Scalable Bayesian Inference with Hardware Accelerators and Normalizing Flows

Thibeau Wouters

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Nikhef

Contents

Parameter estimation

Estimate parameters θ of a model for data d with Bayesian inference:

$$p(\theta|d) \propto p(d|\theta)p(\theta)$$

$$\text{posterior} \propto \text{likelihood} \times \text{prior}$$

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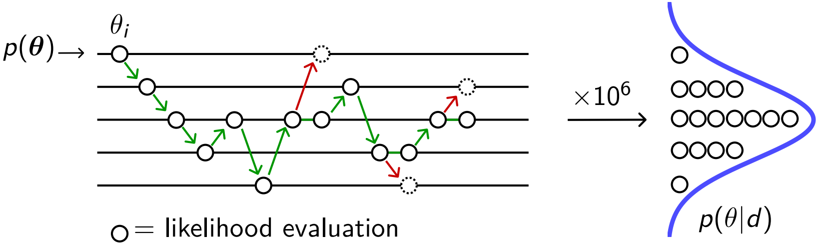
$$\text{posterior} \propto \text{likelihood} \times \text{prior}$$

- Sample the posterior: MCMC or nested sampling
- Propose samples, accept/reject based on likelihood
- $\mathcal{O}(10^6)$ likelihood evaluations: computational bottleneck



Future gravitational wave detectors

Future GW detectors: $10\times$ more sensitive

- $\mathcal{O}(10^5)$ events/year (now: $\mathcal{O}(10^2)$ events/decade)
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Goal: Fast sampling with minimal pretraining: flexible alternative to simulation-based inference [2–6]

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JAX & FLOWMC (Kaze Wong)

Accelerate Python with JAX:

- GPUs
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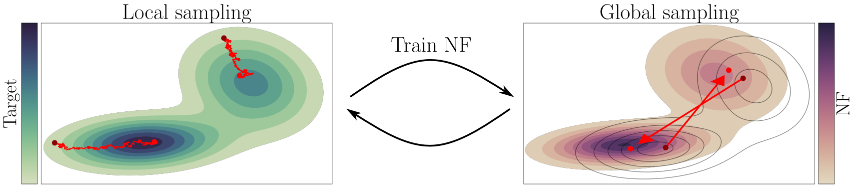

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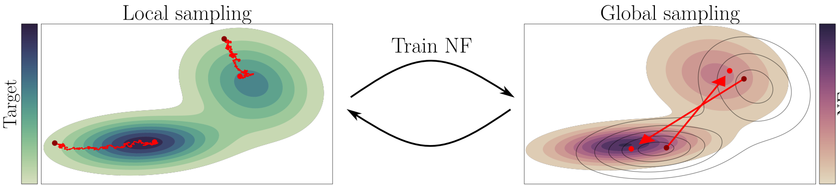
- Also see NESSAI [9, 10], POCOMC [11]



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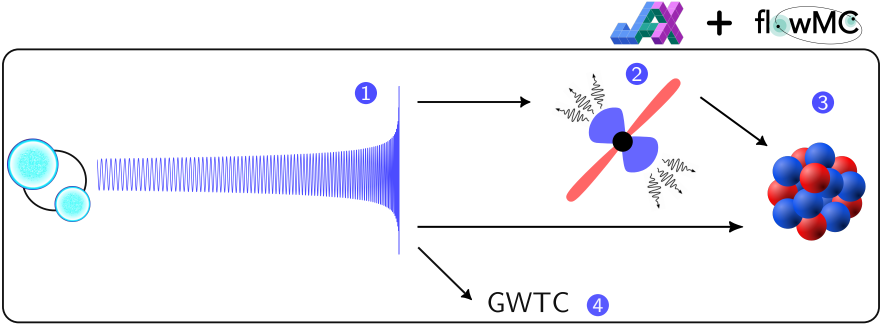
Overview

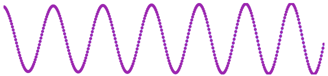
Analyzing a multi-messenger **binary neutron star** signal:

1. **Gravitational waves**
2. Electromagnetic counterparts
3. Nuclear equation of state
4. Gravitational wave transient catalogue



