EMBER: EMULATING GAS FIELDS FROM DARK MATTER SIMULATIONS

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FIRE
Feedback In Realistic Environments

SKACH, 4.10.22

Universität Zürich[UZH]

BARYONS IN GALAXY FORMATION

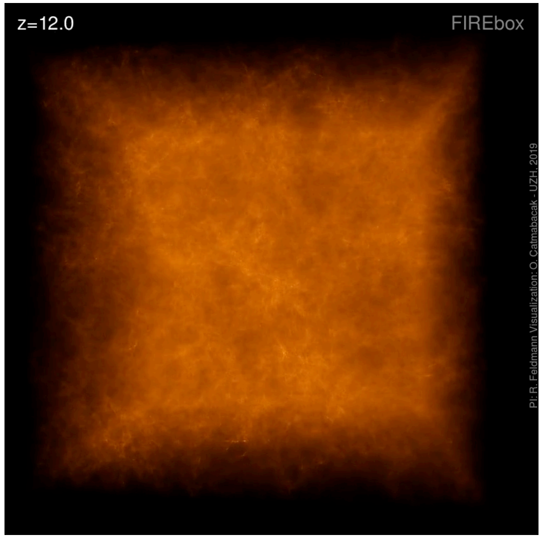
- Baryonic / HI physics on non-linear scales highly complex
- Hydrodynamical simulations are most principled approach:

  + predict baryons on all scales and across cosmic history

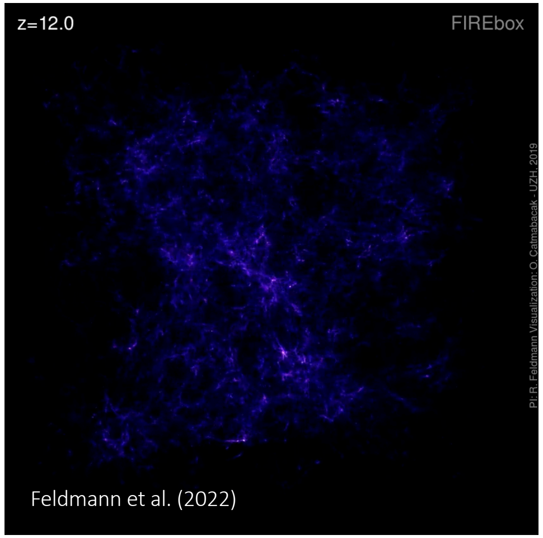
  + can test various physical models (e.g. feedback, UV background evolution, etc.)

  - expensive (computing power, storage, time, money, etc.)
    e.g. Illustris TNG 18 million CPU hours (Nelson et al. 2019)

Dark Matter



Baryons (gas / H_I, stars)



Neural Networks as cosmic emulators can mitigate the large computational costs

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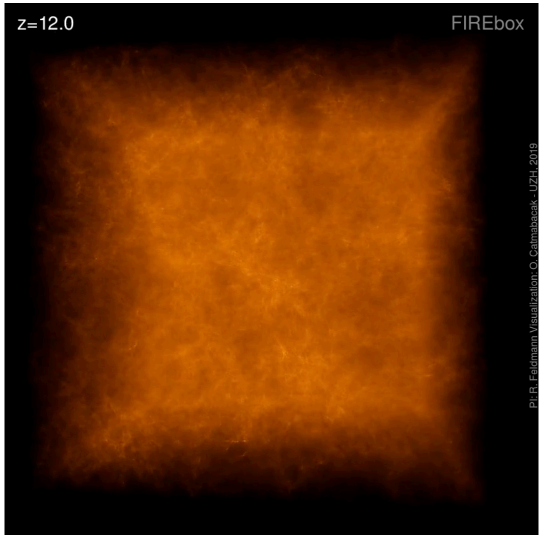

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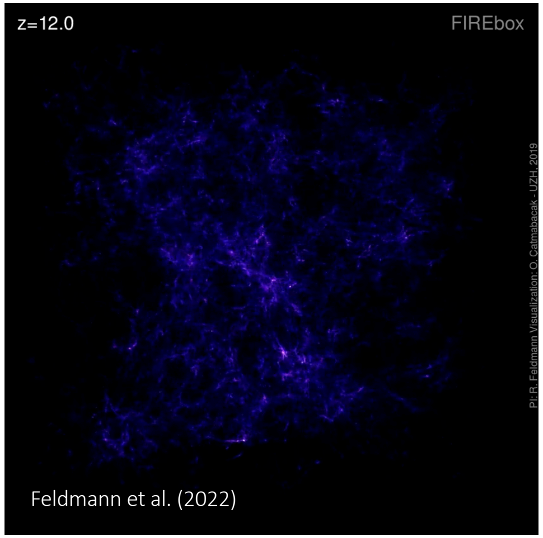

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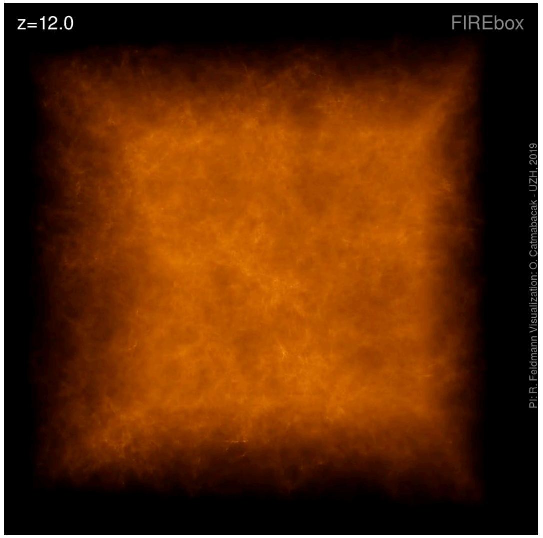

