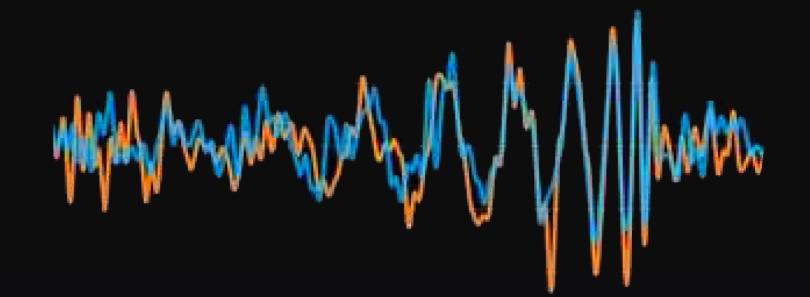


Parameter Estimation of Binary Black Hole Coalescence Using LSTM Neural Networks



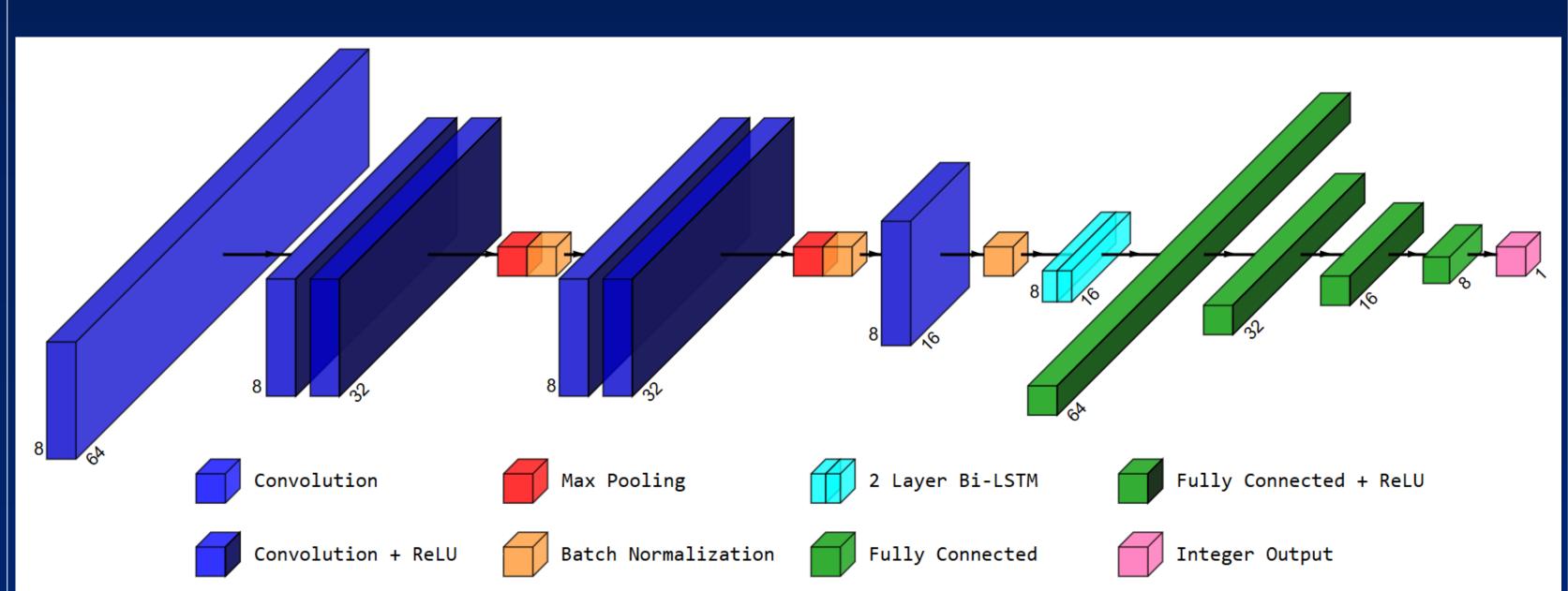
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Abstract

Rapid gravitational wave (GW) data analysis is essential for scientific progress, but traditional data analysis methods are computationally intensive and limited in accuracy. With increasing detection rates, there is a pressing need for more efficient analysis techniques. Recently, machine learning has shown promise in these improvements. This research presents a neural network capable of directly analyzing raw, noisy gravitational wave signals to accurately estimate the chirp mass of binary black hole systems. By circumventing extensive preprocessing, this approach enhances computational efficiency and is capable of more accurate parameter estimation than traditional techniques, advancing the field of gravitational wave astronomy.

