Galaxy Segmentation and Deblending Using Deep Learning

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INTRODUCTION

Goal

This project aims at extending the Astro-RCNN code to include data standardization and normalization measures to improve its performance on real, deep, and varied data

It also aims to train the Astro-RCNN code on deeper data in order to evaluate the performance of the model on deeper simulated data.

Motivation and Past Work

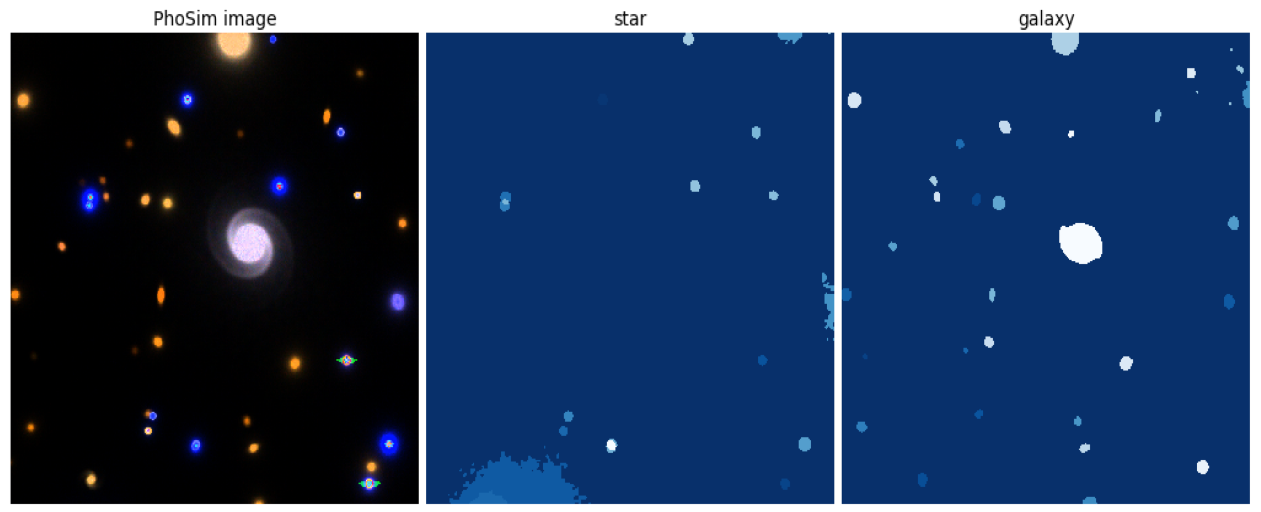
Future astronomical surveys such as such as the Vera Rubin Observatory's (VRO) Legacy Survey of Space and Time (LSST) will generate large volumes of image data, leading to a demand for robust and generalized algorithms to detect, segment and deblend astronomical sources (Burke et al. 2019).

Previous research into the detection and segmentation tasks by Burke et al. (2019) involved using the instance segmentation neural network Mask-RCNN to segment astronomical sources in images and to label the image pixels corresponding to the sources as stars or galaxies. The model, Astro-RCNN, was trained on simulated Phosim (Peterson et al. 2015) 512x512 images meant to replicate the DECam CCD camera.

Data and Methodology

Training Data

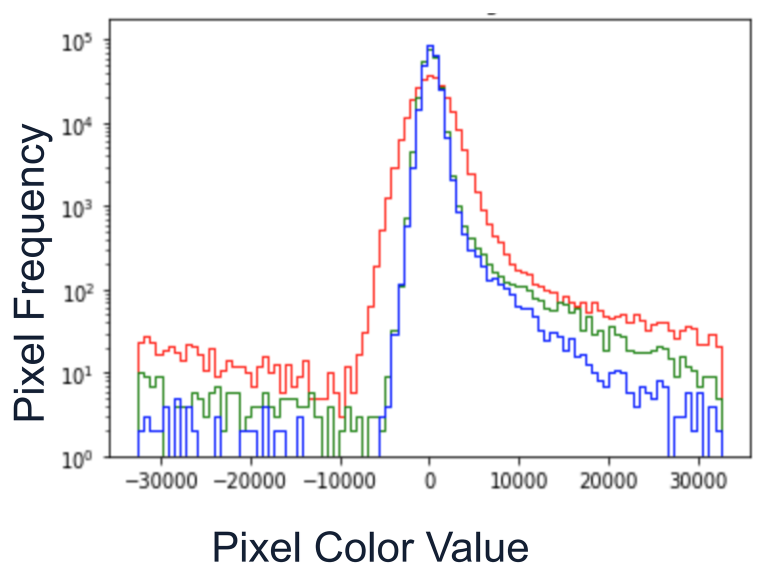
The model was trained on 56 multi-band simulated images and tested on 14 images. The set was simulated using the Phosim software (Peterson et al. 2015), which produced 512x512 images at an exposure time of 500 seconds using the Hyper Suprime Cam instrument specification simulating z, r, and g bands. The simulation speed was increased by not simulating background noise in the images, but instead just simulating the astronomical sources at the magnitude allowed.



Data Standardization and Normalization

In order to extend the Astro-RCNN code to real and varied data, data standardization and normalization is required to account for different backgrounds and magnitudes of astronomical objects.

We implemented the Lupton et al. scheme in order to enhance fainter objects while preserving the integrity and structure of larger and brighter objects in the scene (2004).



