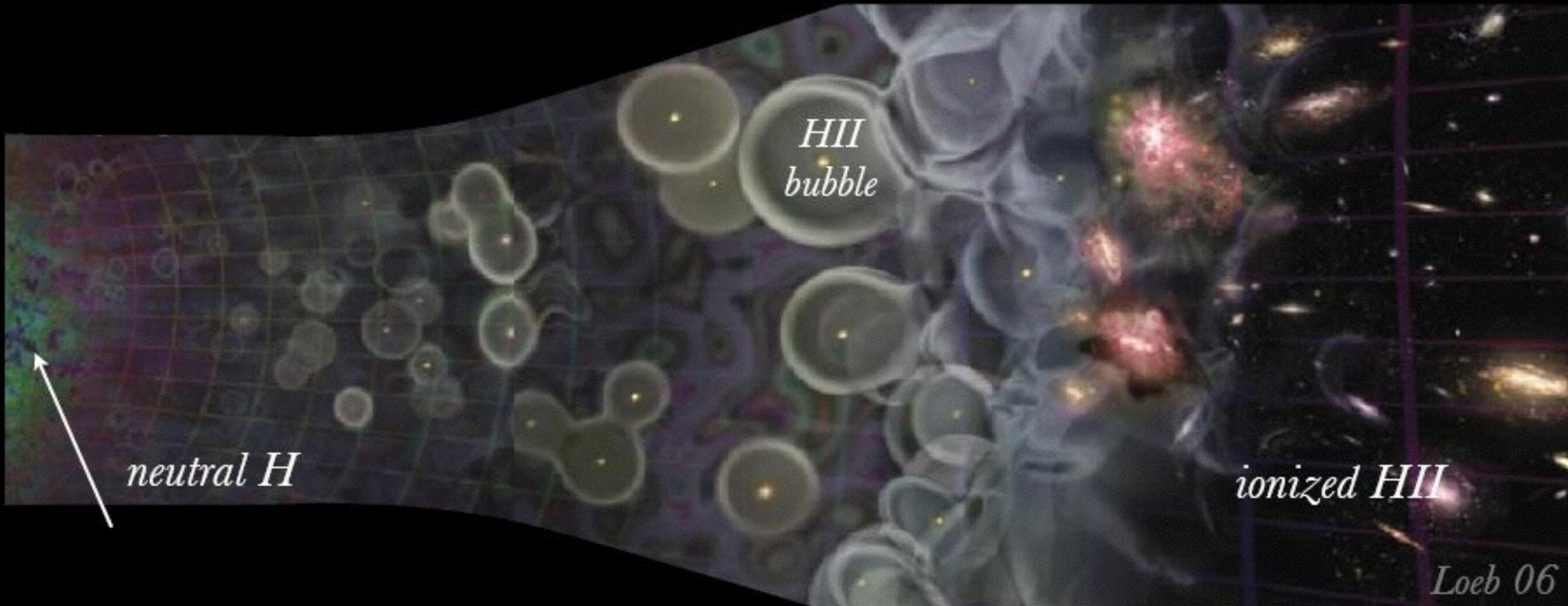

21cm signal analysis with Artificial Neural Networks (ANN)

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with Yi Mao, Benoit Semelin

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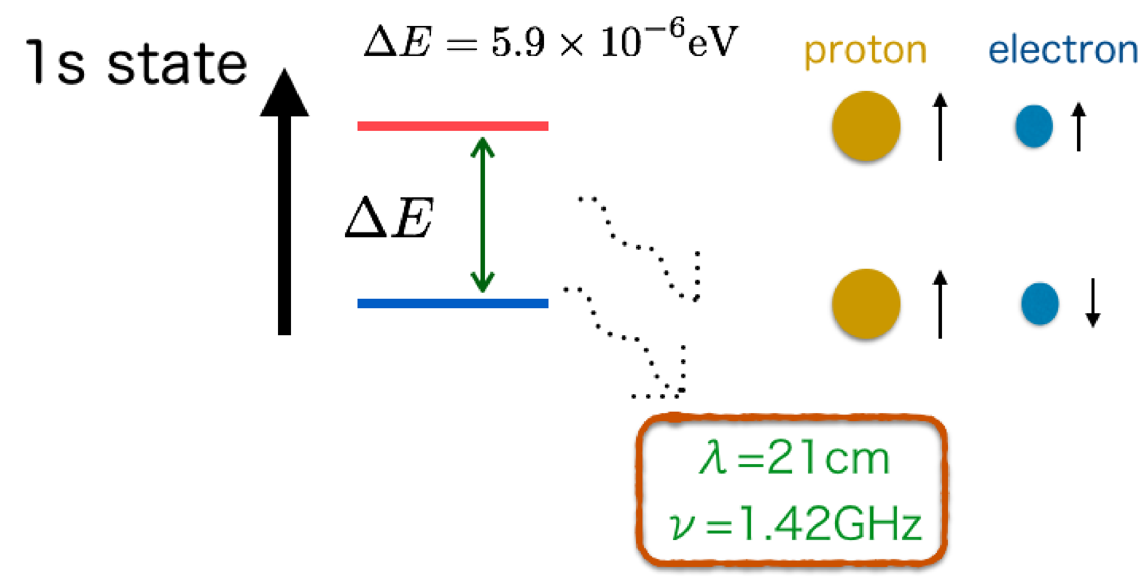
- Introduction (21cm signal, ANN)
- EoR parameter estimation
- Recovering HII size distribution

21cm signal

21cm line radiation :



Neutral hydrogen emits the radiation due to the hyperfine structure.

