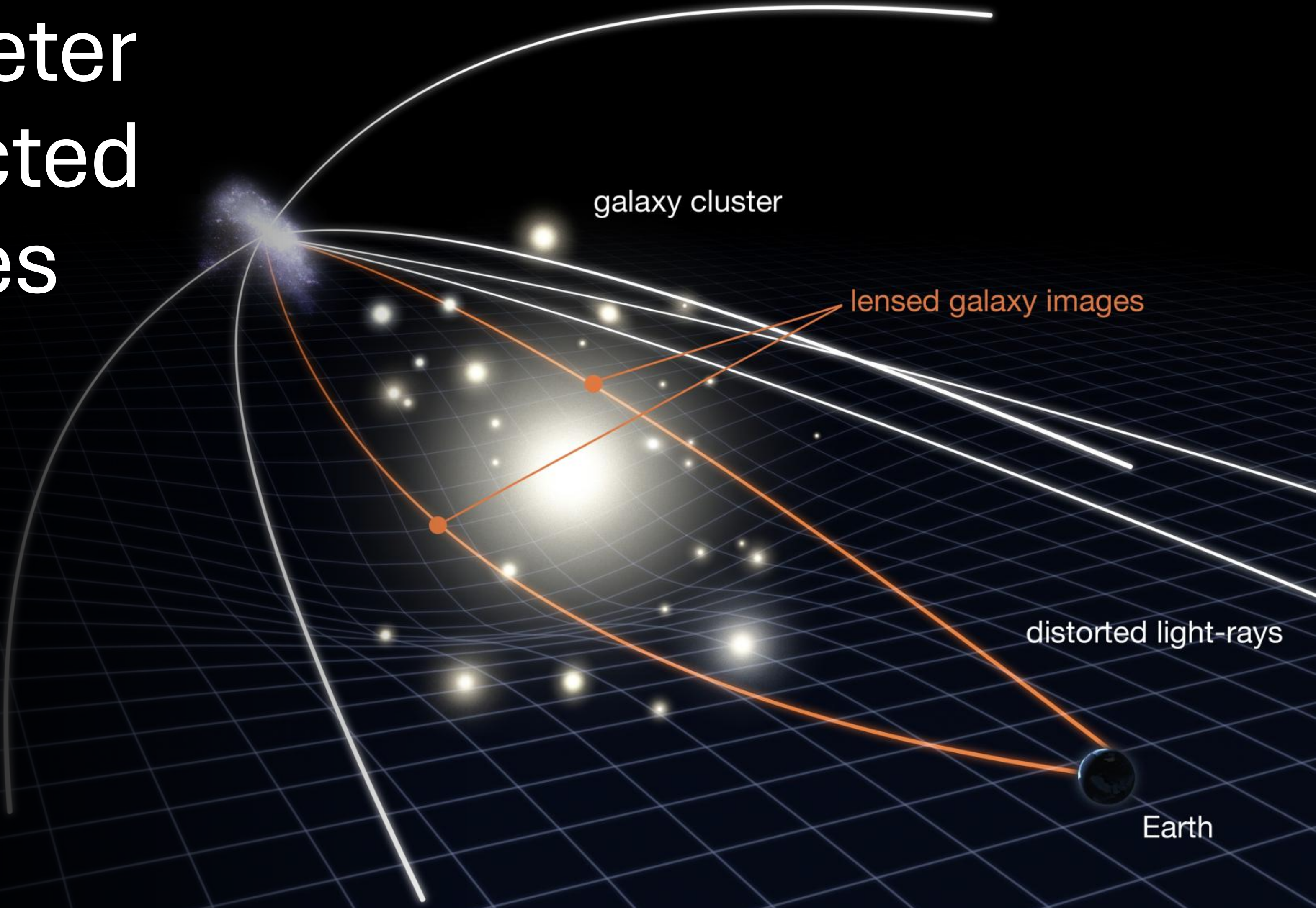
Accelerated parameter estimation of diffracted gravitational waves



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CIEMAT - Madrid

About the project

We develop a framework for accelerated parameter estimation for lensed gravitational waves in the wave-optics regime.

To model these effects, we evaluate the amplification factor using GLoW, an accurate code that computes the frequency-dependent amplification factor for generic lens models and arbitrary impact parameters depending on the lens configuration.

To extract physical parameters from the lensed gravitational wave signals, we employ the DINGO code, a machine learning framework based on neural posterior estimation to evaluate the posterior probability.

We validate the method using point lens. By applying this method we can efficiently perform parameter estimation on diffracted gravitational wave signals, recovering the mass of the lens and the impact parameter independently.

