Title: Strong Gravitational Lensing in the Era of Data-Driven Algorithms

Speakers: Yashar Hezaveh

Series: Cosmology & Gravitation

Date: October 04, 2022 - 11:00 AM

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Abstract: In this talk I will share our recent work in developing statistical models based on machine learning methods. In particular, I will discuss posterior sampling in low- and high-dimensional spaces and connect this to two ongoing projects: measuring the small-scale distribution of dark matter and estimating the expansion rate of the Universe. I will discuss how the speed and the accuracy gained by these models are essential for the large volumes of data from the next generation sky surveys. I will finish by mentioning a few other projects and a new initiative for interdisciplinary collaboration in astrophysics and data sciences.

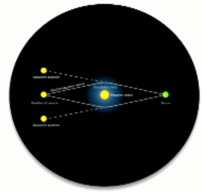
Zoom link: https://pitp.zoom.us/j/98316228305?pwd=UWwrZkIwUG1QZFBkYzc1eVdNSW1Ldz09

Strong Gravitational Lensing with Data-Driven Algorithms

Yashar Hezaveh

Laurence Perreault Levasseur
Neal Dalal
and many more ...

SIMONS FOUNDATION
SCHMIDT FUTURES
Canada
Fonds de recherche Nature et technologies Québec
Université de Montréal
FLATIRON INSTITUTE
Center for Computational Astrophysics



Strong lensing

CIELA

New initiative

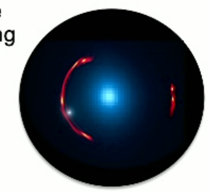
Key questions

OUTLINE

LtU

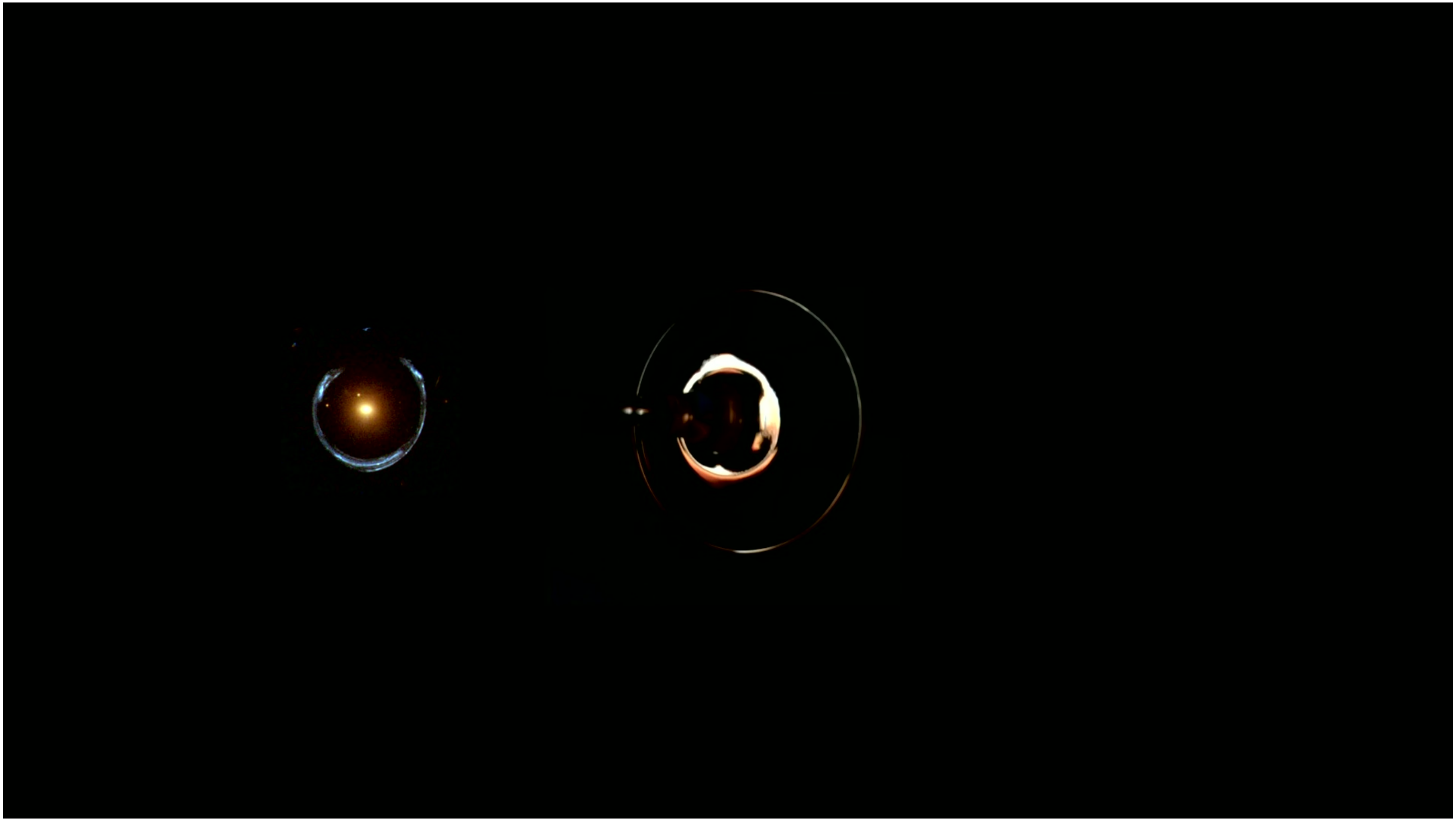
Other ML-related projects

Measuring the SSS with lensing



Our ML work In lensing

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.

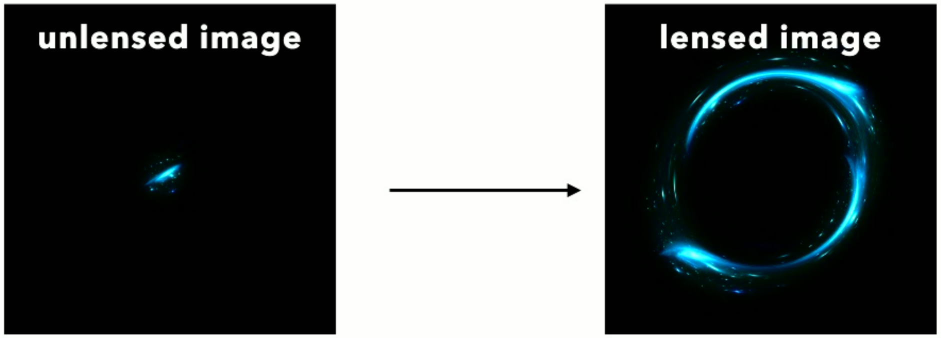
3- Constraining cosmological parameters:

Use time delays in the arrivals of lensed images to measure the **expansion rate of the Universe**.

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:

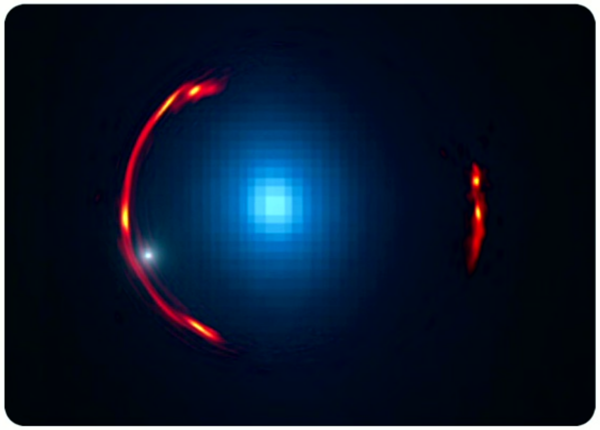
Use lenses to study star formation in the background galaxies

- 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.

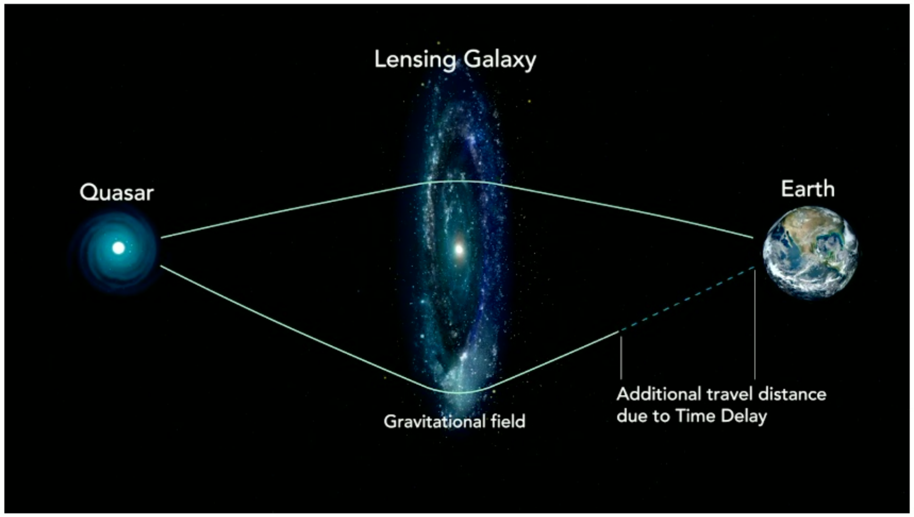
- Distortions in images are caused by **gravity**.
- They can be used to map the **distribution of matter** in the lens.
- Particularly useful for studying **dark matter.**



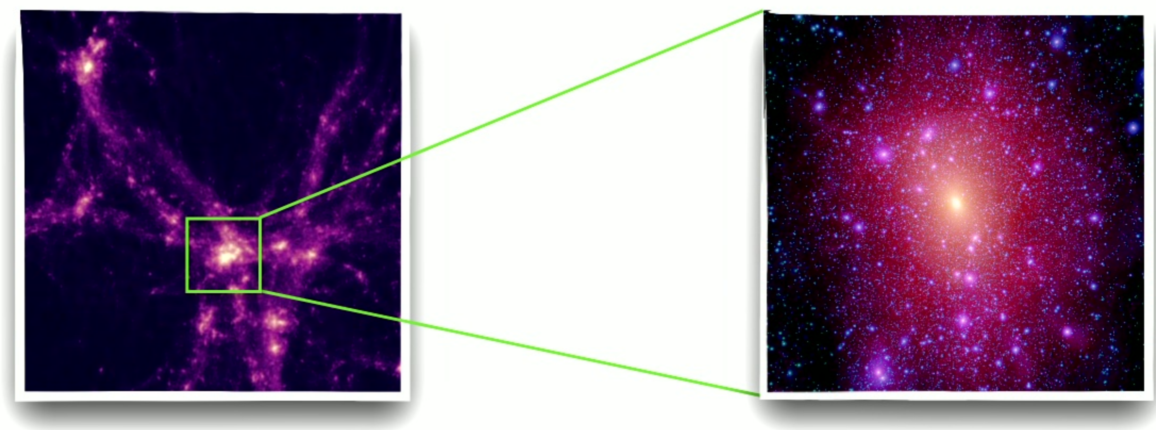
SCIENCE MOTIVATIONS FOR STRONG LENSING

3 - Constraining **cosmological parameters**.

- There is a time delay between the different lensed images.
- If the brightness of the background source fluctuates, one could measure these relative time delays.
- This allows us to measure the **Hubble constant**.



SMALL-SCALE STRUCTURE OF DARK MATTER

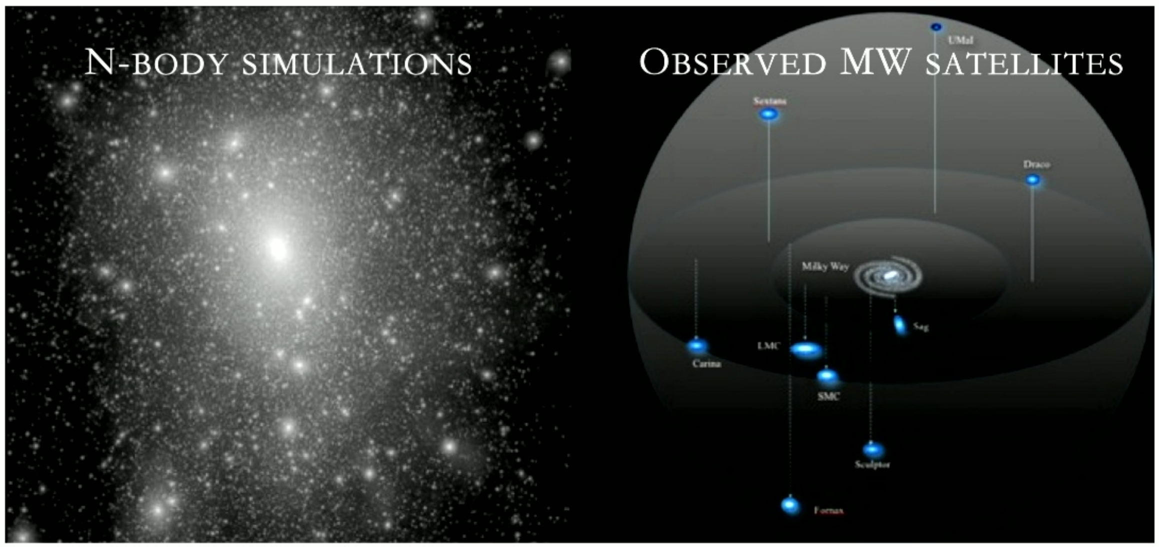


Large scale structure is very well measured.

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

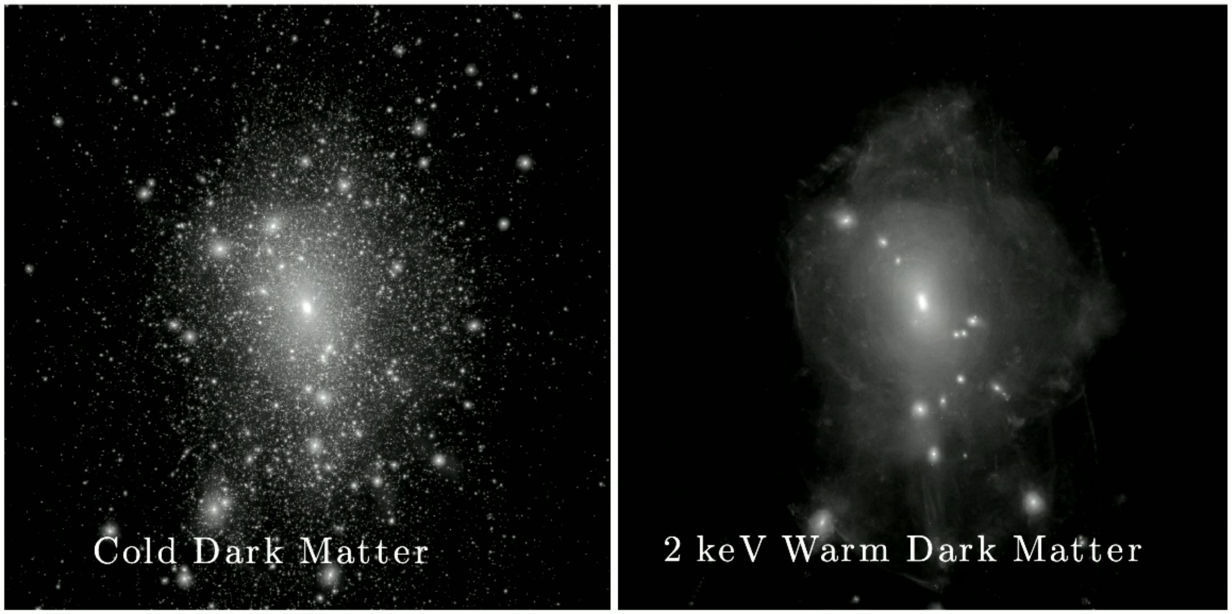


Theory: N~ 10000

Observation N~50

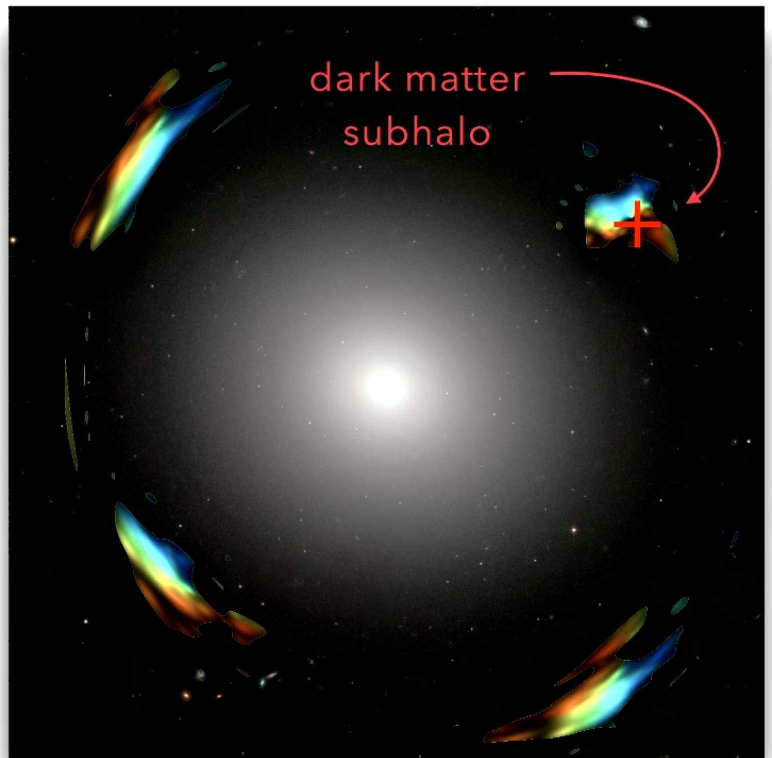
SOLUTIONS

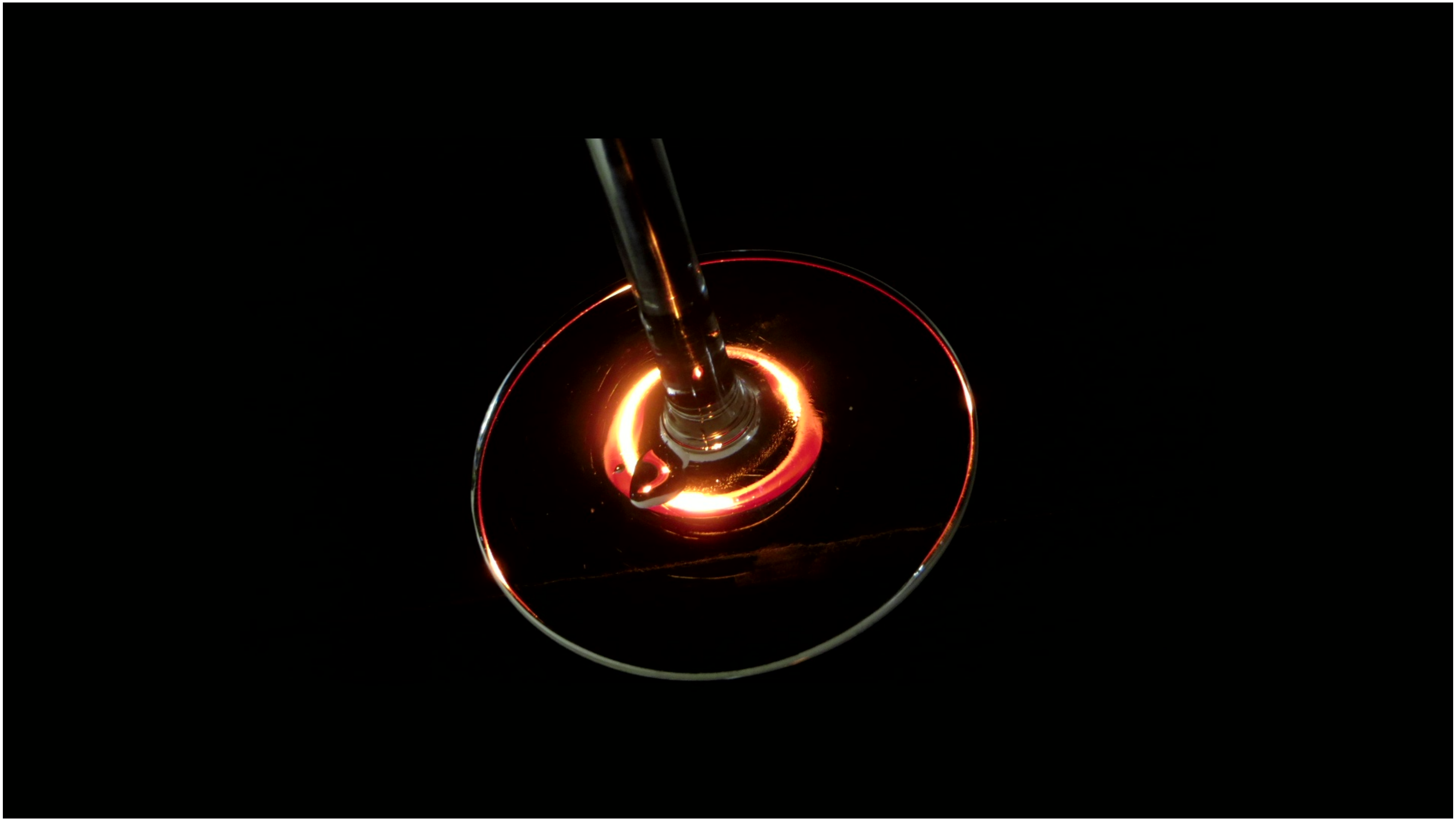
1 - Modify galaxy formation models   2 - Modify dark matter model



