EXTRACTING CLUSTER INFORMATION FROM SMALL-SCALE CMB

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In Collaboration with Louis Legrand and Julien Carron

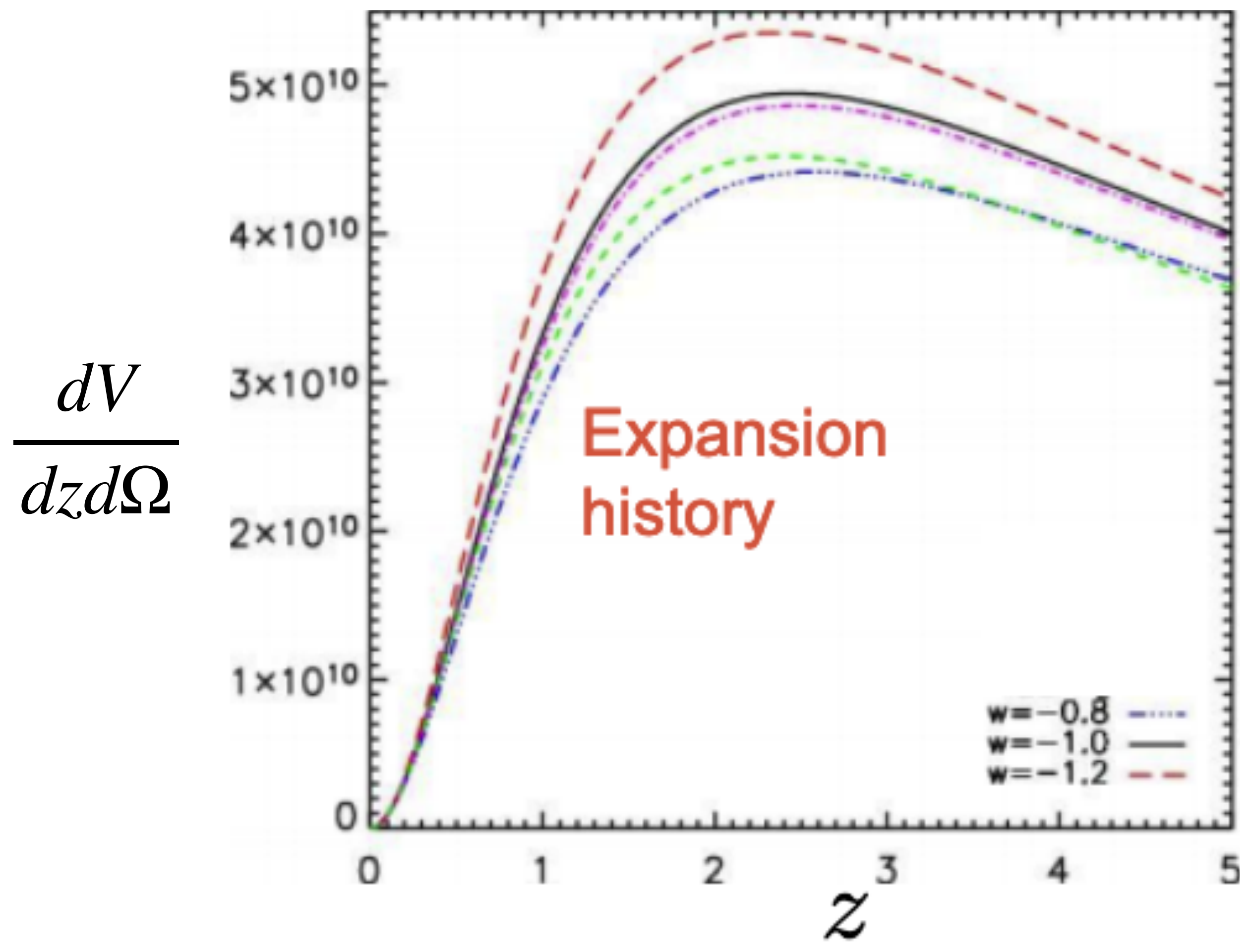
OUTLINE

- Motivation
- Theoretical Model
- Analysis
- Conclusion

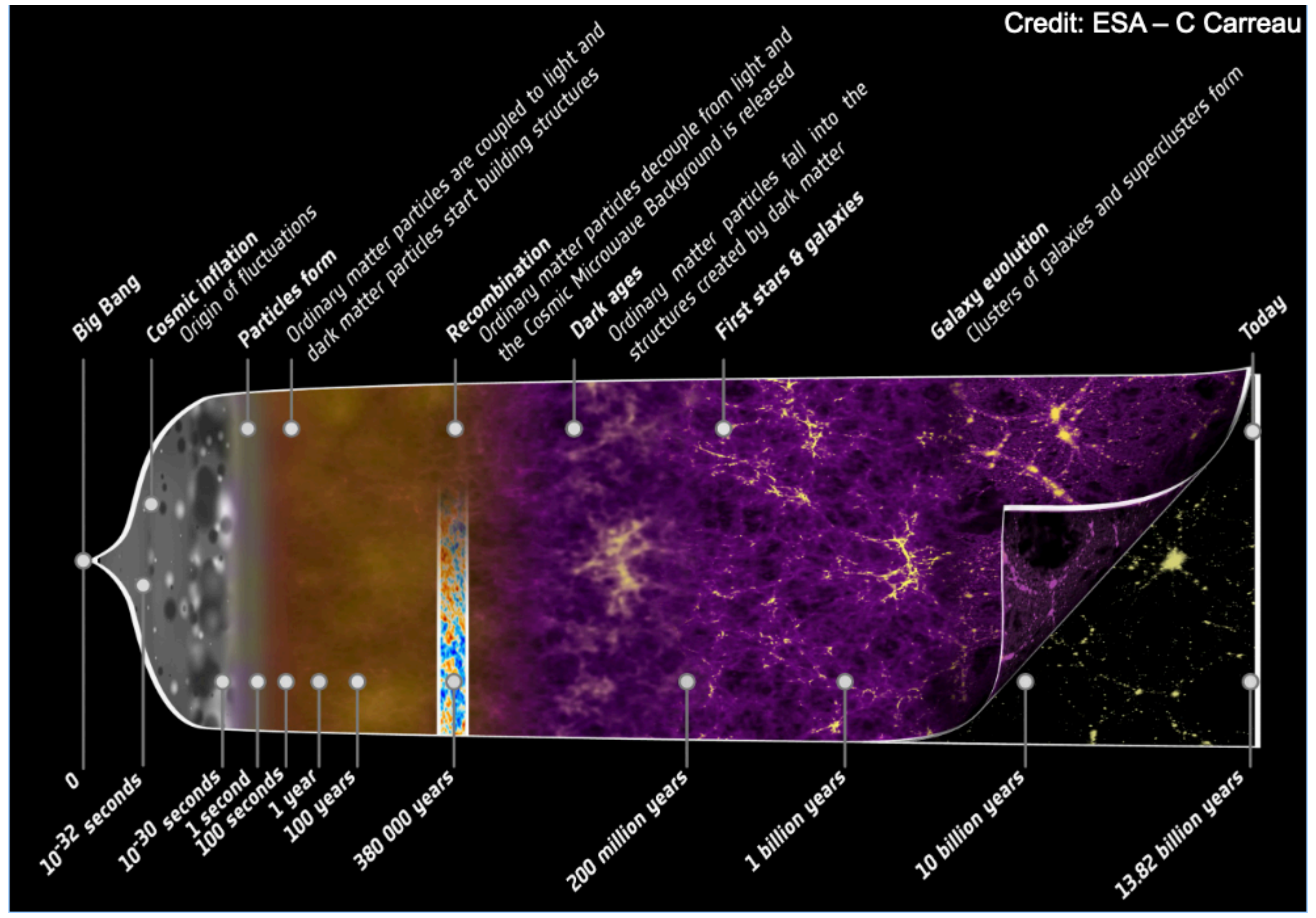
MOTIVATION BEHIND COSMOLOGY WITH CLUSTERS

- Cluster abundances Cosmology

$$\left(\frac{dN}{dMdV}\right) \longrightarrow \text{COSMOLOGICAL CONSTRAINTS}$$



Credit: Koyama & Maartens, 2006



- This history sets bounds on how small and how large a collapsed object can be.
- Uncertainties in cluster mass measurements affects our understanding of the cosmic expansion history

HOW MASS OF CLUSTERS COMES TO THE PICTURE?

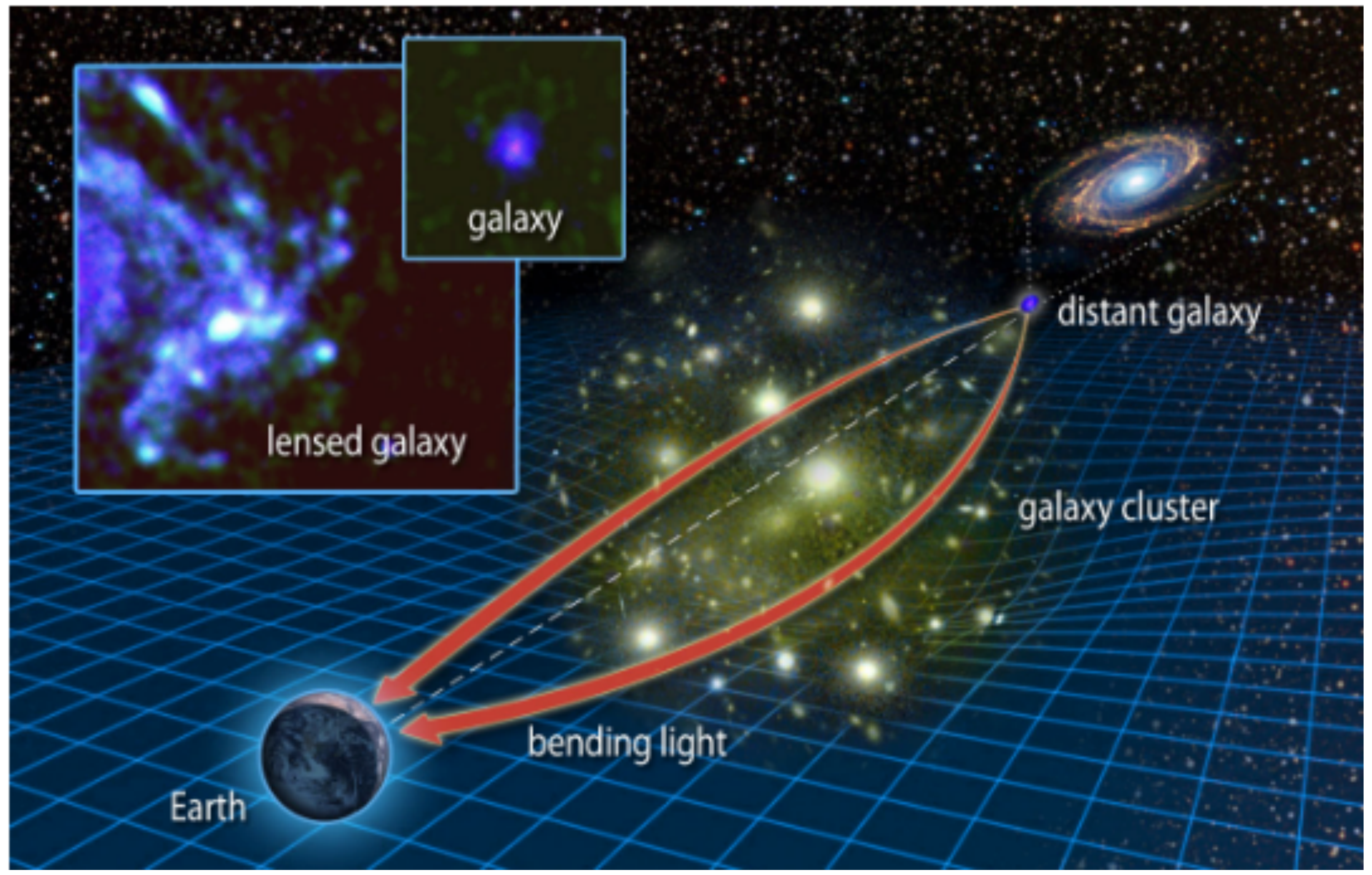
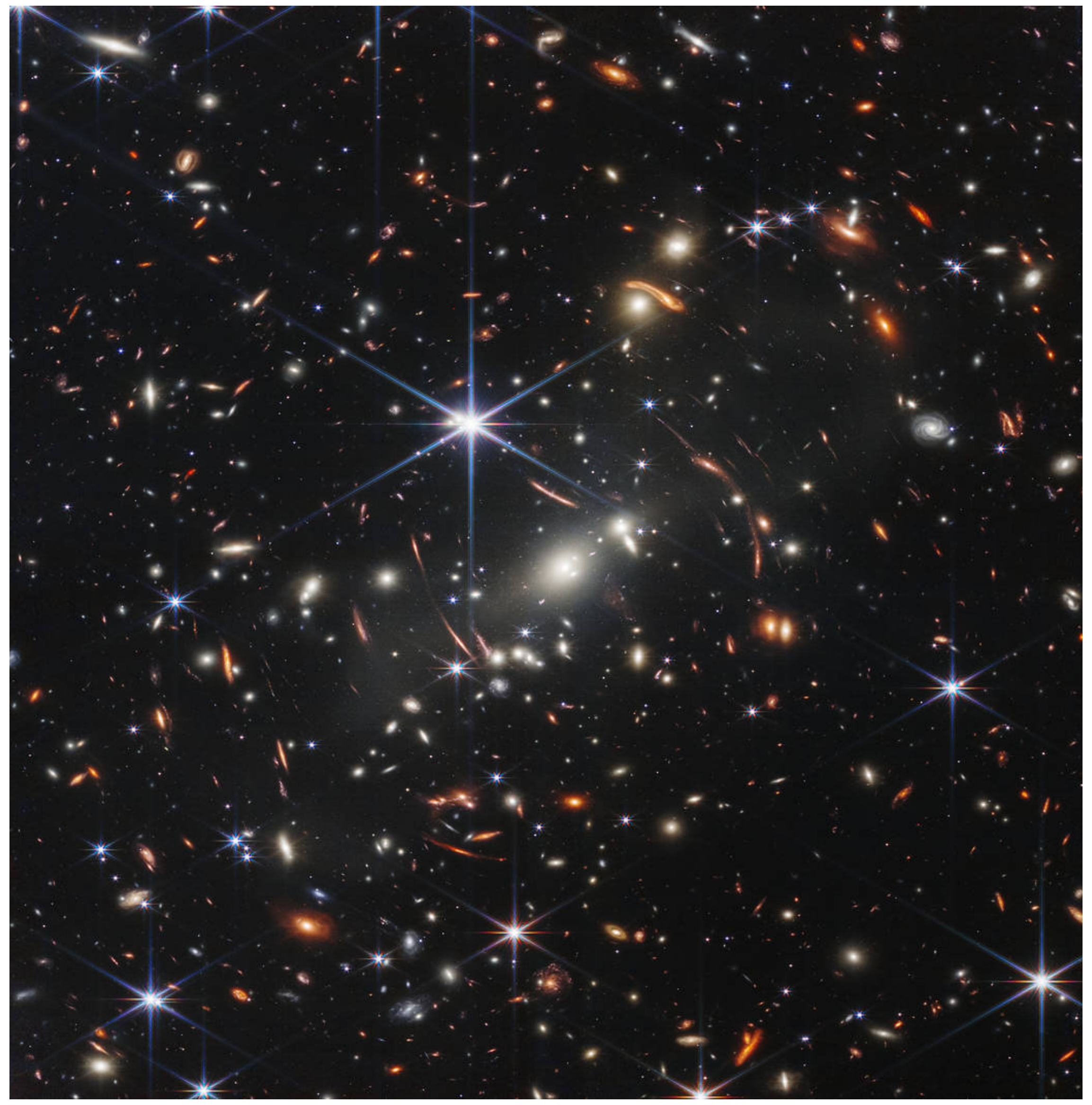


