Submission to the Machine Learning Gravitational Wave Search Challenge 1

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g2net WG1 meeting
Valencia, 12. 4. 2022

MLGWSC-1

- mock data challenge
- BBH signals in long segments
- purely detection
- evaluation metrics
  - false alarm rate
  - sensitive distance
  - runtime
- submission deadline: 14 April 2022

`https://github.com/gwastro/ml-mock-data-challenge-1`

Test data

- 1-month strain in H1 and L1
- IMRPhenomXPHM injections
- 4 levels of complexity

Noise

DS	noise	PSD
1	Gaussian	`aLIGOZeroDetHighPower`
2	Gaussian	random PSD from O3a
3	Gaussian	random PSD from O3a
4	real O3a noise	

Waveforms

DS	spins	modes	masses
1	zero	$l = 2$, $m = \pm 2$	10-50 $M_\odot$
2	aligned	$l = 2$, $m = \pm 2$	such that ≤ 20 s
3	generic	all implemented[1]	such that ≤ 20 s
4	generic	all implemented	such that ≤ 20 s

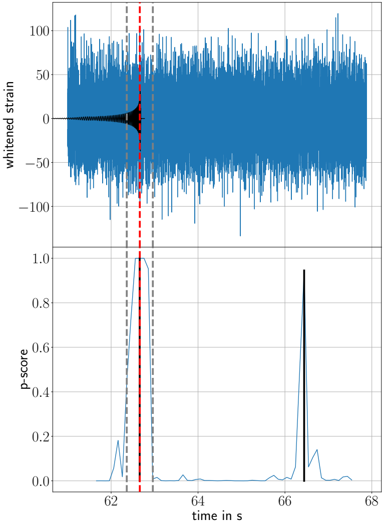
- angles: uniform
- chirp distance: $d_c^2 \in \left(130^2, 350^2\right)$ Mpc^2

[1](2, 2), (2, -2), (2, 1), (2, -1), (3, 3), (3, -3), (3, 2), (3, -2), (4, 4), (4, -4)

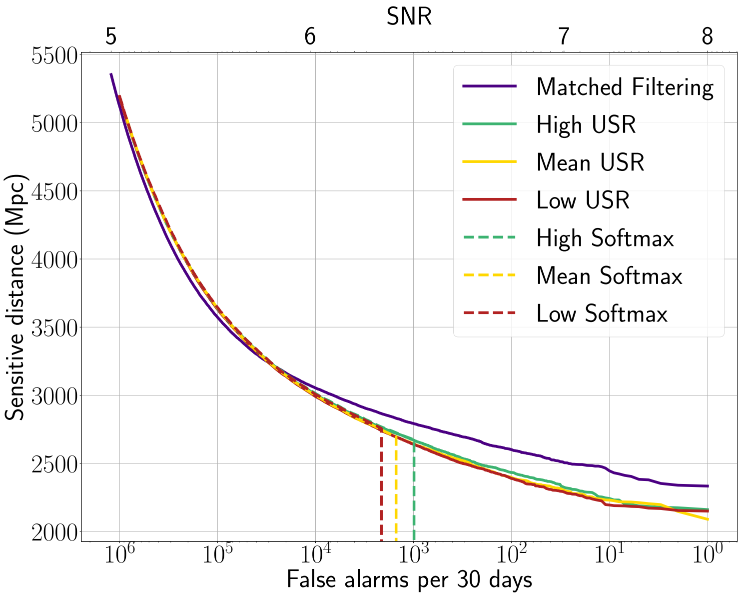
TPI FSU Jena: submission

[Schäfer et al., 2022]

- follows [Gabbard et al., 2018], reproduced results
- USR
- training strategies
- continuous testing



100
50
0
−50
−100
whitened strain
1.0
0.8
0.6
0.4
0.2
0.0
p-score
62
64
66
68
time in s


SNR
5
6
7
8
5500
5000
4500
4000
3500
3000
2500
2000
Sensitive distance (Mpc)
Matched Filtering
High USR
Mean USR
Low USR
High Softmax
Mean Softmax
Low Softmax
10^6
10^5
10^4
10^3
10^2
10^1
10^0
False alarms per 30 days

Training and validation data

1 second segments at a sampling rate of 2048 Hz

Noise

- Real noise from O3a

Waveforms

- generated by `IMRPhenomXPHM`, all implemented HM
- random mass pairs $\in (10M_\odot, 50M_\odot)^2$
- generic spins
- optimal network SNR drawn at runtime
- aligned within window

whitened by the corresponding PSD

Training and validation data

Labels: certain posteriors (1, 0), (0, 1) [Chua and Vallisneri, 2020]

Dataset size:

- training: 10^6
- validation: $2 \cdot 10^5$

pure noise and injections: 1:1

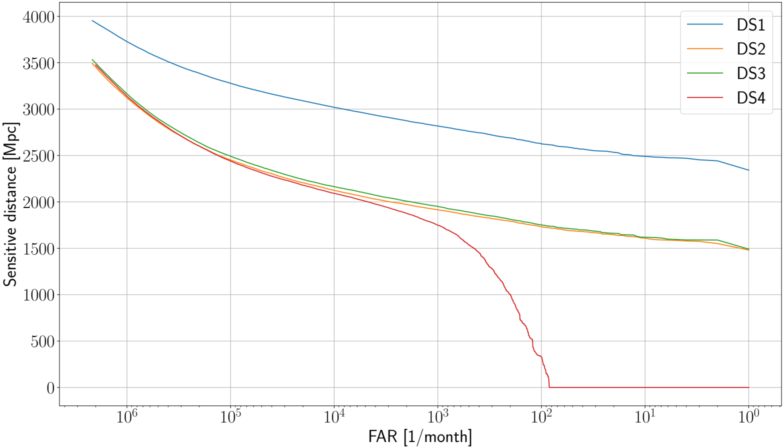
Model

Extension of [Schäfer et al., 2022]

1. 2-channel input
2. batch normalization
3. 12-layer convolutional part, ELU activations
4. 3-layer classifier with dropout, ELU activations
5. softmax

Method

- loss function: binary cross entropy
- optimizer: stochastic Adam, batch size 32
- SNRs drawn randomly at runtime from $[7, 20]$
- implemented in Python using PyTorch
- running on RTX 3090
- using the USR



Sensitive distance [Mpc]
4000
3500
3000
2500
2000
1500
1000
500
0
10^6
10^5
10^4
10^3
10^2
10^1
10^0
FAR [1/month]
DS1
DS2
DS3
DS4

Coincident submission

[Schäfer and Nitz, 2022]

References

Chua, A. J. K. and Vallisneri, M. (2020).
Learning bayesian posteriors with neural networks for gravitational-wave inference.
Phys. Rev. Lett., 124:041102.

Gabbard, H., Williams, M., Hayes, F., and Messenger, C. (2018).
Matching matched filtering with deep networks for gravitational-wave astronomy.
Phys. Rev. Lett., 120:141103.

Schäfer, M. B. and Nitz, A. H. (2022).
From one to many: A deep learning coincident gravitational-wave search.
Phys. Rev. D, 105:043003.

Schäfer, M. B., Zelenka, O., Nitz, A. H., Ohme, F., and Brügmann, B. (2022).
Training strategies for deep learning gravitational-wave searches.
Phys. Rev. D, 105:043002.