AI-Driven Modeling and Inference in Gravitational Wave Astronomy

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AI for GW Astronomy: Overview

Introduction & Motivation

- GW astronomy is entering a data-rich era (LVK, CE, ET, LISA, TaiJi, TianQin)
- Challenges:
  - Recognition: real-time detection (< 1s) for rapid EM follow-up observations
  - Modeling: Noise suppression & waveform generation (mismatch < 0.1%)
  - Inference: fast, reliable parameter estimation (10^4 core hrs currently)
- Traditional methods:
  - computationally expensive （milions of events per yr in the future）
  - difficulty locating global maximum (e.g., EMRIs)

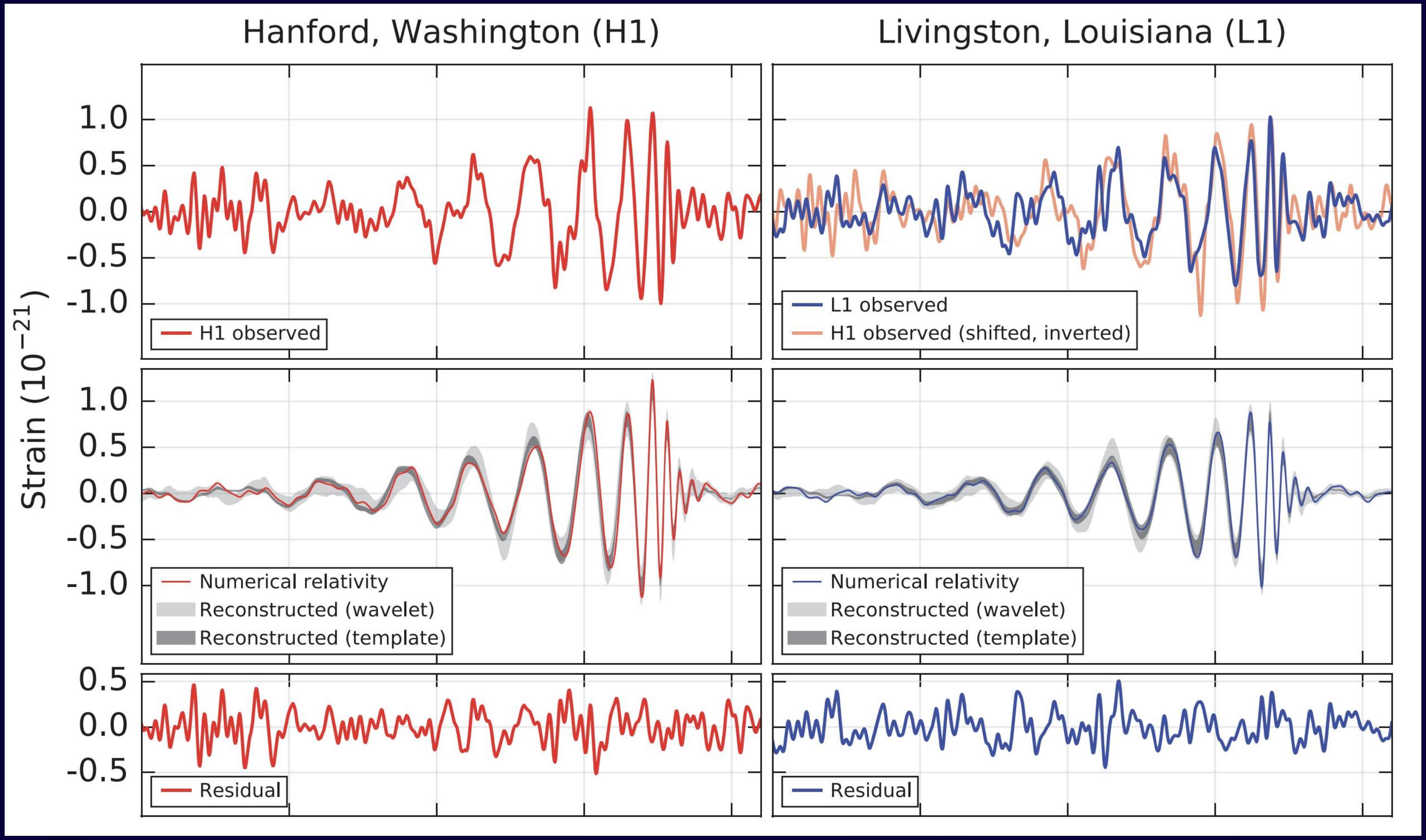
Two promising techniques

- Physics-Informed Neural Networks (PINNs) :
  - Solve PDEs directly using neural networks
  - Embed physical laws into loss function
  - Black hole ringdown/QNMs
  - TENG, BPINN, gradient-PINN,
- Simulation-Based Inference (SBI):
  - Learn complex probability distributions
  - Enable fast Bayesian inference
  - Complementary strengths for inference
  - EMRI searching, microlensing, low snr events, test gravity

02

Waveform Modelling: quasi-normal modes (QNMs)

Waveform Modelling



- Tekowsky Eqn. QNM
- Einstein Eqn. ?

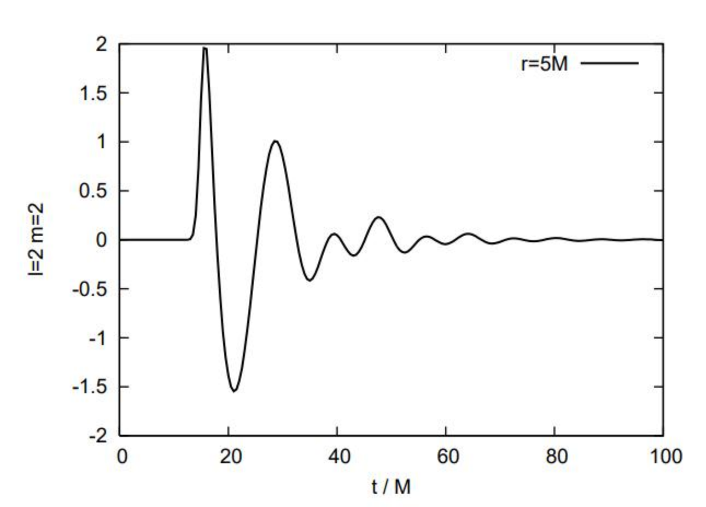
[LIGO & Virgo, 2016, PRL]

