A Neural Network Approach to Model Secondary Dependence of Halo Bias

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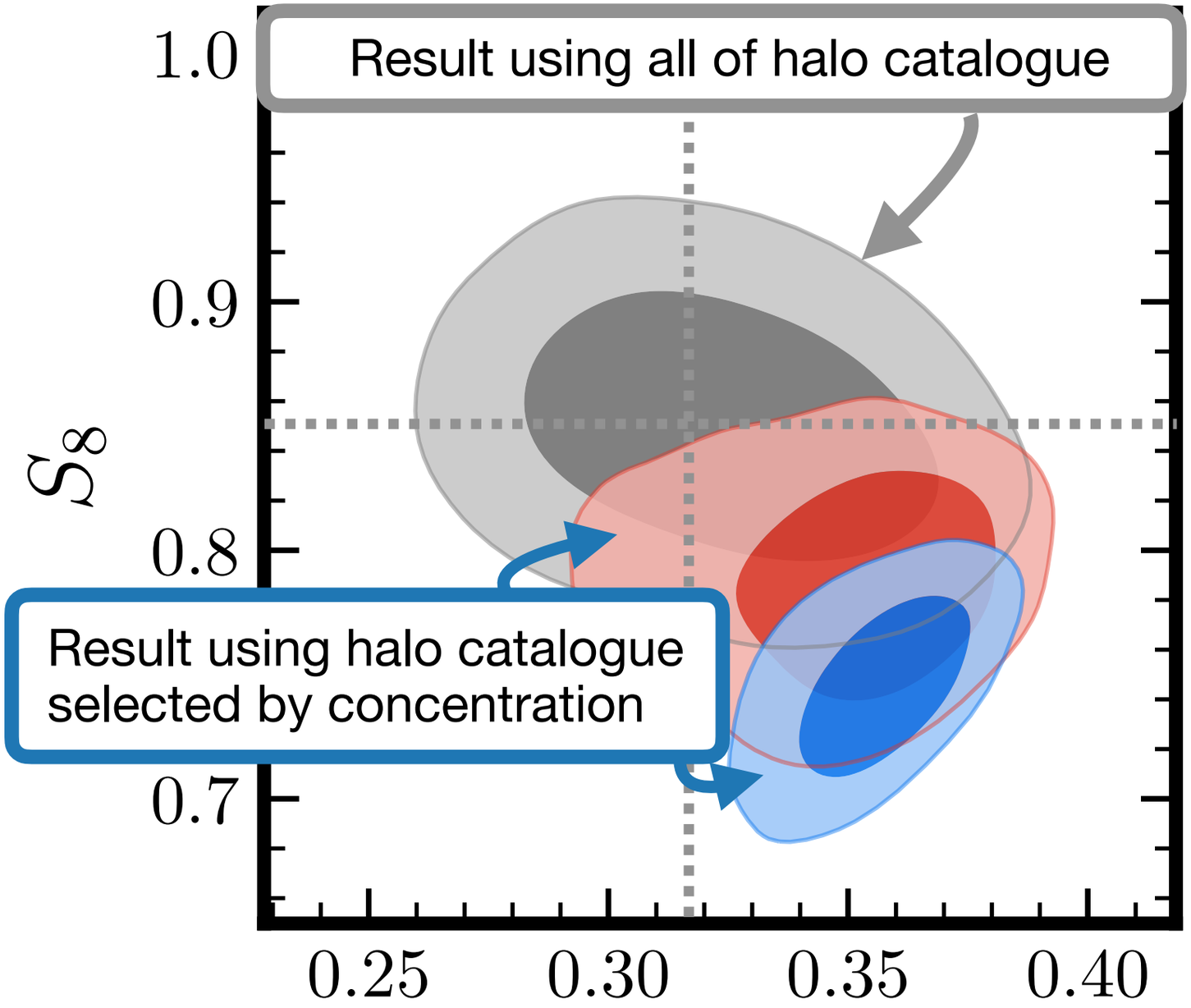
公募研究E01: アセンブリ・バイアス入りの宇宙論エミュレータの開発とΛCDM標準宇宙論の徹底検証

SDSS

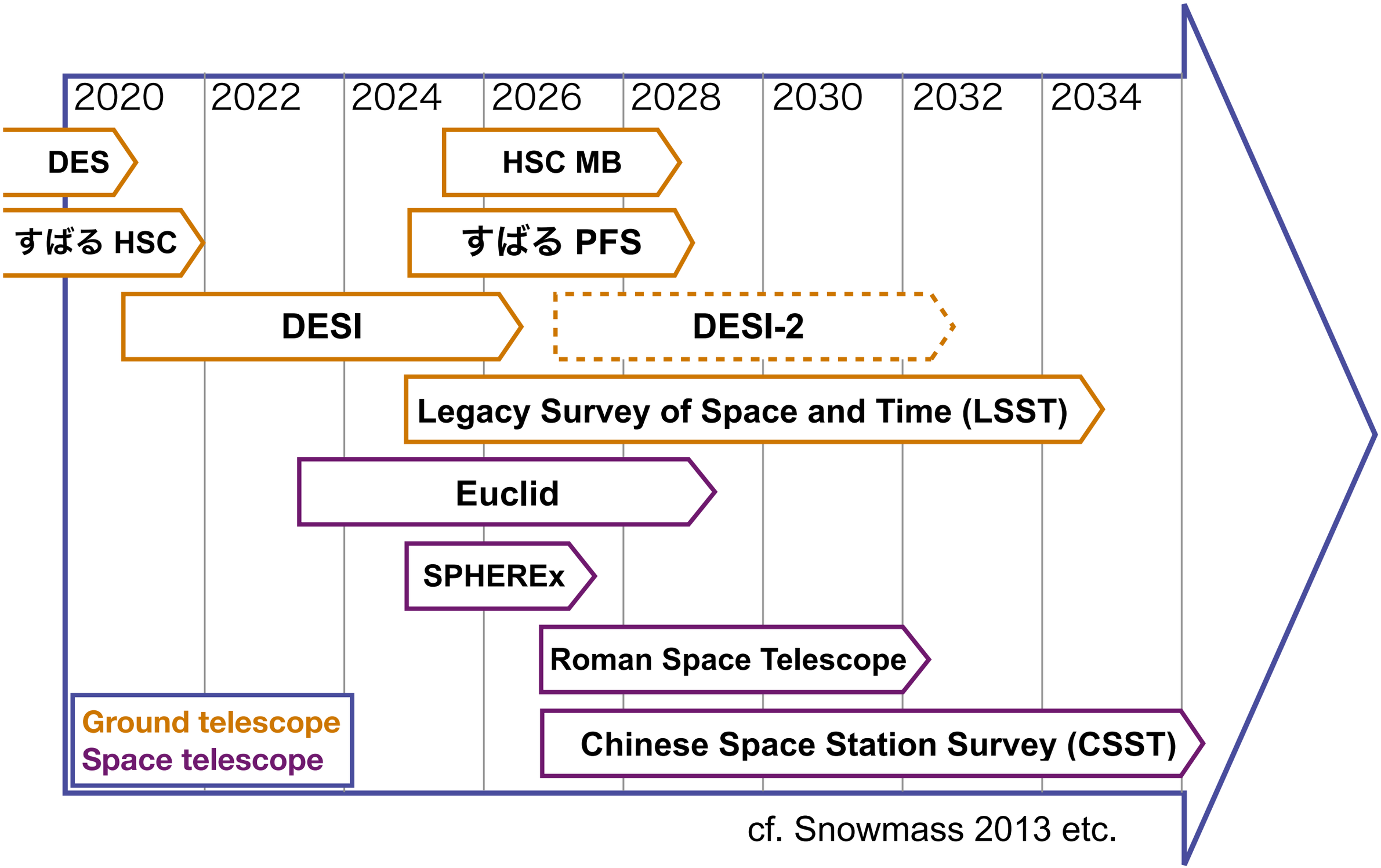
Motivation



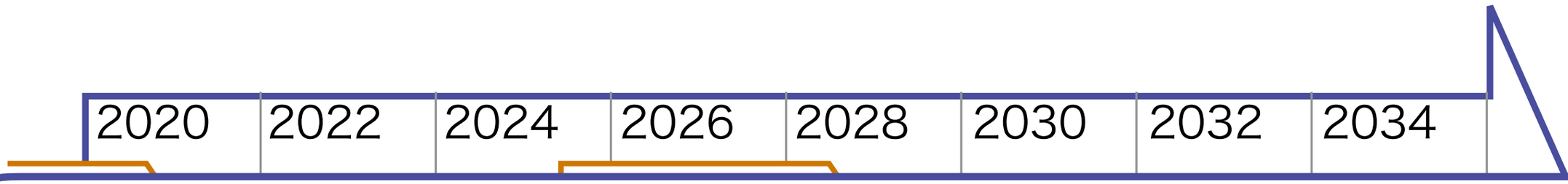
Miyatake et al. 2022b

Construct an emulator
that also predicts secondary dependence parameter

Current & Future Observations



Current & Future Observations



Systematic error > Statistical error

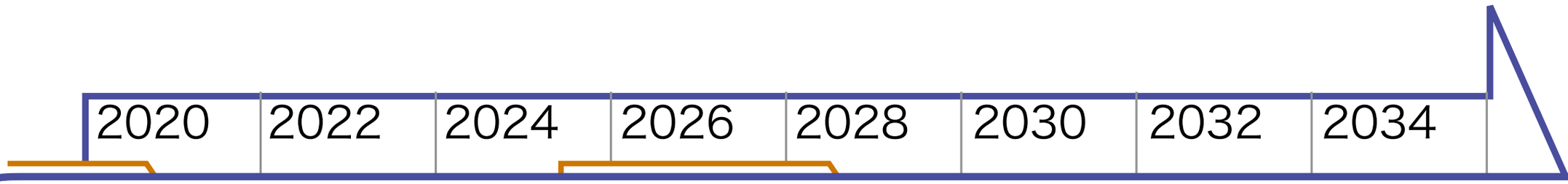
Observational

- Photo-z
- Galaxy shape
- Random catalog etc.

