

Fast neural network surrogate for effective-one-body waveforms from generically precessing binaries

[\[arXiv:2604.14270\]](#)

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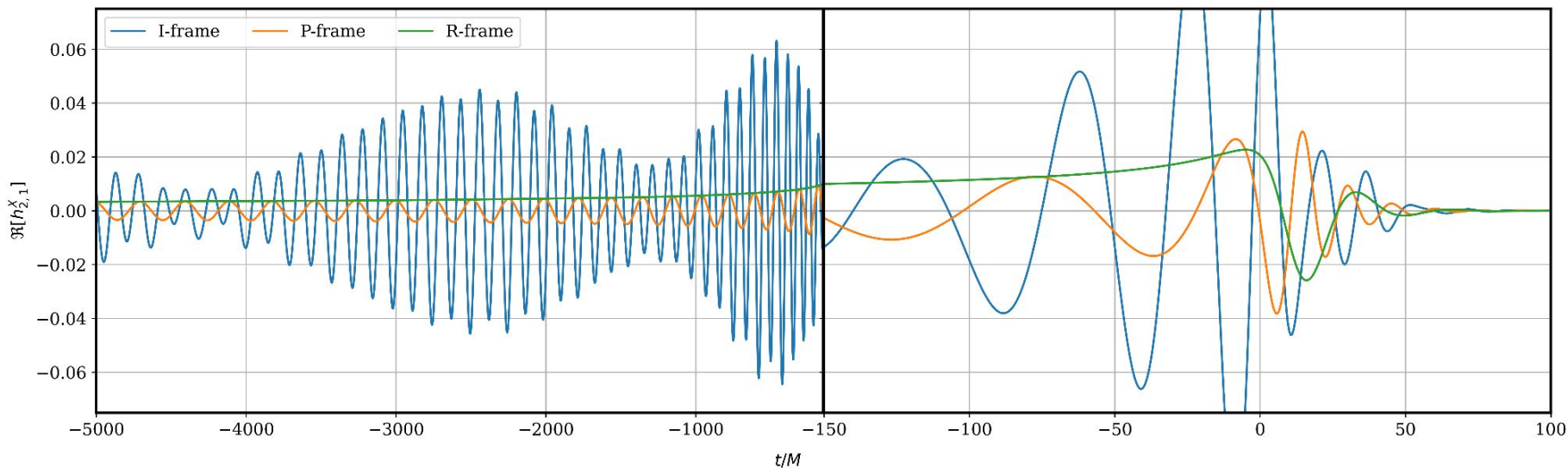
GRAVITATIONAL
WAVE ASTRONOMY

Reduced order surrogate modelling

- **Accurate** and **fast** waveform models needed for gravitational wave data analysis.
- Next-generation detectors need significant extension in waveform model coverage (**duration**, **precession** etc.)
- Surrogate modelling: given a **slow base model**, train a model to **predict** its output for arbitrary parameters in some range.
- Did this for **SEOBNRv5PHM**, a fully precessing, quasicircular EOB model.
[Ramos-Buades+ (2303.18046),...]
- Three basic stages: **decomposition**, **compression** and **prediction**.

Step 1: Waveform decomposition

Analyse precessing waveforms in appropriate frames of reference



I-frame: inertial source frame

P-frame: (non-inertial) co-precessing frame

R-frame: (non-inertial) co-rotating frame

Schmidt+ (1012.2879), Boyle+ (1110.2965),
Schmidt+ (1207.3088), Boyle (1302.2919)