Gravitational waves

- Waveforms on GPU: $\mathcal{O}(10^3)$ faster
- From LALSUITE to JAX: RIPPLE [12]
  - Also see SFTS [13]



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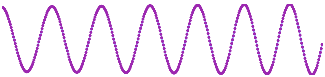

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- ✓ Current detectors
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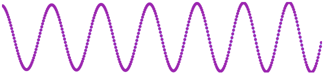
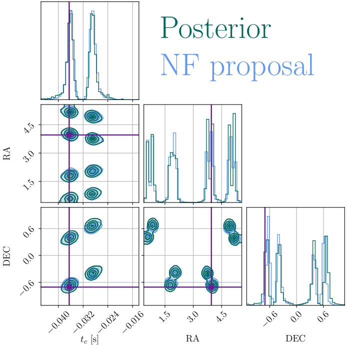


- Parameter estimation: JIM [14, 15]
- ✓ Current detectors
  - Hours → minutes
- Ongoing work for future detectors:
  - Binary neutron star: 13D
  - Einstein Telescope
  - 30 mins on H100 GPU



Overlapping signals (Luca Negri, Justin Janquart, James Alvey, Uddipta Bhardwaj)

- Assess scaling of JIM: BBH+BBH with LIGO-Virgo
  - 2 binary black hole mergers: 22 parameters
  - $M_c^{(1)} = 32M_\odot$, $M_c^{(2)} = 33M_\odot$, $\Delta t = 70$ ms
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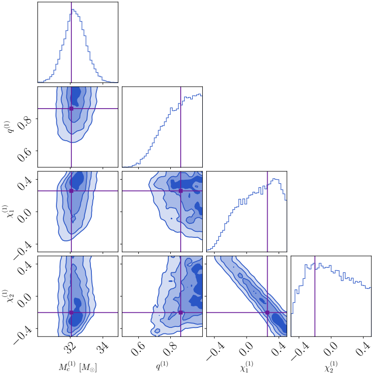
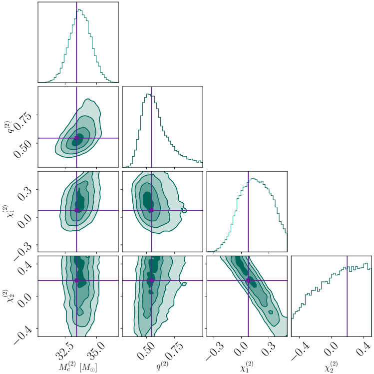
  - 1h28m on H100 (vs 23 days on 16 CPUs [16])





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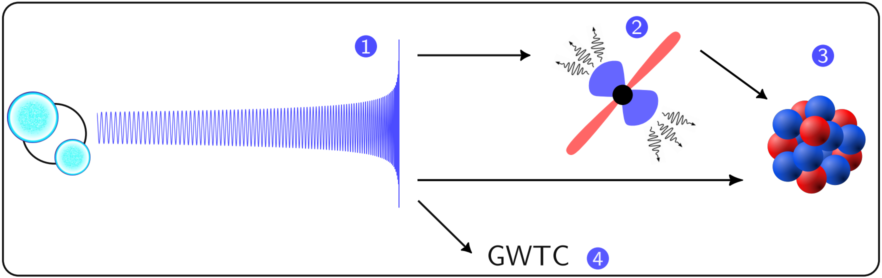
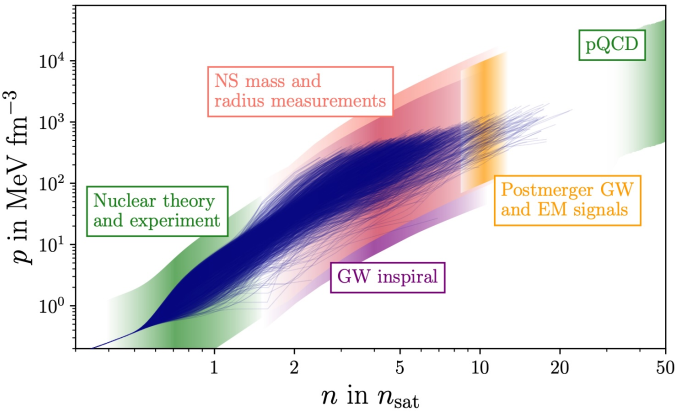


