

# Constraining Reionization Parameters through Bayesian Neural Network and Bayesian Inference

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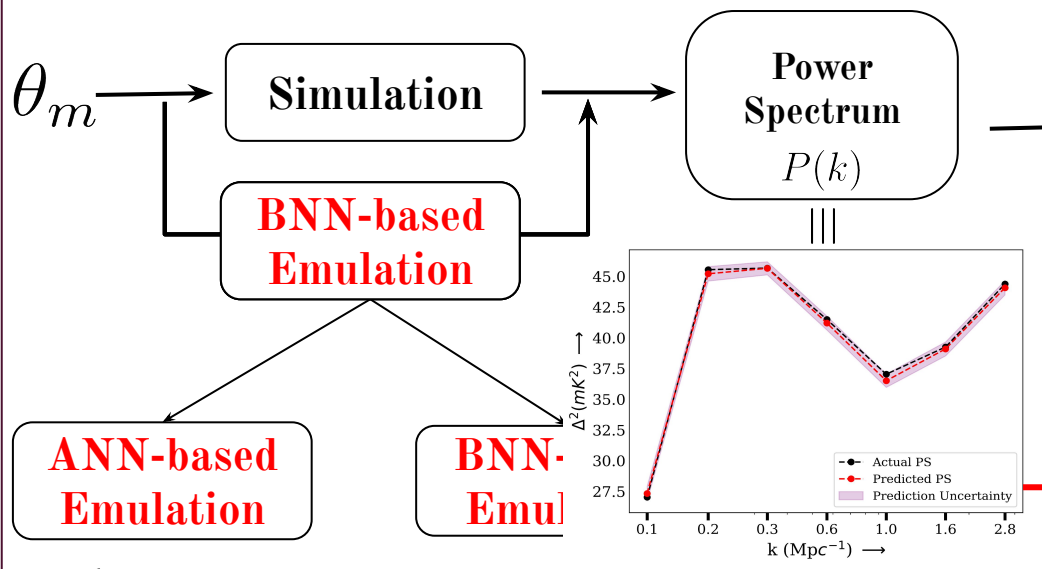
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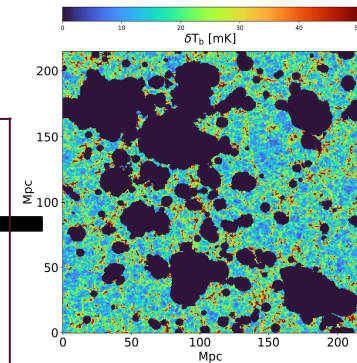
# Forward

