Accelerating parameter estimation of binary neutron star mergers with normalizing flows

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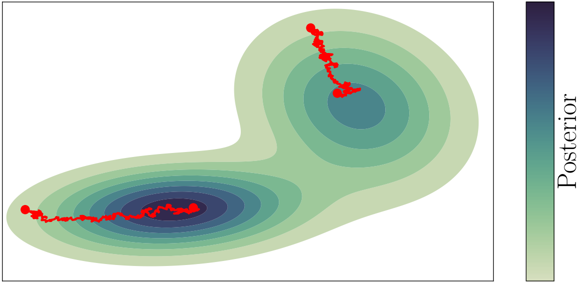
Table of Contents

Parameter estimation

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

$$p(\theta|d) = \frac{p(d|\theta)p(\theta)}{p(d)} = \frac{\text{likelihood} \times \text{prior}}{\text{evidence}}$$

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



Overview

Jim: fast parameter estimation of GW signals with JAX

- MCMC sampler: flowMC
- Waveforms: ripple

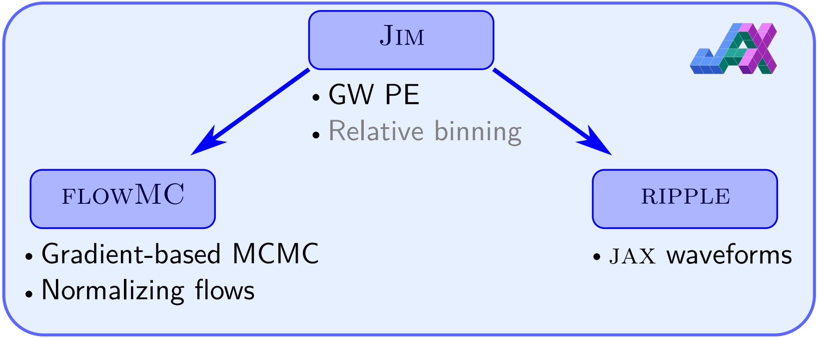
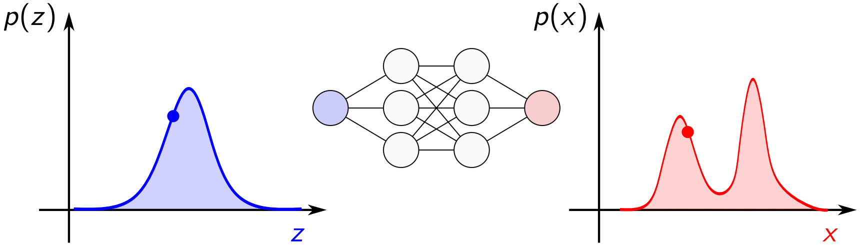


Table of Contents

Normalizing flows

- Generative machine learning model
- Learn mapping between latent and parameter space
- Enable approximate sampling from complicated distributions
- Training data: MCMC samples



FLOWMC: normalizing-flow (NF) enhanced MCMC sampling

1. Gradient-based sampler (local sampler)
2. Train NF with samples from local sampler
3. Sample normalizing flow (global sampler)

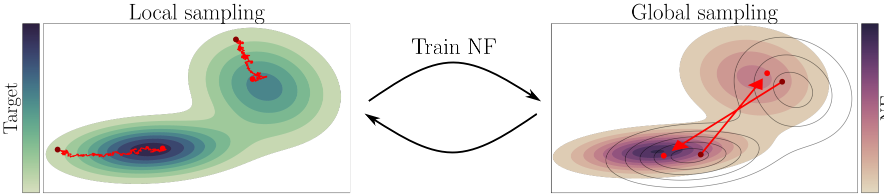


Table of Contents

Results

- Waveforms: `TaylorF2` (`TF2`), `IMRPhenomD_NRTidalv2` (`NRTv2`)
- Jim wall time: (i) computing reference parameters for relative binning, (ii) training NF, (iii) sampling

Event	Waveform	Jim (1 GPU)	pBilby (480 cores)	RB-Bilby (24 cores)	ROQ-Bilby (24 cores)
GW170817	`TF2`	$(9.70 + 17.00)$ min	9.64 h	3.18 h	–
	`NRTv2`	$(5.69 + 28.02)$ min	10.99 h	4.68 h	1.65 h
GW190425	`TF2`	$(5.13 + 16.49)$ min	4.08 h	2.30 h	–
	`NRTv2`	$(6.15 + 15.37)$ min	4.69 h	4.68 h	0.97 h
Injection	`TF2`	24.76 min	–	–	–
	`NRTv2`	18.02 min	–	–	–

(pBilby = Parallel Bilby, RB = relative binning, ROQ = reduced order quadrature)

Environmental impact

JIM is more environmentally friendly than existing pipelines

- Energy consumption for all 204 runs of paper
- Convert to number of trees to capture the emitted CO_2 in a year.

