Disentangling the Gravitational Symphony

Machine Learning for LISA's Global Fit

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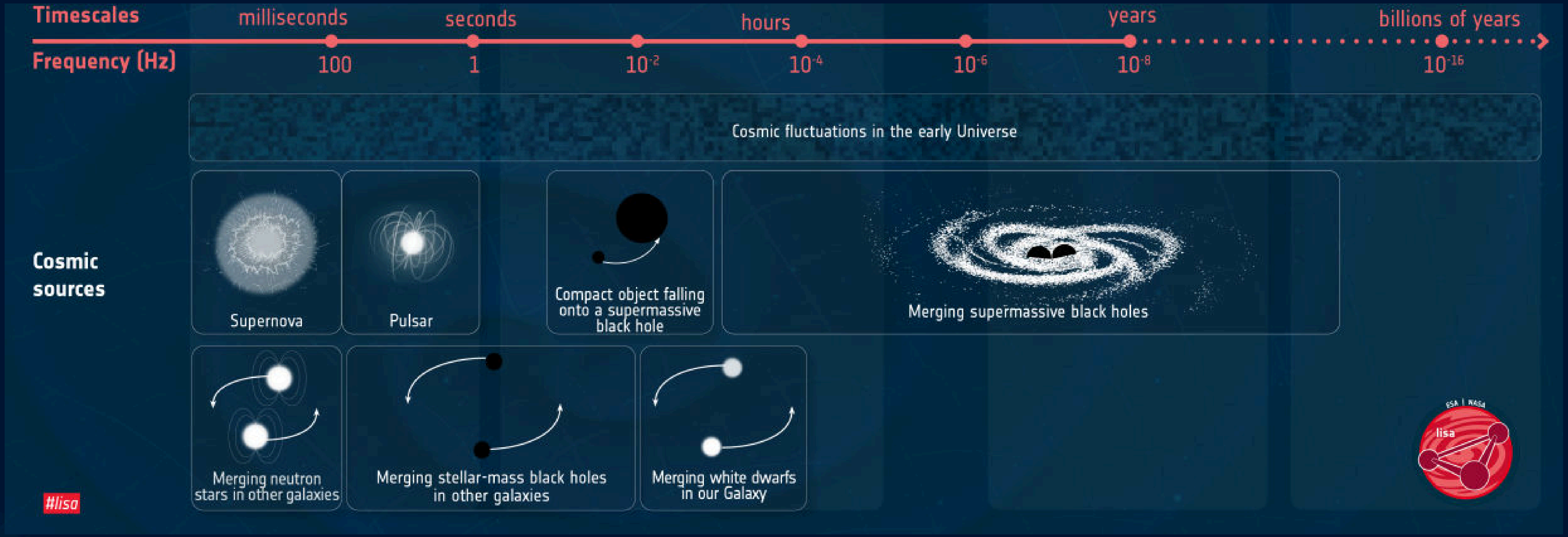
LISA GW Sources



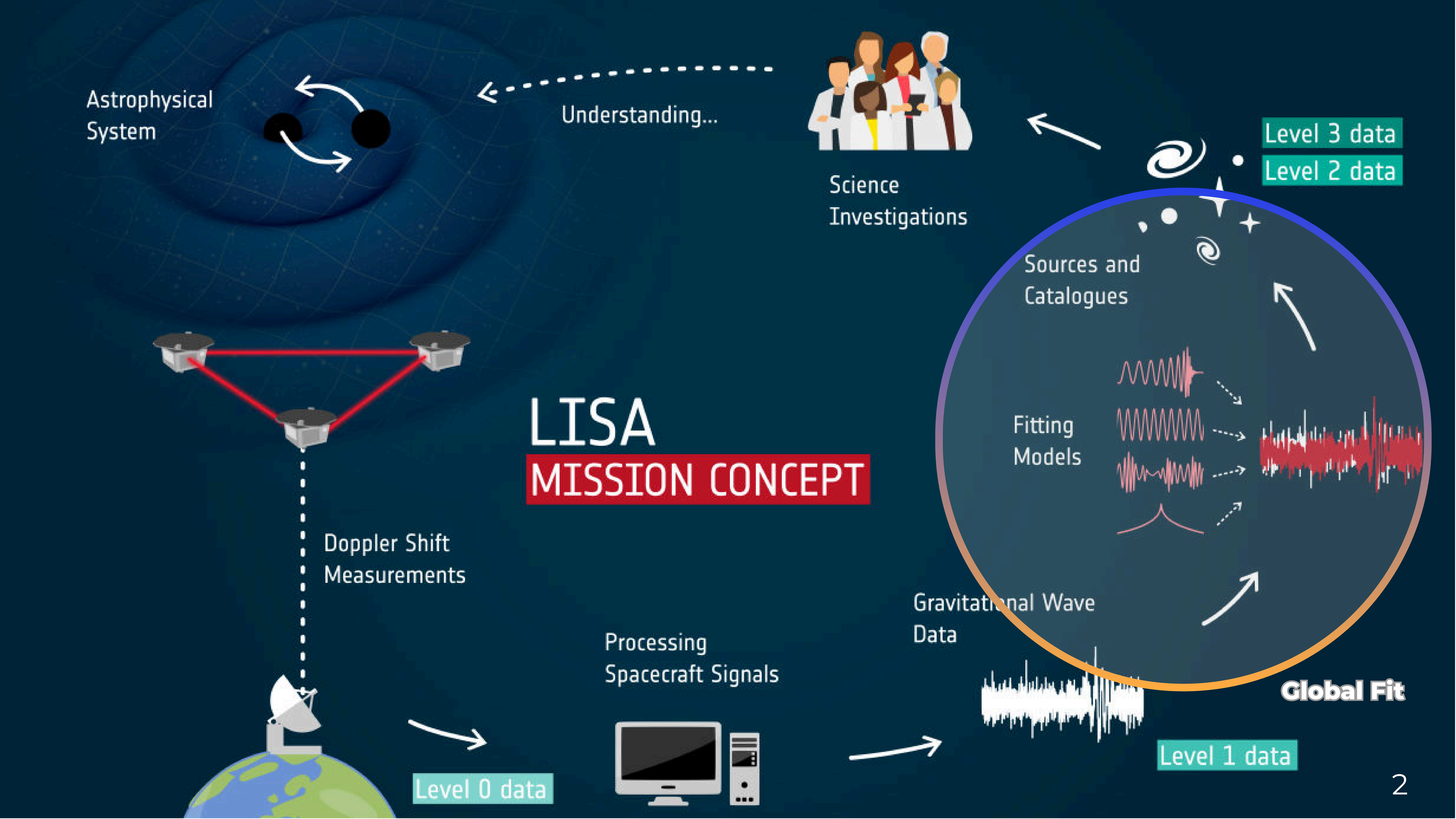
MBHBs : merging massive Black Hole binaries

sBHs : merging stellar-mass Black Holes

EMRIs : extreme mass-ratio inspirals

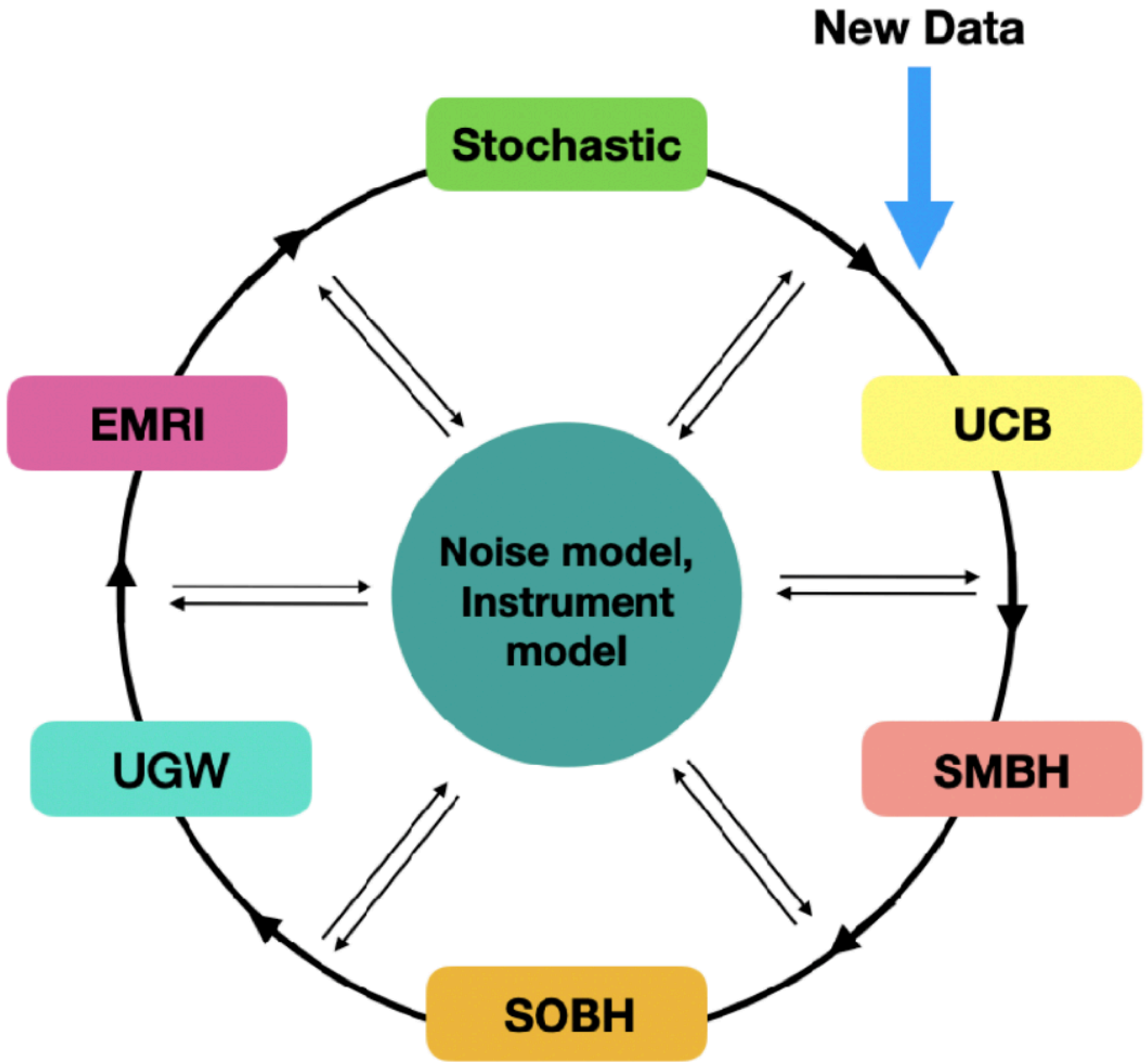
GBs : Galactic binaries (including verification binaries)