The nuclear equation of state

- The equation of state of dense nuclear matter is uncertain [17]
- Neutron stars probe its high density regime
- Solve inverse problem with Bayesian inference



Equation of state

- Parametrization θ_{EOS}: constrain with Bayesian inference

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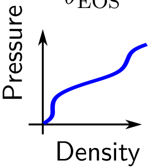
- To predict neutron star properties, we solve the TOV equations: ordinary differential equations (ODEs)

θ_{EOS}



$\longrightarrow$

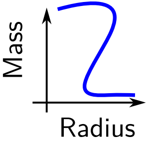
Solve TOV equations

$$\frac{\mathrm{d}p}{\mathrm{d}r} = -\frac{\varepsilon(r)m(r)}{r^2}\frac{\left[1+\frac{p(r)}{\varepsilon(r)}\right]\left[1+\frac{4\pi r^3 p(r)}{m(r)}\right]}{\left[1-\frac{2m(r)}{r}\right]}$$

$$\frac{\mathrm{d}m}{\mathrm{d}r} = 4\pi r^2 \varepsilon(r)\,,$$

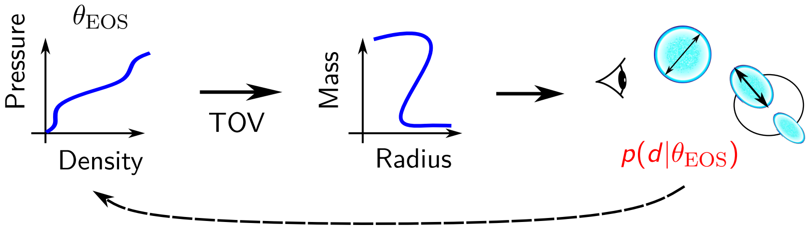
$\longrightarrow$

Neutron stars



Equation of state

- Parametrization θ_{EOS}: constrain with Bayesian inference
- To predict neutron star properties, we solve the TOV equations: ordinary differential equations (ODEs)
- Done for each sample θ_{EOS}: costly likelihood



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- Solving TOV equations (EOS $\rightarrow$ NS) is slow

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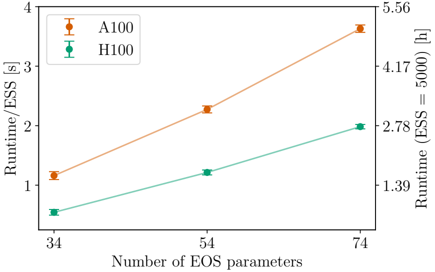
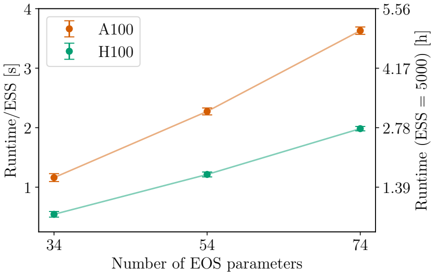
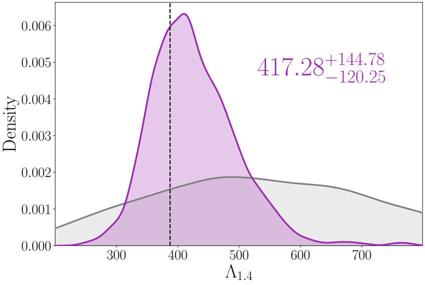
  - No need for ML emulators



JESTER (Peter T.H. Pang)

- Solving TOV equations (EOS $\rightarrow$ NS) is slow
- JESTER [18]: JAX-based TOV solver
  - Full inference in $\sim$hours
  - No need for ML emulators
- End-to-end analysis: from gravitational waves of neutron star mergers to the equation of state
  - Example: 20 BNS in O5





Auto-differentiable ODE solvers

- ODE solvers in JAX are auto-differentiable (DIFFRAX)
- Frame inference as optimization problem:
  - Gradient descent on loss function $\mathcal{L}(\theta_{\rm EOS})$

