



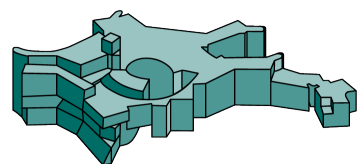
Deep learning insights into cosmological structure formation

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Cosmology From Home, 5 – 16 July 2021



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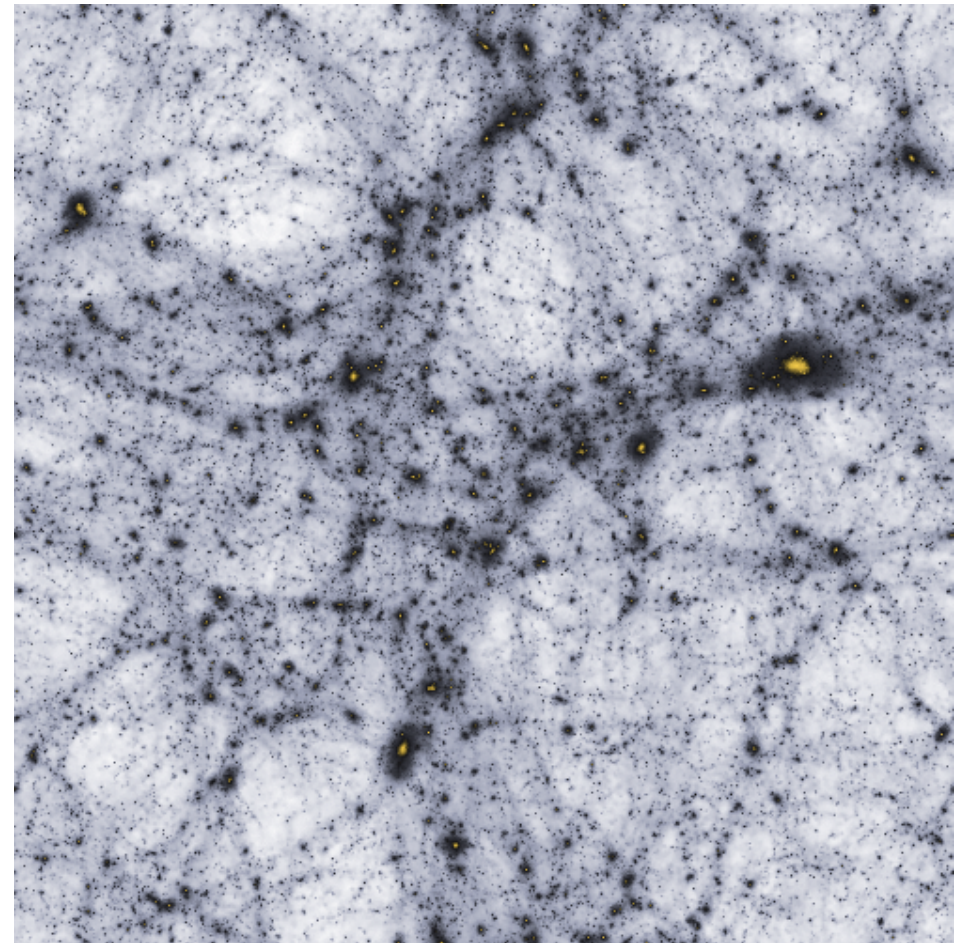
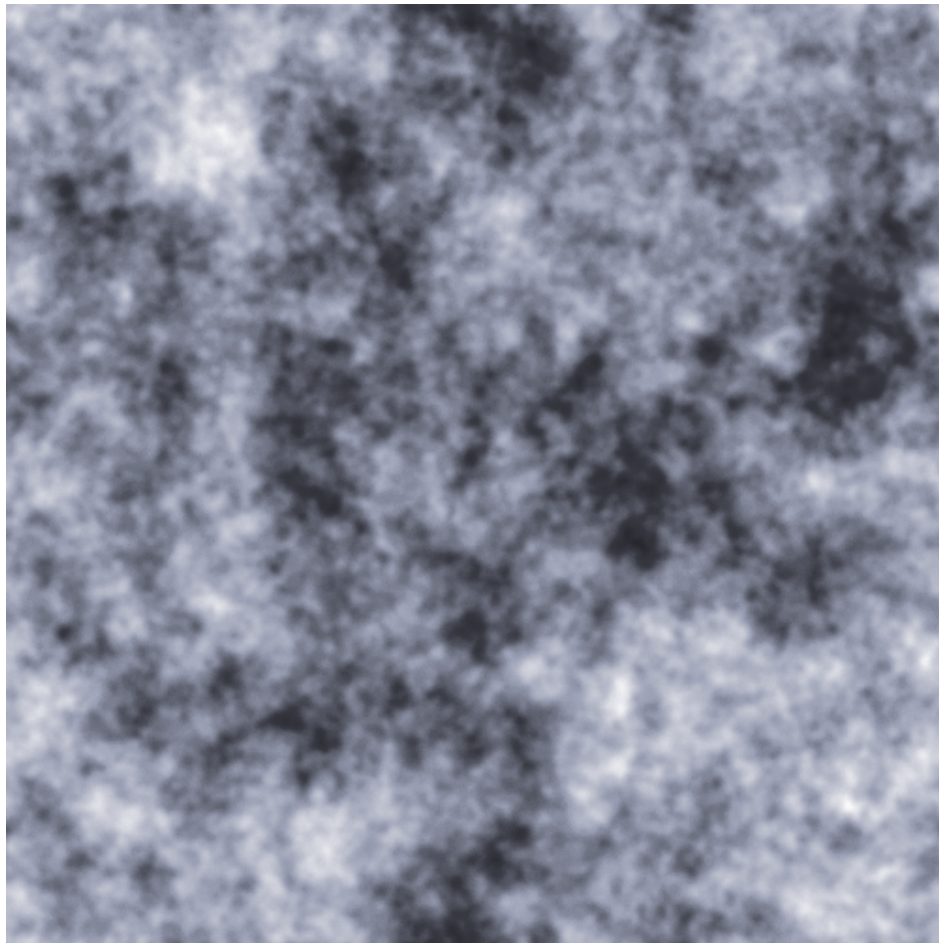
European Research Council

Outline

1. Train a deep learning algorithm to learn mapping between initial conditions and final cosmic structures from N-body simulations
2. Develop techniques to physically interpret the learnt mapping
3. Gain new knowledge about the underlying physics of cosmological structure formation

