Deep Learning Applied to Continuous Gravitational Wave Detection

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Introduction

Gravitational wave (GW) detection sensitivity has advanced drastically over the past decade, but the algorithms required to interpret the associated data still need many developments. Recent efforts [1] to use artificial intelligence for gravitational wave identification have yielded mixed but promising results. Using Deep Neural Networks (DNNs) is significantly more efficient than current approaches in terms of cost, time, and computing power, but is not yet as accurate as other methods. We set out to build a functional DNN that is capable of identifying and analyzing simulated GW data.

Background

GWs are created when accelerating bodies create ripples in spacetime. In September 2015, the Laser Interferometer Gravitational-Wave Observatory (LIGO) detected a brief GW signal from the coalescence of two massive black holes. This initiated gravitational wave astronomy, a new field of astrophysics [2]. Machine learning is also a rapidly growing field, including DNNs which we used in this project. They analyze and process data through multiple layers of transformations.

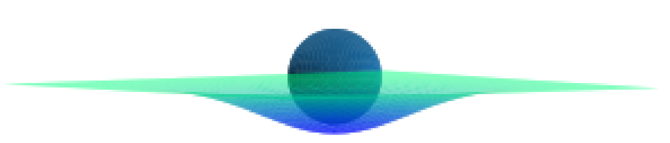

Fig. 1: A body creates a dent in the fabric of spacetime.

Data

Continuous gravitational waves (CWs) should occur when a rotating mass, such as a neutron star, is asymmetric. LIGO has yet to detect CWs, as they have extremely weak signals. Thus, for this project, we generated simulated CW data. In actual LIGO data, the Earth's rotation causes a varying Doppler shift. For this test we left our data as single frequency sine waves, a reasonable approximation to real LIGO data given that the period of the waves we consider is far shorter than 24 hours.

Our data are stored in NPY (NumPy array) files. Creating the DNN model requires an input of 4 arrays: training data, training labels, testing data, and testing labels. Our training sets contain 1600 examples, and our testing sets contain 400 examples. We also generated a data set that was 10 times larger, which we will run when we have the necessary computational resources.

Each wave contains 50,000 points over a time range of 1 second. The sine waves range in frequency from 20 to 1,000 Hertz. All of the waves have an amplitude of 1 and a random phase. We created 5 data set groups, each with a different standard deviation to their Gaussian noise; 0.5, 1, 2, 3, and one that was randomized across all of these values. We trained the DNNs on each amount of noise to examine how performance deteriorated with additional noise.

Fig 2. shows 500-point samples from example waves with specified noise next to the spectra. The corresponding graphs with just noise are also included.