Noise : instrumental noise and GW foreground


Astrophysical
System
Understanding...
Science
Investigations
Level 3 data
Level 2 data
Sources and
Catalogues
Fitting
Models
LISA
MISSION CONCEPT
Doppler Shift
Measurements
Gravitational Wave
Data
Processing
Spacecraft Signals
Global Fit
Level 1 data
Level 0 data

Global Fit via Blocked Sampling

from N. Cornish's talk
Nice, 2023



- Transdimensional Markov Chain Monte Carlo (RJMCMC)
- Blocked Metropolis Hastings—update each component of the signal/noise model in circular sweeps
- Only pass residuals - decouples the analysis types
- Update the fit every ~week as new data arrives

The global fit

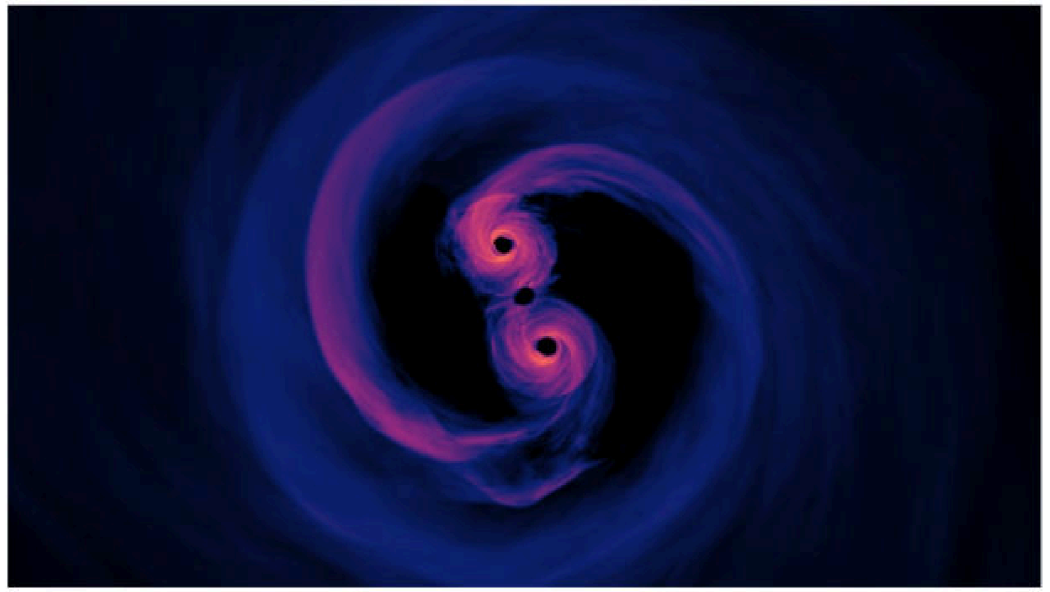
from R. Buscicchio's talk
Toulouse, 2024

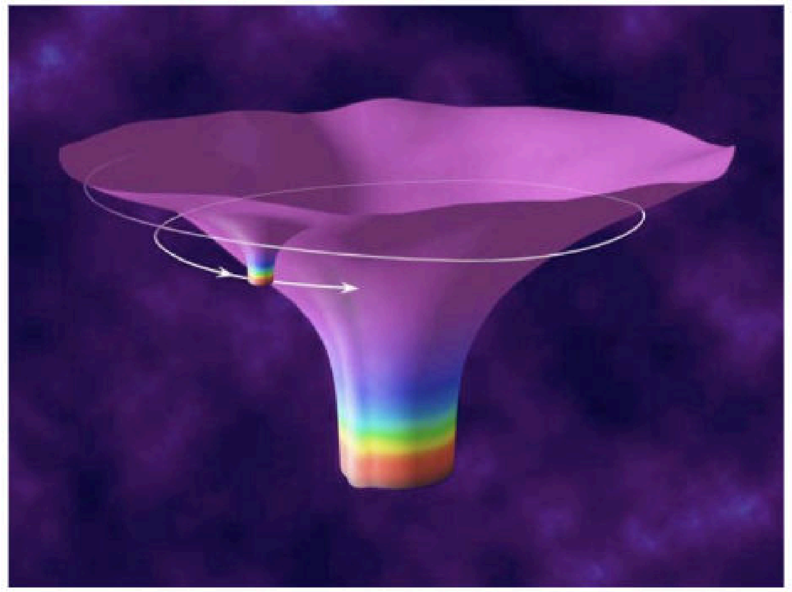
Scores from a penguin cacophony

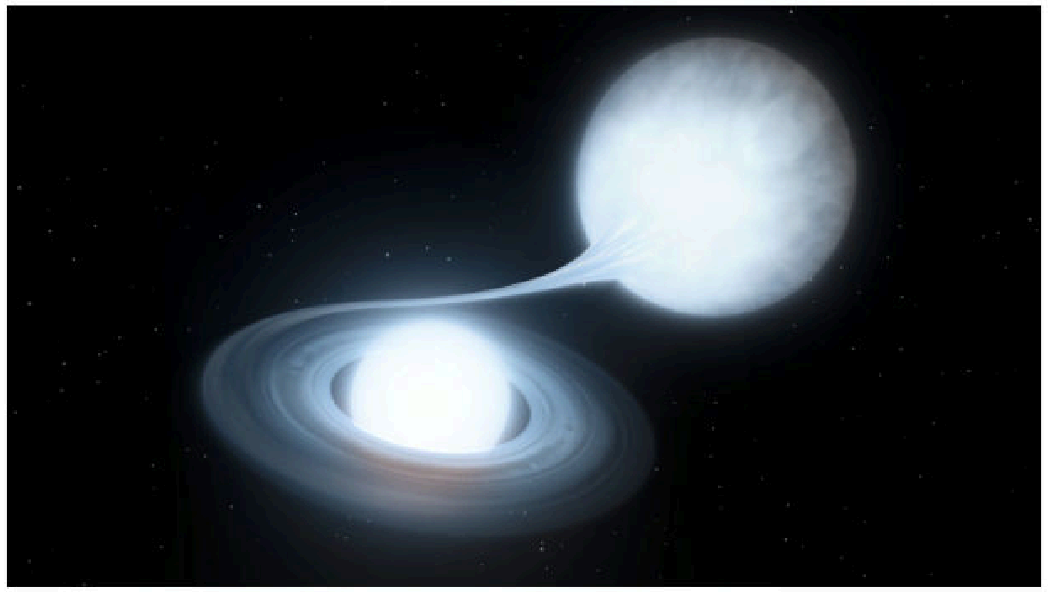
Hundreds

Tens to thousands

Millions







- GWINESS project started in January 2025
- Blind source separation of overlapping gravitational wave signals
- Inspired by music source separation
- Based on SCNet architecture
- Frequency-domain network operating on the Short-Time Fourier Transform
- Simplified Global Fit (for the moment)

Neural network design

Table 2. Comparison with other methods on MUSDB18-HQ (results with a * are tested on the non HQ version). "Extra" represents the quantity of additional data used during training. BSRNN only utilizes mixtures, while the others employ multi-track songs.

Model	Extra	All	drums	bass	other	vocals
HT Demucs [7]	No	7.52	7.94	8.48	5.72	7.93
Hybrid Demucs [6]	No	7.64	8.12	8.43	5.65	8.35
ResUNet* [25]	No	6.73	6.62	6.04	5.29	8.98
BSRNN [8]	No	8.24	9.01	7.22	6.70	10.01
SCNet	No	9.00	10.51	8.82	6.76	9.89
SCNet-large	No	**9.69**	**10.98**	**9.49**	**7.44**	**10.86**
Spleeter* [3]	2500	5.91	6.71	5.51	4.55	6.86
D3Net [26]	1500	6.68	7.36	6.20	5.37	7.80
Hybrid Demucs [6]	800	8.34	9.31	9.13	6.18	8.75
HT Demucs [7]	800	9.00	10.08	**10.39**	6.32	9.20
BSRNN [8]	1750	8.97	10.15	8.16	7.08	10.47
SCNet	235	9.25	10.78	9.21	6.84	10.17
SCNet-large	235	**9.92**	**11.23**	9.86	**7.51**	**11.1**

