DINGO: Neural Posterior Estimation for Gravitational Waves

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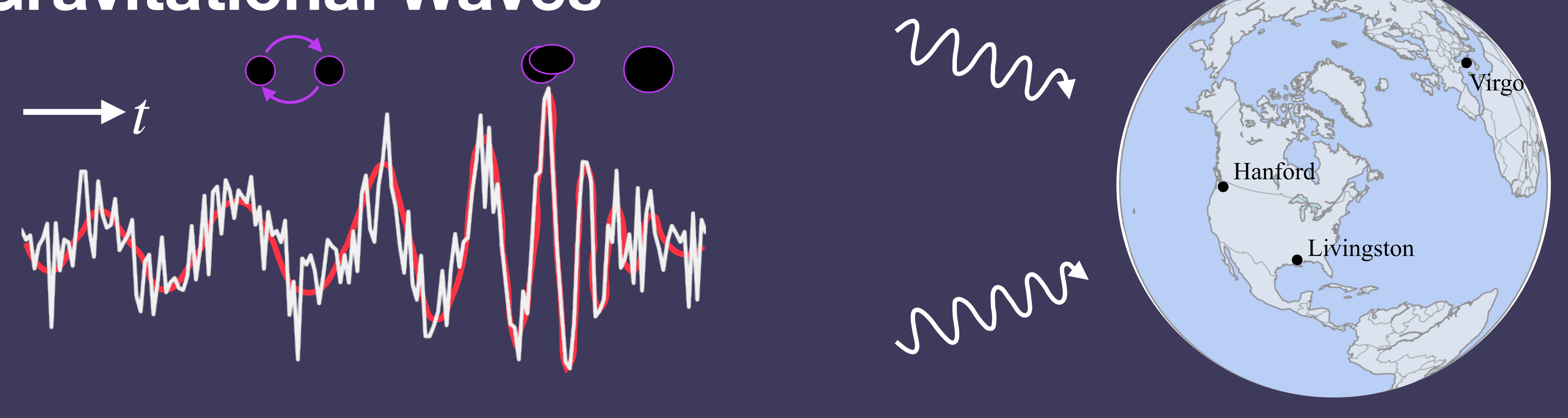
Gravitational Waves



Goal: Analyze signals → posterior distribution of black hole mergers

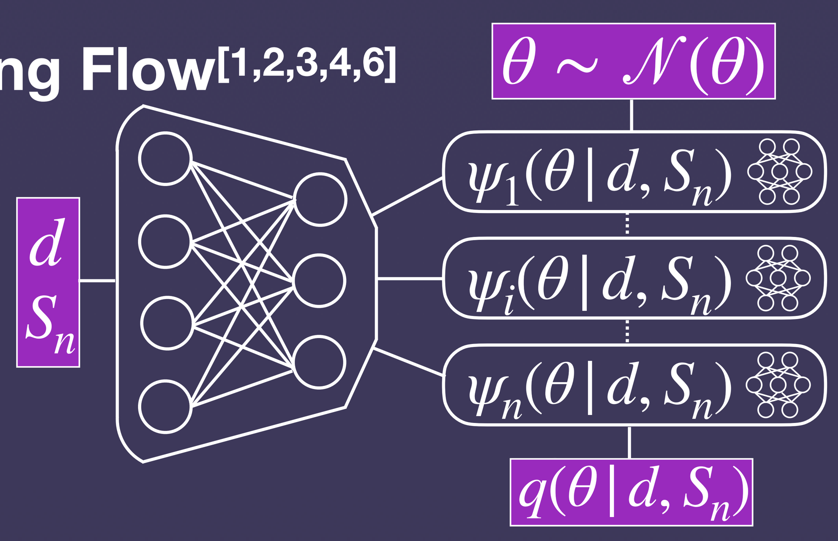
Problem: Standard Bayesian methods ~ hours to weeks for one event
In the future: more signals to analyze

Solution: Use NPE to rapidly obtain posteriors

DINGO (Deep INference for Gravitational wave Observations)

Conditional Normalizing Flow[1,2,3,4,6]

