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GALAXY MERGER ESTIMATION BY MACHINE LEARNING: A NEW METHOD TO CONSTRAIN BLACK HOLE MERGER DETECTION WITH LISA

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Abstract. Understanding the mass assembly history of massive black holes (MBH) in the early universe is a key to constraining their birth and growing processes. The LISA mission is expected to provide key insights through the detection of MBH binaries via gravitational waves (GWs). However, current cosmological simulations face challenges in predicting the growth of intermediate-mass black holes in low-mass galaxies, limiting the accuracy of MBH merger rate estimates. To address this, we present a machine-learning framework using the Illustris-TNG simulation to model galaxy mergers in groups and clusters. By combining these simulated merger histories with VLT/MUSE spectroscopic data up to $z \approx 7$, we improve MBH merger rate predictions. Our model achieves an accuracy of approximately 80%, with an average galaxy merger timescale of $\Delta_T \approx 130$ Myr . Misclassifications, particularly in the non-merger category (33%), are attributed to galaxy's redshift degeneracy and uneven snapshot intervals. This approach enhances predictions for LISA's observational capabilities and advances our understanding of MBH evolution.

Keywords: Galaxies, Merger, Machine Learning, LISA, MUSE

1 Introduction

The existence of Supermassive Black Holes (SMBHs) at the center of massive galaxies is now well-established, supported by stellar velocity dispersion measurements within galactic bulges Kormendy & Ho (2013), the detection of jets from quasars, and direct observations made possible by the Event Horizon Telescope (e.g. M87 observation, Collaboration et al. 2019 or Sagitarius A^*, Collaboration et al. 2022). However, the role of SMBHs in galaxy evolution, particularly during the early universe, remains an open question. Recent discoveries of massive high-redshift galaxies by the James Webb Space Telescope, coupled with mass estimates of their SMBHs (Mezcua et al. 2024), underscore the need for further investigation. The ubiquity of SMBHs across all galaxies, especially in dwarf low-mass galaxies, is still debated, as is the question of when these black holes begin to grow and how they influence the co-evolution of their host galaxies.

The first detection of Gravitational Waves (GWs) by the Advanced LIGO detectors (Abbott et al. 2016) marked a pivotal moment in the study of compact binary systems. The upcoming Laser Interferometer Space Antenna (LISA) promises to extend these studies to the regime of intermediate and supermassive black hole mergers. To maximize the scientific return of the LISA mission, robust estimates of the GW population are essential to inform the development of event disentanglement algorithms. Several cosmological and semi-analytic models have been constructed in an attempt to replicate observed galaxy populations. However, the vast disparity in scale between galaxies and SMBHs introduces significant computational challenges, leading to wide variability in predictions of SMBH merger rates (Habouzit et al. 2022).

Large-scale galaxy surveys typically yield photometric redshifts, which are inherently uncertain. Spectroscopic redshifts, however, have been obtained using the Multi Unit Spectroscopic Explorer (MUSE) (Bacon et al. 2015) mounted on the Very Large Telescope (VLT), enabling deep-field observations of galaxies in various environments up to z $\approx$ 7 (e.g. Richard et al. 2021, Bacon et al. 2023, Epinat et al. 2024). These data have provided valuable estimates of galaxy merger fractions (Ventou, E. et al. 2017, 2019), though comprehensive merger studies accounting for the full galaxy population remain limited. A preliminary framework for predicting

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SMBH merger detection rates for LISA was introduced recently (Contini et al. 2022), but this approach relies on simplified selection criteria based on projected galaxy separations and relative velocities, excluding mergers involving more than two galaxies, thus introducing significant biases in the estimated merger rates.

Recent cosmological simulations now achieve sufficient resolution to model galaxy populations with increasing accuracy, though SMBH dynamics remain an area of improvement. In this work, we propose a machine-learning framework designed to predict galaxy mergers in groups using data from the Illustris TNG-300 (TNG-300) simulation (see next section). By leveraging the detailed merger trees and hierarchical structure of galaxy formation, our model estimates the timescales over which galaxy groups undergo mergers, offering a new approach to predicting SMBH merger rates in preparation for LISA observations.

2 Methodology

The Illustris TNG simulation (Nelson et al. 2021, 2017; Pillepich et al. 2017; Springel et al. 2017; Marinacci et al. 2018; Naiman et al. 2018), is a cosmological, gravo-magneto-hydro-dynamical simulation, divided in 100 snapshots from $z = 20$ up to $z = 0$. Galaxies are identified by a unique index (ID) at each snapshot and a merger tree is provided to determine if a merger occurs between different bodies. The TNG-300 simulation that we use has a comoving width of 205 cMpc.

