Parameter Estimation of Binary Black Hole Coalescence Using LSTM Neural Networks

Thesis by

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Honors Work in Physics
For PHYS-498
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College of Arts and Sciences
Valparaiso University

Spring 2025

Preface

This thesis marks the culmination of my time at Valparaiso University, where I have had the privilege of pursuing my academic passions with much enthusiasm. The journey to this point has been both challenging and rewarding, and it is with much gratitude that I reflect on the support and opportunities that have made this research possible.

My work combines my passion for astrophysics and computation, in an attempt to improve the computational efficiency of gravitational wave data analysis. The inspiration for this project was born from my fascination with the relatively new field of gravitational wave astrophysics and the swiftly expanding world of artificial intelligence and machine learning that we find ourselves in today. Being able to contribute, in however small a way, to this rapidly evolving field has been a deeply fulfilling experience.

I extend my sincerest of thanks to peers new and old, the academic faculty of the Valparaiso University physics, mathematics, and computer science departments, as well as friends and family whose support has been instrumental in my success over the last four years.

This research represents not just the completion of my degree but also the beginning of what I hope will be a lifelong pursuit of knowledge and discovery.

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April 24, 2025

Abstract

The Advanced Laser Interferometer Gravitational Wave Observatory (aLIGO) made its first detection of gravitational waves in 2015. Since then, the rate of event detection has only increased, with a detection being made every 2-3 days during the current observing run, $O4$. This rapid influx of data has the potential to create bottle-necks in data analysis efforts, and can delay the scientific progress which requires it. Traditional gravitational wave data analysis techniques, such as matched filtering, require extremely large template banks of synthetic gravitational waveforms and can often fail to provide meaningful limits on system parameters. Not only is this process computationally intensive, but it also requires a preprocessing of the data. Given the amount of effort this analysis takes, the results leave much to be desired. With recent advances in machine learning, there have been hopes that many of the bottle-necks currently afflicting "big data" may be effectively resolved. This has proven to hold true in many areas of science, even gravitational physics. Machine learning neural networks have already demonstrated the ability to flag whether or not a signal is buried within noise, denoise time-series data and extract the signal, and make accurate parameter estimates. However, the majority of these neural networks still rely on data preprocessing or transformation prior to analysis, raising the question of whether a neural network could instead directly intake raw, noisy, unprocessed time-series signals from a laser interferometer and accurately estimate key system parameters. This thesis covers the development, performance, and analysis of a neural network that, given a time-series of raw, noisy, unprocessed signal from a laser interferometer, can accurately predict the chirp mass of the binary black hole (BBH) system that produced the signal. This advancement has the capability of significantly increasing the computational efficiency of gravitational wave data analysis and yielding more accurate parameter estimates than current techniques.

Contents

Chapter 1

Introduction

1.1 A Brief History of Gravity

The concept of gravity has long captivated scientists, marking one of the most intriguing fields of study in modern physics. Ancient Greek philosophers such as Aristotle believed that objects had a tendency to move back toward their 'natural place.' Thus, objects composed of Earthly elements would fall back to Earth [1]. In modern times, gravity is understood to be a fundamental interaction between massive objects. The evolution of our understanding of gravity was most noteably accelerated by the works of Sir Isaac Newton and Albert Einstein, each of whom revolutionized the way gravity was to be understood.

The first significant leap in understanding gravity came with Sir Isaac Newton's *Philosophiæ Naturalis Principia Mathematica* in 1687. Within, he formulated the Universal Law of Gravitation which postulates that every mass exerts an attractive force on every other mass. Mathematically expressed as Eq. 1.1, Newton's theory unified terrestrial and celestial mechanics, providing a robust framework for predicting planetary orbits, tides, and the trajectory of comets [2].

$$F = G\frac{m_1 m_2}{r^2} \tag{1.1}$$

Despite its success, Newtonian gravity exhibited limitations in extreme circumstances. As astronomical observations became more precise into the 20th century, scientists noted discrepancies (the precession of Mercury's orbit for example) that could not be explained by Newtonian Mechanics, particularly in regions of intense gravitational fields and on cosmic scales [3].

In 1915, Albert Einstein introduced a paradigm shift with his *General Theory of Relativity*, proposing that gravity is not a force acting at a distance but rather a consequence of spacetime curvature caused by mass and energy [4]. A popular analogy compares spacetime to a stretched rubber sheet: placing a heavy object on the sheet creates a depression, causing smaller objects nearby to move towards it, mimicking the attractive force of gravity.

Einstein's theory explained several phenomena that Newton's could not, including the precession of Mercury and the bending of light around massive objects. Einstein's field equations, which mathematically describe how matter and energy influence spacetime curvature, also predict the existence of gravitational waves — ripples in spacetime generated by accelerating massive objects.

1.2 Gravitational Waves

Gravitational waves are ripples in the fabric of spacetime, predicted by Albert Einstein in 1916 as a consequence of his *General Theory of Relativity*. Under specific conditions — massive bodies accelerating — the field equations predict the generation of gravitational waves. Unlike electromagnetic waves, which propagate *through* space, gravitational waves are oscillations in spacetime *itself* allowing them to pass through matter unimpeded. These waves travel at the speed of light and carry energy away from their source [5].

These waves are encoded with information about the source they emanate from. For example, the frequency and amplitude of gravitational waves emitted from a binary black hole merger are directly related to the masses of the black holes and their orbital characteristics. This allows for the inference of a number of system parameters; these efforts being the main subject of this thesis.

Although gravitational waves were a natural consequence of Einstein's field equations, they remained undetected for a whole century. General relativity suggested that binary systems, such as orbiting black holes or neutron stars, should emit gravitational waves. In doing so, the system loses energy and gradually spirals inward until the two bodies merge. The first indirect evidence of gravitational waves came in 1974 through the work of Russell Hulse and Joseph Taylor. The pair studied a binary pulsar system and noted a gradual orbital decay consistent with energy loss due to gravitational wave emission [6]. This discovery provided powerful evidence for not only the existence of gravitational waves, but general relativity as a whole, and led to Hulse and Taylor receiving the Nobel Prize in Physics in 1993.

The direct detection of gravitational waves by the Laser Interferometer Gravitational-Wave Observatory (LIGO) was acheived a century after Einstein published his field equations. The unprecedented precision required to do so was made possible only by incredible advancements in laser interferometry. This detection, resulting from the merger of two intermediate mass black holes, confirmed a fundamental prediction of general relativity and ushered in a new era of physics known as gravitational wave astronomy [7].

1.3 Laser Interferometry

The detection of gravitational waves requires measuring minuscule distortions in spacetime, often to the order of 10^{-18} meters, or $1/1000$ the diameter of a proton. Such extreme precision is achieved through a technique know as laser interferometry, a method which exploits the wave nature of light to detect differential changes in the lengths of two perpendicular arm cavities.

Operating on the principle of interference, a Michelson interferometer consists of a laser source, beam splitter, two perpendicular arms cavities of equal length, and a photodetector. Upon entering the interferometer, the laser is split and sent down the two perpendicular arm cavities. These two beams are reflected back from the end of each arm cavity and recombine at the beam splitter before being sent into the photodetector. Under optimal conditions, upon recombination the two laser beams will destructively interfere resulting in zero light at the photodetector. However, conditions are never optimal and environmental noise and/or gravitational waves will slightly alter the length of each arm cavity; this in turn induces a phase shift between the two beams. This phase shift results in measurable interference intensity variation at the photodector [8, 9].

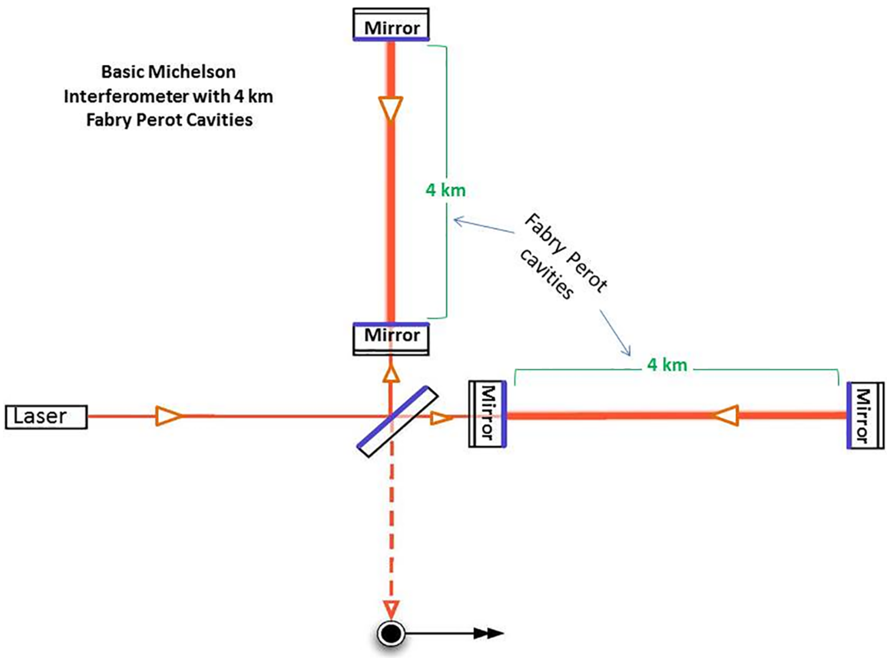

Figure 1.1: A simple schematic of a Michelson interferometer. This is the basis upon which the LIGO detectors are built.

