

Exploring Relationship between Assembly bias and Halo properties toward Dark Emulator II

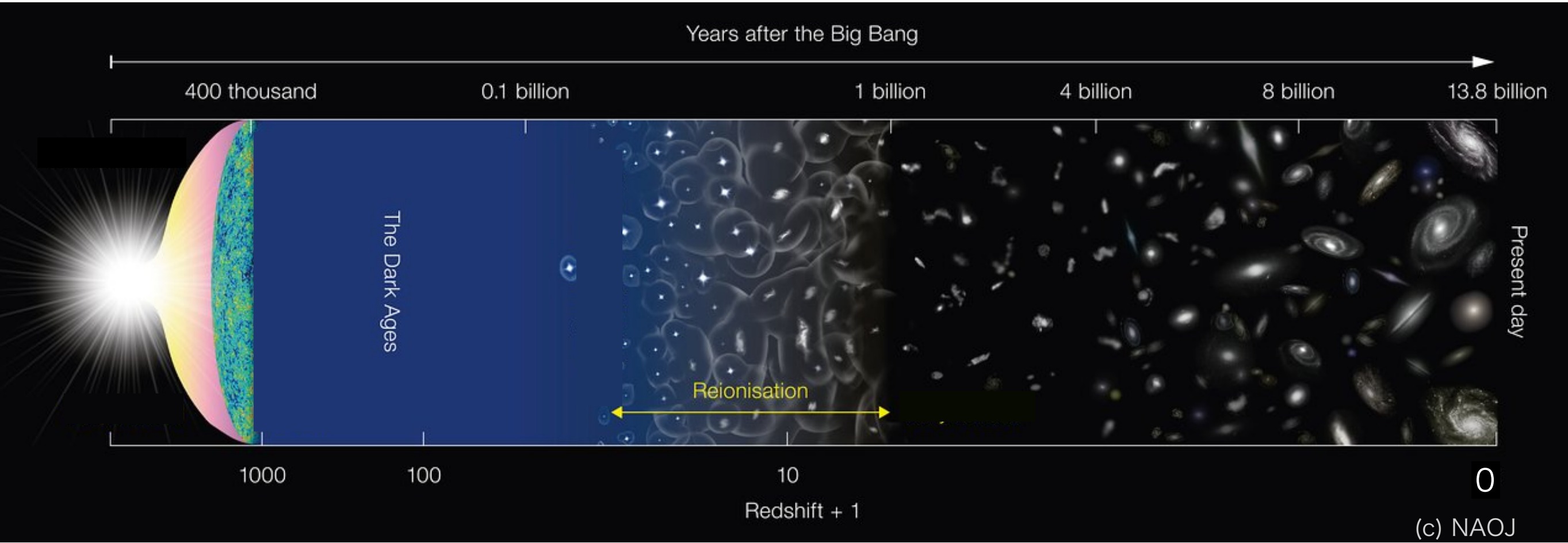
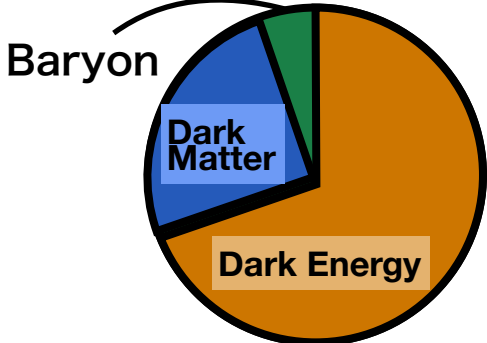
Keitaro Ishikawa (Nagoya U.)

collaborators :

**Takahiro Nishimichi (Kyoto Sangyo U.),
Hironao Miyatake (Nagoya U. KMI),
Satoshi Tanaka (Kyoto U. YITP),
Tomomi Sunayama(U. of Arizona)**

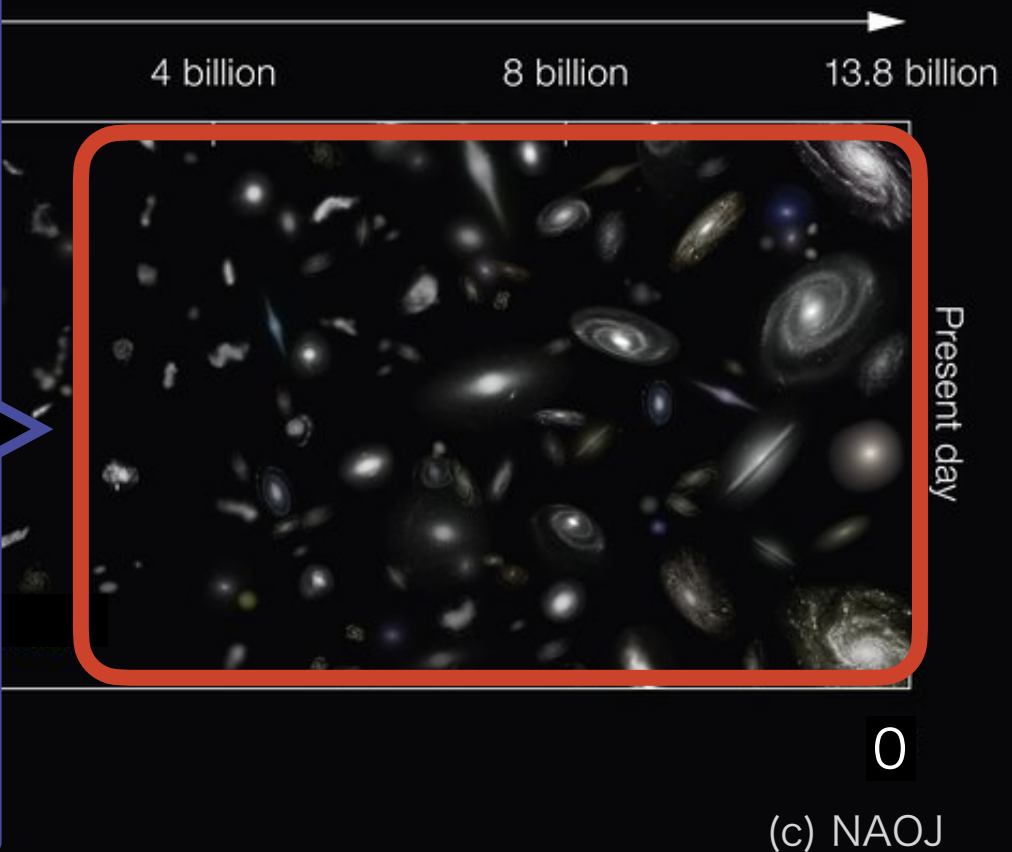
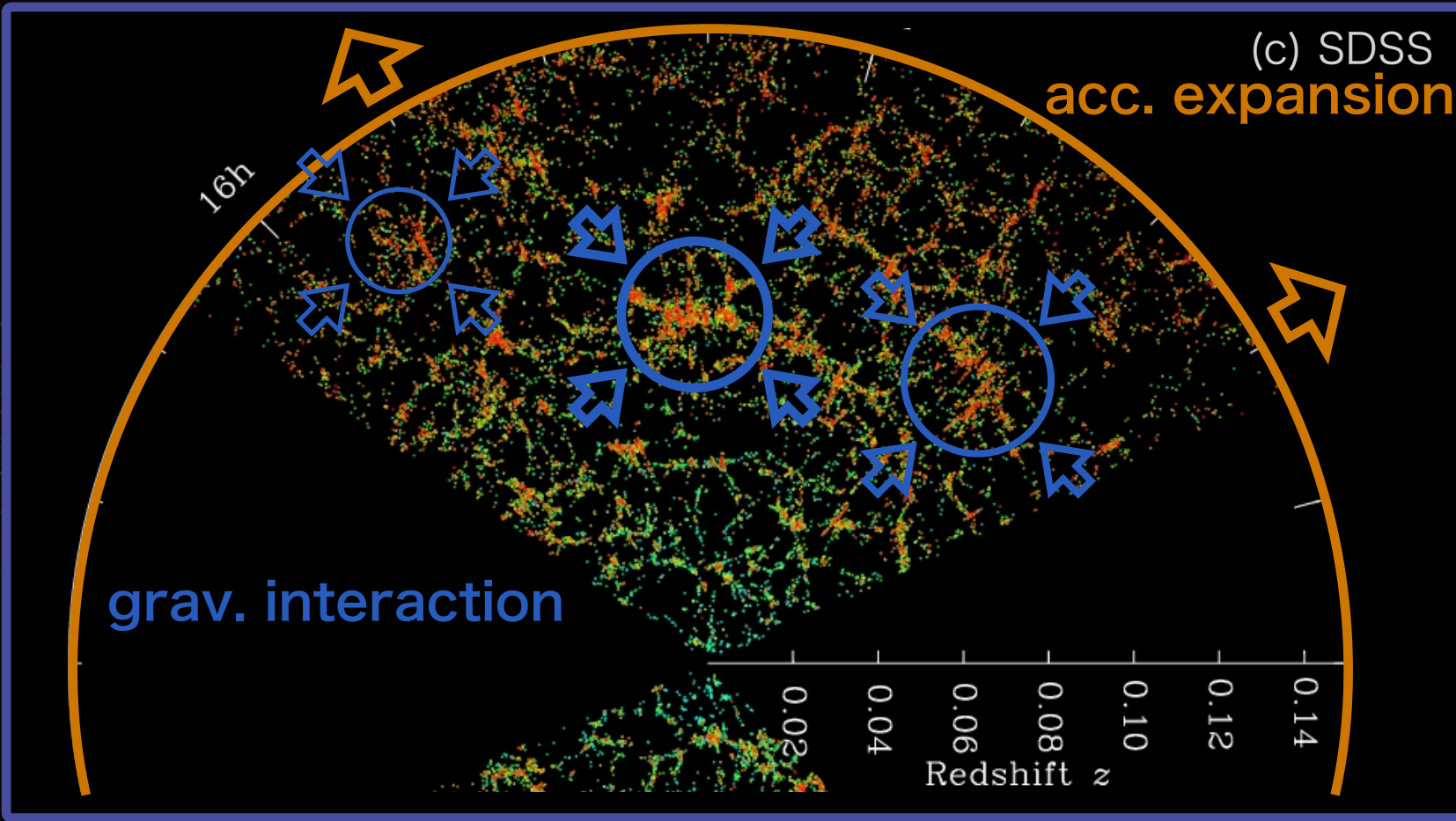
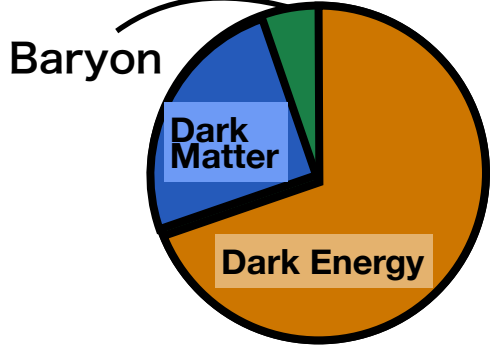
LSS as a Cosmological Probe

