Searches for Compact Binary Coalescence Events using Neural Networks in LIGO/Virgo Second Observation Period

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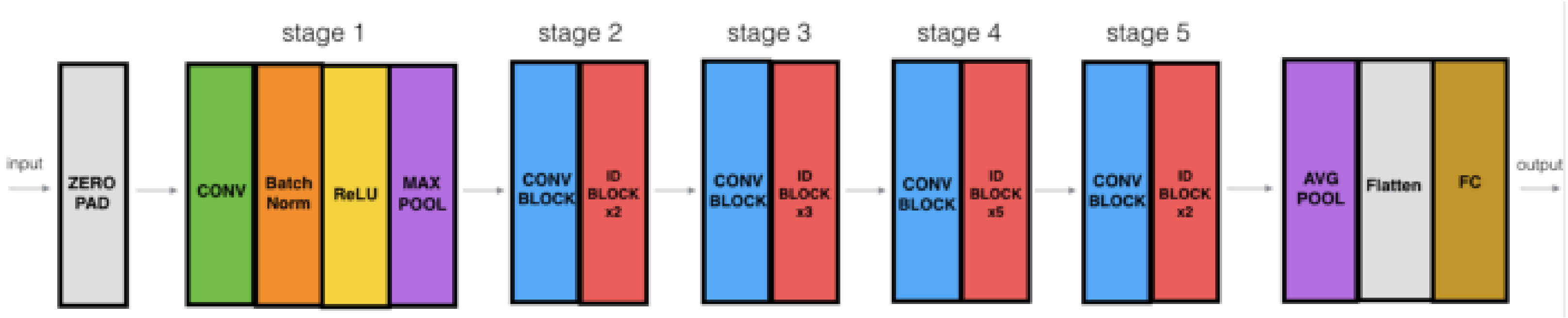
Introduction

- Implemented a CNN for the search of low and high mass CBC events.
- Paper with O2 results accepted in Phys. Rev. D (Phys. Rev. D 103, 062004 arXiv:2012.10702).
- Based on the ResNet50 architecture (arxiv:1512.03385).
- The CNN is trained using O2 LIGO/Virgo Data.
- We study the performance using one and two interferometers as input.
- We want to achieve the highest fraction of detection possible with the lowest amount of false positives.



Input data: Training set

- The training set is generated by creating waveforms using the model IMRPhenomPv2.
- For these templates we vary 7 parameters.
- Parameters are drawn from a uniform distribution.
- The parameter space is divided in two regions: low and high mass.
- The limits in the distance are set accordingly.
- For the low mass case the constraint d_{Eff} < 60 Mpc is added.

$$d_{Eff} = \frac{d_{Real}}{\sqrt{(1+\cos^2(\iota))^2 F_+^2/4 + \cos^2(\iota) F_\times^2}}$$

	Initial	End
Masses ($M_\odot$)	0.19	2.0
Distance (Mpc)	1	50
Right ascension (rad)	0	2π
Declination (rad)	0	π
Polarization (rad)	0	π
Inclination (rad)	0	π/2
Number of signals		160,000

