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Detecting Isolated Mass-Gap Black Holes Using Data-Driven Approaches

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1. Abstract

Isolated mass-gap black holes are a unique type of black hole that fall within a range of masses in which it can be difficult to identify a stellar mass. In this mass-range, both neutron stars and black holes exist these black holes being mass-gap black holes. Current scientific methods utilize statistical analysis to classify such mass-gap stellar masses as black hole, neutron star, etc., but this can be a long and time-consuming process. We propose a novel machine learning driven approach to identifying such objects within the mass-gap automatically using Hubble Space Telescope (HST) microlensing surveys. We develop synthetic data based on existing classifications and compare the classification performance of three different model architectures on the data for a binary classification task. After training a Feed Forward Neural Network, a Radial Basis Function Network, and a Deep Belief Network, we find that the best candidate for mass- gap black hole and neutron star classification is the Feed Forward Neural Network with a test-set classification accuracy of 98.6%.

2. Keywords

Mass-gap, Black holes, Neutron stars, Machine learn-ing, Artificial intelligence

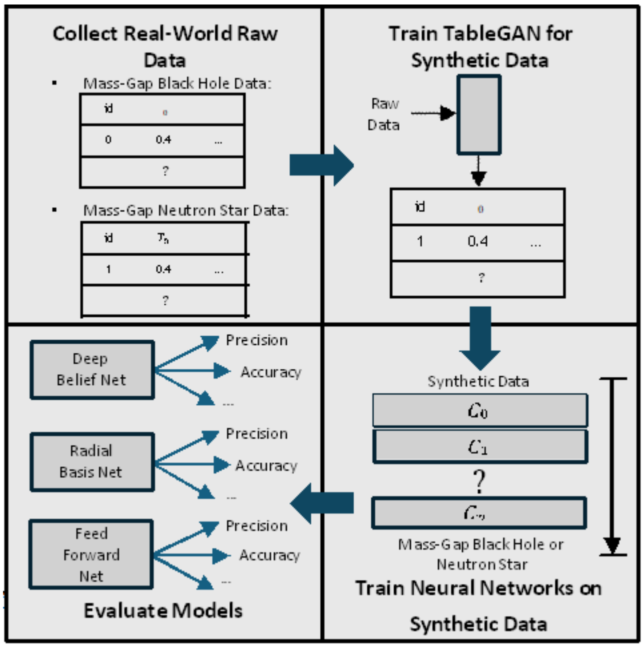
3. Introduction

Isolated mass-gap black holes are a unique type of black hole that fall within a mass range in which black holes are not typically found [1] specifically forming between 2-5M, or solar masses. This range, known as the ”mass gap” serves as an area of uncertainty when differentiating between black holes and neutron stars. A common black hole, known as a stellar mass black hole, is formed when a massive star collapses, leaving behind the remnants which form a black hole. This type of black hole typically has a masses tens of times the mass of the sun, and are relatively well understood in comparison to other types of black holes. Isolated mass-gap black holes, on the other hand, fall within a range in which black holes should not form, known as the ”mass gap” In this range of masses, it can be difficult to predict whether an object is a neutron star or black hole.

A current method for identifying isolated mass gap black holes is gravitational microlensing [7], a technique leveraged by Lam, et al. in a 2022 study [8]. Gravitational microlensing is a technique that leverages the bending of light when a black hole passes a star [7]. The study by Lam et al offers an analysis of five candidate isolated mass-gap black holes, with a specific focus on candidate OB110462. The analysis was conducted through Bayesian inference and the Multi Nest nested sampling routine [9], and concluded that OB110462 is a black hole.

In a preceding study, Lam et al developed a simulation software, PopSyCLE or Population Synthesis Code for Compact Microlensing Events [3], that is designed to simulate microlensing events in the galaxy.