Teukolsky Equation

$$\left[\frac{(r^2+a^2)^2}{\Delta} - a^2\sin^2\theta\right]\frac{\partial^2\psi}{\partial t^2} + \frac{4Mar}{\Delta}\frac{\partial^2\psi}{\partial t\,\partial\varphi} + \left[\frac{a^2}{\Delta}-\frac{1}{\sin^2\theta}\right]\frac{\partial^2\psi}{\partial\varphi^2}$$
$$- \Delta^{-s}\frac{\partial}{\partial r}\left(\Delta^{s+1}\frac{\partial\psi}{\partial r}\right) - \frac{1}{\sin\theta}\frac{\partial}{\partial\theta}\left(\sin\theta\,\frac{\partial\psi}{\partial\theta}\right) - 2s\left[\frac{a(r-M)}{\Delta}+\frac{i\cos\theta}{\sin^2\theta}\right]\frac{\partial\psi}{\partial\varphi}$$
$$- 2s\left[\frac{M(r^2-a^2)}{\Delta} - r - ia\cos\theta\right]\frac{\partial\psi}{\partial t} + (s^2\cot^2\theta - s)\psi = 4\pi\Sigma T\,.$$

$$\Delta(r)R''(r) + (s+1)(2r-1)R'(r) + V(r)R(r) = 0.$$

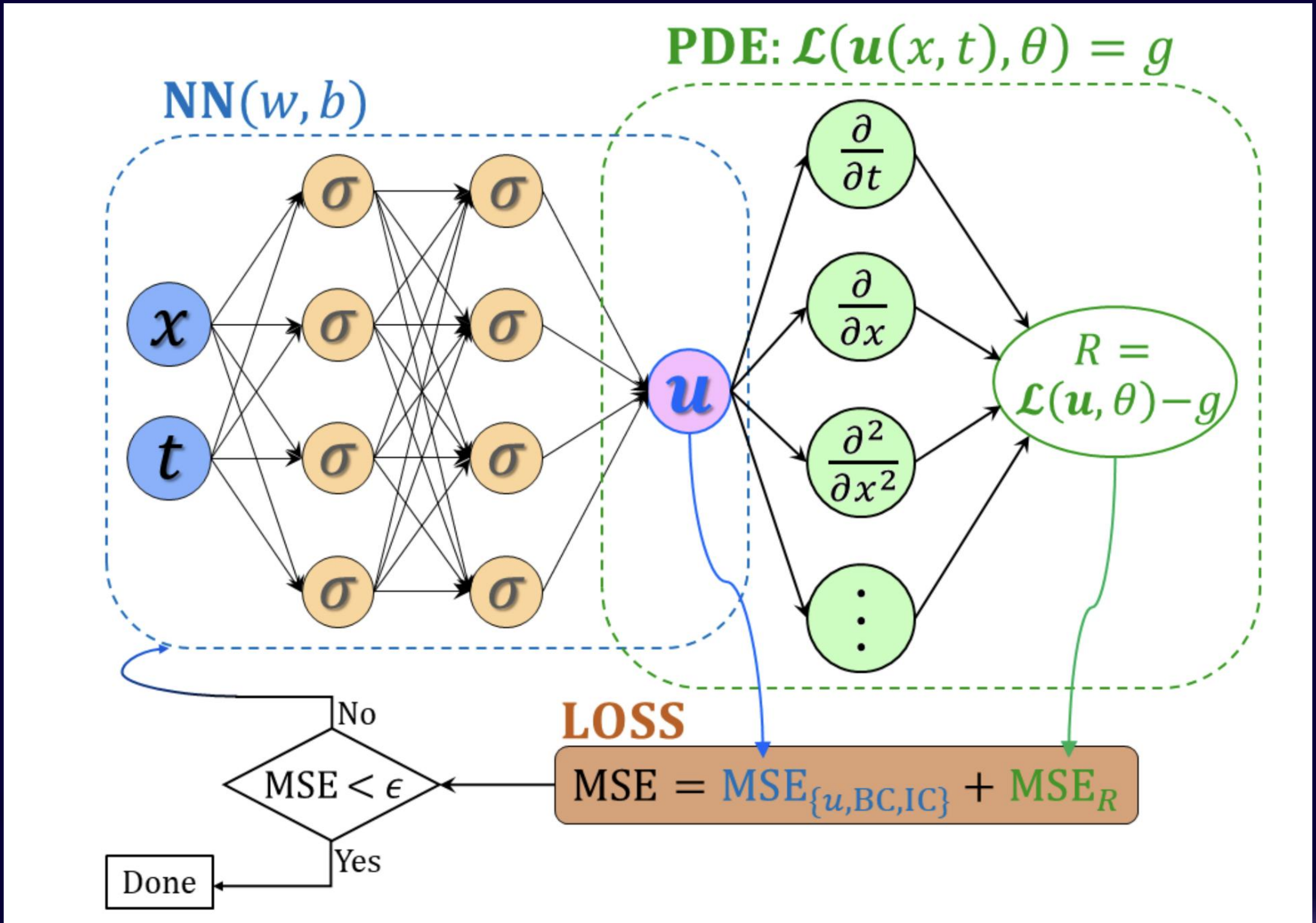
$$(1-u^2)S''(u) - 2uS'(u) + \left[a^2\omega^2u^2 - 2a\omega su + s + A - \frac{(m+su)^2}{1-u^2}\right]S(u) = 0,$$



- Kerr BH perturbations → Teukolsky master eqn. → coupled ODEs for radial & angular parts
- Solve for eigenvalues (ω, A)

[Teukolsky, 1973, ApJ. Dorband+, 2006, PRD]

Physics-Informed Neural Networks (PINNs)

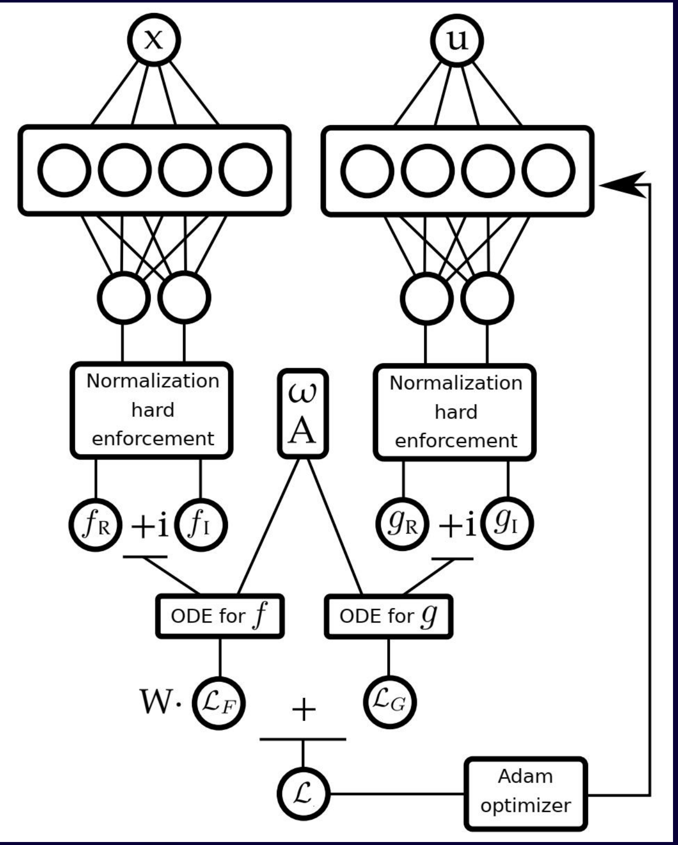


[Meng+ arXiv:1909.10145]

PINN for QNM Extraction

$$\mathcal{L}_F[f(x)] = F_2 f''(x) + F_1 f'(x) + F_0 f(x) = 0,$$
$$\mathcal{L}_G[g(u)] = G_2 g''(u) + G_1 g'(u) + G_0 g(u) = 0,$$

- Coupled ODEs for radial & angular parts
- Goal: Learn eigenvalues (ω, A) from physics loss
- Accuracy: <1% deviation from Leaver's continued fraction method