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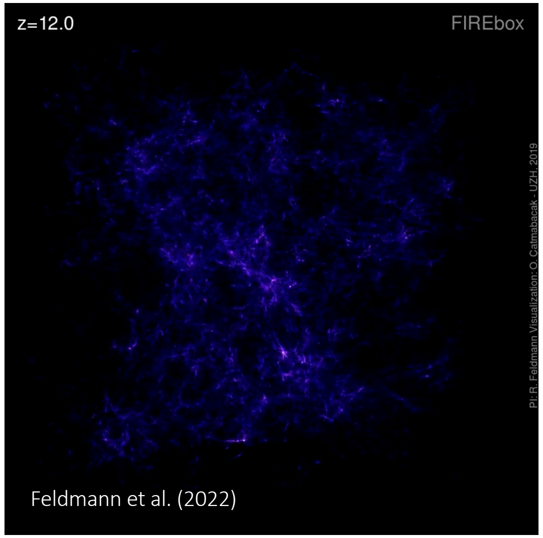

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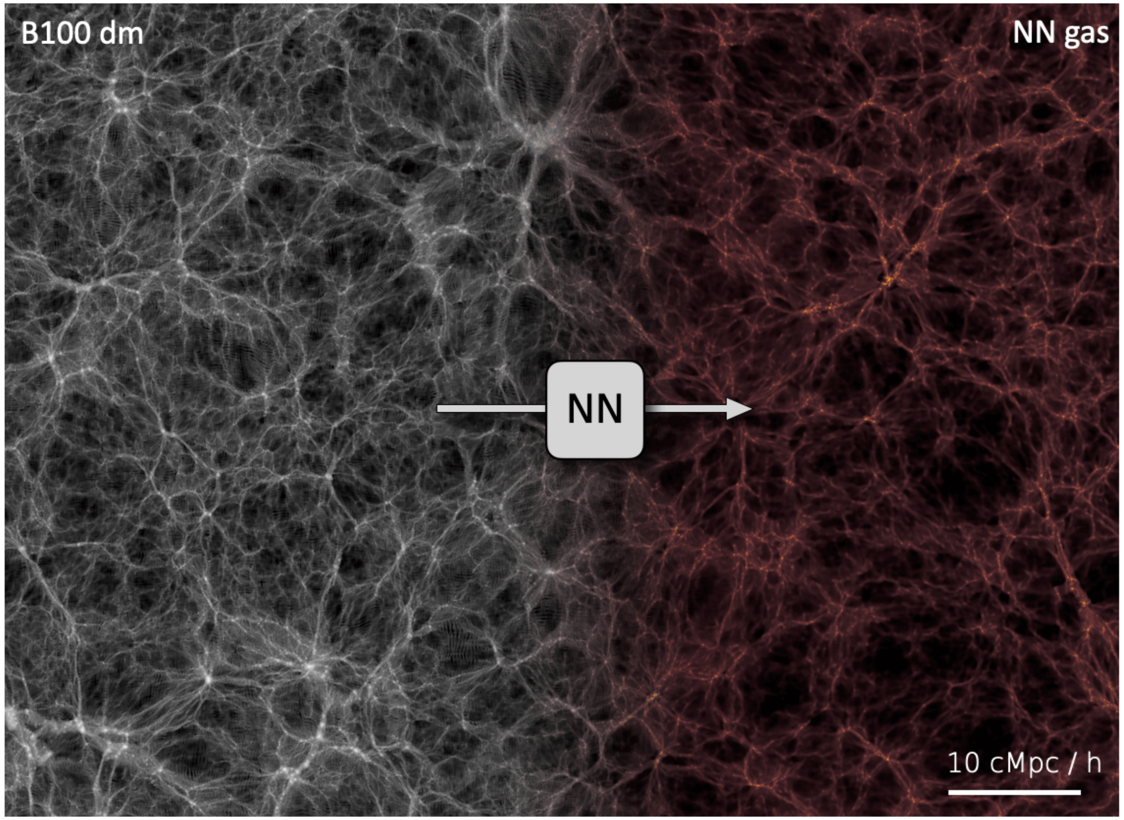
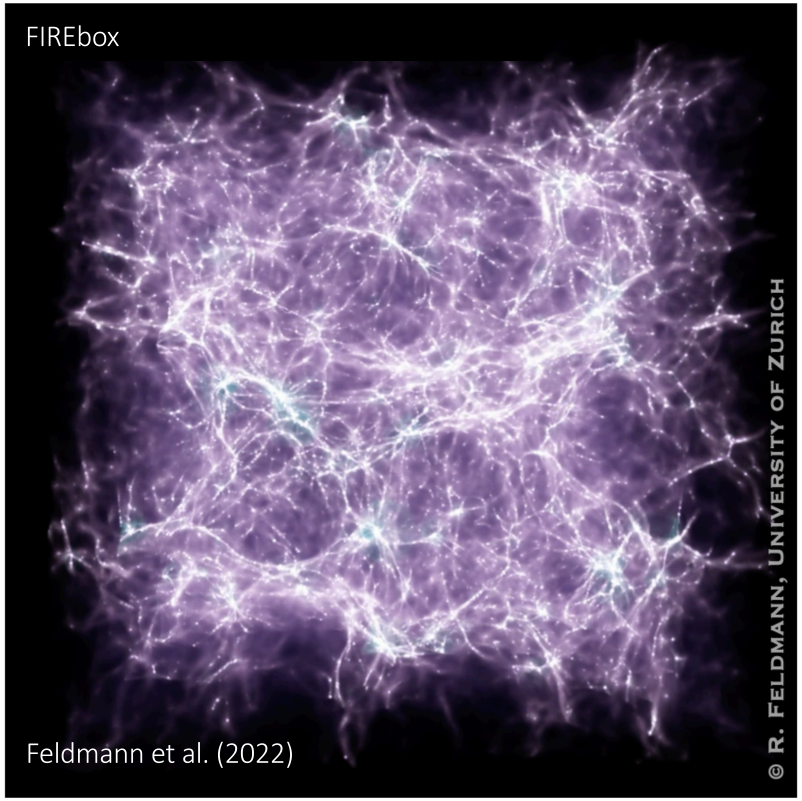
Application