Collaborators:

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Nihar Gupte

Miguel Zumalacarregui

Gravitational Wave (GW) lensing

Point mass: simplest analytical model

Axially symmetric lenses

Singular Isothermal Sphere **(SIS):** common for galaxies

Navarro-Frenk & White density profile: for dark matter halos

Different lens models:
each model predicts different amplification and delays

Deflection of GW paths by massive objects

Well-know phenomenon for electromagnetic waves (light)

DIFFERENT LENSING REGIMES

Geometric Optics Limit: Wavelength ≪ lens size

Multiple images are created at different times (time delays [s - yr]). Each image might have a different magnification

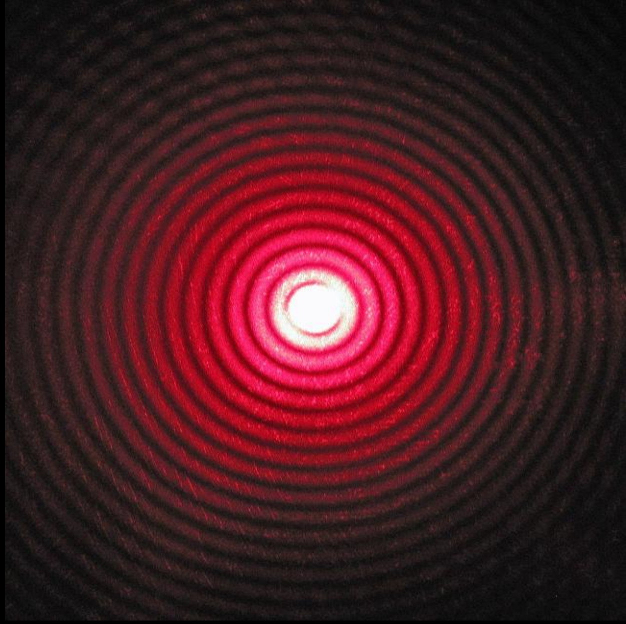
Wave Optics Regime: Wavelength comparable or >> lens size

Diffraction and interference, changing GW amplitude and phase in frequency-dependent ways.

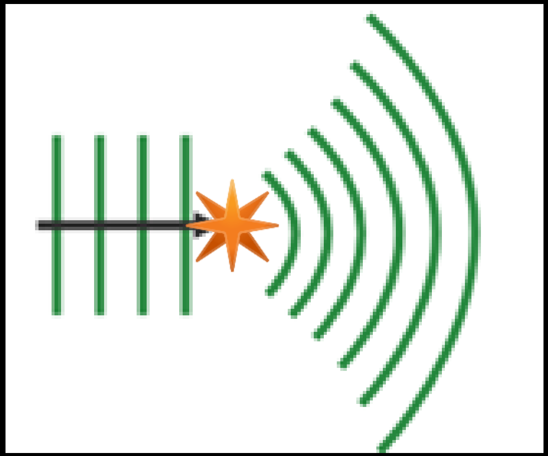
Microlensing: Small objects (stars, black holes)

Macrolensing: Galaxies or clusters

Wave Optic (WO) regime



- Interference and diffraction become significant → beating patterns in the observed GW signal.
- Lens acts like a diffraction screen, bending and spreading the GW as it passes by.
- GW amplitude is modulated by a frequency-dependent amplification.
- Modulations arise from interference between different paths the GW can take.



Observational effects:

- frequency-dependent oscillations in amplitude and phase;
- modulation is related to the time delay between the interfering paths (similar to the interference fringes in optics).

Wave Optic (WO) regime

e.g., see arXiv: 2409.04606

see Hector Villarrubia-Rojo's talk later!

Key quantities:

- Impact parameter $\boxed{\mathbf{y} = \frac{d_L}{d_S}\frac{\boldsymbol{\eta}}{R_{\mathrm{E}}}}$
- Redshifted effective lens mass $M_{Lz} = M_L(1 + z_L)$ $\boxed{M_{Lz} \equiv \frac{\xi_0^2}{4Gd_{\mathrm{eff}}}}$
- Amplification factor $\boxed{F(f) \equiv \frac{\tilde{h}(f)}{\tilde{h}_0(f)}}$

dimensionless frequency $\boxed{w \equiv 8\pi G M_{Lz} f}$

$$\boxed{F(w) = \frac{w}{2\pi \mathrm{i}} \int \mathrm{d}^2 x \exp\left(\mathrm{i} w \tilde{\phi}(\boldsymbol{x}, y)\right)}$$

$w \gg 1$ geometric regime

$w \lesssim 1$ WO regime

Cosmological implications and challenges in detection

Studying GW lensing is important for:

- measuring the Hubble constant;
- constraining dark matter;
- probing cosmic expansion history;
- testing General Relativity.

However:

- identifying whether two events are lensed versions of the same source is statistically and observationally complex;
- careful waveform matching and timing correlation required;
- in the future, an ever-increasing number of events are expected to be detected.