Brightness temperature

$$\delta T_b = \frac{T_\mathrm{S} - T_\gamma}{1+z}(1 - \exp(-\tau_\nu))$$

$$\sim 27 x_\mathrm{H}(1+\delta_m)\left(\frac{H}{dv_r/dr + H}\right)\left(1 - \frac{T_\gamma}{T_\mathrm{S}}\right)\left(\frac{1+z}{10}\frac{0.15}{\Omega_m h^2}\right)^{1/2}\left(\frac{\Omega_b h^2}{0.023}\right)\ [\mathrm{mK}]$$

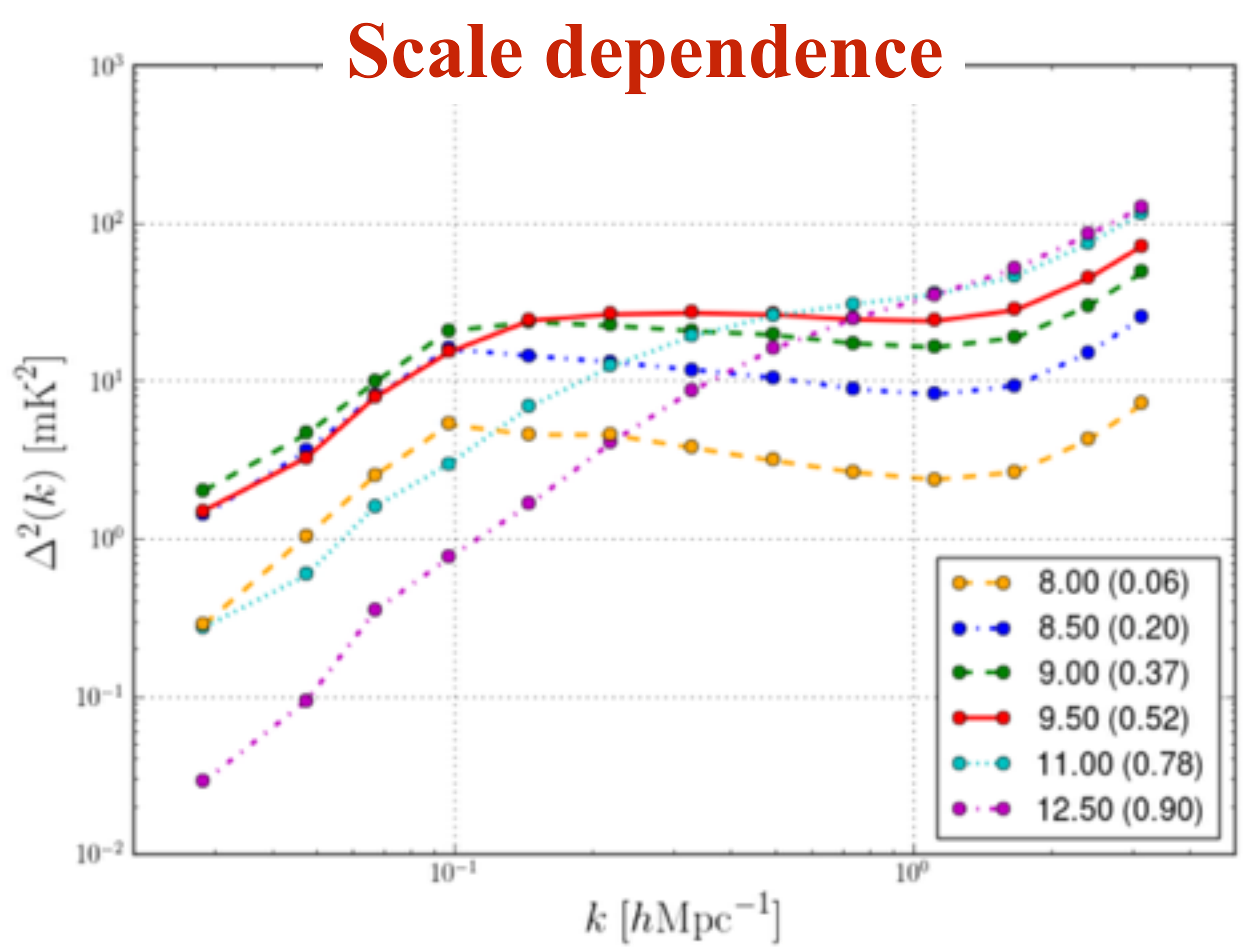
Including both cosmological and astrophysical information

