Measuring dark matter halos in strong lenses with truncated marginal neural ratio estimation

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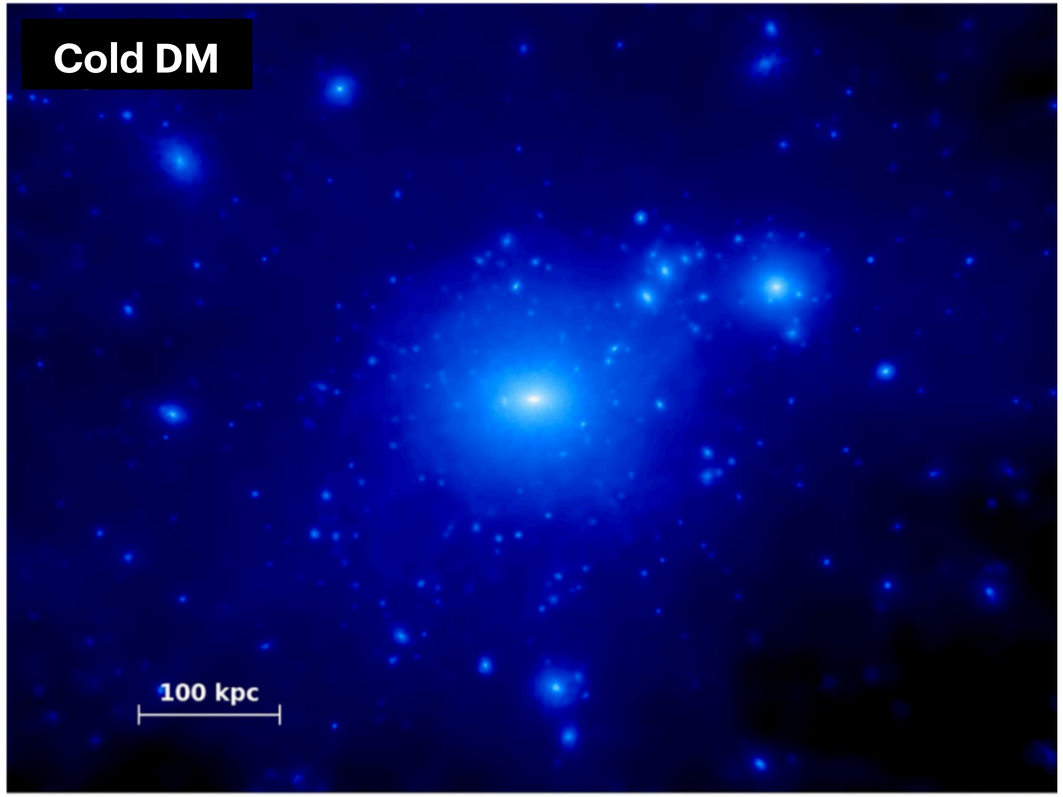
Work with Noemi Anau Montel, Elias Dubbeldam,
Konstantin Karchev and Christoph Weniger