Motivation for ML application

Credit: arXiv:2303.17628

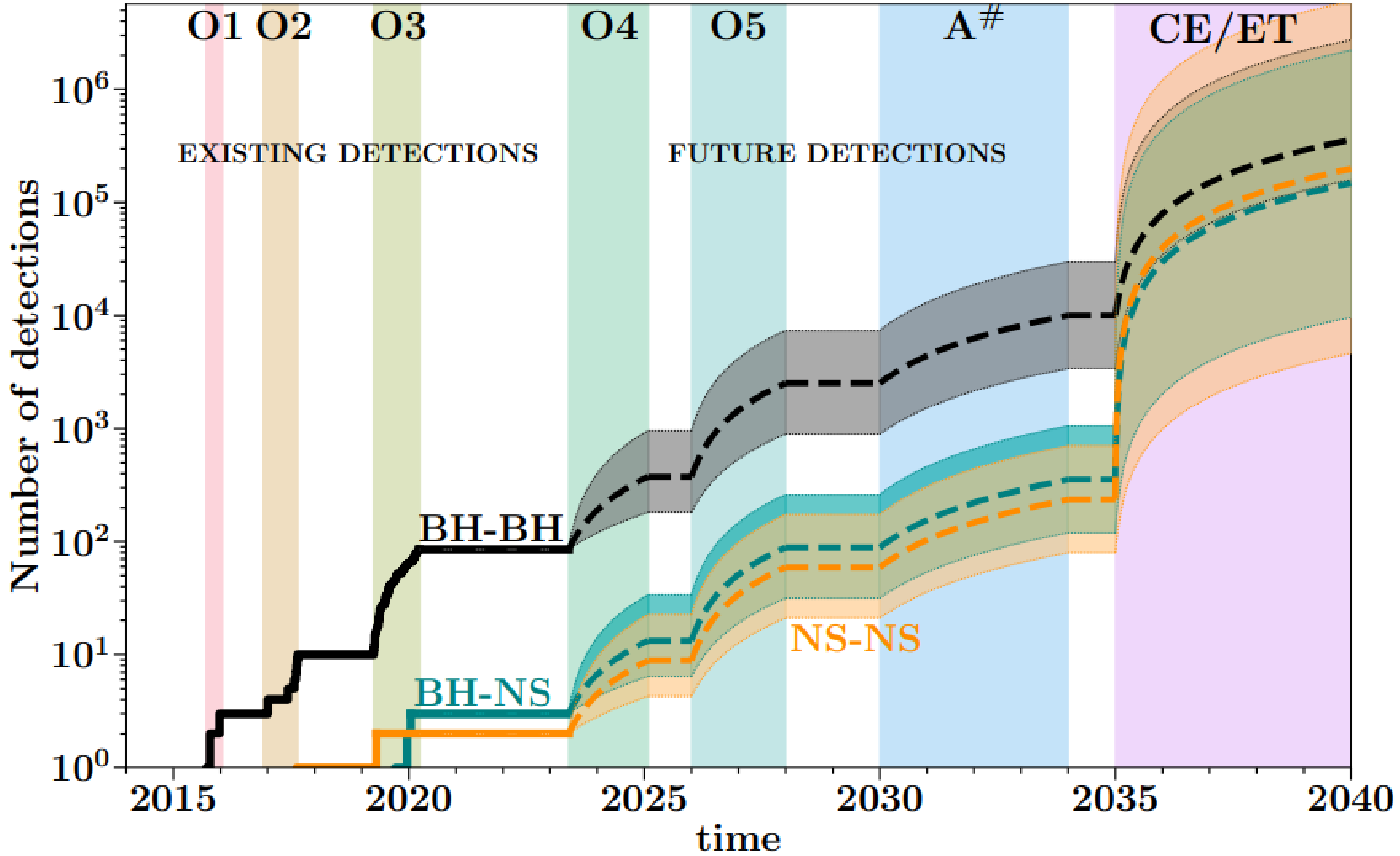


Figure 2. Landscape of the number of detected mergers from binary black holes (BHBH; black), black hole-neutron stars (BHNS; teal), and binary neutron stars (NSNS; orange). See text for more details. The animation shows the catalog as a function of time and is available at Broekgaarden (2024).

We expect to analyse upcoming events (~200 candidates in O4)

GRAVITATIONAL LENSING OF WAVES

GLoW (Gravitational Lensing of Waves)

https://github.com/miguelzuma/GLoW_public

- Numerical methods capable of studying WO lensing phenomena for lenses representing generic matter distributions.
- Computation of time-domain amplification integral, frequency-domain amplification factor, and efficient analytic methods for simple lenses.
- Generation of template banks to search for lensed GW signals that may be missed by regular search pipelines.

Our work: Point Lens in WO framework. We evaluate the amplification factor using GLoW.

For details on GLoW, see Hector Villarrubia-Rojo's talk later!

https://github.com/dingo-gw/dingo

DINGO (Deep Inference for Gravitational-wave Observations)

Analysis of GW data using neural posterior estimation, speeding up inference of astrophysical source parameters.

