Robust parameter estimation on gravitational wave signals from binary neutron star inspirals within minutes

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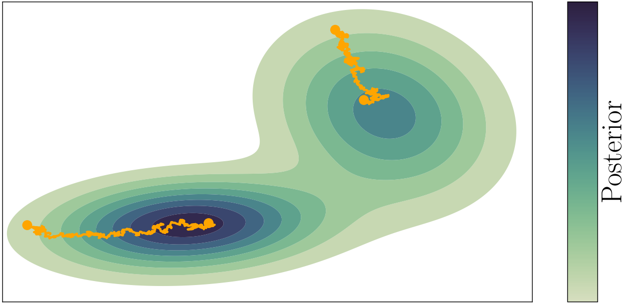
Parameter estimation

- Parameter estimation (PE): get posterior of GW parameters θ

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

- Markov Chain Monte Carlo (MCMC) [1]: computationally expensive for binary neutron stars (BNS)



Methods

We extend JIM [2] to analyze BNS signals:

- JAX: automatic differentiation, GPU acceleration [3]
- Waveforms: `TaylorF2` and `IMRPhenomD_NRTidalv2` in RIPPLE [4]
- Relative binning: speed up likelihood evaluation
- MCMC sampler: FLOWMC [5]
  - Gradient-based sampler (local sampler)
  - Normalizing flows (global sampler)

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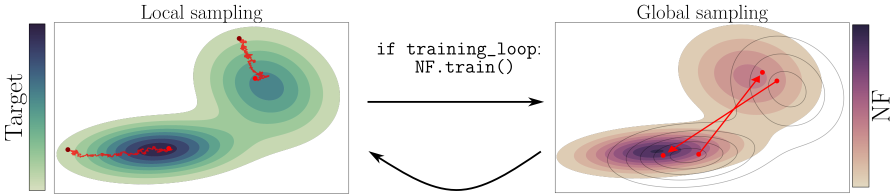
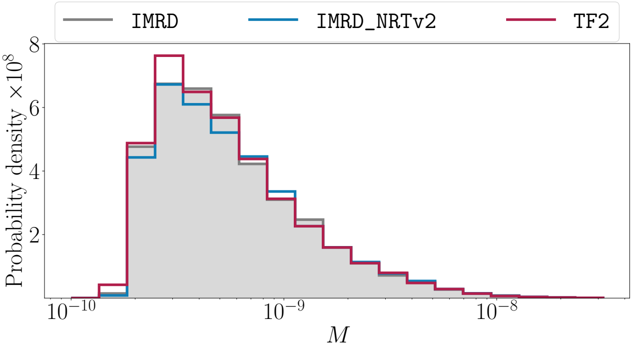


Validation – waveforms

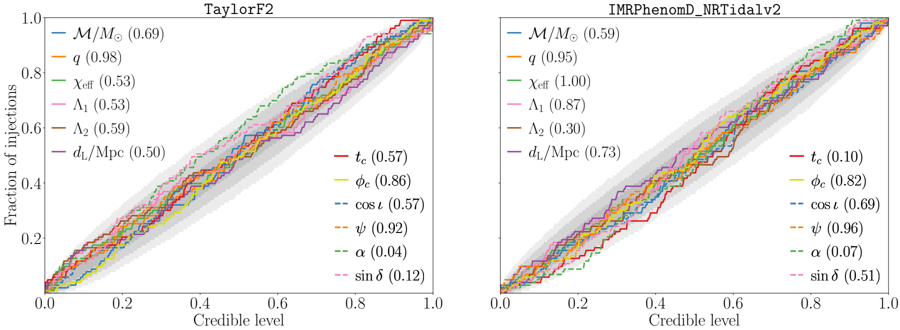
Waveforms implemented in RIPPLE: cross-checked against LALSUITE.
Accuracy sufficient for PE. might also just skip this slide



Validation – p-p plot

We demonstrate the robustness of JIM:

- 100 GW events with HLV at design sensitivity,,
- $T = 128$ s,
- Priors: Table 1.



