



UCL

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

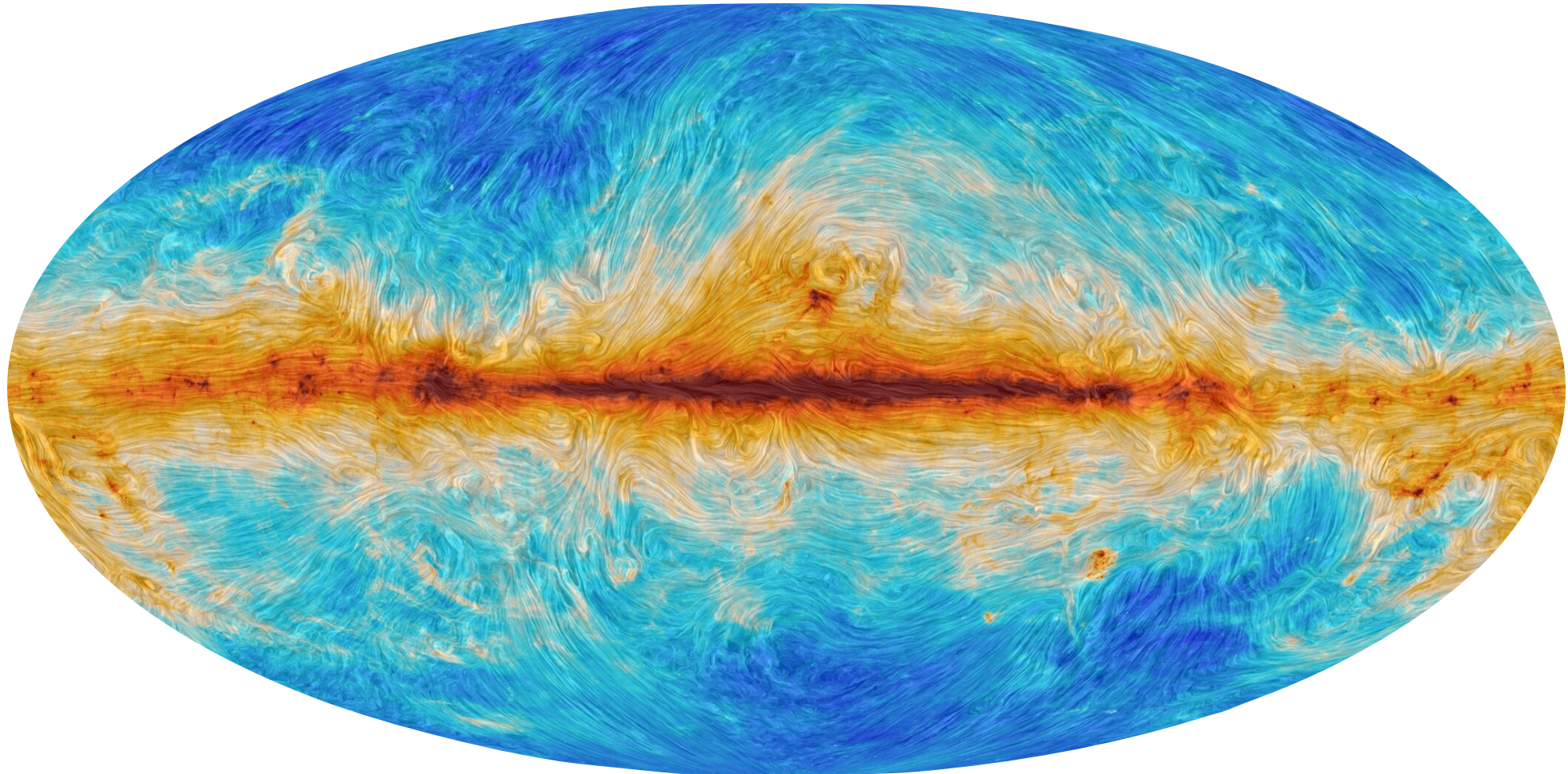
Niall Jeffrey

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

From Planck to the future of the CMB, May 2022

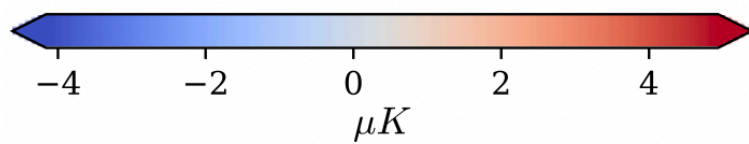
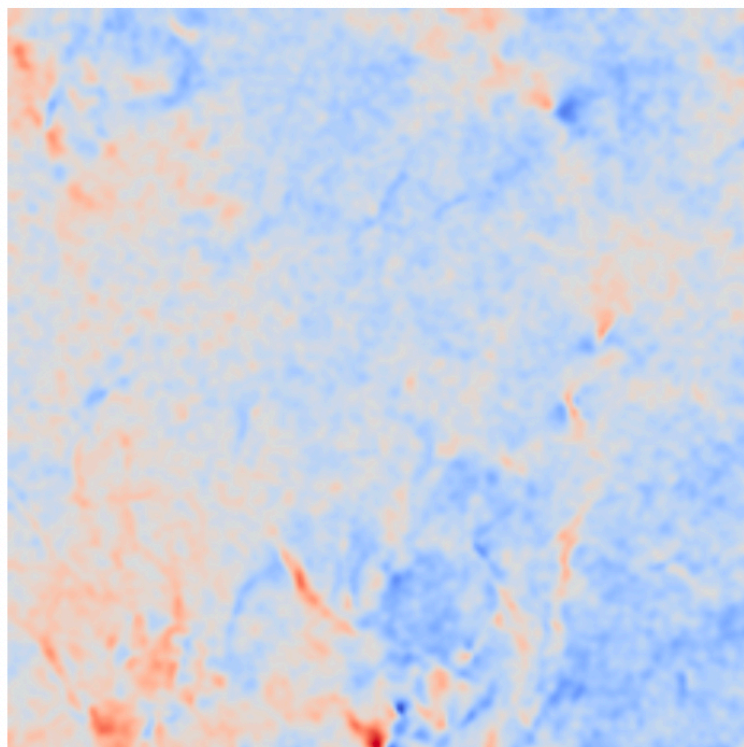
Search for “B-modes” signal of cosmic inflation

image credit: ESA



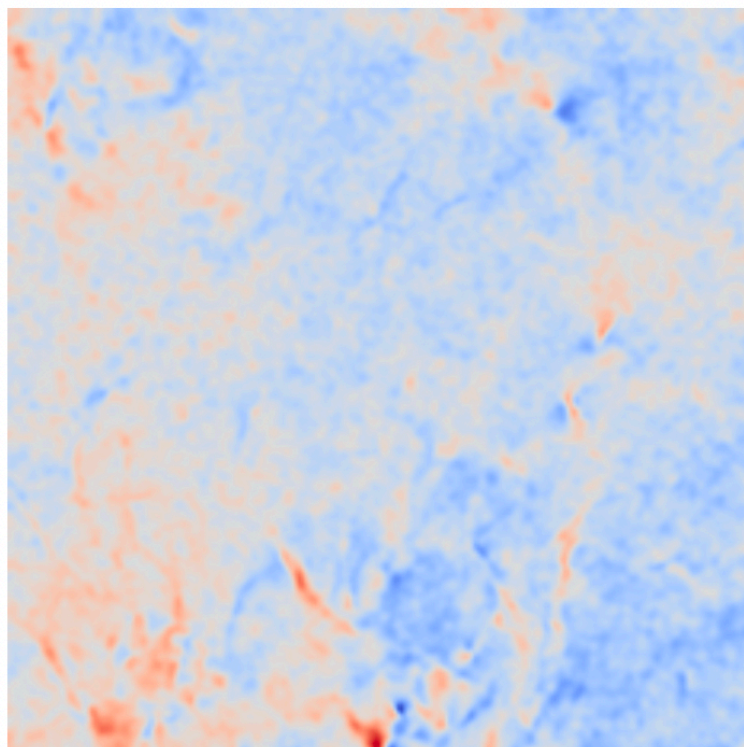
B-mode inference

Data

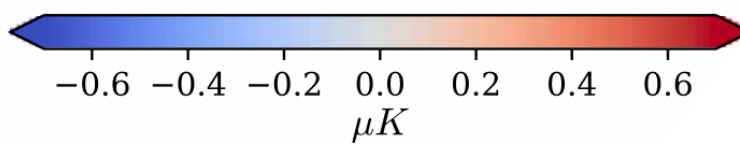
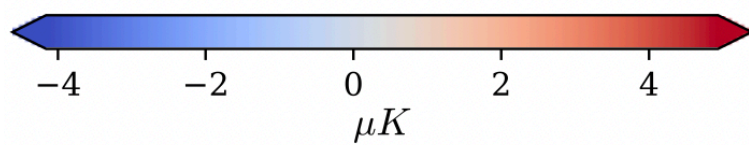
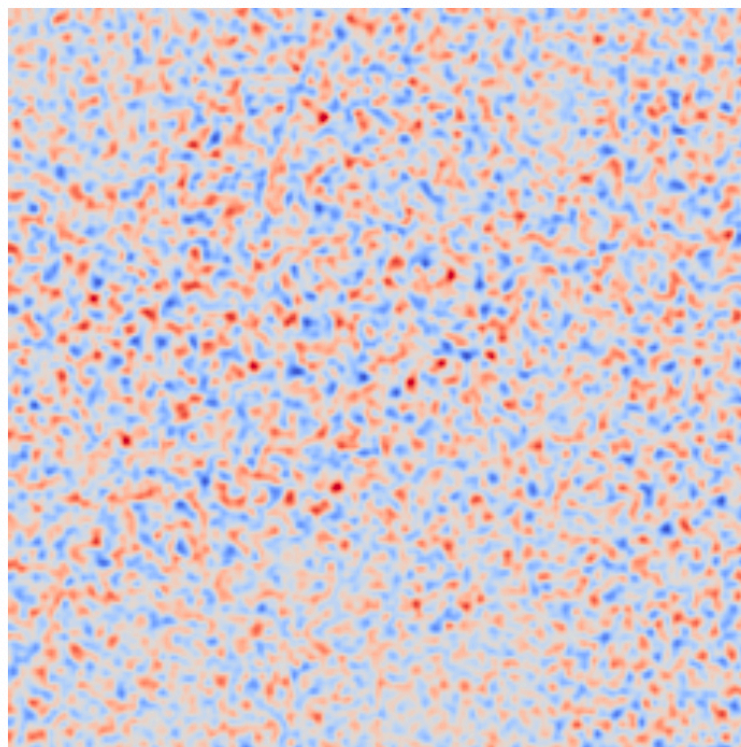


