

'Emulator is all you need' for the Reionization Inference with SKA-Low

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IIT INDORE

The Non-Gaussian Universe,
June 16-19, 2026, FORTH, Iraklio



IIT INDORE



Department of Astronomy, Astrophysics and Space Engineering IIT Indore

We are a unique and first of its kind department (established in 2016) in the IIT system.

Research in Astronomy, Astrophysics, Cosmology, Space, Atmosphere & Remote Sensing....

PhD programme running since 2016

We have four unique Masters' programmes

MSc in Astronomy (since 2018: first of its kind in the IIT system)

MTech in Space Engineering (since 2021)

MS (Research) in Space Science & Engineering (since 2021)

MTech in Advanced Optics and LASER Technology
in collaboration with **RRCAT (host institute for LIGO-India)**

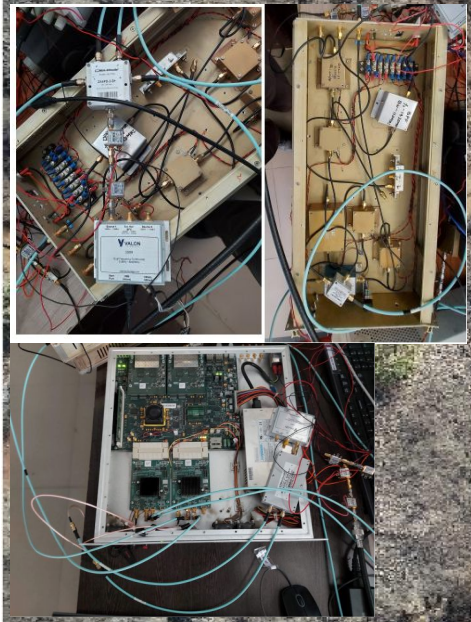
&

BTech in Space Science & Engineering (since July 2023: first of its kind in the IITs)

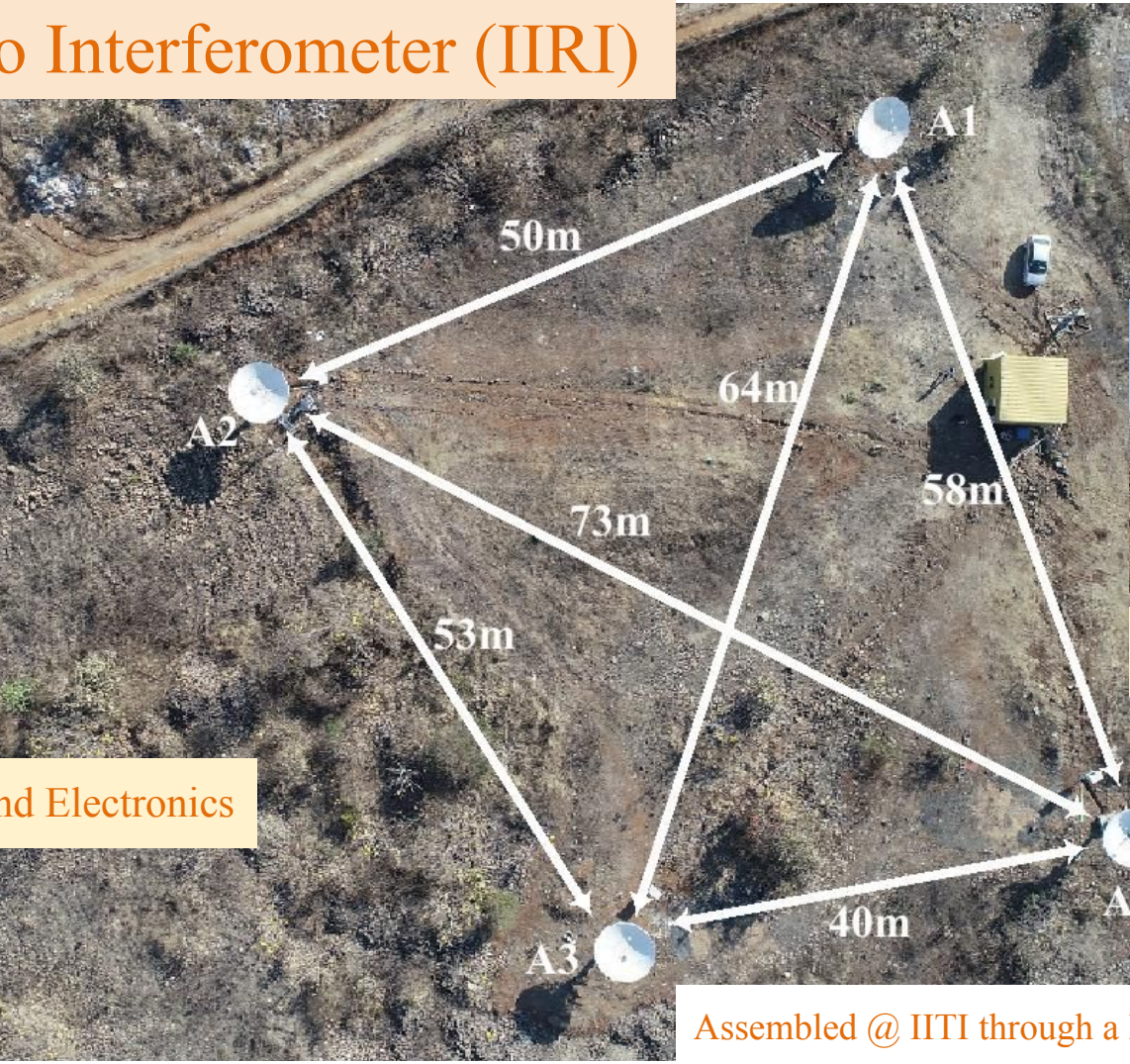


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IIT Indore Radio Interferometer (IIRI)

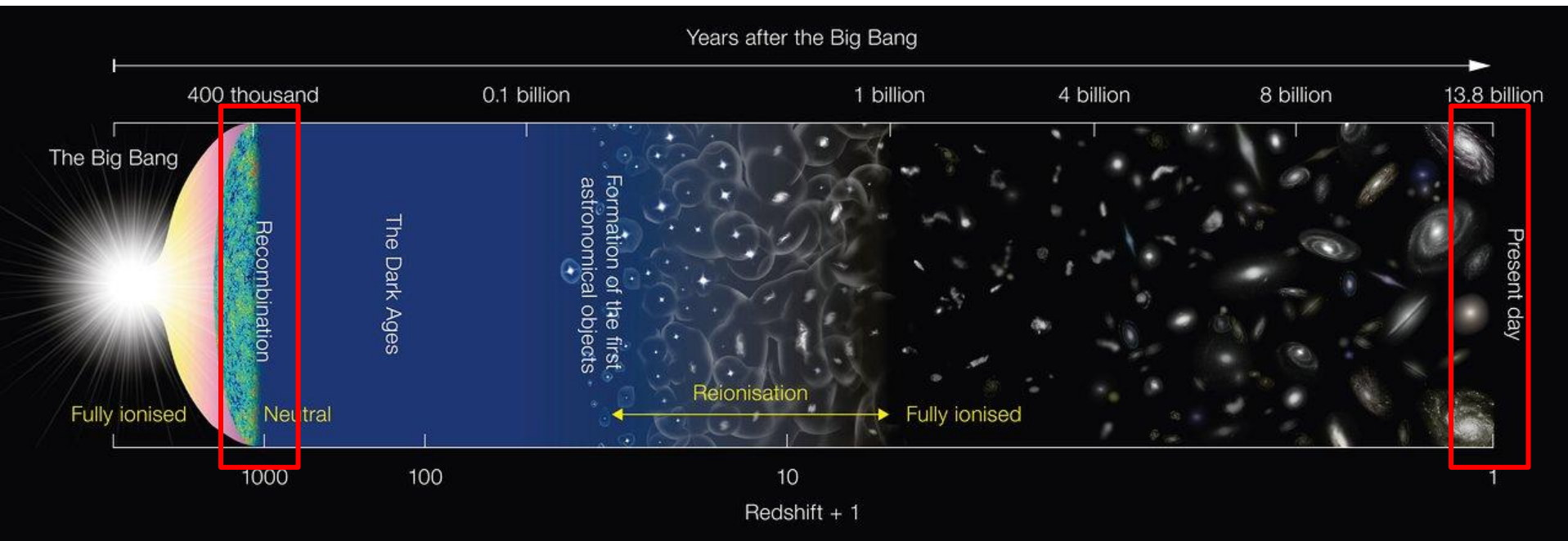


Analog and Digital Backend Electronics



Dishes of IIRI

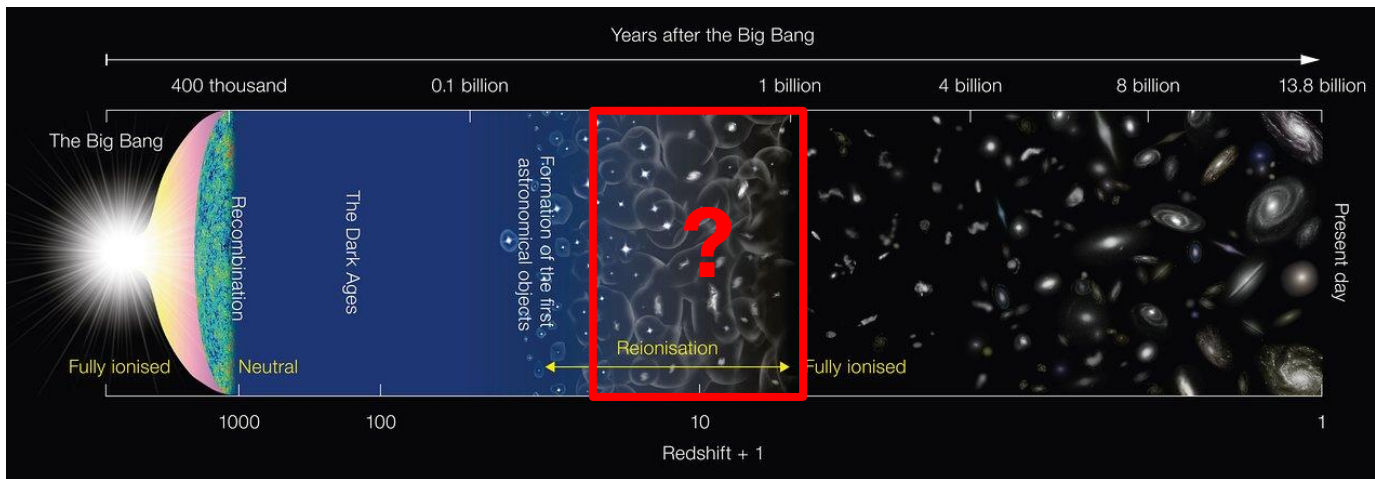
Assembled @ IITI through a DST-SERB grant



How much do we know?

Credit: NAOJ

Epoch of Reionization (EoR)

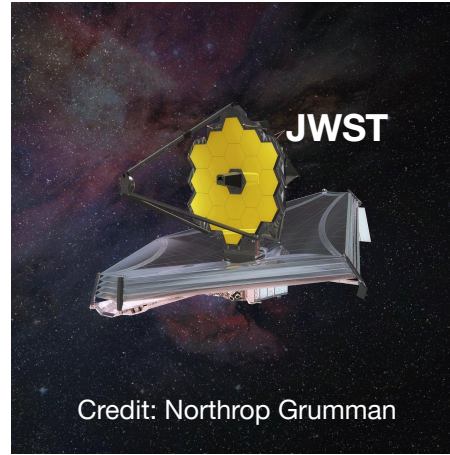


Credit: NAOJ

- First luminous sources (galaxies) were formed
- Ionizing radiation from the luminous sources reionized the neutral IGM

How to probe the EoR universe?

Probing the EoR: galaxies

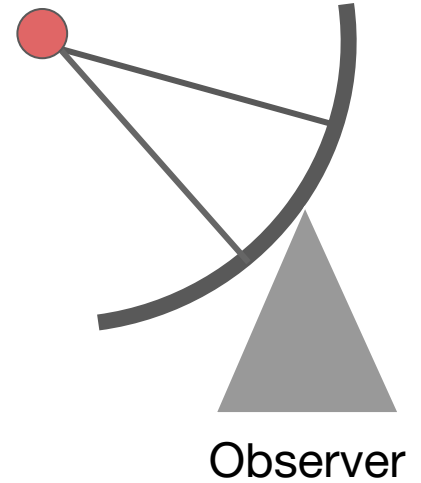
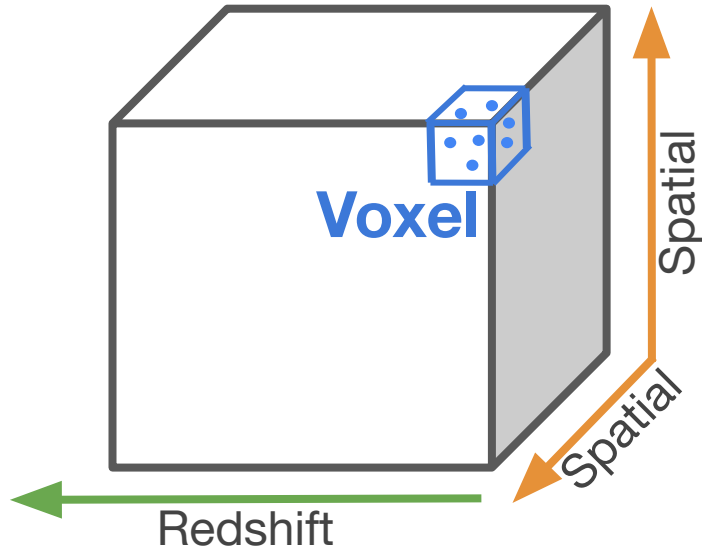


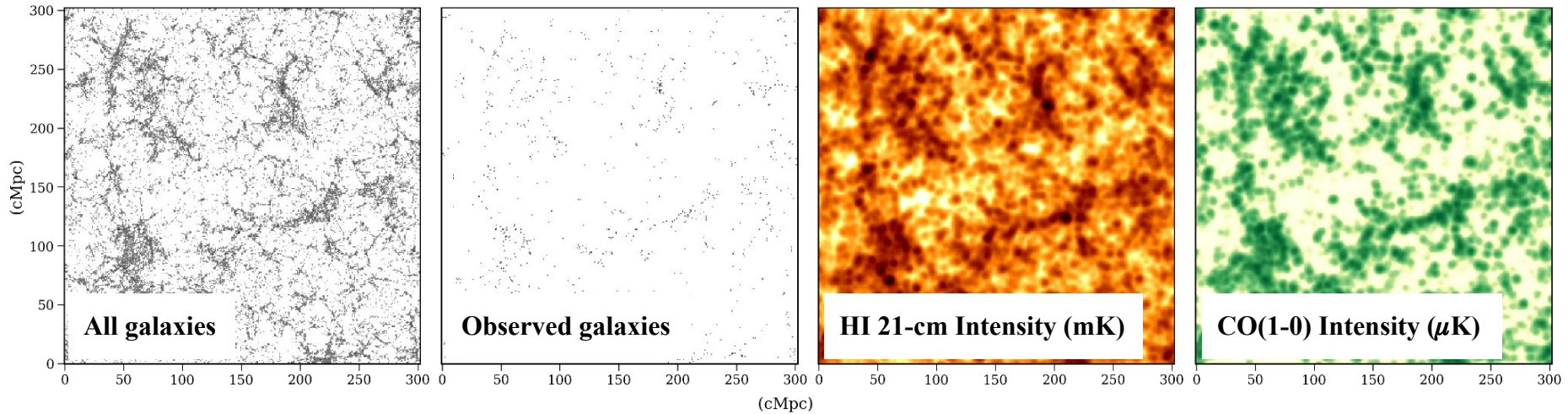
Challenges!

- Demanding sensitivity limits and angular resolutions
- Expensive to operate, therefore it becomes impractical to map large galaxy samples at very high redshifts ($z > 6$)

Line-intensity mapping (LIM)

LIM can probe the large-scale structures by detecting the integrated flux of numerous sources from a comparatively small region (Voxel)





Inference on clustering and morphology biased towards the brightest galaxies

Line Intensity Maps include contributions from faint sources

Line Intensity Mapping

- Maps line emission at a specific observed frequency with low spatial resolution
- Does not resolve individual sources
- Redshift information can be used for tomography

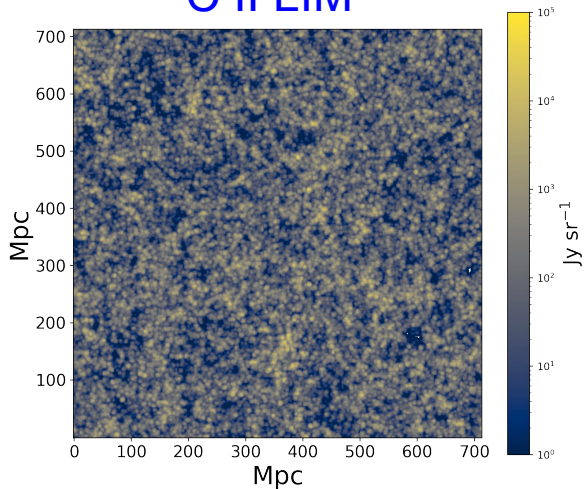
LIM at the EoR

Observing the luminous sources

CII, CO, OII, OIII



C II LIM

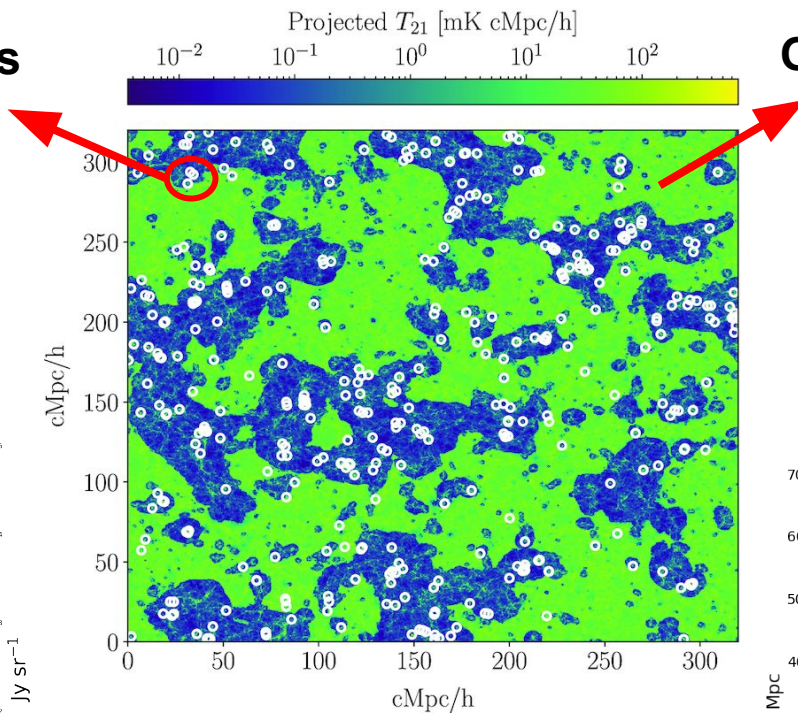
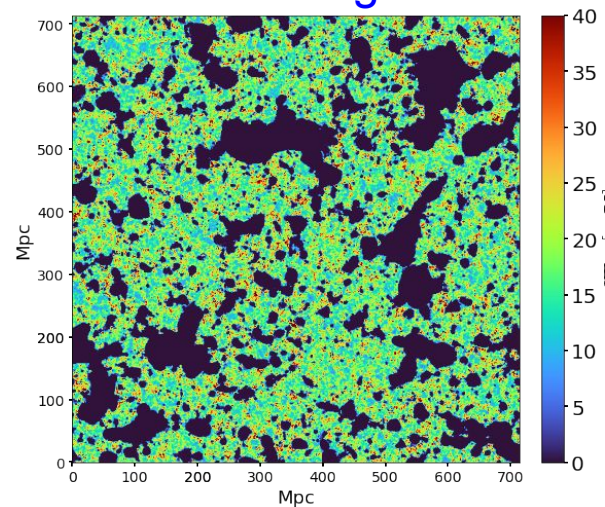


Observing the intergalactic medium

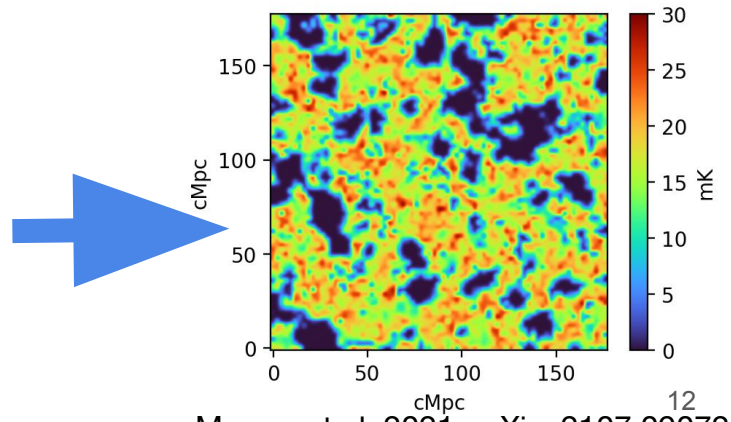
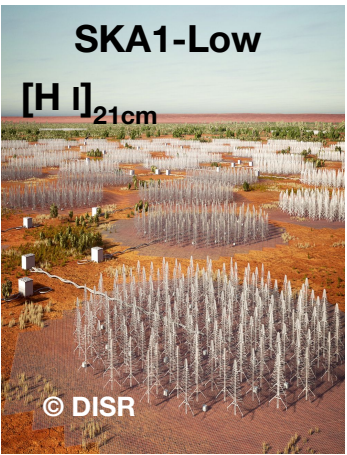
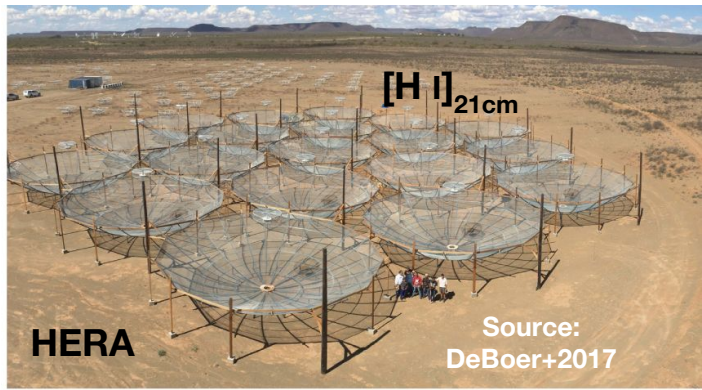
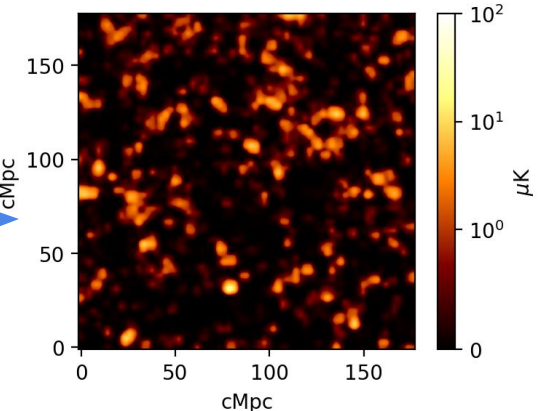
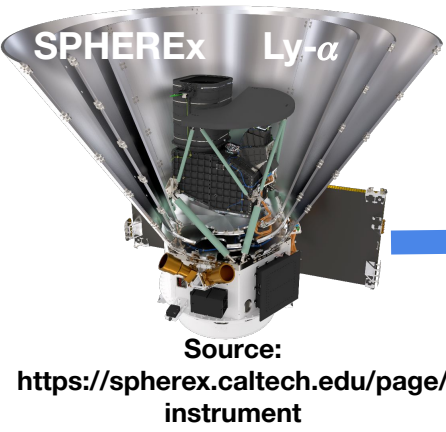
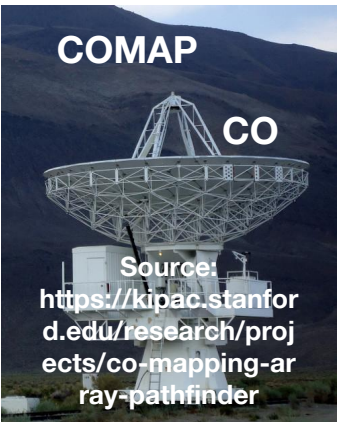
21-cm, Ly α



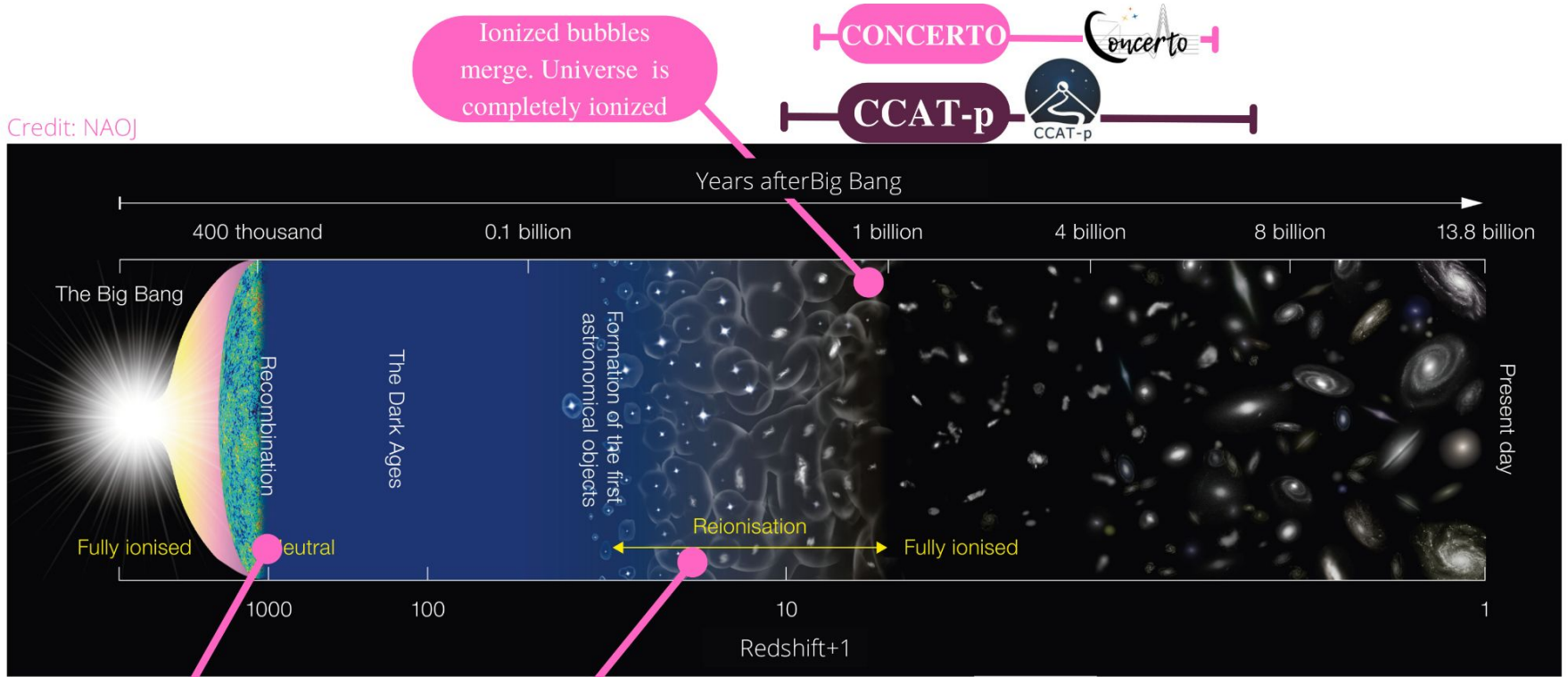
21-cm signal



Probing the EoR with Intensity Mapping: galaxies and IGM



Credit: NAOJ



Ionized bubbles merge. Universe is completely ionized

CONCERTO



CCAT-p



Neutral atoms form. Matter and radiation decouple.

Ionization bubble. form and grow around first galaxies

SKA



uGMRT

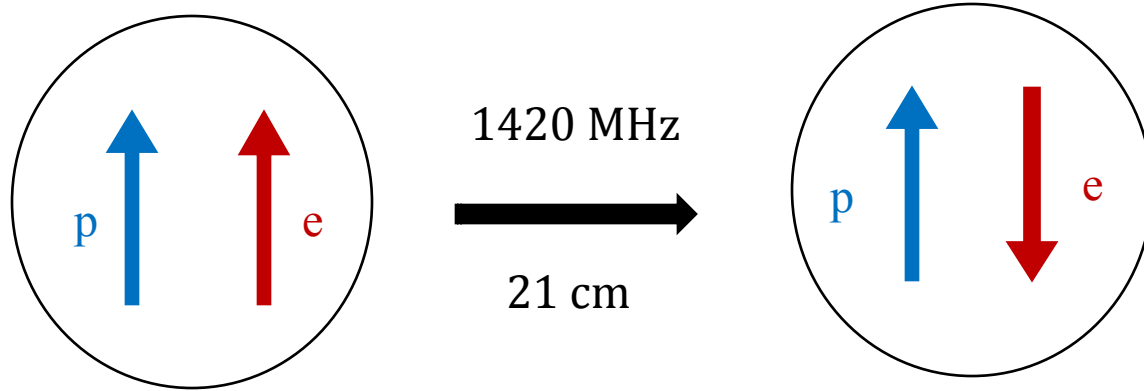


MWA



Observing the Hydrogen (HI)

21-cm Line

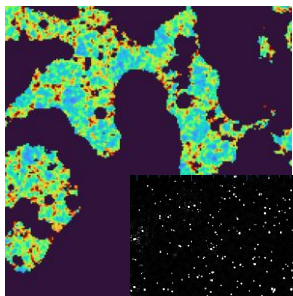


$$\nu_o = 1420 \text{ MHz}/(1+z)$$

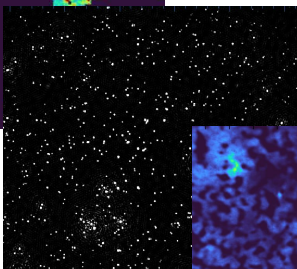
$$\lambda_o = 21 (1+z) \text{ cm}$$

Challenges

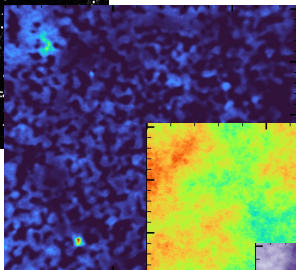
21-cm Signal



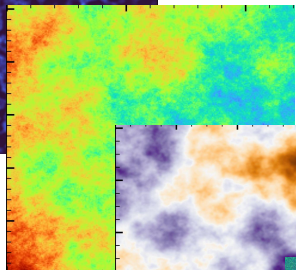
Extragalactic Foregrounds



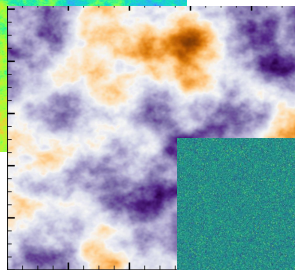
Free-Free Emission



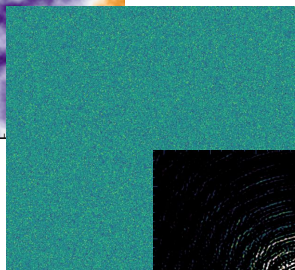
Synchrotron Emission



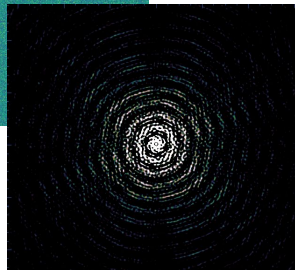
Ionosphere



Instrument noise



Instrument beam



Challenges

System Noise: Possibly Gaussian Random; can be suppressed below signal for long integration time.

Foregrounds: Major components –

i) Galactic Synchrotron Radiation

ii) Extra Galactic Point Sources

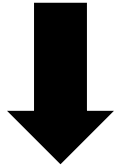
These are few orders of magnitude larger than the signal and are expected to be smooth in frequency therefore can be removed/avoided in principle.

Ionosphere: Turbulence in the ionosphere refracts low frequency radio waves and distorts the apparent magnitude and location of the signal. In principle, this can be corrected for large baselines and wide field of view.

How to quantify the signal?

Basic observable in radio interferometry is **Visibility**

Visibility \equiv Fourier transform of the sky brightness temperature



Power spectrum: $\langle \tilde{T}_b(k_1) \tilde{T}_b(k_2) \rangle = \delta_{k_1+k_2,0} V P(k_1)$



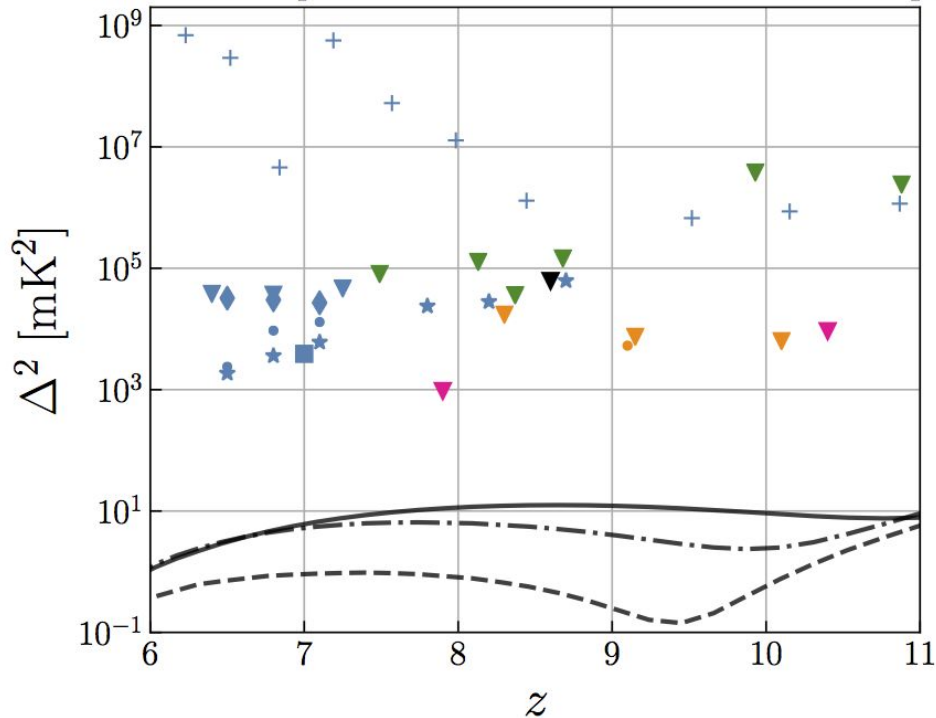
Amplitude of fluctuations
at different length scales

where $k = 2\pi/L$

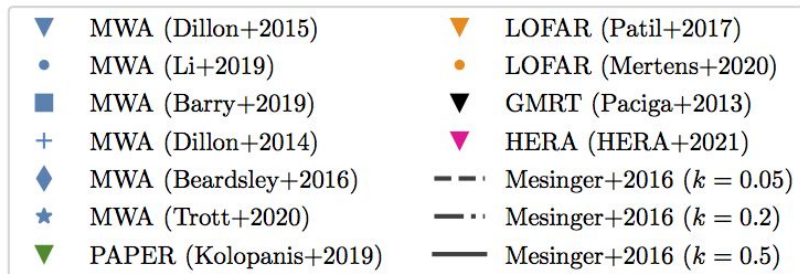
Bharadwaj et al. 2000
(astro-ph/0003200)

******Radio interferometers are not sensitive to the mean of the signal as signal at $k = 0$ is not recorded.

EoR Power Spectrum Limits for $0.05 < k < 0.6 h \text{ Mpc}^{-1}$



**Where do
we stand?**

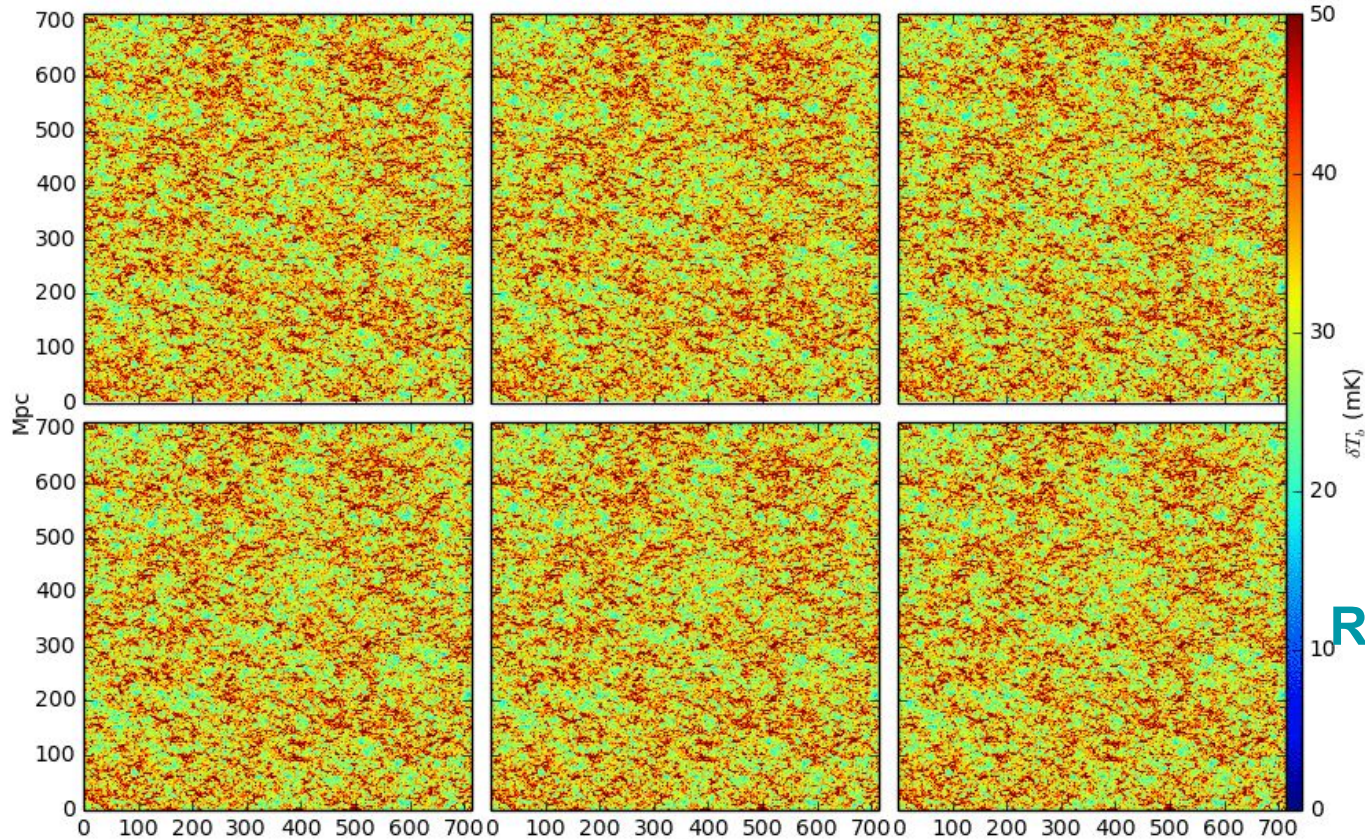


Source:

https://reionization.org/wp-content/uploads/2021/08/eor_limits.png

How does the signal look like?