Astrophysical

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

Current & Future Observations



Systematic error > Statistical error

Need precise theoretical model…

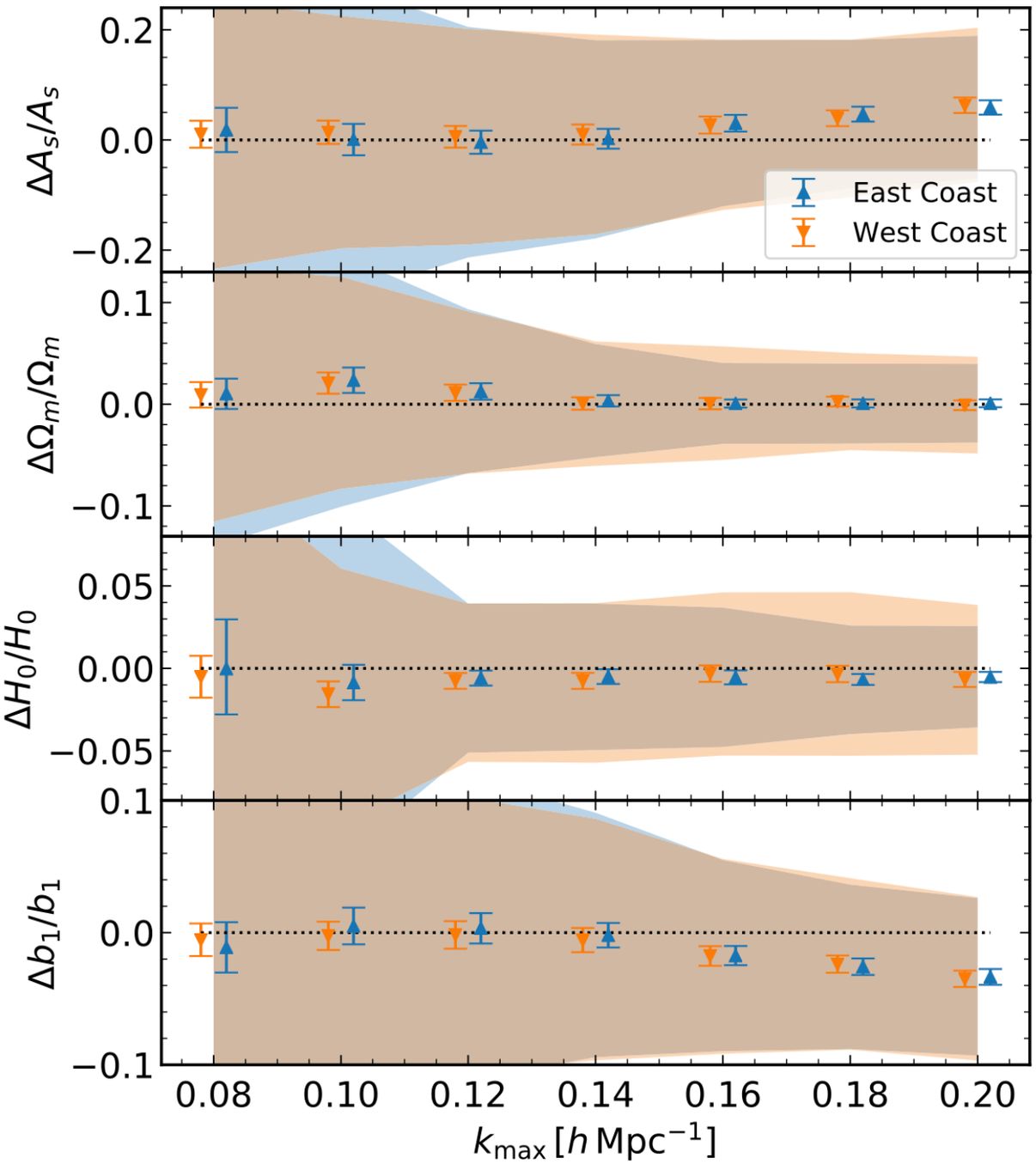
Cosmological emulators calculate
theoretical prediction of structure evolutions rapidly and accurately.

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

etc.

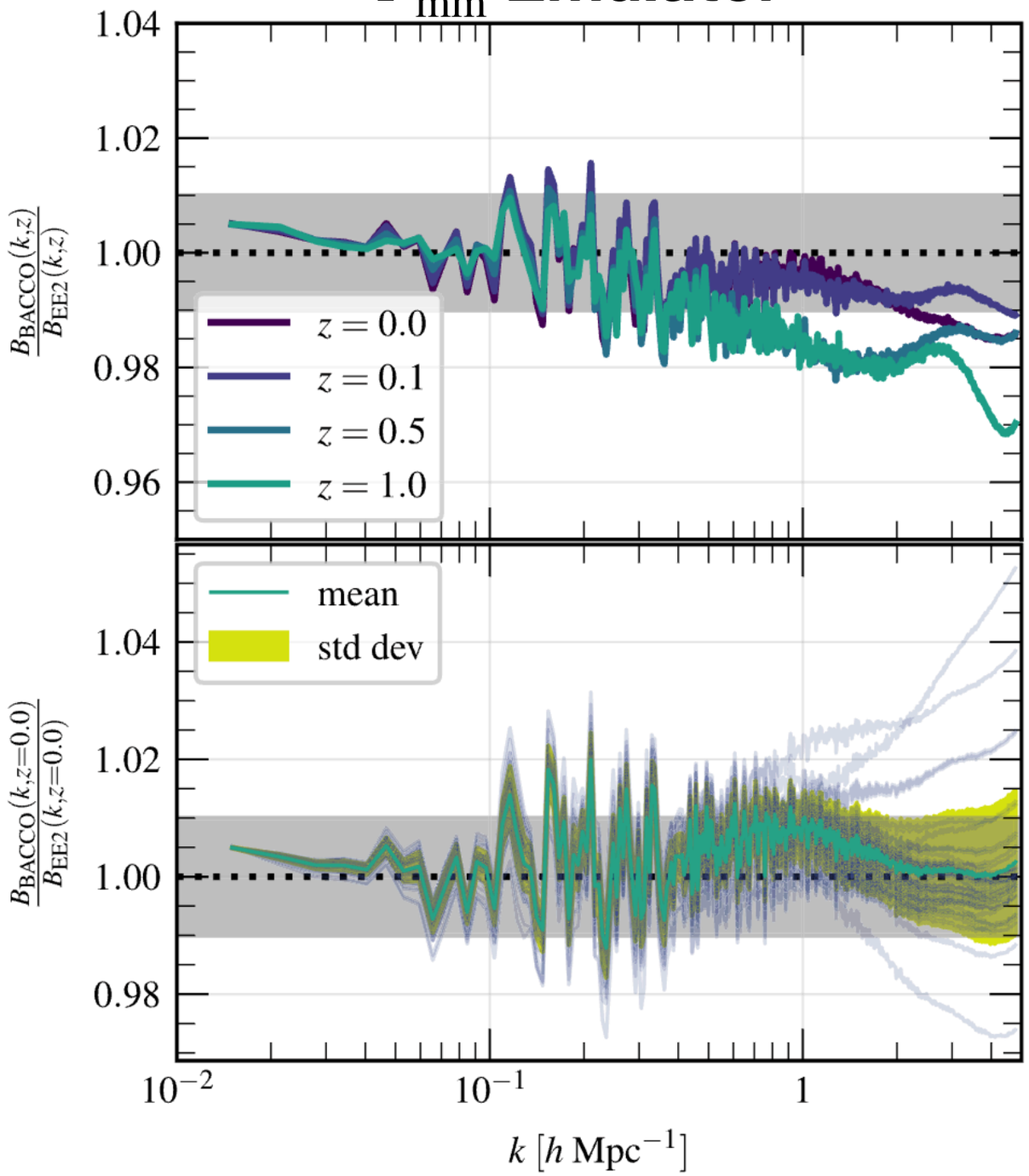
Analysis inclu. non-linear region

Blinded Cosmology Challenge



Nishimichi et al. 2020 (arXiv:2003.08277)

