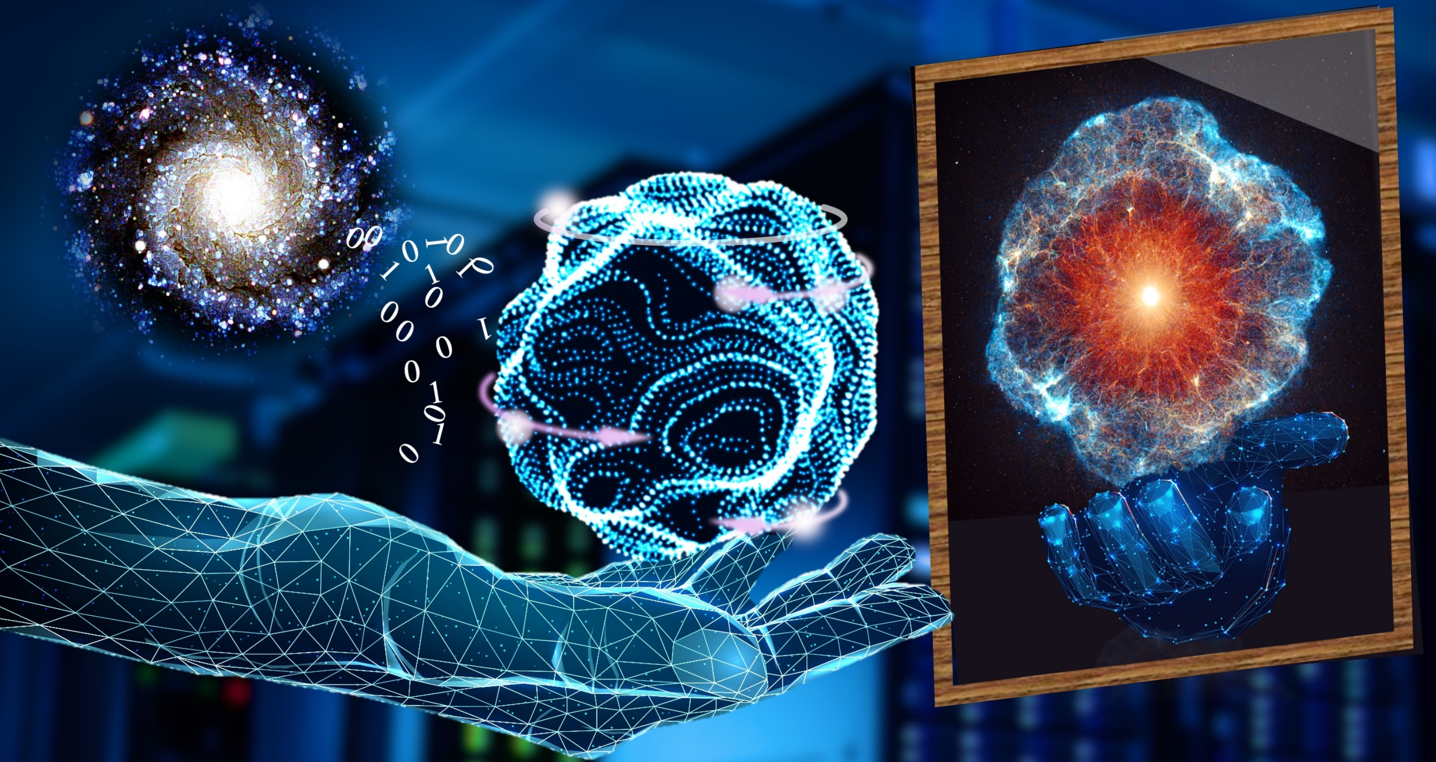

超新星フィードバックのためのサロゲートモデルの開発

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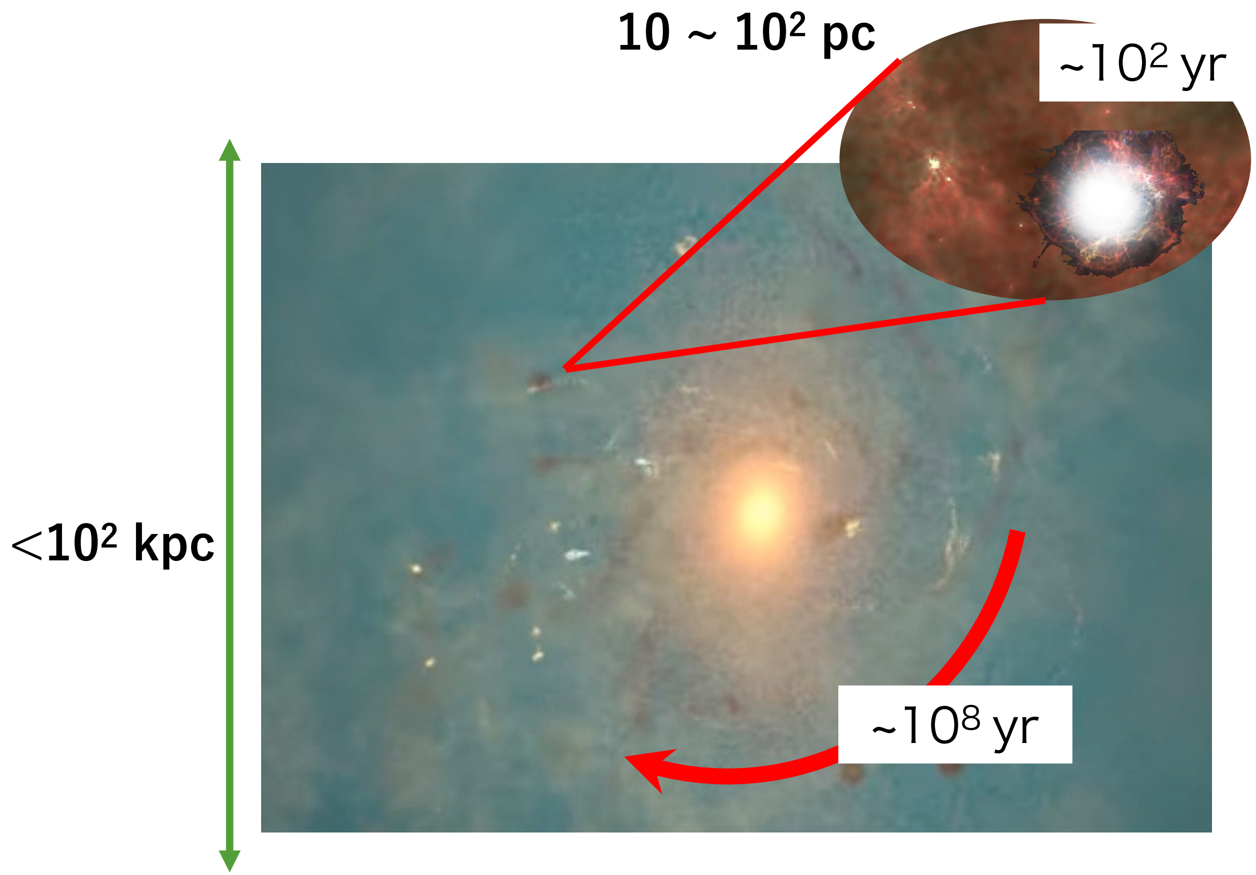
2023/09/06

シミュレーション天文学のこれまでとこれから

Galaxy Simulations Using SPH*



The formation of the galaxy [1].

*SPH: Smoothed Particle Hydrodynamics

[1] https://www.youtube.com/watch?v=DDsUXRfs6ZQ
[2] Applebaum et al. (2021)
[3] Grand et al. (2021)

ASURA-FDPS (N-body/SPH)

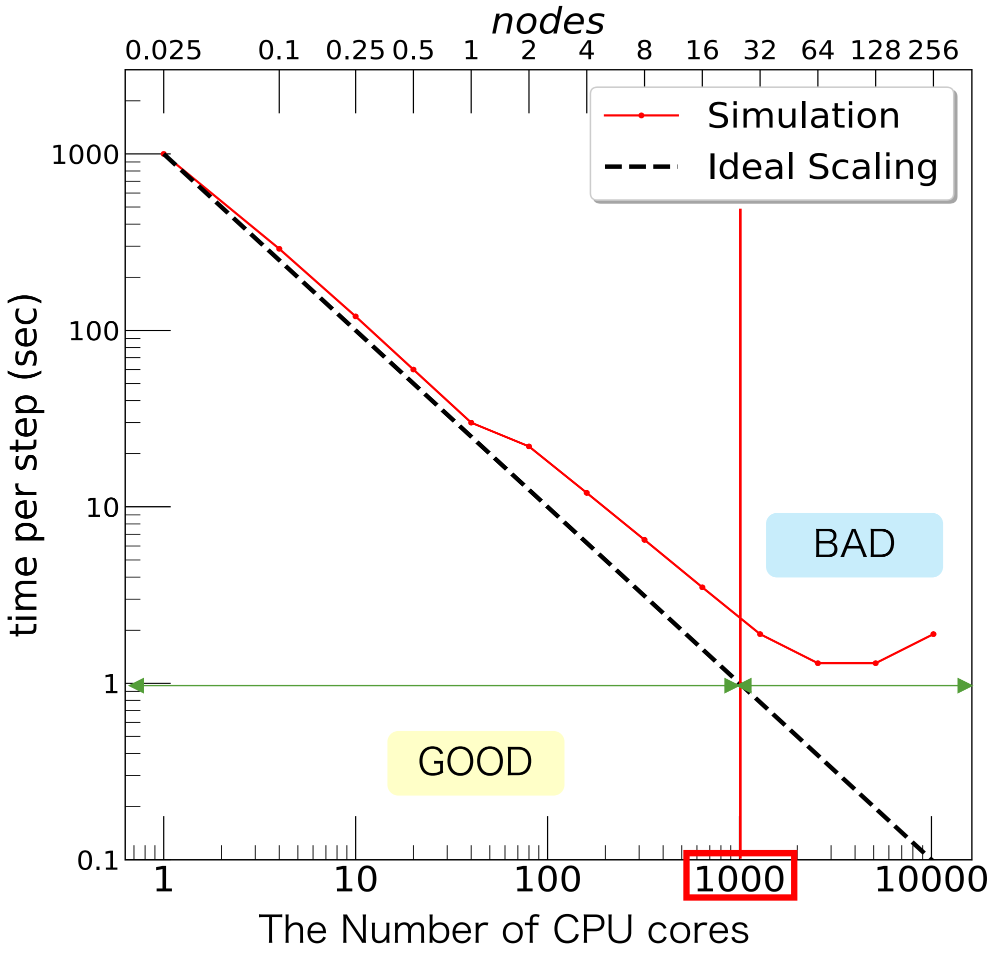
(based on Saitoh+08,09, Iwasawa+16)

- Gravity + Hydrodynamics
  - (DISPH; saitoh+13)
- Radiative Cooling/Heating (Ferland+17)
- Star formation (Hirai in prep.)
- Feedback
  - SNe Ia/IIb, AGB, Neutron star merger
- Chemical evolution (CELib; Saitoh17)
- FUV background

- About to accomplish star-by-star simulations… but…
  - Previous work [2, 3]： $10^3 M_\odot$
  - Our goal (ASURA-FDPS)： $10 M_\odot$

Overheads in Galaxy Formation Simulations

The parallelization efficiency saturates at ~10^3 CPU cores.