$z = 16.095$ $x_{HI} = 1.000$



ReionYuga

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

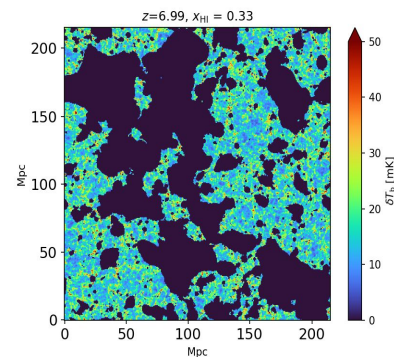
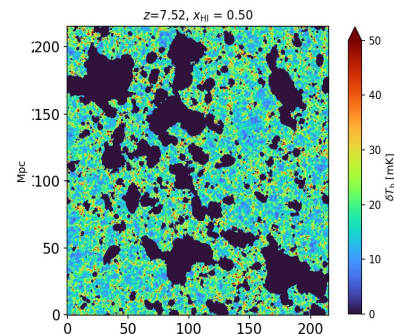
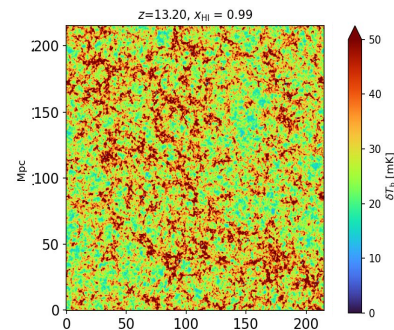
Non-Gaussian EoR 21-cm Signal

- 21-cm signal from EoR is highly **non-Gaussian**.

- Intrinsic: Underlying matter distribution
- Evolving: Distribution & growth of ionized regions

- We need higher order signal statistic to quantify this non-Gaussianity

Evolving ionized regions



Various ways of quantifying non-Gaussianity (in the context of EoR 21-cm signal)

- One point statistics → Skewness, Kurtosis → [Watkinson et al 2014 etc](#)
- Position dependent power spectrum → [Giri et al 2019 etc](#)
- Wavelet Scattering Transforms → [Greig et al 2022, Hoti et al 2024 etc](#)
- Different image based statistics →
Bubble Size Distribution, Minkowski functionals,
Largest Cluster Statistics →
[Iliev et al 2005, 2007, Friedrich et al. 2010, Kakiichi et al. 2017,](#)
[Giri et al. 2017, 2018, Pathak et al 2022, Dasgupta et al 2023 etc](#)

Bispectrum as a summary statistic

Bispectrum

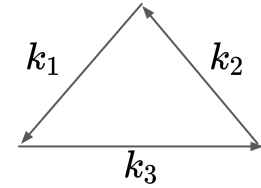
- Fourier equivalent to three point correlation function.
- It quantifies the correlation between different Fourier modes.

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

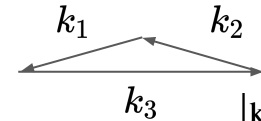
- Normalised Bispectrum

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

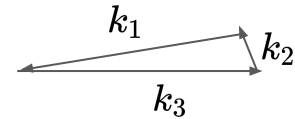
[Majumdar et al. 2018, MNRAS, 476, 4007](#)



Equilateral $|k_1| = |k_2| = |k_3|$

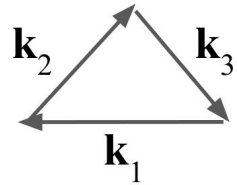
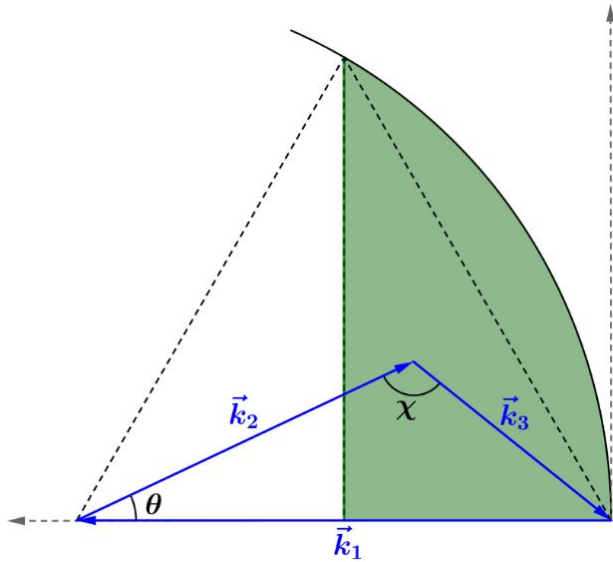


Stretched $|k_1| = |k_2| = |k_3|/2$



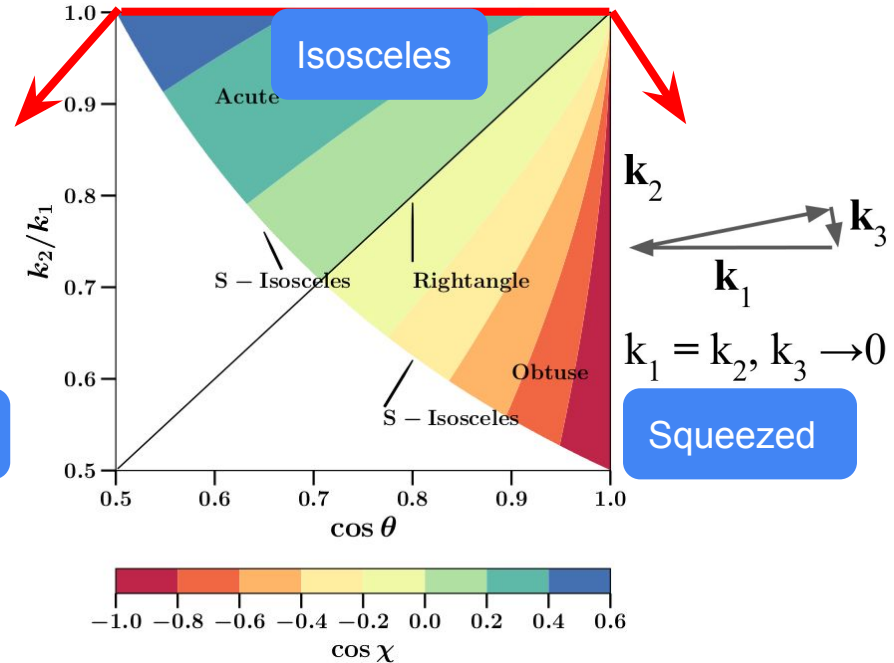
Squeezed Limit $|k_1| \approx |k_3|, |k_2| \rightarrow 0$

Unique triangles in the Fourier space



$$k_1 = k_2 = k_3$$

Equilateral

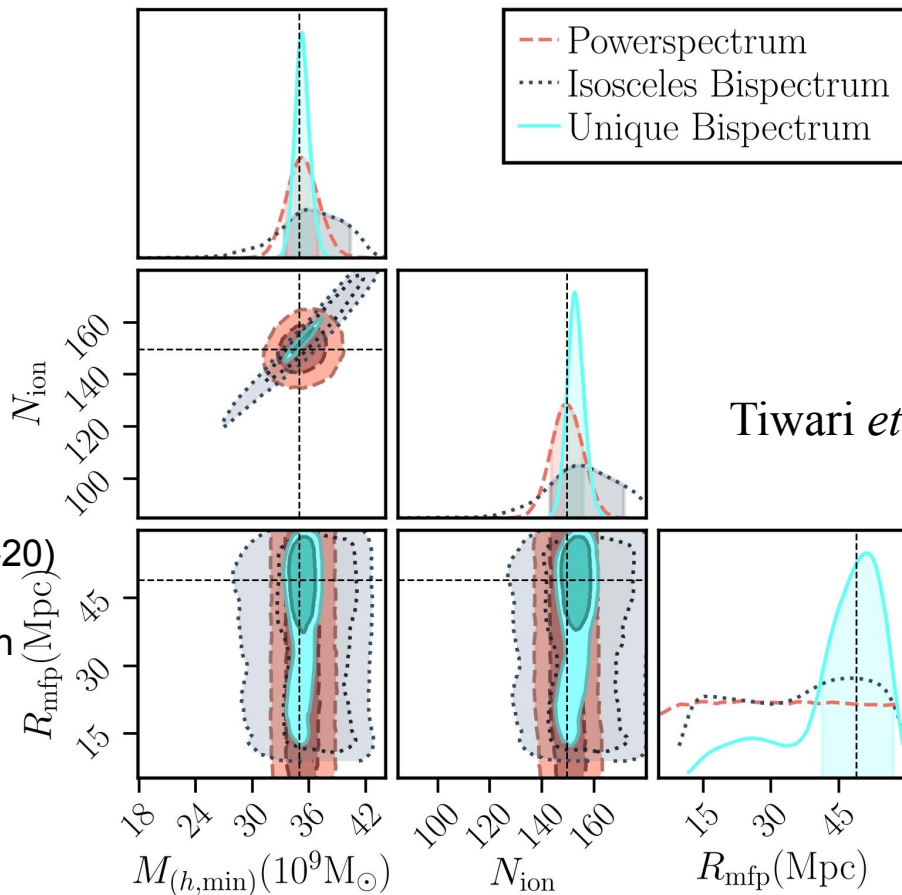


Bispectrum provides better constraints on EoR parameters



Himanshu Tiwari

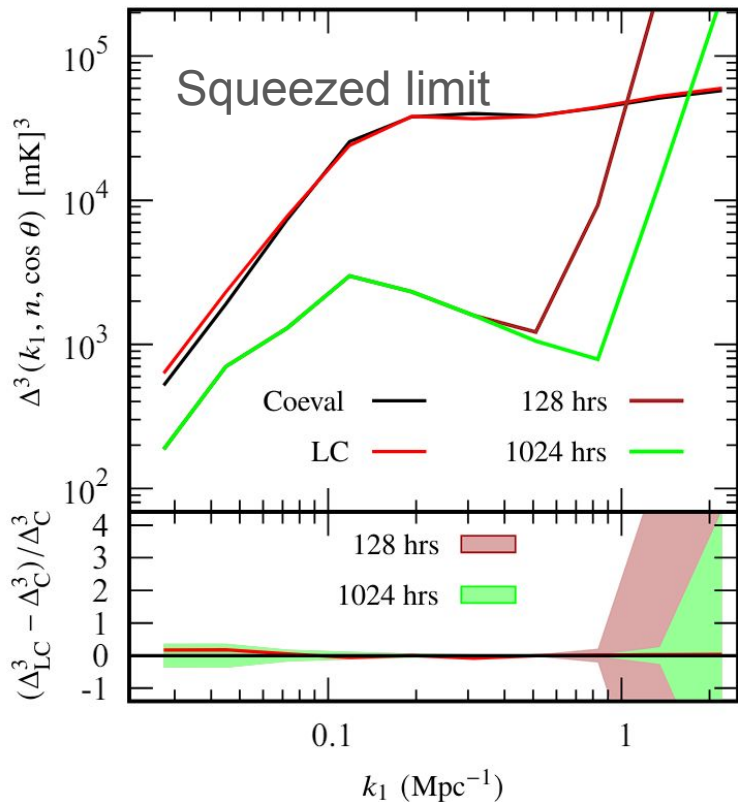
MSc Astronomy IITI (2018-20)
PhD at Curtin Univ. (2024)
Data Scientist at NRI, Perth



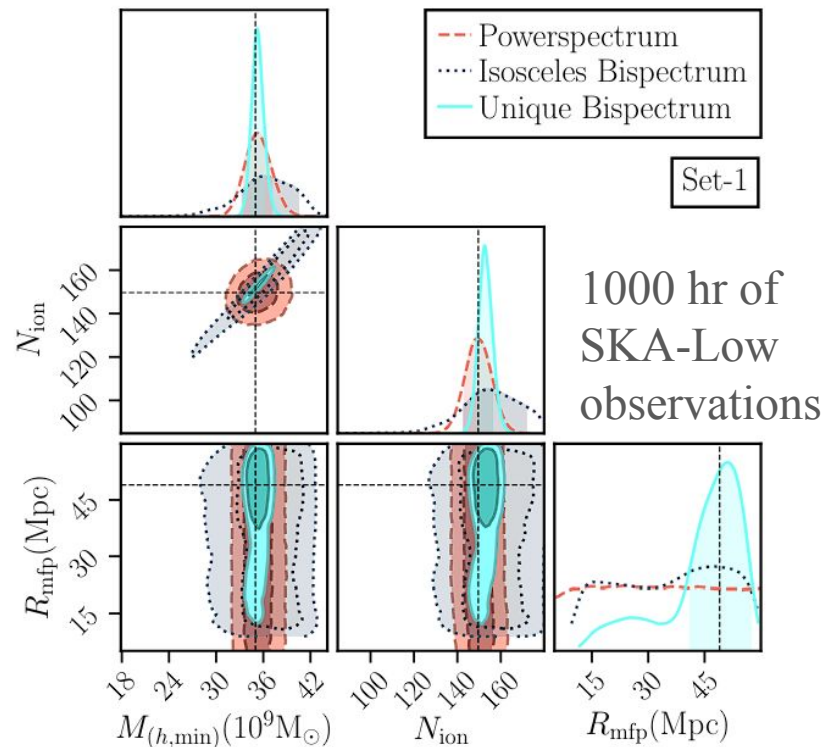
Tiwari *et al* JCAP 04(2022)045

1000 hr of
SKA-Low
observations

Detectability of the bispectrum with SKA-Low

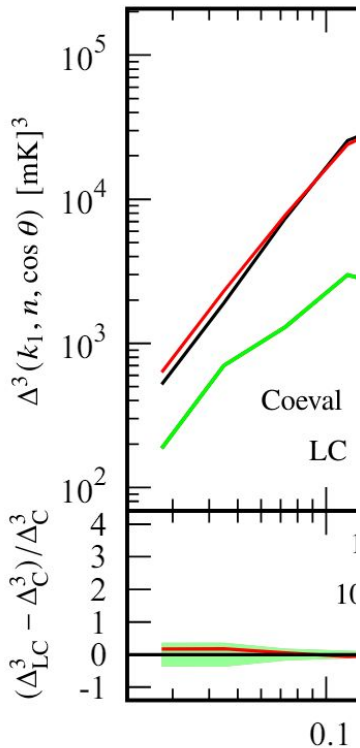


Mondal, ...SM et al 2021 (arXiv:2107.02668)



Tiwari, SM et al 2022(arXiv:2108.07279)

Detectability



Mondal, ...SM

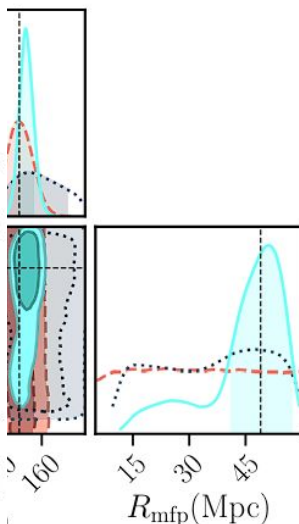
Triangles	Direct	Gridded	Type
EoR0			14m
$k_1 = k_2 = k_3 = 0.007$	$0.166 \pm 2.5e - 7$	$10.4 \pm 4.1e - 8$	Equilateral
$k_1 = 0.2, k_2 = k_3 = 0.1$	-0.266 ± 0.0004	921.2 ± 0.3	Isosceles
$k_1 = 0.4, k_2 = k_3 = 0.2$	2.84 ± 0.0044	-1766.2 ± 0.6	Isosceles
$k_1 = 0.6, k_2 = k_3 = 0.3$	-4.87 ± 0.063	-427.8 ± 5.8	Isosceles
$k_1 = 1.0, k_2 = k_3 = 0.5$	3.45 ± 0.60	129.4 ± 108.9	Isosceles
EoR0			28m
$k_1 = k_2 = k_3 = 0.014$	$-0.019 \pm 1.4e - 7$	$-29.3 \pm 8.1e - 6$	Equilateral
$k_1 = 0.2, k_2 = k_3 = 0.1$	-0.14 ± 0.002	-594.5 ± 4.0	Isosceles
$k_1 = 0.4, k_2 = k_3 = 0.2$	0.360 ± 0.009	948.9 ± 7.2	Isosceles
$k_1 = 0.6, k_2 = k_3 = 0.3$	0.98 ± 0.18	-793.1 ± 37.6	Isosceles
$k_1 = 1.0, k_2 = k_3 = 0.5$	1.08 ± 1.78	19450 ± 752	Isosceles
EoR1			14m
$k_1 = k_2 = k_3 = 0.007$	$-0.004 \pm 1.2e - 8$	$0.61 \pm 3.2e - 9$	Equilateral
$k_1 = 0.2, k_2 = k_3 = 0.1$	0.044 ± 0.0001	-666.5 ± 0.03	Isosceles
$k_1 = 0.4, k_2 = k_3 = 0.2$	0.19 ± 0.0004	3157.0 ± 0.82	Isosceles
$k_1 = 0.6, k_2 = k_3 = 0.3$	-0.064 ± 0.007	-1861.9 ± 0.54	Isosceles
$k_1 = 1.0, k_2 = k_3 = 0.5$	-0.12 ± 0.13	5907.5 ± 56.1	Isosceles
EoR1			28m
$k_1 = k_2 = k_3 = 0.014$	$0.0006 \pm 7.0e - 9$	$17.1 \pm 8.4e - 7$	Equilateral
$k_1 = 0.2, k_2 = k_3 = 0.1$	0.0001 ± 0.0005	927.7 ± 0.43	Isosceles
$k_1 = 0.4, k_2 = k_3 = 0.2$	-0.082 ± 0.002	-245.3 ± 0.15	Isosceles
$k_1 = 0.6, k_2 = k_3 = 0.3$	0.012 ± 0.030	5881.8 ± 10.4	Isosceles
$k_1 = 1.0, k_2 = k_3 = 0.5$	6.2 ± 1.2	4257.6 ± 15.6	Isosceles

with SKA

Trott, ...SM et al 2019

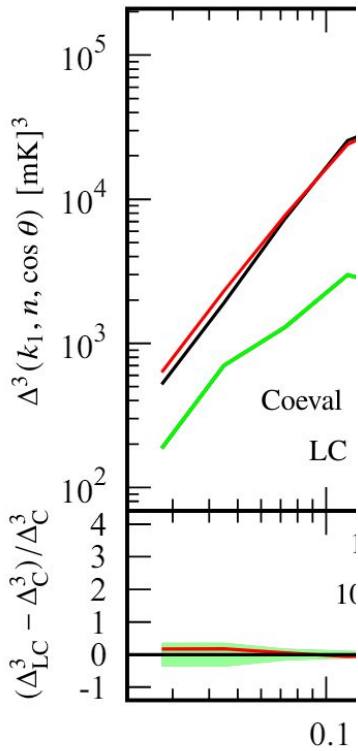
- Powerspectrum
- Isosceles Bispectrum
- Unique Bispectrum

Set-1

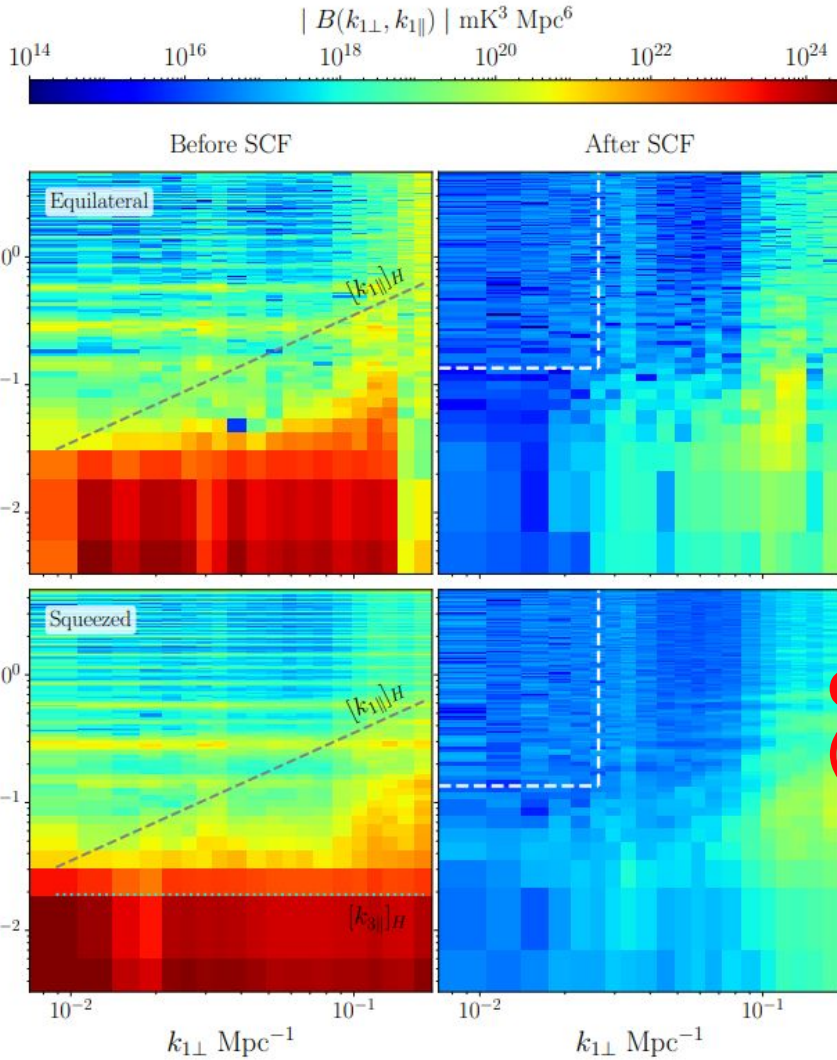


al 2022

Detectability



Mondal, ...SM



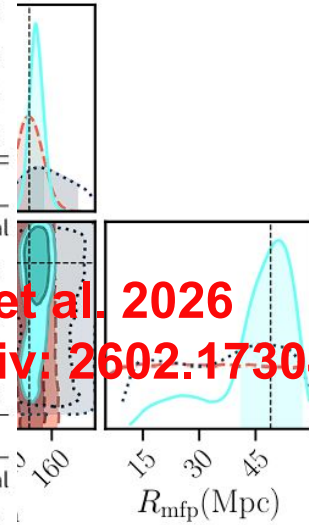
with SKA

...SM et al 2019

- Powerspectrum
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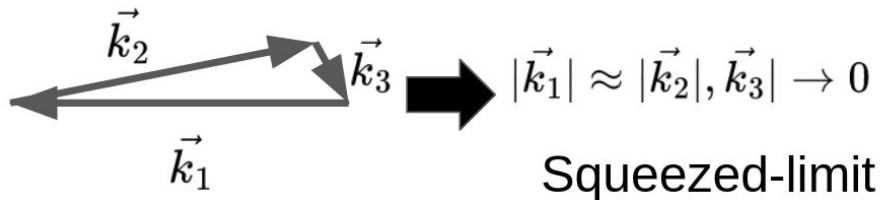
Set-1

Gill et al. 2026
(arXiv: 2602.17304)



al 2022

Squeezed-limit bispectrum



- Among all possible unique k-triangles, **squeezed-limit** triangle bispectrum has **maximum magnitude** (Majumdar et al. 2018, 2020; Hutter et al. 2019, Watkinson et al 2021, Kamran, SM et al. 2021, 2022, Tiwari, SM et al. 2022, Gill, SM et al. 2023, Raste et al. 2024, Gill et al. 2026).
- Highest **detection probability** by **SKA** (Mondal, SM et al. 2021, Tiwari, SM, et al. 2022).

We will focus on large scale ($k_1 \sim 0.16 \text{ Mpc}^{-1}$) squeezed limit bispectrum.



Mohammad Kamran

Postdoc at Trieste Observatory (2026 - Till date)
Postdoc at Uppsala University (2022 - 25)
PhD from IIT Indore (2022)

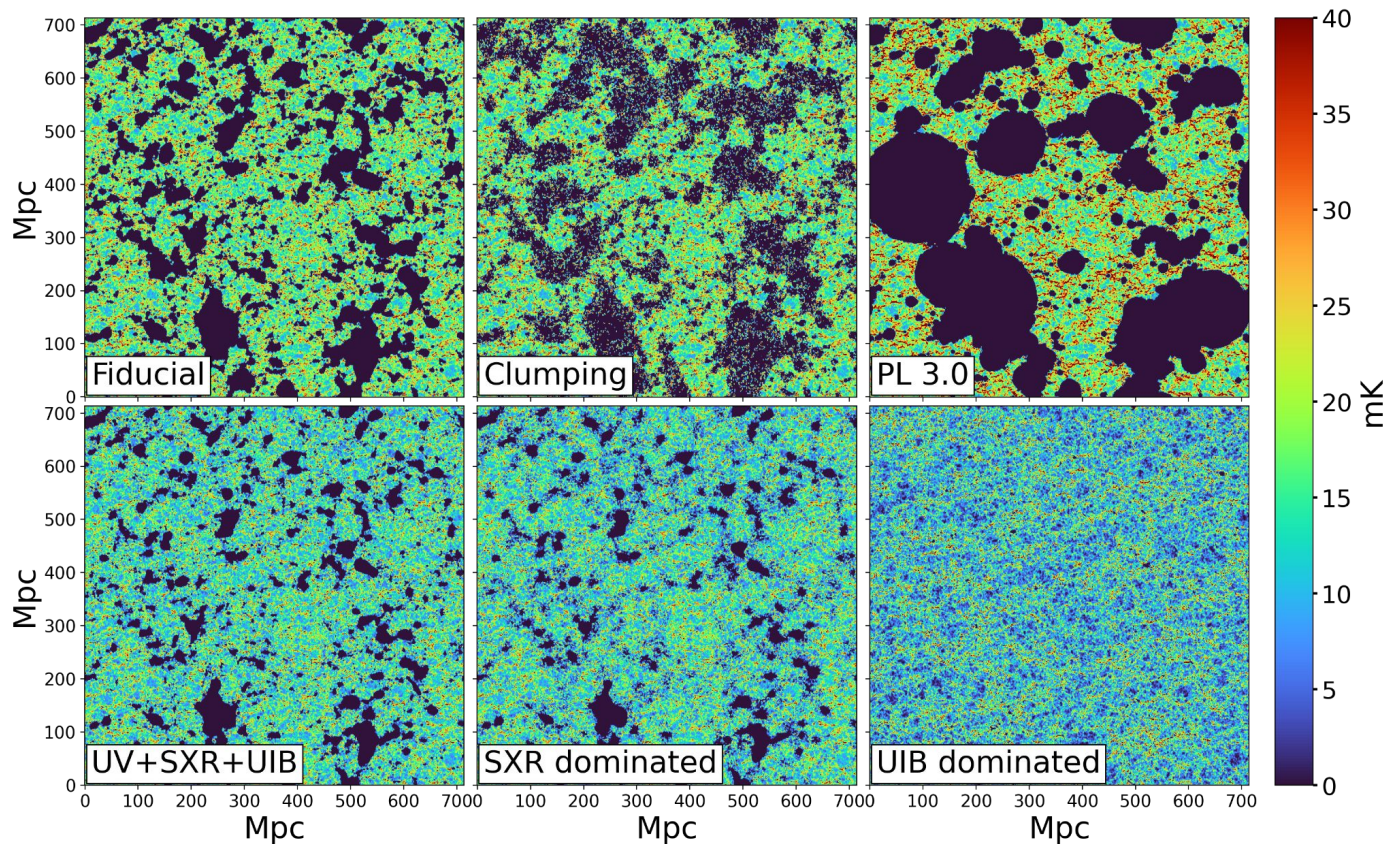


Leon Noble

PhD at IIT Indore (2022 - ongoing)

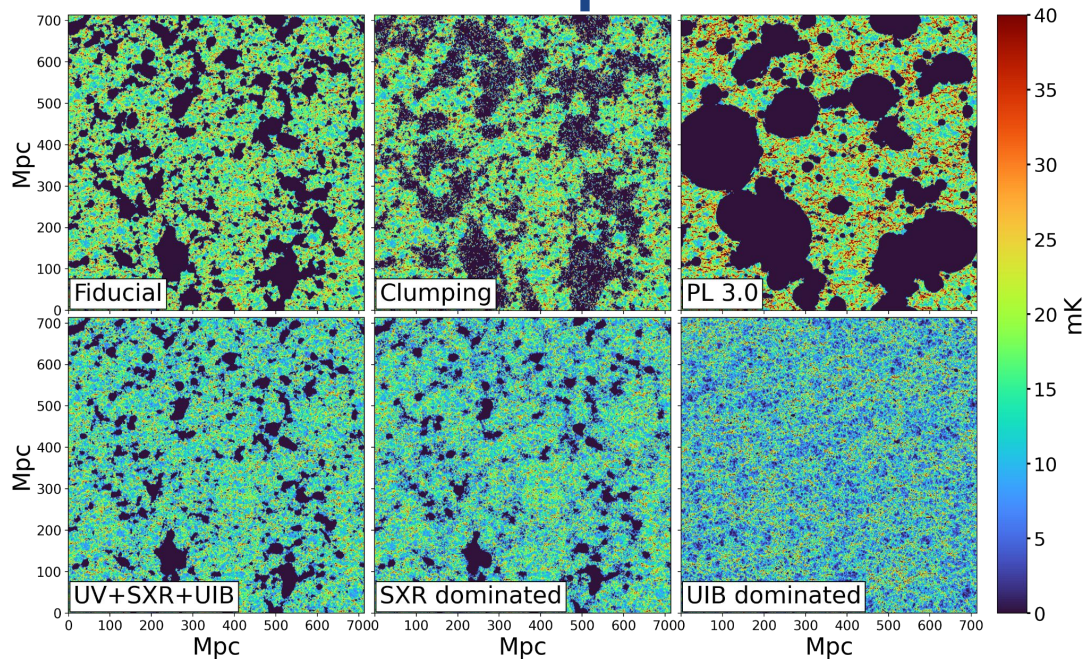
Collaborators: Suman Majumdar (IITI), Chandra Shekhar Murmu (Open University of Israel), Raghunath Ghara (IIT Kharagpur), Garrelt Mellema (Stockholm University), Ilian T. Iliev (University of Sussex) & Jonathan R. Pritchard (MPIfR, Bonn).

