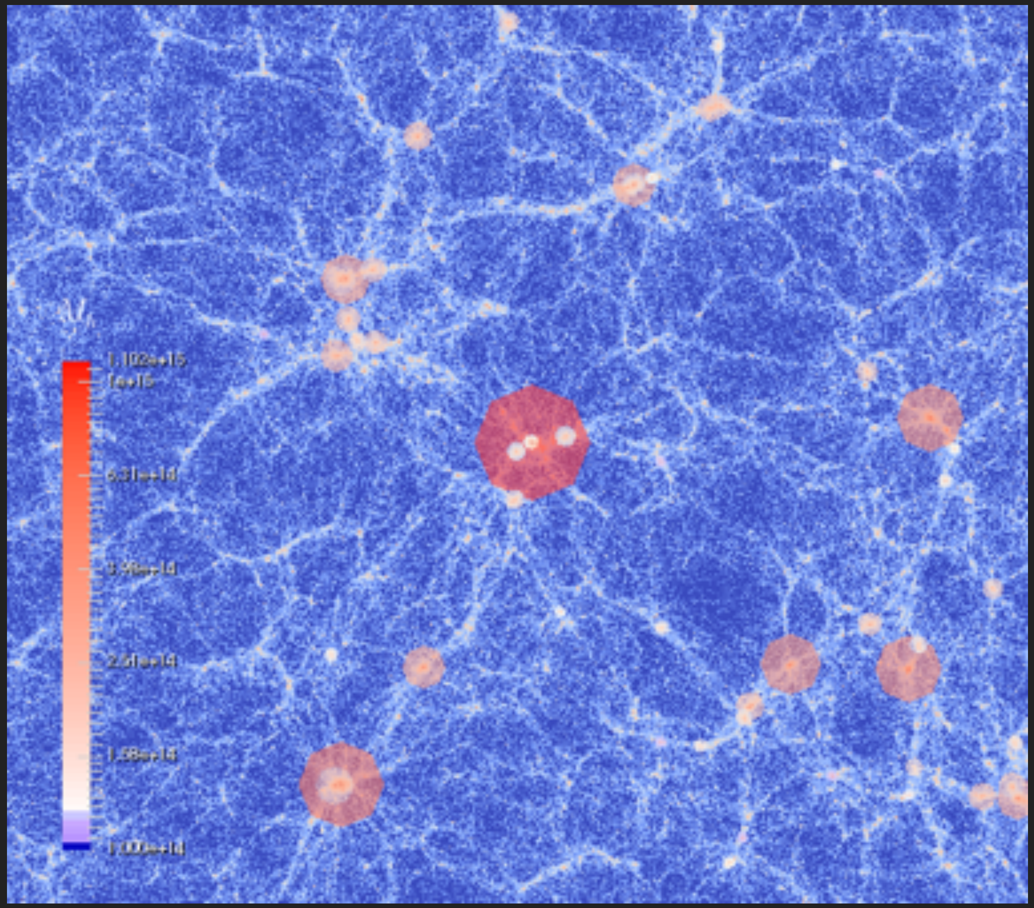
MODELING ISSUES USING N-BODY SIMULATIONS: A CASE FOR SUBARU HSC SURVEY GALAXY-GALAXY LENSING EMULATOR

TAKAHIRO NISHIMICHI (KAVLI IPMU, JST CREST)



- **Kavli IPMU**

Takahiro Nishimichi*
Masahiro Takada
Naoki Yoshida

- **U. Tokyo**

Ken Osato*
Masamune Oguri

- **NAOJ**

Masato Shirasaki*
Takashi Hamana

- **Hirosaki U.**

Ryuichi Takahashi*

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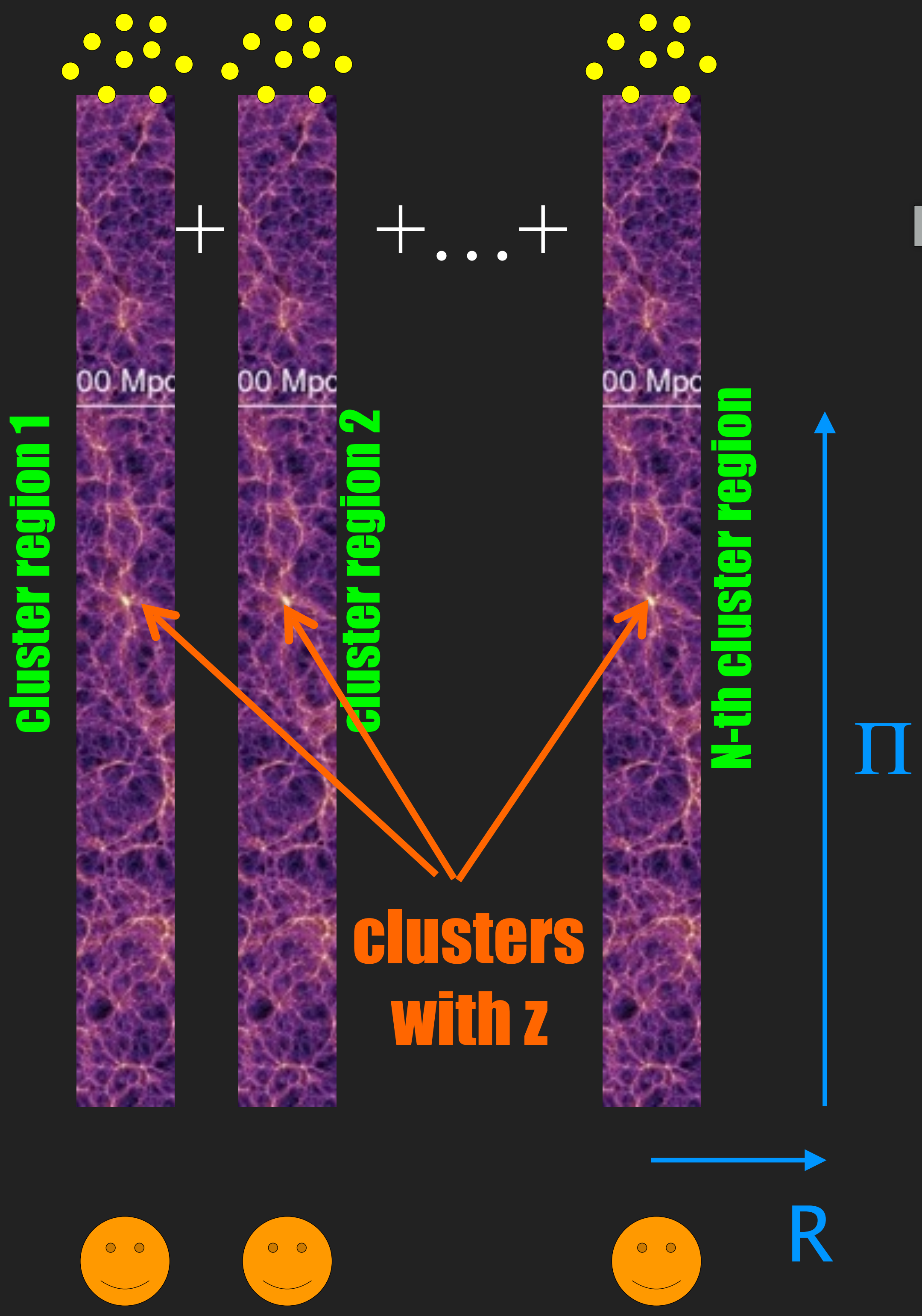
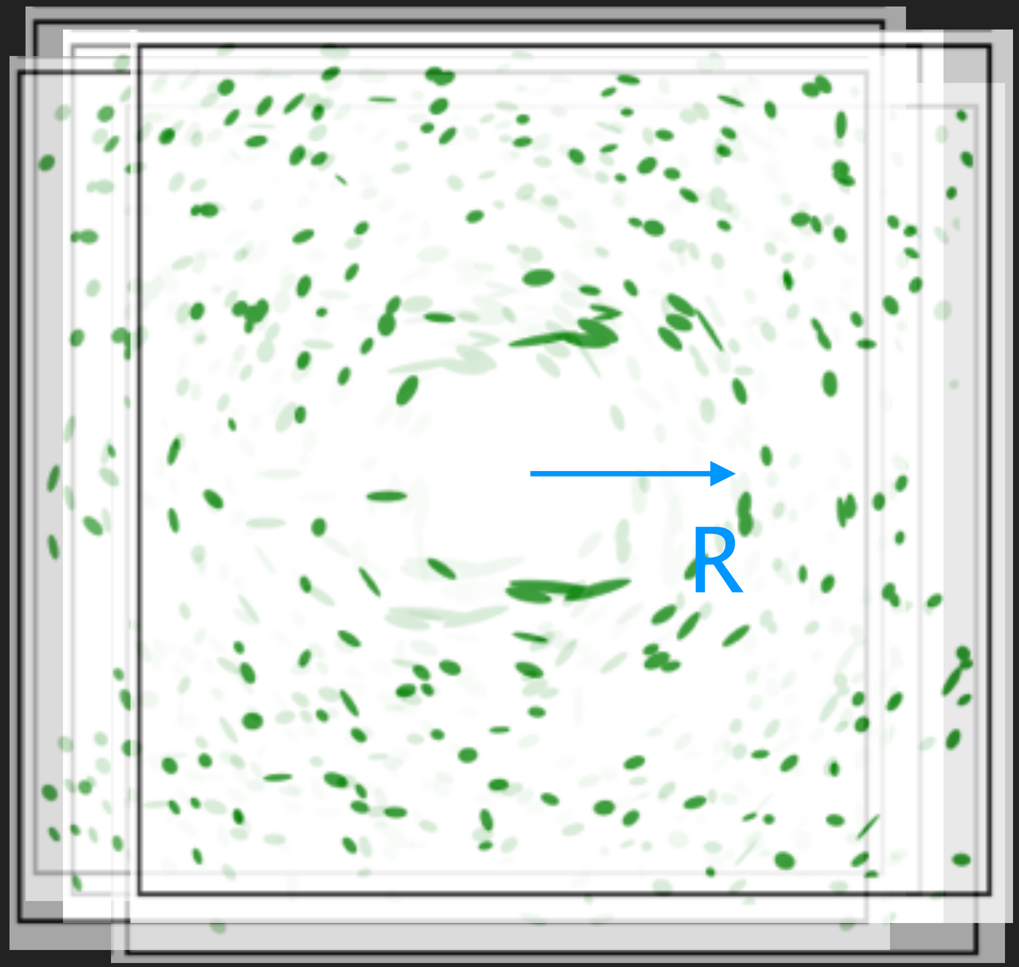
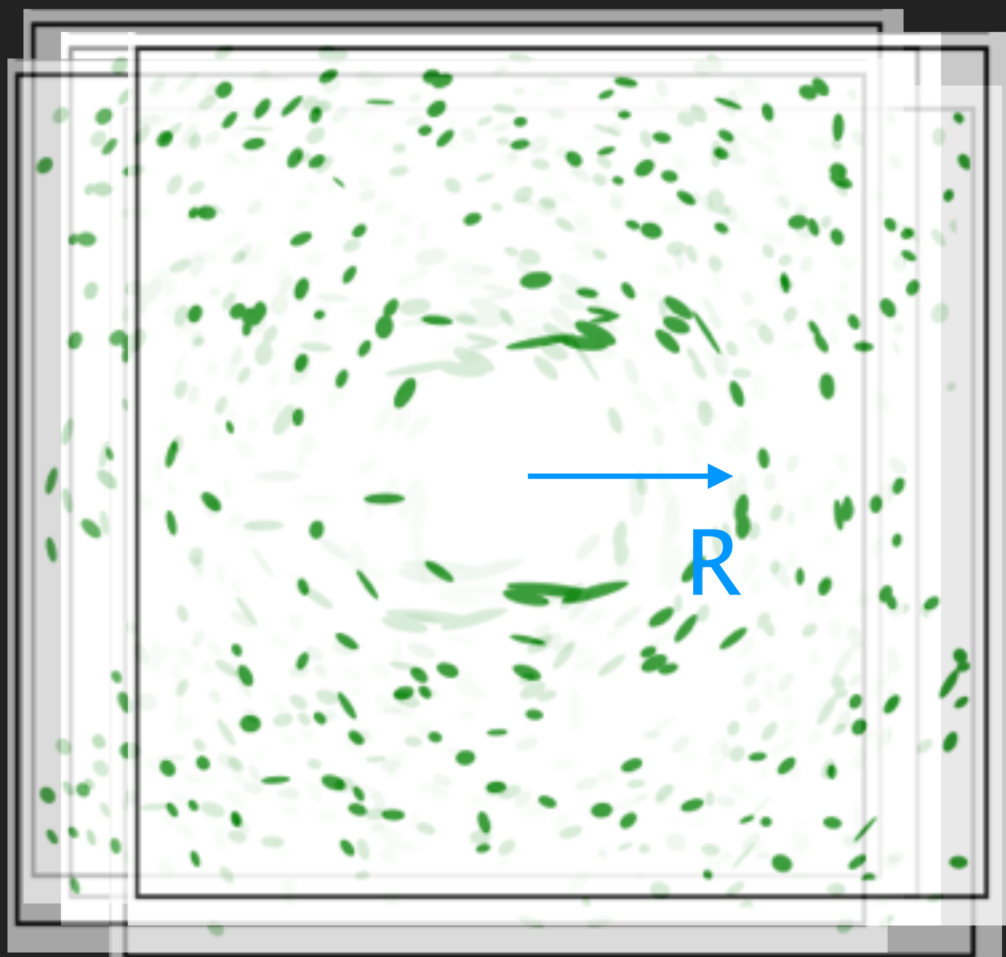
GALAXY(CLUSTER)-GALAXY LENSING

