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Deep Radio Image Segmentation

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Abstract. We show that the U-Net neural network architecture provides an efficient and effective way of locating sources in SKA Data Challenge datasets. The improved performance relative to PyBDSF is quantified and U-Net is proposed as an efficient source finder for real radio surveys.

Keywords. Radio Surveys, Machine Learning, Square Kilometre Array

1. Introduction

In the lead up to the operation of the Square Kilometre Array (SKA), the radio astronomy community has been trialing new methods of image processing and analysis suitable for handling the extremely large volumes of data expected from the new interferometer. The SKA Observatory (SKAO) has released model datasets in the form of simulations considered to be representative of future SKA data. In this work, we use the radio continuum images released in Science Data Challenge 1 (SDC1; Bonaldi *et al.* 2021). The objective of the challenge is to detect, classify, and measure the properties of all the sources within the images. Due to the large datasets, we apply Machine Learning (ML) techniques as a fast and optimised method of source extraction.

The task can be identified as an image segmentation problem. That is we wish to identify areas of interest within the images and classify them. For inspiration we look to the field of biomedical imaging, which hosts a wealth of image segmentation research. We apply U-Net, a neural network based on the encoder-decoder architecture, known for its ability to segment images quickly and accurately whilst only requiring a small dataset for training (Ronneberger, Fischer & Brox 2015). We present this promising method as a novel approach to source extraction in radio astronomical data.

2. Methods

In order to use U-Net for image segmentation we require a labelled training set. The SDC1 data consists of a set of 9 images taken at 3 different observing periods and frequencies. For each frequency, corresponding truth catalogues are provided which contain source information including location, shape and size information. To create our training set we take cutouts 256 x 256 pixels in size from all images of one observing frequency. We use the training catalogue provided, which includes source information for 5% of the field of view, to generate corresponding segmentation maps for each cutout. A segmentation map is an image of the same dimensions as the data cutout, with each pixel classified by a numerical system. In this case, we generate binary segmentation maps which use 0 to represent background and 1 to represent a source. We treat all sources as one class, thus are doing binary classification. We can create these segmentation maps by creating a zero array of dimensions 256 x 256 pixels. We then locate in the training catalogue all sources which exist within the data cutout, and update the zero array to 1 at these locations. We use both the binary segmentation map and the data cutout to train the U-Net, we refer to these as data-map pairs.

We split our data-map pairs 80:10:10 for training, validation and test. The training and validation set are used to train the network, whilst the test set is used for blind analysis of the model. The input data are reduced to a low dimensionality space within which source features are captured. The image is then reconstructed to the original input size. The binary cross entropy loss is minimised between the input and output segmentation. Thus the network learns to predict segmentation maps for new input data.

3. Results

We analyse the quality of the predicted segmentation by assessing the pixel classification accuracy. Since the data are heavily dominated by zero values (background), we also assess the source detection accuracy. We see that U-Net outperforms PyBDSF (Mohan & Rafferty 2015) for almost all metrics. We attribute the superiority of U-Net on pixel classification and source detection accuracy to its higher sensitivity to sources close to the background.

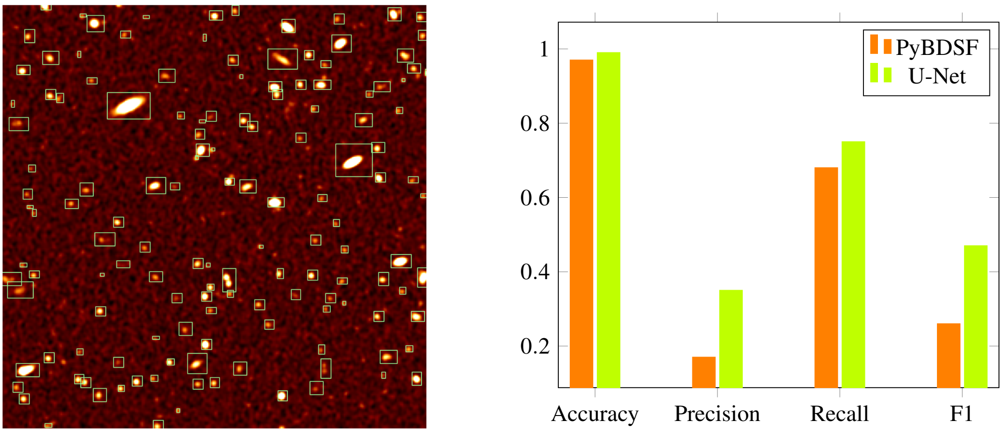

Figure 1: The left hand figure displays a cutout from the test dataset with the bounding boxes of the predicted sources overlaid. The right hand figure shows the comparative metrics of pixel classification for PyBDSF and U-Net. U-Net outperforms PyBDSF over all metrics. The metrics are as follows: accuracy is the proportion of correct predictions within all model predictions; precision is the proportion of the correct positive predictions in all cases classified as positive; recall is the proportion of the true sources the model has predicted; F1 Score is calculated from the precision and recall and varies between 0-1, it is proportional to both precision and recall. In all cases a higher score implies a better model fit.

Initial results imply that U-Net is a highly promising method for source detection in radio images in the SKA era. However, careful tuning of the network parameters is required to ensure the true source distribution is recovered. In future work we will improve parameter estimation in the U-Net pipeline in order to recover the source parameters.

References

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