UNIVERSITY OF AMSTERDAM

GRAPPA
GRavitation AstroParticle Physics Amsterdam

Sequential simulation-based inference for strong gravitational lensing

The importance of reducing data variance

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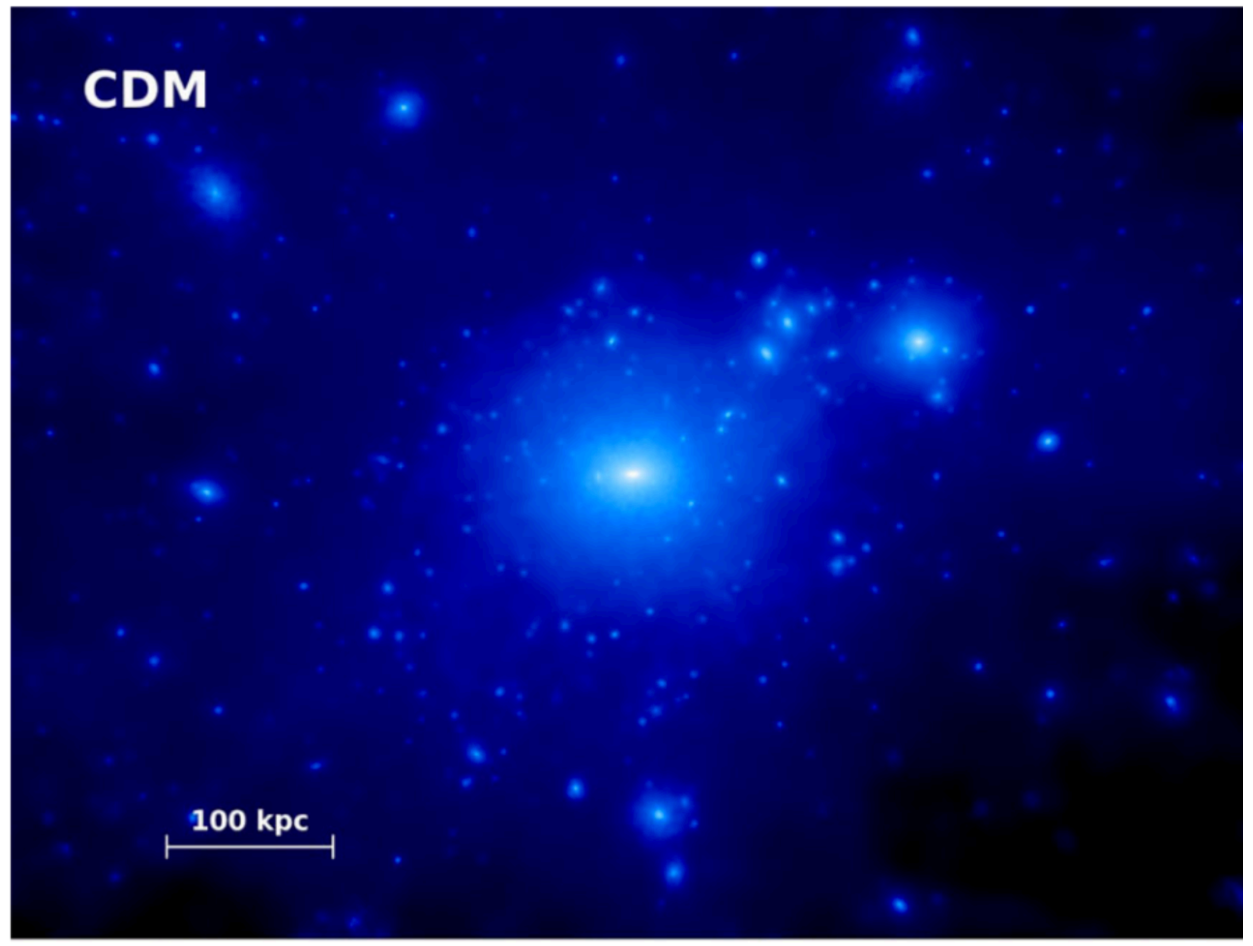
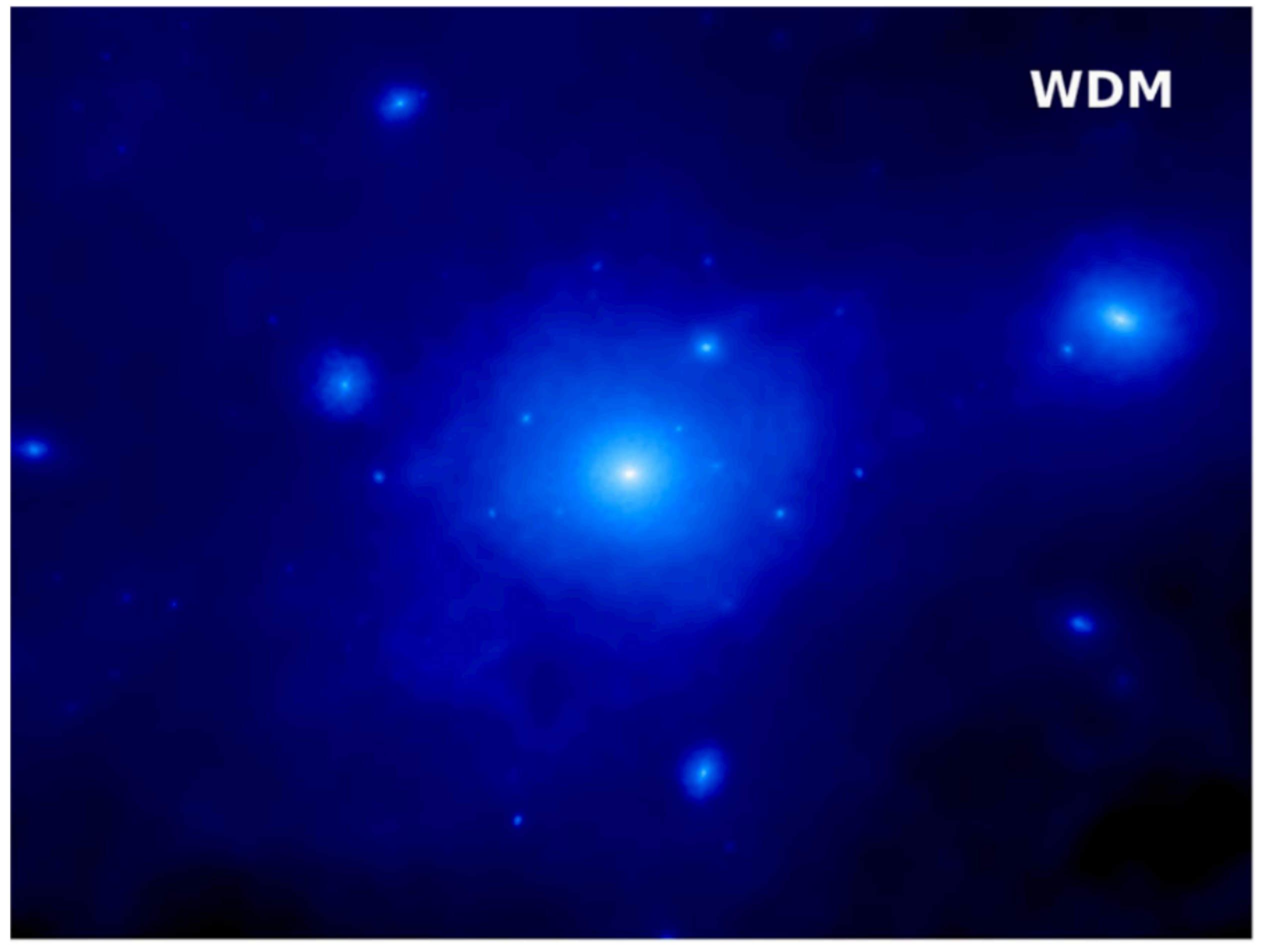
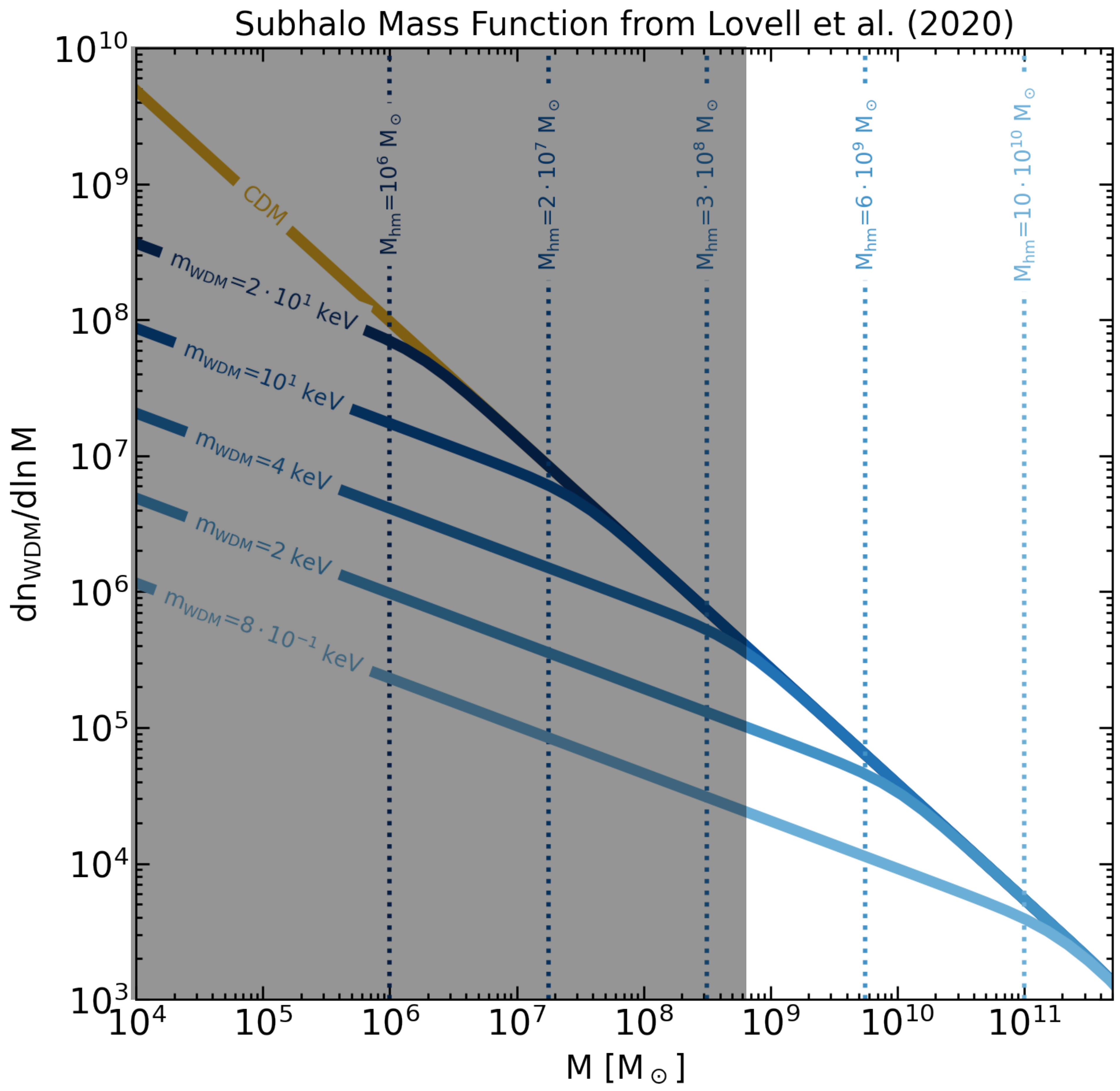
DM physics is encoded in the properties of DM halos