Image credit: Karen Teramura

- The gravitational lensing signature is directly sensitive to the mass of clusters.



galaxy cluster SMACS 0723
Credits: NASA, ESA, CSA, and STScI

- The mass profile of the clusters can be studied through:

1. Strong Lensing distortions of Galaxies
2. Weak Lensing distortions of Galaxies
3. CMB Lensing by the galaxy clusters

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CLUSTER MODEL (NFW PROFILE)

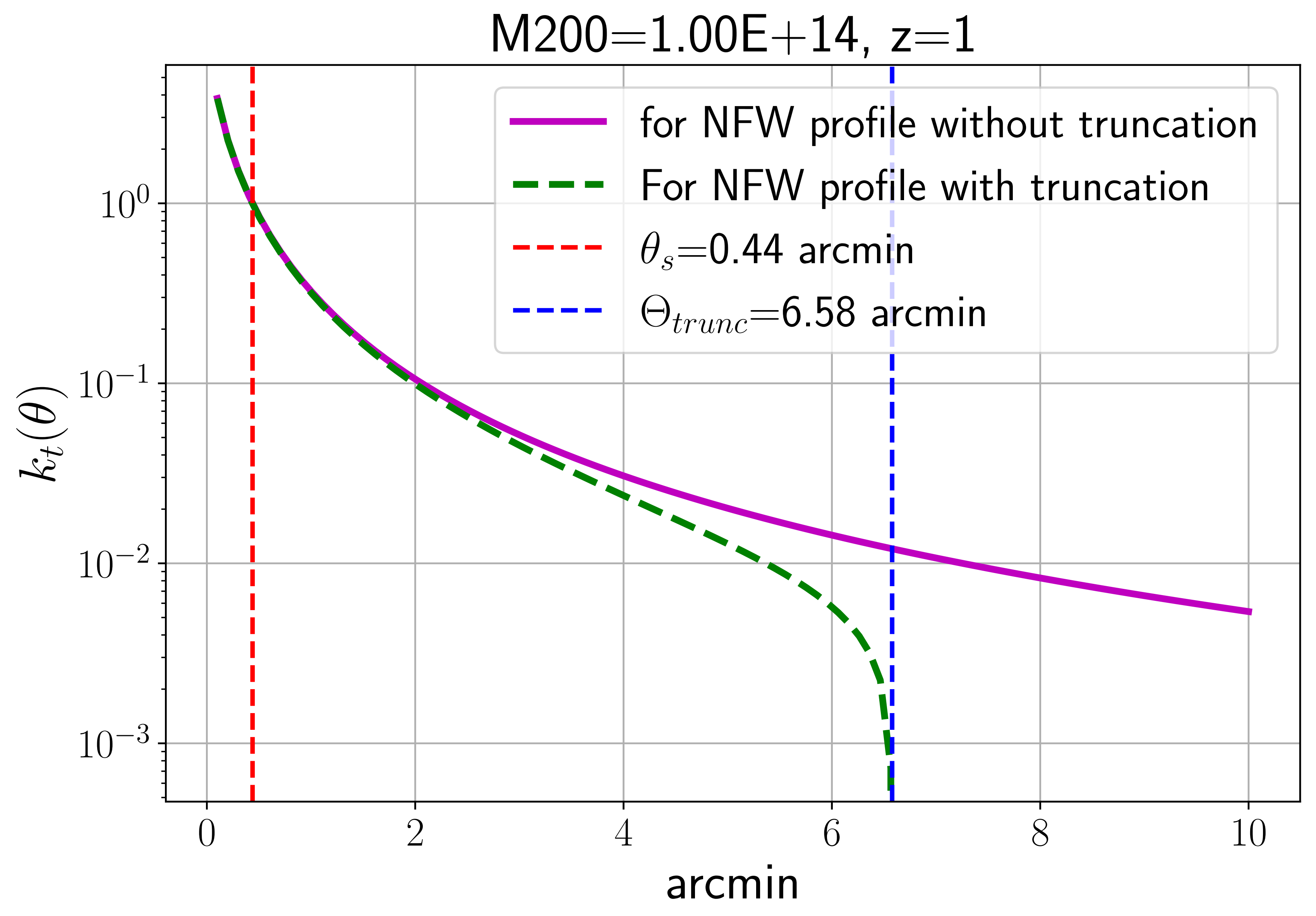
- The halo density profile

$$\rho(r) = \begin{cases} \frac{\rho_0}{(\frac{r}{r_s})(1+\frac{r}{r_s})^2} & \text{if } r < R_{\text{trunc}} \\ 0 & \text{if } r > R_{\text{trunc}} \end{cases},$$

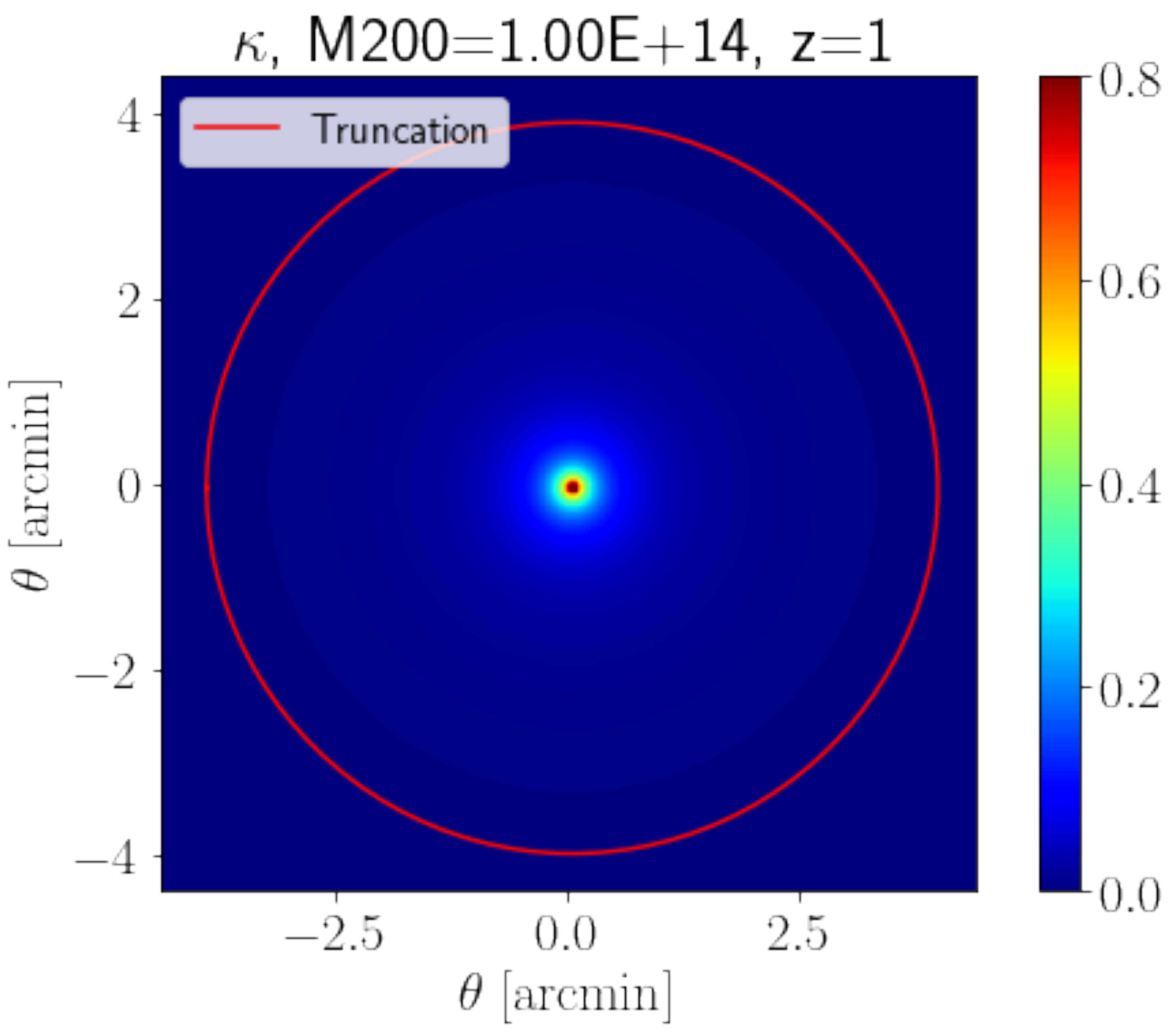
$$\kappa_{cl} = \frac{2\rho_s r_s}{\Sigma_{crit}(z)} g(x), \text{ where } x = \frac{r}{r_s} = \frac{\theta}{\theta_s}$$

