D galaxy modelling
- 3D modelling using point clouds
  - First experiments
- 6D phase-space modelling?

Recap:
Generative Models
For Map-To-Map Translation

Dataset from IllustrisTNG

- projected IllustrisTNG galaxies
- 6 domains:
    - dark-matter, stars, gas,
      HI, temperature, magnetic field
- $\sim$ 2'000 galaxies, (across 6 snapshots)
- $\sim$ 360'000 images
- each galaxy $\geq$ 10'000 particles
- augmented: up to 5x randomly rotated
- scale: 2 dark-matter half-mass radii



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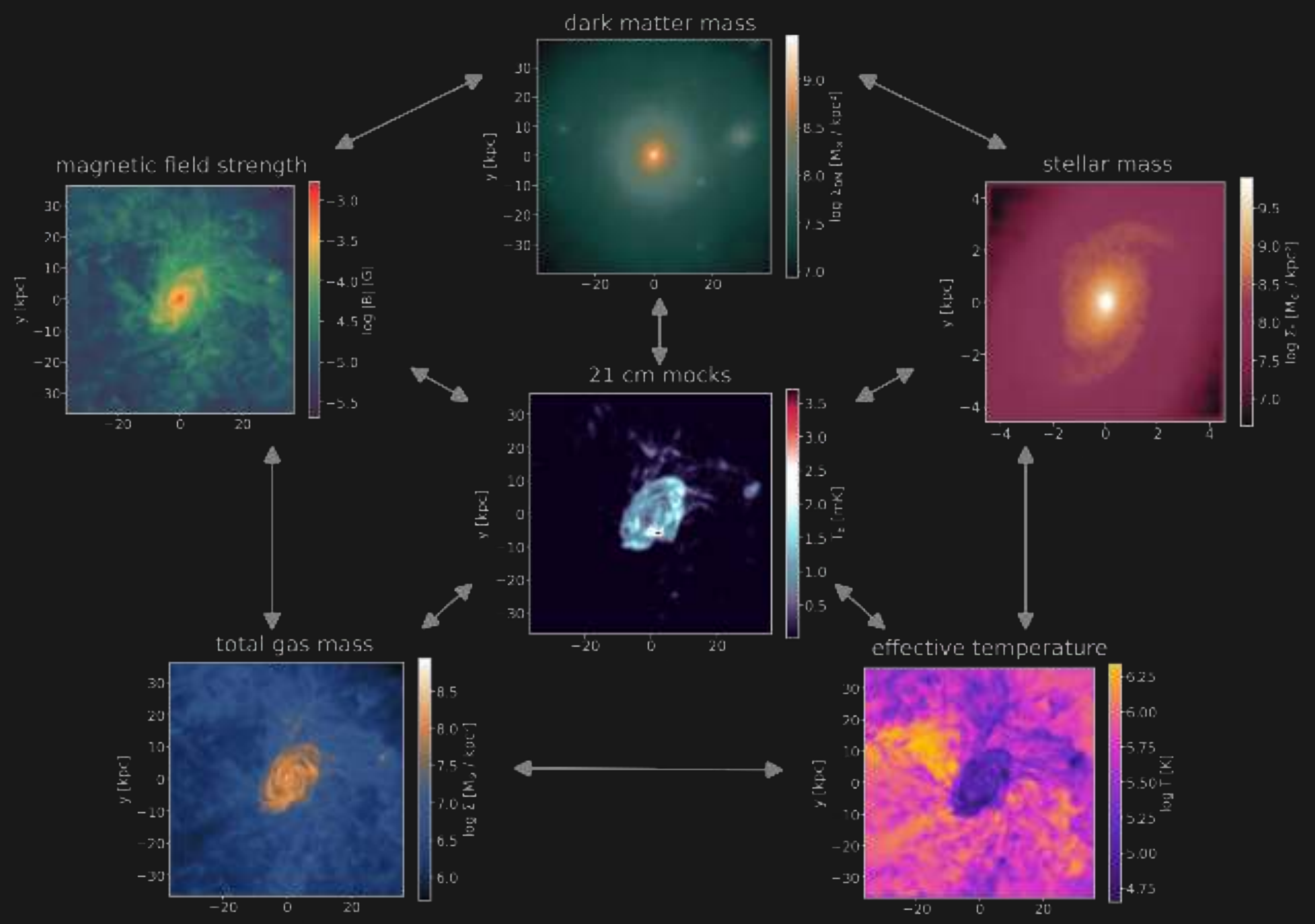