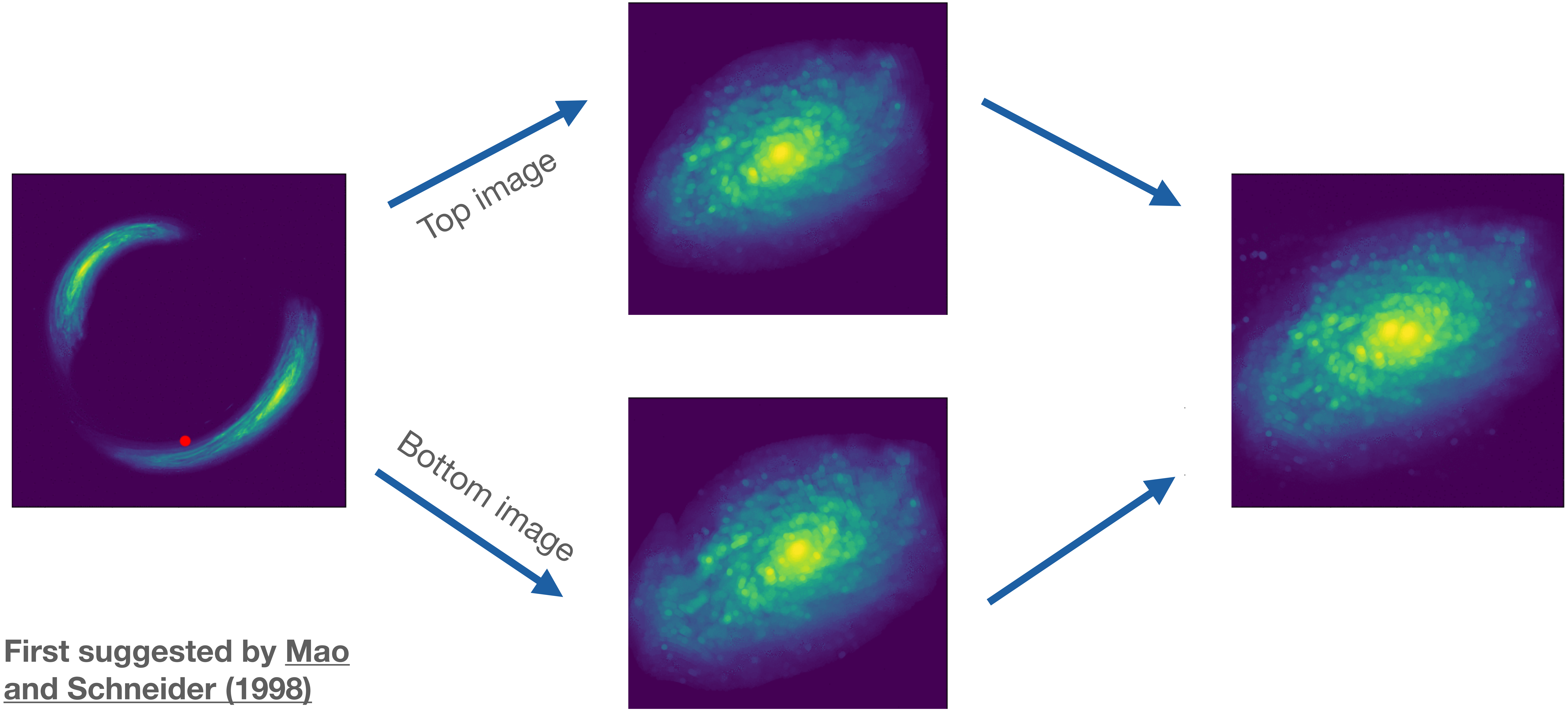






Bœhm et al. (2014)

Why strong gravitational lensing



First suggested by Mao and Schneider (1998)

