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DEEP LEARNING FOR MULTIMESSENGER ASTROPHYSICS: REAL-TIME DISCOVERY AT SCALE

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EXECUTIVE SUMMARY

The observation of two colliding neutron stars in gravitational waves and light marks the beginning of multimessenger astrophysics. To accelerate discovery in this emergent field of science, we pioneered the use of deep learning for rapid detection and characterization of gravitational wave signals. We initially demonstrated this approach using simulated Laser Interferometer Gravitational-Wave Observatory (LIGO) noise. We have now shown for the first time that deep learning can detect and characterize gravitational wave signals in real (nonstationary and non-Gaussian) LIGO data, achieving similar sensitivities and lower errors compared to established LIGO detection algorithms. This new paradigm is far more computationally efficient and resilient to glitches, allowing faster-than-real-time processing of weak gravitational waves in real LIGO data with minimal computational resources and the detection of new classes of gravitational wave sources that may go unnoticed with existing detection algorithms. In addition, the new paradigm is ideally suited to enable real-time multimessenger discovery campaigns.

RESEARCH CHALLENGE

Matched-filtering searches, the most sensitive gravitational wave (GW) detection algorithms used by LIGO, currently target a 3D parameter [1]. Extending these template-matching searches to target the 9D parameter space available to GW detectors is computationally prohibitive [2]. To address these limitations, we pioneered the use of GPU-accelerated deep learning algorithms [3]. Our technique, Deep Filtering, employs a system of two deep convolution neural networks (CNNs) that directly take time-series inputs for both classification and regression.

In our foundational article [3], we showed that CNNs can outperform traditional machine learning methods, reaching sensitivities comparable to matched-filtering for directly processing highly noisy time-series data streams to detect weak GW signals and estimate the parameters of their source in real time, using GW signals injected into simulated LIGO noise.

Deep Filtering demonstrated, for the first time, that machine learning can successfully detect and recover true parameters of real GW signals observed by LIGO, and achieve performance comparable to matched-filtering methods while being several orders of magnitude faster and far more resilient to transient noise artifacts, such as glitches. Furthermore, we showed that after a single training process, Deep Filtering can automatically generalize to noise having new Power Spectral Densities from different LIGO events without retraining.

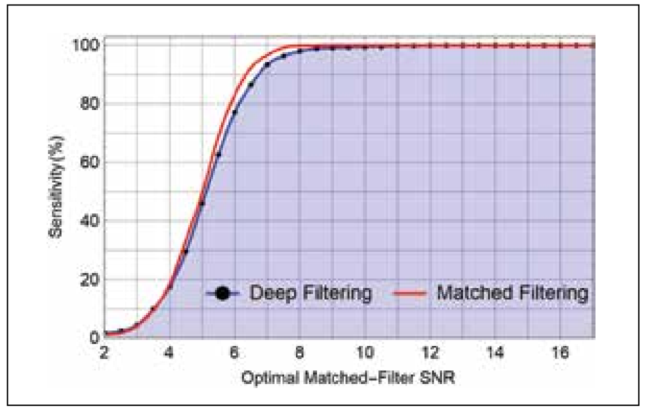

Figure 1: The curve shows the sensitivity of detecting GW signals injected in real LIGO noise from our test set using Deep Filtering and with matched-filtering with the same template bank used for training. These results imply that deep learning is capable of detecting signals significantly weaker than the background noise.

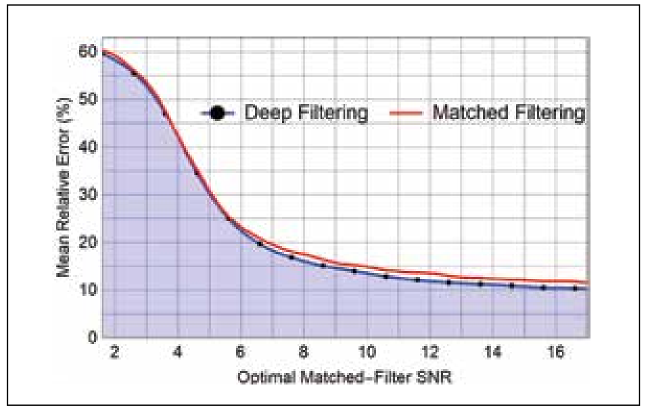

Figure 2: Mean percentage absolute error of estimating masses on testing signals at each SNR, injected in real LIGO noise from events not used for training, compared to matched-filtering using the same template bank that was used for training. Deep learning can interpolate to test set signals with intermediate parameter values.

METHODS & CODES

The training set contained about 2,500 waveform templates, generated with the open source EOB model [4], with black hole component masses between 5 and 75 solar masses sampled in steps of 1 solar mass. The input duration was fixed at 1 second, with a sampling rate of 8,192 Hz. The testing dataset also contained approximately 2,500 templates with intermediate component masses.

We produced copies of each signal by shifting the location of their peaks randomly within the final 0.2 seconds to make the CNNs more resilient to time translations. We obtained real LIGO data from the LIGO Open Science Center (LOSC) around the first three GW events; namely, GW150914, LVT151012, and GW151226. Each event contained 4,096 seconds of real data from each detector. We used noise sampled from GW151226 and LVT151012 for training and validation of our model and noise from GW150914 for testing.

We superimposed different realizations of noise randomly sampled from the training set of real LIGO noise from the two events GW151226 and LVT151012 and injected signals over multiple iterations, thus amplifying the size of the training datasets. The power of the noise was adjusted according to the desired optimal matched-filter signal-to-noise ratio (SNR) for each training round. The inputs were then whitened with the average Power Spectral Densities of the real noise measured at that time period.

We also scaled and mixed different samples of LIGO noise together to artificially produce more training data, and we also added various levels of Gaussian noise to augment the training process. However, the testing results were measured using only pure LIGO noise not used in training with true GW signals or with signals injected from the unaltered test sets.

We used the Wolfram Language neural network functionality, built using the open-source MXNet framework, that uses the cuDNN library for accelerating the training on NVIDIA GPUs. The learning algorithm was ADAM, and other details were the same as before [3]. While training, we used the curriculum learning strategy in our first article [3] to improve the performance and reduce training times of the CNNs while retaining performance at very high SNRs.

RESULTS & IMPACT

This research has shown for the very first time (Figs. 1 and 2) that CNNs can be used for both detection and parameter estimation of GW signals in raw LIGO data [5]. The intrinsic scalability of deep learning can enable fast, automated GW searches covering millions or billions of templates over the full range of parameter-space that is beyond the reach of existing algorithms. Extending Deep Filtering to predict any number of parameters such as spins, eccentricities, etc., or additional classes of signals or noise is as simple as adding an additional neuron for each new parameter, or class, to the final layer and training with noisy waveforms with the corresponding labels. Furthermore, the input dimensions of the CNNs can be enlarged to take time-series inputs from multiple detectors, thus allowing coherent searches and measurements of parameters such as sky locations.

The average time taken for evaluating each of our CNNs per second of data is approximately 85 milliseconds and 540 microseconds using a single CPU core and GPU, respectively, thus enabling analysis even faster than in real time.

WHY BLUE WATERS

Blue Waters played a critical role in creating the numerical relativity waveforms used to train and test deep learning algorithms. In recent developments, Blue Waters has provided the required scale and computational power to construct deep neural networks using distributed learning inolving over 1,024 GPUs.

PUBLICATIONS & DATA SETS

George, D., and E.A. Huerta, Deep learning for real-time gravitational wave detection and parameter estimation: Results with Advanced LIGO data. *Physics Letters B*, 778 (2018), pp. 64–70.