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Self-Supervised Neural Networks for High-Resolution Radio Imaging

Shunyuan Mao

Rice University → CosmicAI (NRAO)

Andrea Isella, Hui Li, Li-Ta Lo, Paris Perdikaris and Kwang Moo Yi

2nd Annual Cosmic Horizons Conference
Charlottesville, Virginia

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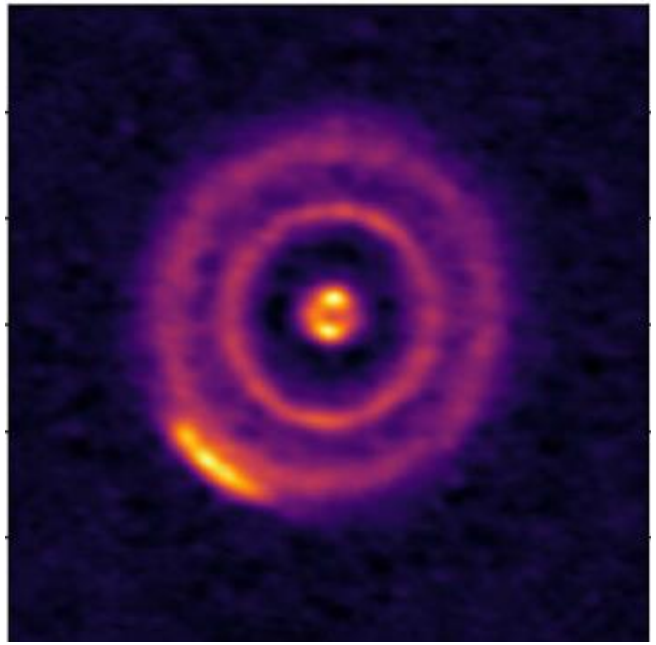
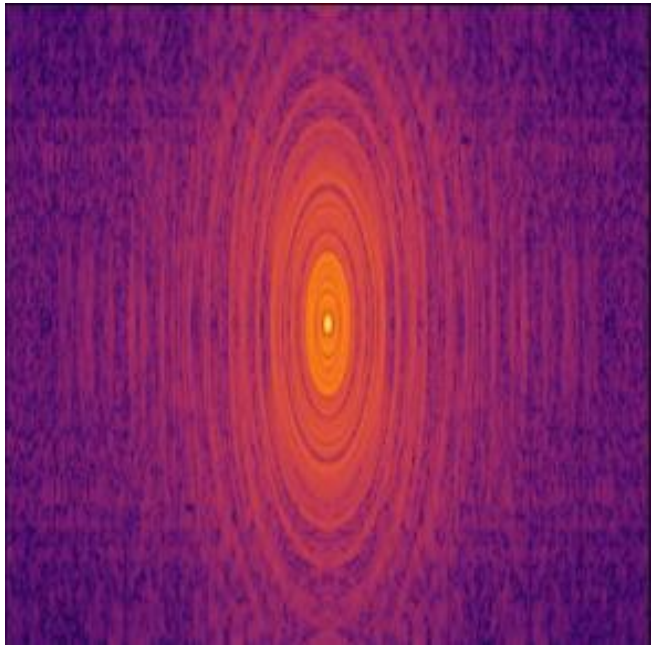
Radio Interferometry: 2D Fourier Transform

Image domain



densely sampled
Fourier transform

Fourier domain



Zawadzki et al. (2023)

