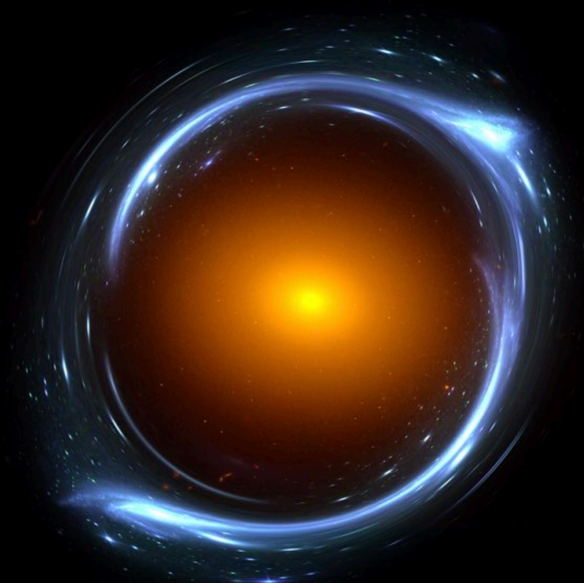
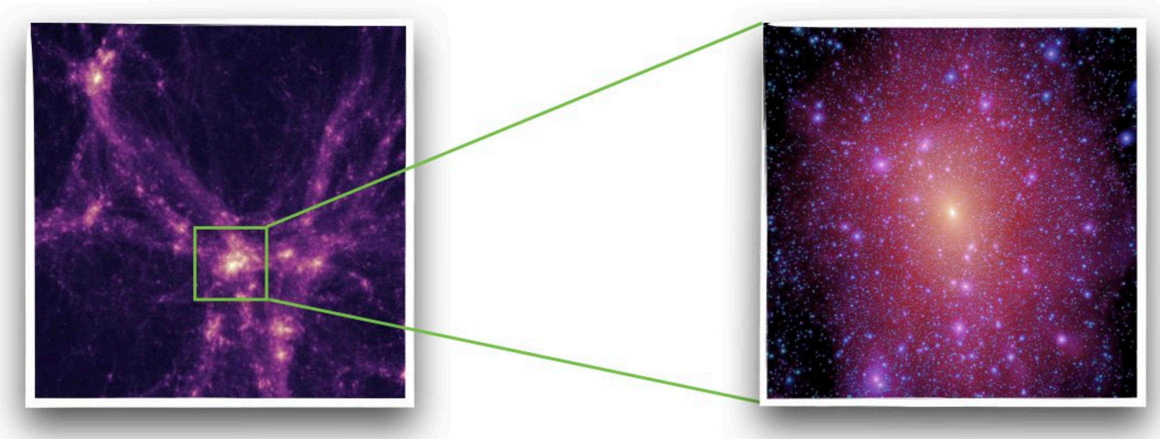
Measuring the mass function of dark matter with observations of gravitational lenses



Yashar Hezaveh
Hubble Fellow - Stanford University

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

Small-scale structure of dark matter

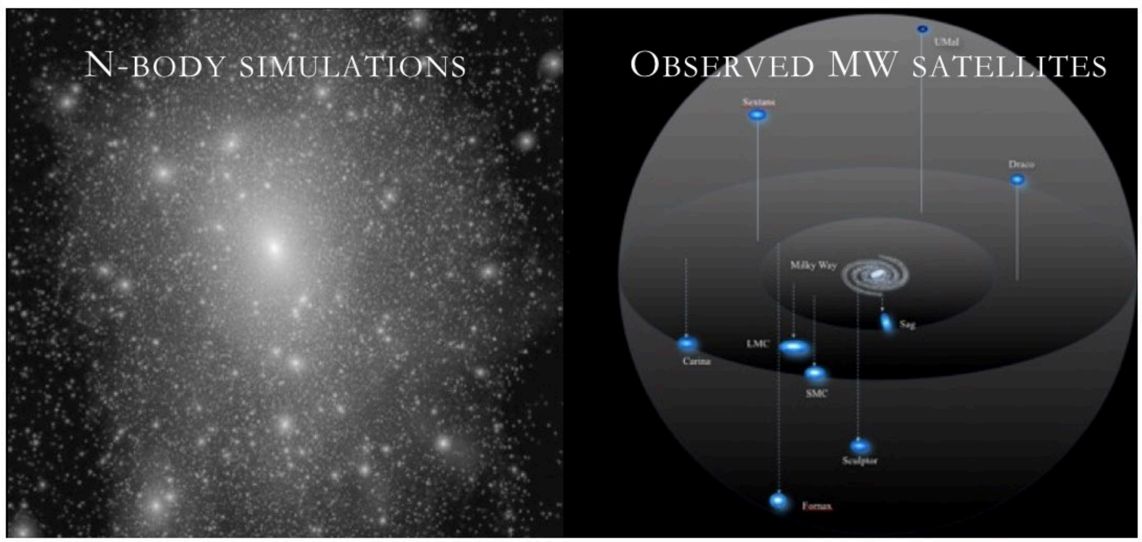


Large scale structure is very well measured.

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

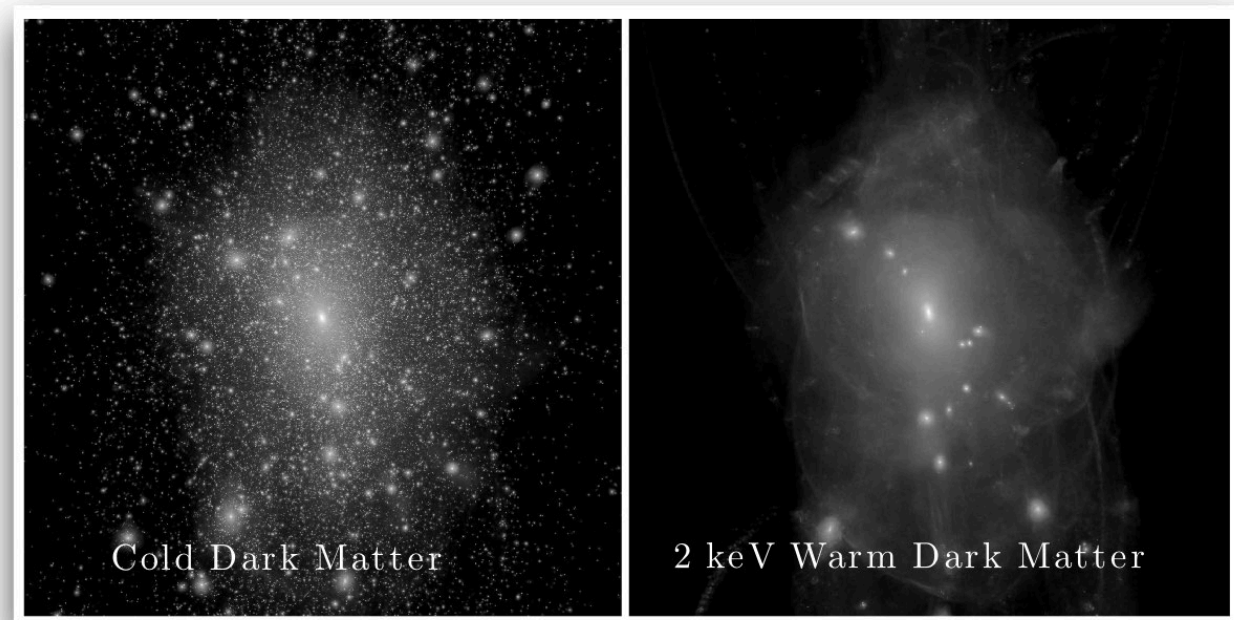


THEORY: N~ 10000 OBSERVATION N~50

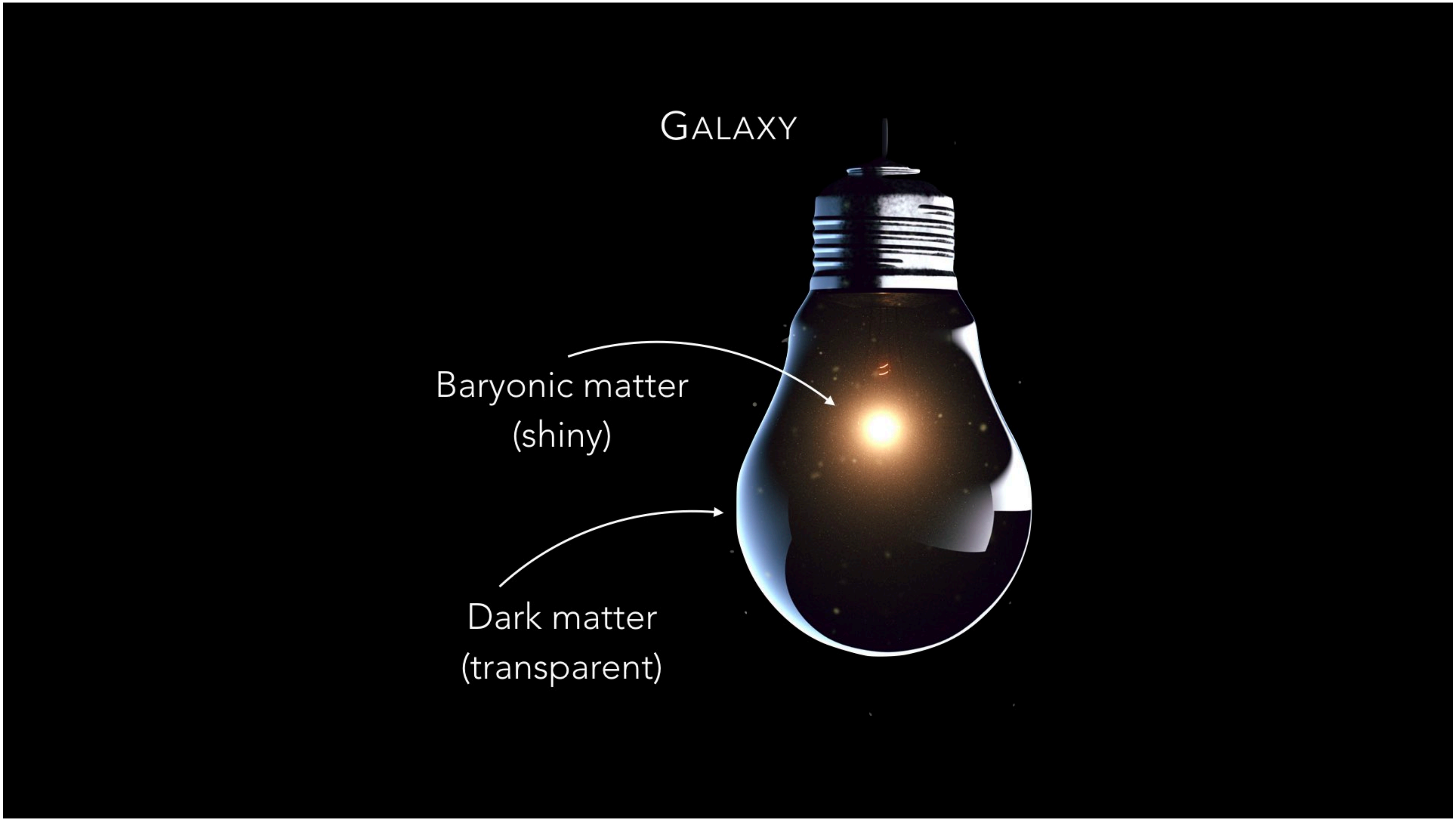
SOLUTIONS

1 - Modify galaxy formation models

2 - Modify dark matter model



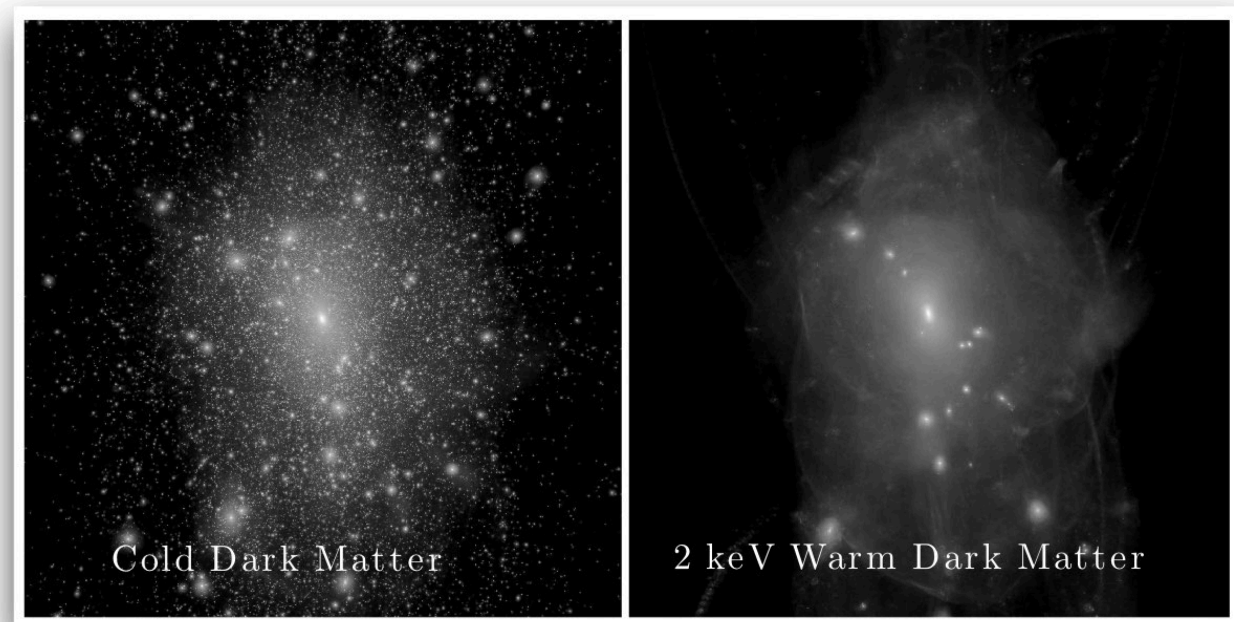
Lovell et al., MNRAS, 2012


GALAXY
Baryonic matter
(shiny)
Dark matter
(transparent)

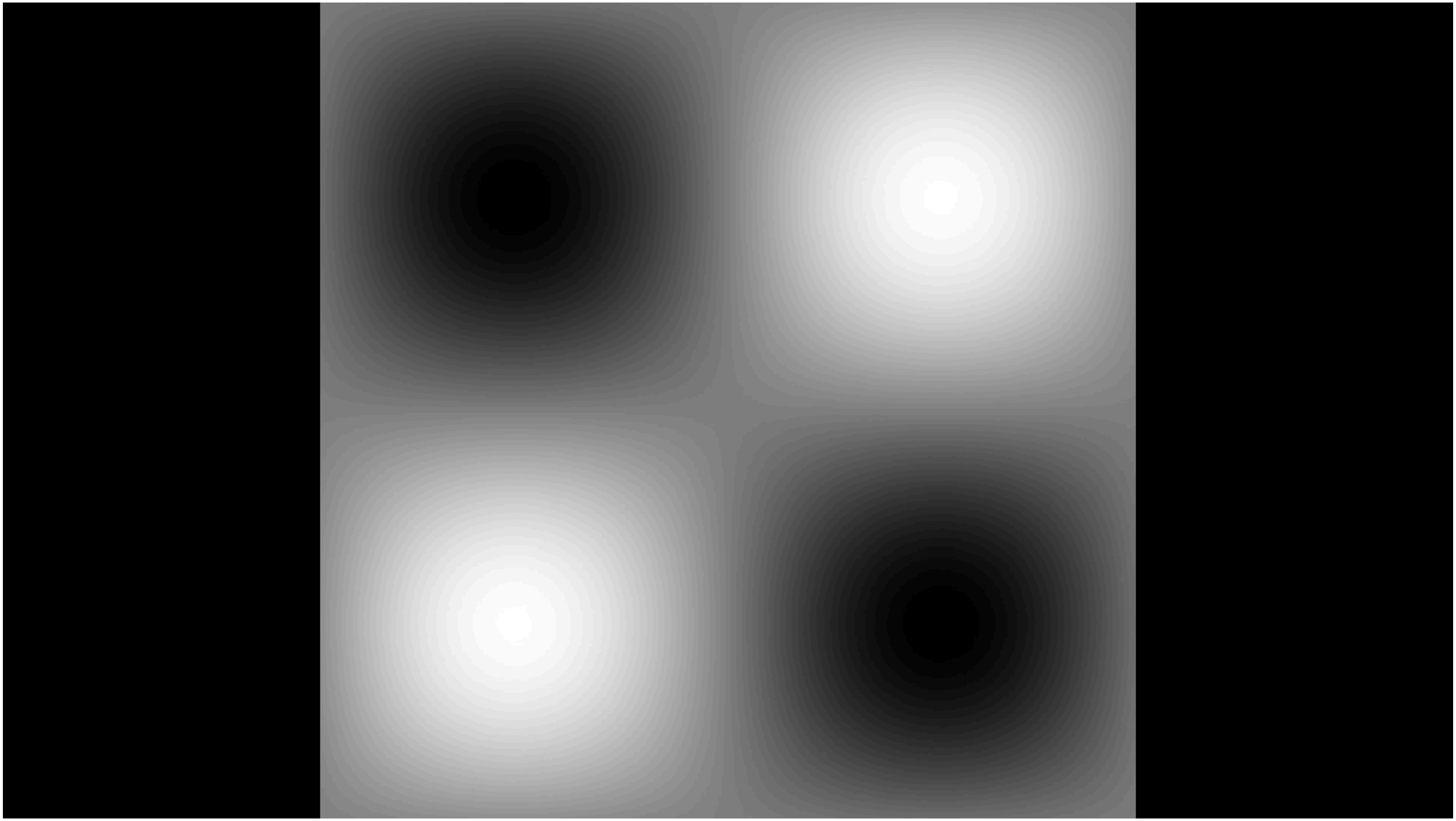
SOLUTIONS

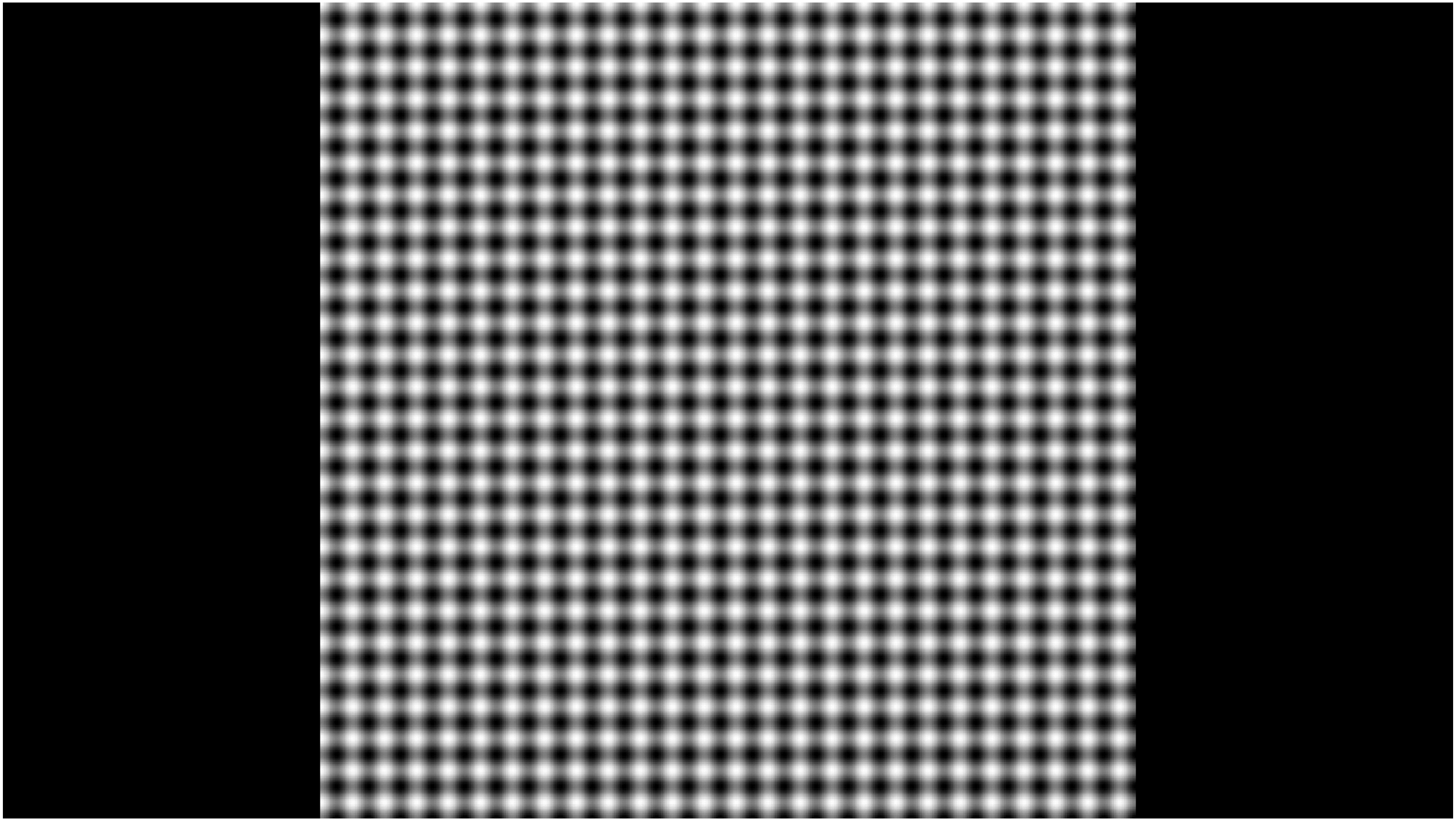
1 - Modify galaxy formation models

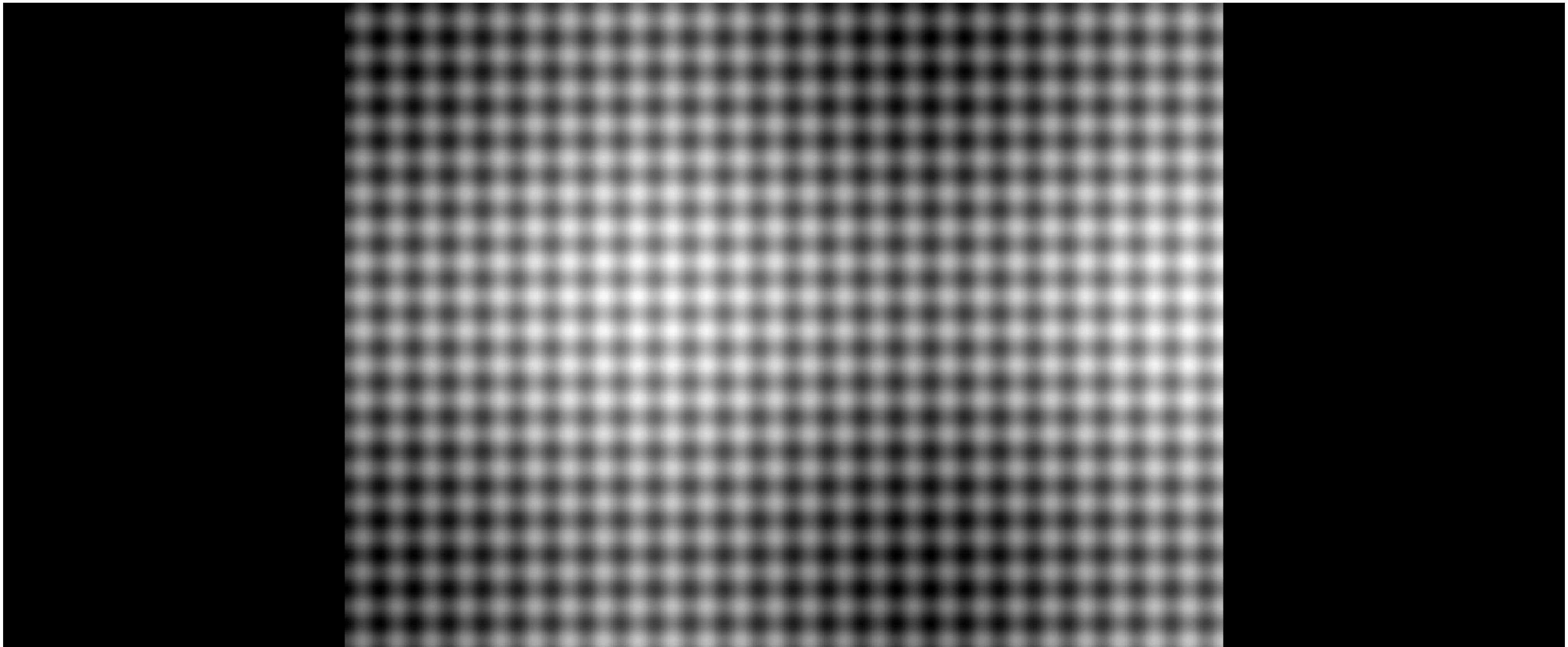
2 - Modify dark matter model

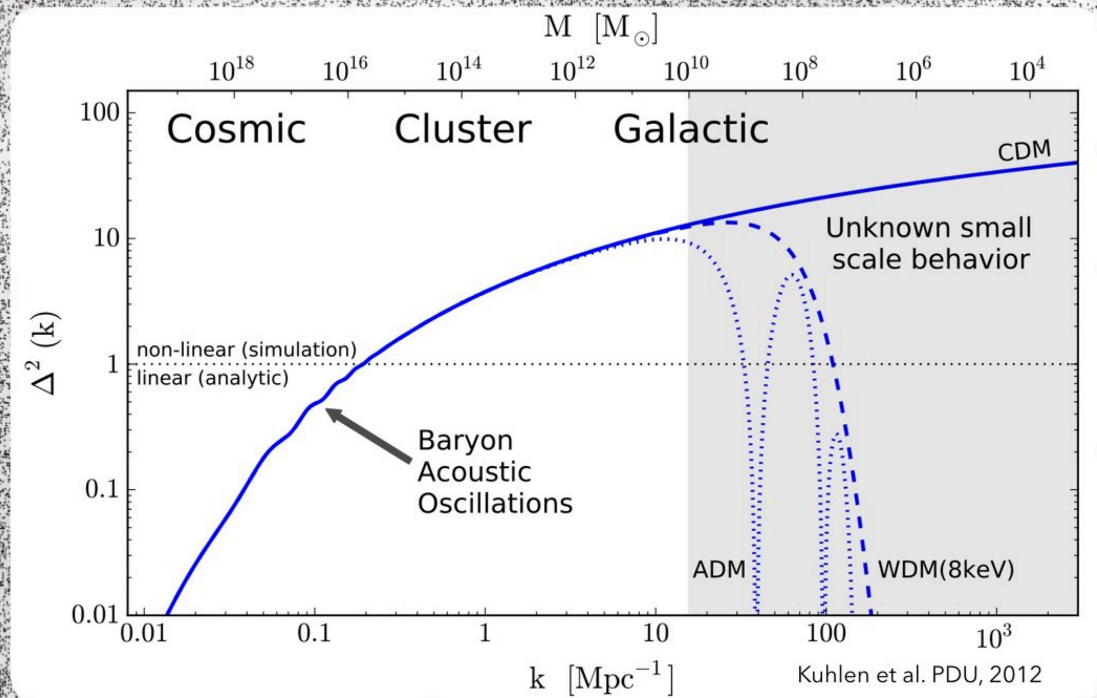


Lovell et al., MNRAS, 2012





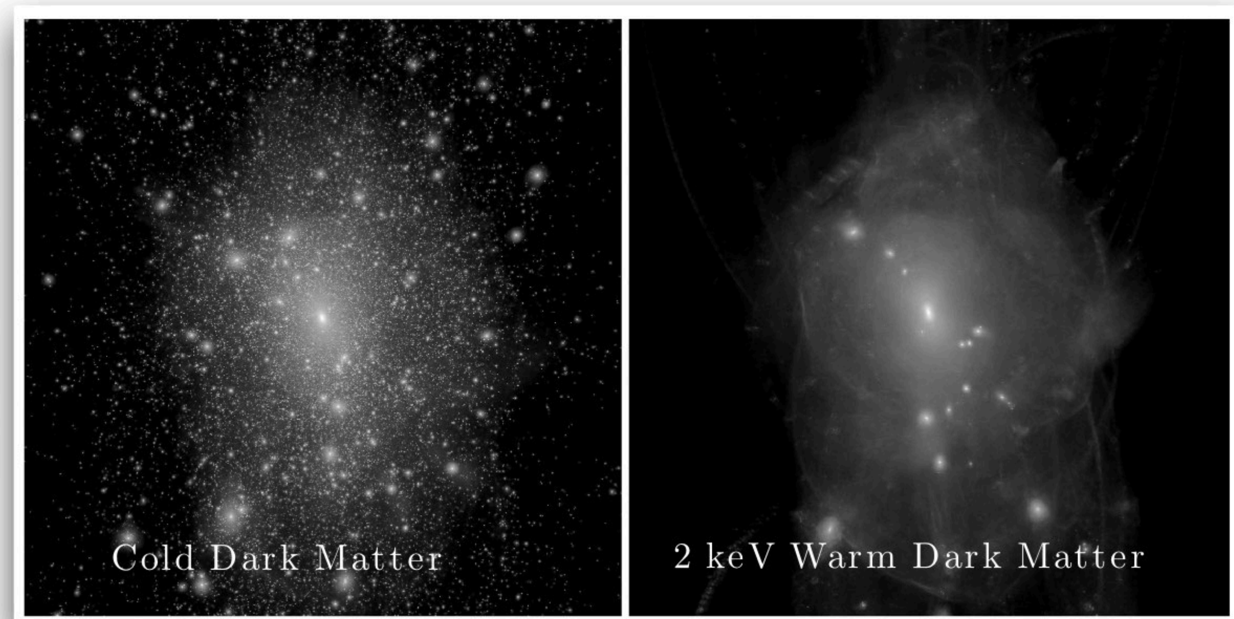




M [M_⊙]
10^18
10^16
10^14
10^12
10^10
10^8
10^6
10^4
Cosmic
Cluster
Galactic
CDM
Unknown small scale behavior
non-linear (simulation)
linear (analytic)
Baryon Acoustic Oscillations
ADM
WDM(8keV)
Δ^2 (k)
100
10
1
0.1
0.01
0.01
0.1
1
10
100
10^3
k [Mpc^-1]
Kuhlen et al. PDU, 2012