Lovell et al., MNRAS, 2012

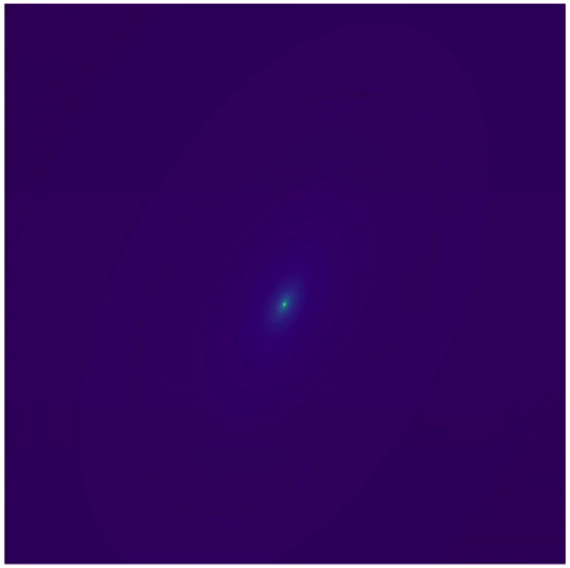
SUBSTRUCTURE LENSING



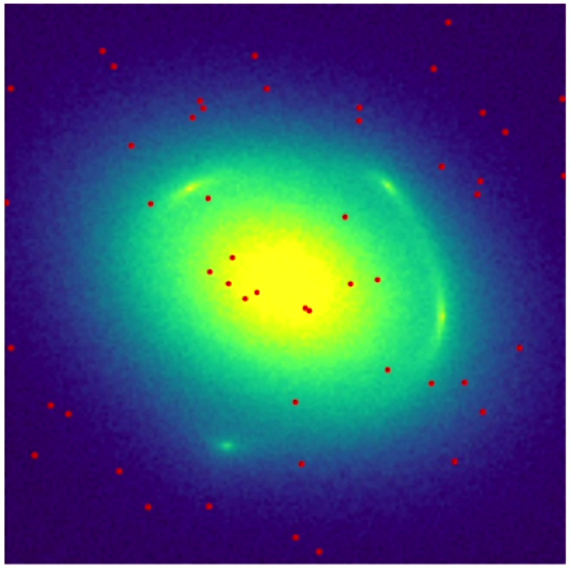


Adam Coogan Research Papers Code Non-work CV

Source



Observation



Adam Coogan

Source parameters

Horizontal position
Vertical position
Orientation
Ellipticity
Sharpness
Size

Telescope

Subhalo parameters

Resample subhalos | Hide subhalos

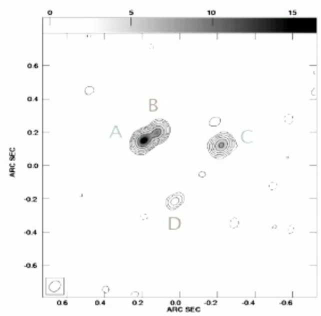
Lens parameters

Orientation
Ellipticity
Einstein radius

Turn off lens light

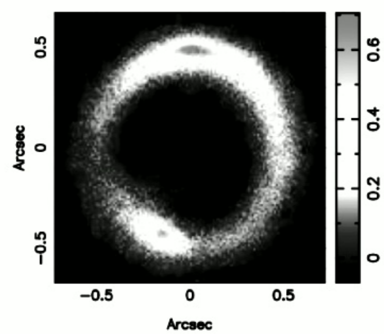
Substructure lensing

Lensed Radio Quasars



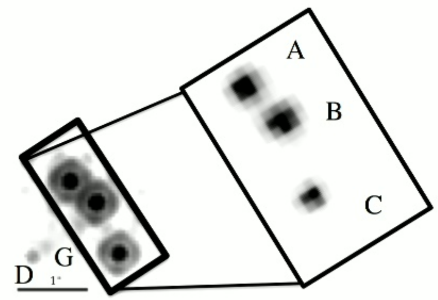
Dalal & Kochanek 2002

Lensed Galaxies (Optical)



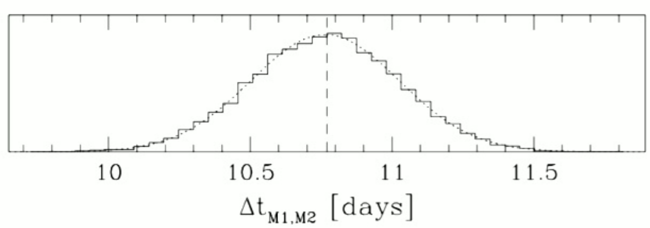
Vegetti et al. 2012

Lensed Optical Quasars



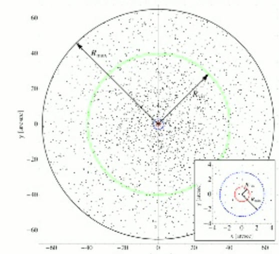
Nierenberg et al. 2014

Effect on time delays between images



Keaton & Moustakas 2009

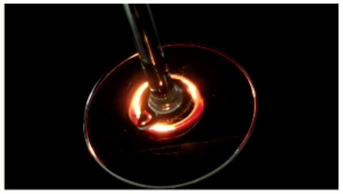
Cumulative effects of all subhalos



Cyr-Racine et al. 2016

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)

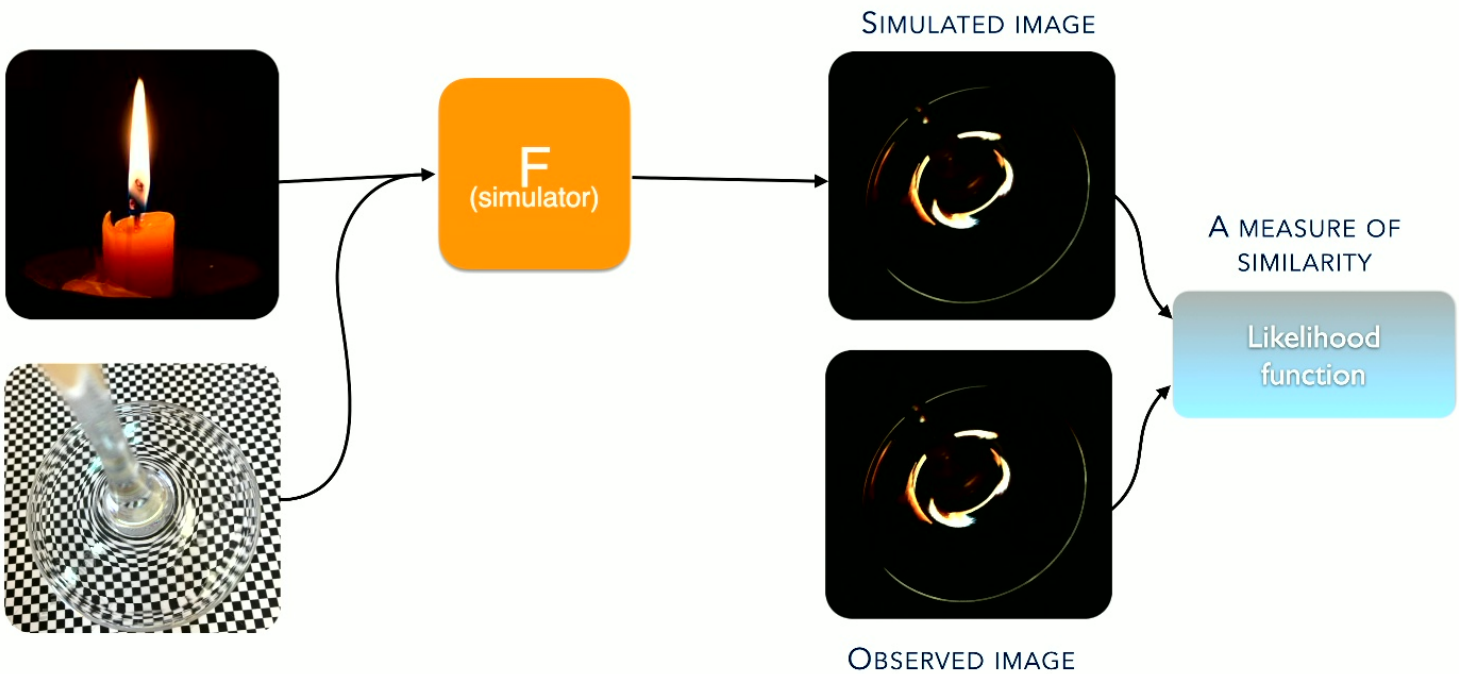
Measuring physical properties from images of strong lenses

Likelihood-based lens modeling

Observed image

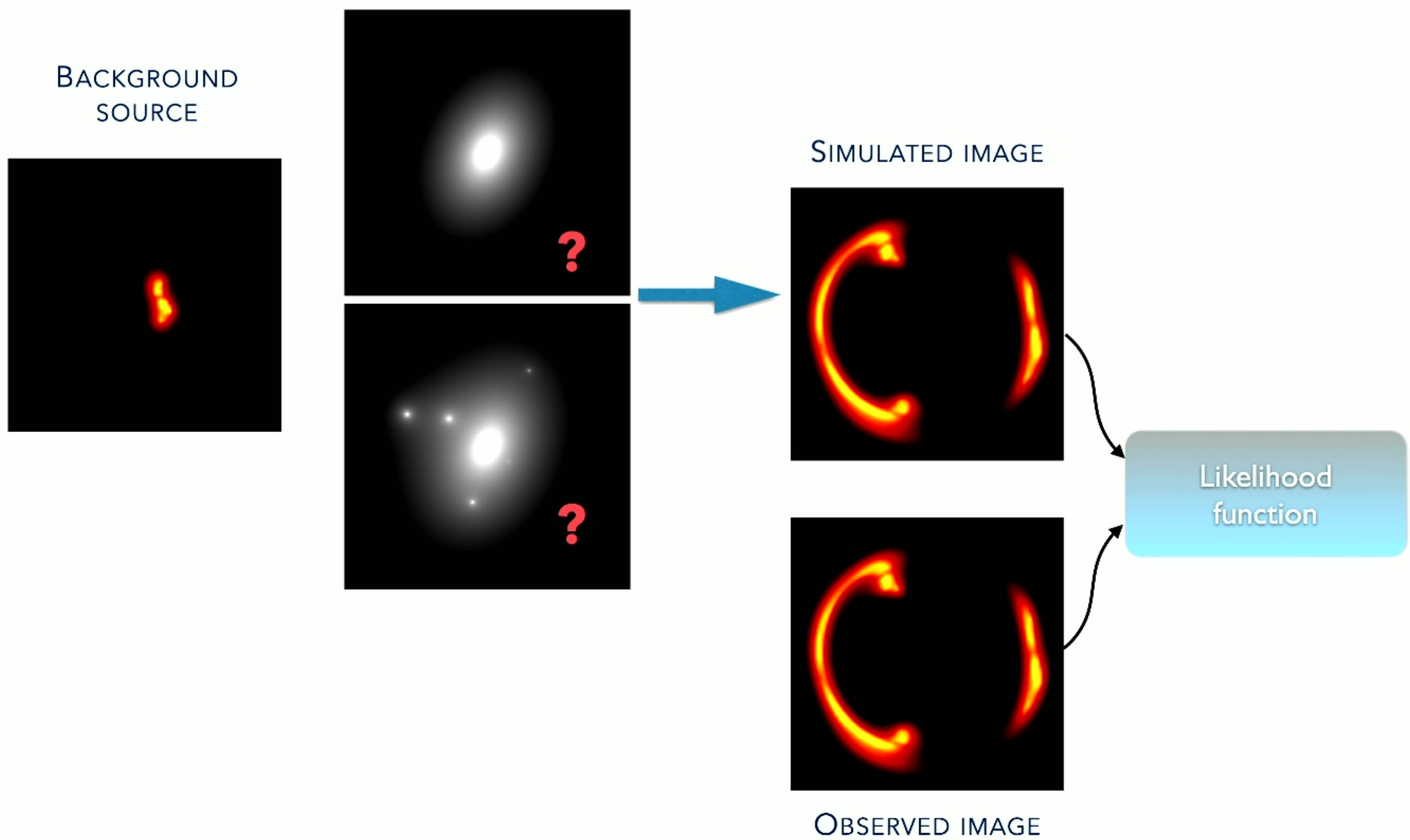
Measuring physical properties from images of strong lenses

Likelihood-based lens modeling

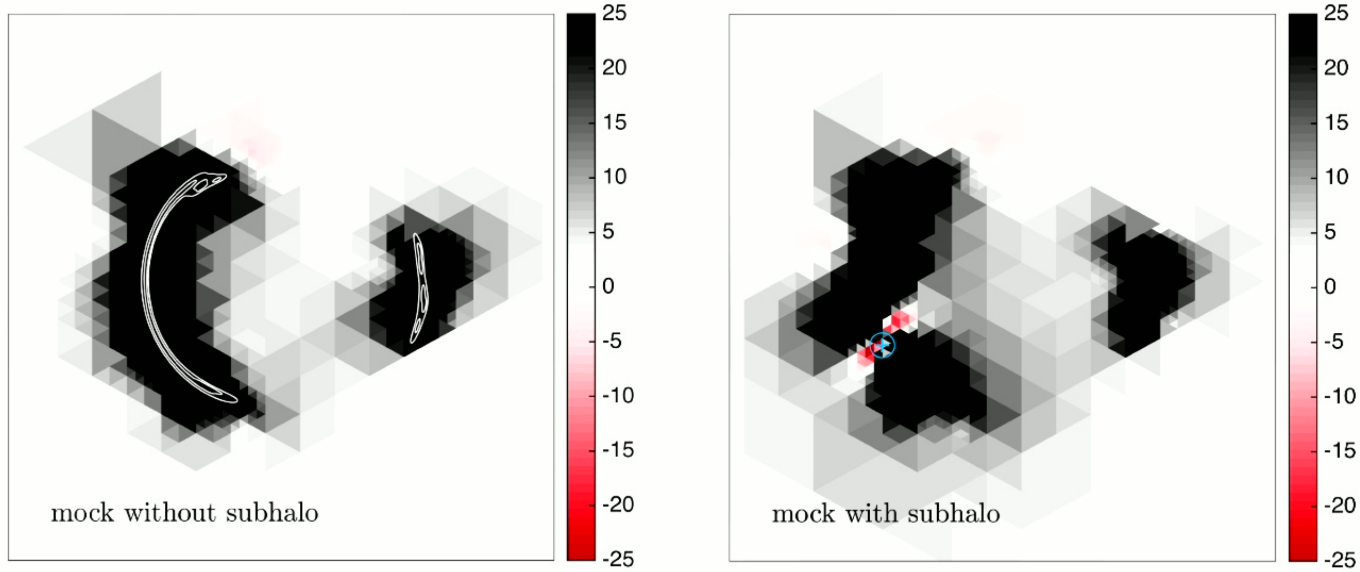


Subhalo detection:

Compare a smooth model with a model which includes subhalos



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)

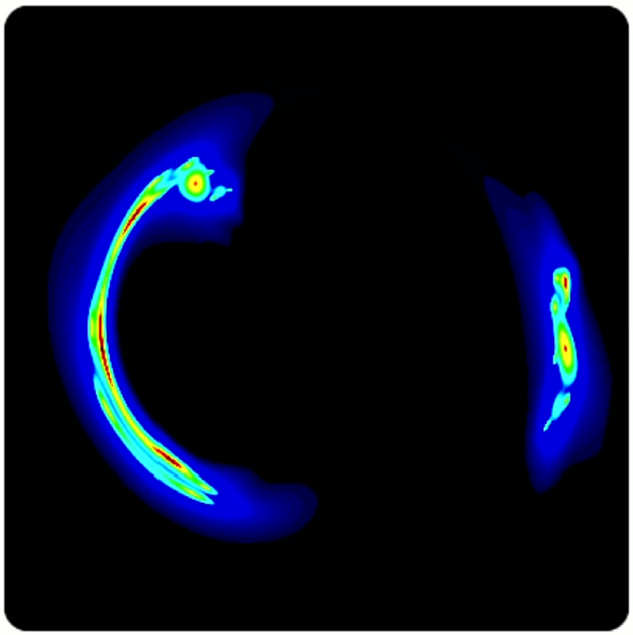
Hezaveh et al. ApJ 2016

Simulated images with and without a subhalo

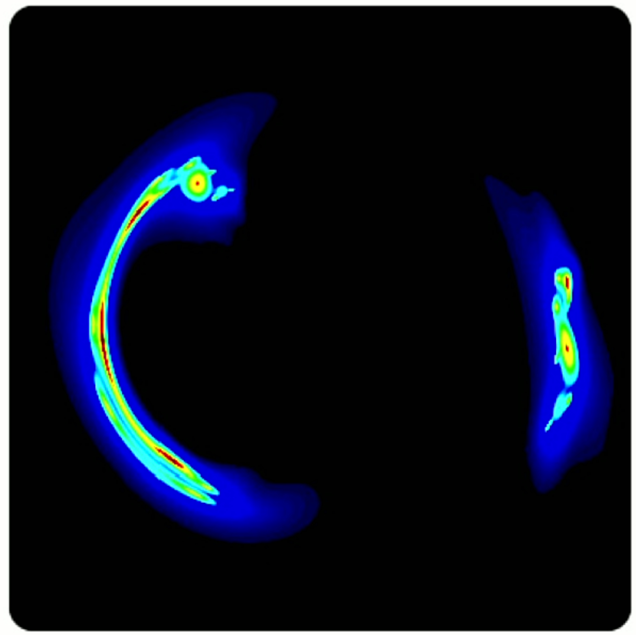
Main lensing galaxy mass ~ 10^{12} M_{sun}