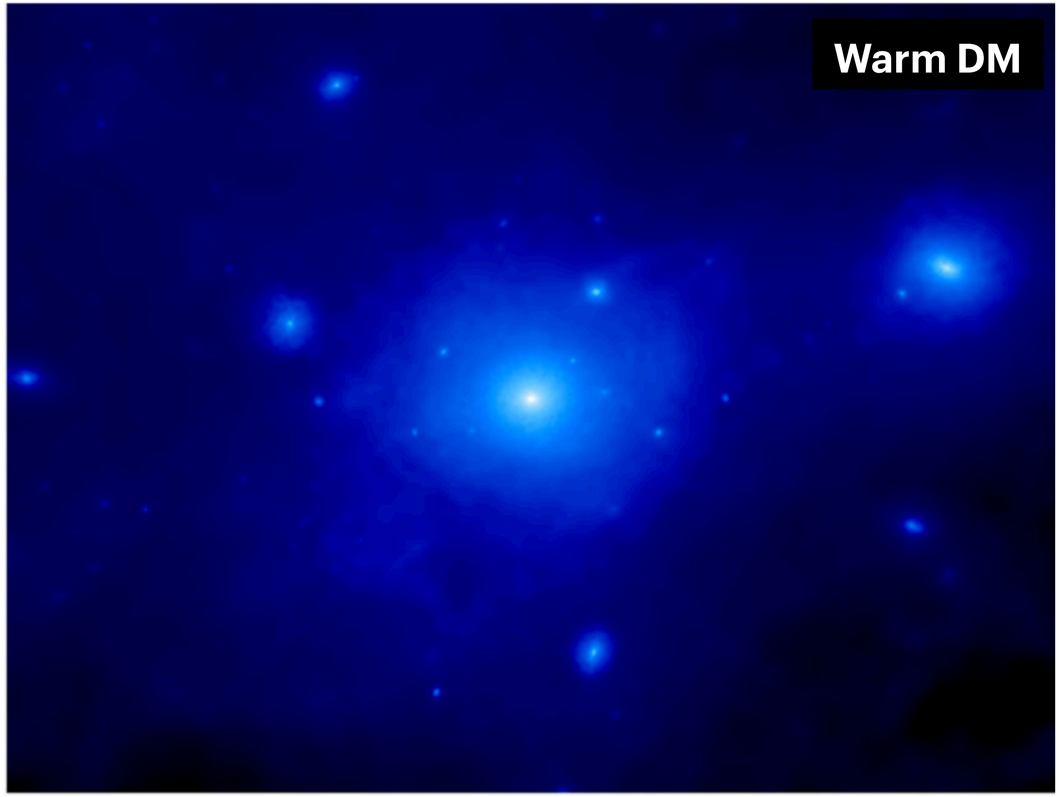
Mila

1910.06157 | 2010.07032 | 2105.09465

LFI Paris, 22 April 2022

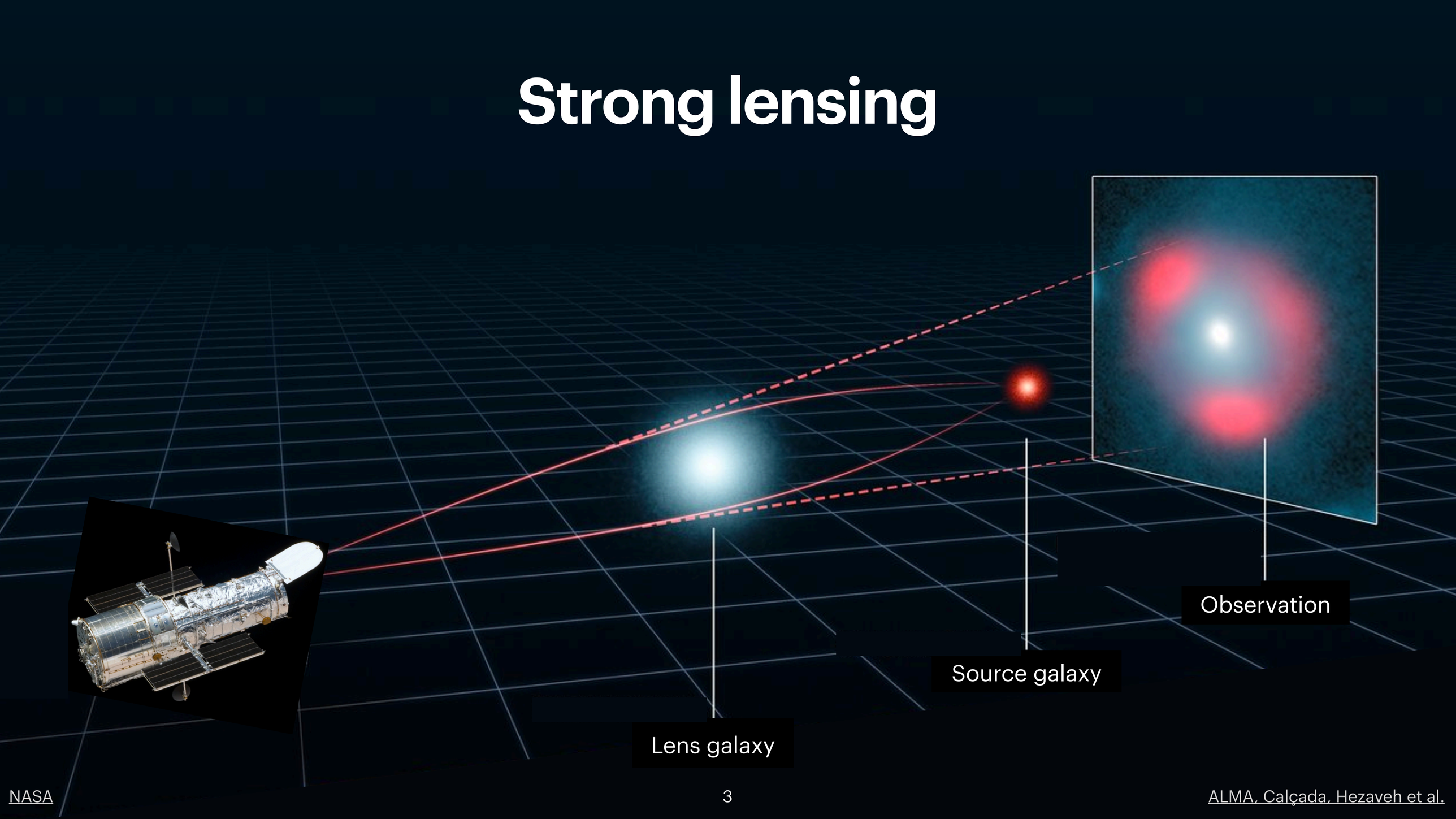
Halos probe dark matter





1404.7012

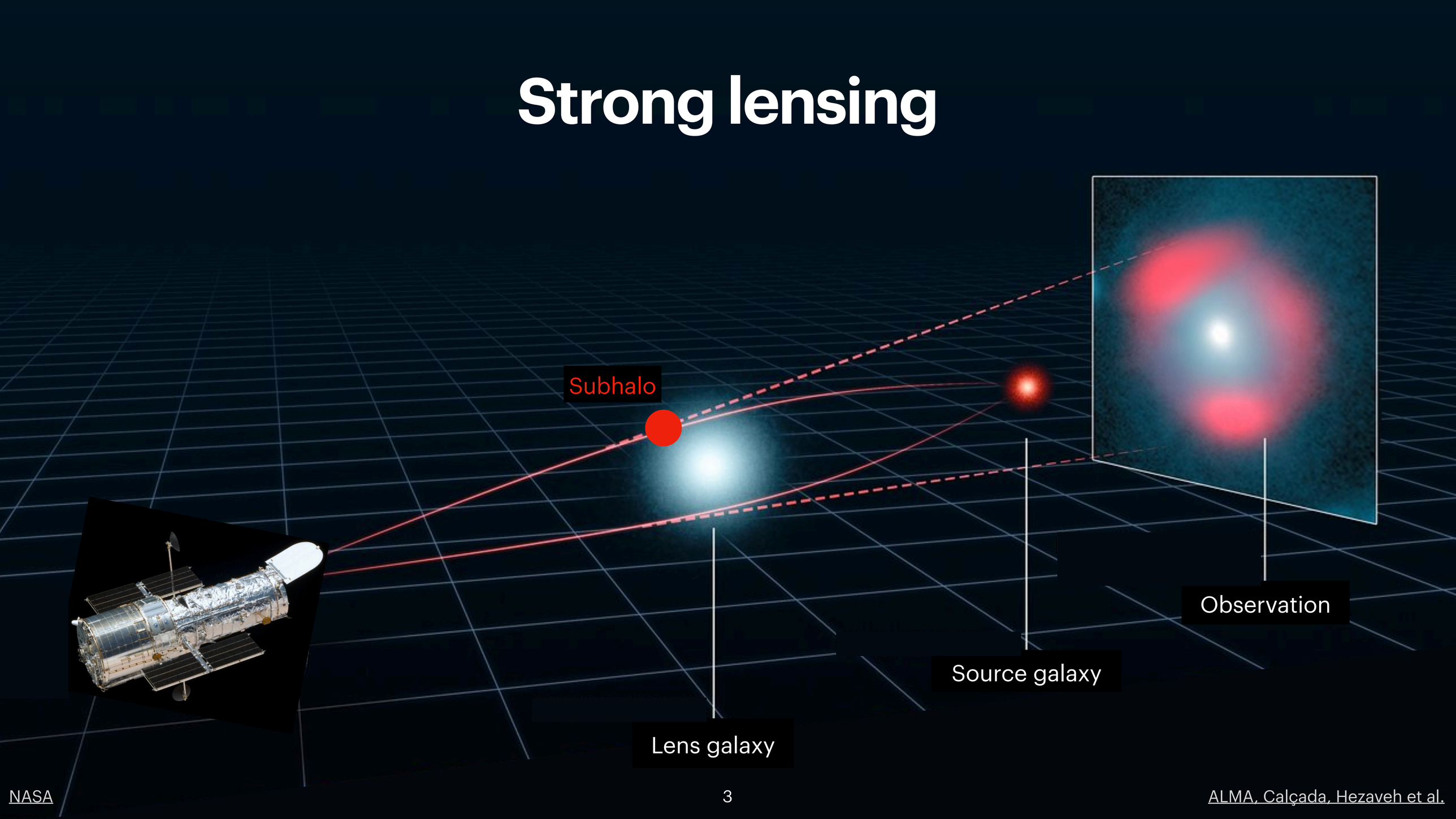
Strong lensing



NASA

ALMA, Calçada, Hezaveh et al.

Strong lensing



NASA

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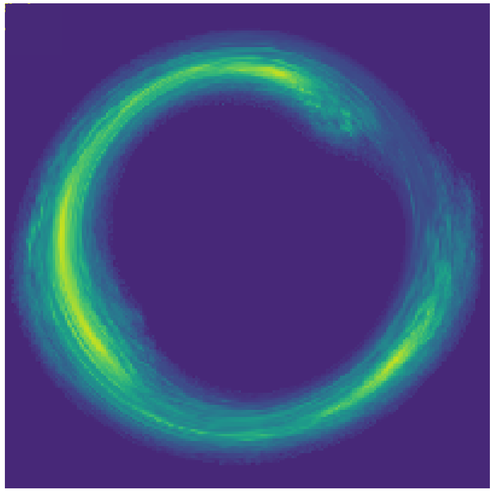
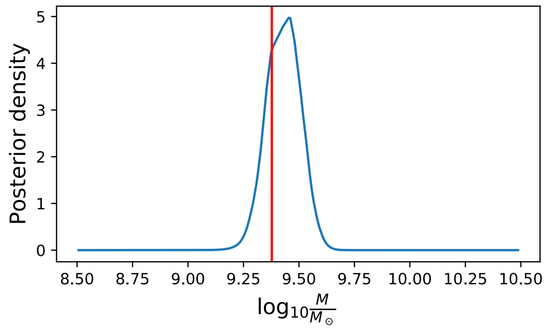
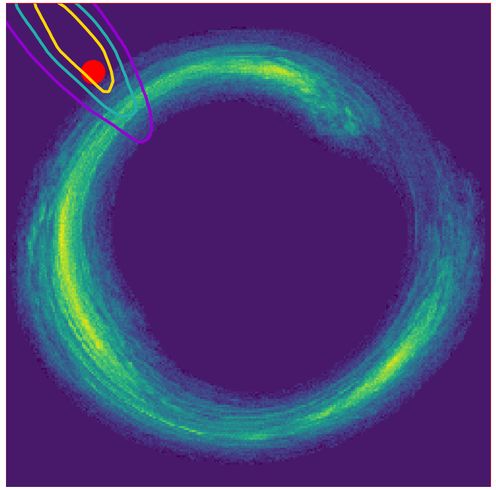
Lensing inference

Observation

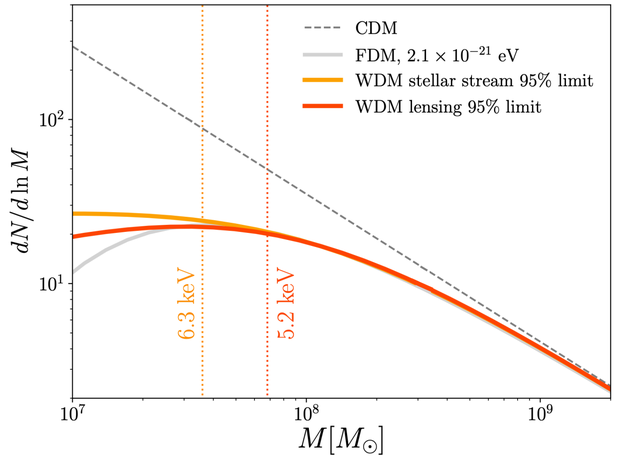


Measure halos' properties





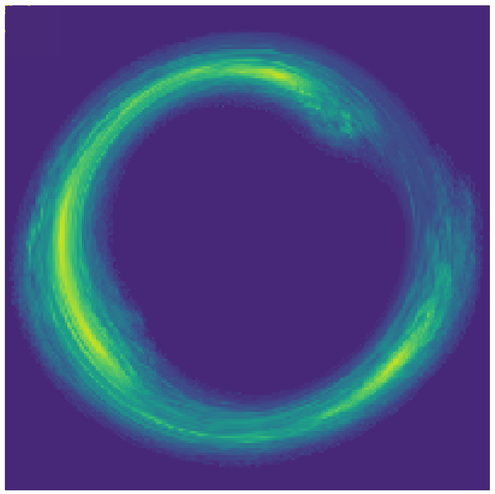
Connect to DM model



2001.05503

Lensing inference

Observation



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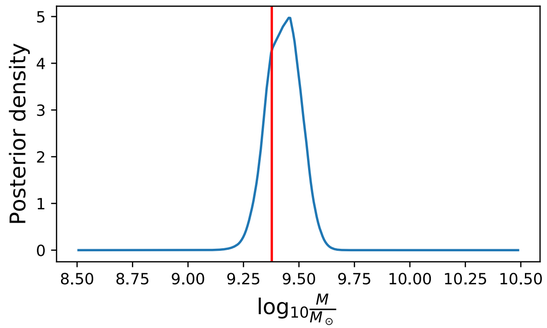

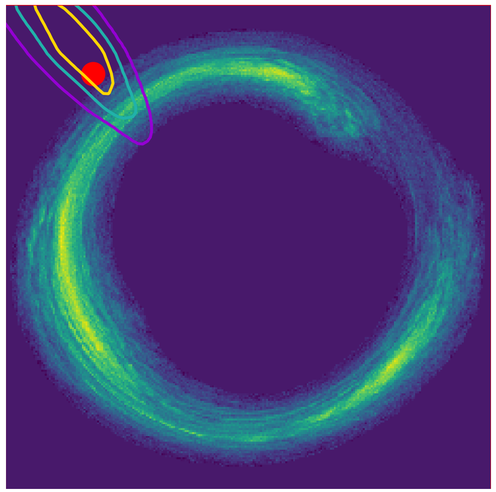

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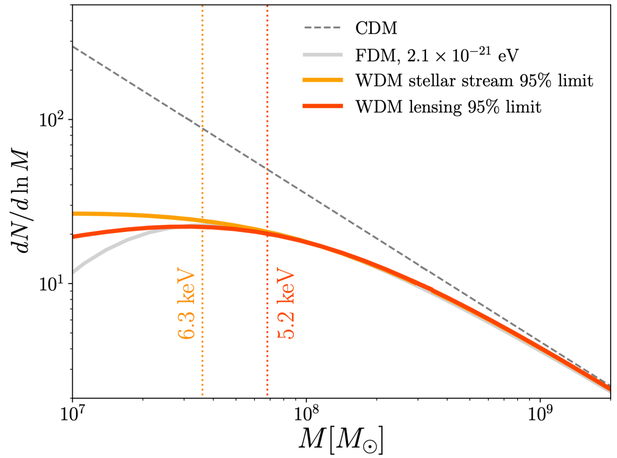
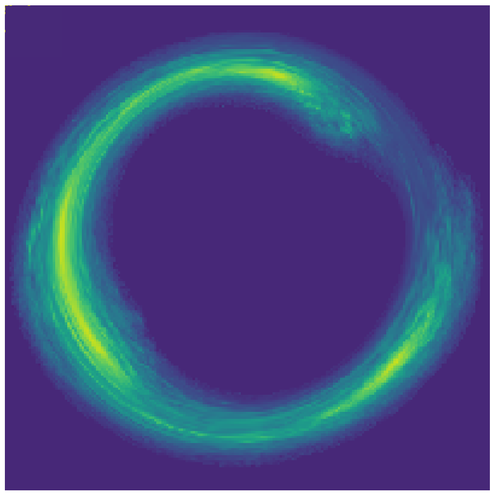


