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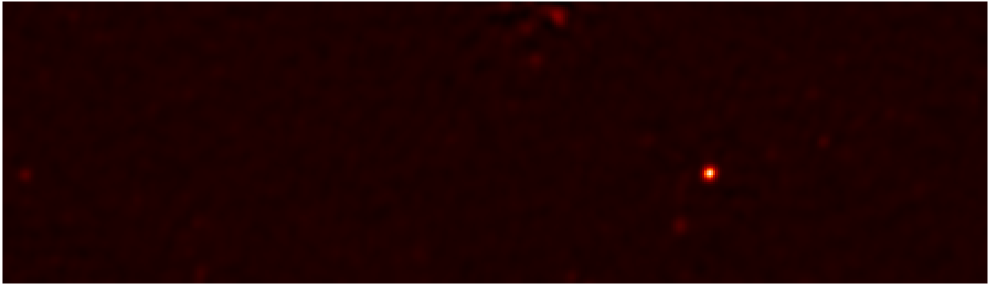


Automated Source Detection in Radio Interferometric Images using Computer Vision

Paul-Simon Blomenkamp

22.10.2021

Radio Interferometry

- Angular resolution is limited by the Rayleigh criterion

$$\Theta = 1{,}22 \frac{\lambda}{D}$$

- Correlate multiple telescopes → large effective diameter D

NRAO/AUI/NSF; J. Hellerman

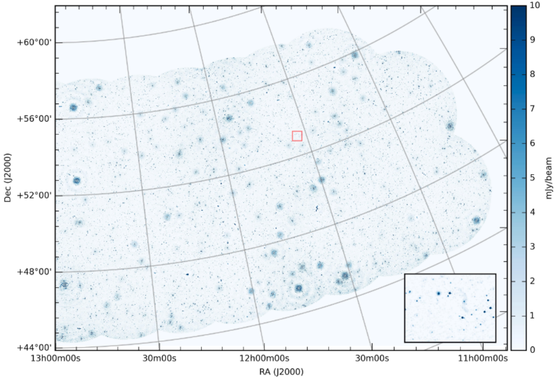
Sky Surveys

- Mostly untargeted search
- Wide field of view
- Backbone of Astronomy
- Rapidly increasing data rates
- Faster, more precise evaluation tools necessary

https://lofar-surveys.org/gallery.html?file=static/gallery/blanksky.png

LOFAR Two Meter Sky Survey

- The **Lo**w **F**requency **Ar**ray
- Survey entire northern sky
- Already more than 300 000 sources
- 770 sources per square degree

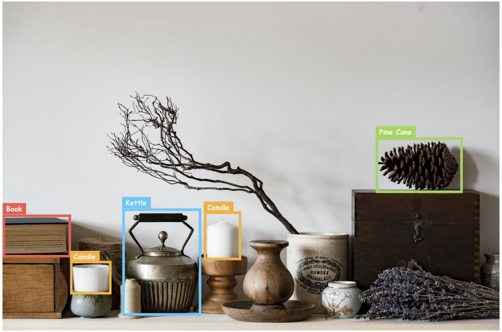


Shimwell, T. W. et al. “The LOFAR Two-metre Sky Survey - I. Survey description and preliminary data release”. In: A&A 598 (2017)

[1] ”LOFAR: The LOw-Frequency ARray” doi.org/10.1051/0004-6361/201220873

Idea

- Use existing techniques from object detection
- Applicable to sky surveys
- Fast and accurate localization and classification
- Requirements:
  - Reliable source detection architecture
  - Realistic dataset



towardsdatascience.com/12-papers-you-should-read-to-understand-object-detection-in-the-deep-learning-era-3390d4a28891

