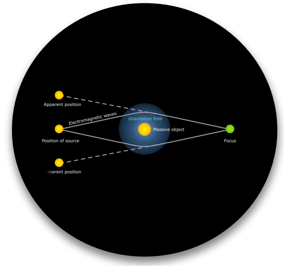
Probing the particle nature of dark matter with strong gravitational lensing

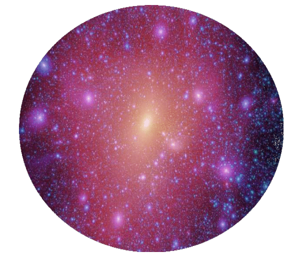
Yashar Hezaveh
University of Montreal
Center for Computational Astrophysics – Flatiron Institute

N. Dalal, G. Holder, L. Perreault Levasseur, D. Marrone, W. Morningstar, Y. Mao
R. Blandford, J. Carlstrom, C. Fassnacht, P. Marshall, N. Murray , J. Vieira, R. Wechsler

OUTLINE



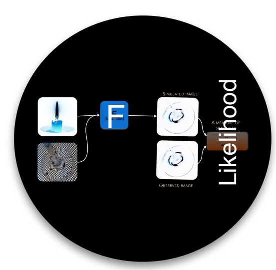
strong lensing

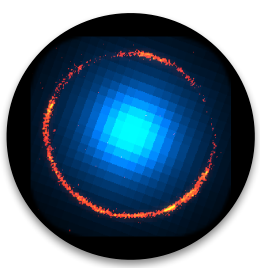


small-scale
distribution
of dark matter

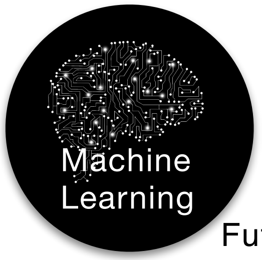
Submm lenses
ALMA
New analysis methods

Analysis methods:
Lens modeling





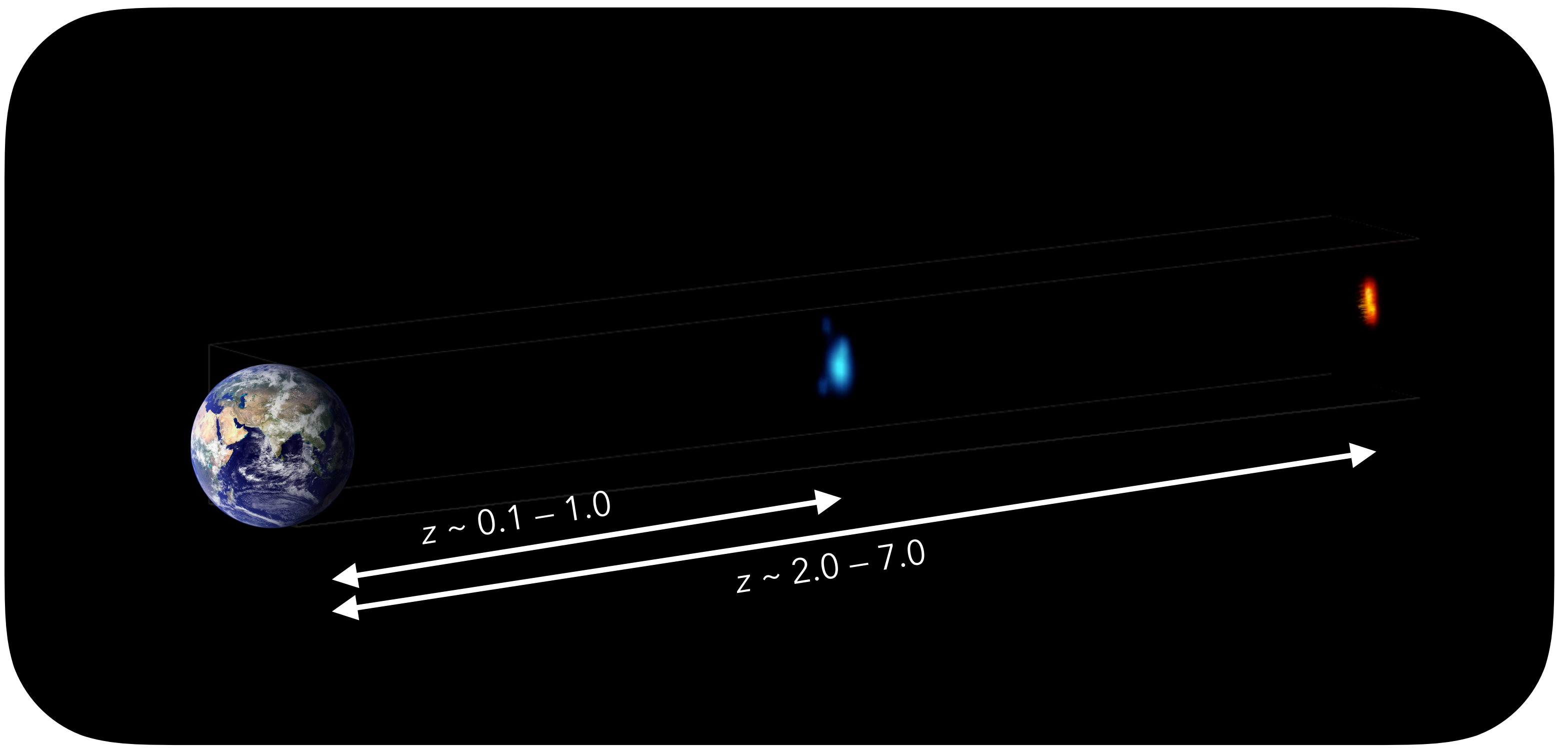
First results
from ALMA

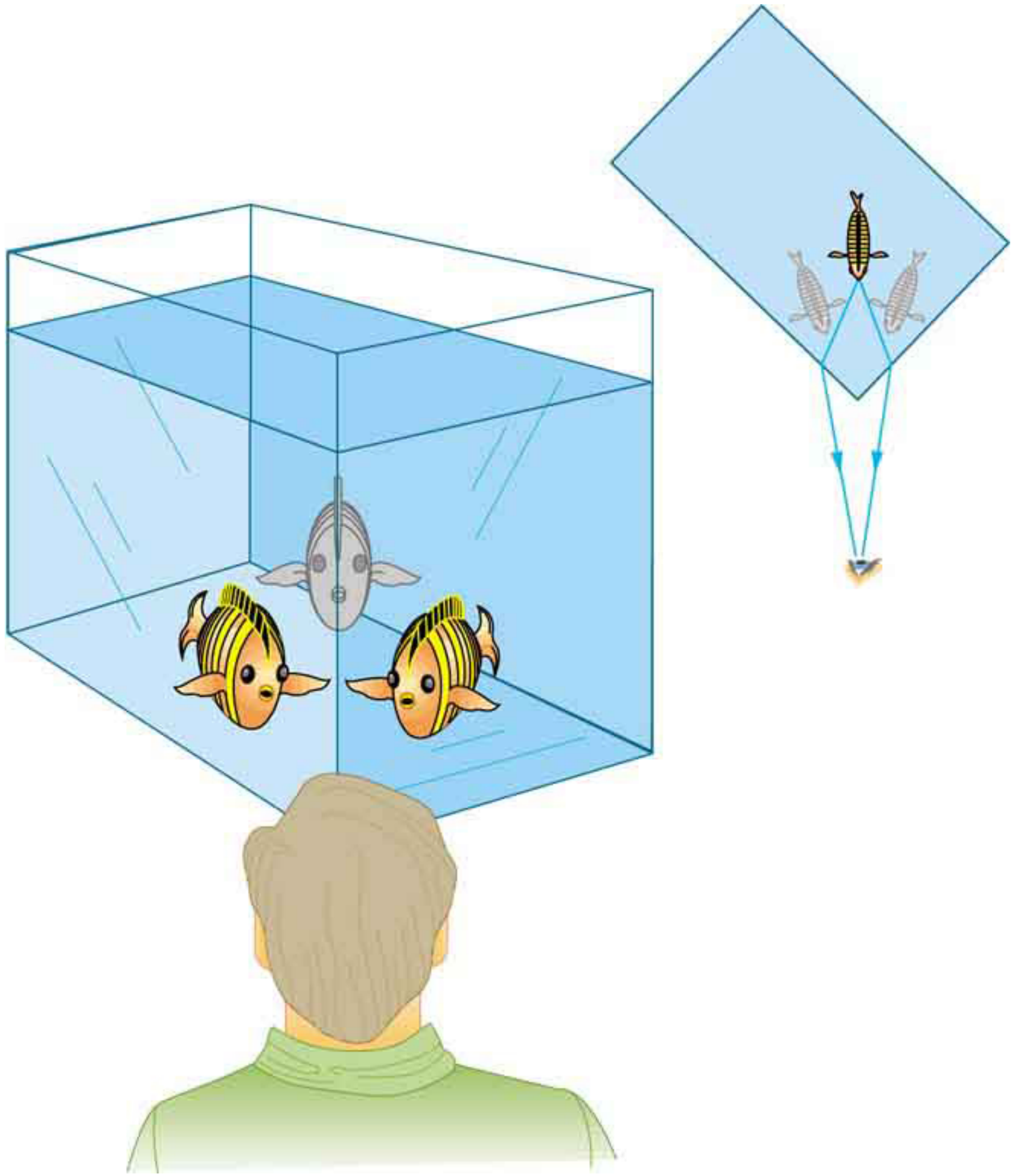


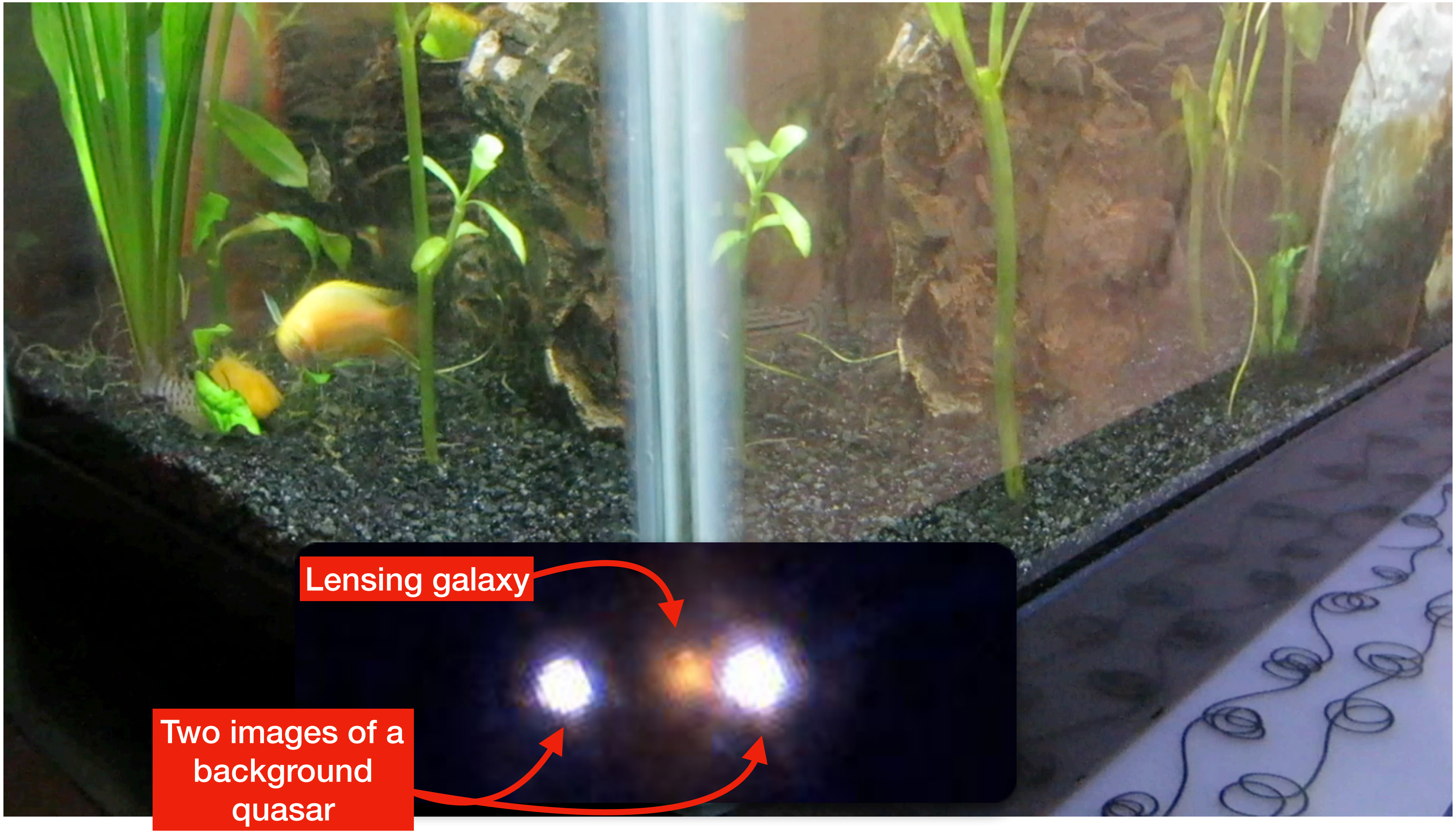
Future directions:
LSST
New telescopes
Machine learning

Strong Gravitational Lensing

Formation of **multiple images** of a single distant object due to the **deflection of its light** by the **gravity** of intervening structures.







Lensing galaxy
Two images of a background quasar

Strong lenses produce arcs

SCIENCE MOTIVATIONS FOR STRONG LENSING

1- Background source:

Use strong lensing as a **cosmic telescope**.

2- Foreground lens:

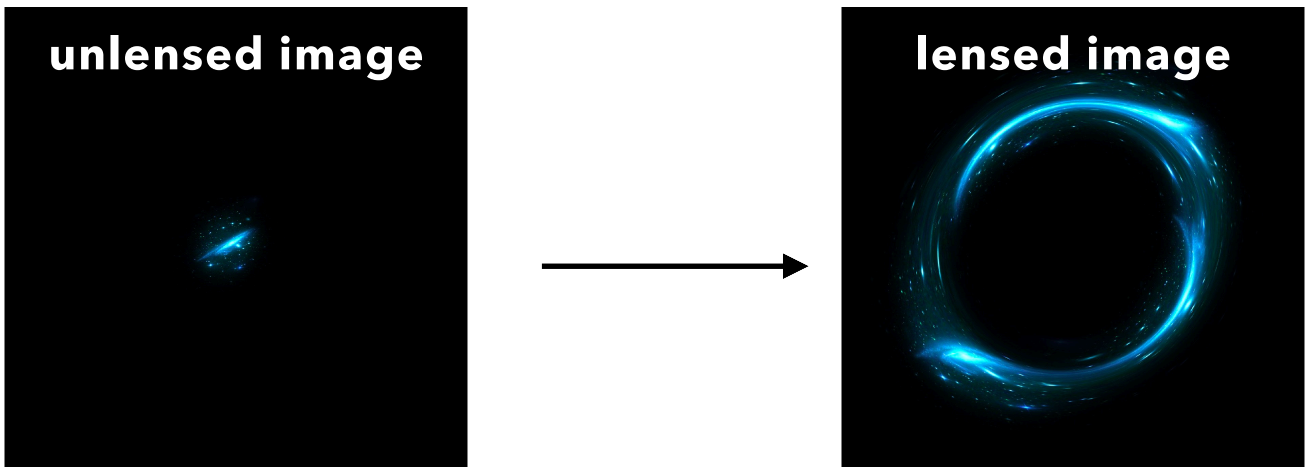
Use lensing to probe the **distribution of matter** in the lensing structures.

*** Other things (cosmology, testing GR, etc.)**

Science motivations for strong lensing

1 - Use strong lensing as a **cosmic telescope**.

- Lensing **magnifies** the images of sources and makes them appear **brighter**.
- This allows us to study some of the most distant galaxies of the universe that would have been otherwise below our sensitivity or resolution limits.



SPT-SMG collaboration:

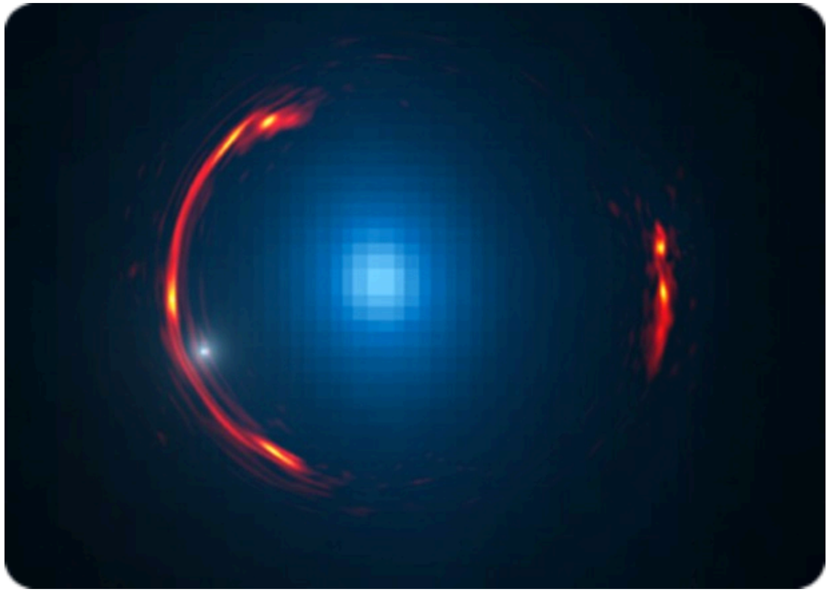
Use lenses to study star formation in the background galaxies

- Vieira et al. 2011
- Greve et al. 2012
- Vieira et al. 2013
- Weiss et al. 2013
- Hezaveh et al. 2013
- Aravena et al. 2013
- Bothwell et al. 2013
- Spilker et al. 2014
- Gullberg et al. 2015
- Spilker et al. 2014
- Gullberg et al. 2015
- Spilker et al. 2015
- Ma et al. 2015
- Welikala et al. 2016
- Bethermin et al. 2016
- Aravena et al. 2016
- Strandet et al. 2016
- Spilker et al. 2016
- Ma et al. 2016
- Strandet et al. 2017

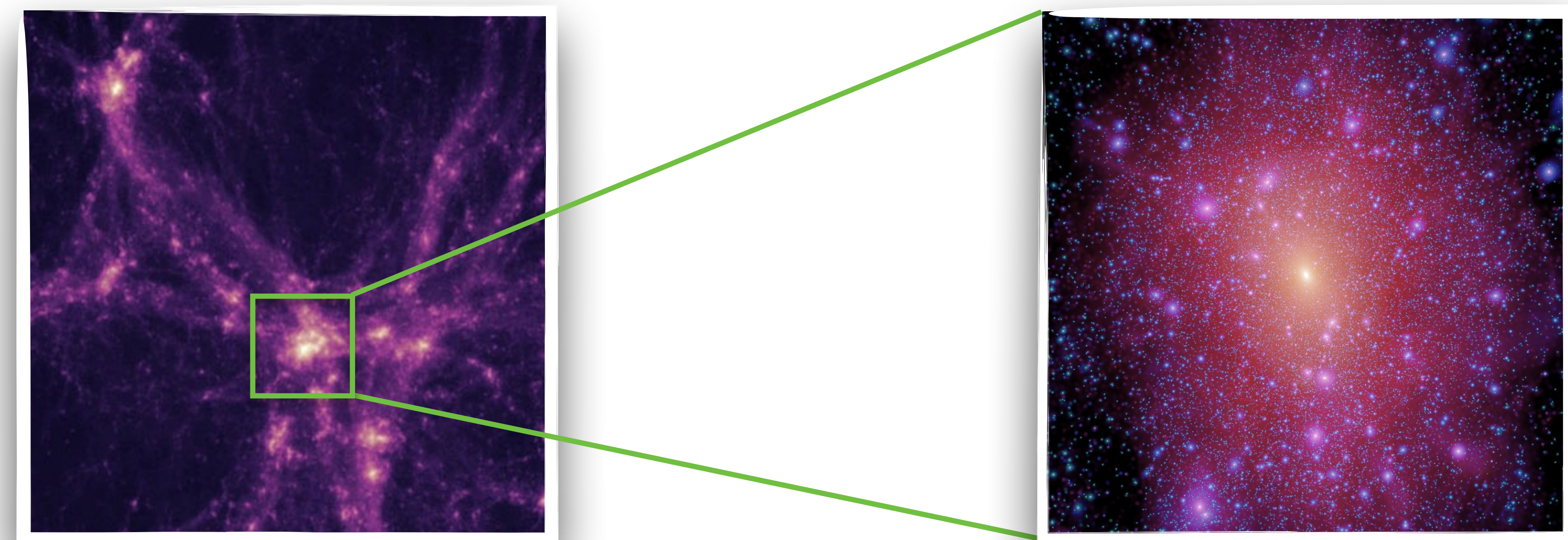
Science motivations for strong lensing

2 - Use lensing to probe the **distribution of matter** in the lensing structures.

- Distortions in images are caused by **gravity**.
- They can be used to map the **distribution of matter** in the lens.
- Particularly useful for studying **dark matter.**



SMALL-SCALE STRUCTURE OF DARK MATTER

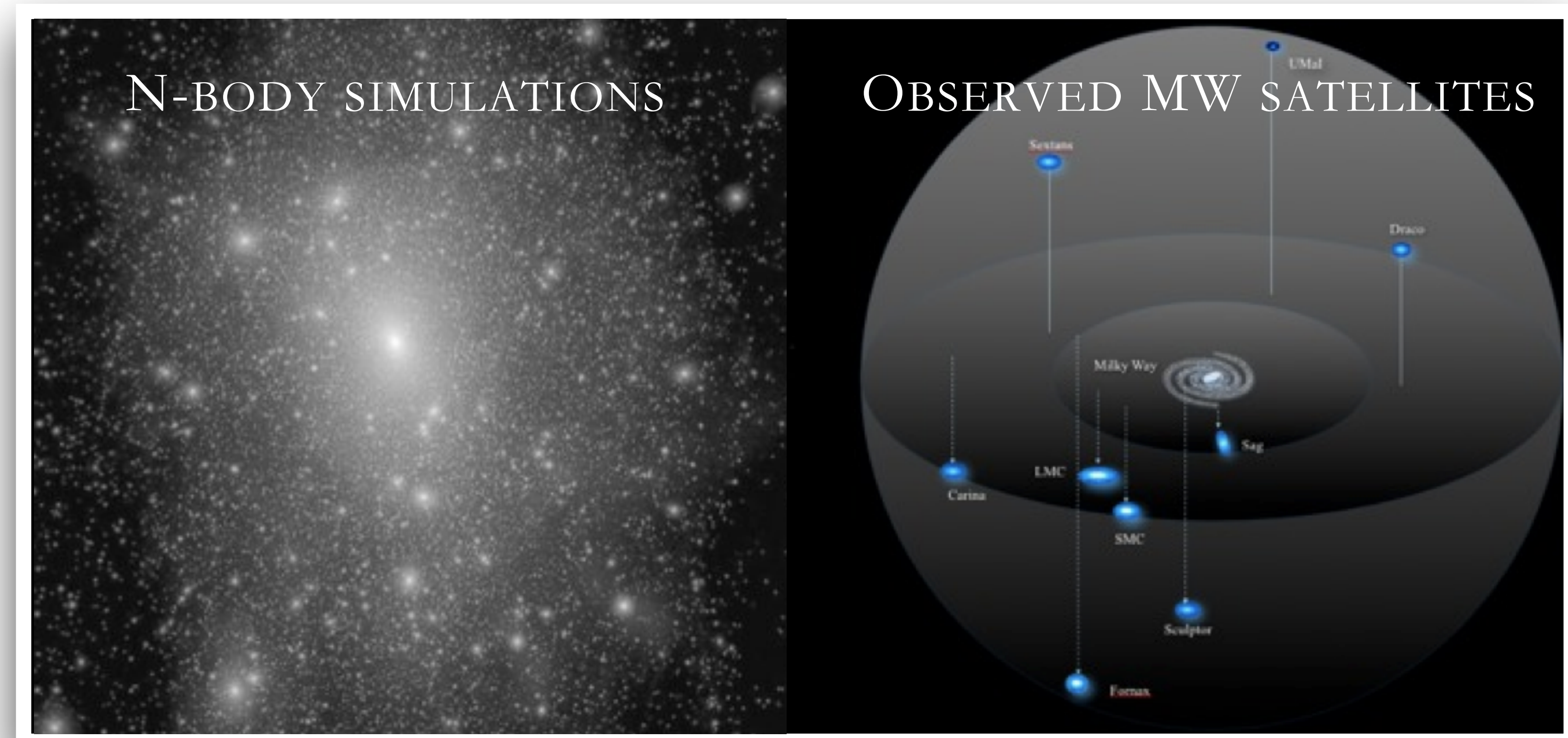


Large scale structure is very well measured.

Small scale distribution of dark matter is not well understood.