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

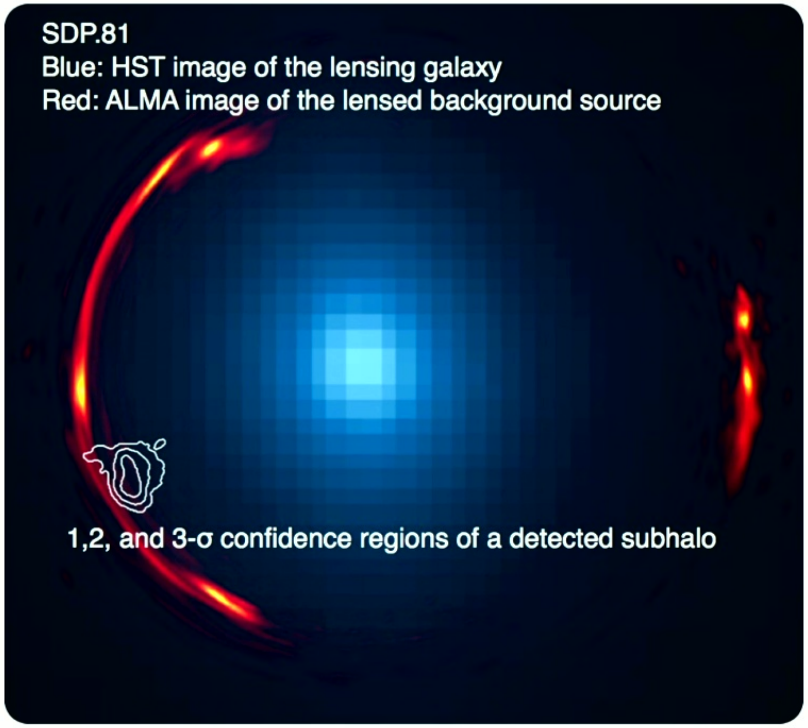
Smooth galaxy



Smooth galaxy + subhalo

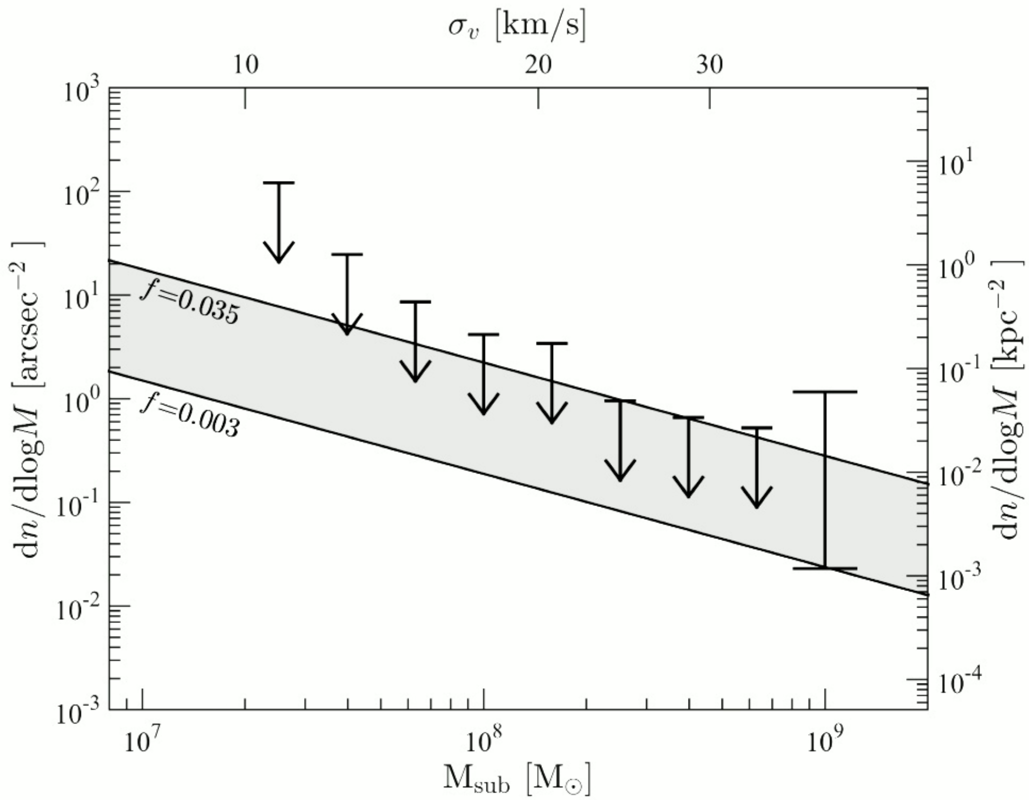


DETECTION OF A 10^9 M_{SUN} SUBHALO



Hezaveh, Dalal, et al. ApJ 2016

Constraints on the mass function of subhalos in the host halo



Hezaveh, Dalal, et al. ApJ 2016

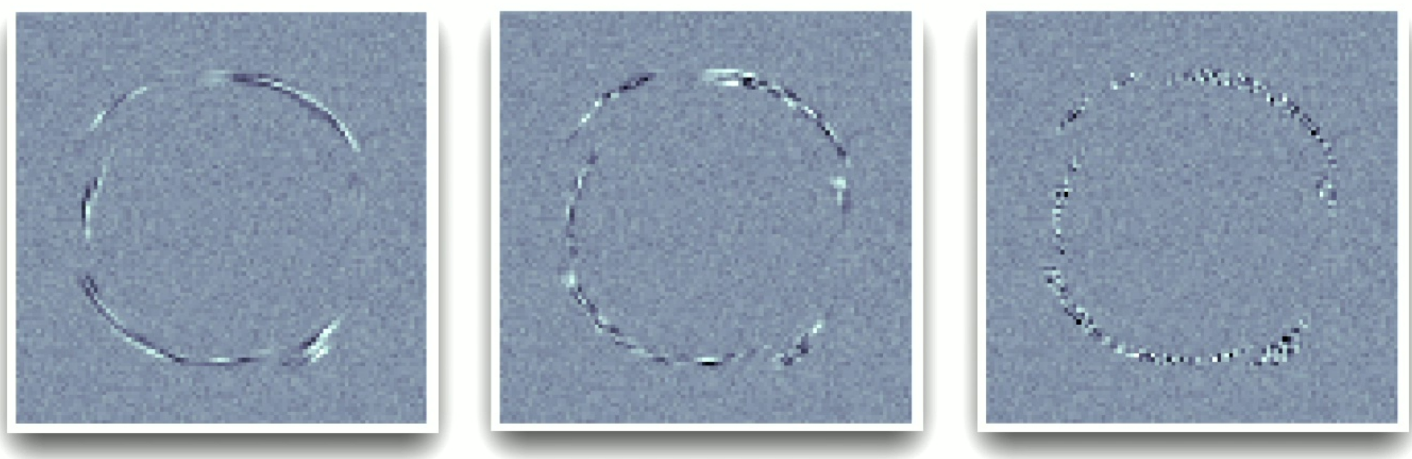
COVARIANCE OF DEFLECTIONS

POWER SPECTRUM OF THE DENSITY FIELD

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

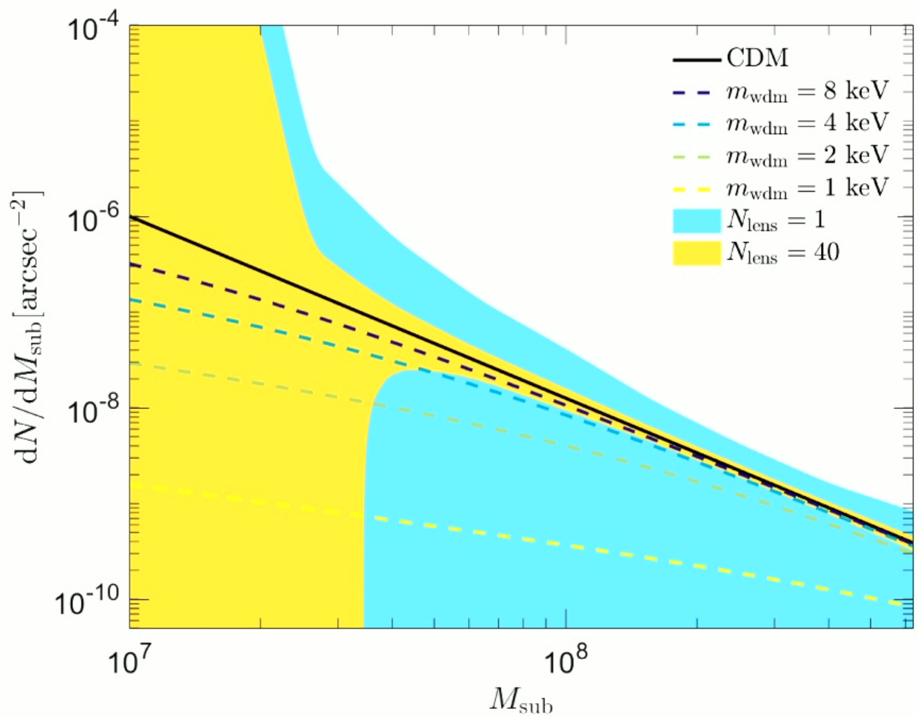
LIKELIHOOD

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

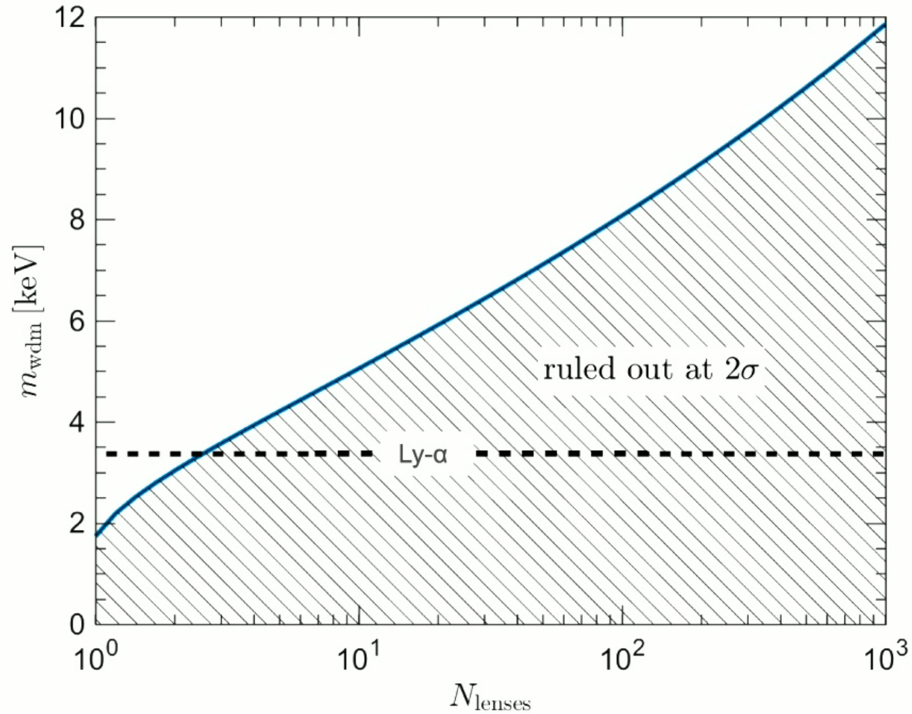


Hezaveh, Dalal, et al., JCAP, 2016

Forecasts for N lenses



Forecasts for N lenses



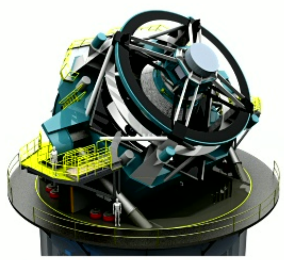
- Extremely Computationally Expensive
- Approximations => Inability to sample the high-dimensional space. Suboptimal priors.

Looking into the future:

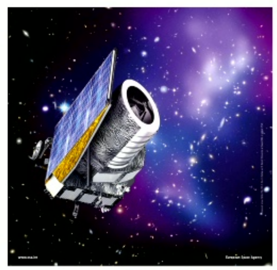
1- New Lenses

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:

3- Analysis Methods

How are we going to analyze 170,000 lenses?

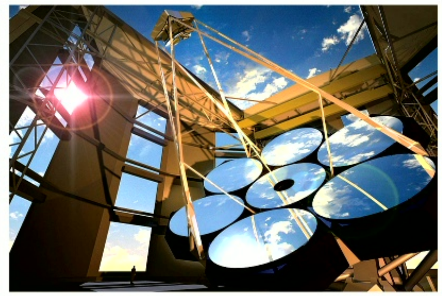
- Lens modeling is **very slow**.
- Even a simple lens model can take 2-3 days of human and CPU time, translating to **1,400 years**!
- Even if we pay 100 people to work on this, it'll be 14 years!
- Old method are simply not feasible.

Lens modeling sweatshop of the future

Looking into the future:

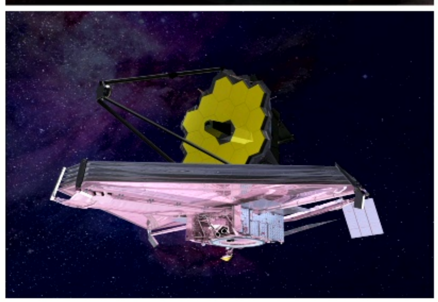
2- Existing and New Telescopes

ALMA



GMT

JWST



TMT

Looking into the future:

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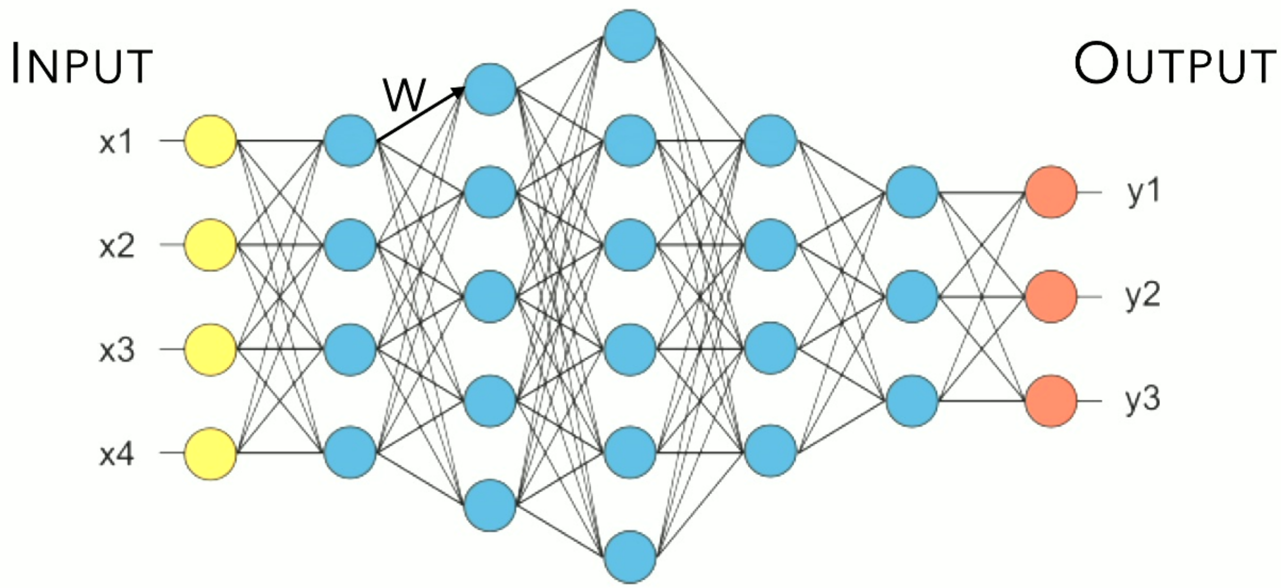
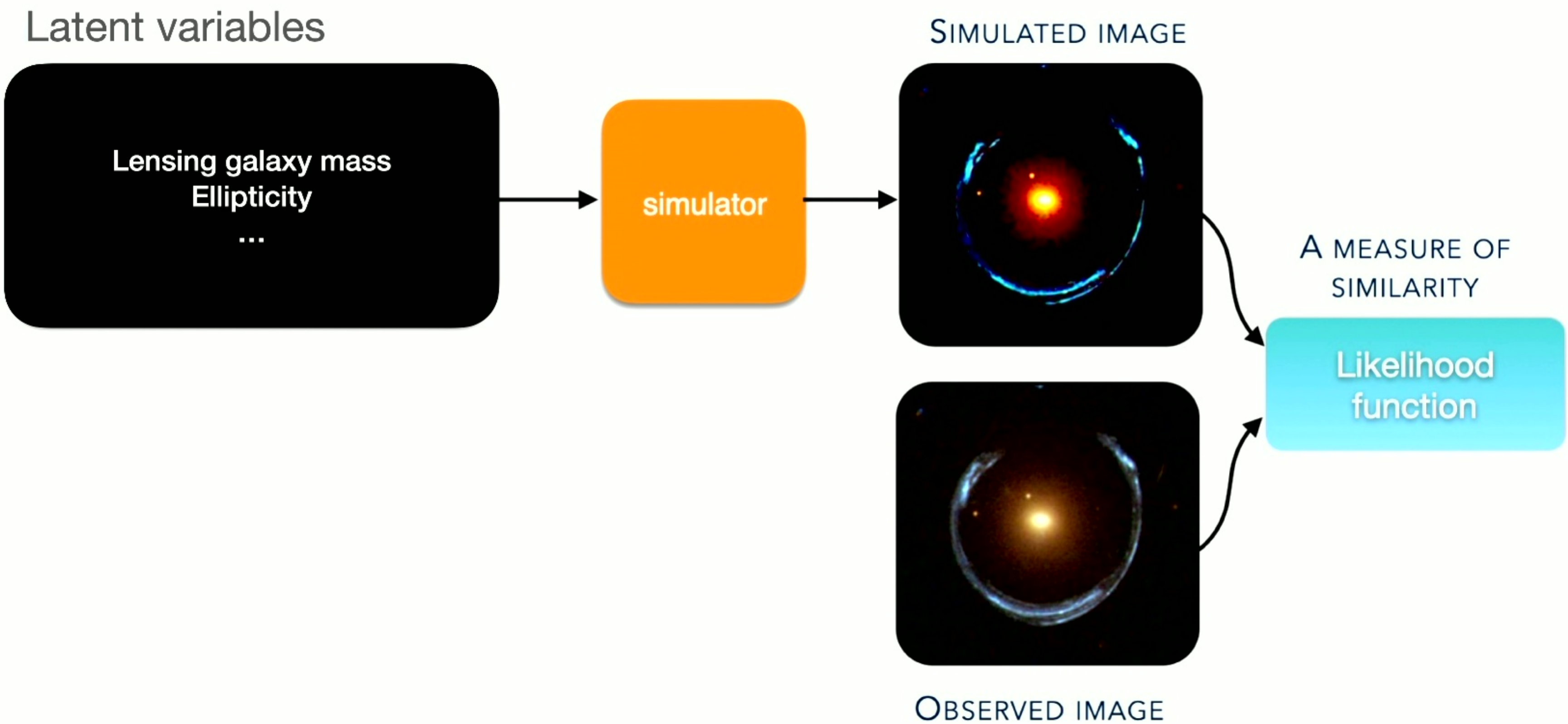
Lens modeling sweatshop of the future

Can we obtain the lens parameters using neural networks?