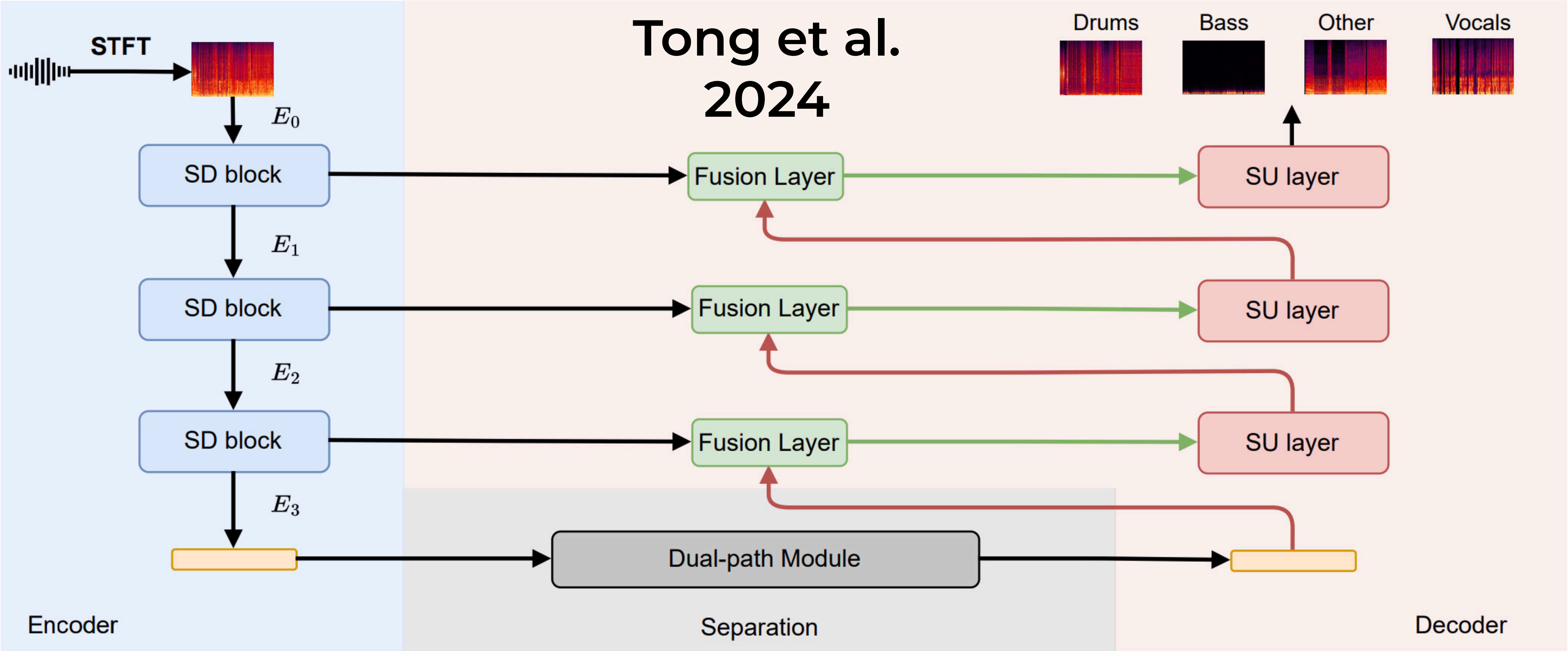
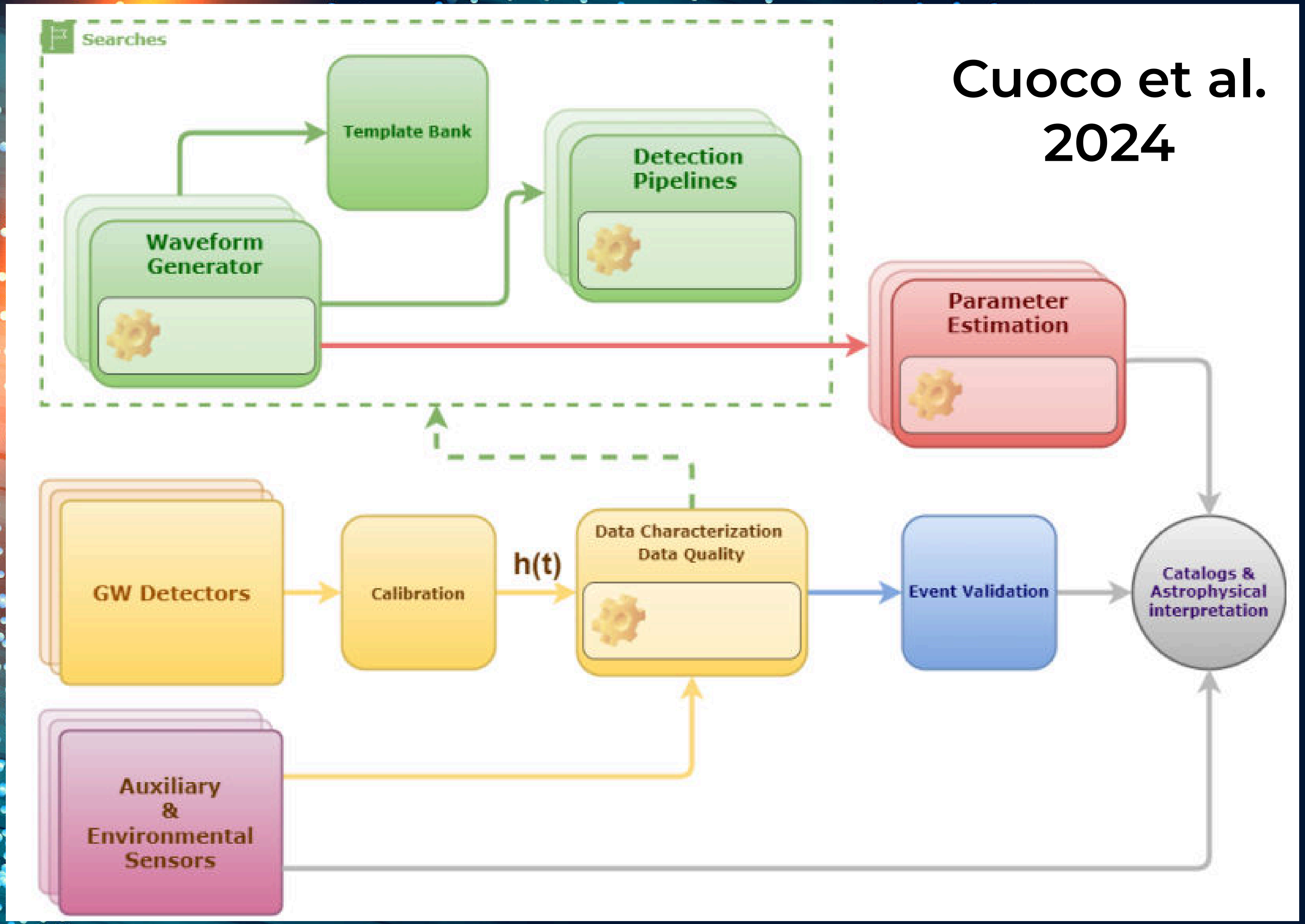


Fig. 1. The overall architecture of SCNet.

https://arxiv.org/pdf/2401.13276

Machine Learning for LISA?

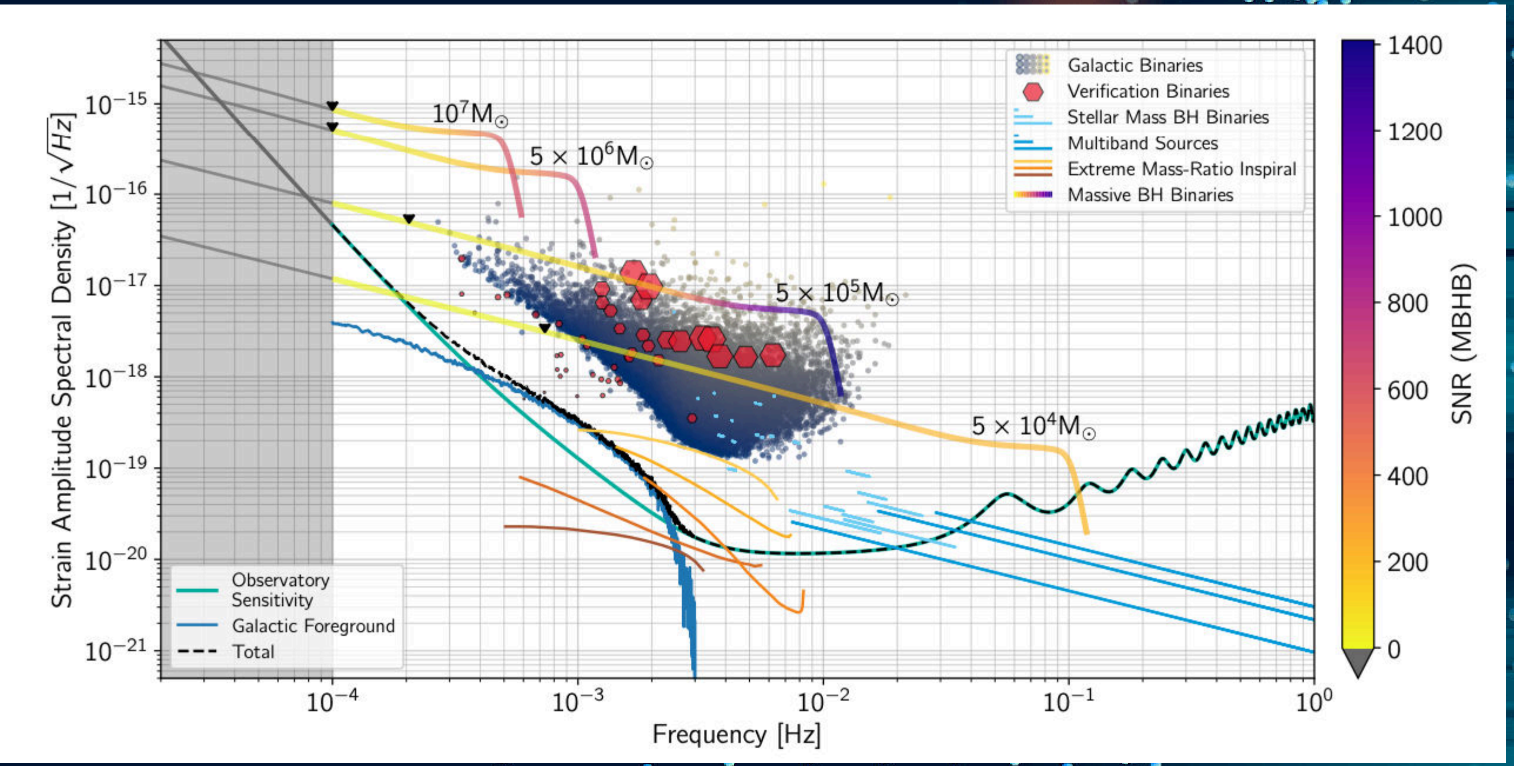


https://arxiv.org/pdf/2412.15046

- Need for scalable and efficient data analysis
- Computational cost of the pure Bayesian inference vs limited resources
- The likehood evaluation is dominated by the waveform computation
- Use of deep learning to accelerate the convergence of the Bayesian inference

Challenges in LISA

- Complex noise structures (including glitches and gaps)
- Need for efficient separation and parameter estimation
- Large number of overlapping sources
- High dimensionality of the model
- Presence of correlated parameters



https://arxiv.org/pdf/2402.07571

GBs : thousands of sources to find (8 parameters each)