Results – GW170817 & GW190425

Comparison against PARALLEL BILBY (PBILBY) for GW170817 and GW190425. Jensen-Shannon (JS) divergences (in bits): I don't want to show all the plots (hard to read/takes long to discuss) and will put them in the appendix, but I also don't like flashing the JS divergences, nobody cares about this, so not sure what to do there

Parameter	TF2	NRTv2	TF2	NRTv2
$\mathcal{M}$	0.001725	0.000516	0.003557	0.002461
q	0.005212	0.007894	0.004837	0.002960
χ_1	0.005633	0.004301	0.002794	0.004825
χ_2	0.003030	0.002671	0.002416	0.003041
Λ_1	0.001062	0.002208	0.008556	0.000783
Λ_2	0.000559	0.002186	0.005808	0.003576
d_L	0.001544	**0.01847**	0.001273	0.002878
ϕ_c	0.003500	0.010714	0.003338	0.006126
$\cos \iota$	0.001615	0.012851	0.006400	0.005279
ψ	0.004048	0.011036	0.001516	0.003730

Results – Runtime

- Real events: including runtime to compute reference parameters for relative binning
- Injections: median runtime

Event	WF	Jim (1 GPU)	pBilby (480 cores)
GW170817	`TF2`	$(9.70 + 17.00)$ min	9.64 h
	`NRTv2`	$(5.69 + 28.02)$ min	10.99 h
GW190425	`TF2`	$(5.13 + 16.49)$ min	4.08 h
	`NRTv2`	$(6.15 + 15.37)$ min	4.69 h
Injection	`TF2`	24.76 min	–
	`NRTv2`	18.02 min	–

Discussion – environmental impact

JIM is 100$\times$ more environmentally friendly than PBILBY

- Energy consumption for all 204 runs
- Power of GPU: 400W, power of CPU: 240W
- Average NL household: 2 810 kWh/year

	kWh	CO_2 [10^3 kg]	Trees†
JIM	33.78	0.01	0.55
PBILBY	3598.53	1.18	59.02

†Number of trees needed to capture the CO_2 emitted in a year.

Conclusion

JIM: a fast and environmentally friendly PE pipeline for GW signals

- Enhance MCMC with
  - JAX,
  - relative binning,
  - gradient-based samplers, and
  - normalizing flows
- $100\times$ more environmentally friendly than PBILBY
- Science cases:
  - low-latency alerts,
  - large-scale population studies, and future generation GW detectors

References

[1] Steve Brooks et al. *Handbook of markov chain monte carlo*. CRC press, 2011.

[2] Kaze WK Wong, Maximiliano Isi, and Thomas DP Edwards. "Fast gravitational wave parameter estimation without compromises". In: *arXiv preprint arXiv:2302.05333* (2023).

[3] Roy Frostig, Matthew James Johnson, and Chris Leary. "Compiling machine learning programs via high-level tracing". In: *Systems for Machine Learning* 4.9 (2018).

[4] Thomas DP Edwards et al. "RIPPLE: Differentiable and Hardware-Accelerated Waveforms for Gravitational Wave Data Analysis". In: *arXiv preprint arXiv:2302.05329* (2023).

[5] Kaze WK Wong, Marylou Gabrié, and Daniel Foreman-Mackey. "FLOWMC: Normalizing-flow enhanced sampling package for probabilistic inference in Jax". In: *arXiv preprint arXiv:2211.06397* (2022).