Generative model architectures

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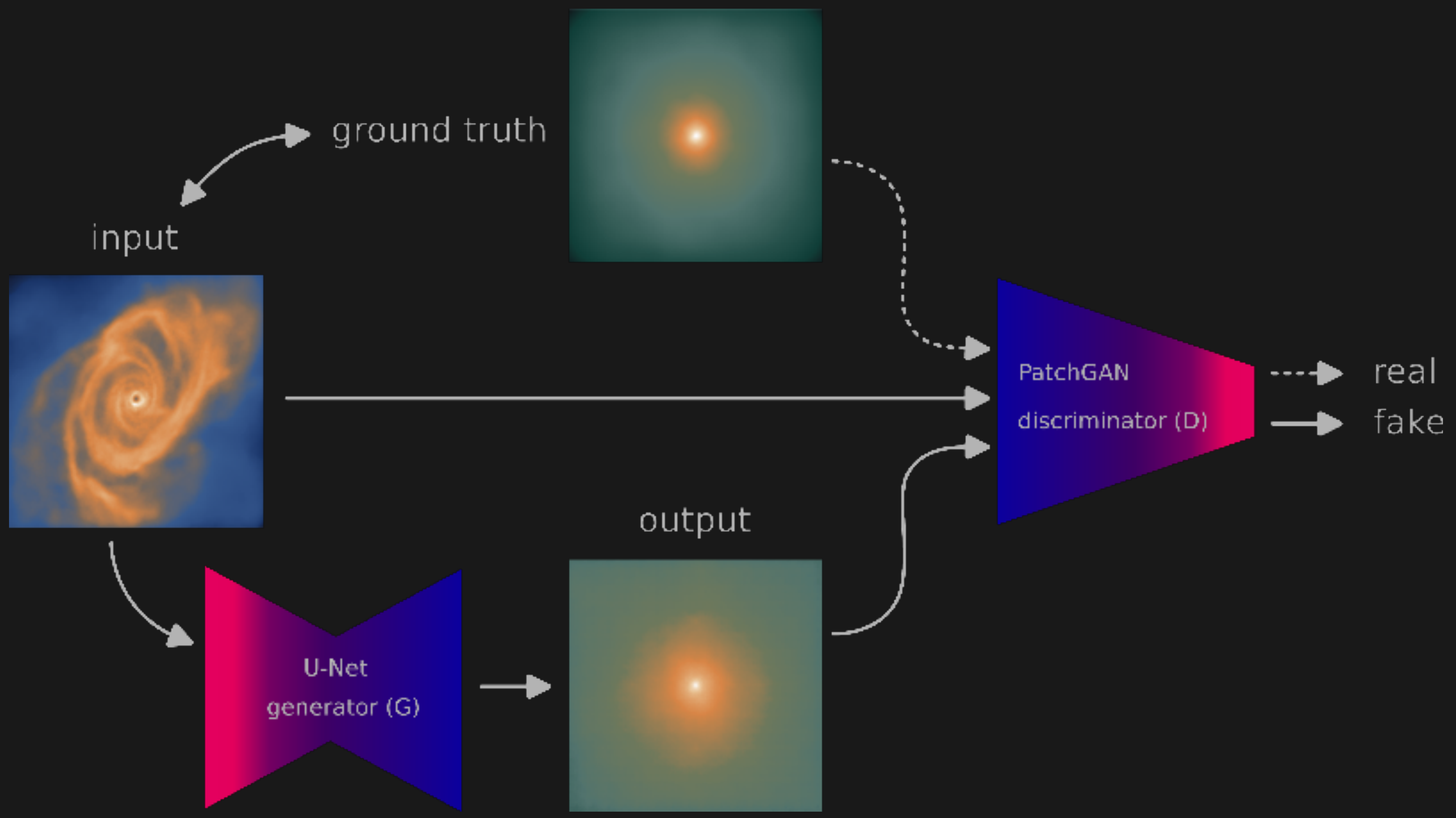
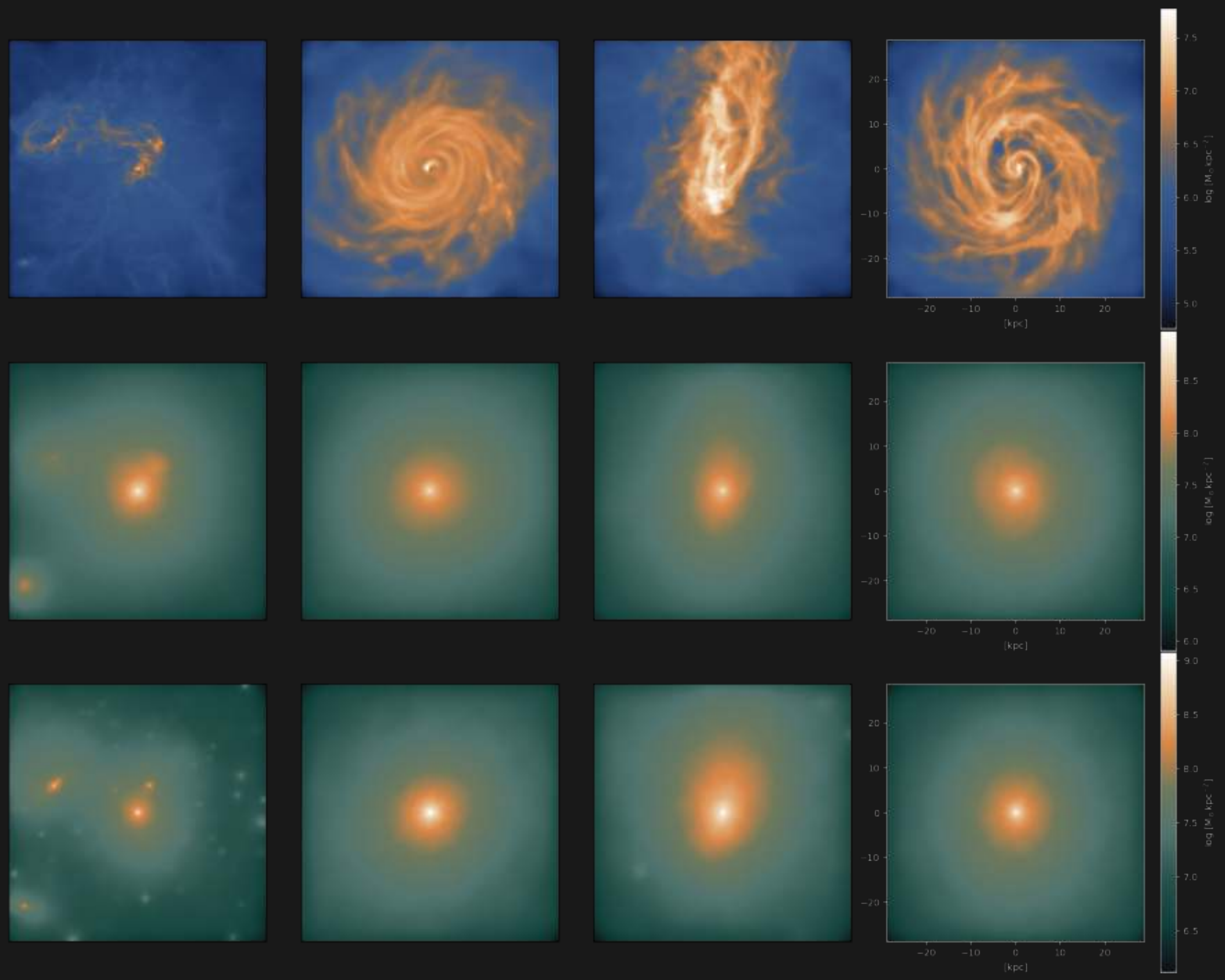
- **cGANs**: lackluster results (see previous talk)
- **Score-based diffusion models**: promising results but really slow
- **InDI** models: more efficient at inference?
- **Diffusion Mamba**: the latest and greatest?