The Laser Interfereometer Gravitational-Wave Observatory (LIGO) Collaboration utilizes two such instruments located in Hanford, Washington and Livingston, Louisiana. Each interferometer is equipped with ultra-stable high-power lasers, 4km-long arm cavities, test masses suspended on quadrupole pendulums, vacuum systems, and much more to ensure the lowest noise environment possible. To further enhance sensitivity, LIGO employs Fabry-Perot cavities within the detector arms to increase the effective path length of the beams, power recycling cavities to boost the circulating laser power, and advanced vibration isolation systems [10, 11].

The world's first detection of gravitational waves by LIGO in 2015 was a landmark achievement in physics [12]. Since then, the global network of gravitational wave interferometers has continued to grow and improve observational capabilities with VIRGO in Europe and KAGRA in Japan. Future upgrades and next-generation detectors such as LIGO Voyager, Einstein Telescope, and Cosmic Explorer aim to extend the observable range by implementing a number of technological advances [13]. Additionally, space-based interferometers such as the Laser Interferometer Space Antenna (LISA) promise to detect lower-frequency gravitational waves [14].

By continually upgrading existing interferometers and ushering in the next generation, physicists will be able to probe much wider swaths of the gravitational wave frequency spectrum. Reaching into both higher and lower frequencies will provide insights into astrophysical phenomena more extreme than those which are already being detected.

1.4 Thesis Outline

Having been oriented with a cursory overview of the modern understanding of gravity and how it came to be, alongside brief introductions to gravitational waves and laser interferometers, one is now prepared for a deeper, more specific dive into the contents of this thesis which will proceed in the following fashion.

First, an intoduction to and discussion of how the data collected at these few massive laser interferometers is interpreted and analyzed in the search for gravitational waves. This will include points on why one might care about gravitational waves in the first place, who is able to search for them in the vast amounts of data, and how that process currently takes place.

Second, is an introduction to and discussion of machine learning and how it has been or could be utilized in this field of research. This will include the apparent benefits and/or drawbacks of using machine learning techniques in doing science of this sort, a casual overview of the most frequently utilized neural network architectures, and an outline of what challenges lay between modern machine learning and its utility in high caliber science.

Third, is a comprehensive telling of the motivation for as well as the production and analysis of, the parameter estimating neural network that is the principle matter of this thesis. This will include discussions of the chosen network architecture, the generation of synthetic time-series data, the training of the neural network, and the evaluation of the neural network's performance. It is within this section of the work that the novelty of this research exists.

Lasty, is an attempt to peer into the future. Here one will find discussions of the potential for real-time gravitational wave data analysis, how advances in machine learning might further contribute to these efforts, a summary of the research completed over the last academic year, what future work might prove to be fruitful, and finally a conclusion to tie everything together.

Chapter 2

Gravitational Wave Data Analysis

2.1 Background

Gravitiational wave (GW) data analysis is an intricate and typically involved process in which extraction, classification, and interpretation of weak astrophysical signals occurs. Unlike traditional electromagnetic astronomy, where signals are often easily discernible from noise, high-confidence GW detection requires sophisticated computational techniques to extract signals which are buried in vast amounts of noise. The sensitivity of current interferometers allows for detection of strain fluctuations on the order of 10^{-21}. This necessitates rigorous data processing pipelines to distinguish true astrophysical events from the presence of significant instrumental and environmental noise sources [7, 15].

GW detectors are laden with a multitude of noise sources including seismic activity, thermal fluctuations, quantum noise, and instrumental imperfections. Looking at the aLIGO noise budget, seismic motion at frequencies below 10 Hz can couple into the detector via ground motion, requiring complicated seismic isolation systems. Also at low frequencies, radiation pressure on the mirrors affect stability. At high frequencies, greater than 100 Hz, a quantum effect (shot noise) introduces uncertainty in the detected signal. Fortunately, the implementation of squeezed vacuum states has significantly improved high-frequency sensitivity [16]. There also exist short-duration noise artifacts, known as glitches, which present a challenge for GW detection and analysis. These artifacts can mimic and obscure true signals, and require statistical or machine learning classification techniques to be properly handled [17].

The raw data from these laser interferometers are digitized at a sampling rate of $16,384$ Hz and undergo multiple stages of preprocessing before astrophysical inference can take place. First, the necessary precise calibration of the detector converts raw photodetector voltage measurements into a measurement of strain, accounting for time-dependent variations in interferometer response [18]. All data in this raw form made publically available through the Gravitational Wave Open Science Center (GWOSC). Downloads can be made of either the $16,384$ Hz data or a version downsampled to $4,064$ Hz [19]. Typically though, before being used, the data will also go through whitening to remove spectral features, band-passing to cut out irrelevent frequencies, and the application of window functions to reduce spectral leakage in Fourier Analysis [20]. The currently prevailing GW data analysis techniques will be discussed later in this chapter.

2.2 Scientific Utility

GW astronomy has bolstered our efforts to understand the cosmos by providing a fundamentally new observational channel which complements traditional electromagnetic, and much more recently neutrino, astronomy. The ability to directly measure ripples in spacetime has a number of significant implications in astrophysics, cosmology, nuclear, and fundamental physics.

First and foremost, the direct observation of compact binary mergers has confirmed a number of hypotheses in astrophysics, including the fact that it is possible for stellar-mass black holes to form and merge within a Hubble time [7], the detection of neutron star merger GW170817 established a direct connection between the mysterious short gamma-ray bursts (SGRBs) and compact binary mergers [21], and GWs also provide key insights into the populations and formation channels of compact binary systems [22].

The tidal interactions between inspiraling neutron stars imprint unique signatures within the GW signal, allowing for the derivation of a neutron star equation of state (EOS), and its corresponding parameters. Each consecutive detection of mergering neutrons stars will allow for further refinement of the EOS and help determine the true nature of dense nuclear matter [23, 24]. On top of this, GWs provide an independent method for measuring the Hubble constant (H_0). The absolute distance to an event can be inferred by the amplitude of its waveform allowing for their use as standard candles, or in this case standard sirens. When followed-up by an EM redshift measurement, these merging neutron stars allow for direct measurement of (H_0). With a growing catalogue of binary neutron star mergers, GW cosmology is expected to yield an incredibly precise measurement of (H_0), potentially resolving—or intensifying—the Hubble tension [23, 25].

Tests of general relativity (GR) in the strong-field regime prove to be convenient with the direct observation of GWs. The inspiral phase of compact binary mergers is thus far well-described by post-Newtonian expansions, but observed deviations from such expansions could point to potential modifications to GR [26]. The ringdown phase of binary black hole mergers can be analyzed to test the "no-hair theorem," which states that a black hole is entirely characterized by its mass and spin [27]. Additionally, the propagation speed of GWs can be used to test for Lorentz invariance violations and place bounds on the mass of the graviton [21]. Not only can GWs be used to confirm physics that has been around for a while, but they can also probe new physics. Primoridal black holes, dark matter, cosmic strings and early universe phase transitions are all in the sights of further gravitational wave detection efforts [28, 29]. Evidently, the scientific utility of GW astronomy extends far beyond just the technical feat of making the detections. As detector sensitivity continues to improve, GW observations promise to unlock new insights into the nature of our universe.

2.3 International Collaboration

GW astronomy is an inherently global scientific indeavor. The detection and analysis of GWs require a complex network of highly sensitive laser interferometers, data processing infrastructure, and a large community of researchers collaborating across multiple disciplines. The LIGO-Virgo-KAGRA (LVK) Collaboration, which combines the efforts and data from the Laser Interferometer Gravitational Wave Observatory (LIGO) in the United States, the Virgo interferometer in Italy, and the Kamioka Gravitational Wave Detector (KAGRA) in Japan, is the predominant international gravitational wave collaboration. The LVK network operates in synchronized observation runs. By doing so, the network allows for increased sky coverage, localization of sources, and greater confidence in detections through cross-validation.

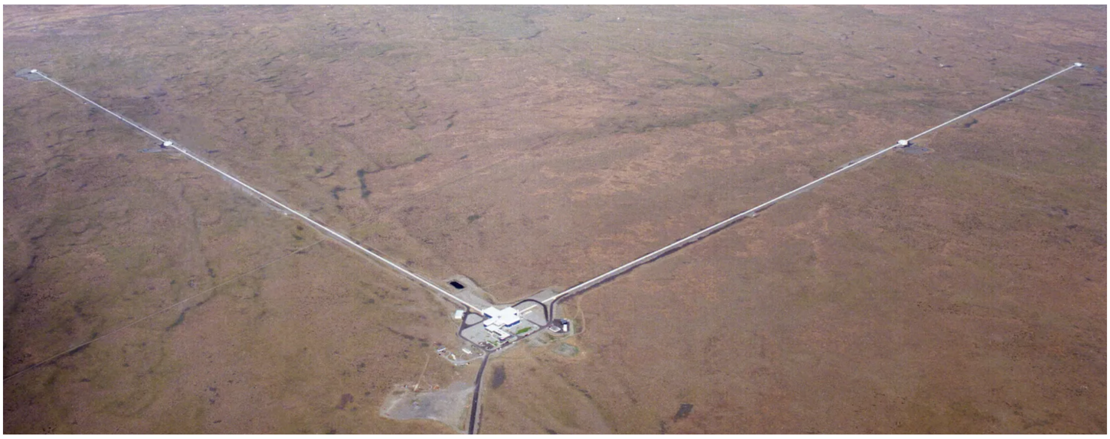

Figure 2.1: An aerial photograph of the LIGO Hanford cite in Hanford, Washington for some sense of scale. The two perpendicular arm cavities are 4km long.

