AI/ML for GW Data Analysis

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The Future of Gravitational-Wave Astronomy — ICTS
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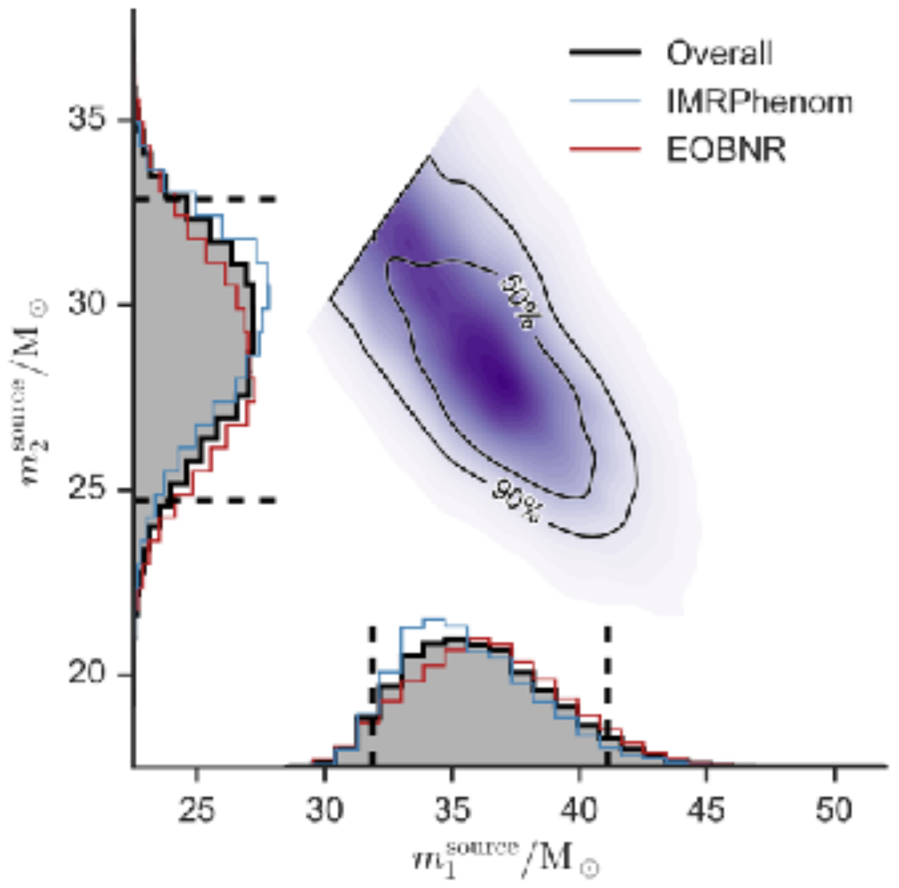
Outline

- Introduction to simulation-based inference
- Potential applications (solution to many problems of Teja)
- Example applications so far
- Conclusions

Challenges of likelihood-based inference

Expensive and imperfect

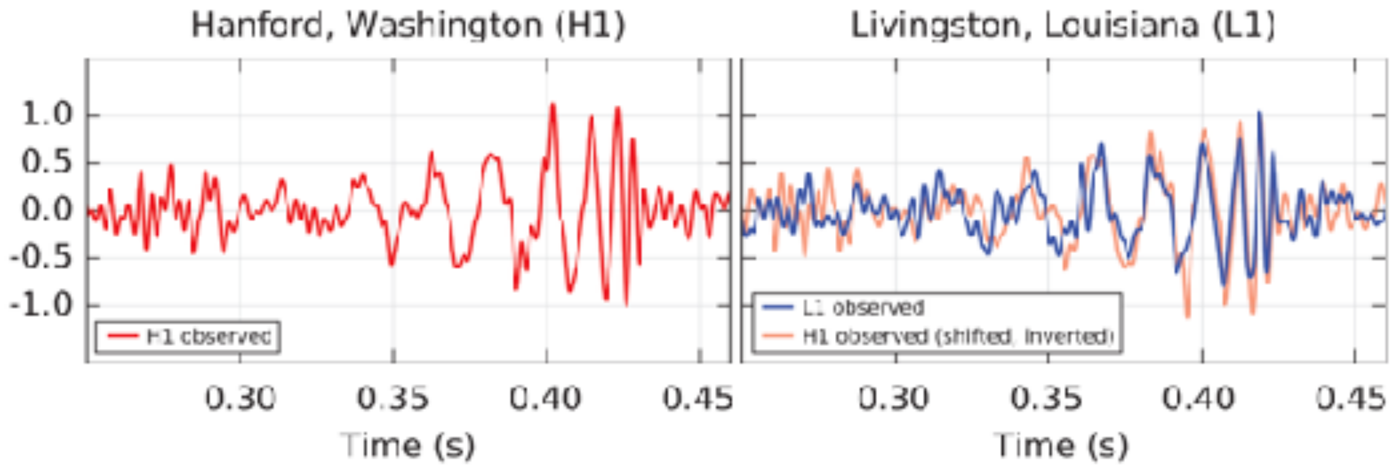
- Bayesian parameter estimation requires sampling the posterior:



parameters

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

data



Based on **evaluating the likelihood**, which can be

1. **Expensive**—costly waveform generation, high data dimensionality.
2. **Approximate or intractable**—non-Gaussian noise, non-stationarity, data gaps.

