Super-Resolving Herschel SPIRE images using Convolutional Neural Networks

Why do we Super-Resolve Herschel SPIRE images?

The Open University

Lynge Lauritsen, Hugh Dickinson, Jane Bromley, Stephen Serjeant, Chen-Fatt Lim, Zhen-Kai Gao, Wei-Hao Wang

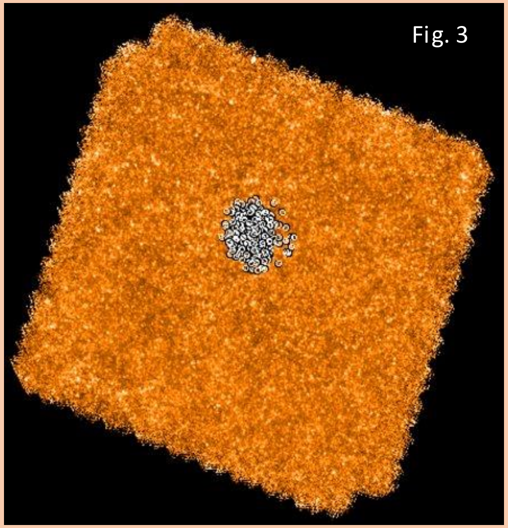
This project aims to Super-Resolve Herschel SPIRE 500 µm maps (fig. 1 show all Herschel SPIRE bands) towards a PSF FWHM comparable to that of the JCMT SCUBA-2 450 µm images (fig. 2).

The improved angular resolution affords the possibility of more reliable multi-wavelength cross-identifications, improved deblending of nearby sources and fainter fundamental confusion limits.

This has allowed JCMT SCUBA-2 to probe submillimetre number counts below 20 mJy, where source confusion becomes problematic in Herschel SPIRE data (table I).

The Herschel SPIRE survey has covered a much wider sky area than JCMT surveys, on fig. 3 the sources identified by the JCMT SCUBA-2 STUDIES survey are overplotted on the Herschel SPIRE 500 µm cosmos map.

Lim et al. 2020, Oliver et al. 2012



Characteristic	Herschel SPIRE			JCMT SCUBA-2
Wavelength	250 µm	350 µm	500 µm	450 µm
PSF FWHM	18.1"	24.9"	36.6"	7.9"
Confusion noise (σ, mJy/beam)	5.8 ± 0.3	6.3 ± 0.4	6.8 ± 0.4	1
Pixel scale	6"	8.33"	12"	1"

Table I: Characteristics of Herschel SPIRE and JCMT SCUBA-2 instruments.

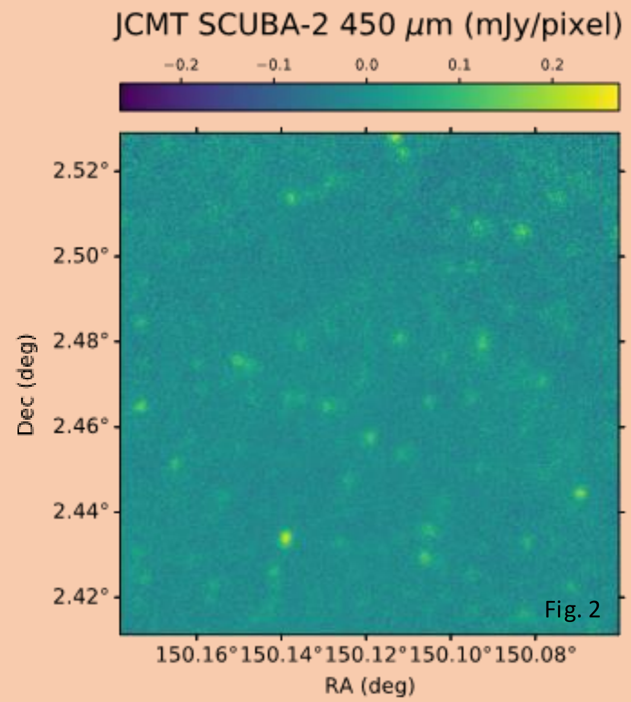
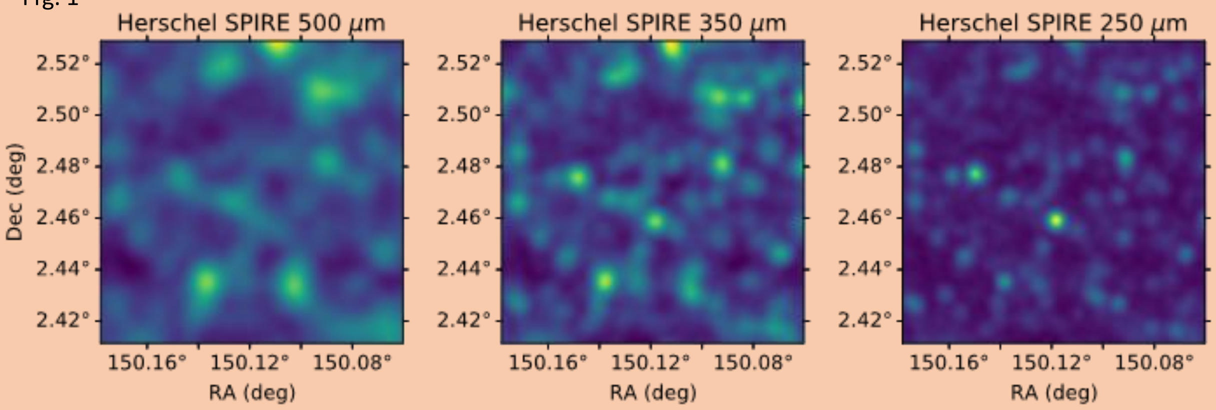


