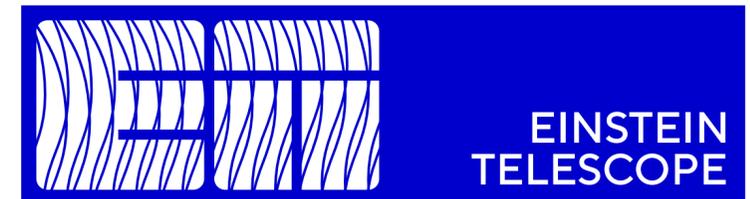


# Data analysis for next-generation gravitational-wave detectors

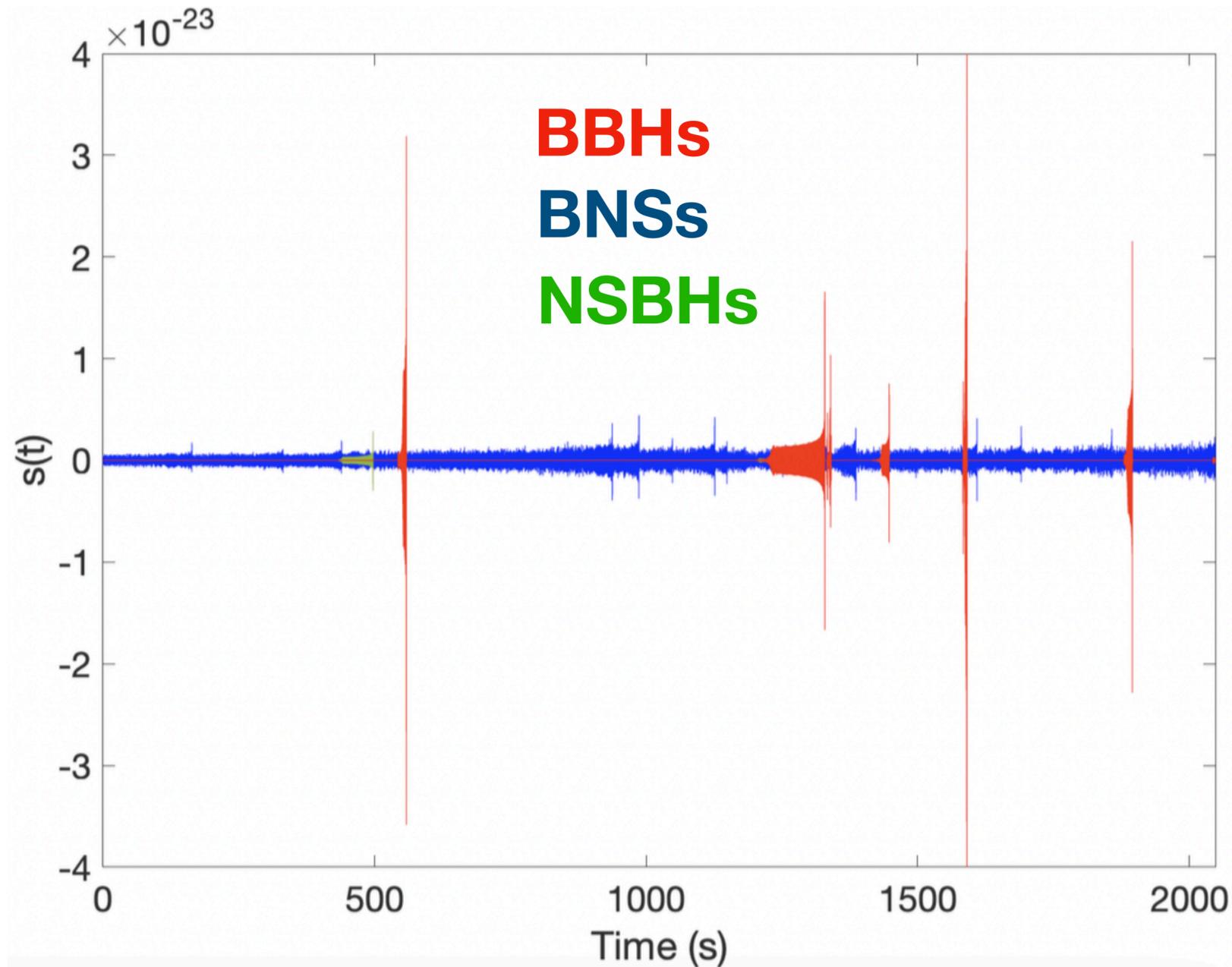
2026 Science Fair

Filippo Santoliquido

23 February 2026



# Next-generation challenges

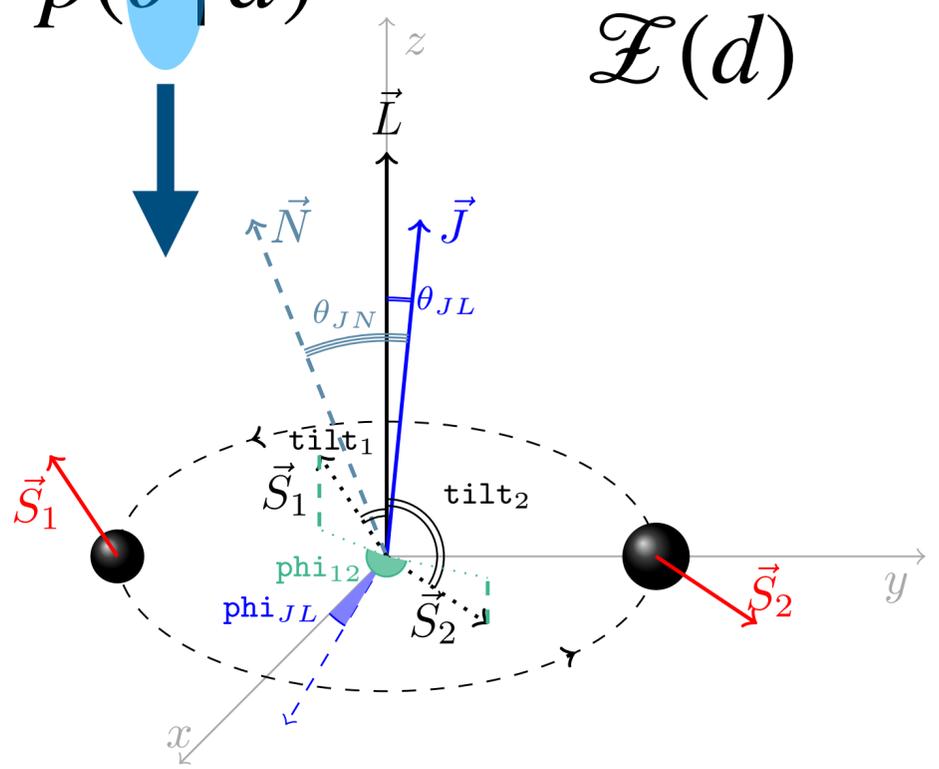


From a data-analysis perspective, **specific problems for ET** include:

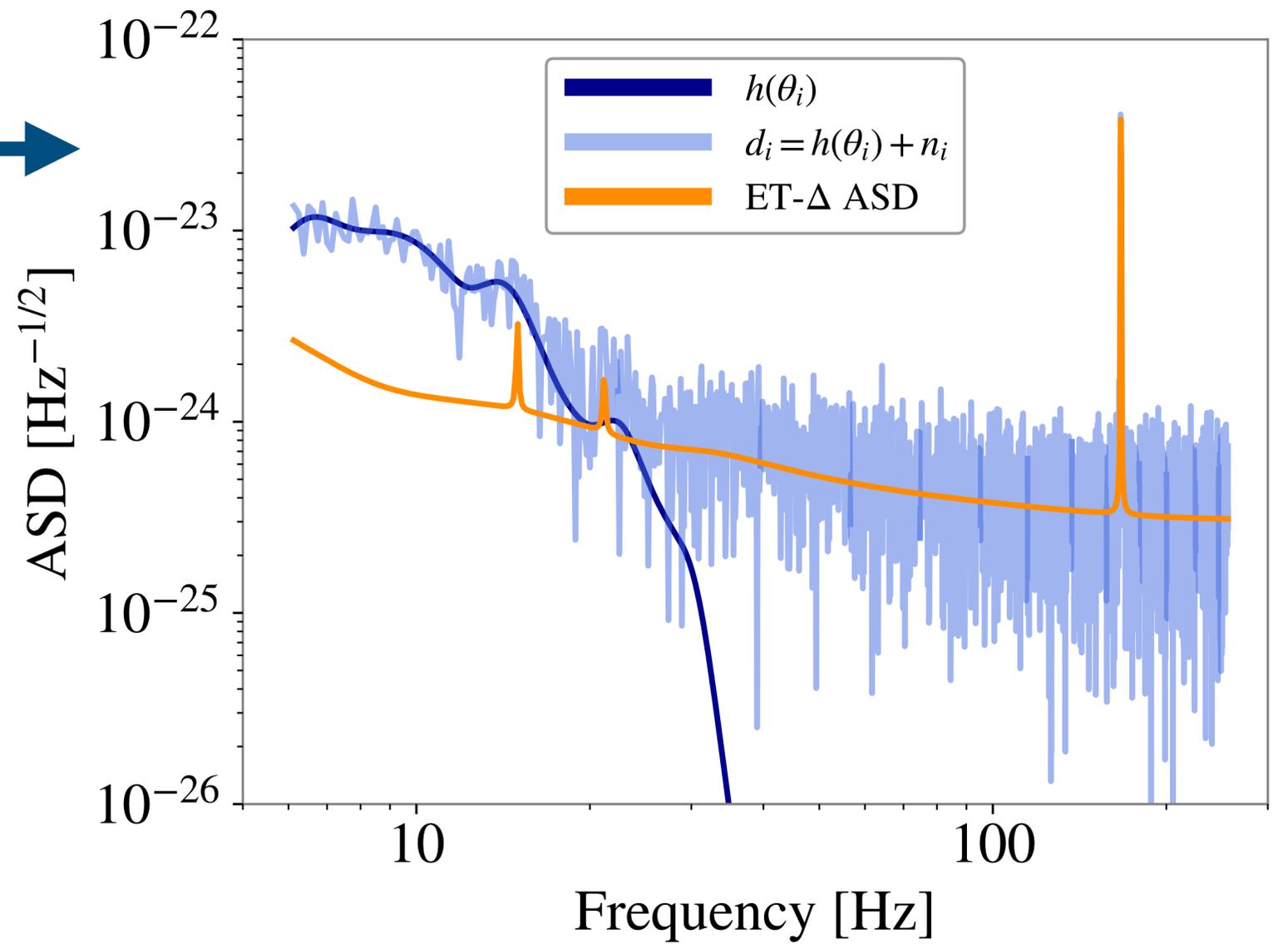
- **long signals** from the increase in frequency bandwidth
- the presence of a **very large number**  $10^5$  **of signals** per year within the sensitivity band
- **Overlapping signals** in the detector's band

# Parameter estimation

$$p(\theta | d) = \frac{\mathcal{L}(d | \theta) \pi(\theta)}{\mathcal{Z}(d)}$$



$$\theta = \{ \mathcal{M}_d, q, d_L, \text{ra}, \text{dec}, \theta_{JN}, \psi, \phi, t_{\text{geocent}}, \chi_1, \chi_2 \}$$



# Likelihood-free inference

Sampling parameters  $\theta$  from the prior  $\theta \sim \pi(\theta)$  and **generating data**  $d = h(\theta) + n$  is **fast**

The diagram illustrates the process of likelihood-free inference. It starts with a text statement about sampling parameters and generating data. A blue arrow points down to a mathematical equation for the posterior distribution  $p(\theta | d)$ . The numerator of the equation,  $\mathcal{L}(d | \theta)\pi(\theta)$ , is enclosed in a blue oval. Another blue arrow points down from the left side of the equation to the next text block.

$$p(\theta | d) = \frac{\mathcal{L}(d | \theta)\pi(\theta)}{p(d)}$$

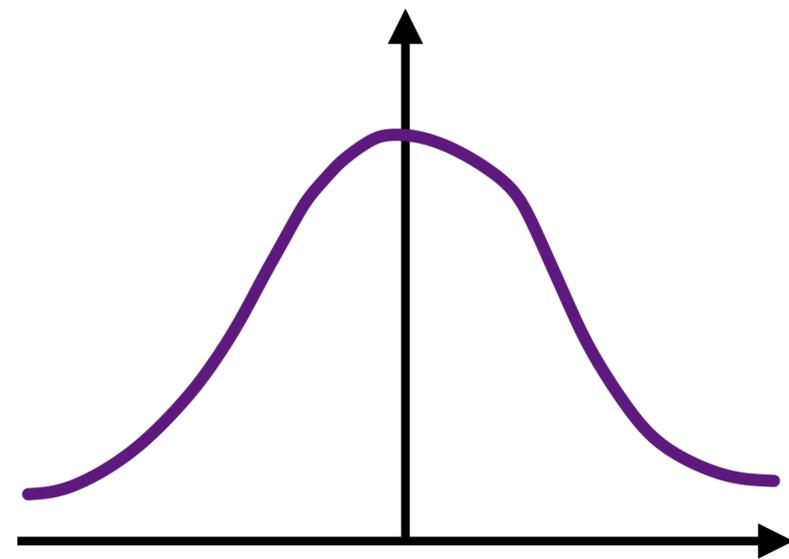
Using  $(\theta, d)$  to construct with **deep learning** an estimator  $q_\phi(\theta | d)$  of  $p(\theta | d)$

Refs. [Lueckmann et al. 2017](#), [Greenberg et al. 2019](#), [Cranmer et al. 2020](#), [Chua et al. 2020](#), [Dax et al. 2023](#)