Figure 1: Schematic of Machine Learning pipeline used to detect mass- gap black holes in this work. First, we collect data from both labelled Hubble Space Telescope (HST) [2] microlensing surveys, and PopSyCLE [3] simulated surveys; compile into a dataset; and feed into a Generative Adversarial Network (GAN) for synthetic data by the TableGAN [4] data synthesis architecture. Then, we train three separate neural networks on the data: a deep belief network [5], a radial basis function network [6], and a feed-forward neural network.



Current approaches to identification of isolated mass-gap black holes have proven to be very tedious due to the magnitude of measurements involved in analysis of mass-gap object data. Data analyzed is derived from gravitational lensing signals. Excluding mass, these measurements have been proven to often be inconclusive when identifying objects in the mass-gap, but successful when determining the presence of these objects in LIGO [10], Virgo [11], KAGRA [12] collaboration studies.

Identifying and characterizing objects found in this mass- gap range has proven to be a challenge for research in this field. Traditional methods have encountered limitations as a result of the complexity and uncertainly involved in the data analysis process. We propose a machine learning approach to classify isolated mass-gap black holes found in the lower mass-gap. Machine learning models are designed to process vasts amount of data, and identify patterns within these datasets. In practical use, a model will be given training data on which it is able to identify these patterns, then evaluated on testing data to observe performance on unseen data. By identifying patterns in gravitational lensing data, in relation to the type of object observed in the mass-gap, a machine learning approach can prove to be proficient in the classification of mass-gap black holes.

A 2021 study by Datta, et al. [13] took the knowledge that the tidal-deformability (TD) and tidal-heating (TH) parameters in gravitational wave detectors have slight differences, and attempted to use this knowledge to discern objects found in the mass-gap. However, the study found limitations in doing so, in that there is a constraint in identifying objects found beyond a certain distance from the detection facility. This suggests that relying fully upon gravitational data obtained from gravitational lensing instruments may have constraints in identifying objects due to changes in the TD and TH parameters as distance increases, when dealing with statistical analysis. The application of machine learning in this context can prove to be proficient, in that a machine learning model is capable of processing large amounts of data, that can encompass many more parameters at once. This will allow the model to identify more complex patterns that involve each of these parameters.

In this study, as shown in fig. 1, we propose a method to determine the feasibility of machine learning in differentiating between mass gap objects as neutron stars or black holes for accelerated detection capabilities. We use the Hubble Space Telescope [2] and PopSyCLE [3] synthetic simulation data used from experiments to train a Deep Belief Network, Radial Basis Function Network, and Feed Forward Neural Network to evaluate the feasibility of this method.

4. Data Preparation

4.1. Data sourcing and compilation

We aggregate the Hubble Space Telescope (HST) [2] and PopSyCLE [3] simulation data from the experiments of Lam et al [8]. Specifically, HST data provides labeled candidates of mass gap black holes and neutron stars and PopSyCLE simulations include labeled, non-massgap black holes and neutron stars. Each microlensing data example holds the time of closes approach in days (t0), the impact parameter (u0), the Einstein crossing time in days (t-E), Einstein radius in milliampere seconds (theta-E), the microlensing parallax (pi-E), the galactic proper motion vector (mu-b-s), the mass of the detected object from the lens (mass-L), the lens-source microlensing parallax (pi-rel), the lens-source galactic proper motion vector (mu-b-rel), the lens-source proper motion vector (mu-rel), and the identity of the object detected a black hole or a neutron star (target).

4.2. Synthetic data generation

Due to the limited number of samples collected from HST microlensing surveys, we design a Generative Adversarial Network (GAN) [14] for generating new data. A GAN is traditionally trained for tasks such as image generation, where a generator G is trained in an adversarial game against discriminator D. G generates samples, which D determines are real samples or samples from G. The goal of the network is to train a generator that can successfully trick D into predicting that the outputs of G are real. We refer the reader to the work of Good fellow, et al. [14] for more specific information on GANs and their learning procedure.

We design a GAN based off of the Table GAN [4] method in order to generate synthetic tabular data. As shown in **Figure 2**, we utilize a convolutional process to filter input noise into microlensing survey data from the data distribution of HST surveys. The process is repeated for 100 epochs. Finally, a total of 6,000 synthetic mass-gap black hole and mass-gap neutron star microlensing candidates from the trained generator are concatenated with the existing microlensing surveys for a total dataset length of 9,000. This composed dataset is given by D_{data}.