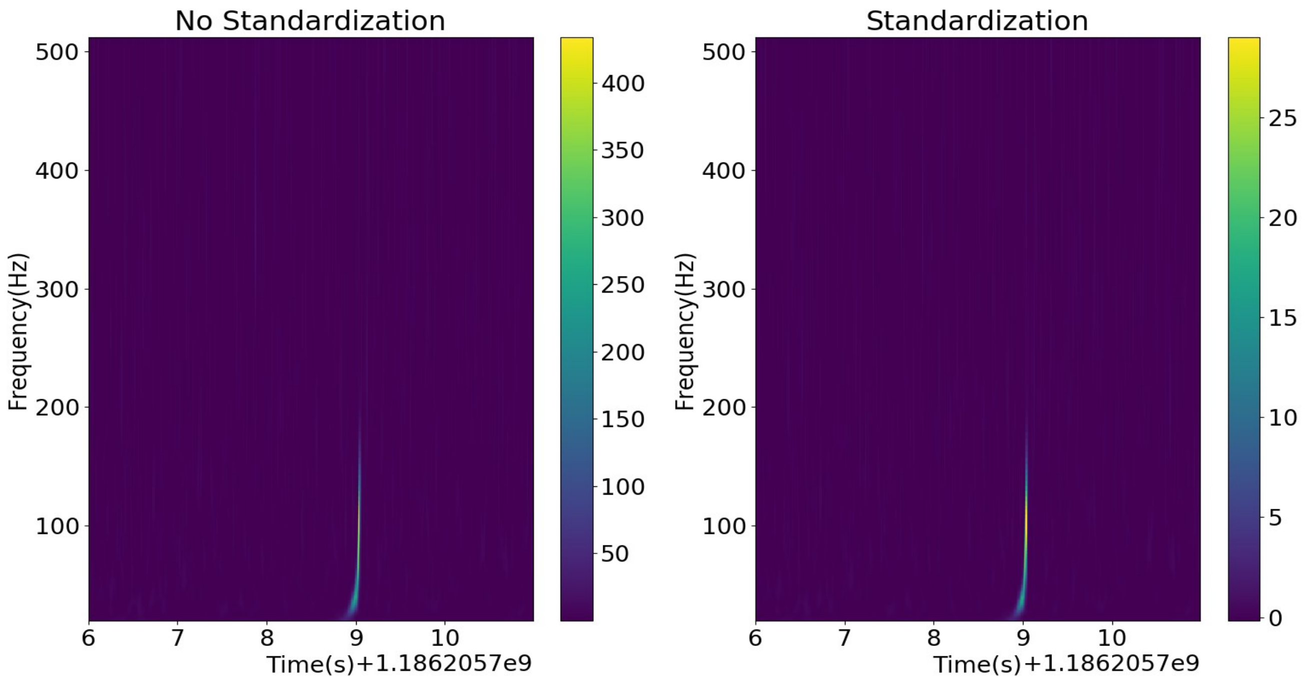
	Initial	End
Masses ($M_\odot$)	25	100
Distance (Mpc)	100	1000
Right ascension (rad)	0	2π
Declination (rad)	0	π
Polarization (rad)	0	π
Inclination (rad)	0	π/2
Number of signals		160,000

- Waveforms are added to O2 data, whitened, sliced in 5s intervals and transformed into a spectrogram.
- Background images are processed in the same way.

Input data: Additional preprocessing

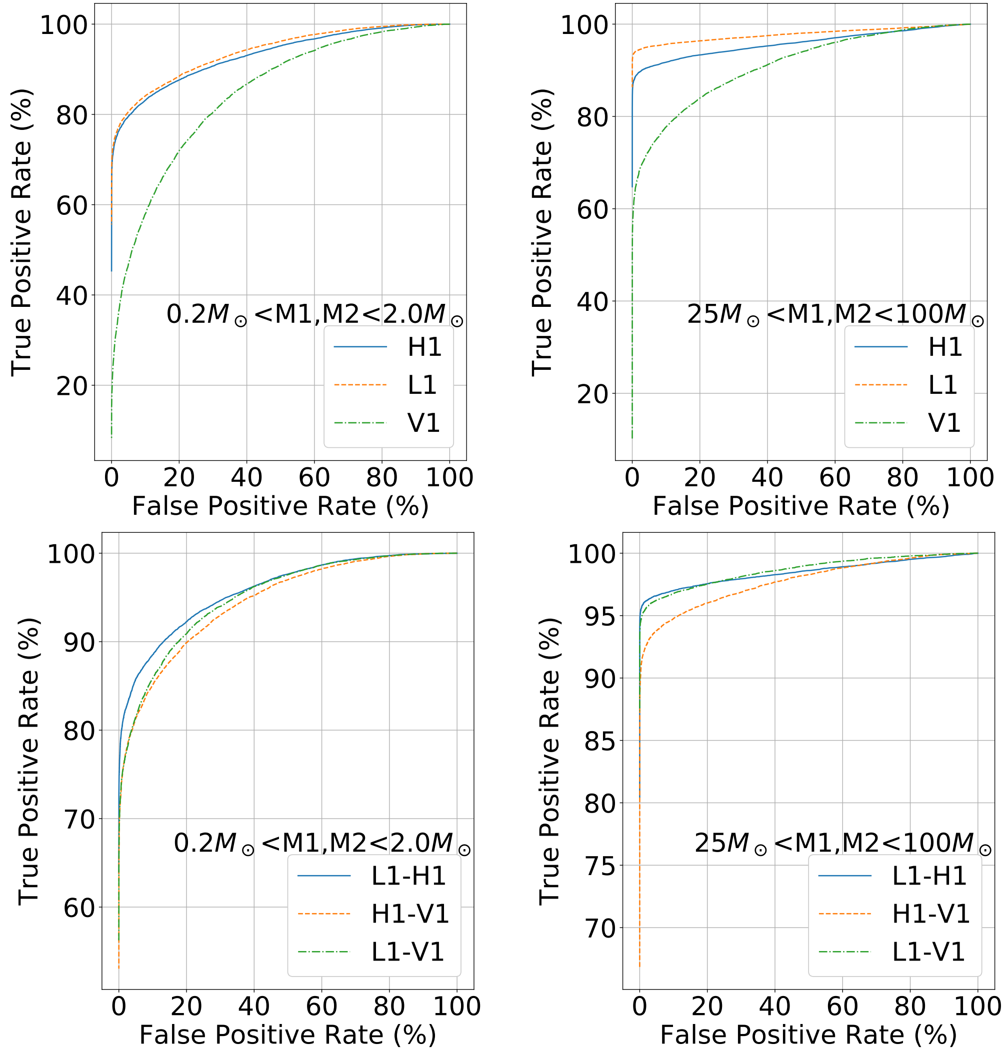
- Inside the ResNet50 architecture there are batch normalization layers.
- Standarization of the data is needed to achieve good performance due to these layers.
- The spectrograms are represented by a matrix.
- For each spectrogram we estimate the mean value and standard deviation of the matrix.
- We substract the matrix by the mean and divide by the standard deviation.
- **Only affects the scale**
- Images are now ready to be used in the CNN.