The Missing Satellites Problem

discrepancy between the number of CDM subhalos and MW dwarf satellites



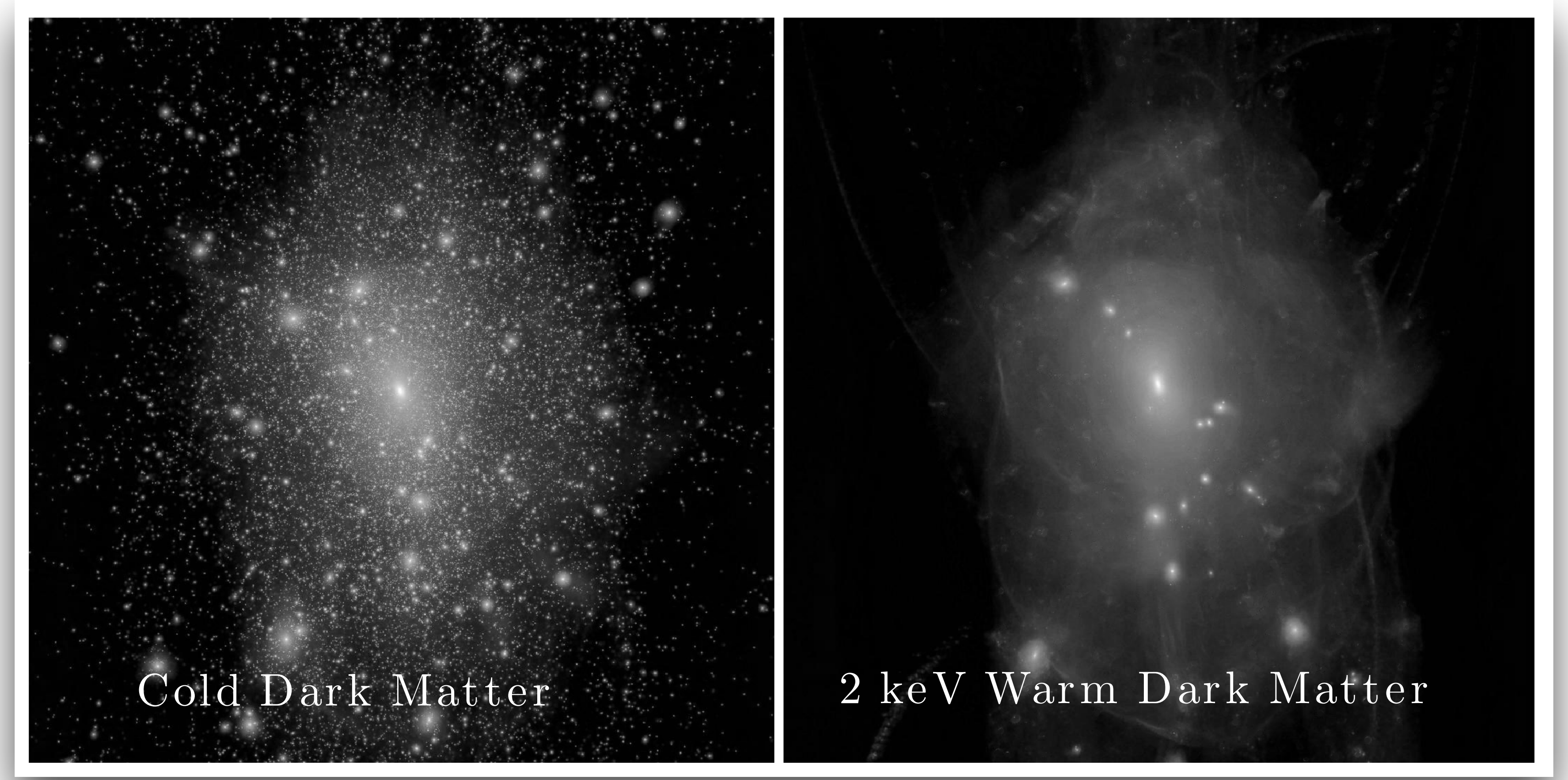
Theory: N~ 10000

Observation N~50

SOLUTIONS

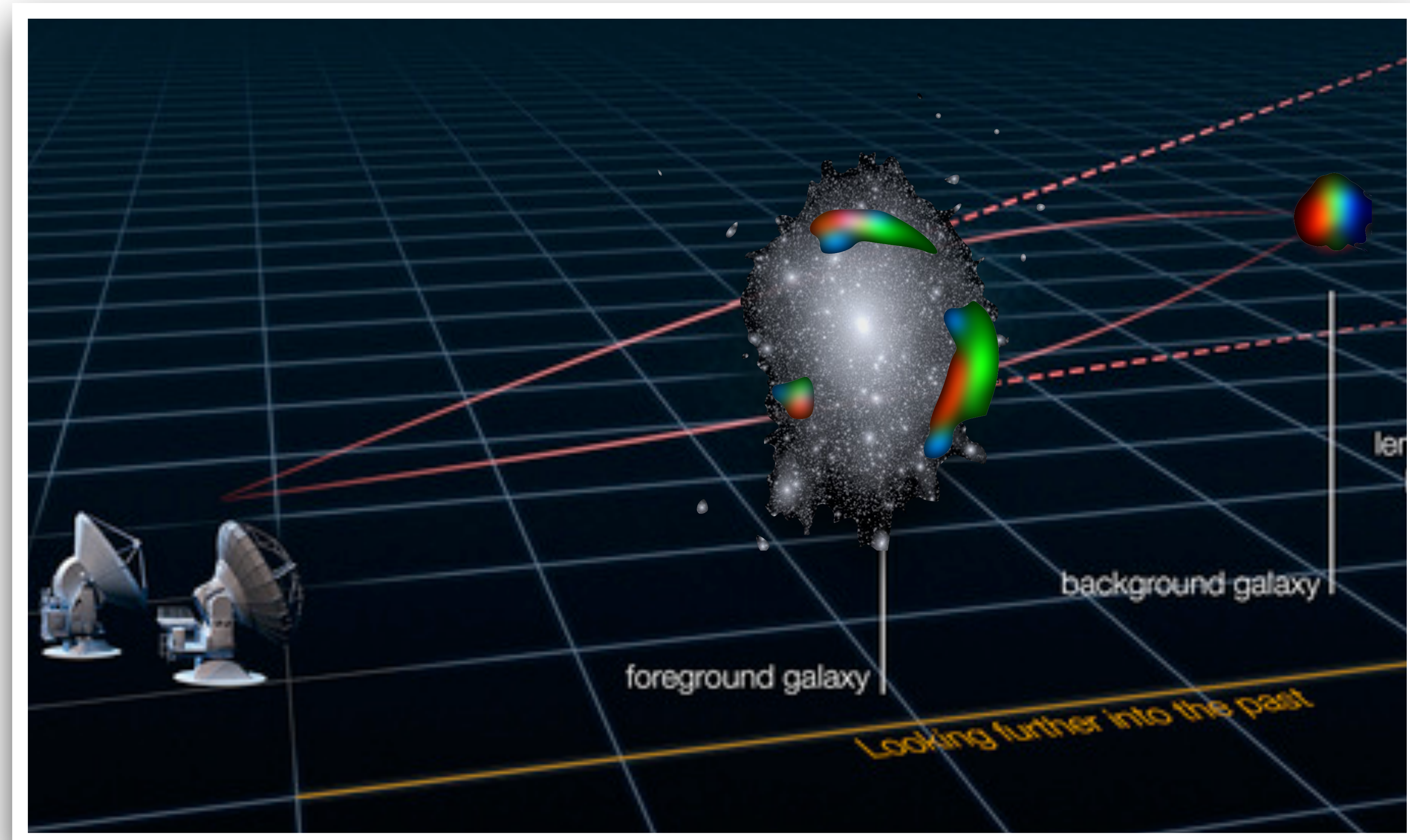
1 - Modify galaxy formation models

2 - Modify the dark matter model

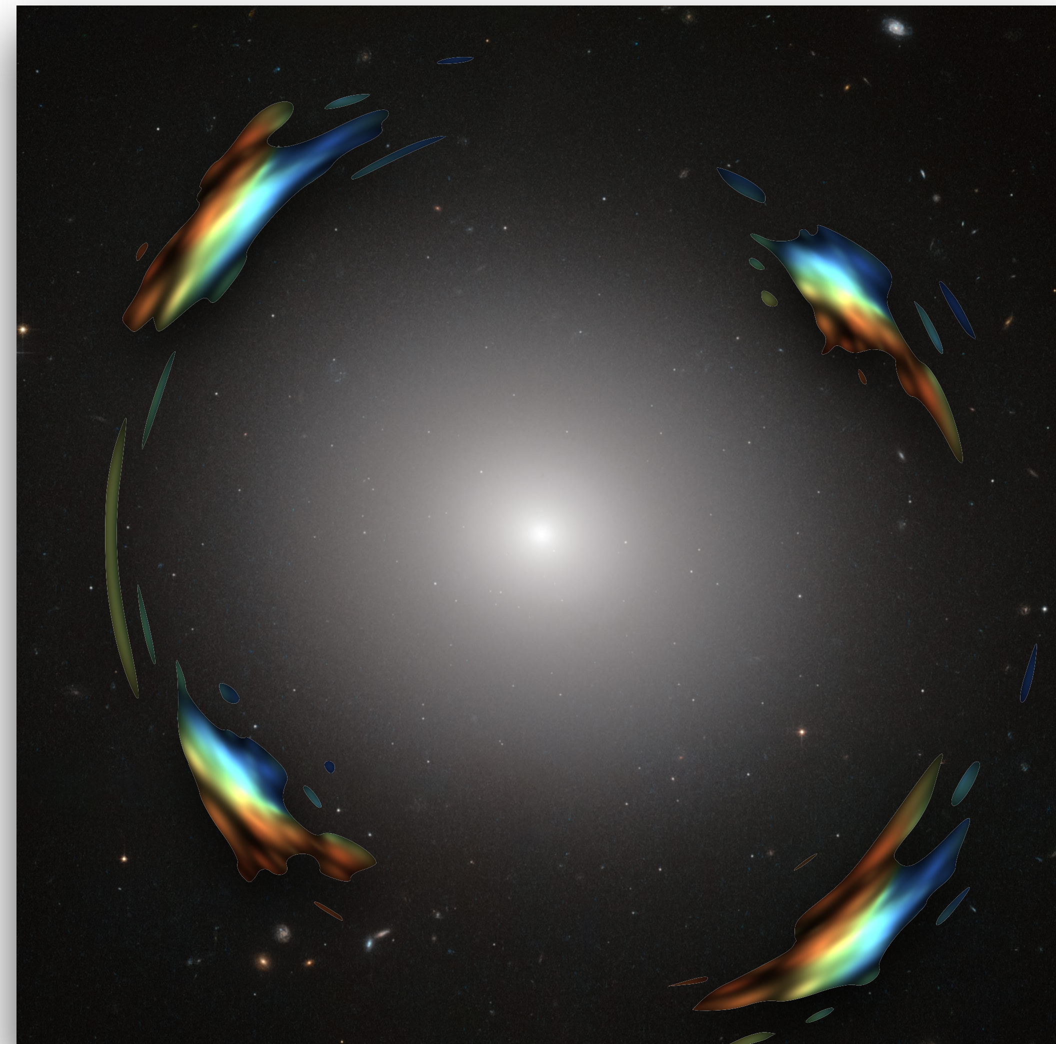


Lovell et al., MNRAS, 2012

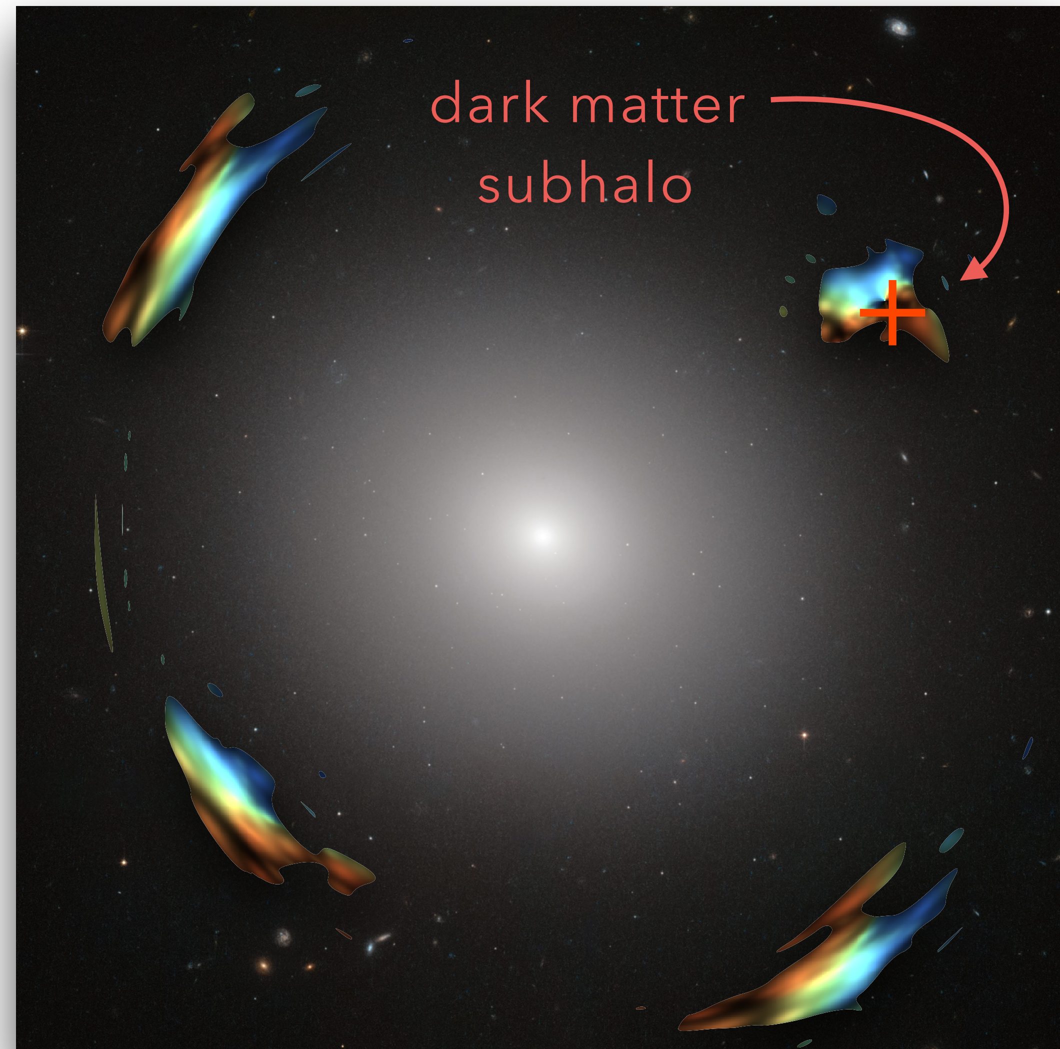
Strong Gravitational Lensing

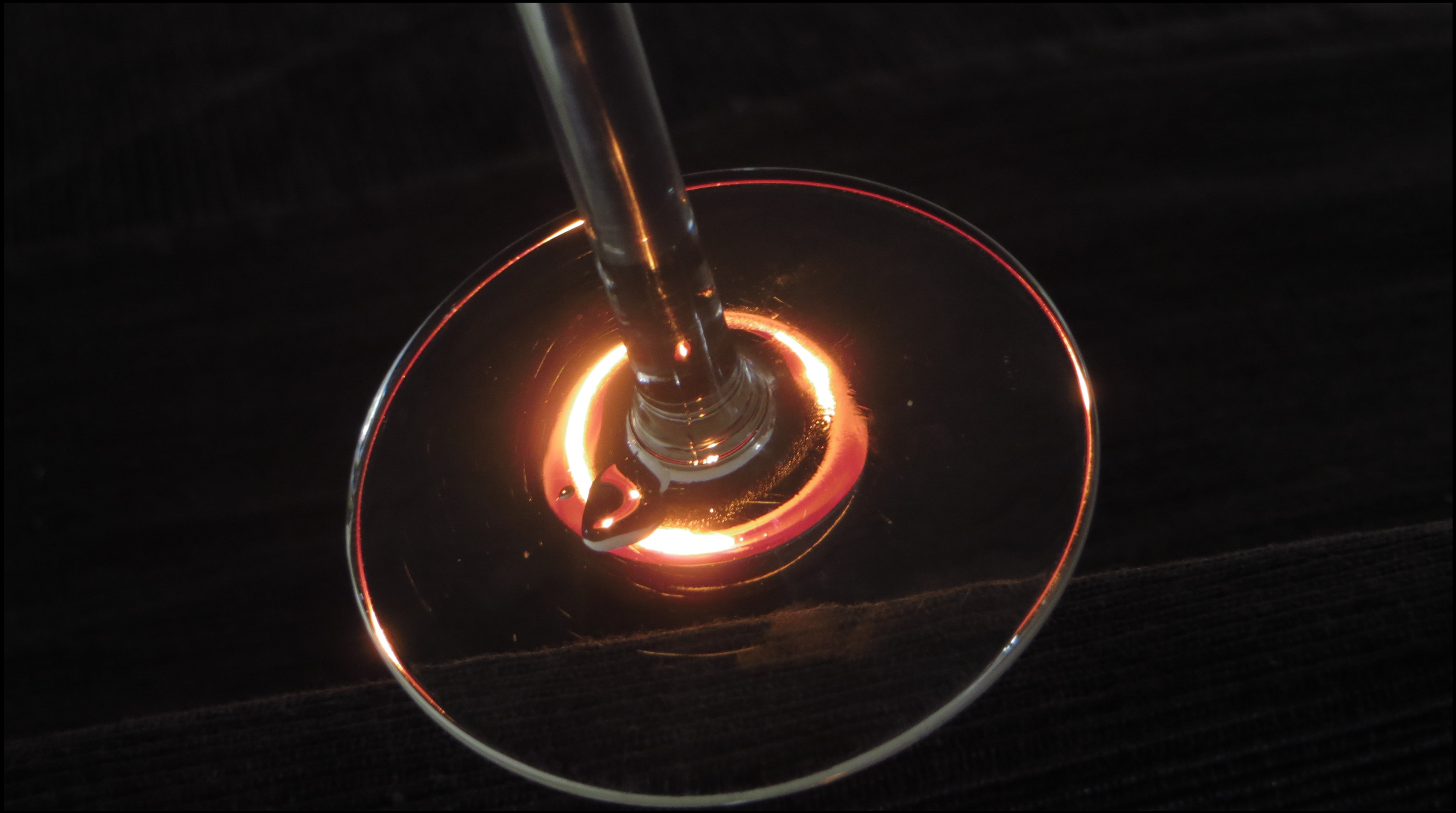


Substructure lensing



Substructure lensing



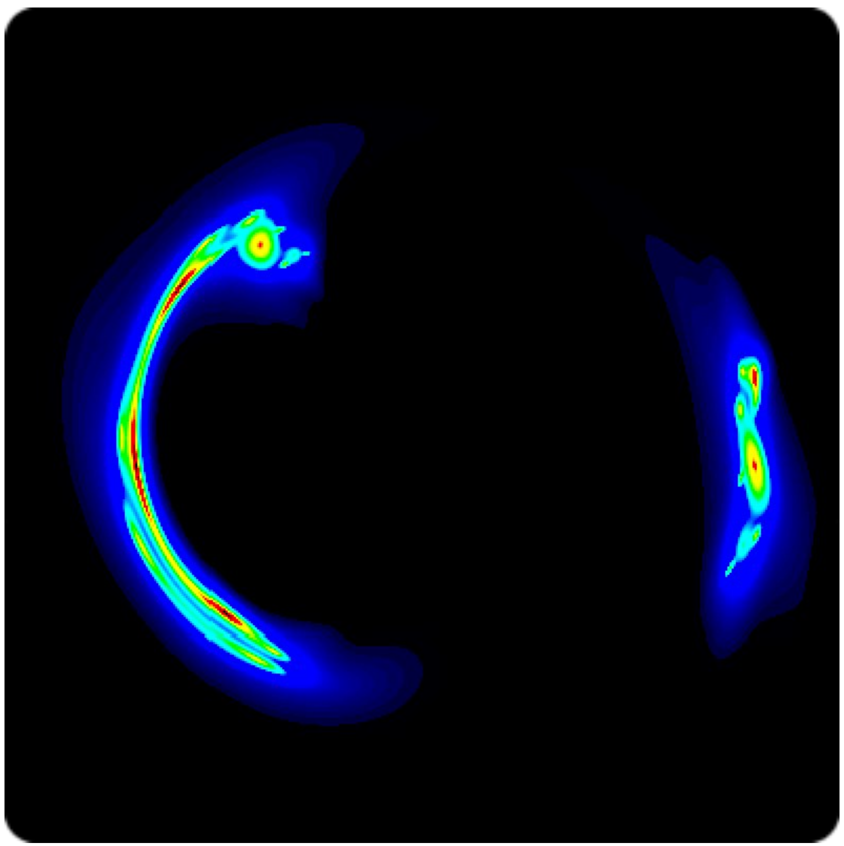


Spot the difference?

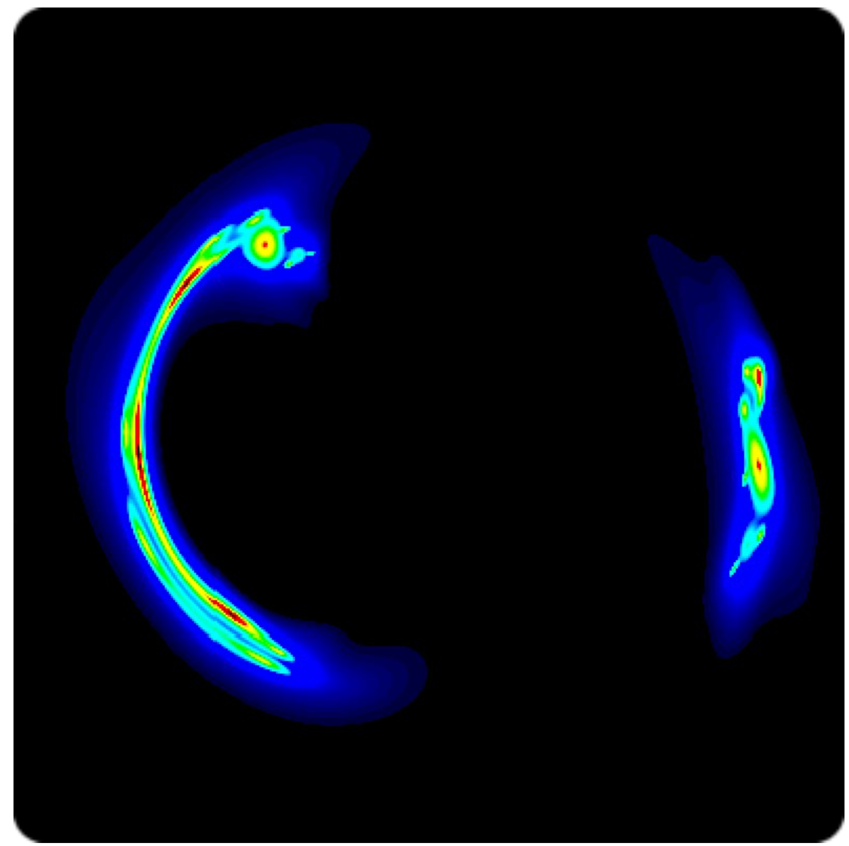
Main lensing galaxy mass ~ 10^{12} — 10^{13} M_{sun}

Subhalo masses ~ 10^{7} — 10^{9} M_{sun}

Smooth galaxy

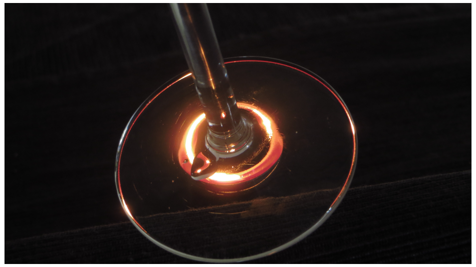


Smooth galaxy + subhalo



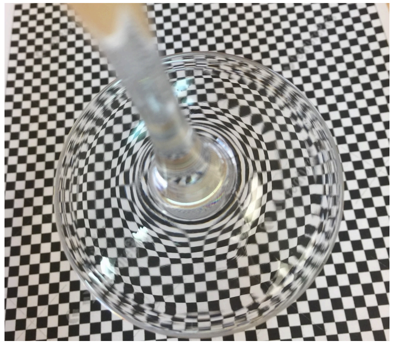
MEASURING PHYSICAL PROPERTIES FROM IMAGES OF STRONG LENSES

Physical properties that can be constrained from lensing images (**lensing parameters**):



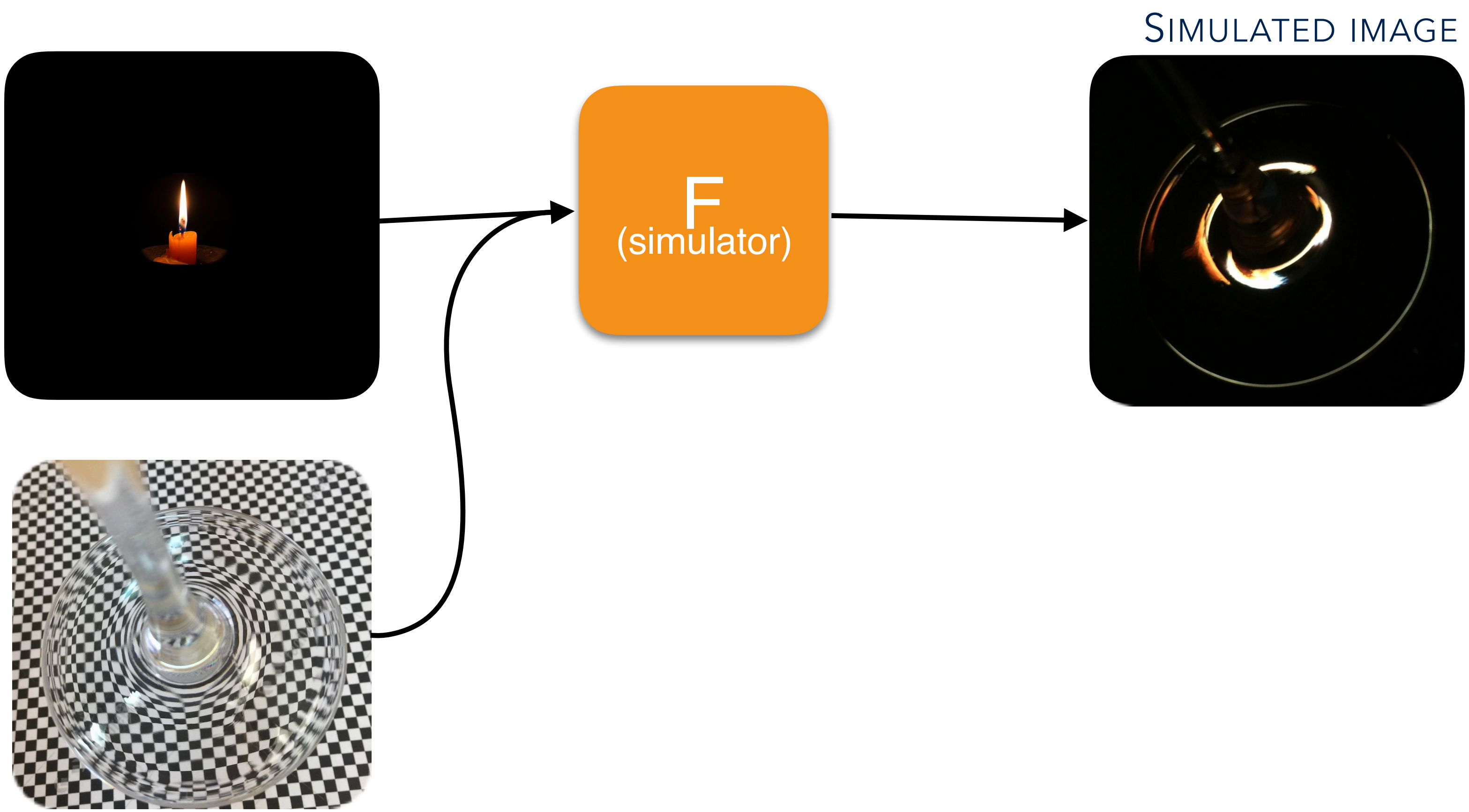
1: Morphology of the background source
(the true, undistorted image of the candle)

2: Matter distribution in the lens
(the shape of the wineglass)



