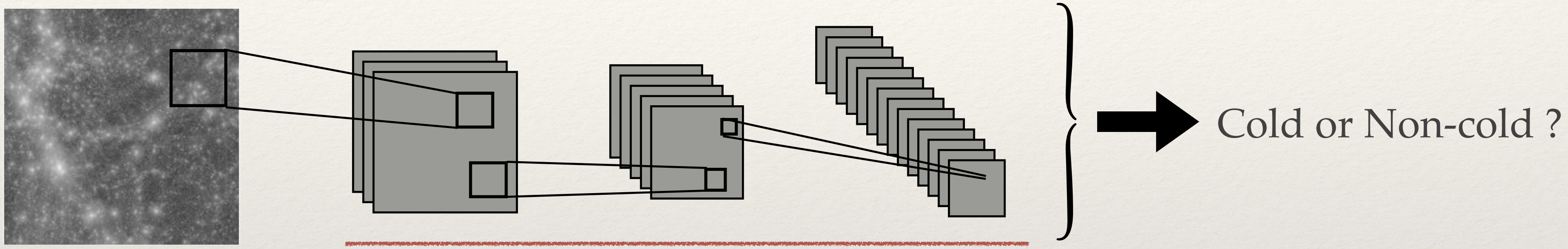
Constraint on dark matter mass by direct analysis of HI density distribution with machine learning

Koya Murakami (D1, Nagoya)

Collaborator :
Atsushi J. Nishizawa (Nagoya)
Kentaro Nagamine (Osaka)
Ikko Shimizu (Shikoku Gakuin)

- **overview**

1. **Distinguish image of dark matter distribution (My previous work, arXiv:2012.03778)**



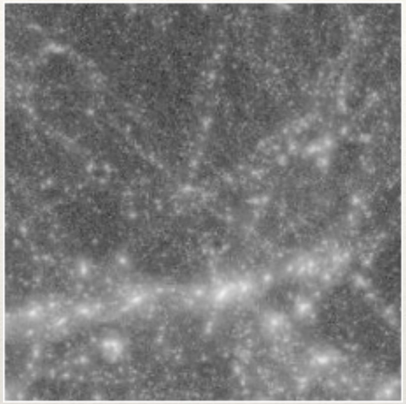
Dark matter distribution
(Cold or Non-cold dark matter)

Machine learning algorithm
(Convolutional Neural Network; CNN)

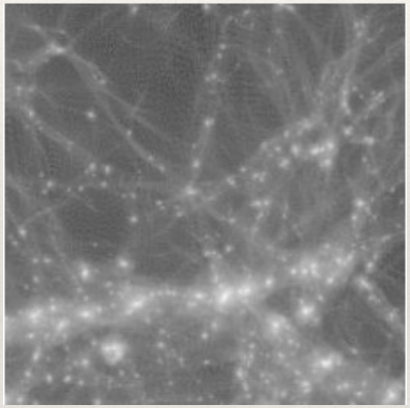
2. **Distinguish image of HI distribution (in progress)**

1. Distinguish image of dark matter distribution

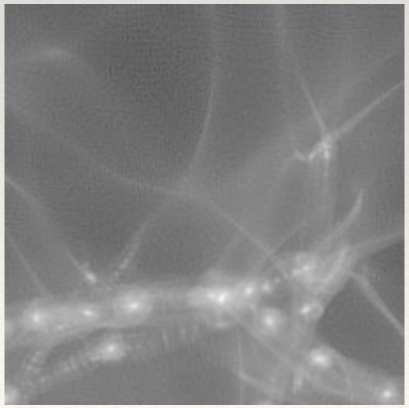
Dark matter mass & dark matter distribution



cold (heavy)

