Accelerating the Computational Modeling of HI with Deep Learning

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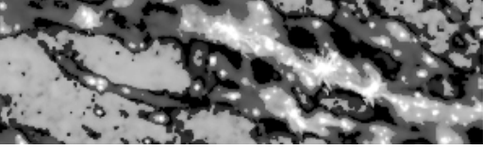
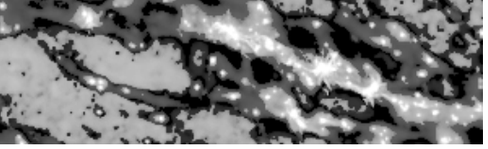
FNSNF Swiss National Science Foundation

University of Zurich[UZH]



The challenge of modeling the distribution of baryons / H_I

- Baryonic / H_I physics on small (non-linear) scales highly complex



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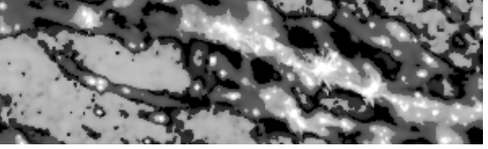
- hydrodynamical simulations most principled approach
  - + predict baryons on all scales and across cosmic history
  - + test physical models (e.g., UV background evolution, feedback)



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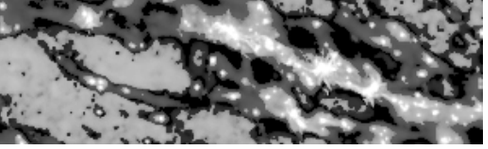

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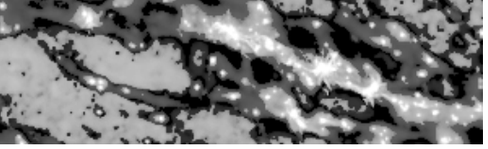

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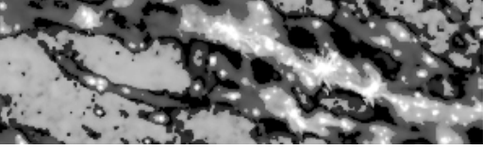

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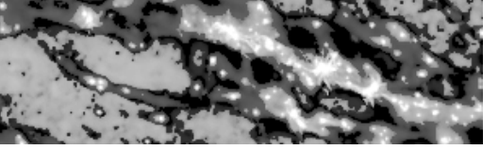
  Once trained, prediction is computationally inexpensive => Emulator

  + Predict baryons for regions of space similar to (but different from) the sim

  + Interpolate to new parameter values, redshifts etc.

  + Upscale to much larger volumes while preserving high resolution



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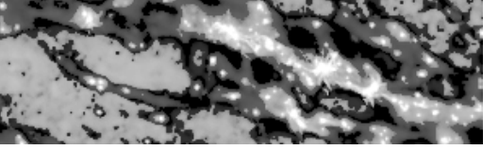

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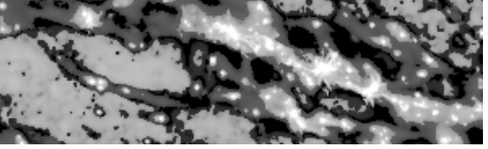

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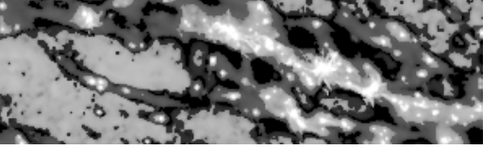

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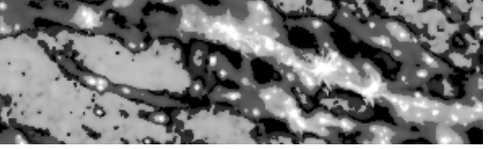

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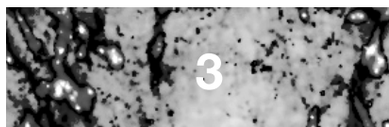

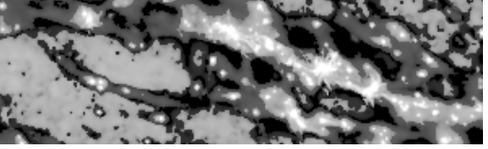

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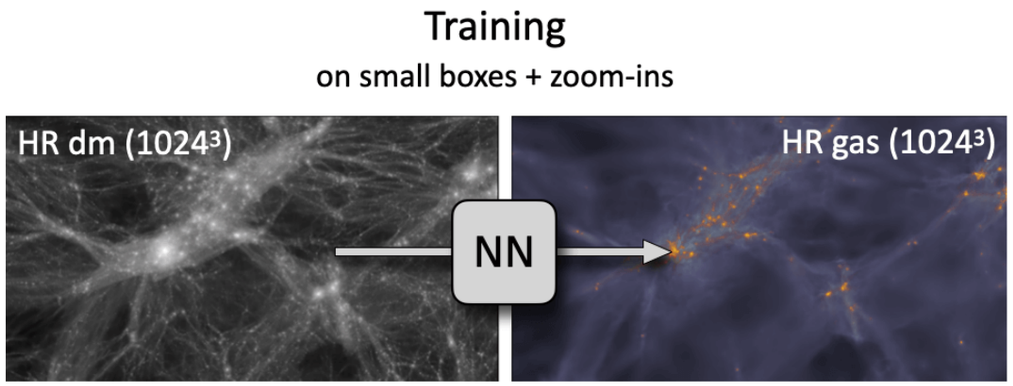

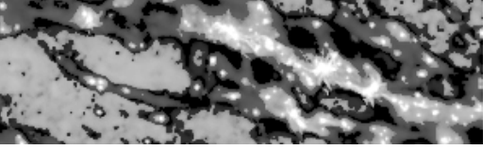

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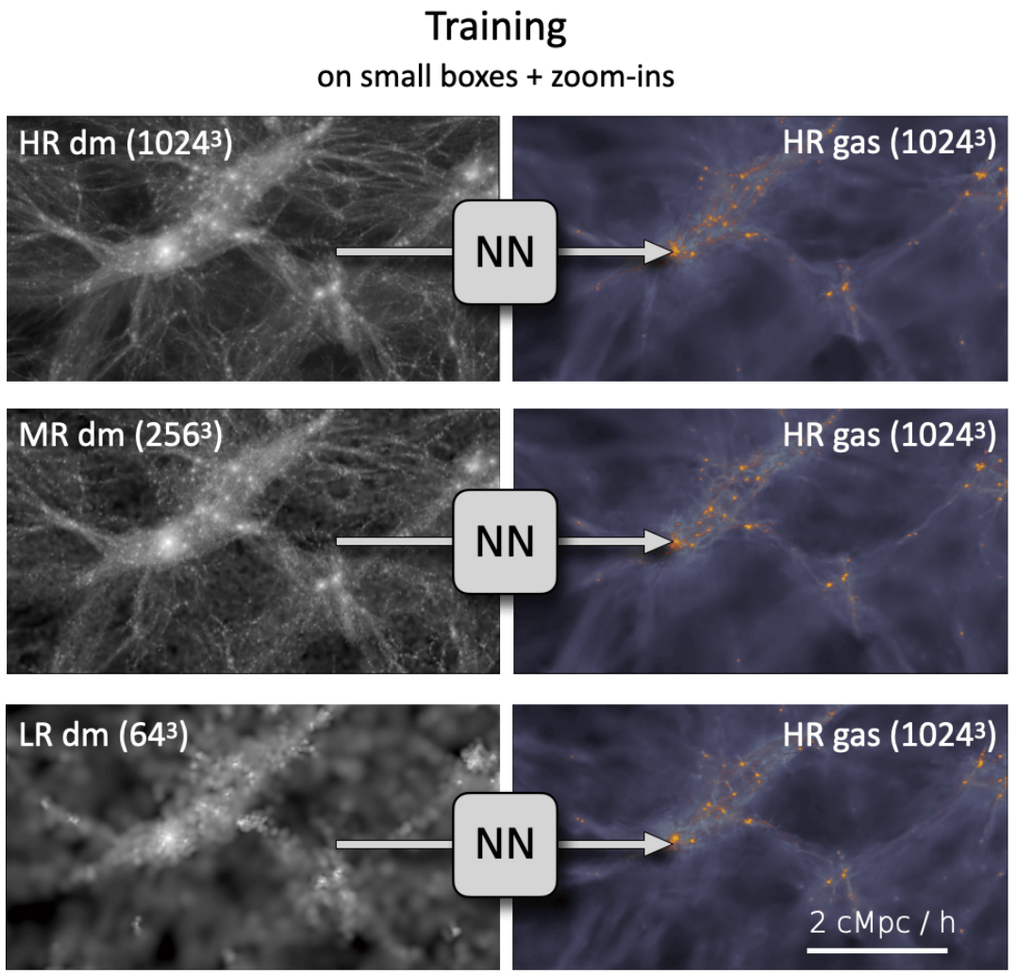