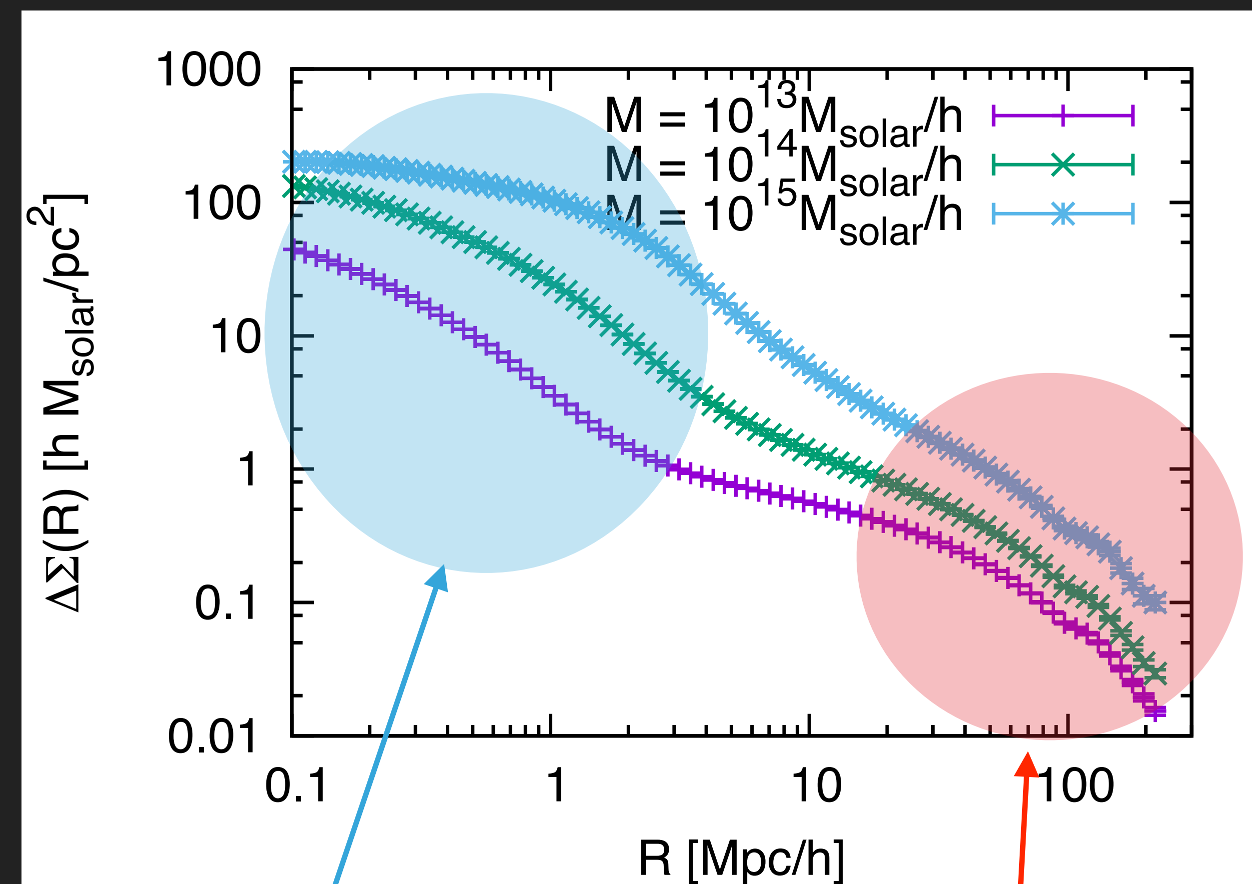




- Lens objects with known z
  - free from projection effect
  - do not have to care too much on the photo-z accuracy
  - can obtain the signal as a function of scale R instead of angle on the sky

G-G LENSING: STACKED WEAK LENSING SIGNAL





1 halo regime

2 halo regime with BAO

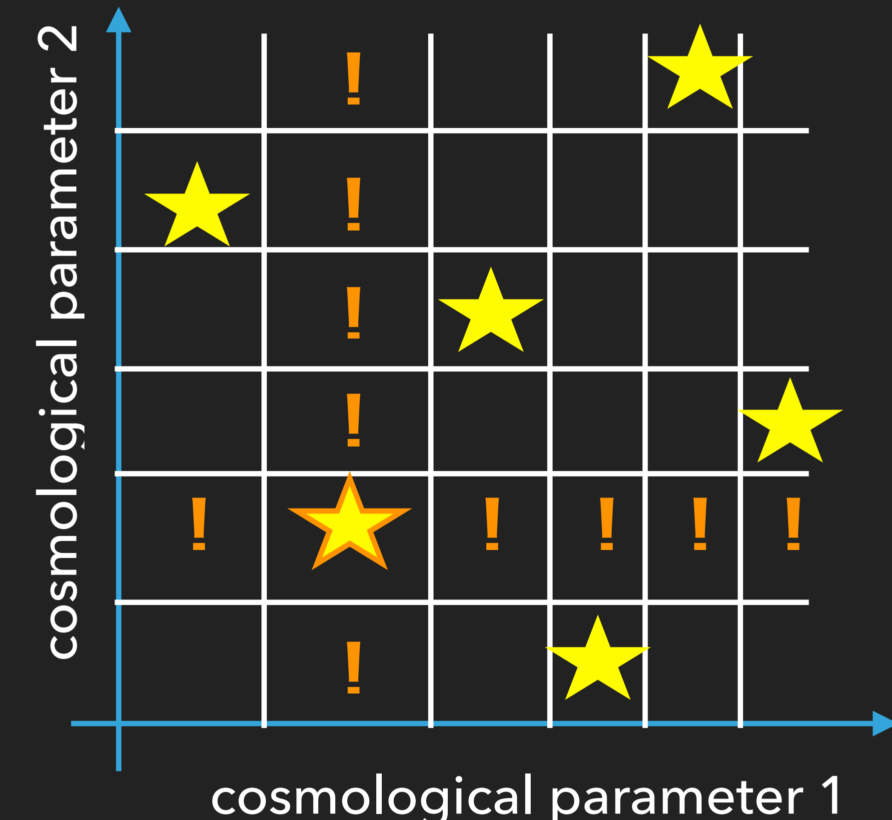
- Wide dynamic range
  - clearly PTs do not apply on small scales
  - analytical bias description still unclear
  - significant volume needed to control large scales
  - cosmological parameter dependence?

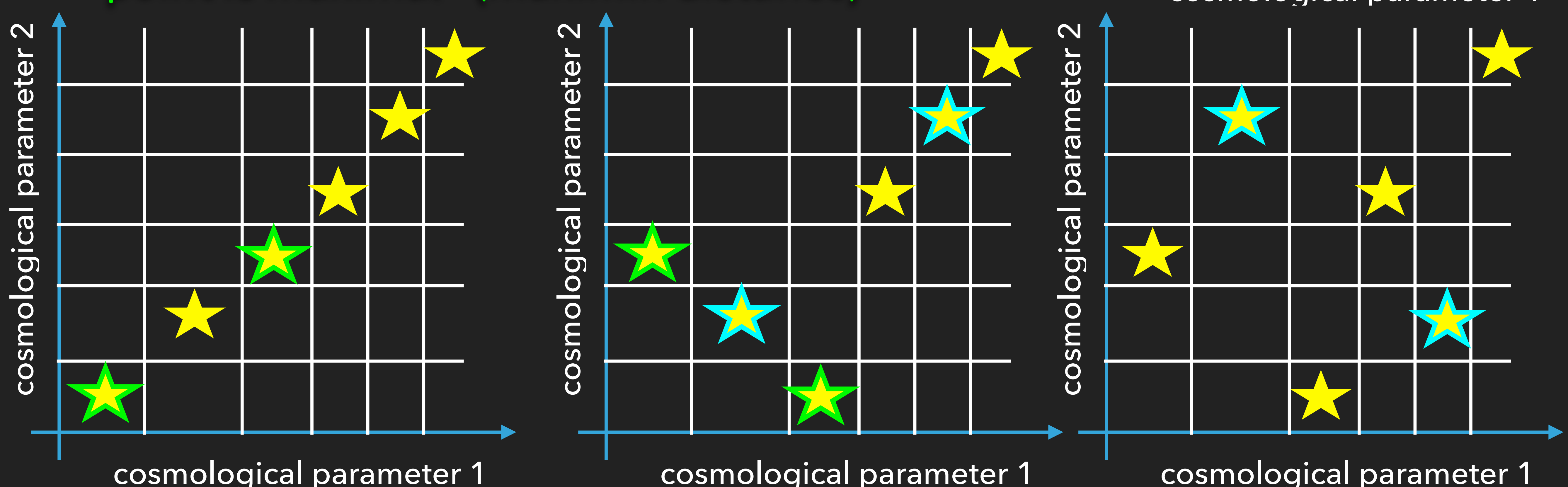
THE GOAL

- ✓ Numerical cosmology: *direct confrontation of obs and sims*
- ✓ Build a *machine* that computes the *halo mass function* and *excess surface mass density* trained by simulation data to predict ***the signal*** in python
  - ✓ covariance is modeled separately
- ✓ Input parameters (6D + α):
  - ✓ cosmological: ω_b, ω_c, Ω_Λ, A_s, n_s, w (flat wCDM) → LH design
  - ✓ + M_h, z (halo mass function)
  - ✓ + M_h, z, R (excess surface mass density)
- ✓ Note that we model *cluster-galaxy lensing signal* first, and thus
  - ✓ ignore subhalos for the moment
  - ✓ parameters to be added: satellite fraction (or HOD params), off-centering, …

EFFICIENT SAMPLING IN MULTI DIMENSIONAL SPACE: LATIN HYPERCUBE

- Each sample is the only one in each axis-aligned hyperplane containing it
  - One can find many realizations of such design (ex. diagonal design)
  - Impose additional condition such as "the sum of the distances to the nearest design point is maximal" (maximin distance)





EFFICIENT SAMPLING IN MULTI DIMENSIONAL SPACE: LATIN HYPERCUBE

fiducial model

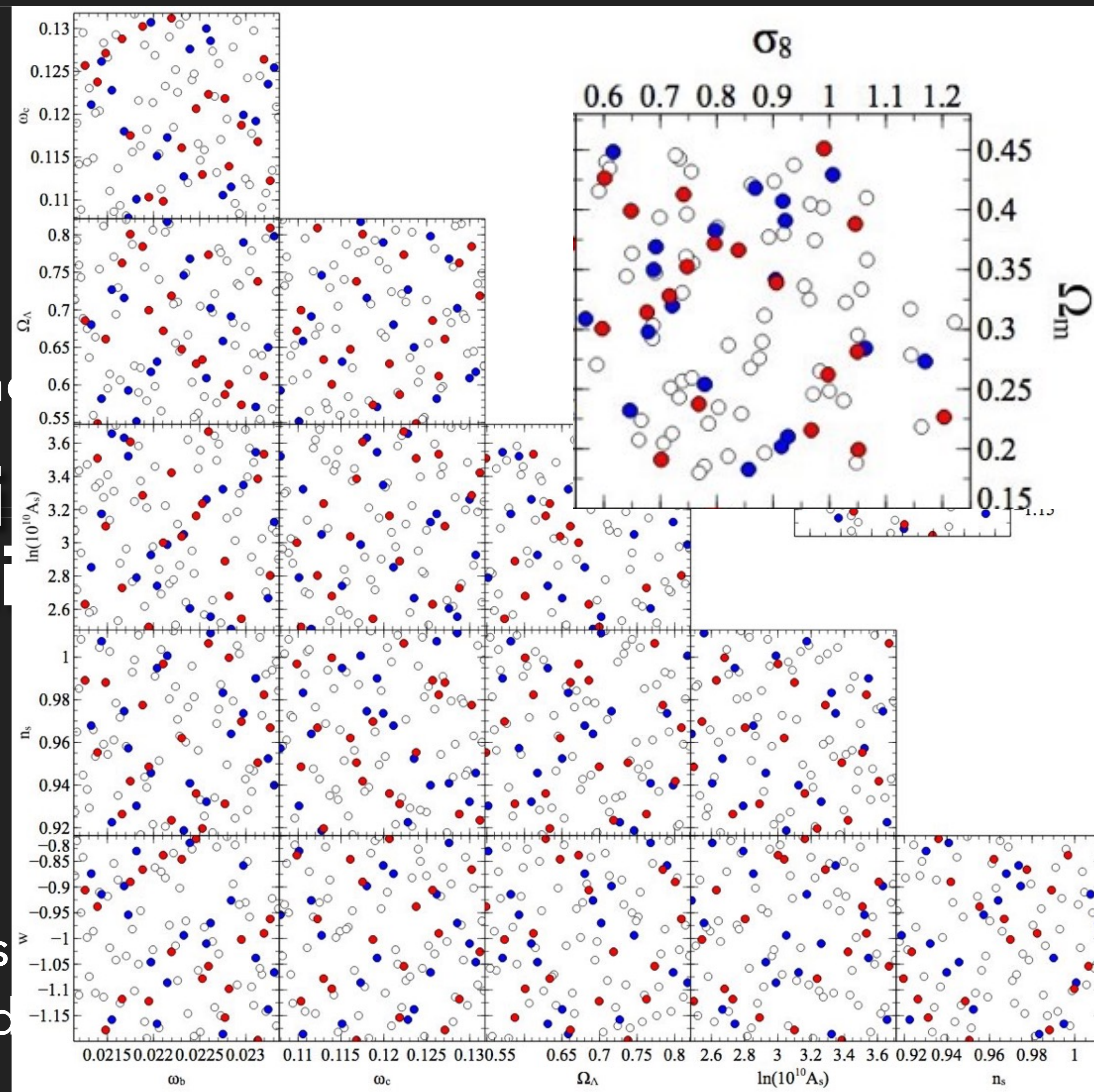
- PLANCK15 flat ΛCDM
- 24 realizations done
- assess statistical error
- check the accuracy of th
  emulator