Impact of the sources of reionization on 21-cm signal



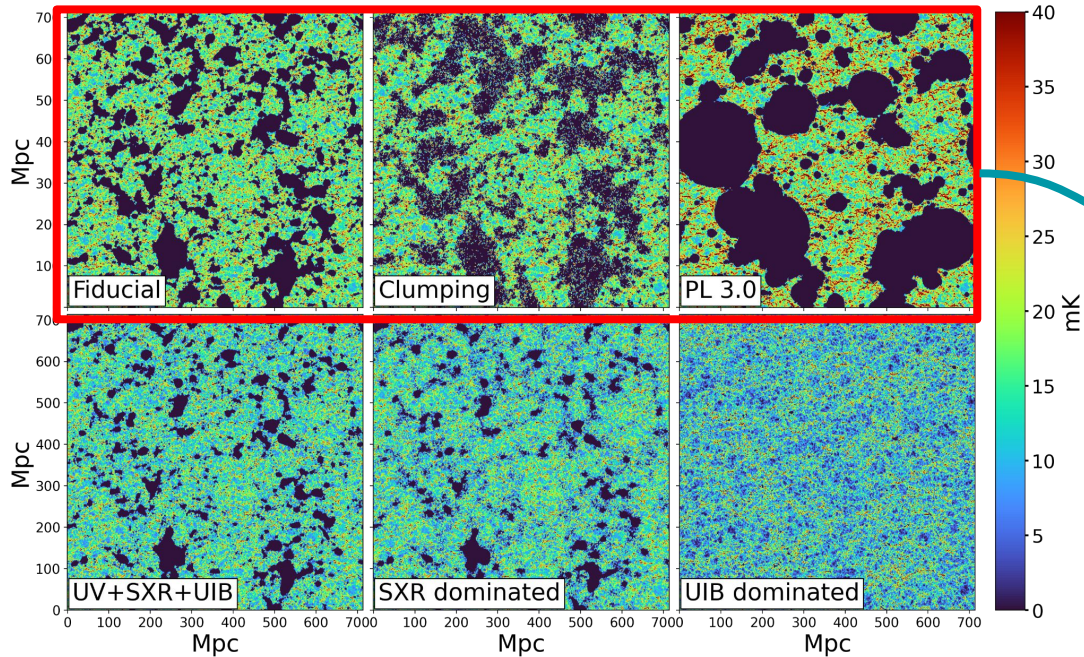
Choudhury et al 2009;
Watkinson et al. 2014;
Majumdar et al. 2016;
Eide et al. 2018;
Hutter et al. 2019;
Watkinson et al. 2021
Pathak et al. 2022;
Raste et al 2024;
Schaeffer et al 2024,.....
and many more

Impact of the sources of reionization on the 21-cm bispectrum



- Impact of various reionization morphologies on the 21-cm bispectrum
- To what extent the 21-cm bispectrum can distinguish between different reionization morphologies

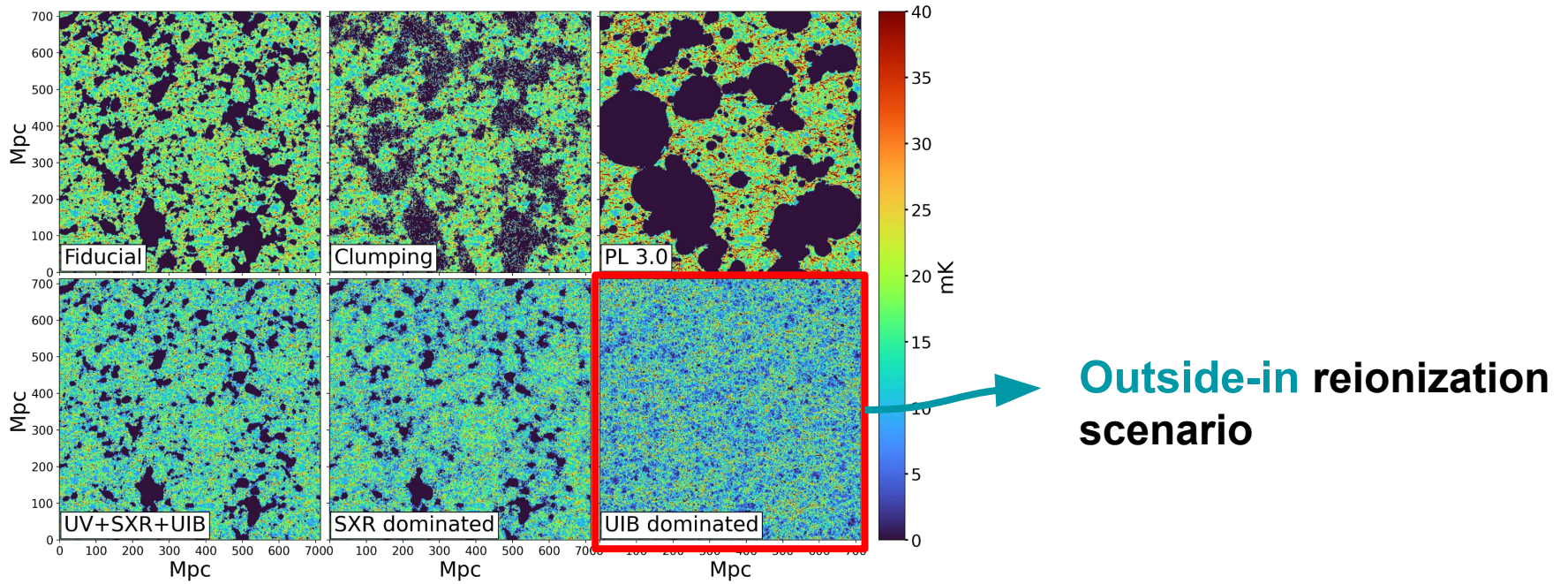
Reionization scenarios



Inside-out reionization scenarios

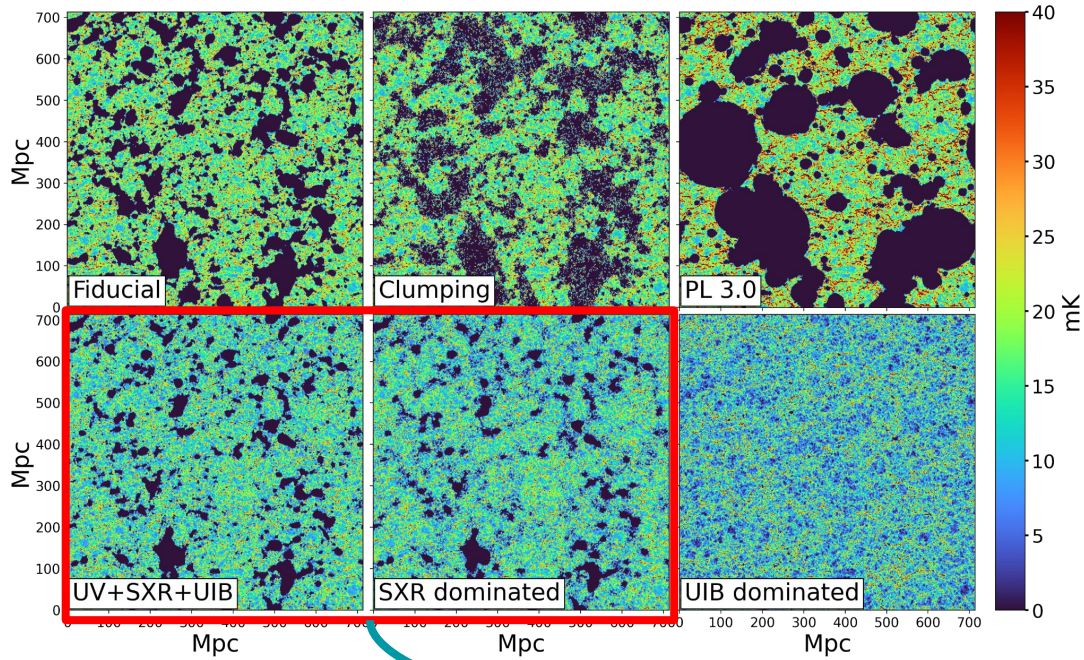
Noble, SM et al. 2024, arXiv: 2406.03118

Reionization scenarios



Noble, SM et al. 2024, arXiv: 2406.03118

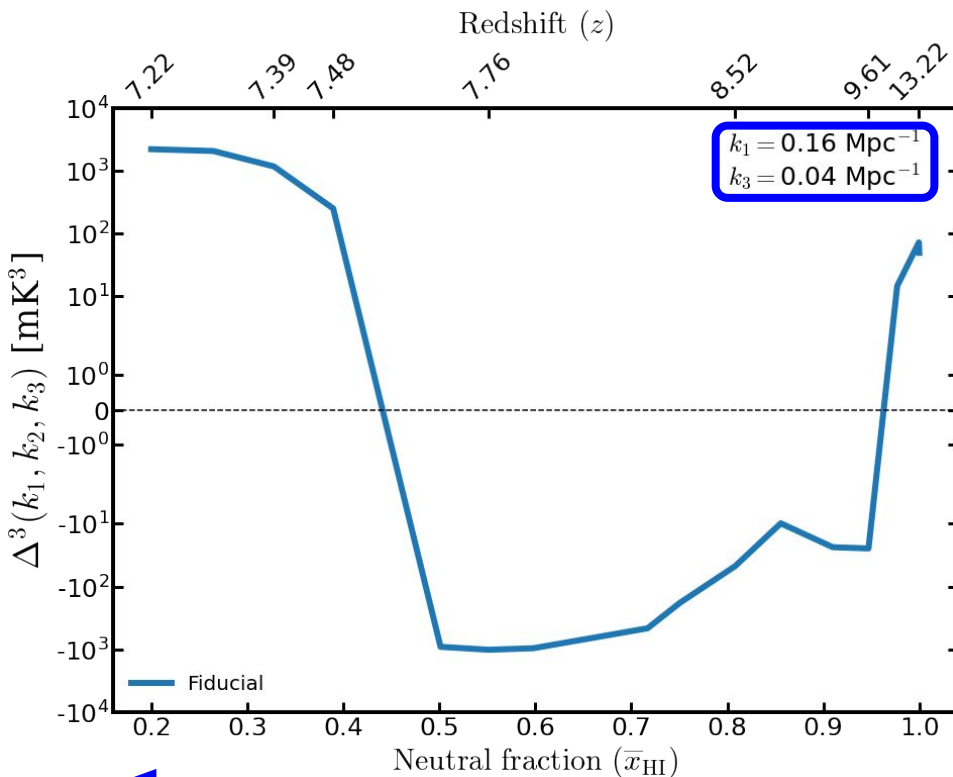
Reionization scenarios



Combination of **inside-out** and **outside-in**

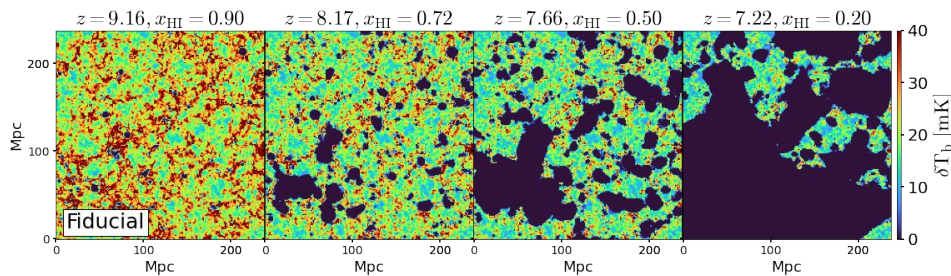
Noble, SM et al. 2024, arXiv: 2406.03118

Evolution of squeezed-limit bispectrum



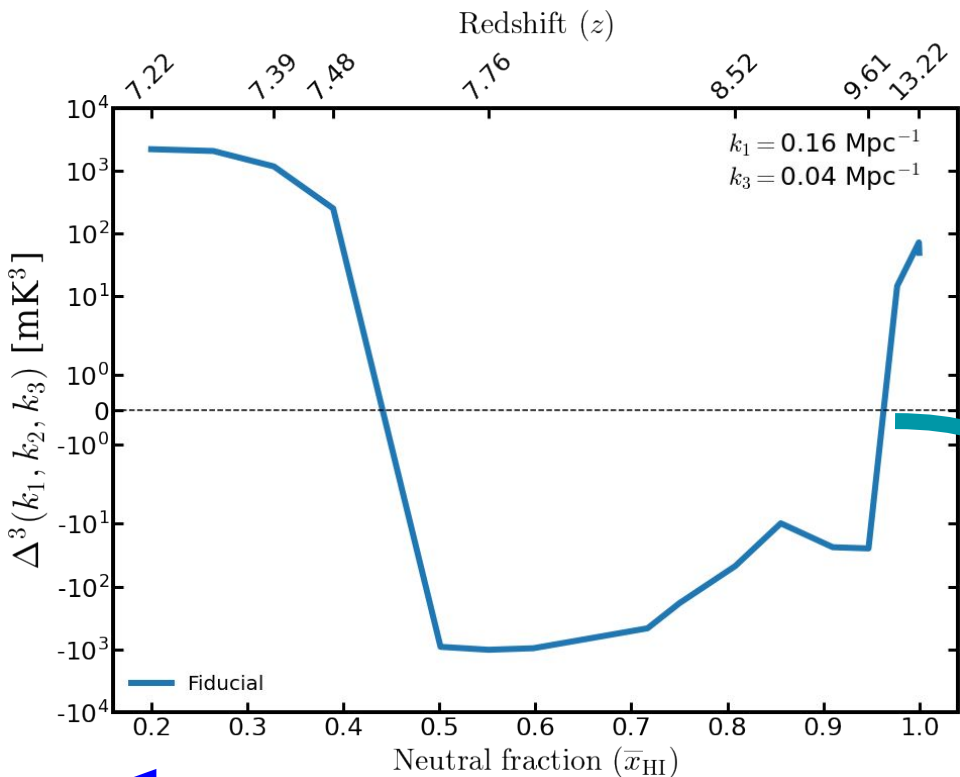
Early stage

Late stage



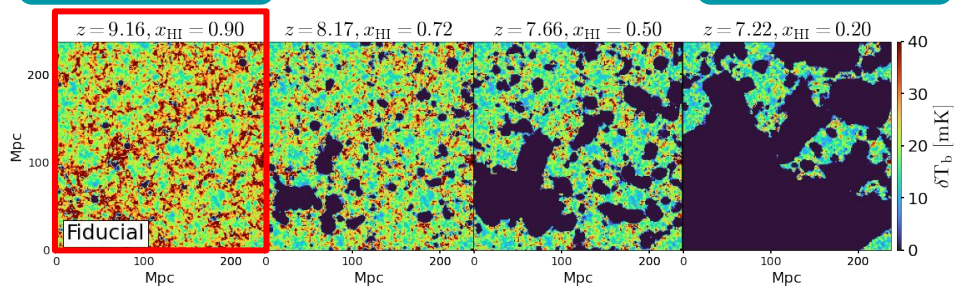
Noble, SM et al. 2024, arXiv: 2406.03118

Evolution of squeezed-limit bispectrum



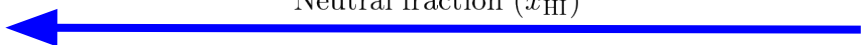
Early stage

Late stage



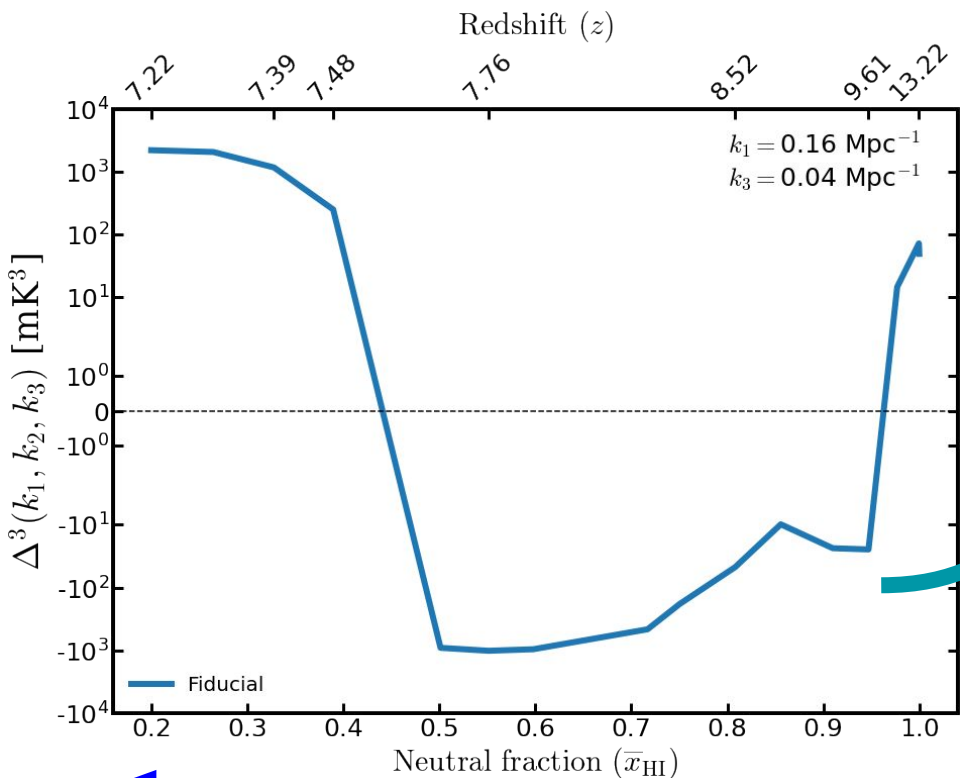
Change in the sign of the bispectrum

Noble, SM et al. 2024, arXiv: 2406.03118



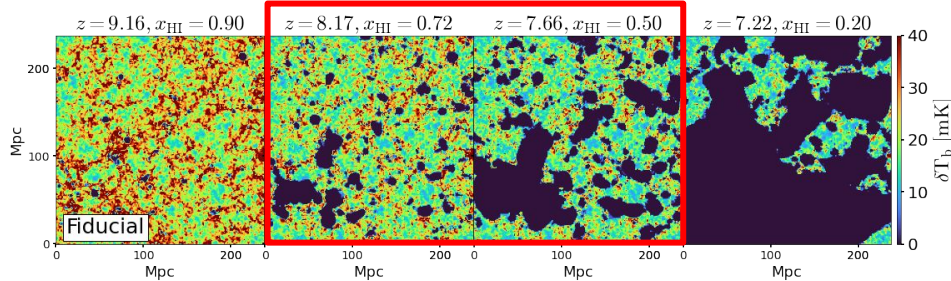
Progress of reionization

Evolution of squeezed-limit bispectrum



Early stage

Late stage

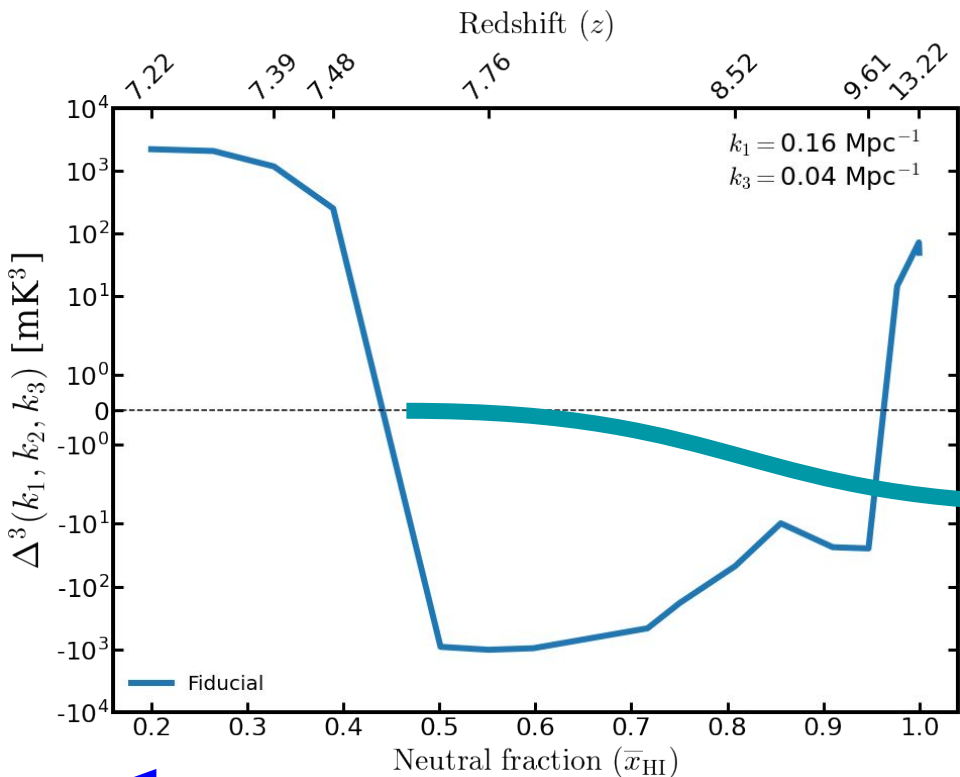


Magnitude of the 21-cm bispectrum increases

Noble, SM et al. 2024, arXiv: 2406.03118

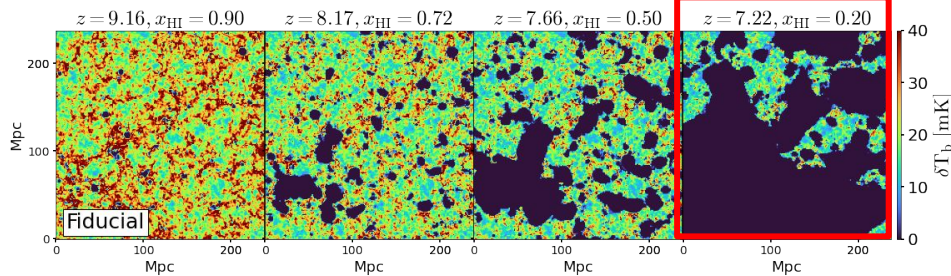
Progress of reionization

Evolution of squeezed-limit bispectrum

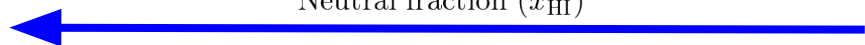


Early stage

Late stage



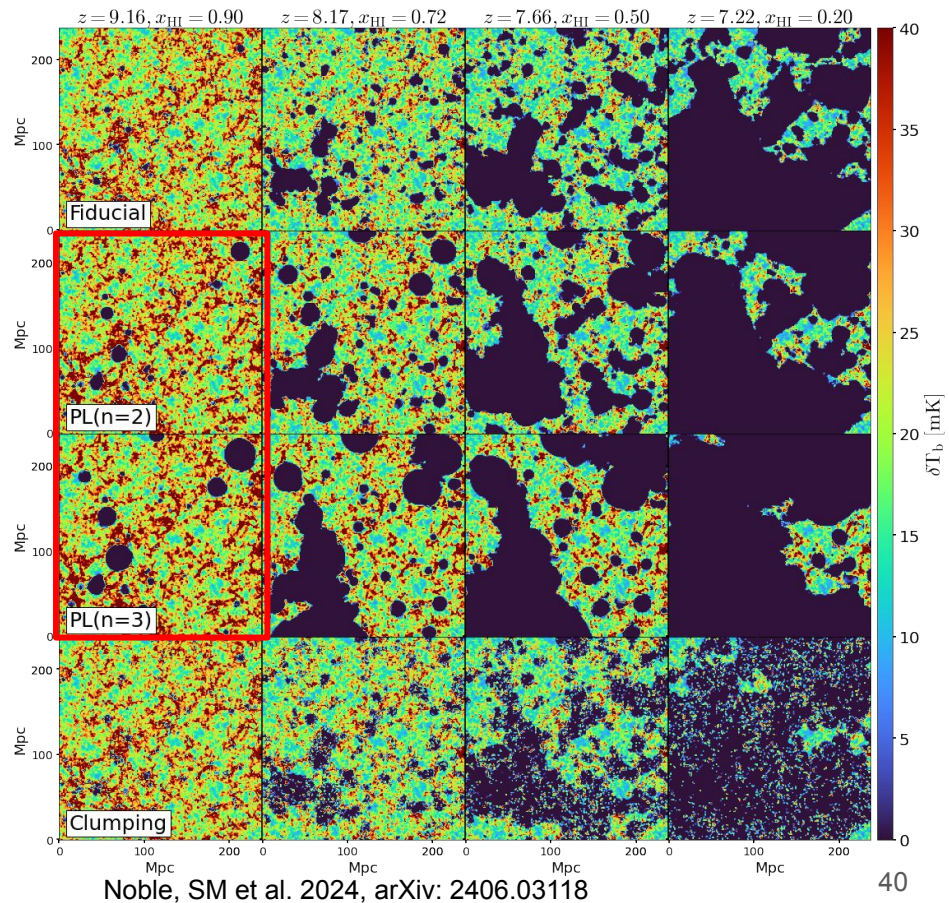
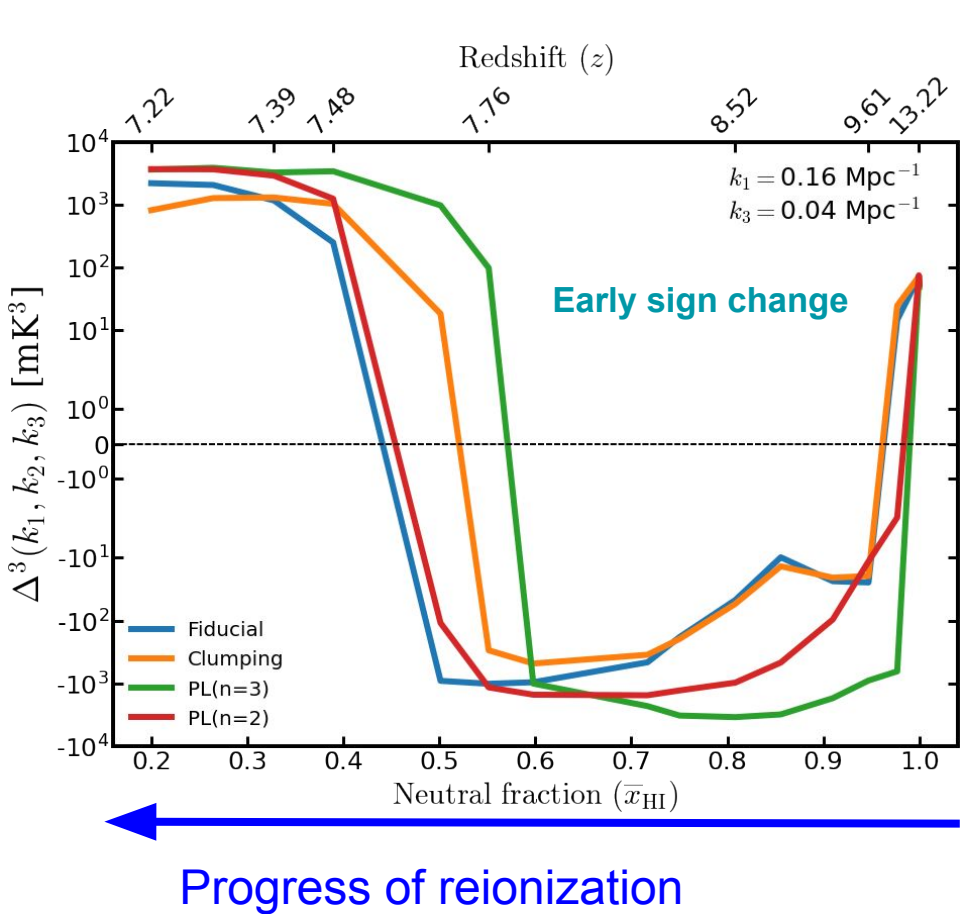
Second sign change in the 21-cm bispectrum



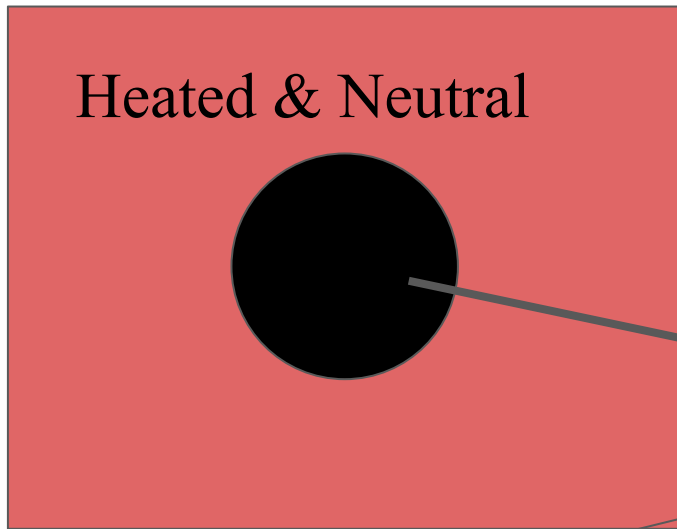
Progress of reionization

Noble, SM et al. 2024, arXiv: 2406.03118

Evolution of squeezed-limit bispectrum: Inside-out scenarios



Interpretation

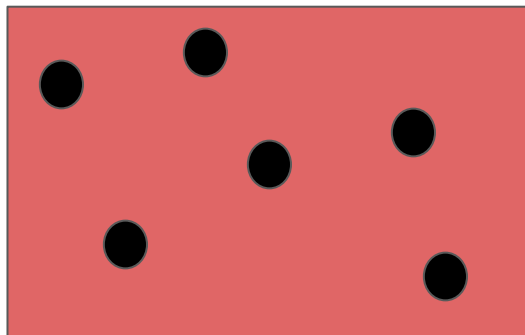


$$\Delta_{21} \propto -W(kR) \left(\sum \exp\{i\mathbf{k} \cdot \mathbf{r}\} \right).$$

Ionized

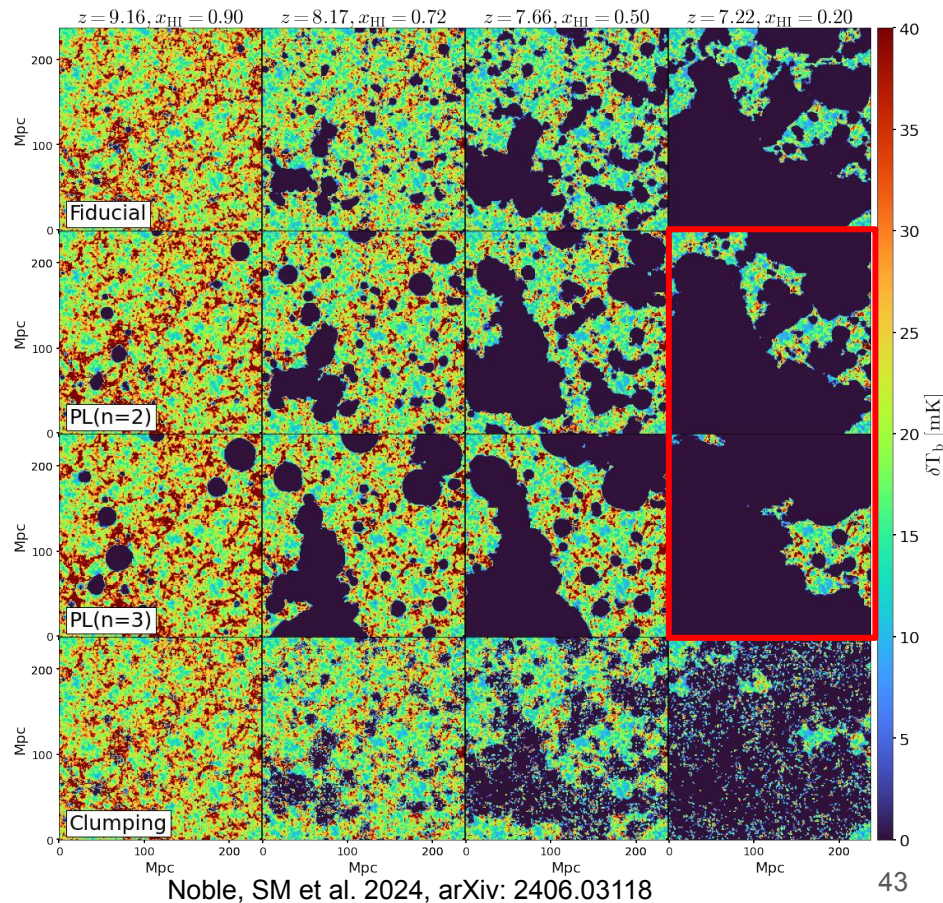
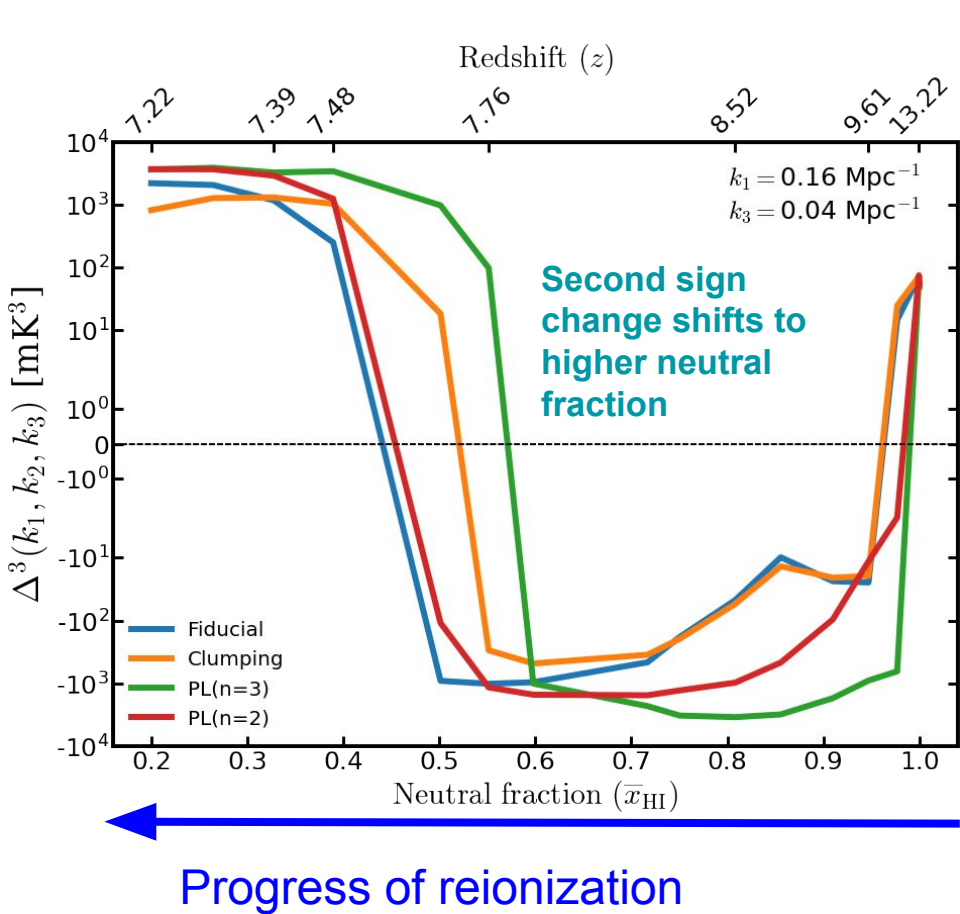
Many non-overlapping
ionized regions

Large scale signal -ve

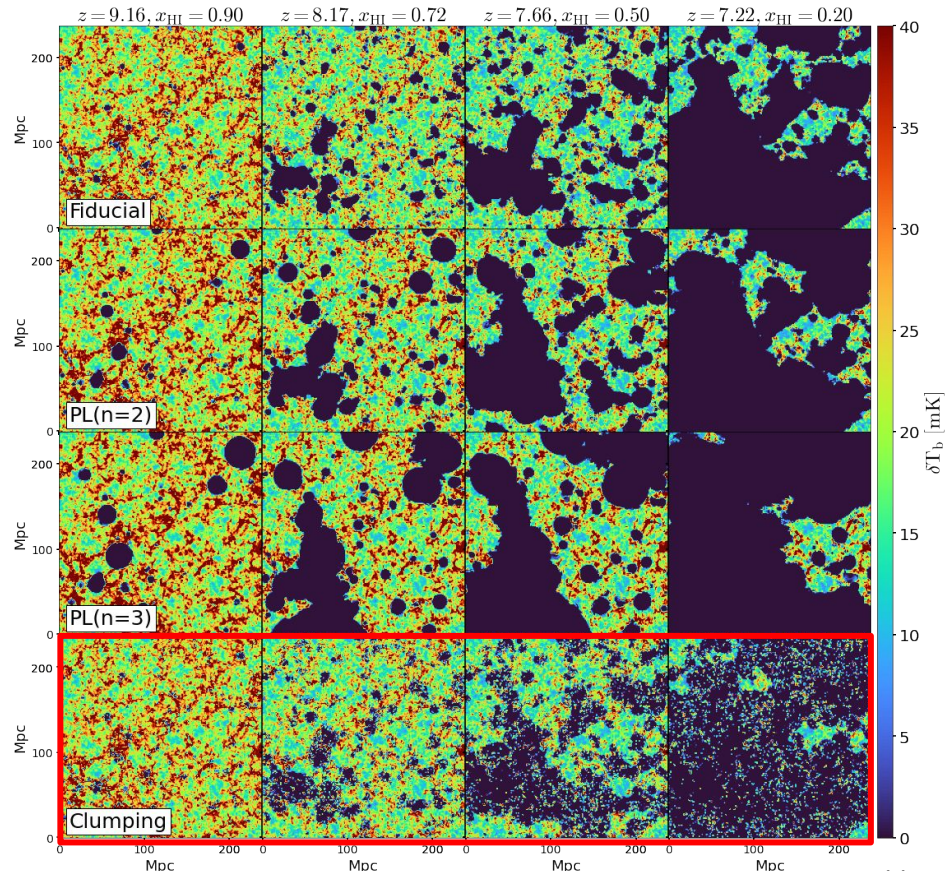
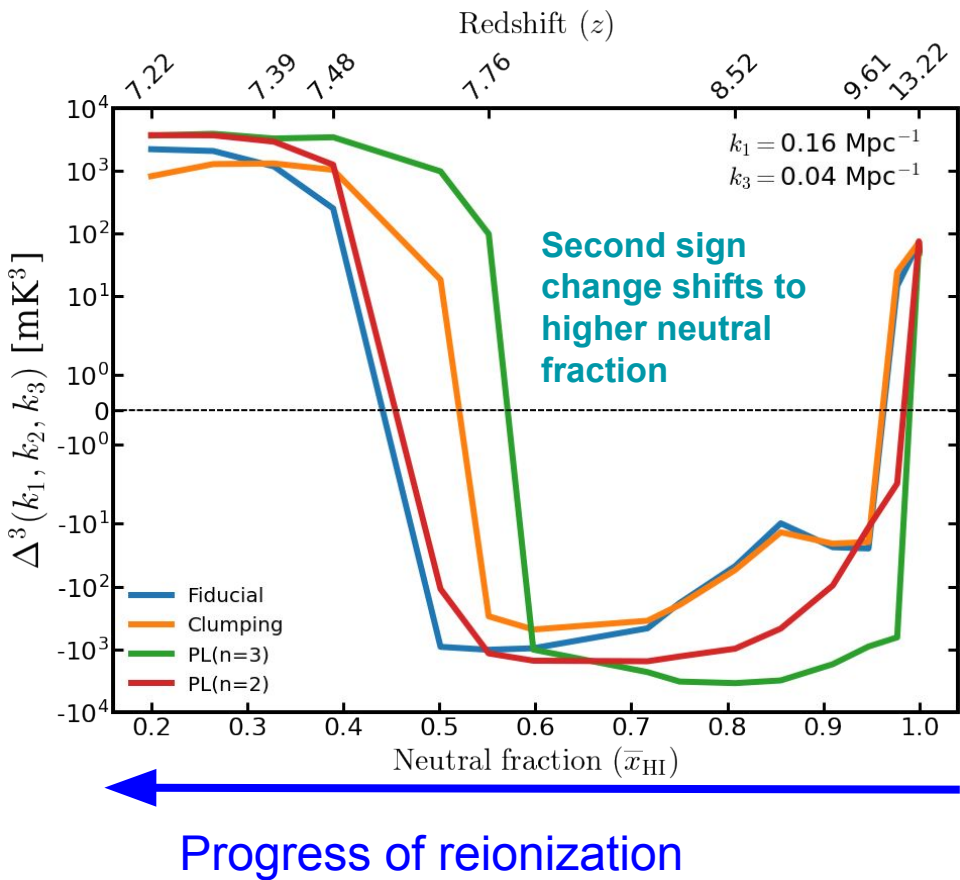


