Deep learning with radio galaxies

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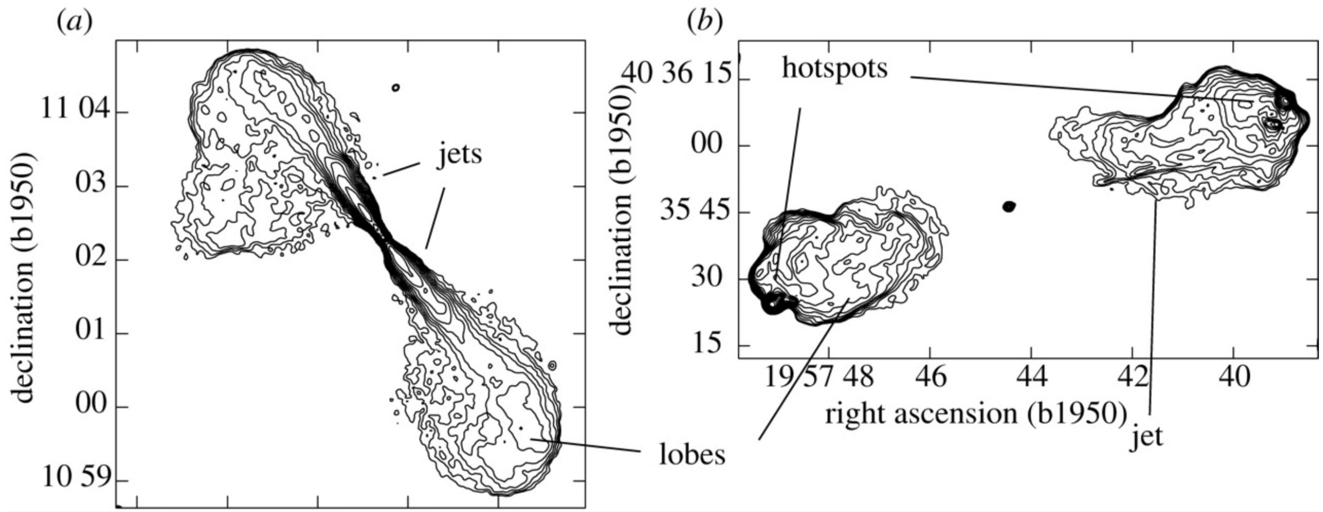
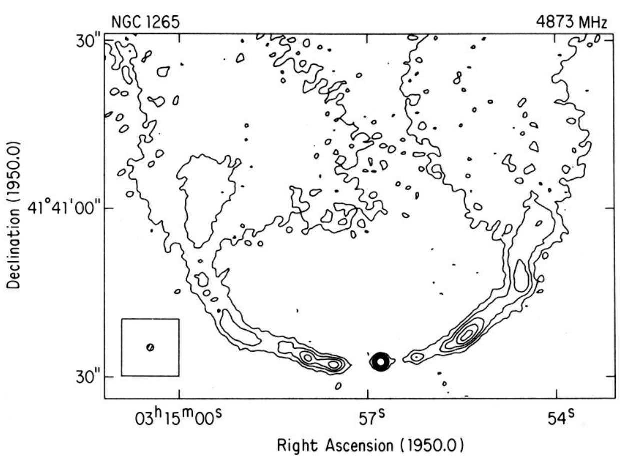
FRI

