

Waveform Systematics for Black Hole Binary Mergers Models

Student: Samuel Clyne, University of Rhode Island
Samuel.Clyne@uri.edu

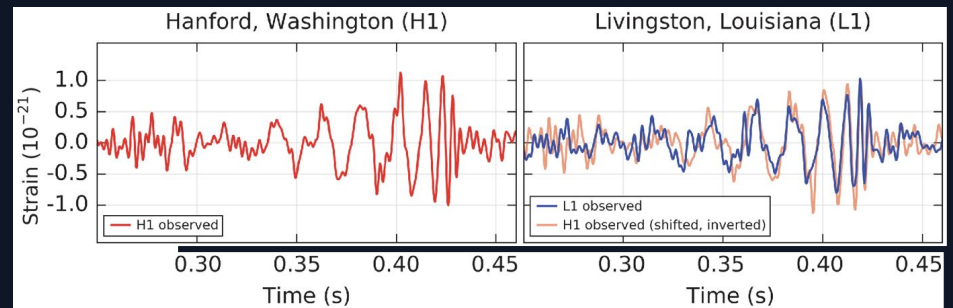
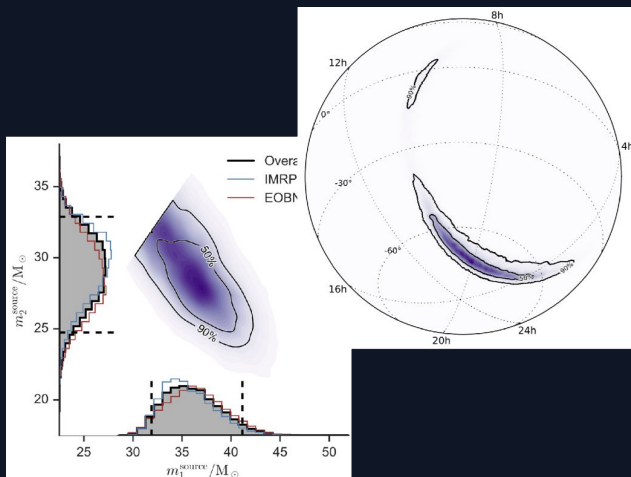
Mentor: Dr Michael Puerrer, URI
mpuerrer@uri.edu

Date April 10, 2024



Waveform Systematics for Black Hole Binary Mergers Models

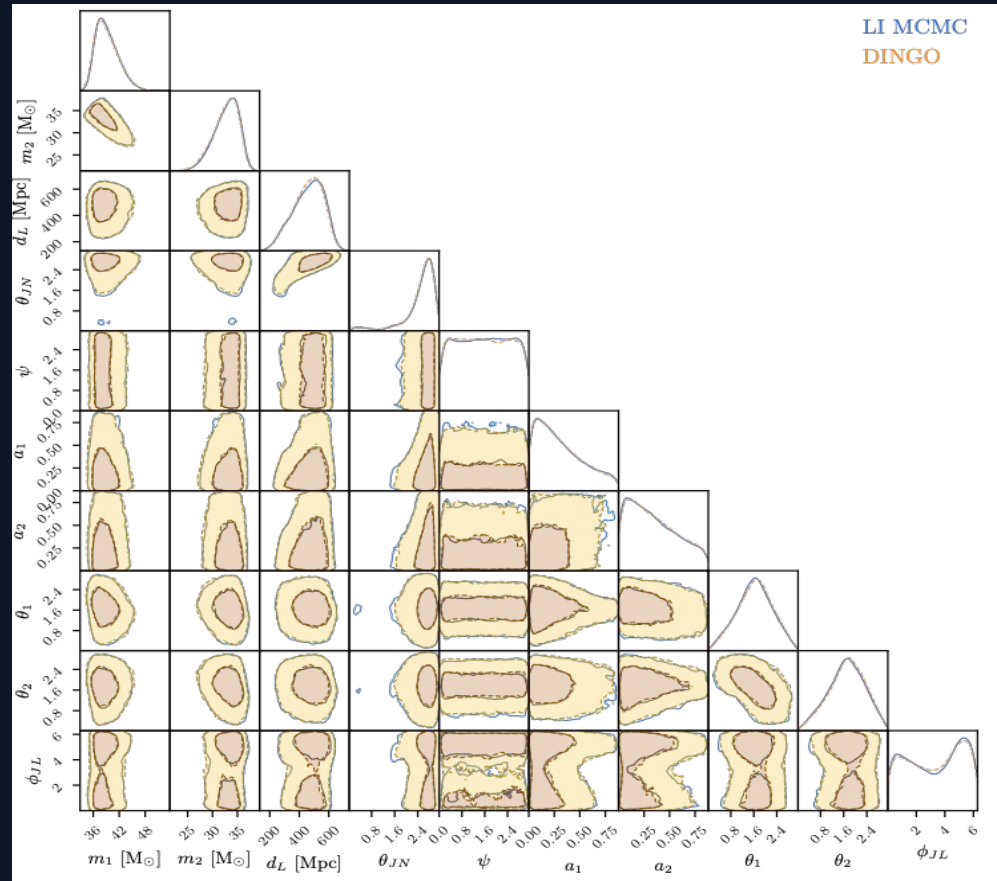
- Black hole mergers can be characterized using gravitational wave data collected at LIGO/Virgo
- Deep Inference for Gravitational-wave observations (DINGO) leverages neural networks to speed up analysis vs traditional methods



