Emulating Baryonic fields from cosmic to galaxy scales with Generative Deep Learning

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References:

Bernardini et al. 2022, arXiv:2110.11970

Feldmann et al. 2023, arXiv:2205.15325

Bernardini et al. in prep

Swiss SKA Days, September 8, 2023

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- Need to understand both formation of (dark matter) structure and the biased tracers accessible to observations

- Most tracers, e.g., galaxies or 21 cm signals, are the product of complex astrophysical processes (“baryonic physics”)

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e.g., Effective Field Theory (e.g., Senatore et al. 2015, Schmidt et al. 2019)

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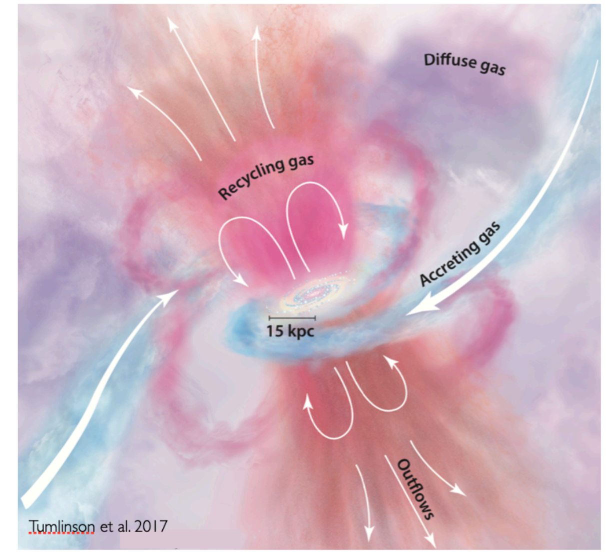
Try to model them

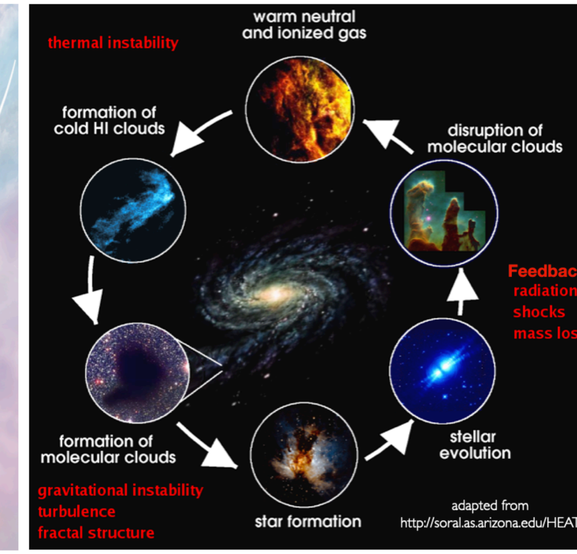
e.g., semi-analytical models, cosmological simulations

- Computationally expensive
- Some of the physics not well understood (e.g., AGN feedback)

Modeling baryons

- Rich / complex physics:
  - Multitude of interacting physical processes
  - Wide range of scales
  - Coupling of scales: Stellar and AGN feedback





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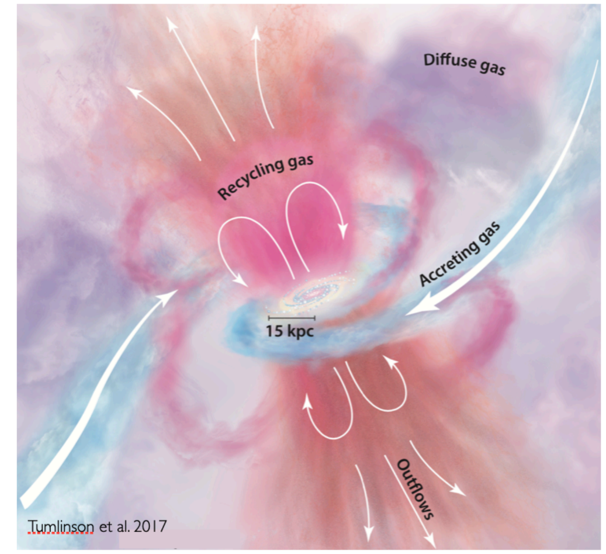
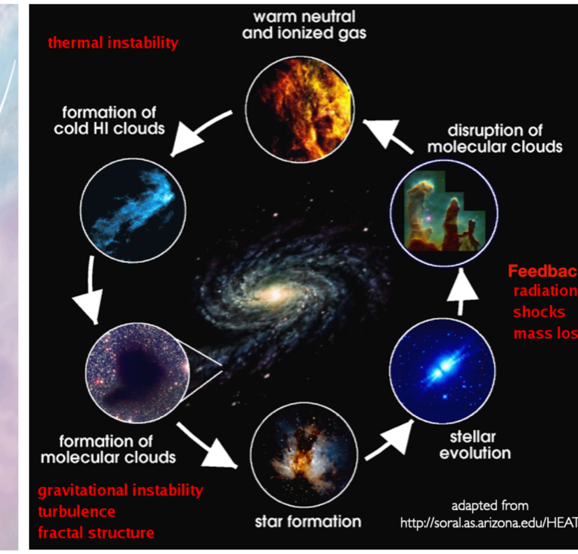


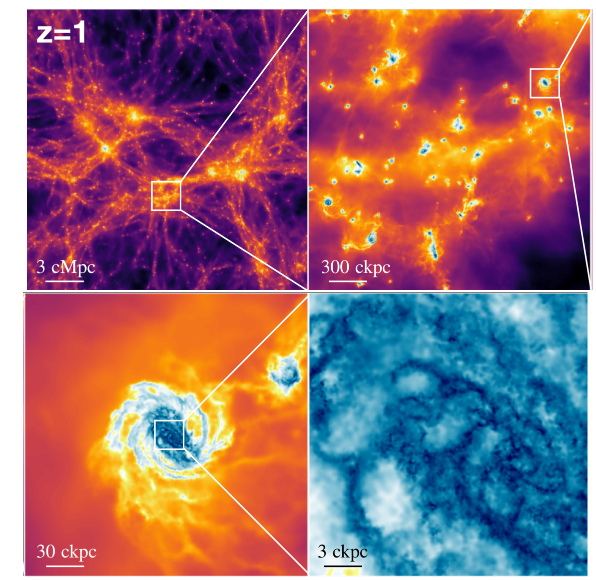


- Hydrodynamical cosmological simulations

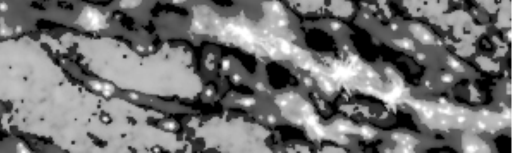
  + predict baryons on all scales and across cosmic history

  + test physical models (e.g., UV background evolution, feedback)

  - high computational cost



RF et al. 2023



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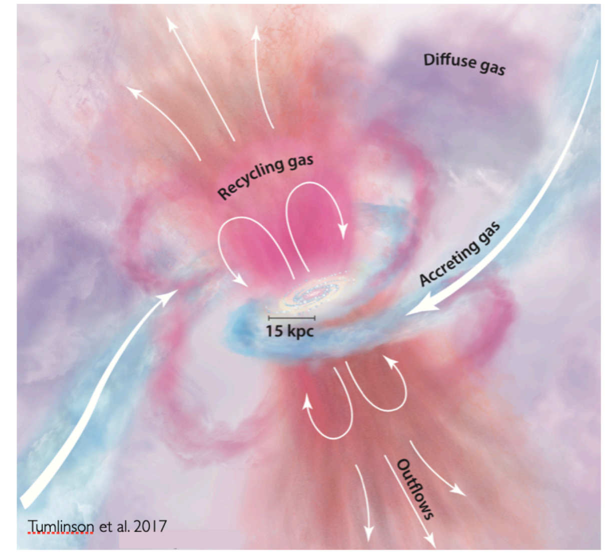

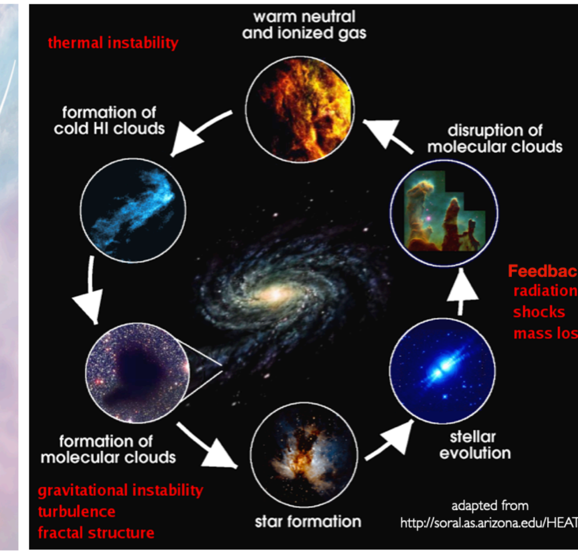

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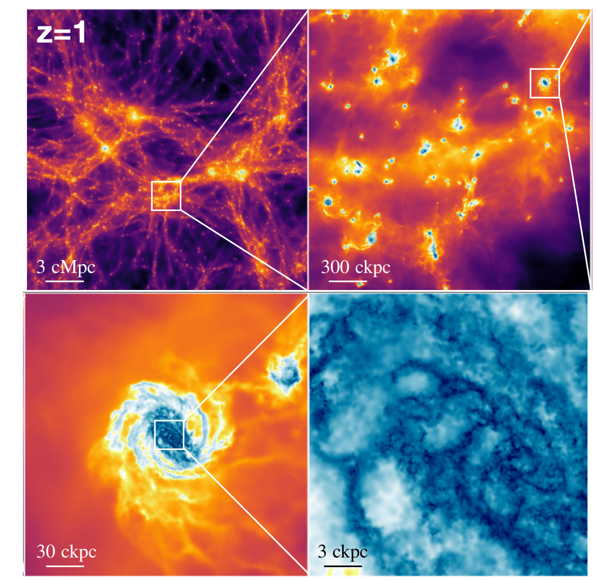

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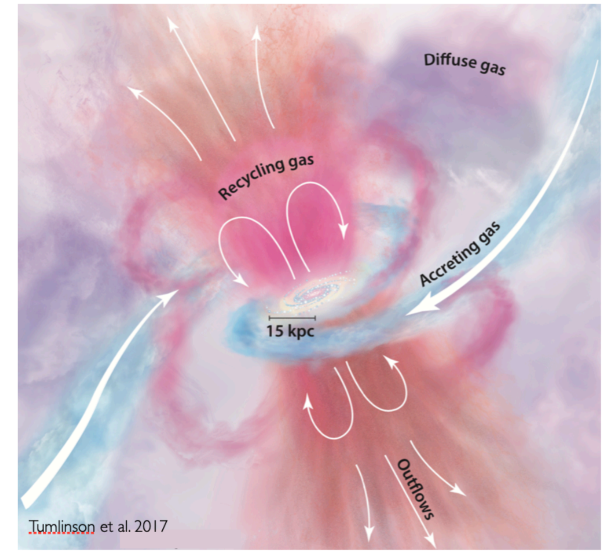

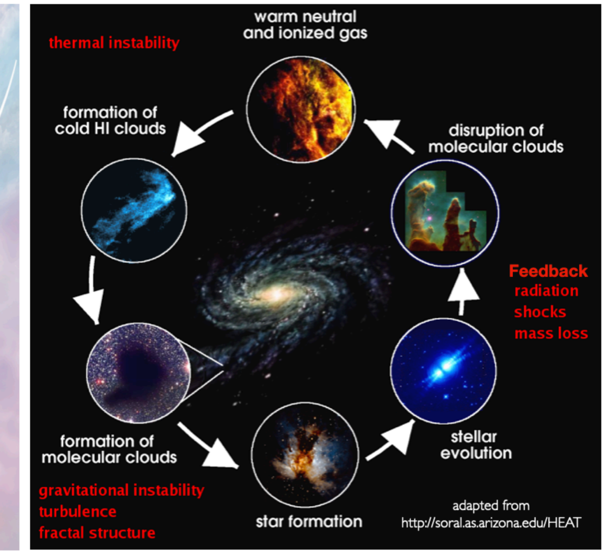

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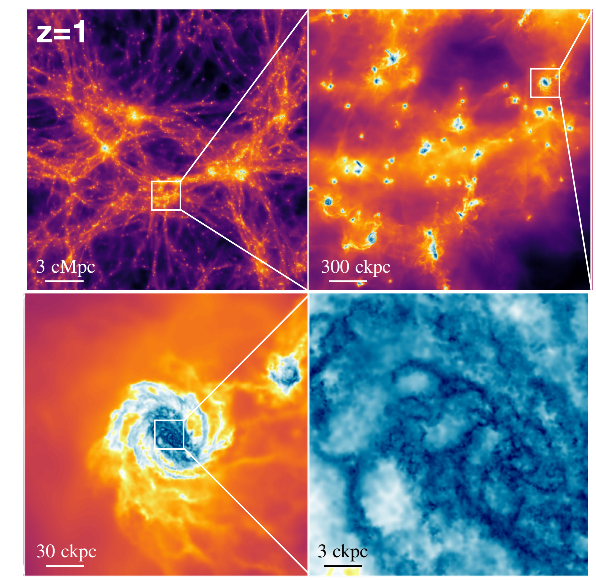

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<u>Idea: Encapsulate simulation results by training deep neural network</u>

- Once trained, prediction is computationally *inexpensive* => Emulator

  \+ Generation of mock catalogs, light cones, covariance matrix calculation

  \+ Interpolate to new parameter values, redshifts etc. => Likelihood-free inference

  \+ Increase resolution ("super-resolution")

  \+ Upscale to much larger volumes while preserving high resolution

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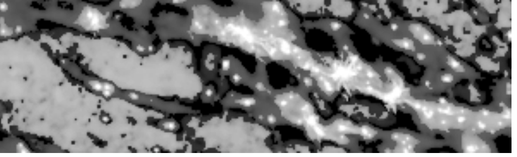
$$p(\Sigma_{\rm gas} | \Sigma_{\rm DM})$$



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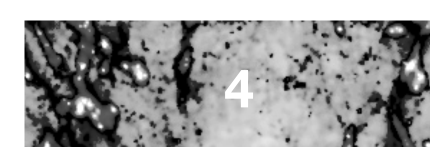

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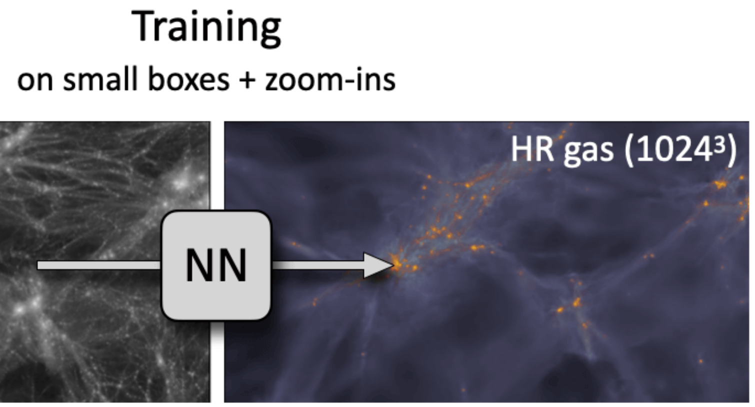