Solutions

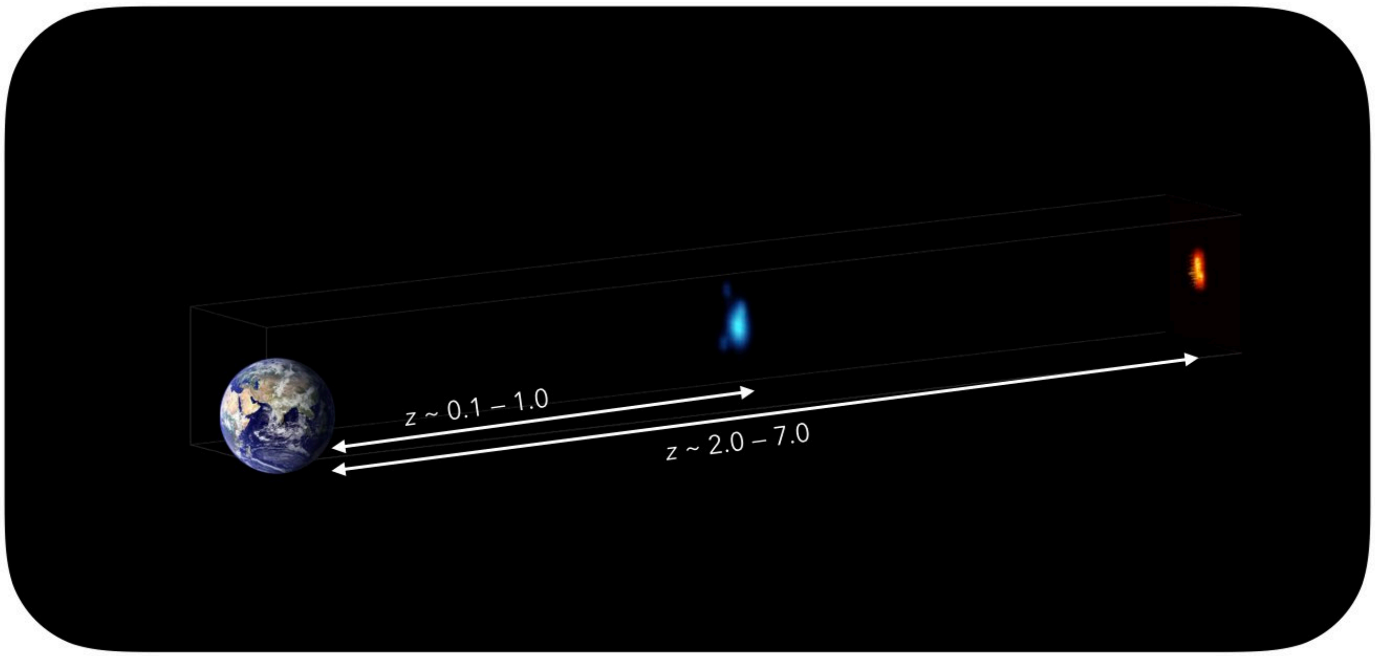
1 - Modify galaxy formation models   2 - Modify dark matter model

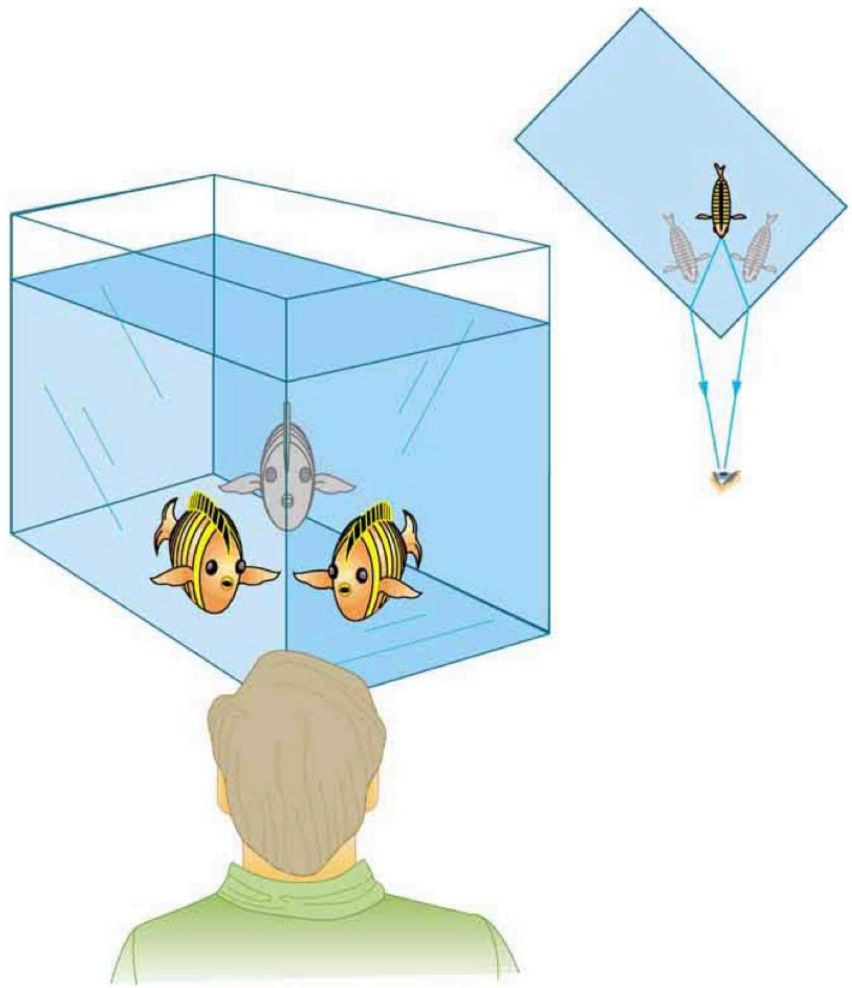


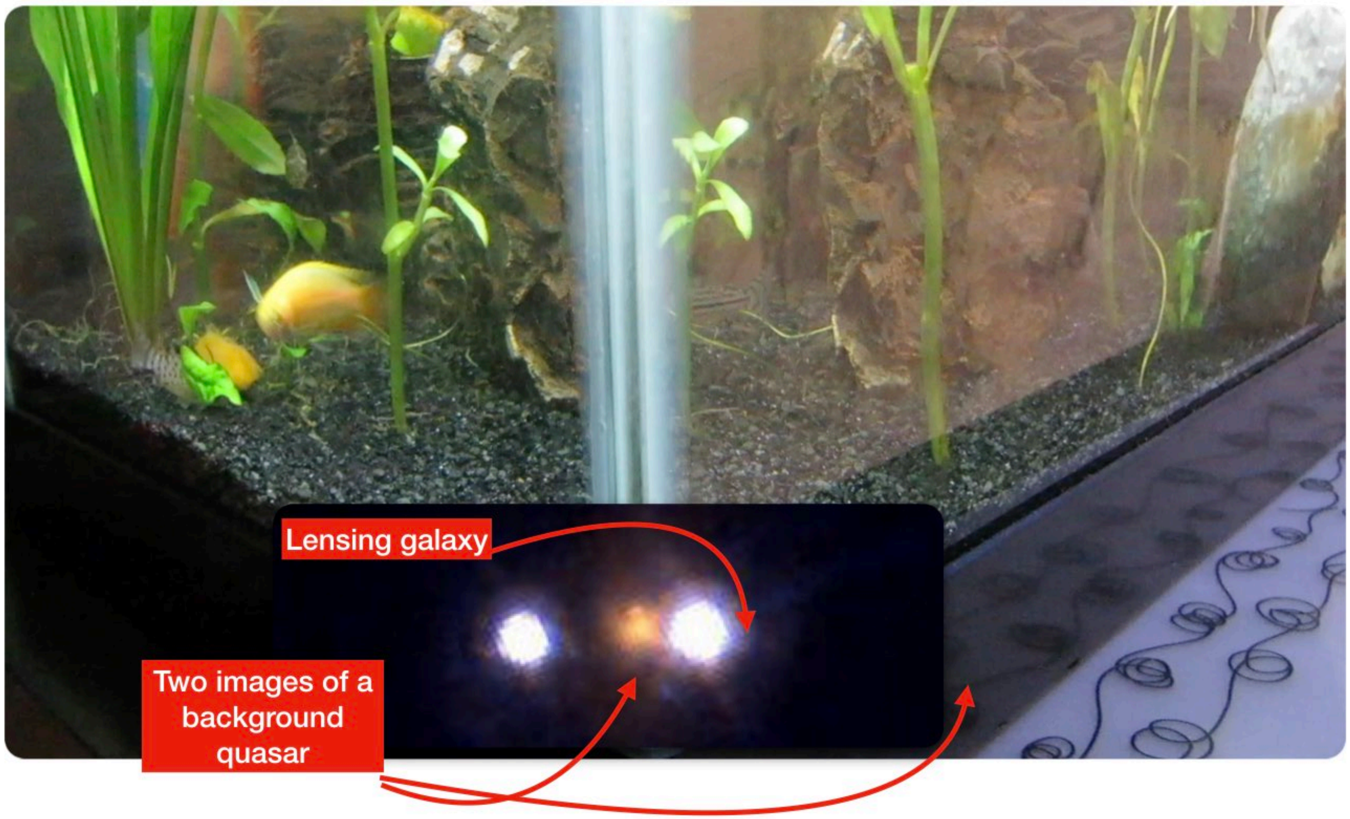
Lovell et al., MNRAS, 2012

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.



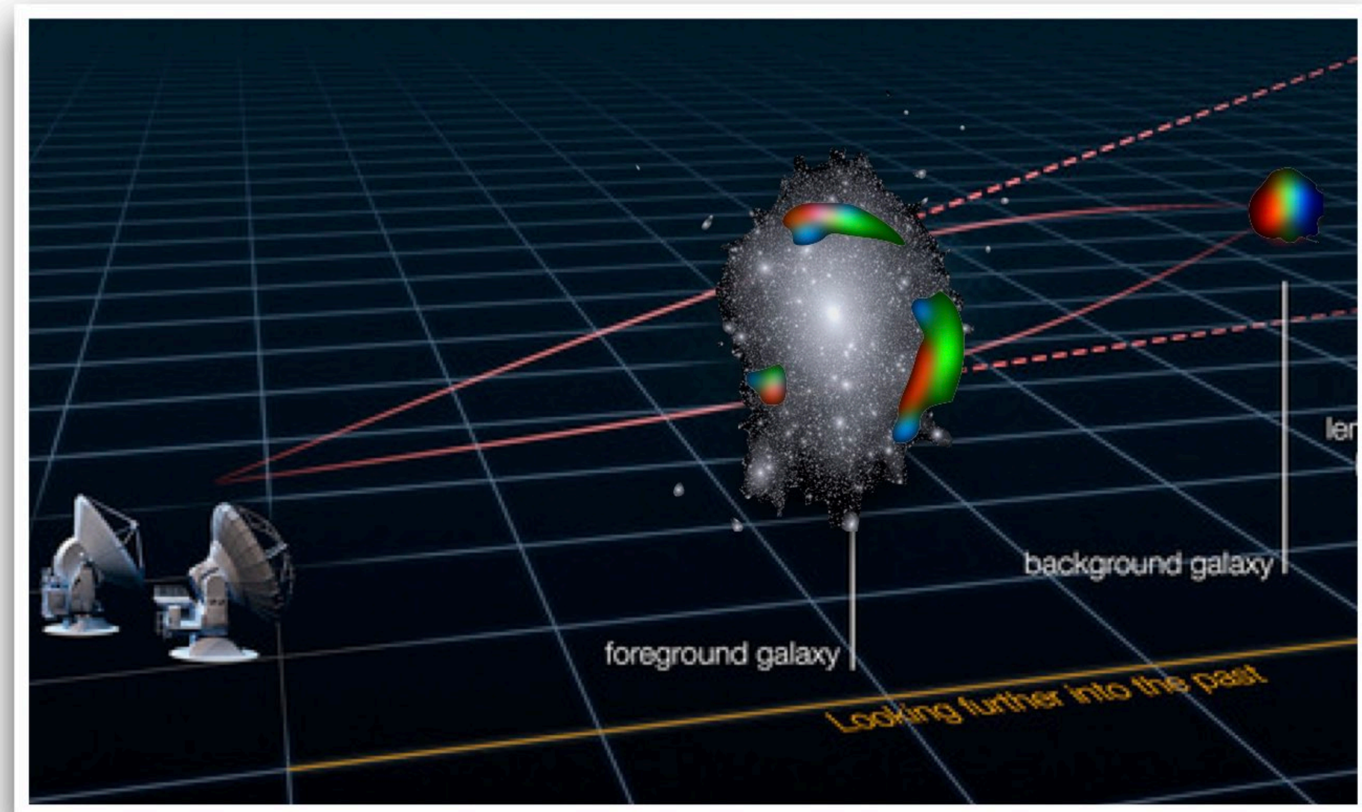




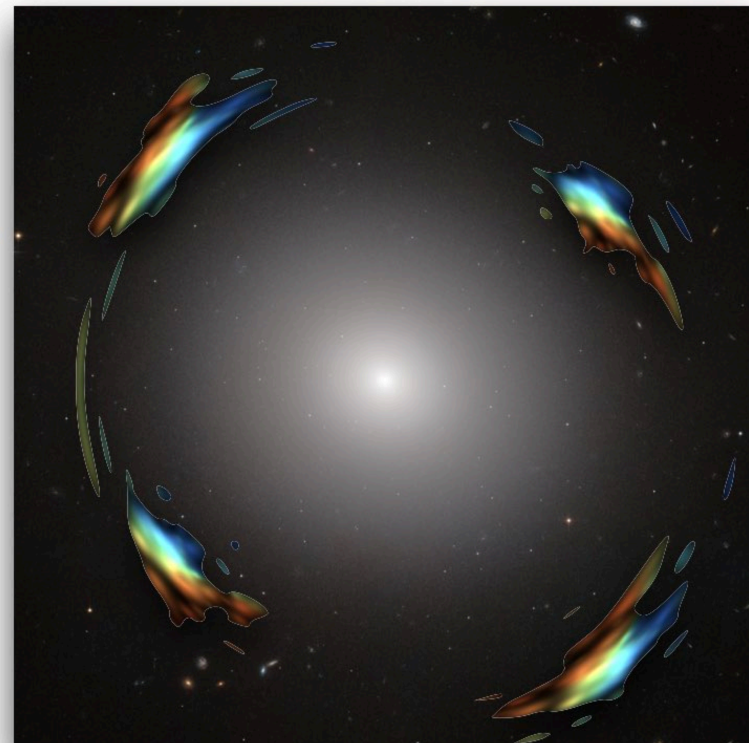
Lensing galaxy
Two images of a background quasar

Strong lenses produce arcs

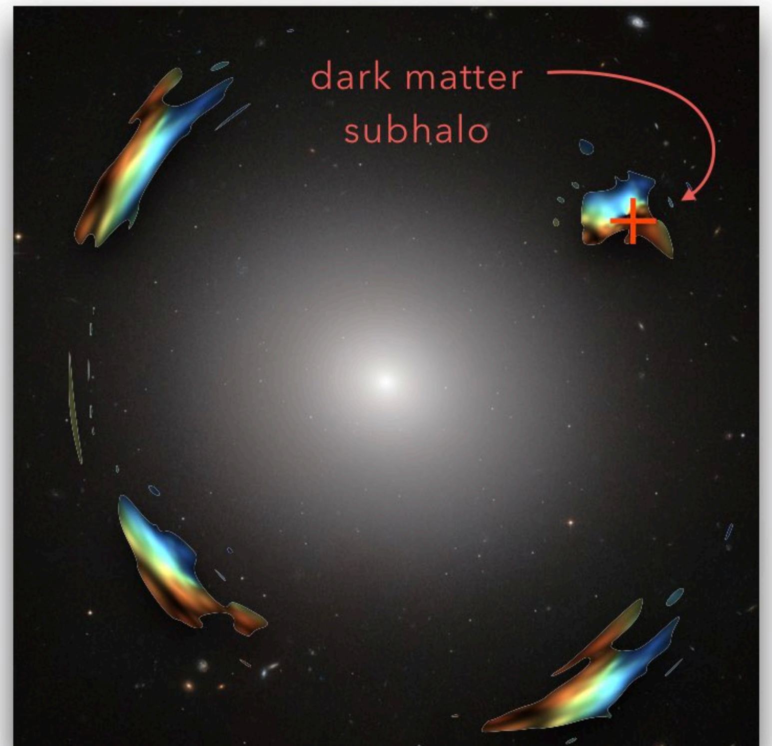
Strong Gravitational Lensing

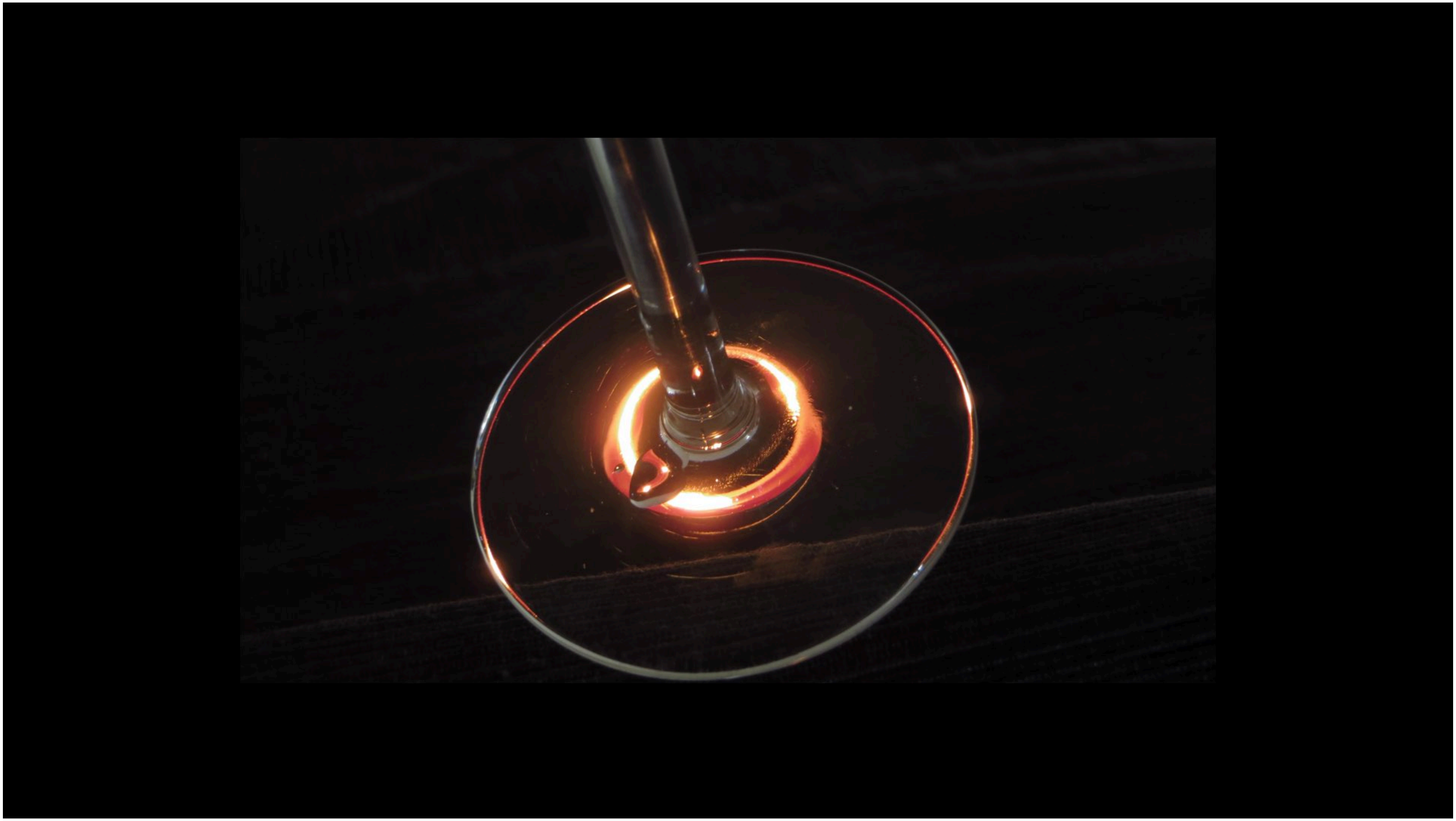


SUBSTRUCTURE LENSING



Substructure lensing



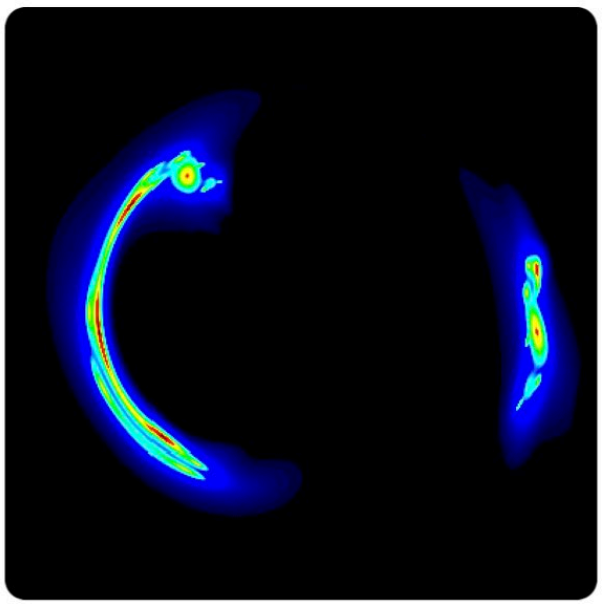


Simulated images with and without a subhalo

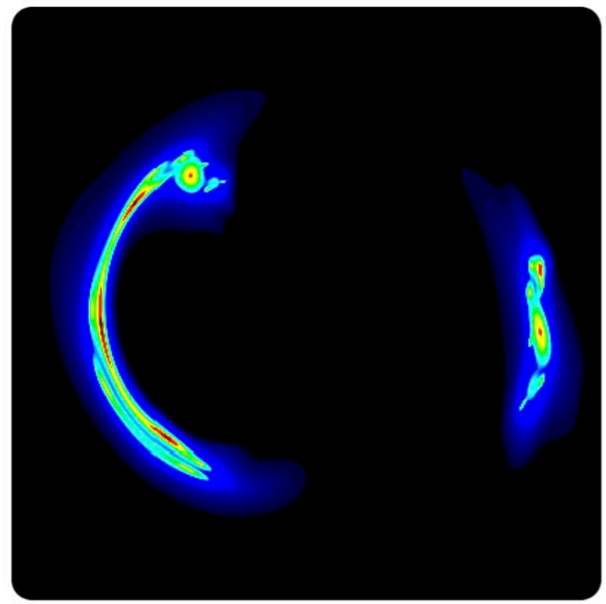
Main lensing galaxy mass ~ 10^{12} M_{sun}