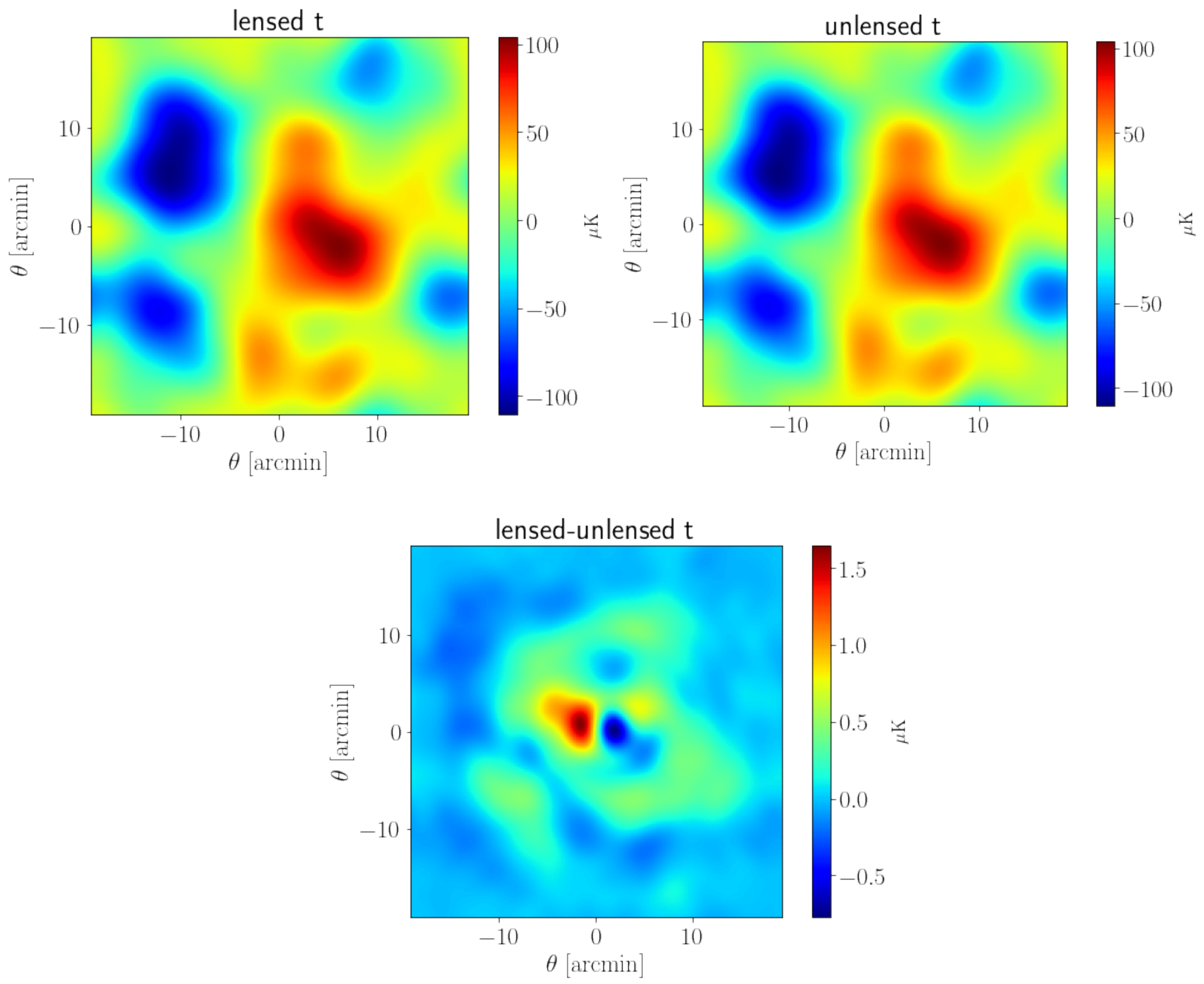
- The convergence profile is

$$\kappa_{cl}(r) = \frac{\Sigma_{cl}(r)}{\Sigma_{crit}(z)}$$



CMB LENSING BY NFW PROFILE





Lensit: https://github.com/carronj/LensIt

THE TEMPLATE FUNCTION

- $\kappa_{cl}(\theta) = \kappa_0 \kappa_t(\theta, \theta_s)$

- $\kappa_t(\theta = \theta_s) = 1$ and $\kappa_{cl}(\theta = \theta_s) = \kappa_0$.

We need an estimator for κ_0

$$\kappa_0 \theta_s^2 \propto \frac{M_{200}}{\Sigma_{crit}(z) d_A(z)}$$

→

$$\frac{\sigma_M}{M} = \frac{\sigma_{k_0}}{\kappa_0}$$

OUTLINE

MINIMUM VARIANCE ESTIMATOR OF κ_0

$$\hat{\kappa}_0 = \frac{\int d^2\vec{l}\ \frac{\kappa^t(\vec{l})\hat{\kappa}(\vec{l})}{N_{\vec{l}}}}{\int d^2\vec{l}\ \frac{|\kappa^t(\vec{l})|^2}{N_{\vec{l}}}}$$

With the inverse variance,

$$\frac{1}{\sigma^2} = \int d^2l\ \frac{|\kappa_l^t|^2}{N_l}$$

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$\hat{\kappa}_l$ = convergence estimated from data

N_l = Noise of the estimation

$= C_l^{\kappa\kappa} + N_0^{\kappa} + N_1^{\kappa}$

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We employ The Maximum a Posterior (MAP) Estimator by Carron et al 2017

- We maximize the log posterior:

$$\ln p(\phi \,|\, X^{dat}) = \ln p(X^{dat} \,|\, \phi) - \frac{1}{2}\sum_L \frac{\phi_L^2}{C_L^{\phi\phi}}$$

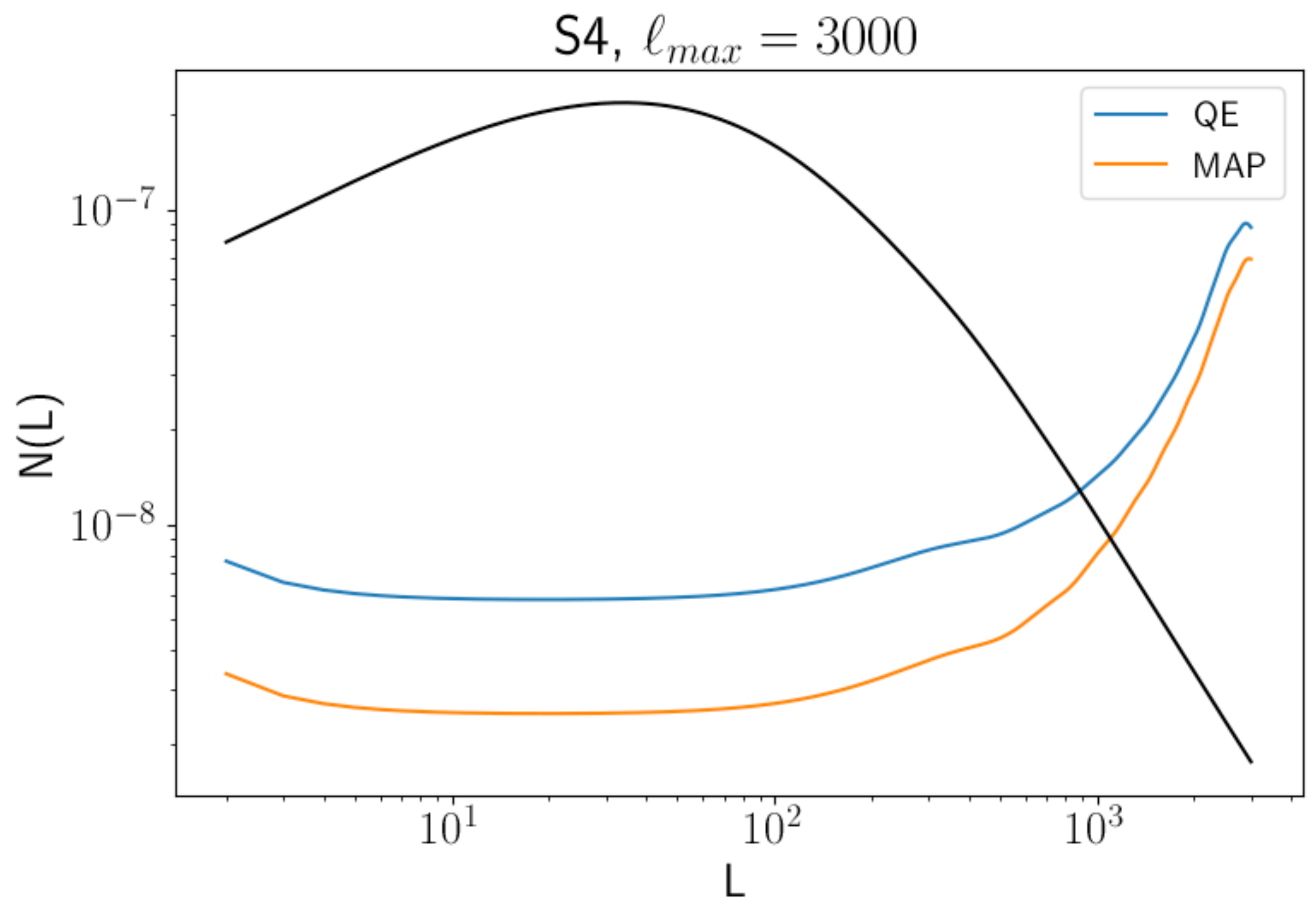
- Using Gradients:

$$g_\phi = \frac{\delta \ln p(X^{dat} \,|\, \phi)}{\delta\phi} = g^{QD} - g^{MF} + g^{PR}$$

