Deep Image Segmentation of the Radio Sky

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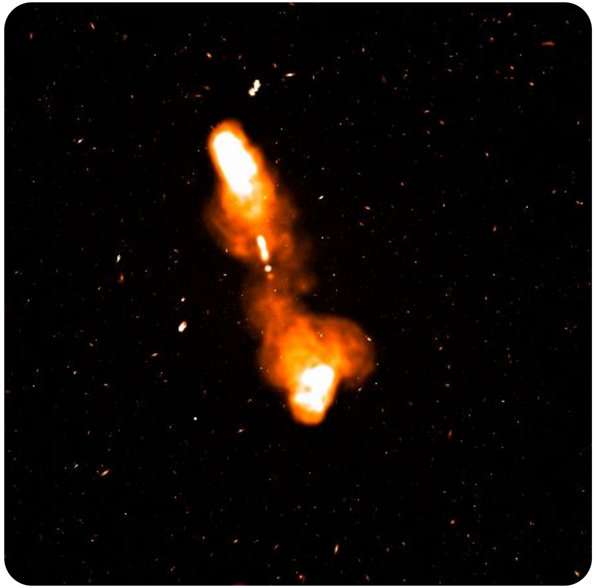
Summary

- → Radio Astronomy’s Big Data Problem
- → Objectives
- → Image Segmentation
- → U-Net

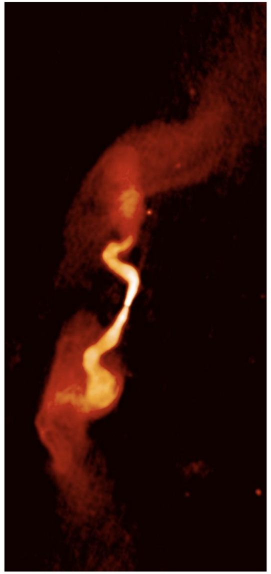


Radio Astronomy's Big Data Problem

- ➔ Large scale observatories will provide a huge influx of data
- ➔ The Square Kilometre Array (**SKA**) will produce data at a rate of **~160 TB/sec**
- ➔ We hope **ML** will provide a solution to this problem

Extragalactic Radio Sources

- ➔ A radio galaxy is an AGN that emits in the radio band of EM spectruM
- ➔ Characterised by bright jets that far extend the galaxy's optical contribution
- ➔ Radio emission is generated via synchrotron emission as mass is accreted onto central black hole



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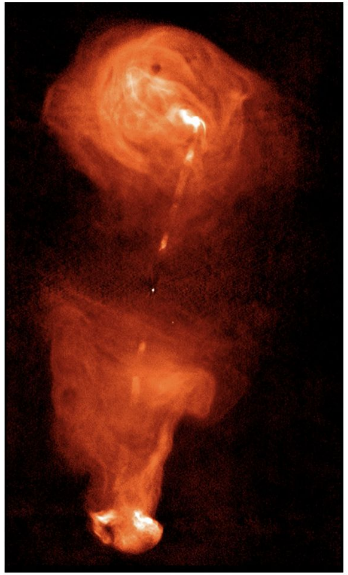

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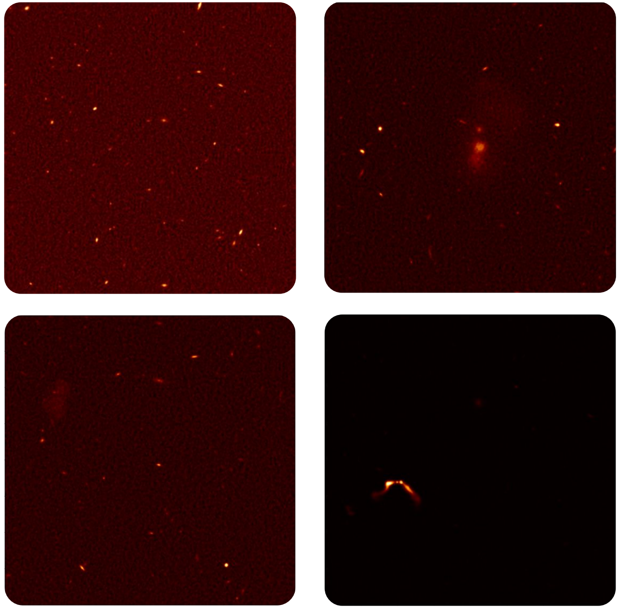
Science Data Challenges

- In the lead up to the launch of the SKA, the SKAO has been releasing model data challenges for analysis by the community
- This work looks at the first data challenge released, **SDC1**
- SDC1 is 2D simulated radio continuum data provided with source location and characteristics labels.