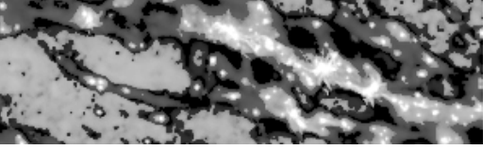

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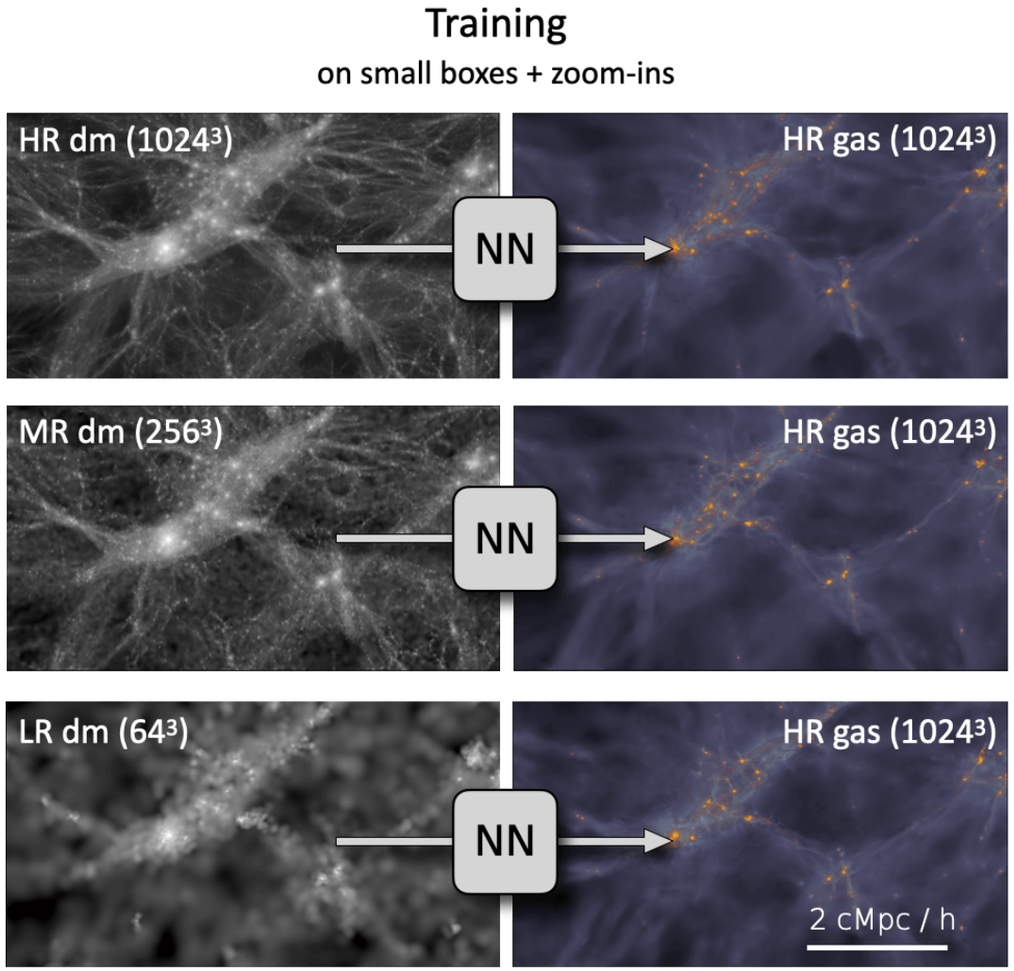
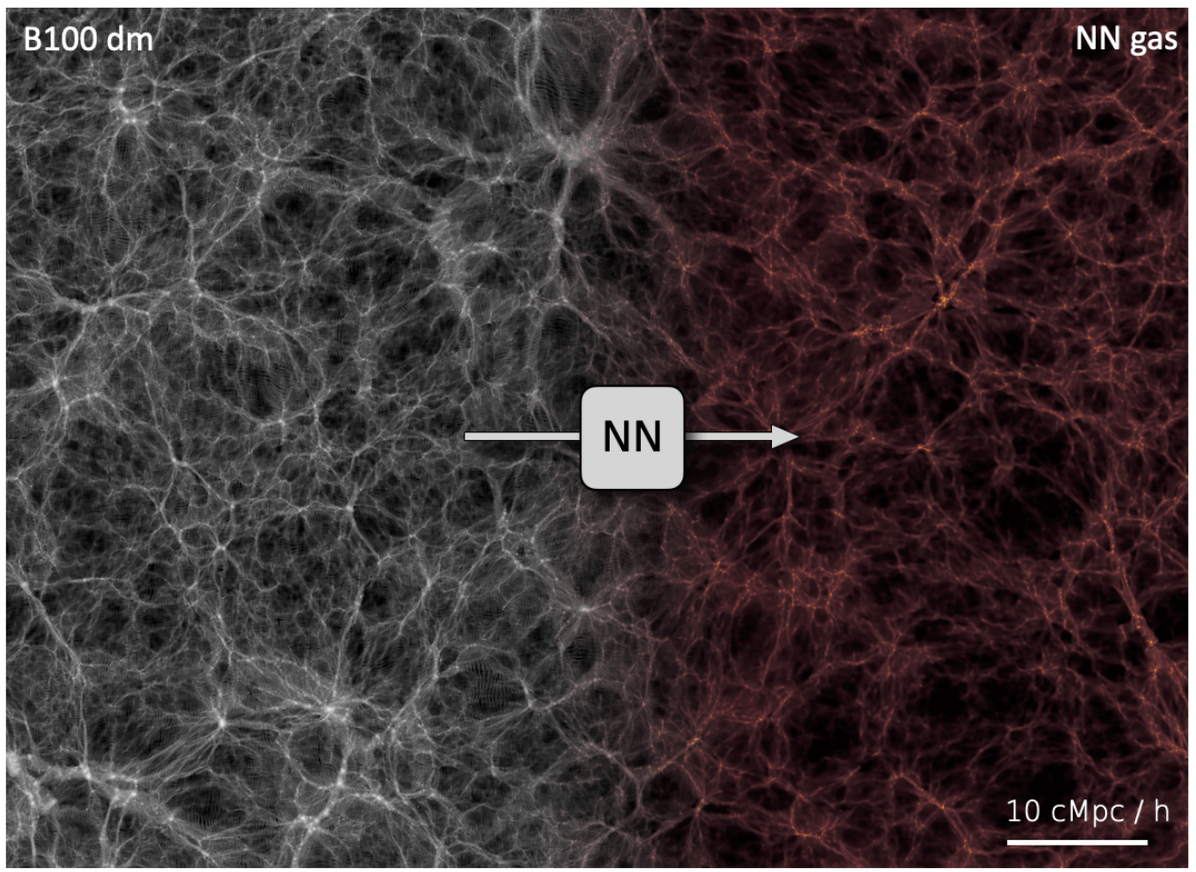
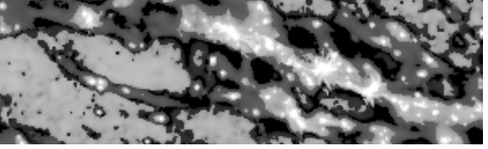




title slide shows part of the B100 map



Simulation data

- Simulations run with GIZMO, FIRE-2 physics

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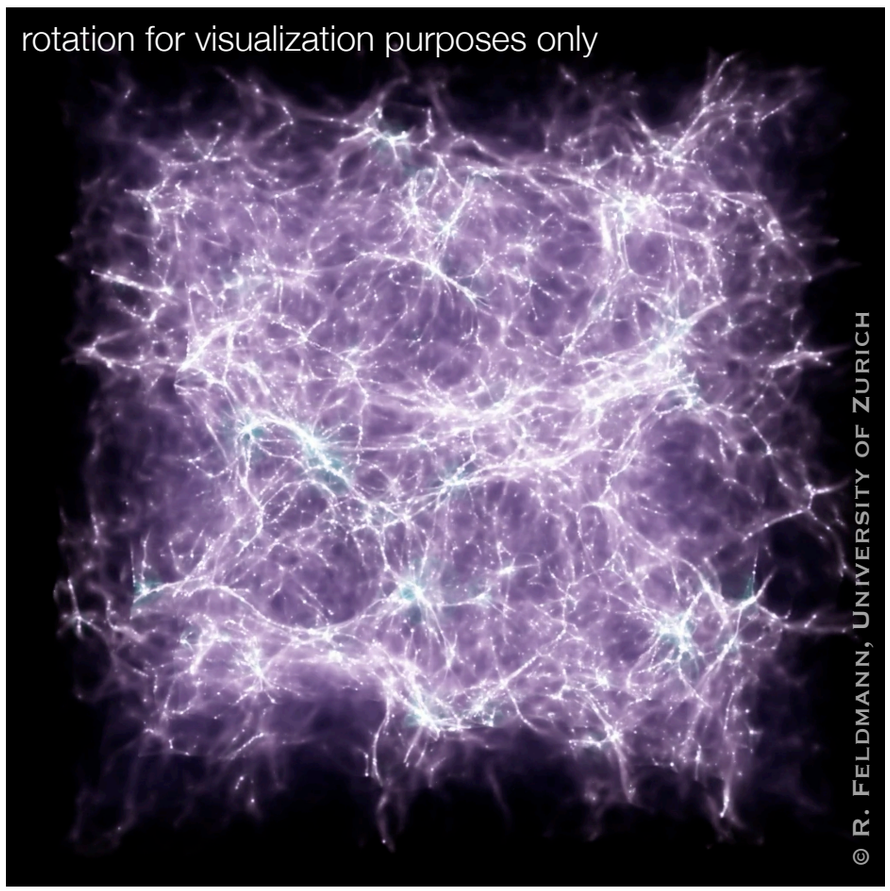
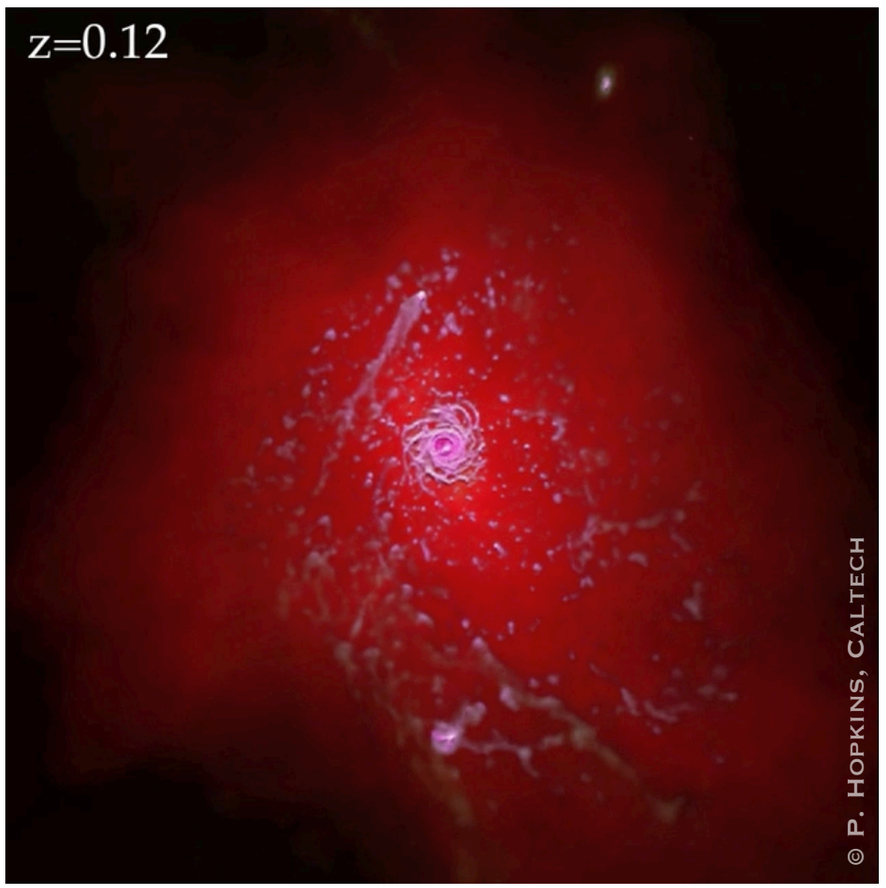
- 2 kinds of simulations:

Cosmological volume



Cosmological zoom-in



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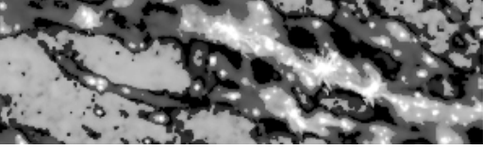

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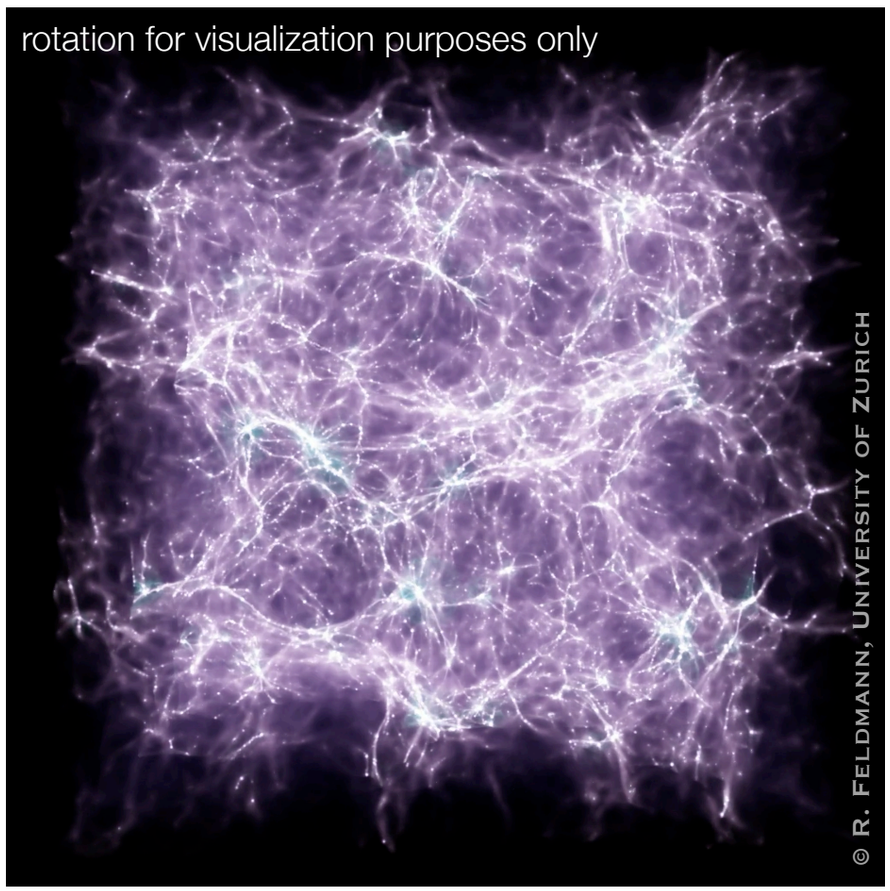

- L = 15 cMpc/h
- 2 billion gas+DM particles
- $m_b \sim 6 \times 10^4\ M_\odot$, $\Delta x \sim$ tens of pc
- RF et al. in prep

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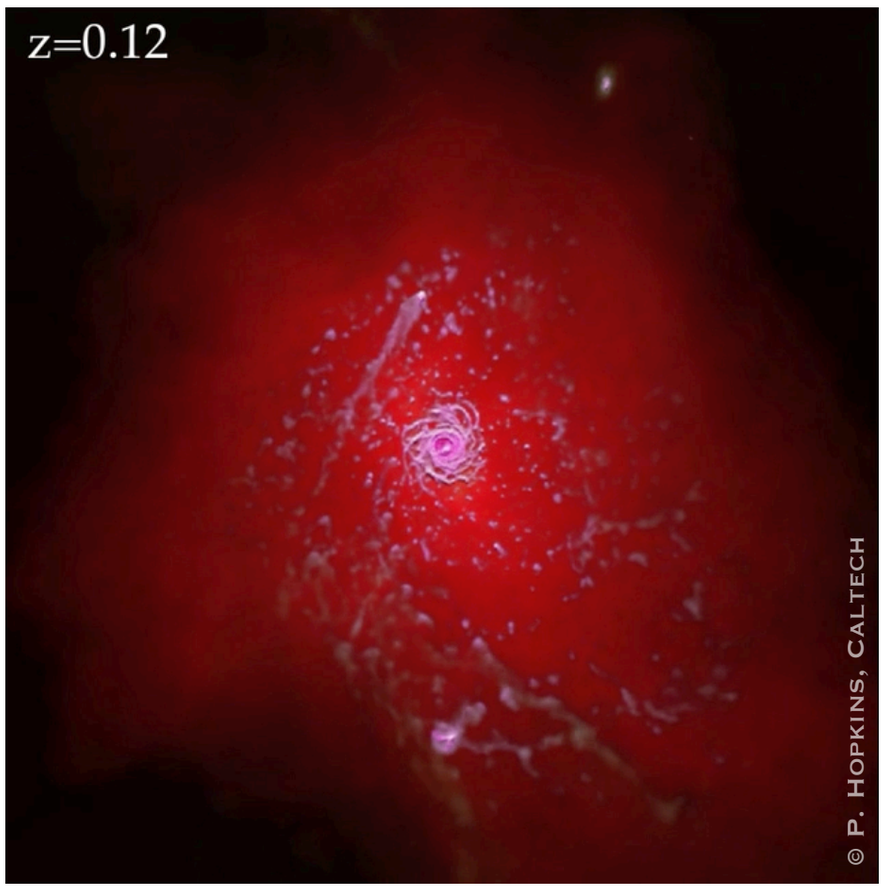

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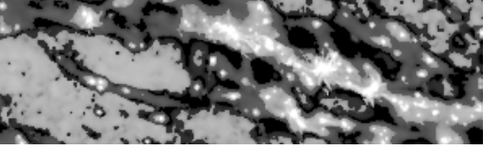

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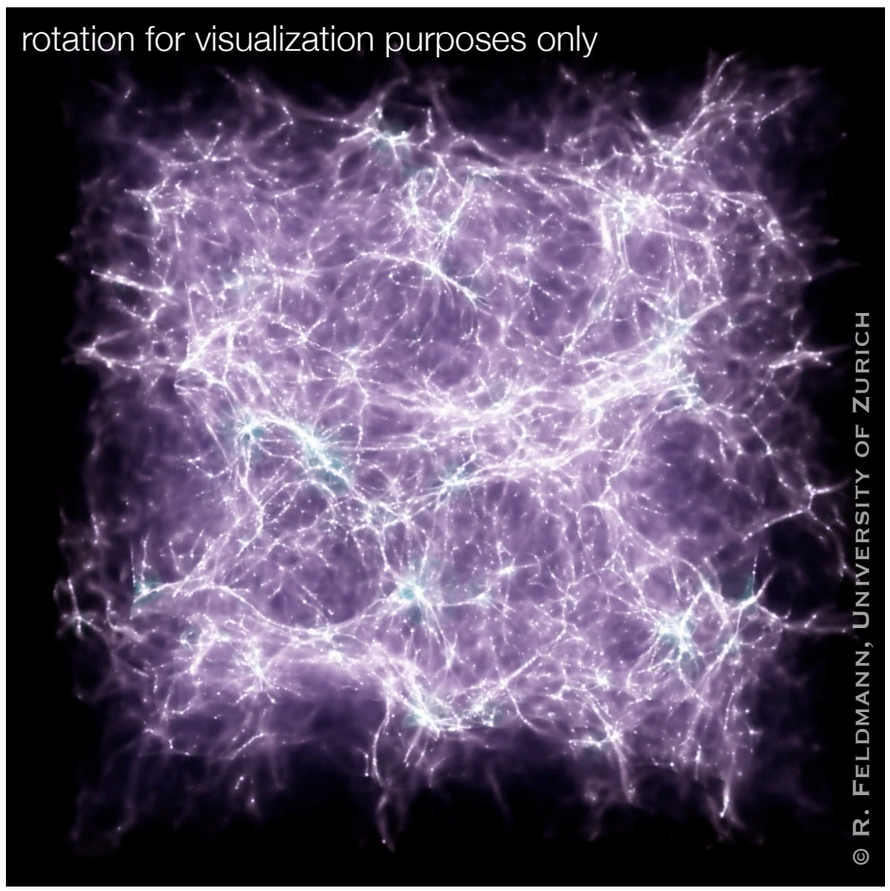