- We use these g_ϕ's iteratively to reach the maximum

IMPROVEMENT OVER QUADRATIC ESTIMATOR

The noise of the estimator



$\Delta_T = \Delta_P/\sqrt{2} = 1\mu K$-arcmin
Beam = 1 arcmin

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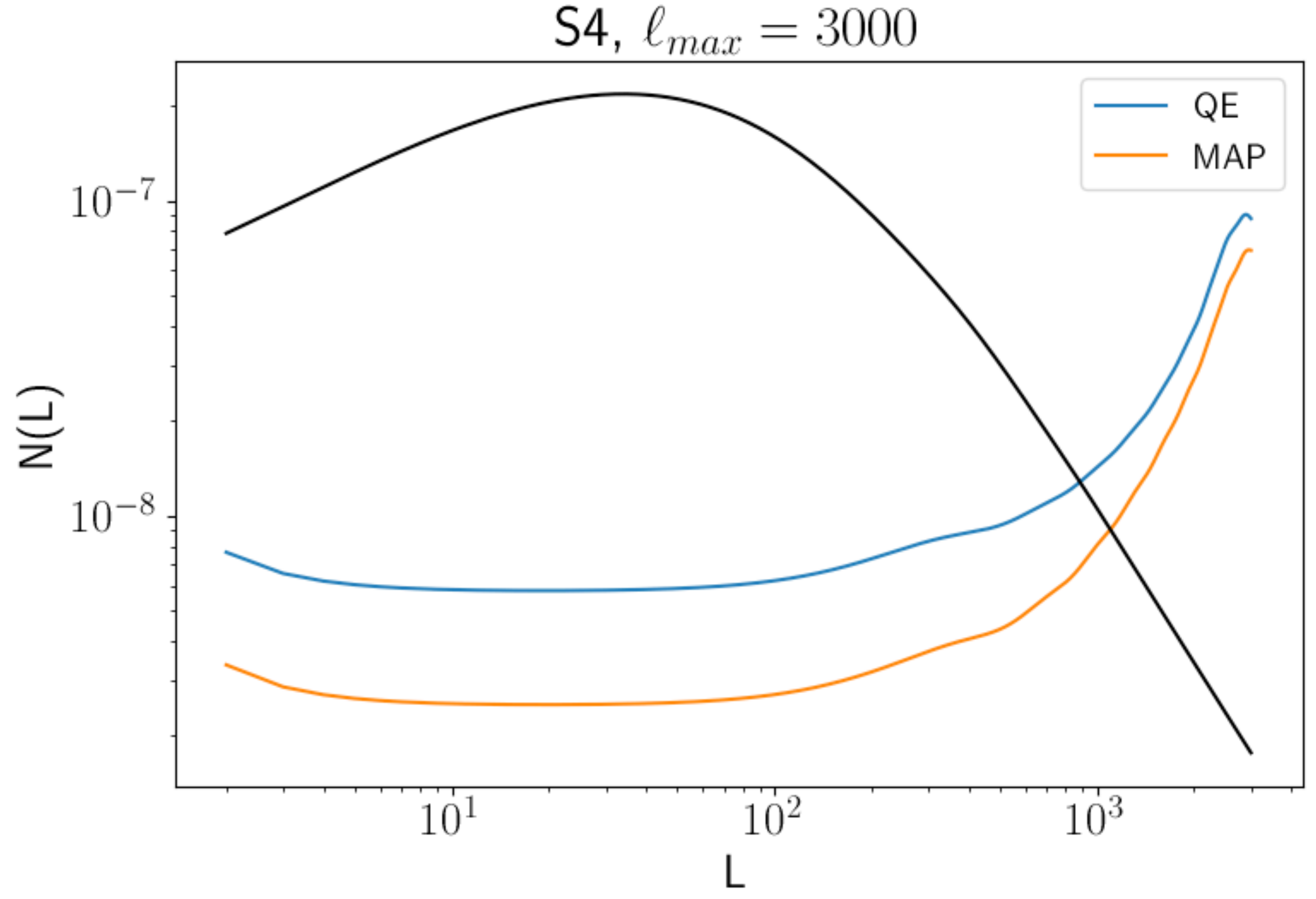
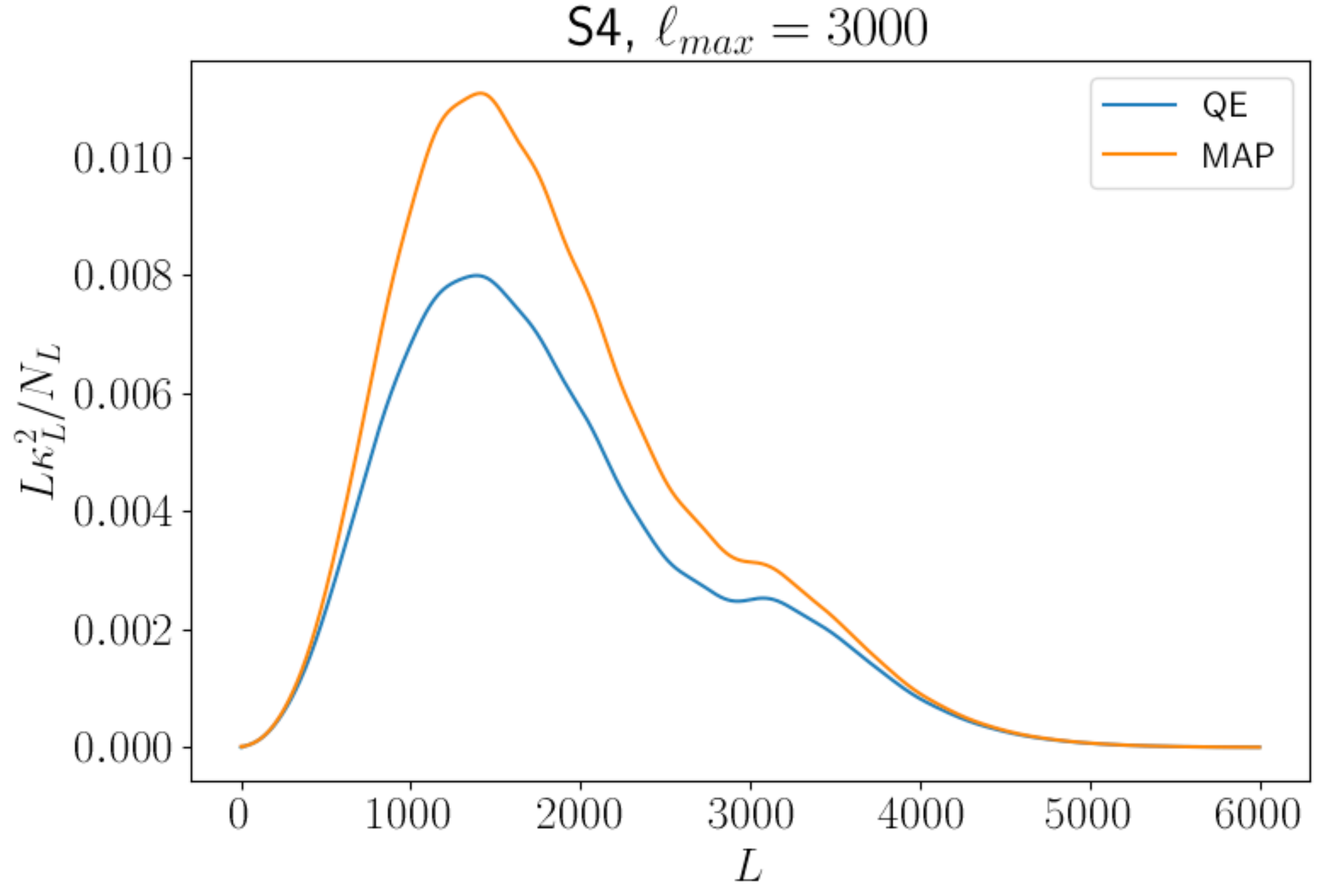
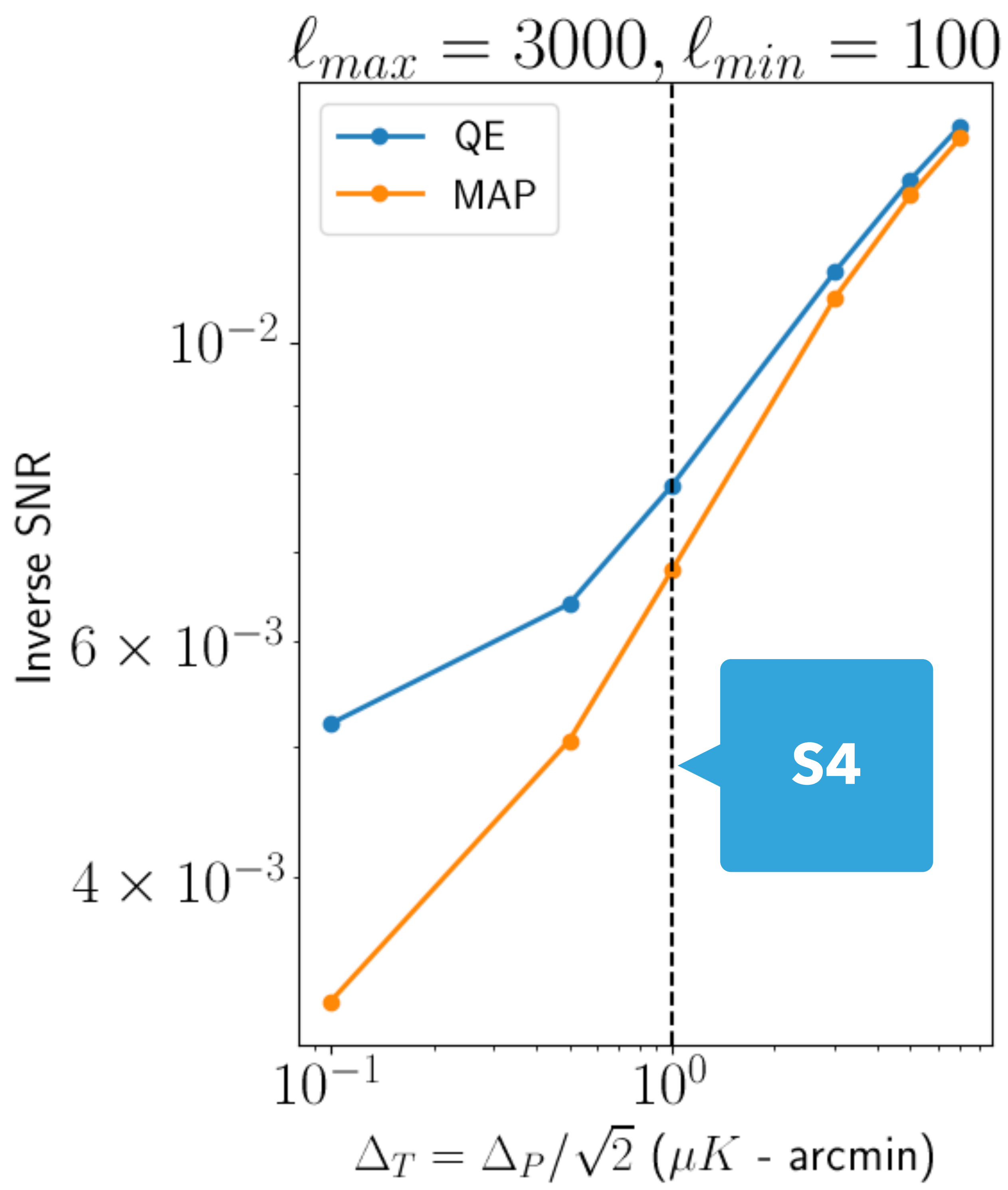


The contribution in $\frac{1}{\sigma^2} = \int d^2l \, \frac{|\kappa_l^t|^2}{N_l}$ comes from certain scales



Inverse SNR for 10^5 clusters



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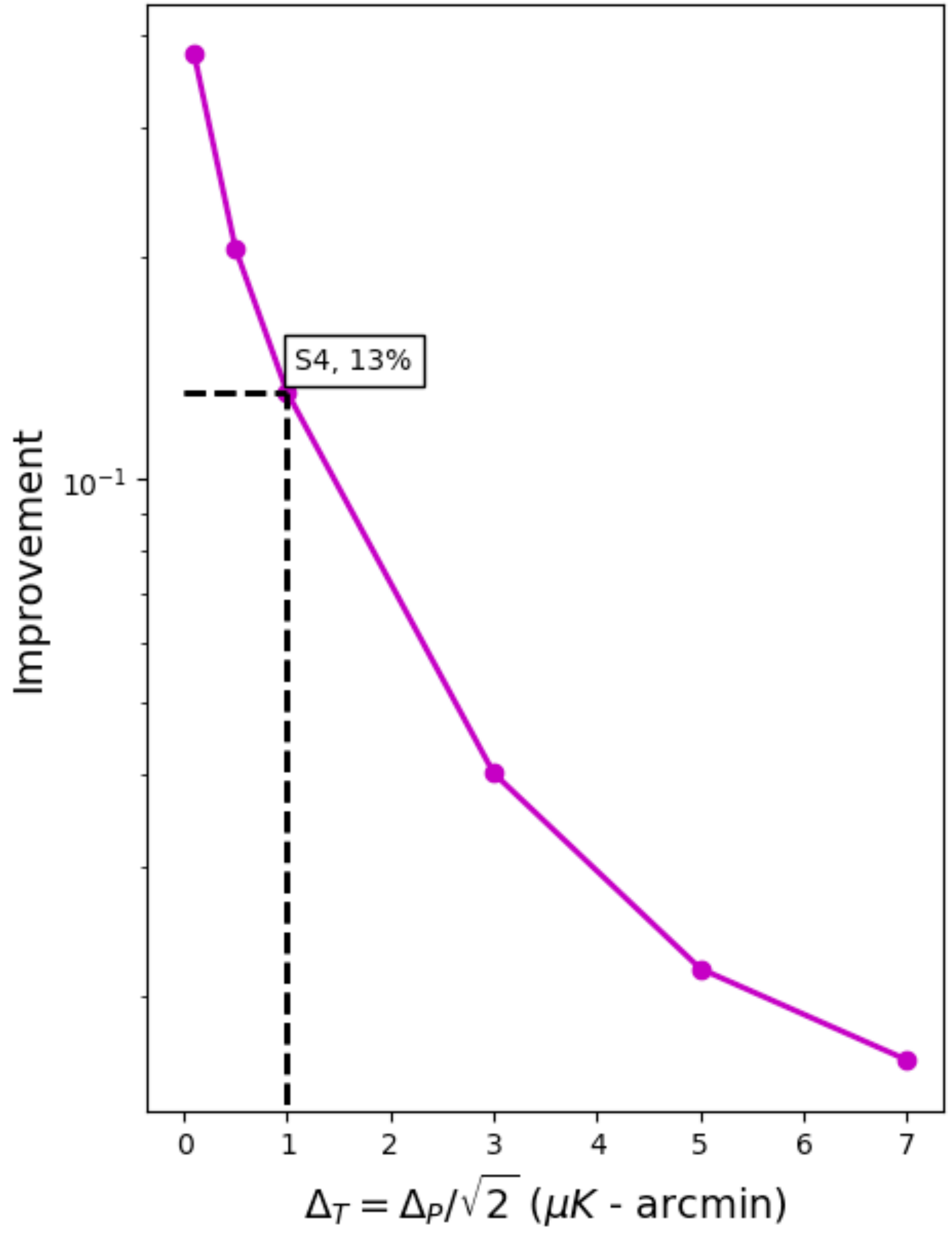
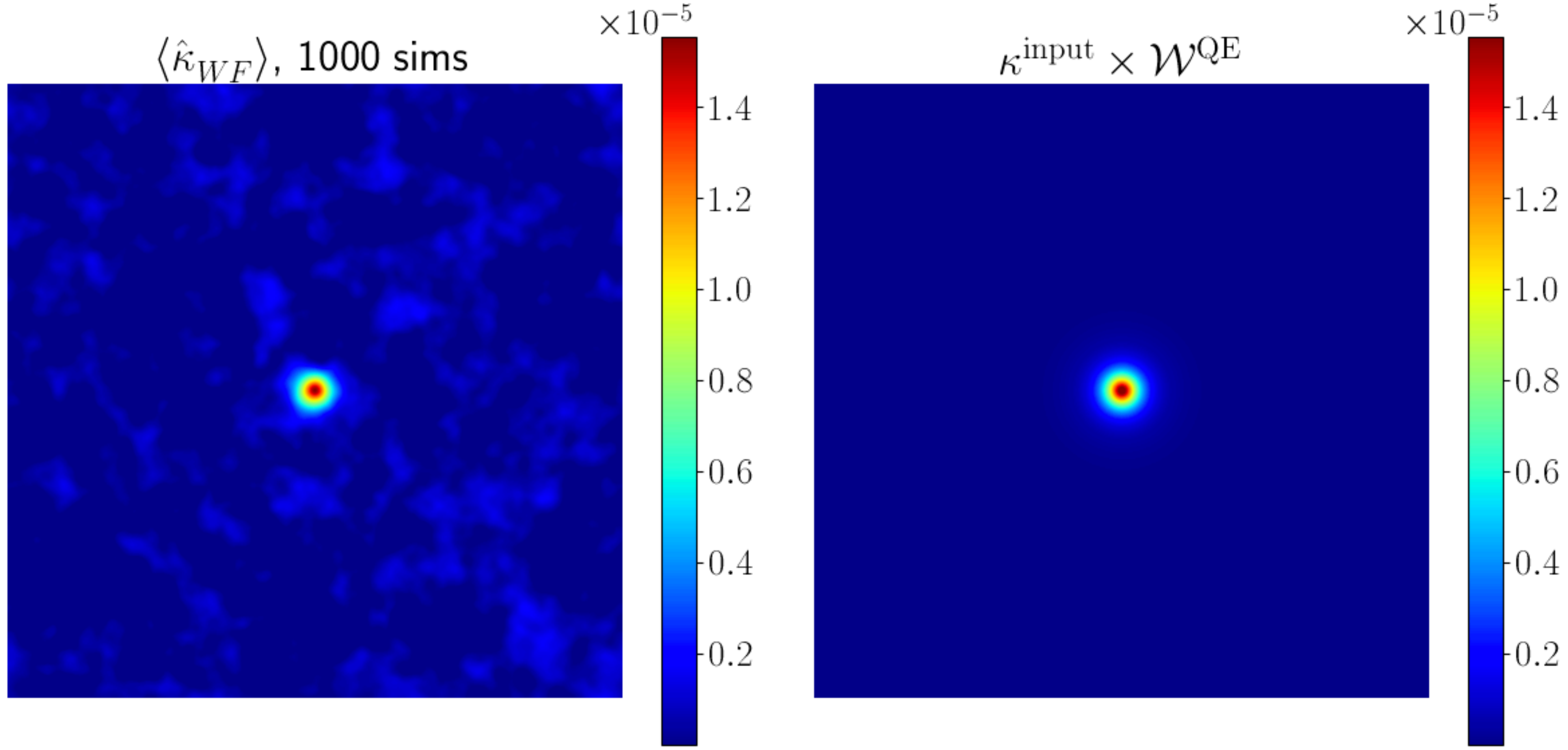
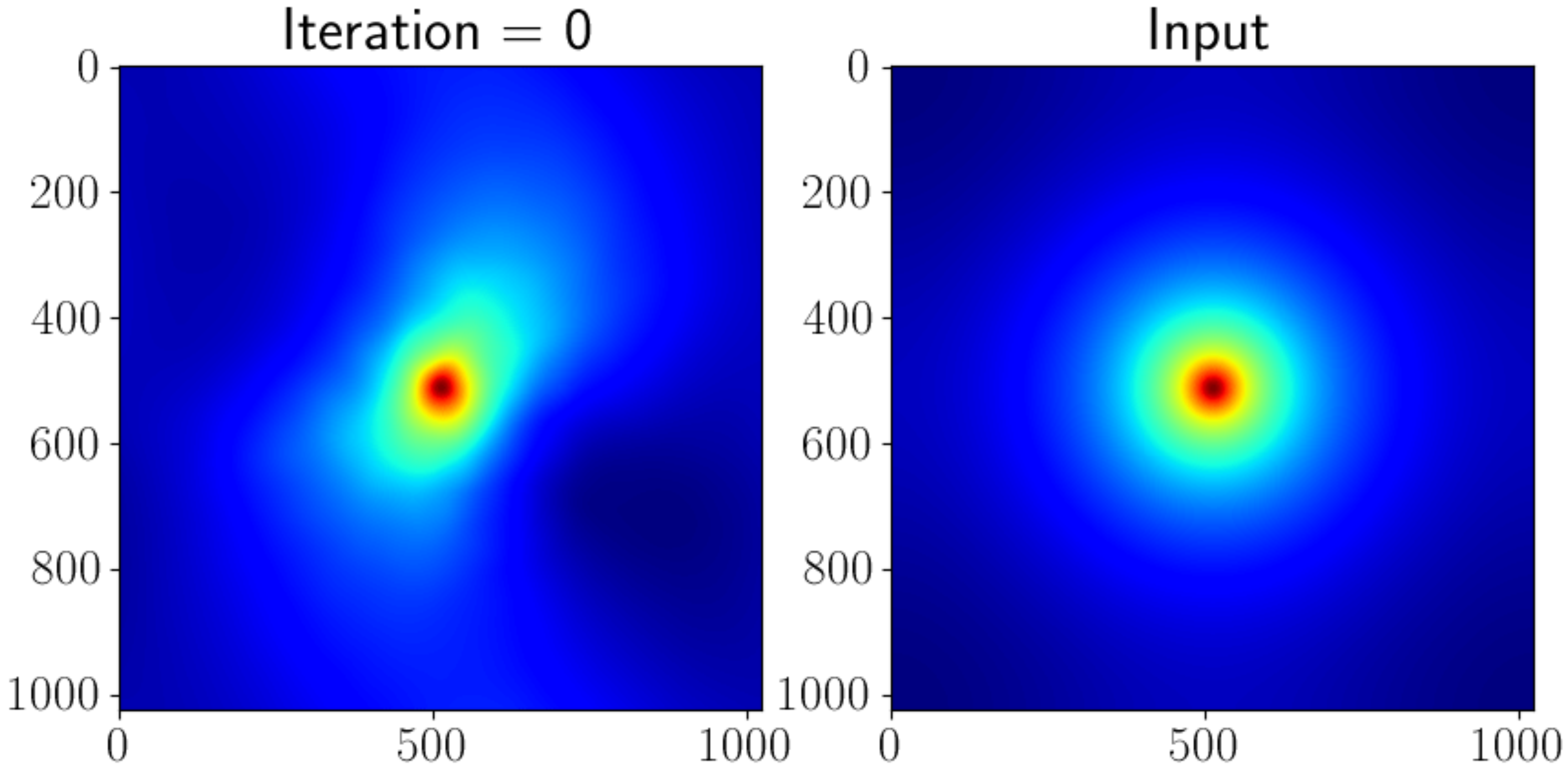