Cosmological structure formation

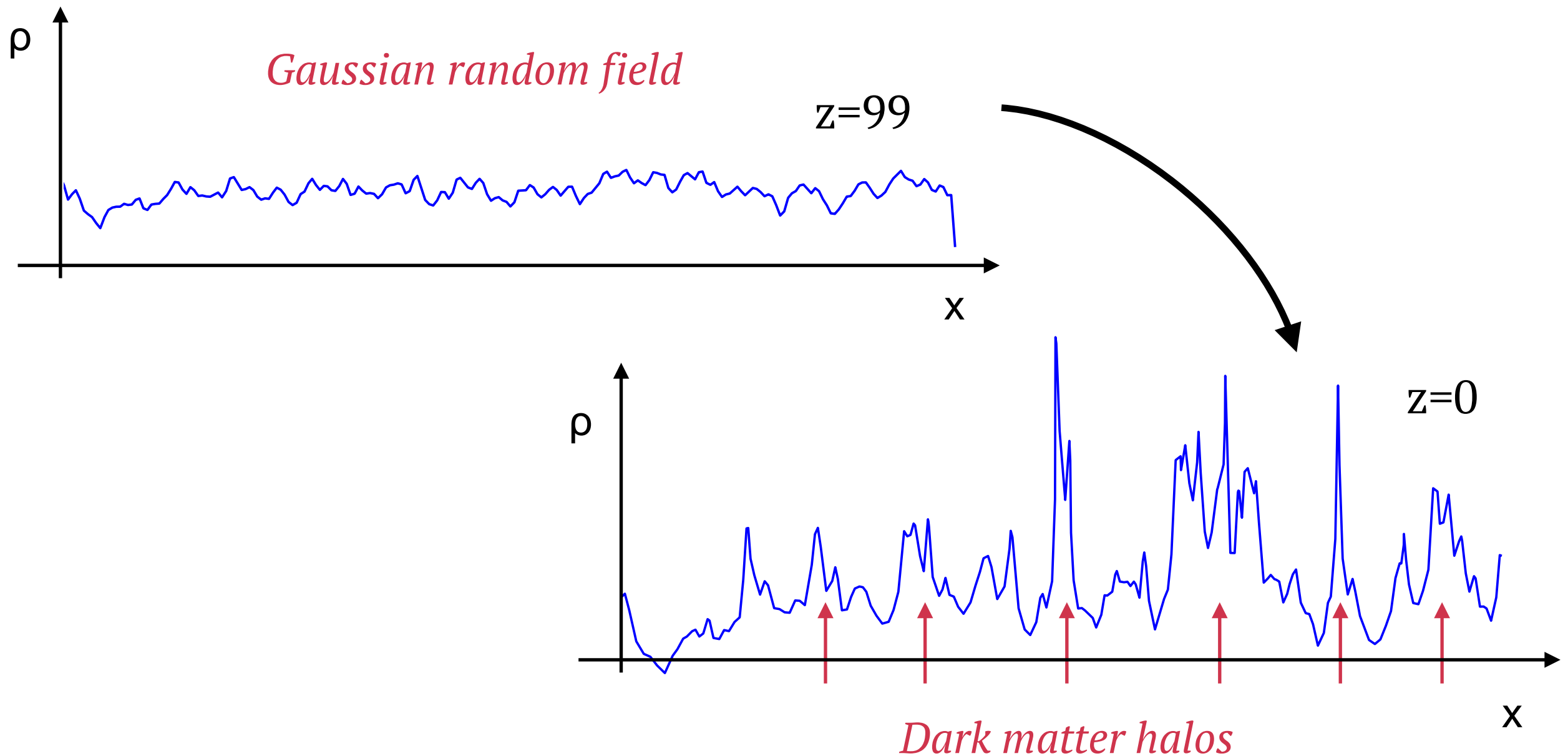
Λ CDM model successfully describes evolution of matter in Universe



*Perturbations in the density of
matter at early times*

*Today's large-scale
structure*

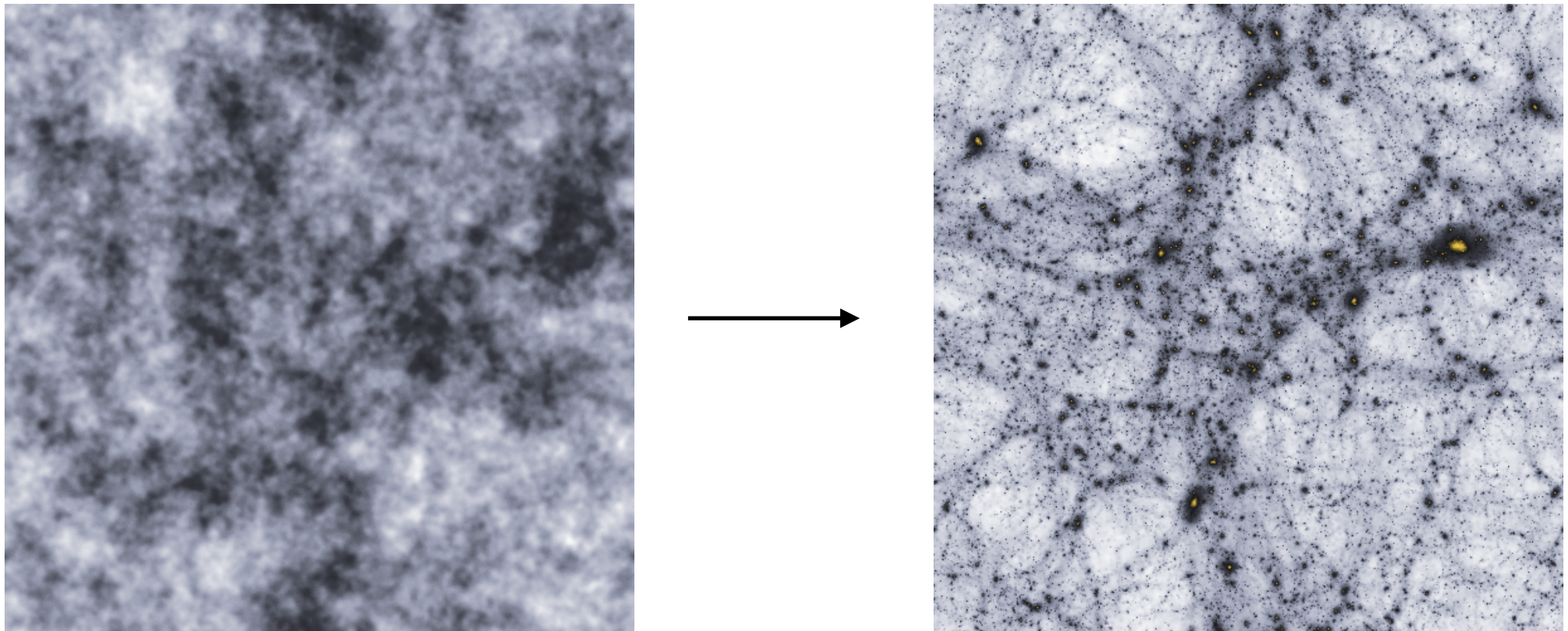
Dark matter halo formation



- **N-body simulations:** most accurate method but difficult to *physically interpret*
- **Analytic models:** provide *qualitative* understanding due to limited model complexity

