

LPENS

LABORATOIRE DE PHYSIQUE
DE L'ÉCOLE NORMALE SUPÉRIEURE

Single frequency CMB B-mode inference with realistic foregrounds from a single training image

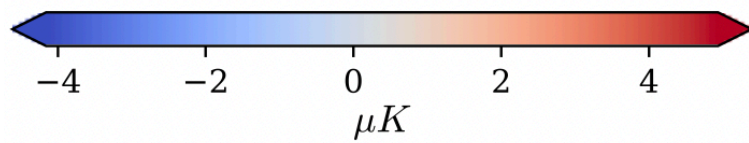
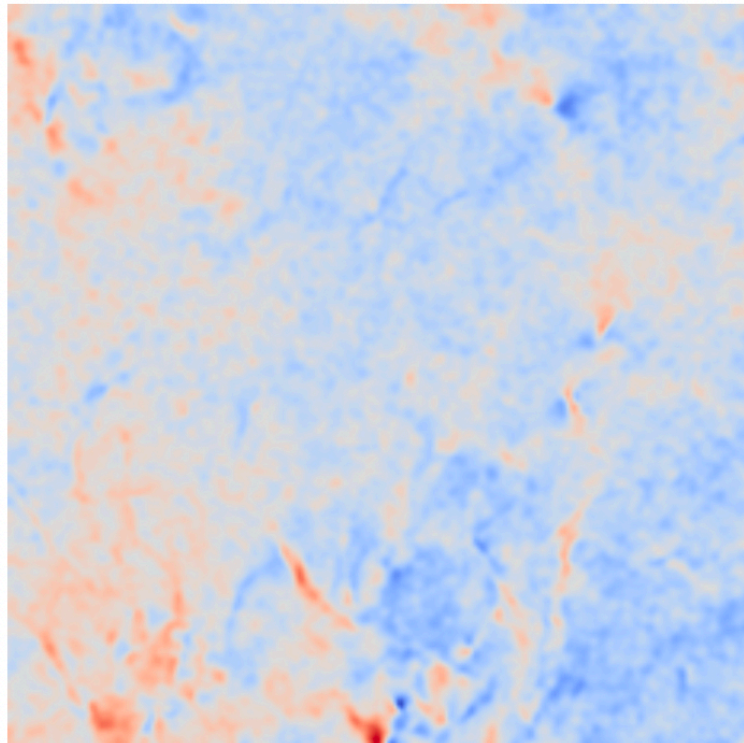
Niall Jeffrey

*François Boulanger, Benjamin Wandelt,
Bruno Regaldo-Saint Blancard, Erwan Allys, François Levrier*



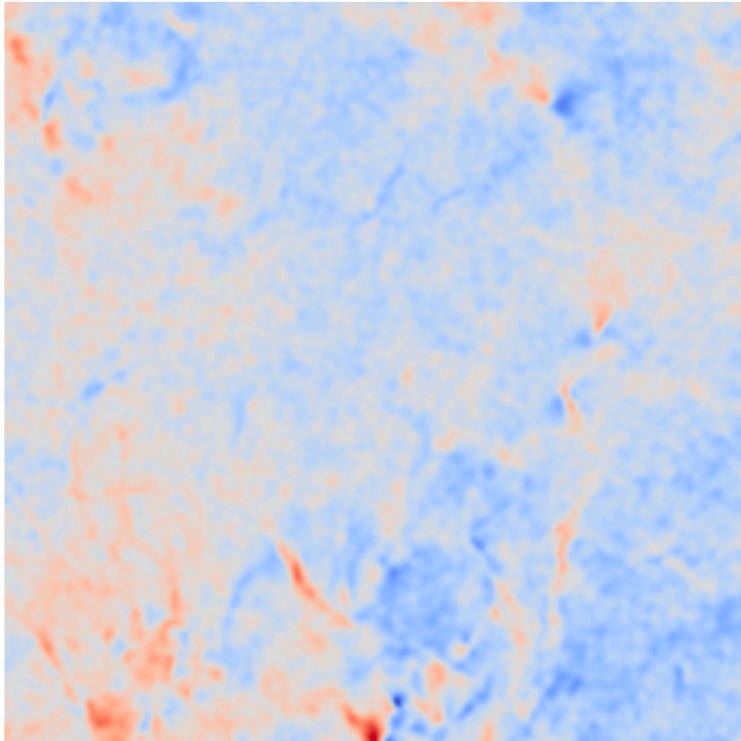
B-mode inference

B-mode data

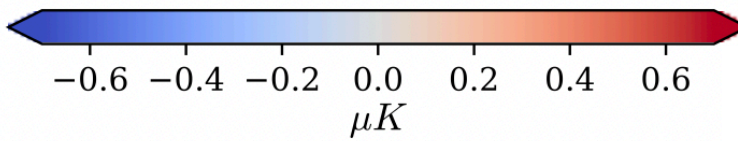
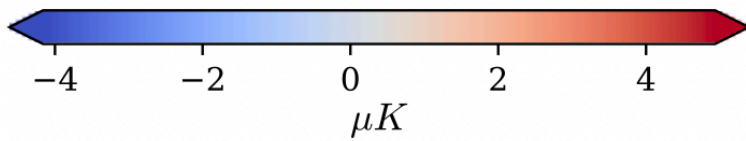
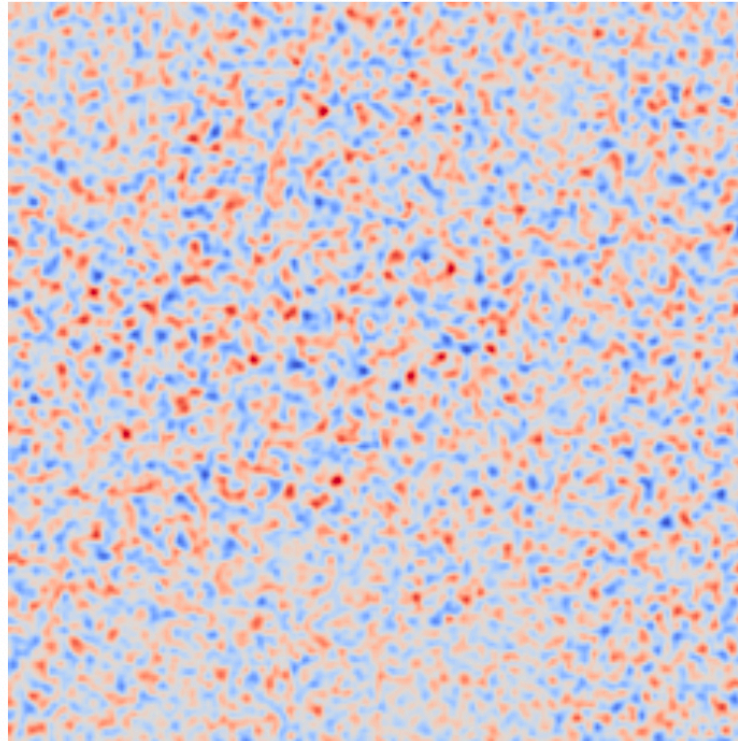