Bharadwaj & Ali 2004
Bharadwaj & Pandey 2005

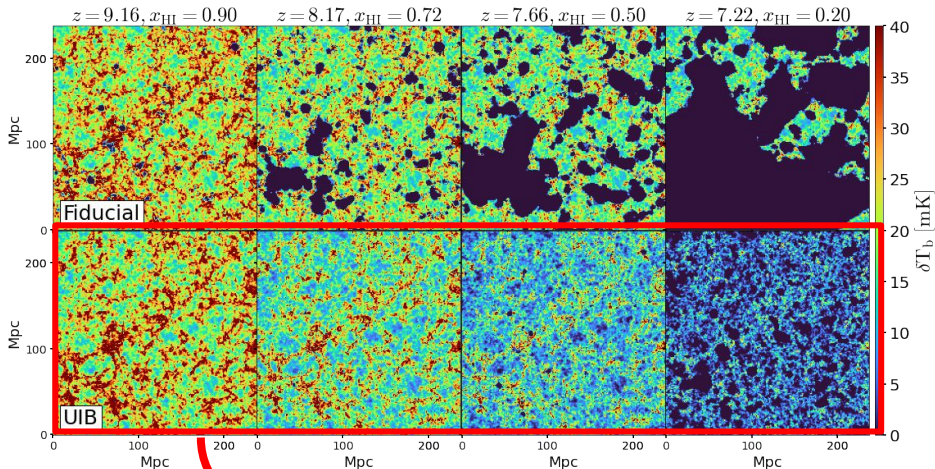
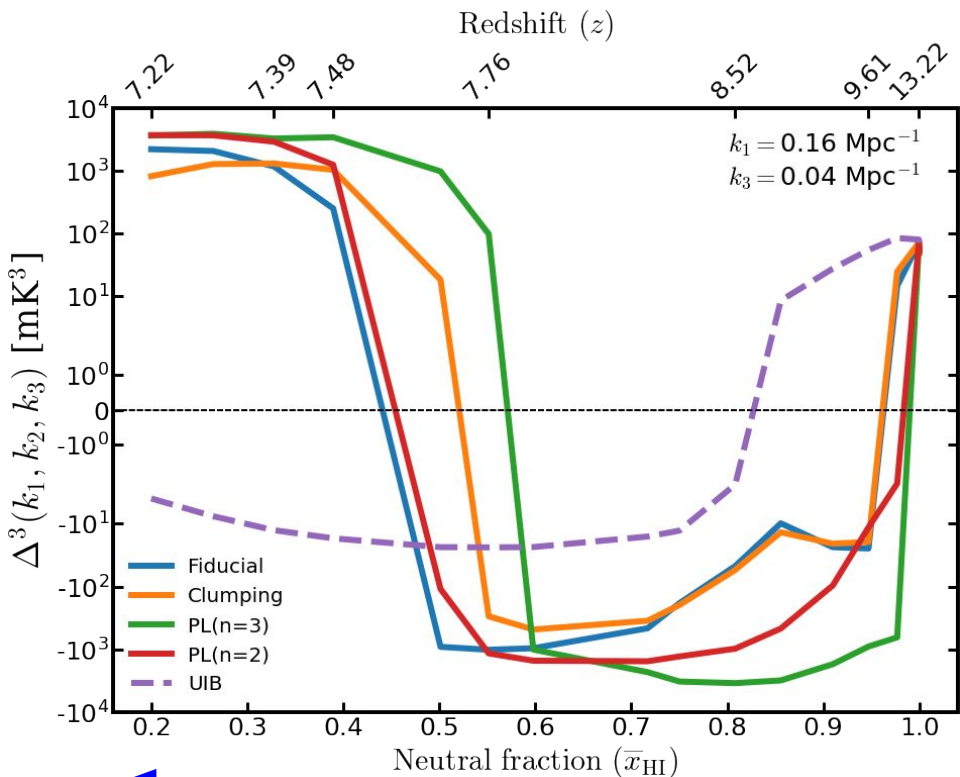
Evolution of squeezed-limit bispectrum: Inside-out scenarios



Evolution of squeezed-limit bispectrum: Inside-out scenarios

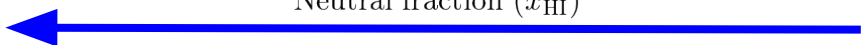


Evolution of squeezed-limit bispectrum: Outside-in scenario



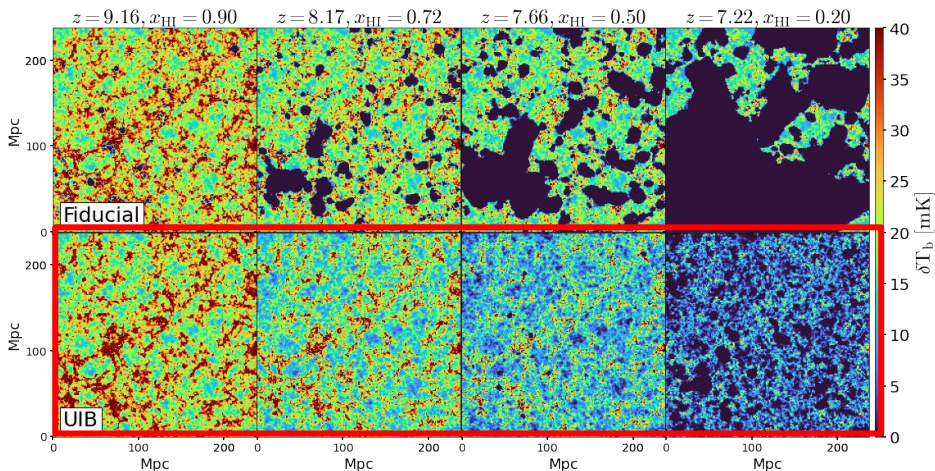
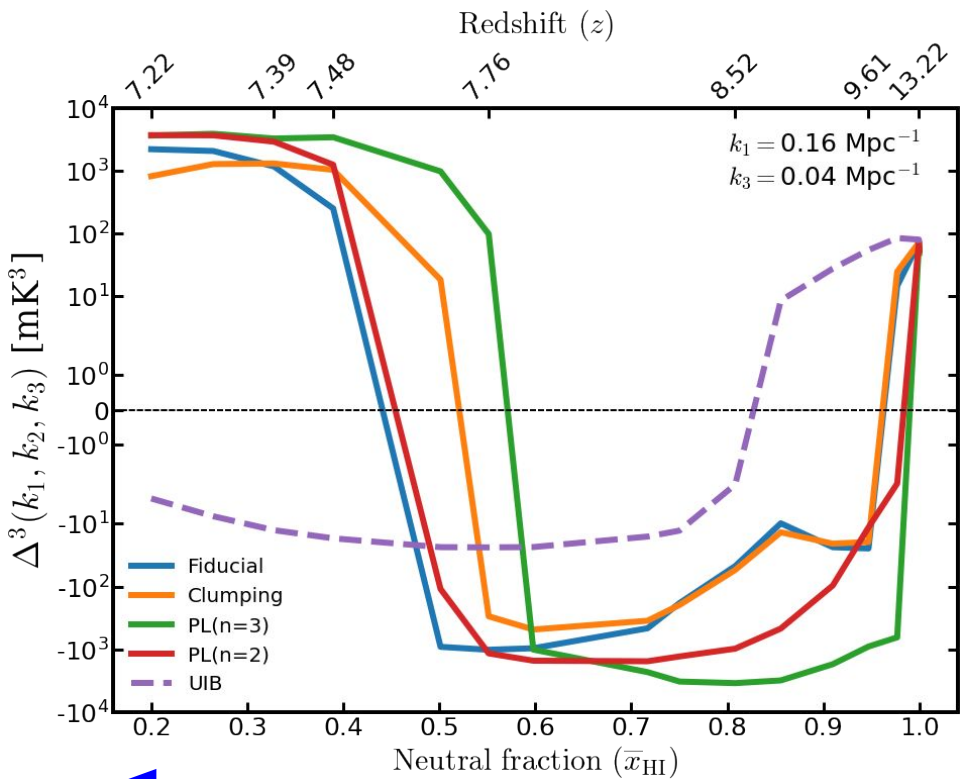
Outside-in reionization scenario

Noble, SM et al. 2024, arXiv: 2406.03118



Progress of reionization

Evolution of squeezed-limit bispectrum: Outside-in scenario

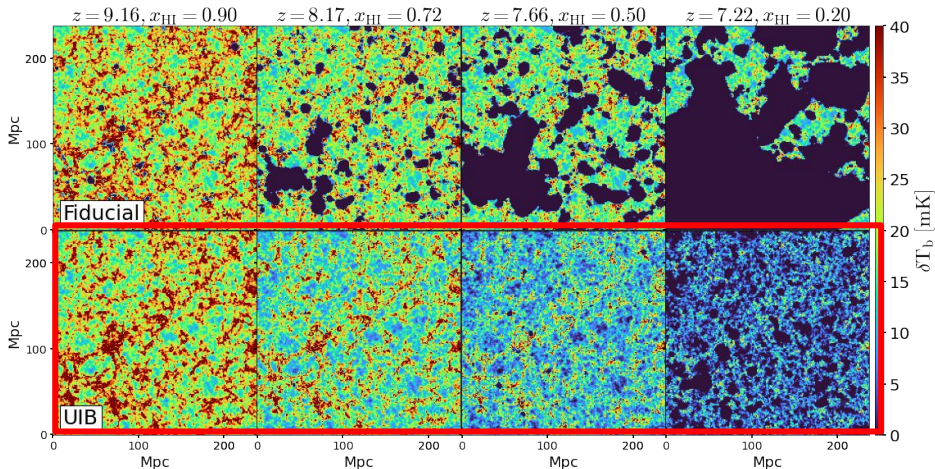
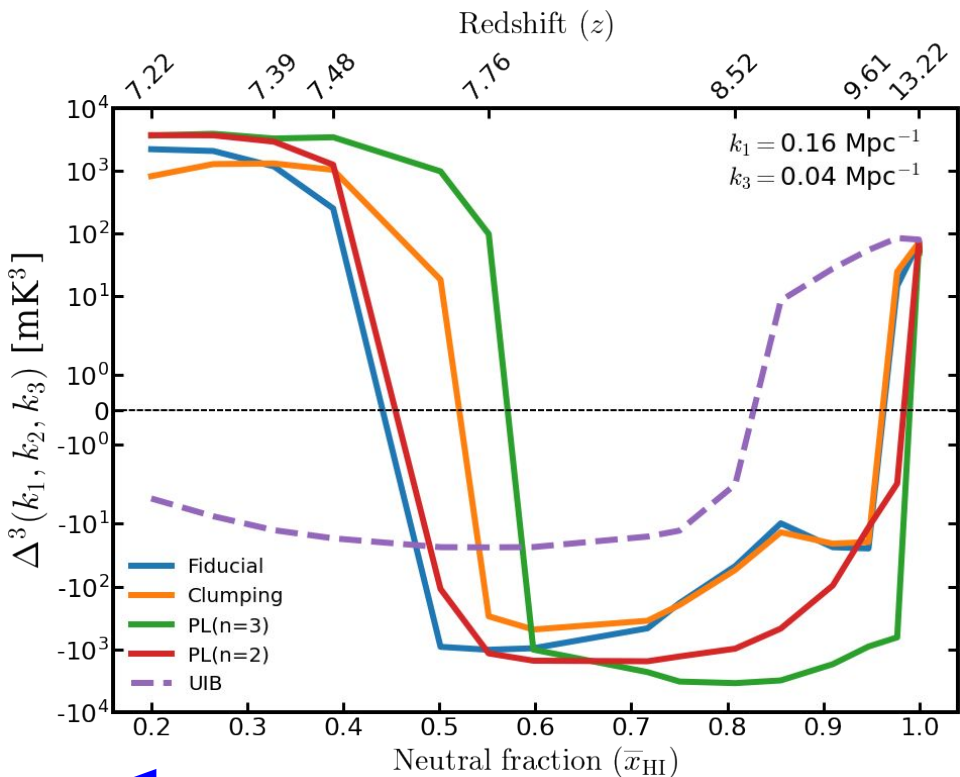


- First change in the sign of bispectrum happens at a later stage of reionization
- Magnitude of the bispectrum is lower than inside-out scenarios

Noble, SM et al. 2024, arXiv: 2406.03118

Progress of reionization

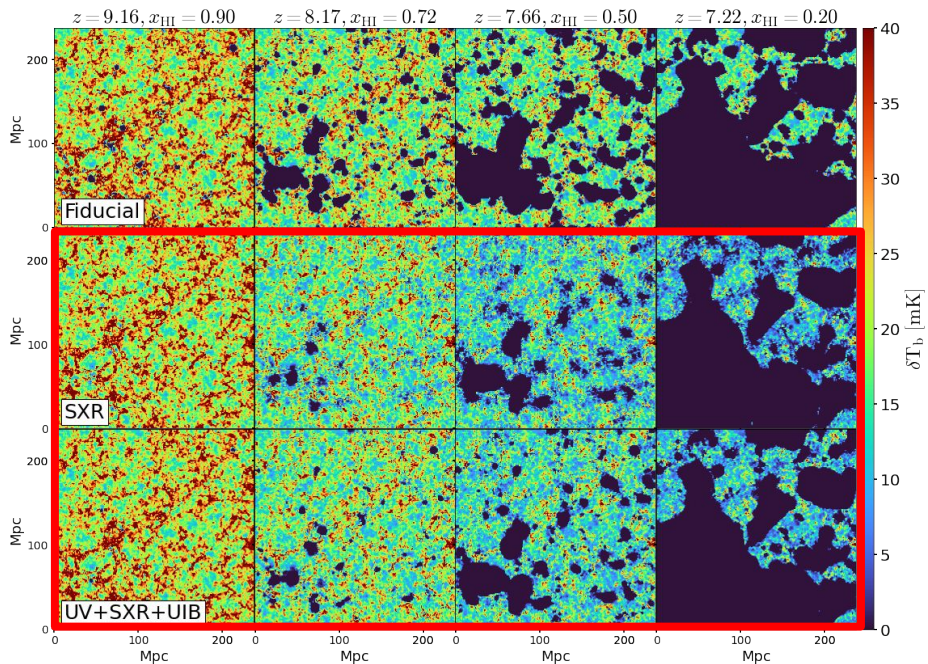
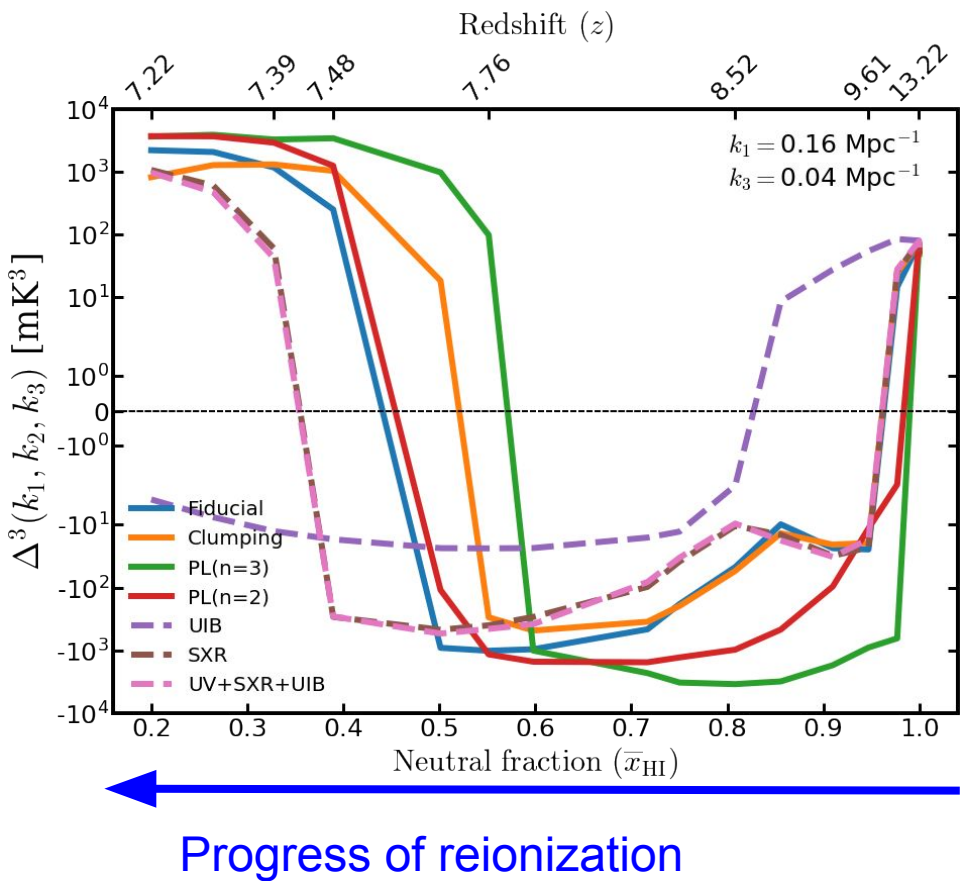
Evolution of squeezed-limit bispectrum: Outside-in scenario



- First change in the sign of bispectrum happens at a late stage of reionization
- Magnitude of the bispectrum is lower than inside-out scenarios
- No change in the **sign of bispectrum** at late stage of reionization

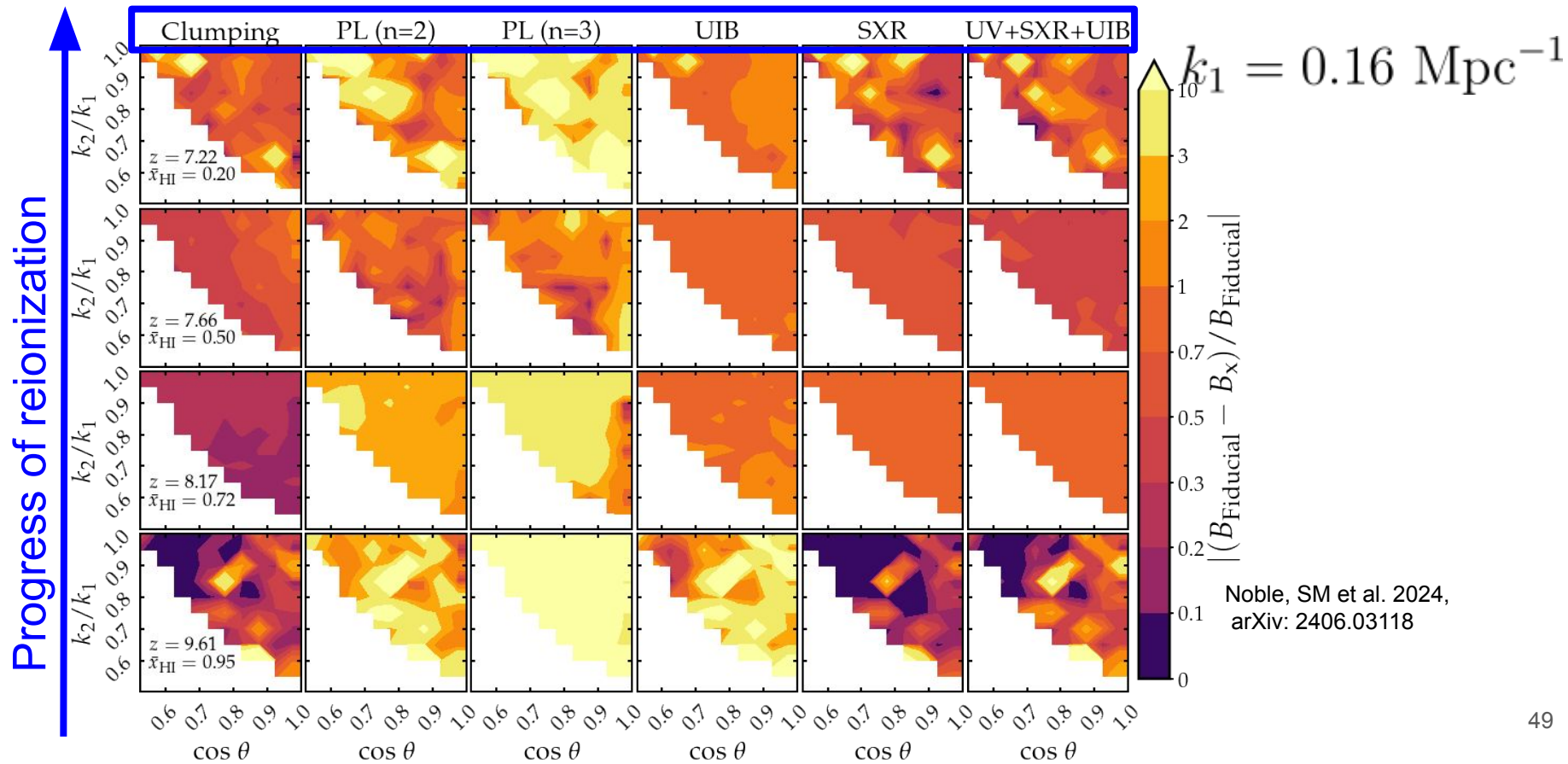
Progress of reionization

Evolution of squeezed-limit bispectrum: Combination of inside-out and outside-in

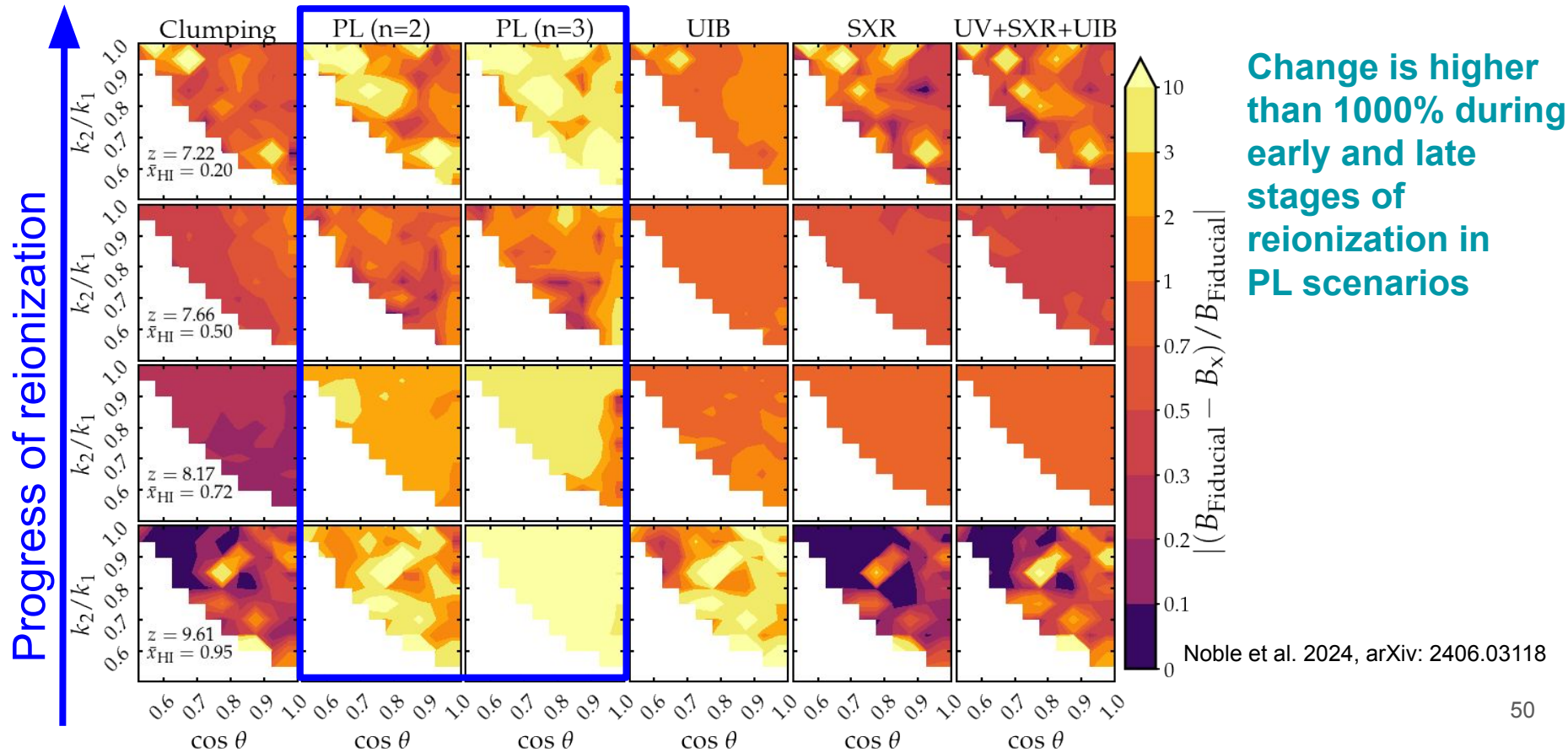


Second sign change shifts to lower neutral fraction

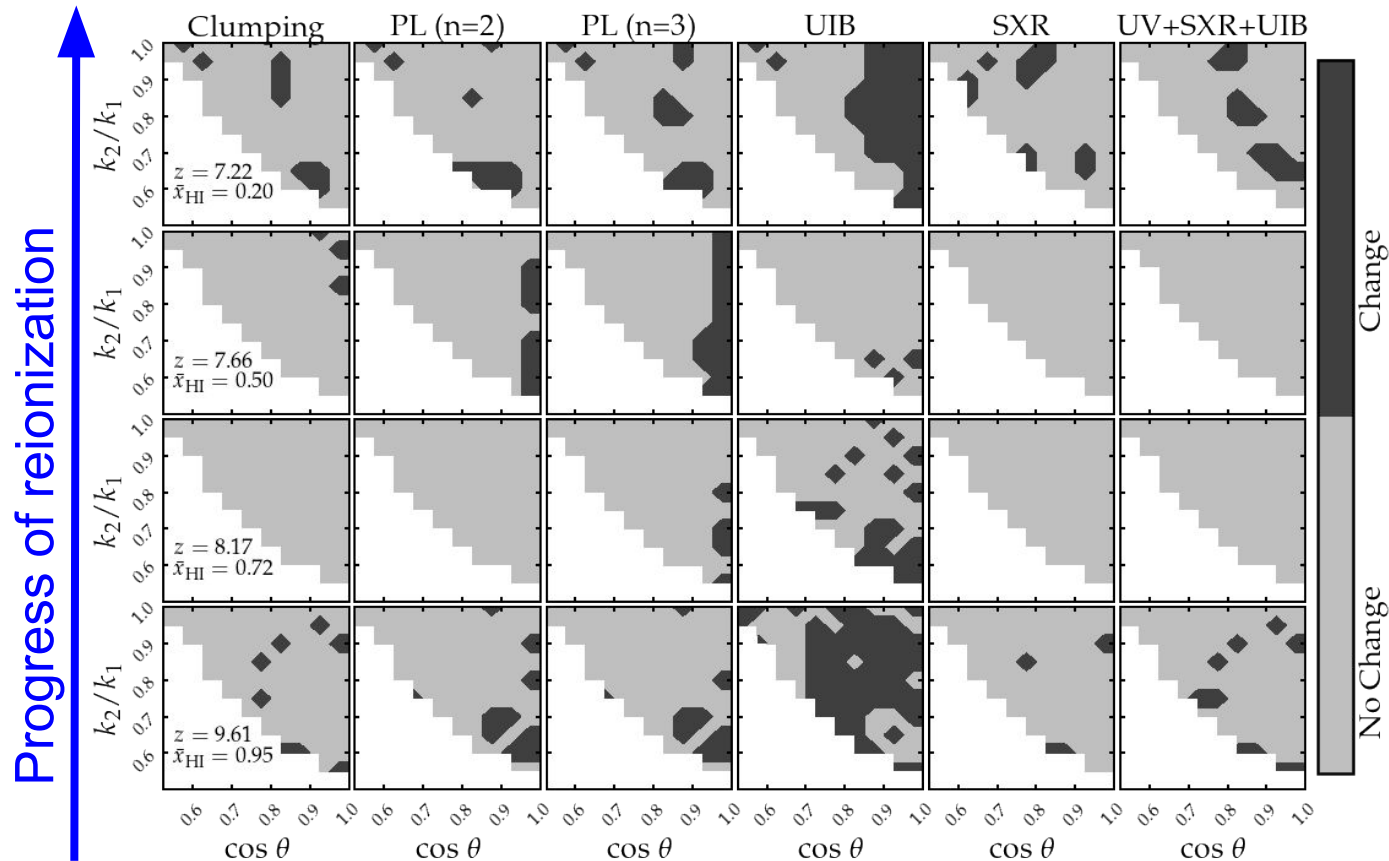
Magnitude differences in 21-cm bispectrum between different reionization scenarios w. r. t. Fiducial



Magnitude differences in 21-cm bispectrum between different reionization scenarios w. r. t. Fiducial

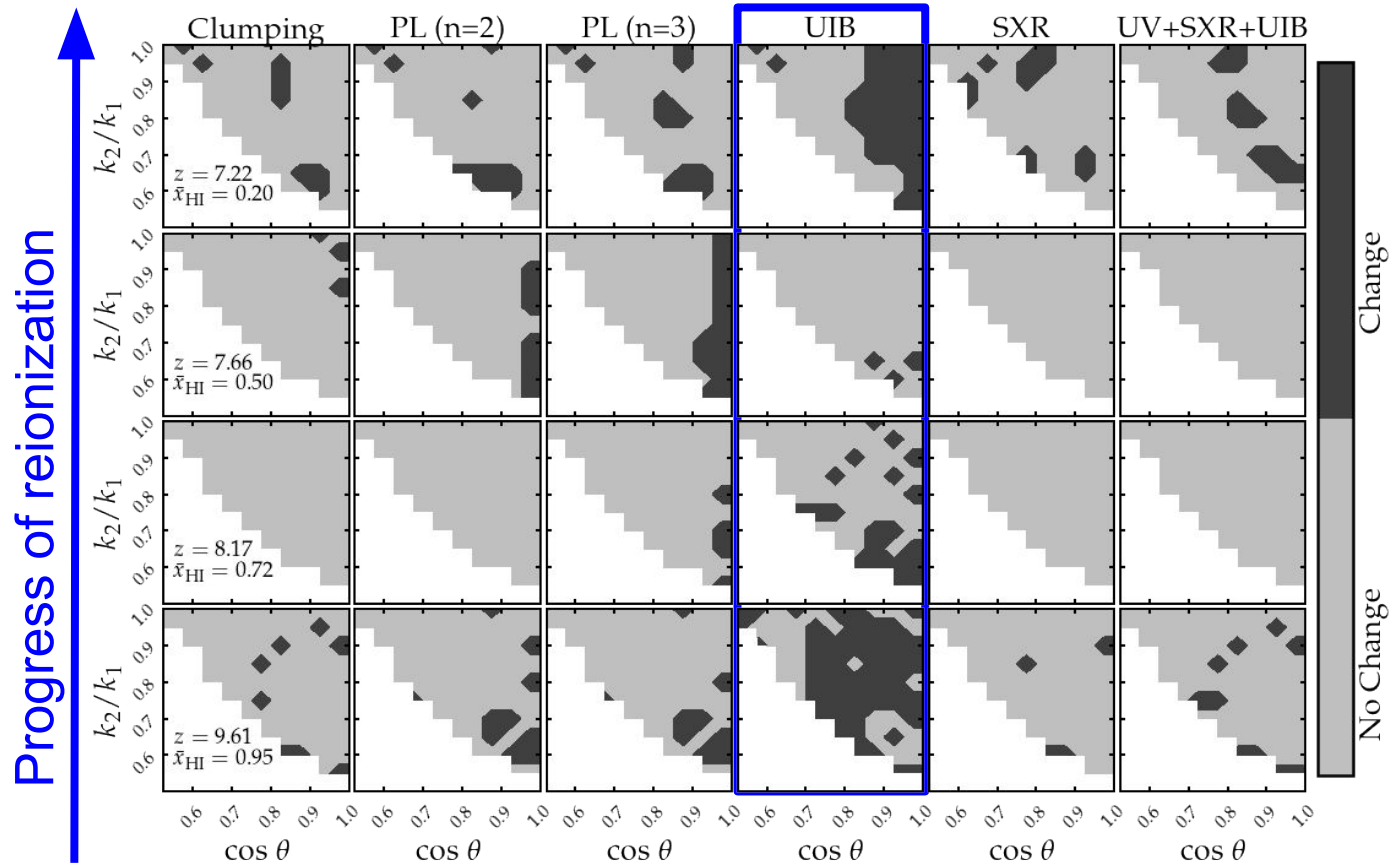


Sign differences in 21-cm bispectrum between different reionization scenarios w. r. t. Fiducial



Noble et al. 2024, arXiv: 2406.03118

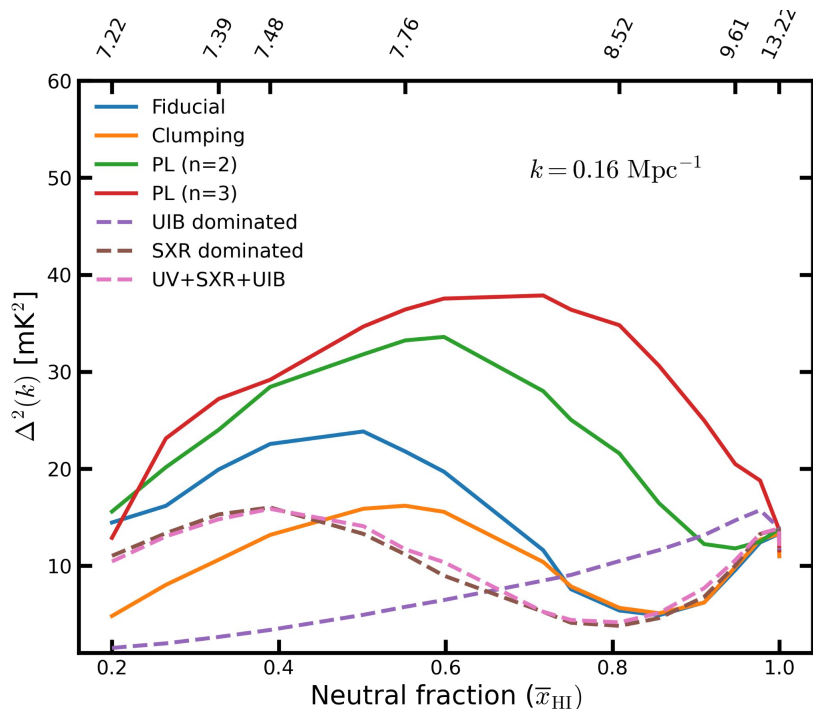
Sign differences in 21-cm bispectrum between different reionization scenarios w. r. t. Fiducial



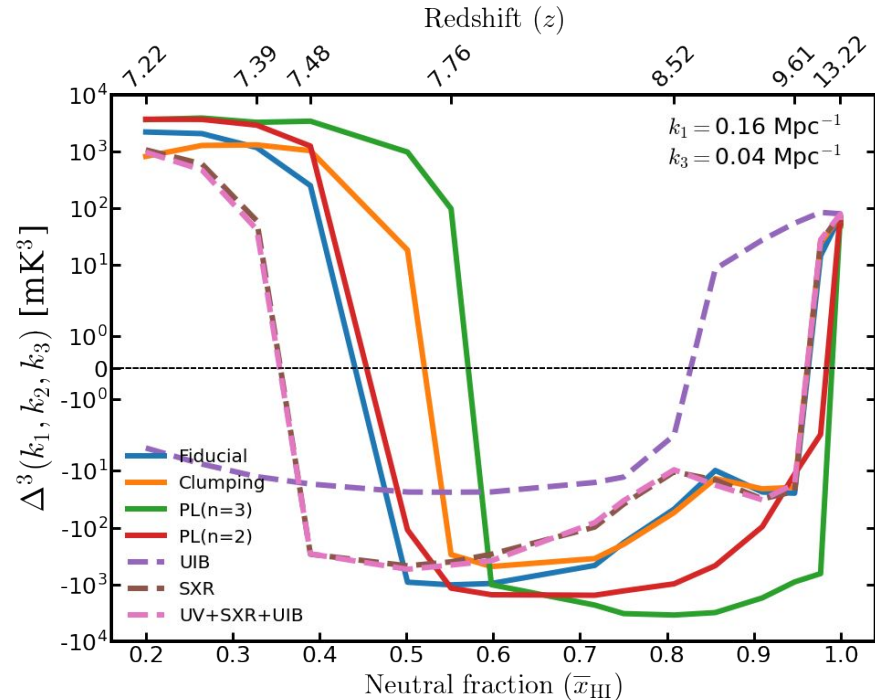
Change is highest
in UIB scenario

Noble et al. 2024, arXiv: 2406.03118

Power spectrum vs bispectrum

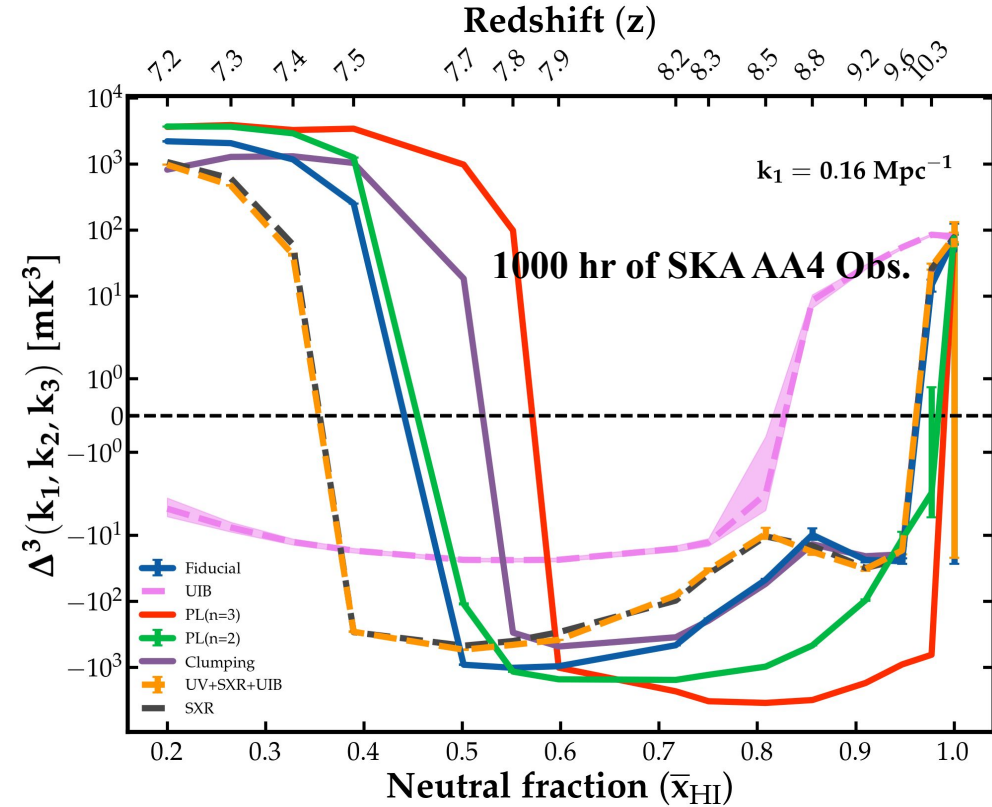


Majumdar et al. 2016, arXiv: 1509.07518



Noble, ..., SM, .. et al. 2024, arXiv: 2406.03118

Summary I



➤ **21-cm bispectrum can capture the time evolving non-Gaussianity in different reionization scenarios.**

➤ **It can distinguish between different reionization scenarios.**

➤ **It can distinguish reionization scenarios better than the 21-cm power spectrum thanks to its sign and sequence of sign changes.**

Forward

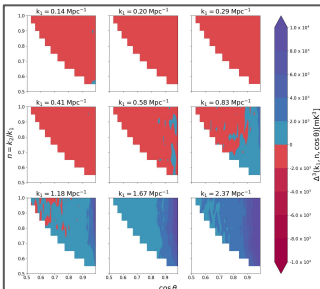
Forward Modeling of Signal Statistics

θ_m

~~Simulation~~

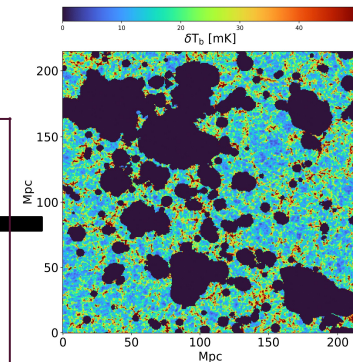
BNN-based Emulation

Bispectrum
 $B(k_1, k_2, k_3)$



Observation

$$D \equiv B_{obs}$$



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

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

Posterior

Bayesian Inference

Backward

Propose new parameters and repeat

GOAL:

Given a dataset: $\mathbf{D} = \{x_i, y_i\}$, we want a **complex, non-linear** parametric function (aka a Neural Net) $y \equiv f(x; \mathbf{w})$, which describes the \mathbf{D} best.