Structures on a scale larger than that of galaxy clusters, which are being formed in a struggle between dark matter and dark energy.



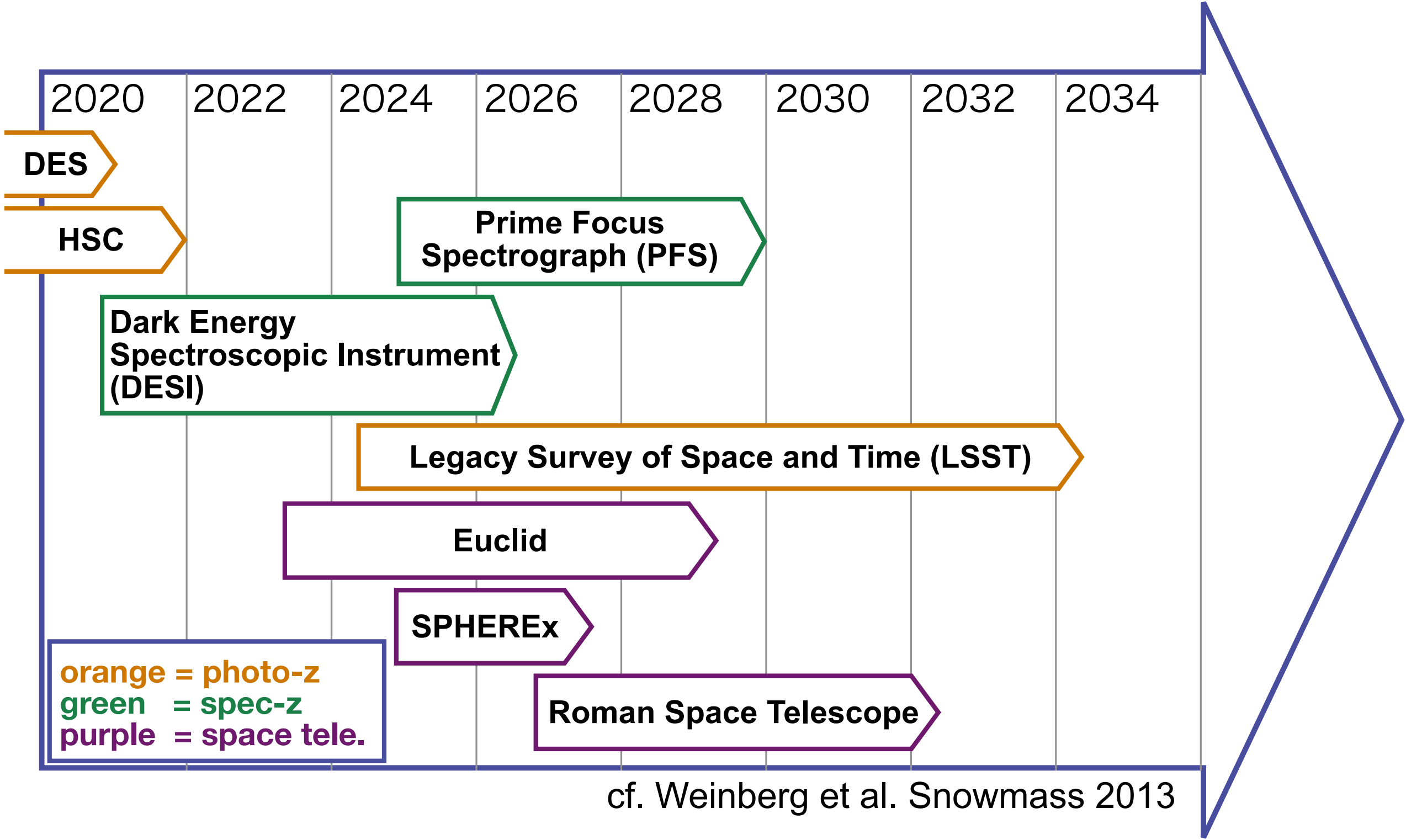
LSS as a Cosmological Probe

Structures on a scale larger than that of galaxy clusters, which are being formed in a struggle between dark matter and dark energy.



To understand nature of **dark energy** and **dark matter** through Large Scale Structure (LSS)

Current & Future Observation



Current & Future Observation

2020 2022 2024 2026 2028 2030 2032 2034

Systematic error > Statistical error

Need precise theoretical model...



Cosmological emulators that calculates theoretical prediction of structure evolutions rapidly and accurately.

- Dark Emulator 2
- MiraTitan IV
- Euclid Emulator 2
- Baccoemu etc.

Current & Future Observation

2020 2022 2024 2026 2028 2030 2032 2034

Systematic error > Statistical error

Observational

- Photo-z cf. KI+2023
- Galaxy shape
- Random catalog etc.

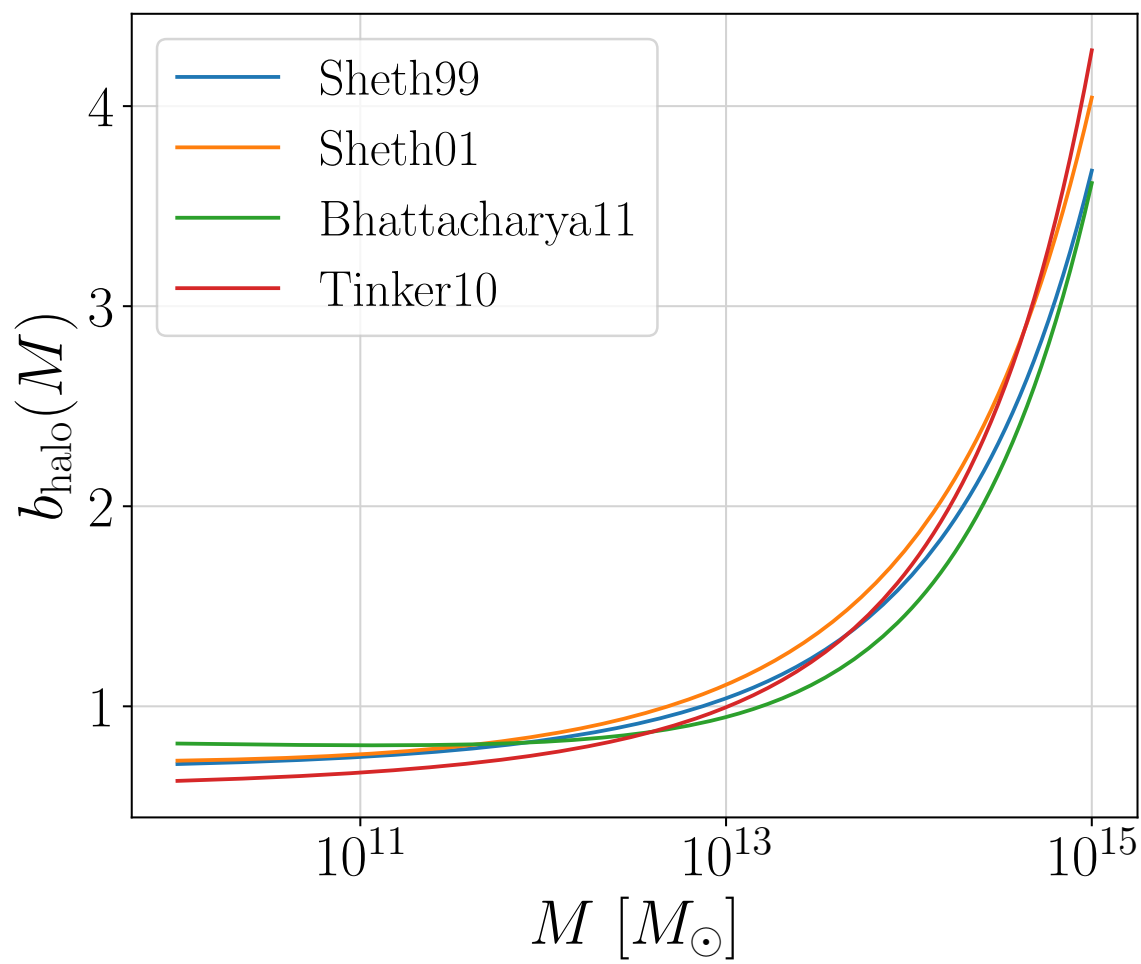
Astrophysical

- **Halo Assembly Bias**
- AGN feedback etc.