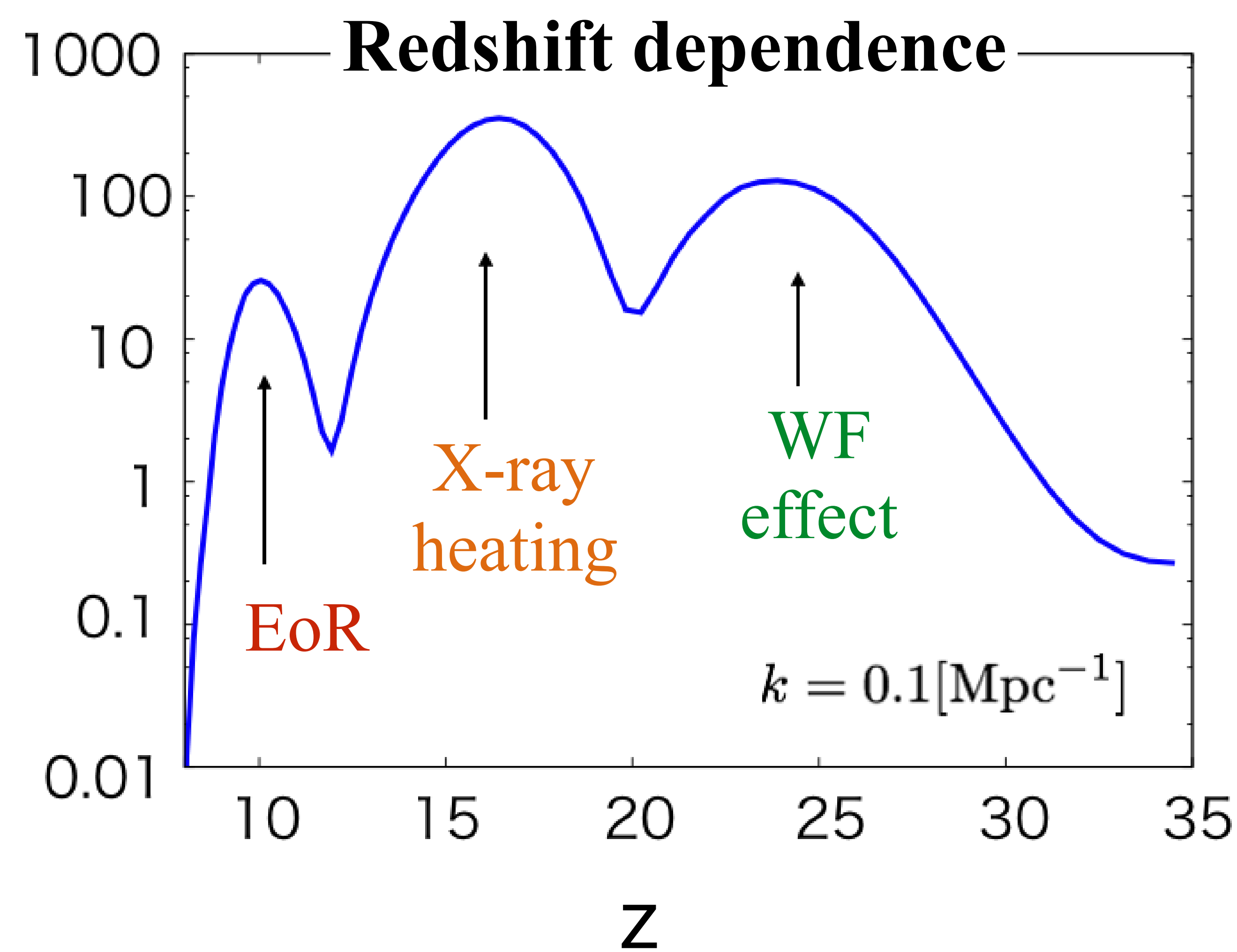
21cm power spectrum

We first aim to detect 21cm signal **statistically**.

21cm power spectrum (PS) : $\langle \delta T_b(\mathbf{k}) \delta T_b(\mathbf{k}^{'}) \rangle = (2\pi)^3 \delta(\mathbf{k}+\mathbf{k}^{'}) P_{21}$

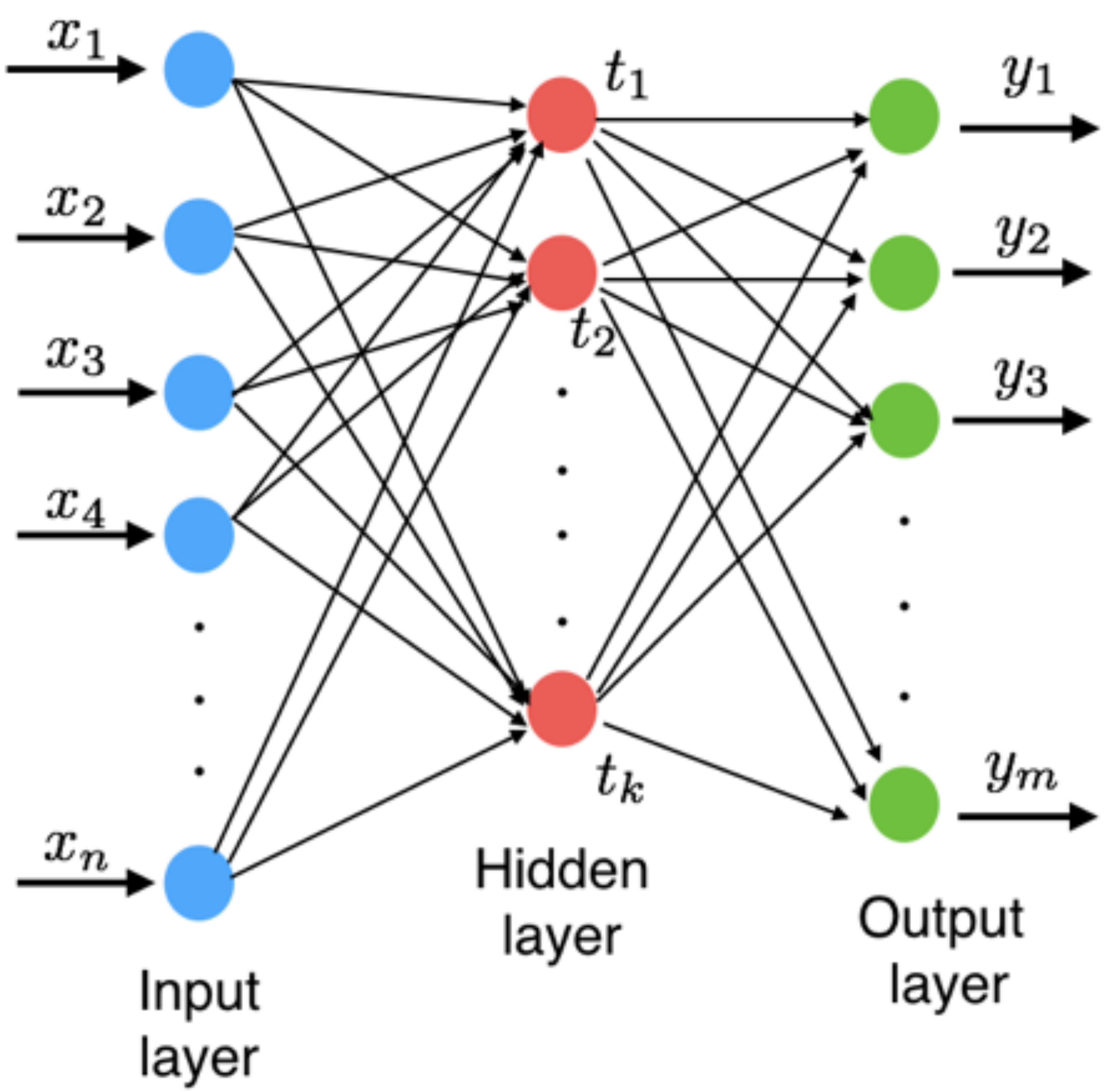
(We use 21cmFAST)





Pober et al (2014)

Artificial Neural Network (ANN)



- ANN consists of input layer, hidden layer and output layer. Each layer has neurons.

