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

Julianna Levanti, Ryan Magee
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, trains an algorithm, and hopes to achieve an output of a more accurate parameter estimation, such as a SkyMap to localize compact binary coalescences.

I. INTRODUCTION

Gravitational Waves (GWs) were first detected in 2015 by the Laser Interferometer Gravitational-Wave Observatory (LIGO) [1]. GWs are physical ripples in the fabric of space and time, stretching and compressing space. GWs originate from compact binary coalescence (CBC), the compact inspiral and merge of two extremely massive objects such as black holes or neutron stars. GWs can also originate from other exotic events in the universe, such as supernovae, but this project will focus solely on CBCs. GWs are detected by laser interferometers such as LIGO, which uses laser interference to measure the impact of passing GWs [1]. Information encoded in the GWs signal from LIGO can give scientists valuable information about each source, like distance and location.

The first binary neutron star merger, detected by LIGO in August 2017, [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 brief gamma-ray burst from the source [3]. The Hubble Space Telescope and The Chandra X-ray Telescope also detected electromagnetic (EM) radiation from the same direction [3]. Further evidence shows that the James Webb Space Telescope detected mid-infrared emission of exotic heavy-element tellurium [4]. Analysis of the GW data and the EM counterparts supported that the progenitor was most likely a binary neutron star merger. The event is important for the understanding of the universe due to its GW and EM counter parts [2, 5, 6] because it is the first open door to multi-messenger astronomy.

Studies have shown efforts towards low-latency GW detection [7]. This project aims to improve the efficiency of data interpretation, specifically localization.

Interferometers complete GW searches and filters data with expected GW forms. The filtering analysis computes a comparison between a large number of modeled CBC waveforms (Figure 1) and the detector output to produce a signal-to-noise ratio (SNR). SNRs can contain GW signals from compact binaries covered by background noise [8]. The data sets in Figure 1 contain waveforms accounting for a variety of masses and spins, which contain information about source parameters, but seem to look similar in appearance. However, these waveforms differ in computational complexity [9].

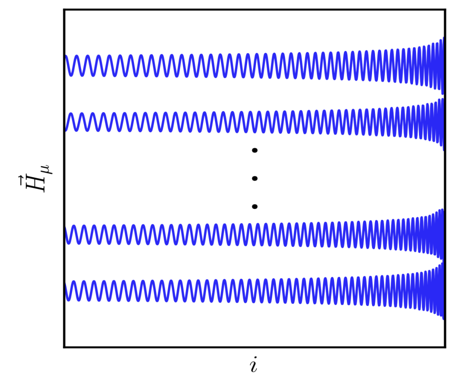

FIG. 1: Original waveform candidates of real GW. $\vec{H}_\mu$ is an arbitrary unit of measurement, referred to as strain. Strain is the distance the lasers are stretched or compressed by a passing gravitational wave, relative to the original length.

GW data from CBCs are dependant on a high number of dimensions and studies face issues in quantifying them [9–11]. The GW strain observed on earth depend on an array of 15 parameters. The parameters are as followed: chirp mass, symmetric mass, luminosity distance, the integration constant, time of coalescence, position of ascension, position of declination, inclination, polarization angle, spin of the primary object which includes the spin itself, the angle, and the orientation, and the spin,angle, and orientation of the secondary object [12]. 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 [9], hence the extreme efforts and costs full parameter estimation process require.

LIGO is able to create low-latency SkyMaps and measure SNRs by imposing constraints on the signal parameter space. Full parameter estimation measures this for many masses which generates more accurate SkyMaps for localization. However, this can take a long time, that it is computationally expensive.

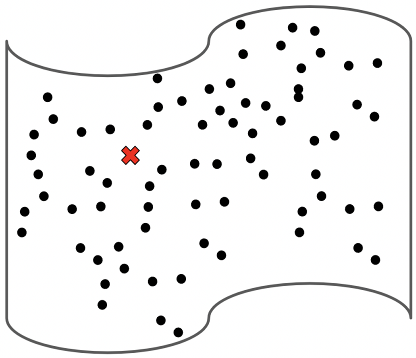

FIG. 2: The figure represents pre-SVD modeled waveforms under a parameter space of a maximum of 4 dimensions. The red X indicates a possible abstract modeled waveform.

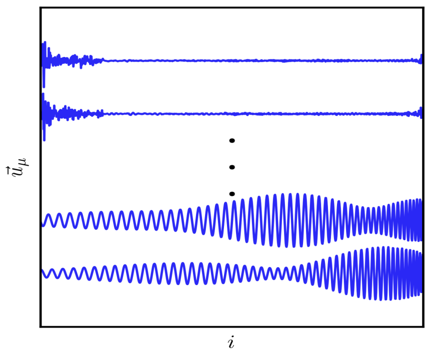

FIG. 3: The result of abstract waveforms computed through SVD using original gravitational waveforms

A. Singular Value Decomposition

We plan to generate SkyMaps more efficiently and accurately by using two strategies, one of which will be using singular value decomposition (SVD) (Equation 1) on original waveforms and mapping them onto an abstract parameter space. Original waveforms can be transformed through SVD which reduces the amount of GW filtering required to analyze a given region of a parameter space of compact binary coalescence [13]. However, the abstract waveforms complied through SVD (Figure 3) do not contain any concrete evidence regarding dimensions we hope to reveal. All of the abstract waveforms are orthogonal and do not overlap with one another [10, 11]. Our project aims to create a structure to reveal dimensions from abstract vectors and localize CBC sources efficiently.