Image credit: SKAO

SDC1

- 9 images
- 3 observing frequencies
- 3 observing periods
- 3 truth catalogues
- 1 catalogue contains > 5 million sources
- 1 image contains > 6500 of these patches



Objectives

→ Detect location of sources

→ Retrieve source parameters

→ Generate a predicted source catalogue that is consistent with the ground truth

→ Improve upon detection rate from traditional software eg. PyBDSF

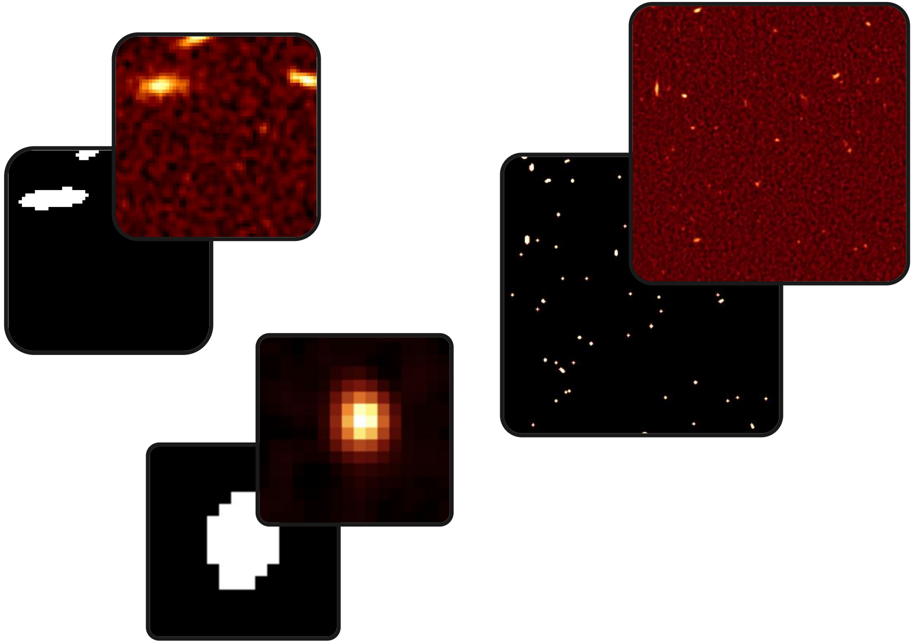
Image Segmentation

- The process of partitioning a digital image into multiple image segments
- Used in machine vision, object detection, medical imaging etc.

Image credit: Research Gate

Binary Segmentation Maps

- All methods were trained using data-segmentation map pairs
- These are generated using labels in truth catalogues
- Pixel-wise labels
- 1 = source
- 0 = background



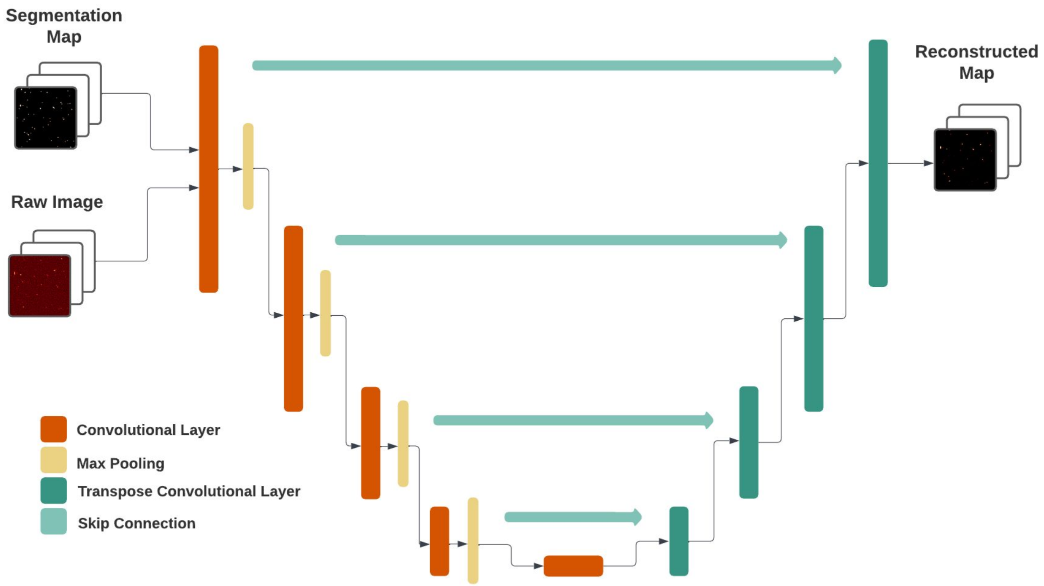
U-Net

- ➔ Worked based on: *U-Net: Convolutional Networks for Biomedical Image Segmentation*
- ➔ Train network using data-segmentation map pairs
- ➔ Network learns segmentation and can predict new maps