Noemi's talk

2001.05503

Lensing inference

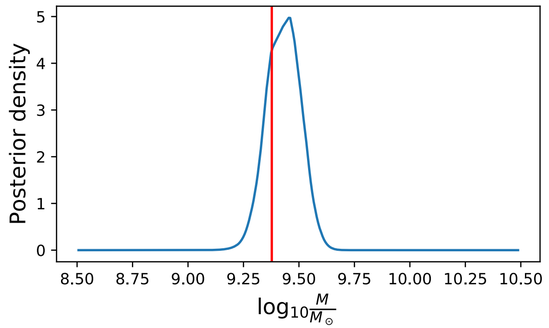
Observation

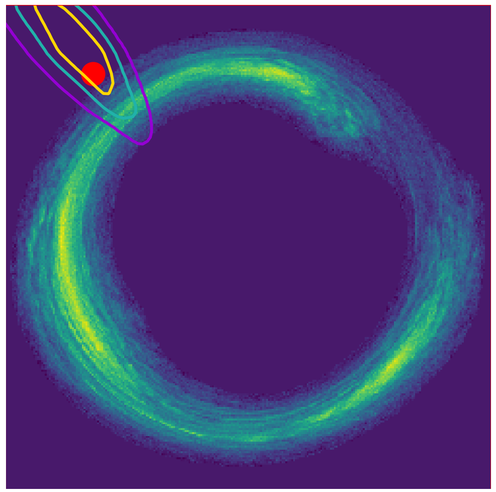


Noemi's talk

Measuring the subhalo distribution function: Elias' talk

Measure halos' properties





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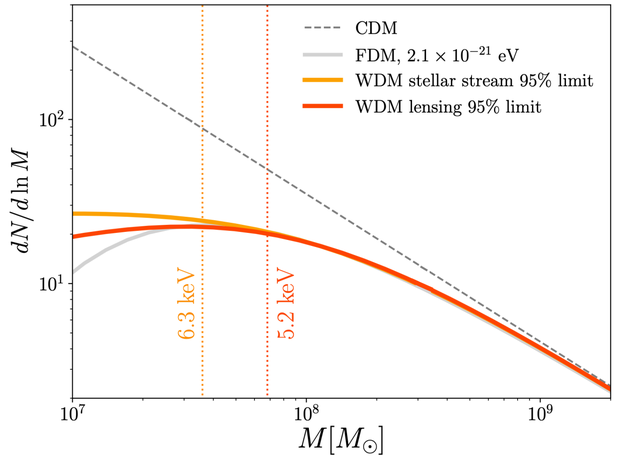

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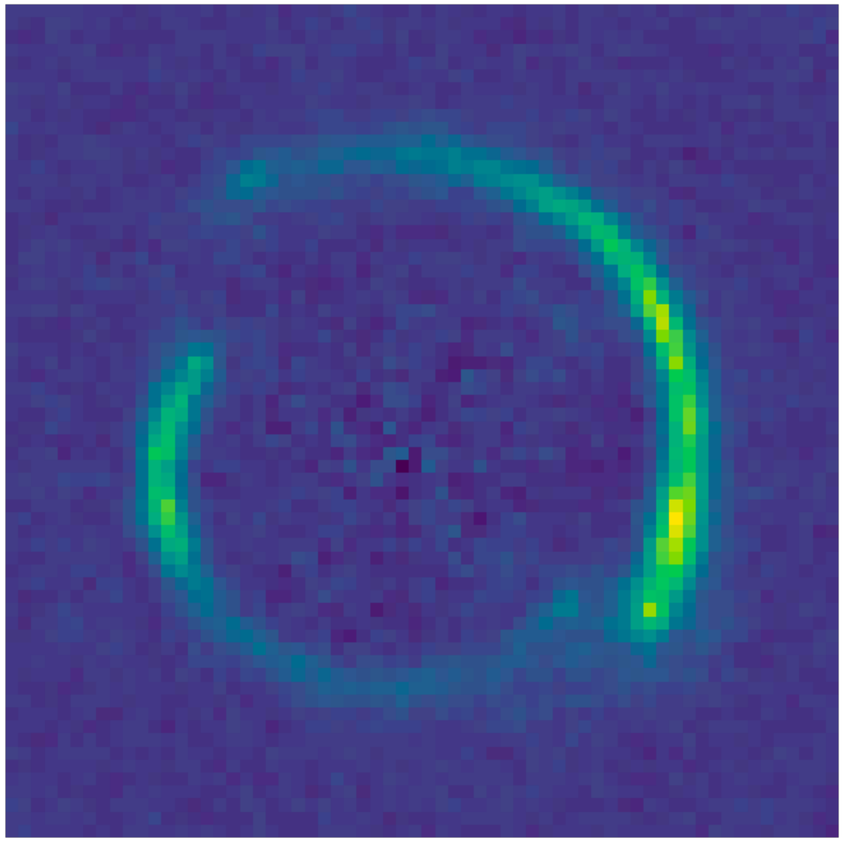
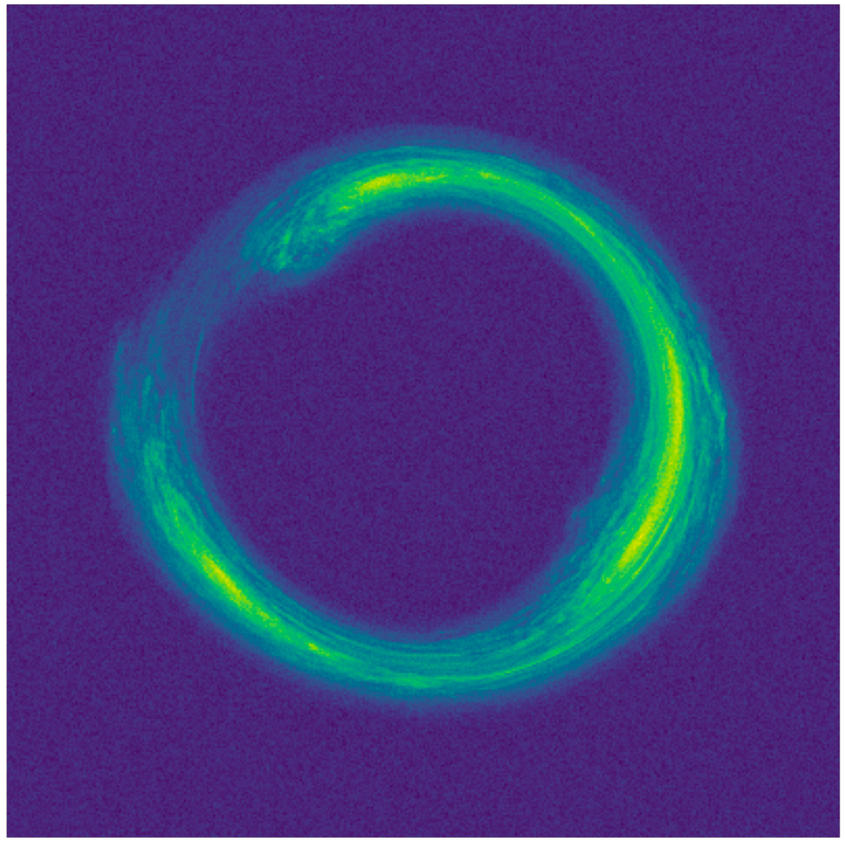
At present



× 100
(HST, Keck)

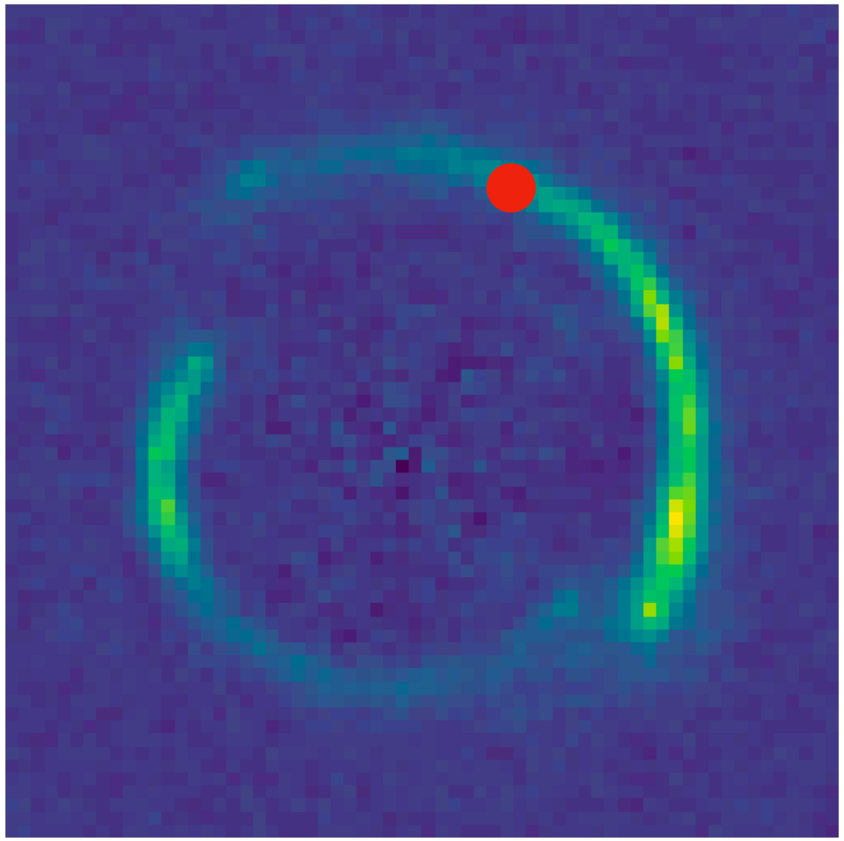
2020s



× 100,000
(Euclid, Rubin, JWST, ELT)

