Autoencoders for Gravitational Waves Detection

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1 Introduction

A Gravitational Wave (GW) is a wave-like disturbance in the curvature of spacetime, generated by accelerated masses. Since it induces a strain in the spacetime, while it passes the distances between objects increase and decrease rhythmically with the same frequency as the wave. GWs have wavelengths from a few kilometers up to the size of the universe. The strongest sources of GWs are related to the violent universe phenomena, such as supernovae, colliding black holes and colliding neutron stars.

Revealing the passage of a GW on the Earth is an extremely challenging task: considering the distances, even for the strongest sources the amplitude of the strain is of order 10^{-18} m. This lead to the construction of the LIGO detector.

LIGO, the **L**aser **I**nterferometer **G**ravitational-wave **O**bservatory is the world's largest GW observatory. It comprises two laser interferometers (Fig 1) whose two arms are 4 km long. The arms are arranged in an L shape and contain a 1.2 m-wide steel vacuum tube, covered by a 10-foot wide, 12-foot tall concrete shelter that protects the tubes from the environment[1]. Basically the LIGO interferometers are Michelson interferometer. Since the passage of a GW distorts the distances along the two arms in a different way at the same time, such passage results in the change of the relative length of the two arms through time:

$$h(t) = \frac{L_y - L_x}{L} \tag{1}$$

where x and y are axes aligned with the directions of the LIGO's arms and $L_x \simeq L_y \simeq L$ is the length of the arms at rest. By recording this quantity (**strain**) as time passes we get a time series. This time series is always dominated by noise, caused by various sources which can be related to the environment (e.g. environmental and seismic noise), intrinsic to the detector itself (e.g. thermal fluctuations of the mirrors or of other parts, shot noise in laser beam) or technical (effects whose influence can be reduced improving the technology, such as interferometer phase fluctuations deriving from instabilities of the laser-beam geometry or from residual gas along the optical path of the beam). Moreover, this

[1] https://www.ligo.caltech.edu/page/what-is-ligo

Figure 1: Aerial views of the LIGO Hanford (left) and the LIGO Livingstone (right) interferometers. From https://www.ligo.caltech.edu/page/ligo-gw-interferometer

noise cannot be modeled as white noise, but rather as a colored broad-band background (Fig. 2) with some spectral peaks, due to the violin modes of the suspensions wires of the apparatus. In addition its distribution could be non-stationary and non-Gaussian. It follows that, in order to reveal a GW it is necessary to perform some pre-processing steps.

The two fundamental pre-processing steps are **whitening** and **bandpass**. The goal of whitening is to make the time series of strain *delta correlated* (each point of the series is correlated only with itself and uncorrelated with any other point). In other terms whitening removes all the correlation of the noise. The whitening procedure can be implemented both in the time domain and in the frequency domain. In the latter case it is performed dividing each point by the noise amplitude in the Fourier domain. In this way the power at all frequencies is normalized and excess power at certain frequencies, which can be related to a GW, becomes more evident. Figure 3 shows an example of the result of the whitening procedure. While in the original signal (left) it is impossible to distinguish the GW, as it is immersed in noise, in the whitened time series (right) it becomes more evident.

The bandpass filter passes frequencies within a certain range and attenuates frequencies outside that range. The LIGO interferometers are sensitive to a broad range of frequencies (from a few Hz to more than 1 kHz), but their sensitivity over this range is not constant, depending on the level of the environmental and of the intrinsic noise

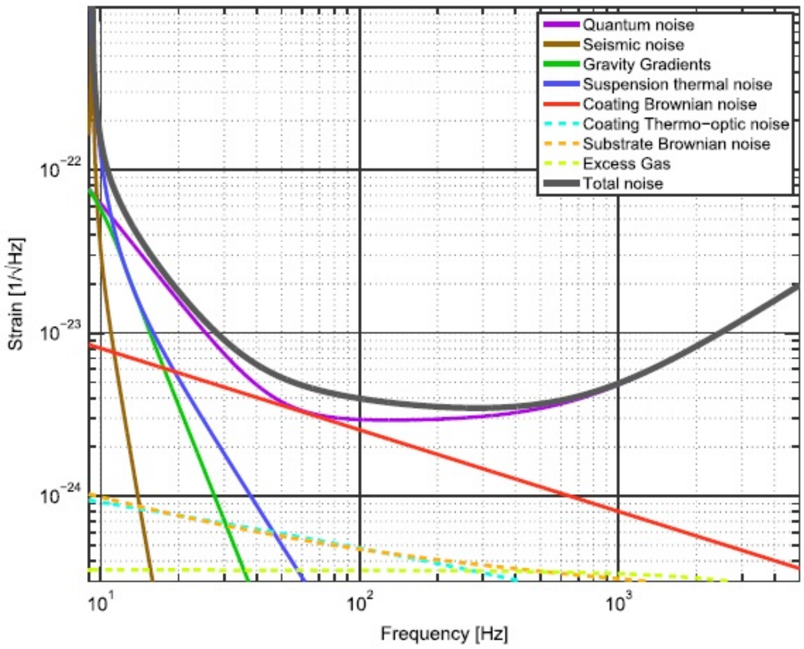

Figure 2: Principal noise terms for the nominal (high power, broadband) mode of operation of Advanced LIGO. From The LIGO Scientific Collaboration et al. (2015).