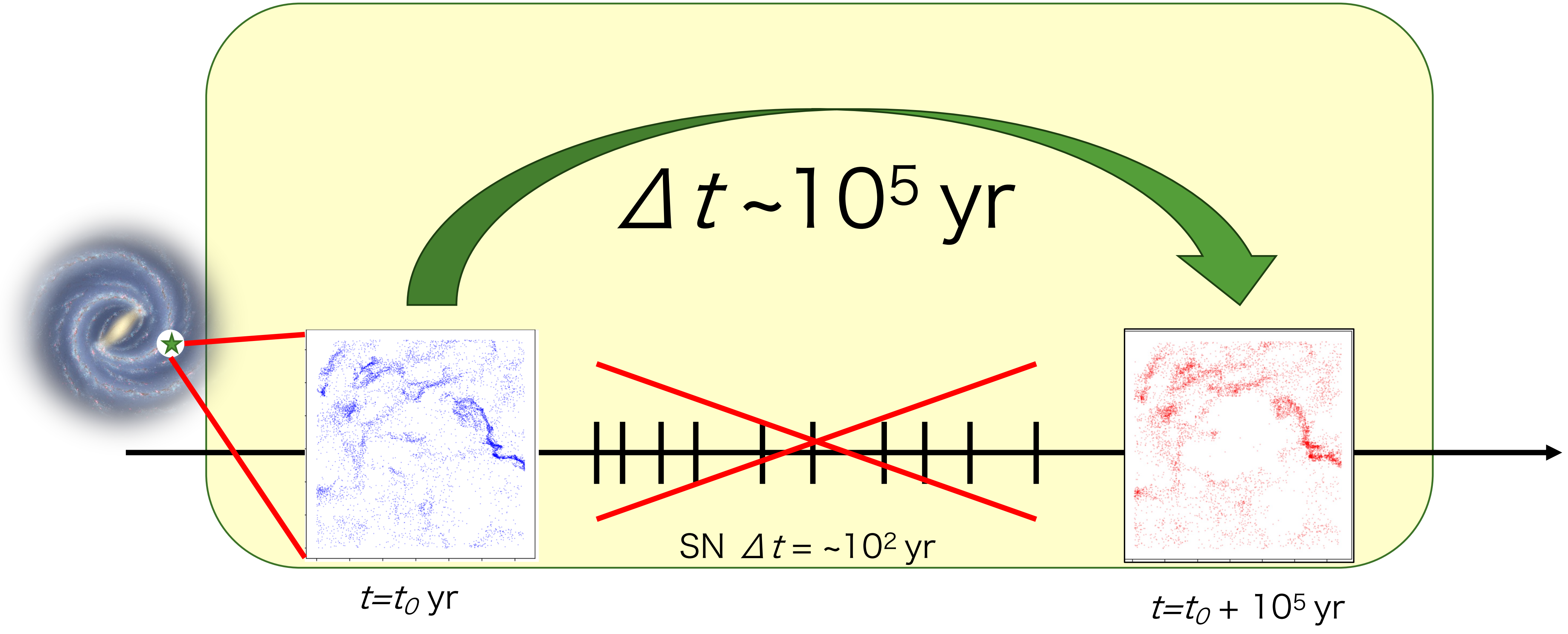
Strong Scaling of GADGET-4
(Based on Figure 63 in Springel et al. 2021)

e.g.,
- GADGET-4(Springel+21)
- DC Justice League (Applebaum+21)
- Fire-2(Hopkins+18)

- Individual Time-stepping
  - Short timescale phenomena (e.g. SNe) require small timesteps.
- Load Imbalance
  - The time for the communication become more significant than the benefit of the parallelization (cf. Amdahl's law).
- The challenge remains even if the latest supercomputers are used (e.g., Fugaku has ~10^6 CPU cores).

How can I avoid the bottleneck?

Sub-grid models



The rest of the region in the galaxy
$\Delta t \sim 10^5$ yr

An analytic method

Sub-grid model (star-by-star dwarf galaxy simulations; Hu+17, Hu19 etc)

1. Timestep: $\Delta t \sim 10^5$ yr
2. Momentum feedback

If $$m_{\rm gas} < 1680\,{\rm M}_\odot E_{51}^{0.87} n_{\rm H}^{-0.26} N_{\rm inj}^{-1}$$

Directly solve it

else:

$$p_{\rm term} = 3.3 \times 10^5\,{\rm M}_\odot\,{\rm km\,s^{-1}}\,E_{51}^{0.93} n_{\rm H}^{-0.13}$$

$$E_{\rm th}^{\rm res} = 0.72 E_{\rm SN} \left(\frac{M_{\rm inj}}{M_{\rm c}}\right)^{-2.17}$$

*Modeled using spherical clouds with a uniform density

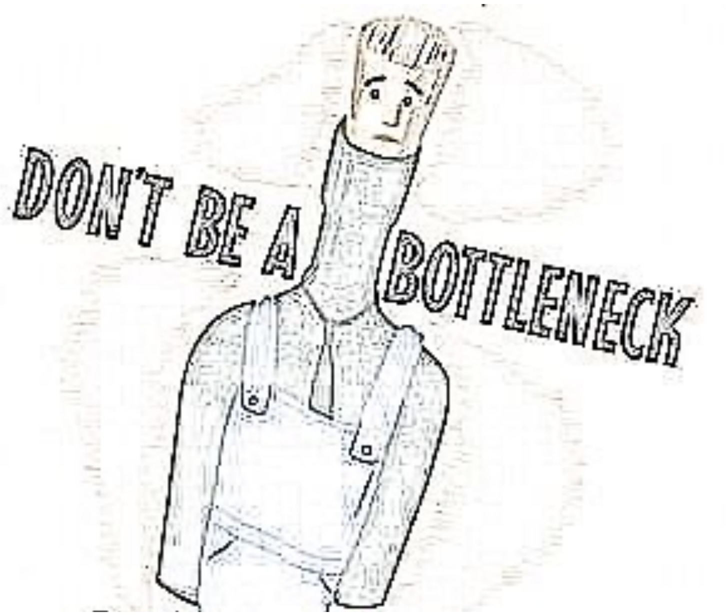
Let's learn the explosions with kernels!

Example. Edge detection

$\otimes$

0	1	0
1	-4	1
0	1	0

$=$



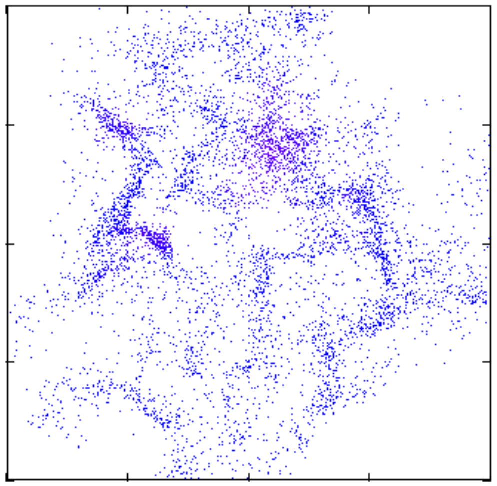
Learnable parameters
(Convolutional Neural Networks)

Training Data (3D cartesian grids)

SN simulations in inhomogeneous turbulent clouds

Temperature	10 [K]
Mean ambient density	40 ~ 60 [cm^{-3}]
Input energy	10^{51} [erg]
Total mass	10^6 [$M_\odot$]
Mass of a gas particle	1 [$M_\odot$]
Softening parameter	2 [pc]

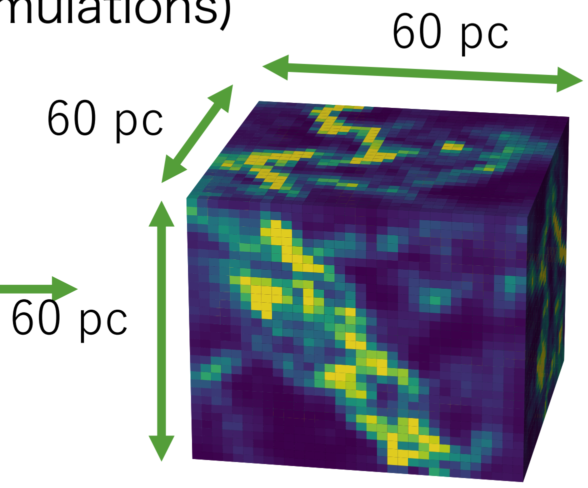
(the equivalent resolution for our galaxy simulations)



Interpolation using

SPH summation

$$\rho_i = \sum_j m_j W(r_{ij}, h_j)$$



32^3 voxels (density distribution)