for enriching large dark matter simulations with baryons



TWO TYPES OF SIMULATIONS

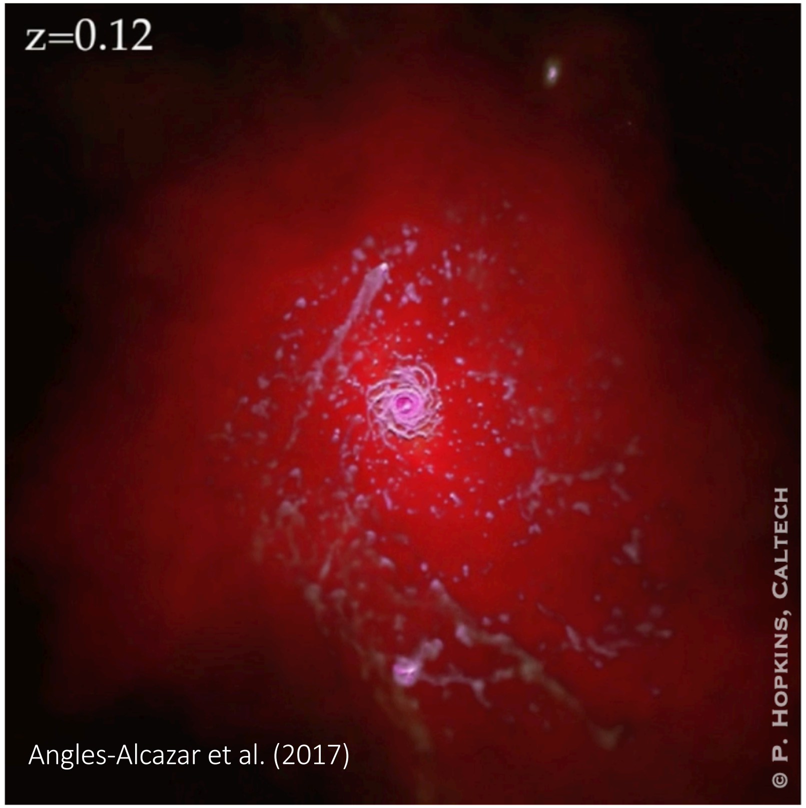
Cosmological volume



Feldmann et al. (2022)

- Boxsize = 22 cMpc, FIRE-2 physics
- 2 x 1024^3 (gas + DM) particles
- $m_b = 6 \cdot 10^4\, M_{\odot}$, Δx tens of pc

Cosmological Zoom-in



Angles-Alcazar et al. (2017)

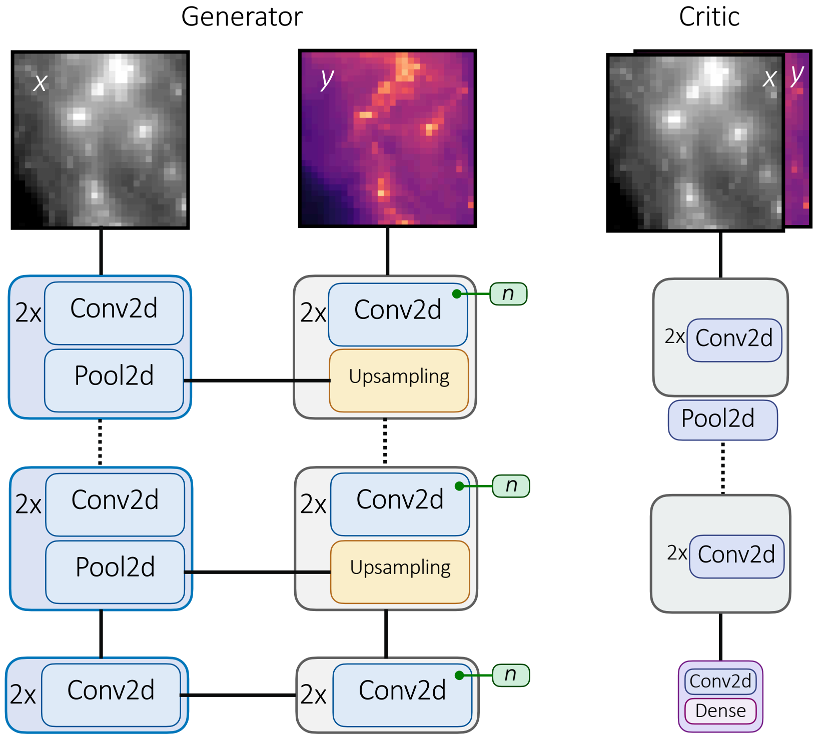
- Few cMpc region, FIRE-2 physics
- 4 massive haloes
- $m_b = 3 \cdot 10^4\, M_{\odot}$, Δx tens of pc