- Narrow band in the frequency domain

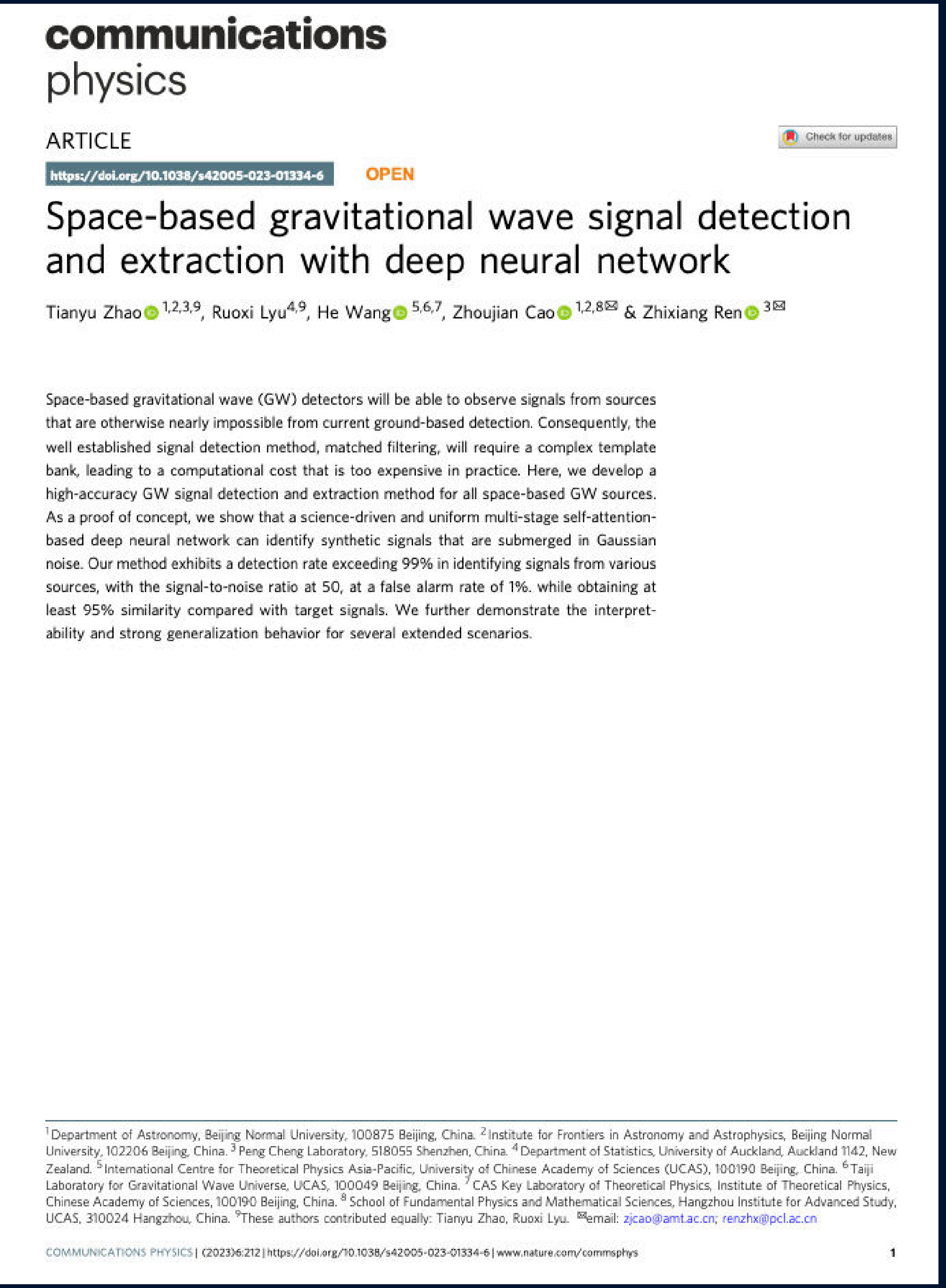
BHBs : not too many sources but tricky parameter estimation

- Transient signals (response varying both with time and frequency)

EMRIs : complex waveforms with multiple harmonics

- Long-lasting sources with low SNR and timescales of several years

Signal denoising



communications
physics

ARTICLE

https://doi.org/10.1038/s42005-023-01334-6 OPEN

Check for updates

Space-based gravitational wave signal detection and extraction with deep neural network

Tianyu Zhao[1,2,3,9], Ruoxi Lyu[4,9], He Wang[5,6,7], Zhoujian Cao[1,2,8✉] & Zhixiang Ren[3✉]

Space-based gravitational wave (GW) detectors will be able to observe signals from sources that are otherwise nearly impossible from current ground-based detection. Consequently, the well established signal detection method, matched filtering, will require a complex template bank, leading to a computational cost that is too expensive in practice. Here, we develop a high-accuracy GW signal detection and extraction method for all space-based GW sources. As a proof of concept, we show that a science-driven and uniform multi-stage self-attention-based deep neural network can identify synthetic signals that are submerged in Gaussian noise. Our method exhibits a detection rate exceeding 99% in identifying signals from various sources, with the signal-to-noise ratio at 50, at a false alarm rate of 1%. while obtaining at least 95% similarity compared with target signals. We further demonstrate the interpret-ability and strong generalization behavior for several extended scenarios.

[1]Department of Astronomy, Beijing Normal University, 100875 Beijing, China. [2]Institute for Frontiers in Astronomy and Astrophysics, Beijing Normal University, 102206 Beijing, China. [3]Peng Cheng Laboratory, 518055 Shenzhen, China. [4]Department of Statistics, University of Auckland, Auckland 1142, New Zealand. [5]International Centre for Theoretical Physics Asia-Pacific, University of Chinese Academy of Sciences (UCAS), 100190 Beijing, China. [6]Taiji Laboratory for Gravitational Wave Universe, UCAS, 100049 Beijing, China. [7]CAS Key Laboratory of Theoretical Physics, Institute of Theoretical Physics, Chinese Academy of Sciences, 100190 Beijing, China. [8]School of Fundamental Physics and Mathematical Sciences, Hangzhou Institute for Advanced Study, UCAS, 310024 Hangzhou, China. [9]These authors contributed equally: Tianyu Zhao, Ruoxi Lyu. ✉email: zjcao@amt.ac.cn; renzhx@pcl.ac.cn

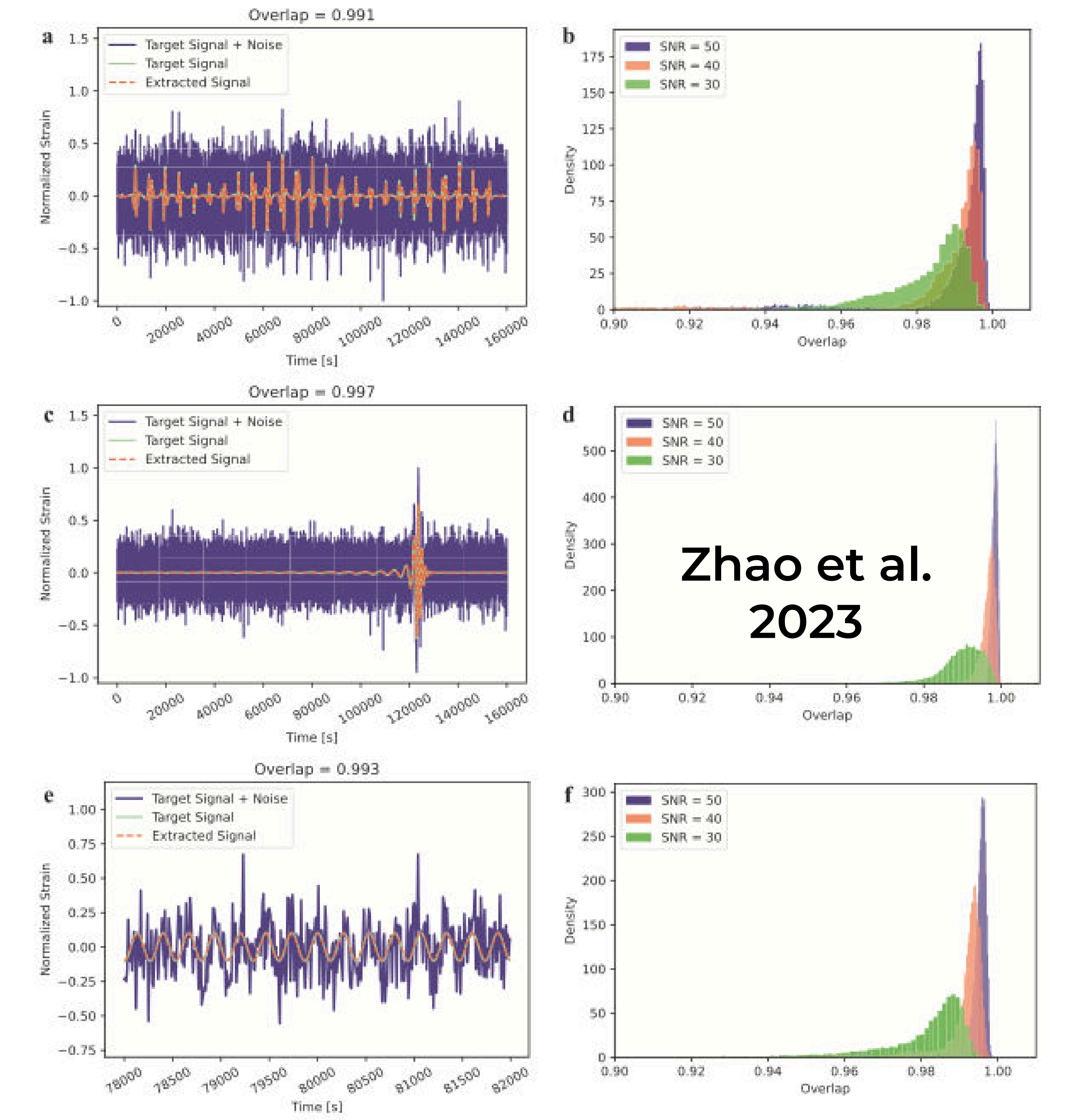


Fig. 4 The signal extraction examples and the overlapping (between the target and extracted signals) distributions for different GW sources. a and **b** EMRI. **c** and **d** MBHB. **e** and **f** BWD. The extracted signal is compared with whitened templates. Only the middle part of the BWD waveform is presented to show the details of the waveform. The overlap between extracted data and waveform templates is shown on the top. The high values indicate the strong performance of our method on signal extraction for different GW sources. Tests on different signal SNRs also show our models' generalization ability.