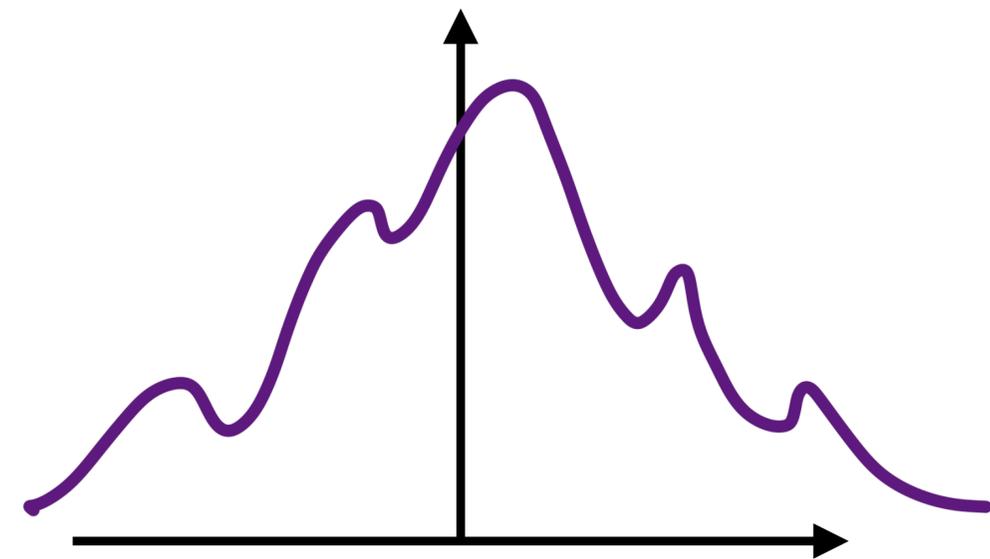


# Normalising flows

They represent a complicated distribution  $q$  using a series of change of variables  $f_d : u \rightarrow \theta$



$$\mathcal{N}^D(0,1)$$

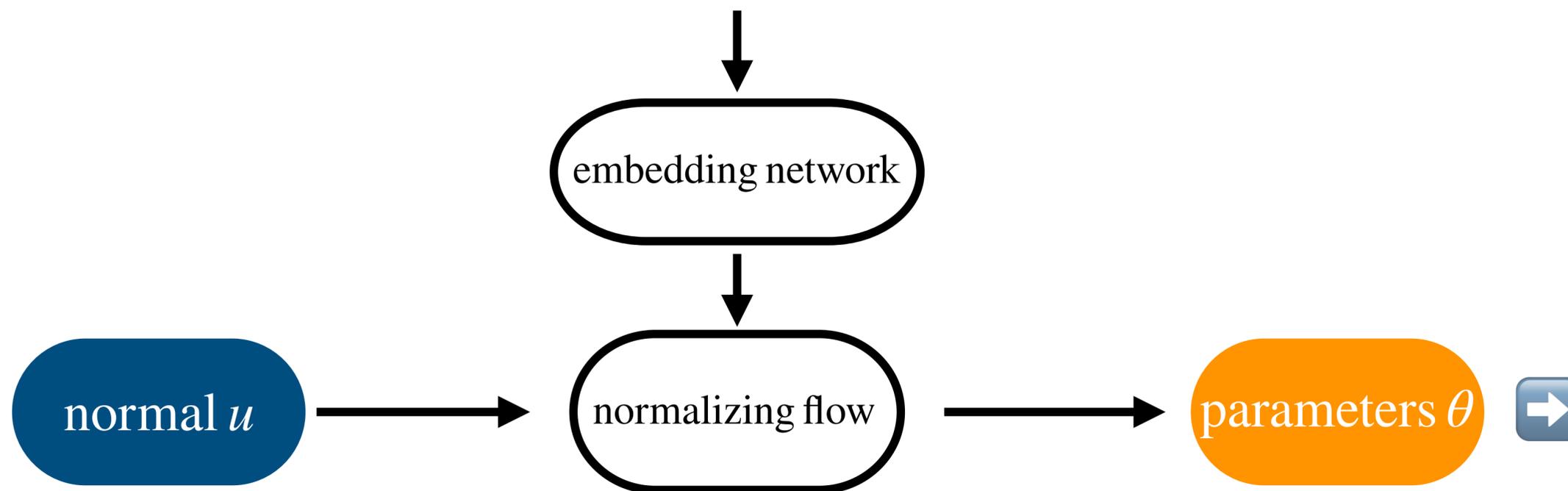
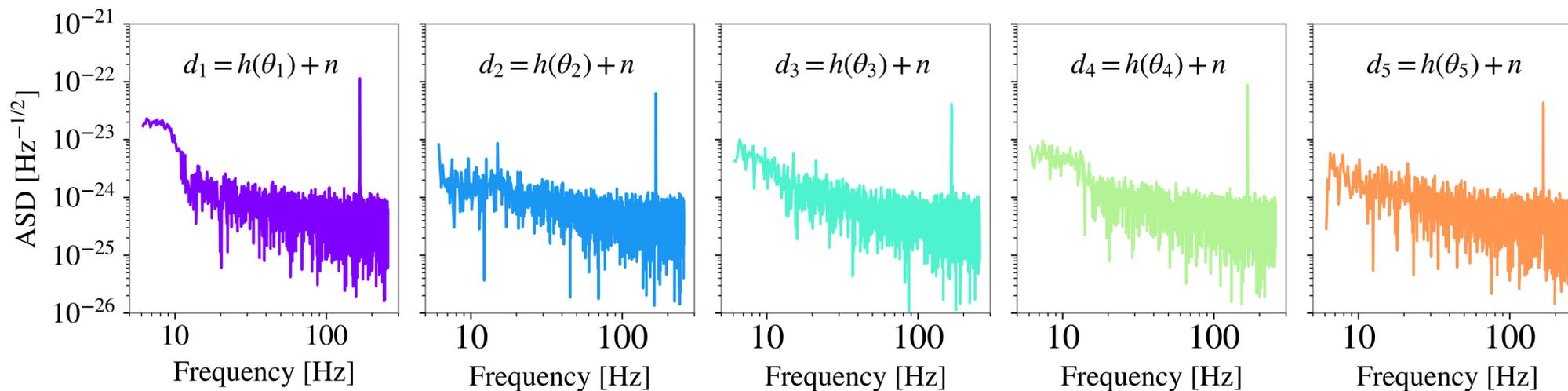
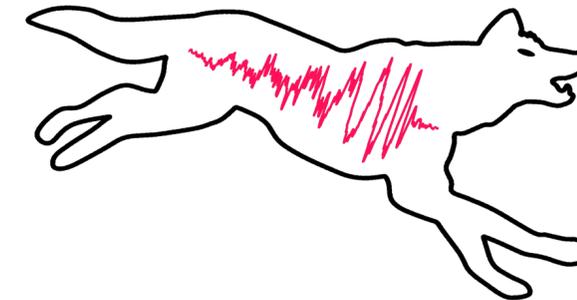


$$q_\phi(\theta | d) = \mathcal{N}^D(0,1)(f_d^{-1}(\theta)) | \det J_{f_d}^{-1} |$$

**Advantages:**

rapidly evaluated and sampled from

# Dingo-IS

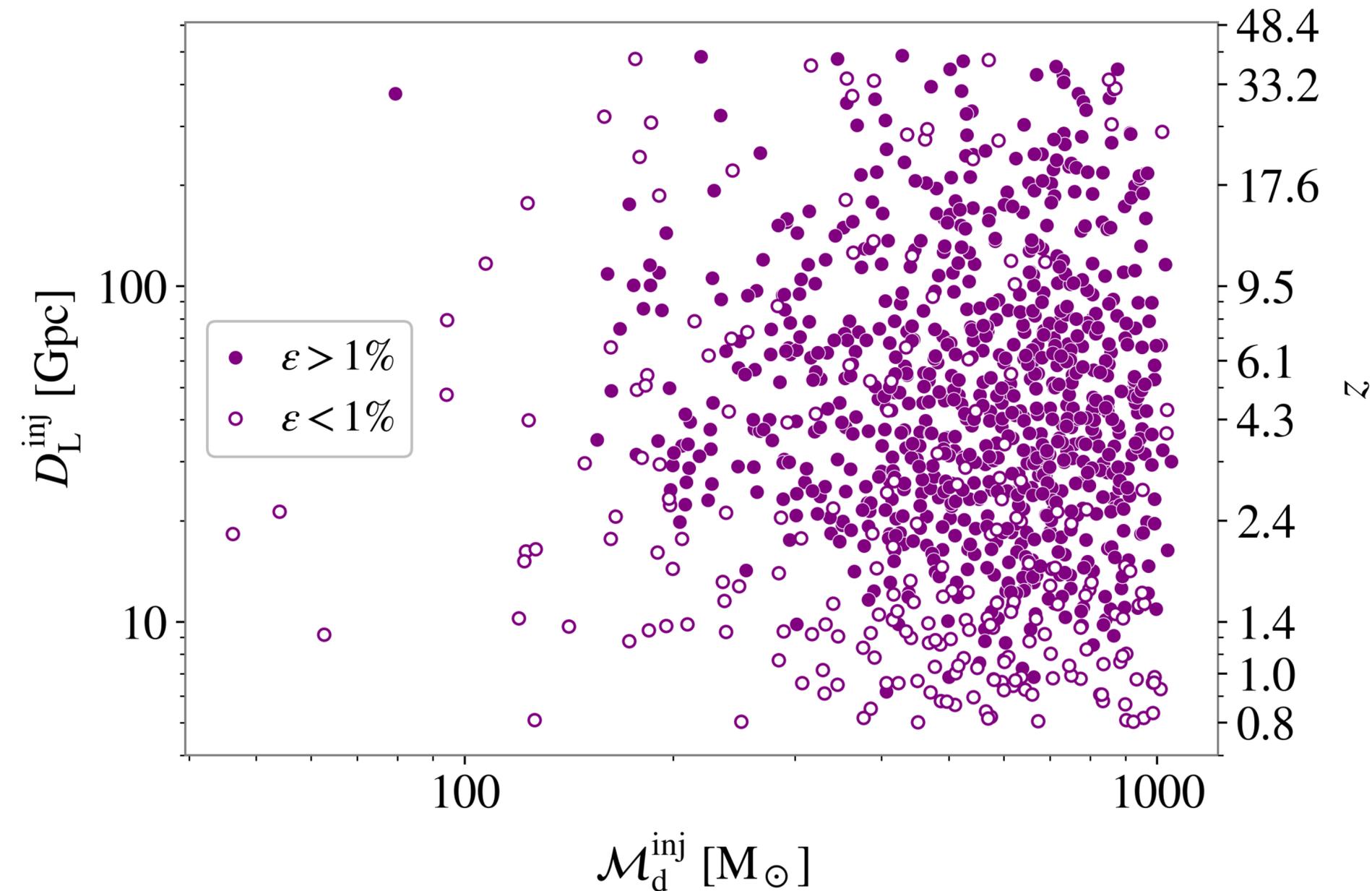


## Importance sampling

$$w_i = \frac{\mathcal{L}(d|\theta)\pi(\theta)}{q_\phi(\theta|d)}$$
$$\text{sample efficiency } \epsilon = \frac{\left(\sum_i w_i\right)^2}{N_s \sum_i w_i^2}$$

Refs. [Green et al. 2020](#), [Green et al. 2021](#), [Dax et al. 2021](#), [Dax et al. 2022](#), [Wildberger et al. 2022](#), [Dax et al. 2023](#), [Dax et al. 2024](#)

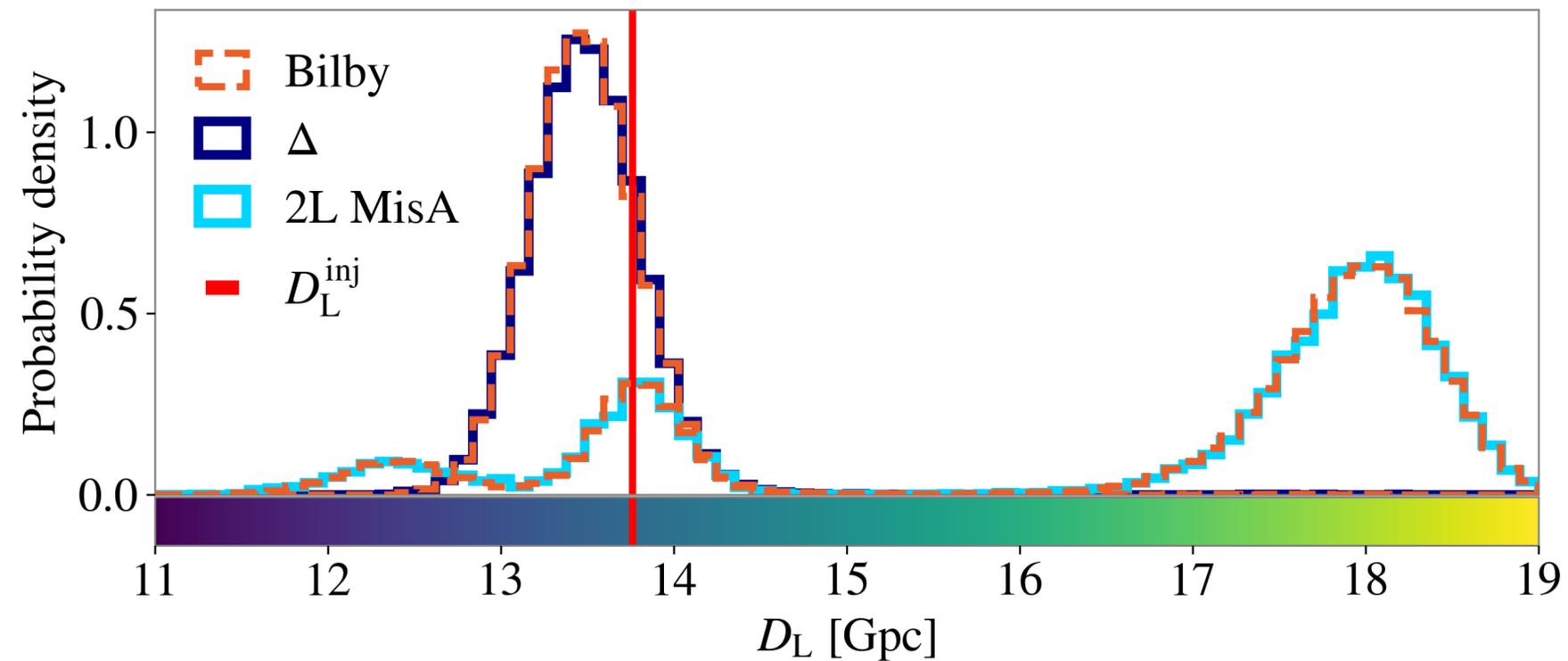
# Short-duration BBHs



- **High-redshift BBHs**  
➡ Pop. III and Primordial
- **Intermediate-mass BBHs**

Refs. [Santoliquido et al. 2023](#), [Mestichelli et al. 2024](#),  
[De Luca et al. 2020](#), [Franciolini et al. 2022](#), [Askar et al. 2023](#), [Arca Sedda et al. 2023](#)

