

JIM for fast parameter estimation of binary neutron star gravitational waves

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[arXiv:2404.11397](https://arxiv.org/abs/2404.11397)

Alslands 2024



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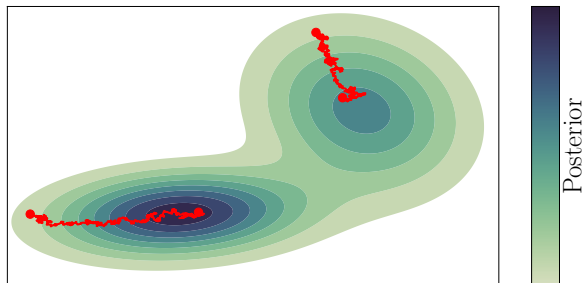
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Parameter estimation

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

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

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

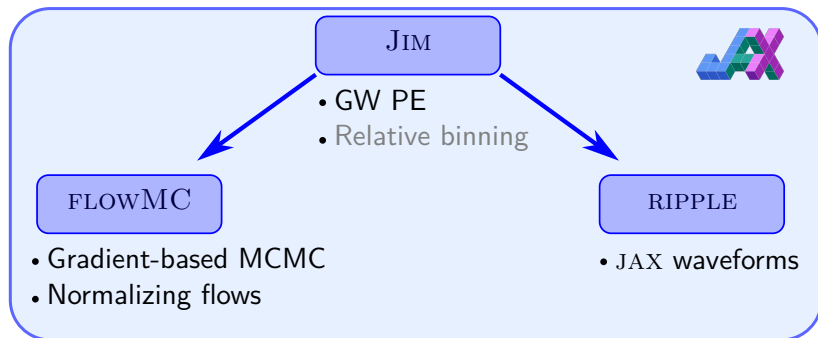


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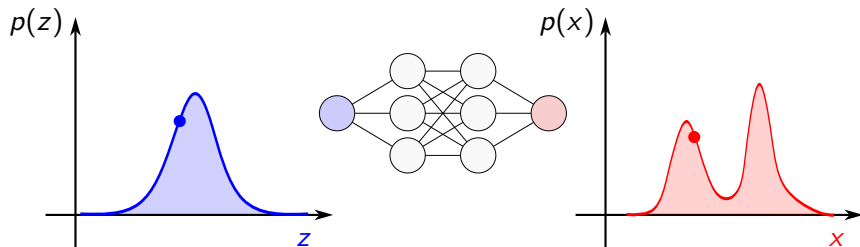
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Normalizing flows

- 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)

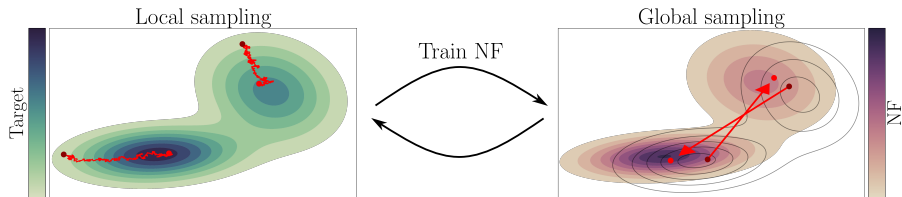


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Results

- 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 CO₂ 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.

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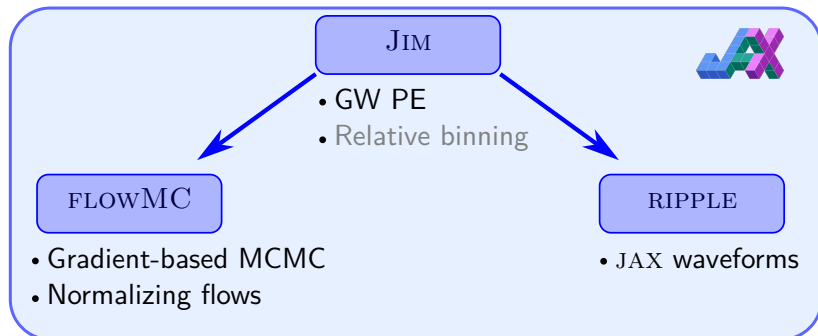
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Conclusion

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

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



Future work/points of discussion

Future applications:

- Future GW detectors, e.g. Einstein Telescope
- Multi-messenger astrophysics: e.g. NMMA [1]

Points of discussion:

- NESSAI, DINGO, JIM,... avoid “fragmentation of effort”?
- Normalizing flows for PE: do's and don'ts?

