

SEOBNRv5PHM_NNSur: a fast neural network waveform surrogate for generically precessing binaries

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Introduction: SEOBNRv5PHM_NNSur7dq10

- We built a reduced order time-domain surrogate model for SEOBNRv5PHM, using neural networks for parameter space fits.
- SEOBNRv5PHM: state-of-the-art EOB model for quasicircular precessing binaries, including higher order modes. [[Ramos-Buades+ \(2303.18046\),...](#)]
- Covers mass ratios up to 1:10, arbitrary spin magnitudes and directions.
- Covers period 10,000M before merger through to 100M after.

Waveform decomposition

- Work in co-orbital frame:

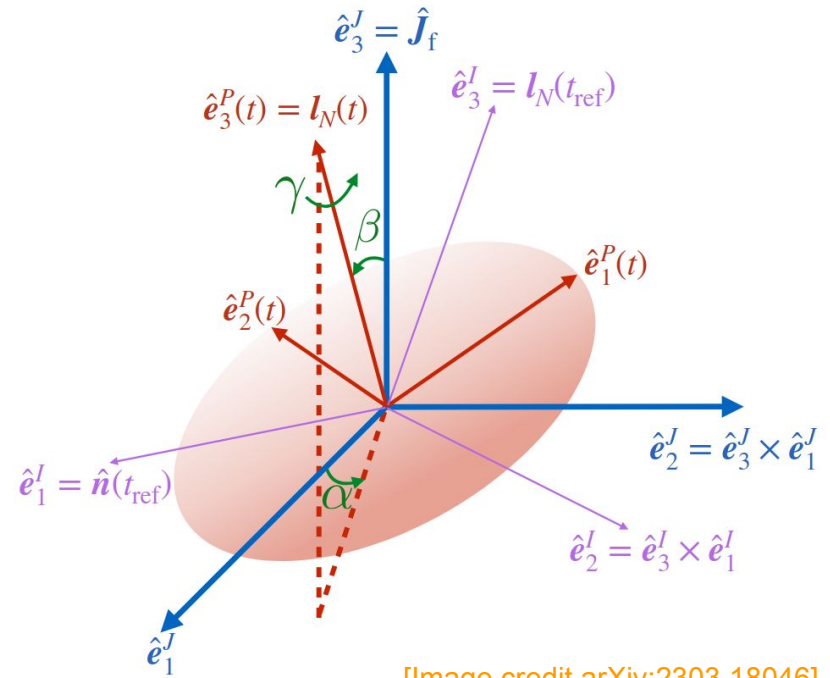
$$\phi_{\text{orb}}(t) := \frac{1}{2} \text{Arg} [h_{22}^{\text{CP}}(t)]$$

$$h_{\ell m}^{\text{CO}}(t) = h_{\ell m}^{\text{CP}}(t) e^{-im\phi_{\text{orb}}(t)}$$

- Rotation from P-frame to inertial frame described by quaternions:

$$\mathbf{q} = \cos\left(\frac{\theta}{2}\right) + \sin\left(\frac{\theta}{2}\right)\hat{\mathbf{n}}$$

- Separate quaternions for $\text{P} \rightarrow \text{J}_f$ and $\text{J}_f \rightarrow \text{I}$ rotations.
- Not currently including P-frame mode asymmetries.



[Image credit arXiv:2303.18046]

We build separate surrogates for the orbital phase, co-orb frame modes and quaternions $\mathbf{q}_{\text{J}_2\text{P}}(t)$ and $\mathbf{q}_{\text{I}_2\text{J}}$

Model structure

For each time-series data piece $f(t; \lambda)$, we...

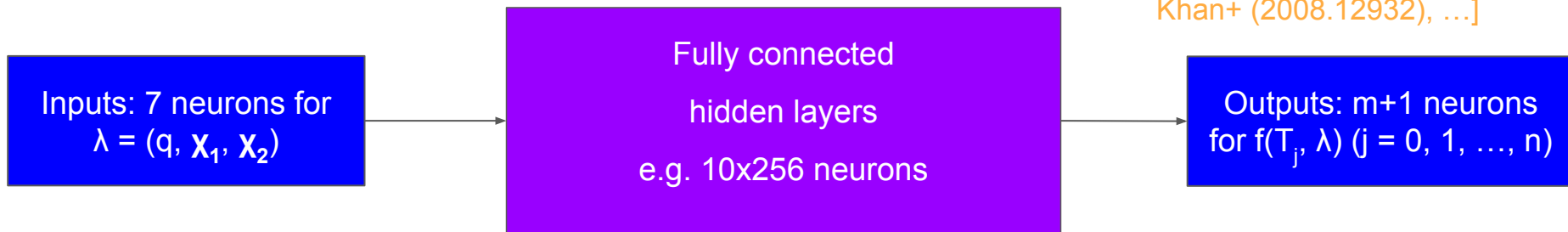
- Use greedy algorithms to find the reduced basis + empirical interpolation matrix $B_i(t)$:

$$f(t, \vec{\lambda}) \approx \text{EI}[f](t, \vec{\lambda}) := \sum_{j=0}^n B_j(t) f(T_j, \vec{\lambda}),$$

[Field+ (1308.3565) and many others....]