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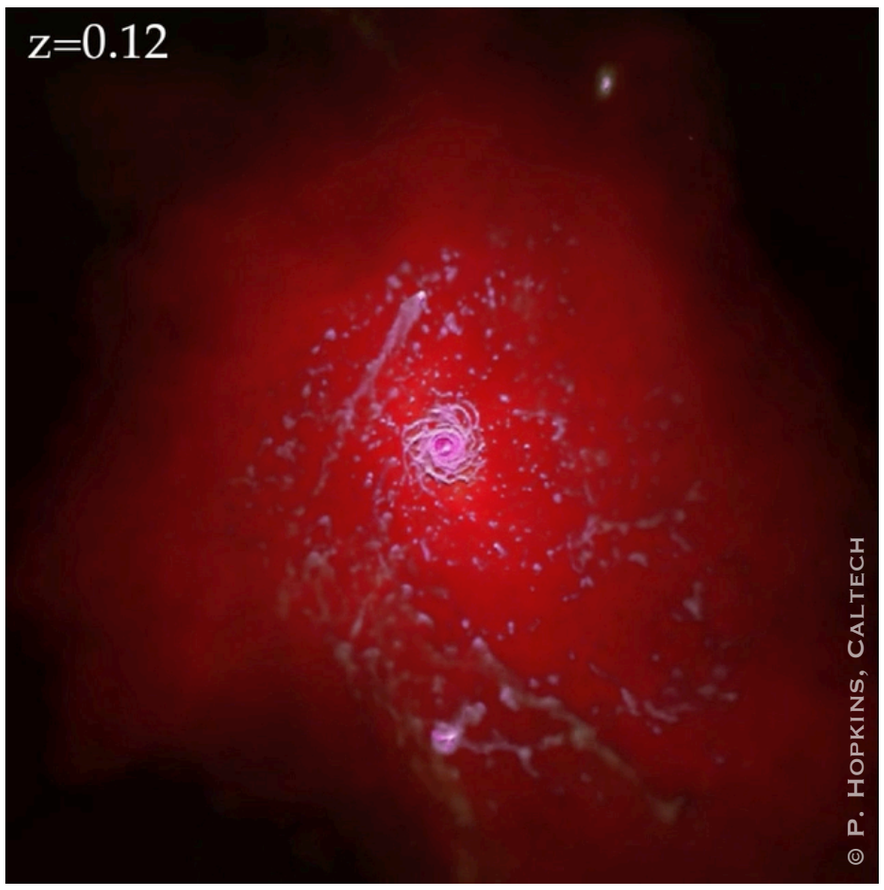
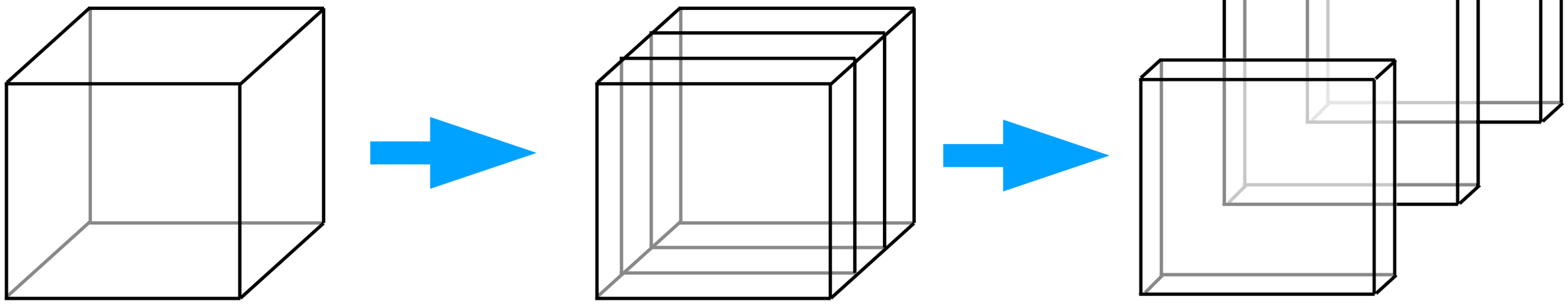


- ~few cMpc region
- 4 massive halos
- $m_b \sim 3 \times 10^4\ M_\odot$, $\Delta x \sim$ tens of pc
- Angles-Alcazar et al. 2017

From FIRE to EMBER

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



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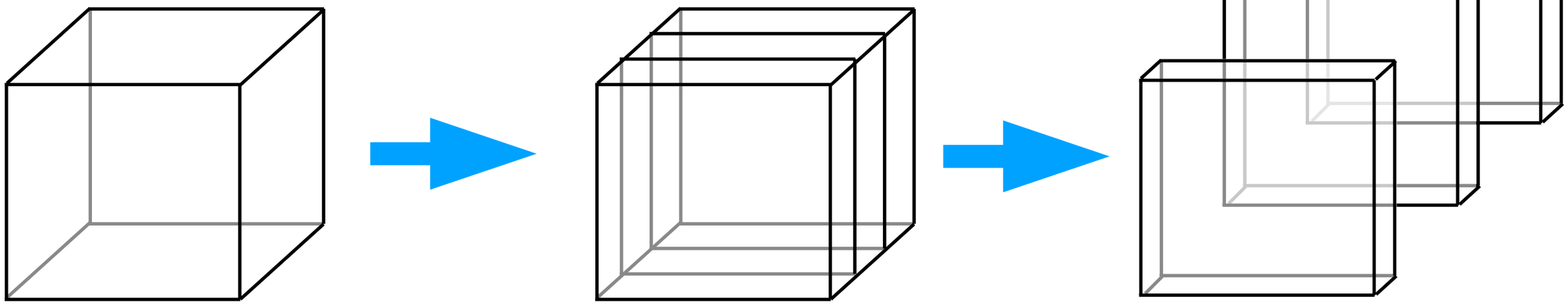
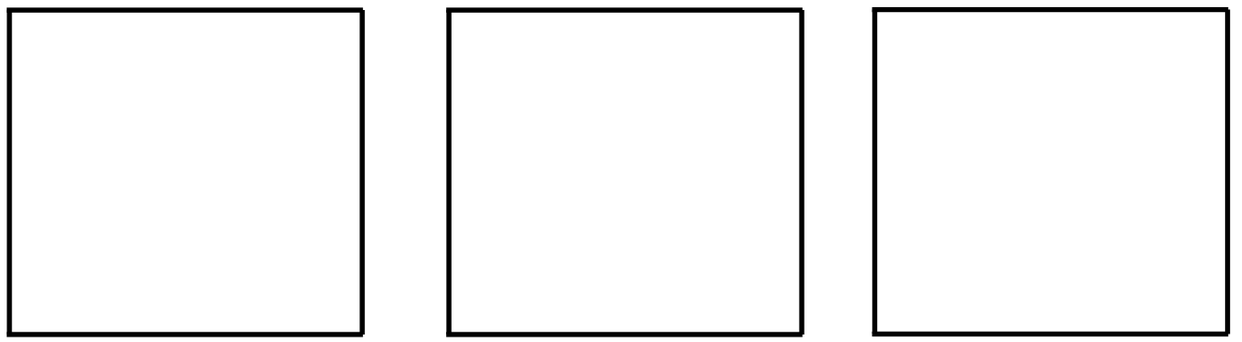


Step 2: Project H_I and DM density fields



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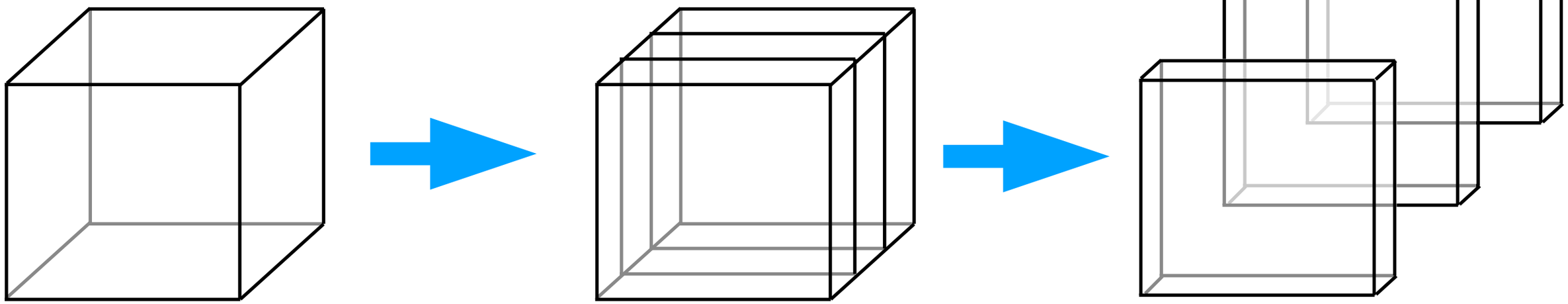

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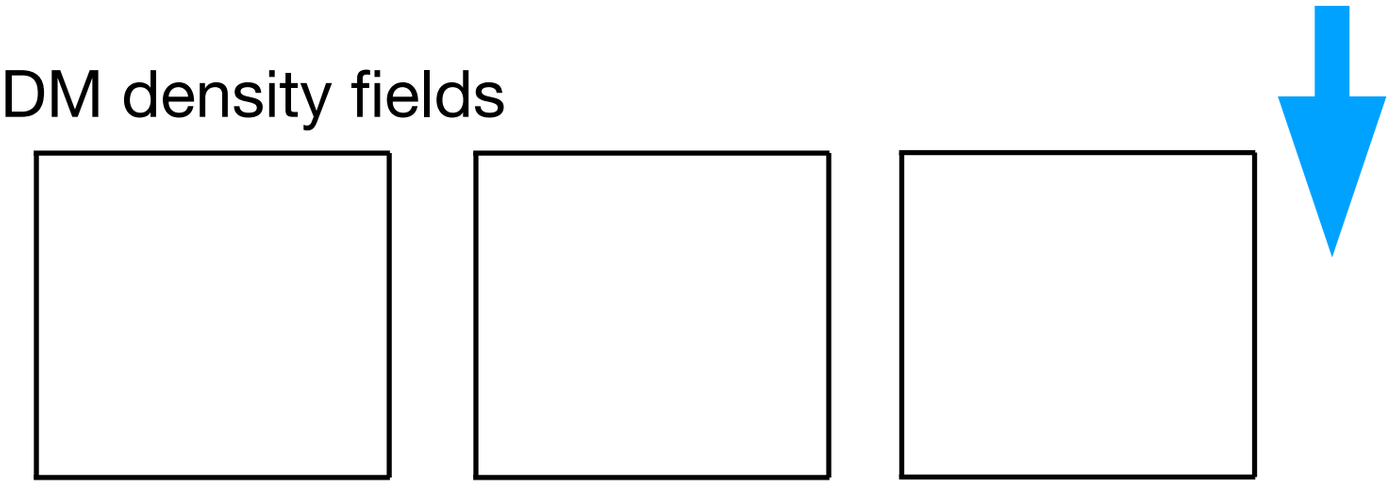
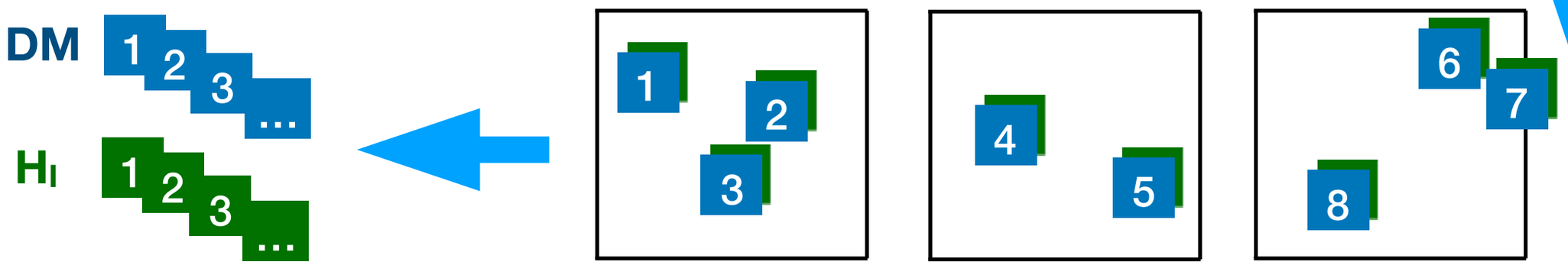