Subhalo masses ~ $10^{7}-10^{9}$ M_{sun}

Smooth galaxy

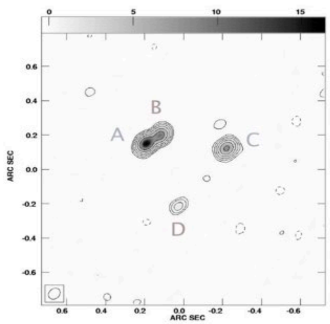


Smooth galaxy + subhalo



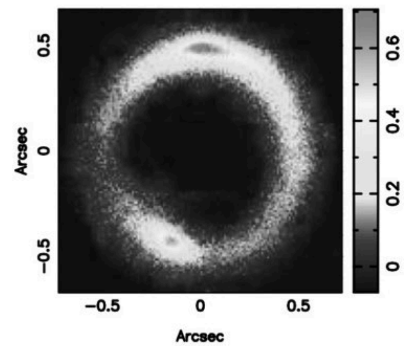
SUBSTRUCTURE LENSING

LENSED RADIO QUASARS



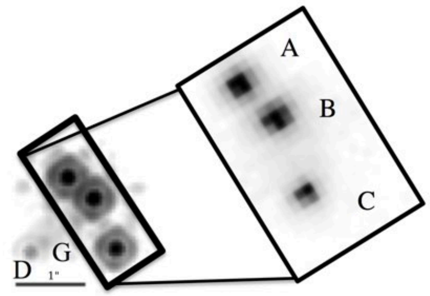
Dalal & Kochanek 2002

LENSED GALAXIES (OPTICAL)



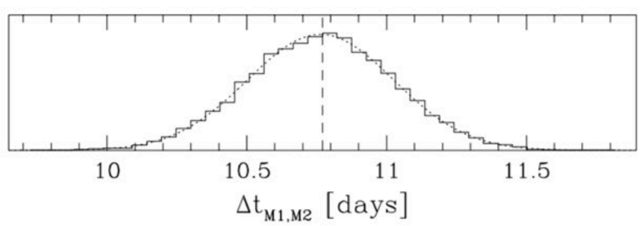
Vegetti et al. 2012

LENSED OPTICAL QUASARS



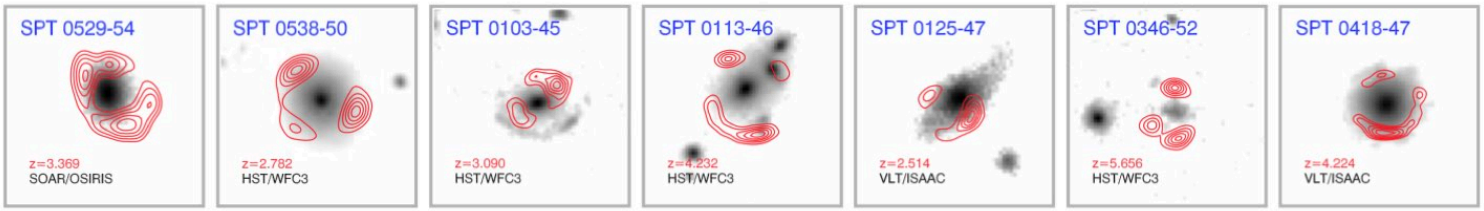
Nierenberg et al. 2014

EFFECT ON TIME DELAYS
BETWEEN IMAGES



Keaton & Moustakas 2009

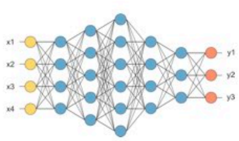
1: A new, large population of strong lenses



Vieira et al. Nature 2013 Hezaveh et al. ApJ. 2013 Weiss et al. ApJ. 2013

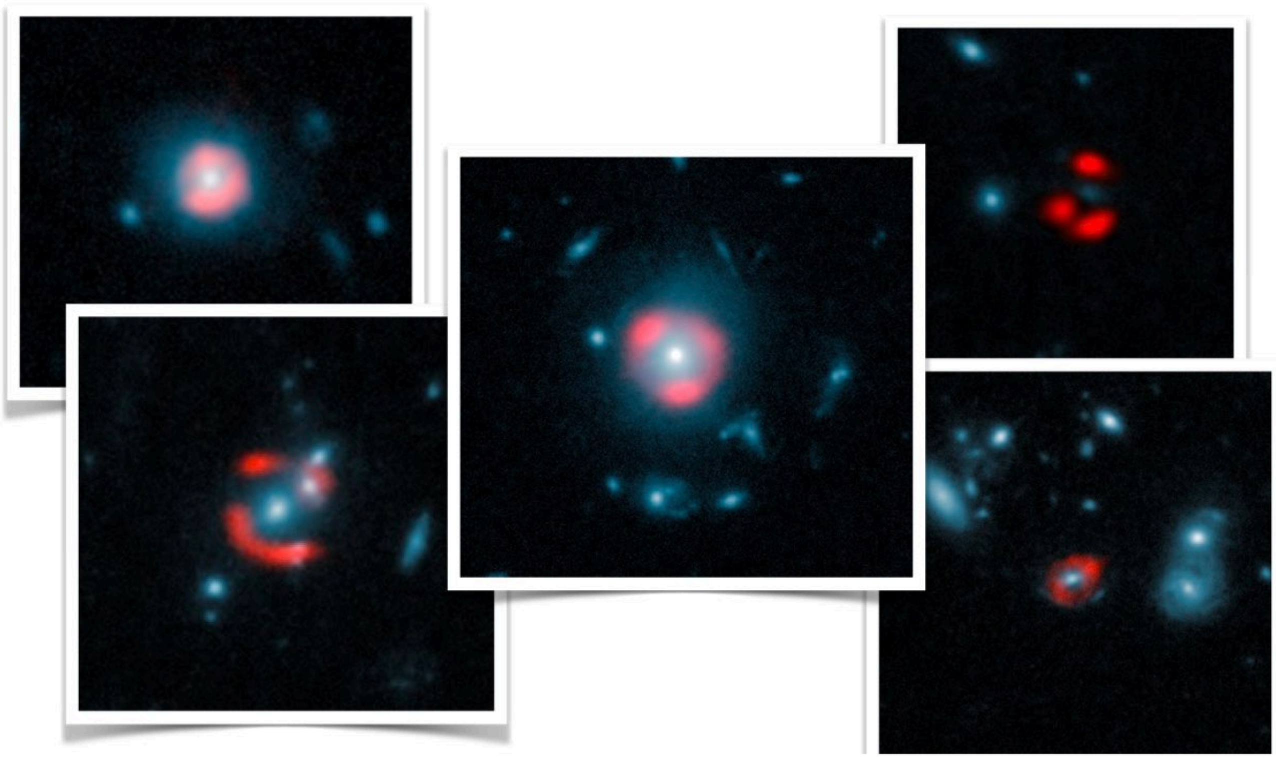
2: A new, revolutionary observatory

3: New analysis methods



- Hezaveh et al. ApJ. 767-9 2013
- Hezaveh et al. ApJ 767-132 2013
- Hezaveh et al. ApJ 823-37 2016
- Hezaveh et al. JCAP 11-048, 2016
- Hezaveh et al. Nature 548-555 2017

SPT-DISCOVERED STRONG LENSES

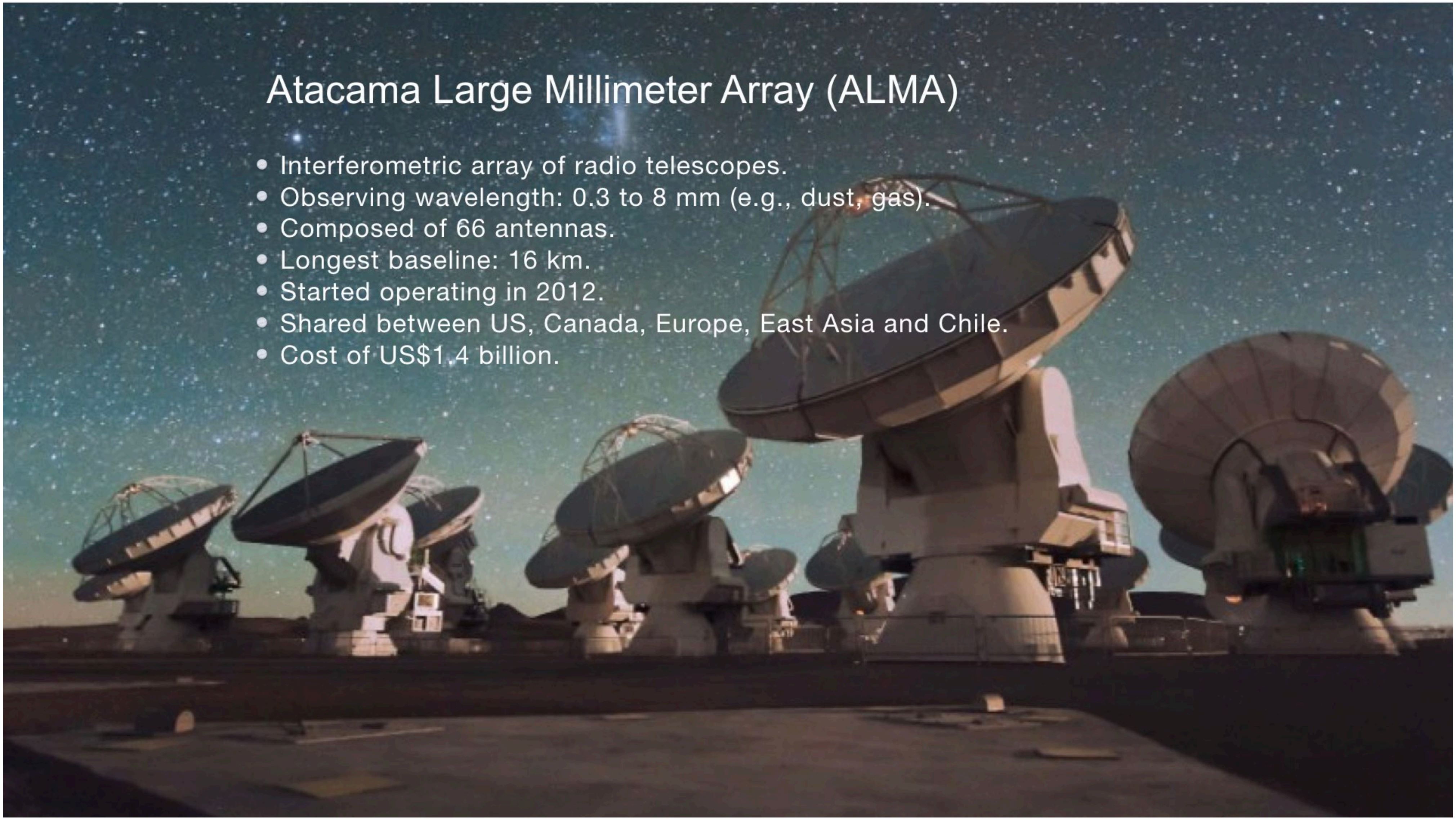


~ 50 (s) ~15 ANTENNAS 0.5 ARCSEC >70 SIGMA DETECTION

Vieira et al., Nature, 2013 Hezaveh et al., ApJ, 2013 Weiss et al., ApJ, 2013

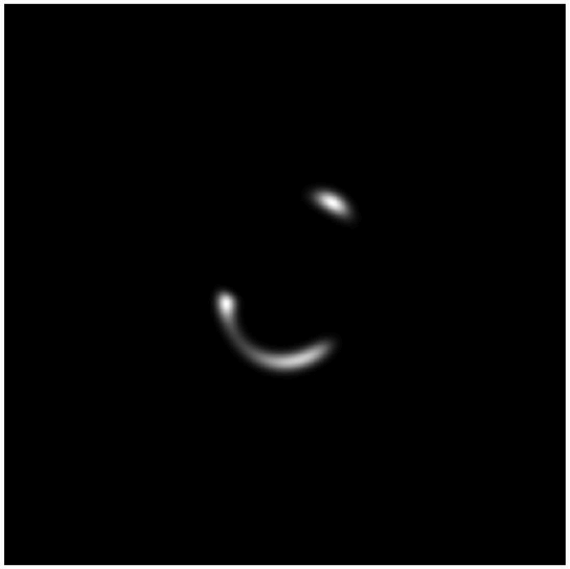
Atacama Large Millimeter Array (ALMA)

- Interferometric array of radio telescopes.
- Observing wavelength: 0.3 to 8 mm (e.g., dust, gas).
- Composed of 66 antennas.
- Longest baseline: 16 km.
- Started operating in 2012.
- Shared between US, Canada, Europe, East Asia and Chile.
- Cost of US$1.4 billion.

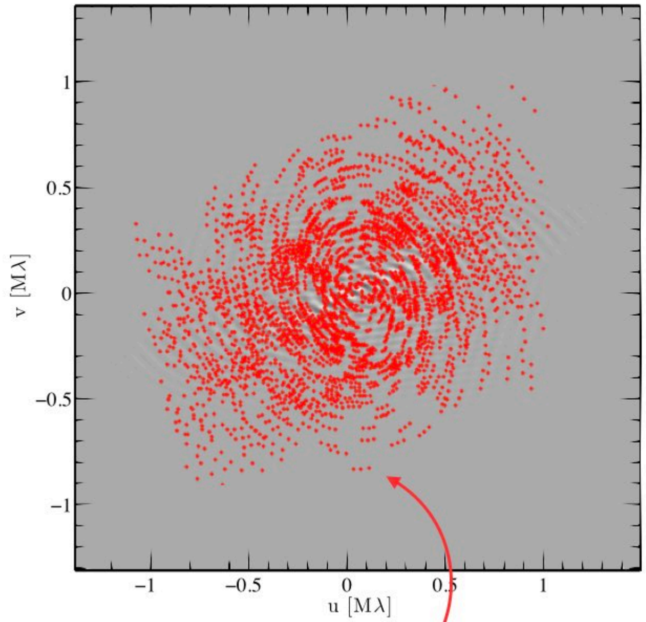


An interferometer measures certain Fourier modes of the sky emission

True image of the sky

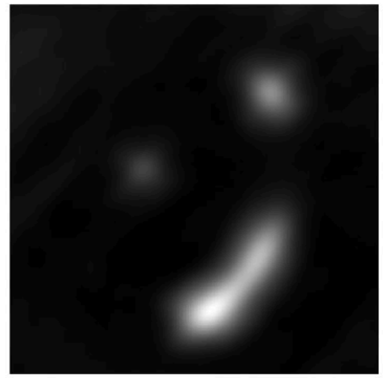


2D Fourier transform

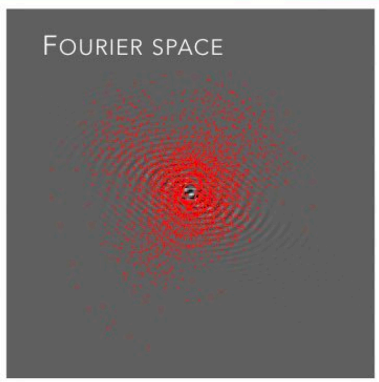


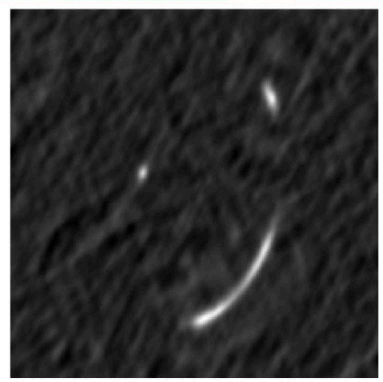
A single measured Fourier mode = a "*visibility*"

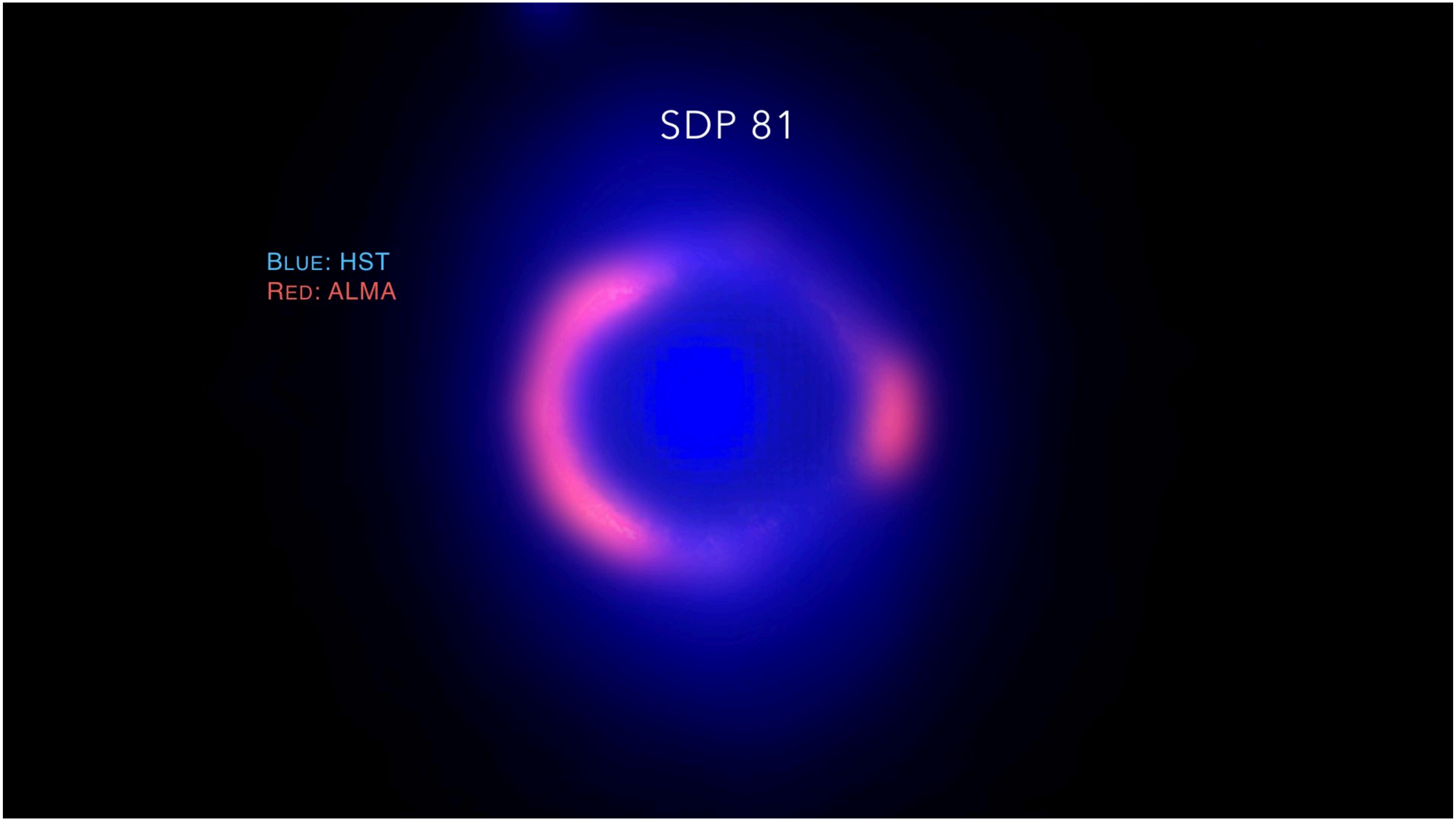
Compact Configuration

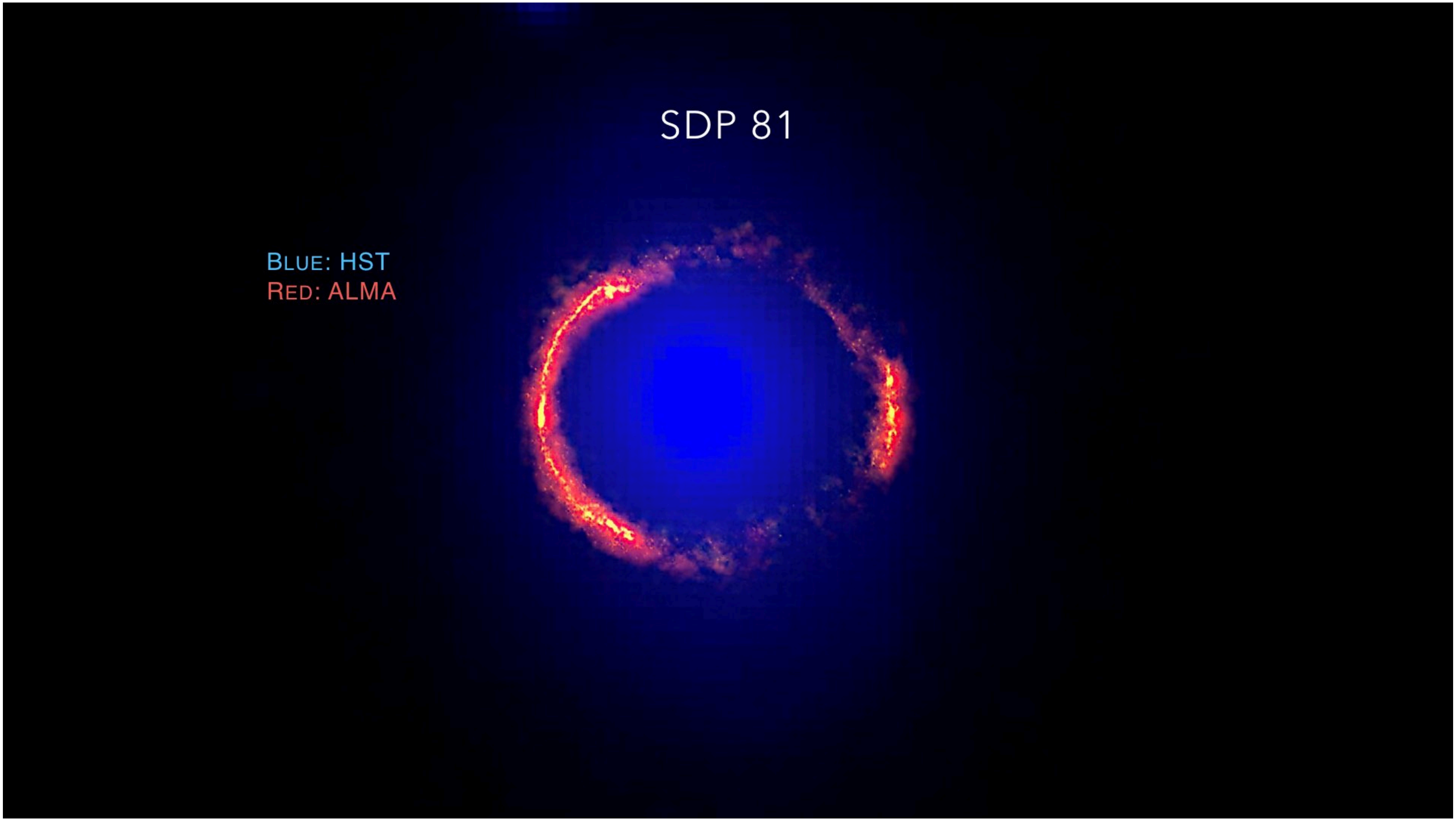


Extended Configuration



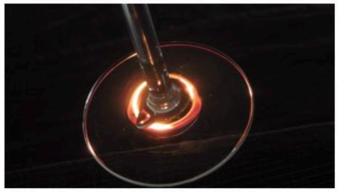



SDP 81
BLUE: HST
RED: ALMA


SDP 81
Blue: HST
Red: ALMA

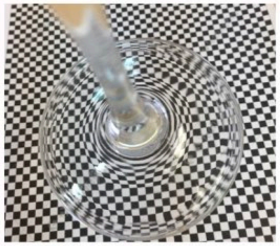
MEASURING PHYSICAL PROPERTIES FROM IMAGES OF STRONG LENSES

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



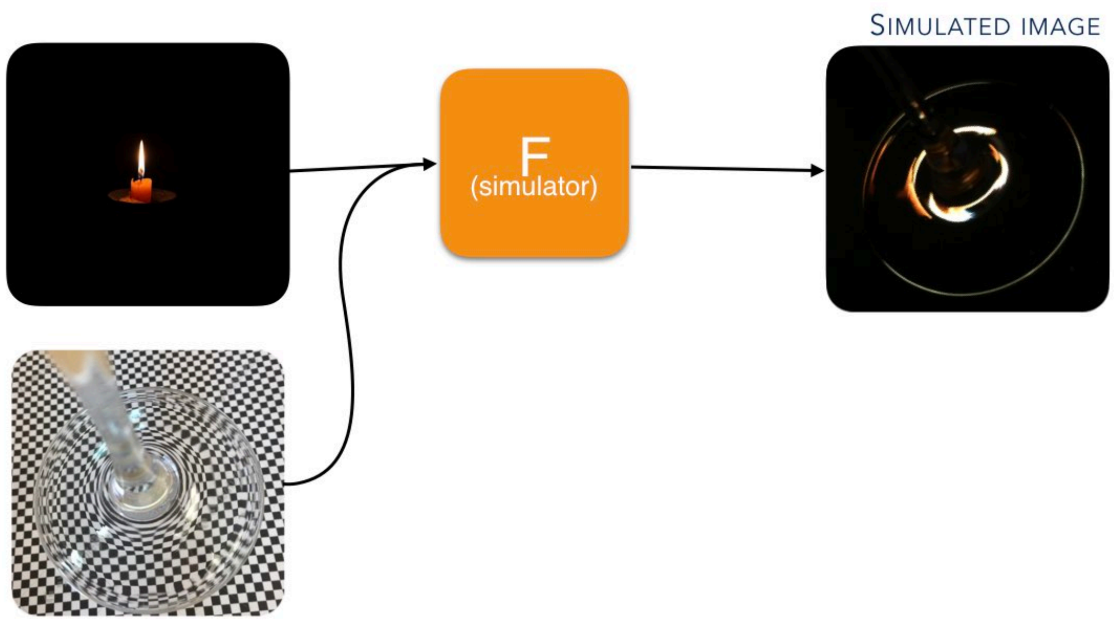
1: Morphology of the background source (the true, undistorted image of the candle)