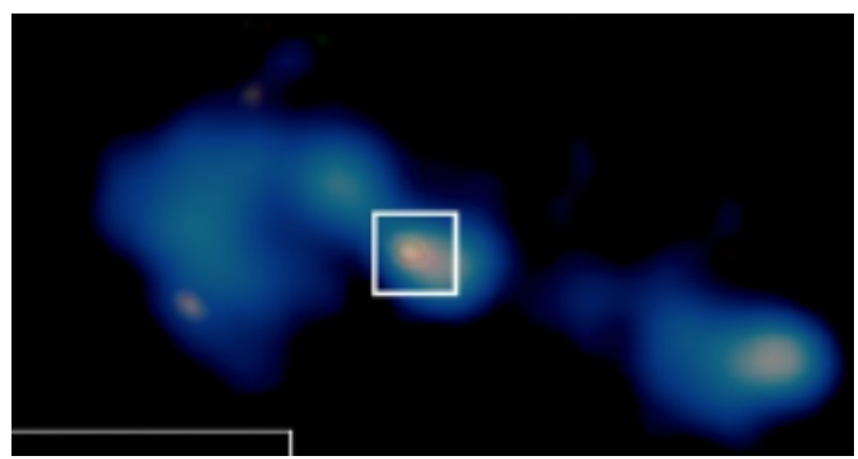
FRII



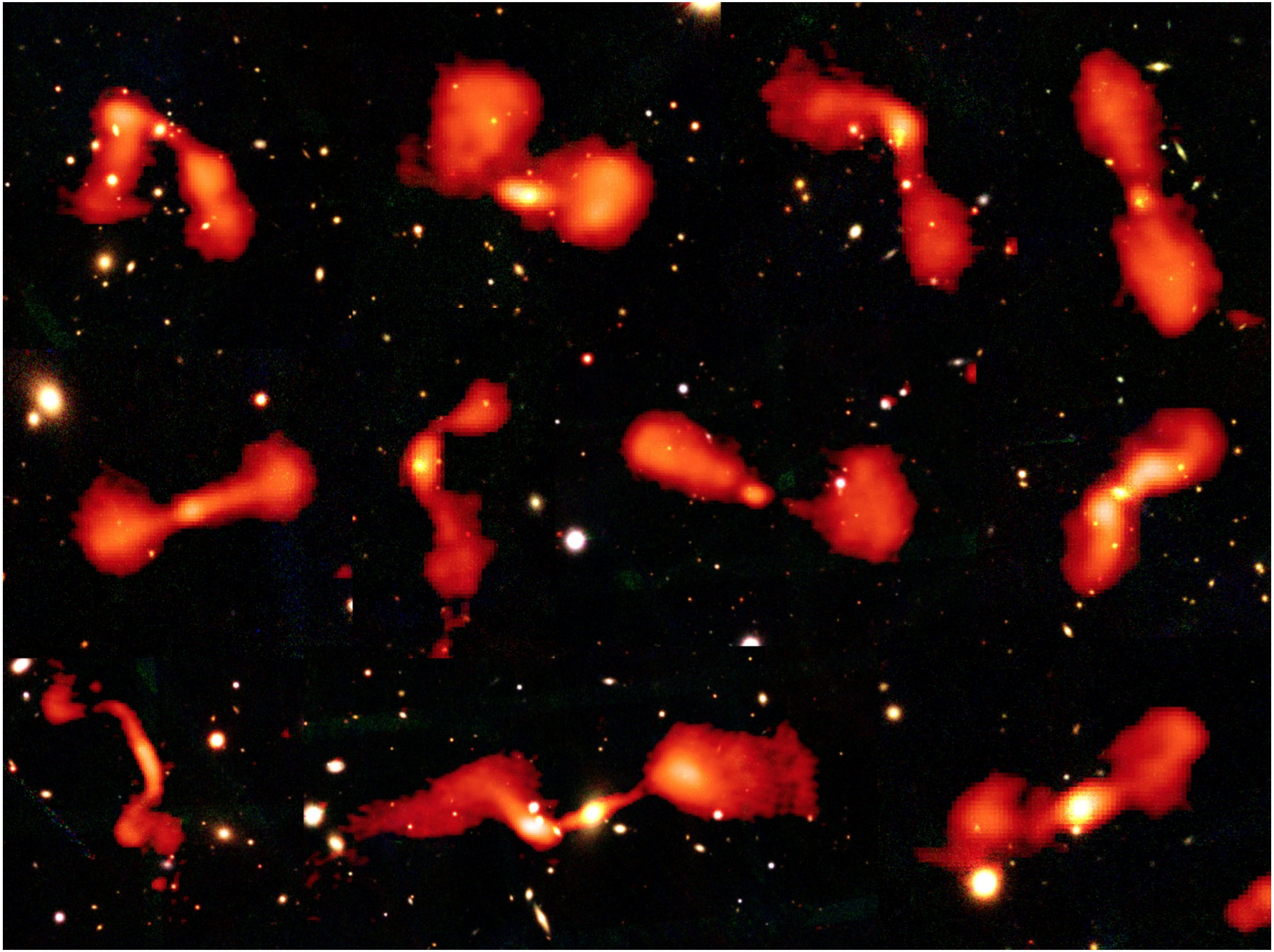
Bent-tailed



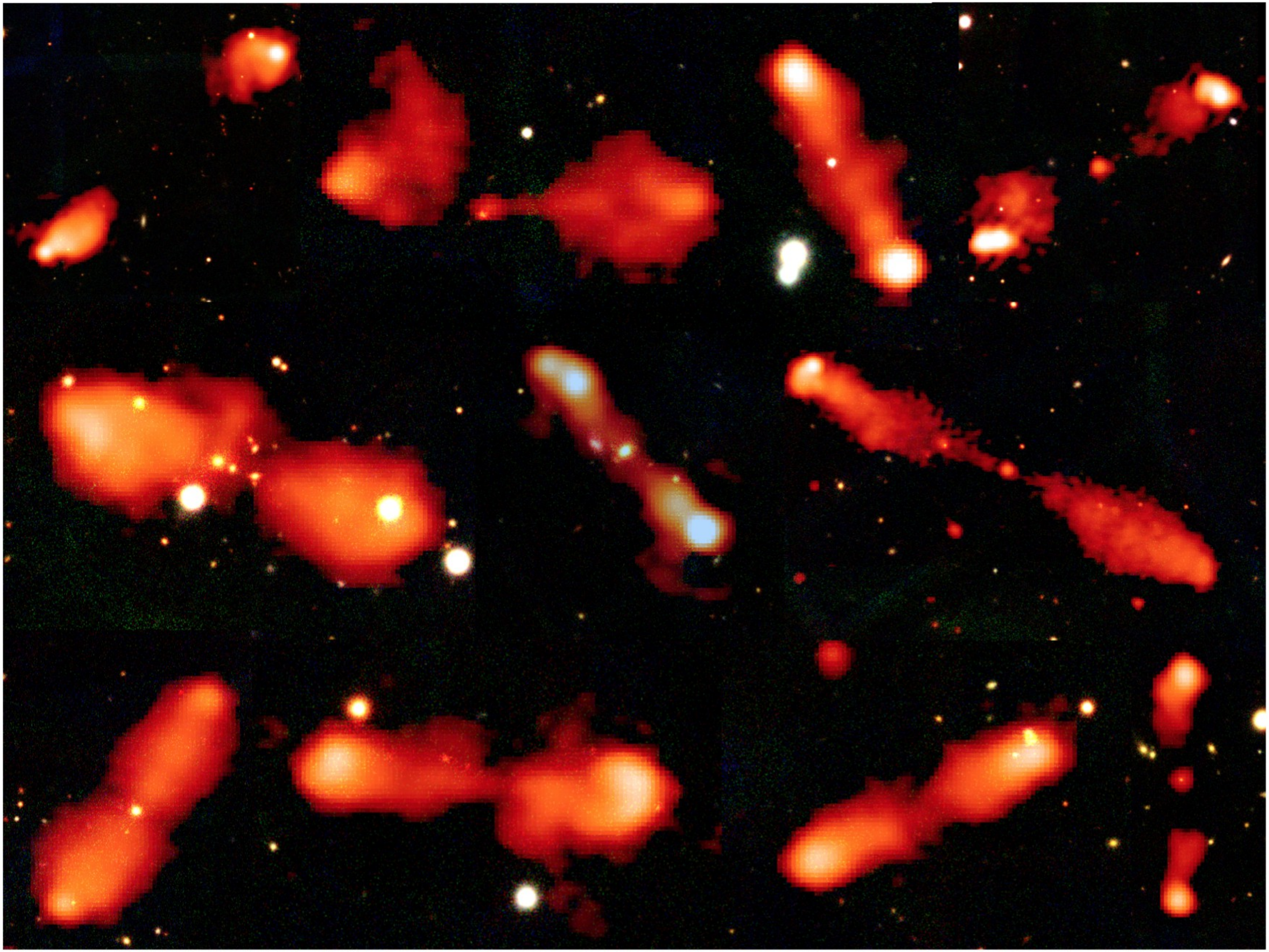
Hybrid



FRI possible morphologies



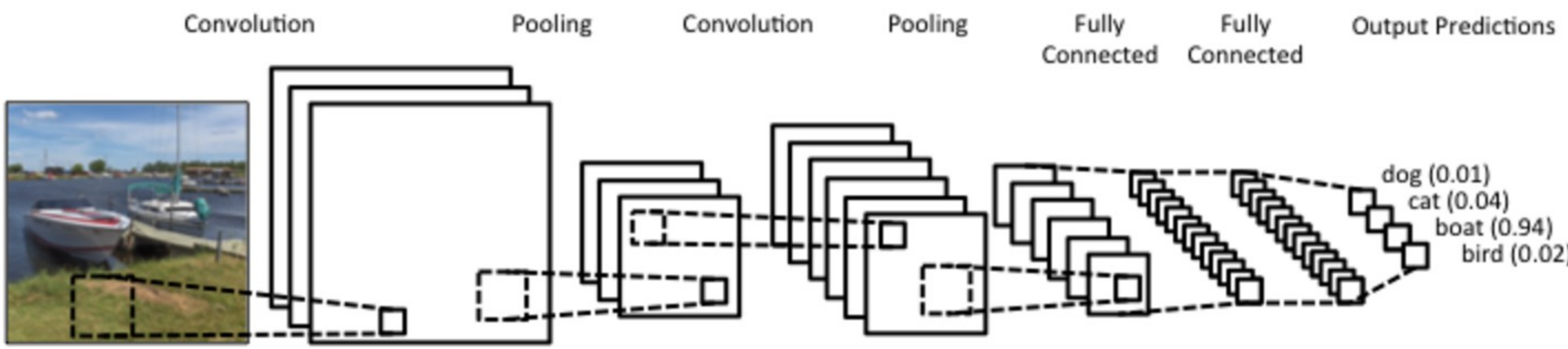
FRII possible morphologies

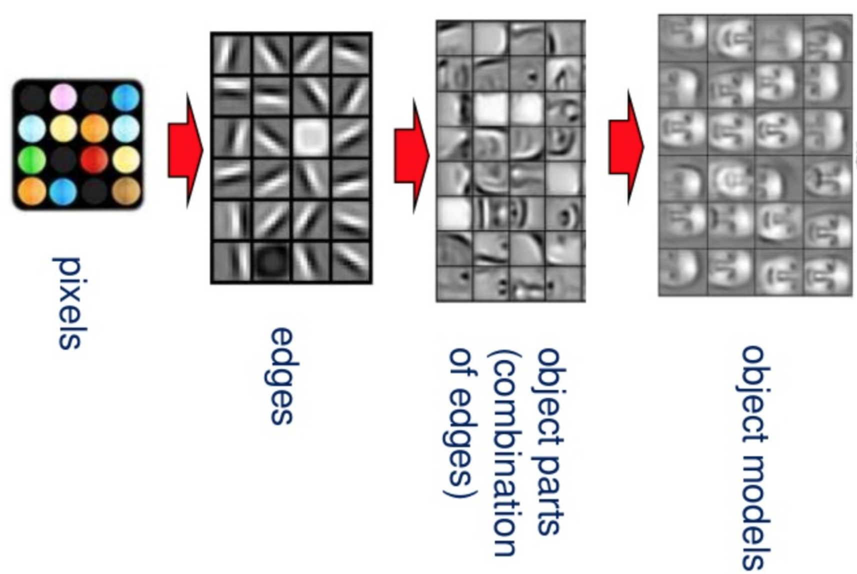


Background

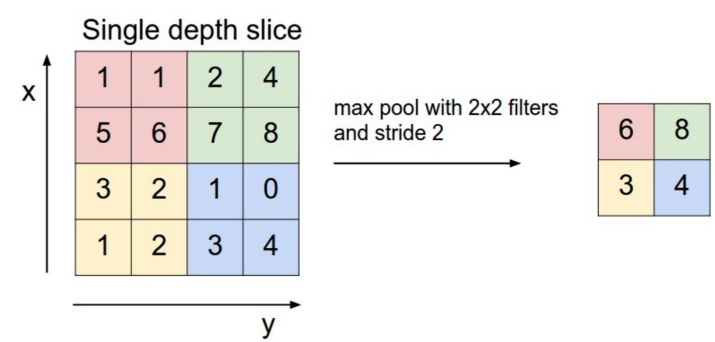
- Important properties can be inferred about the host galaxy based on its morphology
- As more surveys are performed, they detect more sources with increased resolution and sensitivity
- Aim to achieve automatic classification (machine learning)