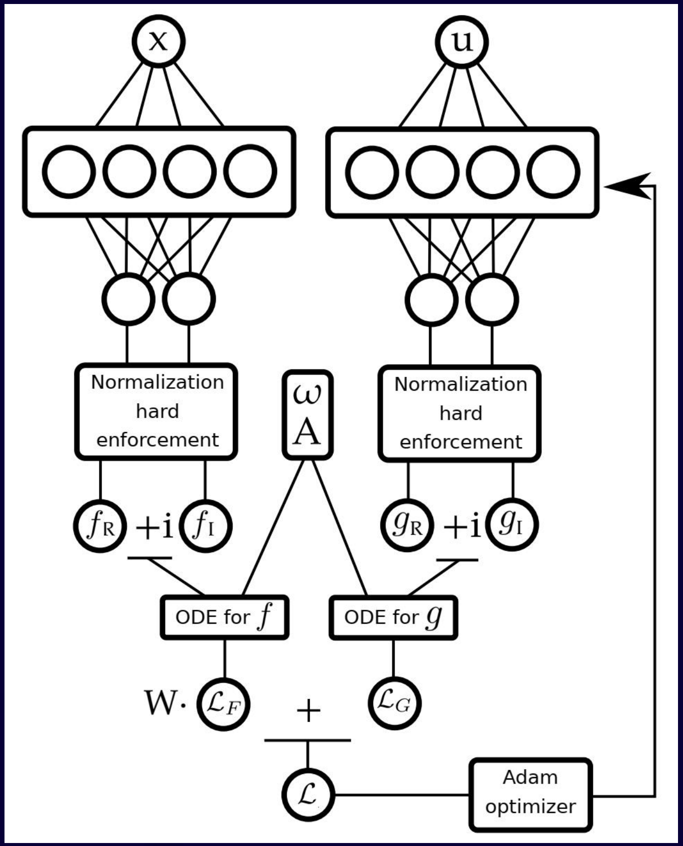


$$\mathcal{L}[\{x_i, u_j\}] =$$
$$= \frac{W}{N_x}\sum_{i=0}^{N_x} |\mathcal{L}_F[f(x_i)]| + \frac{1}{N_u}\sum_{j=0}^{N_u} |\mathcal{L}_G[g(u_j)]|,$$

[Luna+, 2025, PRD]

PINN Architecture

- Input: Radial (x) and angular (u) coords
- Two sub-networks:
  - Nf(x): radial function
  - Ng(u): angular function
- Output: Real/Imag parts of wavefunctions
- Loss = residuals of ODEs
- Parameters ω and A are trainable
- Hard-enforced normalization



$$\mathcal{L}[\{x_i, u_j\}] =$$
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Results – QNM Accuracy

TRUE		w_r	w_i	Re err	Re err
0.74734	-0.17793	0.74734	-0.1778	0	0.07306244
0.75025	-0.1774	0.7504	-0.1774	0.01999334	0
0.75936	-0.17565	0.7595	-0.1758	0.01843658	0.0853971
0.77611	-0.17199	0.7762	-0.1722	0.01159629	0.12210012
0.80384	-0.16431	0.8038	-0.1647	0.00497611	0.23735622
0.82401	-0.15697	0.824	-0.1573	0.00121358	0.21023125
0.84451	-0.14707	0.8464	-0.1485	0.22379842	0.9723261
0.85023	-0.14365	0.8499	-0.1443	0.03881303	0.45248869

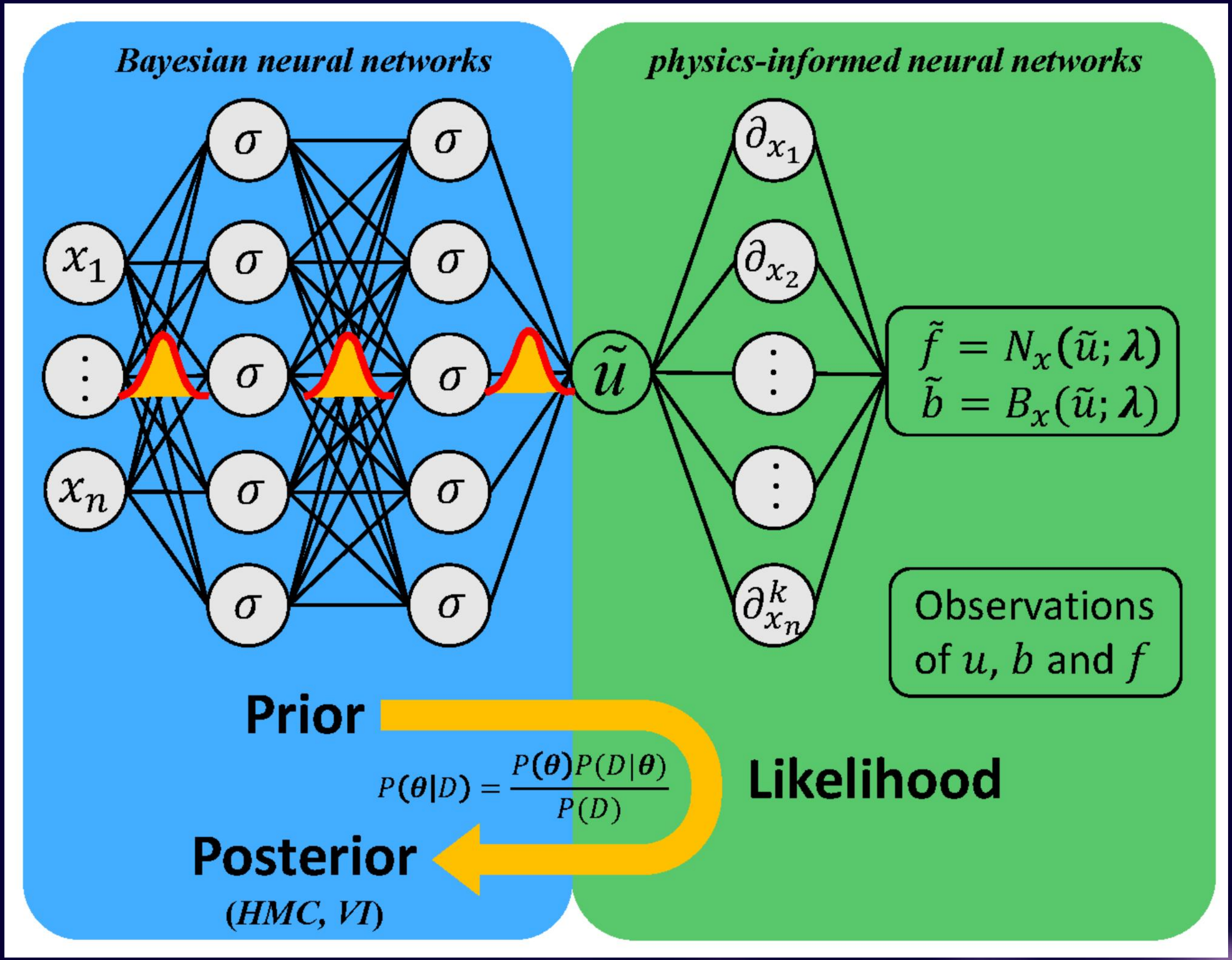
PaddleScience: KAN-Based Linear Layer with Fourier Edge Functions, capture periodic and structured patterns

