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Machine Learning disclosing the edges of galaxies

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Abstract. The next generation of telescope facilities and photometric projects promises not only very large surveyed areas but also staggering depths. This observational step forward will allow us to address new questions such as whether there is any Low Surface Brightness feature related with a physically-motivated definition of the size of a galaxy. Here we introduce galaxy truncations as a suitable size proxy fulfilling these conditions, with full explanations in Buitrago et al. (2023) in prep. Crucially, if one is to infer such galaxy edges or truncations for the plethora of galaxies to be imaged, the only way forward is to apply Machine Learning to derive those. We conducted that study in Fernández-Iglesias et al. (2023) in prep. using ultradeep Hubble Space Telescope imaging for a sample of over one thousand disk galaxies up to $z = 1$ and the current proceedings highlight our more relevant findings.

Key words. Galaxies: sizes – Galaxies: formation and evolution – Astroinformatics – Machine Learning – Galaxies: Machine Learning

1. Introduction

Galaxy size is one of the few direct observables of galaxies but it has been very hard to quantify because galaxies are intrinsically diffuse objects. Many studies have proposed different measurements historically (for an excellent review consult Chamba et al. 2020). Despite their usefulness, all these metrics were arbitrarily established to a greater or lesser extent. However, the next generation of ultradeep surveys and synoptic facilities opens up a new window for determining the true extension of these objects, as we enter in the era of Low Surface Brightness (LSB) analyses enabling the determination of galaxy edges or truncations.

These galaxy edges or truncations are sudden drops of the surface brightness, color and mass profiles in the galaxies' outer parts. They visually coincide with the end of the galaxy disk. They were firstly discovered in Van der Kruit et al. (1979) in edge-on disk galaxies. The authors realized that, even integrating for longer times, the galaxies at study did not change the extent of their surface brightness profiles. Even though these LSB features have been known for many years, it is only now that the depth of state-of-the-art observations allow us to find them. The reader should also bear in mind the fact that truncations and galaxy breaks have been misunderstood as the same feature in some works exploring shallow data, and that other publications prefer to use the name truncations only for edge-on systems (due to how these features were firstly recognized). We will use interchangeably either this name or galaxy edges throughout the current proceedings.

The forthcoming era of LSB observations is not only revolutionary in terms of depth but also in the sheer amount of data to arrive at our computers. For example, Euclid's wide survey (Euclid Collaboration , 2022) will image some 15000 deg^2 of the sky. If we add this aspect to the outstanding depths (3 mag deeper than SDSS, and even 2 mag deeper for the drilling fields) and Hubble Space Telescope (HST)-like spatial resolution, the upshot is that this new space telescope will analyse millions and even billions of sources in the next few years. Thus, the only way to deal with this plethora of objects will be to resort to Machine Learning (ML), at least for pattern-recognition problems such as the one we will present here.

2. Dataset and methodology

Buitrago et al. (2023) in prep. (B23) presents a study of the galaxy edges for a sample of 1052 massive ($M_{stellar} > 10^{10}\ M_{\odot}$) disk (according to Huertas-Company et al. , 2015) galaxies at $z_{spec} < 1.1$ observed with HST in the CANDELS fields. These are among the deepest HST pointings to date, enabling the detection of galaxy truncations without any further complications. The catalogs with information for these galaxies could be found in Santini et al. (2015); Stefanon et al. (2017); Nayyeri et al. (2017); Barro et al. (2019). We took 12×12 arcsec stamps for these galaxies in the F606W (V), F814W (I), F125W (J) and F160W (H) bands (400×400 pixels for the ACS two first bands, resampled to 200×200 pixels to match the WFC3 last two bands). We also created SDSS-equivalent restframe images (as in Buitrago et al. 2017), color images (subtracting these latter ones) and mass

Fig. 1. Example of an original HST RGB image for our galaxy in our sample (left), the label image created out of it (middle) and how the two overlap highlighting where the galaxy edge or truncation is (right). Mind that, because of the proximity of a companion galaxy, the galaxy edge displays a jagged shape.

images (following pixel-by-pixel the recipes in Roediger & Courteau 2015). These three later types of images will be called "astronomic augmentations" (see Section 3).

The truncation values steem from the careful study of the 1D profiles for all the images we mentioned in the previous paragraph (see B23 for more details). The edges appear as sharp drops in the surface brightness and mass profiles. We consequently define our labels as 200×200 pixel images with 1 as a value for pixels belonging to the galaxy at study and 0 otherwise. The galaxy pixels are defined by an ellipse whose semi-major axis has the galaxy edge value, with an axis ratio and position angle representative for the outer parts of the galaxy in the reddest band (H) available (see Fig. 1). Following this rationale, the edges/truncations are the pixels to be found in the boundary between the galaxy pixels and the rest of the pixels.

3. Machine Learning experiments and results

We conducted semantic segmentation by means of U-Nets neural networks having various architectures (Resnet18, Resnet50, EfficientNetB1, EfficientNetB2, EfficientNetB6, DenseNet161, DenseNet201) as encoders. All details could be found in Fernández-Iglesias et al. (2023) in prep. (FI23). We trained our Deep Learning models using a weighted cross entropy loss function, batch size 32, learning rate 10^{-3} and maximum number of training epochs 1000. The metrics we utilized were Precision, Recall and the Sørensen-Dice coefficient (harmonic mean of the other two, and thus more robust to how imbalanced our labels are). Our averaged values for our Base experiment (taking into account only the I, J and H images) for these three metrics are 0.8545, 0.9433 and 0.8851 respectively.

