Generating Binary Black Hole Mergers from Globular Clusters Using Deep Learning

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1. Abstract

Observations of gravitational waves have discovered nearly a hundred mergers of binary black holes. Some of these black hole mergers are believed to originate in the center of globular clusters, which are densely packed groups of stars. Understanding how these globular clusters can produce black hole mergers often involves simulating their behavior using N-body codes. However, many properties of globular clusters that lead to such mergers— such as number of stars, cluster radius, chemical composition, and their position within galaxies — are unknown.

One way to address these uncertainties is by directly comparing N-body simulation results to the observed data. However, this approach faces a significant challenge: N-body simulations are computationally intensive and can take several months for a single stellar cluster. To overcome this, we have developed an emulator using neural networks to mimic the outcomes of astrophysical simulations on stellar clusters.

In this study, we use Normalizing Flows to interpolate astrophysical outcomes derived from the Cluster Monte Carlo (CMC), an N-body simulation code. We optimized our network's performance by fine-tuning the number of training cycles, learning rate, batch sizes, and number of layers in the network, as well as how we normalize the simulation data. Our trained network can accurately predict key properties of black hole mergers such as their masses and time to their mergers. Moreover, we have drastically reduced the computational time required to simulate a single cluster—from months, as necessitated by CMC, to mere seconds.

2. Introduction

Observations of gravitational waves have discovered nearly a hundred mergers of binary black holes. Some of these black hole mergers are believed to originate in the center of Globular Clusters, which are densely packed groups of thousands of stars bound by gravity. The figure on the right showcases the interactions between stellar objects and black holes within these globular clusters that lead to black hole merger events. Over time, these interactions create a binary black hole system that merges to produce a gravitational wave event.

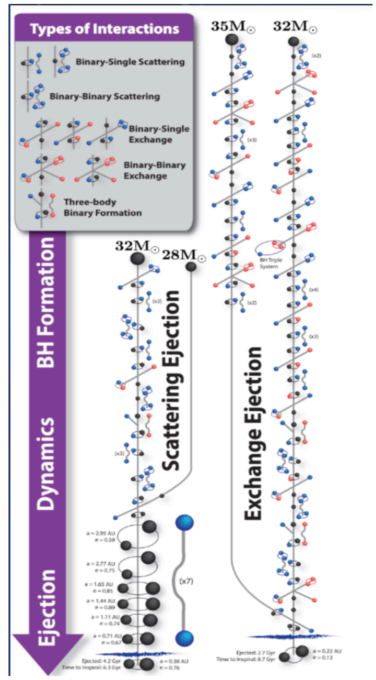

Image credit: [6]

3. Research Objective and Goals

Understanding how these globular Clusters can produce black hole mergers involves simulating their behavior using N-body codes, a computational tool used in astrophysics N-body simulations can allow us to see how clusters evolve over time, which provides insight into the formation & evolution of binary black hole systems, within globular clusters.

Traditional N-body simulations help us understand how black hole binaries form and evolve within stellar clusters. However, these simulations—such as those run using the Cluster Monte Carlo (CMC) Code—are computationally intensive, often taking months to simulate a single cluster. This project aims to develop a generative AI-based emulator using neural networks to approximate the outcomes of astrophysical simulations more efficiently.

- Data Source: Utilize the Cluster Monte Carlo (CMC) dataset for training. Our data contains around 13,000 black hole mergers spread across different cluster properties.
- Generative Model: Apply Normalizing Flows, a class of generative AI models, to emulate complex astrophysical events with reduced computational demand.

4. Framework - Dataset

The Cluster Monte Carlo Code is an N-Body code for collisional stellar dynamics. A set of data (below) was run and saved from this code.

	model_num	rv	rg	Z	N	merger_time(Myr)	id1	id2	m1	m2	merger_channel
0	36	0.5	20.0	0.020	16.0	292.224242	1834592.0	2041552.0	14.100000	13.700000	5
1	36	0.5	20.0	0.020	16.0	361.244899	1755061.0	1376500.0	14.800000	8.060000	5
2	36	0.5	20.0	0.020	16.0	380.915556	841575.0	2378898.0	8.100000	7.340000	5
3	36	0.5	20.0	0.020	16.0	578.985985	1454823.0	1614161.0	8.090000	8.260000	5
4	36	0.5	20.0	0.020	16.0	767.393557	335263.0	1110530.0	7.690000	8.170000	5
...	...	...	...	...	...	...	...	...	...	...	...