Signal $d(f)$
Noise PSD $S_n(f)$



~ 10^7 training examples
~ 10^8 network parameters

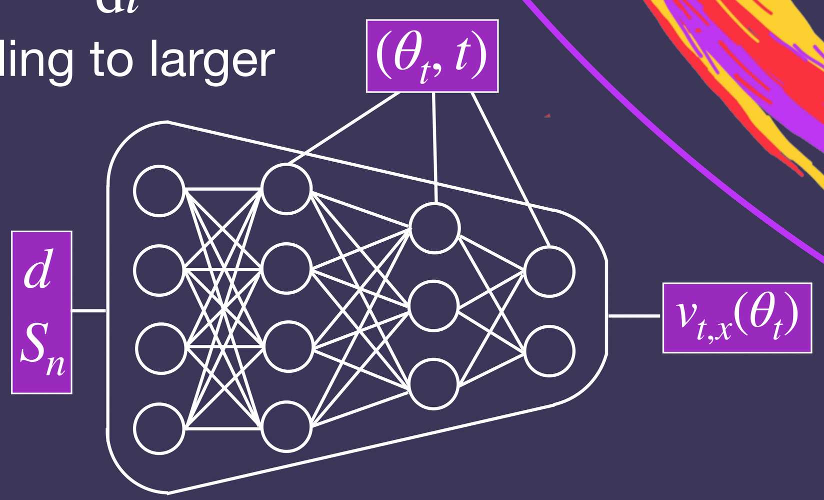
Training: ~ few days
Evaluation: ~ few minutes

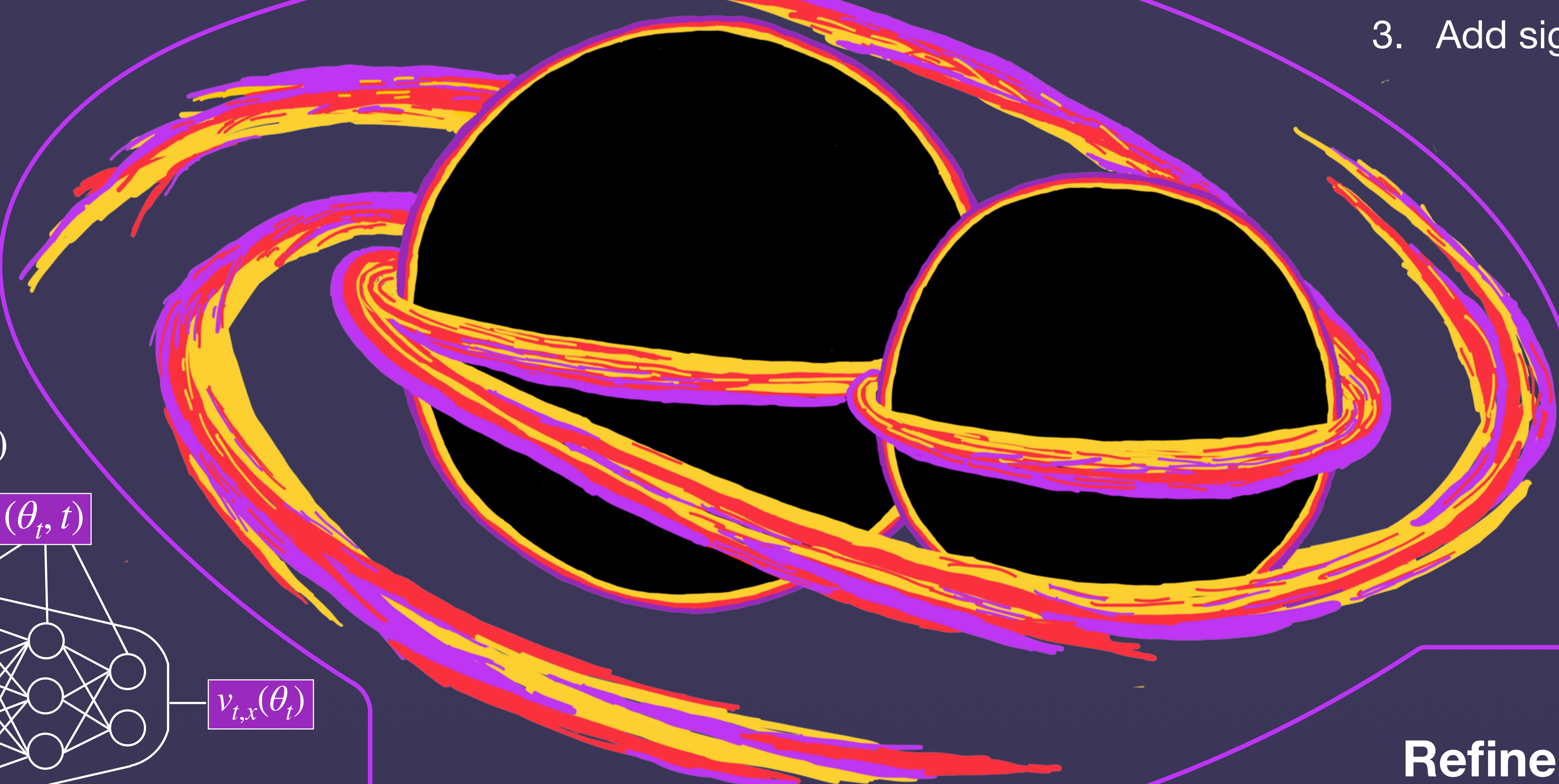
Alternative: Flow Matching[5]

