Investigating Relations Between Denoised GW Structures and the Performance of ML-based GW Analysis

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NATIONAL TSING HUA UNIVERSITY

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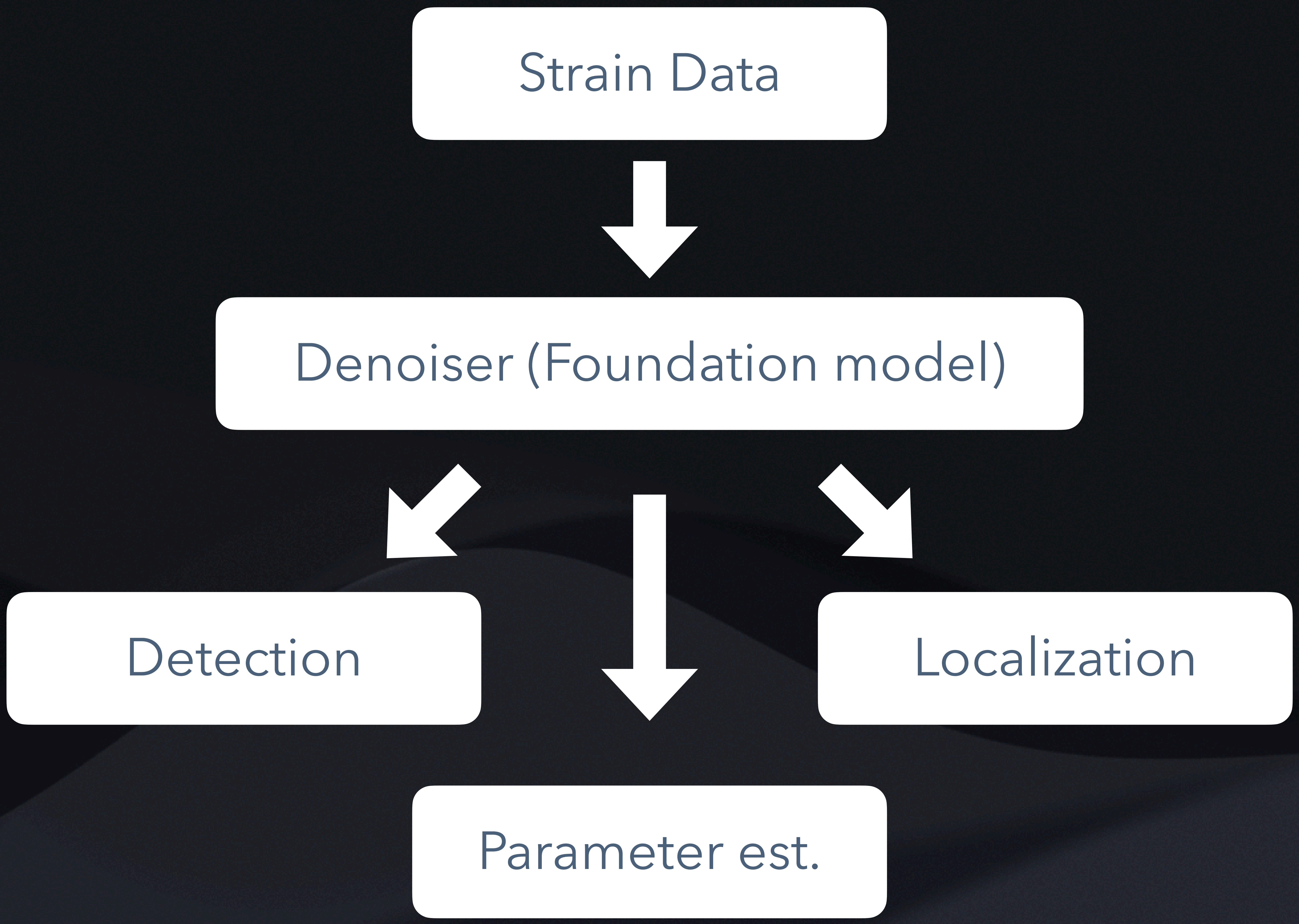
Outline

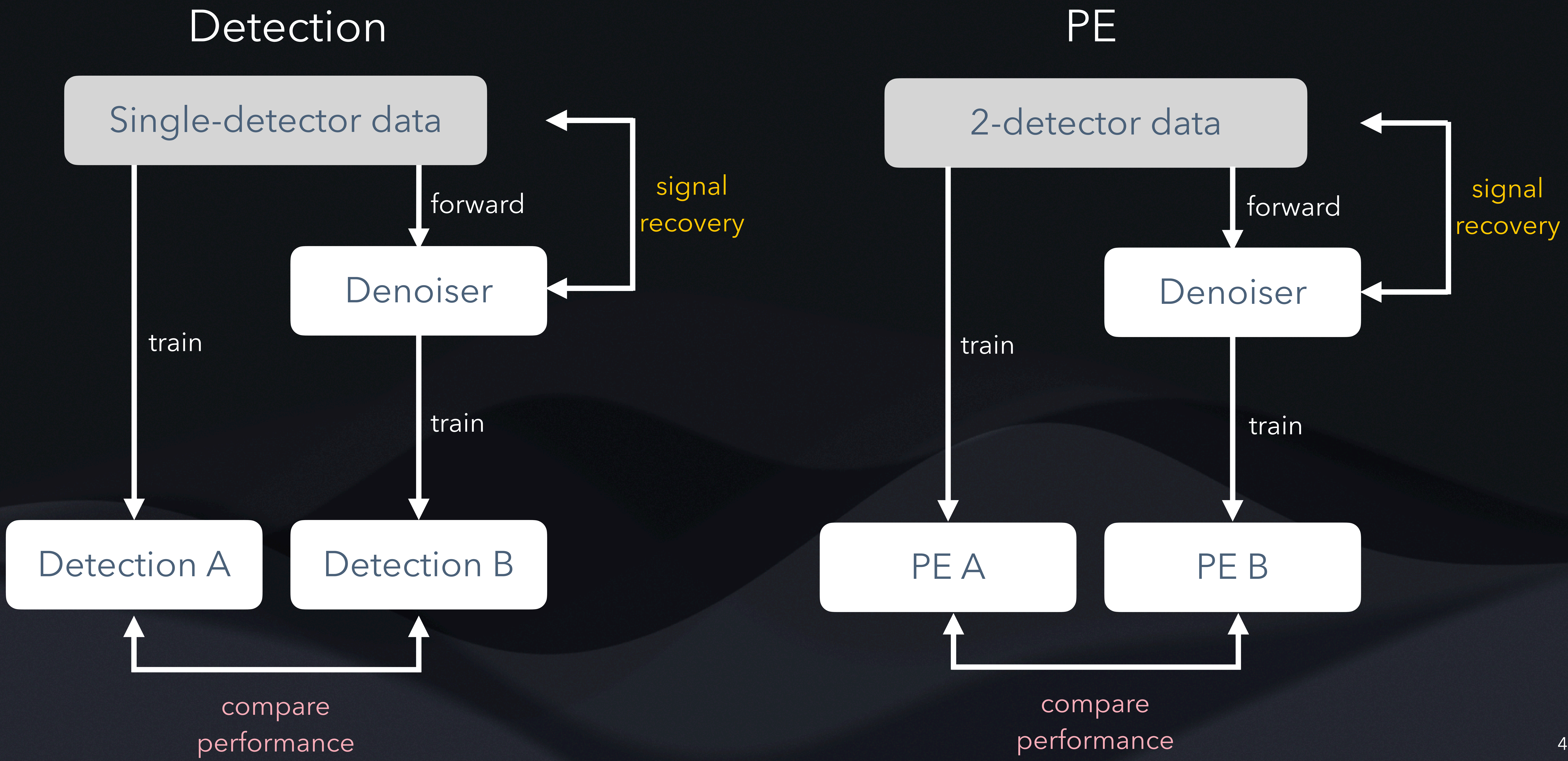
- Introducion and Motivation
- Dataset generation and downstream model setups
- Signal recovery vs. downstream model performances
- Downstream performance with/without denoiser
- Discussion & Conclusion

Denoiser-based GW processing workflow

- Low-latency GW analysis is important in MMA
- In the deep learning framework of GW analysis, the denoiser can be seen as a feature extractor
  - A foundation model
  - Leverage the complexity of downstream models
- In this work, we want to know:
  - The relationship between signal recovery and the performance of downstream tasks
  - Can the denoiser improve the downstream tasks (detection, PE, etc)?