- Train a neural network to predict the values of $\{f(T_j, \lambda): j = 1, 2, \dots, n\}$ at any given value of λ in the training domain:

[Chua+ (1811.05491), Khan+ (2008.12932), ...]



- We use 200k training waveforms to build the reduced basis, and train the networks on 1.2M waveforms (2.2M for the orbital phase)
- Single network to predict the time-independent quaternion q_{12j}

Quaternion downsampling

- Transformation from P-frame to I-frame, e.g.: [Boyle+ (1409.4431)]

$$h_{+}^I(t; \iota, \phi_0) - ih_{\times}^I(t; \iota, \phi_0) = \sum_{\ell, m} \sqrt{\frac{2\ell + 1}{4\pi}} \mathcal{D}_{m,2}^{\ell}(q_f(t; \iota, \phi_0)) h_{\ell m}^P(t),$$

- Expensive to evaluate the Wigner D-matrices at every point on the dense time grid: bottleneck!
- Precession timescale longer than orbital period:
 - Evaluate the quaternions on a sparse time grid (piecewise uniform)
 - Evaluate the D-matrices at the sparse time points
 - Interpolate the D-matrices onto the final waveform time grid
- Saves significant amounts of time in some cases.

Model validity: total mass limits

- Waveform polarizations returned on a fixed geometric time grid $[-10^4M, 100M]$ with spacing $\Delta t = 0.5M$.
- Starting frequency depends on the total mass.
- Require total mass

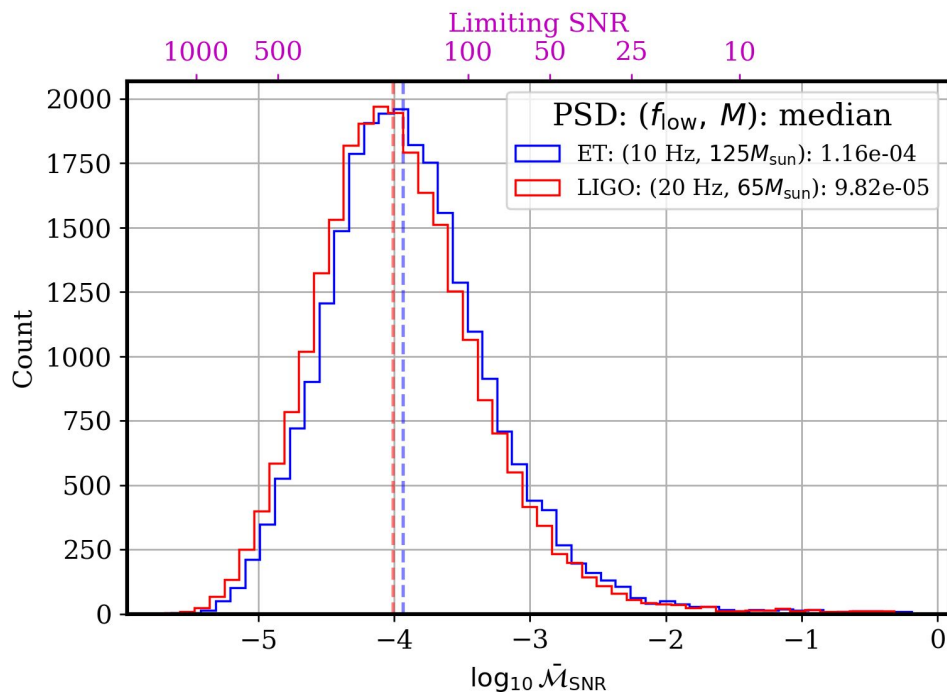
$$(q \leq 10) \\ \mathbf{M > 62.3M_{\text{sun}}}$$

$$(q \leq 4) \\ \mathbf{M > 48.3M_{\text{sun}}}$$

$$(q = 1) \\ \mathbf{M > 41.1M_{\text{sun}}}$$

to ensure starting frequency < 20 Hz for all spin configurations.

