Predicting the Expansion of Supernova Shell for High-Resolution Galaxy Simulations Using Deep Learning

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Contents

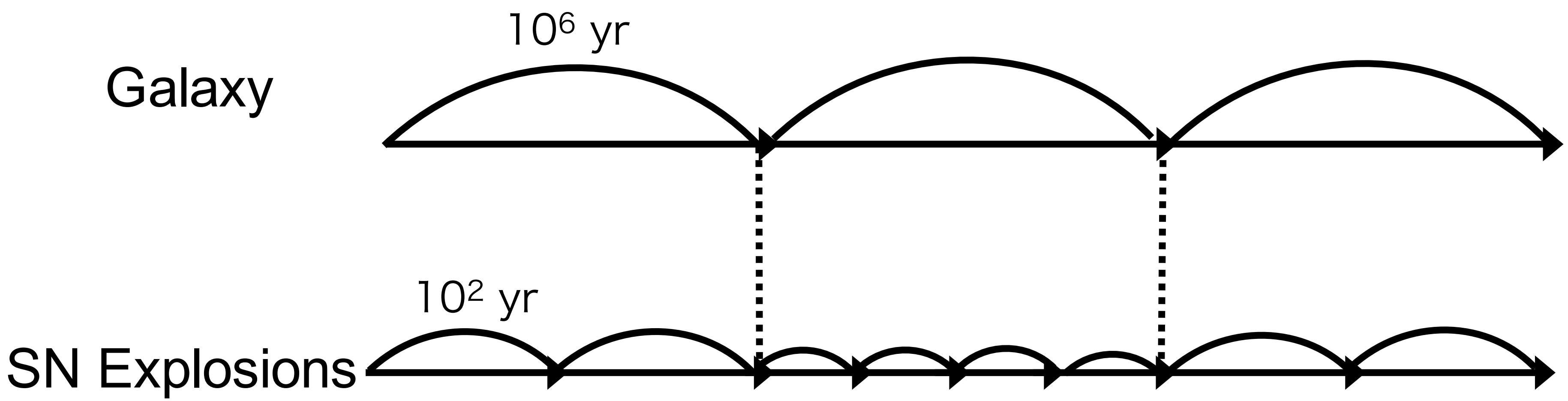
Resolution of Recent Galaxy Simulations

- Recent galaxy simulations come close to reproducing small structures in a stellar scale.
- In the right figure, red and bright regions represent SN.

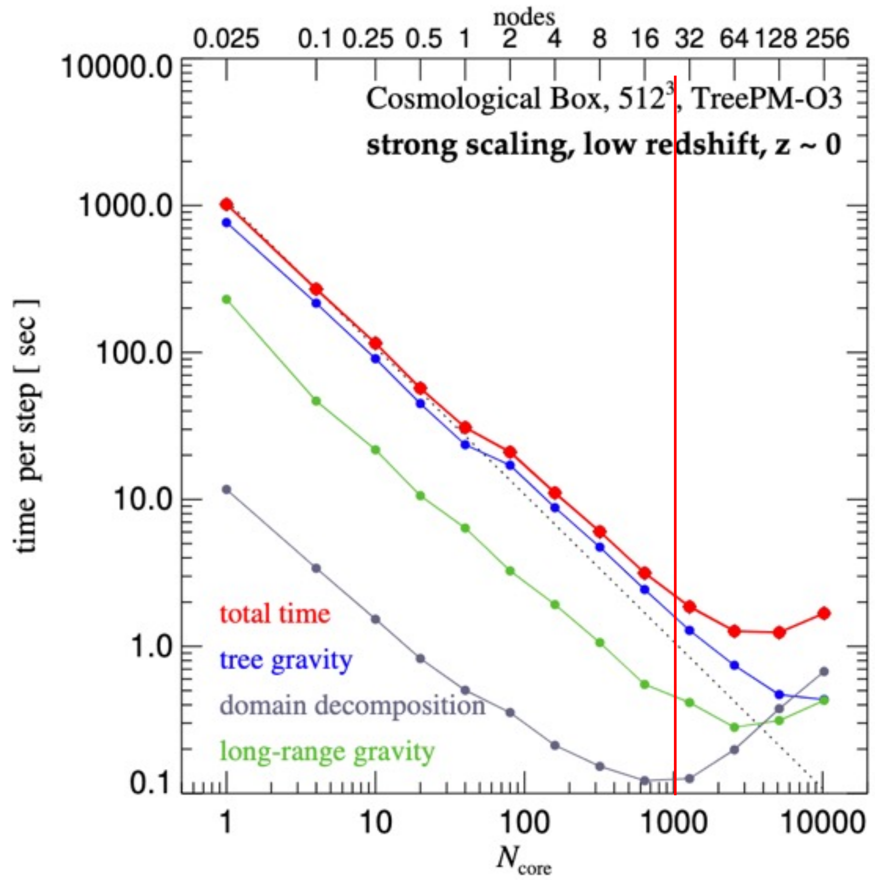
https://4d2u.nao.ac.jp/t/var/download/movie.html