APPLICATION ON SIMULATIONS



AND THE MAGIC OF MAP ESTIMATOR…

QE



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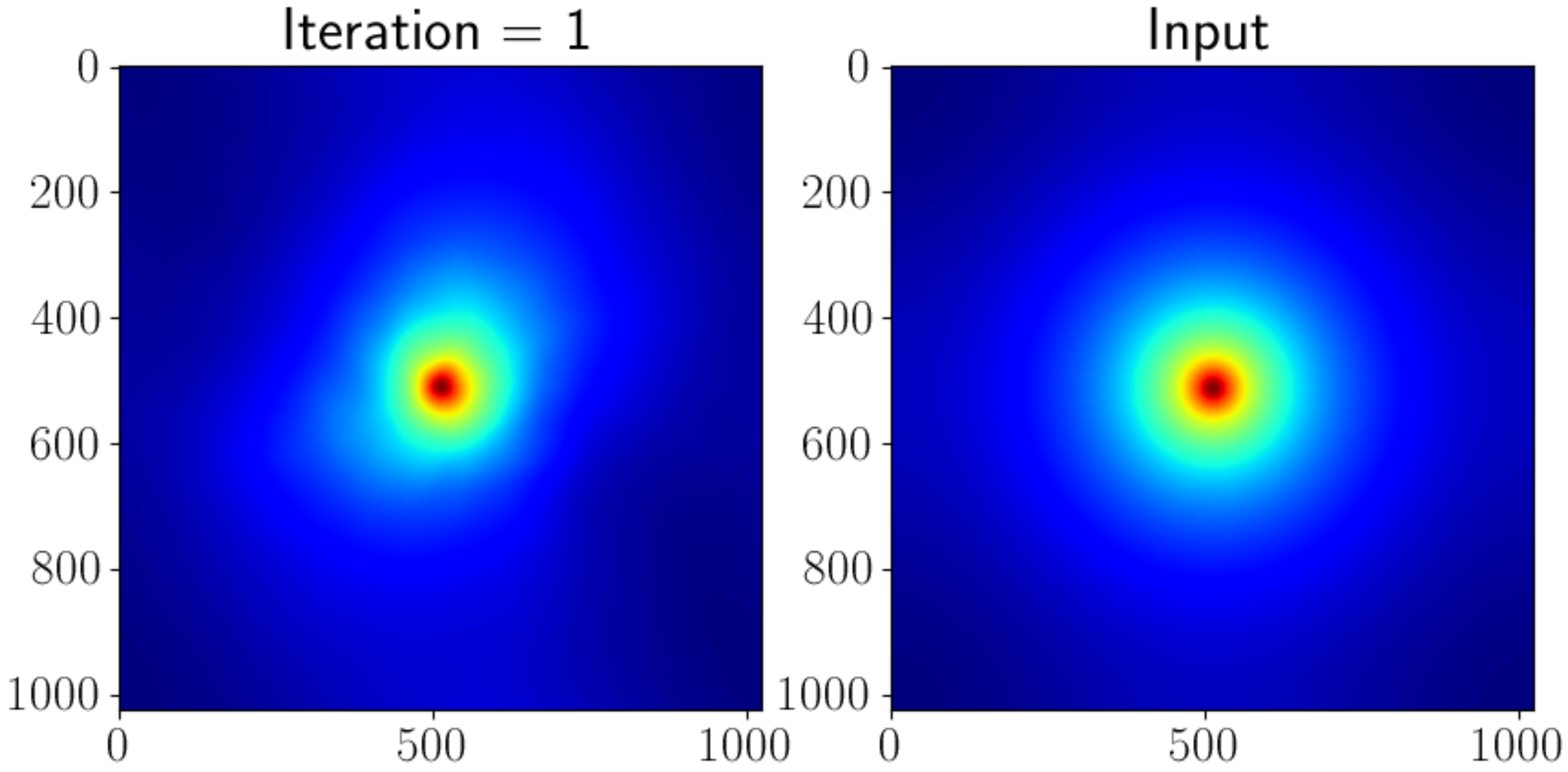

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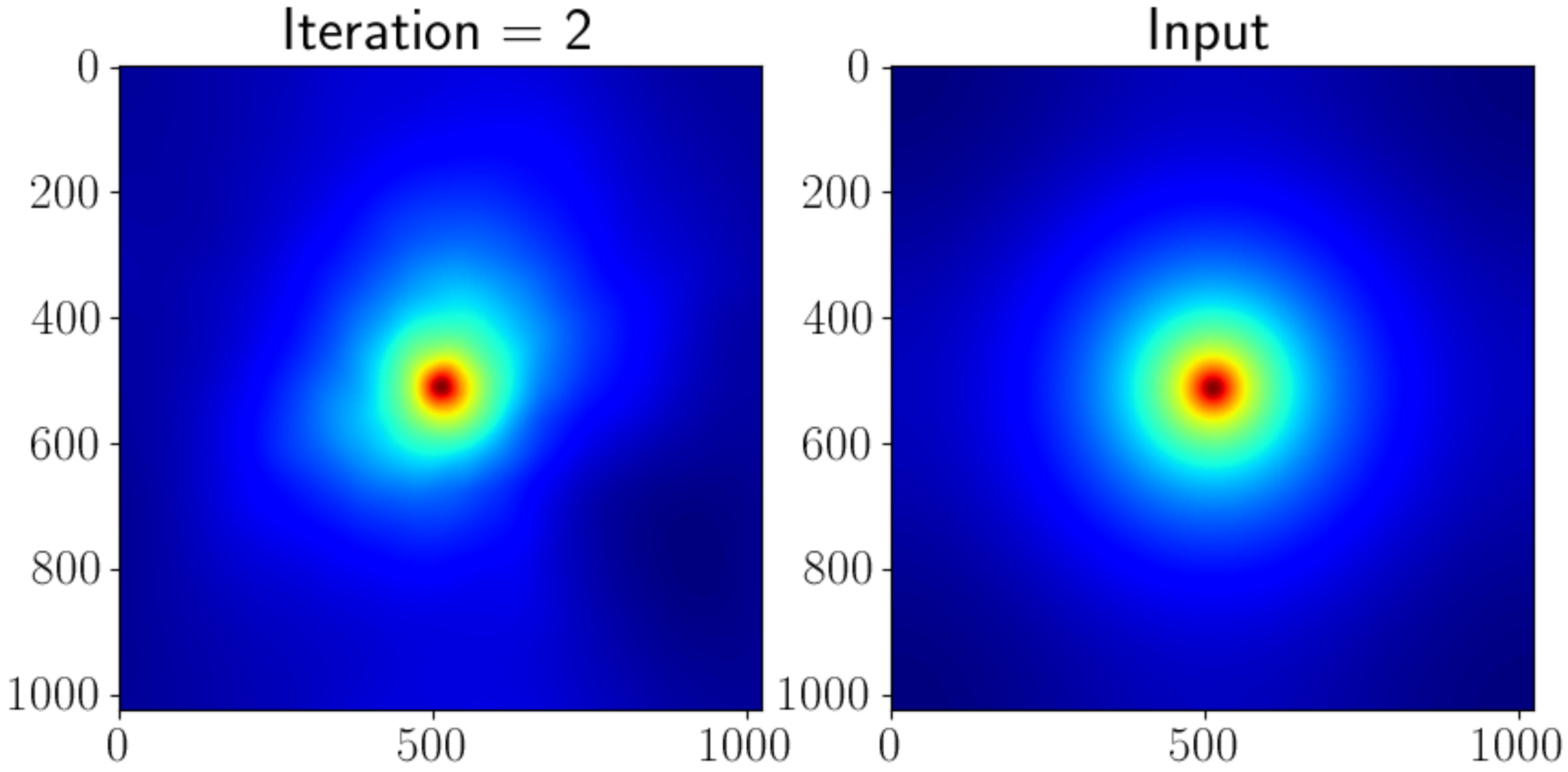

