Targeted dark matter substructure inference with differentiable strong lensing

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Based on 1910.06157, 2010.07032 and 2105.09465

With Marco Chianese, Camila Correa, Kosio Karchev, Noemi Anau Montel and Christoph Weniger

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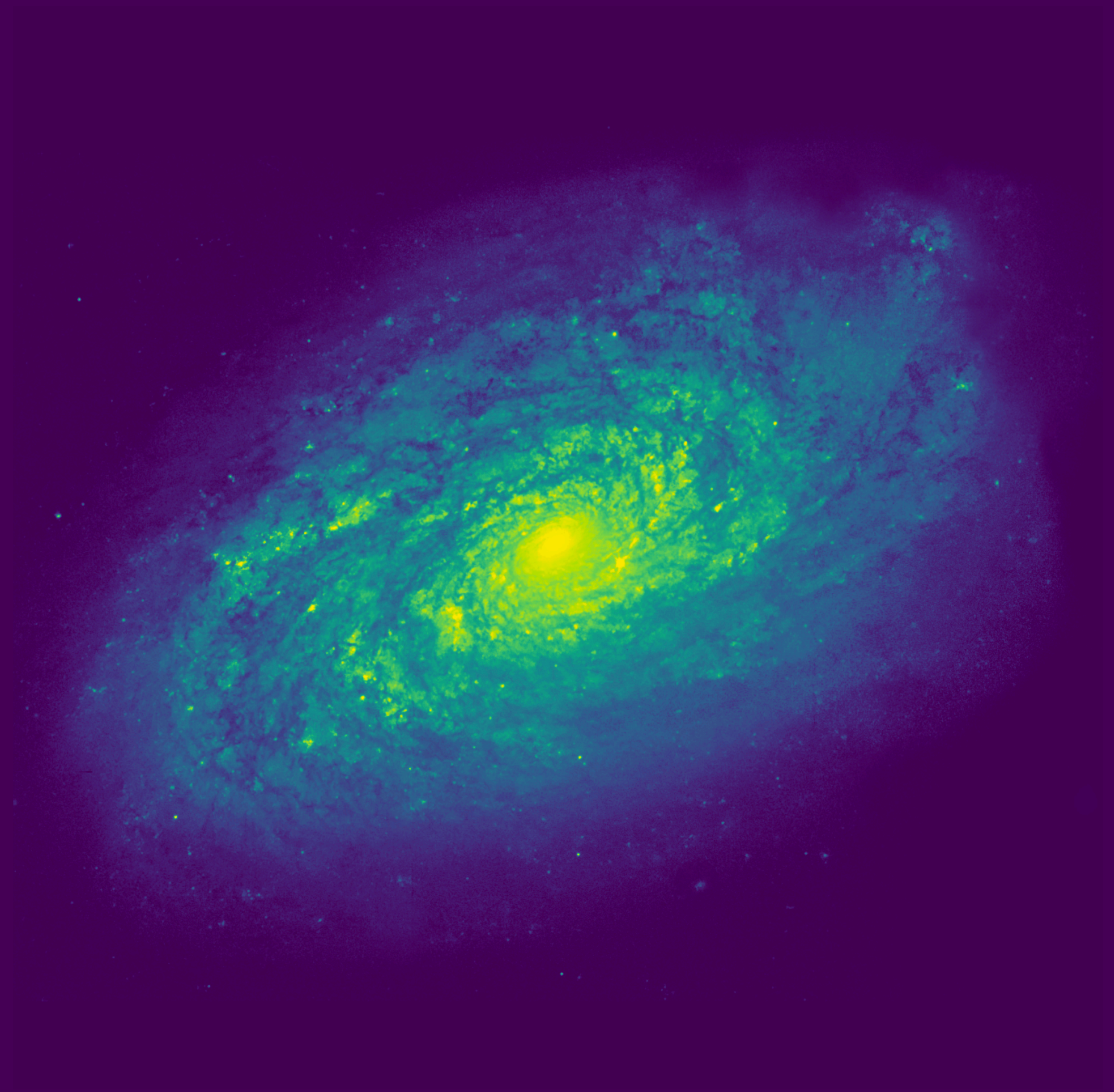
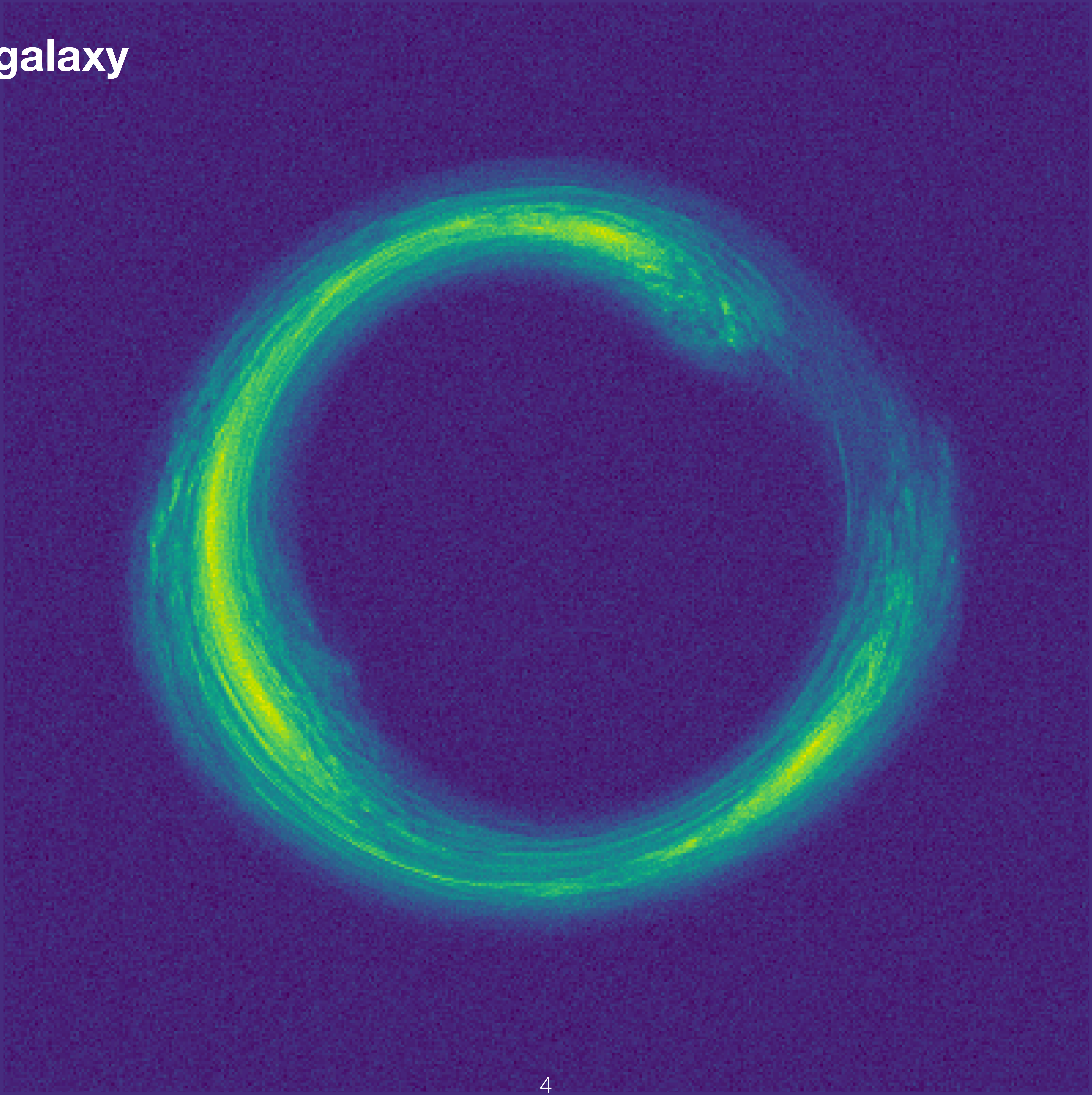
Source galaxy



NGC 4414 (Hubble Heritage Team)