While ground-based detectors such as those in the LVK collaboration are sensitive to stellar-mass binary mergers, the Laser Interferometer Space Antenna (LISA) will expand the range of detection into the low-frequency domain. A collaboration between the European Space Agency (ESA) and NASA, LISA is a space-based interferometer that will be sensitive to supermassive black hole binaries, white dwarf binaries, and potentially new physics in the millihertz frequency range. LISA is set to launch in the 2030s, and consists of three spacecraft that will form an equilateral triangle with arm lengths of 2.5 million kilometers [30]. The addition of LISA to the global network of detectors not only unlocks new astrophysical sources, but could potentially allow for the observation of the same source across different stages of its evolution [31].

Several other projects will eventually contribute to the international GW effort including the Indian Initiative in Gravitational-wave Observations (IndIGO) [32], the Einstein Telecope (ET) is a European collaboration seeking to build an underground interferometer with 10x the sensitivity of current LVK detectors [33], and Cosmic Explorer (CE) is a U.S. led project to build an interferometer with 40-km arms hoping to reach high-redshift sources [34].

Arguably the greatest benefit to international collaboration in GW astronomy is the sharing of data. Embracing an "open science" philosophy, the Gravitational Wave Open Science Center (GWOSC) provides data releases from all LIGO-Virgo observing runs, which enables researchers worldwide to conduct independent analyses [19]. Through the GWOSC, full strain data from GW observations are made available, fostering transparency and enabling non-collaboration researchers to contribute to GW science. The LVK collaboration also releases real-time public alerts for detected GW candidates, enabling rapid EM follow-up by telescopes worldwide [35], projects like Gravity Spy involve citizen scientists in classifying noise artifacts in GW data, improving the performance of machine learning classifiers for event detection [17].

GW science thrives on international collaboration. The integration of LIGO, Virgo, and KAGRA has already revolutionized GW detection. As even more detectors join the GW network, the continued success of its efforts will rely on international collaborations upholding open science policies, data sharing practices, and cross-disciplinary cooperation.

2.4 Prevailing Techniques

With the LIGO-Virgo data publicly available via the GWOSC, researchers around the world have no trouble digging into it. The analysis of GW data relies on a combination of techniques which in the end yield confidence in making detections and accuracy in making source parameter estimates.

With the raw strain data downloaded from the GWOSC, researchers will typically further preprocess it before attempting any sort of analyses. This includes steps such as whitening, band-passing, notching, and the application of window functions [20]. Whitening aims to remove spectral features and produce a uniform intensity across all frequencies. Band-passing cuts out irrelevent frequencies from the data, such as those at which our detectors are not sensitive to GWs. Notching removes specific frequencies from the data to filter out common noise sources like 60Hz power-lines and their subsequent harmonics, and window functions seek to reduce spectral leakage in Fourier analysis. When analyzing large amounts of data, these processes can be especially laborious and hinder efficiency. Hence, the research in this thesis which aims to circumvent this data preprocessing.

Once the data are preprocessed, signal extraction techniques are employed to identify potential GW events. Template-based searches, also known as matched-filtering, compares recorded data against a large bank of precomputed waveform templates produced using numerical relativity and post-Newtonian approximations. By running template waveforms over the real data, one will maximize the signal-to-noise ratio (SNR) of the event, assuming they do indeed match [36].

The matched-filtering process, although effective, is incredibly computationally intensive and time consuming. Considering that one has to produce, store, and repeatedly call tens-of-thousands or hundreds-of-thousands of synthetic waveforms upon each instance of data, the guess and check nature of the process leaves much to be desired.

Nonetheless, after successfully identifying a GW event, Bayesian parameter estimation techniques infer source properties such as masses, spins, and sky location. For example, the LALInference framework applies Markov Chain Monte Carlo (MCMC) and Nested Sampling methods to explore the parameter posterior probability distributions [38]. The accuracy of these parameter estimations is paramount for proper astrophysical interpretation.

Chapter 3

What is Machine Learning

3.1 Background

Machine learning (ML) has rapidly emerged as a powerful tool in many business, scientific, and creative endevours of the modern day. GW data analysis is no exception to this, with ML efforts complementing traditional signal processing and Bayesian inference methods. The application of ML to astrophysics, and most other realms, is motivated by a neural network's ability to process large datasets efficiently, identify patterns that may not be apparent with conventional methods, and provide real-time inference capabilities for detecting and characterizing signals.

ML is a subset of artificial intelligence (AI) that enables computers to learn patterns from data without explicit programming [39]. Unlike traditional statistical methods, ML algorithms improve their performance iteratively by optimizing their parameters through exposure to large amounts of training data. There are three basic types of machine learning. The first is *supervised learning*. In this regime, the neural network is trained on labeled datasets (e.g., known GW waveforms) to learn the complex mapping between an input parameter space and an output parameter space. The second is *unsupervised learning*. In this regime, the neural network identifies hidden patterns in unlabeled data. These first two types of ML are most often used in GW science. The third is *reinforcement learning*. In this regime, the neural network interacts with its environment to maximize a 'reward function.' This can be an incredibly powerful technique especially when training mechanical systems [40], but is not often used in GW science.

The motivation for integrating ML into GW science stems from the challenges posed by traditional data analysis methods. Matched-filtering has been the workhorse of GW data analysis, but requires cross-correlating observational data with hundreds-of-thousands of waveform templates, making it incredibly computationally expensive [7]. ML based classifiers have the potential to dramatically reduce this computational burden by learning waveform features in advance, allowing for near-instantaneous detection and classification. Environmental and detector noise also pose a challenge to traditional signal processing techniques. Trying to find a needle of signal in a haystack of noise could be made much more efficient. ML models trained on real examples of detector and environmental noise can help distinguish true astrophysical signals [17]. While it works well, Bayesian parameter estimation is just as computationally intensive as matched-filtering. ML methods for parameter estimation can help provide accurate real-time parameter estimates [41]. Another drawback of matched filtering is that it requires prior knowledge of the waveforms found in the data. Unsupervised ML models can potentially identify unexpected sources of GWs.

Thus far, ML techniques have proven to be quite successful in analyzing GW data [41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53]. These sources have, across a variety of neural network architectures, managed to predict masses, spins, tidal deformation; learn detector noise profiles; produce early warning merger signals; and more. ML has become an increasingly valuable tool in GW science, offering an array of solutions to the computational challenges posed by traditional analysis techniques. The role it plays will only become more pronounced in coming years.

3.2 Cons of Machine Learning

ML has proven to be a powerful tool in gravitational wave (GW) data analysis, offering significant advantages over traditional methods in terms of speed, efficiency, and adaptability. However, it also introduces several challenges, some of these being interpretability, robustness, and generalizability.

One of the biggest challenges in ML-based GW data analysis is interpretability. Traditional Bayesian inference provides well-defined uncertainties, whereas many ML models, especially deep learning architectures, function as black boxes with decision-making processes that fail to be well understood. While being trained, these deep neural networks (DNNs) are effectively able to produce highly nonlinear emprical mappings between input space and output space. Just because neural networks are able to come to the seemingly correct answer does not mean researchers can properly understand what is going on within them. Without a clear understanding of how a model reaches its conclusions, researchers face difficulties in validating ML-based discoveries and ensuring their scientific credibility.

ML models trained on simulated data often struggle when applied to real detector data due to discrepancies between simulated and actual noise conditions. This issue limits the ability of ML models to generalize across different detectors, observing runs, or configurations. Additionally, obtaining high-quality labeled noise data is challenging because detector glitches and artifacts vary over time. This makes training individual neural networks tailored to specific detectors incredibly burdensome. In order to address this issue, researchers could apply domain adaption techniques that allow the neural network to adapt in-situ.

Unlike Bayesian inference methods, which provide well-defined probability distributions for estimated parameters, many ML models do not naturally output uncertainty estimates. This is problematic in GW science, where precise error bars are essential for astrophysical interpretation. This shortcoming could be addressed using techniques such as conformal prediction. Recent work in uncertainties includes Bayesian deep learning [54] and ensemble learning in which multiple models are trained and the outputs are averaged in order to find uncertainties.

ML presents a transformative opportunity for GW data analysis. However, challenges related to interpretability, generalization, data requirements, and uncertainty quantification must be addressed before ML can be fully integrated into high-precision scientific workflows. Despite these challenges, ongoing research is steadily bridging the gap between ML and traditional methods. Future gravitational wave detections will likely benefit from a symbiotic combination of ML and conventional techniques, optimizing both speed and accuracy.

3.3 Architectures

Neural networks are the maleable mathematical models that allow for "machine learning" to happen. By altering themselves after being exposed to data, these mathematical tools can effectively learn the relationships and patterns within. Neural networks come in all shapes and sizes, and some are often better suited for specific tasks than others. The design of a neural network, also called its architecture, can range from quite simple to incredibly complex. This architecture fundamentally shapes its capacity to learn, represent, and generalize from data. Over the past decade, a variety of architectures have emerged to tackle problems in domains ranging from image recognition and natural language processing to financial modeling and biomedical analysis. These models are characterized by how they process and transform data. Some of the most utilized network architectures are convolutional neural networks (CNNs), recurrent neural networks (RNNs), variational autoencoders (VAEs), transformers, and normalizing flows. An overview of each is presented below.