- Training network with training dataset, ANN can approximate any function which associates input and output values.

$$y = f(x)$$

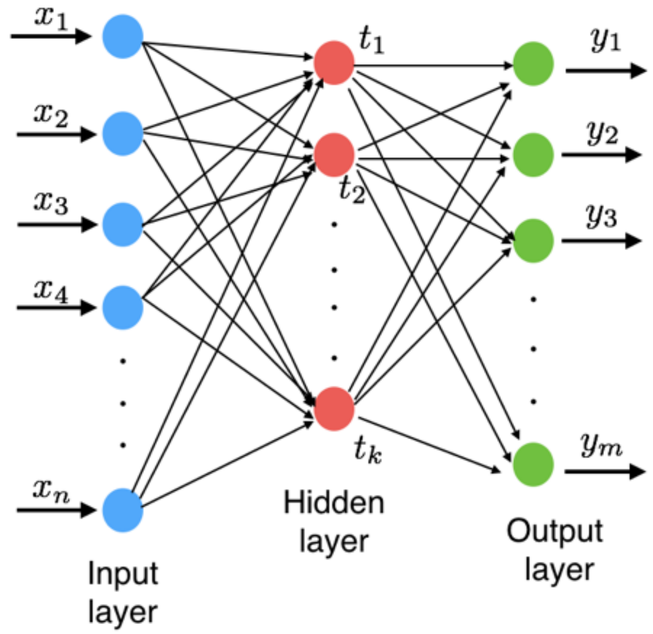
- Applying trained network to unknown data in order to obtain expected value.

$$y_{\mathrm{ANN}} = f(x_{\mathrm{test}})$$

Our strategy

Input

21cm power spectrum



Output

EoR parameters

or

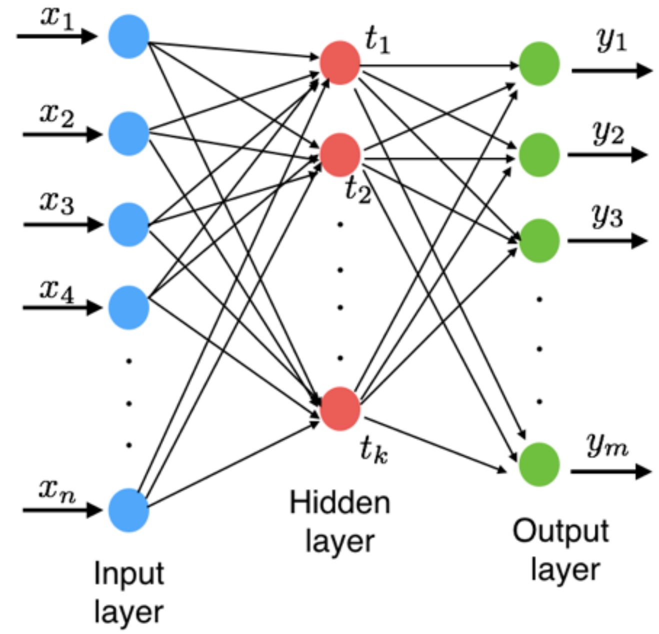
HII size distribution

Our datasets consist of 21cm power spectrum as input data and EoR parameters as output data.

Our strategy ①

Input

21cm power spectrum



Output

EoR parameters

or

HII size distribution

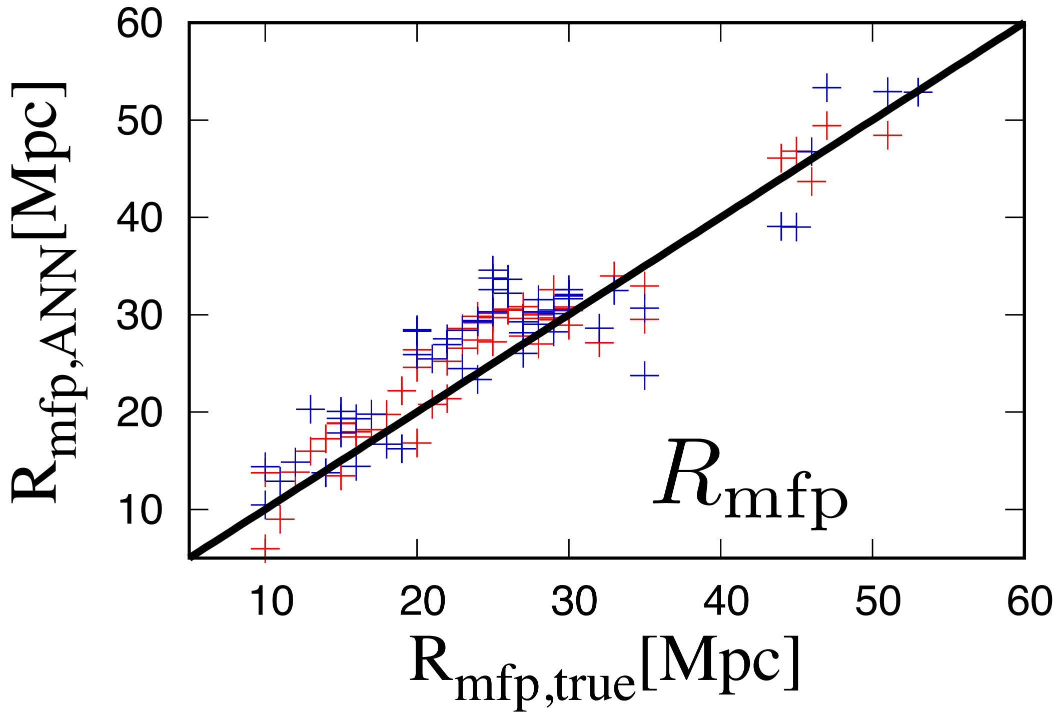
Our datasets consist of 21cm power spectrum as input data and EoR parameters as output data.