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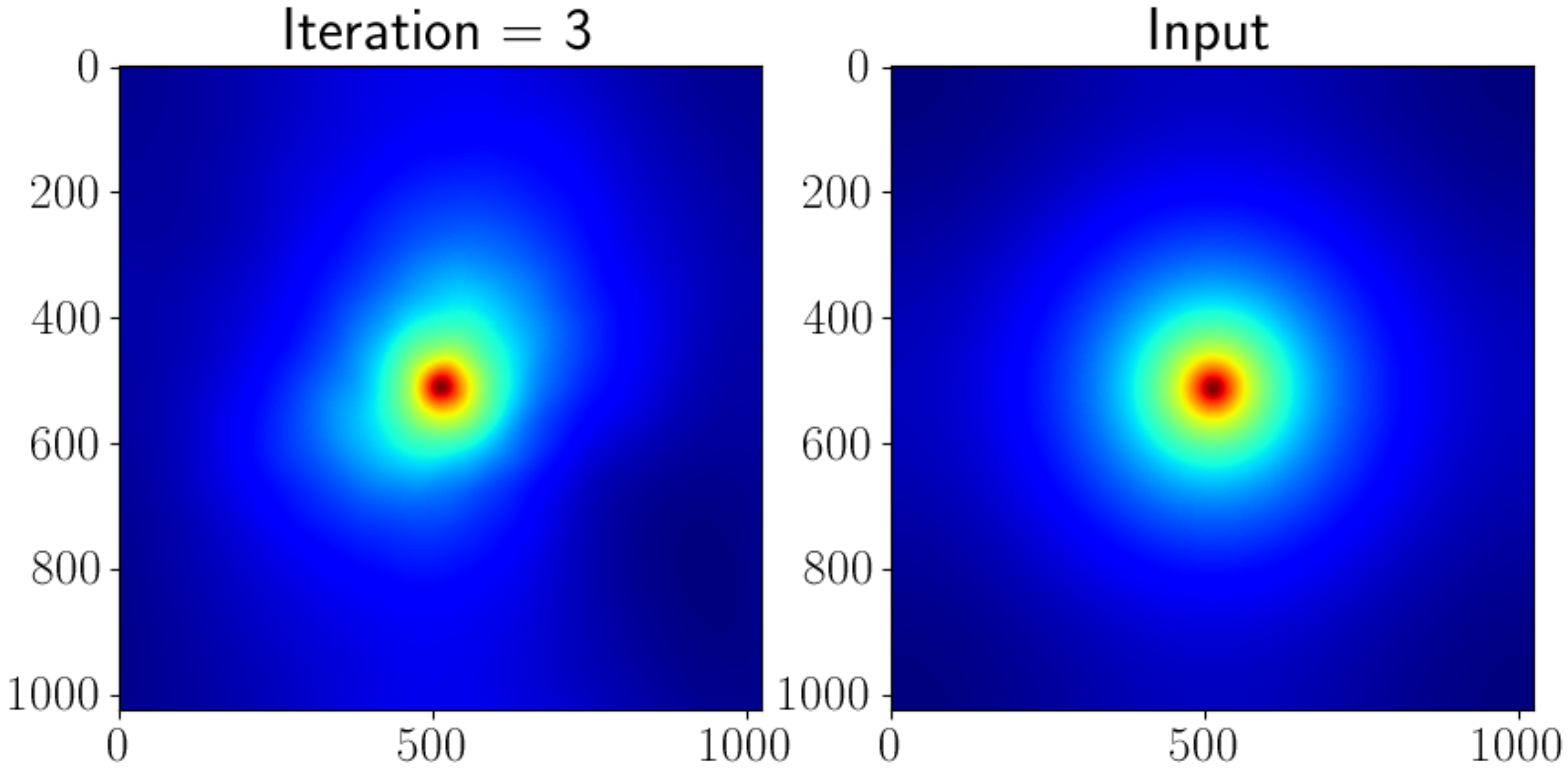

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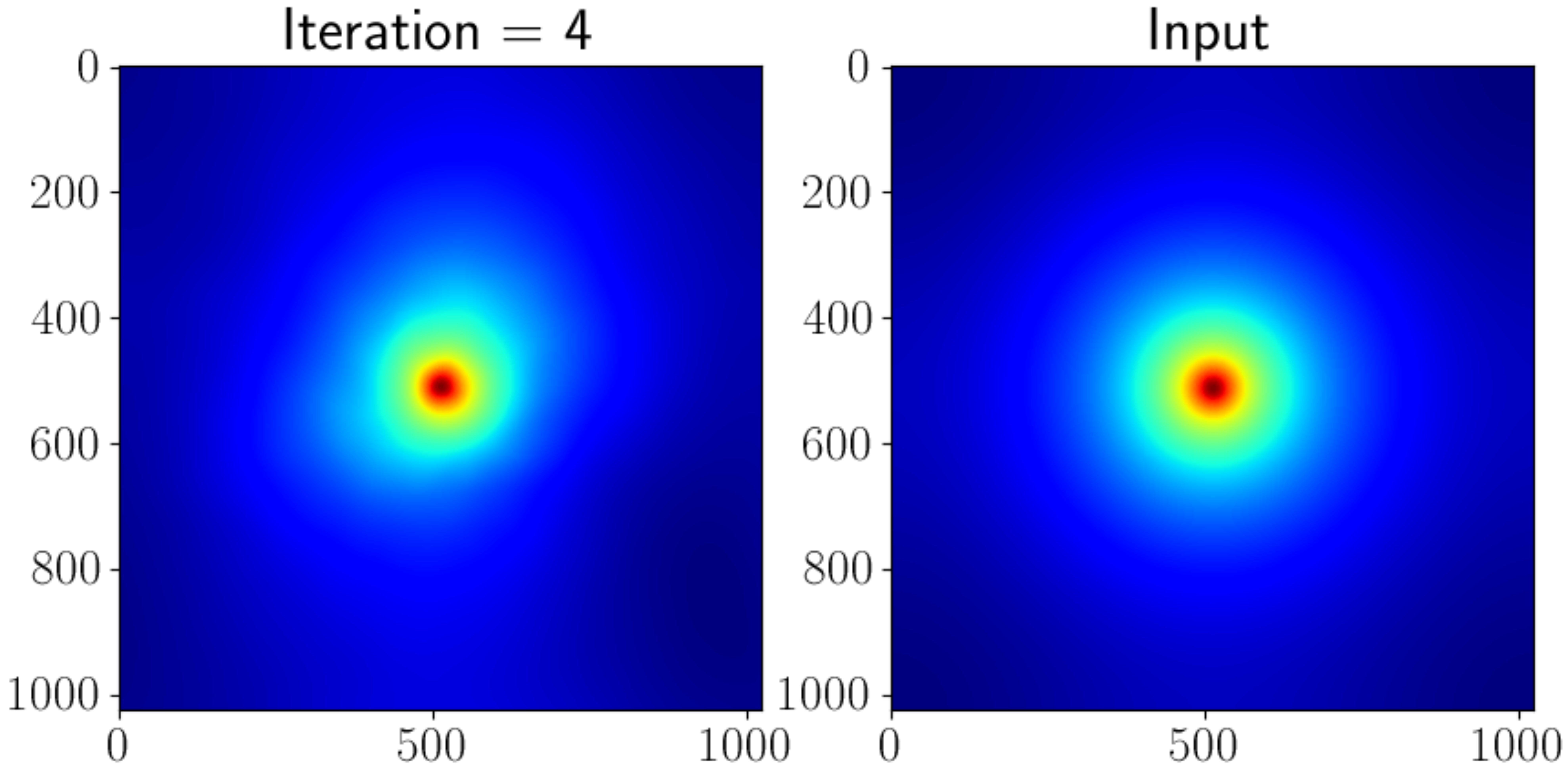

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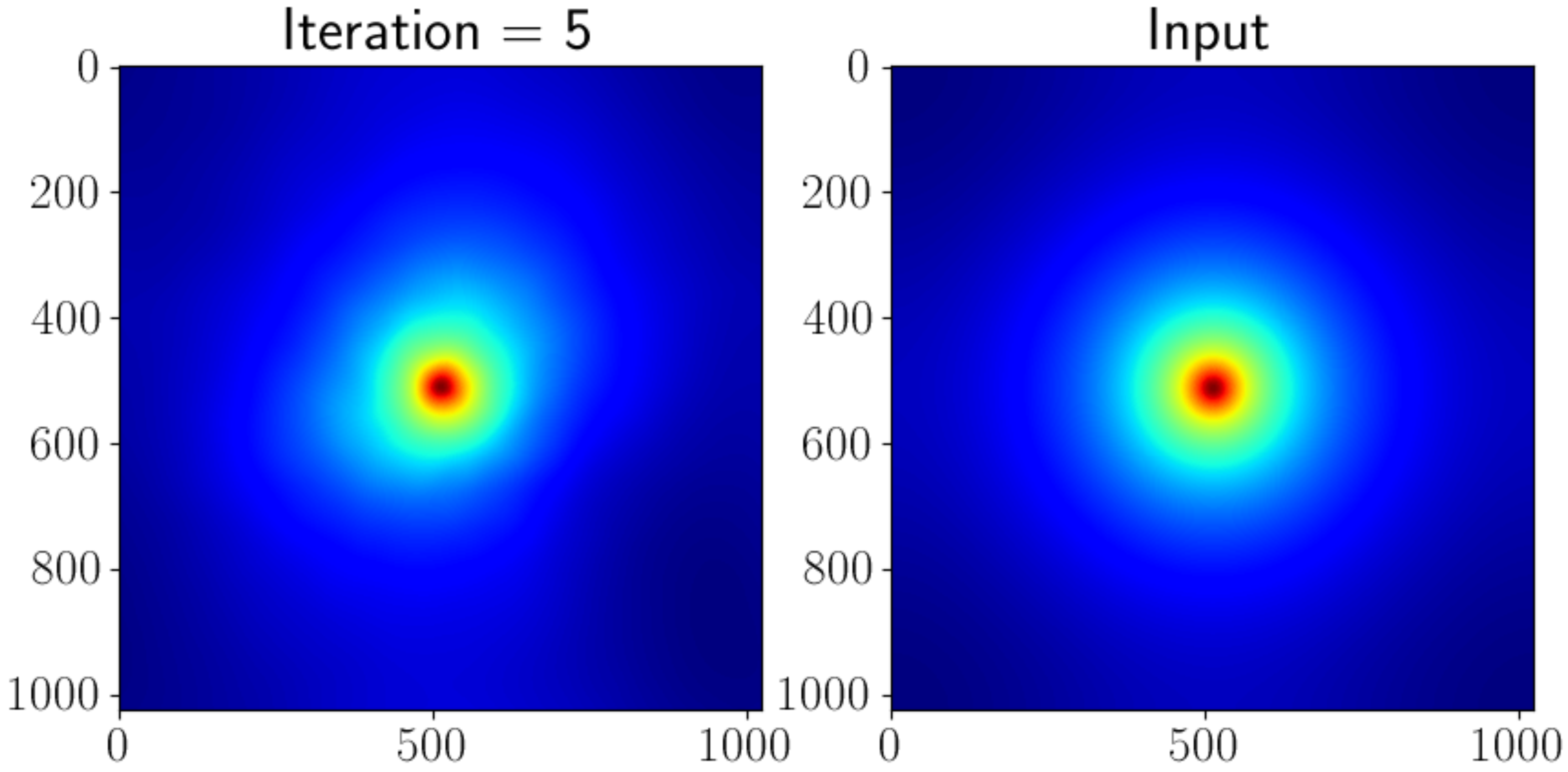