# Multimodal $D_L$

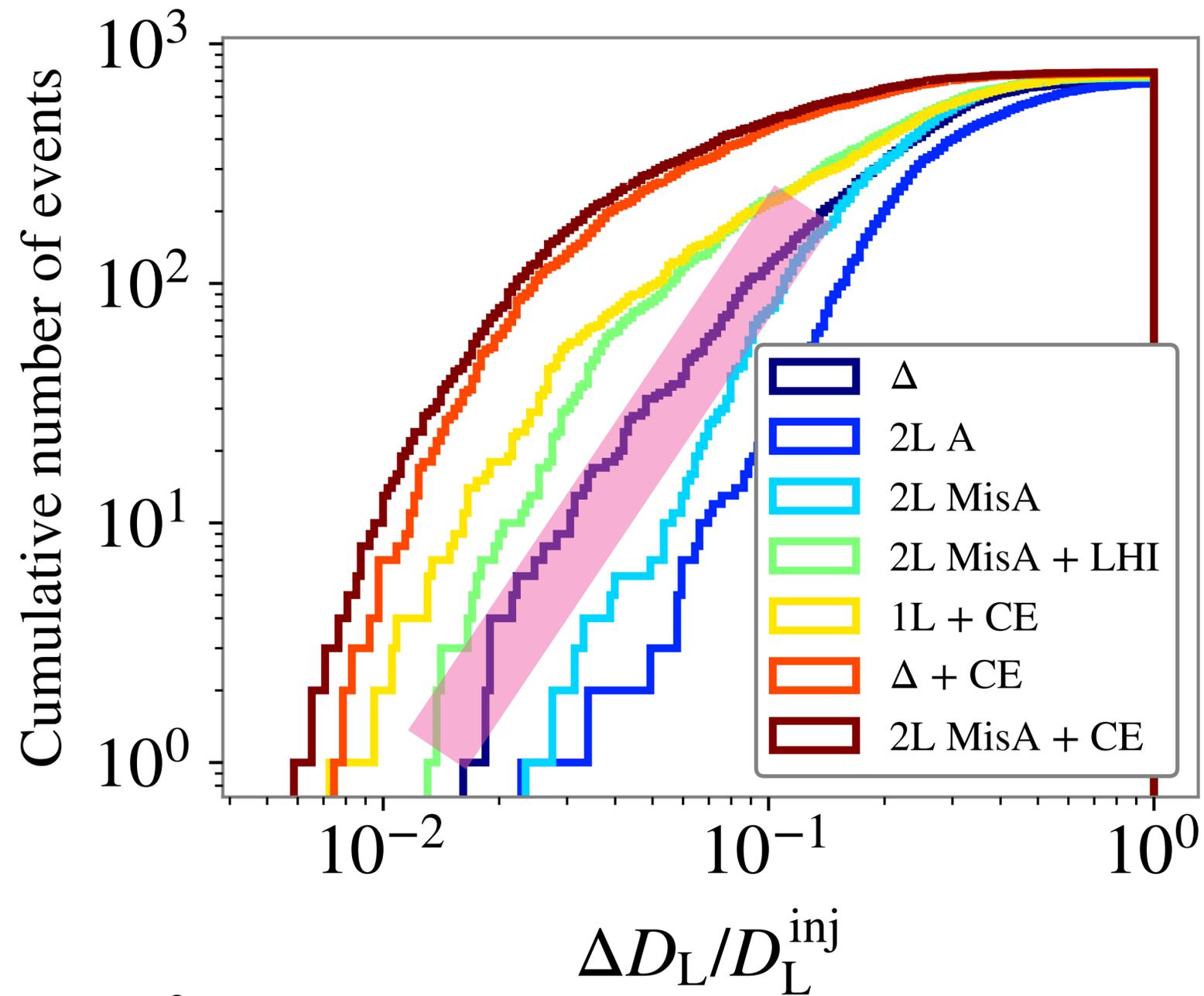


Multimodalities in luminosity distance for 2L MisA

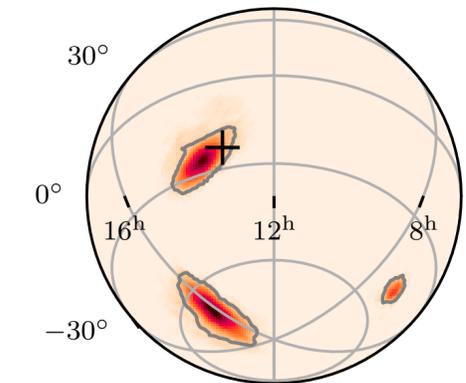
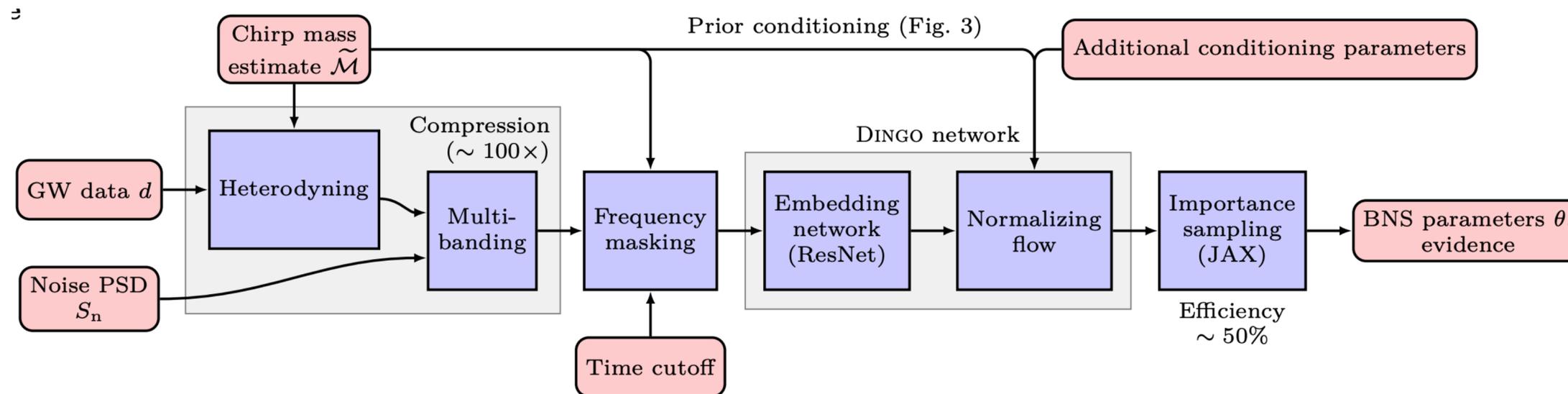
Perfect agreement between Dingo-IS and Bilby

10 min vs. 50 hours

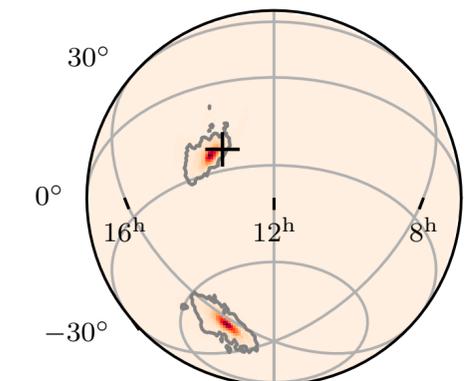
# Luminosity distance performance



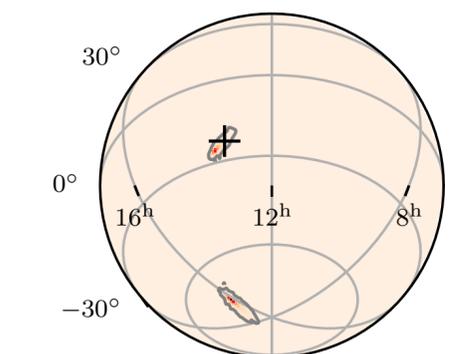
# Dingo-BNS with Cosmic Explorer



$T = -45$  min  
SNR = 82



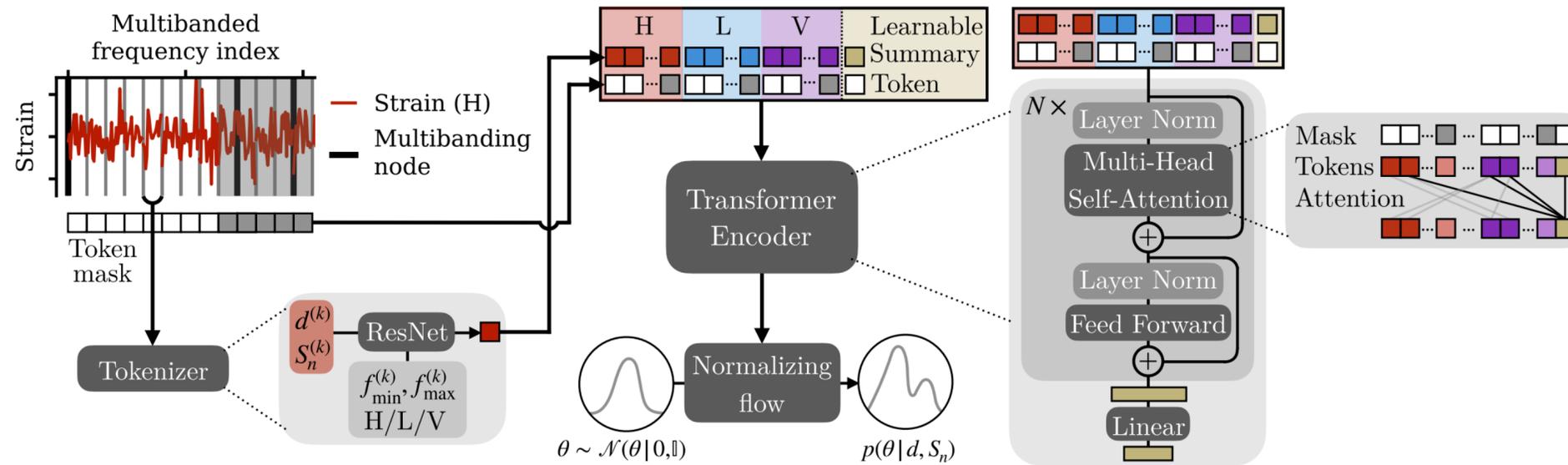
$T = -30$  min  
SNR = 255



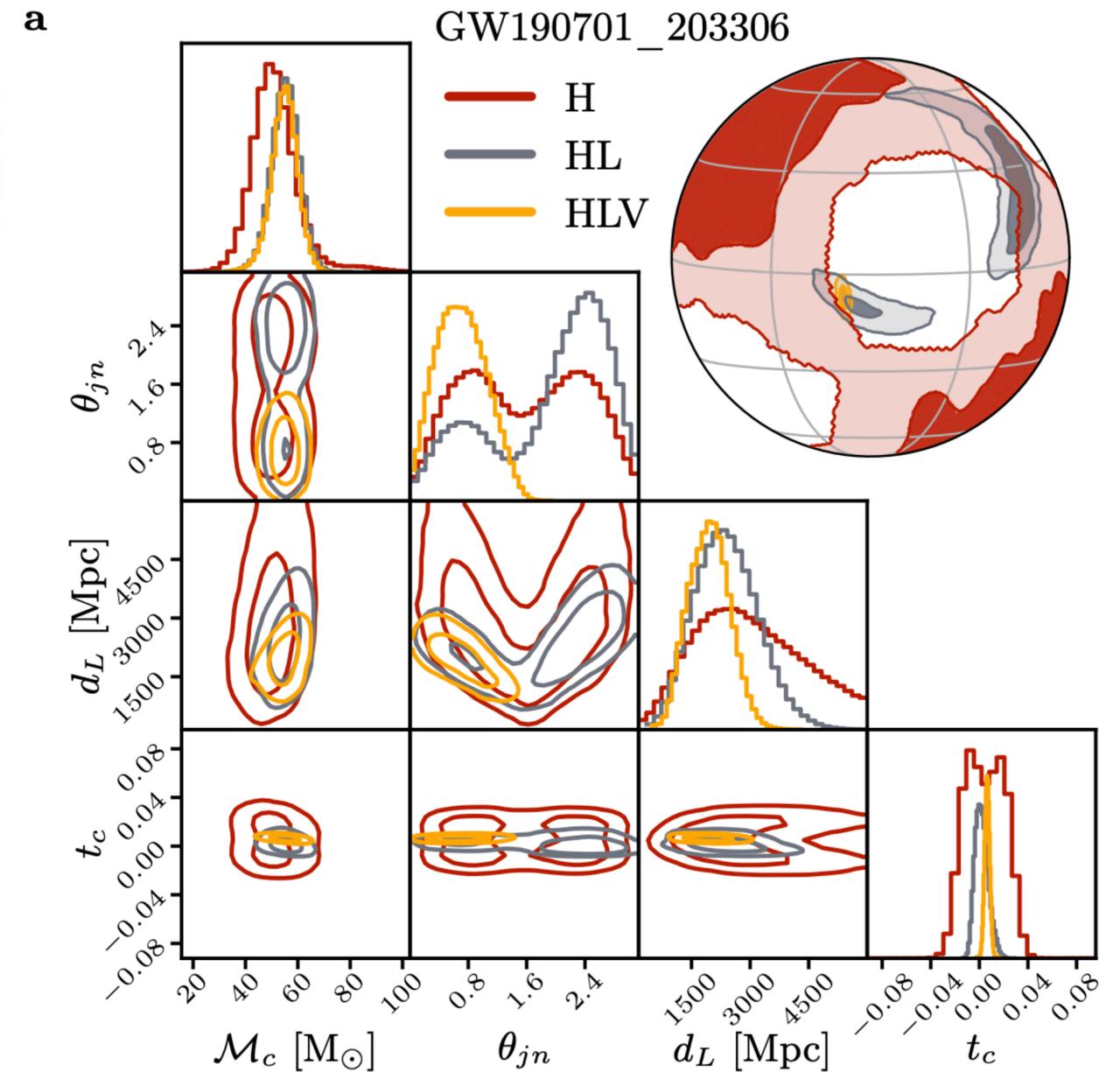
$T = -15$  min  
SNR = 664

**Areas of improvement:** from  $f_{\min} = 5$  Hz, neglecting Earth rotation, signal up to 15 minutes before merger

# Dingo with transformers



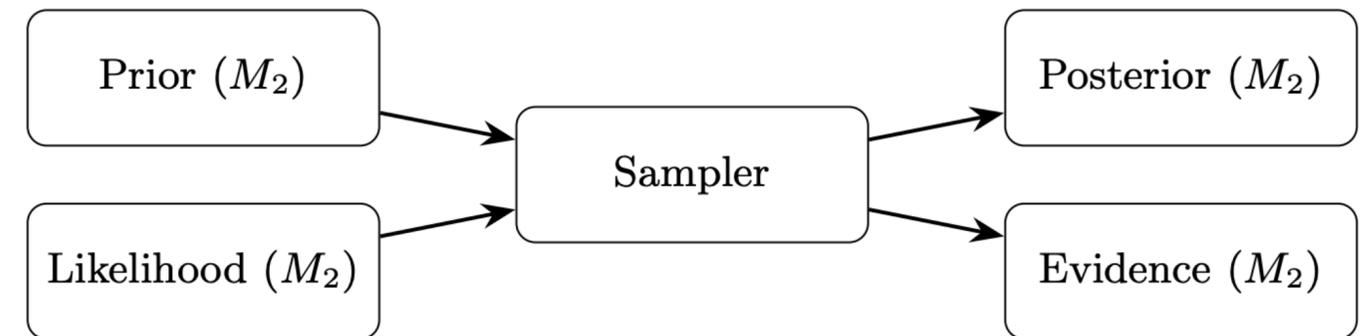
- Train Dingo directly with population priors
- Decrease  $f_{\min} = 2$  Hz
- Expand the range of sources analysed