Aim: rapid predictions for multi-messenger counterparts and in the context of high event rates.

Basis: train a neural network to represent the Bayesian posterior, conditioned on data → amortized inference.

Tasks:

- building training datasets;
- training normalizing flows to estimate the posterior density;
- performing inference on real or simulated data;
- verifying and correcting model results using importance sampling.

Cons: training a network from scratch can be expensive

Pros: gain in time and resources during inference

Parameter inference of GW signals

Goal: Infer physical parameters (masses, spins, distance, inclination, etc.) but also lensing parameters (M_{Lz} and y).

Traditional method: Bayesian inference (e.g., MCMC)

→ problem: slow and costly.

likelihood

prior

Bayes theorem

$$\boxed{p(\theta|d) = \frac{p(d|\theta)p(\theta)}{p(d)}}$$

posterior probability

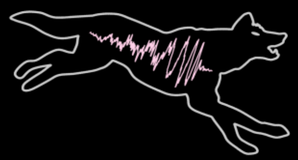
GWs: complex signals + noise

Neural networks can learn the posterior from simulations:

- amortized inference (fast prediction after training);
- scalable to large datasets or fast re-analysis (alerts).

DINGO trains a neural network to directly approximate the posterior

$$\boxed{q(\theta|x) \approx p(\theta|x)}$$



References

arXiv:

2002.07656

2008.03312

2106.12594

2111.13139

2210.05686

2211.08801

Normalizing Flows

- Mapping simple → complex distributions
- Simulate GW data for parameter samples $\theta \sim p(\theta)$
- Train a network on (θ, x) to estimate $p(\theta|x)$
- Use trained network to infer posteriors from real (or mocks) detector data.

GNPE (Group-Equivariant Neural Posterior Estimation)

- NPE: translation times of arrival → interpret such transformations in frequency domain → challenging learning task → limit inference performance on the other parameters.
- GNPE: interpret a much narrower window of arrival times

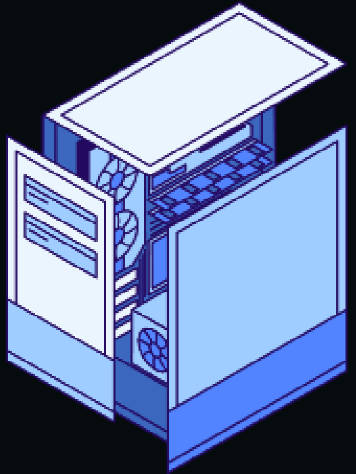
Simplification: GNPE standardizes the times of arrival of the signal in the individual interferometers → however, cost of train another neural network.

Setup

RESOURCES

CLUSTER AT AEI

40 GB GPU



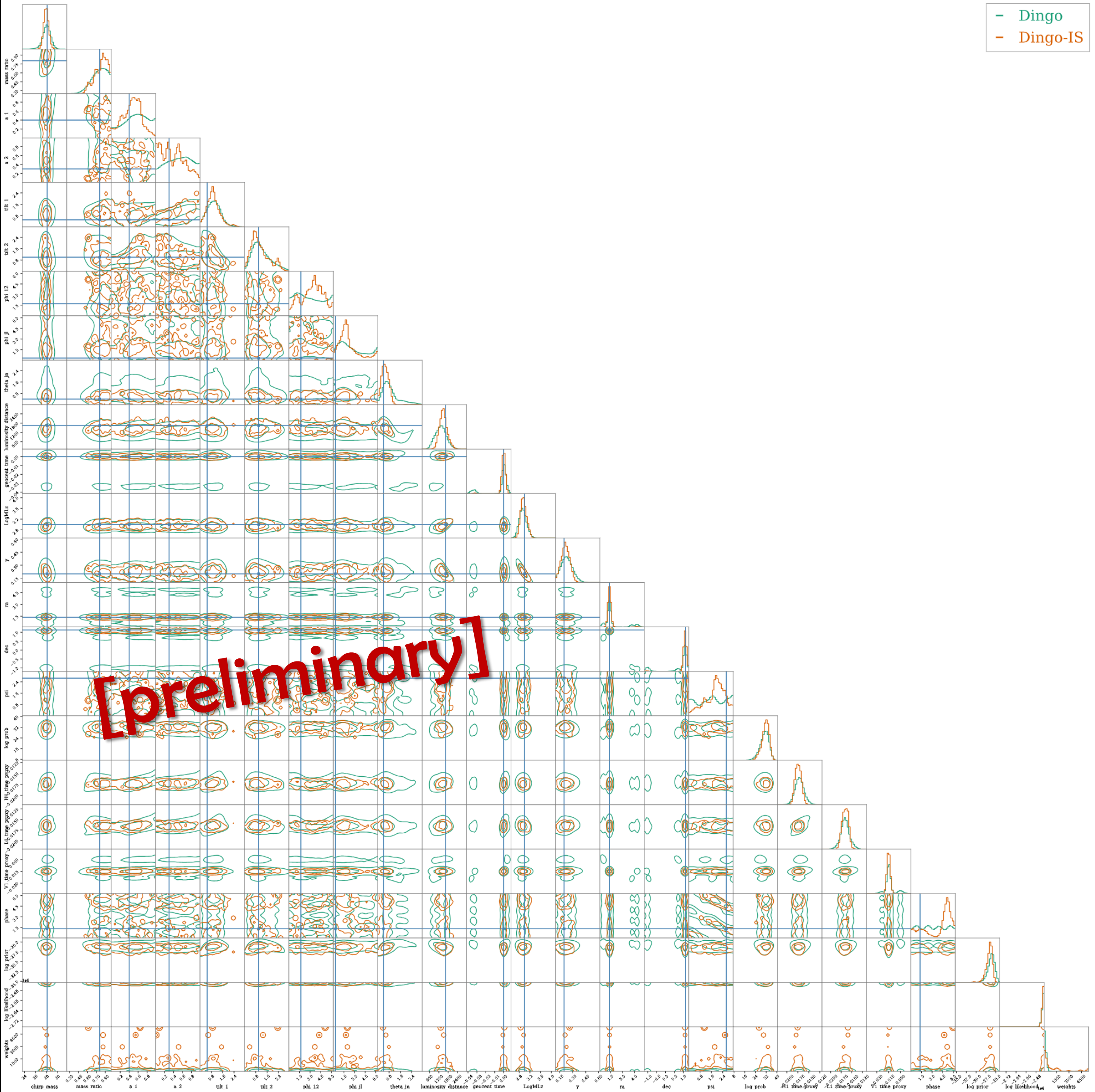
Modification of DINGO: include a transform for lensing effects on waveforms.
Model of the amplification factor → GLoW. Only point lens case.