Architecture

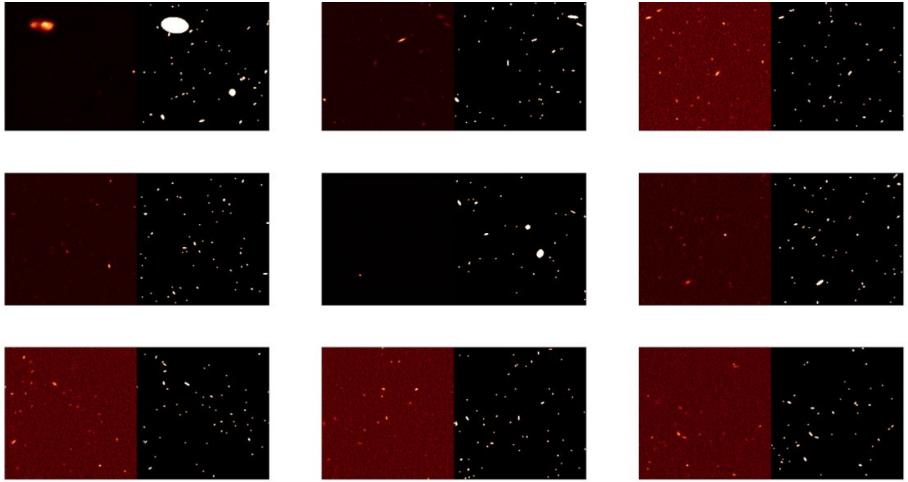
- ➔ Based on Encoder-Decoder architecture
- ➔ End-to-end fully convolutional network
- ➔ No fully connected layer, can accept image of any size
- ➔ Skip connections
    - ◆ concatenate the output of deconvolutional layers with feature maps from the Encoder at the same level
    - ◆ give it “U” shape
    - ◆ model learns to assemble a more precise output

Architecture

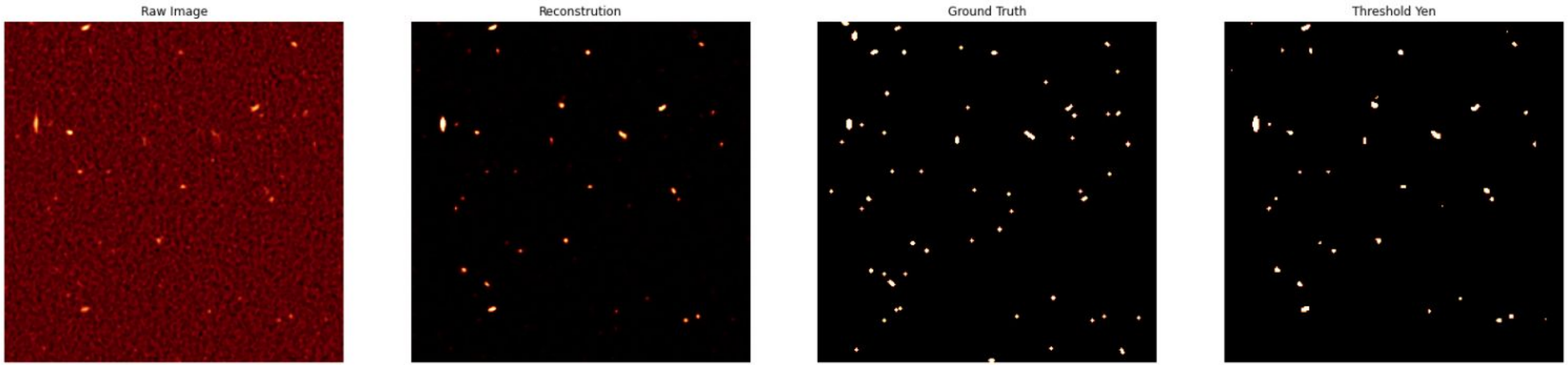


Dataset

- Trained on 256x256 data-map pairs
- Segmentation maps generated from **high S/N sources**
- Used 80:10:10 for train, validation and test datasets
- Small training set - 897 images