Step 1: Waveform decomposition

Break waveform up into pieces with simpler morphology

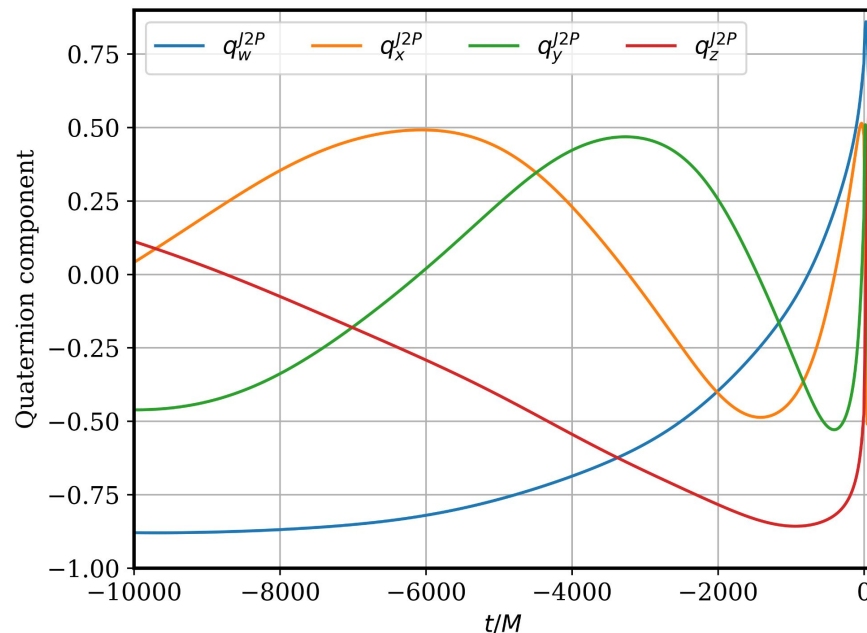
- Quaternions describing rotation from inertial to co-precessing frame:

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

- Orbital phase and co-orbital frame modes:

$$\phi_{\text{orb}}(t) := \frac{1}{2} \arg [h_{2,2}^P(t)] ,$$

$$h_{\ell m}^R(t) = h_{\ell m}^P(t) e^{-im\phi_{\text{orb}}(t)} .$$



Step 1: Waveform decomposition

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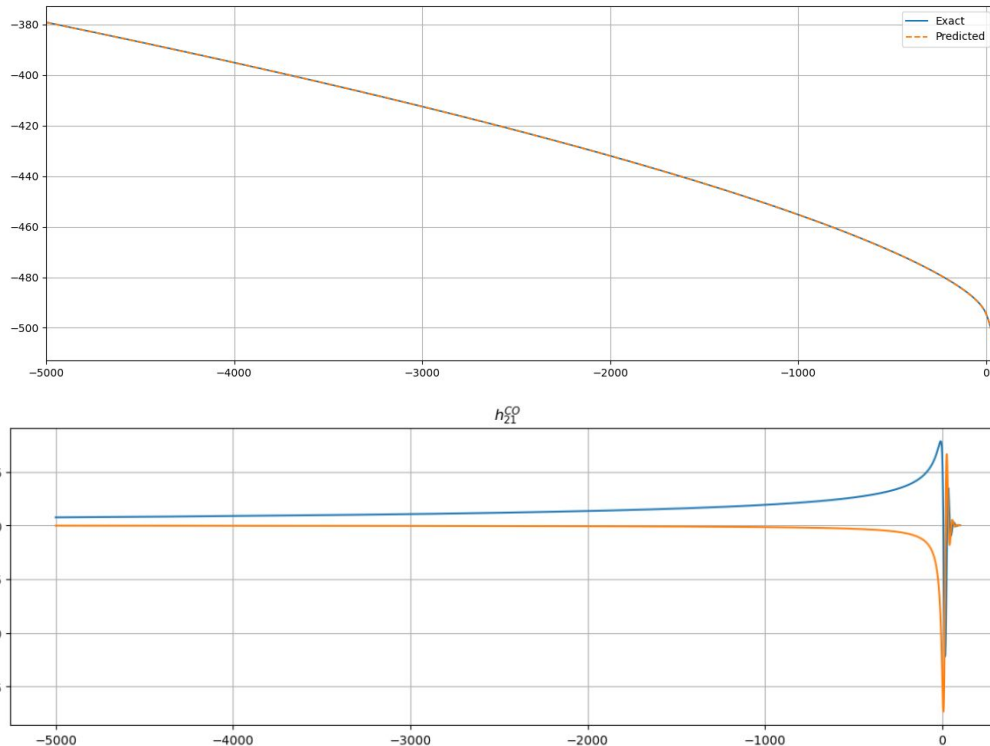
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Step 2: data compression

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

Construct a reduced basis for each waveform data piece

- Waveform pieces can be projected onto a finite dimensional basis $\{e_i(t)\}$:

$$f(t, \vec{\lambda}) \approx \mathcal{P}_n[f](t, \vec{\lambda}) := \sum_{i=1}^n c_i(\vec{\lambda}) e_i(t), \quad (1)$$

Error in approximation (1) can be made arbitrarily small.