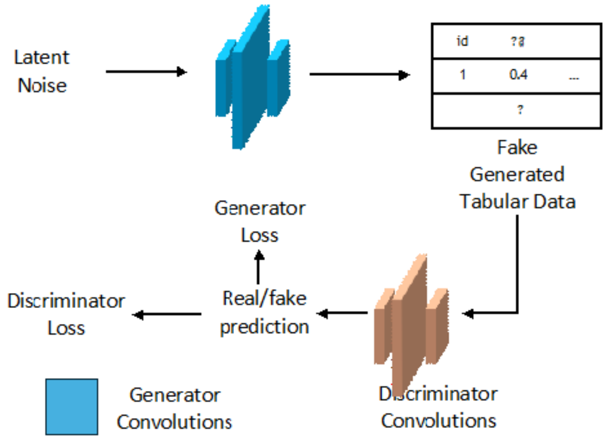
An 80/20 train/validation and test split was then passed on the data.

4.3. Data resampling

The combination of the synthetically generated data along with the original data in D_{data} had very high skew. In order to reduce this skew, resampling was applied through the SMOTE - Tomek link algorithm [15].

By the SMOTE Tomek link algorithm, we iteratively up sample the minority class either mass gap black holes or mass-gap neutron stars and down sample the majority class. Essentially, this method allows for the data to be balanced between both classes.

Figure 2: Due to limited number of microlensing surveys in our dataset, we utilize a GAN [14] predict continuous outputs that resemble those of mass- gap HST microlensing surveys for synthetic data. Specifically, the Table GAN [4] method is adapted for generating synthetic, tabular data for our training pipeline.



5. Model Architectures

5.1. Loss calculations

This problem is bivariate and a binary classification problem with a total of 2 classes: mass-gap black holes and mass-gap neutron stars As such, a categorical cross entropy loss must be applied as the optimization objective for a model learning to distinguish between the 2 classes. This loss is given by the following equation:

$$L_{net} = -\frac{1}{N}\sum_{i}^{N}\sum_{j}^{M} y_{ij} \cdot \log \hat{y}_{ij}, \tag{1}$$

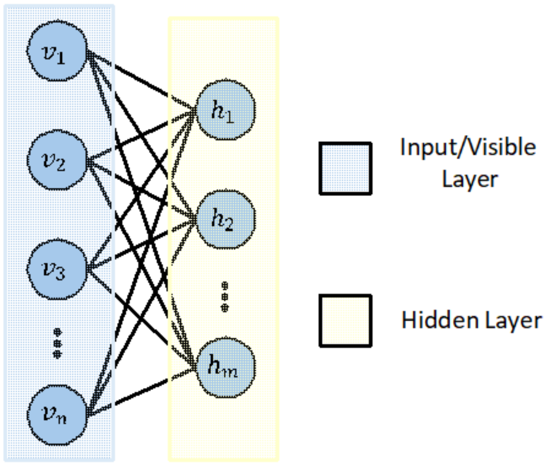
where L_{net} is the categorical cross entropy loss between the predicted set y and the label set y for one of the 2 classes j at a given sample i, with M total classes and N total samples. This optimization objective L_{net} can then be used to train several machine learning pipelines to determine effectiveness and the robustness of machine learning to detect mass-gap objects versus non mass-gap objects. In this work, we train three different network architectures to gauge robustness of the model: A deep belief network [5], a radial basis function network [6], and a simple feed forward neural network. The Results are then compared in Sec. IV.

5.2. Deep belief network

We train a Deep Belief Network, hereafter referred to as a DBN, on the dataset D_{data}.