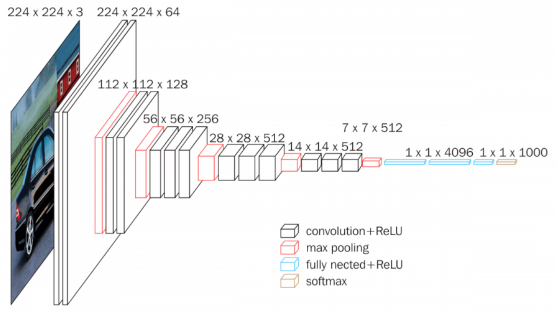
The Architecture

The Architecture

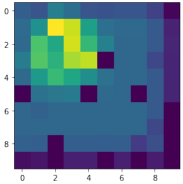
- Challenge: Unknown number of objects in image
- Approach based on SSD300 architecture by Liu et al.
- Use Convolutional Neural Networks (CNN) to create Feature Maps
- Use predefined regions for classification prediction
- Predict offset for the true box coordinates

Feature Maps

- Backbone based on reconfigured VGG-16
  - Single channel
  - 300 × 300 px images
- Trained on four basic classes
- High level maps through additional convolutions
- Decreasing in size → smaller feature maps for larger objects

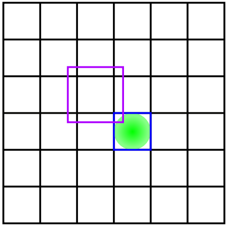


neurohive.io/en/popular-networks/vgg16/



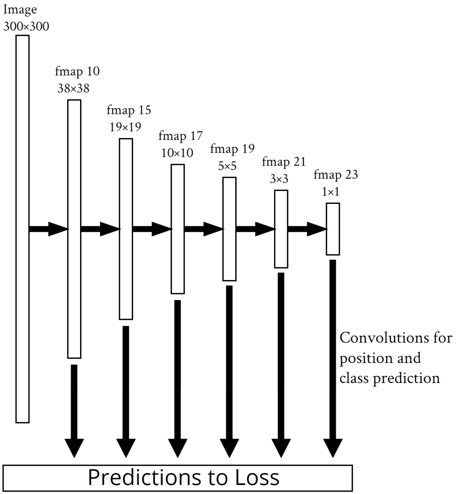
Priors

- Created in each pixel of the feature map
- Multiple priors per pixel possible
- Shape and scale adjusted to dataset
    - Currently: Objects small and best described by square boxes
- Coordinates encoded as offsets to priors
- For each prior a score for each class is predicted



Predictions

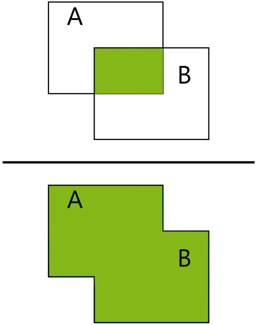
- Two seperate convolutions for each feature map
- For every prior:
  - Predict score for every class including background
  - Predict four offsets



The Jaccard Index

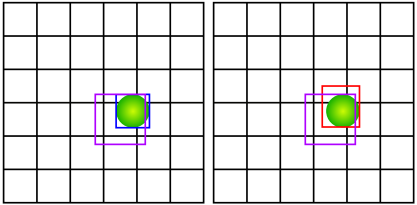
- Measure of similarity of two samples A and B
- Take intersection over the size of the union of both samples

$$J = \frac{|A \cap B|}{|A \cup B|}$$



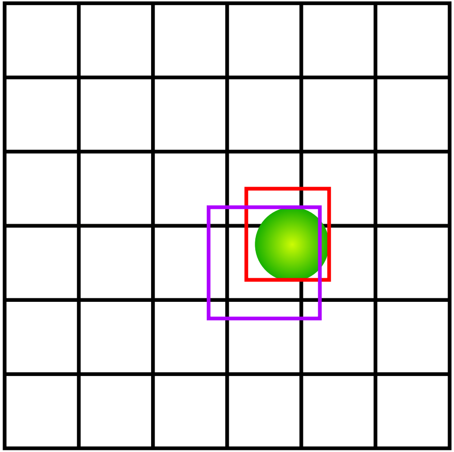
The Loss

- Assign label to each prior based on truth
- If Jaccard index is below threshold → assign background
- Ensure each object has a corresponding prior
  - Find prior that has the maximum overlap for each object
  - Artificially give Jaccard index of 1