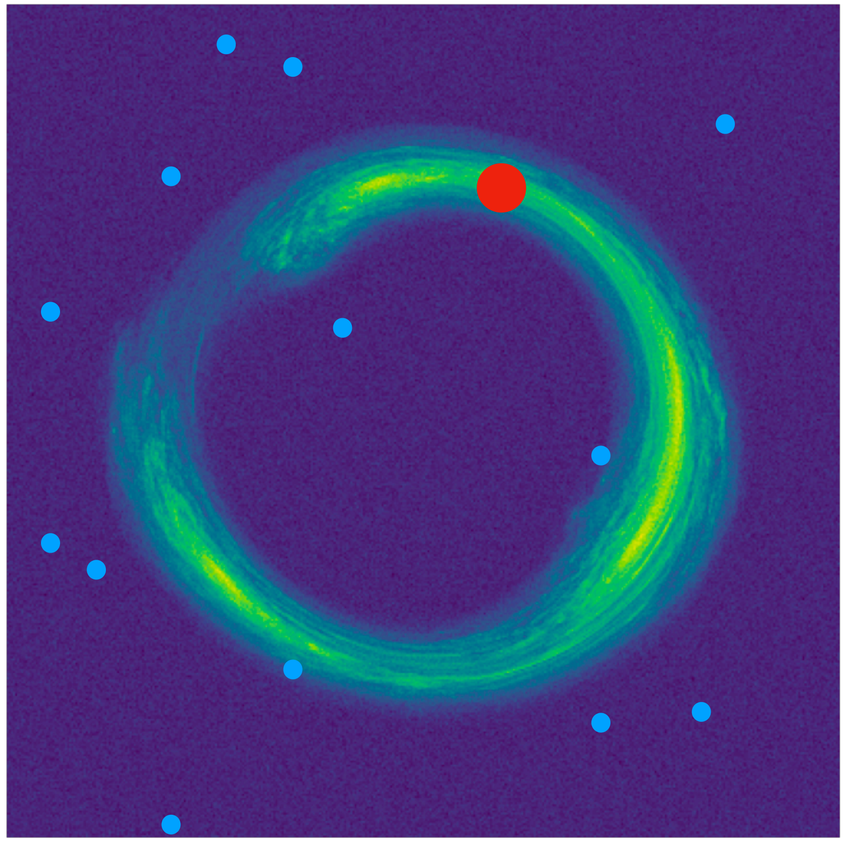
1507.02657

Current analyses



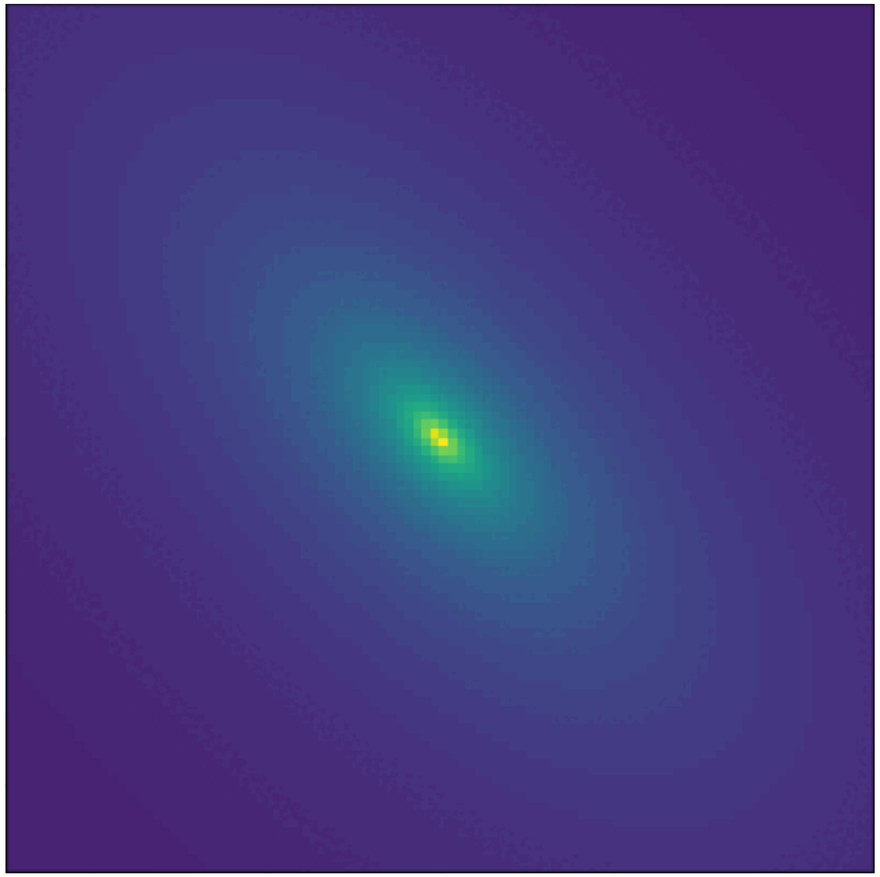
Measures a single halo's properties, marginalized over *particular* lens model

Goal



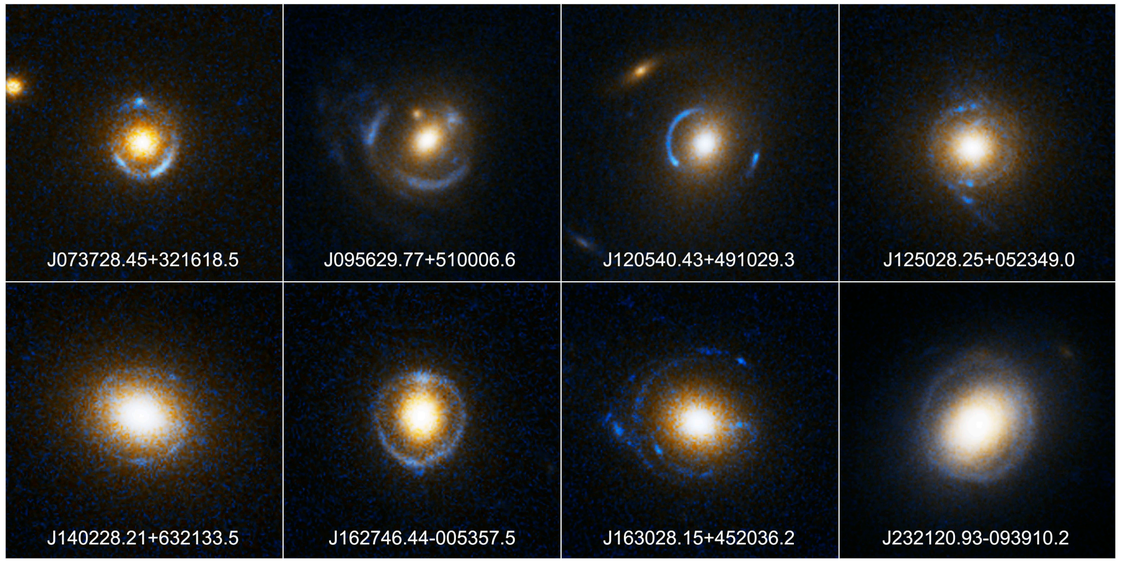
Marginalize over full halo population and generic lens model