## Forward Modeling of Signal Statistics



## Observation

$$D \equiv P_{obs}(k)$$



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

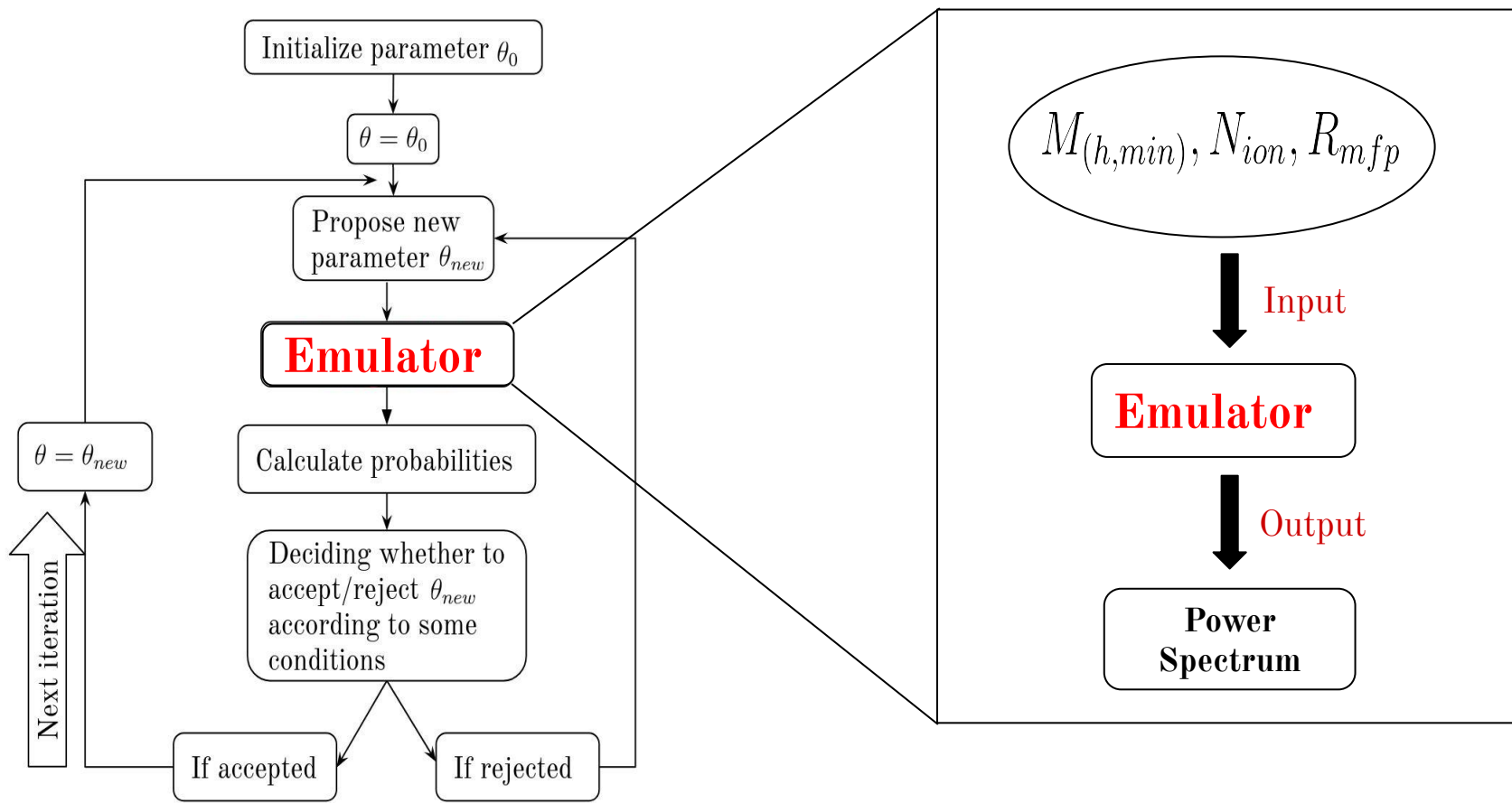
$$\Sigma_{\text{Cov}} = \Sigma_{\text{SV}} + \Sigma_{\text{N}} + \Sigma_{\text{PU}} \leftarrow \text{Posterior}$$

## Bayesian Inference

# Backward

Proposed new parameters and repeat

# MCMC Algorithm

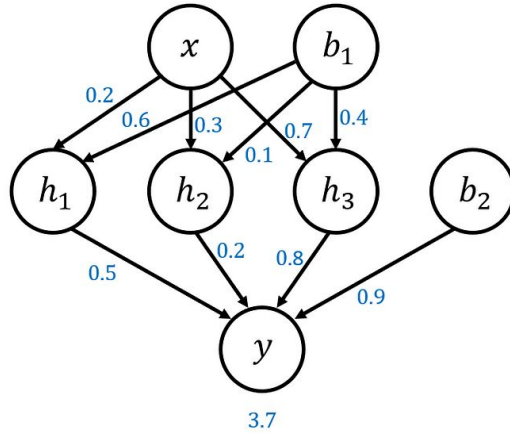


# Aim

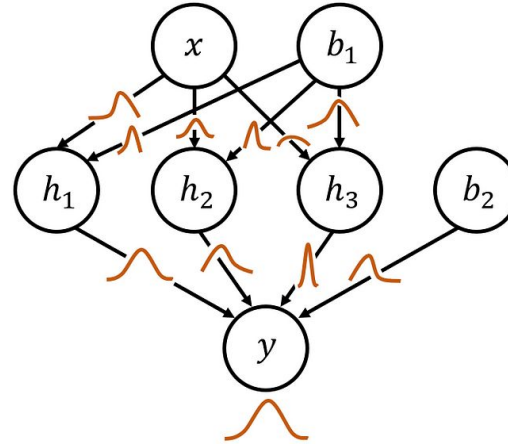
1. Use large data set for the better training of existing ANN-based emulator.
2. Develop a BNN-based emulator to predict the power spectrum along with prediction uncertainty .