$$\hat{X} = \frac{X - \mu_X}{\sigma_X}$$



Training and testing

- 128k Images per interferometer are used, 63% training, 7% validation and 30% testing.
- For each CNN we estimate the ROC (Receiver Operating Characteristic) curve to characterize its performance.
- This performance is described by the True Positive Rate (TPR) and the False Positive Rate (FPR).
- These values depend on the threshold. This threshold is defined as the output such that the CNN has a rate of 25 fakes per day.

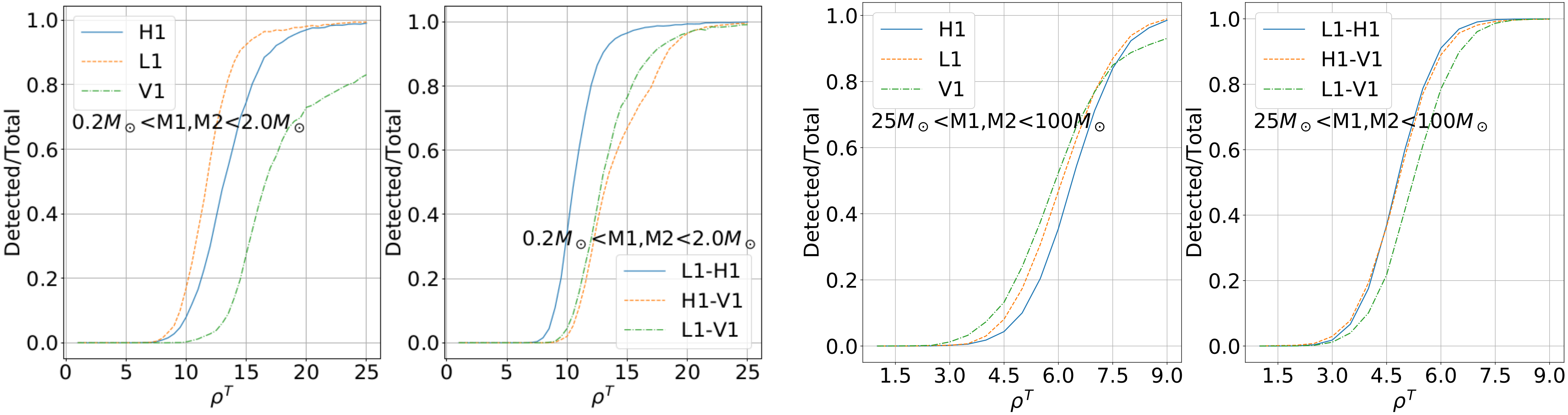


	CNN discriminant (%) low/high mass	TP rate (%) low/high mass	FP rate (%) low/high mass
single interferometer channel			
L1	98/96	70/92	0.09/0.06
H1	98/99	65/84	0.04/0.03
V1	99.7/98	13/52	0.005/0.03
double interferometer channel			
L1 – H1	99/96	74/95	0.06/0.09
L1 – V1	99/97	69/93	0.09/0.04
H1 – V1	99/98	66/88	0.03/0.05

