Using abstract waveforms to infer gravitational wave source properties with machine learning

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LIGO Caltech SURF Pre-Proposal

Due to the recent confirmation of GW170817, a binary neutron star merger, which sent us electromagnetic and gravitational wave data, it is important for astronomers to have the ability to efficiently interpret data. Extensive research has been conducted on low-latency detections, but our goals focus on decreasing time and efforts for data interpretation. Singular value decomposition is applied to original GW form candidates to minimize the efforts of LIGO's filtering analysis. This project inputs signal-to-noise ratios from SVD waveforms into a neural network to achieve an output of a parameter estimation of source dimensions.

I. INTRODUCTION

Gravitational Waves (GW) were first detected in 2015 by the Laser Interferometer Gravitational-Wave Observatory (LIGO) [1]. GW are physical ripples in the fabric of space and time, stretching and compressing space matter. For this project, we will focus on GW that originate from compact binary coalescence (CBC), which consists of the attraction and aggressive combination of two extremely massive objects such as black holes or neutron stars. However, GW can also originate from other exotic events in the universe, such as supernovae. They are detected by laser interferometers such as LIGO, which uses laser interference to measure the impact of passing GW [1]. GW can be detected in other ways, but we will use data from LIGO for the purpose of this project. LIGO can give scientists valuable information about each source, like mass or location.

The first binary neutron star merger [2] was a breakthrough for the understanding of astrophysics. Both the Europeans Space Agency's INTEGRAL telescope and NASA's Fermi Gamma-ray Space telescope observed a short emission of gamma-rays [3]. The Hubble Space Telescope and The Chandra X-ray Telescope also detected radiation from the same direction [3] in August 2017. It was discovered to be a binary neutron star merger. The detection of this merger has allowed us to view this event in two different ways. The event has emitted radiation as well as a GW and is classified as a multi-messenger event [2]. Due to GW, astronomers are able to study characteristics of merging binary systems, such as signal-to-noise ratio (SNR), mass, and electromagnetic radiation [4, 5]. Studies have also shown incredible efforts towards low-latency detection times and efficient data attainment [6]. We have become skilled at low detection times, up to less then a second [5, 6]. This project aims to improve the efficiency of data interpretation. Although attainment time is crucial to this process, our understanding about the physical dimensions of GW, allows us to compare findings with scientists who follow electromagnetic radiation. This is a first open door to multi-messenger astronomy.

Interferometers complete GW searches and automatically filter data with expected GW forms. The filtering analysis computes a comparison between a large number of modeled CBC waveforms and the detector output, which may contain GW signals from compact binaries covered by background noise [7]. The result is a waveform sample space as shown in Figure 1. It is vital to extract as much information as possible from GW and understand how studies face issues when attempting to discover different dimensions [8–10]. These original data sets in Figure 1 contain waveforms which hold information about dimensions and seem to look similar in appearance. However, these waveforms differ in computational complexity [10].

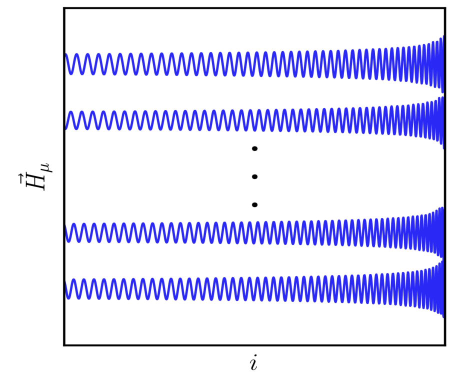

FIG. 1: Original waveform candidates of real GW.

Efforts to decrease attainment times on GW data have been extensive [6] , but many have not studied the efforts needed for low-latency interpretation of GW detections. The process to uncover source dimensions can be expensive and time consuming. Original waveforms can be transformed through singular value decomposition (SVD) which reduces the amount of GW filtering required to analyze a given region of parameter space of compact binary coalescence [11]. However, the abstract waveforms complied through SVD (Figure 3) do not contain any concrete evidence regarding the dimensions we hope to reveal. All of the abstract waveforms exist in unique dimensions and do not overlap with one another [8, 9]. Our project aims to create a structure to reveal these dimensions from abstract vectors to obtain new information efficiently.

The modeled waveforms represented in Figure 1 can be compiled into a parameter space, graphed by up to four selected dimensions shown in Figure 2. Computing abstract waveforms from SVD that will fit in the gaps of the sample space in Figure 3 is one way to apply machine learning. Computationally comparing SVD waveforms

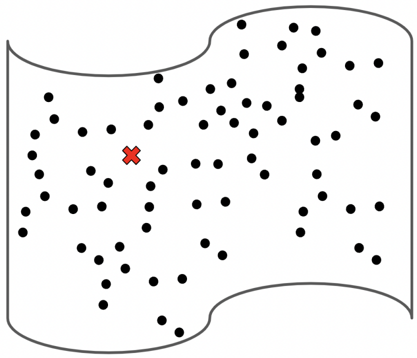

FIG. 2: The figure represents pre-SVD modeled waveforms under a parameter space of a maximum of 4 dimensions. The red X indicates a possible abstract modeled waveform.