Method



Detection
Single-detector data
forward
signal recovery
Denoiser
train
train
Detection A
Detection B
compare performance
PE
2-detector data
forward
signal recovery
Denoiser
train
train
PE A
PE B
compare performance

The denoiser model

- A self-supervised denoiser to extract non-Gaussian features
- The NN itself is not optimized

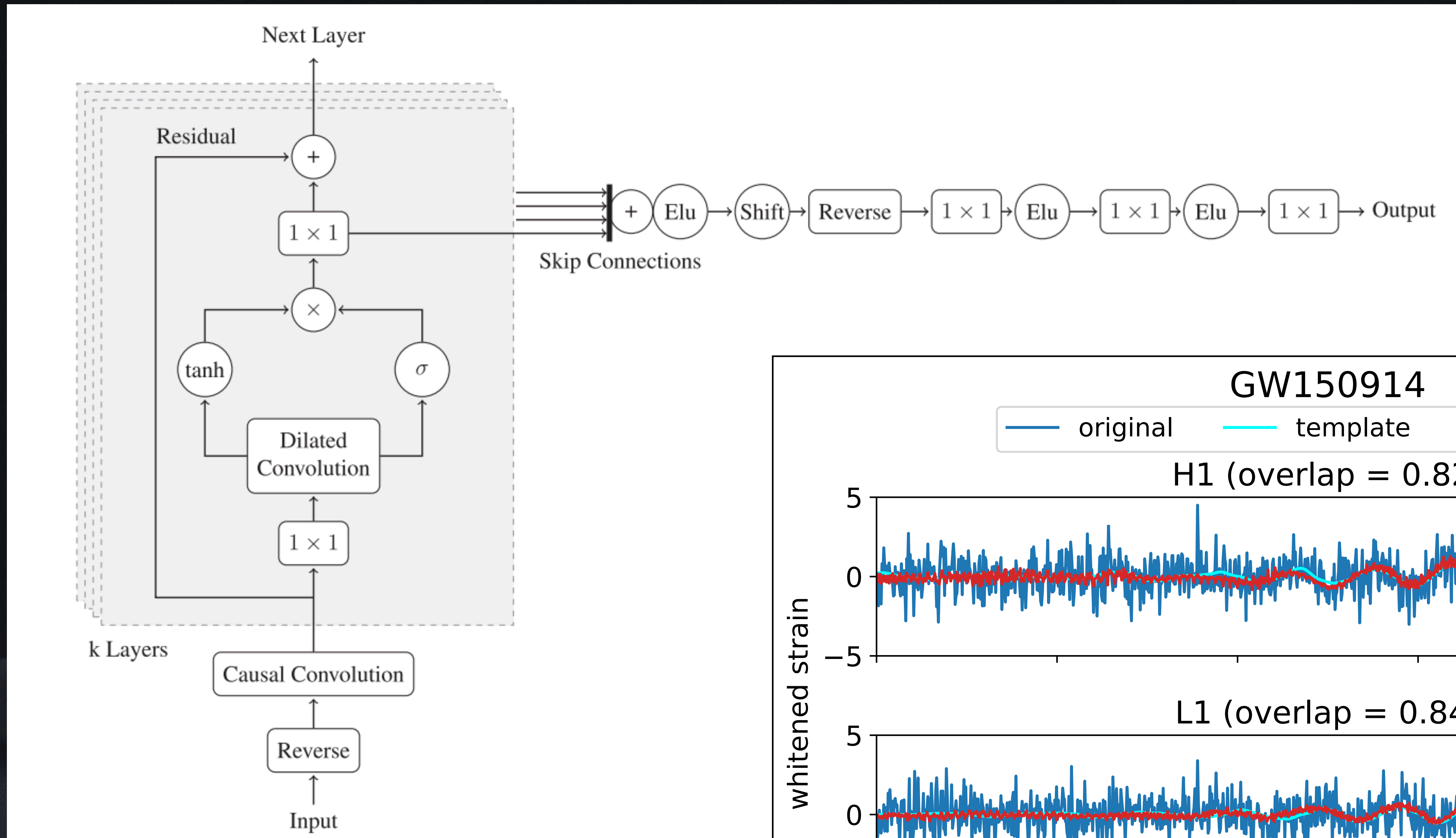
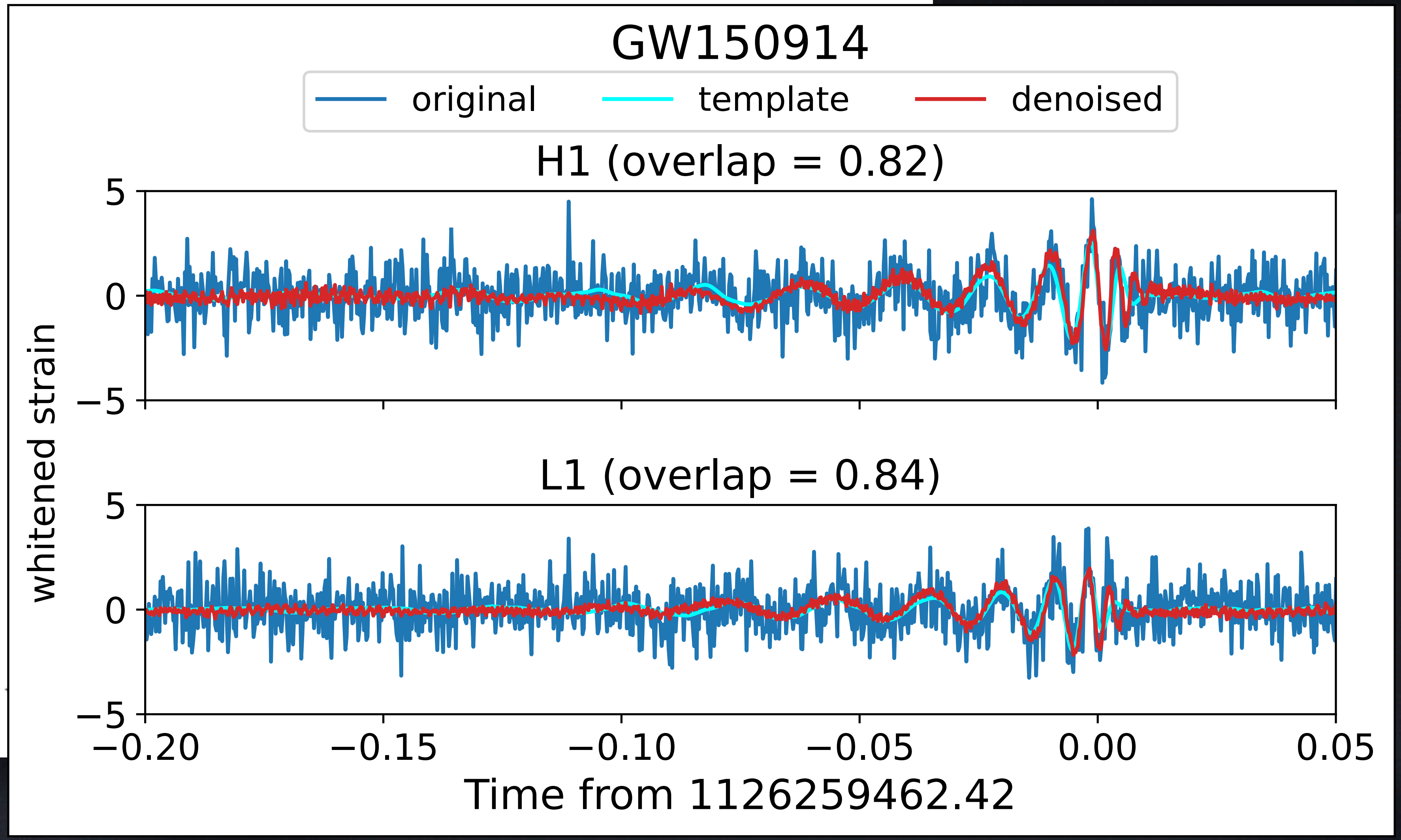
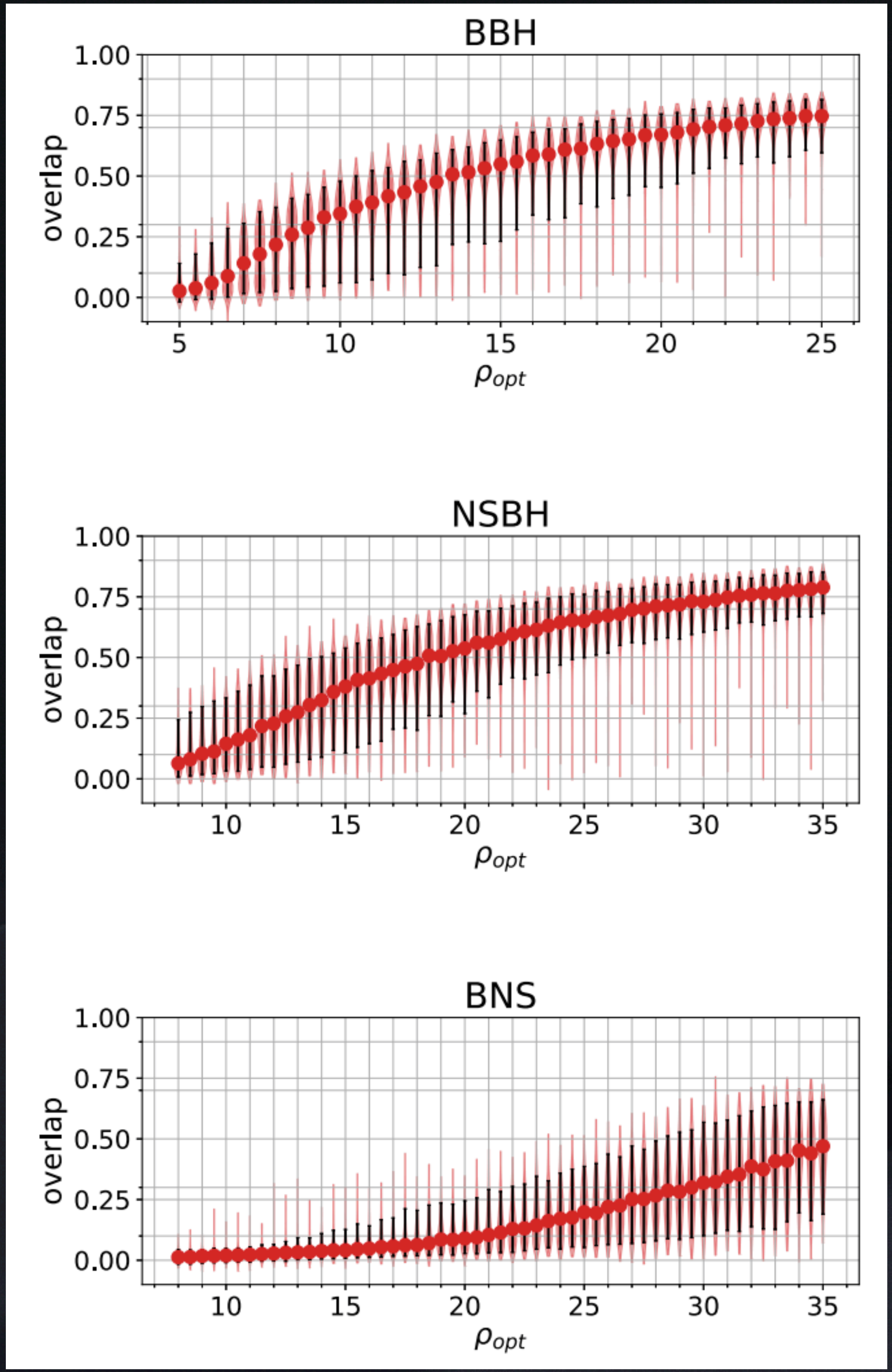


