

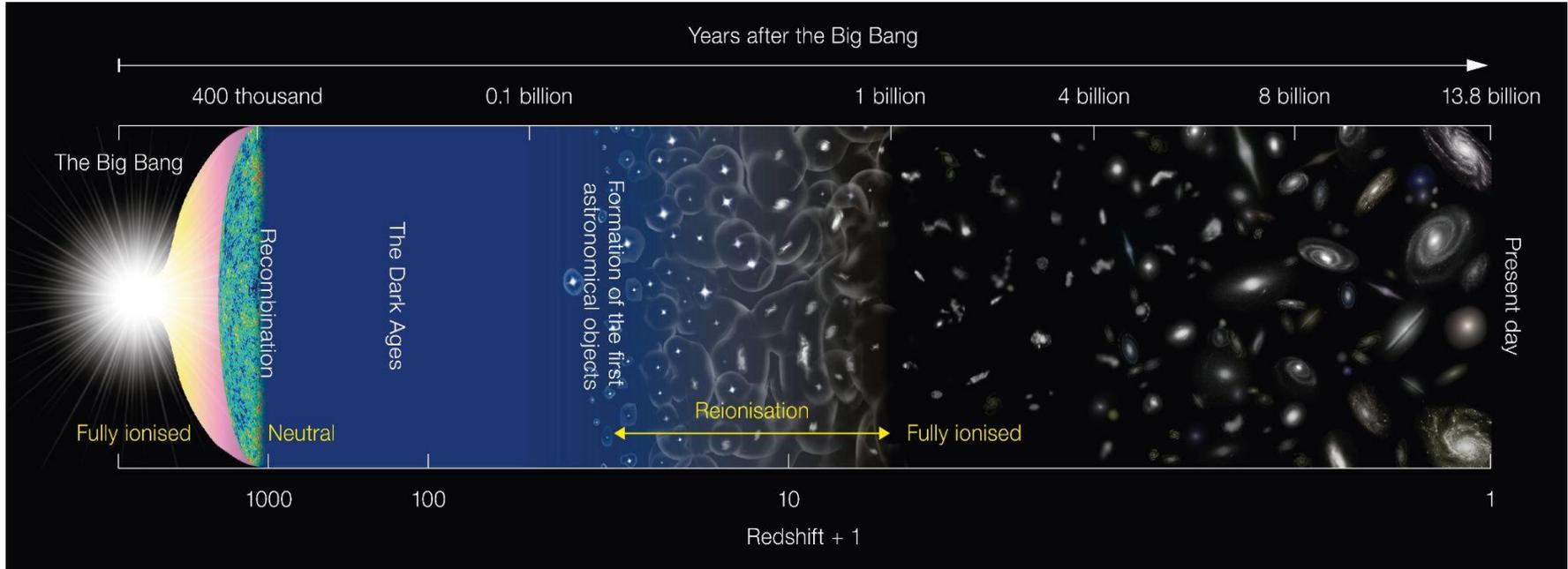
# Constraining Reionization using BNN Emulated 21-cm Bispectrum

Yashrajsinh Mahida

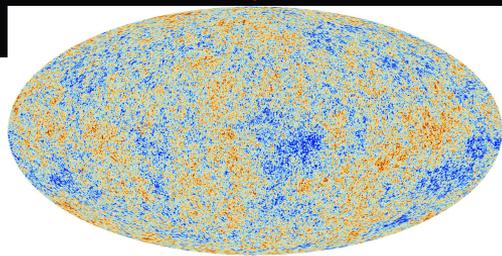
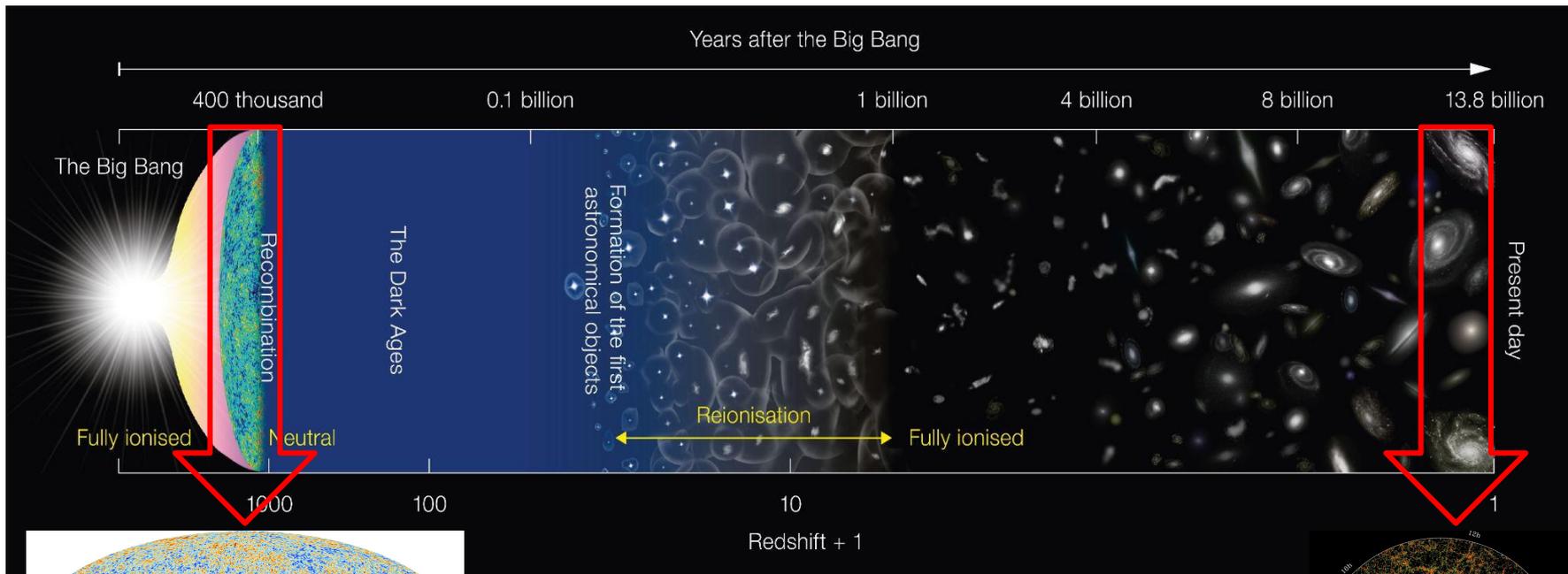
Department of Astronomy, Astrophysics and Space Engineering  
IIT Indore