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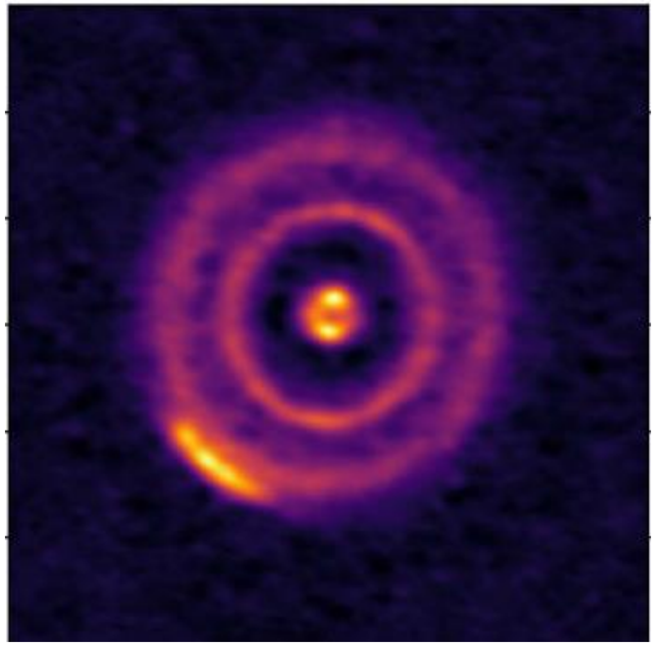
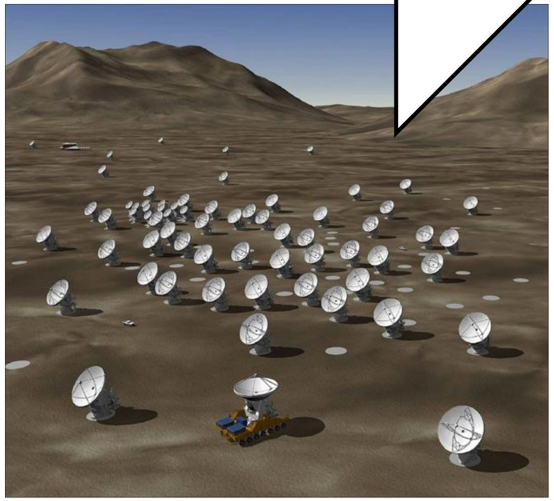
Radio Interferometry: a Sparse Sampling in Fourier Domain

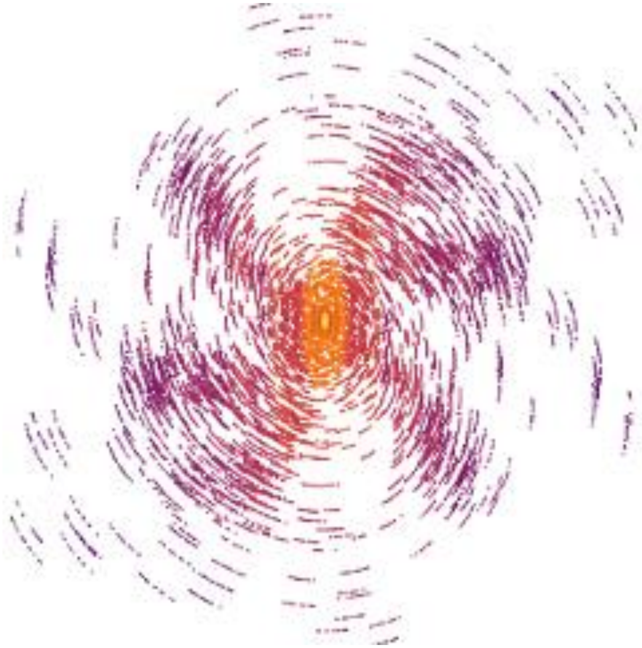
Image domain



sparse sampled
Fourier transform



Fourier domain



Zawadzki et al. (2023)
ALMA

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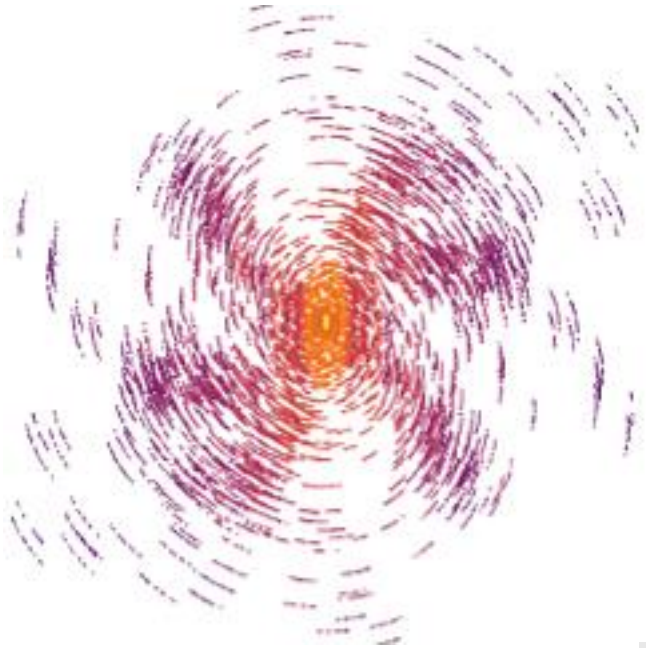
Image Reconstruction in Radio Interferometry

Fourier domain observation



ill-posed inverse problem

Image to reconstruct

?