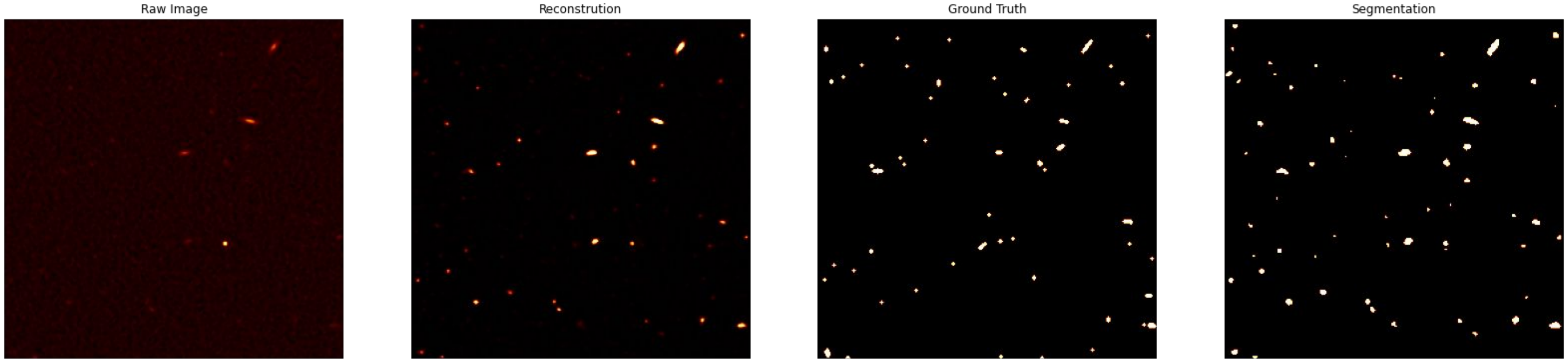
Output



Reconstruction

Connected Components

➔ To get a predicted segmentation map from our reconstruction we use connected components from OpenCV

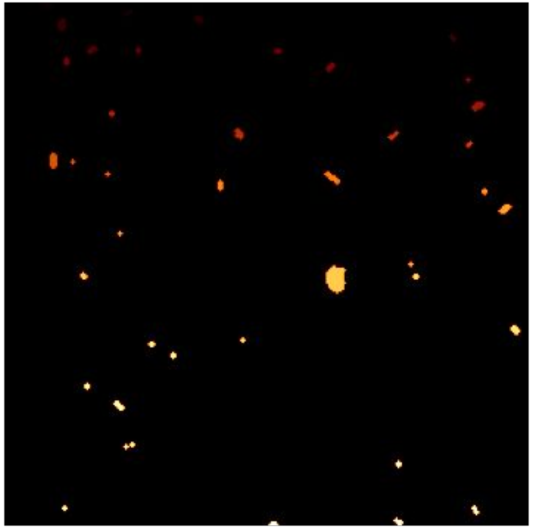


Ground Truth Comparison

- Once we have our connected components we can compare the prediction to the ground truth to understand how well our network is performing

Predicted Labels

True Labels

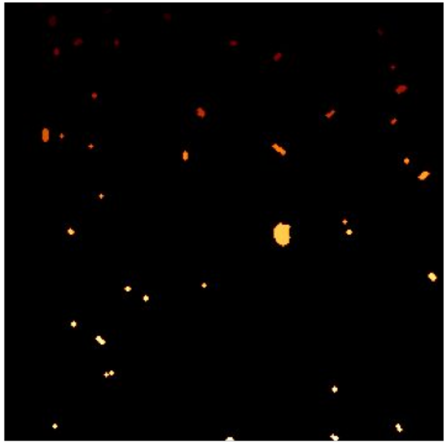


Pixel Wise Metrics

- ➔ Pixel level metrics
- ➔ Direct comparison of each pixel in ground truth and predicted segmentation
- ➔ To check if pixel classification is correct