84 si
avai

varied cosmology

- "sliced" LH design (Ba, Brenneman & Myers '15)
- generate 100 samples eventually
- maxi-min distance LH des
  every 20 models (e.g., red
  points)

e)



SIMULATION PIPELINE

~2TB, 2+2days / 1 run

on analysis servers

prediction

density estimate

final catalog

data analysis

time evolution

mass/profile determination

Gadget2

rockstar

IC generator

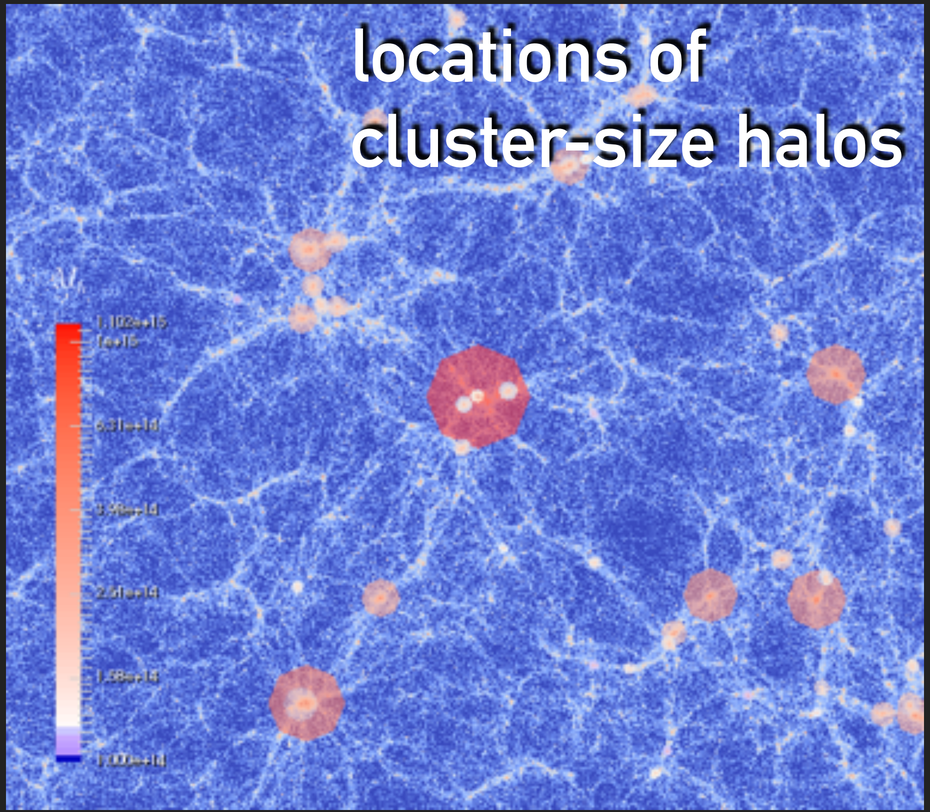
subfind

create "universes"

FOF (on the fly)

object identification

on supercomputer
(XC30 @NAOJ; using 648 CPU cores)



SIMULATION SPEC

- ✓ N of particles: 2048^3
- ✓ box size: $1h^{-1}$Gpc

  resolve a $10^{12}\ h^{-1}M_{solar}$ halo with ~100 particles

- ✓ 2nd-order Lagrangian PT initial condition @ $z_{in}=59$

  (vary slightly for different cosmologies to keep the RMS displacement about 25% of the inter-particle separation)

- ✓ Tree-PM force by L-Gadget2

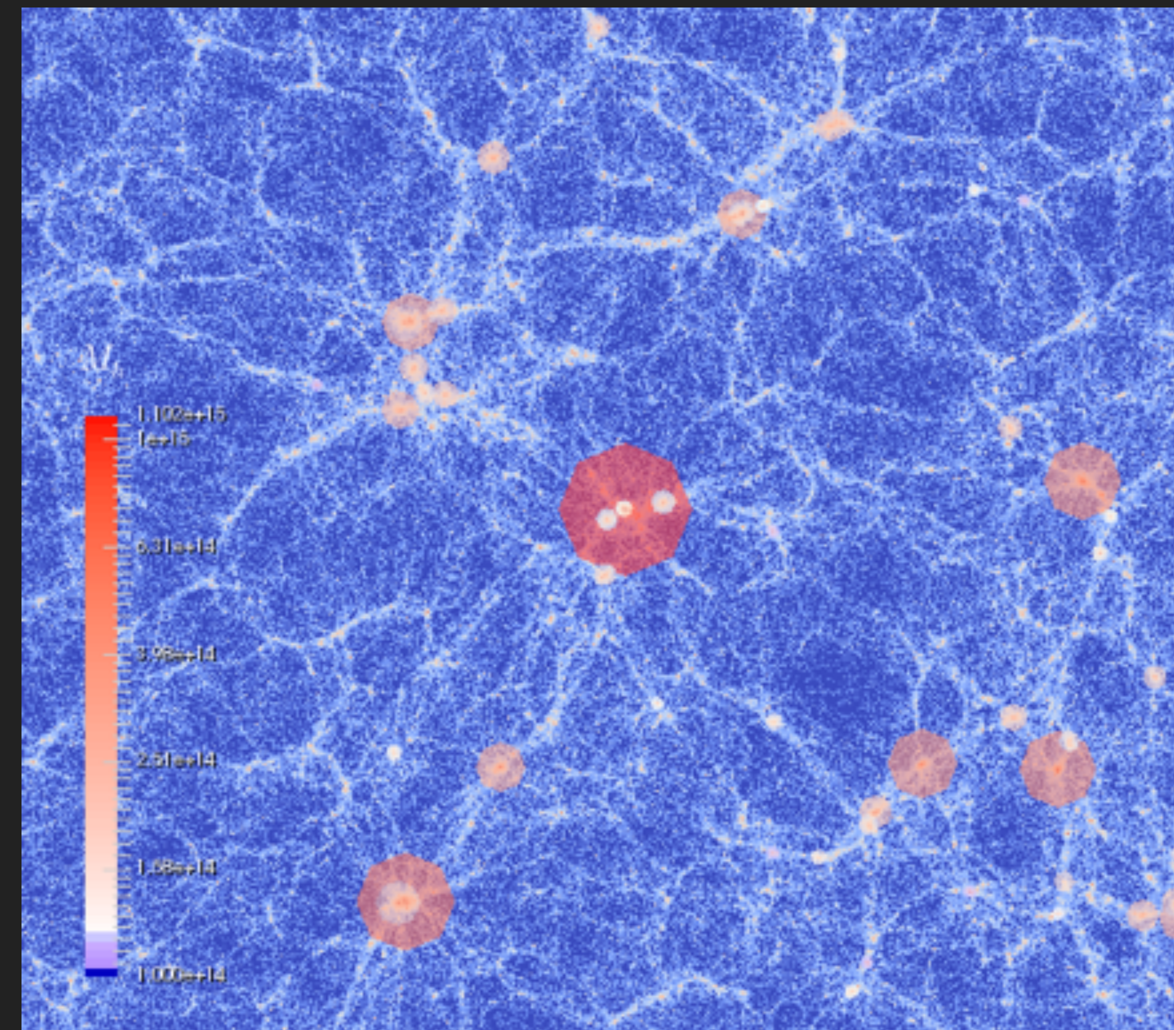
  (w/ 4096^3 PM mesh)

- ✓ 21 outputs in $0 \leqq z \leqq 1.5$

  (equispaced in linear growth factor)

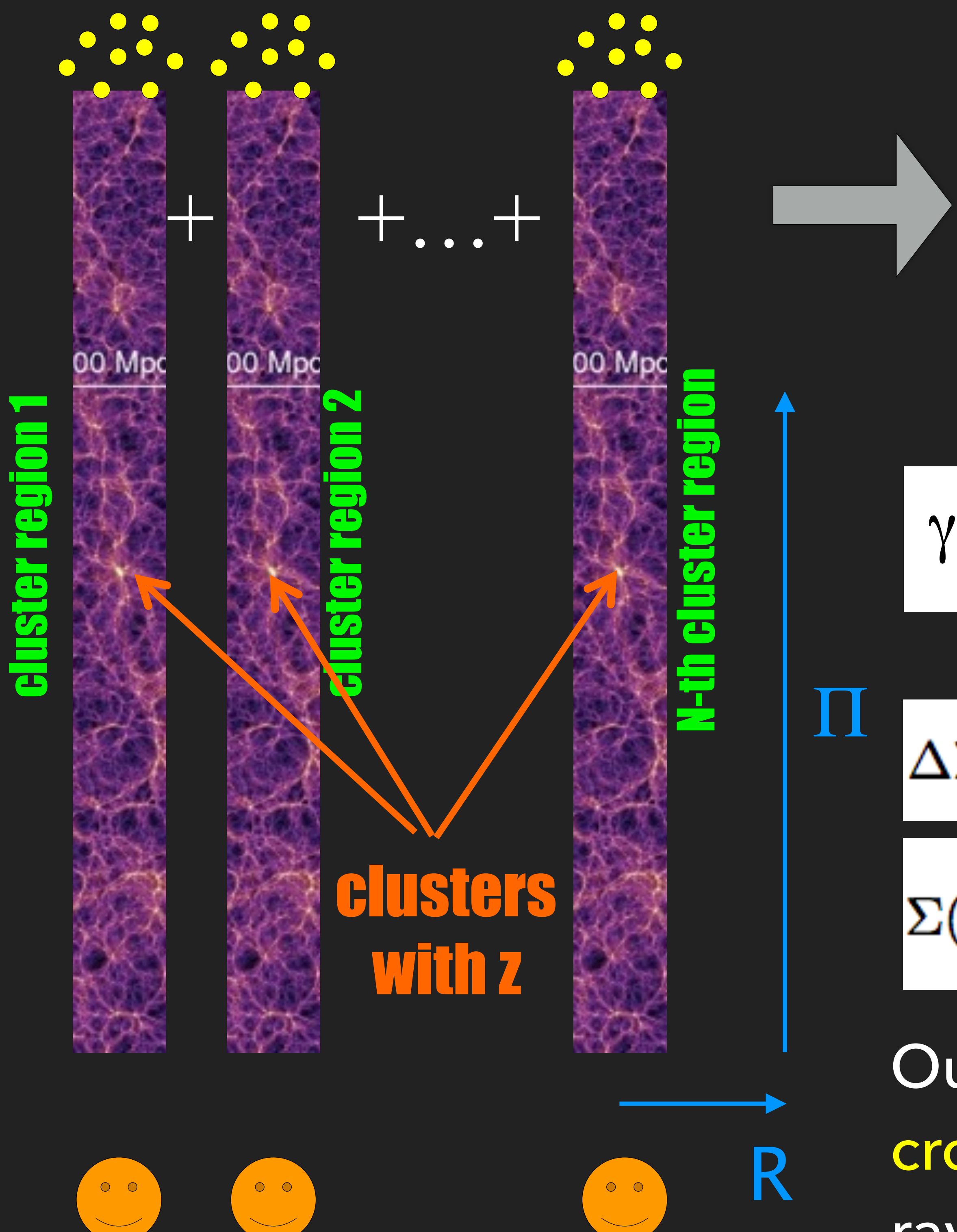
- ✓ Data compression (256GB -> 48GB par snapshot)
  - ✓ positions -> displacement (16 bits par dimension; accuracy ~$1h^{-1}$kpc)
  - ✓ velocity: discard after halo identification
  - ✓ ID: rearrange the order of particles by ID and then discard
  - ✓ already consuming ~200TB in half a year (~observational data)