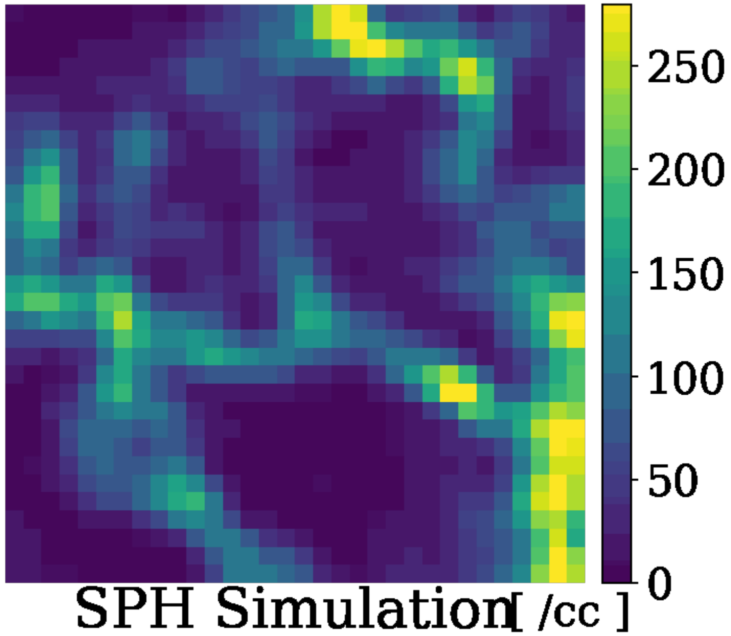
Deep Learning Model

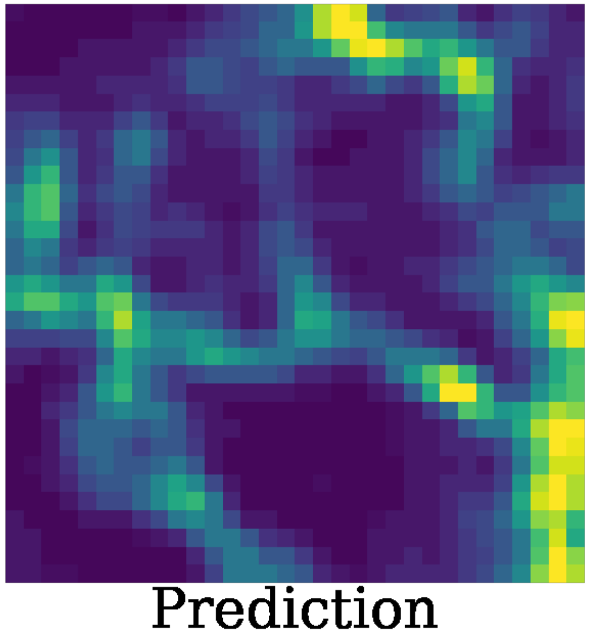
- Memory-In-Memory Network (Wang et al. 2018)
  - Generates 2D video in the future
  - Convolutional Neural Networks (CNNs)
    - Convolution is the operation like inner products.
  - Increased the dimensionality: 2D → 3D

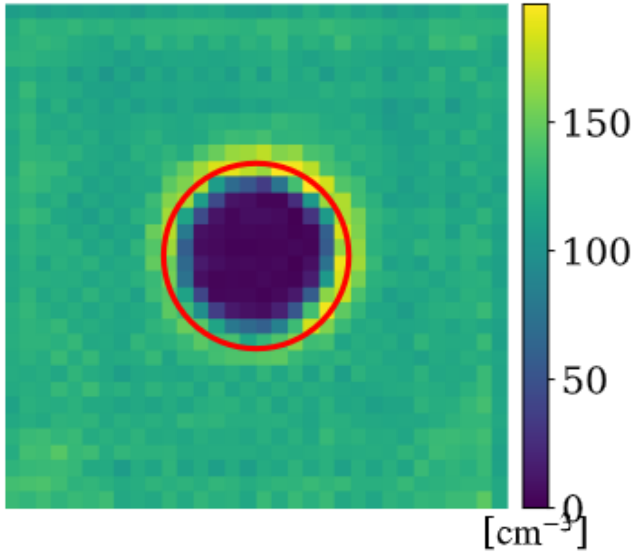
Forecasting the Evolution of the SN Shells in Density

- Taking the initial distribution, the ML model can forecast the spatiotemporal change in density due to a SN explosion.
- Duration: 0.2 Myr

$$R(t) \propto \left(\frac{E_0}{\rho_0}\right)^{1/5} t^{2/5}$$





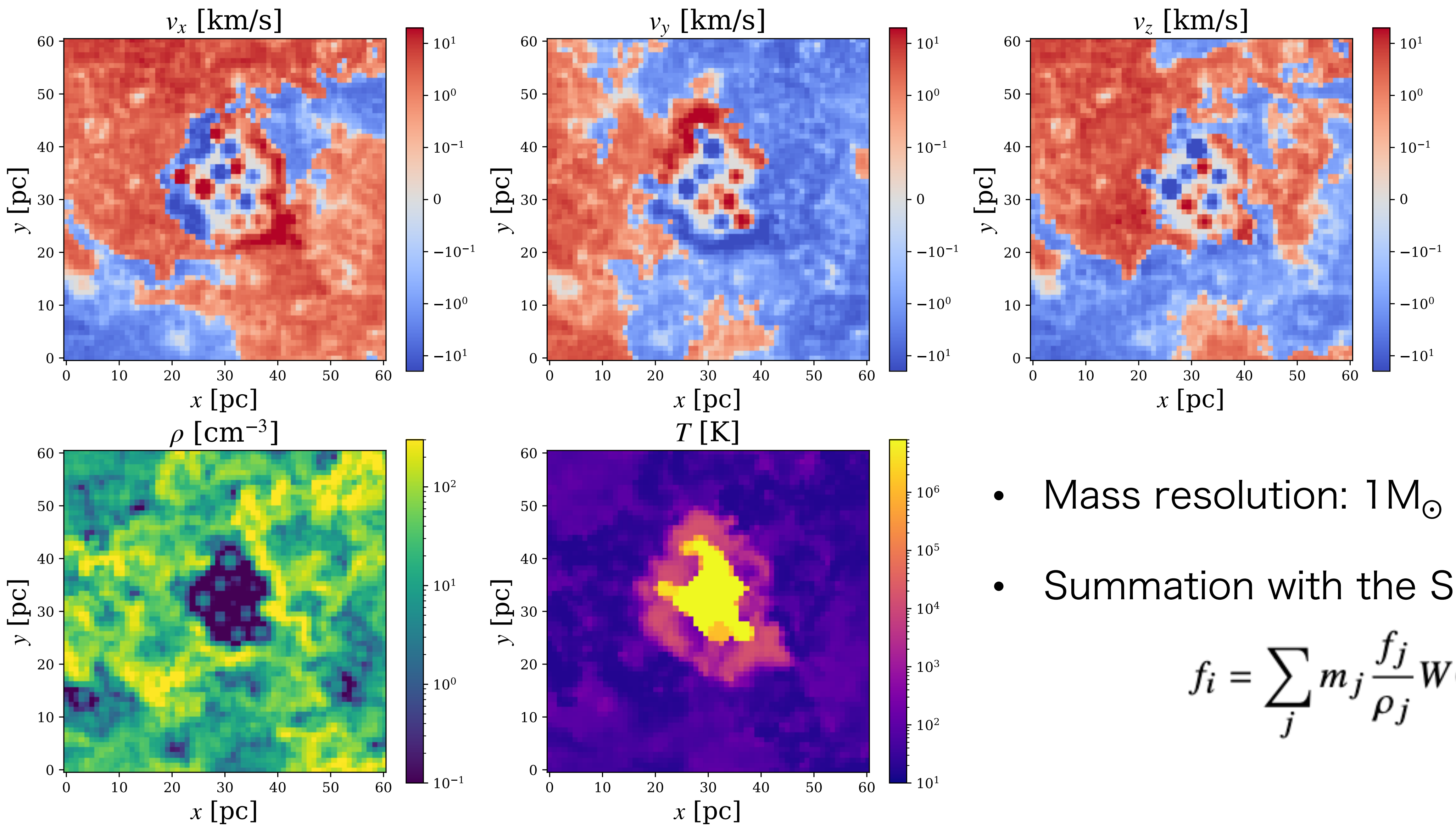


(a) Spherical

Cross section view
Left: Simulation data (ground truth)
Right: Prediction by the 3D-MIM

Hirashima et al. 2023, submitted
arXiv:2302.00026

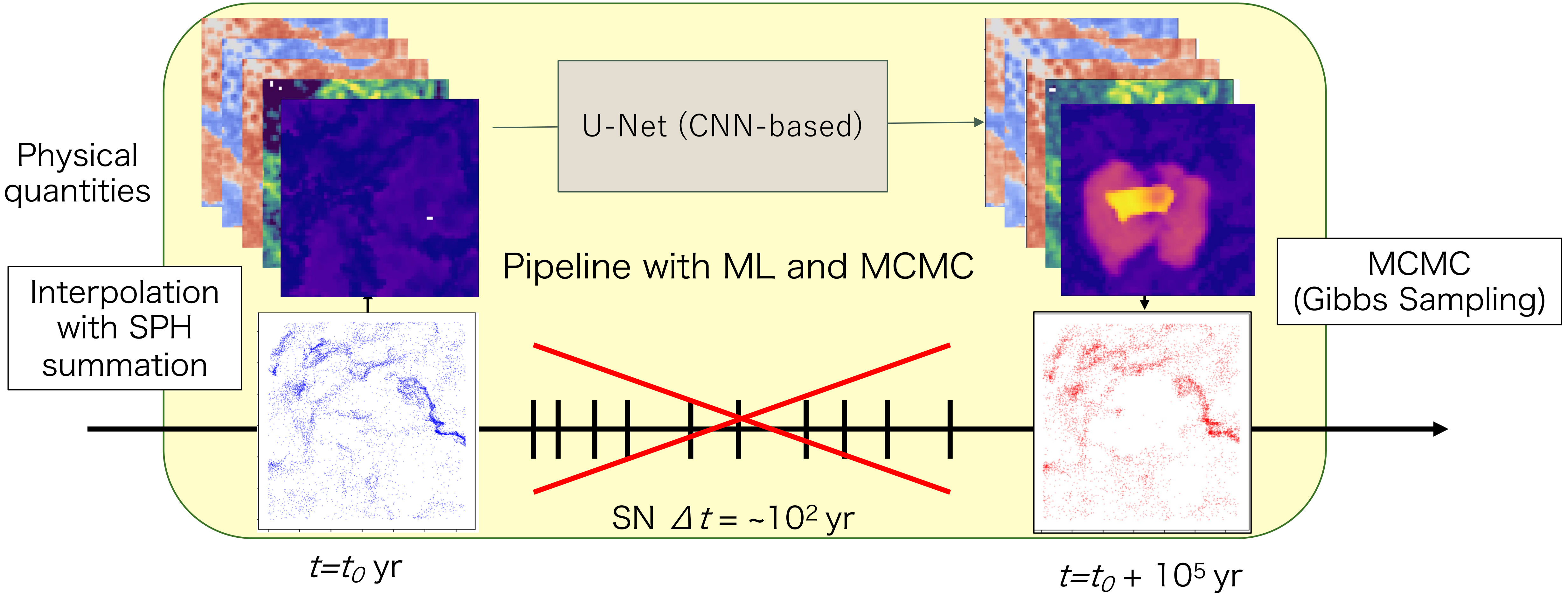
Training Data (3D cartesian grids)