# How ANN & BNN are Different?

**Artificial Neural Network (ANN)**



**Bayesian Neural Network (BNN)**

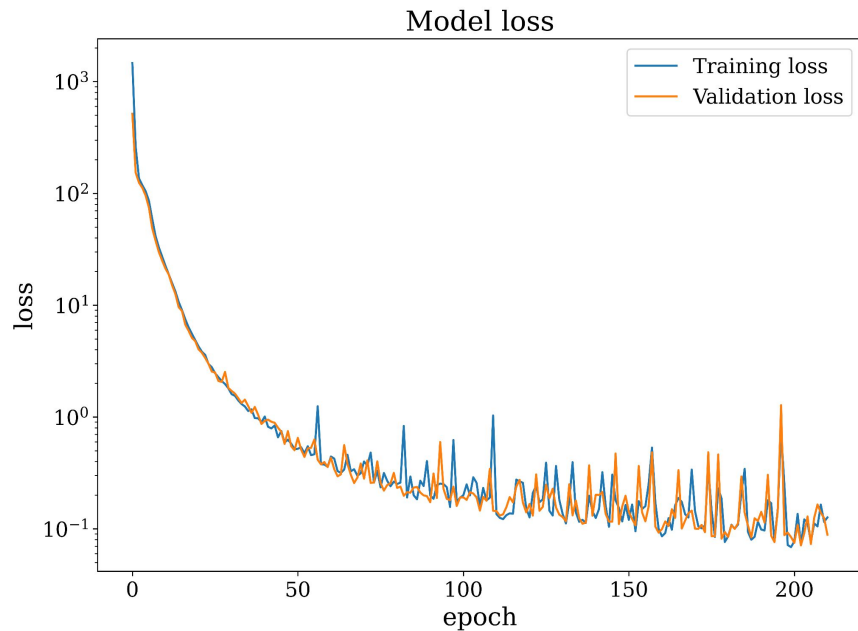


Credit: Medium article by Yeung Wong

# ANN-emulator Architecture

Used an artificial neural network with following tuning parameters