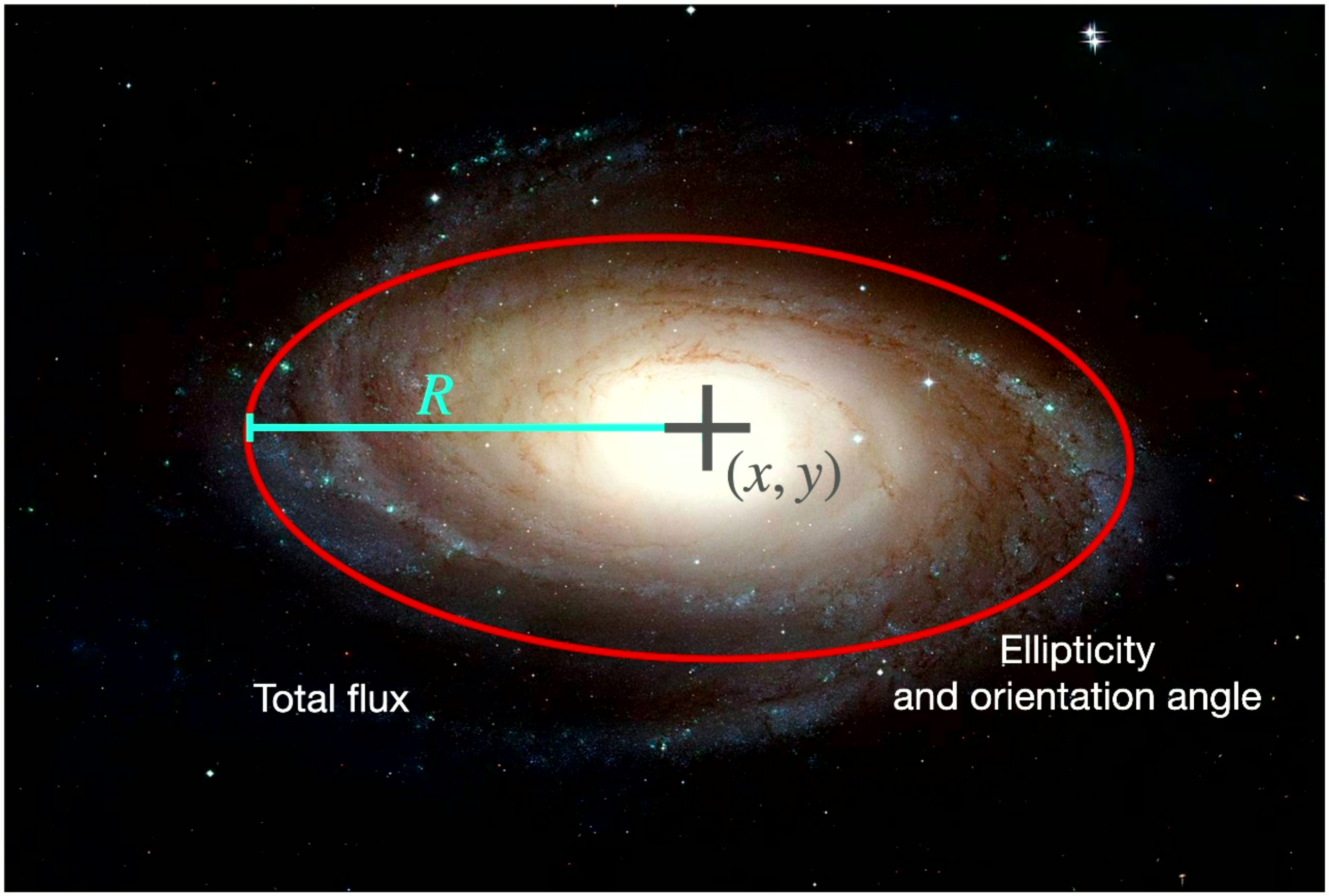


Universal approximation theorem:
Neural nets can approximate *any function* to an *arbitrary accuracy*.

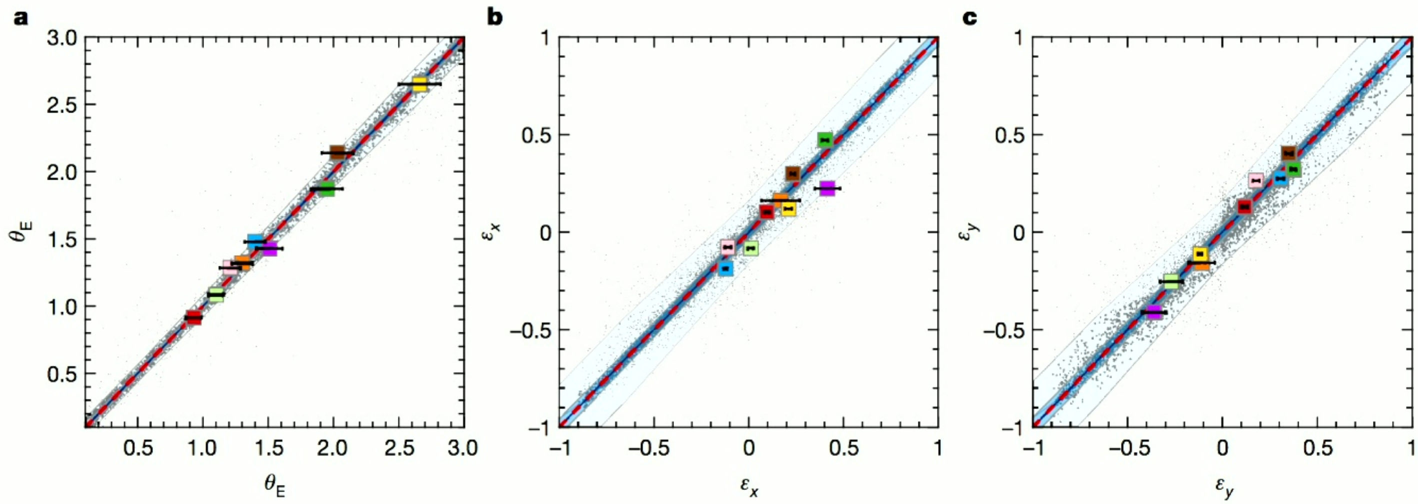


Latent variables
Lensing galaxy mass
Ellipticity
...
simulator
SIMULATED IMAGE
A MEASURE OF SIMILARITY
Likelihood function
OBSERVED IMAGE

Low- vs. high-dimensional representations

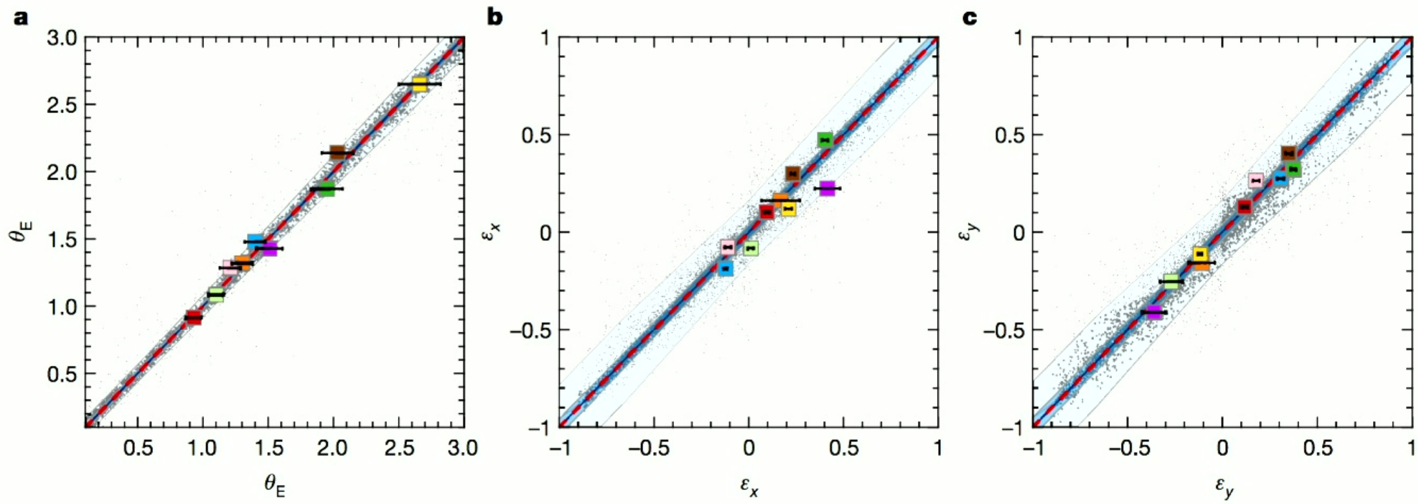


Estimating lensing parameters with neural nets



Hezaveh, Perreault Levasseur, Marshall, Nature, 2017

Estimating lensing parameters with neural nets



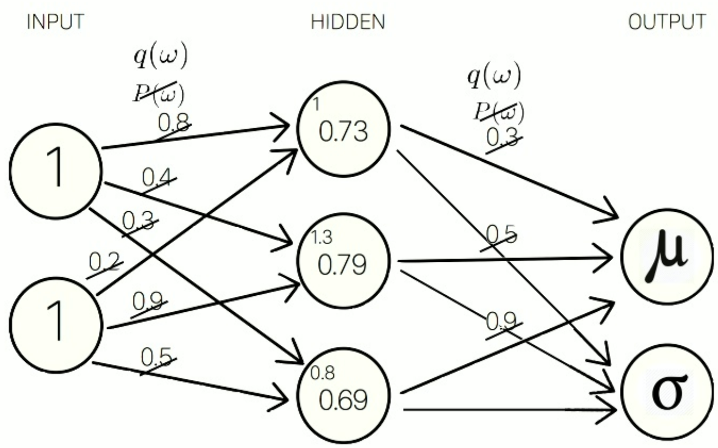
10 million times faster than maximum-likelihood lens modeling.

0.01 seconds on a **single GPU**

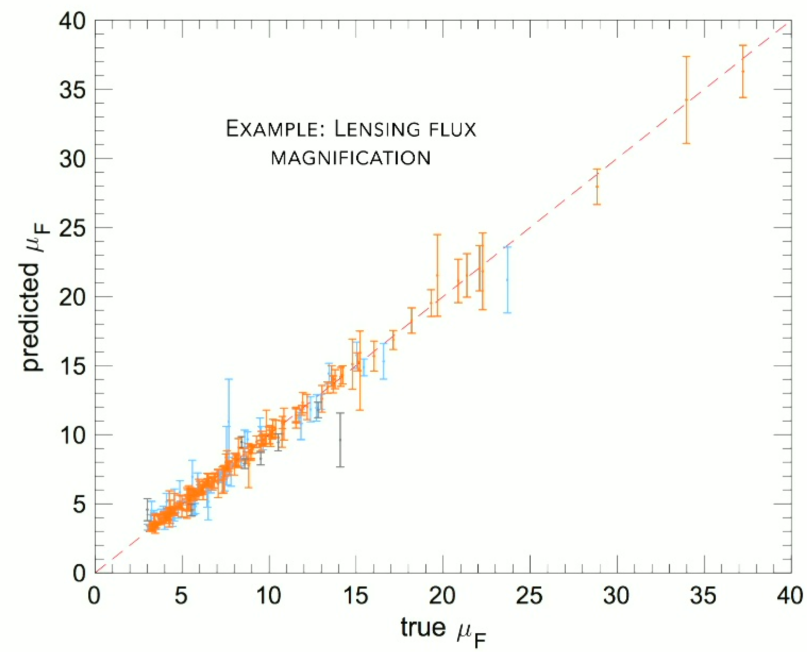
Hezaveh, Perreault Levasseur, Marshall, Nature, 2017

Modeling the posterior

Approximate BNNs

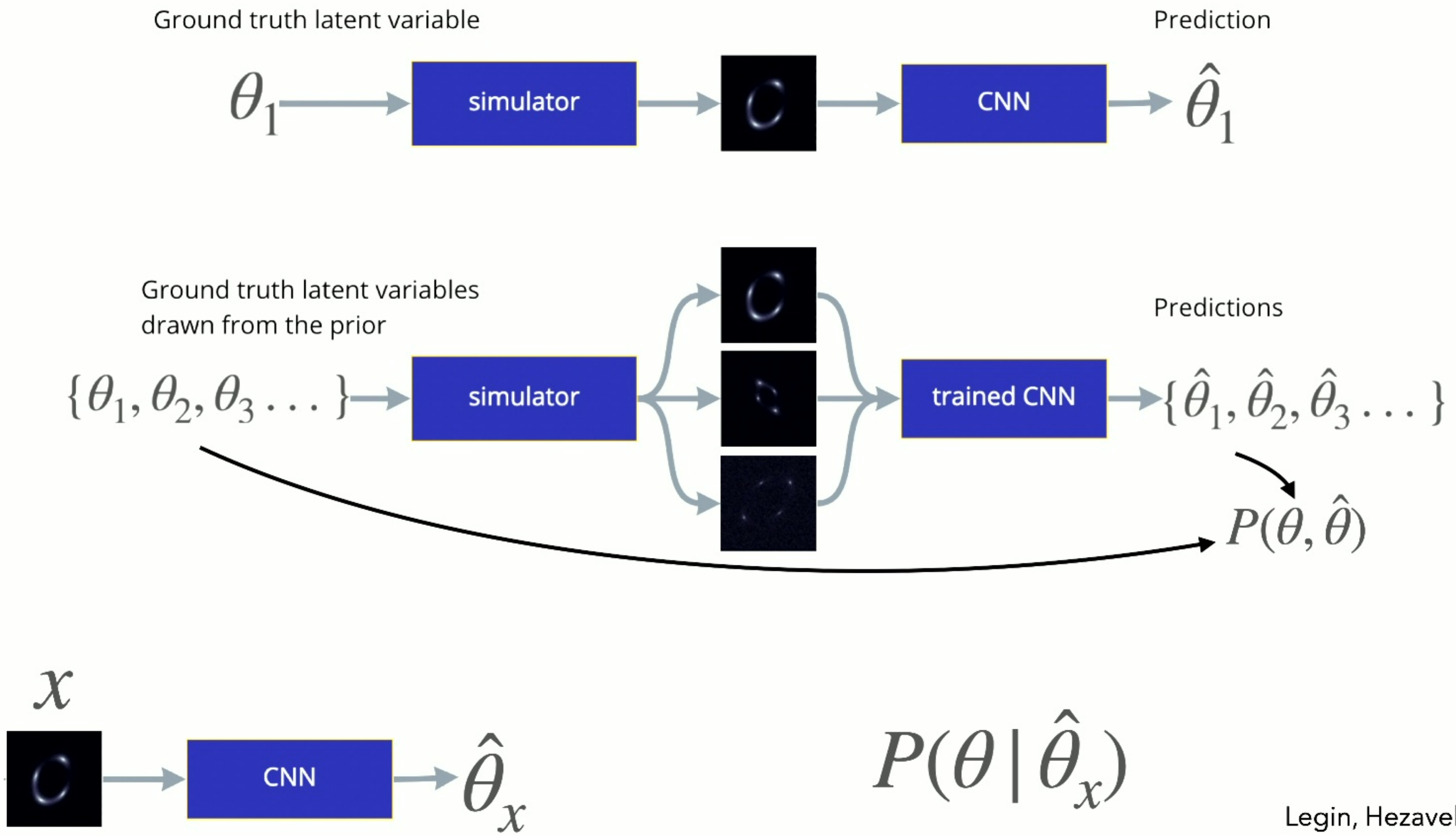


$$\mathcal{L}(\mathbf{y}_n, \hat{\mathbf{y}}_n(\mathbf{x}_n,\omega)) \propto \sum_k \frac{-1}{2\sigma_k^2}||y_{n,k} - \mu_k(\mathbf{x}_n,\omega)||^2 - \frac{1}{2}\log\sigma_k^2$$



Perreault Levasseur, Hezaveh, Wechsler, ApJ, 2017

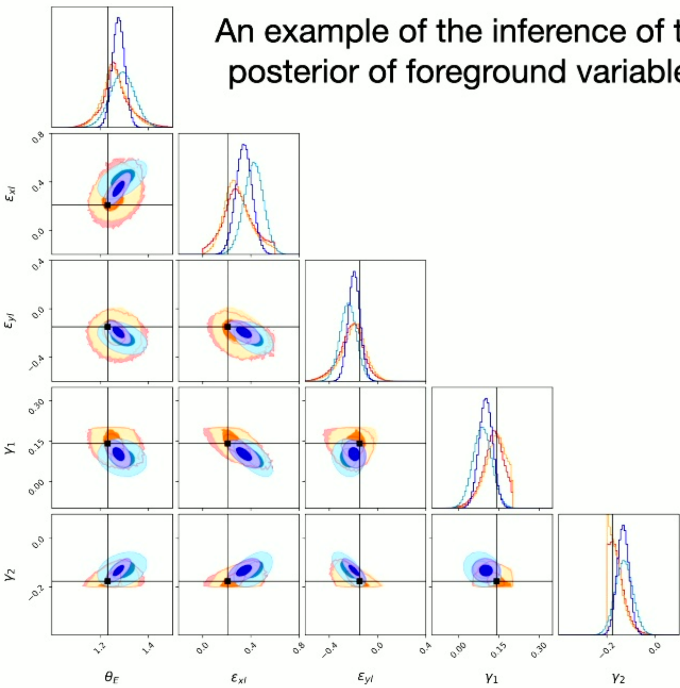
Likelihood-free inference



Ronan Legin

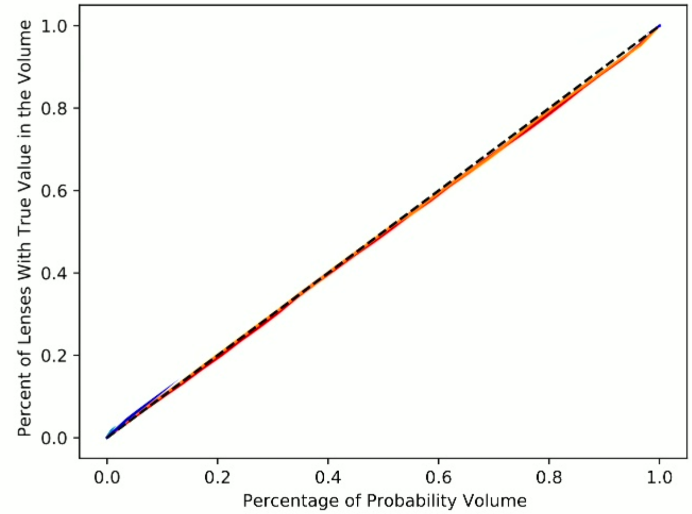
Legin, Hezaveh, Perreault Levasseur, Wandelt
NeurIPS 2021 - Physical Sciences Workshop