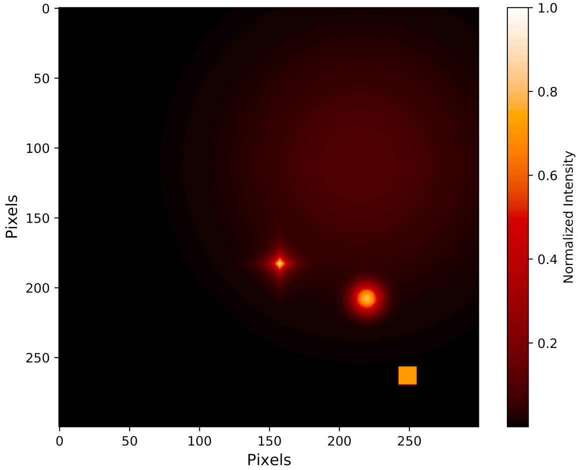
The Loss - Hard Negative Mining

- Don't want to train background detection
- Classification loss:
  - Hard negatives: Background priors with highest loss
  - Loss over fixed ratio of non-background priors and hard negatives
  - Averaged over loss of non-background priors
- Localization loss only over non-background priors
- Total loss is sum of both terms



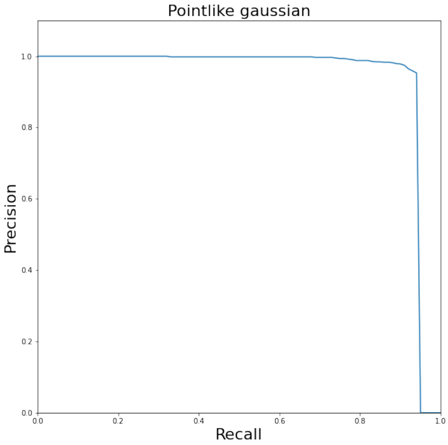
The Toy Data

- Pointlike Gaussians
- Diffuse Gaussians
- Diamonds
- Squares



Mean Average Precision

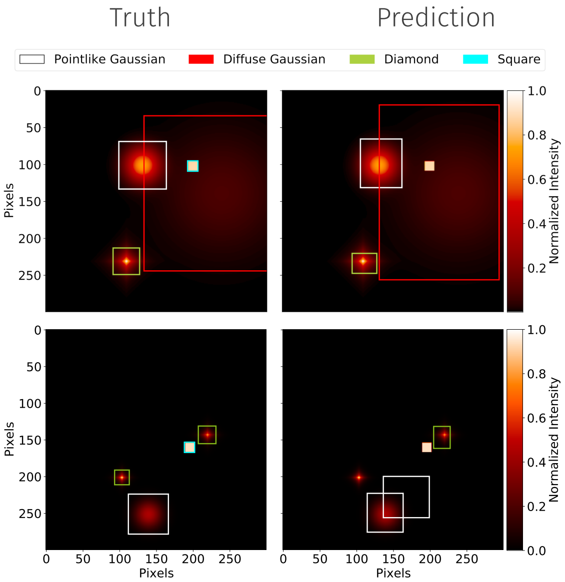
- Measure for performance of model
- AP depends on area under precision-recall curve
- Precision:
$$p = \frac{TP}{TP + FP}$$
- Recall:
$$r = \frac{TP}{TP + FN}$$
- Calculate average precision (AP) for each class then average



