Low-latency Localization and Parameter Estimation of Gravitational Waves Using Probabilistic Deep Learning

確率論的深層学習を用いた重力波の低遅延位置推定とパラメータ推定

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ICRR Research Result Presentation for Fiscal Year 2025

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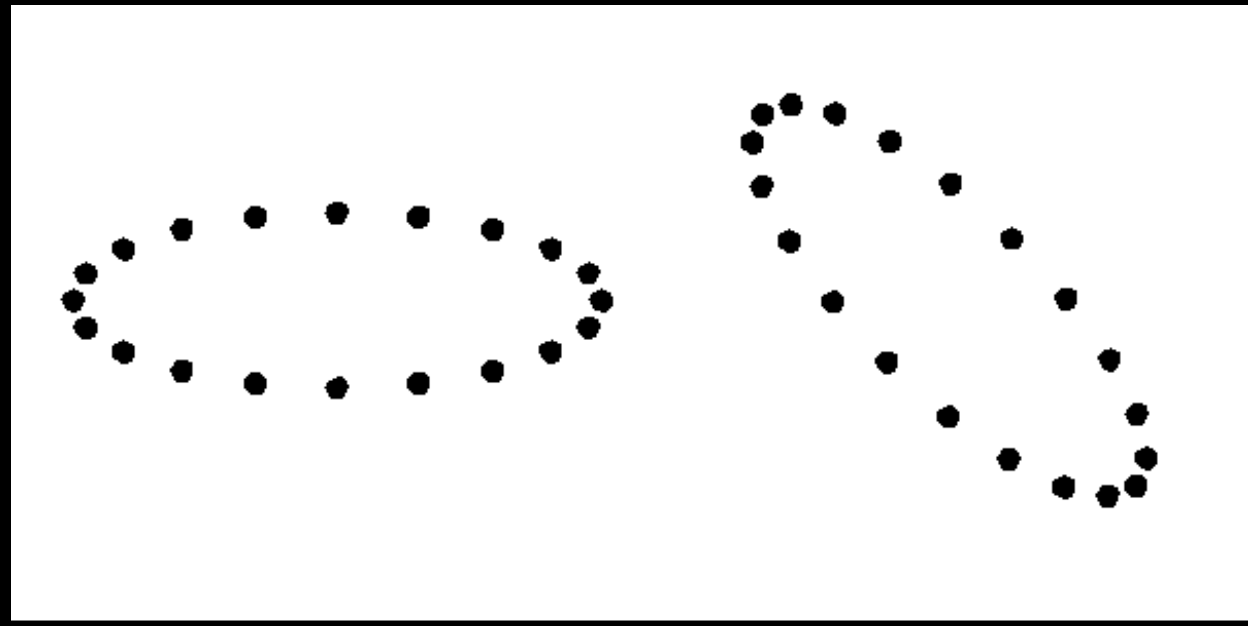
Approved budget: 150,000 yen (travel: 50,000; PC parts: 100,000)

Outline

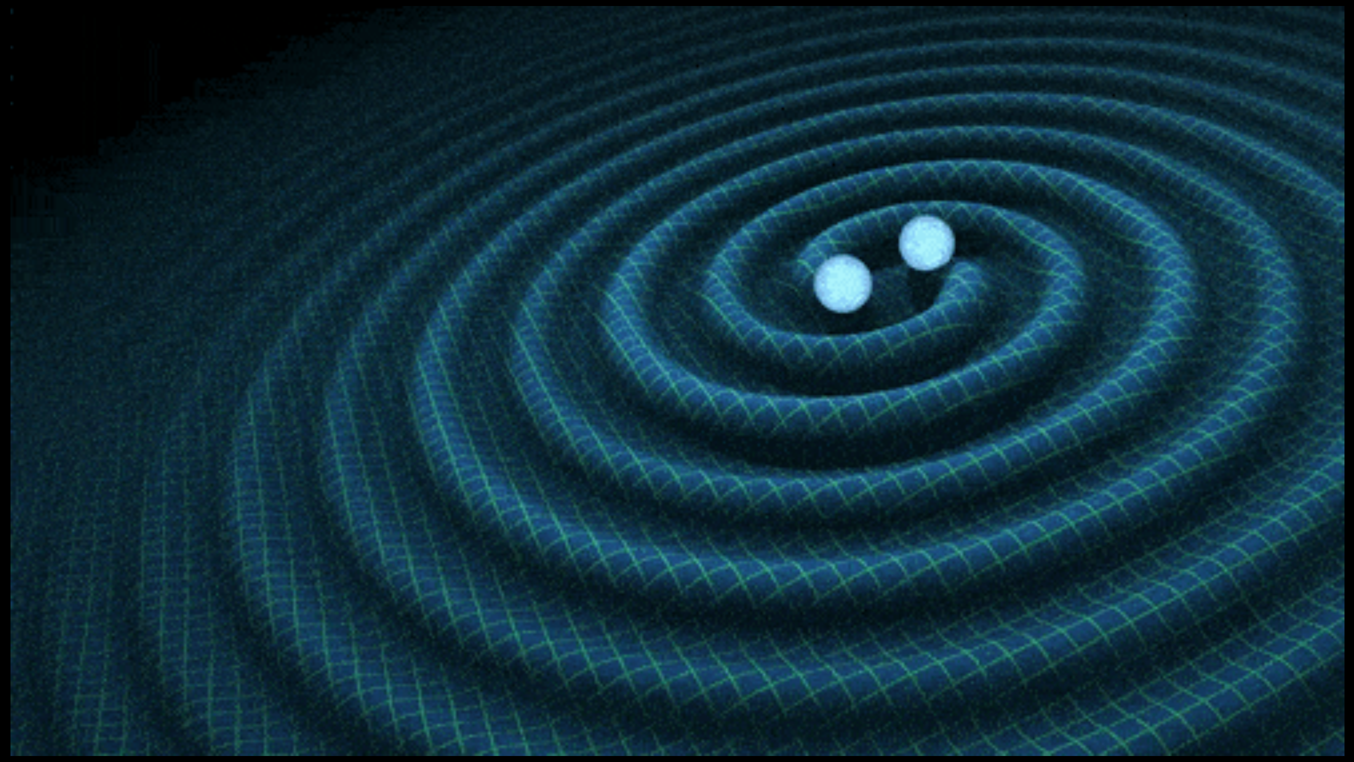
- Introduction to Gravitaional Waves
- Low-latency ML pipeline for GW processing
- Our work this year
- Summary