Testing – Injection test

- Injection test are carried out to understand the performance of the CNN for a signal with a given signal-to-noise ratio (ρ^T).
- ρ is estimated by numerically solving the integral .
- A Tukey window with alpha 1/9 is applied.
- From these test we find that the high mass CNN becomes fully efficient around 8 and the low mass at 16.

$$(\rho^T)^2 = 4 \int_{Fmin}^{Fmax} \frac{|h(f)|^2}{S_n(f)} df$$



O2 Scan

- Using these trainings and the thresholds we ran the CNNs over O2 data.
- For each combination we search for the times where both interferometers are online and in science data taking mode.
- These images were processed in the same way as the simulated events.
- Only difference is that between two consecutive images there is an overlap of 2.5s.
- The ratio of false positives per day achieved is slightly higher than our limit of 25 per day.
- This indicates that the CNNs are triggering on noisy events.

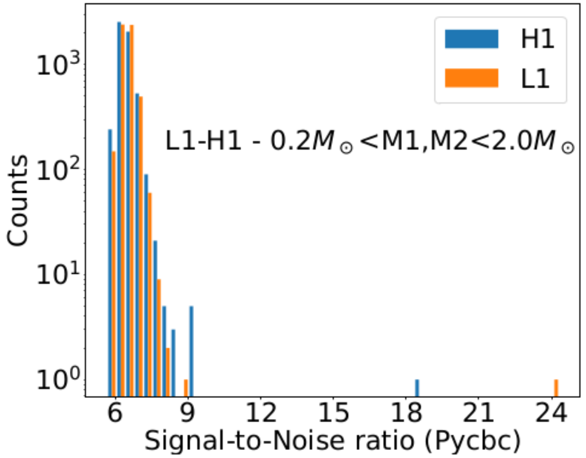
CNNs Response to full O2 scan					
		low mass NN		high mass NN	
CNN	Images	Detected	Events/day	Detected	Events/day
L1-H1	4077233	5496	47	3973	34
H1-V1	584993	439	26	414	24
L1 -V1	601877	3078	178	445	26

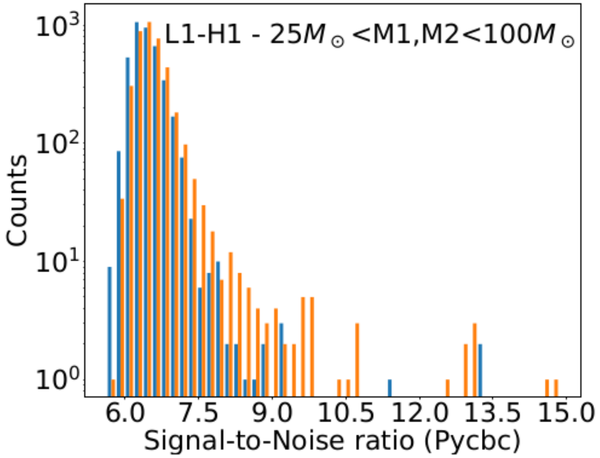
O2 Scan – Results

- We also test the CNNs over the events from the first observation run (O1).
- All the events that are in the scope of the training are detected by the CNNs.
- The missed events have masses out of the training range.
- Comparing the significance of the rest of the triggers of our CNNs we found that a large majority are also detected by the pyCBC pipeline with a signal-to-noise ratio between 6 and 8.
- This indicates that the CNNs are performing similarly to the first steps of dedicated pipelines.

