

Post-Newtonian Theory Informed Data-Driven Approaches in Modeling Eccentric Binary Black-Hole Mergers Waveforms

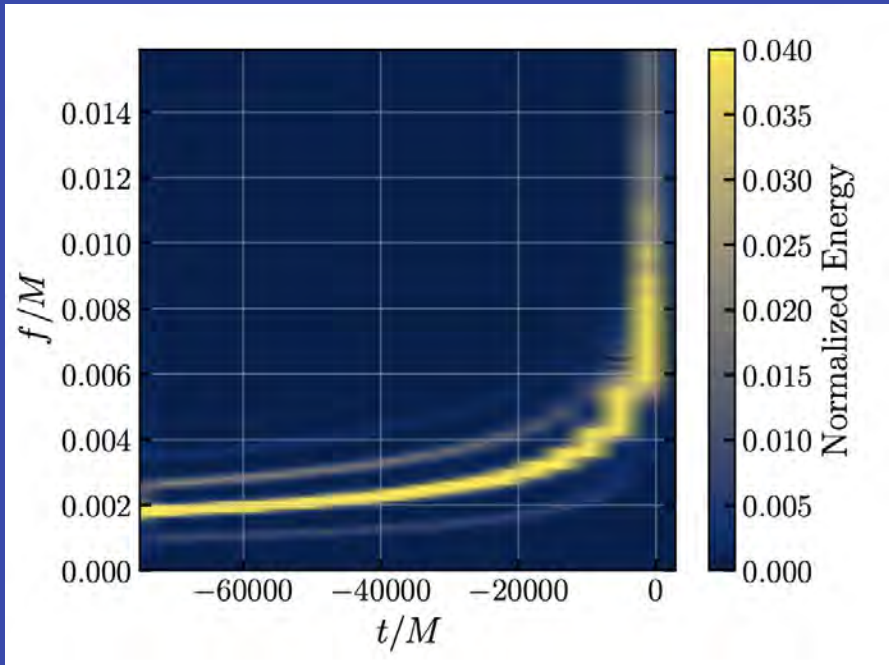
Tousif Islam, Tejaswi Venumadhav, Ajit Mehta, Isha Anantpurkar, Digvijay Wadekar, Javier Roulet, Jonathan Mushkin, Barak Zackay, and Matias Zaldarriaga



Combination of Singular Value Decomposition (SVD) and Signal Processing to extract 'Eccentric Harmonic'



Reduced order model for real-time generation of 'Eccentric Harmonic'



Data-Driven Approaches in Building Template Banks

Tousif Islam, Tejaswi Venumadhav, Ajit Mehta, Isha Anantpurkar, Digvijay Wadekar, Javier Roulet, Jonathan Mushkin, Barak Zackay, and Matias Zaldarriaga

gwIAS-Ecc : efficient template bank for detecting eccentric BBHs

Eccentric harmonic decomposition

K-means clustering

SVD + Random Forest Regression for amplitude/phase modelling

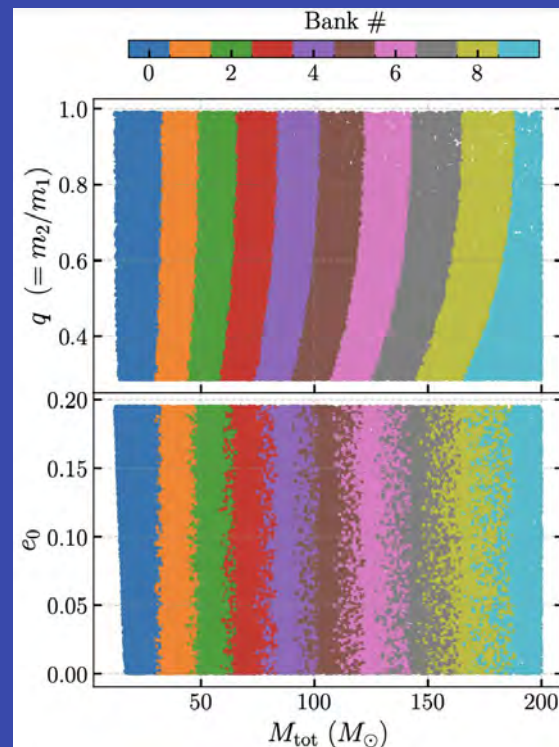
Geometric Placement algorithm

Islam+ 2025, In Preparation

Based on:

Wadekar+ 2025, arXiv:2310.15233

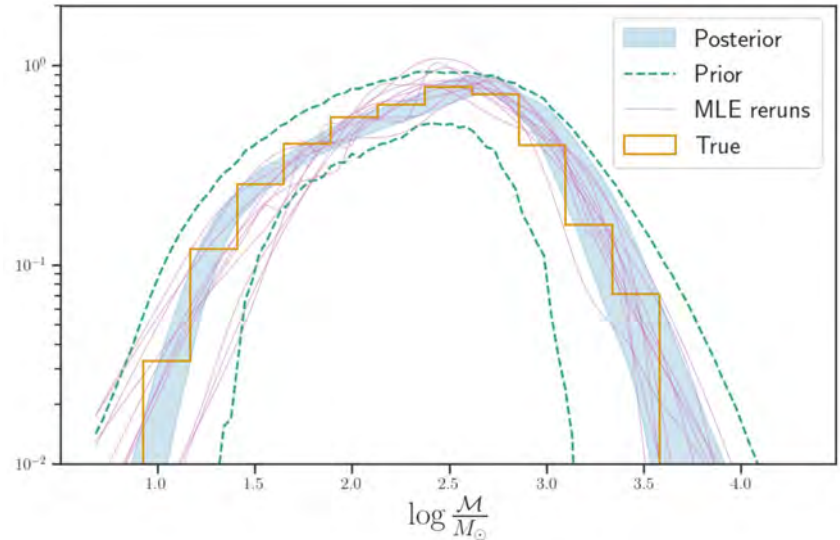
Roulet+ 2019, arXiv:1904.01683



Emulating CBC population synthesis simulations with uncertainty quantification: Bayesian normalizing flows.