- Replace basis expansion (1) with an empirical interpolant:

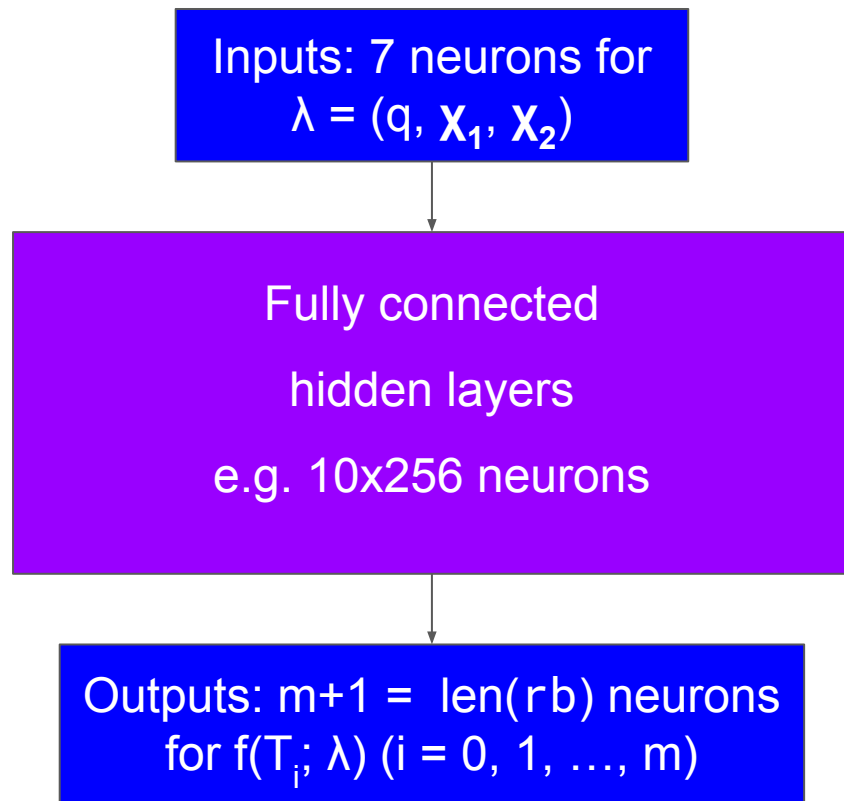
$$f(t, \vec{\lambda}) \approx \text{EI}[f](t, \vec{\lambda}) := \sum_{j=0}^n B_j(t) f(T_j, \vec{\lambda}), \quad (2)$$

Step 3: Prediction

Move from representative to predictive model

- Need to be able to **predict** $f(T_i; \lambda)$ for arbitrary parameters λ , for each T_i .
- Interpolate $f(T_i; \lambda)$ from the training set across parameter space using artificial neural networks
 - Interpolation across 7d parameter space $(q, \mathbf{x}_1, \mathbf{x}_2)$ challenging.
 - Make use of GPU accelerated frameworks.

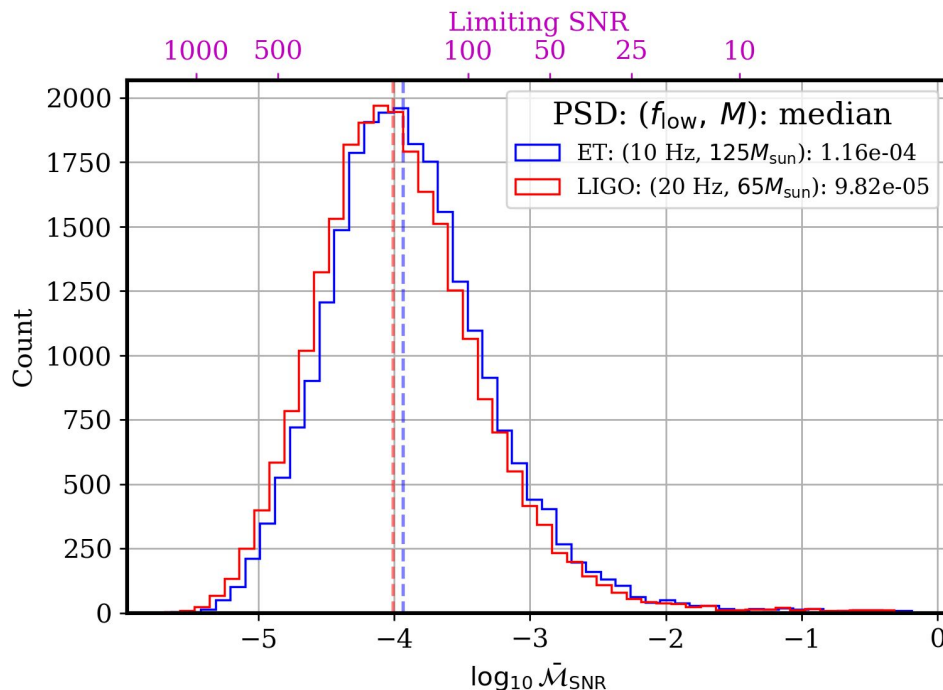
[Chua+ (1811.05491),
Khan+ (2008.12932), ...]