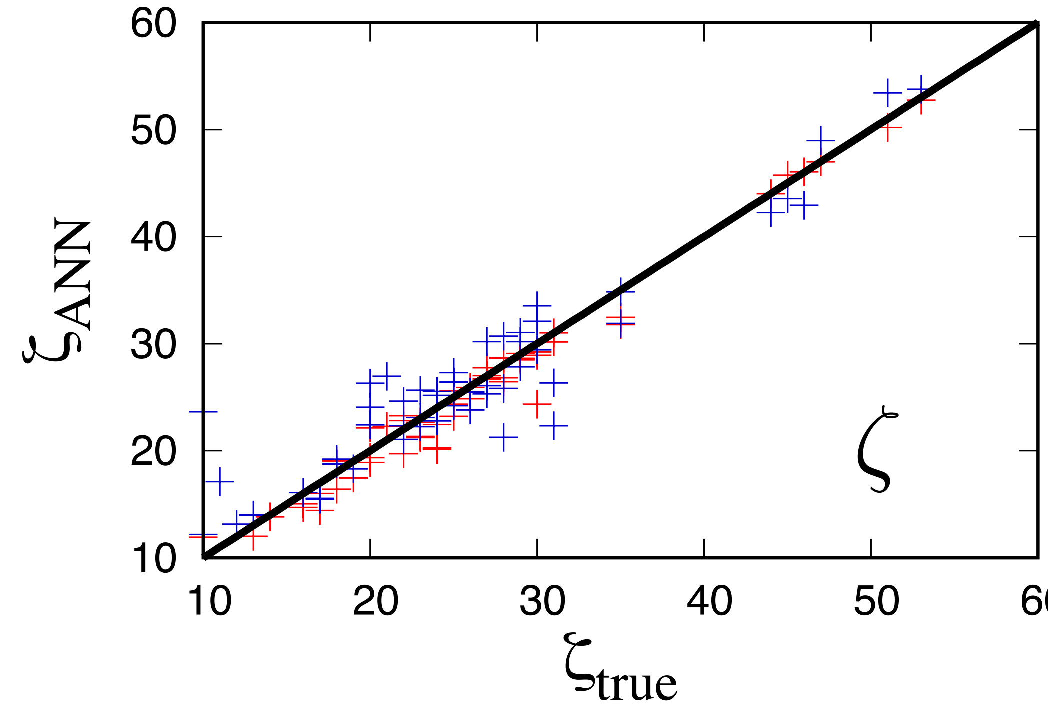
Motivation

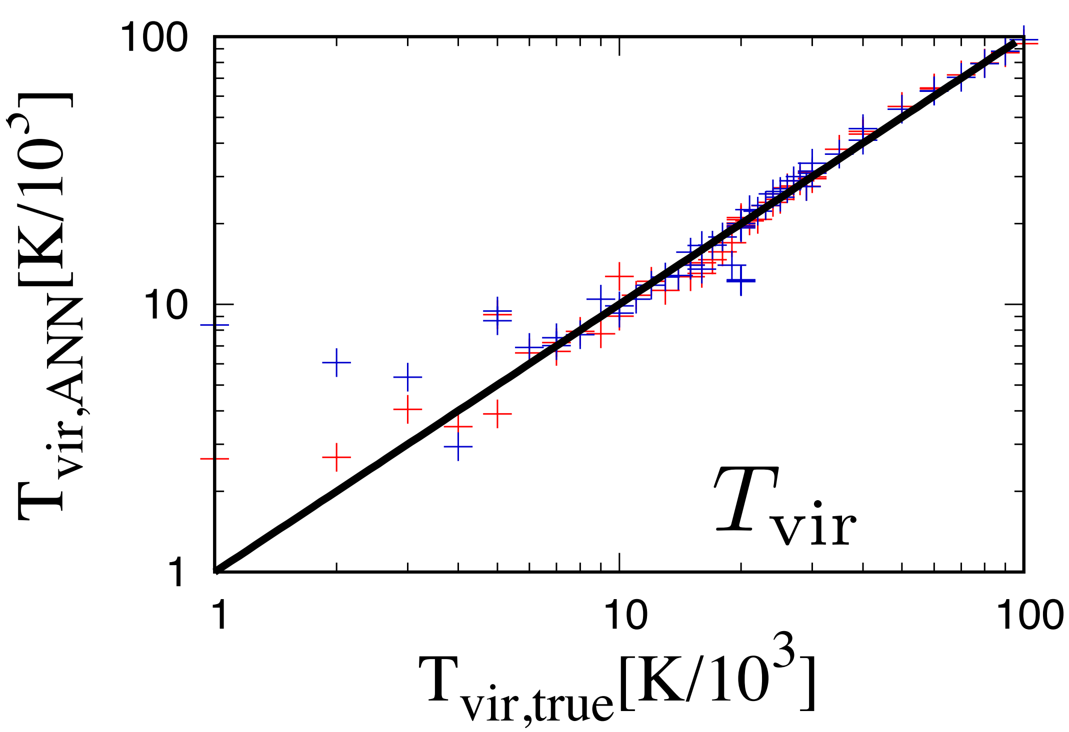
- We usually employ Bayesian inference for parameter estimation (ex. Markov Chain Monte Carlo algorithm).
- It requires likelihood calculation to compare observational (or mock) data with models. This needs calculation cost for each calculation!
- However, **once** we train artificial neural network, we can quickly apply trained network to unknown data.