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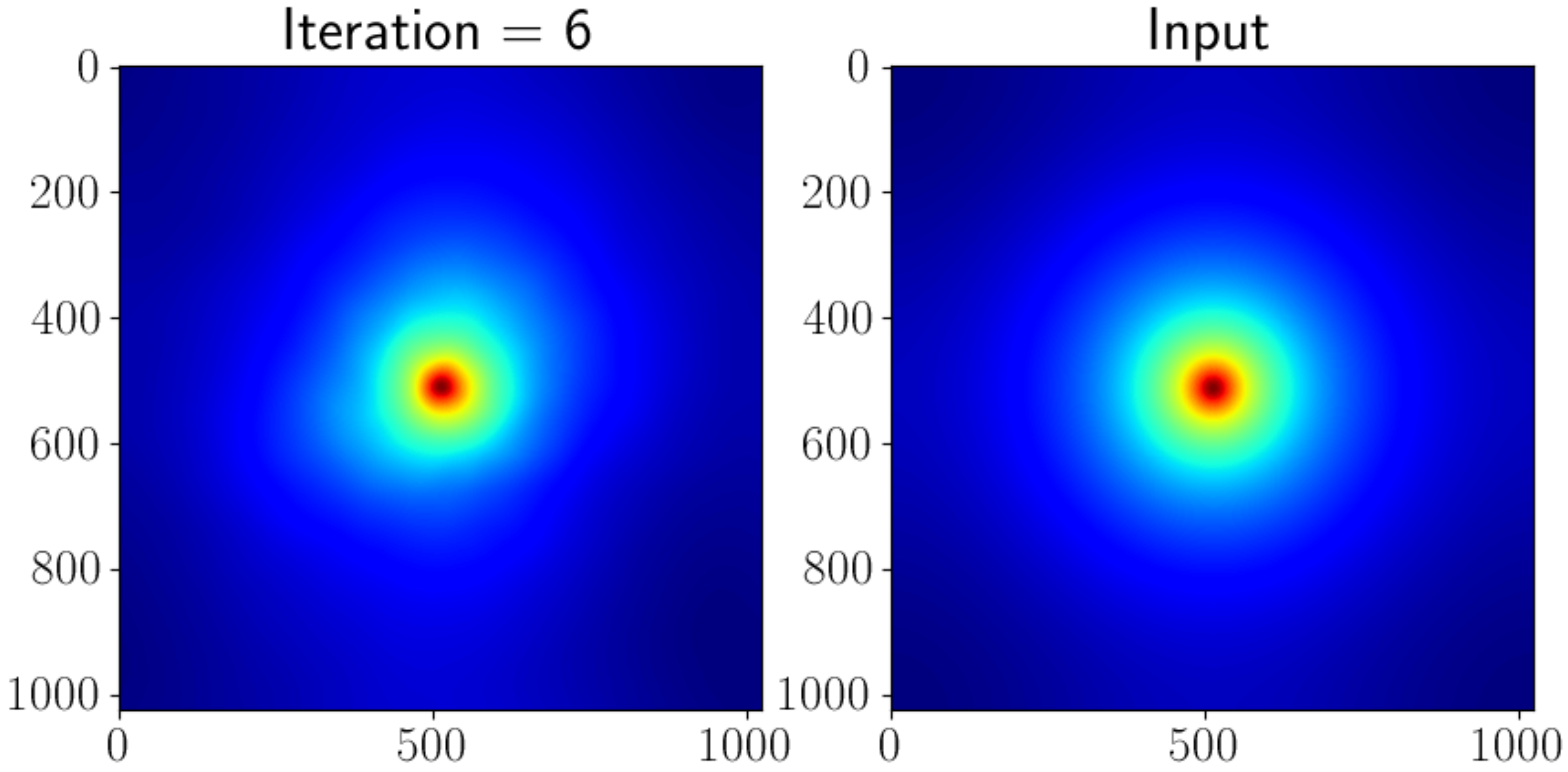

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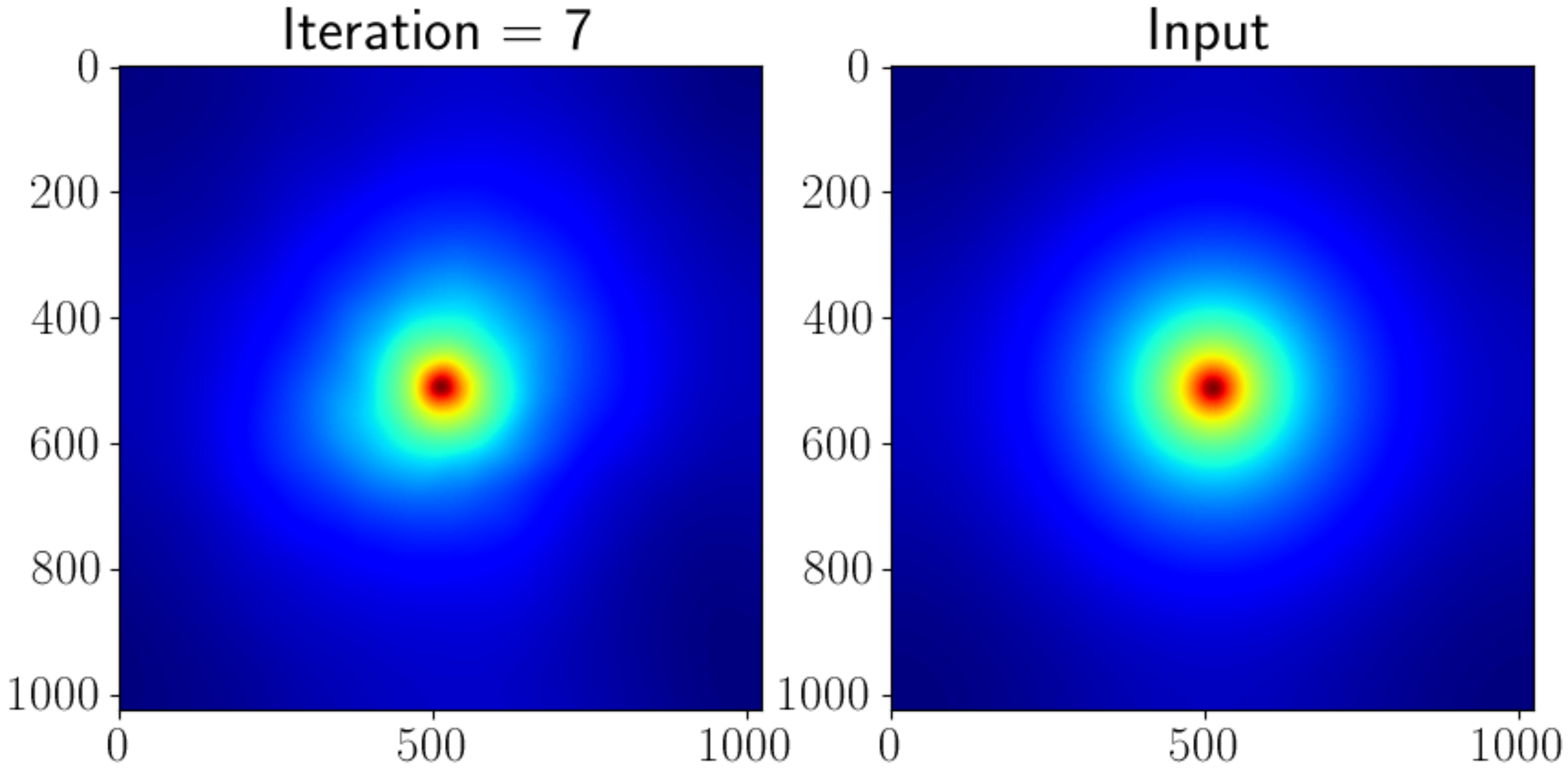

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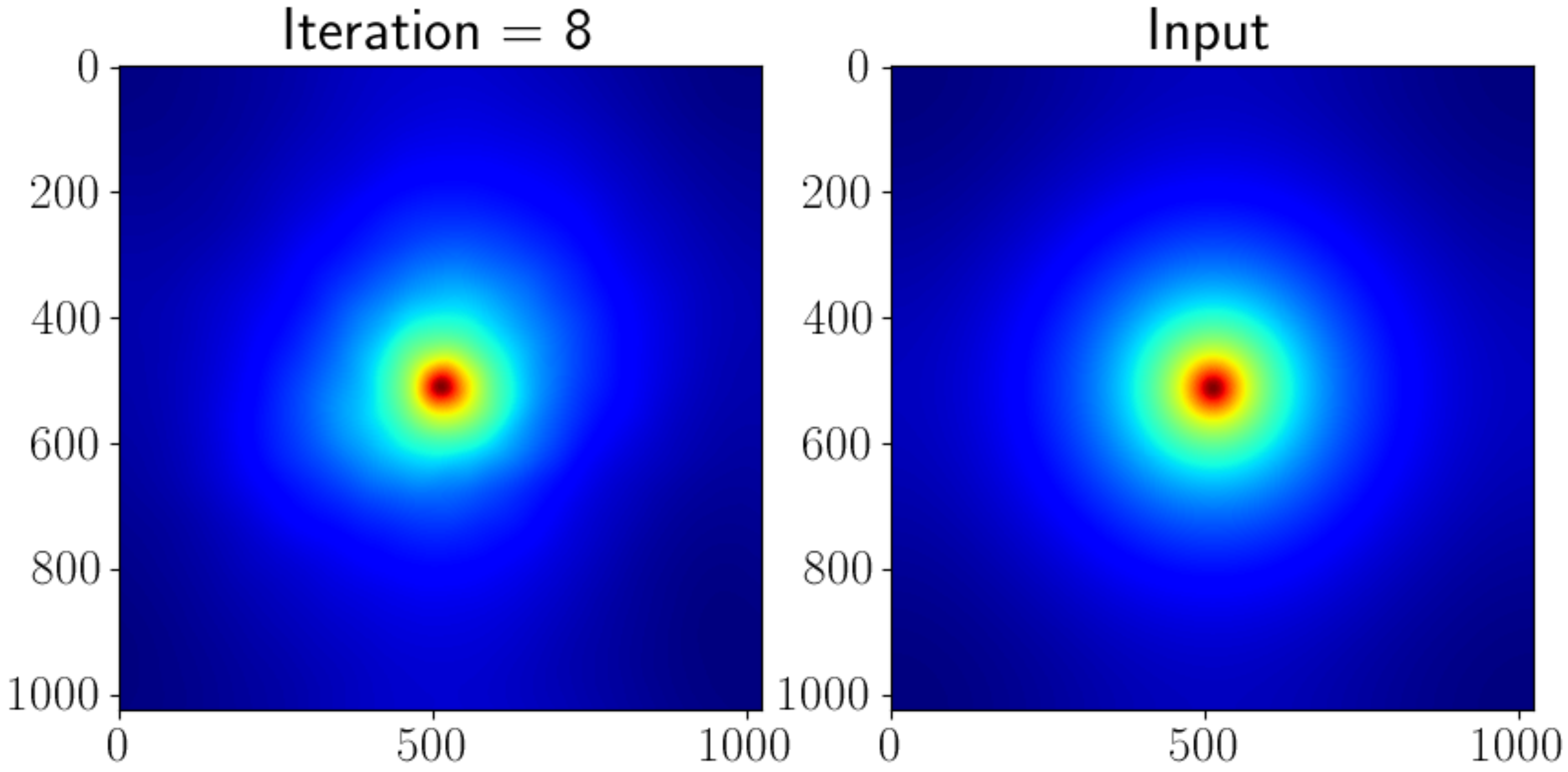

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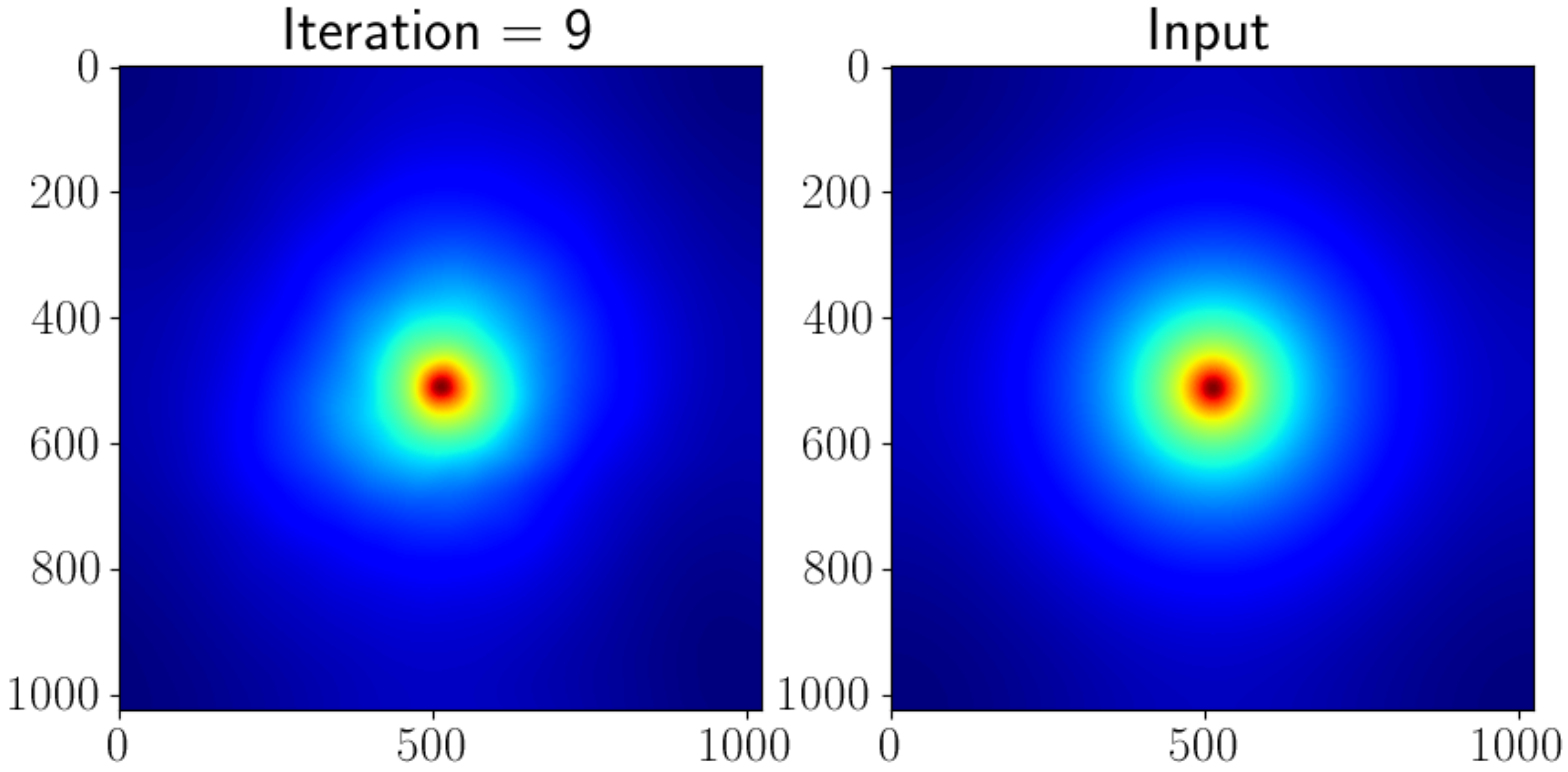