Likelihood-free inference



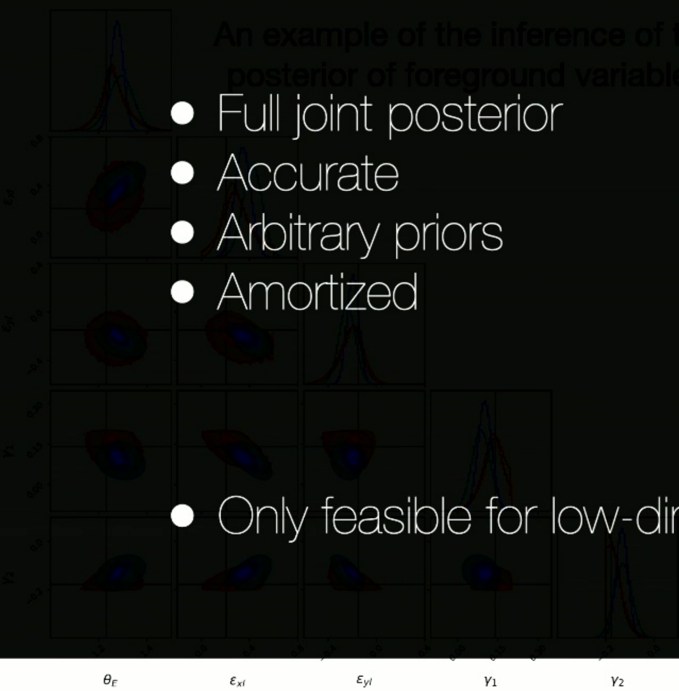
An example of the inference of the posterior of foreground variables

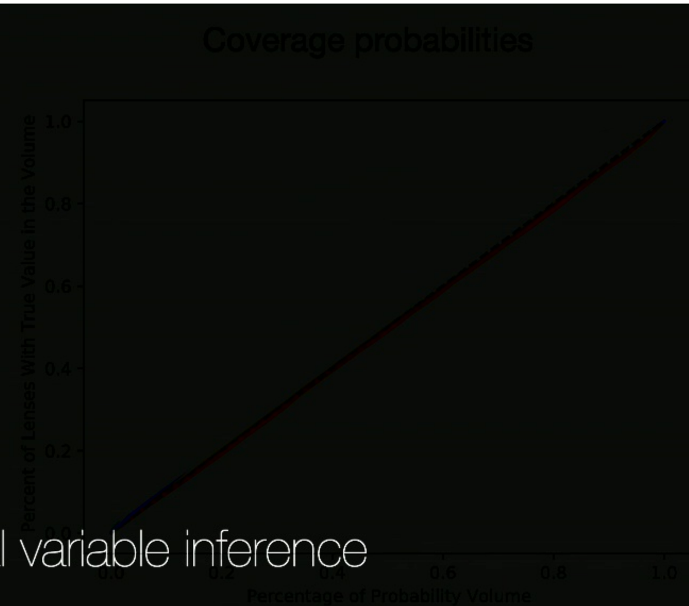
Coverage probabilities



Legin, Hezaveh, Perreault Levasseur, Wandelt
NeurIPS 2021 - Physical Sciences

Likelihood-free inference



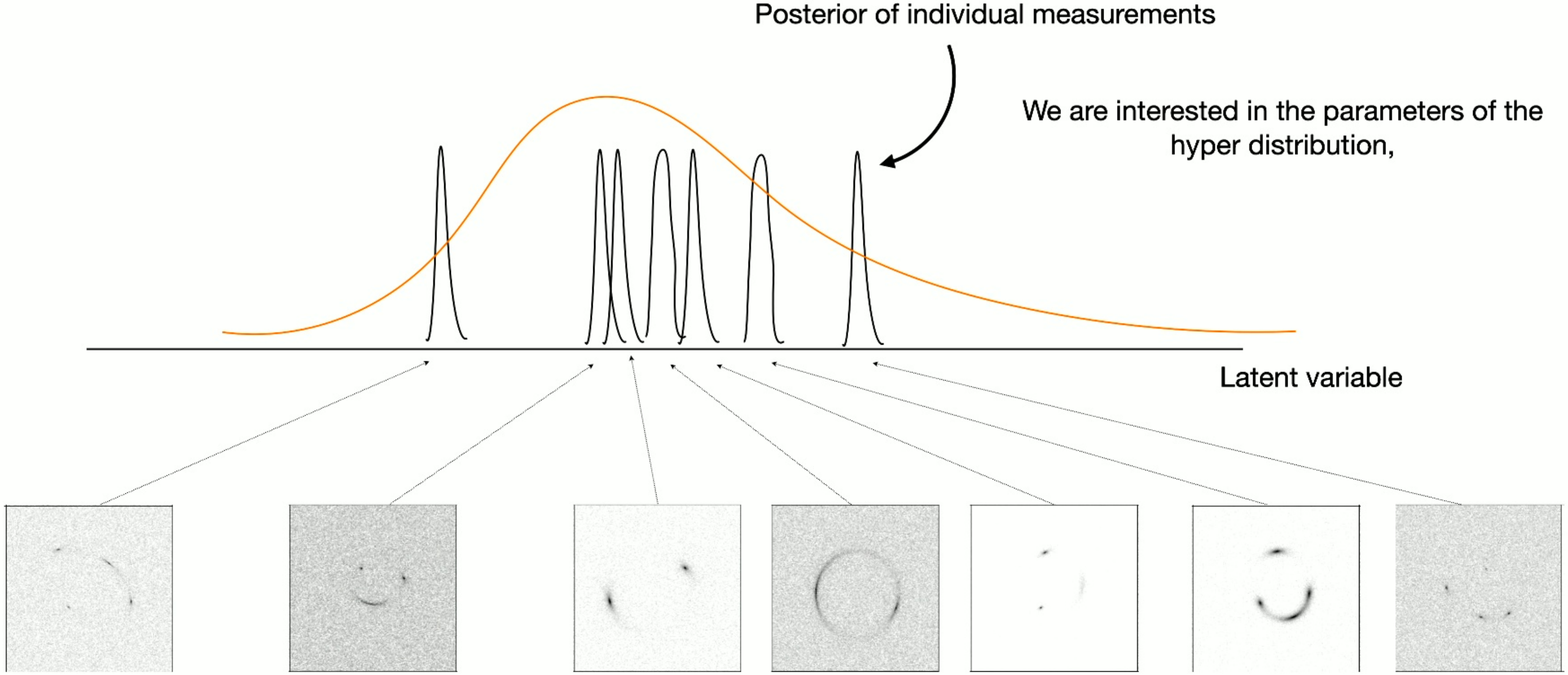


- Full joint posterior
- Accurate
- Arbitrary priors
- Amortized

- Only feasible for low-dimensional variable inference

Legin, Hezaveh, Perreault Levasseur, Wandelt
NeurIPS 2021 - Physical Sciences

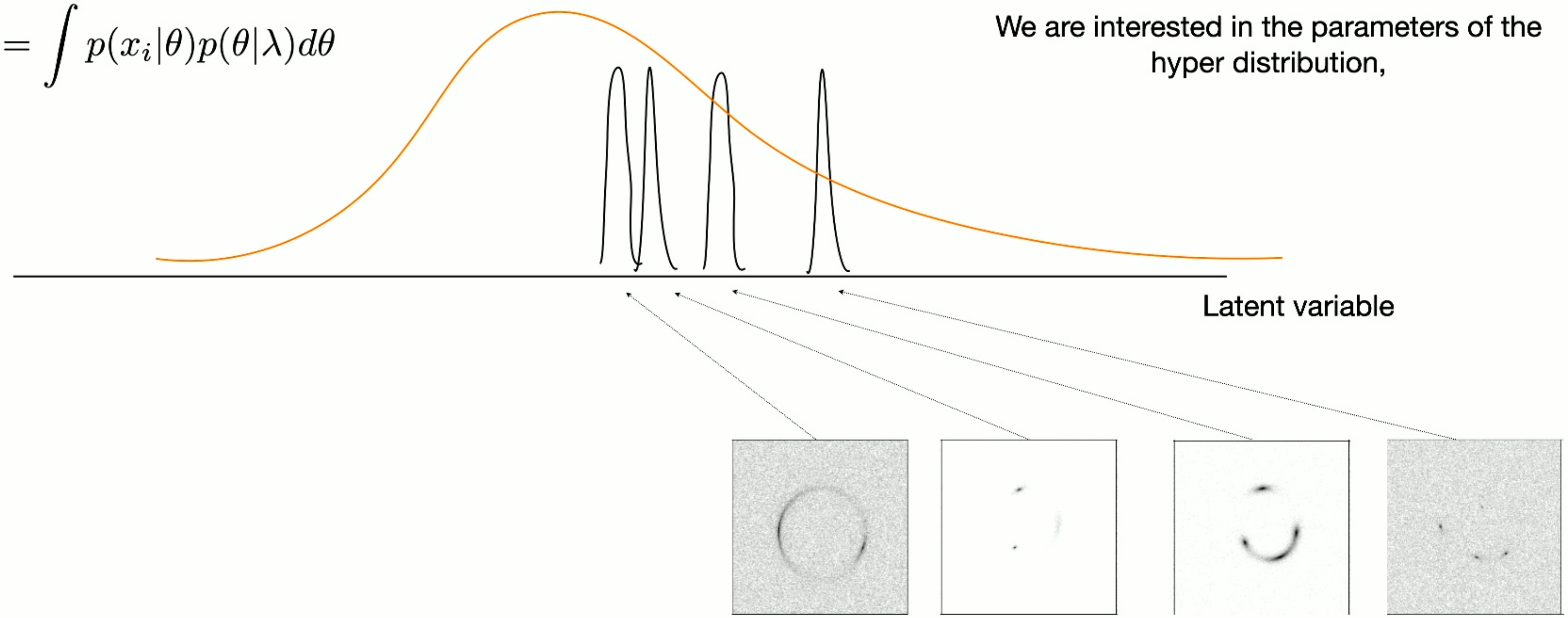
Hierarchical Bayesian inference



Hierarchical Bayesian inference

$$p(\lambda|\{x_i\}) = \frac{p(\lambda)\prod_i p(x_i|\lambda)}{\int d\lambda' p(\lambda')\prod_i p(x_i|\lambda')}$$

$$p(x_i|\lambda) = \int p(x_i|\theta)p(\theta|\lambda)d\theta$$



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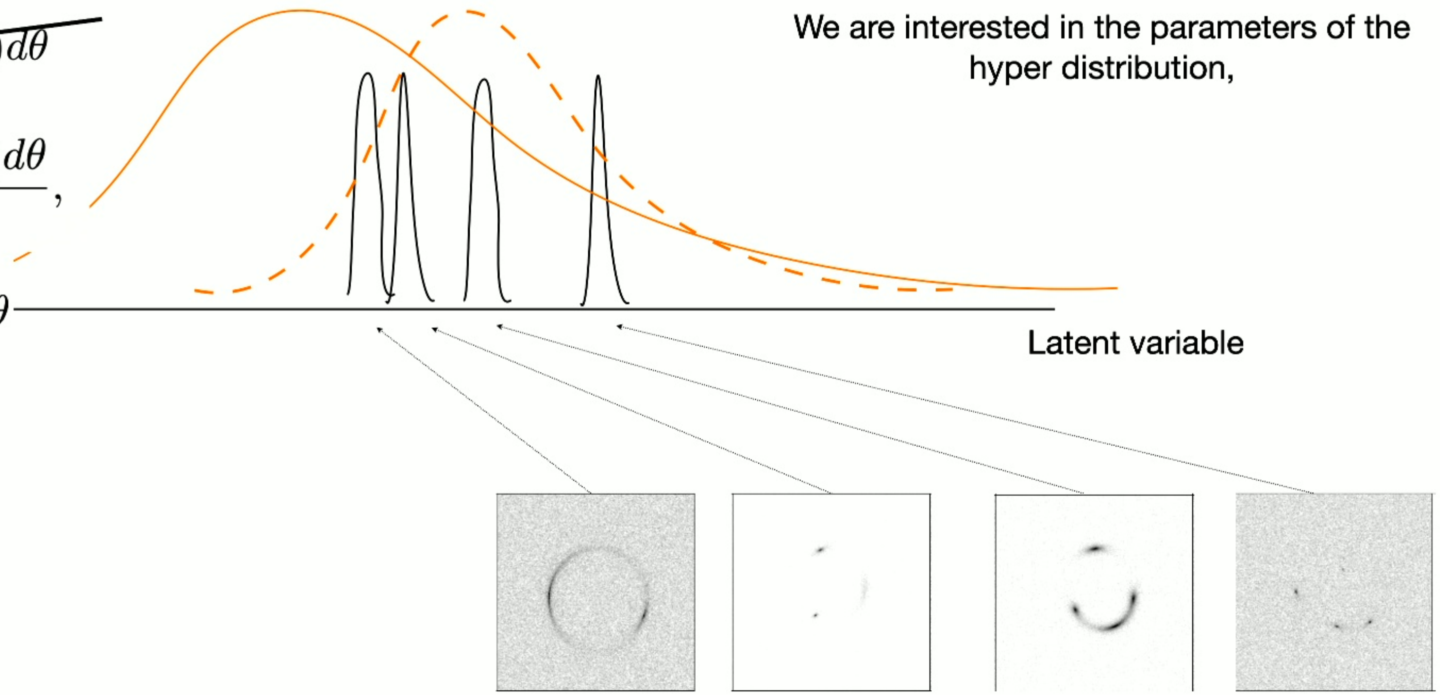
~~$$p(x_i|\lambda) = \int p(x_i|\theta)p(\theta|\lambda)d\theta$$~~

$$p(x_i|\lambda) = \frac{\int p(x_i|\theta)p(\theta|\lambda)d\theta}{\alpha(\lambda)},$$

$$\alpha(\lambda) = \int p_{\rm det}(\theta)p(\theta|\lambda)d\theta$$



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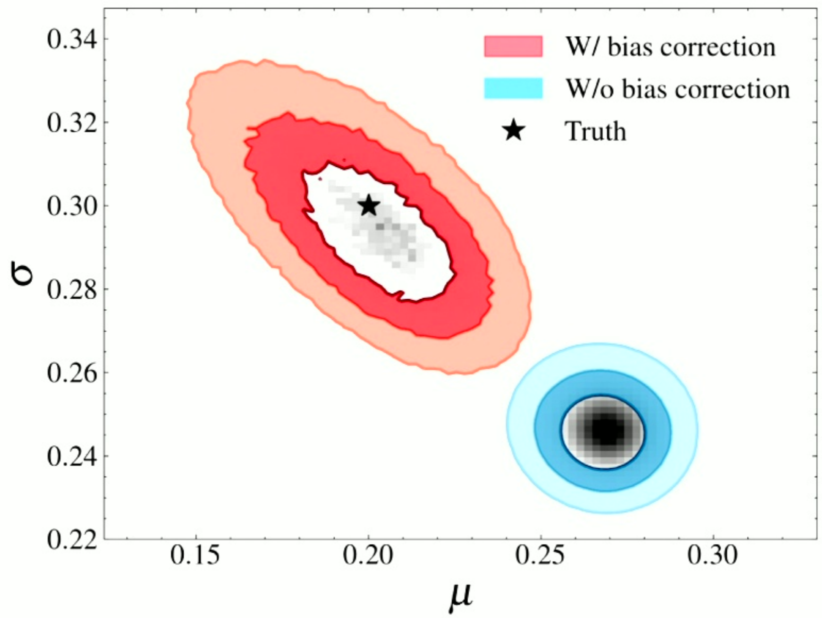


Ronan Legin   Connor Stone

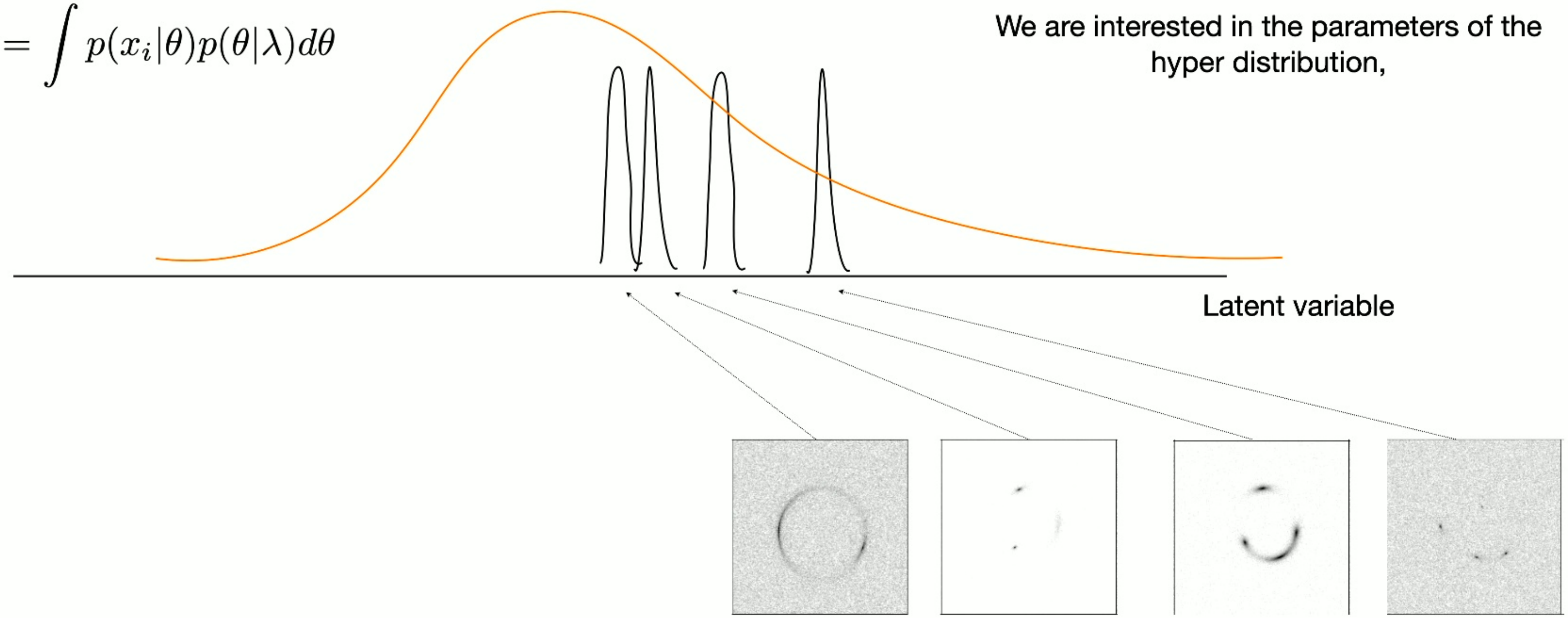
Legin, Stone, Hezaveh, Perreault Levasseur,
ICML 2022 - Machine Learning for Astrophysics