Collaborators: Suman Majumdar, Sanjay Kumar Yadav, Leon Noble



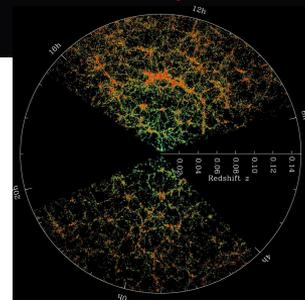


Credit: NAOJ

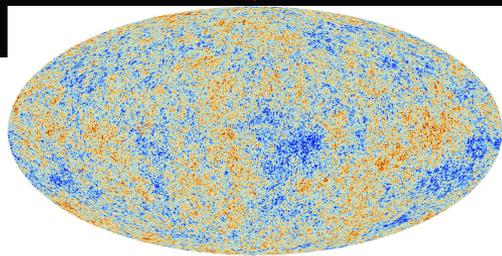
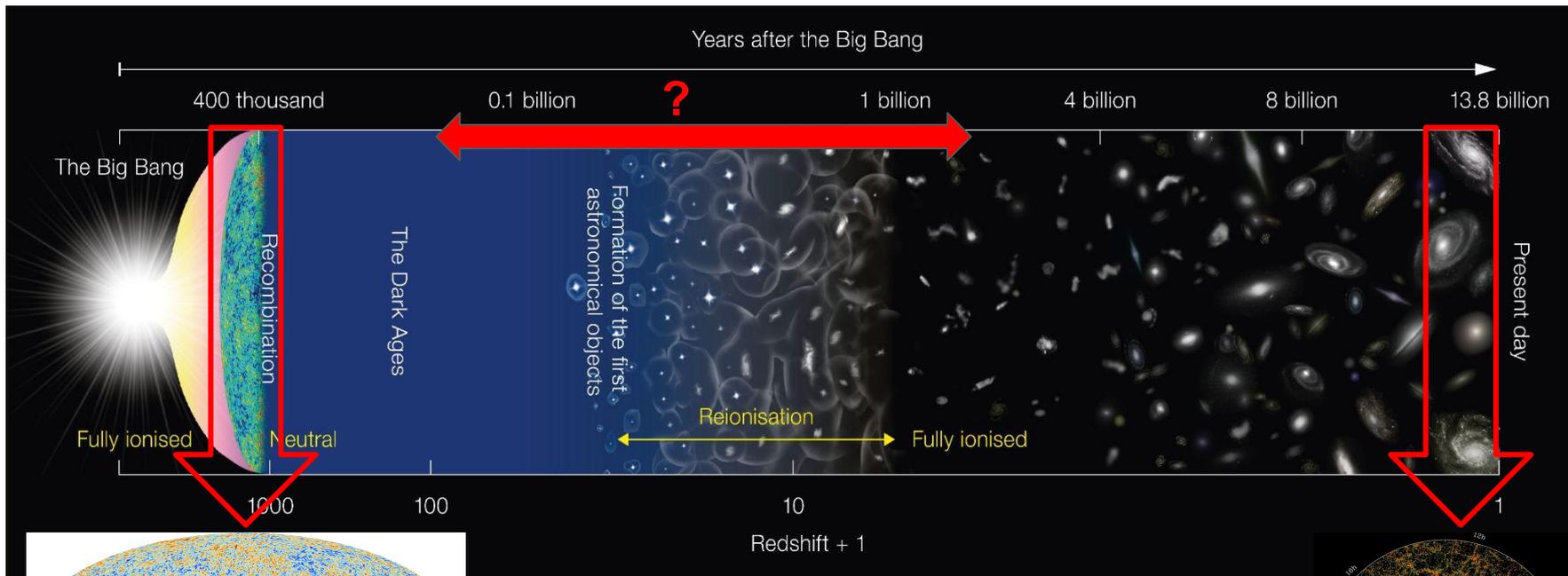


Credit: Planck Collaboration

Credit: NAOJ

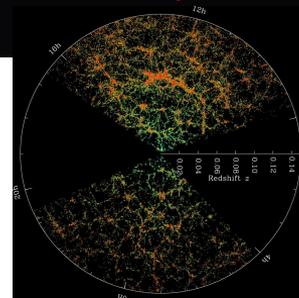


Credit: SDSS



Credit: Planck Collaboration

Credit: NAOJ



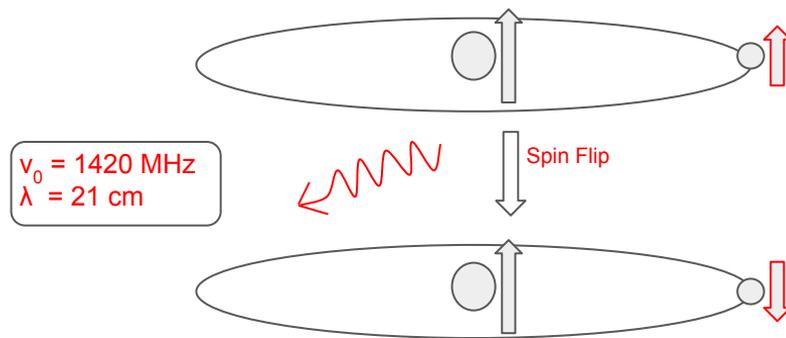
Credit: SDSS

# Epoch of Reionization (EoR)

- It is the least known period of the early Universe.
- It is a period when Intergalactic medium (IGM) was being ionized due to the formation of the first luminous sources.
- It will provide the information of the evolution of the Large-Scale Structure of the Universe.

# 21-cm Line

- The 21 cm line is produced by the hyperfine splitting of the neutral hydrogen caused by the interaction between electron and proton magnetic moments
- Hydrogen was the most abundant element in the IGM during EoR. So, this 21-cm line can work as the perfect tracer for IGM during early Universe



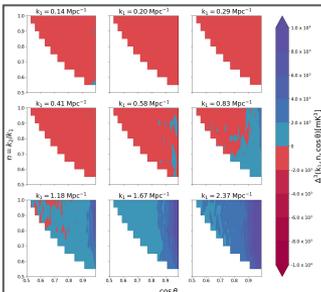
Forward

# Forward Modeling of Signal Statistics

$\theta_m$

Simulation

Summary Statistics



Observation

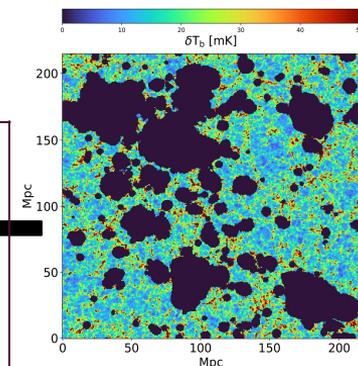
$$D \equiv B_{obs}$$

$$\mathcal{L}(D|M, \theta_m) \rightarrow p(\theta_m|D)$$

$$\Sigma_{Cov} = \Sigma_{SV}$$

Posterior

Bayesian Inference



Proposed new parameters and repeat

Backward

Forward

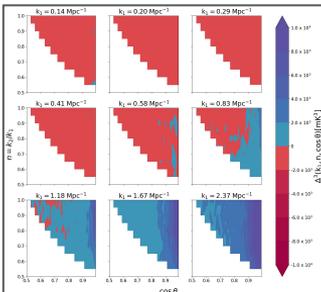
# Forward Modeling of Signal Statistics

$\theta_m$

~~Simulation~~

Emulation

Summary Statistics



Observation

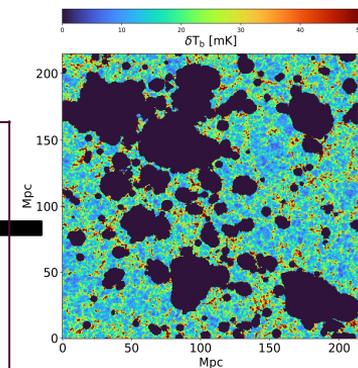
$$D \equiv B_{obs}$$

$$\mathcal{L}(D|M, \theta_m) \rightarrow p(\theta_m|D)$$

$$\Sigma_{Cov} = \Sigma_{SV}$$

Posterior

Bayesian Inference



Proposed new parameters and repeat

Backward

Forward

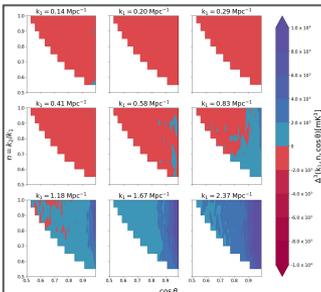
# Forward Modeling of Signal Statistics

$\theta_m$

~~Simulation~~

ANN-based Emulation

Summary Statistics



Observation

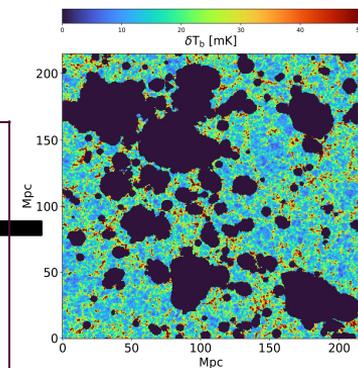
$$D \equiv B_{obs}$$

$$\mathcal{L}(D|M, \theta_m) \rightarrow p(\theta_m|D)$$

$$\Sigma_{Cov} = \Sigma_{SV}$$

Posterior

Bayesian Inference



Proposed new parameters and repeat

Backward

Forward

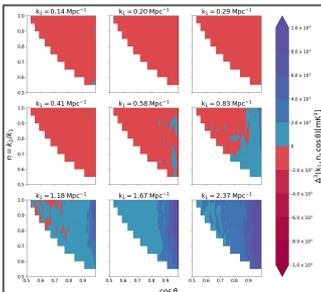
# Forward Modeling of Signal Statistics

$\theta_m$

~~Simulation~~

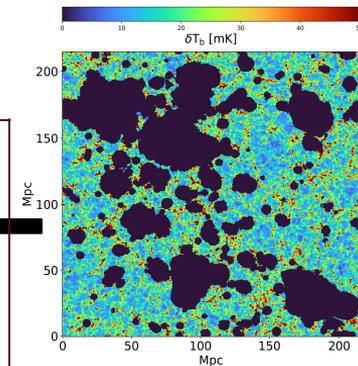
BNN-based Emulation

Summary Statistics



Observation

$$D \equiv B_{obs}$$



$$\mathcal{L}(D|M, \theta_m) \rightarrow p(\theta_m|D)$$

$$\Sigma_{Cov} = \Sigma_{SV} + \Sigma_{PU}$$

Posterior

Bayesian Inference

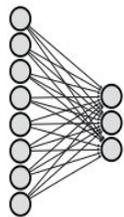
Backward

Proposed new parameters and repeat

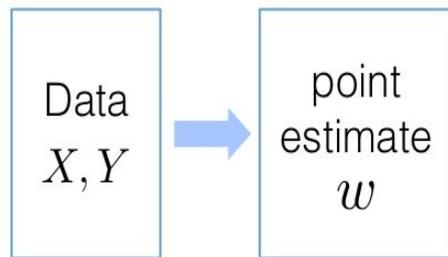
## Deterministic neural network

Weights:

deterministic weights



Training:

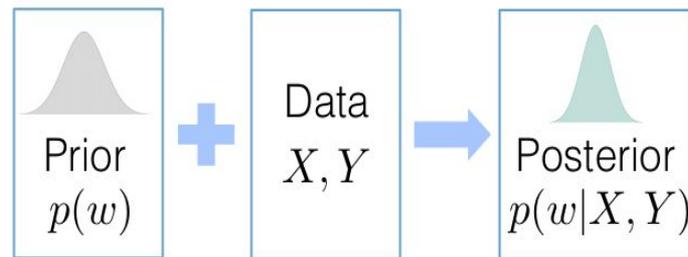
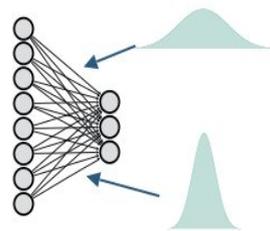


Prediction:

$$p(y_* | x_*, w)$$

## Bayesian neural network

stochastic weights



$$\mathbb{E}_{p(w|X, Y)} p(y_* | x_*, w)$$

# Generating The Training Dataset

21-cm Brightness Temperature Map for given set of Parameters

## Reionization Parameters:

$M_{(halo,min)}$  = Minimum halo mass that can host the ionizing sources

$N_{ion}$  = Dimensionless parameter which relates the host halos and ionizing photons produced by them.

$R_{m,fp}$  = The mean free path of the ionizing photons.

Reionization Code: <https://github.com/rajeshmondal18/ReionYuga>

Ref: Choudhury et al. 2009 (<http://adsabs.harvard.edu/abs/2009MNRAS.394..960C>),

Majumdar et al. 2014 (<http://adsabs.harvard.edu/abs/2014MNRAS.443.2843M>)

Mondal et al. 2017 (<http://adsabs.harvard.edu/abs/2017MNRAS.464.2992M>),

**Power spectrum as a summary statistic**

# ANN-emulator Architecture

Layers	Neurons	Activation Function
Input Layer	3	-
Hidden Layer 1	1024	ELU
Hidden Layer 2	512	ELU
Hidden Layer 3	256	ELU
Hidden Layer 4	128	ELU
Hidden Layer 5	64	ELU
Hidden Layer 6	32	ELU
Output Layer	7	-

## ANN-emulator Architecture

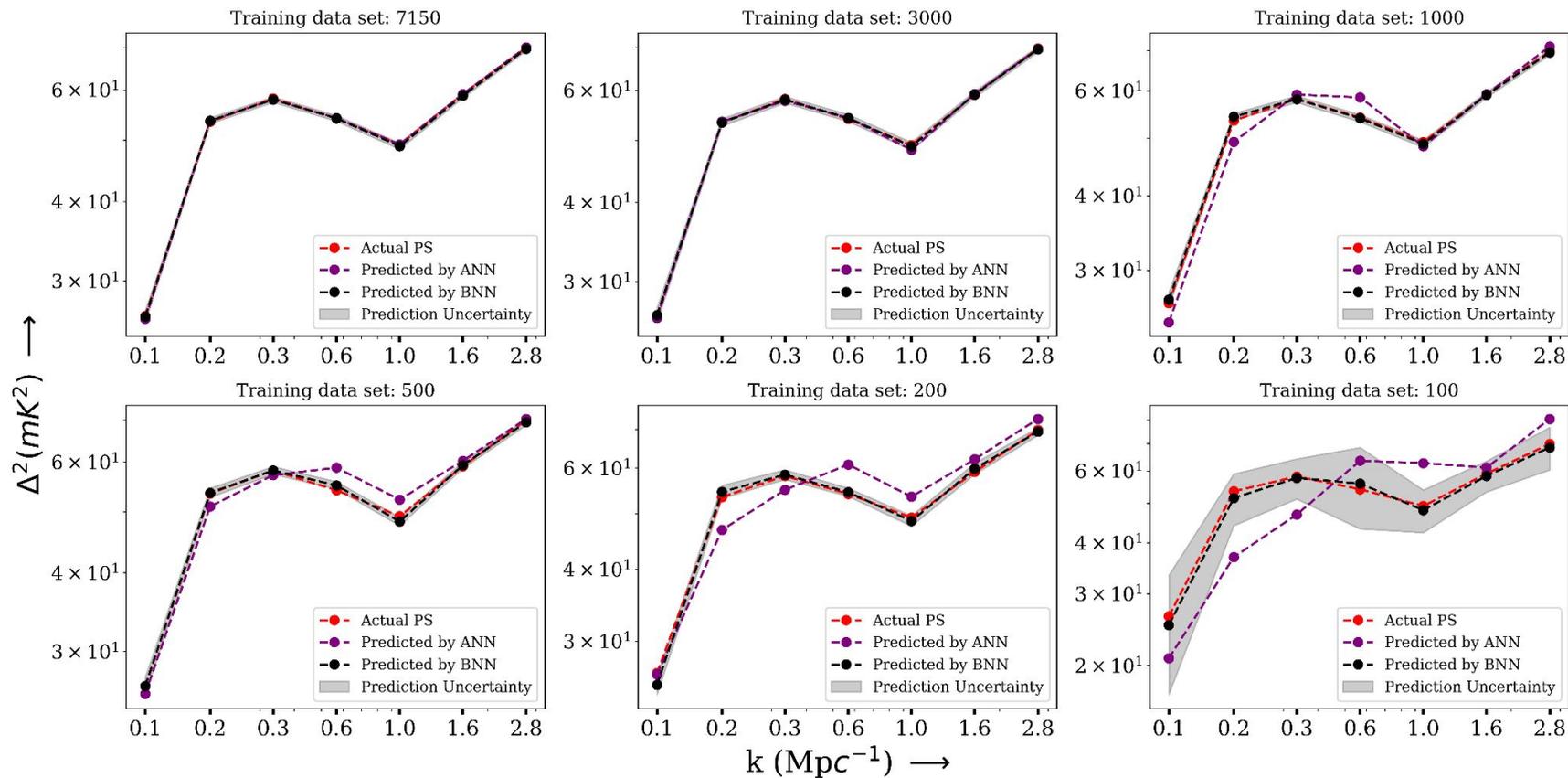
Layers	Neurons	Activation Function
Input Layer	3	-
Hidden Layer 1	1024	ELU
Hidden Layer 2	512	ELU
Hidden Layer 3	256	ELU
Hidden Layer 4	128	ELU
Hidden Layer 5	64	ELU
Hidden Layer 6	32	ELU
Output Layer	7	-

## BNN-emulator Architecture

Layers	Neurons	Activation Function
Input Layer	3	-
Hidden Layer 1	50	ELU
Hidden Layer 2	100	ELU
Hidden Layer 3	50	ELU
Output Layer	7	-