→ **Hard to scale to future detectors.**

Simulation-based inference

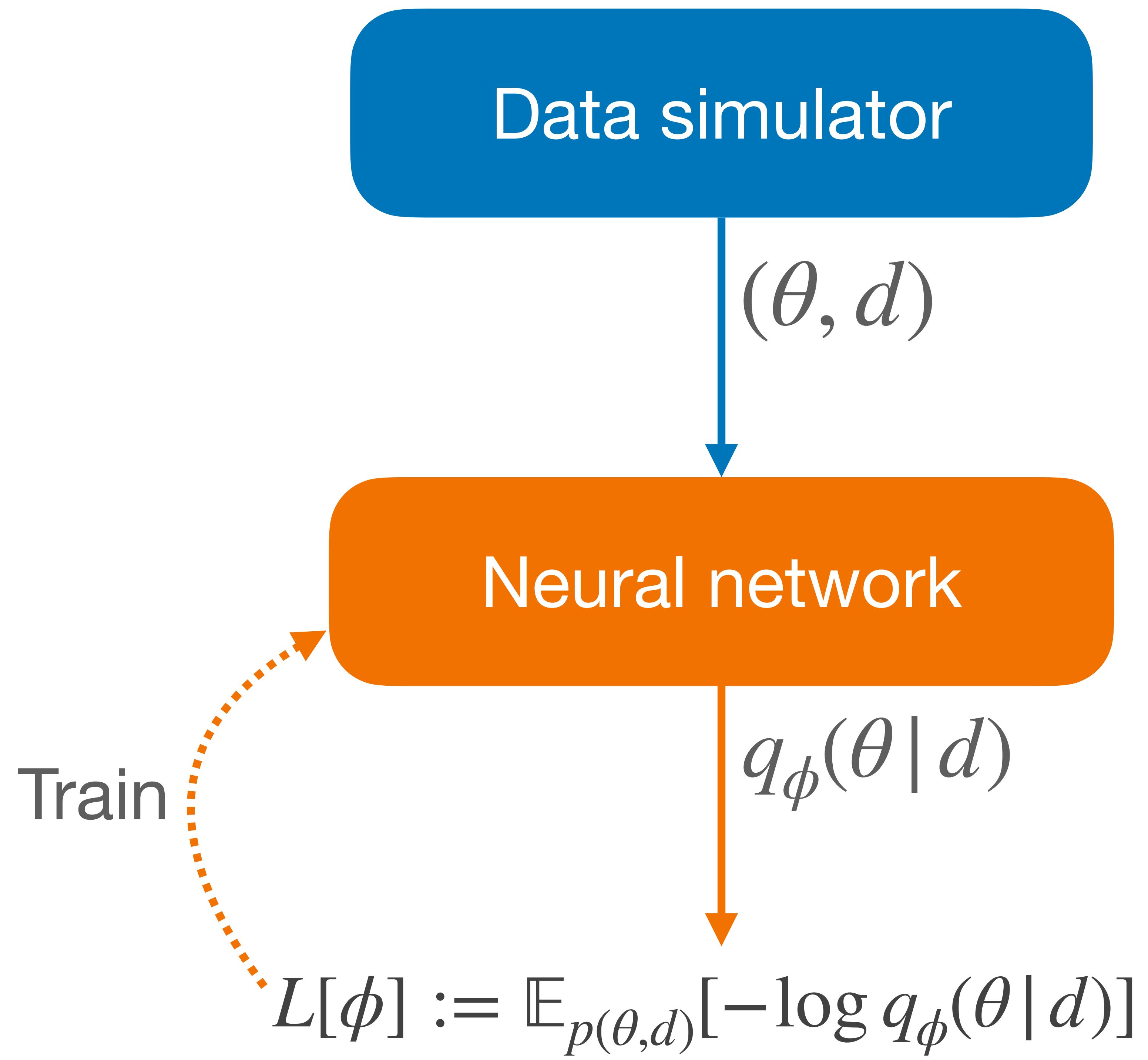
Core idea

- Replace likelihood evaluation with simulation:
  Generate synthetic data $d \sim p(d\,|\,\theta)$.

- Use these simulations to train neural networks to infer parameters:
  Learn the posterior,

$$q_\phi(\theta\,|\,d) \approx p(\theta\,|\,d)$$

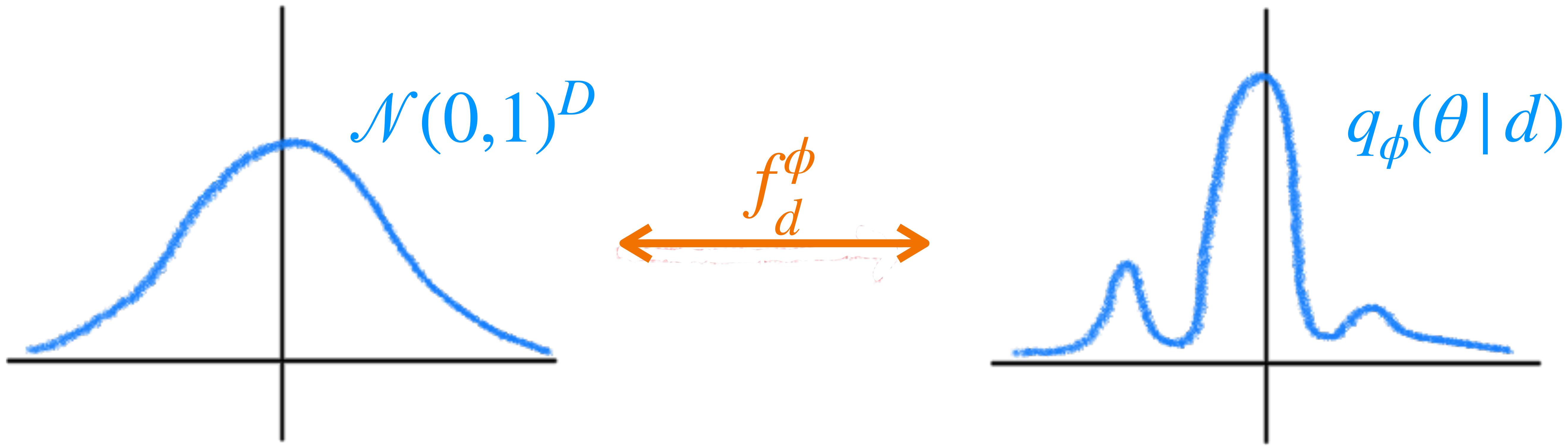
(No need to know the likelihood explicitly — works even when $p(d\,|\,\theta)$ intractable.)