the Number of Calculation

- SN explosions occur in much smaller time scale than the galaxy evolves.
- They should be calculated using small timesteps. This increases the number of calculations.



Overhead of Communication Time



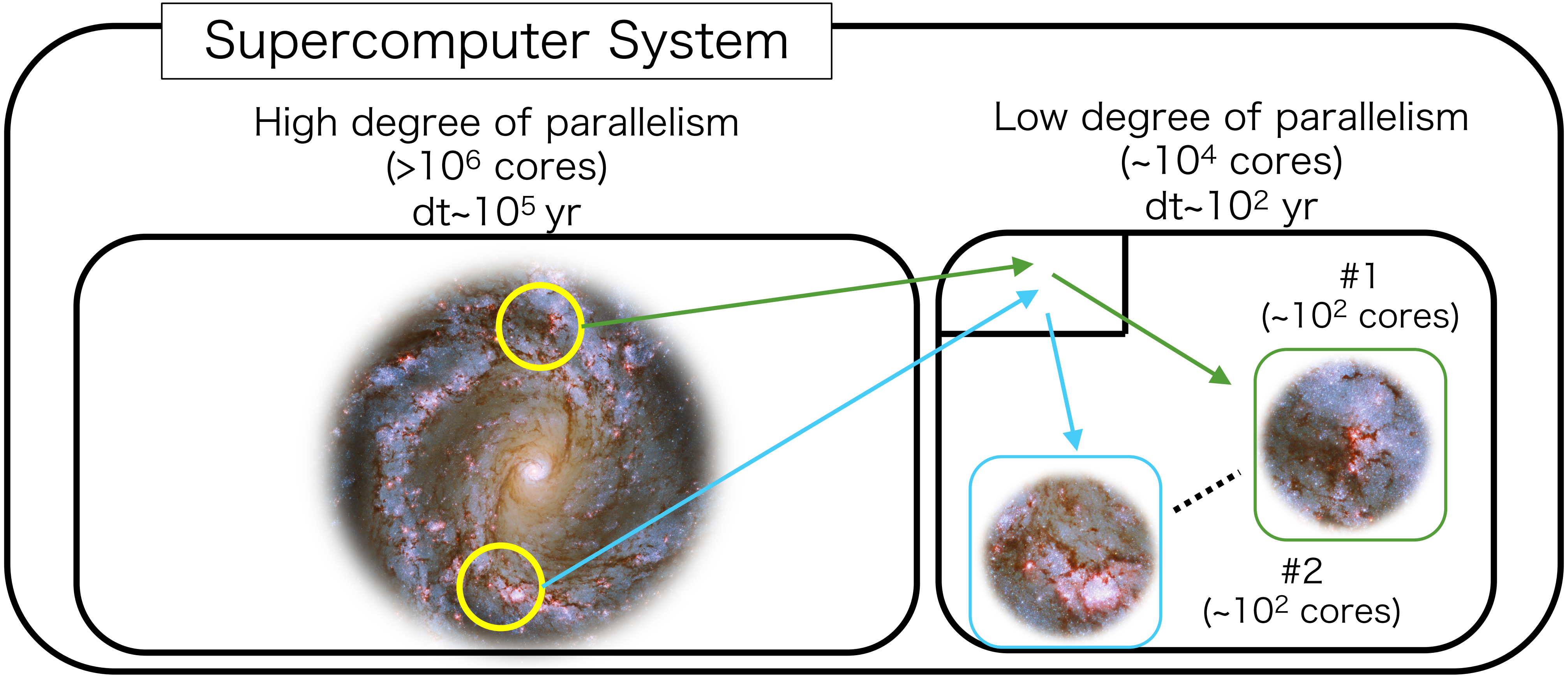
Strong Scaling of GADGET-4

(Springel et al. (2013), Figure 63)

- FUGAKU has more than 10^6 CPU cores.
- If we use more than 10^4 cores, efficiency gets worse because integrations need sync data per timestep between CPUs.
- Time for data transfer per timestep is bottleneck.
- If we integrate compact regions as isolated regions, we can decrease the number of communication.

How to Reduce the Num of Communication

- Compact regions need large number of integration and communication.
- Integrate compact regions as isolated regions.



ESA/Hubble & NASA, ESO, J. Lee and the PHANGS-HST Team

Why and How We Predict Expansions of SN

- Before the integration, we need to predict the particles that will have smaller time steps in the future and assign them to isolated regions.
