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

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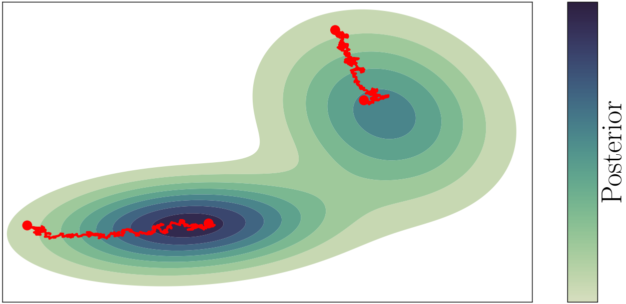
Parameter estimation

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

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

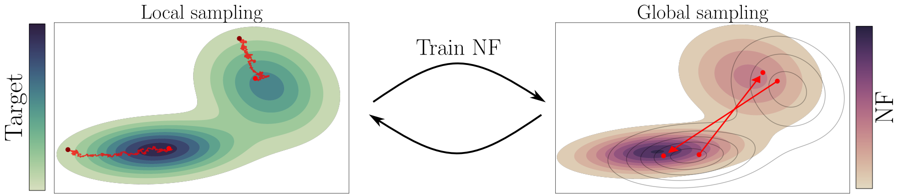
- **Problem:** Markov Chain Monte Carlo (MCMC): computationally expensive for binary neutron stars (BNS)



Methods

We extend JIM [1] to analyze BNS signals:

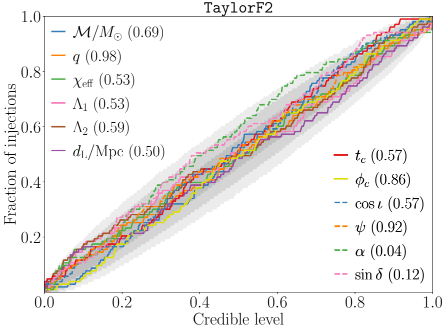
- JAX: automatic differentiation, GPU acceleration [2]
- Waveforms: `TaylorF2` and `IMRPhenomD_NRTidalv2` in RIPPLE [3]
- Relative binning: speed up likelihood evaluation [4, 5]
- MCMC sampler: FLOWMC [6]
  - Gradient-based sampler: "local sampler"
  - Normalizing flows (NF): "global sampler"

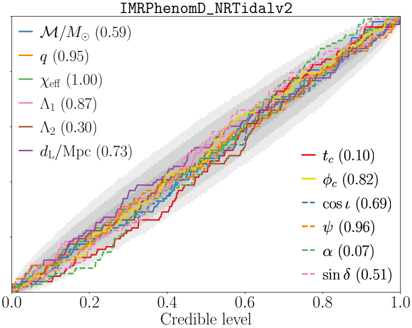


Validation – p-p plot

We demonstrate the robustness of JIM:

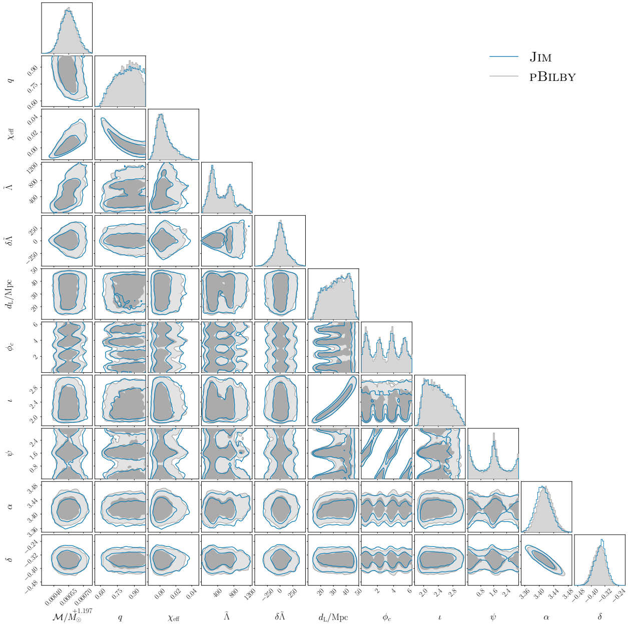
- 100 GW events with HLV at design sensitivity and $T = 128$ s,
- `NRTv2`: reference waveform relative binning without taper,
- Priors: Table 1.