Simulation-based inference

Neural posterior estimation with flexible density estimators

- For SBI, it is common to use a normalizing flow. Represents a complex distribution q using an invertible mapping $f_d^\phi : u \mapsto \theta$ from a simpler distribution:



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

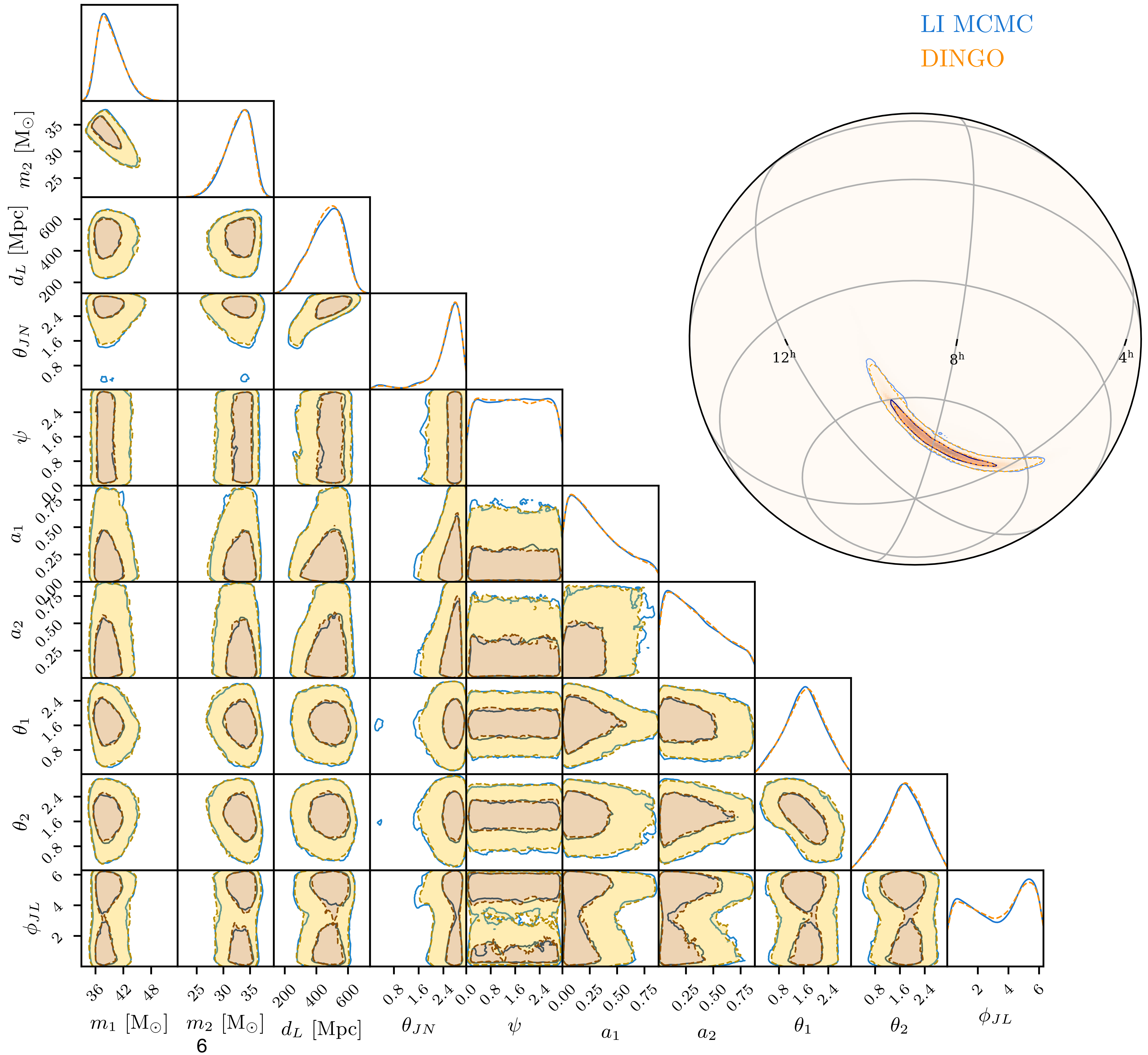
- f_d^ϕ parametrized using neural networks
- Alternatives (more powerful): diffusion models, flow matching

LVK BBHs

GW150914

- $\theta \sim p(\theta)$
  $d = h(\theta) + n, \quad n \sim p_{S_\mathrm{n}}(n)$
- Train on ~10^7 simulations for ~ 1 week.
- Inference in seconds to minutes.
- Model can also handle varying PSDs,

$$q_\phi(\theta \mid d, S_\mathrm{n})$$

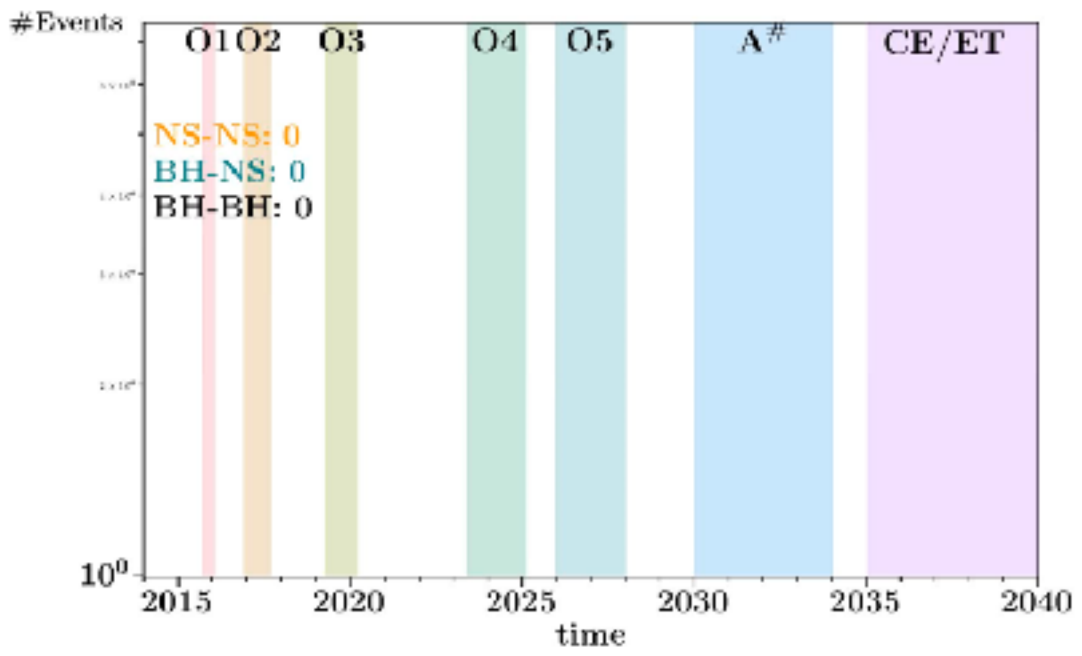


Dax, SRG+ (PRL 2021)