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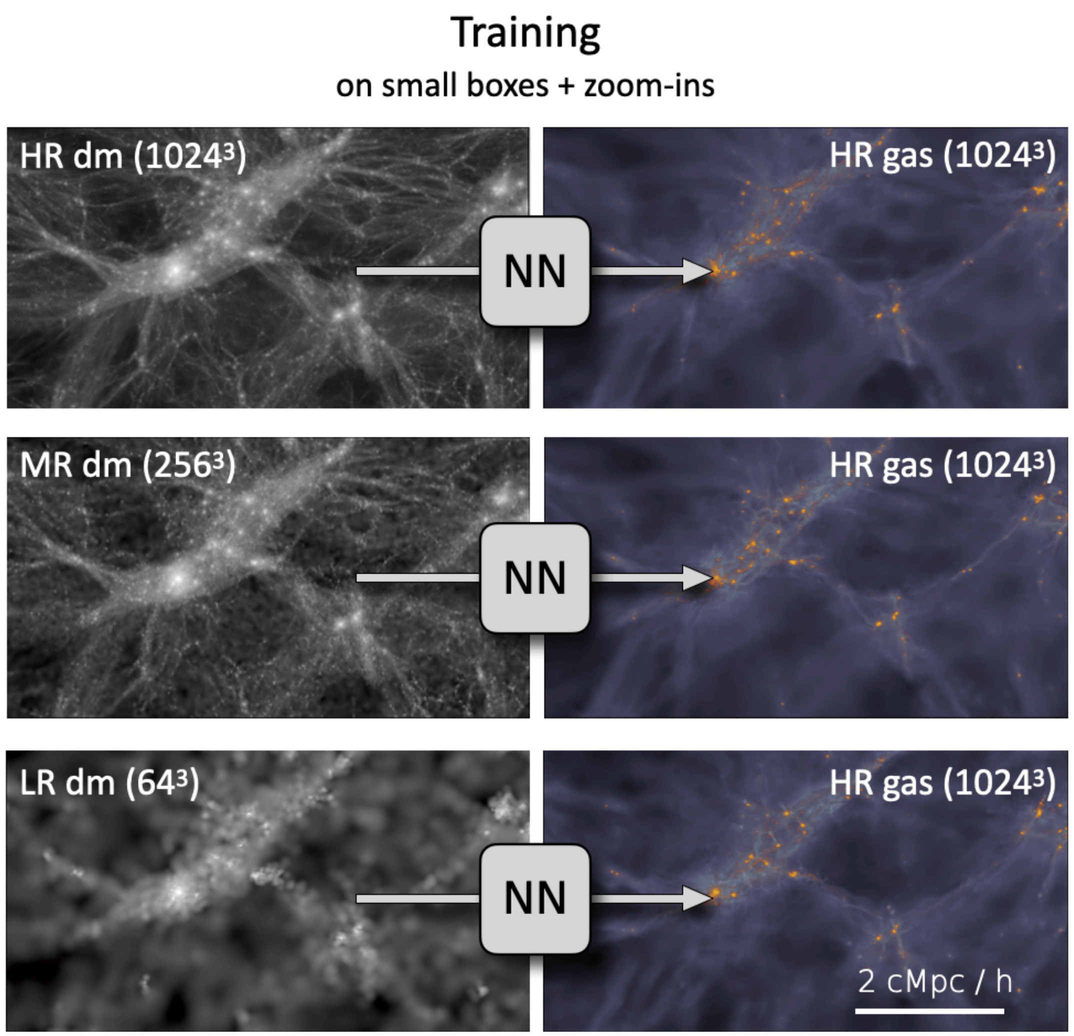

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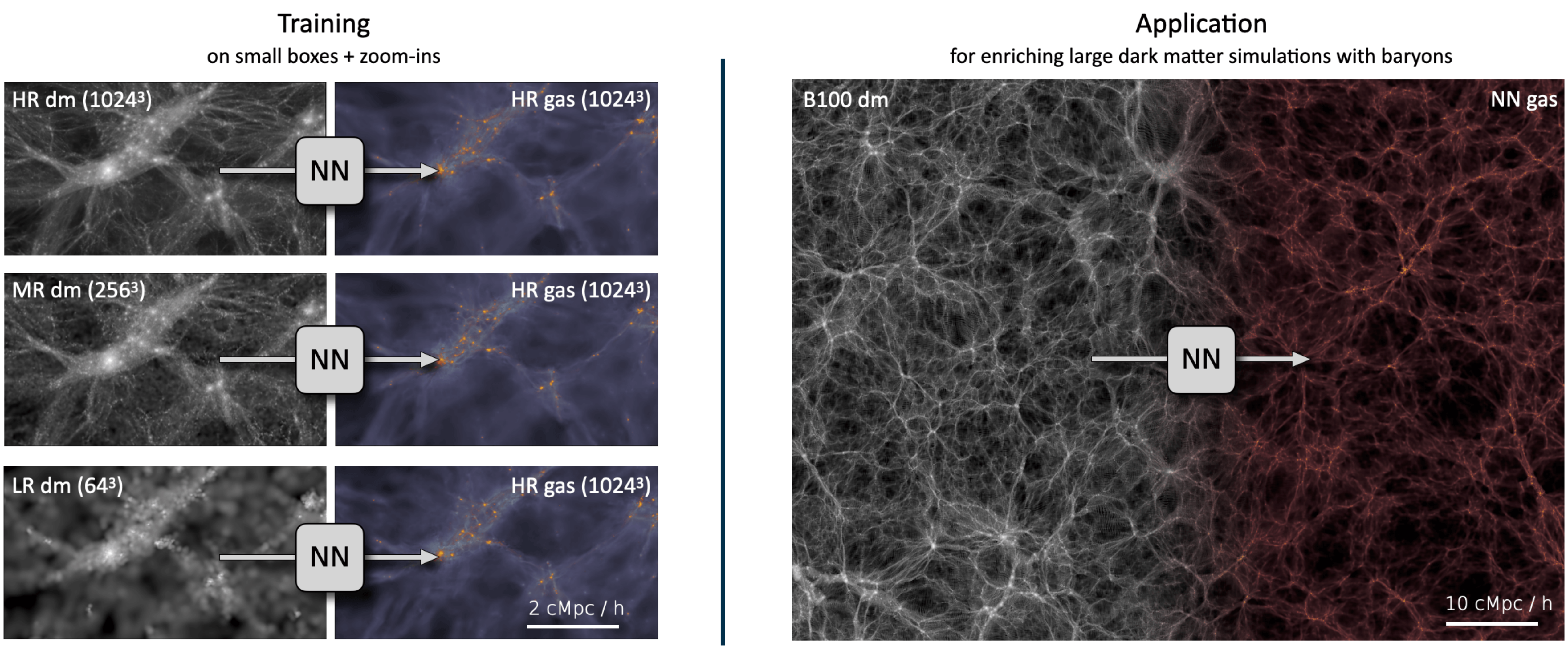

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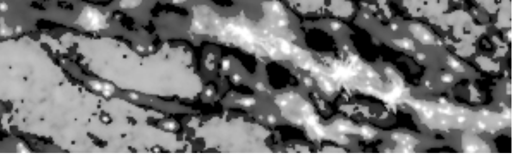
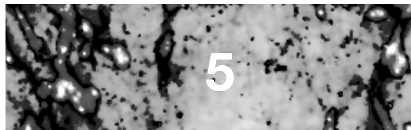
title slide shows part of the B100 map



Emulating observational data on the field level

Input	Output	Posterior	Note	Reference	
Noise	HI field	Yes	3-d, Δx~35 kpc/h	Zamudio-Fernandez et al. 2019	
DM map, Noise	electron pressure map	Yes	2d, Δx~200 kpc/h, tSZ	Tröster et al. 2019	
DM field	elec. pressure, density, momentum fields	No	3d, Δx~100 kpc, tSZ, kSZ	Thiele et al. 2020	
DM field	HI field	No	3d, Δx~140 kpc/h	Wadekar et al. 2021	
DM field	gas density, temp., velocity field	No	3d, Δx~20 kpc/h	Harrington et al. 2021	
DM field, Noise	gas density, temp., velocity field	Yes	3d, Δx~40 kpc/h	Horowitz et al. 2021	
DM maps	HI maps	Yes	2d, Δx~400 kpc/h	Hassan et al. 2022	
DM maps	HI maps, gas maps	Yes	2d, Δx~3.6 kpc/h	Bernardini et al. 2022	**EMBER**
DM maps, l.o.s. velocities	gas maps, temp., velocity, HI maps	Yes	2d, variable resolution	Bernardini et al. in prep	**EMBER-2**



Simulation data

- Simulations run with GIZMO, FIRE-2 physics

FIRE
Feedback In Realistic Environments

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- 2 kinds of simulations:

Cosmological volume

Cosmological zoom-in

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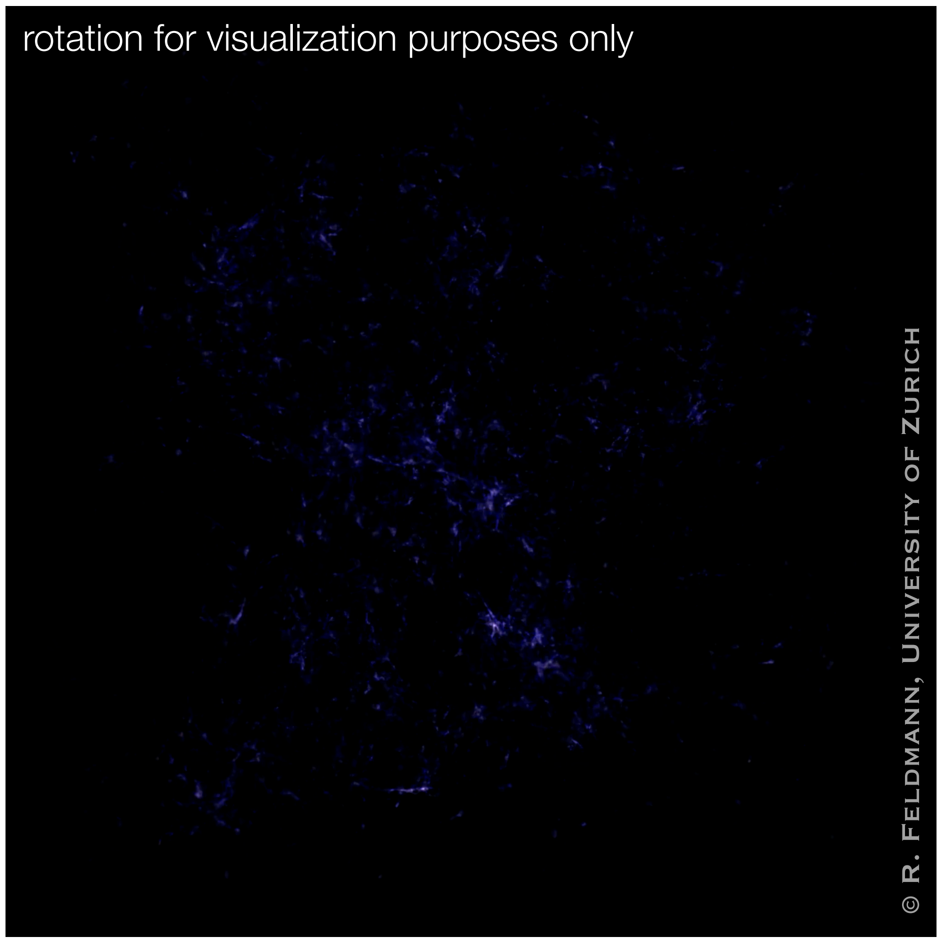

FIREbox (RF et al. 2023 arXiv:2205.15325)

- L = 22 cMpc
- 2 billion (gas+DM) particles
- $m_b \sim 6 \times 10^4\, M_\odot$, $\Delta x \sim$ tens of pc

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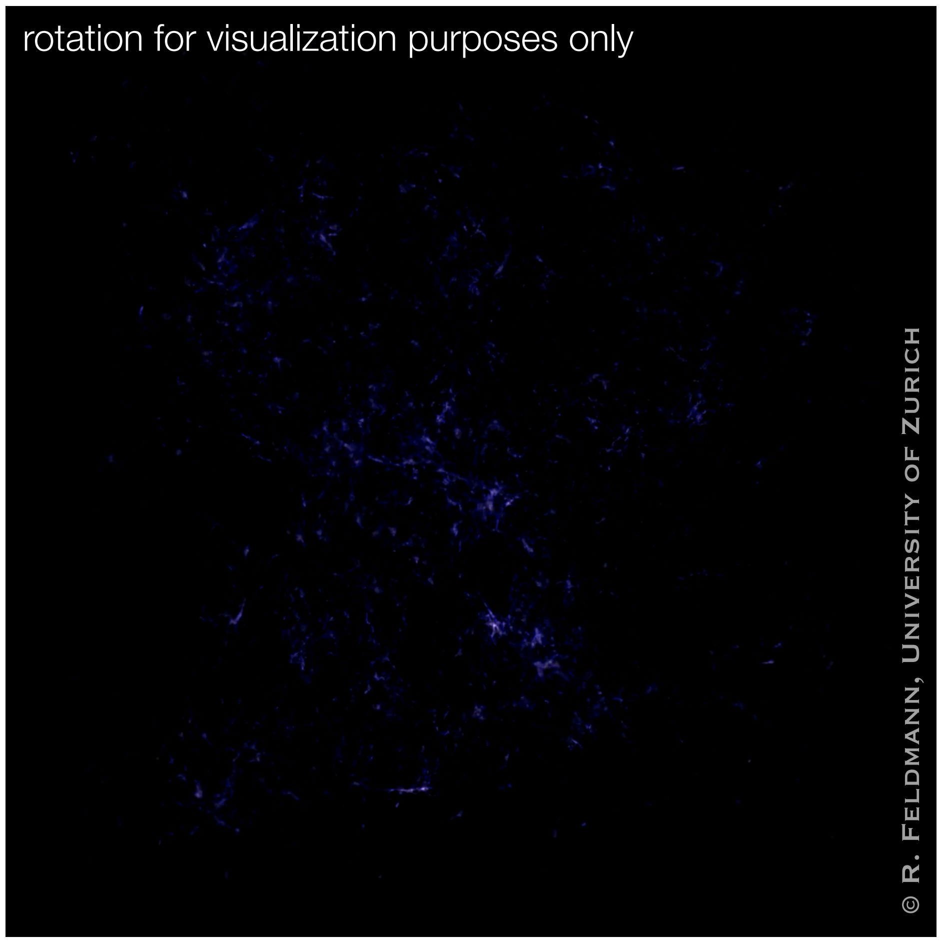

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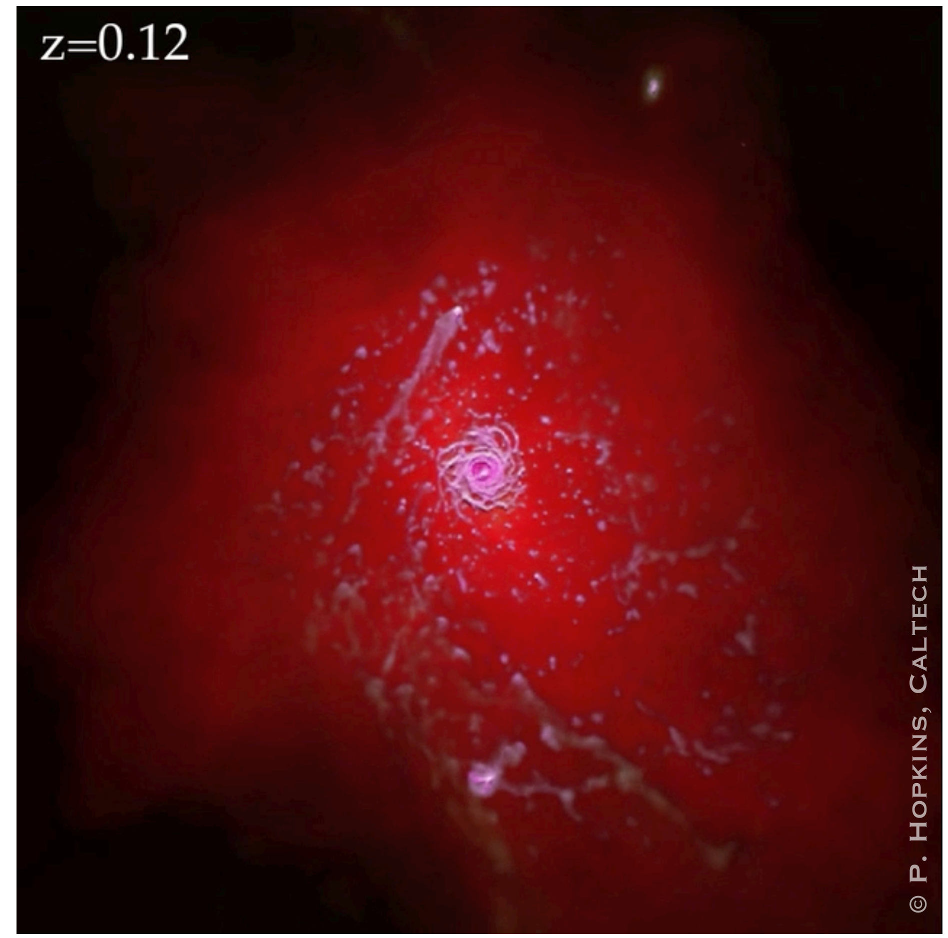
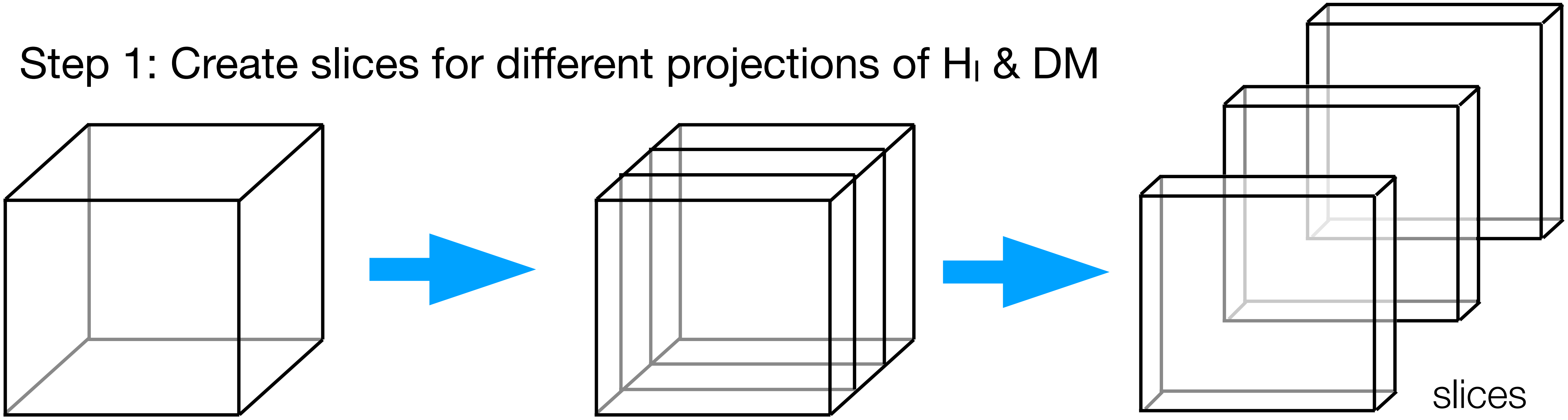