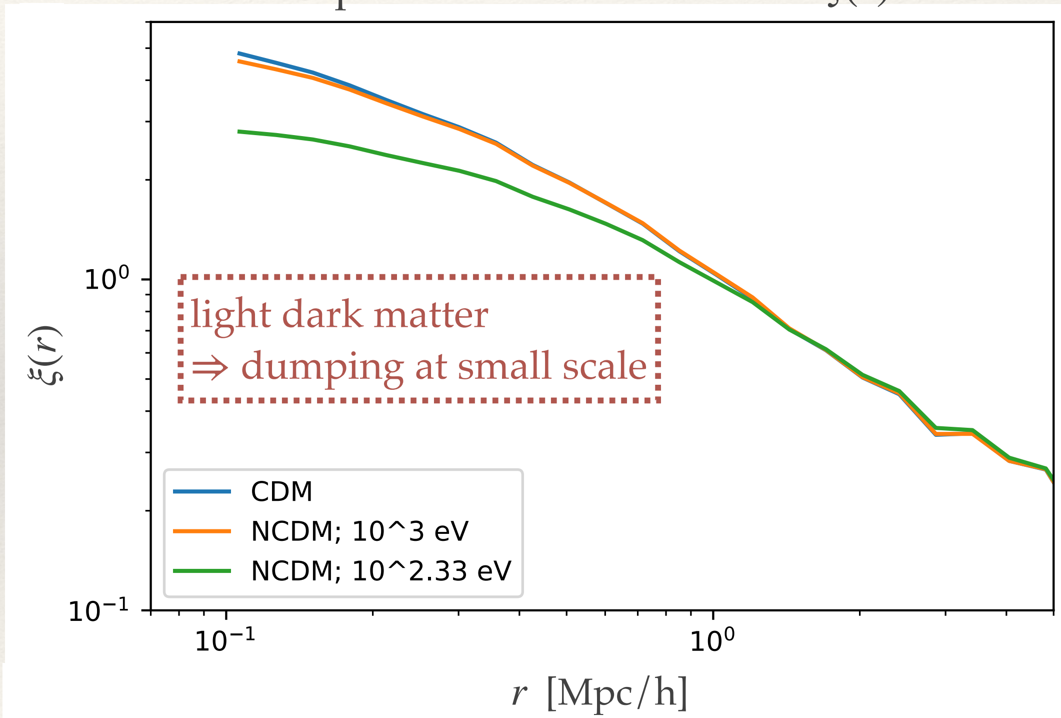


non-cold 1 keV



non-cold 0.2 keV

2D Two-point correlation function $\xi(r)$



1. Distinguish image of dark matter distribution

Dark matter mass & dark matter distribution

- Two-point correlation

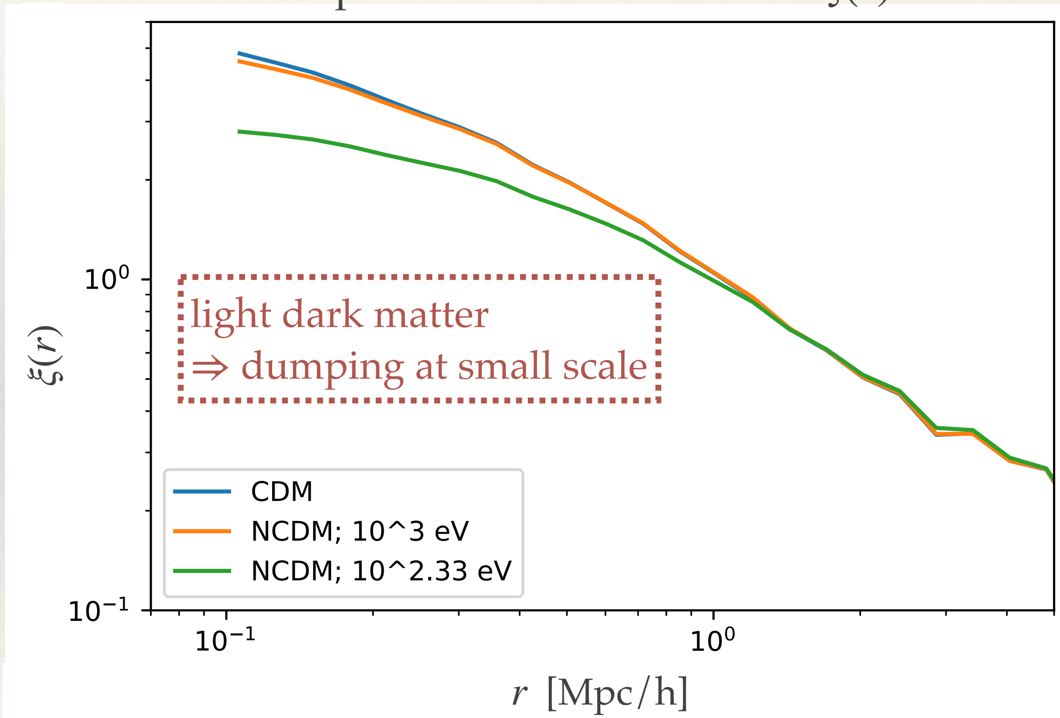
  => extract all information when distribution follows Gaussian

