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**Accelerating Gravitational Wave Parameter Estimation using Machine Learning**

Over the course of my fellowship, I propose the development of a novel likelihood-free machine learning method to rapidly infer the properties of gravitational wave source parameters. Gravitational waves (GWs), small perturbations in the fabric of space-time, are produced by some of the most violent events in the universe, such as colliding neutron stars and stellar mass black holes. My proposed method uses a form of machine learning known as conditional variational autoencoders [1], well known for their ability to estimate conditional probability distributions. When fully deployed, this method will have a dramatic impact on the speed with which we can identify events, forming the basis for GW parameter estimation in the future.

The goal of the Advanced Laser Interferometer Gravitational-wave Observatory (LIGO) Virgo Kagra Collaboration (LVK) is to directly detect, characterise and learn about the universe through GWs using large-scale [Michelson-Morley Interferometers](https://en.wikipedia.org/wiki/Michelson%E2%80%93Morley_experiment). The first direct detection of GWs from a pair of merging black holes was made on September 14th, 2015 [3], for this and subsequent detections the [2017 Nobel Prize](https://www.nobelprize.org/prizes/physics/2017/press-release/) was awarded. These instruments are intrinsically noisy and are affected by many external noise sources (i.e. seismic, thermal, quantum shot noise, etc.). We use Bayesian inference techniques to account for the uncertainty the noise contributes when estimating physical source parameters of detections [4]. Unfortunately, Bayesian inference techniques are computationally costly and can take between days and weeks to run [5]. As the sensitivity of our detectors improves we will see a dramatic rise in detections and therefore an increased computational cost. This is dwarfed by the equivalent rise in detections for the proposed next generation detectors where, with current approaches, the detection rate will far exceed the rate at which signals can be analysed [6]. As such, there is an urgent need for more efficient algorithms.

Multi-messenger observations aim to observe both the GW and the electromagnetic (EM) emission (or neutrino flux) from common astronomical events [7]. Such observations allow us to combine information from multiple independent instruments and mediums in order to gain further understanding of fundamental astrophysical phenomena, such as the Hubble Constant which governs the expansion rate of the universe [8]. The speed with which GW events can be localised on the sky by the LVK is crucial for rapid follow-up with other telescopes. As some classes of EM emission from events decay rapidly, current processing times can adversely affect the quality of EM observations and the science output gained from them.

The approach that I have developed using CVAEs not only reproduces the optimal Bayesian results, it can do so ~6 orders of magnitude faster than existing techniques, giving observers accurate sky localisation within less than a second. I have already recently demonstrated that my proposed low-latency machine learning method works in a simplified scenario (manuscript currently with referees at Nature Physics [9]), but there is still much work left to be done in order to deal with more realistic events. My approach has been shown to work well with merging binary black holes (two black holes rotating about a common center of mass) having durations of ~1s. However, other signals with strong probability of EM signatures such as merging binary neutron stars can have durations on the order of 1000s of seconds. I have shown that my method works well under idealised noise conditions (i.e. Gaussian noise), but LVK detectors are known to have non-Gaussian noise properties which may change as a function of time. Optimised sampling methods and further research on neural network architecture will be needed to handle such events in the future. Over the course of this fellowship I will:

* Develop new techniques to handle increasingly complex signals, including binary neutron stars and neutron star black hole mergers with longer durations.
* Consider optimal strategies to deal with realistic detector noise.
* Develop the existing code into a user-friendly software package to be made available to the GW community at large.

In addition to my most recent work, I have led many other machine learning projects over the past several years. During the 2016-2017 academic year I was awarded a 10-month [Fulbright Fellowship](https://en.wikipedia.org/wiki/Fulbright_Program) from the U.S. Department of State to study and perform research at the Max Planck Institute for Gravitational Physics in Hannover, Germany. I focused on data quality improvements within the LVK GW search. Using several machine learning techniques (restricted Boltzmann machines, deep fully connected neural networks, etc), as well as other statistical approaches, I developed an automatic flagging system to identify noise artefacts hindering the search for GWs. Following my Fulbright Fellowship, I led the development of a deep convolutional neural network for identifying binary black hole GW signals in simulated detector noise [10]. We showed that a network can be trained to match the sensitivity of the standard matched filtering analysis used at the core of GW searches. This work was one of the first papers to show that machine learning is a viable solution to many of the problems in our field, with added massive speed gains. As the LVK detectors reach their design sensitivity goals, sub-second identification of events will become crucial to handling the influx of expected signals. Such performance gains reduce the time between identifying an event and alerting other telescopes around the world, thus improving observation time dramatically. This paper has been published in Physical Review Letters.

The future of GW astronomy is bright and I believe machine learning will not only be able to replicate, but also exceed the performance of existing methods. I have already shown that this is possible, but there is still much left to be done to fully realize this goal including: the addition of more complex GW signals, inclusion of realistic noise and to package this method into a user-friendly tool for the greater scientific community. This fellowship will allow me access to some of the best hardware and researchers in machine learning and physics, further strengthening efforts to enhance my approach. When widely used, this proposed technique will have a dramatic impact on the speed with which we can identify events and allow us to gain new insights towards a greater fundamental understanding of our universe.

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