cGANs

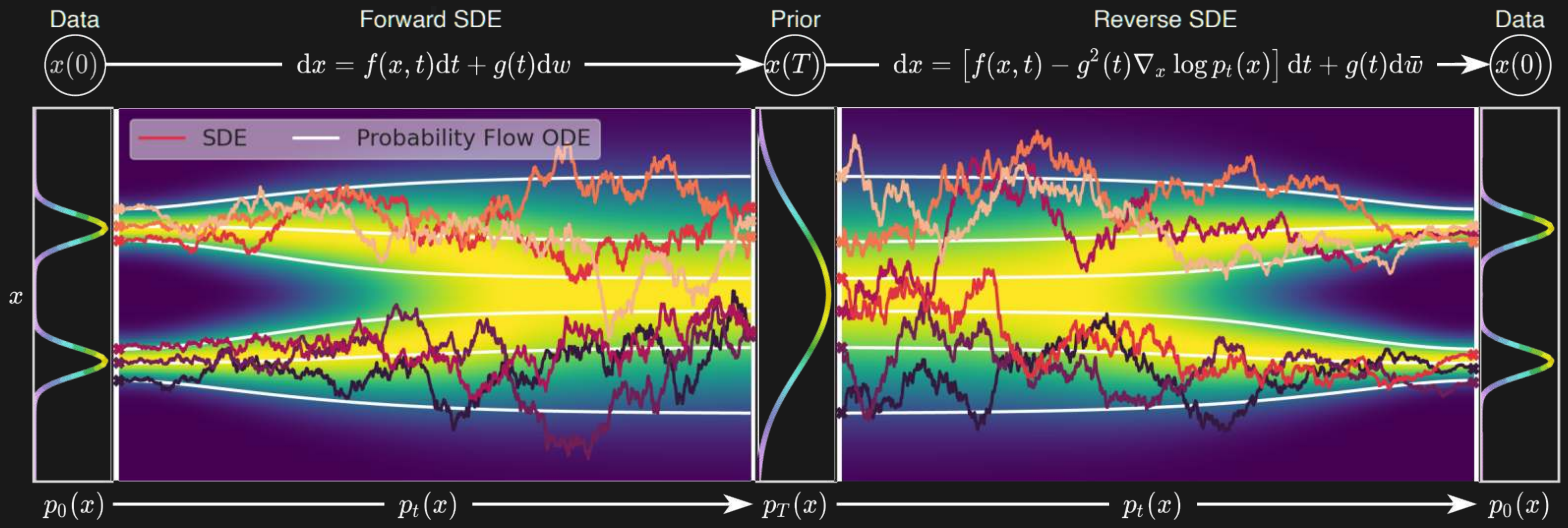


pix2pix scheme



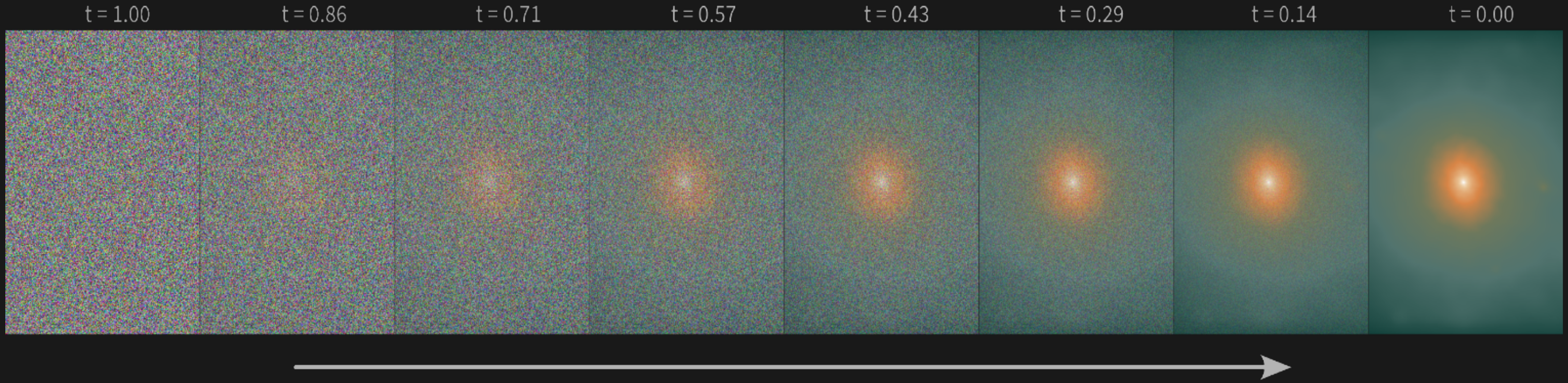
cGAN(Gas) → DM: data, prediction, and ground truth (from top to bottom)

Score-based diffusion (SDM)

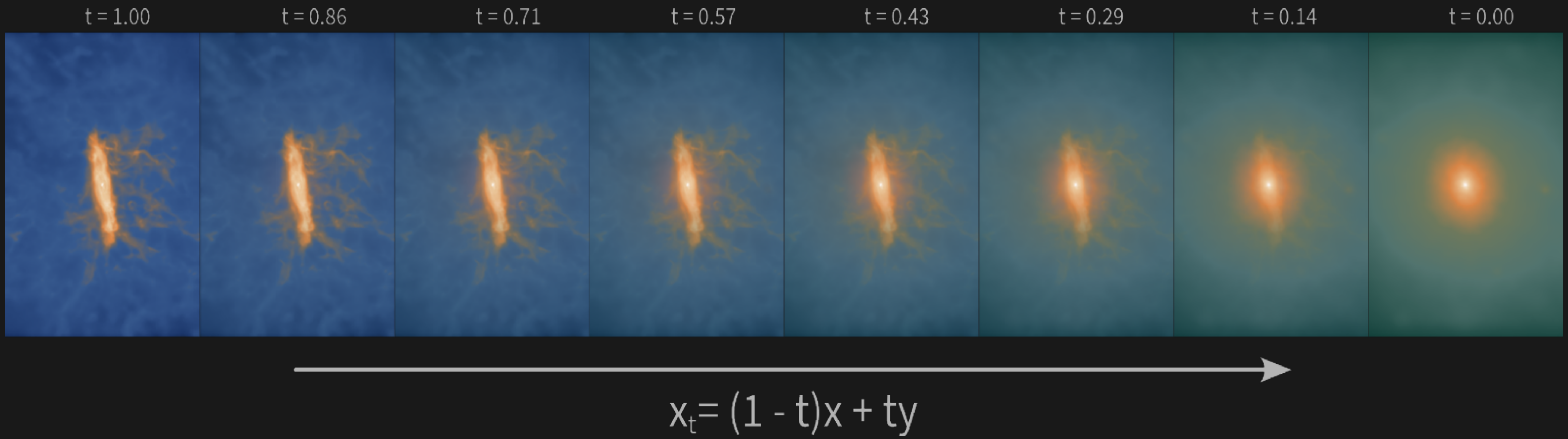


Score-based diffusion: Song et al. (2021)

Noise schedule

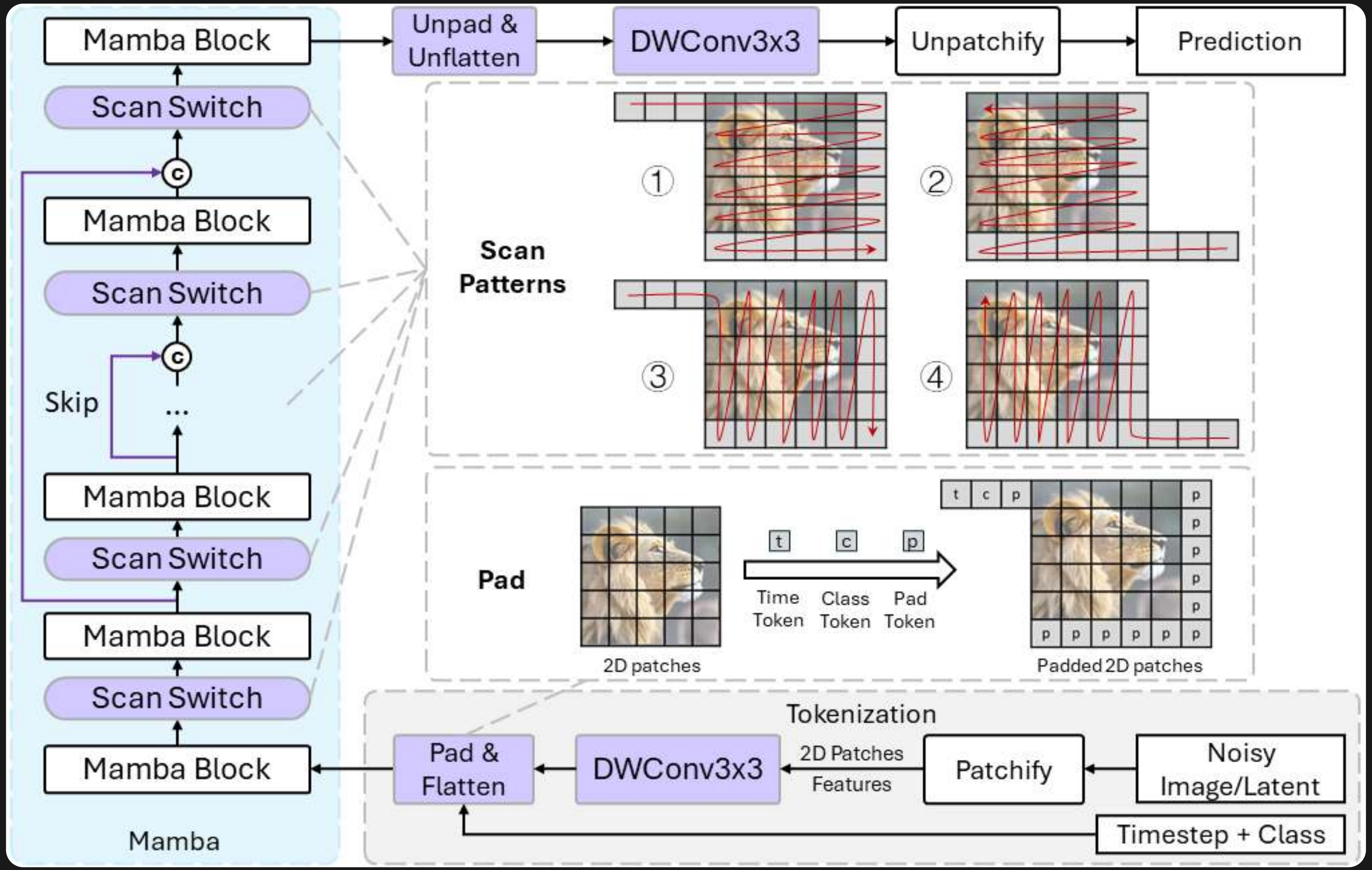


Inversion by Direct Iteration (InDI)