SEOBNRv5PHM_NNSur7dq10

- Reduced bases trained using 200k training waveforms.
- Neural networks trained on 1.2M waveforms (2.2M for the orbital phase)
- Covers mass ratios $q = m_1/m_2$ up to $q=10$, arbitrary spin magnitudes and directions.
- Returns time domain waveform, stretching from time 10,000M before merger through to 100M after.
- (2,2)-mode starting frequency < 20 Hz for all $M > 62.3M_{\text{sun}}$.

Results: faithfulness to SEOBNRv5PHM



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

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

- Conservative estimate of “limiting SNR”,

$$\rho < \sqrt{\frac{N}{2\mathcal{M}_f}}.$$

above which we expect bias

Results: computational cost

Mean cost per waveform (wall time/batch size, averaged over parameter combinations)

	Wall time	Speedup ³
Laptop CPU¹ [single wf]	12.52ms	5.2x
Laptop GPU² [single wf]	13.01ms	5.0x
Laptop GPU² [250x batch]	0.93ms	71x
Nvidia A100 [1500 batch]	0.16ms	410x
Nvidia A100 [1500 batch, No copy to host] ⁴	0.081ms	810x

¹ Single-thread on Intel Core Ultra 7 155H

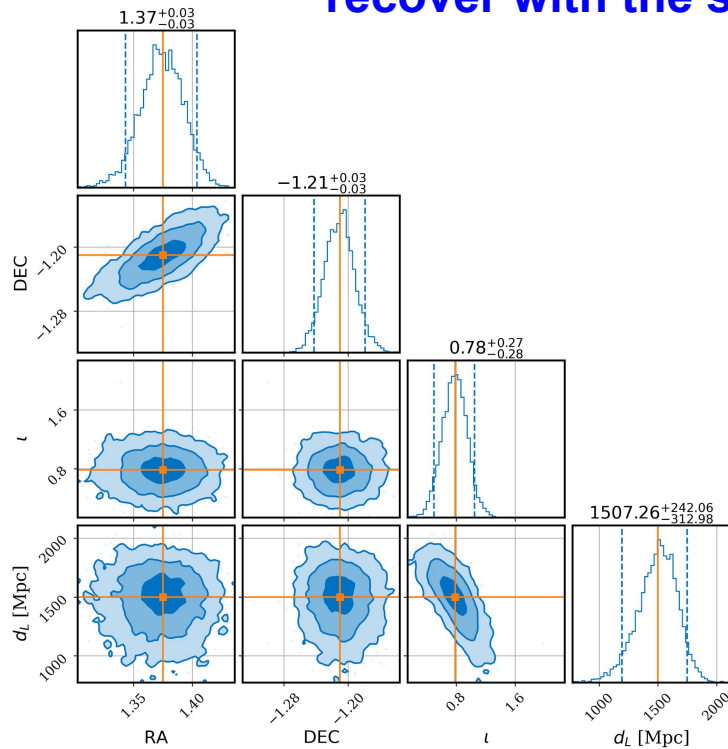
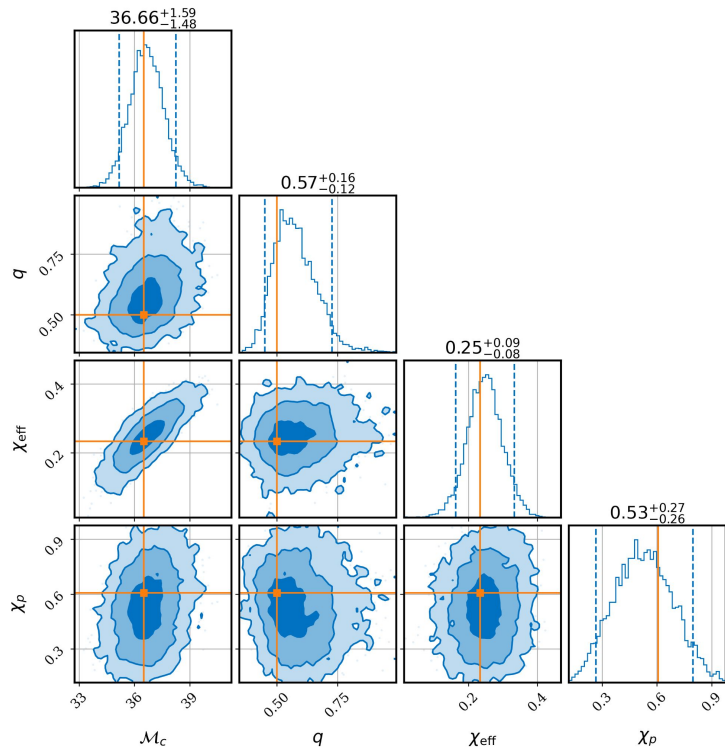
² Nvidia RTX 1000 Ada