2.1 Dataset preparation

In order to ensure consistency between our dataset and the galaxy population observed in the MUSE/VLT deep fields, we impose a lower stellar mass limit of 10^7 M$\odot$. This threshold allows us to focus on a statistically significant subset of galaxies while maintaining observational relevance. For each simulation snapshot where the redshift is $z < 7.5$, we randomly select a position within the TNG-300 cosmological simulation, confining this selection to cubic volumes (hereafter referred to as "mini-boxes") of dimensions 1.5, 5, or 10 Mpc. For every mini-box, we generate 15 random viewing angles to simulate diverse observational perspectives. From each of these projections, we subsequently extract the key observational parameters: right ascension (RA), declination (DEC), stellar mass (M), and redshift (z) for every galaxy present within the mini-box. This methodological approach ensures a robust statistical sampling and mitigates orientation-based selection effects. To accurately identify galaxy mergers, we trace the unique galaxy indices across consecutive snapshots. A merger event is identified when two or more galaxies share the same index in the subsequent snapshot, signaling a physical merger process. However, in certain cases, galaxies may undergo a "Fly-By" event, wherein they pass near each other but do not merge. In these scenarios, the galaxy IDs will differ between snapshots, introducing potential biases. To address this, we cross-verify galaxy IDs across two consecutive snapshots, thus reducing the likelihood of misidentifying non-mergers as mergers. To balance the dataset and prevent the perceptron model from being skewed towards the dominant non-merger cases during training, we ensure an equal representation of merger and non-merger populations. This stratified sampling approach enhances the model's ability to distinguish between merger and non-merger scenarios. Moreover, to prevent gradient divergence during the training process, we normalize each feature in the dataset to the range $[-1, 1]$, with the exception of the merger status, which is binary encoded as 0 for non-mergers and 1 for mergers. The timescale for mergers, corresponding to the 1 label, is observed to vary between 30 Myr and 225 Myr, with a mean merging timescale of approximately 130 Myr. This normalization ensures stable convergence during training and allows for a more interpretable classification task. The dataset employed in this study is restricted to cases where pairs of galaxies were identified within the mini-boxes, resulting in a selection of 867 030 galaxy pairs.

2.2 Machine Learning

The architecture employed in this work is a multi-layer perceptron (MLP) implemented using the Python library **PyTorch**. The model consists of four fully connected layers, with 32, 64, 128, and 2 neurons, respectively. Each hidden layer is activated using a Rectified Linear Unit (ReLU) function, while the output layer utilizes a Sigmoid activation function to facilitate binary classification. To optimize model performance, we adopt an adaptive batch size strategy, starting from 8 and increasing to 2048, alongside a dynamic learning rate, initially set at 10^{-3} and gradually reduced to 10^{-5} over 2500 training epochs. The loss function used is Cross-Entropy, which serves as the validation metric during training. The dataset is split into 70% for training and 30% for testing, ensuring robust model evaluation and minimizing overfitting.

3 Results and Discussion

The perceptron is capable of identifying galaxy mergers with an accuracy of approximately 80%. A confusion matrix, presented in Fig.1, illustrates the classification performance. The training loss and validation loss (Fig.2) exhibit a consistent decline as the number of epochs increases, indicating that the model progressively improves in fitting the data. Initially, the training loss decreases more rapidly, while the validation loss follows a more gradual decline, suggesting a convergence towards generalization. Both losses stabilize as the model approaches 2500 epochs, indicating diminishing returns in further optimization. In parallel, the accuracy of the model shows a steady increase, with early epochs marked by rapid improvement, followed by a more gradual rise as the model approaches its optimal performance, reaching a plateau at approximately 80%. This trend signifies the model's growing capacity to correctly classify data while mitigating overfitting

Most misclassifications occur within the non-merger category, with around 33% incorrectly labeled, compared to approximately 7% for recent mergers. The underlying cause remains unclear; potential explanations include redshift degeneracy induced by the galaxies's proper velocities or the uneven time intervals between snapshots, which can vary by up to a factor of two.