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



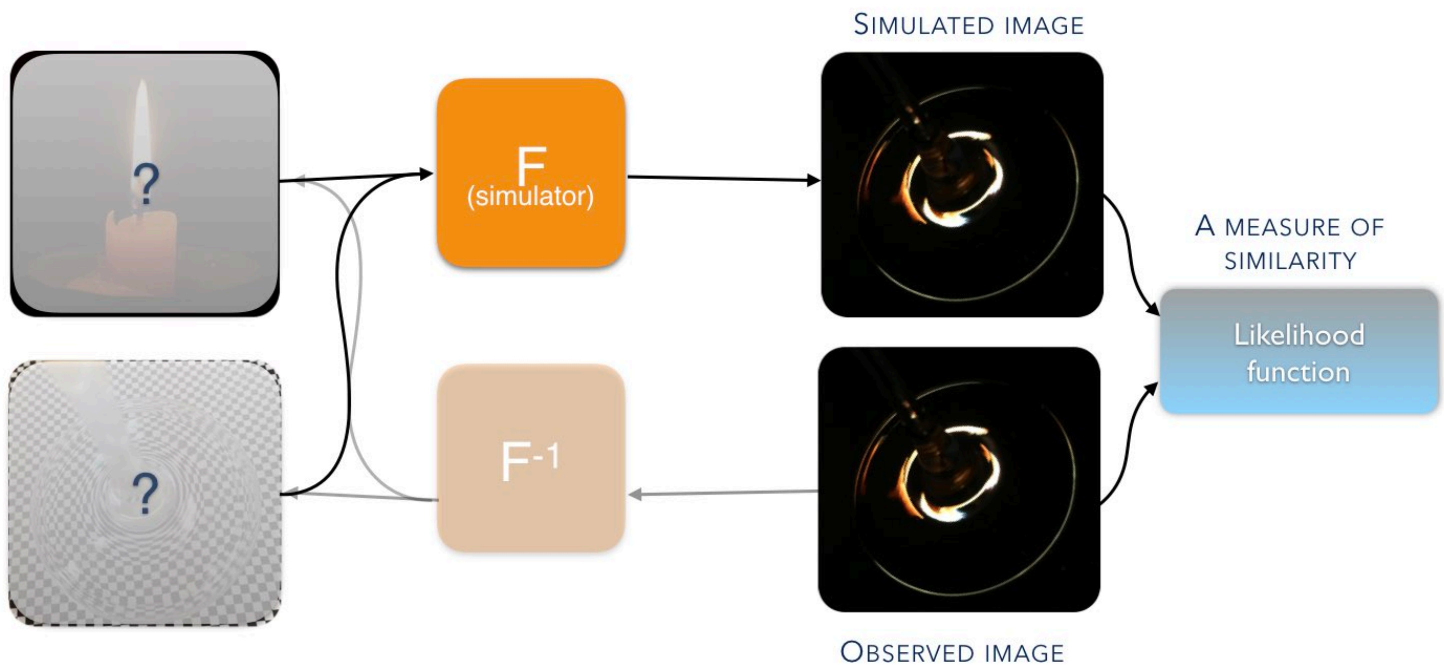
Measuring physical properties from images of strong lenses

simulating lenses



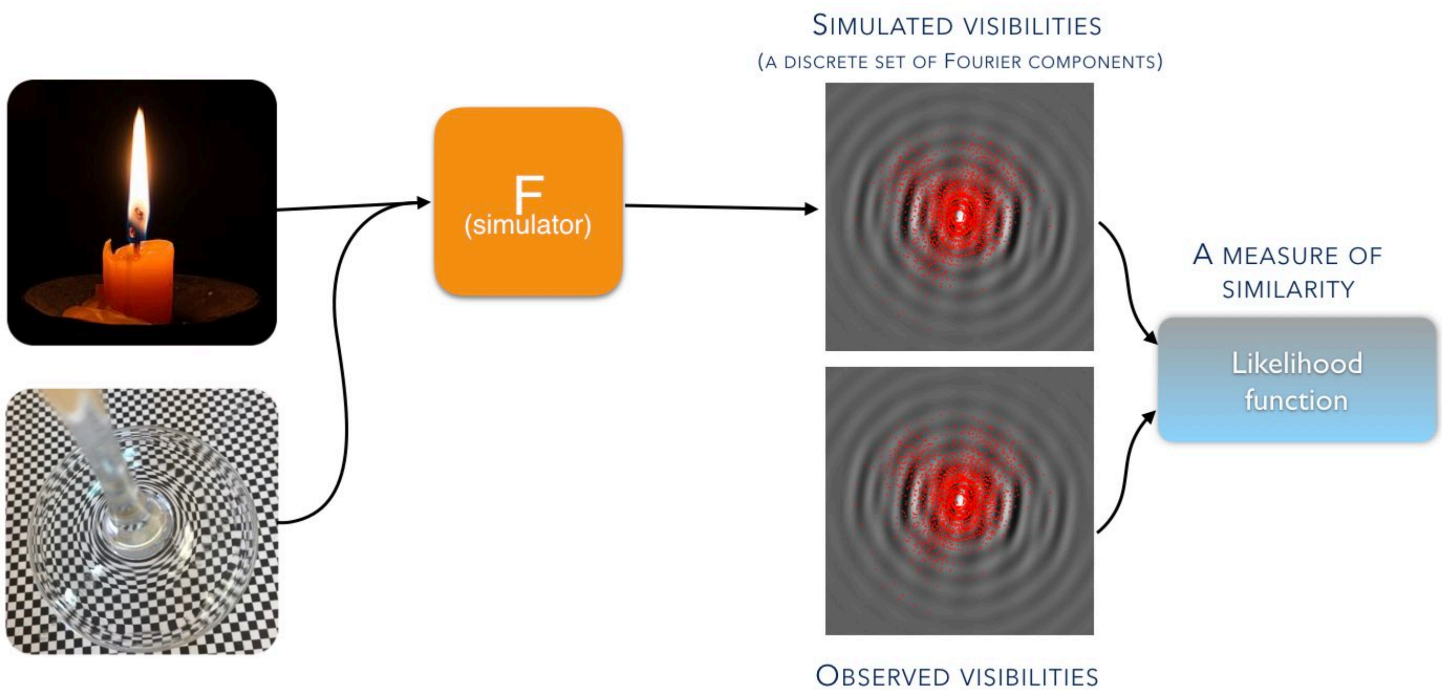
Measuring physical properties from images of strong lenses

maximum likelihood lens modeling



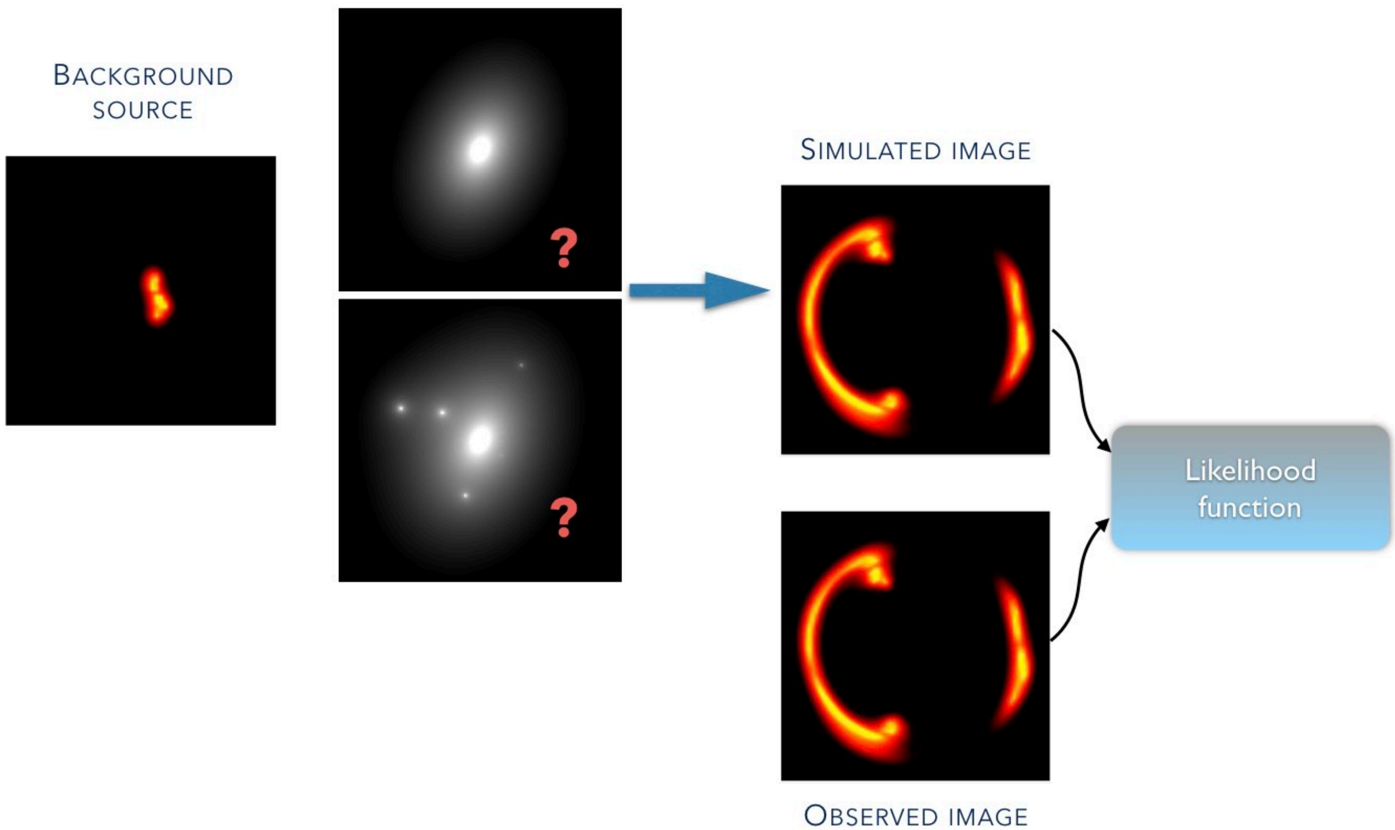
MEASURING PHYSICAL PROPERTIES FROM IMAGES OF STRONG LENSES

maximum likelihood lens modeling



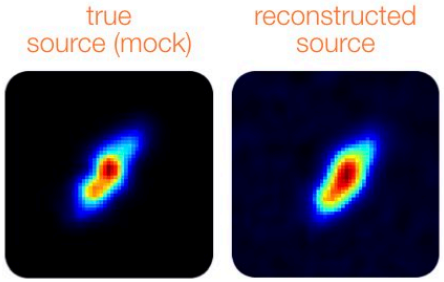
Subhalo detection:

Compare a smooth model with a model which includes subhalos

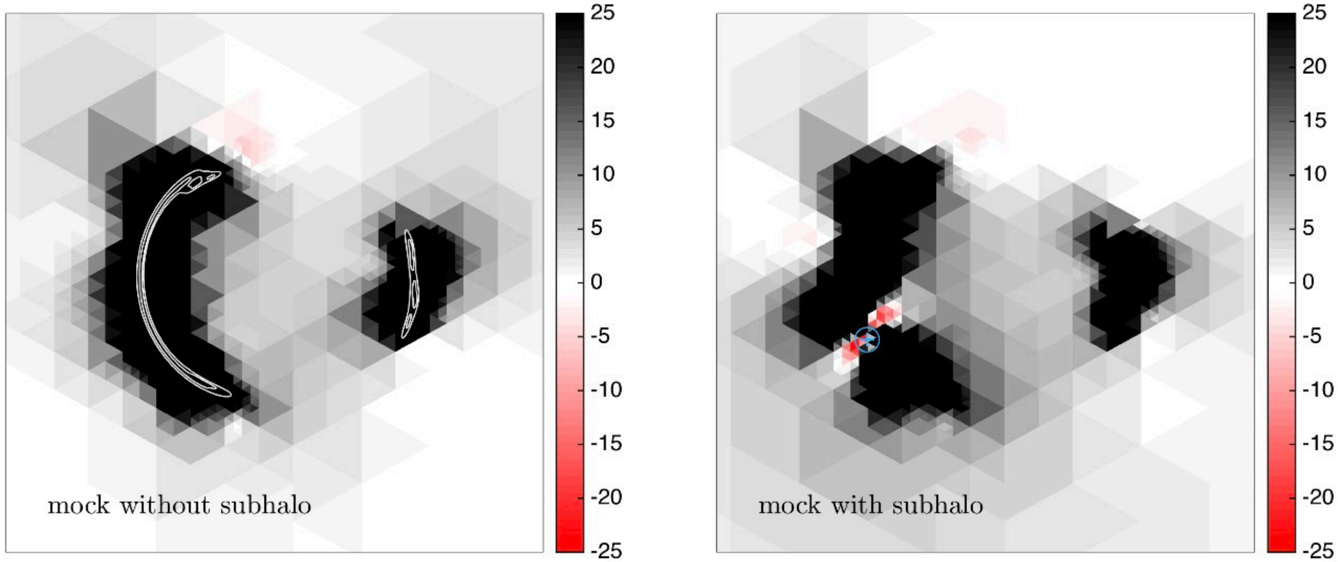


Lens modeling pipeline

- Pixelated background source reconstruction.
- Perturbative, linear subhalo search.
- Distributed computations 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)

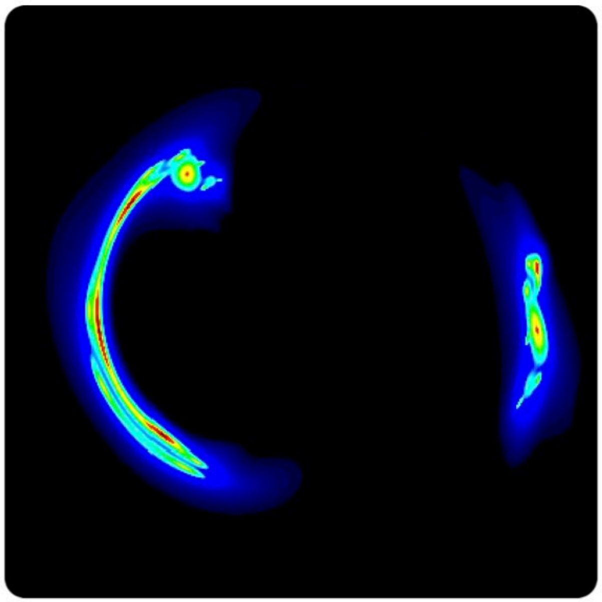
Hezaveh et al. ApJ 2016

SIMULATED IMAGES WITH AND WITHOUT A SUBHALO

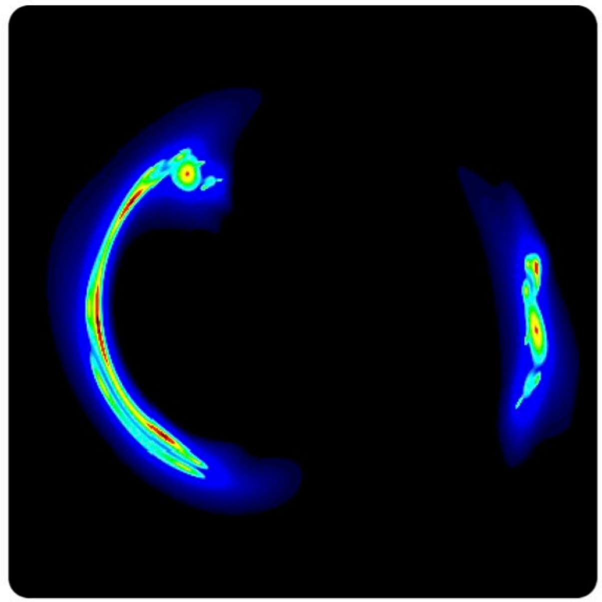
Main lensing galaxy mass ~ 10^{12} M_{sun}

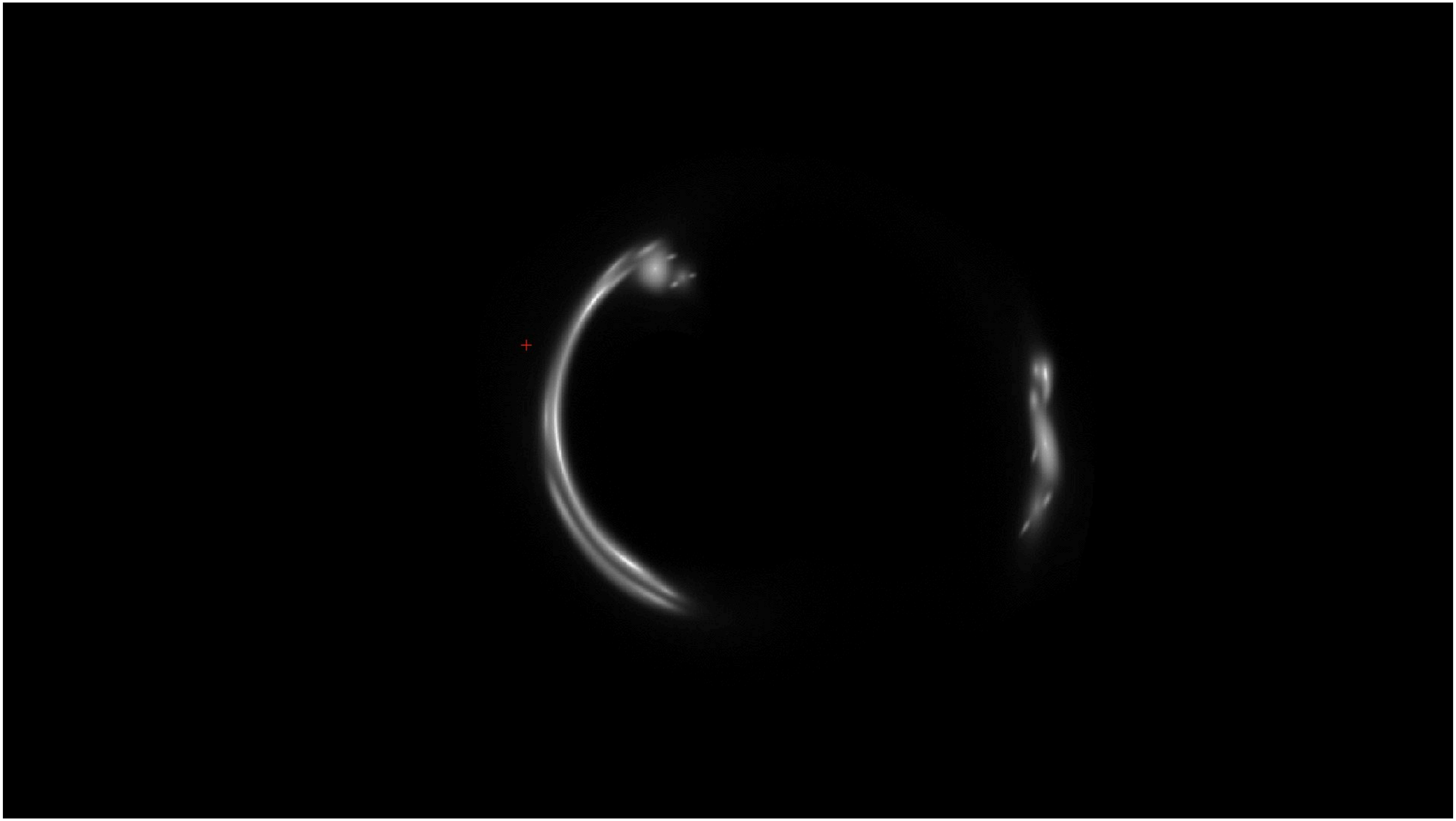
Subhalo masses ~ $10^{7} - 10^{9}$ M_{sun}