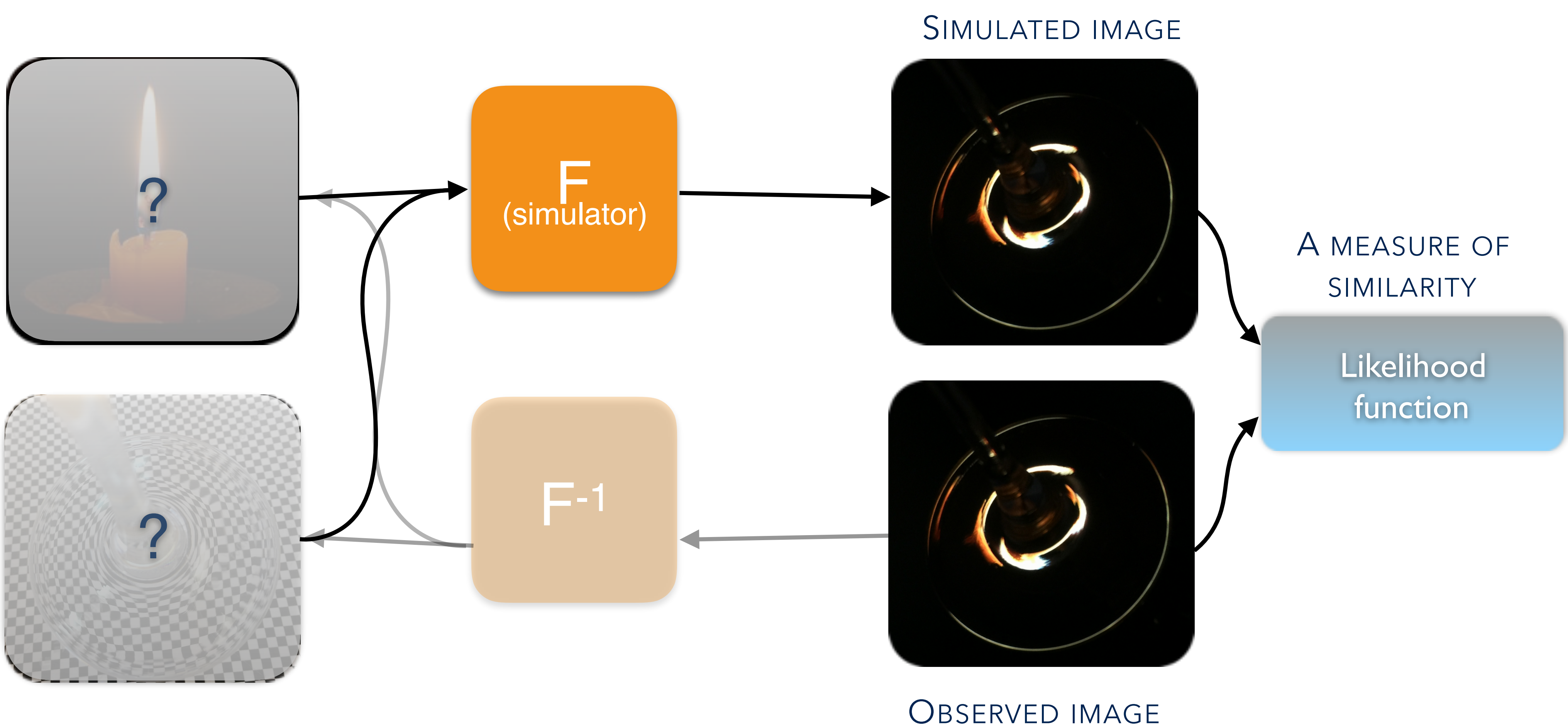
MEASURING PHYSICAL PROPERTIES FROM IMAGES OF STRONG LENSES

simulating lenses



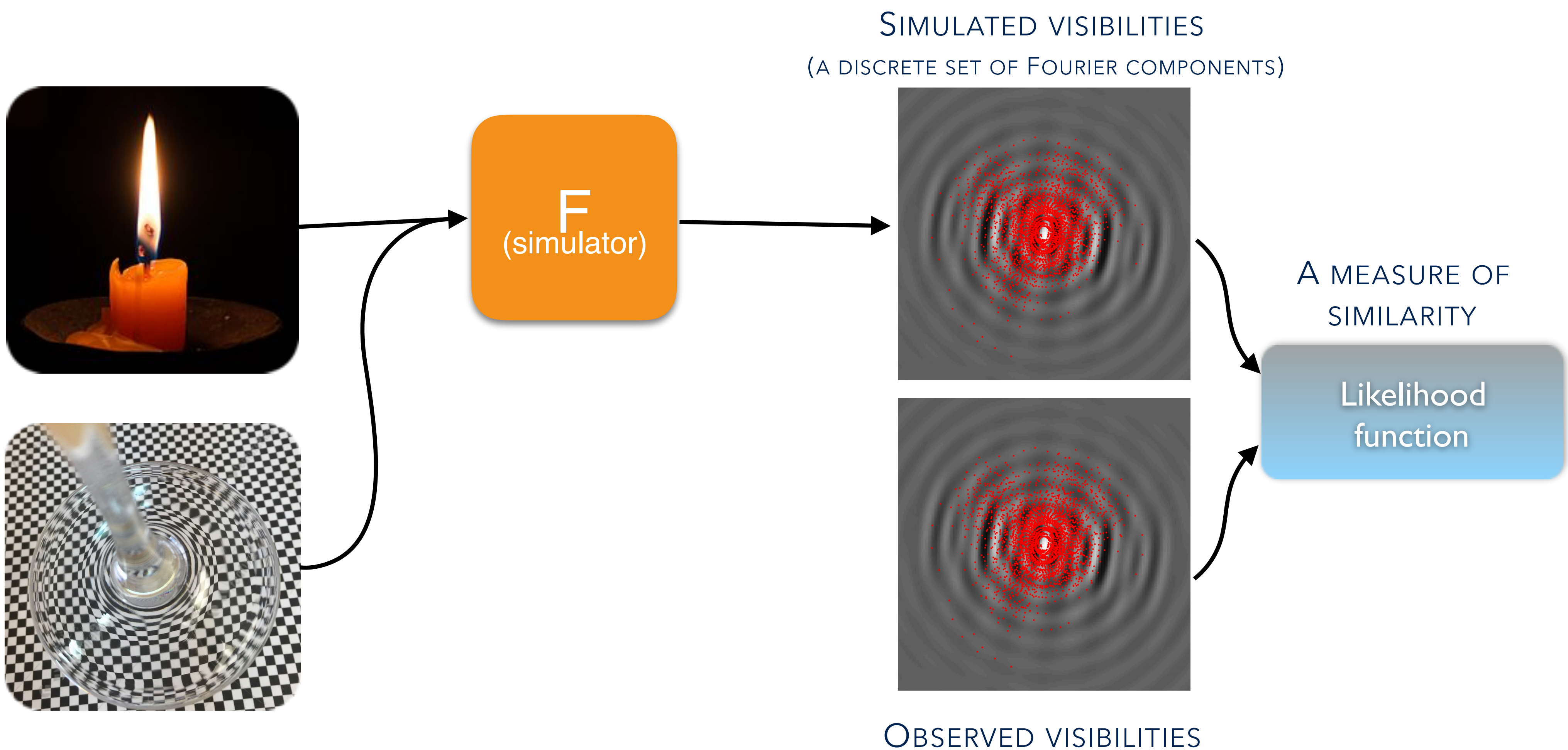
Measuring physical properties from images of strong lenses

maximum likelihood lens modeling



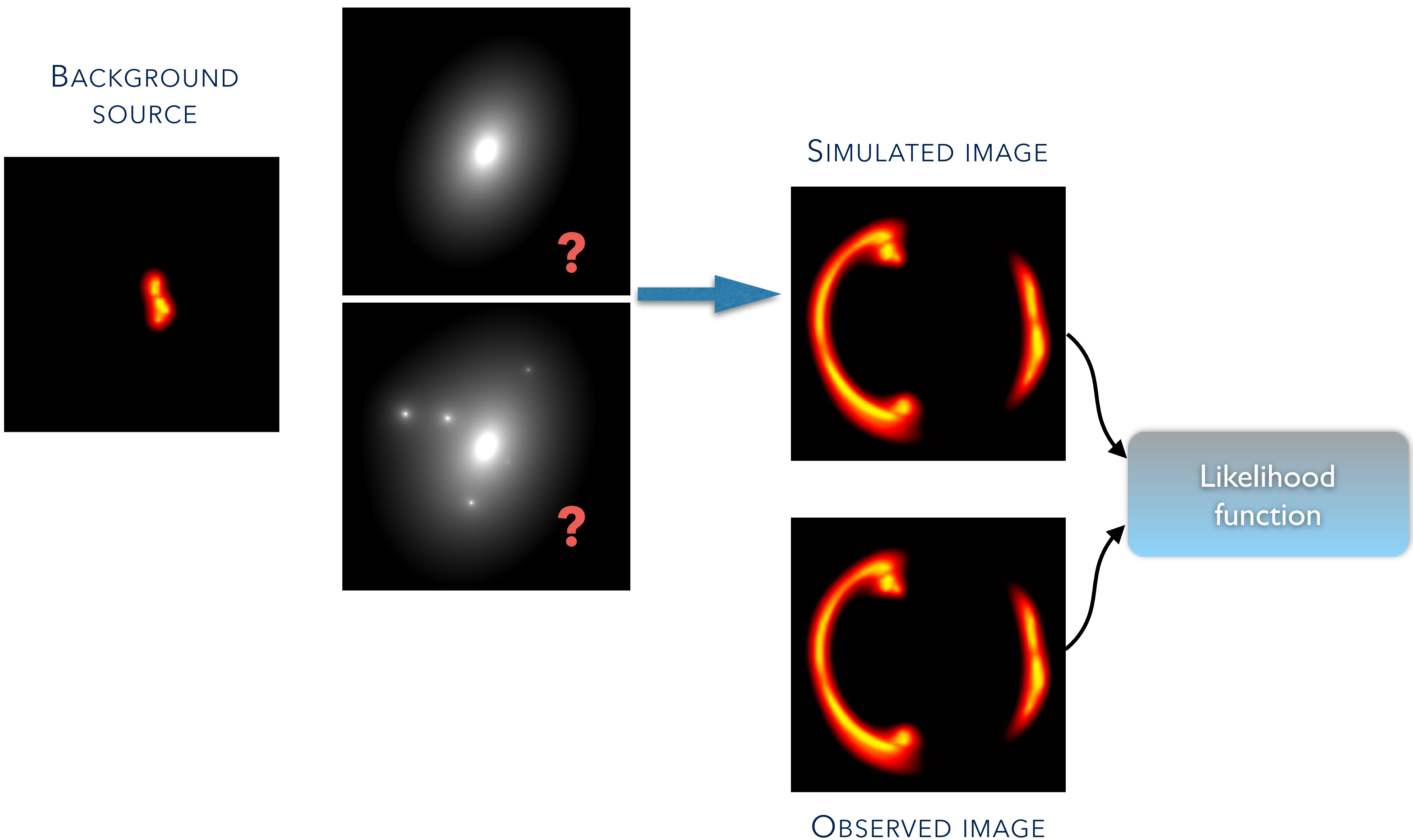
Measuring physical properties from images of strong lenses

maximum likelihood lens modeling



Subhalo detection:

Compare a smooth model with a model which includes subhalos



LENS MODELING PIPELINE

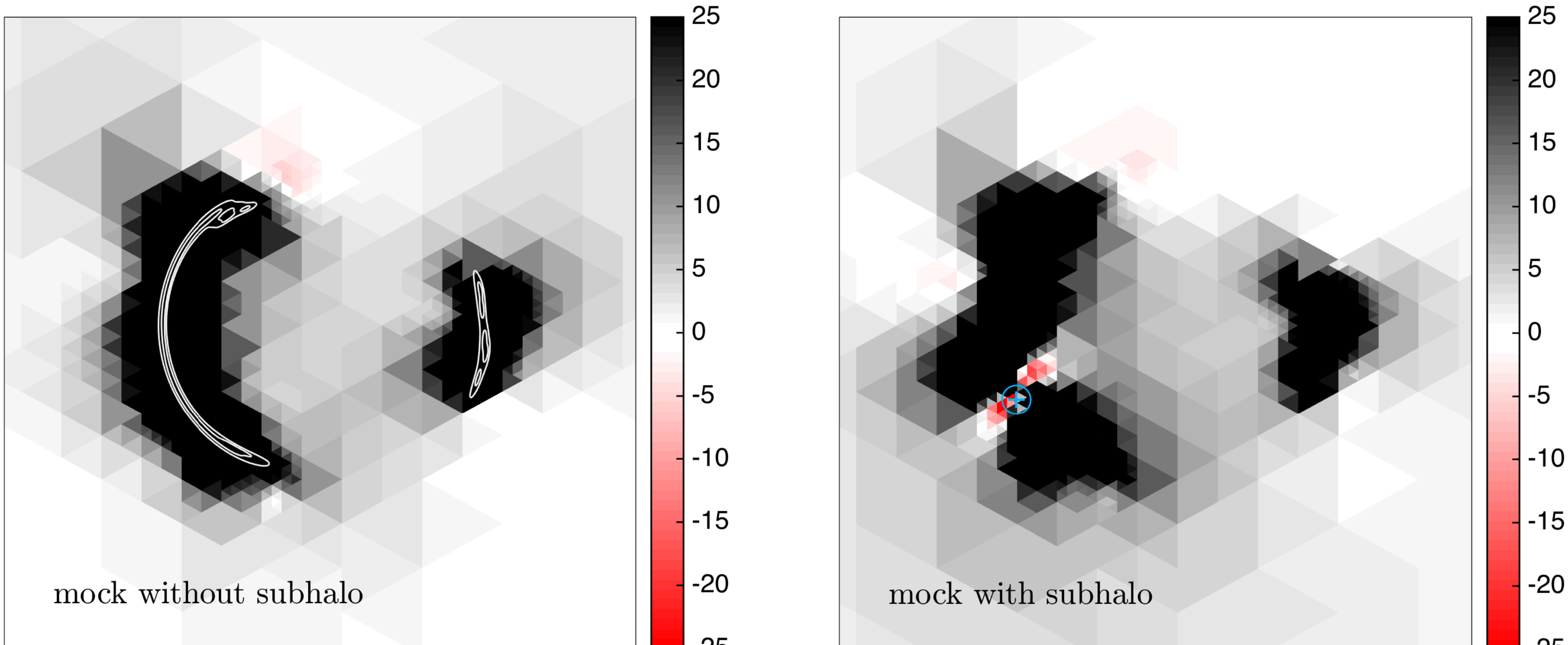
Problem:

- Millions of visibilities.
- Tens of thousands of parameters.
- Dense linear algebra operations on terabyte-sized matrices.

Solution:

- Ripples: Distributed computations with MPI on thousands of cores.
- Extensively tested on simulated data.

PROBABILITY OF THE PRESENCE OF A SUBHALO



Greyscale: difference in log posterior between a model which includes a subhalo and a smooth model (no subhalos)

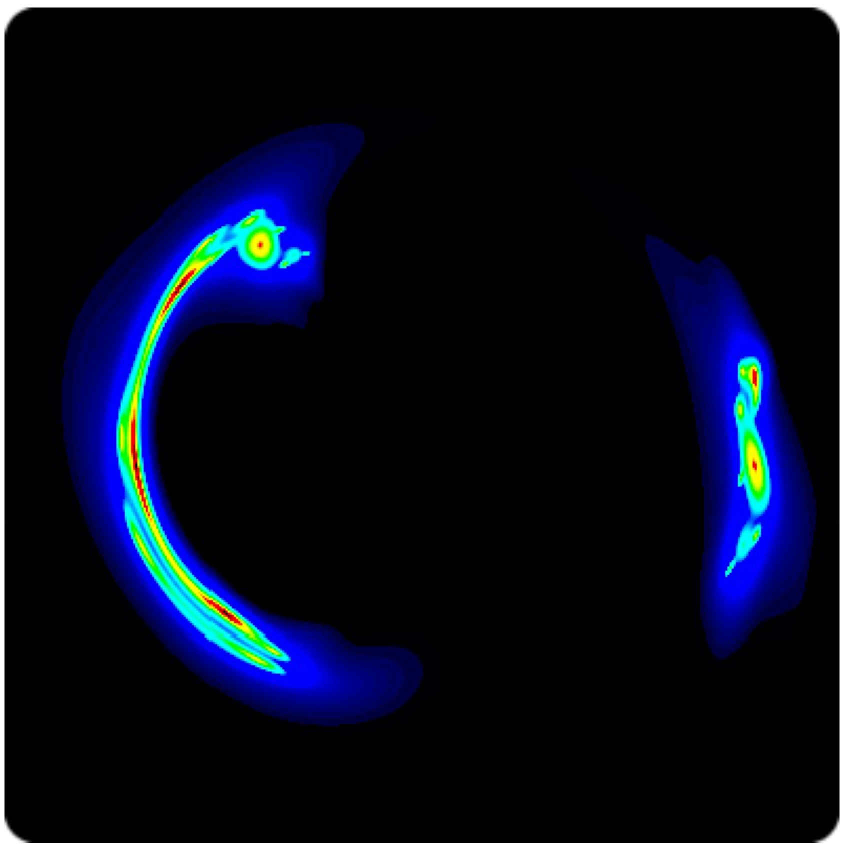
Hezaveh et al. ApJ 2016

Simulated images with and without a subhalo

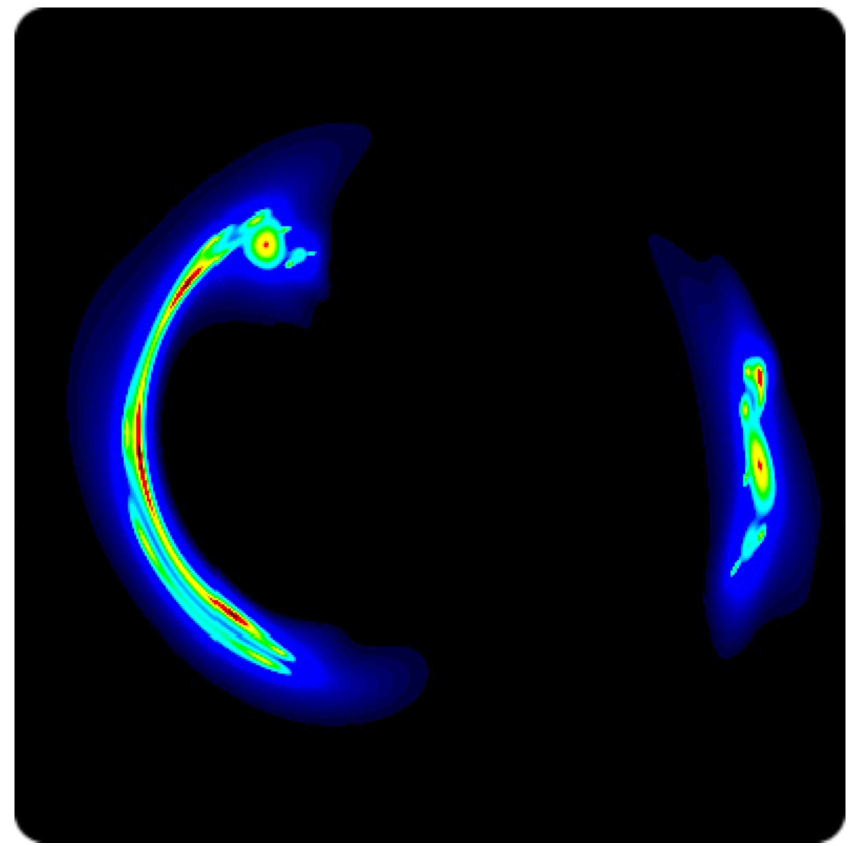
Main lensing galaxy mass ~ 10^{12} M_{sun}