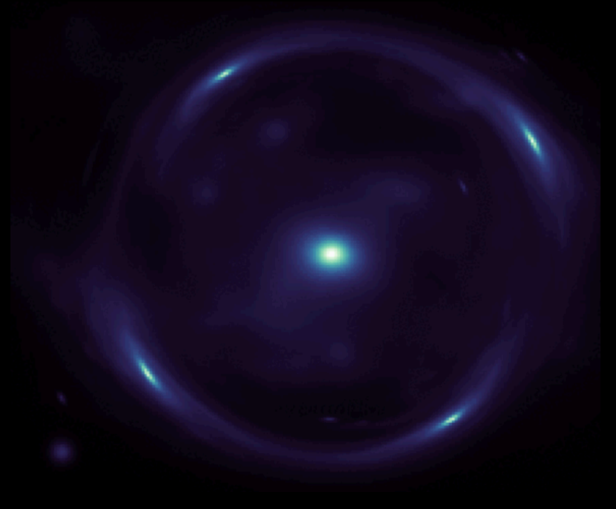
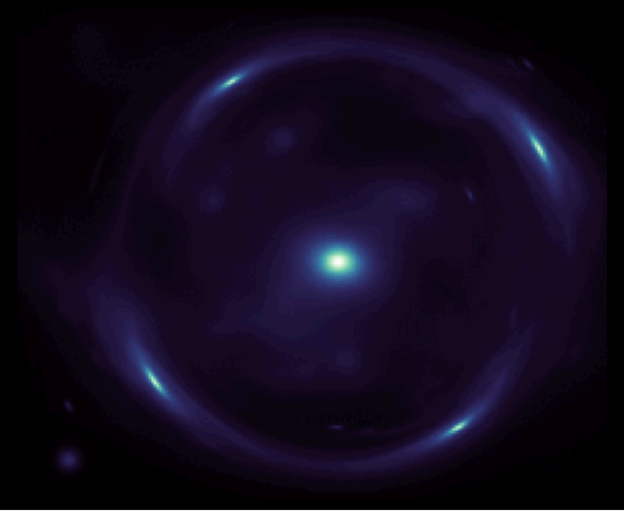
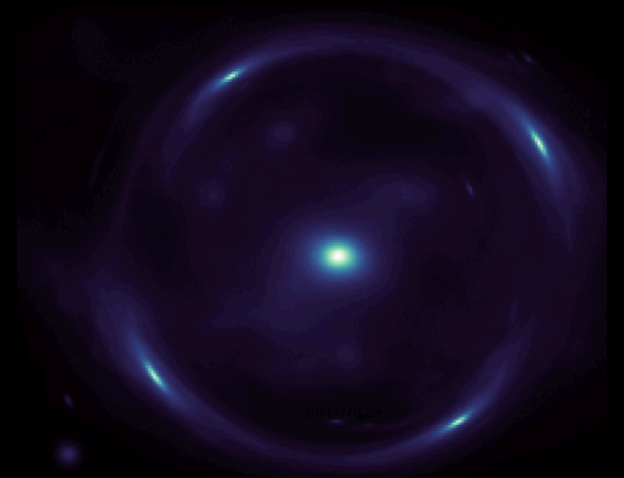
Gif credit: Adam Coogan

Strong gravitational lensing in reality

Searching for *tiny* signatures in *diverse* and *complex* observations, with *mountains* of *high-quality* data to come.

Strong gravitational lensing in reality

An inference challenge

$p(z \,|$  $) =$ $p($  $| \, z)$ / $p($  $)$ $p(z)$

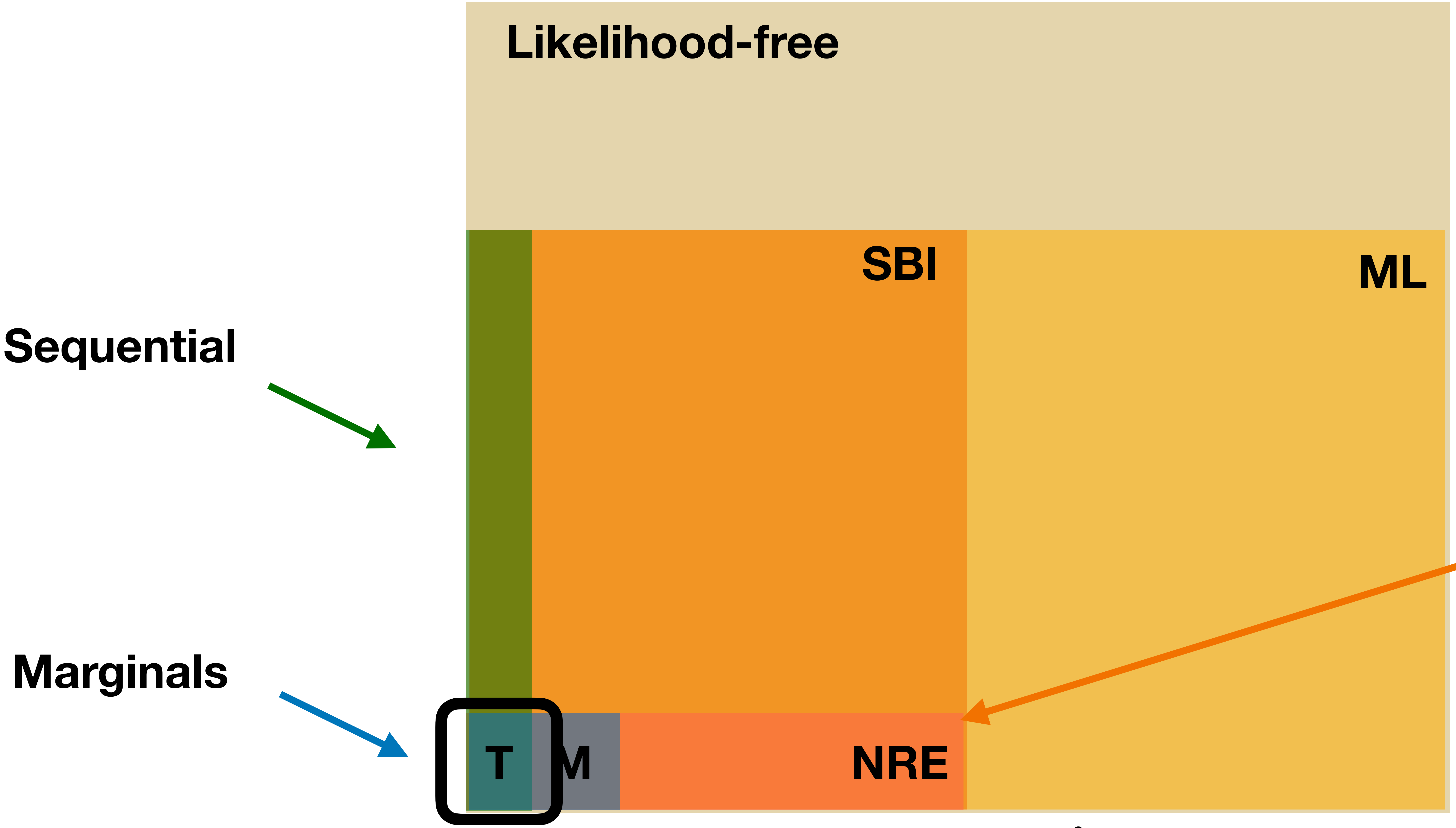
Searching for *tiny* signatures in *diverse* and *complex* observations, with *mountains* of *high-quality* data to come.

Truncated Marginal Neural Ratio Estimation

A sequential simulation-based inference technique

For more information:

- Hermans et al. (2019)
- Miller et al. (2020)
- Miller et al. (2021)
- ***swyft*** package



Neural Ratio Estimation

$$r(x; z) = \frac{p(z\,|\,x)}{p(z)} = \frac{p(x\,|\,z)}{p(x)} = \frac{p(x, z)}{p(x)p(z)}$$