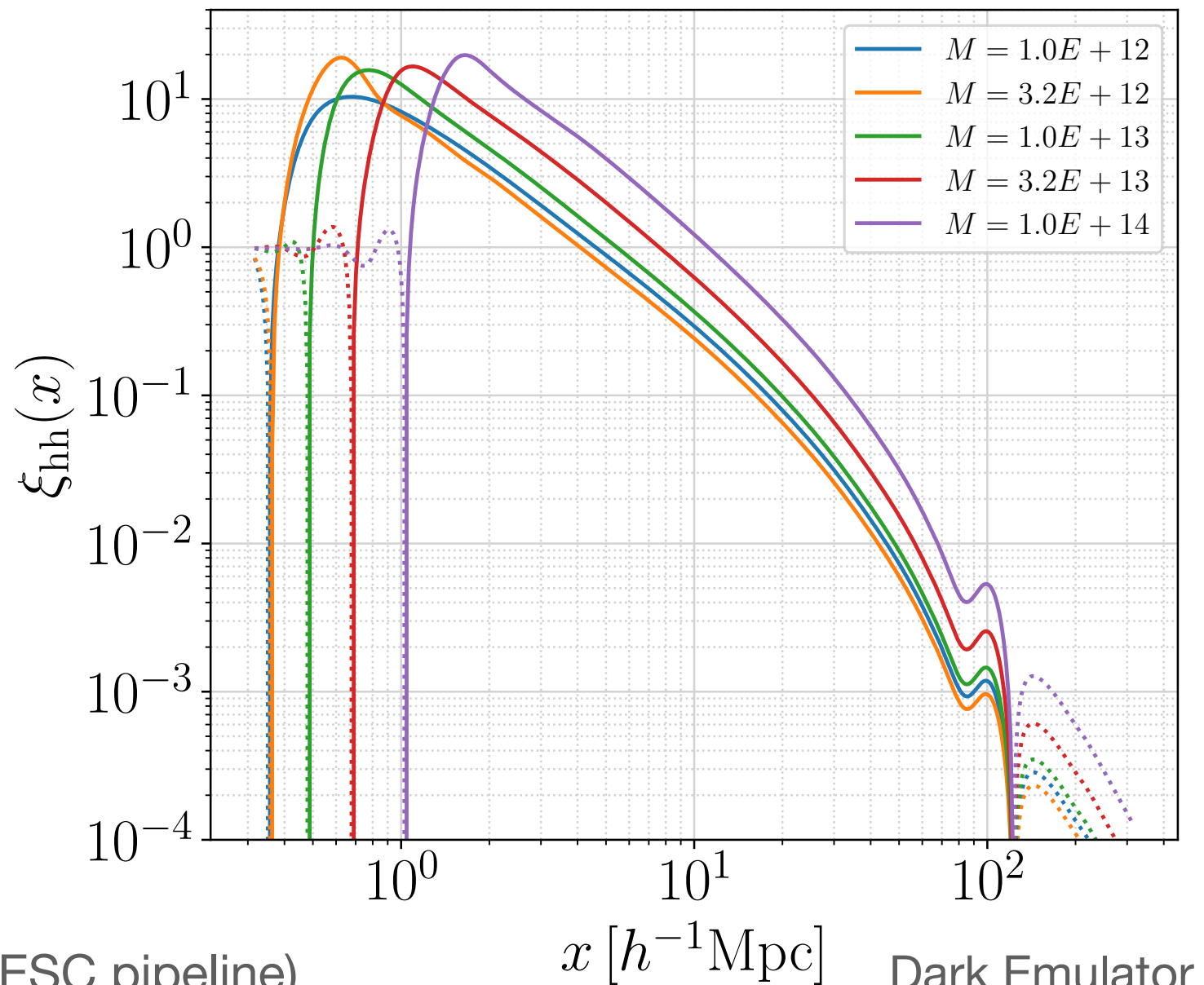
What is halo assembly bias?

linear halo bias

$$\delta_{\text{halo}} = b_{\text{halo}}^{\text{lin}}(M, z) \delta_{\text{m}}$$



cf. CCL (LSST DESC pipeline)



Dark Emulator

The linear halo bias *primarily* depends on halo mass.

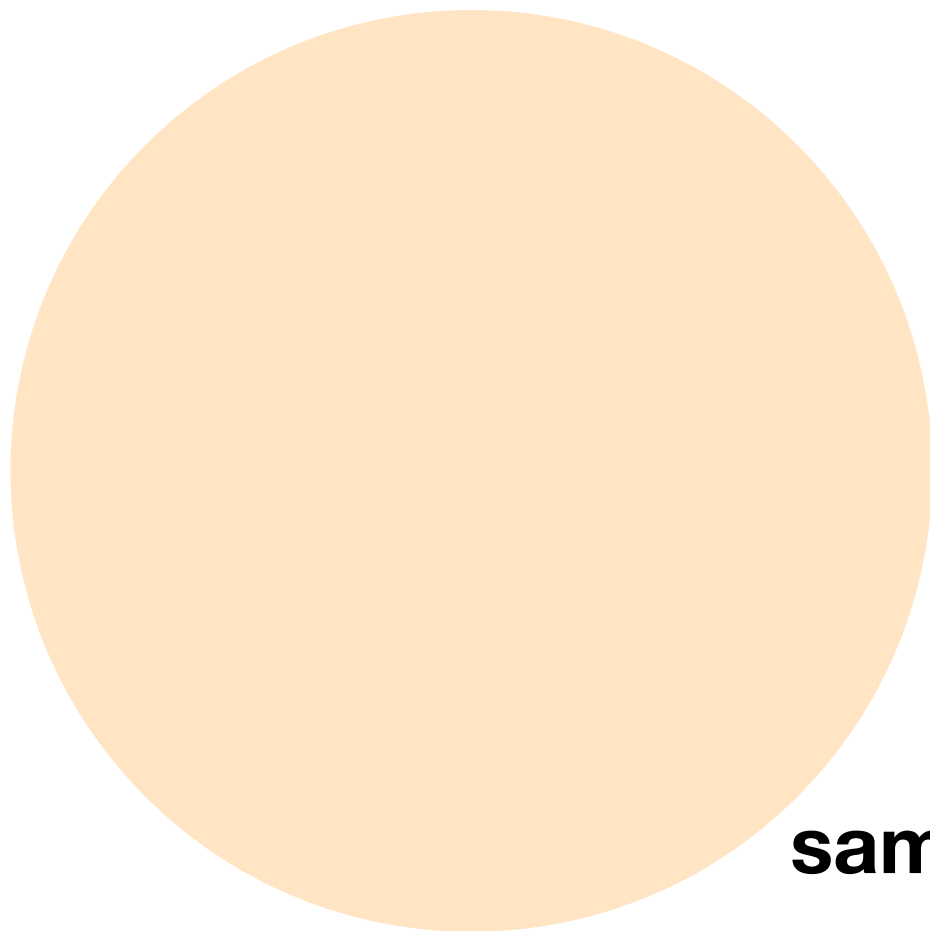
What is halo assembly bias?

Secondary dependence
on physical quantities other than halo mass

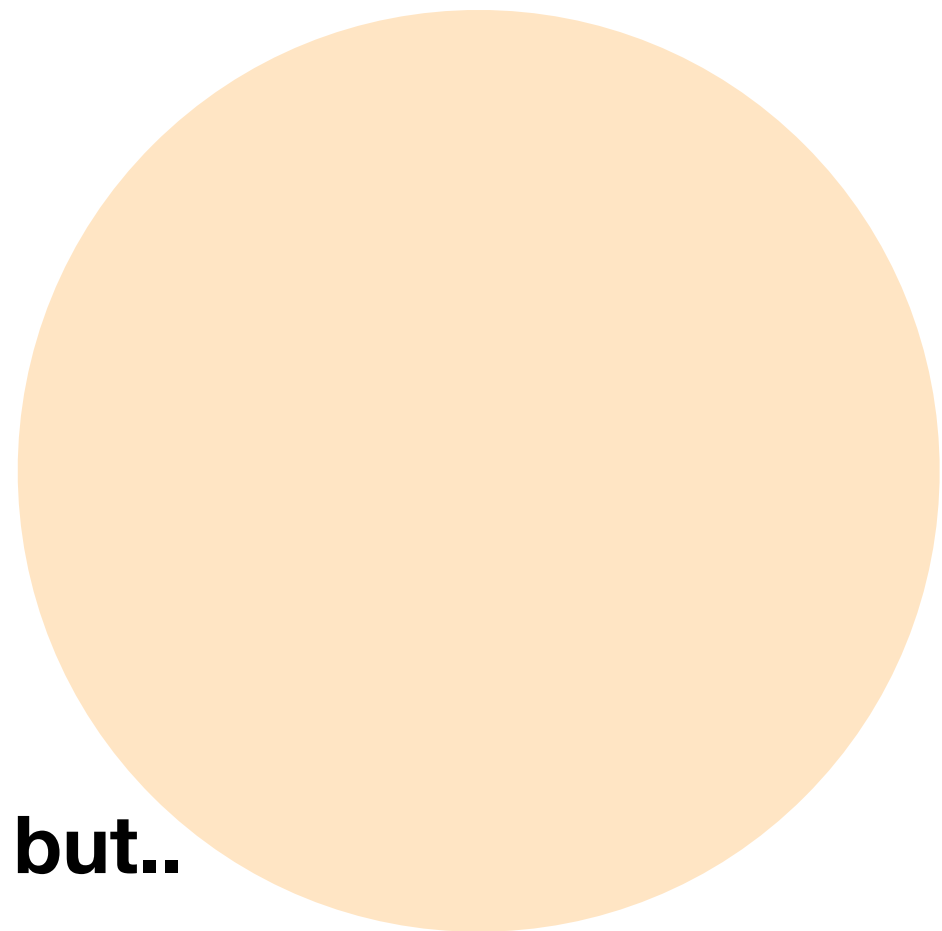
concentration, local overdensity, assembly history, ...