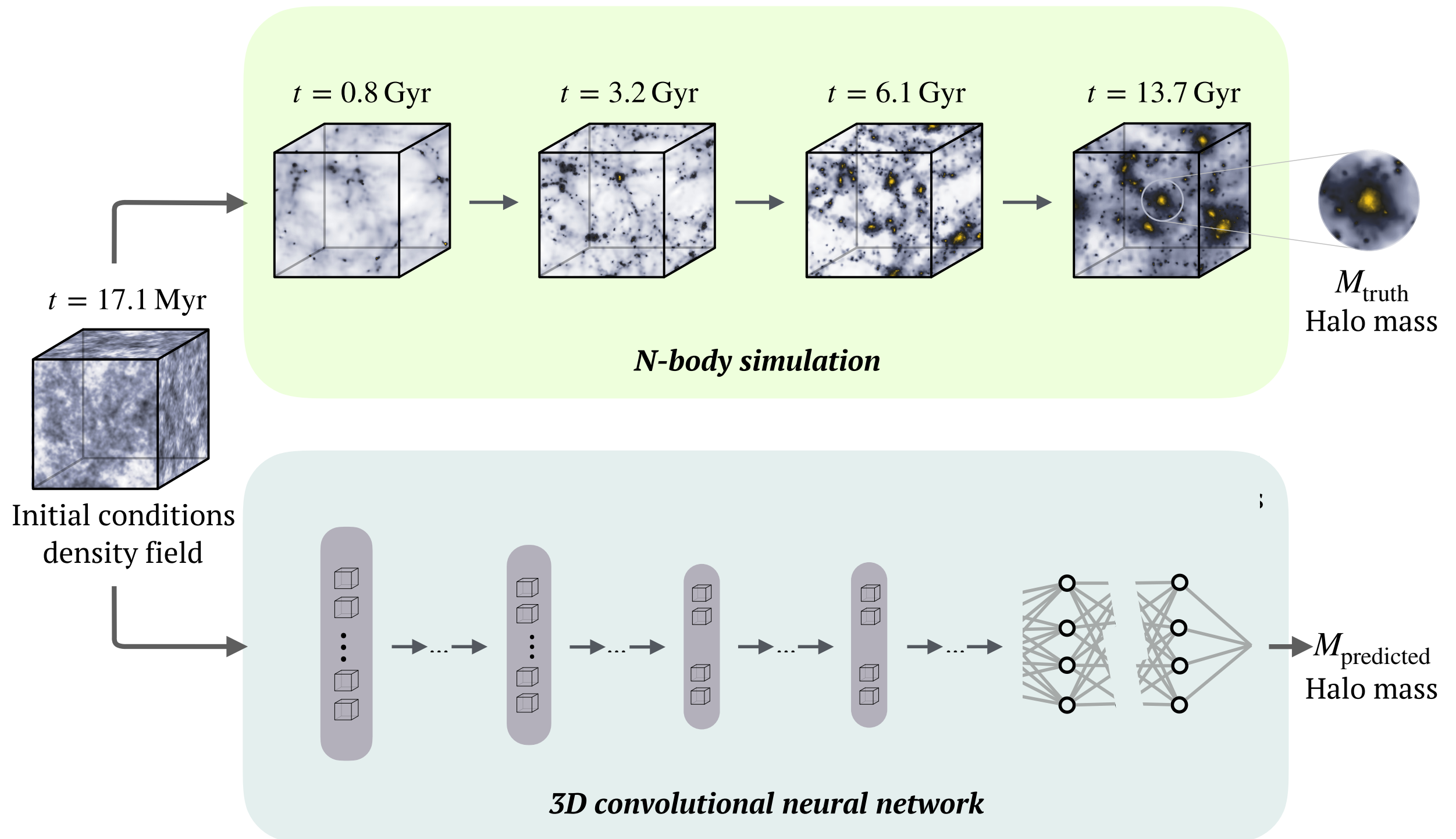
Insights into dark matter halo collapse from ML?

Approach: Train ML algorithm to learn mapping between initial conditions and dark matter halos from N-body simulations

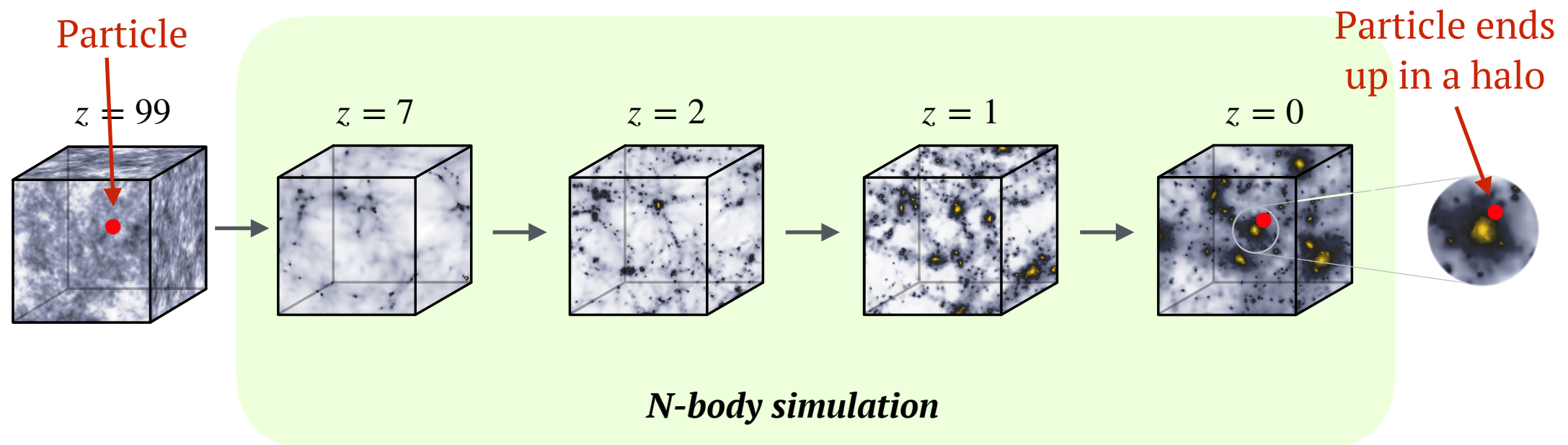


Aim: gain new physical insights into dark matter halo formation

A deep learning (DL) approach to halo formation

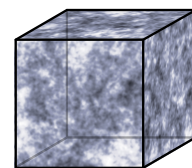


ICs-to-halo mass mapping for every particle

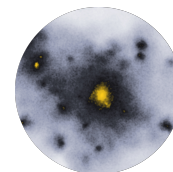


Input:

Initial density field centred on particle's position



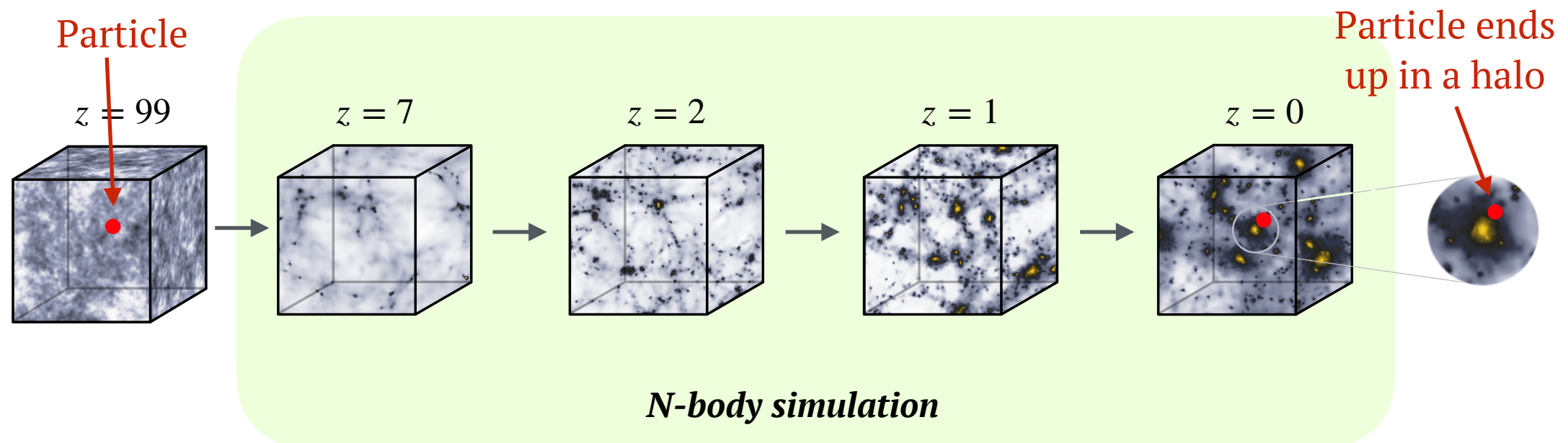
CNN



Output:

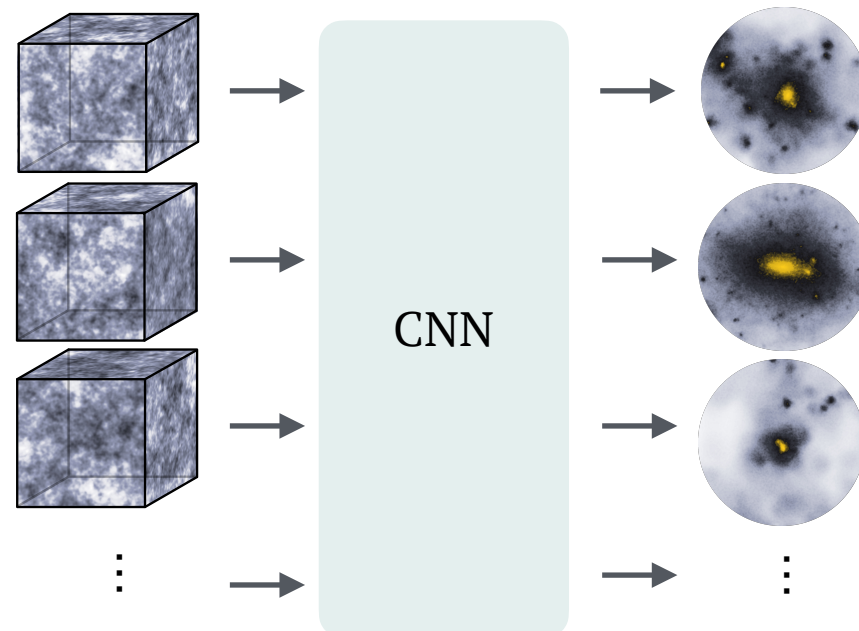
Mass of halo to which particle belongs at $z = 0$

Construct ICs-to-halo mass mapping for every particle



Input:

Initial density field centred on particle's position

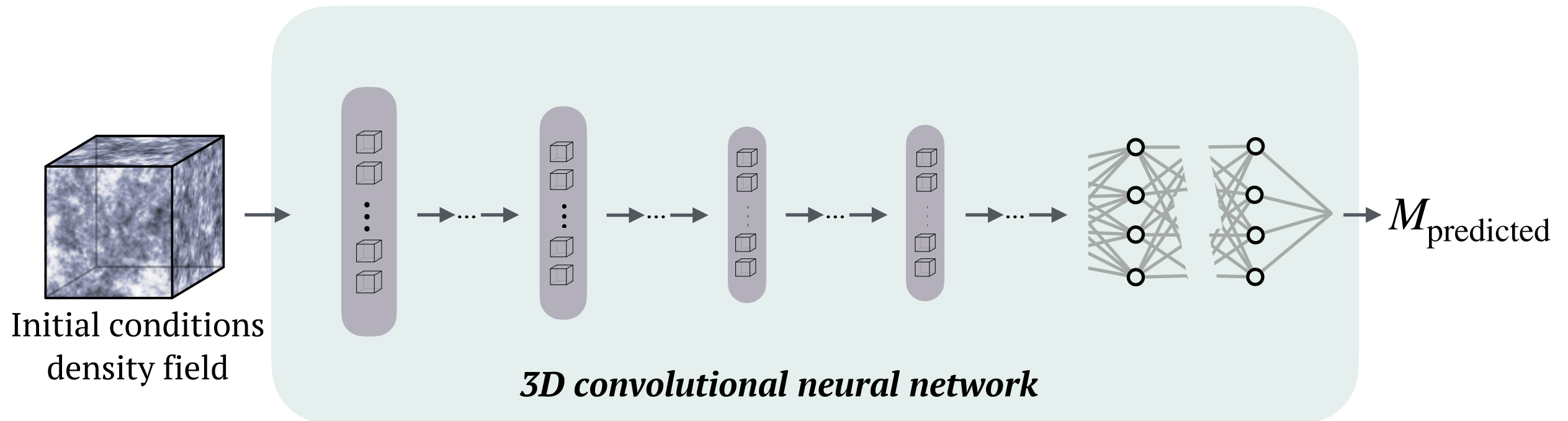


Output:

Mass of halo to which particle belongs at $z = 0$

By training network on many particles across many simulations, model learns to identify aspects of initial density field relevant to final halo mass

Why convolutional neural networks?