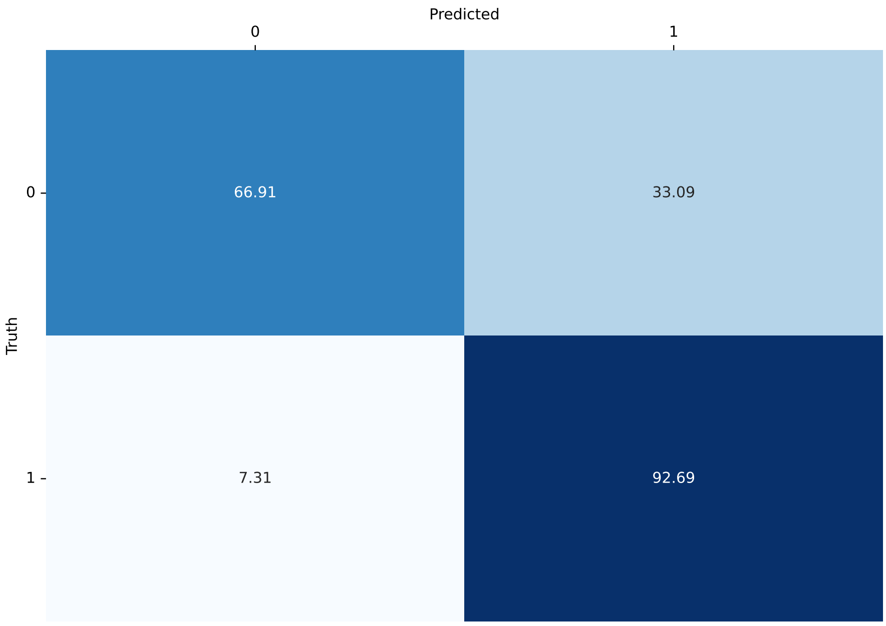

Fig. 1. Confusion matrix: Predicted versus real values with their relative fractions. 0 for the non-merger case and 1 for the merger case.

Since in this training method the amount of epochs is fixed, the algorithm does not manage to reach the learning limit which might cause the remaining error. Improvements can still be made by adjusting the learning rate when the loss reaches a plateau and with a regular increase in the batch size. We are still working on improving the merging timescale estimate to a higher value.

4 Conclusions and perspectives

In this study, we developed a machine-learning framework using a multi-layer perceptron (MLP) to predict galaxy mergers based on data from the Illustris TNG-300 simulation. The model achieved an accuracy of approximately 80%, effectively distinguishing between merger and non-merger events. Our evaluation metrics revealed that both training and validation losses steadily decreased over the 2500 training epochs, with diminishing returns in optimization observed towards the later epochs. The model accurately captured merger events occurring on timescales ranging from 30 Myr to 225 Myr, with an average merger timescale of around 130 Myr. This result suggests that the model is nearing optimal performance for this task, although further improvements are possible through refinements in the learning rate schedule and batch size increments. Notably, the majority of misclassifications occurred within the non-merger category, with around 33% incorrectly classified, compared

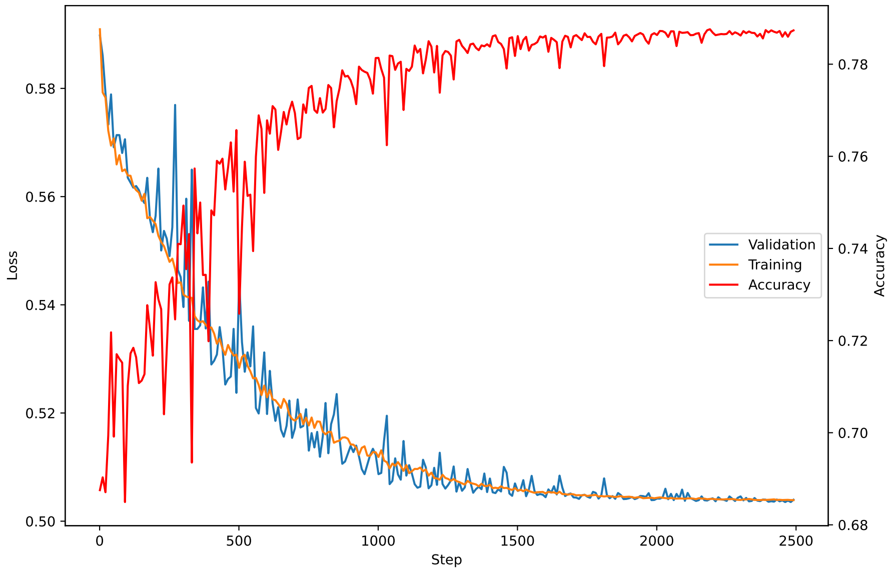

Fig. 2. The training and validation loss (orange and blue curves, respectively) and the model accuracy (red) over 2500 epochs.For clarity, only one dot out of every twenty is shown.

to only 7% for recent mergers. This discrepancy may be attributed to redshift degeneracy induced by the galaxies' proper velocities or to the varying time intervals between simulation snapshots, which can differ by up to a factor of two. While the current model demonstrates robust performance, there is room for enhancement. Adjusting the learning rate when the loss plateaus could potentially reduce the residual error. Additionally, expanding the model to account for mergers within galaxy groups, rather than just pairs, represents a promising avenue for future work. Incorporating group interactions would offer a more comprehensive understanding of hierarchical galaxy evolution and provide a more accurate estimation of supermassive black hole merger rates. Overall, our approach lays the groundwork for improving the prediction of galaxy mergers and advancing our understanding in preparation for upcoming LISA observations.

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