- Mass resolution: $1M_\odot$
- Summation with the SPH kernel

$$f_i = \sum_j m_j \frac{f_j}{\rho_j} W(r_{ij}, h).$$

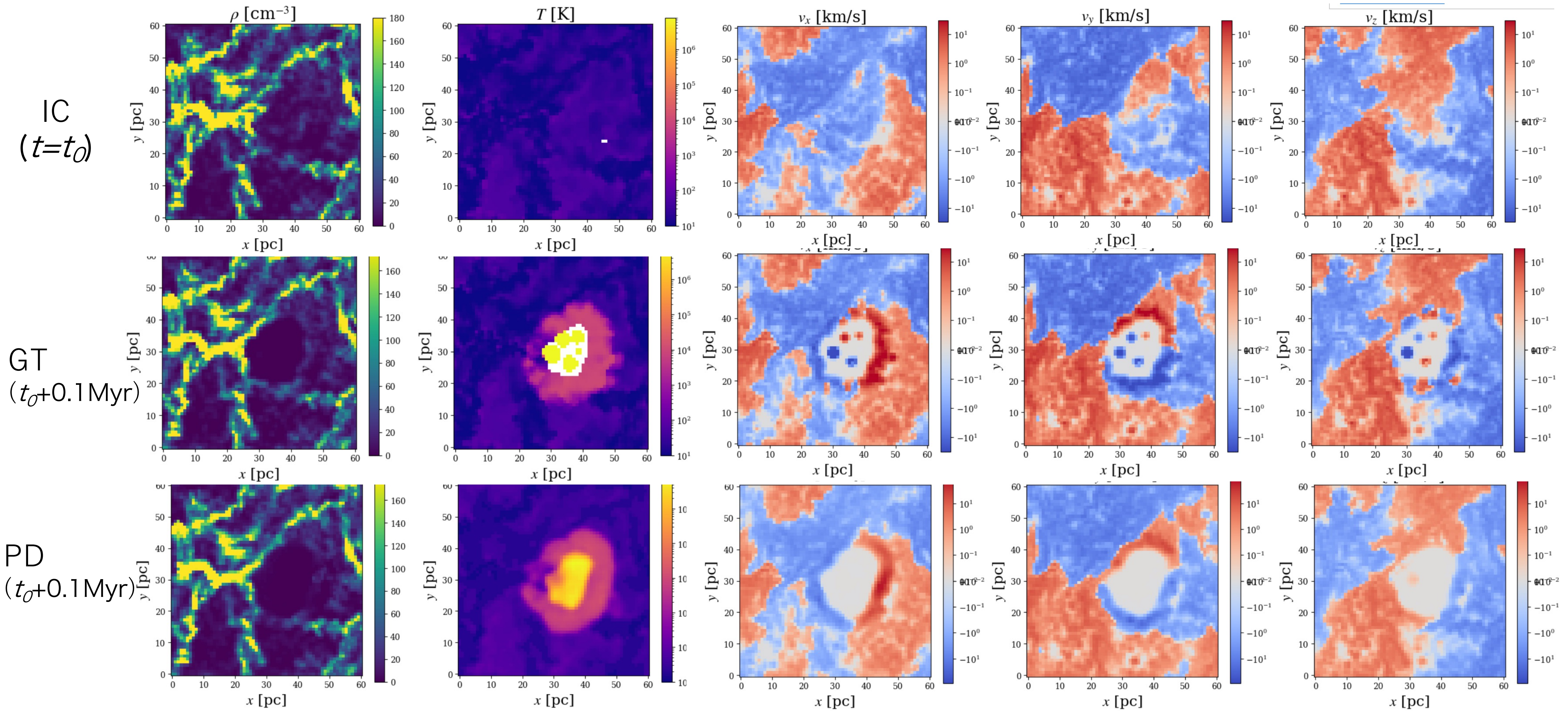
Surrogate modeling for SN feedback



The rest of the region in the galaxy
Δt ~10^5 yr

Prediction results #1

Blocked by the dense filament

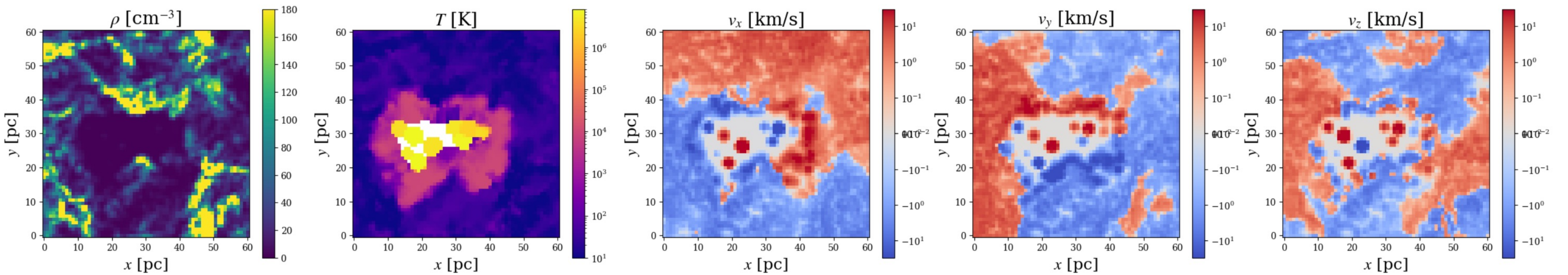


Prediction result #2

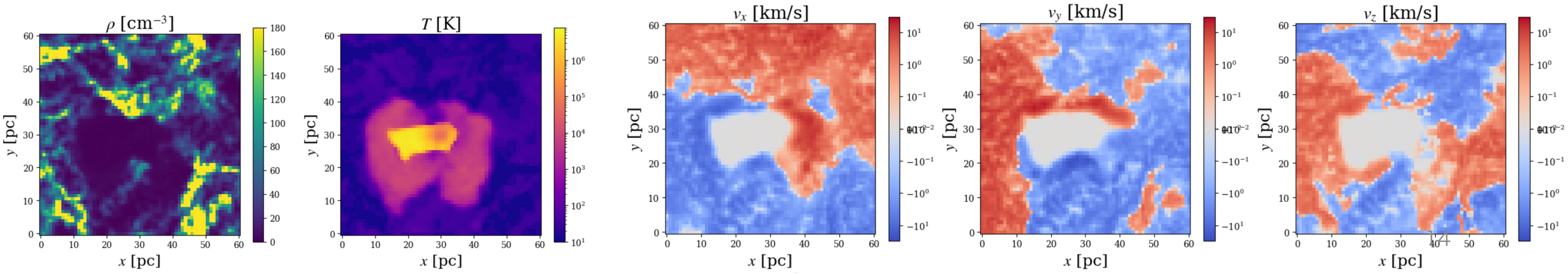
Relatively inhomogeneous case

Ground Truth (t_0+0.1Myr)

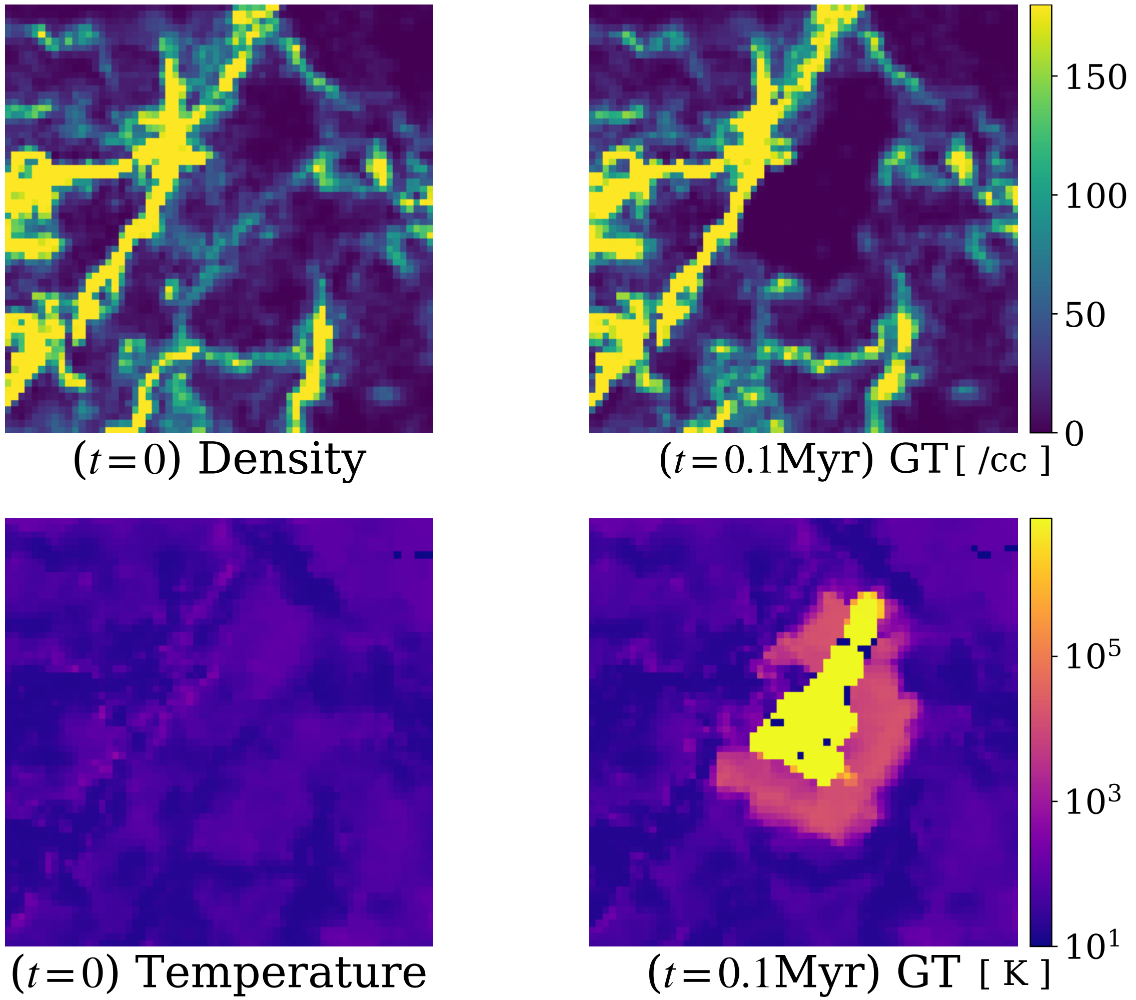
Density Temperature x-velocity y-velocity z-velocity