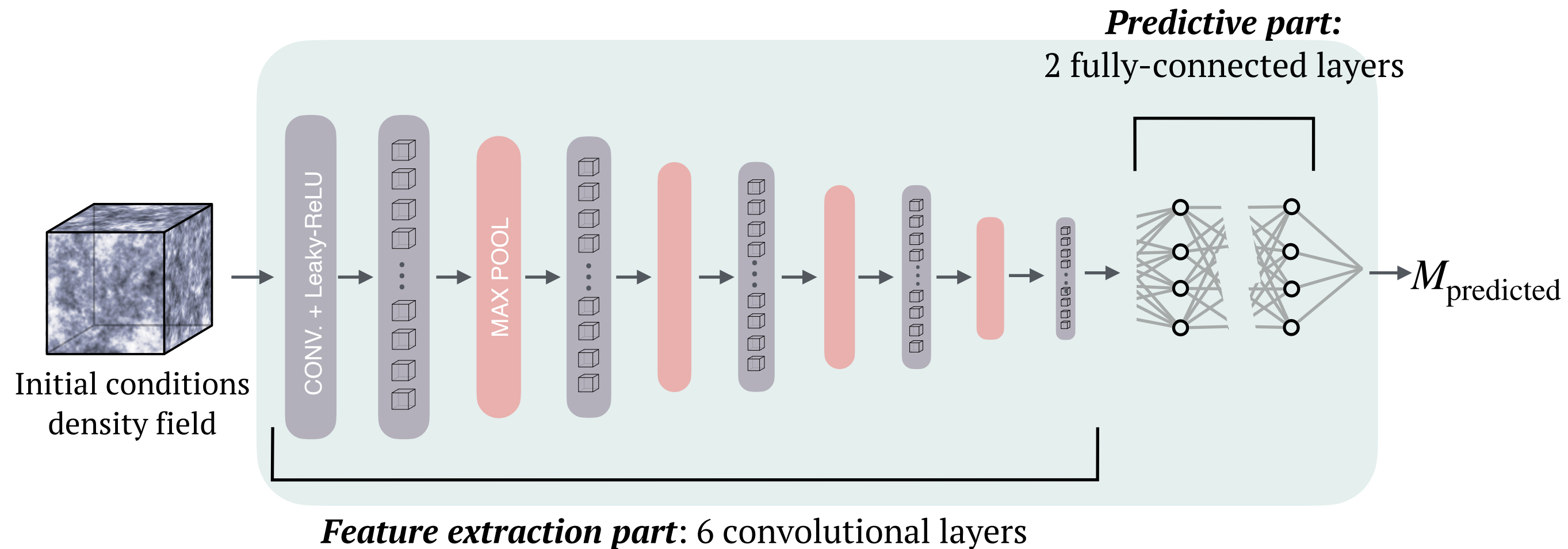
Advantages:

- no *featurization*: CNN learns directly from ICs “raw data”
- CNN identifies which ICs features are relevant for halo mass

Disadvantages:

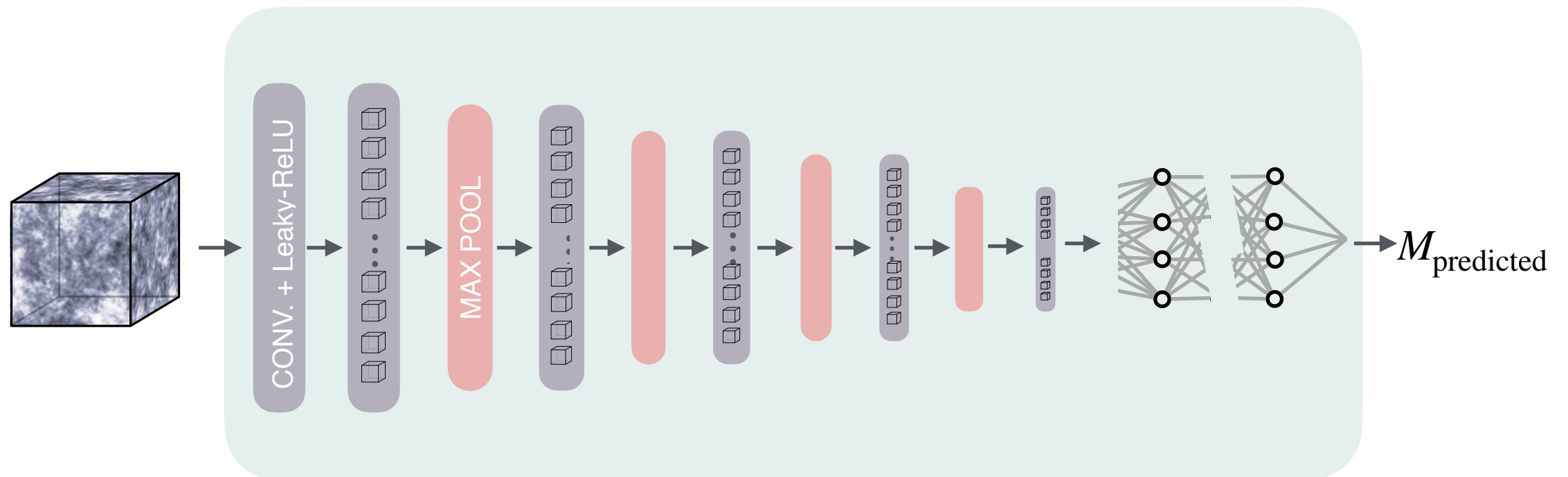
- DL algorithms are “black-box” algorithms
- *how do we extract physical knowledge from a DL algorithm?*

The CNN model



- Input convolved with kernels, s.t. each kernel detects a specific feature
- Features extracted hierarchically: low-level to high-level features

Training the CNN model



Find the set of parameters \vec{w} that minimise the loss function:

$$\text{Loss} = \mathcal{L}_{\text{pred}}(M_{\text{true}}(x), M_{\text{predicted}}(x, w)) + \mathcal{L}_{\text{reg}}(w)$$

Predictive term:

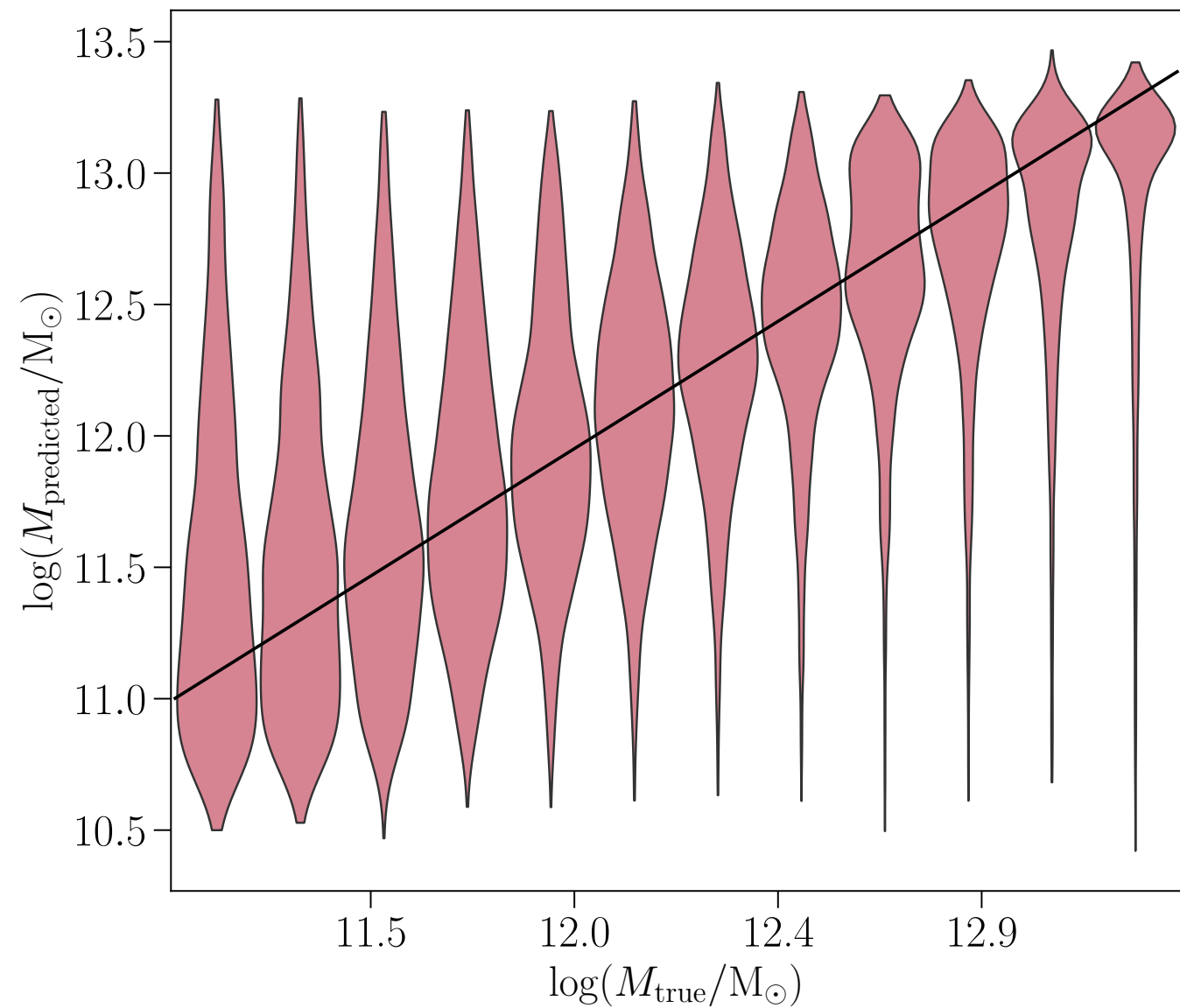
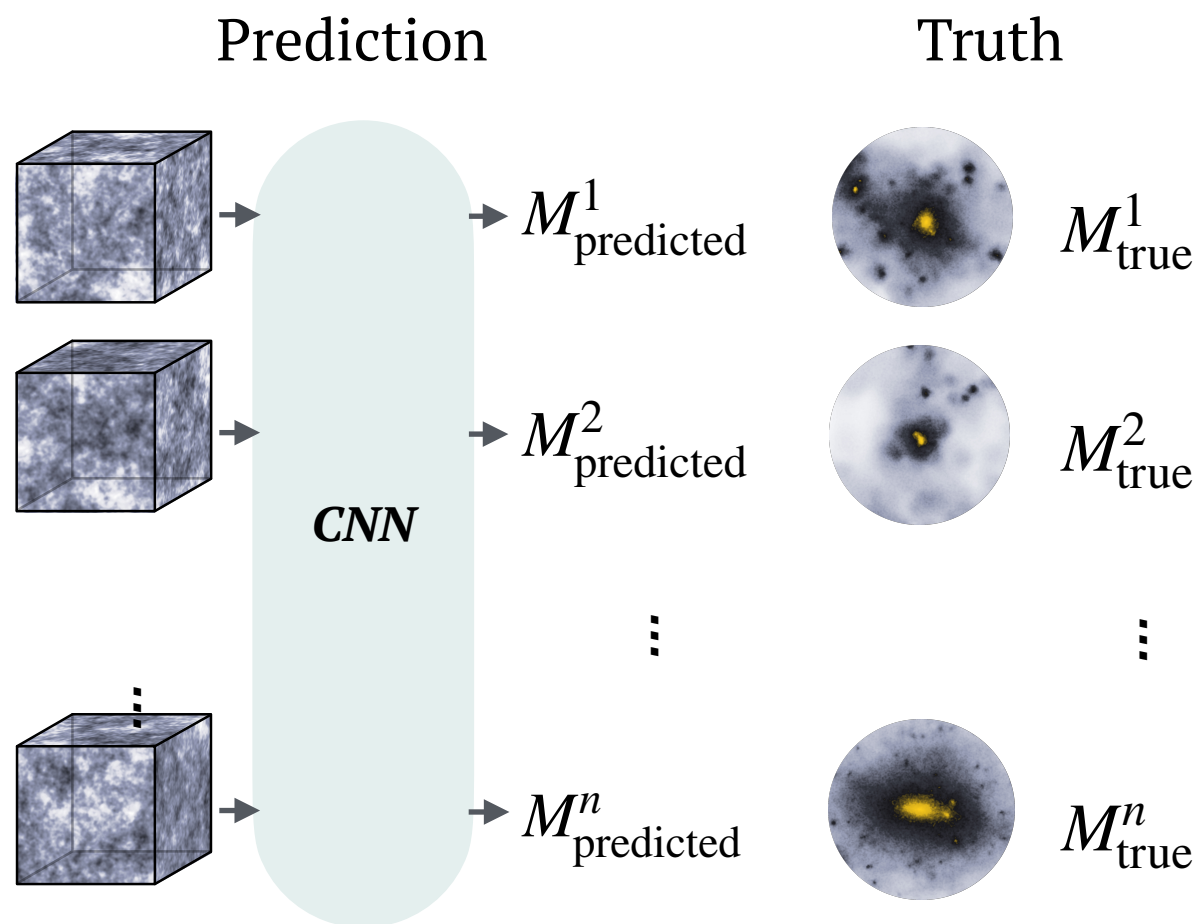
Negative log of a Cauchy likelihood