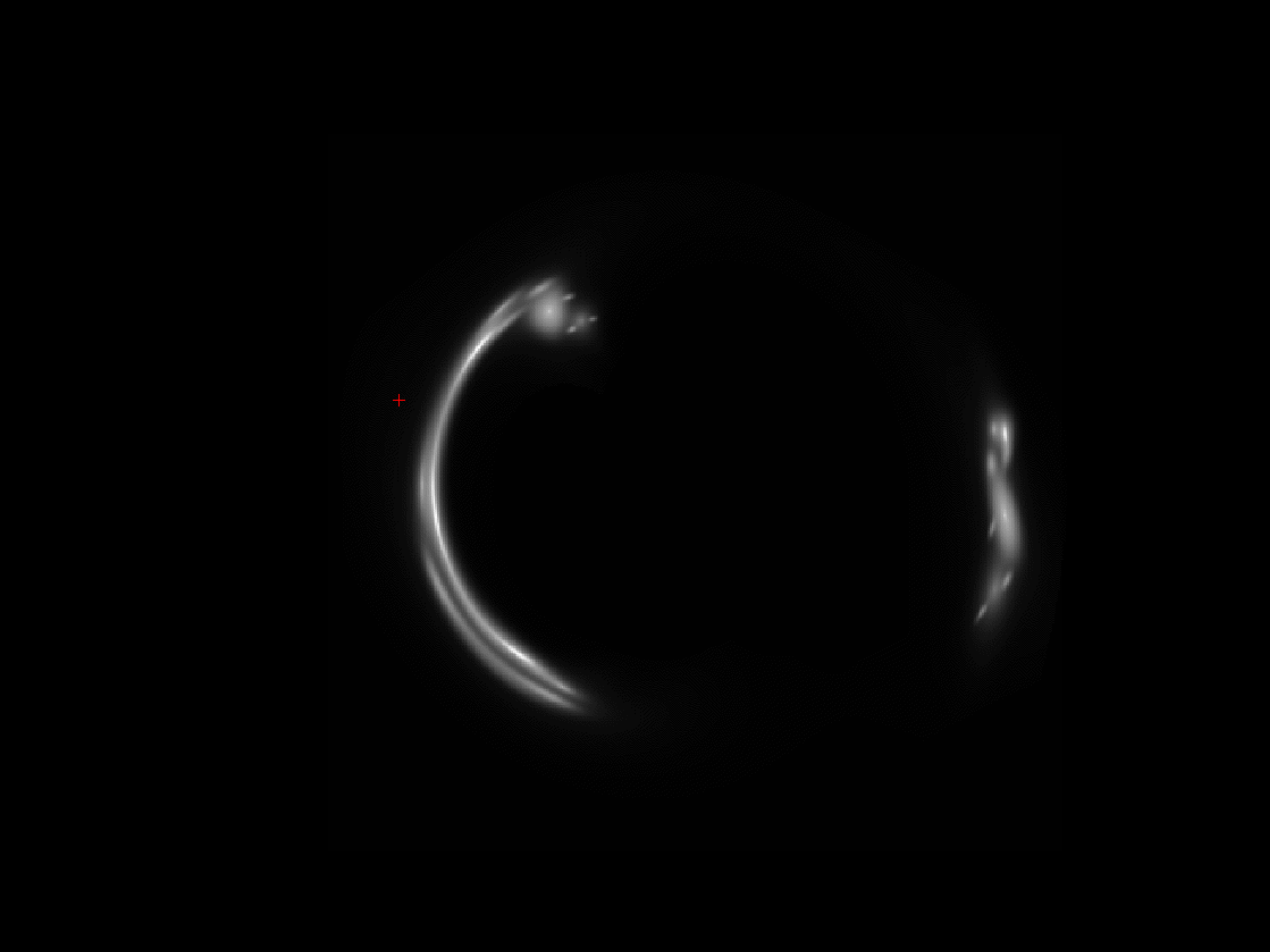
Subhalo masses ~ 10^{7}—10^{9} M_{sun}

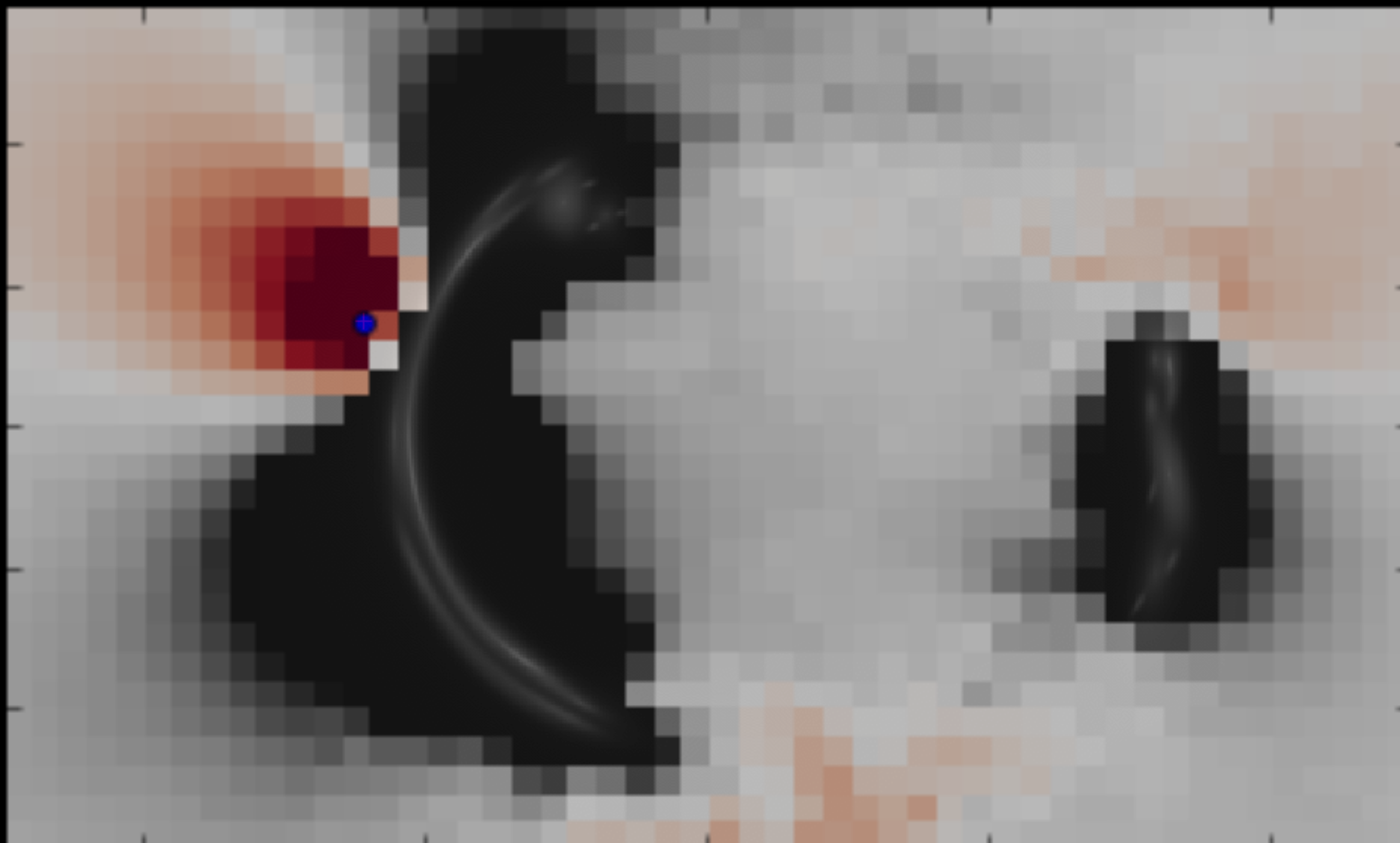
Smooth galaxy



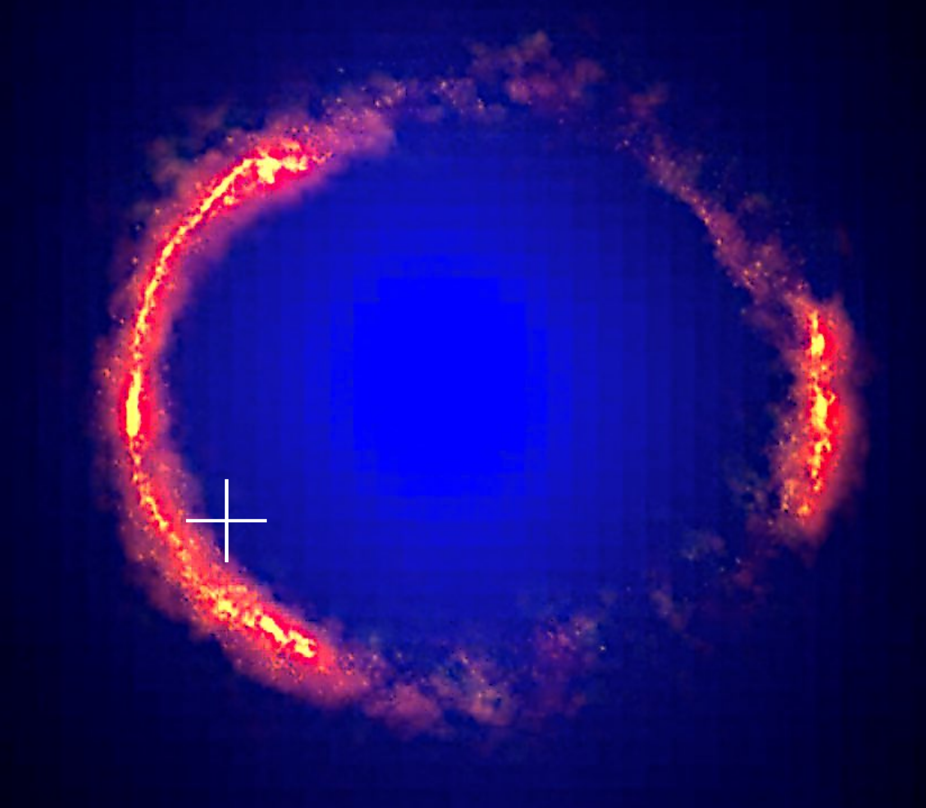
Smooth galaxy + subhalo





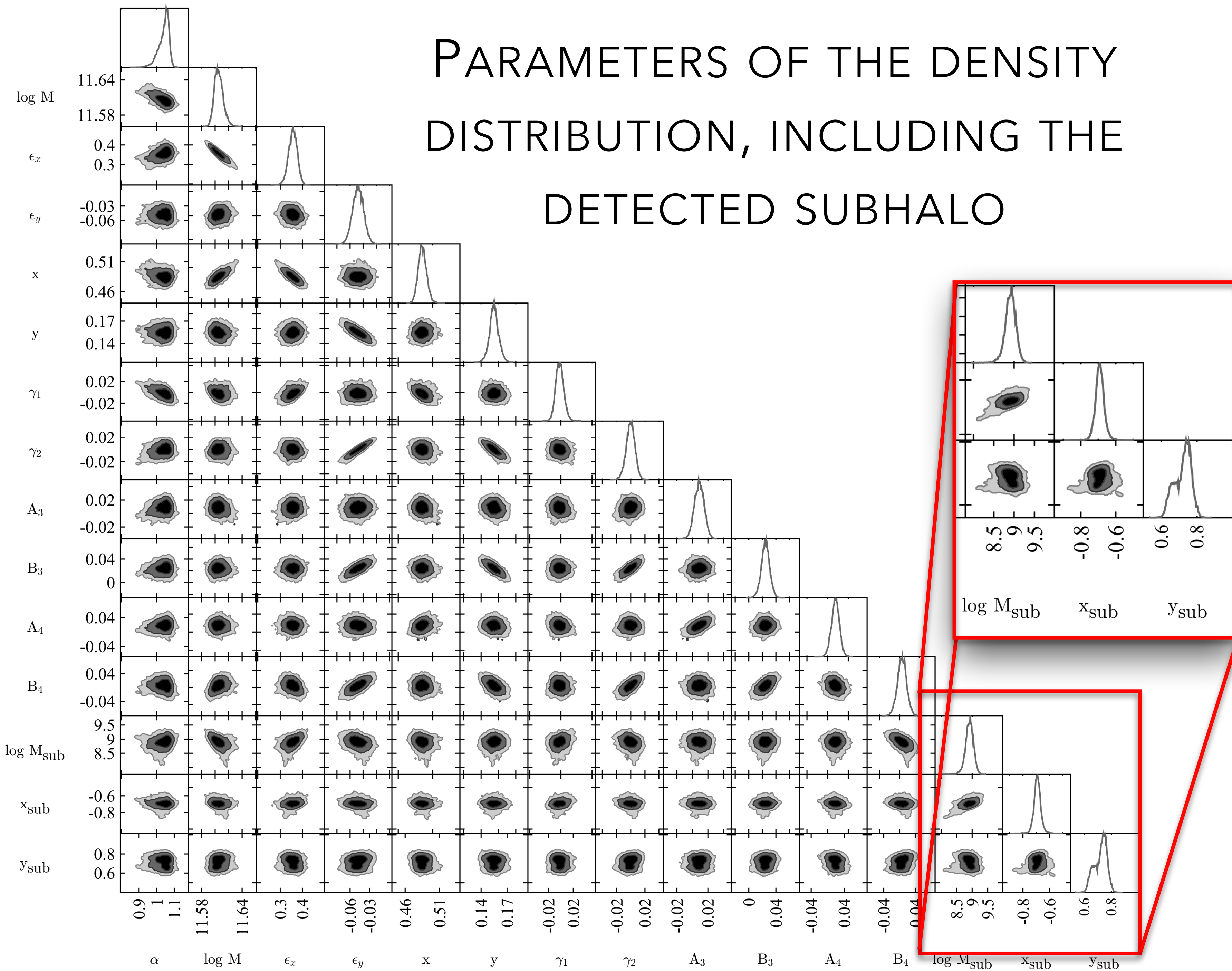


Detection of a 10^9 M_{sun} subhalo in SDP.81



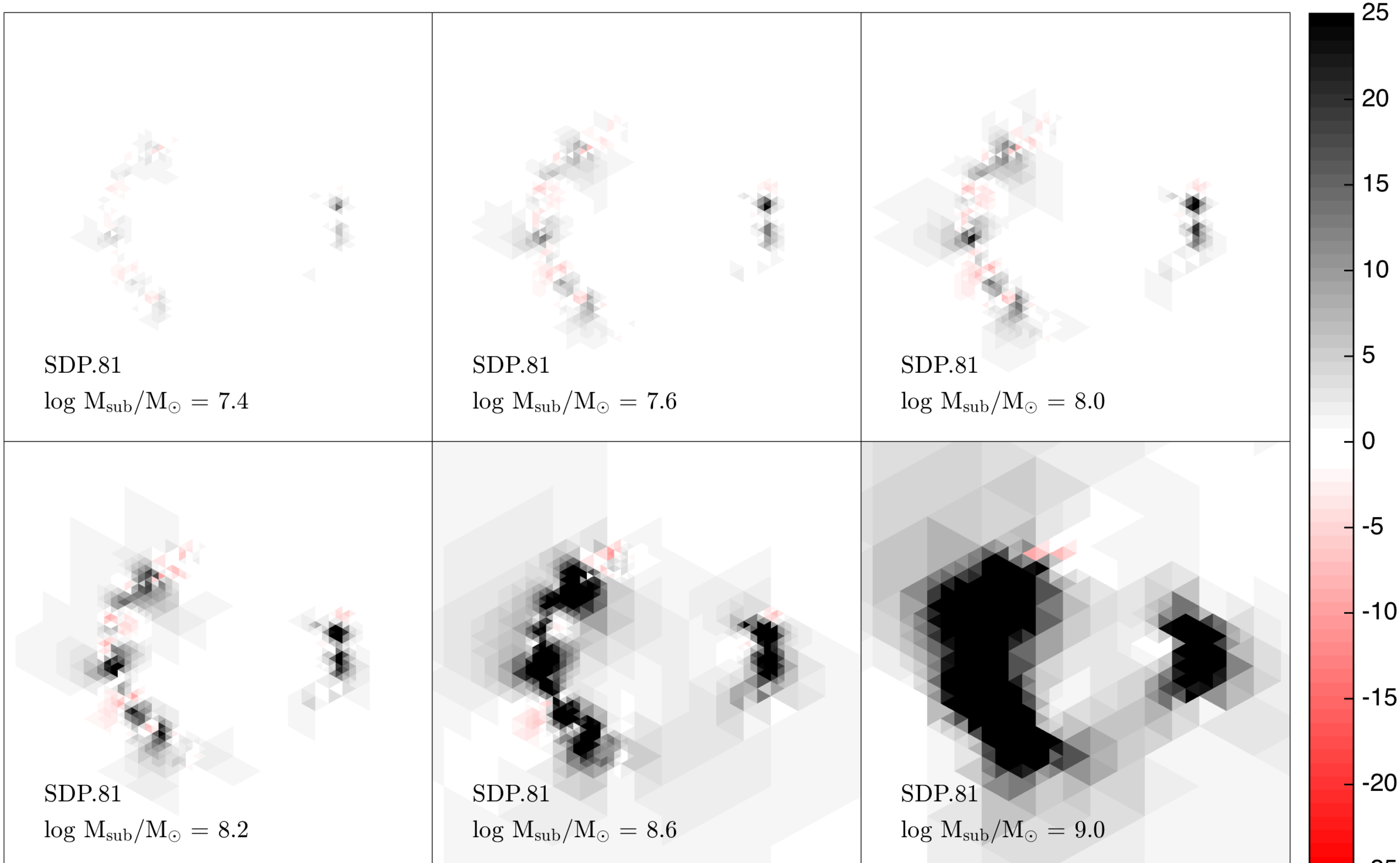
Hezaveh et al. ApJ 2016

PARAMETERS OF THE DENSITY DISTRIBUTION, INCLUDING THE DETECTED SUBHALO



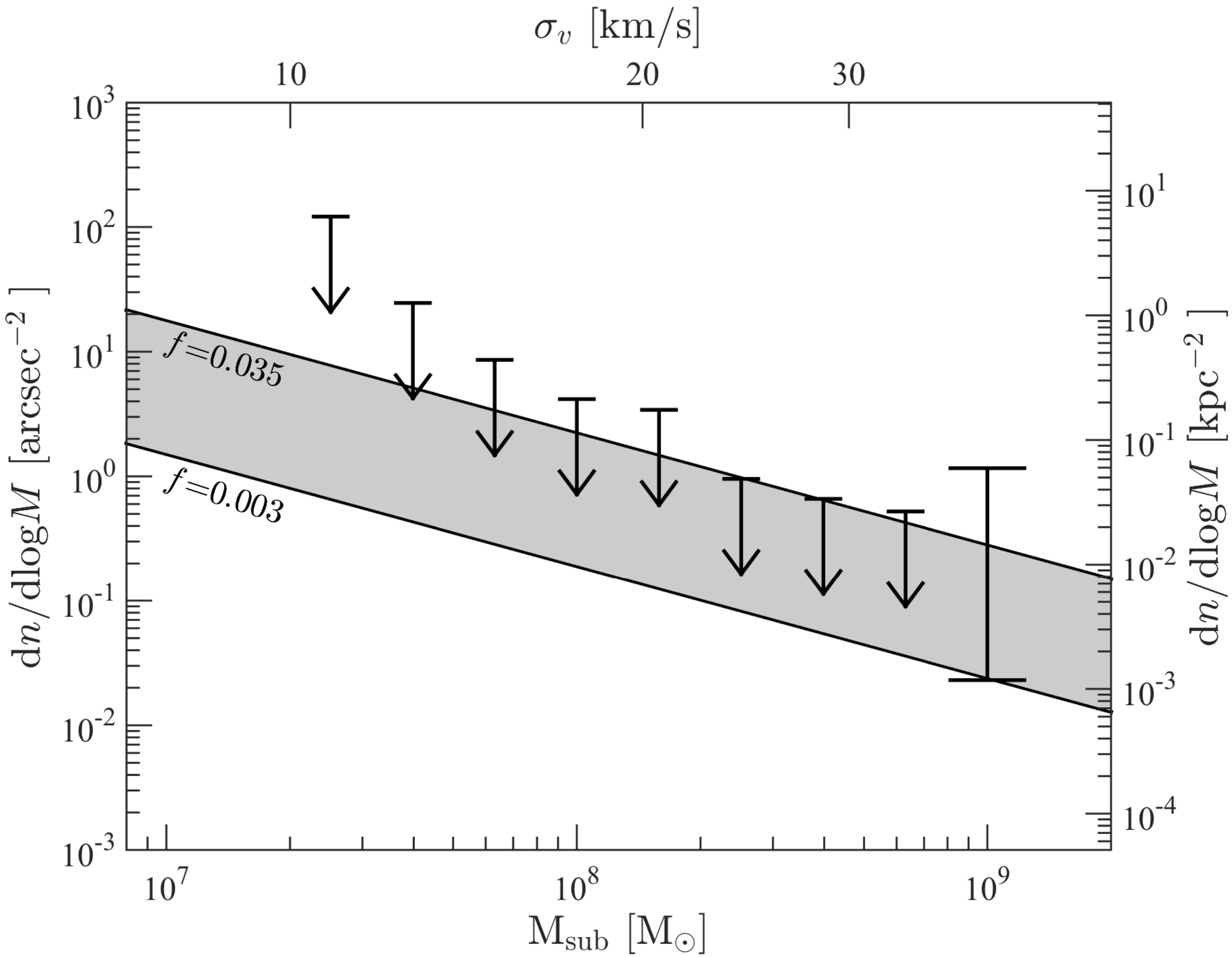
Hezaveh et al. ApJ 2016

EXCLUSION MAPS FOR OTHER SUBHALOS



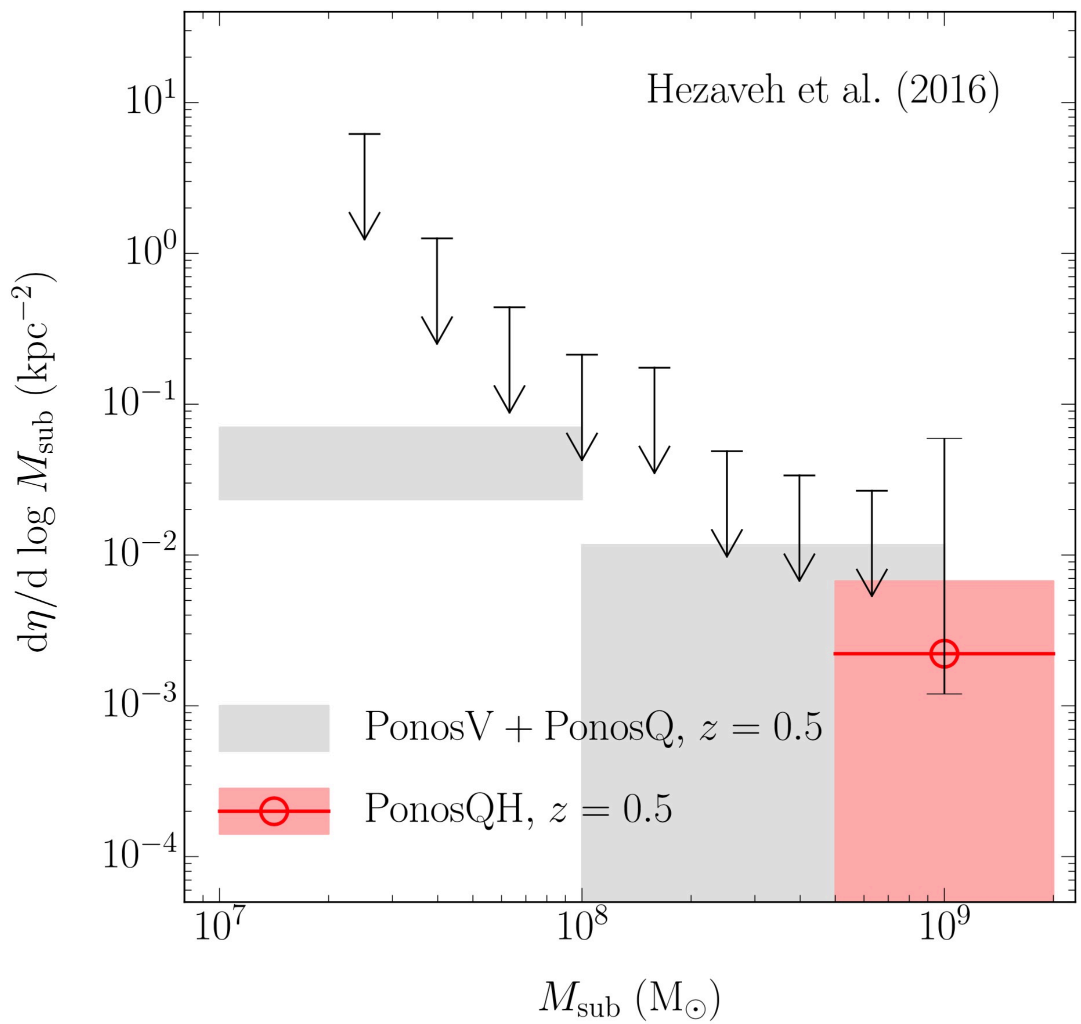
Hezaveh et al. ApJ 2016

Constraints on the mass function of subhalos in the host halo



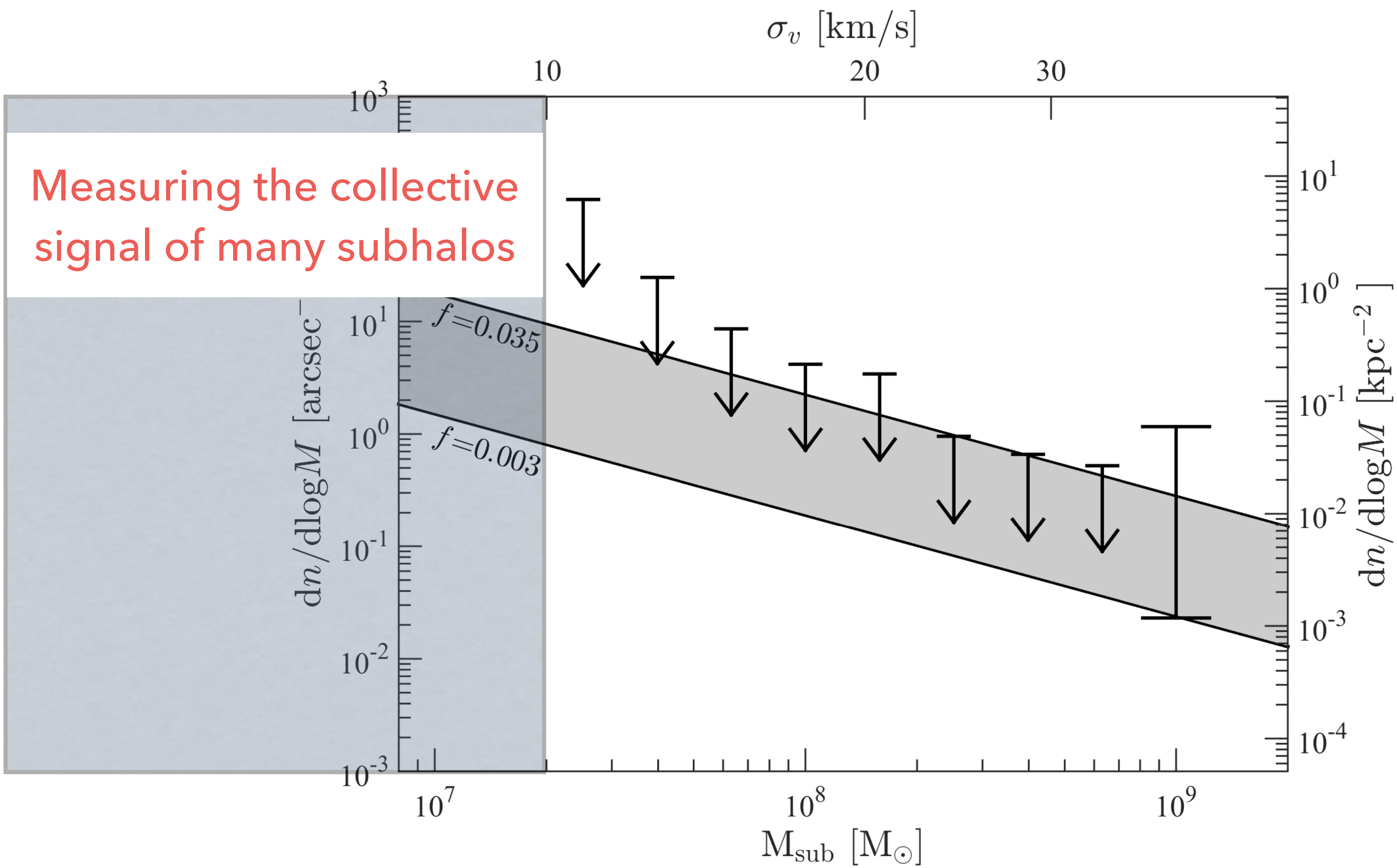
Hezaveh et al. ApJ 2016

Comparison to theoretical predictions



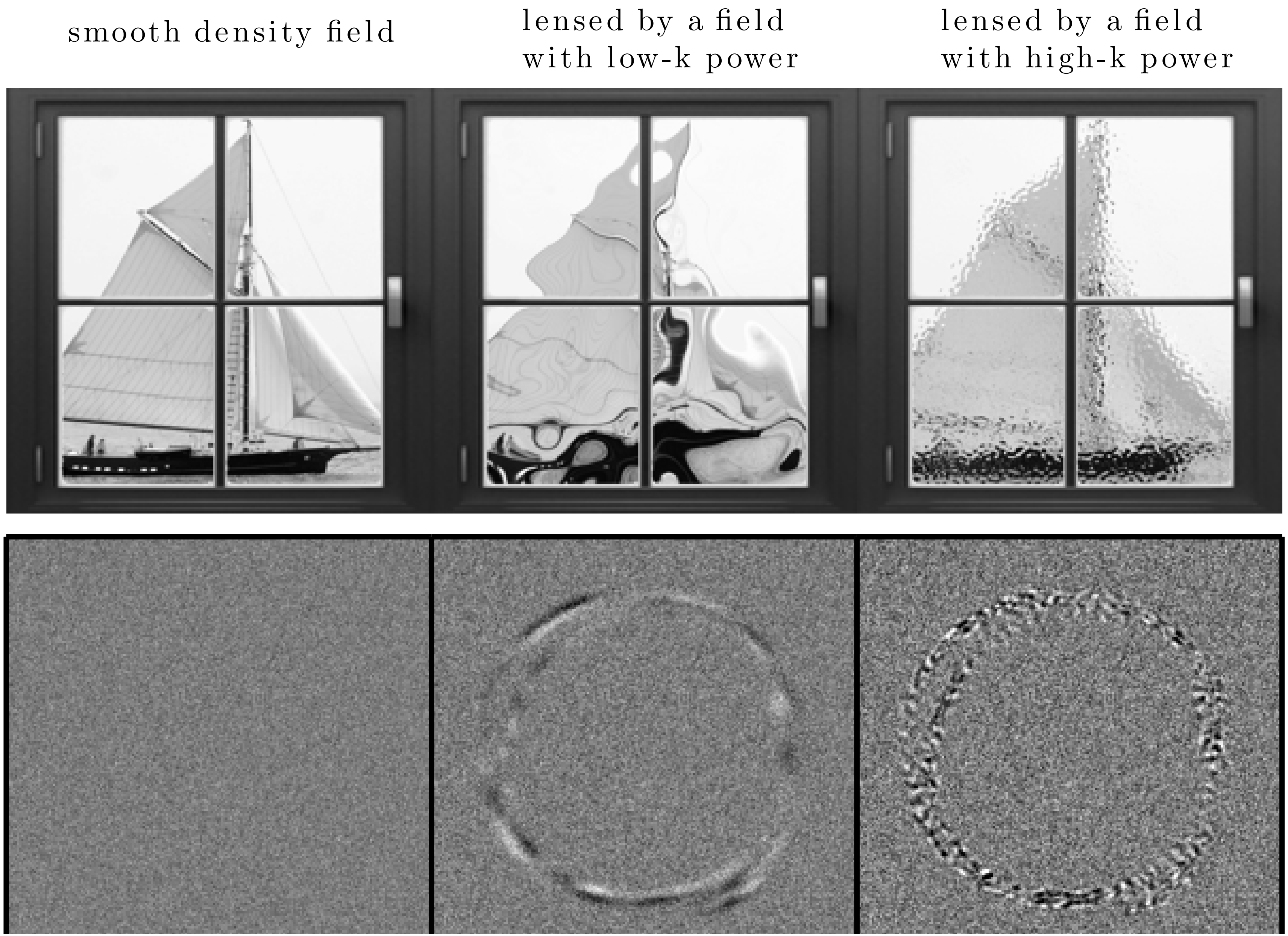
Fiacconi, Madau et al. ApJ, 2016

HOW TO IMPROVE OUR CONSTRAINTS



Hezaveh et al. ApJ 2016

Surface brightness correlations



Surface brightness correlations => power spectrum of the density field

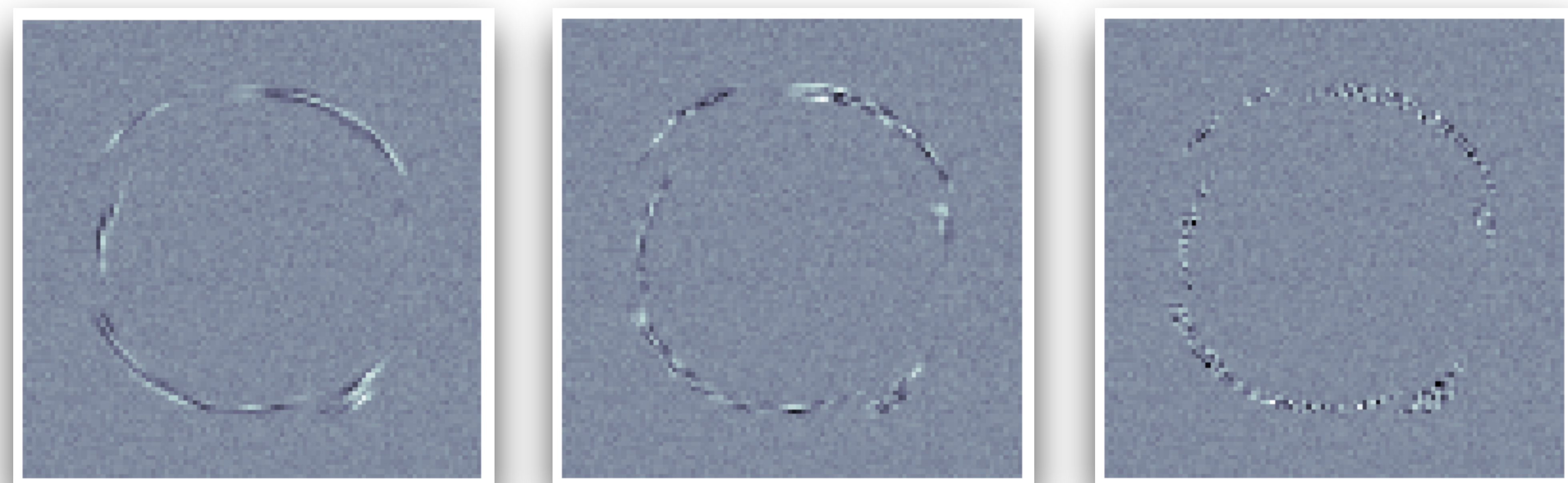
Covariance of deflections

Power spectrum of the density field

$$\mathbf{C}_\alpha = \langle \alpha_i(\vec{x})\,\alpha_j(\vec{x}+\vec{r})\rangle = 4\int P(k)\left(\frac{\delta_{ij}}{k^2 r}J_1(kr) - \frac{r_i r_j}{k r^2}J_2(kr)\right)dk$$