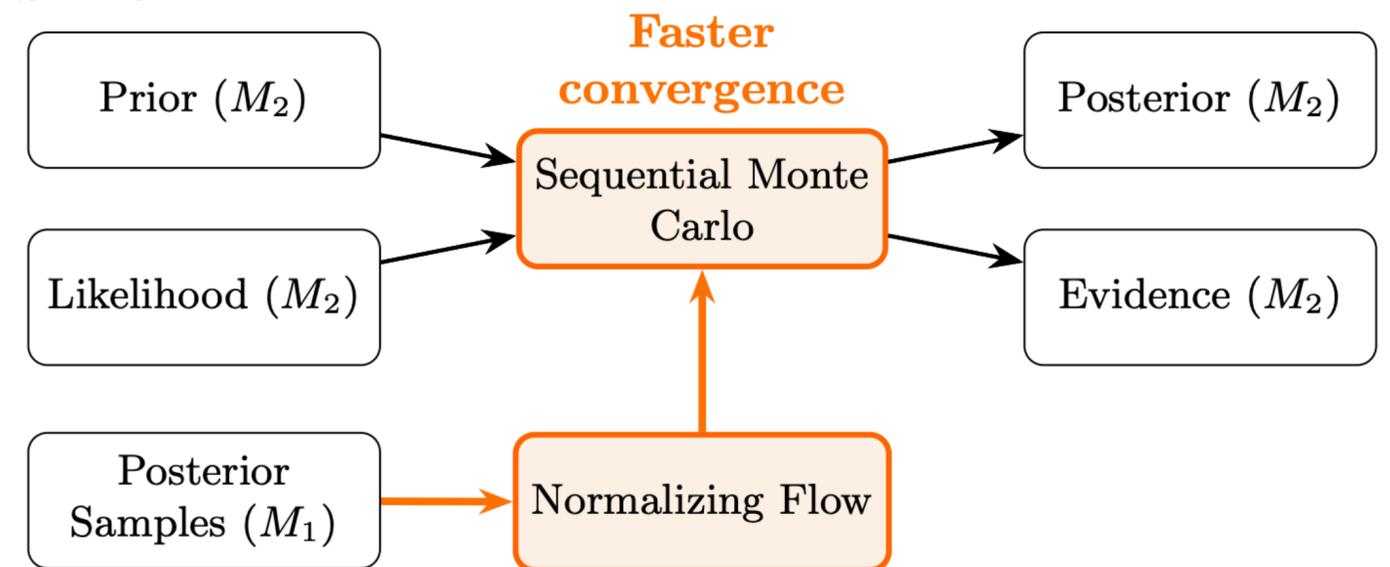
# aspire-dingo

Starting point: Posterior Samples ( $M_1$ ), New Model ( $M_2$ )

## Traditional inference



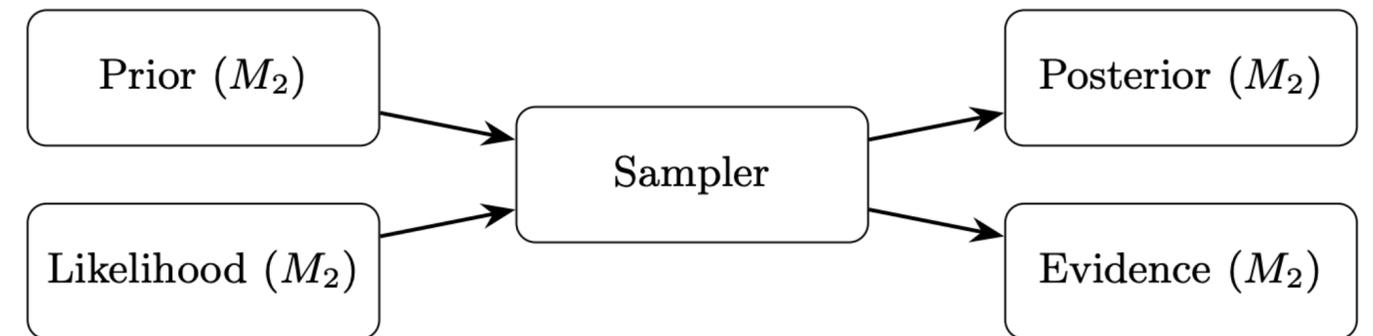
## ASPIRE



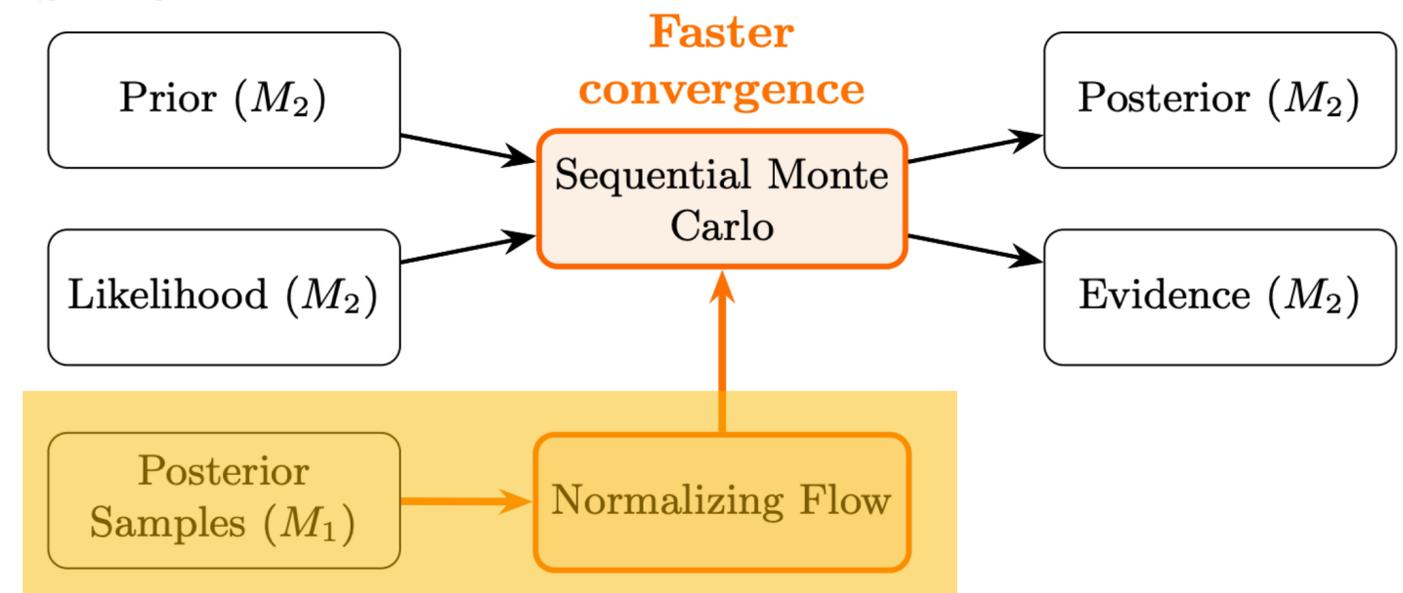
# aspire-dingo

Starting point: Posterior Samples ( $M_1$ ), New Model ( $M_2$ )

## Traditional inference



## ASPIRE



We already have access to trained normalising flows!  
Natural extension to make aspire work with dingo.

**THIS IS GAME CHANGER!**

Especially because aspire-dingo allows PE of high-SNR events



# Short course

- **“Foundations of gravitational-wave and multimessenger data analysis”**
- Filippo’s lectures: **13, 20, 22 May**
- Biswajit’s lectures: **11, 15, 16 June**
- This course provides a foundational **introduction to gravitational wave data analysis**, covering key concepts and standard Bayesian inference techniques used to analyse data from the LIGO, Virgo, and KAGRA detectors. We will also explore **analysis methods** recently developed **for next-generation observatories** such as the Einstein Telescope, including Fisher-matrix approximations and accelerated yet accurate **deep-learning– based approaches**. The course will also examine the multi-messenger opportunities for advancing our understanding of GRB physics. We will discuss observational strategies with current and future facilities, including the use of early-warning alerts. Particular emphasis will be placed on the largely unexplored high-energy gamma-ray domain (GeV–TeV) and its role in constraining jet physics and radiation mechanisms within the broader framework of multi-messenger astronomy. **The course will be highly hands-on**, with practical sessions designed to teach the essential Python tools commonly used in the gravitational wave community.

# Contributions

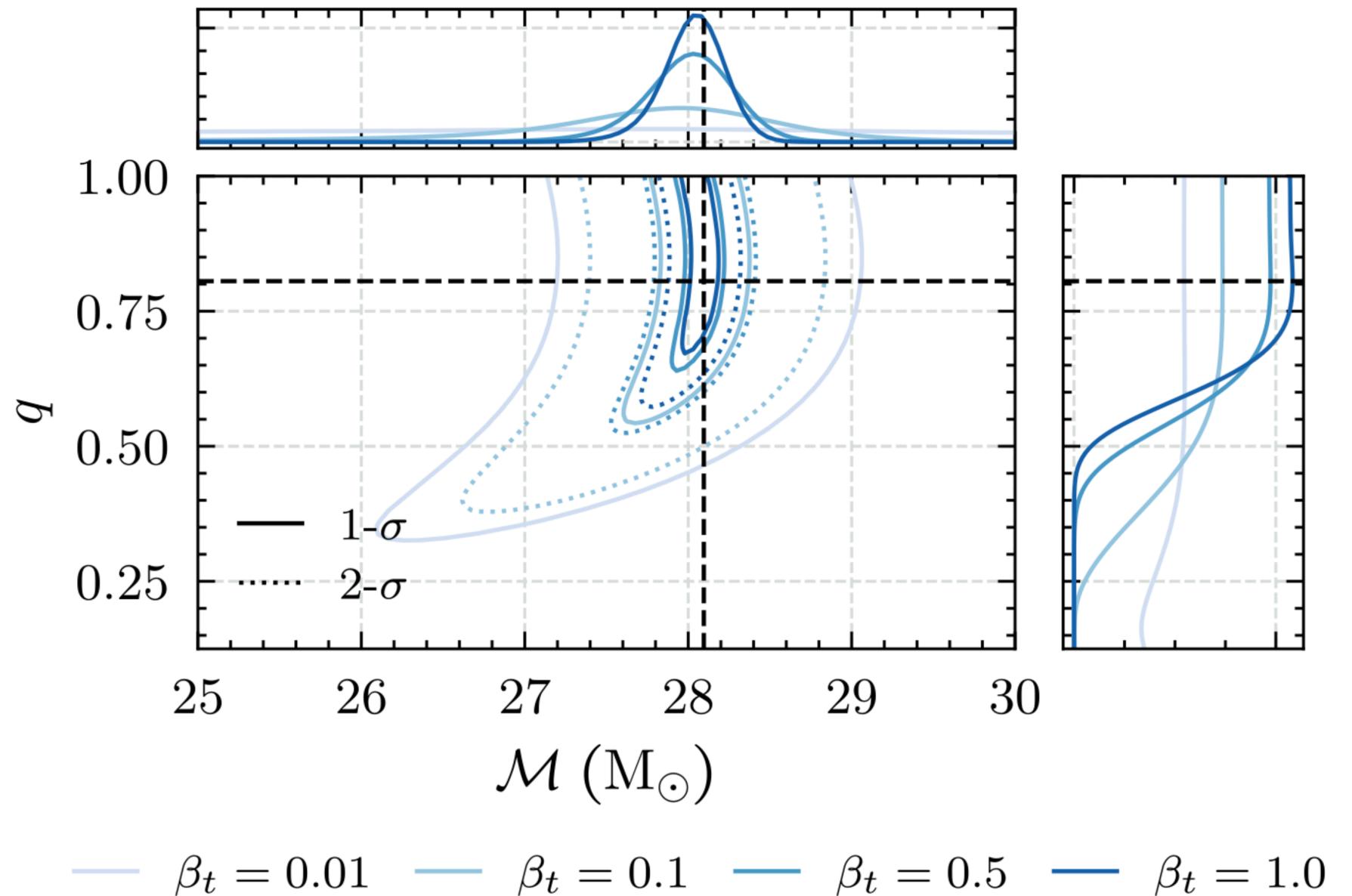
- The Einstein Telescope calls for a **pragmatic shift** in data analysis technique
- Addressing these challenges is **essential and feasible**
- We have the *unique* opportunity to **develop new technologies**