So, we want to know the network parameters (OR as we call them: “**Weights**”)

PROBLEM:

How to get \mathbf{w} s, so that the network output $y(x)$ is optimised for the input-output pairs of \mathbf{D} and make prediction .

Neural networks

- Complex arrangement of neurons
- Can “approximate” any function specially for **complex, non-linear** data
- Trained from data by Minimising the Loss function
 - With (form of) stochastic gradient descent
 - Efficient with “automatic differentiation”
 - And backpropagation

Fundamental Architecture of ANNs

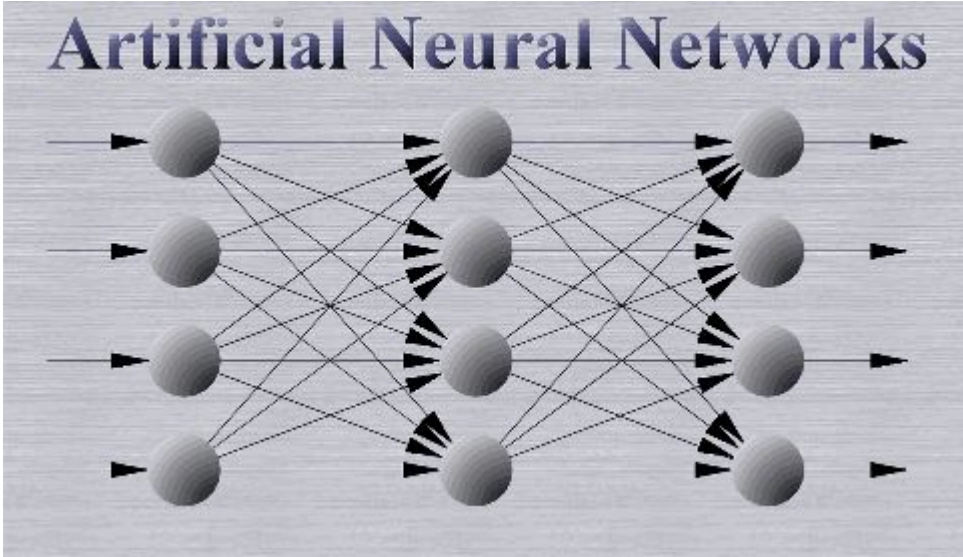
Input layer



Hidden layer(s)



Output layer

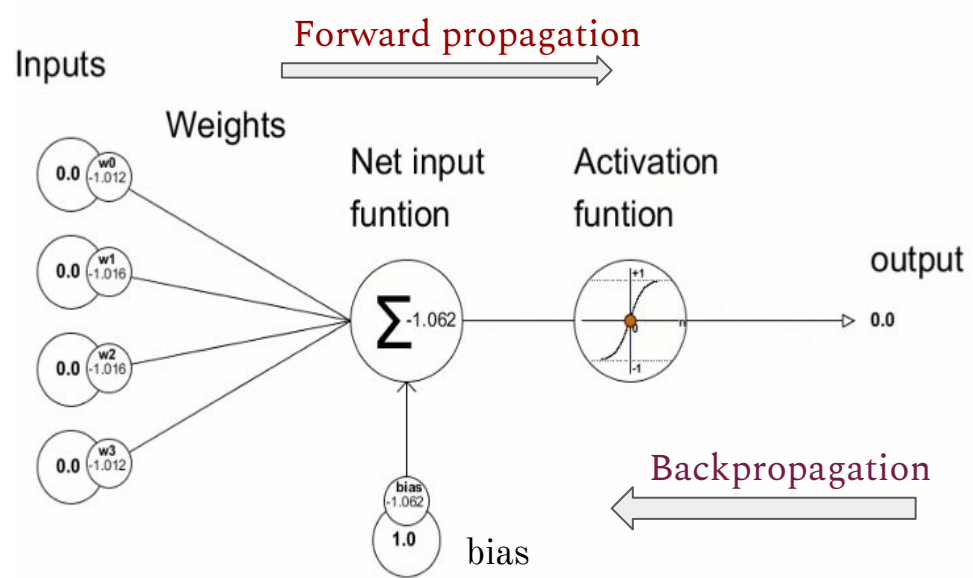


Single Neuron



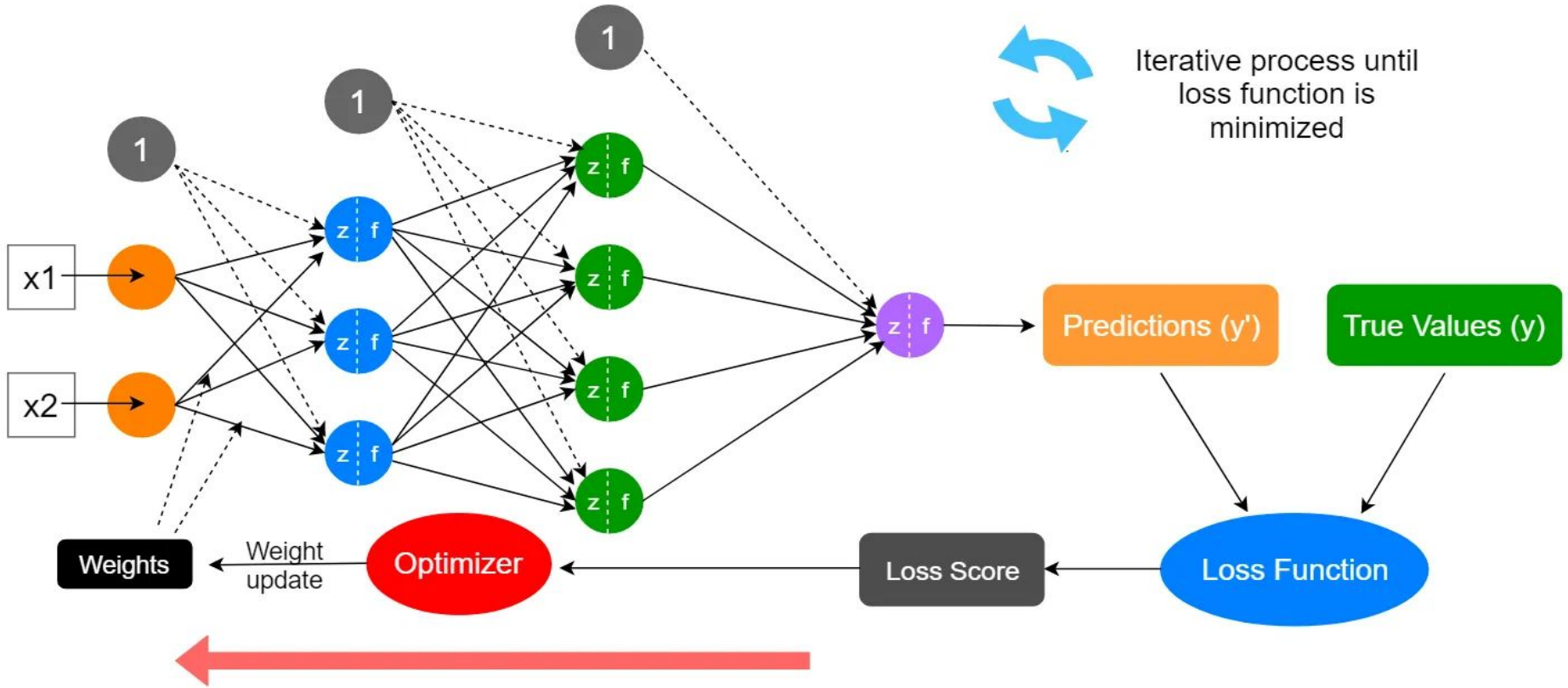
The fundamental unit of an ANN

This is how information flows through a neuron



Animation credit : [Prabhakar](#)

Forward Propagation



Backward Propagation



Backpropagation

➡ Propagation of errors in backward direction using Gradient Descent

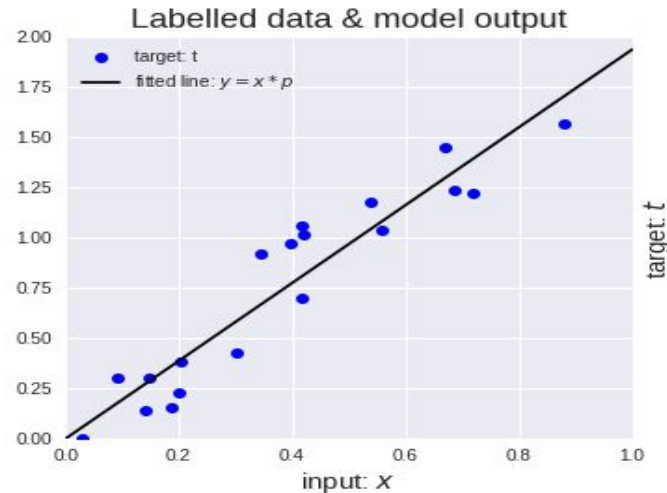
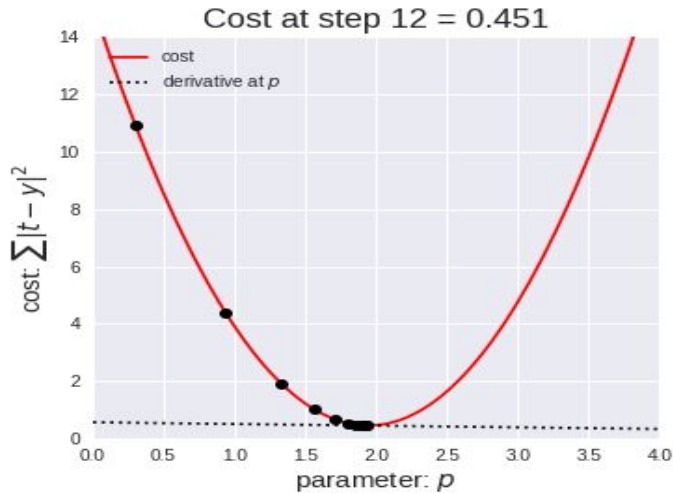
Loss/cost function

$$J = \frac{1}{m} \sum_{i=1}^m (y_{true}^{(i)} - y_{pred}^{(i)})^2$$

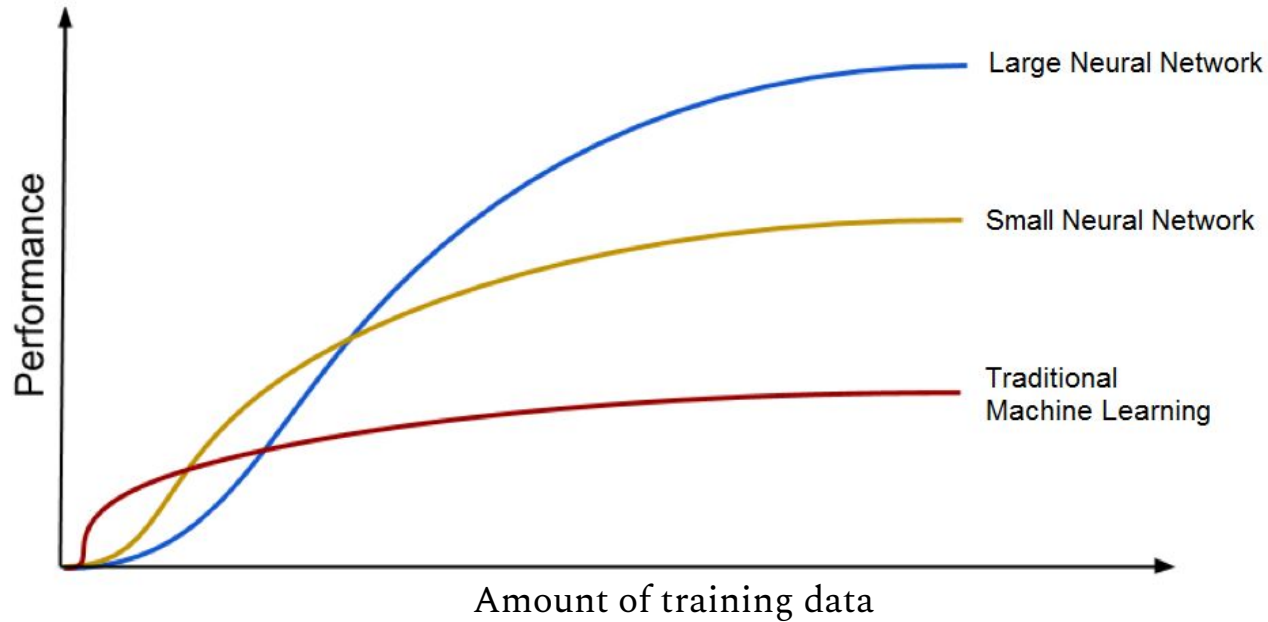
weight and bias updation during training

$$w_{t+1} = w_t - \alpha \frac{\partial J}{\partial w_t}$$

$$b_{t+1} = b_t - \alpha \frac{\partial J}{\partial b_t}$$



Performance of ANNs with amount of data



Deterministic neural network

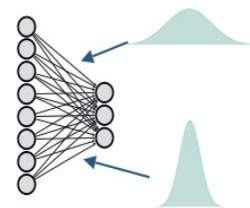
Bayesian neural network

Weights:

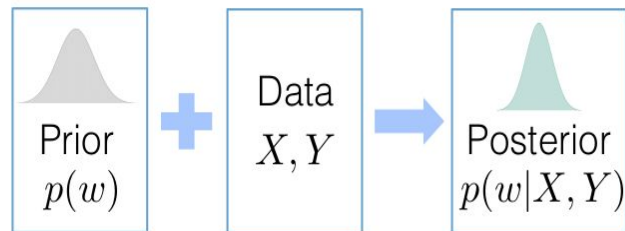
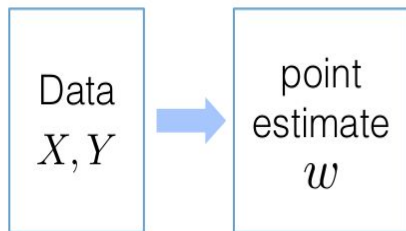
deterministic weights



stochastic weights



Training:



Prediction:

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

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



Prasad Rajesh Posture
MSc Astronomy IITI (2023-25)



Yashrajsinh Mahida
PhD IITI (2023-ongoing)



Sanjay Kumar Yadav
MSc Astronomy IITI (2022-24)

Collaborators: Suman Majumdar, Leon Noble, Chandra Shekhar Murmu, Saswata Dasgupta, Sohini Dutta, Himanshu Tiwari, Abinash Kumar Shaw

Generating 21-cm Bispectrum 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_{mfp} = The mean free path of the ionizing photons.

7203 parameter combinations, of which 80% for training 20% for validations

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

Ref: [Choudhury et al. 2009](#),
[Majumdar et al. 2014](#),
[Mondal et al. 2017](#),

Generating 21-cm Bispectrum Training Dataset

21-cm Brightness Temperature Map for given set of Parameters

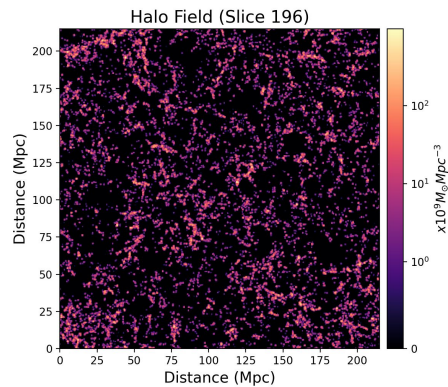
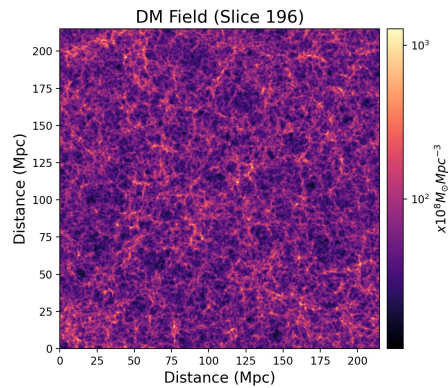


Large scale semi-numerical simulations for 21-cm LIM signals from EoR: ReionYuga.

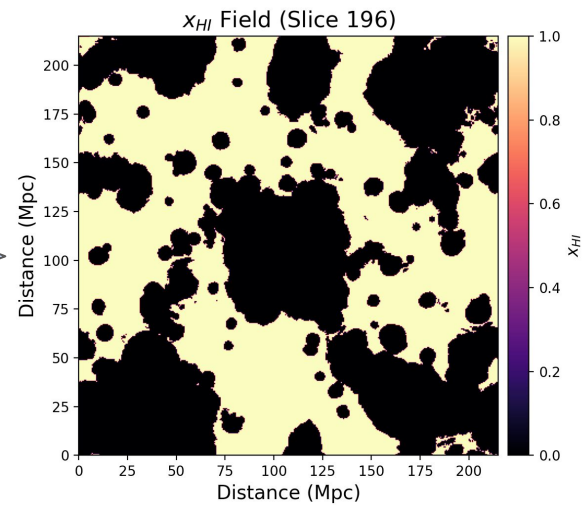
PM N-body dark matter field \rightarrow FoF halo field \rightarrow Excursion set formalism to identify cells as ionized or neutral, for a given set of reionization parameters \rightarrow convert it to brightness temperature maps.

7203 parameter combinations, of which 80% for training 20% for validations.

Reionization Simulation: <https://github.com/rajeshmondal18/ReionYuga>
[Choudhury et al. 2009](#), [Majumdar et al. 2014](#), [Mondal et al. 2017](#),



+ Reionization Parameters



Emulator Architectures and Performance

ANN Emulator Architecture

First Four k1 bins

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	

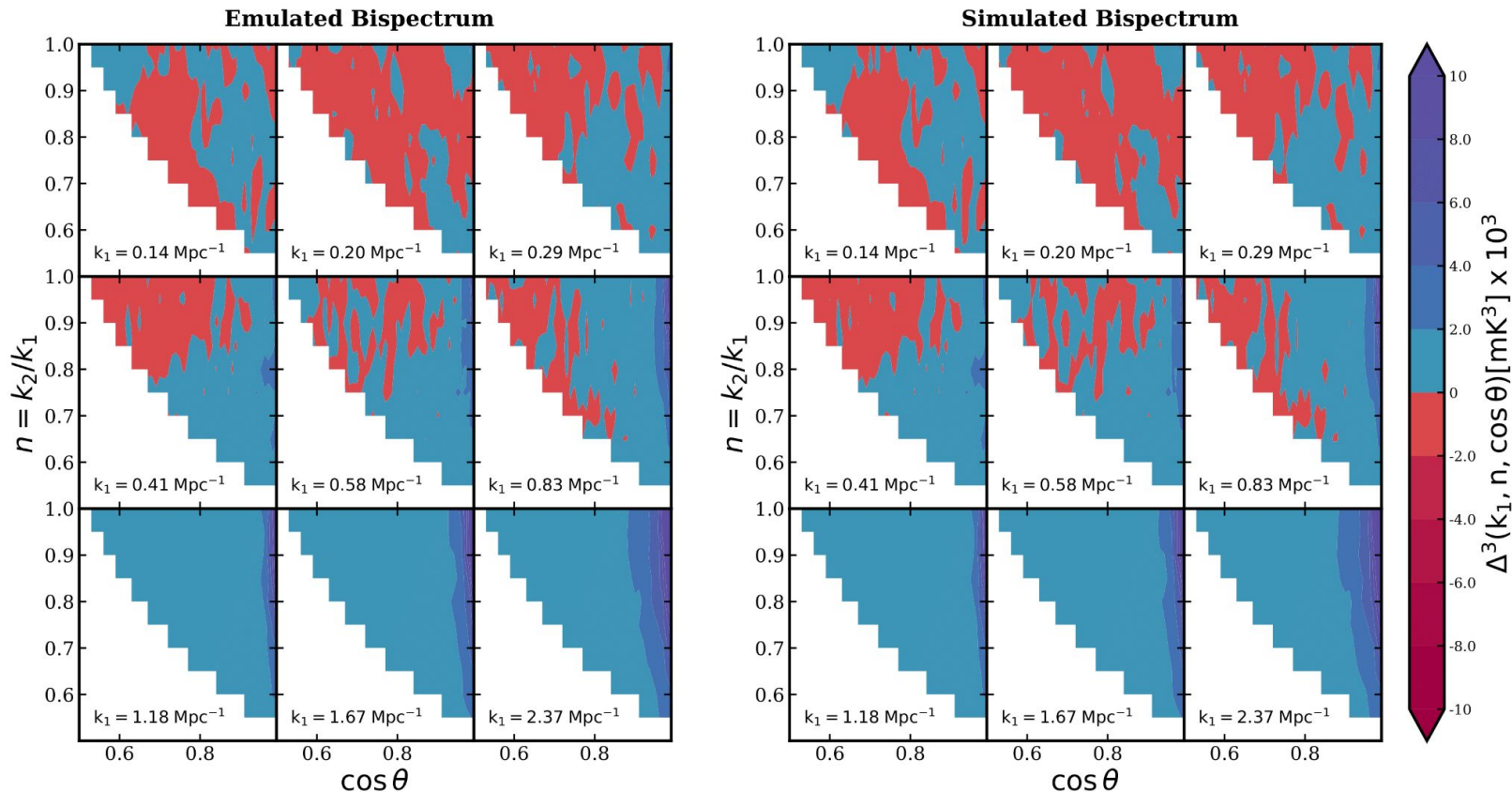
Remaining Five k1 bins

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	

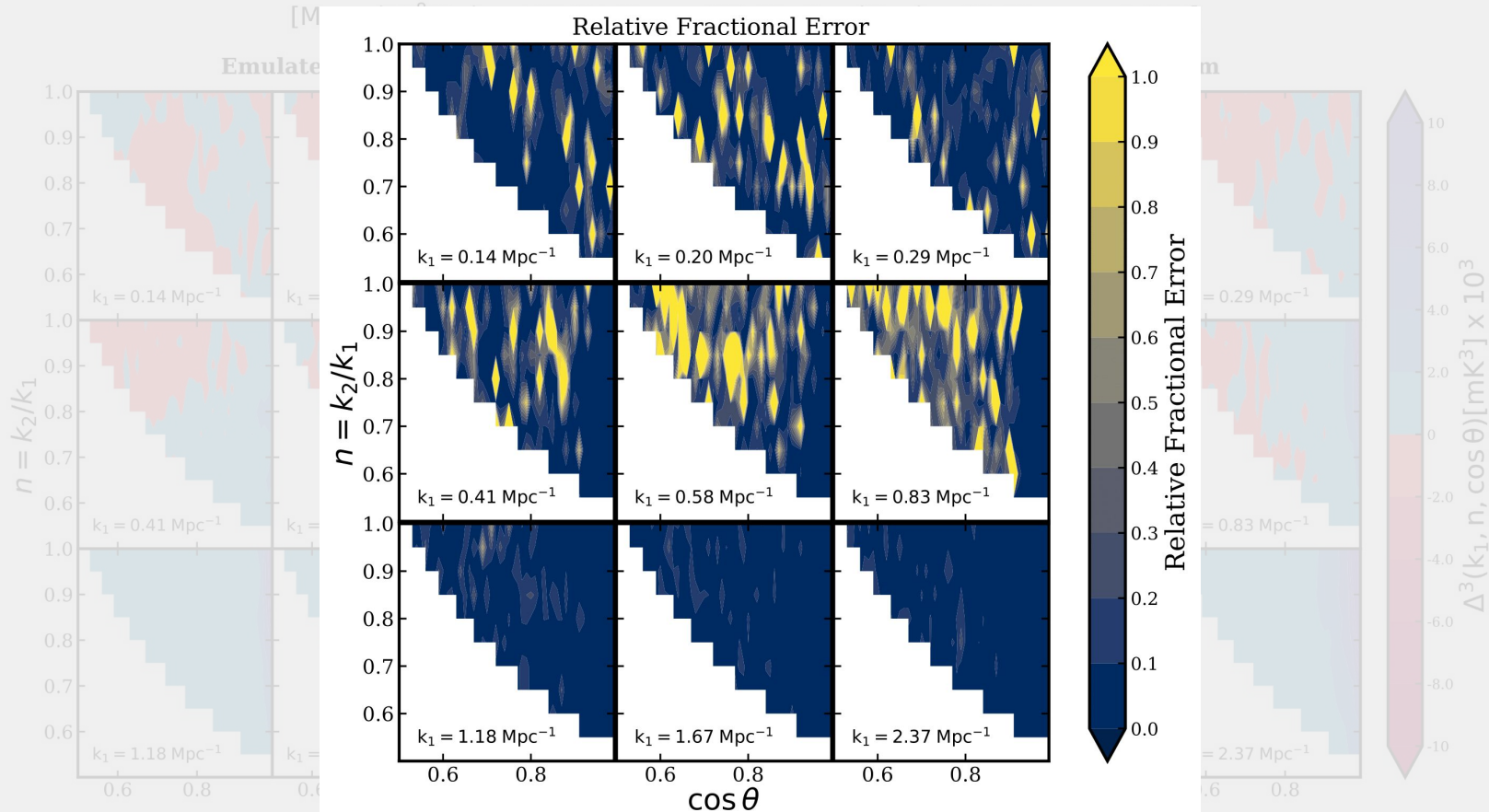
Loss Function = MSE (Mean Squared Error)

Bispectrum Prediction using ANN

$[M_{h,\min}(10^8 M_\odot) = 467.37, N_{\text{ion}} = 181.05, R_{\text{mfp}}(\text{Mpc}) = 12.65, x_{\text{HI}} = 0.377]$



Bispectrum Prediction using ANN



BNN Emulator Architecture

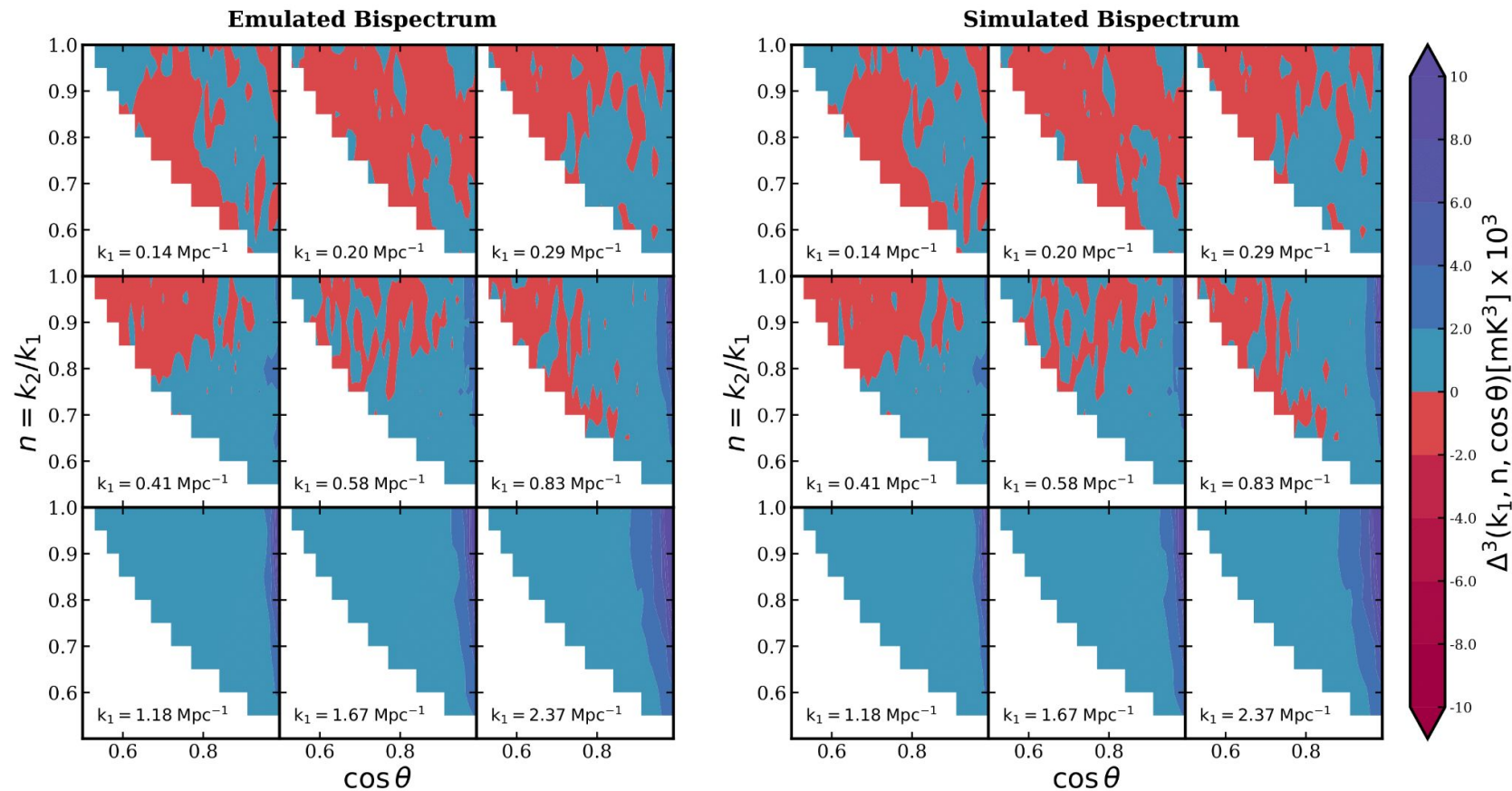
For All k1 bins

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	

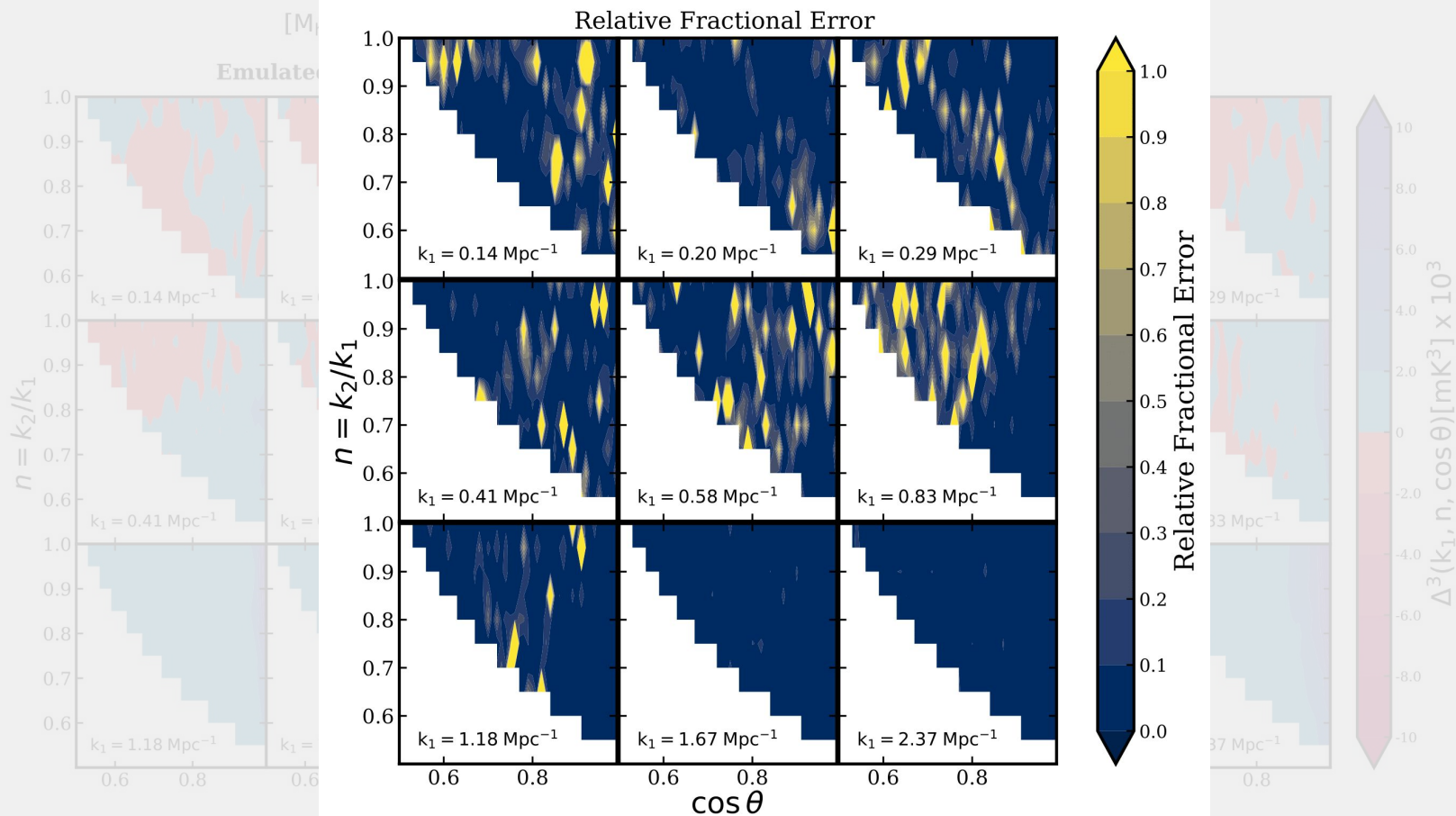
- Prior distribution of weights & biases
⇒ Gaussian
- Likelihood function ⇒
Multivariate Gaussian