# Comparison of ANN & BNN-emulator prediction with different training data sets sizes

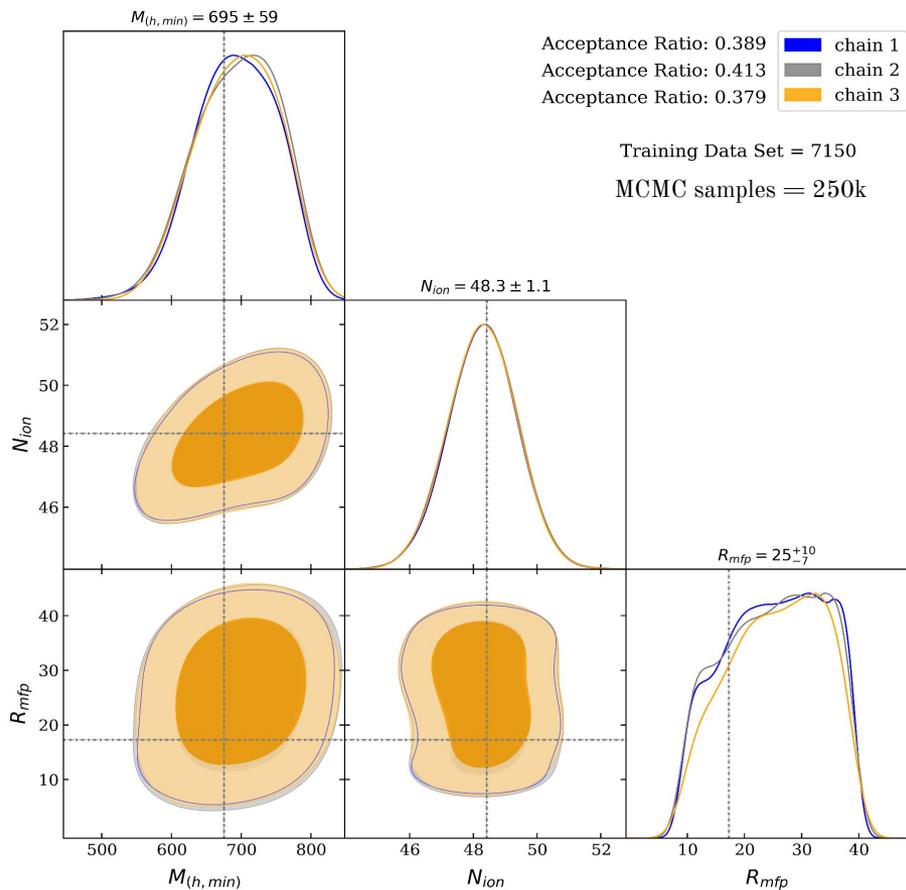
Power spectrum at  $x_{HI} = 0.541$



# Constraints on Parameters: Test set-1

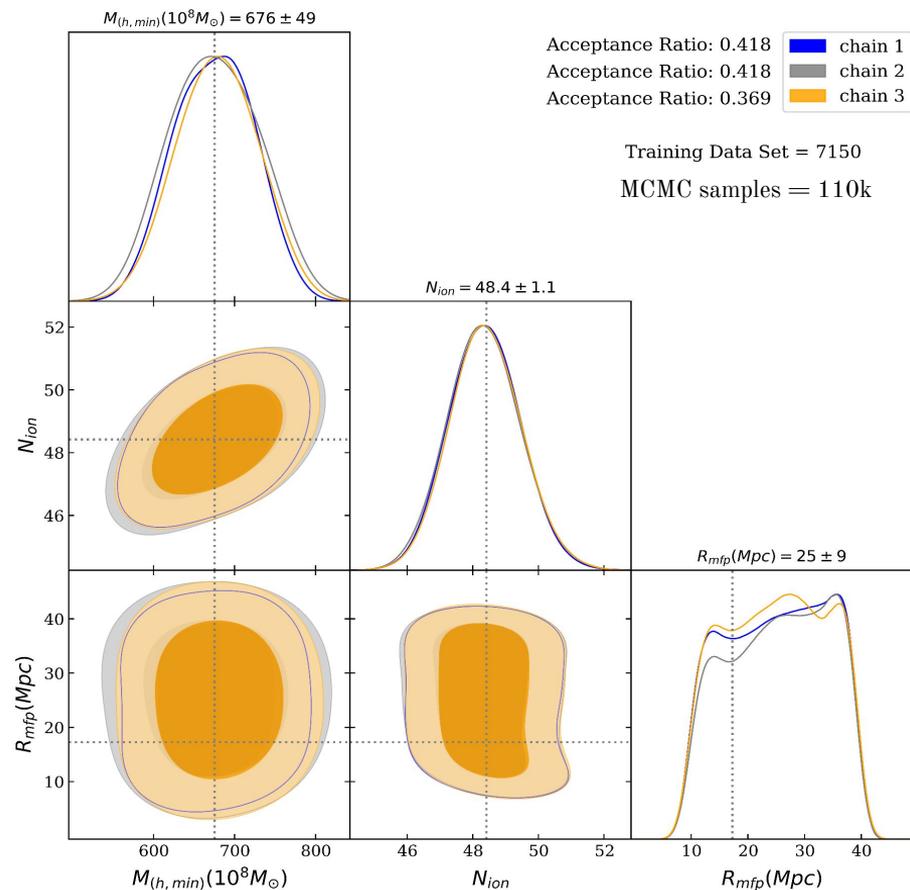
Constrained using ANN at  $X_{HI} = 0.84$

True Parameters:  $M_{(h, min)}(10^8 M_\odot) = 675.26$ ,  $N_{ion} = 48.42$ ,  $R_{mfp}(Mpc) = 17.26$



Constrained using BNN at  $X_{HI} = 0.84$

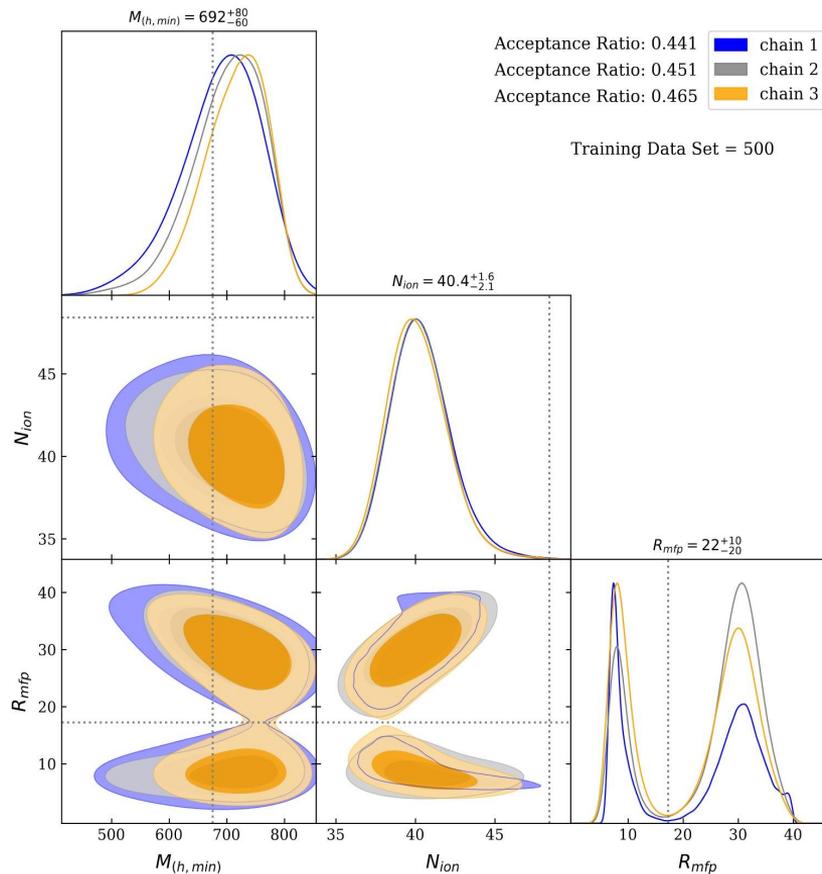
True Parameters:  $M_{(h, min)}(10^8 M_\odot) = 675.26$ ,  $N_{ion} = 48.42$ ,  $R_{mfp}(Mpc) = 17.26$



# With dataset size of 500: Test set-1

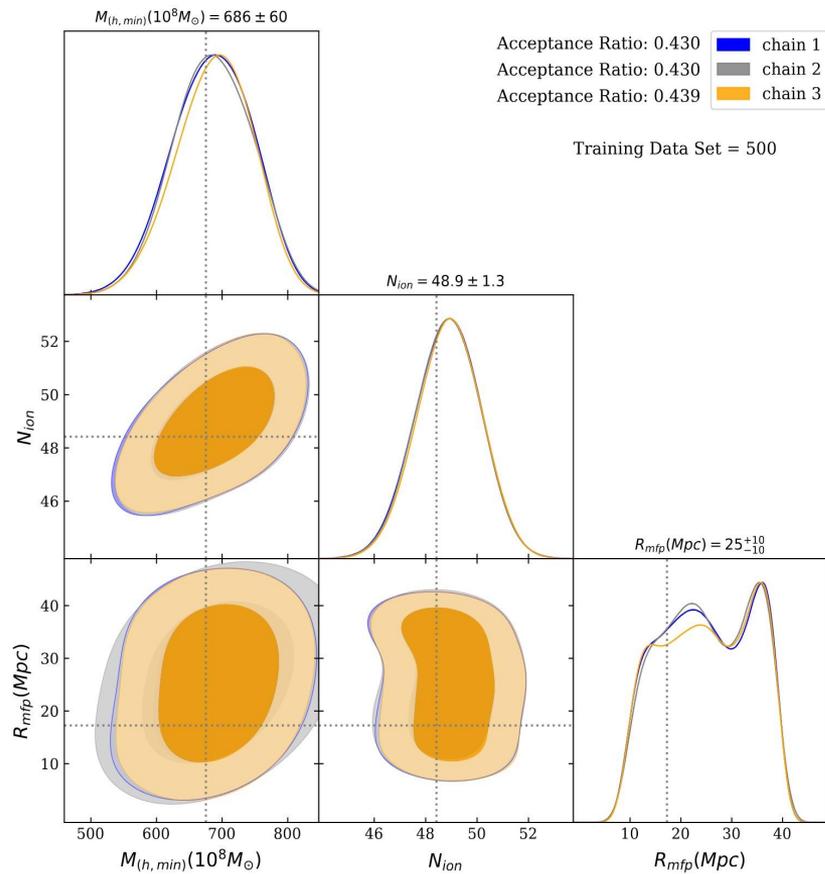
Constrained using ANN at  $x_{HI} = 0.84$

