

Representations of Extreme Mass Ratio Inspiral Signals for Identification

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EMRI Search and Inference within the LISA Global Fit - Part II
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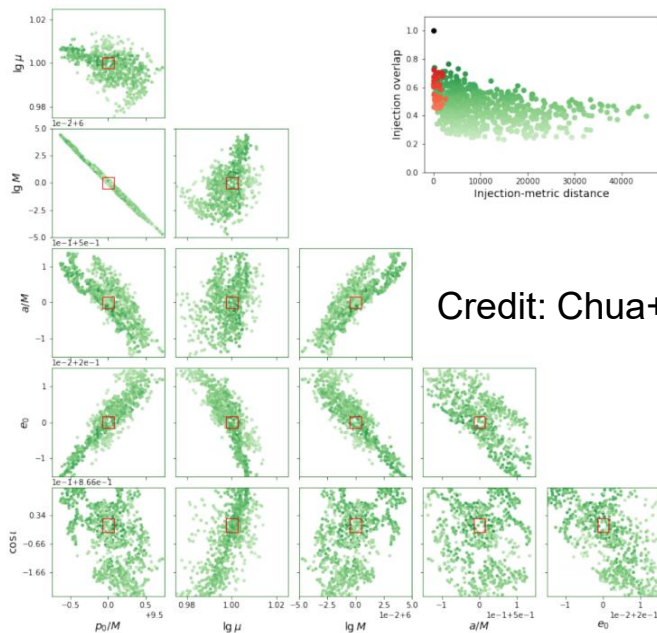
Plan of this talk

1. **Scientific motivation:** why month-scale data matter
2. **Core challenge:** compression efficiency versus information loss
3. **Diagnostic framework:** what information should an encoder preserve?
4. **Validation:** PCA, wavelet, regression embedding, and normalizing flow
5. **Summary & Outlook**

EMRI signals are information-rich but inference-hostile.



- EMRIs contain many harmonics and several orbital timescales.
- These local matches produce secondary likelihood modes.



Credit: Chua+2021

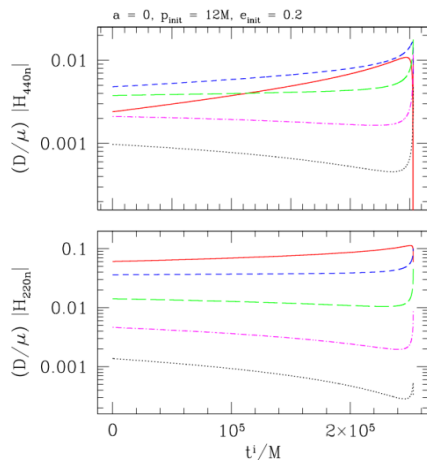
$$\delta\theta \sim 10^{-3}$$



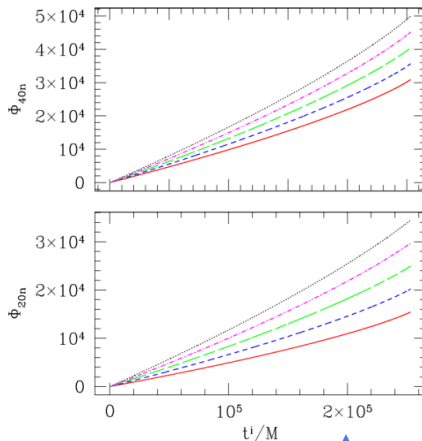
Why EMRIs require long and coherent observations

- Small local phase differences can become measurable after months of observation.

Credit: Hughes+2024

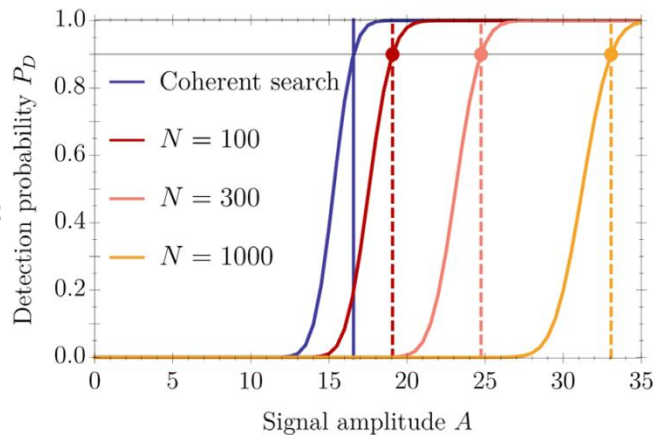


$2 \times 10^6 \text{ s}$



$2 \times 10^6 \text{ s}$

Credit: Chua+2017



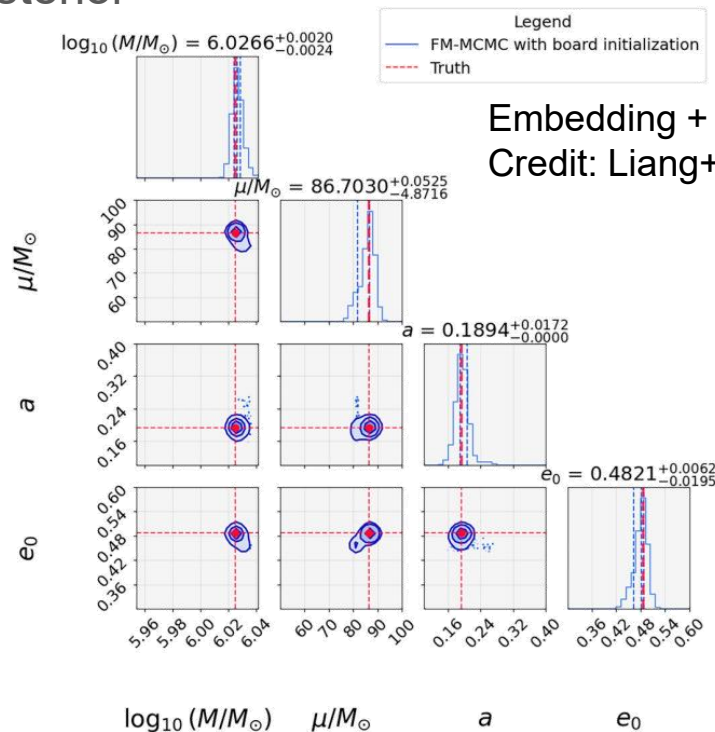
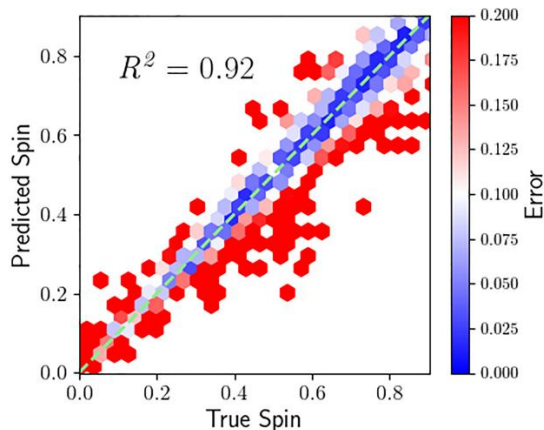
Detection threshold