$P_{\rm mm}$ Emulator

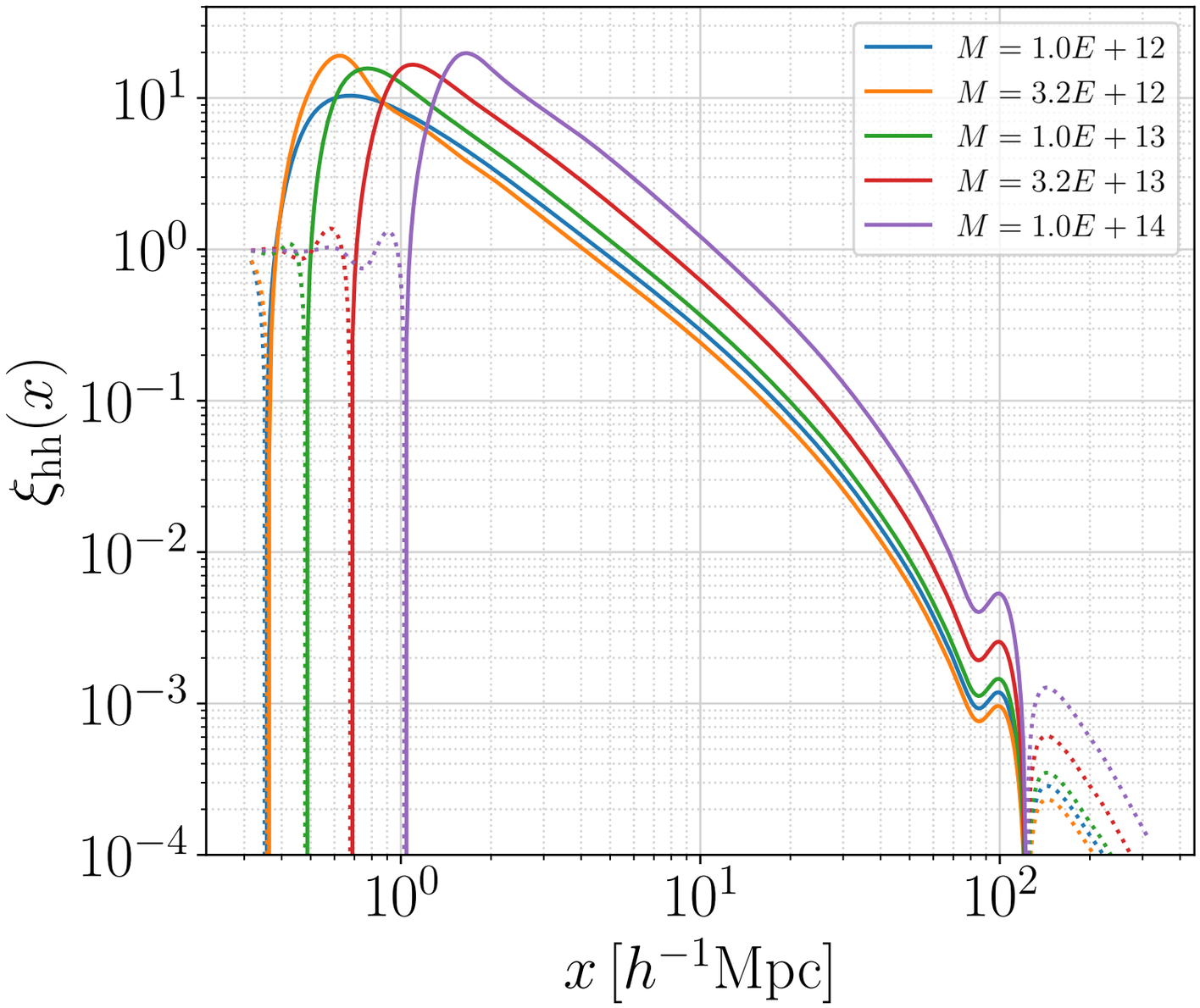


EuclidEmulator2 (2021)

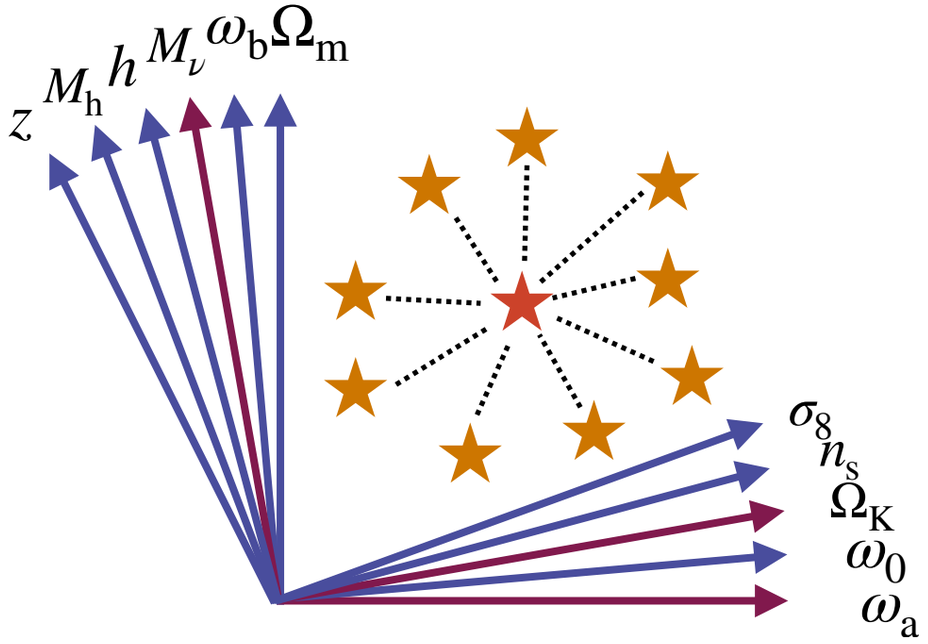
Halo Emulator: Dark Emulator

T. Nishimichi et al. 2019

is besed on N-body simu., learns statistics using Gaussian process.



Real / Configuration space

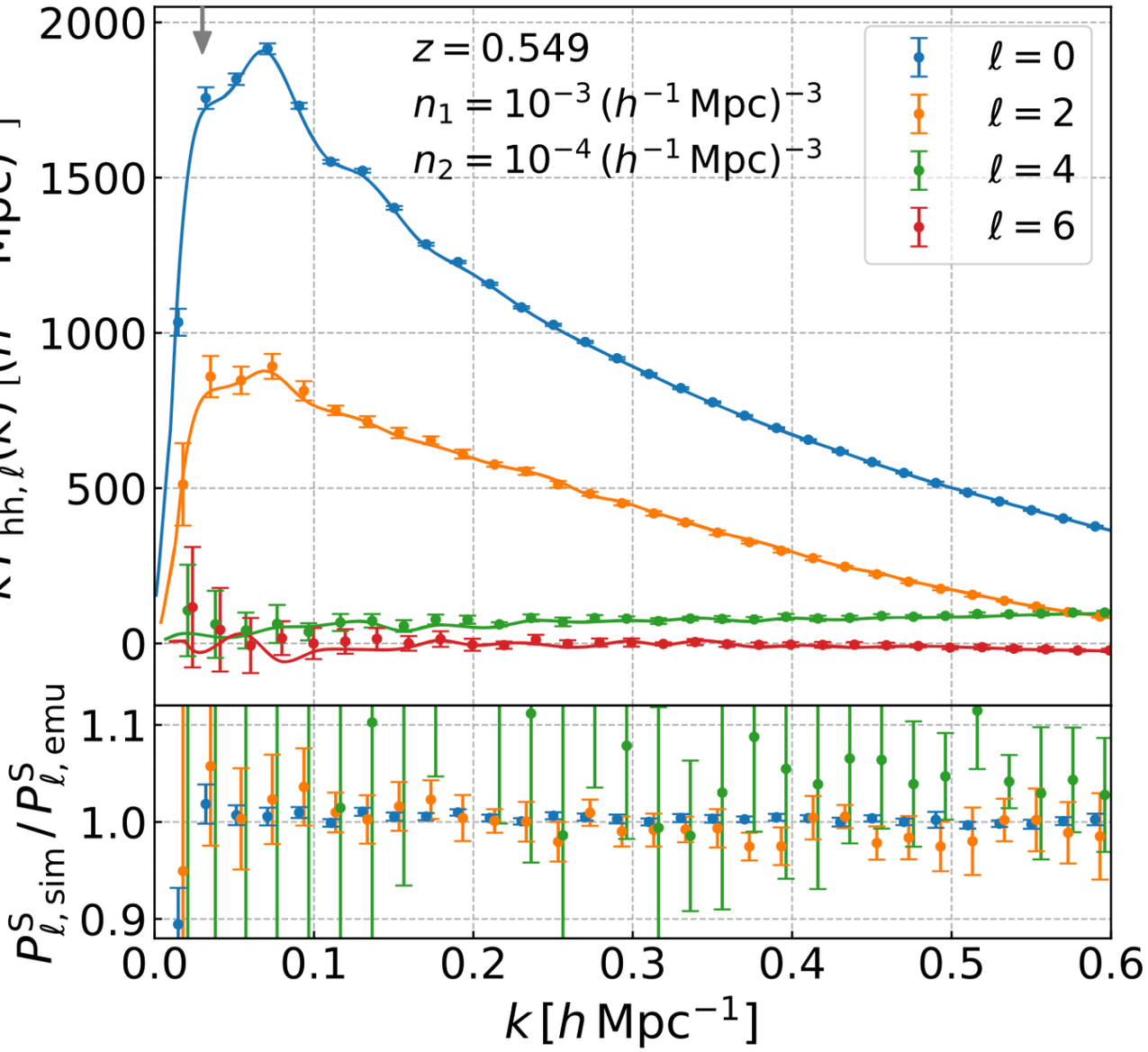


Dark Emulator I
Dark Emulator II (soon!)