Gravitational Waves

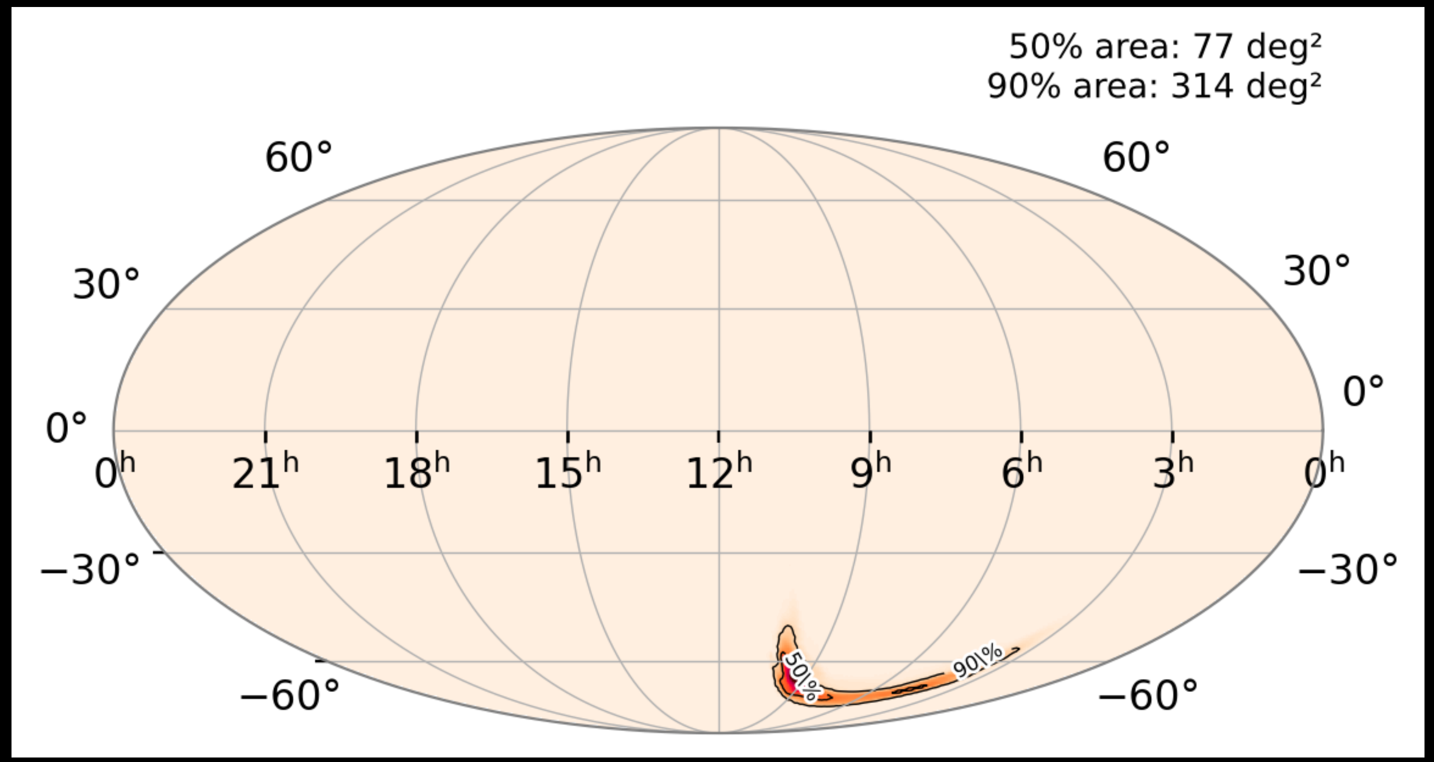
Polarizations:



(So far detected) Sources:

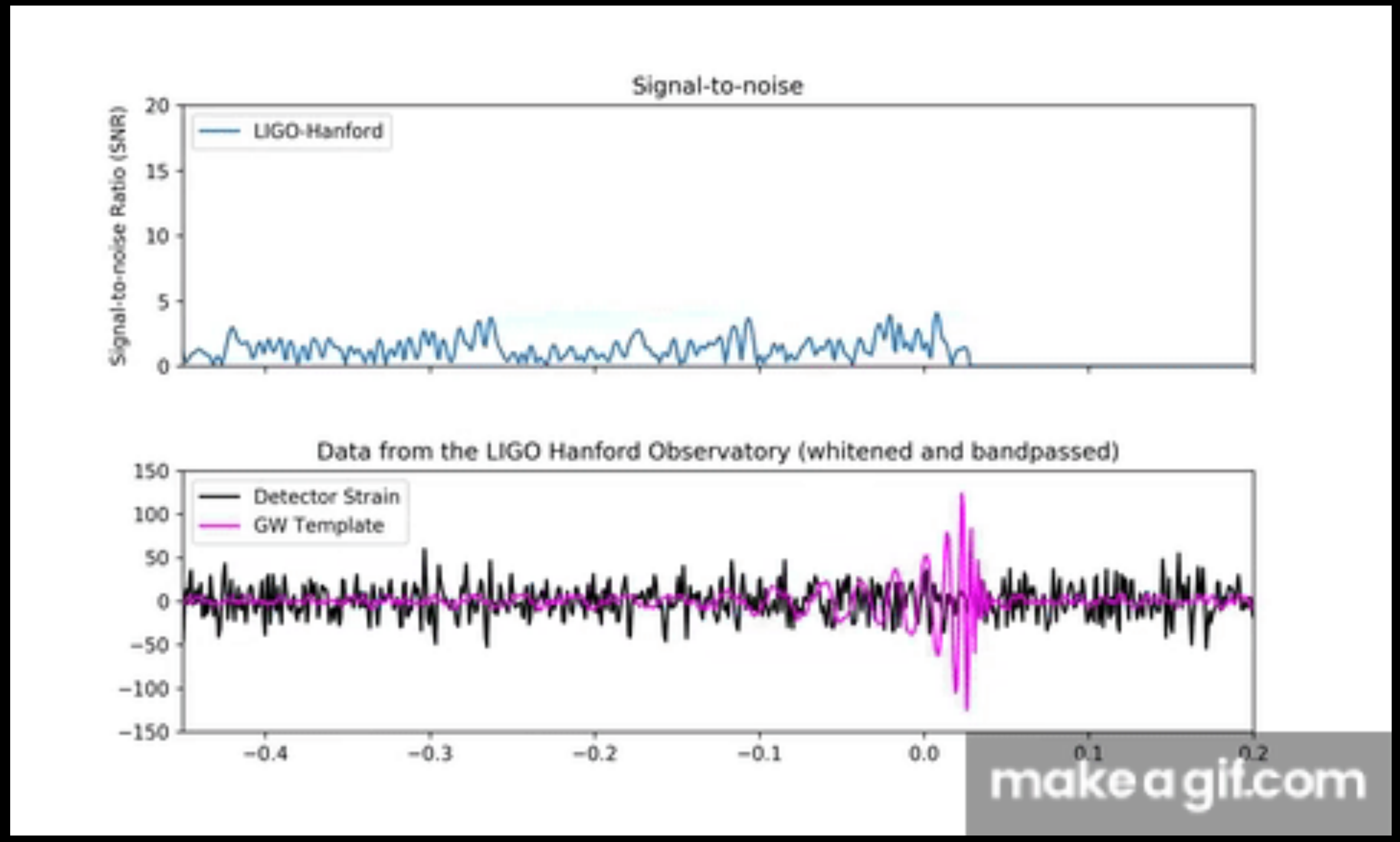


Localization:

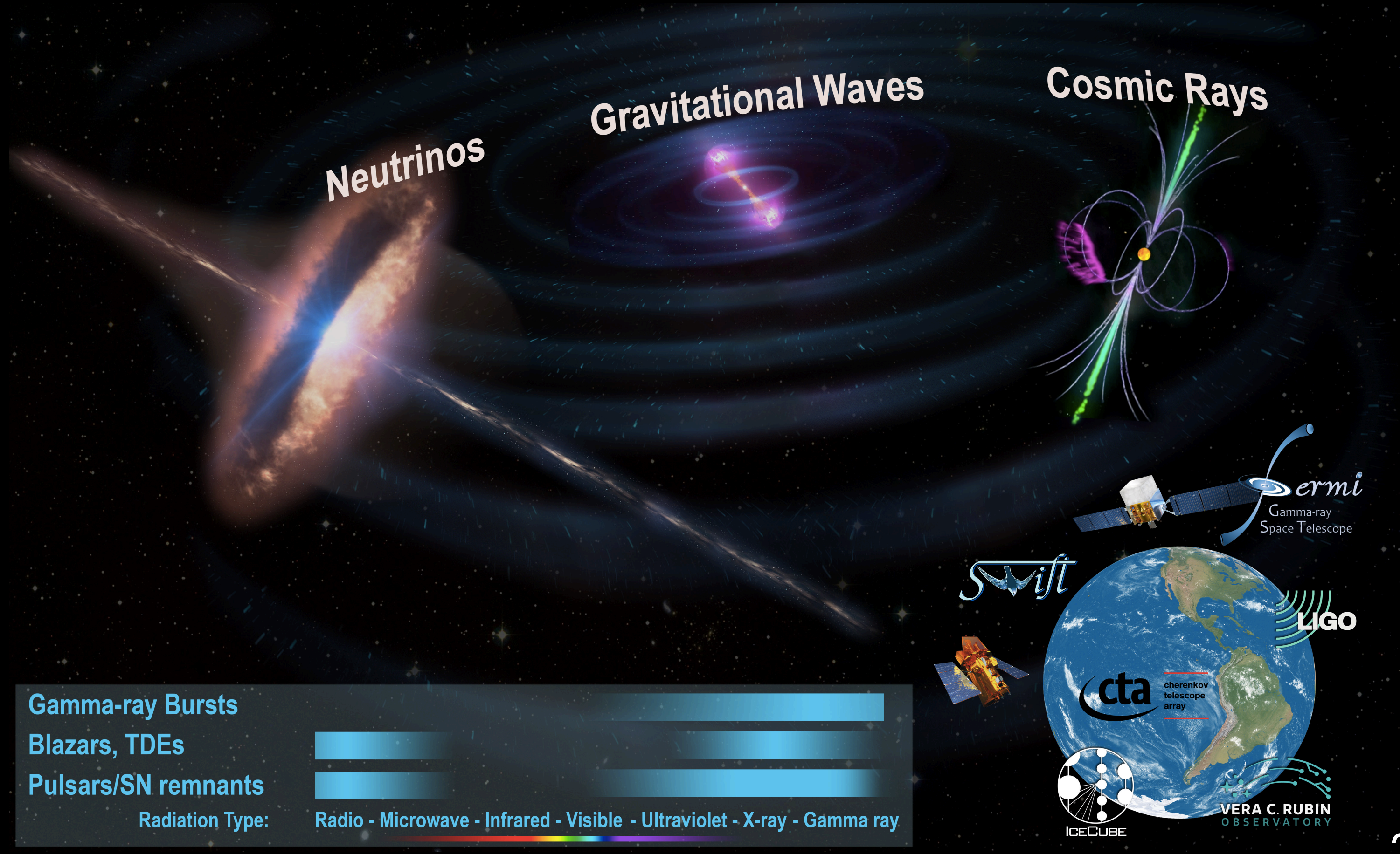


Detection:

Searches:

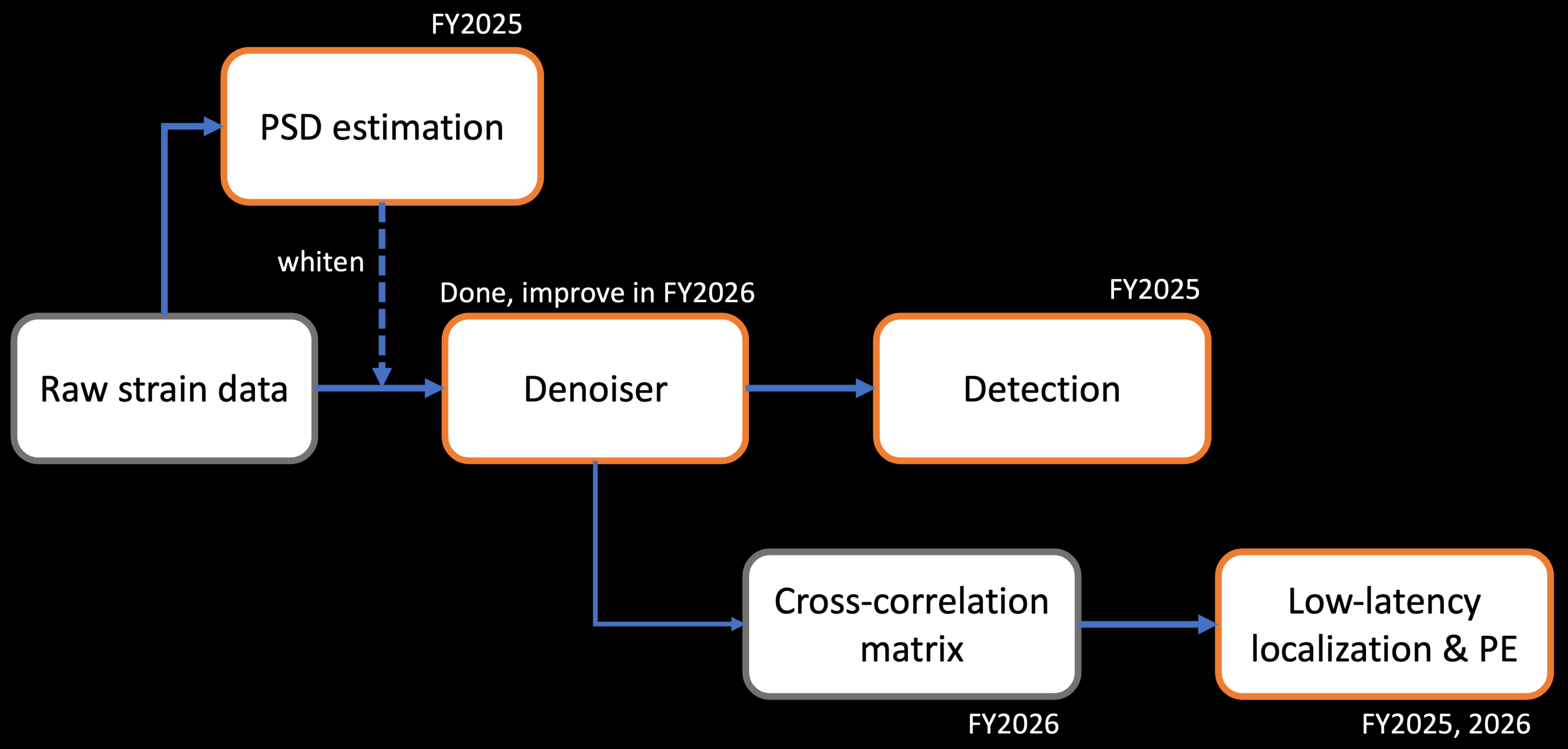


Multi-messenger Astronomy (MMA):



(Proposed) Low-latency GW Pipeline

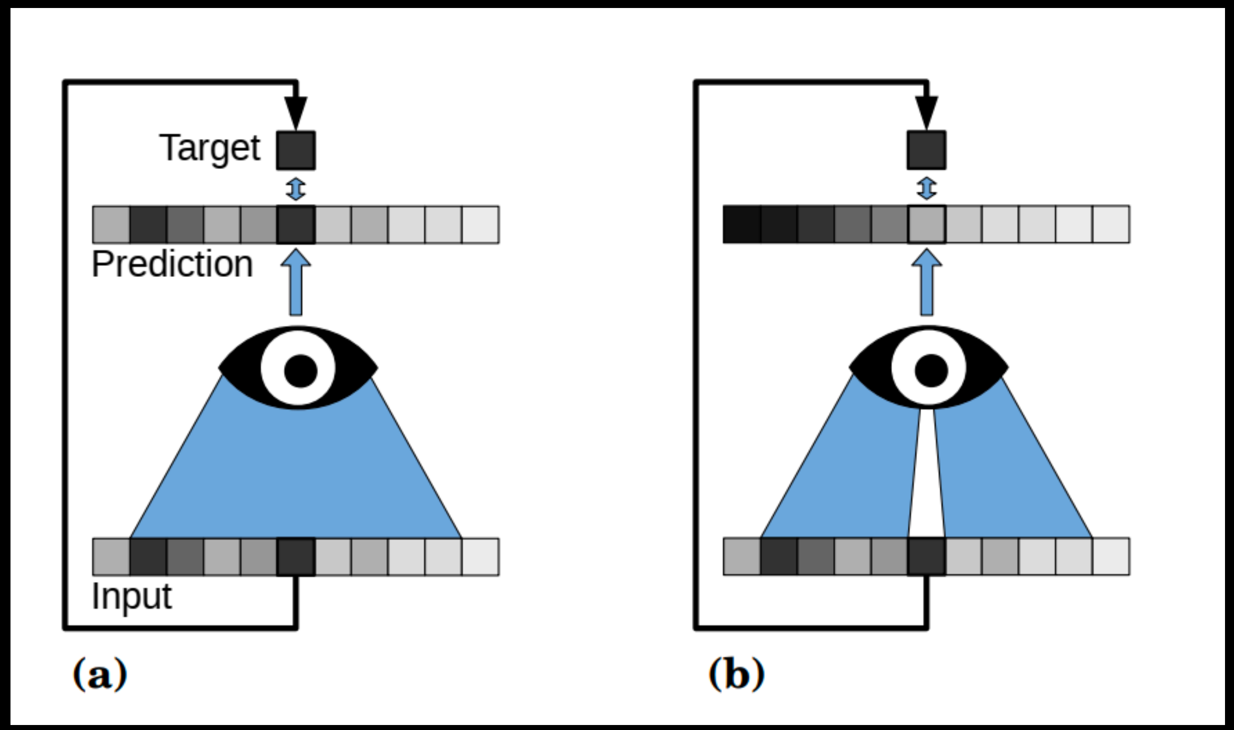
- We aim to build a machine-learning-only pipeline that can detect, localize, perform fast parameter estimation with low latency, and estimate uncertainty.
- The denoiser serves as a general feature extractor. We are keeping improving the performance.
- In FY2025, we investigated the relationship between denoised features and downstream tasks and developed a novel noise background estimator.
- Expected to test our pipeline on LIGO-Virgo-KAGRA data before O5 (2027).