Challenges
- Sparse sampling
- Signal to noise ratio $\lesssim 1$

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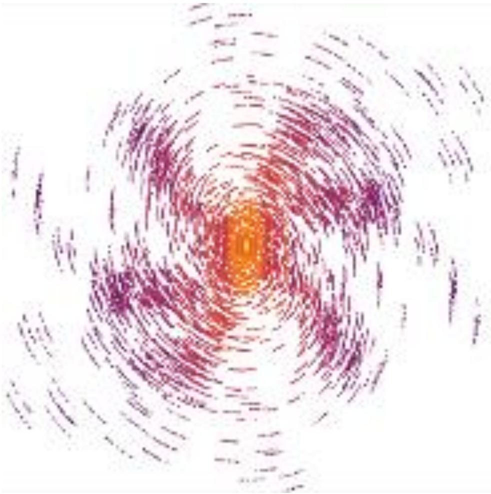
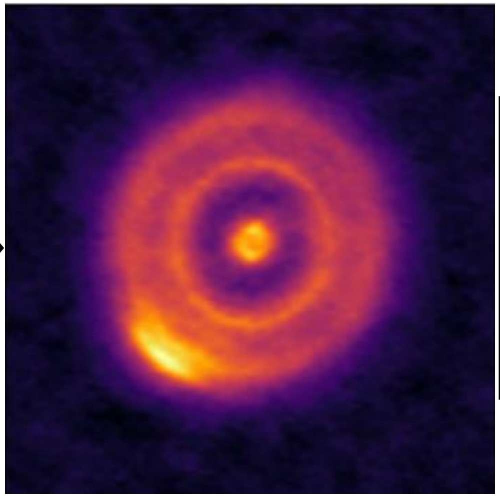
Traditional Method CLEAN Struggles for Extended Objects

Radio telescope observation



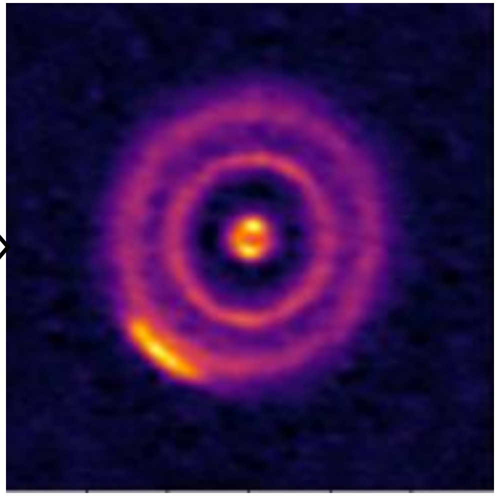
Interpolate & Inverse Fourier Transform

Image blurred with artifacts



Fit with Point Sources and Gaussians

Image cleaned



Issues
Point Spread Function is non-Gaussian
Need infinite point sources to reconstruct extended objects

Andrews et al. (2018)
Zawadzki et al. (2023)