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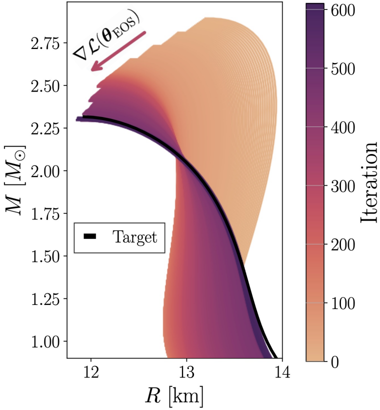
- Frame inference as optimization problem:
  - Gradient descent on loss function $\mathcal{L}(\theta_{\mathrm{EOS}})$

$$\mathcal{L}(\boldsymbol{\theta}_{\mathrm{EOS}}) = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{R_i(\boldsymbol{\theta}_{\mathrm{EOS}}) - \hat{R}_i}{\hat{R}_i}\right|$$



Contents

Conclusion

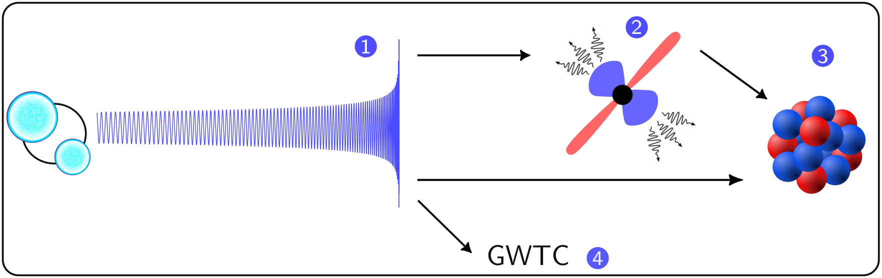
- Progress on scalable Bayesian inference, with minimal pre-training
- Hybrid acceleration: GPUs + normalizing flow proposals
  - JAX/GPU: faster likelihoods
  - flowMC: sampling converges faster
- Simulators in JAX can remove the need for emulators (GW, TOV)
- Auto-differentiable ODE solvers: inference as optimization problem

Let's talk!

Thank you for your attention!

Software written in JAX:

- FLOWMC [7, 8]
- JIM [14, 15] 1 2 4
- FIESTA 2
- JESTER [18] (built with DIFFRAX) 3
- HARMONIC [19–21]



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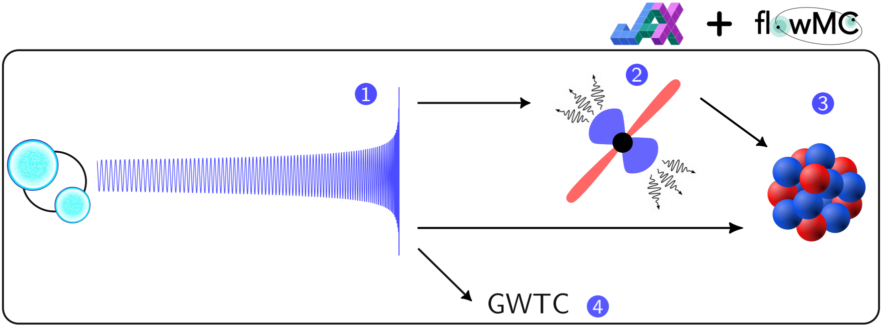

Electromagnetic counterparts (Hauke Koehn, Tim Dietrich)

- BNS mergers lead to kilonovae, gamma-ray bursts (afterglows)
- Numerical models are expensive (e.g. AFTERGLOWPY [24])

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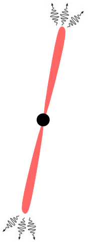
- Numerical models are expensive (e.g. AFTERGLOWPY [24])
- Neural network emulators for inference: FIESTA