TMNRE for strong gravitational lensing

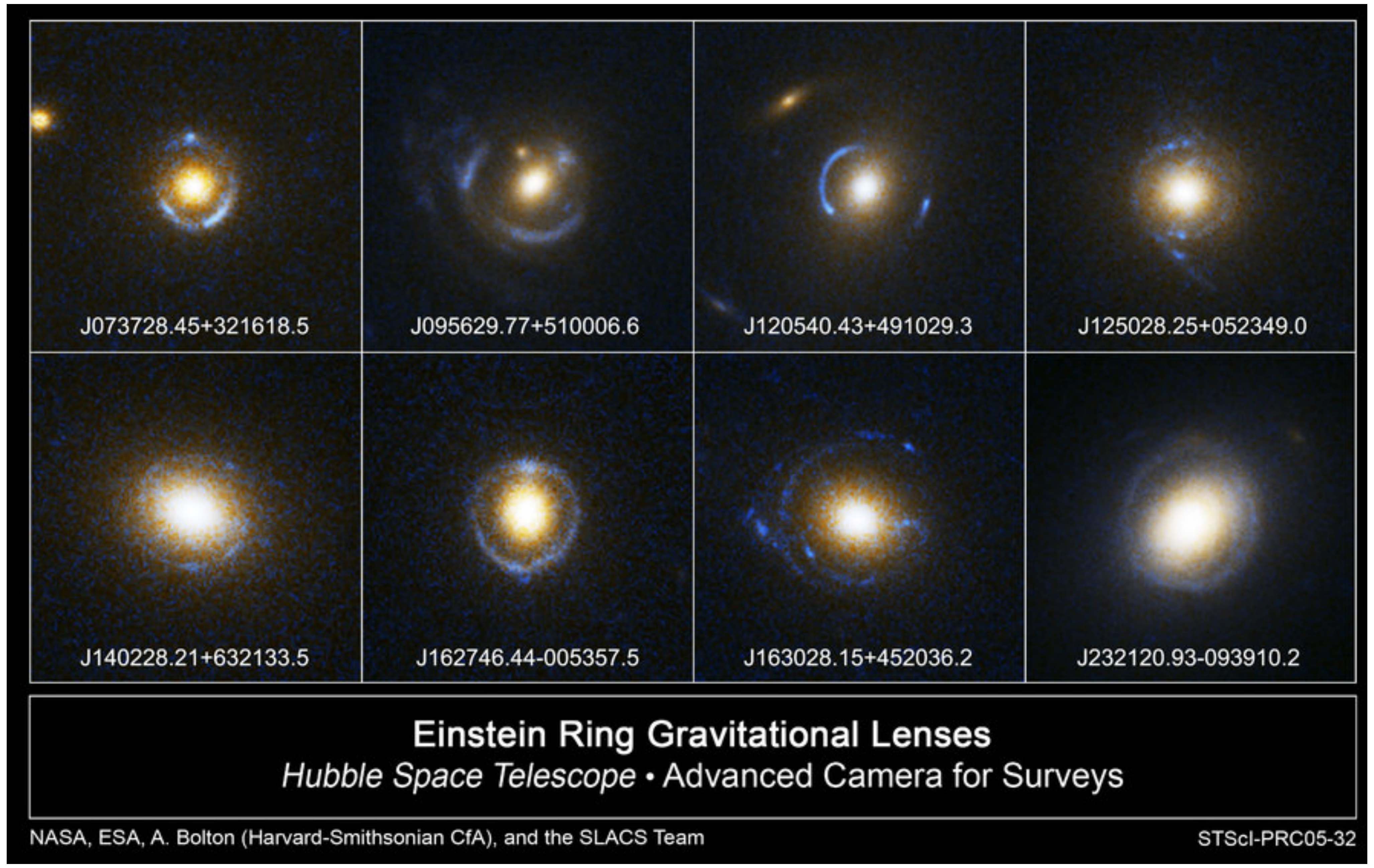
Where it can help

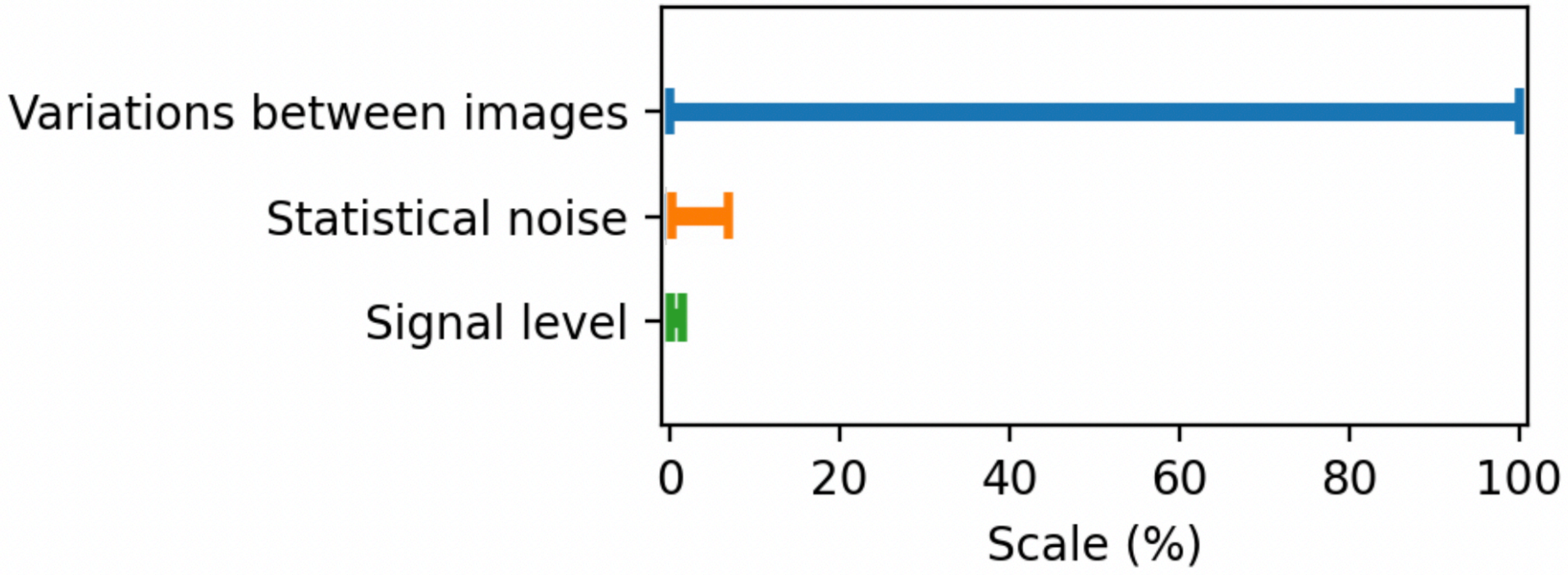
SBI → Can handle complex forward models
Improve realism of the model without dealing with an **intractable likelihood**.

NRE → "Painless"
Rephrases parameter inference into a **binary classification problem**. It composes well with marginalisation and prior truncation.

M → Higher flexibility and simulation efficiency
We can **cherry-pick** the parameters we are interested in, marginalizing over the rest (e.g. numerous source, lens and halos' parameter).

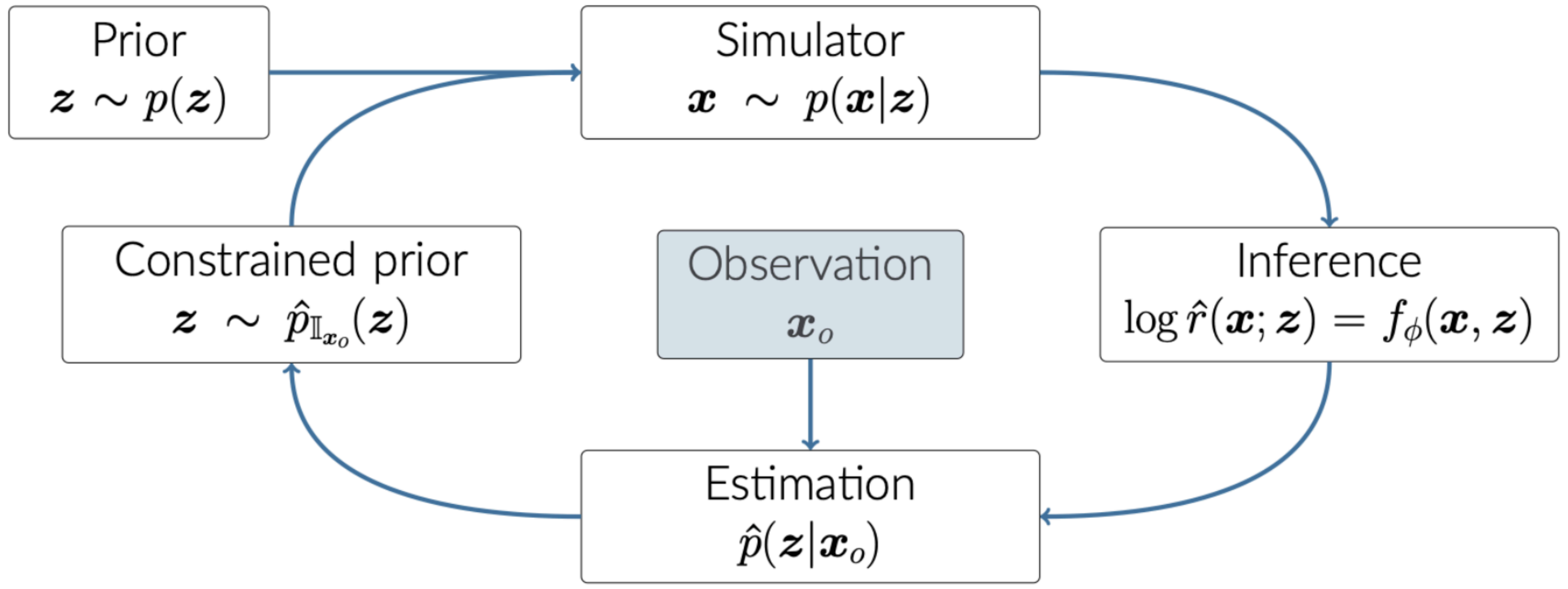
T → Learning with high-precision
Targeting the inference enables being sensitive to an extremely **small signal** compared to noise and variations between image.



