Understanding real galaxy mergers through simulations and deep learning

William J. Pearson¹

1. National Centre for Nuclear Research, Pasteura 7, 02-093 Warszawa, Poland

Galaxy mergers are events that underpin how our Universe grows and evolves. Despite their importance, knowing exactly what is and is not a real galaxy merger is not as simple as it seems. Equally, knowing how far along in a merger is for real galaxy mergers is a non-trivial issue, beyond a simplistic pre-coalescence, coalescence and post-coalescence categorisation. Due to the long times scales involved, on the order of a billion years, we cannot wait and watch mergers occur and evolve to solve these issues. Thus, merger detections can be uncertain and it is difficult to follow the physical processes inside mergers as a merger progresses.

Simulations do not have these problems. Zoom in simulations allow us to closely follow two colliding galaxies and observe how physical properties change and evolve. Cosmological simulations allow us to gather a large number of known galaxy mergers for statistical samples. Thus, being able to use simulations with known truths of if a galaxy is a merger and known times before or after a merger event to identify and classify galaxy mergers would be a powerful tool.

This paper will discuss how we can take the images and truths from simulations and apply them to the real Universe through deep learning. It will explore how this can allow us to gain a base truth for what is a merger and identify how far along real mergers are. From this, we can have a sneak peak at the kind of science that is right around the corner using these cutting edge techniques.

1 Introduction

Galaxy mergers underpin our current understanding of how galaxies grow and evolve. Under the current cold dark matter paradigm, dark matter halos merge and grow hierarchically causing the baryonic matter within them to also merge.

These galaxy-galaxy interactions are known to influence the properties of the merging galaxies. Mergers are known to change the morphologies, with material driven into the centre of the galaxies and spiral galaxies being disrupted to form ellipticals (Somerville & Davé, 2015). A wealth of studies have also looked into how the star-formation rates and active galactic nuclei accretion are influenced by these collisions (e.g. Knapen et al., 2015; Ellison et al., 2019; Pearson et al., 2019; Gao et al., 2020). However, determining the exact time before or after a merger event in the real universe is non-trivial. Thus, determining exactly when these physical changes occur during the merger is a non-trivial task in the real universe.

However, within a simulation it is possible to know the exact time before or after a merger event. Thus, if we can use the information from a simulation and apply this knowledge to observations, it would be possible to estimate the time before or after a merger event for galaxy mergers observed in the real universe. The first steps towards this have only recently been attempted in Koppula et al. (2021).

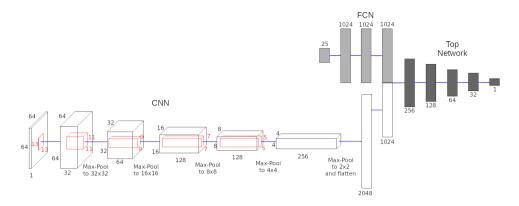


Fig. 1: Schematic for the current neural network. Input is on the left, with a 64×64 image and 25 morphological parameters. Output is on the right with a single neuron. White layers form the CNN, light grey layers form the FCN and dark grey layers are the Top Network. Shape of layers is given for each layer with size of kernels for the CNN in red.

2 Deep Learning for Merger Time

To use simulations to determine the merger time of real galaxy mergers, we employ deep learning. Using simulated galaxy images and their morphologies, a neural network is trained to determine the time before or after the galaxy merger. This uses a combination of a traditional, fully connected neural network (FCN) and a convolutional neural network (CNN), which are combined together with a fully connected neural network dubbed the "Top Network" as shown in the Fig. 1.

For the simulated galaxies, mergers from the Illustris TNG simulation (Pillepich et al., 2018; Springel et al., 2018; Nelson et al., 2019) were used. This provides a larger number of galaxy mergers across a range of redshifts in a cosmological context. However, the time-resolution of the Illustris TNG simulation is low: 127 Myr between the snapshots used that are closest together. To increase the time-resolution, the galaxies identified as mergers are simulated between snapshots. This is done using a simple particle, gravity simulation which treats each galaxy in the merger as a point mass and the merging galaxies are allowed to evolve under gravity. The first passage is then used as the point when the merger occurs.

The hybrid FCN and CNN is trained with the galaxy images and morphologies and the higher-resolution times before or after a merger event.

3 Future Prospects

This work is still ongoing, with the network being tweaked to improve performance. Once the final network architecture has been determined, the simulated galaxies will be edited to appear like galaxies from the Kilo Degree Survey (KiDS, de Jong et al., 2013). This is with a view to applying the network to pre-selected KiDS galaxy mergers. These will include KiDS galaxies selected as mergers by a CNN in Pearson et al. (2019), examples of which are shown in Fig. 2.

Once the network has been applied to the KiDS images, we will, for the first time, be able to trace temporal physical changes during a galaxy merger, from a statistical

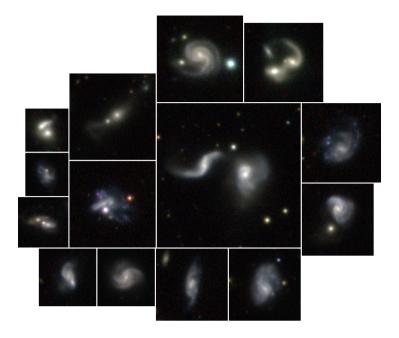


Fig. 2: Example KiDS galaxy mergers, identified by a CNN in Pearson et al. (2019), whose time before or after a merge will be determined.

perspective. The star-formation rate of the merging galaxies will be compared to the star-formation rate of non-merging systems. This will allow the change in star-formation rate to be tracked as a galaxy merger evolves in the real universe. This will then be compared to results from simulations so we can study any differences between what we think we should see and what actually happens during a merger.

Acknowledgements. This work has been supported by the Polish National Science Center project UMO-2020/37/B/ST9/00466

References

de Jong, J. T. A., et al., The Messenger 154, 44 (2013)

Ellison, S. L., et al., MNRAS 487, 2, 2491 (2019)

Gao, F., et al., A&A 637, A94 (2020)

Knapen, J. H., Cisternas, M., Querejeta, M., MNRAS 454, 2, 1742 (2015)

Koppula, S., et al., arXiv e-prints arXiv:2102.05182 (2021)

Nelson, D., et al., Computational Astrophysics and Cosmology 6, 1, 2 (2019)

Pearson, W. J., et al., A&A 631, A51 (2019)

Pillepich, A., et al., MNRAS 473, 3, 4077 (2018)

Somerville, R. S., Davé, R., ARA&A 53, 51 (2015)

Springel, V., et al., MNRAS 475, 1, 676 (2018)