Deep Learning For Gravitational Wave Astrophysics

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INTRODUCTION

AIM
Match-filtering is SLOW: A template bank for all black hole binaries requires over 300k waveforms, each thousands of samples long. To use this template bank further involves convoluting it with strain data in all locations in all channels. This is slow and expensive.

Sub-optimal: While mathematically optimal on Gaussian noise, LIGO noise is non-Gaussian and non-stationary. It also lacks generalization, meaning what’s out of the template bank is ignored, hence search sensitivity is limited by size of template bank.

Go Faster: Deep learning is known for parameter re-use and compression in approximating distributions from samples. Both the distribution of LIGO noise and binary black hole waveforms are smooth, reasonably consistent, and free to sample from. Thus, deep learning may accelerate the detection process with less overhead and larger template banks.

METHOD
Concurrent Non-Causal Wavenet: We adopt a modified version of Wavenet[2] that runs concurrently on each channel, and the pair-wise differences of each channel. A small final CNN is used to combine outputs from all Wavenets to produce the final detection.

RESULTS
Detection Sensitivity:
We found our model accurate enough to detect almost all real events without retraining, even those with low SNR without retraining to adjust for power-spectrum-density. Due to the lack of real detections, we also benchmark model sensitivity on injected datasets.

Detection Accuracy:

Computational Performance:
Our model is capable of processing four seconds of dual-channel data per second on one NVIDIA V100, achieving real-time performance even with spinning template bank.

CONCLUSIONS
We have developed a deep learning model that is as sensitive as matched-filtering, but significantly faster and that requires minimal re-training to adjust for changes in the sensitivity of the detectors.

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