Waveform Systematics for Black Hole Binary Mergers Models

DINGO

- Train on simulated data (Gaussian noise + GW signal)
- Training: ~1 week (NVIDIA A100)
- Inference: ~ 1 minute [GPU]; ~ hours with *importance sampling* [CPU]
- Posterior and evidence match with traditional samplers (~ 1 nat)

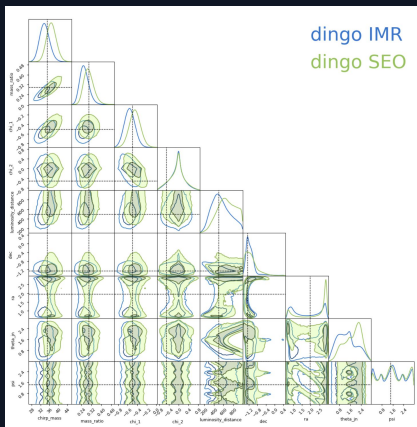


Code: <https://github.com/dingo-gw/dingo>

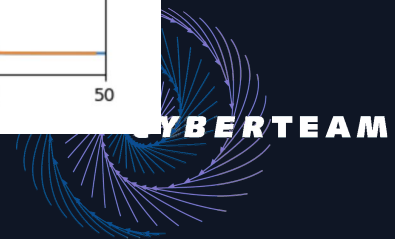
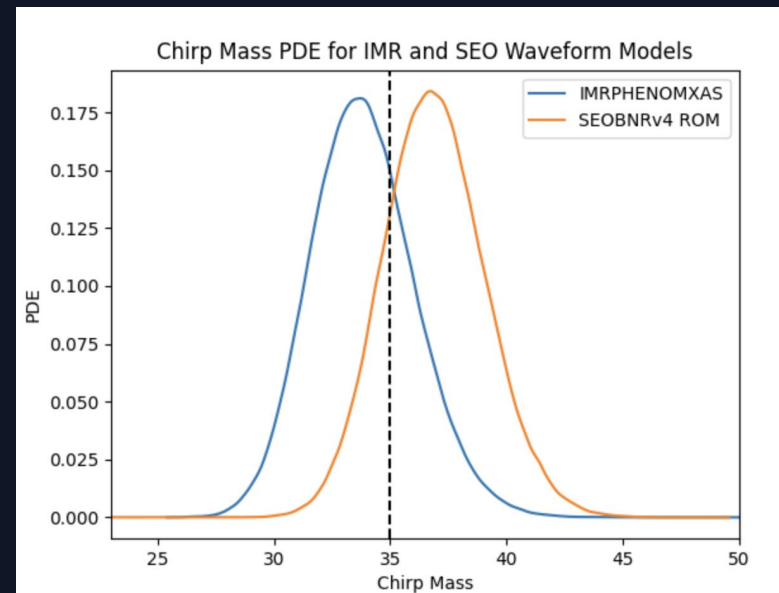