Convolutional neural networks





Pooling



http://www.wildml.com/2015/11/understanding-convolutional-neural-networks-for-nlp/

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Radio Galaxy Zoo: compact and extended radio source classification with deep learning

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ABSTRACT

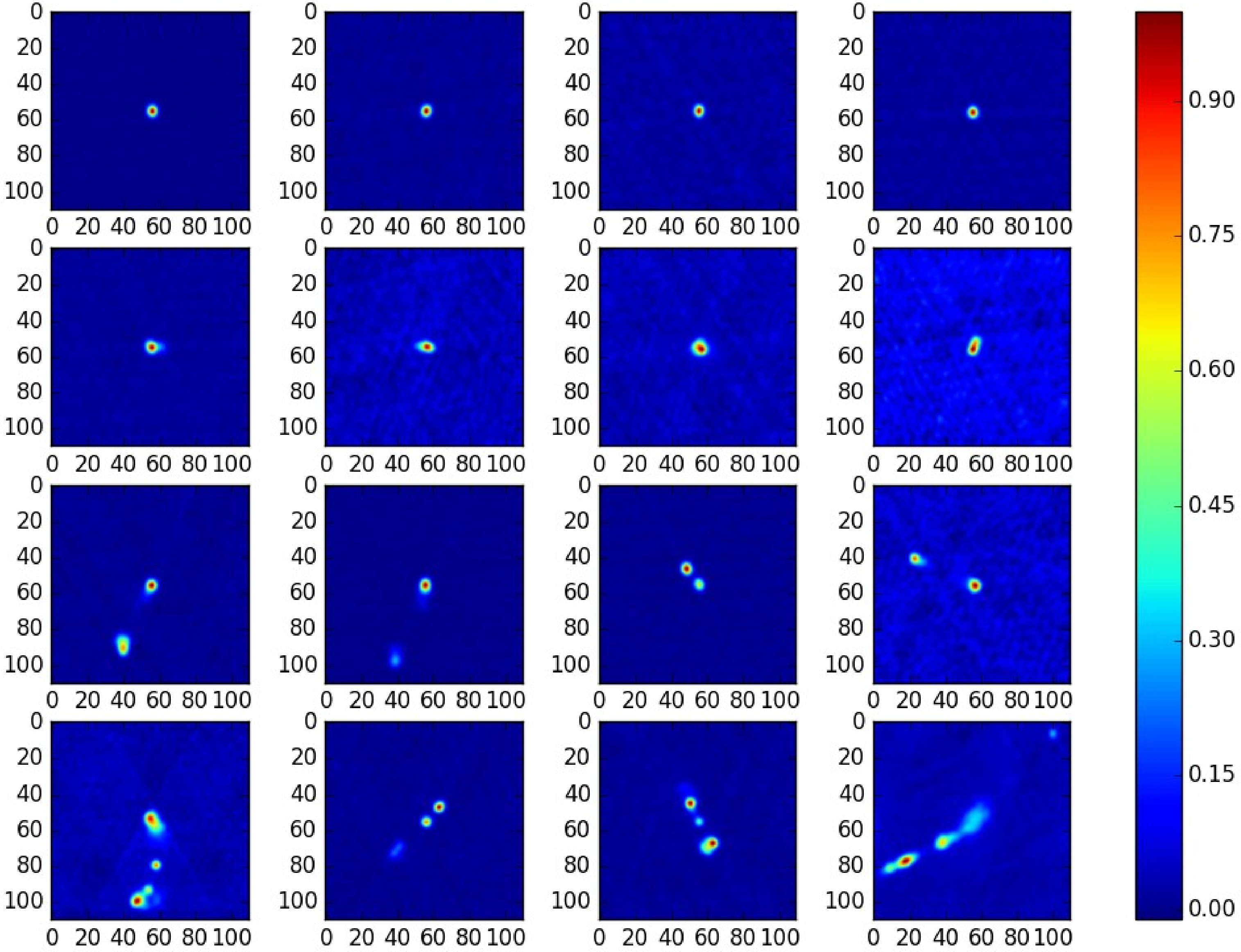
Machine learning techniques have been increasingly useful in astronomical applications over the last few years, for example in the morphological classification of galaxies. Convolutional neural networks have proven to be highly effective in classifying objects in image data. In the context of radio-interferometric imaging in astronomy, we looked for ways to identify multiple components of individual sources. To this effect, we design a convolutional neural network to differentiate between different morphology classes using sources from the Radio Galaxy Zoo (RGZ) citizen science project. In this first step, we focus on exploring the factors that affect the performance of such neural networks, such as the amount of training data, number and nature of layers, and the hyperparameters. We begin with a simple experiment in which we only differentiate between two extreme morphologies, using compact and multiple-component extended sources. We found that a three-convolutional layer architecture yielded very good results, achieving a classification accuracy of 97.4 per cent on a test data set. The same architecture was then tested on a four-class problem where we let the network classify sources into compact and three classes of extended sources, achieving a test accuracy of 93.5 per cent. The best-performing convolutional neural network set-up has been verified against RGZ Data Release 1 where a final test accuracy of 94.8 per cent was obtained, using both original and augmented images. The use of sigma clipping does not offer a significant benefit overall, except in cases with a small number of training images.

Key words: instrumentation: miscellaneous – methods: miscellaneous – techniques: miscellaneous – radio continuum: galaxies.

Radio Galaxy Zoo (RGZ) data provided

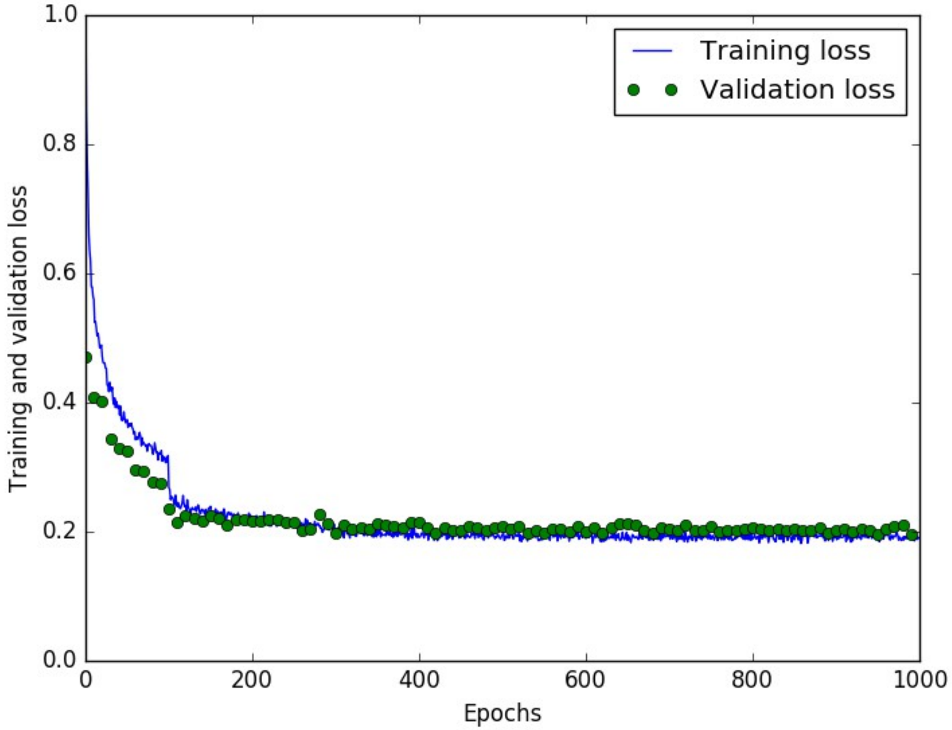
- Image data of 206399 galaxies, from fits files
- No label data provided
- Single channel
- Typically (132,132) pixels
- Images contain different numbers of components
- Used PyBDSF (Python Blob Detector and Source Finder) to help organise the data