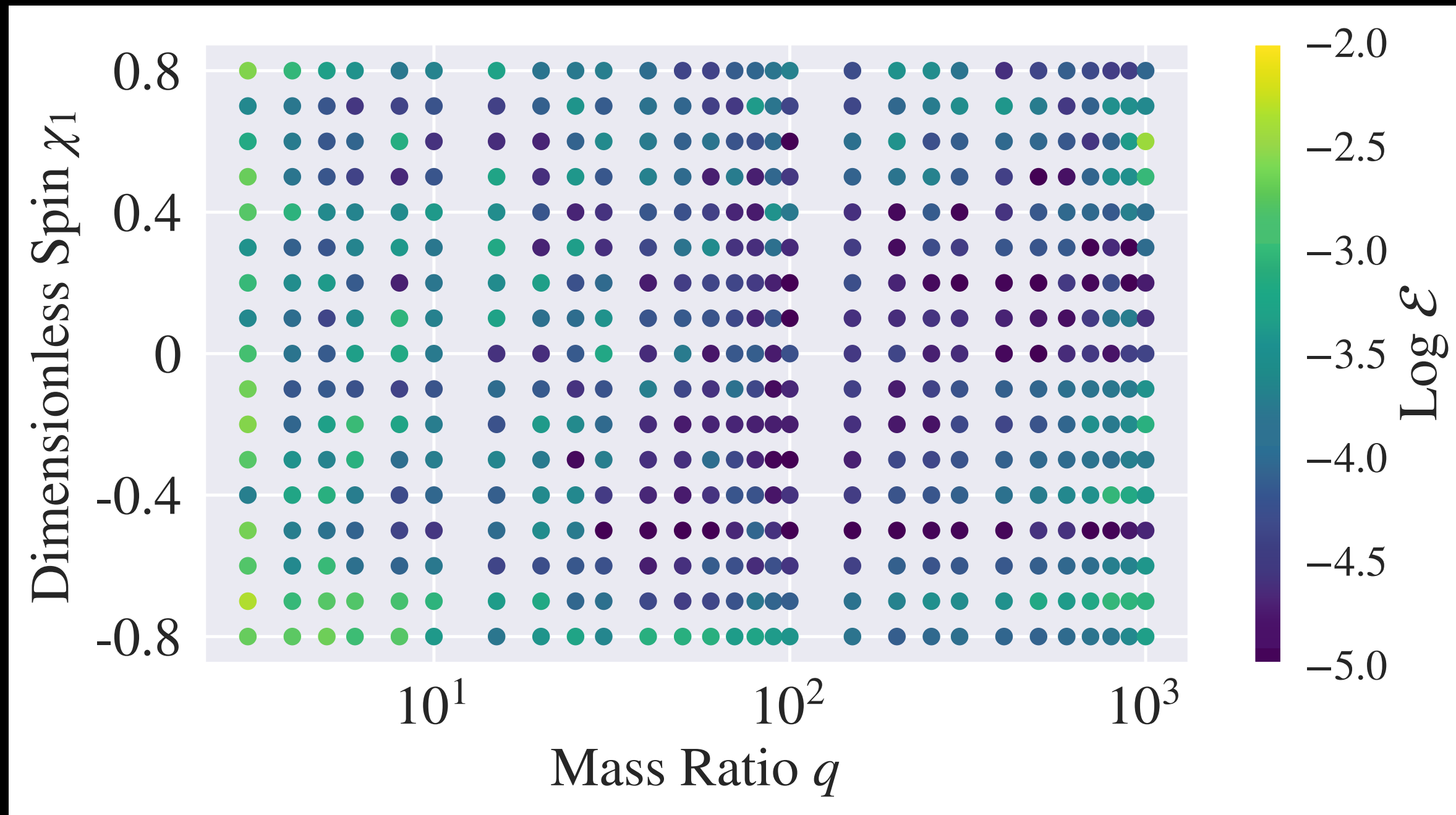
Anarya Ray

- **Flows can emulate PopSynth:** constrain astrophysics from GWTC
[Colloms et al 2025 \(2503.03819\)](#)
- Training of flows are susceptible to **epistemic and aleatoric uncertainties.**
- To **quantify** and marginalize: **Flows made of Bayesian networks**