Results: faithfulness to SEOBNRv5PHM



- Mismatches with SNR-weighted average over inclination, phase and polarisation.

$$\bar{\mathcal{M}}_{\text{SNR}} := 1 - \left(\frac{\sum_i \mathcal{M}_i^3 \rho_i^3}{\sum_i \rho_i^3} \right)^{1/3}$$

- Orbital phase model is greatest source of error, followed by the quaternion models.

Results: computational cost

Mean cost per waveform (wall time/batch size)

	With DS	Without DS	Best-case speedup ³
Laptop CPU¹ [single wf]	12.52ms	15.47ms	5.2x
Laptop GPU² [single wf]	13.79ms	13.38ms	4.9x
Laptop GPU² [250x batch]	0.93ms	1.82ms	71x
Nvidia A100 [1500 batch]	0.16ms	0.25ms	410x

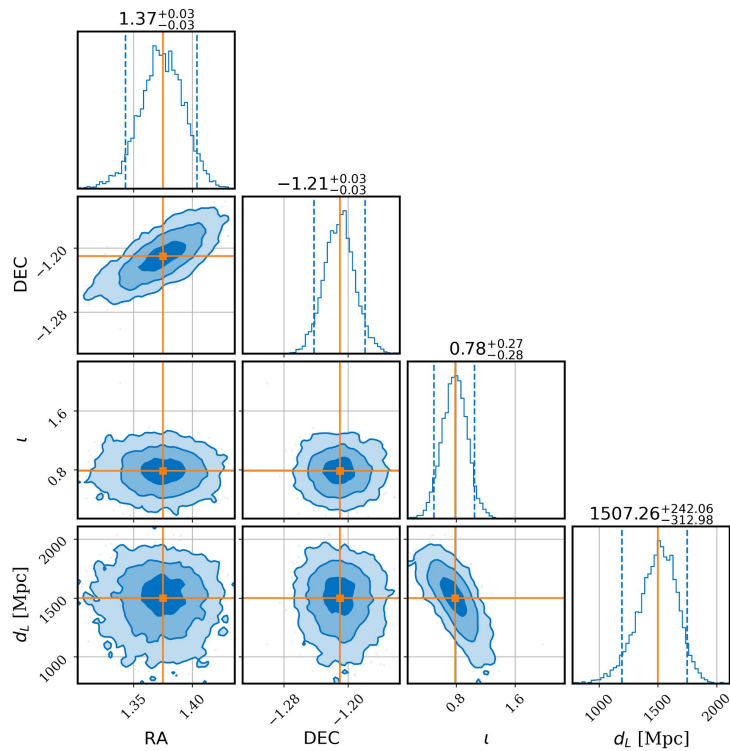
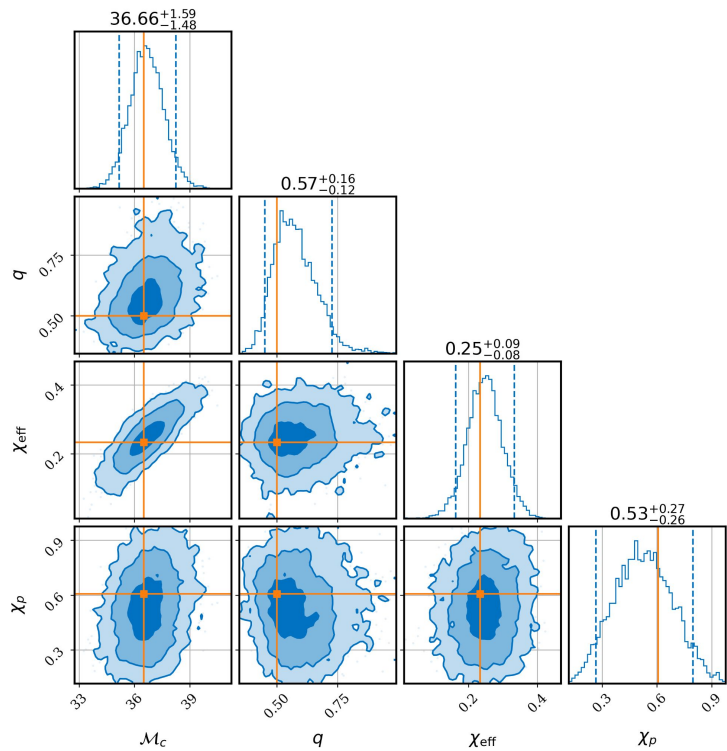
¹ Single-thread on Intel Core Ultra 7 155H