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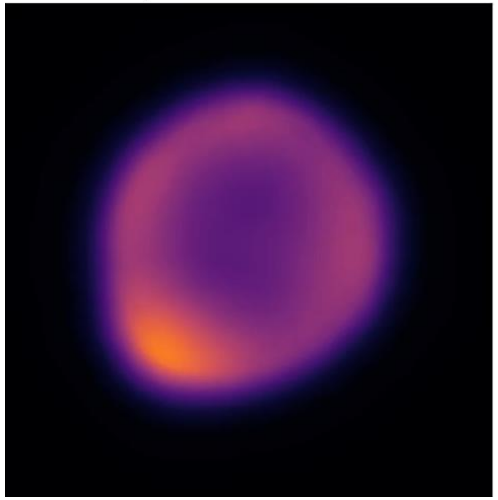
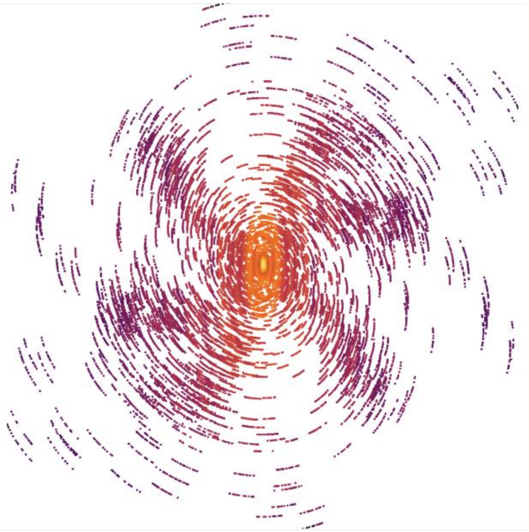
Our Approach:
Fitting Neural Network to Visibility

Image domain

Epoch 000000



Fourier domain



Neural Network (NN)

Loss: FFT(NN) – observational data

Iterate NN parameters

Self-Supervised: No ground truth or prior needed for training
Generalization: Versatile to any array configuration or morphology
Efficiency: 2 seconds / epoch, 5 minutes to convergence (A100 GPU)

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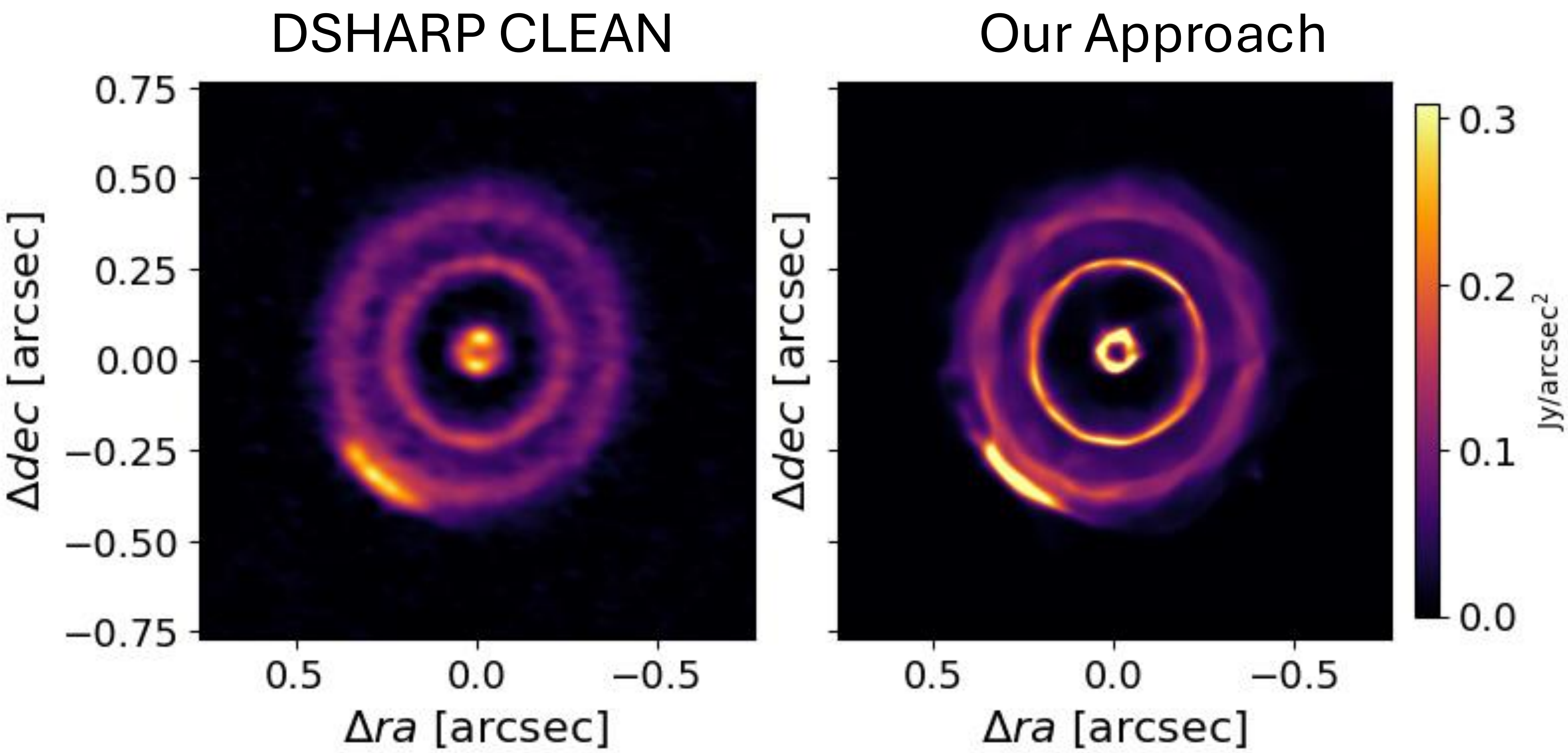
Reconstruction of Real Observation HD 143006