B. Machine Learning

The modeled waveforms represented in Figure 1 can be compiled into a parameter space shown in Figure 2. Computing abstract waveforms from SVD that will fit in the gaps of the sample space in Figure 3 through a neural network is an example of how apply machine learning. Computationally comparing SVD waveforms 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 a GW source. The use of a neural network has been confirmed and tested as a reliable structure for a machine learning algorithm [14].

II. PROJECT PLAN

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 SNRs 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 localization parameter estimation and demonstrate localization dimension probability. SkyMaps will be centralized on source localization and distance.

The project will consist of generating SkyMaps more efficiently and accurately, by 1) using abstract waveforms formulated by Singular Value Decomposition and 2) utilizing machine learning techniques such as Simulation Based Inference (SBI) that would reduce computational costs while producing a low-latency, SkyMap result.

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 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 [7]:

$$h = \sum a_\mu u^\mu \tag{1}$$

where h are physical waveforms, a are reconstruction coefficients or overlaps, and u are the new, abstract basis vectors, all indexed by μ [13]. 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 true SNR from the cosmos can be expensive to compute through GW filtering.

Machine learning can help us find more efficient ways to interpret strain data. Past strain data and the corresponding outputs (SkyMap values that were previously formulated) will be fed into an SBI motivated framework. We will indicate a parameter set, run simulations to train the algorithm, allow it to learn the shape of our current data, and build a posterior. From this, we can then input SVD SNRs and hope for an outcome that tells us characteristics about the source, quicker than using the original waveforms. Our final goal will be to construct an accurate SkyMap showing the 50% and 90% confidence areas of the sky where the source is located.

To justify our project, we researched two SkyMap algorithms. BAYESTAR, which computes low-latency SkyMaps by assuming a singular mass [15], and BILBY, which takes many masses into account for a better localized SkyMap [16]. However, BILBY has a computing time on the order of hours to days. We extracted data in square degrees and compared the two systems in 50% and 90% confidence areas. To filter data and study true results, criteria have been set at signal-to-noise signal greater than 9, and a false alarm ratio (FAR) less than 3.171e-9 (1 in 10 years) or less than 6.342e-8 (1 in 6 months).

Evidence shows that although BILBY's complex computations can be prolonged, it can produce a more accurate SkyMaps than BAYESTAR's low-latency algorithm. The project strives to achieve each algorithm's strengths of low-latency and more accurate localization with the use of SVDs and machine learning.

When applying abstract waveforms and SNR to the creation of the SkyMap parameter estimation, we can decipher which models fit the estimation, while looking for higher probabilities for the 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 within abstract waveforms.

By utilizing LALApps, a public collection of gravitational wave data, we are able to set values for each parameter and initiate a variety of distances to binary coalescence gravitational wave sources. We have generated simulated signals to be used in the training network. Due to the high level of dimensions applicable to the binary coalescences, all parameters in the LALApps configuration were kept fixed at a selected measurement, which allowed distance to be a free parameter.

We hope our project of applying SVD and machine learning will introduce a low-latency method of accurate localization from abstract waveforms efficiently and inexpensively.

III. IMPLICATIONS

Data attainment and detection times have been minimized in recent research. Data interpretation still requires extreme expenses and efforts. The goal to calculate physical 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.

[1] B. P. Abbott et al. (LIGO Scientific), Phys. Rev. D **95**, 062003 (2017), arXiv:1602.03845 [gr-qc].

[2] B. P. Abbott et al. (LIGO Scientific, Virgo), Phys. Rev. Lett. **119**, 161101 (2017), arXiv:1710.05832 [gr-qc].

[3] NASA ESA (2017).

[4] A. Levan et al., (2023), arXiv:2307.02098 [astro-ph.HE].

[5] R. Magee et al., Astrophys. J. Lett. **910**, L21 (2021), arXiv:2102.04555 [astro-ph.HE].

[6] B. P. Abbott, R. Abbott, T. D. Abbott, Abernathy, and others., .

[7] K. Cannon et al., Astrophys. J. **748**, 136 (2012), arXiv:1107.2665 [astro-ph.IM].

[8] A. Reza, A. Dasgupta, and A. S. Sengupta, (2021), arXiv:2101.03226 [gr-qc].

[9] J. Veitch et al., Phys. Rev. D **91**, 042003 (2015), arXiv:1409.7215 [gr-qc].

[10] K. Cannon, C. Hanna, and D. Keppel, Phys. Rev. D **84**, 084003 (2011), arXiv:1101.4939 [gr-qc].

[11] K. Cannon, C. Hanna, and D. Keppel, Phys. Rev. D **85**, 081504 (2012), arXiv:1108.5618 [gr-qc].

[12] V. Raymond, M. V. van der Sluys, I. Mandel, V. Kalogera, C. Rover, and N. Christensen, Class. Quant. Grav. **27**, 114009 (2010), arXiv:0912.3746 [gr-qc].

[13] K. Cannon, A. Chapman, C. Hanna, D. Keppel, A. C. Searle, and A. J. Weinstein, Phys. Rev. D **82**, 044025 (2010), arXiv:1005.0012 [gr-qc].

[14] R. Qiu, P. G. Krastev, K. Gill, and E. Berger, Phys. Lett. B **840**, 137850 (2023), arXiv:2210.15888 [astro-ph.IM].

[15] L. P. Singer and L. R. Price, Phys. Rev. D **93**, 024013 (2016), arXiv:1508.03634 [gr-qc].

[16] P. Baral, S. Morisaki, I. Magaña Hernandez, and J. Creighton, (2023), arXiv:2304.09889 [astro-ph.HE].