InDI's iteration scheme following Delbracio & Milanfar (2023)

Diffusion Mamba (DiM)



DiM architecture Teng et al. (2024)

From 2D To 3D Models

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- observations inherently have 2D spatial resolution
- astrophysical structures are inherently 3D
- modelling difficulties:
    - inherent 3D features, different 2D perspectives
    - degeneracies
    - computational costs, …

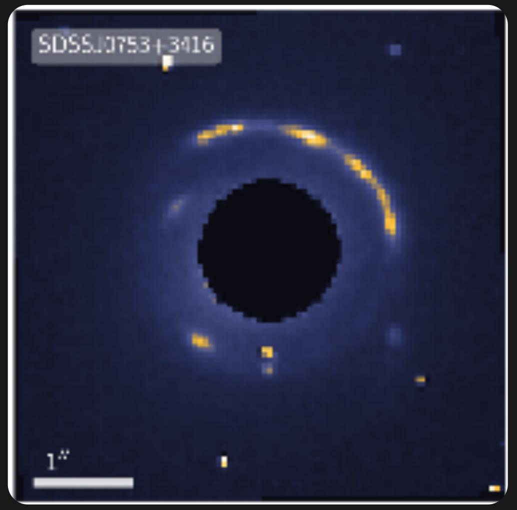
Inherent 3D shapes

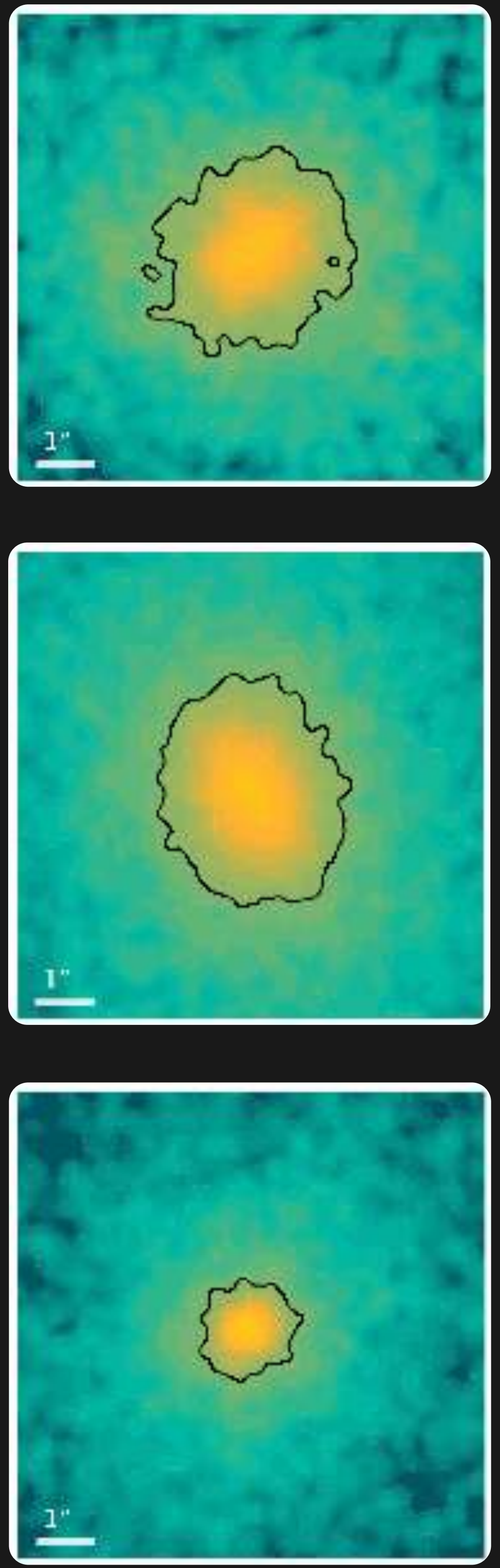
APOD 2019 June 29: M83

APOD 2024 June 6: NGC 4565

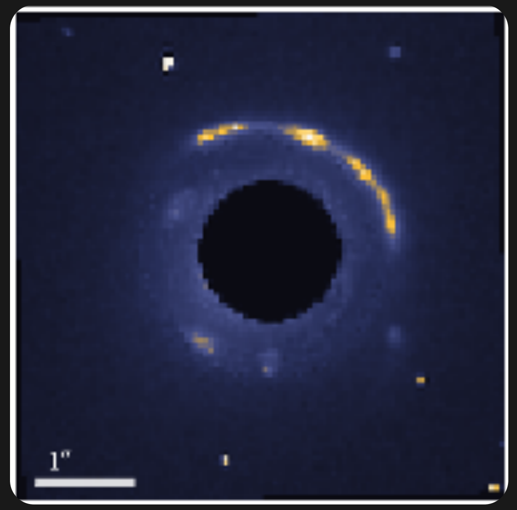
Degeneracies

original image





reconstruction



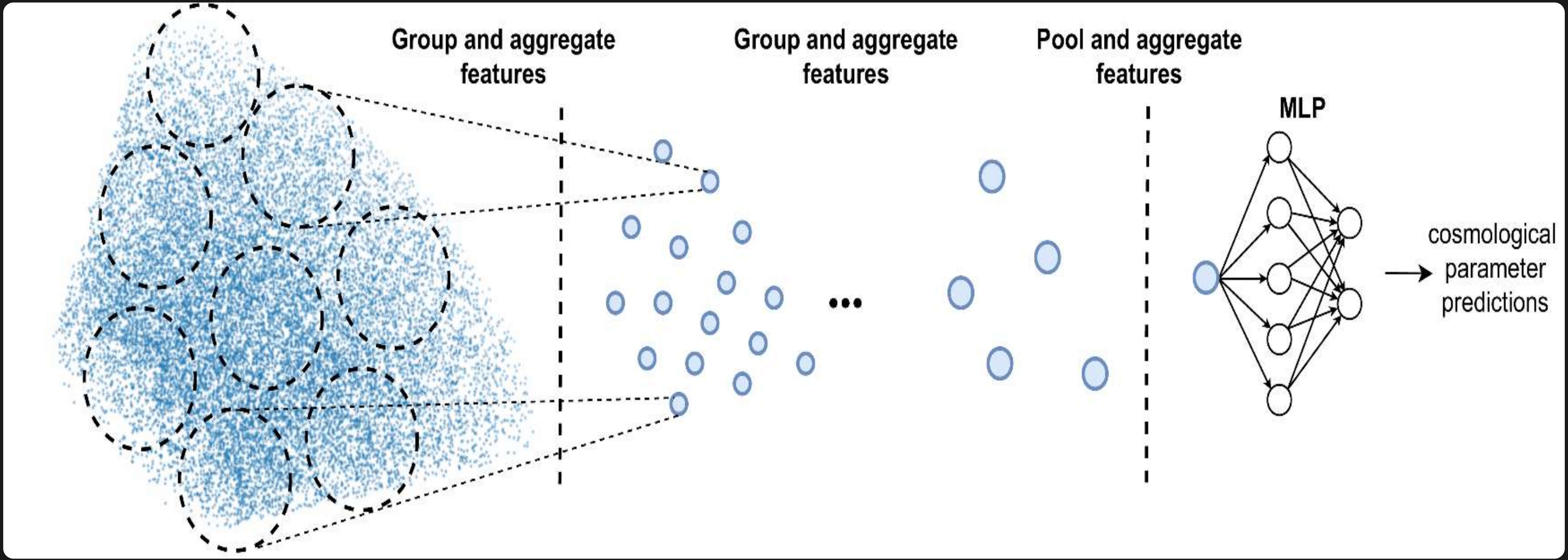
All valid model solutions: Denzel et al. (2021)