Image created by researcher

Properties of the cluster (Input):

- rv = varial radius
- rg = position in galaxy
- Z = metallicity (chemical composition)
- N = Number of stars

Properties of binary black holes (Output):

- m1 = mass of heavier black hole
- m2 = mass of lighter black hole
- Merger time = time from the simulation until the black holes merge
- Merger channel = the way/process through which these black holes merge

4. Data Normalization

Normalization is a data preparation technique used in machine learning to transform the column in a dataset to a similar scale. This helps to improve the speed and accuracy of our neural network. Ultimately, the model's results will need to be transformed back through the inverse of these functions. The figure is shown below:

Model Input Columns

Variable	Original Domain	Transformation	Resulting Domain
rv	[0.5, 2]	rv/2	[0.25, 1]
rg	[2, 20]	rg/20	[0.1, 1]
Z	[0.002, 0.02]	log_10 (Z/0.02)	[-2,0]
N	[2*10^5, 32*10^5]	log_2 (N)	[17.6, 21.6]

Model Output Columns

Variable	Original Domain	Transformation	Resulting Domain
m1	[5, 253.3]	log_10(m1+m2)	[0.99, 2.46]
m2	[5, 147.7]	min(m1/m2, m2/m1)	[0.0035, 1]
Merger Time (t)	[6.25, 13,984.5]	log_10 (t/0.02)	[0.79, 4.15]
Merger Channel	[1, 5] (classification, integer)	none	[1, 5]

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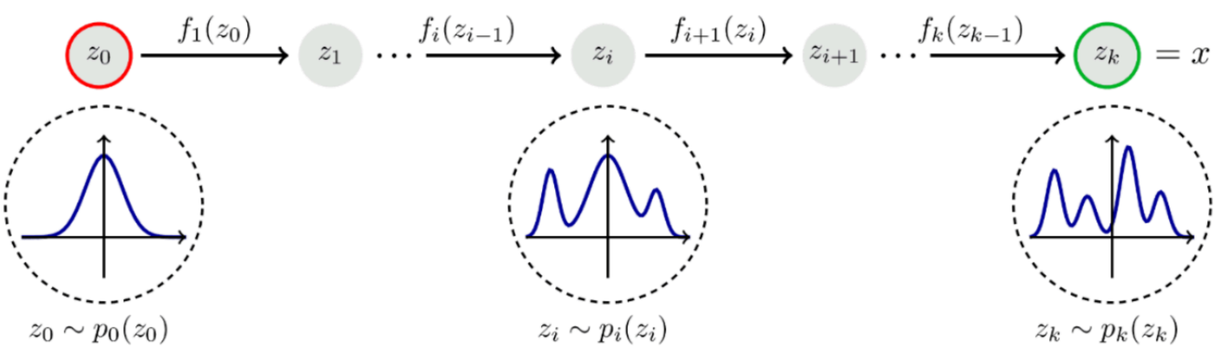
6. Methodology: Normalizing Flows

Normalizing flows help model complex distributions of binary black hole properties (like masses, time delay, and merger channels) by transforming a simple, known distribution (e.g., Gaussian) into one that matches the CMC data. This is done through a series of invertible transformations that progressively reshape the base distribution to approximate the true distribution of black hole attributes. Key Steps:

1. Start with a Base Distribution: Begin with a simple probability distribution.
2. Apply Transformations: A sequence of transformations reshapes this base distribution to match the complex patterns in black hole distributions.
3. Calculate Probabilities: By applying the change of variables, the model provides exact probability densities for black hole characteristics, making it effective for likelihood estimation and data generation.

Image credit (below): [1]



Simple Distribution → Learning Transformations → Complex Distribution

We trained our model on 136 distinct properties of unique globular clusters, resulting in a dataset of 13,000 black hole mergers. We optimized the training process by maximizing the likelihood of the observed data as we tuned hyperparameters. The model architecture consists of 10 layers, each containing 1,024 hidden units.

7. Data Analysis

To illustrate our findings, we present a comparison of binary black hole (BBH) properties between CMC and our network for a globular cluster characterized with rv = 1 pc, rg = 20 pc, Z = 0.02 solar metallicity, N = 32 x 10^5 stars. The results are shown as histograms depicting the following key properties: the sum of black hole masses (m1 + m2), the mass ratio (q), the merger time, and the classifications of the merger channels.