Four-class problem



Results for four classes

- 3 conv + 2 dense layer architecture, using original and augmented images
- Overall accuracy 93.5%

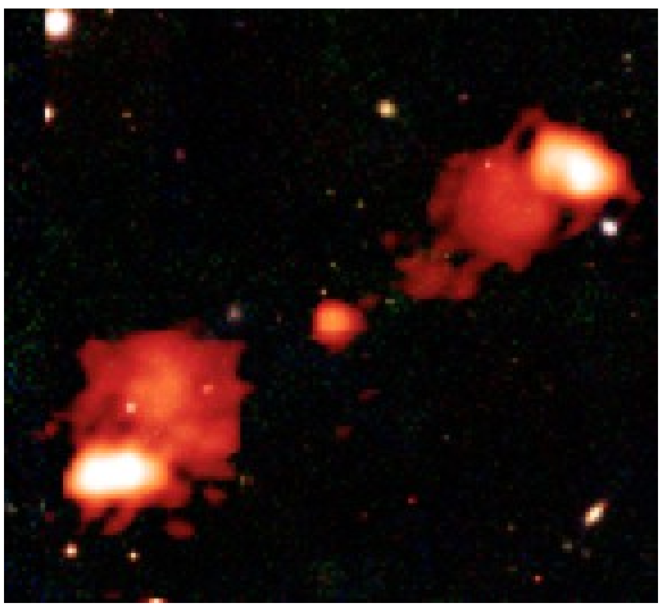


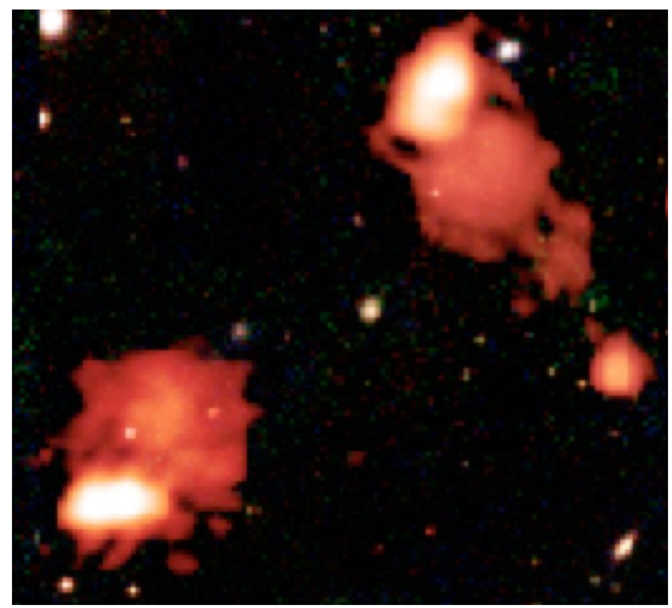
Cross-check with DR1

- Accuracy up to 94.8%
- High accuracy is influenced by the larger sample of compact, single, and two-component extended sources
- Poorer metrics achieved on the multiple-component extended sources

Drawback of convolutional neural networks

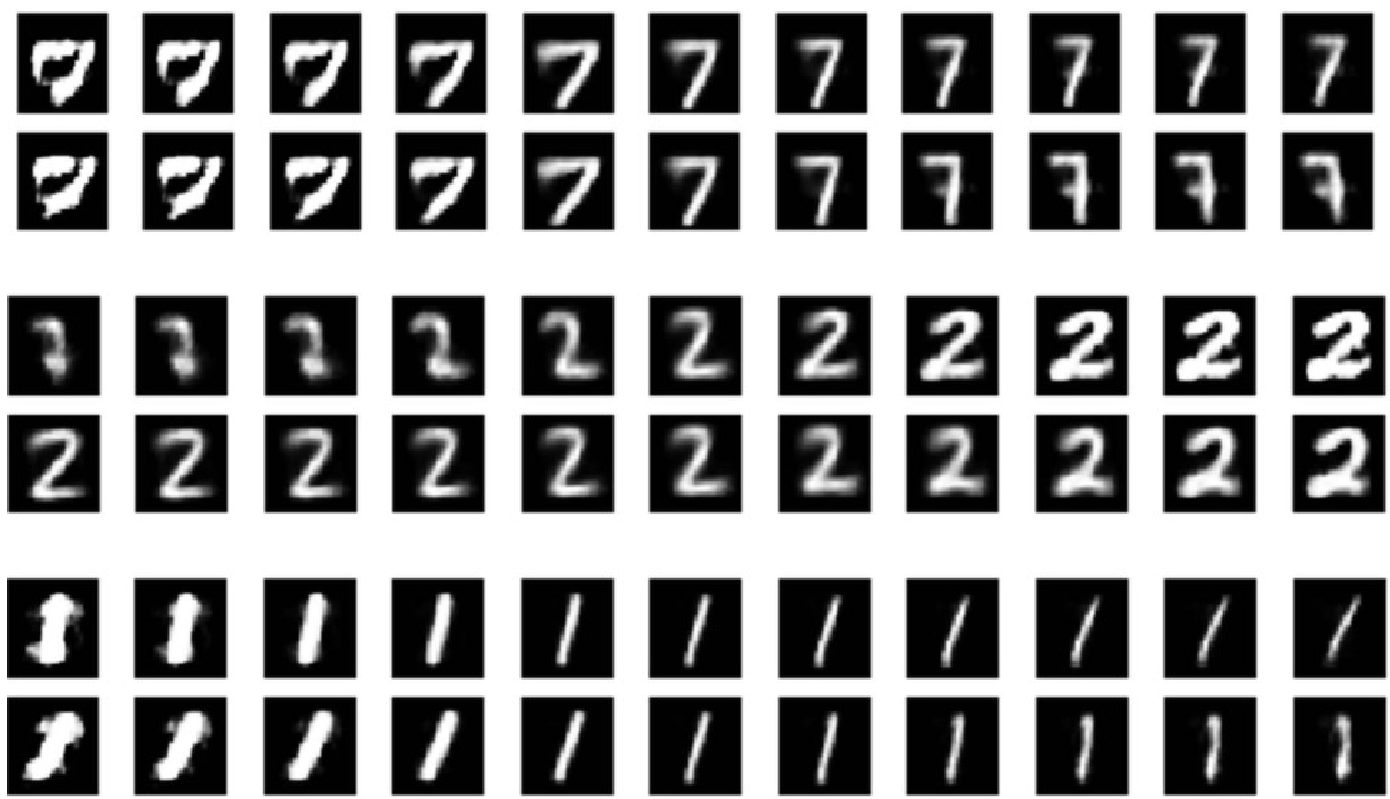
- Relative location of features within image is not preserved, due to pooling operation
- Lack of rotational invariance





Capsule networks

- Designed to preserve hierarchical relationships in images (Sabour, Frosst, Hinton (2017))
- A capsule consists of a group of neurons that attempt to extract possible variations of the subject in the image (e.g. Thickness and deformation)