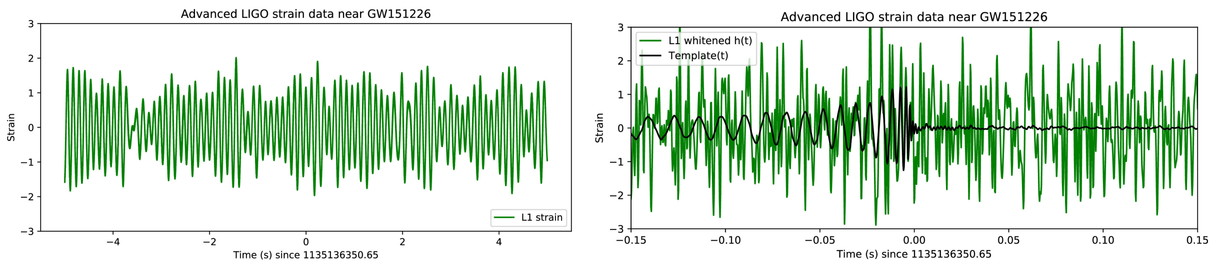

Figure 3: Time series containing a GW signal (GW151226) immersed in noise. Since the signal is noise-dominated, in the original time series (left) it is impossible to distinguish the GW. On the right the same signal after whitening is shown. The black line is the best matching template. Source Corizzo et al. (2020)

(Fig. 2). The bandpass filter attenuates the frequencies bands at the extremes of the measurement range, which are particularly affected by noise, and also focuses the area of the spectrum in which the detection of a signal of astrophysical interest is expected.

2 GW detection: traditional approach vs ML

Once the pre-processing has been carried out, the detection of GWs can take place. The traditional approach used for the detection of GWs from LIGO's time series signal is based on **matched filtering algorithms.** These algorithms basically scan the time series trying to match an optimal waveform template, among all those contained in a GW waveforms database. This approach has a twofold drawback: it requires the knowledge of the gravitational waves waveforms, and this can be not true for all the possible sources. Moreover it is (very) computationally expensive, especially in the case of large waveforms template databases. Also, it is prone to errors due to *glitches*, non-stationary instrument artifacts which can can mimic a GW wave.

Deep learning methodologies offer an efficient alternative. Indeed, the peculiar feature of ML techniques, that of generalizing ("learning") directly from data, becoming able to make predictions without the need to be explicitly programmed on a case-by-case basis, is well suited to the GWs detection task, when one thinks of it as a *classification* (anomaly vs noise) problem. We define **anomaly** as a rare, transient feature in the time series that differs significantly from the background noise of the instrument. Such an anomaly may represent a GW or an instrumental glitch. Through deep learning techniques it is possible to perform a fast and effective detection of these anomalies, which can be better analyzed at a later time. The problem put in these terms is independent from a theoretical model, and therefore more robust. In addition, the computational load is concentrated in the training phase, while the classification (detection) phase, which is the most scientifically relevant, can benefit of the efficiency of NNs, which opens up to near real-time analysis of LIGO signals.

3 AEs for anomaly detection

An **autoencoder (AE)** is a neural network that learns to reconstruct its input with the highest possible accuracy. It has an hidden layer that contains the so called *code* or *latent representation*, which is a compressed representation of the input. An AE is composed by two parts:

1. The *encoder*, which maps the input to the latent representation. It consists of the input layer and one ore more hidden layers with progressively smaller dimensions. In this way the input is compressed and the central part of the networks contains only the most relevant aspects of the input data.

2. The *decoder*, which maps the code to the output, i.e. it reconstructs the input based on the code. The decoder is made up of one or more progressively bigger hidden layers, and of the output layer, which has the same dimension of the input layer.

During the training phase the AE tries to minimize the reconstruction error (loss), i.e. the distance between the input and its reconstruction, according to an appropriate metric. Since AEs are meant to reproduce their input, and not to predict a target value given an input, they are unsupervised learning models.

The idea behind the use of AEs in anomaly detection is to make them learn the feature of the noise. For each training instance the reconstruction error is calculated and a threshold is set. This threshold is calculated every time the AE is trained,

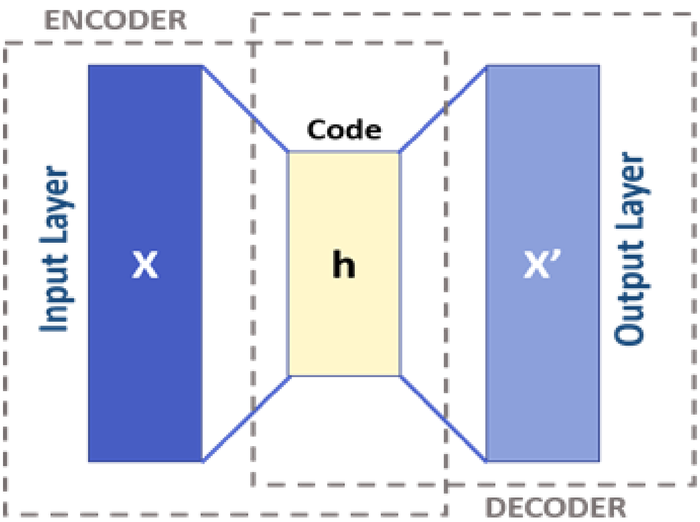

Figure 4: Basic diagram of an autoencoder. From https://en.wikipedia.org/wiki/Autoencoder.

and represents the upper extreme for deciding whether a new event should be considered noise or non-noise. For a new instance at prediction time, if the reconstruction error exceeds the threshold, then it is assumed that the instance belongs to a data distribution different from the one of the training instances. In other words this instance is classified as an anomaly which, as already stated, can be a real GW or a glitch, and therefore requires further analysis.

The big advantage of this method is that for the training we can exploit data representing potentially all kind of noises which affect the instrument. In addition these data are many more than those related to the confirmed GWs. Also, this technique allows to classify new, unseen signals based only on the reconstruction error, thus excluding the need for a theoretical model describing the astrophysical signal we expect to observe.

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