Real and Redshift / Fourie space

Halo Emulator

Y. Kobayashi et al. 2020b



$$P_{\mathrm{halo}}(k, z; \mathrm{cosmo}; M_{\mathrm{halo}})$$

Not model
halo assembly bias yet

HOD

Connect halo distri. and
a number of gals, gal. distri.

$$P_{\mathrm{gal}}(k, z)$$

Accuracy: $l = 0 : 1\,\%$, $l = 2 : 5\,\%$ @ $k < 0.6$ $[h/\mathrm{Mpc}]$

Halo Assembly Bias

Secondary dependence
on physical quantities other than halo mass

$$\delta_{\rm halo} = b^{\rm lin}_{\rm halo}(M_{\rm halo}, z)\delta_{\rm m}$$

▽ Confirmed on simulations

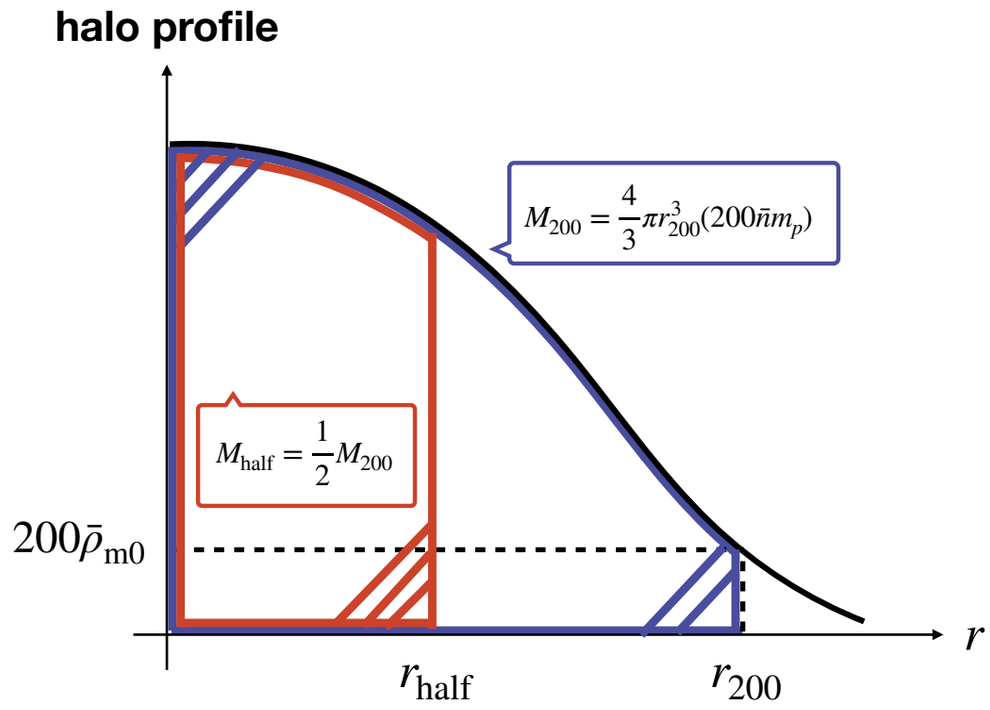
$$\delta_{\rm halo} = b^{\rm lin}_{\rm halo}(M_{\rm halo}, c, z)\delta_{\rm m}$$

ex. Wechsler et al. 2006

Ex. : **Concentration**

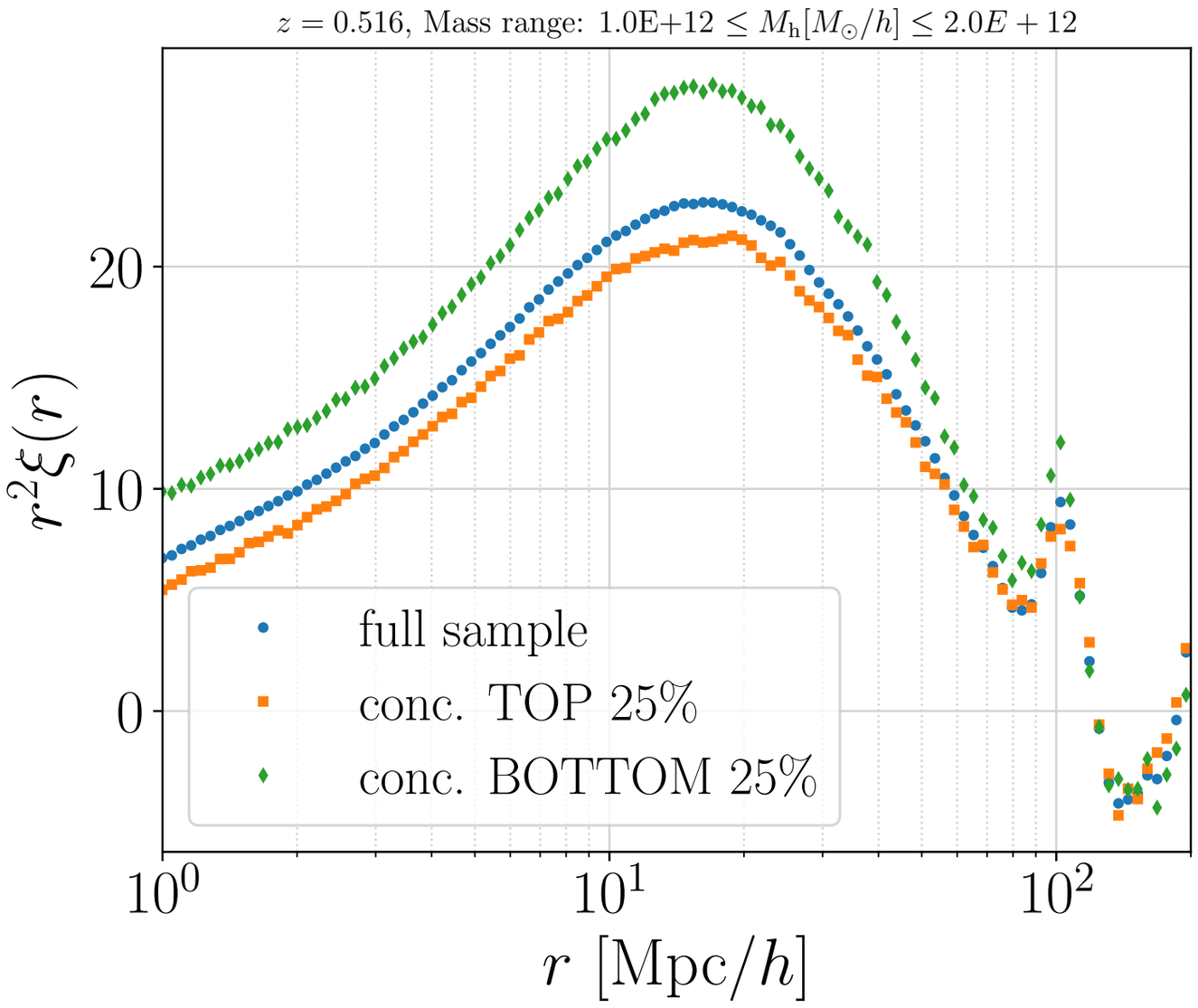
halo profile dependence

$$c \equiv \frac{r_{200}}{r_{\rm half}}$$



Halo Assembly Bias

Secondary dependence



early-forming
(= high concentration)

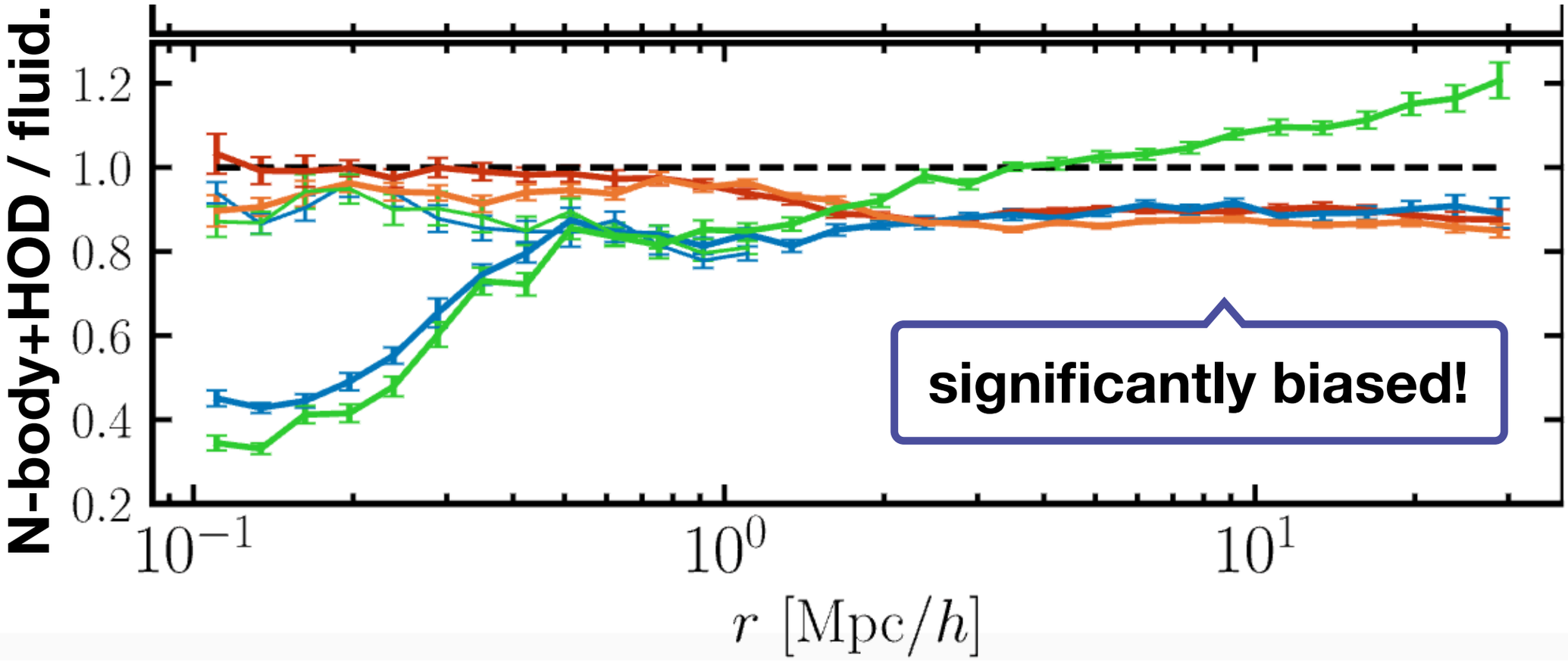
less strong clustering

late-forming
(= low concentration)