EoR parameters

z=9, 10, 11. 21cm PS including thermal noise and cosmic variance







Red : z=9,10,11
Blue : z=9

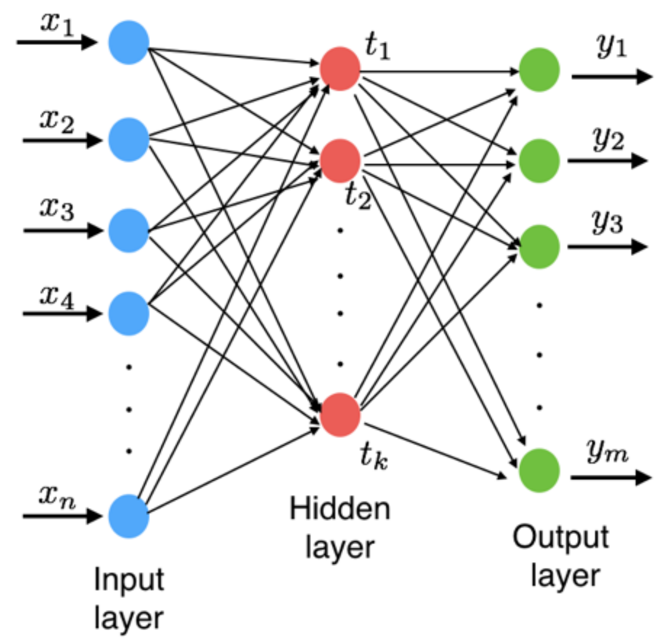
Shimabukuro & Semelin (2017)

Reconstructed parameters are good agreement with true ones.

Our strategy ②

Input

21cm power spectrum



Output

EoR parameters

or

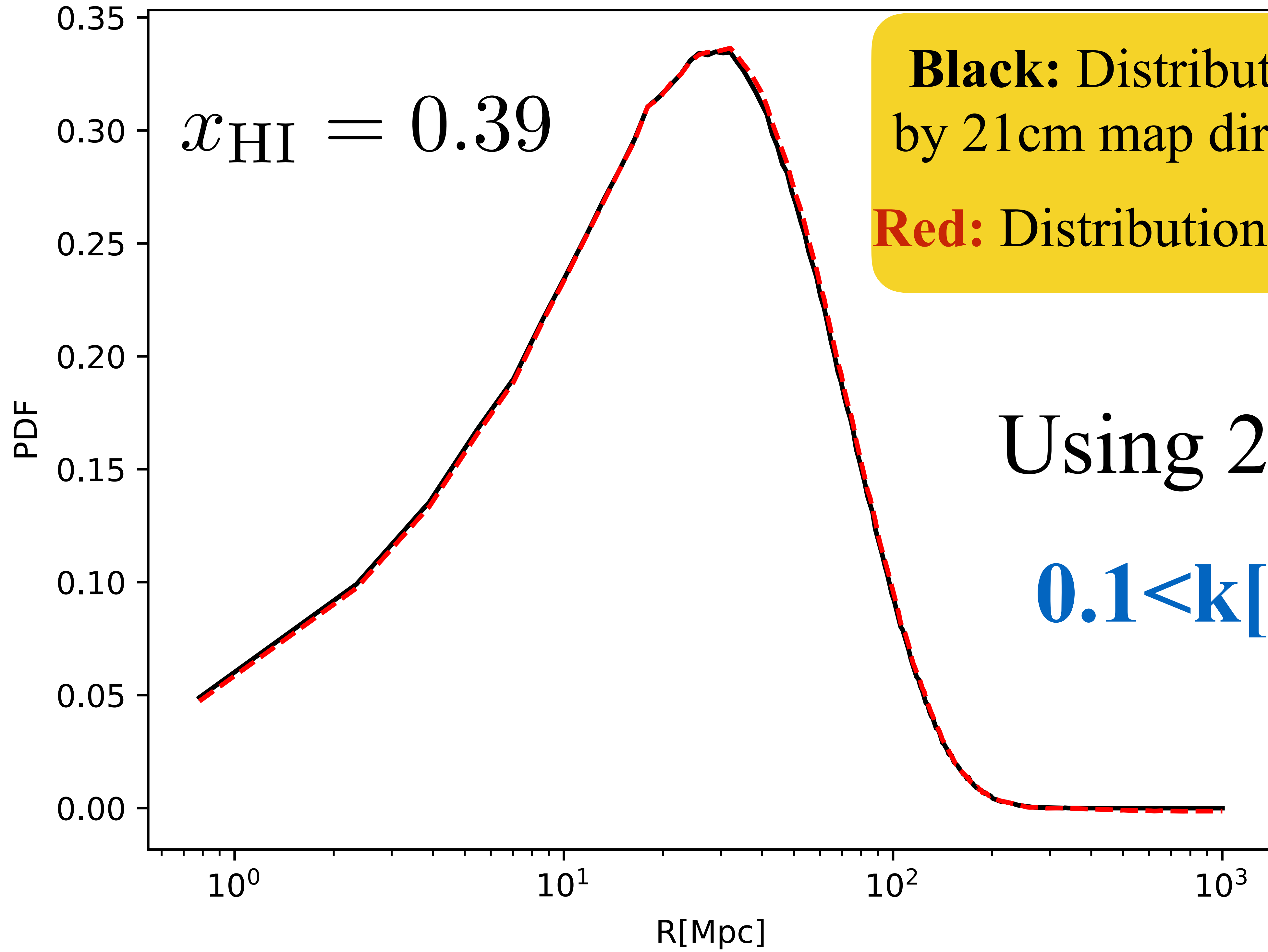
HII size distribution

Our datasets consist of 21cm power spectrum as input data and b
ubble size distribution as output data.

Motivation

- Measuring HII size distribution helps us understand what ionising sources are dominant at the EoR.
- Some previous studies measure HII size distribution from 21cm 3D map directly.
- From observational aspects, we require good angular resolution to make 21cm map.
- Therefore, I attempt to recover HII size distribution from 21cm PS that does not require making 21cm map.