https://www.nature.com/articles/s42005-023-01334-6

Signal denoising

Zhao et al. 2023

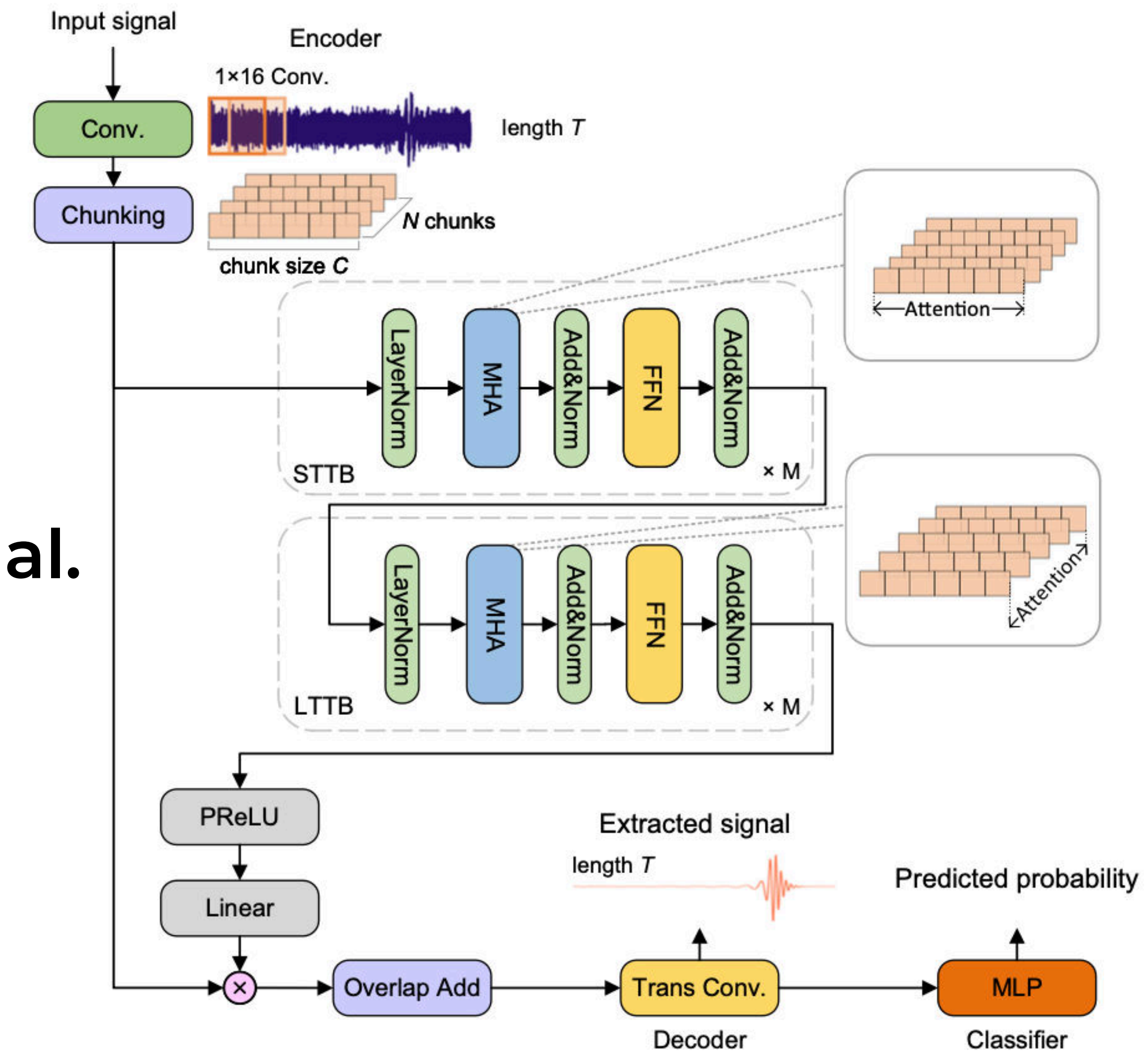


Fig. 1 The overall architecture of our Transformer based deep neural network. Beginning with a convolutional network-based encoder, data is transformed and feed into the Transformer-based extraction network. This network composed of several Short-Term Transformer Blocks (STTB) and Long-Term Transformer Blocks (LTTB), excels in capturing both local and global dependencies within the GW data, aimed at extracting GW signals. The final stage is a multi-layer perception-based classifier, responsible for the signal detection and provide a predicted probability.

https://www.nature.com/articles/s42005-023-01334-6

Table 1 Summary of parameter setups in EMRI signal simulation.

Parameter	Lower bound	Upper bound
M	$10^5 M_\odot$	$10^7 M_\odot$
a	10^{-3}	0.99
e_0	10^{-3}	0.5
$\cos \iota$	-1	1

Table 2 Summary of parameter setups in MBHB signal simulation.

Parameter	Lower bound	Upper bound
M_{tot}	$10^6 M_\odot$	$10^8 M_\odot$
q	0.01	1
s_1^z	-0.99	0.99
s_2^z	-0.99	0.99

Table 3 Summary of parameter setups in BWD signal simulation.

Parameter	f	$\dot{f}$
Range-1	[0.1, 4]mHz	$[-3\times10^{-17}, 6\times10^{-16}]\mathrm{Hz}^2$
Range-2	[4, 15]mHz	$[-3\times10^{-15}, 4\times10^{-14}]\mathrm{Hz}^2$

Signal denoising & separation

Houba 2025

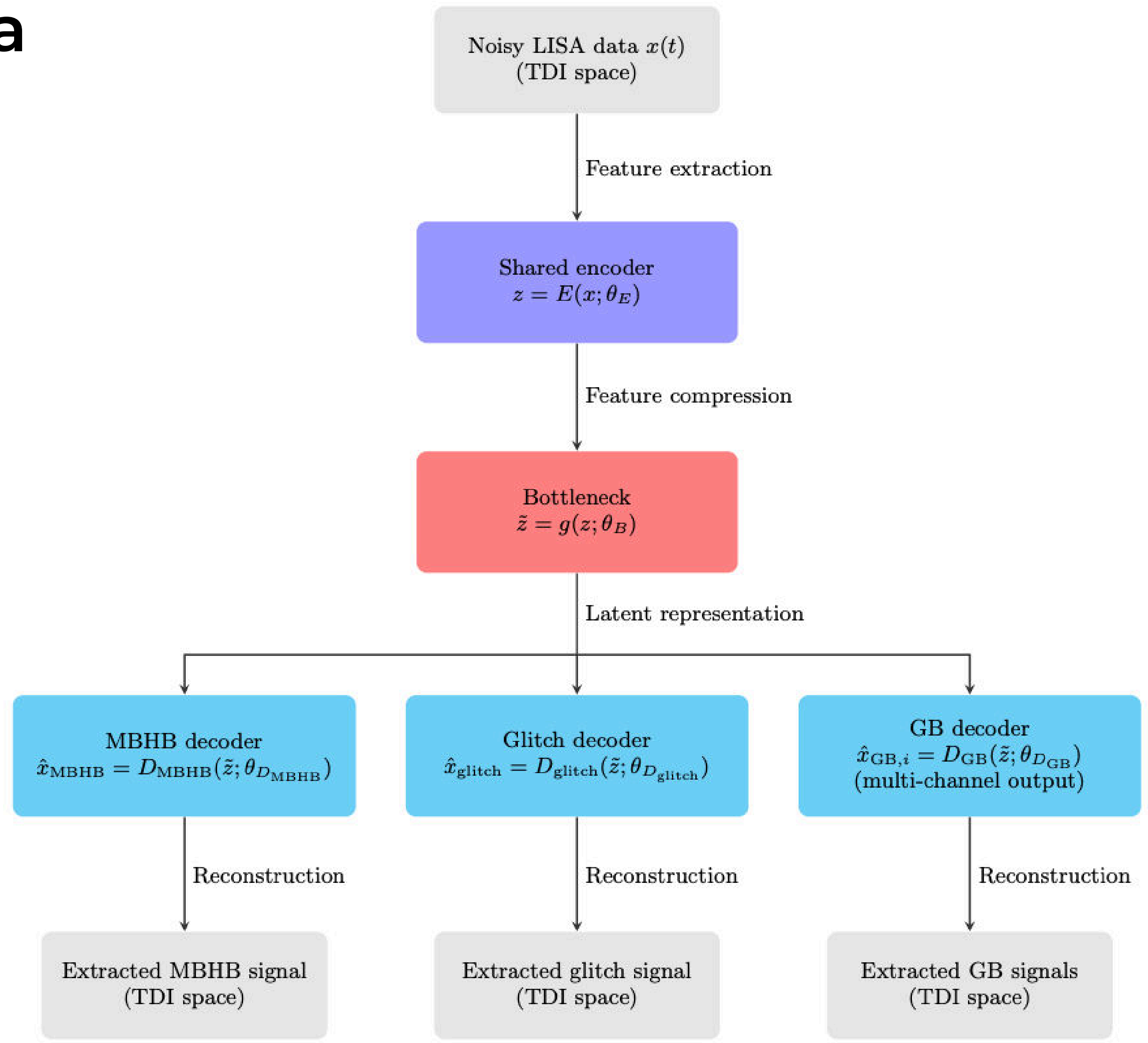
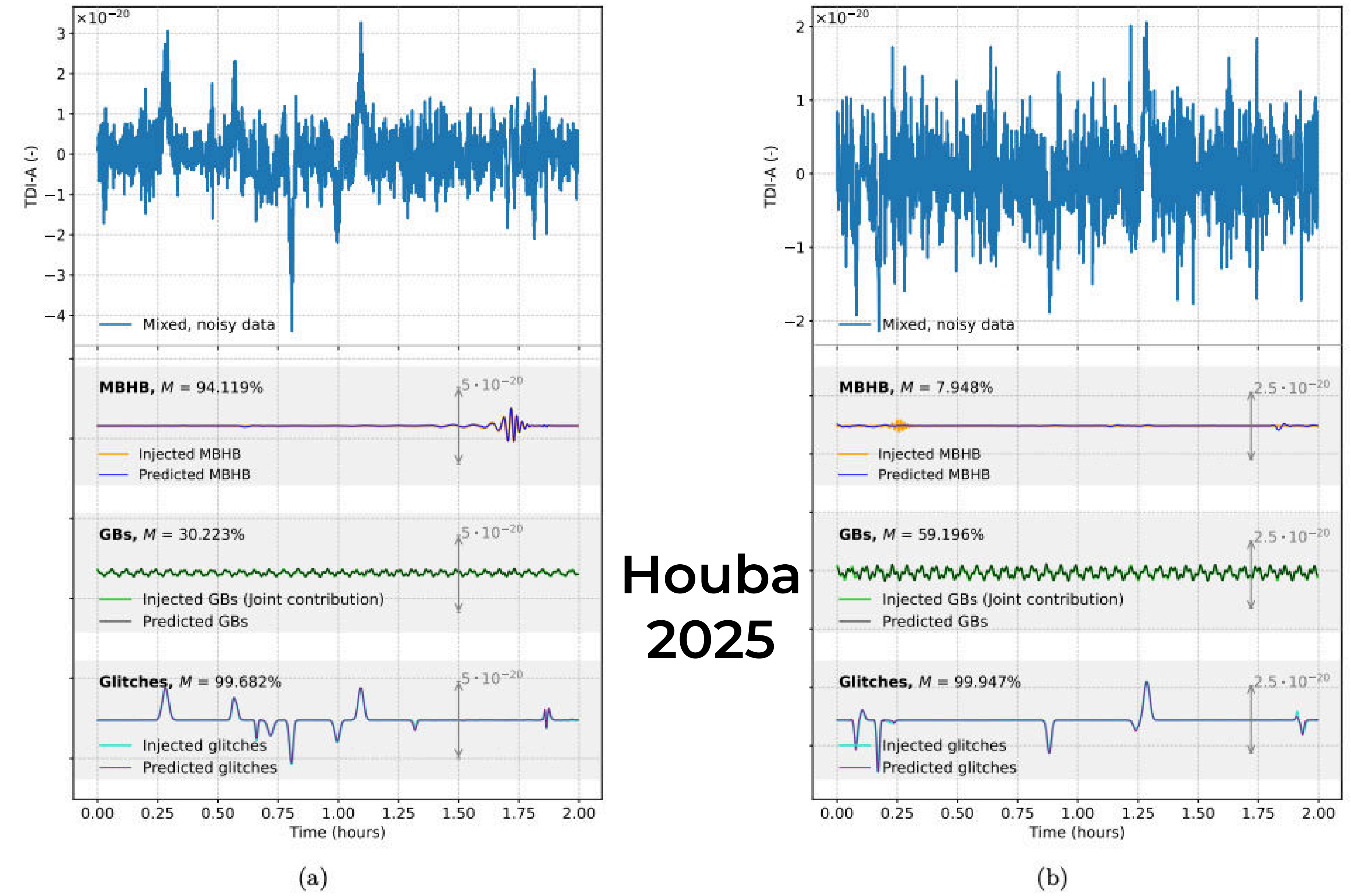