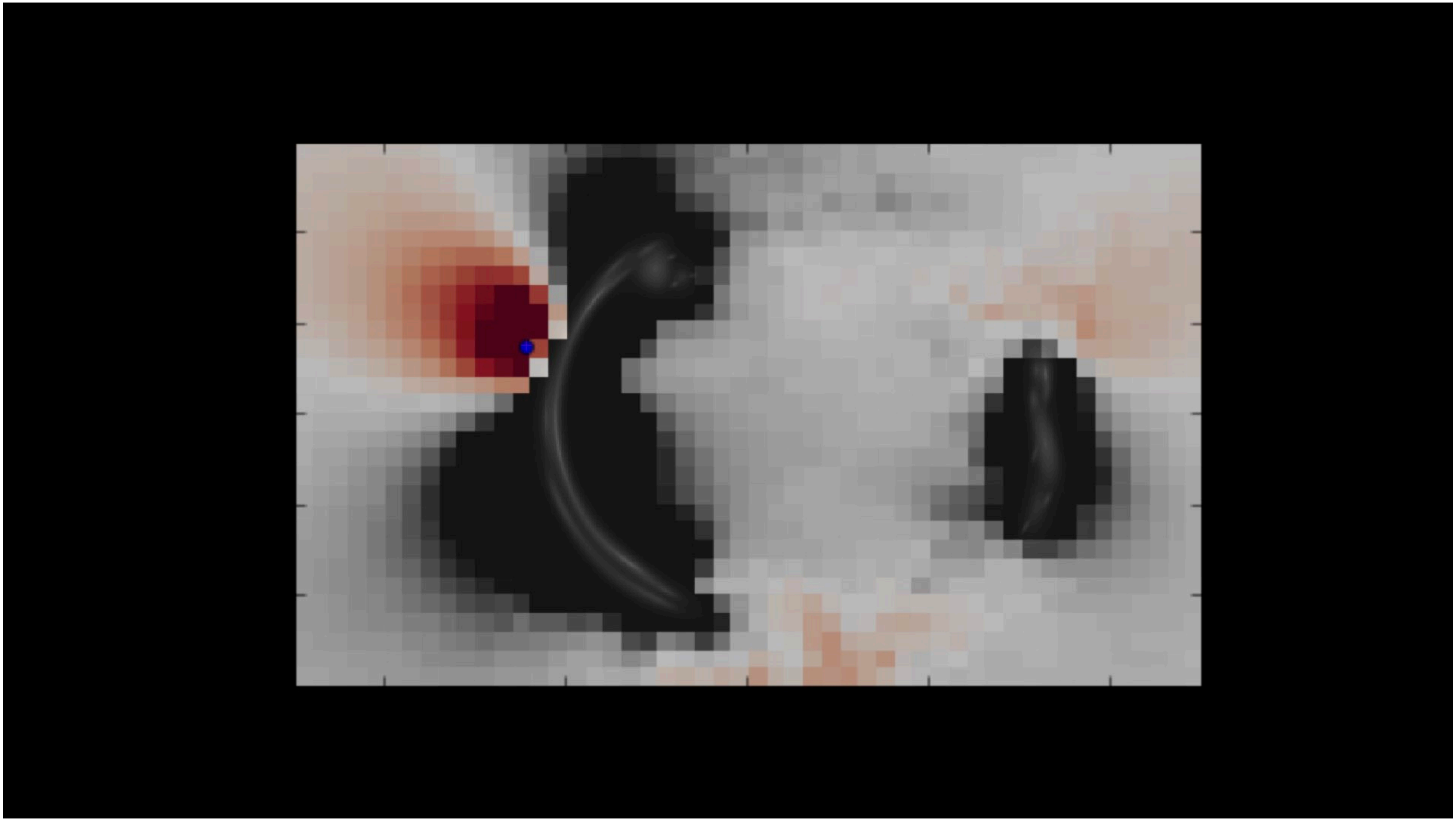
SMOOTH GALAXY



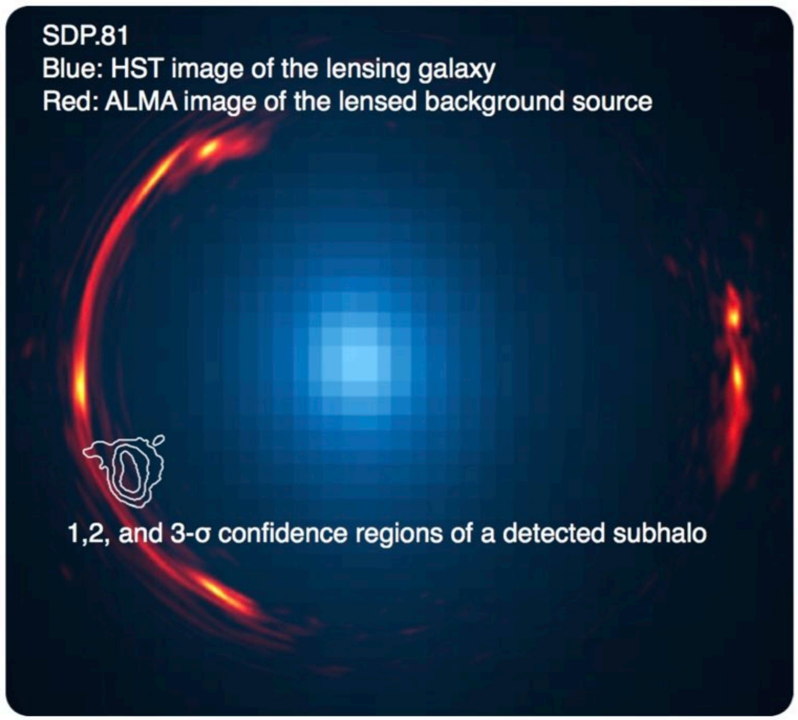
SMOOTH GALAXY + SUBHALO





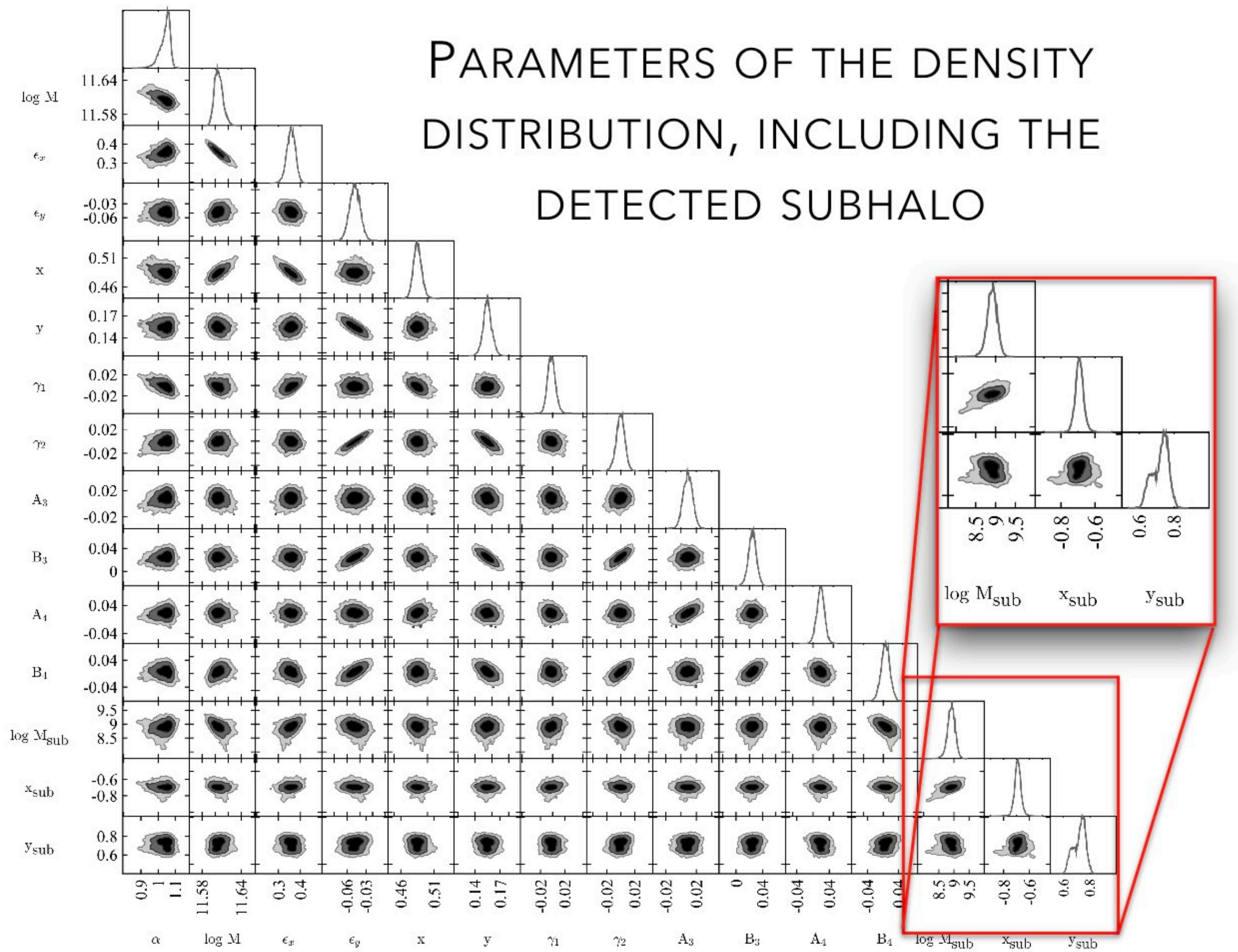


DETECTION OF A 10^9 M_{SUN} SUBHALO



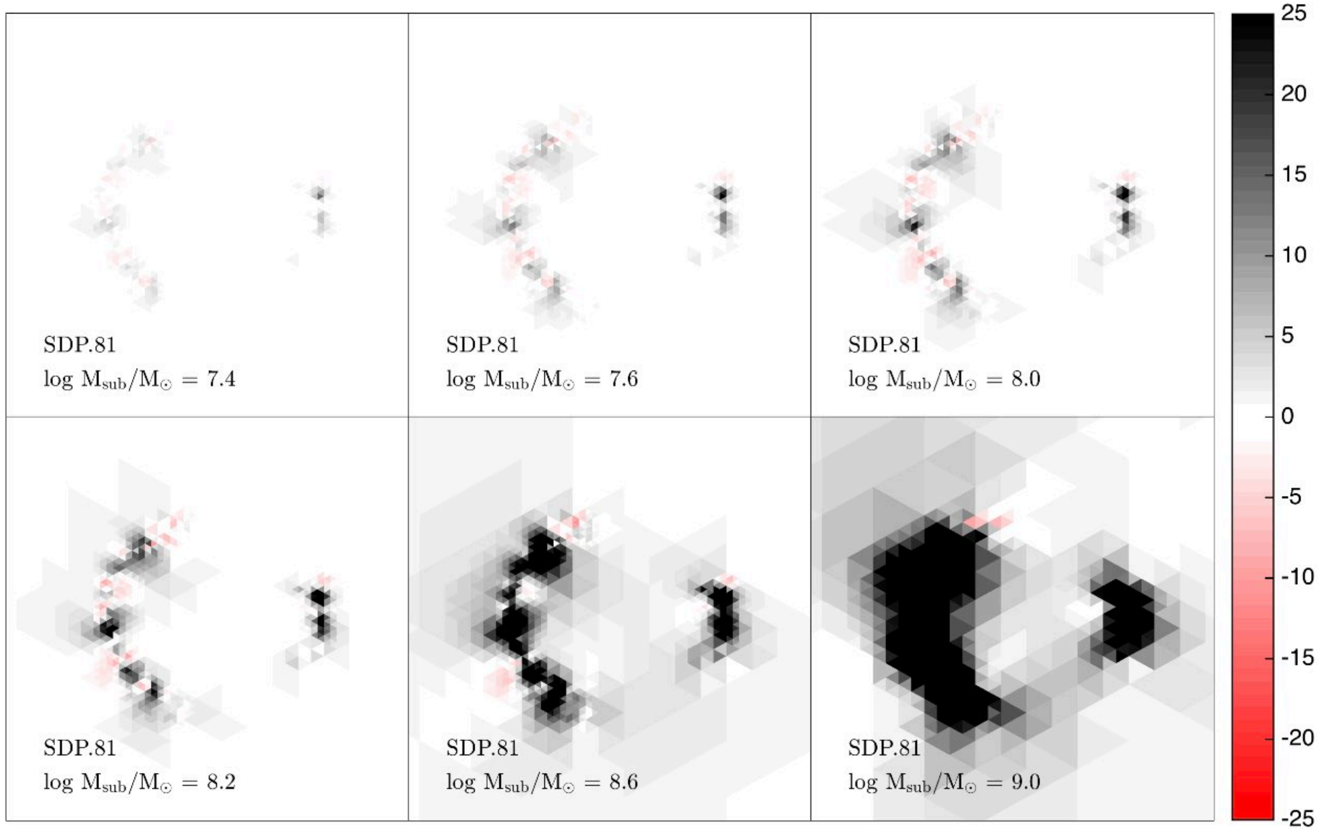
Hezaveh et al. ApJ 2016

PARAMETERS OF THE DENSITY DISTRIBUTION, INCLUDING THE DETECTED SUBHALO



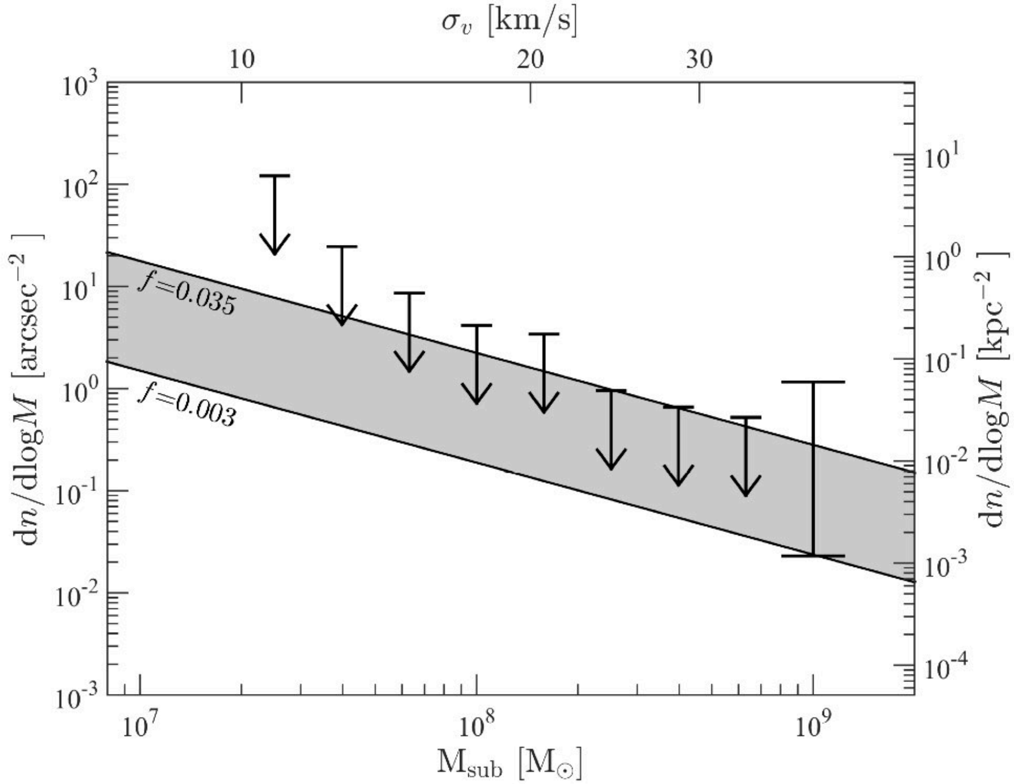
Hezaveh et al. ApJ 2016

Exclusion maps for other subhalos



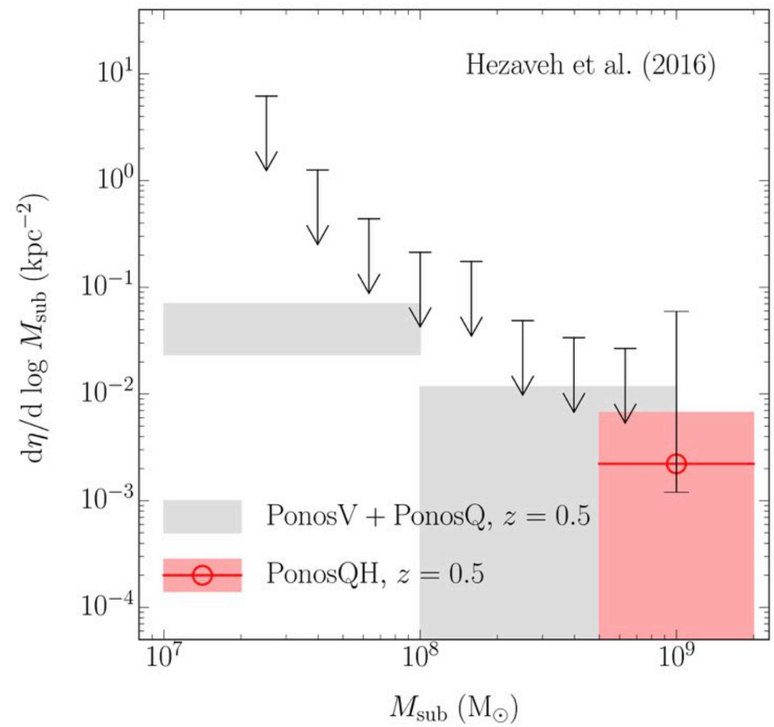
Hezaveh et al. ApJ 2016

CONSTRAINTS ON THE MASS FUNCTION OF SUBHALOS IN THE HOST HALO



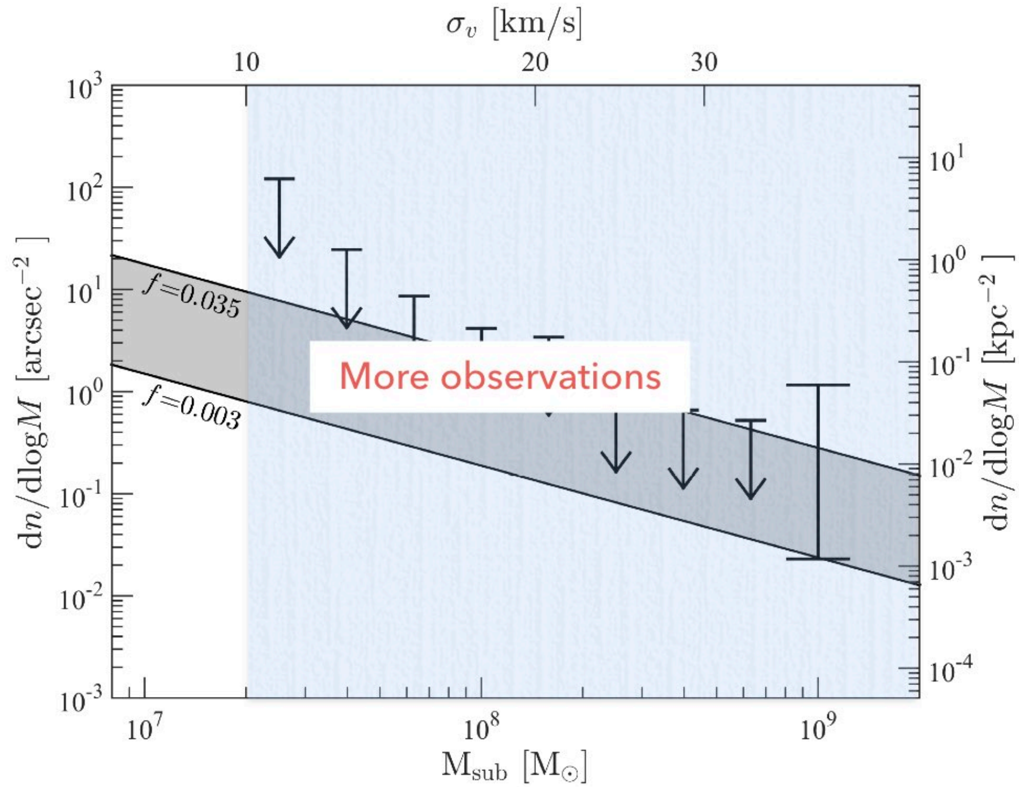
Hezaveh et al. ApJ 2016

Comparison to theoretical predictions



Fiacconi, Madau et al. ApJ, 2016

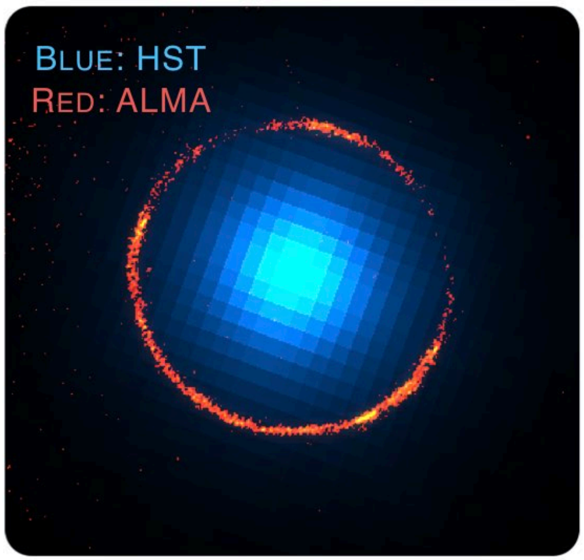
HOW TO IMPROVE OUR CONSTRAINTS



Hezaveh et al. ApJ 2016

SPT 0418

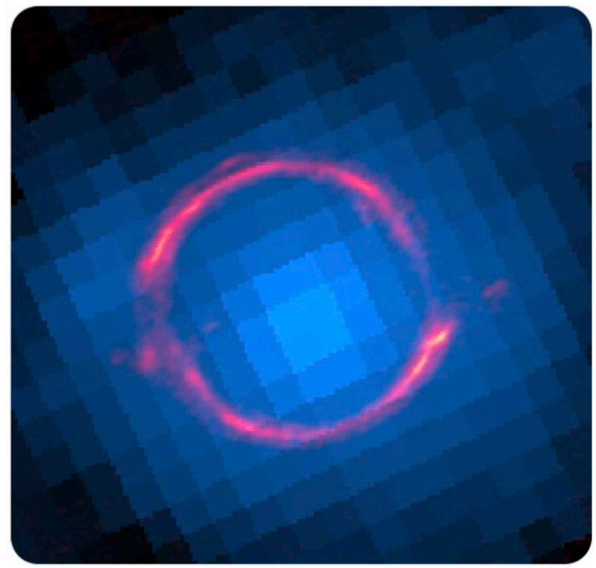
0.025 arcsec resolution (2018)



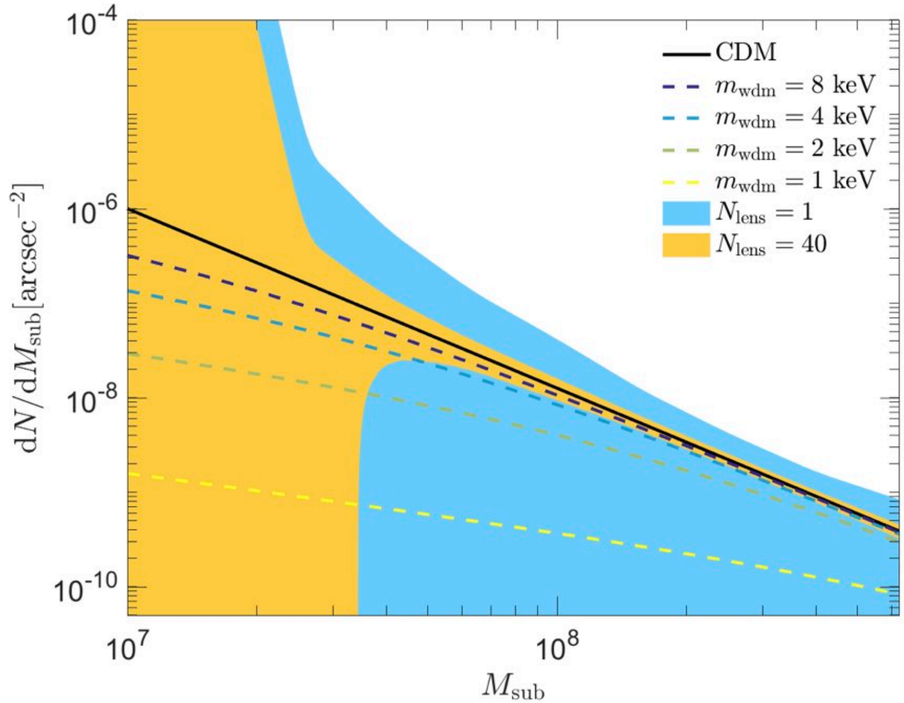
12 hours with JWST in ERS

SPT 0532

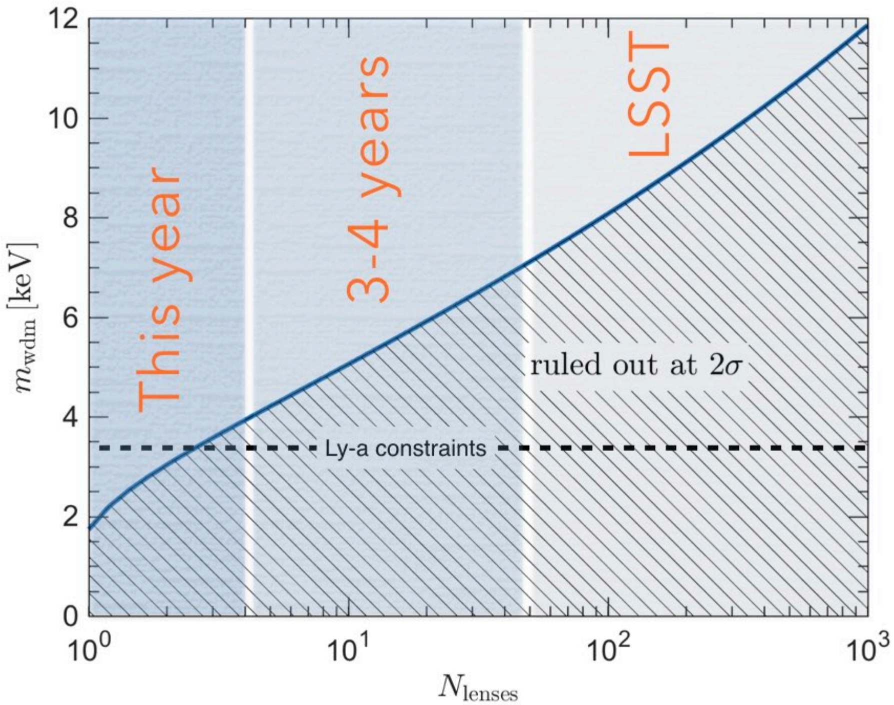
0.025 arcsec resolution (2018)