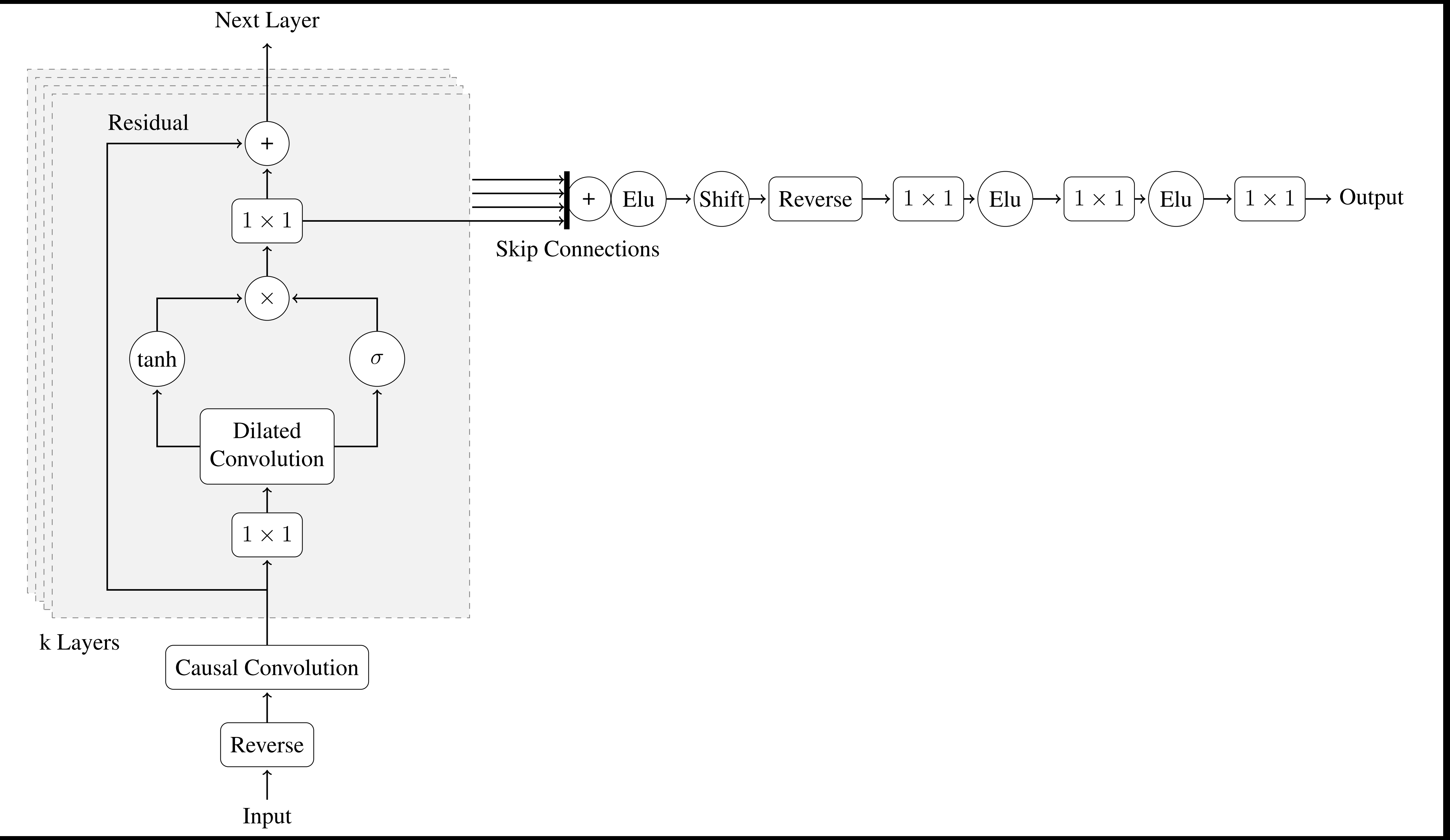
GW Denoiser

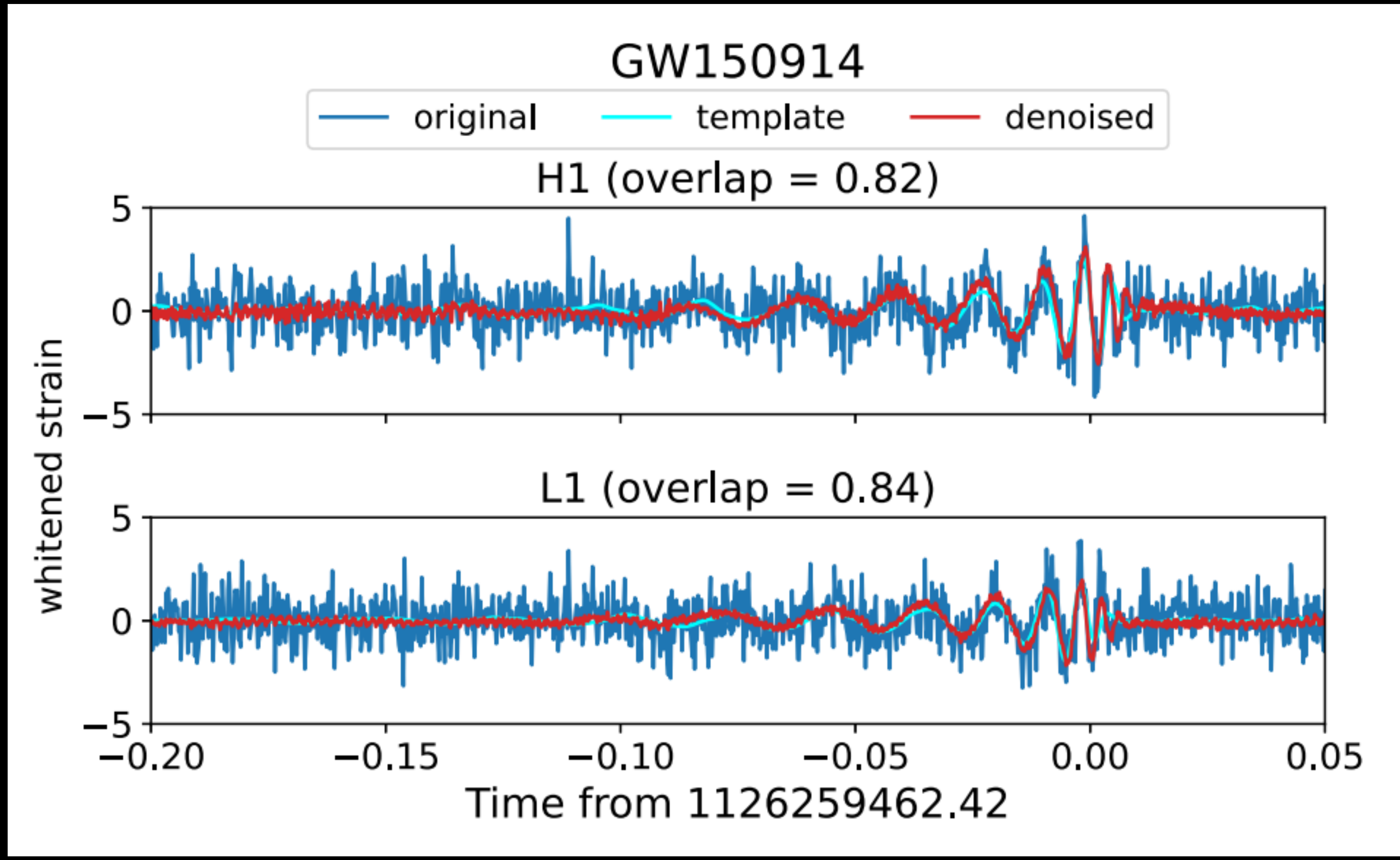
- Using self-supervised learning to clean the Gaussian noise from whitened strain data.