First Results

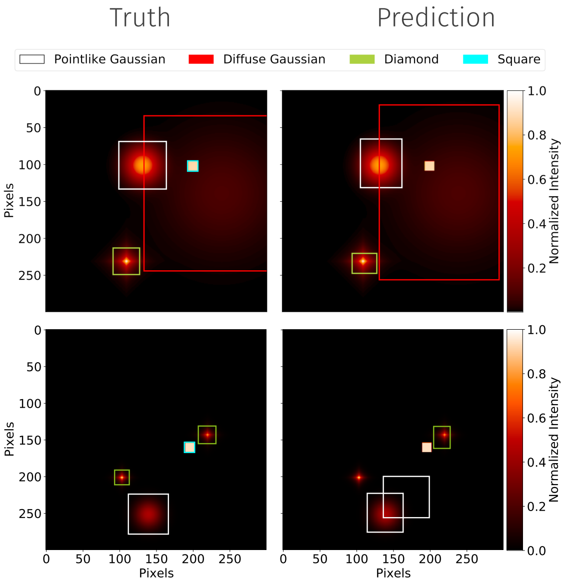
Results

- Training on 30.000 images for 100 epochs
- Min score of 0.3 for prediction
- Max overlap of $J = 0.45$ between predictions



Results

- Training on 30.000 images for 100 epochs
- Min score of 0.3 for prediction
- Max overlap of $J = 0.45$ between predictions
- Main issue: Inability to find small objects

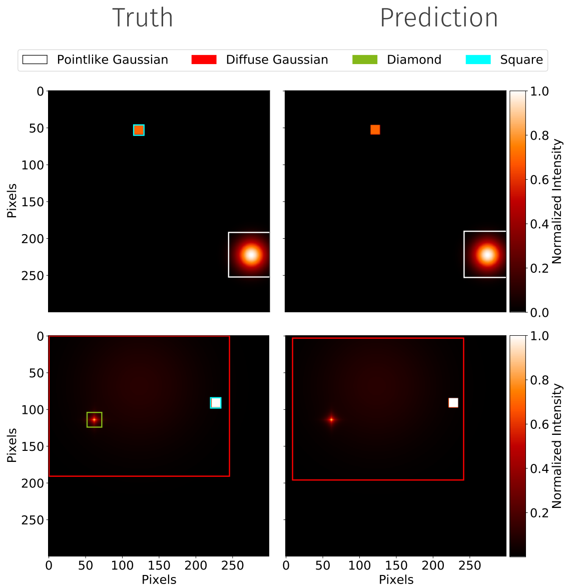


Results

Average precision AP values for the four source classes with the SSD300 architecture.

Class	AP
Pointlike gaussian	0.789
Diffuse gaussian	0.799
Diamond	0.420
Square	0.091
mAP	0.525

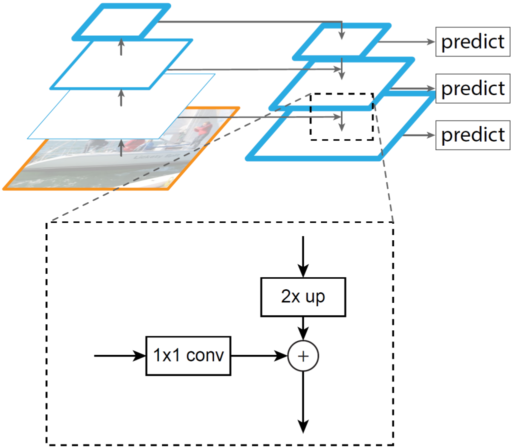
- Idea: Use higher resolution feature maps



Improvements

FPN - Feature Pyramid Network

- Small features lost on low resolution maps
- Earlier maps have fewer convolutions applied → low semantic value
- <u>Solution</u>:
  - Combine deeper feature maps with high resolution map
  - Upsample deepest feature map
  - Add feature map with corresponding resolution
  - Make predictions and repeat