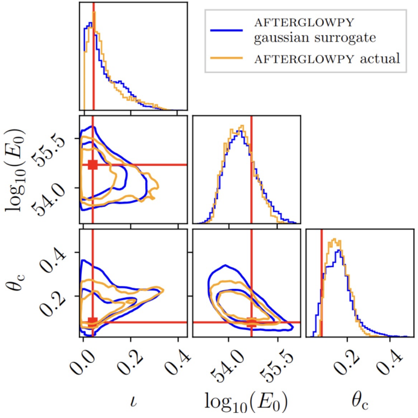


FIESTA

- 1m36s
- 1 H100 GPU

AFTERGLOWPY

- 4 hours
- 30 CPUs



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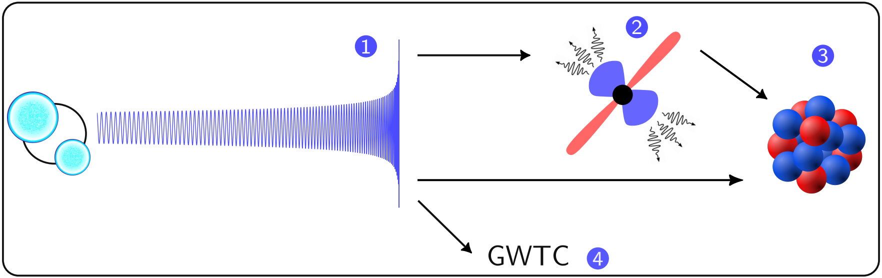
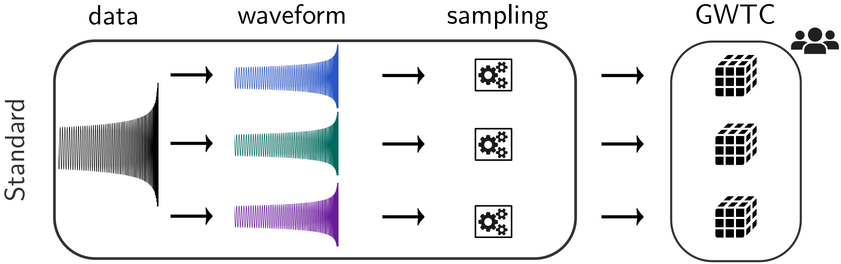


Constructing GWTCs (Thomas Ng, Kaze Wong)

GWTCs do not scale well in memory:

- GWTC stores several samples (different waveforms)
- Standard: fixed sample size, $\sim$ 100 MB



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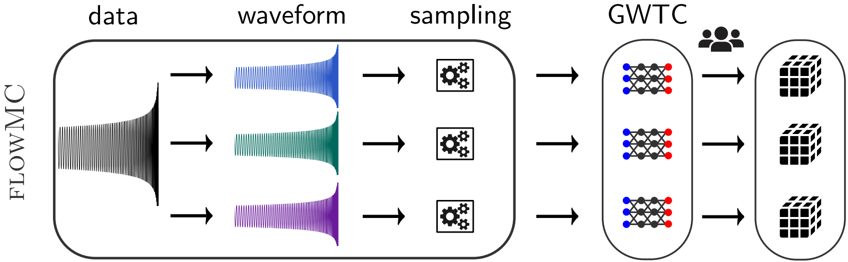
- FLOWMC: generate samples from normalizing flows, $\sim$ 10 MB
  - Also see Michael Williams' talk/poster



Evidence calculation: HARMONIC I

Evidence Z can be computed from posterior samples with HARMONIC [19] with the harmonic mean estimator

$$\rho \equiv \mathbb{E}_{P(\theta|d)}\left[\frac{1}{L(\theta)}\right] = \int \mathrm{d}\theta \frac{1}{\mathcal{L}(\theta)} P(\theta|d) = \int \mathrm{d}\theta \frac{1}{\mathcal{L}(\theta)} \frac{\mathcal{L}(\theta)\pi(\theta)}{Z} = \frac{1}{Z}$$

Therefore, estimate ρ with posterior samples:

$$\hat{\rho} = \frac{1}{N}\sum_{i=1}^{N} \frac{1}{\mathcal{L}(\theta)}, \quad \theta_i \sim P(\theta|d)$$

