

Evaluating Summary Statistics with Mutual Information for Cosmological Inference

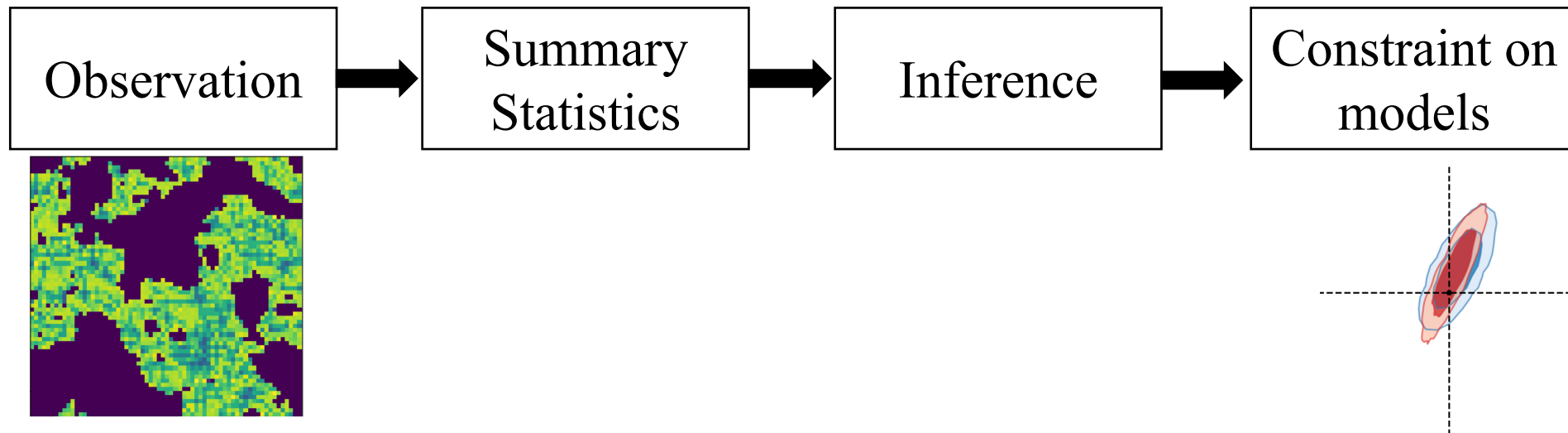
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In collaboration with

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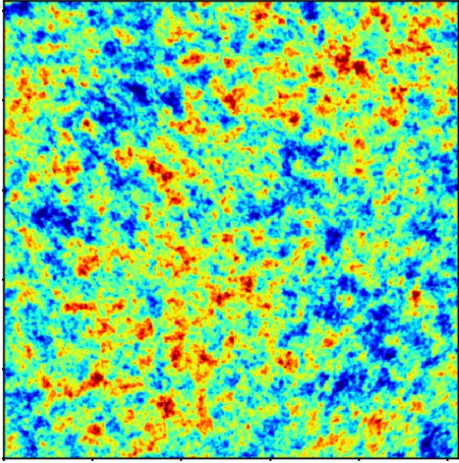
Tsinghua University

Statistical Inference in Cosmology



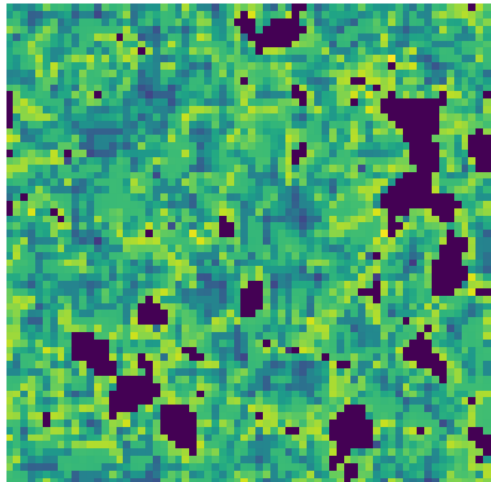
How to select optimal statistics ?