Learn vector field:

$$\frac{d\theta_t}{dt} = v_{t,x}(\theta_t)$$

→ better scaling to larger architectures





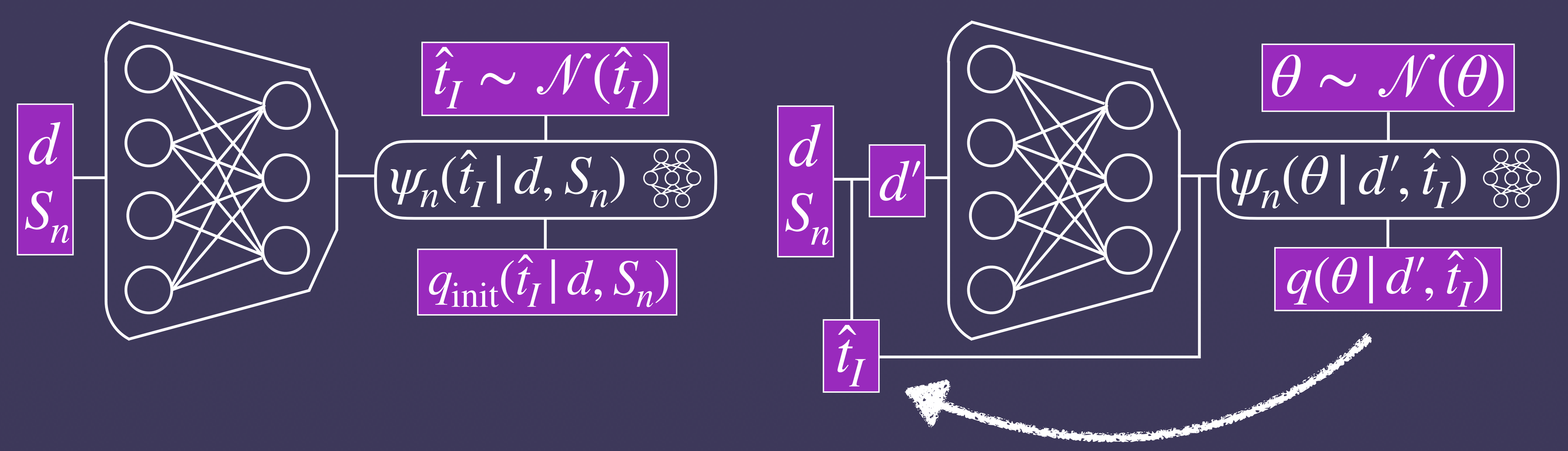
Challenges

Time-Shifts between Detectors[1,2]

- Large impact of time-shift on frequency-domain signal: $d \cdot e^{2\pi i f \delta t}$
- Difficult to learn just from data

→ Include equivariances by using Group-Equivariant NPE (GNPE)

- Idea: standardize data around time $t_I = 0, I \in \{L, V, K\}$

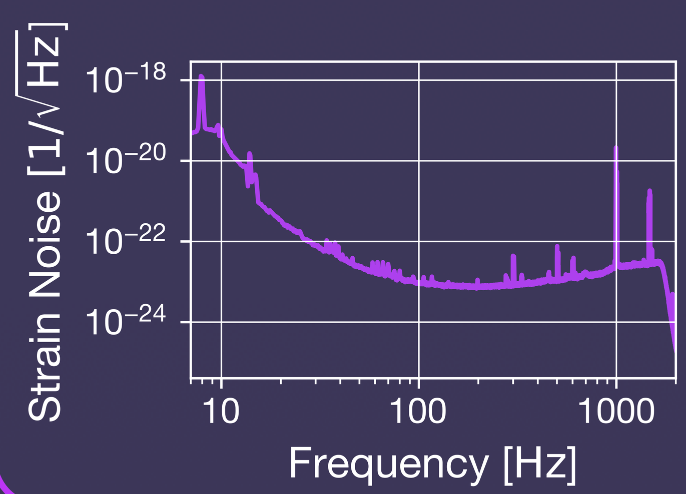


Shifts in the Detector Noise

Detector noise varies from event to event

→ Augment training data to include collection of PSDs $\{S_n^{(i)}(f)\}$

1. Sample $S_n^{(i)}(f) \sim p(S_n)$
2. Generate noise $n^{(i)} \sim \mathcal{N}(0, S_n^{(i)})$
3. Add signal $d^{(i)} = h(\theta^{(i)}) + n^{(i)}$



Validation and Refinement with NPE-IS[3]

- Compare learned NPE density and likelihood

$$w_i \propto \frac{p(d\,|\,\theta_i)p(\theta_i)}{q(\theta_i\,|\,d)}$$

Likelihood · Prior
Proposal (NPE)