- By predicting the density change after a SN explosion, we attempt to predict the particles.

- I tried to predict 3D density maps using deep learning model with extended Memory-In-Memory Network.
- For training data, we used the result of simulations of the expansion of a SN's ejecta shell in the turbulent ISM, evolved by some Myrs.

the Prediction by MIM Network

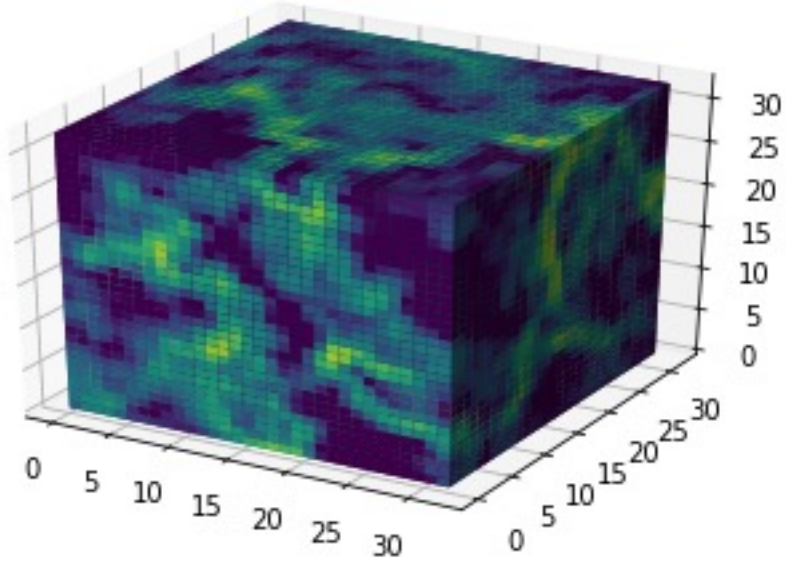
- Memory-In-Memory Network (Y. Wang et al. (2018)) learns the changes in a couple of frames in videos.
- This model can take 10 frames as input and predict 10 frames in the future.

- Red: 10 frames as input
- Blue: predicted 10 frames in the future
- Left: Ground Truth
- Right: Prediction

https://github.com/Yunbo426/MIM

Extending MIM to the 3D Prediction Model

- MIM can learn and predict only **2D** images.
- We need to predict changes in the **3D** distribution of physical quantities.
- Improved MIM through increasing the dimension of the data format and network.