more strong clustering

Galaxy Assembly Bias

B. Hadzhiyska et al. 2023 (MillenniumTNG project)

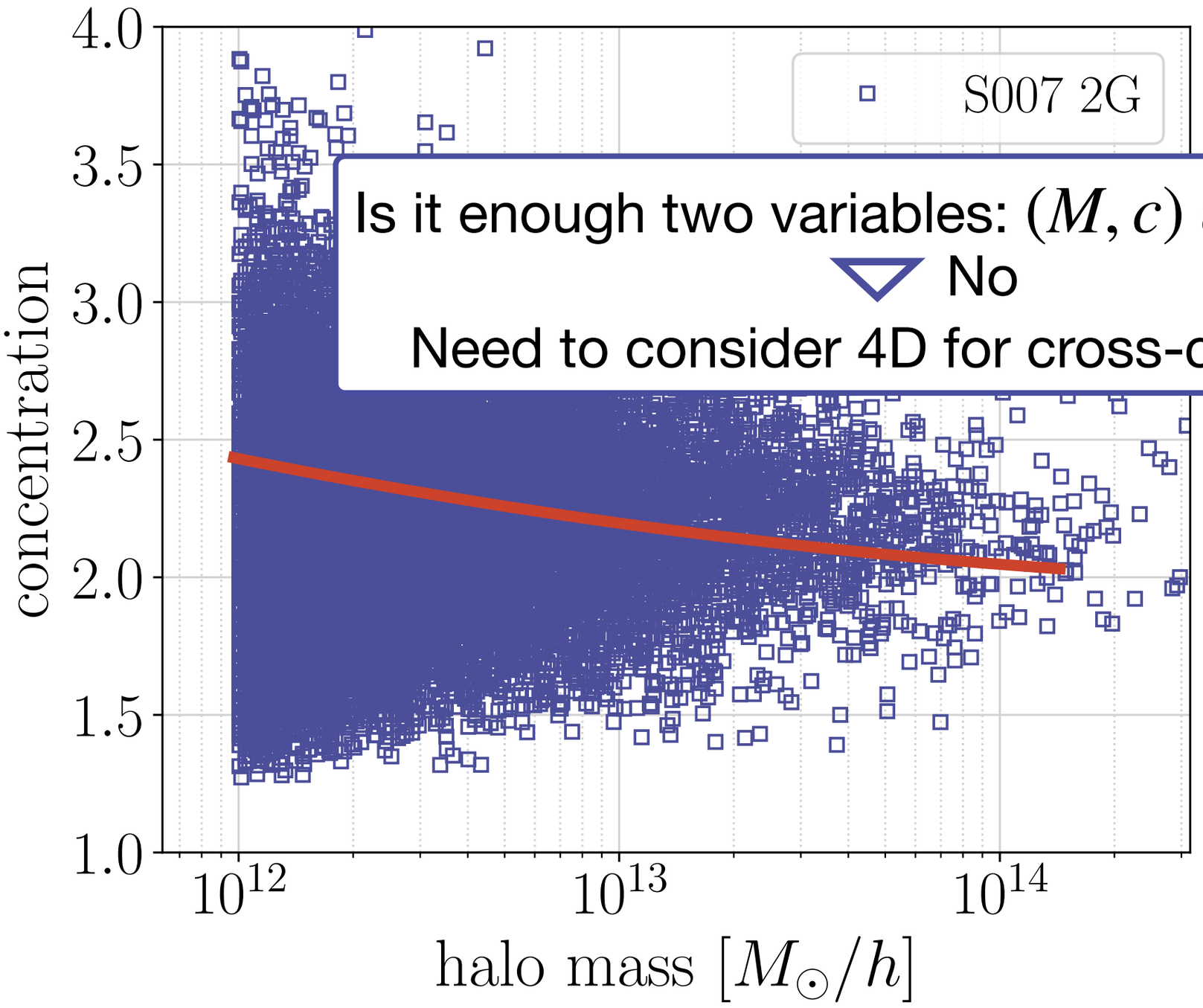


Success or failure of galaxy formation (**galaxy bias**) has possibility that depends on halo envs. other than halo mass

▷ Galaxy assembly bias

To consider $P_{\rm h}(k; M_{\rm h}, c) \to P_{\rm g}(k)$

Relationship between halo mass and concentration



Is it enough two variables: (M, c) as a inputs?

No

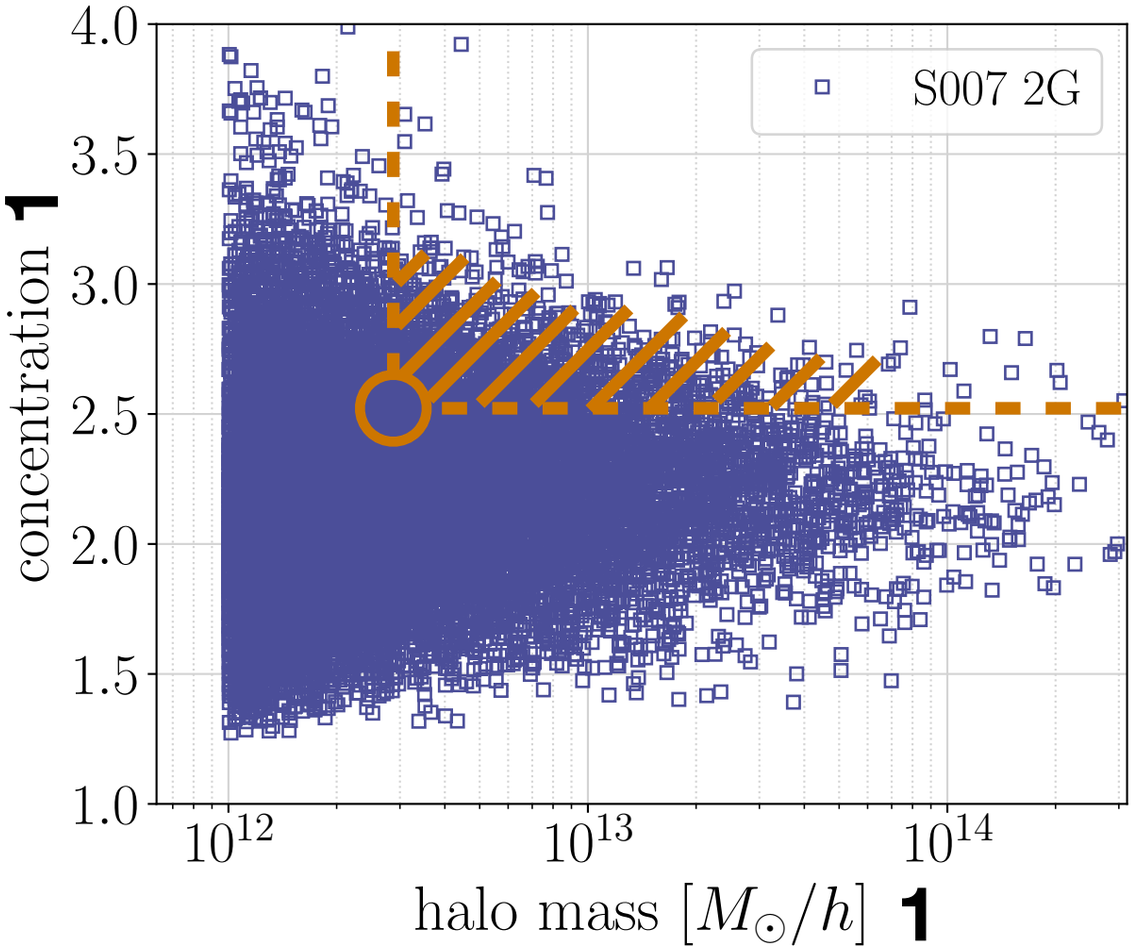
Need to consider 4D for cross-correlation

Implement assembly bias effect

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

・sample range: $12 \leq \log_{10} M \leq 15,\ 1 \leq c \leq 4$

⇨ Check out all the cross-corr.



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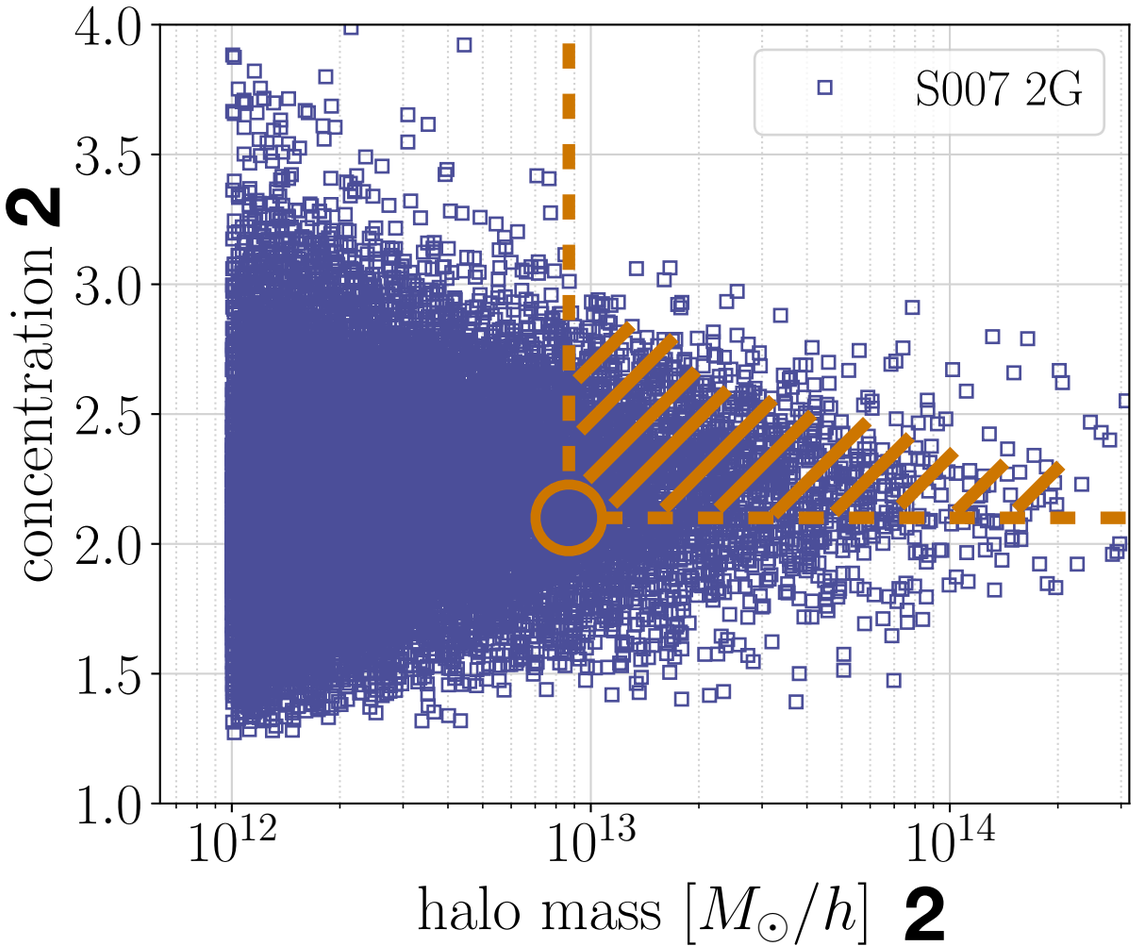