B-mode inference

B-mode data

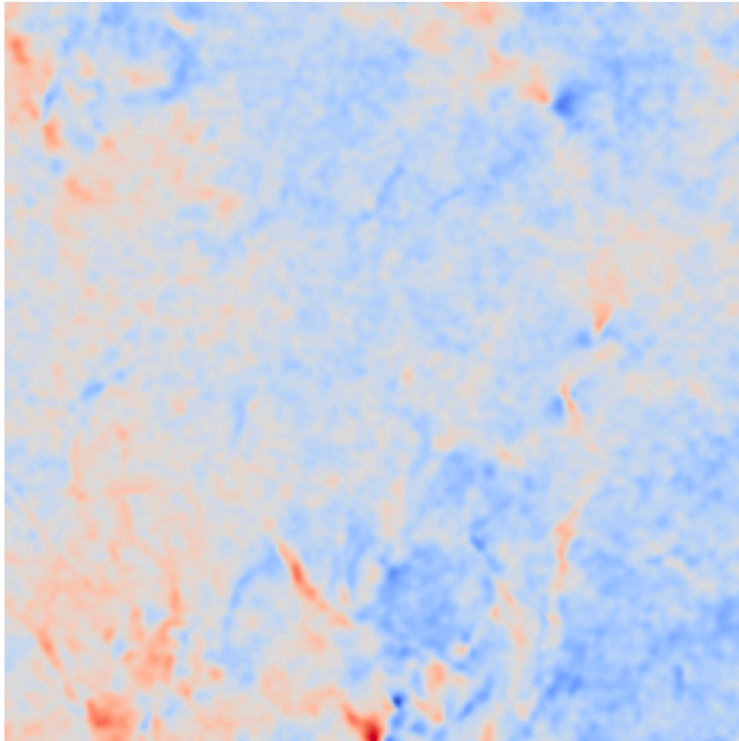


Posterior mean

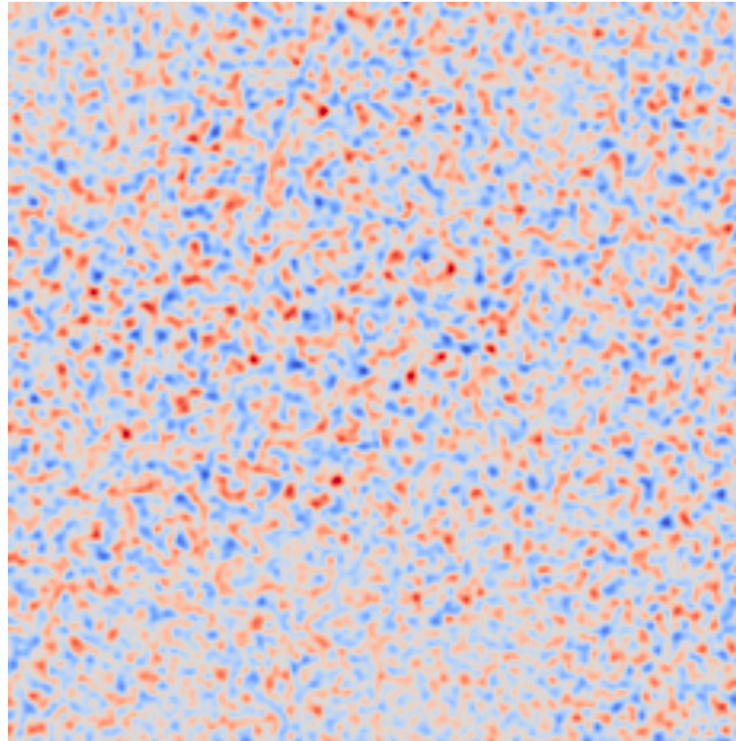


B-mode inference

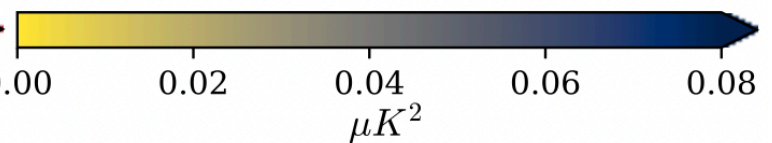
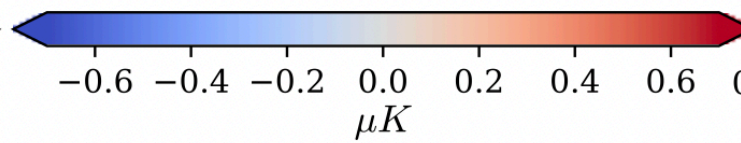
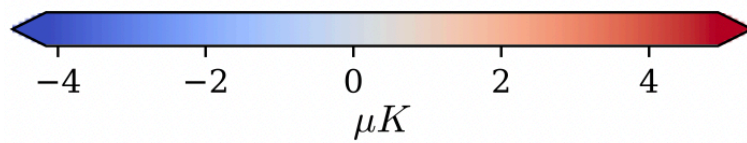
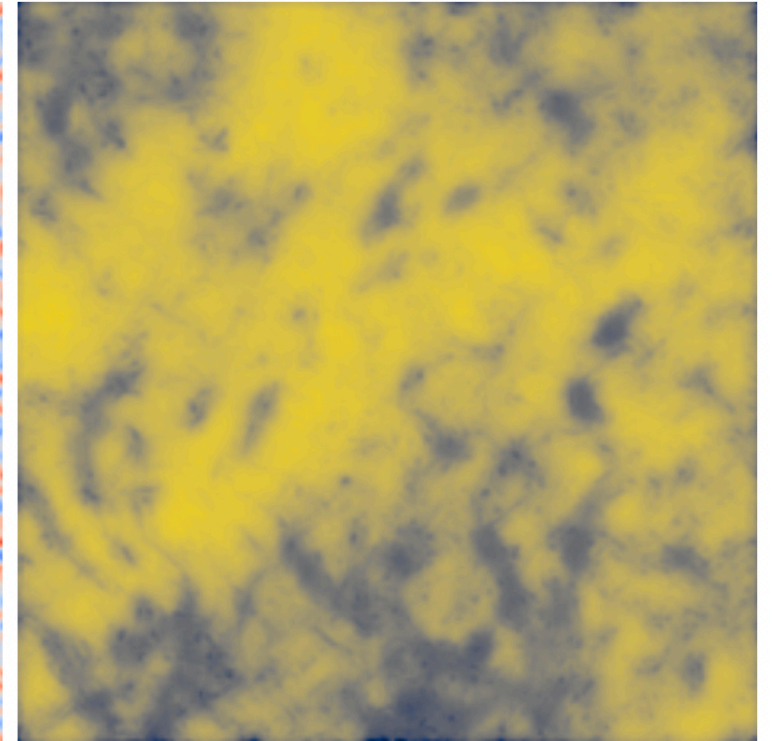
B-mode data



Posterior mean



Posterior marginal variance



Outline

1. *High-dimensional likelihood-free inference*
2. *Realistic forward model*
3. *Posterior validation*

01

High-dimensional likelihood-free:
Moment Networks

Parameter inference

1. Possible “data” \mathbf{d}
2. Unknown parameters: \mathbf{S} signal

$$p(\mathbf{s} | \mathbf{d}) \propto p(\mathbf{d} | \mathbf{s}) p(\mathbf{s})$$

Likelihood-free inference

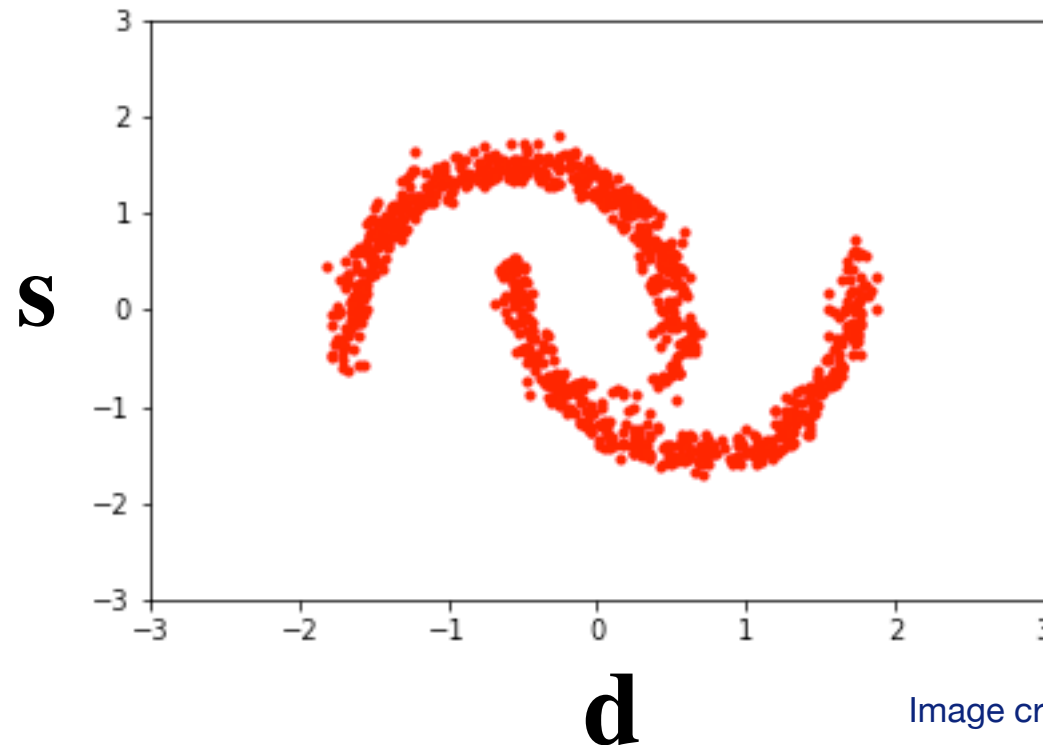
$$\{\mathbf{d}_i, \mathbf{s}_i\}$$

- I. \mathbf{d}_i are simulated data vector summary statistics (inc. noise)
- II. Draw \mathbf{d}_i from the distribution $p(\mathbf{d} | \mathbf{s}_i)$ by running a simulation

Likelihood-free inference

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Normalizing flow

Neural density estimation method

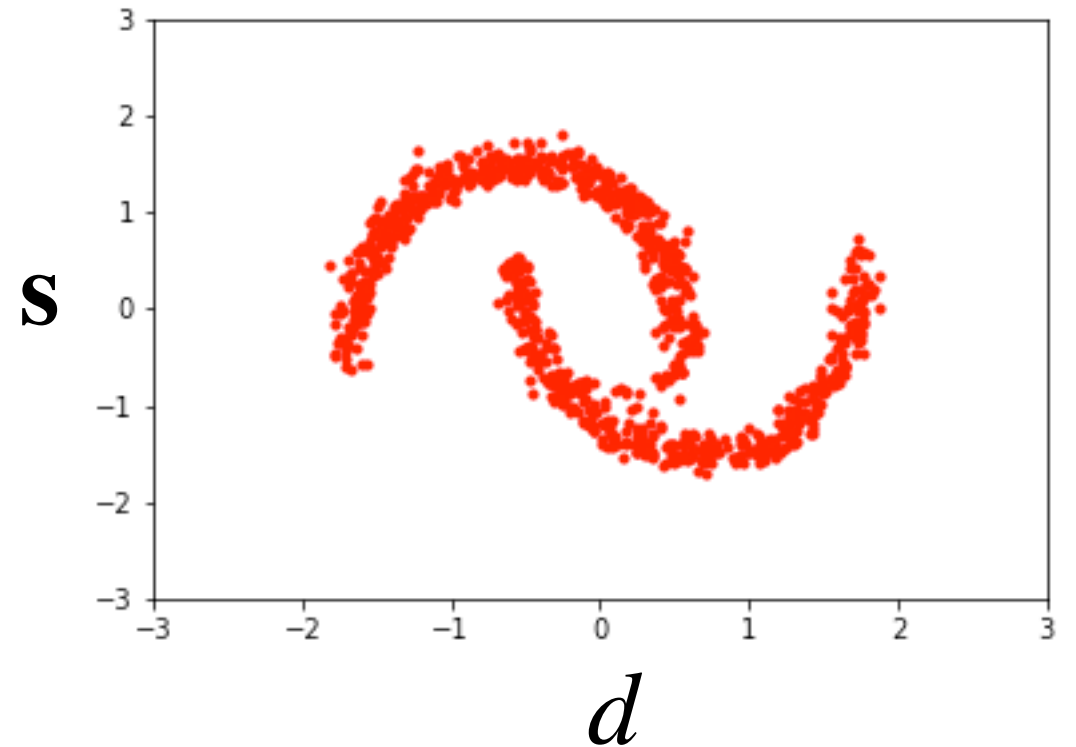
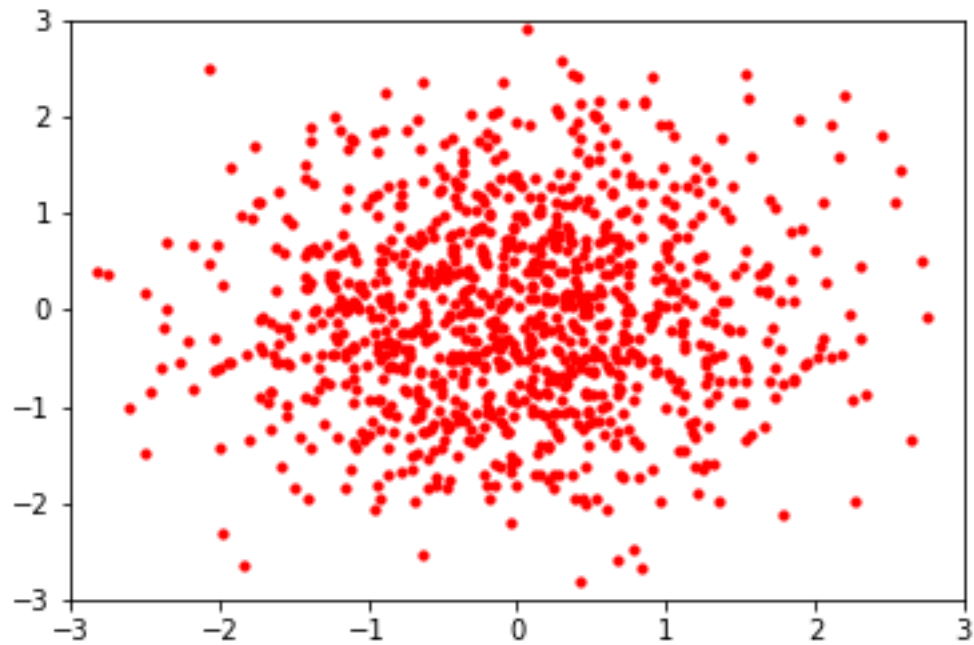