3D data format which represents density distribution

Training Data for our DL Model

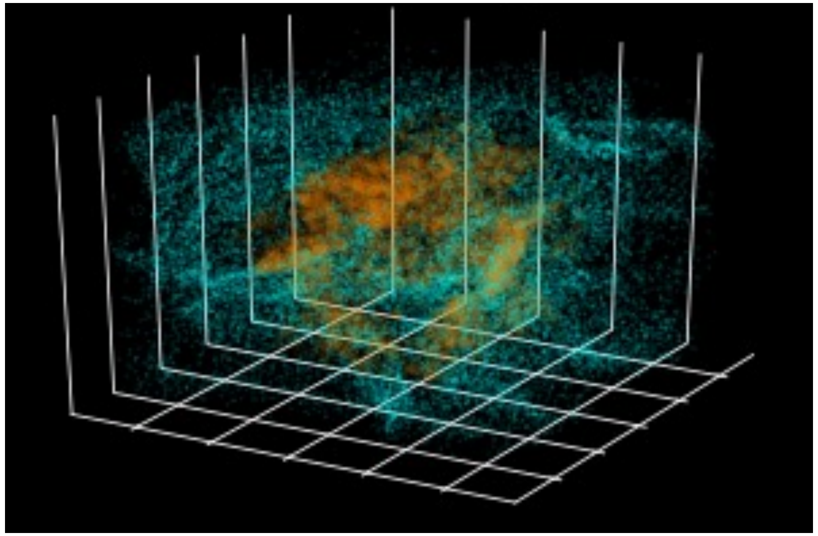
- To predict the expansion of SN shell, I used the results of SN explosion simulations as ground truth and training data for DL.

Table 1 Initial condition of ISM.

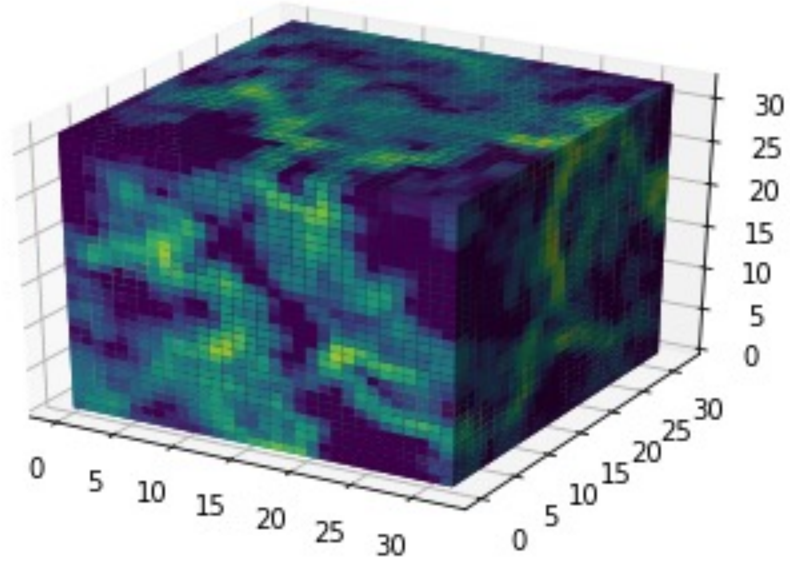
Temperature	10 [K]
Input Energy	10^{51} [erg]
Total mass	10^{6} [$M_\odot$]
Mass of a gas particle	10 [$M_\odot$]
Time for SN	1.2 [Myr]
Length of SN expansion	0.2 [Myr]
Softening Parameter	3 [pc]

Voxel Data as Training Data

- Volume + picture + element -> Voxel
- Convert particle data of SPH simulations to voxel data.
- The value of voxel represents the physical quantity at that point obtained by SPH kernel function.