Point-cloud models for 3D modelling

Data type: point cloud

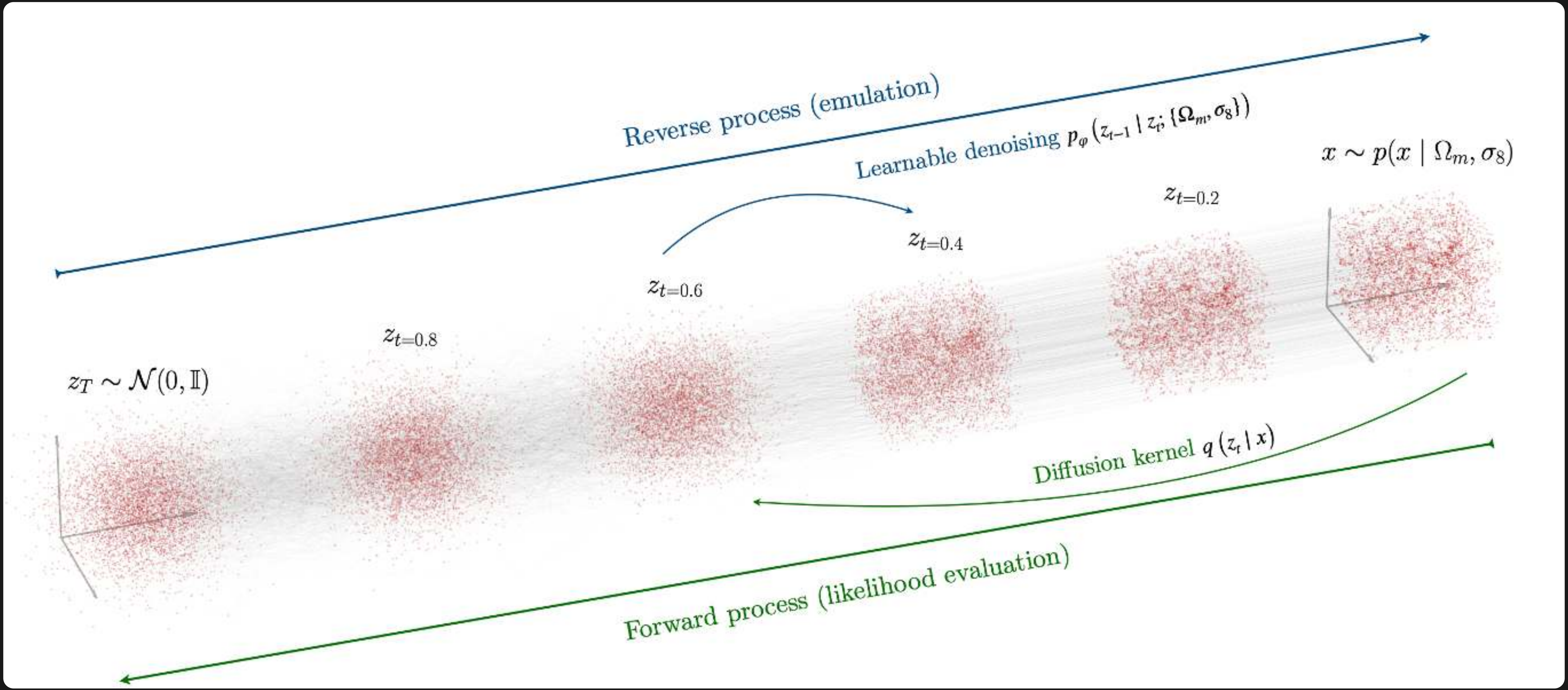
x	y	z	[Mass]	[E]
4	8	1	-	-
5	1	6	-	
2	3	4	2	-
3	4	3	5	-
5	9	1	3	-
9	6	9	4	-
…	…	…	…	-

For Cosmological Inference



Anagnostidis et al. (2022)

For Emulation of DM simulations (Quijote)