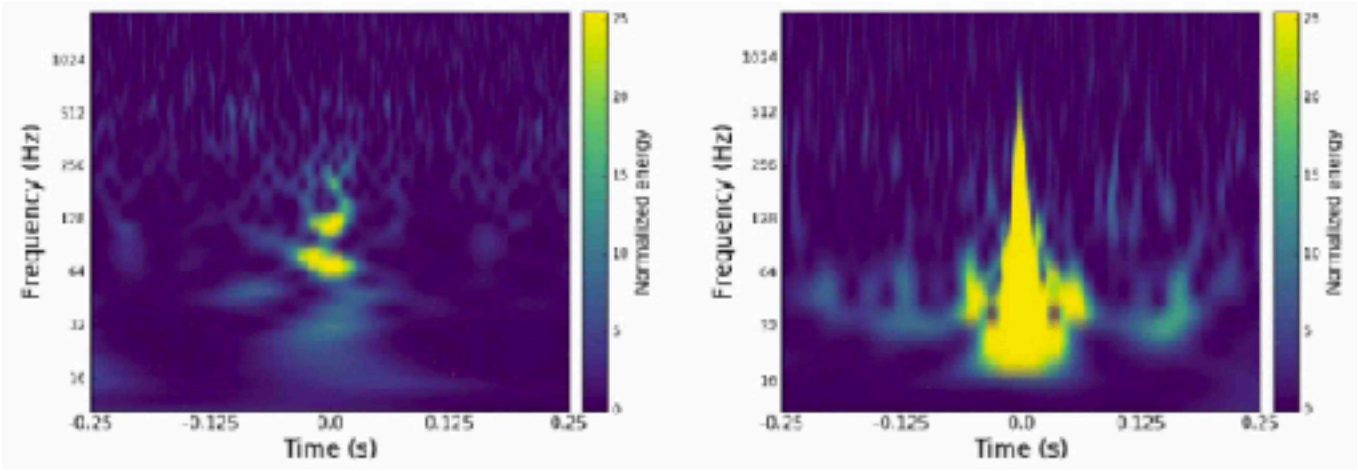
The Future of Gravitational-Wave Astronomy

Opportunities with SBI

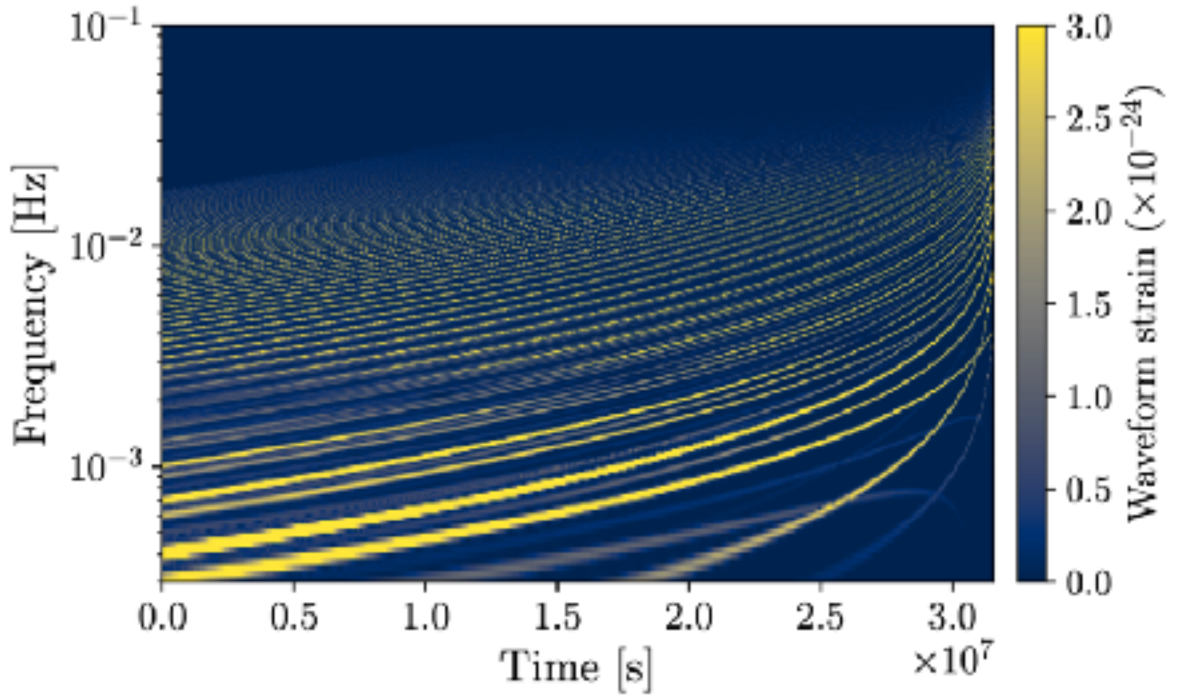
- **Speed:** Handle huge event rates; real-time alerts; many analyses



- **Noise:** Treat non-Gaussian artifacts and non-stationarities



- **Flexibility:**



  Time or time-frequency domain

  Gaps in data

  Marginalize nuisance signals (Enrico's talk)