=

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

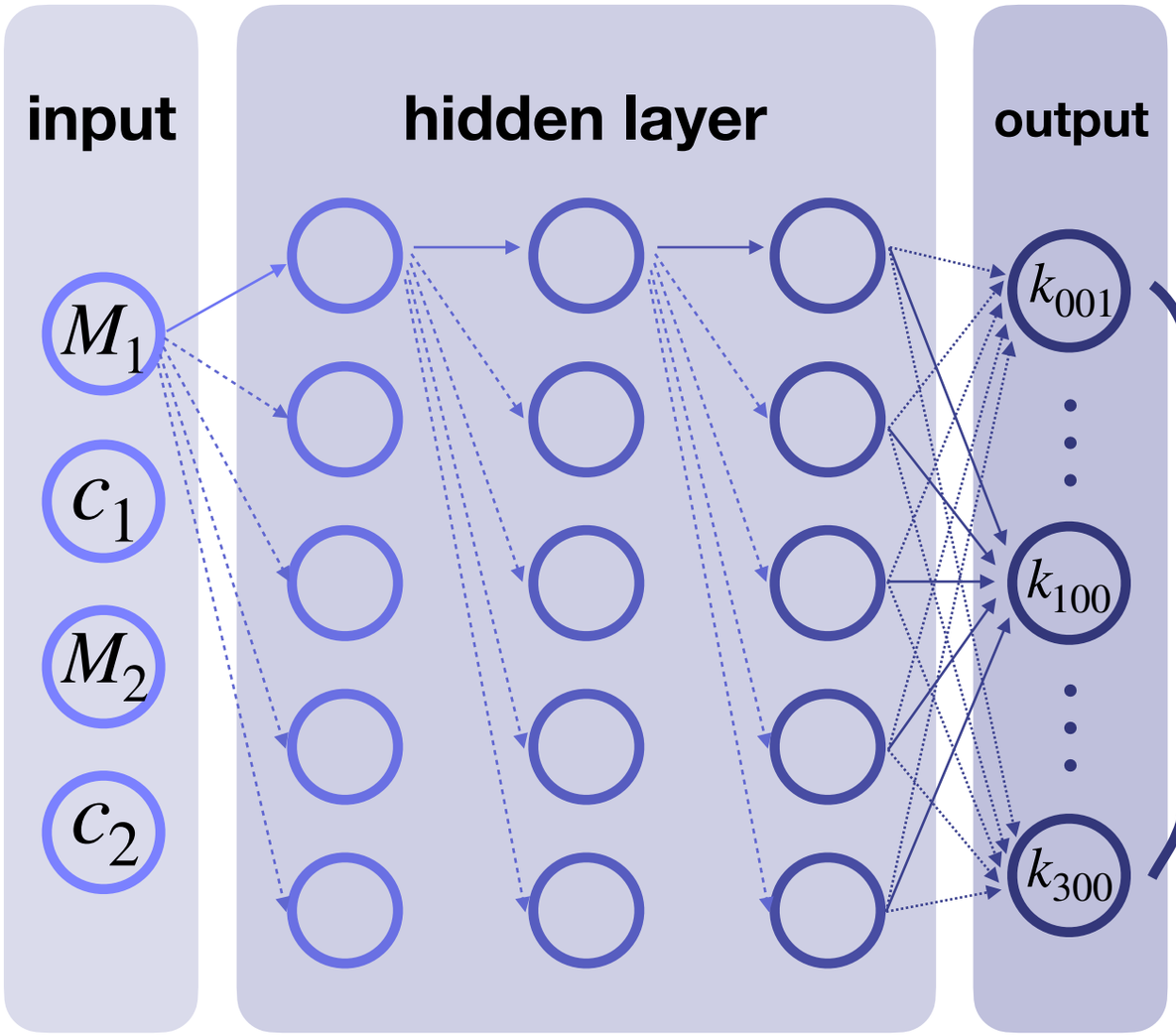
Measure in real-space, redshift-space ($l = 0,2,4,6$)

*normalizing flow + scrambled Sobol sequence

Implement assembly bias effect

Feed Forward Neural Network (FFNN)

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



- loss function: RMSE
- k : [3×10^{-3},50] [h/Mpc]
- **suppressing cosmic variance using propagator method**

- sample size: 39,120
  (90%: train, validation, 10%: test)

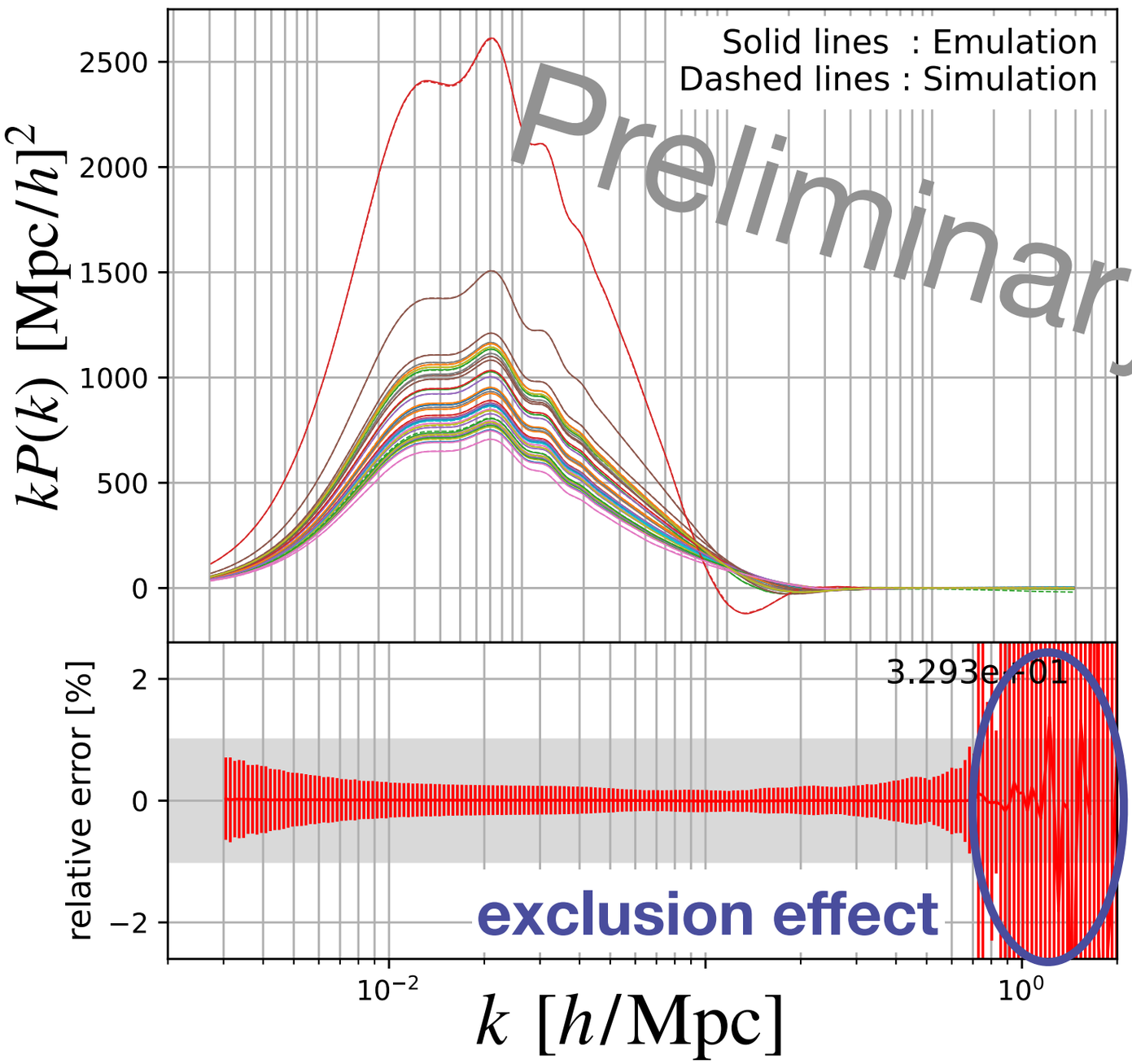
- automatic survey of hyper params
  (hidden layer, # of neuron, batch size, scheduler, initial learning rate, epoch)