NEURAL NETWORK MODEL

- Goal: We want a generative model (NN) that can synthesize H_I from dark matter on the field level:
  - condition: x = dark matter map
  - noise: n = drawn from $N(0, 1)$
  - target: y = H_I map
  - → model stochasticity $p(y\,|\,x)$
- Generative adversarial Network (wgan)
  - fully convolutional generator
  - paired with standard critic network
- Training by minimizing respective losses:

$$L_G = -\,C(\text{fake})$$

$$L_C = +\,C(\text{fake}) - C(\text{real}) + \text{reg}\,.$$



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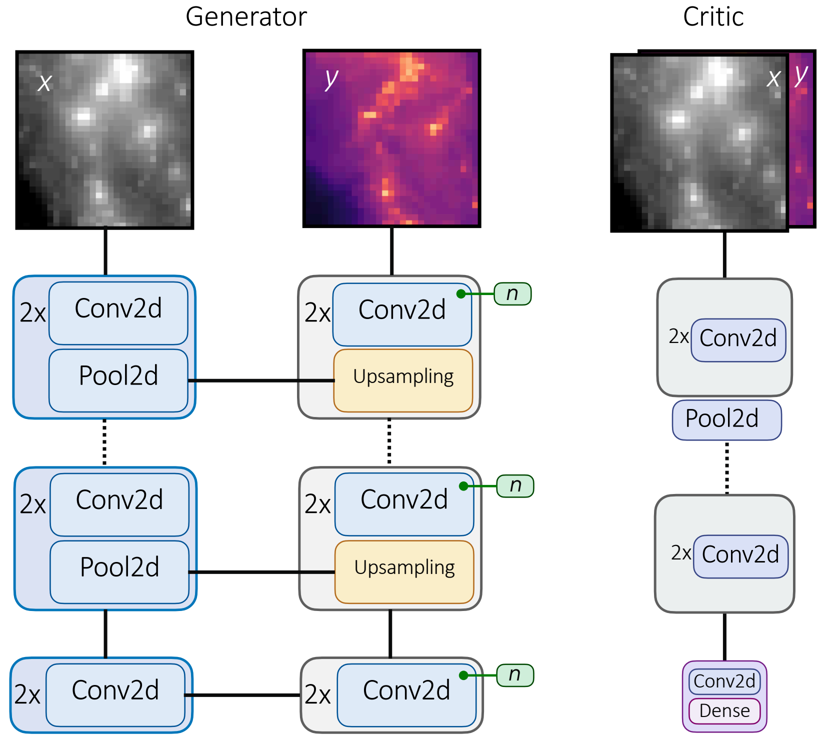

ds

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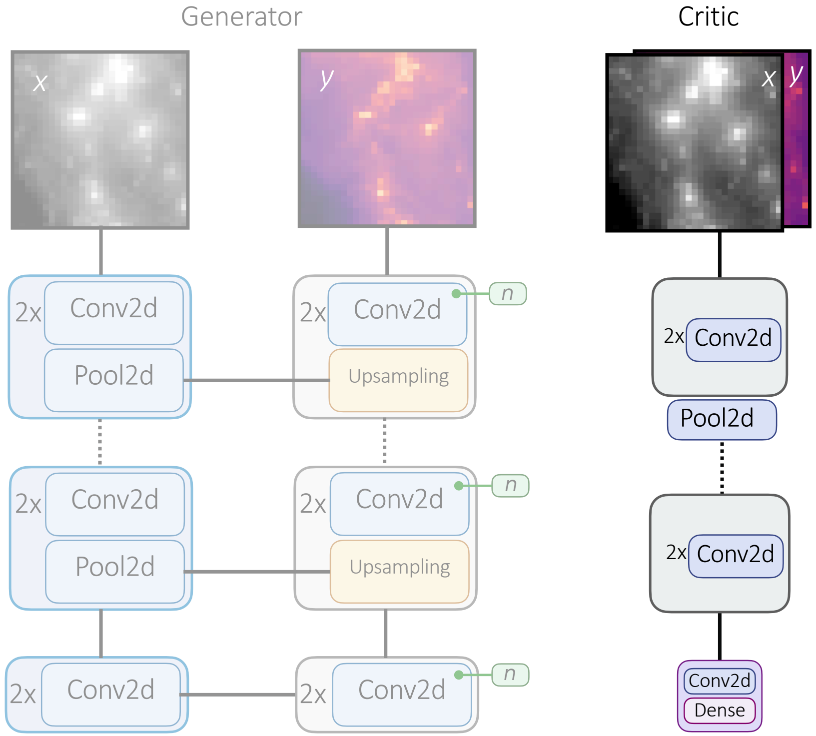

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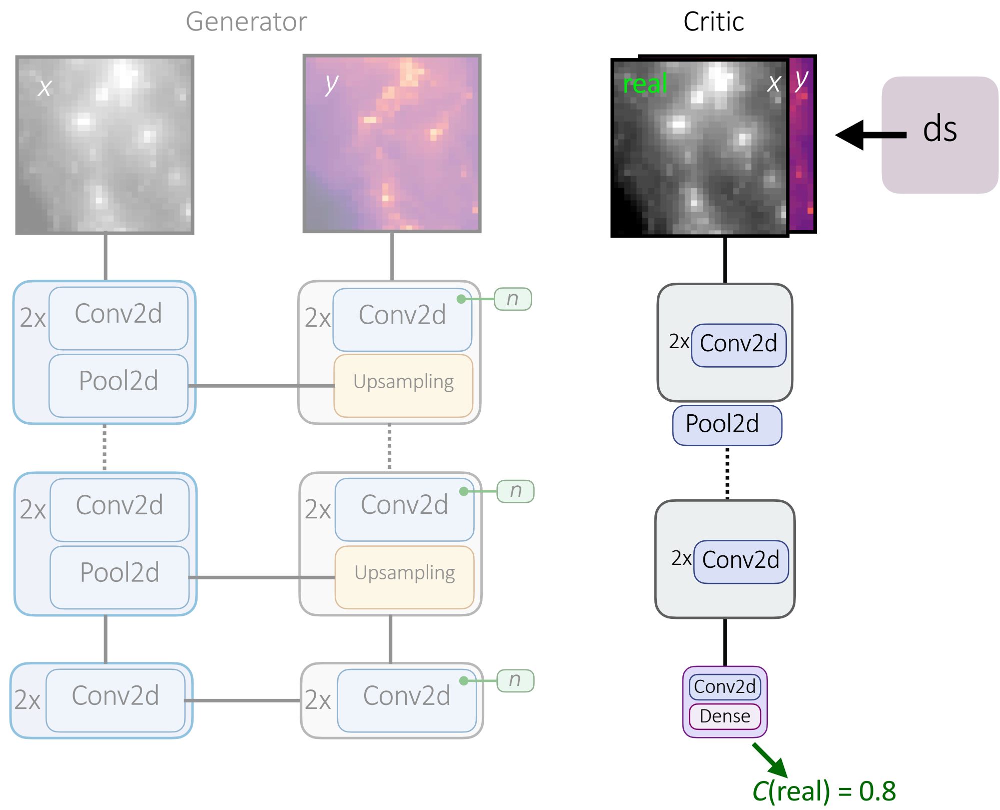