- With the blind-spot neural network, we can train the denoiser without providing clean references.



A. Krull et al, CVPR 2019

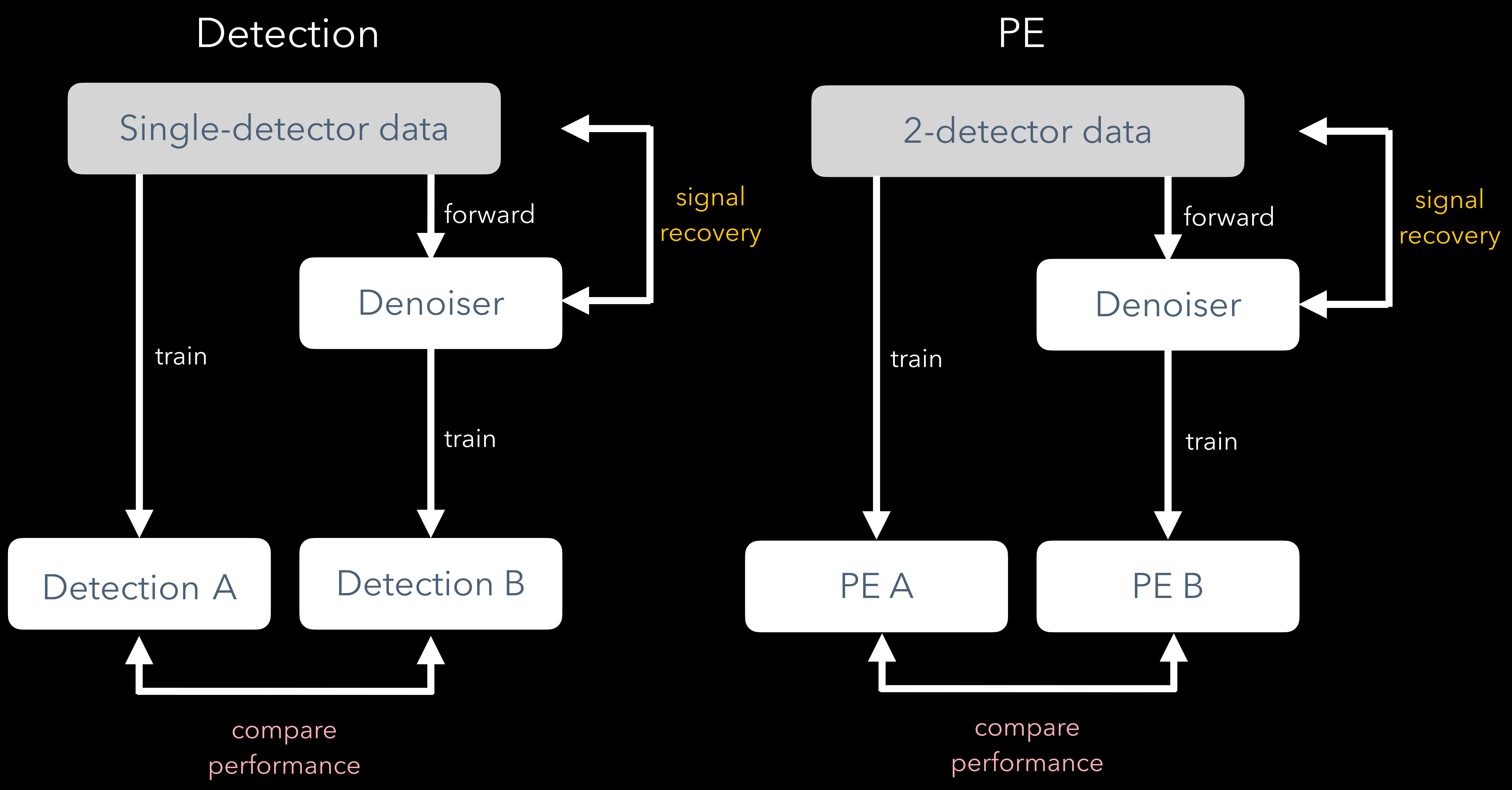




Y. C. Lin & A. Kong, Phys. Rev. D 111, 063520 (2025)

Our work in this year (I)

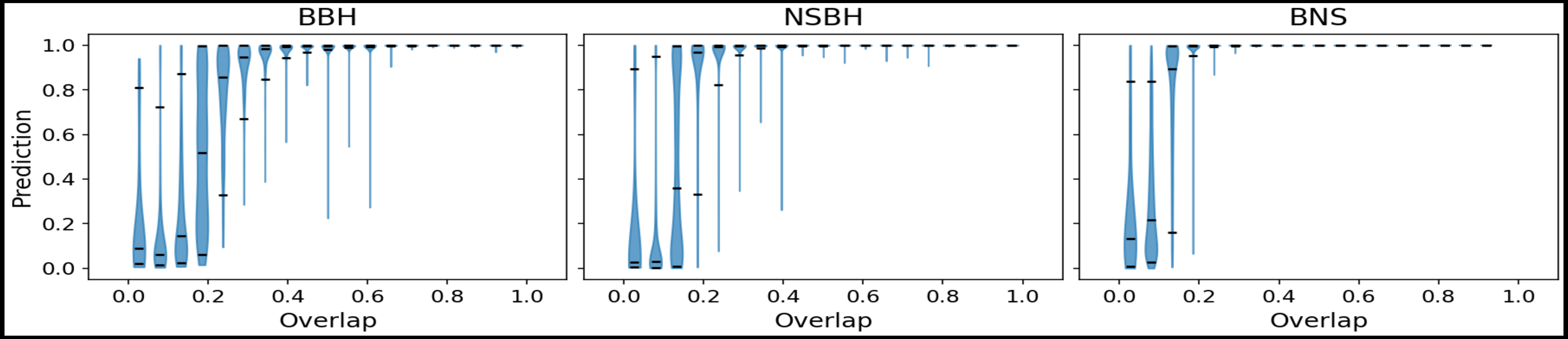
- We first tested deterministic models in FY2025 and will switch to probabilistic models in FY2026.
- We investigated the relationship between signal recovery and the performance of downstream tasks
- Use simple CNNs to build detection and PE models (predict m_1, m_2)
- Trained on 80k 2-sec segments with GW injection