Pipeline for generating multiple overtones

	Real part of ω		Luna+
a	PINN	Leaver	% error
0	0.74981	0.74734	0.330
0.1	0.75137	0.75025	0.149
0.2	0.76151	0.75936	0.282
0.3	0.77758	0.77611	0.190
0.4	0.80571	0.80384	0.233
0.45	0.82380	0.82401	0.025
0.49	0.83974	0.84451	0.564
0.4999	0.84589	0.85023	0.511

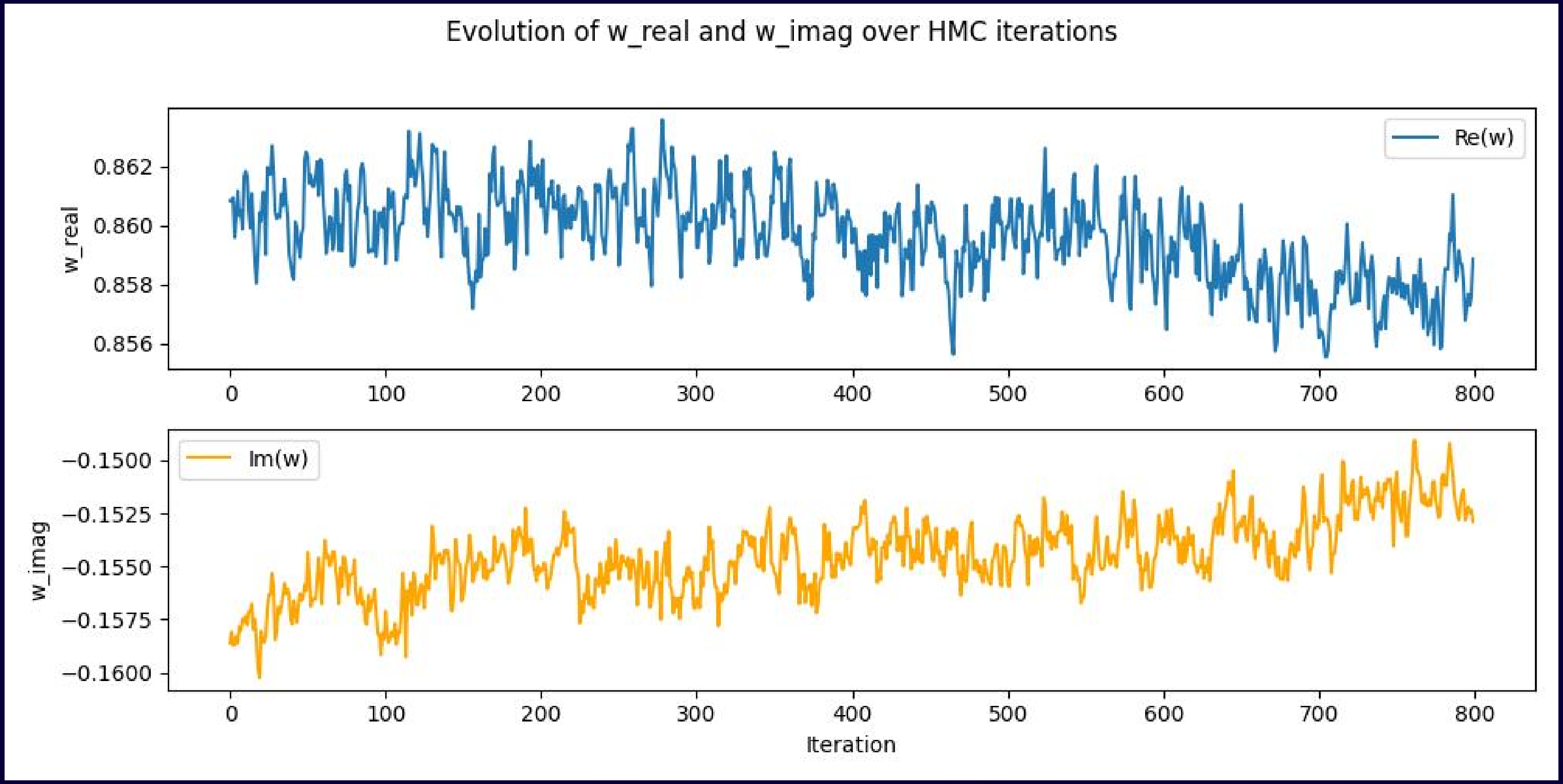
Collaborators: Hanlin Song, Haohao Gu, Bo Liang, Sensen He

Results – QNM with B-PINN



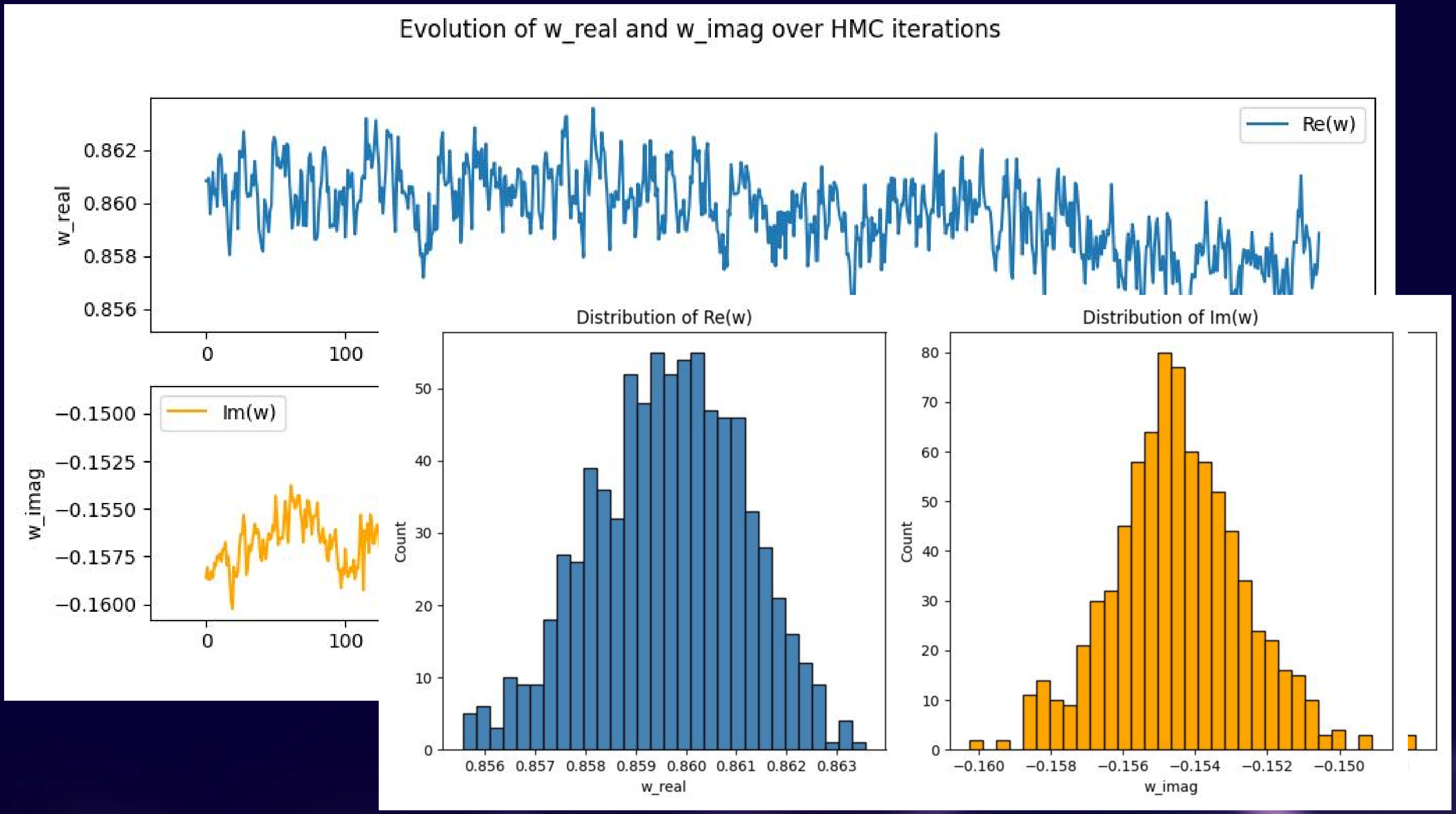
[Yang+ arXiv:2003.06097]

