# Machine Learning Methods for Imaging with Interferometers

Christopher Danner[1,2], Richard Dodson[1], Foivos Diakogiannis[2], Samuel Lai[2], Andreas Wicenec[1], Ivy Wong[1,2], Nithyanandan Thyagarajan[2]

[1]ICRAR, University of Western Australia, Crawley, WA
[2]CSIRO, Australian Resources Research Centre, Kensington, WA

## Introduction

Machine learning (ML) imaging is an active field of research, primarily focused on compact images at the field center (e.g. GenDIRECT[1] , kine[2]). Unlike the Event Horizon Telescope[3] (EHT), SKA-Low[4] will generate huge, complex wide field images of the sky, containing 1000's of sources. These images require a lot of time to deconvolve. In this project, we will explore how different ML networks can be applied to deconvolve complex images, with the goal of building a framework that is capable of quickly and accurately deconvolving complex images.

## Data & Modeling

We generated ~2,100 2,048x2,048 synthetic images using OSKAR[5]. Each image contained five elliptical Gaussian sources, with the coordinates, flux, size, and orientation all randomized. Each radio source had a total flux ranging from 1xe$^{-4}$-2 Jy/beam and was always at least 12 arc-minutes apart from other sources.

We trained a modified Residual Network (ResNet[6]) with a 'dirty' sub-image paired with the corresponding parameters of the radio source. The ResNet would view the 'dirty' sub-image, then determine the source's center coordinates, total flux, size, and orientation. Each of the guesses were scored using a Mean Squared Error loss function and weighted to prevent any one parameter from dominating the loss. Then, the network's internal parameters were updated using the summed loss. At the end of each iteration, we ran the validation set against the updated ResNet.

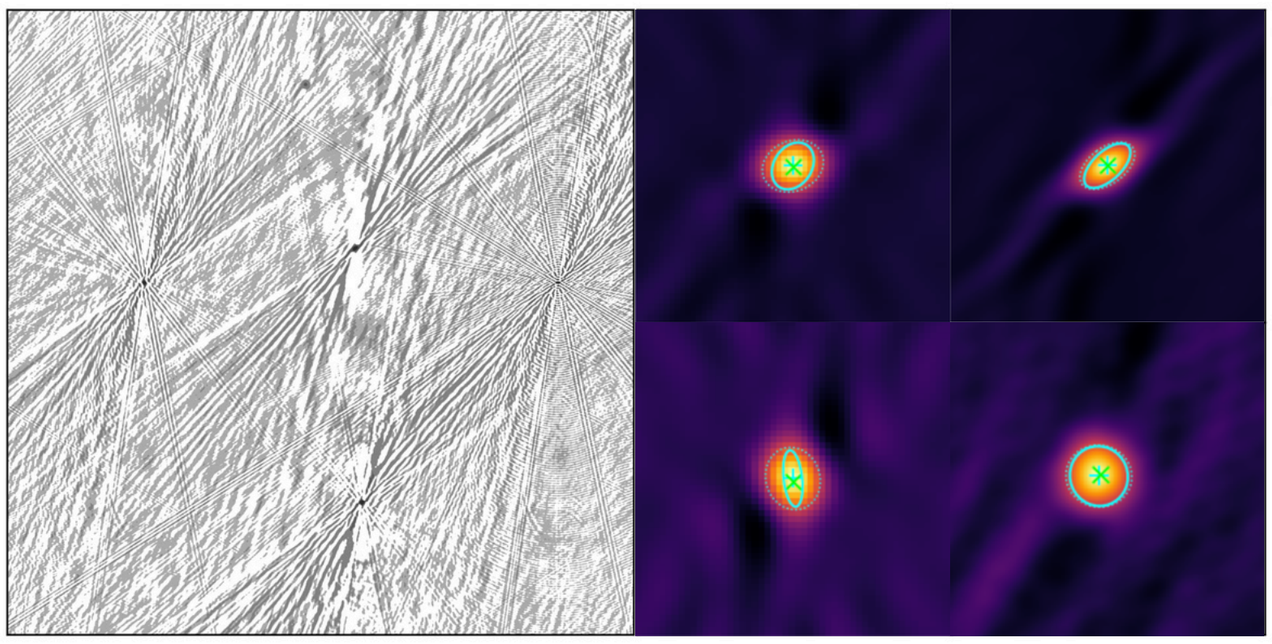


**Figure 1. Left:** Synthetic 'dirty' (i.e. not deconvolved) image generated using OSKAR. Each image contained five Gaussian sources whose locations were always separated by at least 12 arc-minutes. Despite being physically separated, the sidelobes, generated by the point spread function (PSF), still interfere with the other sources. **Right:** 128x128 pixel subimages of 'dirty' image. Each sub-image contains one radio source. The solid cyan line outlines the true shape of the radio source, the dashed line outlines the source's shape when convolved with the beam, and the mark in the middle is the source center. This is the training data for the ResNet.