- dark matter mass affect itself distribution

  at small scale -> large non-Gaussianity

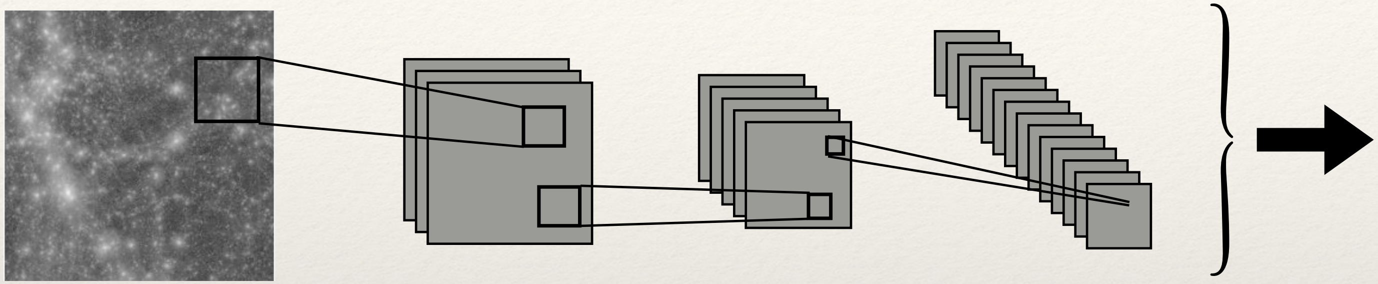
Machine learning extract more information than two-point correlation?

2D Two-point correlation function $\xi(r)$



1. Distinguish image of dark matter distribution

Convolutional Neural Network



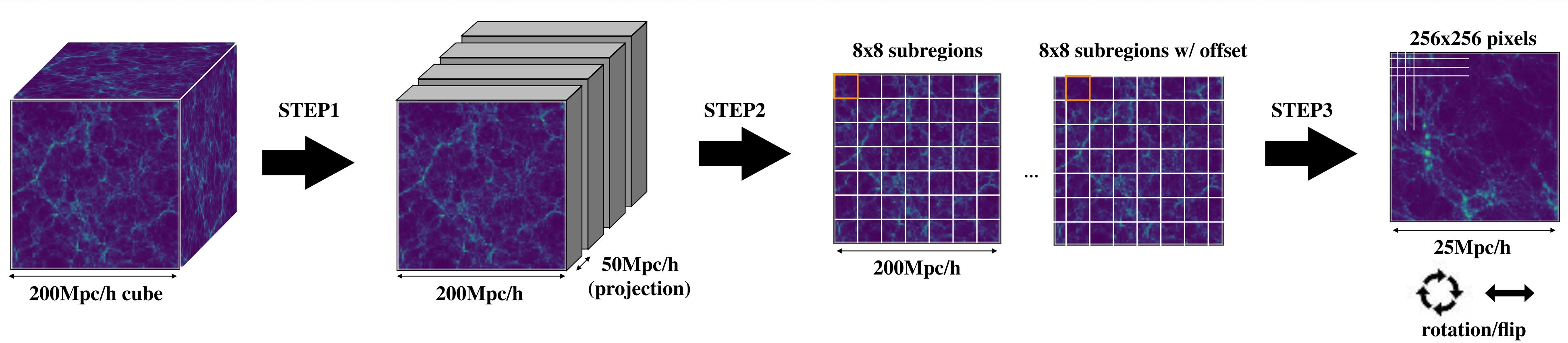
Cold or Non-cold ?