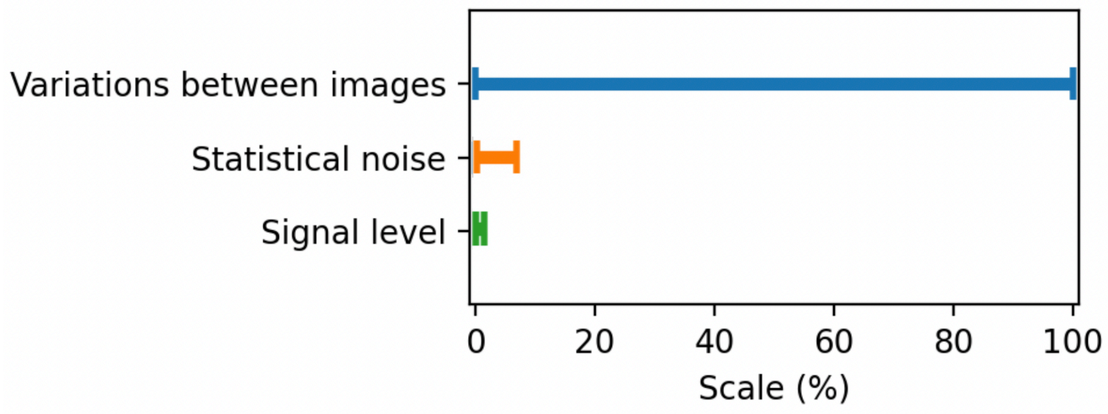
Inference challenges



Inference challenges

- Signal is small compared to noise and variations between images



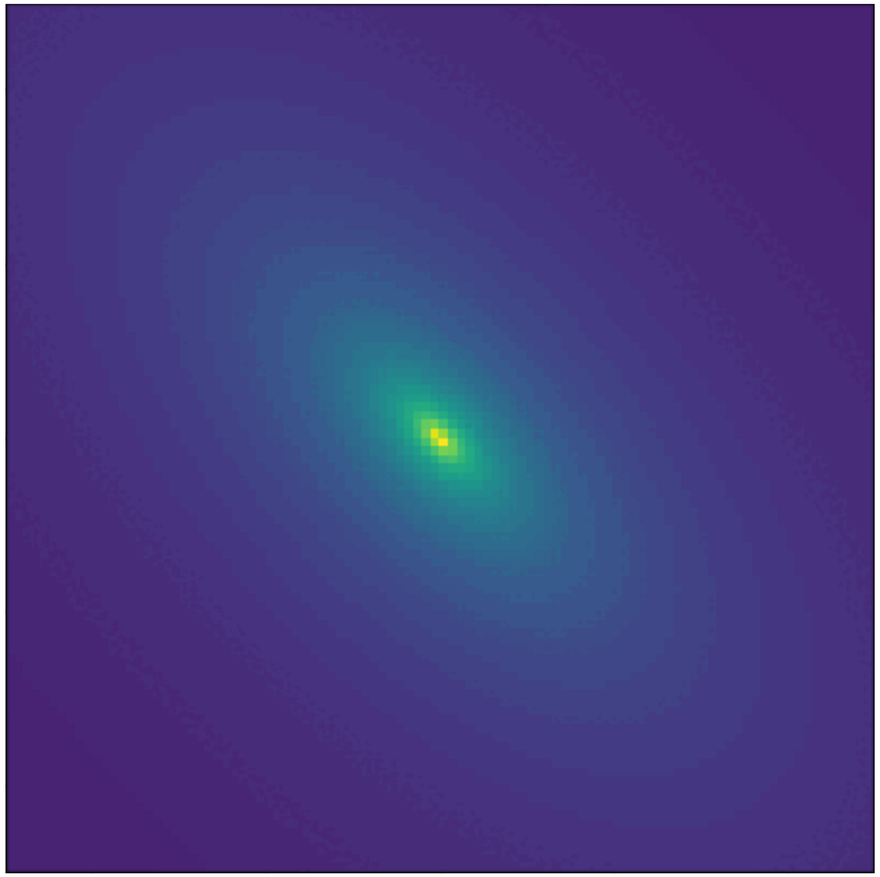


Slide credit: Noemi Anau Montel

Inference challenges

- Signal is small compared to noise and variations between images

- Marginalization over numerous source, lens and halo parameters



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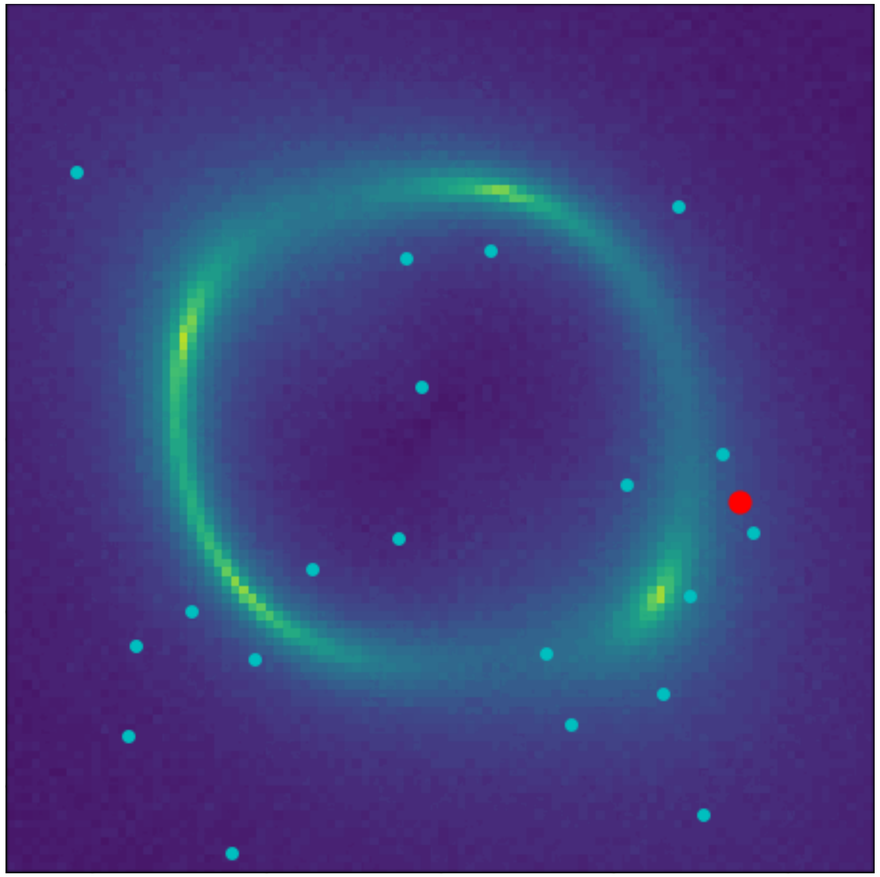
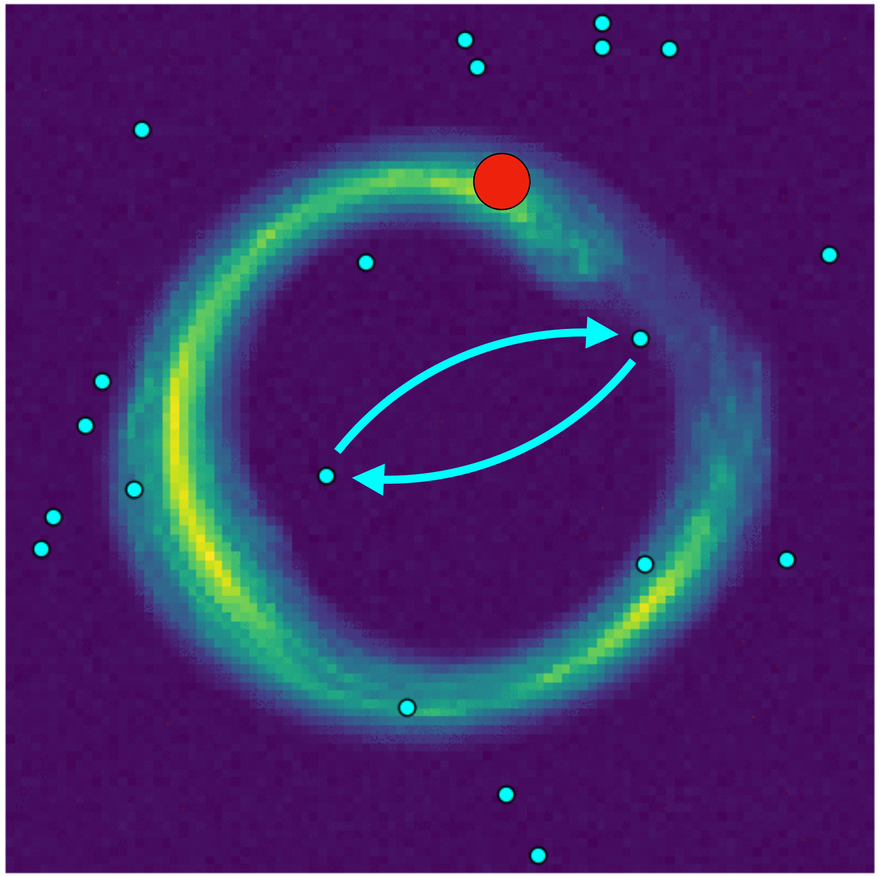


Inference challenges

- Signal is small compared to noise and variations between images
- Marginalization over numerous source, lens and halo parameters
- Joint posterior has ~$N_{sub}!$ modes; likelihood can be intractable



Truncated marginal neural ratio estimation

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- Direct marginal inference of subhalo posteriors over $O(10^3\text{-}10^5)$ source, lens and subhalo population parameters

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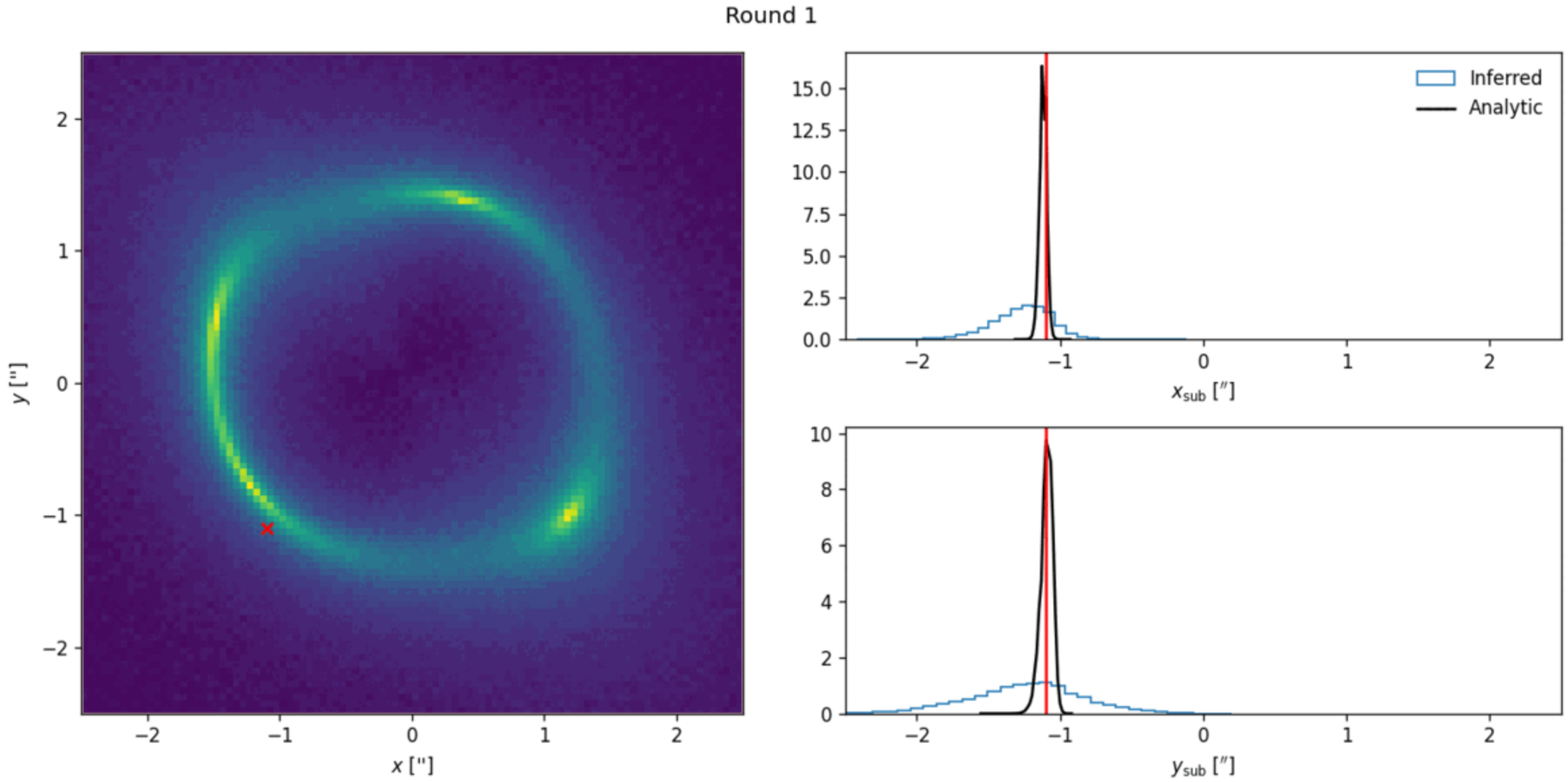
- Truncation enables targeted inference to uncover tiny signals

Truncated marginal neural ratio estimation

- Direct marginal inference of subhalo posteriors over $O(10^3\text{-}10^5)$ source, lens and subhalo population parameters
- Truncation enables targeted inference to uncover tiny signals
- Can leverage simple classifier CNNs and the `swyft` package

1. Analytically-tractable case

Lens, source and halo mass fixed



Good agreement with analytic calculation after several rounds of truncation

Preliminary!