CNNs are specialized neural networks designed to extract spatial hierarchies of features from data with grid-like topology, such as images. Originally introduced for image classification [55], CNNs excel at learning local patterns using shared filters. CNNs are widely used in medical imaging and video classification. They operate by applying convolutional filters across input data, allowing them to detect edges, textures, and shapes at various levels of abstraction. In GW research, CNNs have been leveraged to detect GW signals by treating spectrogram representations as images. [51] demonstrated that CNNs trained on simulated LIGO data could match the sensitivity of traditional matched filtering while operating orders of magnitude faster.

RNNs are designed for sequential data, where inputs are temporally or logically ordered. They maintain a hidden state that evolves over time which makes them suitable for tasks like speech recognition, text generation, and time-series forecasting. However, RNNs suffer from vanishing or exploding gradients during training. This makes it difficult for them to pick up on long-term dependencies. In an effort to address this, long short-term memory (LSTMs) networks were developed [56]. These networks introduce memory cells and gating mechanisms that better retain long-term patterns. In GW research, RNNs strength in capturing dynamic relationships has been applied to detect signals and make parameter estimates [44].

VAEs, as well as standard autoencoders, are unsupervised learning architectures that learn compact, latent representations of data through an encoder-decoder framework. These networks can identify and separate genuine signals from noise without without labelled training data, and have been successfully employed to reconstruct GW waveforms from noisy data.

Transformers, initially developed for natural language processing, incorporate so-called attention mechanisms. Rather than relying on recurrence, seeing the data multiple times, transformers focus only on relevent pieces of data. This makes them incredibly efficient.

Normalizing flows are a family of invertible probabilistic models that map simple probability distributions such as Gaussian functions to complex posterior distributions using a sequence of invertible transformations. They are able to combine the accuracy of Bayesian inference with the efficiency of ML. Despite being far less common than CNNs and RNNs due to their complexity, normalizing flows are gaining traction due to their balance in speed, interpretability, and statistical rigor, making them attractive alternatives to Markov-Chain Monte-Carlo (MCMC) sampling methods.

The choice of neural network architecture depends heavily on the task at hand. In this research, on making parameter estimates from unprocessed GW data, I use a RNN architecture that contains convolutional layers for feature extraction, LSTM layers for temporal dependencies, and fully connected layers to ensure the network has enough complexity to produce a sufficient mapping from input to output space.

3.4 ML Challenges

Despite its promise, the application of ML in many scientific fields requiring high precision and interpretability remains an open and evolving challenge. While many of the architectures above demonstrate high performance in an array of use cases, their full integration into scientific workflows is hindered by several limitations.

One of the largest challenges in applying ML to scientific domains is the availability of training data. Unlike consumer-focused ML applications backed by large companies and teams of engineers, where obtaining or producing vast amounts of data is a feasible option, scientific undertakings often have much less financial support and therefore less ability to procure data. Well structured and labeled data is simply scarce and difficult to produce. In GW physics, there exist only about 200 real detections with accompanying data. Hence, researchers rely on synthetic gravitational wave data produced using numerical relativity, and even this takes large amounts of computational effort. Synthetic data, while convenient, may not perfectly capture the true complexity of a whatever real data one is looking to use. Efforts such as data augmentation, transfer learning, and unsupervised learning are all being explored to remedy this shortcoming, but none will perfectly make up for it.

Neural networks also struggle with generalization and robustness. Many models, when trained on synthetic data, will fail to perform well when exposed to real-world conditions due to the network overfitting to noise charactersitics, data resolution, or more. This challenge is especially relevent in GW science, where the detector environments are dynamic. Additionally, it is unrealistic to train just one model and use it on data from all detectors. Each detector has a unique noise profile and sensitivity that must be individually captured by separate neural networks. Domain adaption techniques such as transfer learning could one day resolve these types of issues.

In fields of study where explainability and reproducability are necessary, most ML models act as black-boxes. Input goes in and output comes out without much, if any, understanding of what happens in-between. For ML models to be integrated in rigorous scientific workflows, neural networks need to be transparent and their analysis processes well understood. There is an inherent tension between the probabilistic interpretable framework of physics and the blurry data-driven nature of neural networks. Without interpretability, it is difficult for ML to be trusted by the broader scientific community.

ML models often output deterministic predicitions lacking any type of calibrated uncertainty estimate. This is typically a non-starter in most scientific fields where understanding the error in your measurement or estimate is crucial. While methods like Bayesian neural networks, normalizing flows, conformal prediction, and ensemble training are beginning to pave a pathway for uncertainty estimation in ML, they are not yet efficient and widely adopted. Moreover, these statistical errors are not easily comparable to those of traditional techniques.

ML is poised to become a powerful complement to traditional scientific analyses, but getting to this point requires addressing some of the key challenges above. As these issues become progressively resolved through interdisciplinary efforts, ML will become an all the more accepted and utilized tool.

Chapter 4

Enabling Faster GW Data Analysis

4.1 Introduction to the Project

This research was undertaken as Senior Honors Work in the Valparaiso University Department of Physics and Astronomy. The goal of this research is to demonstrate that a neural network is capable of accurately estimating key system parameters of binary black hole (BBH) coelescence, with the caviate that the data be unprocessed. This is motivated by the fact that all other research on this topic relies on data that has been preprocessed (i.e. transformed into a spectrogram, whitened, etc). Therefore, it will be demonstrated that a recurrent neural network comprising layers of convolutions, max pooling, batch normalization, bidirectional long short-term memory (LSTM) cells, and dense layers is capable of taking an input 1D time-series of raw unprocessed strain data and outputting an accurate estimate of the BBH systems chirp mass. This is assuming that the input time-series does in fact contain the signal from a BBH coalescence.

Were this neural network placed in series with another machine learning model capable of flagging a BBH coalescence event in a data stream, such as [51]'s *Deep Filtering* technique, it could yield real-time chirp mass estimation resulting in a much improved and streamlined data analysis process. With an accurate chirp mass estimate, one would reduce the size of the template bank required to further analyze the signal with matched filtering by orders of magnitude. An accurate estimate of the chirp mass also has the potential to produce more well-defined priors for Bayesian analysis techniques. Essentially, the neural network produced in this research has the potential to greatly increase the rate at which GW data analysis can occur.

Due to the fact that there exist so few real observations of gravitational waves ($\sim$200), the data used in this research was synthetically generated to resemble that of an aLIGO detector.

4.2 Data Preparation

As described above, the data used in this research was synthetically generated. Utilizing the CUDA acceleration of an NVIDIA RTX 3080 Ti for computational efficiency, the binary black hole (BBH) coalescence waveforms and detector noise were generated with the *PyCBC* python package. As a proof-of-concept study, I consider only non-spinning BBHs labled by component masses m_1 and m_2. Additionally, the inclination of, and distance to, the binary system are also defined.

Parameters	Symbols	Distributions	Ranges	Units
primary mass	m_1	Uniform	$[5, 100]$	M_{sol}
secondary mass	m_2	Uniform	$[5, 100]$	M_{sol}
inclination	i	Uniform	$[0, \pi]$	radians
distance	d	Uniform	$[500, 4000]$	Mpc

Table 4.1: Parameters and respective distributions and ranges used to generate the synthetic binary black hole coalescence waveforms.

Using [44] as a template, I utilize the *SEOBNRv4_ opt* waveform approximant and a sampling rate of 4096 Hz to generate the data. After randomly sampling the four parameters above, the *PyCBC* function *get_ td_ waveform* is used to generate the waveform corresponding to such a system. Both the plus (+) and cross (×) polarizations are produced from a single 'detector.' Unlike [46], I combine the plus and cross polarization with Eq. 4.1 in an effort to encode as much information about the source system as possible. This combination makes it possible to break the degeneracy between distance and inclination [46].

$$h_{+,\times} = h_+ \frac{1 + \cos^2 i}{2} + h_\times \cos i \tag{4.1}$$

With the polarizations combined into a single waveform, it is then cushioned with arrays of zeros to achieve a length of 27,500 timesteps, or roughly 6.714 seconds. This length was chosen arbitrarily. In order to then generate realistic detector noise, I do as [44] and produce Gaussian noise using a specified power spectral density (PSD) defined by *PyCBC's aLIGOZeroDetHighPower*. The timeseries of noise is then generated using the *noise_from_psd* function.

With signal and noise timeseries of the same length, they are converted to the frequency domain and summed together before being returned to the time domain. Because the signal and noise are treated as completely indpendent sources, summing in the frequency domain ensures a linear transformation that respects the statistical properties of each. This effectively combines the signal and noise into what I will henceforth refer to as a synthetic observation. The above process was repeated to produce a complete dataset of 10^5 synthetic observations that are used to train and evaluate the neural network produced in this research.