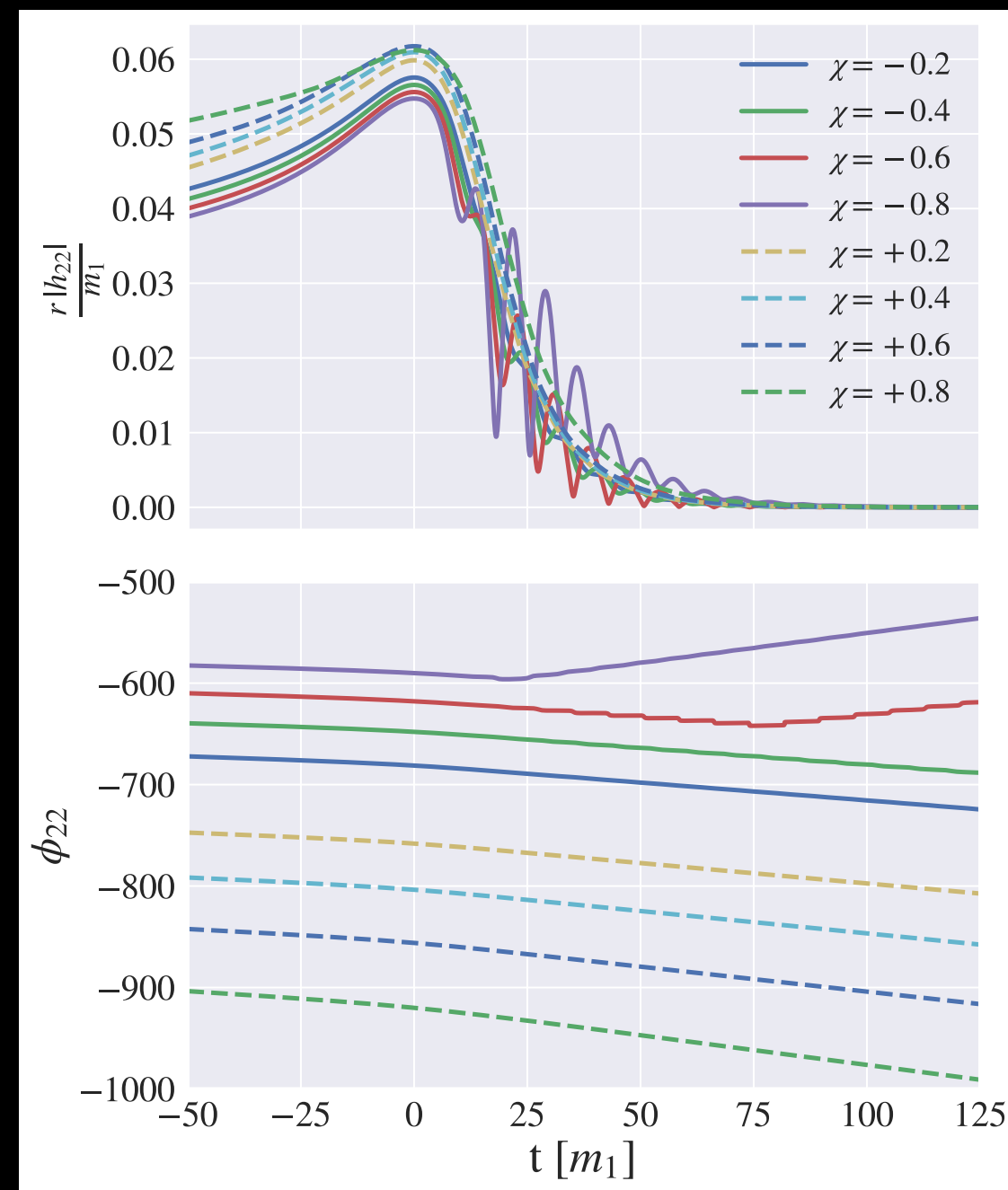
Modeling spinning IMRIs

The need for speed

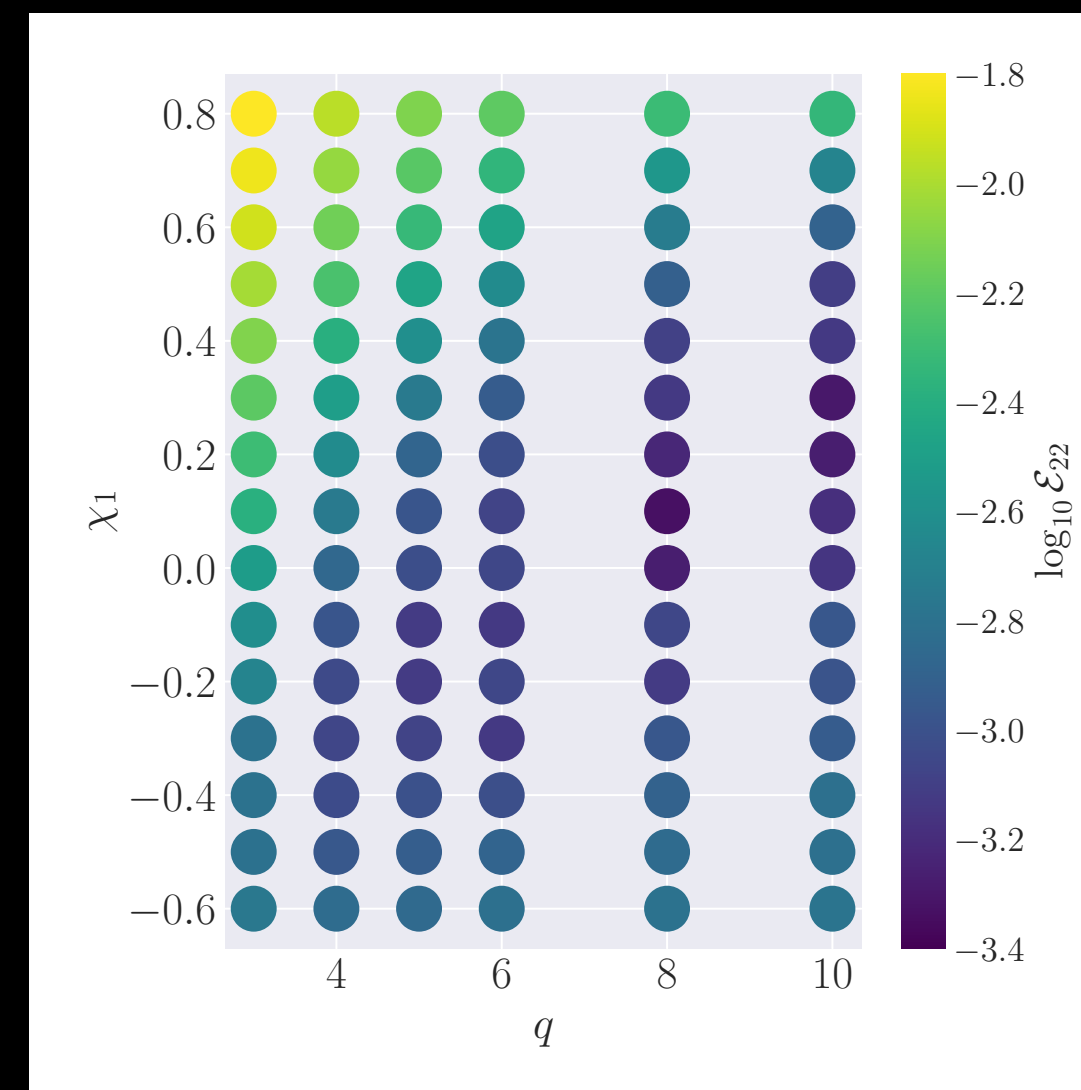


- BHPTNR2dq1e3 : a **fast** and **accurate** surrogate model for point-particle black hole perturbation theory waveform
- Parameter span: $q \in [3, 1000]$ and $\chi_1 \in [-0.8, +0.8]$
- Includes higher order modes up to $\ell \leq 4$
- Median time-domain mismatch error $\sim 8 \times 10^{-5}$
- Evaluation speed: hours to few milliseconds