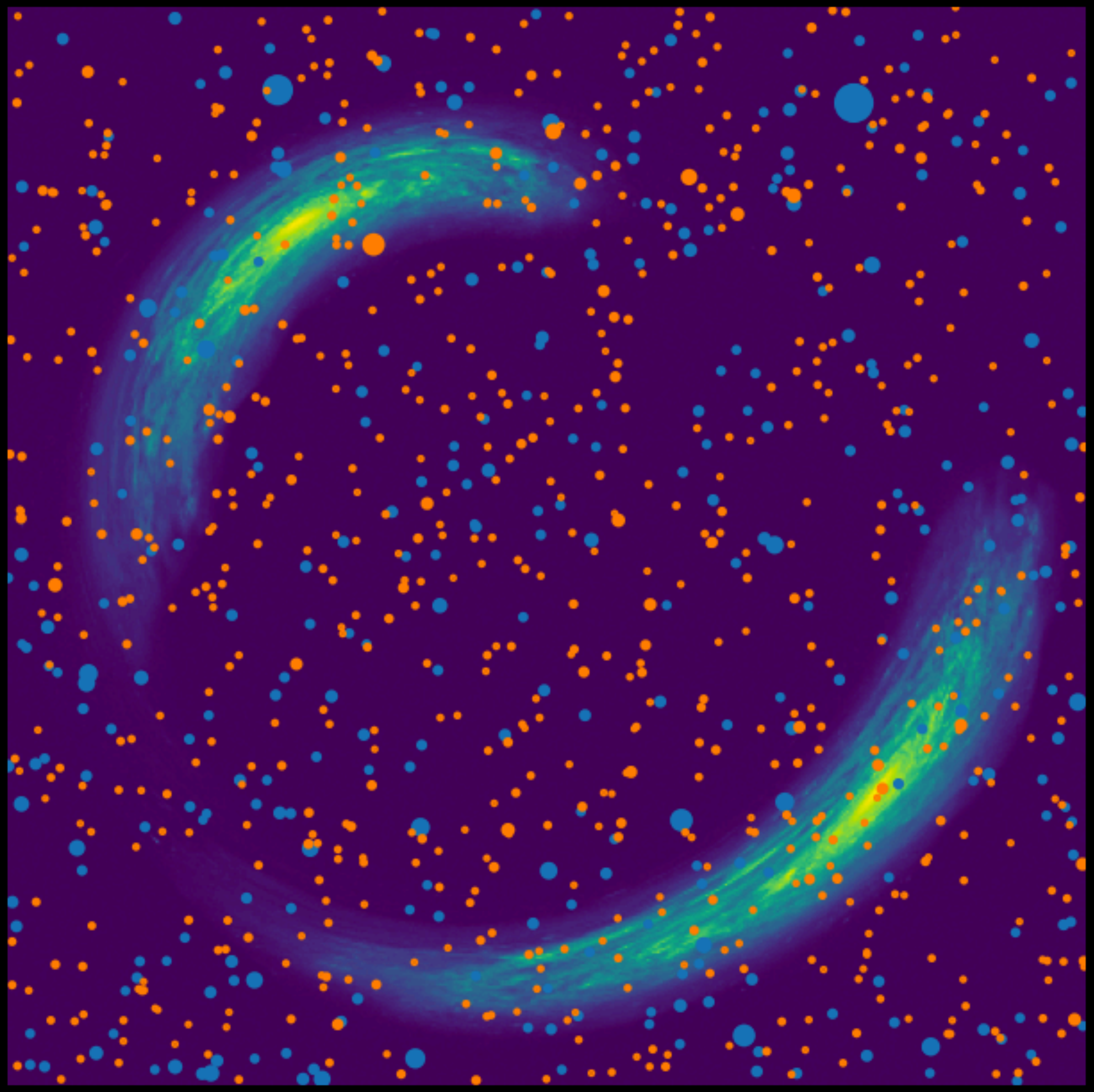
Lens mass

Lensed galaxy



NASA

ALMA, L. Calçada, Y. Hezaveh et al.



Goal: *marginal* posteriors for

- Number of subhalos
- Heaviest subhalo's properties
- Lower bound on masses

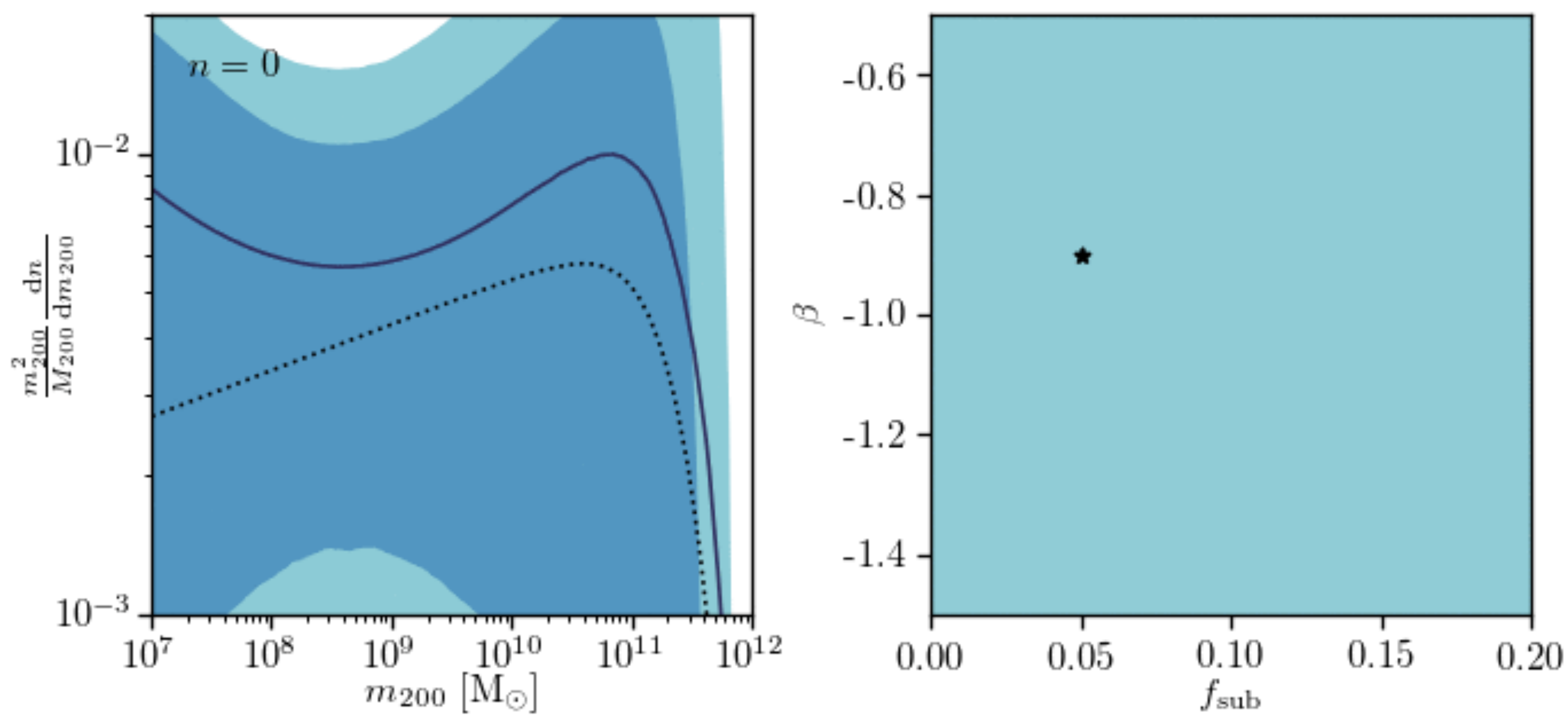
Typical inference:

- *Joint* posterior — not scalable to e.g. multiple subhalos
- No source uncertainties

E.g. Vegetti & Koopmans 0805.0201

Simulation-based inference with
neural ratio estimation

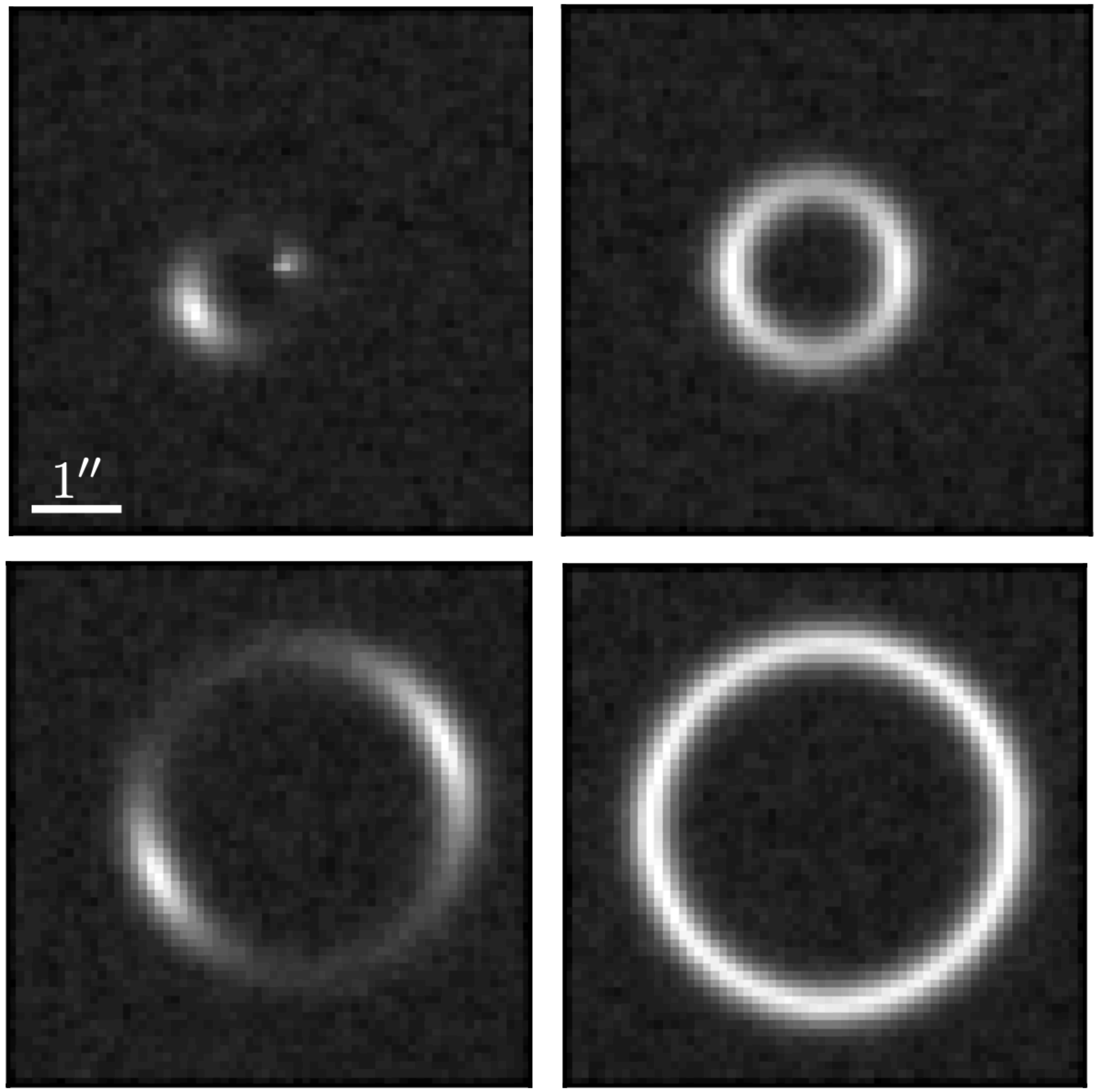
Observations   Mass function   Population parameters