CMB



→ Power Spectrum

21cm



Spatial Correlation

→ Power Spectrum, Bispectrum

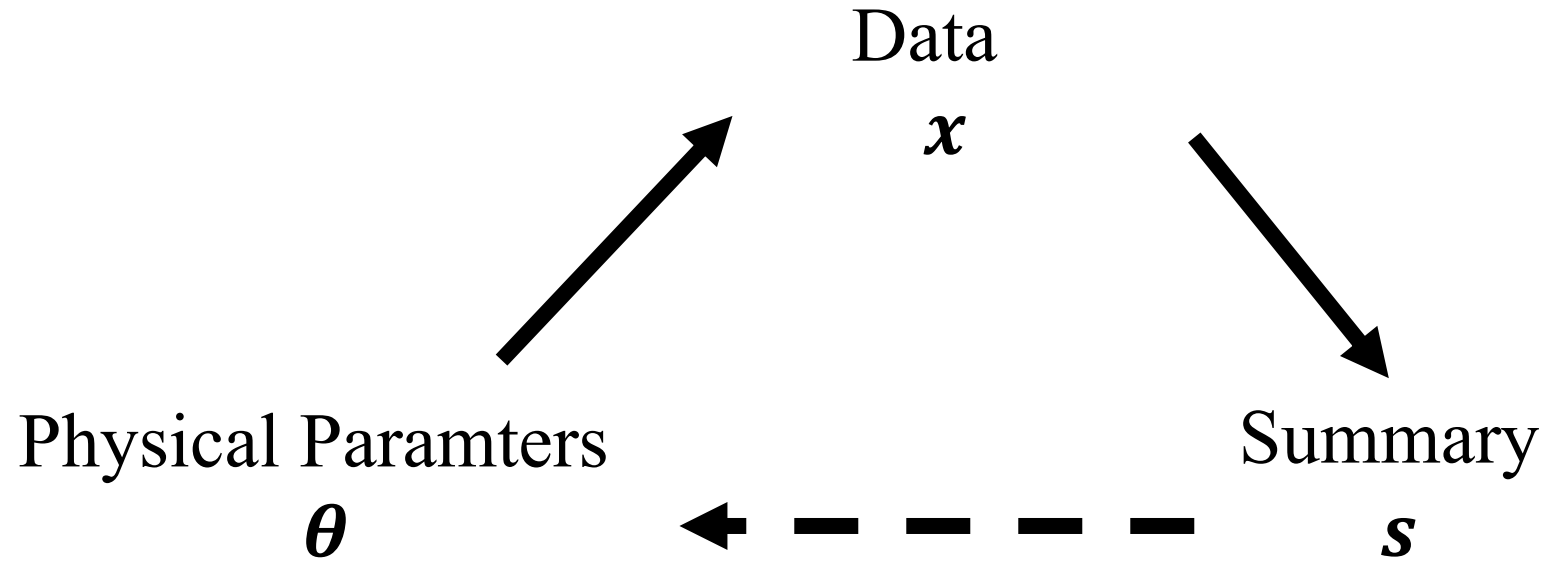
Morphological Properties

→ Minkowski Functionals / Bubble Size Distribution

Signal decomposition

→ Wavelet Transform

How to select optimal statistics ?



1. Through theoretic interpretation
2. Fisher Analysis
3. Running inferences with one mock observation

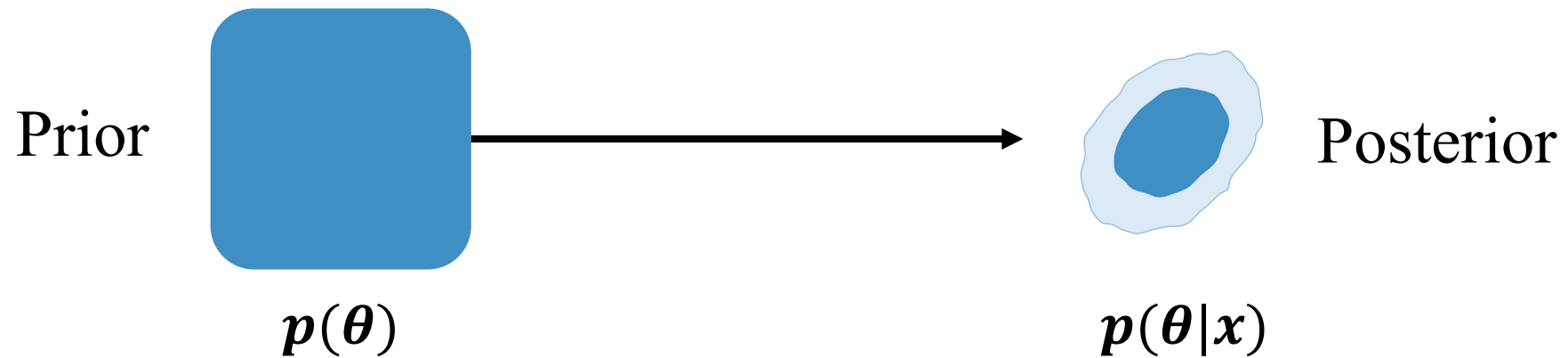
Method: Mutual information

Mutual information

$$I(\theta; x) = \mathbf{D}_{KL}[p(\theta, x) || p(\theta)p(x)] = E_{p(x)}[\mathbf{D}_{KL}(p(\theta|x) || p(\theta))]$$

MI is a fundamental measure of Statistical Dependence.

It quantifies how much uncertainty is reduced in θ given x



Method: Mutual information

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MI is a fundamental measure of Statistical Dependence.

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How to estimate mutual information?

$$I(\theta; x) \equiv E_{p(\theta, x)} \left[\log \frac{p(\theta|x)}{p(\theta)} \right] \approx E_{p(\theta, x)} \left[\log \frac{q(\theta|x)}{p(\theta)} \right]$$

Variational Lower Bound

Summary Statistics Considered in this work

Power Spectrum

$$\langle \delta(k)\delta(k') \rangle = (2\pi)^3 \delta^D(k+k')P(k)$$

Bispectrum

$$\langle \delta(k_1)\delta(k_2)\delta(k_3) \rangle = (2\pi)^3 \delta^D(k_1+k_2+k_3)B(k_1, k_2, k_3)$$