The Neural Network

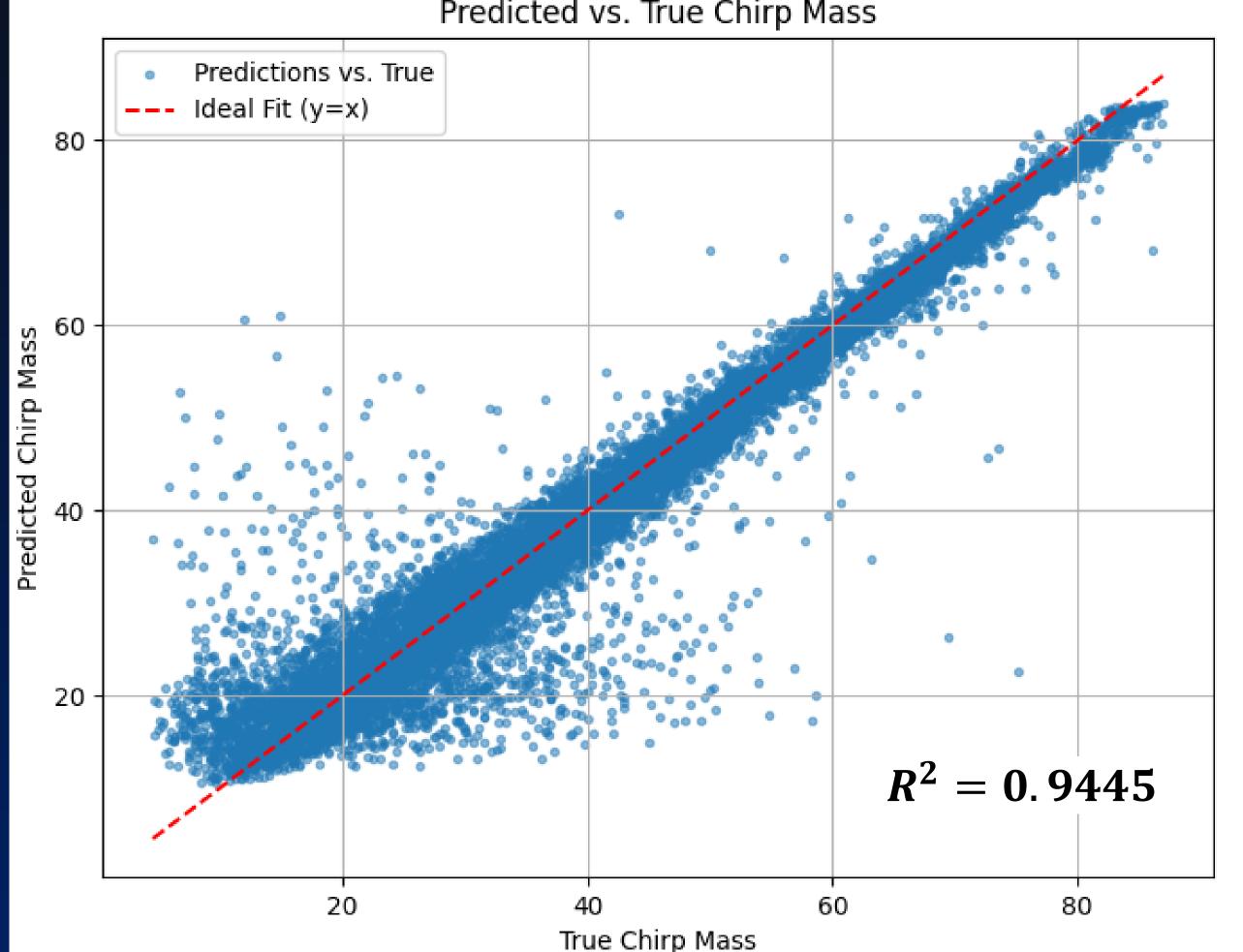
- A hybrid neural network structure containing Convolution, LSTM, and Dense layers
- Optimized via random search of hyperparameter space with Optuna package
- The model contains 18,009 total tunable parameters requiring 89.9 KB of storage