Image credit: Eric Jang

Moment Network:

Side-step density estimation for likelihood-free inference

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Side-step density estimation for likelihood-free inference

- I. Hierarchy of Networks
- II. Optimization objective use square loss

$$J_0 = \int \|\mathbf{s} - \mathcal{F}(\mathbf{d})\|^2 p(\mathbf{d}, \mathbf{s}) \, d\mathbf{d} \, d\mathbf{s}$$

Moment Network:

Side-step density estimation for likelihood-free inference

- I. Hierarchy of Networks
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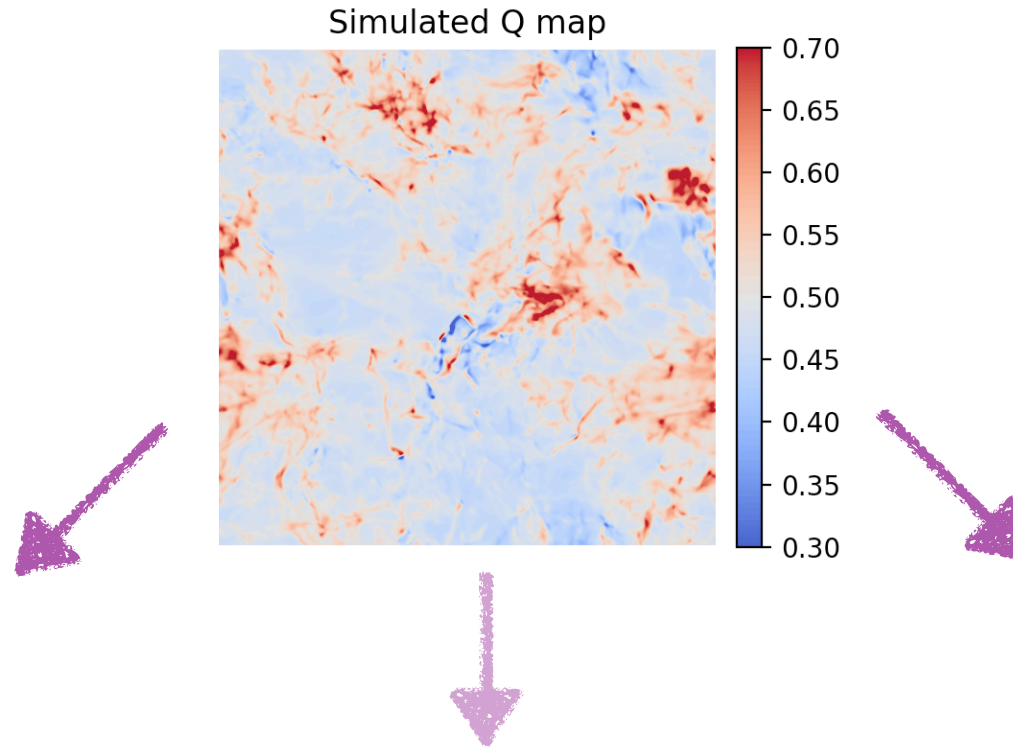
$$J_0 = \int \|\mathbf{s} - \mathcal{F}(\mathbf{d})\|^2 p(\mathbf{d}, \mathbf{s}) \, d\mathbf{d} \, d\mathbf{s}$$

$$J_1 = \int \left\| (\mathbf{s} - \mathcal{F}_{\text{fixed}}(\mathbf{d}))^2 - \mathcal{G}(\mathbf{d}) \right\|^2 p(\mathbf{d}, \mathbf{s}) \, d\mathbf{d} \, d\mathbf{s}$$

02

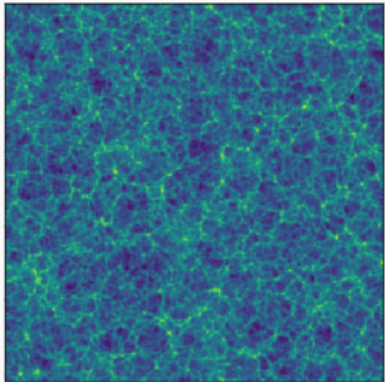
*Forward model &
B-mode inference*

Generative model for data?

