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Deep convolutional neural network to characterize transient noise in gravitational-wave detectors

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Summary. — Gravitational-wave detectors are affected by many noise sources, including transient events called glitches, originating from instrumental or environmental disturbances, that make the noise of a detector far from being stationary and gaussian. Glitches affect data quality, and can mimic astrophysical signals or even mask them. Therefore, it is fundamental to recognize these transients in order to cluster them in families of similar morphology and investigate their origin. In this paper we discuss the possibility of tackling this task with a deep convolutional neural network.

1. – Introduction

In 2015, Advanced LIGO detected the first gravitational waves from the coalescence of two black holes [1], opening a new window on the study of the Universe. During the subsequent observing runs (O2, O3) tens of events were detected [2] by Advanced LIGO [3] and Advanced Virgo [4], including the coalescence of neutron star-neutron star and neutron star-black hole systems, for a total of 90 confirmed events [5].

The characterization of these detectors is a primary task in order to recognize the main sources of noise and optimize the sensitivity of detectors [6].

The dominant contributions to the noise of an interferometer can be described as a stationary and Gaussian random process [7], whose statistics is completely determined by the mean and the power spectral density (PSD), essentially related to instrument design and due to fundamental noise sources [8].

However, the noise of the interferometers presents also transient components produced by the complex interactions among detector subsystems or with the surrounding environment [8]. These noise transients are called glitches and they make the noise of a gravitational-waves detector not stationary and not gaussian [7]. Glitches have an impact on the gravitational wave data quality, by increasing the false alarm rate; in addition, short time-scale glitches can mimic true gravitational waves signals [9]. Furthermore, glitches can be superposed with a gravitational-wave signal and compromise the estimation of the source parameters, as happened for GW170817 [10]. Therefore, in order to investigate the impact of transient noise on the detectors it is important to identify and characterize these glitches [8]. Moreover, in order to further investigate their origin or model them to de-noise the raw data, a first step consists in classifying glitches in families, according to their morphology.

Machine learning techniques seem to be very promising to tackle this problem. Past studies have shown how deep neural networks can be effective to classify images of spectrograms of different transient signals. For instance, in [11] it was shown that a deep convolutional neural network (CNN) is able to classify spectrograms of simulated transient signals with an accuracy of $\sim$99%, while in [12] a CNN is used to classify spectrograms of real LIGO signals with an accuracy of $\sim$97%. Moreover, [13] showed that convolutional neural networks are effective to distinguish between gravitational-wave signal from different core-collapse supernovae models and noise transients, using both time series and their spectrograms.

In this paper we explore the possibility of classifying directly the time series of simulated transients with a custom convolutional neural network, which can be useful for the future development of low-latency pipelines. Thanks to a custom set of simulations of transient signals embedded in the detector colored noise, we train a convolutional neural-network classifier, with the goal to predict if a certain signal is a glitch or not and to define its class.

2. – Dataset preparation

In order to test the ability of CNN1D to classify transient signals, we prepared a simulated set of time series that include glitches and signals of astrophysical origin, such as coalescences of compact binary objects. This approach was also adopted in previous works [11] and it allows to evaluate classification performance depending on the parameters of the simulated signals. More precisely, as in [11], we have simulated six different transients which are: Gaussian glitch, Sin-Gaussian glitch, Scattered-like glitch, Whistle-like glitch and the astrophysical signals Chirp-like and Ringdown-like.

These classes emulate a wide variety of observed glitches, referred to as blips, and a more specific type associated to scattered light in the interferometers and to the beating of radio signals with the Voltage Controlled Oscillators [8]. In addition, also the parameters of these signals are taken as in [11], in order to mimic signals observed in Advanced LIGO and Virgo, during the second observing runs (O2). The amplitude of each transient is scaled according to a given optimal signal-to-noise ratio (SNR) [14]; for our simulation we uniformly extracted the SNR values for the glitches between 8 and 50 and between 8 and 40 for the astrophysical signals.

These transients are then linearly superposed on the colored Gaussian noise of Virgo, estimated from its PSD during O2 with an algorithm inspired by [15].

Moreover, we have also included a class of signals without glitches so that our pipeline can be employed as a trigger to detect transient signals in the raw data.

For each family of signals we have generated 2000 time series of 2 s centered around the transient for a total of 14000 samples. The sampling frequency is chosen to be 8 kHz which is a good compromise between the computational cost and the information content of each time series. Figure 1 shows examples of transient signals from the simulated dataset with no background colored noise.