FIG. 2: Deep source separation framework for LISA data, where a shared encoder compresses the TDI input, and decoders reconstruct MBHBs, GBs and glitches. Since the input data denotes a TDI channel, the separated and decoded output signals are represented in the TDI space, as well.

https://arxiv.org/pdf/2503.10398

- Proof-of-concept
- Exclude EMRI waveforms
- Very simple neural network model
- Time-domain analysis (2h signal)
- TDI data as input
- Multi-channel output for GBs
- Latent space representation

Signal denoising & separation



Houba 2025

FIG. 7: Comparison of injected waveforms and model predictions for a low-amplitude MBHB merger buried in stationary noise. In panel (a), the deep source separation framework successfully detects and reconstructs the MBHB signal. However, in (b), where the signal amplitude is further diminished, the model fails. In such cases, further investigation is needed to determine whether the issue lies in the shared encoder or the MBHB decoder head.

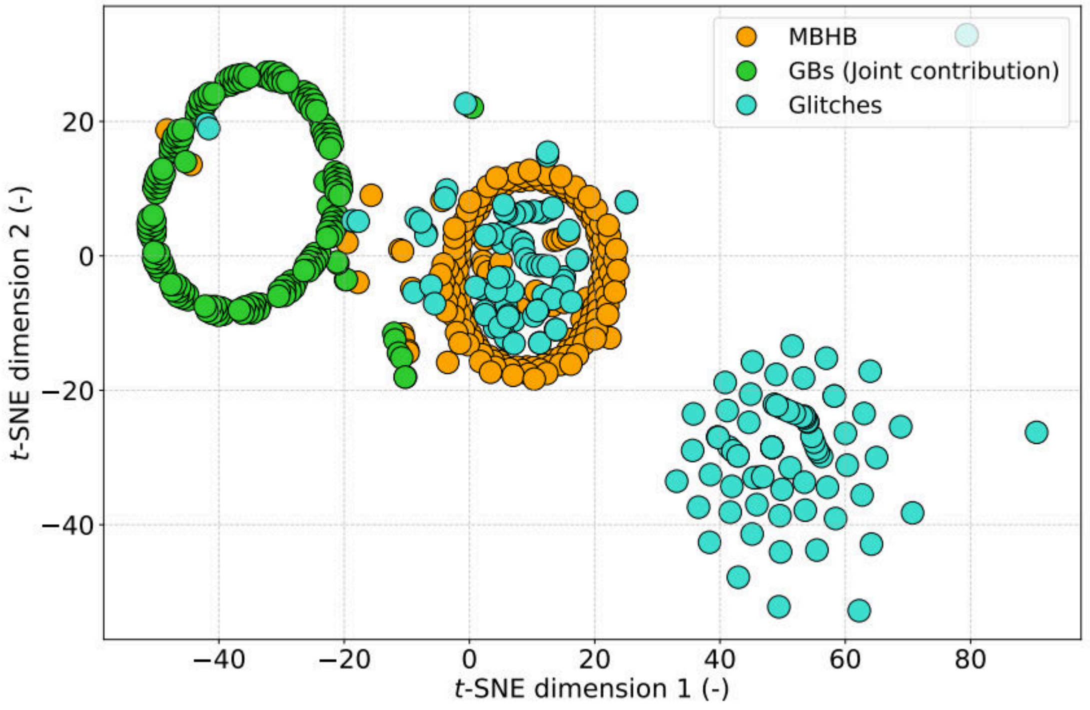
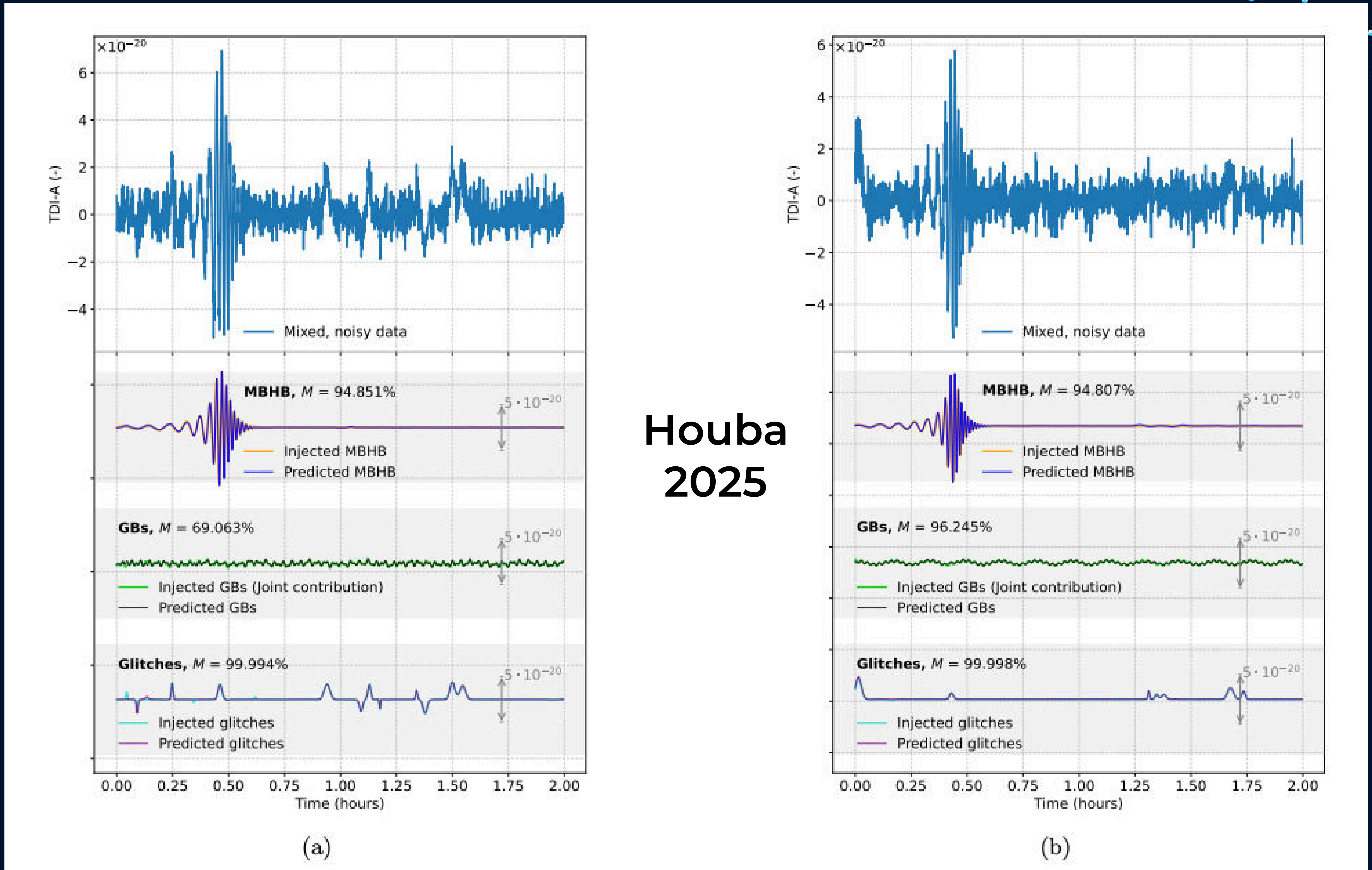


FIG. 4: t-SNE projection of bottleneck-encoded features derived from the normalized time series data in Fig. 3, illustrating clustering of merging MBHBs, GBs, and glitches. Note that separating sources within an abstract feature space beyond traditional temporal and spectral domains denotes a reorientation of methodology in LISA data analysis.