Prediction (t_0+0.1Myr)

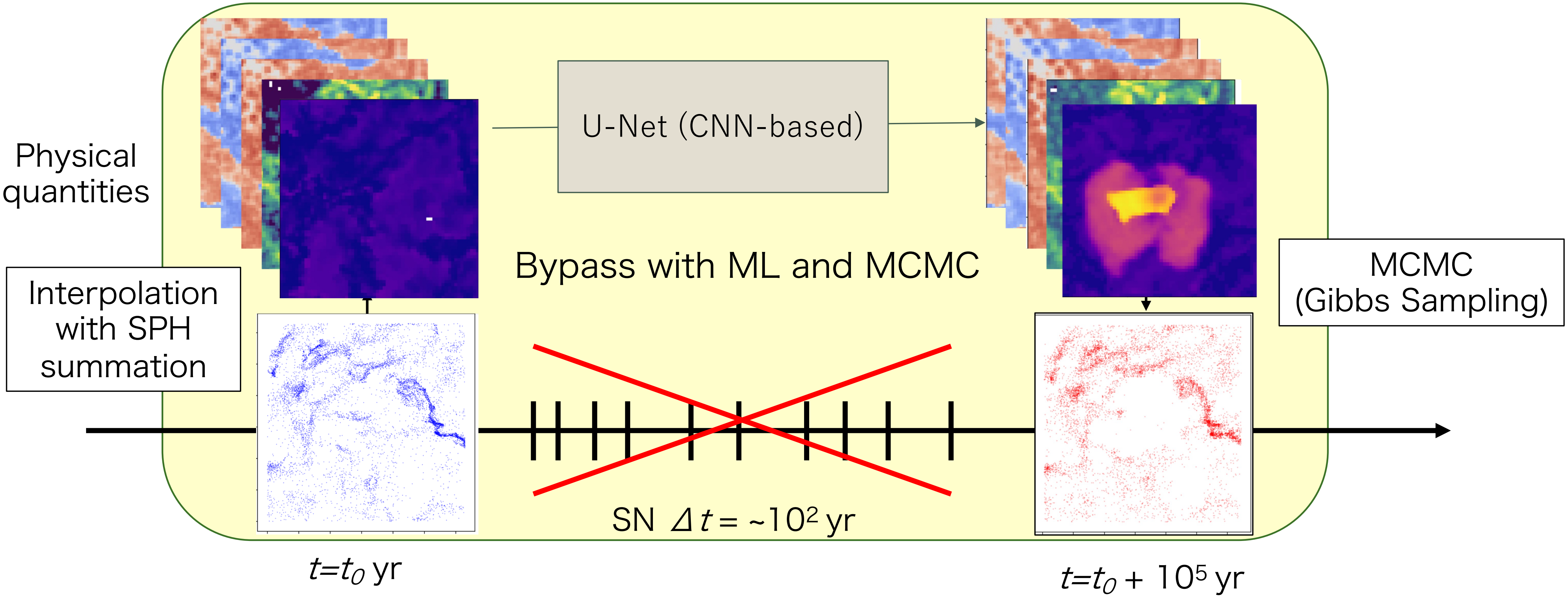


Prediction results #3



Error
3% (density)
65% (thermal energy)

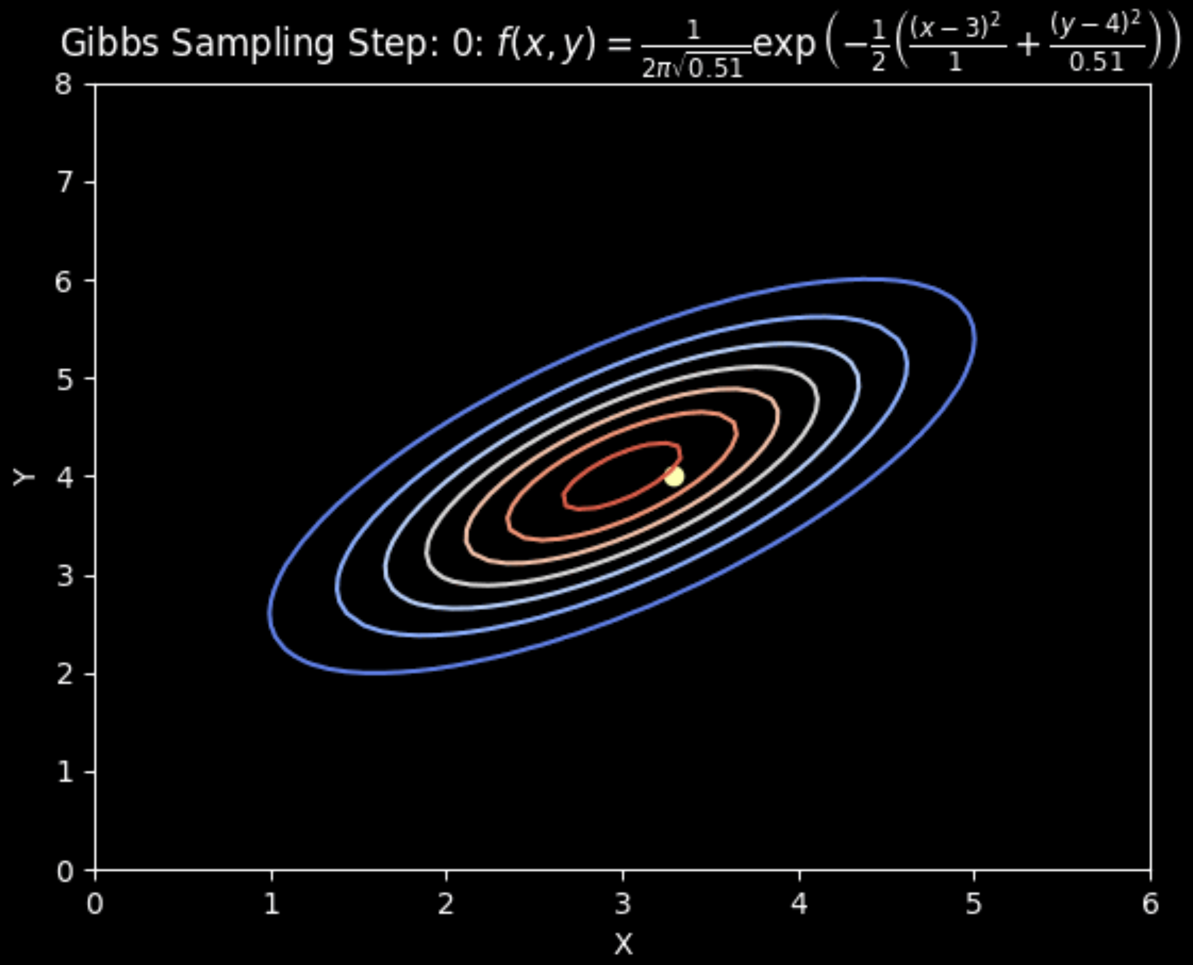
Surrogate modeling for SN feedback



The rest of the region in the galaxy
$\Delta t \sim 10^5$ yr

Gibbs Sampling (2D)

- Initialize X^0, Y^0
- for $j = 1, 2, 3, \cdots$ do
- sample $X^j \sim p(X \mid Y^{j-1})$
- sample $Y^j \sim p(Y \mid X^{j-1})$
- end for

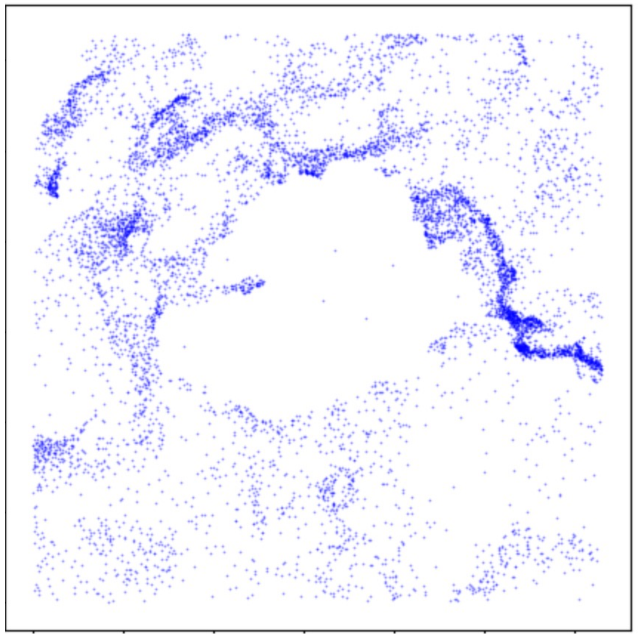


Validation 1 | Gibbs Sampling

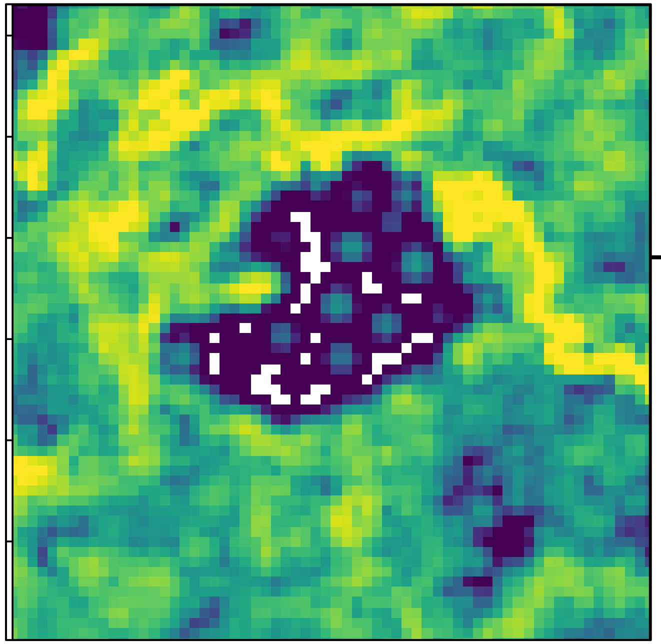
The particle distribution is sampled by a Markov chain Monte Carlo method.