Hierarchical Bayesian inference

$$p(\lambda|\{x_i\}) = \frac{p(\lambda)\prod_i p(x_i|\lambda)}{\int d\lambda' p(\lambda')\prod_i p(x_i|\lambda')}$$

$$p(x_i|\lambda) = \int p(x_i|\theta)p(\theta|\lambda)d\theta$$

We are interested in the parameters of the hyper distribution,



Neural Ratio Estimators

$P(x, \theta)$

Class #1

$\{(x_1, \theta_1), (x_2, \theta_2), \ldots, , (x_N, \theta_N)\}$

$P(x)P(\theta)$

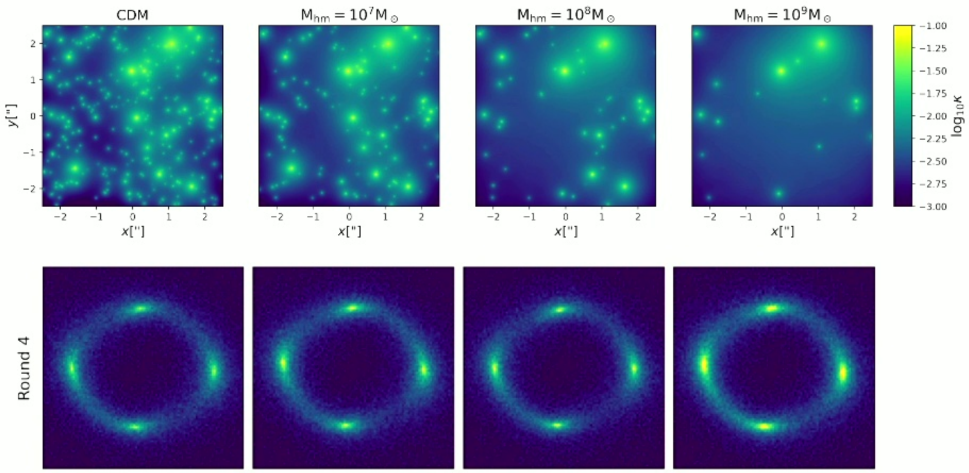
Class #2

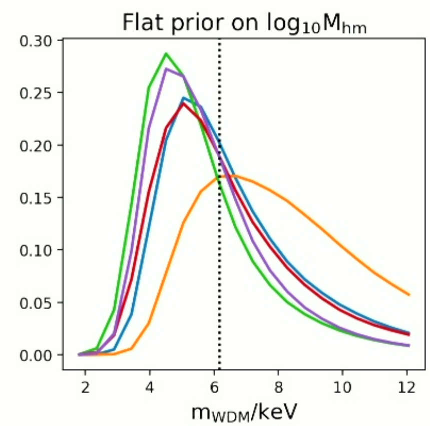
$\{(x_1, \theta_1), (x_2, \theta_2), \ldots, , (x_M, \theta_M)\}$

Classify

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

Estimating the dark matter particle temperature with Neural Ratio Estimators



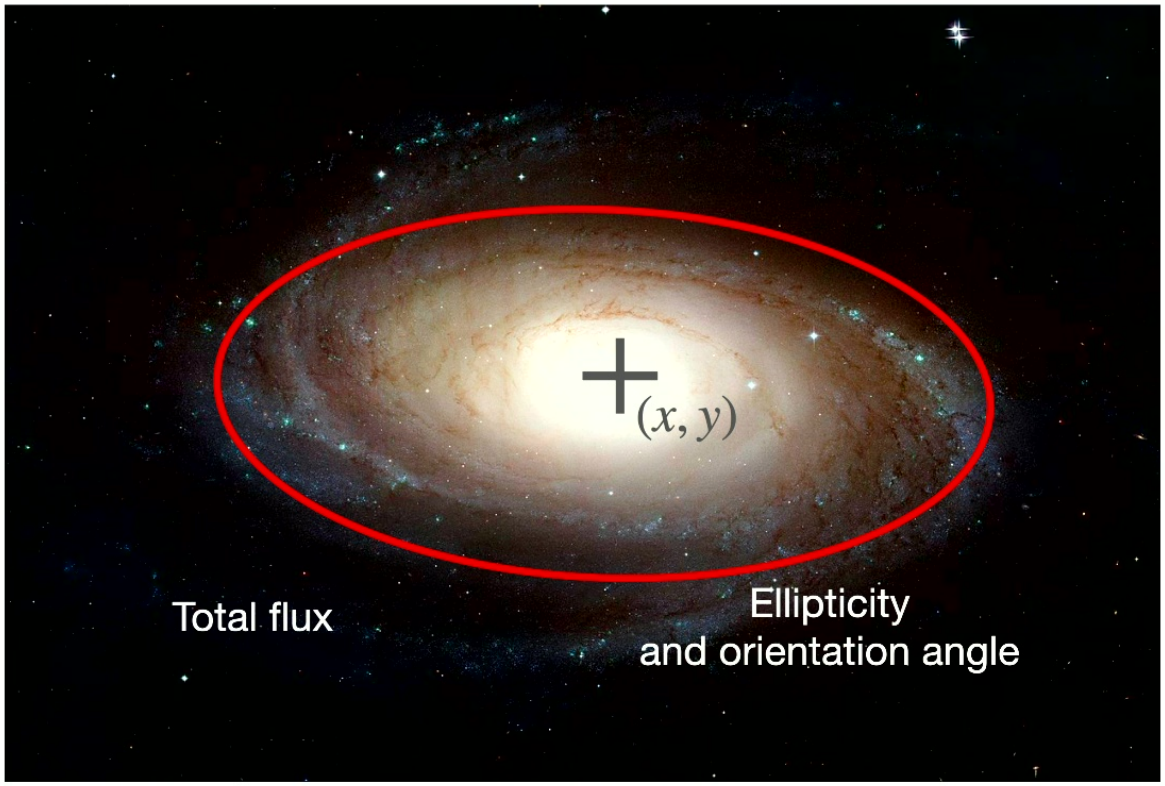


Adam Coogan

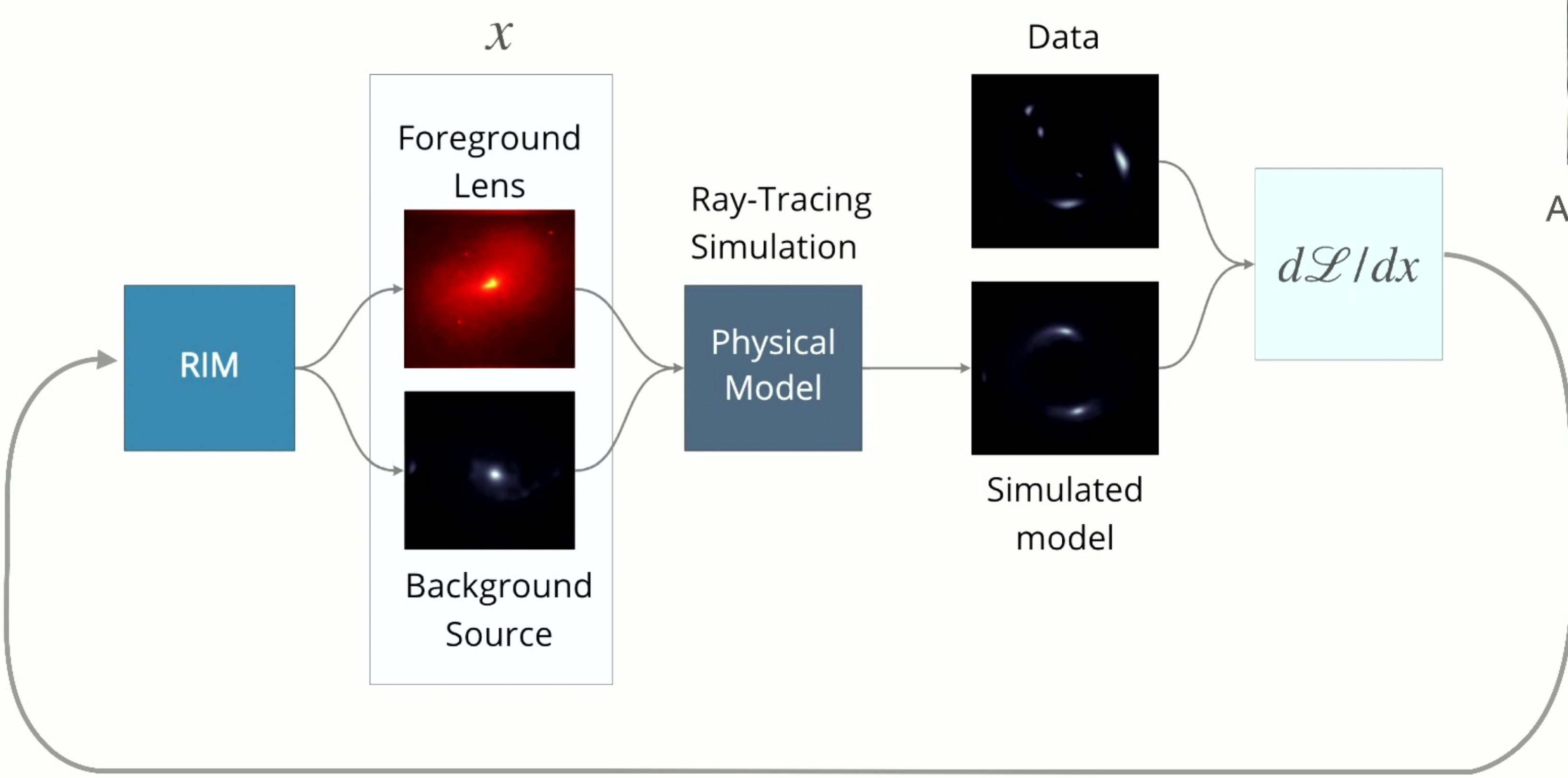
Anau Montel, Coogan et al. 2022

Coogan et al.
NeurIPS 2020 - Physical Sciences

High-dimensional (pixelated) representations

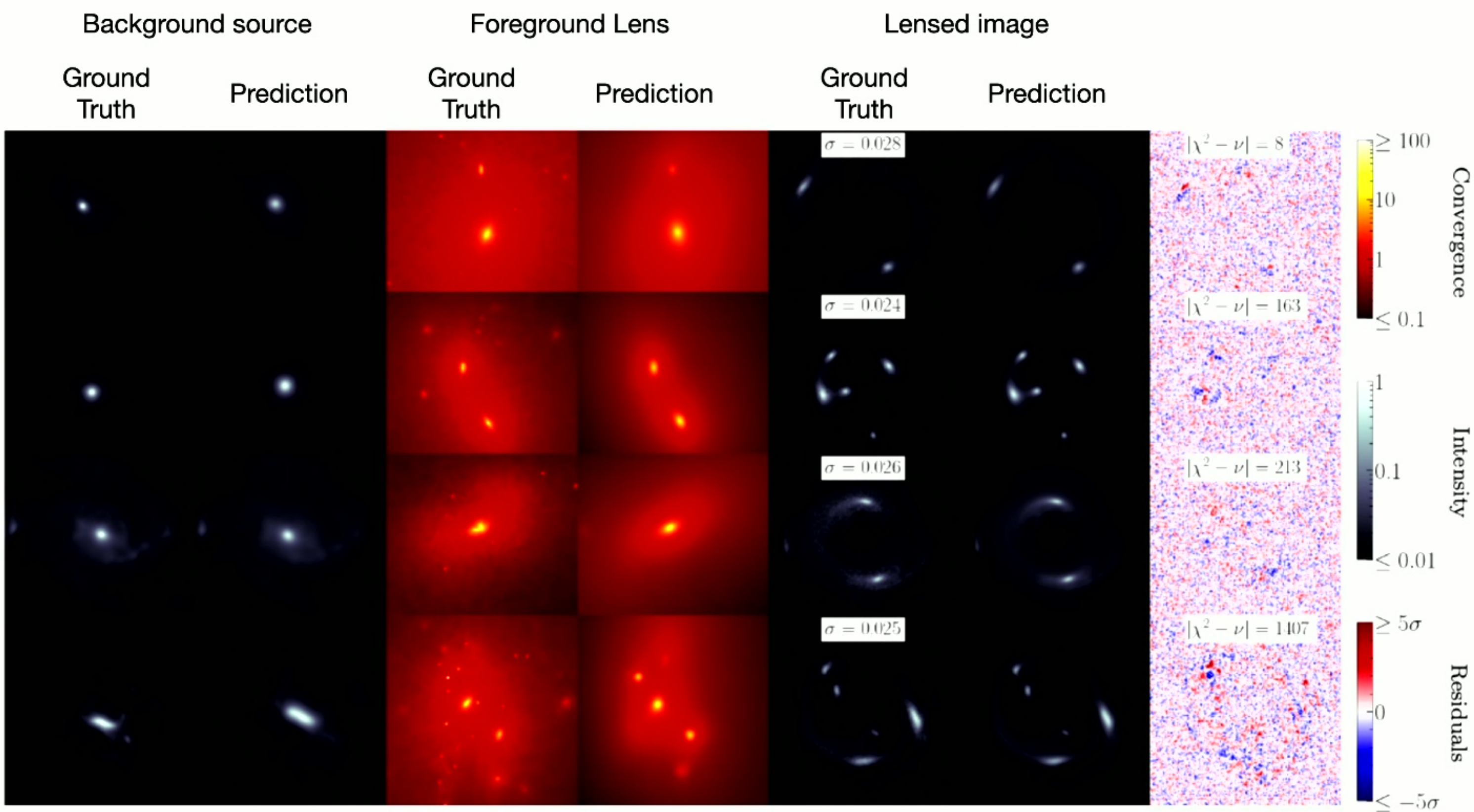


The Recurrent Inference Machine



Alexandre Adam

The Recurrent Inference Machine



Adam, Perreault Levasseur, Hezaveh, Welling
ICML 2022 - Machine Learning for Astrophysics Workshop

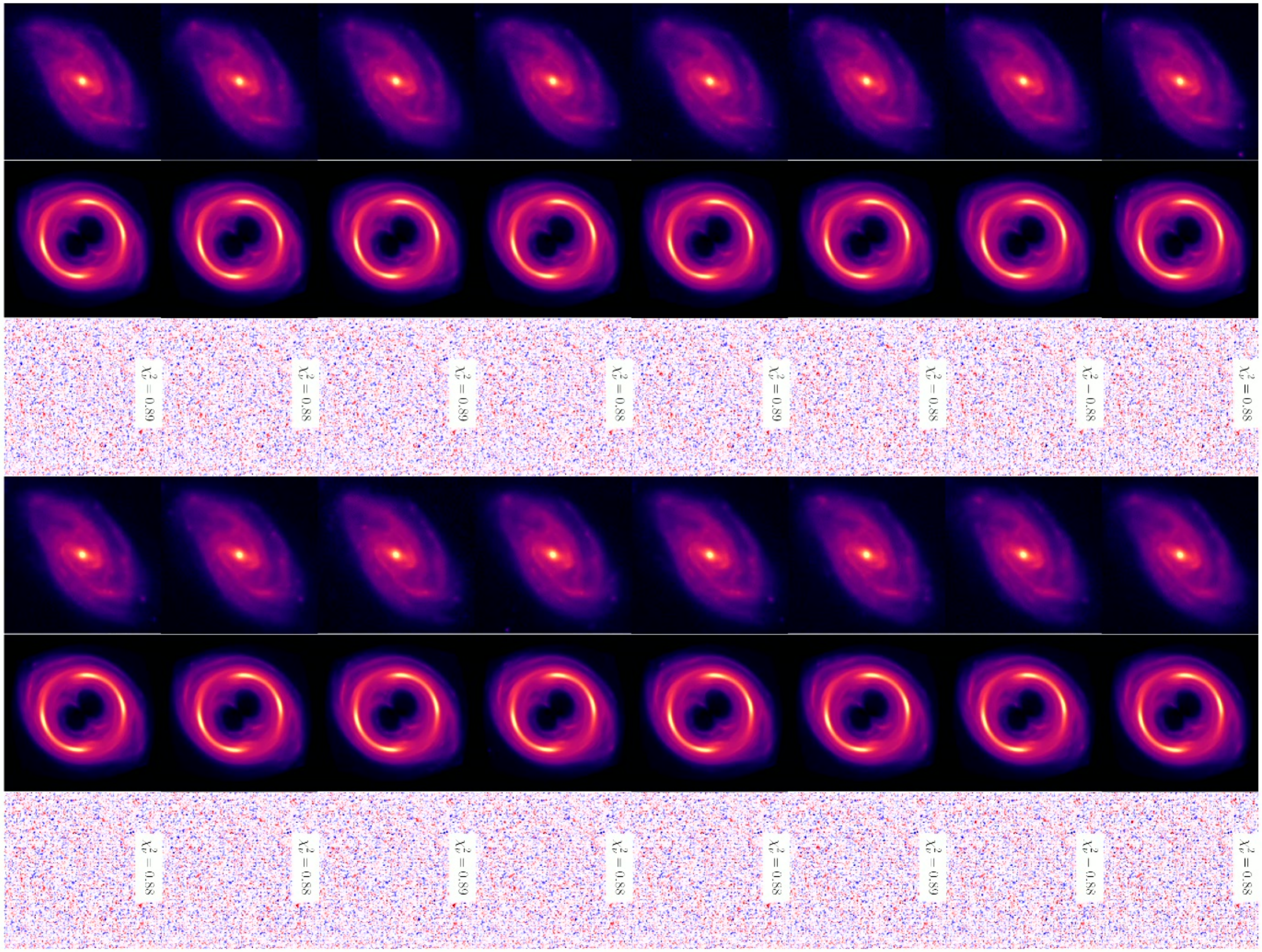
Estimating the posteriors of high-dimensional (pixelated) representations

$$\log p(\mathbf{x} \mid \mathbf{data}) = \log p(\mathbf{data} \mid \mathbf{x}) + \log p(\mathbf{x}) - \log p(\mathbf{data})$$

$$\nabla_{\mathbf{x}} \log p(\mathbf{x} \mid \mathbf{data}) = \nabla_{\mathbf{x}} \log p(\mathbf{data} \mid \mathbf{x}) + \nabla_{\mathbf{x}} \log p(\mathbf{x})$$

Learned from training data

Langevin Sampling $\mathbf{x}_{i+1} \leftarrow \mathbf{x}_i + \epsilon \nabla_{\mathbf{x}} \log p(\mathbf{x}) + \sqrt{2\epsilon}\, \mathbf{z}_i, \quad i = 0, 1, \cdots, K,$