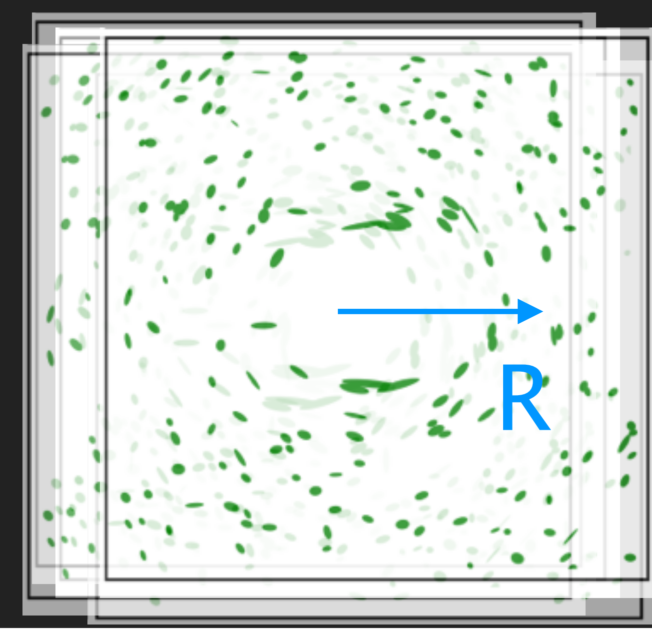
OUR HALO CATALOGS



- ✓ Halo finder
  - ✓ FOF + Subfind
  - ✓ Rockstar (+ merger tree by consistent-trees)
- ✓ Grow sphere centered at
  - ✓ core center (rockstar)
  - ✓ most bound particle (subfind)
- ✓ until the interior density reaches 200ρ_m to determine M_200m
  - ✓ measure and store the density profile at the same time
- ✓ Exclude “satellites” when the center is within r_200m
- ✓ density profile is stored for each halo up to 5Mpc/h
  - ✓ g-g lens signal is obtained immediately once the mass bin, weight and off-centering profile are given

G-G LENSING: STACKED WEAK LENSING SIGNAL





Oguri & Takada '11

$$\gamma_+^{\mathrm{obs}}(\theta_i) = \gamma_+^{\mathrm{cluster}}(\theta_i) + \underline{\gamma_+^{\mathrm{LSS}}(\theta_i)} + \varepsilon_+(\theta_i)$$

projection effect

$$\Delta\Sigma(R) = \gamma_t(R)\Sigma_c = \overline{\Sigma}(<R) - \Sigma(R),$$

$$\Sigma(R) = \overline{\rho} \int \left[1 + \xi_{\mathrm{gm}}\left(\sqrt{R^2 + \Pi^2}\right)\right] d\Pi,$$

Our target statistics is basically the halo-matter cross-correlation function; we do not perform ray-tracing simulations

MEASURING G-G LENSING SIGNAL

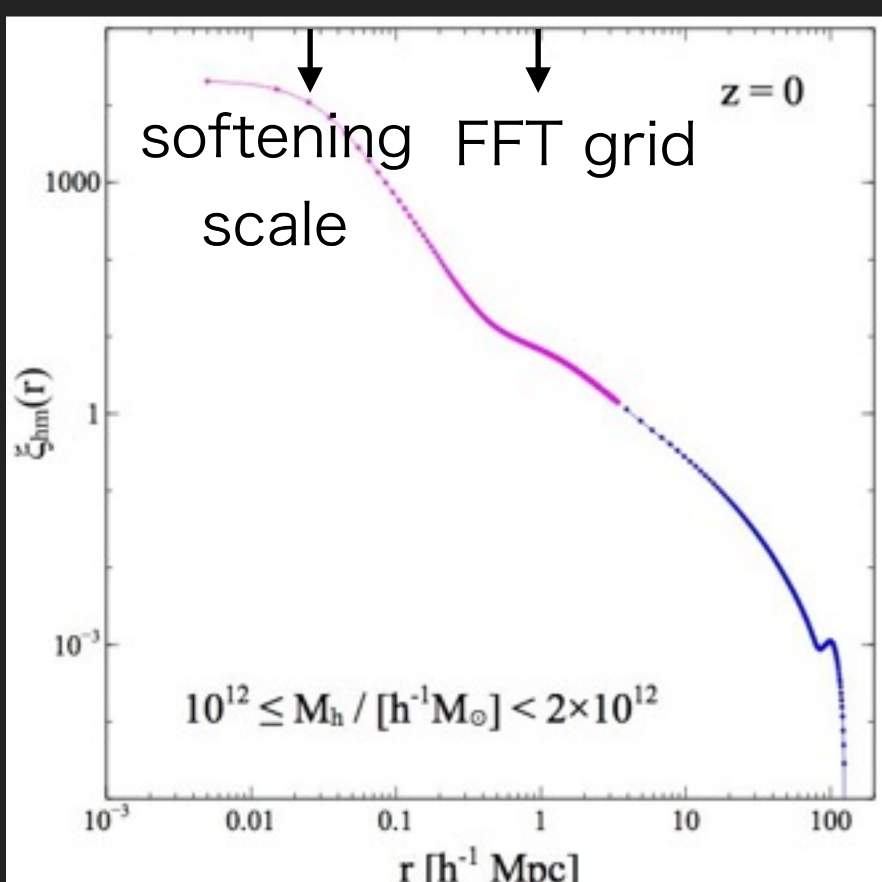
- Work in 3D
- And then projection onto 2D
- Better statistics than working in 3D from the beginning
- Hybrid Fourier-direct scheme

Measure 3D cross spectrum in Fourier space

$P_{\rm hm}(\vec{k})$ (on 1024^3 mesh by FFT)

Inverse FFT to real space and take the spherical average

$$\xi_{\rm hm}(\vec{r}) \xrightarrow[\text{spherical avg.}]{} \xi_{\rm hm}(r)$$



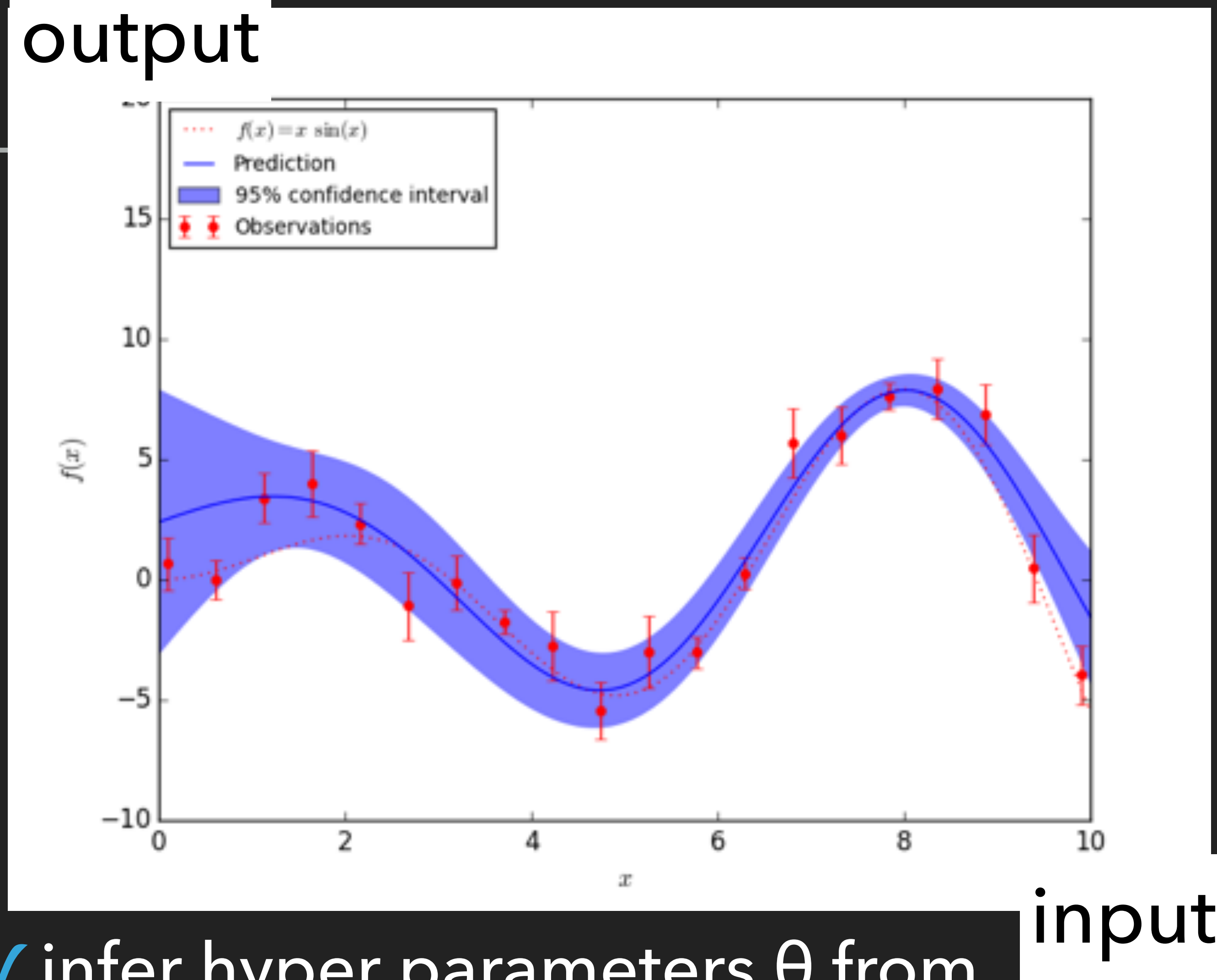
$\xi_{\rm hm}$ on small scale from direct pair count

Finally project onto 2D to have $\Sigma(R)$ and then $\Delta\Sigma(R)$

$$\Sigma(R) = \overline{\rho} \int \left[1 + \xi_{\rm gm}\left(\sqrt{R^2 + \Pi^2}\right)\right] {\rm d}\Pi$$

Easier accuracy control than working in 2D, and quicker than direct pair counting alone

GAUSSIAN PROCESS



- A kind of machine learning that interpolates in function space
  - non-parametric Bayesian inference
  - quick in high dimension input space
- Basic quantities (c.f., normal distribution)
  - mean function (cf. mean)
  - covariance function (cf. variance)
- mean can be anything, set zero usually
- covariance function is characterized by a simple function with several hyper parameters

ex. $$C(\mathbf{x}, \mathbf{x}'; \boldsymbol{\theta}) = \theta_1 \exp\left[-\frac{1}{2}\sum_{i=1}^{I}\frac{(x_i - x_i')^2}{r_i^2}\right] + \theta_2.$$

✓ infer hyper parameters θ from training data (x_i, t_i)

✓ Given any input x_{N+1}, infer t_{N+1} from θ and (x_i, t_i)

$$P(t_{N+1} \,|\, \mathbf{t}_N) \propto \exp\left[-\frac{1}{2}\begin{bmatrix}\mathbf{t}_N & t_{N+1}\end{bmatrix}\mathbf{C}_{N+1}^{-1}\begin{bmatrix}\mathbf{t}_N \\ t_{N+1}\end{bmatrix}\right].$$

answer: $$\begin{aligned}\hat{t}_{N+1} &= \mathbf{k}^T\mathbf{C}_N^{-1}\mathbf{t}_N \\ \sigma_{\hat{t}_{N+1}}^2 &= \kappa - \mathbf{k}^T\mathbf{C}_N^{-1}\mathbf{k}.\end{aligned}$$

OUR HMF EMULATOR

- fit by the well-established functional form:

$$f(\sigma) = A[\sigma^{-a} + b] \exp\left[-\frac{c}{\sigma^2}\right]$$

  - sim data is noisy at the high-mass tail
  - resolution issue at low-mass → down weight

- Construct Gaussian Processes for A, a, and c for each z that interpolate in the 6D cosmological parameter space

- Convert mass to σ using classy

- For a given cosmology, z and M dependence is interpolated by spline

OUR HMF EMULATOR: HOW DOES IT WORK

jupyter hmf_demo Last Checkpoint: Last Wednesday at 5:03 PM (autosaved)

File Edit View Insert Cell Kernel Help

Code CellToolbar

In [101]:
```
cparam = np.array([[0.02225,0.1198,0.6844,3.094,0.9645,-1]]) # planck 2015
set_cosmo(cparam)
set_MF()
```