SPH summation

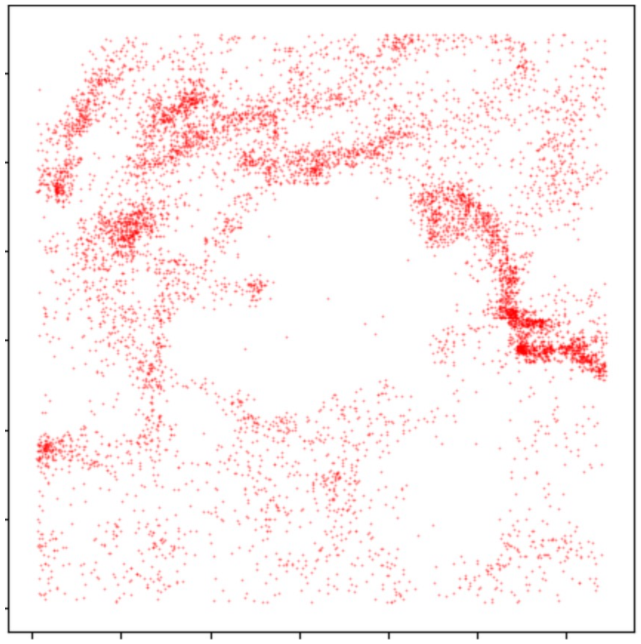
MCMC
(Gibbs Sampling)



SPH
($t = t_0 +$ 0.1Myr)

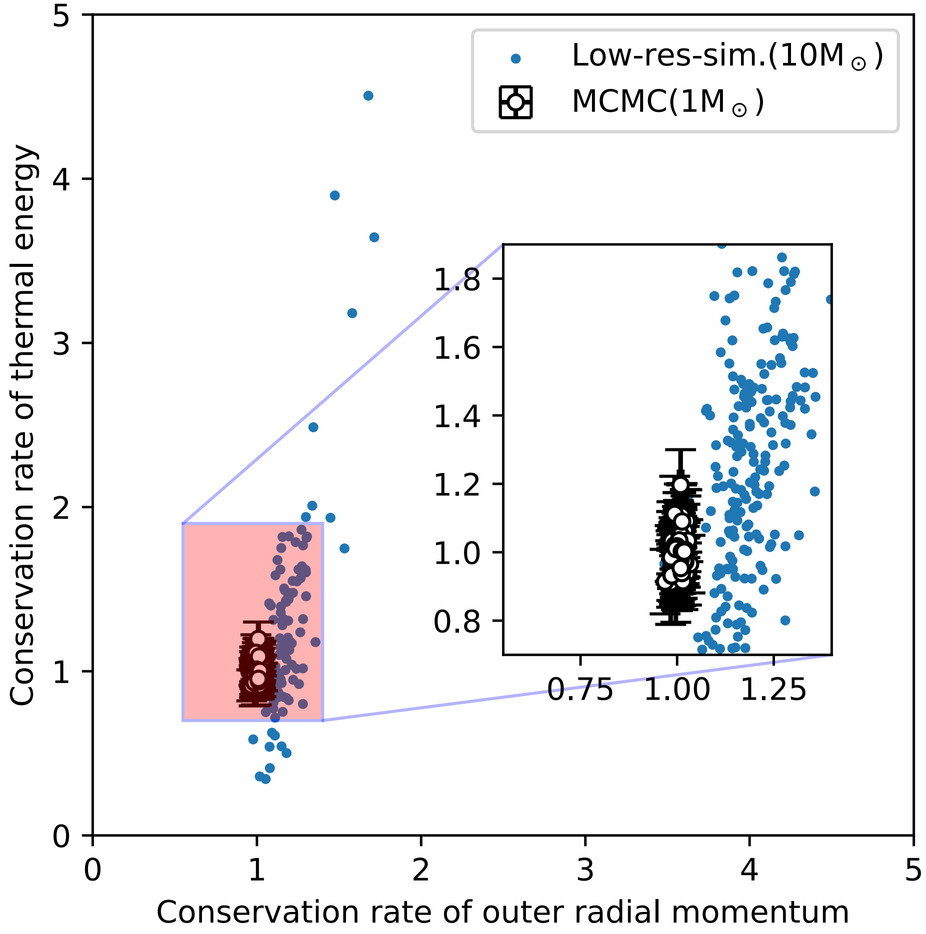


3D cartesian grids of density
~ 3D probability density function



Error due to the Gibbs Sampling (Preliminary)

$$y = \frac{E_{\rm thermal,pred}}{E_{\rm thermal,true}}$$

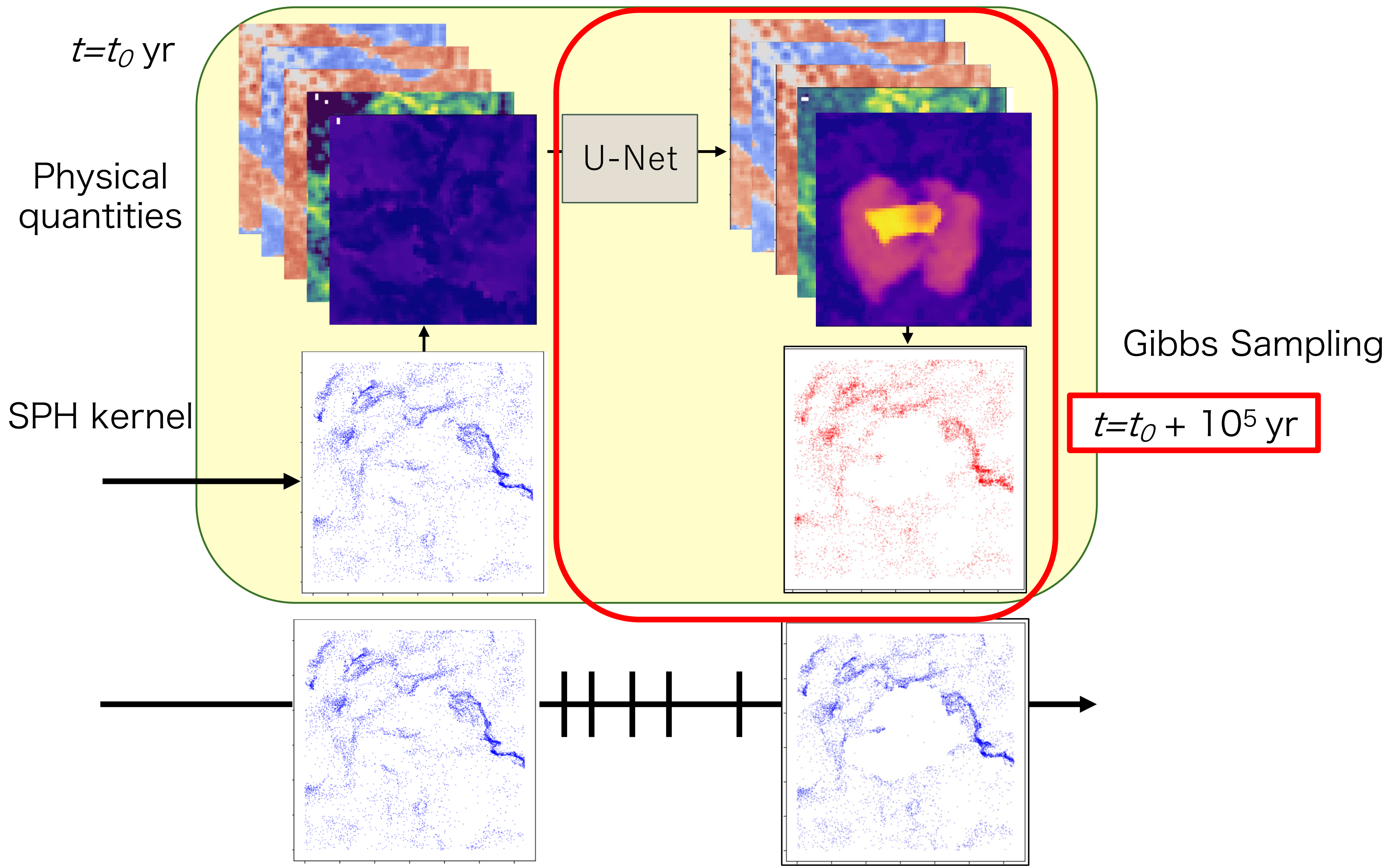


$$x = \frac{p_{\rm radial,pred}}{p_{\rm radial,true}}$$

- Benchmark: Low-res-sim. (Blue, 300)
- Sampling: MCMC (Black, 100)