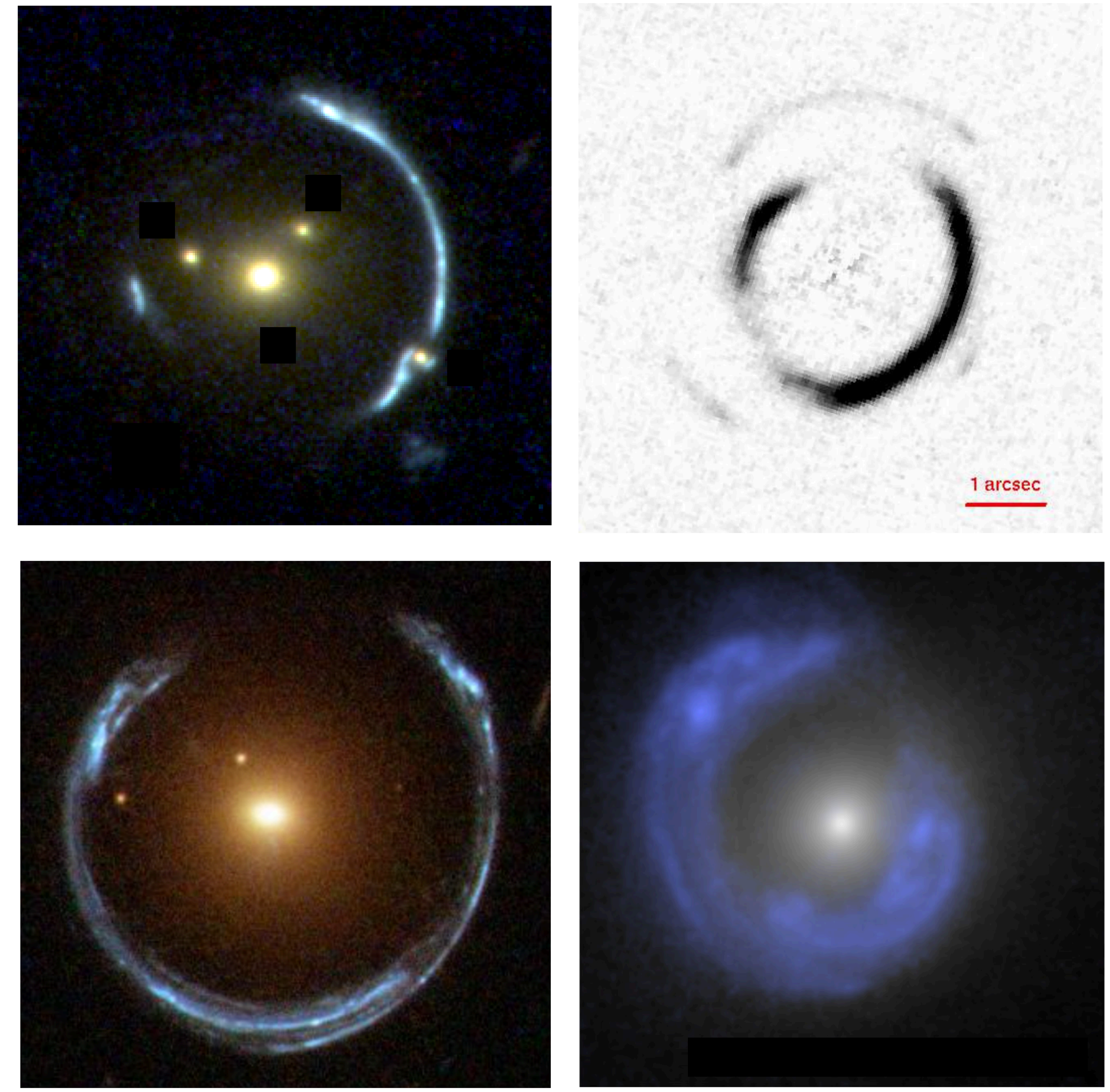


Scaling to real images?

Johann Brehmer et al 2019, ApJ 886 49

swyft (Miller et al 2020, arXiv:2107.01214)



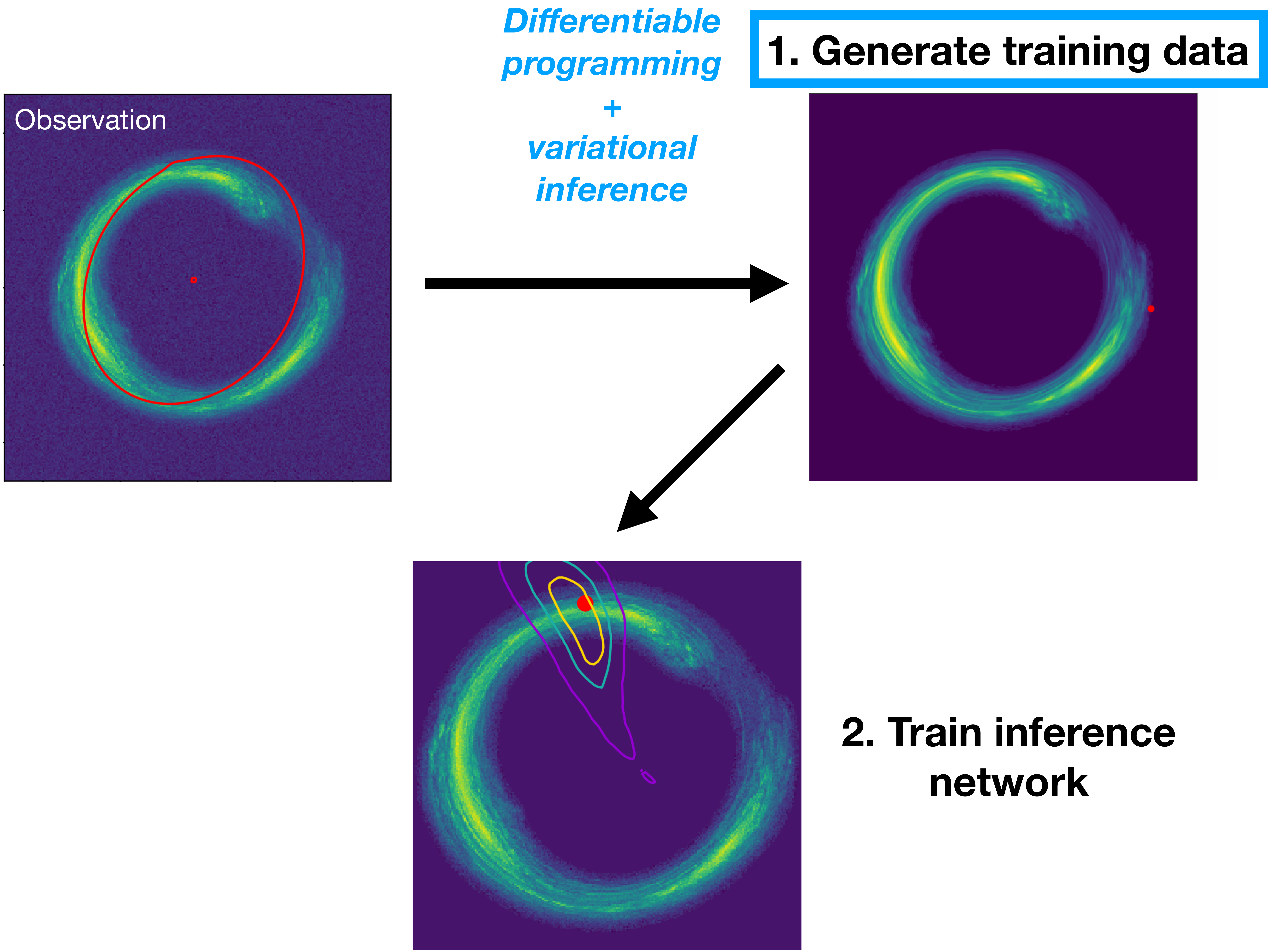


Large variations make training hard.