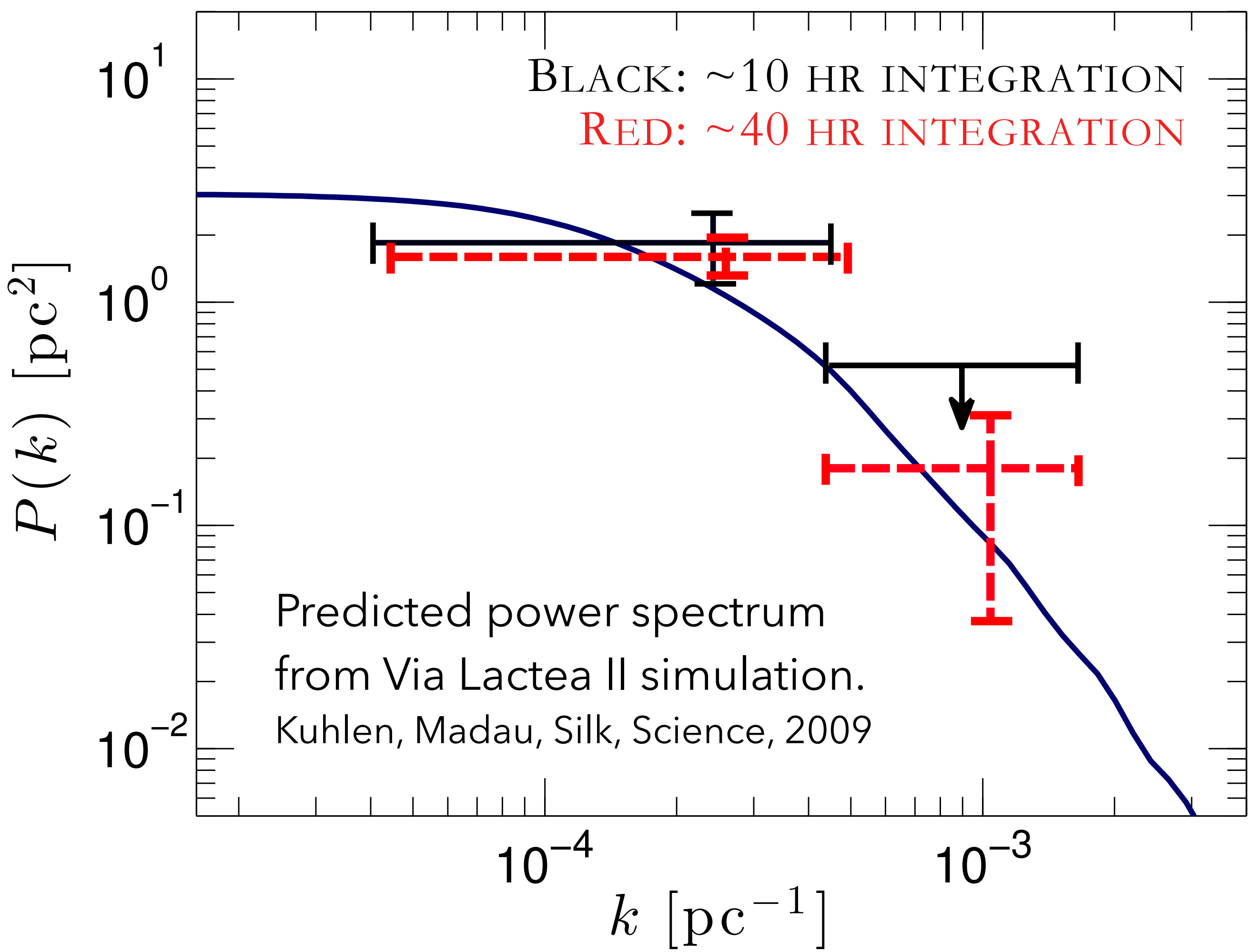
Likelihood

$$\mathcal{L}(C_\alpha) = (|C_N|\,|C_\alpha|\,|C_p||M|)^{-1/2} e^{\frac{1}{2}B^T\,M\,B}\quad e^{-\frac{1}{2}(\boldsymbol{\Delta O}^T C_N^{-1}\boldsymbol{\Delta O}+\boldsymbol{p}_0 C_p^{-1}\boldsymbol{p}_0)}$$



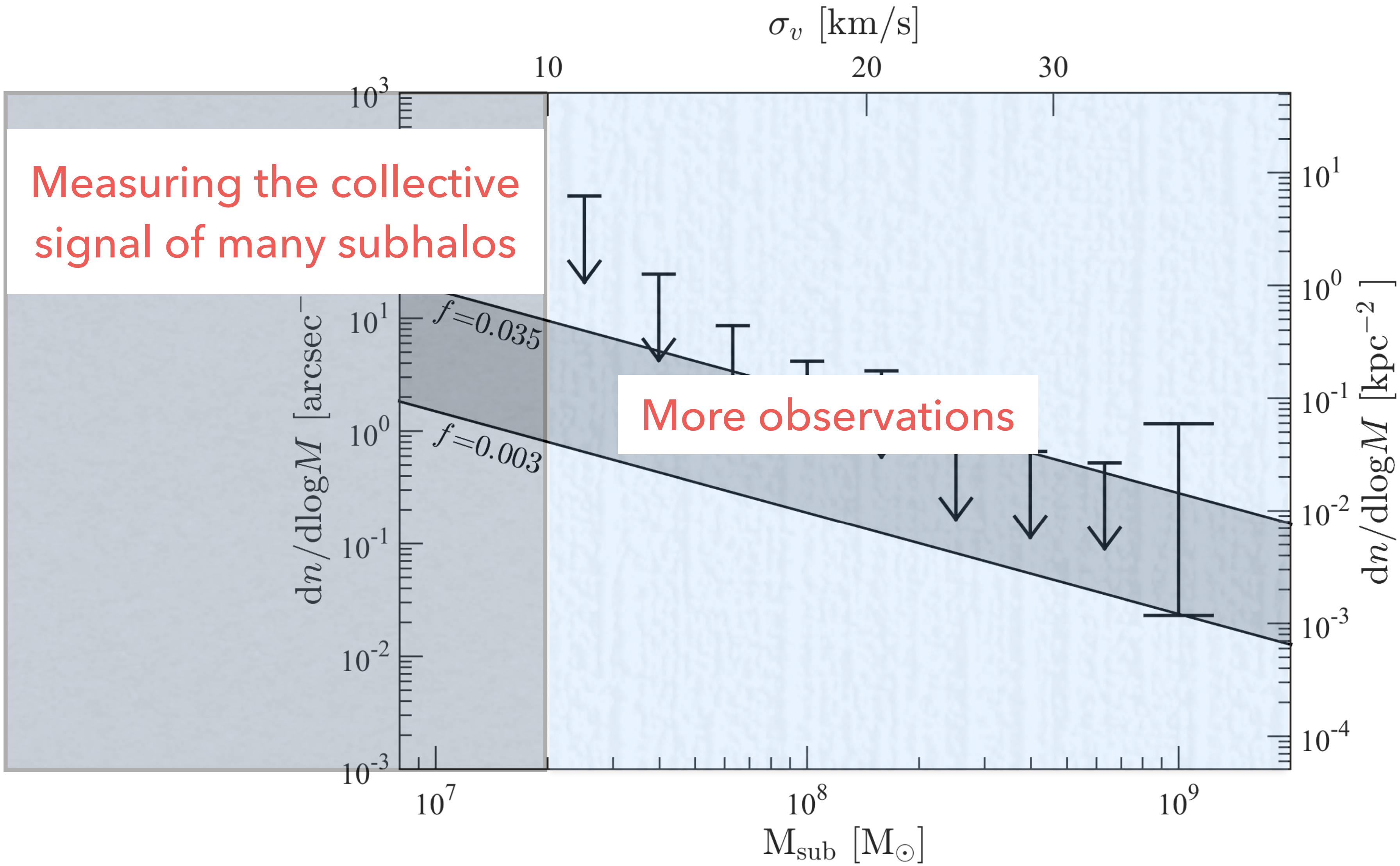
Hezaveh et al., JCAP, 2016

Forecast for measuring the DM subhalo Power Spectrum with ALMA



Hezaveh et al., JCAP, 2016

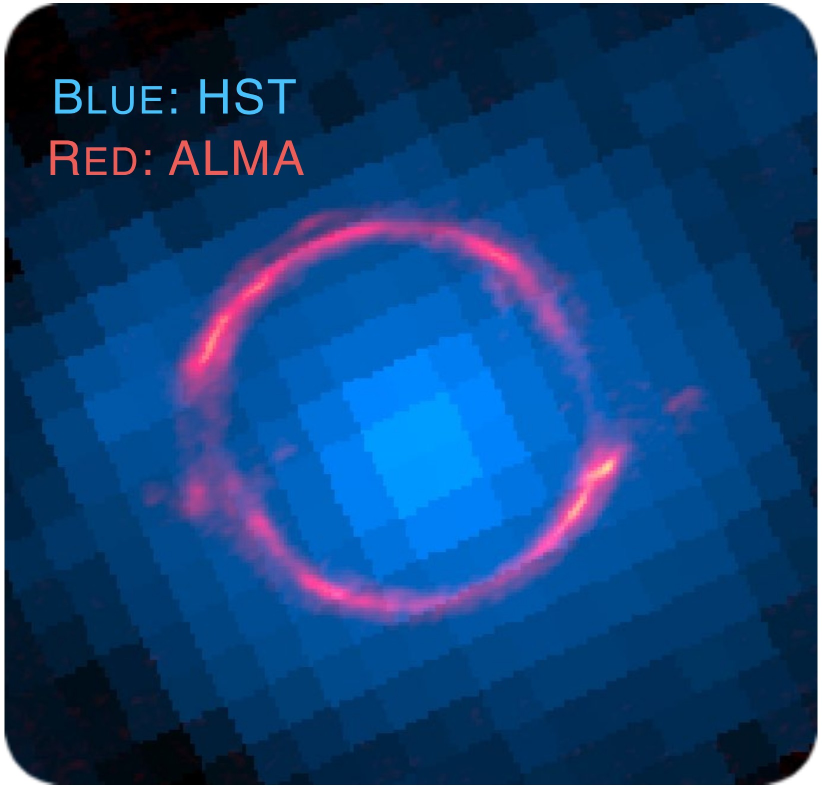
How to improve our constraints



Hezaveh et al. ApJ 2016

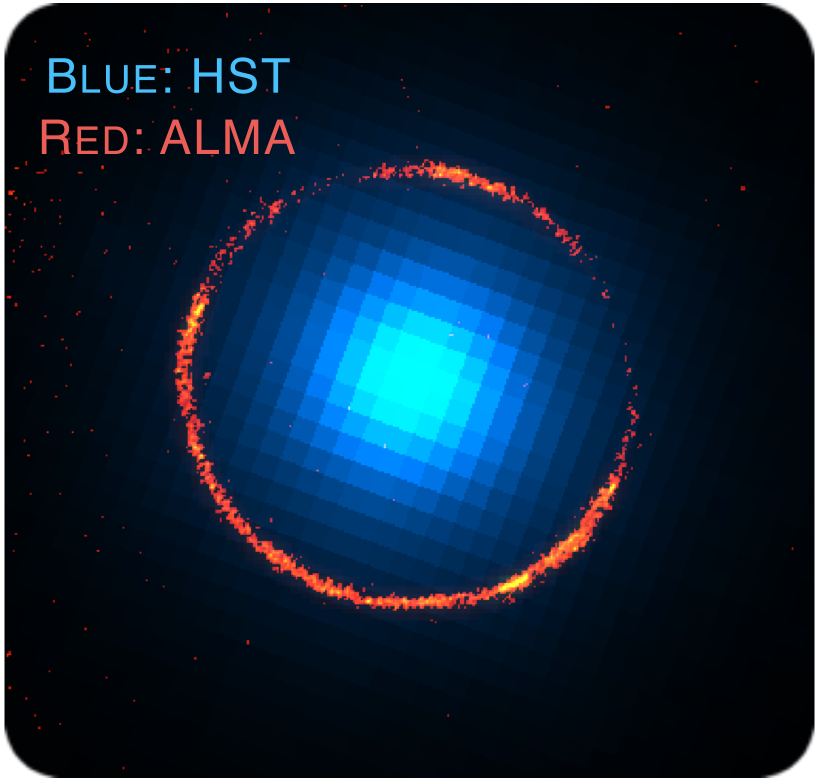
SPT 0532

0.025 ARCSEC RESOLUTION (2018)



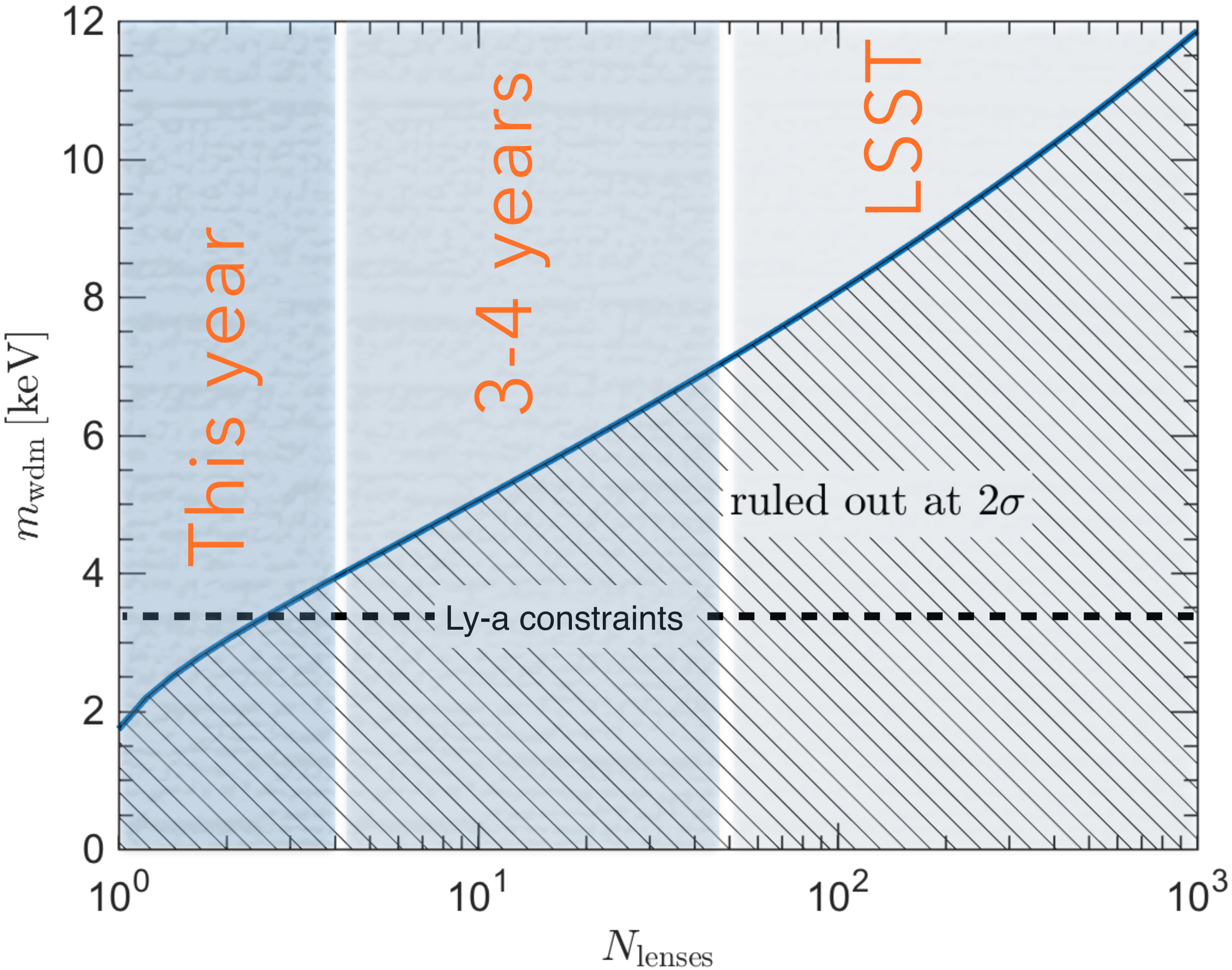
SPT 0418

0.025 ARCSEC RESOLUTION (2018)



12 hours with JWST in ERS

Forecasts for N lenses



Looking into the future

1- New Lenses

2- New Telescopes

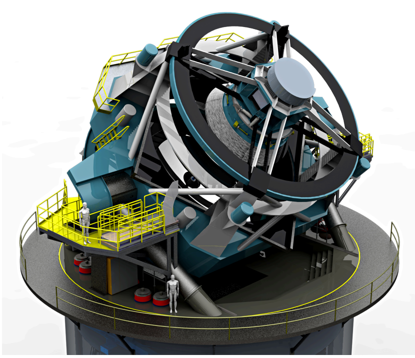
3- New Analysis Methods

Looking into the future:

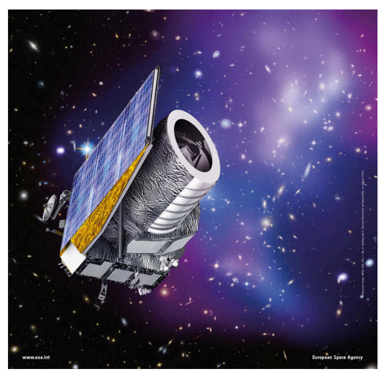
1- New Lenses

For future surveys we find that, assuming Poisson limited lens galaxy subtraction, searches of the DES, LSST, and Euclid data sets should discover **2400**, **120000**, and **170000** galaxy–galaxy strong lenses, respectively

Collett, ApJ. 2015



LSST



Euclid consortium

WIDE-FIELD INFRARED SURVEY TELESCOPE
WFIRST
ASTROPHYSICS • DARK ENERGY • EXOPLANETS

WHY DO WE NEED SO MANY LENSES?

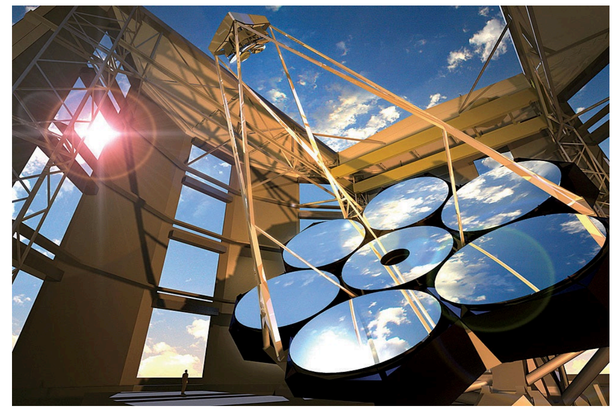
1- Statistical precision from the analysis of a large population.

2- Finding rare systems:
- Lensed supernovae
- Double-plane lenses
- Lensing systems at extreme redshifts

Looking into the future:

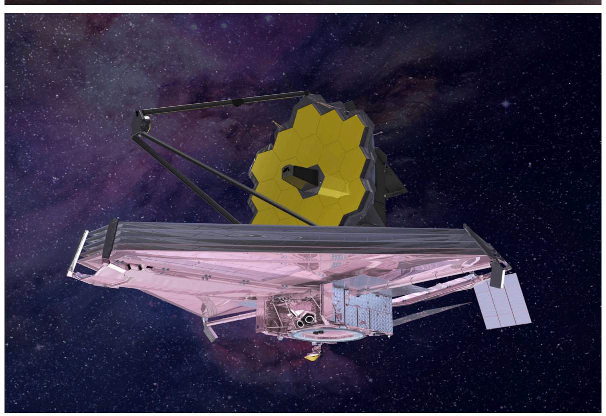
2- Existing and New Telescopes

ALMA
In operation



GMT
2020s

JWST
???



TMT
2020s

Looking into the future:

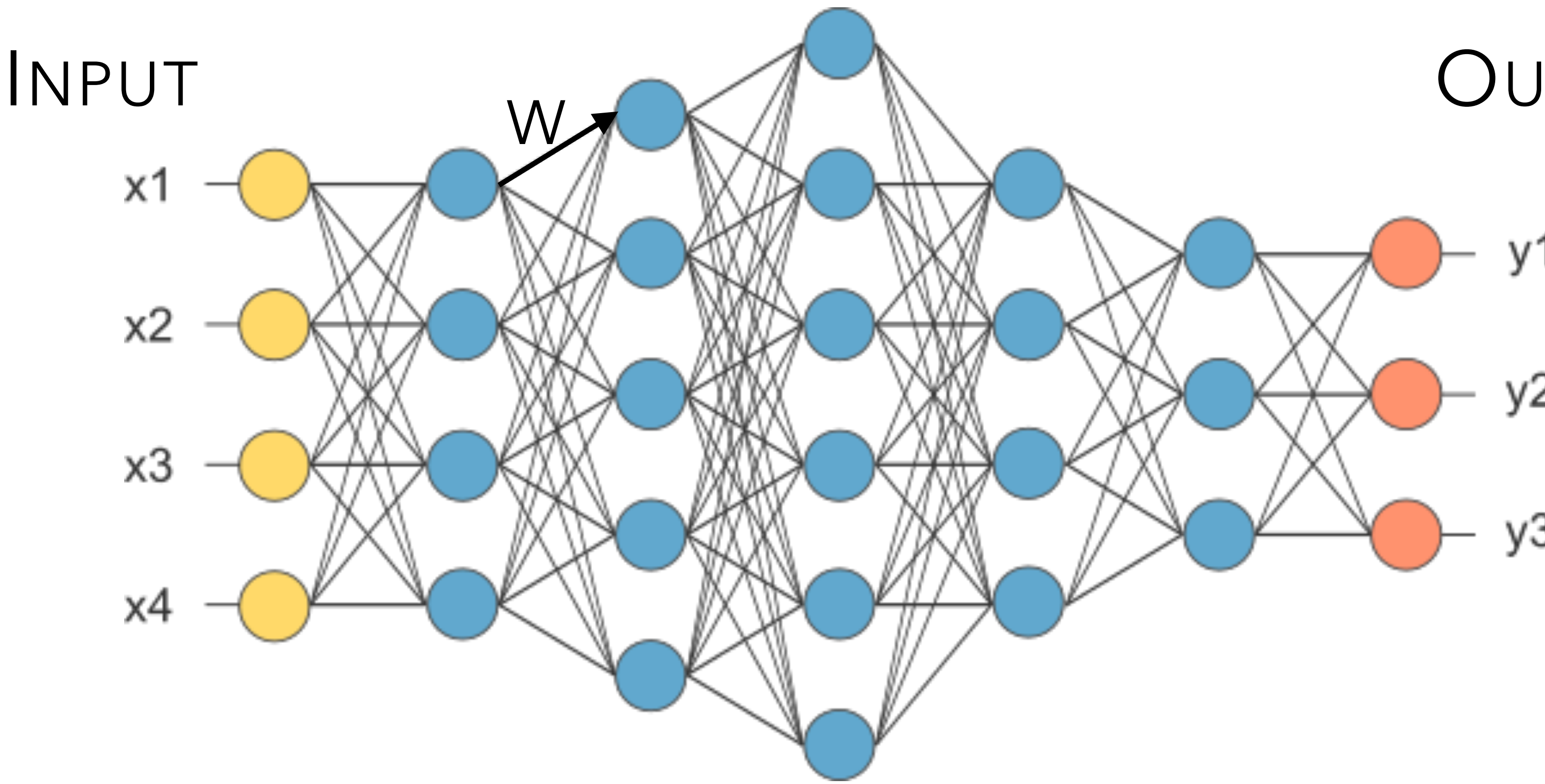
3- Analysis Methods

How are we going to analyze 170,000 lenses?

- Lens modeling is **very slow**.
- Even a simple lens model can take 2-3 days of human and CPU time, translating to **1,400 years**!
- Even if we pay 100 people to work on this, it'll be 14 years!
- Old method are simply not feasible.

Lens modeling sweatshop of 2022

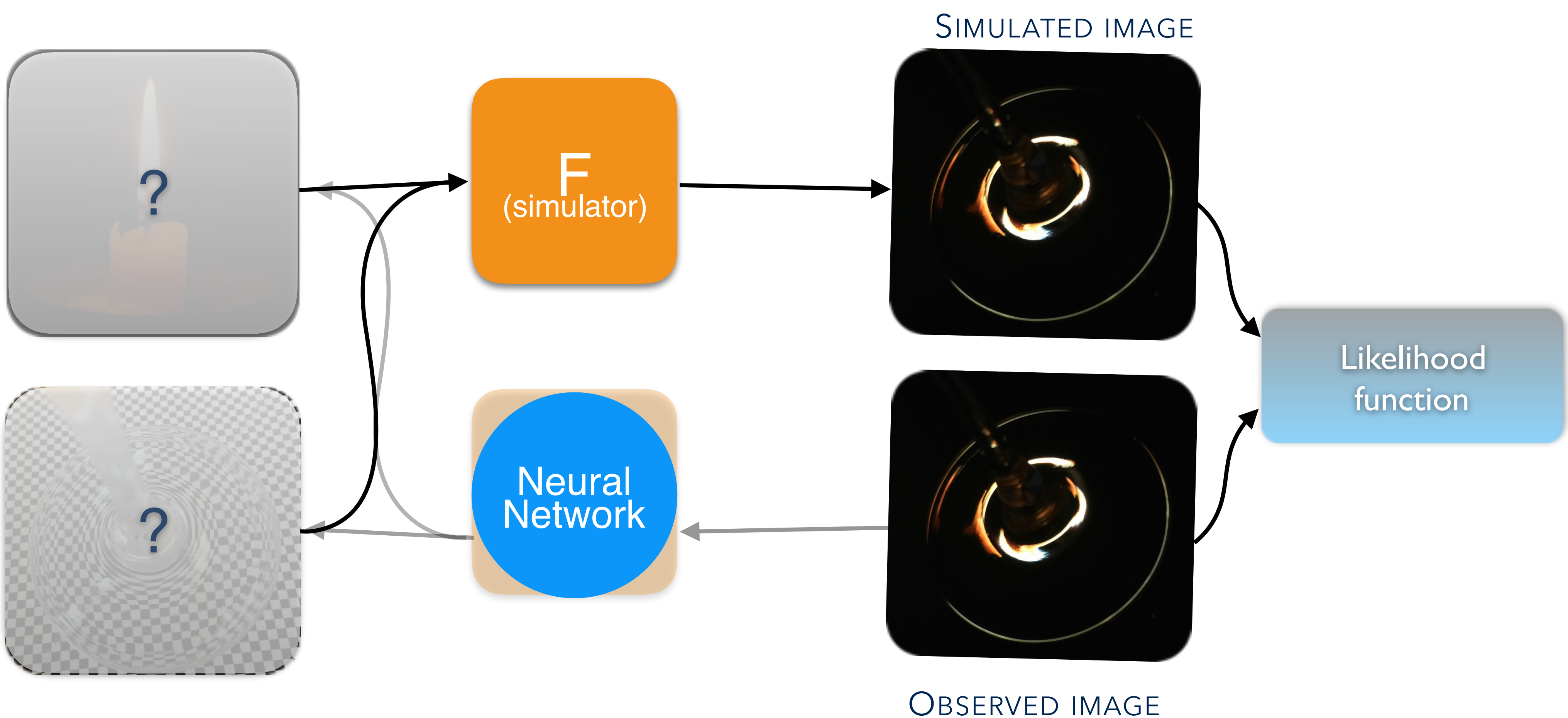
Can we obtain the lens parameters using neural networks?