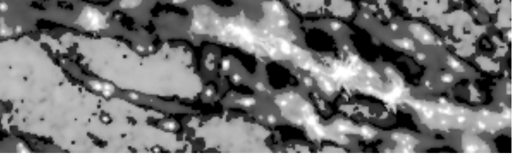
MassiveFIRE (RF+2016, Angles-Alcazar+2017)

- ~few cMpc region
- 4 massive halos
- $m_b \sim 3 \times 10^4\, M_\odot$, $\Delta x \sim$ tens of pc

From FIRE to EMBER

Step 1: Create slices for different projections of H_I & DM





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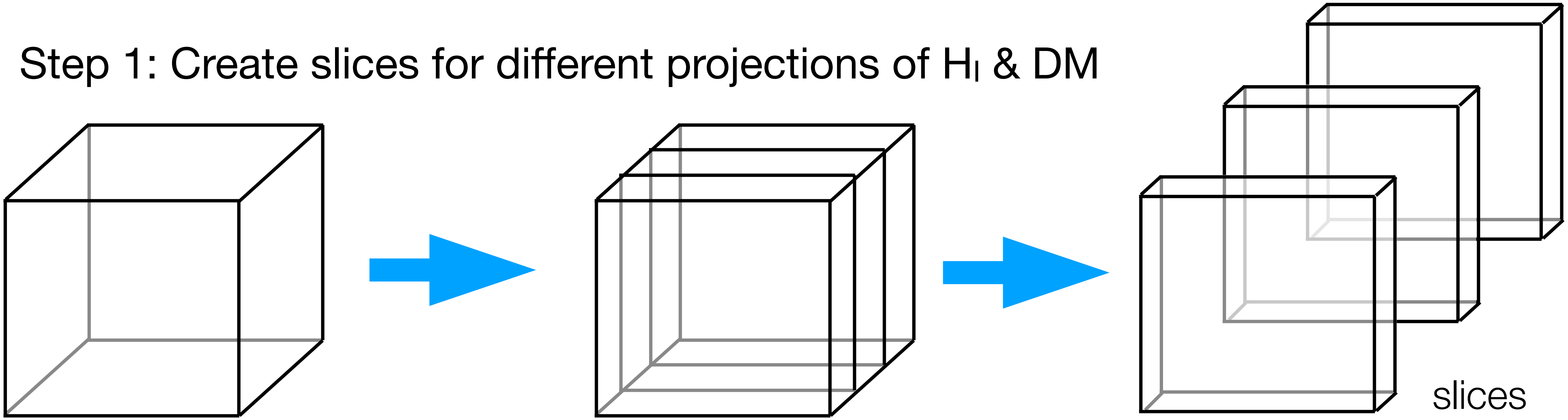
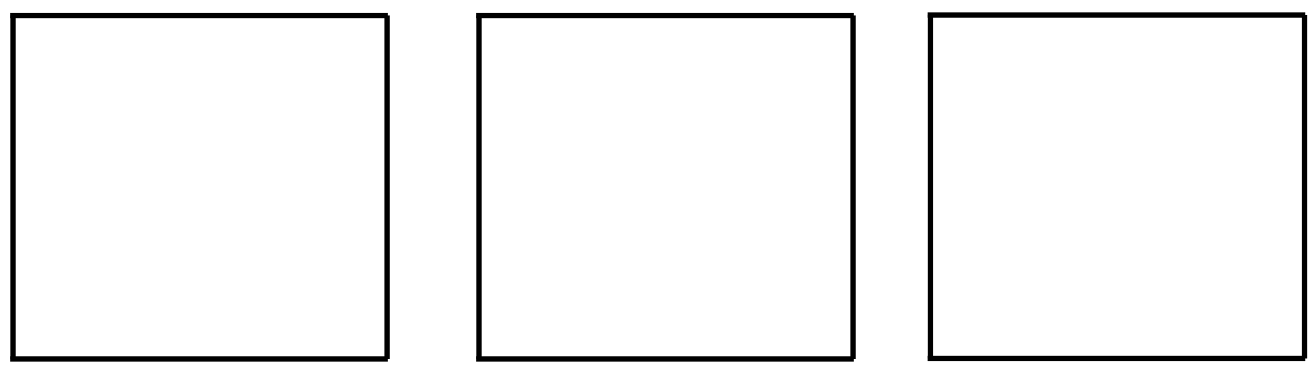
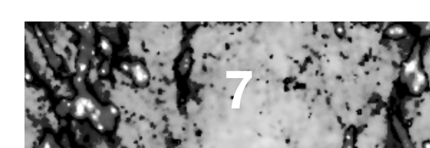


Step 2: Project H_I and DM density fields





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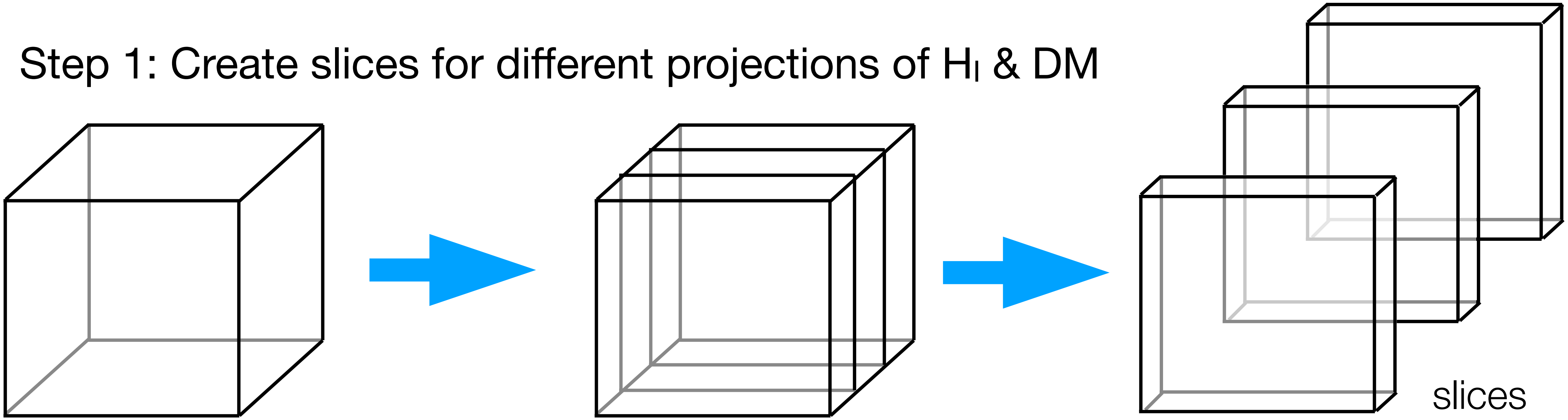

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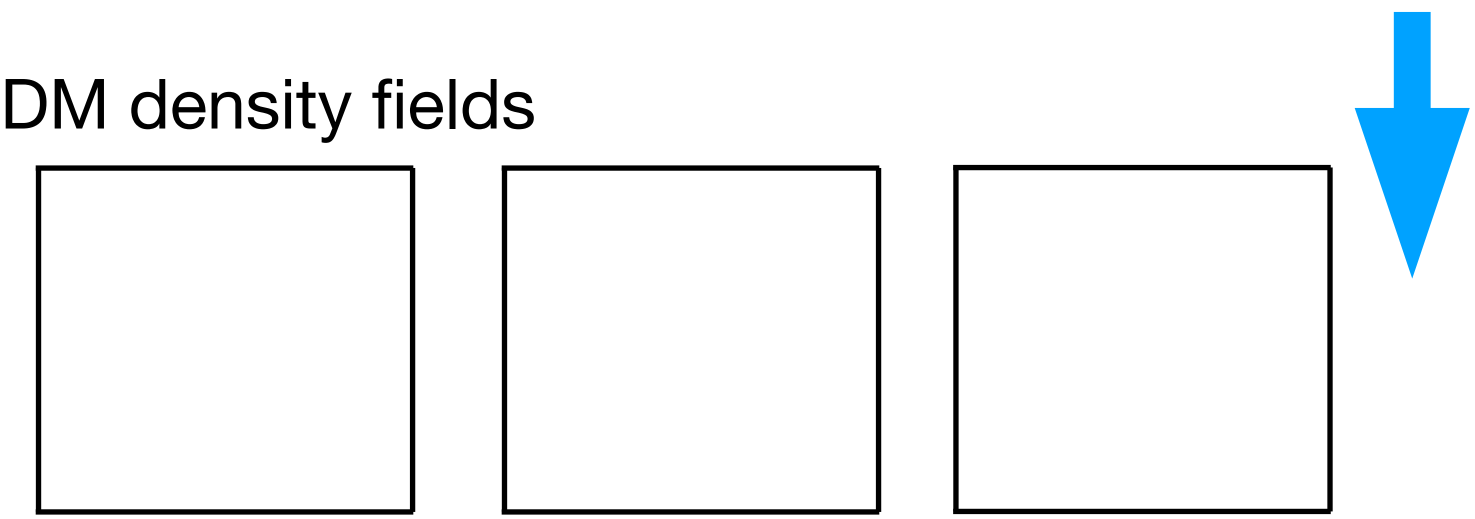
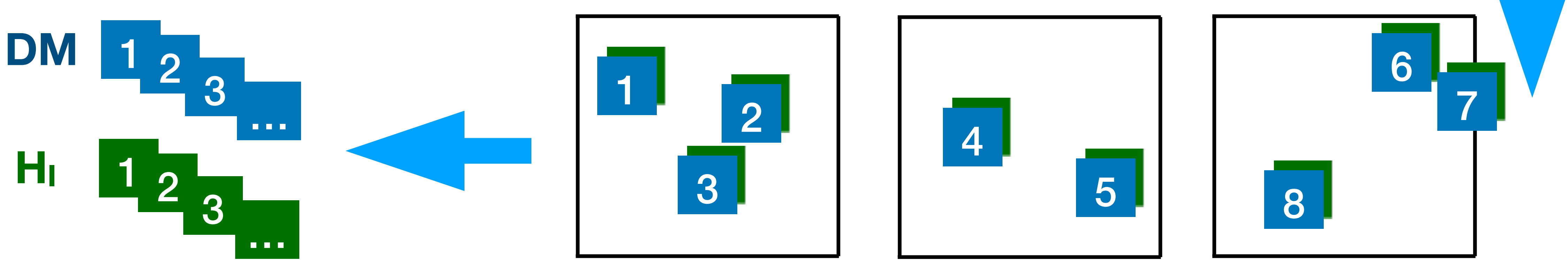


Step 3: Extract 512x512 pixel tiles randomly



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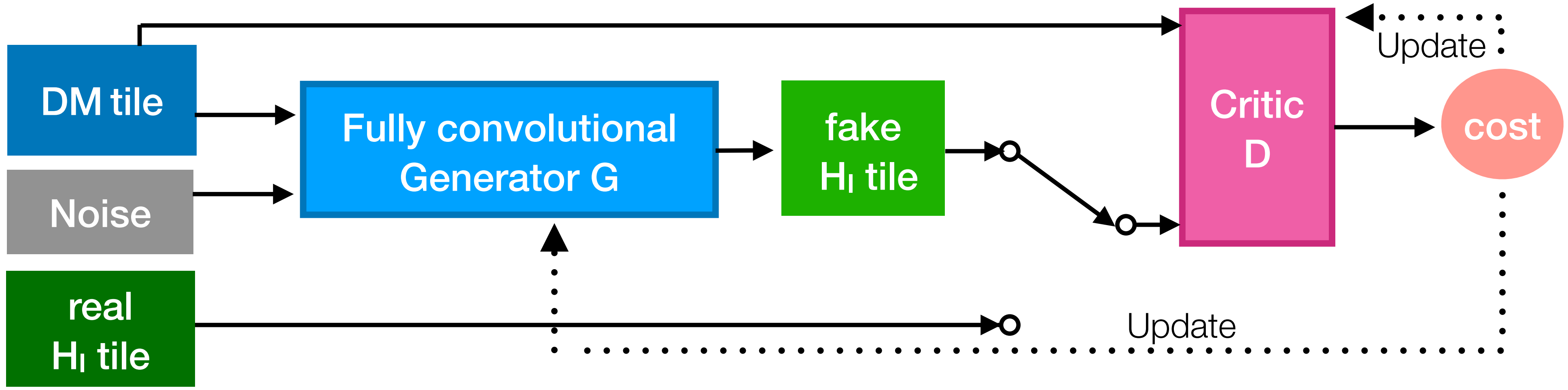

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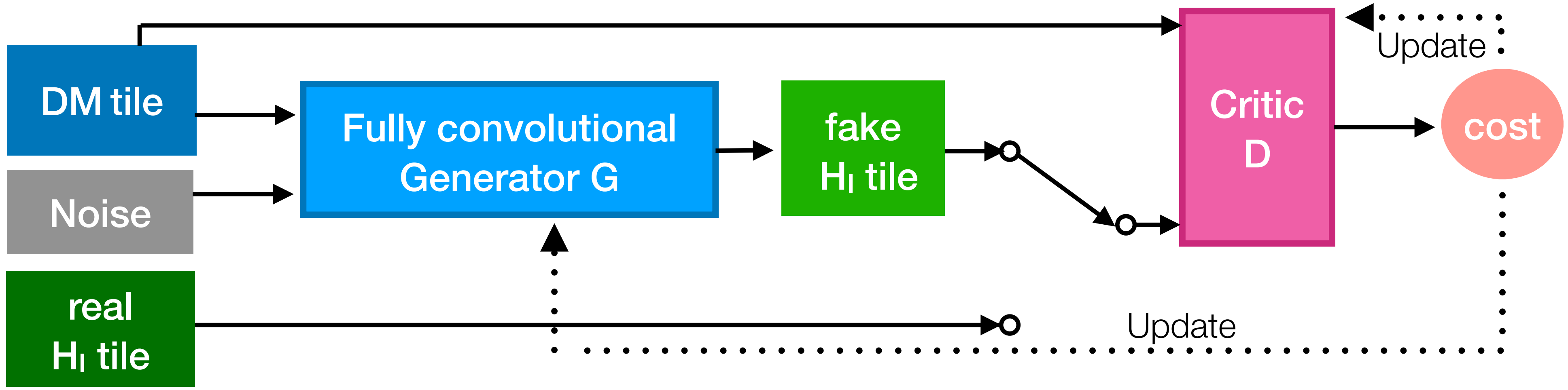