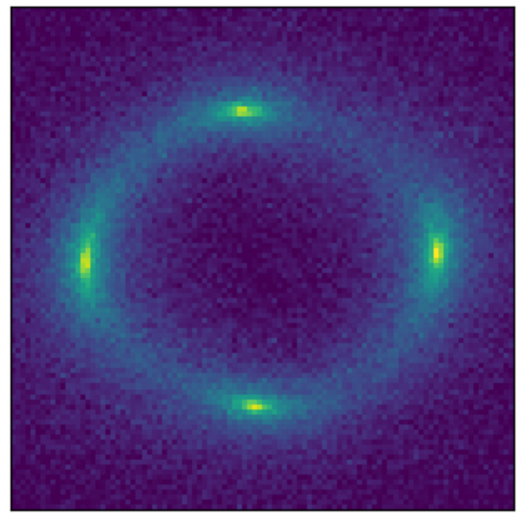


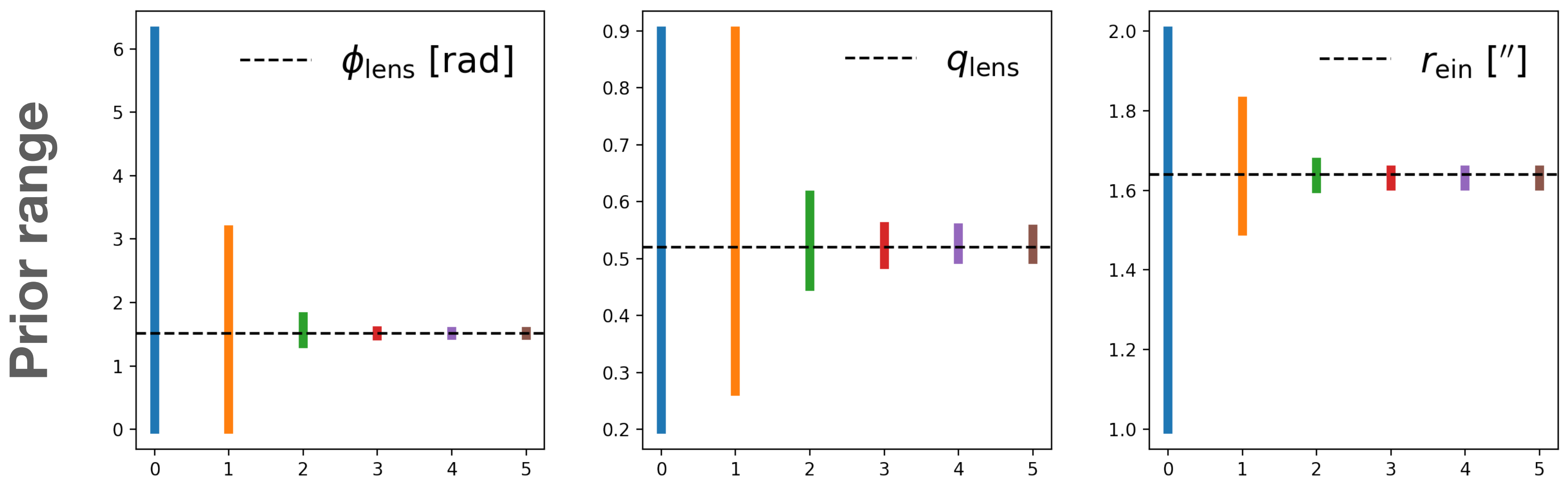
TMNRE for strong gravitational lensing

Reducing data variance

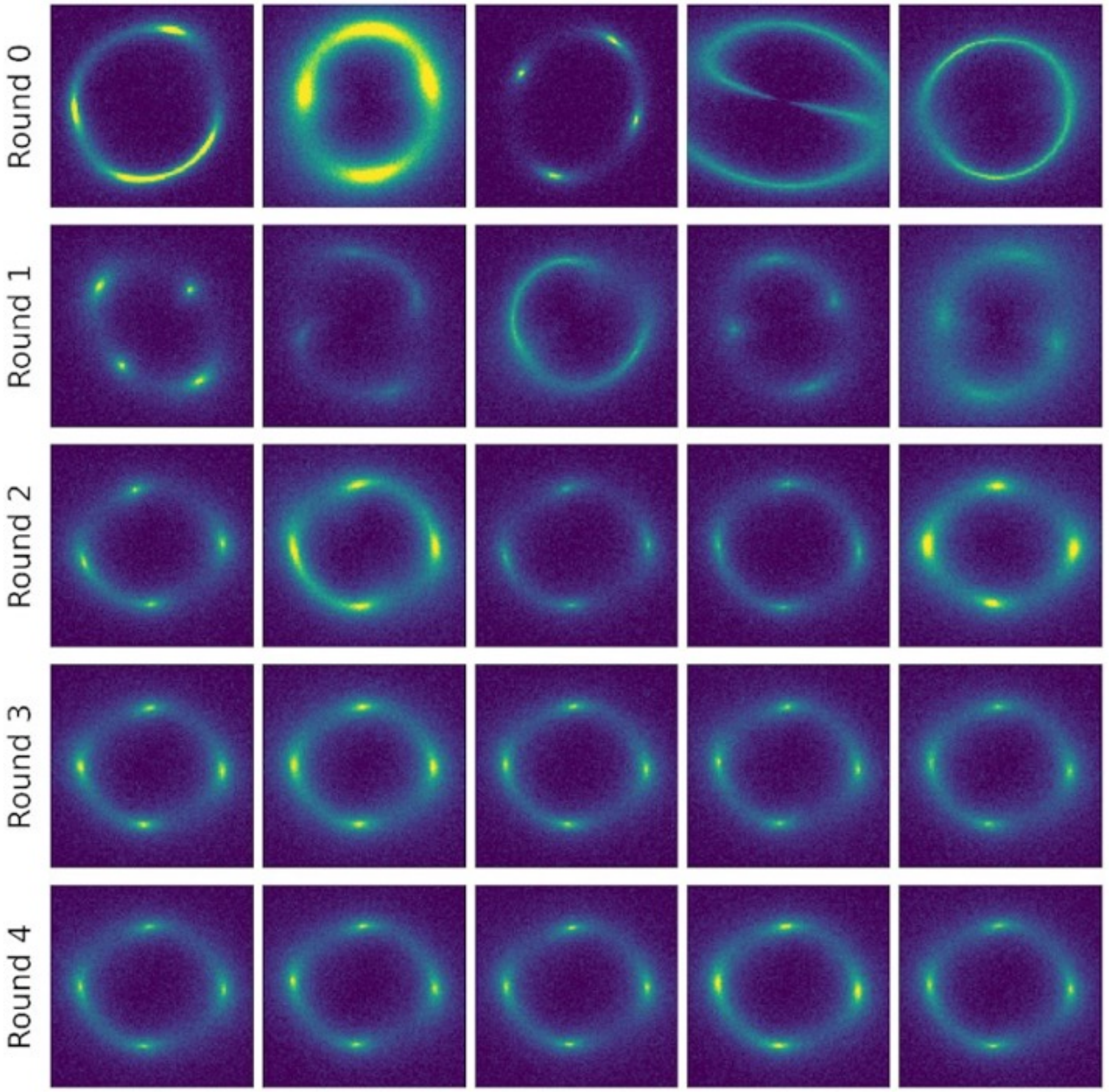


Target mock observation





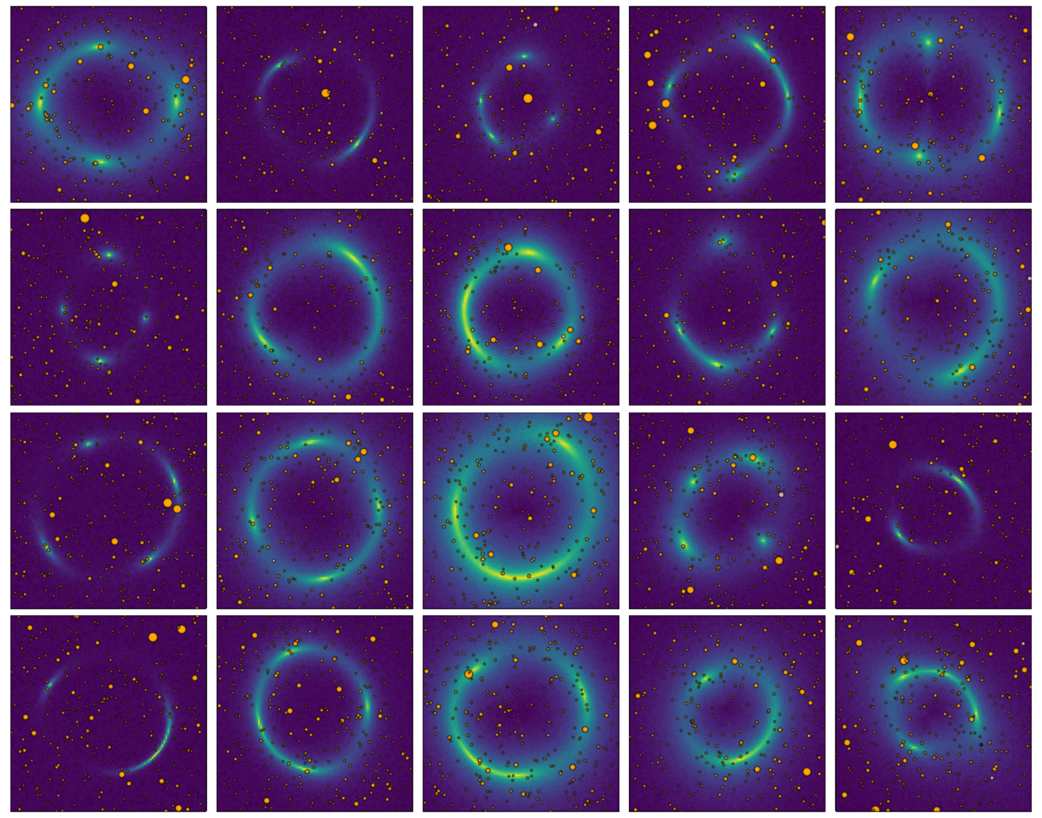
Targeted training data

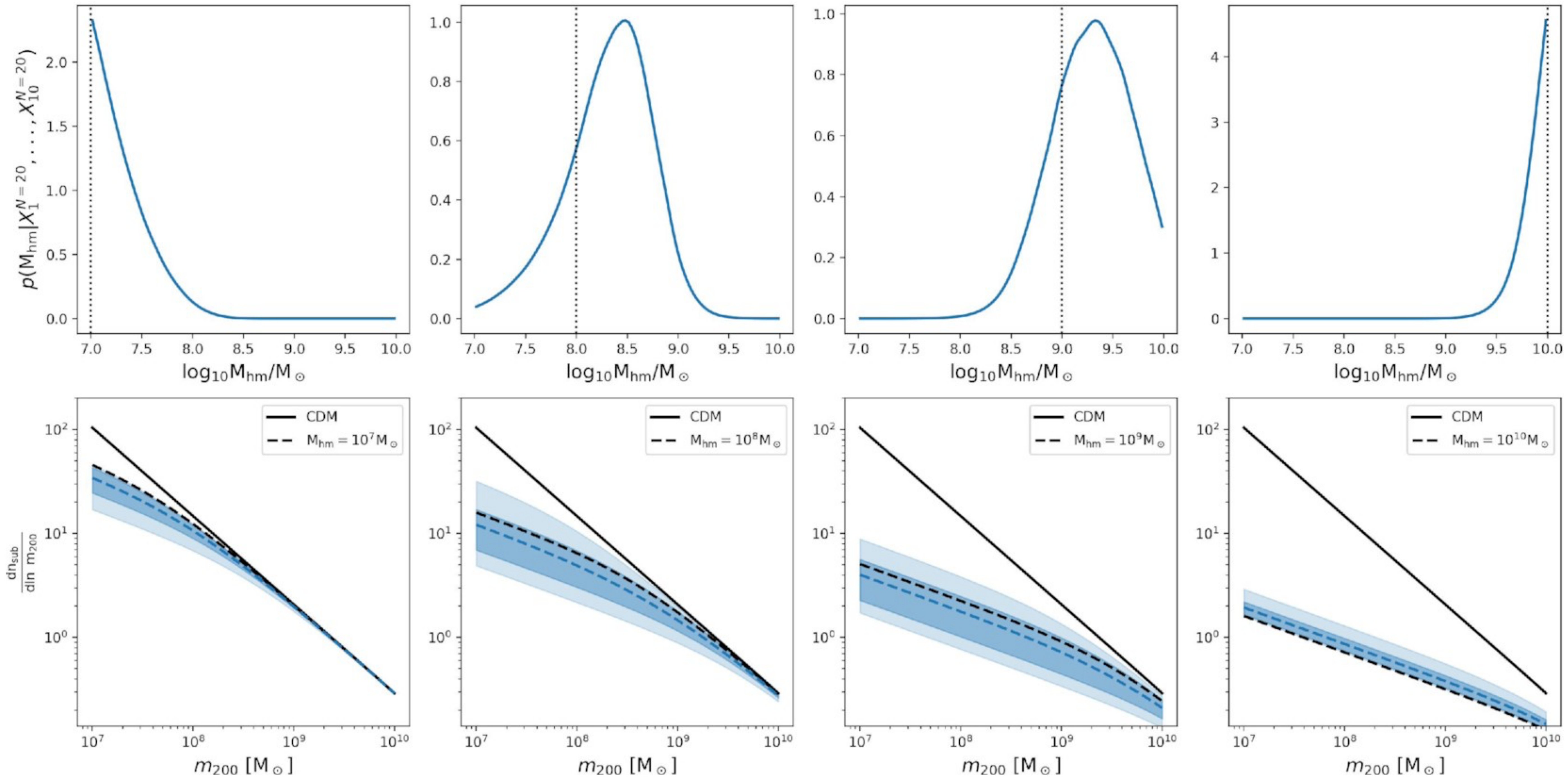