Bispectrum Prediction using BNN

$[M_{h, \min}(10^8 M_{\odot}) = 467.37, N_{\text{ion}} = 181.05, R_{\text{mfp}}(\text{Mpc}) = 12.65, x_{\text{HI}} = 0.377]$

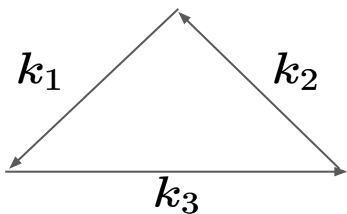


Bispectrum Prediction using BNN



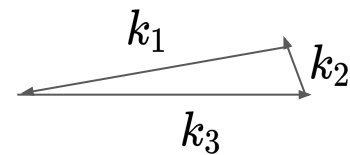
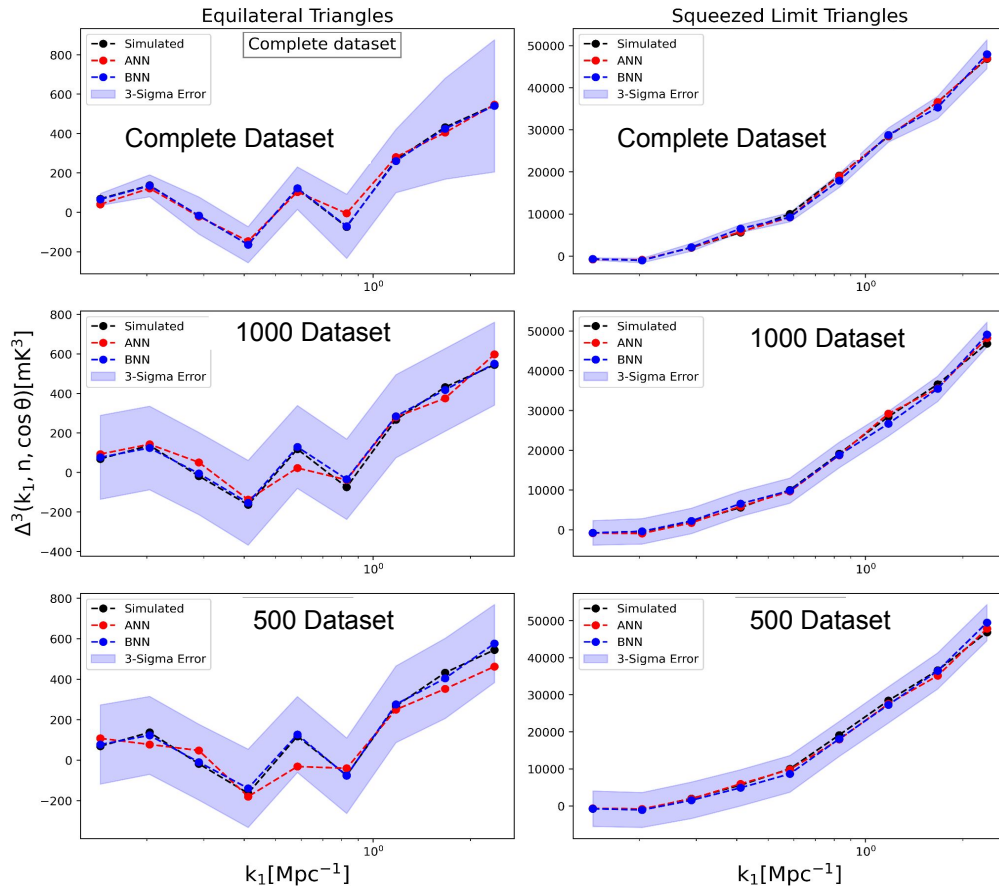
Prediction Comparison

$[M_{h, \min}(10^8 M_{\odot}) = 467.37, N_{\text{ion}} = 181.05, R_{\text{mfp}}(\text{Mpc}) = 12.65, x_{\text{HI}} = 0.377]$



Equilateral

$$|k_1| = |k_2| = |k_3|$$

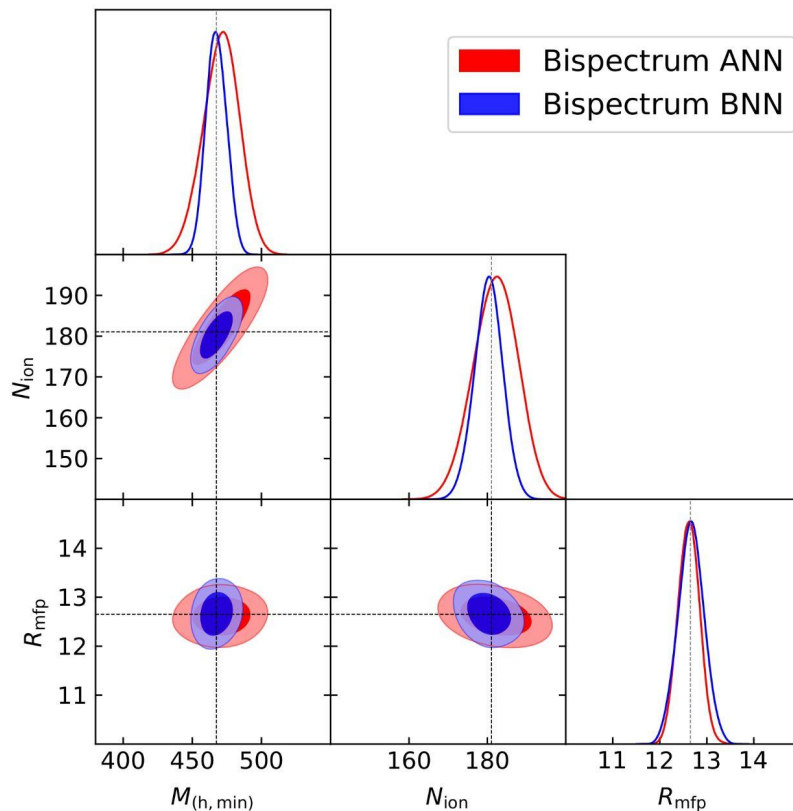


**Squeezed
Limit**

$$|k_1| \approx |k_3|, |k_2| \rightarrow 0$$

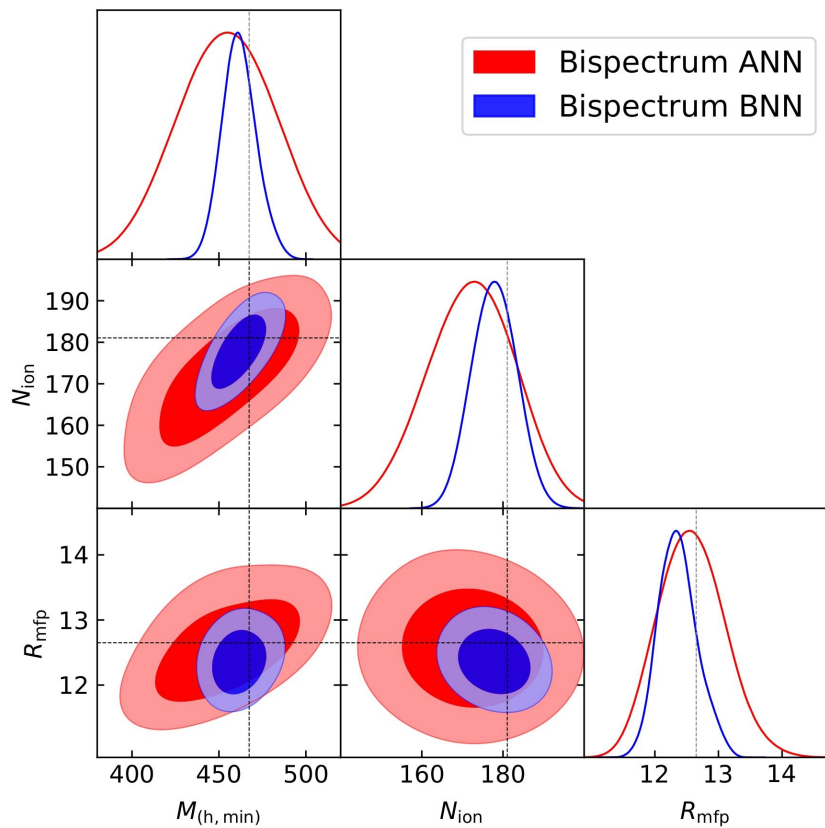
Parameter Estimation: (ANN vs BNN)

$[M_{h, \min}(10^8 M_{\odot}) = 467.37, N_{\text{ion}} = 181.05, R_{\text{mfp}}(\text{Mpc}) = 12.65, \bar{x}_{\text{HI}} = 0.377]$

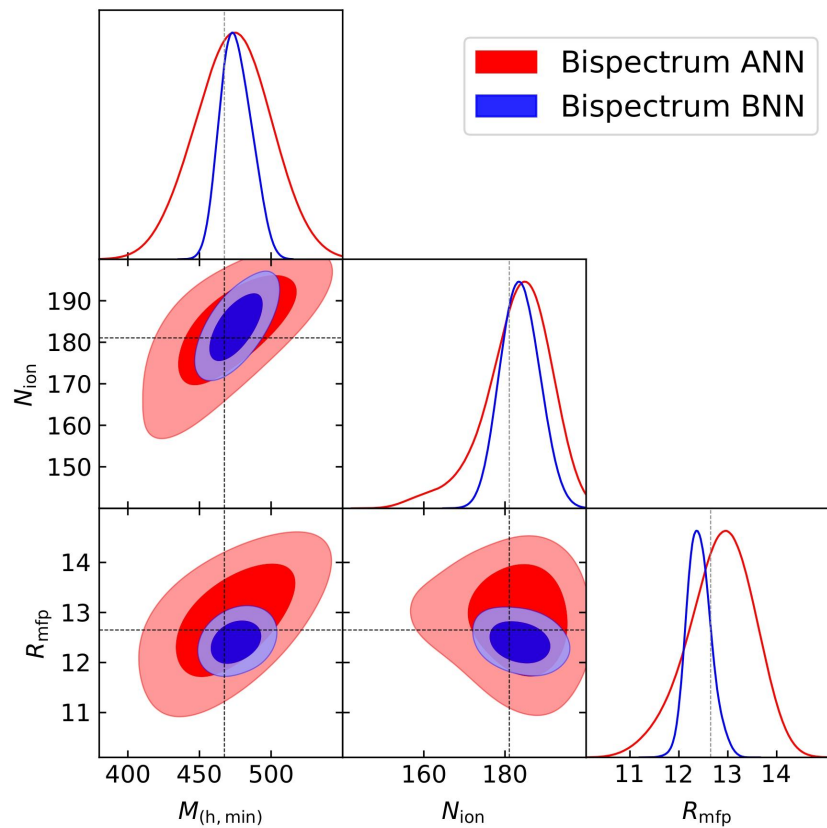


Parameter Estimation: (ANN vs BNN)

1000 dataset

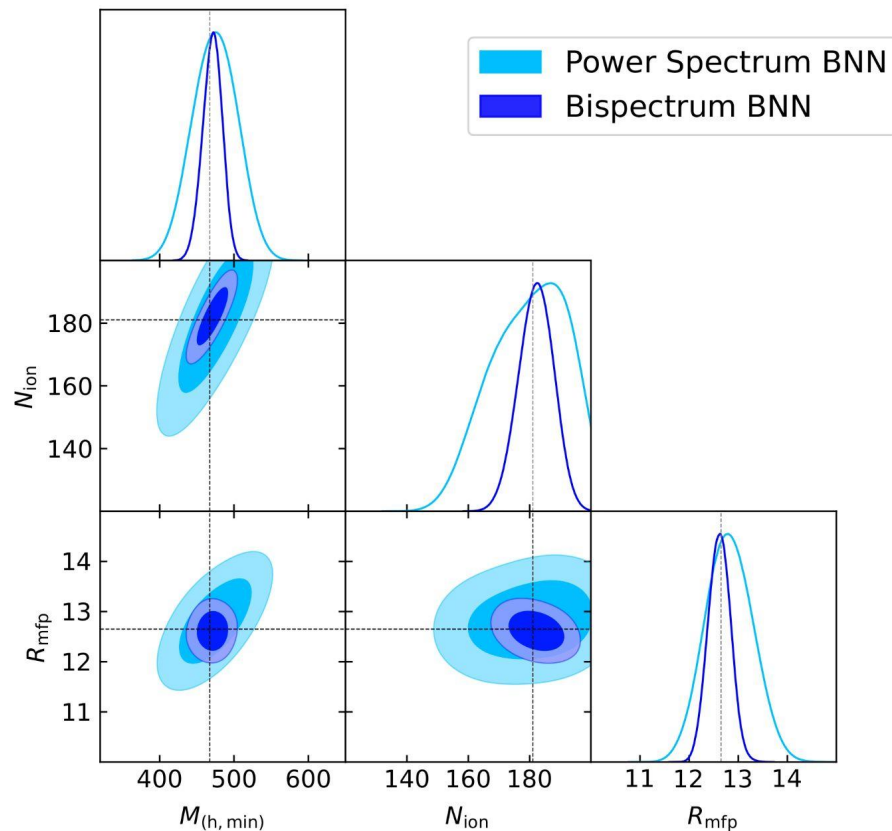


500 dataset



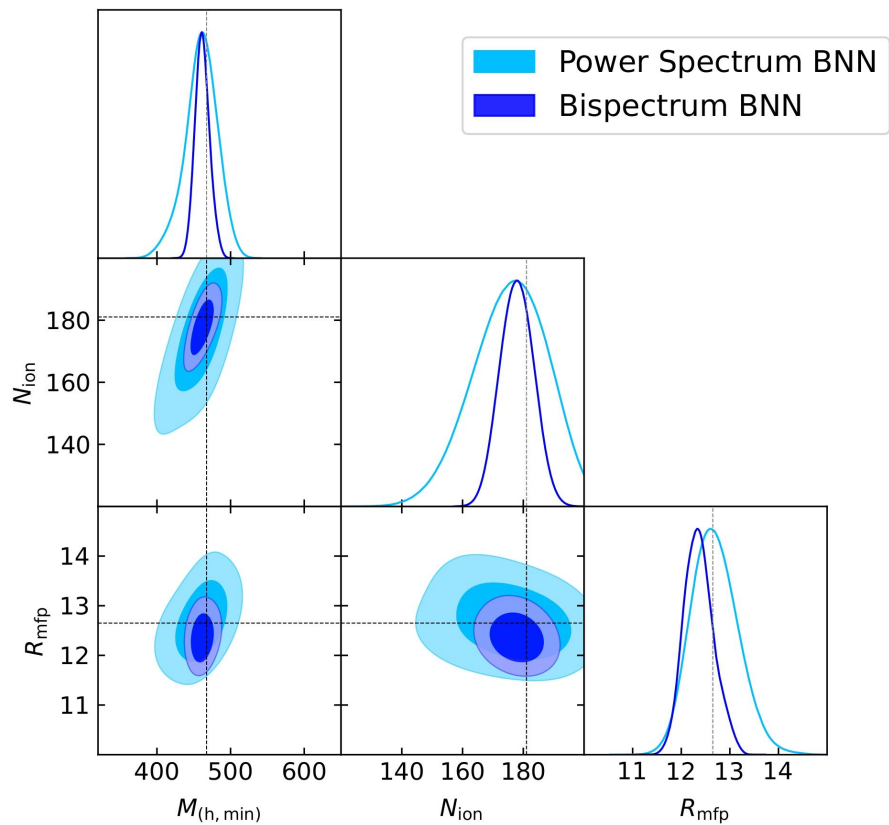
Parameter Estimation: (Power spectrum vs Bispectrum)

$[M_{h, \min}(10^8 M_{\odot}) = 467.37, N_{\text{ion}} = 181.05, R_{\text{mfp}}(\text{Mpc}) = 12.65, \bar{x}_{\text{HI}} = 0.377]$

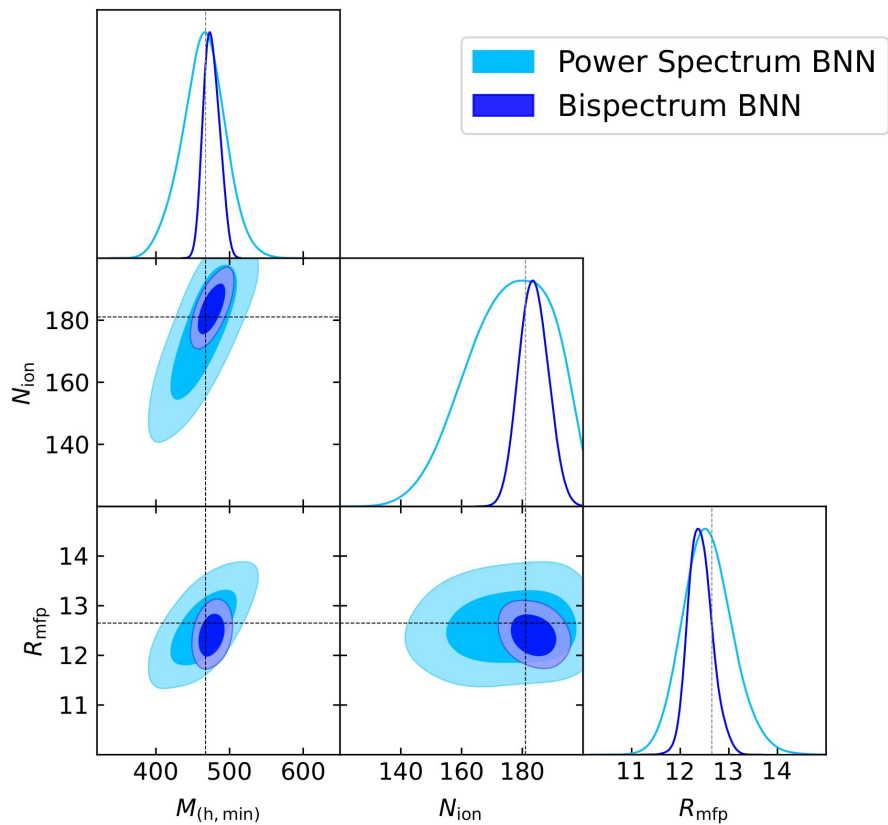


Parameter Estimation: (Power spectrum vs Bispectrum)

1000 dataset

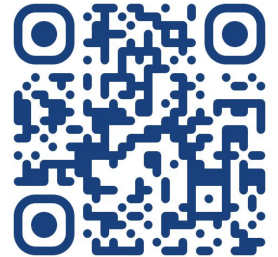


500 dataset



From ANN to BNN: Inferring reionization parameters using uncertainty-aware emulators of 21-cm summaries

Authors: Yashrajsinh Mahida, Sanjay Kumar Yadav, Suman Majumdar, Leon Noble, Chandra Shekhar Murmu, Saswata Dasgupta, Sohini Dutta, Himanshu Tiwari, Abinash Kumar Shaw



Summary: II

- 21-cm signal is highly non-Gaussian. So, **we use bispectrum** for the parameter estimation
- **ANNs** provide only point value prediction. They **cannot quantify the uncertainties** in their prediction.
- We use **BNNs**, which provide the posterior distribution of predicted signal. They **are better at quantifying the model uncertainty**.
- We show that **BNNs give better and robust estimation** of the EoR 21-cm bispectrum compared to ANNs.

However

- Even Higher-order statistics (e.g. Bispectrum) cannot describe the non-Gaussian EoR 21-cm field completely. It does not contain the phase information.
- We need all N-point statistics to fully describe the field.

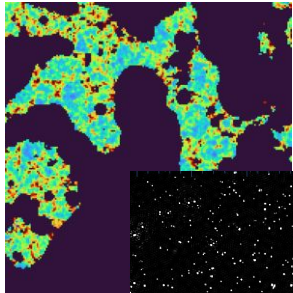
We can use the observable Fields directly



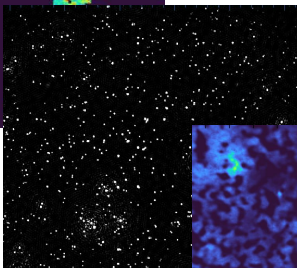
Towards Field-Level Inference of Reionization Parameters

Challenges

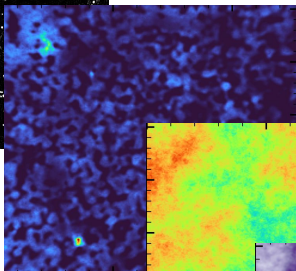
21-cm Signal



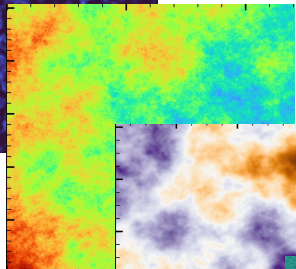
Extragalactic Foregrounds



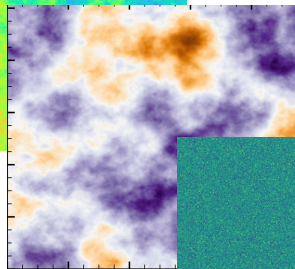
Free-Free Emission



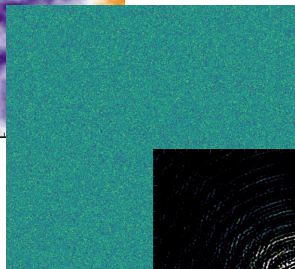
Synchrotron Emission



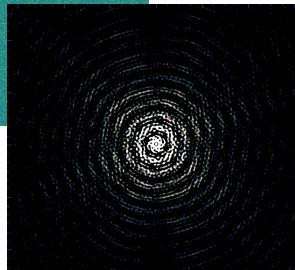
Ionosphere



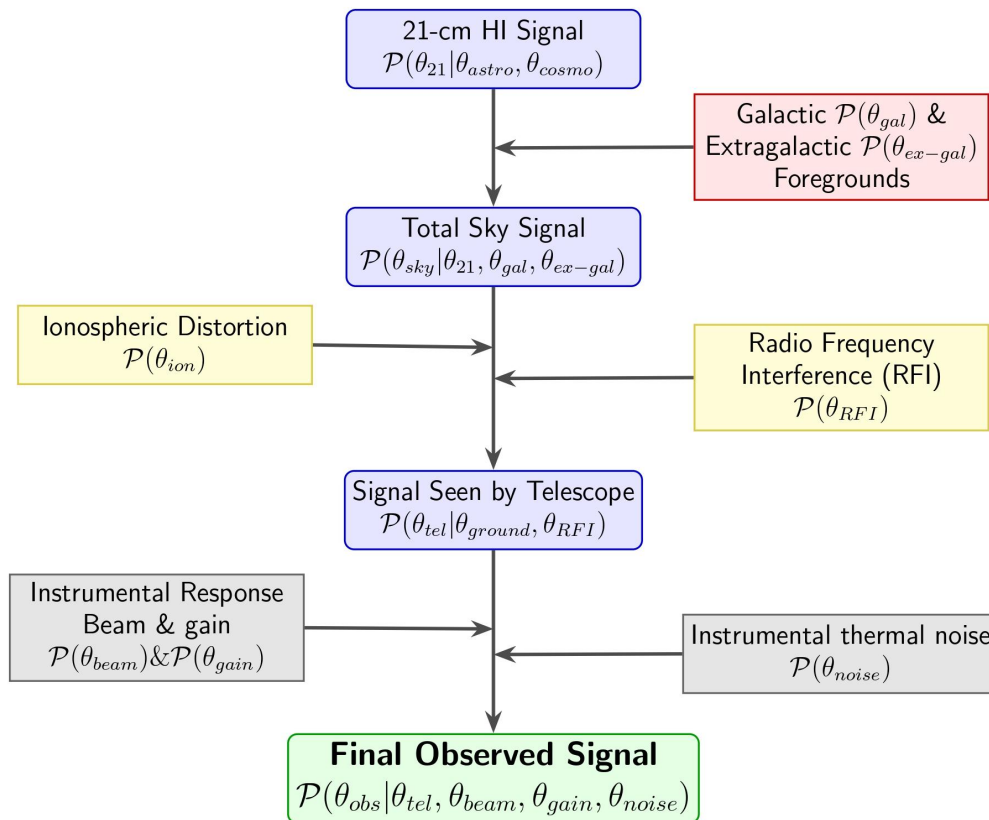
Instrument noise

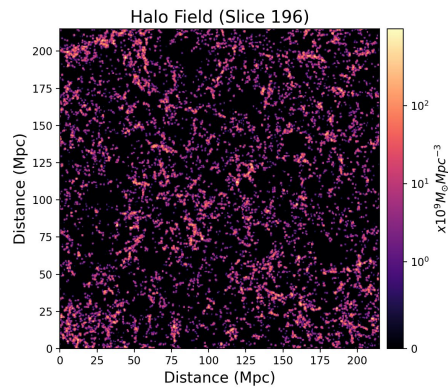
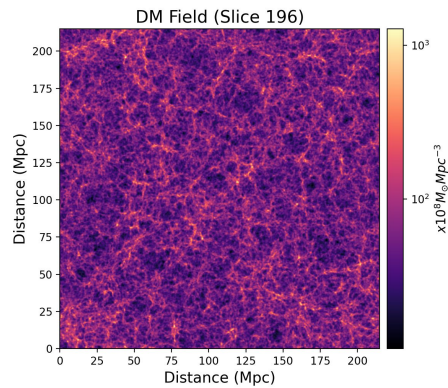


Instrument beam

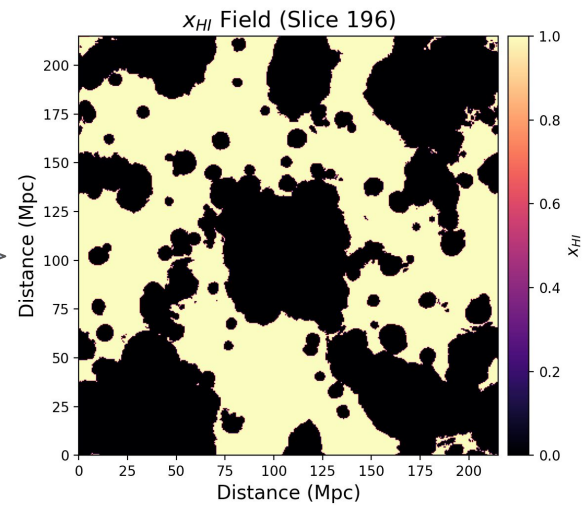


Hierarchical Forward Modeling of Signal





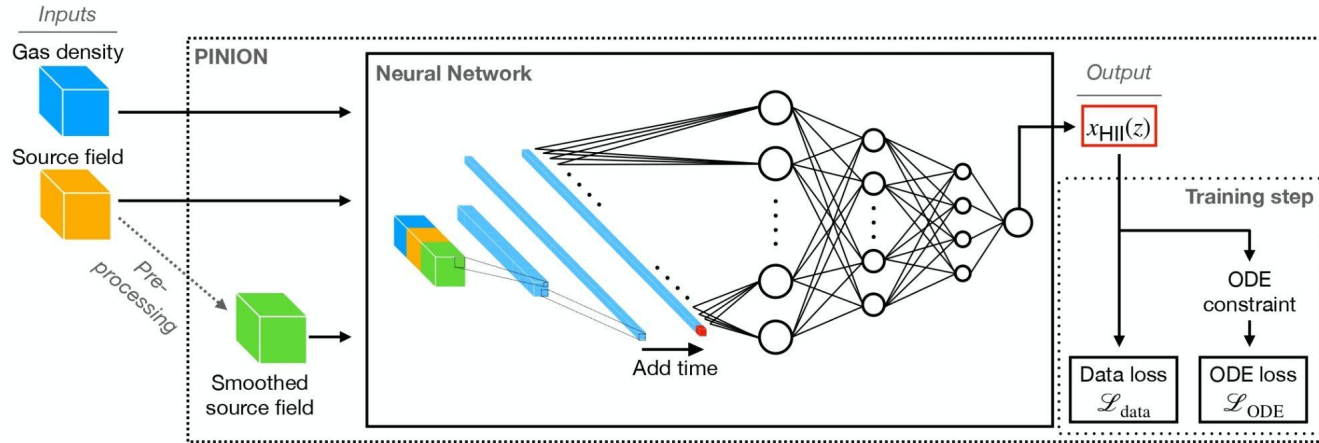
+ Reionization Parameters



Previous Field Emulation Efforts

Use of CNN for Emulation & Its Drawbacks

PINION Architecture



Korber et al., 2023, MNRAS, 521(1), [arxiv:2208.13803](https://arxiv.org/abs/2208.13803)

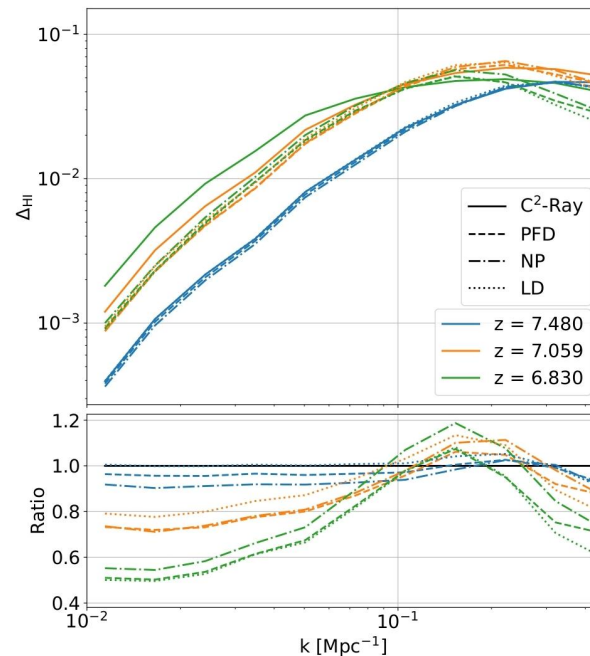
$$\lambda_{\nu\text{HI}}(z) \approx \frac{c}{H(z)} \times 0.1 \left(\frac{1+z}{4} \right)^{-2.55}$$

Choudhury et al., 2009, arXiv, [arxiv:0904.4596](https://arxiv.org/abs/0904.4596)

Use of CNN for Emulation & Its Drawbacks

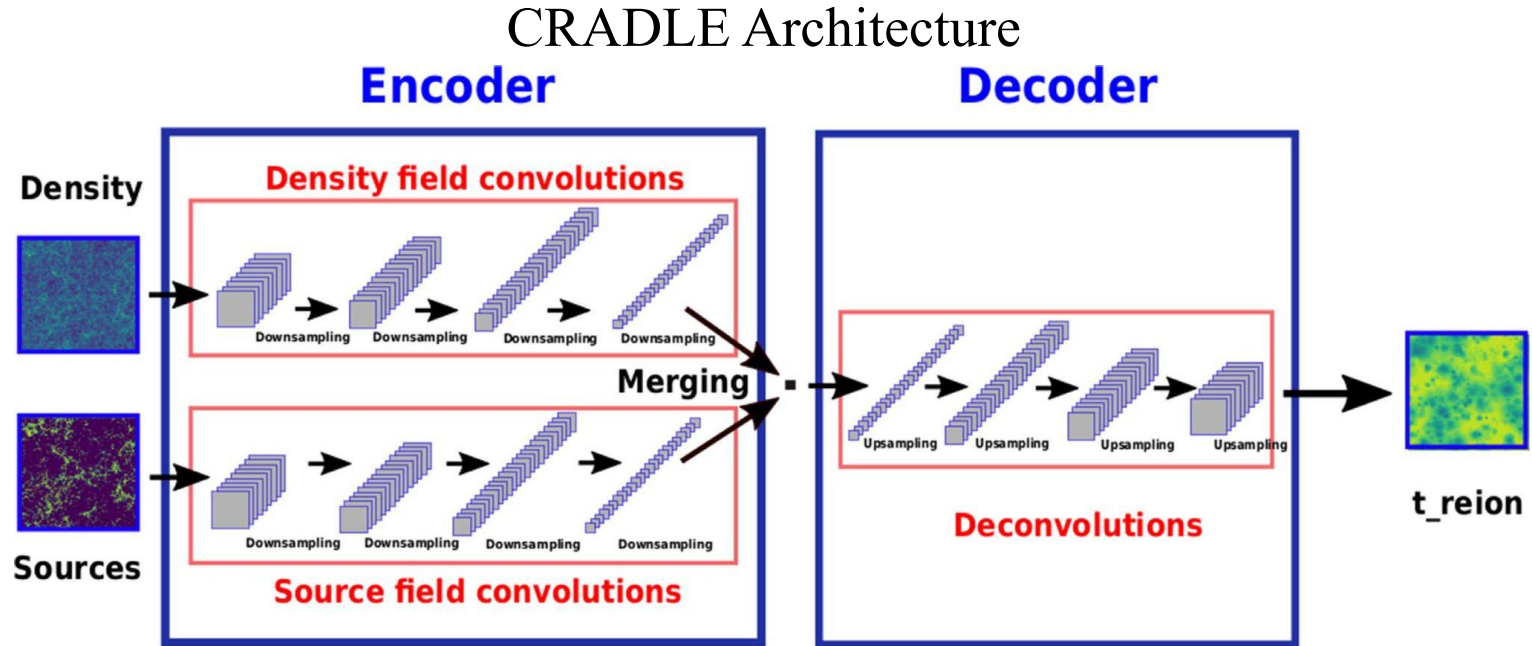
Drawbacks of PINION

- ❖ An arbitrary smoothing of the input fields have been done which is not well motivated.
- ❖ Takes subvolume of size 7^3 instead of entire cube to predict the ionized fraction on a single grid point.
- ❖ Underpredicts the large scale variations of the signal at the late stages of the EoR.



Korber et al., 2023, MNRAS, 521(1),
[arxiv:2208.13803](https://arxiv.org/abs/2208.13803)

Use of CNN for Emulation & Its Drawbacks

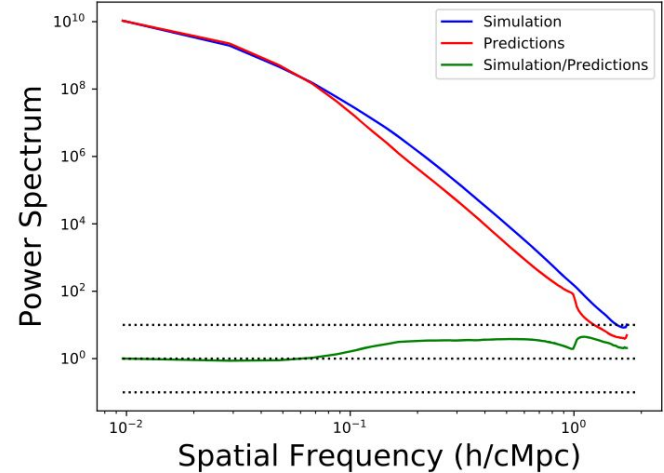


Chardin et al., 2019, MNRAS, 490(1), [arxiv:2110.08037](https://arxiv.org/abs/2110.08037)

Use of CNN for Emulation & Its Drawbacks

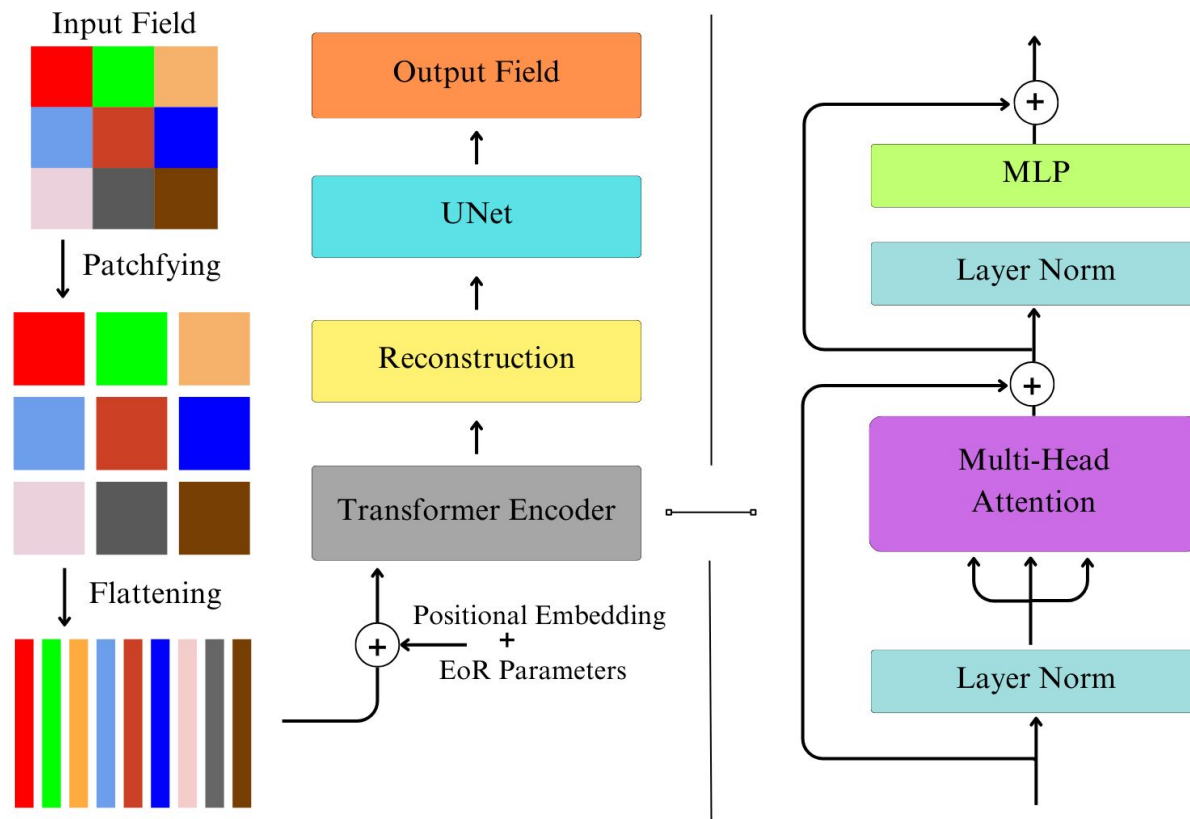
Drawbacks of CRADLE

- ❖ 3D cube is broken into 2D slices which are treated as independent inputs.
- ❖ Influence of sources across the slices are not considered.
- ❖ Smoothing with Gaussian kernel of size 3.75 cMpch^{-1} is done.
- ❖ Underpredicts small scale variations due to smoothing of inputs.