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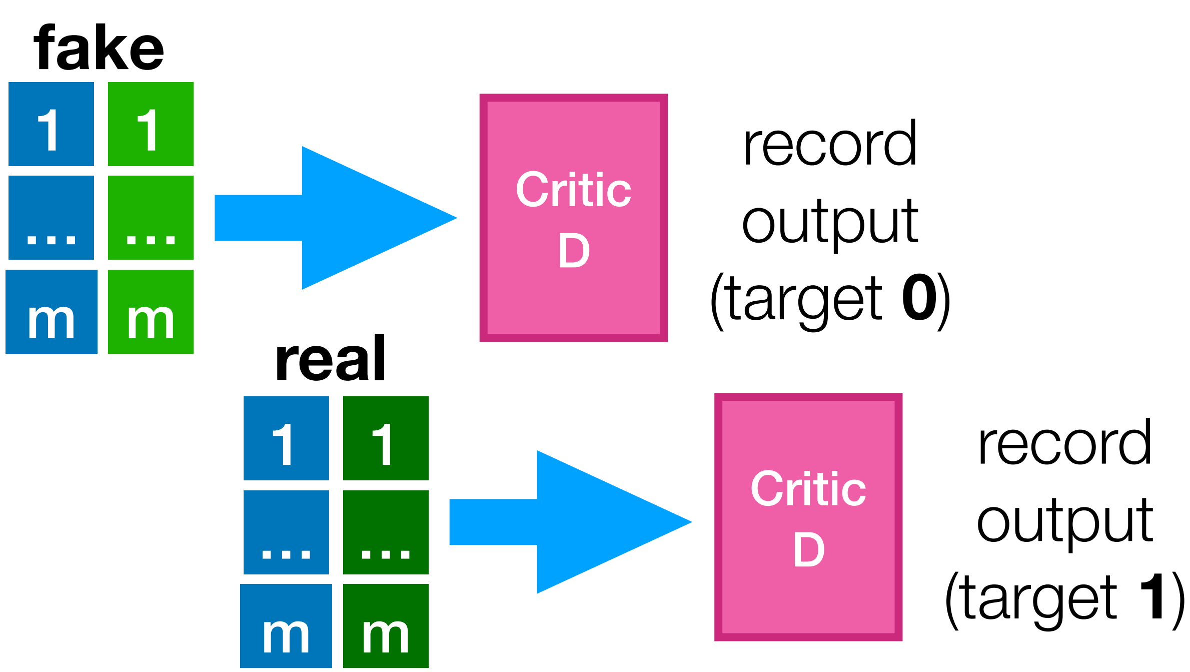

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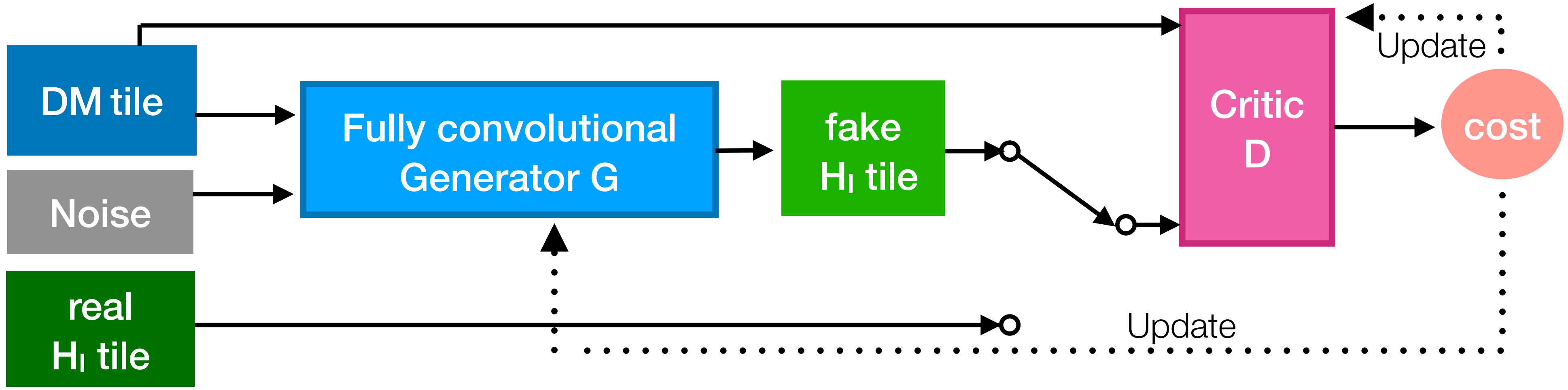

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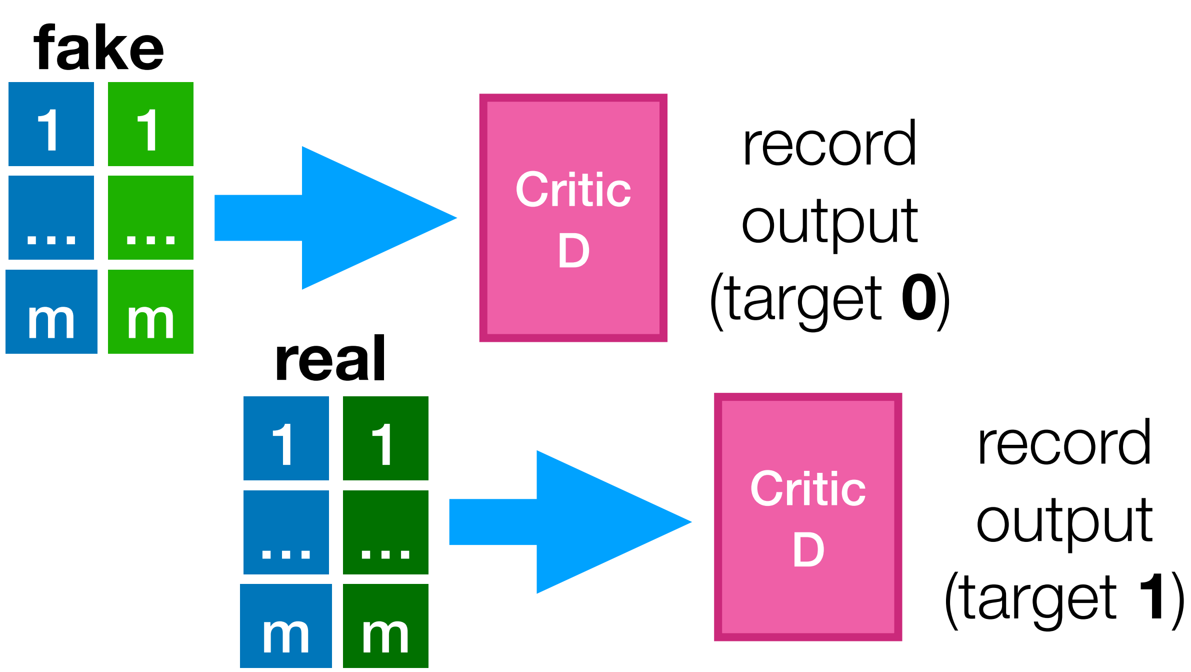

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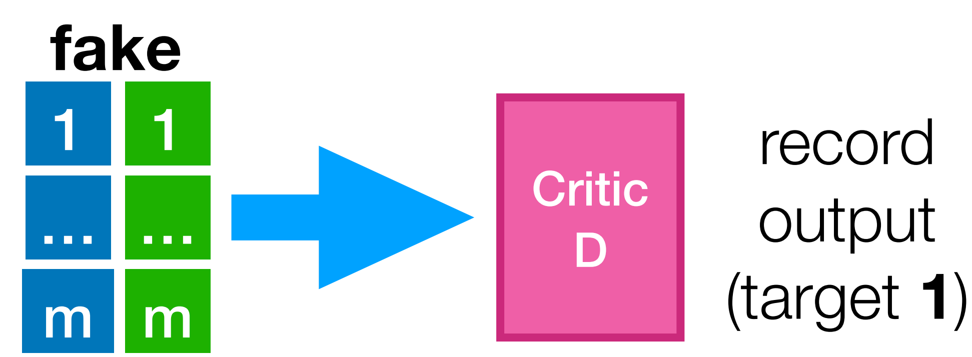

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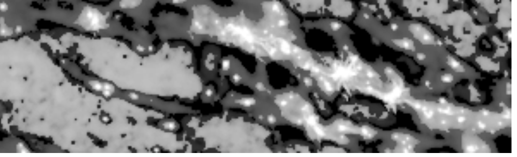

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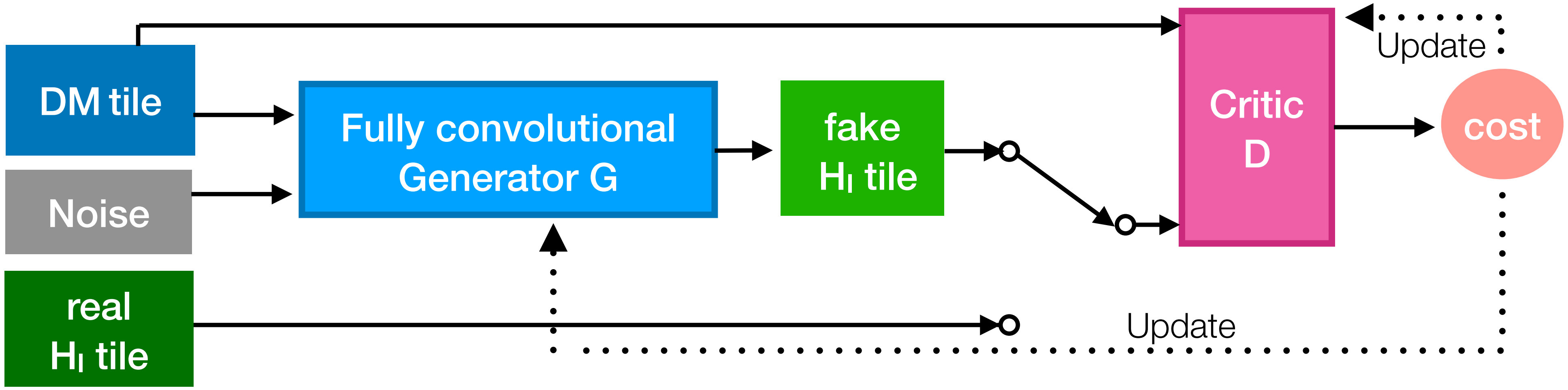

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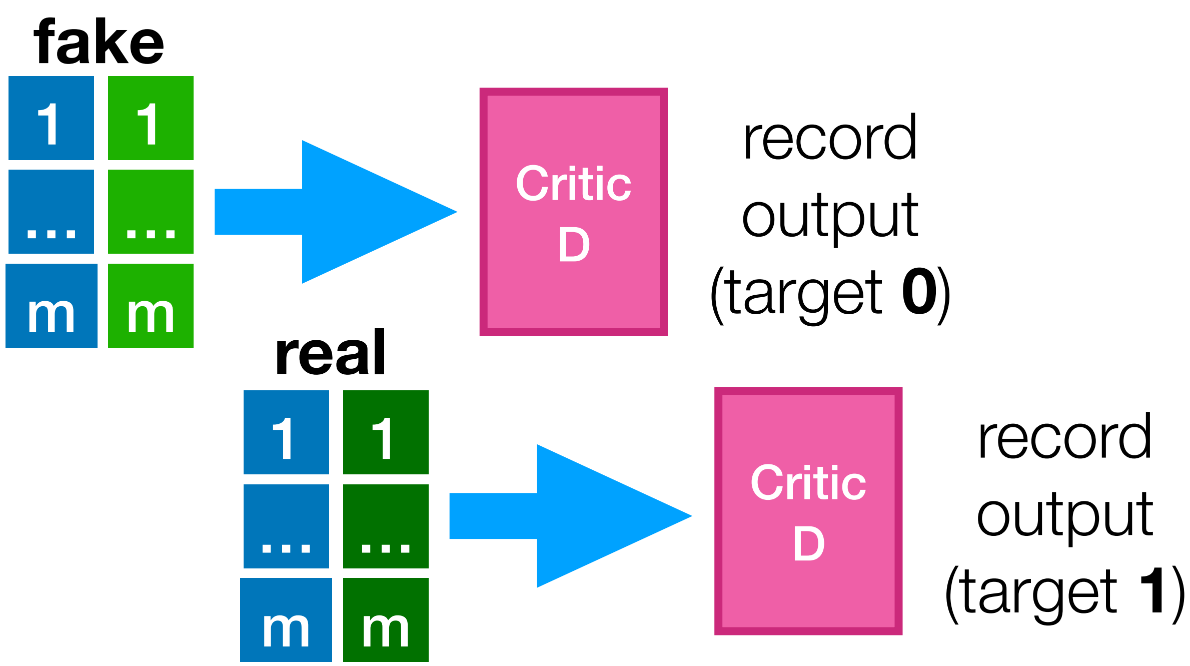

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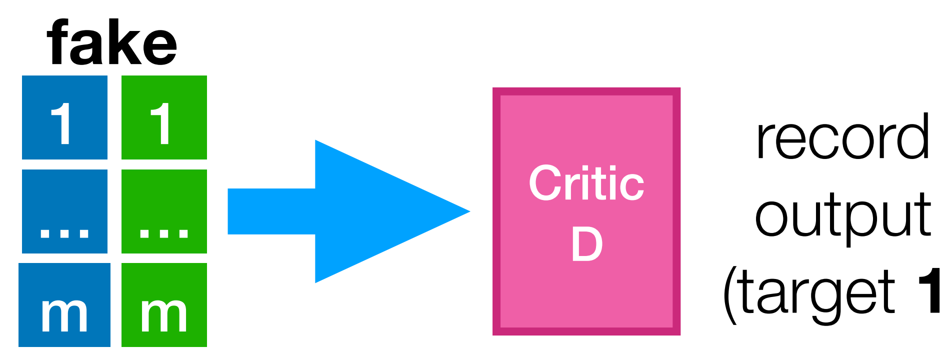

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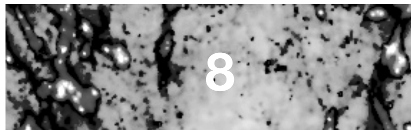
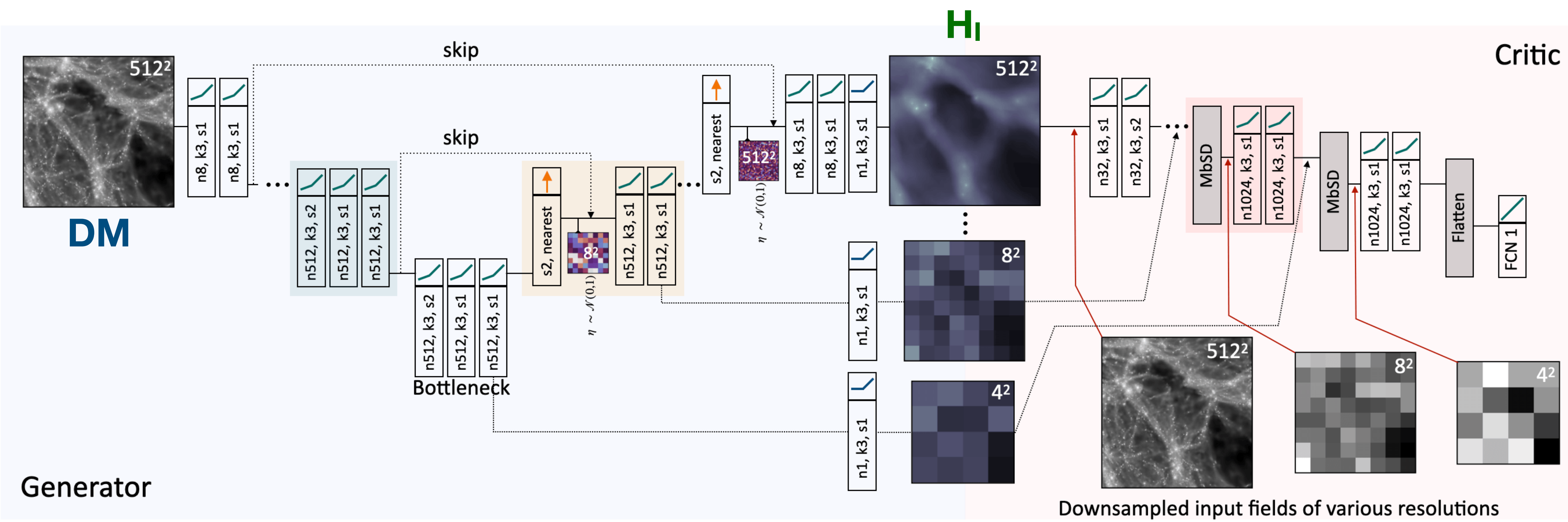
Step 3: Continue with step 1