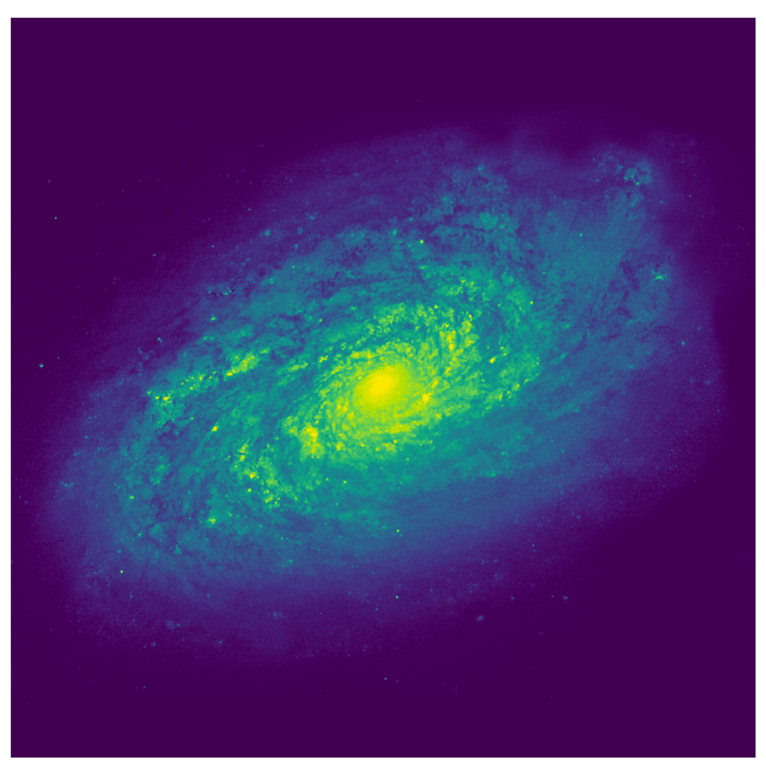
Our approach: targeted inference

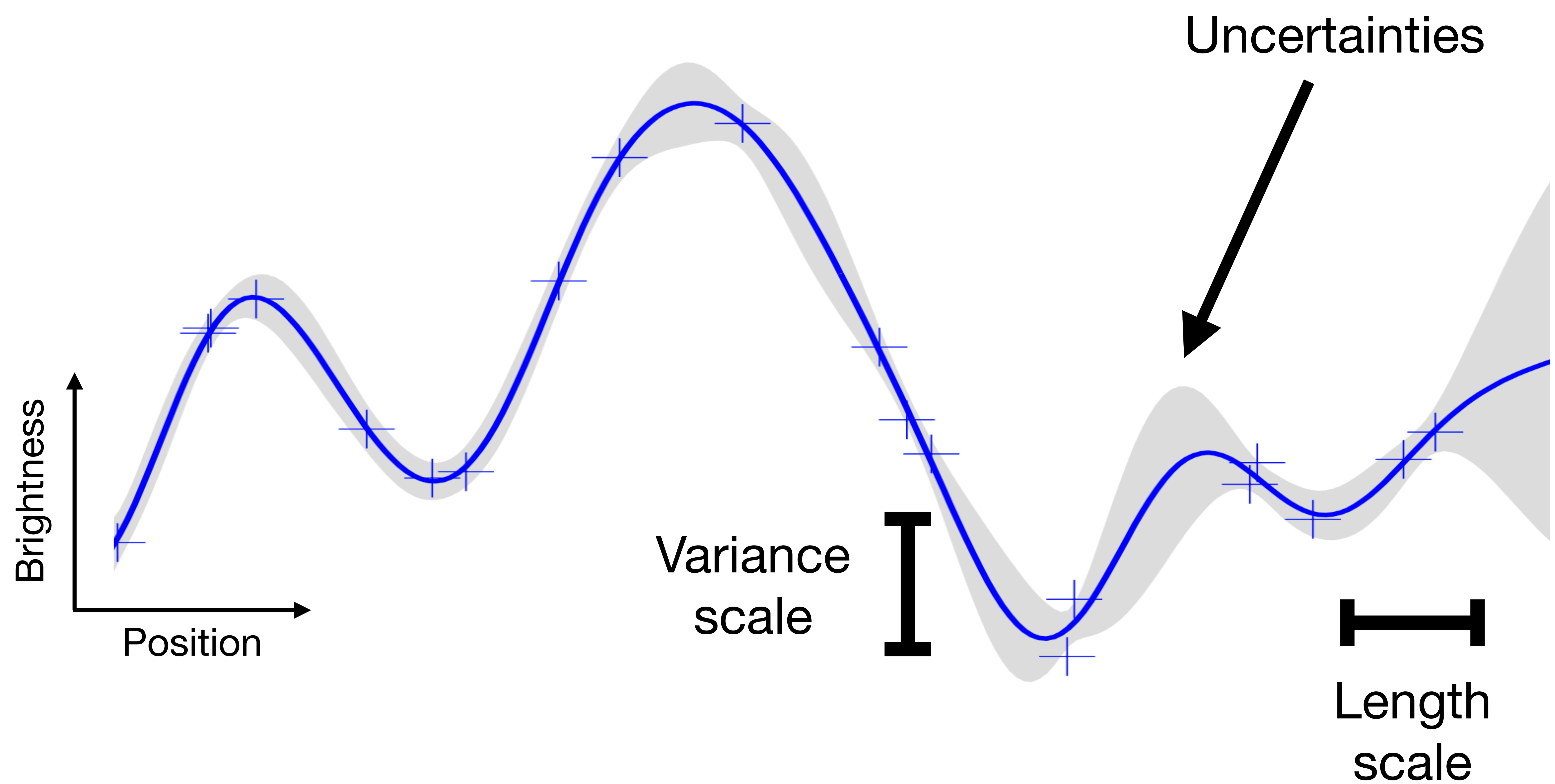
Vegetti et al 2010, MNRAS 407 1
ESA/Hubble & NASA

Gavazzi et al 2008, ApJ 677 1046
Bolton et al 2008, ApJ 682 964


Differentiable
programming
+
variational
inference
1. Generate training data
Observation
2. Train inference
network

Gaussian process source modeling





Directly models covariance in source plane

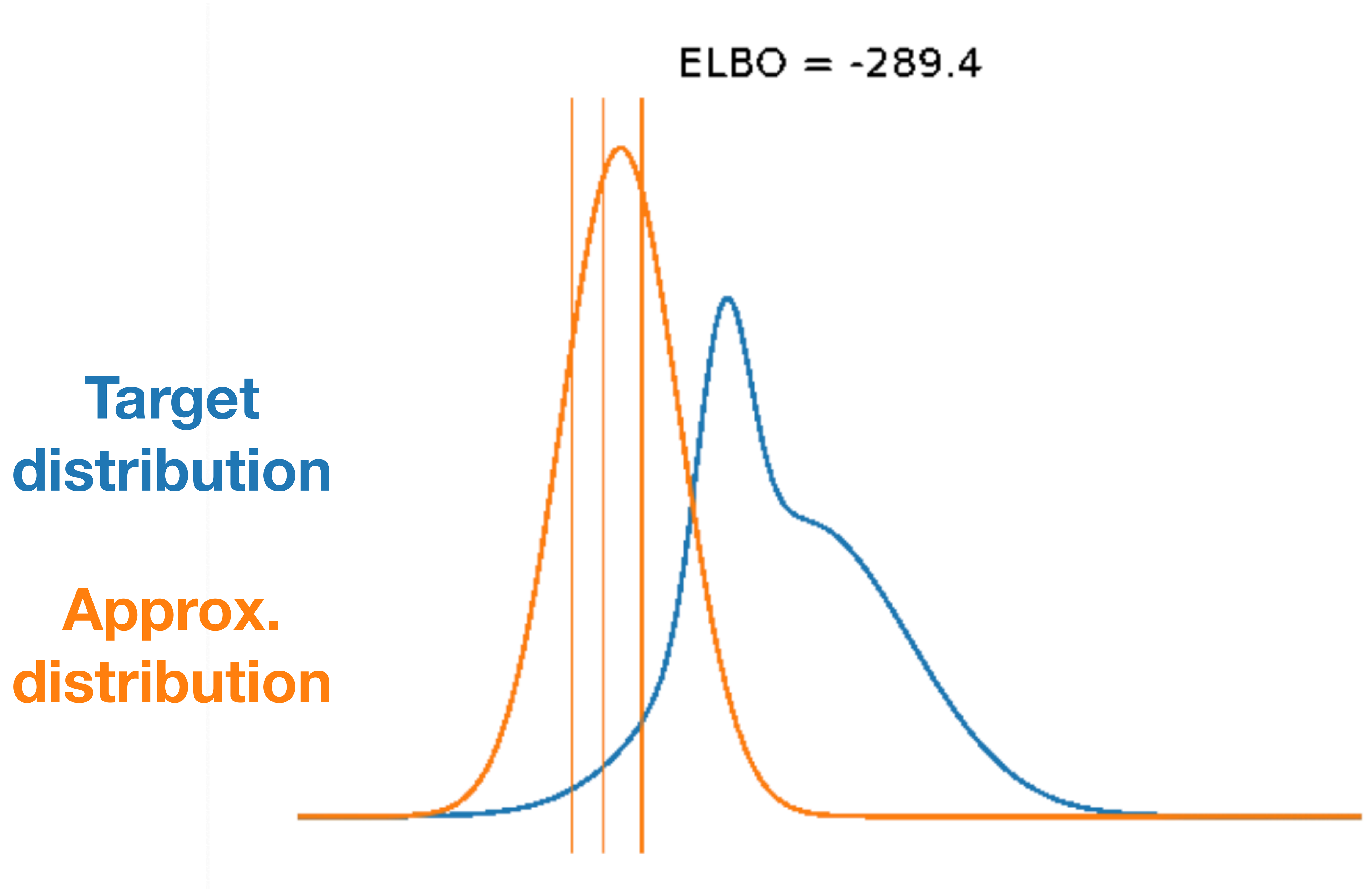
Interpretable hyperparams, uncertainties

Rasmussen & Williams, 2006 (GPs for ML)

Issues with O(10^5 x 10^5) lens-dependent covariance matrix:

- **Source parameter posteriors**
- **Evidence maximization for hyperparam optimization**