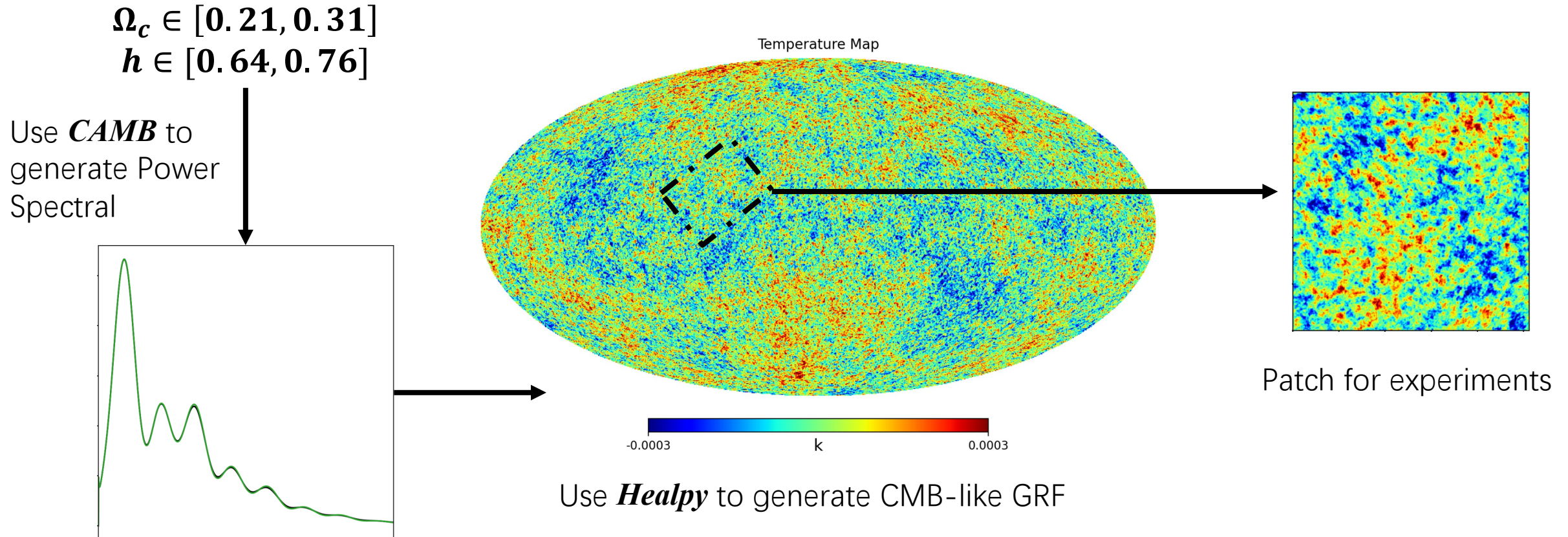
Scattering Transform

$$S\delta[\lambda_1, \dots, \lambda_k] = |\psi_{\lambda_k} \star \dots \star \psi_1 \star \delta|$$

Use designed wavelets to convolve the field
(Anden & Mallat 2014, Eickenberg et al. 2017,2018)

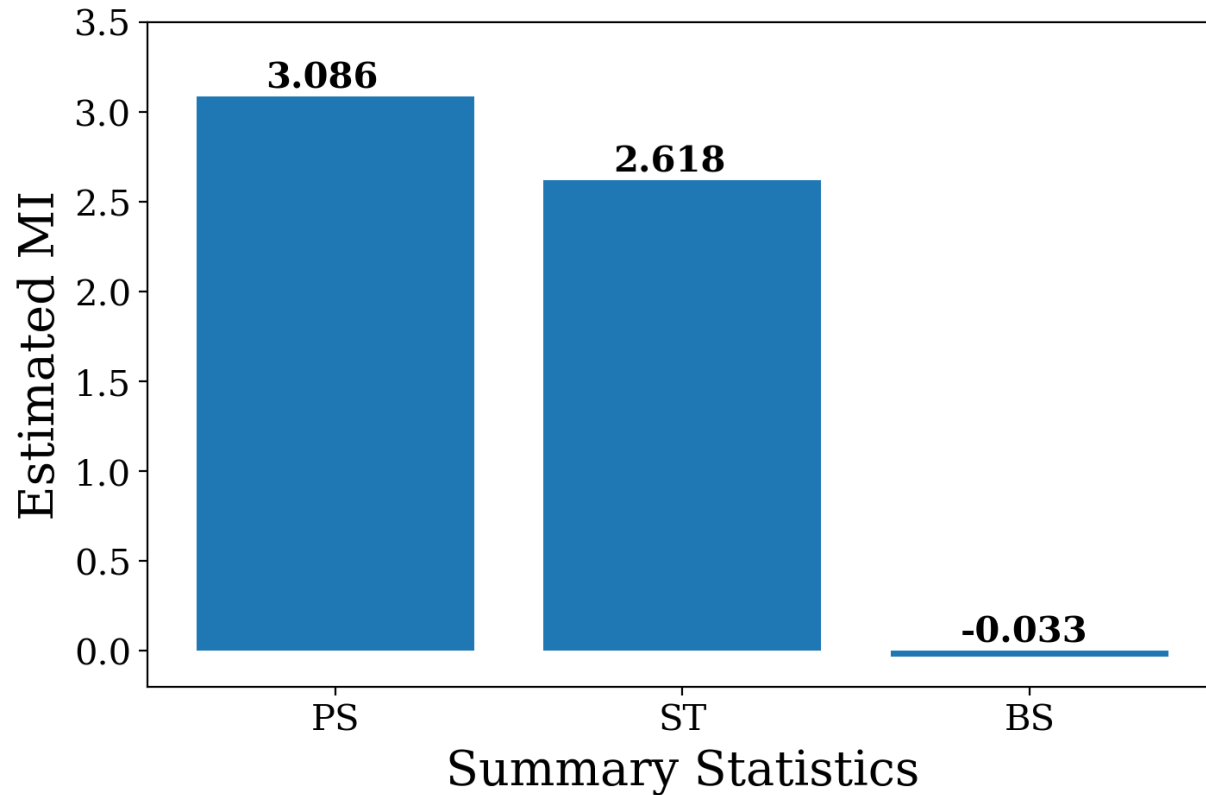
Experiments I:

Validate the method in CMB-like Gaussian random fields(GRF)



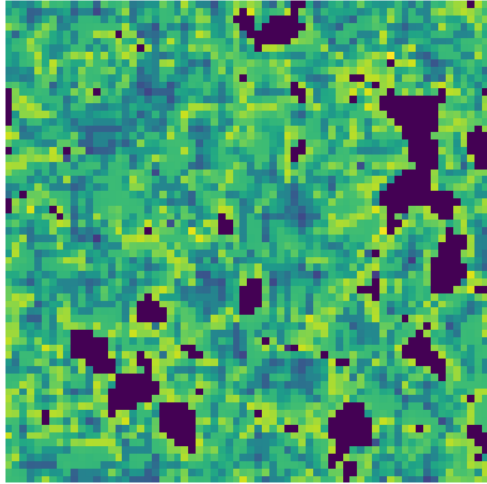
Experiments I:

Validate the method in CMB-like Gaussian random fields(GRF)



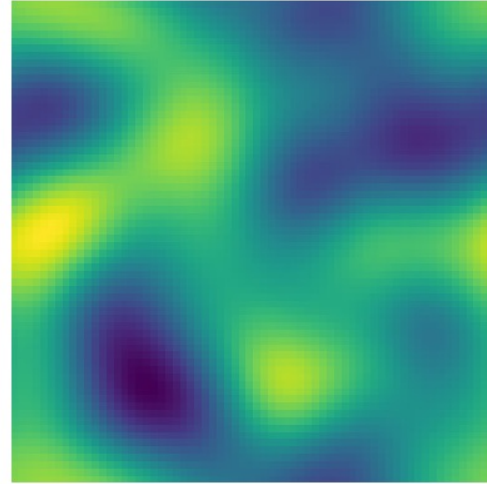
PS is optimal and BS contains no information

Experiments II: Evaluate Statistics in an EoR inference Task

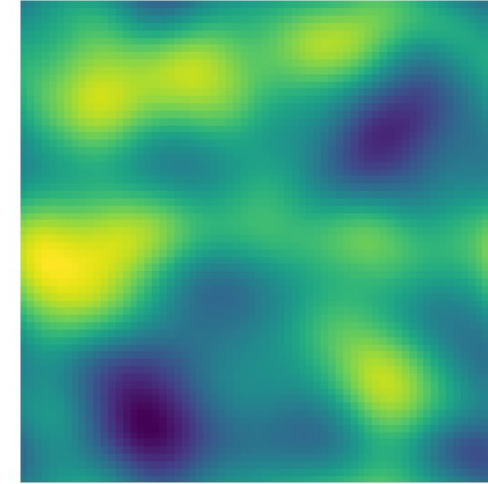


Pure 21cm signal
(simulated by 21cmFAST)

Mesinger & Furlanetto (2007)



+Thermal Noise
(SKA1-low configuration)



+Residual Foreground
(GSM model +SVD)

Zheng et al. (2017)



Reionization Parameters

ζ the ionizing efficiency

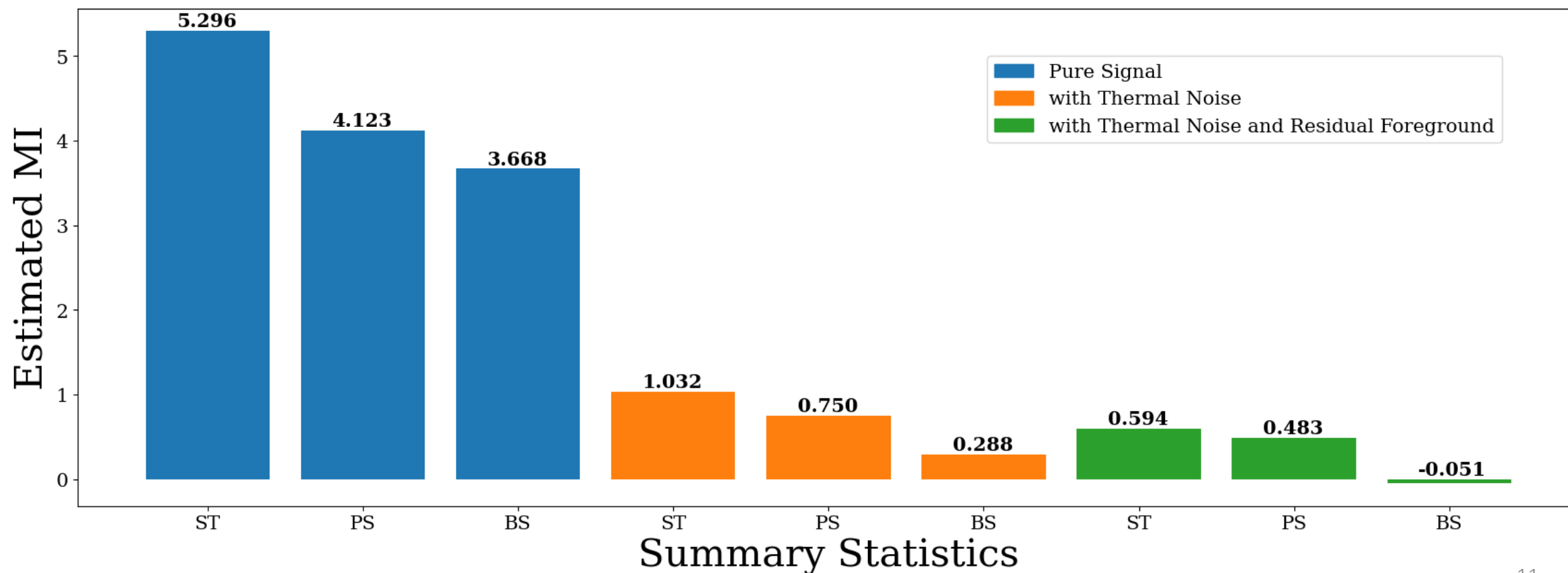
T_{vir} the minimum virial temperature of halos
that host ionizing sources

