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Matched Filtering using Neural Networks

Galit Alter*

Department of Space Technology, Debre Tabor University, Debre, Ethiopia

About the Study

Gravitational wave science is a pioneering field with rapidly evolving data analysis methodologies and is currently inventing by absorbing deep learning techniques. Most of the sophisticated flagship searches in this area rely on proven true principles of consistent filtering at the core. This article makes important observations about the relationship between new deep learning and traditional methods. Coordinated filtering is formally equivalent to a particular neural network. This means that neural networks can be constructed analytically to implement exact matching filtering, further training with data, and adding complexity to improve performance. In addition, the proposed neural network architecture shows that it is superior to matching filtering, both with and without prior knowledge of parameter distributions. Given in advance, the proposed neural network can approach statistically optimal performance.

We also propose and study two different neural network architectures, MNet-Shallow and MNet-Deep. Both can implement matched filtering at initialization and train on the data. Although the structure of MNet-Shallow is simple, MNet-Deep is more flexible and can handle a wider range of distributions. Our theoretical findings are supported by experiments using real LIGO data and synthetic injections. Here, the proposed method goes far beyond compliant filtering for false positives. By matching filtering and basic equivalence of neural networks, we define a "standard light source of complexity" and characterize the relative complexity of different approaches for searching gravity wave signals in a common framework. You can also get a glimpse of interpretability, an interesting symmetry that can provide clues as to how neural networks tackle the problem of finding signals with overwhelming noise. Finally, our results suggest a new perspective on the role of deep learning in gravitational wave detection.

An abundance of prior works has been using deep learning methods to detect gravitational waves. Convolutional neural networks have been shown to be able to discriminate gravitational waves and their parameters from binary black holes and binary neutron stars with performance similar to the matched filtering searches currently used in LIGO, Virgo, and KARGA. In addition, this machine learning (ML) technique can be applied to glitch and noise transient identification, signal classification and parameter estimation, data denoising, and more. Although these pieces feature neural networks that can approach the performance of matched filtering, they are still often applied or displayed as "black box" models. This makes it difficult to evaluate the statistical evidence provided by the neural network and include this evidence in the downstream analysis. To explore the potential for improved performance.

Neural networks, we abstractly formulate the gravitational wave detection problem as the detection of a parametric signal family. We show that within this framework it can also be used as a primary starting point for learning analytically constructed networks from data. The result is a signal classifier that outperforms initialization, that is, "stands on the shoulders of giants." Such learning can be applied to both scenarios with and without prior distribution of parameters. In particular, when a prior distribution is given, we show that the learned neural network can (empirically) approach the statistically optimal performance.

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Address for Correspondence: *Galit Alter, Department of Space Technology, Debre Tabor University, Debre, Ethiopia; Tel: +251931883823; E-mail: altergalit@gmail.com*

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