ex. The case we focus on halo that has higher than typical collapsing mass

early-forming



late-forming



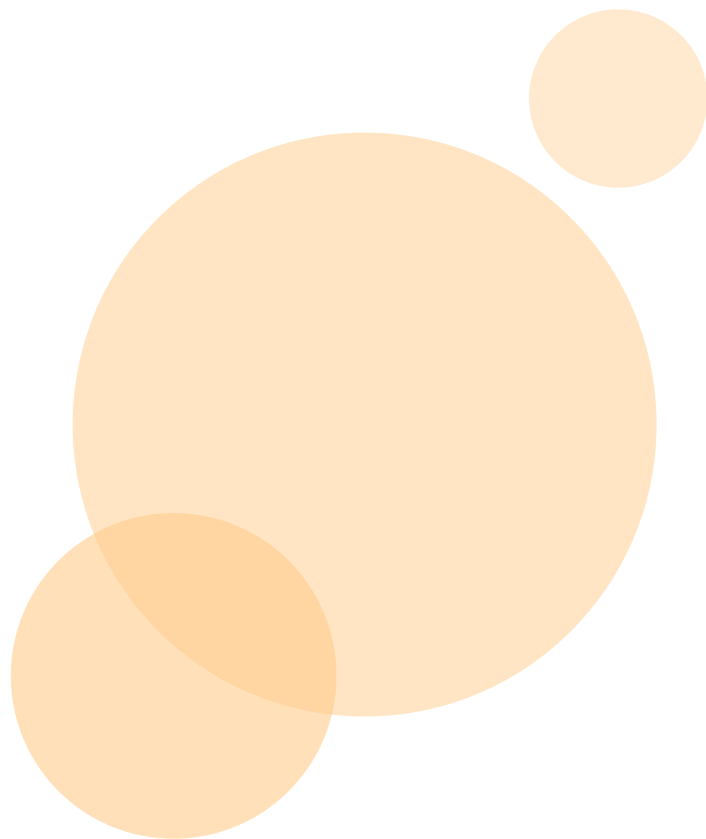
same mass, but..

What is halo assembly bias?

Secondary dependence
on physical quantities other than halo mass

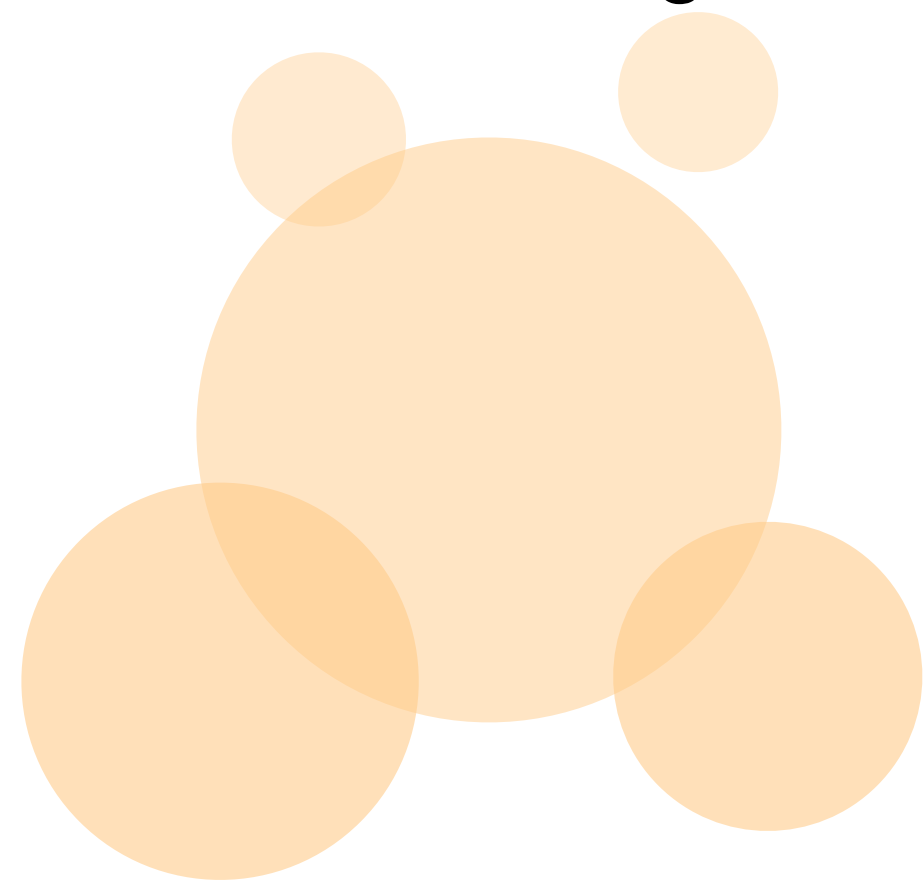
ex. The case we focus on halo that has higher than typical collapsing mass

early-forming



less strong clustering

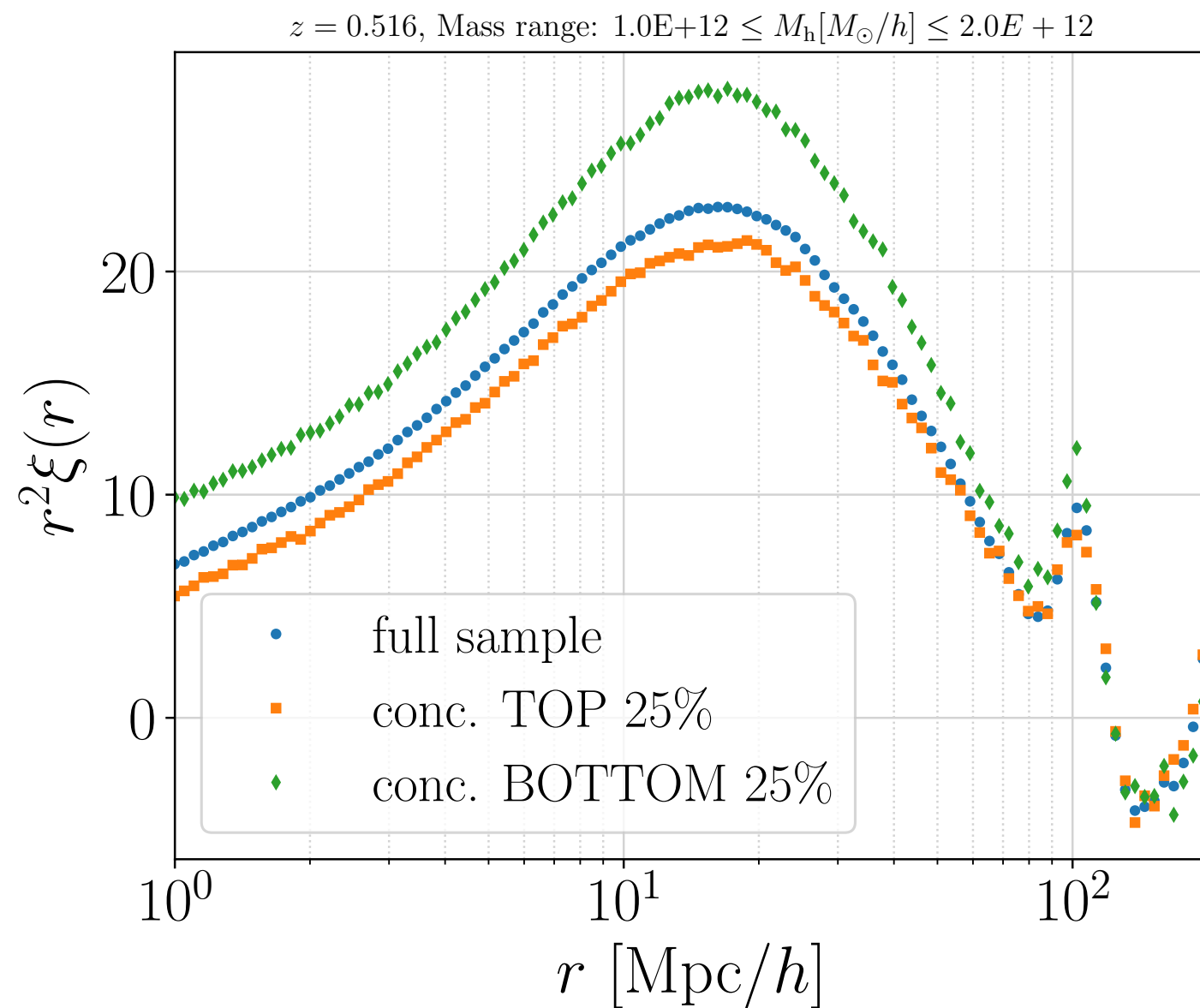
late-forming



more strong clustering

What is halo assembly bias?