Step 3: Extract 512x512 pixel tiles randomly



Overview of the EMBER architecture

Training:

Step1

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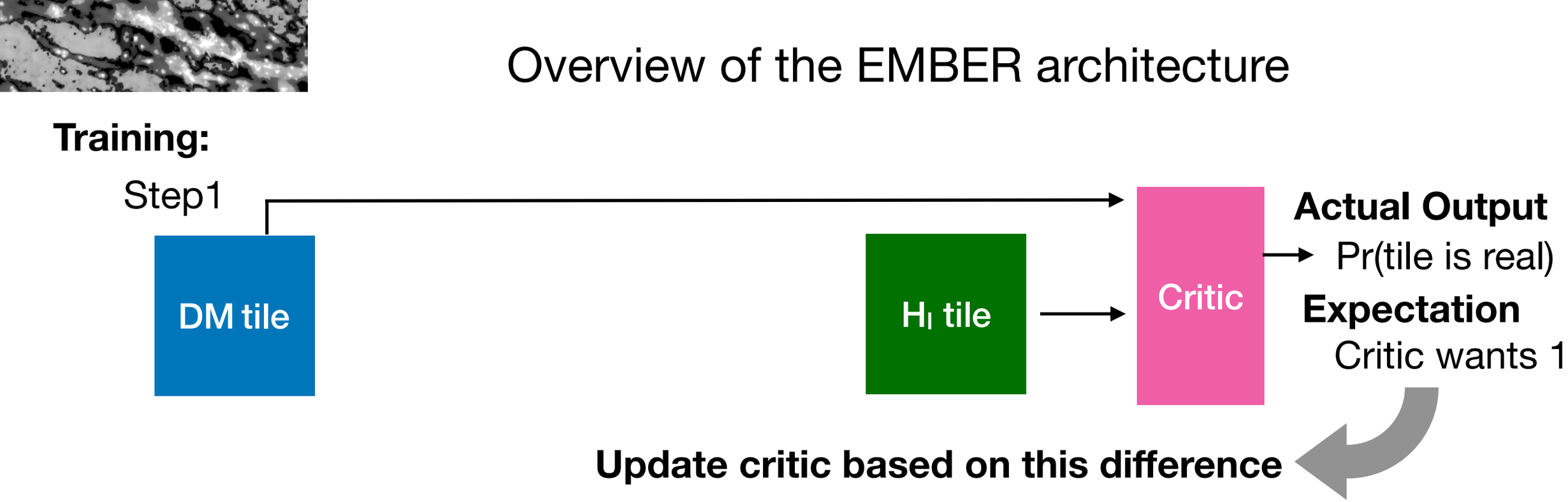

Overview of the EMBER architecture

Training:

Step1

DM tile

H_I tile

Critic

Actual Output

Pr(tile is real)

Expectation

Critic wants 1

Update critic based on this difference

Step 2

DM tile

Noise

Fully convolutional Generator

predicted H_I tile

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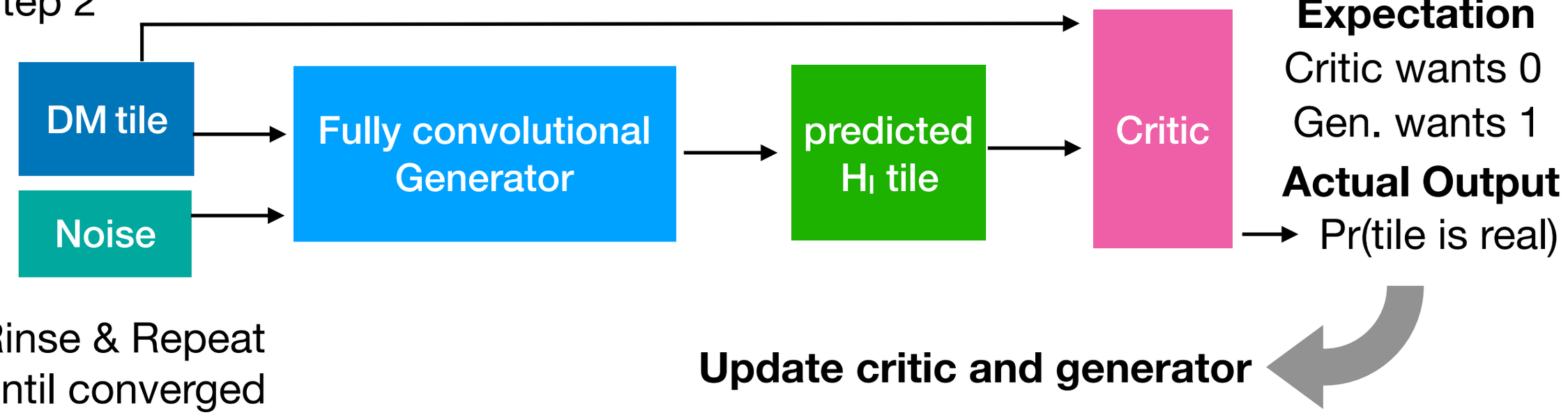
Step 2



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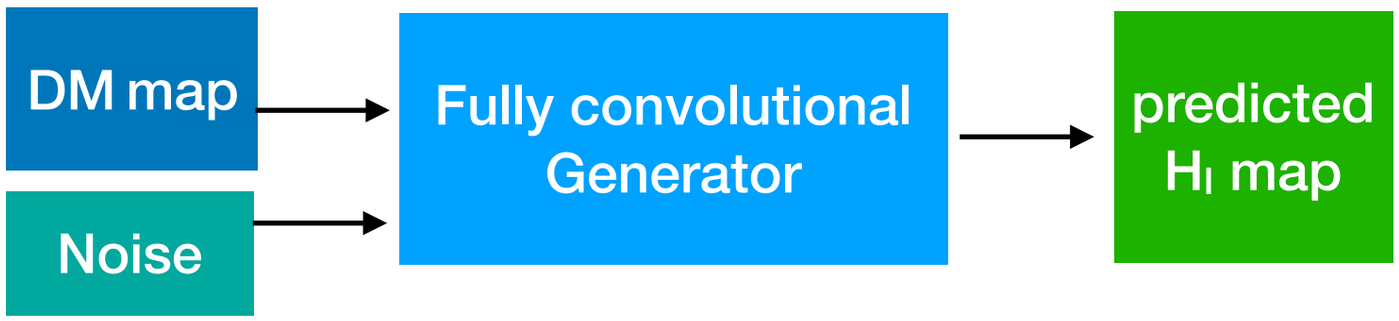
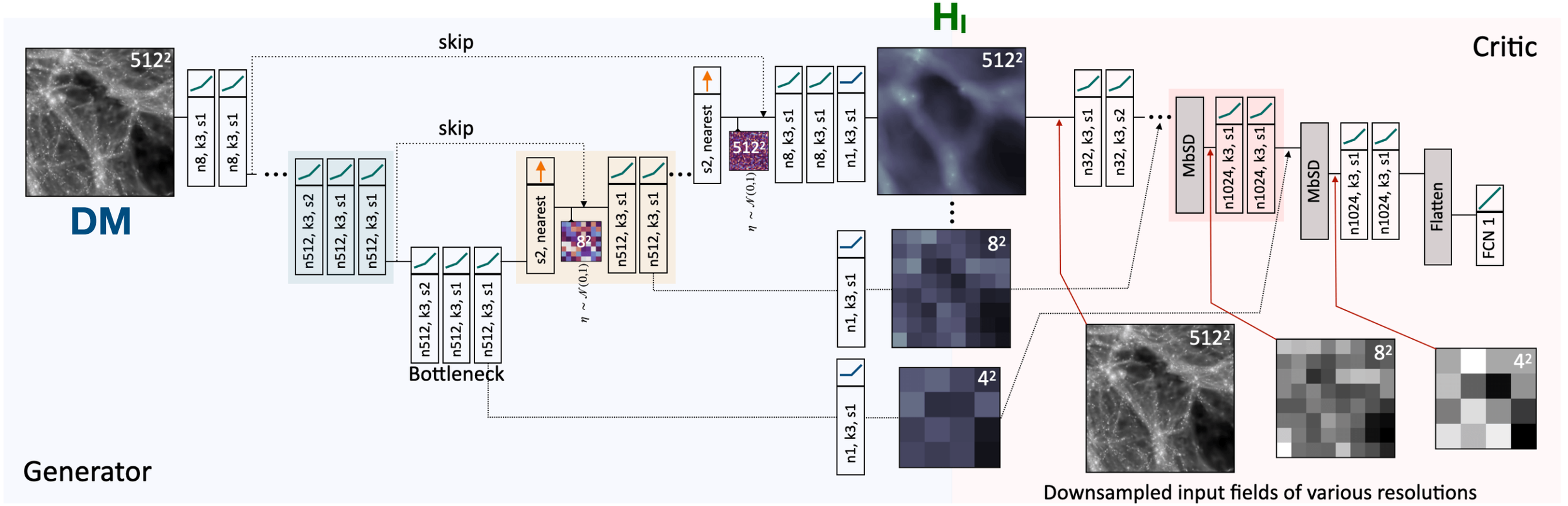
Application:



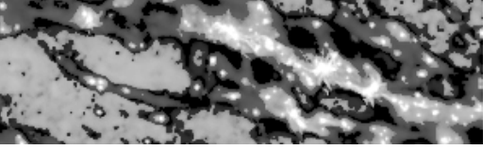
A detailed view of the EMBER architecture

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)

