Deep Learning with HPC Simulations for Extracting Hidden Signals: Detecting Gravitational Waves*

Extended Abstract†

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ABSTRACT

We introduce Deep Filtering, a new machine learning method for end-to-end time-series signal processing, which combines two deep *one-dimensional* convolutional neural networks for classification and regression to detect and characterize signals much weaker than the background noise. We trained this method with a novel curriculum learning scheme on data derived from HPC simulations and applied it for gravitational wave analysis specifically for mergers of black holes and demonstrated that it significantly outperforms conventional machine learning techniques, is far more efficient than matched-filtering, offering several orders of magnitude speed-up, allowing real-time processing of raw big data with minimal resources, and extends the range of gravitational waves that can be detected by LIGO. This initiates a new paradigm for scientific research which employs massively-parallel numerical simulations to train artificial intelligence algorithms that exploit emerging hardware architectures such as deep-learning-optimized GPUs. Our approach offers a unique framework to enable coincident detection campaigns of gravitational wave sources and their electromagnetic counterparts.

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SUMMARY

A new era of gravitational wave (**GW**) astronomy has begun, with the recent Nobel-prize-winning discovery of GWs from a binary Black Hole merger announced by LIGO in 2016 [1] followed by several more GW events [2]. High-Performance Computing (**HPC**) plays a central role in GW astrophysics since numerical relativity simulations, that solve Einstein's field equations for sources of GWs such as black-holes, neutron stars, and supernovae, are required to create template banks used to extract GW signals from the highly noisy data streams and to infer the astrophysical properties (parameters) of the source by comparison [1,2].

GWs alone allow us to observe exotic events that do not emit light and probe the structure of the Universe, the behavior of gravity in the strong-field regime, the formation and evolution of black-holes, and possibly the nature of Dark Matter and Dark Energy [1,2]. The future of astronomy is multimessenger astrophysics in which we expect to *hear* an event first through our GW detectors, then immediately turn our telescopes around to *see* it, and also *feel* it via neutrino and other astro-particle detectors. These real-time multimessenger observations will lead to ground-breaking insights about the universe. However, current data analysis pipelines are limited by the computational costs of signal processing and the inability to scale to all types of sources [3].

Existing methods to extract weak GW signals rely on matched-filtering, a *template matching* technique requiring repeated comparisons of data streams against over 300,000 templates [3]. Even with thousands of CPUs, the flagship searches for modeled sources are restricted to a small subset, i.e., quasi-circular and spin-aligned compact binaries. The computational complexity of matched-filtering explodes exponentially with the number of templates. Therefore, targeting the full parameter-space of astrophysically motivated sources is computationally infeasible even with exascale resources.

Therefore, an efficient alternative method for simultaneous real-time analysis of big data collected by multiple observational instruments is necessary to enable real-time multimessenger astrophysics. Artificial Intelligence (**AI**), based on deep learning with artificial neural networks [4], is rapidly becoming a ubiquitous technology that is revolutionizing every industry today. Deep learning thrives on big data and has recently achieved dramatic successes, in every field of AI ranging from image/speech recognition and synthesis, to self-driving vehicles, to health care, to language understanding and translation [4]. Rather than performing template matching, deep learning algorithms have been shown to learn complex patterns relating inputs, leading to huge algorithmic speed-ups and scalability [4].

To overcome the limitations of existing methods, we developed Deep Filtering, a new highly scalable method for directly processing raw 1D data using deep learning, which enables real-time detection and parameter estimation of GW signals hidden in extremely noisy time-series data [5]. While Convolutional Neural Networks (CNNs) are typically applied to images or spectrograms, here we show that a

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system of two 1D CNNs can directly process raw 1D time-series data for classification and regression of extremely noisy signals. This approach is particularly appealing for data analysis as it diverts all the intensive computation to a *one-time* training process, therefore allowing us to scale to template banks of any size and still perform analysis rapidly with minimal resources. Whereas LIGO's highly optimized search algorithms still require thousands of dedicated CPUs to operate, we show that our DNNs can be evaluated faster than real-time with a single CPU and very intensive searches can be easily carried out with one GPU.

To demonstrate this method, we specifically designed and trained two deep 1D CNNs, with a novel curriculum learning training procedure, with gradually increasing noise levels, using templates derived from HPC numerical relativity simulations of black hole mergers, to analyze data streams from LIGO. The first CNN recognizes the presence of gravitational waves and the second one estimates the mass of each black hole. We show for the first time that 1D CNNs can be used for both signal detection and multiple-parameter estimation directly from highly noisy time-series data, once trained with templates of the expected signals, and that deep CNNs outperform traditional machine learning algorithms and reach accuracies comparable to optimized matched-filtering methods, while being several orders of magnitude faster, and extends the range of detectable signals.

Our results strongly indicate that CNNs are highly efficient and versatile tools for directly processing any raw noisy data streams to identify signals, or transient noise [6], and can be widely applied in other disciplines of engineering, science, and technology, ranging from weather and earthquake prediction to finance. Furthermore, we introduce a new paradigm to accelerate scientific discovery by using data from massively-parallel HPC simulations on traditional supercomputers to train artificial intelligence algorithms that exploit emergent hardware such as deep-learning-optimized GPUs, FPGAs, and neuromorphic chips.

It is evident that GW astronomy, multimessenger astrophysics, HPC simulations, and AI based on deep learning with innovative hardware architectures, will each play a dominant role in the near future. This work offers the first opportunity to merge these exciting fields to accelerate scientific discovery by initiating a new paradigm for interdisciplinary research and by integrating expertise in observational astronomy, theoretical and computational physics, data science, signal processing, and computer science to observe events and gain scientific insights that may otherwise be missed.

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