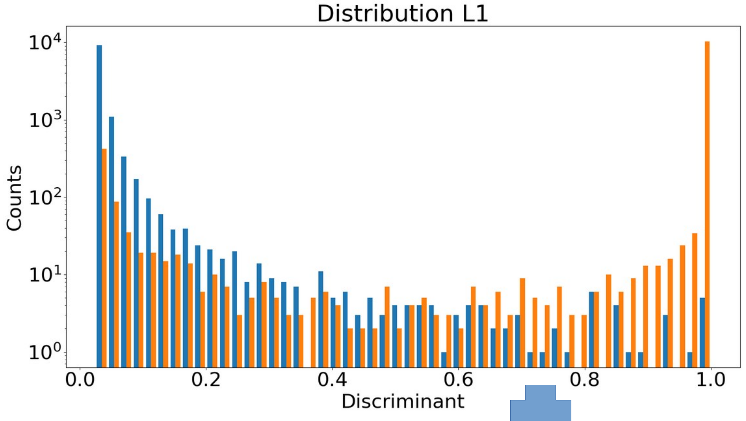
CNNs response to O1+O2 catalog

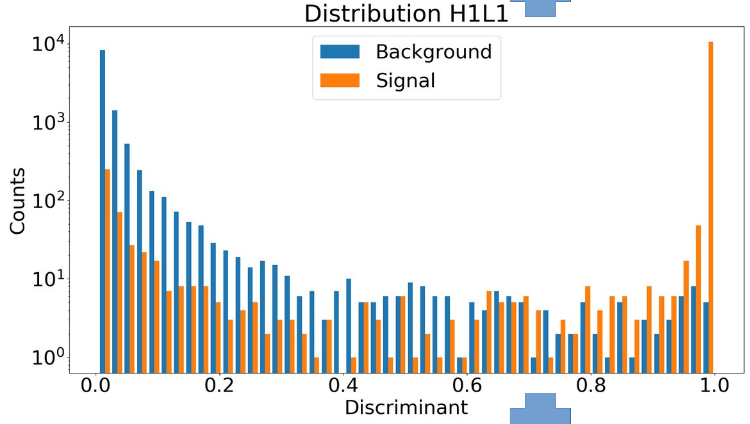
	low mass		high mass	
Event	CNN value	Detected (Y/N)	CNN value	Detected (Y/N)
GW170104	0.001	N	1.0	Y
GW170608	0.02	N	0.008	N
GW170729	0.1	N	1.0	Y
GW170809	0.15	N	1.0	Y
GW170814	0.01	N	1.0	Y
GW170817	1.0	Y	0.04	N
GW170818	0.003	N	1.0	Y
GW170823	0.05	N	1.0	Y
GW150914 (O1)	0.24	N	1.0	Y
GW151012 (O1)	0.06	N	0.95	N
GW151226 (O1)	0.29	N	0.08	N