  Multi-band or multi-messenger inference

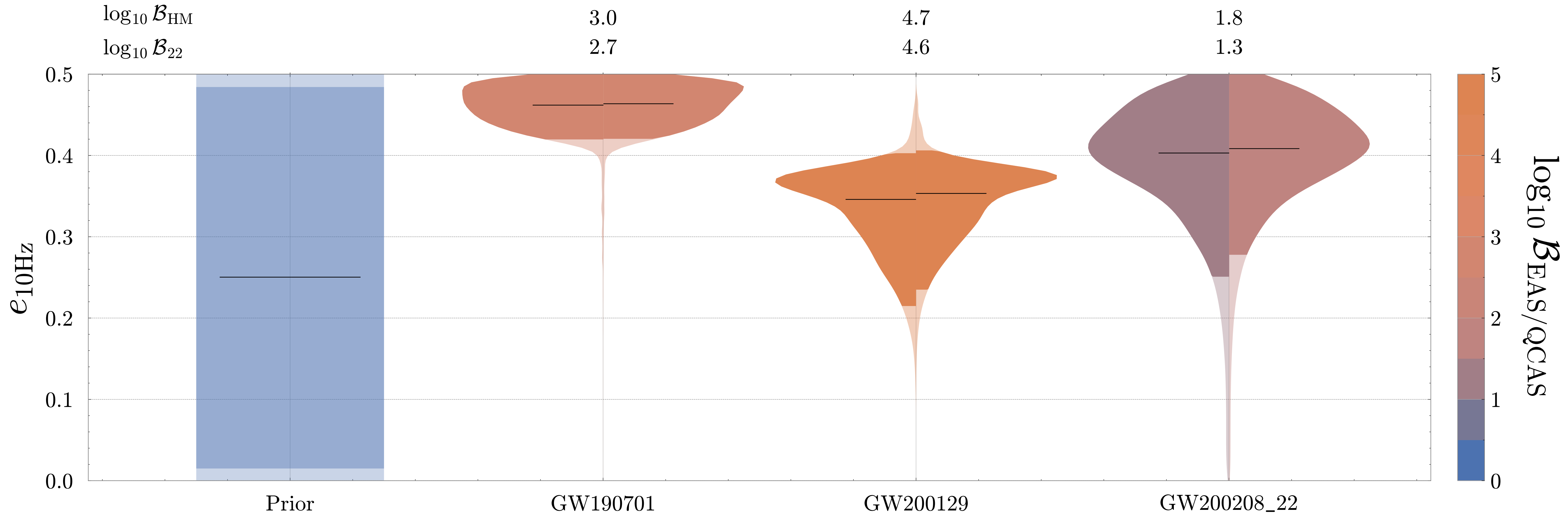
  Condition on external data

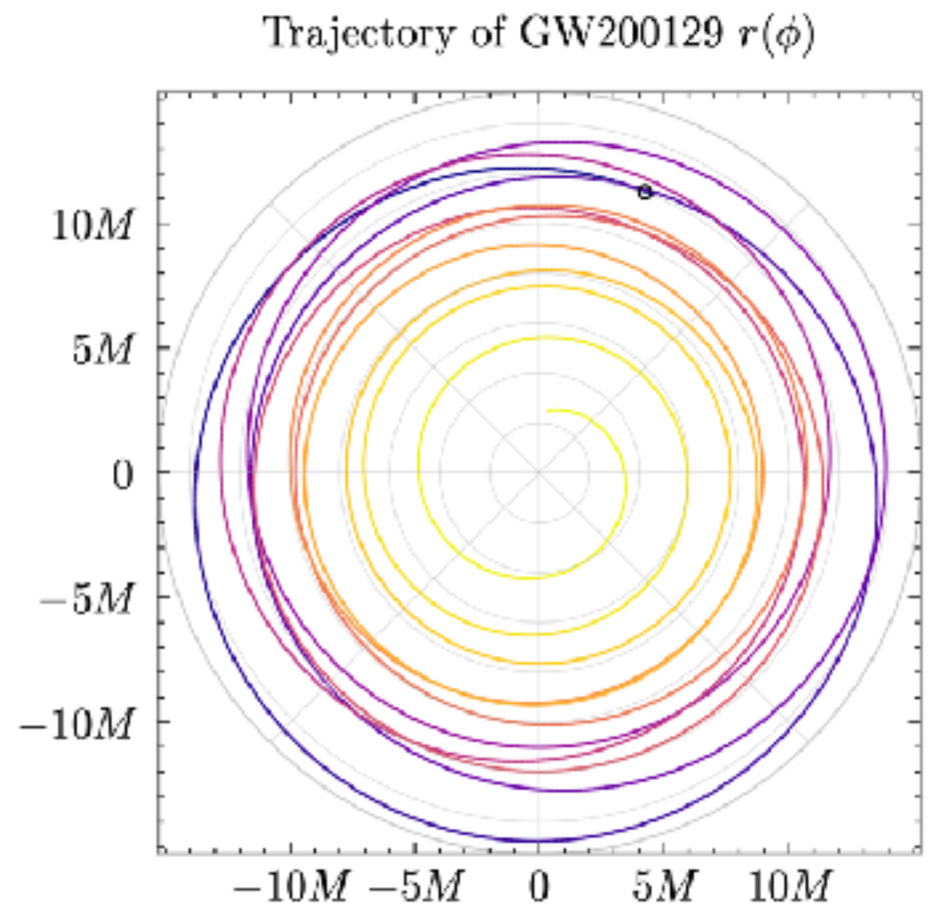
Example applications

Eccentric binary inference

Fast inference enables more analyses

- Eccentricity analyses with SEOBNRv4EHM are generally very expensive:
    - Nested sampling, ~2 weeks on 320 cores
    - Dingo, ~1 hour each including importance sampling
- Analyzed 57 events from GWTC-3 and obtained evidence for eccentricity in three.