True Parameters:  $M_{(h,min)}(10^8 M_\odot) = 675.26$ ,  $N_{ion} = 48.42$ ,  $R_{mfp}(Mpc) = 17.26$



Constrained using BNN at  $x_{HI} = 0.84$

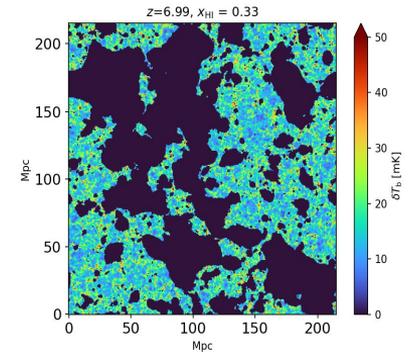
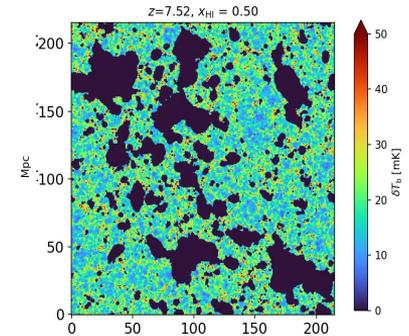
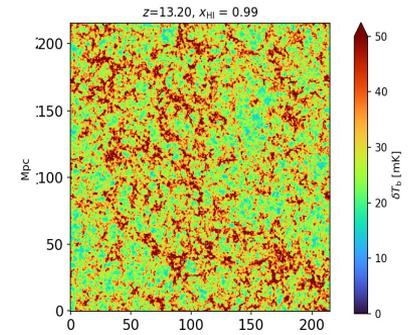
True Parameters:  $M_{(h,min)}(10^8 M_\odot) = 675.26$ ,  $N_{ion} = 48.42$ ,  $R_{mfp}(Mpc) = 17.26$



**BUT**  
**Power spectrum is NOT an optimal statistic**

# Probing the Non-Gaussianity

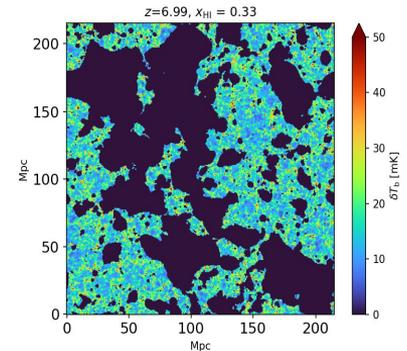
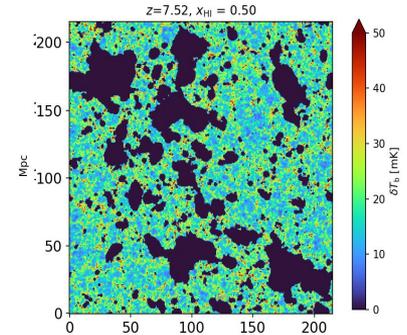
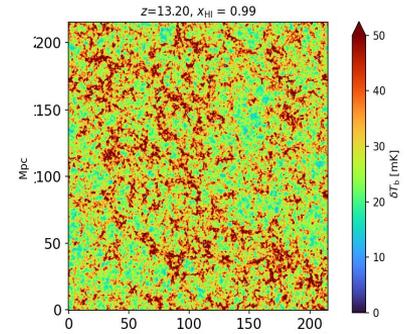
Increasing non-Gaussianity



# Probing the Non-Gaussianity

- 21-cm signal from EoR is highly **non-Gaussian**.
  - **Intrinsic**: Underlying matter density distribution
  - **Evolving**: Distribution of ionizing regions
- We need higher order signal statistic like Bispectrum to quantify this non-Gaussianity

Increasing non-Gaussianity



**Bispectrum as a summary statistic**

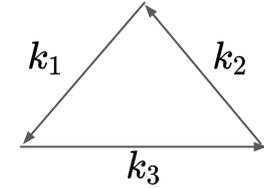
# Bispectrum

- Fourier equivalent to three point correlation function.
- It quantifies the correlation between different Fourier modes.

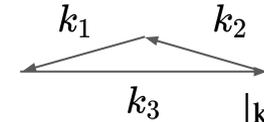
$$\langle \Delta_b(k_1) \Delta_b(k_2) \Delta_b(k_3) \rangle = V \delta_{(k_1+k_2+k_3,0)}^K B_b(k_1, k_2, k_3)$$

- Normalised Bispectrum

$$\Delta^3(k_1, k_2, k_3) = \frac{k_1^3 k_2^3}{(2\pi^2)^2} B(k_1, k_2, k_3)$$

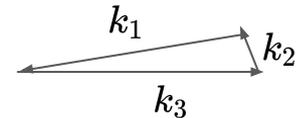


**Equilateral**  $|\mathbf{k}_1| = |\mathbf{k}_2| = |\mathbf{k}_3|$



**Stretched**

$|\mathbf{k}_1| = |\mathbf{k}_2| = |\mathbf{k}_3|/2$



**Squeezed**  $|\mathbf{k}_1| \approx |\mathbf{k}_3|, |\mathbf{k}_2| \rightarrow 0$

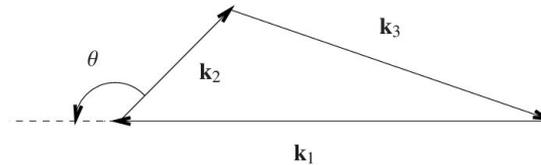
# Generating 21-cm Bispectrum Training Dataset

## Bispectrum Estimation

- We estimate the bispectrum using the binned bispectrum estimator which is defined as the average  $B$  inside the semi-spherical bin corresponding to the  $m^{\text{th}}$  triangle configuration

$$\widehat{B}_m(k_1, k_2, k_3) = \frac{1}{N_{tri} V} \sum_{[k_1 + k_2 + k_3 = 0] \in m} \Delta(k_1) \Delta(k_2) \Delta(k_3)$$

- Parametrization for triangle configuration



$$\frac{k_2}{k_1} = n$$

$$\frac{k_1 \cdot k_2}{k_1 k_2} = -\cos \theta$$

Ref: [Majumdar et al. 2018, MNRAS, 476, 4007](#)  
[Bharadwaj et al. 2020, MNRAS, 493, 594](#)  
[Majumdar et al. 2020, MNRAS, 499, 5090](#)