FIG. 1. Overview of the blind-spot





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Dataset generation

- H1 and L1 O3b data as background
- Detection:
  - Single detector 2s data (H1 or L1)
  - Whitened
  - train: 81920, val: 4096 samples
  - testing: 512 per SNR in [5, 40]
- PE:
  - Two-detector 2s data (H1L1)
  - Whitened
  - train: 40960, test: 4096 samples
  - testing: 512 per SNR in [5, 40]

approx. for BBH	SEOBNRv4_opt
approx. for BHNS	SEOBNRv4_opt
approx. for BNS	TaylorT4
m_{BH}	$[3, 75]\ M_\odot$
m_{NS}	$[1.4, 3]\ M_\odot$
$q = m_1/m_2$	$[1, 10]$
RA	$[0, 2\pi]$
dec	$[-\pi/2, \pi/2]$
ψ	$[0, 2\pi]$
ρ_{opt}	$[5, 30], [10, 35], [10, 40]$

Detection model

Input (8192 x 1)
Conv1D (16,8)
Conv1D (32,8)
Conv1D (64,8)
Conv1D (128,4)
Flatten
Dense (64) / ReLU
Dense (32) / ReLU
Dense (1) / Sigmoid
$p \in [0,1]$

Conv1D
ReLU
MaxPool1D (4,4)
BatchNorm

Training:
50 epochs
cross-entropy loss

PE model

Input (8192 x 2)
Conv1D (32,8)
Conv1D (64,8)
Conv1D (128,8)
Conv1D (256,4)
Flatten
Dense (64) / ReLU
Dense (64) / ReLU
Dense (2)
(m_1, m_2)