Results – GW170817 & GW190425

- Compare with PBILBY
- Cornerplots: Figure 1, 2, 3, 4
- Jensen-Shannon divergences: Table 2
- GW170817, `TaylorF2`:



Results – Runtime

- Real events: includes (i) runtime to compute reference parameters for relative binning, (ii) training NF, (iii) sampling
- Injections: median runtime
- 1 GPU (A100) – vs – 480 cores (Intel Skylake Xeon Platinum 8174)

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× 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 emitted CO_2 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
- Analyze BNS in 15 – 30 minutes of sampling time
- $100\times$ more environmentally friendly than PBILBY
- Science cases:
  - low-latency alerts,
  - large-scale population studies, and future generation GW detectors

References

[1] Kaze WK Wong, Maximiliano Isi, and Thomas DP Edwards. "Fast gravitational wave parameter estimation without compromises". In: *arXiv preprint arXiv:2302.05333* (2023). Available at: `https://github.com/kazewong/jim`.

[2] Roy Frostig, Matthew James Johnson, and Chris Leary. "Compiling machine learning programs via high-level tracing". In: *Systems for Machine Learning* 4.9 (2018). Available at: `https://github.com/google/jax`.

[3] Thomas DP Edwards et al. "RIPPLE: Differentiable and Hardware-Accelerated Waveforms for Gravitational Wave Data Analysis". In: *arXiv preprint arXiv:2302.05329* (2023). Available at: `https://github.com/tedwards2412/ripple/`.

[4] Kruthi Krishna et al. "Accelerated parameter estimation in Bilby with relative binning". In: (Dec. 2023). arXiv: `2312.06009 [gr-qc]`.

[5] Barak Zackay, Liang Dai, and Tejaswi Venumadhav. "Relative Binning and Fast Likelihood Evaluation for Gravitational Wave Parameter Estimation". In: (June 2018). arXiv: `1806.08792 [astro-ph.IM]`.

[6] 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). Available at: `https://github.com/kazewong/flowMC`.

[7] Patrick Kidger and Cristian Garcia. EQUINOX*: neural networks in JAX via callable PyTrees and filtered transformations*. Available at: `https://github.com/patrick-kidger/equinox`. 2021. arXiv: `2111.00254 [cs.LG]`.

APPENDIX

Normalizing flow

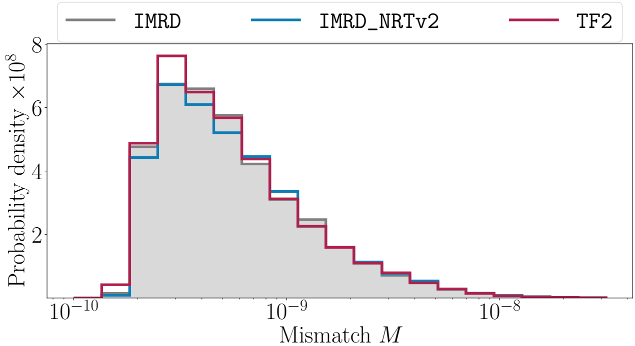
Normalizing flows details:

- Rational-quadratic neural spline flows
- 10 layers, 8 bins
- 128 neurons in hidden layers
- Adam optimizer, learning rate decayed (polynomial schedule)
- Deep learning library: EQUINOX [7]

Validation – Mismatch waveforms

Cross-check against LALSUITE: mismatch histogram based on 10 000 waveforms, from uniform samples with following ranges:

Parameter	Range
Component masses	$[0.5M_\odot, 3M_\odot]$
Component aligned spins	$[-0.05, 0.05]$
Dimensionless tidal deformabilities	$[0, 5000]$
Inclination angle	$[0, \pi]$



Priors

Table 1: Prior ranges used in our analyses. 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	$[0, 2\pi]$	$[0, 2\pi]$	$[0, 2\pi]$
$\sin\delta$	$[-1, 1]$	$[-1, 1]$	$[-1, 1]$