³ Average SEOB cost = 65.6ms per waveform

⁴ Keeping the final result in GPU memory rather than copying back to the CPU-accessible memory.

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

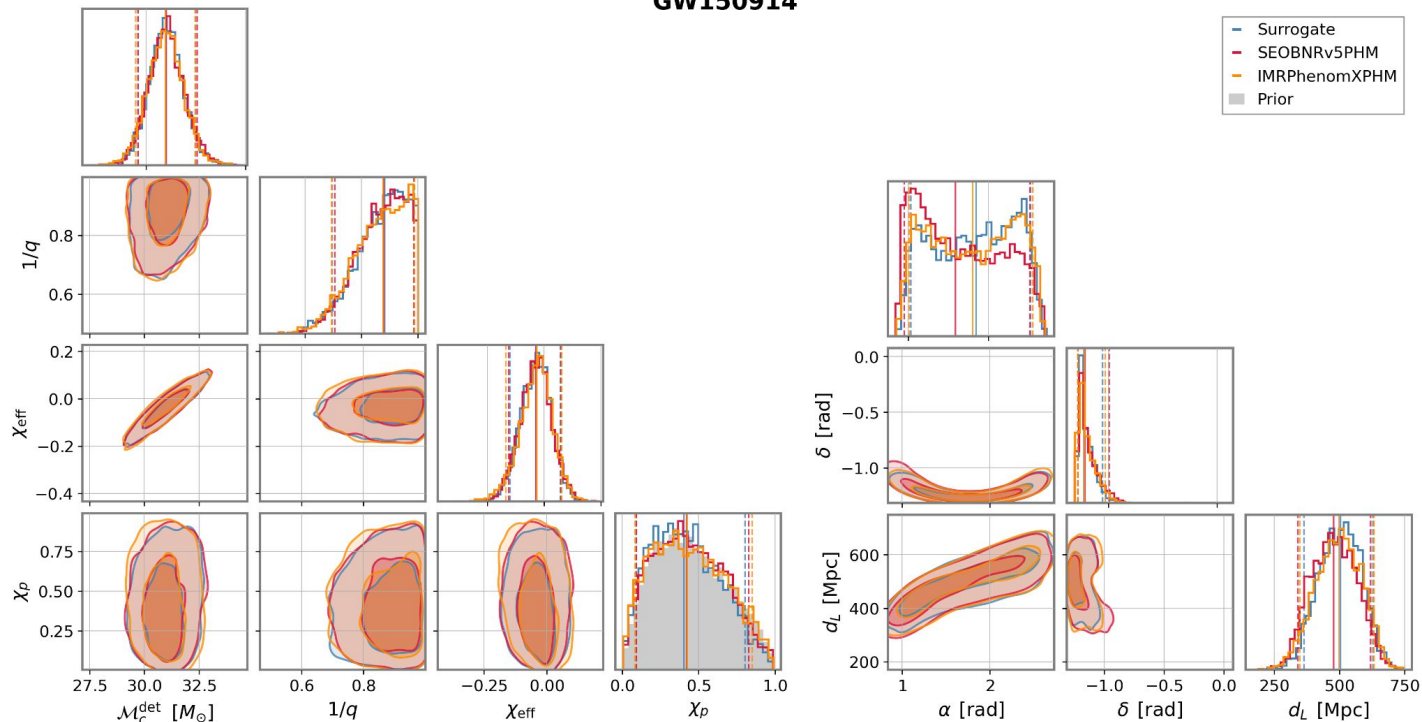
Network
(HLV)
optimal
SNR ~ 25.7

$$\chi_{\text{eff}} := \frac{q|\vec{\chi}_1| \cos \theta_1 + |\vec{\chi}_2| \cos \theta_2}{1 + q},$$

$$\chi_p := \max \left\{ |\vec{\chi}_1| \sin \theta_1, \frac{(4 + 3q)}{(4q + 3)q} |\vec{\chi}_2| \sin \theta_2 \right\}.$$