Secondary dependence



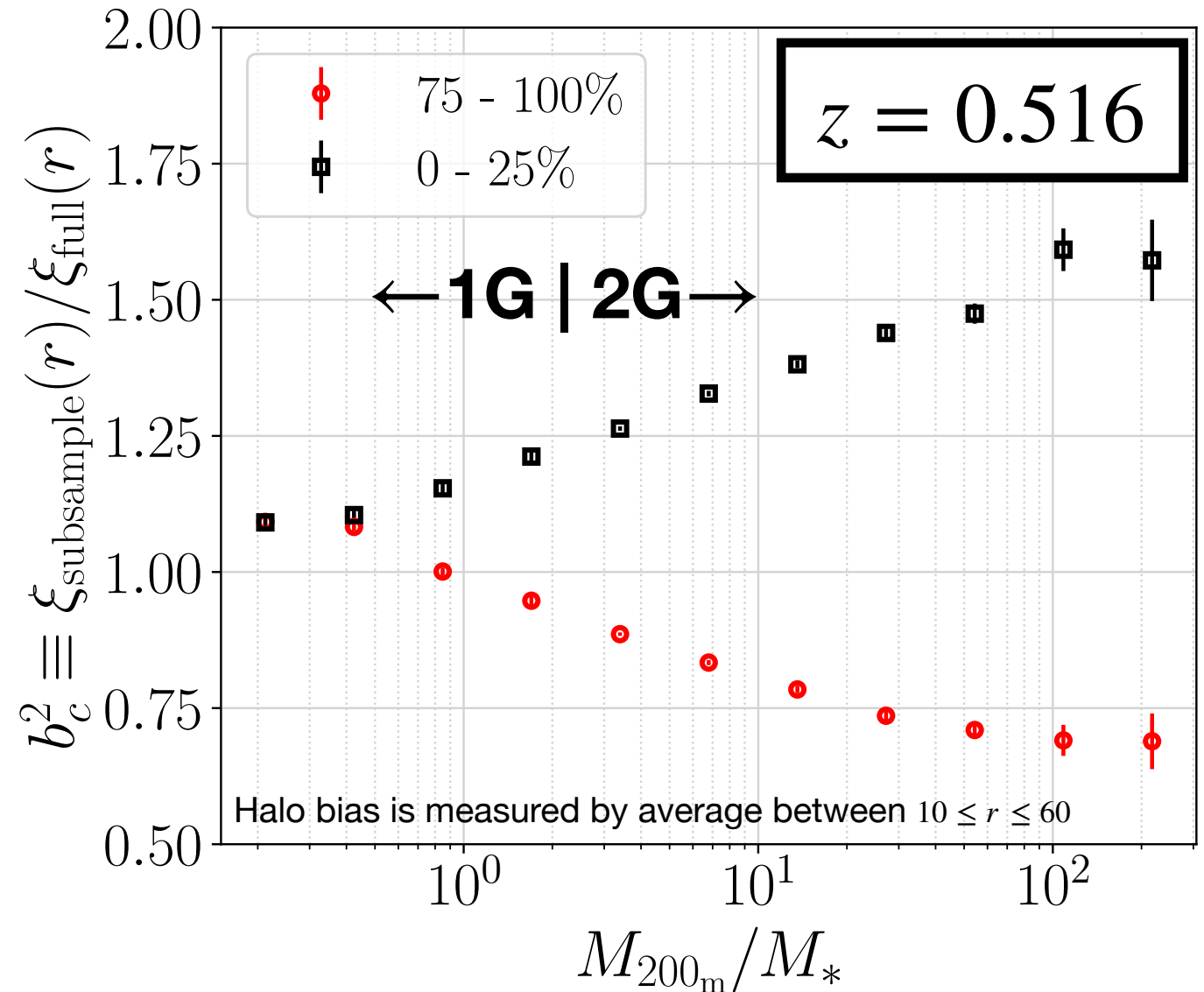
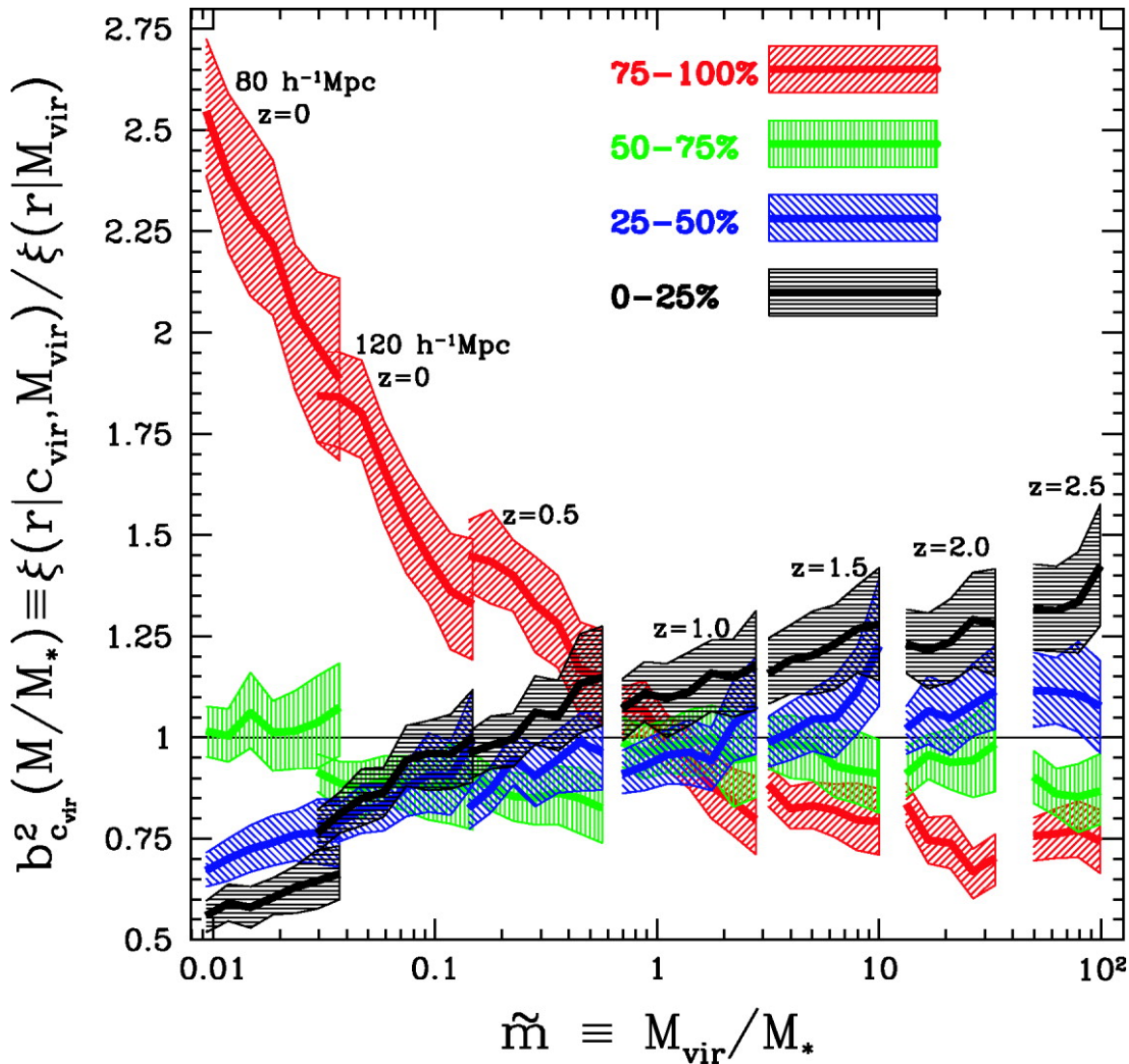
early-forming
(= **high** concentration)
less strong clustering

late-forming
(= **low** concentration)
more strong clustering

Non-trivial dependence

Wechsler et al. 2006

Dark Quest II (in prep.)