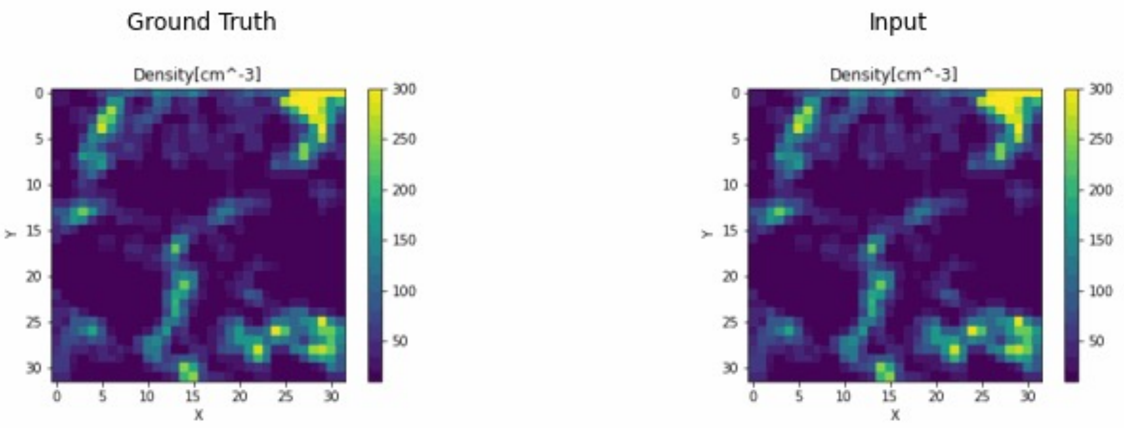
SPH Kernel Function



Particle Data (SPH):Orange particles represent the target particles which are hot and high-velocity.

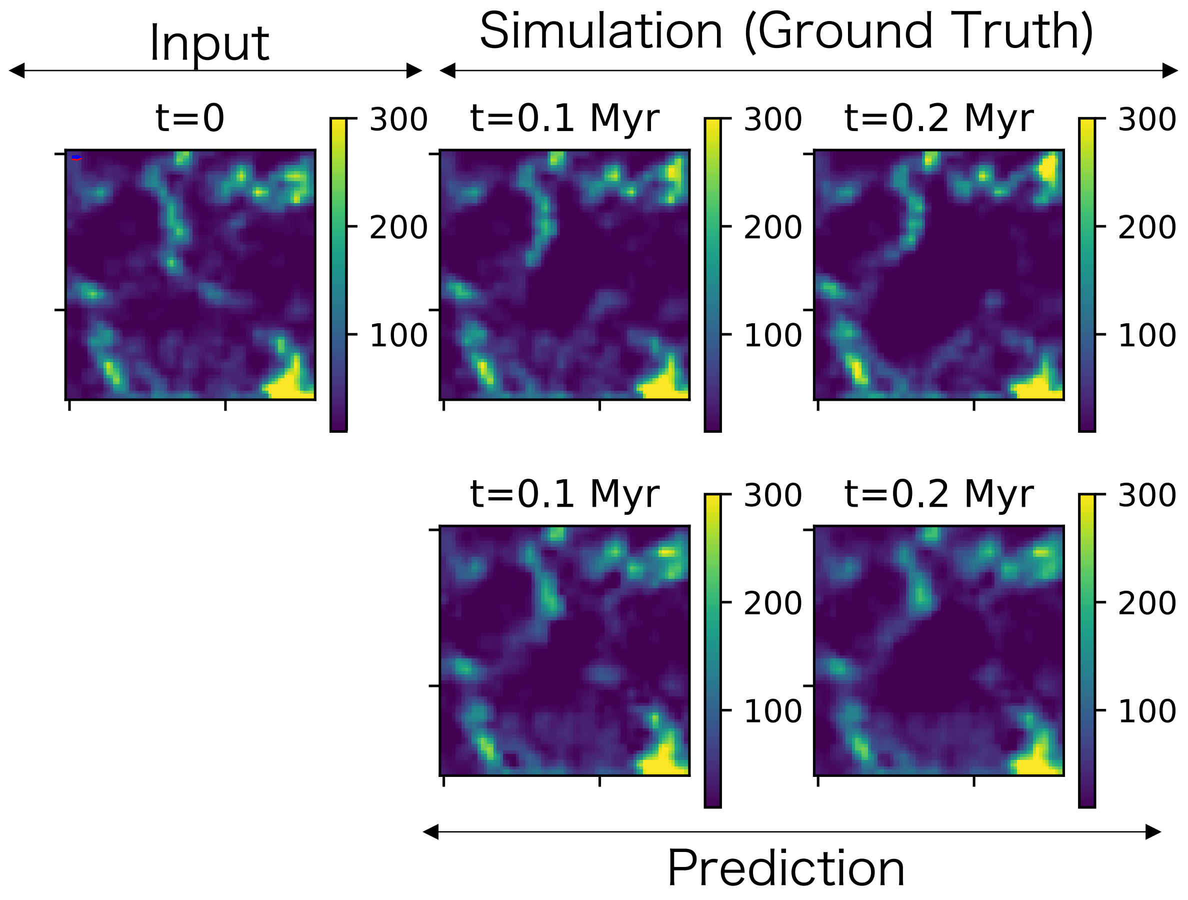
Voxel Data (Density)