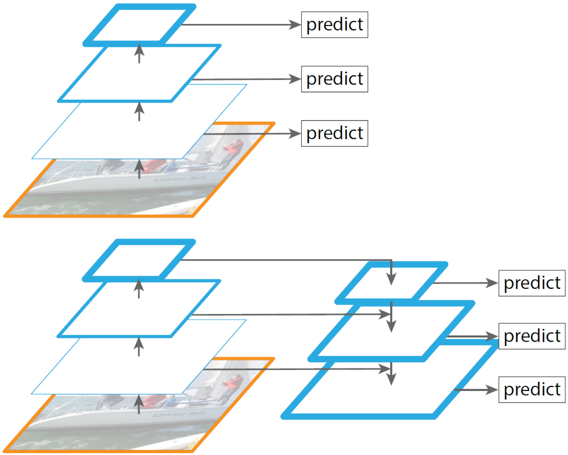


T. Lin, P. Dollár, R. Girshick, K. He, B. Hariharan and S. Belongie, "Feature Pyramid Networks for Object Detection," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 2017, pp. 936-944, doi: 10.1109CVPR.2017.106.

Improvements

- Implement Feature Pyramid Network
- Include higher resolution feature map
- Use additional aspect ratios

$\Rightarrow$ 18 018 Priors



T. Lin, P. Dollár, R. Girshick, K. He, B. Hariharan and S. Belongie, "Feature Pyramid Networks for Object Detection," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 2017, pp. 936-944, doi: 10.1109CVPR.2017.106.

Comparison of Results

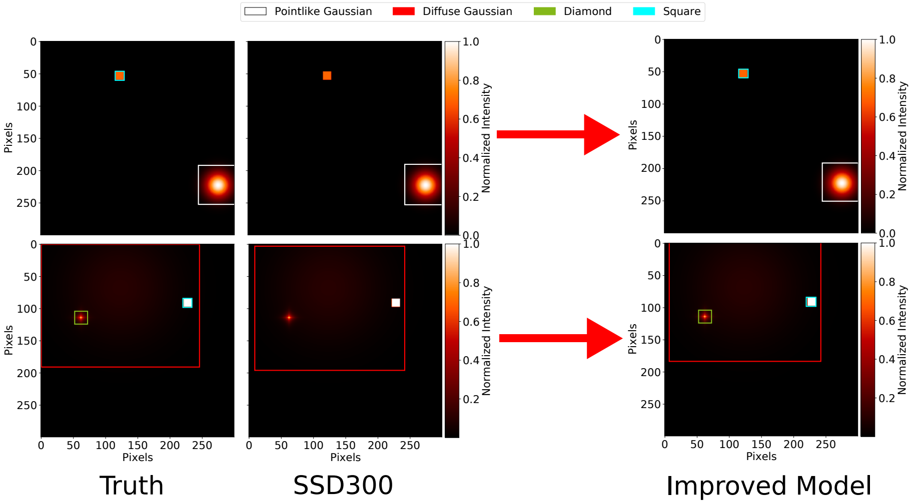
- Old Architecture

Class	AP
Pointlike gaussian	0.789
Diffuse gaussian	0.799
Diamond	0.420
Square	0.091
mAP	0.525