https://arxiv.org/pdf/2503.10398

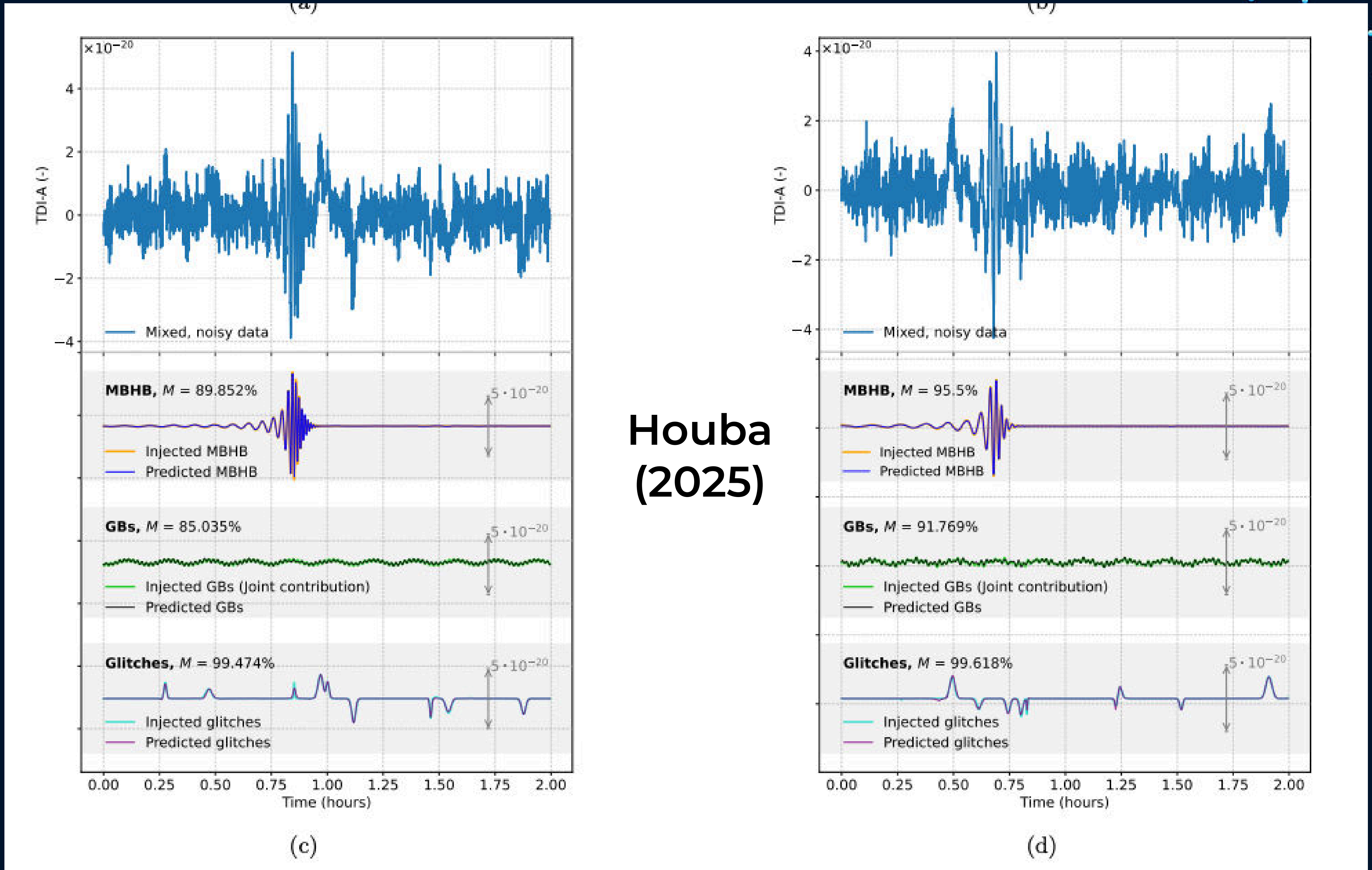
Signal denoising & separation



when glitches overlap with the MBHB merger phase

https://arxiv.org/pdf/2503.10398

Signal denoising & separation



Houba (2025)

when glitches occur during the MBHB ringdown

https://arxiv.org/pdf/2503.10398


GWINESS
GRAVITATIONAL WAVE INFERENCE
NEURAL SOURCE SEPARATION
Data Input
Drop HDF5 files here
or
Browse Files
Loaded File:
Name: mixed_test.hdf5
Size: 6.43 GB
Modified: 29/04/2025 16:35:38
Analysis Tools
Spectrogram
Parameter
Correlation
Source Information
MBHB GW150914-like 2.3 Gpc
EMRI Extreme Mass Ratio 4.1 Gpc
Galactic White Dwarf Binary 8 kpc
Visualization Controls
Fullscreen
Item: 10
Start
Stop
Mixed Input
Export
MBHB
Focus
Log Amplitude
Frequency (Hz)
Time (days)
Time Domain
Sampling Rate: 0.1 Hz
Separated Outputs
Hide
All
Show
MBHB Massive Black Hole Binary
SNR: 24.5
Frequency: 0.01-0.1 Hz
EMRI Extreme Mass Ratio Inspiral
SNR: 18.2
Frequency: 0.001-0.01 Hz
Galactic White Dwarf Binary
SNR: 32.7
Frequency: 0.1-1 Hz
Residual Remaining Noise
Power: 0.05
Frequency: Full Band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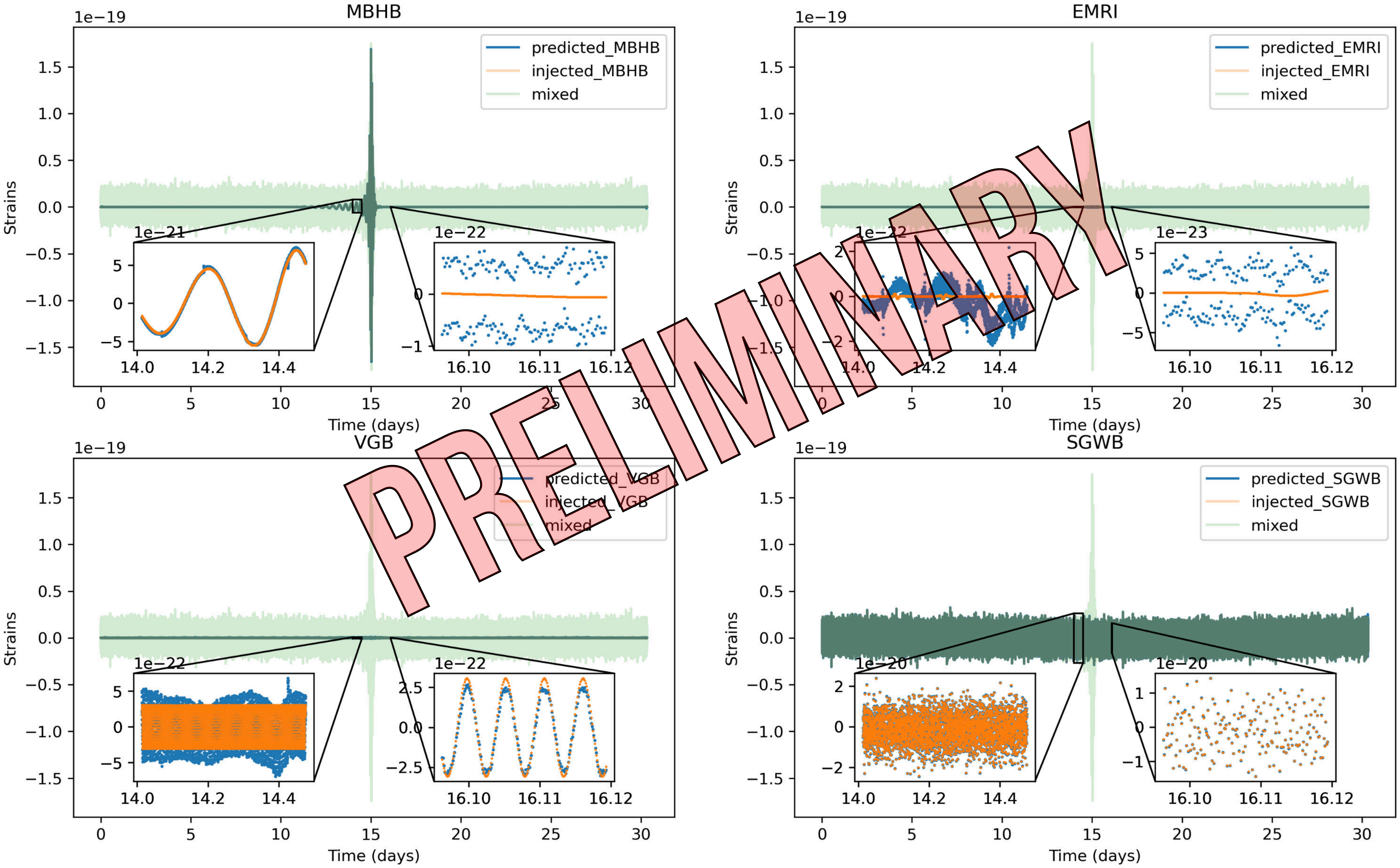
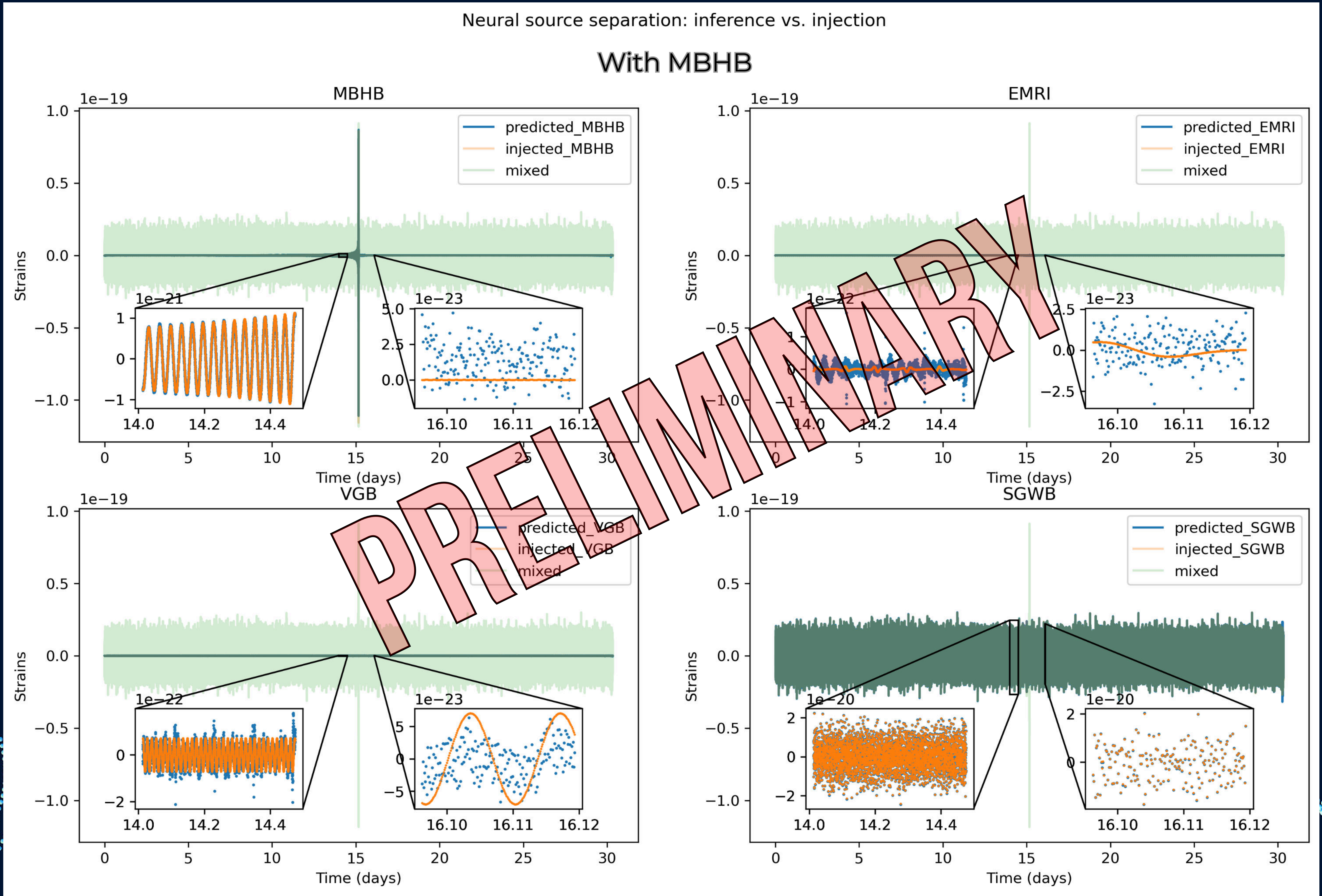
Residual Remaining Noise
Power: 0.05
Frequency: Full Band