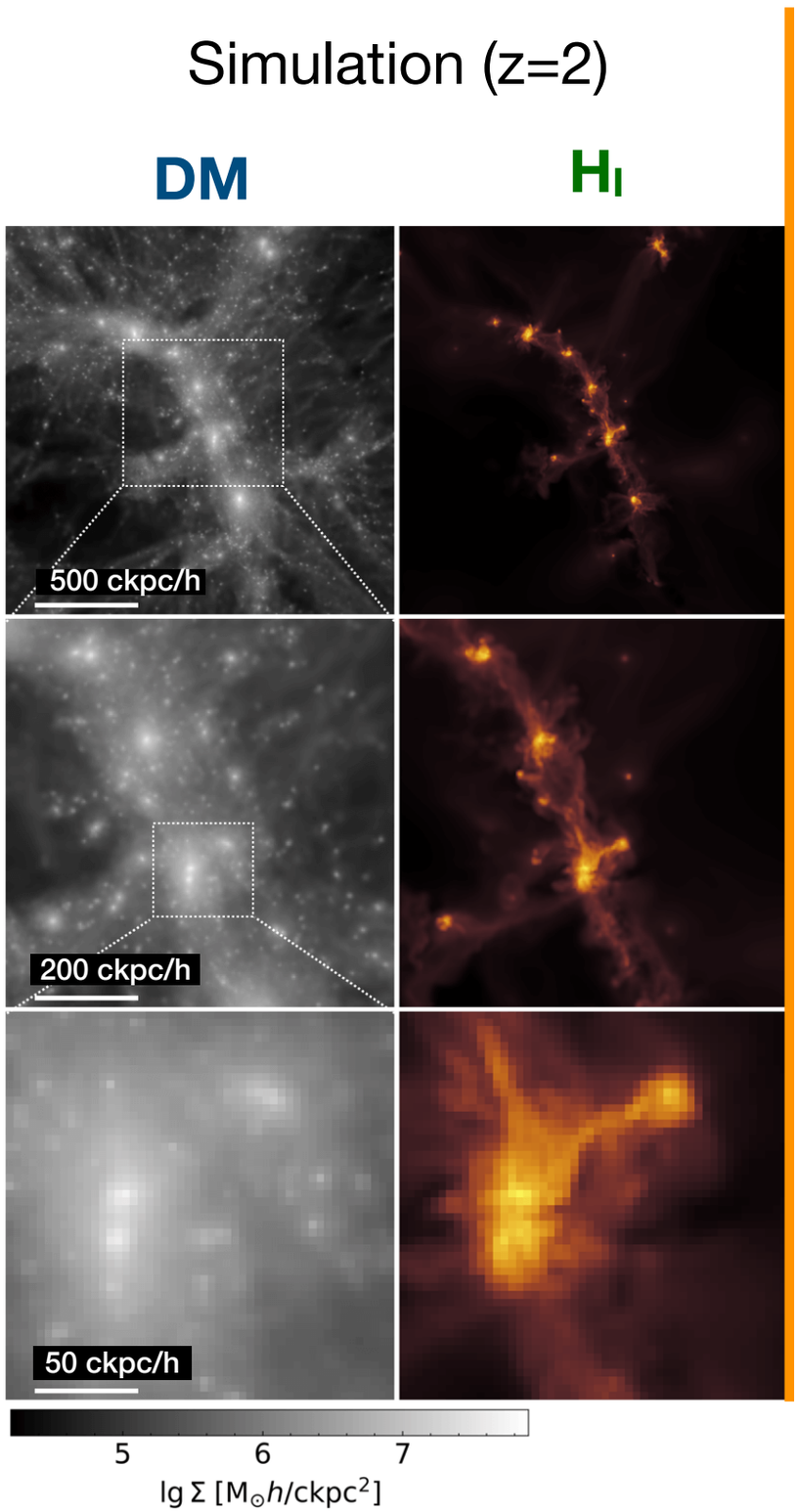


Bernardini, RF, et al. submitted



How well does it work?

Simulation (z=2)



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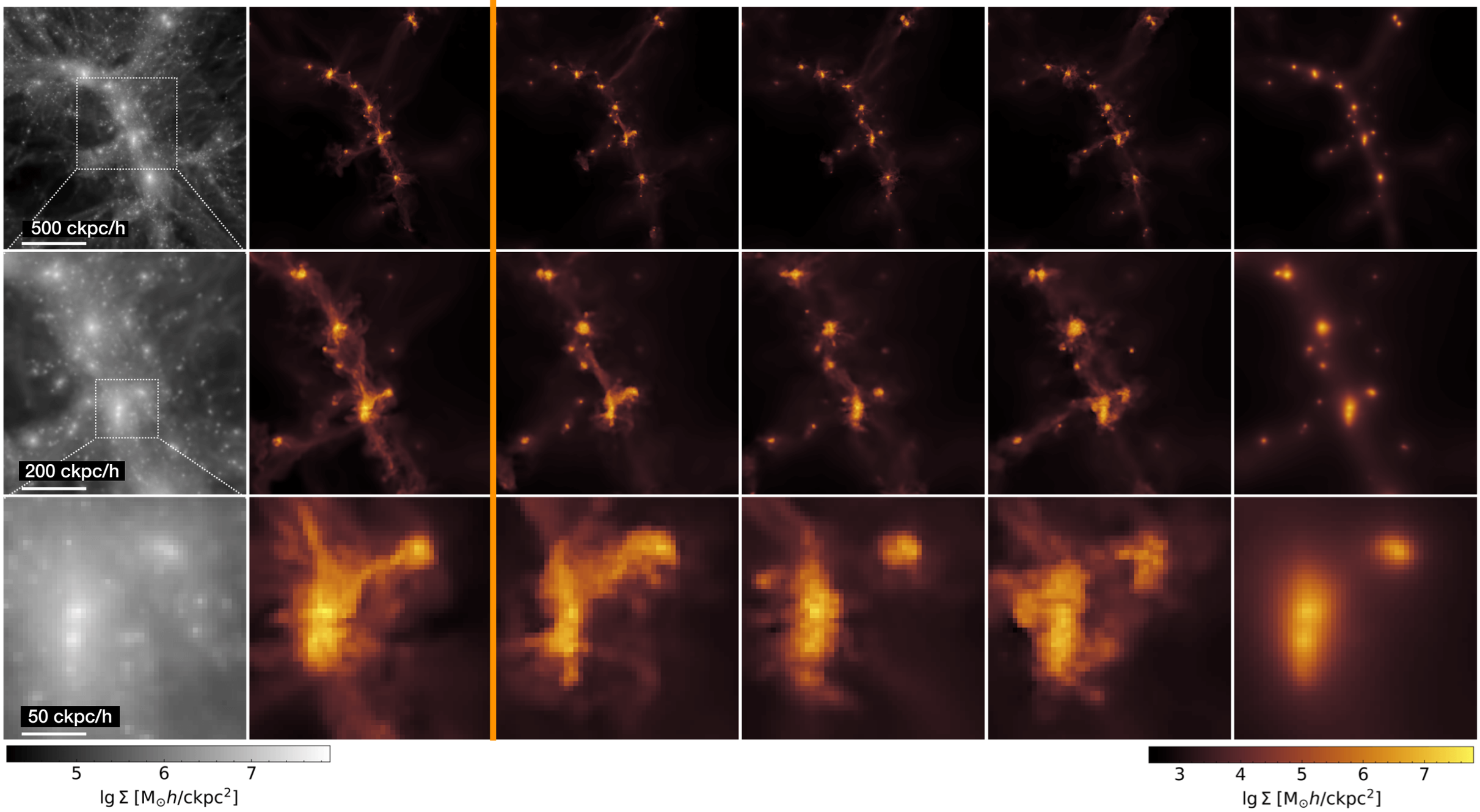
DM | **H_I** | WGAN | WGAN | WGAN | pure U-NET



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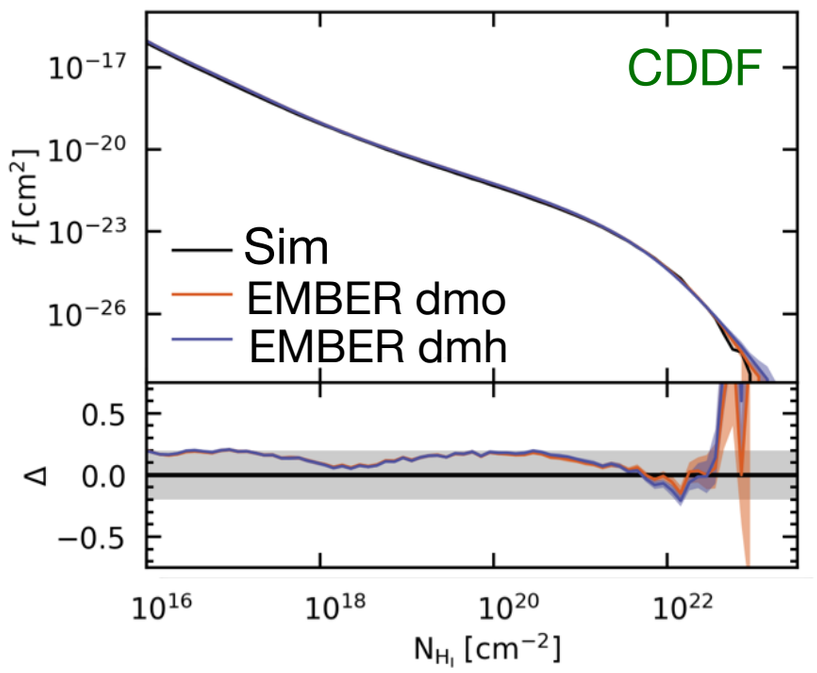