# Backup slides

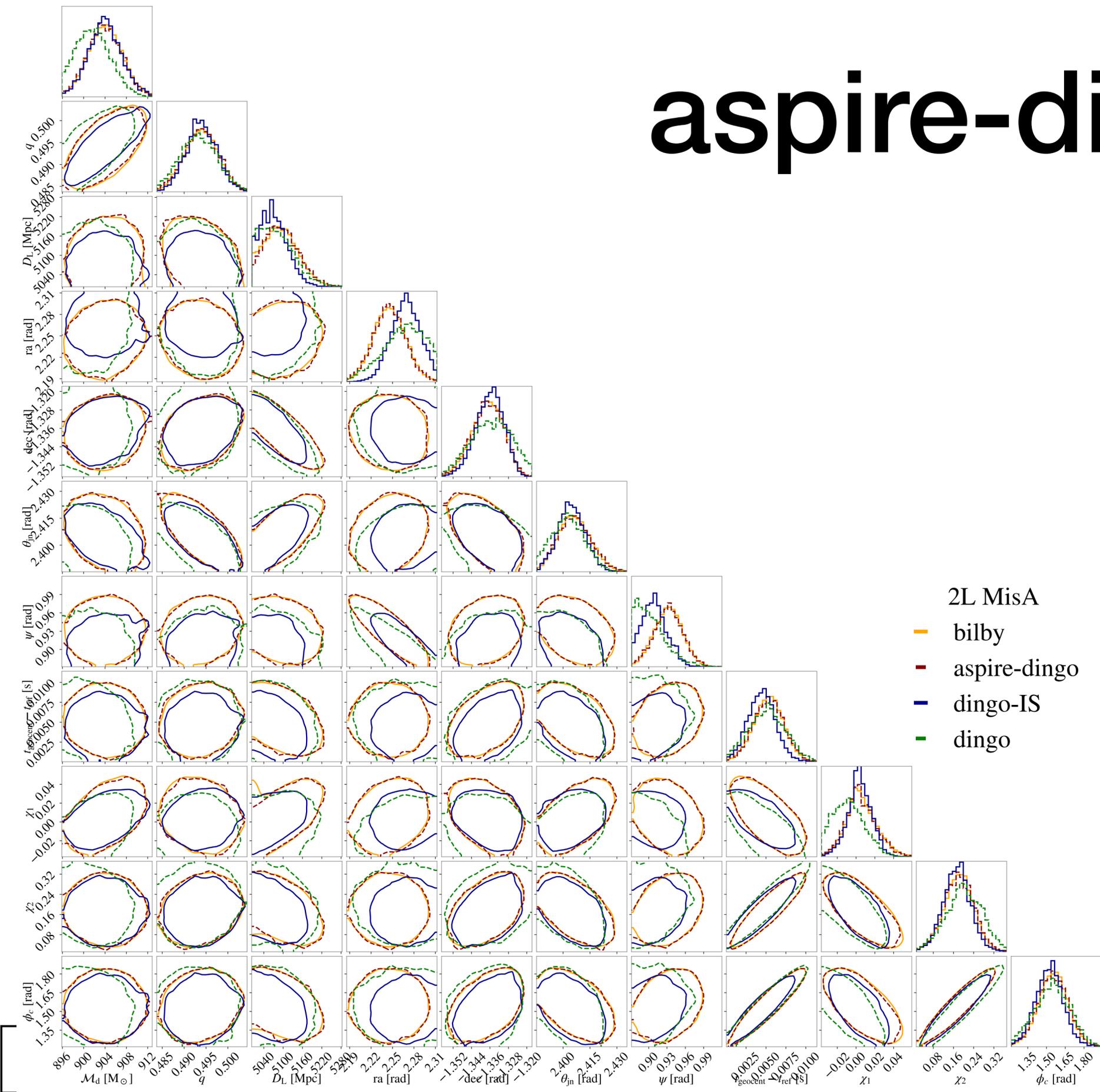
# Solution: sequential Monte Carlo

- $p_t(\theta | d) = \frac{\mathcal{L}(d | \theta)^{\beta_t} \pi(\theta)}{Z_t}$

- Where  $\beta_t \in [0,1]$



# aspire-dingo

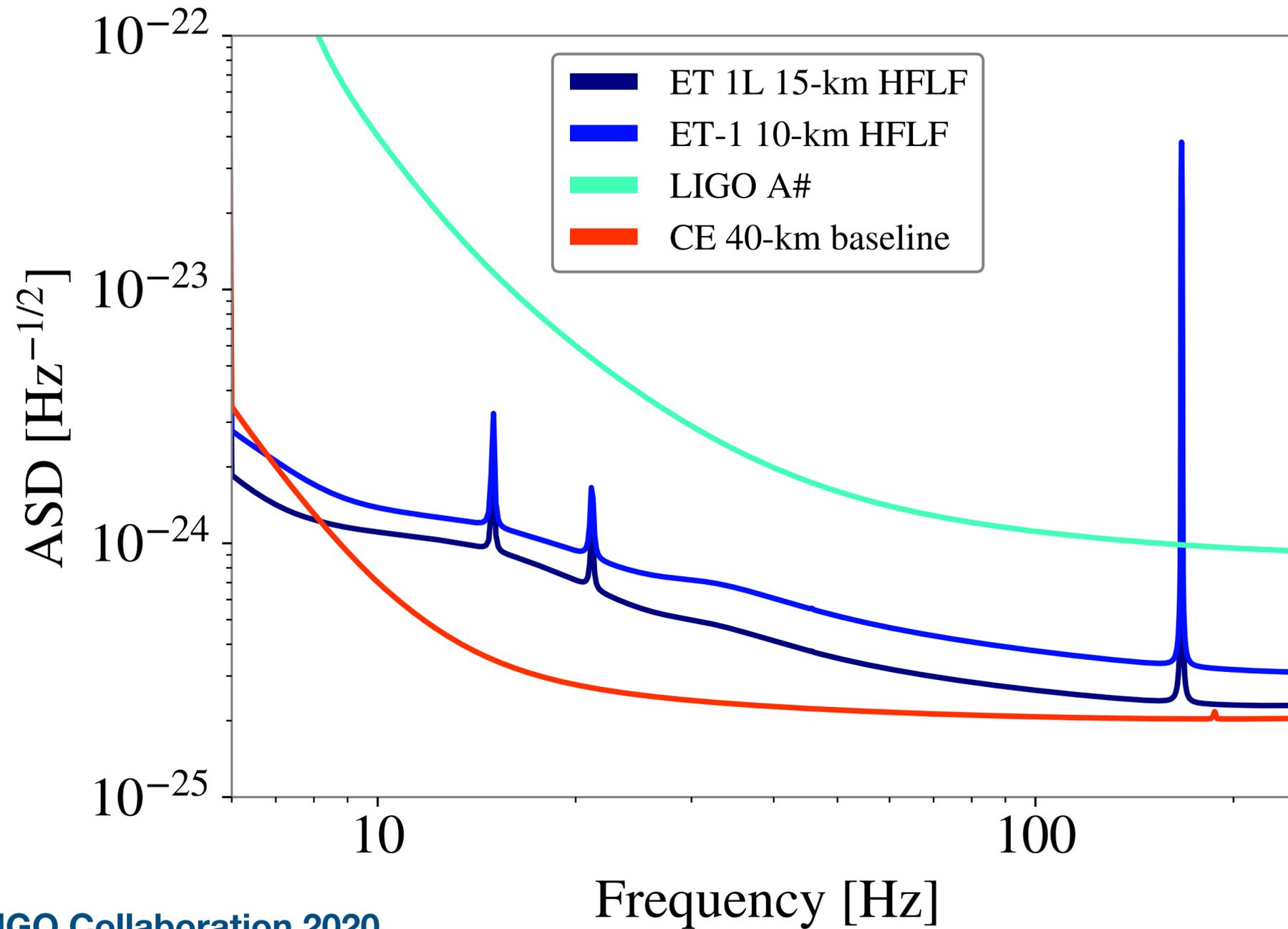


2L MisA  
 - bilby  
 - aspire-dingo  
 - dingo-IS  
 - dingo

**Sample efficiency very low ~0.02%**  
**With very high SNR ~ 650**

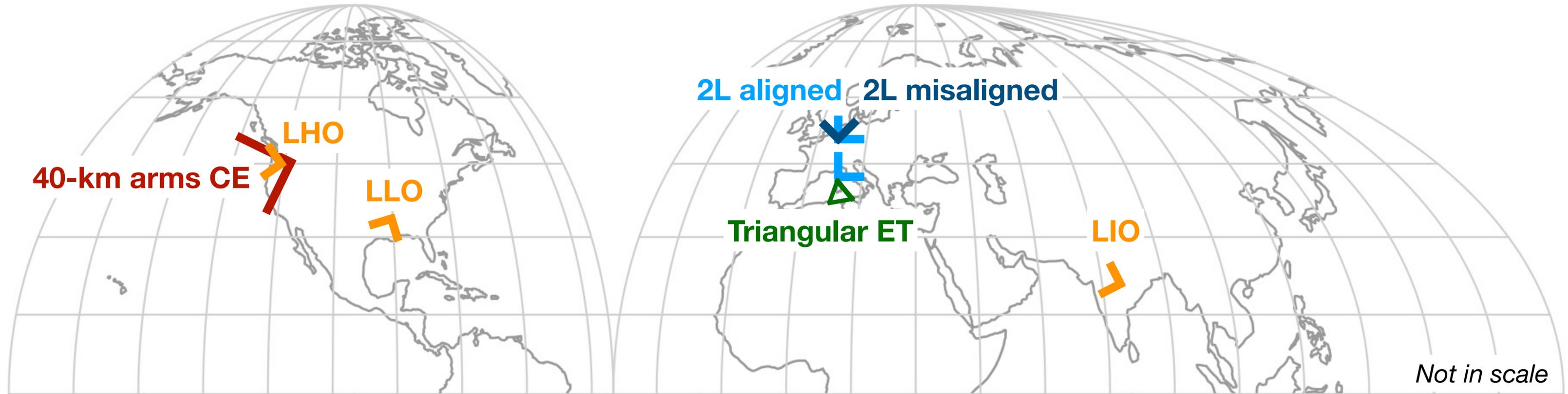
Computing times:  
 - dingo : < 1 s  
 - aspire-dingo: 7 hours  
 - bilby: 12 hours  
 - dingo-IS: 20 hours

# Amplitude spectral densities



Refs. [ET Collaboration 2023](#), [LIGO Collaboration 2020](#),  
[S. Kandhasamy & S. Bose 2020](#), [CE Collaboration 2022](#)

# Configurations



$\Delta$   
2L A  
2L MisA

2L MisA + LHI  
1L + CE  
2L MisA + CE  
 $\Delta$  + CE

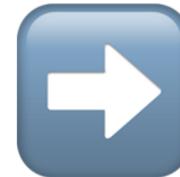
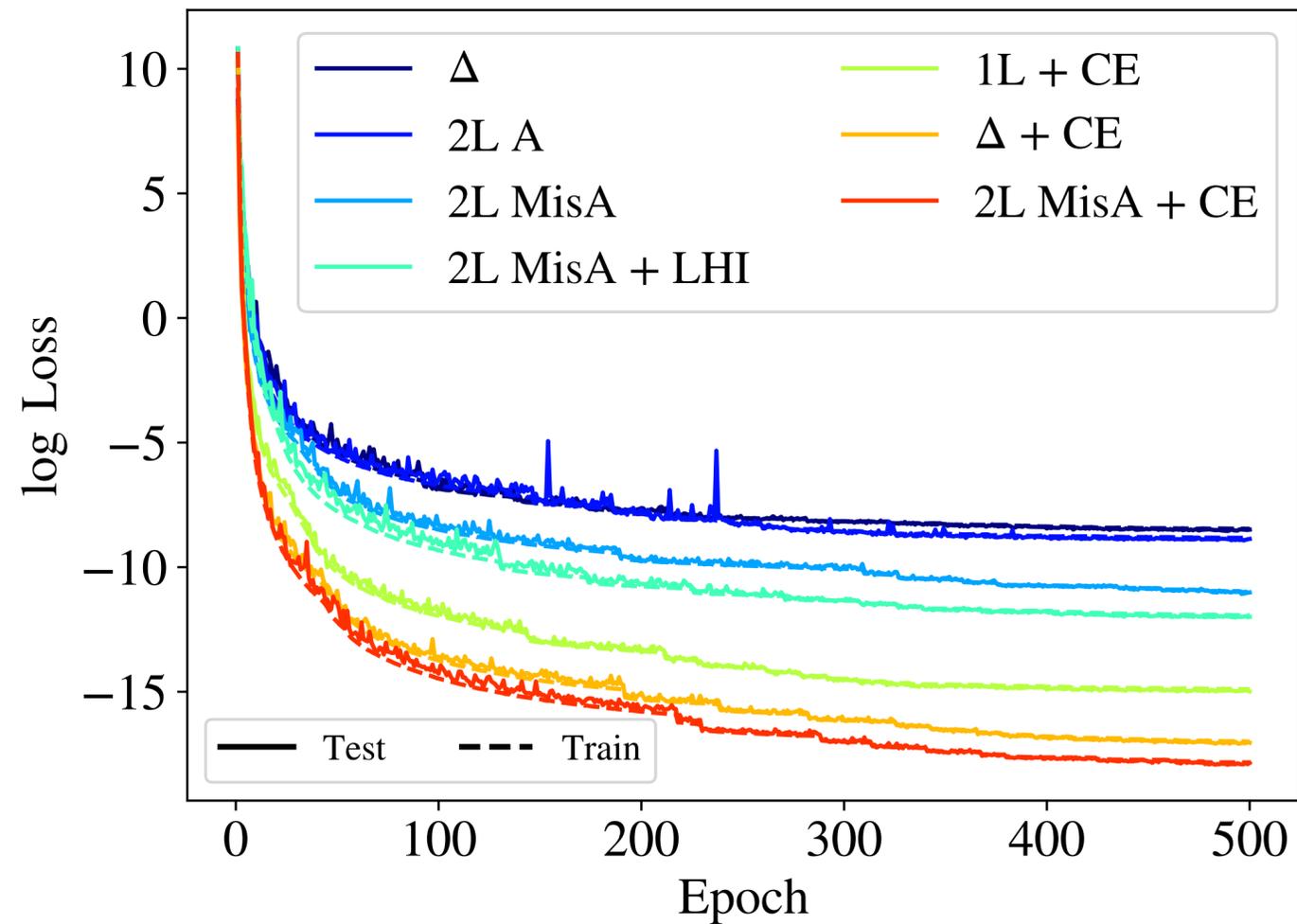
# High-redshift sources