References

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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

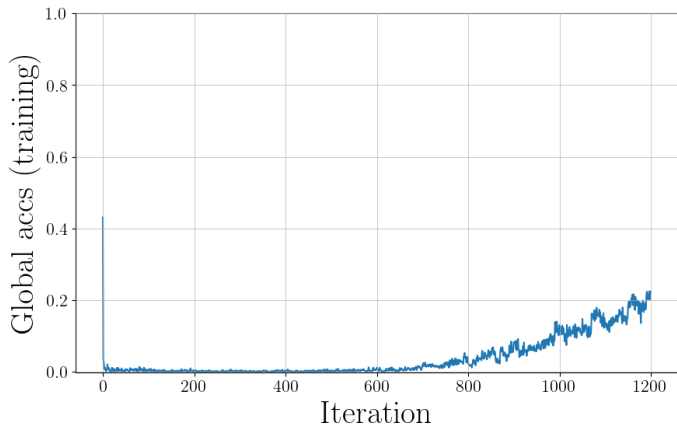
Loss function: KL divergence on sampled data

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

Stopping criterion

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

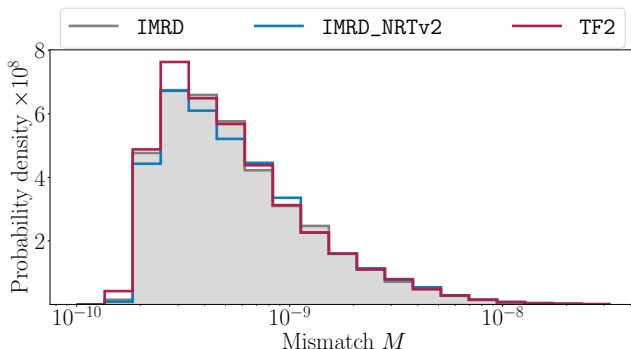
Example: GW170817, TaylorF2 with 20%:



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.

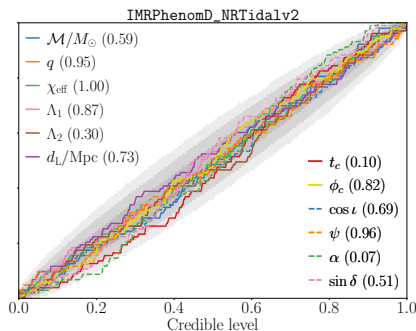
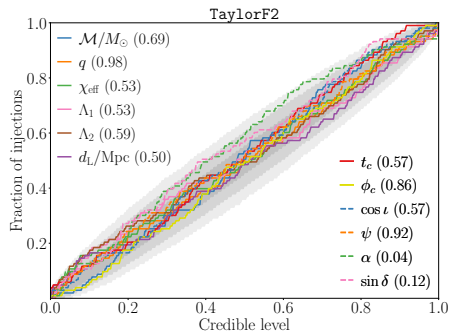


Table 1: Prior ranges used in our analyses. All priors are uniform priors with the specified range.

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 [Mpc]	[30, 300]	[1, 75]	[1, 500]
t_c [s]	[-0.1, 0.1]	[-0.1, 0.1]	[-0.1, 0.1]
ϕ_c	[0, 2π]	[0, 2π]	[0, 2π]
$\cos \iota$	[-1, 1]	[-1, 1]	[-1, 1]
ψ	[0, π]	[0, π]	[0, π]
α	[0, 2π]	[0, 2π]	[0, 2π]
$\sin \delta$	[-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 $[0, 1]$.