B-mode inference

Data

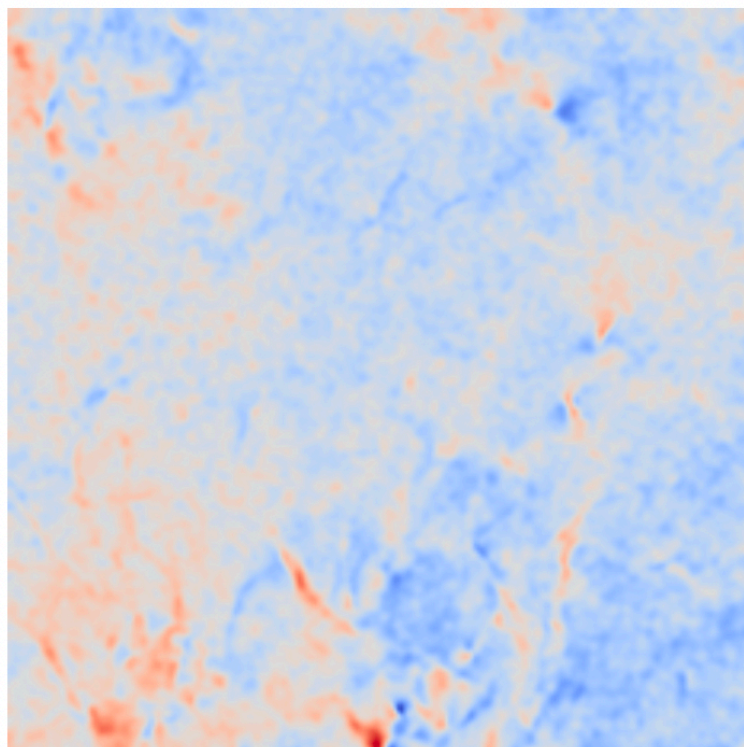


Posterior mean

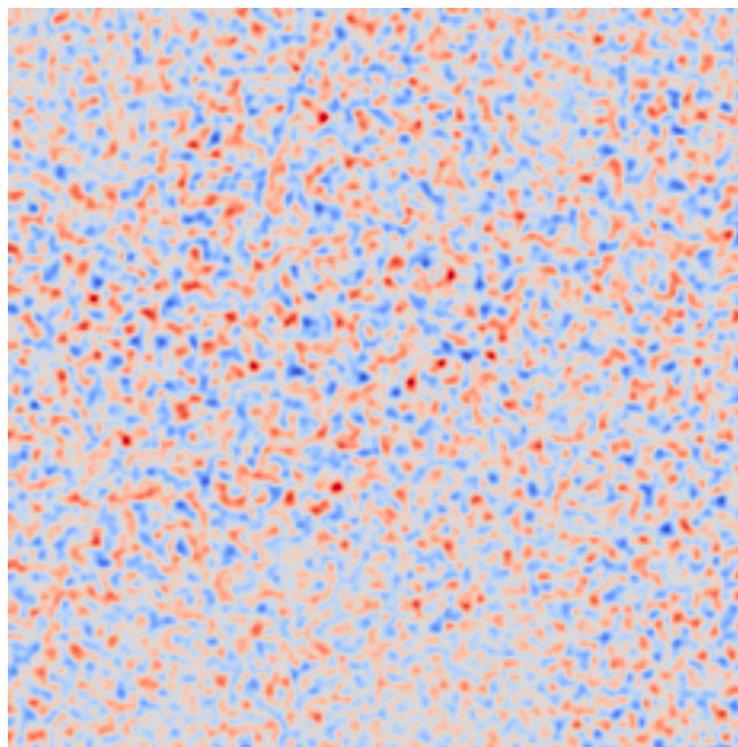


B-mode inference

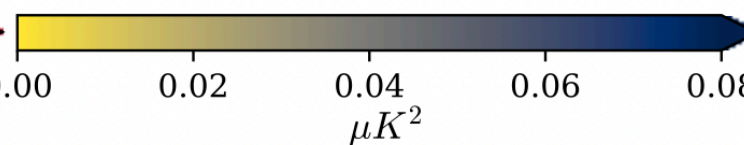
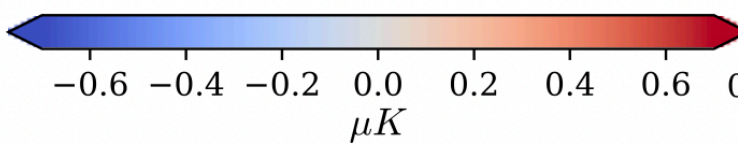
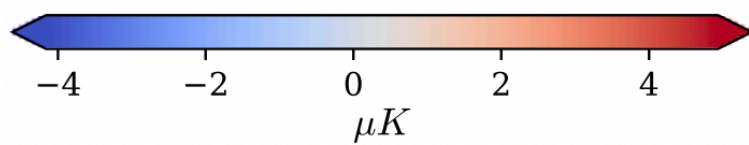
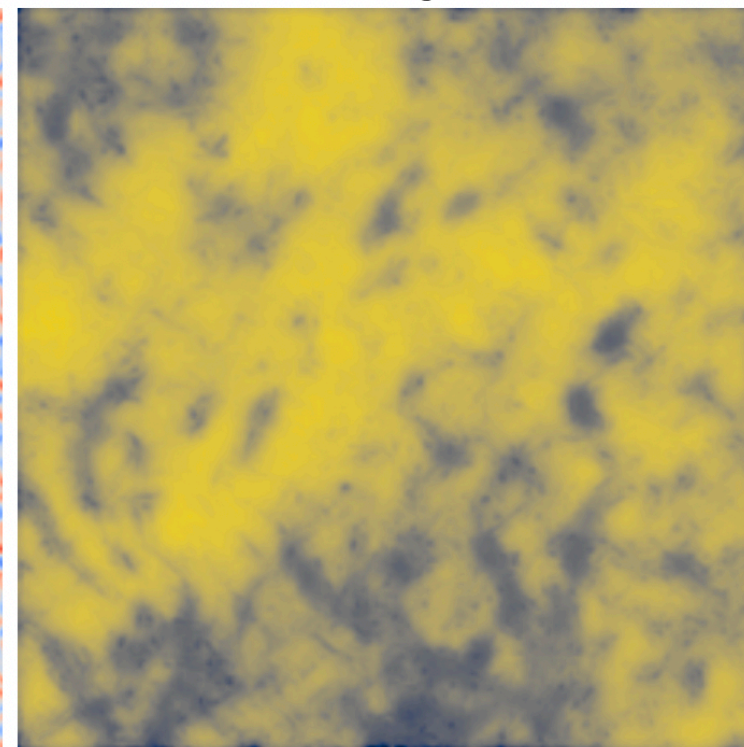
Data



Posterior mean



Posterior marginal variance



Outline

1. Likelihood-free inference
2. Realistic foreground synthesis
3. Posterior validation
4. Neural foreground generator

1. Likelihood-free inference (in high-dimension)

Why “likelihood-free”?

Observed summary statistic d_o & unknown parameters θ

Why “likelihood-free”?

Observed summary statistic d_o & unknown parameters θ

$$p(\theta | d_o) \propto p(d_o | \theta) p(\theta)$$

LIKELIHOOD

A diagram illustrating the components of the equation $p(\theta | d_o) \propto p(d_o | \theta) p(\theta)$. A blue arrow points from the word "LIKELIHOOD" to the term $p(d_o | \theta)$ in the equation. Another blue arrow points from the word "PRIOR" to the term $p(\theta)$ in the equation.

PRIOR

Density-estimation likelihood-free

$$p(d | \theta) ?$$

Density-estimation likelihood-free

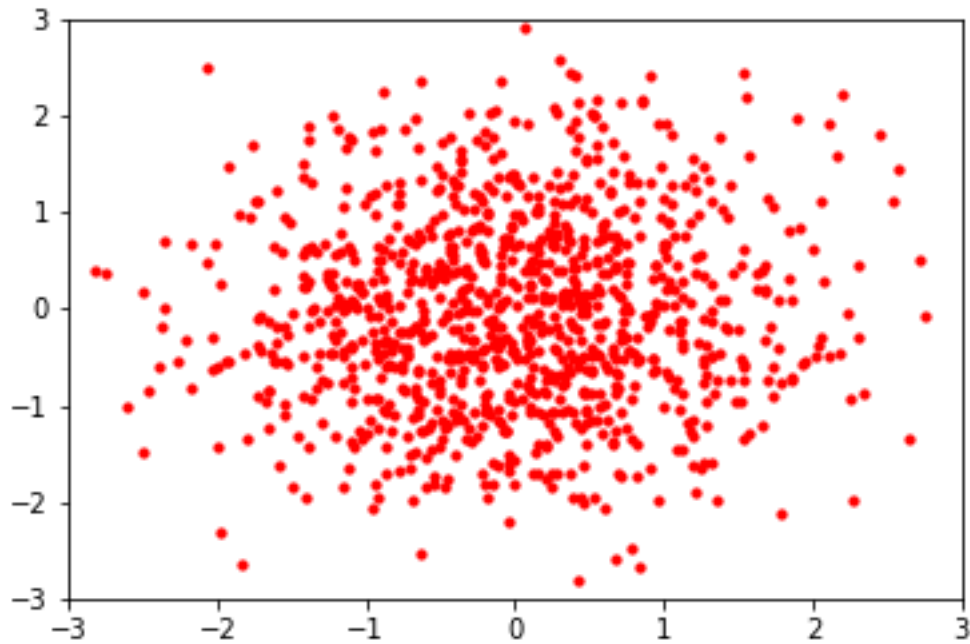
$$p(d | \theta) ?$$

Draw d_i from the distribution $p(d | \theta_i)$ by running a simulation:

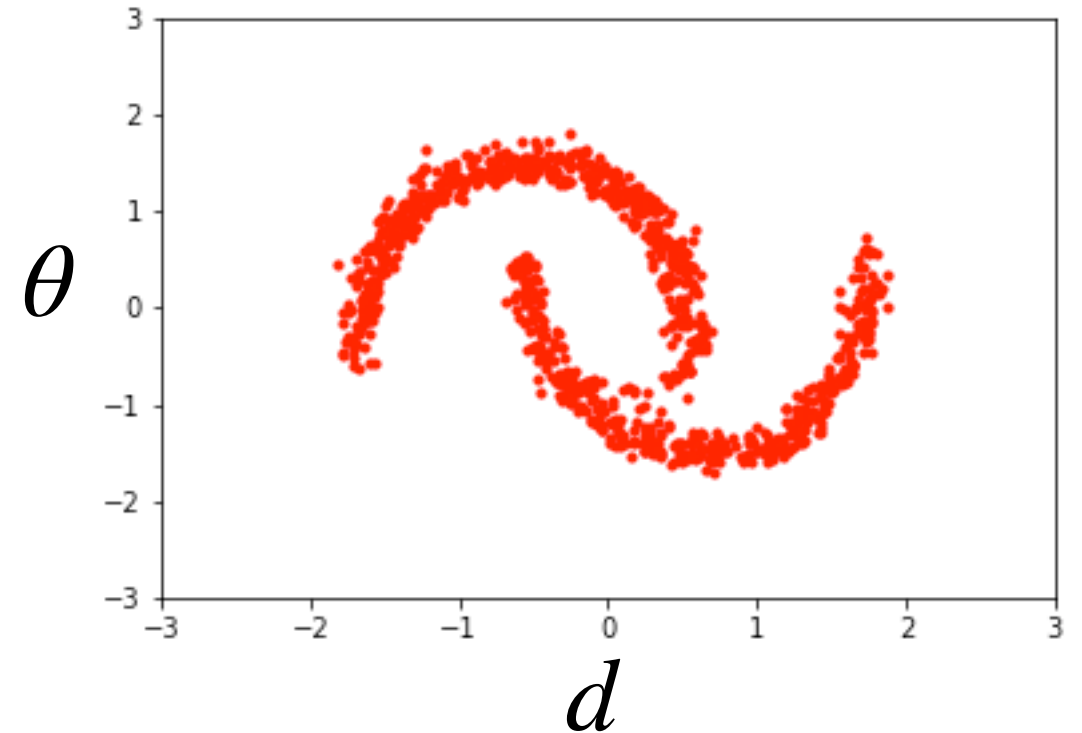
$$\{d_i, \theta_i\}$$

Estimate density from simulations: $p(d | \theta)$

Image credit: Eric Jang



Normalising Flow



Simulated data realizations

Moment Networks

NJ & Wandelt 2011.05991

1. Hierarchy of networks
2. Estimate marginal posterior moments

Moment Networks

NJ & Wandelt 2011.05991

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2. Estimate marginal posterior moments