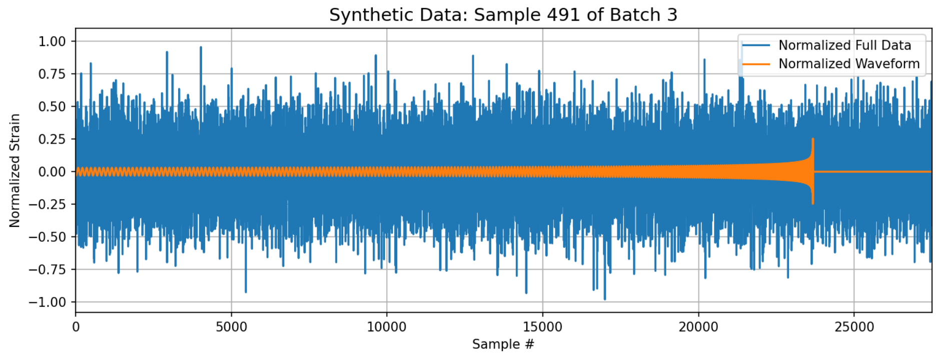

Figure 4.1: A single synthetic observation produced for this research (in blue), overlayed by the pure GW waveform (orange) that is contained within. The parameters corresponding to this event are [chirp mass: 4.66 solar masses, inclination: 0.6 radians, distance: 889 Mpc, peak SNR: 10.84].

Adjacent to the production of each synthetic observation, the system's chirp mass, inclination, distance to event, and peak signal-to-noise (SNR) ratio were calculated and stored as labels for the data. While inclination and distance were able to be immediately retreived from the sampling process, chirp mass and peak SNR had to be calculated post-facto. The chirp mass variable captures the frequency evolution of the BBH signal and is calculated using Eq. 4.2. The peak SNR ratio was determined by first matched filtering the synthetic observation against its own noiseless waveform using the *PyCBC matched_filter* function, and then the maximum value of the matched filtering process was stored as *peak_ SNR*.

$$\mathcal{M}_{chirp} = \frac{(m_1 m_2)^{3/5}}{(m_1 + m_2)^{1/5}} \tag{4.2}$$

It should be noted that, for the sake of computational efficiency and memory limitations, the final synthetic observations composing the full dataset were band-passed so as to allow only frequencies within the 30 - 1,000 Hz range. This is the range of frequencies at which the aLIGO detectors are sensitive enough to make meaningful detections. Frequencies outside this range are dominated by instrumental and environmental noise. Additionally, the amplitude of each synthetic observation is scaled to ± 1 to ensure a relative ease in the training process for the neural network, but the signal is invariant under this scaling transformation. This is the entirety of the minimal preprocessing that occurs in this research, and theoretically neither step is necessary if the appropriate computational resources are available.

The 10^5 synthetic observations were converted to memory efficient JSON strings and labled with their corresponding chirp mass, distance, inclination, and peak SNR and temporarily organized in a *pandas* dataframe before being saved as 100 .csv files of 1,000 synthetic observation each. These 100 .csv files were then converted into a single custom *PyTorch* dataset before being subsequently split into training (70% of full dataset), validation (15% of full dataset), and testing (15% of full dataset) datasets.

Additionally, to better aid in the evaluation of the machine learning model, three further datasets of 10^4 samples were produced using the same procedure. The first comprised only pure signal waveforms lacking any noise. The second comprised only noise lacking any signal waveform. The third being a collection of full synthetic observations, but subsequently binned by their *peak_SNR* in order to evaluate performance at different thresholds. The data preparation stage of the research is thus complete.

4.3 Model Devlopement

Developing a machine learning model is oftentimes considered more of an art than an exact science. Therefore, I found two models recently published in the literature and evaluated them for their ability to make parameter estimates. My machine learning development package of choice is *PyTorch*. Each model was trained with the same data, batch size, loss function, optimizer, and learning rate for the same number of epochs in an effort to make a fair comparison. The first was [45]'s neural network which utilizes first a number of LSTM cells and then a number of dense layers. Originally intended to learn and predict the complex noise couplings within GW data [45], this model was incapable of performing accurate parameter estimation. It could do little more than predict the mean value of each of the parameter distributions.

The second model was [57]'s deep learning neural network. This original version includes convolution, max pooling, batch normalization, LSTM, flatten, and dense layers. Rather than analyzing a timeseries of strain data, this model was originally intended to analyze an SNR timeseries and make a binary classification. Either the SNR timeseries demonstrated that there was a GW merger event during that stretch of time, or there was not. In no way was it intended to make parameter estimates. However, this model exceeded expectations and was able to readily estimate the chirp mass of a BBH merger given the synthetic observation.

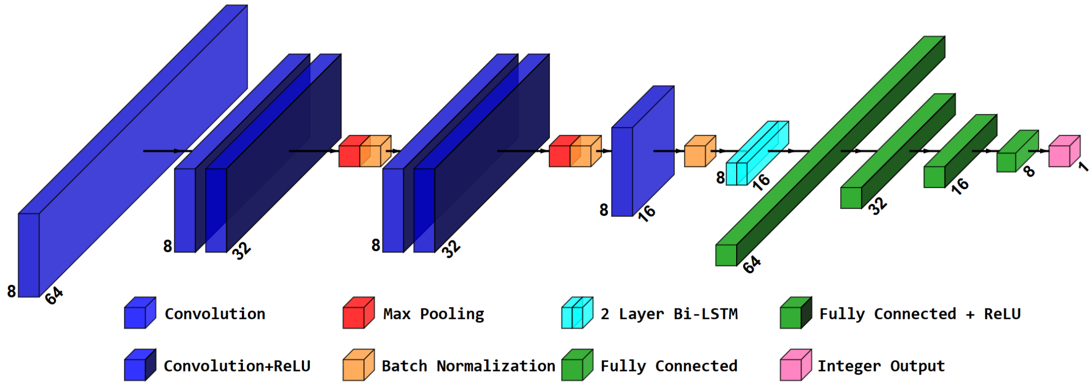

Figure 4.2: This is a visual representation of my neural network that performs chirp mass regression, which is an optimized form of [57]'s neural network that originally performed binary classification for event detection.

Additionally, I tested a modified version of [57]'s deep learning neural network. This modified version lacked any LSTM cells in order to determine their influence. The model was still able to make chirp mass predictions, but with noticeably less accuracy and precision. Therefore, with evidence of the utility of LSTM layers, I proceeded with [57]'s deep learning neural network.

Hyperparameter	Value
batch size	32
learning rate	1×10^{-5}
dropout probability	0.05
max pooling kernel size	3
# LSTM layers	2

Table 4.2: The optimized hyperparameters used to train the finalized neural network. Note that my deep learning network includes 2 LSTM layers while [57]'s contains only 1.

In an effort to further optimize this deep learning neural network, it's hyperparameters and structure were tuned using the *Optuna* Python package. This package allows for a random exploration of the hyperparameter and network structure space in relation to the loss function of the training neural network. By finding the hyperparameter and structural configuration which minimizes the loss most efficiently, one can produce an optimized neural network. The optimized network and hyperparameters are detailed in Table 4.2 and Figure 4.2.

The training dataset of synthetic observations that composed 70% of the original was used to train the optimized model. It trained for 100 epochs over the course of about two hours. After each epoch, the model's loss was evaluated on both the training dataset and the validation dataset. As is expected with proper training, the validation loss remained below the train loss, informing me that the model was not overfitting to the training data. With the model tuned and trained, its performance can be further evaluated.

4.4 Model Evaluation

The neural network was given a number of datasets to analyze in an effort to evaluate its performance. The first was the test dataset of synthetic observations that composed 15% of the original. This dataset was not tailored in any particular fashion and is meant to be representative of the parameter space the model was trained on. It serves as a general evaluation of the model's performance.

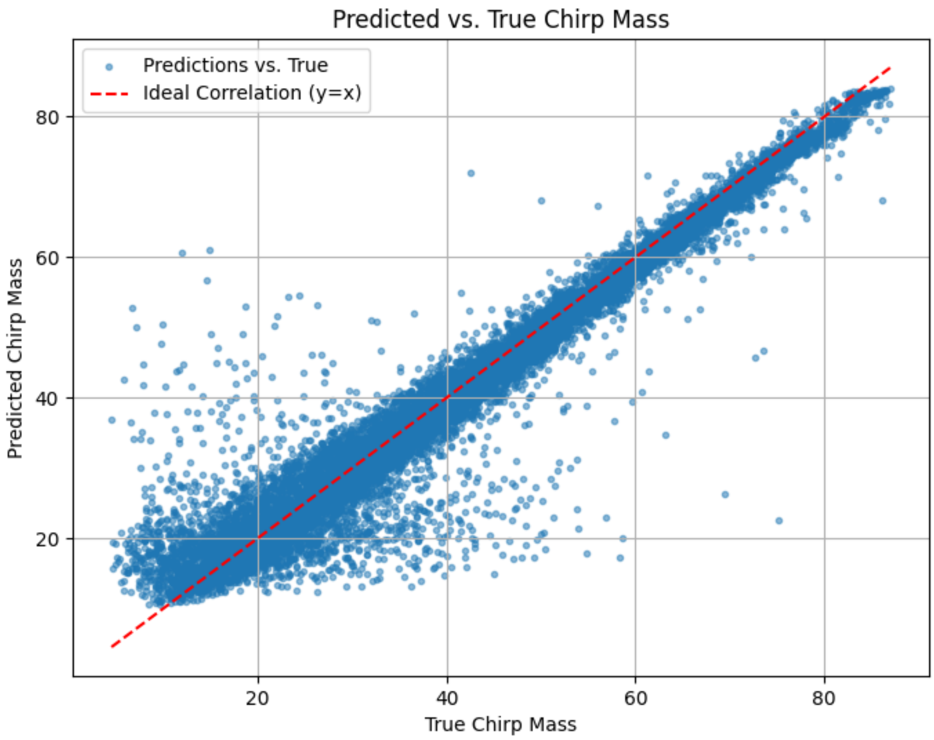

Figure 4.3: True chirp masses vs the neural network's predicted chirp masses of the test dataset's synthetic observations. This data has an R^2 value of 0.9445.