arxiv:2205.09126

From images to dark matter

Constraining DM with an *ensamble* of lenses

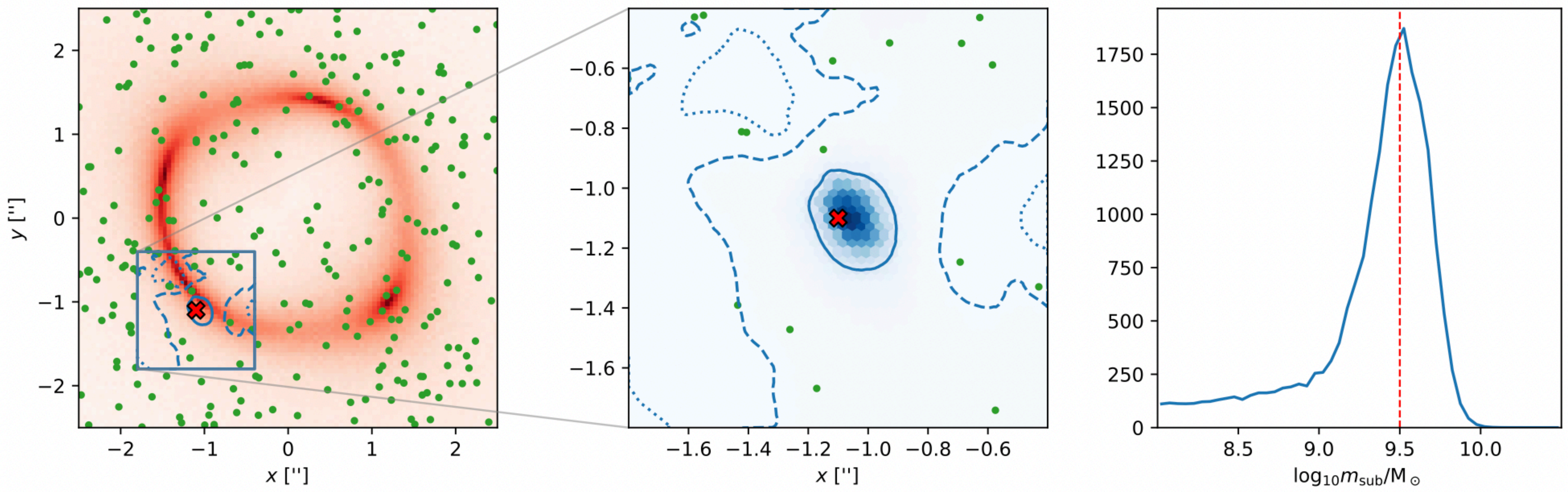




Results for subhalo mass function cutoff mass obtained by fully marginalising over main lens, source, and realistic population of subhalos and line-of-sight halos.