Neural source separation: inference vs. injection

With MBHB

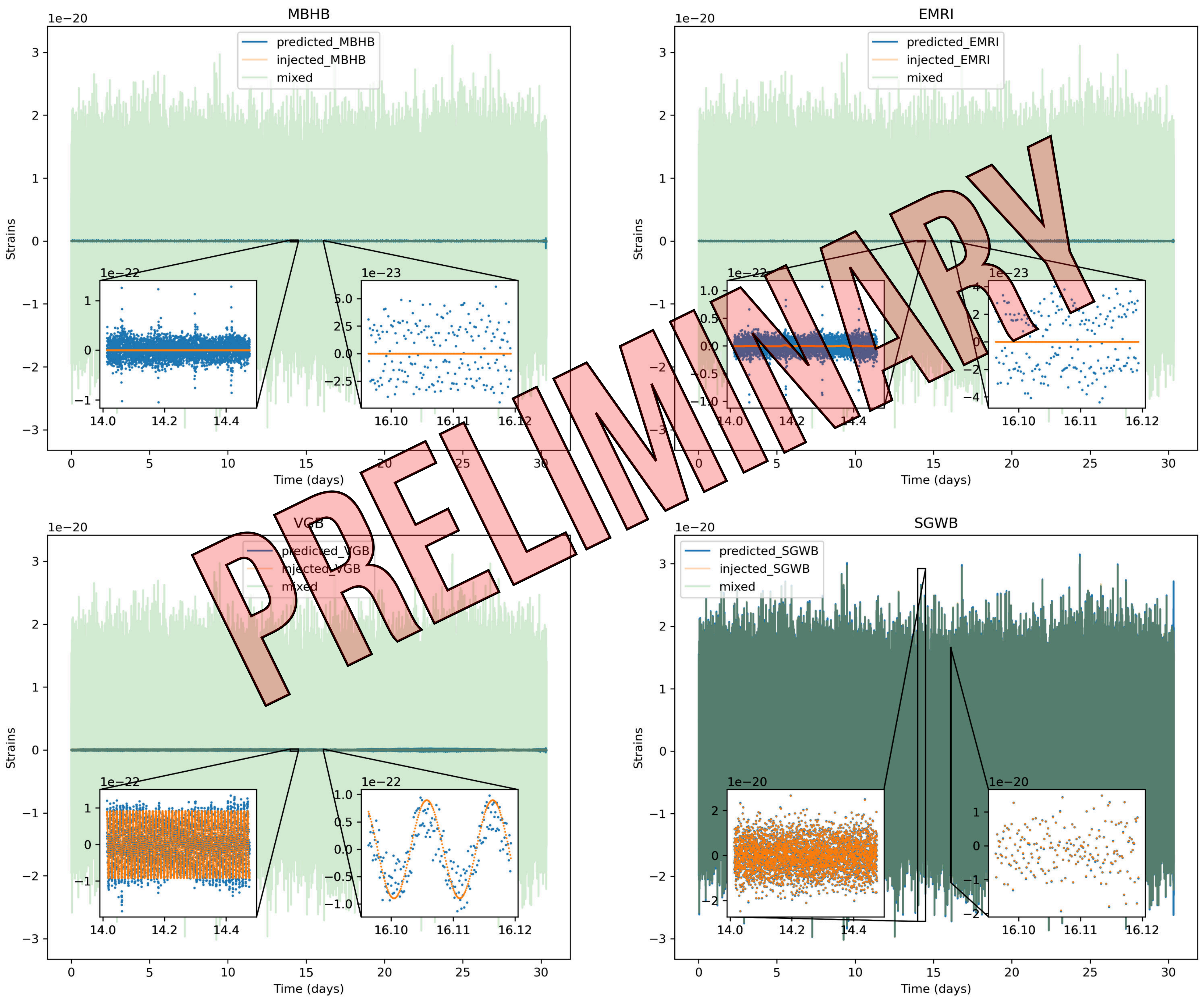


With MBHB


Neural source separation: inference vs. injection
MBHB
EMRI
VGB
SGWB
predicted_MBHB
injected_MBHB
mixed
predicted_EMRI
injected_EMRI
predicted_VGB
injected_VGB
predicted_SGWB
injected_SGWB
Strains
Time (days)
PRELIMINARY

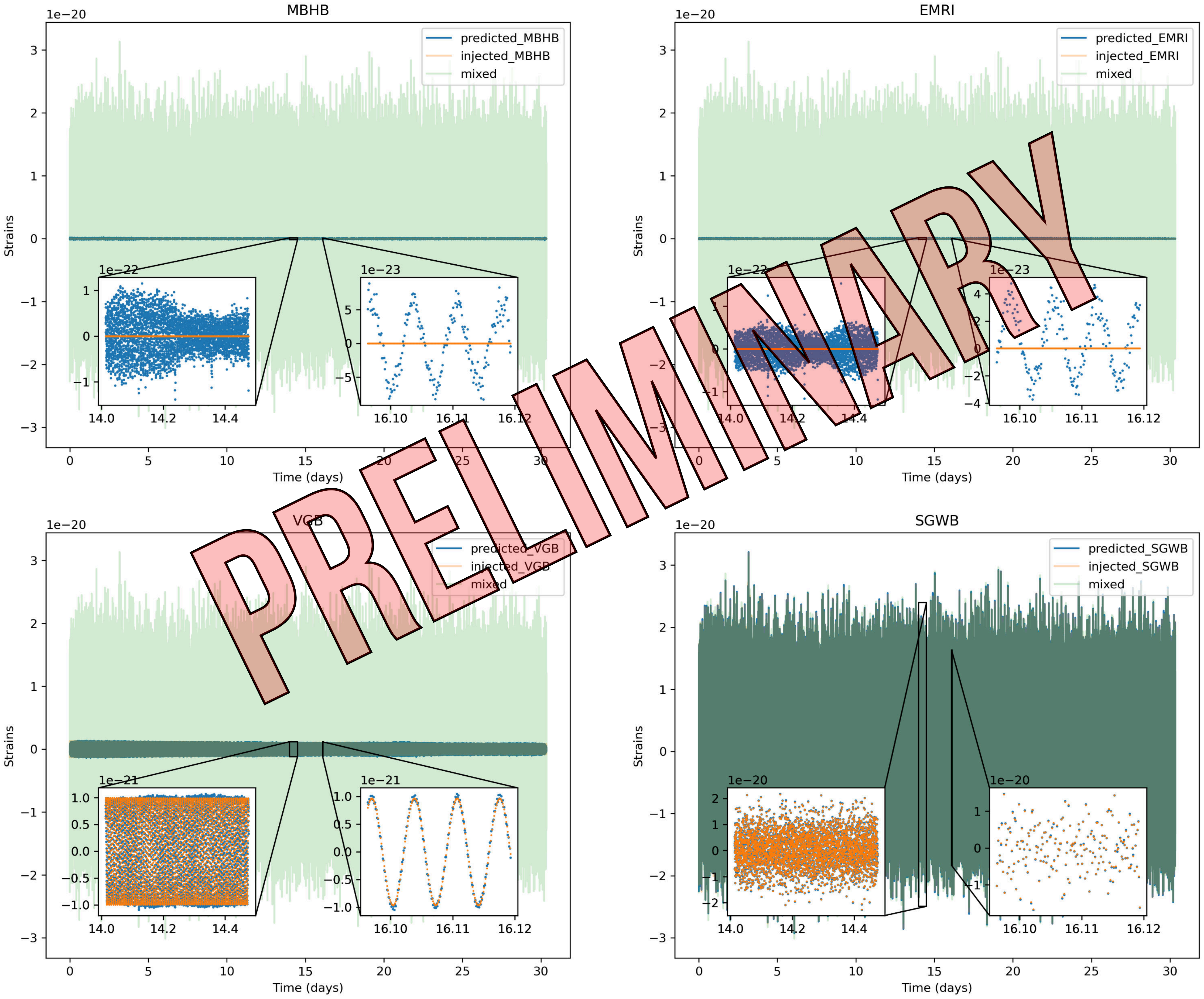
Neural source separation: inference vs. injection

Without MBHB



Neural source separation: inference vs. injection

Without MBHB



Conclusion

The GWINESS approach requires further investigation:

- hyperparameter tuning
- parameter estimation with variational autoencoder
- many overlapping sources

Data quality, algorithm selection, and computational resources can all impact its effectiveness.

While the benefits are clear, there are also many challenges to consider.

Thanks!

Do you have any questions?