Dark matter distribution

- Machine learning algorithm for image analysis
- extract information from image with trained filters
- We use N-body simulation data for training and testing machine learning

1. Distinguish image of dark matter distribution

Image of dark matter distribution



Number of particle : 512^3
Box size : 200 Mpc/h
Cosmological param : Planck Collaboration et al. (2018)
Image size : 25 Mpc/h
Pix size : ~ 0.1 Mpc /h
1 CDM + 9 NCDM models

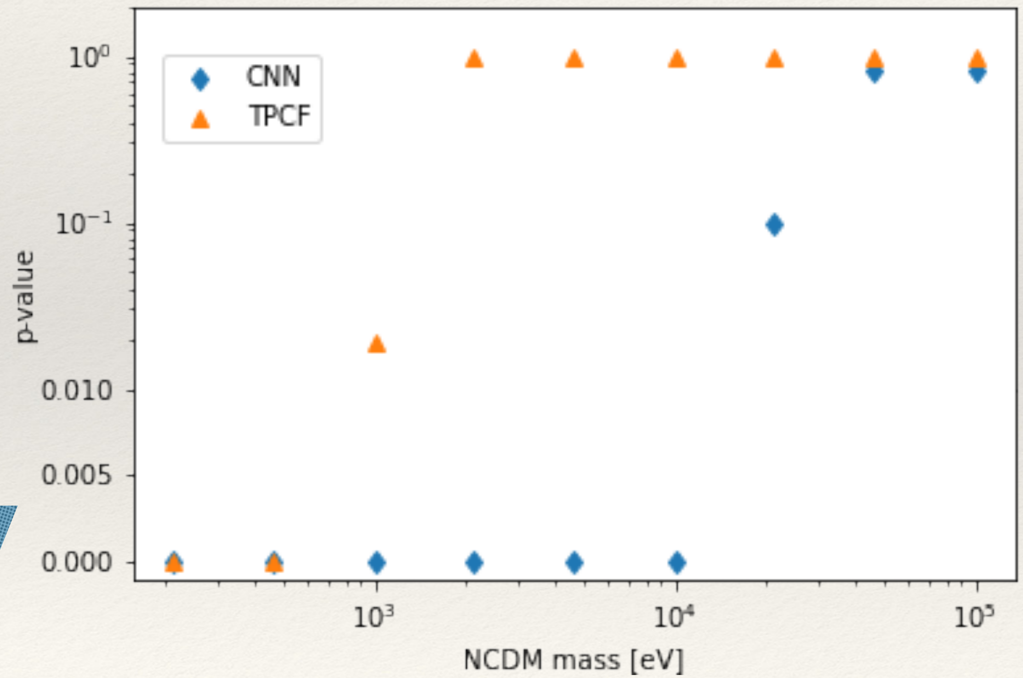
1. Distinguish image of dark matter distribution

distinguish NCDM from CDM ⇒Machine learning vs. two-point correlation

$$\chi^2 = (D_{CDM} - D_{NCDM})C^{-1}(D_{CDM} - D_{NCDM})^T$$ ⇒ compare p-value

$\xi(r)$ or output from machine learning method

Distinguished well



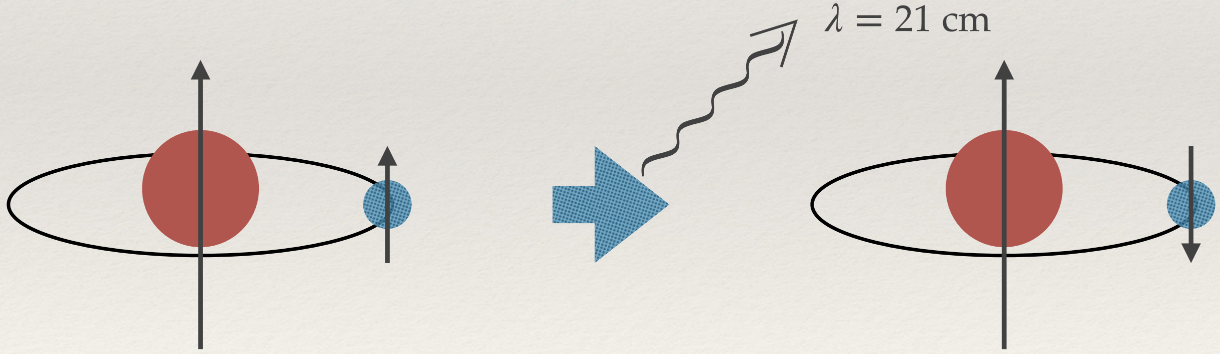
Machine learning algorithm show
better performance than two-point correlation