`'chirp_mass'`: `UniformInComponentsChirpMass(minimum=40, maximum=1100)`

`'luminosity_distance'`: `UniformSourceFrame(minimum=5_000.0, maximum=500_000.0)`

waveform approximant = `IMRPhenomXPHM`

# Training



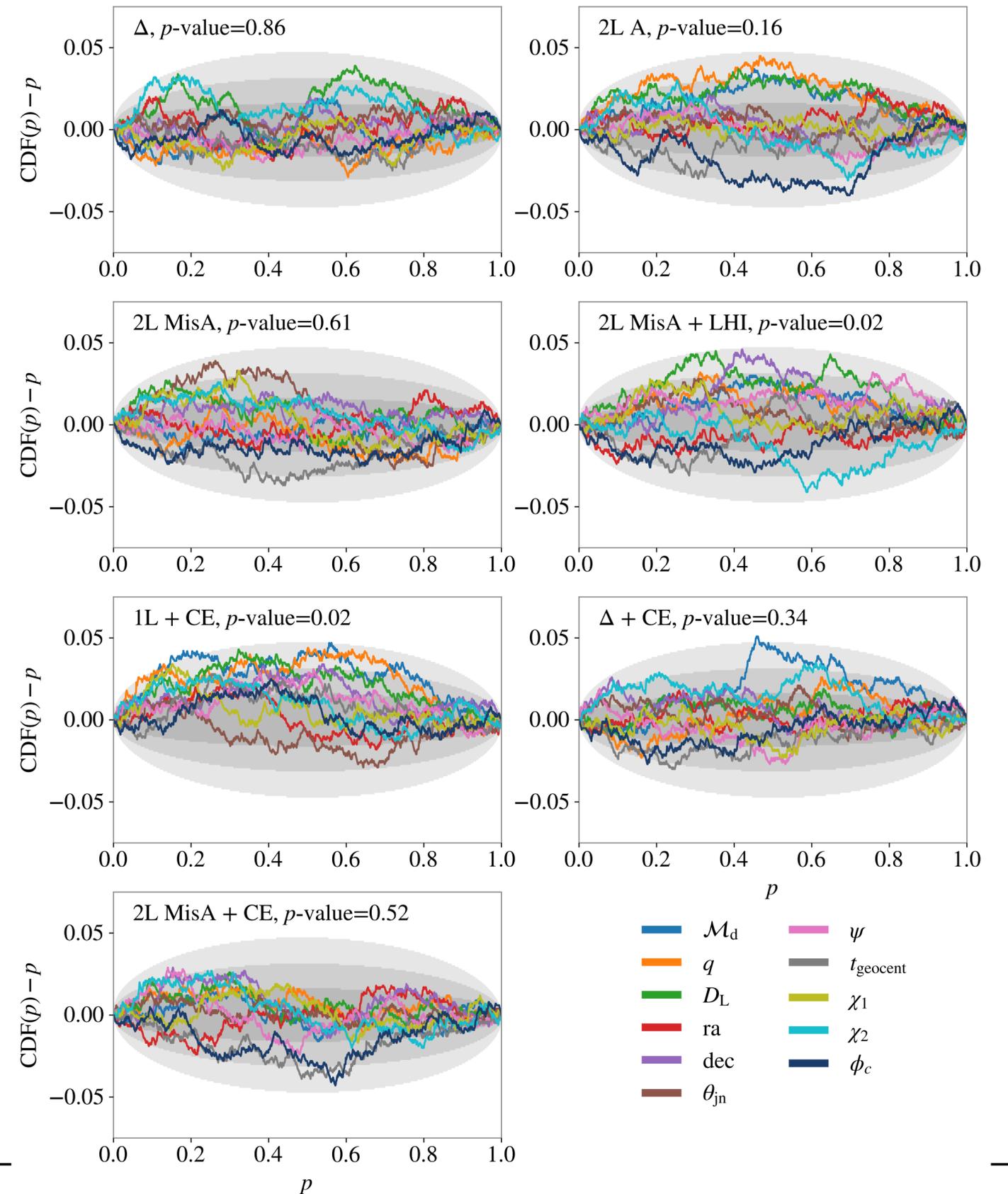
# Injections

- Randomly sample 1000 BBHs from the priors
- Use the same injection parameters for all configurations.
- Obtain  $10^5$  posterior samples and importance weights for each injection.

# P-P plots

	$\Delta$	2L A	2L MisA	2L MisA + LHI	1L + CE	$\Delta$ + CE	2L MisA + CE
$\mathcal{M}_d$	0.72	0.12	0.92	0.29	0.02	0.01	0.91
$q$	0.35	0.03	0.59	0.23	0.04	0.47	0.76
$D_L$	0.08	0.12	0.42	0.03	0.04	0.84	0.47
ra	0.79	0.53	0.73	0.59	0.71	0.90	0.57
dec	0.80	0.71	0.76	0.03	0.19	0.47	0.34
$\theta_{jn}$	0.92	0.96	0.09	0.37	0.34	0.72	0.98
$\psi$	0.79	0.72	0.92	0.23	0.25	0.43	0.35
$t_{\text{geocent}}$	0.55	0.30	0.12	0.27	0.37	0.29	0.08
$\chi_1$	0.55	1.00	0.21	0.41	0.19	0.61	0.83
$\chi_2$	0.21	0.28	0.47	0.06	0.42	0.15	0.43
$\phi_c$	0.89	0.07	0.50	0.33	0.50	0.44	0.04

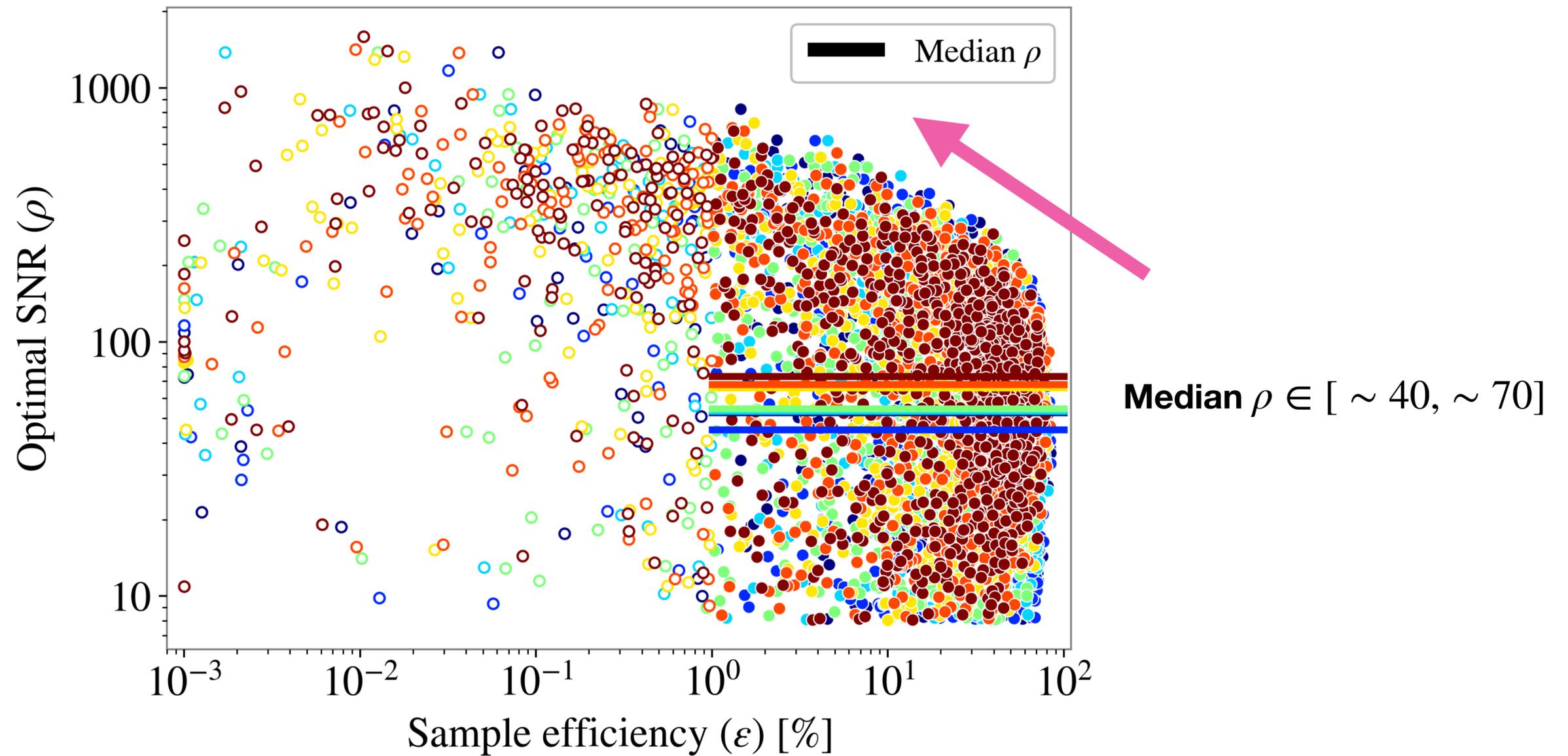
**Table 4.**  $p$ -values (color-coded) for each GW parameter (rows) across different detector configurations (columns). See Figure 7 and Appendix C for details.



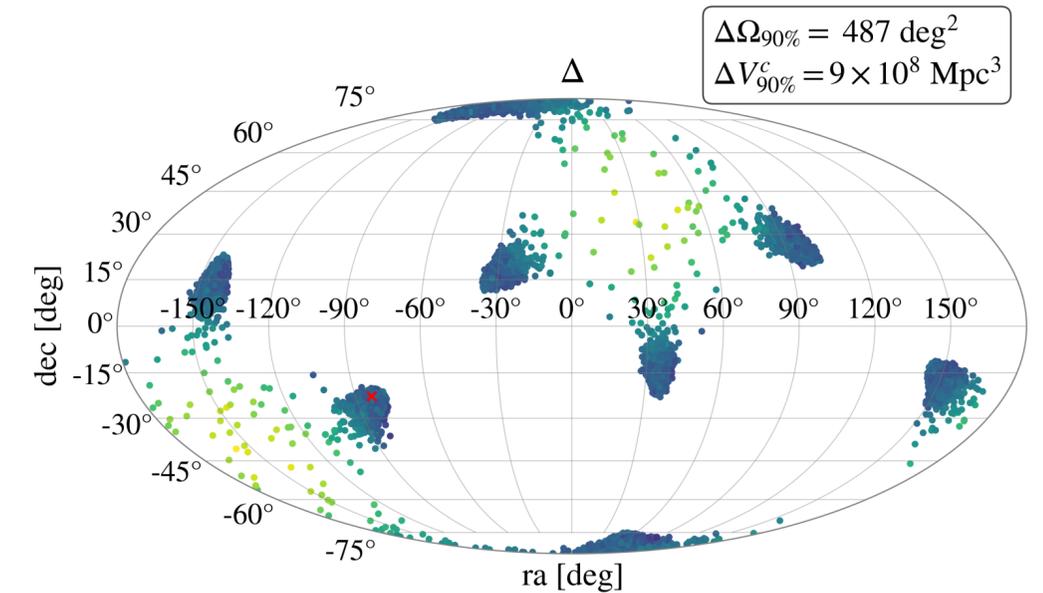
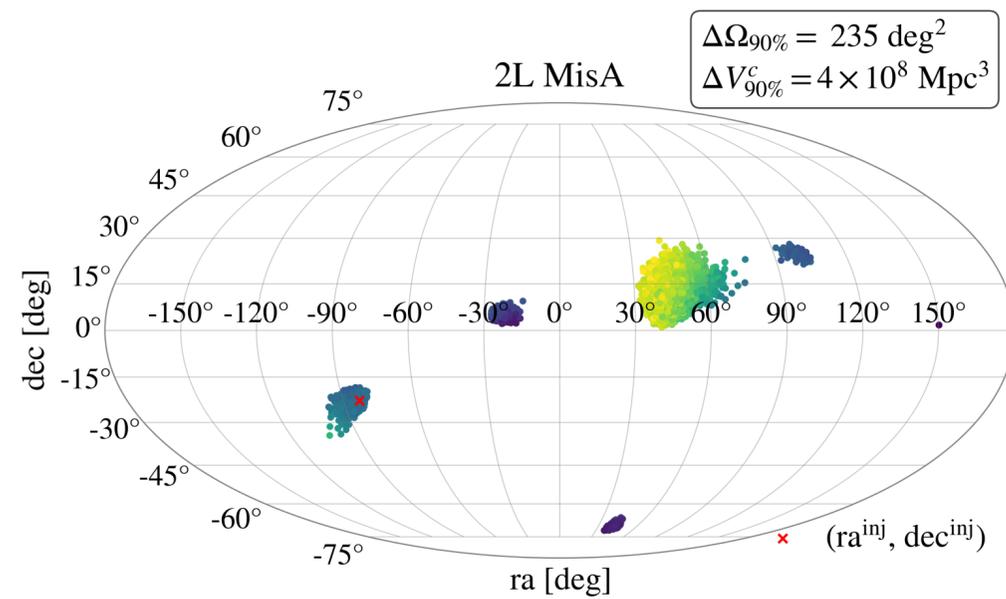
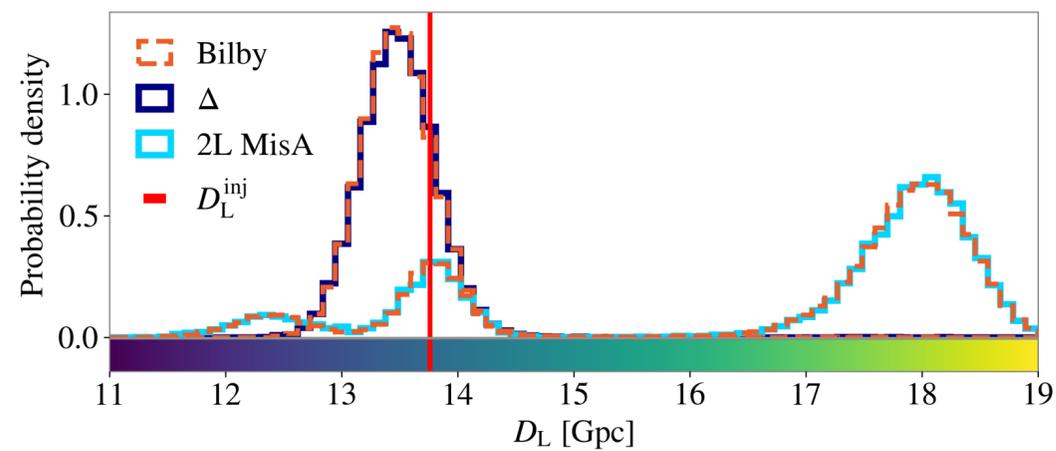
# Sample efficiency

Higher sample efficiency  
wrt [Santoliquido et al. 2025a](#)