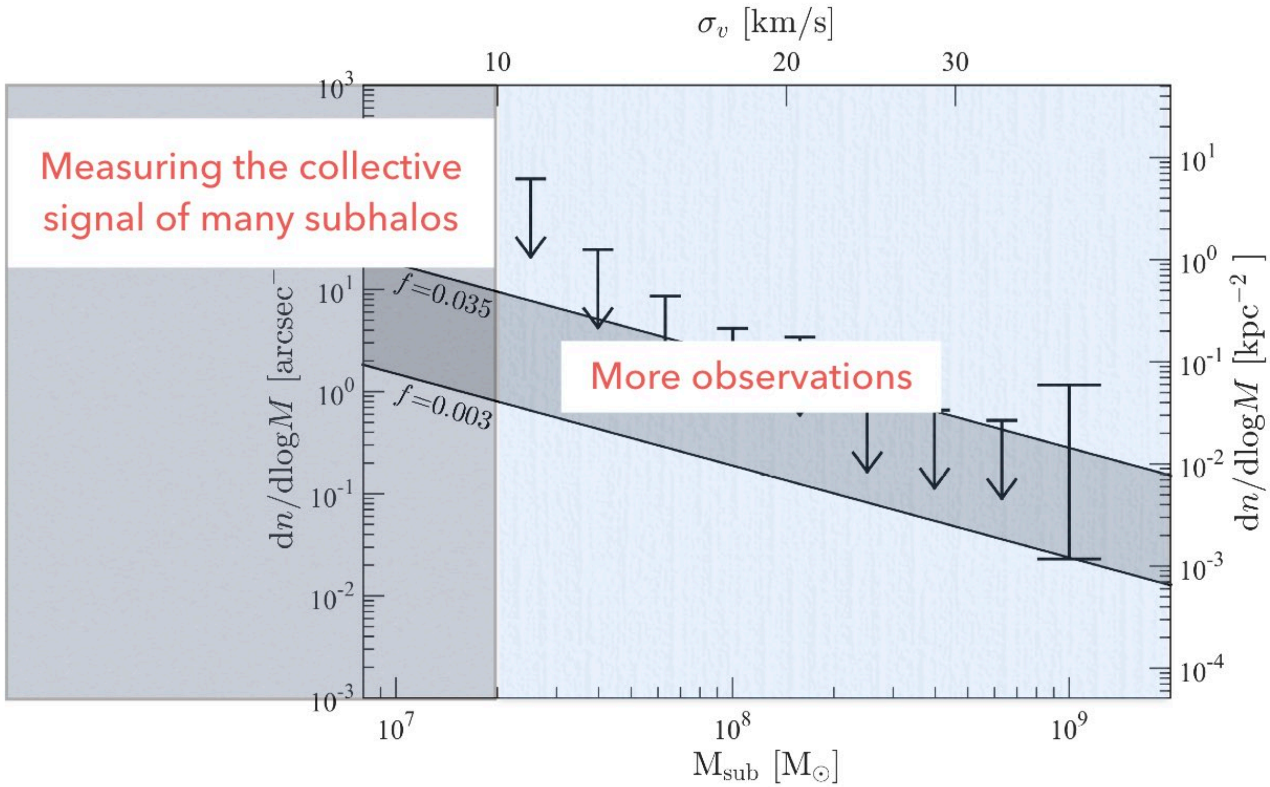
Forecasts for N lenses



FORECASTS FOR N LENSES

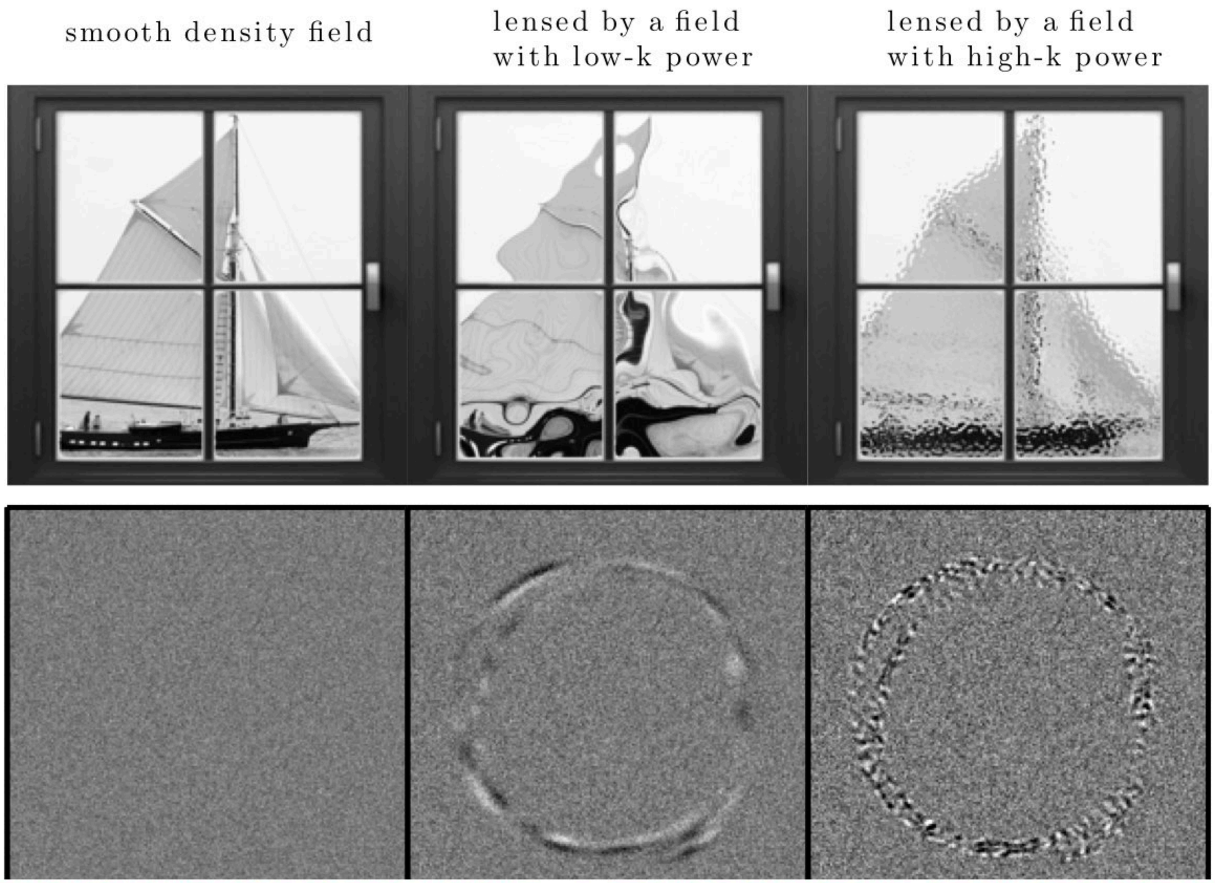


How to improve our constraints



Hezaveh et al. ApJ 2016

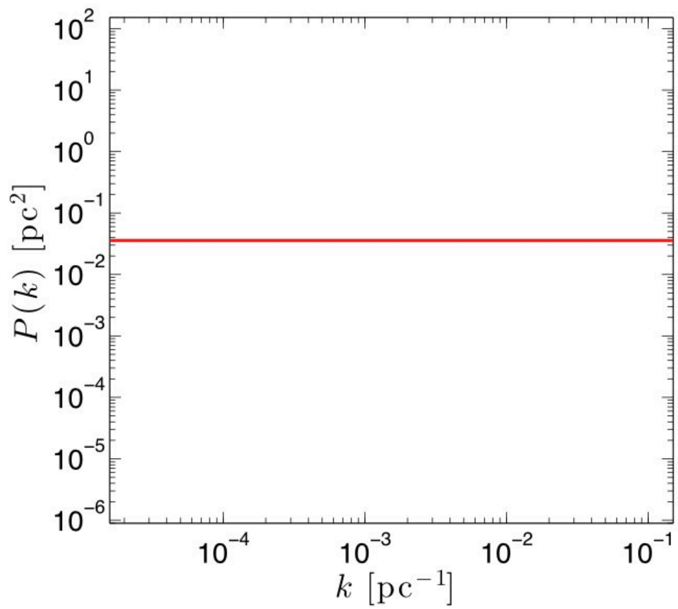
SURFACE BRIGHTNESS CORRELATIONS



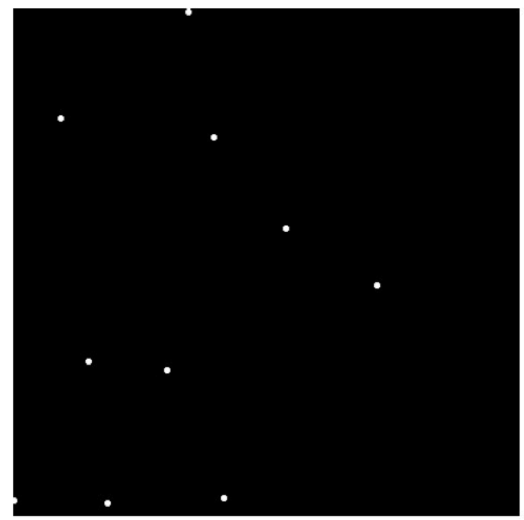
SURFACE BRIGHTNESS CORRELATIONS => POWER SPECTRUM OF THE DENSITY FIELD

DM subhalo density Power Spectrum

Power spectrum



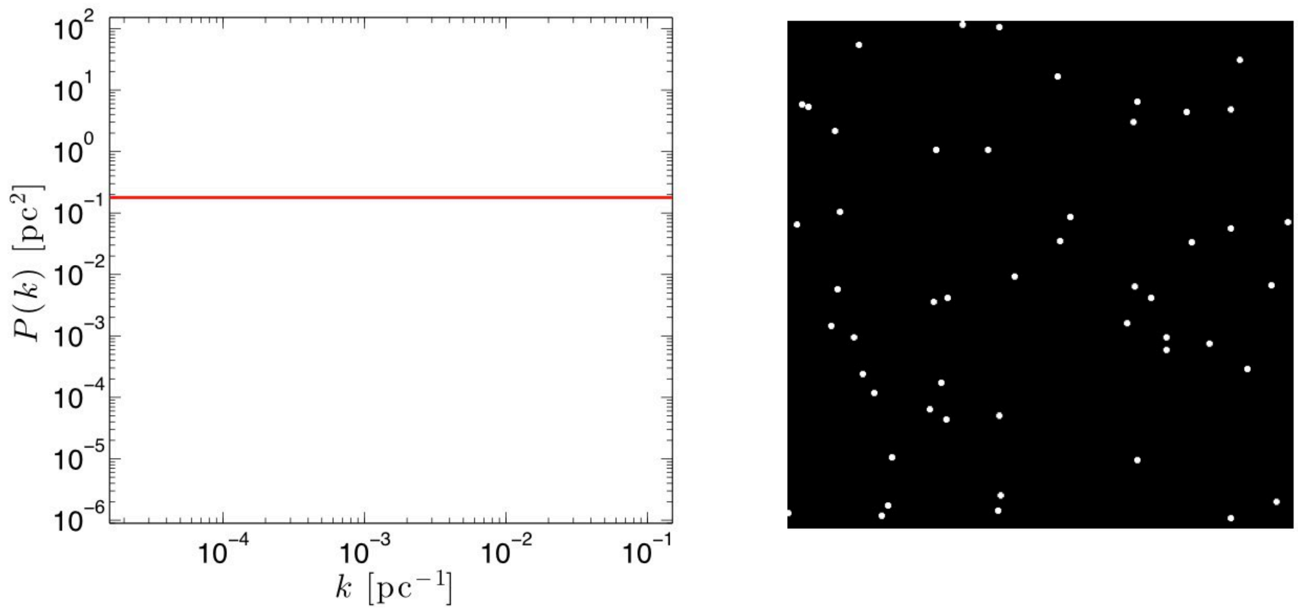
Density map



DM subhalo density Power Spectrum

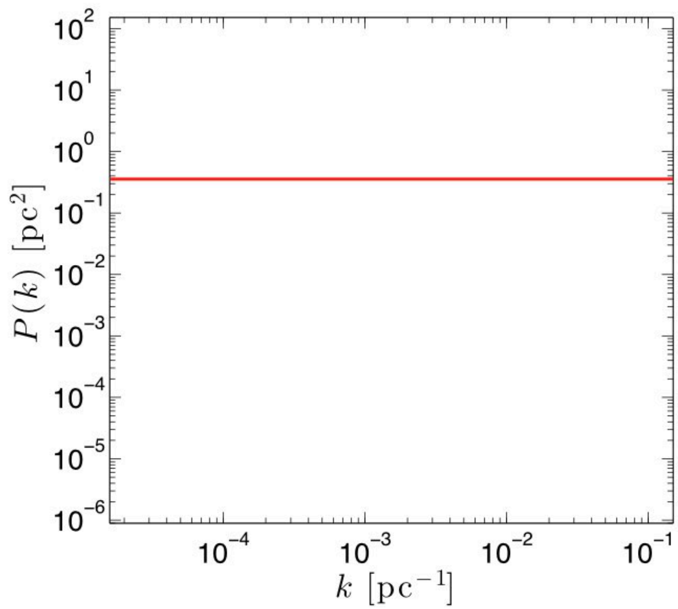
Power spectrum

Density map

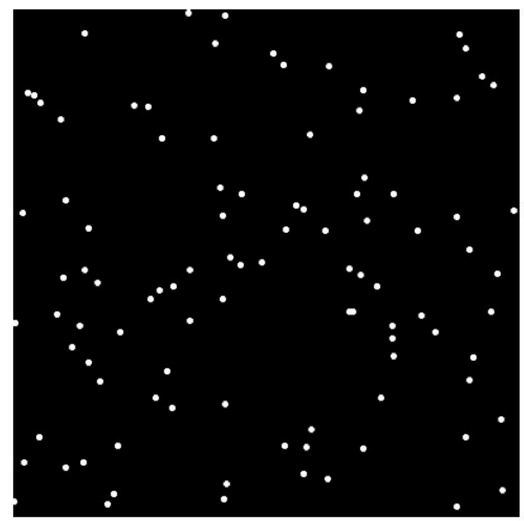


DM SUBHALO DENSITY POWER SPECTRUM

POWER SPECTRUM

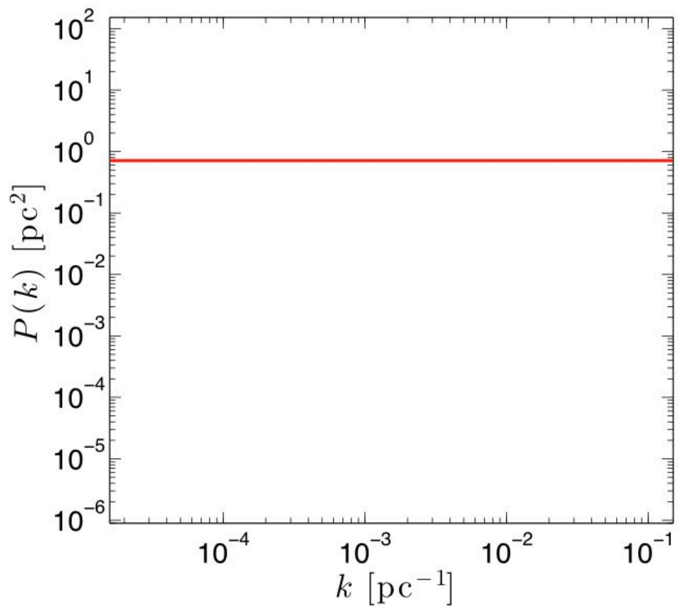


DENSITY MAP

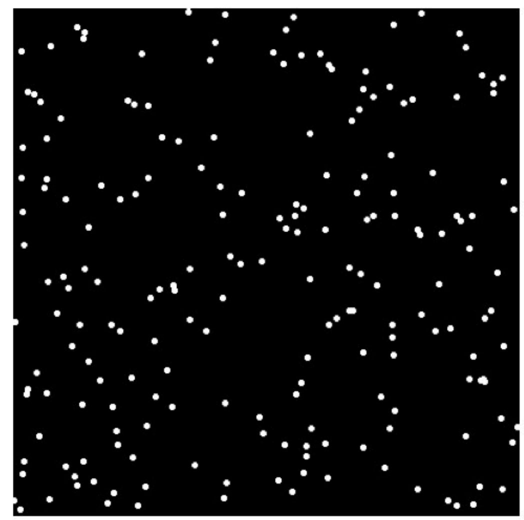


DM subhalo density Power Spectrum

Power spectrum

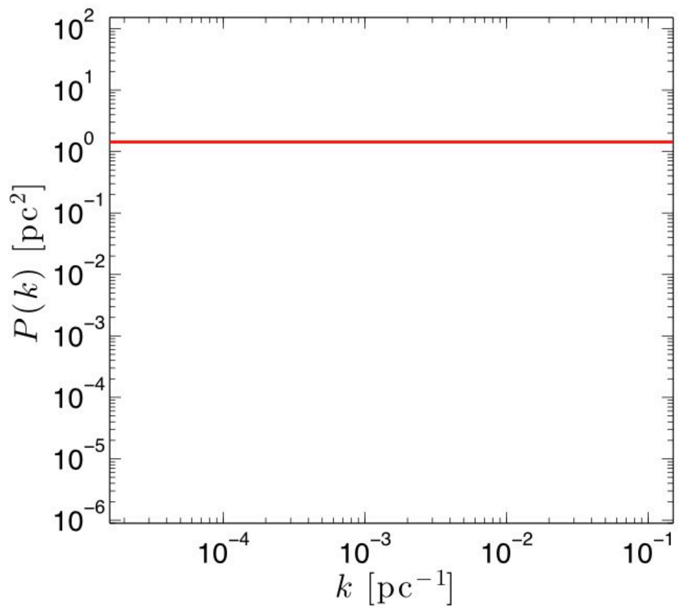


Density map

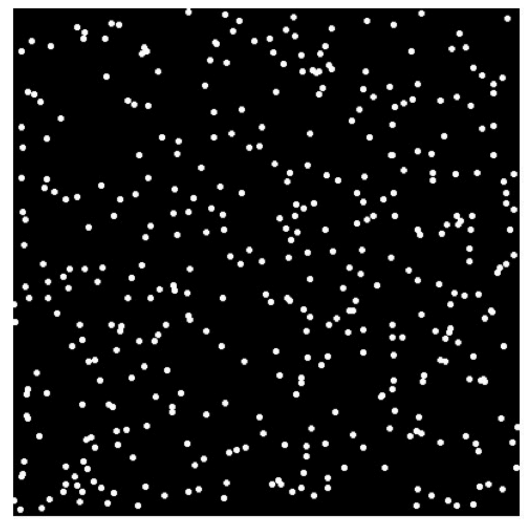


DM subhalo density Power Spectrum

Power spectrum

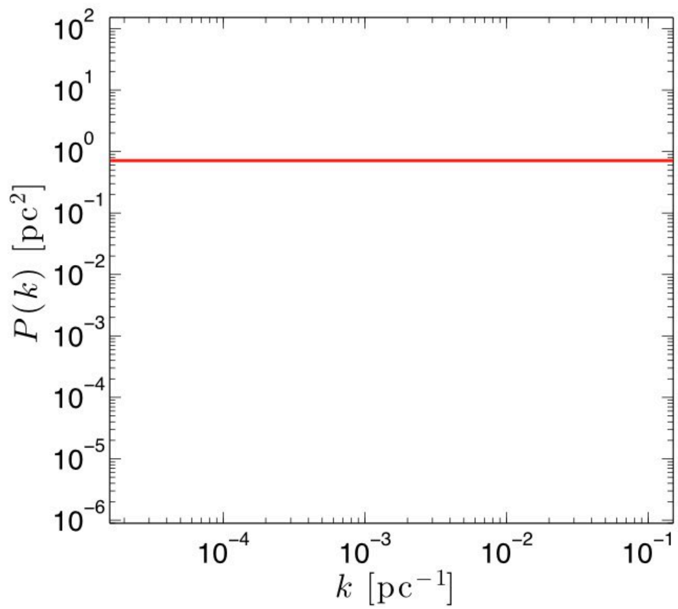


Density map

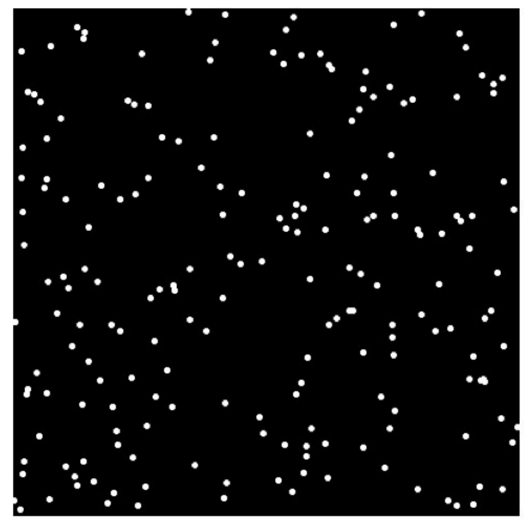


DM subhalo density Power Spectrum

Power spectrum

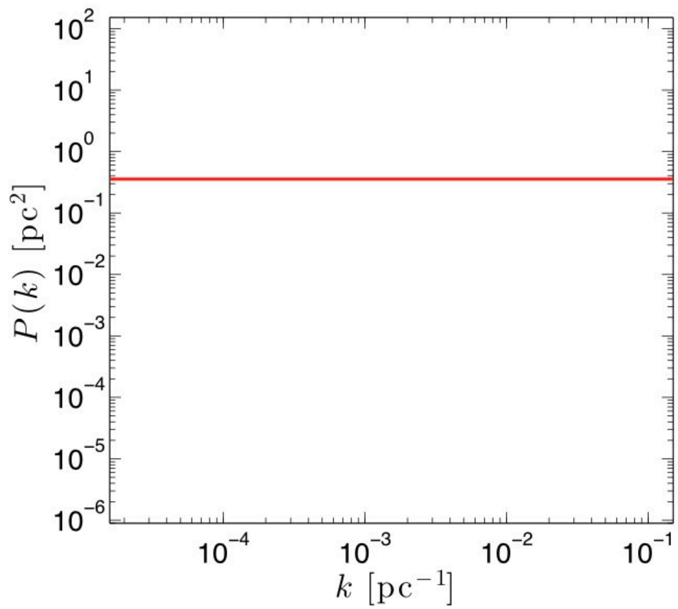


Density map

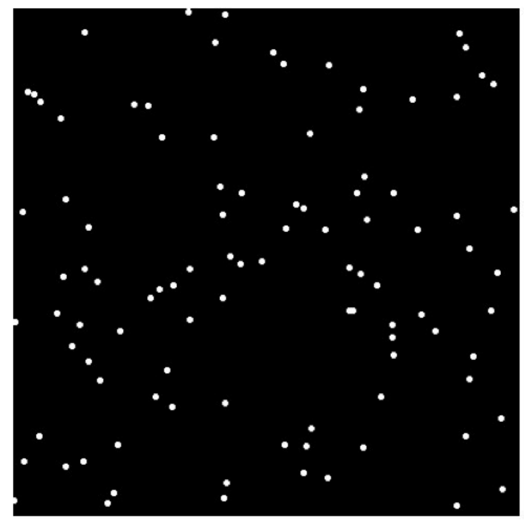


DM subhalo density Power Spectrum

Power spectrum

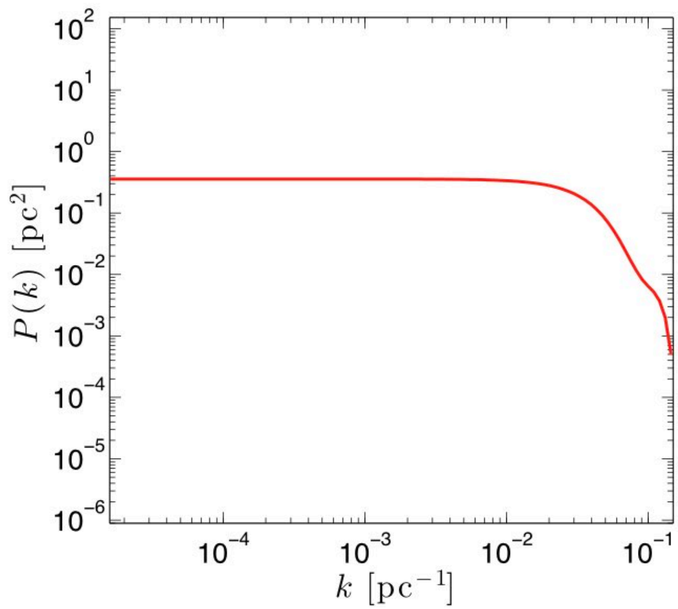


Density map

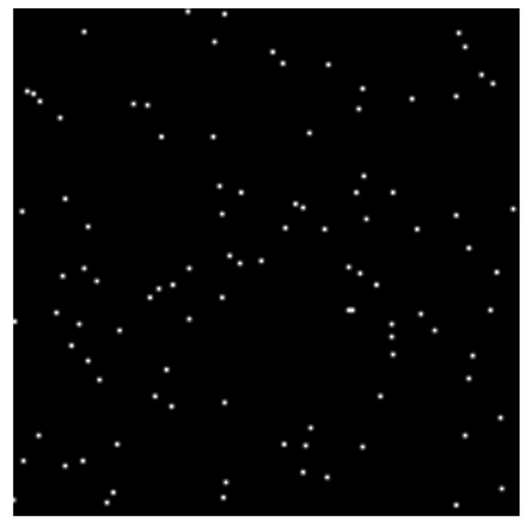


DM subhalo density Power Spectrum

Power spectrum

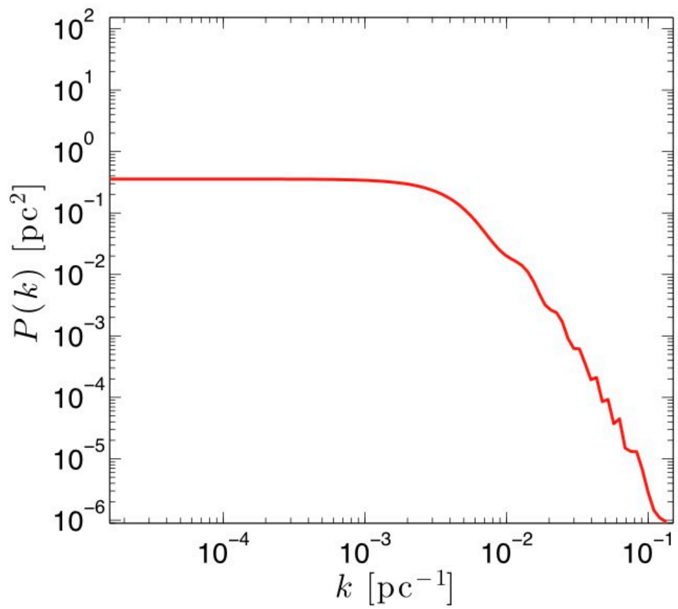


Density map

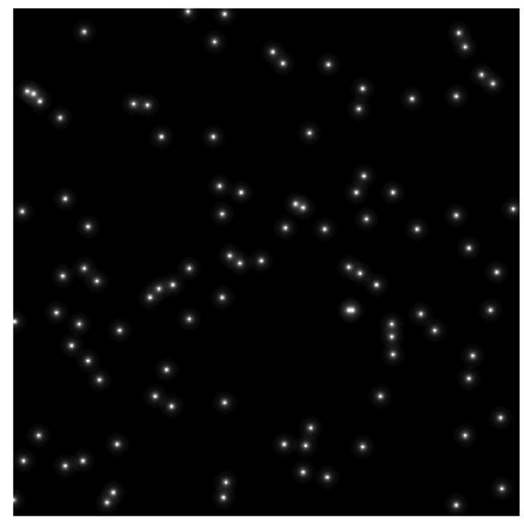


DM subhalo density Power Spectrum

Power spectrum

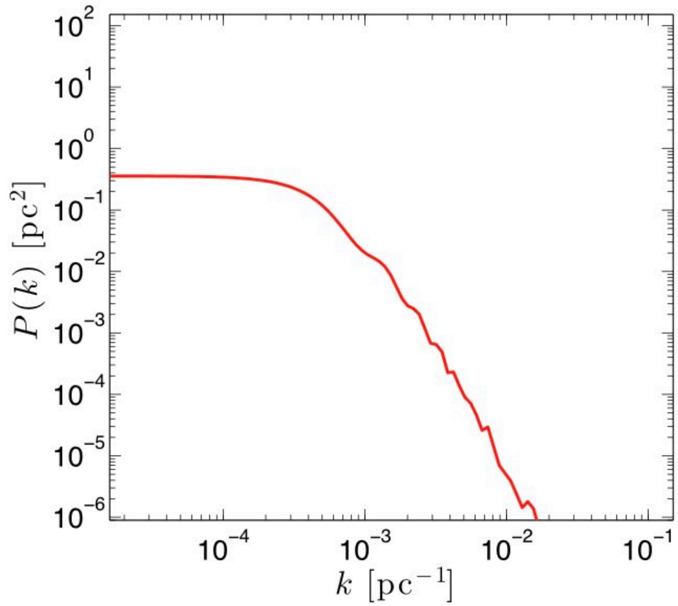


Density map

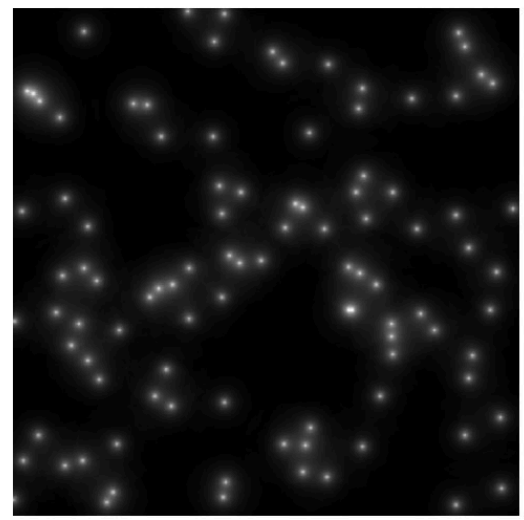


DM SUBHALO DENSITY POWER SPECTRUM

POWER SPECTRUM

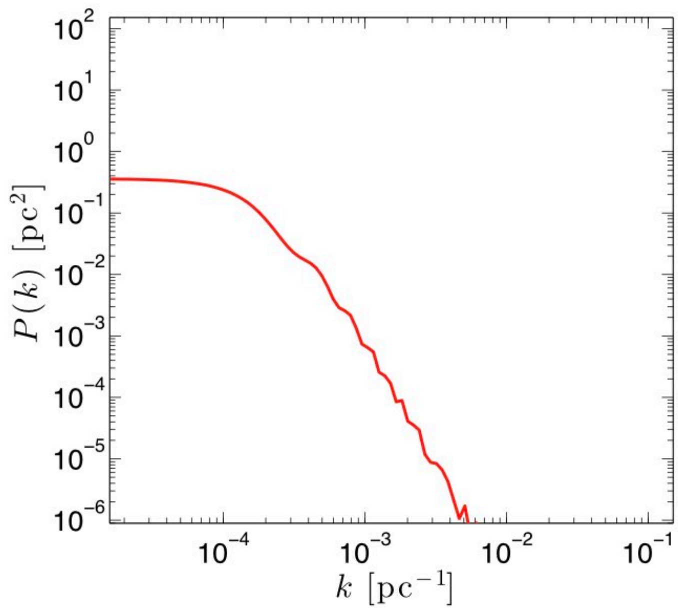


DENSITY MAP

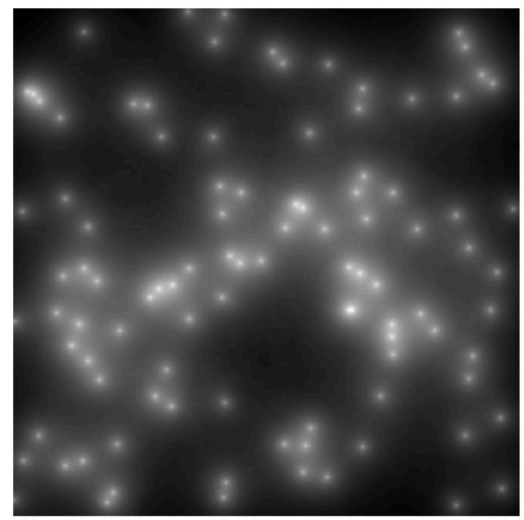


DM subhalo density Power Spectrum

Power spectrum



Density map



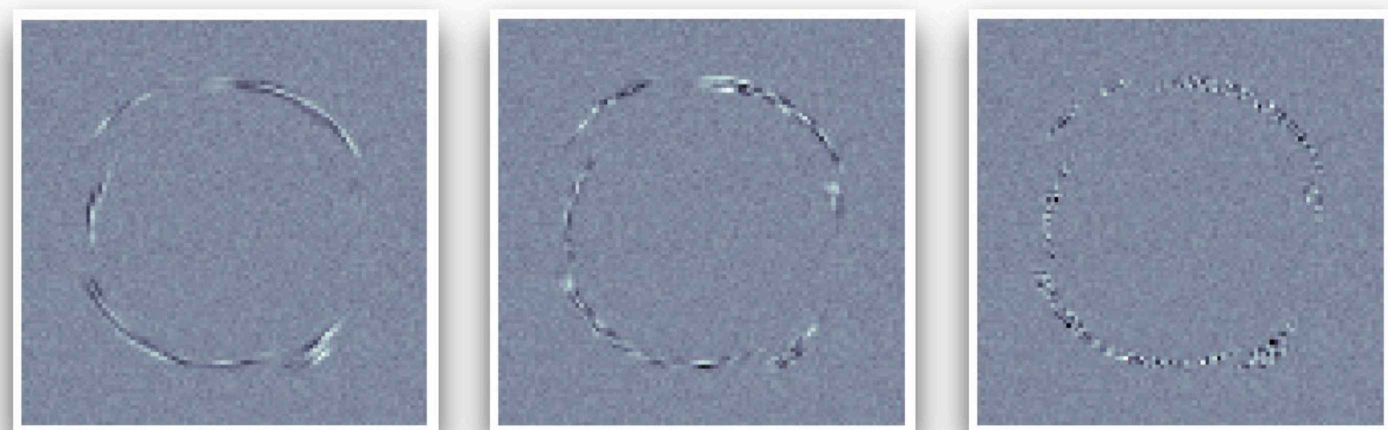
Covariance of deflections

Power spectrum of the Density Field

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

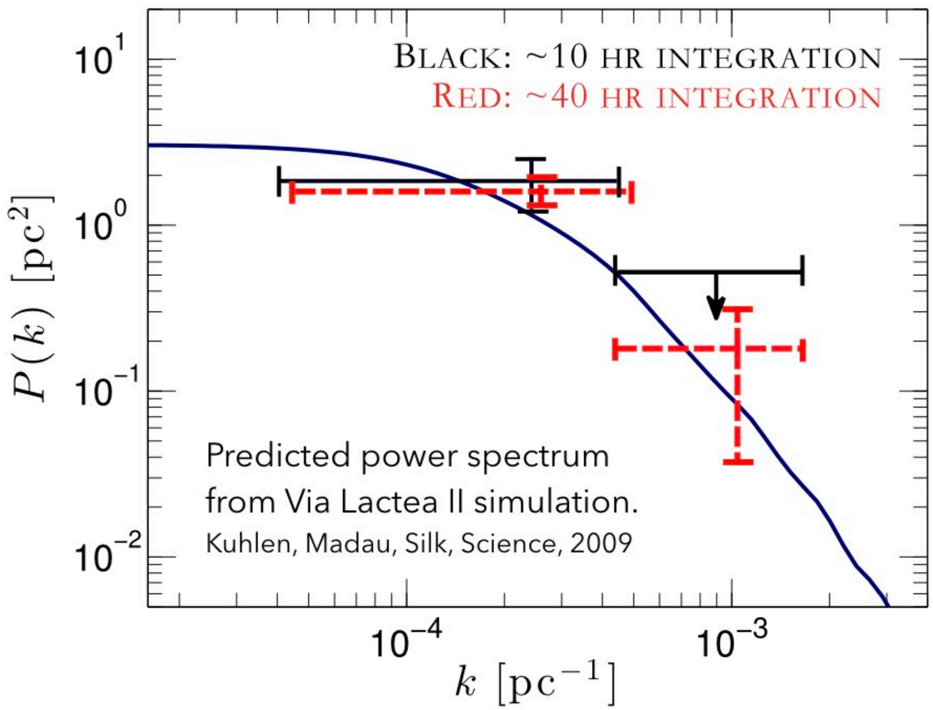
Likelihood

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



Hezaveh et al., JCAP, 2016

Forecast for measuring the DM subhalo Power Spectrum with ALMA



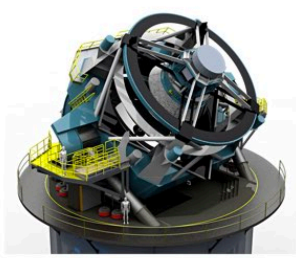
Hezaveh et al., JCAP, 2016

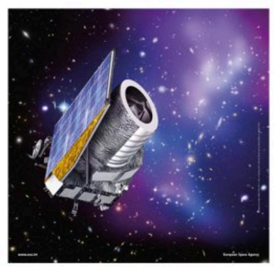
Looking into the future:

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?

