Exploring the Link Between the Star Formation History and the Morphology of Galaxies

On galaxy-wide scales, the physical appearance of galaxies is correlated with their past star formation activity. On the smallest scales within galaxies, the local star formation rate (SFR) is correlated with the local gas density (also referred to as the Kennicutt-Schmidt law). How the SFR of a galaxy has changed over time is called the star formation history (SFH) of the galaxy, and offers great insight into the physical phenomena regulating a galaxy's star formation activity over time. This includes things such as stellar and AGN feedback, galaxy mergers, and other processes. The link between the morphology (i.e the physical structure) of galaxies and the underlying processes that regulate star forming activity in galaxies is well documented in the literature. This leads us to conjecture that the very same physical phenomena that regulate star formation in galaxies are also responsible for the morphological appearance of the galaxies. Hence, if we can better understand which morphological features of a galaxy link with it's current and past star formation activity we can have a better understanding of the physical phenomena that drive galaxy evolution.

Much of the current literature uses summary statistics to quantify morphology, which do not take into account features like bars and spiral arms. To make a more detailed assessment of the morphology-SFH correlation, we instead adopt a non-parametric approach, training a convolutional neural network (CNN) to predict masses and SFRs (which both depend on the SFH) using galaxy images that contain their full morphology information. For the training we use the SDSS-IV MaNGA galaxy sample because it is an IFU survey meaning we have much more spectral data to work with compared to other surveys. Another big focus of the project was making sure the network was interpretable and not just a "black box". Often when dealing with machine learning we tend to care just about the ability of the network to make accurate predictions, and not so much what it is actually doing when making the predictions. When doing science however, understanding the learning process of the network is also very important as that can give us insights that can help form new physical theories. Additionally, we want to ensure the network is learning to do physical analysis and not simply memorizing patterns in the images. We focused on interpretability of the trained network using Class Activation Mapping (CAM), such as Grad-CAM and Eigen-CAM, to see what parts of galaxy images the network is focusing on to make its predictions. With this, we explored which morphological features of galaxies have the greatest impact on predicted star formation history parameters, and used it to gain insights on the links between the underlying physical processes regulating star formation in galaxies.

After training this network, we find that the CNN was able to take in a given galaxy image (taken using a telescope) and interpret key physical features in order to predict the galaxy's SFR and stellar mass. Our key results are that we can predict galaxy masses to 0.21 dex accuracy and SFRs to 0.33 dex accuracy for the MaNGA sample. Additionally, we were able to see that the network was actually learning to recognize physical structures in the galaxy (such as bars, bulges and spiral arms), and not simply memorizing physically irrelevant parts of the images. The results of Eigen-CAM on one galaxy is shown below, where the closer the colour is to yellow the more the network is focusing on that region to make its prediction. In this figure, notice how the network is able to pickout the spiral arms from the background galaxy. Future plans for this project include expanding the network to be able to predict how the SFR changes in time (SFH). While doing this we will continue to work with CAM methods to interpret what the network is learning, and use this to make the network even better at learning to pick out key morphological features.

Eigen-CAM heatmap of what parts of the galaxy the network is focusing on to make its predictions

1.0

0.8

0.6

0.4

0.2

0.0



Galaxy image taken from a telescope and part of the SDSS MaNGA survey