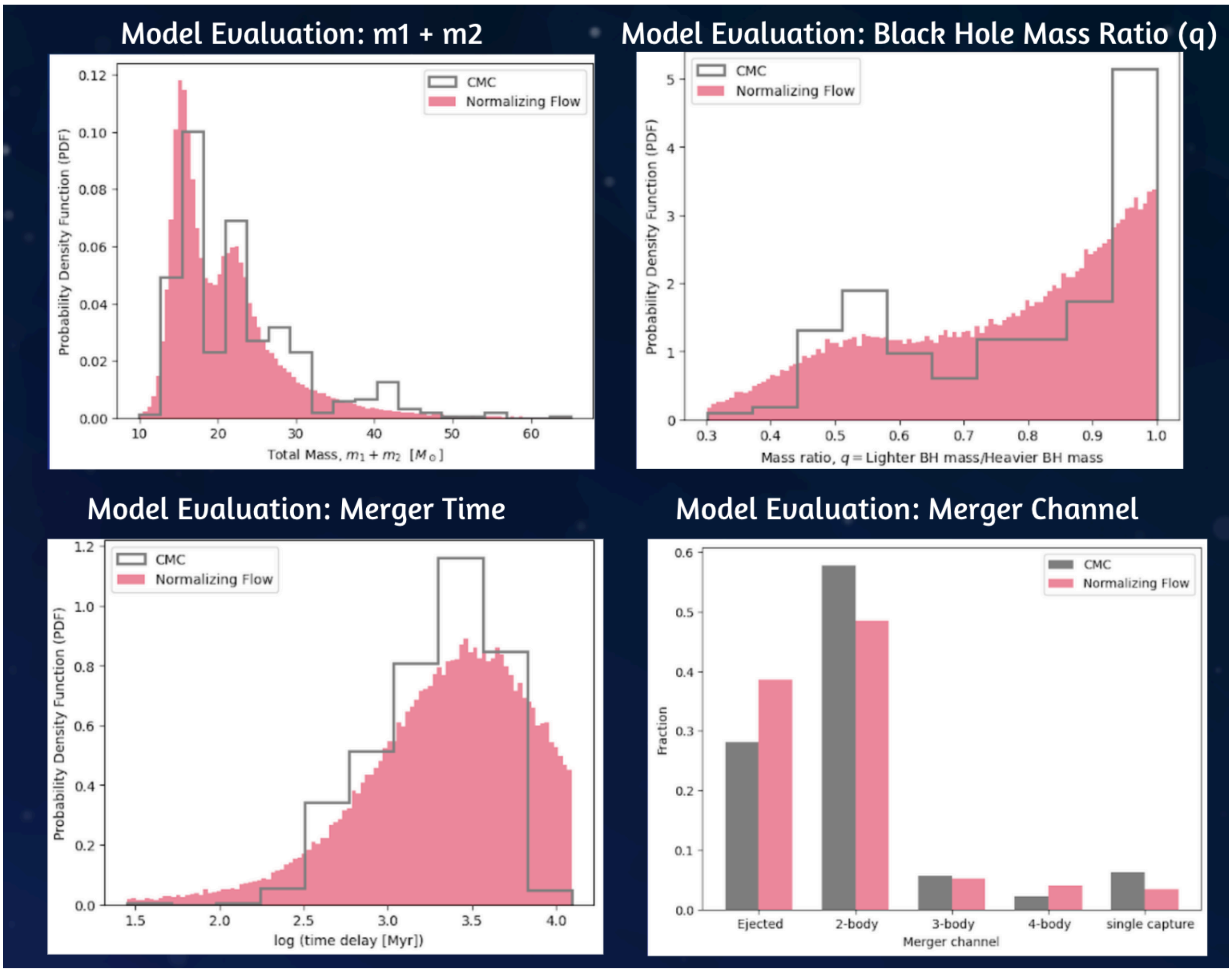


Image created by researcher

8. Conclusion

We developed a normalizing flow network to create an accurate simulation model for binary black hole mergers in globular clusters. The trained neural networks efficiently generate outputs based on conditional inputs related to globular clusters that host these mergers. Moreover, we have drastically reduce the computational time to simulate a single cluster -- from months, as necessitated by the Cluster Monte Carlo Code, to mere seconds using machine learning. The Normalizing Flow network directly provides likelihoods that can be applied in Bayesian analysis of globular cluster properties.

9. References

[1]https://tikz.net/normalizing-flow/

[2]https://clustermontecarlo.github.io/CMC-COSMIC/src/index.html (dataset)

[3]https://medium.com/@jain.sm/normalizing-flows-an-intutive-explana-13b92dcfe643

[4]https://uvadlc-notebooks.readthedocs.io/en/latest/tutorial_notebooks/tutorial11/NF_image_modeling.html [5]https://github.com/ikostrikov/pytorch-flows (flows architecture) [6] https://arxiv.org/pdf/1604.04254.pdf

[7]https://www.sci.news/astronomy/globular-star-clusters-repeated-merging-multiple-black-holes-05906.html