Waveform Systematics for Black Hole Binary Mergers Models

- Imperfections in gravitational waveform models can lead to significant bias in estimating parameters
- Goal: create a visual map of discrepancies between the posteriors for different models to guide model improvements
- Method: Analyze grid of 100 mock injections varying mass ratio from 1 to 8 and varying spin from -0.9 to 0.9 using simple waveform models



Posterior plot example for single grid point



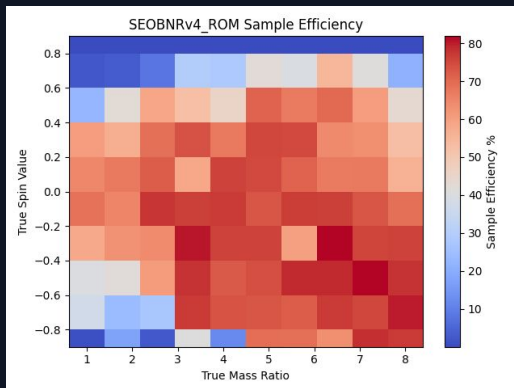
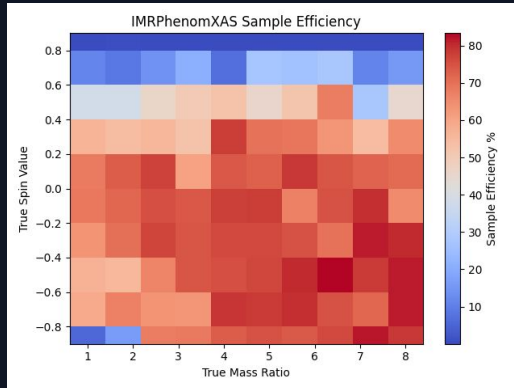
Waveform Systematics for Black Hole Binary Mergers Models

- Timeframe
 - Start Date: October 1, 2023
 - End date: March 31, 2024



Waveform Systematics for Black Hole Binary Mergers Models

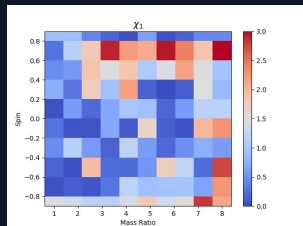
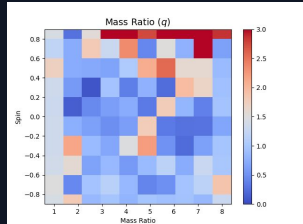
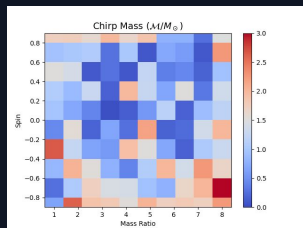
Results



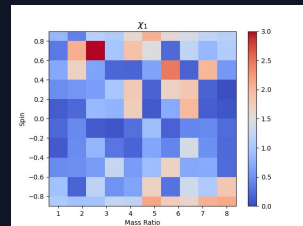
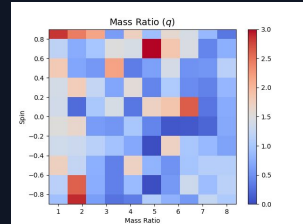
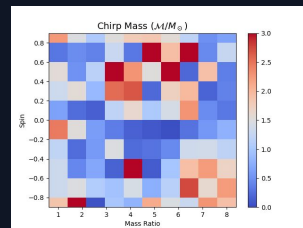
- Trained networks conditioned on two waveform models (IMRPHENOMXAS and SEOBNRv4_ROM)
- Used *importance sampling* to verify grid space where models perform well
- Results here indicate at very high spins neither network performs well