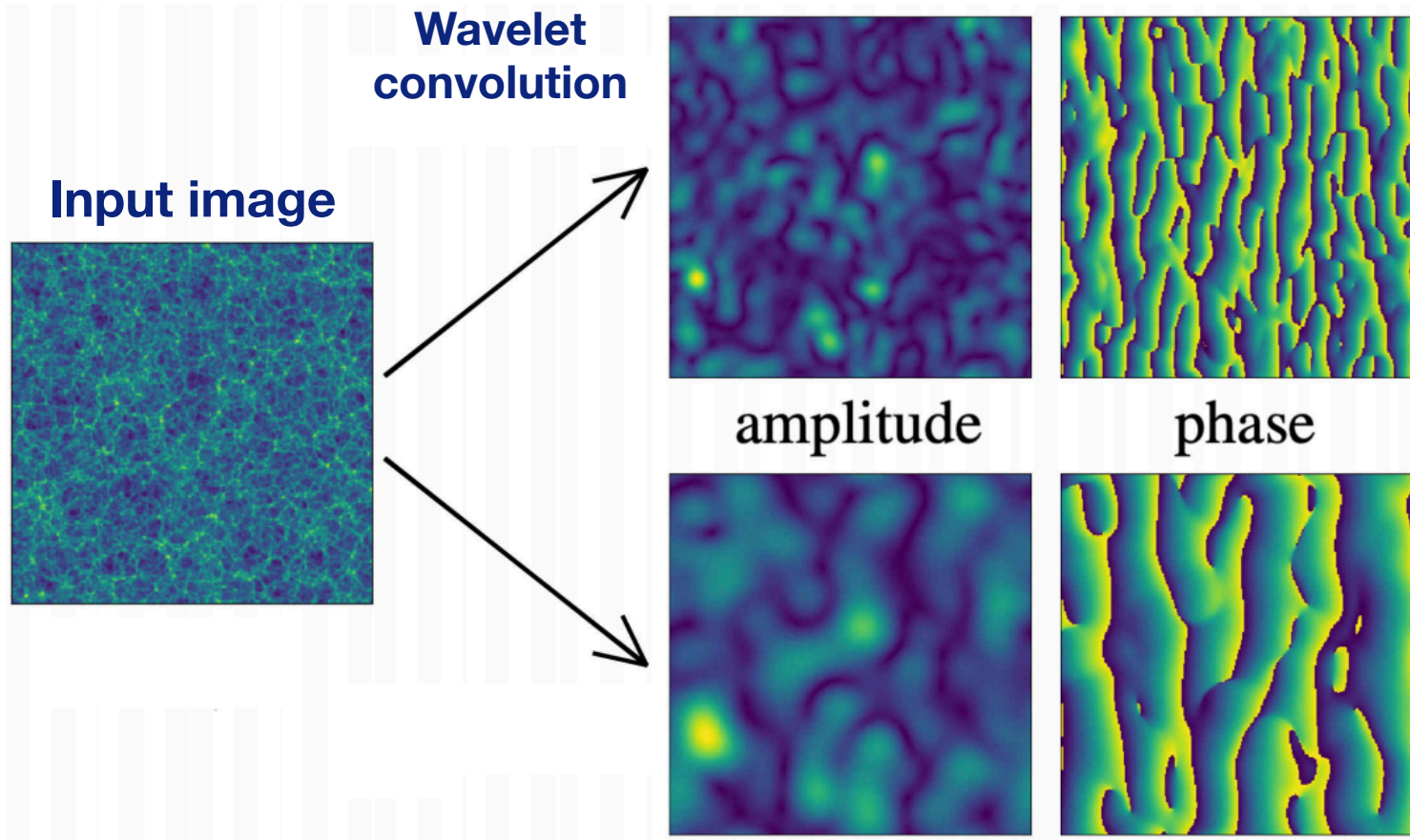


Wavelet Phase Harmonics

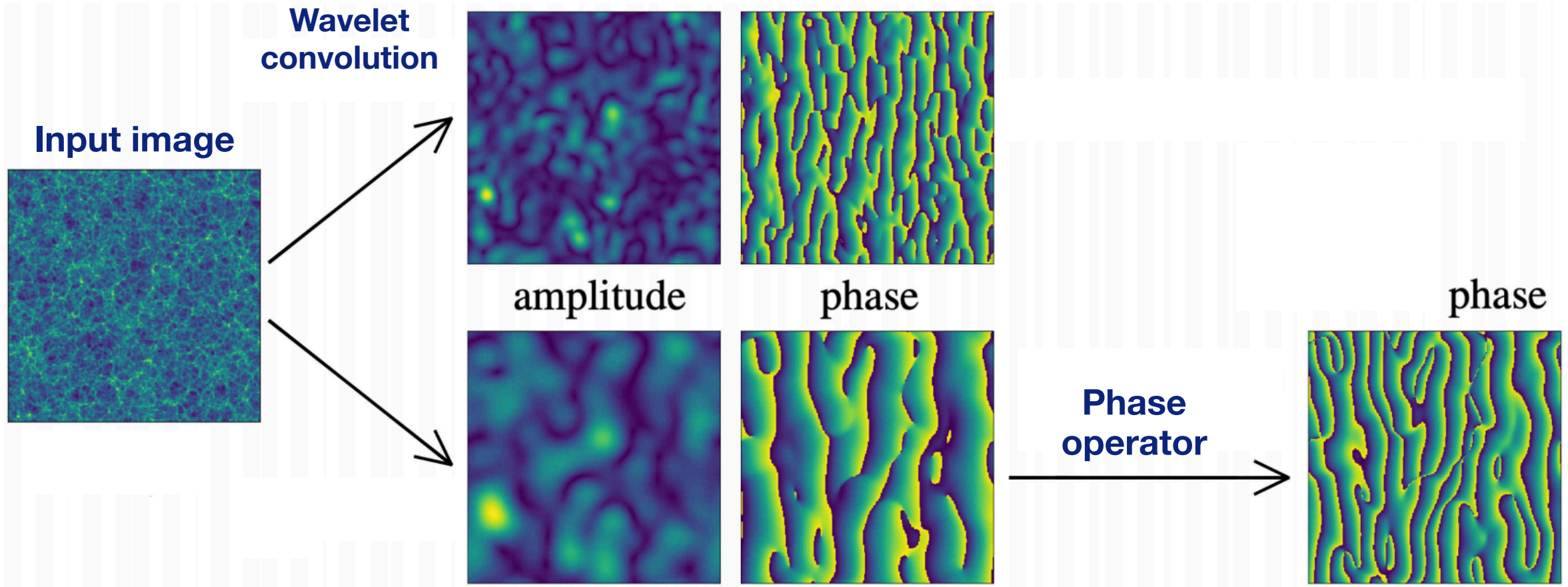
Input image



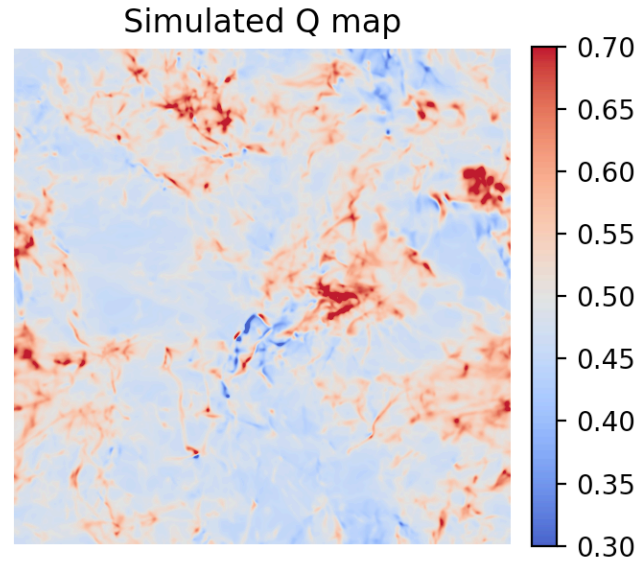
Wavelet Phase Harmonics



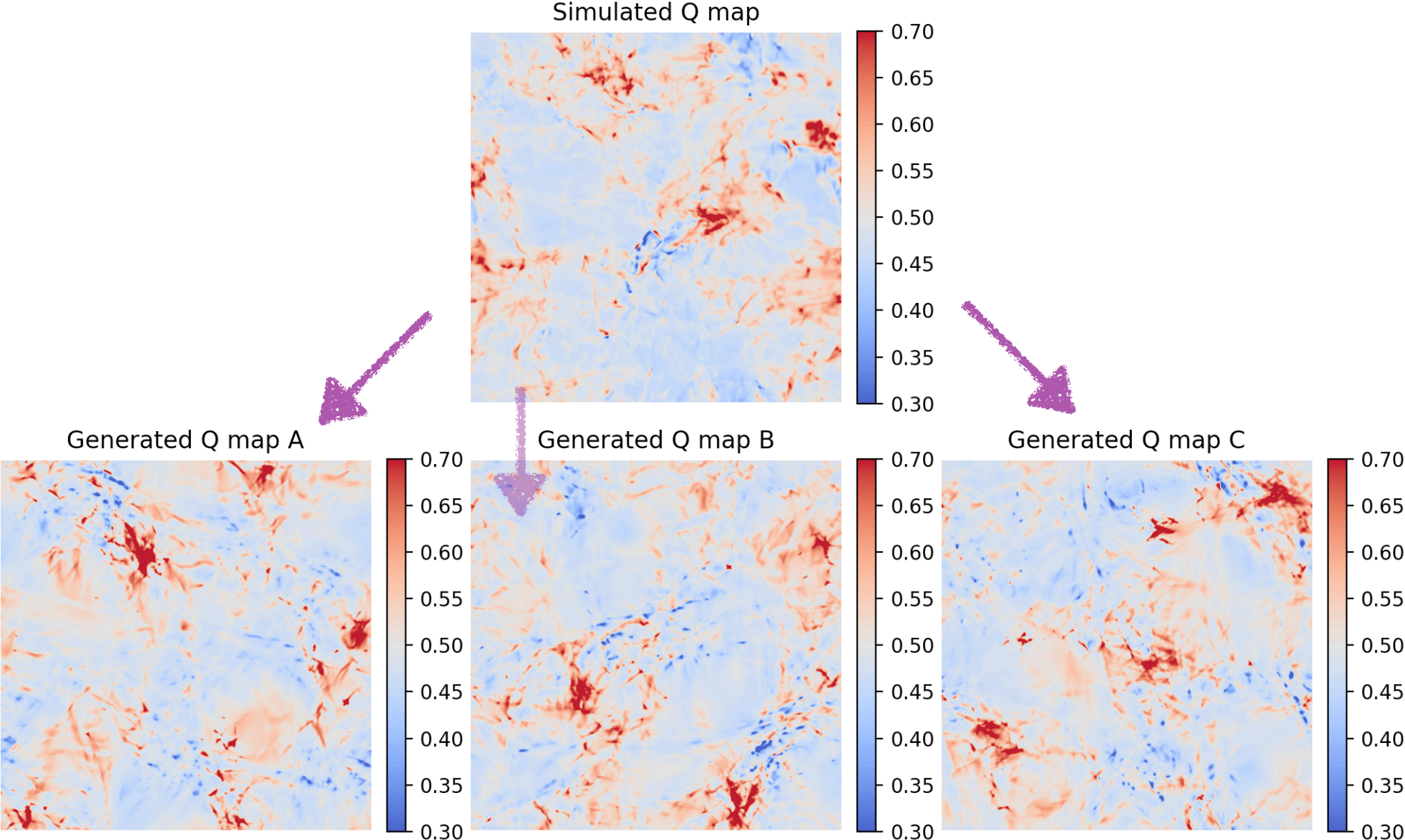
Wavelet Phase Harmonics



Generative model for data

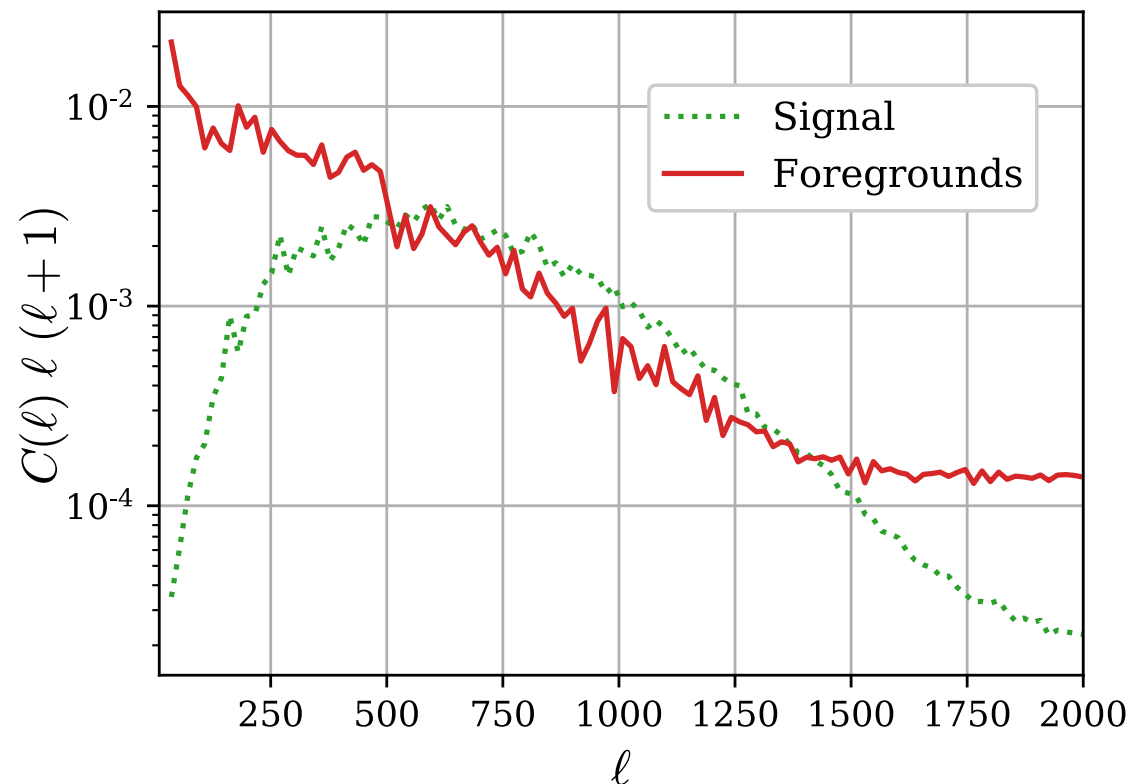


Generative model for data



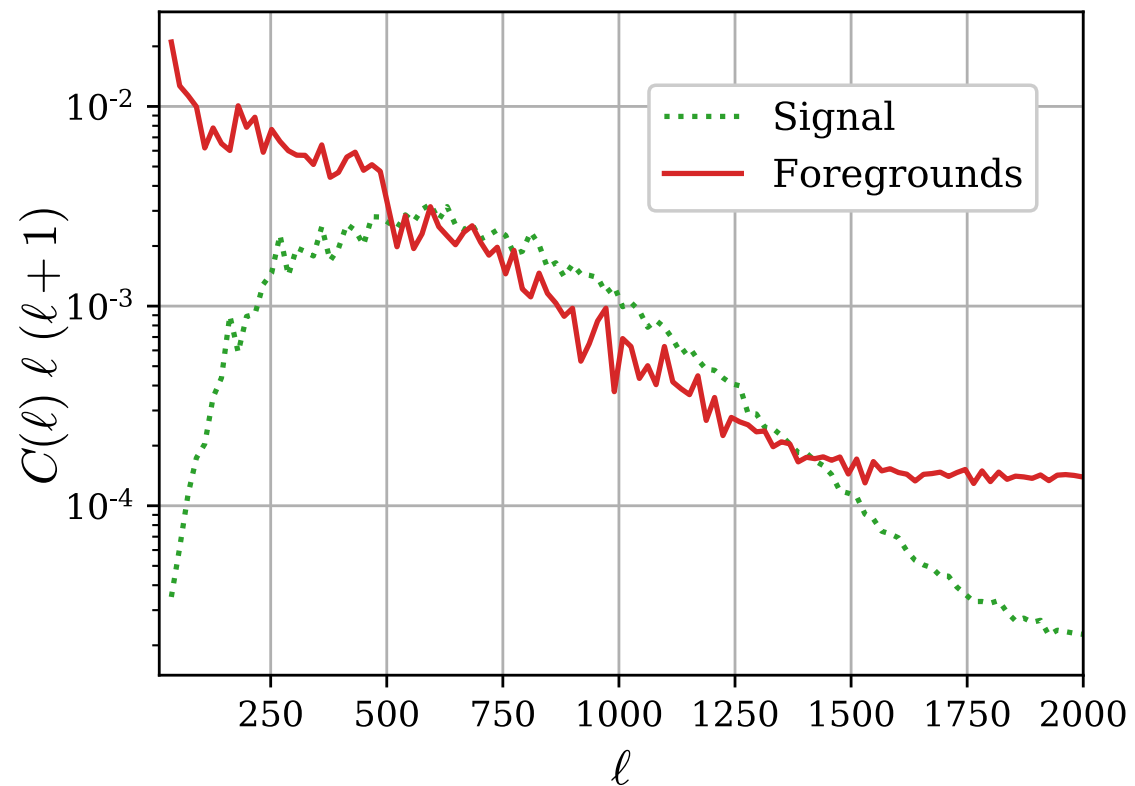
Model parameters from prior