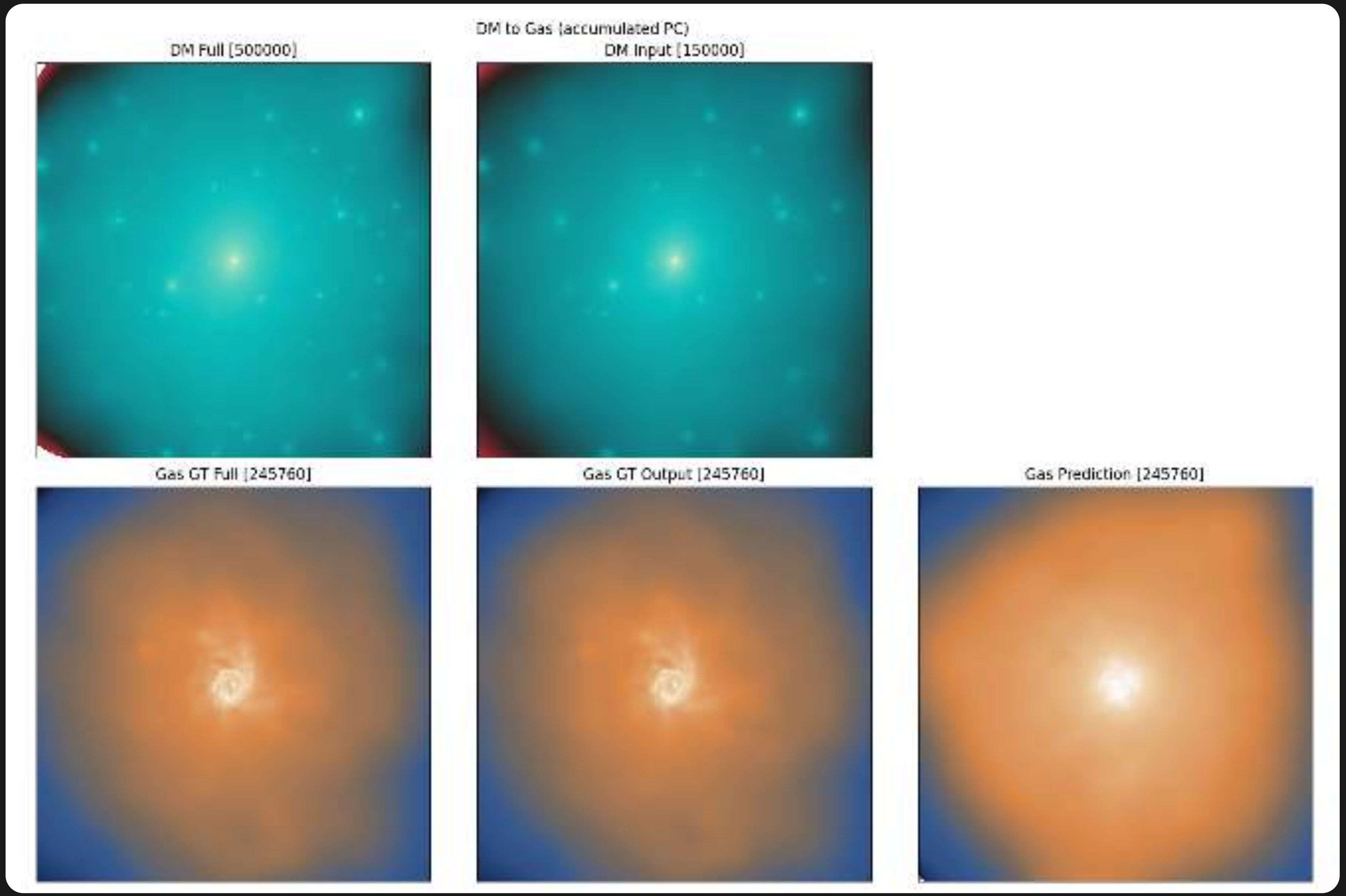


Cuesta-Lazaro & Mishra-Sharma (2023)

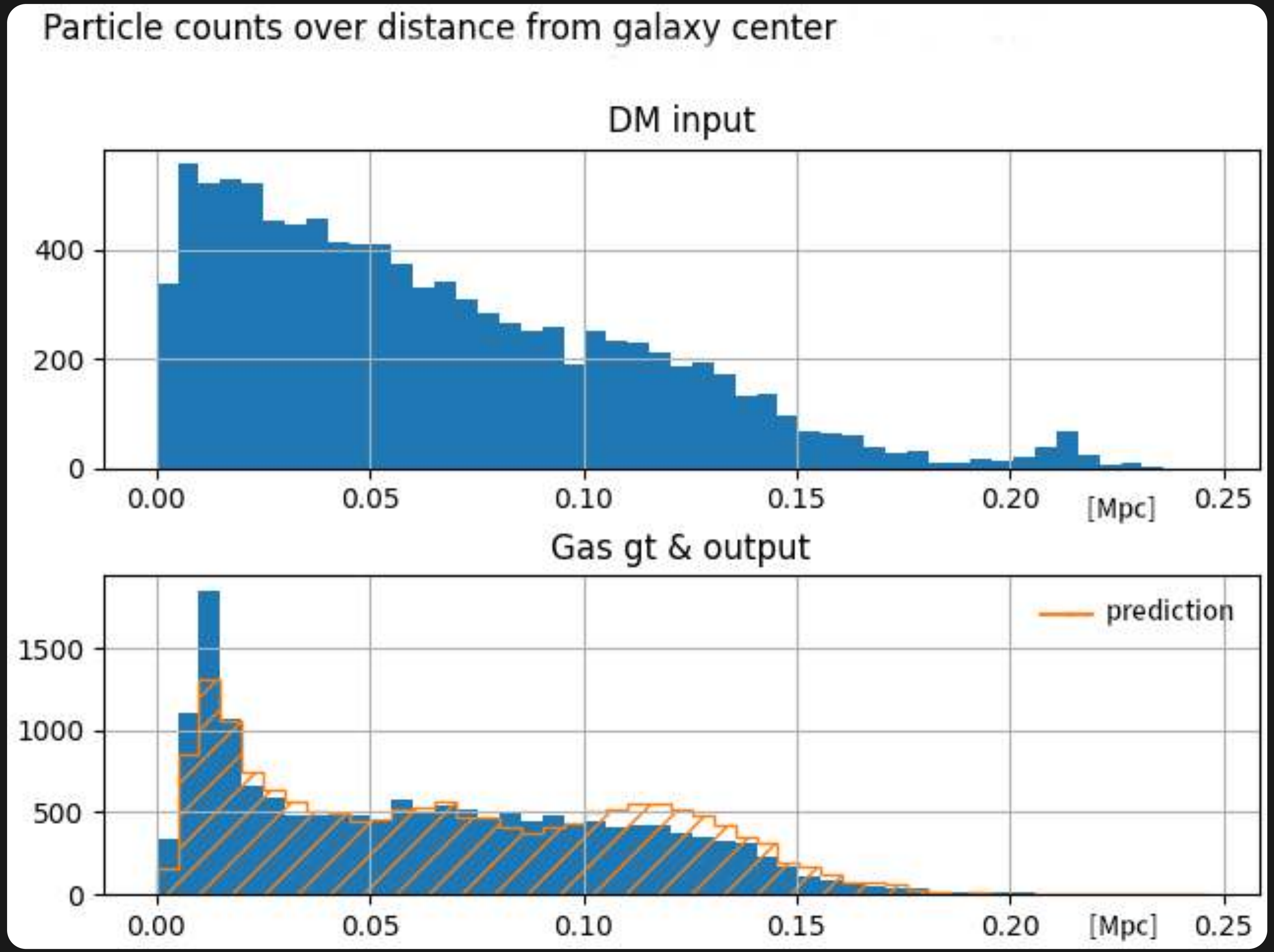
Experiments Using Transformers

- AdaPoinTr architecture
- Task: point cloud "completion"
- Limitations:
  - input: max. ~10'000 particles
  - output: max. ~16'000 particles
    $\longrightarrow$ Iterative generation
    $\longrightarrow$ subsampling input
- by Master student: Raphael Emberger

The "Good"

