Accelerating gravitational wave signal discoveries and analyses with deep learning (IOP)

Intended promotor(s): *dr. C. Weniger (GRAPPA, ITFA); IvI promotor*
Intended co-promotor(s): *dr. S. Nissanke (GRAPPA, API, IHEF); lab manager*

Background:

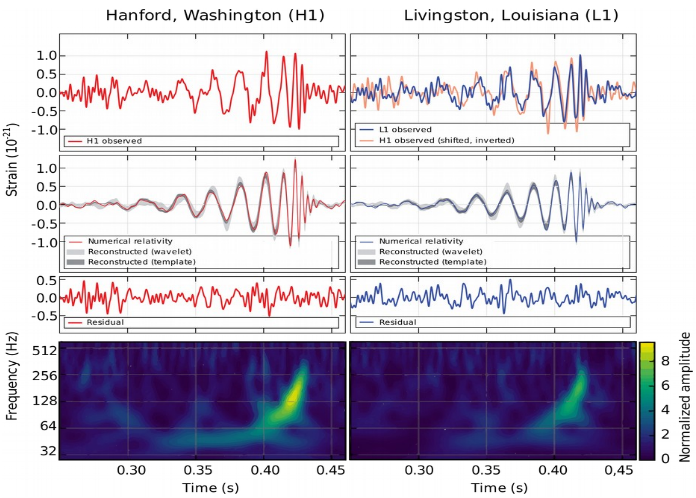

Figure 3: First measurements of GW signals in time and frequency space. LIGO measurement of the GWs at the Livingston (right) and Hanford (left) detectors. From [1].

The breakthrough discovery of the first graviational wave (GW) signal in September 2015 (Nobel Prize 2017) has opened a new window to the Universe (Fig. 1). GWs are generated by the merger of compact objects (neutron stars and black holes, NSs and BHs respectively). Detailed analyses of the signal waveforms during the initial inspiral, merger and final ringdown phase provide crucial information about properties of the progenitor and final objects, including for instance their masses and the enclosing environment. These measurements are critical for understanding the astrophysical origin and fate of compact objects, allow to probe gravity in the strong field region, provide new cosmological probes for dark energy and dark matter.

GW signals from compact mergers are modelled in a number of ways, ranging from semi-analytical calculations with the effective one-body (EOB) approximation to computationally expensive numerical relativity (NR) and hydrodynamical simulations. Generating individual waveforms with EOB or NR takes from minutes to many days or even months (NR). As a consequence, parameter inference with commonly used Monte Carlo samplers requires weeks or months, even for signal models with a reduced parameter set. This is a major bottleneck in current GW research, which hinders an exhaustive study of all aspects of GW signals, and significantly impairs timely multi-wavelength follow-ups. Recent developments in deep learning and differentiable programming have the potential to accelerate both the signal identification and parameter inference in numerous ways, potentially by orders of magnitude, which would have significant, potentially groundbreaking, impact on all fronts of GW research.

Aims:

The specific goals of the project are (a) training of a surrogate model for GW signals in order to accelerate the generation of waveforms, likely by orders of magnitude; (b) development and exploration of new methods for fast and accurate parameter inference; and (c) increasing the scope and diversity of GW searches and analysis by successively increasing the model complexity, including for instance spin information.

Approach:

Task 1 (yrs 1+2): Training of surrogate generative model for GW signals; publication of method (*deliverable 1*) and scientific results (*deliverable 2*). **Task 2 (yrs 3+4):** Usage of surrogate model and other techniques for parameter inference of GW signals, publication of scientific results (*deliverable 3*). Extension of surrogate model to larger variety of signals; publication of scientific results (*deliverable 4*). Thesis write-up (*deliverable 5*).

From an AI perspective, we are interested in parameter regression and parameterized (surrogate) models for wave functions. We aim at accurate posterior distributions and Bayesian evidence calculations. Furthermore, generative models for waveforms would ideally allow a direct connection with the physical interpretation of the compact binary systems. Training data comes from multiple source (EOB, NR, like outlined above), and will be typically labeled with 10-20 parameters. We plan to use existing template databases with millions of waveforms, as well as generate new ones using the EOB method, if necessary (in collaboration with one of the world-leading GW source modelling experts dr. Tanja Hindere, a D-ITP fellow). However, for NS-NS mergers, only a very sparse training data set is available.

We will use supervised learning of deconvolutional neural networks (DNNs) to define surrogate models against which we can compare other methods [2,3]. We then plan to train neural networks expressed as ordinary differential equations (ODE) [4], and to identify via sparsity constraints minimal sets of equations that faithfully reproduce the training data. We expect that this approach does not only allow a physical interpretation of the learned waveform dynamics in terms of traditional equations of motion, but also provides a better regularization in situations with sparse training data (like for binary NS mergers) than DNNs.

On the parameter regression side, we will train a traditional convolutional neural net (CNN) again as baseline model (see [2] for previous work). We will then use the differentiable surrogate waveform models from task 1 as input into Bayesian methods to explore the posterior distributions of the physical parameters. Besides standard Hamiltonian Monte Carlo (HMC) [5], we will also test recent extensions based on expressive parameterizations of posterior distributions, and compare accuracy and speed of the methods.

Impact:

The application of AI techniques in the analysis of GWs has just begun to be explored [2-6]. In this project, we would build the first surrogate models for GW signals using AI techniques using our unique cutting-edge expertise. Further planned innovations are the usage of auto-differentiable NN models in HMC sampling, the training of ODEs to improve interpretability and physical regularization of sparse training data. If succesful, the results of this project would have significant, if not ground-breaking, impact on GW research, on the speed with which electromagnetic and other messenger follow-up observations can be initiated, and the accuracy of parameter regression. On the AI side, the project will deliver a comparison between "traditional" generative and regression models using CNNs and DNNs, and new approaches connected to, e.g., ODE solvers, as well as various advanced sampling techniques and extensions of HMC methods.

References:

[1] The LIGO Scientific Collaboration & the Virgo Collaboration. Observation of Gravitational Waves from a Binary Black Hole Merger (2016).

[2] Shen, H., Huerta, E. A. & Zhao, Z. Deep Learning at Scale for Gravitational Wave Parameter Estimation of Binary Black Hole Mergers (2019).

[3] Shen, H., George, D., Huerta, E. A. & Zhao, Z. Denoising Gravitational Waves with Enhanced Deep Recurrent Denoising Auto-Encoders (2019).

[4] Chen, R. T. Q., Rubanova, Y., Bettencourt, J. & Duvenaud, D. Neural Ordinary Differential Equations (2018).

[5] Bouffanais, Y. & Porter, E. K. Bayesian Inference for Binary Neutron Star Inspirals Using a Hamiltonian Monte Carlo Algorithm (2018).

[6] George, D. & Huerta, E. A. Deep Learning for Real-time Gravitational Wave Detection and Parameter Estimation with LIGO Data (2017).