Subhalo's parameters inference

Effect of the perturber population on subhalo measurements

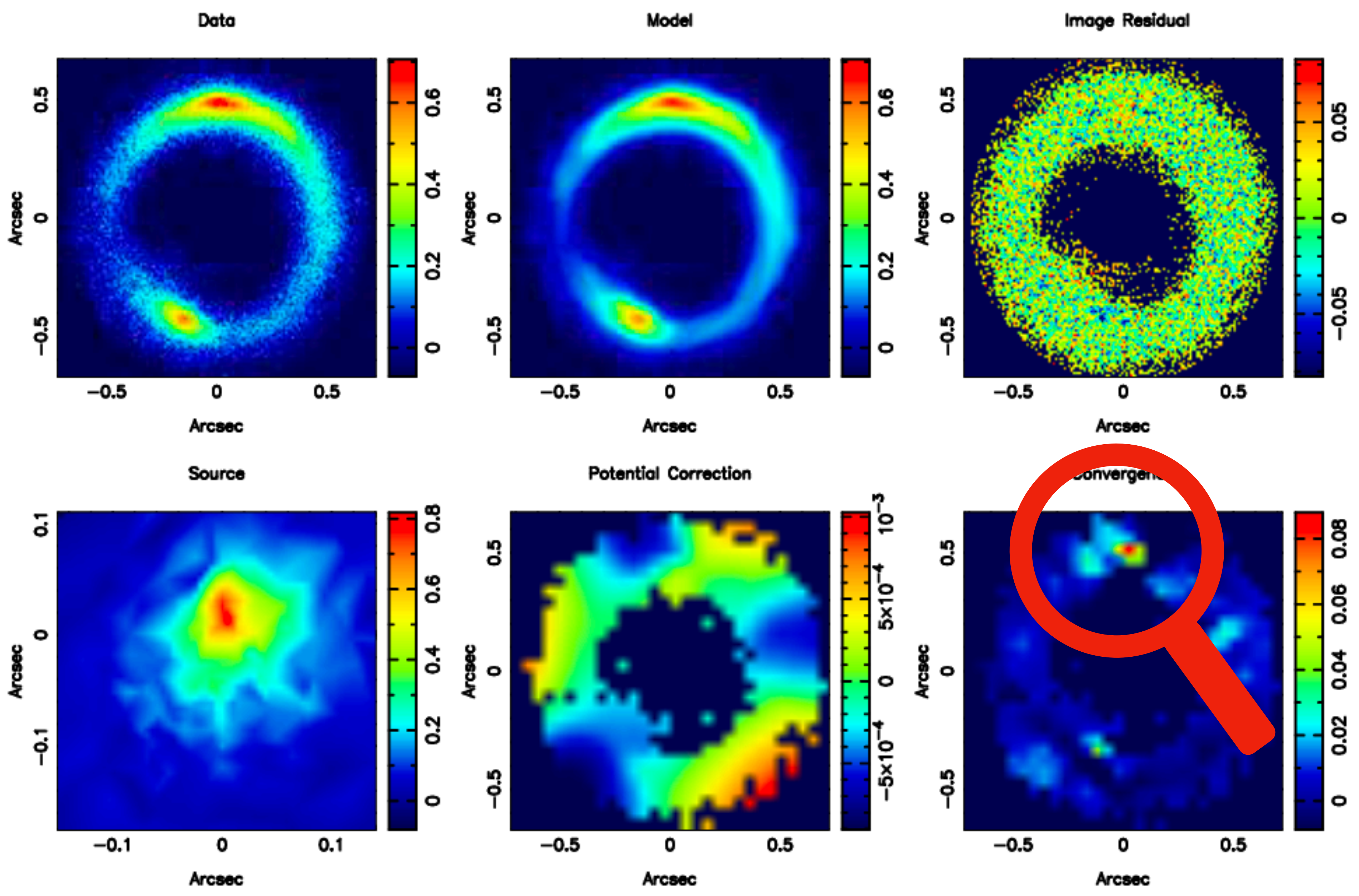


Results for position and mass of individual heavy small-scale halo obtained by fully marginalising over main lens, source, and realistic population of subhalos and line-of-sight halos.