Fig. 1



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The Network

The Neural Network used in this project is an Auto-encoder in a U-NET configuration. The basic schematic of the network is shown below. The network contains 8 convolutional layers to reduce the image to a 2x2x512 embedded layer, and 8 de-convolutional layers.

All layers except the last de-convolutional layer is followed by Batch Normalisation and an activation layer (LeakyReLU). The three first de-convolutional layers is also followed by a dropout layer.

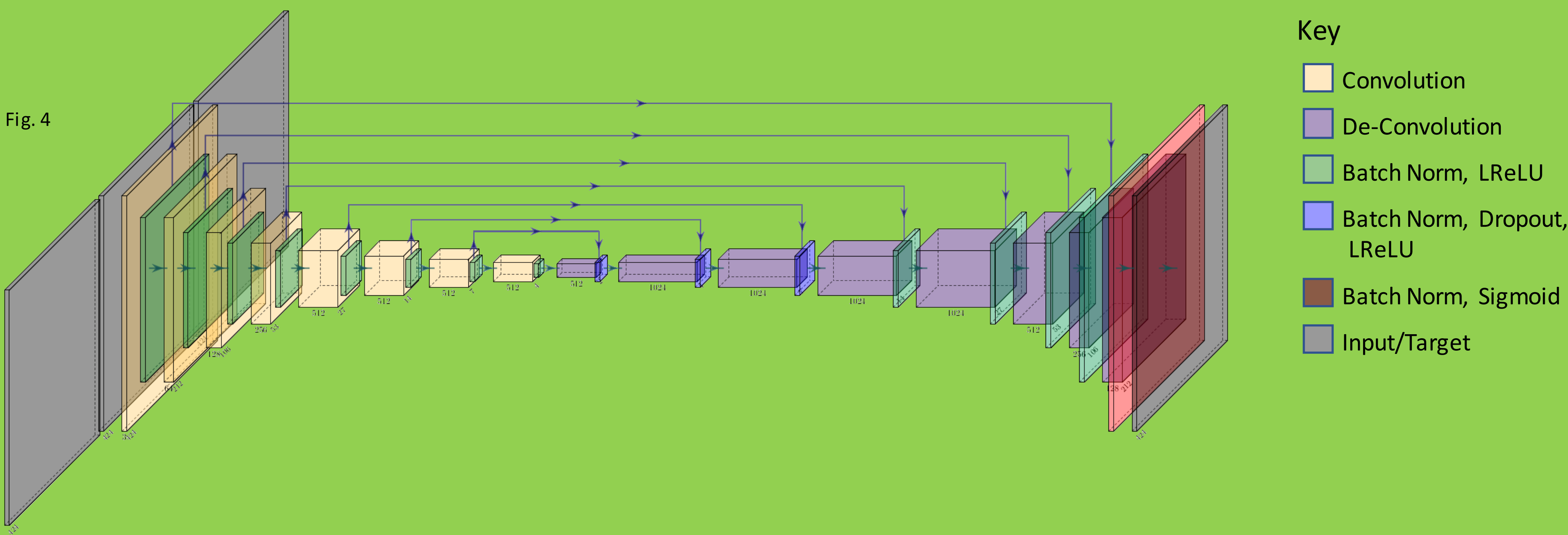
The final de-convolutional layer is followed by a Sigmoid activation function. The Sigmoid activation was chosen to enforce the output value to range from 0 to 1, preventing the prediction of negative values suppressing the noise characteristics of the JCMT SCUBA-2 images.