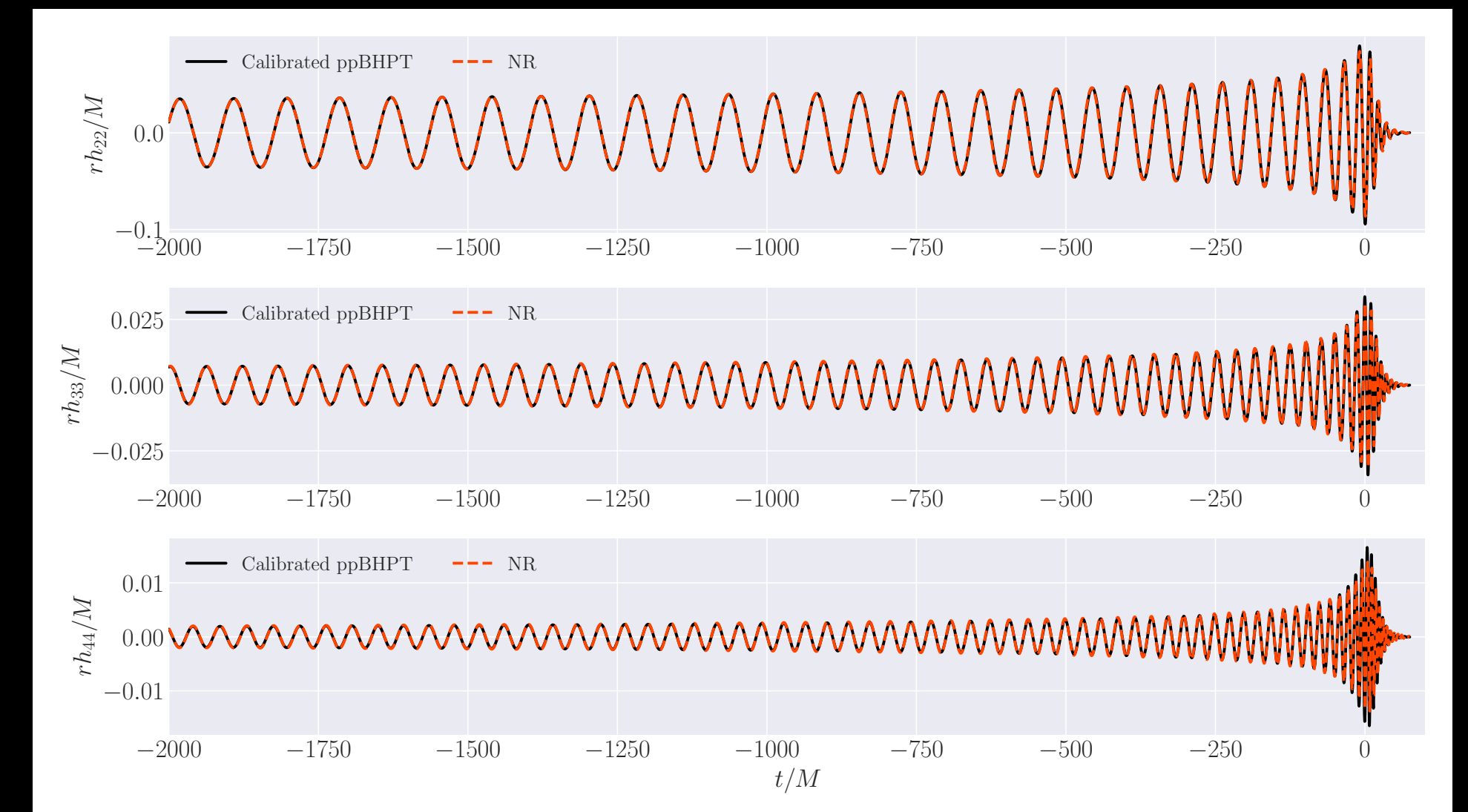
Highlights



Domain Decomposition



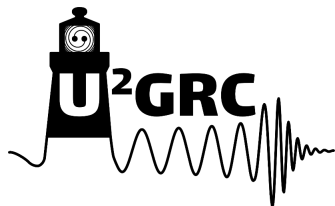
Time Domain Error
after calibration



NR vs rescaled-ppBHPT

Rapid Identification and Classification of Eccentric Gravitational Wave Inspirals with Machine Learning

Scientific Machine Learning in GW Astronomy Workshop
ICERM, Brown University, June 2025