Fast Inference: precision gap in multi-stage pipelines

- Possible failure mode or broad posterior

Unet extraction + VGG regression
Credit: Yun+2024



Embedding + Flow-matching
Credit: Liang+2026

Question



- Information bottleneck:

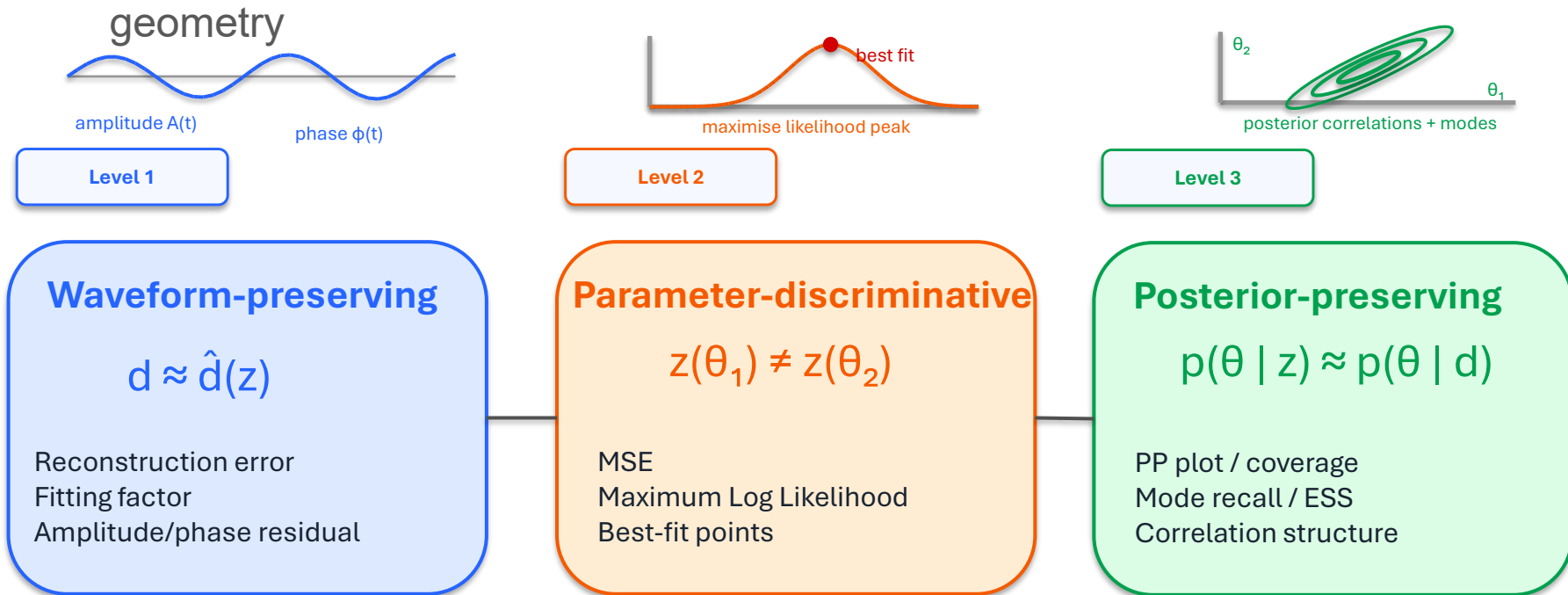
Does the encoder preserve the phase and harmonic information needed to distinguish parameters?

Can the learned posterior match the precision of classic Bayesian inference?



A three-level diagnostic framework

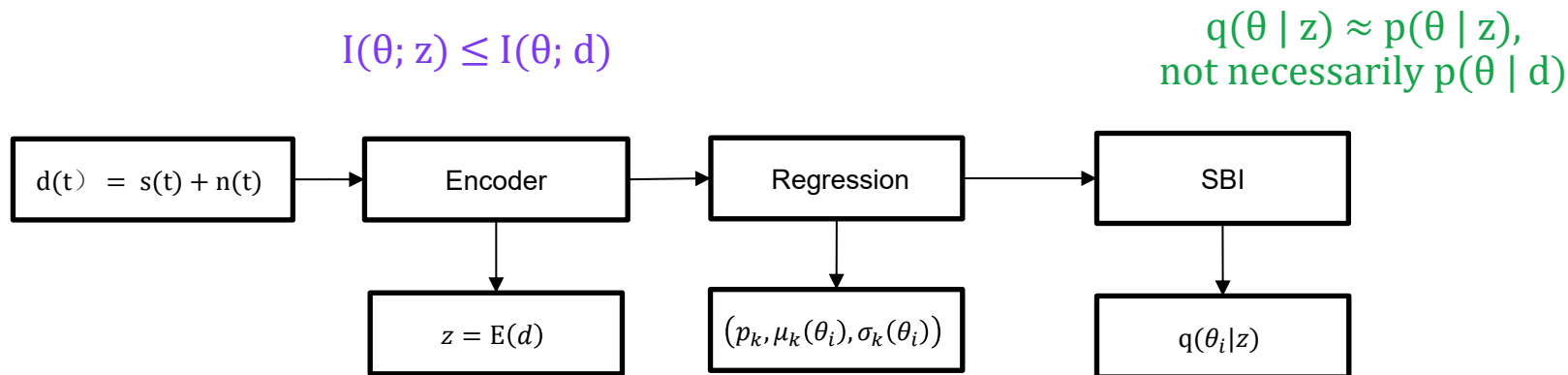
- From waveform compression to parameter information and posterior