Evidence calculation: HARMONIC II

Can be interpreted as importance sampling

$$\rho = \int \mathrm{d}\theta \frac{1}{Z} \frac{\pi(\theta)}{P(\theta|d)} P(\theta|d) \,,$$

but with target = prior and sampling density = posterior. Therefore, importance sampling is inefficient – how to solve?
New proposal:

$$\begin{aligned}\rho &= \mathbb{E}_{P(\theta|d)} \left[\frac{\varphi(\theta)}{\mathcal{L}(\theta)\pi(\theta)} \right] \\ &= \int \mathrm{d}\theta \, \frac{\varphi(\theta)}{\mathcal{L}(\theta)\pi(\theta)} \, P(\theta|d) \\ &= \int \mathrm{d}\theta \, \frac{\varphi(\theta)}{\mathcal{L}(\theta)\pi(\theta)} \, \frac{\mathcal{L}(\theta)\pi(\theta)}{Z} = \frac{1}{Z}\end{aligned}$$

Evidence calculation: HARMONIC III

Use the following estimator:

$$\hat{\rho} = \frac{1}{N} \sum_{i=1}^{N} \frac{\varphi(\theta_i)}{\mathcal{L}(\theta_i)\pi(\theta_i)}, \quad \theta_i \sim P(\theta|d)$$

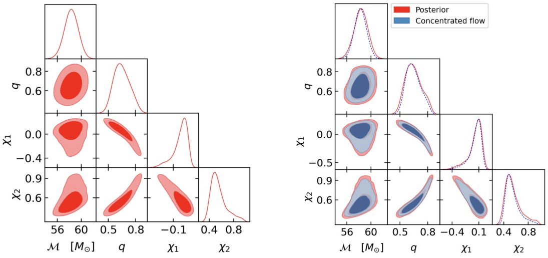
Replace the target distribution π with φ: only requirement is that it is normalized

In practice, this can be achieved with a normalizing flow [20].

This has been verified to give accurate evidences (similar values as nested sampling) when GW posteriors are used [21].

Table 1: Total wall times to compute the evidence estimates for the examples discussed in the main text. We run BILBY on 16 CPU cores and JIM + `harmonic` on 1 GPU.

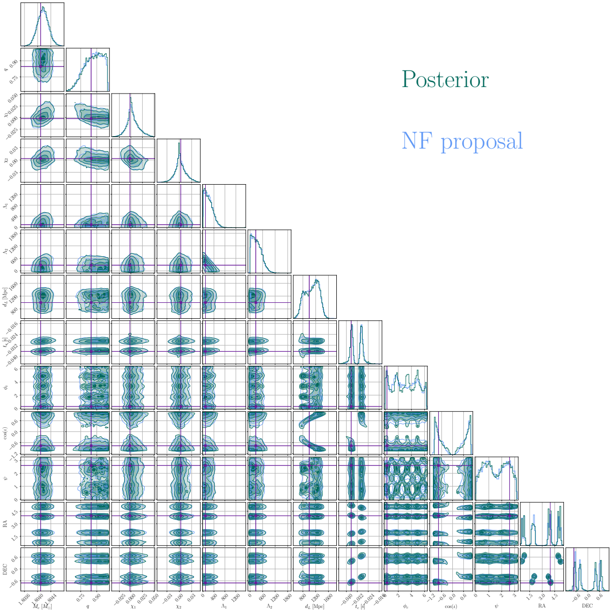
Example	Method	$\log(z)$	Sampling time	Evidence estimation time
4D	BILBY	390.33 ± 0.11	31.3 min	–
	JIM + `harmonic`	$390.360^{+0.006}_{-0.006}$	3.4 min	1.9 min
11D	BILBY	378.29 ± 0.15	3.5 h	–
	JIM + `harmonic`	$378.420^{+0.09}_{-0.08}$	11.8 min	2.4 min