- Evaluation measure: Effective Sample Size

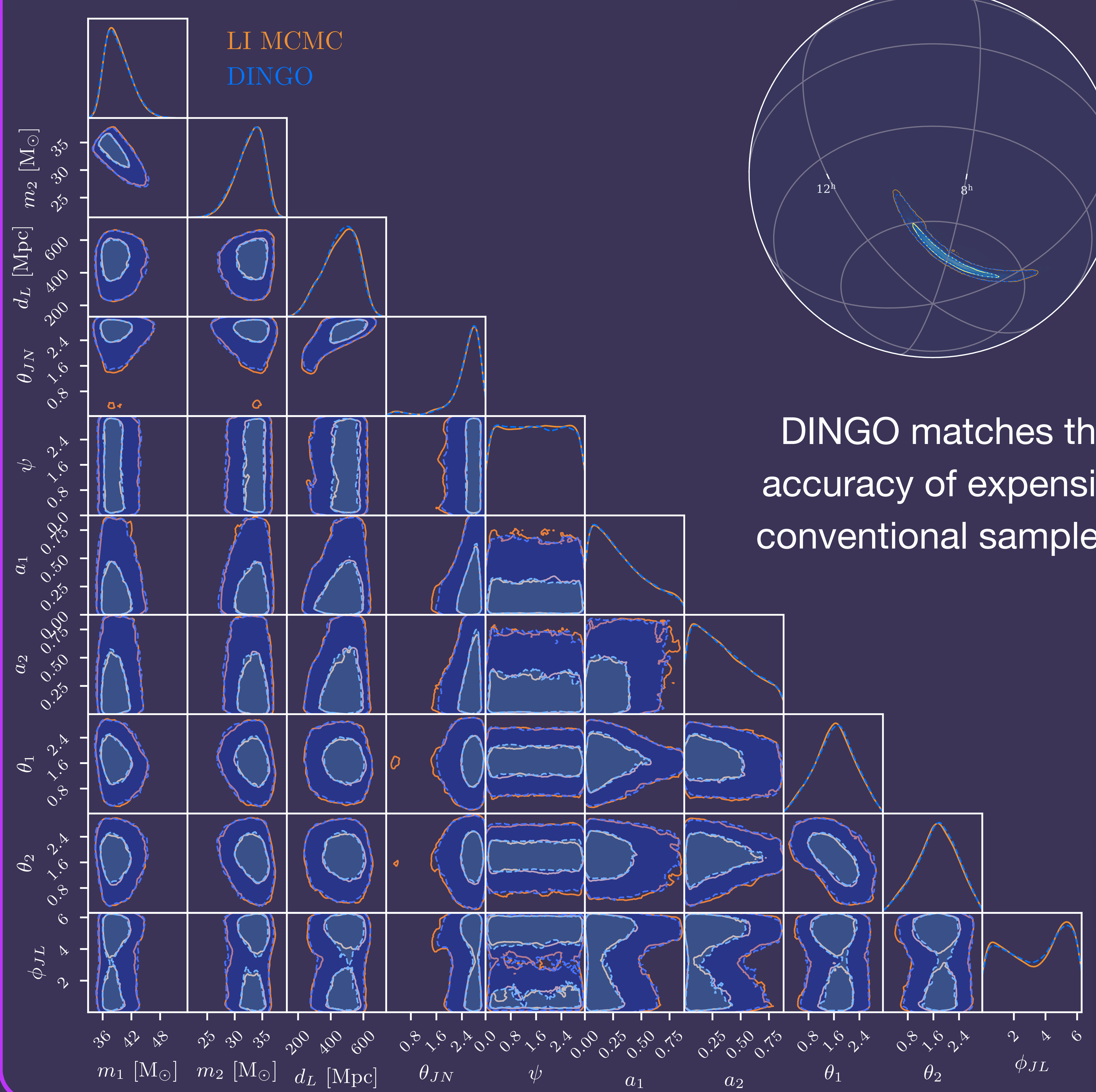
$$n_{\text{eff}} = \frac{\left(\sum_i w_i\right)^2}{\sum_i w_i^2}$$

- Estimate evidence:

$$p(d) \approx \frac{1}{N}\sum_{i=1}^{N} w_i$$

→ Efficient model comparison via Bayes factor
→ Enables large scale studies

Results for GW150914[1]



DINGO matches the accuracy of expensive conventional samplers.

New Physics Results[5]

- DINGO allows for joint analysis of large number of events
  → Study populations, e.g. eccentricity[6]
- Code reviewed for analysis of events in Ligo-Virgo-KAGRA Collaboration

References

[1] Dax+, Real-Time GW Science with NPE, PRL 2021
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[4] Wildberger+, Adapting to Noise Distribution Shifts in GW Inference, PRD 2023
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[6] Gupte+, Evidence for Eccentricity in the Population of BBH observed by LVK, arXiv 2024