Experiments: MI-based comparison of statistics in an EoR Inference task

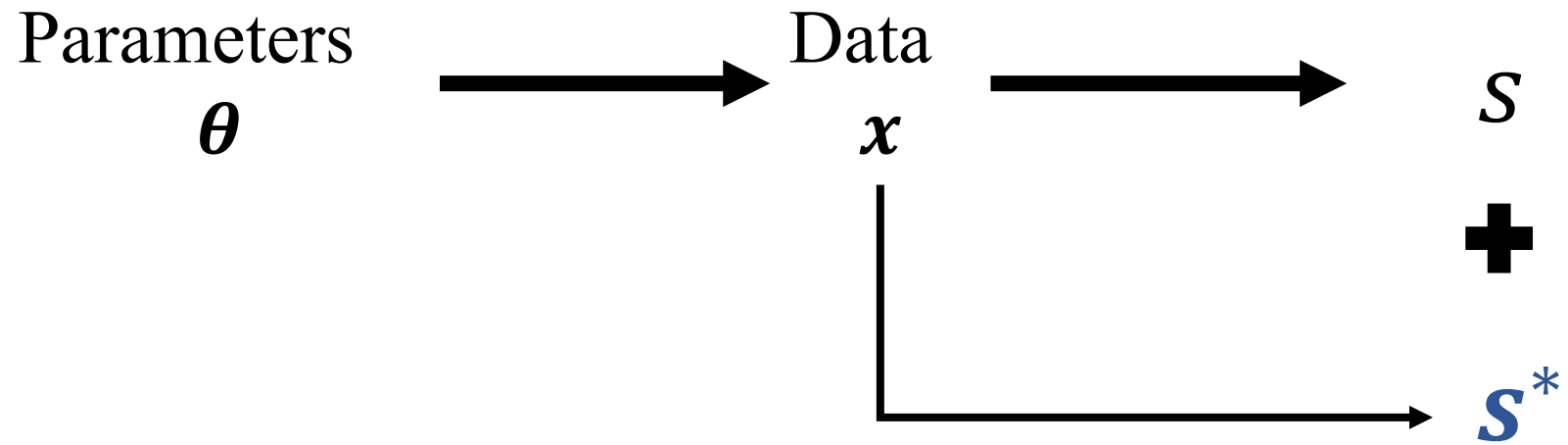
ST: Wavelet Transform

PS: Power spectrum

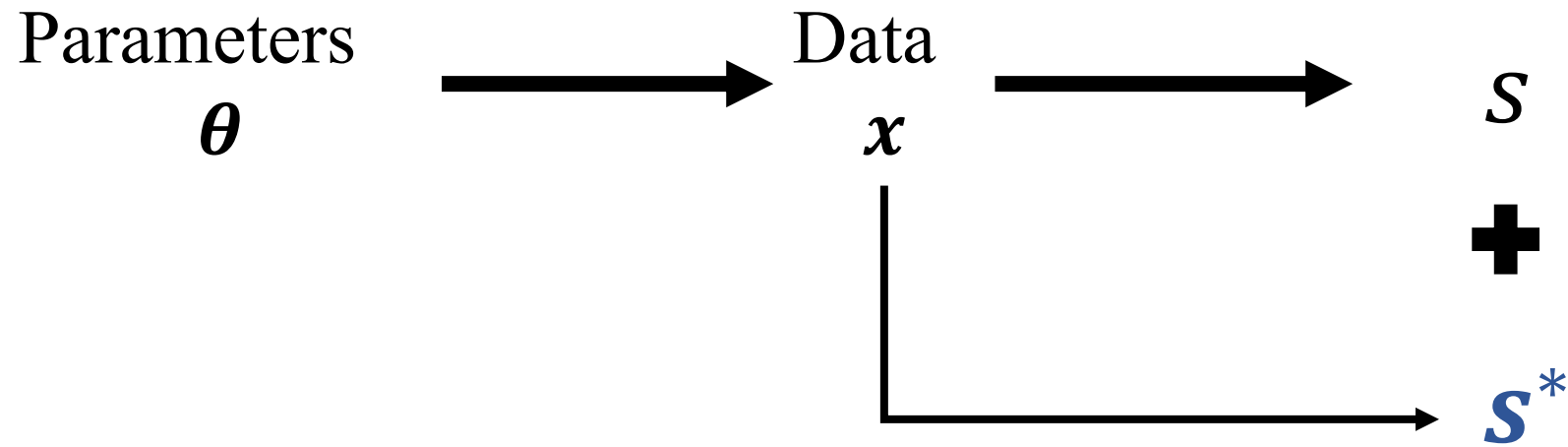
BS: Bispectrum



Mutual Information for evaluating Complementary Summary

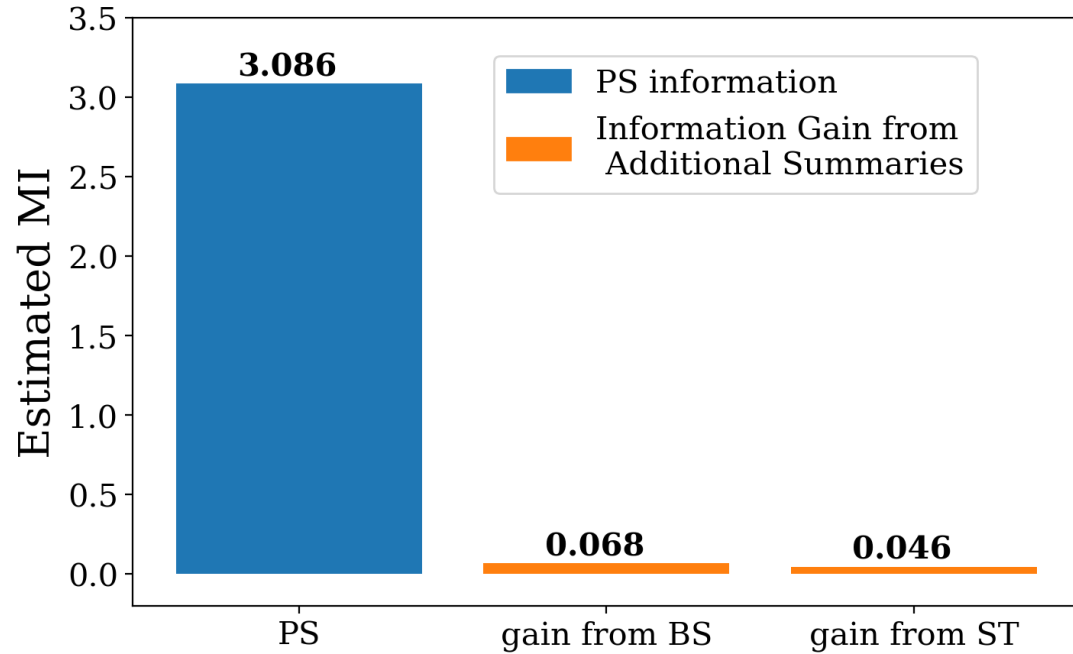


Mutual Information for evaluating Complementary Summary