The input images are 424''x424'' cutouts from the Herschel COSMOS data, and the images are linearly interpolated to a pixel scale of 1'' to match the desired output pixel scales.

The training was done using a combination of simulated data, and data from the Herschel SPIRE cosmos maps combined with data from the JCMT SCUBA-2 STUDIES survey.

Each epoch the network was trained first on simulated data, and then refined on the observational data to learn the characteristics inherent in observational data.

Fig. 4



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Results I

The bottom row of fig. 5 shows the interpolated Herschel SPIRE images used as input for the network, while the top row shows the Super-resolved and target JCMT SCUBA-2 images.

While reconstructed sources can generally be individually identified in the 250 µm Herschel SPIRE image, the relative fluxes of the reconstructed sources appears to closely correlate with the fluxes at comparable locations in the 500 µm Herschel SPIRE image.

Fig. 5

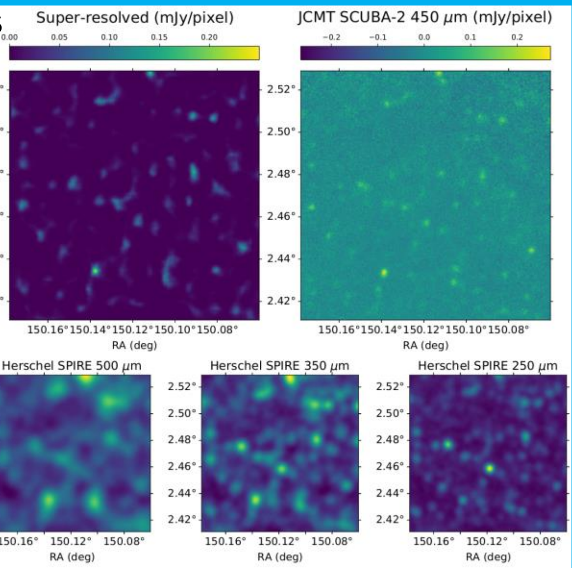


Fig. 6 shows the astrometric error between the target location for sources identified in the Super-resolved image, and the reconstructed location.

A strength of this approach is the ability to generally reconstruct sources insude ~ 10'' of the expected location of a JCMT SCUBA-2 450 µm source.

Some sources shows large astrometric errors. This is likely due to artifacts in the network output being wrongly identified as possible sources.

Fig. 6

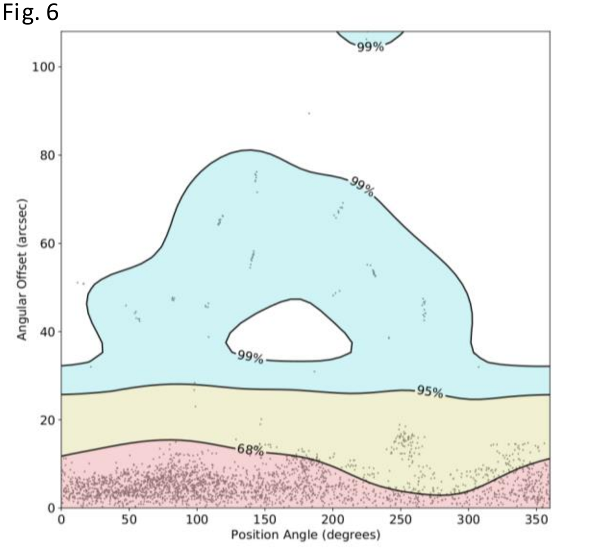
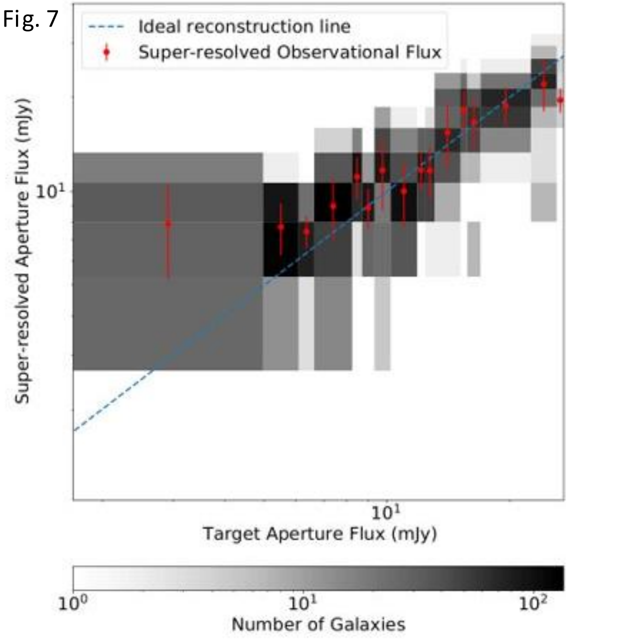


Fig. 7 is a plot of the reconstructed flux in the super-resolved images plotted against the flux of the closest identified source in the target images.