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

- Chirp Mass can be accurately estimated from a noisy strain timeseries without the need for preprocessing
- Neural Network performance suffers in low SNR regimes, but *LIGO's detection threshold* is currently an SNR of 8
- Machine Learning solutions can perform parameter estimation *near instantaneously*
- **Initially trying to estimate 4 parameters**, this network architecture could only *reliably track 1 parameter*
- This neural network struggles to accurately estimate chirp masses at the extremes of the parameter space.
- There is a *definitive linear correlation between true* and predicted chirp masses evidenced by R^2 > 0.99
- Residual plots exhibit more order as SNR decreases, implying some sort of *inherent bias in the model*

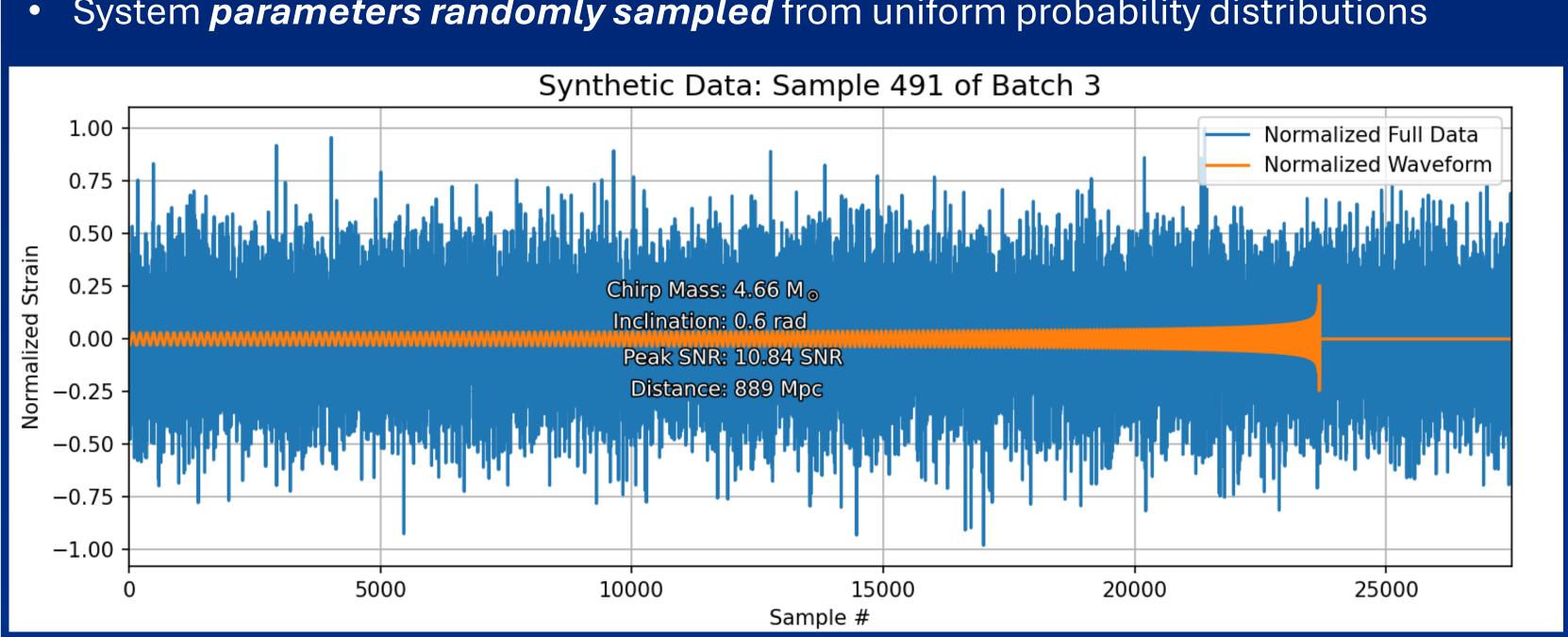
Results and Impact Predicted vs. True Chirp Mass