A DBN can be described as an ensemble model which contains several Restricted Boltzmann Machines (RBMs) [5] linked to each other. A RBM is a simple neural network with two layers an input layer along with one hidden layer, as shown in **Figure 3**. The simplicity of the network enables it to be used in more complex network ensembles while also learning useful data representations. RBMs are popular for tasks including classification and basic regression due to their restricted design meaning that, within the same layer, nodes are not interconnected, allowing individual nodes to pass data more relevant to the classification task.

Figure 3: Schematic of Restricted Boltzmann Machine [5] architecture and design. There is an input visible layer along with a hidden layer acting as the output layer of the model.



Stacking several RBMs together forms a DBN, a set of *overlapping* RBMs as shown in fig. 4. Each individual RBM can learn specific representations and the ensemble learns from the higher order of non-linearity. In this work, we train a DBN model with 10 visible units each along with an input layer connected to the model. This network is then trained for 20 epochs.

5.3. Radial basis function network

A Radial Basis Function Network (RBFN) [6] is made up of several Radial Basis Functions (RBFs). The RBFs are attached together as "nodes" within a network to act as a composite radial basis function network.

The radial basis function is a simple neural network that is given by three layers an input layer with no activation or weights, a hidden layer, and a final output layer. Mathematically, the inputs are given by an input vector x such that

$$x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

where n is the number of input features and each value corresponds to a particular input node within the RBF's input layer. The hidden layer then acts upon the input values x using guassian functions, computing

$$x_{hidden} = \begin{bmatrix} \sum_{i}^{n} a_1 e^{-\frac{(x_i - b_1)^2}{2c_1^2}} \\ \sum_{i}^{n} a_2 e^{-\frac{(x_i - b_2)^2}{2c_2^2}} \\ \vdots \\ \sum_{i}^{n} a_j e^{-\frac{(x_i - b_j)^2}{2c_j^2}} \end{bmatrix},$$

Figure 4: Schematic of Deep Belief Network [5] architecture and design. Overlapping RBMs are constructed to form the DBN architecture.

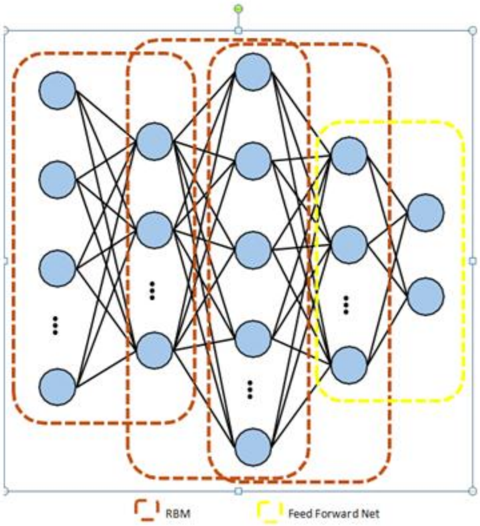
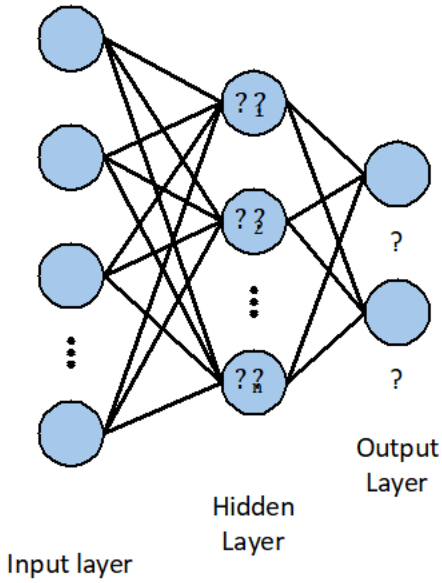


Figure 5: Schematic of Radial Basis Function Network [6] architecture and design. The Radial Basis Functions are used to create an ensemble RBFN. The three layer model consists of an input layer, a hidden layer with radial basis, Gaussian activations, and the final layer consists of simple summation nodes.