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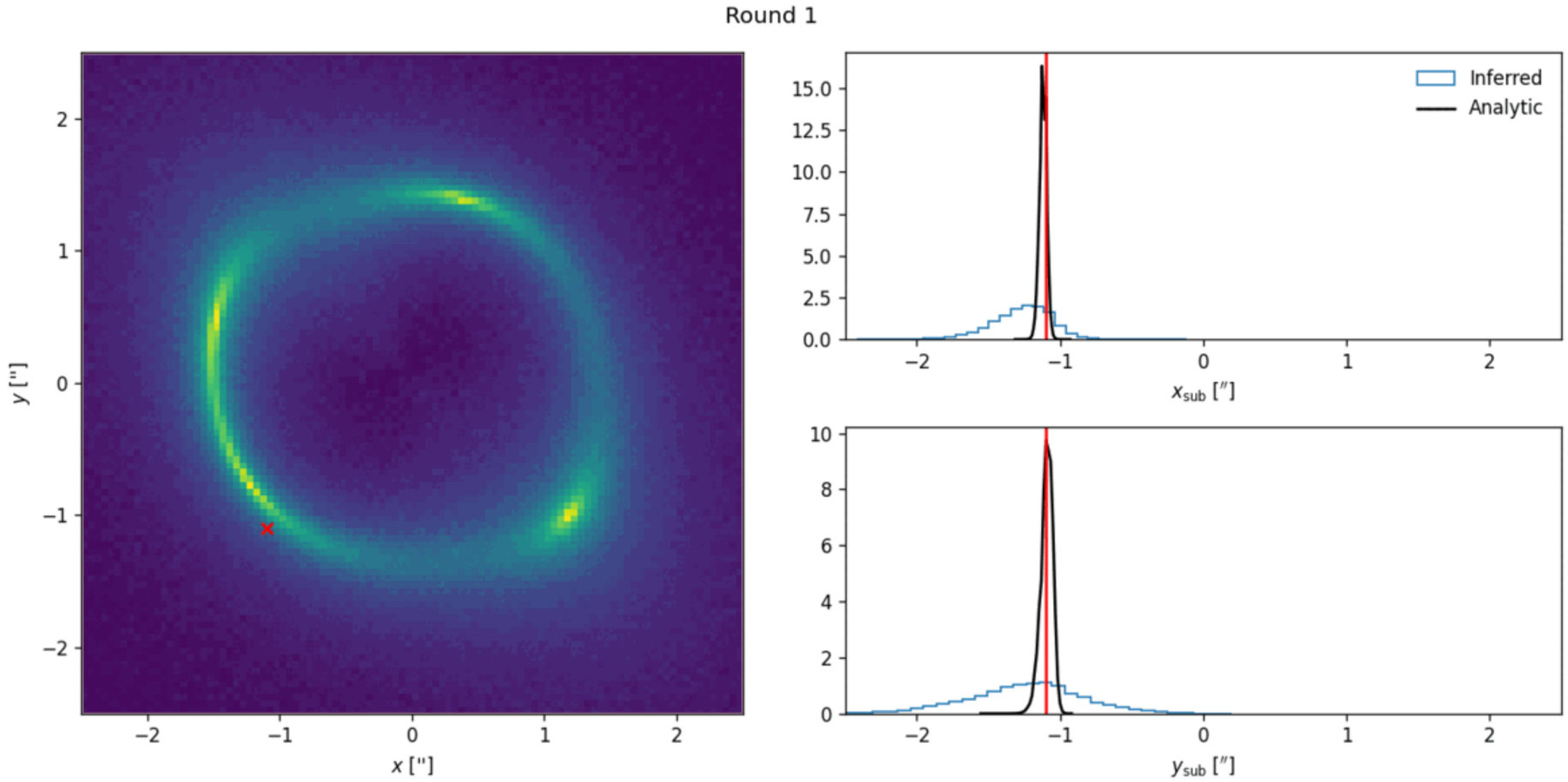
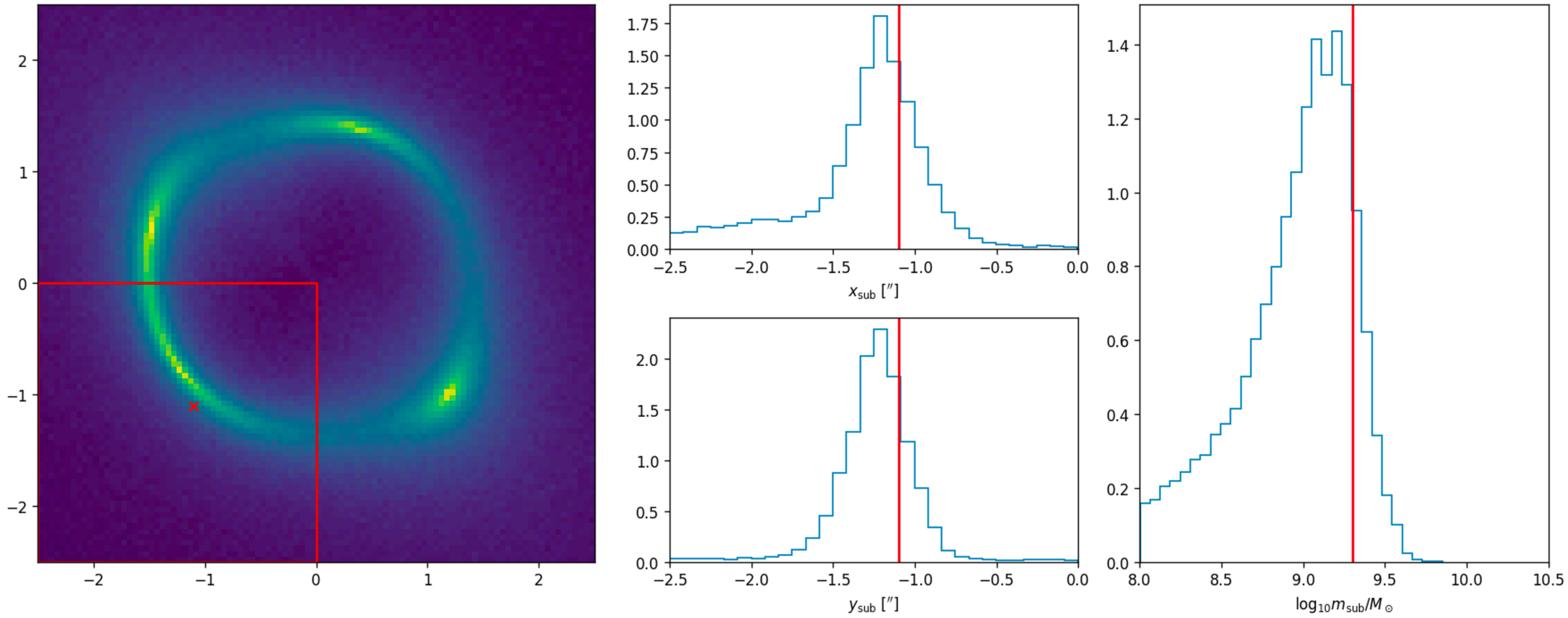
Lens, source and halo mass fixed



Good agreement with analytic calculation after several rounds of truncation

Preliminary!

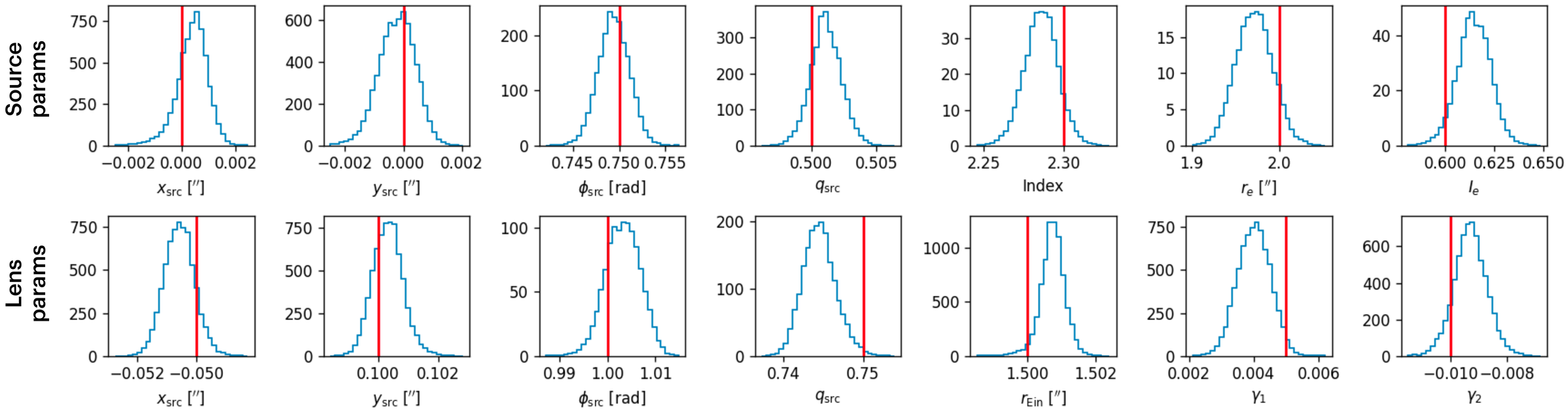
2. One halo, simple source model



Can marginalize over source and lens parameters...

Preliminary!