Validation data example "A"
(signal dominated $\ell \sim 1000$)

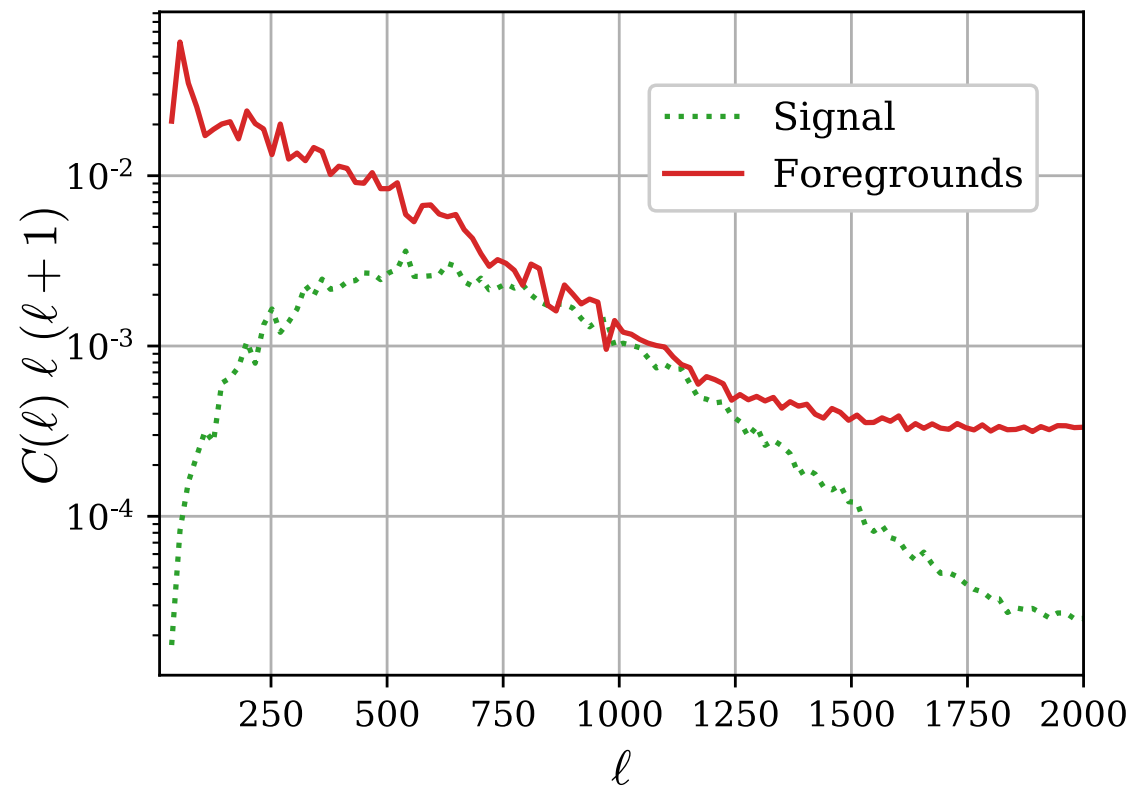


Model parameters from prior

Validation data example "A"
(signal dominated $\ell \sim 1000$)



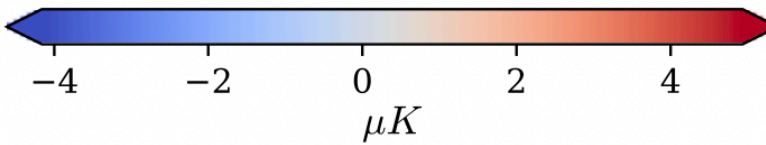
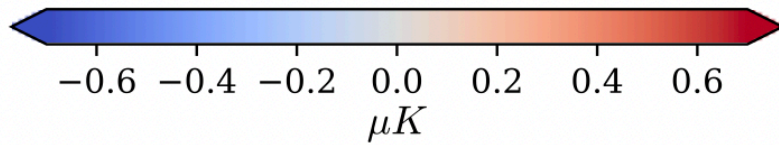
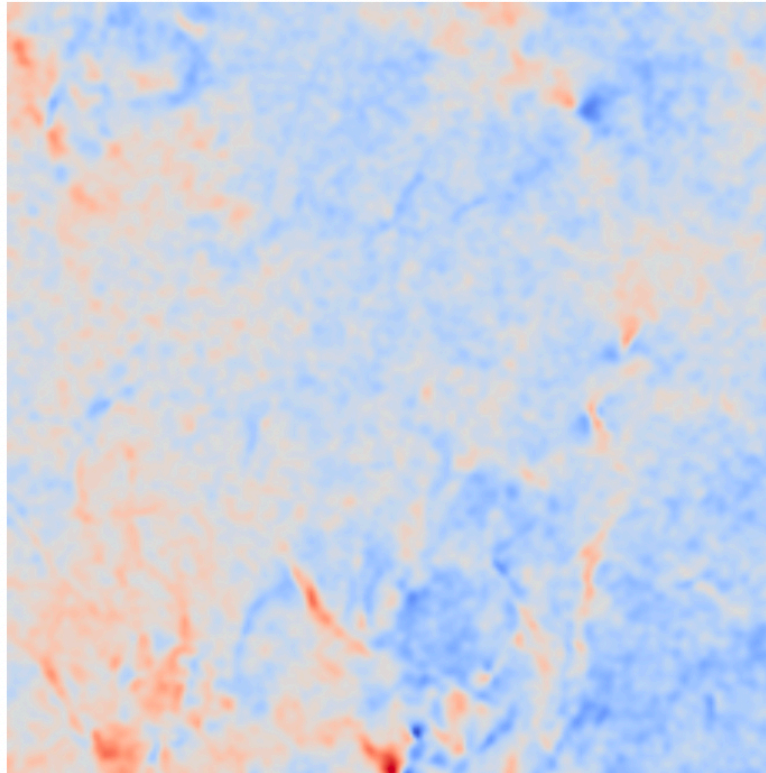
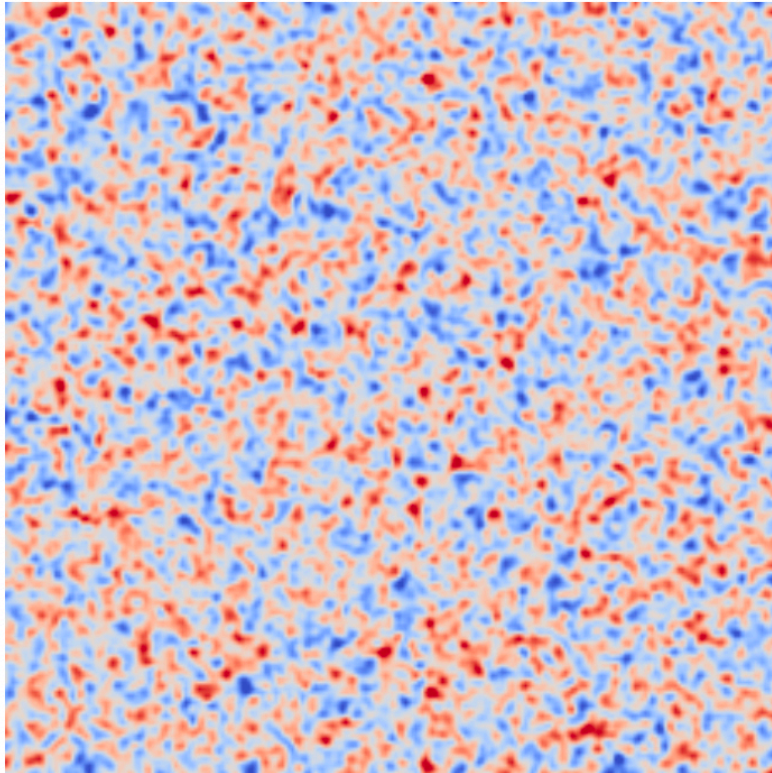
Validation data example "B"
(foreground dominated $\ell \sim 1000$)