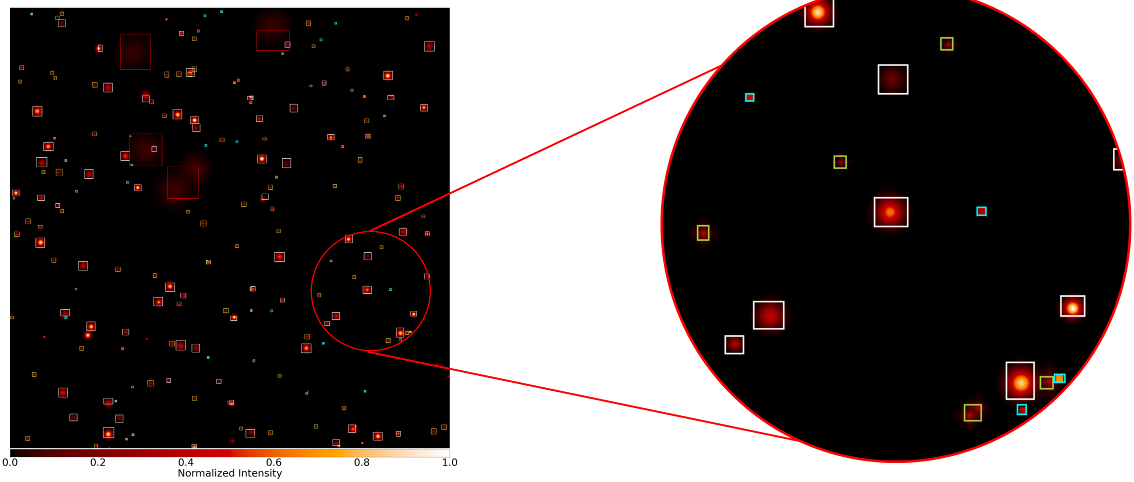
- FPN Architecture

Class	AP
Pointlike gaussian	0.902
Diffuse gaussian	0.693
Diamond	0.905
Square	0.726
mAP	0.807

FPN Results

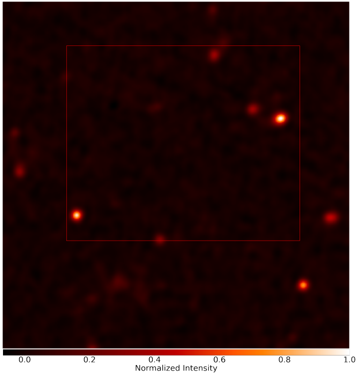

Pointlike Gaussian
Diffuse Gaussian
Diamond
Square
Pixels
Normalized Intensity
Truth
SSD300
Improved Model

Sources	True positives	False positives	False negatives
200	182	21	18

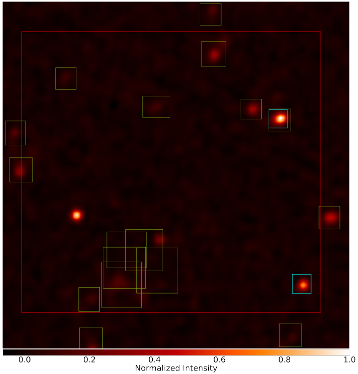


Testing on LOFAR Data

- LOFAR preliminary data release (LoTSS PDR)
- Analyze 300×300 px tiles



SSD300



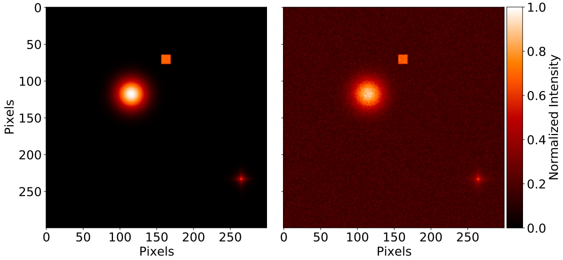
Improved Architecture

Noisy Data

Gaussian Noise

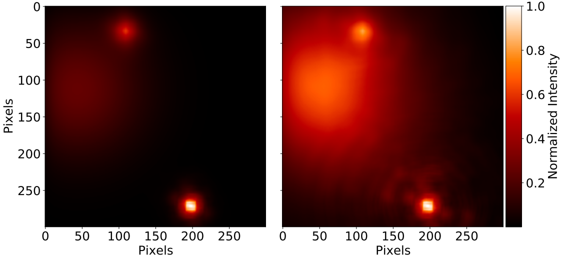
- Simulate random noise in Measurement
- Add random value $n_{\tilde{p}}$ from Gaussian distribution to pixel

$$p = \tilde{p} + n_{\tilde{p}}$$



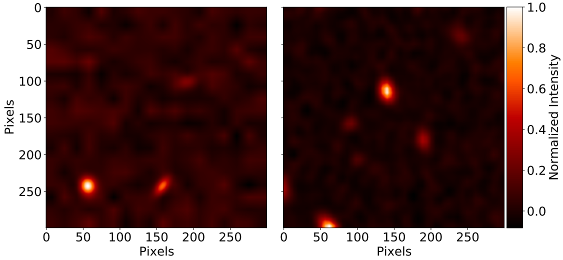
Beam Noise

- Convolution of true brightness distribution with beam
- Use beam from real LOFAR measurement
- Adjust noise intensity with additional 2D Gaussian