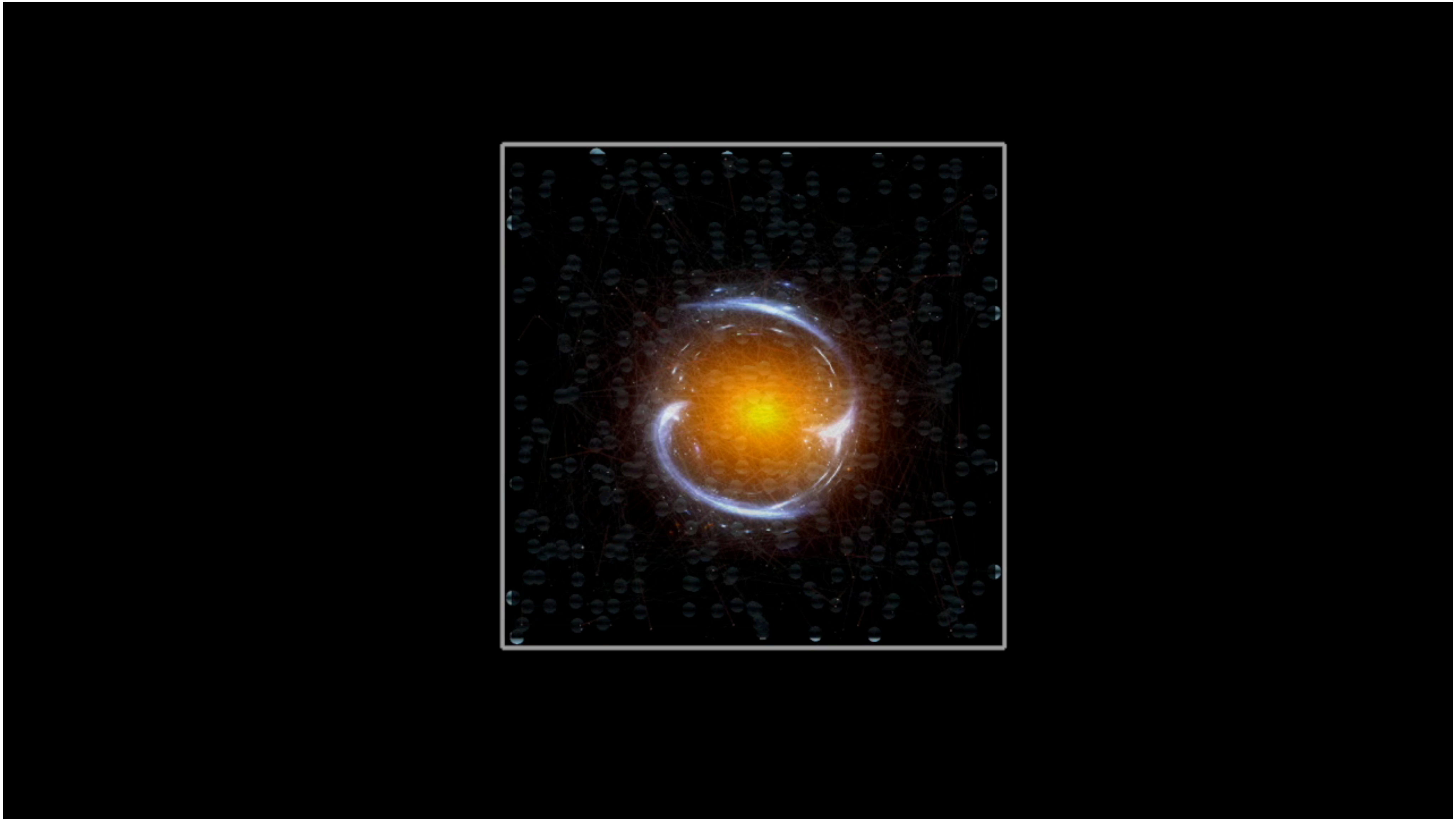
Universal approximation theorem:
Neural nets can approximate *any function* to an *arbitrary accuracy*.

Measuring physical properties from images of strong lenses

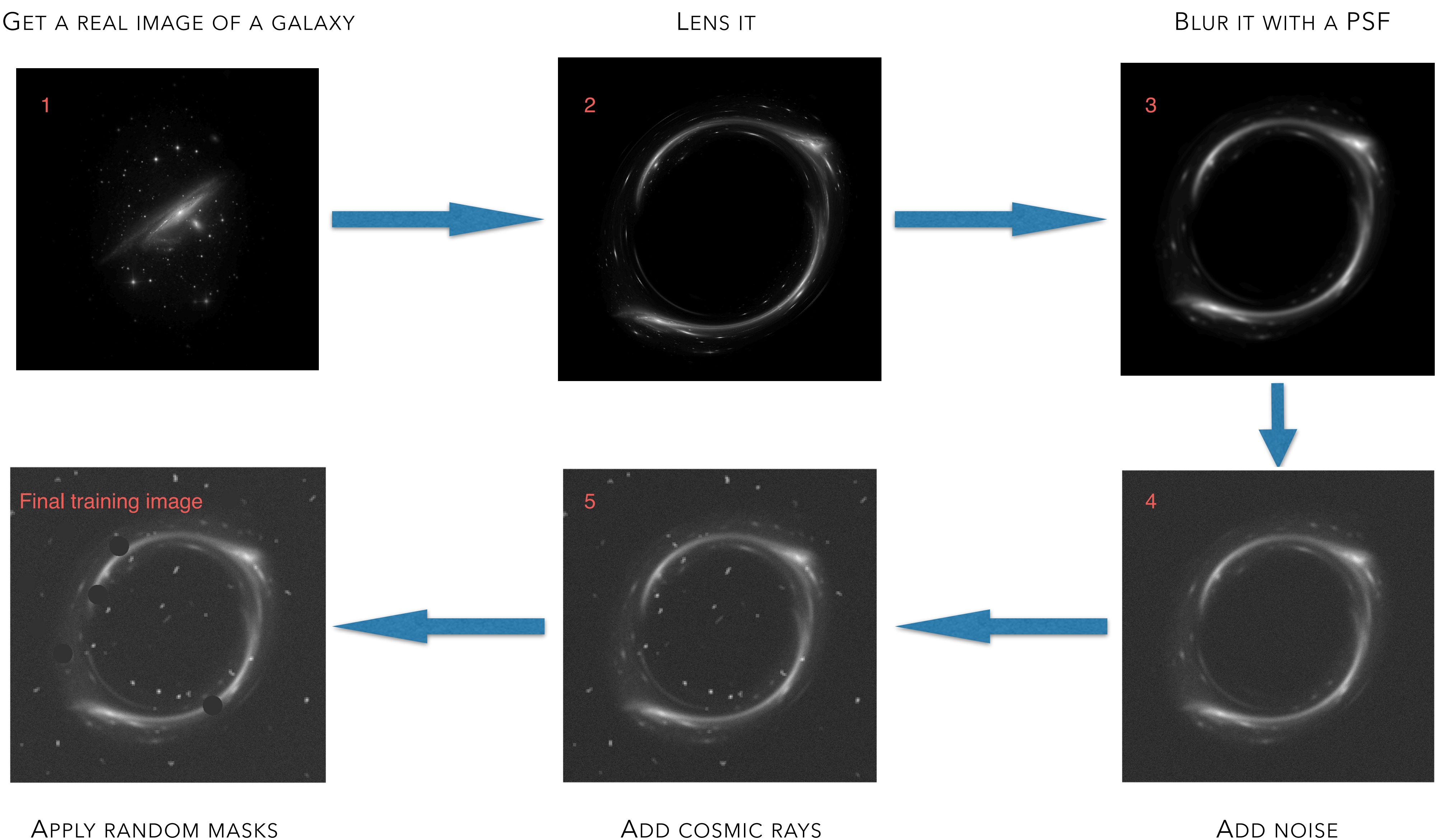
maximum likelihood lens modeling



NEURAL NETWORK OUTPUTS: LENSING PARAMETERS

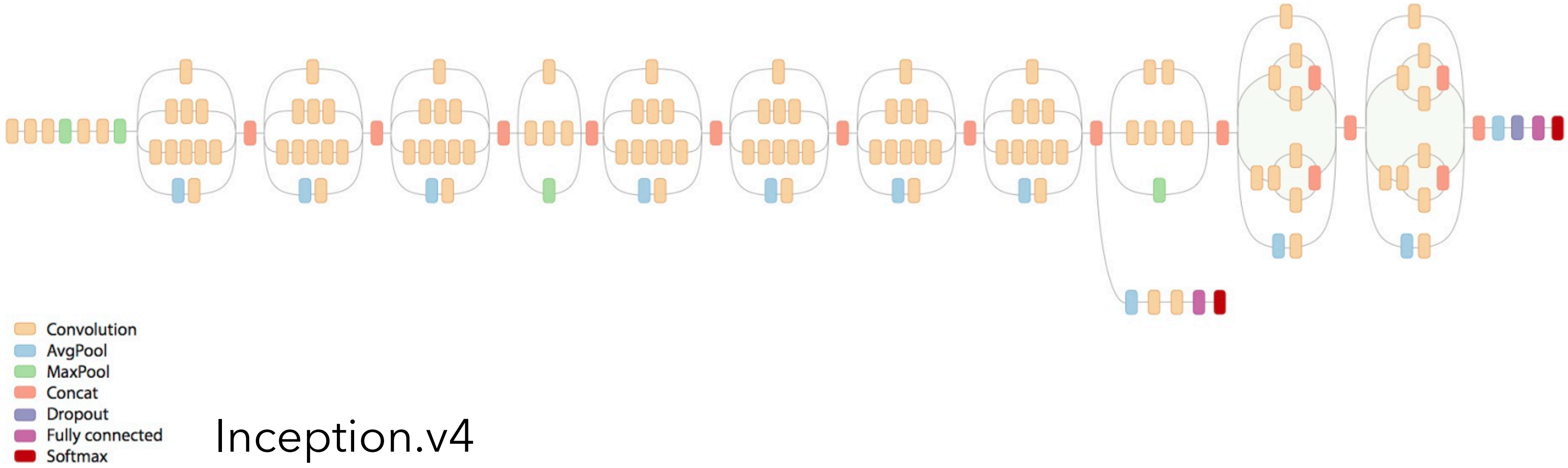


Producing the training data



TRAINING

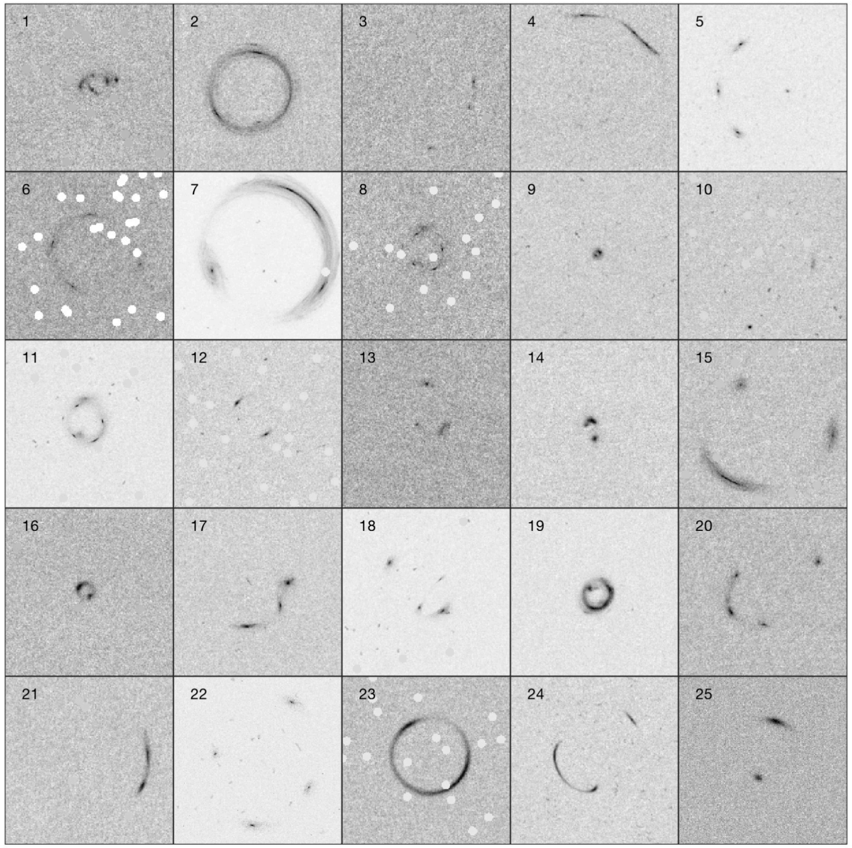
- Half a million (simulated) images for training.
- Trained multiple networks: e.g., Inception.v4 (hundreds of layers)
- Training time: About 1-2 day(s) on a single GPU



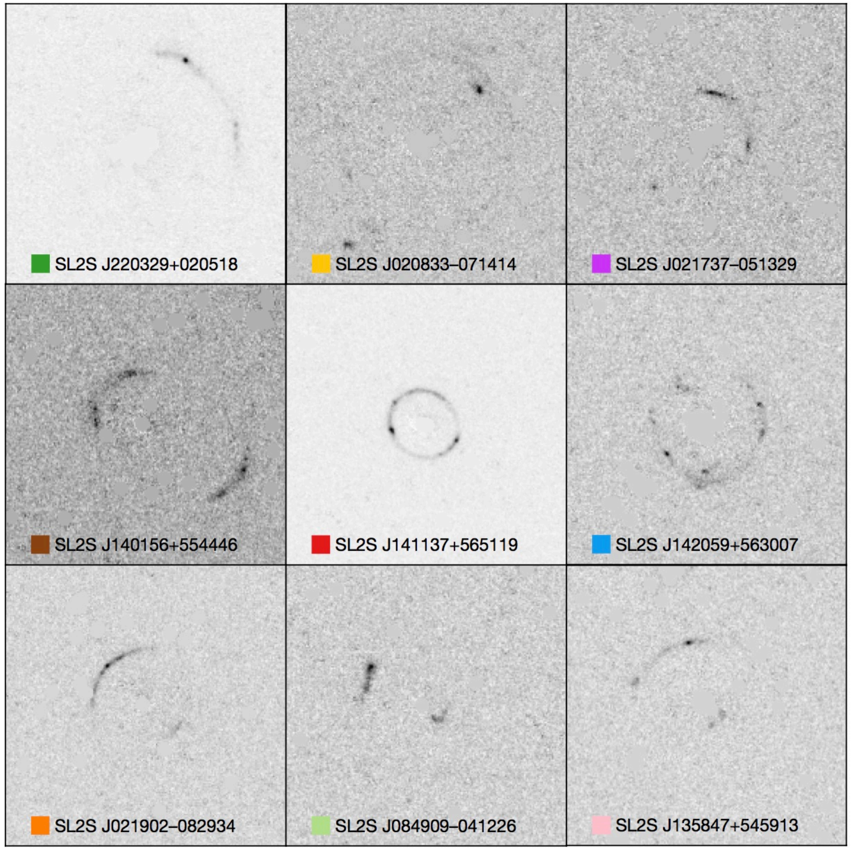
Inception.v4

TEST DATA

10,000 SIMULATED IMAGES

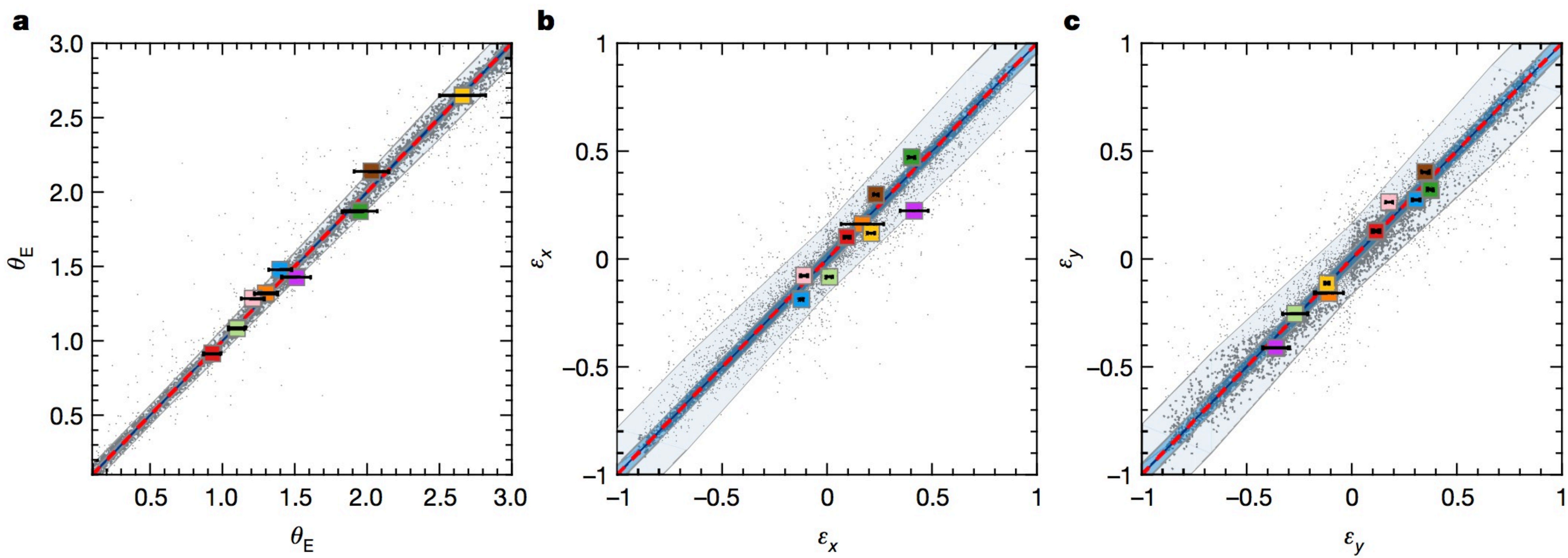


9 *HST* IMAGES



Hezaveh, Perreault Levasseur, Marshall, Nature, 2017

Estimating lensing parameters with neural nets



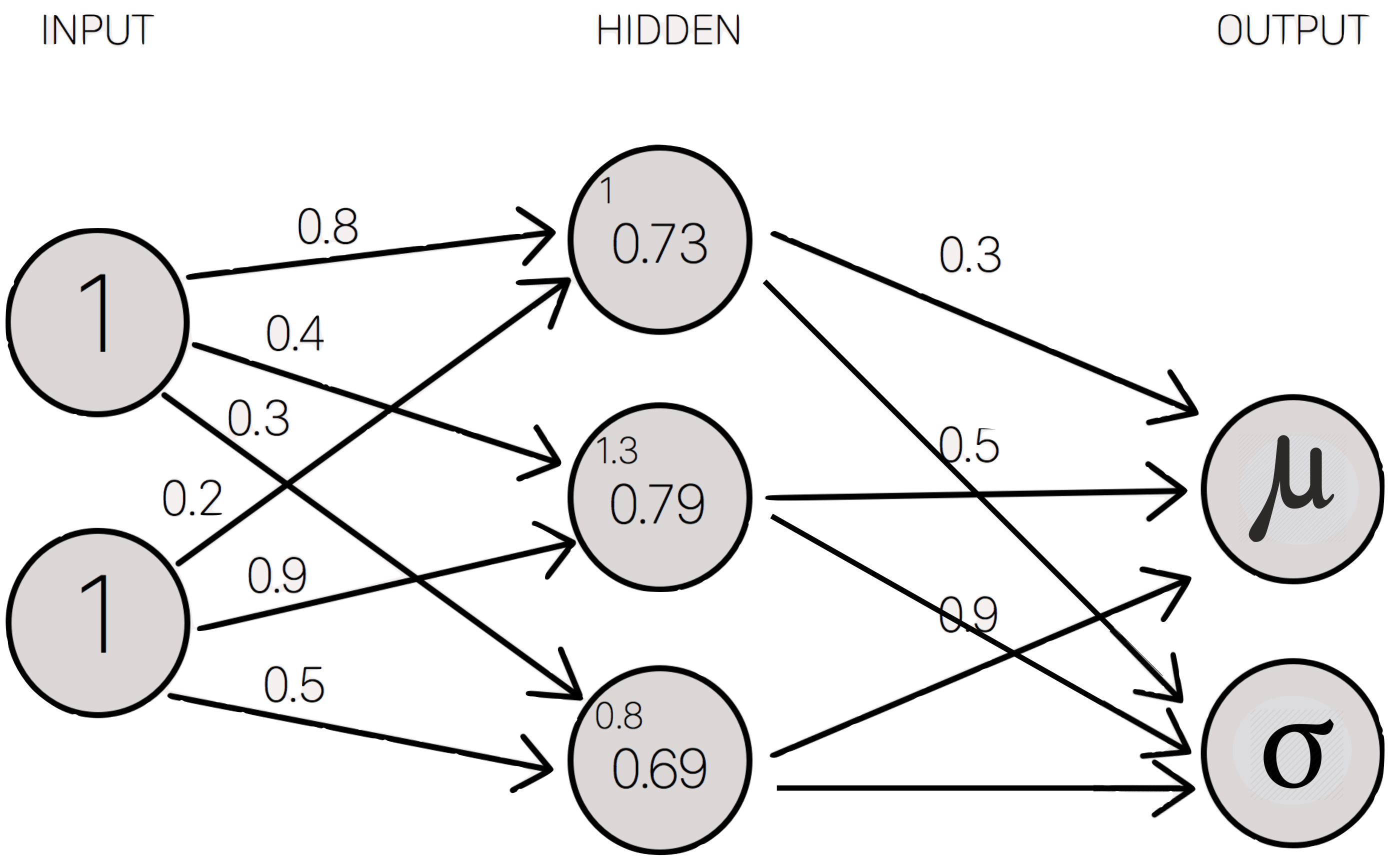
10 million times faster than max-likelihood lens modeling.