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	-



Loss function = Mean squared error (MSE)

# BNN-emulator Architecture

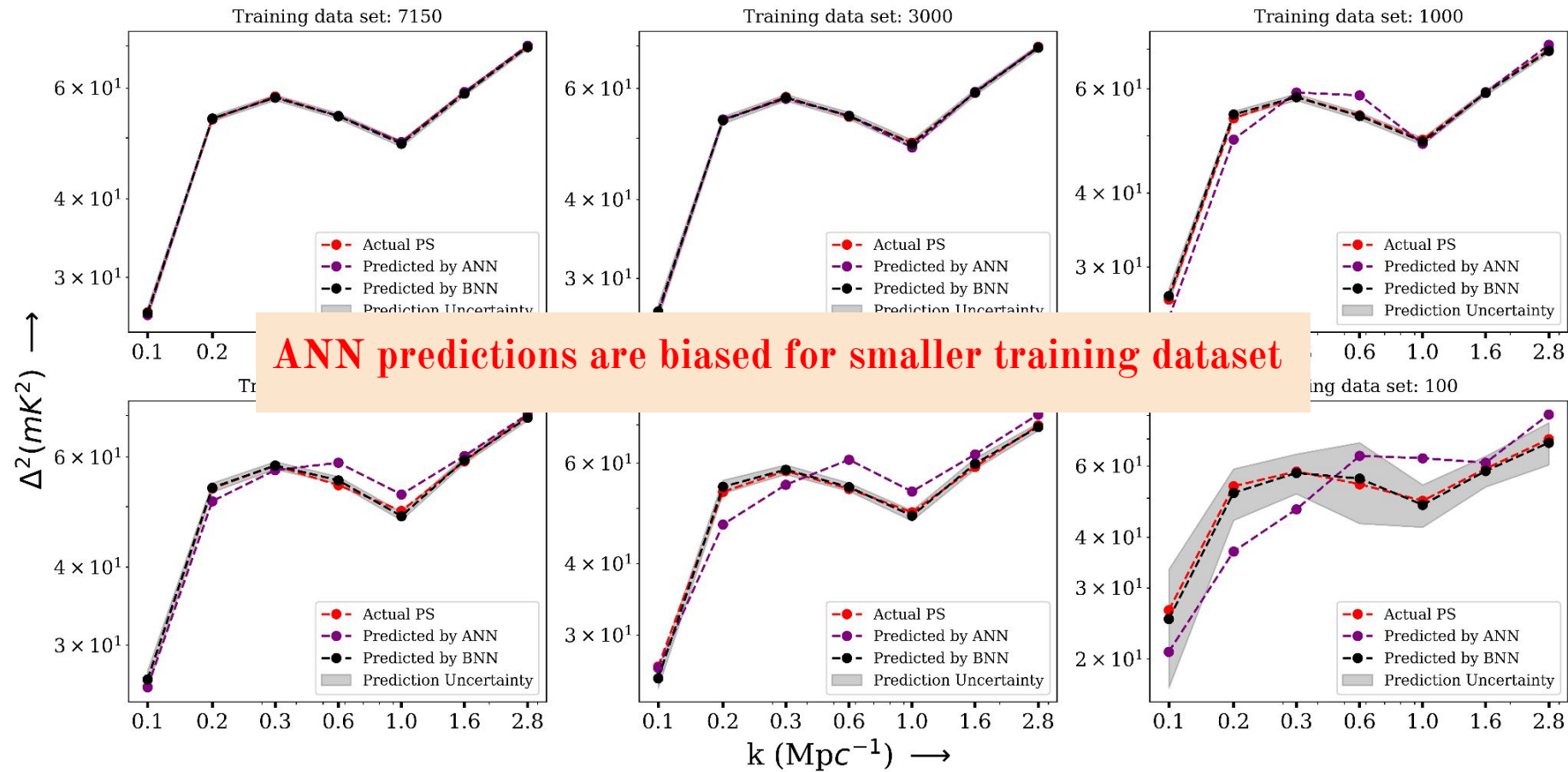
Used a Bayesian neural network with following tuning parameters