A detailed view of the EMBER architecture

Fiducial architecture

- Fully convolutional Generator = U-Net with noise injection
- conditional GAN using multi-scale mapping
- normalization scheme: $$\tilde{x} = \frac{1}{k} \log \left[\left(\frac{x}{x_0} \right)^q + 1 \right]$$
- Cost function:
  - perceptual loss based on image similarity index & MSLE
  - Wasserstein metric for adversarial loss (WGAN)



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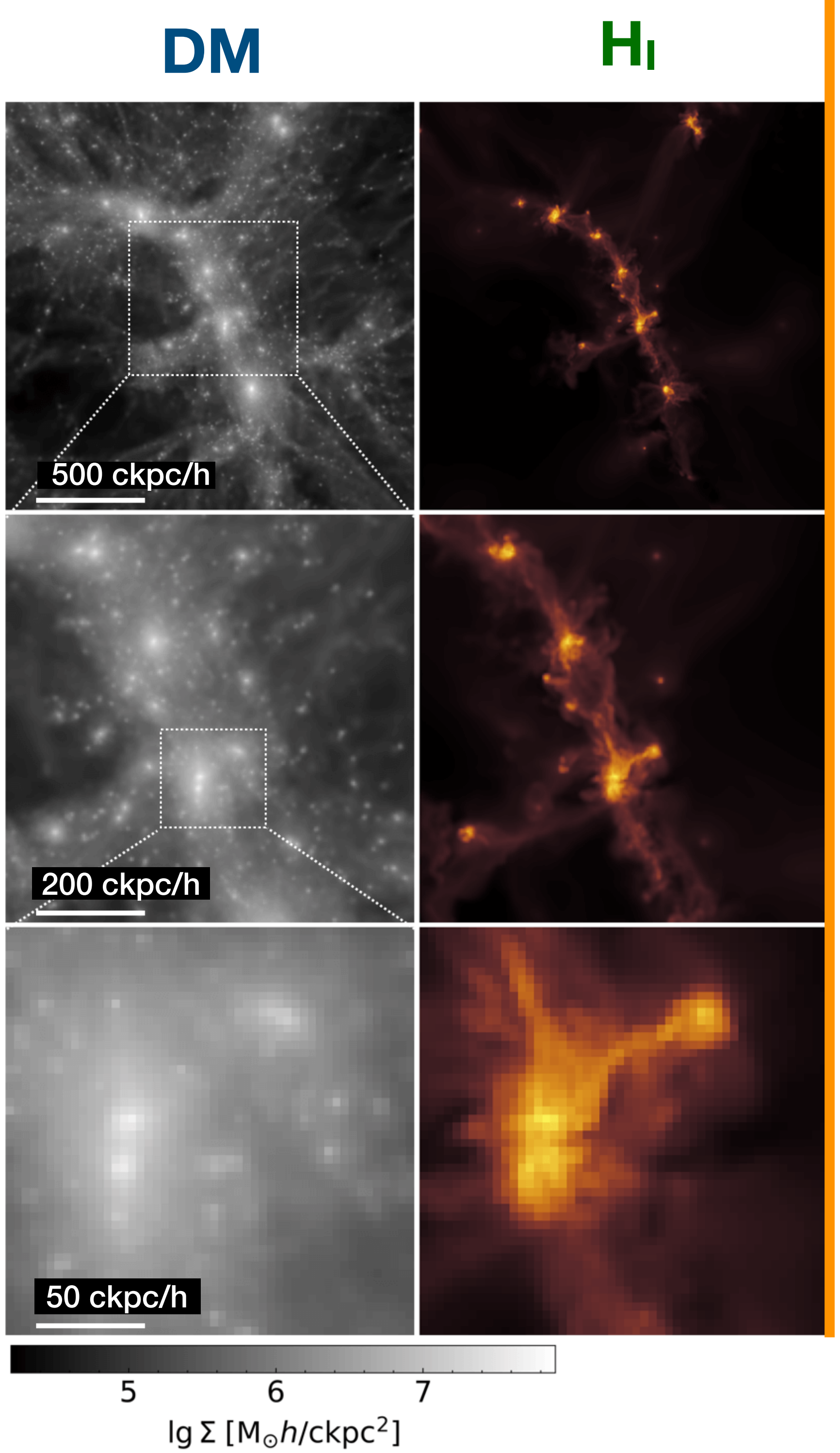
How well does it work?

Simulation (z=2)



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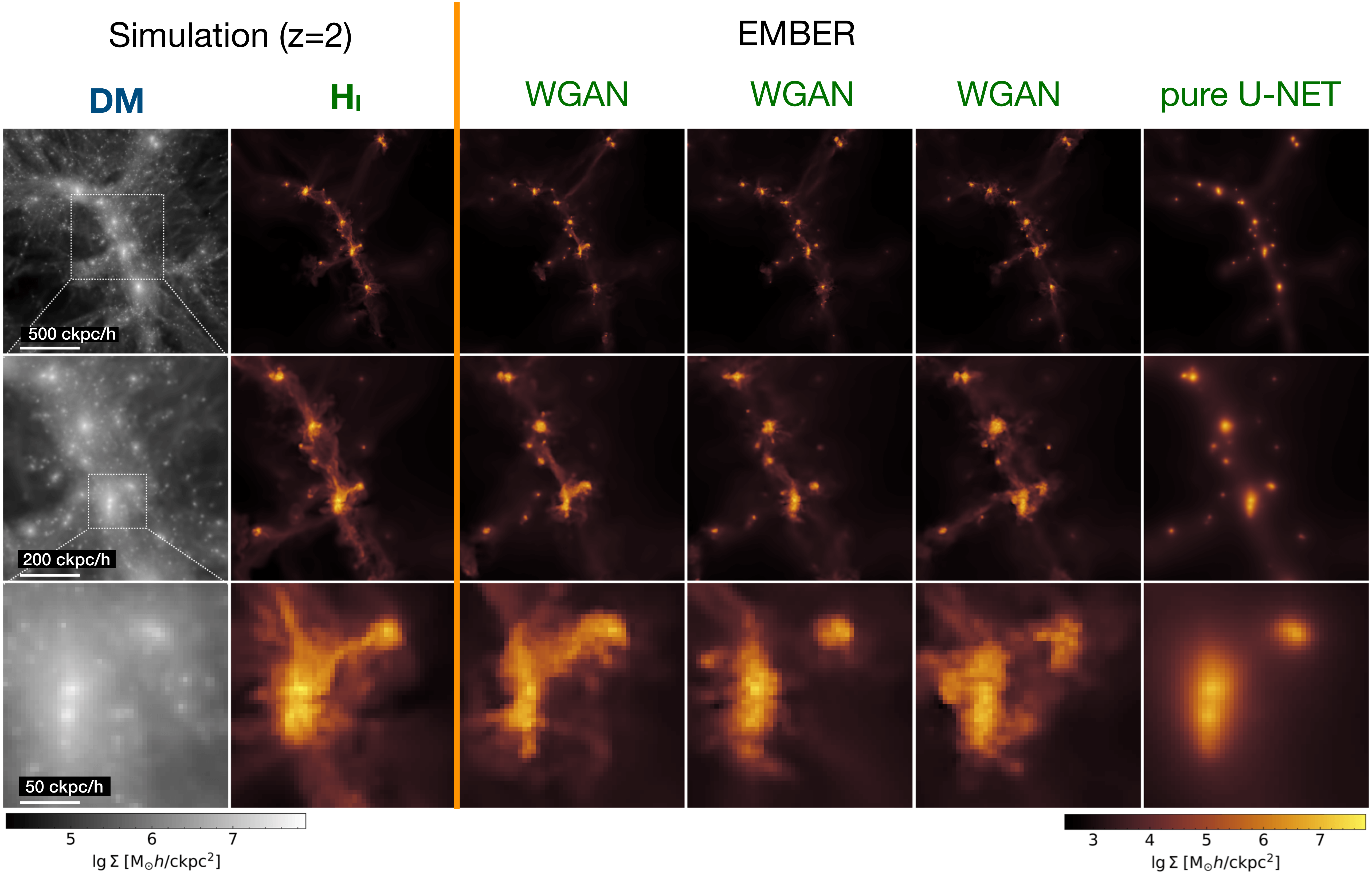

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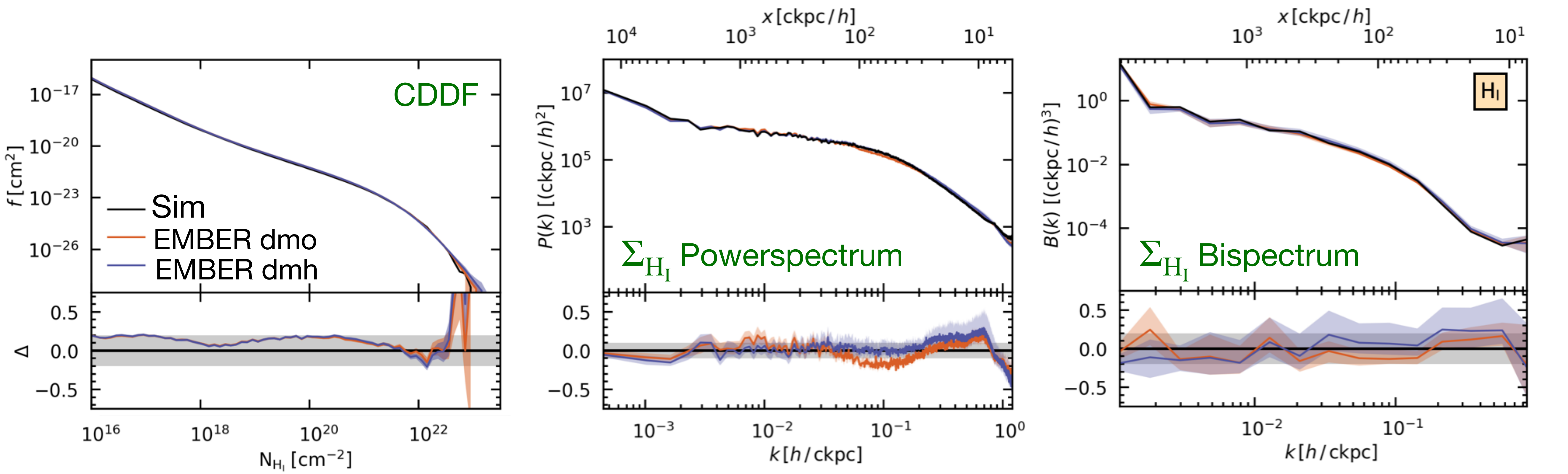
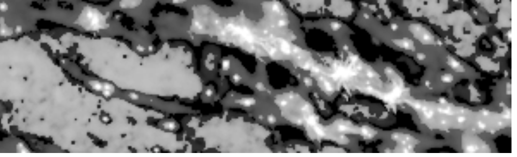


- Agreement to within 10-20% down to galactic scales!



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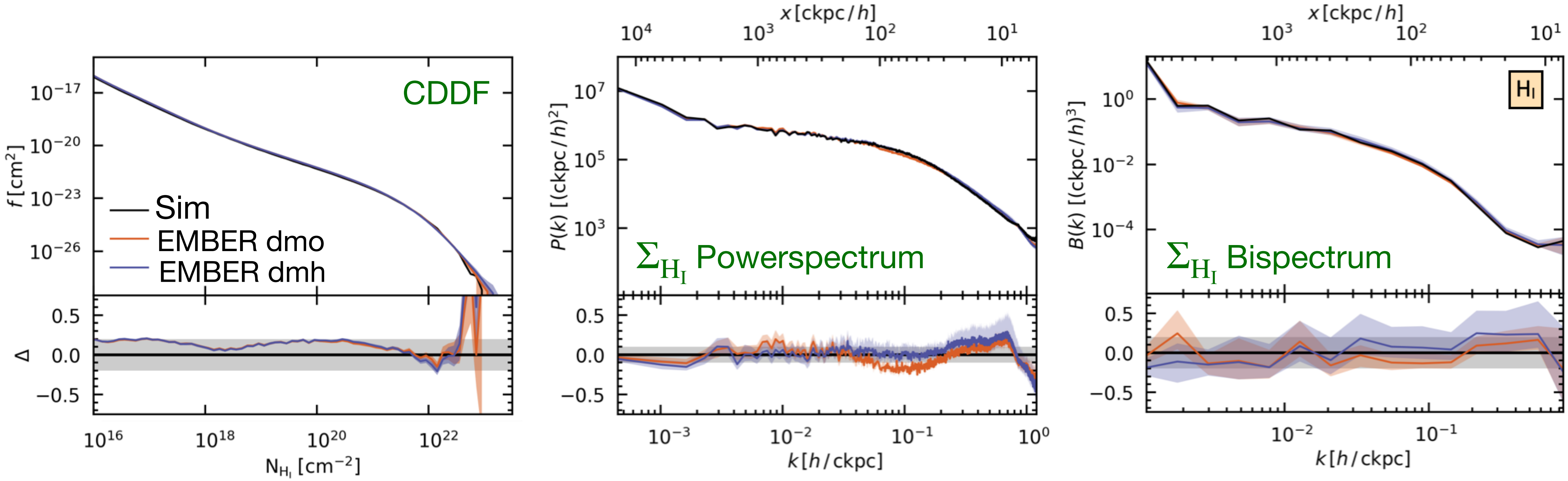

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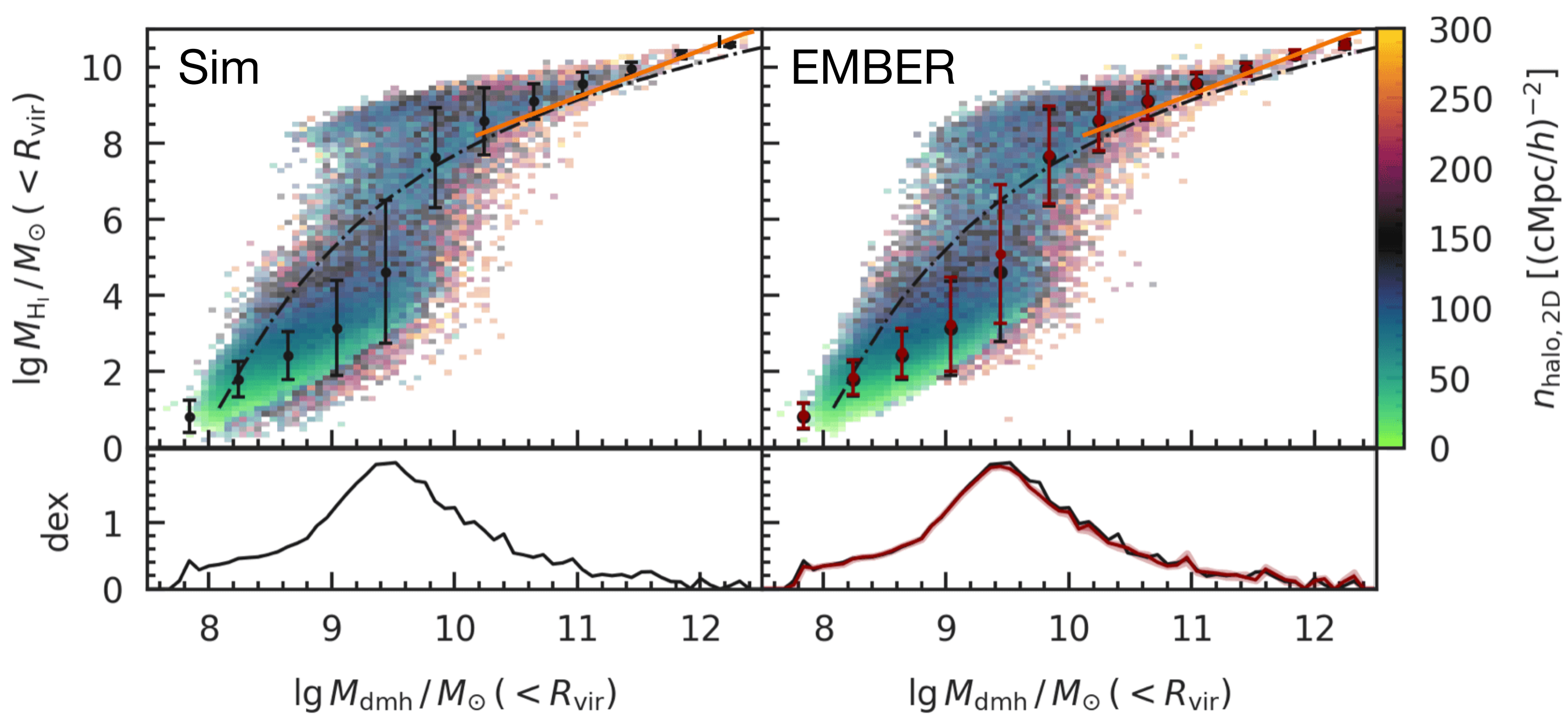
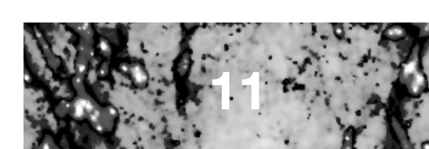
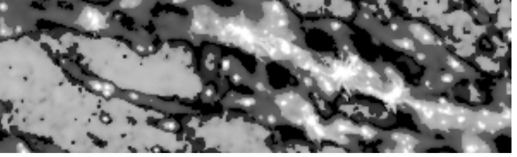