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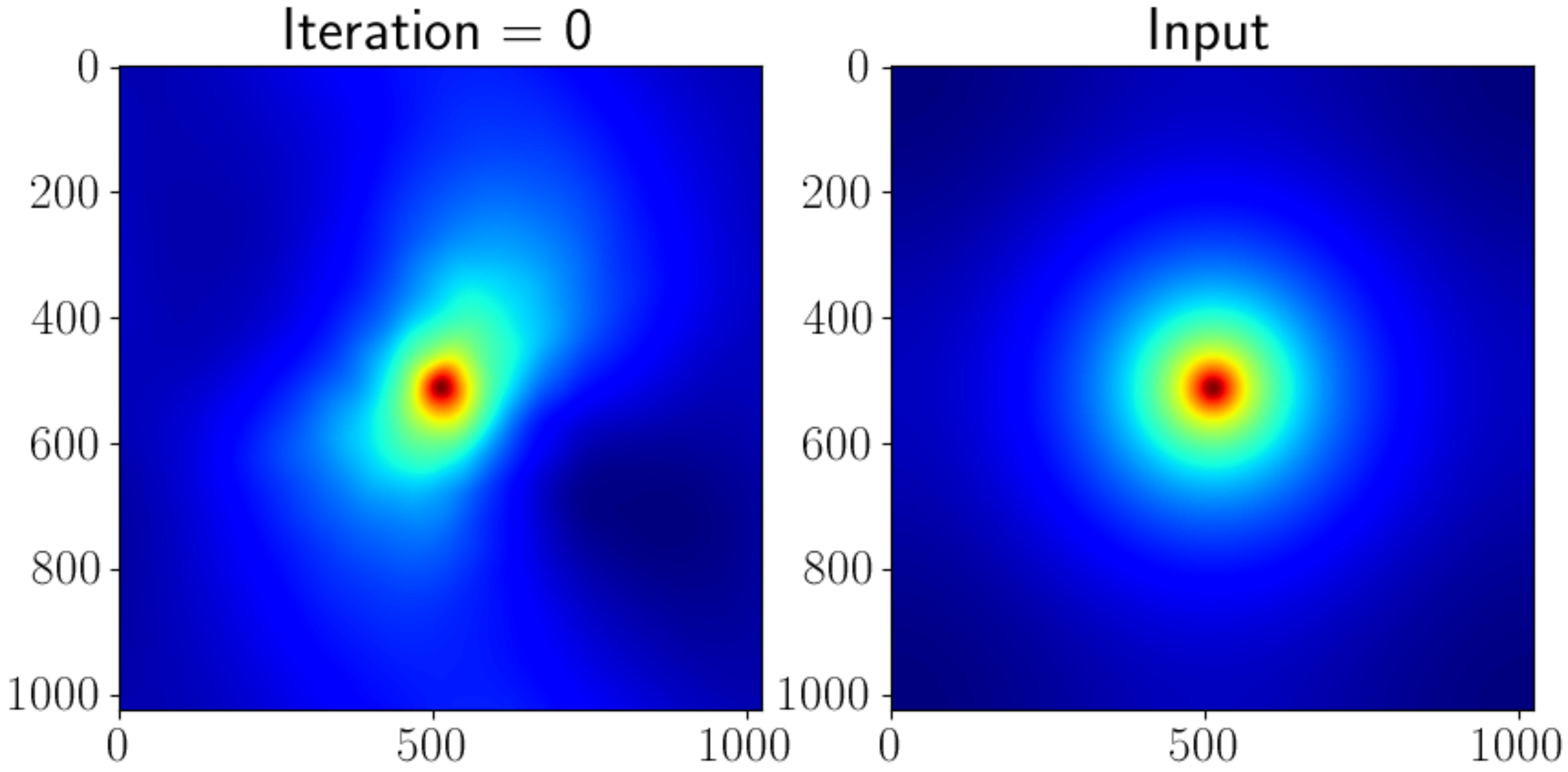

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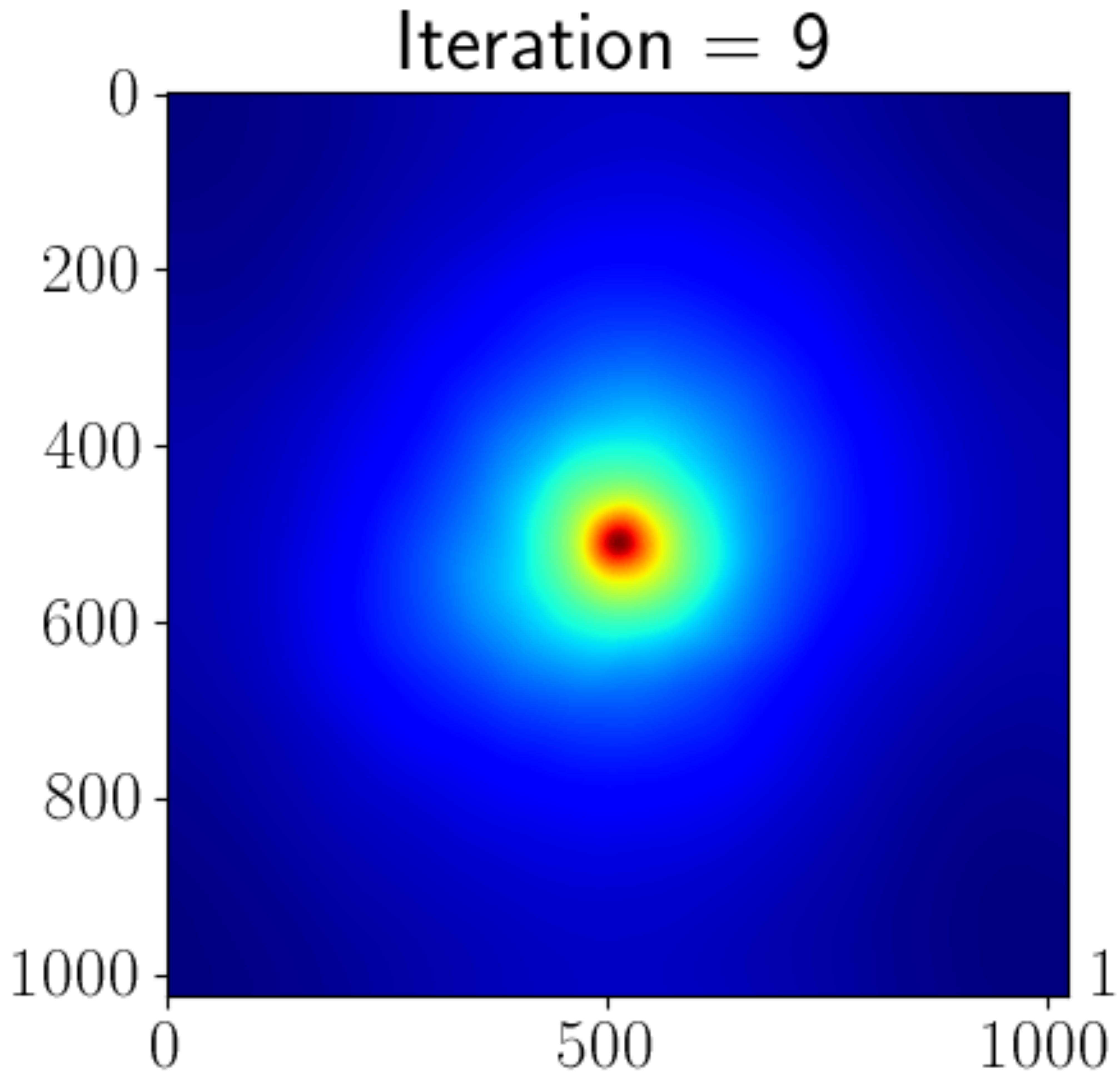

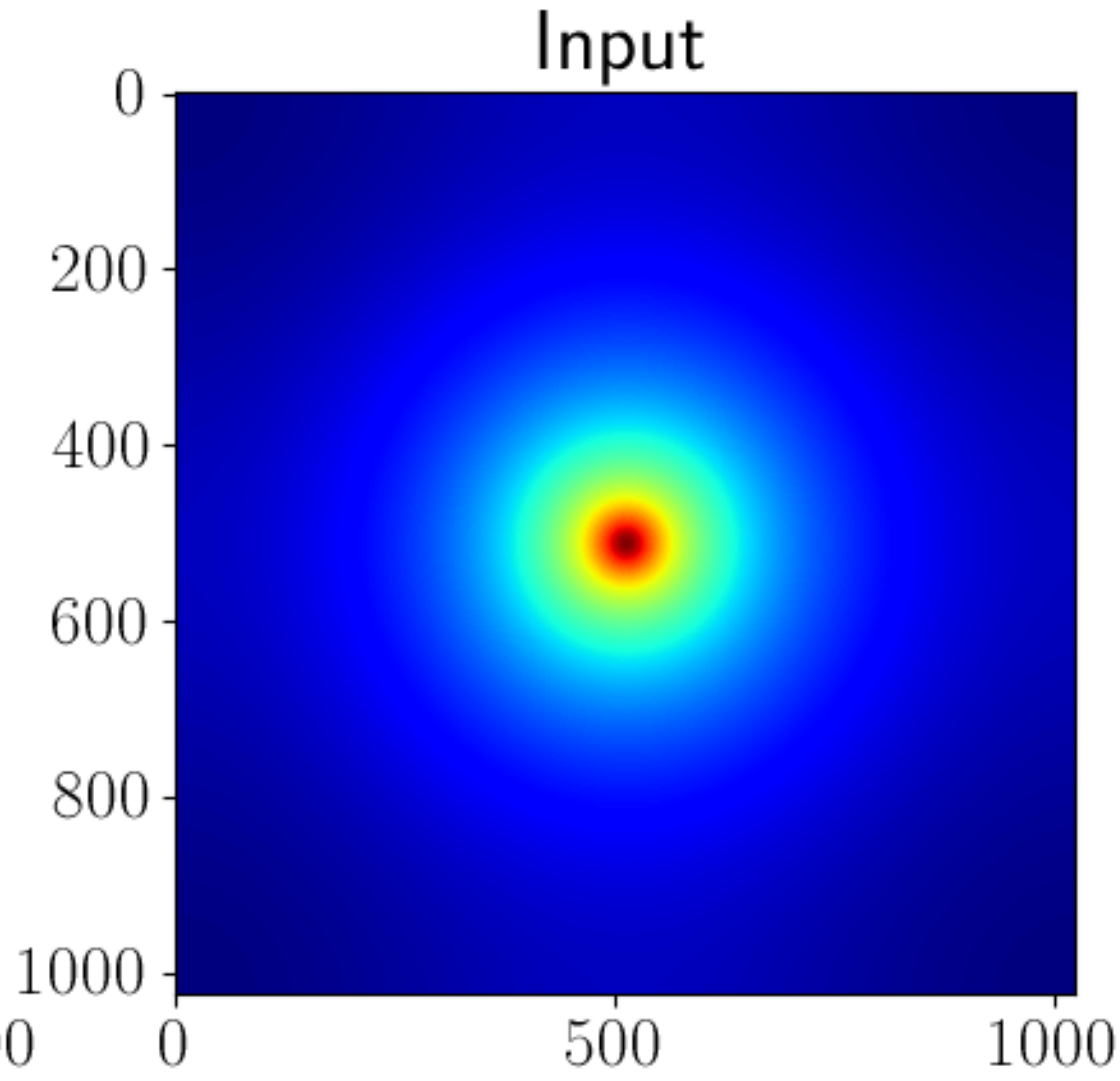

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- We worked on an estimator, if you show a patch of CMB which is lensed by a galaxy cluster, it will estimate its mass (κ_0).
- In the estimator κ_0, we use iterative estimate (MAP estimator) of $\hat{\kappa}$, instead of a quadratic estimator.
- We forecast improvement using our estimator, for CMB-S4 like experiment.
- We test our estimator on Mock data, which is lensed by galaxy-clusters.
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