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Adaptation of a Convolutional Neural Network–based Pipeline to Detect Short Gravitational Wave Bursts

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Abstract

We present a machine learning based pipeline to analyze unmodeled gravitational wave (GW) transients of less than 10 s. The convolutional neural network (CNN) is based on a U-NET architecture and takes as input data from GW interferometers represented as time-frequency maps, returning a spectrogram without the background noise. The CNN has been trained on simulated data, using a generated Gaussian background noise and injecting GW signals from core-collapse supernovae (CCSNe) simulations. The pipeline is able to successfully denoise spectrograms and recognize as signals also CCSNe waveforms for which it has not been trained on.

Keywords: gravitational waves, data analysis, machine learning

1. Introduction

The difficulty of detecting unmodeled gravitational wave (GW) transients, commonly named GW bursts, lies mostly in the impracticability of performing a matched filtering search. The main problem is therefore to find a way to distinguish a potential GW signal from a detector noise transient. Convolutional Neural Networks (CNN) can be suitably used to overcome this problem, as they are frequently used as noise-removal filters in image processing [1]. The work we present here is about a prototype adaptation of a CNN named ALBUS (Anomaly detection for Long-duration BUrsts Searches [2]) to the search for short-duration GW bursts, i.e., unmodeled GW transients with a duration of 10 s. Both ALBUS and its new companion, which we will call ASBUS, act as denoisers in the GW-detection pipeline named GWpyxel [3].

2. GW Data

In order to be analyzed through our neural network, the data from a single GW detector is first whitened. A short fast Fourier transform is then applied and the result is displayed in a 10.375 s long spectrogram covering the 0–2048 Hz frequency range. The data used for the results presented here is fully simulated. We sample the Gaussian noise from a given power spectral density ("aLIGO175MpcT1800545" from the PyCBC library [4]).

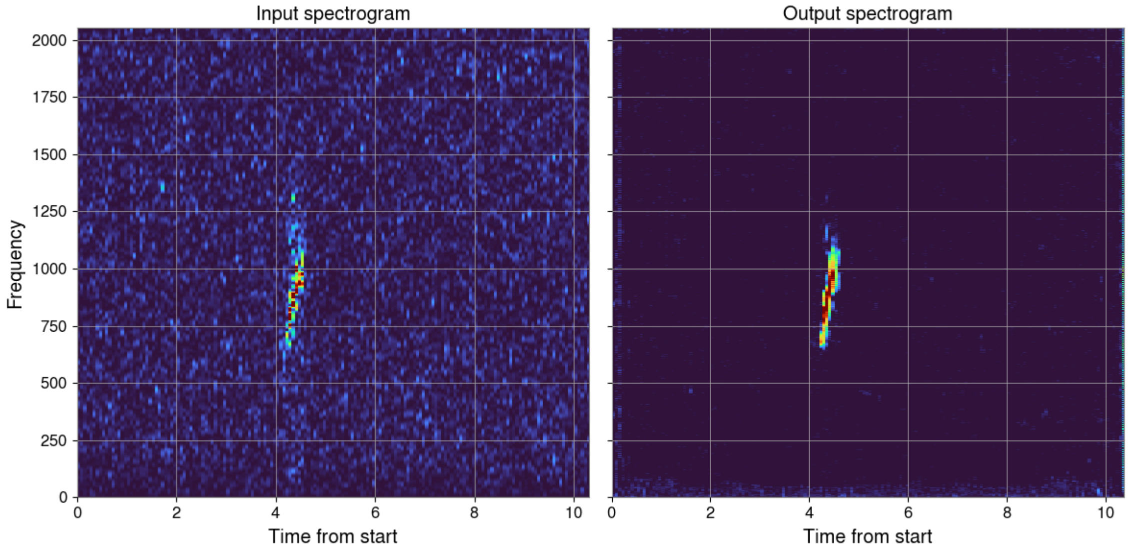

Figure 1: (*Left*) Time–frequency map of a CCSN gravitational waveform (s18; [6]) injected in Gaussian noise that is given as an input to ASBUS. (*Right*) Corresponding output map showing the injected GW signal extracted from the noise.