Method		Trees
JIM		0.55
PBILBY		59.02
RB-BILBY		1.49
ROQ-BILBY	sampling	0.52
	precompute[‡]	0.44

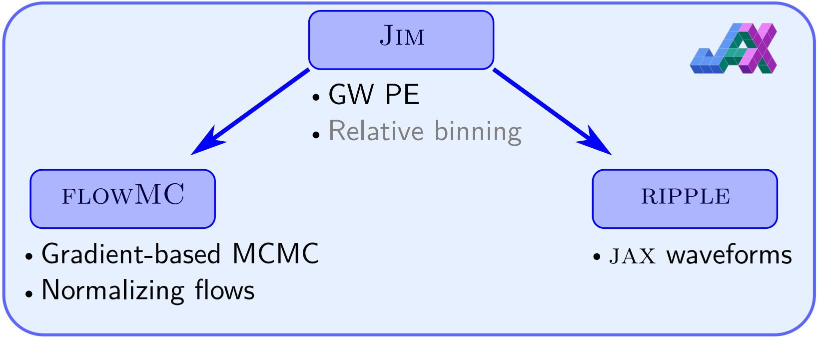
[†]Estimated cost to build ROQ bases.

Table of Contents

Conclusion

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

- TaylorF2 and IMRPhenomD_NRTidalv2 in ripple
- Parameter estimation of BNS in 15 – 30 minutes sampling time without pretraining



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] 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/.

[3] Marylou Gabrié, Grant M Rotskoff, and Eric Vanden-Eijnden. "Efficient bayesian sampling using normalizing flows to assist markov chain monte carlo methods". In: *arXiv preprint arXiv:2107.08001* (2021).

[4] 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.

[5] 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.

[6] 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].

[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 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

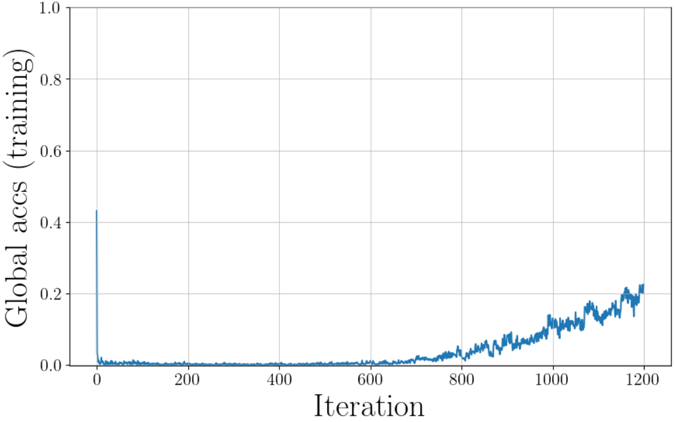
Loss function: KL divergence on sampled data

$$\mathcal{L}(T) = -\frac{1}{n}\sum_{i=1}^{n} \log \hat{\rho}(x_i)$$

Stopping criterion

We stop training the NF if we achieve a mean Metropolis-Hastings acceptance rate of 10% (20%) for real events (injections).

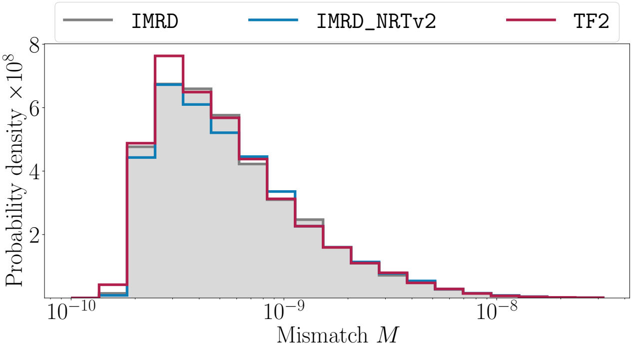
Example: GW170817, `TaylorF2` with 20%:



Validation – Mismatch waveforms

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

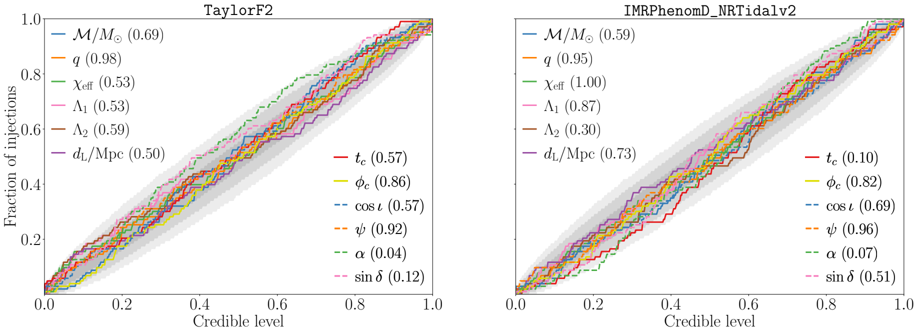
Parameter	Range
Component masses	$[0.5M_\odot, 3M_\odot]$
Component aligned spins	$[-0.05, 0.05]$
Dimensionless tidal deformabilities	$[0, 5000]$
Inclination angle	$[0, \pi]$



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.