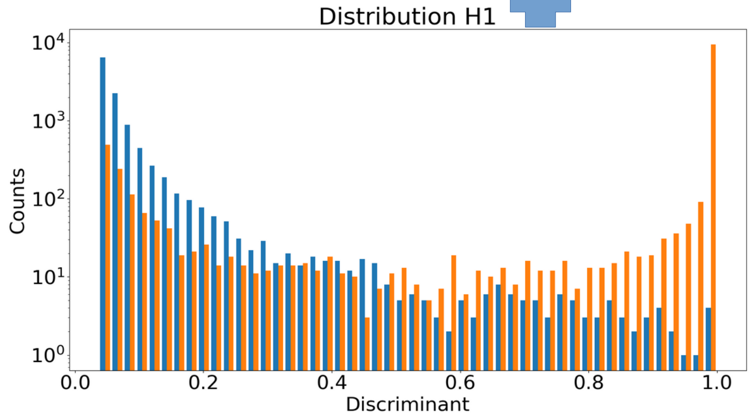




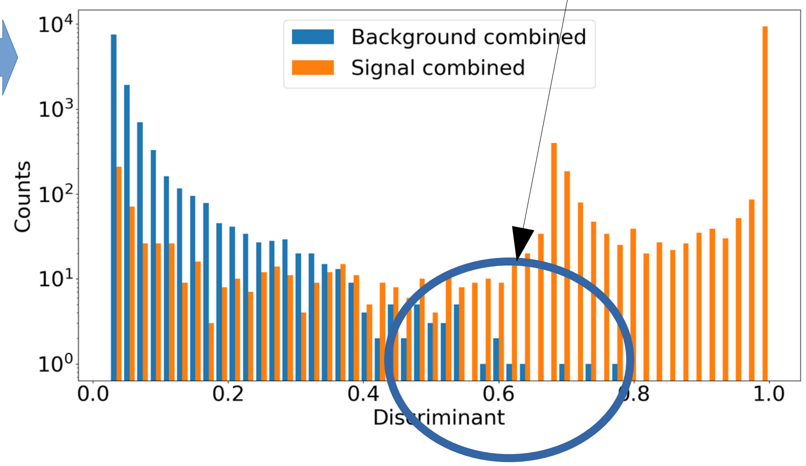
Improving the false rate

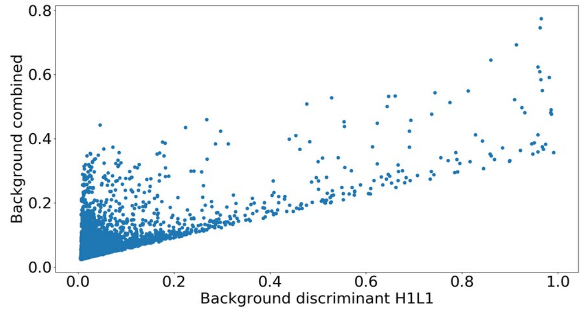


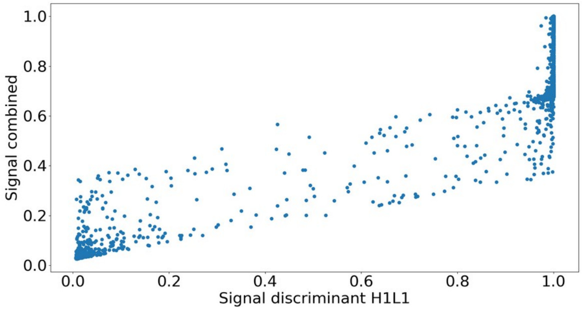




- The excess of false rates can be decreased by combining the output of the NNs for pairs and single interferometers.
- To each image we assign as value for the discriminant, P_{imag}, the average of the different outputs: $P_{imag}=(P_{2ITF}+P_{ITF1}+P_{ITF2})/3$.
- Chirp like glitches due to being visible only in one interferometer will have P_{2ITF}~1 and P_{ITF1}~1 but P_{ITF2}~0.
- This allows us to have much more control over the false rate.







Effects on O2 scan

- The discriminant for some events decreases noticeably and some accuracy is lost.
- However by using this method, the amount of fakes is sharply reduced.
- There is a trade-off between accuracy and purity of our CNNs.
- In the tables you can see the difference in performance achieved by using this method for arbitrary thresholds → .9 for low mass and .8 for high mass.
- The level of reduction in the fake rate can go as high as 41 times lower than the original.

CNNs Response to full O2 scan

	low mass NN (threshold .9)		high mass NN (threshold .8)	
CNN	Detected	Events/day	Detected	Events/day
L1-H1	5496 → 315	47 → 3	3973 → 96	34 → 0.81
H1-V1	439 → 253	26 → 15	414 → 109	24 → 6
L1 -V1	3078 → 930	178 → 53	445 → 38	26 → 2

CNNs response to O2 catalog

	Low mass		High mass	
Event	**2 ITFs Value**	**Combined**	**2 ITFs Value**	**Combined**
GW170104	0.001	0.13	1.0	1.0
GW170608	0.02	0.39	0.008	0.06
GW170729	0.1	0.34	1.0	1.0
GW170809	0.15	0.41	1.0	0.88
GW170814	0.01	0.43	1.0	1.0
GW170817	1.0	0.93	0.04	0.16
GW170818	0.003	0.41	1.0	0.7
GW170823	0.05	0.34	1.0	1.0

Conclusions

- CNNs are usable for the detection of CBC events.
- Results published in Phys. Rev. D 103, 062004.
- The O2 catalog events in the scope of the training were properly detected.
- The performance can be improved by combining the output from different CNNs.
- We are applying this method to O3 data.
- Working in the proper estimation of the significance for each image.
- Plan to test the CNNs online.