2. One halo, simple source model



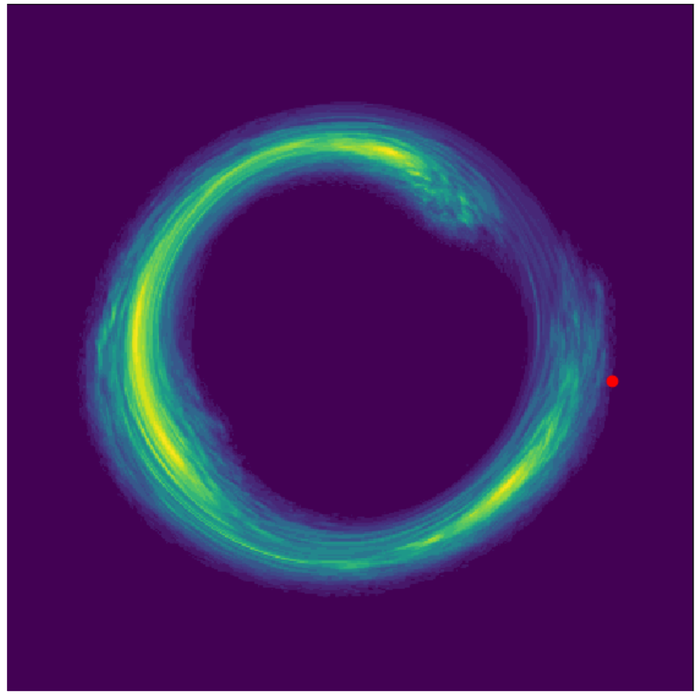
...and simultaneously infer their posteriors

Preliminary!

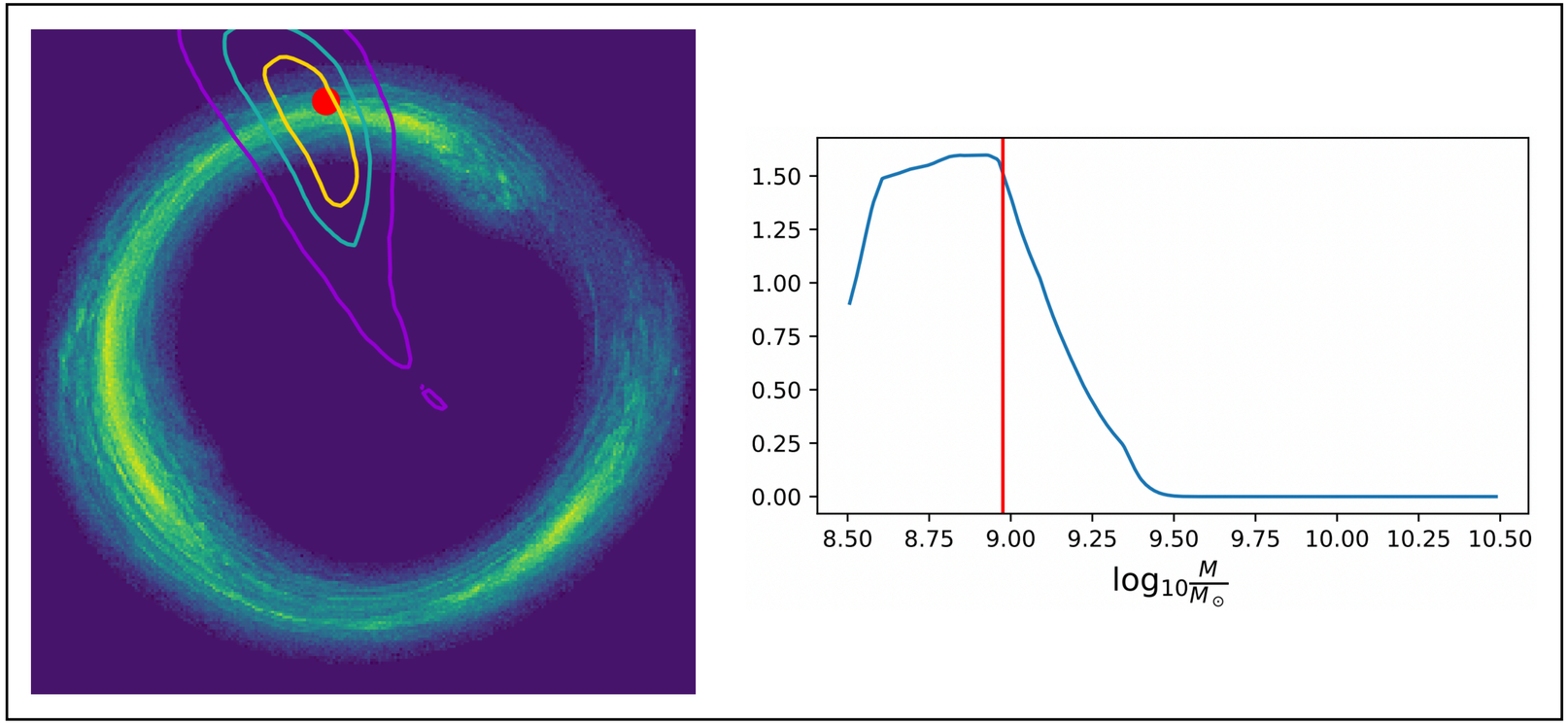
3. One halo, Gaussian process source

First constrain lens and source with variational inference, then apply TMNRE

Training data



Inference



Marginalized over O(10^5) source and lens parameters

• = $10^8 - 10^{11.5}\,M_\odot$ subhalo

2010.07032, 2105.09465

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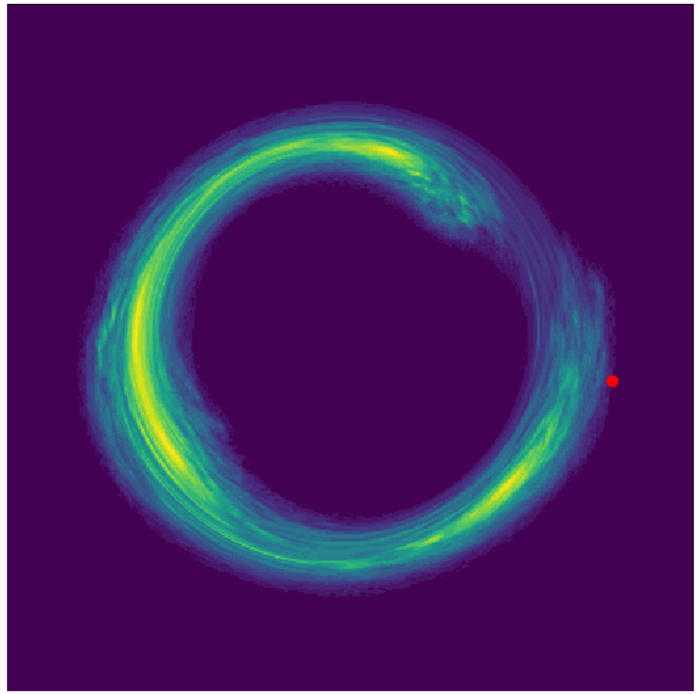

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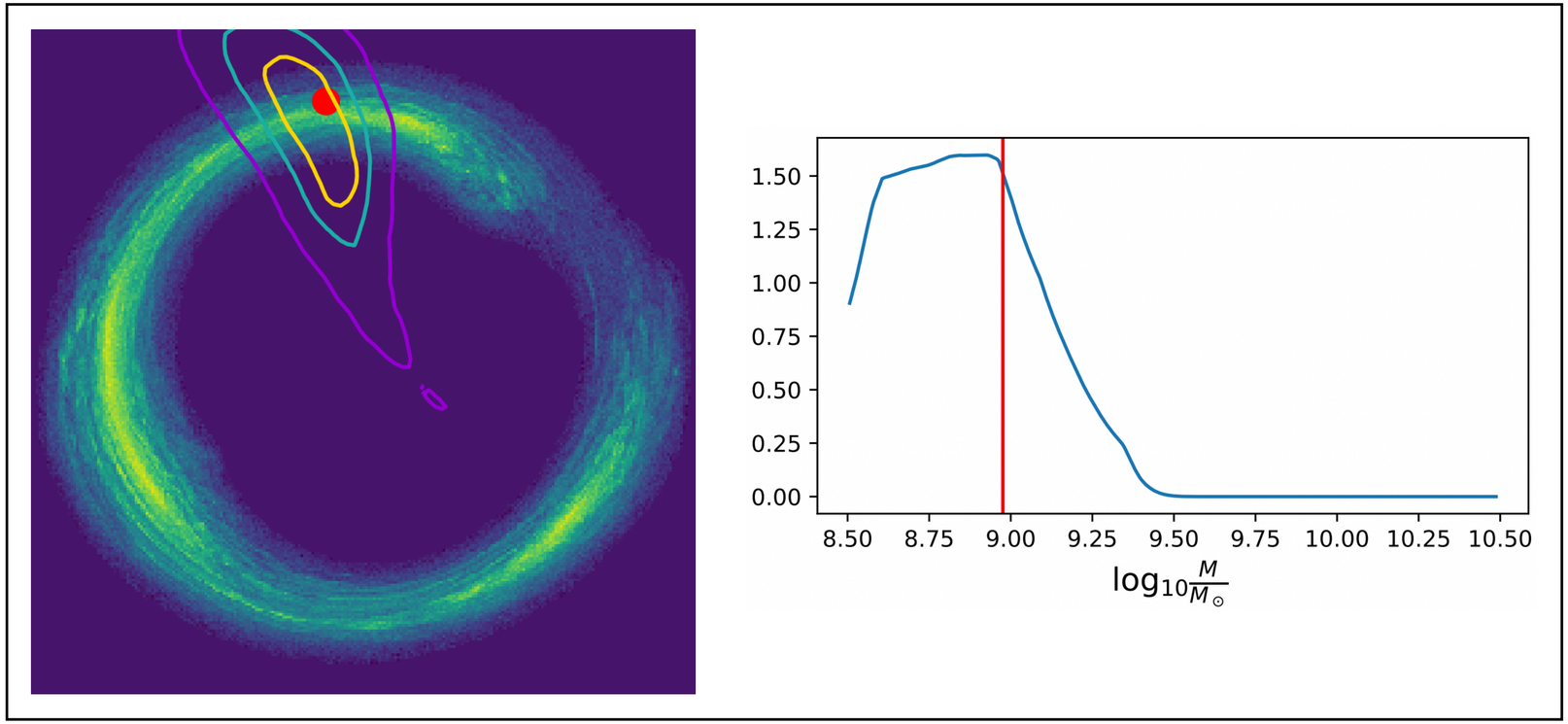