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

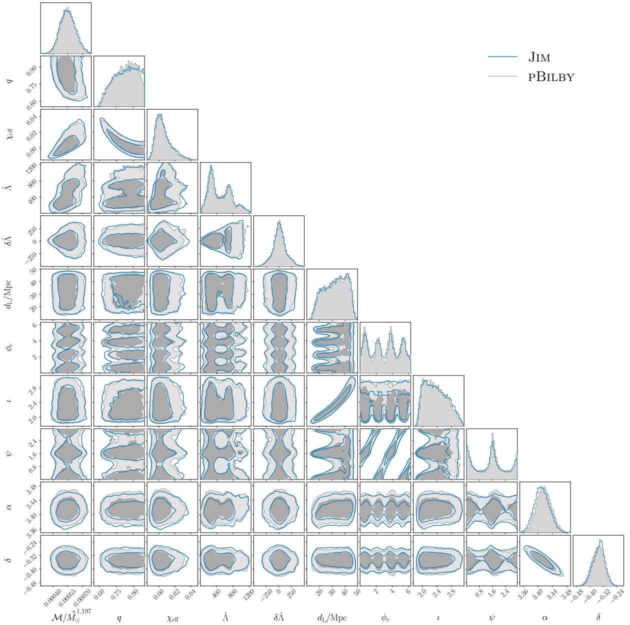
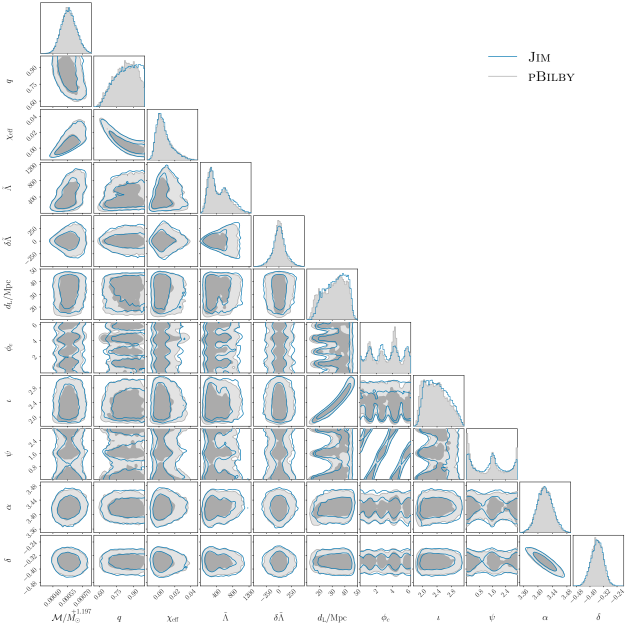
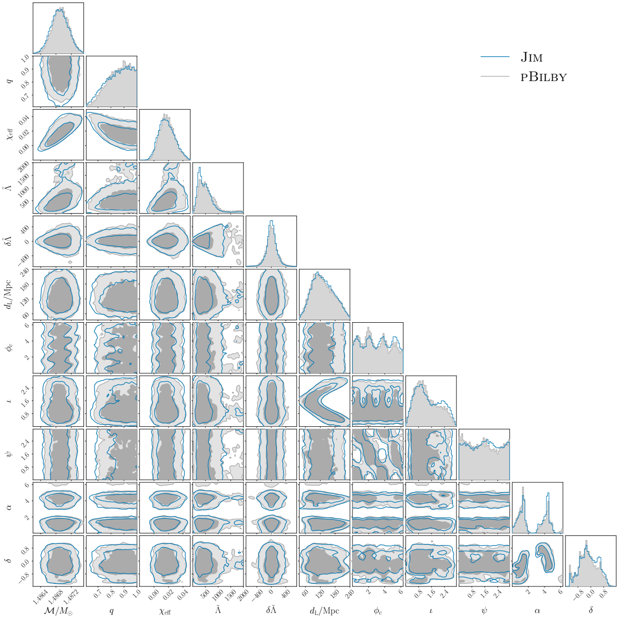


Figure 2


Jim
pBilby
$\mathcal{M}/M_\odot^{+1.197}$
q
$\chi_{\rm eff}$
$\tilde{\Lambda}$
$\delta\tilde{\Lambda}$
$d_{\rm L}/{\rm Mpc}$
ϕ_c
ι
ψ
α
δ

GW190425 with TaylorF2

Figure 3



GW190425 with IMRPhenomD_NRTidalv2

Figure 4