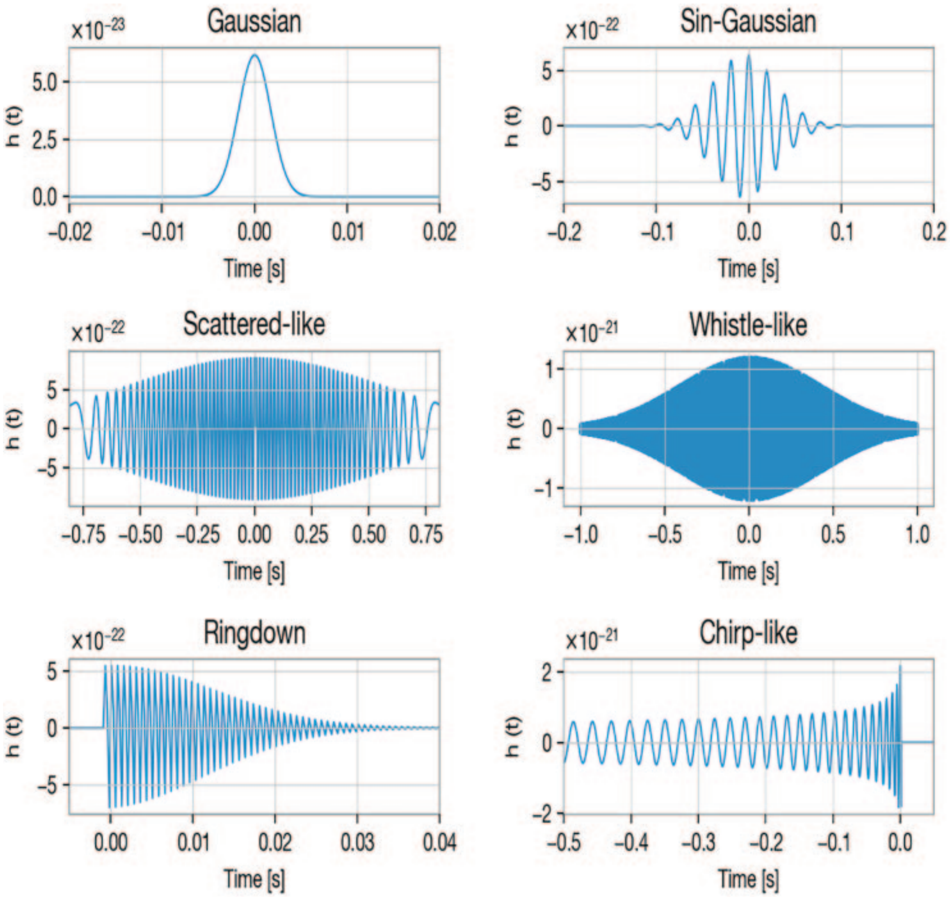

Fig. 1. – Examples of time series of the dataset: Gaussian with SNR ~ 9.5; Sin-Gaussian SNR ~ 32; Ringdown SNR ~ 26; Chirp-like SNR ~ 9; Scattered light SNR ~ 12; Whistle-like SNR ~ 18.

3. – Description of the pipeline

Before applying any detection and classification pipeline, the time series are conditioned by applying a whitening procedure [7] and a band-pass filter between 16 Hz and 3200 kHz, implemented in the GWpy library [16], so that the presence of a transient signal in the raw data becomes more obvious. Lastly, the simulated data are randomly divided into train (70%), validation (15%) and test (15%) sets. The train set is used to train the network, while to determine the best architecture we evaluated its performances on the validation dataset. Finally, the test set is used only to assess the performance of the chosen optimal network architecture.

After these steps, each time series is processed by a deep CNN, whose structure is well suited for exploiting the local structure of our input data. Moreover, this architecture, once trained, is computationally efficient, allowing the classification to be performed in low latency.

The architecture that we proposed is based on three blocks of convolutional layers followed by two blocks of fully connected layers for the purposes of classification. We used the categorical cross entropy [17] as loss function to tune the parameters of the neural network and Adam algorithm [18] for its optimization. Indeed, with this neural network we have defined a function that is able to map each time series to an array of seven elements, where the i-th element is the probability that the input belongs to the i-th class.

4. – Results

Once the network has been trained on a Tesla T4 GPU, transient signals of the test set can be classified with $\sim$99% of overall accuracy in a short ($<$1 s) time. The accuracy is a common metric to assess the performance of a neural network and it is defined as the fraction of correctly labelled signals over the whole dataset of signals.

Therefore, we have shown that a deep convolutional neural network can be effectively employed for classifying signals recorded by gravitational-wave detectors, reaching performances comparable to those obtained in the literature based on the classification of spectrograms, but with the advantage of being faster, which makes our pipeline suitable for low latency analysis applications.

Machine learning offers new, powerful tools to analyze data in the gravitational-wave field and it will be even more useful for the next generation of detectors, where the large number of events will make the low-latency noise characterization more urgent and crucial.

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