0.01 seconds on a **single GPU**

Hezaveh, Perreault Levasseur, Marshall, Nature, 2017

Standard Neural Networks:

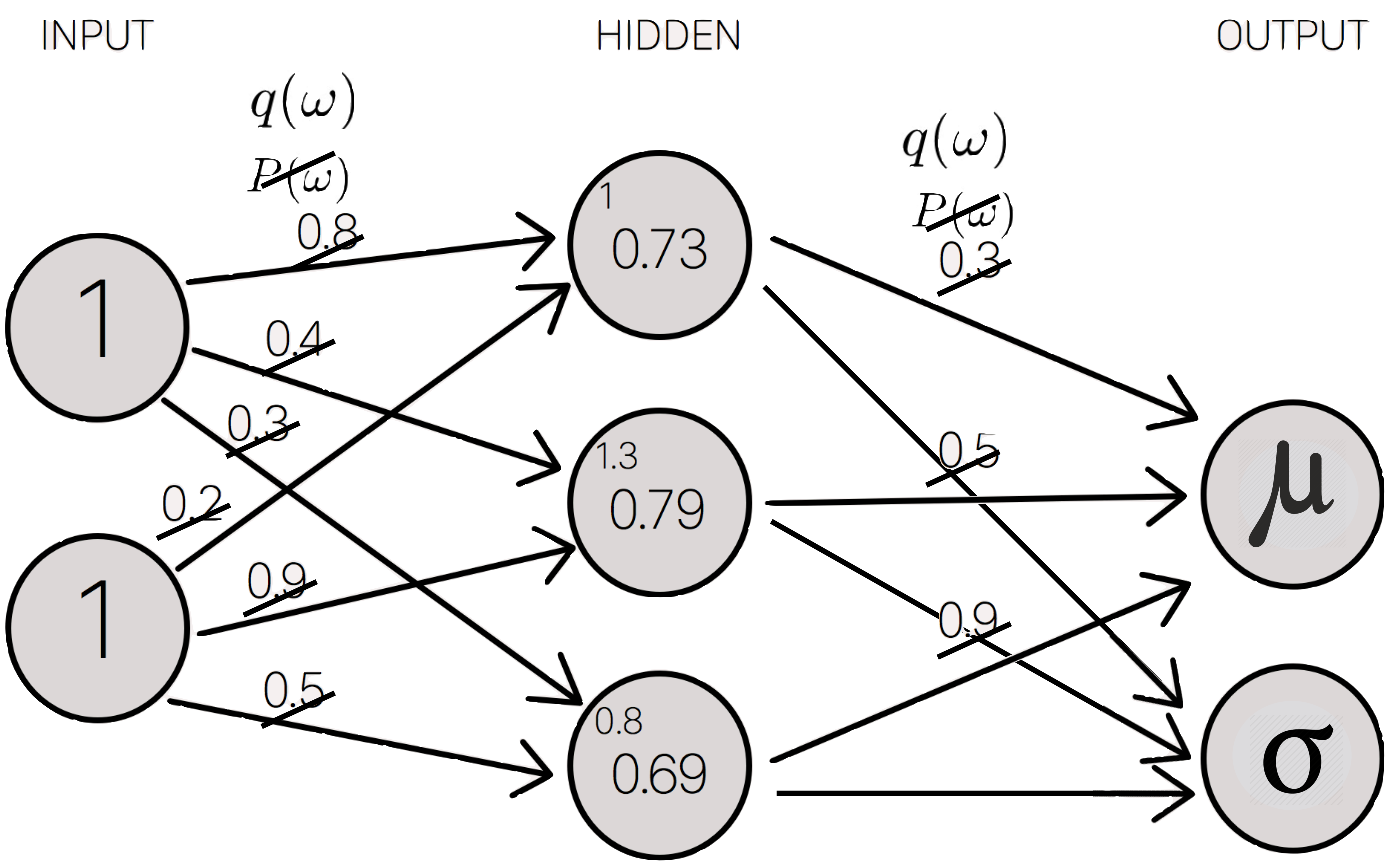
Weights have fixed, deterministic values



$$\mathcal{L}(\mathbf{y}_n, \hat{\mathbf{y}}_n(\mathbf{x}_n, \omega)) \propto \sum_k \frac{-1}{2\sigma_k^2} ||y_{n,k} - \mu_k(\mathbf{x}_n, \omega)||^2 - \frac{1}{2} \log \sigma_k^2$$

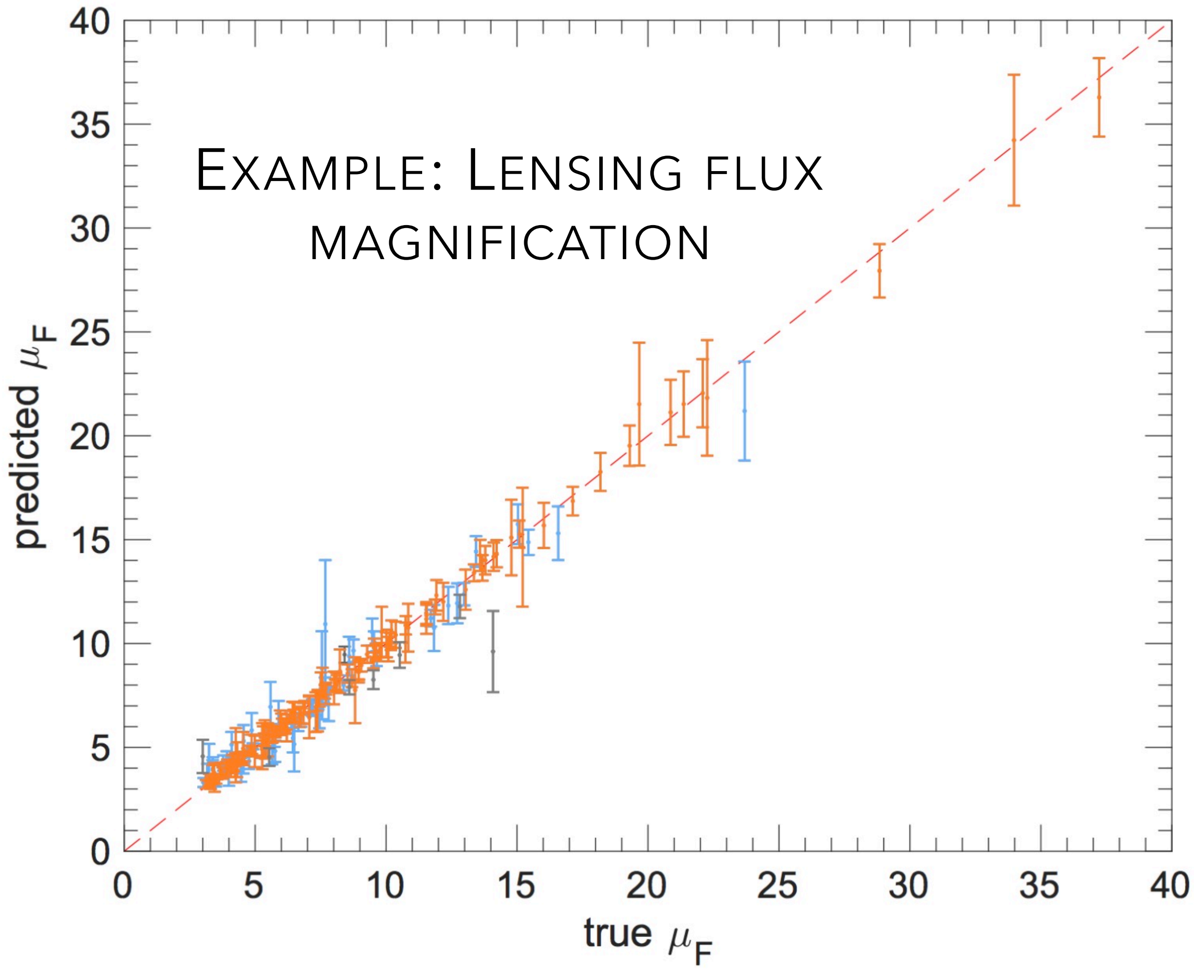
Bayesian Neural Networks:

WEIGHTS ARE DEFINED BY PROBABILITY DISTRIBUTIONS



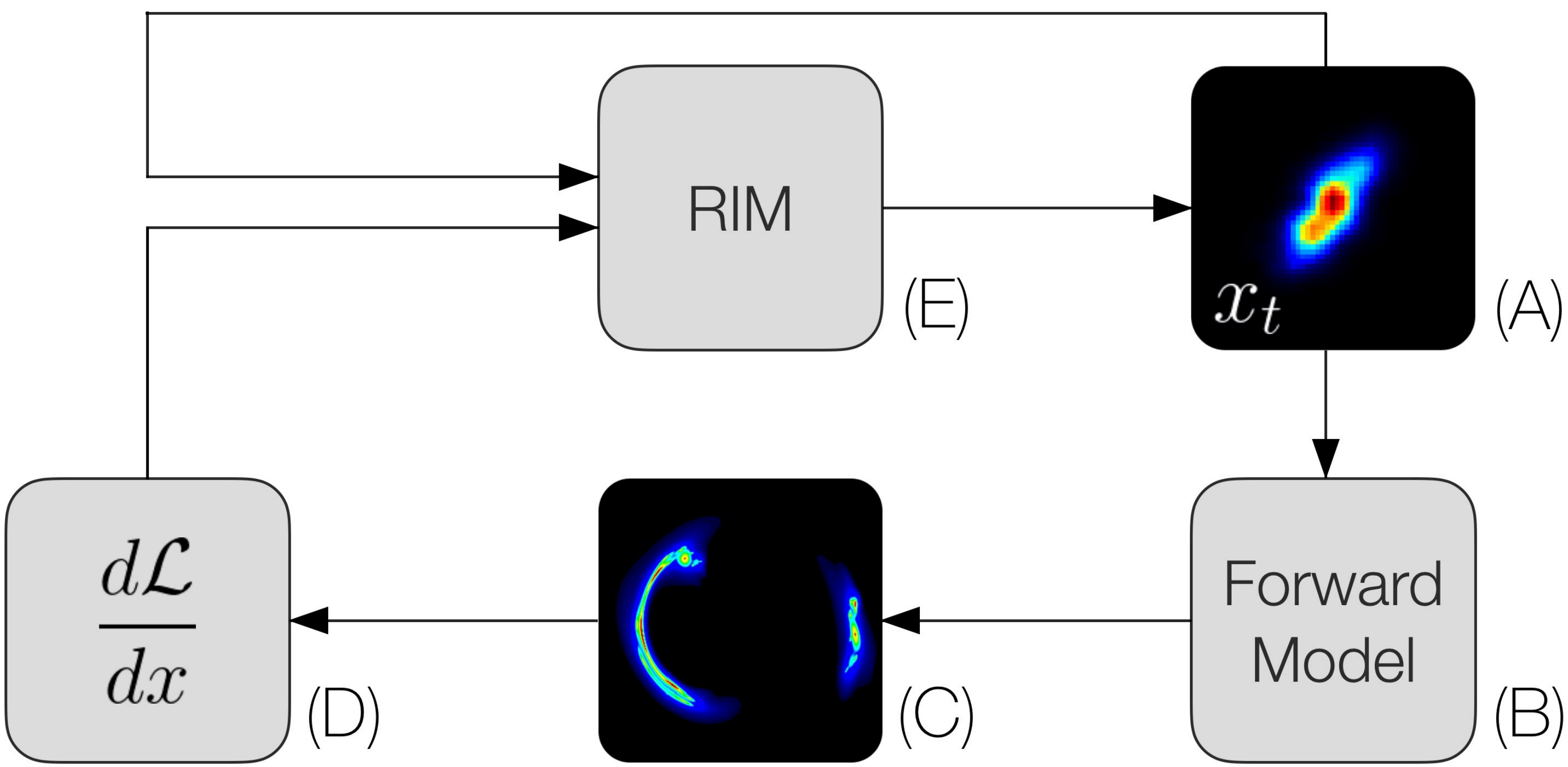
$$\mathcal{L}(\mathbf{y}_n, \hat{\mathbf{y}}_n(\mathbf{x}_n, \omega)) \propto \sum_k \frac{-1}{2\sigma_k^2} ||y_{n,k} - \mu_k(\mathbf{x}_n, \omega)||^2 - \frac{1}{2} \log \sigma_k^2$$

Uncertainties of the estimated parameters



Perreault Levasseur, Hezaveh, Wechsler, ApJL, 2017

Reconstructing the background sources with the Recurrent Inference Machine



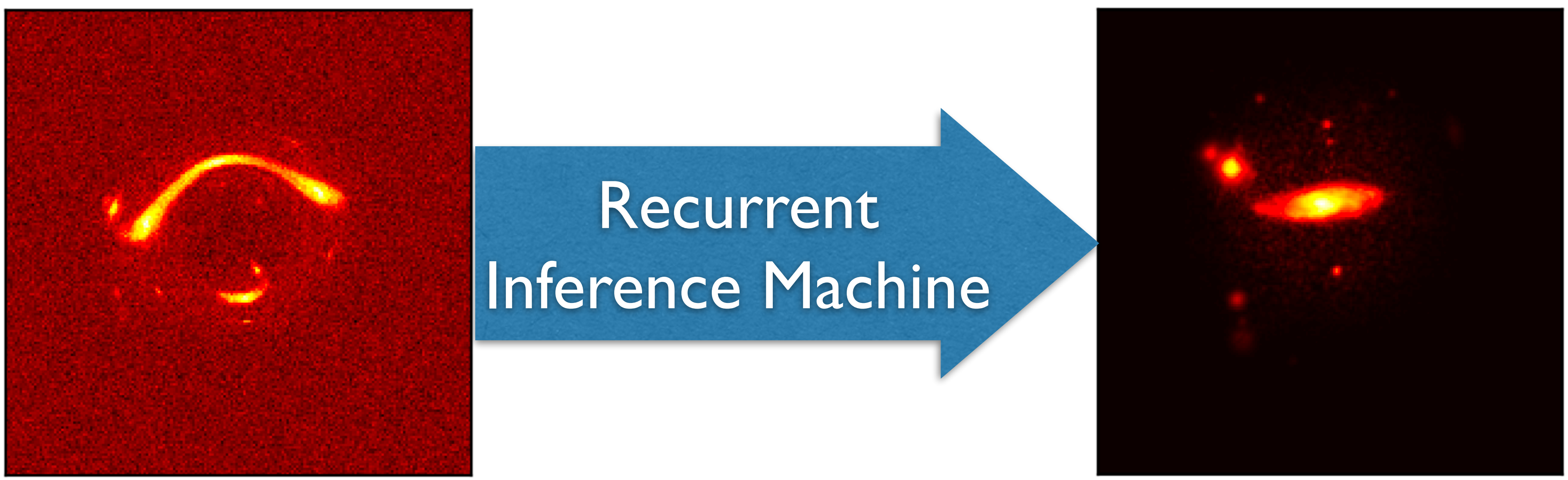
Morningstar, Perreault Levasseur, Hezaveh et al. 2019

Reconstructing the background sources with the Recurrent Inference Machine

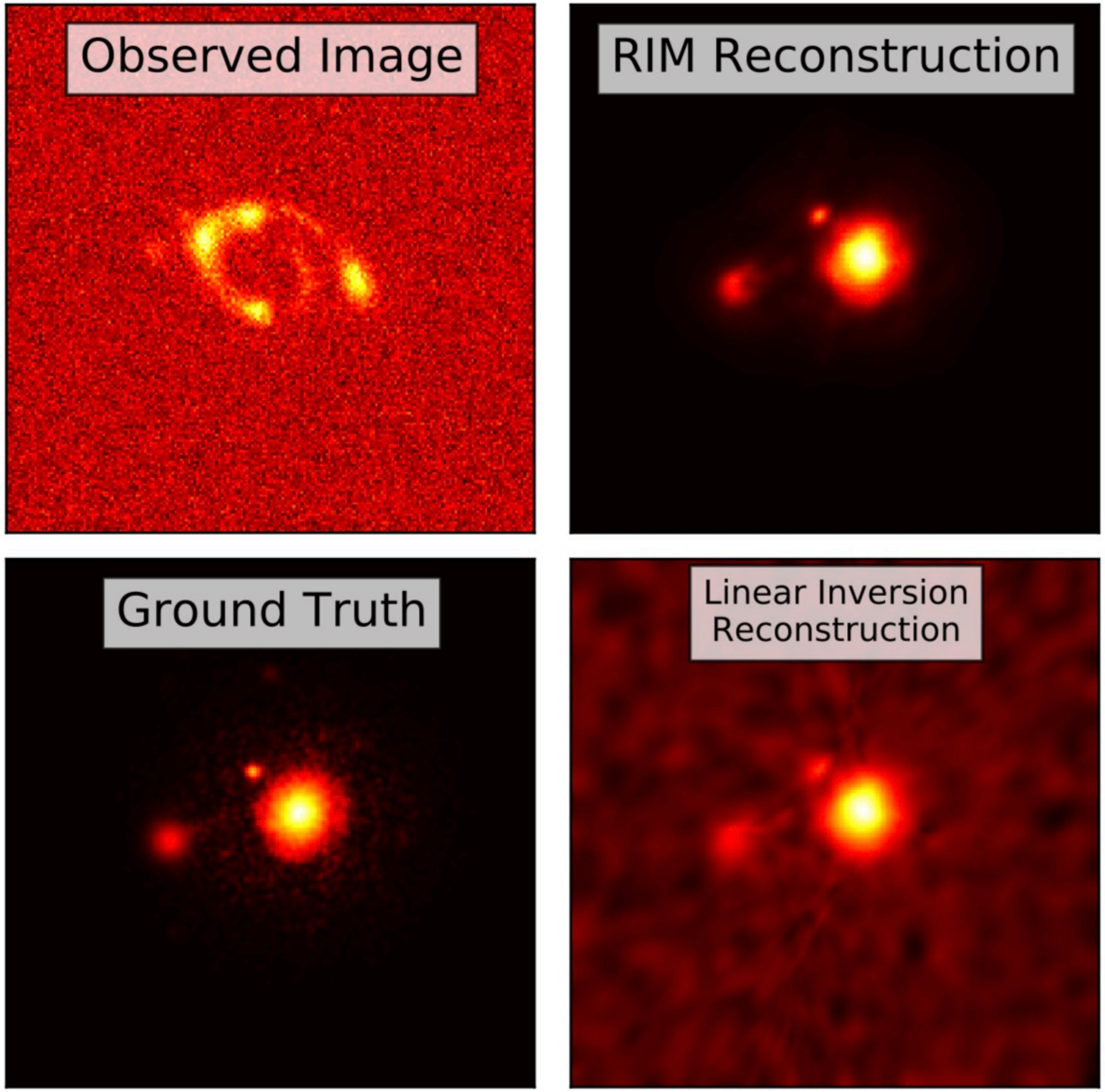
Observed image

Reconstructed source

True source

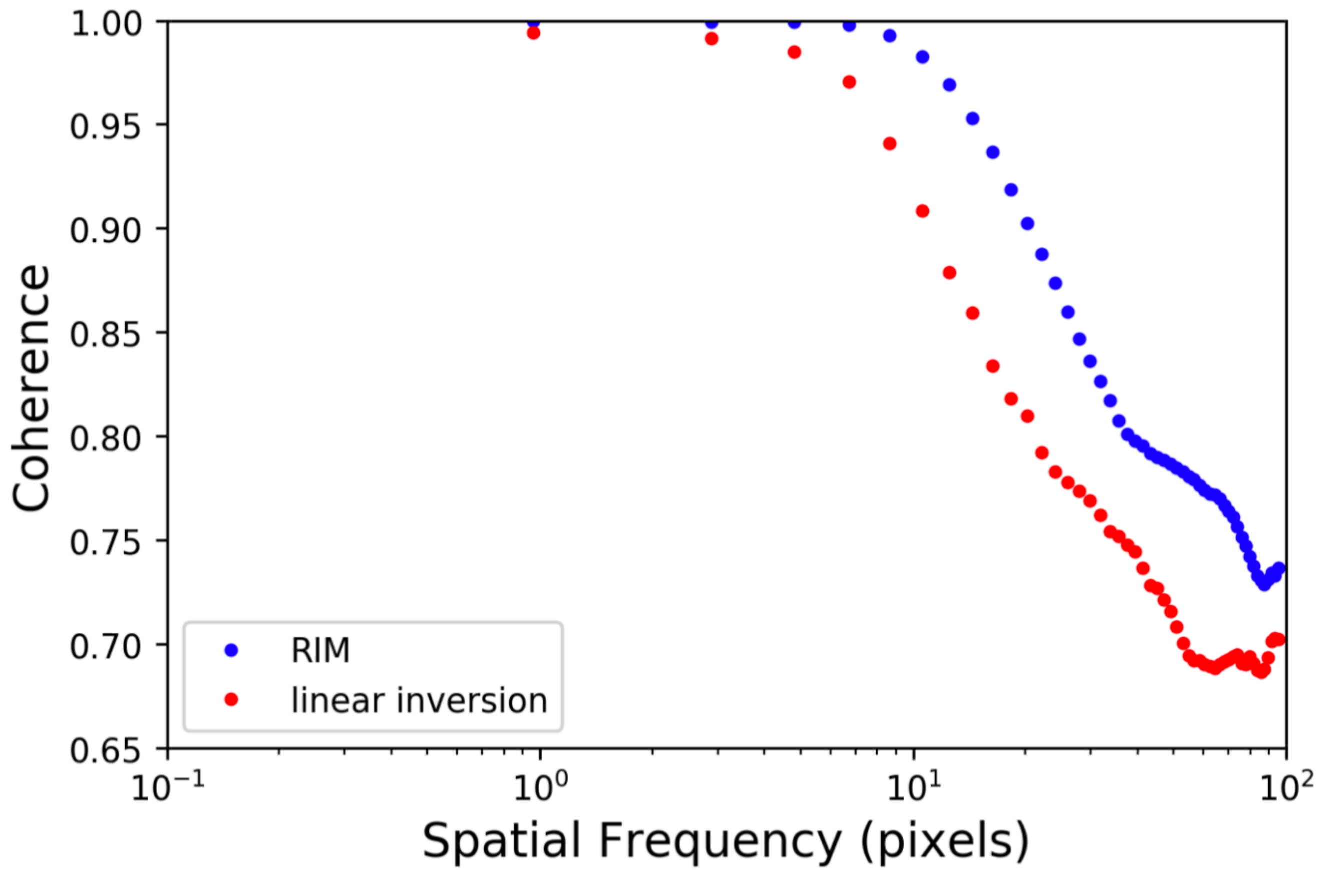


Morningstar, Perreault Levasseur, Hezaveh et al. 2019

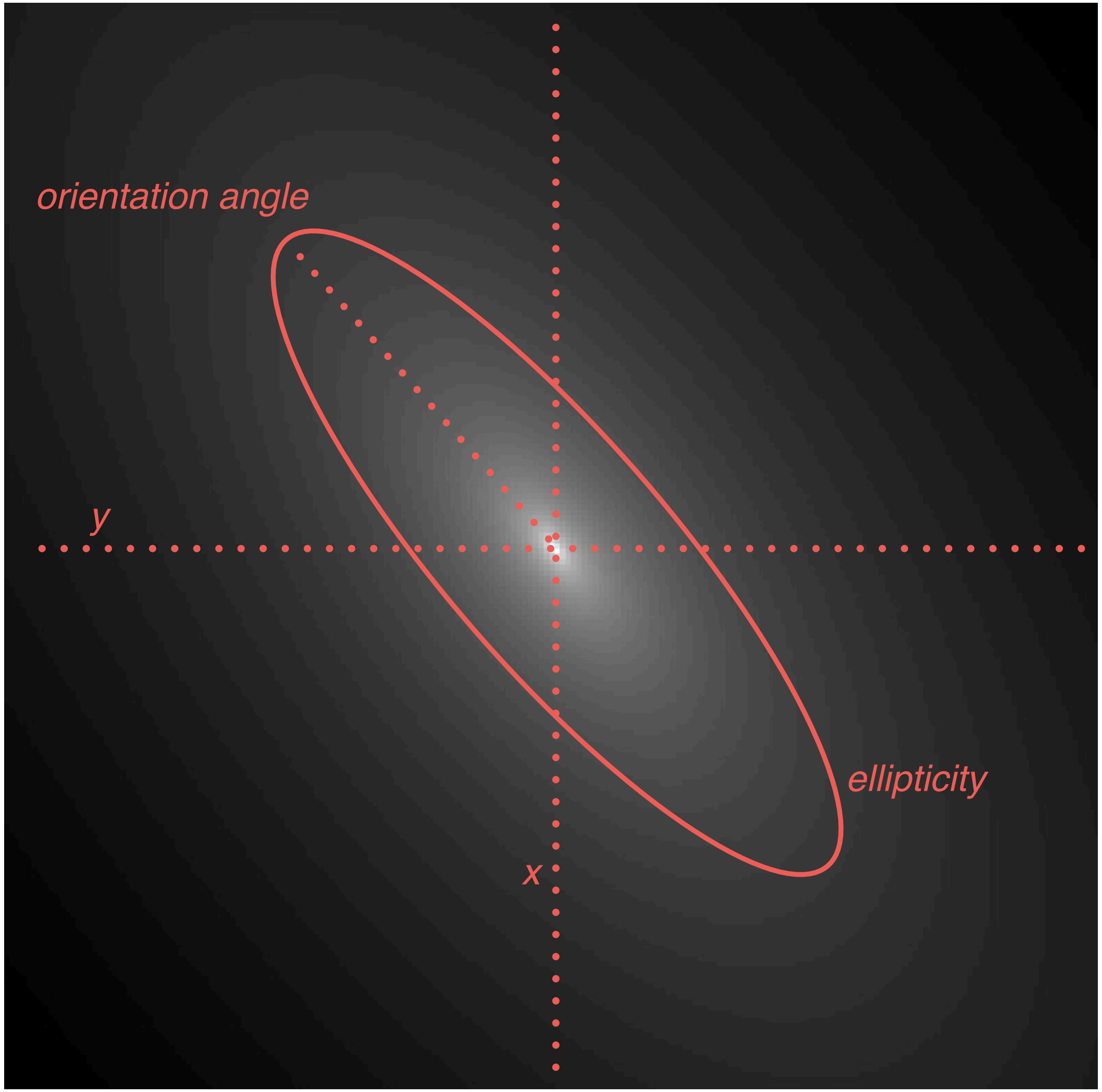


Morningstar, Perreault Levasseur, Hezaveh et al. 2019

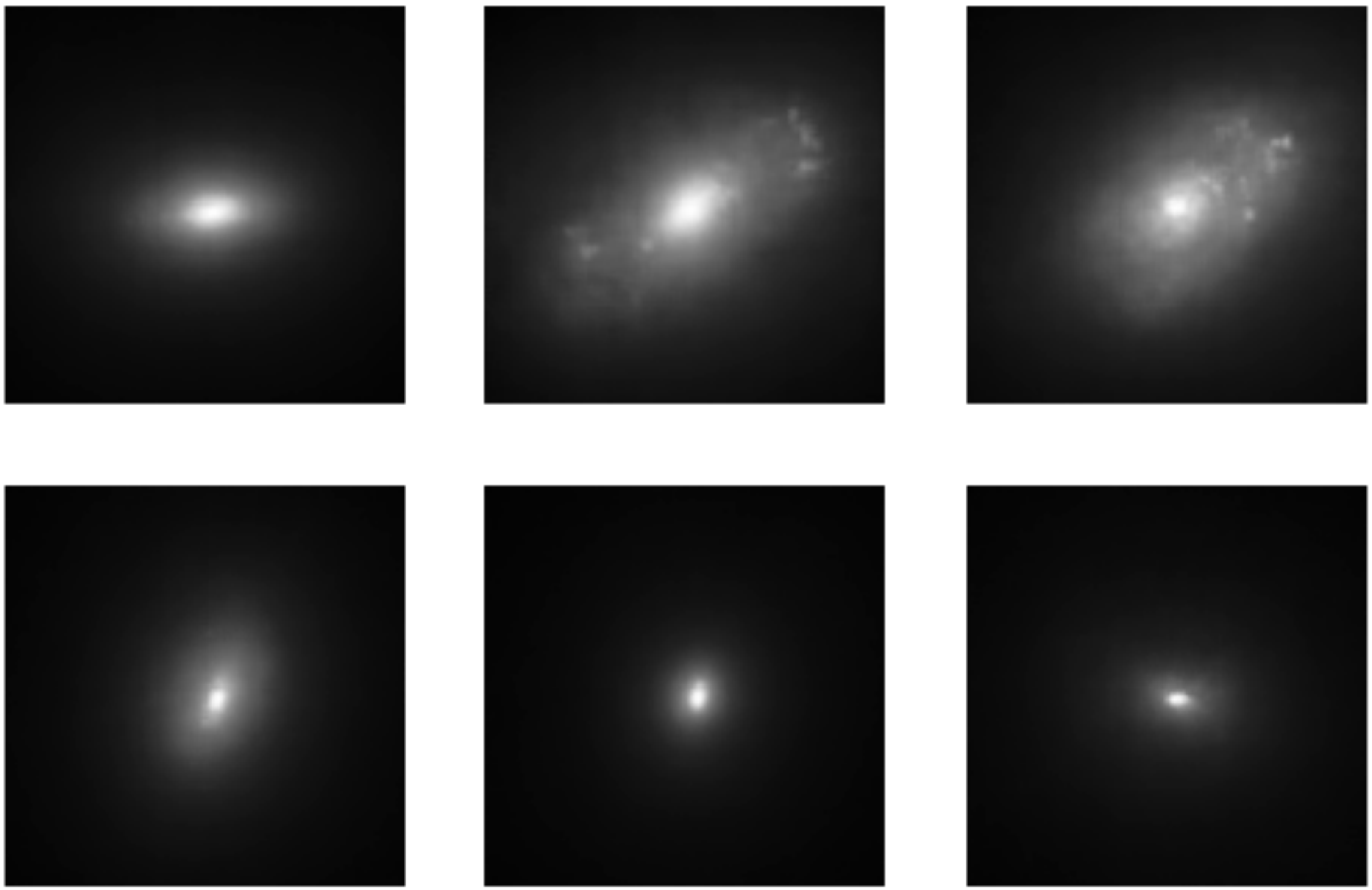
Background source reconstruction: Comparison to maximum likelihood methods