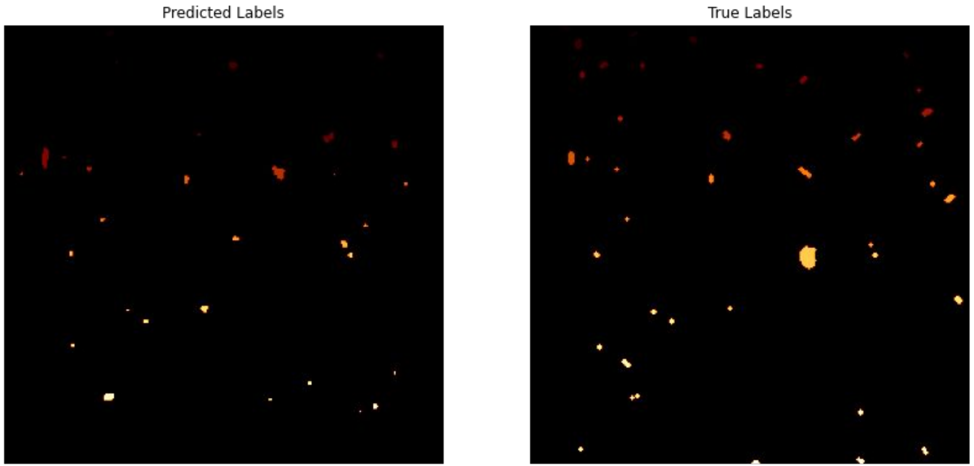
Predicted Labels

True Labels

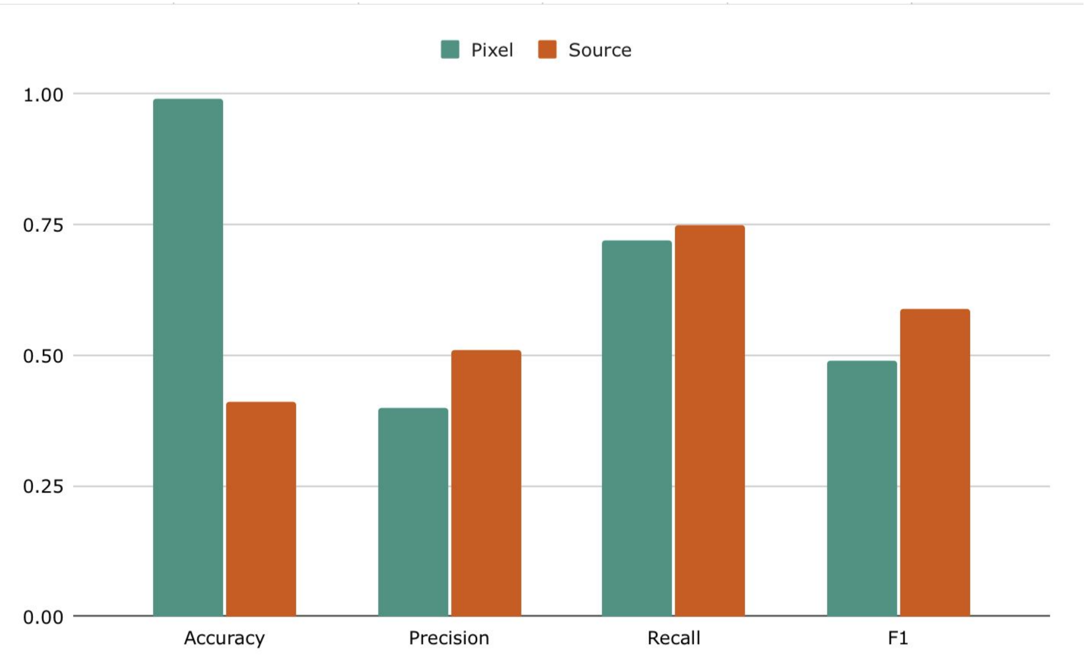


Source Wise Metrics

- ➔ Dataset is heavily imbalanced
- ➔ Majority of pixels are 0
- ➔ Calculate metrics for only the sources (1s)
- ➔ Determine ‘true’ detections
- ➔ Recover FP/FN/TP/TN values