We can see in Figure 4.4 that the model does quite well. There is a well-defined linear trend matching what should be expected. The scatter becomes more prominent as the chirp mass decreases. This is also to be expected as there is a correlation between chirp mass and SNR. The smaller the chirp mass, the less signal received, and the harder it is to do meaningful analysis on the noisy data.

Figure 4.4: The residual plot of figure Figure 4.4. Clearly exhibiting some form of order in its scatter. This is not yet understood.

Taking a look at the residual plot, there is clearly some sort of well defined order. This is an unexpected result and the origin of such order is not yet understood. This effect grows more prominent in further analyses of the performance in specific SNR regimes. Plotting a histogram of these residuals, we see that most of the predicted chirp masses are indeed good estimates.

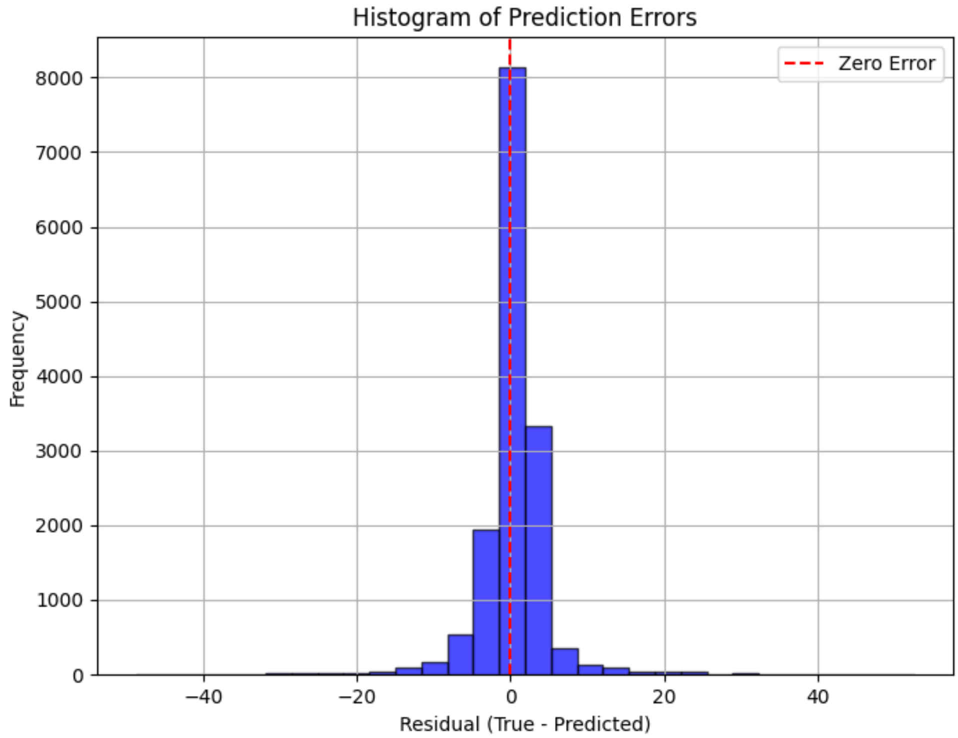

Figure 4.5: The residuals of Figure 4.5 in histogram form. We see a well defined peak indictating that a majority of the estimates made by the neural network are indeed accurate.

Were the neural network to perform perfectly, one would expect a residual of zero. Doing some simple statistics on this set of residuals we find the average residual to be $0.47 \pm 4.38 M_{sol}$. This corresponds to a z-score of 0.11. Thus, our mean residual value lies well within the range of what we could expect to measure by chance. The neural network is calculating the correct results most of the time.

Getting more specific in the analysis, I put together a number of datasets with bounds on the peak SNR value associated with the synthetic observations they contained. The performance of the neural network in these different SNR regimes is captured in Table 4.3

Interestingly, nothing sticks out as completely unusual. The performance is fairly even across all peak SNR regimes, except for the $0 < SNR < 5$ which has a much larger standard deviation of the residuals, a much worse R^2 value, and a larger mean residual. It should be noted that the official LIGO threshold of "network SNR" for declaring a detection is 8 [58]. Network SNR means the cumulative SNR of all detectors that happen to pick up the event. This is different than the peak SNR I am calculating for the synthetic detections of a single detector, but it is no surprise that analysis becomes much more difficult in these low SNR regimes. Therefore, the drop in performance of the neural network is no surprise.

Peak SNR Range	R^2 Value	Mean Residual	Std. Dev. of Residual
$0 < SNR < 5$	0.417	1.443	9.241
$5 < SNR < 20$	0.959	0.092	3.558
$20 < SNR < 35$	0.990	0.629	1.594
$35 < SNR < 50$	0.993	0.509	1.336
$50 < SNR < 65$	0.993	0.601	1.220
$65 < SNR < 80$	0.993	0.620	1.092
$80 < SNR$	0.992	0.859	0.837

Table 4.3: A summary of the neural network's performance at different SNR levels. Note that this is the peak SNR as described earlier.

The true vs. predicted, residual, and residual histogram plots of each SNR regime also fail to reveal anything too insightful. Attested to by the high R^2 values, there is high correlation between true and predicted in all cases. The residual plots appear more random at higher SNR levels, and slowly become more ordered as SNR falls. This hints at the fact that there is a linear relationship between residual and chirp mass at low SNRs, but not much more. The standard deviation of the residual becoming smaller at large SNRs, and larger at small SNRs, may simply be a function of the correlation between chirp mass and SNR.

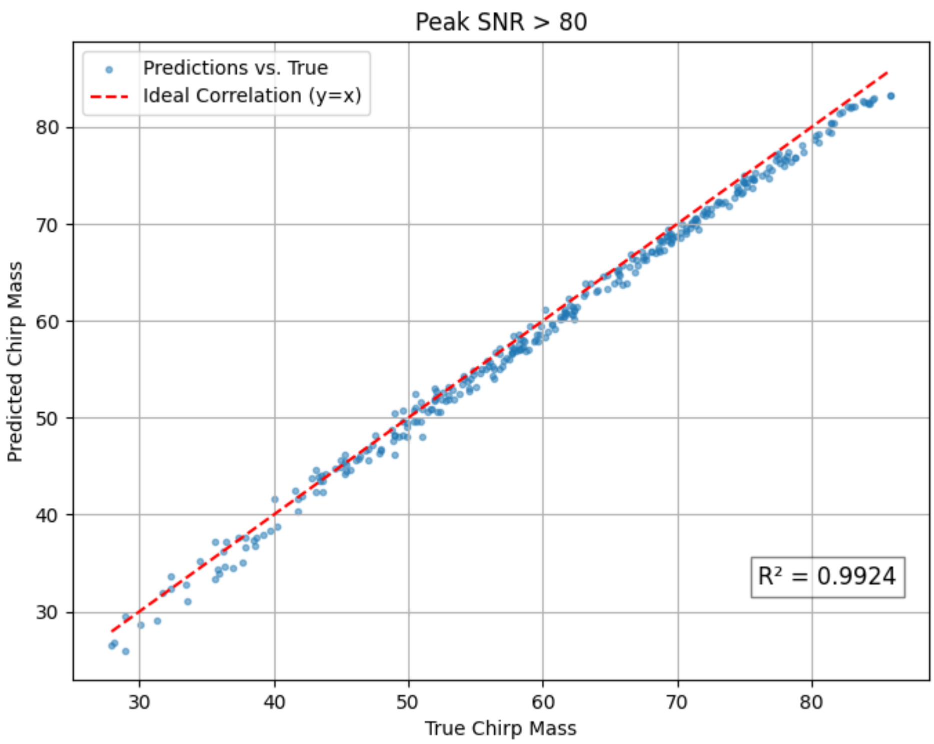

Figure 4.6: True vs. predicted plot for events with SNR > 80.

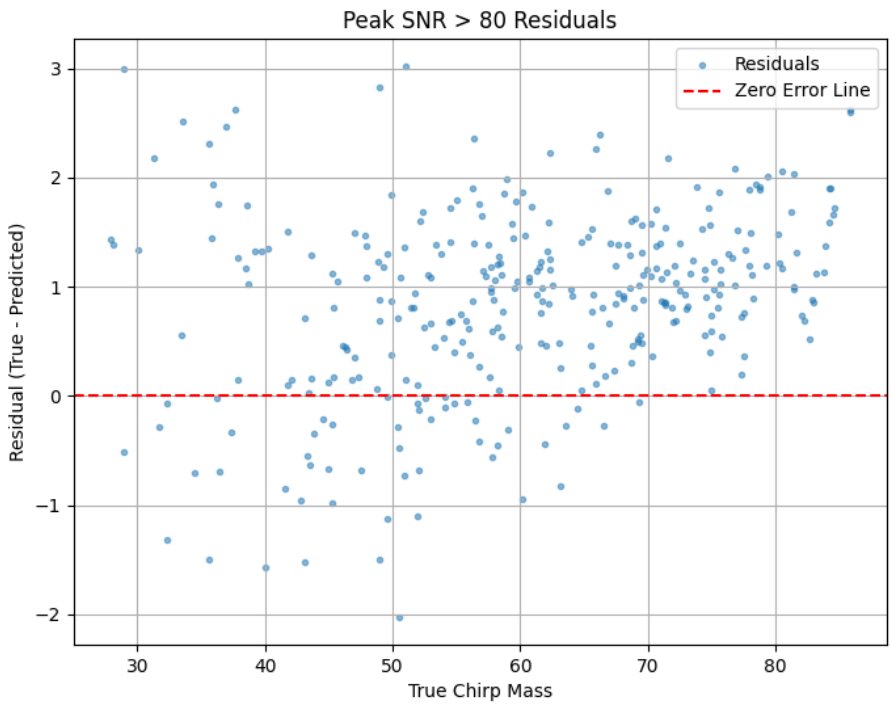

Figure 4.7: The residual plot for events with SNR > 80.