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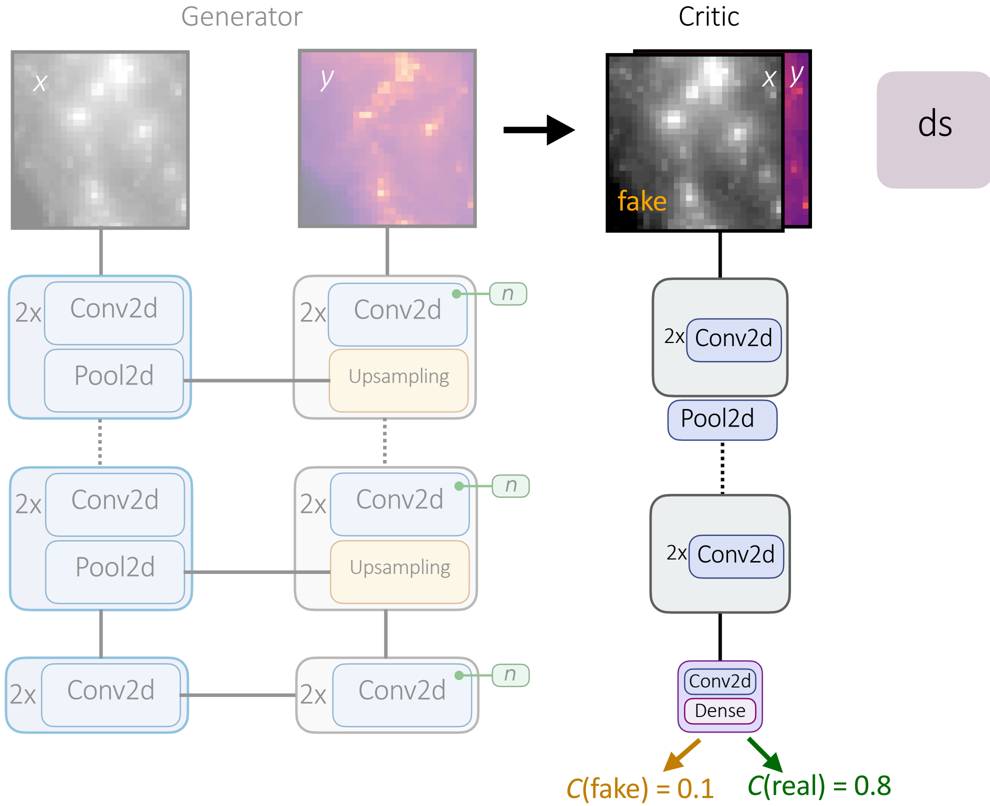
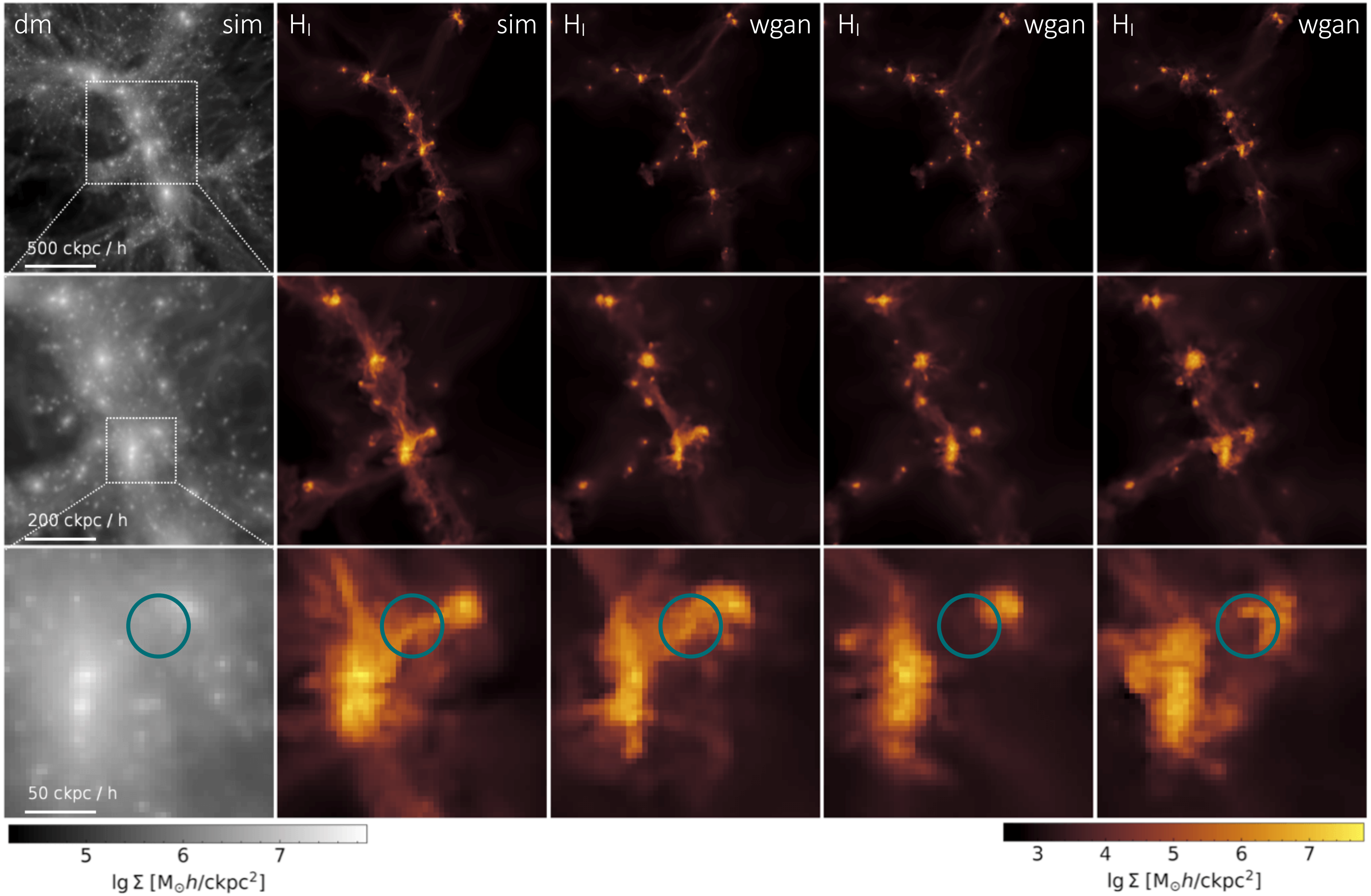
→ update network parameters until converged