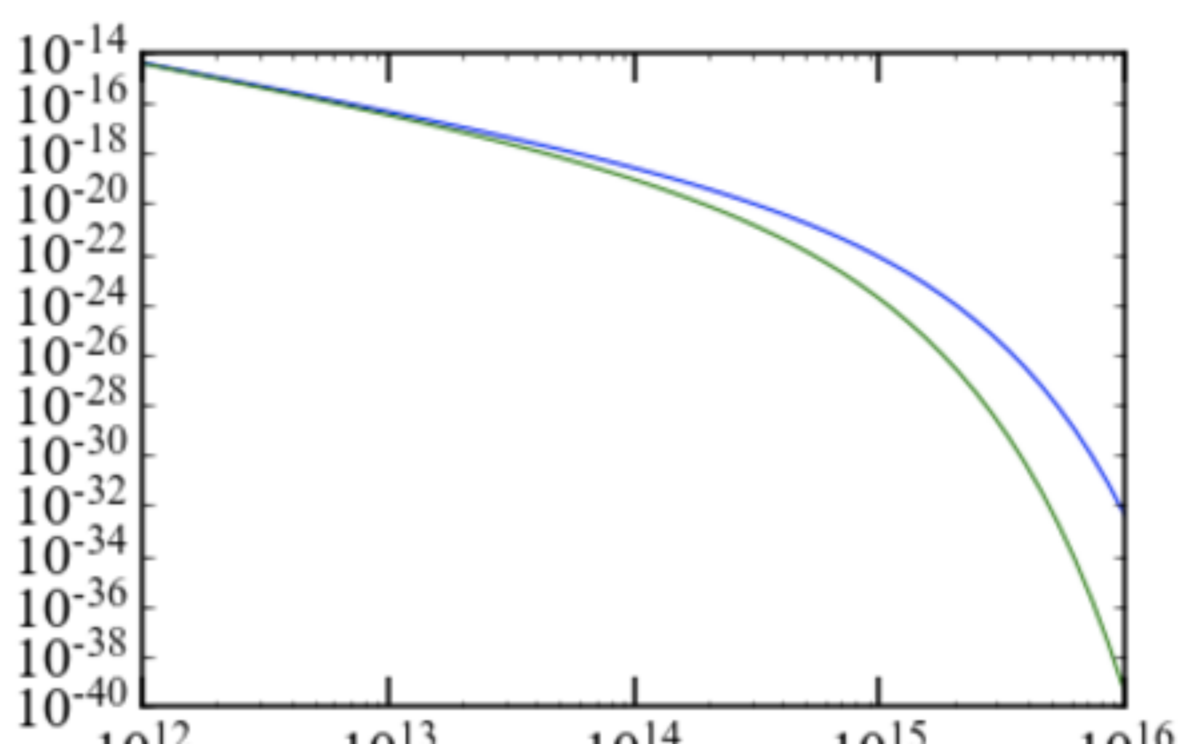
~10s

~25ms

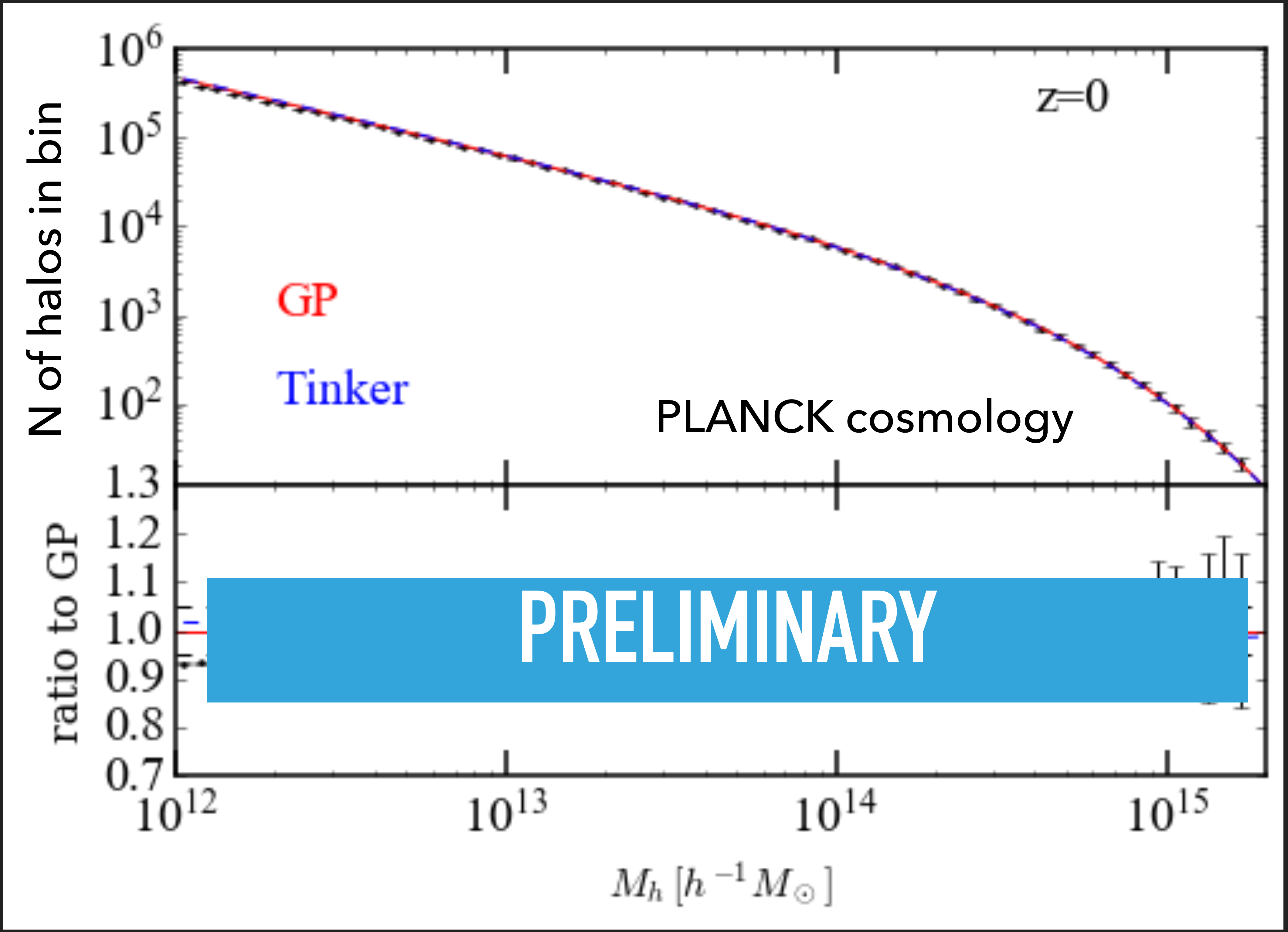
In [109]:
```
logMh=np.linspace(12,16,60)
z = 0.5
plt.loglog(10**logMh,10**f_interp(logMh,z))
z = 1
plt.loglog(10**logMh,10**f_interp(logMh,z))
```

~300μs

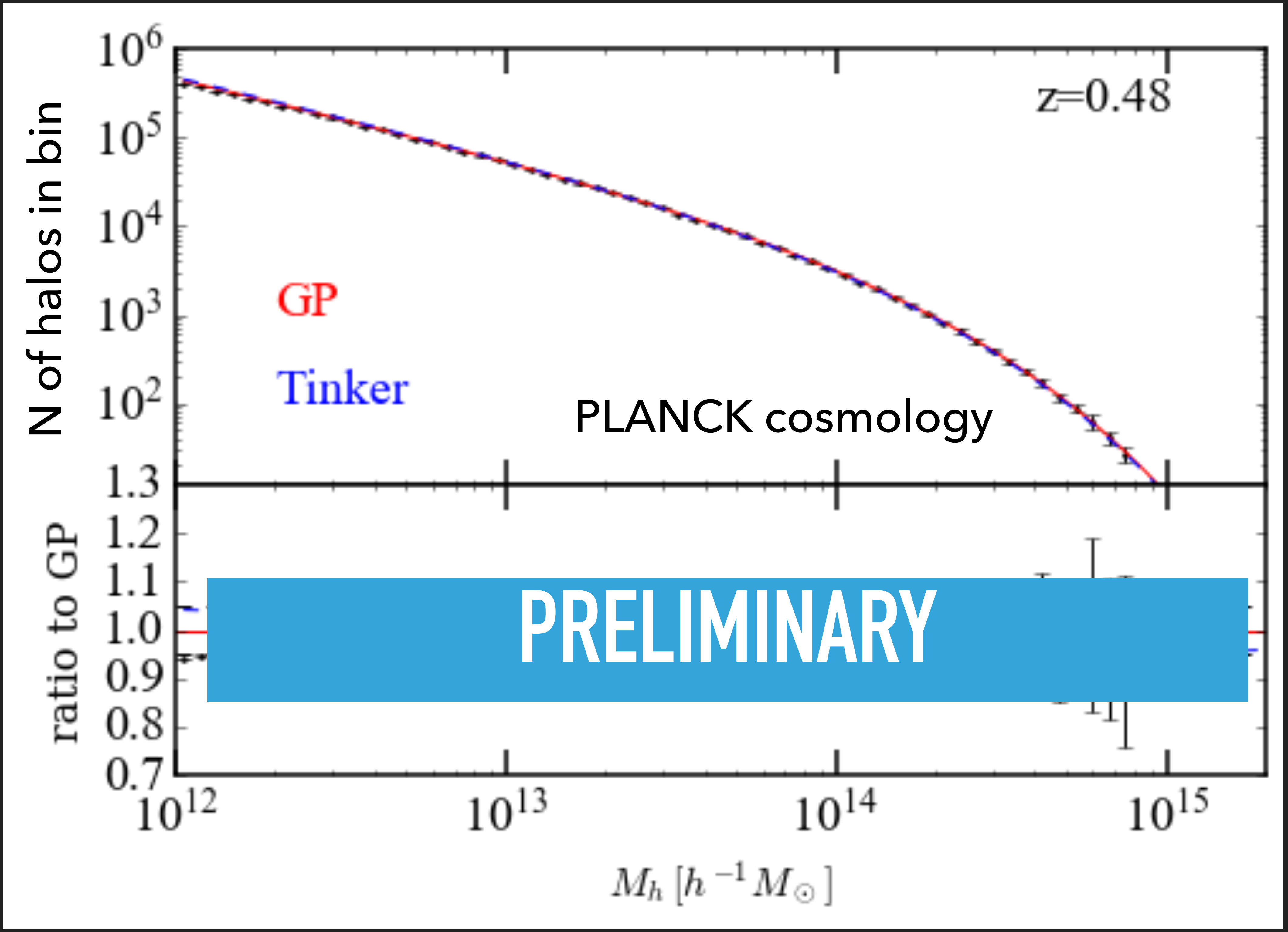
Out[109]: [<matplotlib.lines.Line2D at 0x130c11390>]



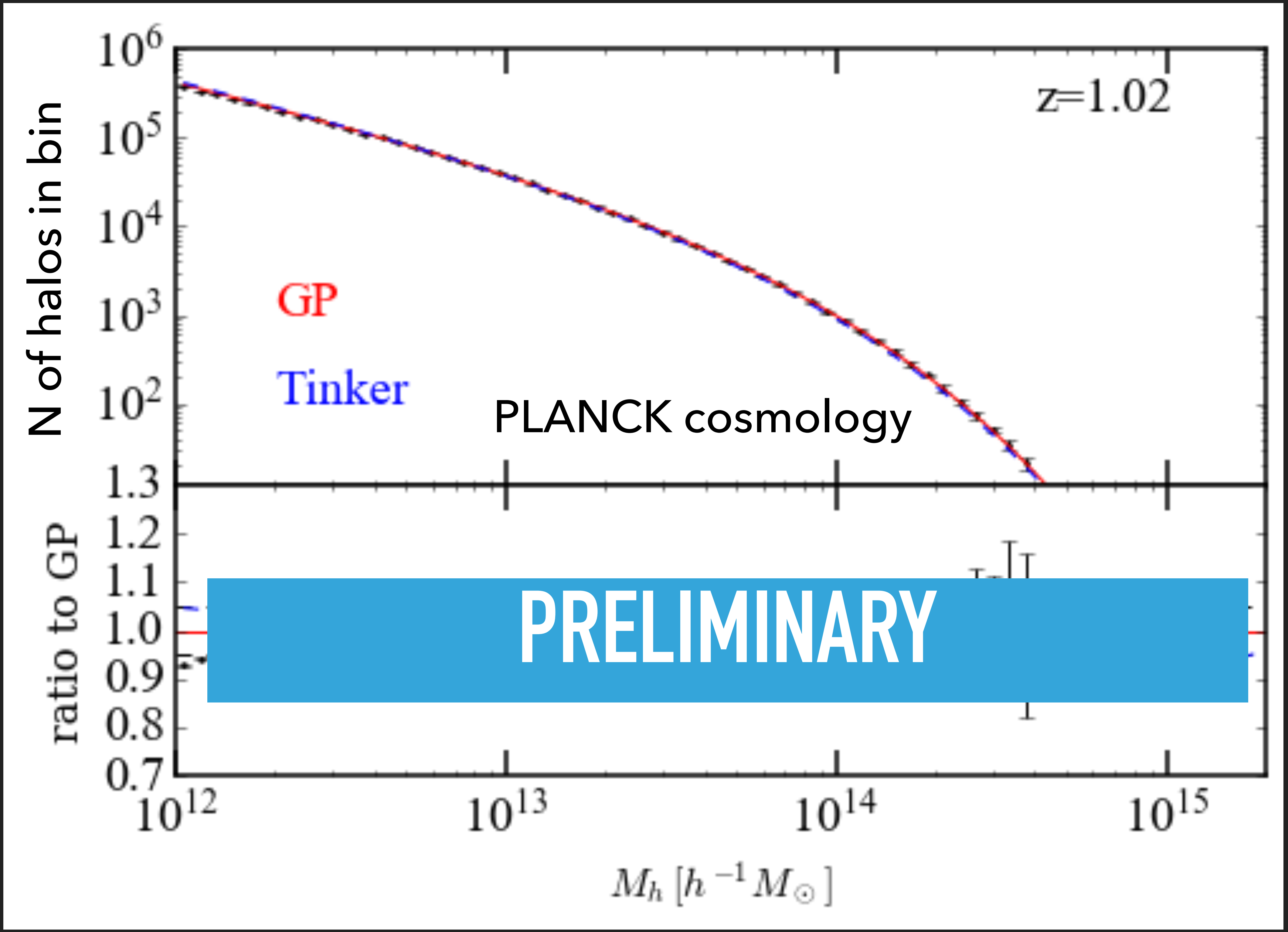
OUR HMF EMULATOR PERFORMANCE



OUR HMF EMULATOR PERFORMANCE



OUR HMF EMULATOR PERFORMANCE



OUR ΔΣ EMULATOR

- construct *mass limit samples* and measure ΔΣ(R)
- at each (z, n_h) decompose ΔΣ(R) by PCA
  - use n_h, instead of M_min to have similar noise level
  - the first 10 PCs are sufficient
- Construct Gaussian Processes for each of the 10 PC coefficients for each (z, n_h) that interpolate in the 6D cosmological parameter space
- Prediction
  - GP evaluates the 10 PCs for every (z, n_h) for a given cosmology
  - Revert them to ΔΣ(R)
  - Finally, (z, n_h, R) dependence is interpolated by 3D spline
- Use HMF GP to convert M_min to n_h

jupyter dsigma_demo Last Checkpoint: 3 minutes ago (autosaved)