² Nvidia RTX 1000 Ada

³ Average SEOB cost = 65.6ms per waveform

Results: injection-recovery

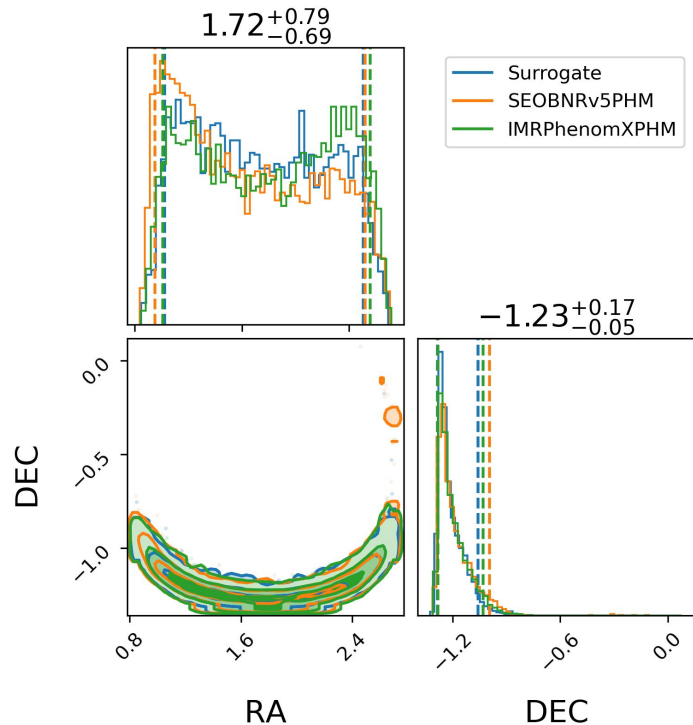
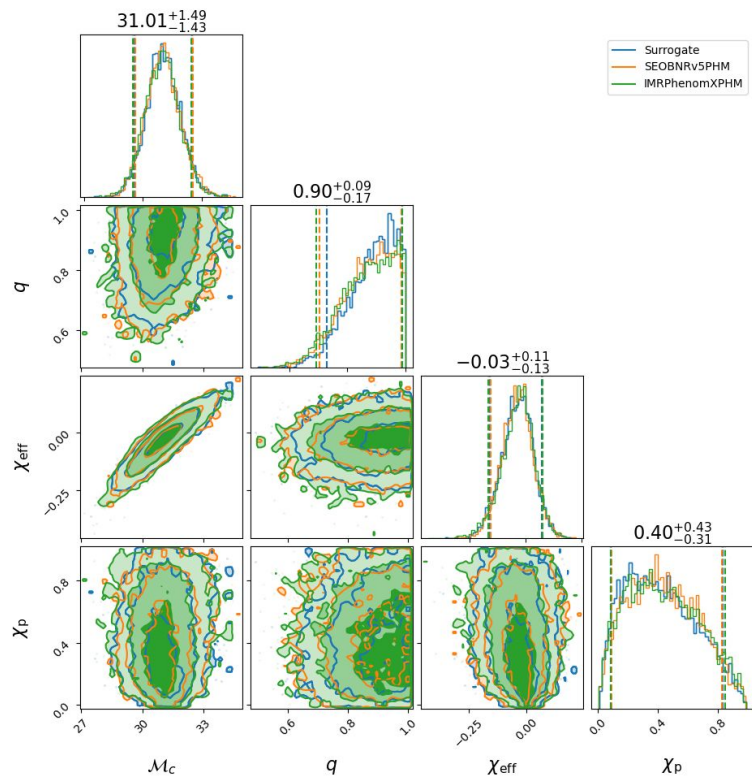
Inject SEOBNRv5PHM into zero noise, recover with the surrogate



	Injected
m_1	60.0
m_2	30.0
a_1	0.7
θ_1	$\pi/3$
a_2	0.0

Network
(HLV)
optimal
SNR ~ 25.7

Results: GW150914



	Sur	SEOB	XPHM
Wall time	22hr 56m	63hr 49m	9hr 10m

8s segment, nlive=1000, npool=32

~ 2.8x speedup compared to SEOBNRv5PHM

Conclusions

- Demonstrated neural network surrogate approach for 7d precessing problem.
- Median model mismatches $\sim 1e-4$ against base SEOBNRv5PHM.
- Speedup $\sim 5x$ for single waveform on a laptop CPU or GPU
- Surrogate achieves best (average) performance when evaluating large waveform batches on the GPU.
- Demonstrated practical application of surrogate to PE, with significant speedup over SEOBNRv5PHM.

Thank you for listening