VISUAL PERFORMANCE

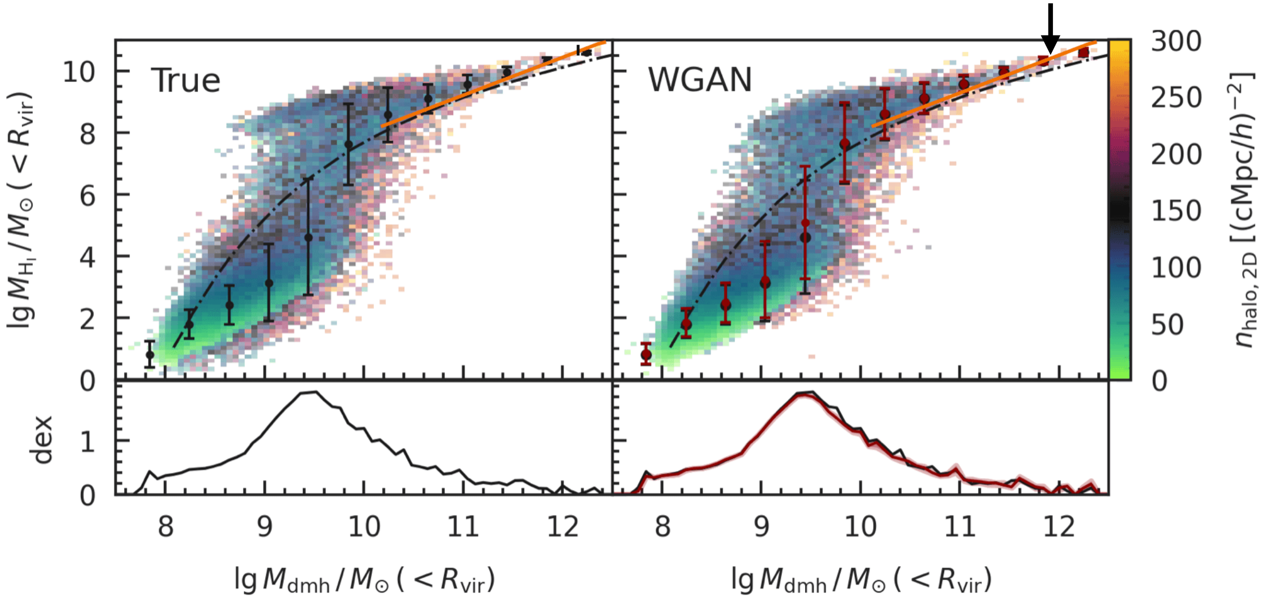


DM TO HI MASS RELATION

- NN is a halo-free method!
- Measure **projected** masses within R_{vir}
- For $M_{dm} \geq 10^{10} M_{\odot}$: main predictor is M_{dm}

  For $M_{dm} < 10^{10} M_{\odot}$: strong importance of environmental information
- Indirectly we find **no** strong dependence on dynamical information on the DM to H_I relation

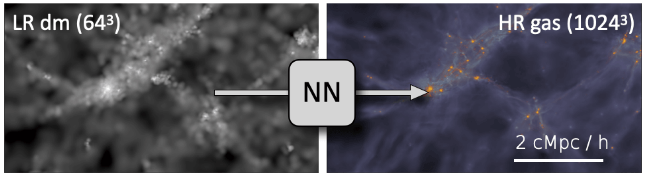
Padmanabhan & Kulkarni (2017)



NN can model DM to H_I mass relation beyond the regime of analytical models down to dwarf galaxy scales

MODEL APPLICATION: UPSCALING

- Train from LR dm to HR H_I



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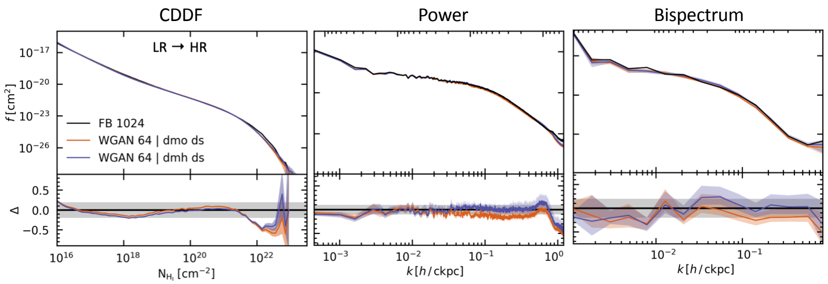