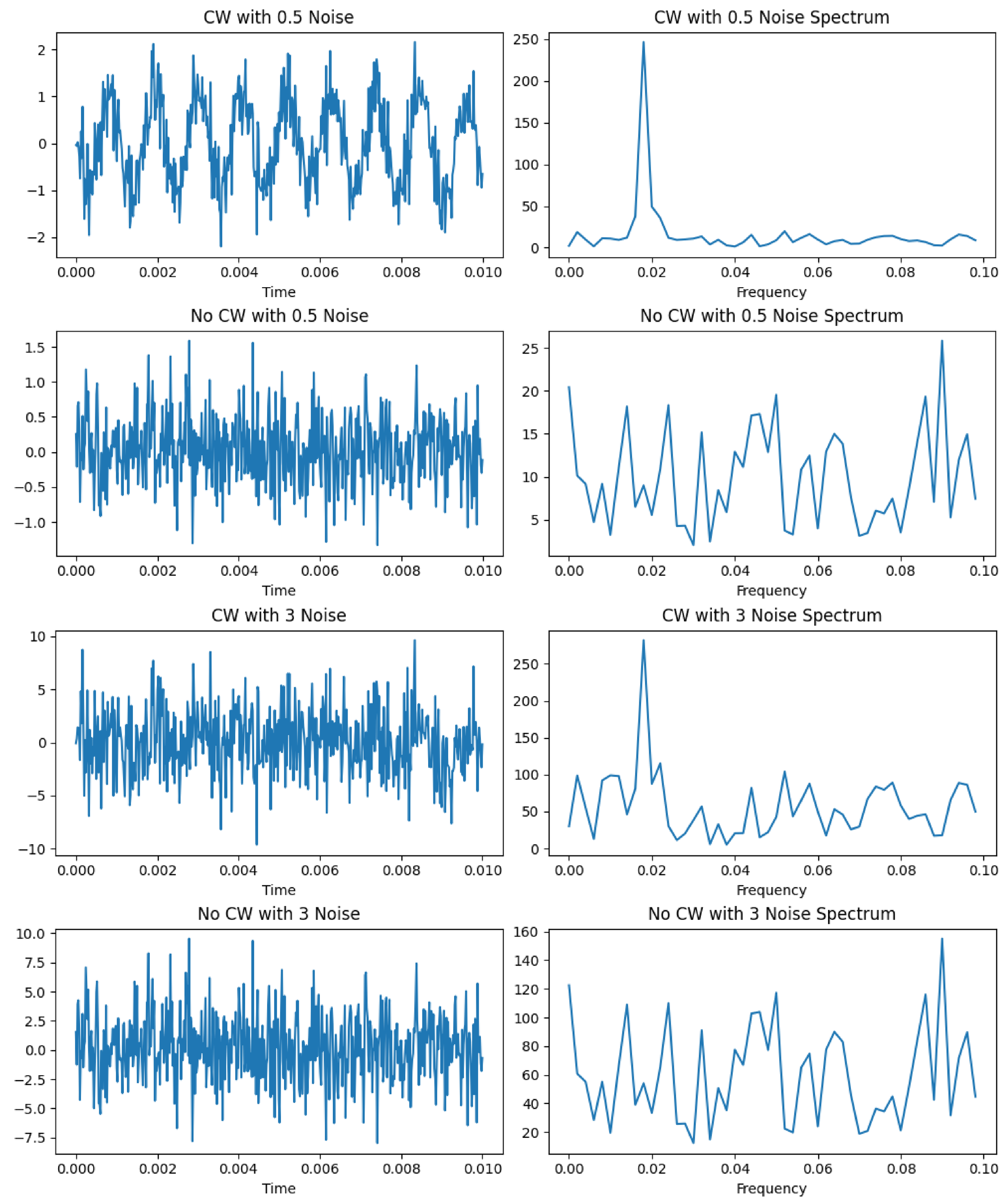

Fig. 2: Data with a standard deviation in Gaussian noise of 0.5 and 3.

Findings

We tested each neural network thrice, and the accuracies can be viewed in Fig 3. This shows that the DNN, like many humans, finds features better in the Fourier transform of the data than in the time domain signal. As expected, the accuracy of the DNN went down with noisier data. We also found that the more data that were given to the network, the better it performed. This leads us to believe that if there were substantially more data, the DNN would be able to recognize even very noisy waves at a high rate. Unfortunately, we did not have access to a powerful enough computer to generate substantially more than 2,000 examples for each group.

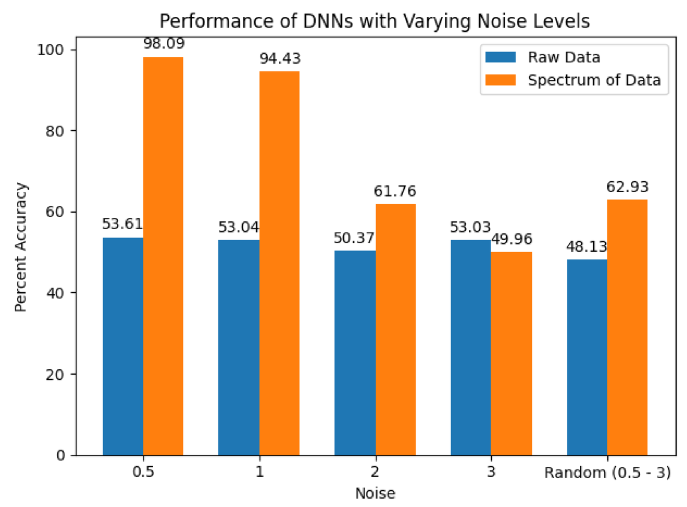

Fig. 3: Average accuracy for various data.

Fig 4. shows how accuracy improves during the training process. Notably, some of the higher noise groups did not level off in the same way as the 0.5 noise group did. It is conceivable that if we had more training time the accuracies would continue to improve.

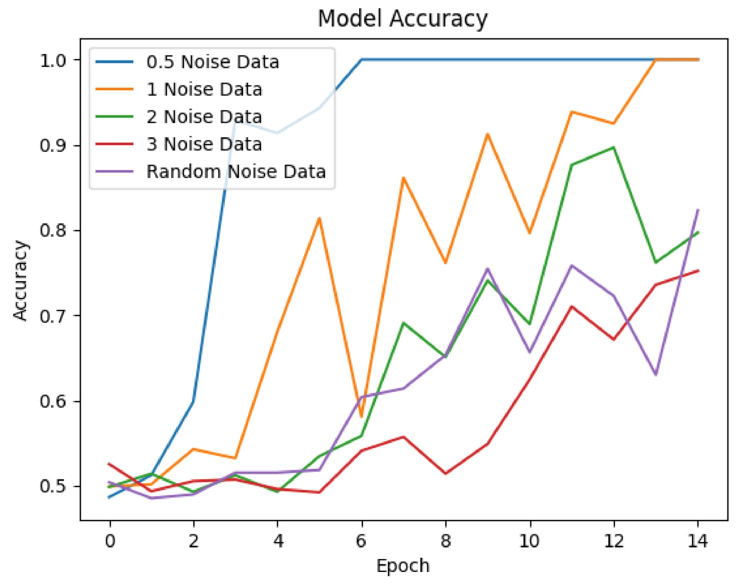

Fig. 4: DNN accuracy at each training epoch.

Our neural network serves as a proof of concept that DNNs can be used in GW detection. While our data were simulated due to the lack of CW observation, we believe that our approach can be applicable to future classification efforts. In contrast to matched filtering, the process was simple, time effective, and cheap. Our DNN and data generation are also very scalable to be used with larger amounts of data on stronger computers.

Acknowledgements

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References

[1] C. Dreissigacker. "Deep-Learning Continuous Gravitational Waves". In: *Physical Review D* 100 (Aug. 2019), p. 044009.

[2] *What are Gravitational Waves?* `https://www.ligo.caltech.edu/page/what-are-gw`. Accessed: 2021-11-16.