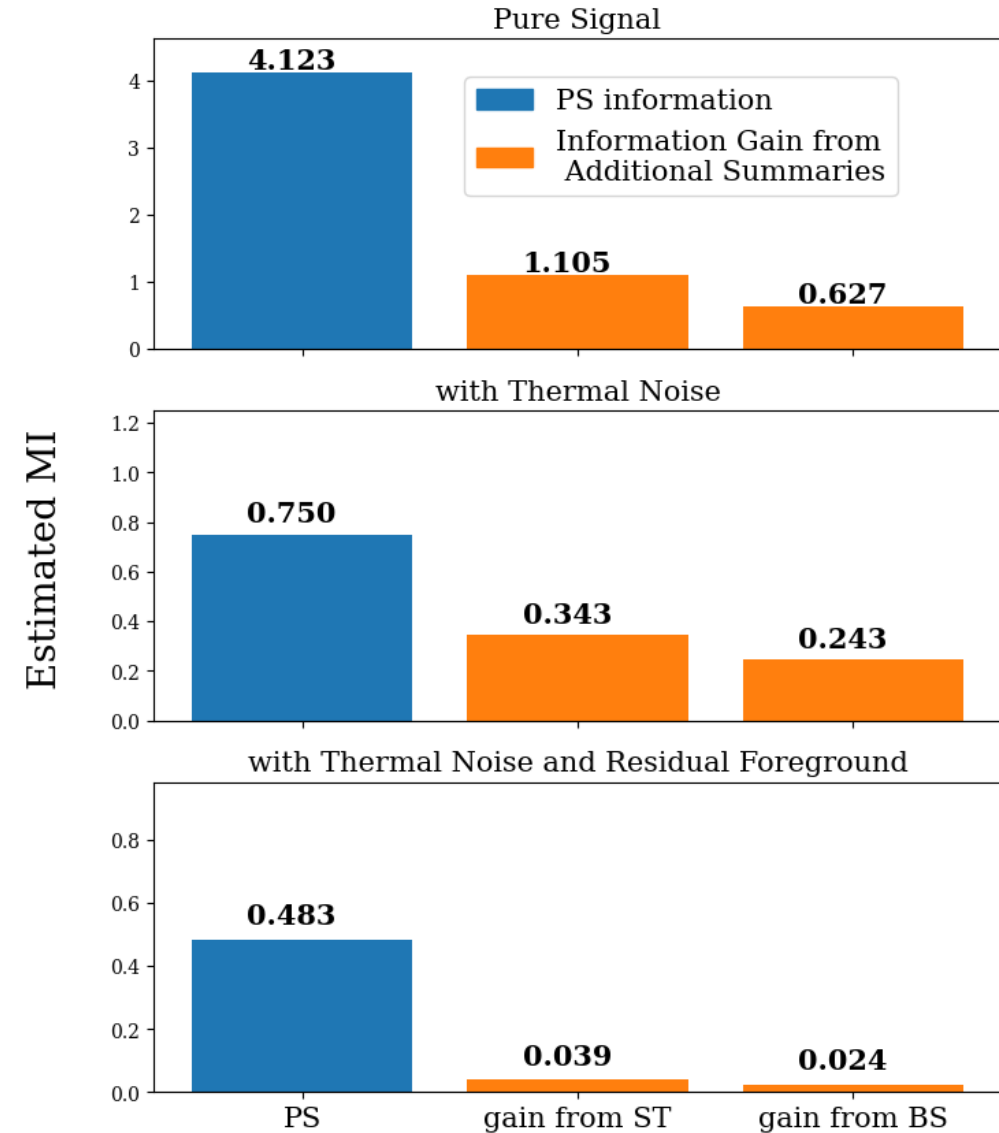


Conditional Mutual Information: $I(\theta; S^* | S)$

Mutual Information for evaluating Complementary Summary



CMB Experiment



21cm Experiment

Mutual Information for Learning Summaries

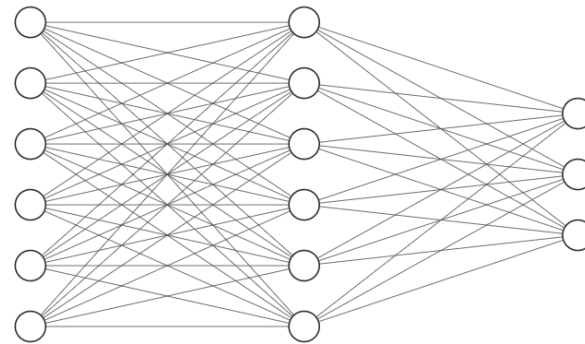
1. Learn a new optimal summary by maximizing mutual information