Prediction of the Expansion of a SN's shell



- Cross-sectional views of 3D-density map
- Input: Only one 3D-density map before the explosion
- Output: 19 3D-density maps every 3333 yrs.
- Our model can learn changes in density caused by SN.

Prediction of the Expansion of a SN's shell



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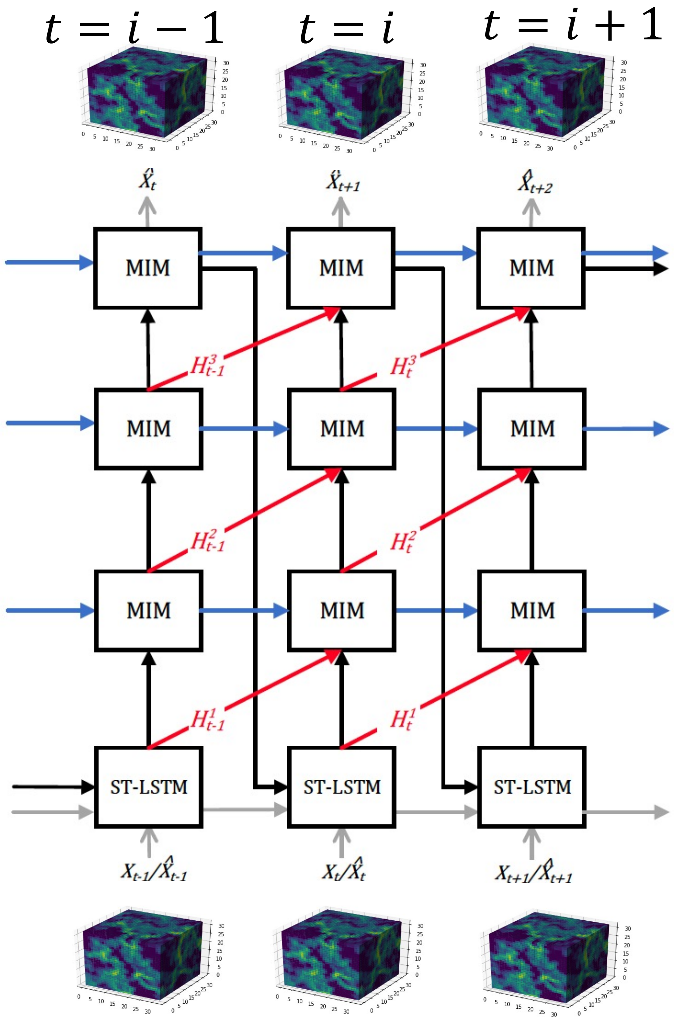
Method Details



Output: predicted frames

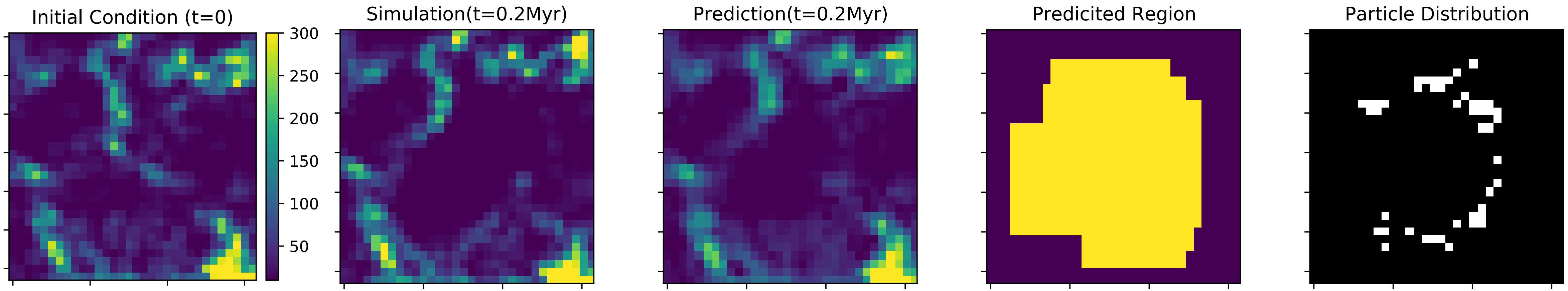
- Extended MIM learnes changes in the **3D** distribution of physical quantities.
- Red flows transmit the difference in pixel (voxel) values between a couple of frames.