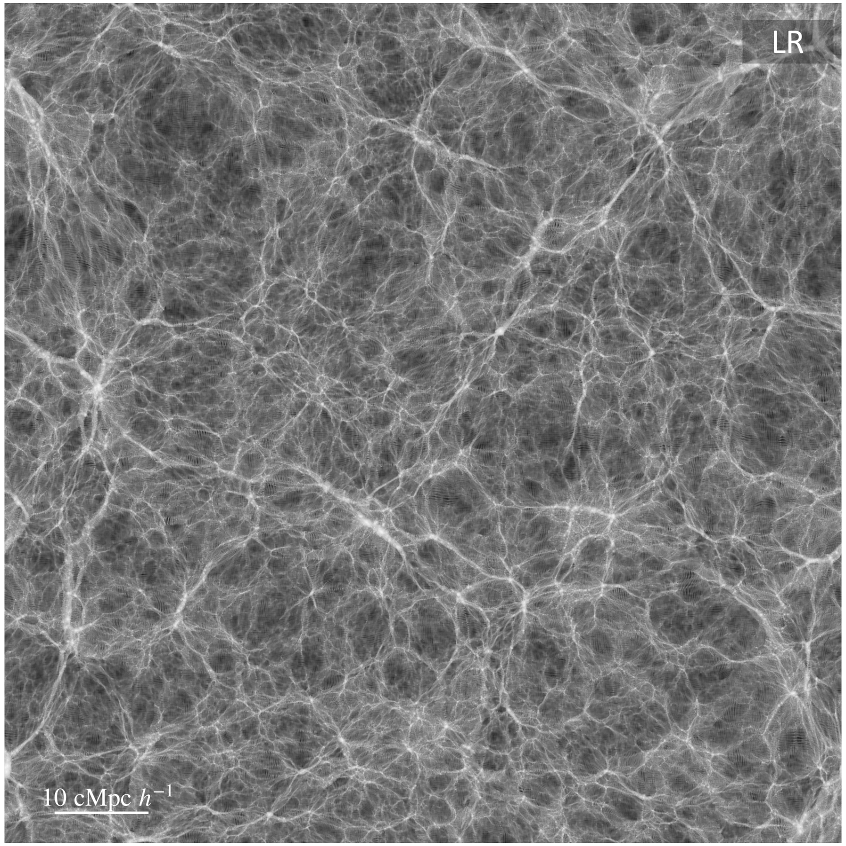

Emulator for upscaling on the field level
→ creation of large HR mocks

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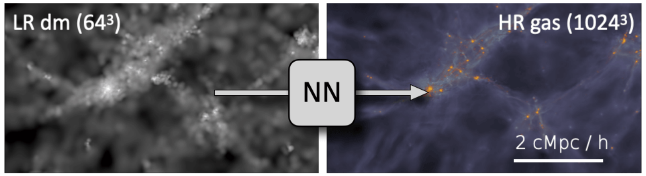

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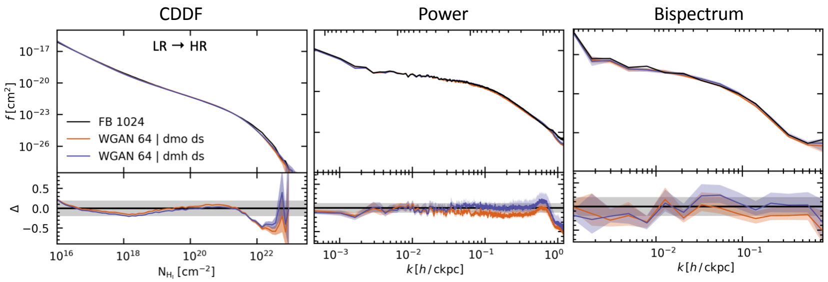