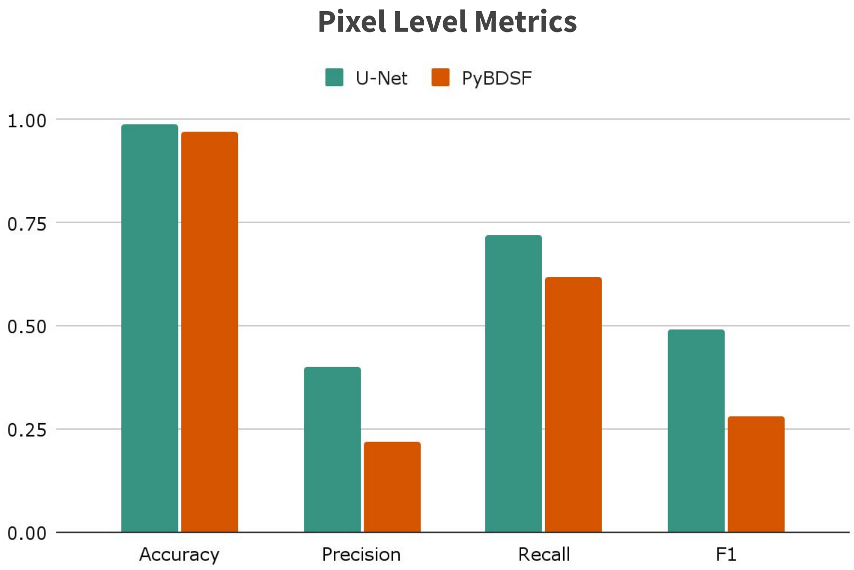
Comparison

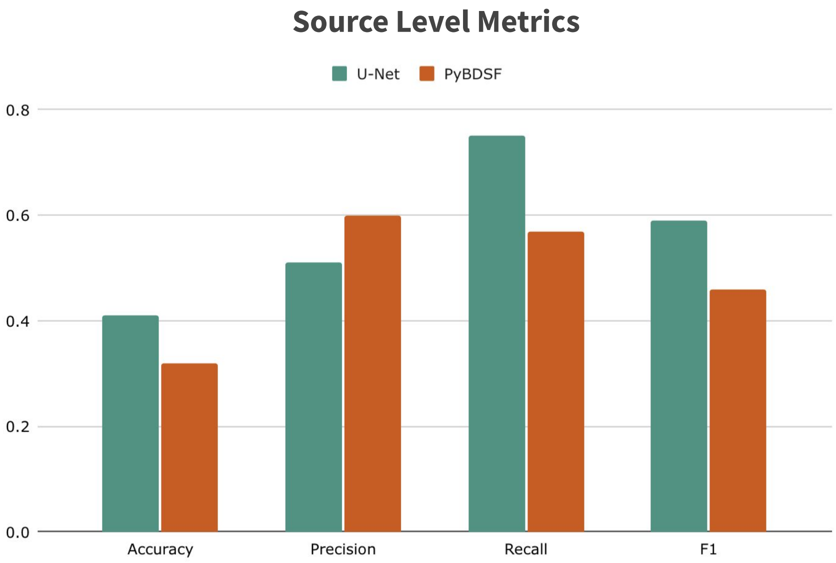

Pixel
Source
1.00
0.75
0.50
0.25
0.00
Accuracy
Precision
Recall
F1

Comparison to PyBDSF

- ➔ PyBDSF is a widely used source detection software in astronomy
- ➔ We run our test images through PyBDSF and perform the same post-processing and analysis to caclulate the metrics