- 2L A (96%)
- $\Delta$  (96%)
- 2L MisA (94%)
- 2L MisA + LHI (93%)
- 1L + CE (89%)
- $\Delta$  + CE (88%)
- 2L MisA + CE (85%)

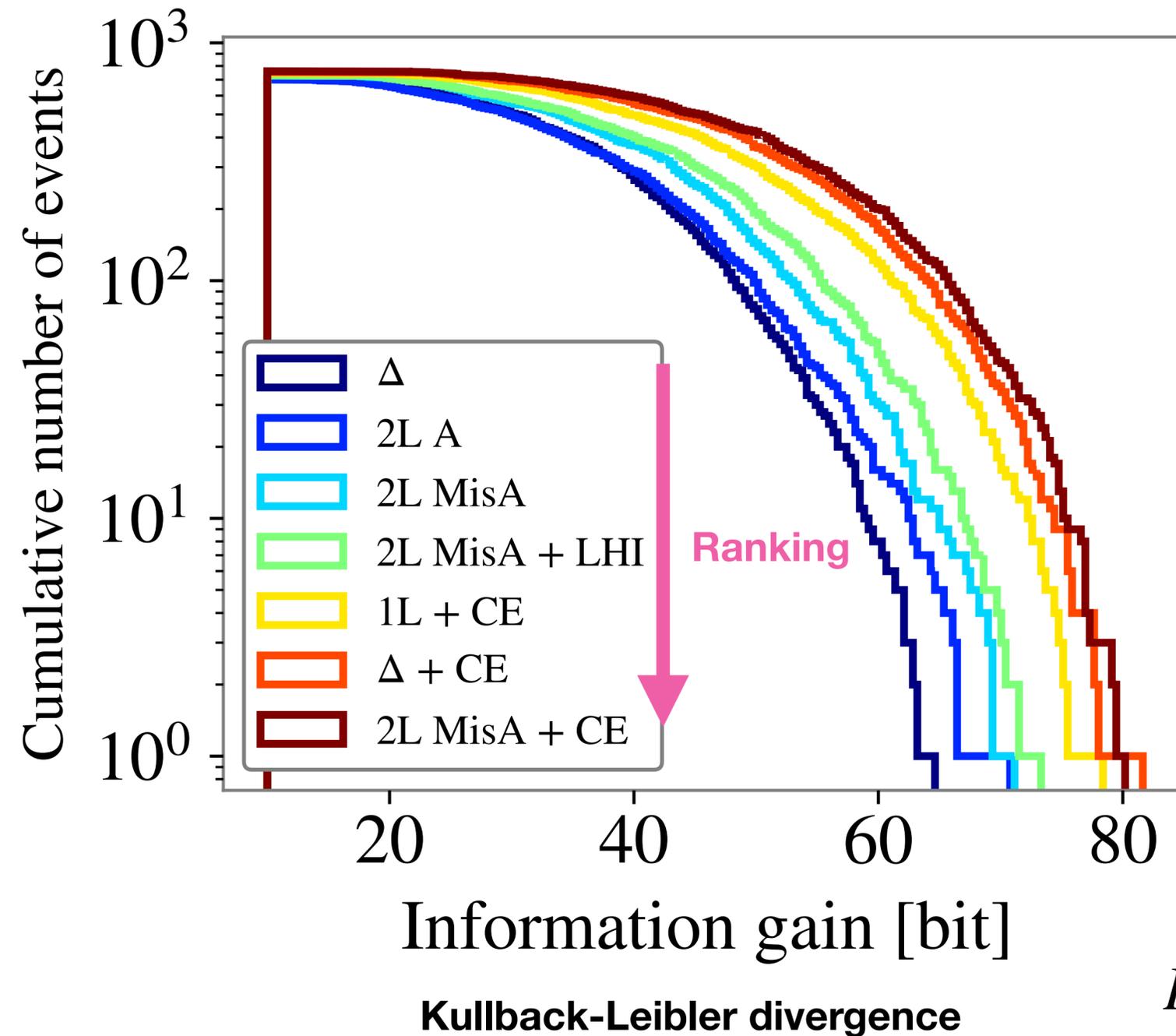


# Multimodal posteriors



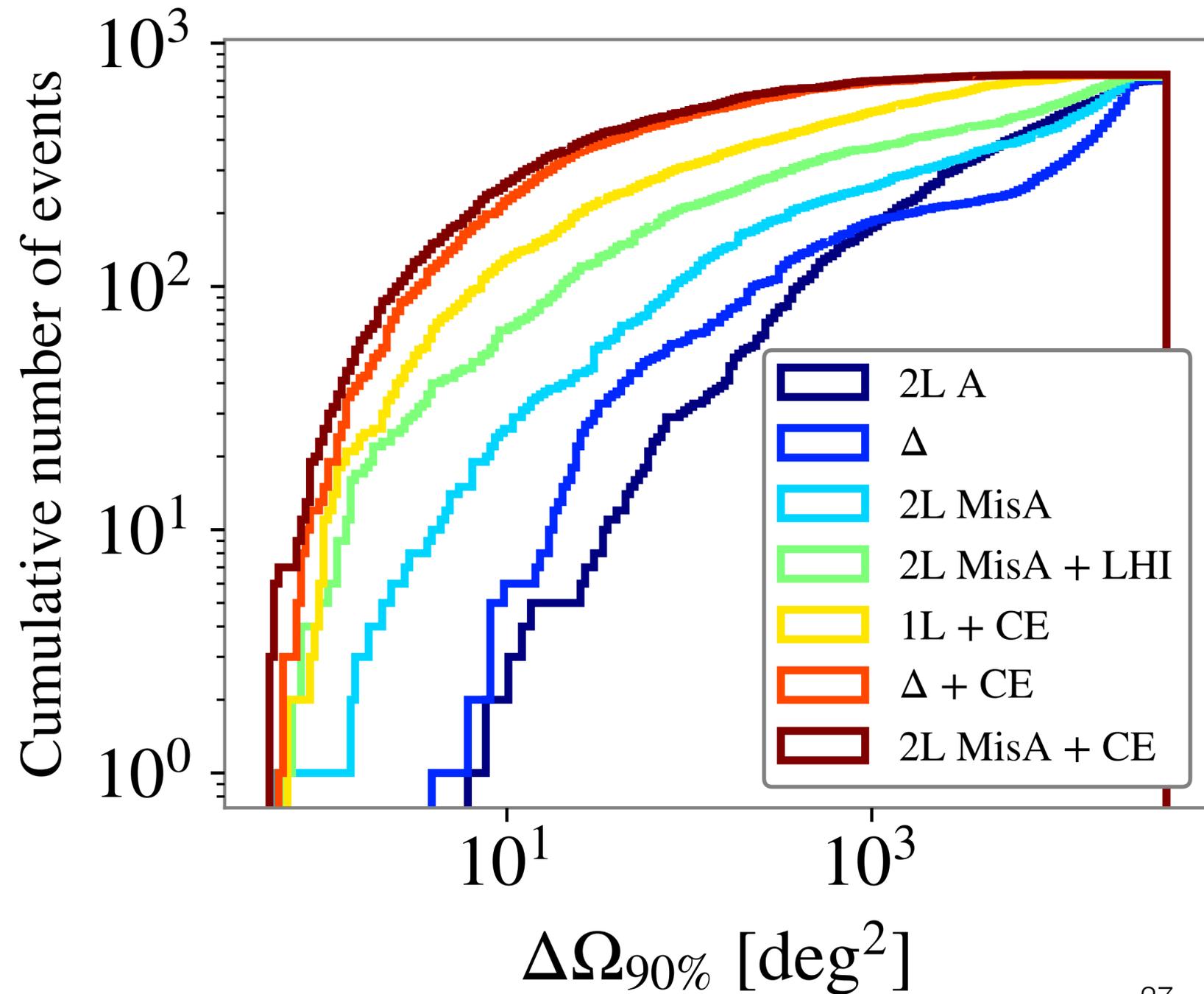
**Eight-fold sky degeneracy**  
extensively discussed in  
[Santoliquido et al. 2025a](#)

# Parameter estimation performance



$$I = \int d\theta p(\theta | d) \log_2 \frac{p(\theta | d)}{\pi(\theta)}$$

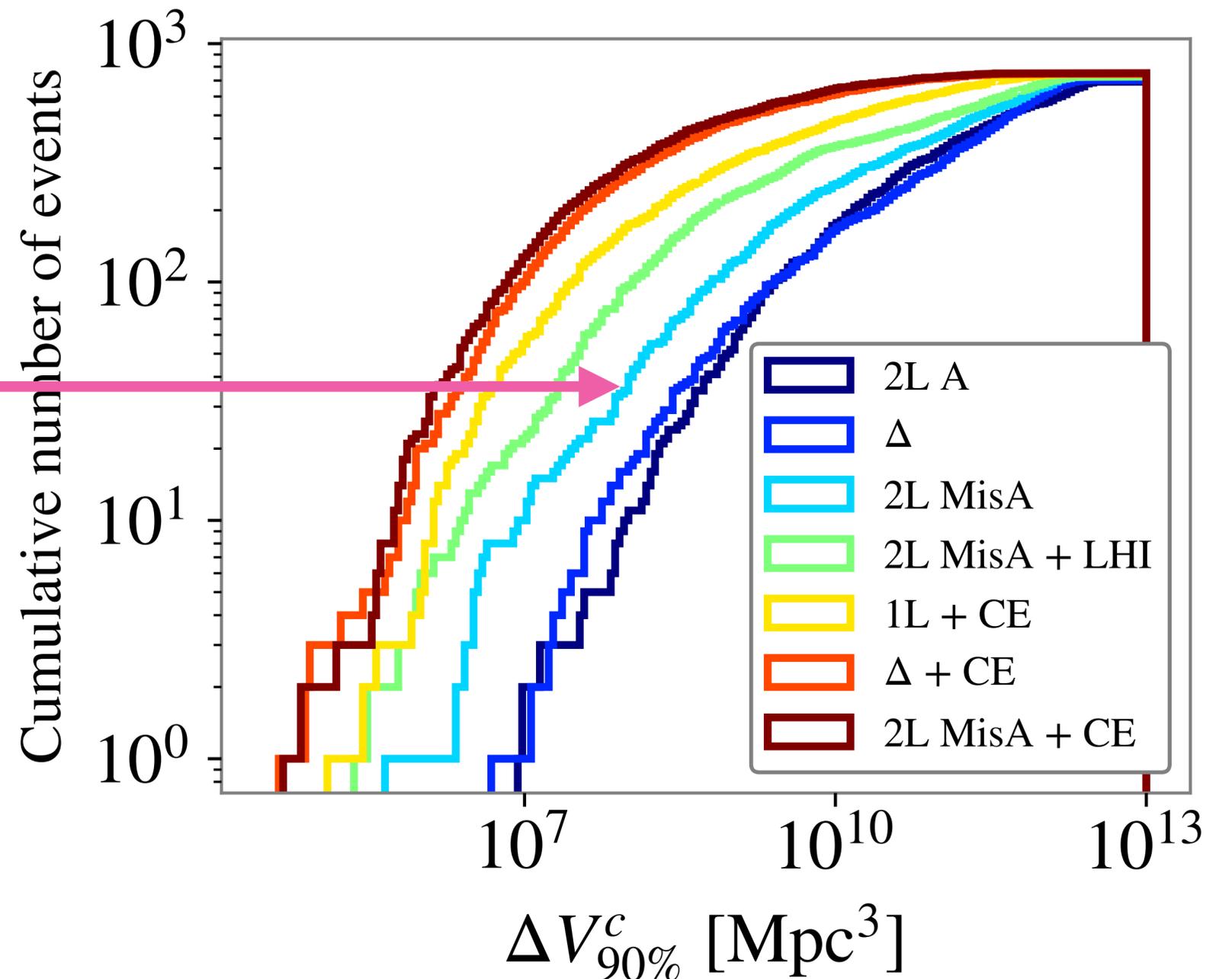
# Sky localisation performance



— Improvement in sky localisation with 2L MisA configuration wrt to  $\Delta$  due to less sky modes

# Volume localisation performance

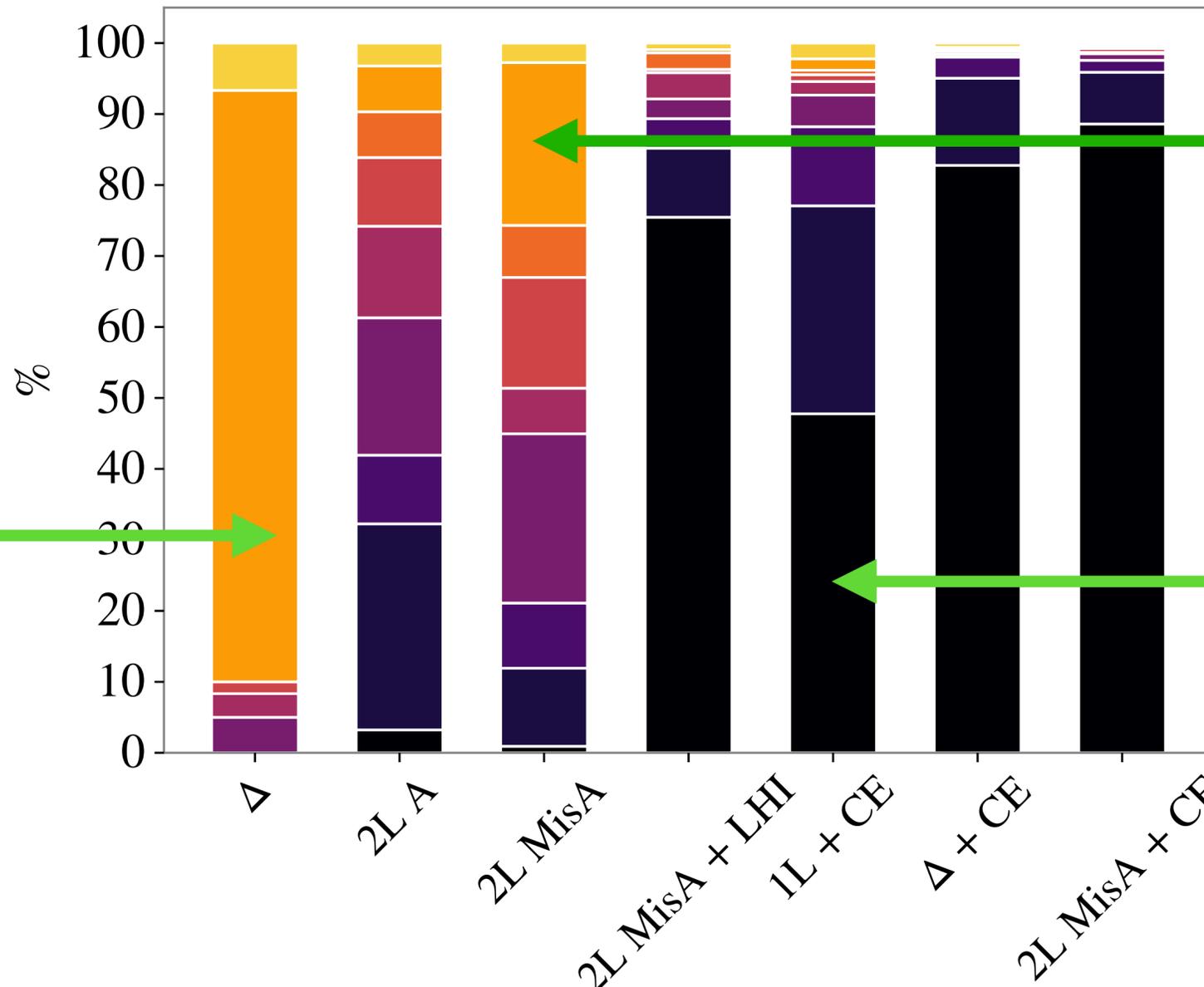
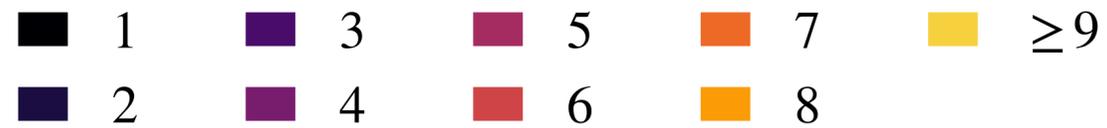
Large **improvement in volume localisation** with **2L MisA** configuration. Impact on several science cases (e.g., dark siren cosmology)