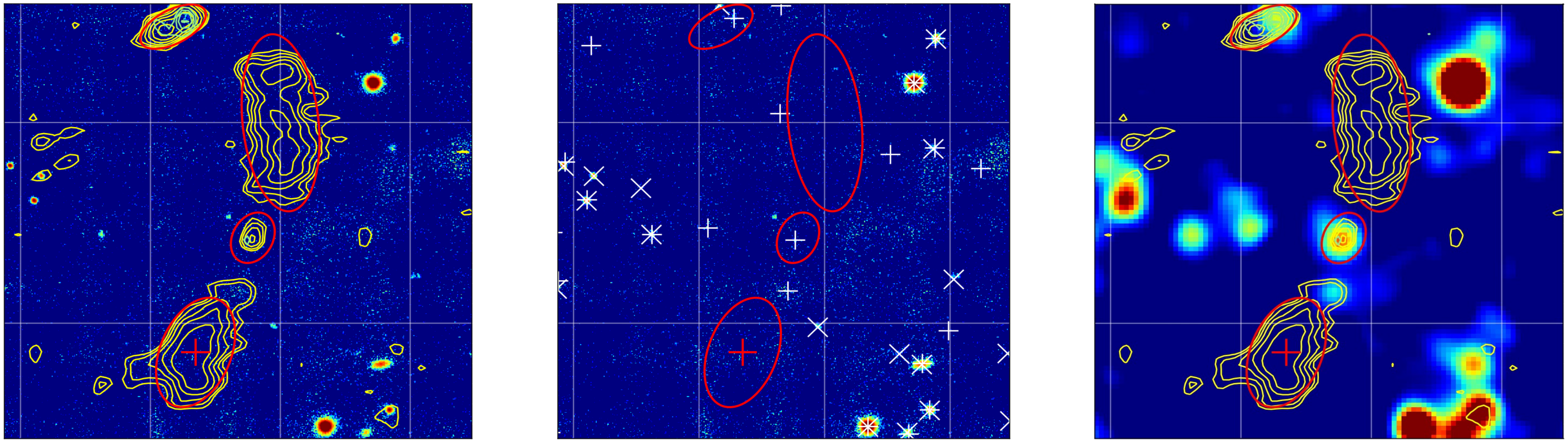


Recent work

- Morphological classification of radio galaxies: Capsule networks versus Convolutional Neural Networks (V. Lukic, M. Bruggen, B.Mingo, J.H. Croston, G. Kasieczka, P.N. Best)
  - Submitted to MNRAS
- Sources from the LOFAR LoTSS HetDex field

Recent work

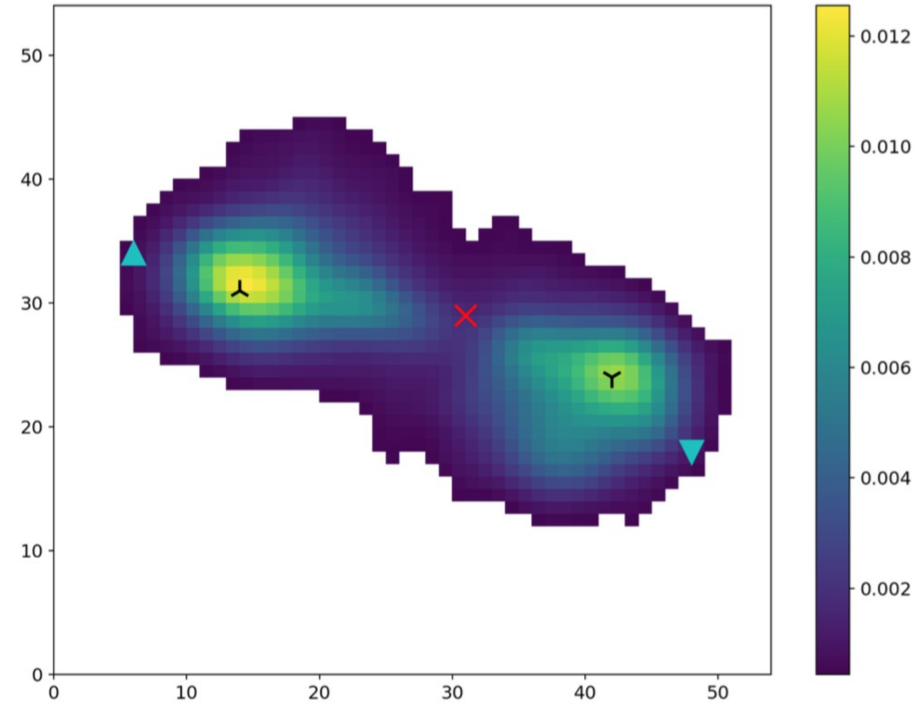
- Cross-identification of radio sources with optical source
  - Sources < 15 arcsec : Maximum likelihood technique
  - Sources > 15 arcsec : Inspected by expert astronomers

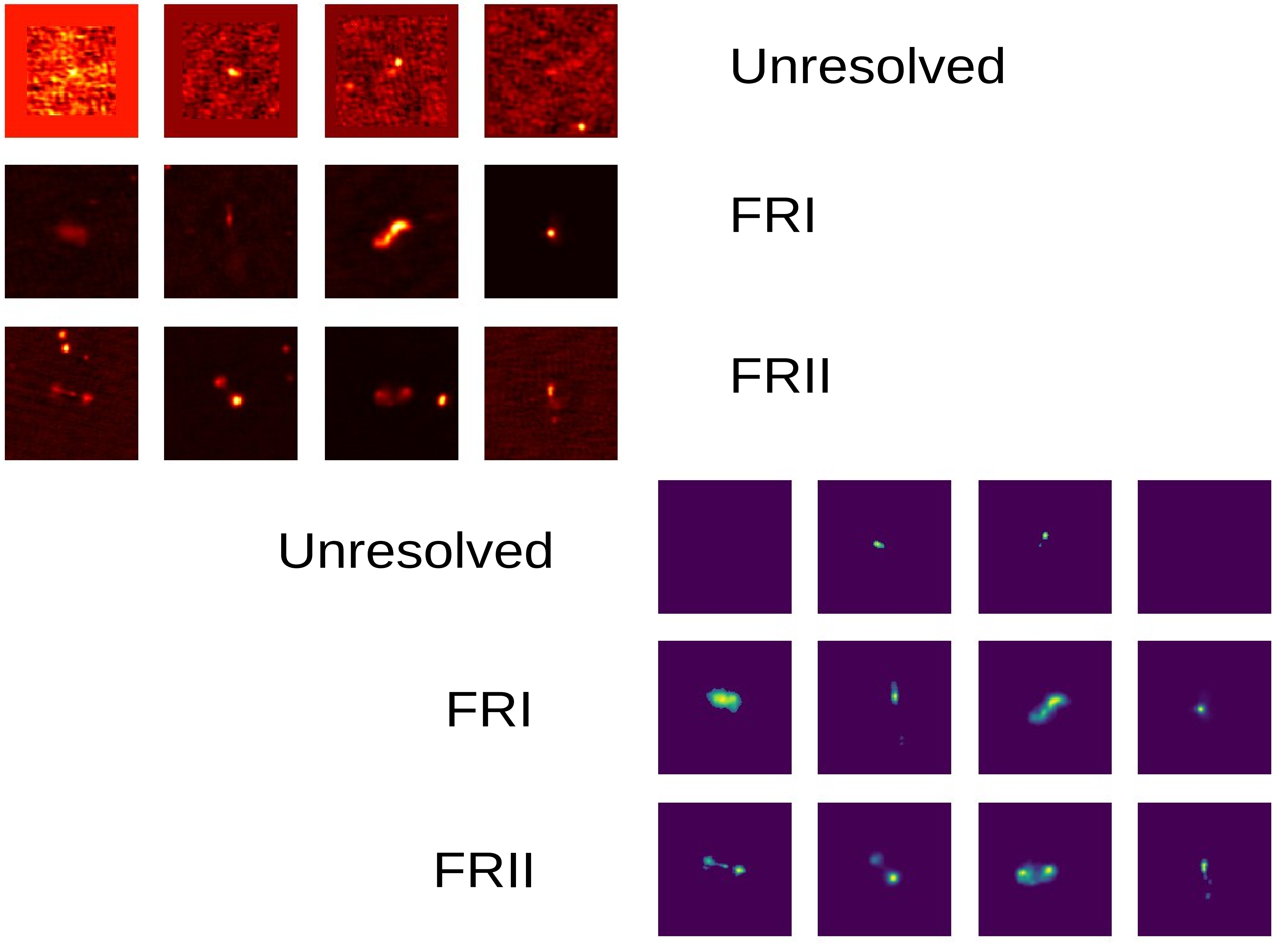


Recent work

- 2901 images with classifications:
  - Unresolved, FRI, FRII
  - Fits file cutouts and 4rms sigma-clipped numpy arrays
  - Labels generated using automated technique on 4rms images, FRIs and FRIIs cross-checked by a third party
  - Applied image augmentation (Translation, rotation, flipping)