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Tests: Neural Network Imaging of Synthetic Observation

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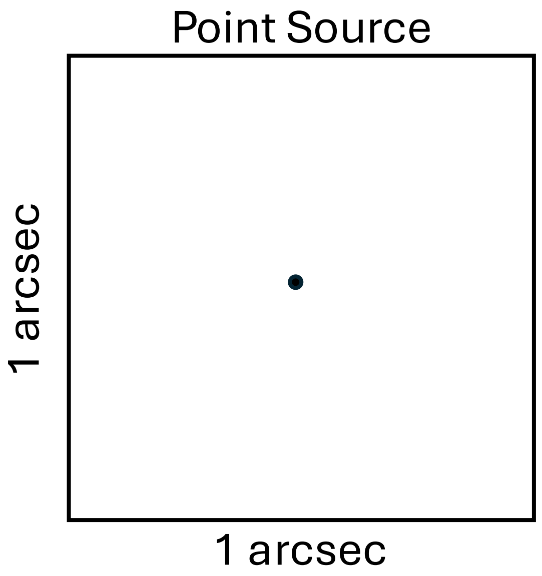
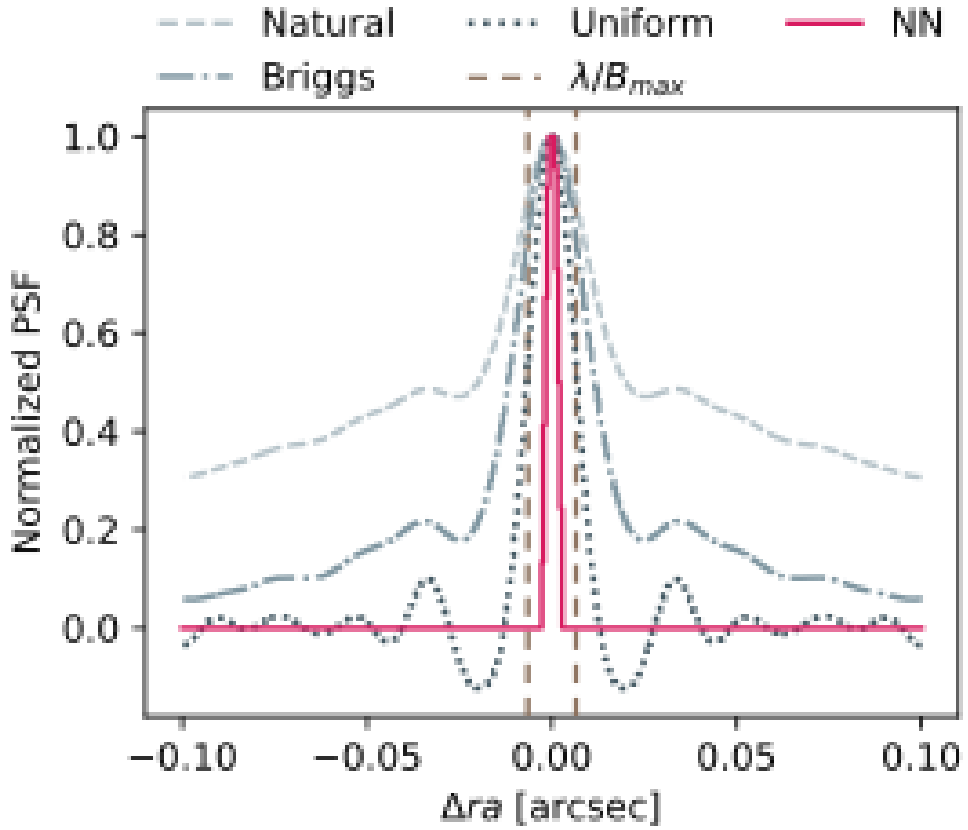
NN → 4-10× Sharper PSF and Less Sidelobes