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

Moment Networks

NJ & Wandelt 2011.05991

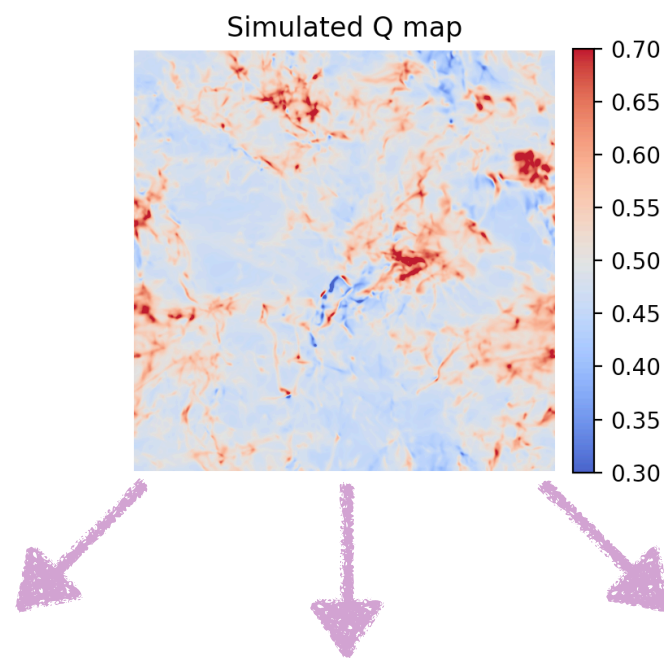
1. Hierarchy of networks
2. Estimate marginal posterior moments

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

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

2. Forward model & B-mode inference

Generative model for data

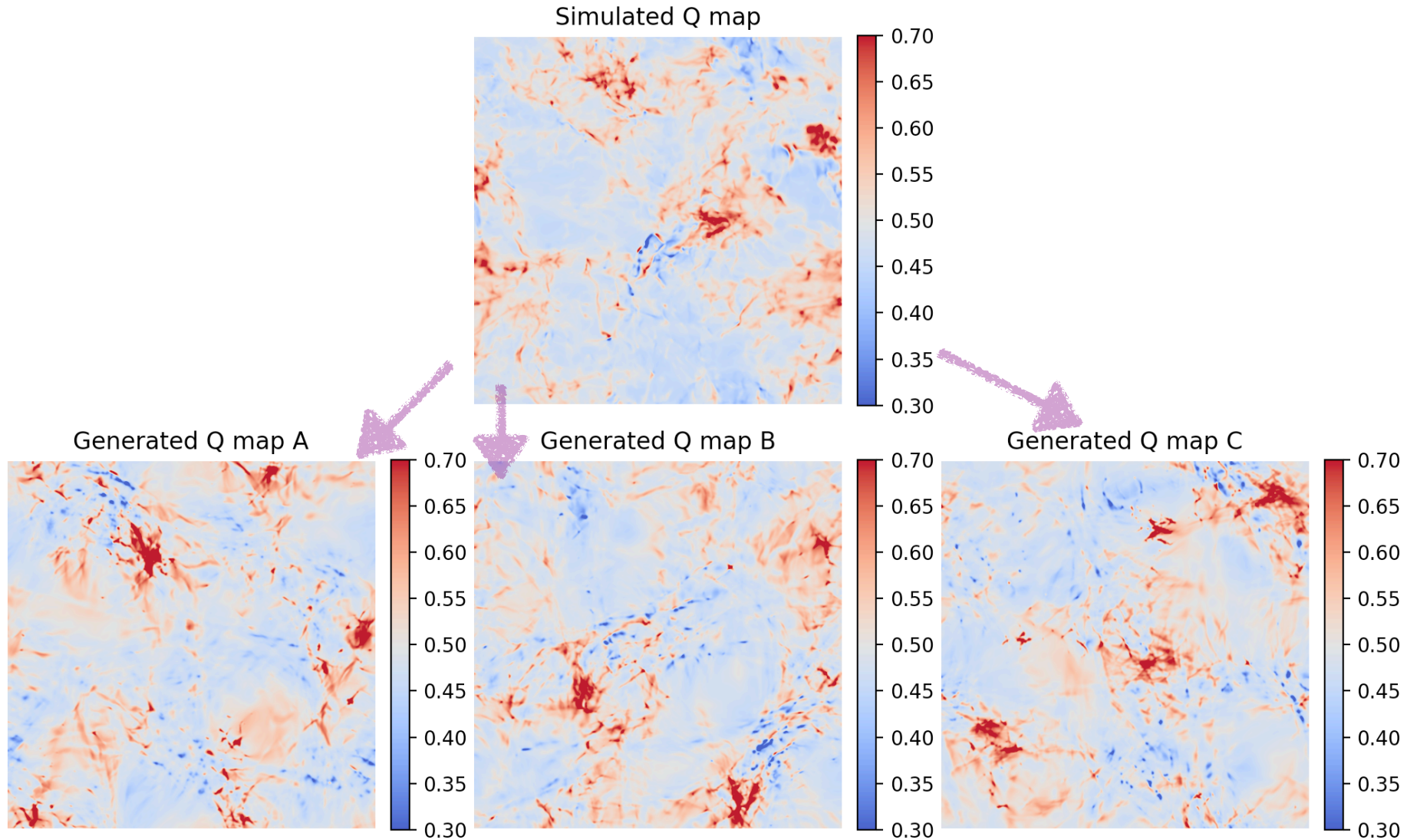


Wavelet Phase Harmonics

$$\phi(f)_{p_1=0, p_2=1} = \text{Cov} \left(\psi_{j_1, l_1} \circledast f(\vec{x}) , \|\psi_{j_2, l_2} \circledast f(\vec{x} + \vec{\tau})\|_1 \right)$$

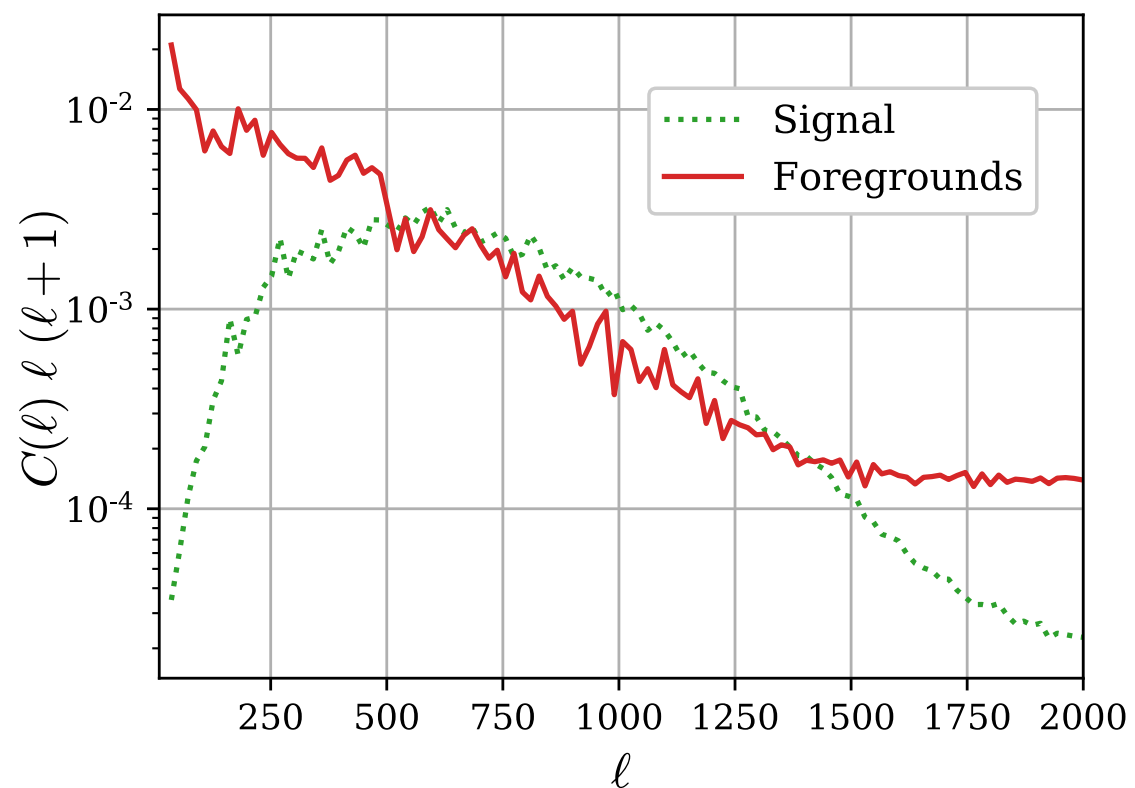
(see Allys++ 2006.06298)