File Edit View Insert Cell Kernel Help | Python 2

Code CellToolbar

Read out pre-computed PCA basis function + GP

In [3]:
```
basis = [[joblib.load('basis/S%03d_dens%02d_basis.pkl' % (snap,ndens)) for ndens in range(0,10)] for snap in range(0,21)]
dsig_gp = [[joblib.load('gp/S%03d_dens%02d_gp.pkl' % (snap,ndens)) for ndens in range(0,10)] for snap in range(0,21)]
```

Prepare a table for 3D spline

In [96]:
```
def prep_dsigma_template(params):
    global d_gp
    d_gp = np.zeros((21,10,81))
    for snap in range(0,21):
        for ndens in range(0,10):
            d_gp_pca=dsig_gp[snap][ndens].predict(params)
            d_gp[snap,ndens,] = basis[snap][ndens].inverse_transform(d_gp_pca)[0,]
```

Inputs:

- scale factor
- number density (or halo mass)
- projected distance

In [59]:
```
z=0.25
ascale = 1./(1+z)
Rplot = np.logspace(-1,2.3,100) # in h^{-1}Mpc
Mmin = 1e14 # in h^{-1}M_\odot
```

```
# PLANCK 2015
cparam = np.array([[0.02225,0.1198,0.6844,3.094,0.9645,-1]])
set_cosmo(cparam)
set_redshift(z)
lognh = mh_to_logdens(Mmin)
plt.loglog(Rplot,get_dsigma(ascale, lognh, Rplot),lw=2,color='red')
```

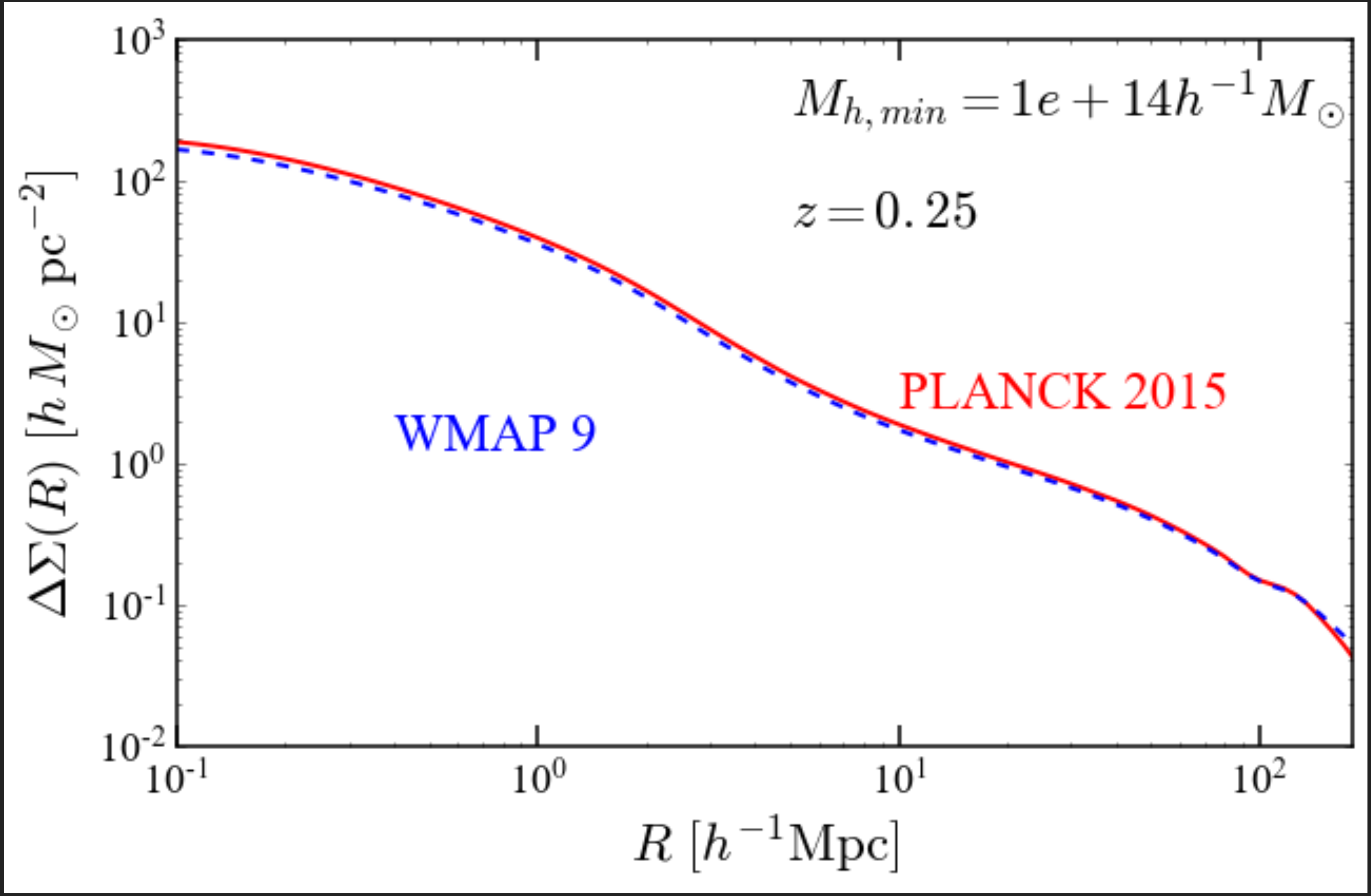
give your cosmological params ~5s

and redshifts ~600ms; HMF GP called inside

convert M_min to n_h ~50μs

Evaluate !! ~1ms

OUR ΔΣ EMULATOR DEMONSTRATIONS



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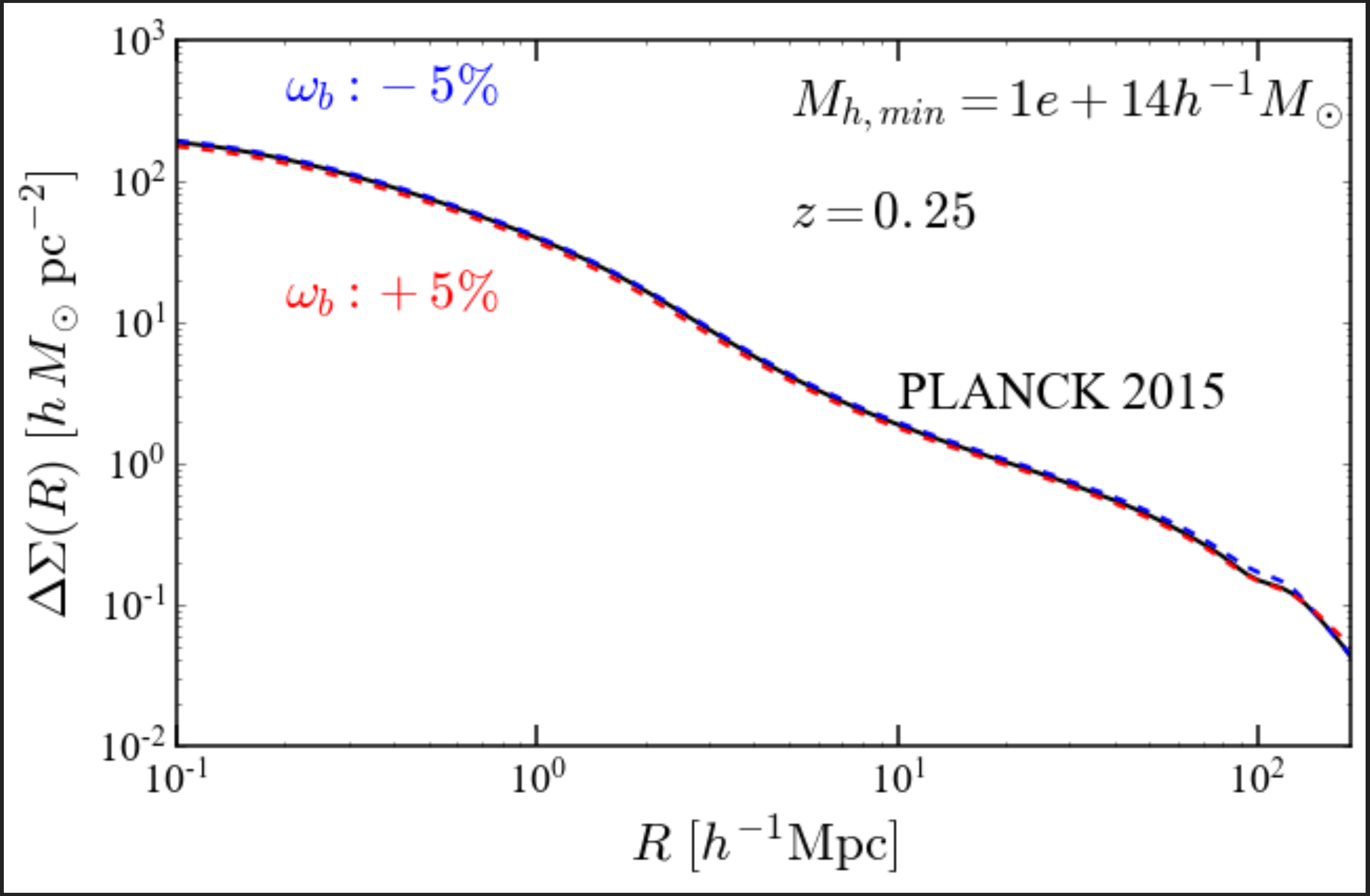

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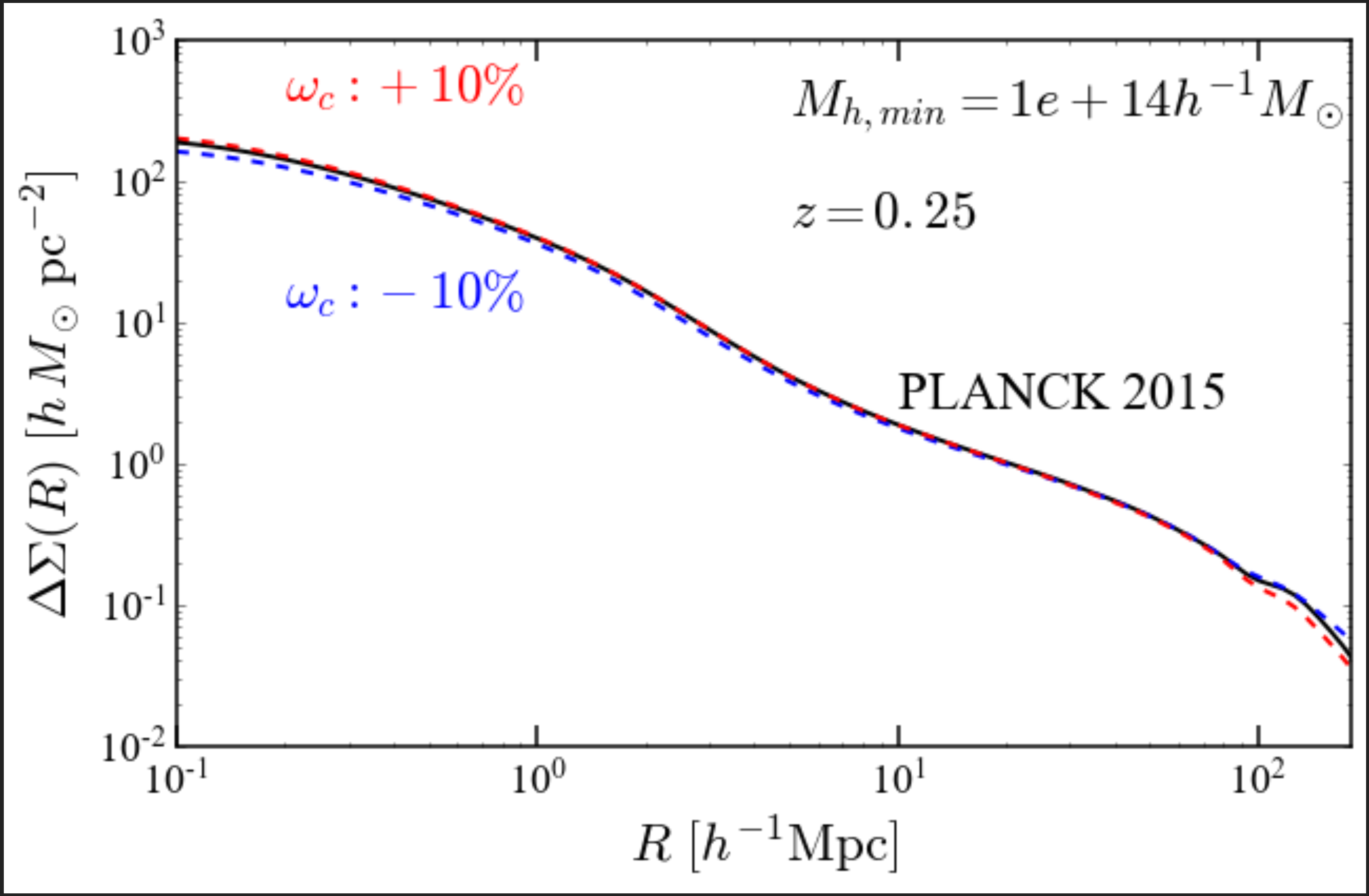