Waveform Systematics for Black Hole Binary Mergers Models

IMRPhenomXAS



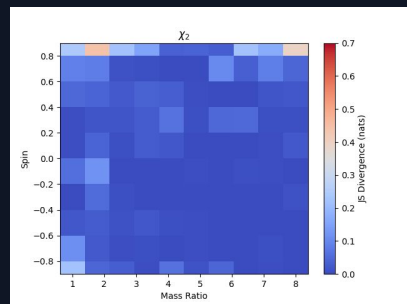
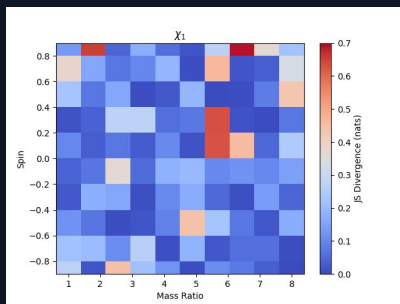
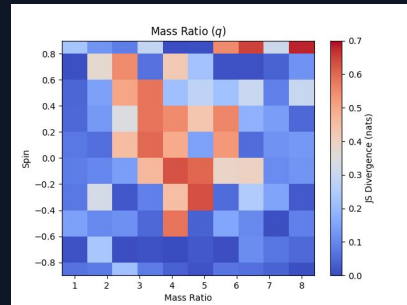
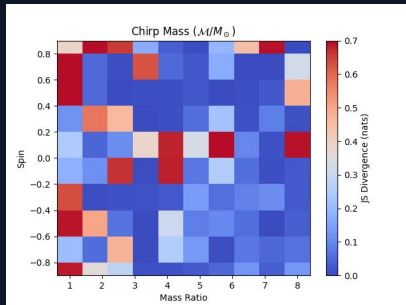
SEOBNRv4 ROM



- For both models biases in a number of parameters are high for large spin magnitudes
- biases tend to be small for moderate spins, irrespective of mass-ratio.
- Biases at high spin magnitudes may be partly due to the spin prior used to train networks being constrained to $[-0.9, 0.9]$ which can cause railing.



Waveform Systematics for Black Hole Binary Mergers Models



- Used Jensen Shannon divergence to compare models
- Moderate JS-Divergence value, suggesting similar posteriors
 - indistinguishability threshold of 0.002


$$JS(P||Q) = \frac{1}{2}KL(P||\frac{P+Q}{2}) + \frac{1}{2}KL(Q||\frac{P+Q}{2}) \quad KL(P||Q) = \sum_x P(x) \log\left(\frac{P(x)}{Q(x)}\right)$$

Jensen-Shannon Divergence Values		
Parameter	Median	St.Dev
Chirp Mass (M/M_{\odot})	0.072 nats	0.237 nats
Mass Ratio (q)	0.120 nats	0.201 nats
Spin 1 (χ_1)	0.096 nats	0.158 nats
Spin 2 (χ_2)	0.008 nats	0.075 nats



Publications/Contributions

- Poster presentation at LIGO-VIRGO-KAGRA March Meeting in Baton Rouge, LA
- URI AI Lab Poster Competition (April 29)



Mapping Systematic Effects of Waveform Models on Parameter Estimation with Dingo

Samuel Clyne¹, Michael Pürer², Stephen Green³, Nihar Gupta^{3,4}, Alessandra Buonanno^{2,5}, Jonathan Gair⁶, Maximilian Dax⁷, Jonas Wildberger⁸, Jakob Macker^{1,8}, Bernhard Schölkopf⁹

¹U. of Rhode Island, ²Max Planck Institute for Gravitational Physics, ³U. of Maryland, ⁴Max Planck Institute for Intelligent Systems, ⁵U. of Nottingham, ⁶U. of Tübingen

Bayesian Inference

Bayesian inference is a powerful tool to determine the probability distribution of a collection of variables given some data with strong priors to gravitational wave parameter estimation.

$P(\theta)$ - Prior distribution of variable
 $P(\theta|D)$ - Likelihood function
 $P(\theta)$ - Evidence (normalizing factor)

$$P(\theta|D) = \frac{P(\theta)P(D|\theta)}{P(D)}$$

The posterior distribution can be obtained through stochastic sampling with algorithms such as Markov Chain Monte Carlo and related sampling.