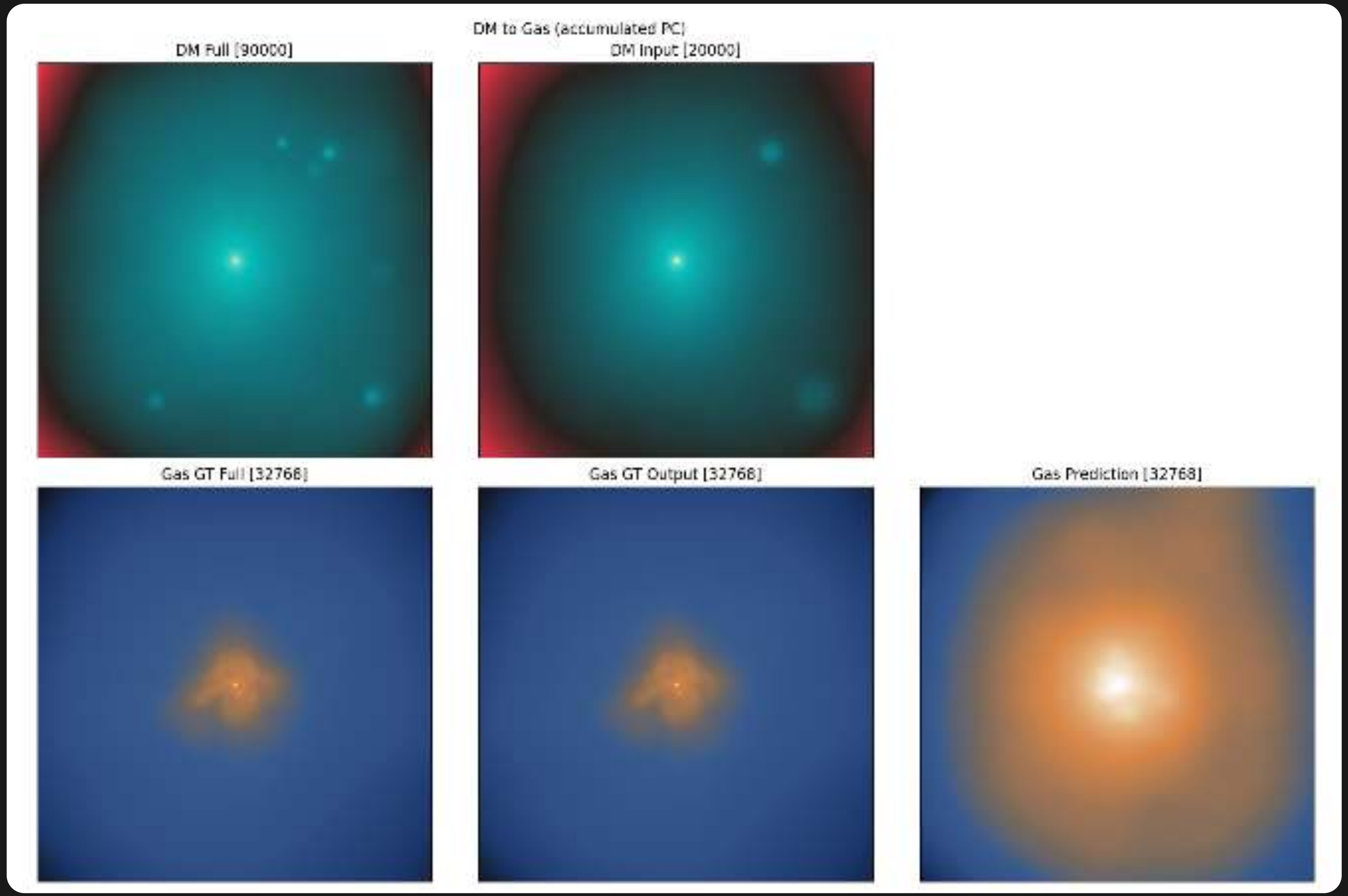


AdaPoinTr (Yu et al. 2023) on TNG50 galaxies: DM → gas



Radial profiles of particle numbers

The "Bad"



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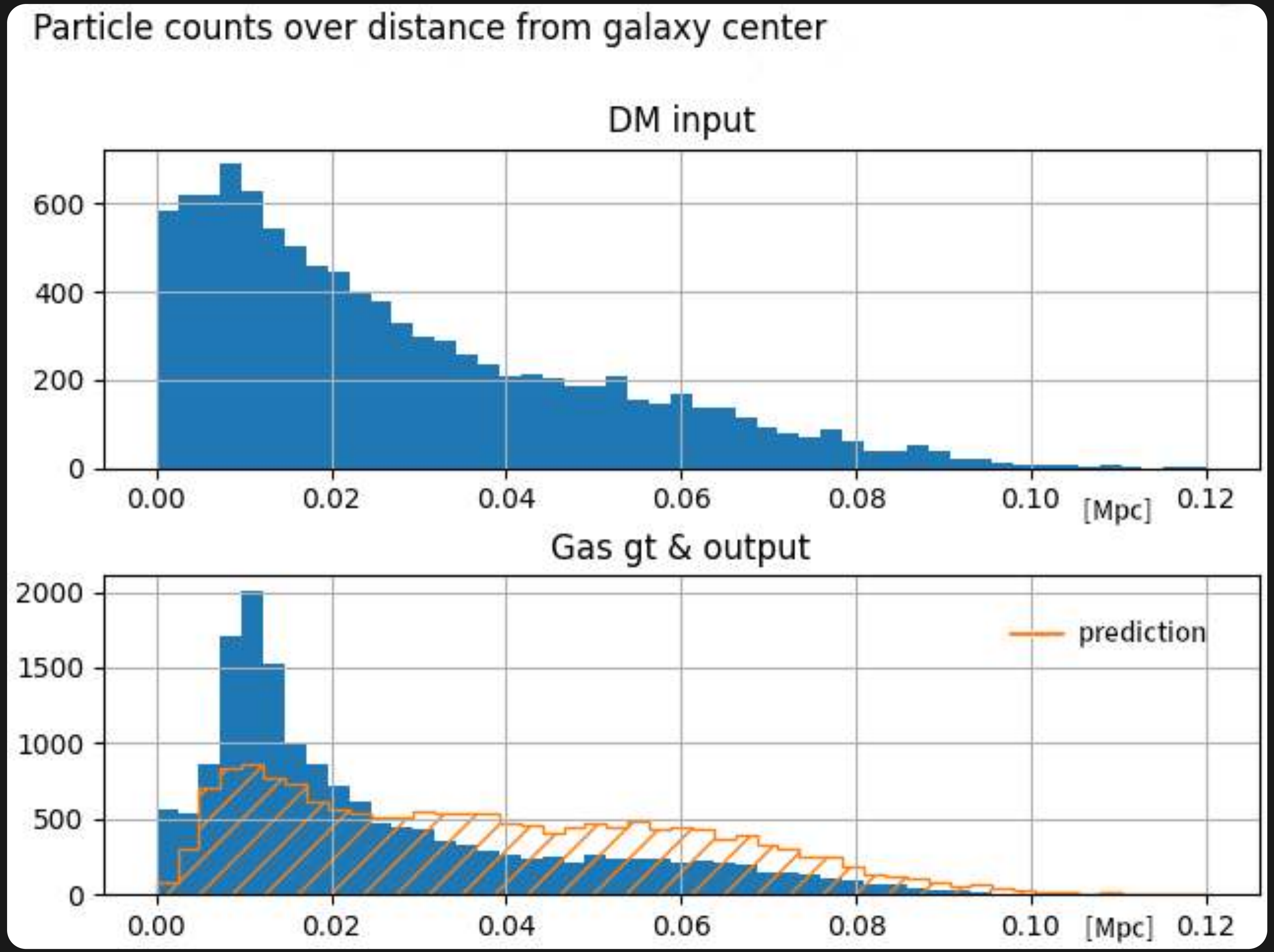
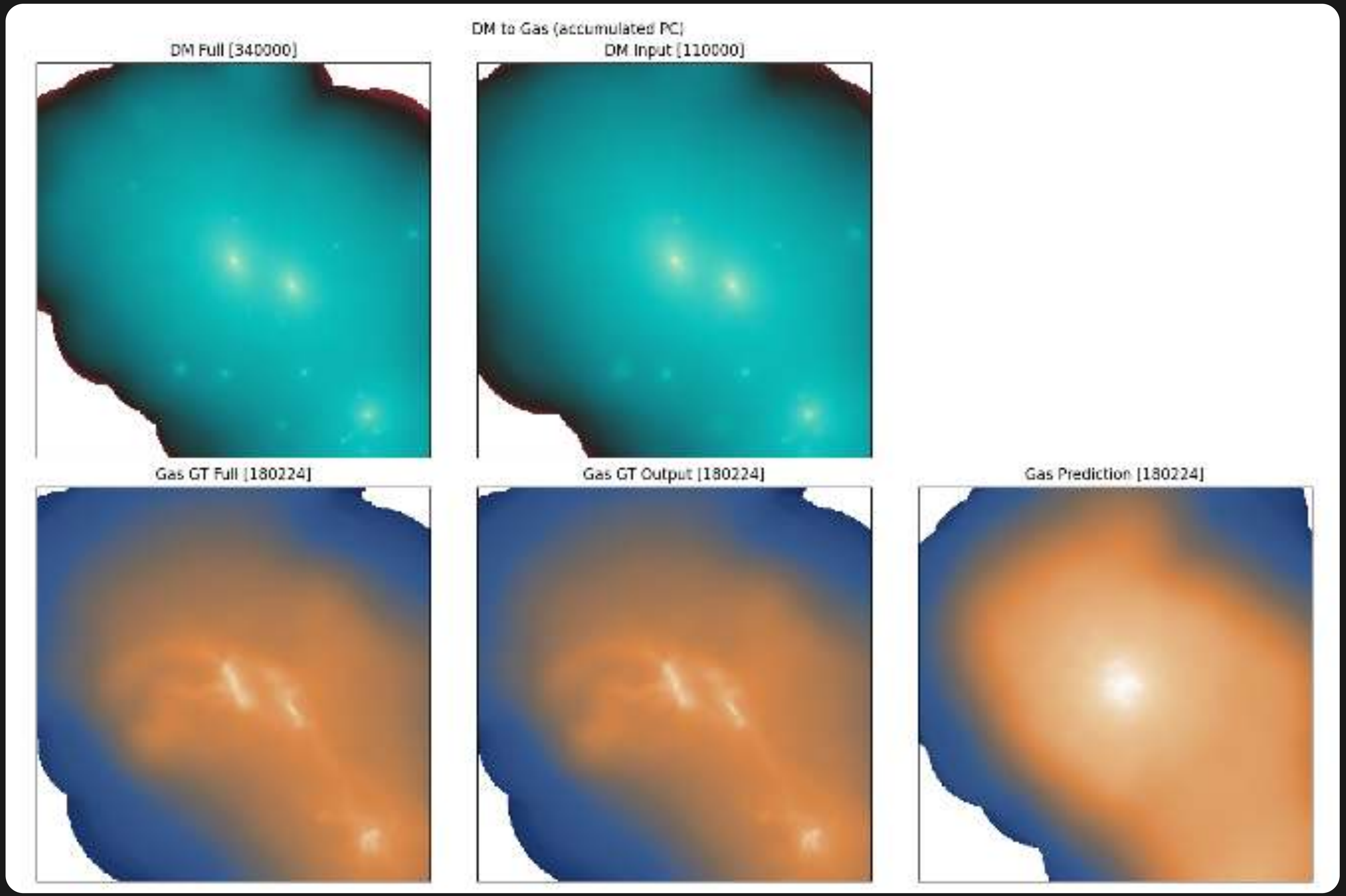