Machine learning for EMRI identification

- Fast identification: localize parameter-informative regions before full PE.
- A downstream simulation-based inference(SBI) can only learn the posterior conditioned on the latent representation

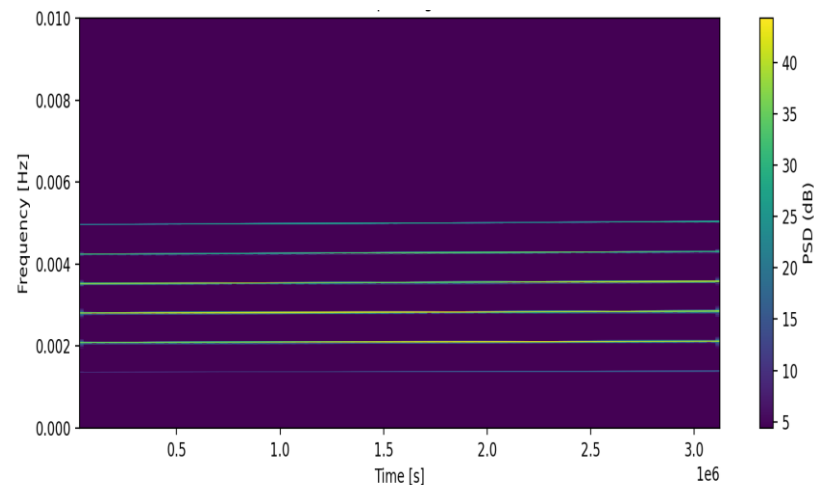
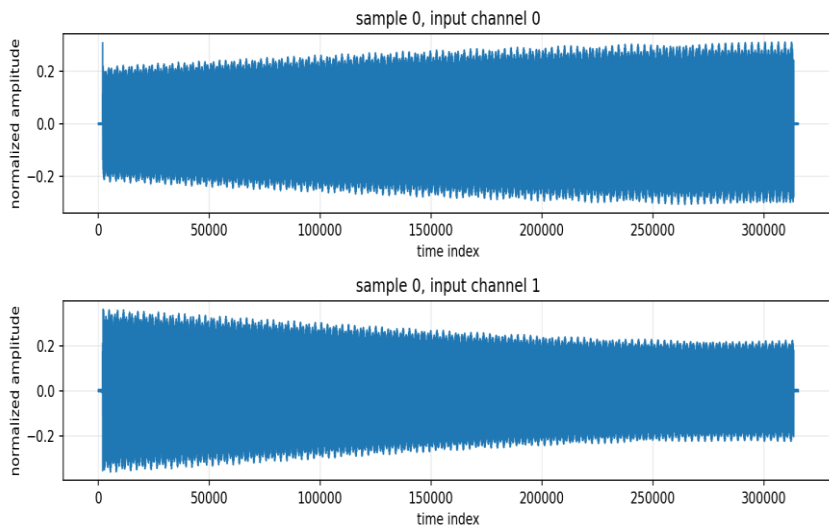




Mock LISA signal: 2nd TDI simulation

- 0.1 year, $dt=10$ seconds, (3, 315580),
- **Pn5AAKWaveform**

Credit: Chua+2021



small chirp rate shift



Prior selection: intrinsic parameters

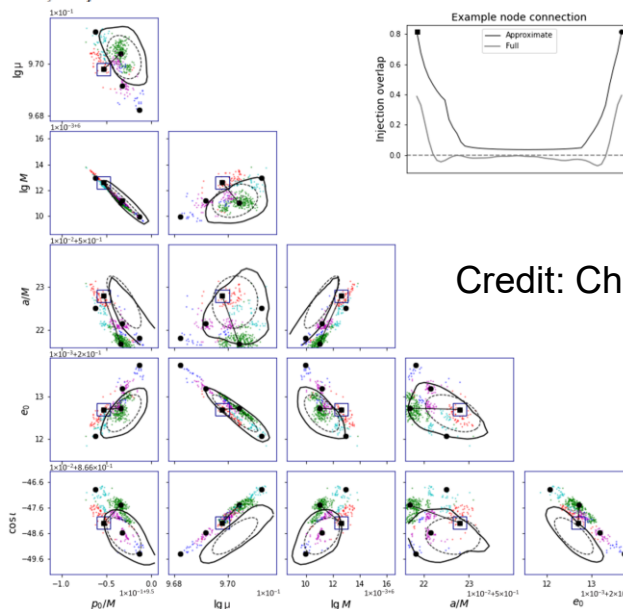
- 6-dim parameters: $\theta_{inj} = (\lg \mu, \lg M, \frac{a}{M}, \frac{p_0}{M}, e_0, \cos \iota)$

$$\theta_{inj} = (1, 6, 0.5, 9.5, 0.2, 0.866), \quad \delta\theta = (0.5, 1, 3, 15, 0.3, 5) \times 10^{-3}.$$

$$\theta_A - \theta_{inj} = (-30, 13, 228, -53, 13, -482) \times 10^{-3}.$$

Parameter-sensitive features

- M** frequency scale
- μ** radiation-reaction timescale $\longrightarrow$ chirp rate
- a** Kerr frequencies and precession
- p_0** initial orbital scale, correlated with M
- e_0** harmonic power distribution