Results: GW150914

GW150914



	Sur	SEOB	XPHM
Wall time	19hr 54m	63hr 49m	9hr 10m

~ 3.2x speedup compared to SEOBNRv5PHM

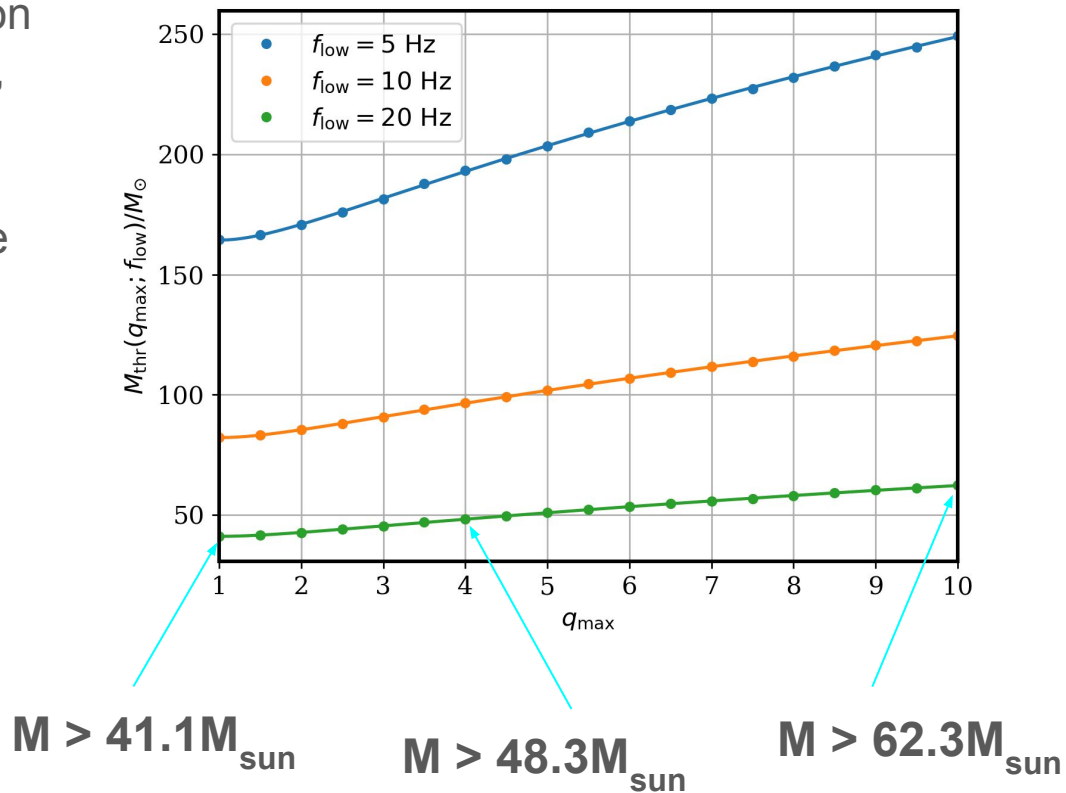
Conclusions

- 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.
 - Waveforms in as little as 81us amortized cost.
- Demonstrated practical application of surrogate to PE, with significant speedup over SEOBNRv5PHM.
 - Full potential requires samplers that can exploit batched waveform evaluation.