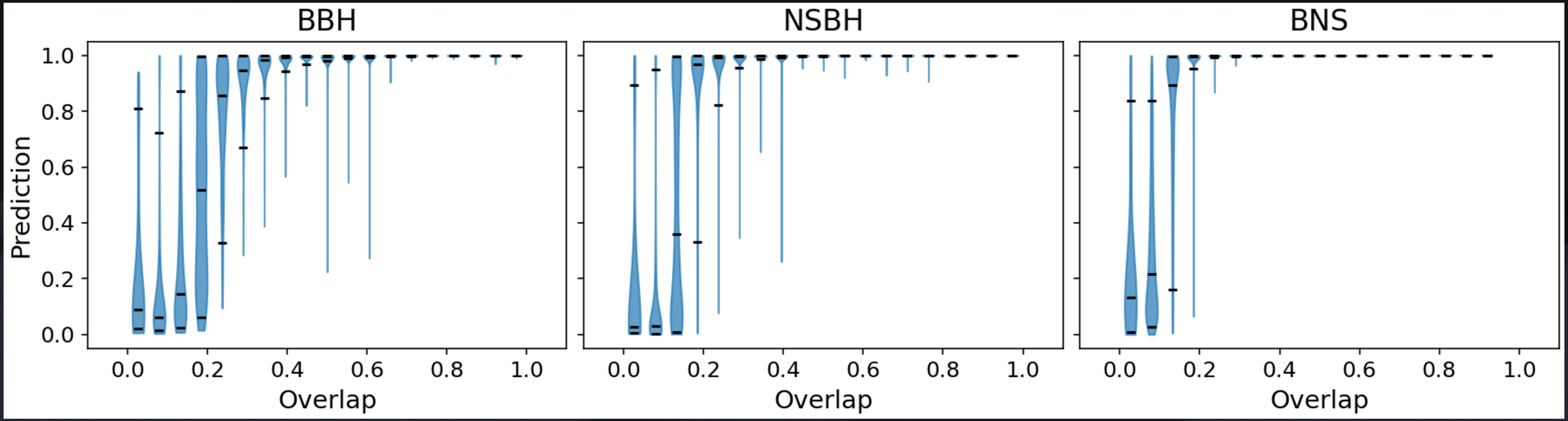
Training:
100 epochs
MAPE loss

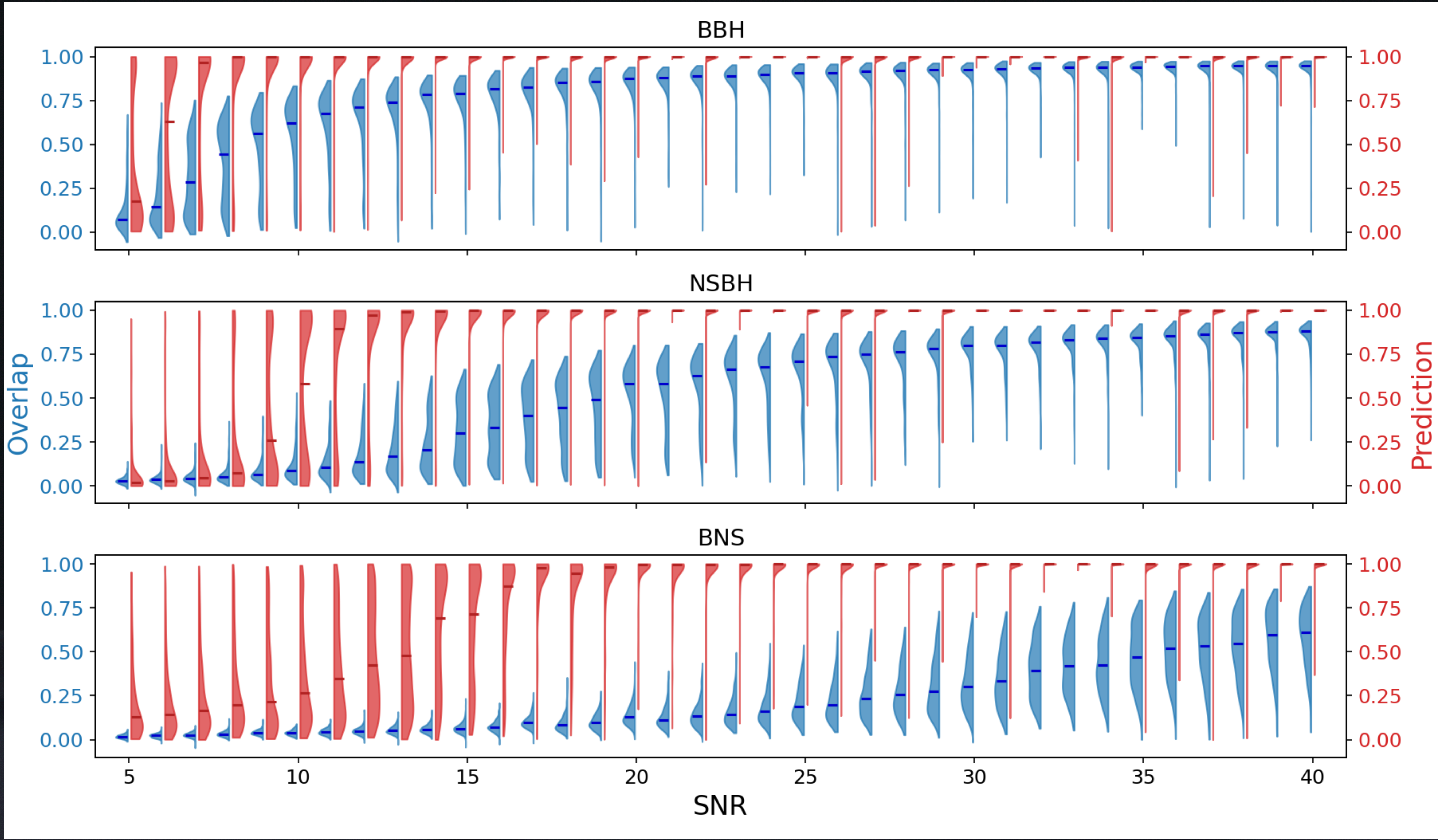
Signal recovery vs. Detection

- Use overlap to quantify signal recovery:

$$\mathcal{O} = \frac{(h|s)}{\sqrt{(h|h)}\sqrt{(s|s)}}$$

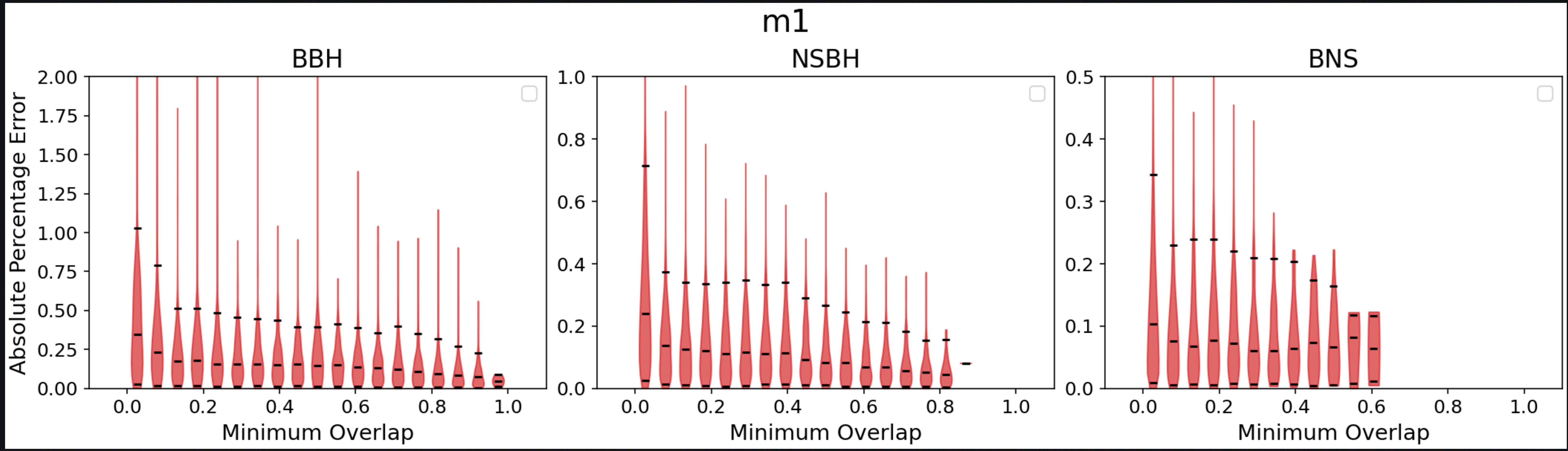
- The model can make confident predictions when $\mathcal{O} > 0.2$ for BBH and NSBH, and 0.1 for BNS.