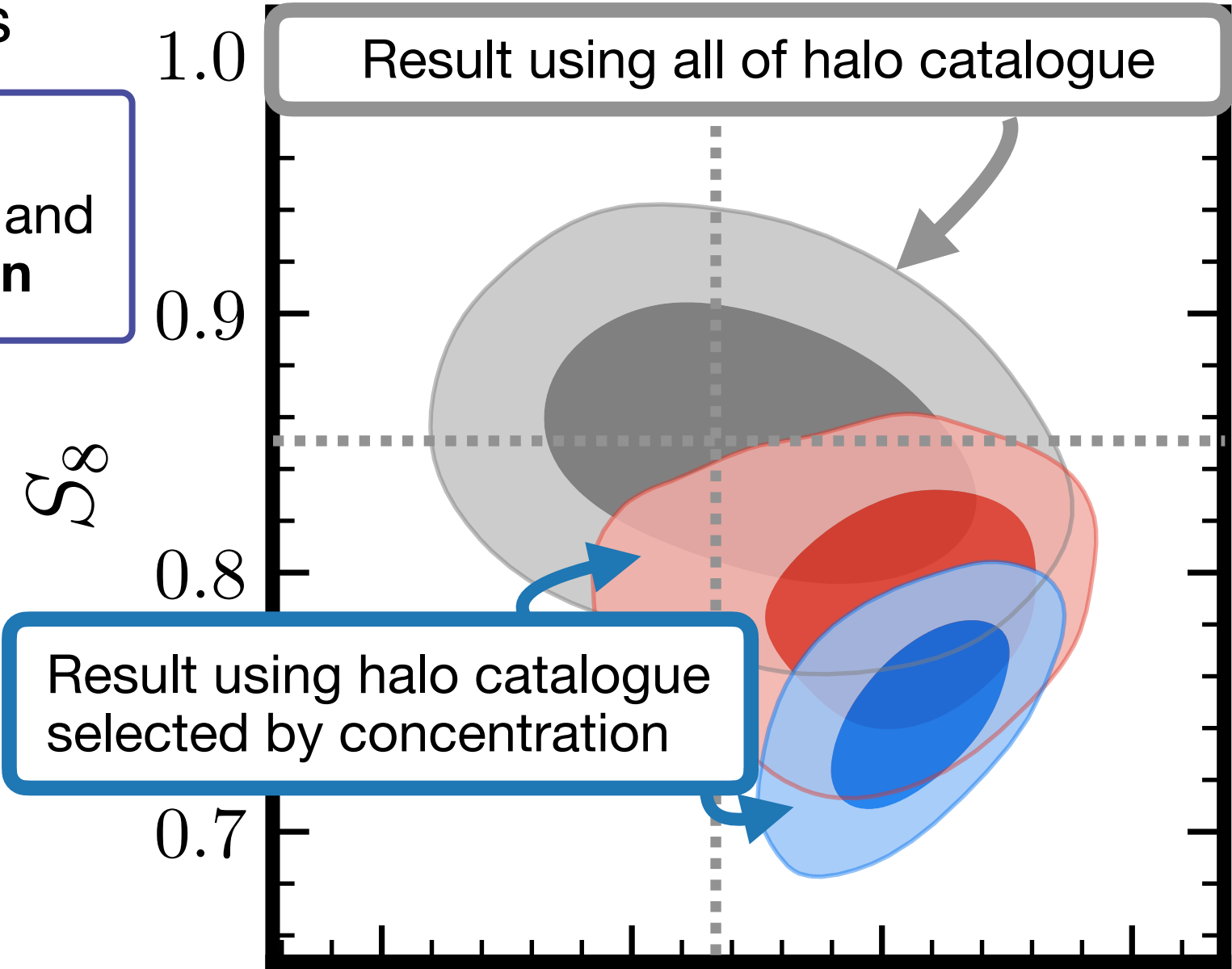
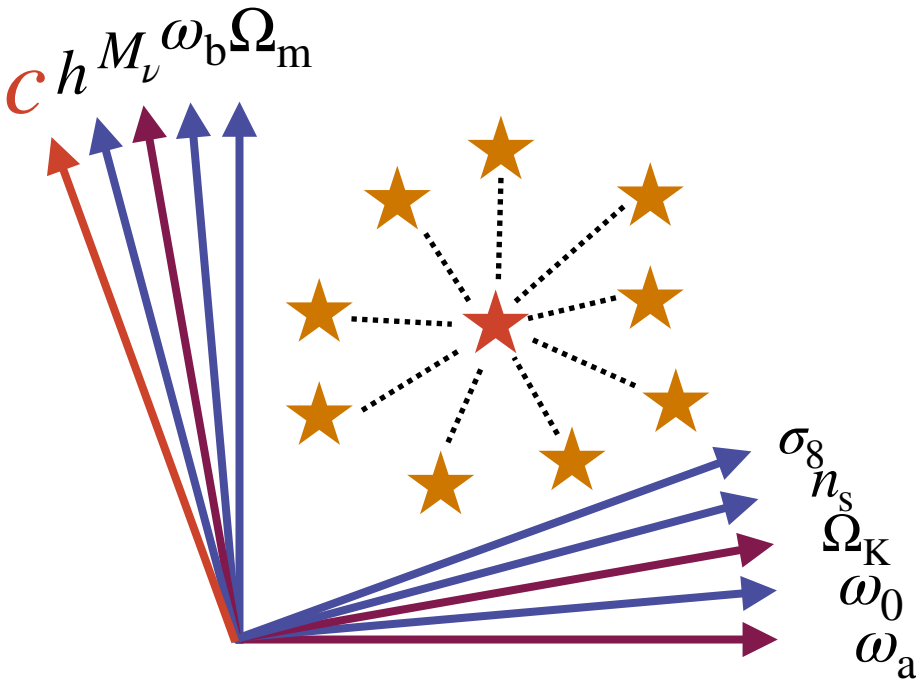


- Non-trivial dependence between halo mass and concentration
- Smaller systematic error is required in the future → Need to consider

It affects cosmological params.

Dark Emulator mock analysis

The cosmological emulator based on N-body that enables fast and accurate **halo statistics calculation**



Construct an emulator that **also predicts assembly bias parameters**

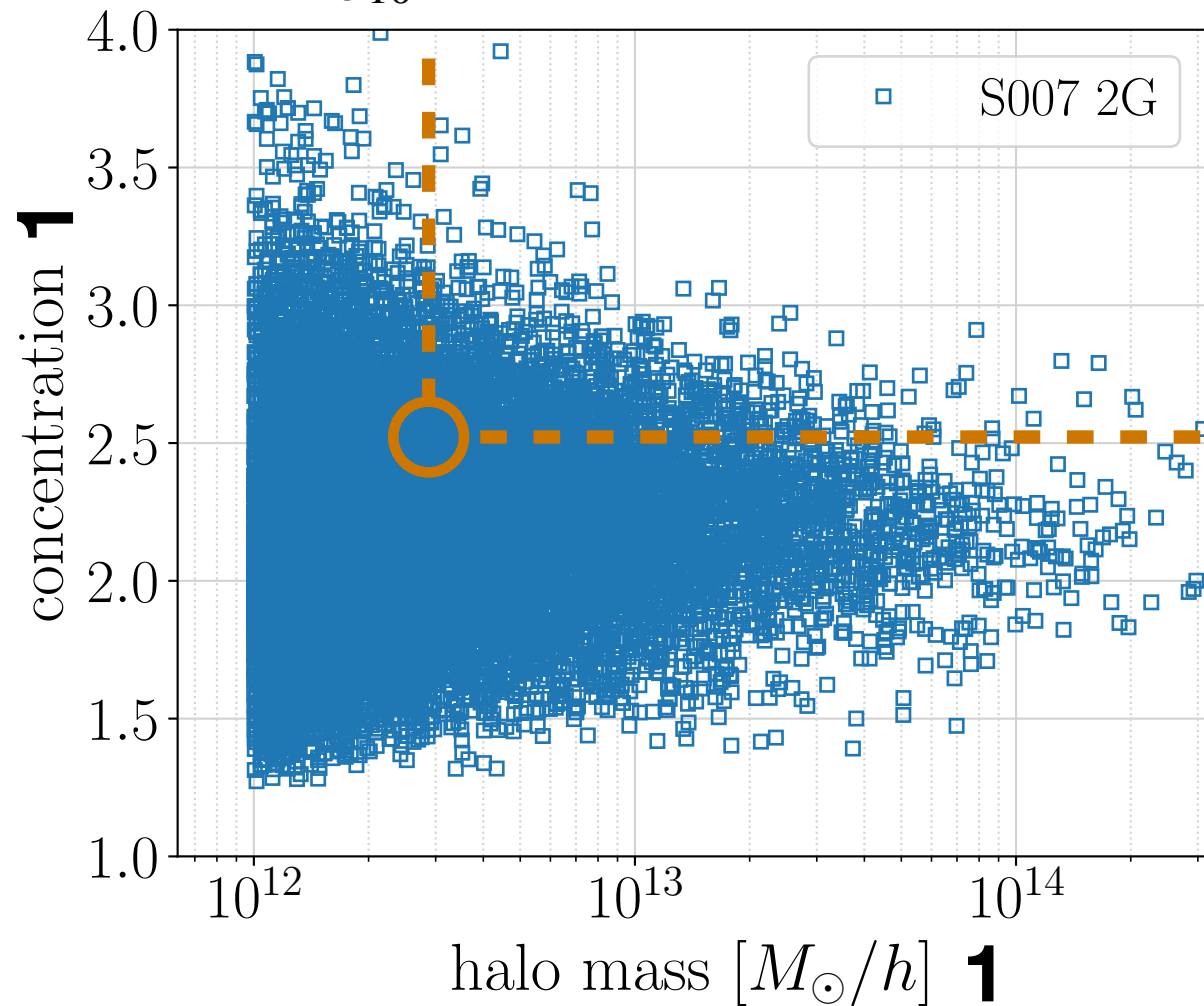
To implement assembly bias effect

Efficiently sample $M_{\text{threshold}}, c_{\text{threshold}}$ in 4D space

• sample range:

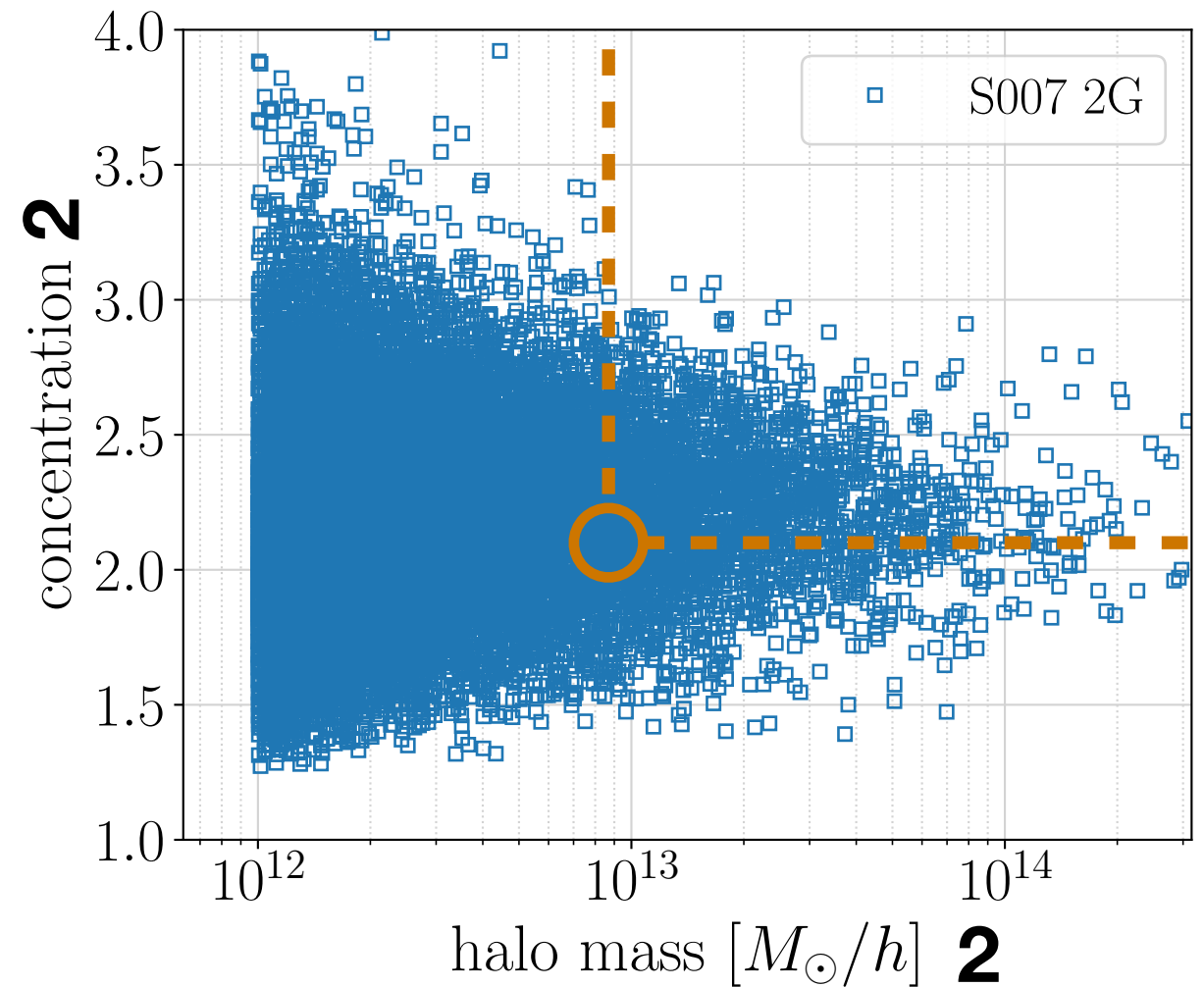
$$12 \leq \log_{10} M \leq 15, 1 \leq c \leq 4$$

➔ Check out all the cross-corr.



×

||



$$\langle \delta_{\text{halo}}(> M_1, > c_1) \delta_{\text{halo}}(> M_2, > c_2) \rangle$$

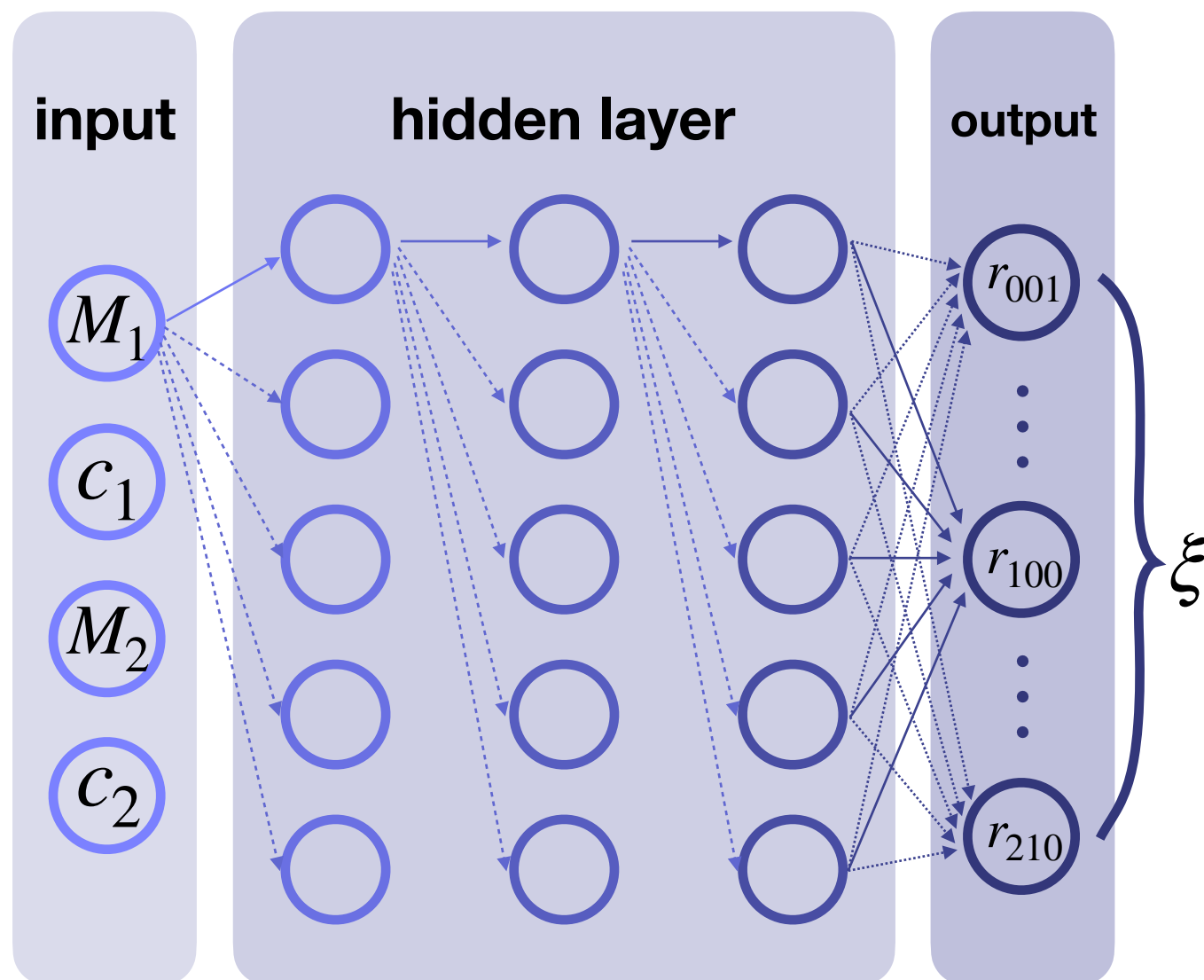
Measure in real-space, redshift-space ($l = 0, 2, 4, 6$)

*normalizing flow + scrambled Sobol sequence

To implement assembly bias effect

◆ Feed Forward Neural Network (FFNN)

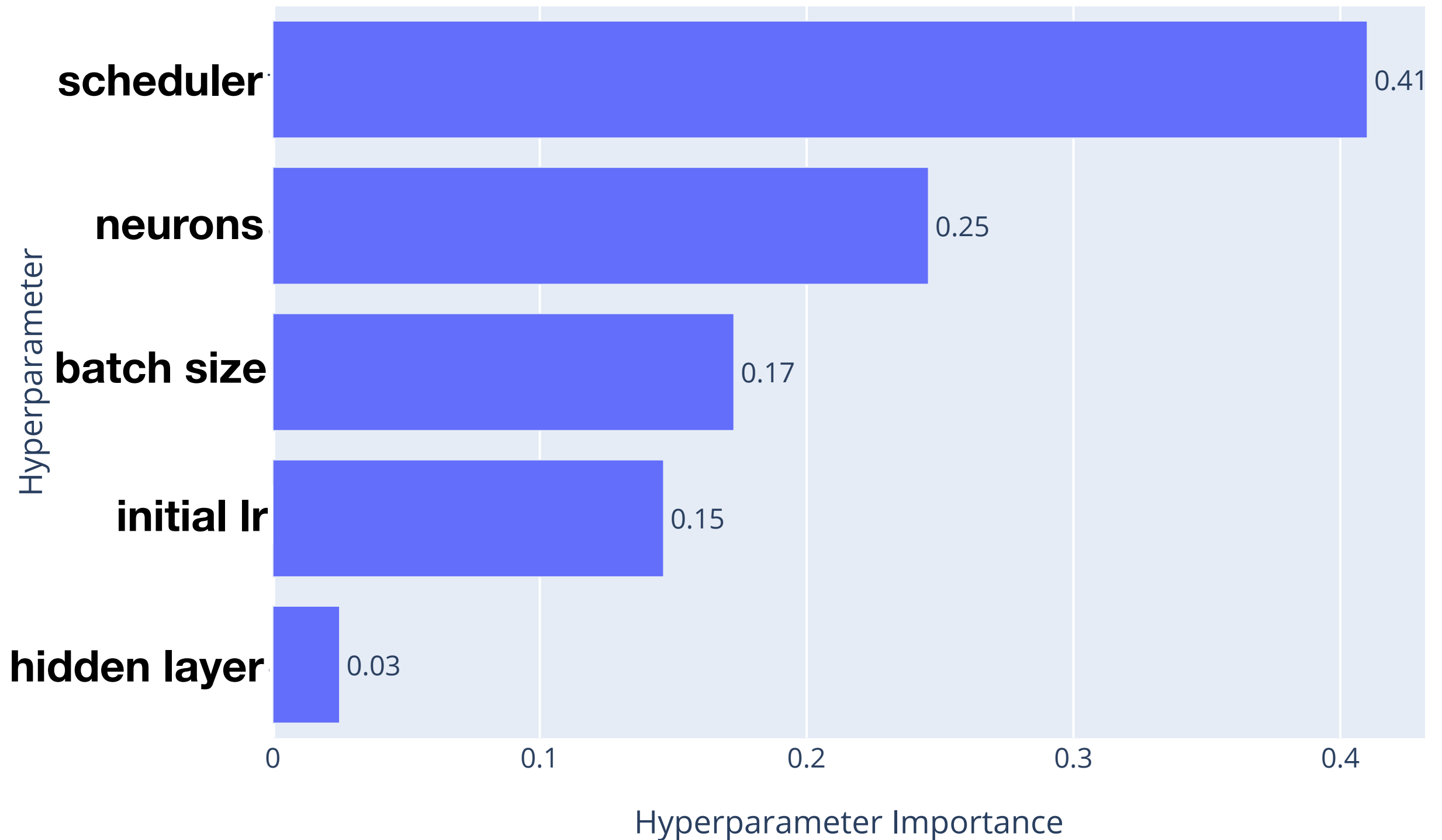
Regress cross-corr. as a function of $M_{\text{threshold}}$, $C_{\text{threshold}}$