Credit: Chua+2021



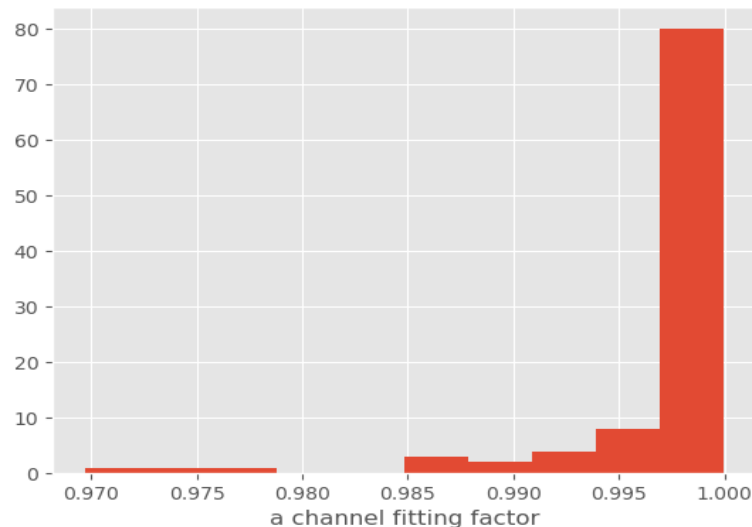
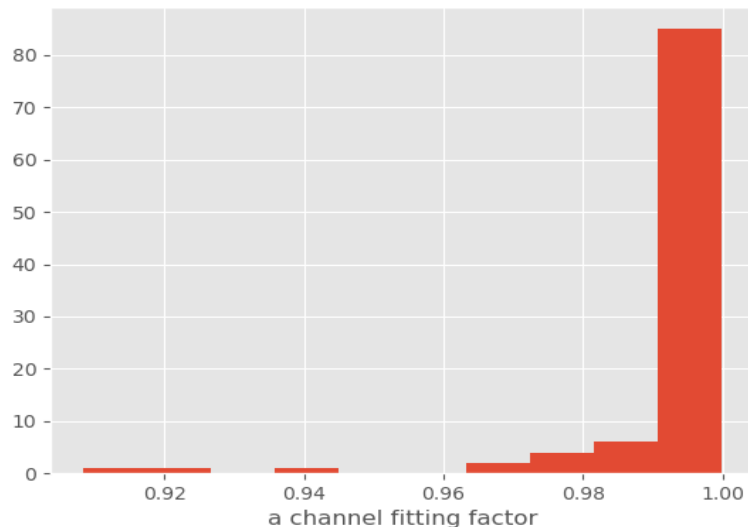
Level 1 Results: Waveform-preserving representation

PCA, wavelet, autoencoder



Fitting factor for the PCA reconstruction

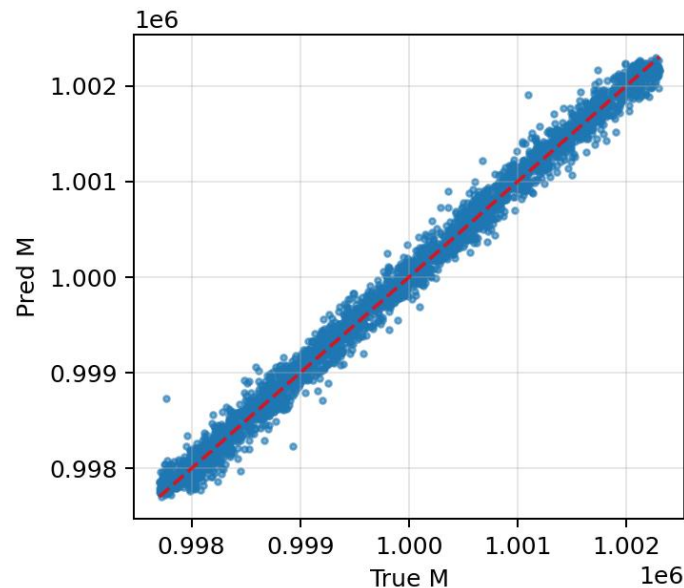
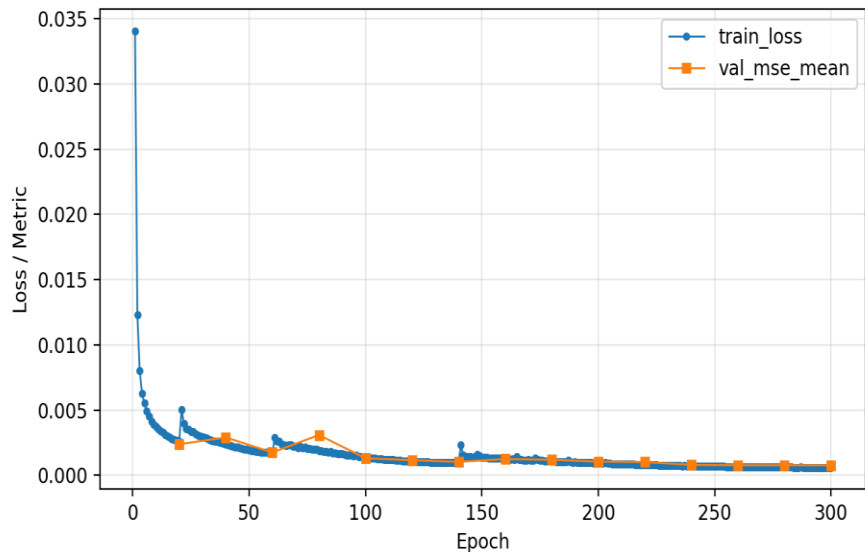
- PCA components: 500, 600.
- Compression factor: $315580/600 \sim 526$



PCA -> ResNet : M



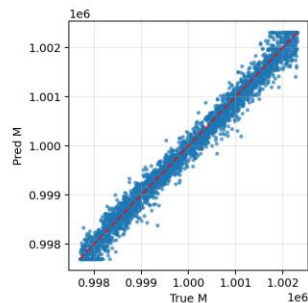
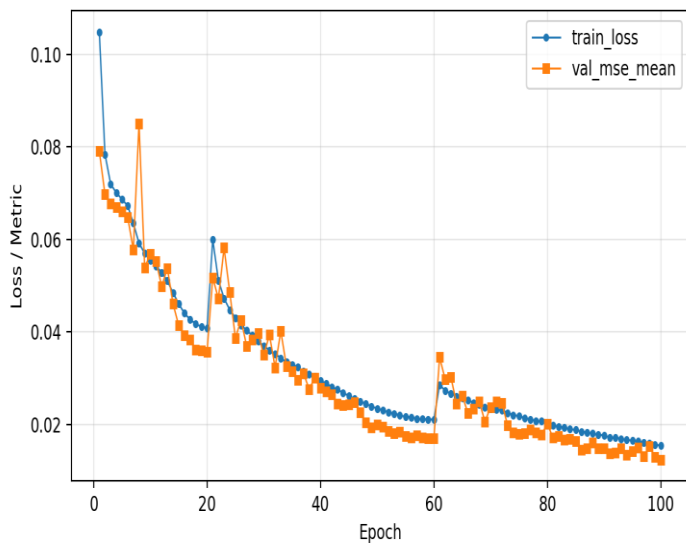
- Low efficiency in late epochs: Use a new schedule with warm up after 80th epoch