Results – QNM with B-PINN



Collaborators: Youyi Ni, Songyu Ren, Zhengqi Zhou, Zihao Wang

Results – QNM with B-PINN



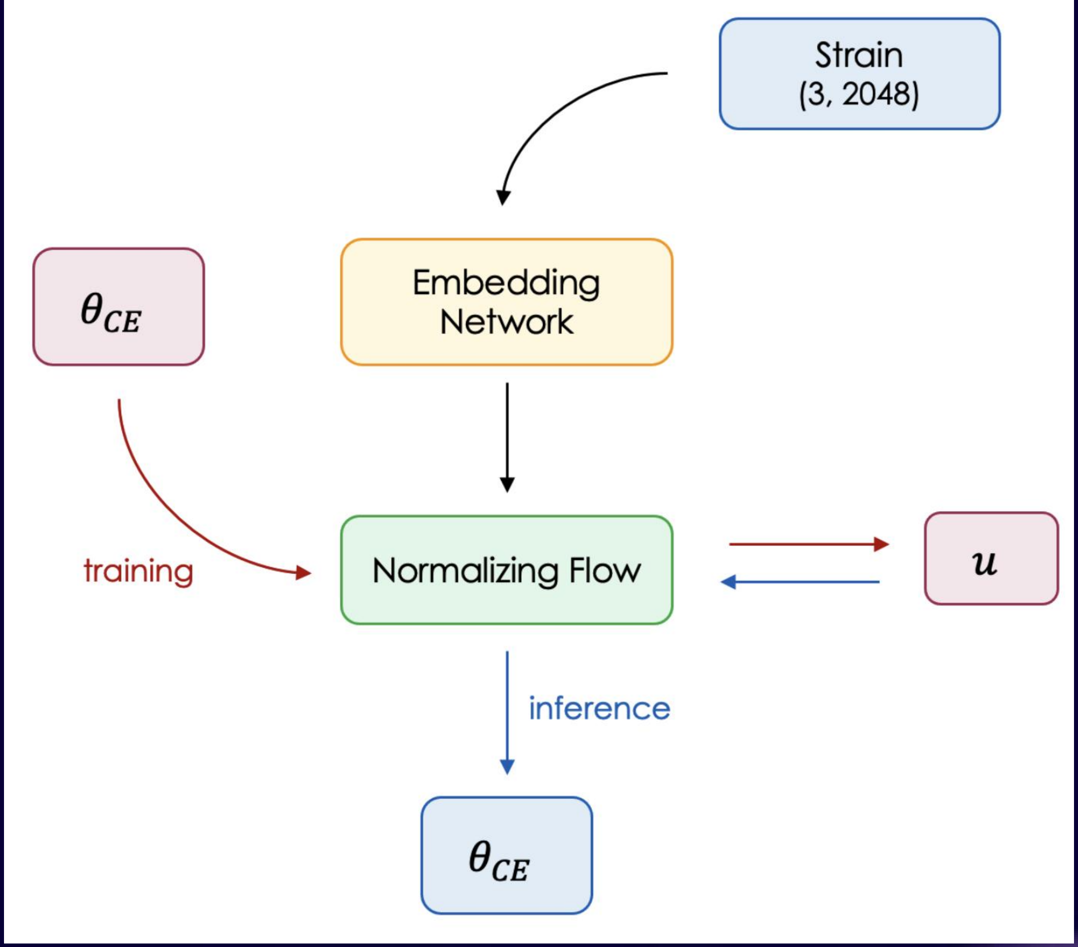
03

Detection and Inference

Detection and Inference

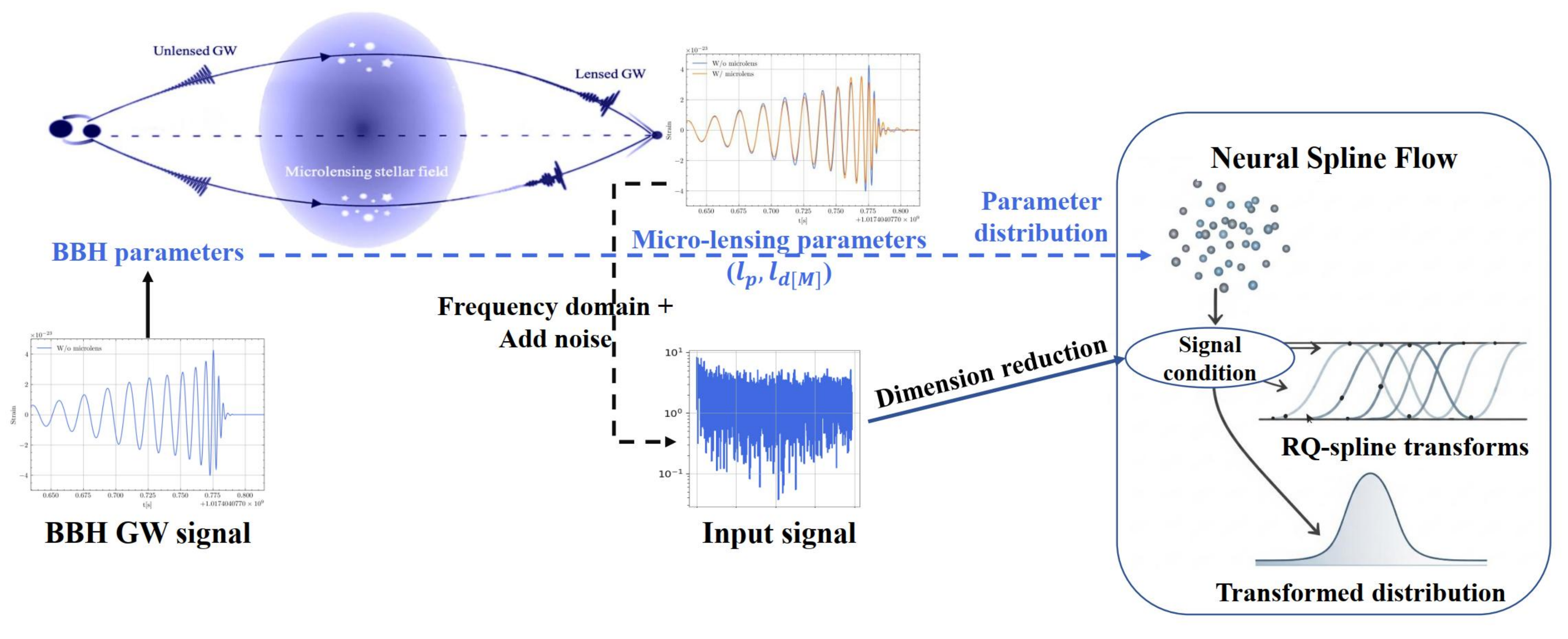
- GW-YOLO: [Soni+ arXiv:2508.17399], detect events with realistic noise
- BNS: DeepHMC [Perret+ arXiv:2505.02589], Dingo [Dax+ 2025]
- Close encounters: [Santi+ arXiv:2404.12028]
- Zhoujian Cao's group on waveform modeling, denoising and signal recognition
- Microlensing [Su+ 2025]
- EMRIs:
  - non-spinning SMBH: [Strub+ arXiv:2505.17814; Cole+ arXiv:2505.16795]:
  - Kerr EMRIs: FM-MCMC [Liang+ 2025]