- loss function: χ^2
- covariance: Jackknife
- r : [0.1, 200] Mpc/h
- suppress cosmic variance
- sample size: 24,780
(90% of # : train, validation, 10%: test)
- automatic survey of hyper params
(hidden layer, # of neuron, batch size, scheduler, initial learning rate)
- ✧ consider cosmological dependence as a future work

Result: hyper parameters search

◆ Real space



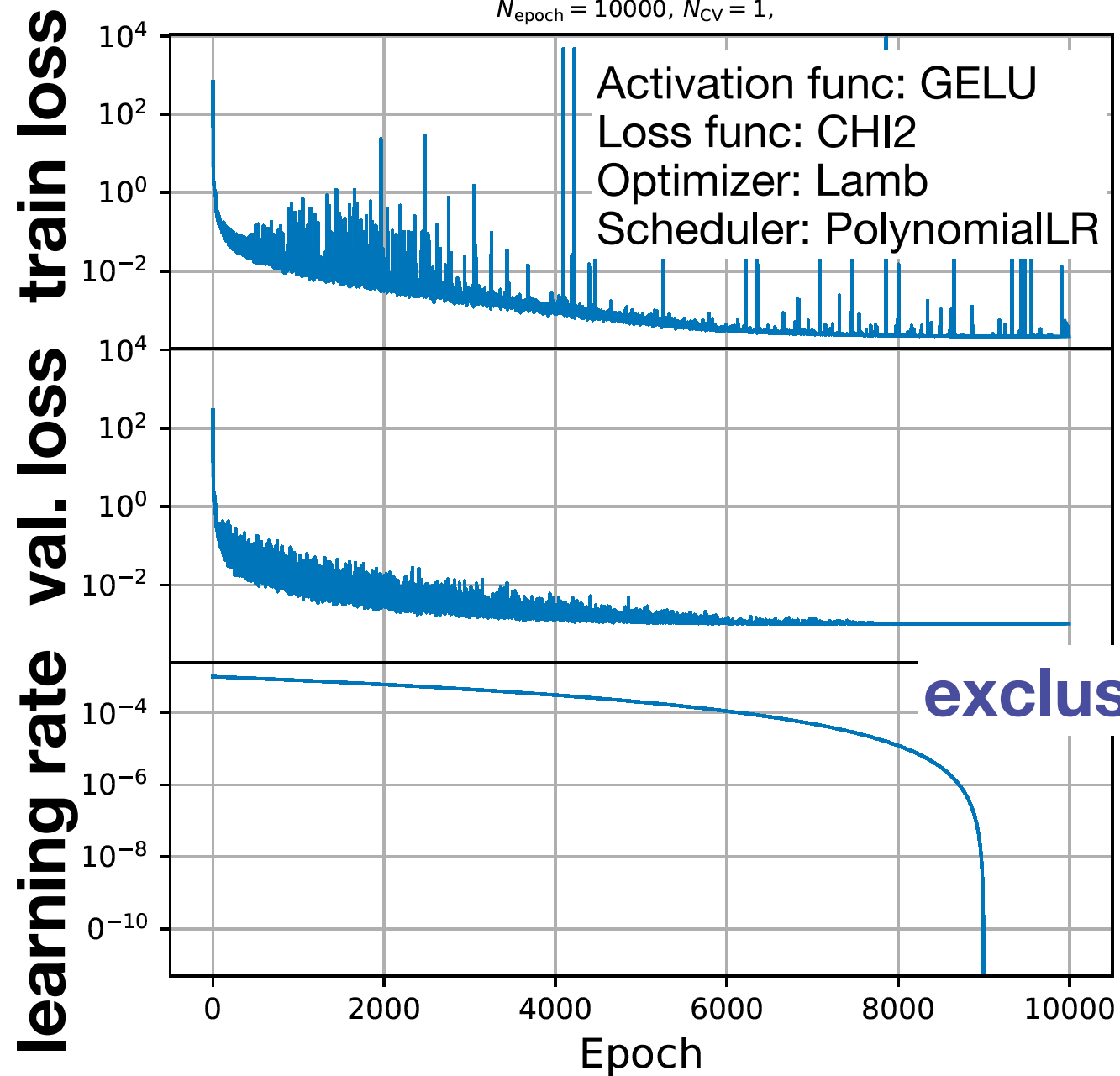
Result: achieve 1% accuracy (2-40 [Mpc/h])

Real space

loss function

$N_{\text{param}} = 4, N_{\text{batch}} = 256, N_{\text{hidden}} = 8, N_{\text{net}} = 1000,$
 $N_{\text{epoch}} = 10000, N_{\text{CV}} = 1,$

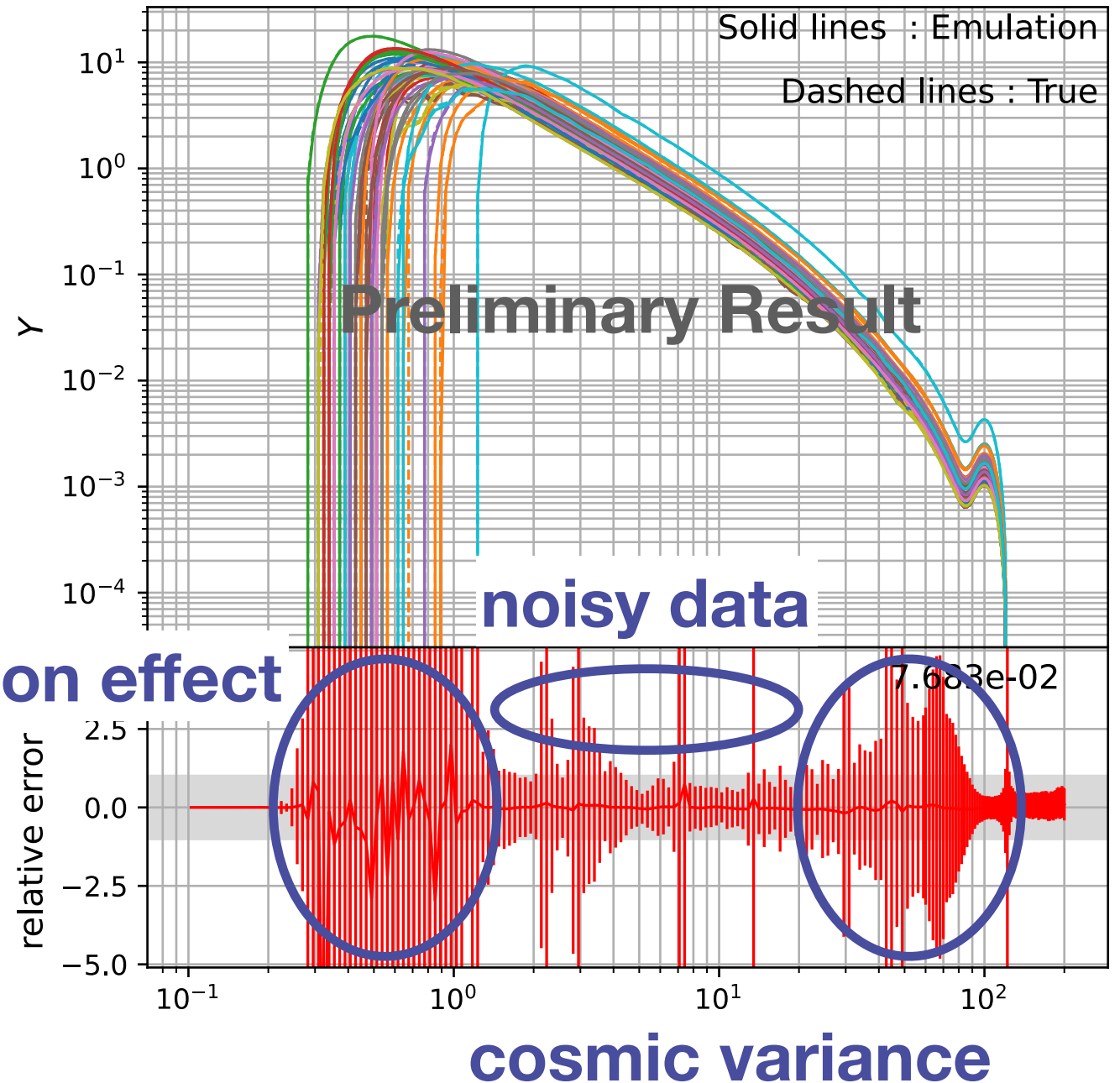
Activation func: GELU
 Loss func: CHI2
 Optimizer: Lamb
 Scheduler: PolynomialLR



correlation function (test data)

20240622_191335_994046.pth

Solid lines : Emulation
 Dashed lines : True



exclusion effect

Summary

- ✓ The goal of this study:
 - **Implement halo assembly bias effect into Dark Emulator II**
- ✓ What exactly do we do?:
 - **Efficiently sample in multi-dimensional space**
 - **Learn params. dependence in 4D input space by FFNN**
- ✓ Result:
 - Achieved 1% accuracy (2-40 [Mpc/h]) in prediction on FFNN
 - Automatic hyper parameters search with **Optuna**
- ✓ Next Step:
 - Redshift dependence
 - Cosmological parameters dependence
 - **Implementing Dark Emulator 1 into Roman analytical pipeline**