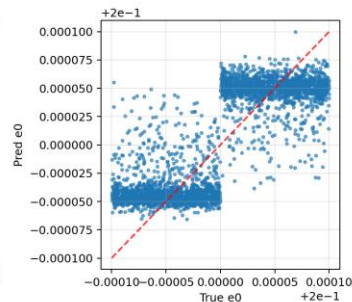
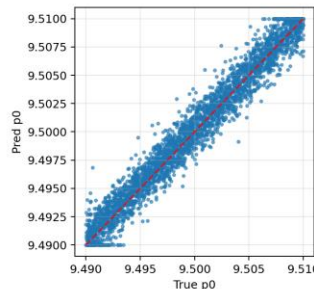
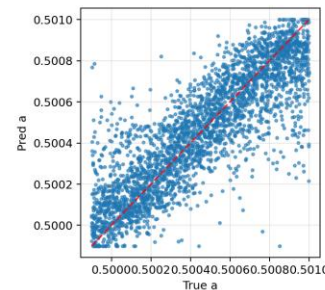
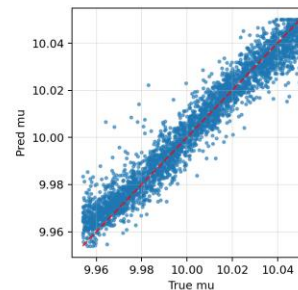


PCA -> ResNet: (M, μ, a, p_0, e_0)

- Output without any **activation function**



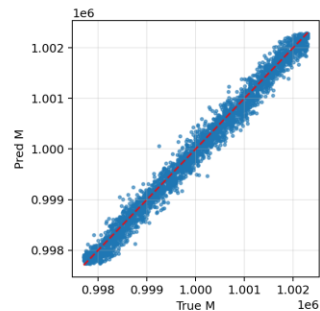
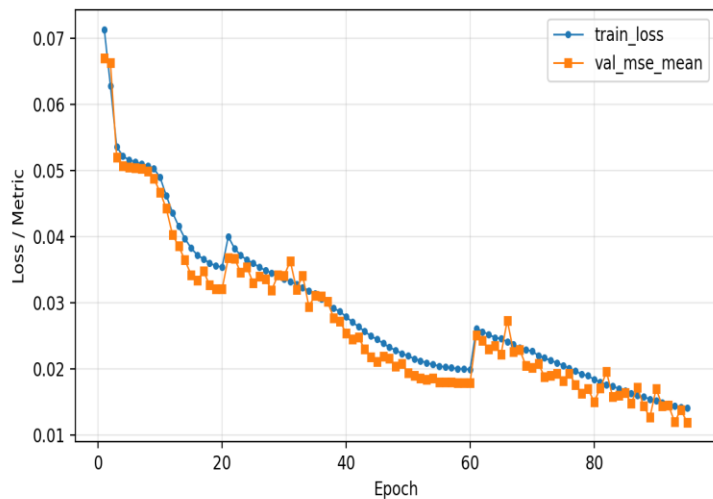
Physical space theta: pred vs true (y=x reference)



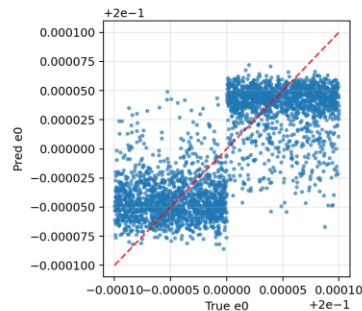
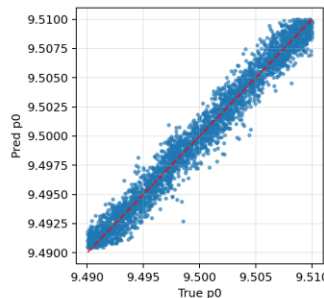
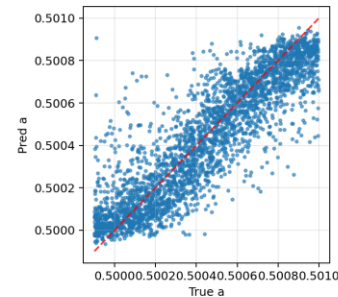
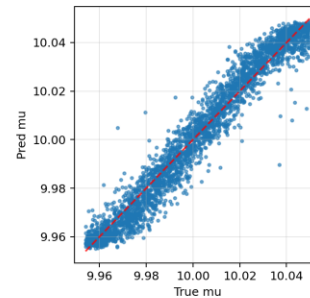


Wavelet+PCA->ResNet: L=6, A,D5, 600 components

- Ntrain=1e5, Nval=1e4



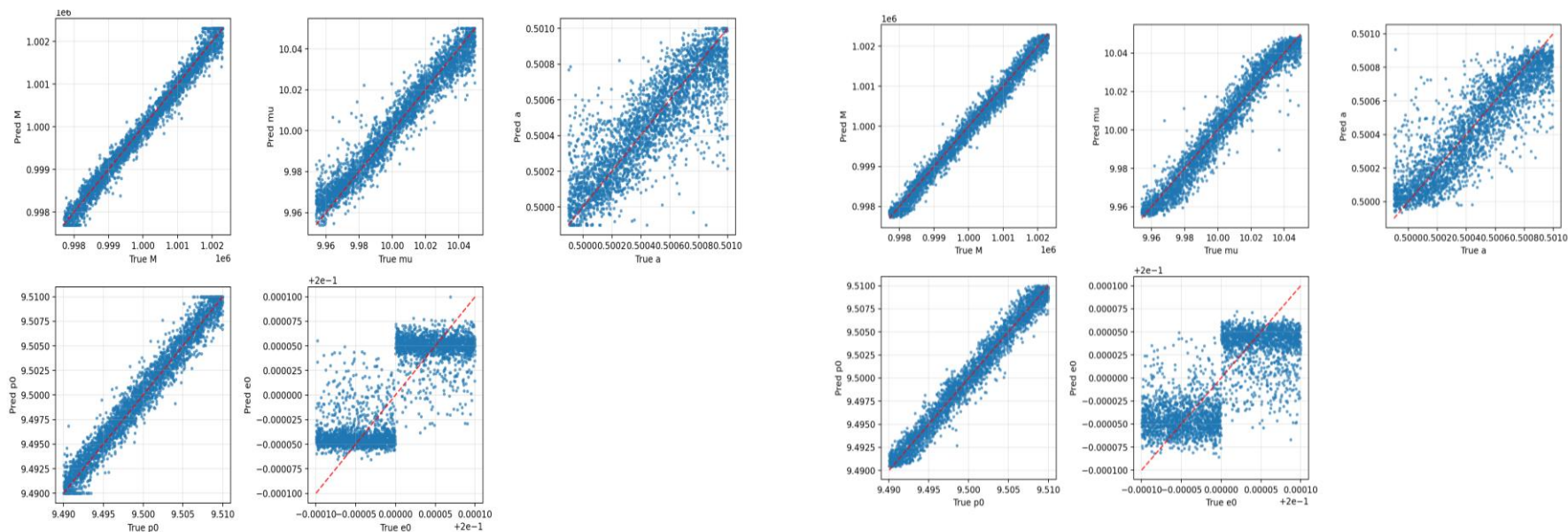
Physical space theta: pred vs true (y=x reference)