HII bubble size distribution



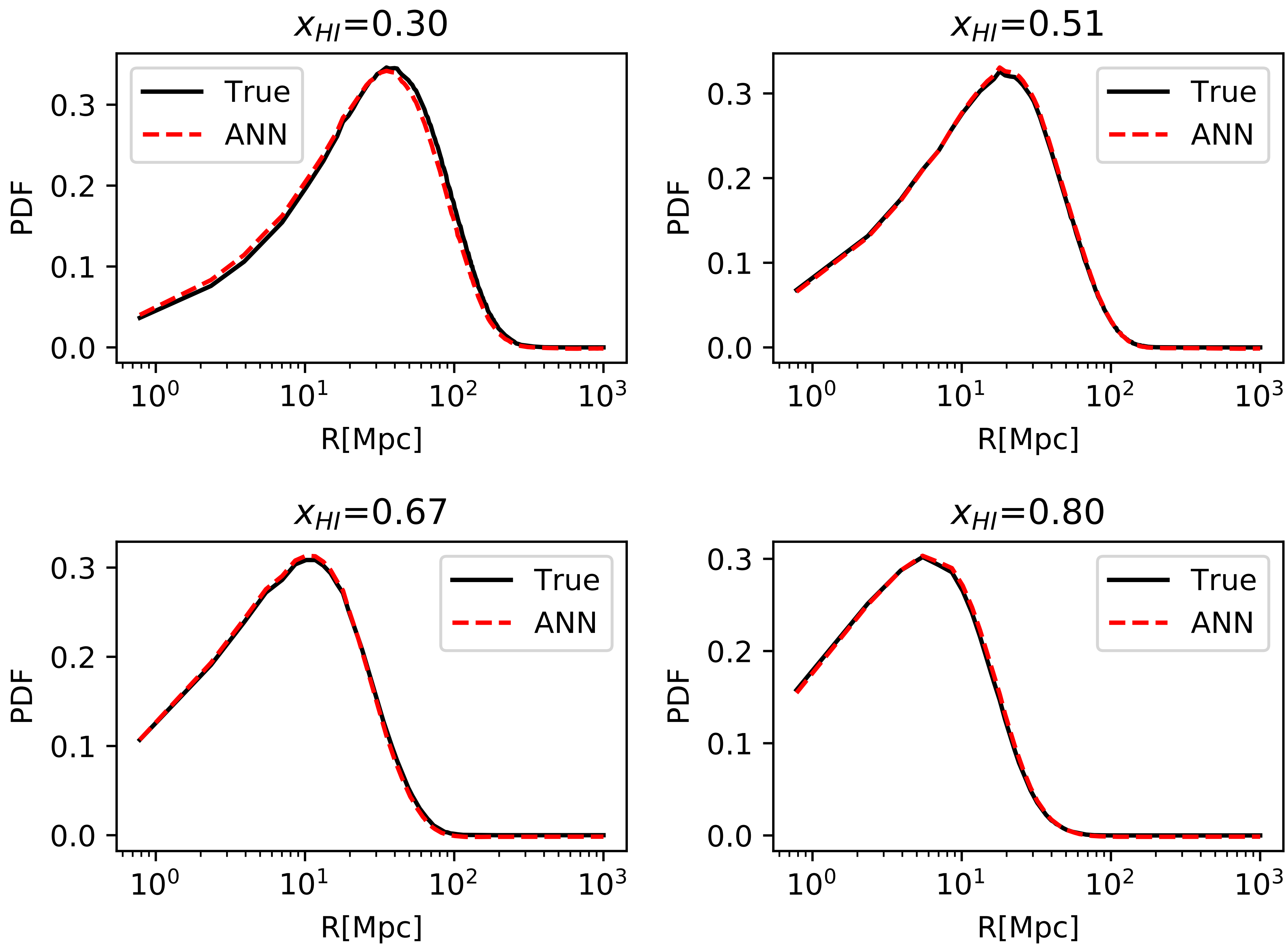
Black: Distribution obtained by 21cm map directly