Moreover, we added another four experiments, taking into account the aforementioned astronomic augmentations (see Section 2). We called them this way because they are variations of the input data based on our astrophysical knowledge. These extra experiments were Visual (Base adding RGB images using the different possible combinations of the HST bands), Sloan (Base and using the SDSS-equivalent restframe bands), Color (Base plus color images) and Mass (Base plus mass images). The introduction of these astronomic augmentations improves the performance of our deep learning models because all Dice values increase in comparison with the Base experiment (see Fig. 2).

Nevertheless, the power of these astronomic augmentations lies in the fact that the induced variability makes the neural networks learn different features. We created ensembles to improve the quality of our segmentation. Different algorithms combined their pixel-by-pixel results using the mode (i.e. a "democratic-vote"). Each ensemble utilizes the results from our 35 segmentation networks (5 experiments times 7 different possible encoders) taking 3 of them at a time, yielding a final 6545 possible ensembles. Remarkably, 65% of them retrieve better (i.e. greater) Dice values than the ones obtained for individual models. The best configuration is the one taking EfficientNetB6, Resnet18 and DenseNet161 trained with Mass-type astronomic augmentations (Precision: 0.9016, Recall: 0.9353, Dice: 0.9104).

4. Conclusions

Galaxy edges aka truncations are very promising features to allow us to finally derive physically-motivated galaxy sizes. However, in order to achieve our aims, it is necessary to analyse sufficiently deep images that are also conveniently reduced to preserve the LSB signal (Buitrago et al. , 2017; Akhlaghi et al. , 2019). In addition, for the swarm of data to arrive in the coming years from the synoptic facilities, it will be mandatory to create the Machine Learning tools to derive these quantities as the human astronomers will not be able to visually check all the required inputs.

We derived the galaxy edge position for a sample of 1052 intermediate massive disk galaxies at $z < 1.1$ in B23. FI23, that is the study from where this proceedings is based, used the previous results as labels for a Deep Learning study of the retrieval of these LSB features. Specifically, it uses a series of U-Nets with different architectures of neural networks as encoders, in order to derive these truncation positions. To ensure the machine learns as humans do, we created a series of "astronomic augmentations", i.e. augmentations with astronomical meanings (surface brightness, color and mass maps). By making use of them, the metrics of our study improve in comparison with the Base model.

The variability of inputs also ensures that the neural networks learn in a different manner. This is the reason why we furthermore built all possible ensembles of the different combinations of the neural networks available in order to vote, on a pixel-by-pixel basis, which pixels belong to each galaxy at study and thus determining the position of the galaxy edges. Almost two thirds of such ensembles improve the best model's performance and thus our best neural network uses this technique (combining EfficientNetB6, Resnet18 and DenseNet161 using always the Mass astronomic augmentations).

Future facilities will transform our knowledge of not only low-mass very distant galaxies but also the high-mass low-z ones by deriving the long-sought physically-motivated galaxy sizes. This will have profound implications in the galaxy assembly, both for the baryonic and dark-matter components. Ours is a step further in the application of this methodology for the extremely large galaxy samples to arrive in the near future. We also hope that similar techniques and augmentations could be applied to

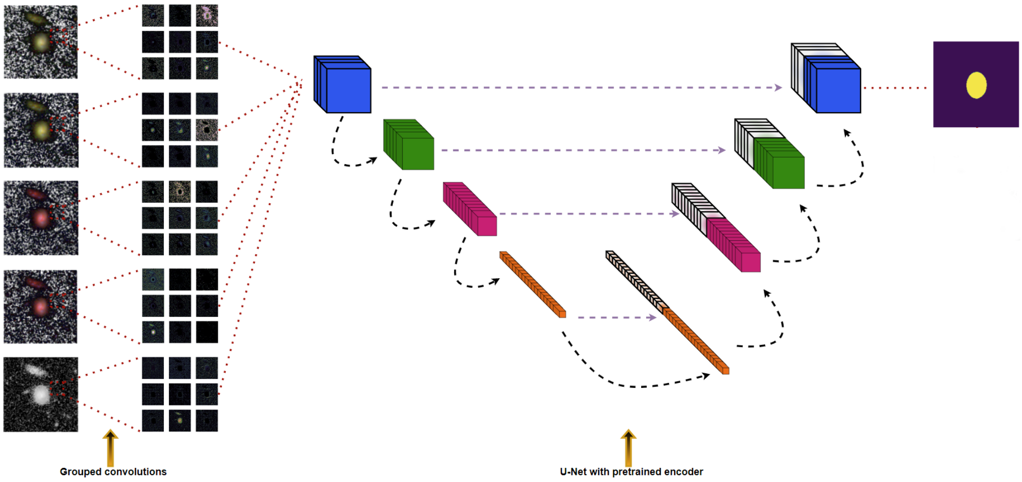

Fig. 2. Layout of our U-Net configuration, using different images as inputs (including astronomic augmentations and performing grouped convolutions). The final outcome will be another 200×200 pixel image that will be matched with the galaxy label in order to derive the metrics that tell us how well we identify the pixels that belong to the central galaxy, and consequently its galaxy edge or truncation.

tackle similar problems related with the visual appearance of galaxies, like galaxy deblending or the identification of tidal tails.

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