Simulation-based inference



[Santi+ arXiv:2404.12028]

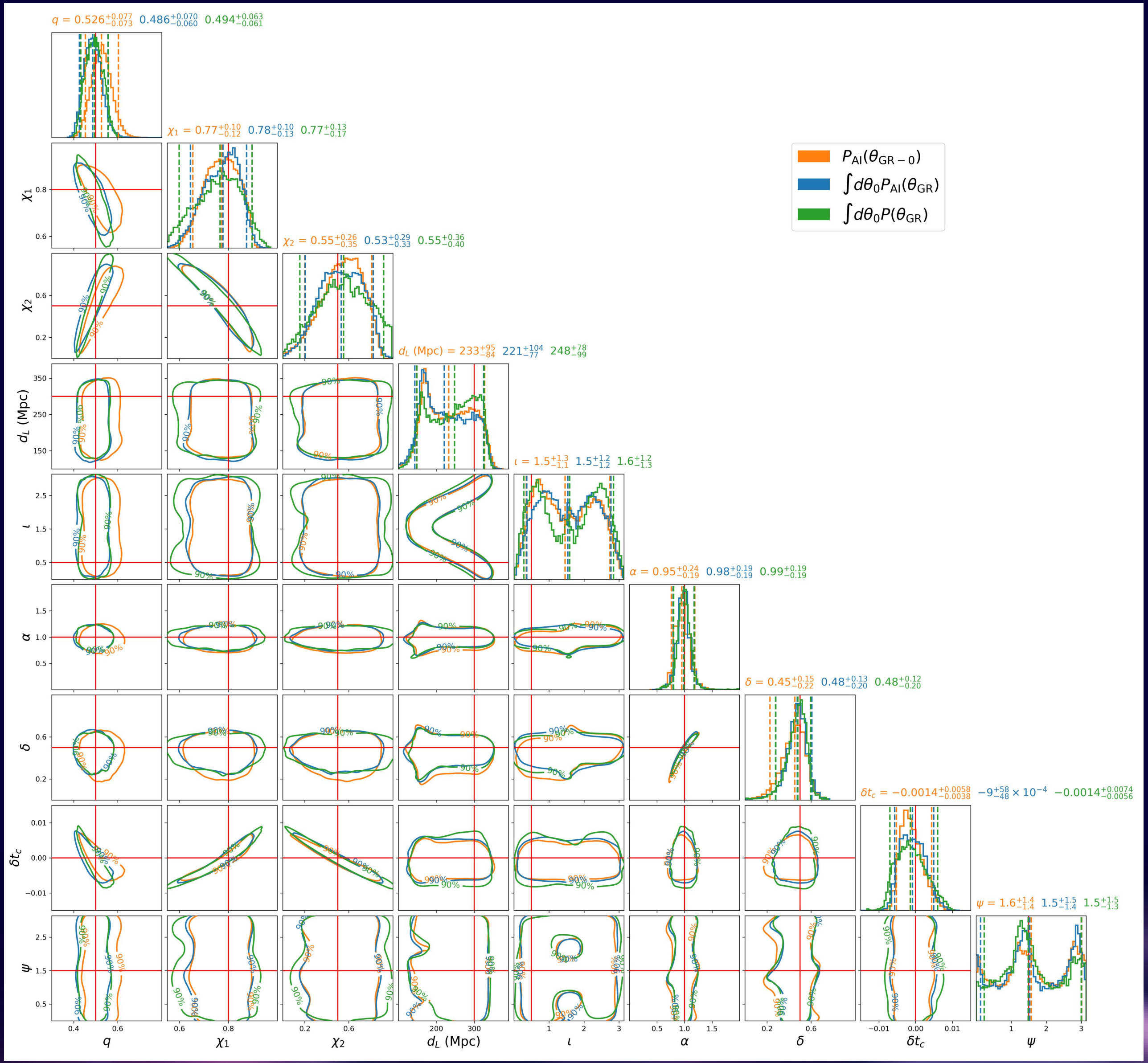
Microlensed Gravitational Waves



[Zhaoqi Su+ 2025]