synthetic visibility
simobserve
with DSAHRP coverage
and noise



$\lambda/\sqrt{\max(u^2+v^2)}$	0.013"
CLEAN (Natural)	0.031”
CLEAN (Uniform)	0.012”
Our Network	0.003”

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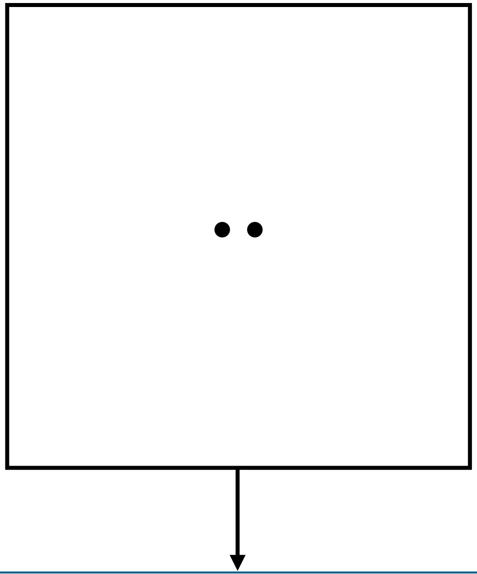
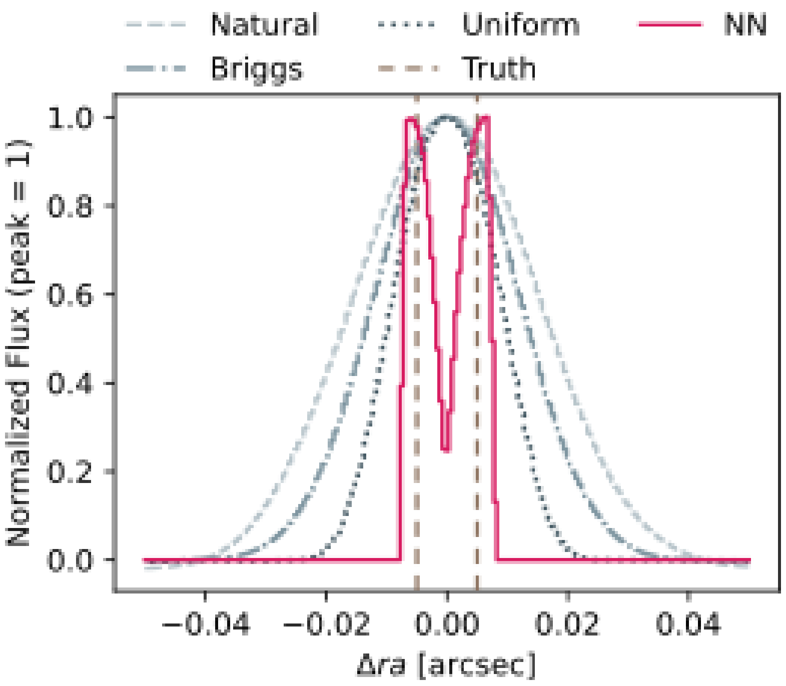
NN → Higher Resolution