# Generating 21-cm Bispectrum Training Dataset

## Bispectrum Estimation

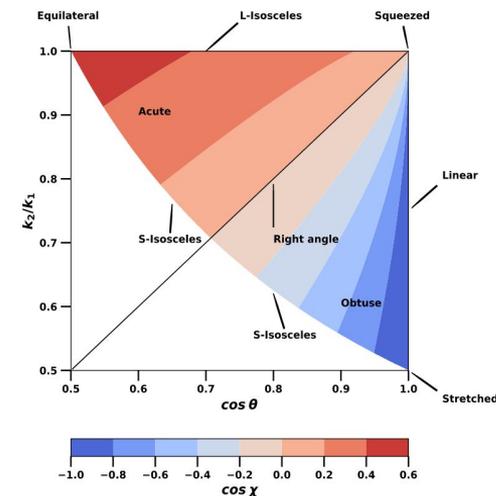
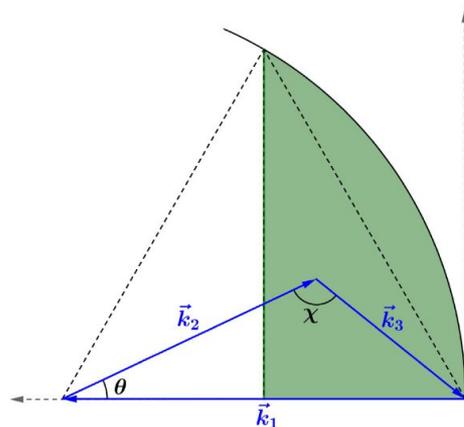
Unique triangle conditions:

$$k_1 \geq k_2 \geq k_3$$

$$0.5 \leq n \leq 1.0$$

$$0.5 \leq \cos \theta \leq 1.0$$

$$n \cos \theta \geq 0.5$$



Ref: [Majumdar et al. 2018, MNRAS, 476, 4007](#)  
[Bharadwaj et al. 2020, MNRAS, 493, 594](#)  
[Majumdar et al. 2020, MNRAS, 499, 5090](#)

# ANN Emulator Architecture

## First Four k1 modes

Layers	Nodes	Activation Function
Input Layer	3	
Hidden Layer 1	2255	ReLU
Hidden Layer 2	1524	ReLU
Hidden Layer 3	1008	ReLU
Output Layer 1 [For Magnitude]	328	
Output Layer 2 [For Sign]	328	

## Remaining Five k1 modes

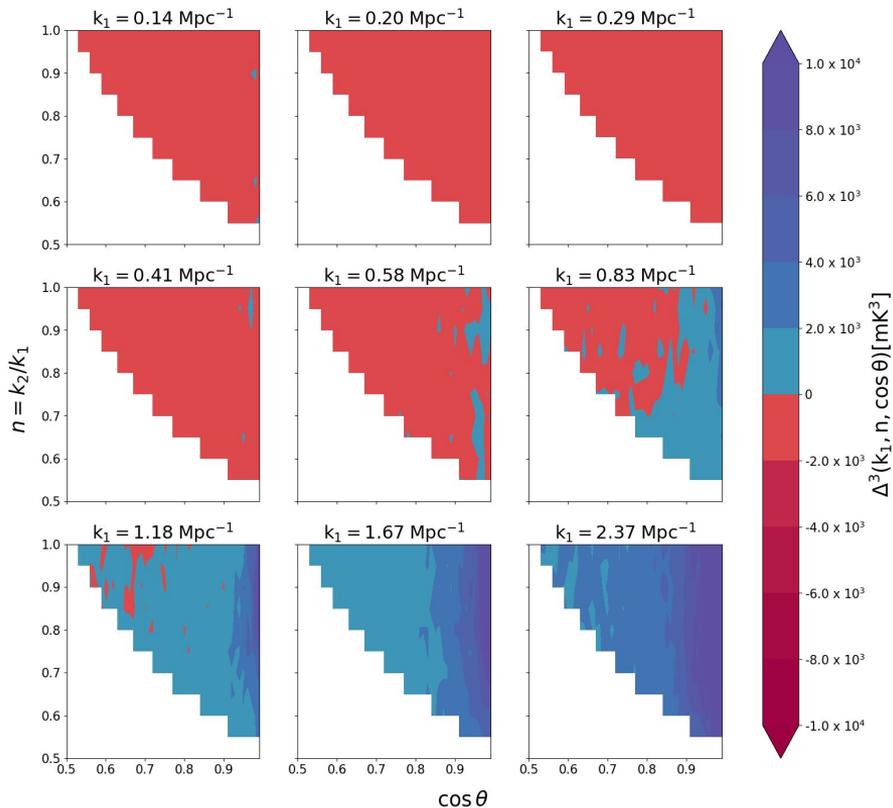
Layers	Nodes	Activation Function
Input Layer	3	
Hidden Layer 1	2255	ReLU
Hidden Layer 2	1524	ReLU
Hidden Layer 3	1008	ReLU
Hidden Layer 4	956	
Output Layer 1 [For Magnitude]	328	
Output Layer 2 [For Sign]	328	

Loss Function = MSE (Mean Squared Error)

# Bispectrum Prediction using ANN

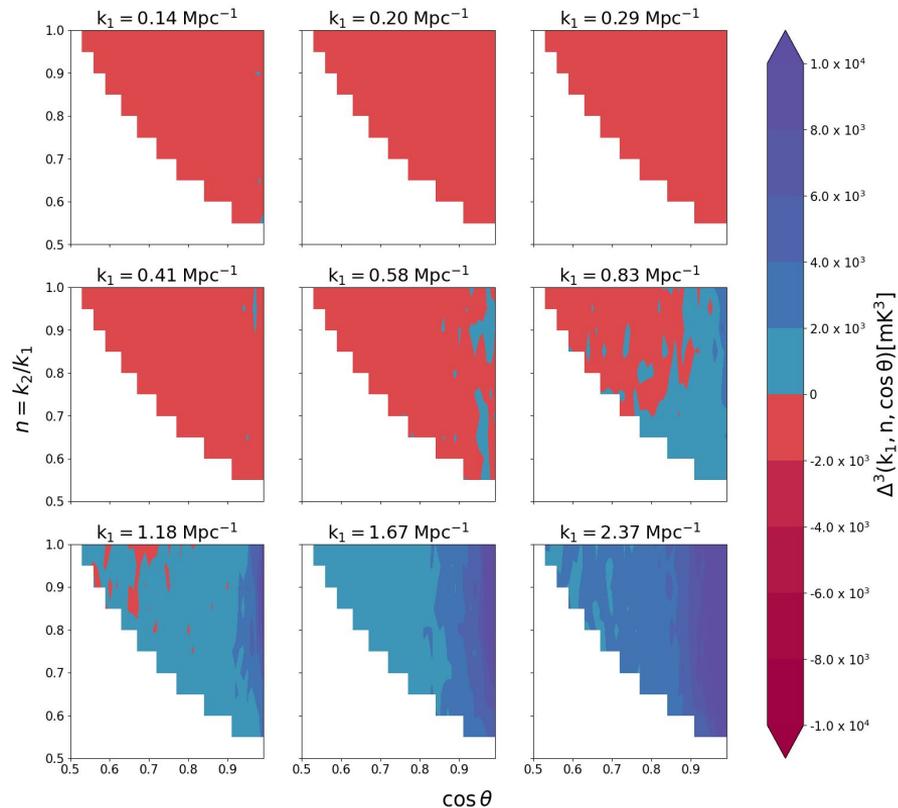
Simulate Bispectrum

$[M_{h,\min}(10^8 M_\odot) = 675.26, N_{\text{ion}} = 48.42, R_{\text{mfp}}(\text{Mpc}) = 17.26, x_{\text{HI}} = 0.844]$



Emulate Bispectrum

$[M_{h,\min}(10^8 M_\odot) = 675.26, N_{\text{ion}} = 48.42, R_{\text{mfp}}(\text{Mpc}) = 17.26, x_{\text{HI}} = 0.844]$