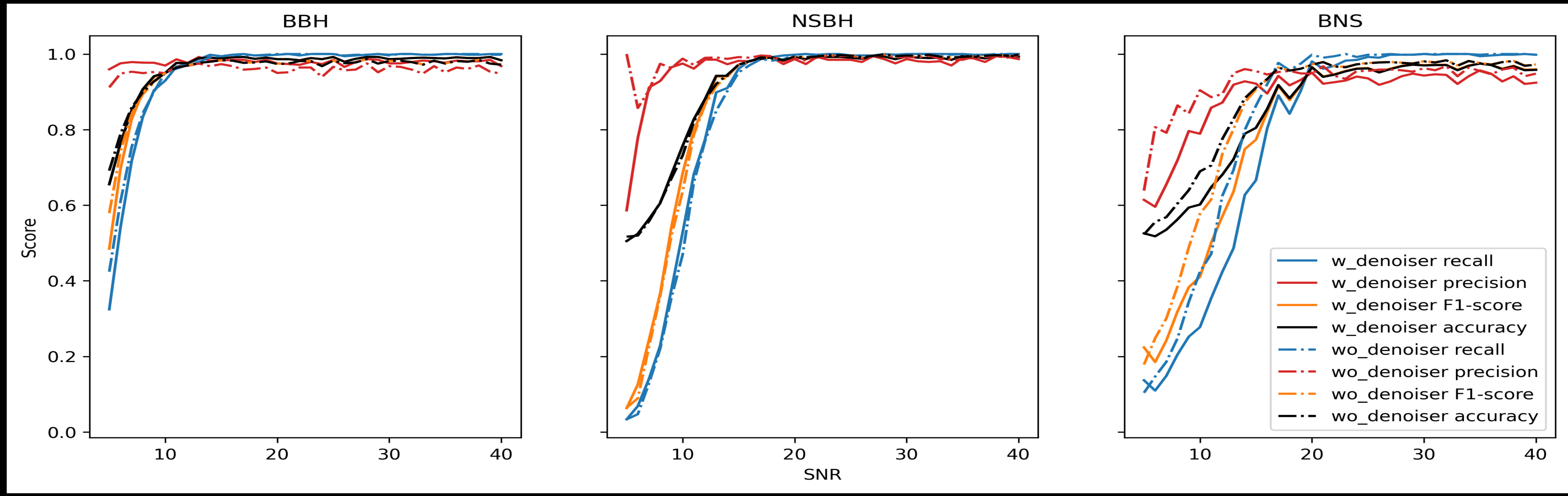


Y. C. Lin & A. Kong, In prep.

Our work in this year (I)

- Use overlap to quantify signal recovery: $\mathcal{O} = \dfrac{(h|s)}{\sqrt{(h|h)}\sqrt{(s|s)}}$
- The model can make confident predictions when $\mathcal{O} > 0.2$ for BBH and NSBH, and 0.1 for BNS.
- Insignificant improvement with the denoiser, and poor denoising degrades the model's performance.

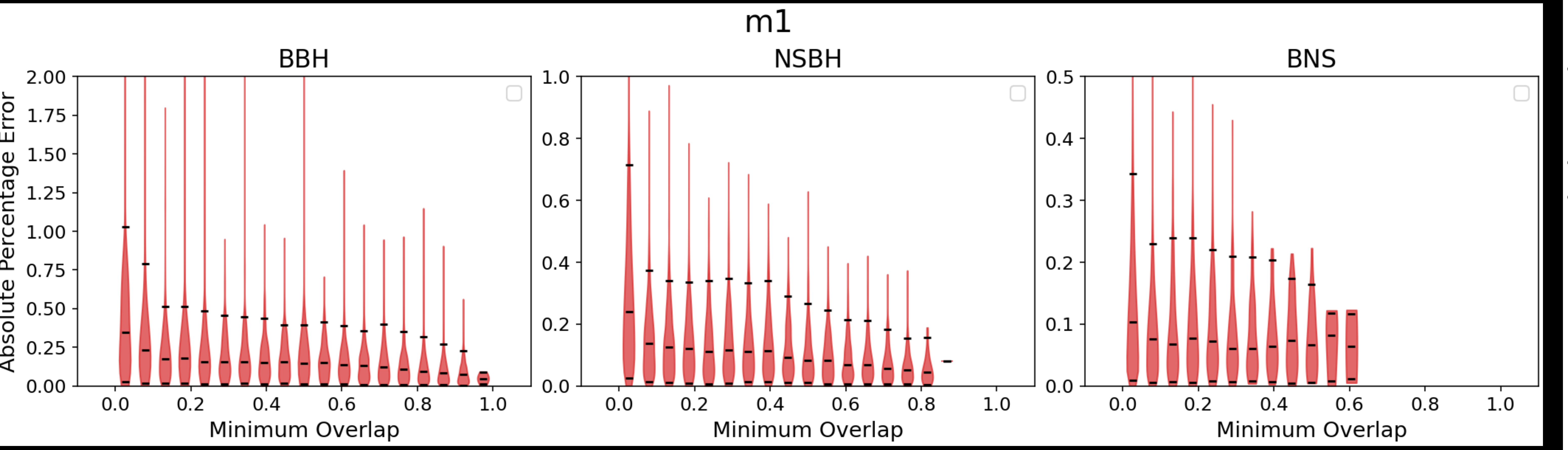


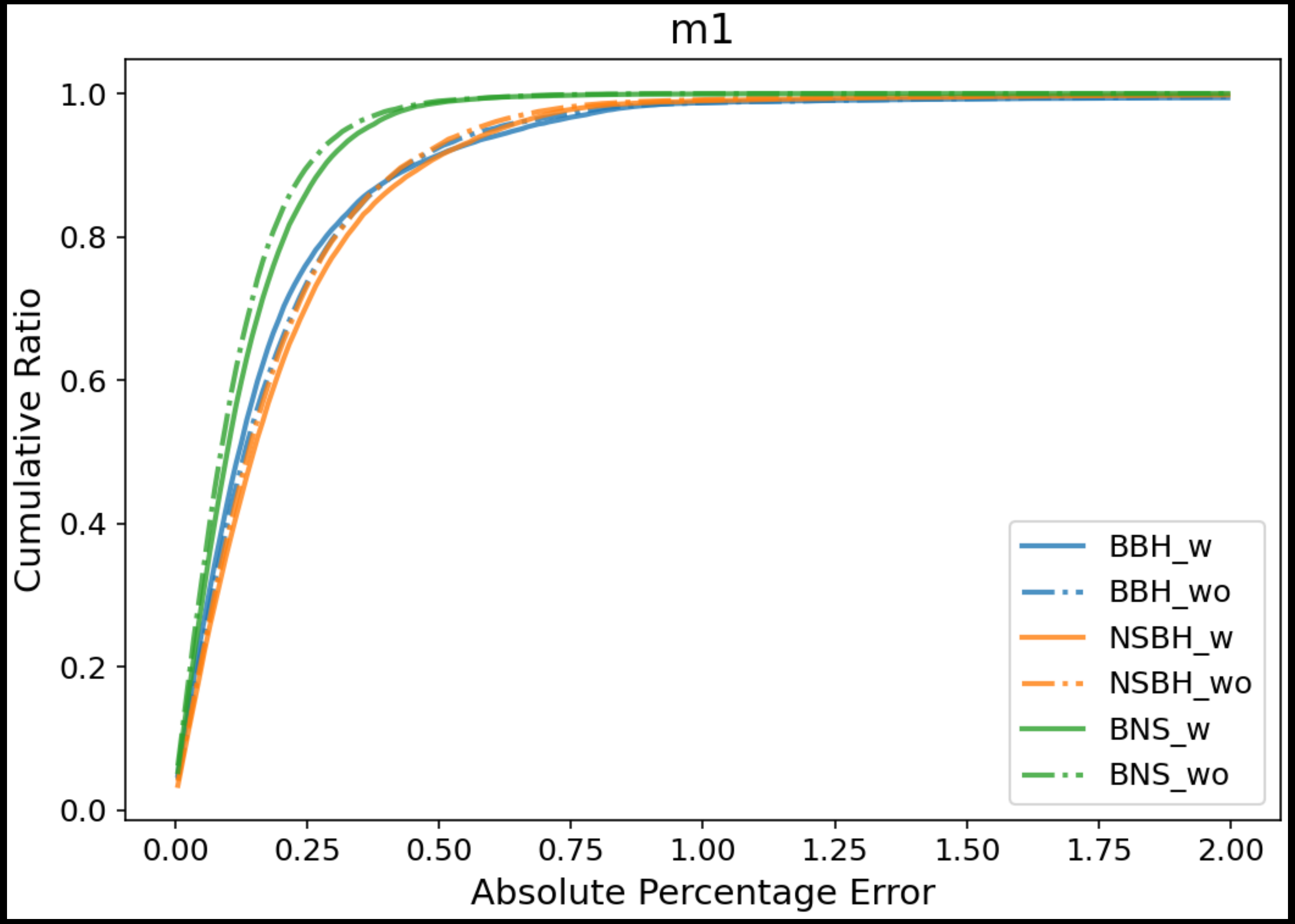


Y. C. Lin & A. Kong, In prep.

Our work in this year (I)

- For PE, loss decreased as overlap increased, but overall performance is not good.
- Random sky location for the injection and two-detector input made the result hard to interpret.
- Still has insignificant improvement with the denoiser.
- We will further improve the denoiser and consider a different training scheme in FY2026.