Adhrit Ravichandran

Graduate Student, C.S.C.D.R, University of Massachusetts Dartmouth

with Aditya Vijaykumar^{1,2}, Prayush Kumar², Shasvath Kapadia^{2,3}

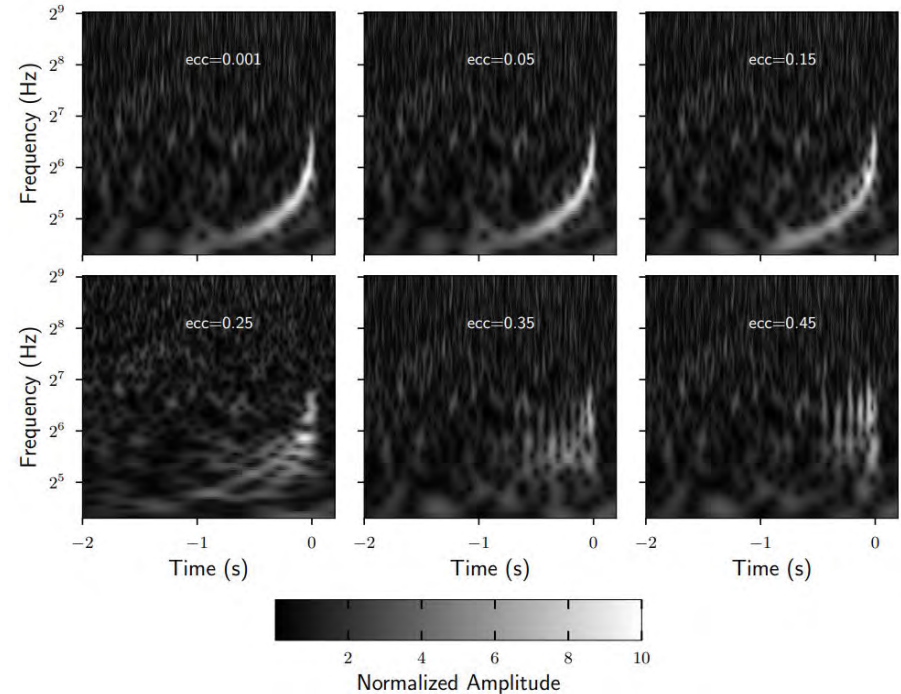
University of Toronto¹

International Center for Theoretical Sciences, Bengaluru, India²

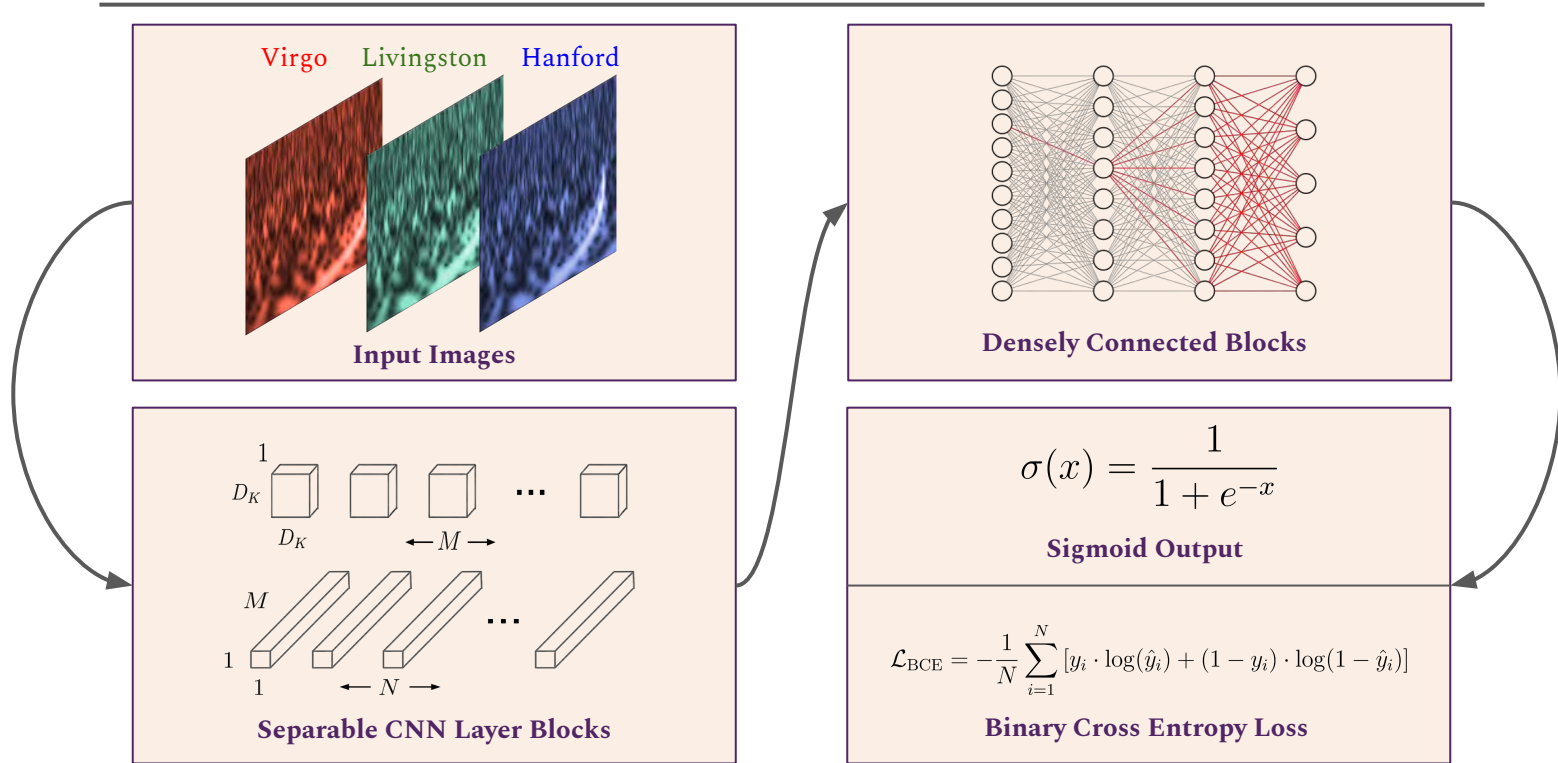
Inter University Center for Astronomy and Astrophysics, Pune, India³

Primary Idea

- PE with eccentricity is computationally expensive
- Eccentricity \rightarrow observable changes in $qscan$
- Propose a neural network to rapidly identify eccentric GW signals from $qscans$ to streamline downstream LIGO analysis.



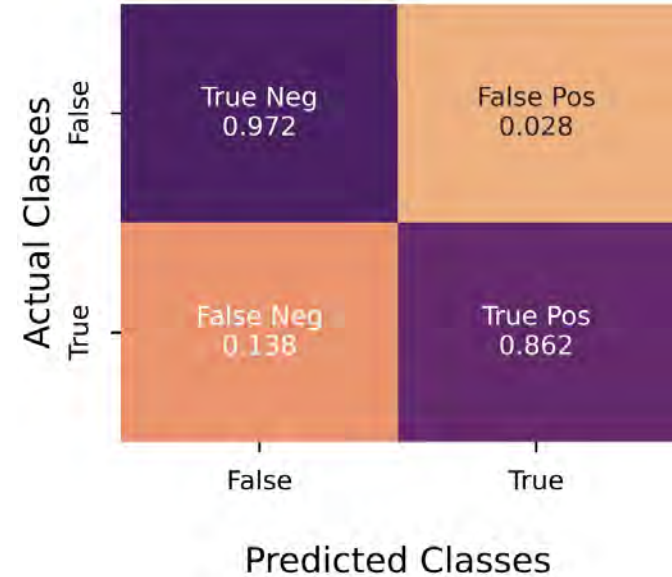
Flow of Information



- **Ratio of Computational Cost** (*Separable CNN / Standard CNN*) = $N^{-1} + (\text{input_layer_size})^{-2}$

Results

e	Accuracy	M	Accuracy	ρ	Accuracy
0	0.972	20-30	0.829	15-25	0.912
0-0.1	0.875	30-40	0.886	25-35	0.948
0.1-0.2	0.918	40-50	0.915	35-45	0.964
0.2-0.3	0.993	50-60	0.933	45-55	0.964
0.3-0.4	0.999	60-70	0.945	55-65	0.979
0.4-0.5	0.999	70-80	0.947	65-75	0.985
				75-85	0.952