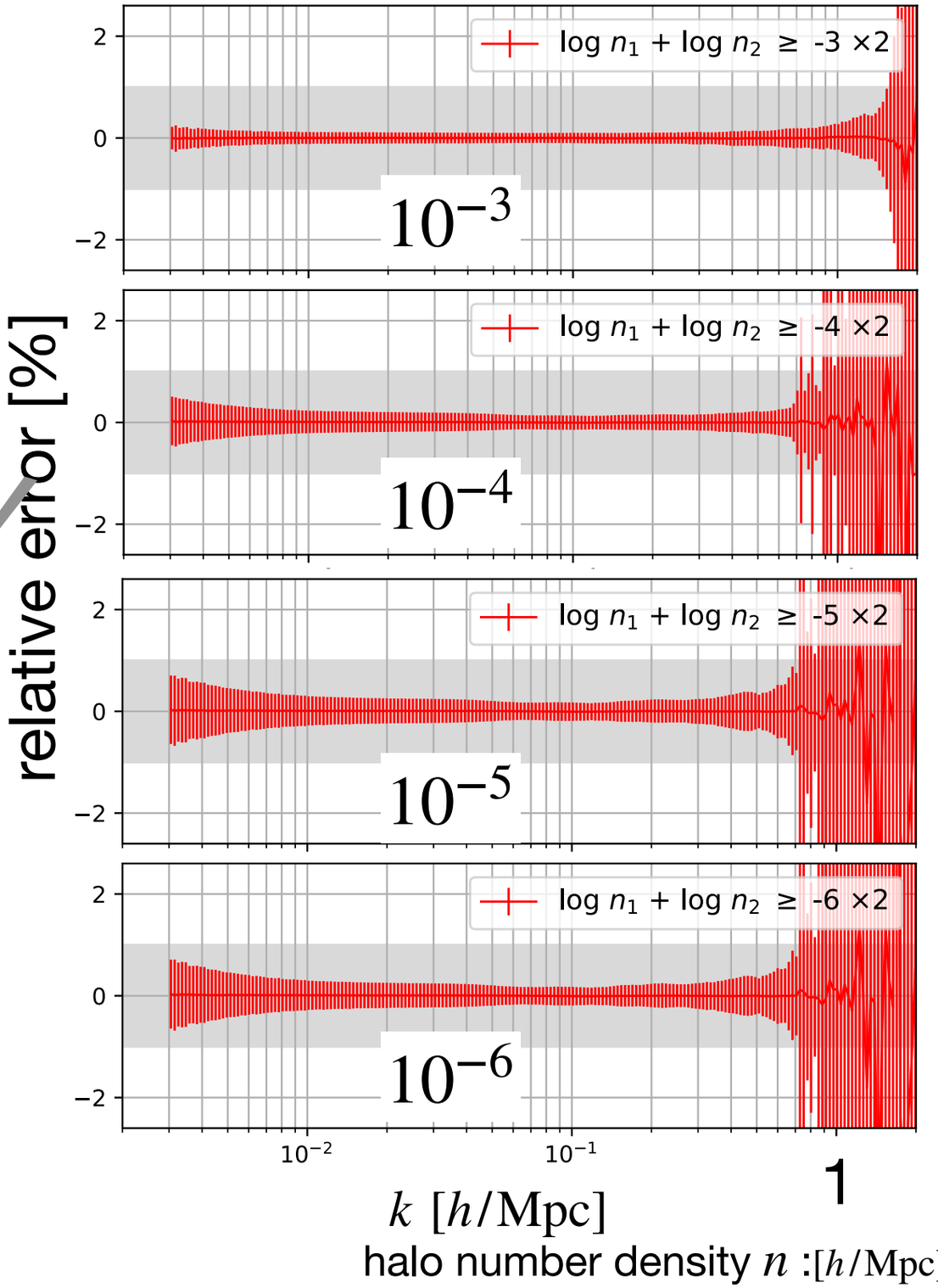
※ consider cosmological dependence as a future work

Result: achieve 1% accuracy

Redshift space (ell = 0)

power spectrum (test data)

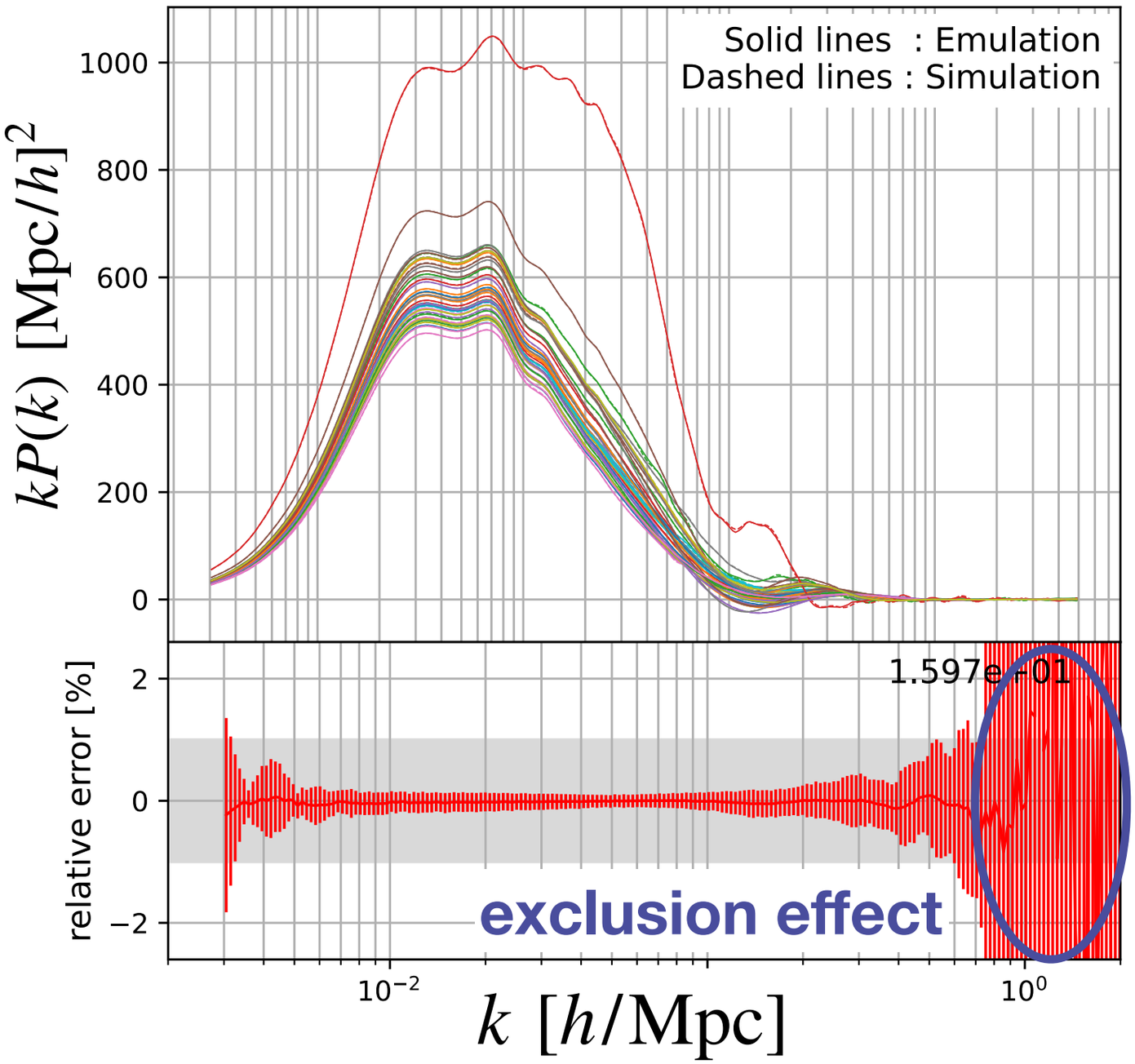


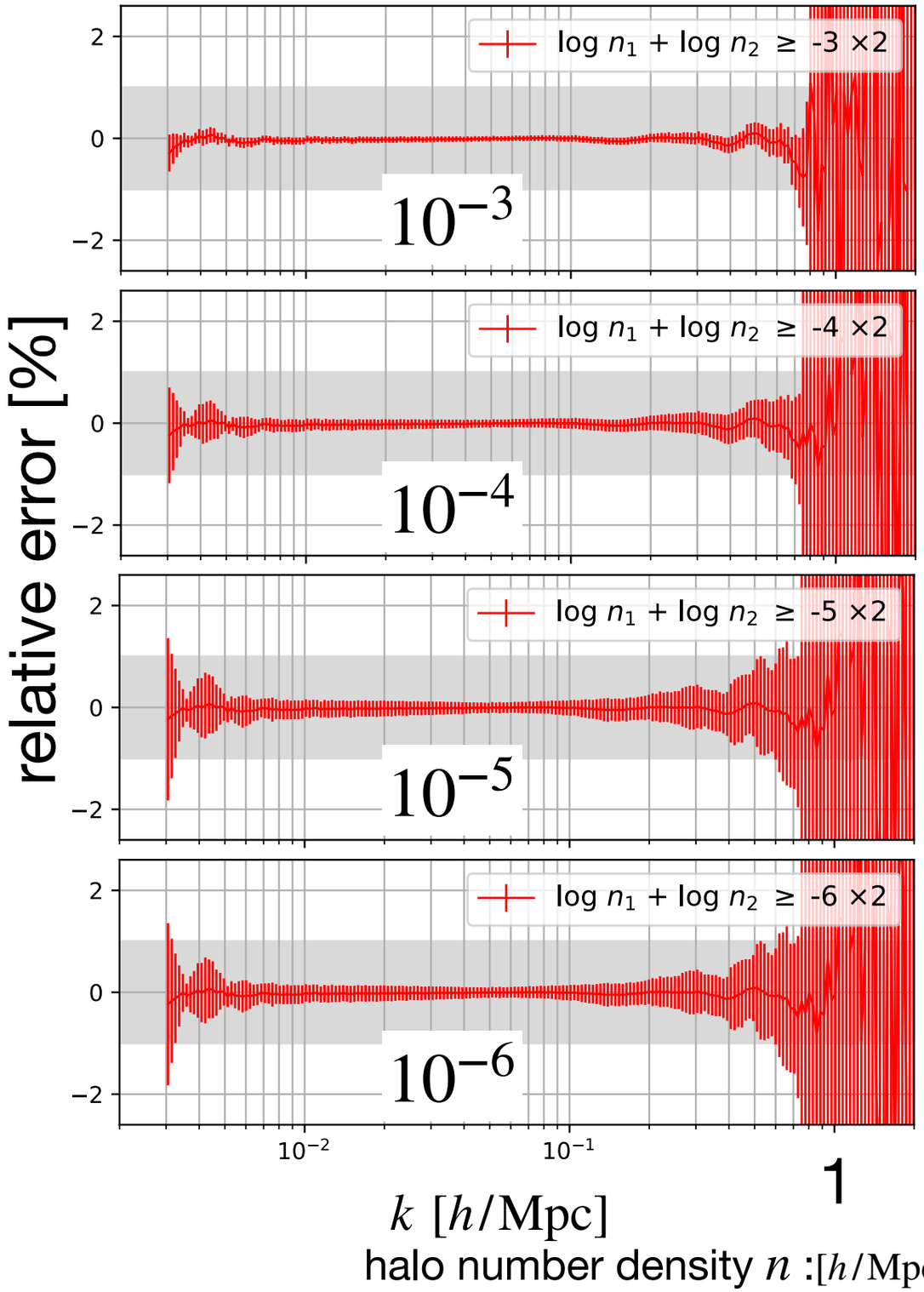


Result: achieve 1% accuracy

Redshift space (ell = 2)