For a given set of j hidden layer nodes with learnable parameters a, b and c such that

$$a = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_j \end{bmatrix}, a_j \in \mathbb{R}; \qquad b = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_j \end{bmatrix}, b_j \in \mathbb{R};$$

$$c = \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_j \end{bmatrix}, c_j \in \mathbb{R}.$$

Finally, the output layer takes the vector x_{hidden} and computes a summation over the vector to determine the output value Y such that

$$y = \sum_i x_{hidden_i}.$$

We then train this model for 20 epochs as with the DBN described in Sec. III-B.

D. Feed Forward Neural Network

A simple feed forward neural network is implemented as the third model in our comparison. We employ simple linear layers along with ReLu activations after each linear layer. We apply 2 hidden layers along with one output layer that ends in a soft max activation function. We then train this model for 20 epochs as with the DBN described in Sec. III-B.

E. Training Details

After implementing all model architectures, each network was trained for 20 epochs, as stated before. Additionally, a learning rate of 0.001 was used for all models and the loss L_{net} was computed as the optimization objective. The Adam [16] optimizer was used as the optimization framework.

6. Results

6.1. Metrics

For metrics, we utilize classification accuracy, precision, recall and F1 score. For clarity, the metrics are defined as follows:

$$\text{accuracy} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives} + \text{True Negatives} + \text{False Negatives}},$$

$$\text{precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}},$$

$$\text{recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}},$$

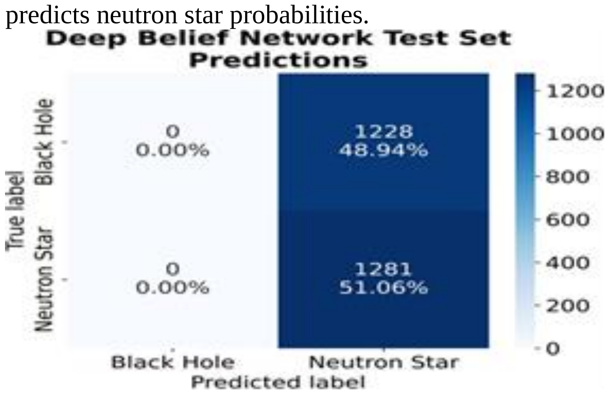
$$\text{F1} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}.$$

6.2. Network comparison

We test all models on the test set of roughly 2,500 examples. The corresponding precision, recall, accuracy, and F1 scores are then given.

The Deep Belief Network generally performs poorly on the test dataset, achieving high recall but low accuracy and precision. As shown in **Figure 6**, the confusion matrix shows that the Deep Belief Network is unable to learn the non-linearity of the classification problem.

Figure 6: Confusion matrix of the Deep Belief Network predictions on the test set. The Deep Belief Network performs poorly and learns an incorrect representation it only predicts neutron star probabilities.

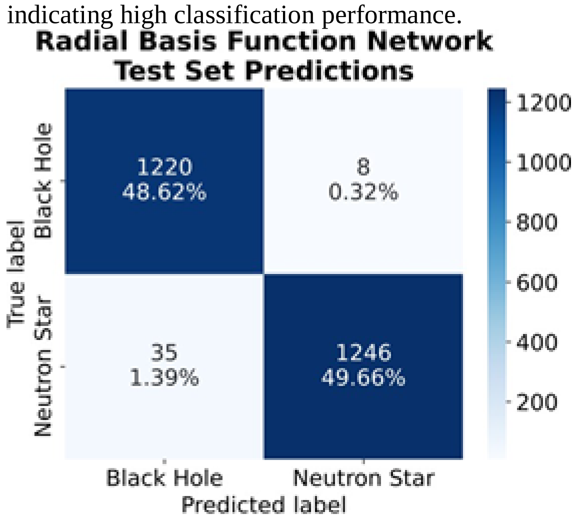


Unlike the Deep Belief Network, the Radial Basis Function Network performs well across the classification tasks due to its neural network node-like structure. The model achieves both high accuracy, precision, F1, and recall as shown in fig. 7.

Table 1: Model Scores on Test Set.