3. CNN and Training

The architecture of ASBUS is based on a pixel-to-pixel U-Net CNN [5], taking spectrograms as inputs and ideally returning a spectrogram containing only the GW signal. An example is shown in Fig. 1. The target maps are generated from spectrograms containing just a simulated GW transient without noise. Those images are passed through an edge-detecting algorithm, with a threshold on the edge strength depending on the strain amplitude of the injected signal. The pixel regions found this way are then clustered together. For this test of the CNN, we trained it on four different models of Core-Collapse SuperNovae (CCSNe) waveforms: s25, s9 [7]; mesa20_pert [8]; s18 [6]. The training and validation loss curves are displayed in Fig. 2.

4. Results

The CNN successfully detects CCSNe waveforms, both for models used in the training set and for other CCSNe waveform models. Figure 3 shows the sigmoid fit for the detection efficiency curve as a function of distance for the s18 waveform from [6]. Table 1 shows the 10%, 50% and 90% exclusion distances corresponding to other CCSNe GW waveform models.

5. Conclusions

We showed that a U-Net CNN architecture can successfully act as a noise-removal filter for short, unmodeled GW transients represented in spectrograms. We plan to train ASBUS on

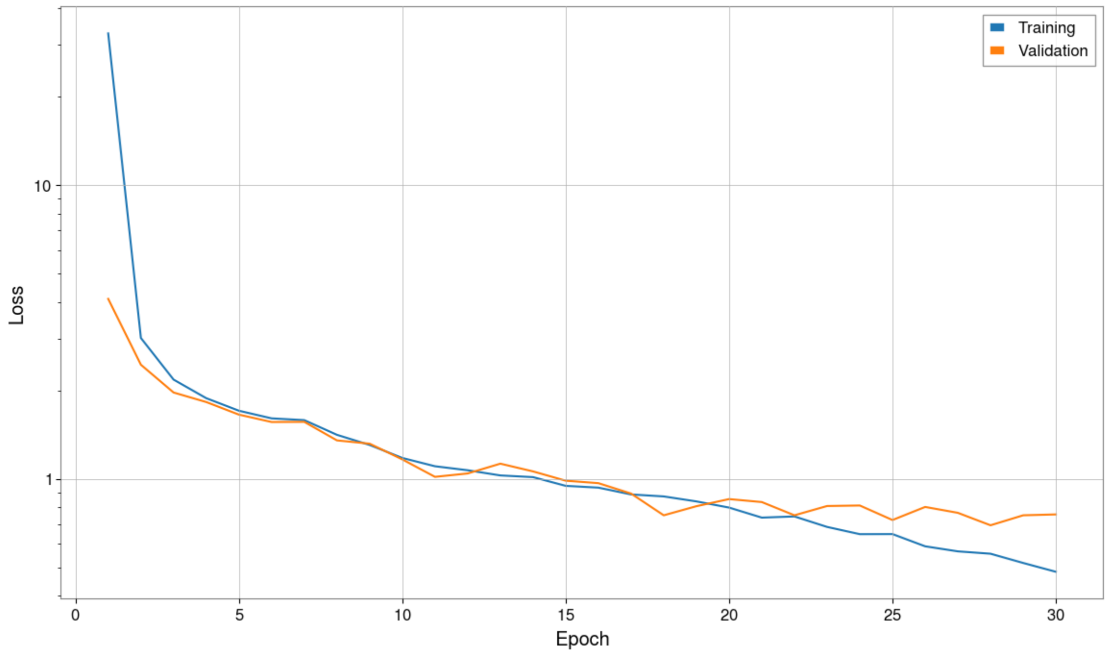

Figure 2: Training and validation loss curves for the training of ASBUS.