Refs. [Schutz 1986](#), [Del Pozzo 2012](#), [Libanore et al. 2021](#),  
[Gair et al. 2023](#), [Borghi et al. 2024](#)

# Sky modes

Number of sky modes in  $\Delta\Omega_{90\%} \leq 100 \text{ deg}^2$



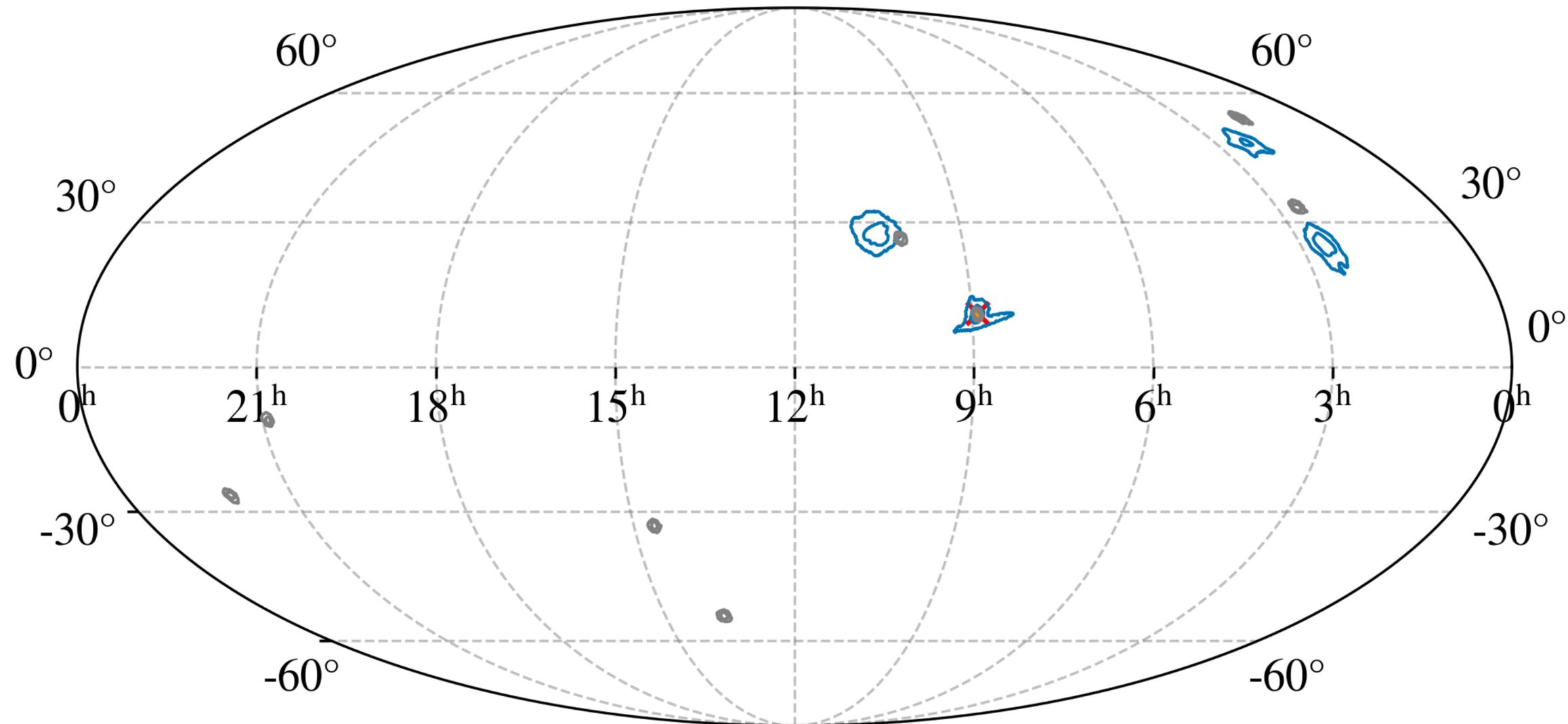
$\Delta$ , > 80% of sources with **eight sky modes**

2L MisA, ~ 20% of sources with **eight sky modes**

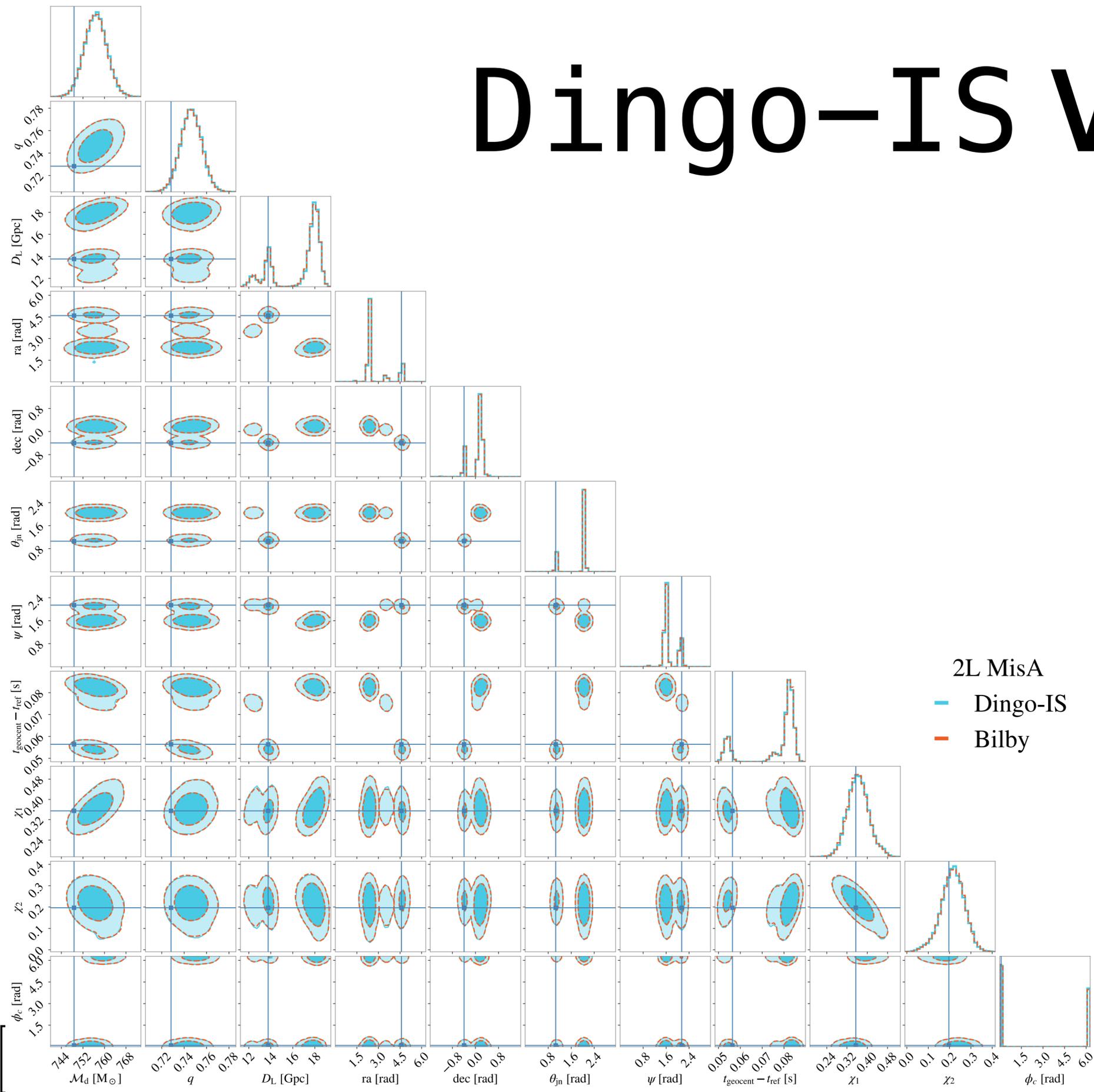
For 1L + CE, ~ 50% of sources with **one sky mode**

# Sky modes

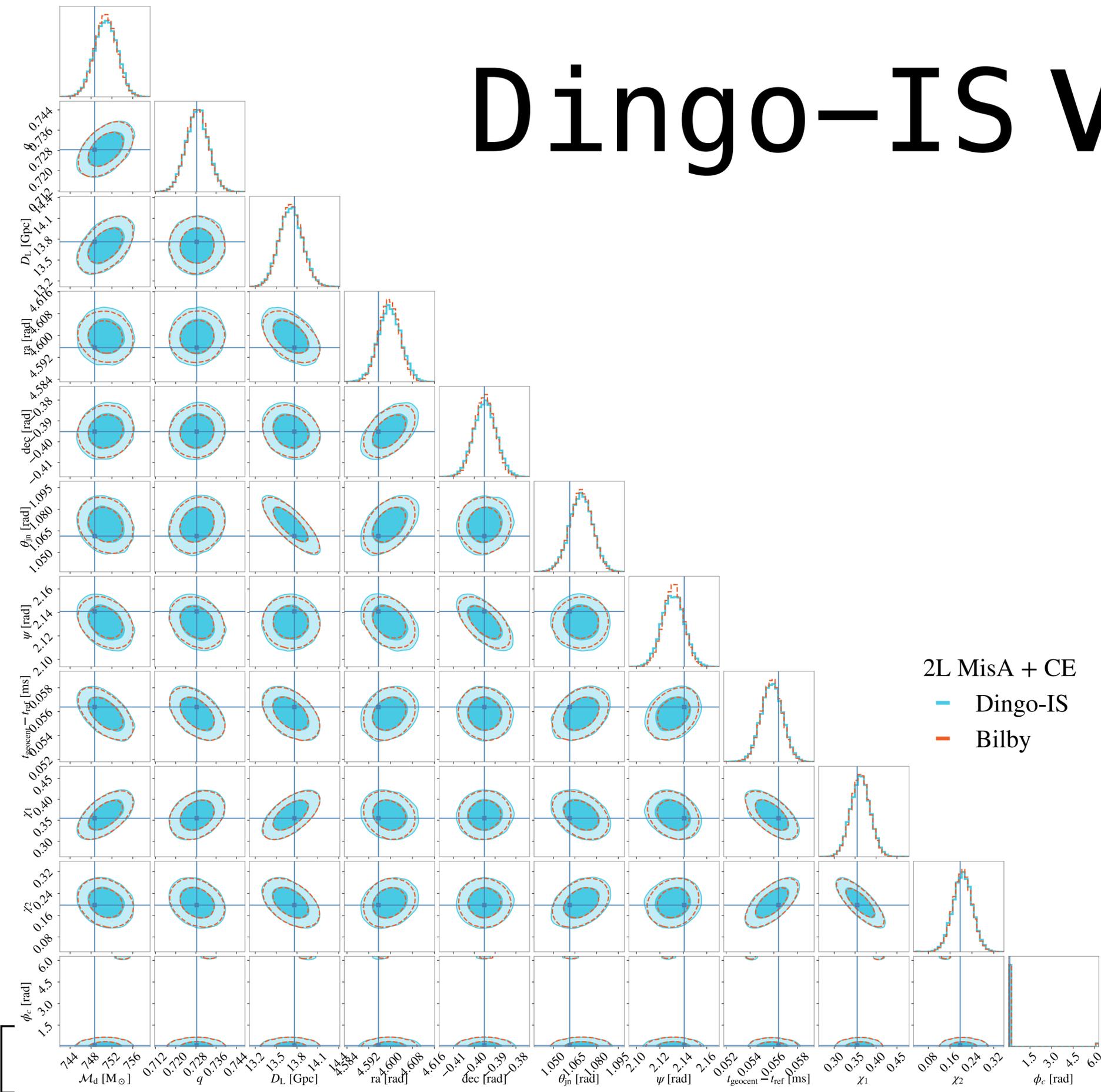
- ✗  $(\text{ra}^{\text{inj}}, \text{dec}^{\text{inj}})$
- 2L MisA,  $\mathcal{M}_d^{\text{inj}} = 145.3 M_{\odot}$ ,  $\Delta\Omega_{90\%} = 194 \text{ deg}^2$
- 2L MisA,  $\mathcal{M}_d^{\text{inj}} = 55.5 M_{\odot}$ ,  $\Delta\Omega_{90\%} = 3 \text{ deg}^2$
- $\Delta$ ,  $\mathcal{M}_d^{\text{inj}} = 55.5 M_{\odot}$ ,  $\Delta\Omega_{90\%} = 50 \text{ deg}^2$



# Dingo-IS VS Bilby



# Dingo-IS VS Bilby



# Parameter estimation performance