$$\max_S I(\theta; S(x))$$

Parameters
 θ



Data
 x



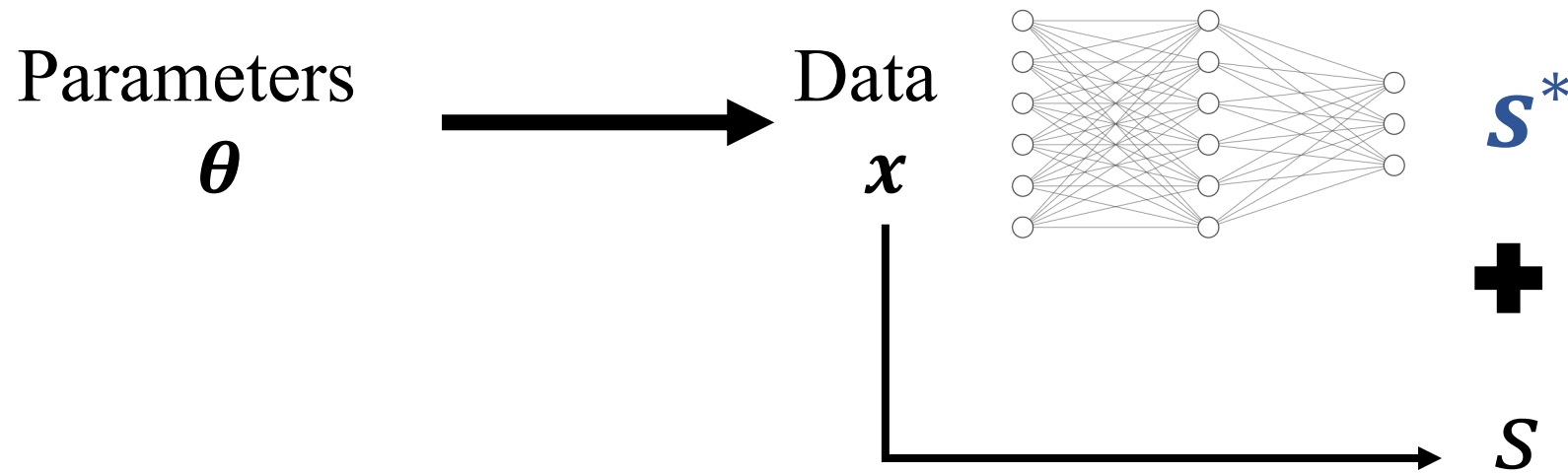
Compressor Neural Network
 S

Summary
 s

Mutual Information for Learning Summaries

2. Learn a **complementary** summary by maximizing **conditional** mutual information

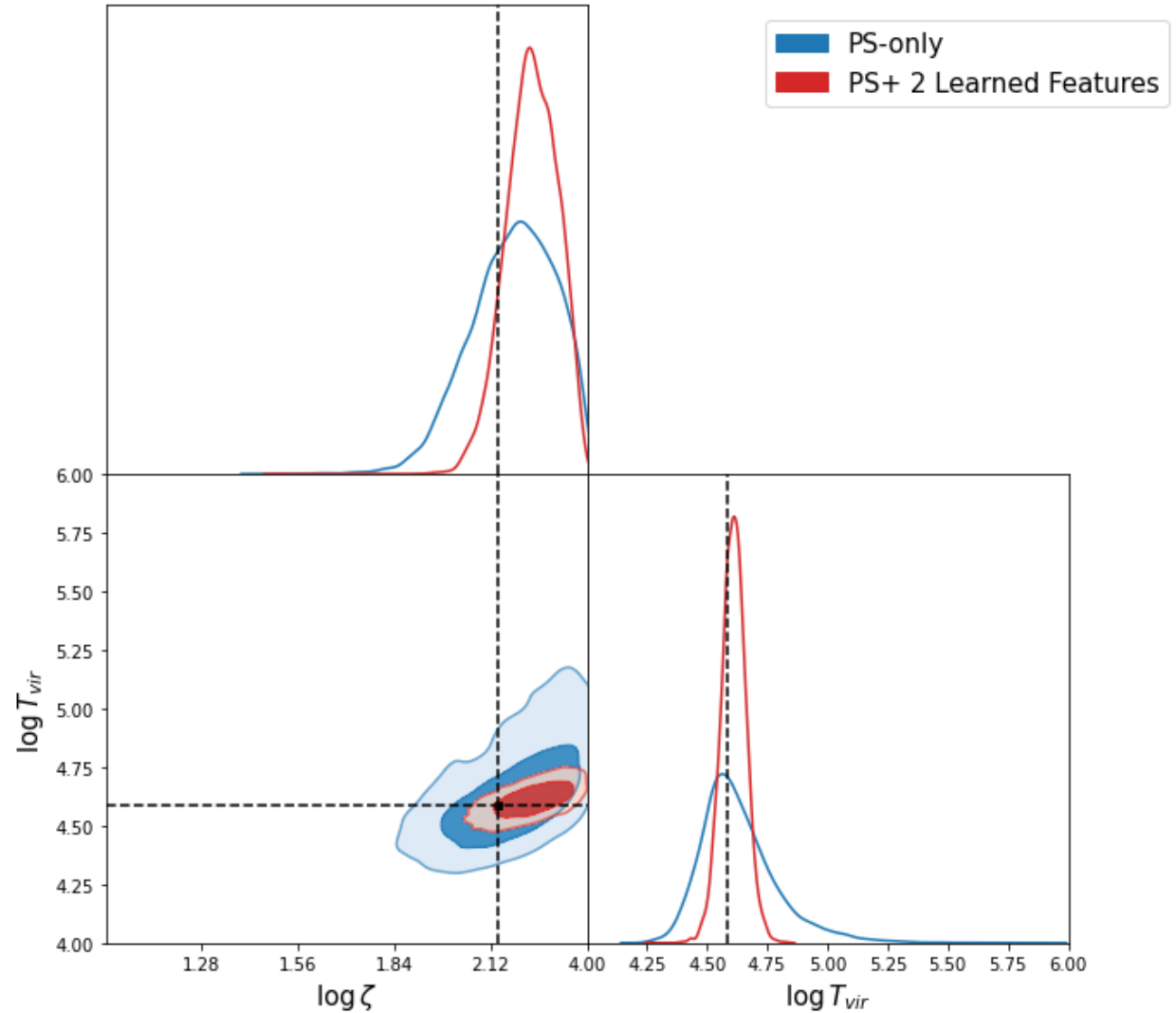
$$\max_S I(\theta; S^*(x) | S)$$



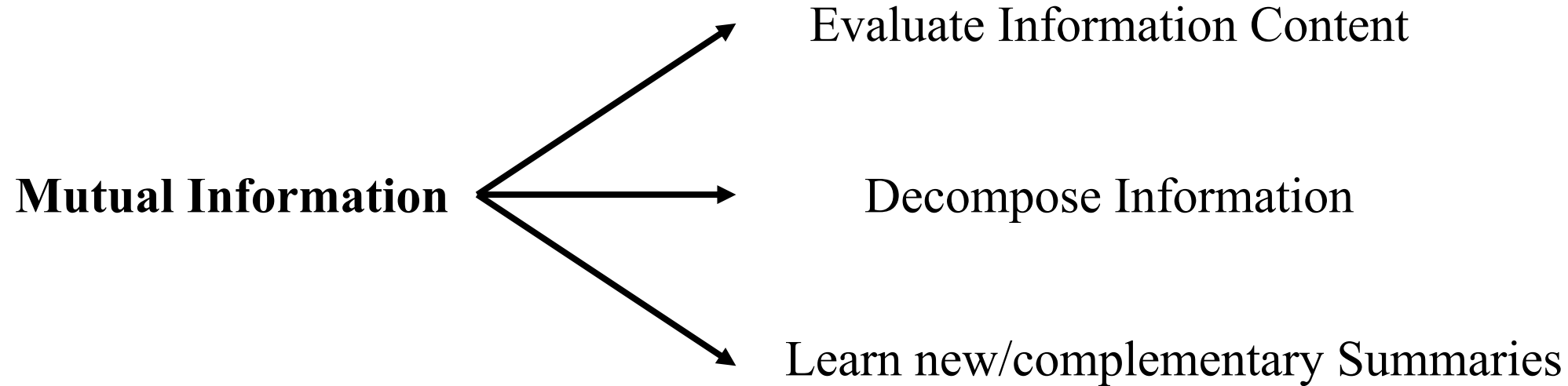
2. Learn a **complementary** summary by maximizing **conditional** mutual information

Learn **two complementary features** for Power Spectrum

Experiment:
Infer Reionization Parameter from 21cm images.



Summary



More Details:

ICML 2023 AI4Astro Workshop: <https://arxiv.org/abs/2307.04994>

1–2 additional papers are expected to be released next month.

Part of the experimental results can be found on: <https://github.com/suicee/MI4StatsEval>