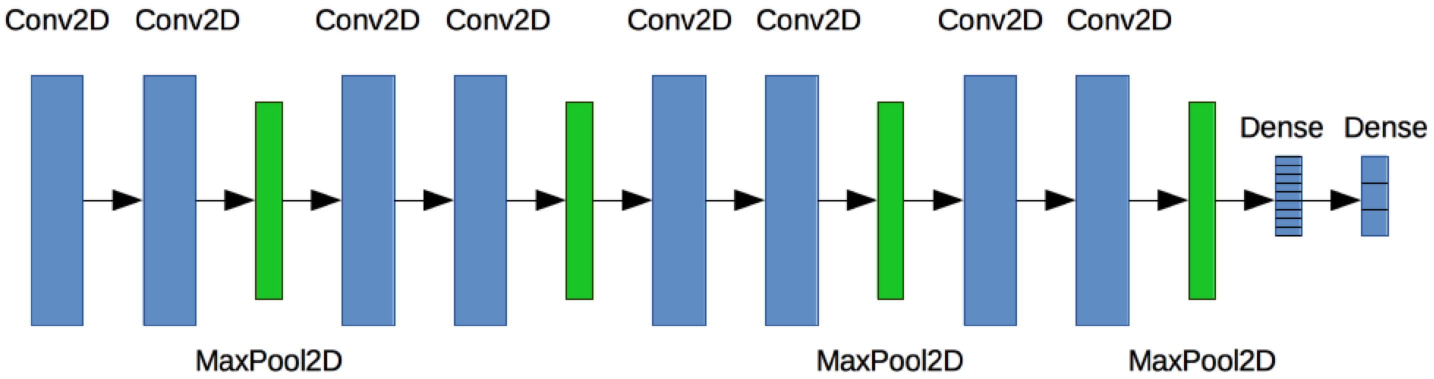
Class	# Original	# Augmented	# Total
Unresolved	1457	4371	5828
FRI	984	5904	6888
FRII	460	2760	3220
Total	2901	13035	15936




Unresolved
FRI
FRII
Unresolved
FRI
FRII

Convolutional neural networks

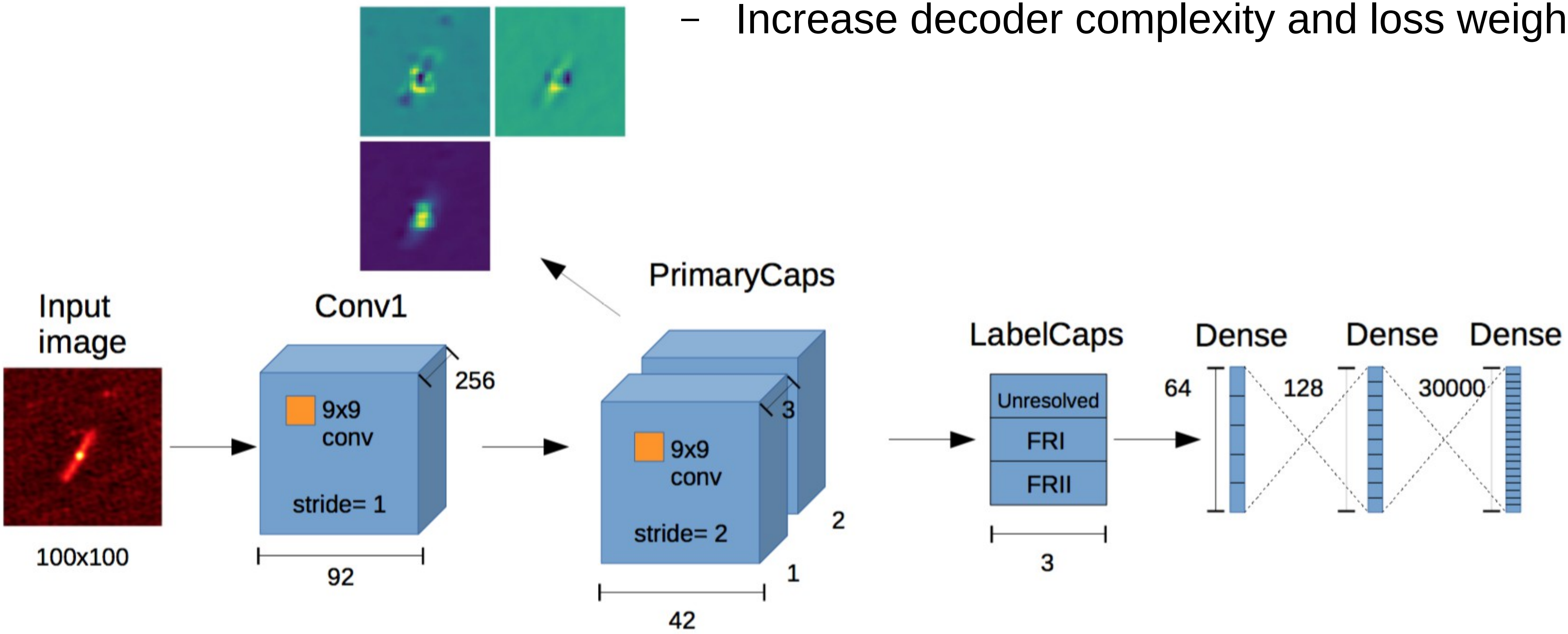
- ConvNet-4 and ConvNet-8



- Learning rate 0.001, cross-entropy cost function
- Train for 50 epochs, batch size of 100
- Adam optimizer

Capsule network

- Default
- Increase size of filters and stride
- Increase decoder complexity and loss weight

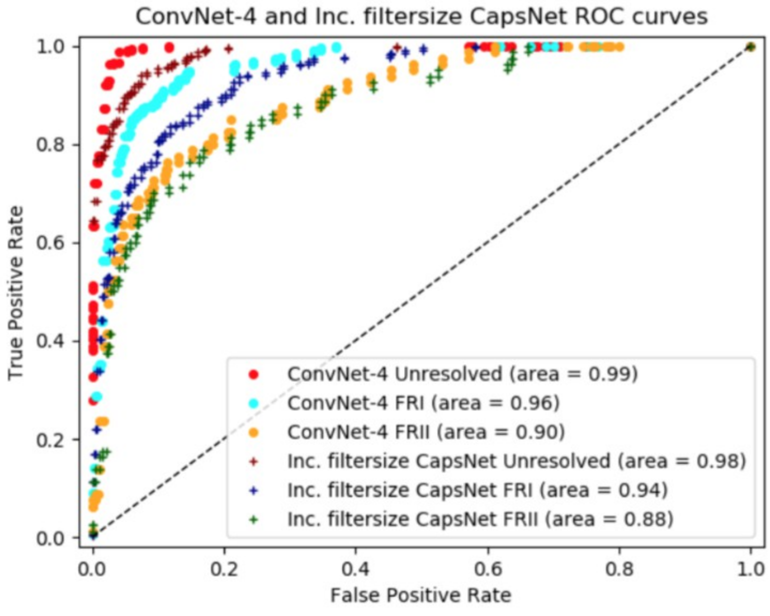


Datasets tested

- Original images - fits (79% training and 21% for validation and testing)
- Original images – 4rms numpy arrays
- Original + augmented images
- 5 training runs and calculate 95% confidence interval

Results

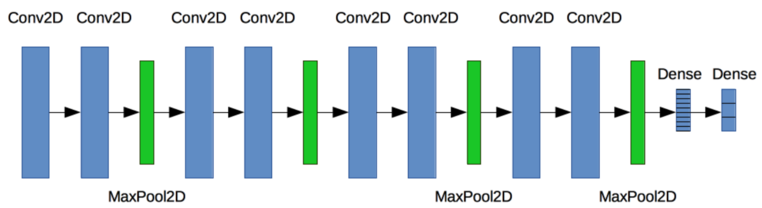
- Original data (79% training and 21% testing)
  - 4 and 8 layer convolutional network achieves overall accuracies of 88.7% and 91.2% respectively
  - Capsule network variations achieve overall accuracies between 82.9% and 84.2%
  - Unresolved sources are recovered best, followed by FRIs and FRIIs