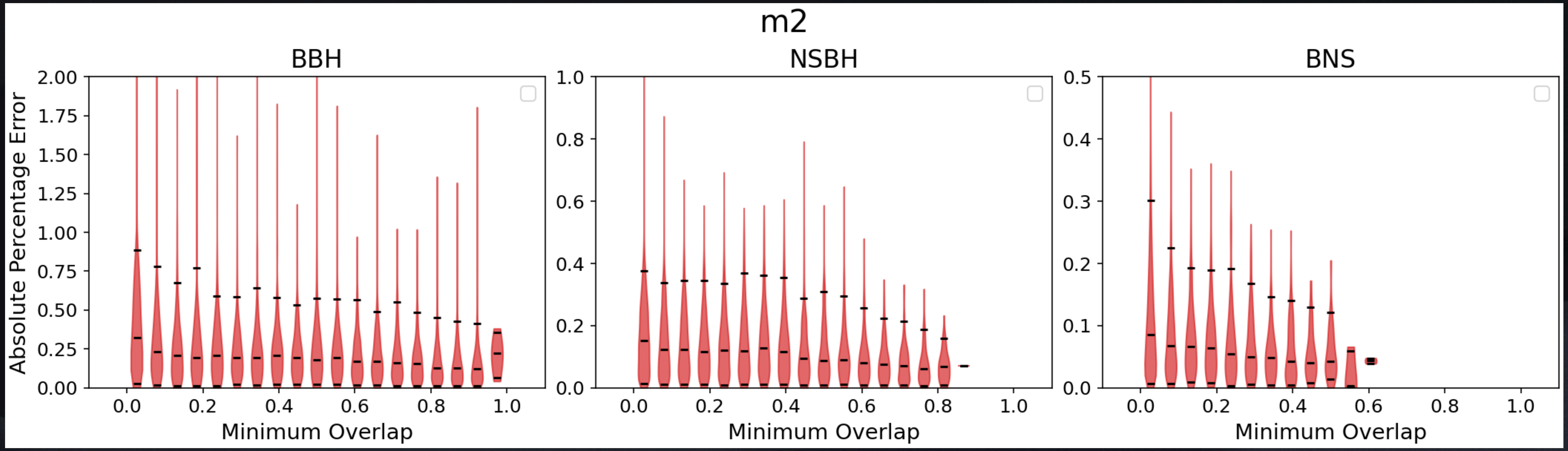


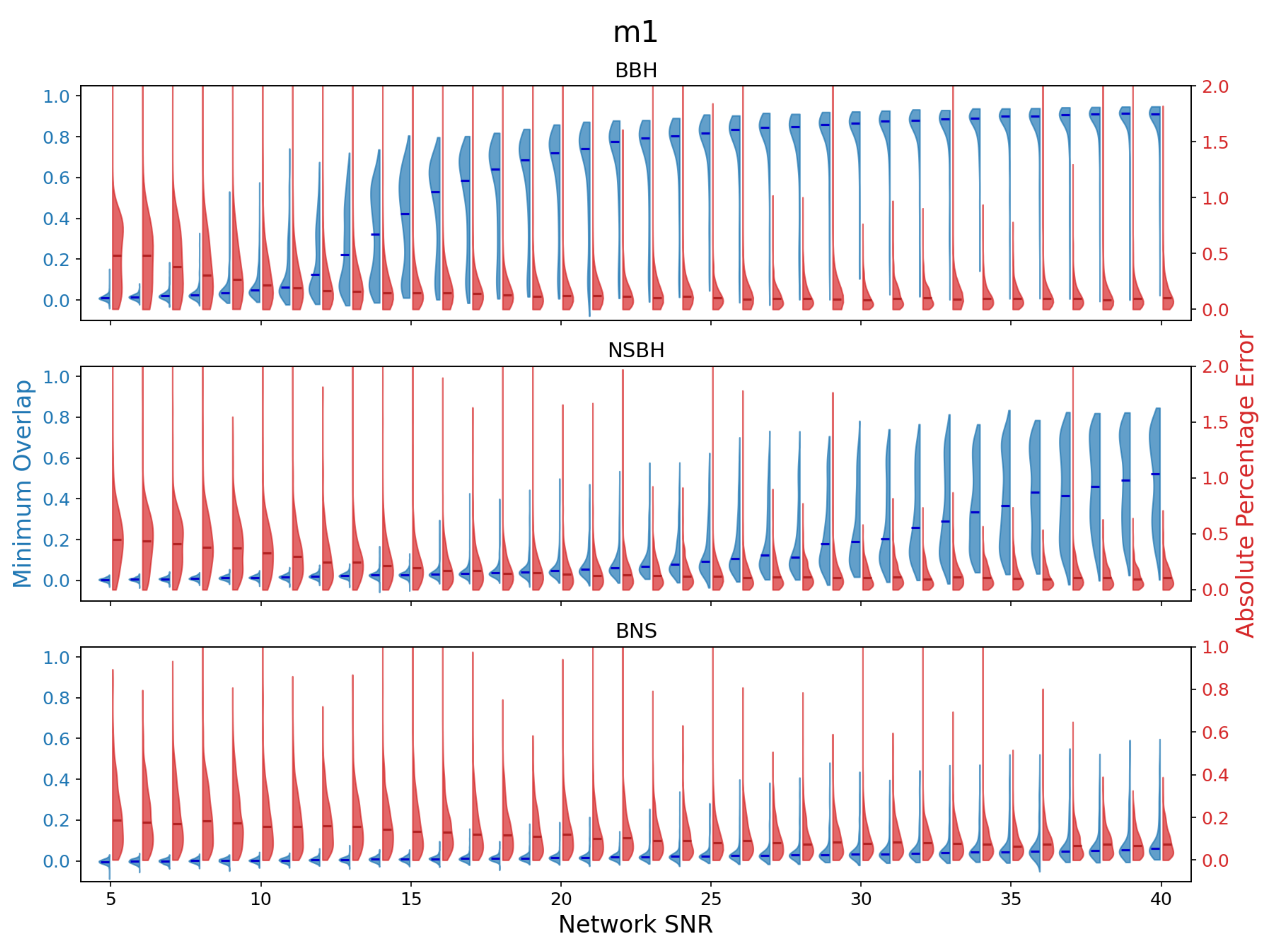

BBH
NSBH
BNS
Overlap
Prediction
SNR
1.00
0.75
0.50
0.25
0.00
5
10
15
20
25
30
35
40

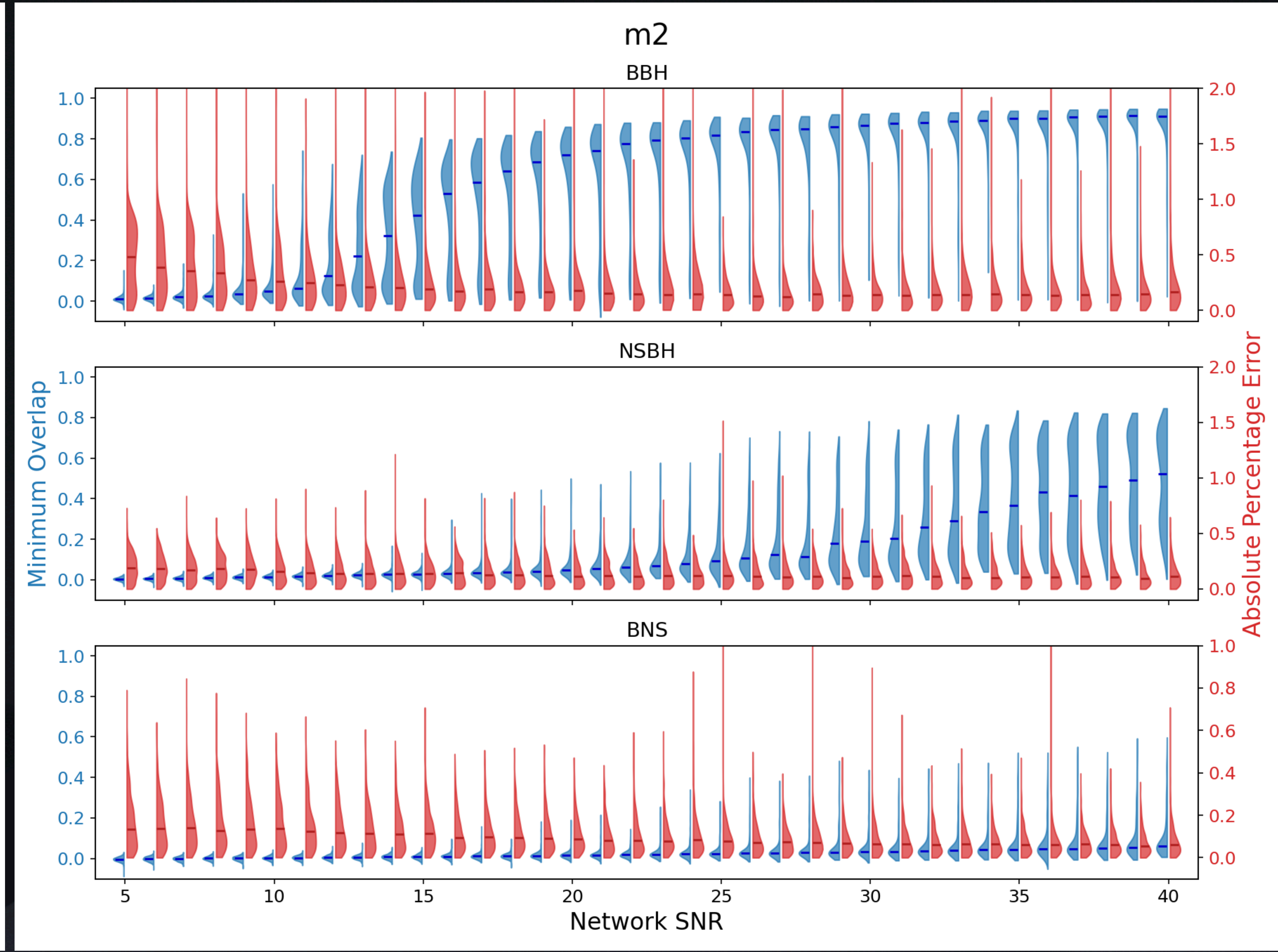
Signal recovery vs. PE

- Loss decreased as overlap increased
- Overall performance is not good
- Random sky location for the injection and two-detector input made the result hard to interpret