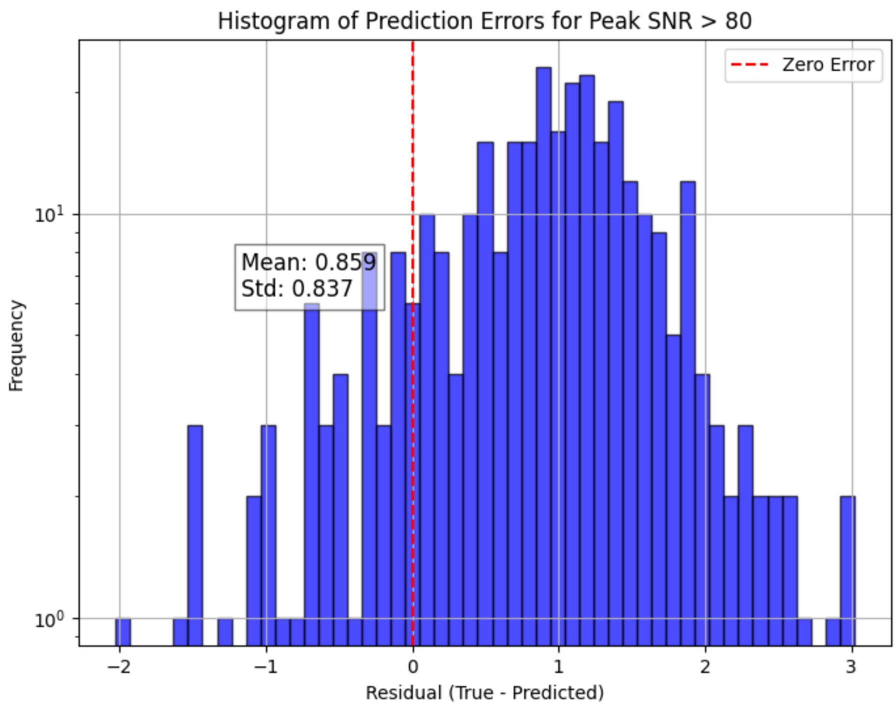

Figure 4.8: The residual histogram plot for events with SNR > 80.

Furthering the analysis, I produced two more datasets of size 10^4, one containing pure waveform signals lacking any form of noise and the other containing only noise without any embedded signal. The goal of these two datasets is to determine what the neural network is doing with the signal and noise seperately.

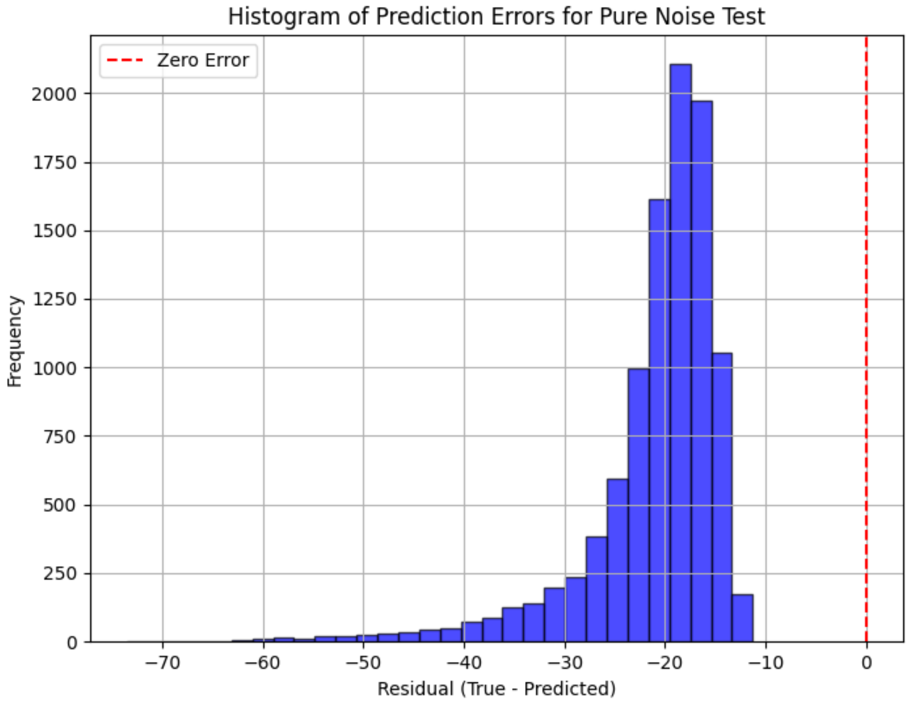

Figure 4.9: The residual histogram plot for pure noise injections.

Because there is no signal within the data, the neural network should theoretically have no chirp mass to estimate, but because the network assumes there is a signal within the detection, it will give an estimate regardless. The distibution of residuals is strongly peaked around -19, with a skew further into the negatives. This suggests to me that the network has picked up some biases from the training process. Perhaps it is picking up on and coupling to imperceptible statistical variation in the Gaussian noise used. Future research should be aimed at answering this question.

The pure signal dataset yielded results even more intriguing than those of the pure noise. While making quite accurate predictions for most of the range of chirp masses, the neural network fails to accurately predict extremely small and extremely large chirp masses. There are very noteable tails diverging from the linear trend in the true vs. predicted plot, and the residual plot also exhibits these large tails and perhaps even some periodicity.

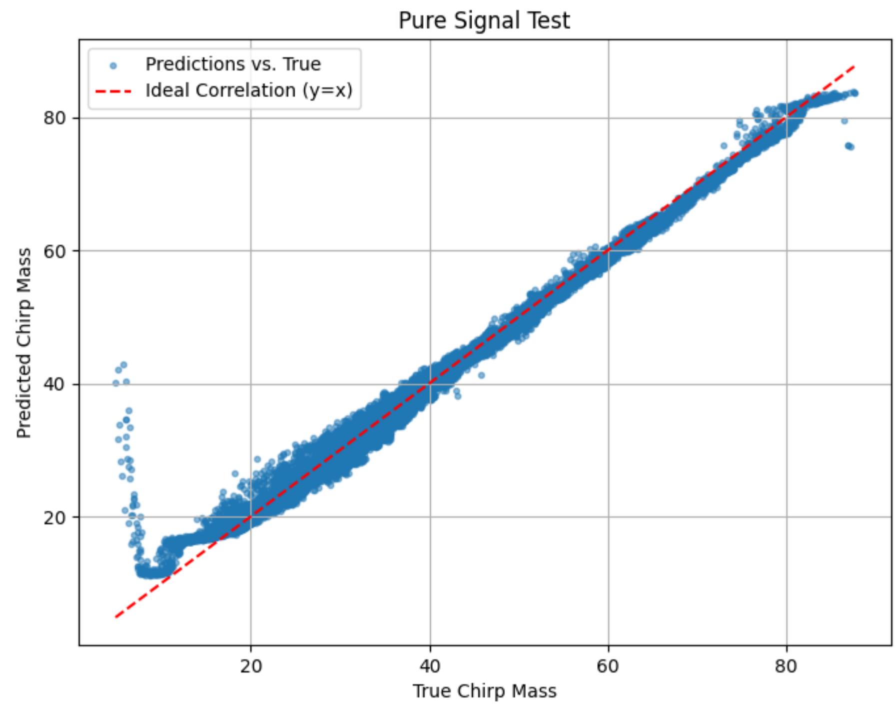

Figure 4.10: True vs. predicted plot for pure signal injections.

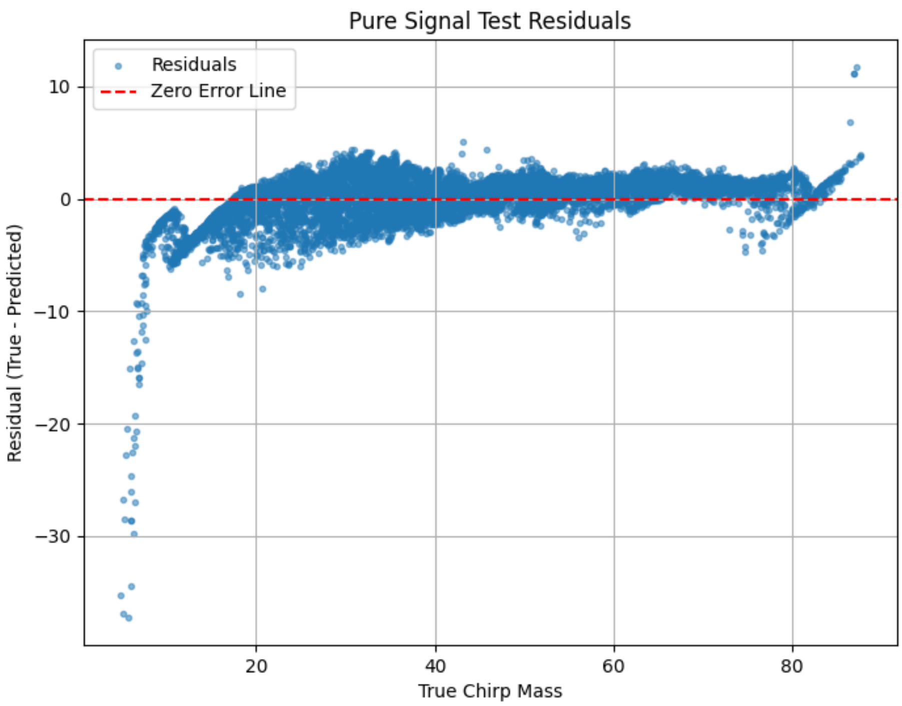

Figure 4.11: The residual plot for pure signal injections.