$\chi^2_\nu = 0.89$
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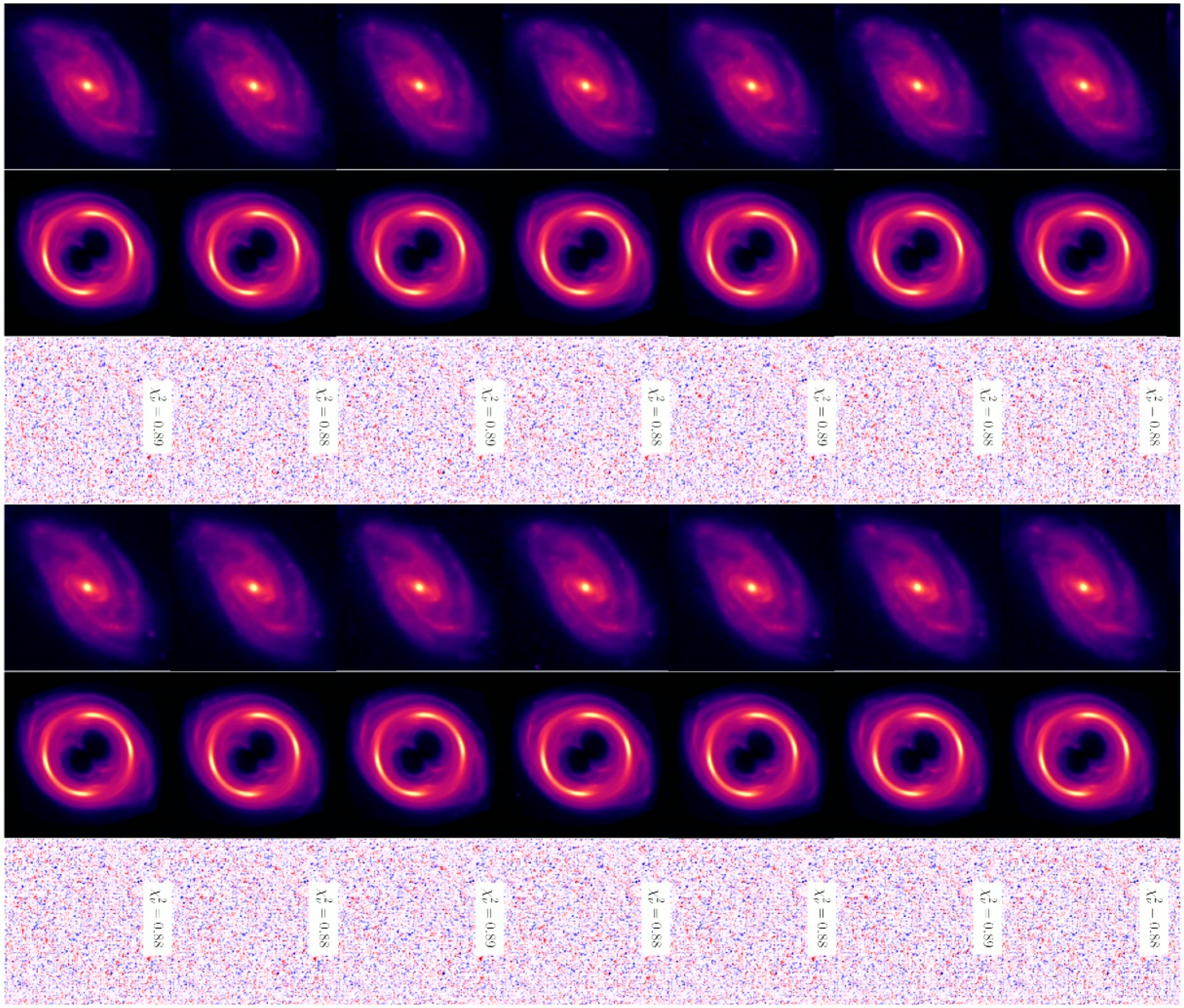
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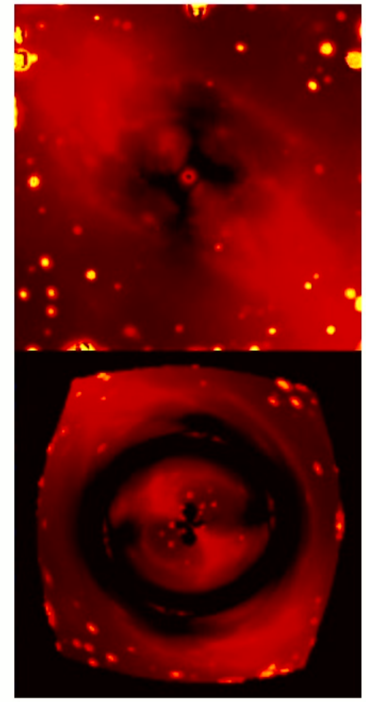
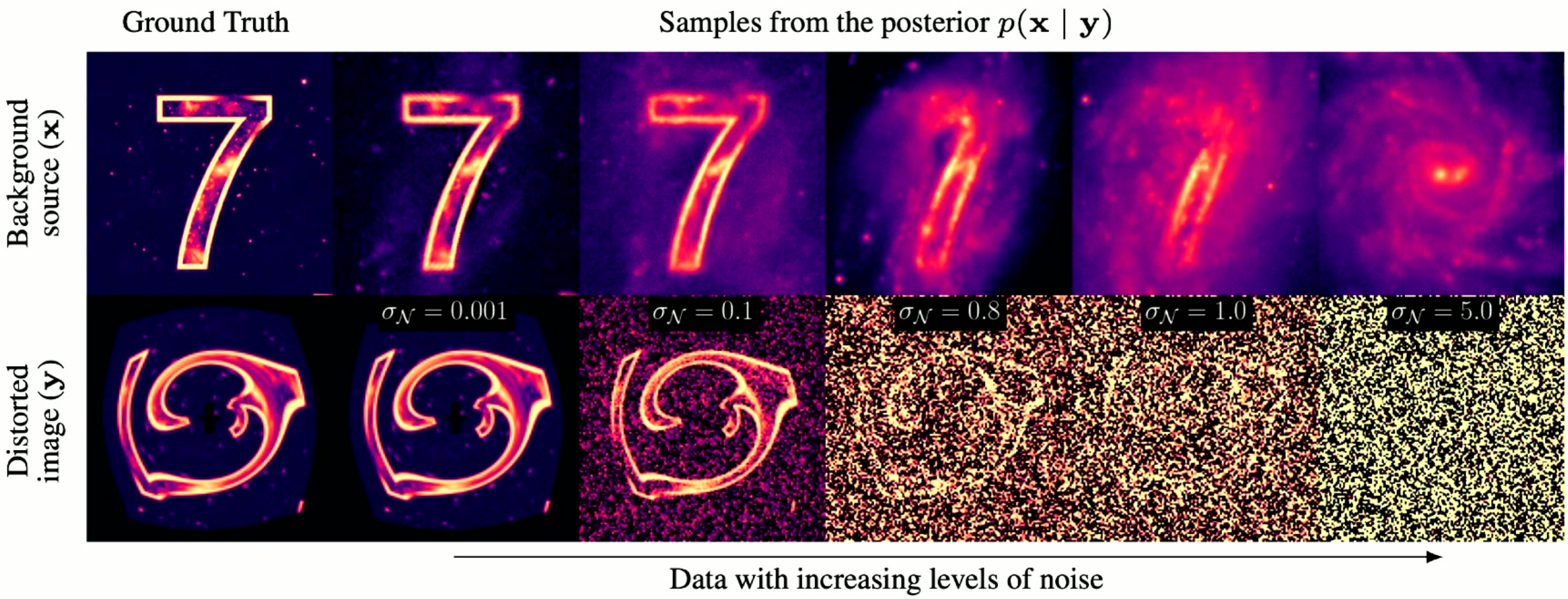
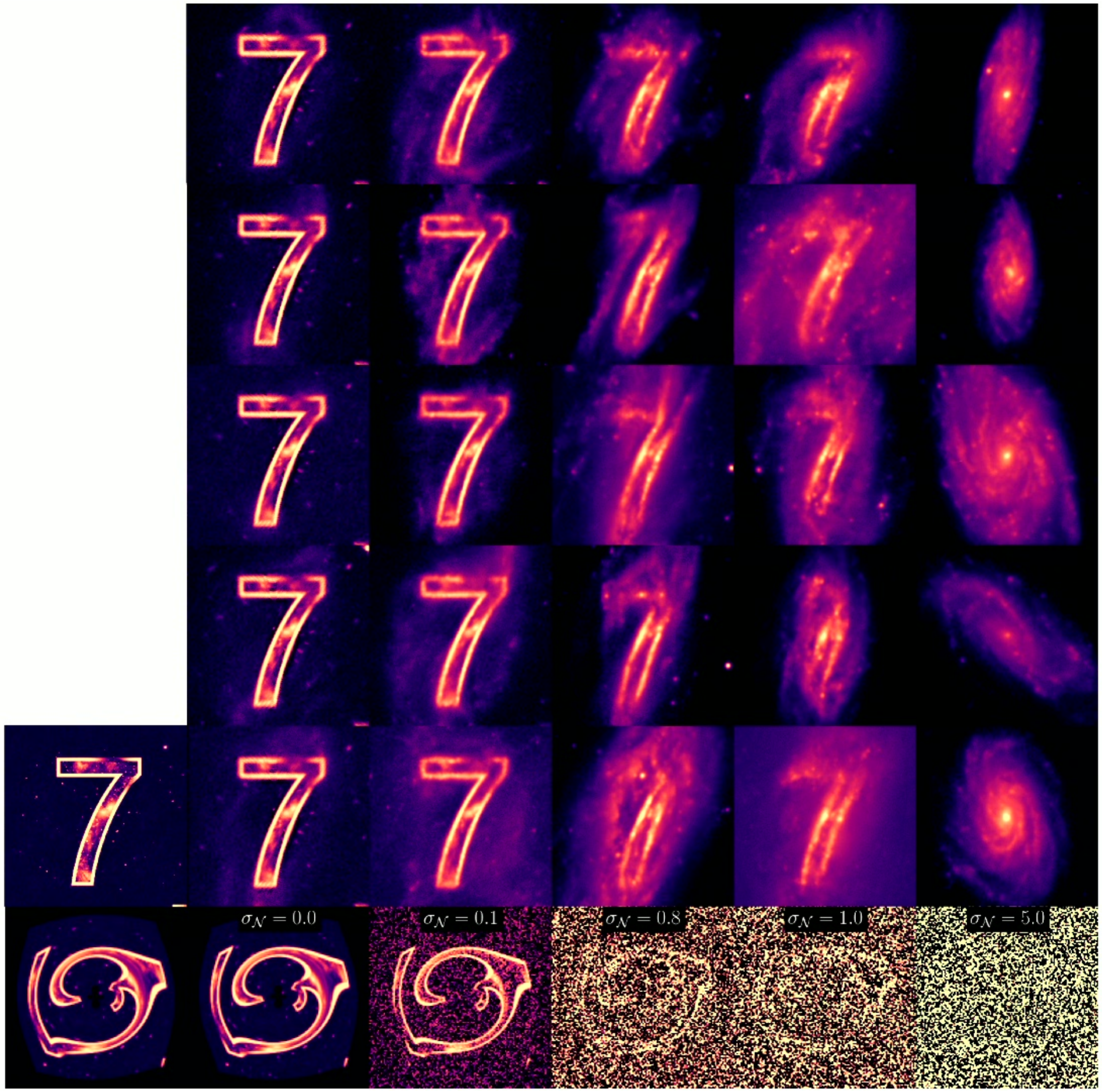
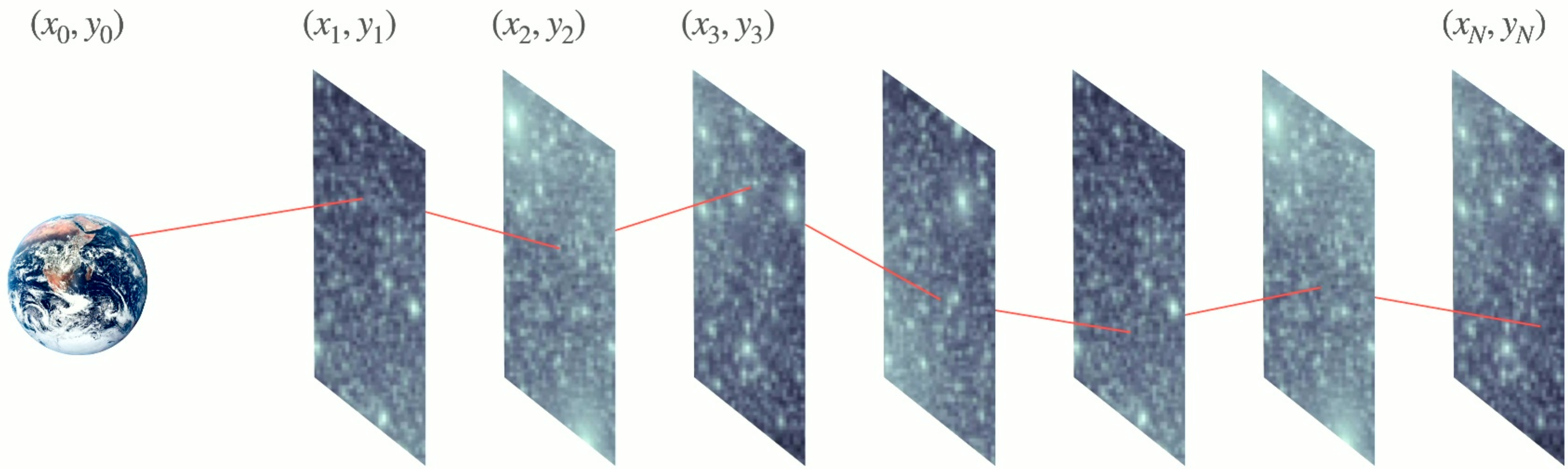


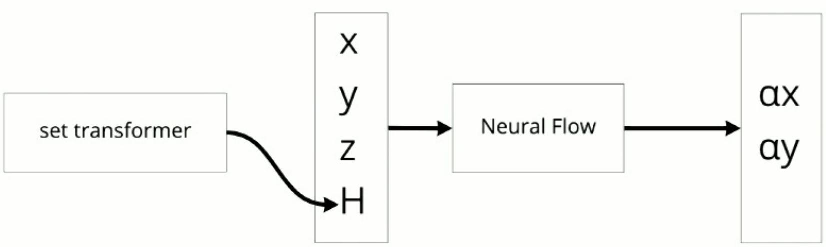
Out of distribution tests




$\sigma_{\mathcal{N}} = 0.0$
$\sigma_{\mathcal{N}} = 0.1$
$\sigma_{\mathcal{N}} = 0.8$
$\sigma_{\mathcal{N}} = 1.0$
$\sigma_{\mathcal{N}} = 5.0$

Speeding up the simulations

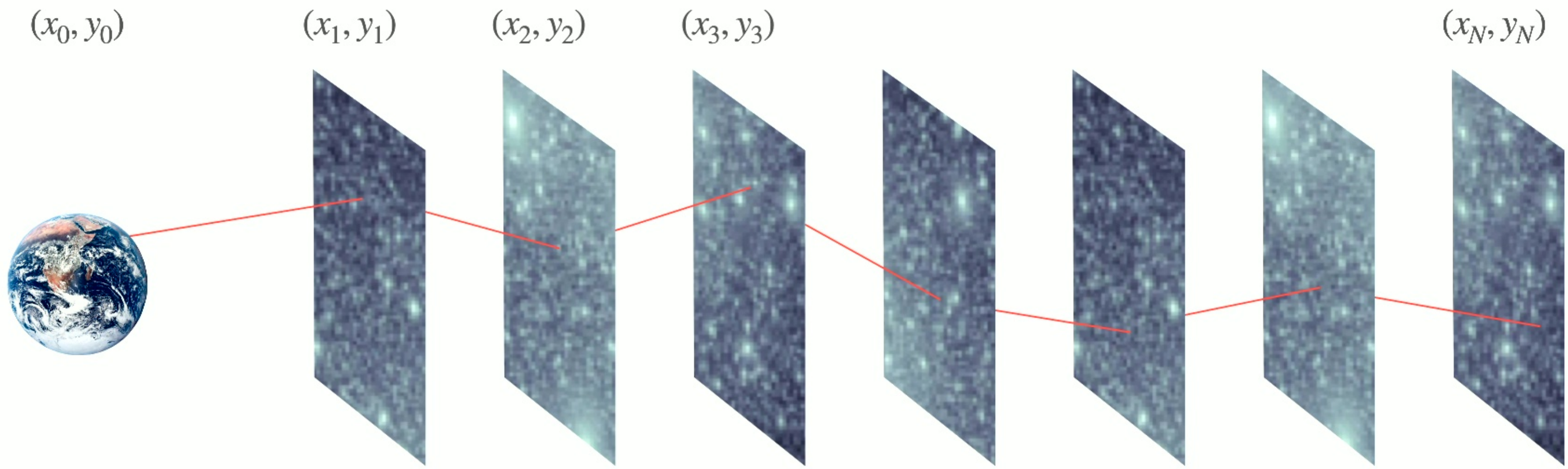


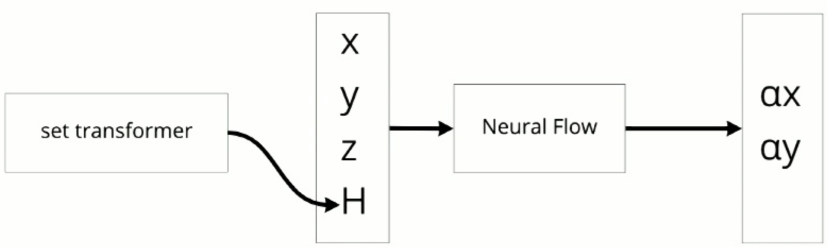


Charles Wilson

Adam Coogan

Speeding up the simulations





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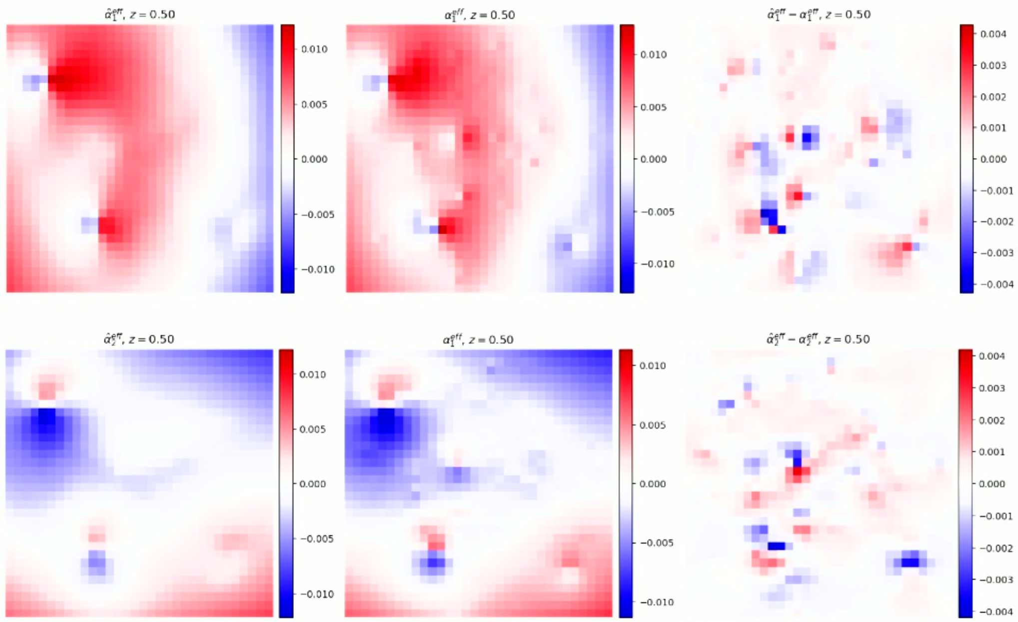
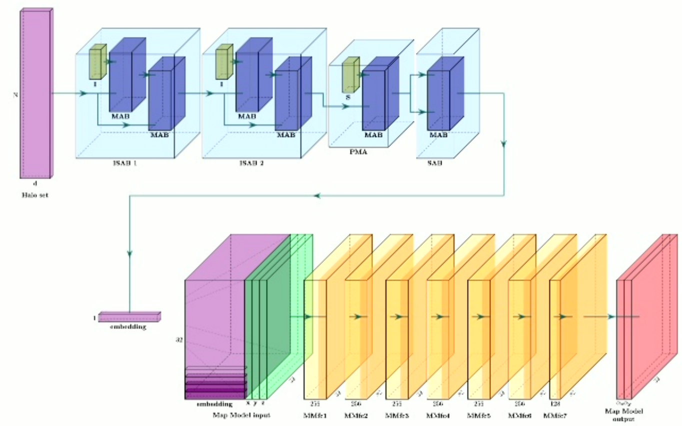
Speeding up the simulations