Comparison to PyBDSF

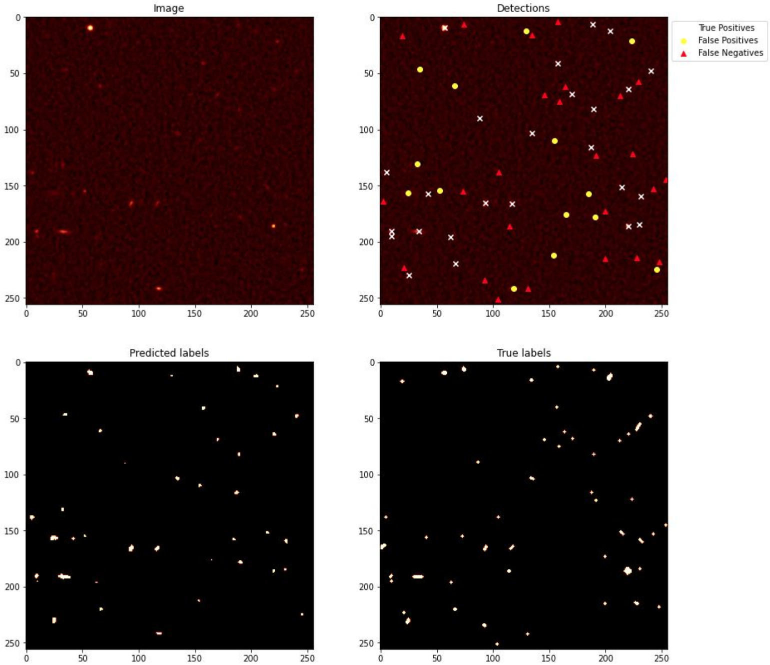




Source Wise Metrics

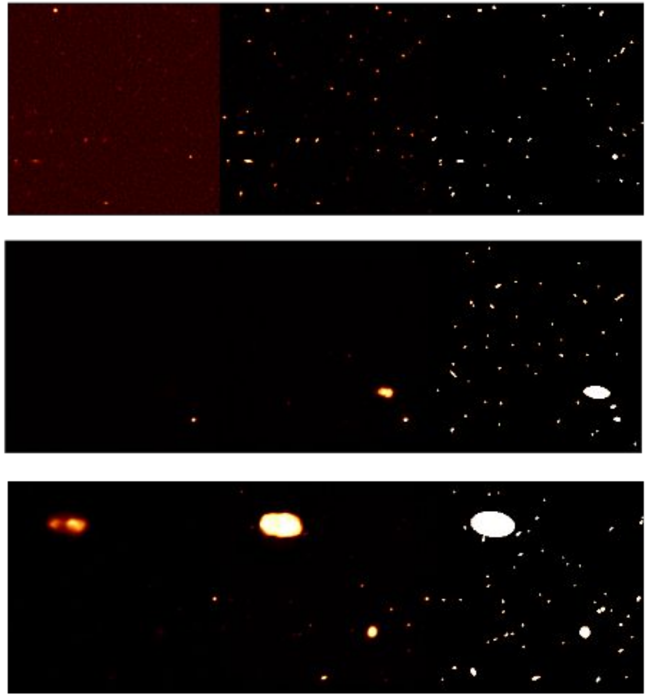
➔ High false positive rate

➔ Network is misclassifying noise as sources

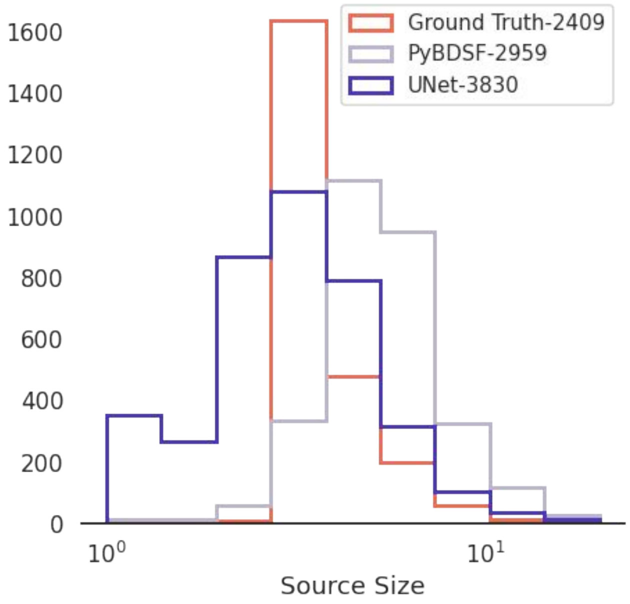


Surface Brightness

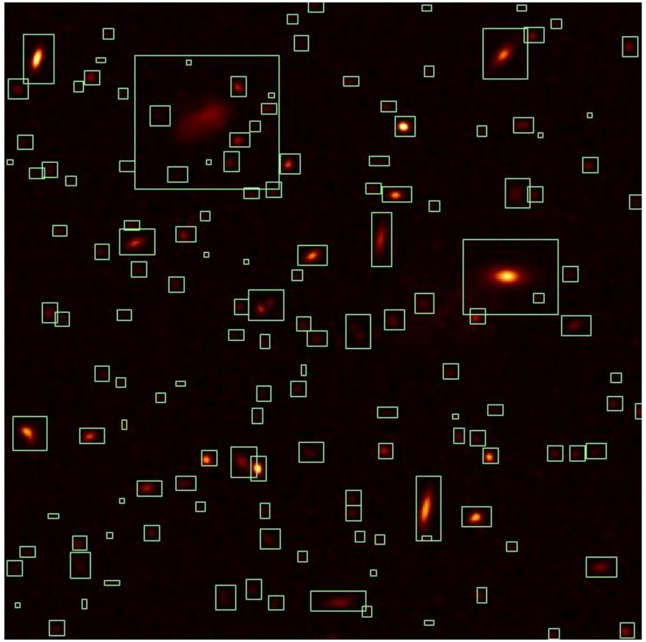
- ➔ Some cutouts have a broad surface brightness range
- ➔ The network struggles to detect the fainter sources in these cases
- ➔ This gives us a high false negative rate
- ➔ Which brings down the overall scores for all cutouts
- ➔ Have tried using histogram equalisation and logging input