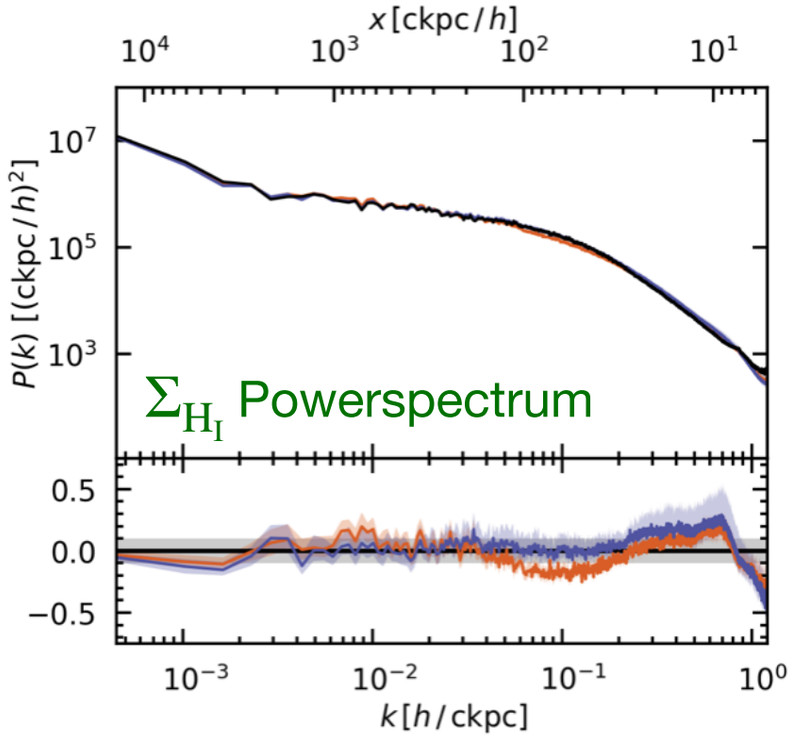

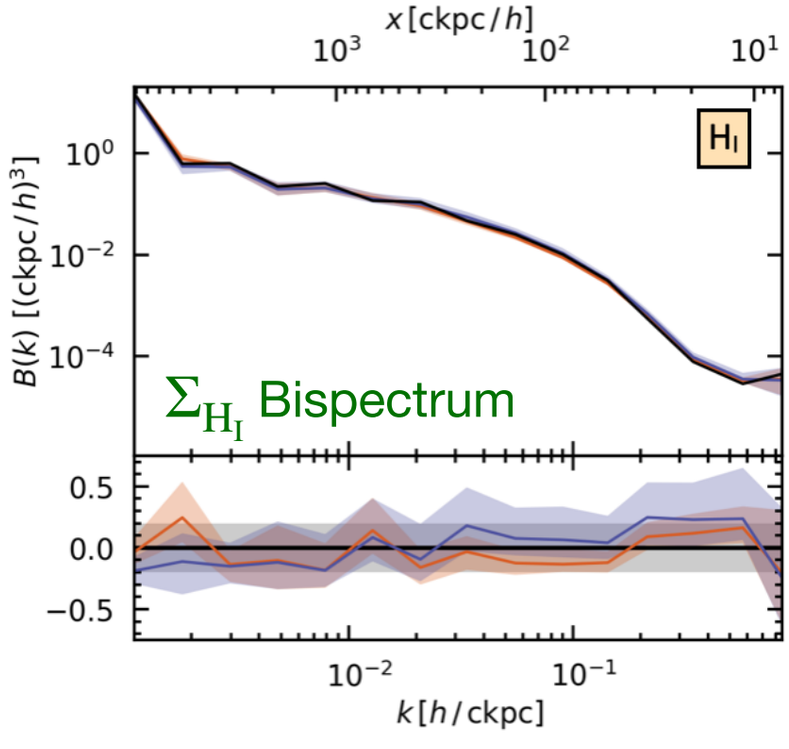

- Agreement to within 10-20% down to galactic scales!

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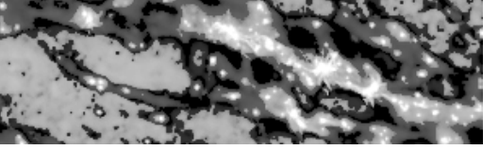

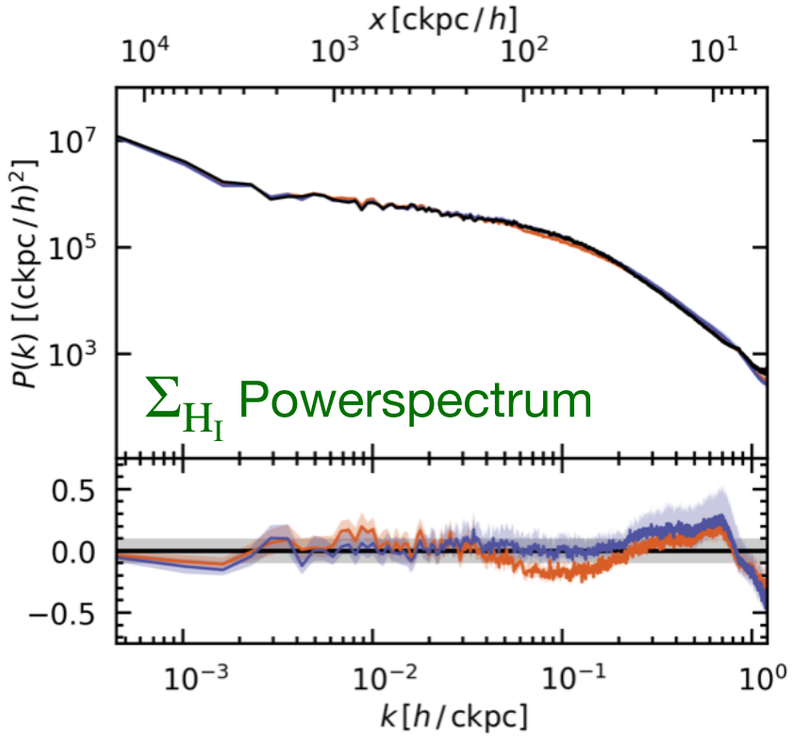

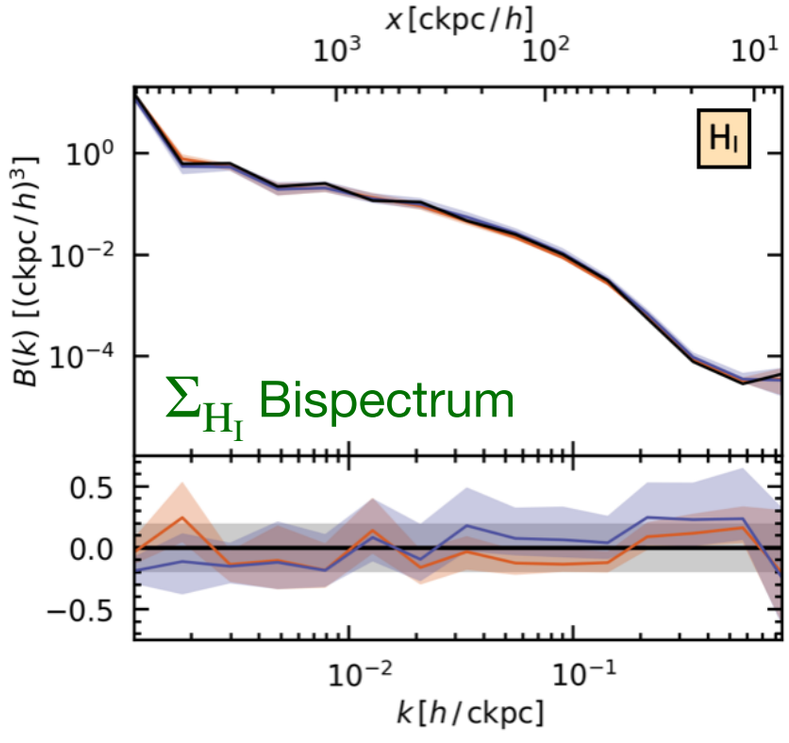

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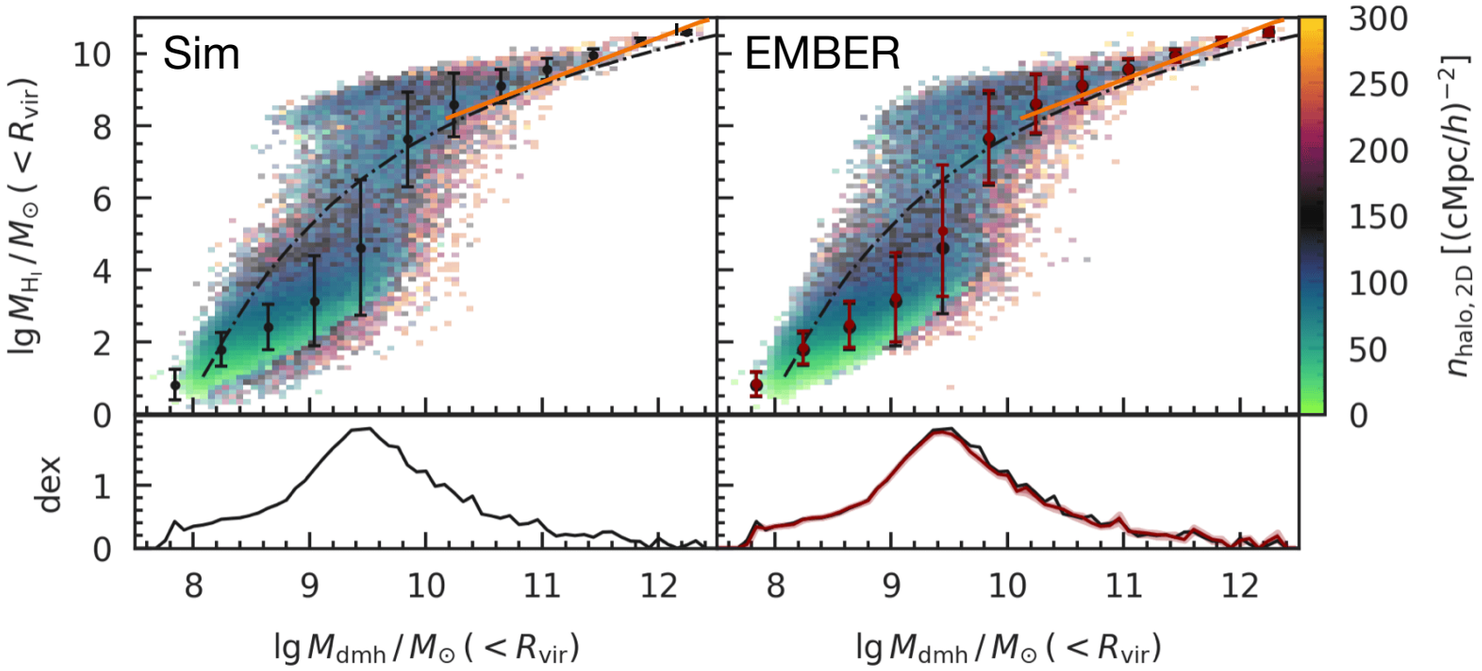
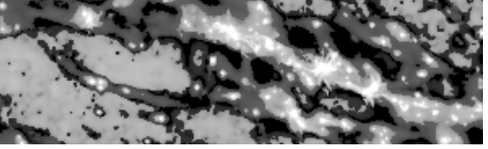
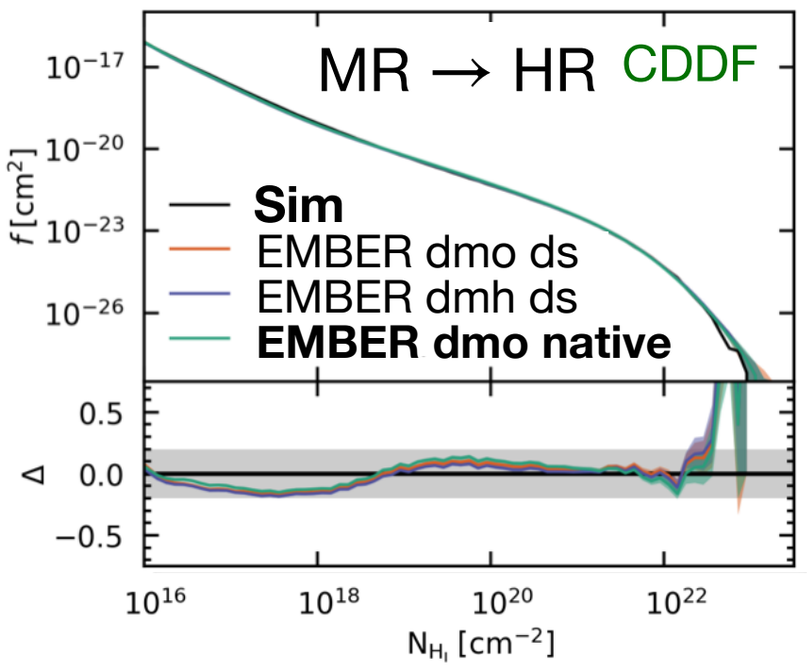