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	-

- Prior distribution of weights & biases  $\Rightarrow$  Gaussian  $X \sim \mathcal{N}(0, 5)$
- Likelihood function  $\Rightarrow$  Multivariate Gaussian

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

Power spectrum at  $x_{HI} = 0.541$

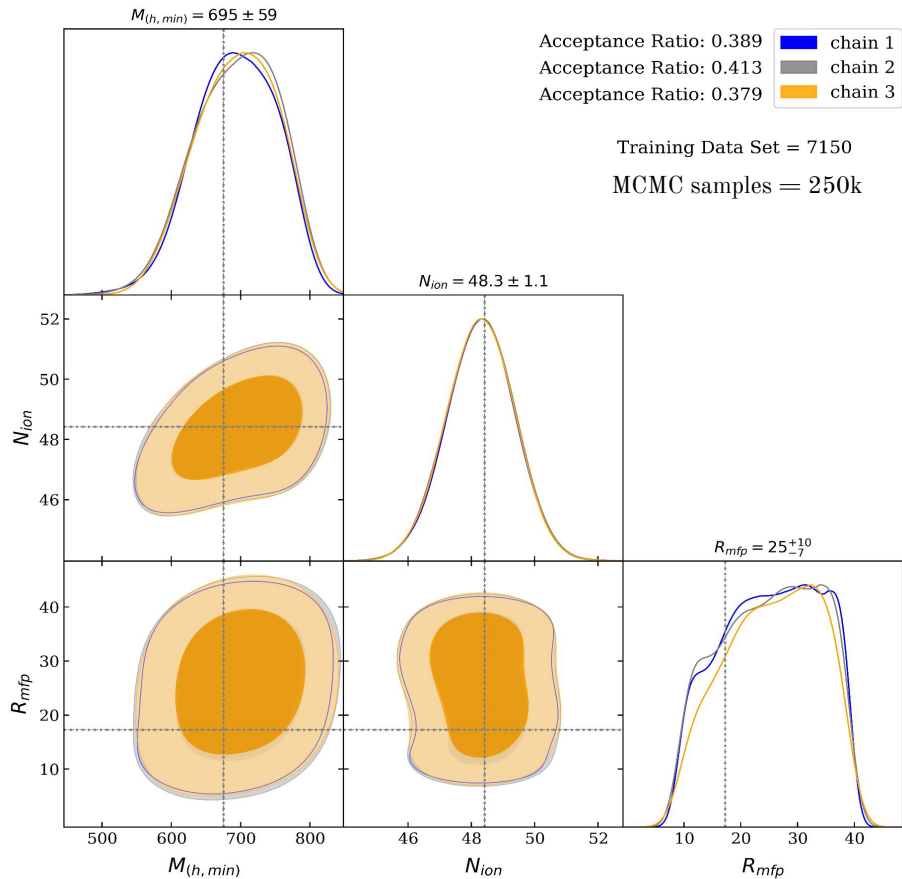




# Constraints on Parameters using emulators trained with whole dataset (7150 datapoint)

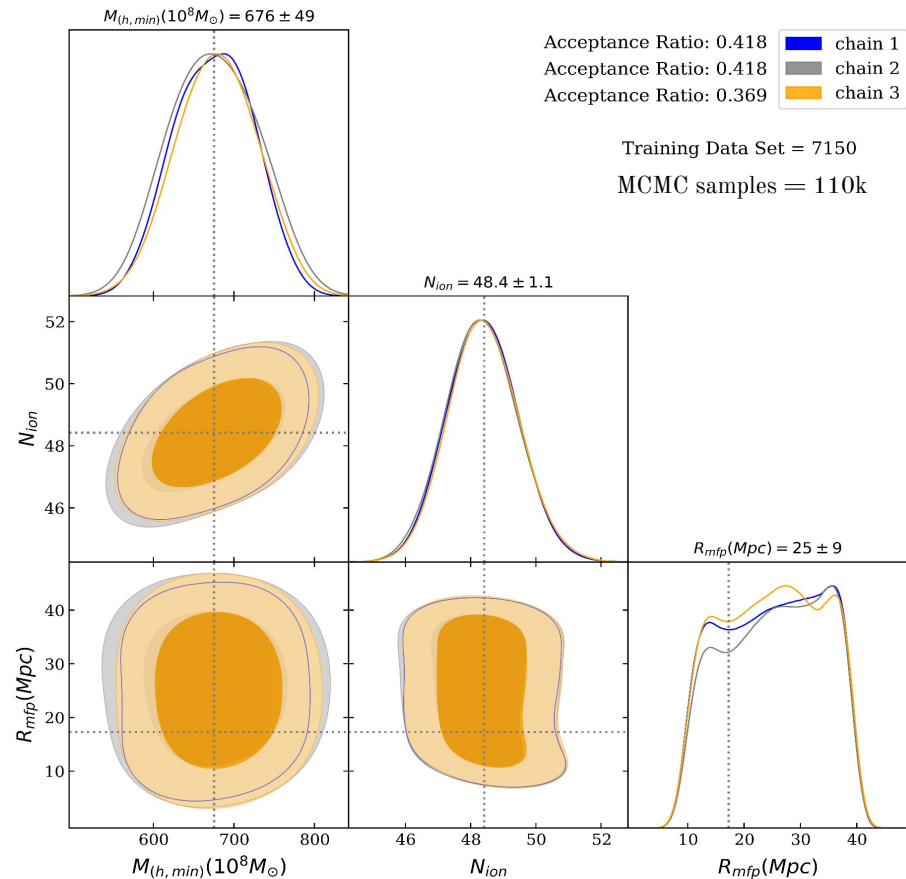
Constrained using ANN at  $X_{HI} = 0.84$