Regularization term:

Priors on the weights to
(i) regularise network & reduce overfitting
(ii) compress the model (sparsity)

Halo mass predictions from the initial conditions

Test model on dark matter particles from independent simulations



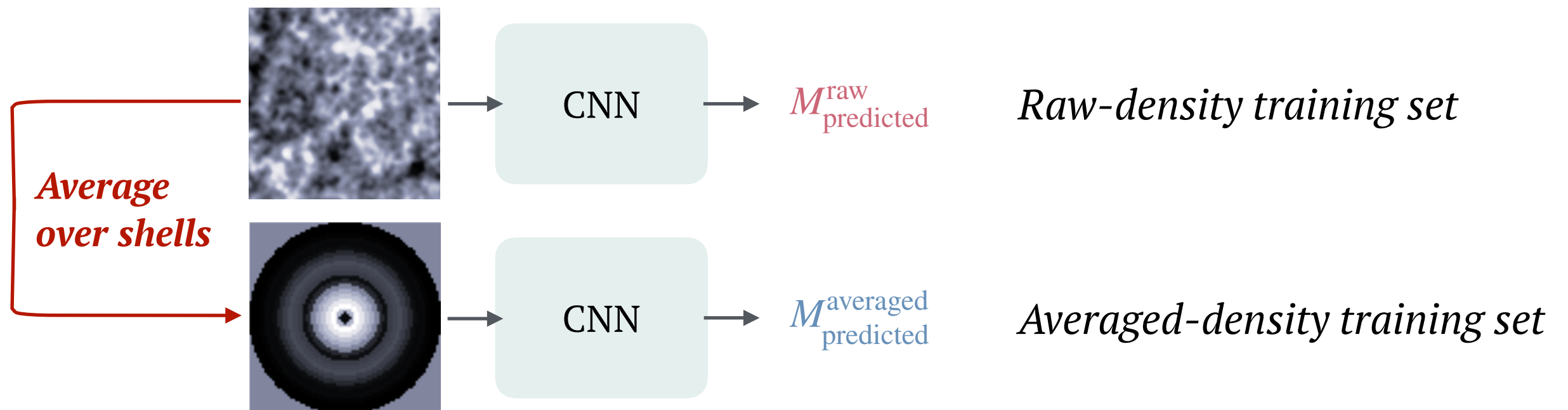
Interpreting the DL model

Interpretability technique:

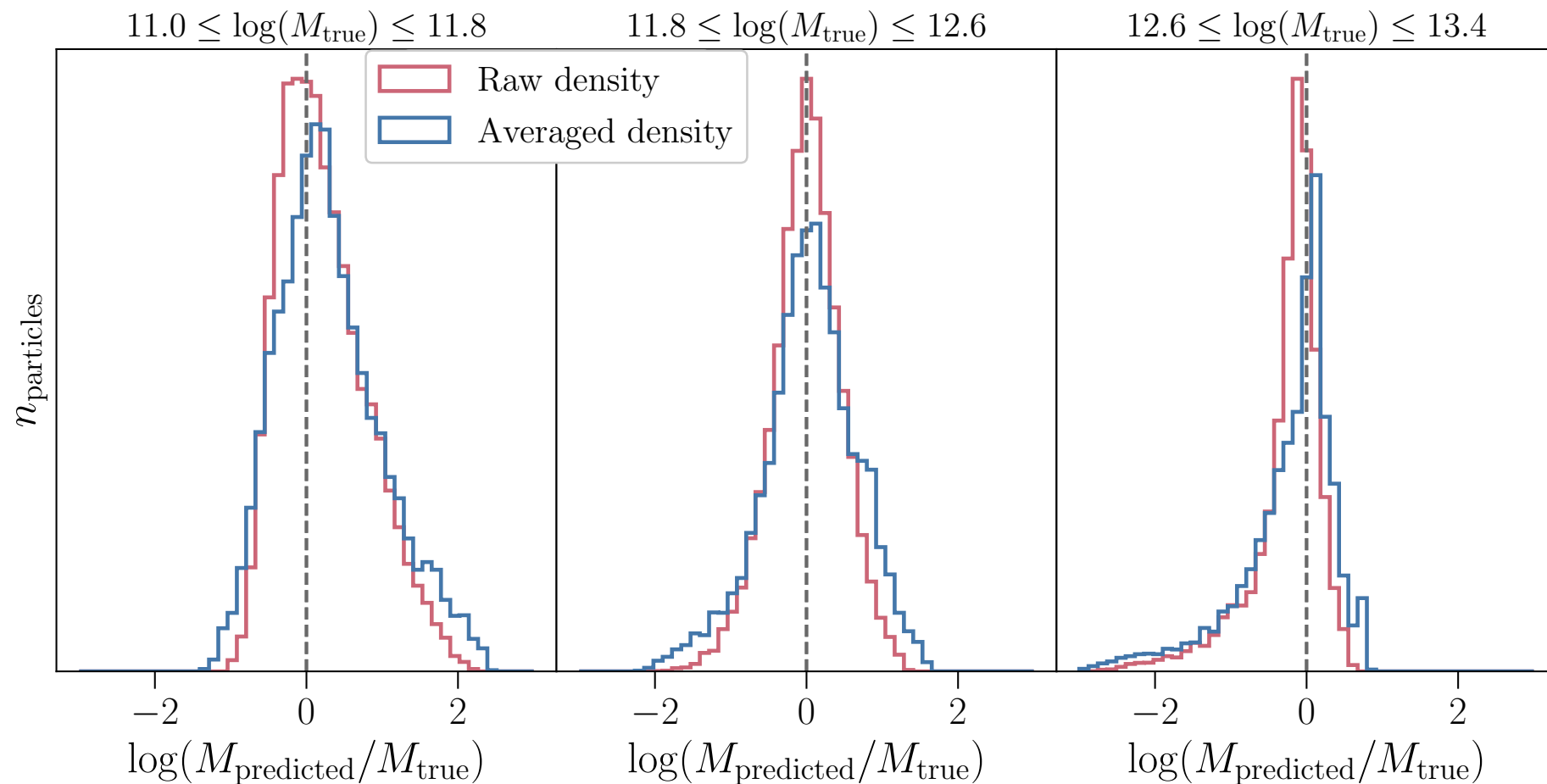
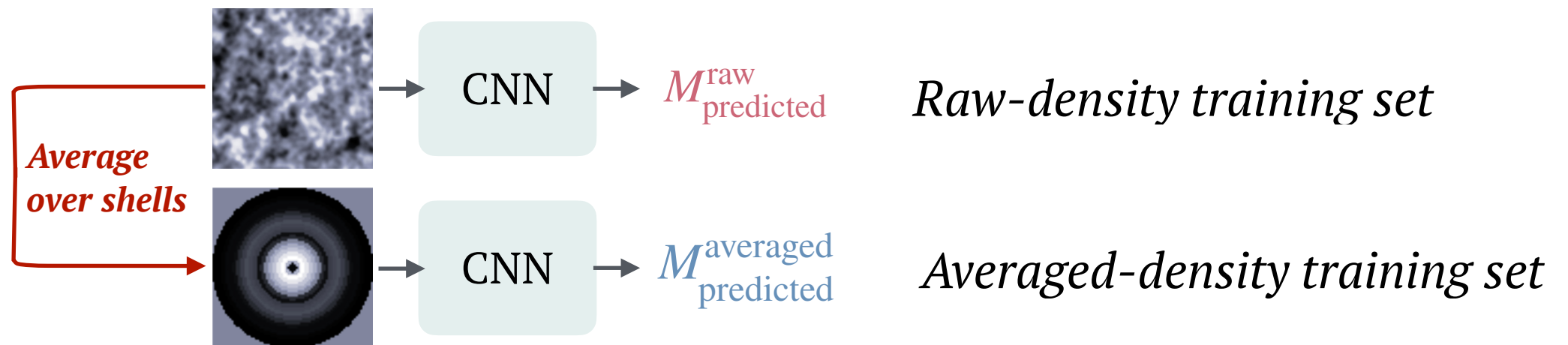
1. Remove part of the information carried by inputs & re-train model
2. Measure the resulting change in the model's performance.