B-mode inference

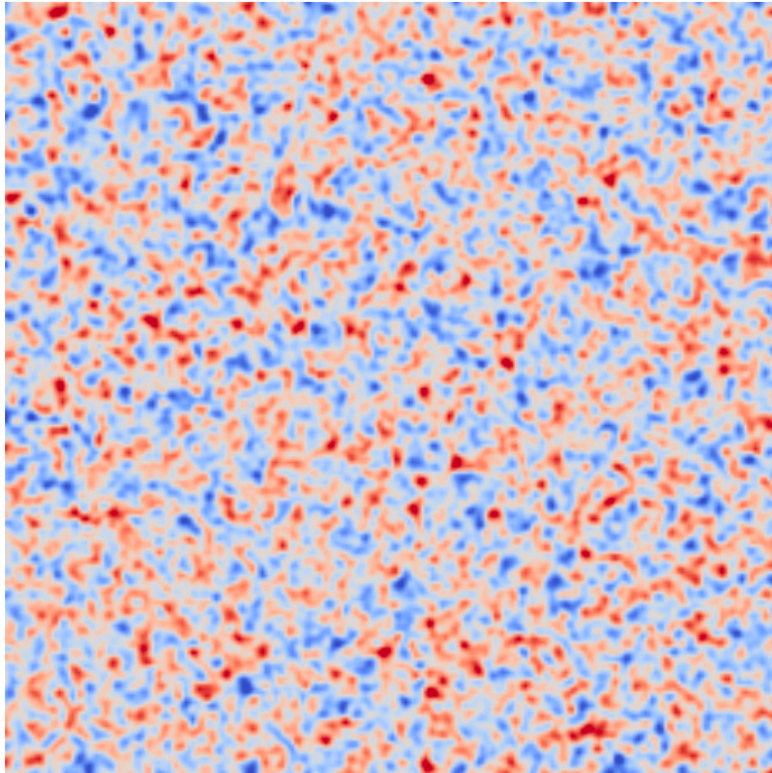
B-mode truth

B-mode data

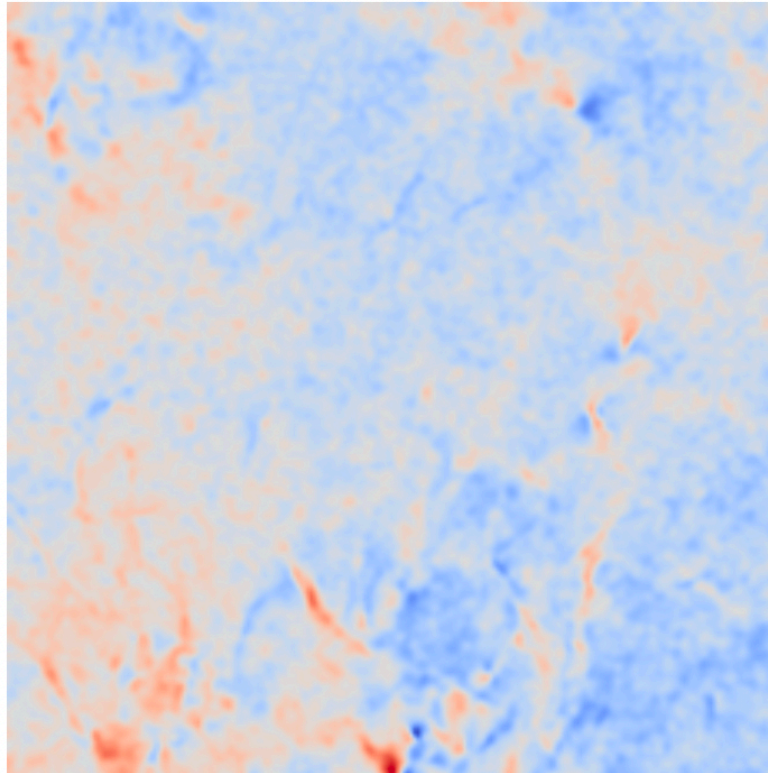


B-mode inference

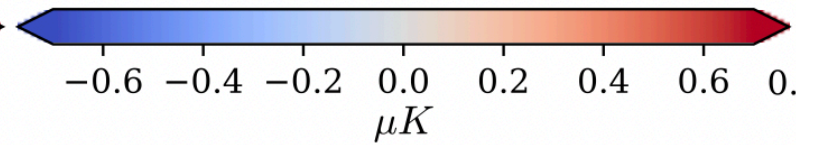
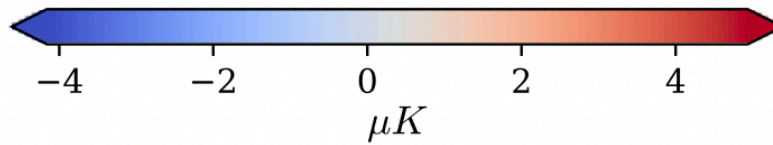
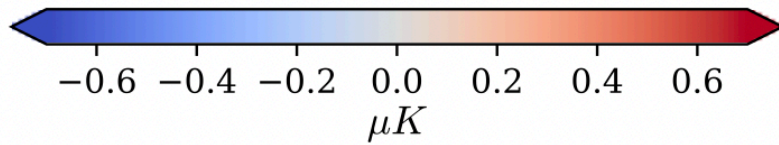
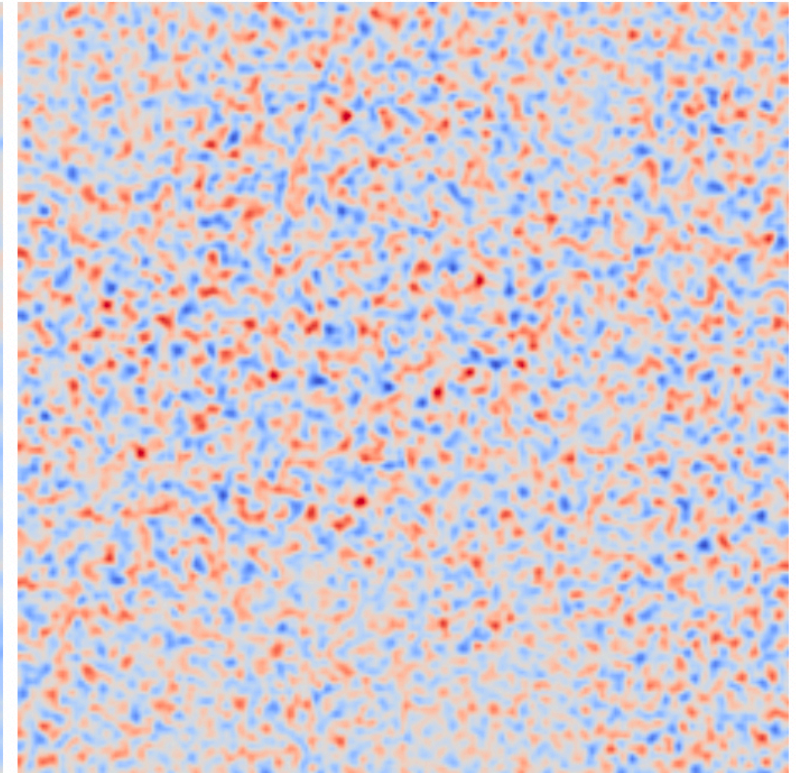
B-mode truth



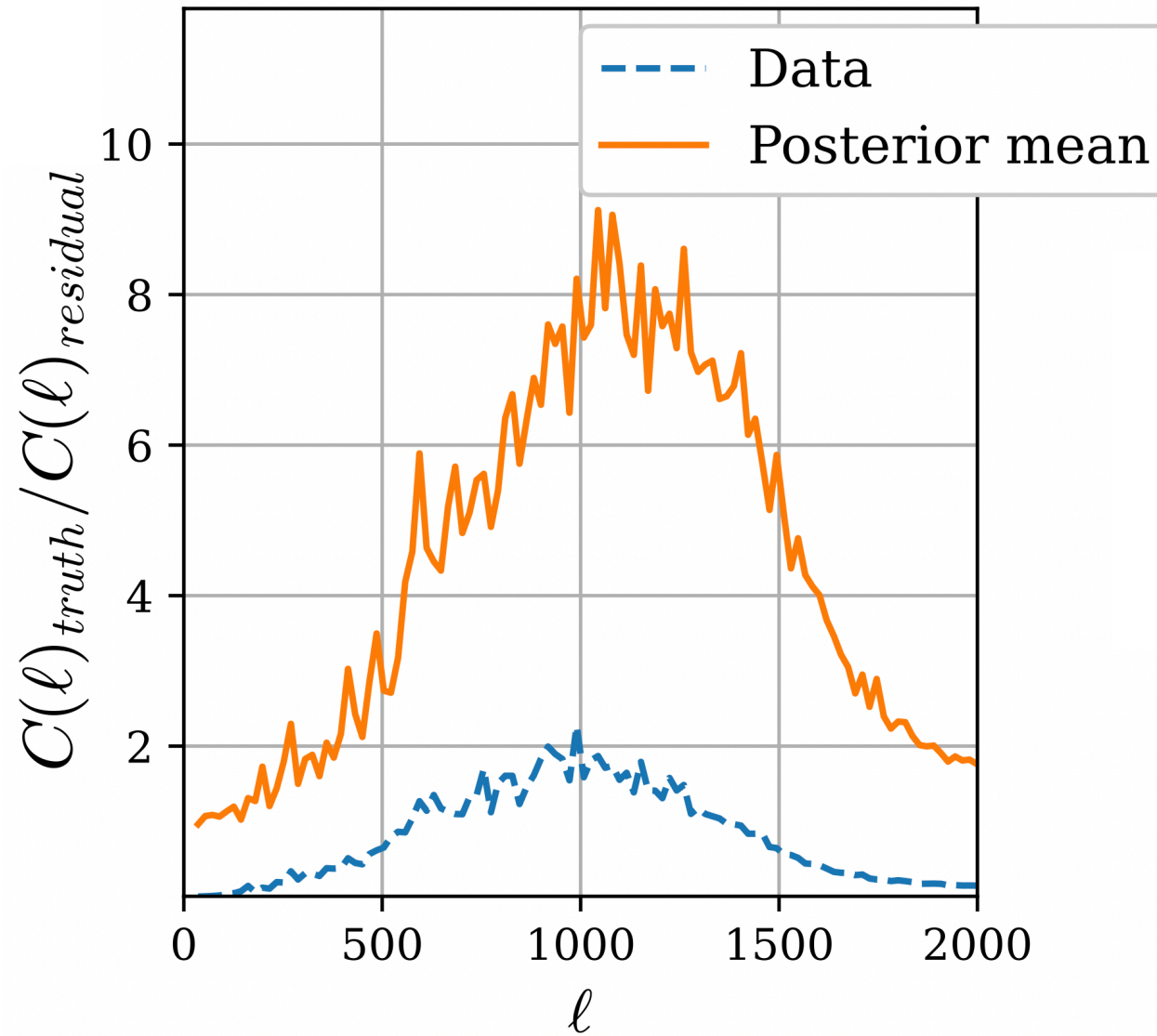
B-mode data



Posterior mean



Recovered “signal-to-noise”