# Bispectrum Prediction using ANN

Simulate Bispectrum

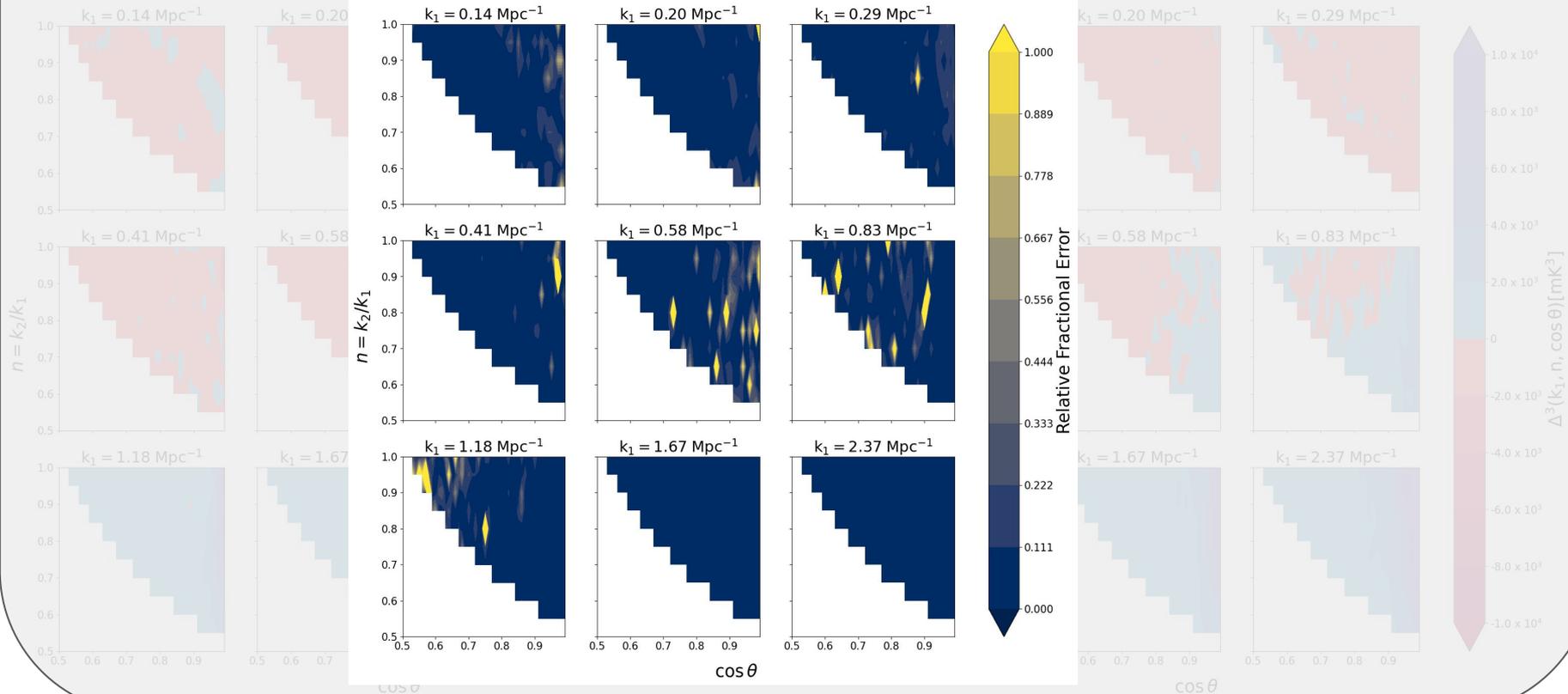
Relative Error

Emulate Bispectrum

$[M_{h,\min}(10^8 M_\odot) = 467.37, N_{\text{ion}} = 143.16, R_{\text{mfp}}(\text{Mpc}) = 8.04, x_{\text{HI}} = 0.543]$

$[M_{h,\min}(10^8 M_\odot) = 675.26, N_{\text{ion}} = 48.42, R_{\text{mfp}}(\text{Mpc}) = 17.26, x_{\text{HI}} = 0.844]$

$[M_{h,\min}(10^8 M_\odot) = 750.0, N_{\text{ion}} = 143.16, R_{\text{mfp}}(\text{Mpc}) = 8.04, x_{\text{HI}} = 0.543]$



# BNN Emulator Architecture

For All k1 modes

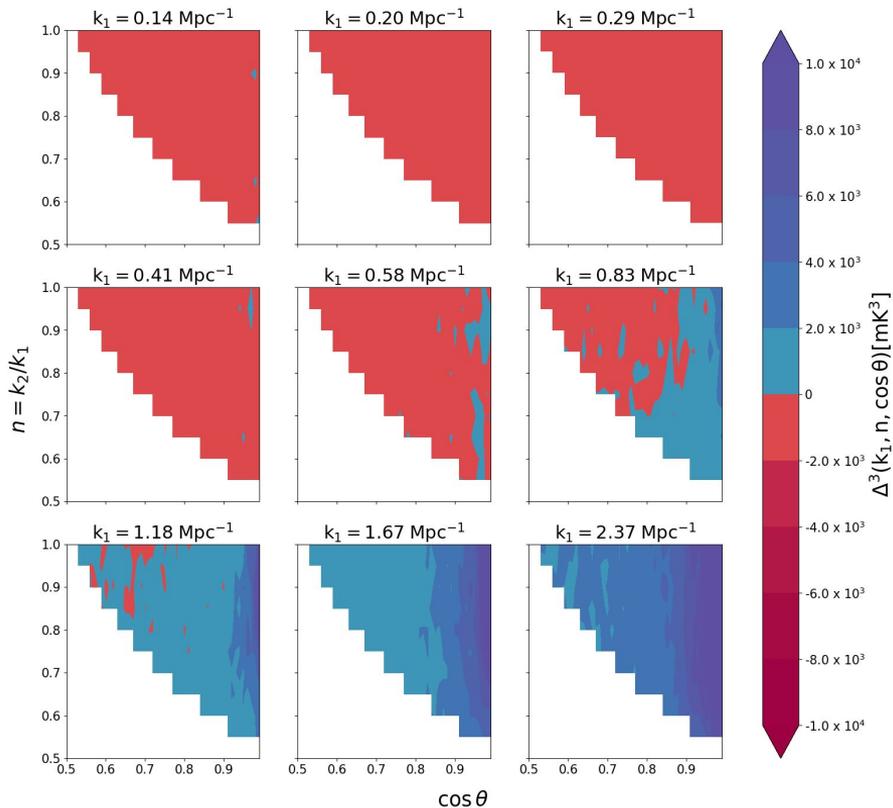
Layers	Nodes	Activation Function
Input Layer	3	
Hidden Layer 1	128	ELU
Hidden Layer 2	256	ELU
Hidden Layer 3	512	ELU
Output Layer	328	

- Prior distribution of weights & biases  
⇒ Gaussian
- Likelihood function ⇒ Multivariate Gaussian

# Bispectrum Prediction using BNN

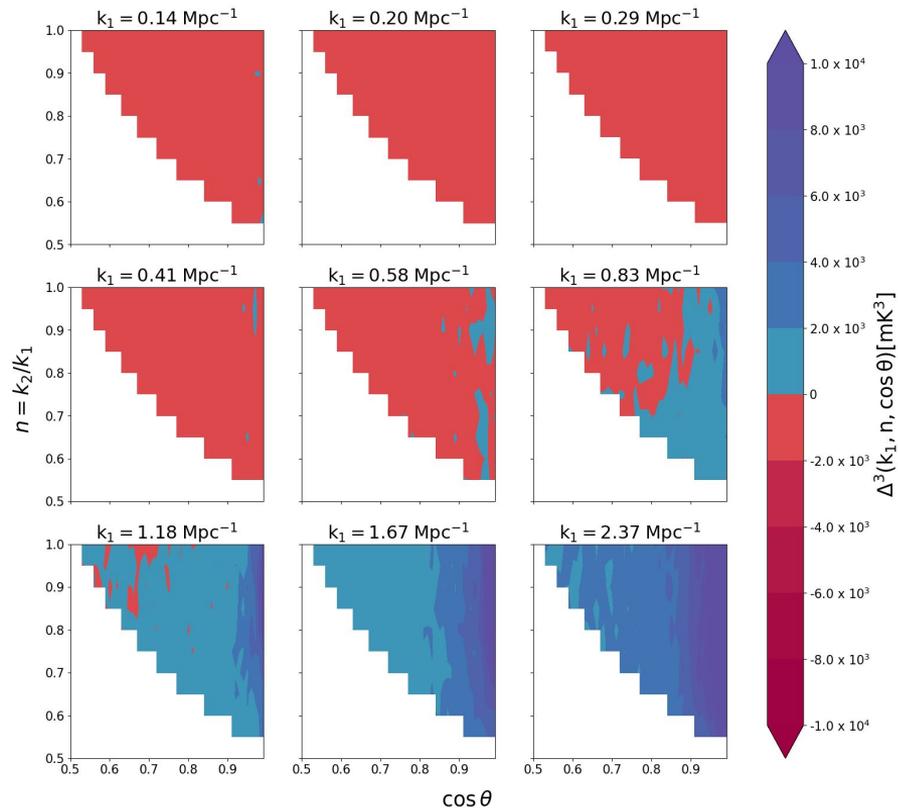
Simulate Bispectrum

$[M_{h,\min}(10^8 M_\odot) = 675.26, N_{\text{ion}} = 48.42, R_{\text{mfp}}(\text{Mpc}) = 17.26, x_{\text{HI}} = 0.844]$



Emulate Bispectrum

$[M_{h,\min}(10^8 M_\odot) = 675.26, N_{\text{ion}} = 48.42, R_{\text{mfp}}(\text{Mpc}) = 17.26, x_{\text{HI}} = 0.844]$