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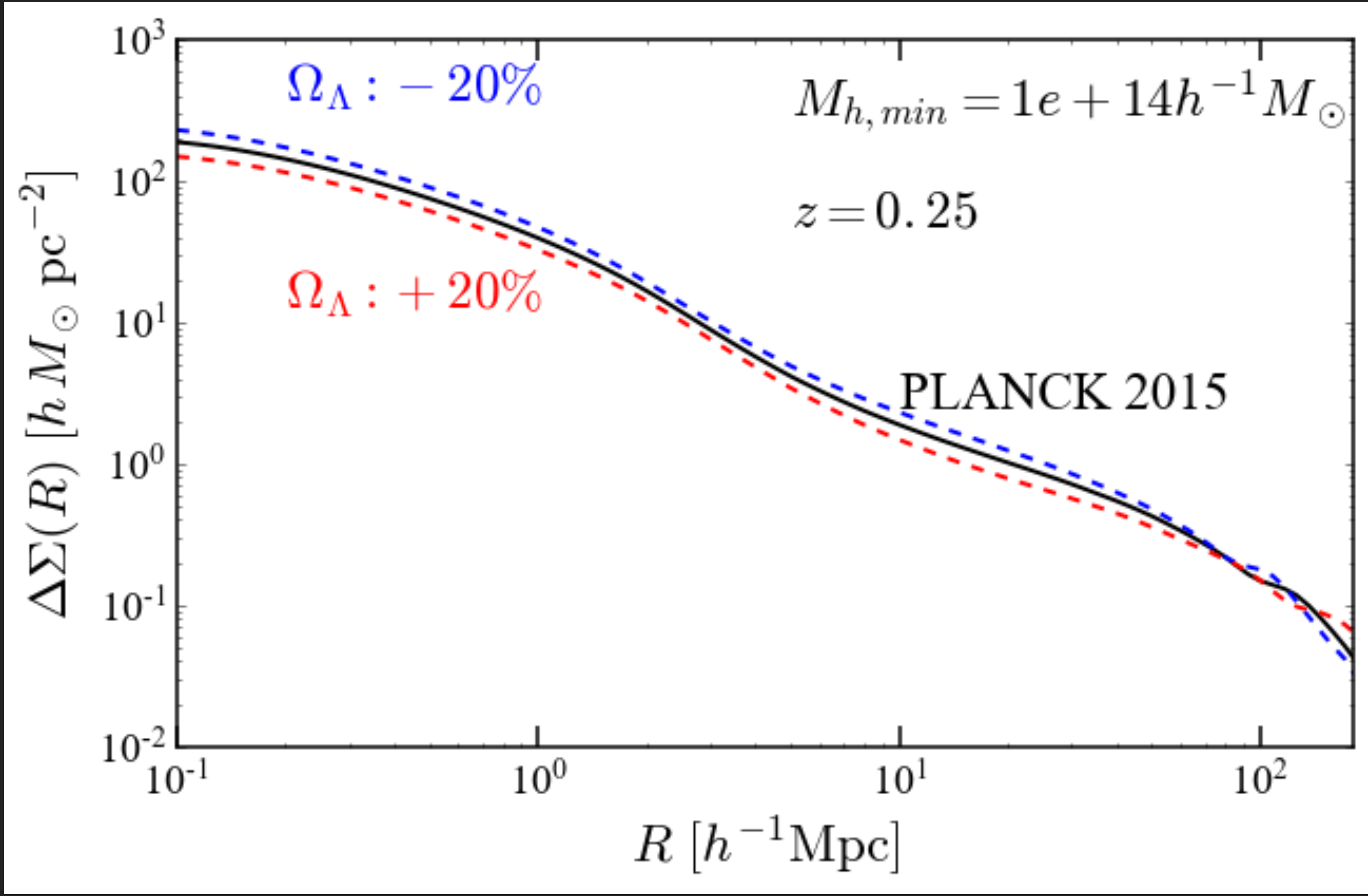

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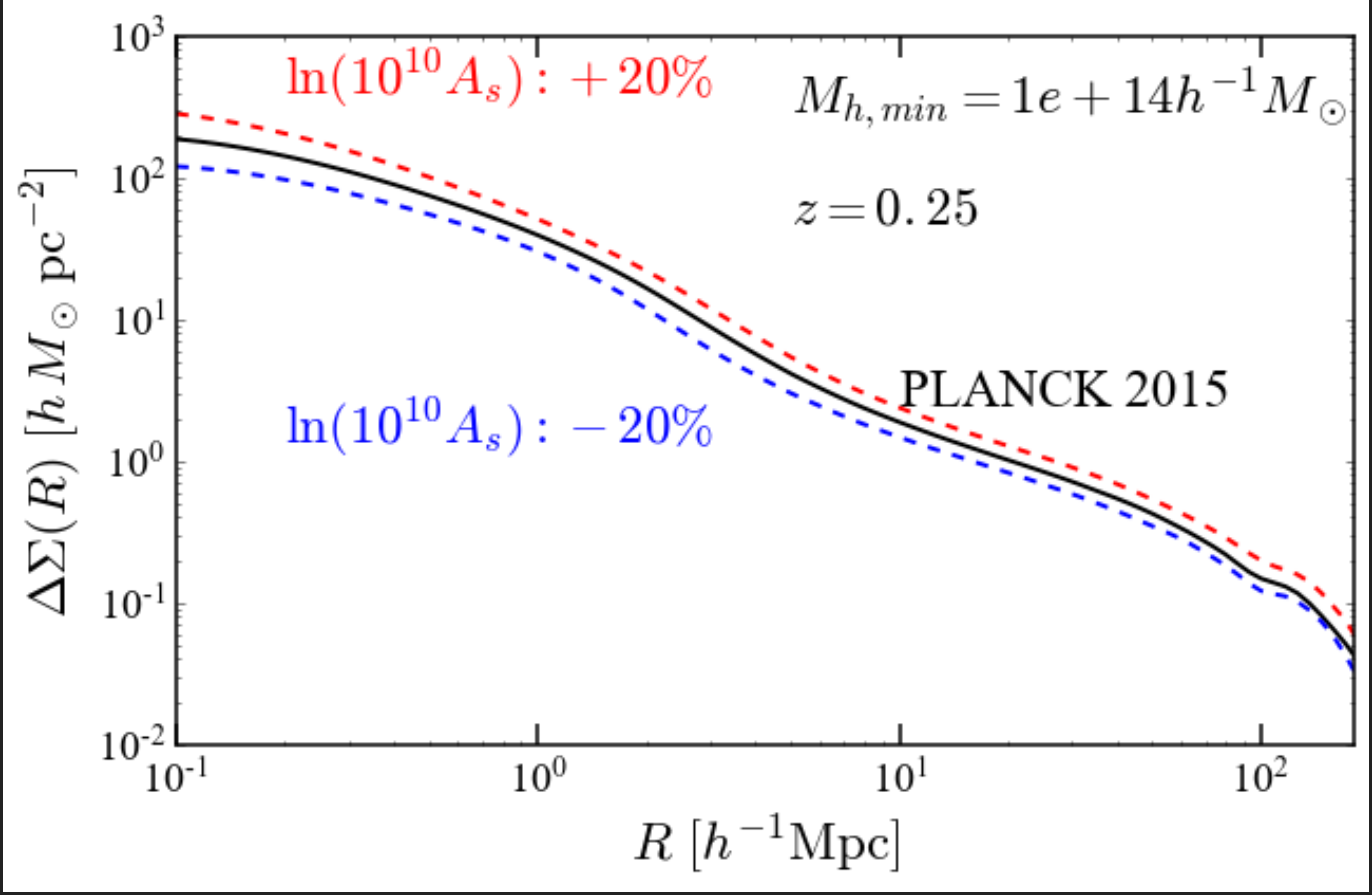

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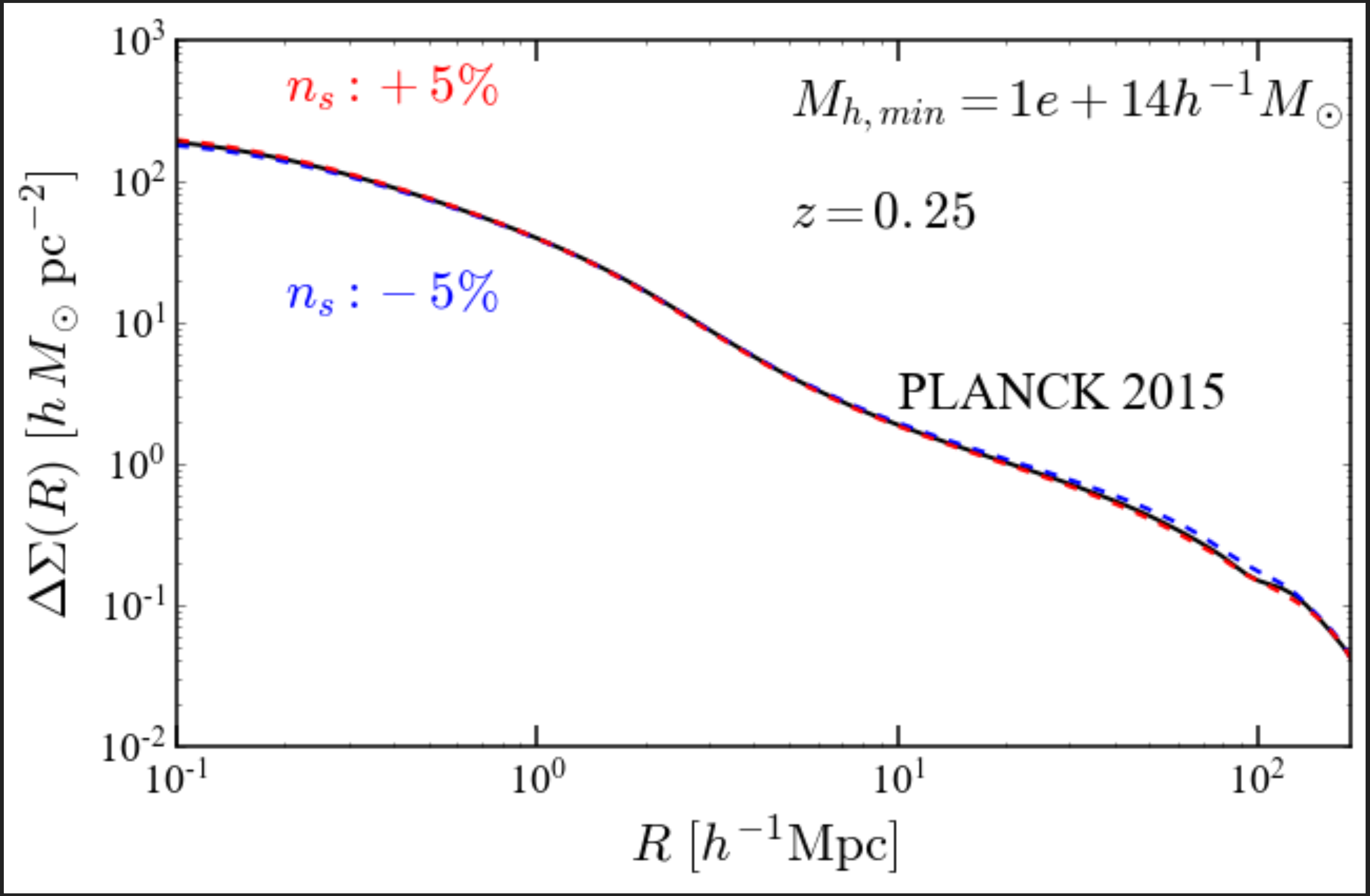