Generative for foregrounds



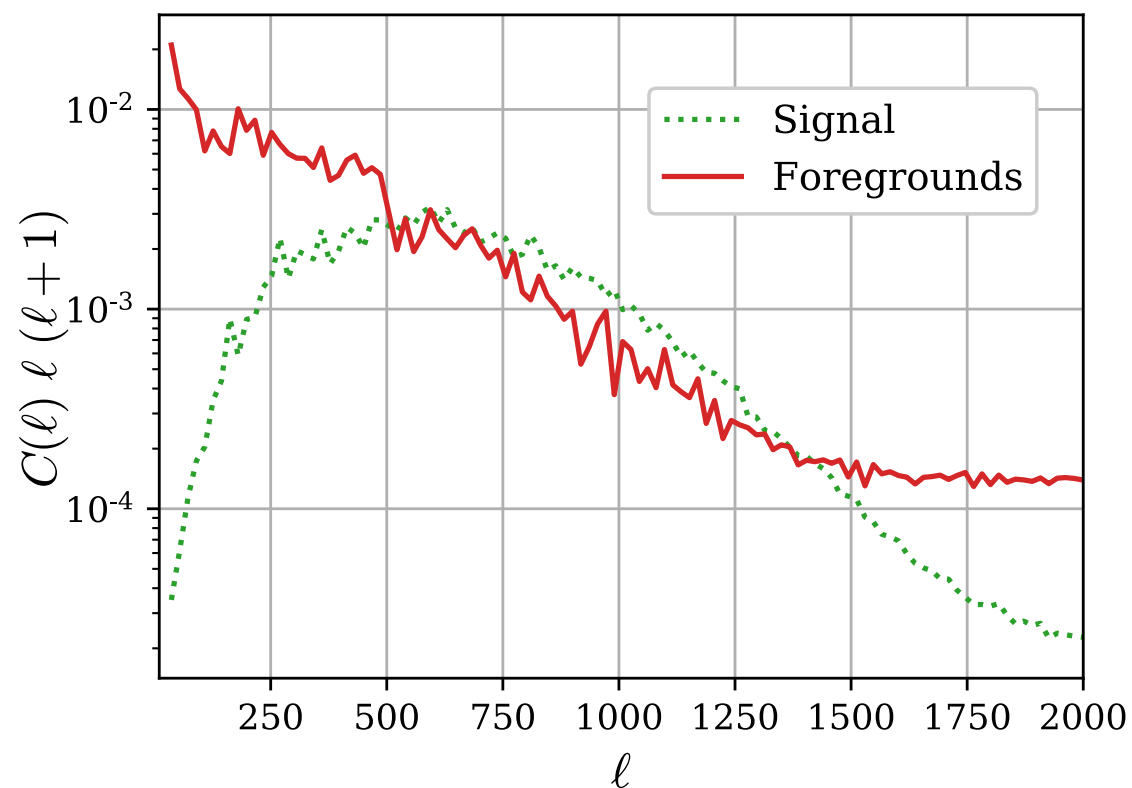
Nuisance parameters from prior

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

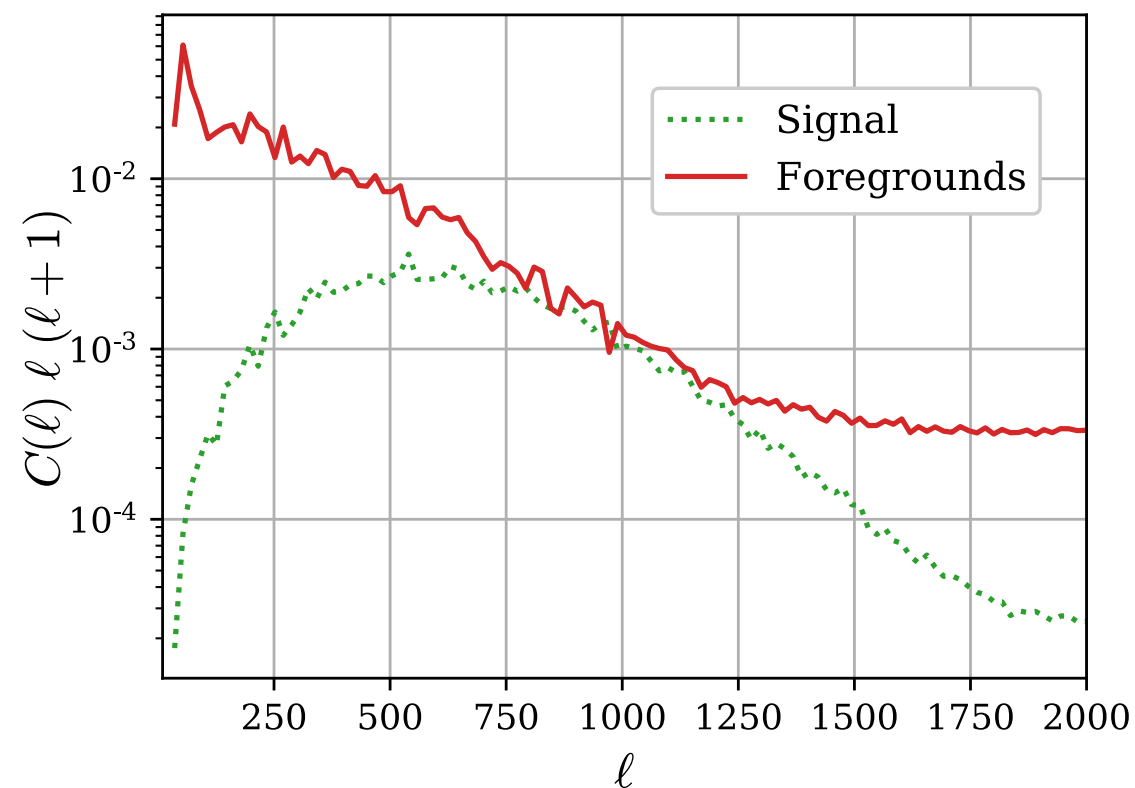


Nuisance parameters from prior

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



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



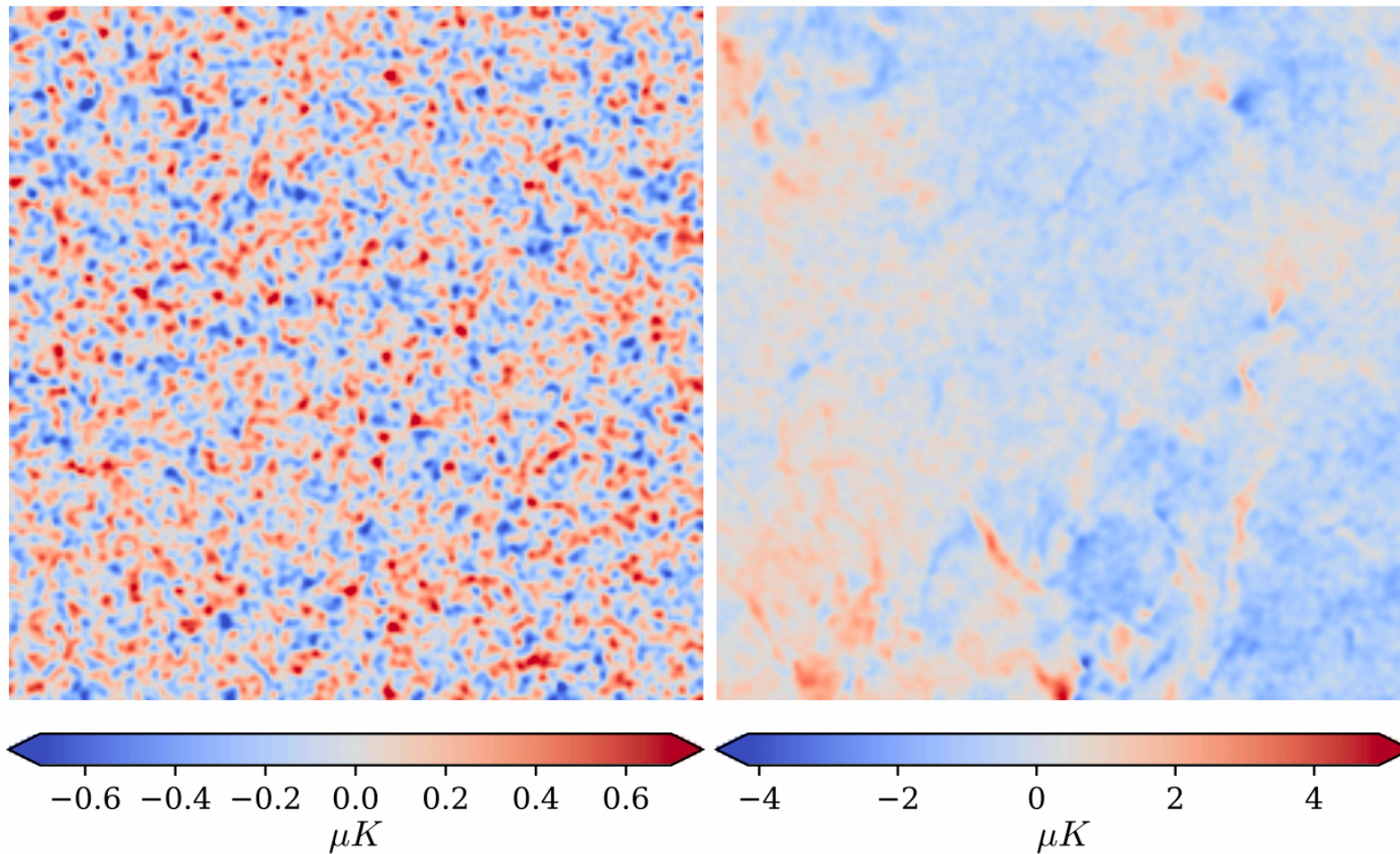
We now have:

CMB simulation ✓

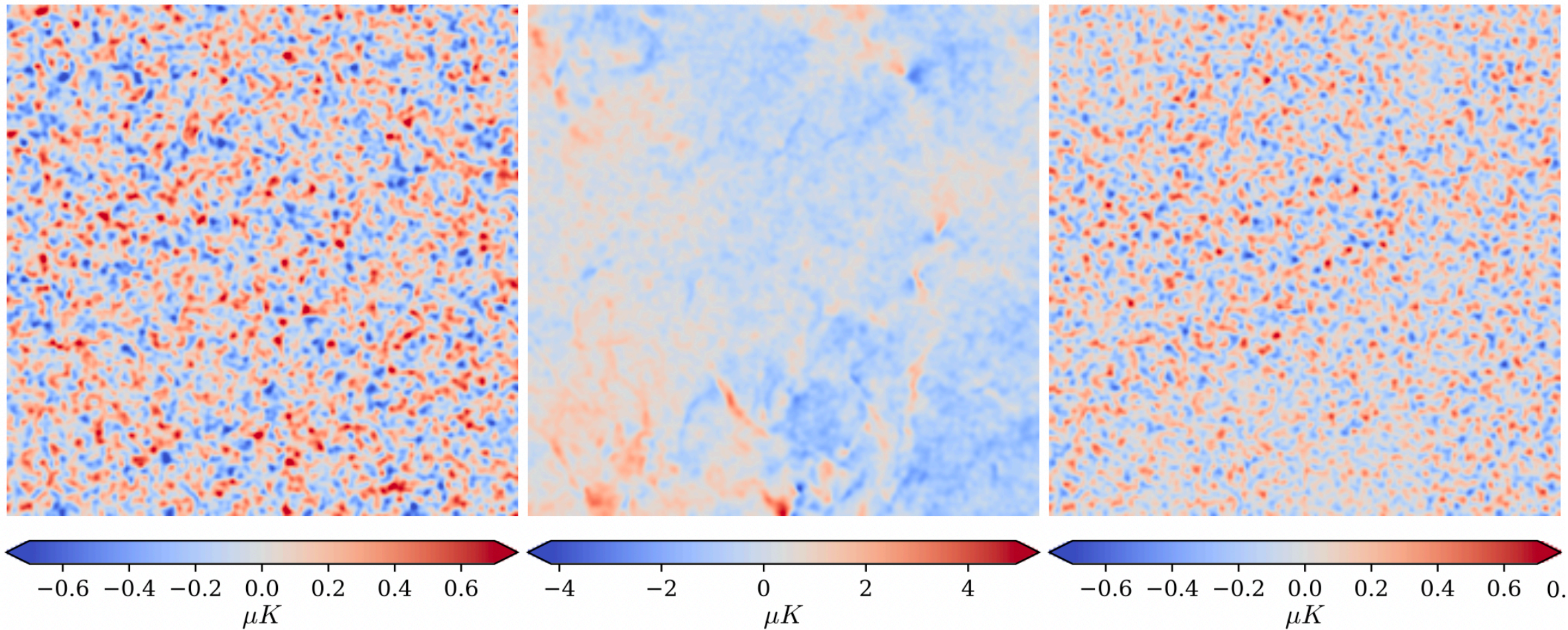
Foreground “synthesiser” ✓

Inference tool (Moment Network) ✓

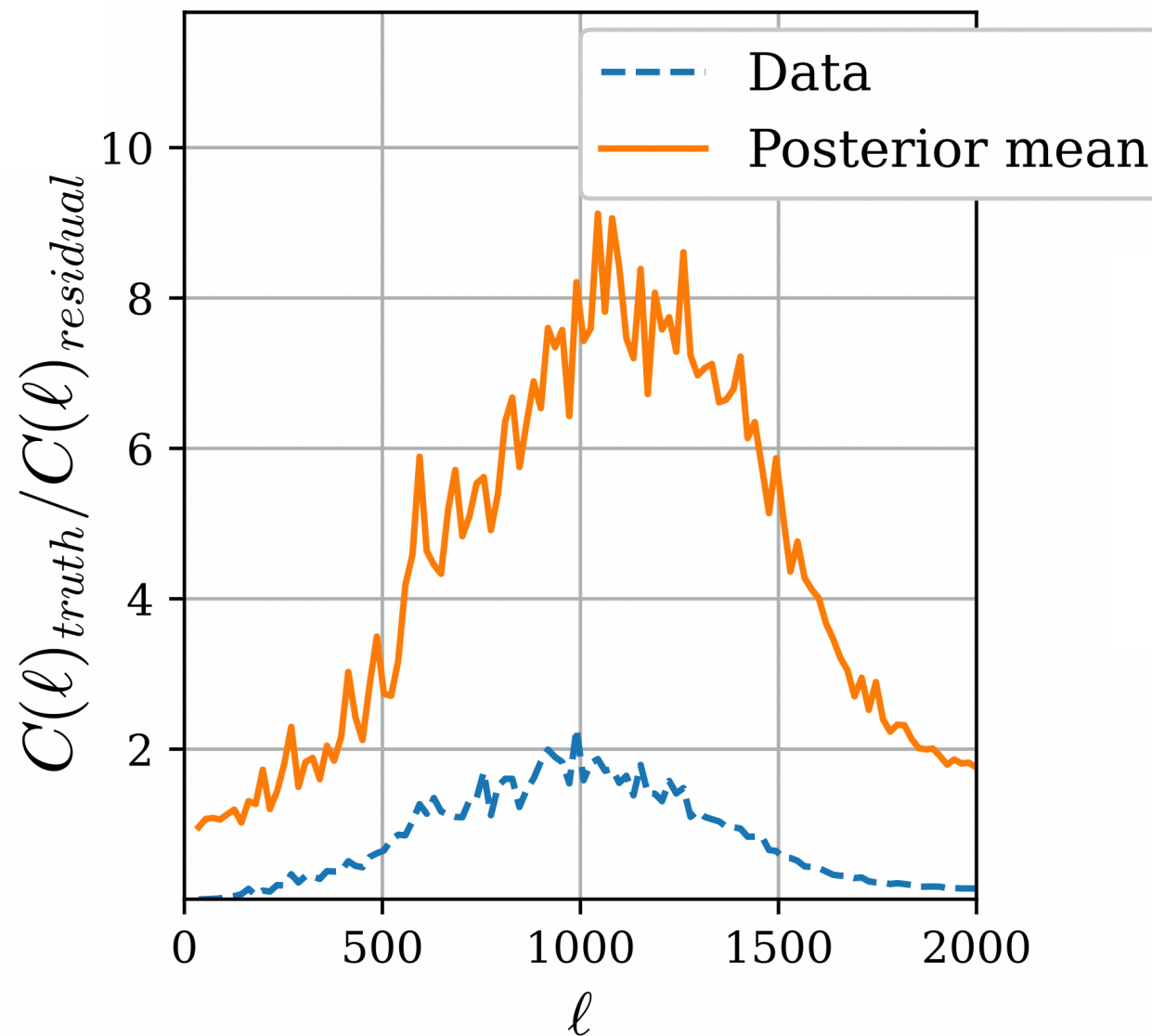
B-mode inference



B-mode inference



Recovered “signal-to-noise”



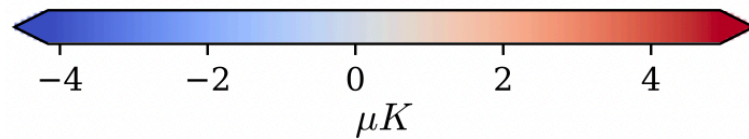
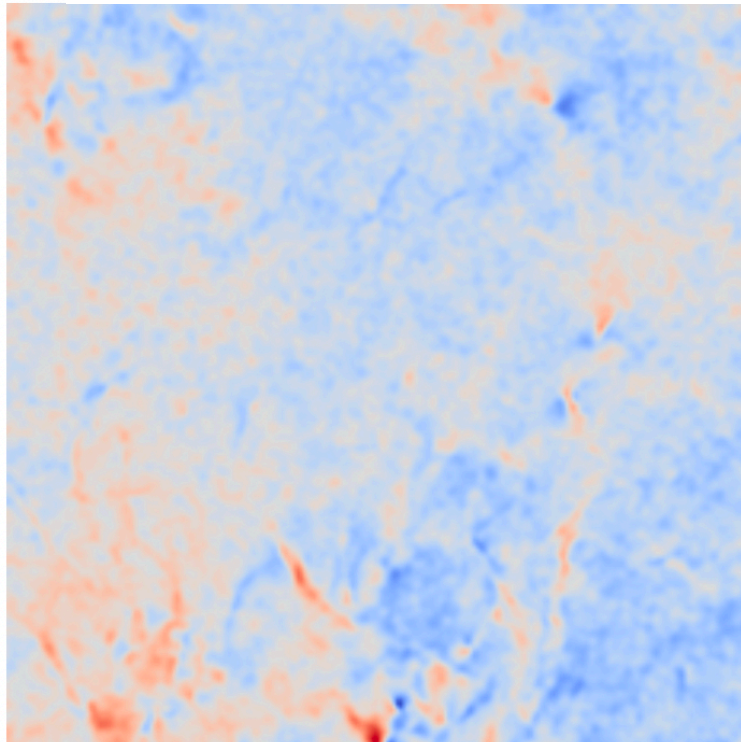
3. Posterior validation

How can we test the posterior?

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

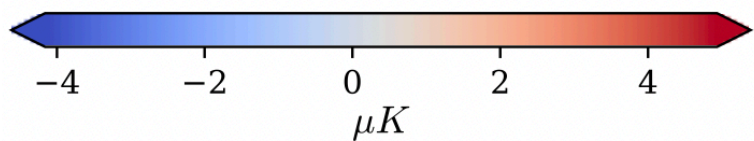
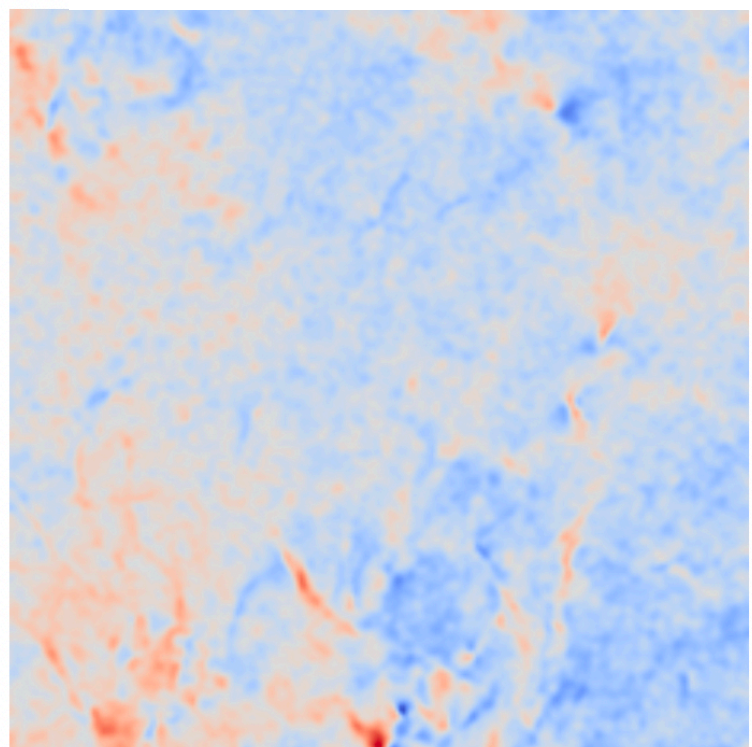
Naive Gaussian model:

Data

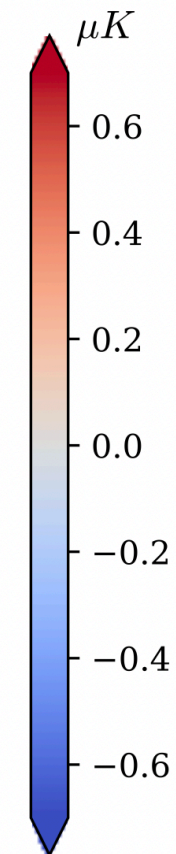
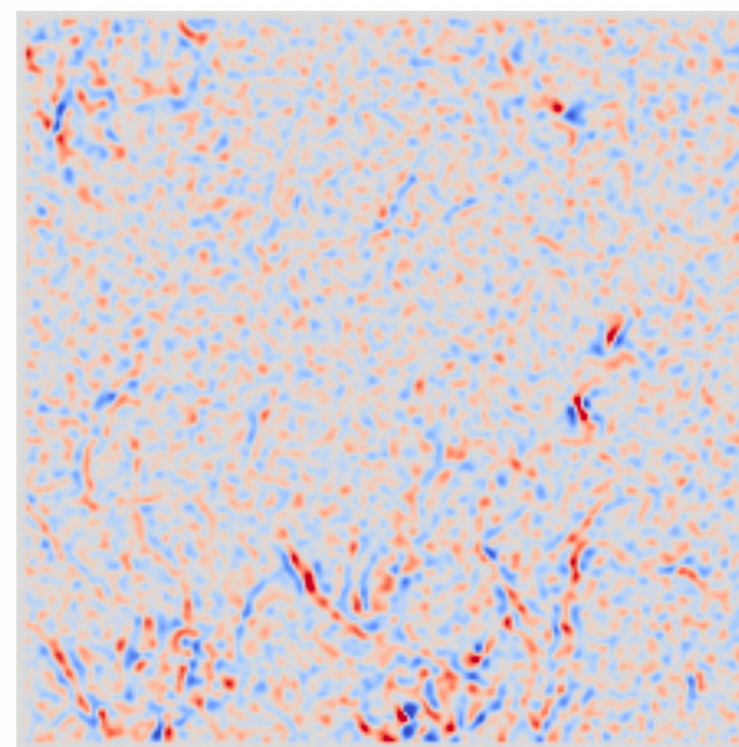


Naive Gaussian model:

Data

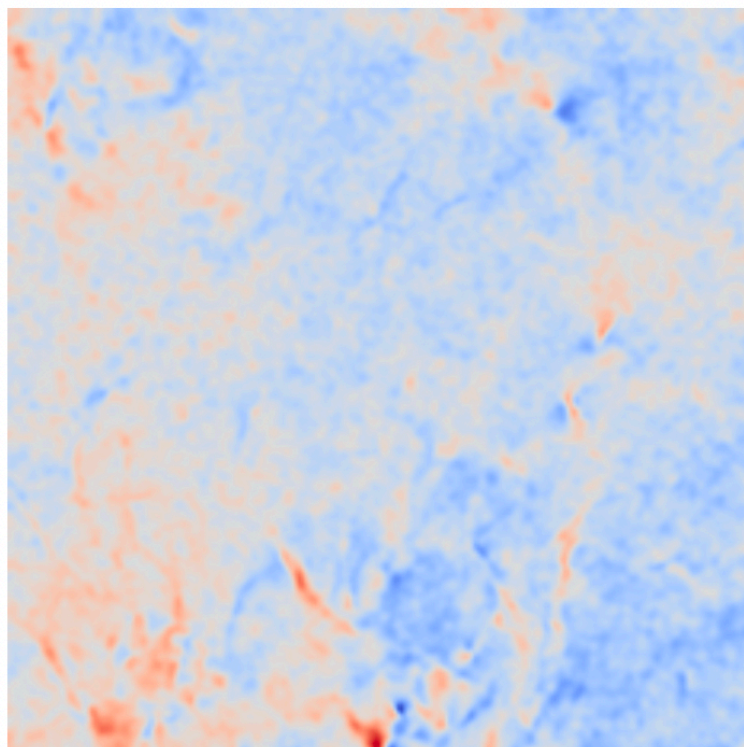


Posterior mean

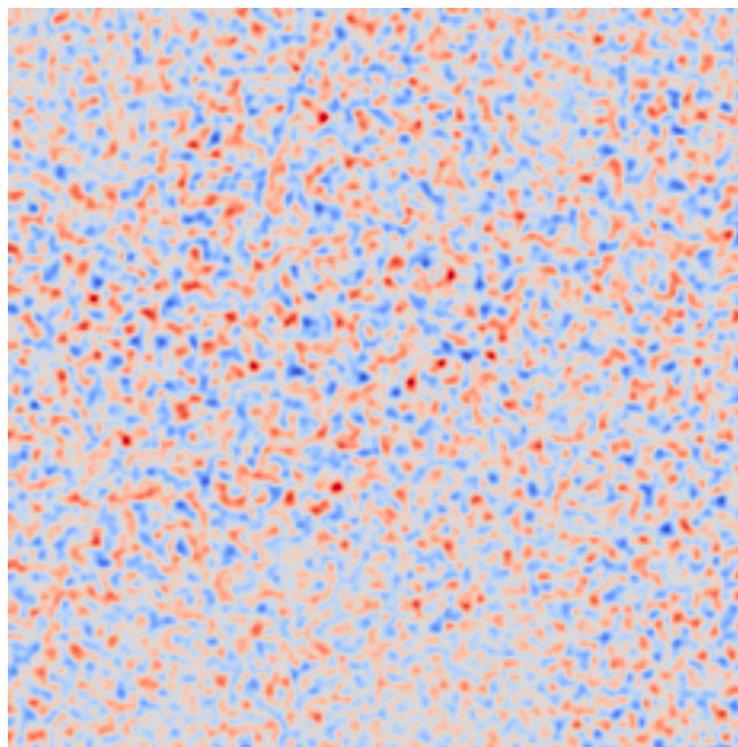


Validation of posterior

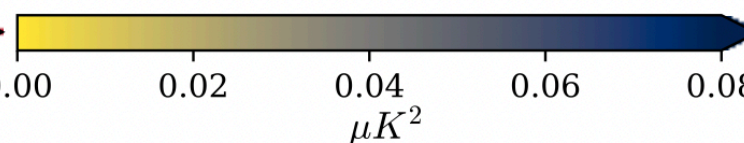
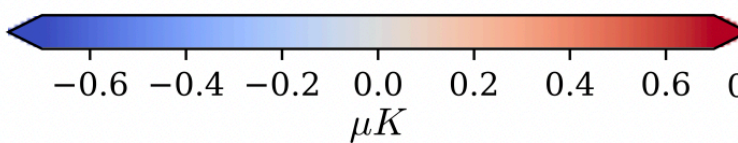
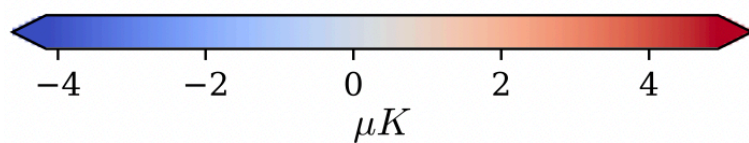
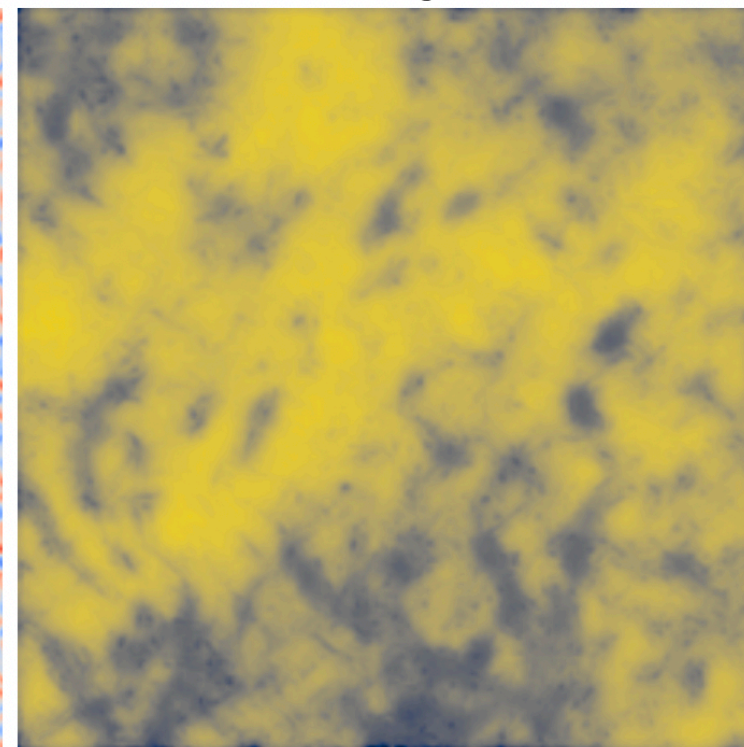
Data