	Precision	Recall	Accuracy	F1
Deep Belief Network	0.511	1.00	0.511	0.676
Radial Basis Function Network	0.994	0.973	0.983	0.983
Feed Forward Network	0.997	0.976	0.986	0.986

Figure 7: Confusion matrix of the Radial Basis Function Network predictions on the test set. The Radial Basis Function Network far outperforms the Deep Belief Network. A visible diagonal is apparent on the confusion matrix indicating high classification performance.



The Feed Forward Neural Network also performs well, achieving a strong downward diagonal slope in the confusion matrix shown in fig. 8.

Finally, we compare all three models across the evaluation metrics. We find that the Feed Forward Neural Network and the Radial Basis Function Network both perform well, with the Feed Forward Neural Network achieving the highest classification accuracy. This can be attributed to the Feed Forward Neural Network's ability to understand more non-linear data relationships.

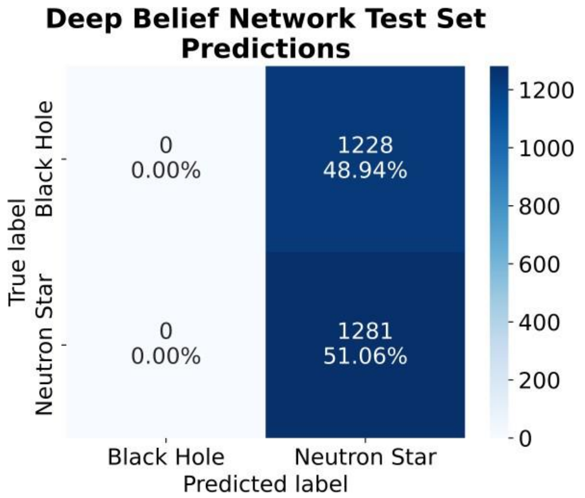
Furthermore, we note that both the Feed Forward and Radial Basis Networks have slight difficult in classifying the black hole and both have a ą 1% false negative rate. This could be attributed to remaining skew in the data even after resampling.

7. Conclusions and Future Work

We report three machine learning models a deep belief network, radial basis function network, and a feed forward neural network that have the ability to discern between objects within the mass-gap range as neutron stars or black holes. Our custom data pipeline enables higher quality learning on existing, small sample sized datasets.

We find that both the radial basis function network and feed forward neural network considerably outperform the deep belief network, illustrating the degree of non-linearity of mass- gap objects as well as the ability for heuristics to distinguish between stellar objects within the mass-gap range.

Figure 8: Confusion matrix of the Feed Forward Neural Network predictions on the test set. The Feed Forward Network has results comparable to those of the Radial Basis Function Network. The confusion matrix illustrates a strong diagonal indicating high classification performance.



Our work provides insight into the formation of black holes within the mass-gap. The phenomenon of stellar objects, to the extent of current literature, is still not fully understood, the ability to distinguish between different objects that form in this range of masses is critical in the continued research of this class of black hole and neutron star.

The implementation of machine learning into this problem can be applied in further research to better classify future mass-gap objects, as the data derived from gravitational lensing is highly complex and intricate, creating limitations for direct statistical analysis to discern objects found in the mass gap. Ultimately, our proposed solution finds promising results in identifying these objects.

Future work could include larger sample sizes of *unlabeled* gravitational lensing data in order to learn an unsupervised or weakly-supervised model for stellar object classification, though this was outside the focus of our work as we aimed to specifically distinguish between neutron stars and black holes within the mass-gap to aid the discovery of black holes within the mass gap.

Other ongoing work includes incorporating larger, labeled samples within our dataset in order to reduce the number of generated samples within the training and testing dataset. This would also enable the model to better learn patterns within the data for higher and more reliable performance.

The reported models can be used in future studies analyzing mass-gap data through the gravitational lensing medium in order to expedite results and ultimately improve understanding of patterns within mass-gap black hole and mass-gap neutron star formation along with their non-mass gap counterparts. Finally, the presented work has the ability to significantly improve the quality of scientific understanding of the mass gap.

8. Author Note

The authors declare no competing interests in this study.

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