Red: Distribution obtained by ANN

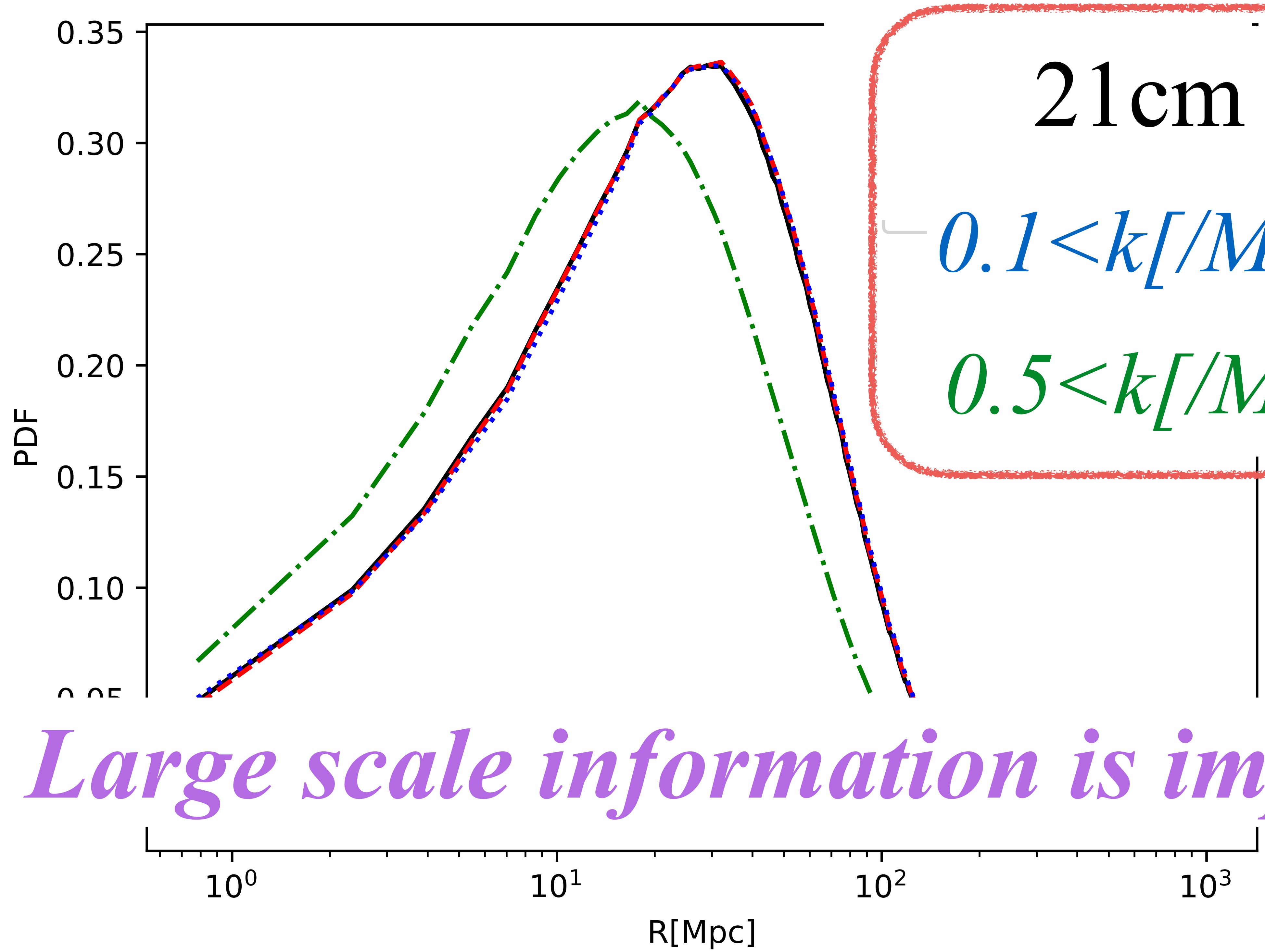
Using 21cm PS at

0.1<k[/Mpc]<1

HII bubble size distribution



HII bubble size distribution



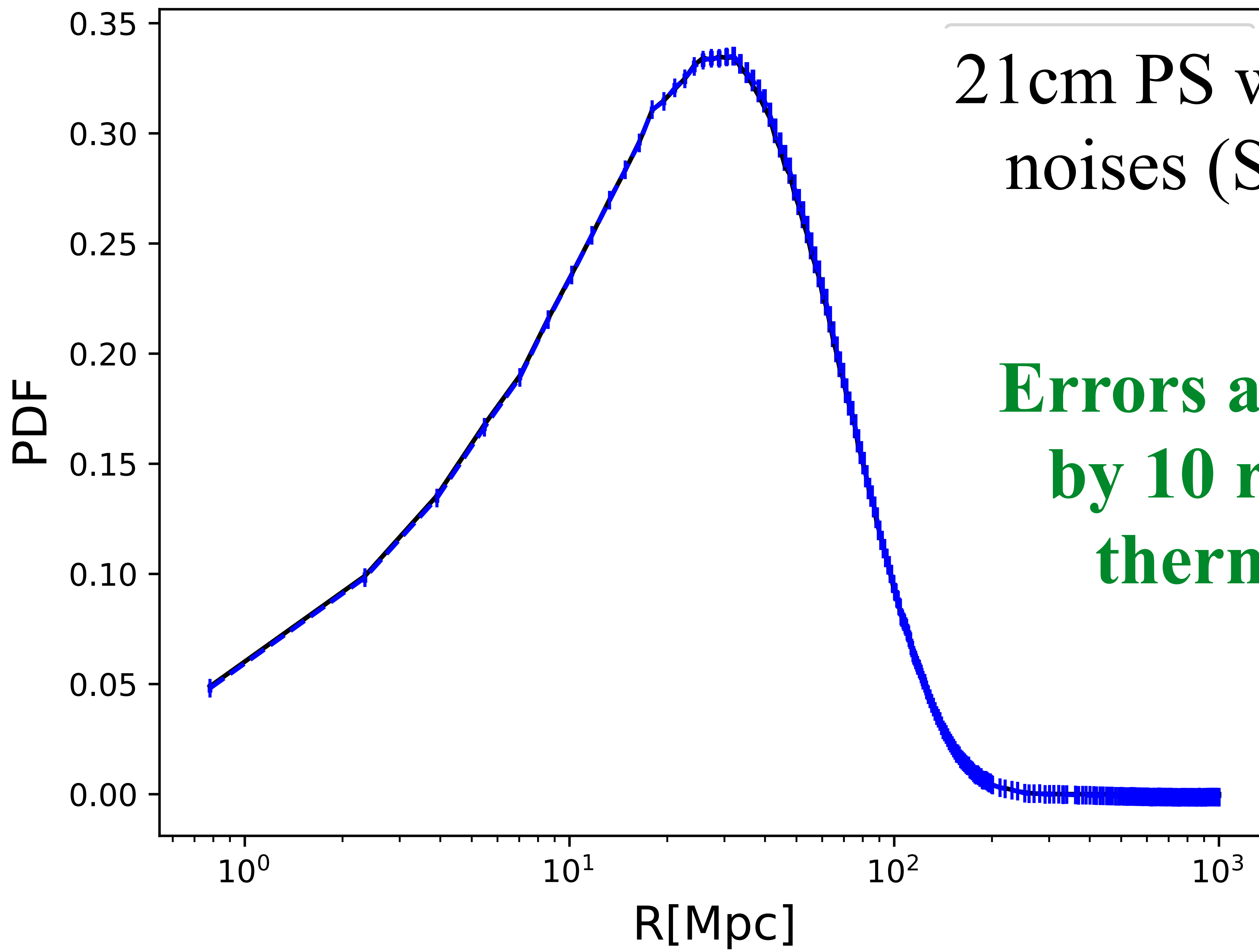
21cm PS at

0.1<k[/Mpc]<0.5

0.5<k[/Mpc]<1

Large scale information is important

HII bubble size distribution



21cm PS with thermal noises (SKA level)

Errors are estimated by 10 realizations thermal noises

Summary

- We applied artificial neural networks (ANN) to analysis of 21cm signal.
- We reconstruct EoR parameters and HII size distribution from 21cm PS with ANN.
- Reconstructed EoR parameters and HII size distribution are good agreement with true values.
- (Future work) Are there other 21cm observables which we can apply machine learning to ?