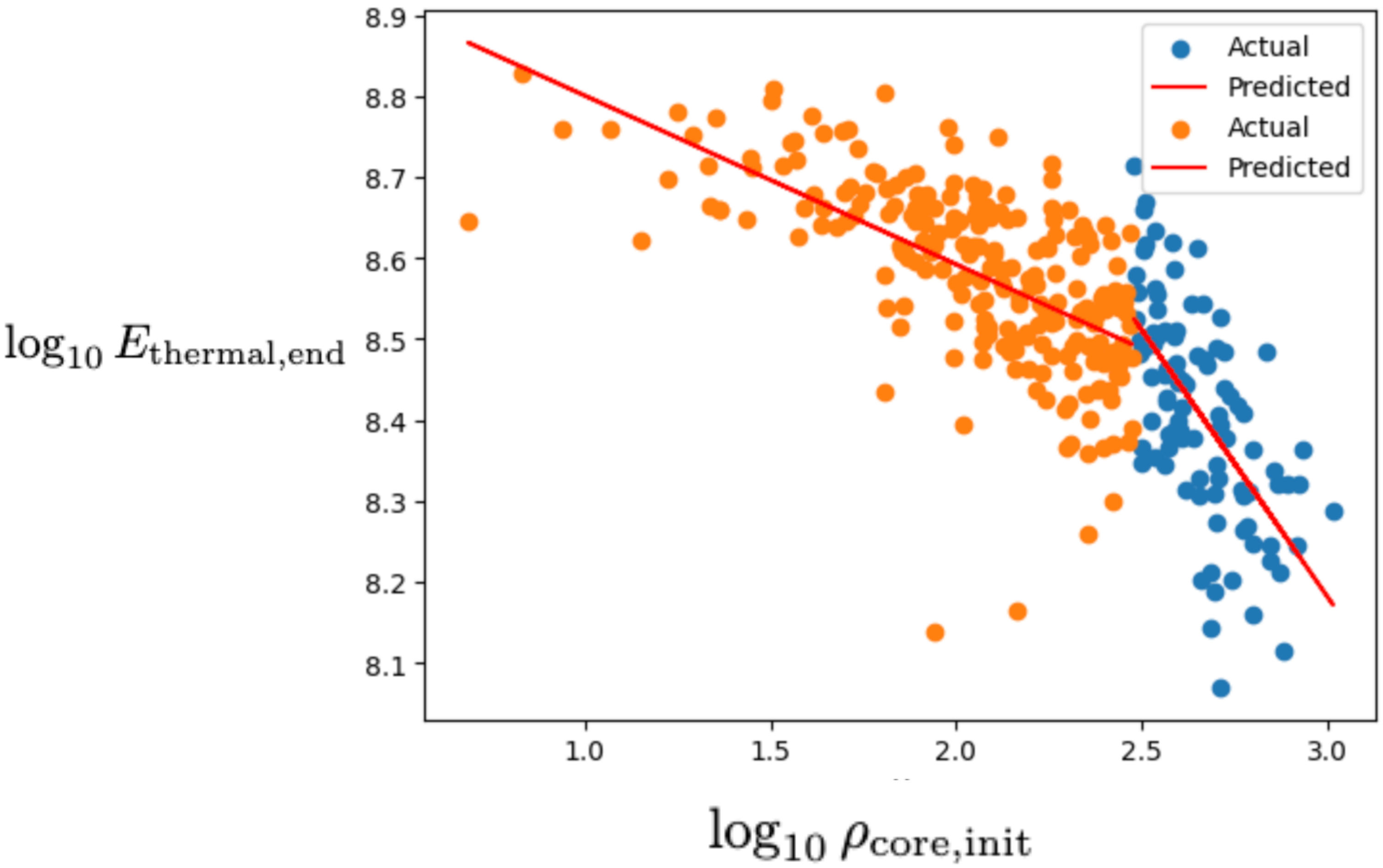
- "momentum is more easily characterized as it is conserved at late times" (Kim+15)
- For galaxy evolutions, radial momentum and thermal energy matter.

Validation 2 | ML + MCMC



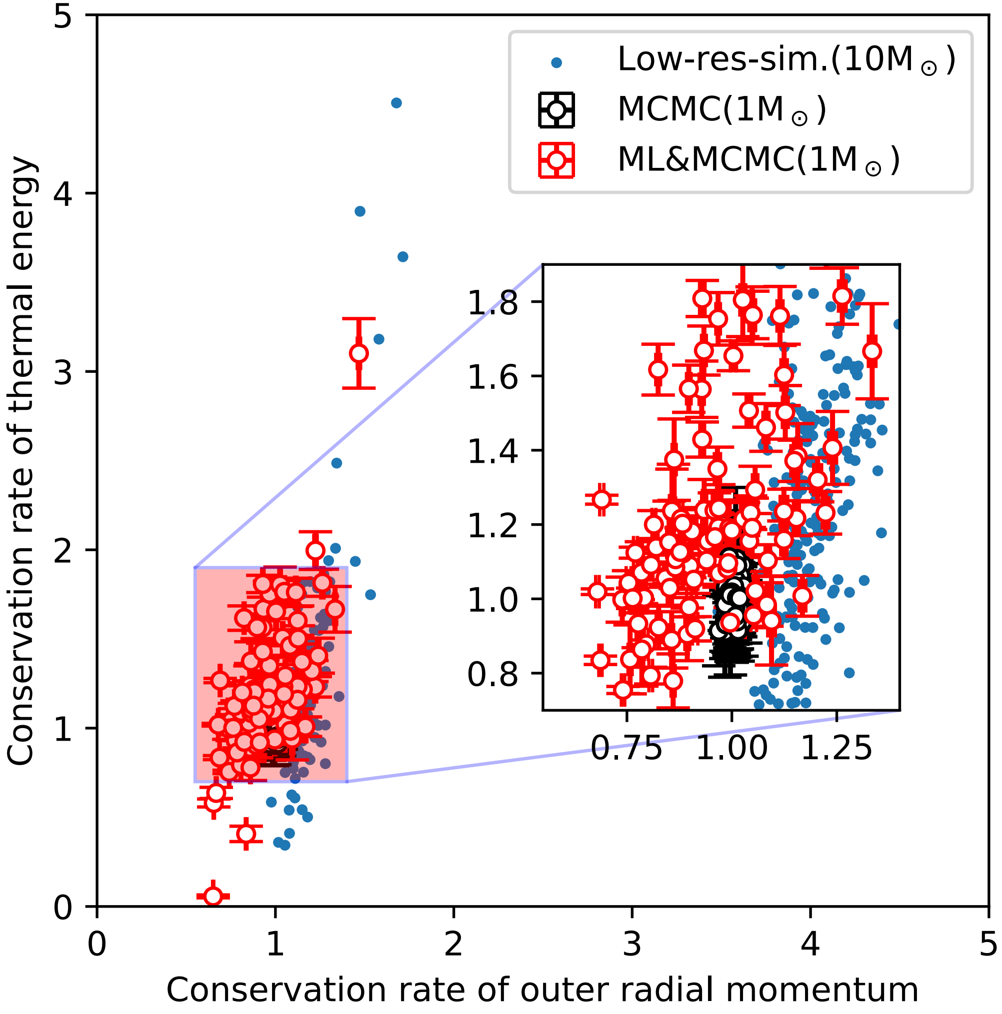
Constrain of thermal energy

(Roughly) fit an initial density – final thermal energy relation



Error due to the ML model (Preliminary)

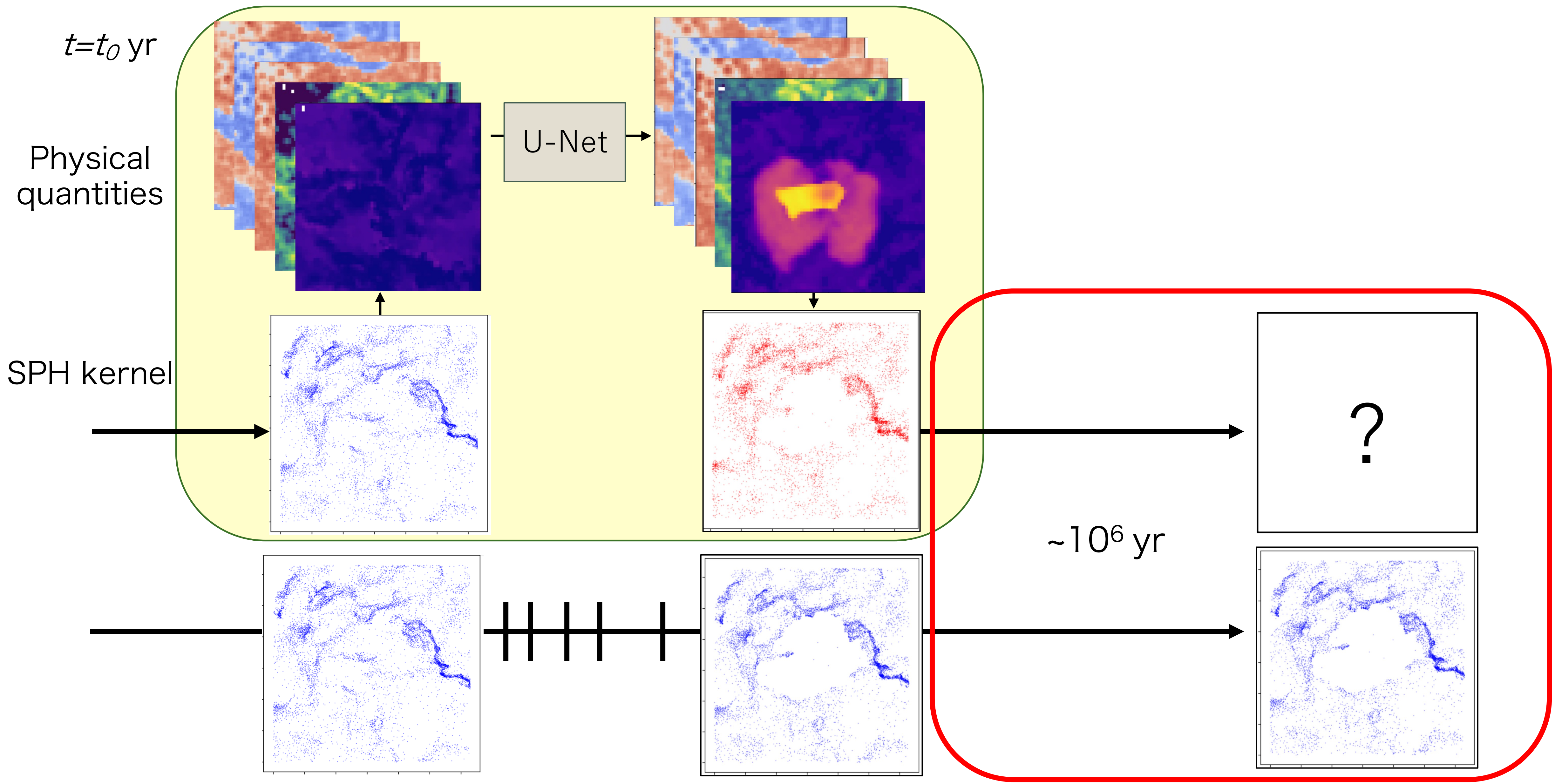
$$y = \frac{E_{\text{thermal,pred}}}{E_{\text{thermal,true}}}$$