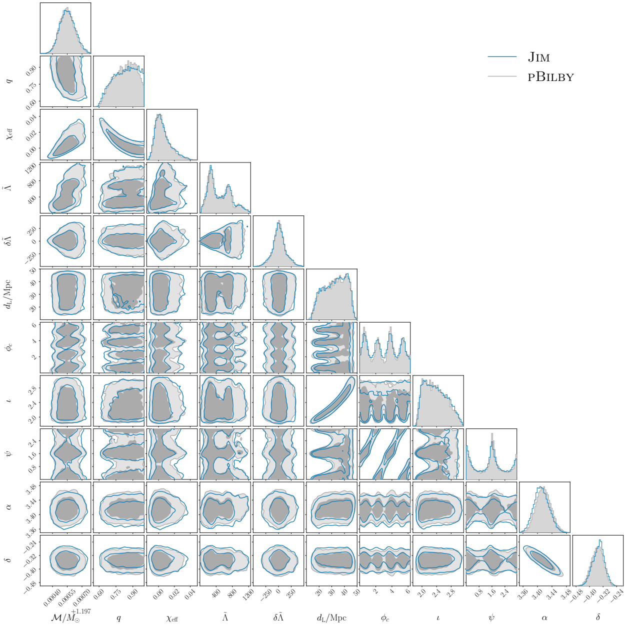
BACK-UP SLIDES

Priors

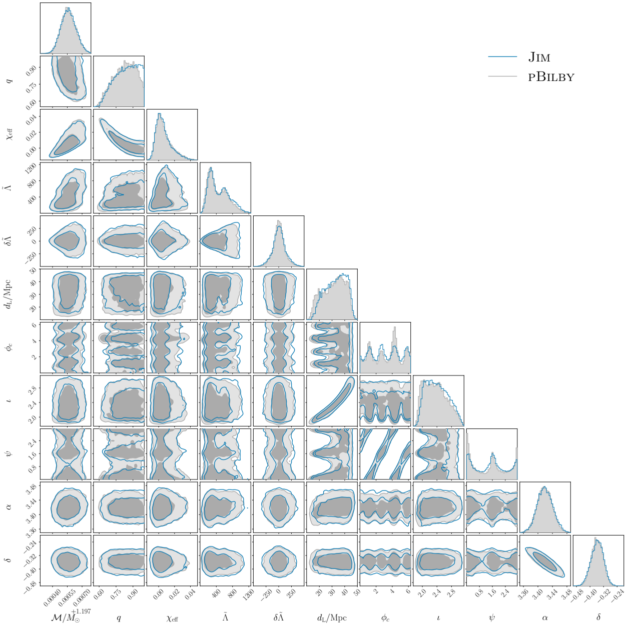
All priors are uniform priors with the specified range.

Parameter	Injection	GW170817	GW190425
$\mathcal{M}$ $[M_\odot]$	$[0.88, 2.61]$	$[1.18, 1.21]$	$[1.485, 1.490]$
q	$[0.5, 1]$	$[0.125, 1]$	$[0.125, 1]$
χ_i	$[-0.05, 0.05]$	$[-0.05, 0.05]$	$[-0.05, 0.05]$
Λ_i	$[0, 5000]$	$[0, 5000]$	$[0, 5000]$
d_L $[\mathrm{Mpc}]$	$[30, 300]$	$[1, 75]$	$[1, 500]$
t_c $[\mathrm{s}]$	$[-0.1, 0.1]$	$[-0.1, 0.1]$	$[-0.1, 0.1]$
ϕ_c	$[0, 2\pi]$	$[0, 2\pi]$	$[0, 2\pi]$
$\cos\iota$	$[-1, 1]$	$[-1, 1]$	$[-1, 1]$
ψ	$[0, \pi]$	$[0, \pi]$	$[0, \pi]$
α	$[0, 2\pi]$	$[0, 2\pi]$	$[0, 2\pi]$
$\sin\delta$	$[-1, 1]$	$[-1, 1]$	$[-1, 1]$

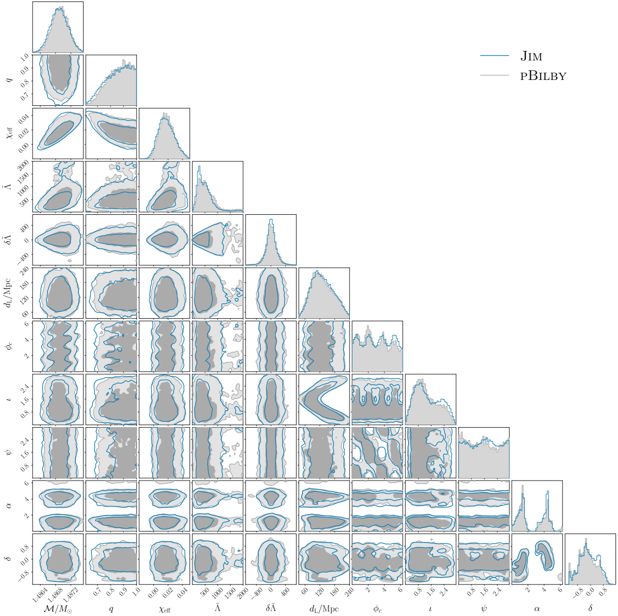
GW170817 TaylorF2



GW170817 IMRPhenomD_NRTidalv2



GW190425 TaylorF2



GW190425 IMRPhenomD_NRTidalv2