ResNet 5-dimensional parameter point estimation

- Ntrain=1e5, Nval=1e4
- Left: PCA only Right: wavelet L=6 + PCA, **2** bands(A/D6,D5)



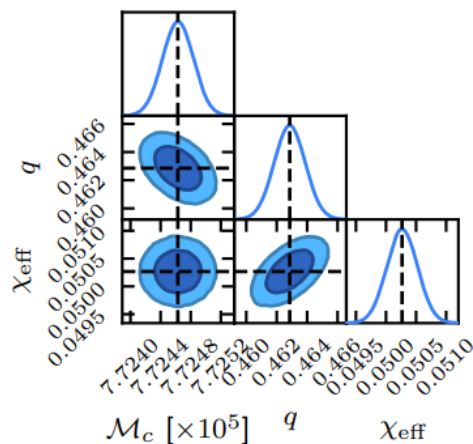
Waveform reconstruction could preserve the wrong coordinates



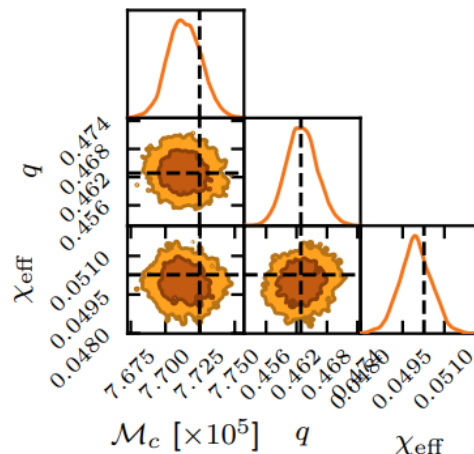
- Autoencoder + SBI/SNL for MBHB: residual

Credit: Iván Martín Vilchez +2025, 2406.00565

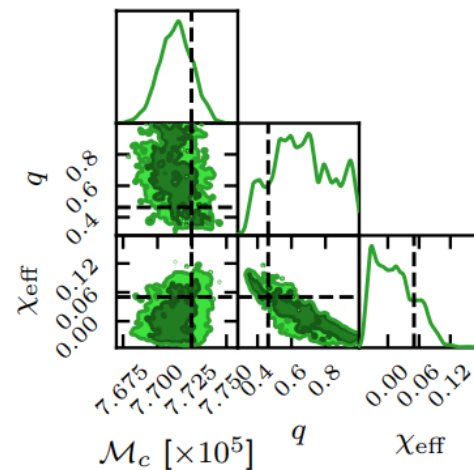
	Noise-free	Noisy	Noise
Random	3.0266	3.5556	2.0007
PCA-128	1.7647	2.2897	1.0143
Noisy PCA-128	1.2801	1.8087	0.9785
Autoencoder	0.1794	0.7867	0.9919
Denoising autoencoder	0.1458	0.1398	0.0005



(a) Eryn



(b) SNL-PCA



(c) SNL-AE



Level 2 Results: Parameter-discriminative representation

Gaussian Regression

Regression based on the CNN detection model



TABLE III. The architecture of the CNN.

	Layers	Kernel number	Kernel size	Activation function
1	Input	...	Matrix(size: 2×262144)	...
2	Convolution	32	Matrix(size: 1×34)	relu
3	Pooling	16	Matrix(size: 1×8)	relu
4	Convolution	16	Matrix(size: 1×8)	relu
5	Pooling	16	Matrix(size: 1×6)	relu
6	Convolution	16	Matrix(size: 1×6)	relu
7	Pooling	16	Matrix(size: 1×4)	relu
8	Flatten	...	...	...
9	Dense	...	Vector(size: 128)	relu
10	Dense	...	Vector(size: 32)	relu
11	Output	...	Vector(size: 2)	softmax