100 000 generated waveforms in frequency domain
Approximant: IMRPhenomXPHM - asd dataset: H1, L1, V1 - observing run: O3

Training time
NPE: ~2 weeks GNPE: ~2 weeks (but less required memory)

Time inference (on 17 parameters)
DINGO-IS: ~15 minutes Bilby: ~2 days

Results



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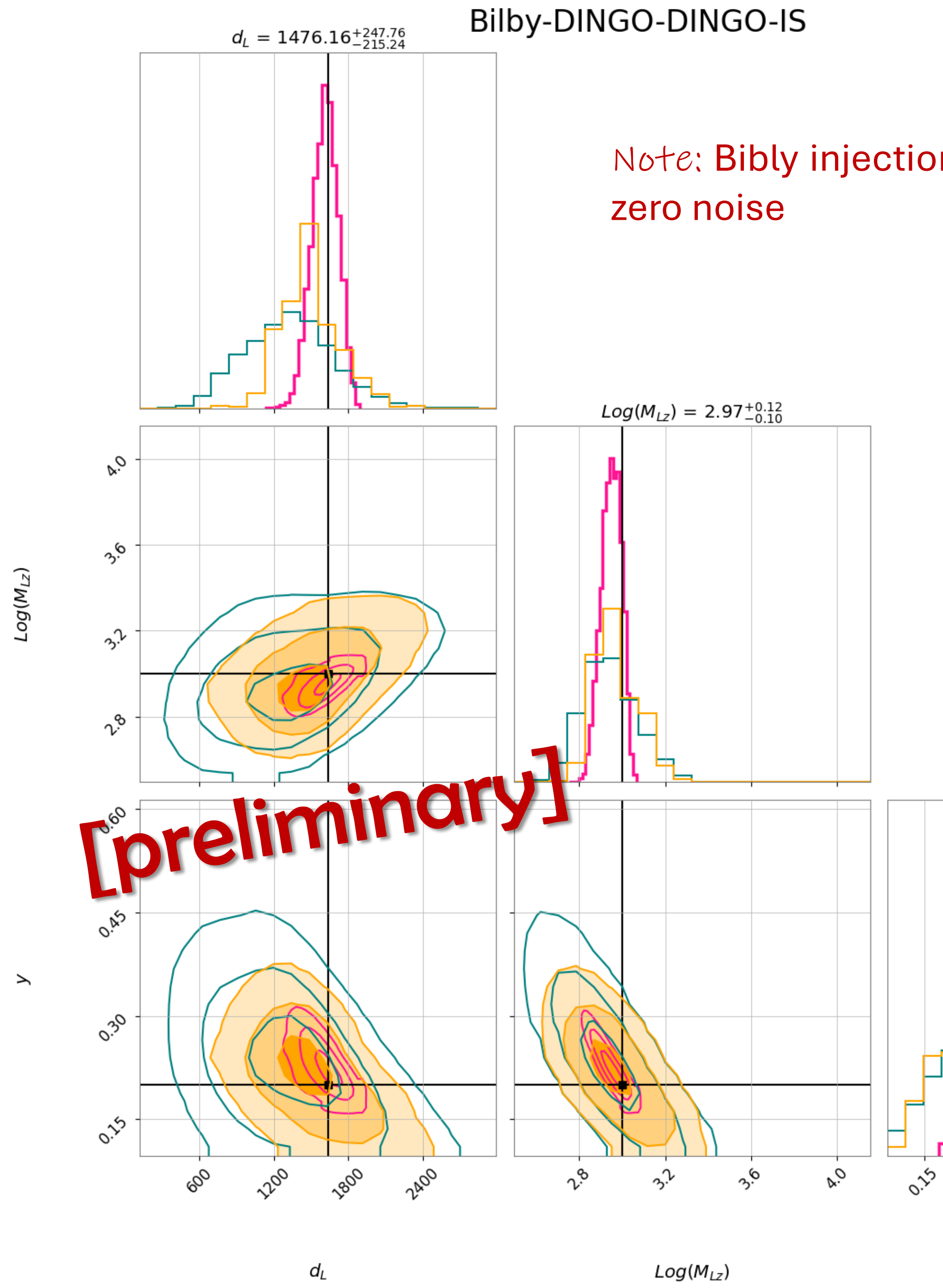
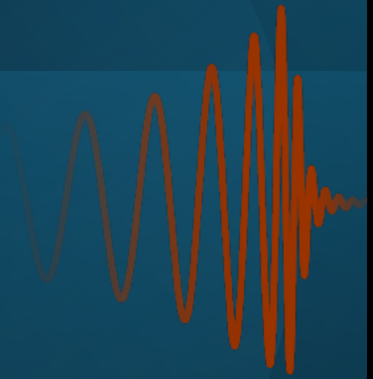
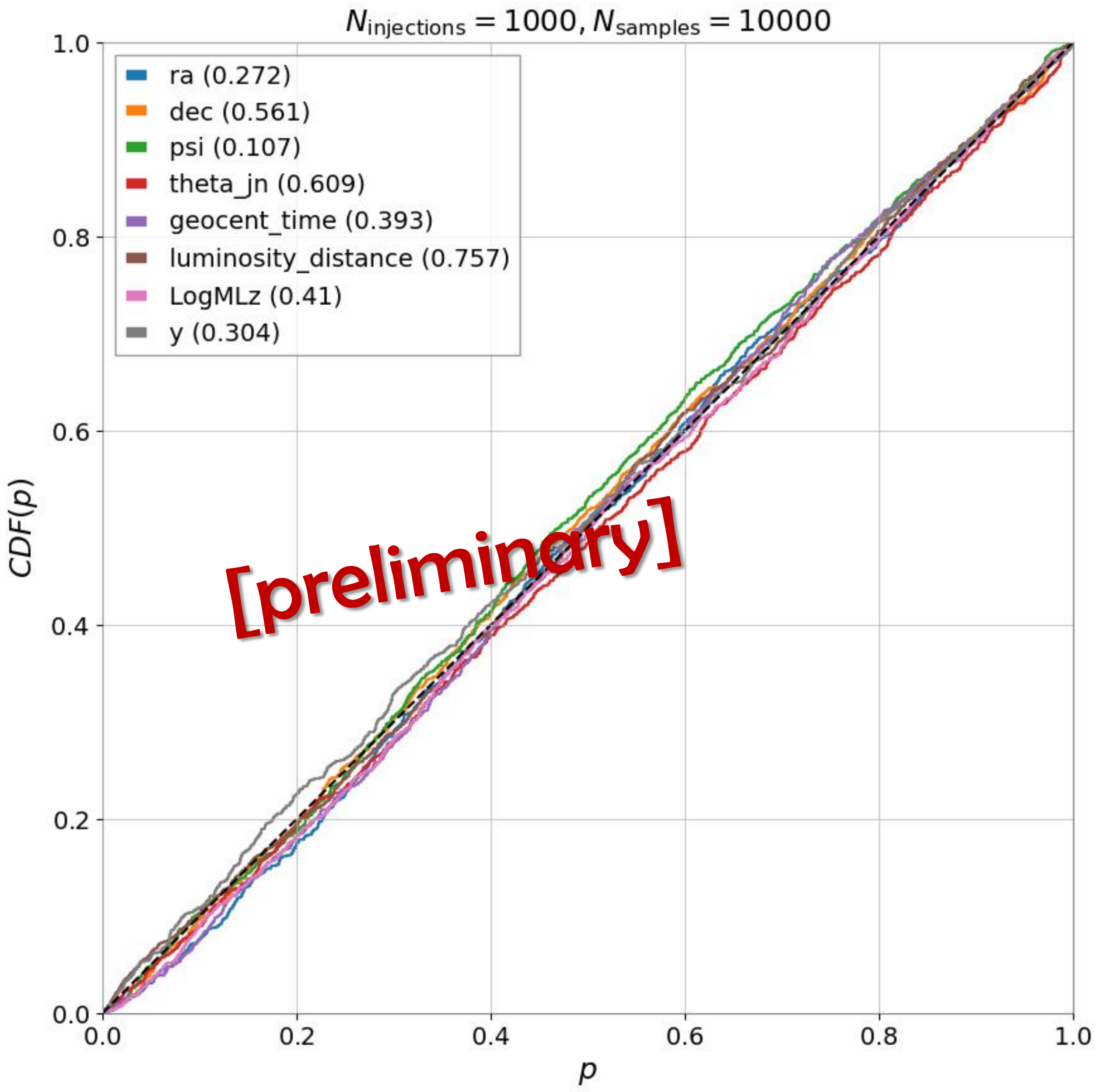