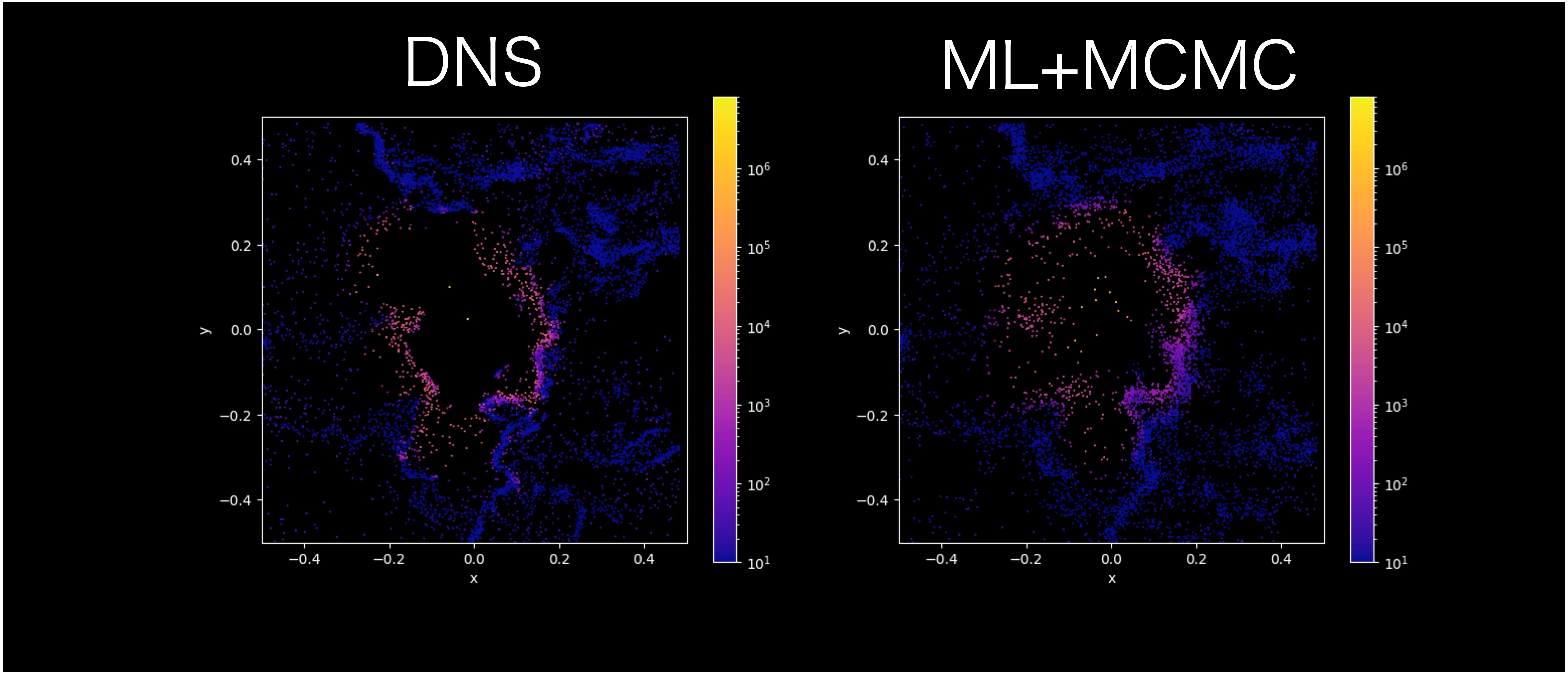
$$x = \frac{p_{\text{radial,pred}}}{p_{\text{radial,true}}}$$

- Benchmark: Low-res-sim. (Blue, 300)
- Prediction: ML+MCMC (Red, 100)

Experiment | Rerun the simulation

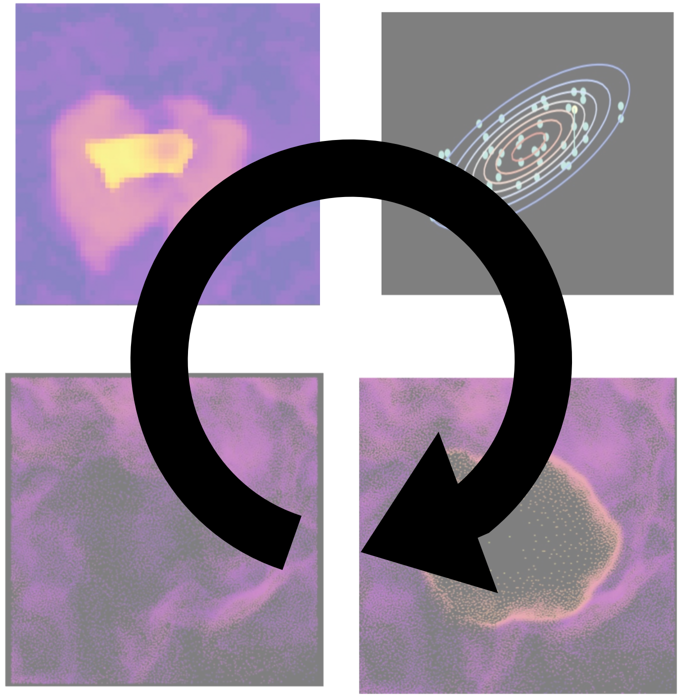


Restart Run from 0.1 Myr（Preliminary)

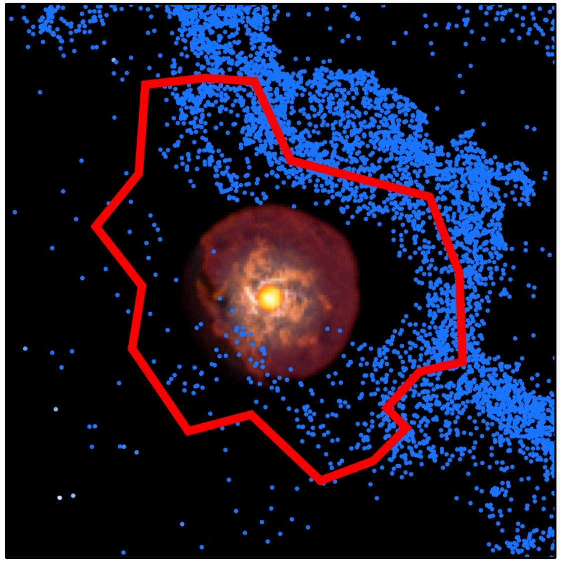


To conclude

Surrogate modeling



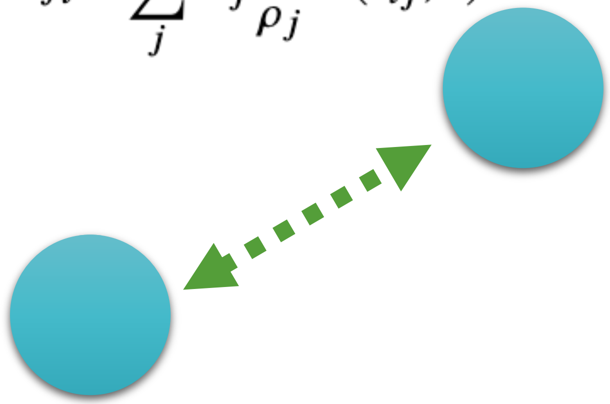
Individual timestep (with Hamiltonian Splitting)



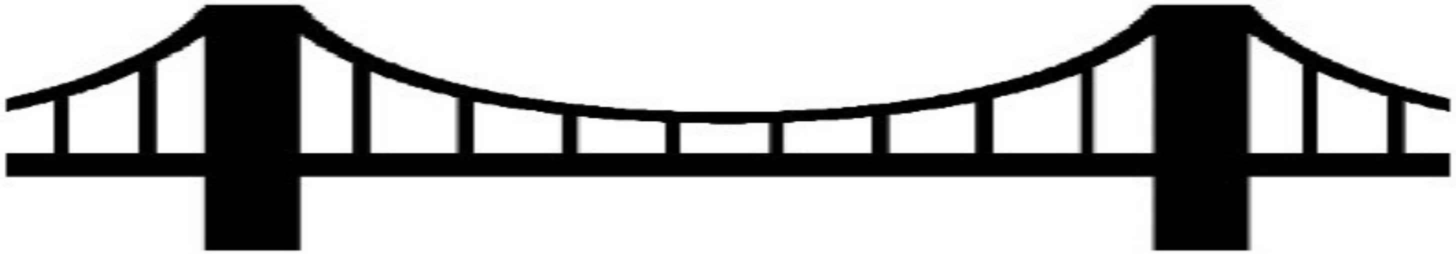
cf. Hirashima et al. 2023, submitted
arXiv:2302.00026

Direct Numerical Simulations

$$f_i = \sum_j m_j \frac{f_j}{\rho_j} W(r_{ij}, h).$$



- Stochastic
- Fast



- Deterministic
- Expensive

Summary and Future Work

- An approach for surrogating SN simulations with ML and MCMC
- Need more accurate predictions
  - try generative models?
- Need higher-res simulations
  - Preparing for higher resolution (0.1 Msun) simulations
- Try particle-based models (e.g. Graph Neural Networks)

Thank You!!!!