Radial profiles of particle numbers

The "Ugly"



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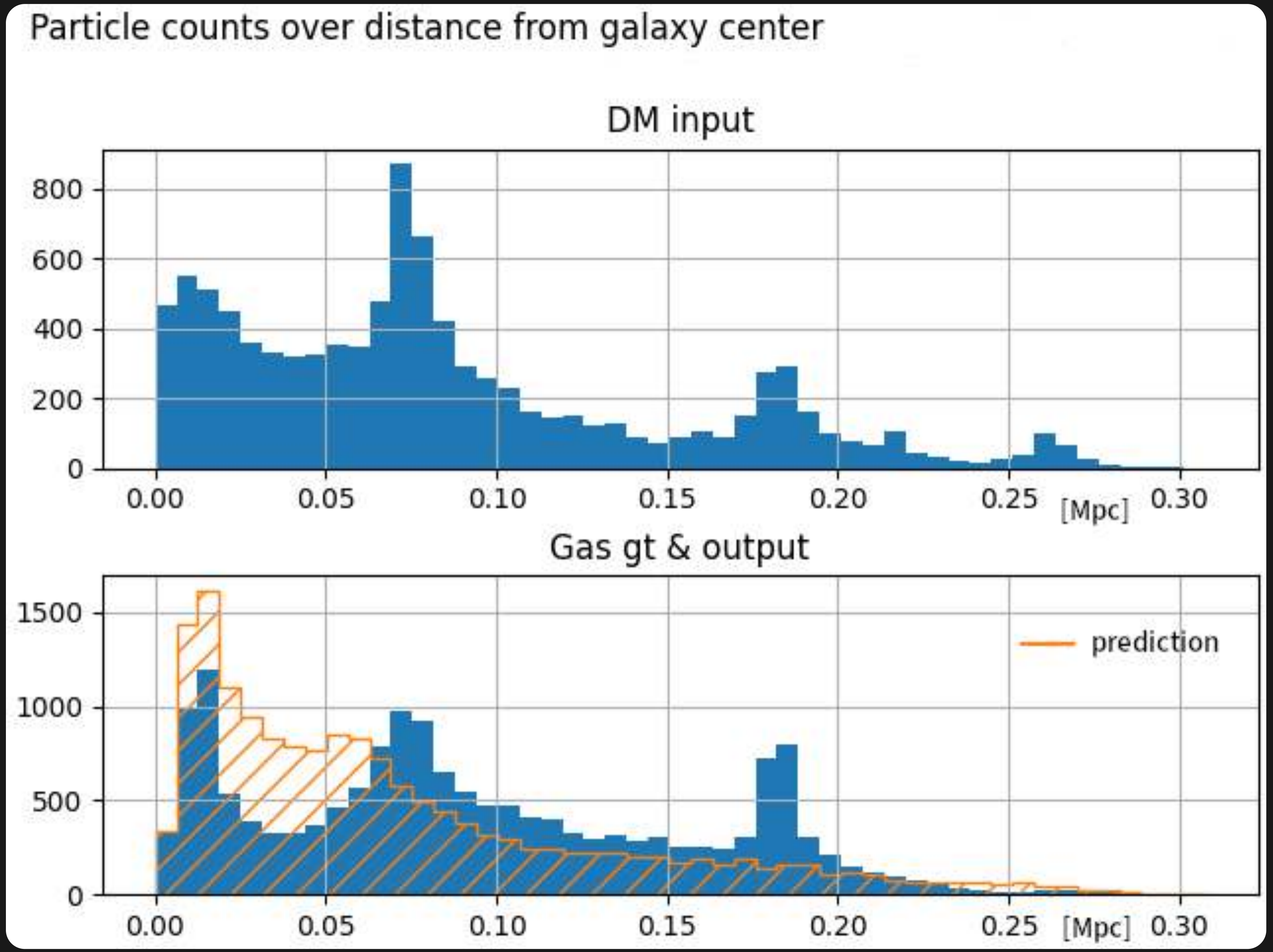

Radial profiles of particle numbers

Towards "Phase-Space-Point" Models

- expand feature vector to: mass, momenta/velocities, potential, …
- problems:
  - already barely computationally tractable
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    $\longrightarrow$ optimization: quantization, pruning, data parallelism, sharding, …
    $\longrightarrow$ better subsampling strategies
    $\longrightarrow$ self-consistency checks? regularizations?

Contact

https://phdenzel.github.io/

Email: philipp.denzel@zhaw.ch

References

- SDM: Song et al. (2021)
- InDI: Delbracio & Milanfar (2023)
- DiM: Teng et al. (2024)
- PointNet for summary statistics: Anagnostidis et al. (2022)
- Point cloud generation for galaxy surveys: Cuesta-Lazaro & Mishra-Sharma (2023)
- AdaPoinTr architecture: Yu et al. (2023)
- Cosmology from point clouds: Chatterjee & Villaescusa-Navarro (2024)

Created by phdenzel.