Rough Gaussian Noise

- Images from real data must be upsampled and show large scale artifacts
- Create low resolution grid with random values
- Upsample and add to data



Custom simulation (left) and SKA Data Challenge (right)

Perfomance

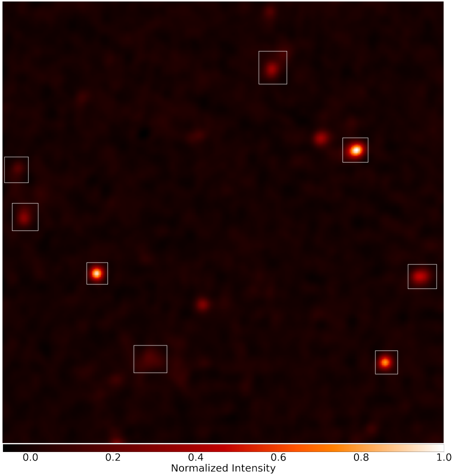
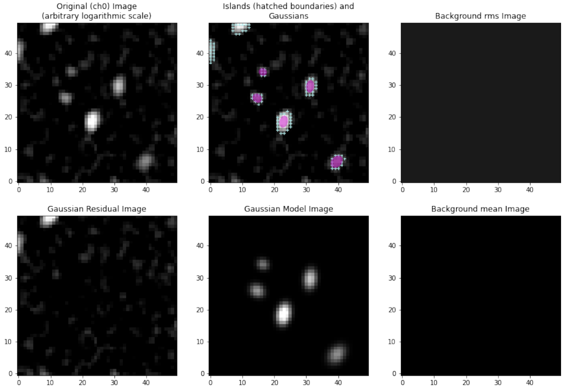


Image taken from LOFAR preliminary data release (LoTSS PDR)

Evaluation and Comparison to PyBDSF

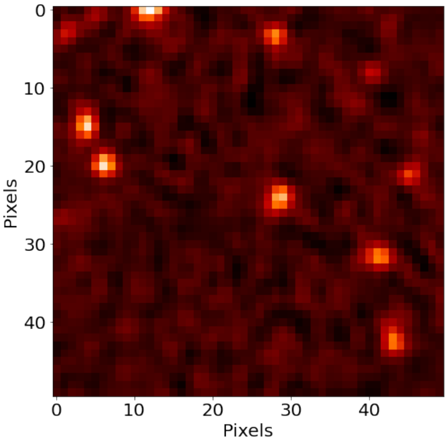
PyBDSF

- Established source detection tool
- Designed for LOFAR
- Fits Gaussians to islands of emission



SKA Data Challenge #1 (SDC)

- Sophisticated Simulations
- Contain ground truth data
- Smaller Sources →50 pixel cutouts