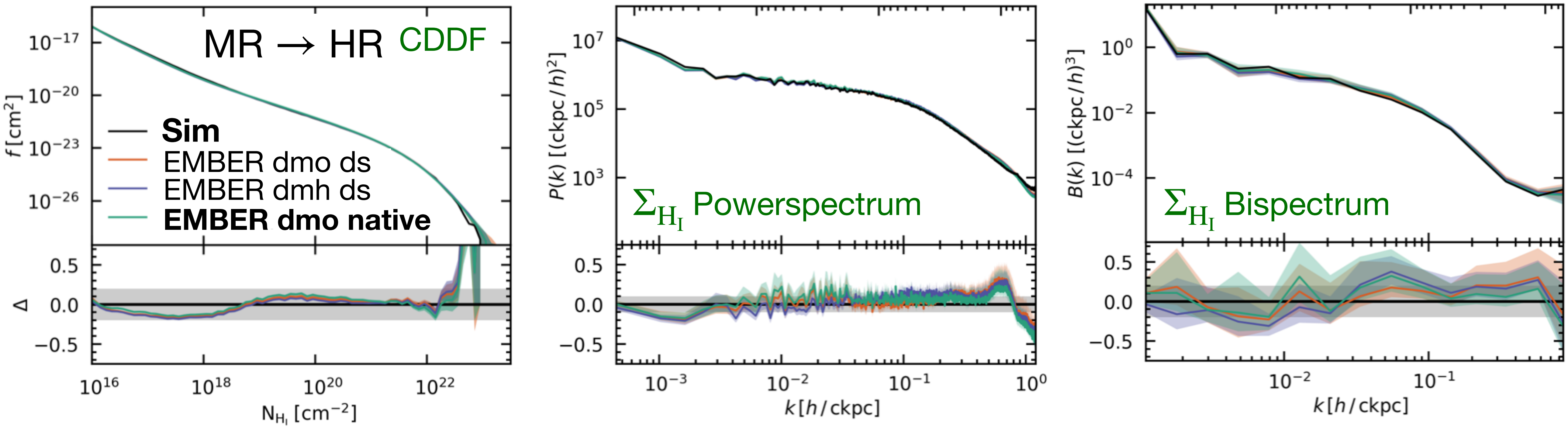
- Reproduces (projected) $\mathrm{H_I}$ masses in halos and scatter!



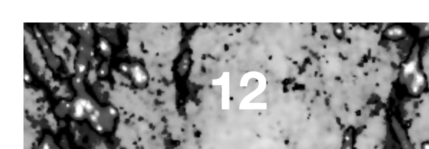


Upscaling

- Goal: create high-resolution HI maps from low resolution DM simulations



- 10-20% accurate when using 64x lower resolution DM maps



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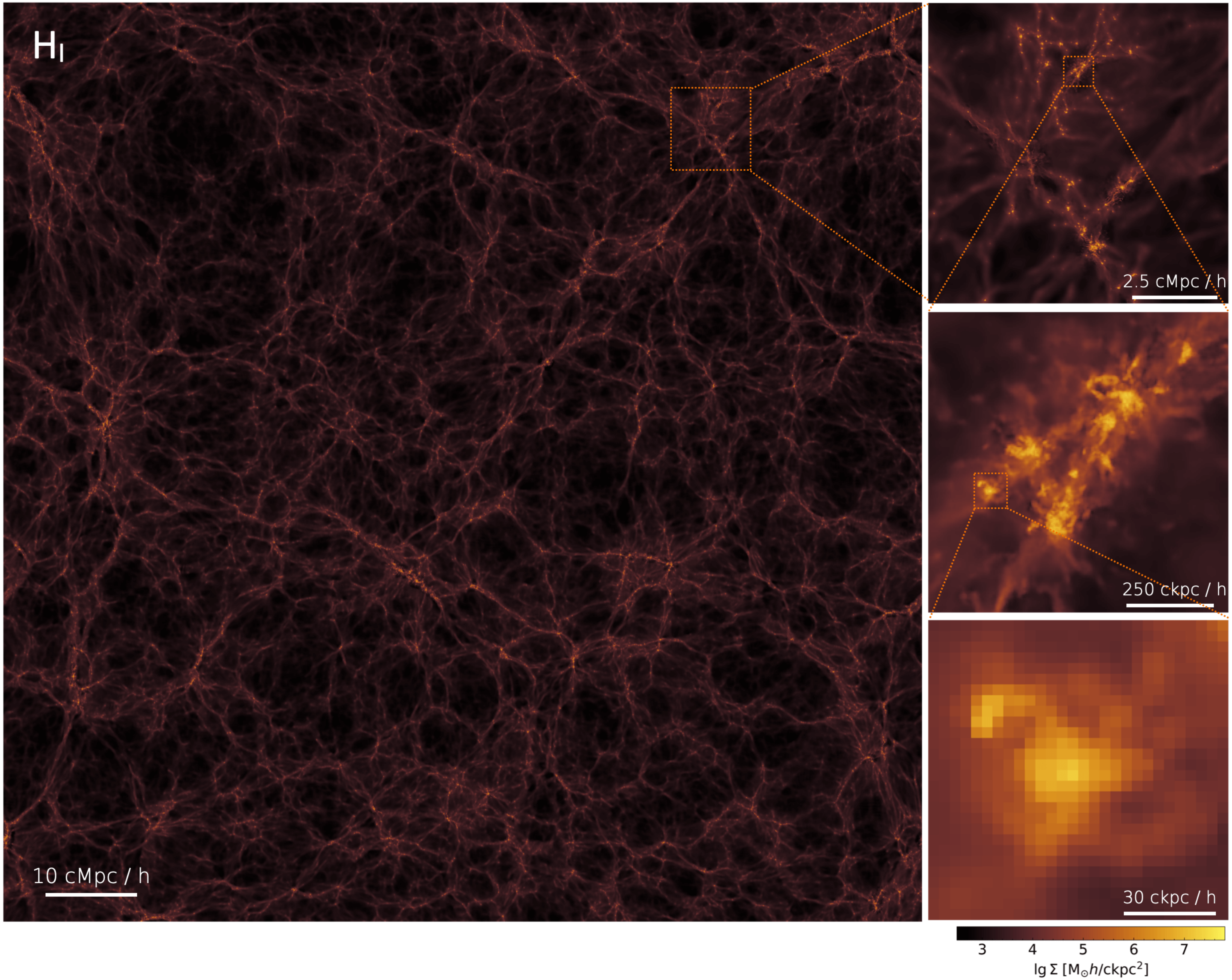

H$_{I}$
10 cMpc / h
2.5 cMpc / h
250 ckpc / h
30 ckpc / h
3 4 5 6 7
lg Σ [M$_\odot$$h$/ckpc^2]

Next steps

EMBER

- Training comparably expensive (~1 GPU-week)
- Makes predictions for fixed redshift
- Makes prediction for fixed output resolution
- Only single output (e.g., HI mass map or gas mass map)

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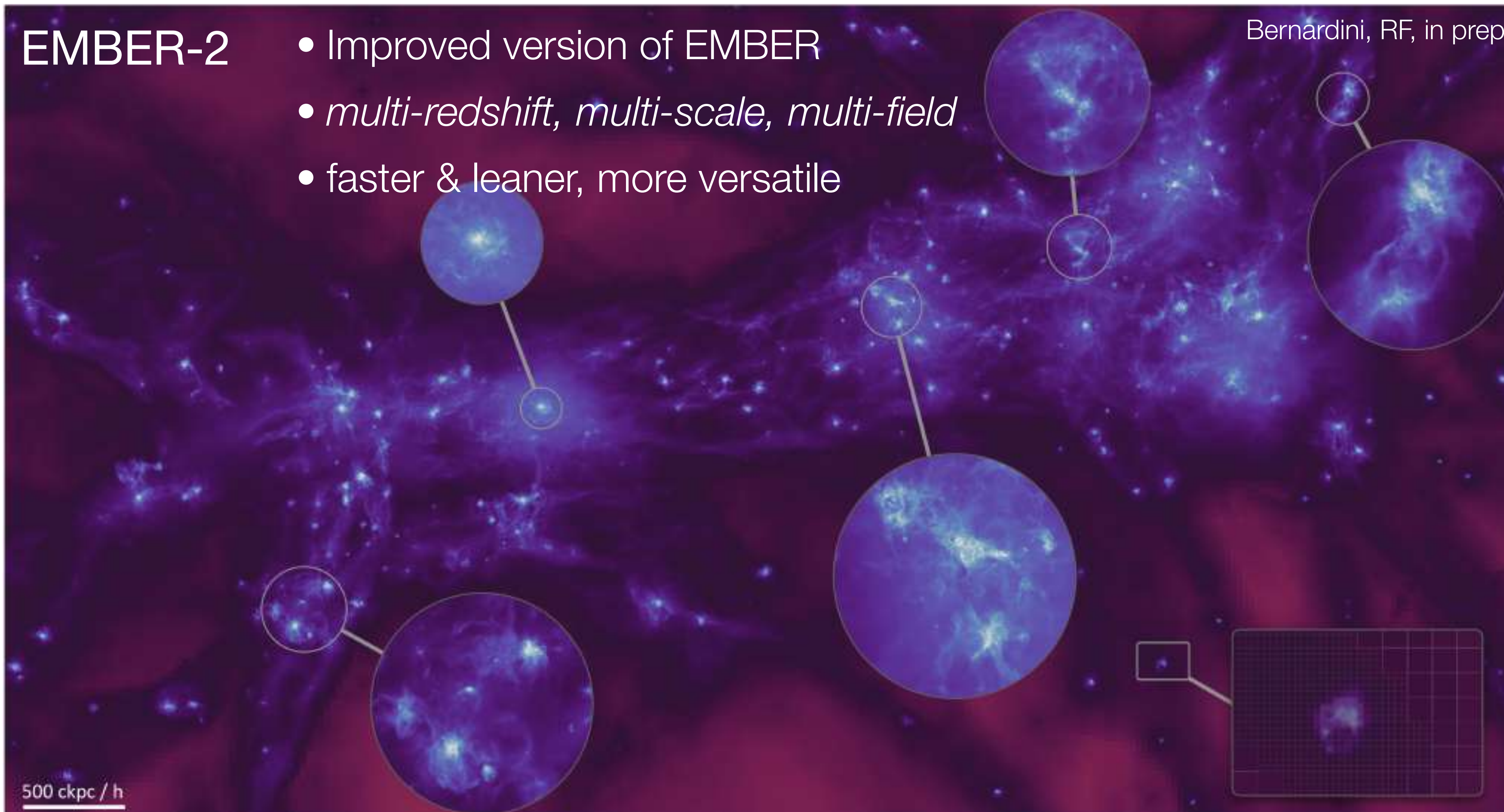
EMBER-2

- Improved version of EMBER
- *multi-redshift, multi-scale, multi-field*
- faster & leaner, more versatile

Bernardini, RF, in prep



Challenges for EMBER-2

Achieving multi-redshift capability

Coupling between DM and HI strongly redshift dependent, network would become too large if using standard convolutions

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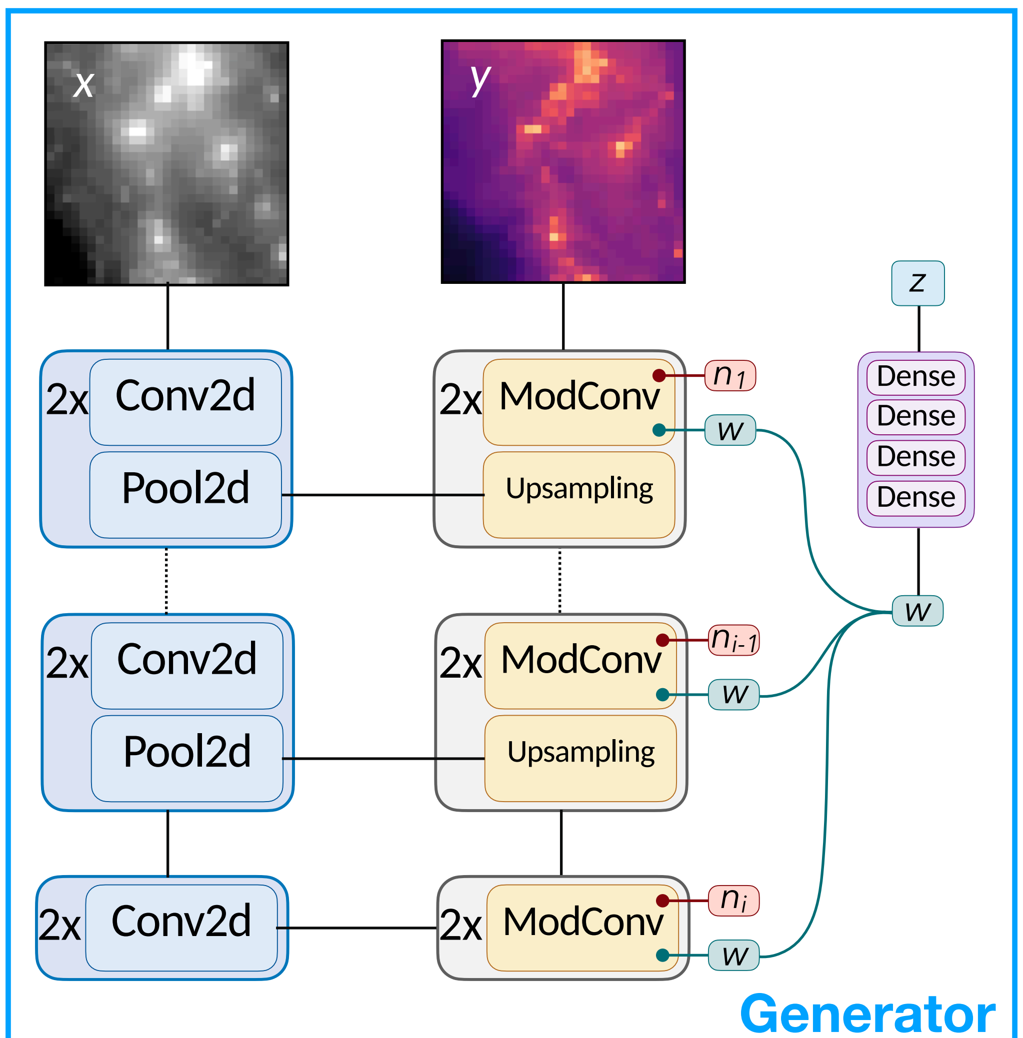