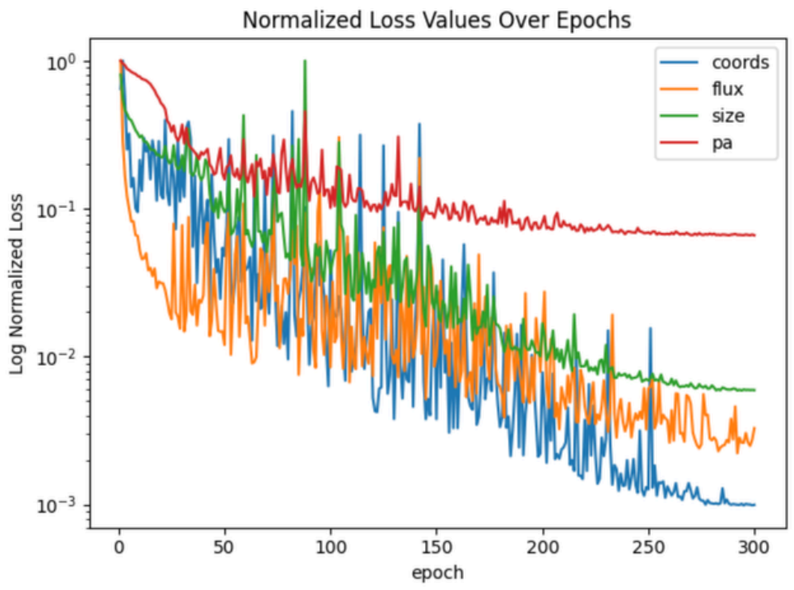



**Figure 2.** Combined plot of returned loss values over 300 epochs. The framework was trained to take into account input from four loss values: the center coordinates (blue line), the total integrated flux (orange line), the source size (green line), and the position angle (red line) of the source.

## References

1. L. Samuel et al., 2025, PASA, 42(148)
2. M. Foschi et al., 2026, Nature, 657, 900-905
3. Event Horizon Telescope Collaboration et al., 2019, AJL, 875(1)
4. P. E. Dewdney et al., 2009, IEEE, 97(8), 1482-1496
5. F. Dulwich et al., 2009, SKADS
6. K. He et al., 2016, IEEE, 1(1)

**Email: christopher.danner@research.edu.au**

## Results

After 300 iterations, the ResNet model was able to locate 95% of all elliptical Gaussian sources. Of these sources, the median RA and DEC coordinates were offset by ~3xe$^{-3}$ and ~4xe$^{-3}$ of the beam, respectively. This means that every coordinate estimate was off by less than a pixel. The median relative flux error was 1.2%, with 95% of the flux estimates having a relative flux error below 4%. Lastly, the median FWHM_major and FWHM_minor sizes were offset by ~-6x3$^{-3}$ and ~4xe$^{-3}$ of the beam, respectively.

The remaining 5% of sources were all incredibly faint compared to other sources in the same image. Any time a bright source (~1 Jy/beam) was generated near a very dim source (~1 mJy/beam), the sidelobes from the bright source completely covered the dim source. A second major cycle is required to find remaining dim sources.

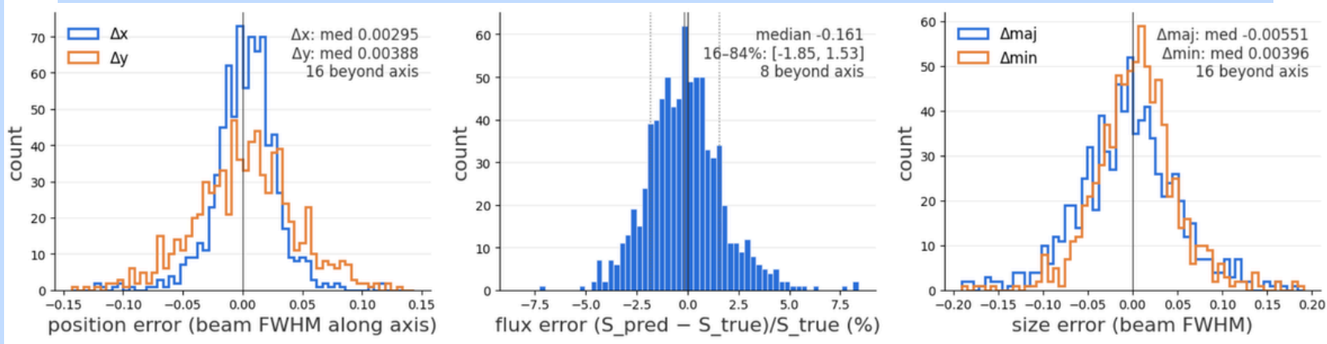



**Figure 3. Left:** Position error histogram. The blue line (x) highlights the RA offset whereas the orange line (y) highlights the DEC offset. Both offsets are measured with respect to resolution. **Center:** Integrated flux error histogram. **Right:** Size error histogram. The blue line (maj) highlights the Full Width Half Max (FWHM) major offset whereas the orange line (min) highlights the FWHM minor offset.