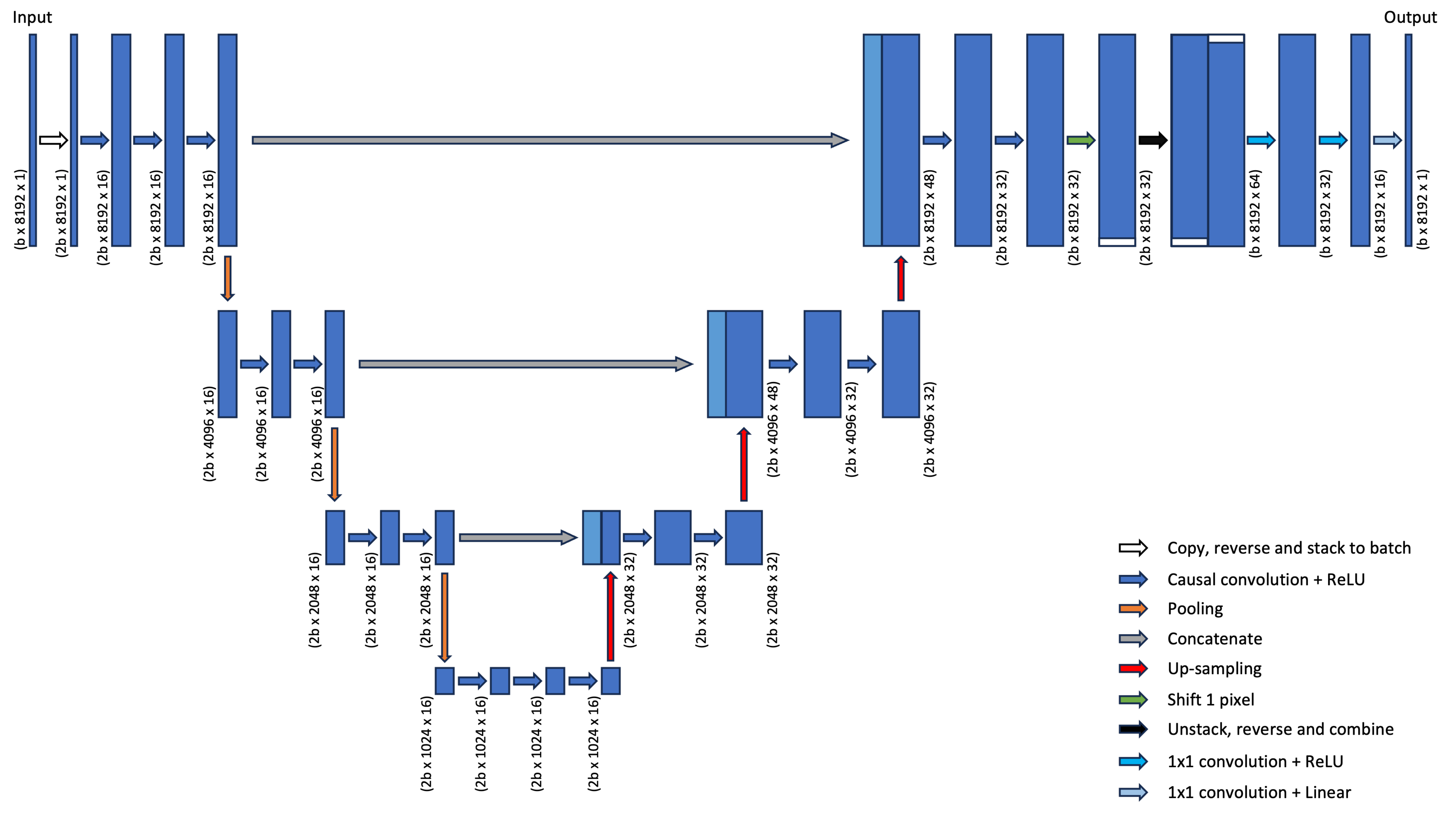




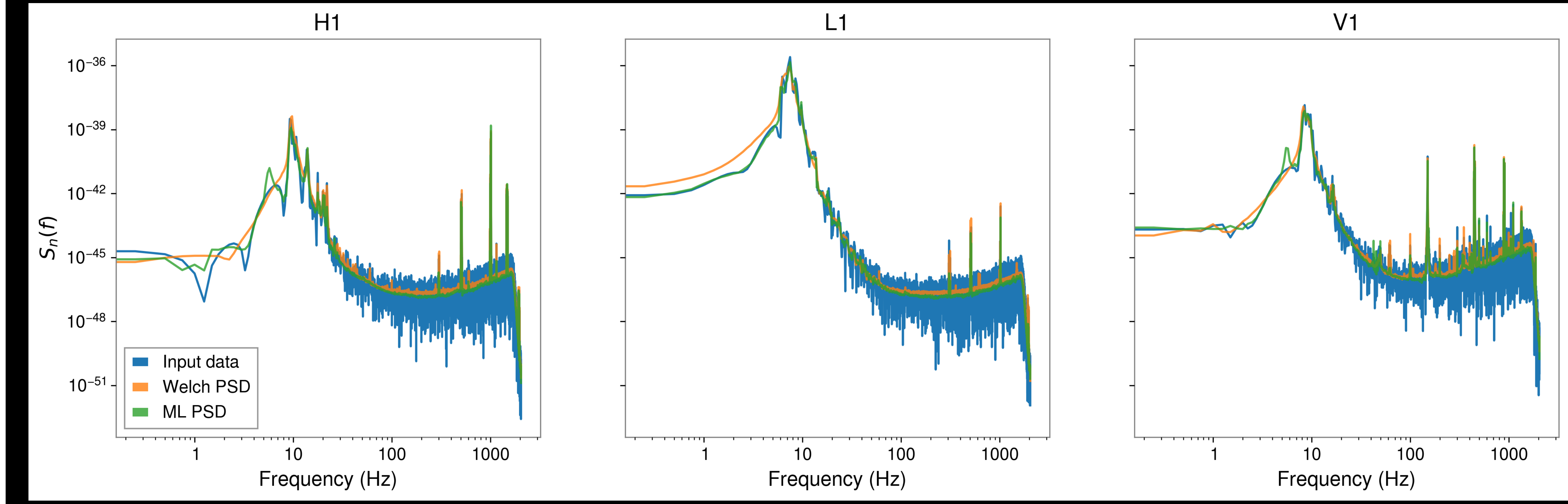
Y. C. Lin & A. Kong, In prep.

Our work in this year (II)

- We found that sometimes whitened data has dips in the spectrum, causing the denoiser to generate noise. We suspected the dips were due to non-stationary line noise in the previous segments.
- We developed a self-supervised ML model to estimate a pseudo PSD directly from the data power spectrum we are analyzing.