Input: a couple of previous frames

Y. Wang et al. (2018) Fig. 4

Apply DL to picking up particles

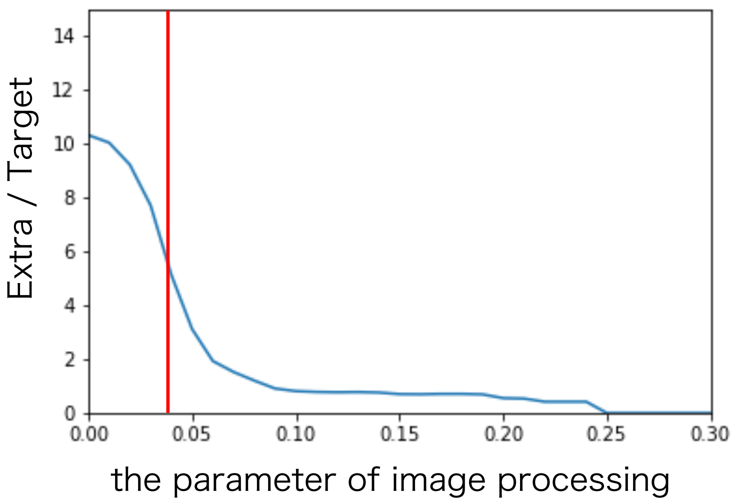
- There are particles with small time-steps in the boundary of SN ejecta's shell.
- Using predicted density maps, I enclosed the region where the density greatly reduced.



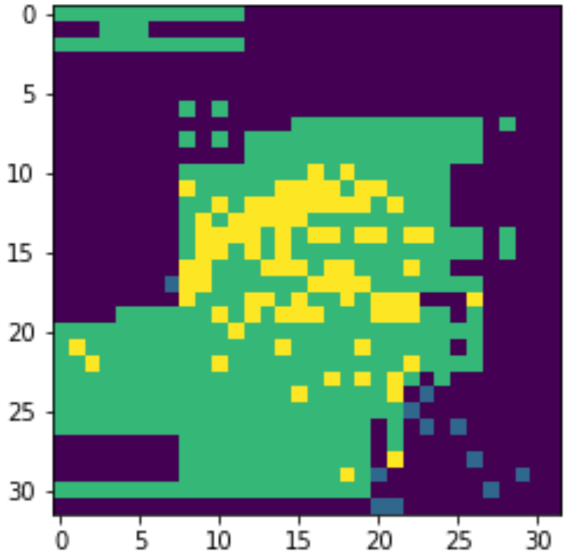
Current Performance of the Algorithm

- Target particles, which experienced T>100K and dt < 5e4 yr.
- When we capture 90% target particles, we also do about five times as many extra particles as target particles.
- We must make the shape of predicted regions closer to the particle distribution.

Capture ratio of the target particles.



Ratio of the num of captured extra particles to the num of captured target particles .



Green: enclosed region
Yellow: captured targets
Blue: missed targets

Summary and Future Works

- I made a trained model which predict time evolution of density to shell expansion of SN in 3D using extended MIM network.
- I am developing the algorithm which detect small time-step particles using predicted 3D density maps.
- The algorithm also allocate large timestep particles to isolated regions although it can allocate about 100% small timestep particles.

- Removing noise of training data.
- searching optimal parameters (e.g. filleter size, etc…).