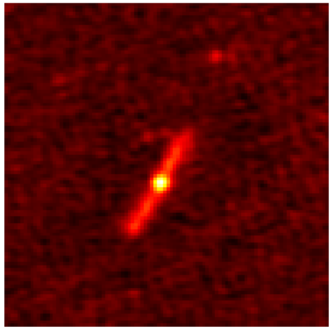


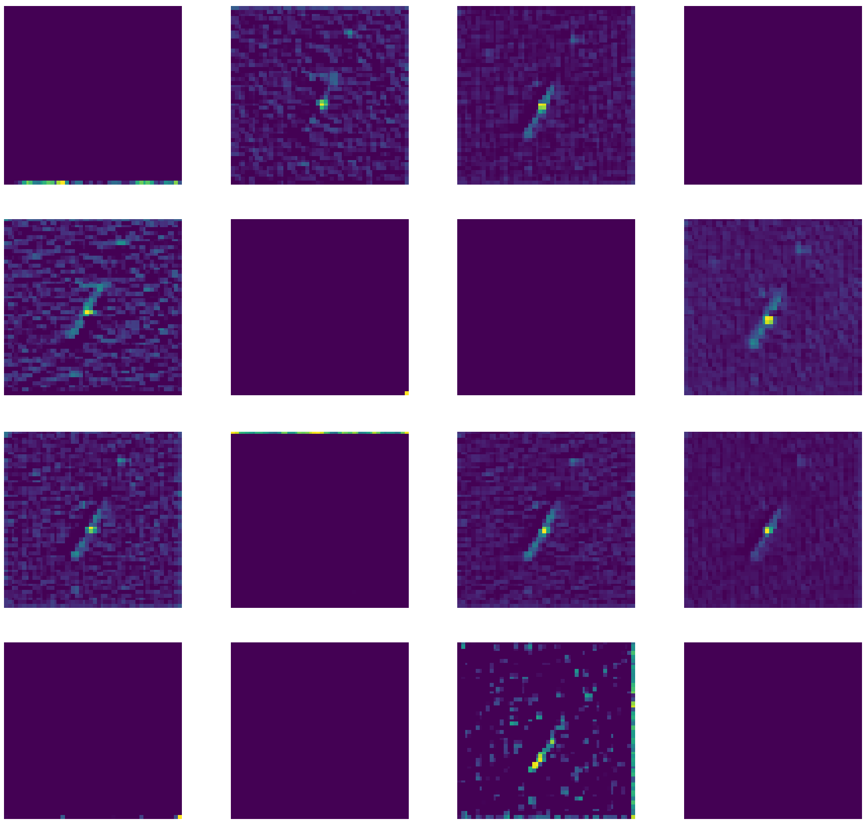
Results

- Using original + augmented data achieves the same results as using transfer learning (94.5% accuracy)
  - Transfer learning network trained on ImageNet images and using the Inception-v2 network
- Best results are obtained using 4rms masked numpy arrays (96.5%)
  - Both models (CapsNet and ConvNet) benefit from the removal of noise and potential unassociated sources
  - No augmentation has been applied to this dataset