Our solution: variational inference



Inference through optimization

Variational inference

+

Novel covariance factorization to eliminate matrix inversions

+

Differentiable lensing physics

+

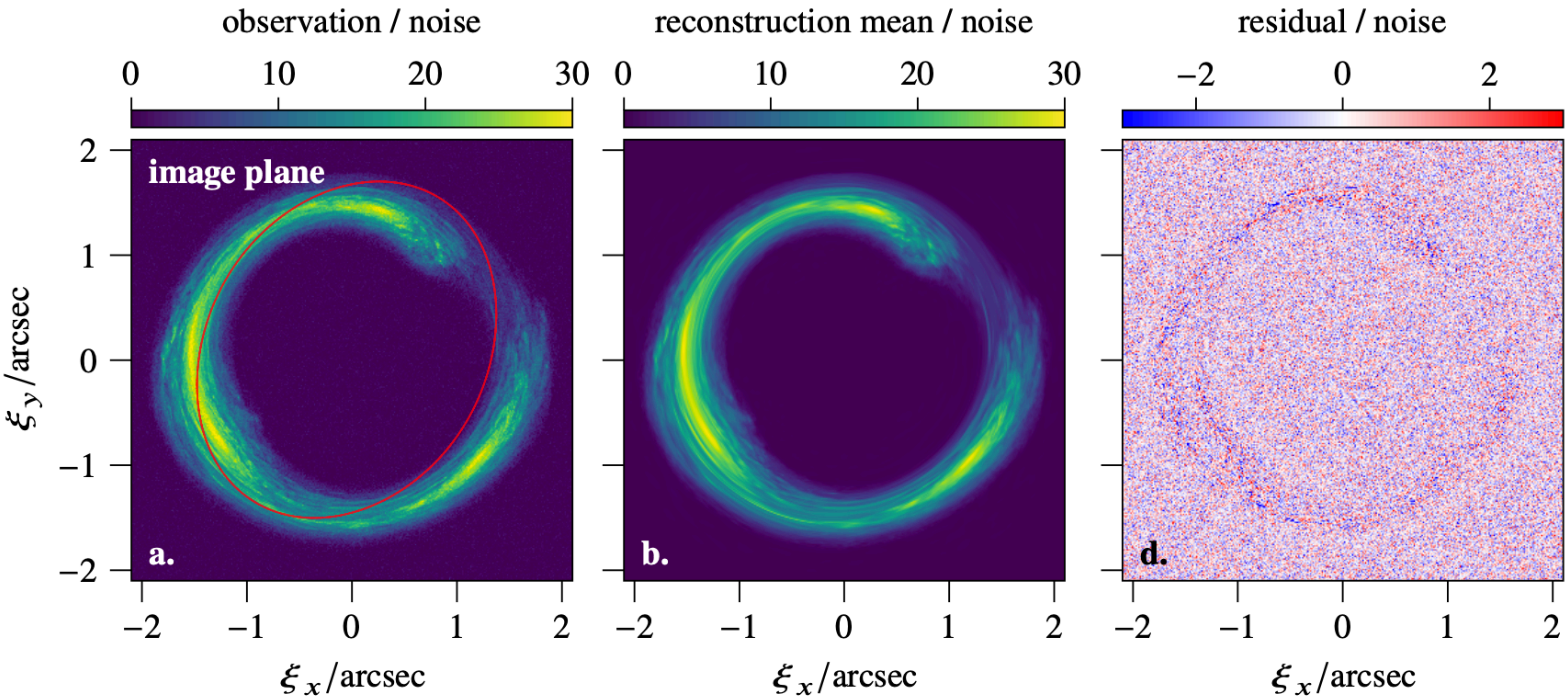
PyTorch KeOps

=

Simultaneously fit lens + source posteriors + hyperparams

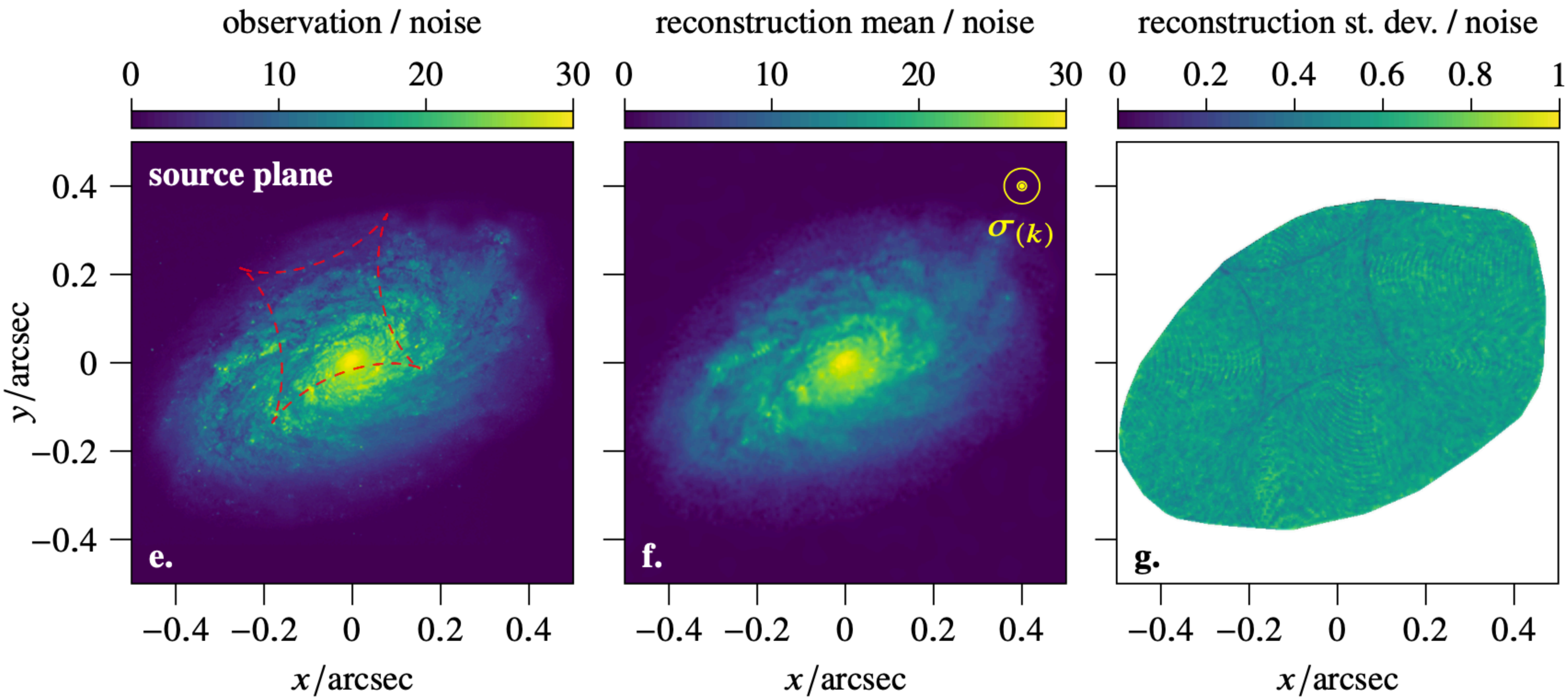