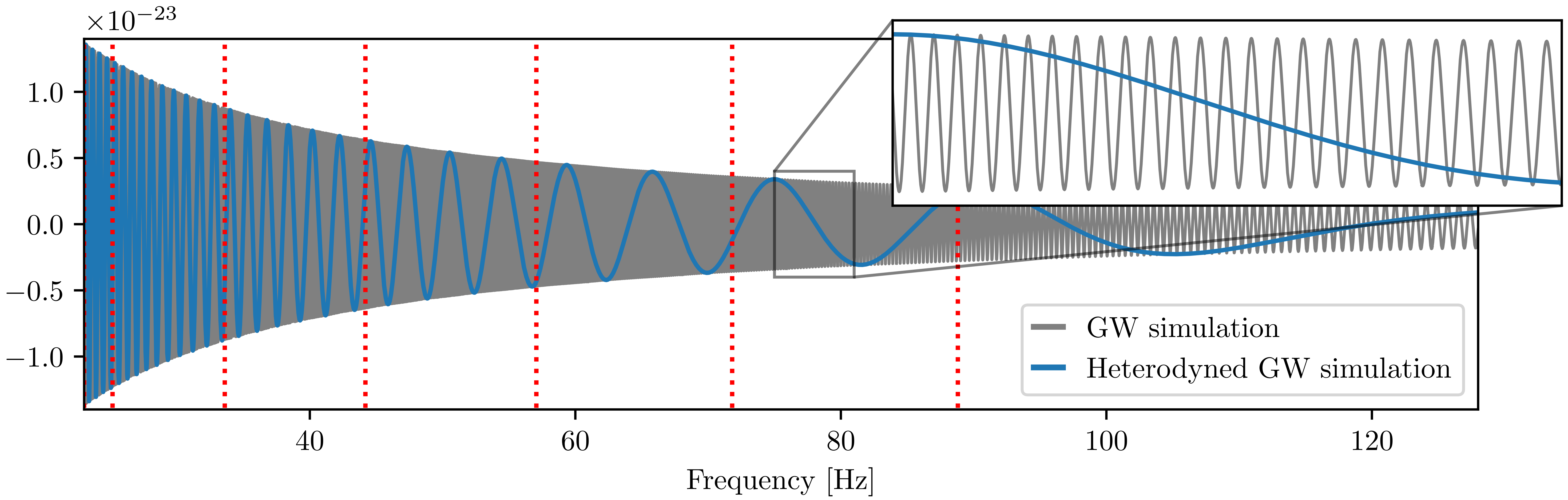


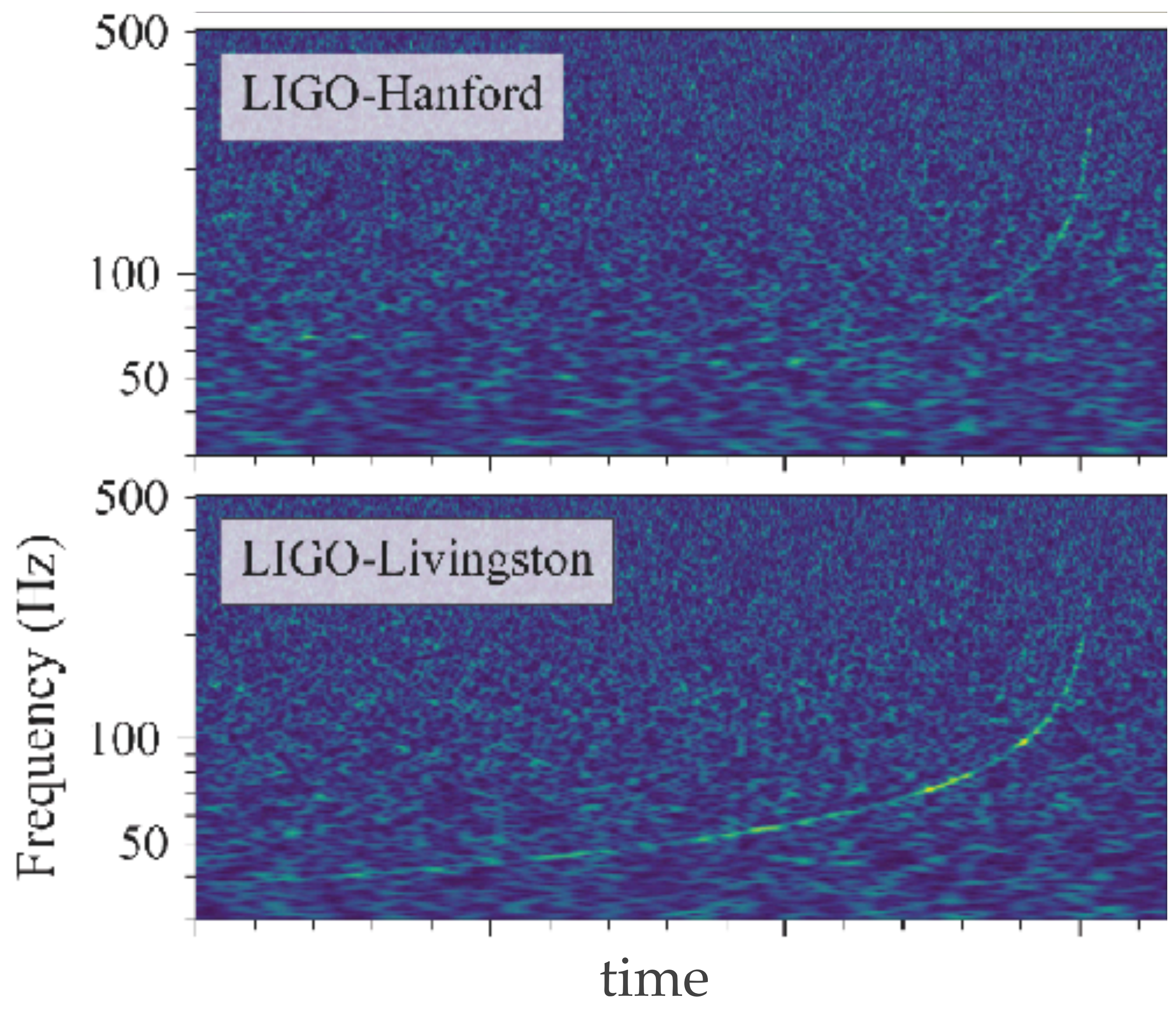


Binary neutron stars

Fast multi-messenger alerts

- Train prior-conditioned networks $q_\phi(\theta \,|\, d, \tilde{M}_{\text{chirp}})$, where the data d are simplified using heterodyning (with respect to $\tilde{M}_{\text{chirp}}$).
- Simplified data representation enables effective training.