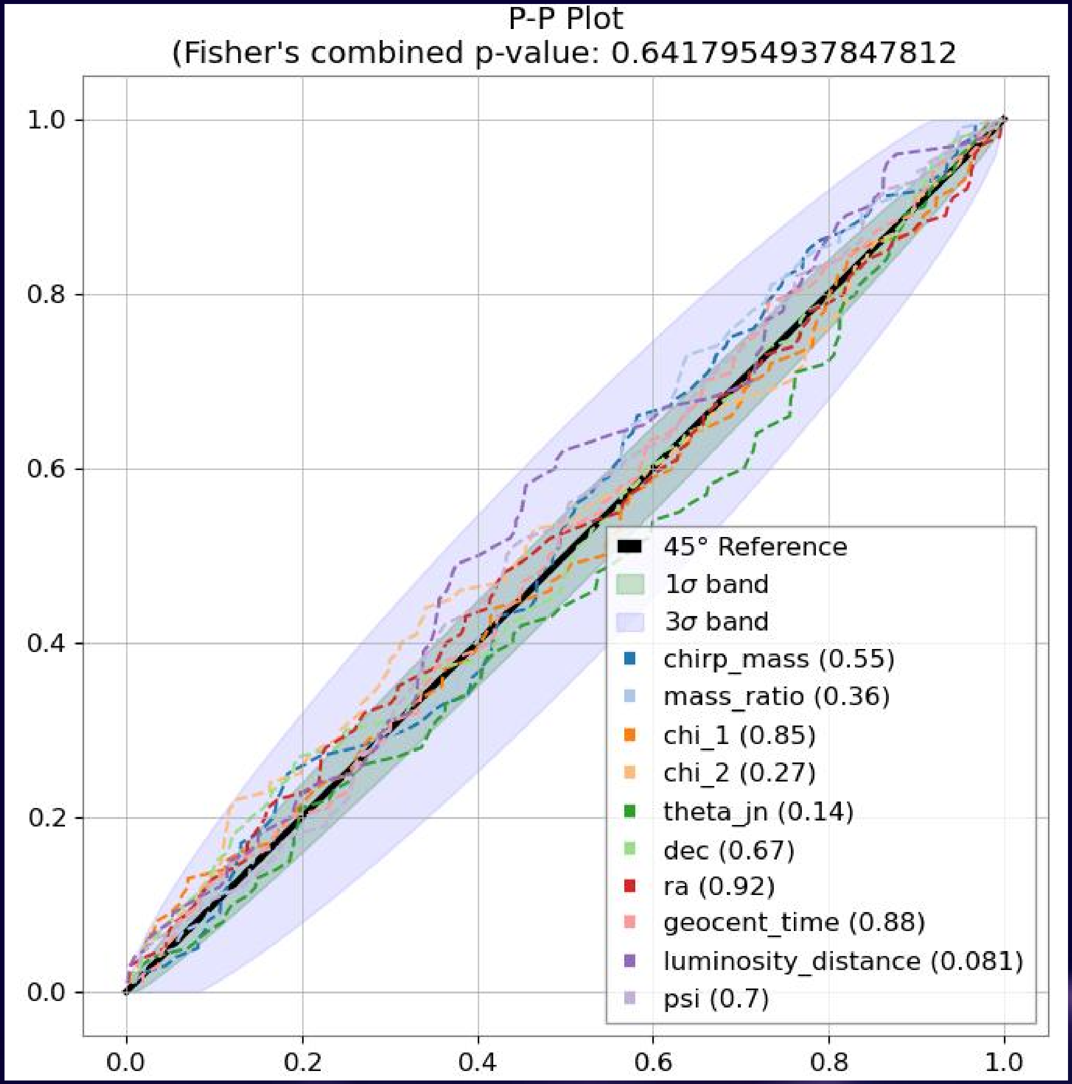
Collaborators: Zhaoqi Su, Xikai Shan, Junyao Zhang, Yebin Liu, Shude Mao, Huan Yang