Parameter	GW170817		GW190425	
	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

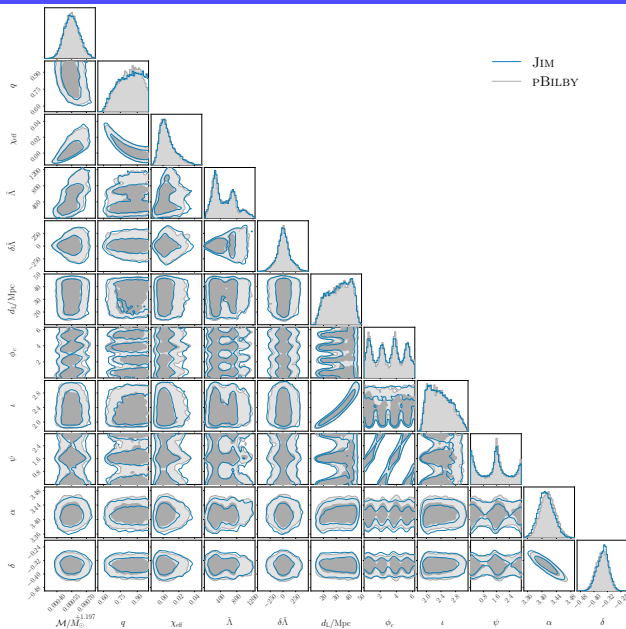
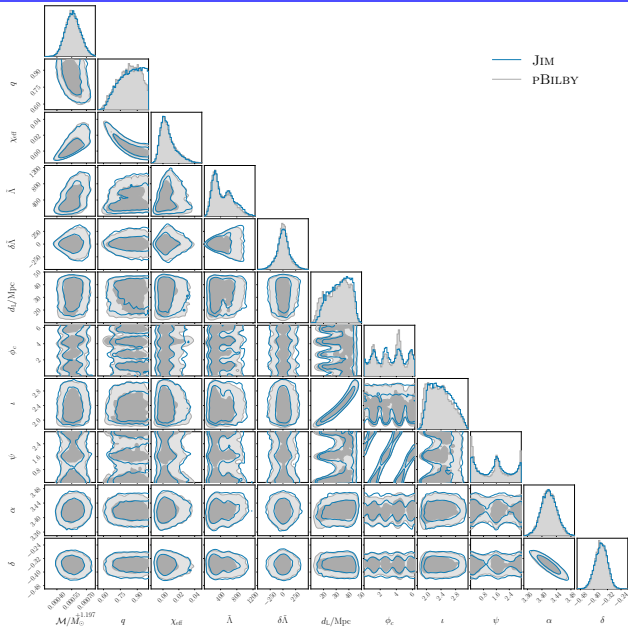


Figure 2



GW190425 with TaylorF2

Figure 3

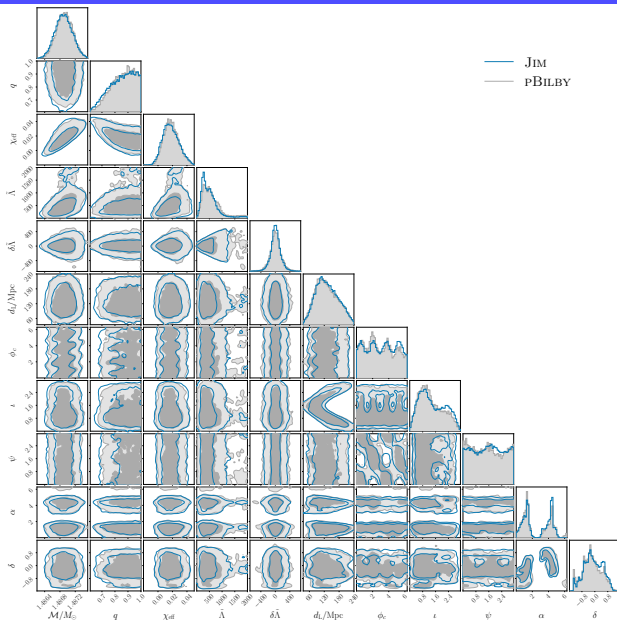


Figure 4