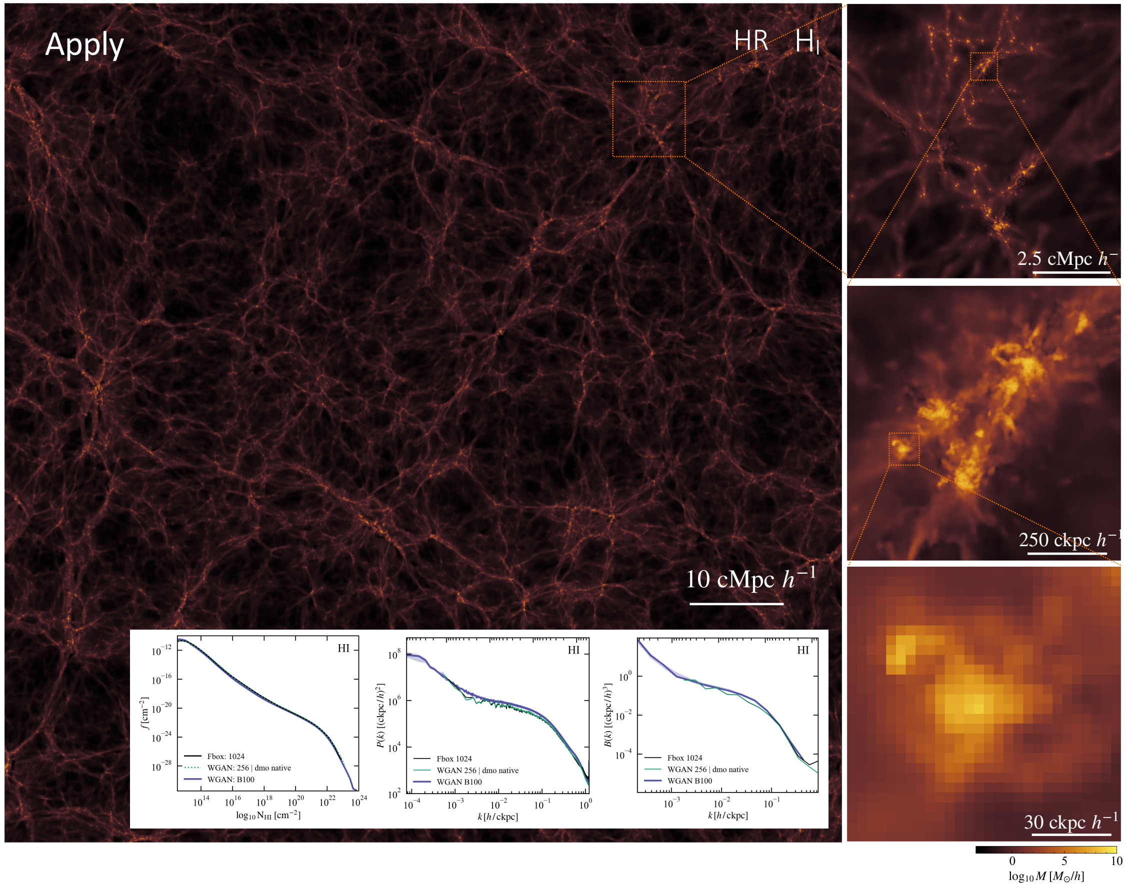

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SUMMARY

- Advantages

  + Fast! (10^3 x faster than simulation)

  + Emulation on the field level

  + Upscaling to larger volumes
    designed to emulate HR gas for large volumes

  + Captures stochasticity: infinte realizations possible

- Disadvantages

  - Not scale-free
    Need to retrain for different pixel and mass resolutions

  - Black box approach
    which dm features are key for the emulation?

- Limitations

  + Dataset specific: need to retrain for different simulations, cosmologies, resolutions, etc. (vs. semi-analytical models)

  + Completely data driven:
    learns by experience, not directly trained on the physics

- Future improvements

  o Extend to more target fields: H_2, stars, etc.

  o Include additional dm predictors
    dynamical information (e.g. velocity dispersion)

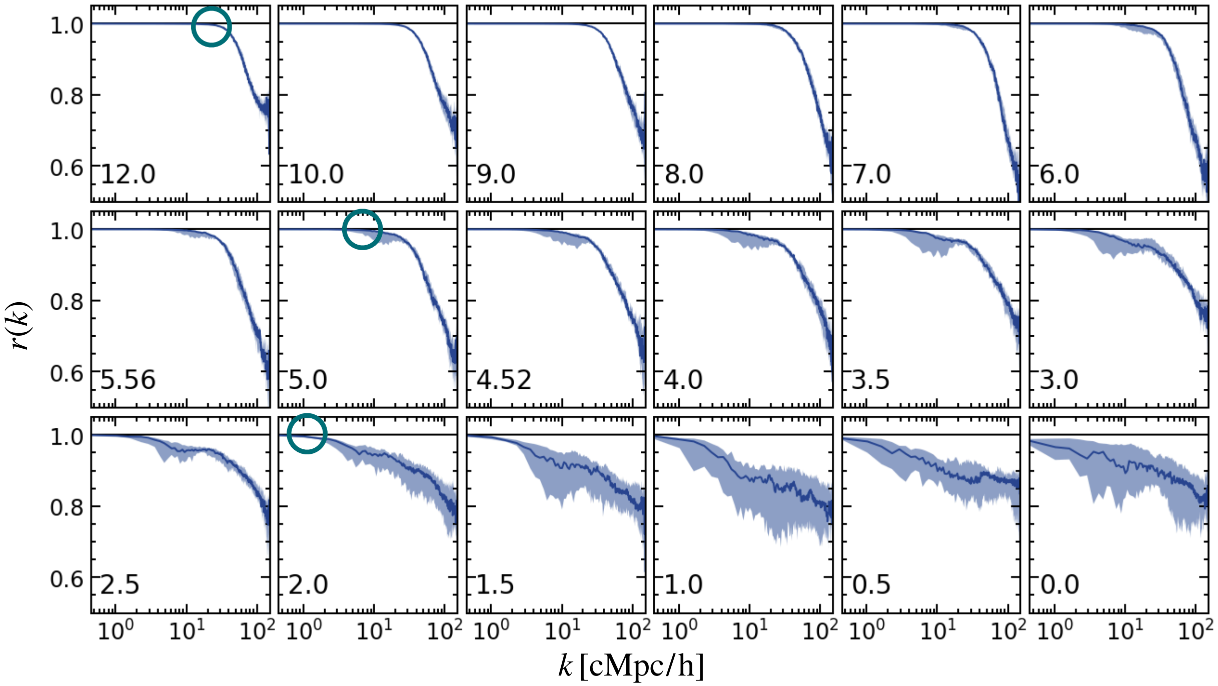
  o Synthesize information from multiple snapshots
    interpolate along time axis

MB+ (2021): *From EMBER to FIRE: predicting high resolution baryon fields from dark matter simulations with Deep Learning*
arxiv.org/abs/2110.11970

BACKUP SLIDES

SPECTRAL ASPECTS

- Power Spectrum: $P(k) \sim < \delta_k \delta_{k'} >$
  - Histogram of Fourier amplitudes
  - Fourier transform of the 2-point correlation function
- Cross correlations: $r(k) = P_{mb}/(P_m P_b)^{1/2}$
  - which scales are directly correlated?
  - decoupling scale → importance of stochasticity
- Bispectrum: $B(k) \sim < \delta_k \delta_{k'} \delta_{k''} >$
  - sensitive to Fourier phase shifts



The correlation from Dark Matter to Baryons is both deterministic and stochastic, depending on the scale of interest!

UPSAMPLING MODELS: PERFORMANCE