03

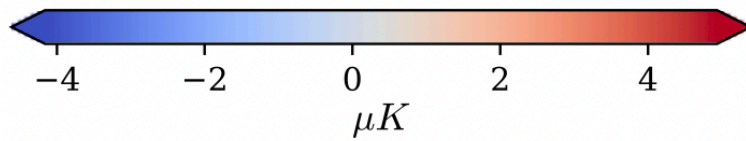
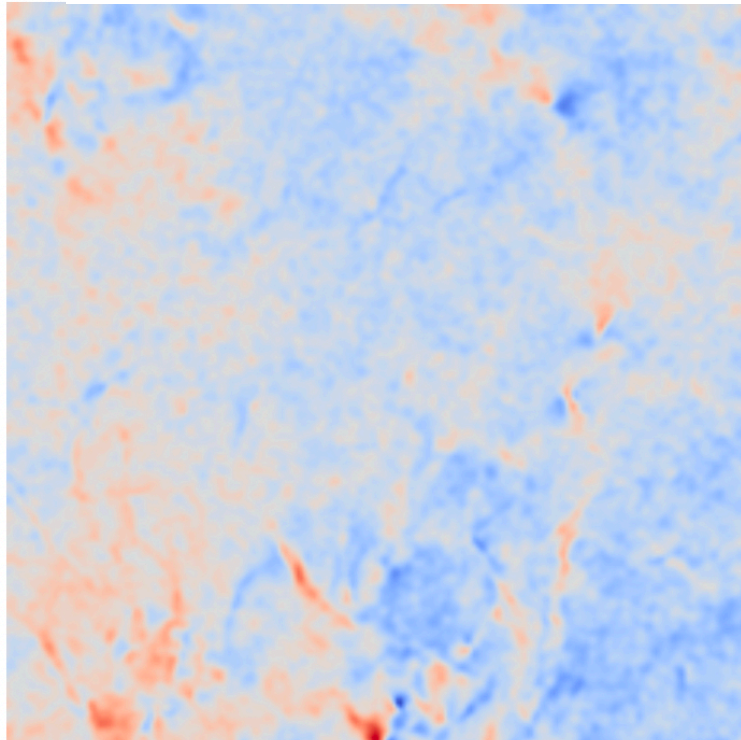
Posterior validation

How can we test the posterior?

What does the “wrong” answer look like...

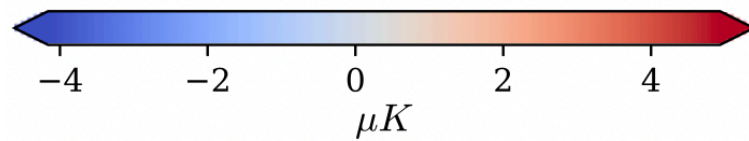
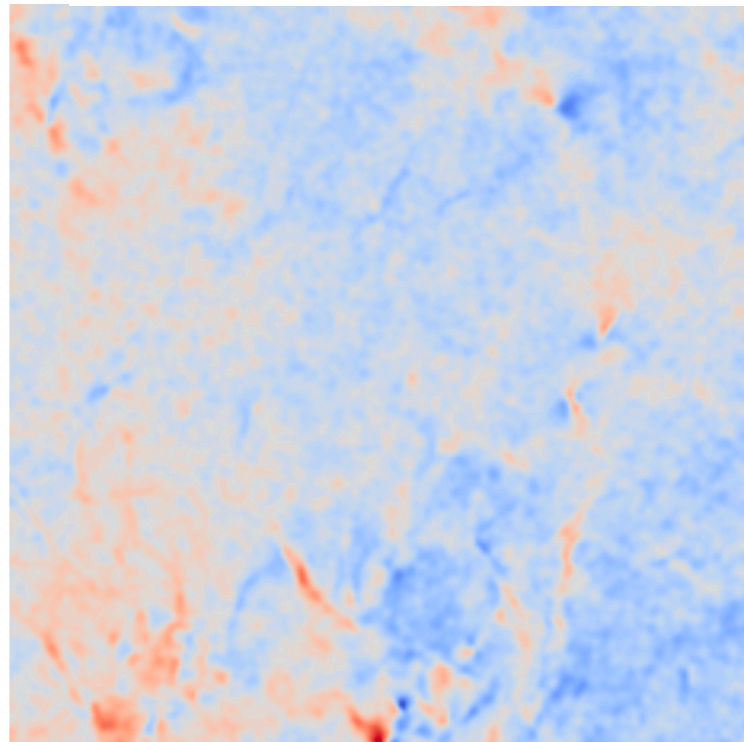
Naive Gaussian model:

B-mode data

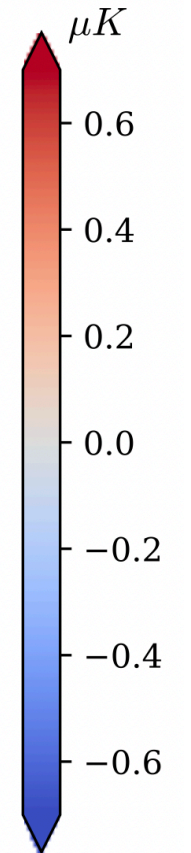
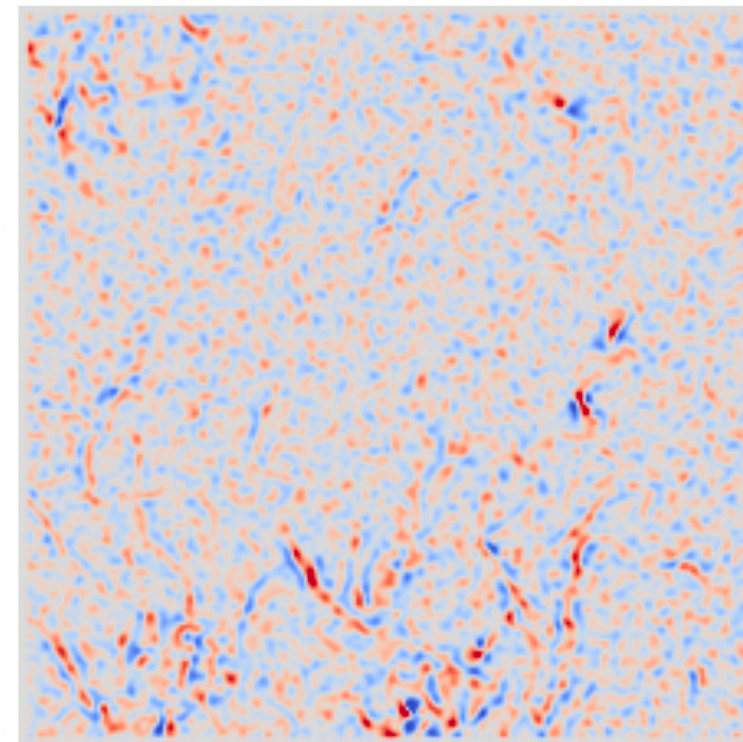


Naive Gaussian model:

B-mode data

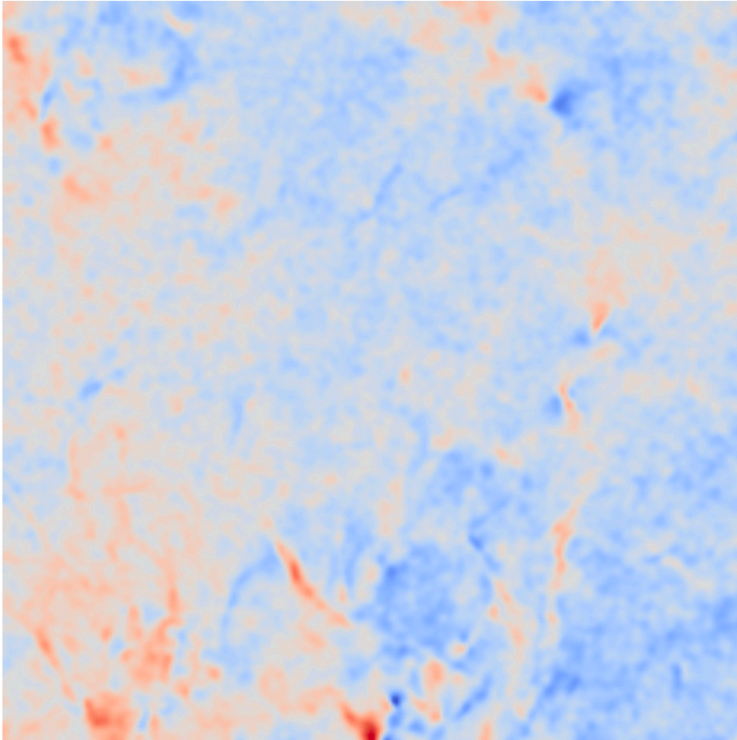


Posterior mean

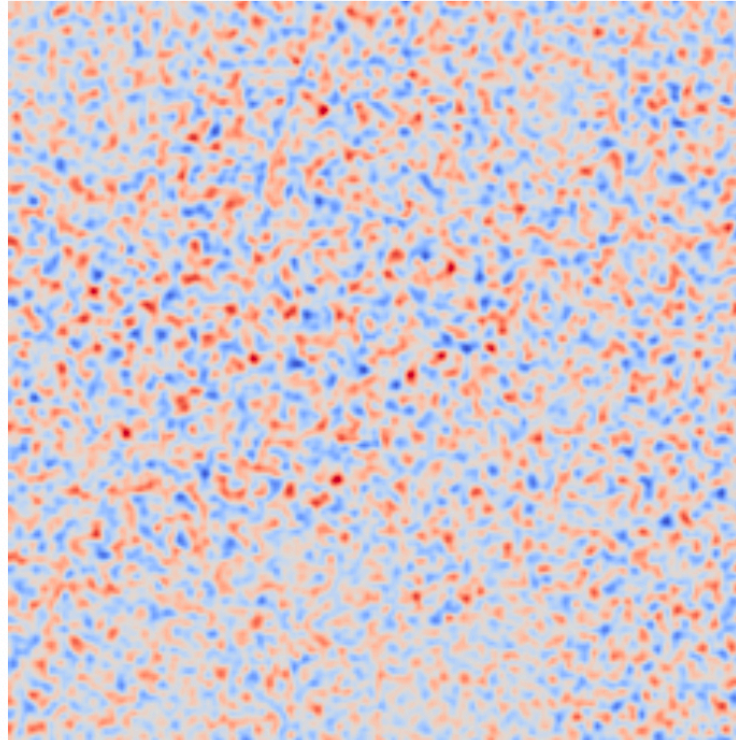


Validation of posterior

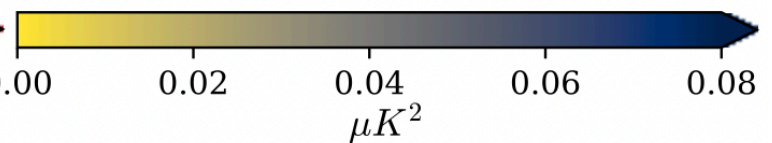
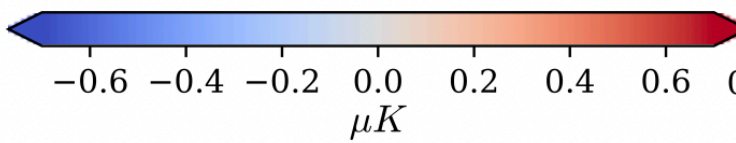
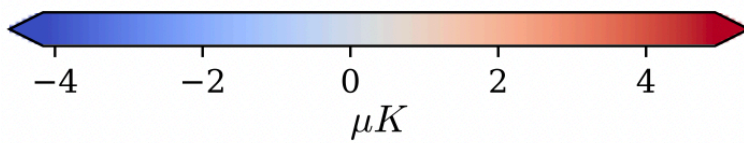
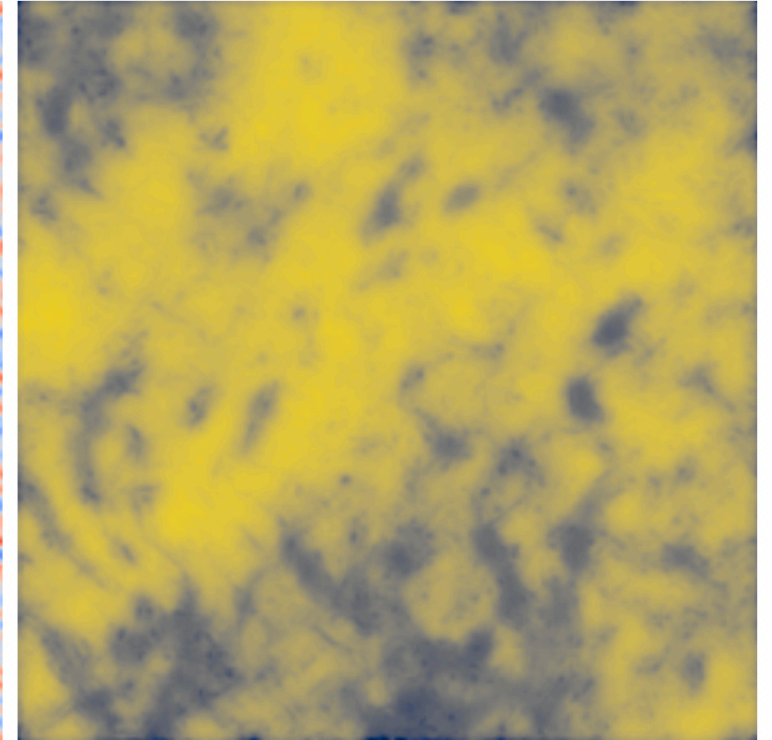
B-mode data



Posterior mean



Posterior marginal variance



Rescaled residuals

$$(\mu_B - s_B) / \sigma_B$$

POSTERIOR
MEAN



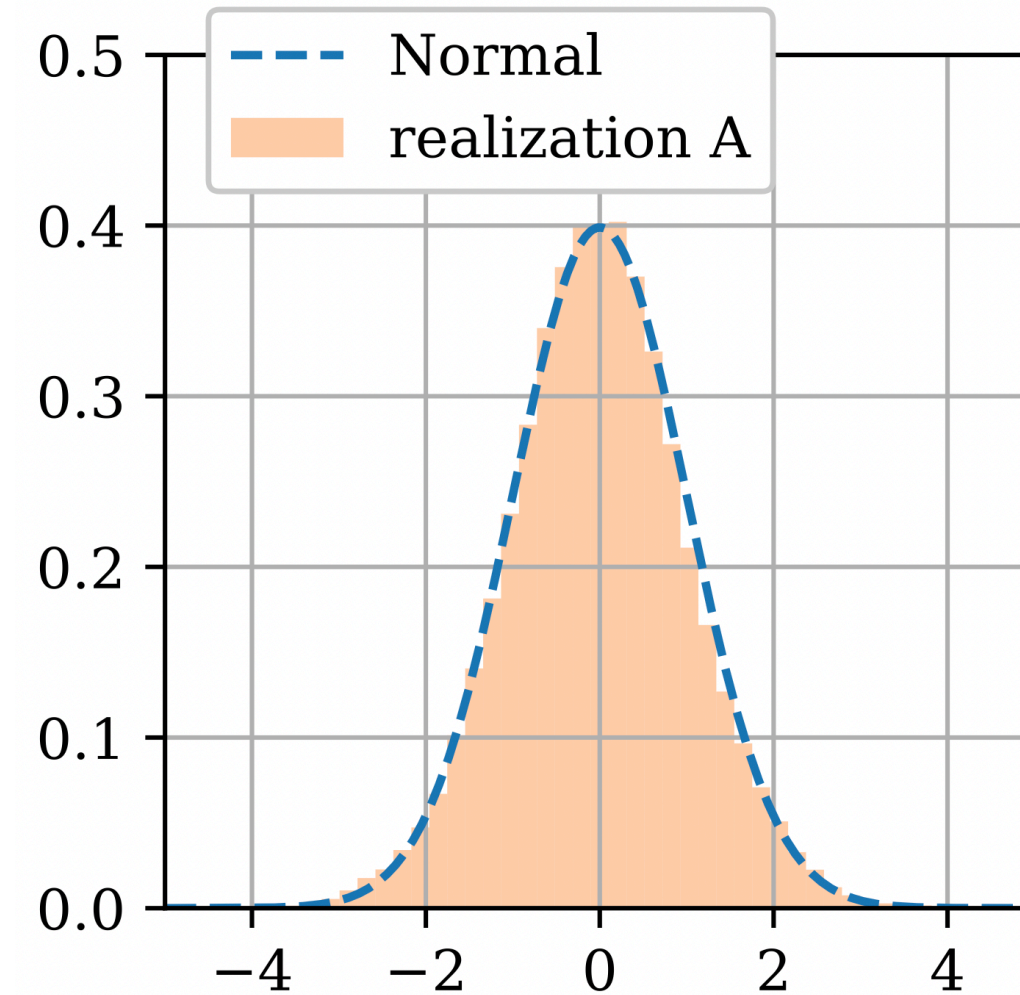
TRUE PIXEL
VALUE



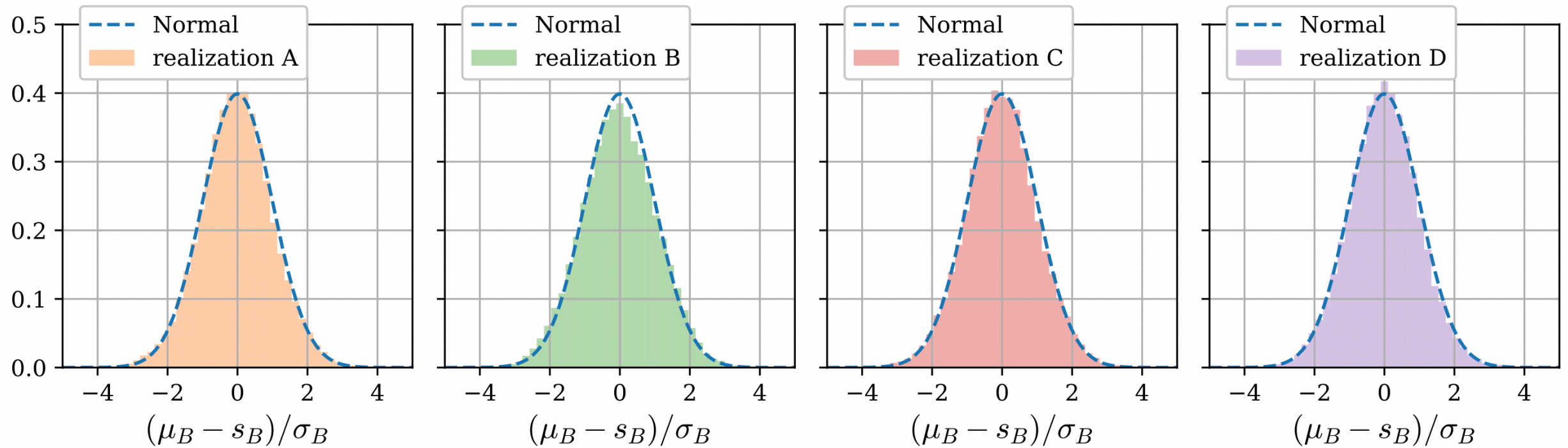
POSTERIOR
VARIANCE

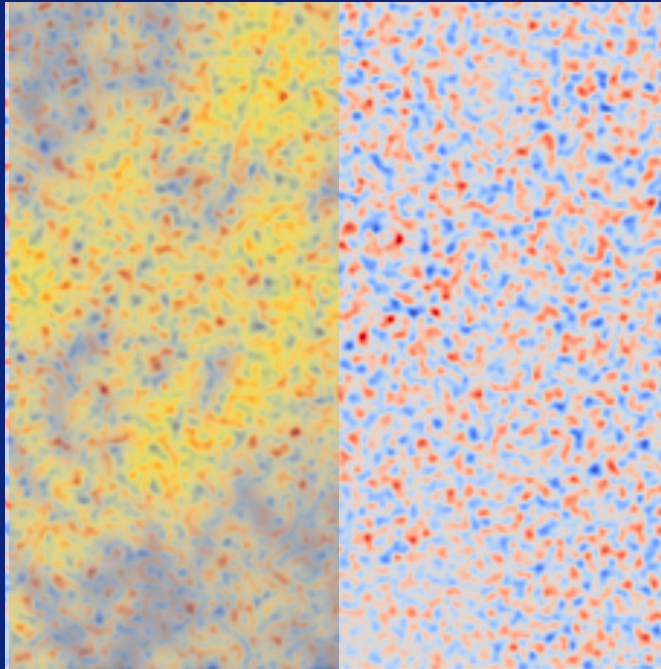


Rescaled residuals



Posterior estimates are excellent:





Merci !