Posterior mean



Posterior marginal variance



Rescaled residuals

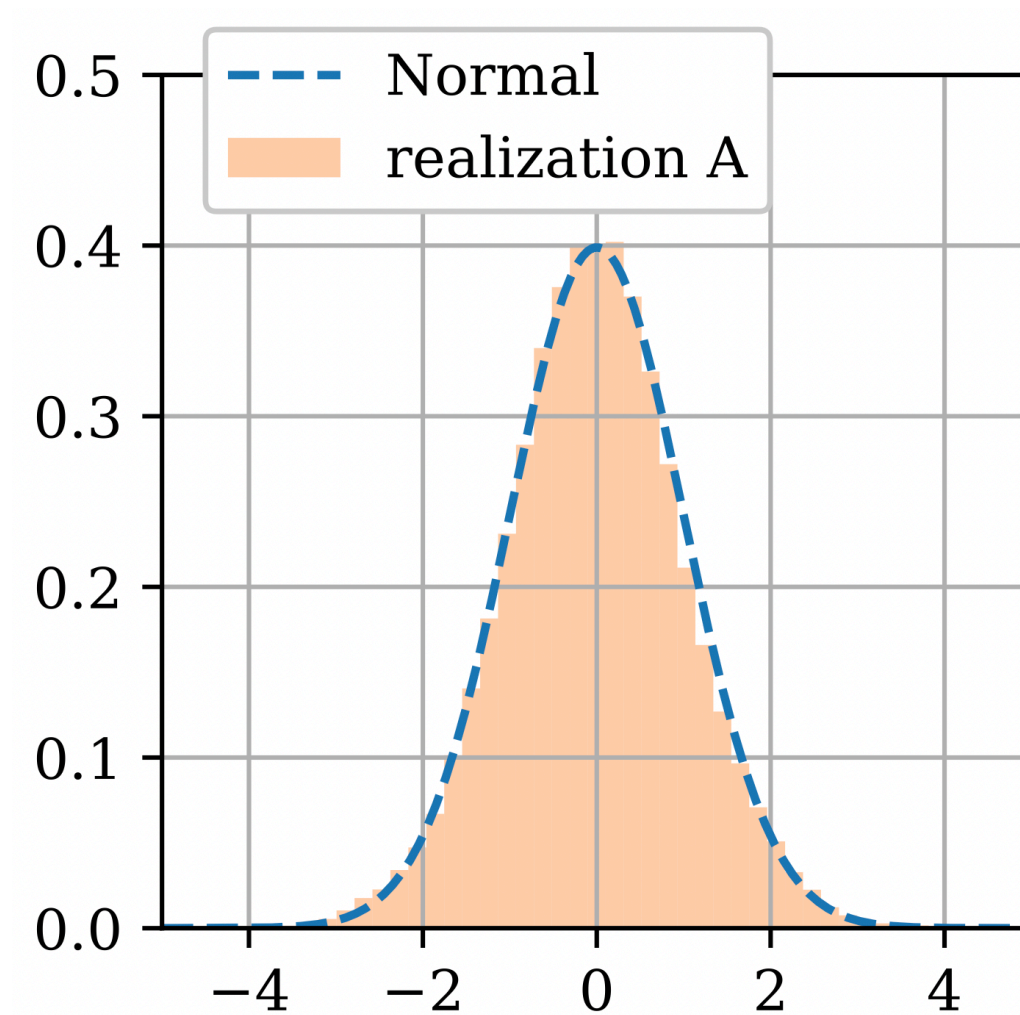
$$(\mu_B - s_B) / \sigma_B$$

POSTERIOR
MEAN

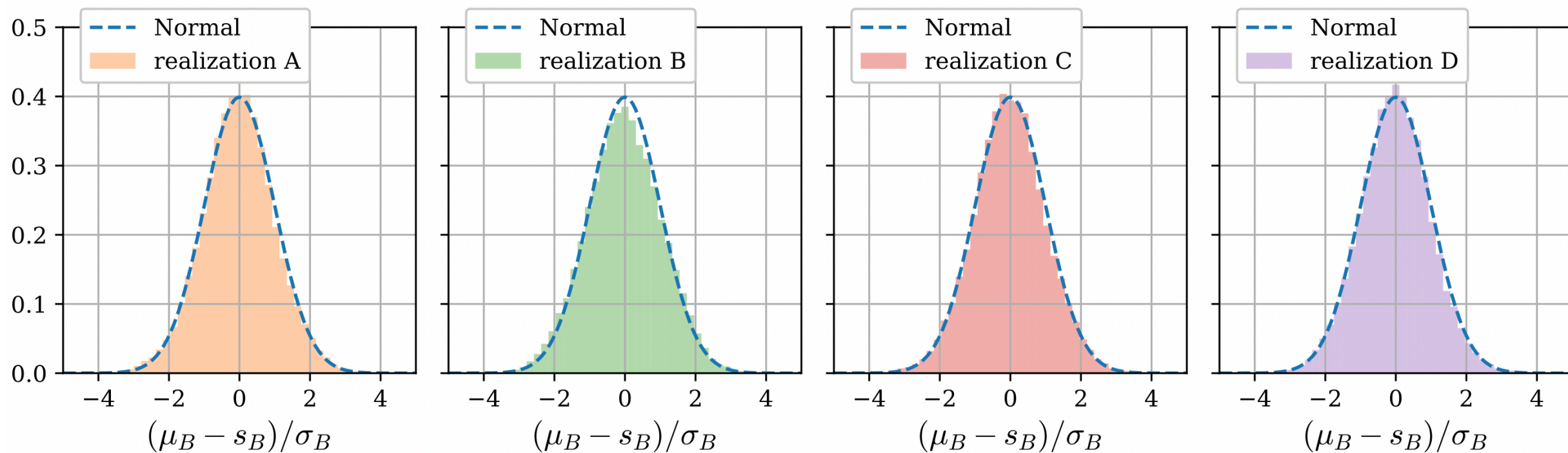
TRUE PIXEL
VALUE

POSTERIOR
VARIANCE

Rescaled residuals



Posterior estimates are excellent

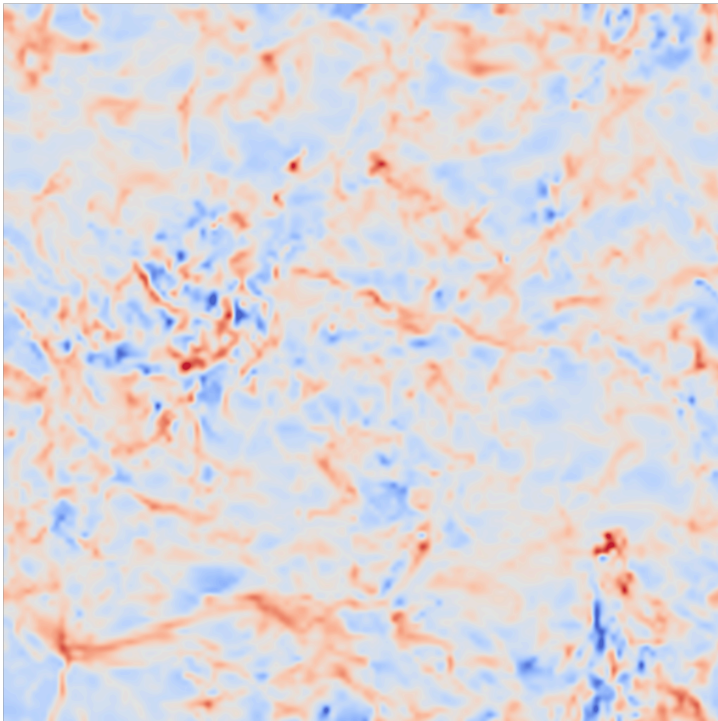


4. Neural foreground generator (in progress!)

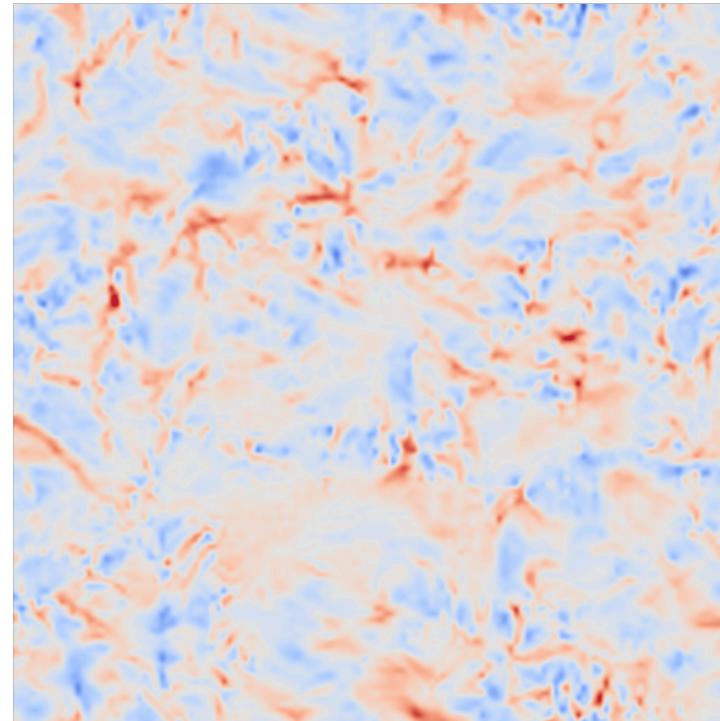
Standard synthesis procedure

1. Measure target wavelet phase coefficients: ϕ^*
2. Generate foreground image f with coefficients $\phi(f) = \phi^*$

Target (simulation)