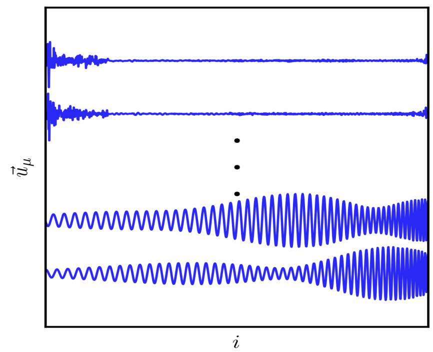

FIG. 3: The result of abstract waveforms from SVD computed using original gravitational waveforms

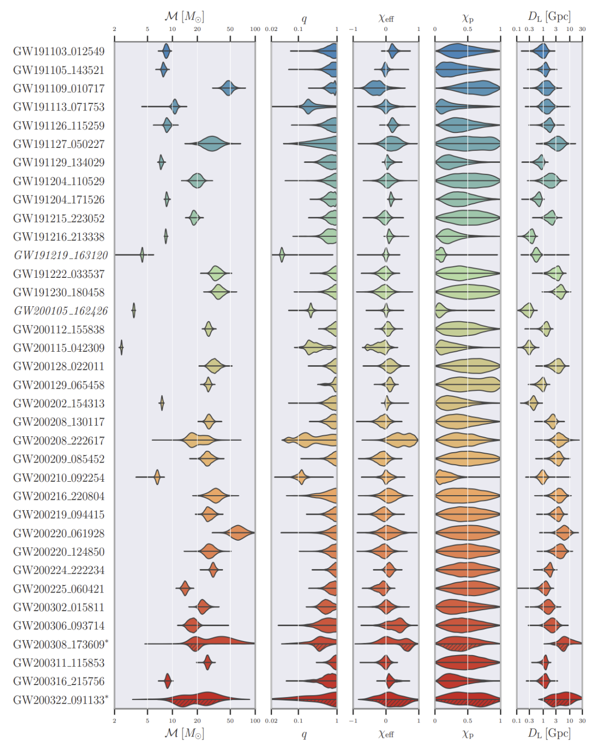

FIG. 4: An example of a parameter estimation that we hope to produce using SVD, abstract waveforms instead of original wave forms. For each event (y-axis) the estimation shows parameters for possible values of the specified dimension. The more spread data for each event, the more uncertain we are about the value of the dimension [13].

with original waveforms can be an extensive process. Instead of waiting to map the SVD for comparison with the original waveforms, our project looks to use the abstract waveforms through a neural network to discover the physical properties of GW. The use of a neural network has been confirmed and tested as a reliable structure for a machine learning algorithm [12].

Normally, waveforms that are filtered into GW candidates will be applied to an equation to map a Bayesian inference parameter estimation, and demonstrate property probabilities of the CBC. However, this process is expensive and time-consuming. The proposed project will use neural networks to connect abstract waveforms that are produced by SVD to the physical properties of GW candidates. SNR time series will be computed from SVD waveforms, which than will be ingested into a neural network to compile a parameter estimation and demonstrate dimension probability. This estimation space, shown in Figure 4, has the potential to hold important information regarding specific dimensions of GW, solely created through abstract waveforms.

II. PROJECT PLAN

Our first goal is to use the neural network to create a sample of abstract waveforms from the original waveforms. Using SVD, Equation 1 is applied to waveforms shown in Figure 1. Abstract waveforms (Figure 3) will automatically produce a SNR which is fed into the neural network, to achieve a possible parameter distribution.

Since filtering analysis can be computationally expensive, we want to reduce the expenses of GW filtering, and apply SVD to the original waveforms [6]:

$$h = \sum a_\mu u^\mu \quad (1)$$

where h are physical waveforms, a are reconstruction coefficients or overlaps, and u are the new, abstract basis vectors [11]. We can easily view more extreme differences between the wave forms after SVD transformation. Also, a smaller set of data is obtained through SVD. The abstract vectors are formulated from real GW data, but the calculation of real waves from the cosmos can be expensive to compute through GW filtering.

After SVD transformation to compute abstract waveforms, each wave is scanned with an abstract model to compute a SNR. The SNR is applied to an equation that maps a Bayesian inference parameter estimation. The Bayesian framework allows the evaluation of the probability of dimensions [10] of abstract waveforms. However, this is where we will use the neural network instead of a complicated computation. Directly using Bayesian calculations to map the parameter estimation can be costly and contain extensive efforts. To avoid this, we will apply machine learning to SNRs to discover values in a variety of different dimensions. We aim to minimize interpretation time with the use of a neural network through machine learning to map an inference parameter estimation.

When applying abstract waveforms and SNR to the creation of the parameter estimation, we can decipher which models fit the estimation, while looking for higher probabilities for each dimension. Indicating more probable models and tracing back to our neural network, we can identify the value of factor a from Equation 1 to better understand the quantitative values of the individual dimensions in-bedded in abstract waveforms. Awareness of the size of the parameter space is vital to the probability results. It is difficult to apply these methods over a fixed sample of data, as well as a fixed number of dimensions to attain quality results [10], hence the extreme efforts and costs this process would require. We hope our project of applying SVD and machine learning will introduce a simplistic method of data interpretation from abstract waveforms efficiently and inexpensively.

III. IMPLICATIONS

Data attainment and detection times have been minimized in recent research. Data interpretation lies in a realm of expenses and extreme efforts. The goal to calculate physics properties of the CBC from the abstract waveforms efficiently will allow a beginning to instantaneous review of possible overlaps in GW with EM data. This multi-messenger cooperation allows astronomers to view the universe through a lens never examined before.

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