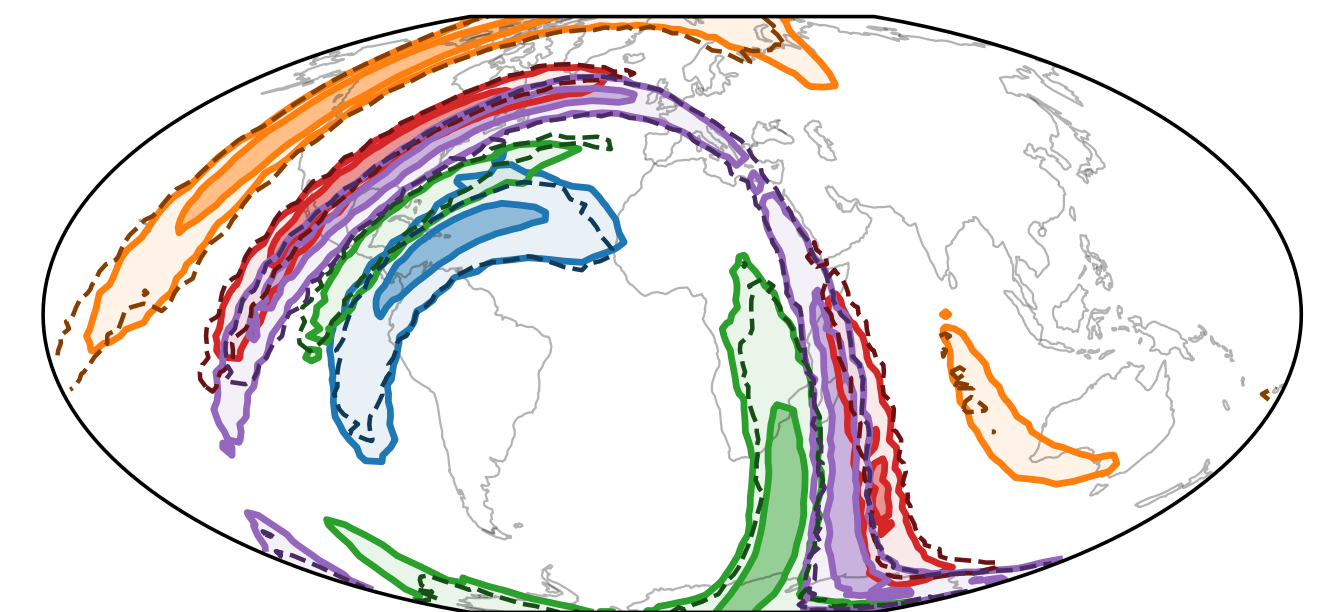
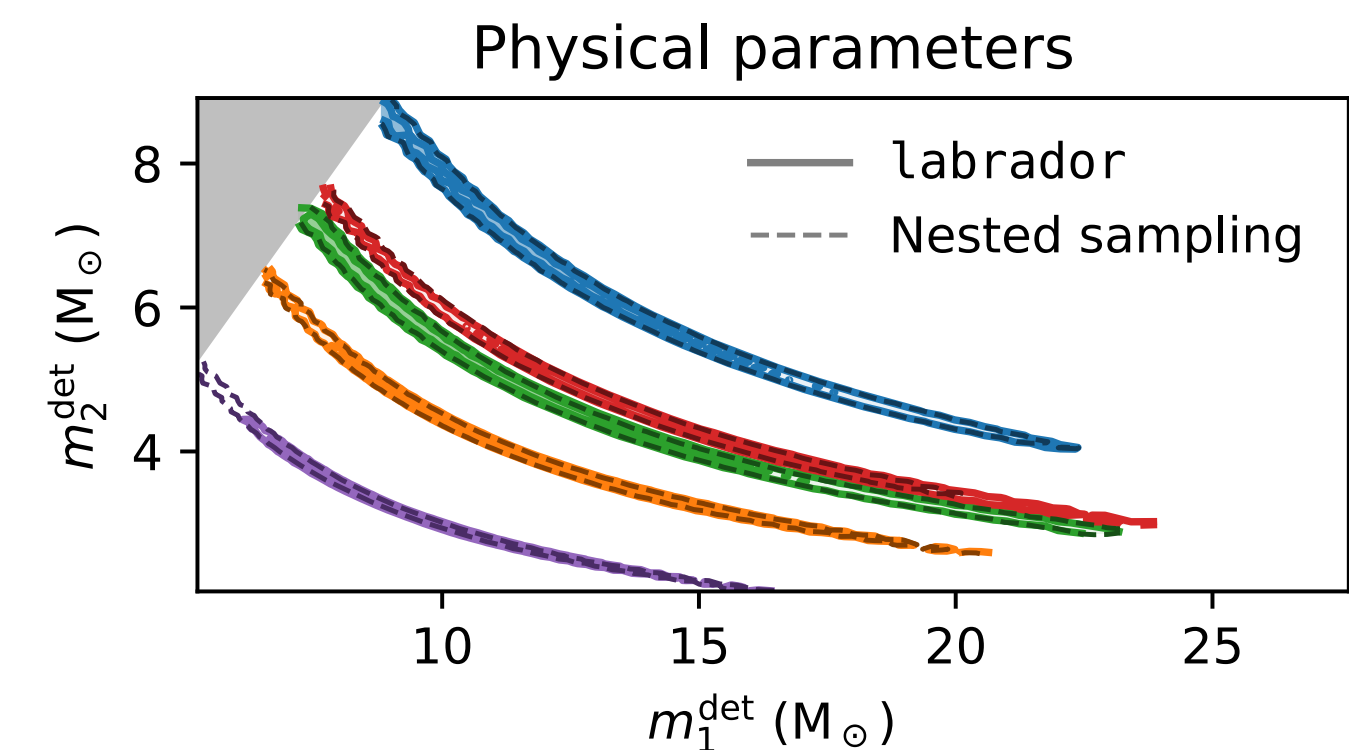
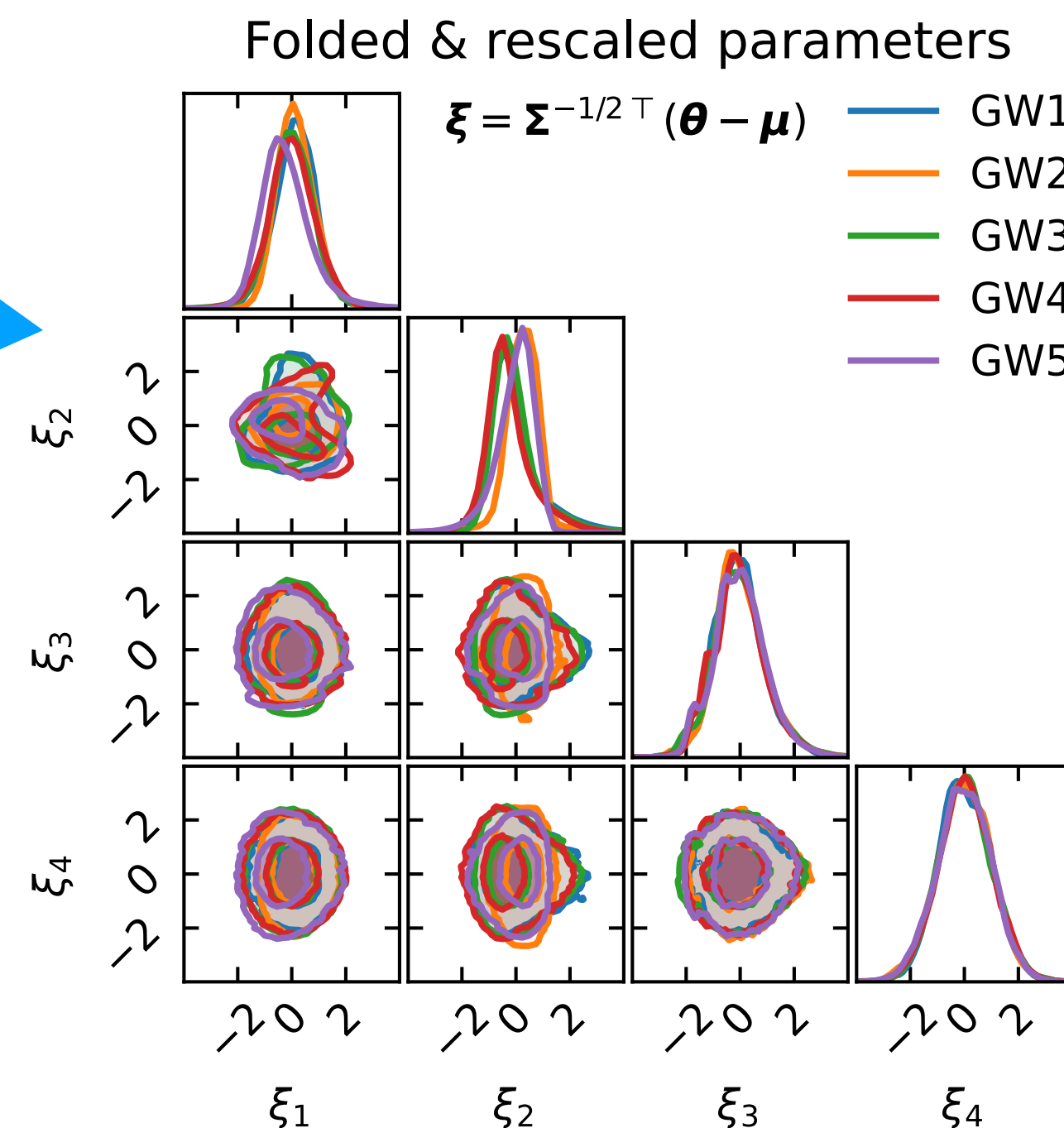
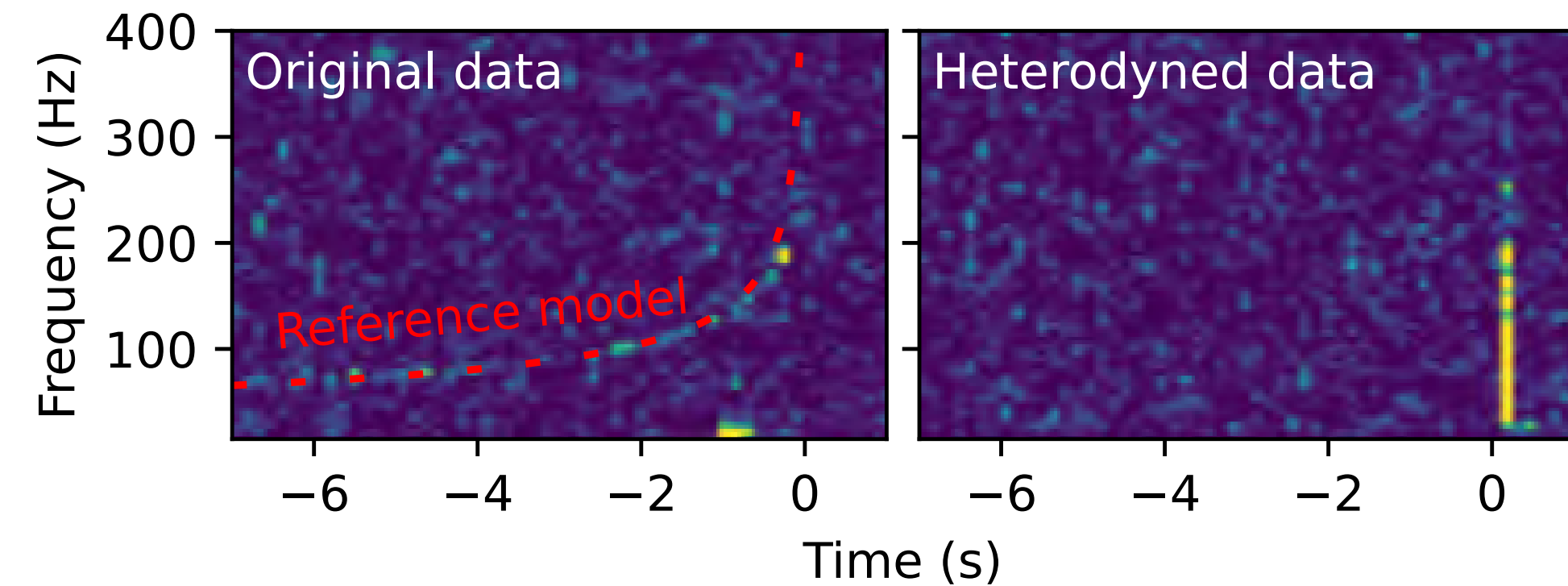