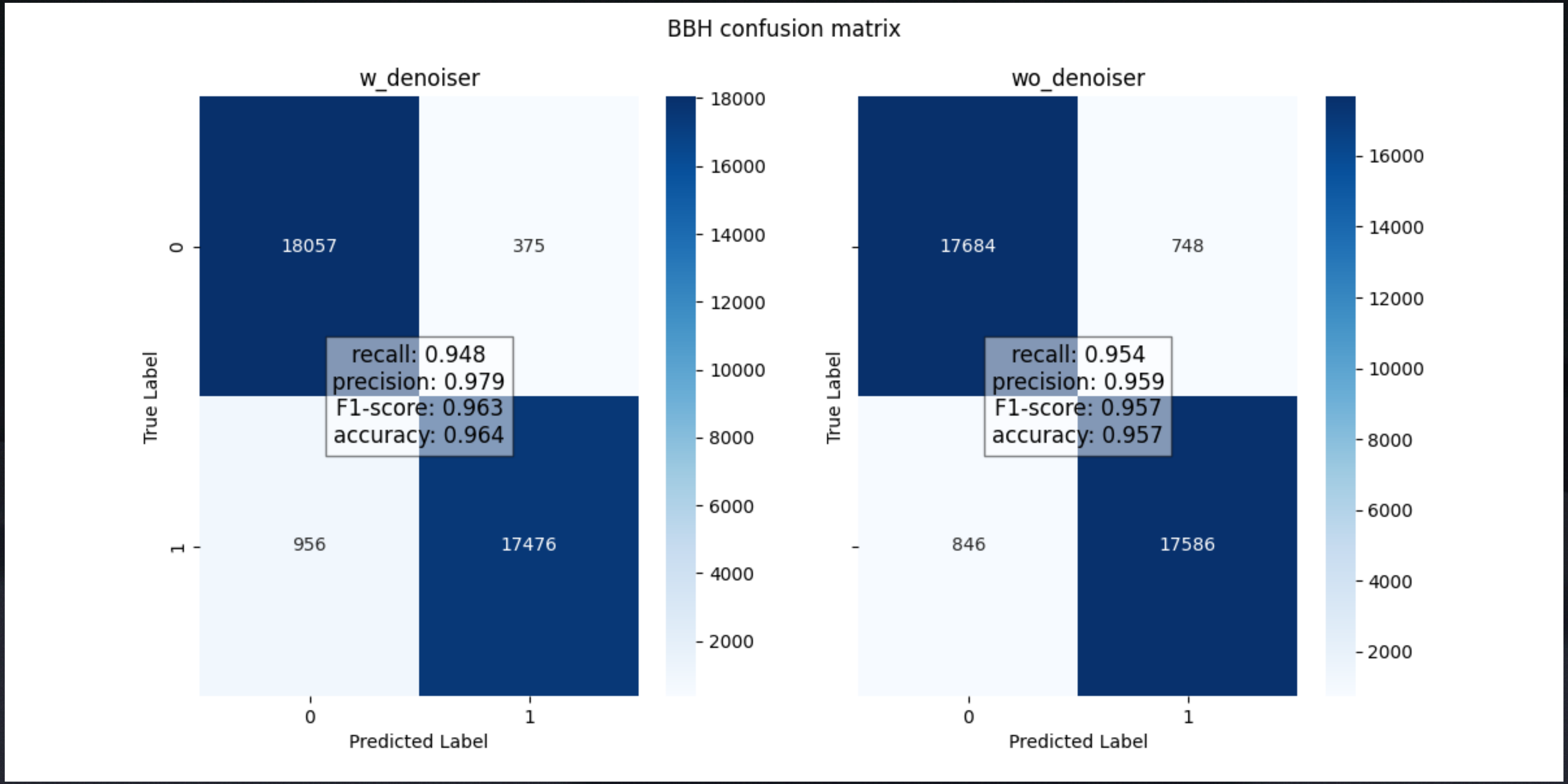



m1
BBH
NSBH
BNS
Minimum Overlap
Absolute Percentage Error
Network SNR


m2
BBH
NSBH
BNS
Minimum Overlap
Absolute Percentage Error
Network SNR

Detection performance w/wo denoiser

- Insignificant improvement with denoiser
- Poor denoising degrades models' performance



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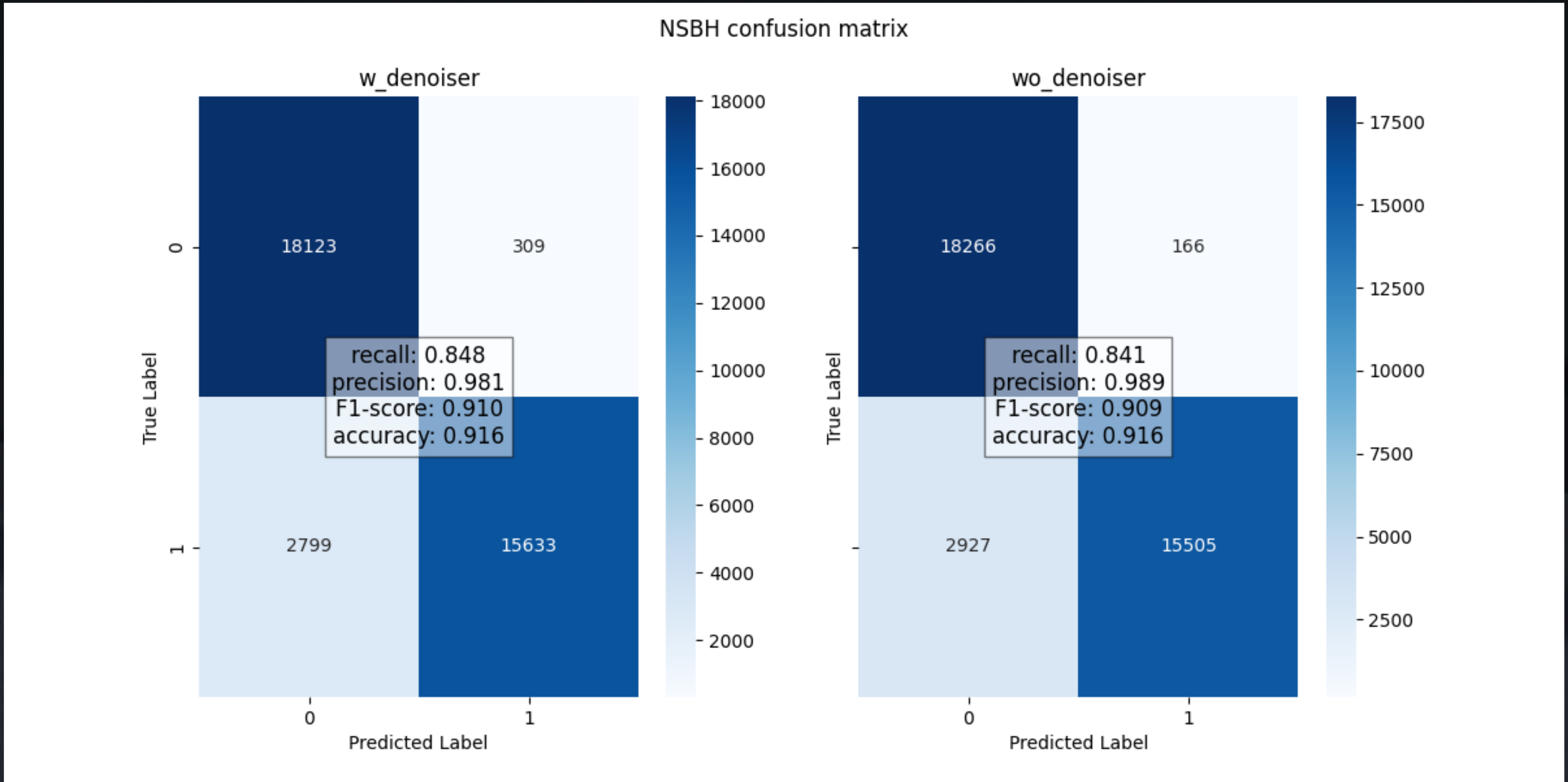