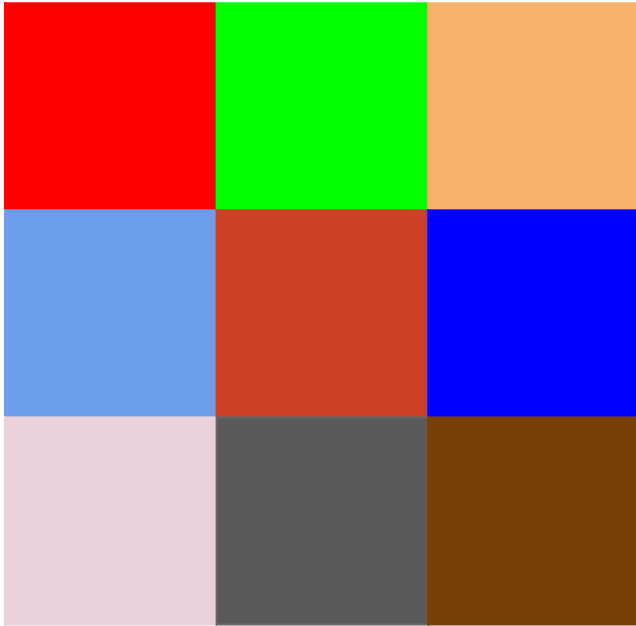
Chardin et al., 2019, MNRAS, 490(1),
[arxiv:2110.08037](https://arxiv.org/abs/2110.08037)

UNet integrated Vision Transformer (CosmoUiT)

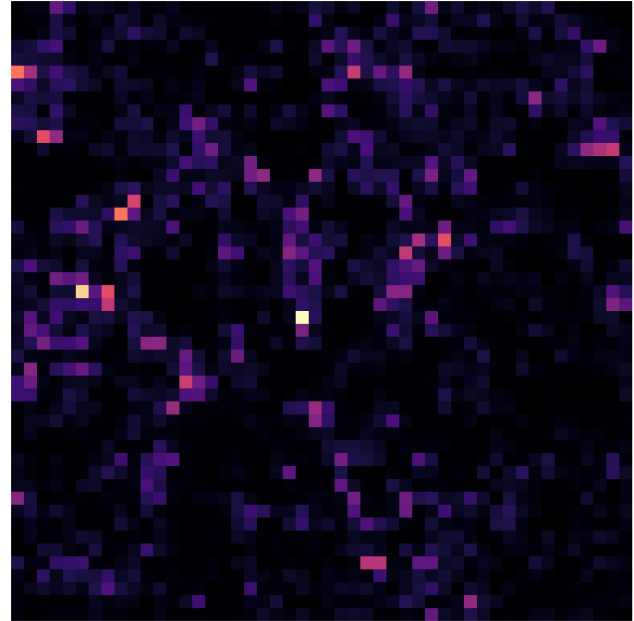


Input Field

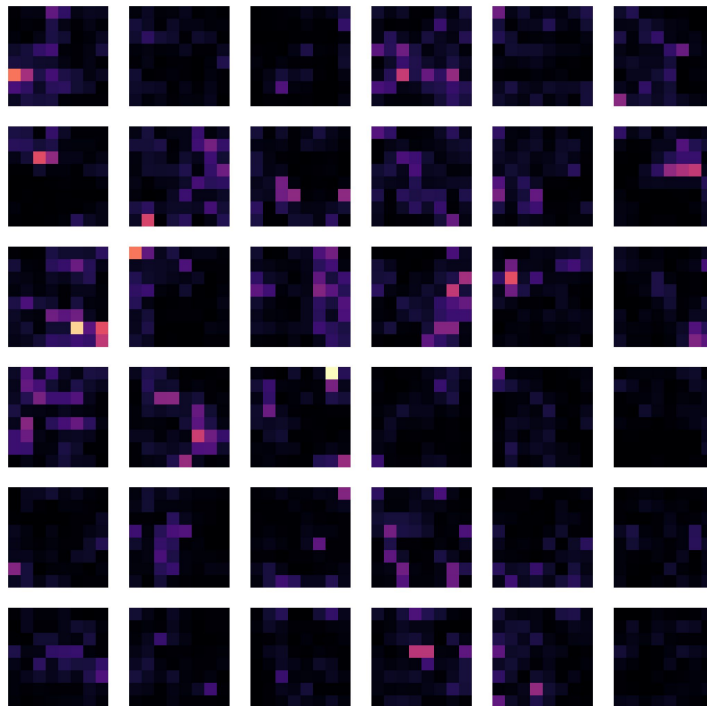
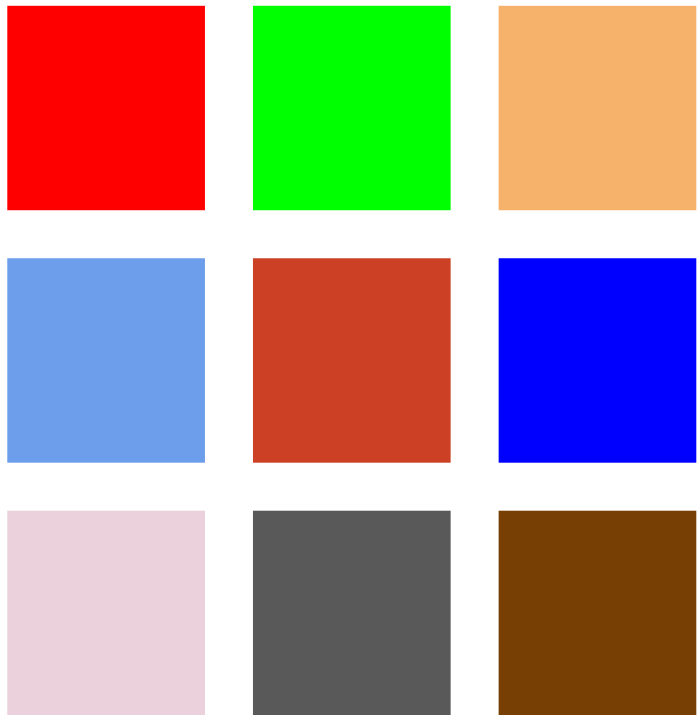
Toy Field



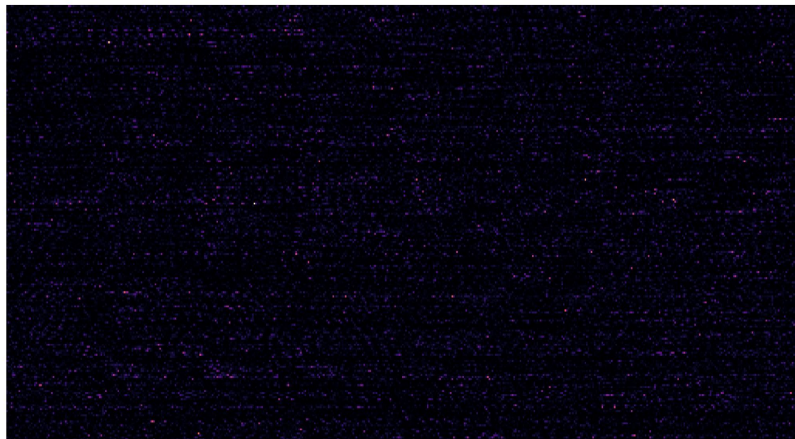
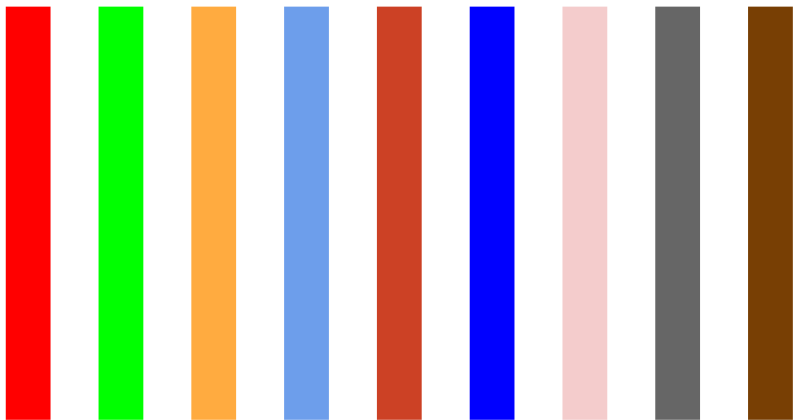
Halo Field



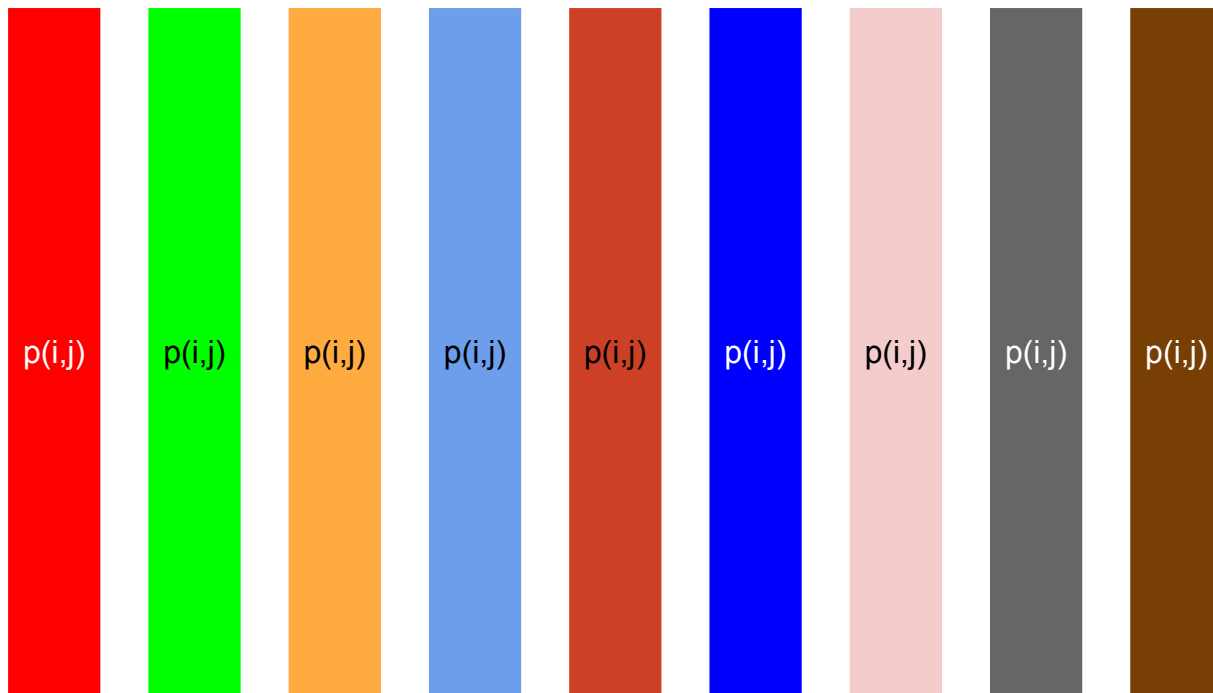
Patchfying



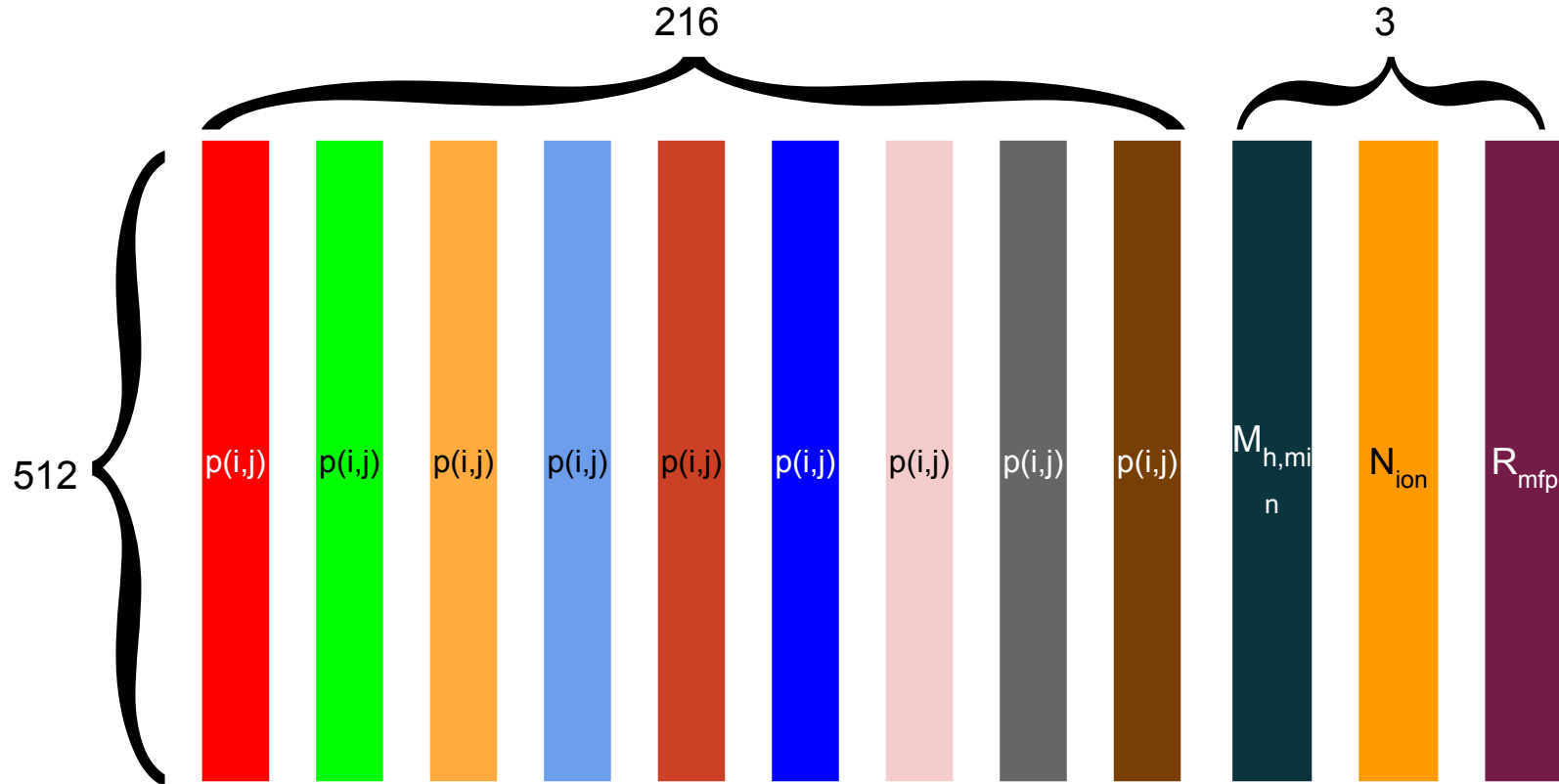
Flattening



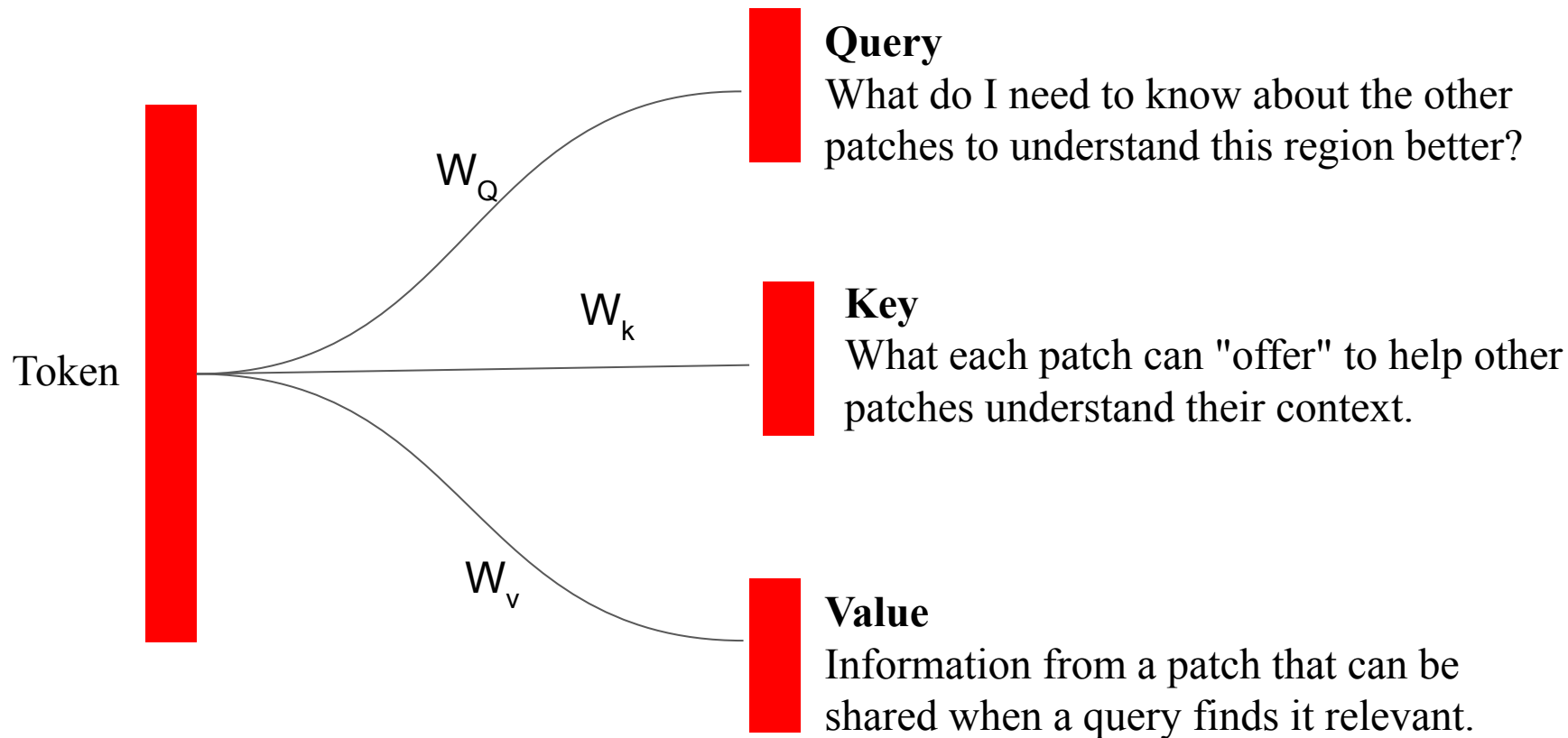
Positional Embedding



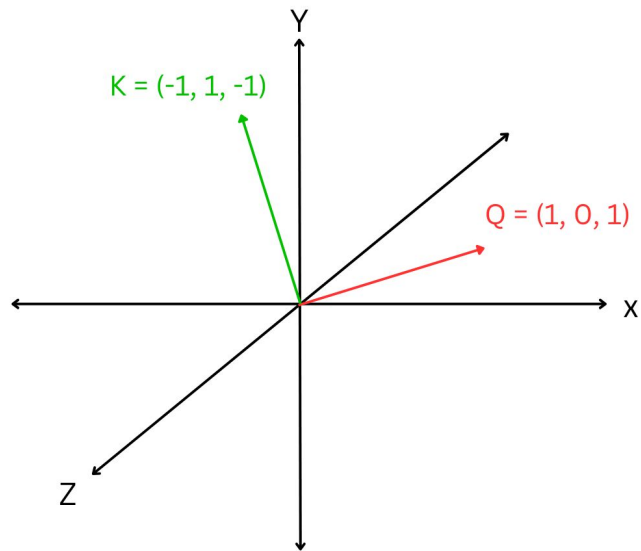
Integrating EoR Parameters



Query, Key and Value through Linear Projection

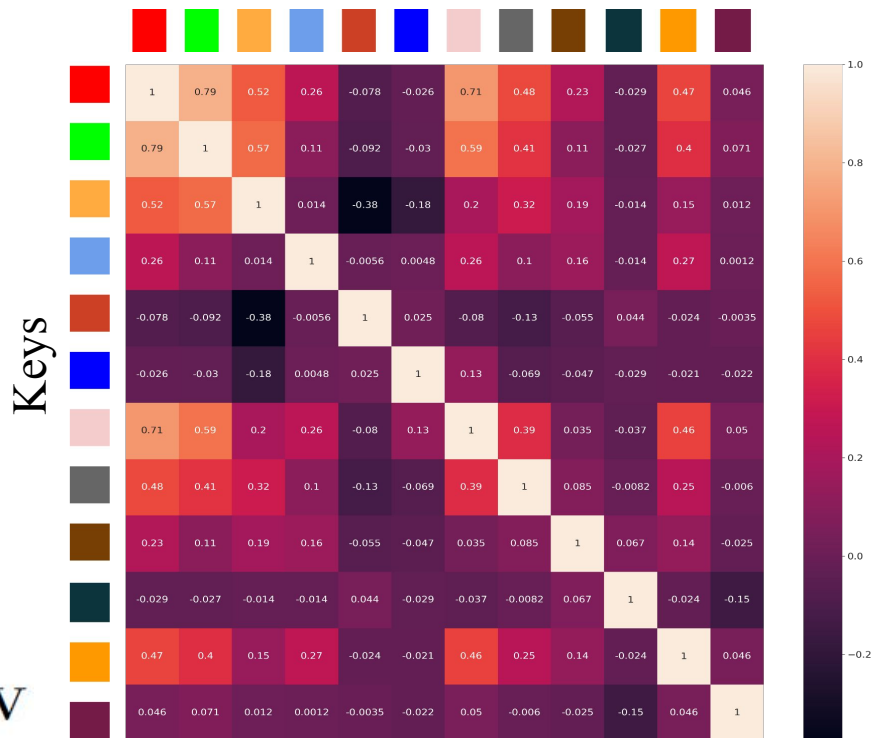


Attention Score

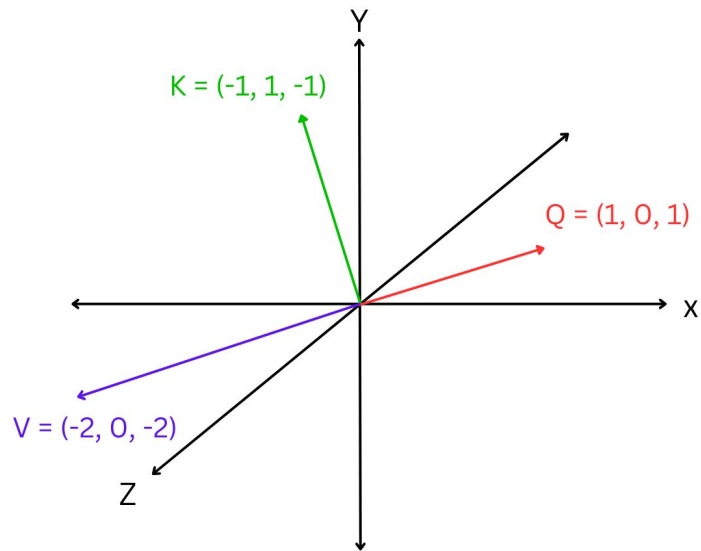


$$\text{Attention}(Q, K, V) = \text{softmax} \left(\frac{QK^T}{\sqrt{D_H}} \right) V$$

Dot Product Queries



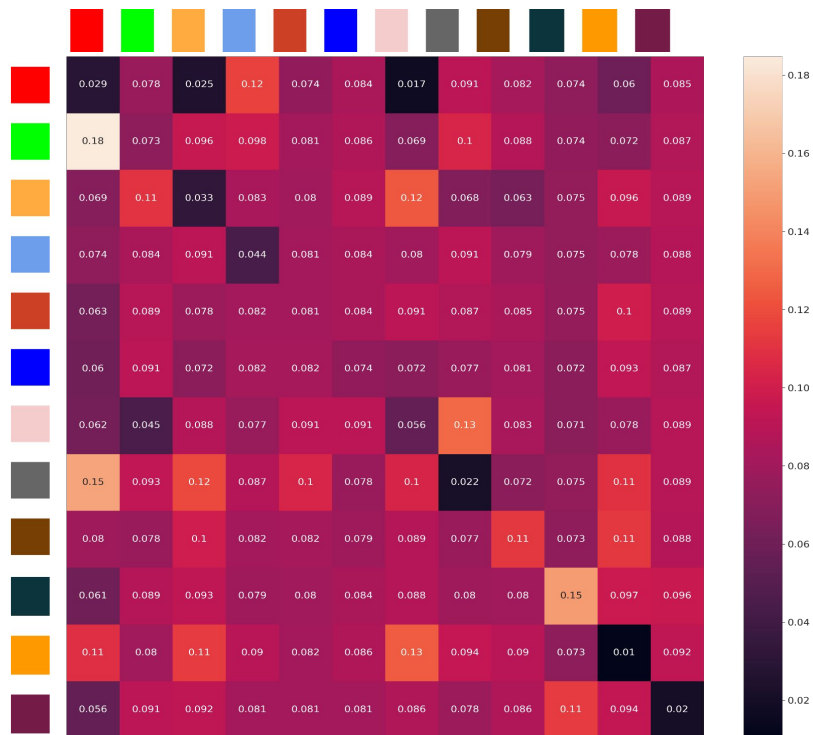
Attention Score



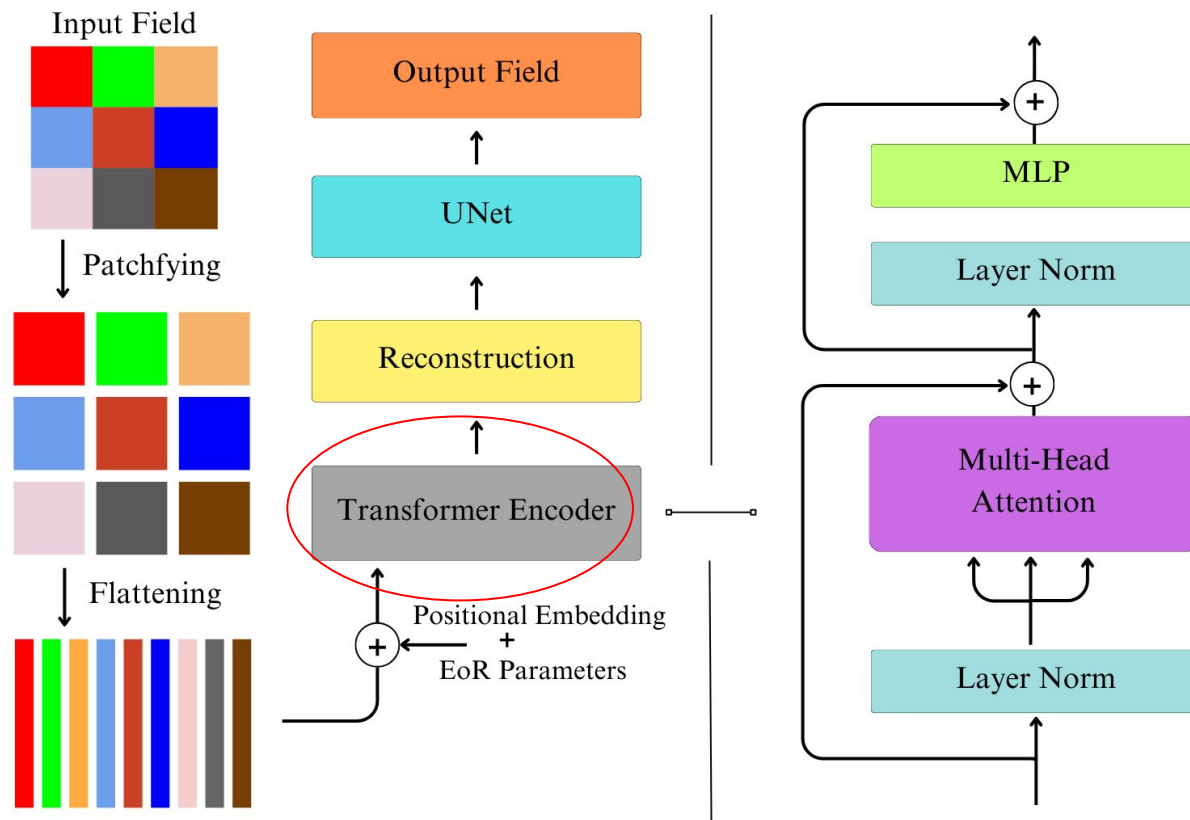
$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax} \left(\frac{\mathbf{QK}^T}{\sqrt{D_H}} \right) \mathbf{V}$$

Attention Score

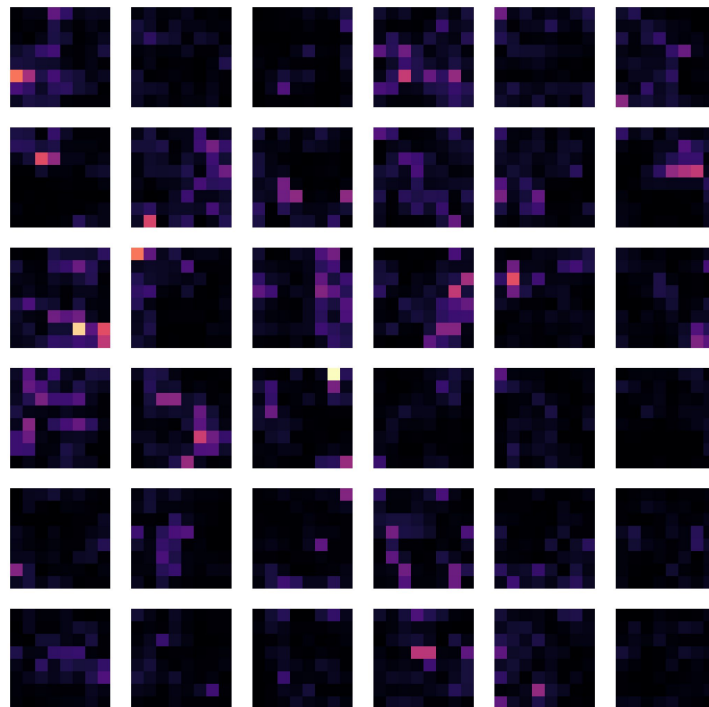
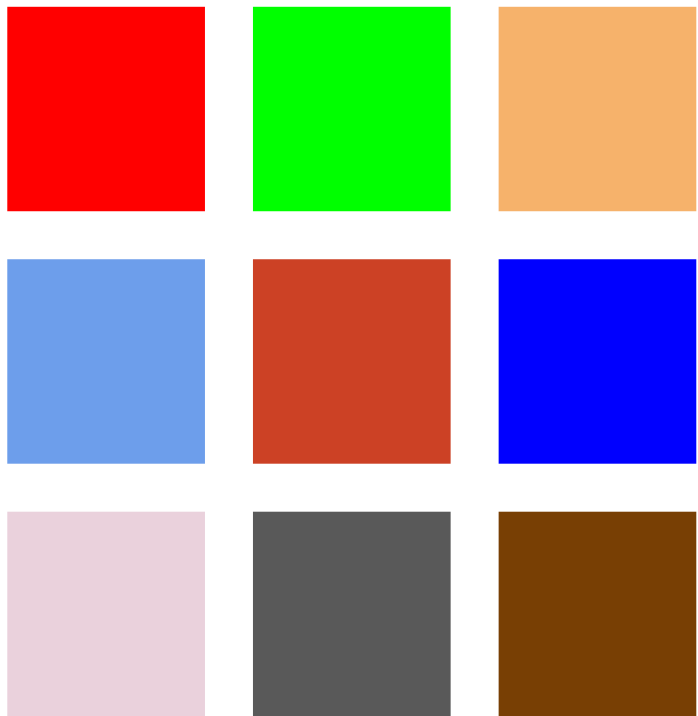
Values



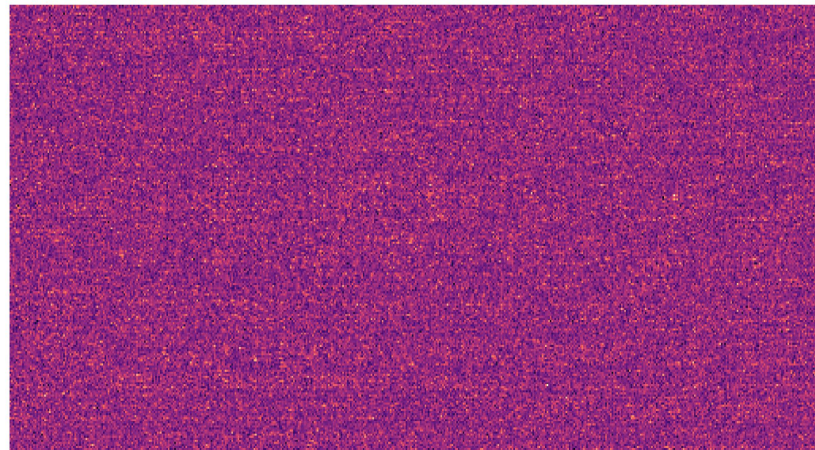
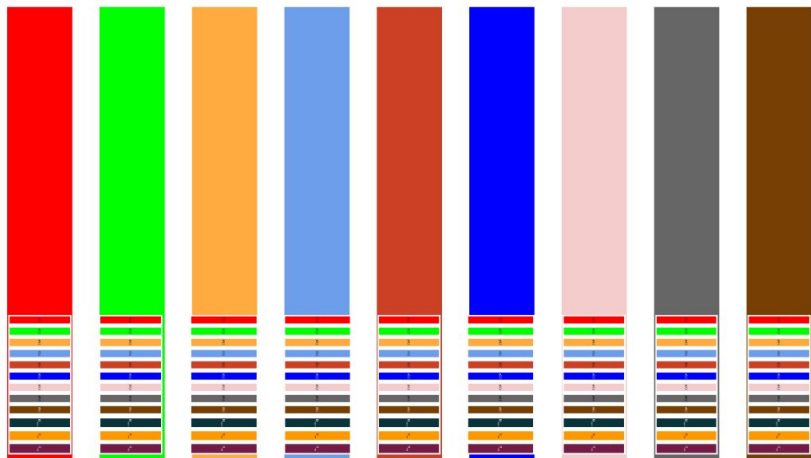
UNet integrated Vision Transformer (CosmoUiT)