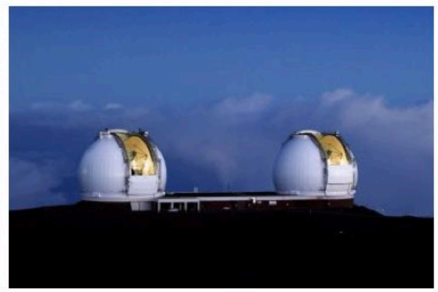
1- Statistical precision from the analysis of a large population.

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

Looking into the future:

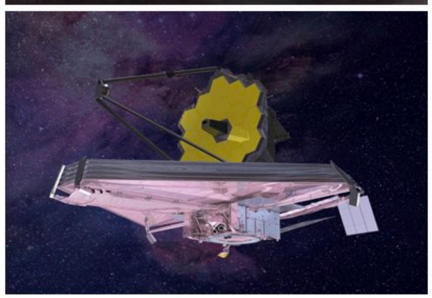
2- Existing and New Telescopes

ALMA
In operation



Keck
In operation

JWST
2019



TMT
2020s

Looking into the future:

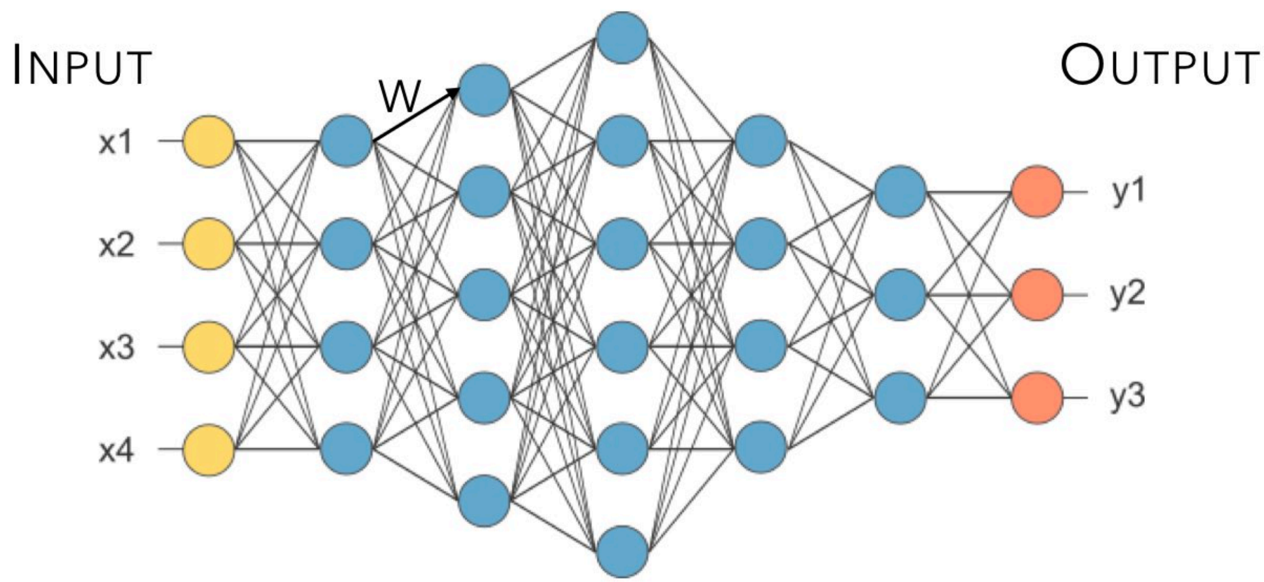
3- Analysis Methods

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

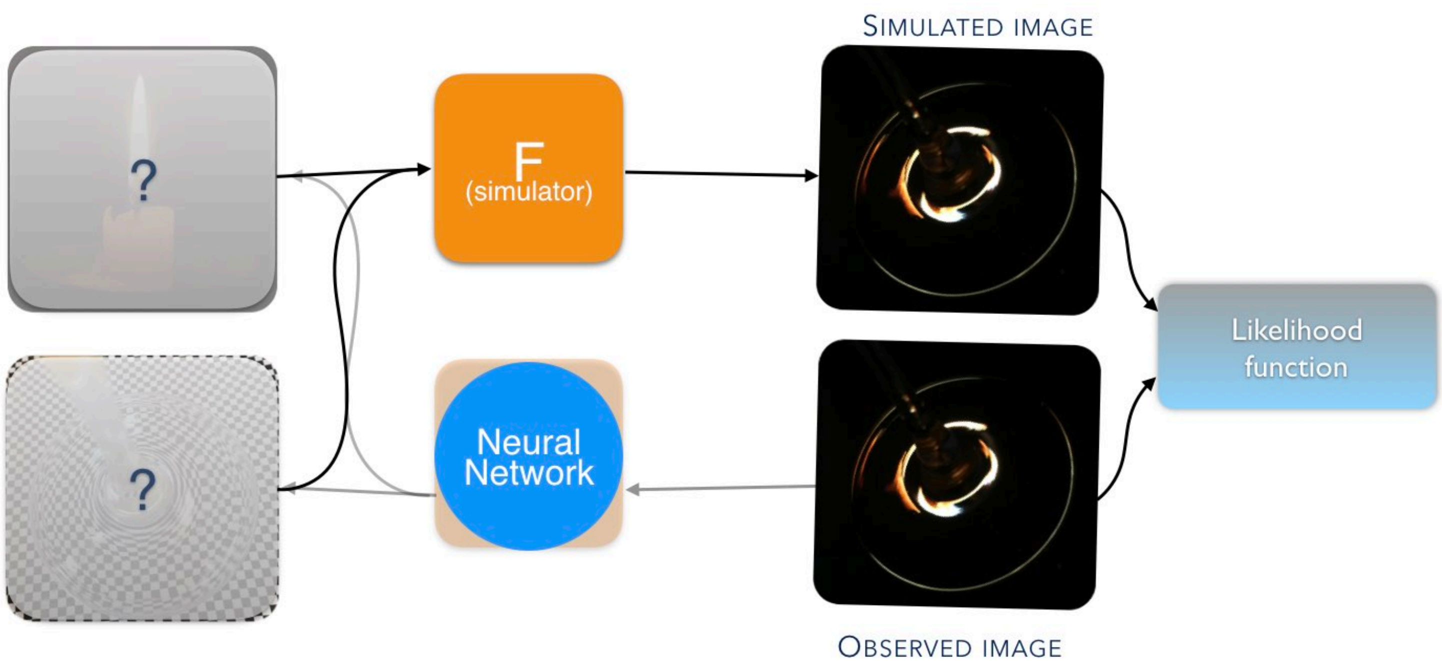
CAN WE OBTAIN THE LENS PARAMETERS USING NEURAL NETWORKS?



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

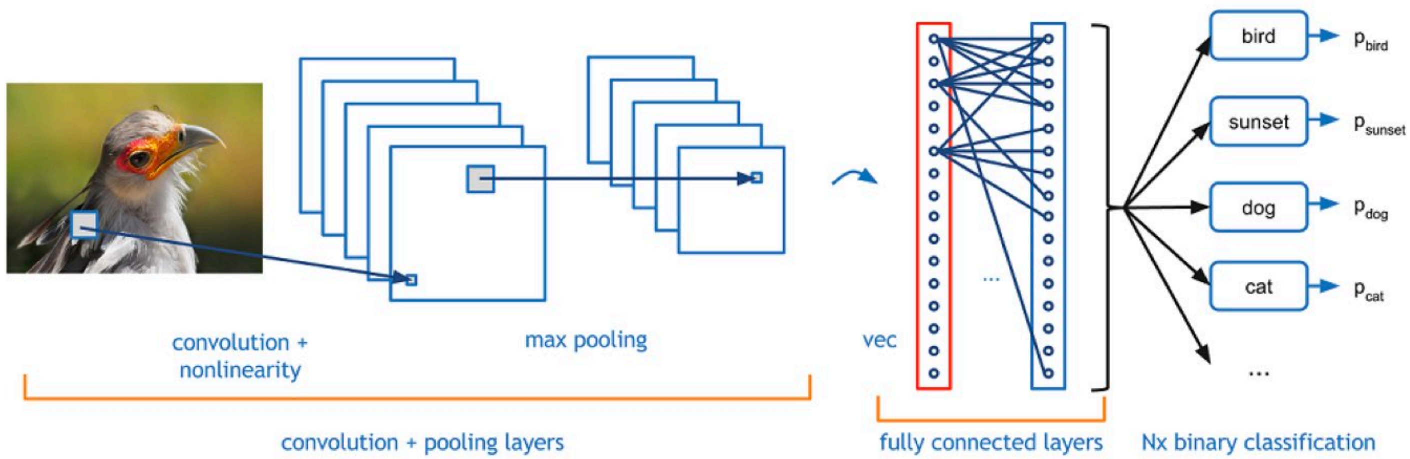
Measuring physical properties from images of strong lenses

maximum likelihood lens modeling



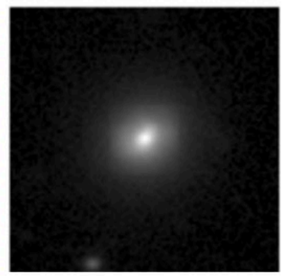
COMPUTER VISION: CONVOLUTIONAL NEURAL NETWORKS

COMMONLY USED FOR IMAGE RECOGNITION AND CLASSIFICATION



Convolutional Neural Networks: Previously used for lens discovery (Classification)

They can be trained to classify images:
Two classes: lenses vs. non-lenses



CMU DeepLens: Deep Learning For Automatic Image-based Galaxy-Galaxy Strong Lens Finding

François Lanusse,[1*] Quanbin Ma,[2] Nan Li,[3,4] Thomas E. Collett,[5] Chun-Liang Li,[2] Siamak Ravanbakhsh,[2] Rachel Mandelbaum[1] and Barnabás Póczos[2]

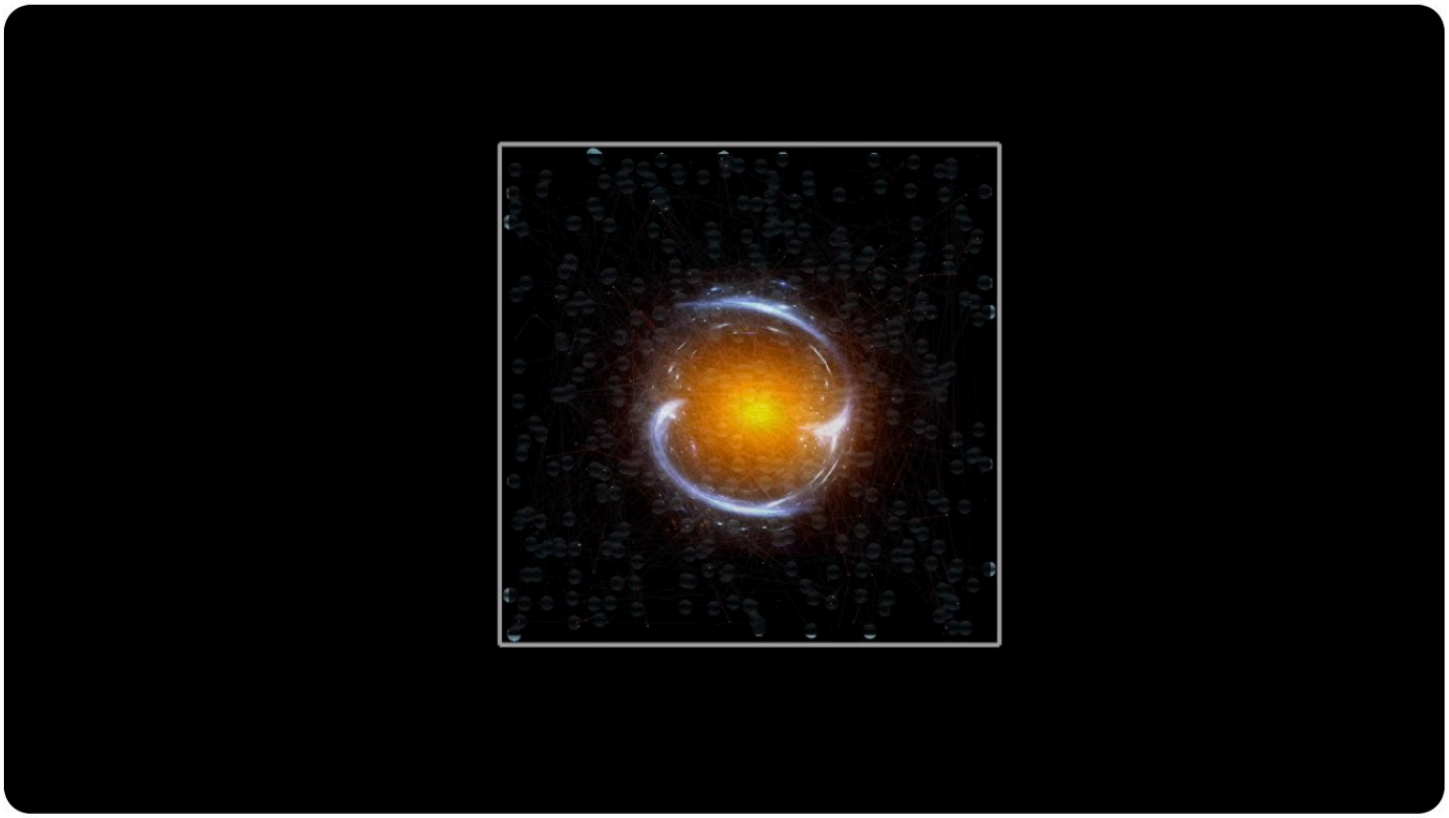
[1] *McWilliams Center for Cosmology, Department of Physics, Carnegie Mellon University, Pittsburgh, PA 15213, USA*
[2] *School of Computer Science, Carnegie Mellon University, Pittsburgh, PA 15213, USA*
[3] *High Energy Physics Division, Argonne National Laboratory, Lemont, IL 60439, USA*
[4] *Department of Astronomy & Astrophysics, The University of Chicago, 5640 South Ellis Avenue, Chicago, IL 60637, USA*
[5] *Institute of Cosmology and Gravitation, University of Portsmouth, Burnaby Rd, Portsmouth, PO1 3FX, UK*

Finding Strong Gravitational Lenses in the Kilo Degree Survey with Convolutional Neural Networks

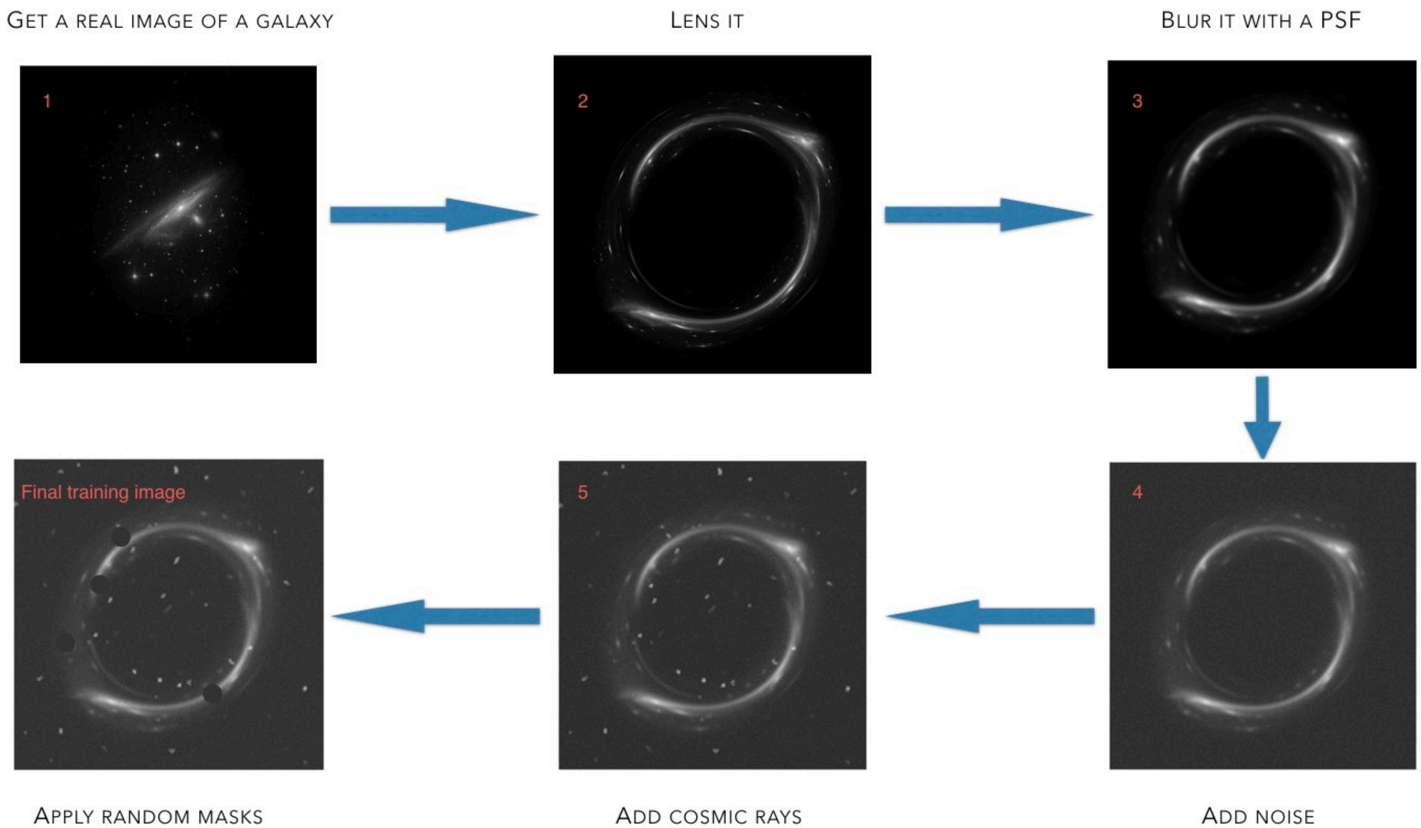
C. E. Petrillo[1*], C. Tortora[1], S. Chatterjee[1], G. Vernardos[1], L. V. E. Koopmans[1], G. Verdoes Kleijn[1], N. R. Napolitano[2], G. Covone[3], P. Schneider[4], A. Grado[2], J. McFarland[1]

[1] *Kapteyn Astronomical Institute, University of Groningen, Postbus 800, 9700 AV, Groningen, The Netherlands*
[2] *INAF - Osservatorio Astronomico di Capodimonte, Salita Moiariello, 16, 80131 Napoli, Italy*
[3] *Dipartimento di Scienze Fisiche, Università di Napoli Federico II, Compl. Univ. Monte S. Angelo, 80126 Napoli, Italy*
[4] *Argelander-Institut für Astronomie, Auf dem Hügel 71, D-53121 Bonn, Germany*

Neural network outputs: lensing parameters

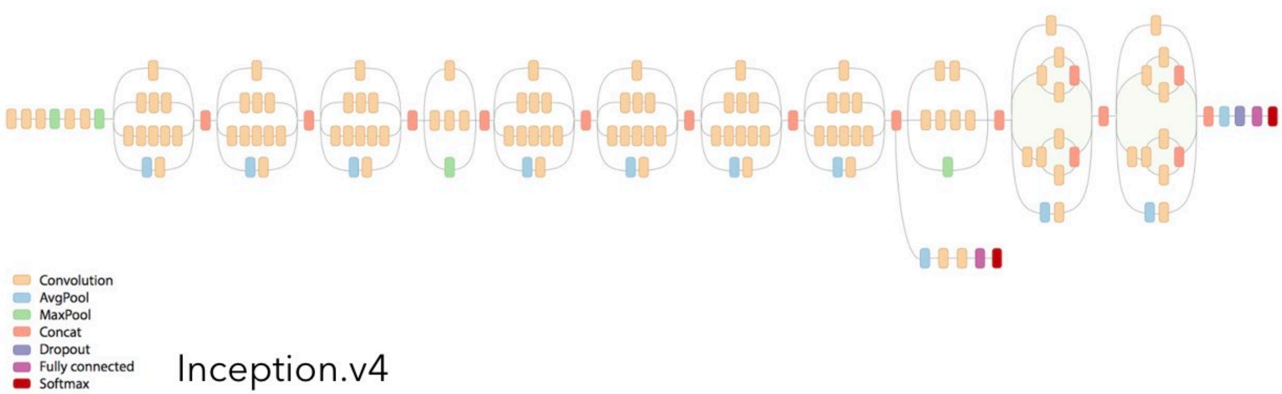


Producing the training data



Training

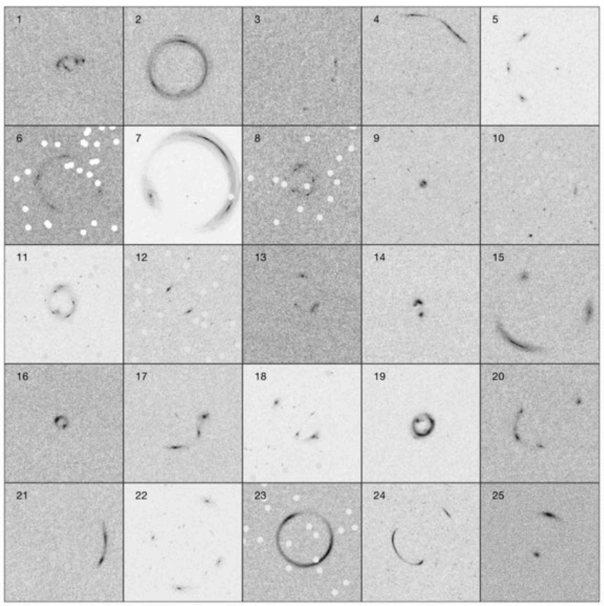
- Half a million (simulated) images for training.
- Trained multiple networks: e.g., Inception.v4 (hundreds of layers)
- Training time: About 1-2 day(s) on a single GPU



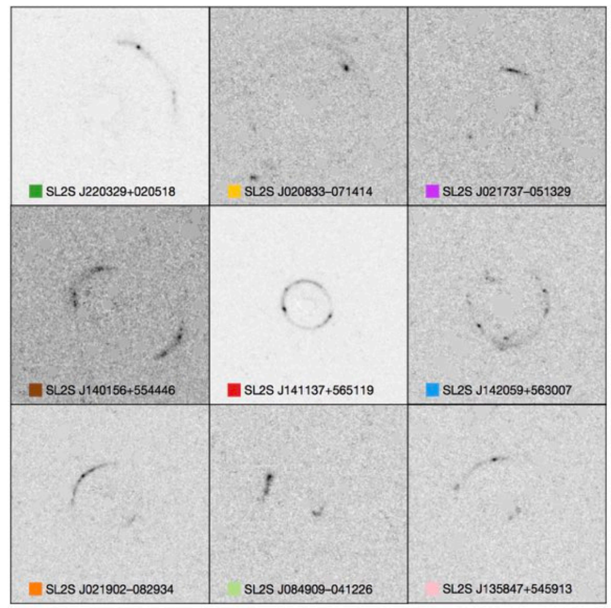
Inception.v4

Test data

10,000 Simulated images

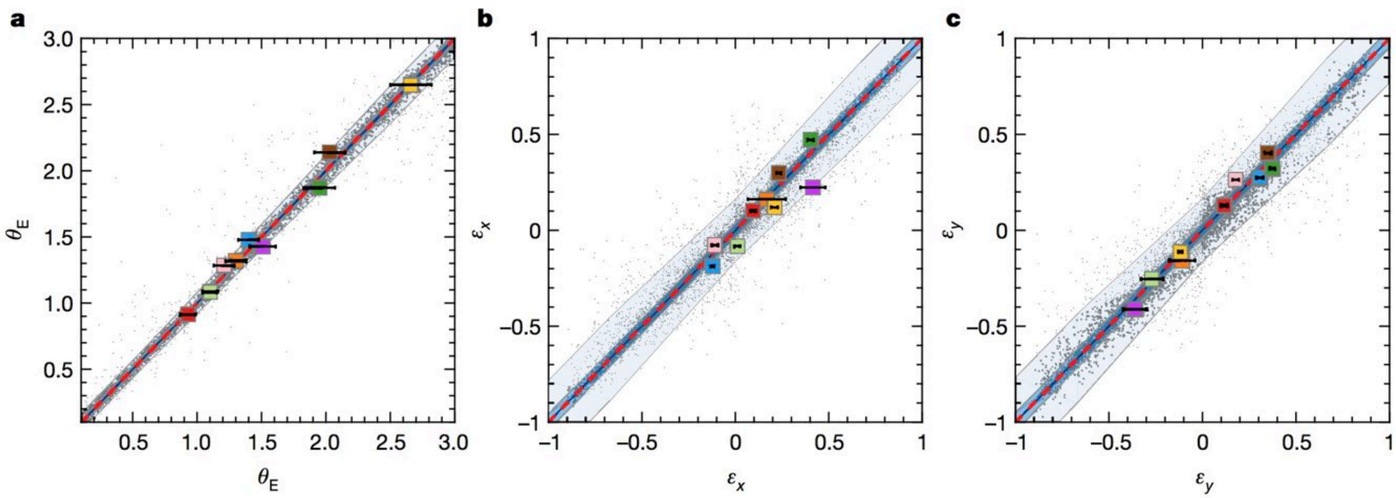


9 *HST* images



Hezaveh, Perreault, Marshall, Nature, 2017

ESTIMATING LENSING PARAMETERS WITH NEURAL NETS



10 million times faster than ML lens modeling.