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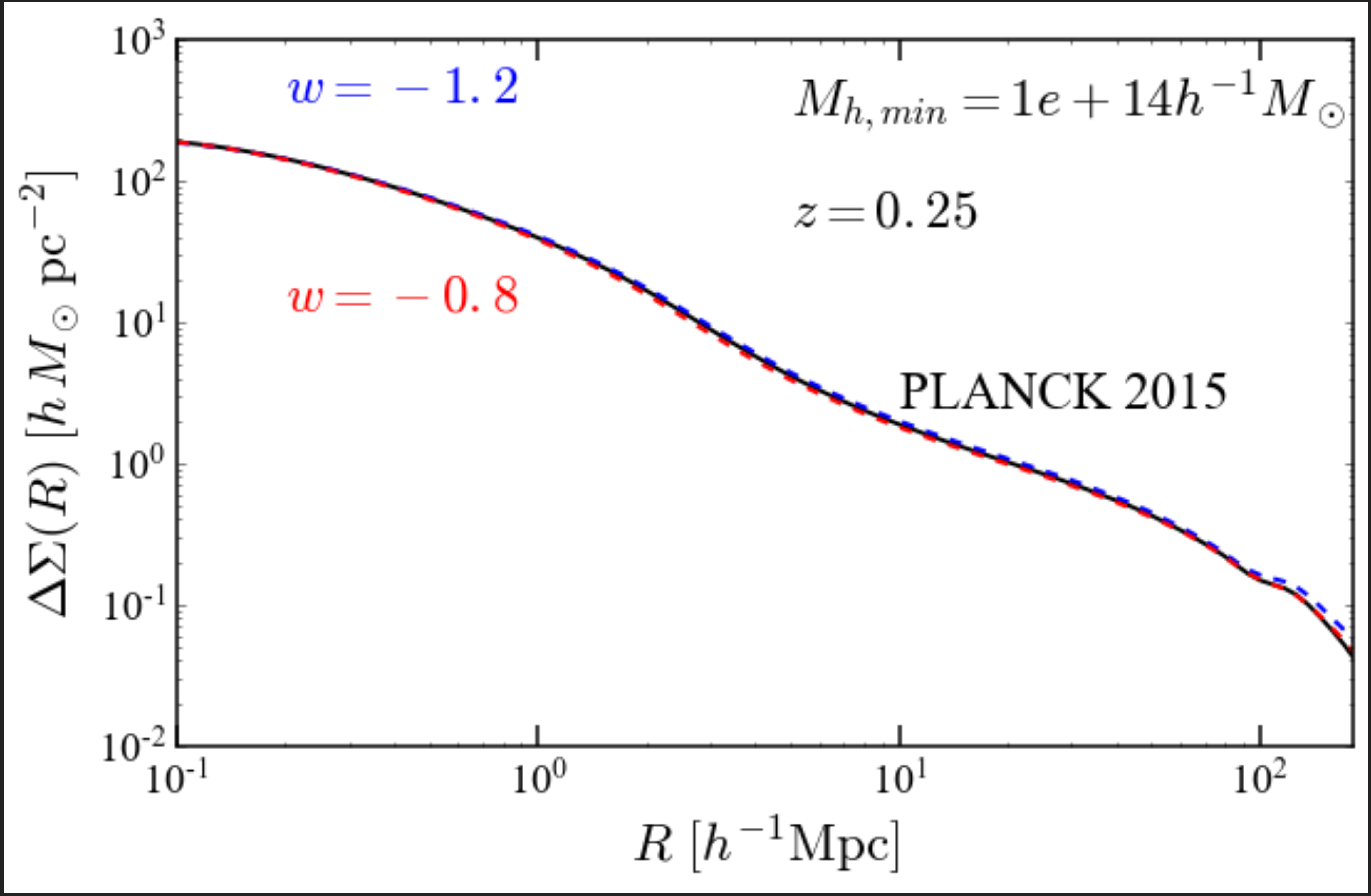

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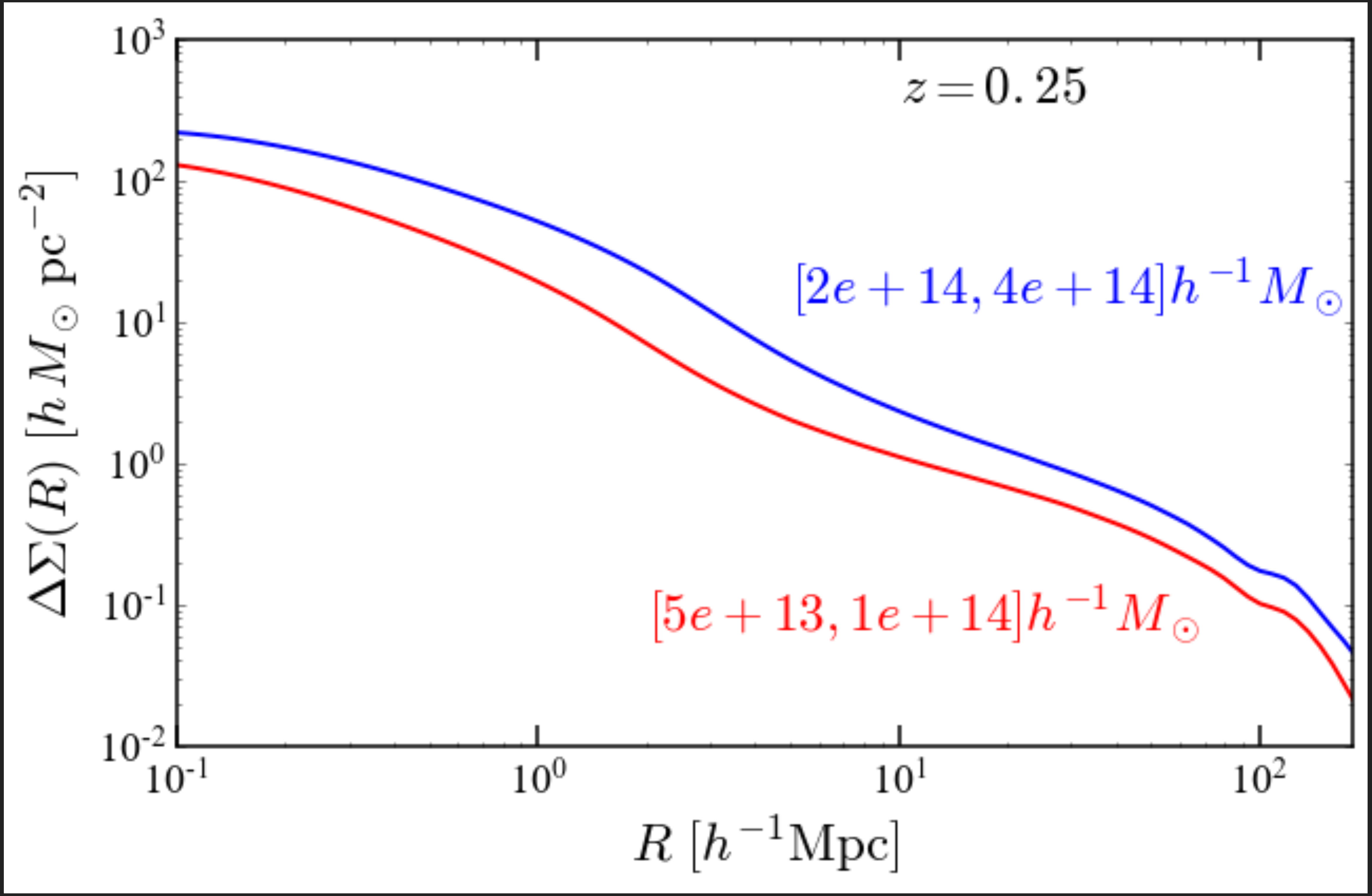
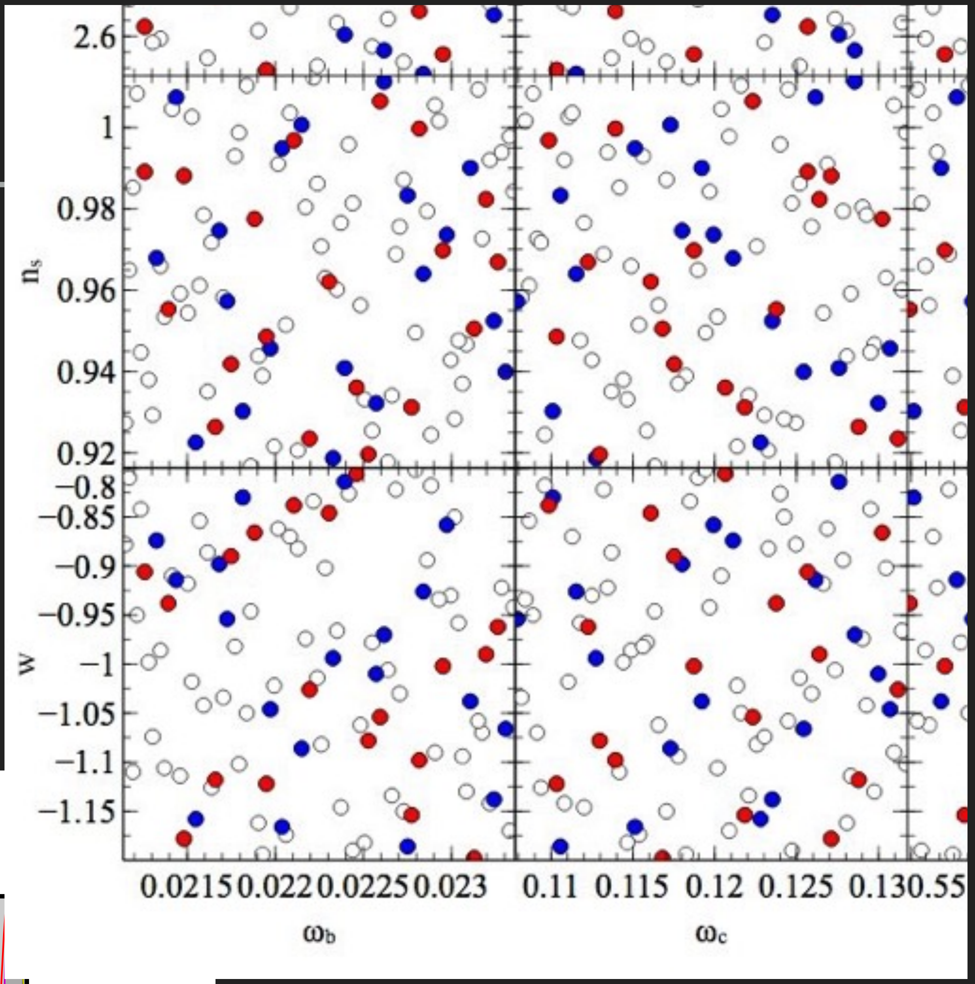
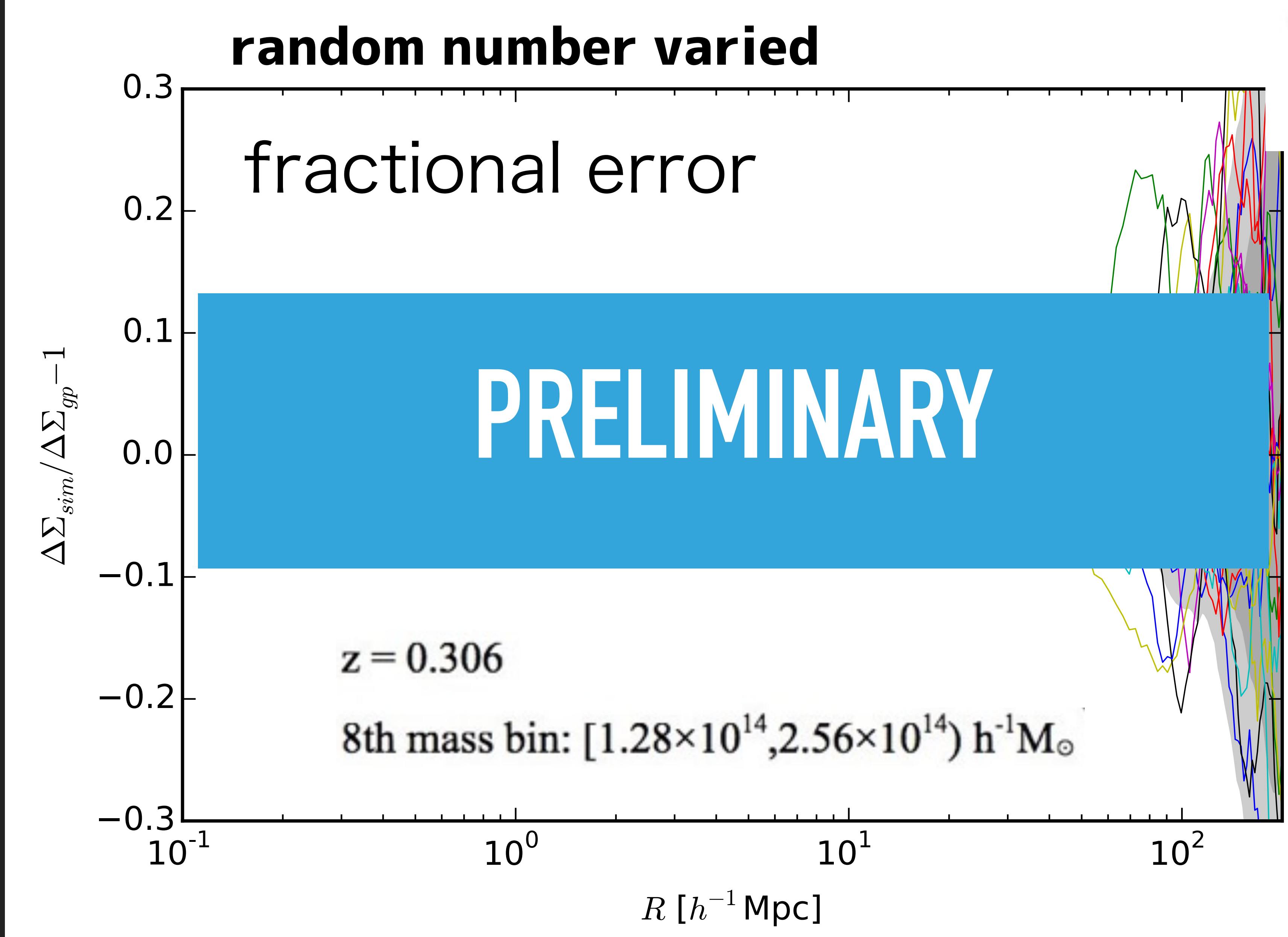


GAUSSIAN PROCESS ACCURACY

training with 20 models (red)
validation with 20 other models (blue)





SUMMARY

- Modeling the halo mass function and galaxy-galaxy lensing signal
  - Latin hypercube design + fitting/GP/spline
  - handy emulator in python almost ready
  - accuracy test undergoing, naively expect 5% accuracy
- To come
  - RSD emulator to combine g-g lensing and 3D clustering
  - further extension under discussion
    - e.g., non-flat, w0-wa cosmologies