Non-deterministic Inference

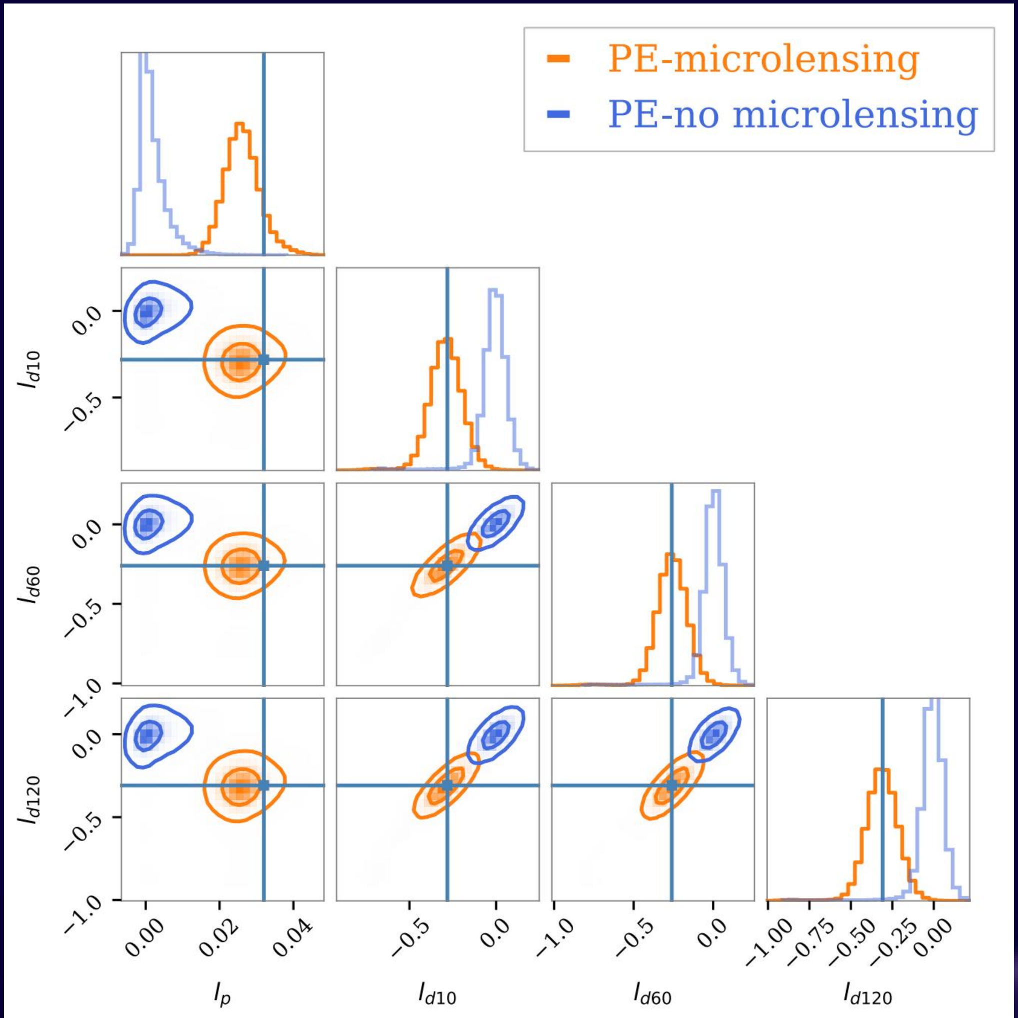


Su+ 2025

Probability – probability plot

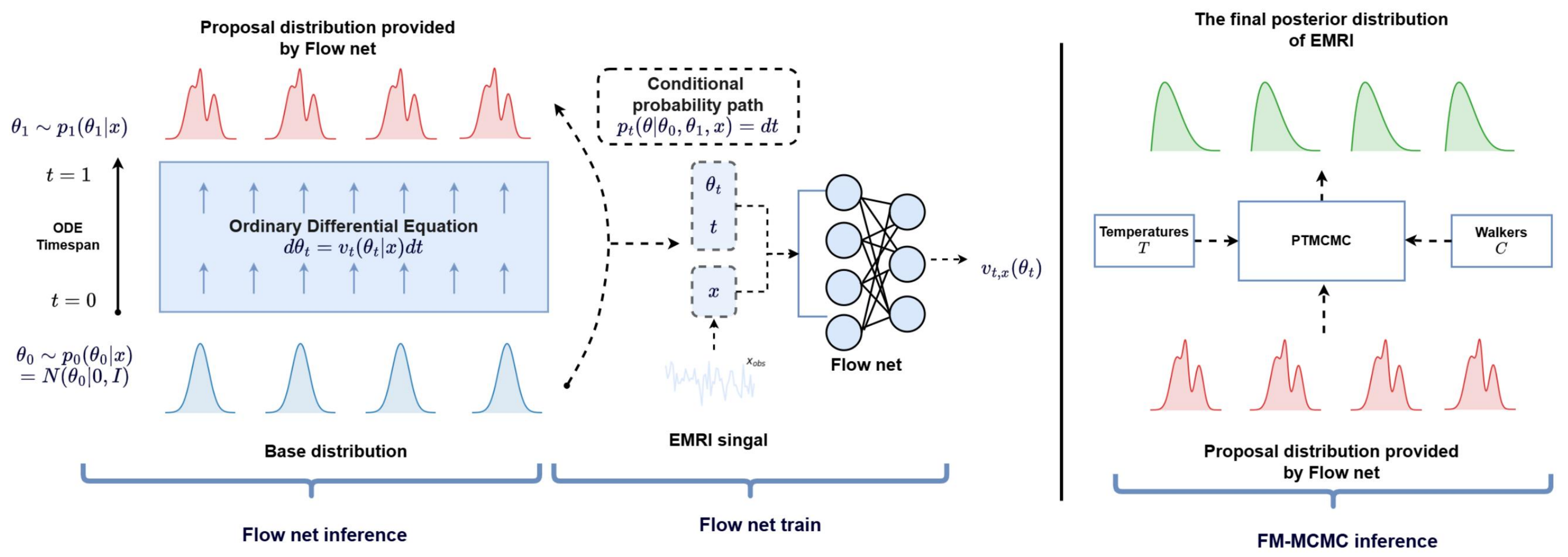


Detection of the microlensing signal



Su+ 2025

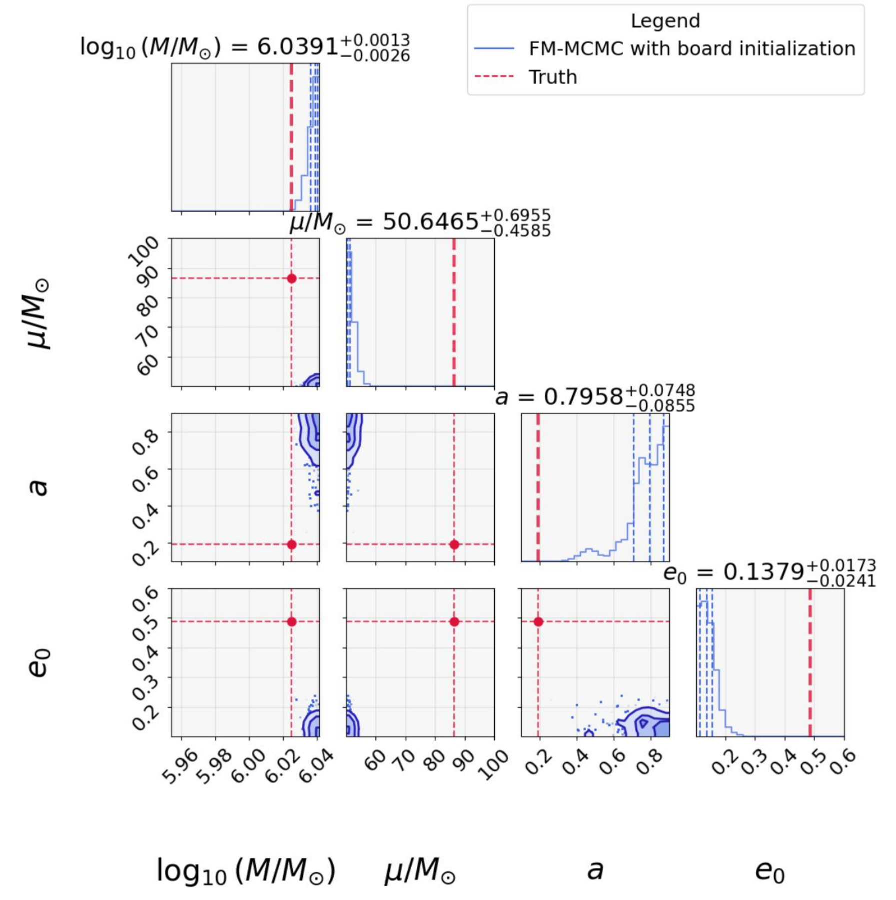
EMRIs recognition and estimation

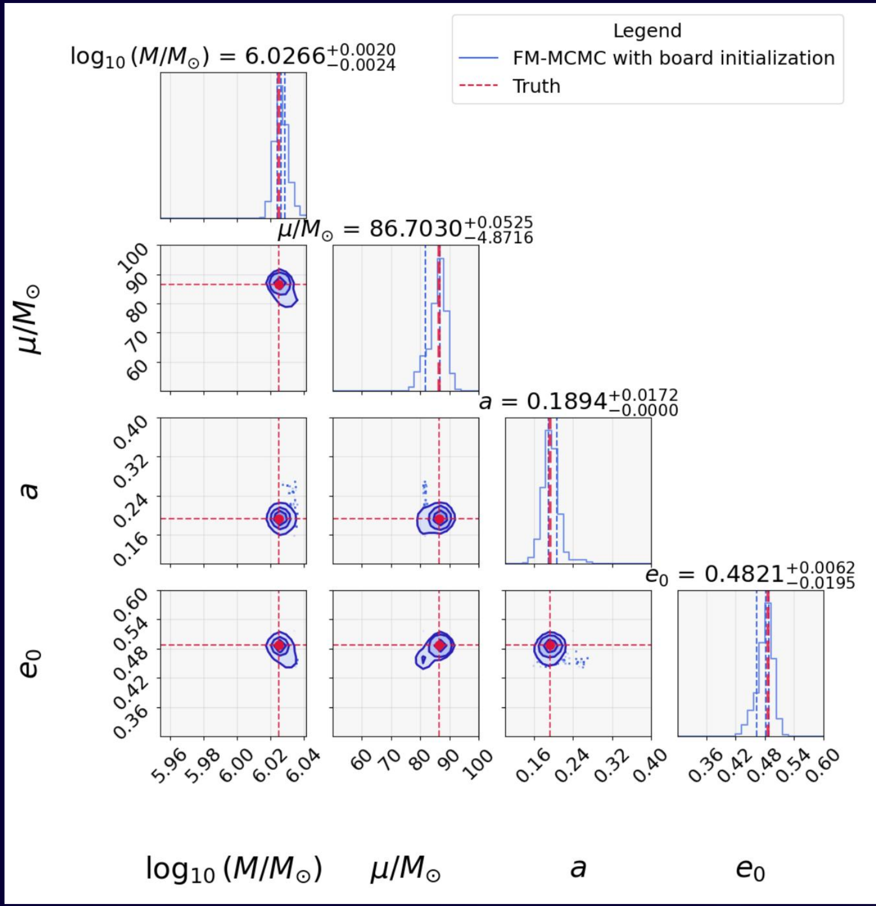


Collaborators: Bo Liang, Chang Liu, Hanlin Song, Tianyu Zhao, Manjia Liang, Yuxiang Xu, Li-e Qiang, Minghui Du, Peng Xu, Wei-Liang Qian, Ziren Luo

Liang+ 2025

Normalizing Flows for EMRIs





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Future Outlook

Future Outlook

- PINNs and NFs are powerful for GW modeling and inference for next generation detectors (ET, LISA， TaiJi, TianQIn)

- Can be integrated into real-time pipelines

- AI is shaping next-gen multi-messenger astrophysics

Thanks