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



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

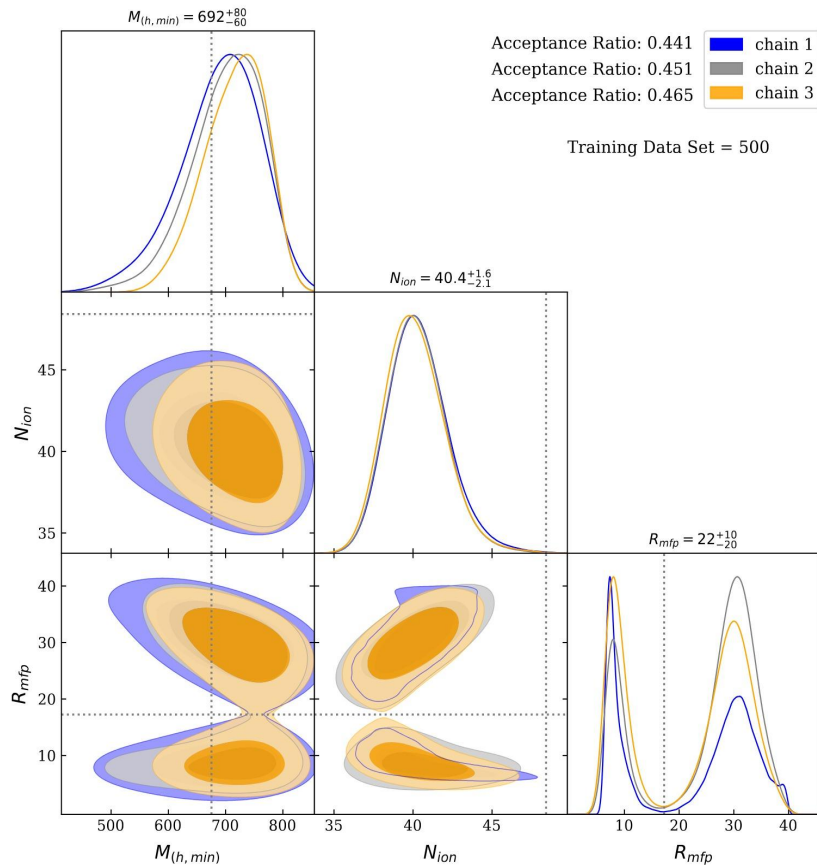
True Parameters:  $M_{(h,min)}(10^8 M_\odot) = 675.26$ ,  $N_{ion} = 48.42$ ,  $R_{mfp}(\text{Mpc}) = 17.26$



# Emulators trained with only 500 data points

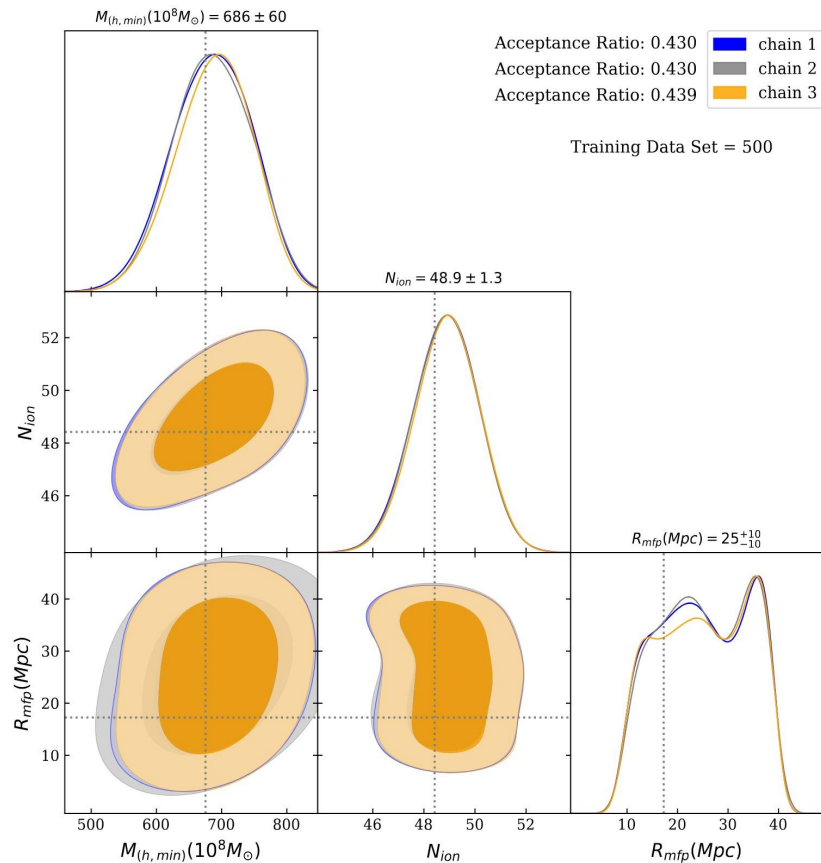
Constrained using ANN at  $x_{HI} = 0.84$