Gradient descent synthesis



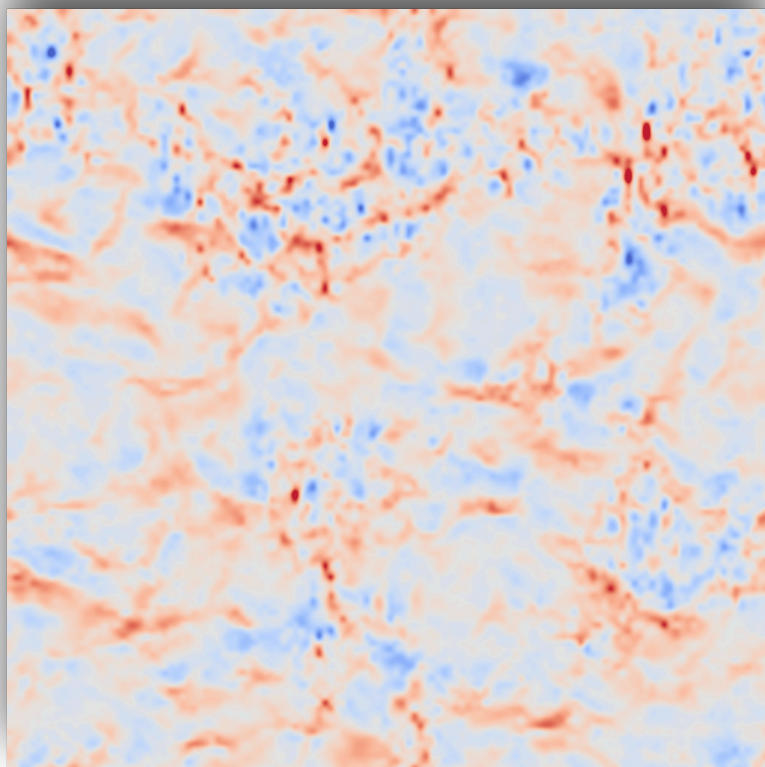
Neural foreground sampler

$$z_i \sim \mathcal{N}(0, \Sigma)$$

$$f_i = W(z_i) \quad \text{such that} \quad \langle \phi(f_i) \rangle = \phi^*$$

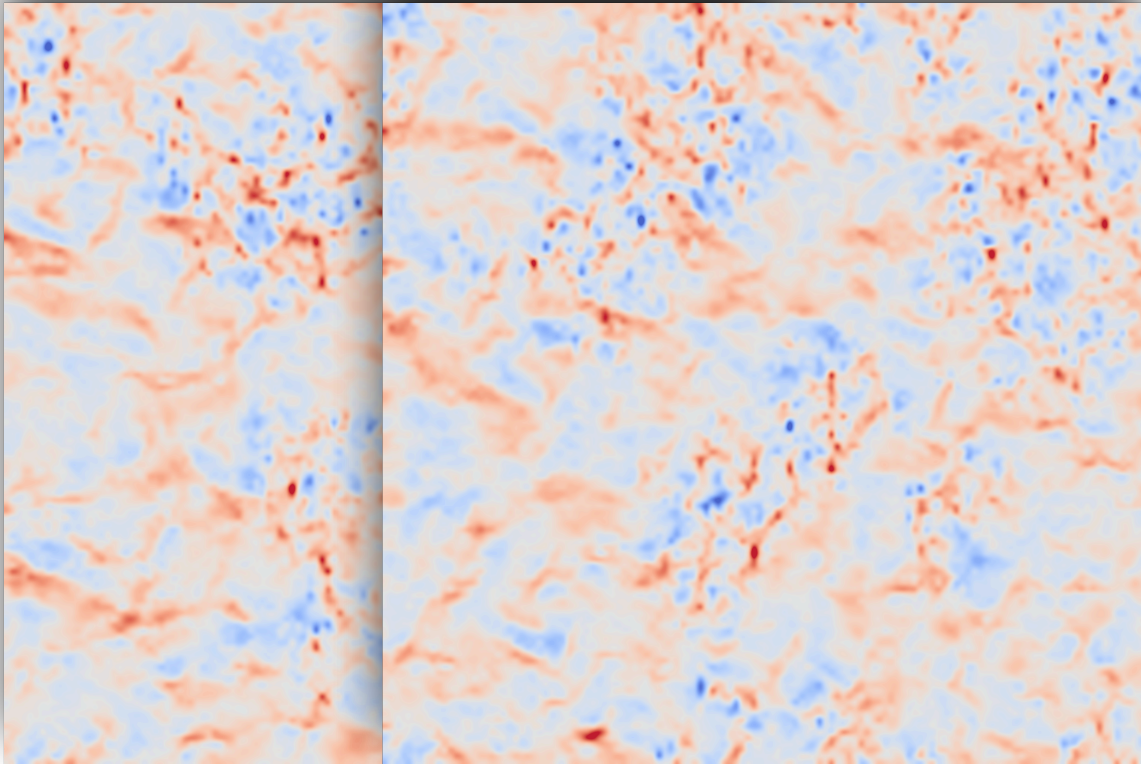
Neural foreground sampler

$$f_i \sim p(f | \phi^*)$$



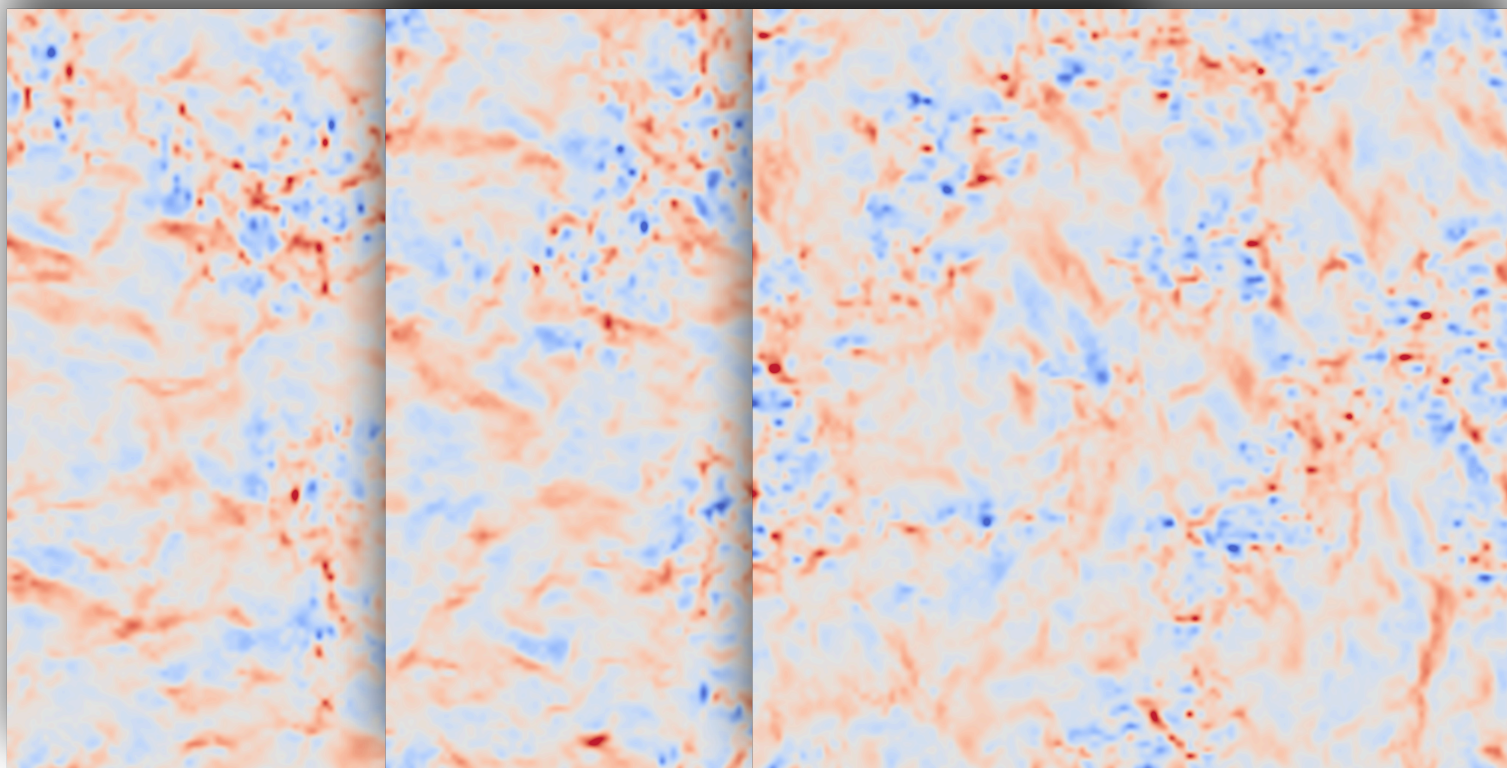
Neural foreground sampler

$$f_i \sim p(f | \phi^*)$$



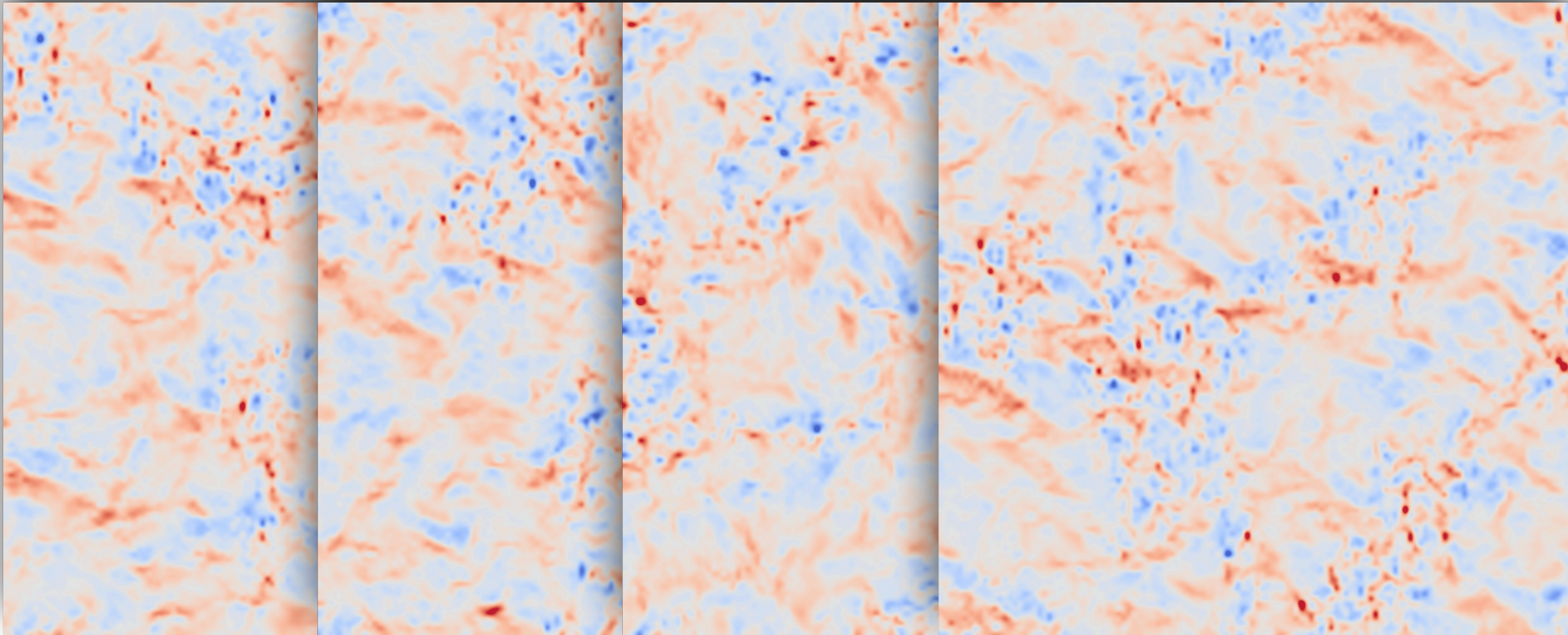
Neural foreground sampler

$$f_i \sim p(f | \phi^*)$$



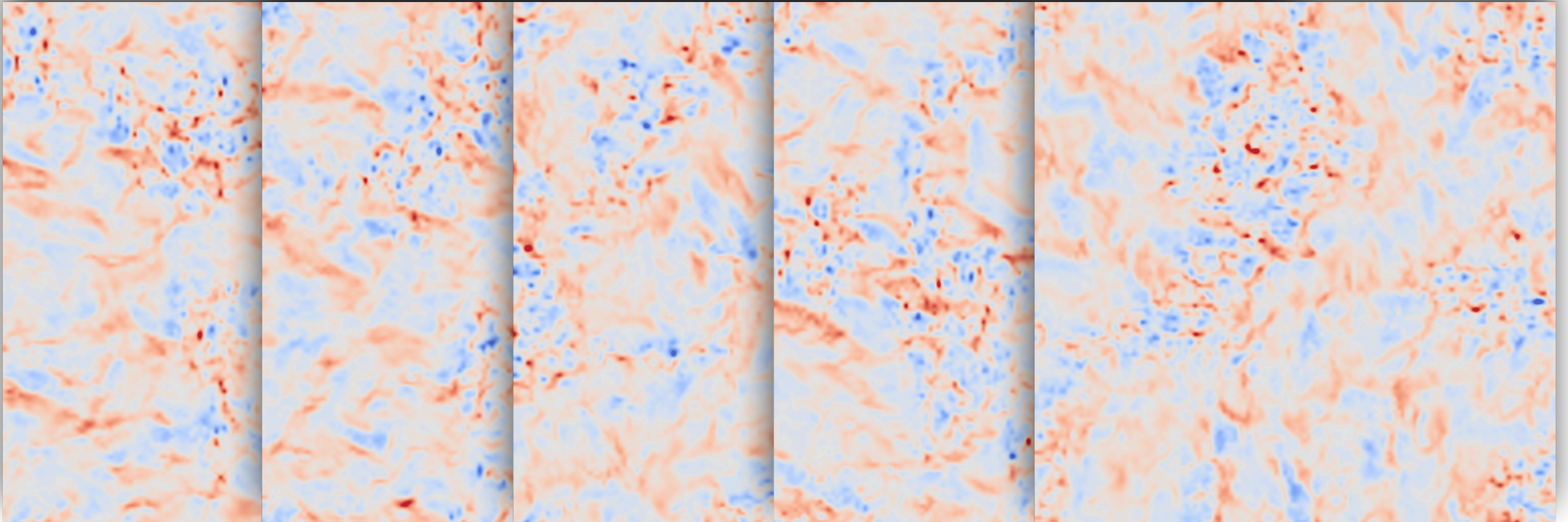
Neural foreground sampler

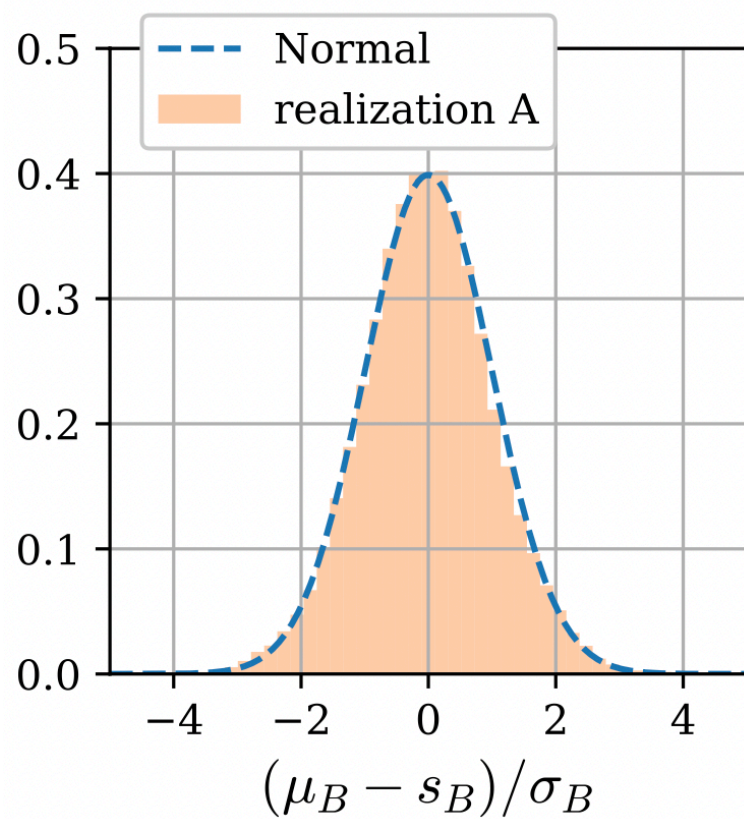
$$f_i \sim p(f | \phi^*)$$



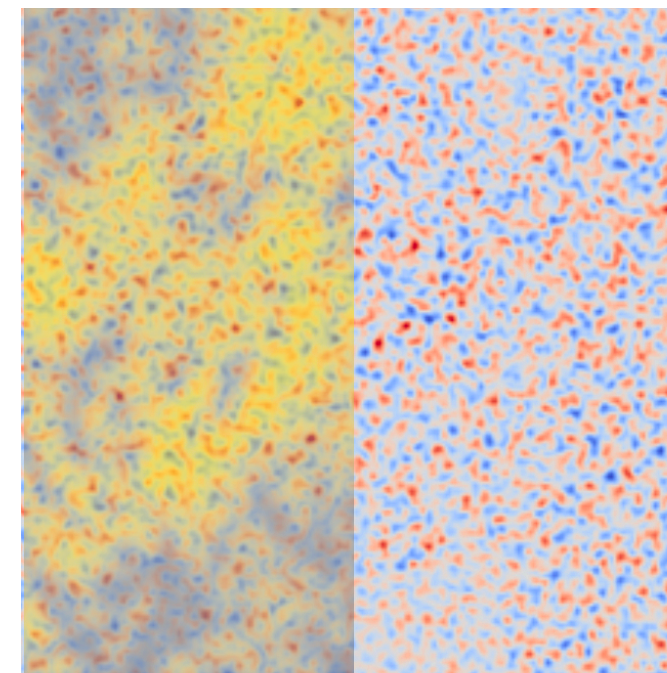
Neural foreground sampler

$$f_i \sim p(f | \phi^*)$$





Grazie!



NJ & Wandelt 2011.05991

NJ, Boulanger, Wandelt et al. 2111.01138