Application:

1. Remove anisotropic information from the initial density field



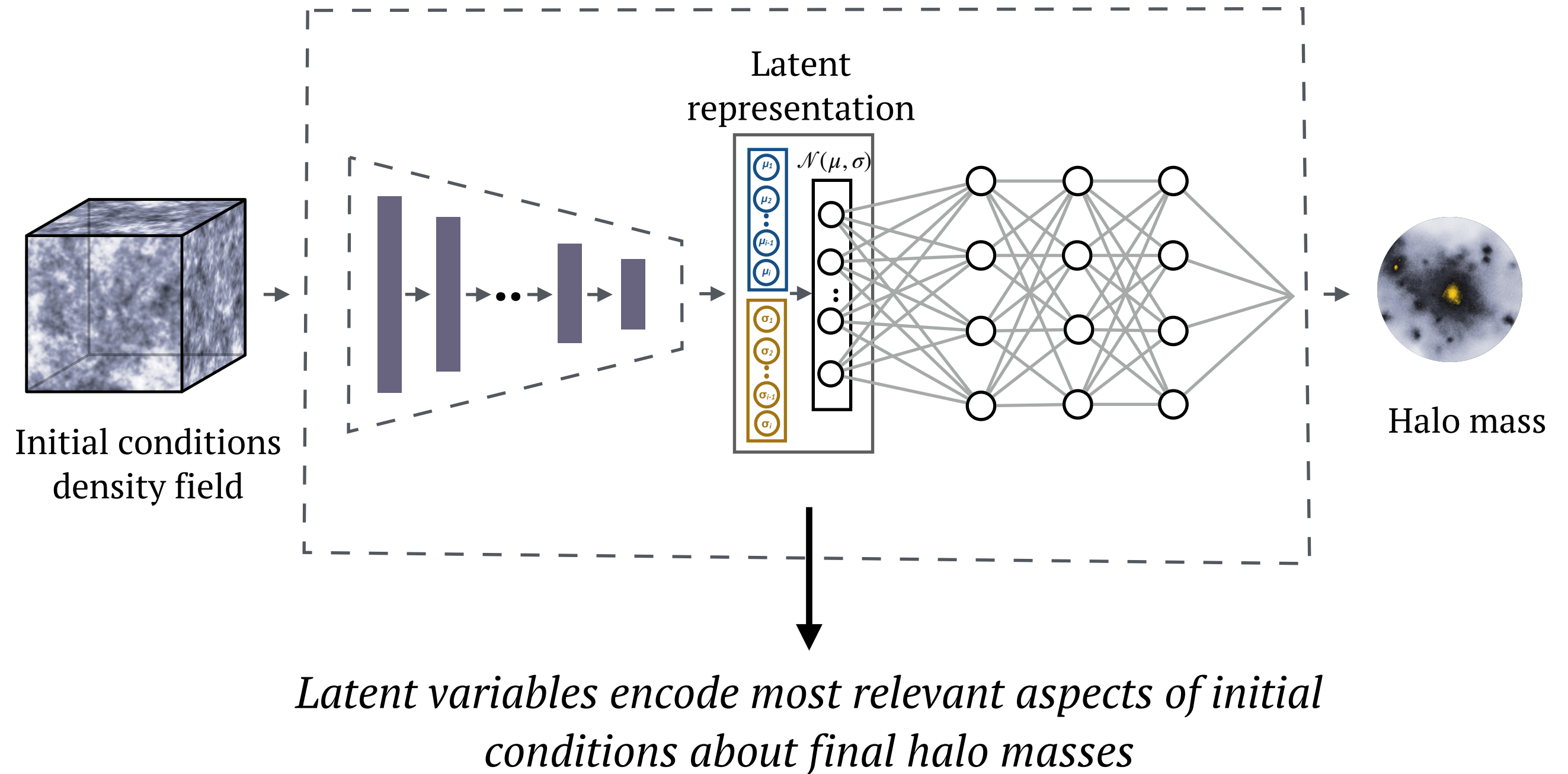
Interpreting the learnt mapping between ICs and halos



Anisotropic information plays no role in establishing final halo masses

Work in progress: knowledge extraction

Supervised variational encoder



Conclusions

- Interpretable DL framework enabled new insights into role of anisotropic information in initial density field in establishing final halo masses
- **Work in progress:** employing “supervised variational encoder” to extract new physical knowledge about cosmological structure formation
- **Future work:** application to other properties of halos & other cosmic structures such as voids

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