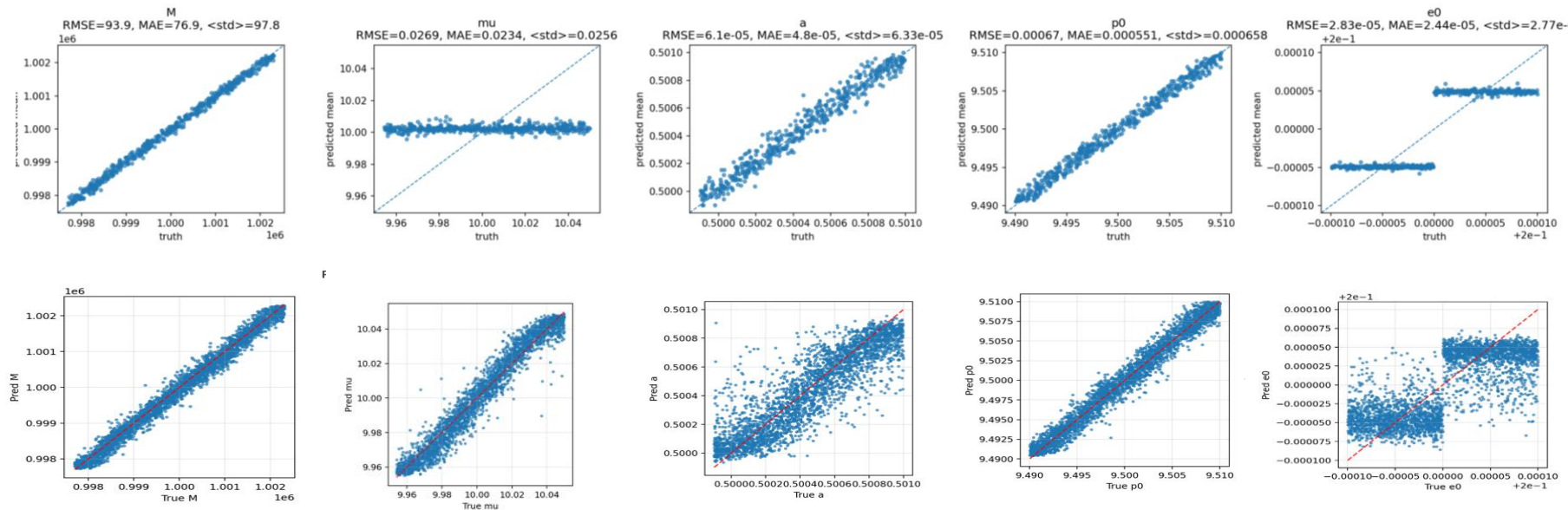
X.-T. Zhang +2022

Output (mean, var)

Noise-free CNN vs Wavelet+pca : Ntrain=1e5



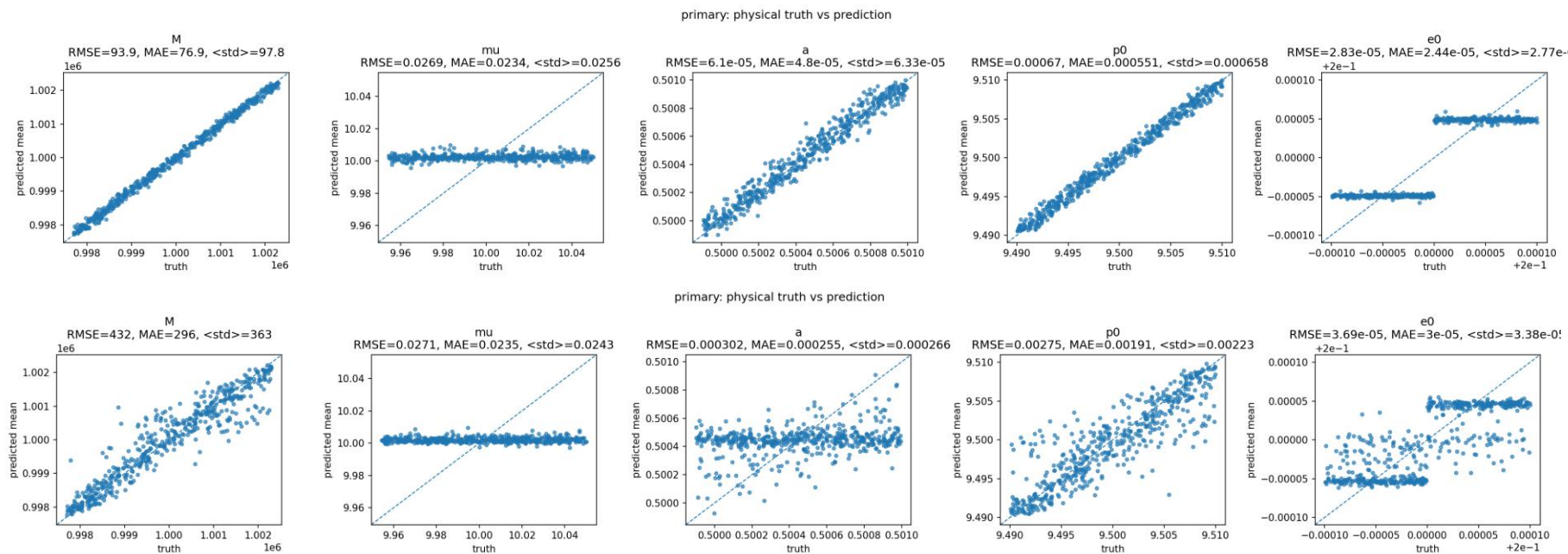
- Ntest=500, **upper**: new regression model, **bottom**: previous best result



Noise-free CNN vs SNR(50,120)

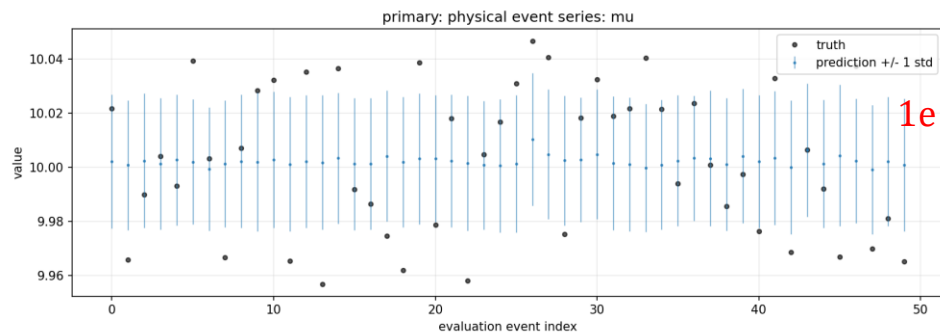
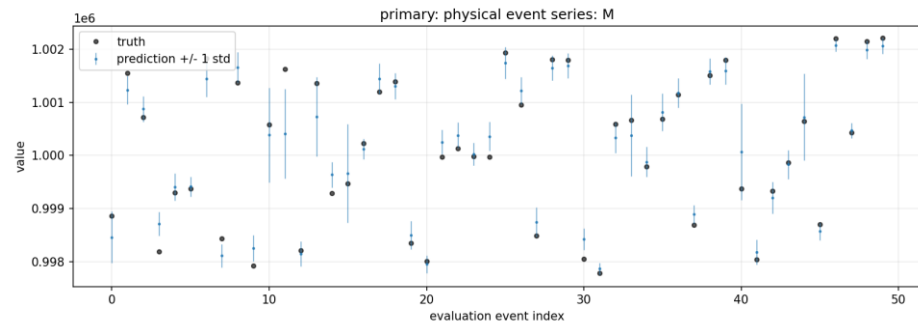


- $N_{\text{test}}=500$, **upper**: noisy free regression, **bottom**: noisy regression