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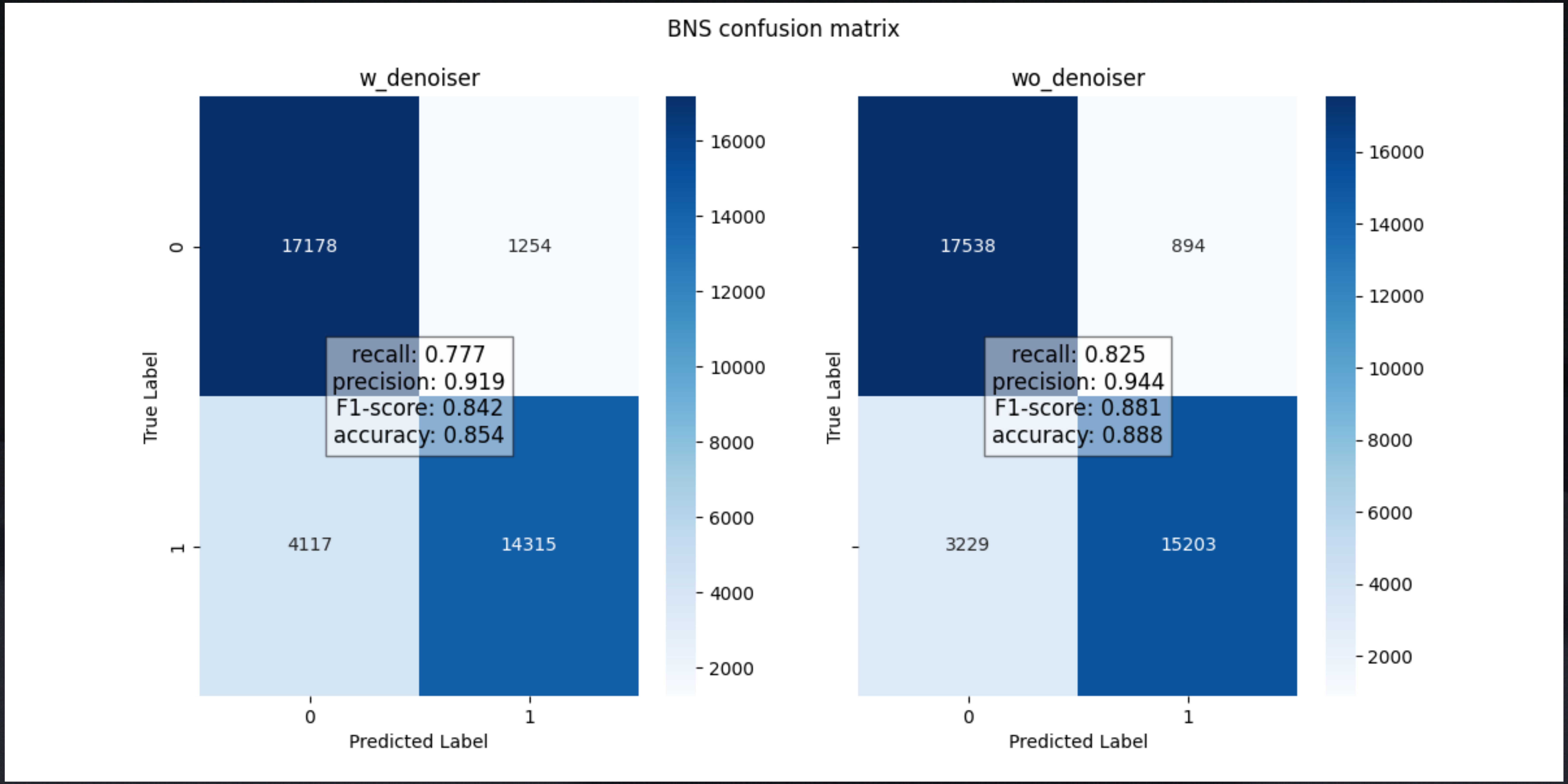