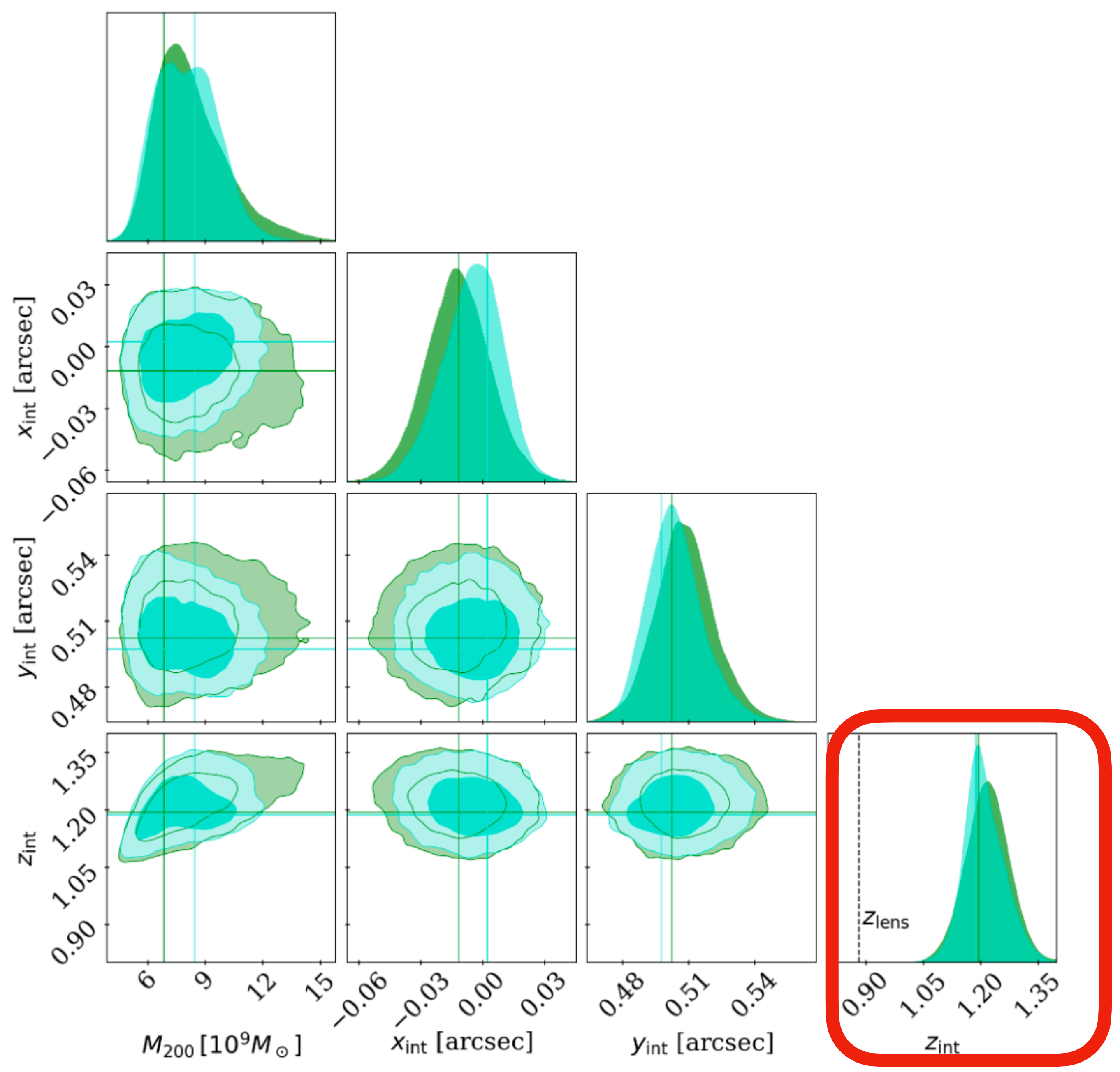
Towards analysing lensing data with ML

JVAS B1938+666: a case study

Vegetti et al. (2012) → detection



Şengül et al. (2021) → interloper



PRELIMINARY

JVAS B1938+666: a case study

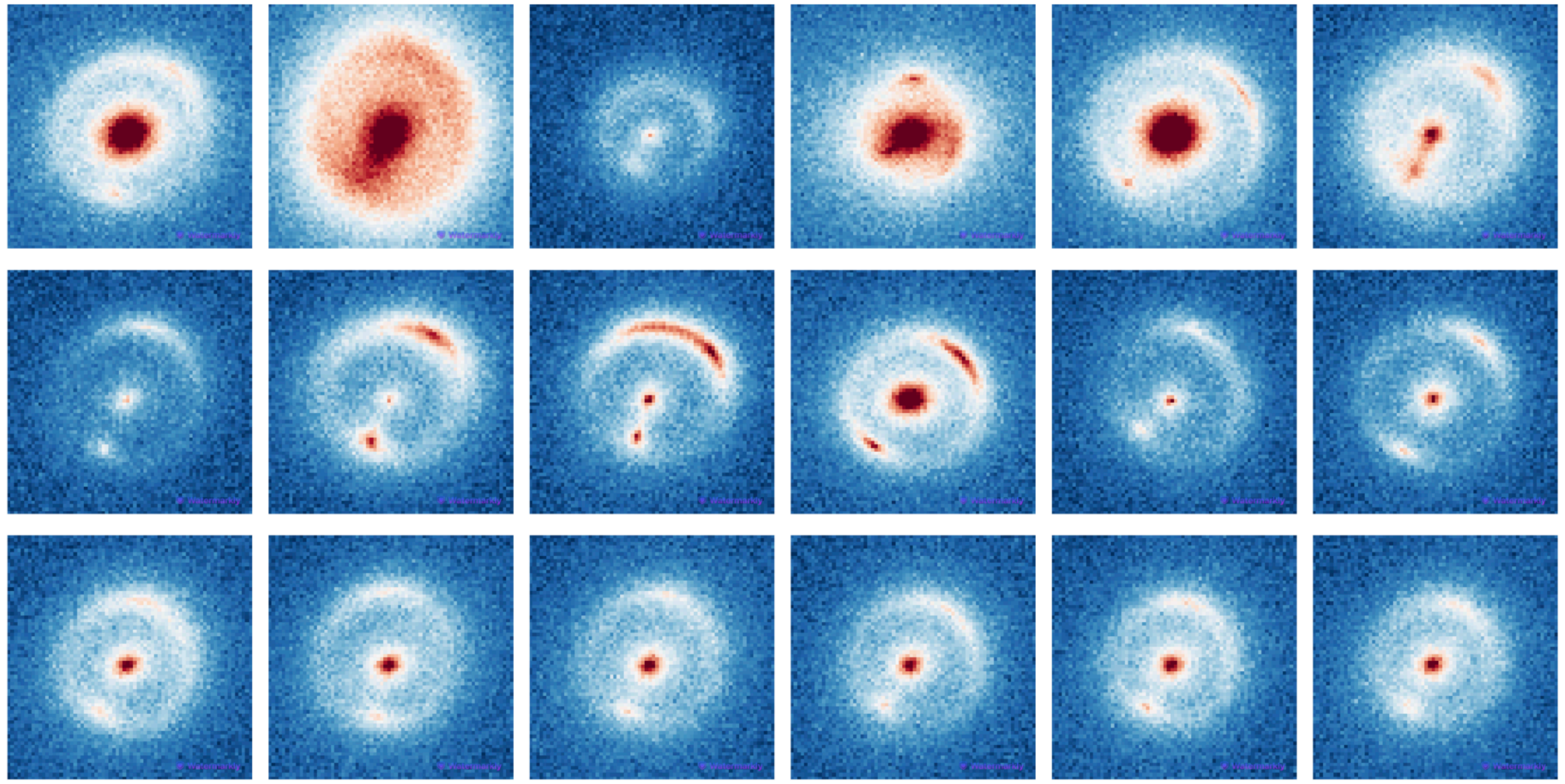
Including lens light variations

Targeted training data

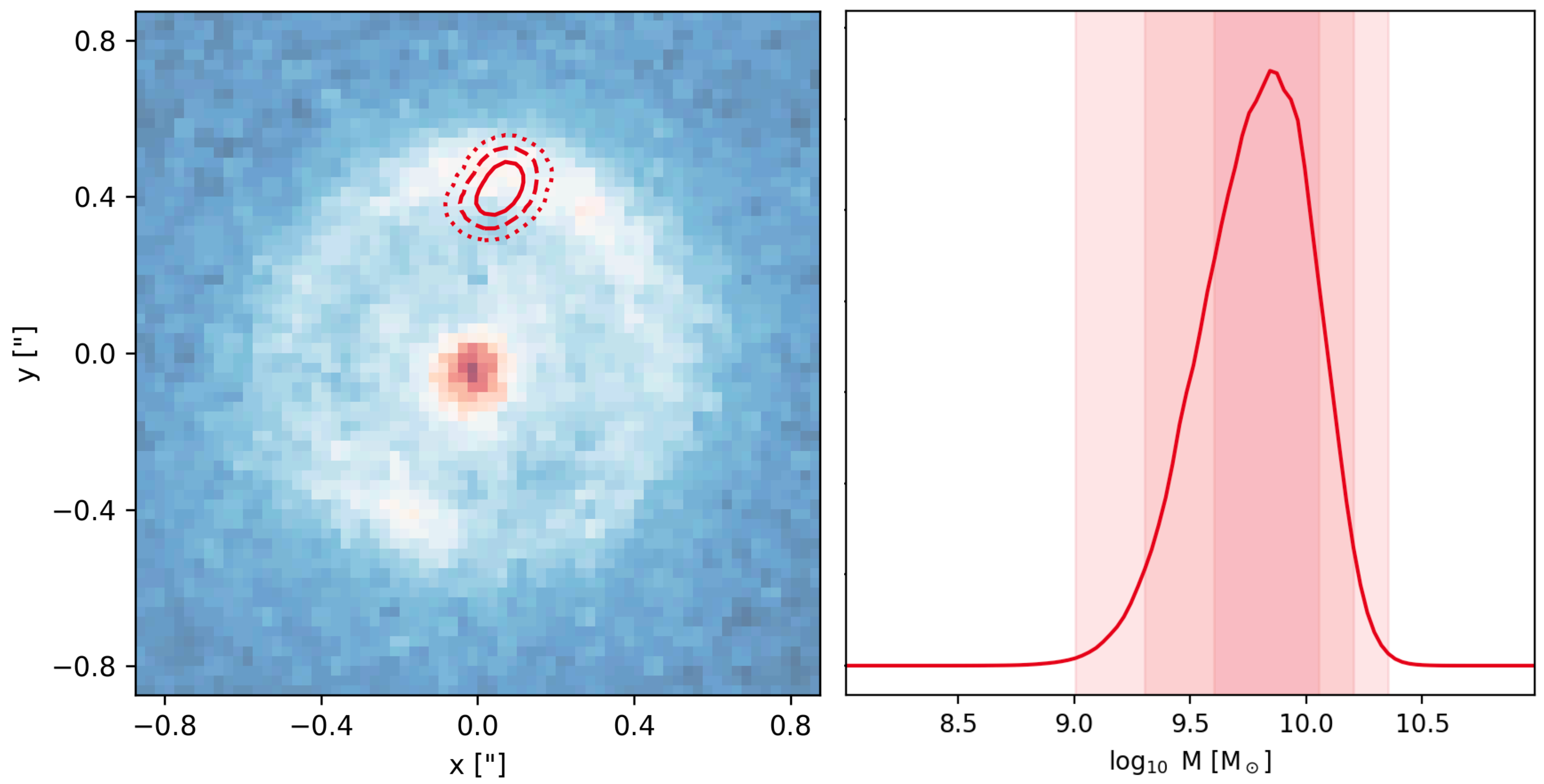
Initial round

Intermediate round

Final round



Results



We are able to locate and infer the mass of the substructure. Promising results, but still a long road!

Summary

Motivation: DM lensing analyses challenge

Searching for *tiny* signatures in *diverse* and *complex* observations, with *mountains* of *high-quality* data to come.

Technique: TMNRE

- implicit likelihood ⟶ improve realism of the model
- marginals ⟶ high-efficiency
- truncation ⟶ high-precision

⟶ results with **full marginalisation** over light, lens, source and small-scale halos population

Applications:

- **collective** substructure **properties**
- **individual** heavy subhalo **parameter inference**
- **JVAS B1938+666**