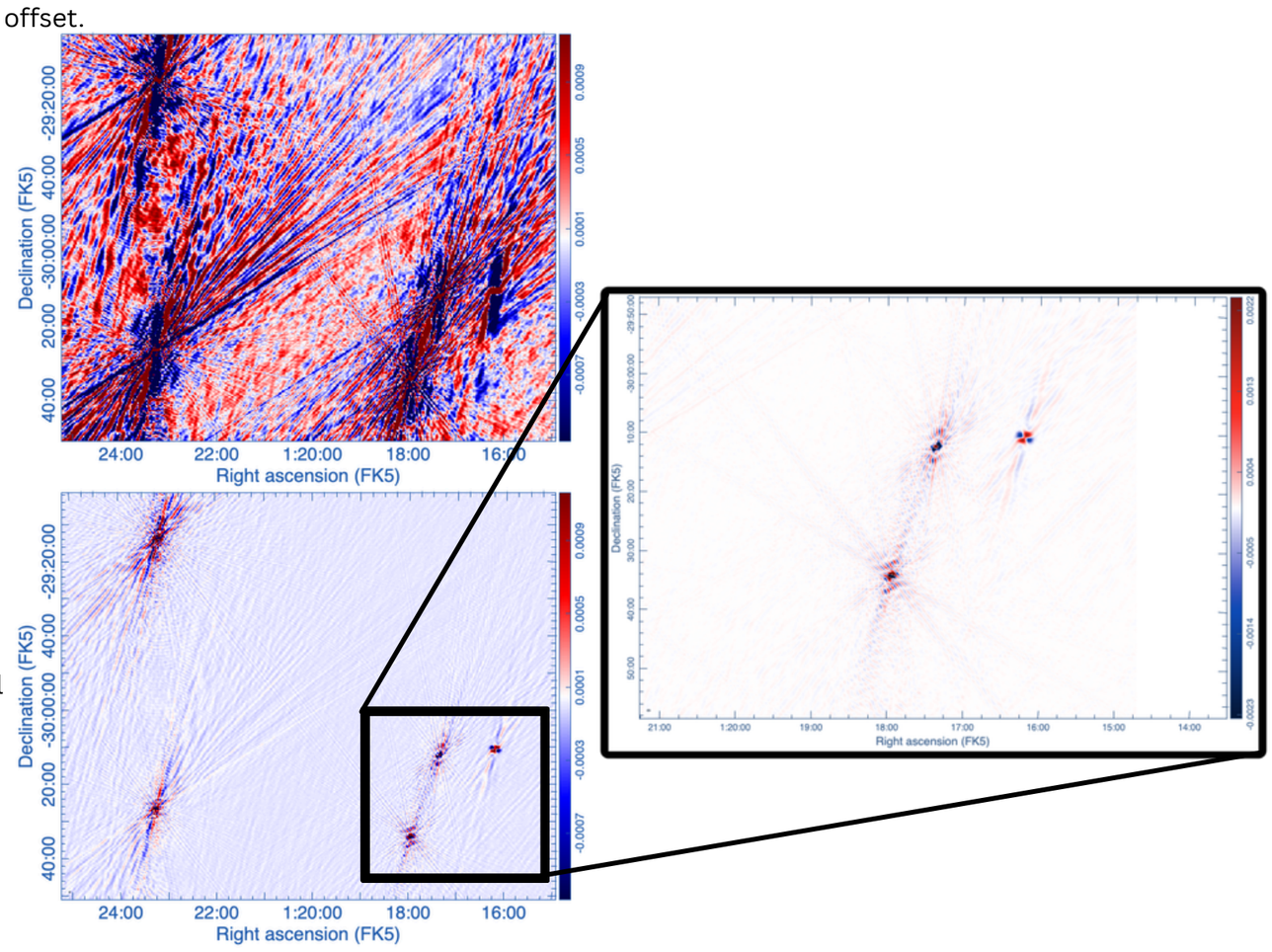



**Figure 4. Top Left:** Another 'dirty' image containing 5 elliptical sources. The flux values are distinguished based on color, with positive flux values appearing red and negative appearing blue. **Bottom Left:** Subtracted image, obtained by subtracting the model predicted by the ResNEt framework. **Right:** Zoomed in image of 3 elliptical sources relatively close together. Despite being close enough for their sidelobes to overlap in the 'dirty' image, they can now be processed in isolation.

## Conclusion

- Future frameworks will use image segmentation, followed eventually by replacing image inputs with visibilities
- The current ResNet model can locate 95% of sources with median coordinate and size offsets at ~6xe$^{-3}$ of the beam or less and median relative flux error at 1.2%.
- With a few major cycles, all sources can be deconvolved.
- More advanced frameworks will be necessary to detect and map both adjacent and complex objects.
- Future frameworks will be built to produce a deconvolved image of the original 'dirty' image.