Note: Bibly injection has zero noise

Results

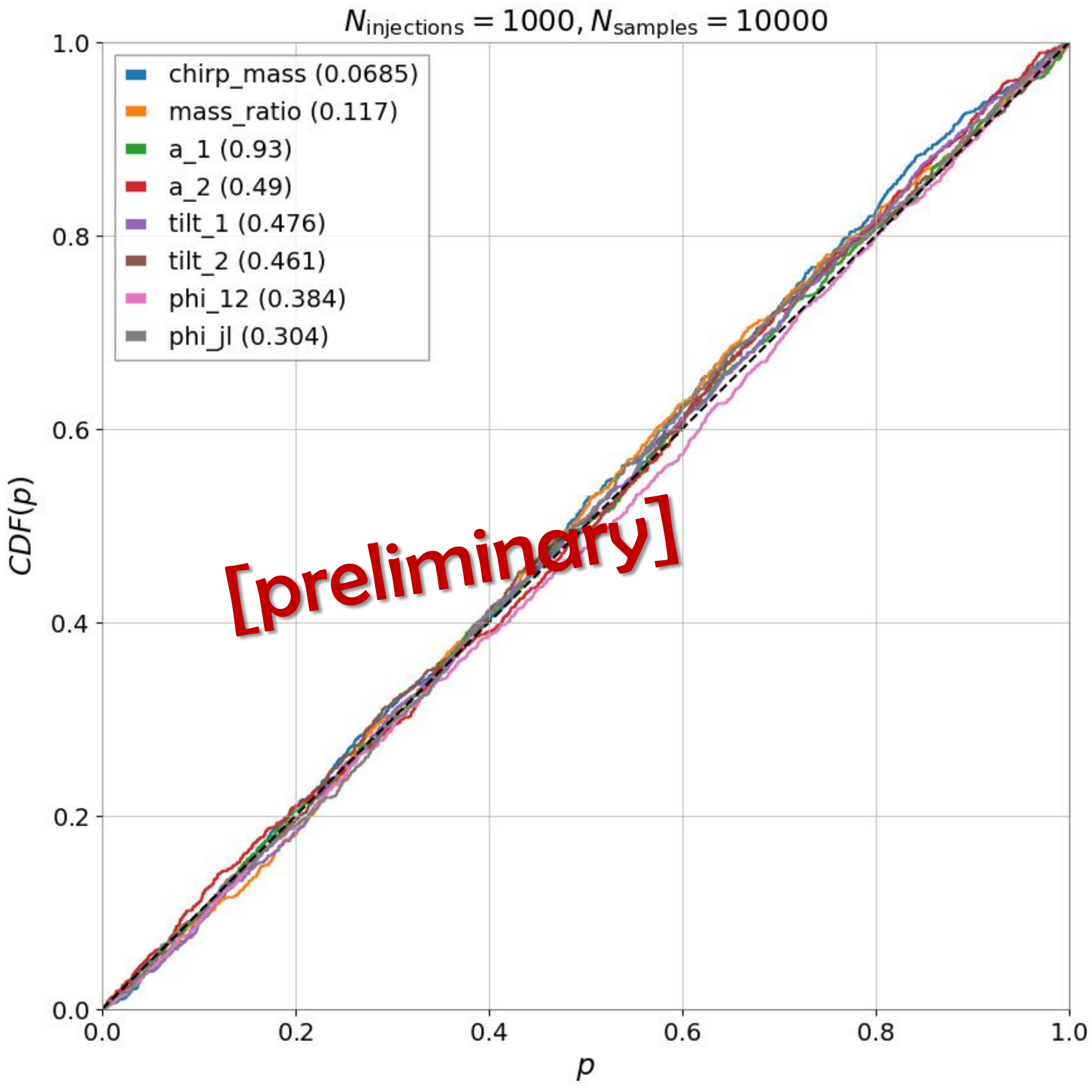


Exstrinsic parameters



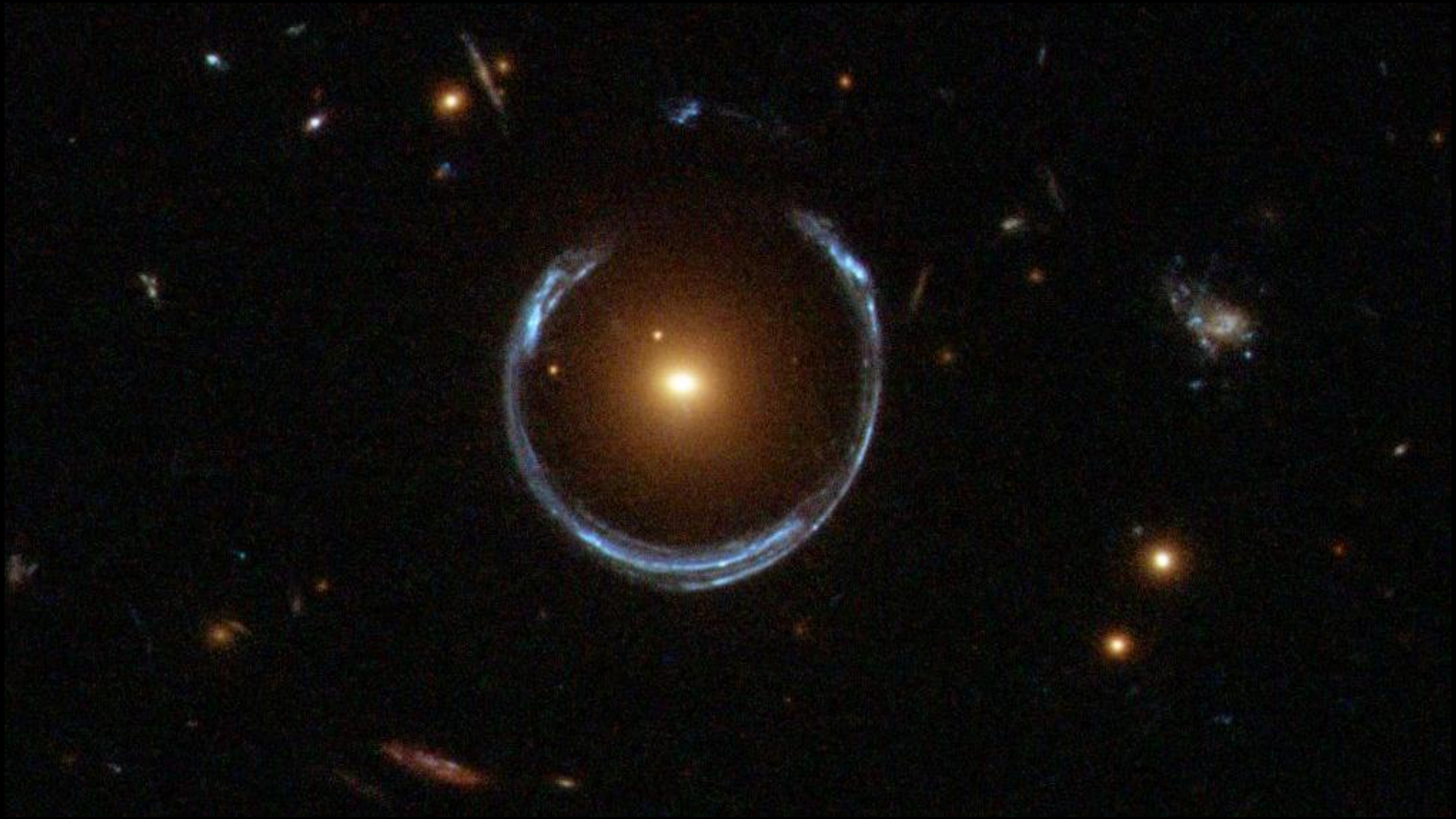
Results

Intrinsic parameters



Summary & future prospects

- GW lensing offers a new window into cosmology and astrophysics.
- Test of dark matter, constraining cosmological parameters, identifying structure in the Universe, exploring exotic compact objects.
- Discriminating lensing effects in GW signals can be difficult and would require complex analysis techniques. Machine learning can represent an useful tool to handle it.
- Expectation to analyse upcoming events: ~200 candidates in O4.
- In particular, neural posterior estimation enables fast, flexible inference of GW source parameters, avoiding expensive sampling and likelihood evaluations.
- GLoW: accurate lens profiles evaluation and amplification factor computation.
- DINGO: accurate GWs parameter estimation and significantly reduction of computational time.
- Future: generalization to other lens profiles.



Thank you for your attention!