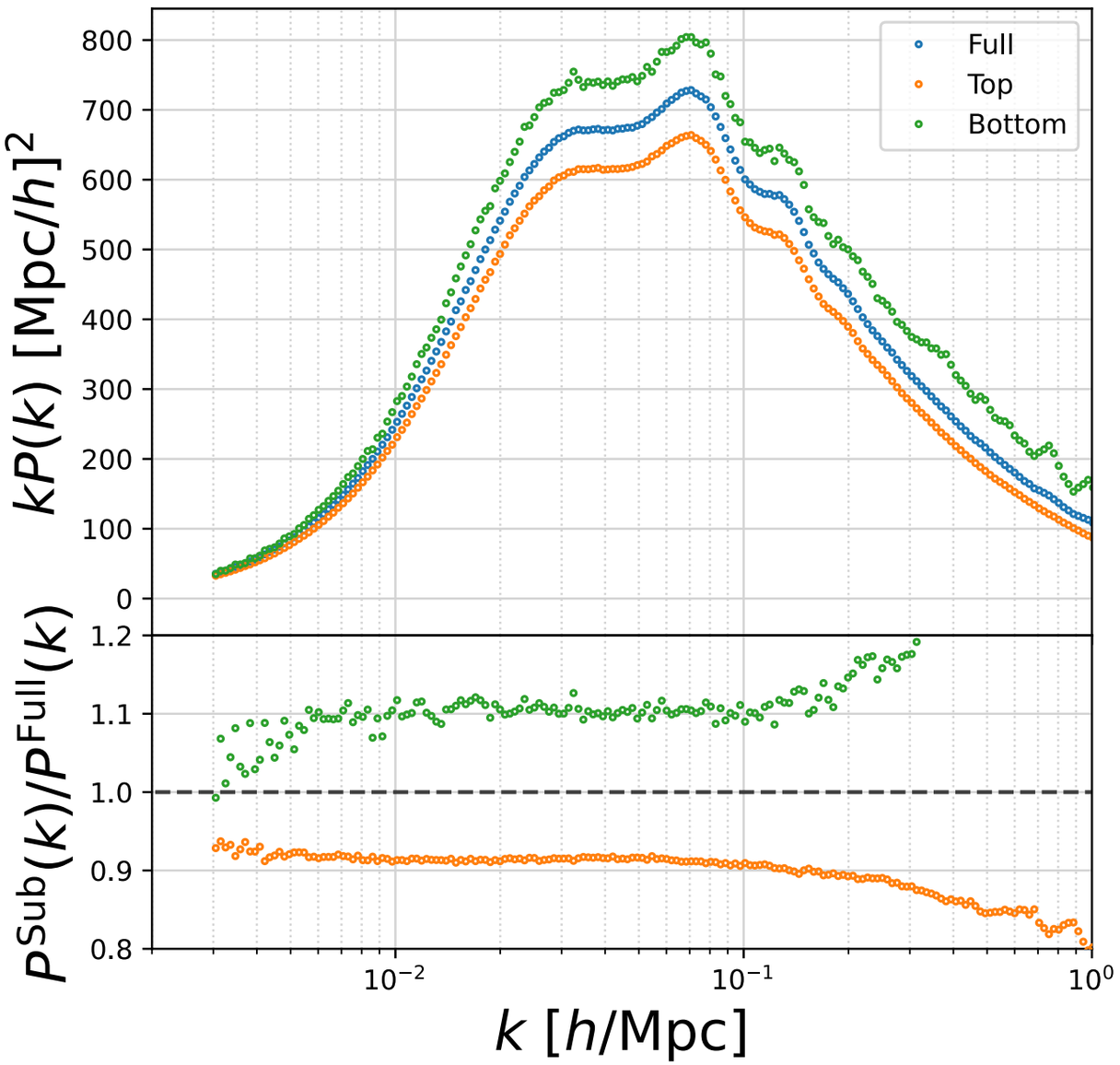
power spectrum (test data)



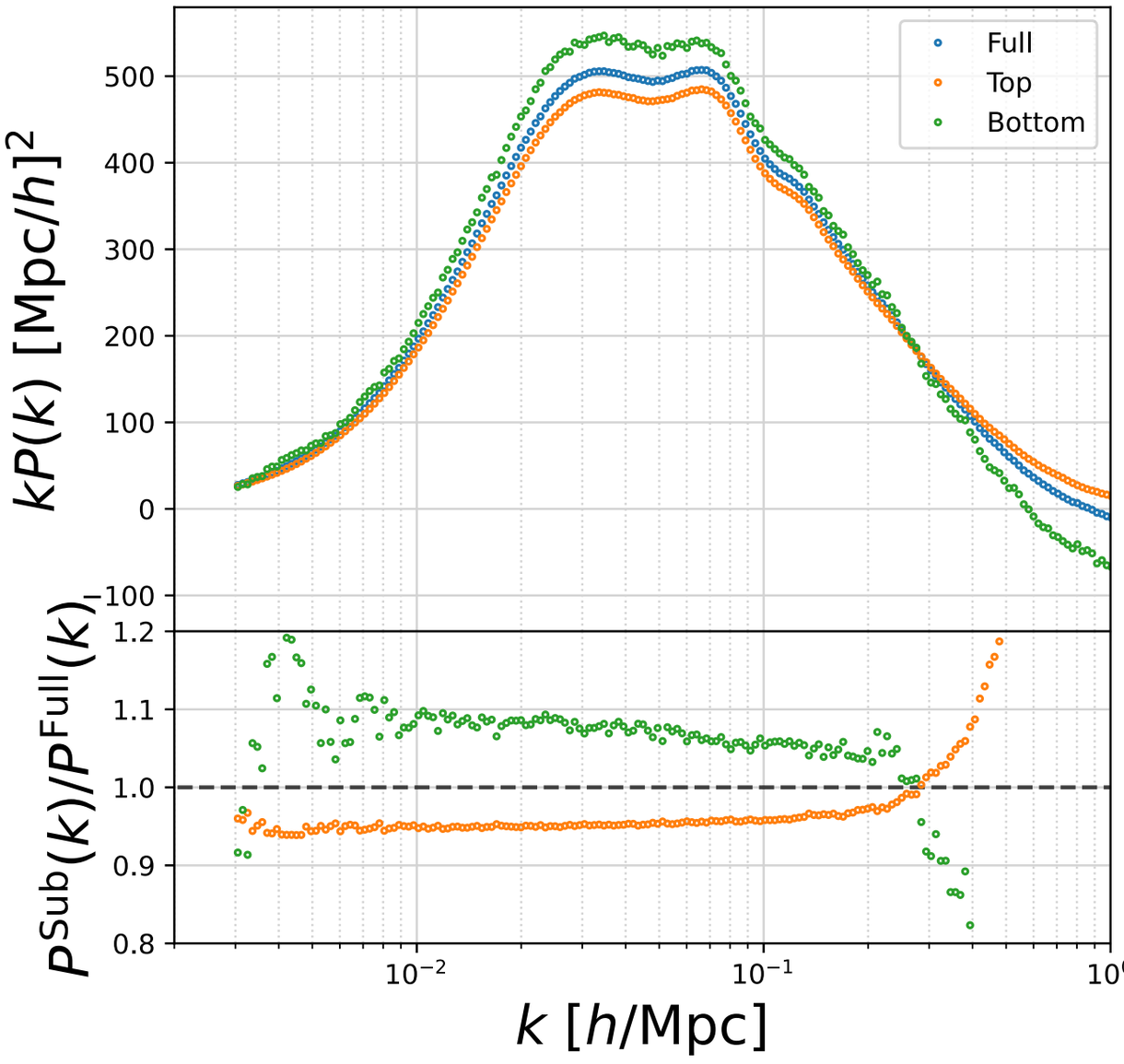


Prediction ($\log_{10} M_{\rm h} = 12.3$)

$l = 0$



$l = 2$



$$P_0(k) = \left(1 + \frac{2}{3}\beta + \frac{1}{5}\beta^2\right) P^{\rm real}_{\rm halo}(k)$$

$$P_2(k) = \left(\frac{4}{3}\beta + \frac{4}{7}\beta^2\right) P^{\rm real}_{\rm halo}(k)$$

Summary

- The goal of this study:
  - **Implement halo assembly bias effect into Dark Emulator II**
- Result:
  - Achieved 1% accuracy ($k < 1$ [Mpc/h]) in prediction on FFNN
- Next Step:
  - Redshift / Cosmological parameters dependence
  - Develop halo mass concentration function
- Infrastructure work:
  - **Implement Dark Emulator I into Roman/LSST analytical pipeline**