Morningstar, Perreault Levasseur, Hezaveh et al. 2019


orientation angle
y
ellipticity
x

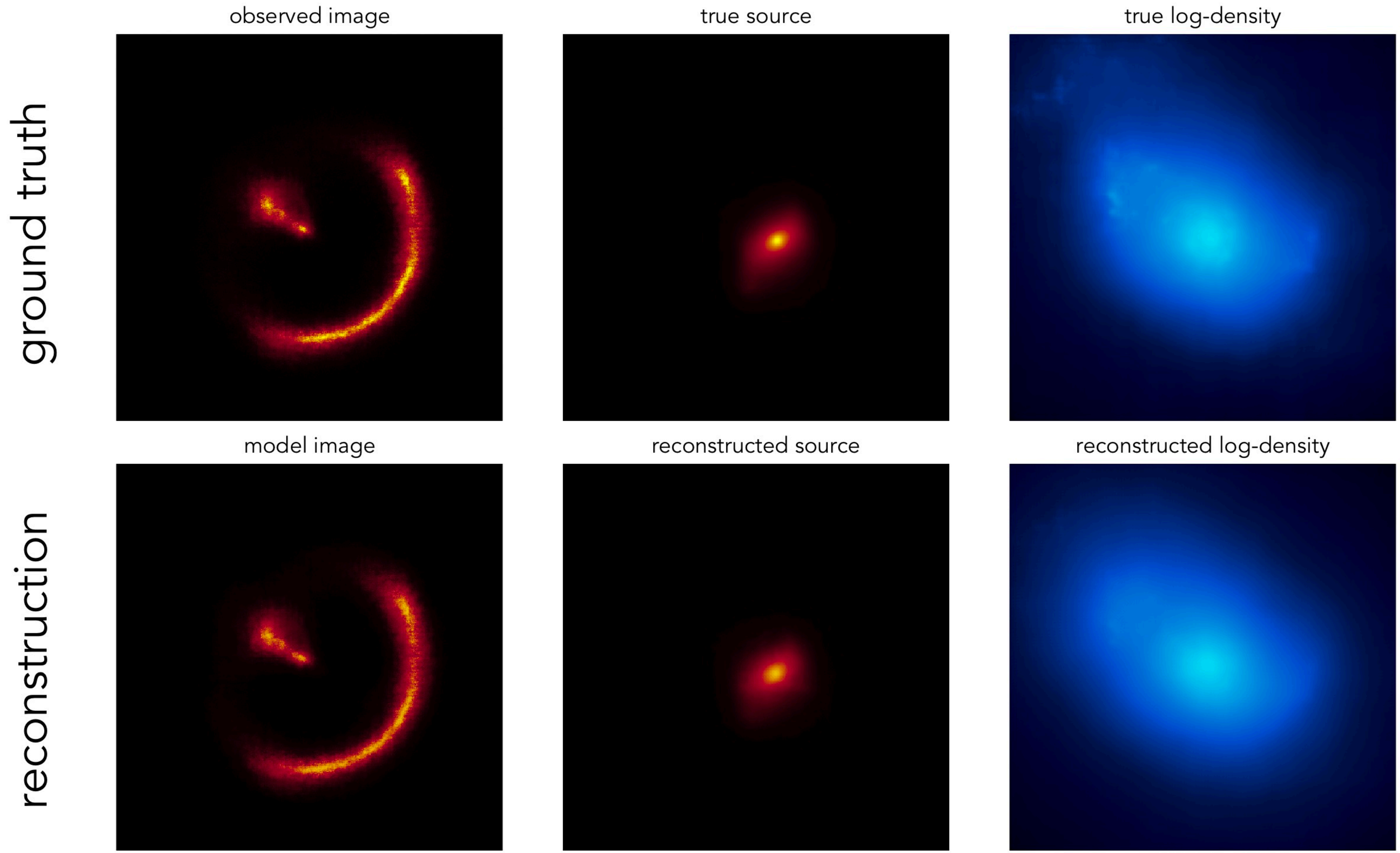
Train on cosmological simulations



IllustrisTNG simulation

Perreault Levasseur, et al. in prep

Train on cosmological simulations

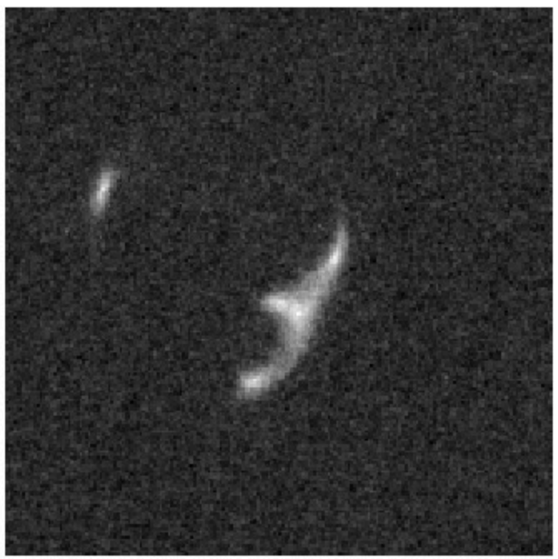


Perreault Levasseur, et al. in prep

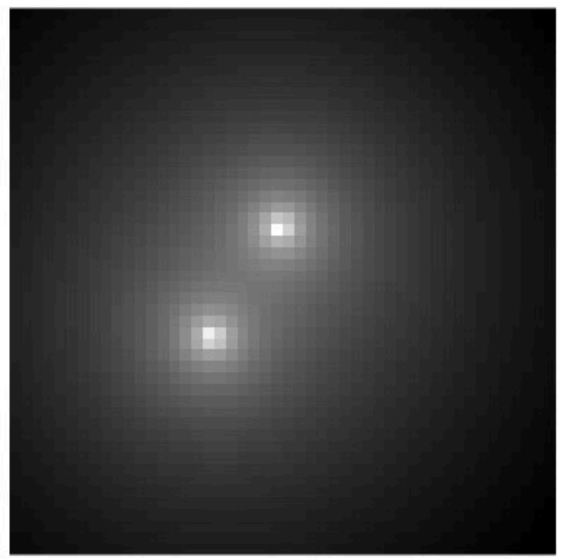
Pixellated density map reconstruction

Observation

(Networks' input)



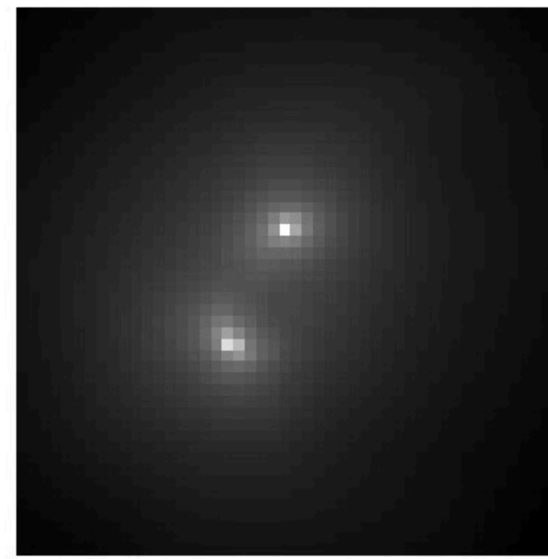
True density map



(log projected density)

Prediction

(Networks' output)

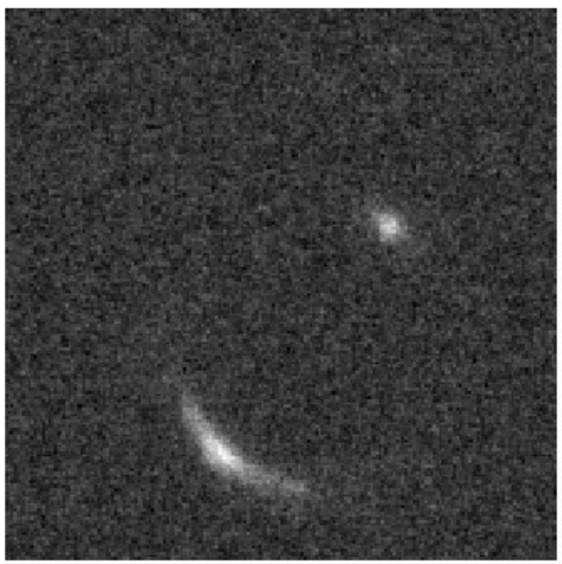


(log projected density)

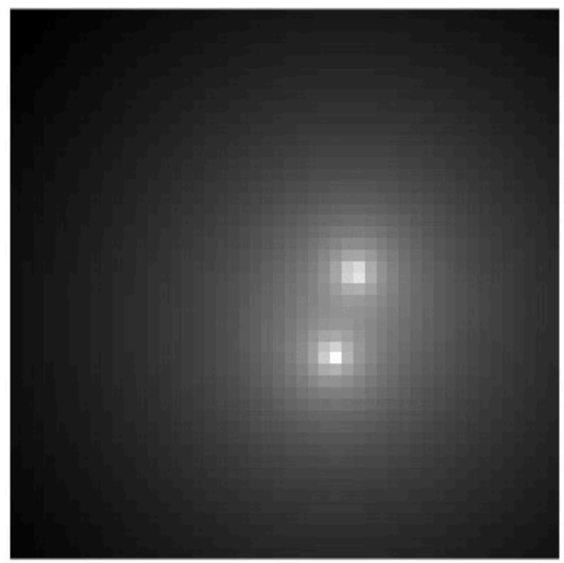
Perreault Levasseur, et al. in prep

Pixellated density map reconstruction

Observation
(Networks' input)

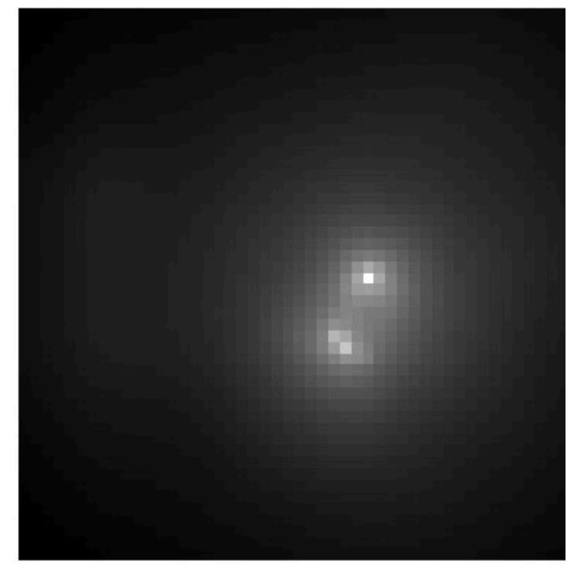


True density map



(log projected density)

Prediction
(Networks' output)

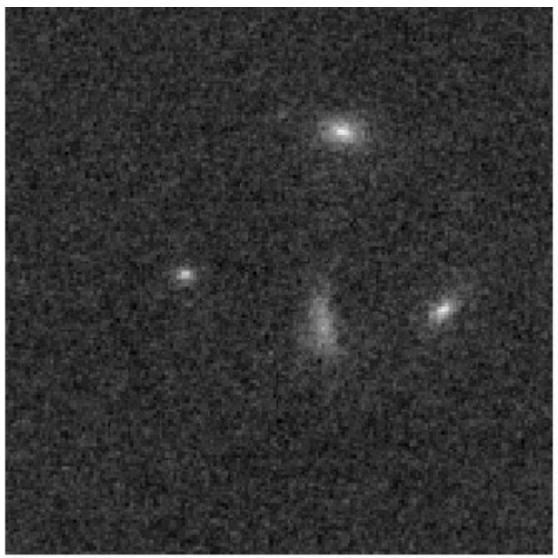


(log projected density)

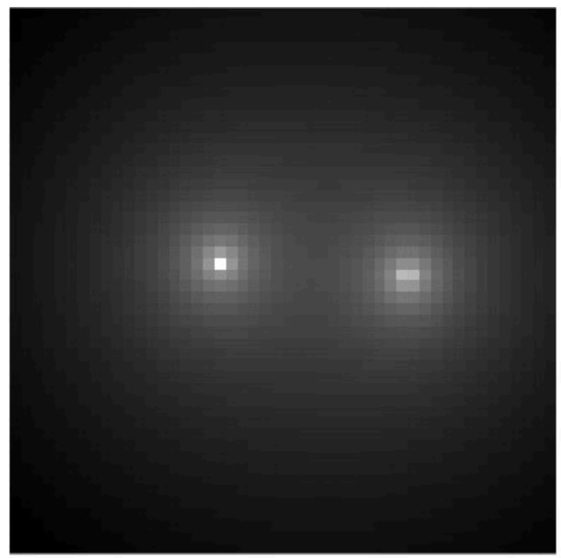
Perreault Levasseur, et al. in prep

Pixellated density map reconstruction

Observation
(Networks' input)

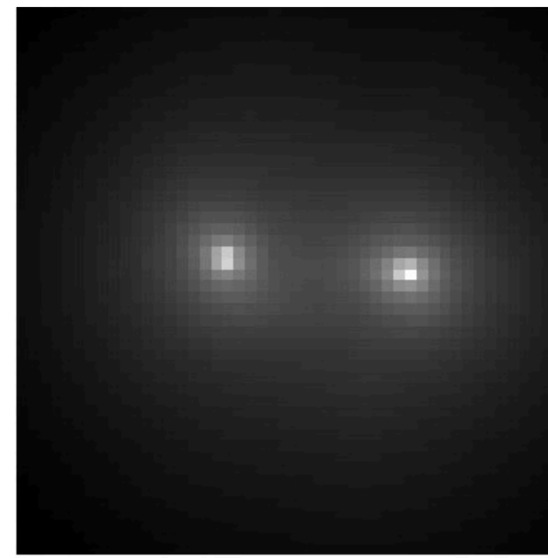


True density map



(log projected density)

Prediction
(Networks' output)

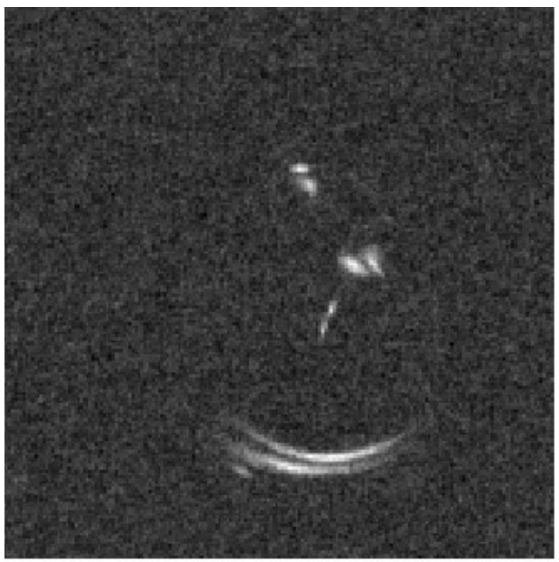


(log projected density)

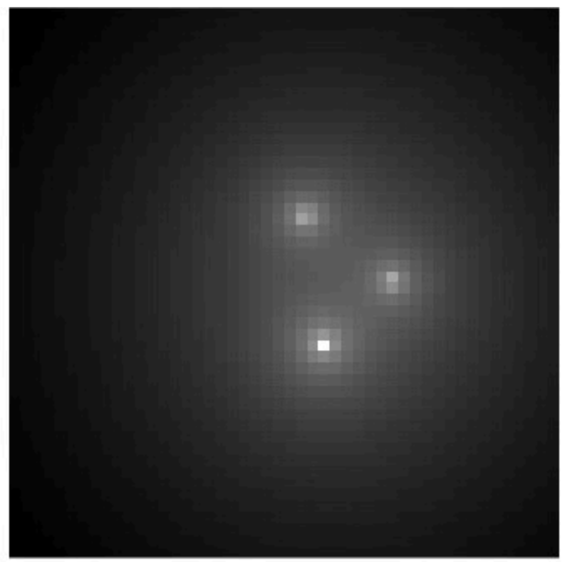
Perreault Levasseur, et al. in prep

Could these networks ever generalize beyond their training data?

Observation
(Networks' input)



True density map

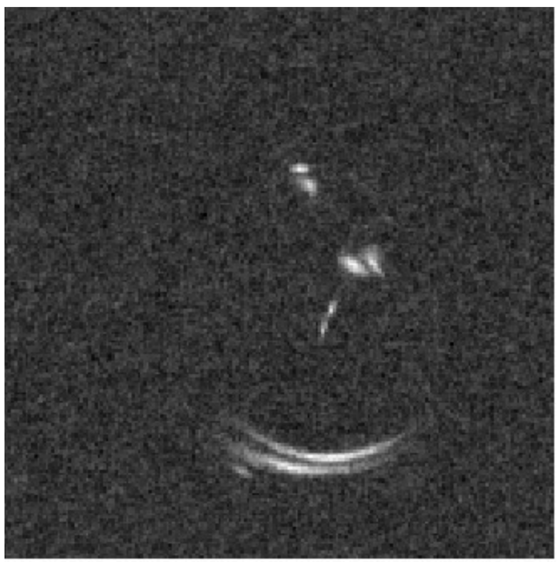


Prediction
(Networks' output)

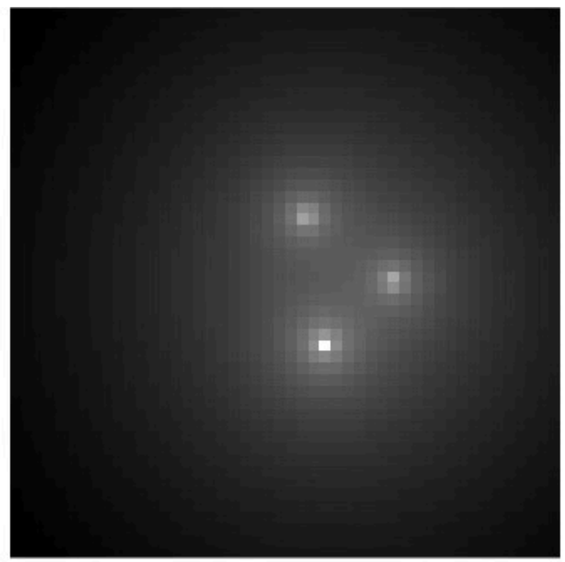
Perreault Levasseur, et al. in prep

Could these networks ever generalize beyond their training data?

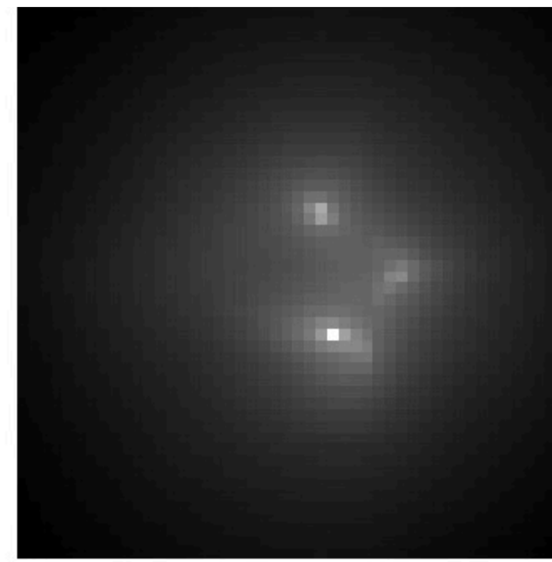
Observation
(Networks' input)



True density map



Prediction
(Networks' output)

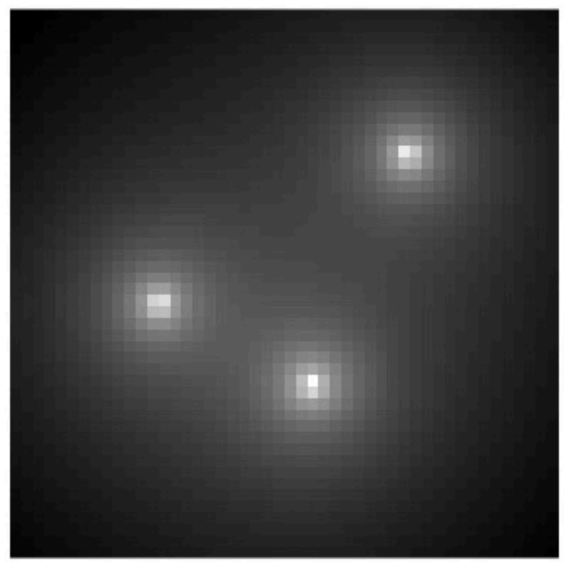


Perreault Levasseur, et al. in prep

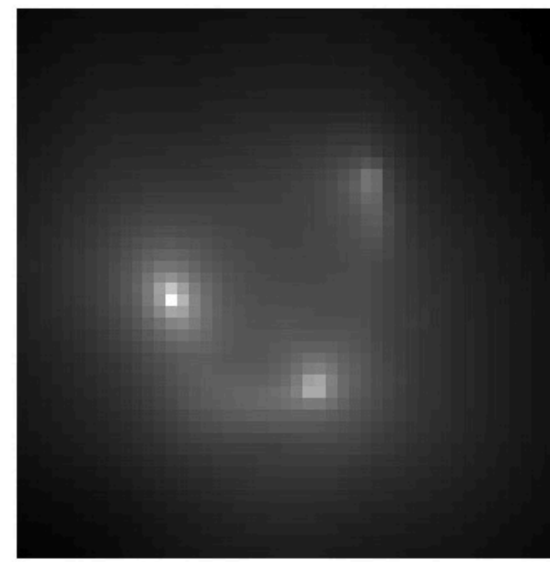
Could these networks ever generalize beyond their training data?

Observation
(Networks' input)

True density map



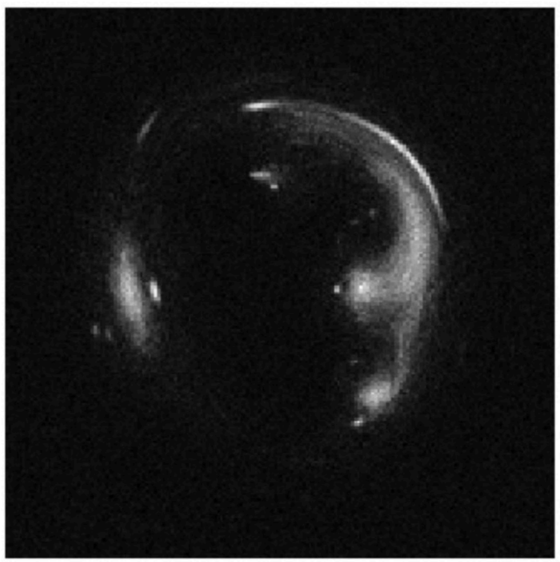
Prediction
(Networks' output)



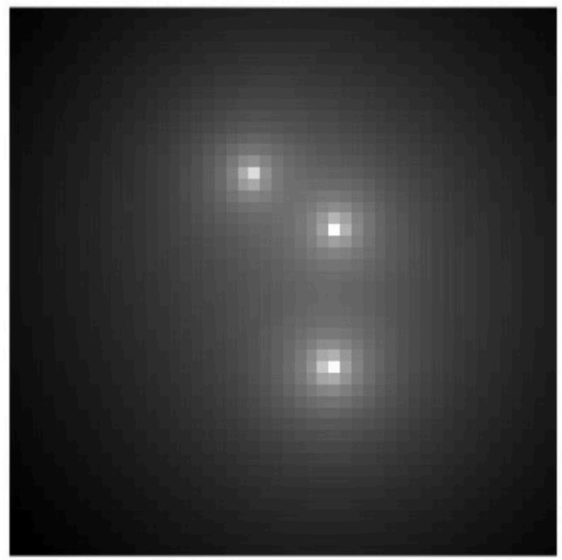
Perreault Levasseur, et al. in prep

Could these networks ever generalize beyond their training data?

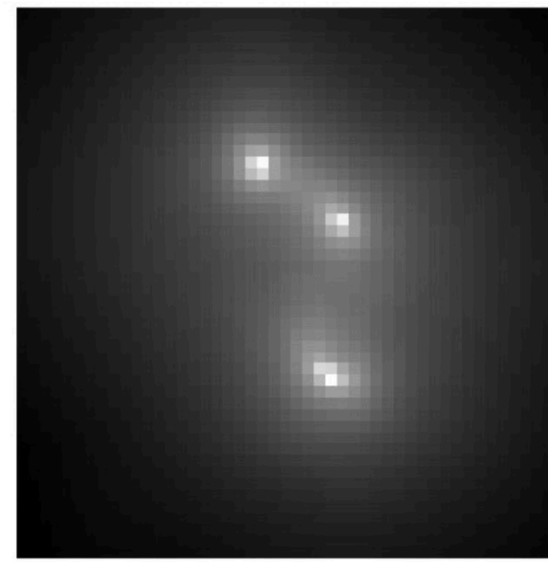
Observation
(Networks' input)



True density map



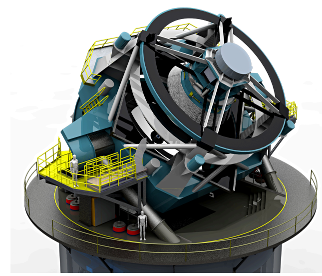
Prediction
(Networks' output)



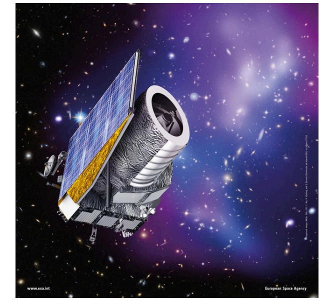
Perreault Levasseur, et al. in prep

LENSES

WIDE-FIELD INFRARED SURVEY TELESCOPE
WFIRST
ASTROPHYSICS • DARK ENERGY • EXOPLANETS



LSST

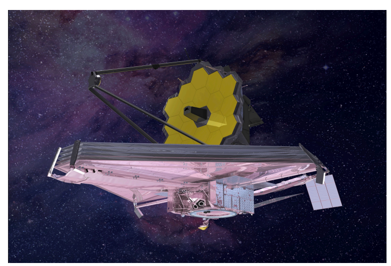


Euclid consortium

TELESCOPES

ALMA

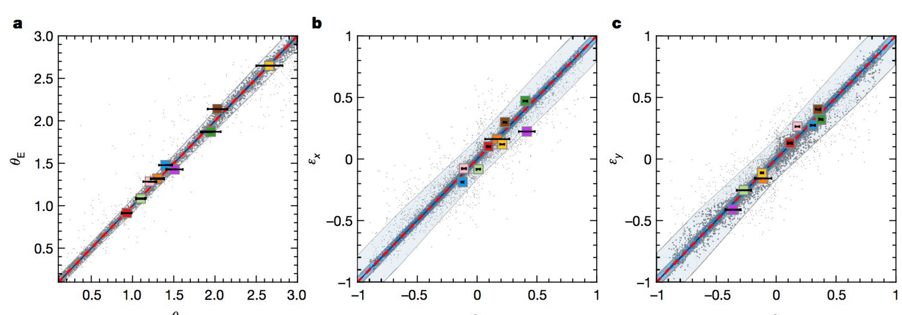
JWST



TMT

GMT

ANALYSIS METHODS



Thank you!