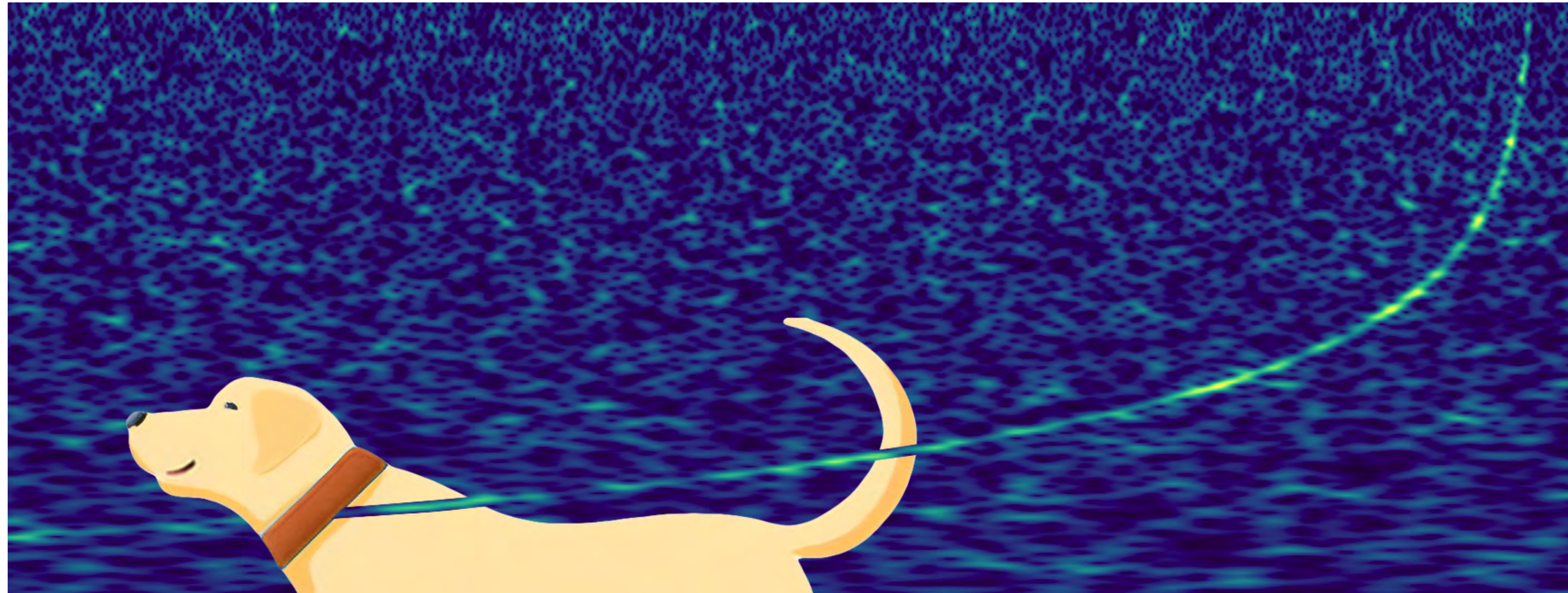
Labrador: easy-to-train gravitational wave inference