Methods and Motivation

We train neural networks on datasets of SEOBNRv4_ROM¹ and IMRPhenomXAS² approximations. Models are trained on the ML detector network with synthetic ASDs from O3. Mock injections using the NRHybridSurf3pp³ approximation are analyzed over a grid of varying mass ratio and spin values, with all other parameters held constant. We aim to quantify the bias of the above SEOBNR and IMRPhenom waveform families, which cover a larger parameter space compared to the NRHybridSurf waveform family which is more constrained but offers higher accuracy. We compare posteriors across the grid using the Jensen-Shannon divergence as a measure of similarity.

Jensen-Shannon Divergence
 Symmetric measure of similarity between two probability distributions

$$JS(P||Q) = \frac{1}{2}KL(P||P_{\text{mix}}) + \frac{1}{2}KL(Q||P_{\text{mix}}) \quad KL(P||Q) = \sum_i P(x_i) \log\left(\frac{P(x_i)}{Q(x_i)}\right)$$

Waveform Models

- SEOBNRv4_ROM - Effective-one-body reduced order model approximation
- IMRPhenomXAS - Phenomenological waveform approximation
- NRHybridSurf3pp - Numerical relativity surrogate approximation

In this initial study all waveform approximations are restricted to dominant (2,2) mode. The chosen detector sensitivity and injection distance lead to a median SNR of ~250, allowing us to probe how well Dingo works in the high SNR limit. We use a fixed noise realization for all injections.

Results

Normalized bias

For both models biases in a number of parameters are high for large spin magnitudes, while biases tend to be small for moderate spins, irrespective of mass-ratio. Biases at high spin magnitudes may be partly due to the spin prior used to train networks being constrained to (-0.5, 0.5) which can cause railing.

JS-divergence

In general, the JS-divergence between EOB and Phenom posteriors is moderate suggesting that these models have similar posterior distributions. The JS-divergence values are well above the customary misdiagnosability threshold of 0.002 nats [8] and can reach values of ~0.5 nats in some cases, indicating strong disagreement.

While bias in the spin of the secondary can be high, this behavior is consistent for both models resulting in low low-divergence values.

Parameter	SEOBNRv4_ROM	IMRPhenomXAS
Chirp Mass M_{chirp} [M _⊙]	0.075 bias	0.075 bias
Mass Ratio q	0.100 bias	0.100 bias
Spin χ_{1z}	0.000 bias	0.000 bias
Spin χ_{2z}	0.000 bias	0.000 bias

Injection Parameters used for study

Parameter	Injection Parameter
Chirp Mass M_{chirp} [M _⊙]	30M _⊙
Mass Ratio q	0.100
Spin χ_{1z}	0.0
Spin χ_{2z}	0.0
Spin χ_{1x}	0.0
Spin χ_{2x}	0.0
Spin χ_{1y}	0.0
Spin χ_{2y}	0.0
Right Ascension [rad]	1.58775 rad
Declination [rad]	0.20233 rad
Inclination Angle [rad]	0.5 rad
Phase [rad]	0.0 rad

DINGO

The Deep Inference for Gravitational Wave Observations (DINGO) is a python package that delivers fast and accurate gravitational wave inference results using normalized flow neural networks. Networks are trained to approximate Bayesian posteriors. DINGO obtains results 2-3x orders of magnitude faster than traditional stochastic sampling codes.

DINGO tasks:

- Build training datasets: waveforms + noise
- Train normalizing flows to estimate posterior density
- Perform inference on real or simulated data
- Verify and improve posteriors with importance sampling (DINGO-ISP)


Importance Sampling
 Importance sampling generates importance weights for a given posterior. It can be used with DINGO to verify and correct results.