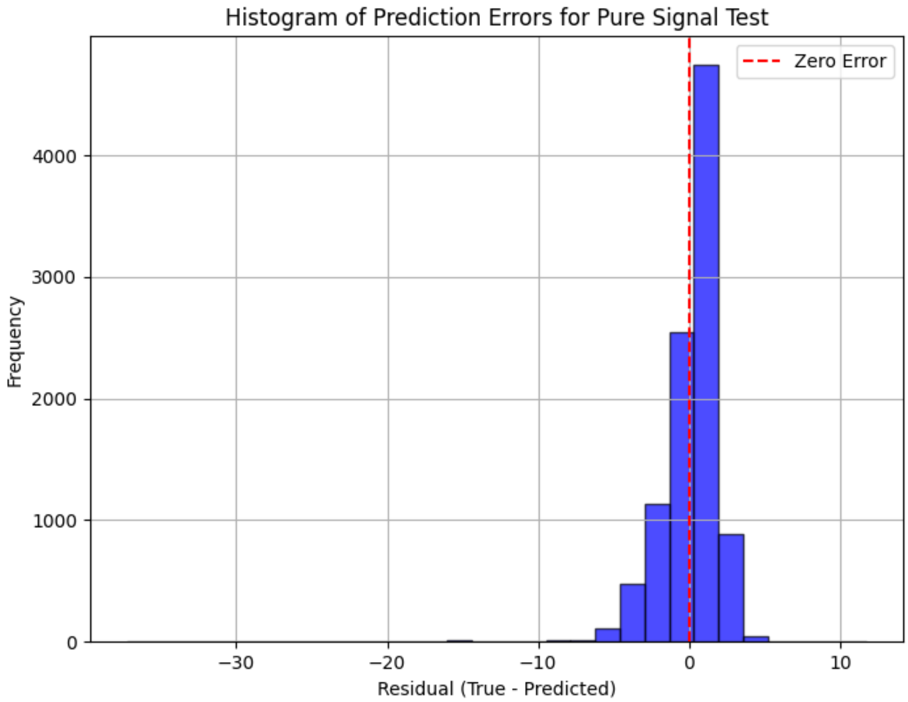

Figure 4.12: The residual histogram plot for pure signal injections.

These tails appear to be a classic instance of edge effects. I hypothesize that they are due to the size of the parameter space the neural network was trained on, this being the same size of parameter space it was tested on. Perhaps if trained on a parameter space larger than it would be tested on, these edge cases would no longer be prevelent. On the other hand, it may be due to the manner in which the convolutional layers are applied to the data once it enters the neural network. These kernels have less information to work with at the edges of the timeseries than they do in the middle of them.It also happens to be the case that these extremes of chirp masses manifest at the beginning and ends of the timeseries data. Systems with larger chirp masses coalesce much more readily as they emit more gravitational radiation. Systems with smaller chirp masses shed gravitational radiation much more slowly, and therefore coalesce at a more leisurely rate.

I incidentally overlooked, during the data preparation phase of this research, that *PyCBC* correlates the length of timeseries with the chirp mass of the system when generating synthetic waveforms unless told otherwise. Therefore, there exists within the dataset that the network was trained on a correlation between the synthetic observations' chirp mass and the position or index of the actual chirp, and therefore of peak SNR, within the timeseries. Based on the analysis already performed, I don't believe this to be the manner by which the neural network is making its chirp mass predictions, but it should be investigated in future research nonetheless.

Chapter 5

Towards More Efficient Analysis

5.1 Real Time Analysis

The ability to perform real-time analysis of gravitational wave (GW) data represents a critical step in unlocking the full scientific potential of GW astronomy. As new detectors come online and the sensitivity of existing detectors increase, so too will the frequency of event detections. Efficient near-instantaneous analysis enables electromagnetic follow-up, an invaluable tool for multimessenger astrophysics, but this requires minimizing the latency between signal detection and scientific interpretation.

Currently, the LVK collaboration utilizes several low-latency pipelines desgned to detect and classify GW events within minutes. These include, GstLAL [59], PyCBC Live [60], and cWB [61]. Despite impressive efforts, these systems often give up accuracy for the sake of speed, thus allowing for quicker public notification. Much of the paramter estimation and sky localization is refined in post-processing over the course of extended periods of time.

Achieving robust real-time GW data anlysis will therefore require navigating several obstacles including computation, noise and glitch characterization, parameter estimation, and synchronization across multiple detectors. As detection rates increase and parameter spaces expand, keeping up with the computational demand becomes more difficult. Short-duration noise artifacts can sometimes mimic true signals and cause false alarms. Rapid parameter estimation techniques are still being developed to work accurately and precisely. On top of it all, with a network of multiple detectors, gathering all available data to utilize in one place still poses a challenge.

Looking forward, there is no doubt that low-latency pipelines for real-time analysis will rely on machine learning techniques such as those developed in this very research and elsewhere.

5.2 Summary and Future Work

This thesis set out to explore a promising avenue in GW data analysis, one that aims to enhance both the efficiency and accuracy of such work through the application of machine learning. Specifically, I introduced and evaluated a neural network capable of estimating the chirp mass of binary black hole coalescences directly from raw, noisy, unprocessed strain time-series data. The central hypothesis and motivation driving this research was that parameter estimation, a typically multi-step and resource-intensive procedure, could be meaningfully accelerated without compromising accuracy by developing the appropriate deep learning architecture.

The model designed in this research used a hybrid neural network structure comprising convolutional layers for feature extraction, LSTM layers for learning temporal dependencies, and fully connected layers for final regression. Trained entirely on synthetic observations generated via *PyCBC*, the model exhibits strong correlation between true and predicted chirp masses across a wide array of SNR regimes. Even without intensive preprocessing such as whitening, notching, or transformation into spectrograms, the neural network demonstrated high accuracy, especially in moderate-to-high peak SNR conditions, with an R^2 value exceeding 0.99 in most regimes.

This performance suggests that deep neural networks can indeed learn to extract astrophysical parameters directly from interferometer-like data, a finding that could reduce reliance on conventional matched-filtering techniques. Moreover, the size and storage efficiency of the model (~90 KB) further demonstrates its potential for deployment in an analysis pipeline. However, this research has also left several open questions to be undertaken in future work.

Evaluation of this neural network revealed distinct biases and apparent edge effects, particularly at the extremes of the chirp mass distribution. This may be an artifact of the parameter space bounds or the inherent structure of the training dataset. Future work should explore widening the parameter space to prevent learned edge behaviors and testing for correlation between chirp mass and the chirp's location in the timeseries to rule out unwarranted temporal cues.

The model's robustness across different noise environments remains a challenge. While it performed well with synthetic Gaussian noise, its performance on real detector noise is yet to be validated. Future work in this area should explore transfer learning with real data from the GWOSC and perhaps even domain adaption tecnniques.

The current neural network focuses solely on chirp mass estimation, as it was entirely unsuccessful in predicting distance or inclination, and very brief undocumented testing seems to point to the fact that it is marginally successful in estimating peak SNR. However, GW signals encode multiple parameters including mass ratios, spins, and more. Future extensions of this work could explore methods for estimating multiple parameters simultaneously or even integrating this network with one capable of flagging events in continuous datastreams.

Of utmost importance is the fact that parameter estimation without uncertainty is scientifically incomplete. Conformal prediction, Bayesian deep learning, and normalizing flows all offer paths toward reliable uncertainty quantification. Further research in these areas will better help ML solutions integrate with statistically rigorous scientific pipelines.

Finally, the lighweight nature of this model opens up the possibility for deployment in live detector settings. It could be run in conjunction with other smaller networks on just about any modern computer. When paired with detection networks, this architecture could contribute to a future real-time analysis stack.

This research has demonstrated that it is possible to unite data-heavy astrophysics and modern machine learning by building architectures that are fast, effective, and scientifically grounded. It provides a robust foundation for more expansive efforts in parameter estimation and the eventual integration of neural networks into trusted scientific workflows. The path to a fully autonomous GW data analysis will be long, but this work contributes a small, yet meaningful, step in that direction.

5.3 Outlook

I am personally incredibly excited for the future of gravitational wave astronomy and the technical challenges that come along with it. Where there are problems to solve, there are also many eager people willing to sit down and attempt to solve them. I believe that the part machine learning plays in sciences of all kinds will continue to expand at ever increasing speeds, and am eager to make further impact in this particular field. Beyond this bachelor honors thesis and my time at Valparaiso University, I am excited to attend graduate school at the Australian National University (ANU) Center for Gravitational Astrophysics (CGA). There, I will continue my studies of gravitational physics and its intersection with machine learning as I pursue my graduate degree.

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