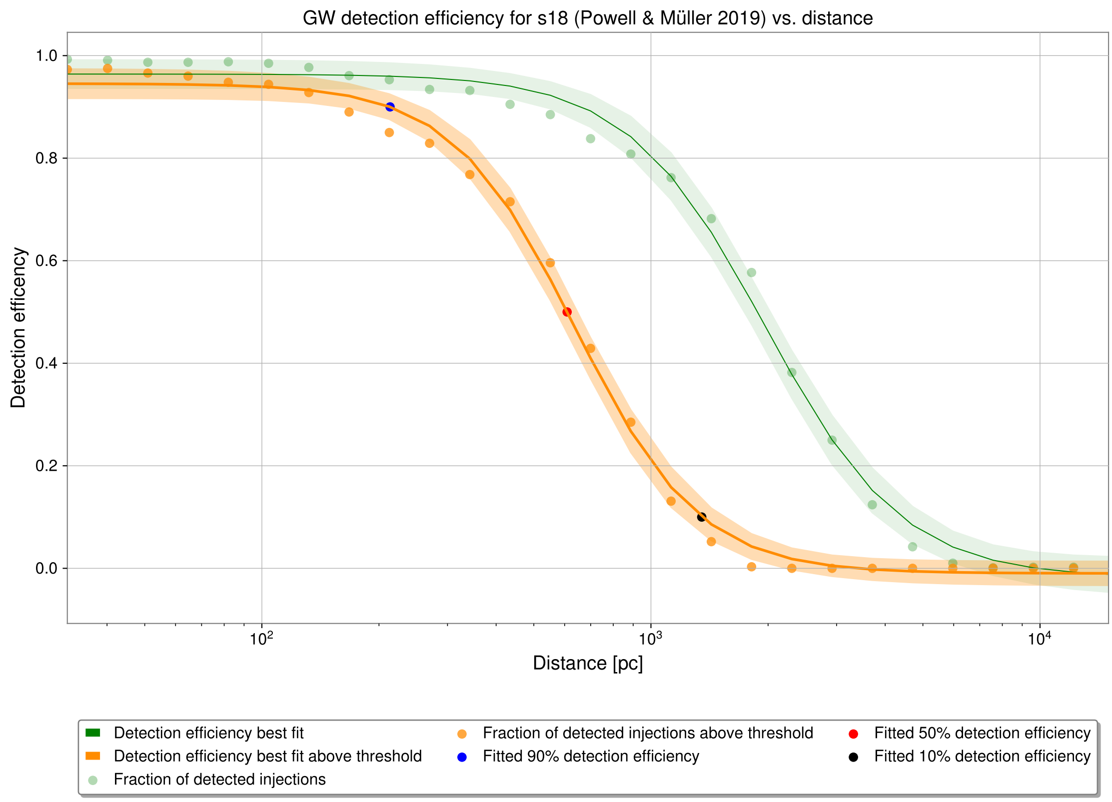

Figure 3: GWpyxel detection efficiency curves for the s18 CCSN waveform [6]. The green and the orange curves are, respectively, obtained with and without putting a threshold on detection statistics obtained simulating five years of background. The black, red and blue dots represent, respectively, the 10%, 50% and 90% exclusion distances.

Table 1: Preliminary exclusion distances for some test CCSNe-waveform models.

		Exclusion distances [kpc]		
Waveform model	**Ref.**	**10%**	**50%**	**90%**
mesa_pert 20	[8]	0.26	0.13	0.06
s18	[6]	1.34	0.62	0.22
s3.5*	[6]	0.75	0.35	0.11
m39*	[9]	4.41	1.76	0.76

* Models not used in the training set.

other simulated waveforms from possible GW sources, like eccentric CBCs, cosmic strings or pulsar glitches. The choice of analyzing single detector data is challenging, due to the presence of glitches (non-Gaussian and non-stationary noise transients) which can mimic GW transients and cannot be suppressed using cross-correlated data between two detectors. However, given the ability of the ALBUS/ASBUS CNN architecture to be trained to identify and even classify glitches [10], the pipeline looks promising for the analysis of single-detector data.

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Further Information

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Conflicts of interest

The author declares that there is no conflict of interest.

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