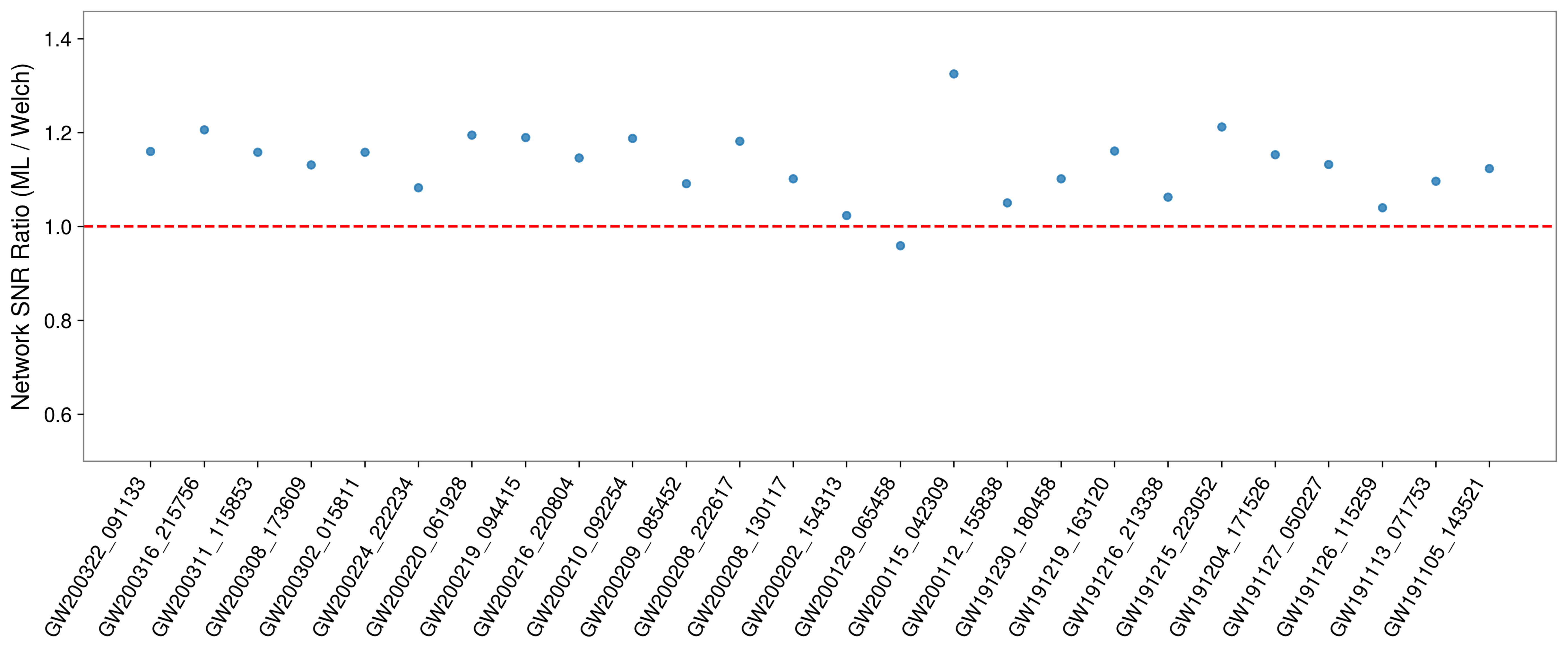
GW200224_222234



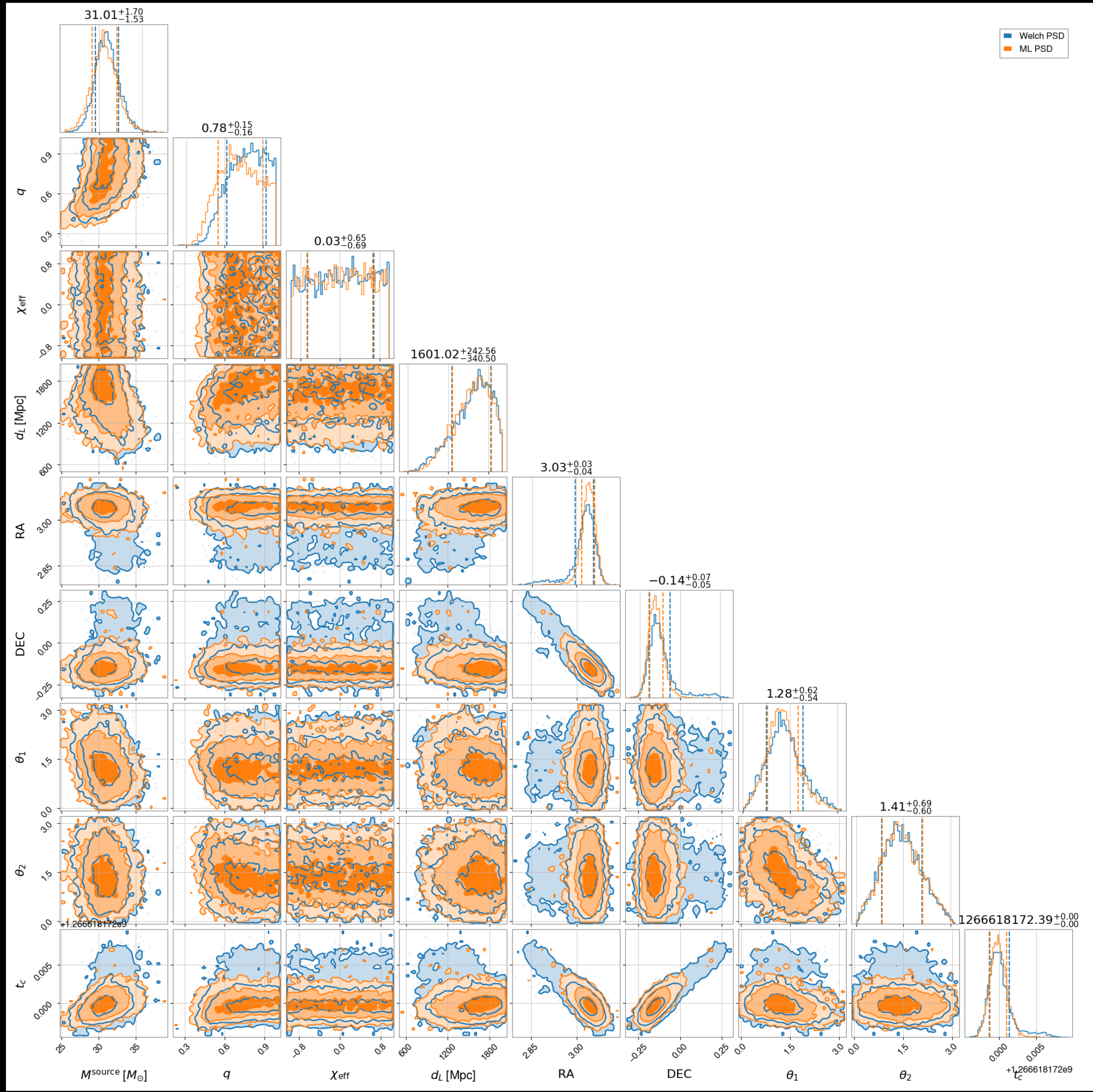
Y. C. Lin & A. Kong, In prep.

Our work in this year (II)

- Our method improved the matched filter SNR of GWTC-3 events.
- Also improved the PE results of the event GW200224_222234.
- We will conduct more tests in the next year.
  - FAR, Gaussianity, etc.



Y. C. Lin & A. Kong, In prep.



Summary

- In this project, we aim to develop a low-latency ML pipeline to detect GWs and perform fast PE
- This year, we investigated the relationship between the denoised signal and performance of downstream tasks, and developed a self-supervised model to estimate the pseudo PSD directly from the data power spectrum.
- We will further improve the denoiser and conduct additional investigations into our work this year.
- The budget this year was used for travel and the purchase of computer parts. We thank ICRR for the support.

Thanks for your attention!