Karchev, Coogan, Weniger 2105.09465

Variational inference results



Mean reconstruction of high-res image near noise level

Karchev, Coogan, Weniger 2105.09465

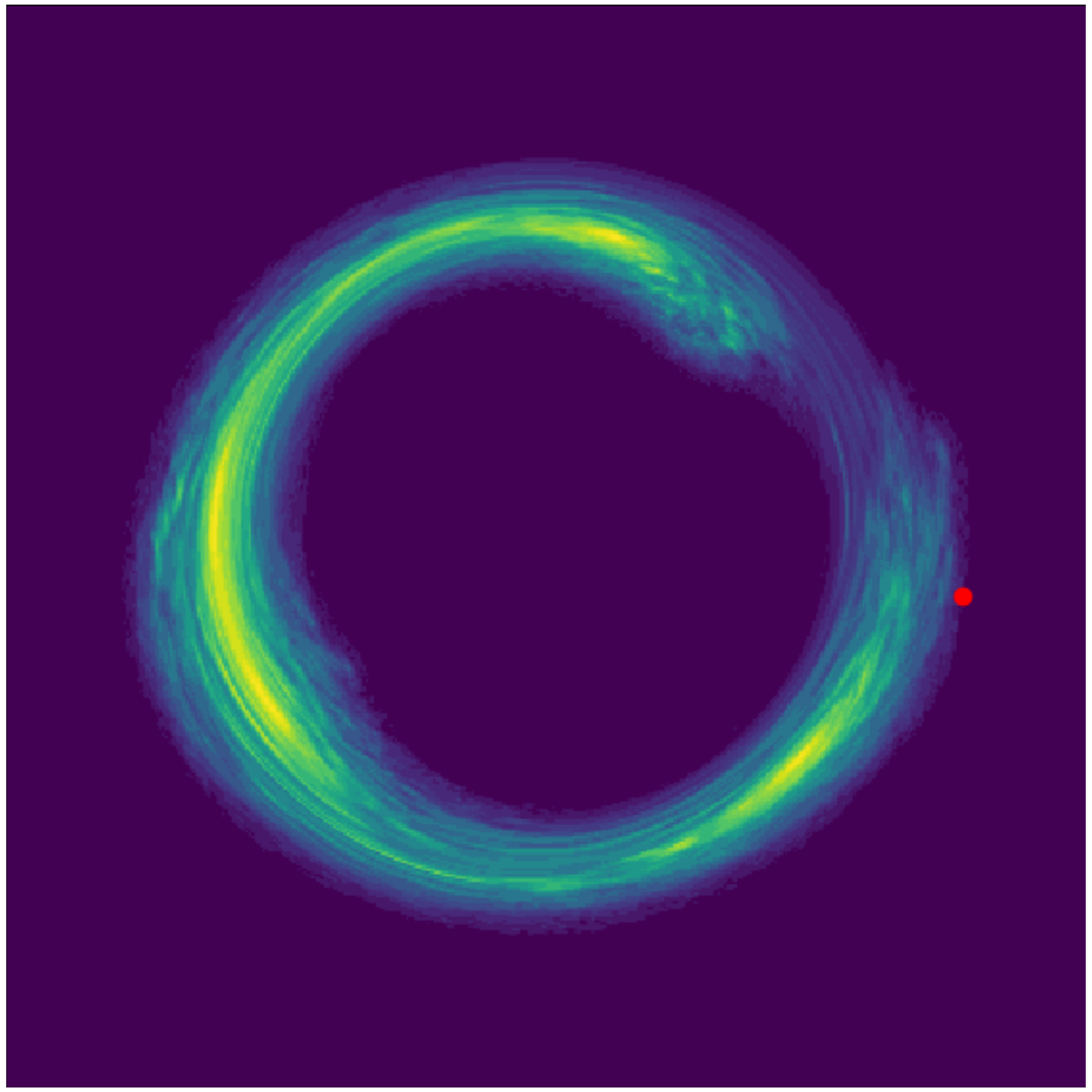


Excellent mean source reconstruction, along with uncertainties

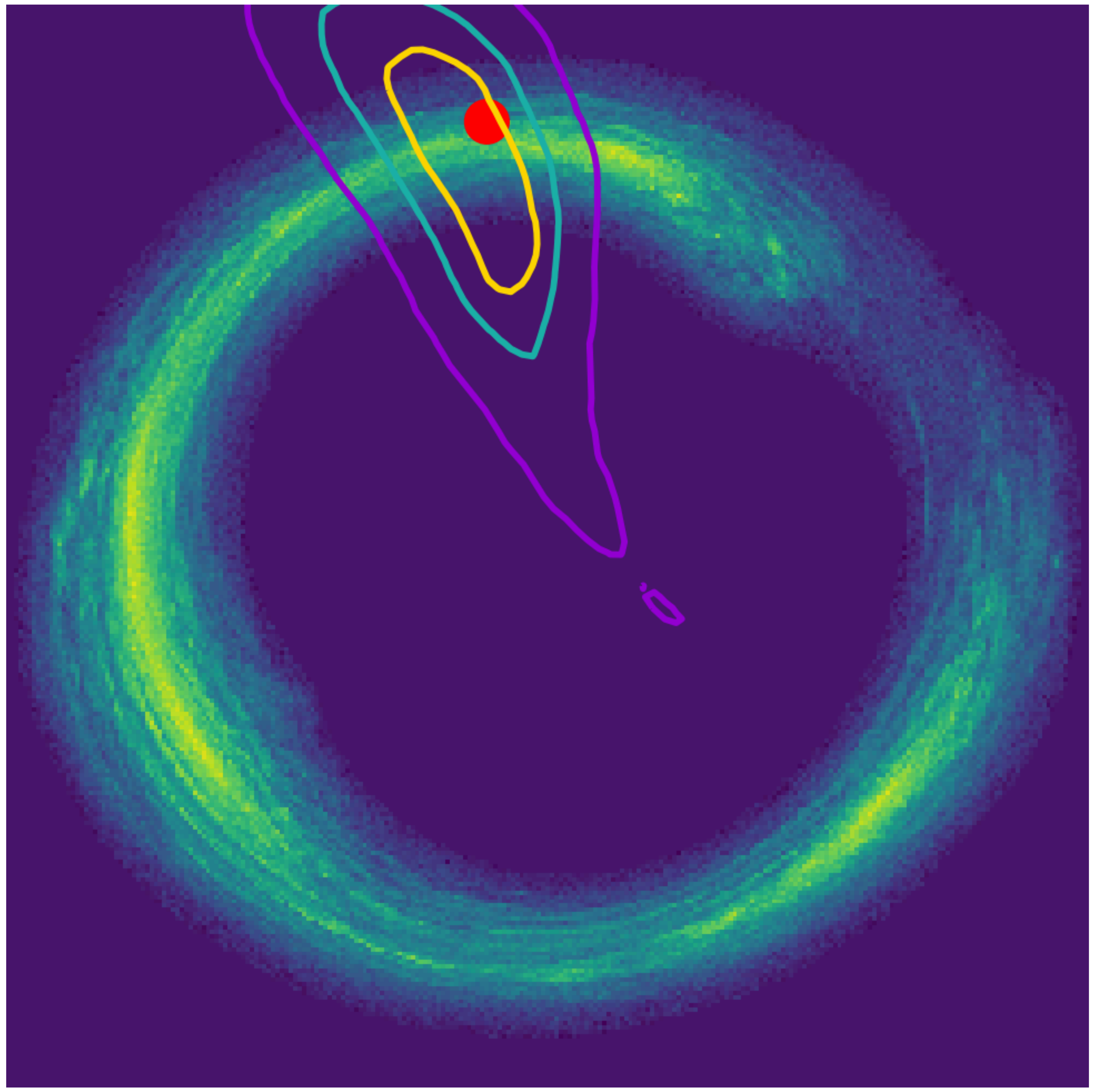
Karchev, Coogan, Weniger 2105.09465

Targeted inference examples