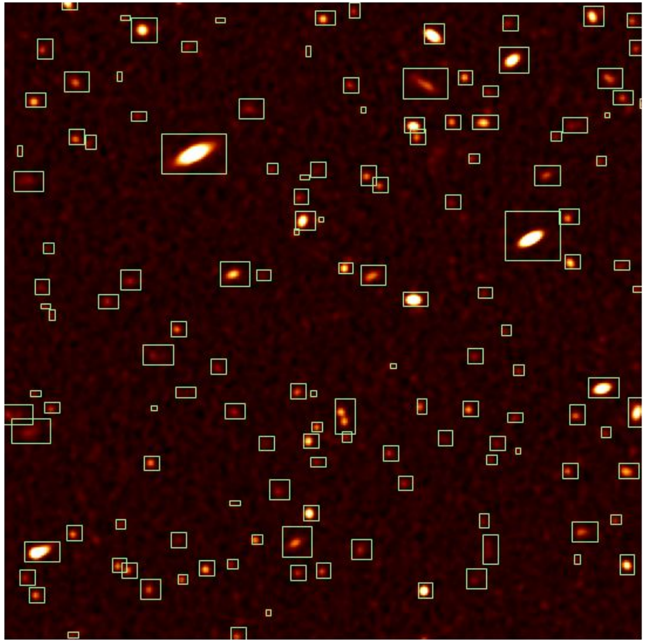


Source Size Recovery



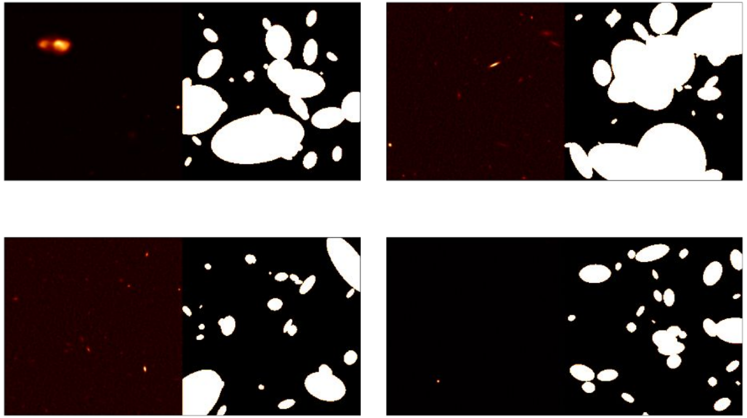
Source Finder





Next Steps

- Denoise input images using deep-image-prior
- Comparison to ProFound
- Recover the source parameters
- Recover all of the **low S/N sources**



Thank you!
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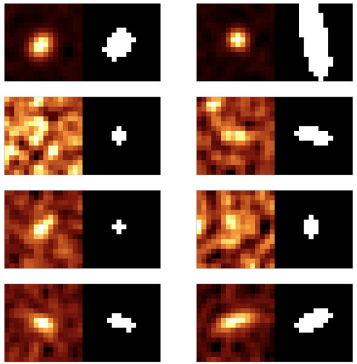
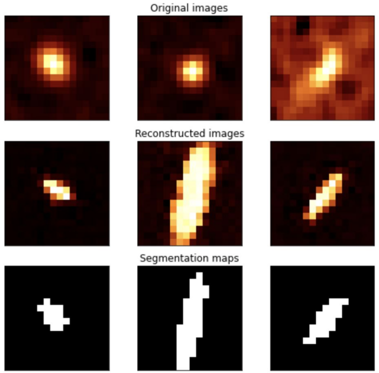
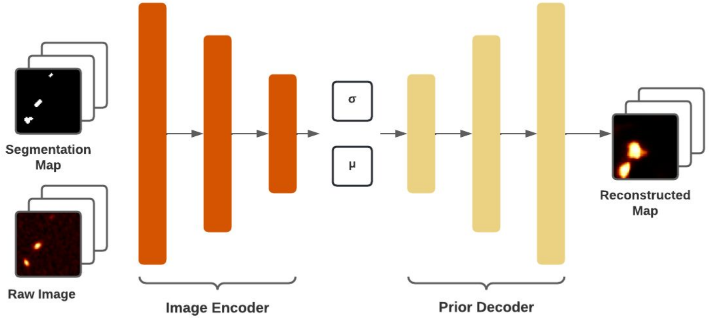
Variational Autoencoder

- ➔ Work based on: [Anatomical Priors in Convolutional Networks for Unsupervised Biomedical Segmentation]
- ➔ Trained on 16x16 data-map pairs
- ➔ Trained network by reducing the loss between the reconstruction and the segmentation map
- ➔ Network then learns the segmentation
- ➔ Network can predict segmentation map for new input data







Convolutional Autoencoder

- ➔ Trained on 60x60 data-map pairs
- ➔ Trained network by reducing the loss between the reconstruction and the segmentation map