0.01 seconds on a **single GPU**

Hezaveh, Perreault, Marshall, Nature, 2017

UNCERTAINTIES

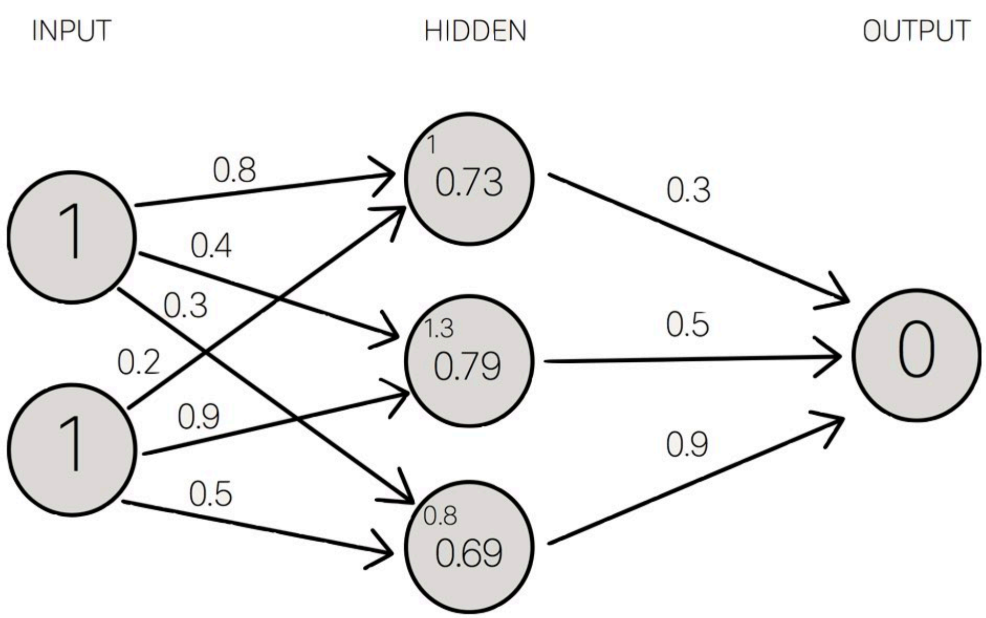
- Make networks predict their uncertainties:
  Instead of predicting a point estimate of lens parameters, make NNs predict a *distribution*, defined by a handful of parameters.

- Example: Gaussian

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

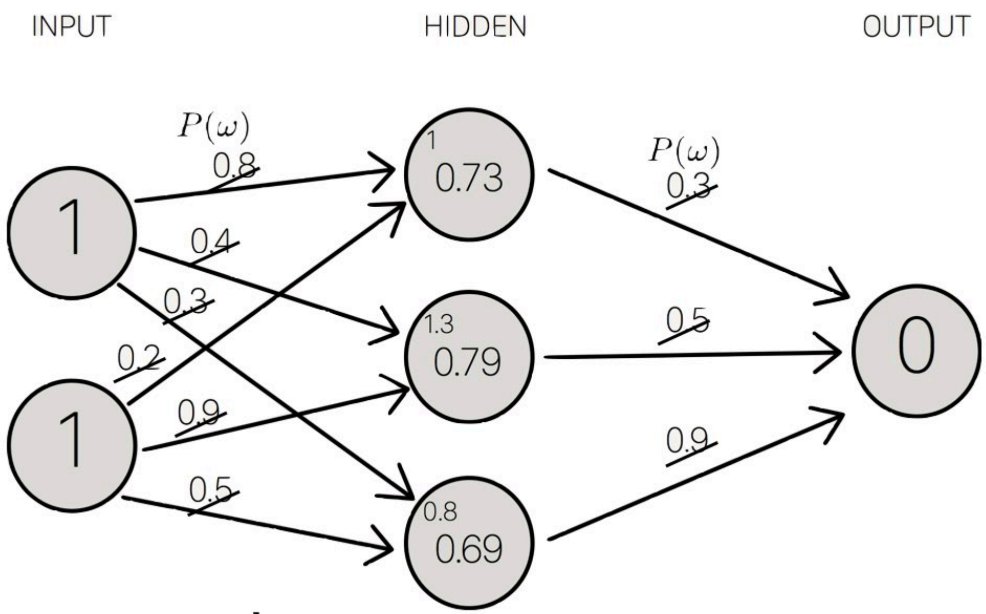
Standard Neural Networks:

Weights have fixed, deterministic values



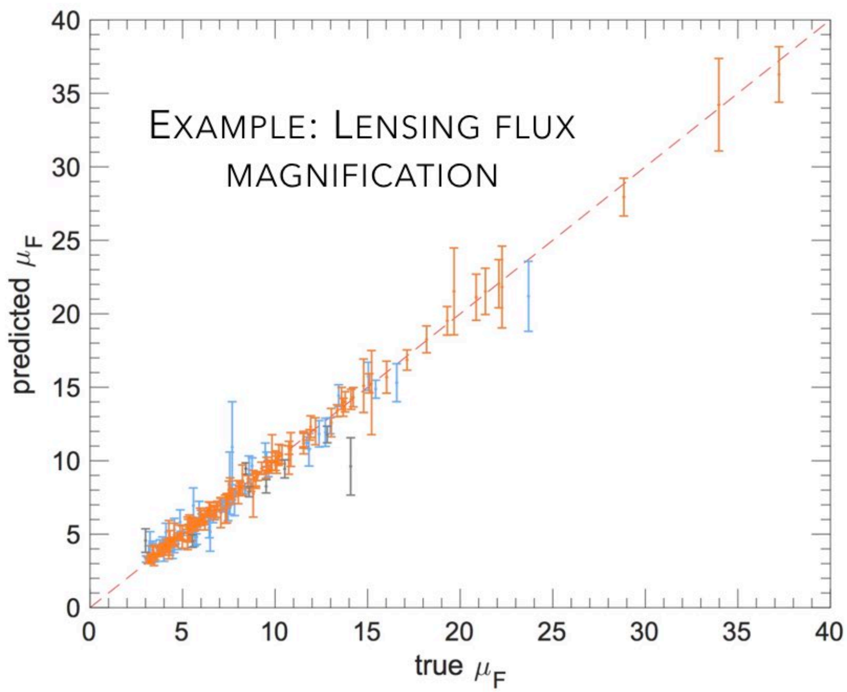
BAYESIAN NEURAL NETWORKS:

WEIGHTS ARE DEFINED BY PROBABILITY DISTRIBUTIONS

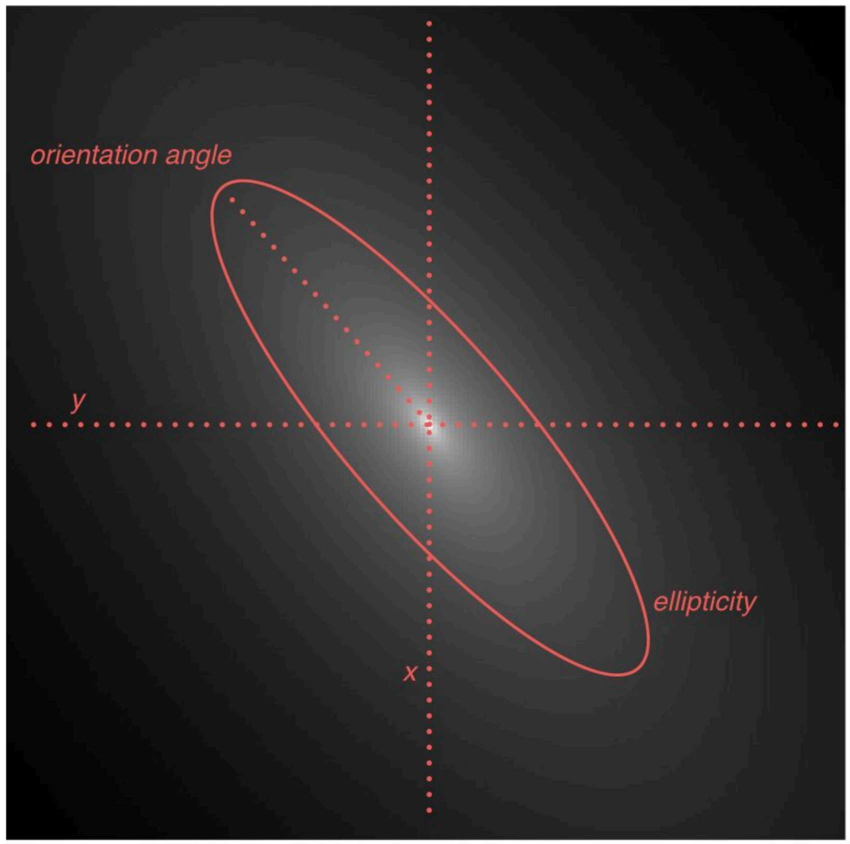


[USING VARIATIONAL INFERENCE]

Uncertainties of the estimated parameters

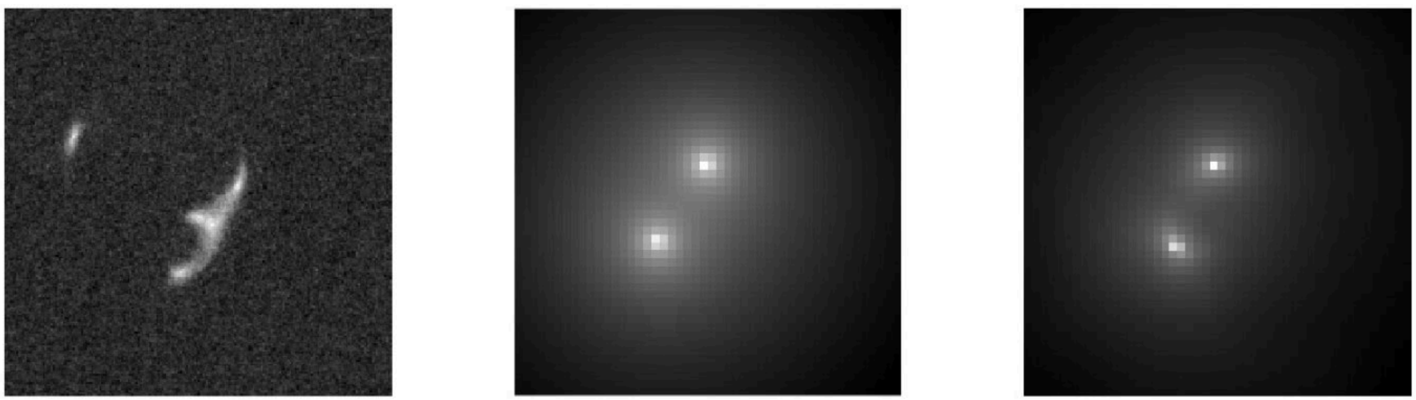


Perreault, Hezaveh, Wechsler, ApJL, 2017


orientation angle
y
ellipticity
x

Pixellated density map reconstruction

Observation (Networks' input) | True density map | Prediction (Networks' output)



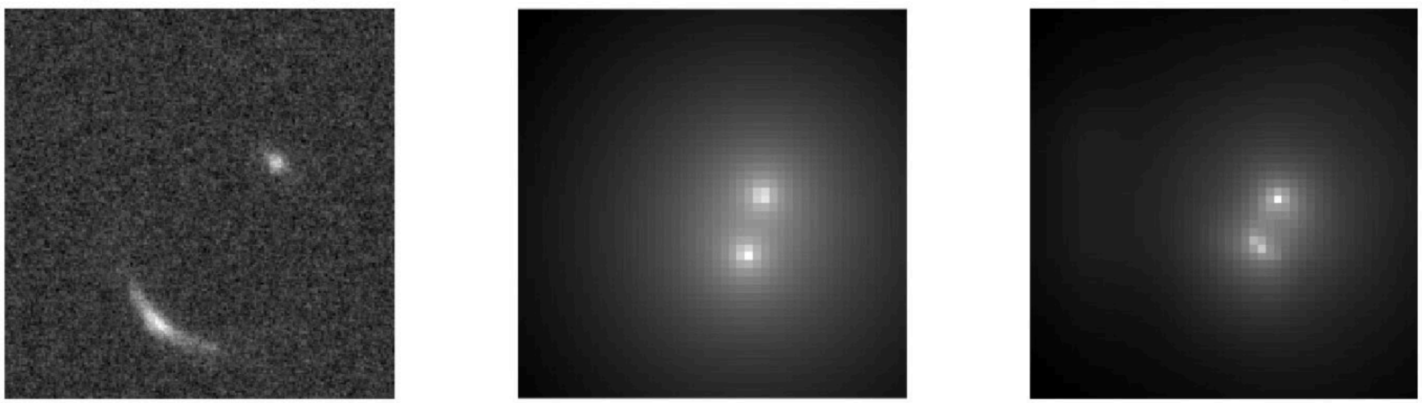
(log projected density) (log projected density)

Pixellated density map reconstruction

Observation (Networks' input)

True density map

Prediction (Networks' output)



(log projected density)

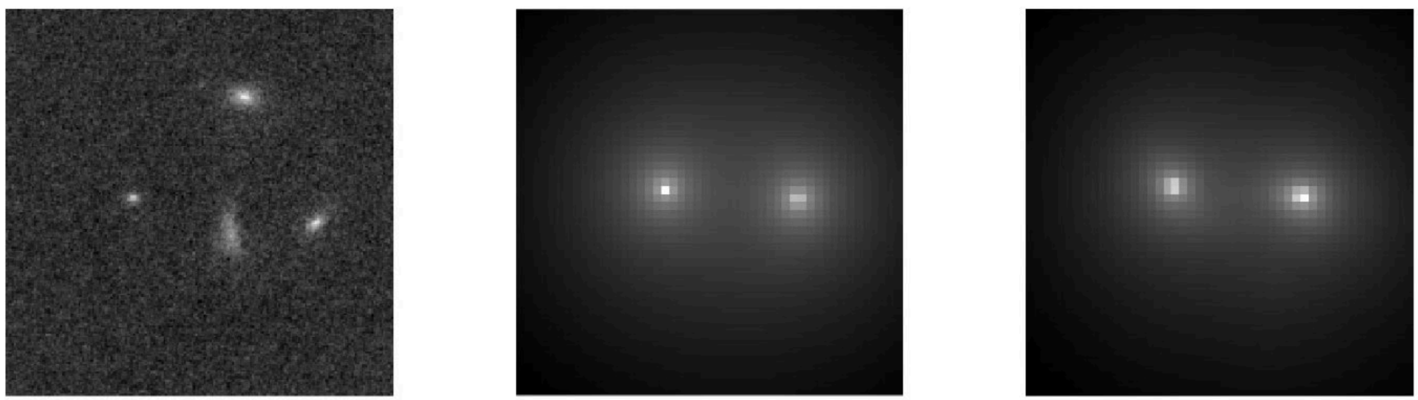
(log projected density)

Pixellated density map reconstruction

Observation
(Networks' input)

True density map

Prediction
(Networks' output)

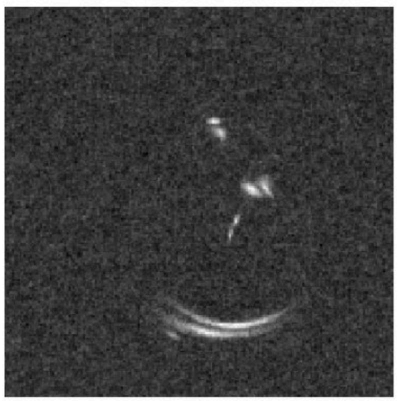


(log projected density)

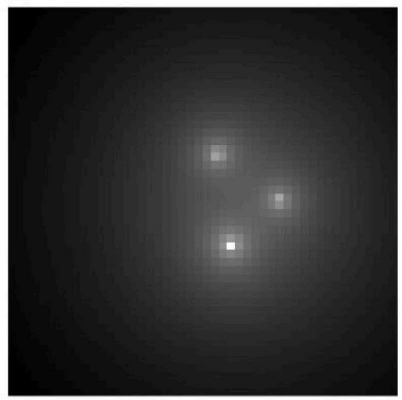
(log projected density)

Could these networks ever generalize beyond their training data?

Observation
(Networks' input)

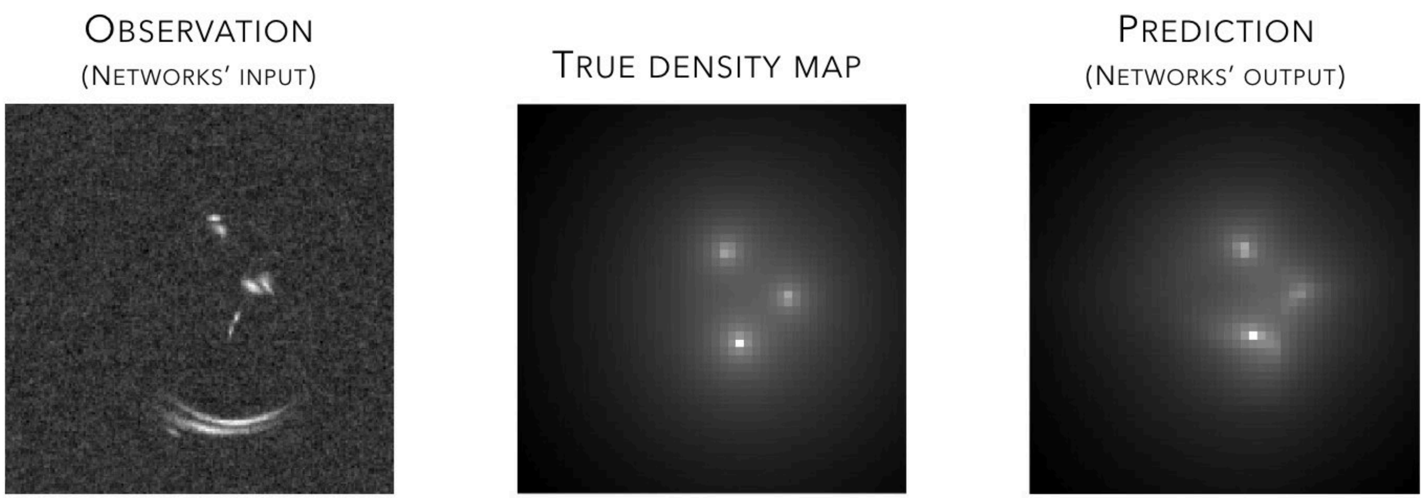


True density map



Prediction
(Networks' output)

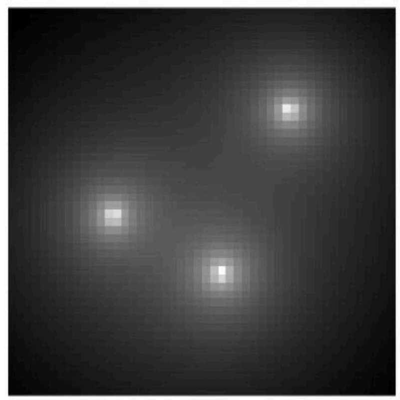
Could these networks ever generalize beyond their training data?



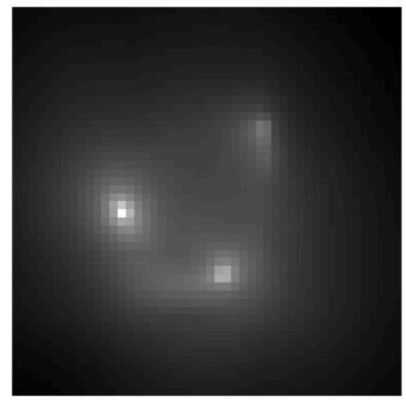
Could these networks ever generalize beyond their training data?

Observation
(Networks' input)

True density map

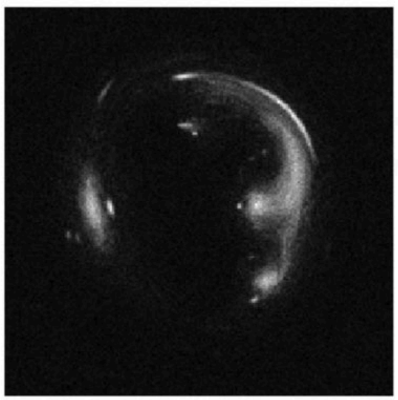


Prediction
(Networks' output)

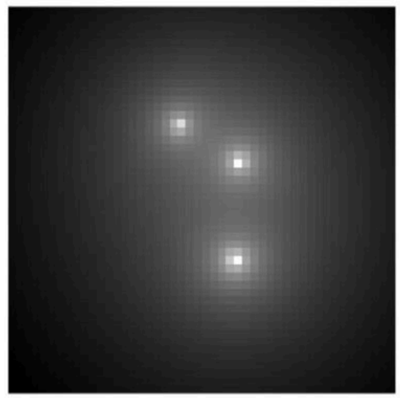


COULD THESE NETWORKS EVER GENERALIZE BEYOND THEIR TRAINING DATA?

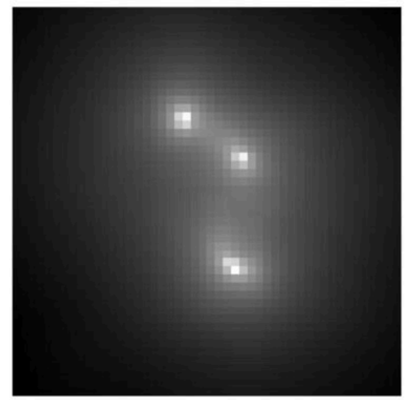
OBSERVATION
(NETWORKS' INPUT)



TRUE DENSITY MAP

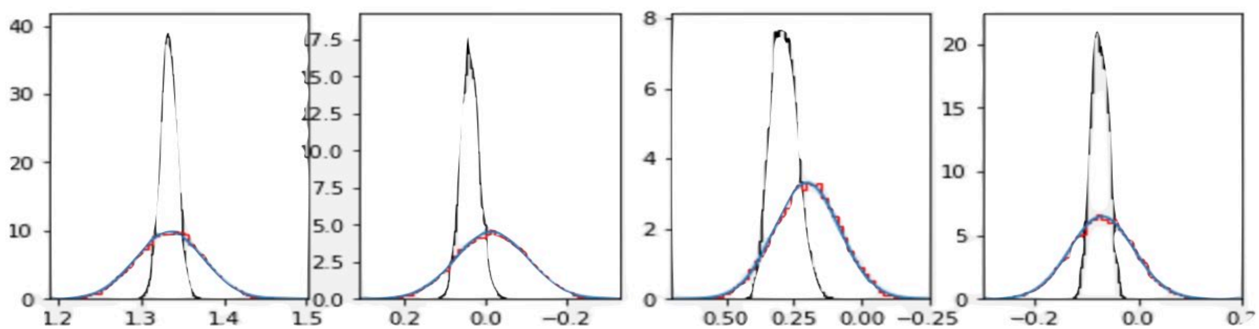


PREDICTION
(NETWORKS' OUTPUT)



Extension to interferometric data

SPT 0529:
Max-likelihood lens modeling (black)
Neural Networks (red/blue)



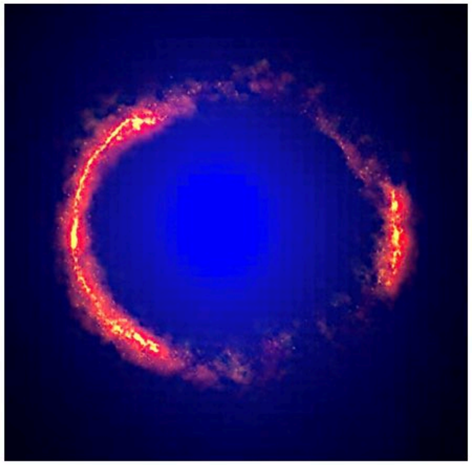
Morningstar et al. (in prep)

Summary

- The small scale distribution of dark matter is an important test of dark matter models.

- ALMA observations of lensed submm sources are extremely sensitive probes of subhalos.

- With large number of lenses from wide surveys and machine learning methods, in the coming years, we are poised to see significant advances in this field.



Thank you!