# Bispectrum Prediction using BNN

Simulate Bispectrum

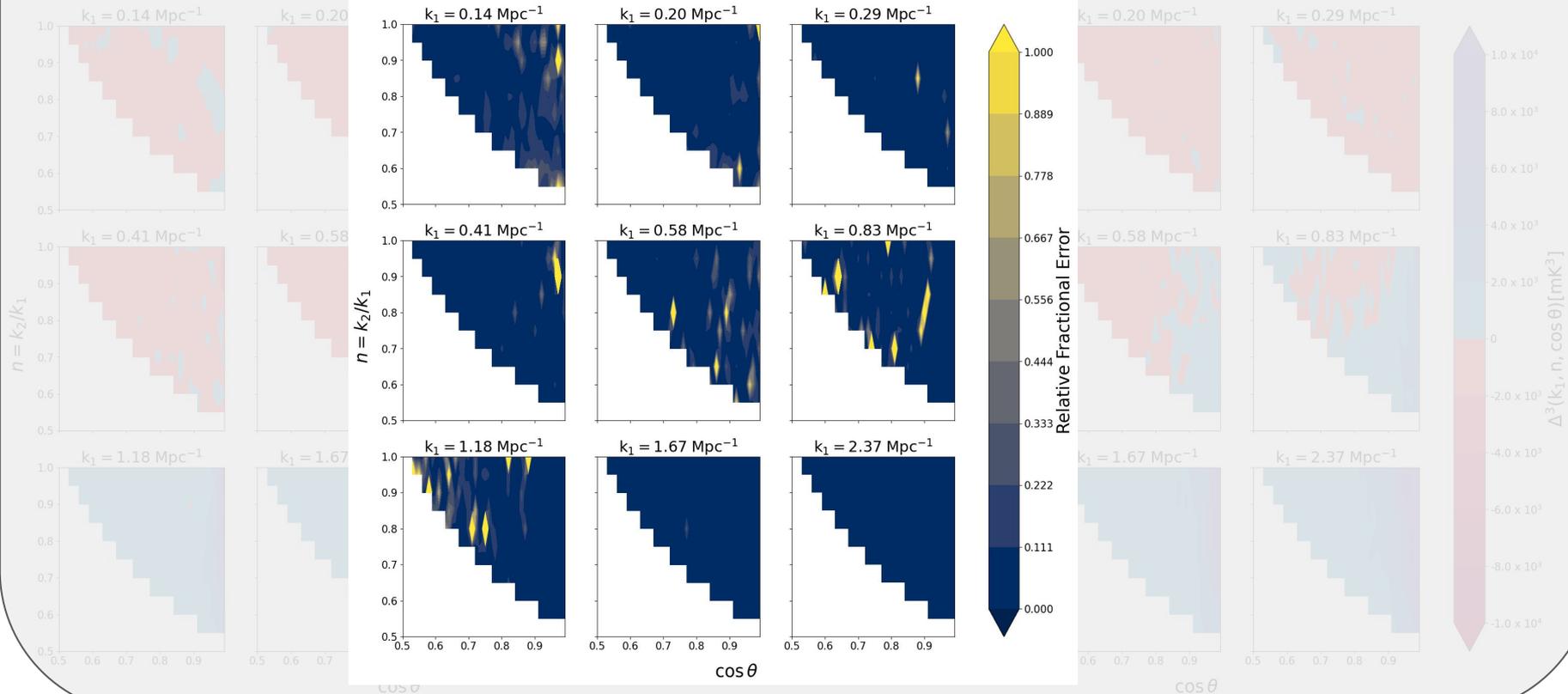
Relative Error

Emulate Bispectrum

$[M_{h,\min}(10^8 M_\odot) = 467.37, N_{\text{ion}} = 143.16, R_{\text{mfp}}(\text{Mpc}) = 8.04, x_{\text{HI}} = 0.543]$

$[M_{h,\min}(10^8 M_\odot) = 675.26, N_{\text{ion}} = 48.42, R_{\text{mfp}}(\text{Mpc}) = 17.26, x_{\text{HI}} = 0.844]$

$[M_{h,\min}(10^8 M_\odot) = 7, N_{\text{ion}} = 143.16, R_{\text{mfp}}(\text{Mpc}) = 8.04, x_{\text{HI}} = 0.543]$

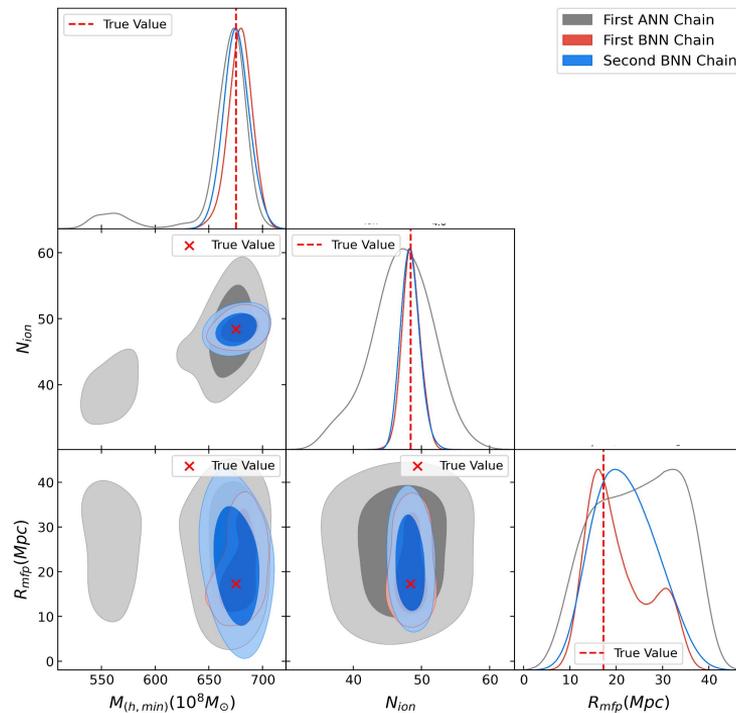






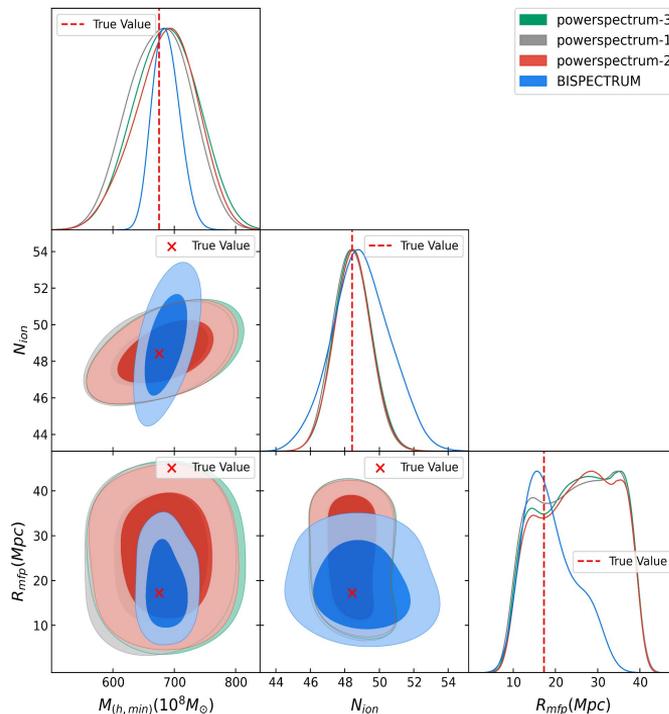
# Comparing Parameter Constraints of BNN with ANN

$[M_{h,\min}(10^8 M_{\odot}) = 675.26, N_{\text{ion}} = 48.42, R_{\text{mfp}}(\text{Mpc}) = 17.26, x_{\text{HI}} = 0.844]$



# Comparing Parameter Constraints of Bispectrum with Power Spectrum

$[M_{h,\min}(10^8 M_\odot) = 675.26, N_{\text{ion}} = 48.42, R_{\text{mfp}}(\text{Mpc}) = 17.26, x_{\text{HI}} = 0.844]$



## Summary

- 21-cm signal is highly non-Gaussian. So, we use bispectrum for the parameter estimation
- ANNs provide only point value prediction. So, we cannot quantify the uncertainty in their prediction.
- We use BNNs, which provide the posterior distribution of predicted signal. So, they are better at quantifying the model uncertainty.
- We show that BNNs give better constraints of the EoR parameters than ANNs.
- Bispectrum provides tighter constraints than power spectrum.

- New data set with large number of samples.
- In this set samples are uniformly distributed.