Patchified Field

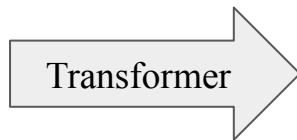


Transformer Output

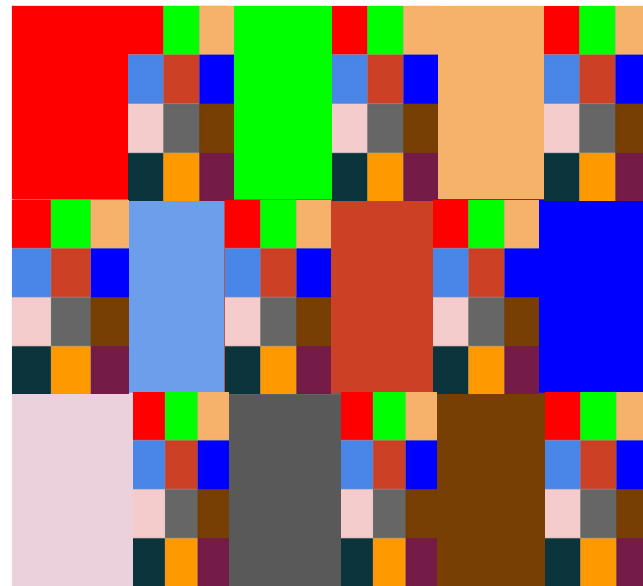


Reconstructed Field

Original Field

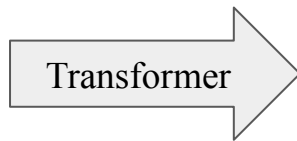
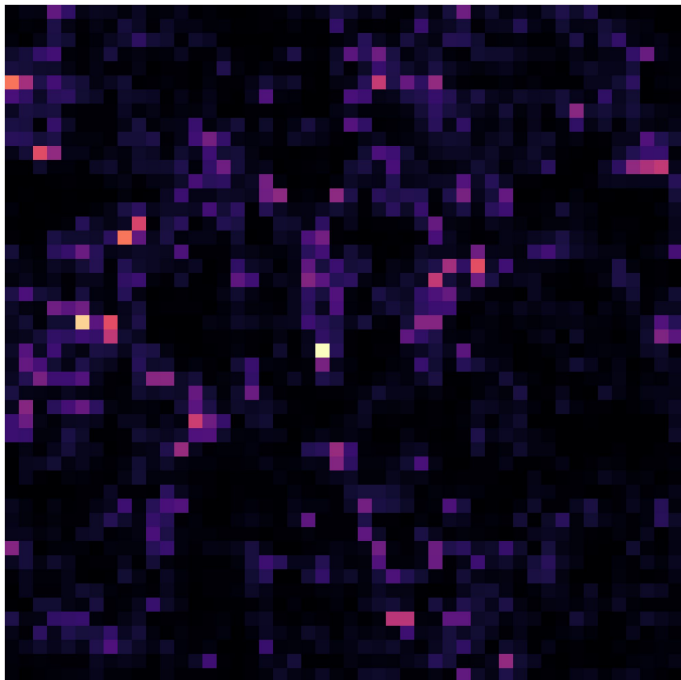


Reconstructed Field

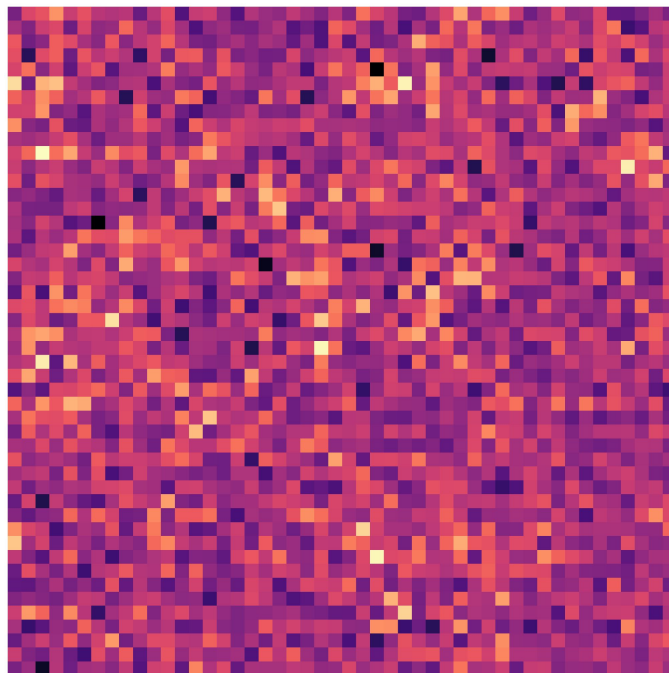


Reconstructed Field

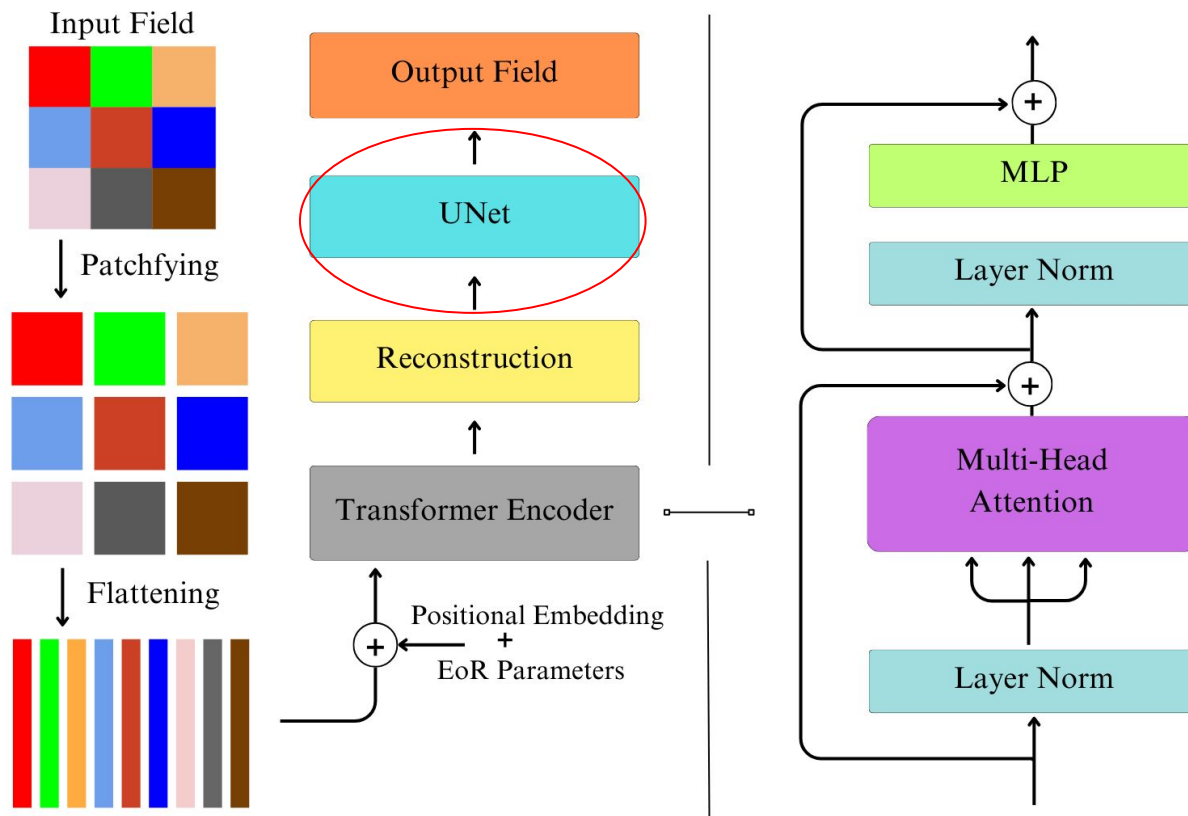
Original Field



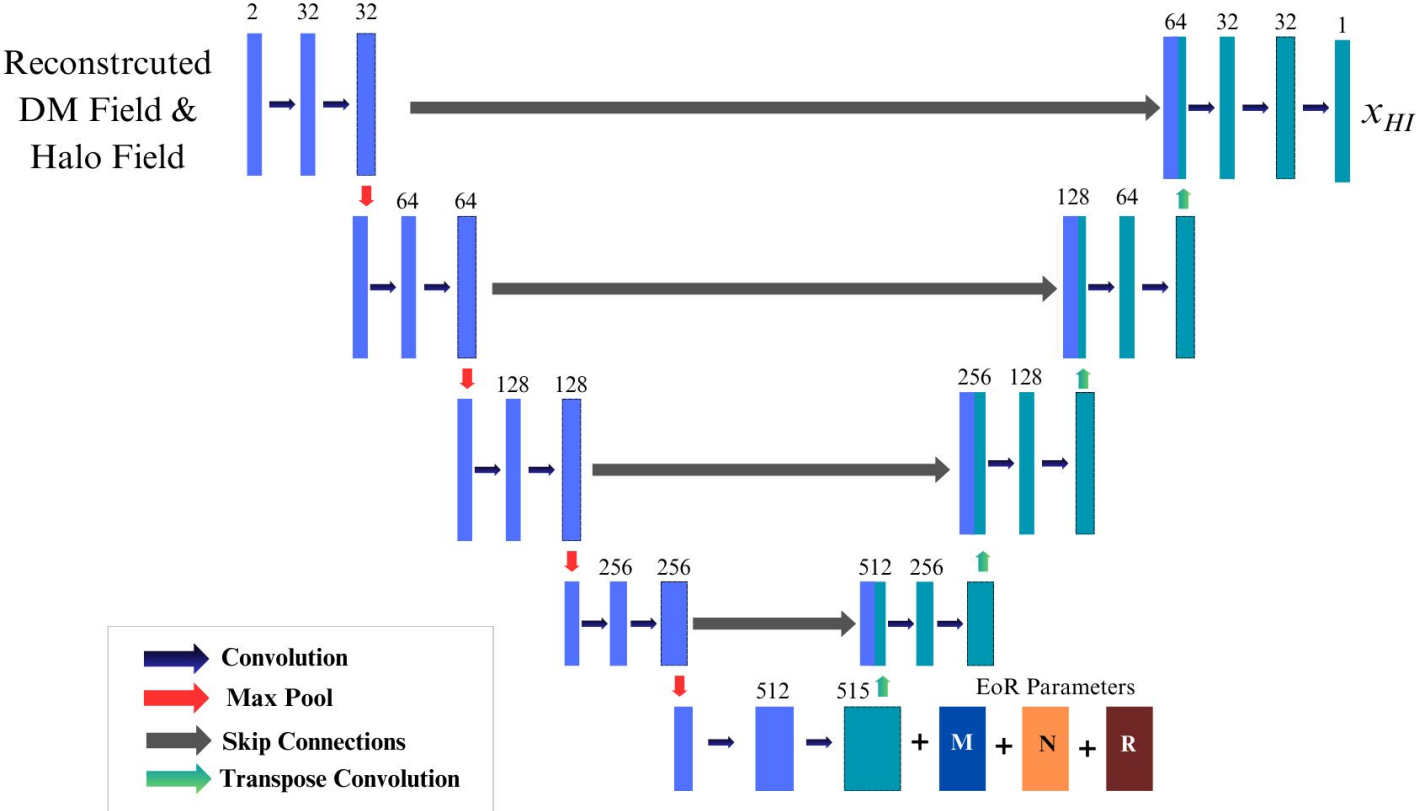
Reconstructed Field



UNet integrated Vision Transformer (CosmoUiT)



UNet Architecture



UNet Architecture

Training Data Set : CosmoUIT

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

Simulated 21-cm fields within a box of 384 Mpc for following parameters:

- ❖ **Minimum Halo Mass, $M_{h,min}$** : $10 \times 10^8 M_{\odot} \leq M_{h,min} \leq 800 \times 10^8 M_{\odot}$
- ❖ **Ionizing Photon Emitting Efficiency, N_{ion}** : $10 < N_{ion} < 200$
- ❖ **Maximal Distance travelled by Ionizing Photons, R_{mfp}** : $1.12 \leq R_{mfp} \leq 40.32$ Mpc

7203 parameter combinations, of which 80% for training 20% for validations

GPU Specifications: CosmoUIT

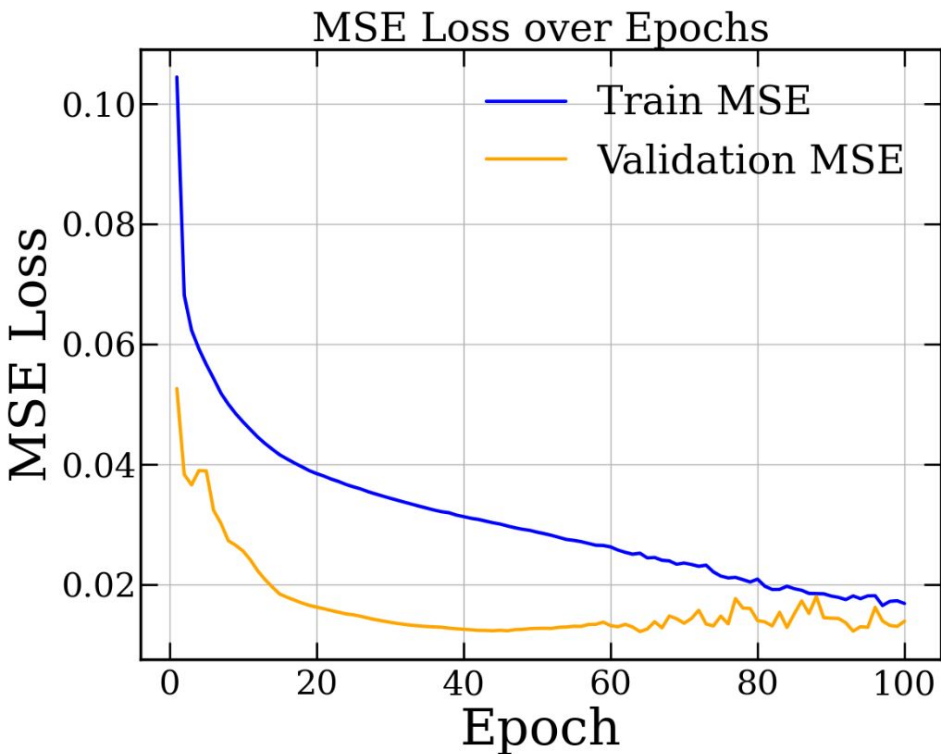
Device Name: NVIDIA A100-SXM4-40GB

Total Memory Used: 30 GB

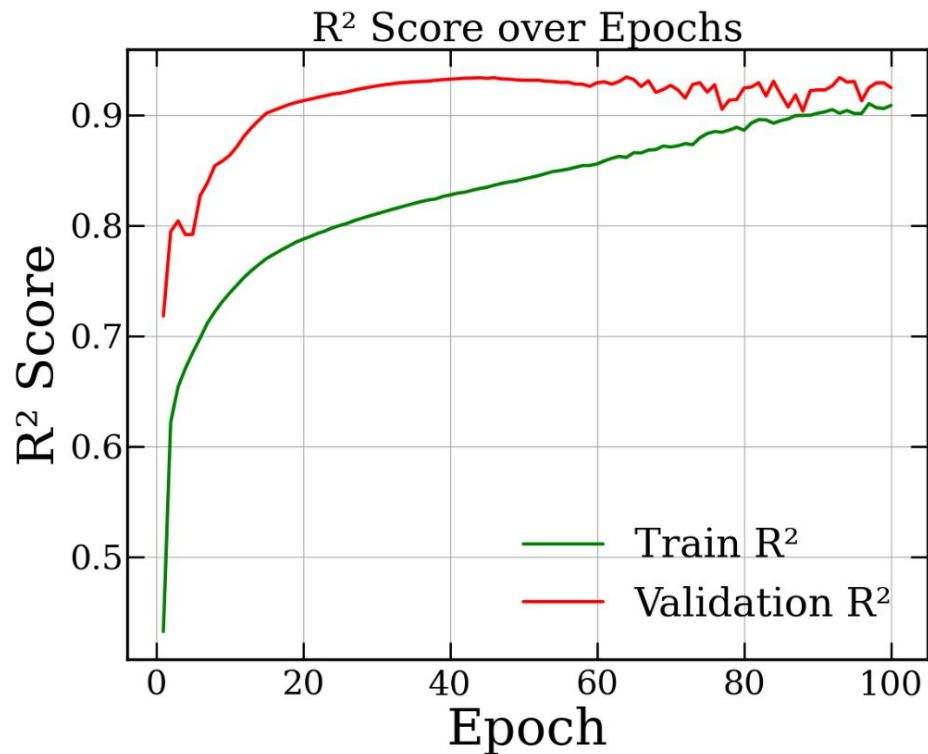
Batch size: 16

Training Time: 100 hrs for 100 epochs

Loss and R² for CosmoUIT



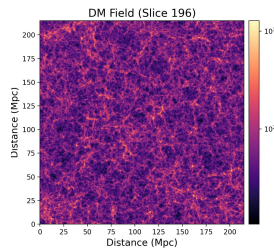
Validation Loss: 0.01385
Training Loss: 0.01678



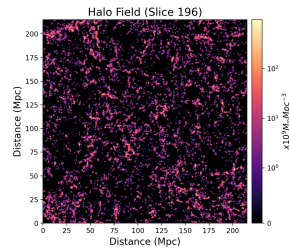
Validation R²: 0.925
Training R²: 0.9091

CosmoUiT: Field-Level Emulator (3D Coeval Cubes)

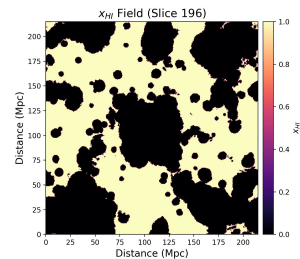
Dark Matter Density field



Halo Density field

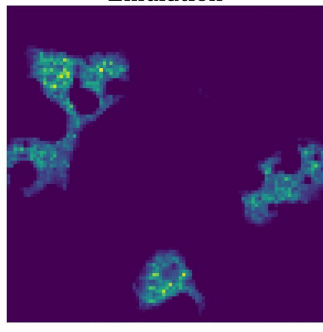


+ Reionisation Parameters

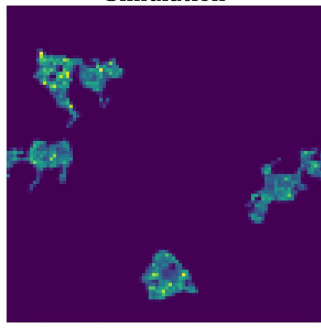


$\bar{x}_{\text{HI}} = 0.1$, $M_{\text{h, min}} = 259$, $N_{\text{ion}} = 133.68$, $R_{\text{mfp}} = 35.71$, $\text{MSE} = 4.197$, $R^2 = 0.86$, $\text{SSIM} = 0.88$

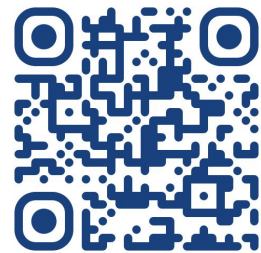
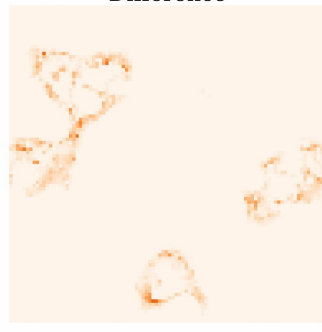
Emulation



Simulation



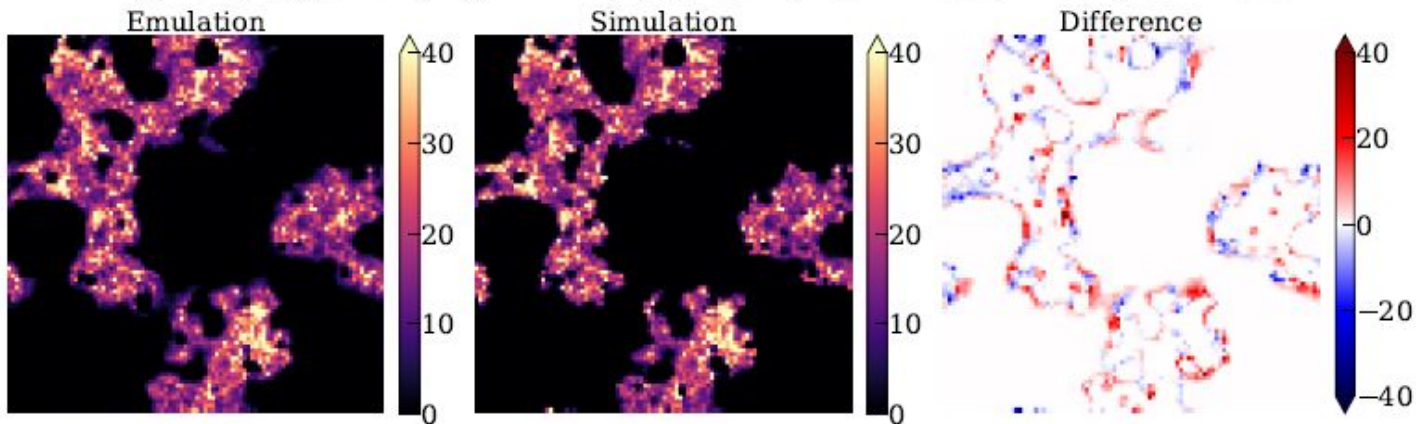
Difference



Posture, Mahida et al.
2026 (JCAP)
(arXiv: 2510.01121)

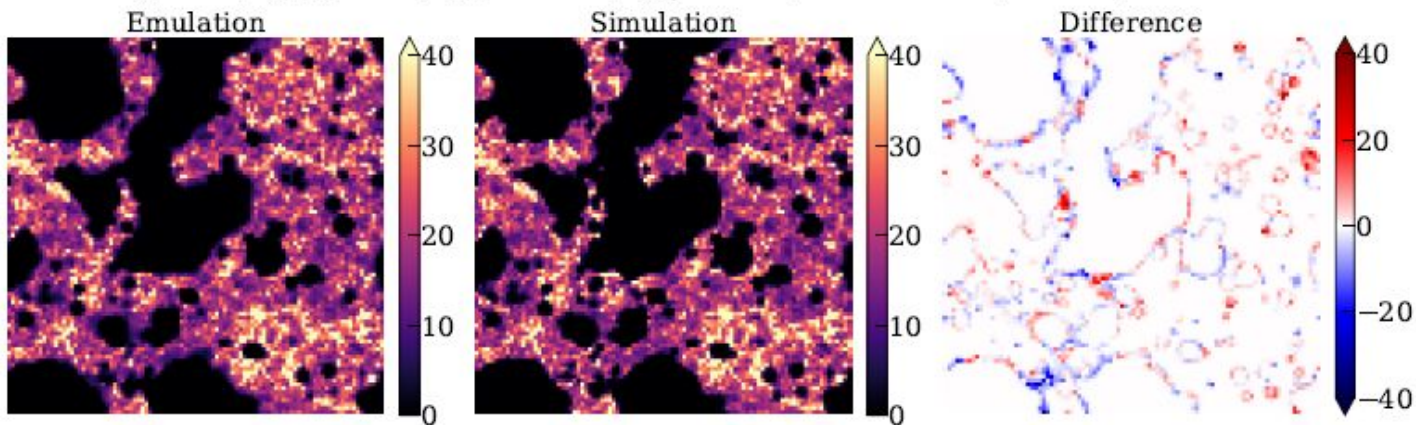
Emulated 21-cm Maps

$\bar{x}_{\text{HI}} = 0.3$, $M_{\text{h,min}} = 342$, $N_{\text{ion}} = 124.21$, $R_{\text{mfp}} = 35.71$, $\text{MSE} = 12.259$, $R^2 = 0.91$, $\text{SSIM} = 0.90$



SSIM ~ 1
=> High
structural
similarity

$\bar{x}_{\text{HI}} = 0.5$, $M_{\text{h,min}} = 467$, $N_{\text{ion}} = 124.21$, $R_{\text{mfp}} = 33.40$, $\text{MSE} = 10.972$, $R^2 = 0.94$, $\text{SSIM} = 0.95$

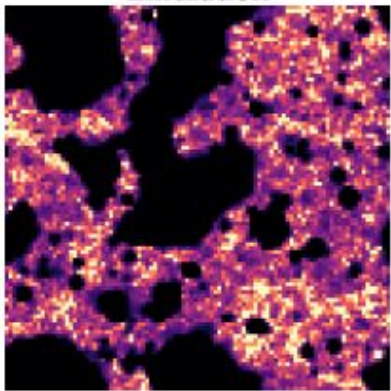


$$\text{SSIM}(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

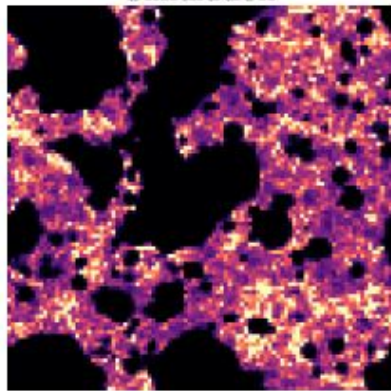
Emulated 21-cm Maps

$\bar{x}_{\text{HI}} = 0.5$, $M_{\text{h,min}} = 467$, $N_{\text{ion}} = 124.21$, $R_{\text{mfp}} = 33.40$, $\text{MSE} = 10.972$, $R^2 = 0.94$, $\text{SSIM} = 0.95$

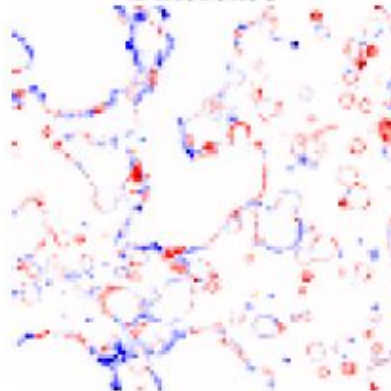
Emulation



Simulation



Difference

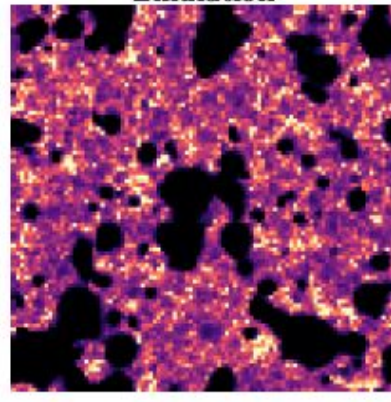


SSIM ~ 1
=> High structural similarity

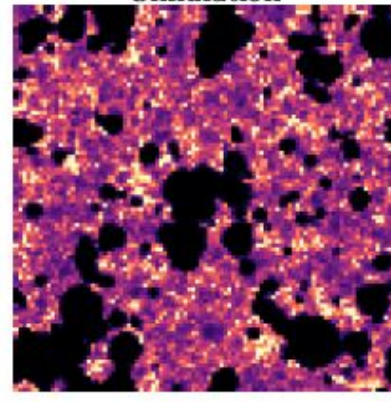
$$\text{SSIM}(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

$\bar{x}_{\text{HI}} = 0.7$, $M_{\text{h,min}} = 675$, $N_{\text{ion}} = 114.74$, $R_{\text{mfp}} = 26.48$, $\text{MSE} = 8.503$, $R^2 = 0.94$, $\text{SSIM} = 0.95$

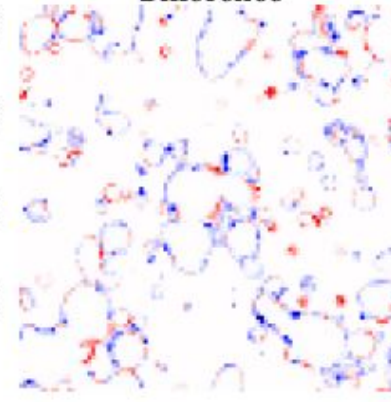
Emulation



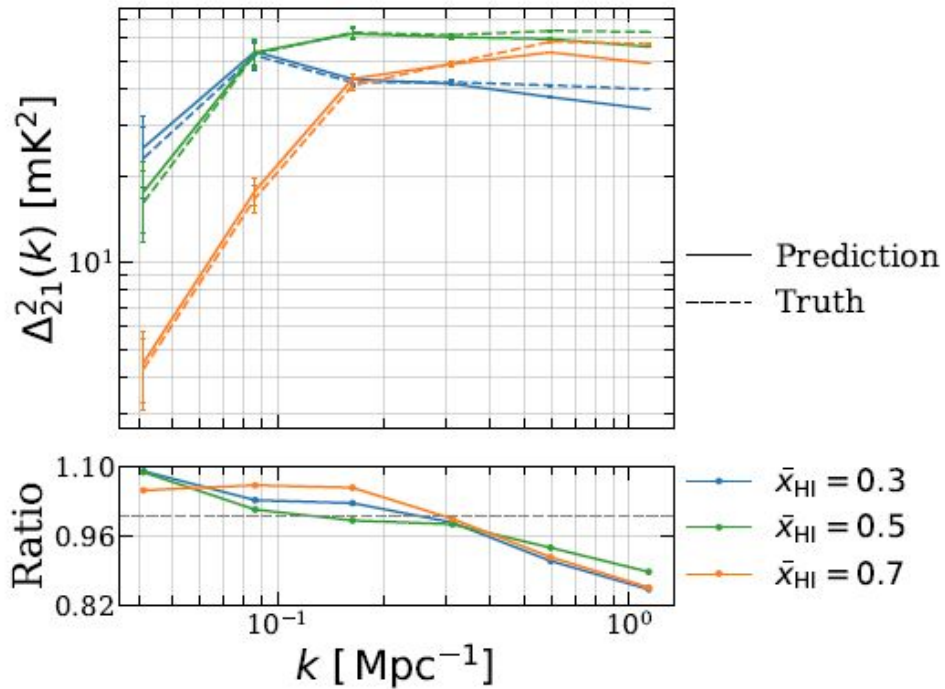
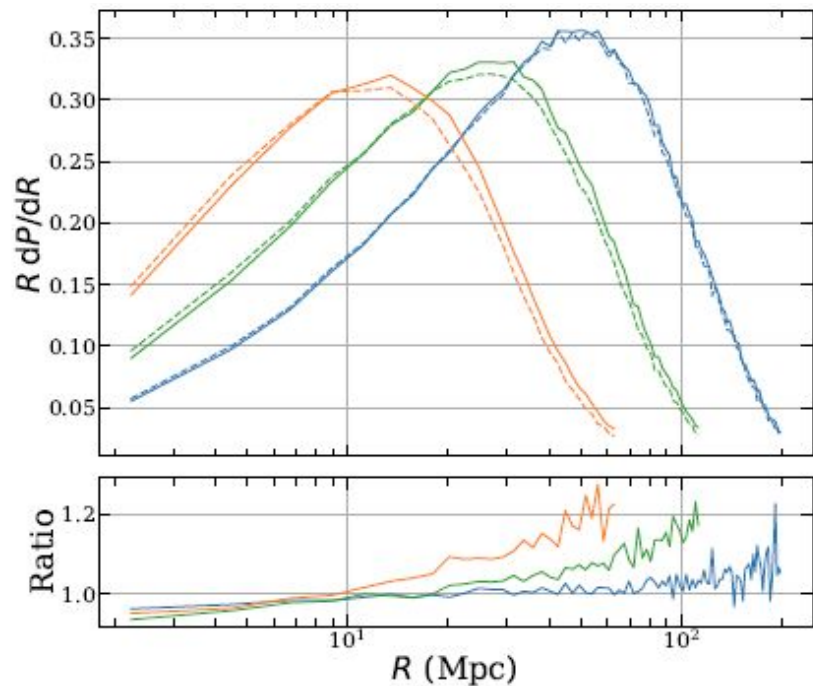
Simulation



Difference

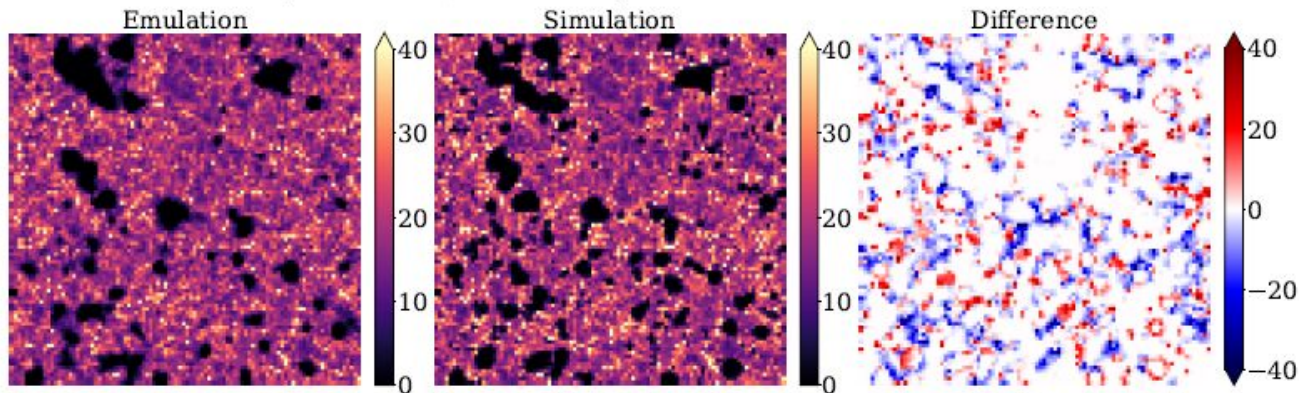


HII Region Size Distribution and Power Spectrum

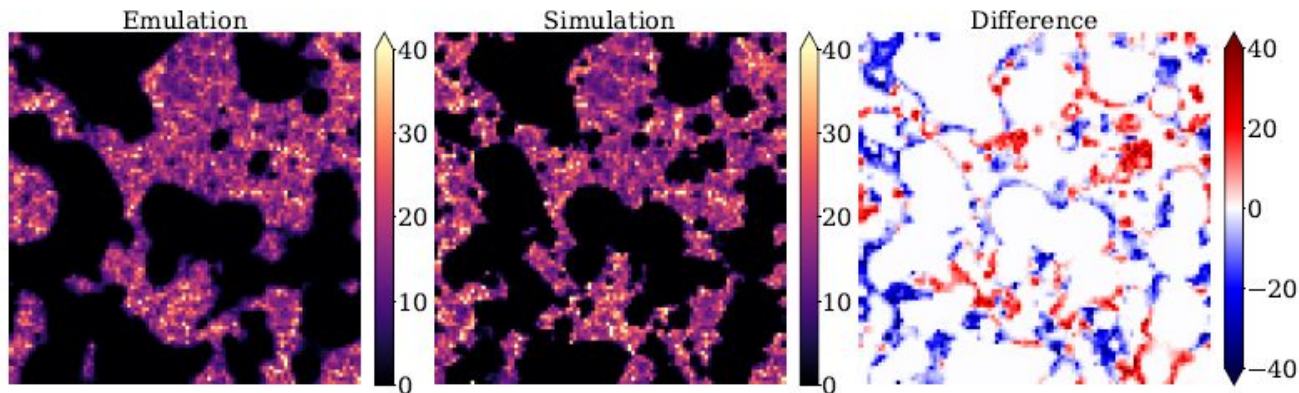


Generalization for Different Dark Matter and Halo Fields

$\bar{x}_{\text{HI}} = 0.8$, $M_{h, \text{min}} = 166$, $N_{\text{ion}} = 40.84$, $R_{\text{mfp}} = 7.58$, $\text{MSE} = 55.078$, $R^2 = 0.37$, $\text{SSIM} = 0.61$



$\bar{x}_{\text{HI}} = 0.4$, $M_{h, \text{min}} = 404$, $N_{\text{ion}} = 160.21$, $R_{\text{mfp}} = 19.78$, $\text{MSE} = 69.869$, $R^2 = 0.39$, $\text{SSIM} = 0.54$



Summary: III

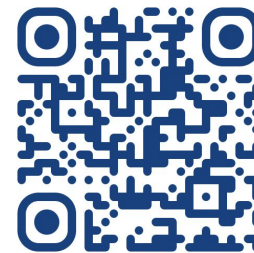
- `CosmoUiT` can predict the 3D 21-cm field for given input reionization parameters, dark matter and halo fields.
- Transformers can capture the large-scale effects and UNet captures the small scale effects of the reionization.
- `CosmoUiT` as a hybrid architecture effectively predicts both large and small scale features of the ionisation field.
- `CosmoUiT` works considerably well for the out of domain input fields.

Further Development

- Upgrade `CosmoUIT` to predict the entire lightcones of the 21-cm field for given input reionization parameters.
- Train `CosmoUIT` for other simulations; both semi-numerical and radiative transfer.
- Make it more robust by training it for a large ensemble of Nbody realizations.

CosmoUiT: A Vision Transformer-UNet Hybrid for Fast and Accurate Emulation of 21-cm Maps from the Epoch of Reionization

Authors: Prasad Rajesh Posture, Yashrajsinh Mahida, Suman Majumdar, Leon Noble



Posture, Mahida et al.
2026 (JCAP)
(arXiv: 2510.01121)