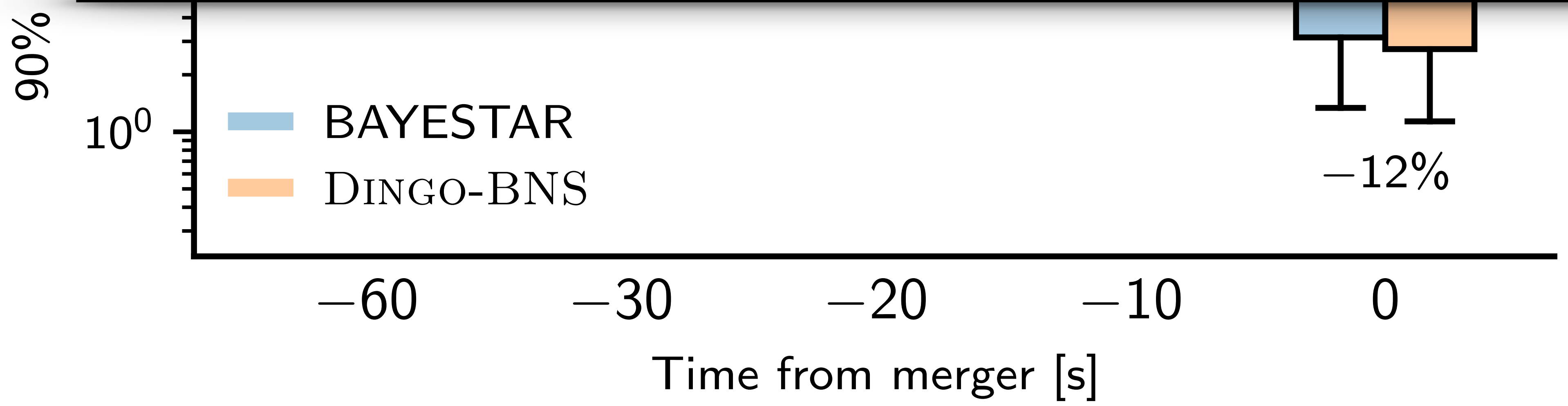


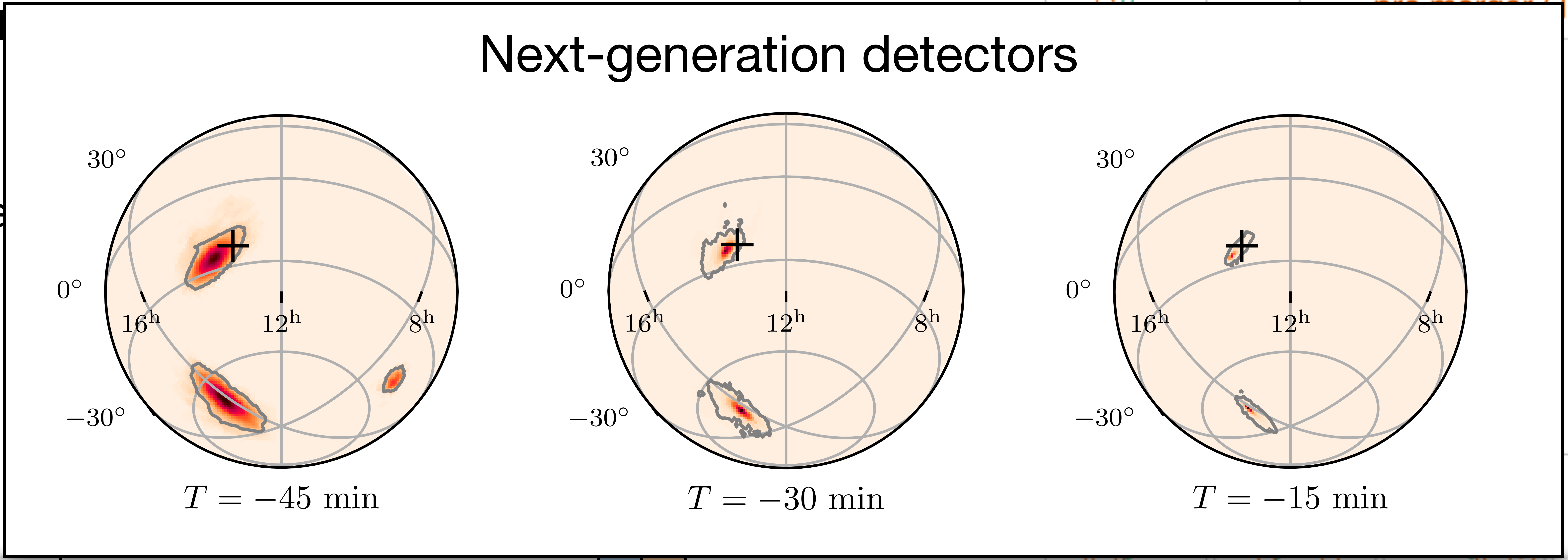


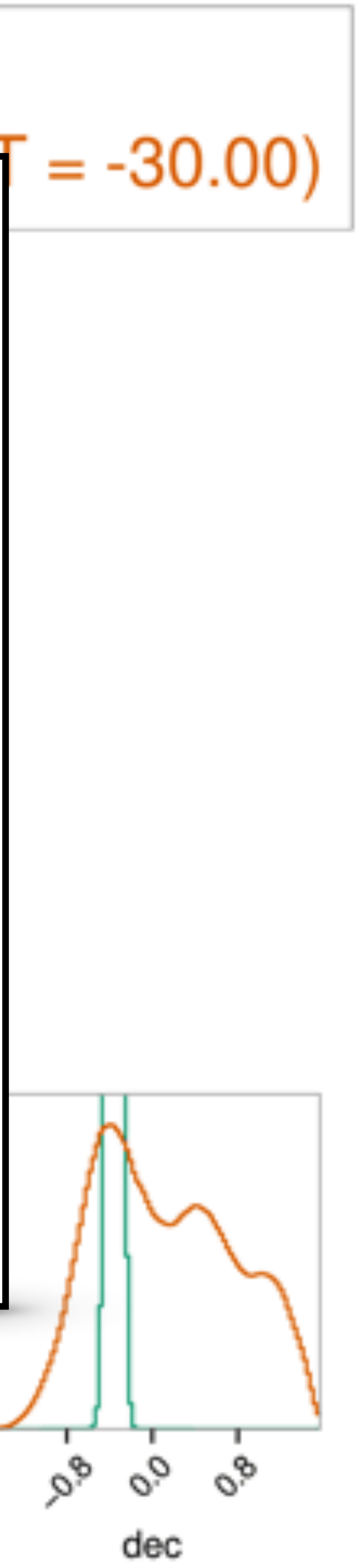
Binary neutron stars

Pre-merger inference

- Full dat
- No spe



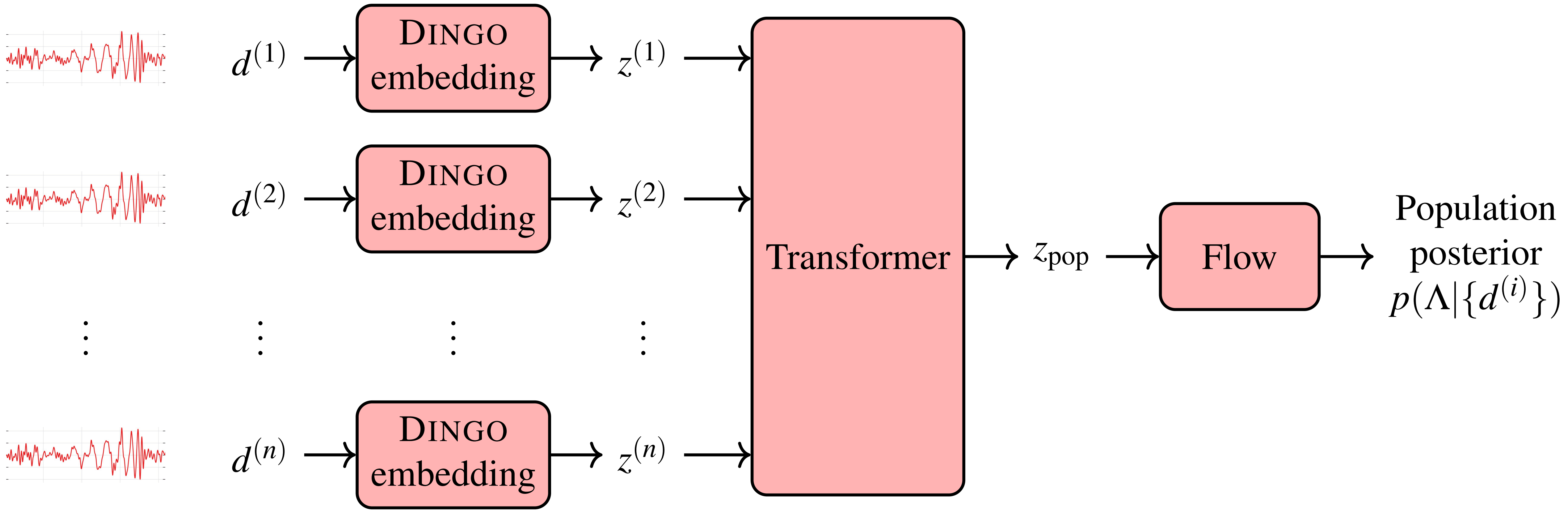


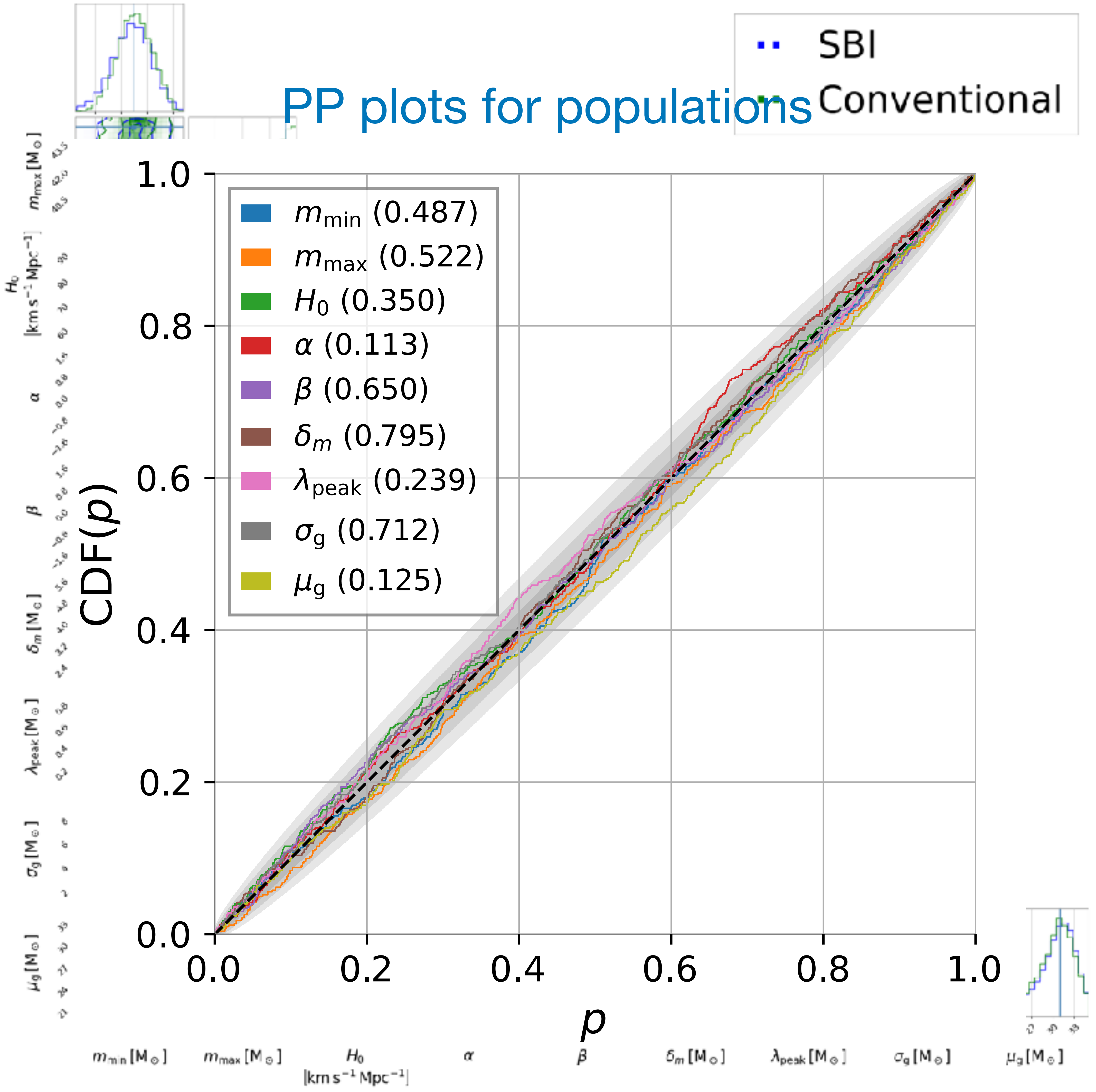


Population inference

Neural hierarchical posteriors

- Compare astrophysical simulations directly to data, including selection effects.





Conclusions

Simulation-based inference enables fast, accurate, and flexible inference

- **Prospects include**
  - Extensions to future detectors (time-frequency analyses, multiple events, huge event rates)
  - Realistic noise (non-stationary noise, non-Gaussian artifacts, gaps in data)
  - Population inference
- **Key challenges**
  - Amount of training data needed
  - How to deal with systematics
  - Scalability of training and network reusability across applications

Thank you!