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

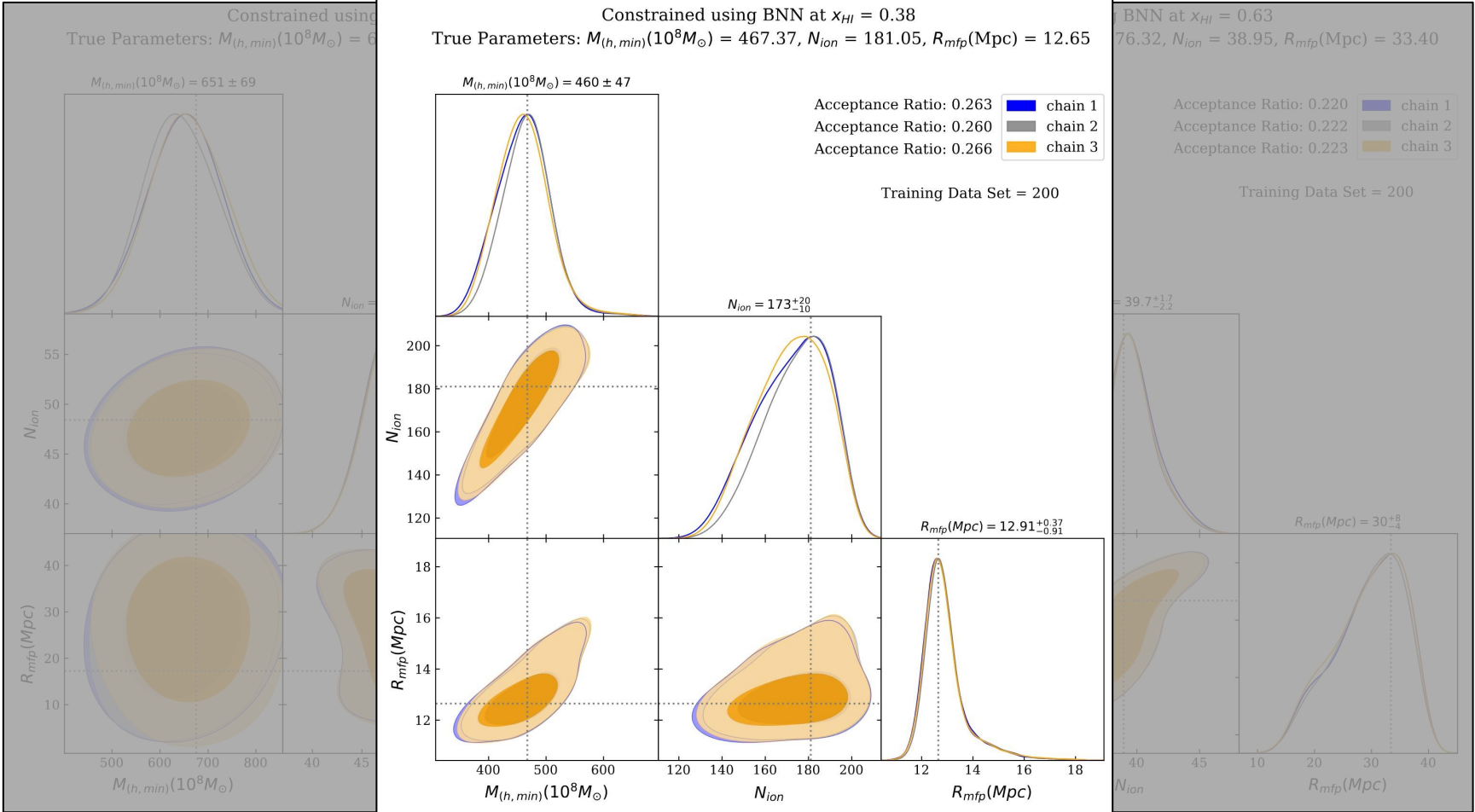


Constrained using BNN at  $x_{HI} = 0.84$

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



# Inference by BNN, trained with only 200 data points



# Summary of work

- Developed a BNN-based emulator to get the prediction uncertainty along with predictions.
- Tested the robustness of the ANN and BNN emulators with different sizes of training datasets and found that BNNs remain robust even with small datasets, while ANN predictions are biased with smaller data sets.
- Used these emulators as a model to constrained the EoR model parameters via Bayesian inference using MCMC.
- Found that BNN-based emulators, trained with small dataset size are remain robust while making inference using MCMC framework. However ANN-based model are not able to infer parameters when trained with small dataset size.
- BNN-based emulators can be used in the scenarios where datasets are small.

## Further scopes

- BNN-based emulators can be used for higher order statistics i.e. bispectrum.
- BNN-based emulator can be trained for multiple redshifts.
- We will use this emulator in SKA Science Data Challenge (SKA SDC-3).