The normal threshold used when calculating number counts based on Herschel SPIRE images tends to be > 20 mJy. A strength of this network is the ability to have good flux reconstruction down to < 10 mJy, which allows a significant improvement on what can normally be expected from Herschel SPIRE data.

Fig. 7



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Results II

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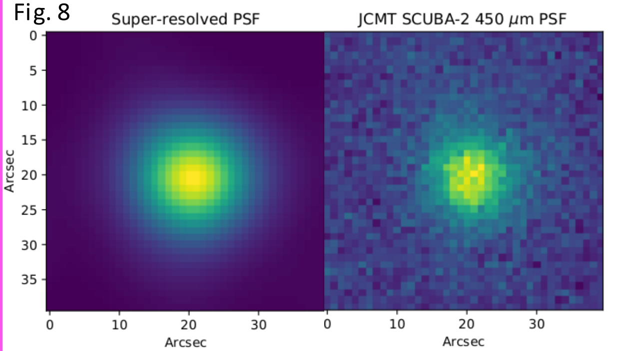
A key target of the project was to improve the angular resolution of the Herschel SPIRE data and push the PSF FWHM towards that found in the JCMT SCUBA-2 450 µm images.

Figs. 8 and 9 show the comparison between the stacked reconstructed PSFs and the stacked target PSFs of the JCMT SCUBA-2 instrument.

The smoother appearance of the PSF of the super-resolved data compared to the JCMT SCUBA-2 data is probably a consequence of the noise suppression caused by using a sigmoid activation function in the final layer of the network.

Fig. 8



Figs. 10 and 11 show the purity and completeness plots of the network for various source flux densities.

The purity is calculated by the equation

$$\frac{TP}{TP+FP}$$

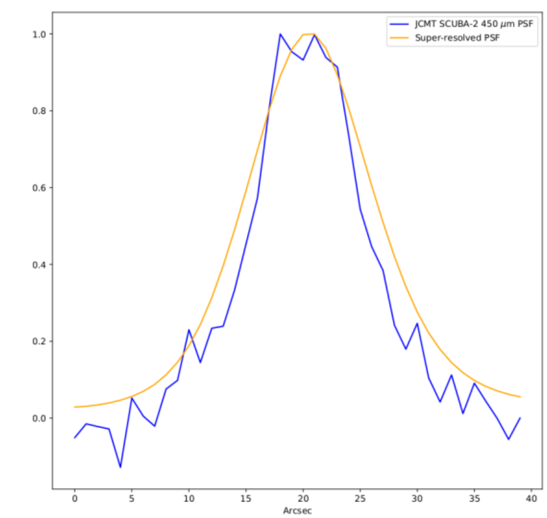
with *TP* being the true positives and *FP* the false positives.

The completeness is calculated by

$$\frac{TP}{TP+FN}$$

with *FN* being the false negatives.

Fig. 9



The purity of the reconstructed data is heavily dependent on the reconstructed source flux density. Similarly, the completeness is heavily dependent on the JCMT SCUBA-2 450 µm source flux density. While purity is generally high and completeness is > 60% at 10 mJy, the network excels especially above 15mJy with completeness above 95%.

Fig. 10

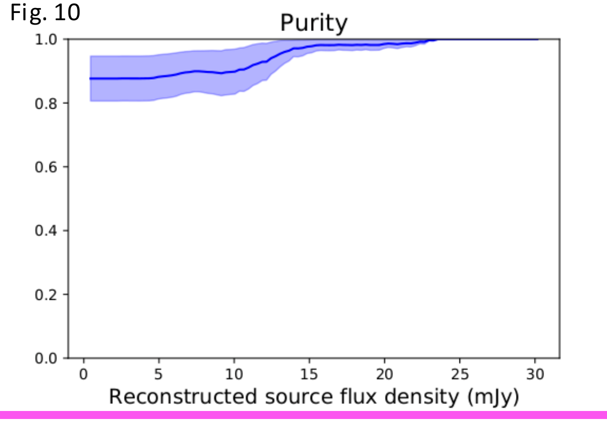


Fig. 11