Marginalized over O(10^5) source and lens parameters

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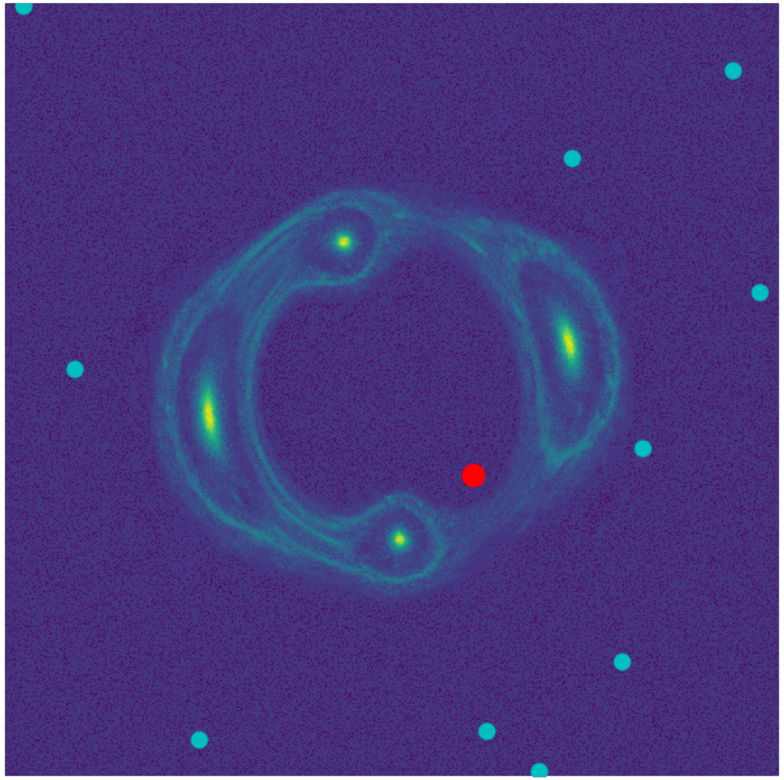
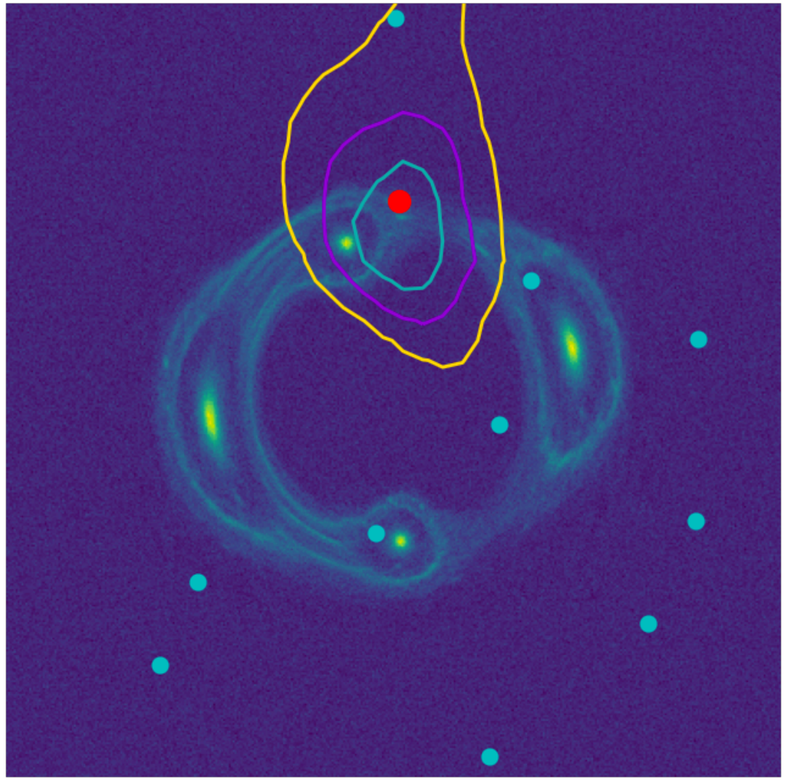
2010.07032, 2105.09465

4. Multiple subhalos, Gaussian process source

Training data



Inference



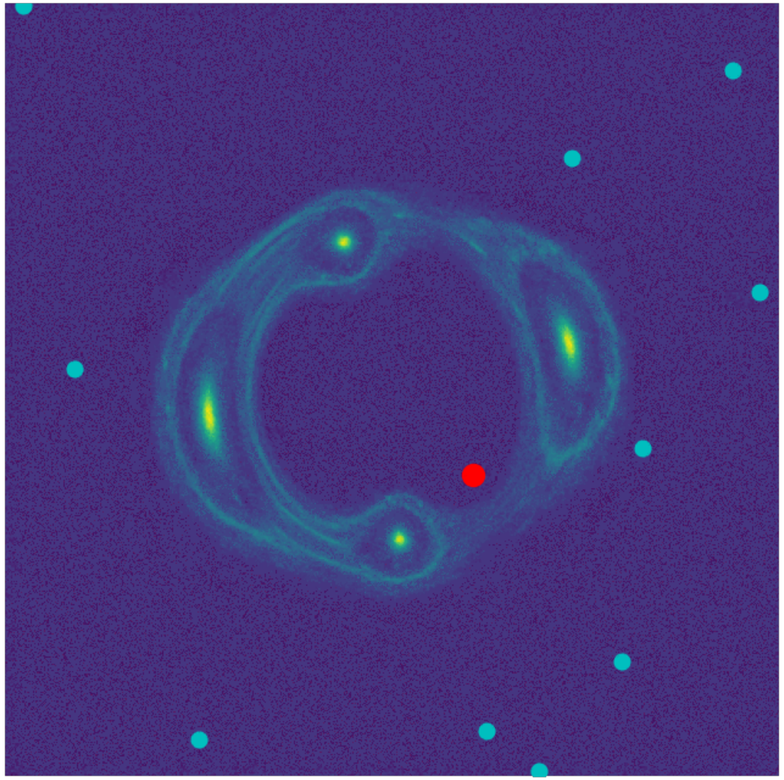
Marginalized over source, lens and halo population

• = $5 \times 10^9\,M_\odot$, • = $10^8 - 10^9\,M_\odot$

Preliminary!

4. Multiple subhalos, Gaussian process source

Training data



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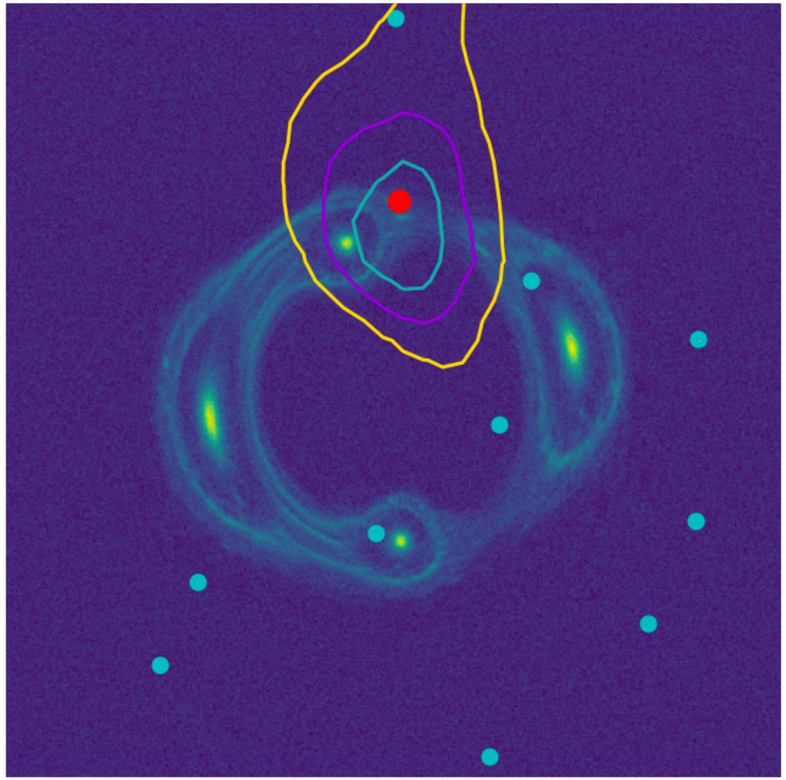

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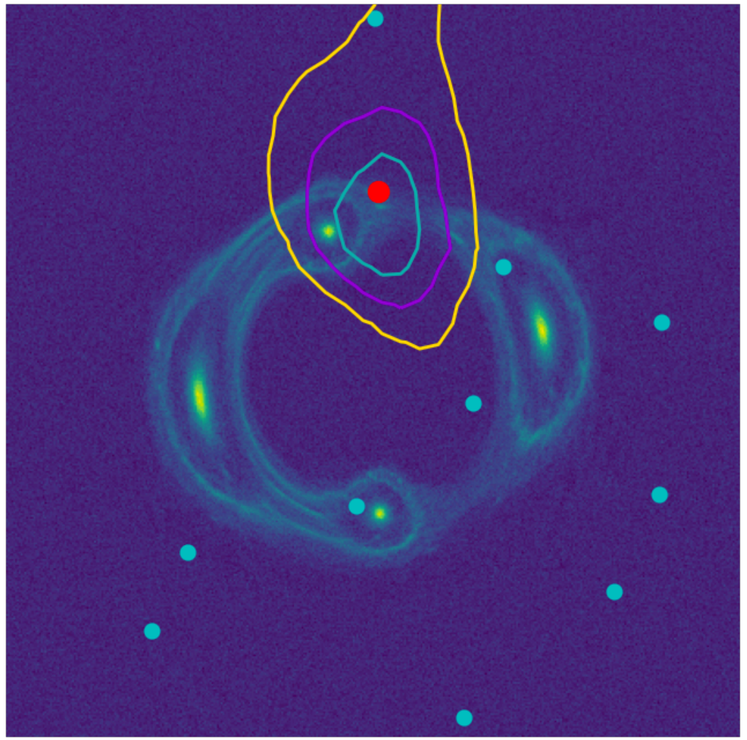
• = $5 \times 10^9\,M_\odot$, • = $10^8 - 10^9\,M_\odot$

Preliminary!

Conclusions

- Measuring individual halos is an important component of dark matter lensing analyses
- TMNRE enables fully marginalizing over lens, source *and halo population*
- Next steps: replace variational inference step with TMNRE, integrate with other subhalo analyses, and apply to real data



Thank you!