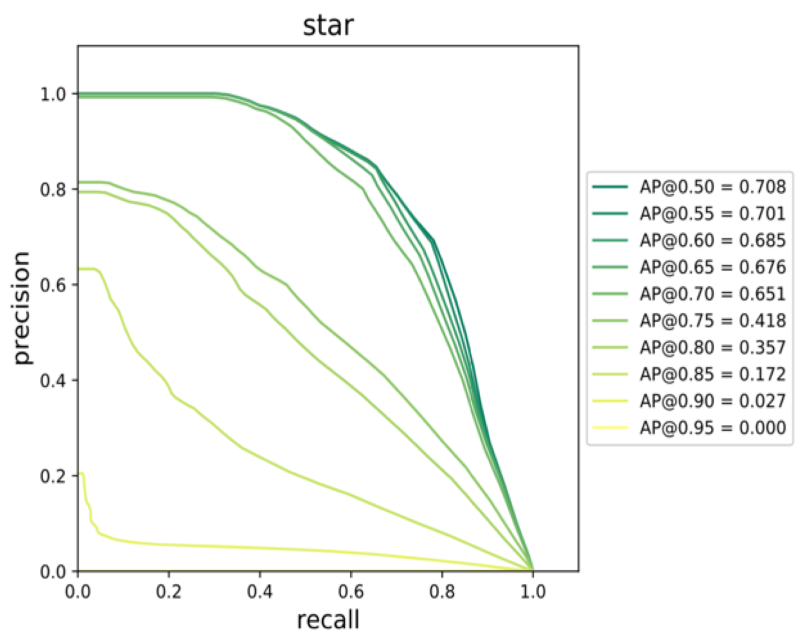
Network Implementation and Training

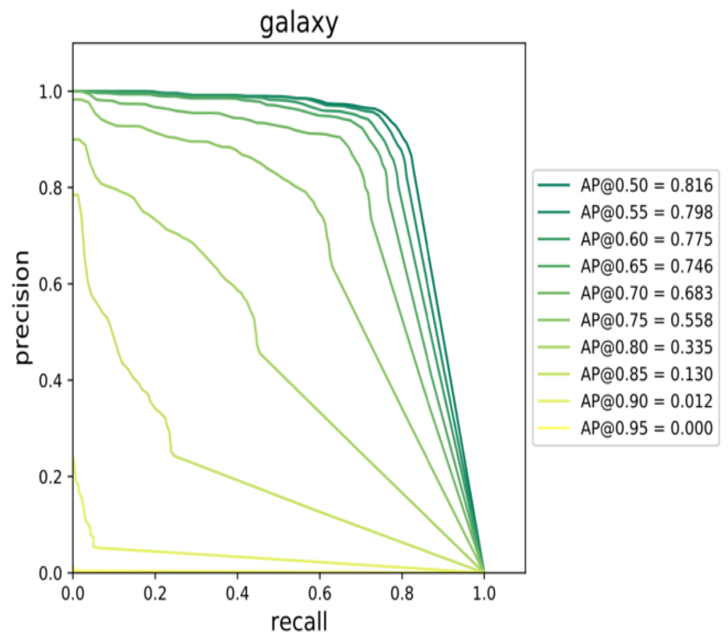
The training is done in 4 steps. The first step trains only the head layers of Mask-RCNN, and the following steps train all the layers. The optimization algorithm used was stochastic gradient descent with momentum and with each of the 4 steps the learning rate decreased but a constant learning momentum of 0.9 was used.

Gradient with Momentum Update Formula:

$$z^{j+1} = \beta z^j + \nabla f(\theta^j)$$
$$\theta^{j+1} = \theta^j - \alpha z^{j+1}$$

Network Performance





The discrete IOU thresholds here are {0.50, 0.55, …, 0.90, 0.95 } with step size of 0.05.

The curves are generated by averaging precision and recall values over testing set of 14 simulated images at various detection confidences

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

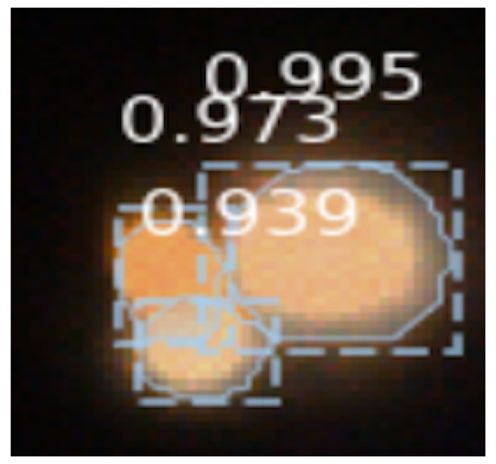
$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

$$AP\ Score = Area\ under\ Precision - Recall\ Cuve$$

$$IOU = \frac{Area\ of\ Overlap}{Area\ of\ Union}$$

Testing on an independent set simulated with the same software and parameters as the training set, we measure an AP score of 0.816 for galaxies and 0.708 for stars at an IOU threshold of 0.5.

We can also see the deblending capabilities of our code in simulated images with detection Masks overlayed on partially blended sources



CONCLUSIONS

From our results with a limited training set, it is evident that our code is capable of segmenting our blended galaxies, and of training to recognize objects in dense and crowded scenes.

Future steps include generating training data to better recognize objects in real ultra-deep fields, and extending the current code to recover source profiles of detected objects

Acknowledgements

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References

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