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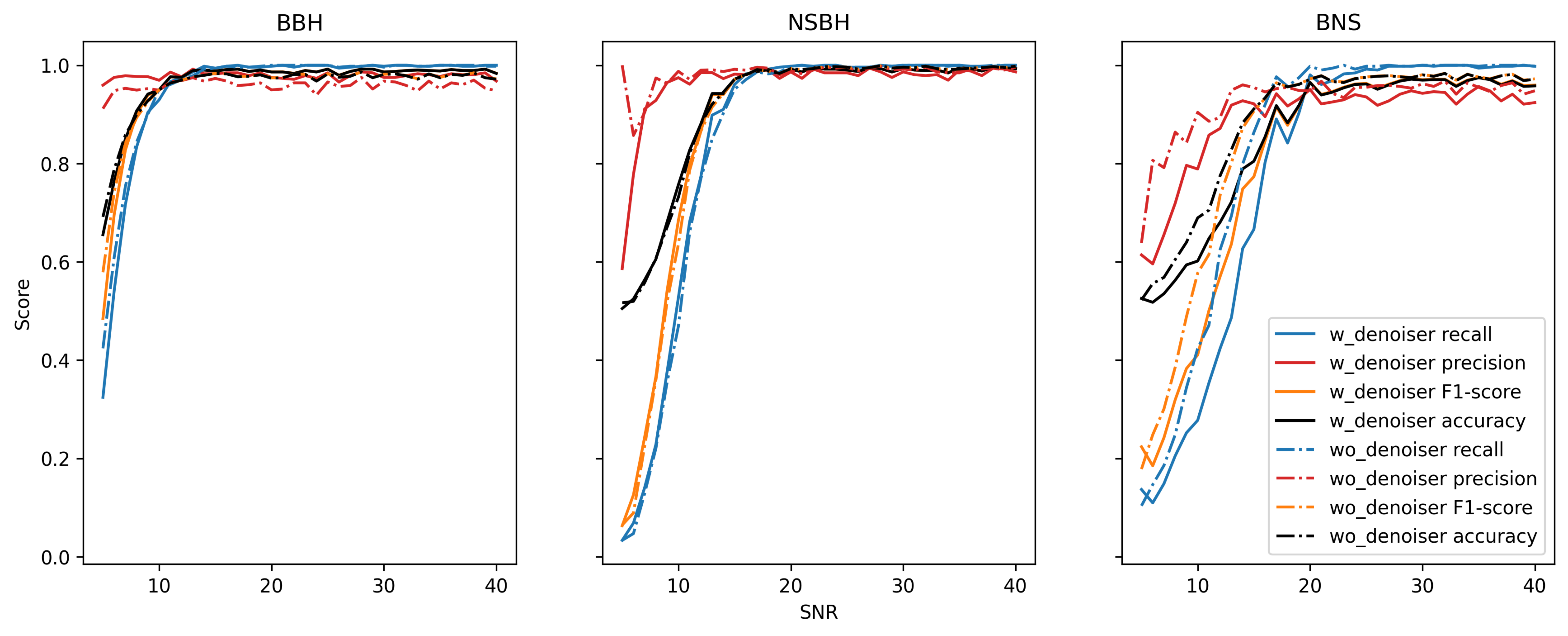
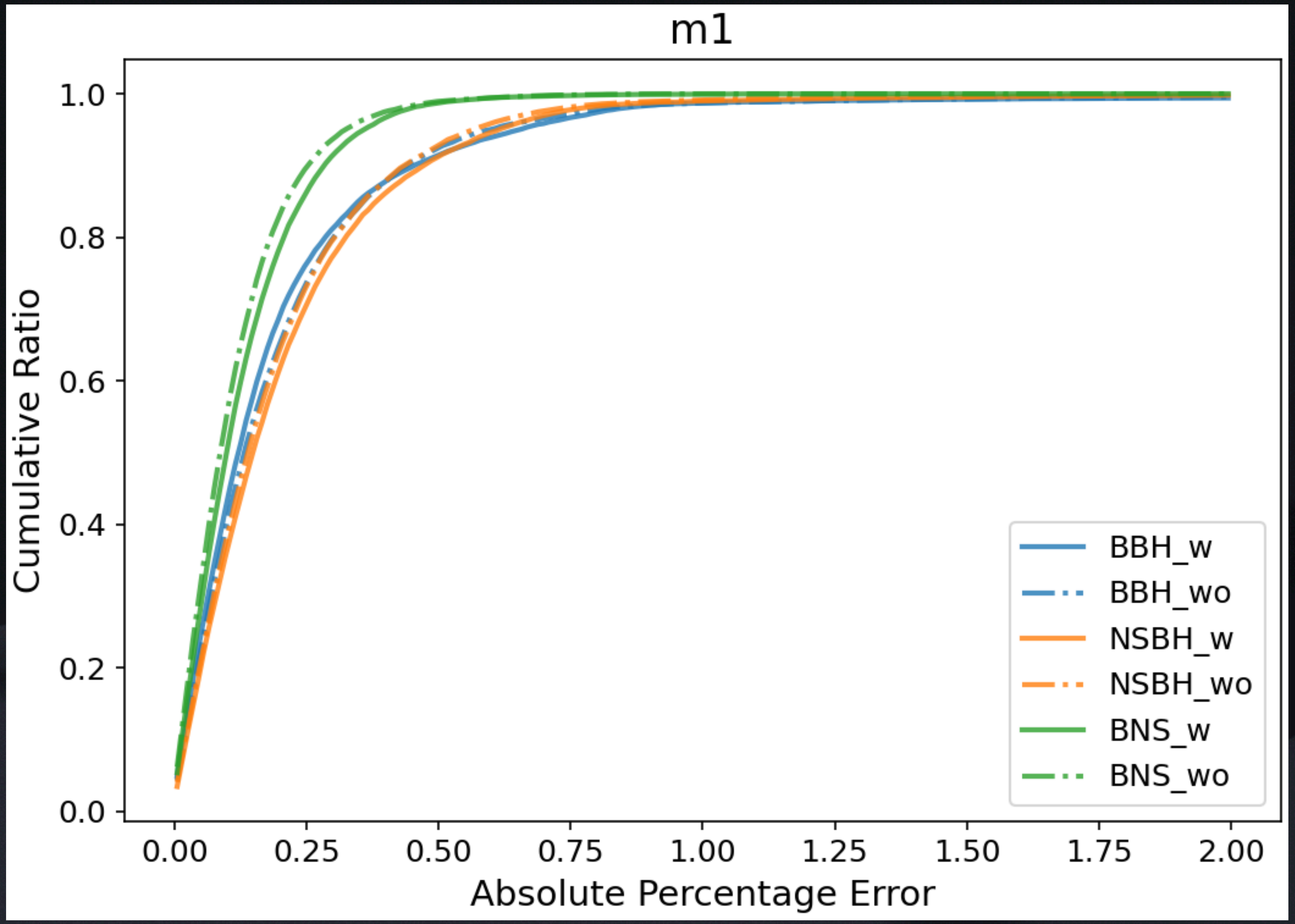
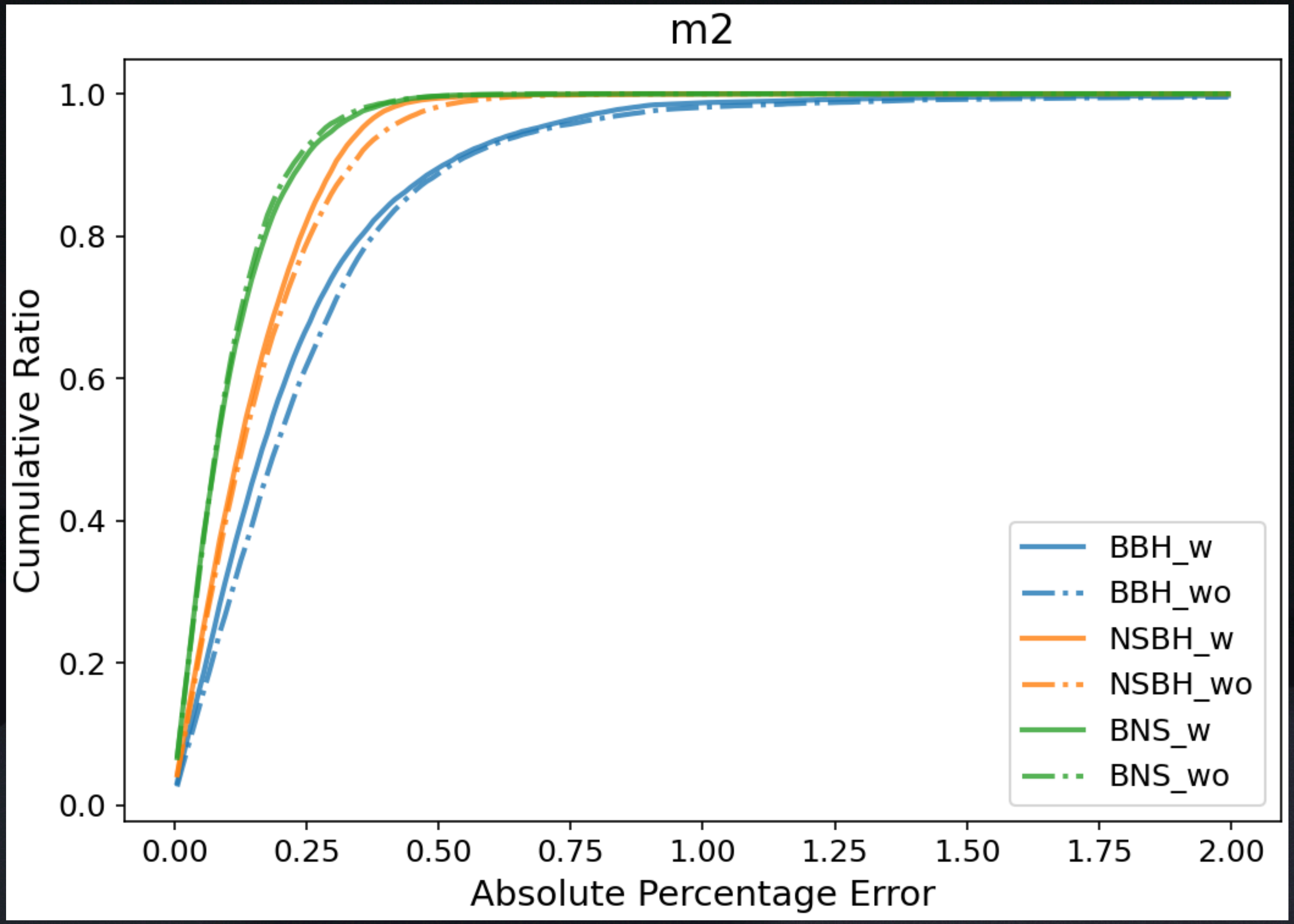


PE performance w/wo denoiser

- Similar trend to the detection performance





Summary

- For the detection task, a deep learning model only requires a small portion of the GW features
  - A very simple NN already does the job well
- For PE tasks, the prediction error decreases as more GW features are used
  - Need to rethink our current method for more specific investigations
- Currently, the use of a denoiser has little improvement on the downstream task performance
  - Using an encoder as the foundation model could be more efficient
- Future works:
  - Focusing on extracting inspiral features
  - Design more specific methods to test PE