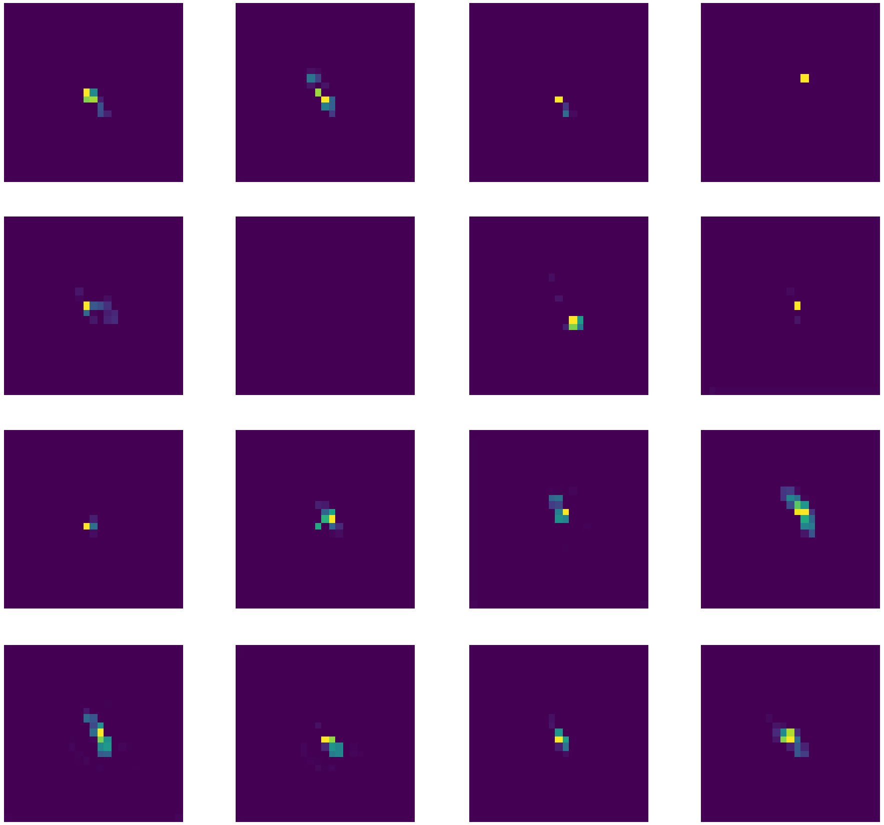
Features detected by ConvNet-8





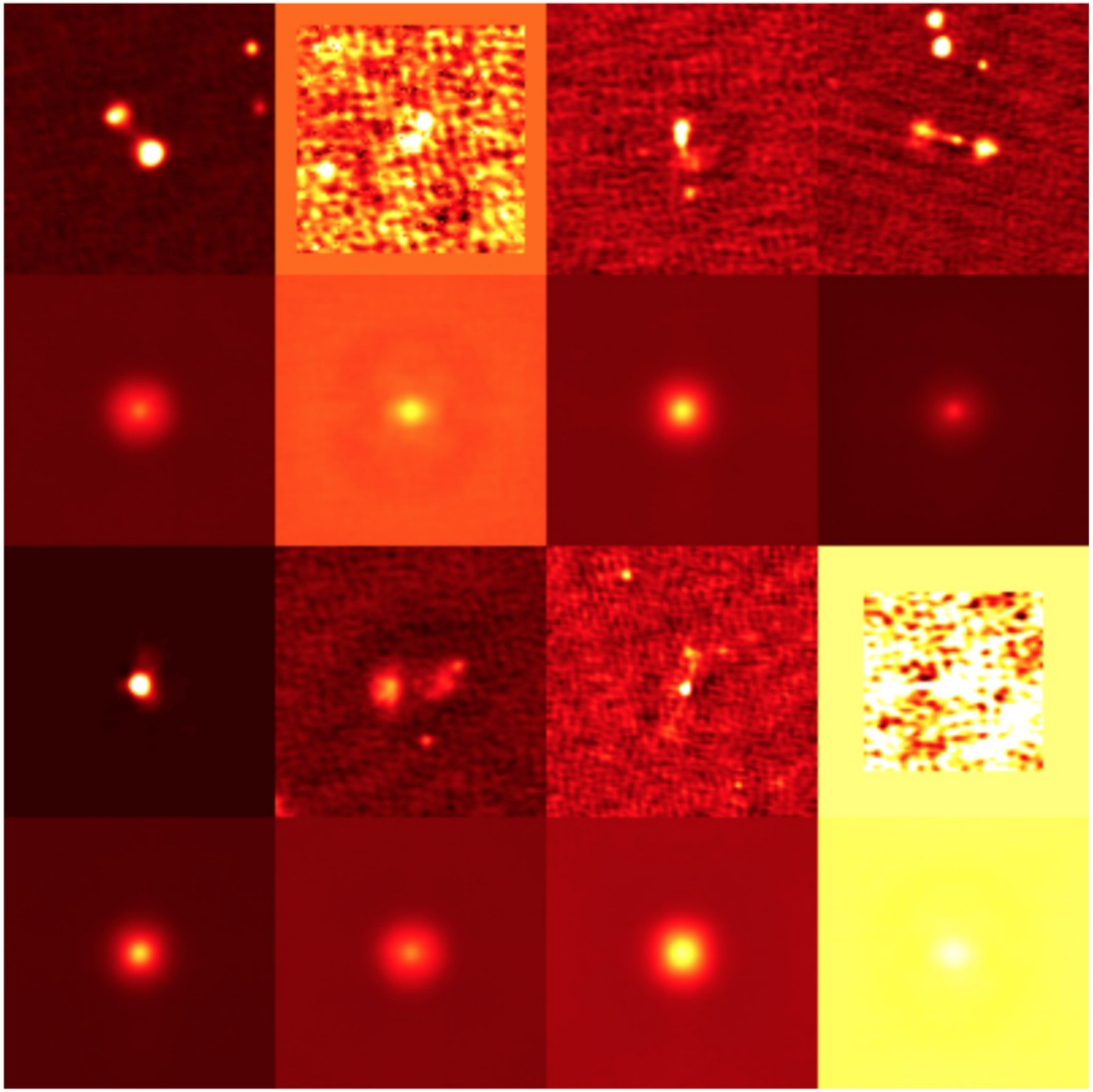


2nd



4th

Real and reconstructed images of CapsNet using (128,256) decoder with weight=5

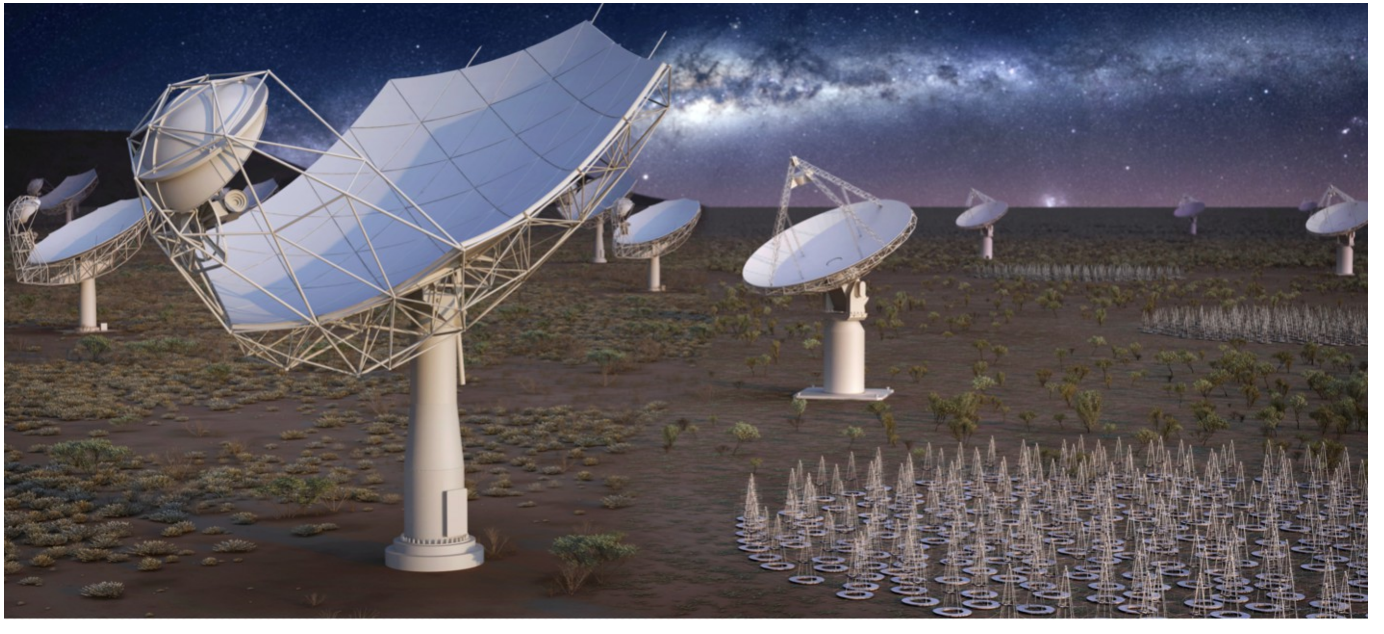


Possible reasons for performance

- Capsule network does not cope as successfully perhaps due to preserving all (signal + noise) features
- Pooling operation in convolutional networks appears to be advantageous in helping to reduce the effect of noise and intruding sources
- Pooling appears to give more degrees of freedom for morphology

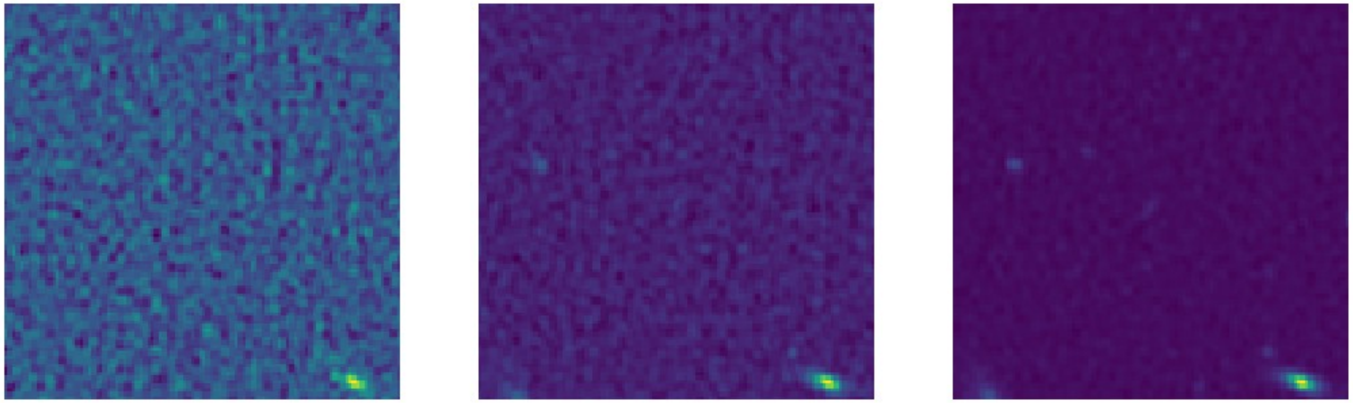
Current work

- Square kilometer array (SKA) is the worlds largest radio telescope
  - >1 square kilometer of collecting area
  - Eventually will use thousands of dishes and up to a million low frequency antennas
  - Will discover up to 500 million sources



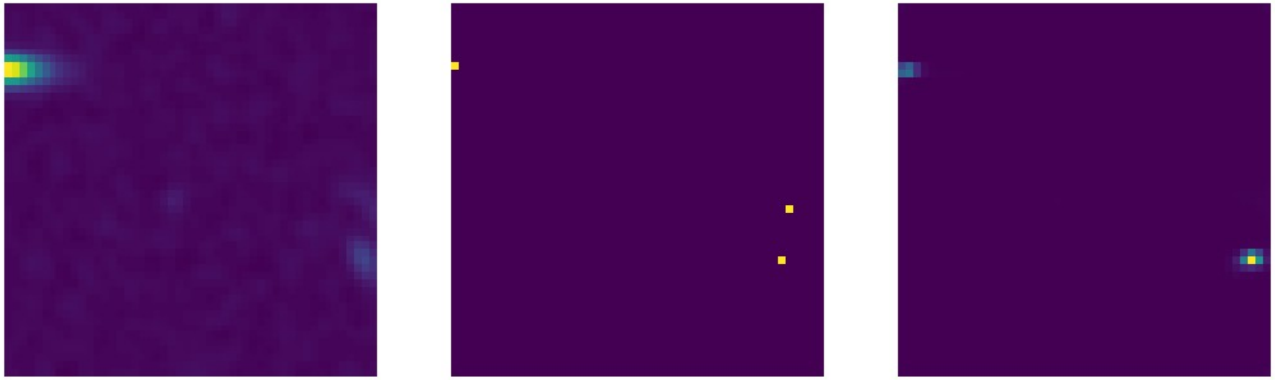
Current work

- SKA data challenge
  - Find, characterise and classify sources at 3 different frequencies (560,1400 and 9200 MHz) and 3 different exposure times (8h,100h,1000h)
- 3 separate training sets provided for the 3 frequencies



Current work

- Source-finding with autoencoders



- Characterisation and classification with general deep learning framework
  - Predicting flux, size of source, angle using regression
  - Classification into one of AGN-steep, AGN-flat or star-forming

Summary

- Machine learning is essential in analysing data from future astronomical surveys
- First work showed that it is possible to predict the classifications of citizen scientists given # peaks and # components with up to 94.8% accuracy
- Recent work shows performance of convolutional network surpasses that of capsule network models
  - CapsNet may have trouble distinguishing signal from noise as it preserves the local information within an image
- Currently exploring autoencoder performance in source-finding, and general DNN methods for characterisation and classification in the SKA data challenge