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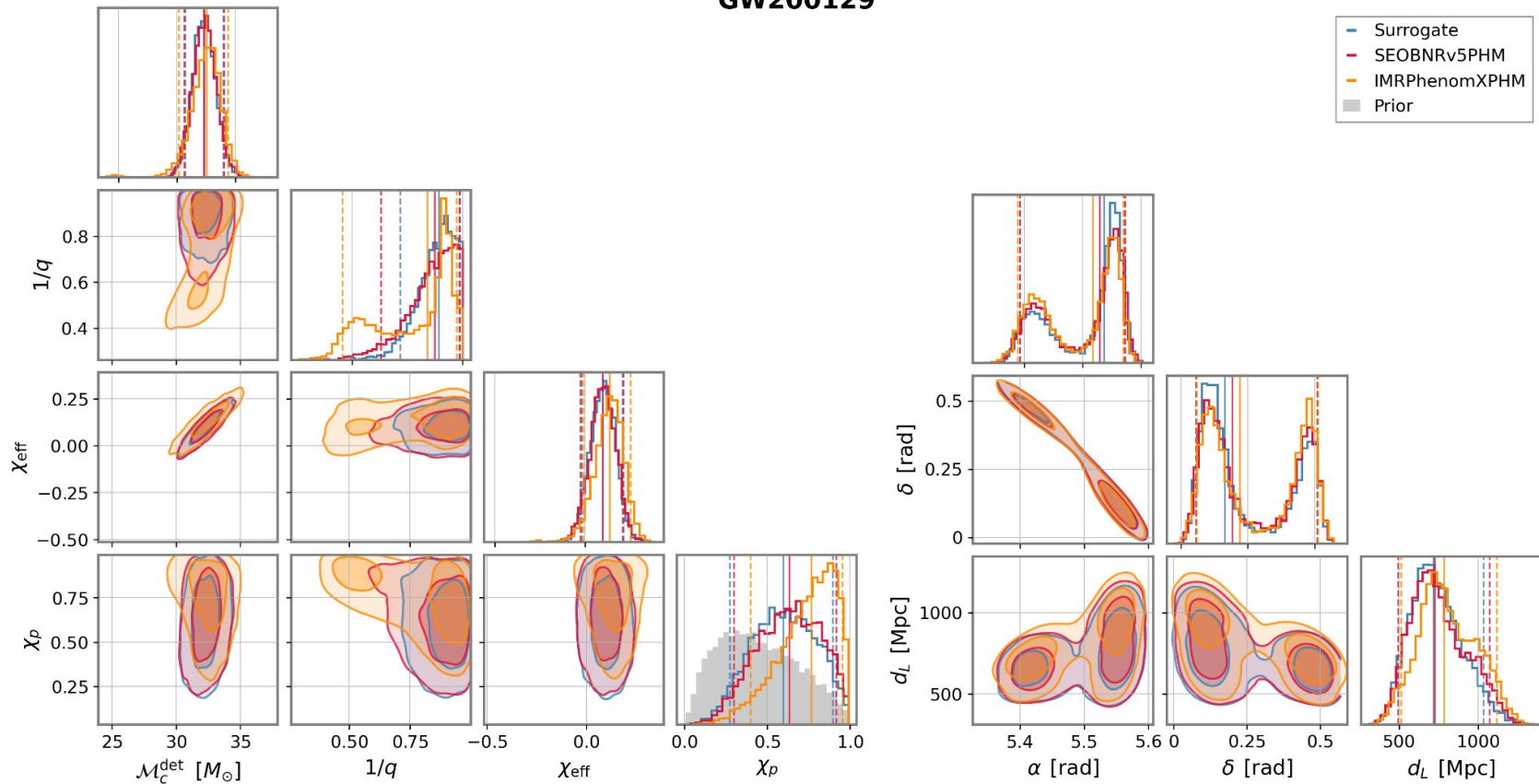
Bonus slide: threshold mass

- Waveform polarizations returned on a fixed geometric time grid $[-10^4 M, 100M]$ with spacing $\Delta t = 0.5M$.
- Starting frequency depends on the total mass.
- Threshold mass (right): minimum mass such that (2,2) mode starts below 5, 10, 20 Hz whenever $M > M_{\text{thr}}$.
- $M_{\text{thr}} = 1.2 \times 10^7 M_{\text{sun}}$ for $f_{\text{low}} = 0.1$ mHz, $q_{\text{max}} = 10$



Bonus slide: GW200129

GW200129



Bonus slide: GW250114

GW250114