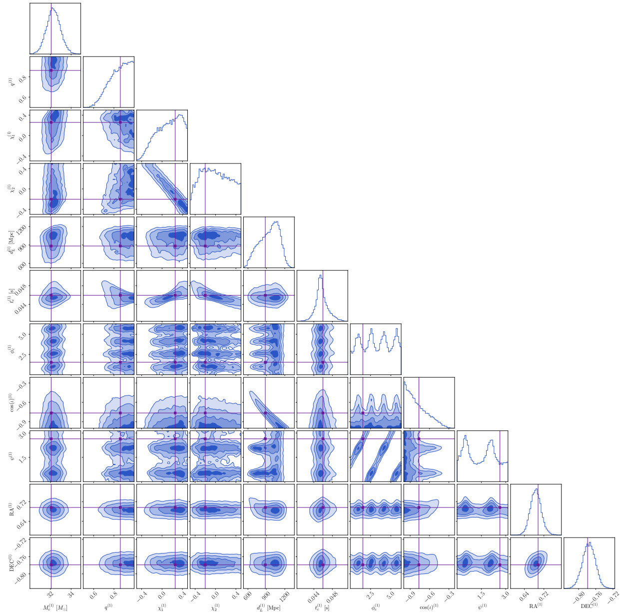
(a) BILBY (b) JIM + `harmonic`

Figure 1: Corner plots for the 4-dimensional posterior samples from (a) BILBY and (b) JIM used for inference (solid red) alongside the concentrated flow at $T = 0.8$ used in the learned harmonic mean (dashed blue).

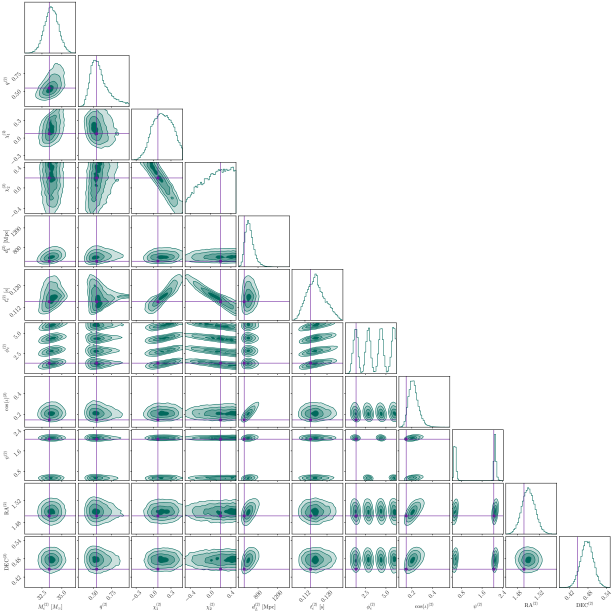
BNS in ET-Δ example: all parameters



Overlapping signals: all parameters signal A

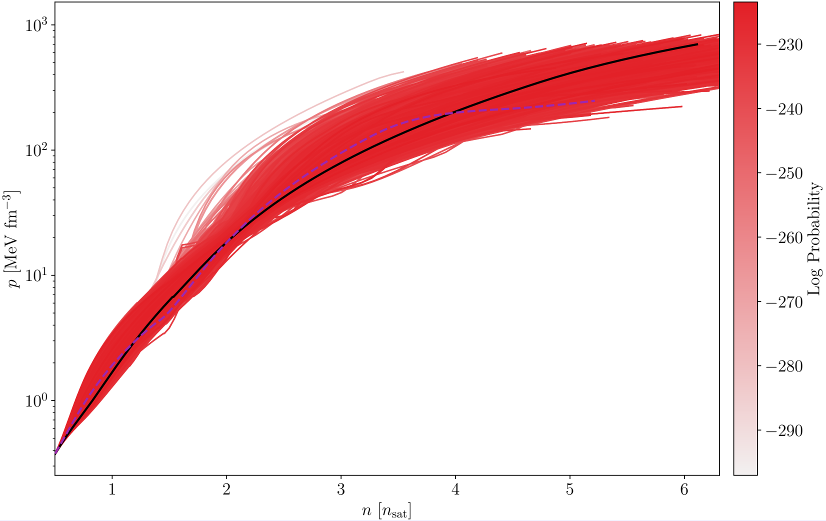


Overlapping signals: all parameters signal B



Equation of state O5 projection with 20 BNS: EOS

- **Purple**: target
- **Red**: posterior EOS samples (**black**: maximum log posterior)



Equation of state O5 projection with 20 BNS: NS