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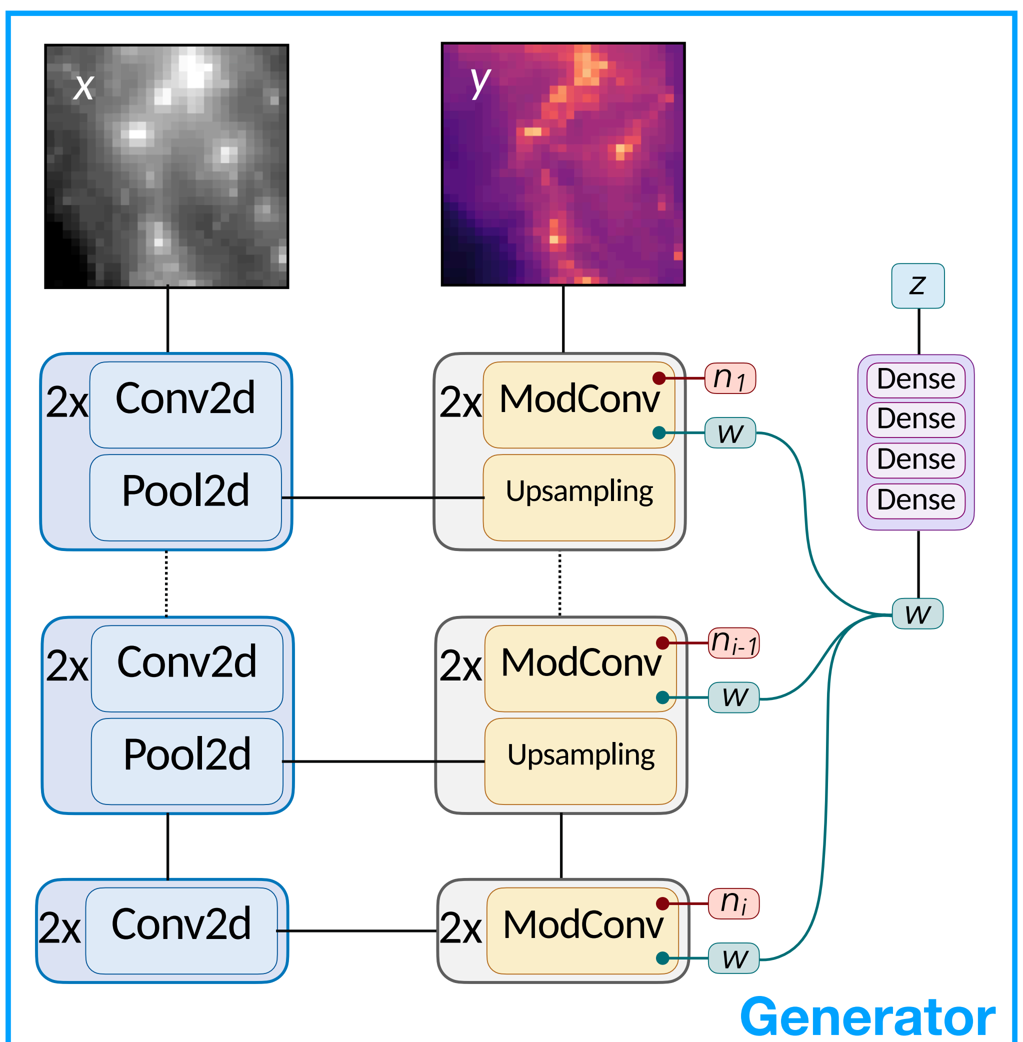

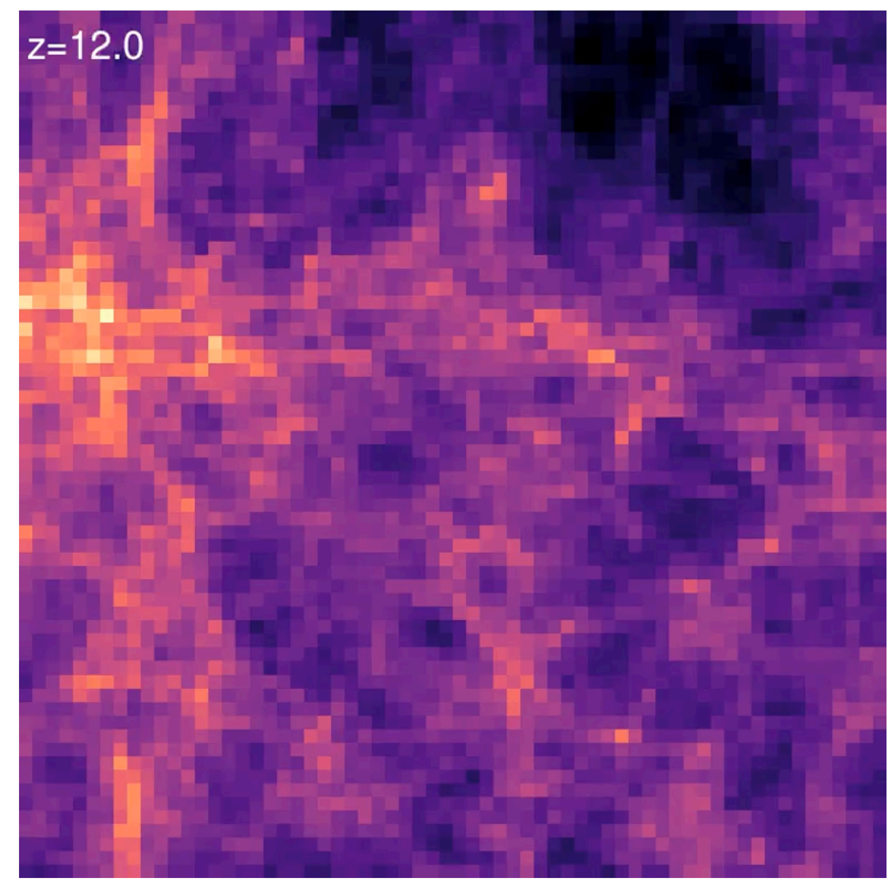

Changing “redshift” while keeping DM map fixed

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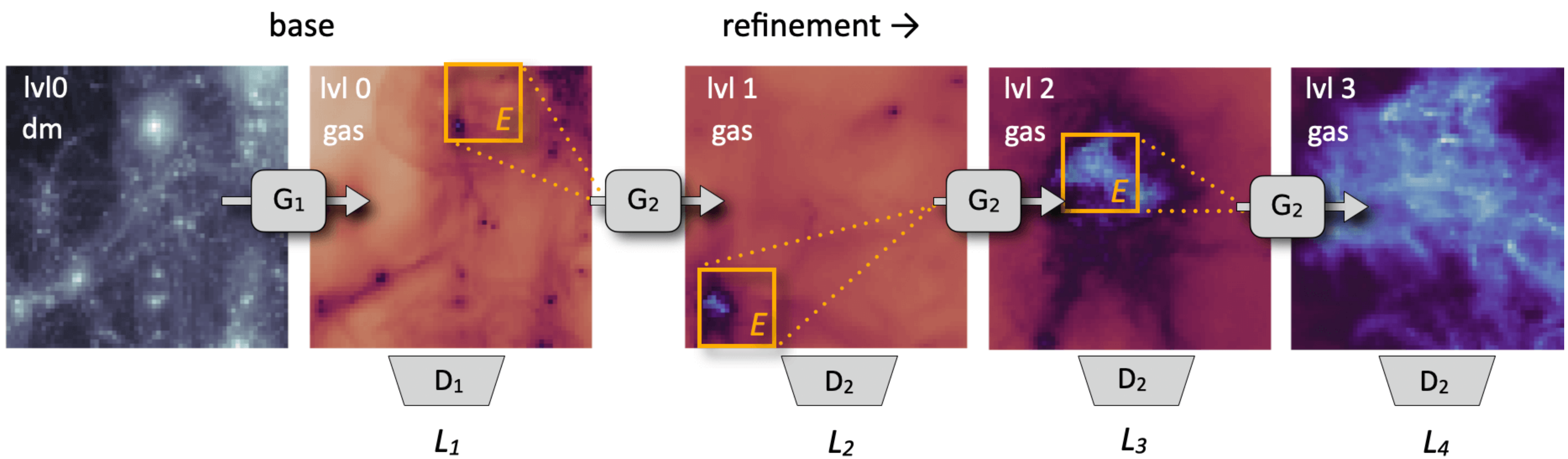

Combine **base network** which learns large scale features and a **refinement network** which adds small-scale features given large scale features

Resolution level injected as context information (Style2-GAN) directly into the modulation of the convolution kernel of the refinement network

Achieving multi-field capability

- Consistency between output fields, e.g., temperature, density etc.
- Enable additional input fields $(\Sigma_{\rm DM}, v^{\rm rad}_{\rm DM}) \rightarrow (\Sigma_{\rm gas}, v^{\rm rad}_{\rm gas}, T_{\rm gas}, \Sigma_{\rm HI})$

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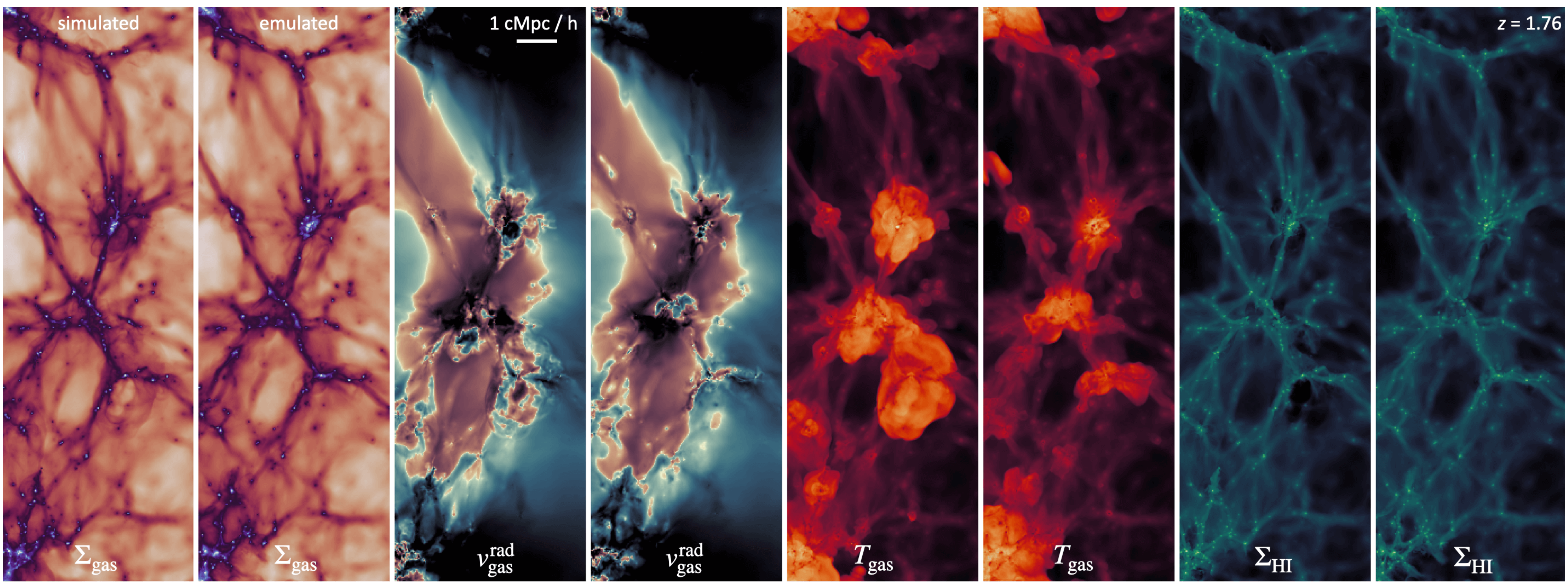
Solution:

Conceptually straightforward: Include extra fields as additional channels

Sim **EMBER-2** **Sim** **EMBER-2** **Sim** **EMBER-2** **Sim** **EMBER-2**



First look at EMBER-2 performance

- EMBER 2.0 significantly leaner, faster

	# params [1e6]	Training time [d]	Inference time	Redshift	Tilesize
EMBER-1	80	7	minutes	z=2 fixed	1.8 cMpc/h
EMBER-2	18	2	seconds	z=12 to 1	1.8 cMpc/h

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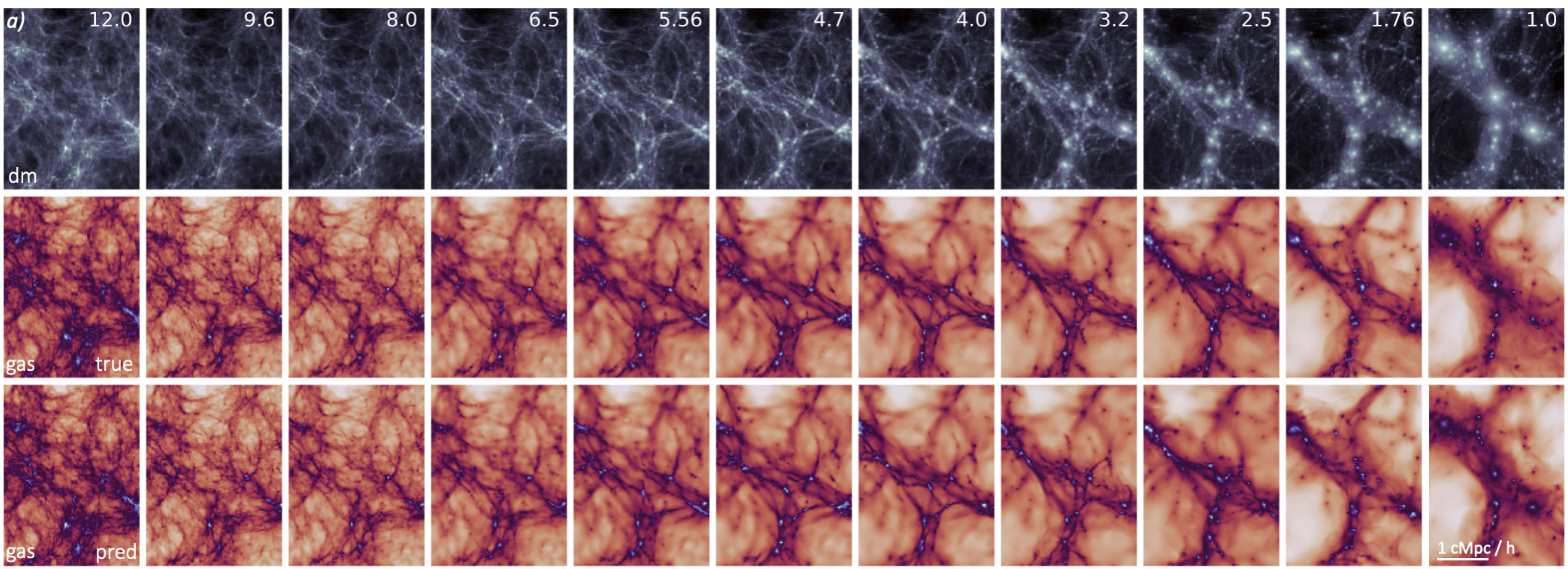
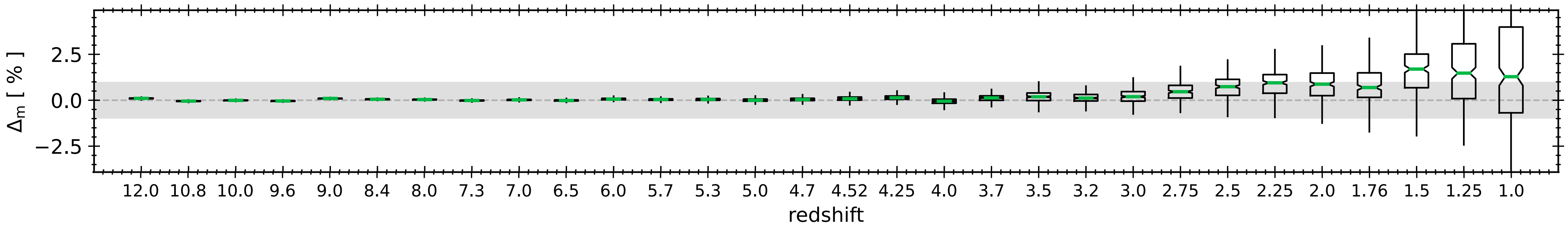
- Visually accurate predictions for any redshift z=1-12



First look at EMBER-2 performance

- Excellent mass conservation for slices (~1%)