Inference: single subhalo



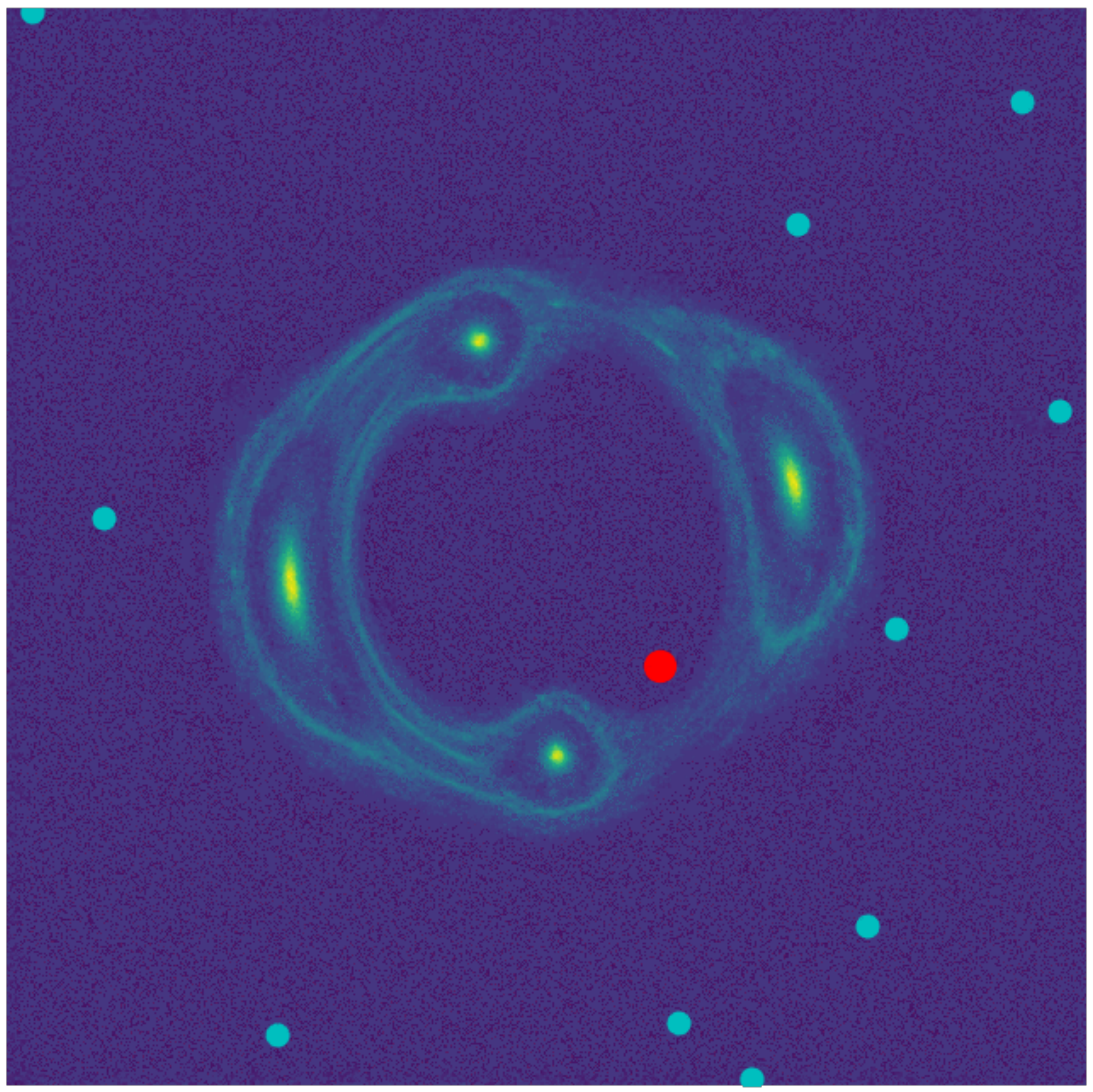
Training data



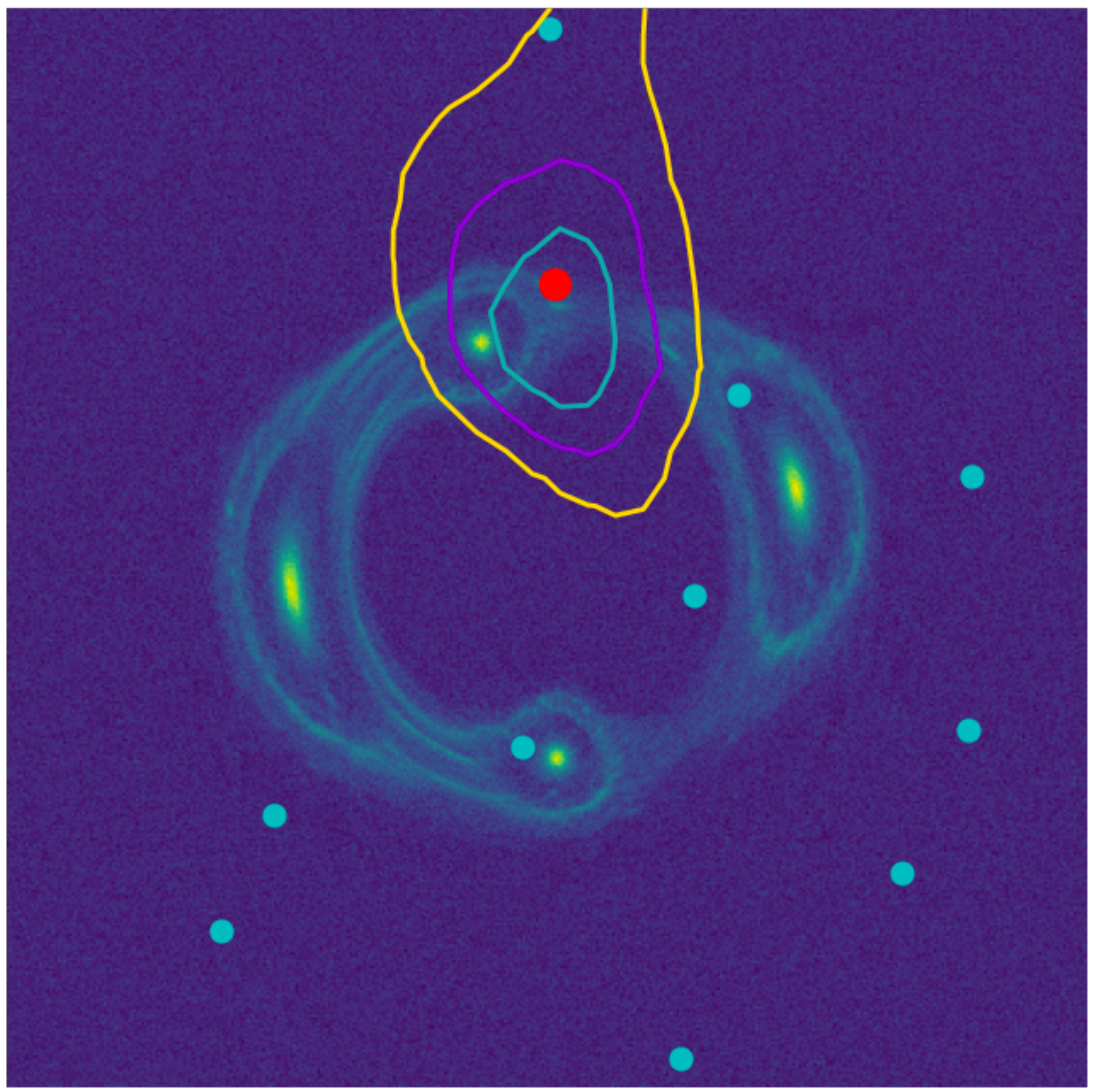
Marginal posterior

Coogan, Karchev, Weniger 2010.07032

Inference: single heavy subhalo



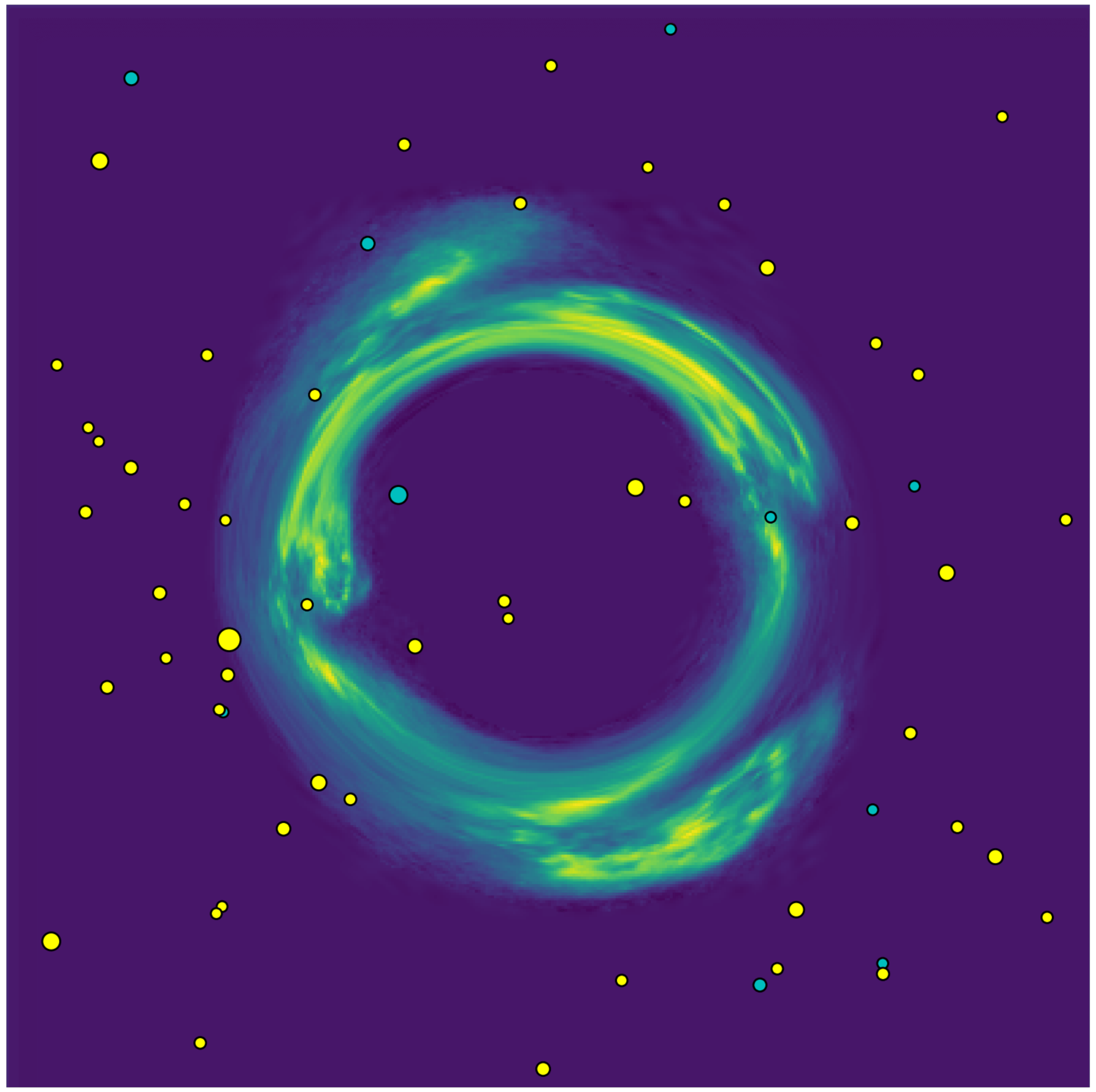
Training data



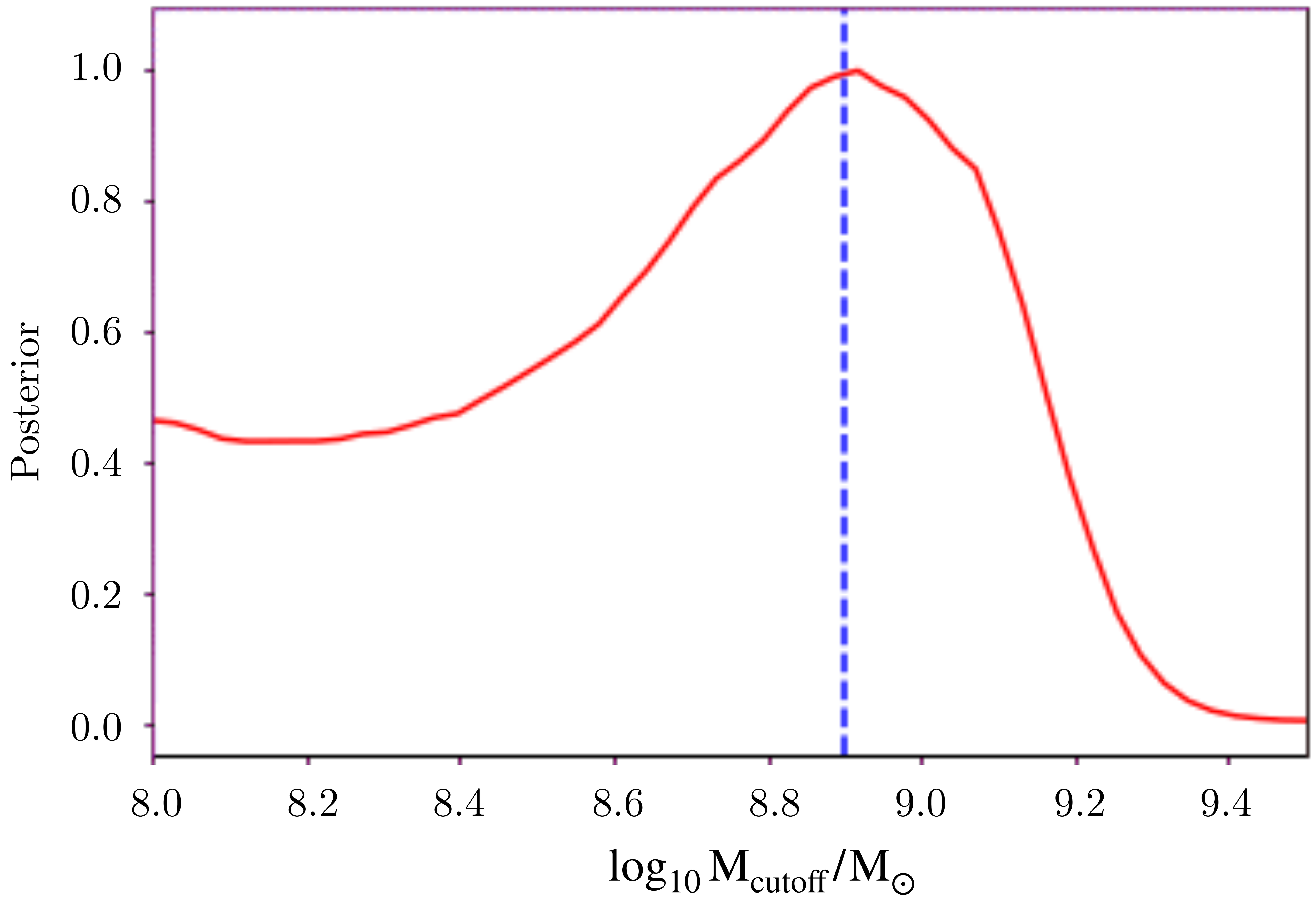
Marginal posterior

* Very preliminary!