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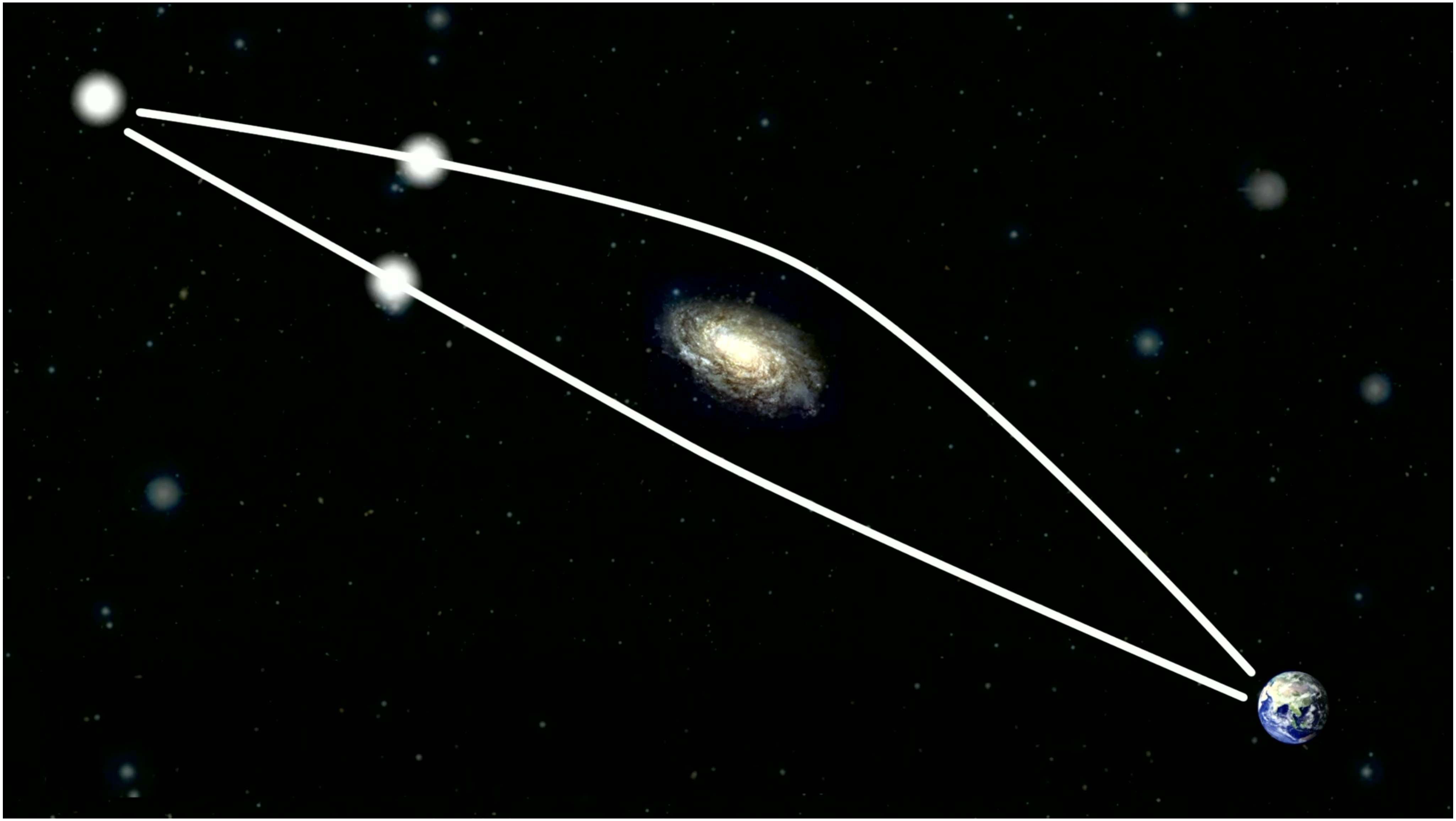
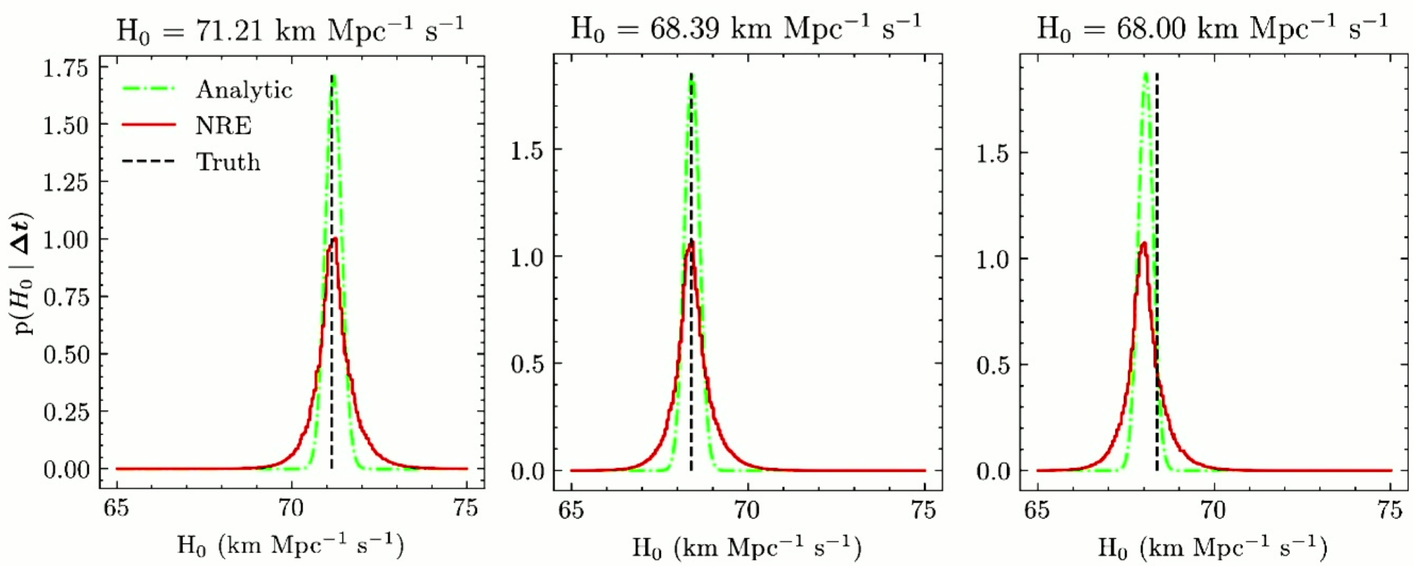
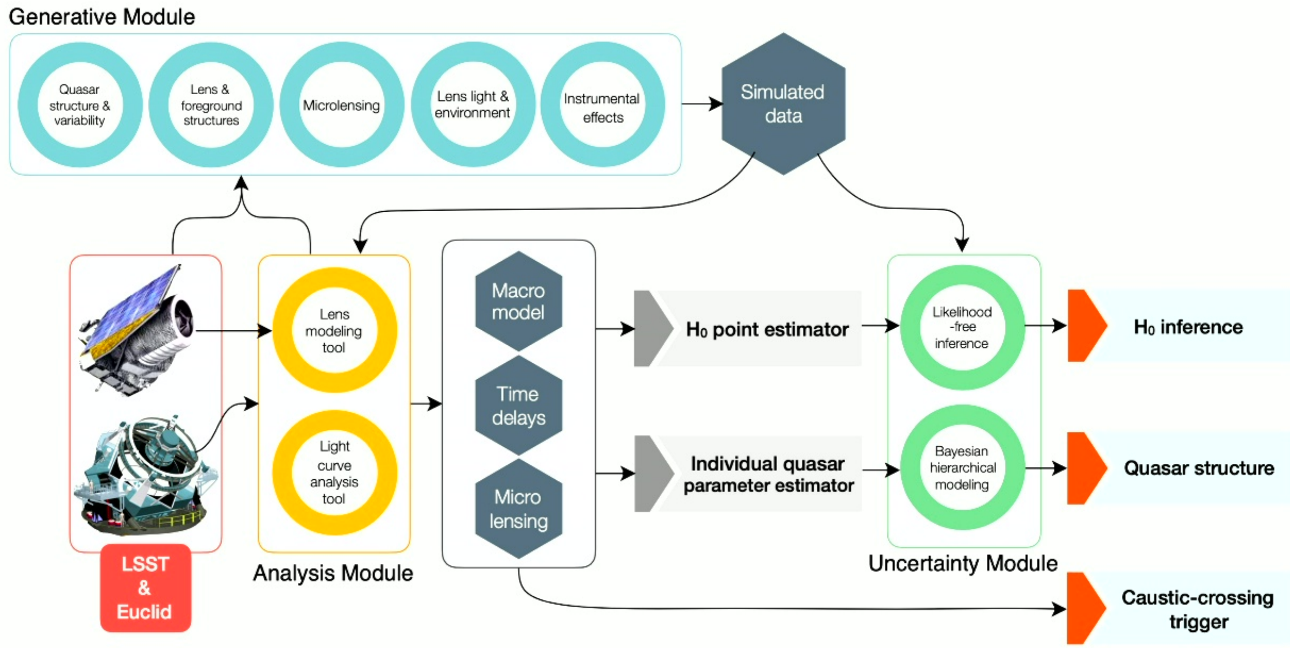


H_0 Inference with Neural Ratio Estimators



Ève Campeau-Poirier

An analysis pipeline for strong lensing data



SCHMIDT FUTURES

FLATIRON INSTITUTE Center for Computational Astrophysics

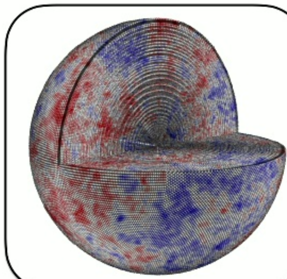
Université de Montréal

CUNY

Project Goals

Use cosmological observations to infer:

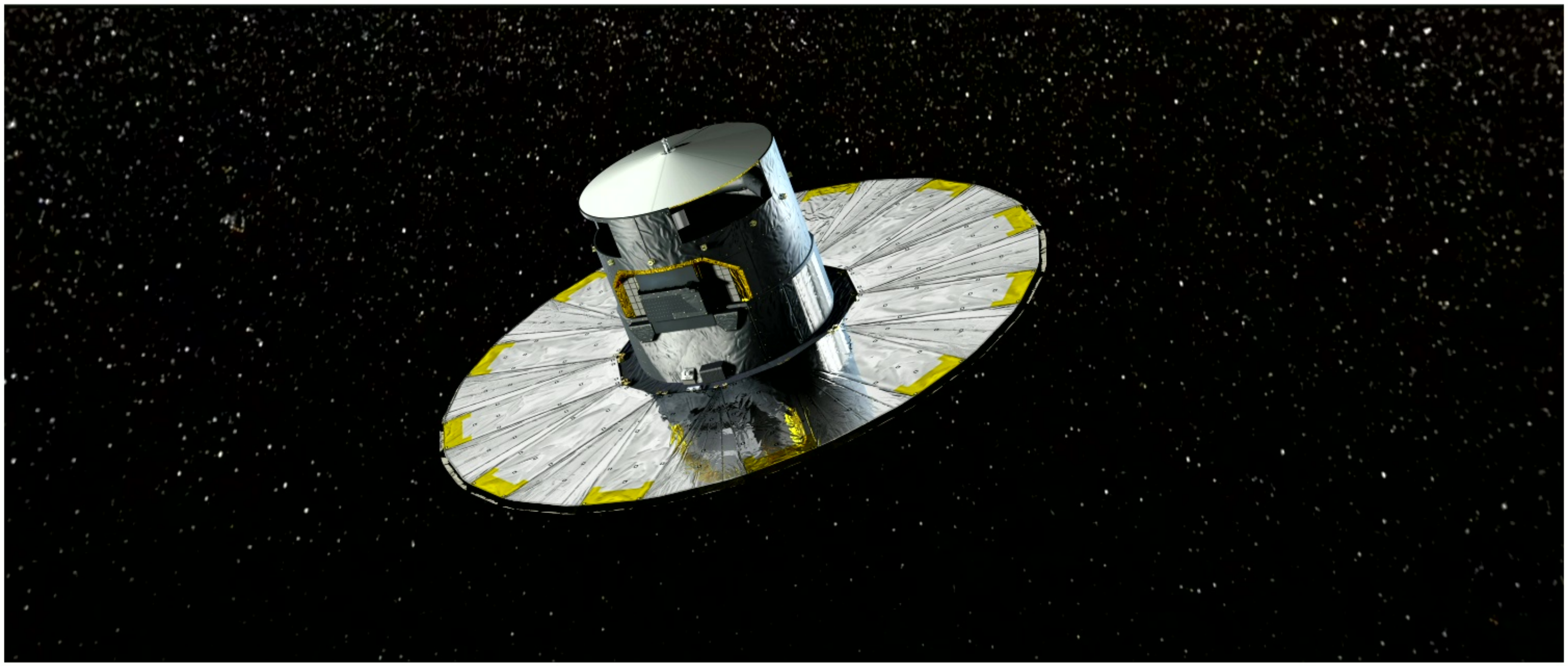
INITIAL CONDITIONS OF THE UNIVERSE:
PHASES AND AMPLITUDES



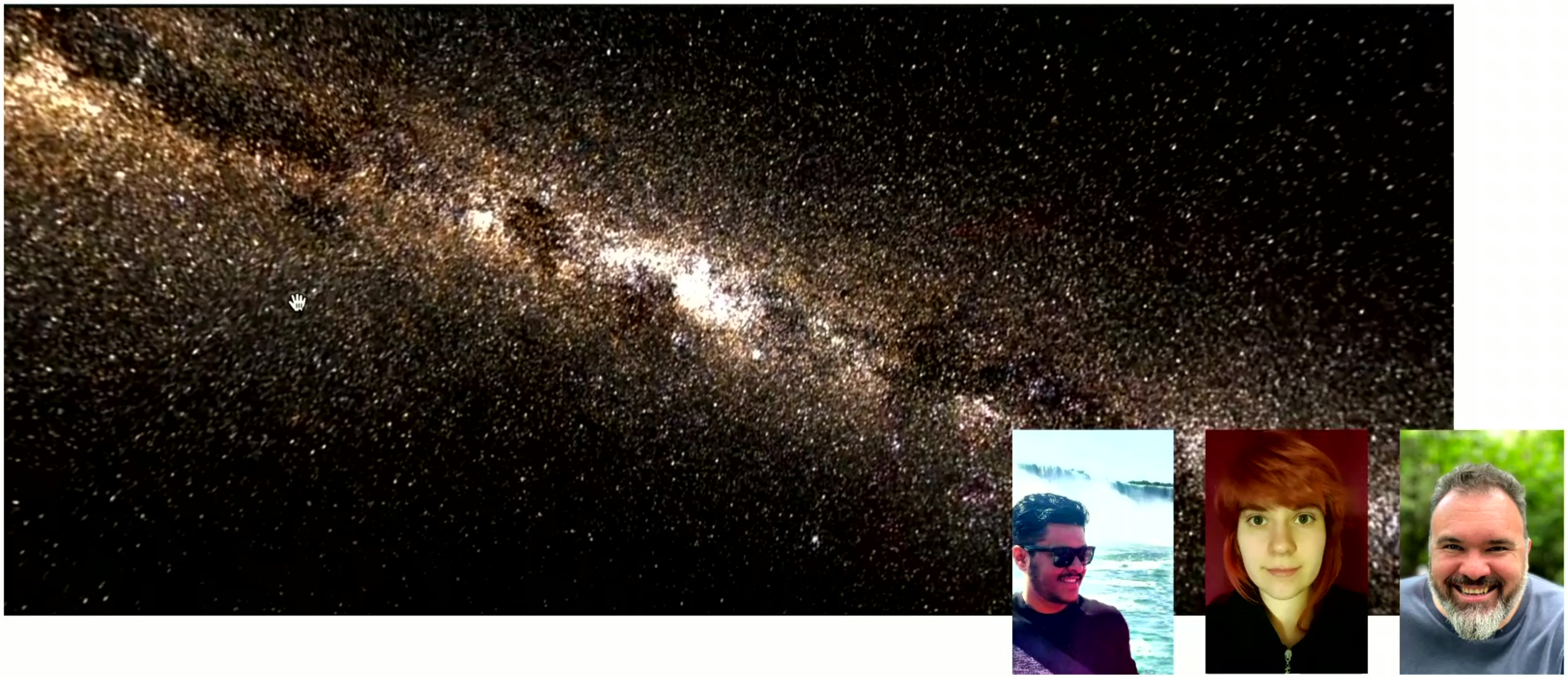
COSMOLOGICAL PARAMETERS

$\Omega_m, \Omega_b, m_\nu, \ldots$
$\Omega_\Lambda, \mathrm{w}_0, w_a, \ldots$

Unsupervised learning for anomaly detection in GAIA data



Unsupervised learning for anomaly detection in GAIA data



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Posterior sampling with GFlowNets and Reinforcement Learning

Pablo Lemos

Laura Leuzzi

Modeling strong lenses on cluster scales

Measuring the masses of SMBH with resolved kinematics and gravitational lensing

David Chemaly

Hasti Nafisi

Adjusting priors for closed-form linear inversions

Quantifying dark matter subhalos with LSST

Andreas Filipp

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Combining stellar population and strong lens modelling on galactic scales

Lensing posterior estimation with interferometric data and score-based priors

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Posterior estimation with variational inference

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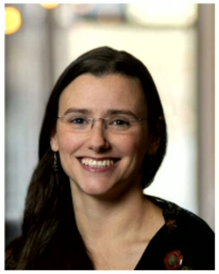
Astrophysics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Astrophysics


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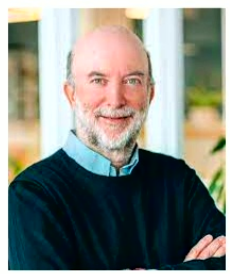
Statistics


Yoshua Bengio
Mila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