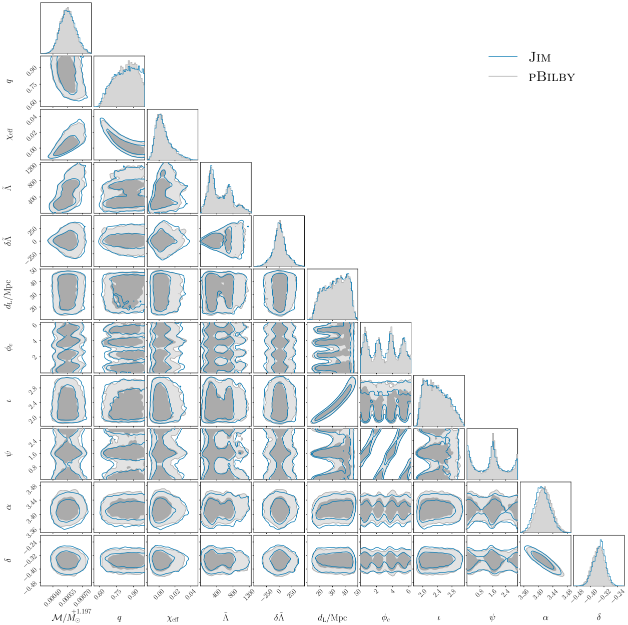
GW170817 & GW190425: Jensen-Shannon divergences

Table 2: Jensen-Shannon divergences (in bits) between the marginal posterior obtained for GW170817 and GW190425 using `TaylorF2` and `IMRPhenomD_NRTidalv2` with Jim and pBilby, with the highest value of each comparison in bold. The divergences are bound between $[0, 1]$.

	GW170817		GW190425	
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
α	**0.014008**	0.001258	**0.009822**	**0.012291**
$\sin\delta$	0.009570	0.001761	0.008934	0.009228

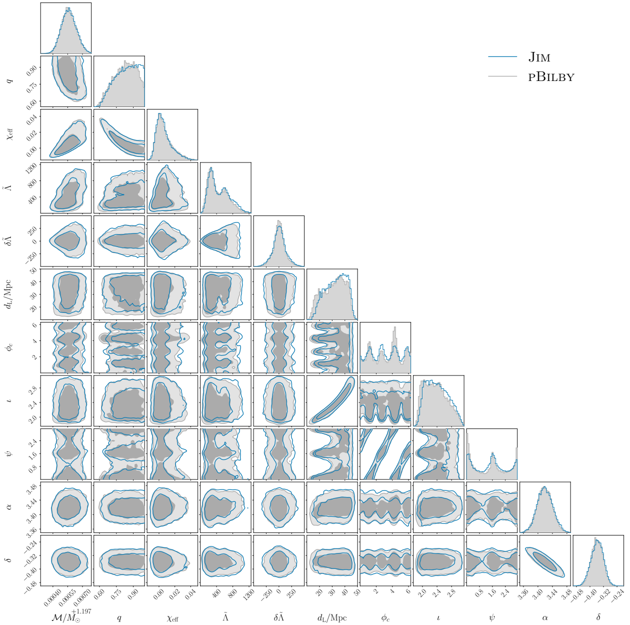
GW170817 with TaylorF2

Figure 1



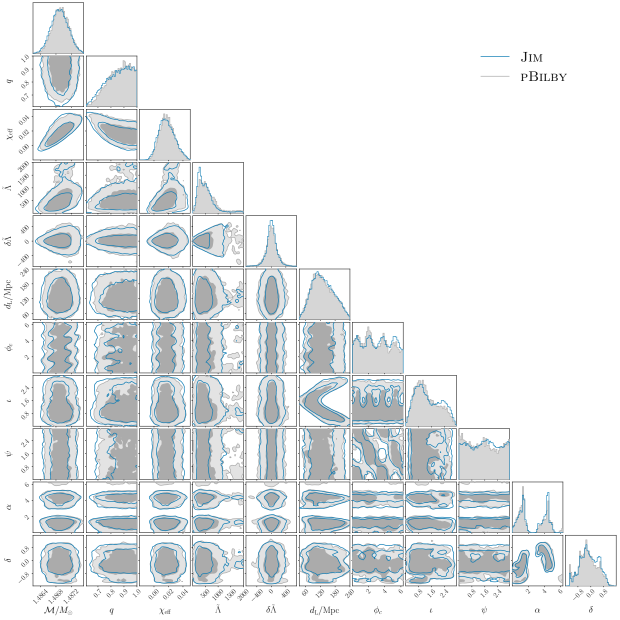
GW170817 with IMRPhenomD_NRTidalv2

Figure 2



GW190425 with TaylorF2

Figure 3



GW190425 with IMRPhenomD_NRTidalv2

Figure 4