Inference: mass function cutoff



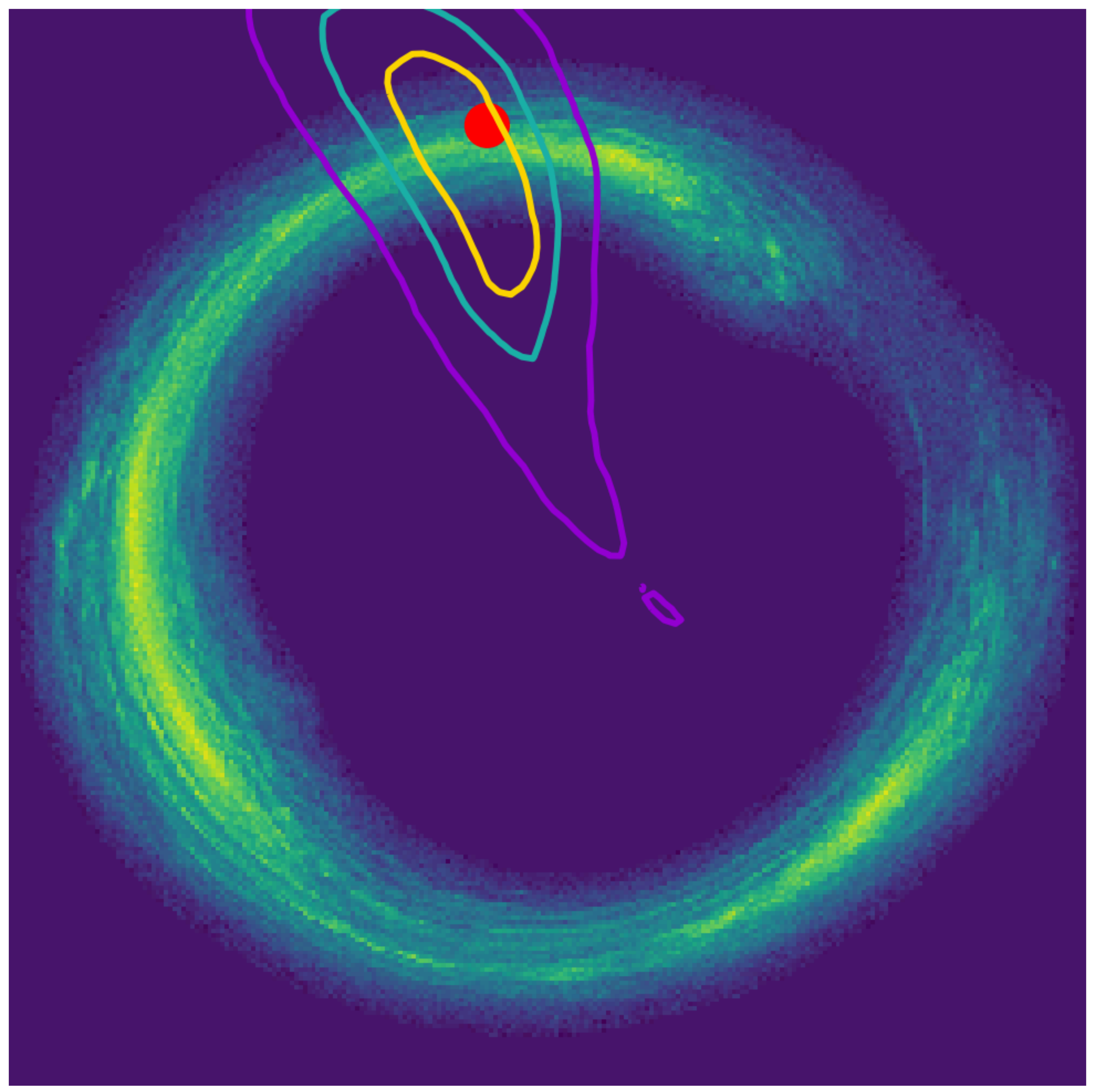
Training data

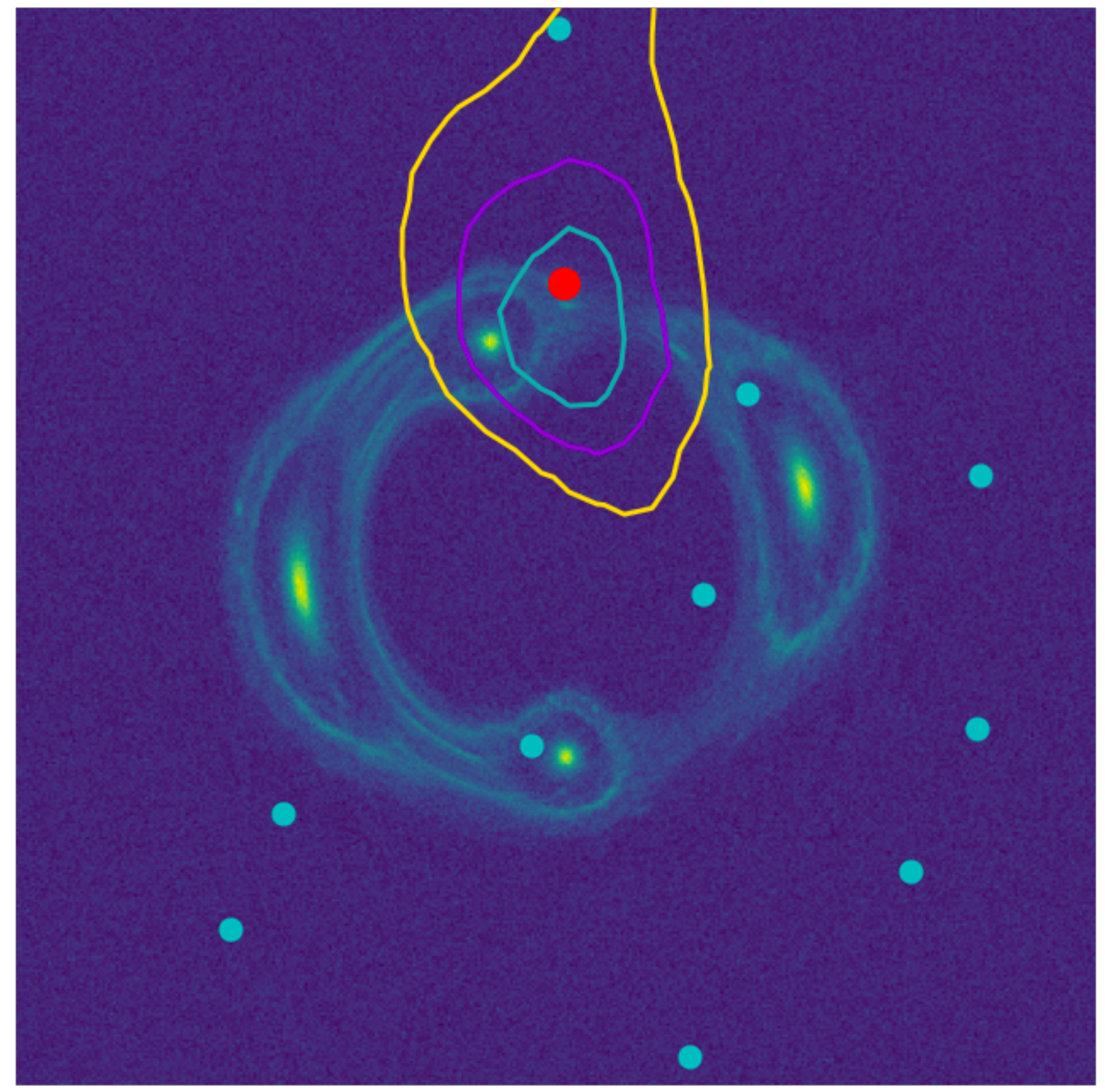


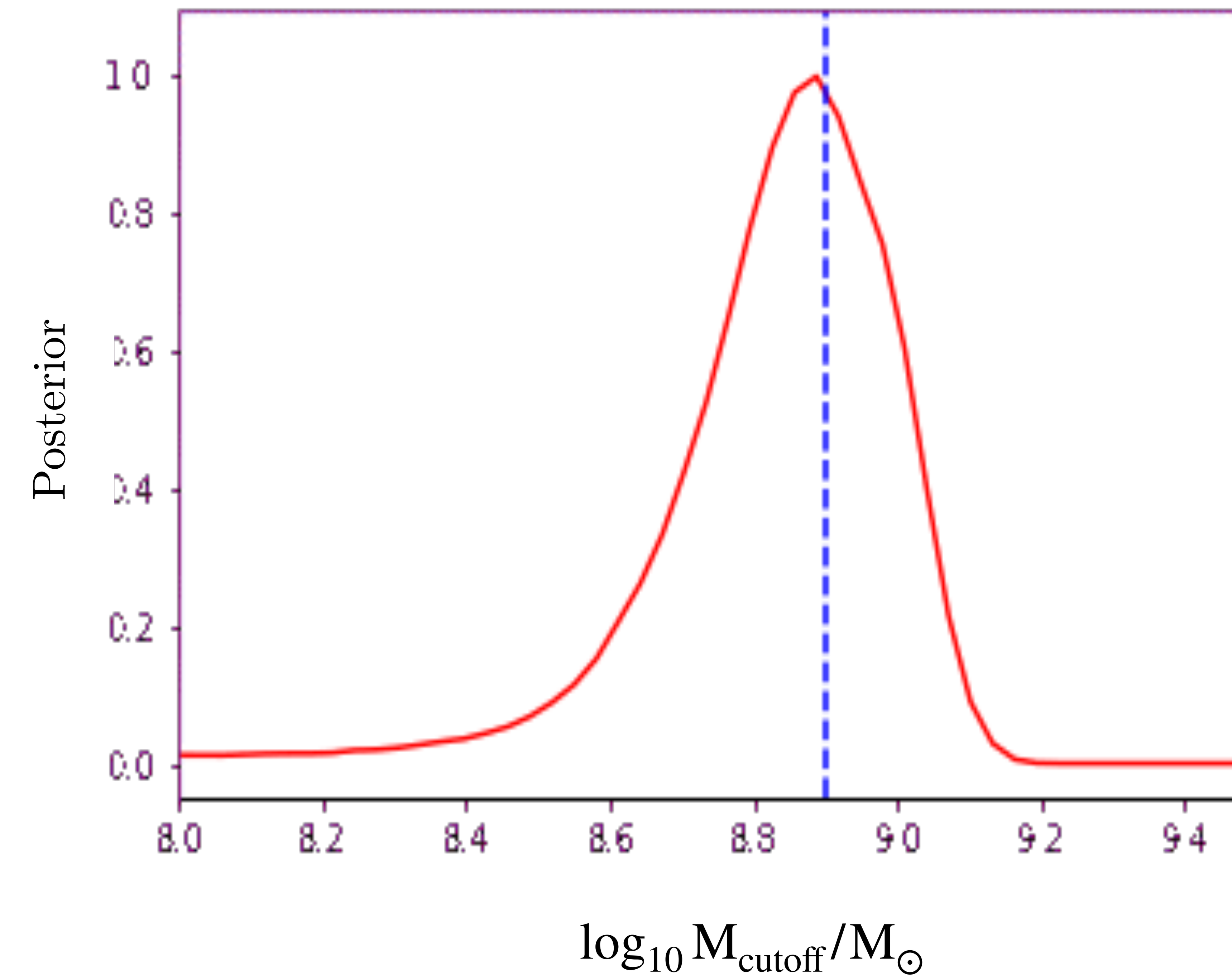
Marginal posterior (50 observations)

*** Very preliminary!**

Animation credit: Noemi Anau Montel







Marginalized over $O(10^5)$ source, lens and subhalo parameters by neural nets

Conclusion

- Developed targeted inference strategy for lensing analysis

  1. Constrain lens + source with variational inference and novel approximate Gaussian process

  2. Apply simulation-based inference to get exact marginal posteriors with neural networks

- Result: marginal posteriors for subhalo parameters, marginalized over thousands of nuisance parameters

- (Almost) ready for application to existing and upcoming data

- Potentially useful for other analyses?

Thanks!