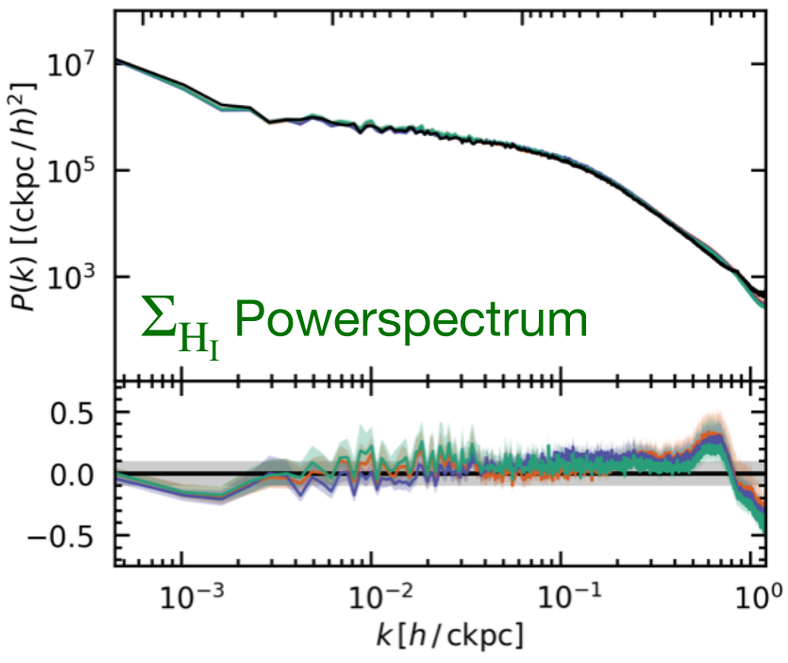
- Reproduces (projected) H_I masses in halos and scatter!

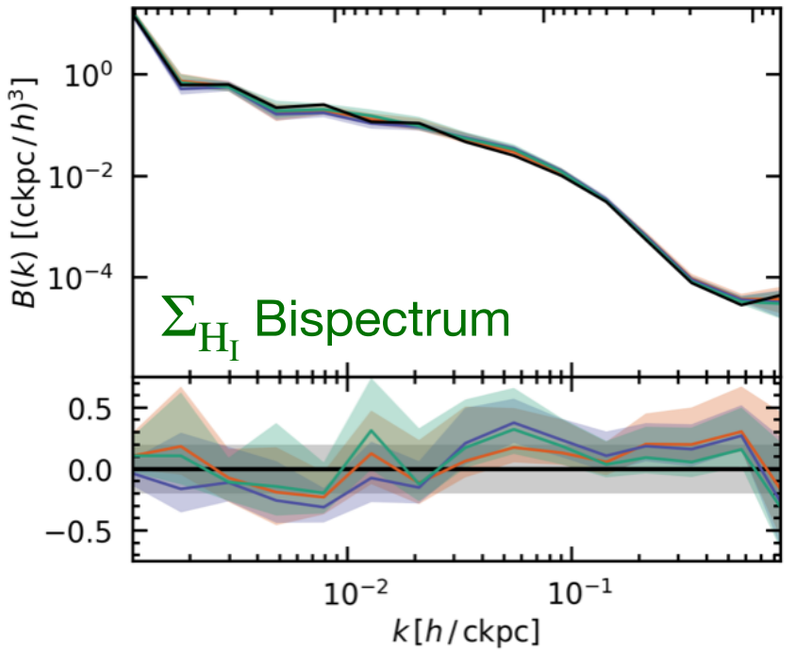


Upscaling

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

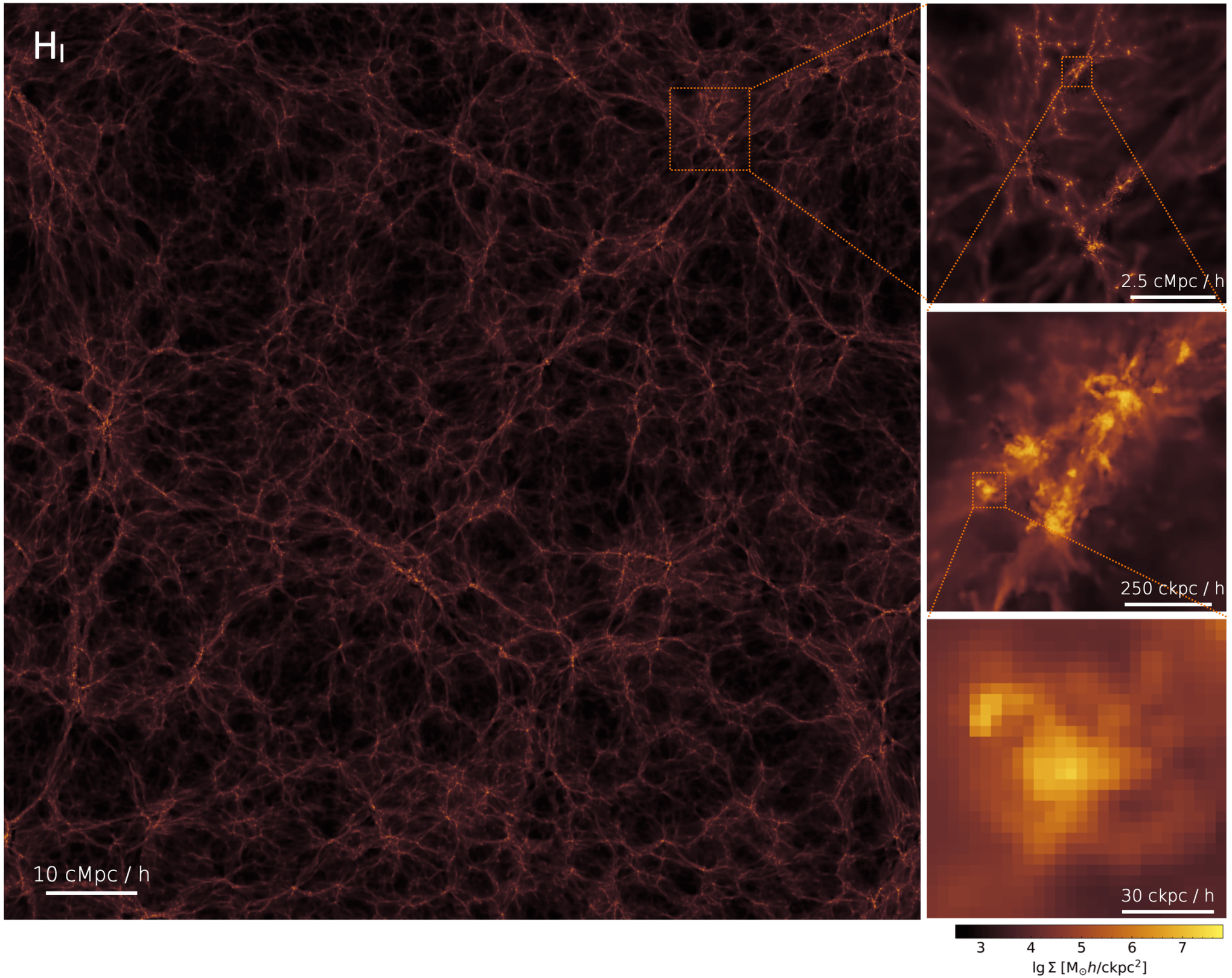


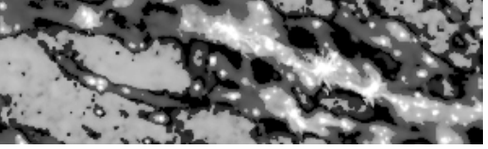




- 10-20% accurate when using 64x lower resolution DM maps

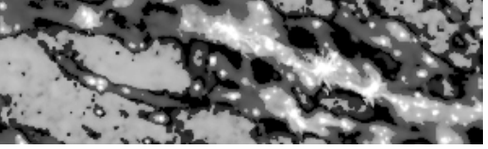
Upscaling


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]



Summary

- Introduced EMBER: stochastic, conditional, convolutional GAN that learns baryon maps from cosmological, hydrodynamical simulations
- High-resolution FIRE simulations used for training
- 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
- Reasonably accurate prediction from 64 x lower resolution DM maps, allows upscaling to larger volumes



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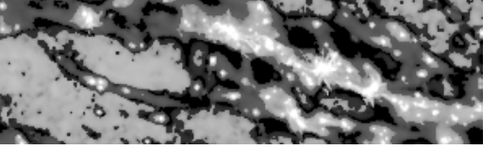
Future extensions

- Additional input fields (e.g., DM velocity)
- Different output fields (gas temperature, pressure etc)
- Redshift interpolation



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Thank you