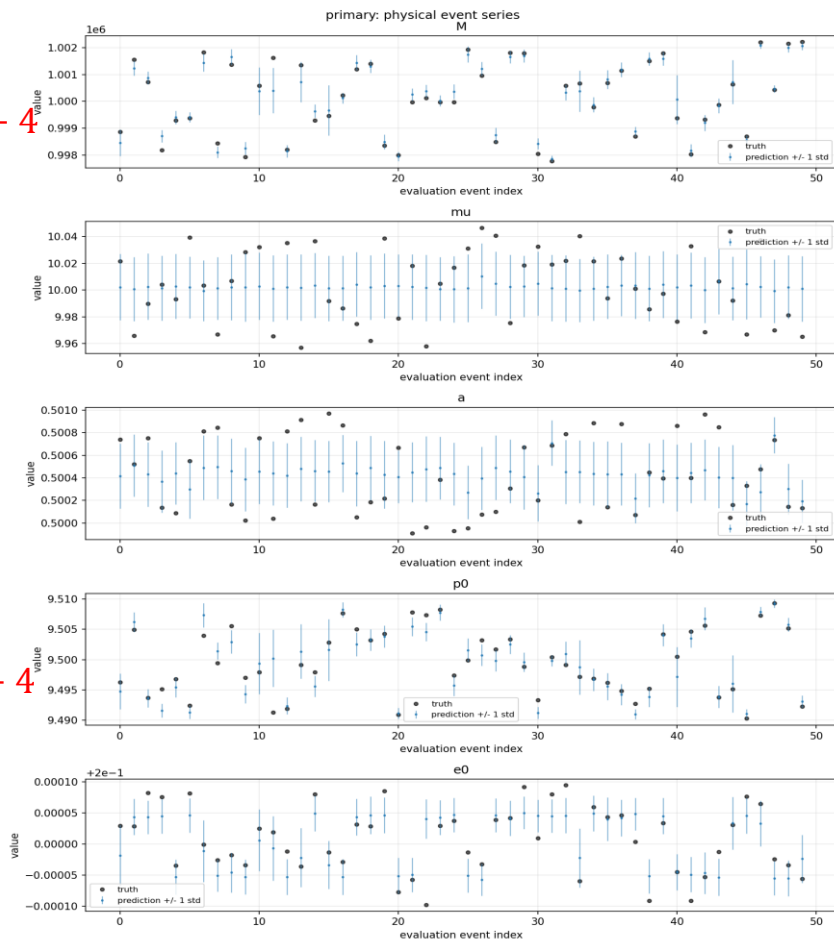


Noisy signals evaluation: (μ, σ)

$1e-4$



$1e-4$

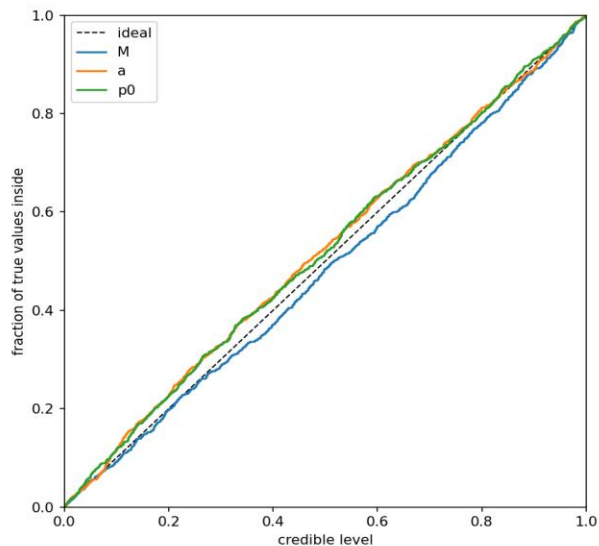




Level 3 Results: Posterior-preserving representation Normalizing flow

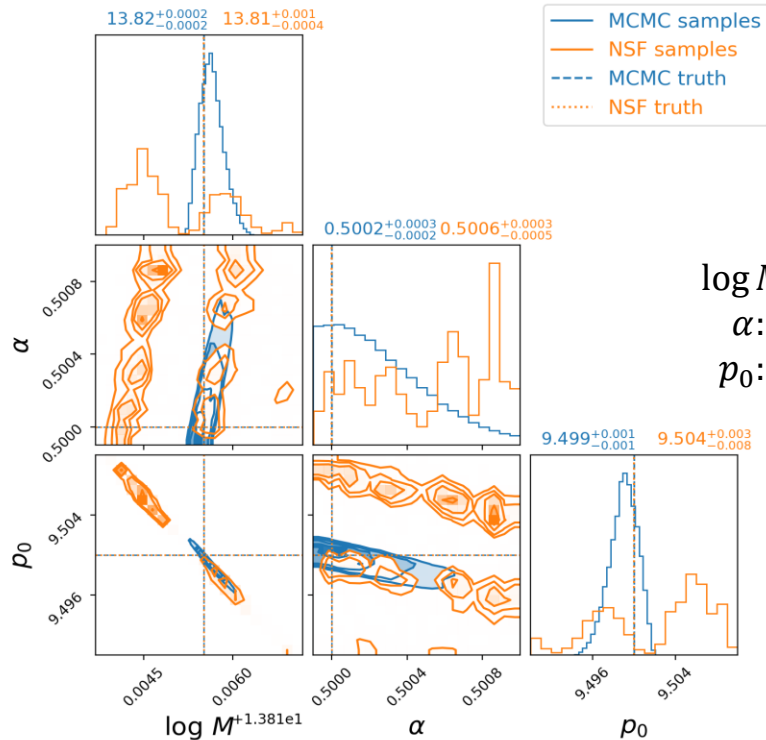
CNN embedding + SBI results:

$$\theta_{\text{inj}} = (1, 6, 0.5, 9.5, 0.2, 0.866),$$



Ntest=1000, Nsamples=5000

"M": [997700.064, 1002305.24]
 "mu": [9.954, 10.05],
 "a": [0.4999, 0.501],
 "p0": [9.49, 9.51],
 "e0": [0.1999, 0.2001],
 "x0": [0.8655, 0.8665],



Take-home message

For EMRIs, the central object to preserve is not the waveform itself, but the posterior-relevant phase information that controls physical interpretation.

- 1 Reconstruction features is not sufficient for EMRI inference.
- 2 Parameter-aware diagnostics reveal where information is lost.
- 3 Next: multiscale-representation-conditioned flow and mode-recall tests.

Thank you · Questions?



Thank you for your attention!