2. Distinguish image of HI distribution (in progress)

Previous work : use dark matter distribution

⇔real observation : cannot observe dark matter distribution directly

HI distribution can be observed through 21 cm Intensity mapping



Neutral hydrogen

2. Distinguish image of HI distribution (in progress)

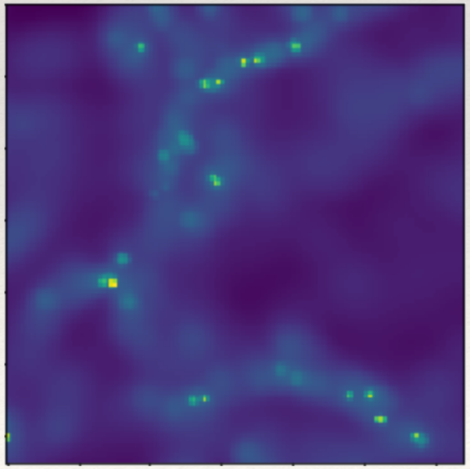
Analysis of HI distribution with machine learning

HI distribution are affected by self-shielding, UVB model, etc.

⇒these have effect on the analysis with machine learning ?

Three simulation (K. Nagamine et al., 2021) => HI distribution image

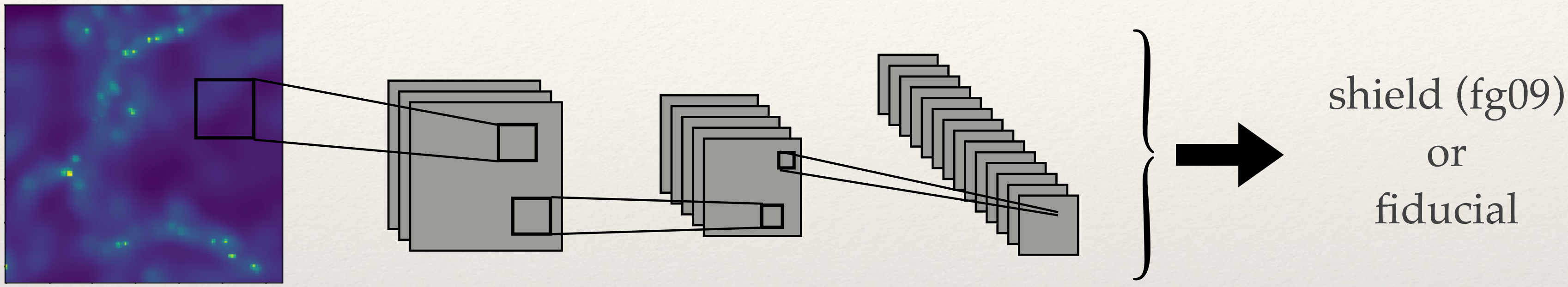
fiducial : no self-shielding
shield : with self-shielding
fg09 : UVB model (Faucher-Giguère et al., 2009)



1 pix ~ 0.1 Mpc/h

2. Distinguish image of HI distribution (in progress)

Distinguish shield or fg09 from fiducial with machine learning



HI density distribution

Machine learning algorithm distinguish models well

~99 % test images are distinguished correctly in either case (shield or fg09 vs. fiducial).

We cannot ignore the difference from models (UVB model etc.) affect HI distribution when constraint on dark matter mass

Summary

- machine learning algorithm have better performance than two-point correlation when constraint on dark matter mass with dark matter distribution from N-body simu.
- models such as self-shielding have effect on machine learning analysis sufficiently.

Future work

- discuss appropriate machine learning method for analysis of HI distribution
- hydrodynamic simulations with various dark matter mass, UVB model, etc
  test machine learning for these data