- $w_i(\theta)$ - Conditional density from neural network, approximates $p(\theta|D)$
- w_i - Importance Weights
- N_{eff} - Number of effective samples


$$w_i = \frac{p(\theta|D)}{q(\theta|D)} \quad \theta_{\text{eff}} = \frac{\theta_i}{w_i}$$

Parameter	SEOBNRv4_ROM	IMRPhenomXAS
Chirp Mass [M _⊙]	0.075 bias	0.075 bias
Mass Ratio	0.100 bias	0.100 bias
Spin χ_{1z}	0.000 bias	0.000 bias
Spin χ_{2z}	0.000 bias	0.000 bias
Spin χ_{1x}	0.000 bias	0.000 bias
Spin χ_{2x}	0.000 bias	0.000 bias
Spin χ_{1y}	0.000 bias	0.000 bias
Spin χ_{2y}	0.000 bias	0.000 bias
Right Ascension [rad]	1.58775 rad	1.58775 rad
Declination [rad]	0.20233 rad	0.20233 rad
Inclination Angle [rad]	0.5 rad	0.5 rad
Phase [rad]	0.0 rad	0.0 rad

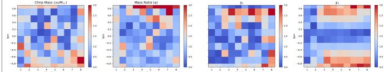
Posterior for SEOBNRv4_ROM injection analyzed with DINGO-ISP with $\chi_{1z} = 0.3, \chi_{2z} = 0.138$. Injection results obtained in ~1 hour.



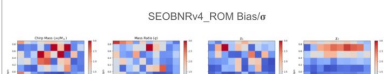
Posterior for injection analyzed with DINGO with $\chi_{1z} = 0.1, \chi_{2z} = 0.205$.




IMRPhenomXAS Bias



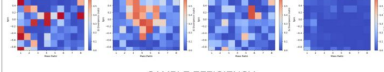
SEOBNRv4_ROM Bias



JENSEN-SHANNON DIVERGENCE



SAMPLE EFFICIENCY



Importance Sampling sampling efficiency for DINGO networks (n = 400,000). Neither network performs well at very high spin.

Future Work

- We will compare JS-divergence results with misdiagnosability between EOB and Phenom models, even though the match does not directly translate to the bias seen in parameter estimation.
- We will extend the study to incorporate models trained on waveform datasets using higher order modes and precession for the effective-one-body and phenomenological approximations.
- We will also incorporate DINGO models trained on NR-surrogate waveform models including higher order modes.

References

[1] M. Pürer, S. Green, S. Hild, and B. Schölkopf, “Fast time gravitational wave space with neural generative models,” *Physical Review Letters*, vol. 125, p. 211101, 2020.

[2] S. Green, S. Hild, and B. Schölkopf, “Fast time gravitational wave space with neural generative models,” *Physical Review Letters*, vol. 125, p. 211101, 2020.

[3] S. Green, S. Hild, and B. Schölkopf, “Fast time gravitational wave space with neural generative models,” *Physical Review Letters*, vol. 125, p. 211101, 2020.

[4] S. Green, S. Hild, and B. Schölkopf, “Fast time gravitational wave space with neural generative models,” *Physical Review Letters*, vol. 125, p. 211101, 2020.

[5] S. Green, S. Hild, and B. Schölkopf, “Fast time gravitational wave space with neural generative models,” *Physical Review Letters*, vol. 125, p. 211101, 2020.

[6] S. Green, S. Hild, and B. Schölkopf, “Fast time gravitational wave space with neural generative models,” *Physical Review Letters*, vol. 125, p. 211101, 2020.

[7] S. Green, S. Hild, and B. Schölkopf, “Fast time gravitational wave space with neural generative models,” *Physical Review Letters*, vol. 125, p. 211101, 2020.

[8] S. Green, S. Hild, and B. Schölkopf, “Fast time gravitational wave space with neural generative models,” *Physical Review Letters*, vol. 125, p. 211101, 2020.

LIGO-G240337
samuel.clyne@uri.edu

Challenges

- Initial plan to compare 3 models, but could not get reliable results within timeframe
- Low sample efficiency at high spins limit the scope of study



Lessons Learned

- Much Stronger understanding of Black Hole Binary Parameter Estimation
- Gained Practical experience training neural networks on HPC resource
- Learned to write efficient scripts to run in HPC
- Ready to apply skills learned during study to more complex models