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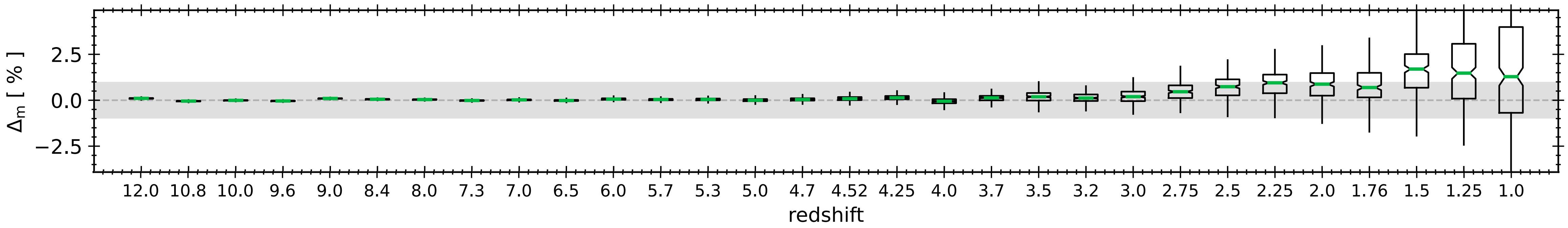
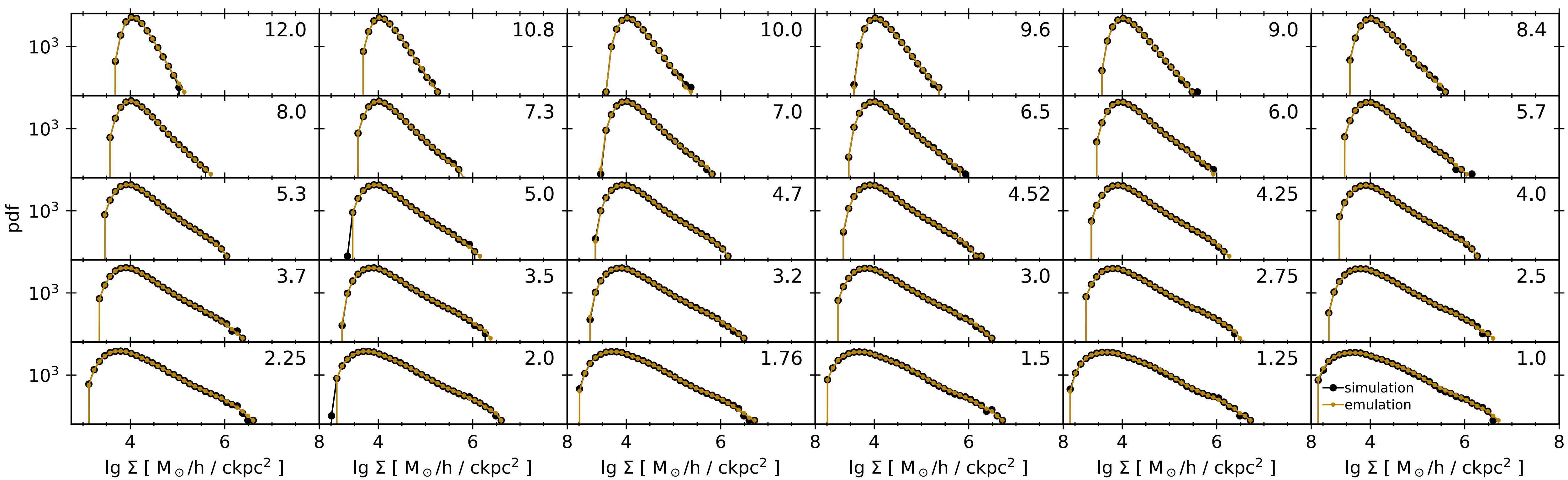
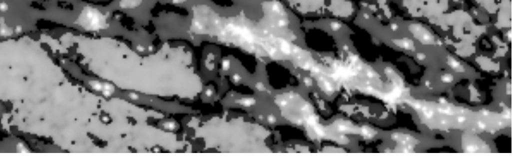


- Excellent agreement for the pixel probability density functions





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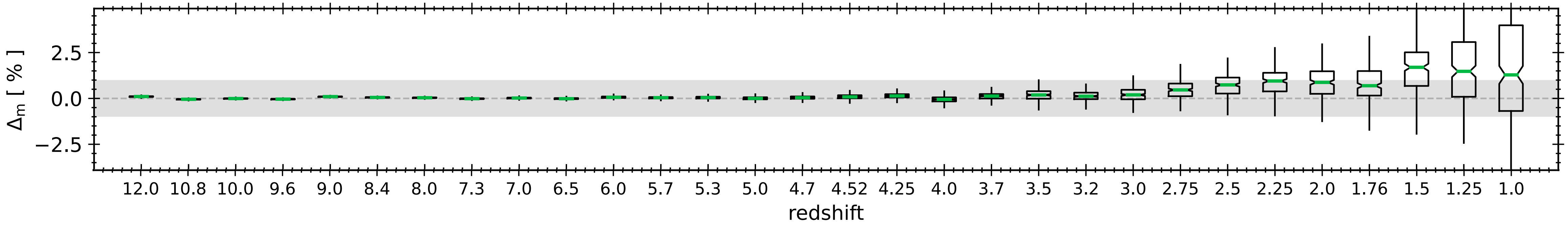

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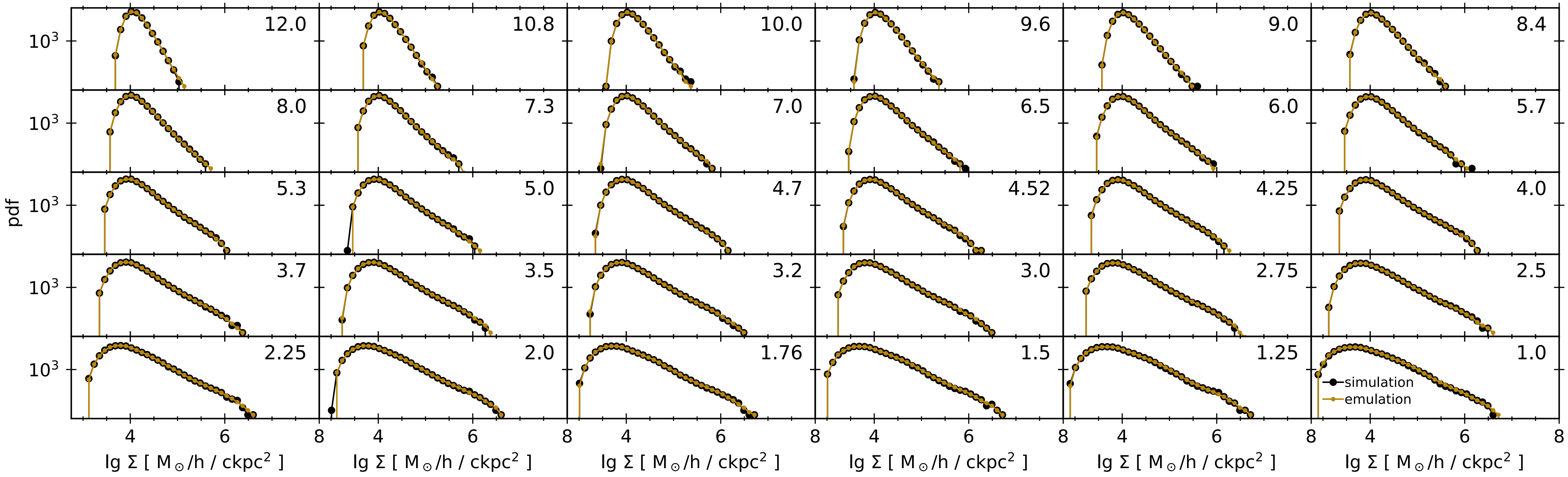
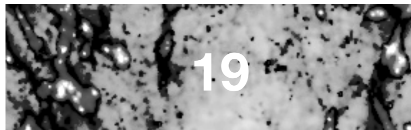
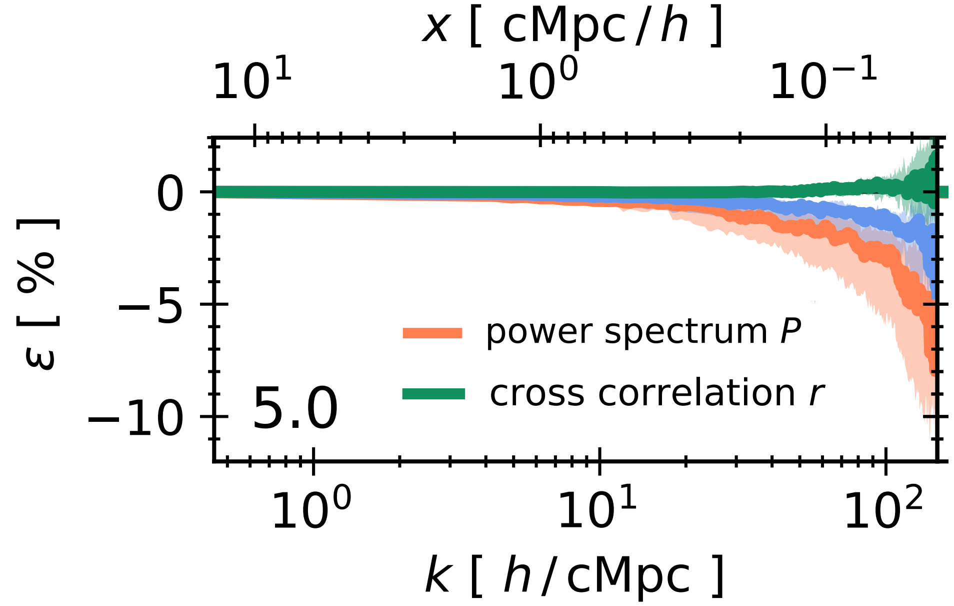


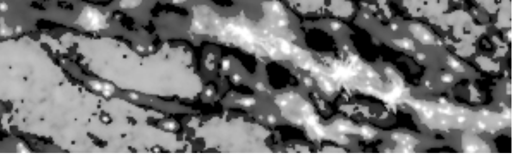
- What about higher order statistics?



First look at EMBER-2 performance

- Often employed metric to measure performance of emulator is power-spectrum
- Small box => high variance
- Test: modify slices by lowering mass in 5 most massive pixels by 10%





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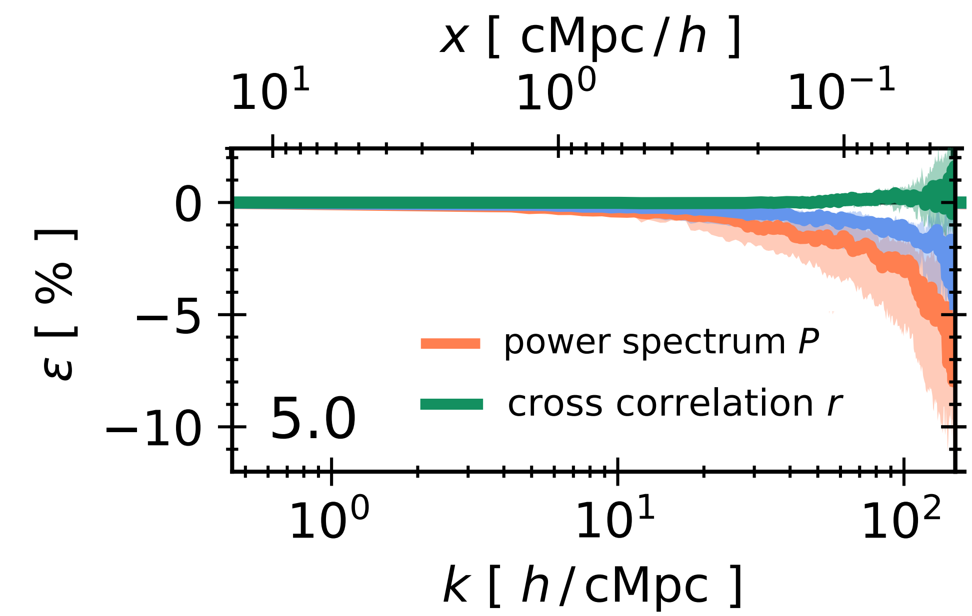
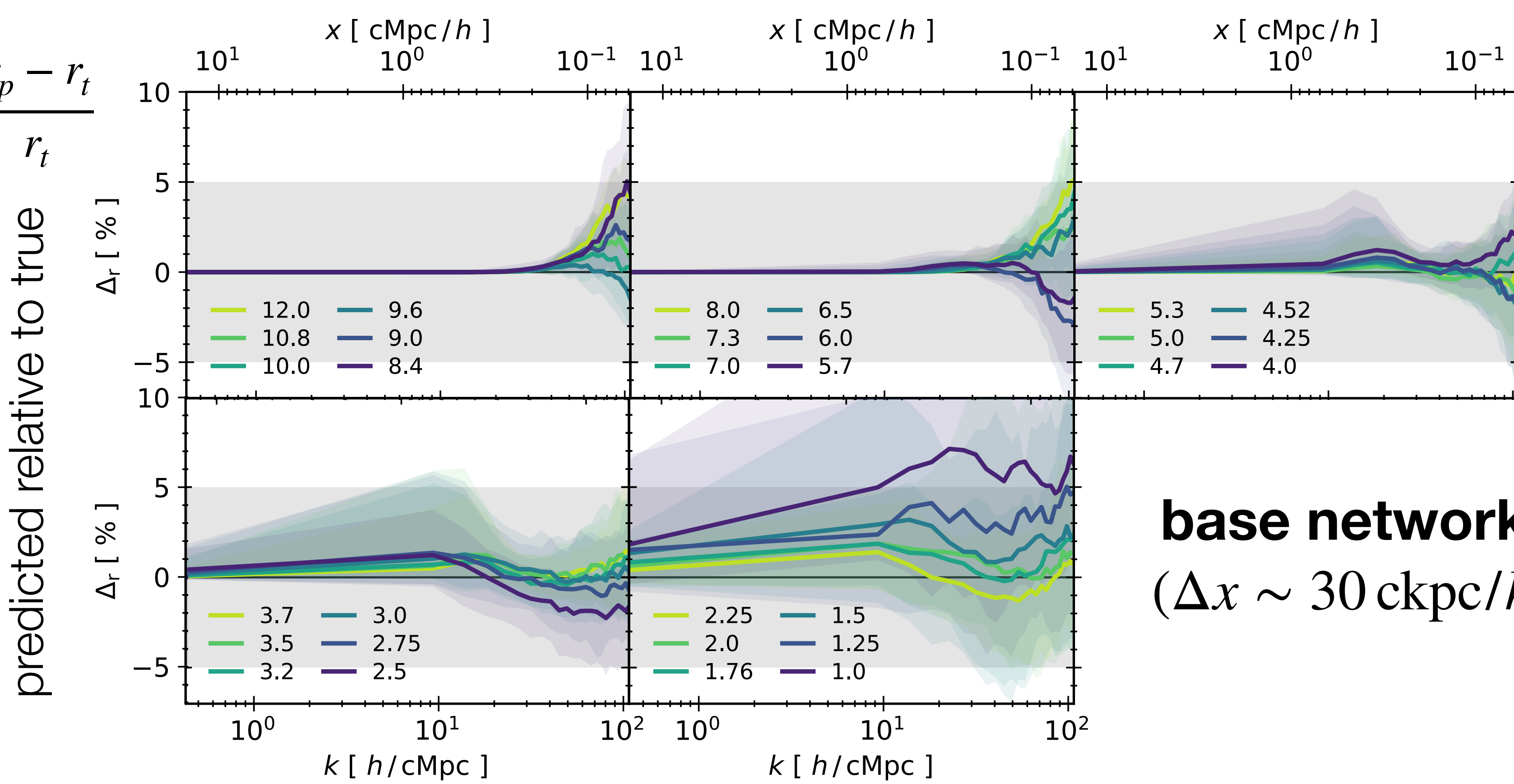


- Better performance metric: cross correlation between DM map and gas map:

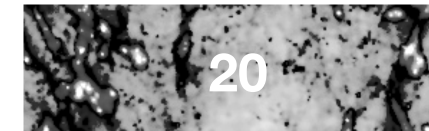
$$r(k) = P^{\times}_{dm,g} / (P_{dm} P_g)^{1/2}$$

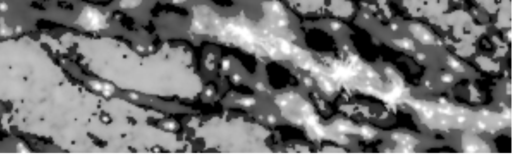
$$\Delta r = \frac{r_p - r_t}{r_t}$$



base network!
$(\Delta x \sim 30\,\mathrm{ckpc}/h)$

➜ Cross-correlation reproduced to better than ~5% at z=1-12 up to ~50 ckpc





Summary

- Deep Learning techniques can reduce computational cost of calculating baryonic fields compared with high-resolution (hydrodynamical) simulations

- EMBER: stochastic, conditional, convolutional GAN that learns baryon maps from cosmological, hydrodynamical simulations; trained on FIRE simulations
- 10-20% accurate mapping down to galactic scales (~tens of kpc) for CDDF, powerspectrum, and bispectrum
- Entirely halo-free method, but can make accurate predictions for halo based properties (including scatter) down to low halo masses; upscaling to large volumes

- EMBER-2: upgraded version of EMBER with new architecture
- Adds *multi-redshift*, *multi-scale*, and *multi-field* capabilities
- Faster to train, faster to run, more versatile