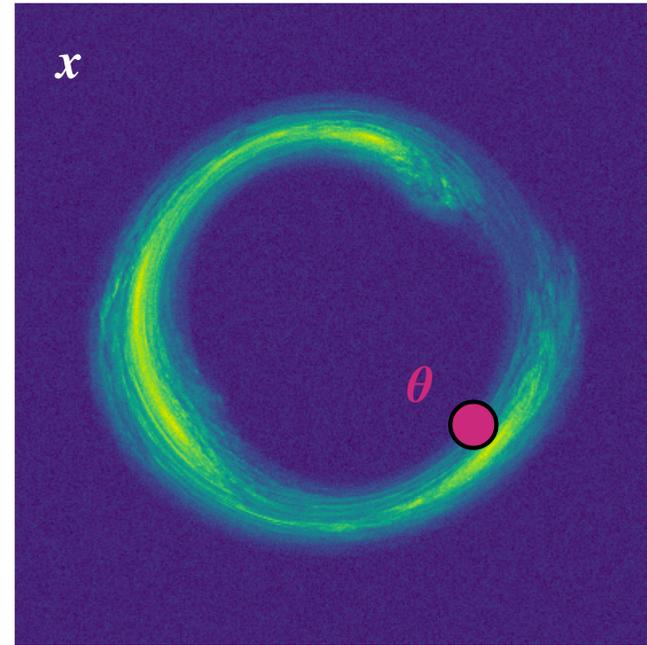


Precision searches for subhalos in strong lensing images with targeted inference networks

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Goal: robustly measure **individual dark matter subhalos' parameters**

Problem: need to *marginalize* over $O(10^3-10^5)$ nuisance parameters



$$p(\theta | x) = \int d^n \eta p(\theta, \eta | x)$$

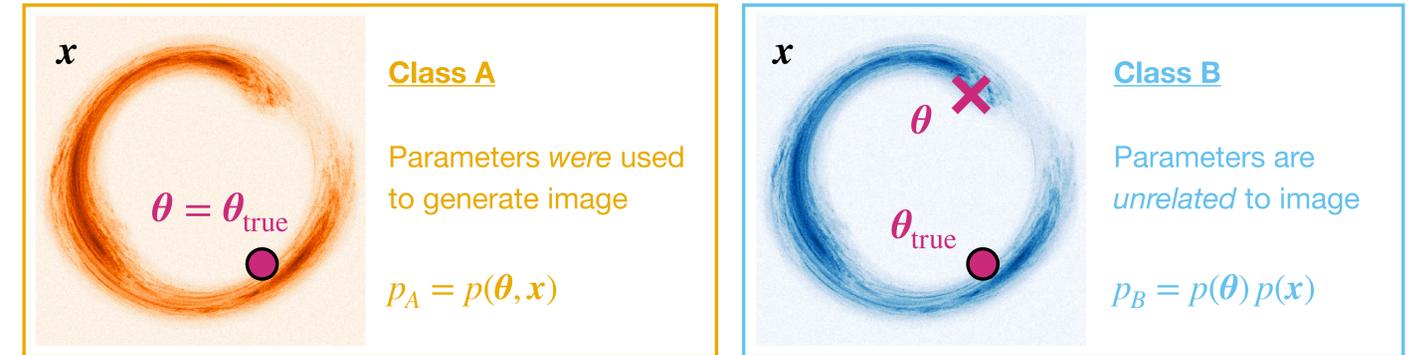
Observation x → Marginal posterior $p(\theta | x)$
Source and lens parameters θ, η → Joint posterior $p(\theta, \eta | x)$

Techniques like MCMC and nested sampling sample the joint posterior.

Intractable here due to **high dimensionality**.

Neural likelihood-to-evidence ratio estimation: rephrases marginal posterior inference as equivalent *classification problem*

“Given an (subhalo parameter, image) pair (θ, x) , does the subhalo in x actually have parameters θ ?”



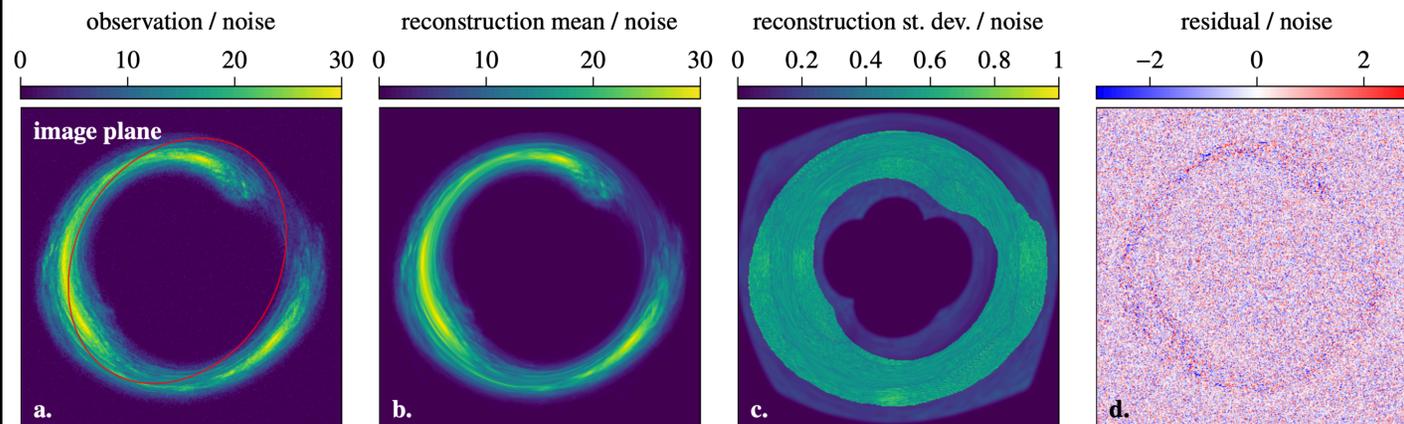
Classification network directly learns $\frac{p_A}{p_B} = \frac{p(\theta | x)}{p(\theta)}$ ← Marginal posterior

Nuisance parameters marginalized via *random sampling* during training

Targeted inference: sample **nuisance params** consistent with observation

We've developed a fast, differentiable lensing model using an approximate Gaussian process source and variational hyperparameter optimization. Enables fitting a variational posterior for $O(10^5)$ source and lens parameters using gradient-based optimization, then *sample from it to generate training data*.

→ See [Konstantin Karchev's poster for more details](#)



Results

Analysis of mock **high-resolution image**

Accurate marginal posteriors for subhalo position and mass from a simple inference network trained on just 10,000 targeted samples

Posteriors are marginalized over **174,458 source and lens parameters!**

→ See [Noemi Anau Montel's talk for extension to inferring parameters for a population of perturbers](#)