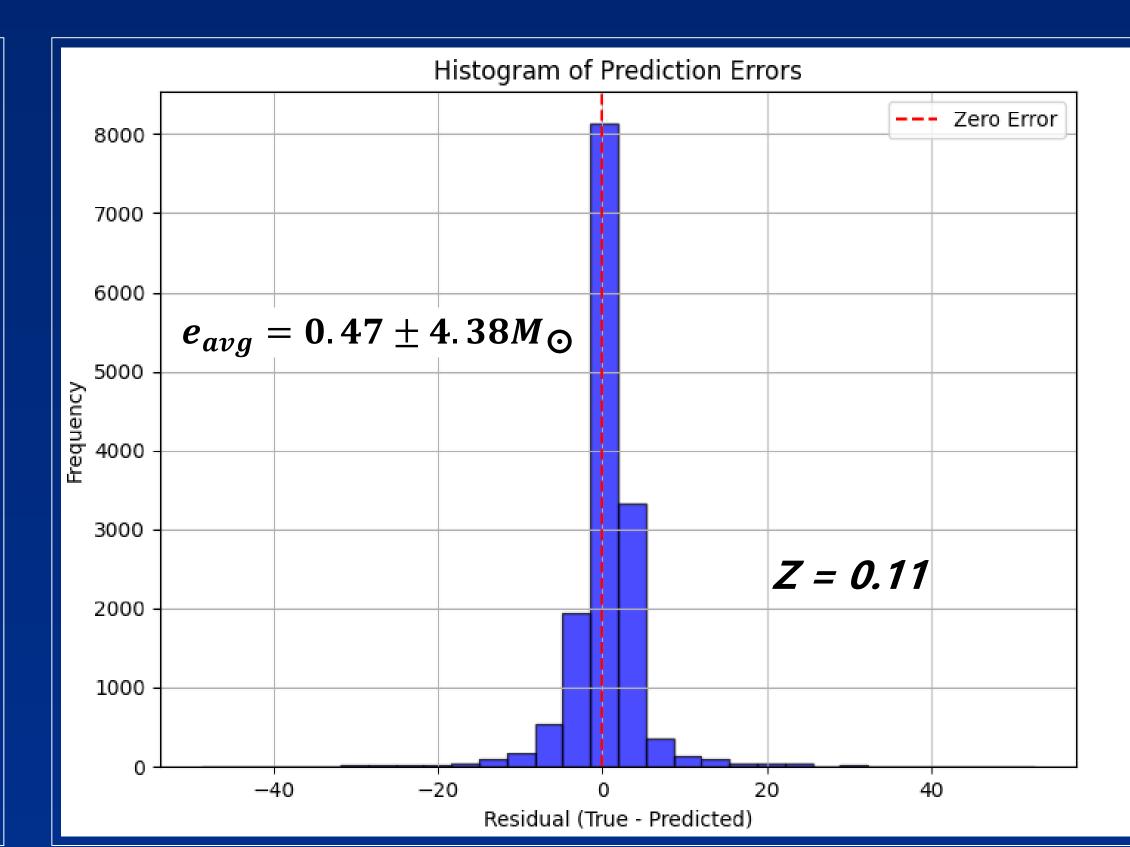


Peak SNR Range	R^2 Value	Mean Residual	Std. Dev. of Residual
0 < SNR < 5	0.417	1.443	9.241
5 < SNR < 20	0.959	0.092	3.558
20 < SNR < 35	0.990	0.629	1.594
35 < SNR < 50	0.993	0.509	1.336
50 < SNR < 65	0.993	0.601	1.220
65 < SNR < 80	0.993	0.620	1.092
80 < SNR	0.992	0.859	0.837

Synthetic Data

- Produced a total of **1.3E+5** samples of data to train and evaluate the neural network
- Synthetic Observations, Pure Signal, Pure Noise, SNR Regimes *using PyCBC*
- System *parameters randomly sampled* from uniform probability distributions





Conclusion and Future Work

- Neural Networks can indeed extract astrophysical parameters from minimally processed interferometer-like data. Extensions of this work should aim to *estimate multiple system parameters* simultaneously.
- When *paired with other light-weight neural networks* capable of flagging and trimming detections out of continuous data streams, this model could work as part of a real-time data analysis stack.
- Evaluation of this model revealed *inherent biases and edge effects* in its *predictions*, particularly at the extremes of the parameter space. These phenomena should attempt to be resolved in future work.
- Parameter estimation without robust uncertainty measurements is scientifically incomplete. Continued efforts should prioritize the integration of uncertainty quantification for individual estimates.