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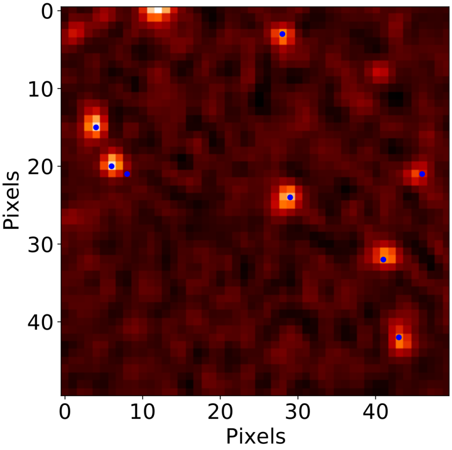
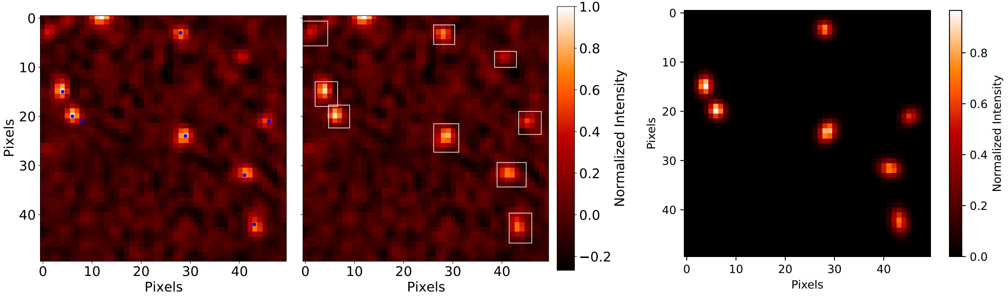
SKA Data Challenge #1

- Truth Catalog contains (x,y)-Coordinates
- Evaluation:
  - Collapse predicted boxes to points
  - FP if prediction more than 5% of image resolution away from truth



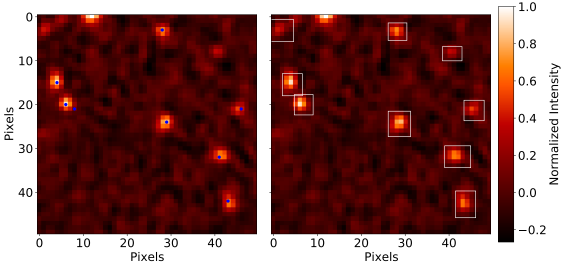
Detection Results



Detection Results

- Testing on 2500 SDC images
- Wall times
  - PyBDSF: $28\,\mathrm{min}$
  - This work: $5\,\mathrm{min}$

	Sources	False positives
Truth	15520	-
PyBDSF	11569	3681
This work	8542	2503

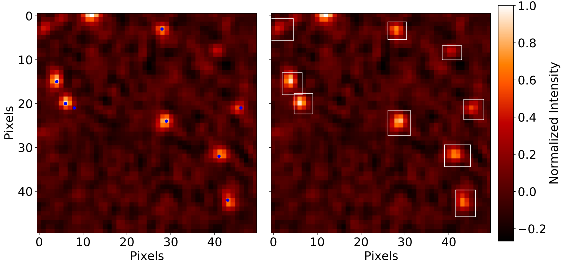


Outlook

Current Results

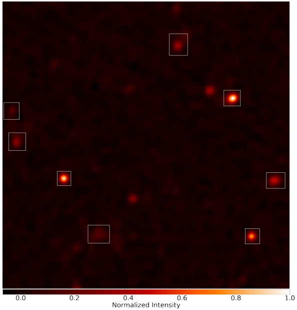
	Sources	False positives
Truth	15520	-
PyBDSF	11569	3681
This work	8542	2503

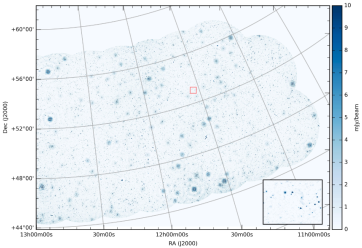
- Competitive with established tools
- Fewer true positives but much faster
- Great potential for further improvements



Outlook - Sky Surveys

- Training on SDC data
- Loss adjustments
- Use of super resolution





ui.adsabs.harvard.edu/abs/2017A%26A...598A.104S

- Localization Loss

$$L_1 = \sum_{i=1}^{n} \left| y_{\text{true}} - y_{\text{predicted}} \right| \tag{1}$$

- Classification Loss

$$L_{\text{Cross Entropy}} = -\sum_{\forall x} p_{\text{true}}(x) \log \left(p_{\text{predicted}}(x) \right) \tag{2}$$