Javier Roulet, Marco Crisostomi, Lucy Thomas, Katerina Chatziioannou (Caltech)

Goal: amortized simulation-based inference, but simplifying the problem using gravitational-wave knowledge

- Compress data by heterodyning against an *optimized* waveform
- Standardize posteriors by folding parameters with known symmetries, and rescaling by a predicted mean and covariance





labrador

Stay tuned for article and code...

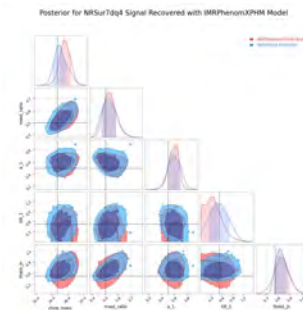
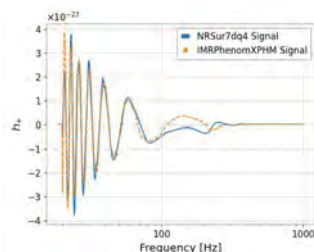
Mapping Systematic Effects of Waveform Models on Gravitational-Wave Parameter Estimation with DINGO

Samuel Clyne¹, Michael Pürrer¹, Stephen Green², Nihar Gupte^{2,3}

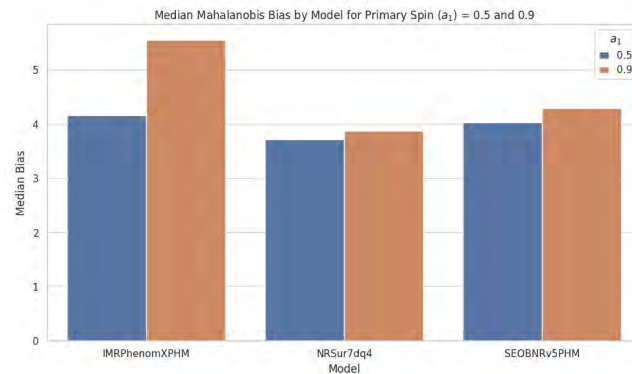
¹U. of Rhode Island, ²U. of Nottingham, ³Max Planck Institute for Gravitational Physics, ⁴U. Of Maryland,



- Discrepancies between waveform models and true signals lead to discrepancies between posteriors
- We aim to map posterior discrepancies across a grid of parameter to guide future waveform model improvement
- Bias in **1D posteriors and 7D posteriors - Mahalanobis Bias** used as metric



Injection Parameters Varied	
Parameter	Injection Value
Mass Ratio q	[1,4] (4 points)
a_1	[0.5,0.9] (2 points)
θ_1	$[0, \frac{\pi}{2}]$ (4 points)
Inclination θ_{JN}	$[0, \frac{\pi}{2}]$ (4 points)
Detectors	HLV



BUILDING NEXT-GENERATION GRAVITATIONAL WAVE SEARCHES

Kanchan Soni, Alexander Nitz



Fully Coherent Bayesian Search Pipeline

- **Develop** a fully coherent Bayesian search pipeline for gravitational-wave detection
- **Integrate** with the open-source **PyCBC** GW analysis toolkit
- **Enable** reproducible results for current and future LIGO–Virgo–KAGRA observing runs