Two Point Sources

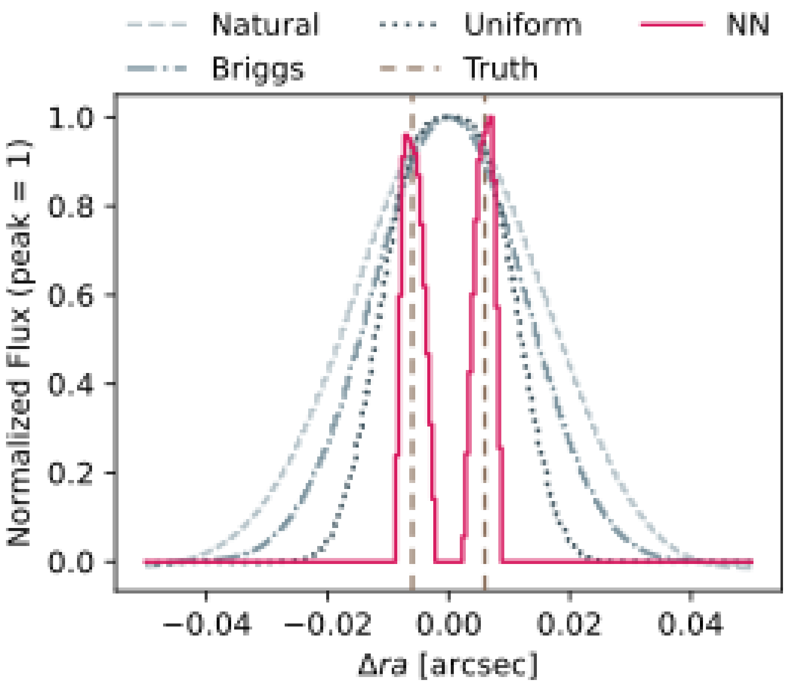


synthetic visibility
simobserve
with DSAHRP coverage
and noise

0.010”



0.012”



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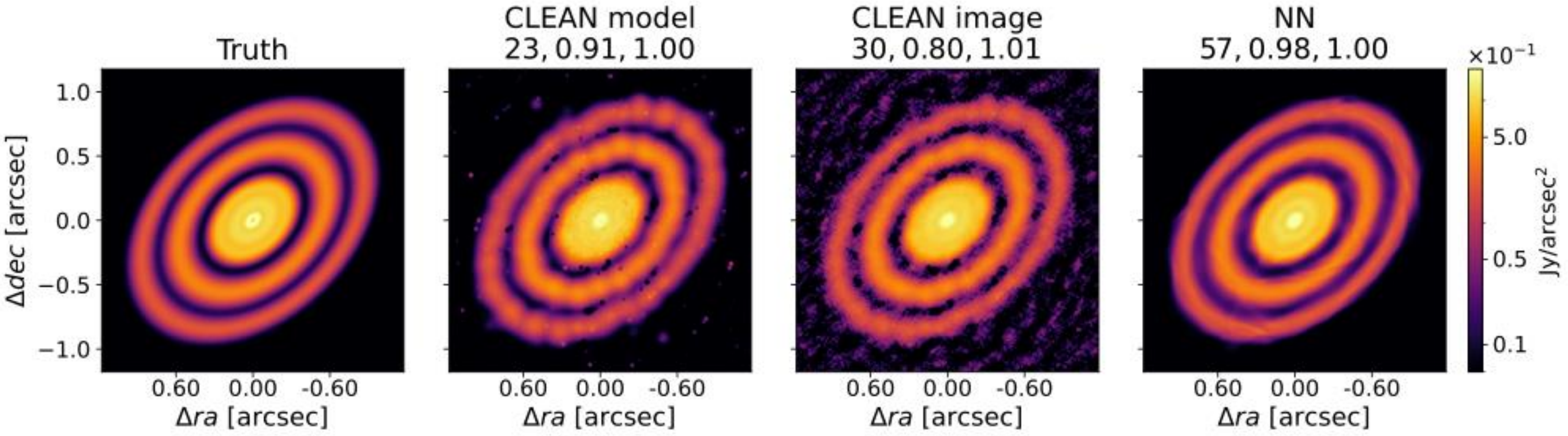
NN → Higher Image Fidelity



Three scores comparing reconstructed images (CLEAN/NN) with ground truth image

Left: Fidelity Middle: Structure Similarity Right: Flux Ratio

Higher → Reconstruction closer to ground truth

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Applications: Neural Network Imaging of Real Observational Data

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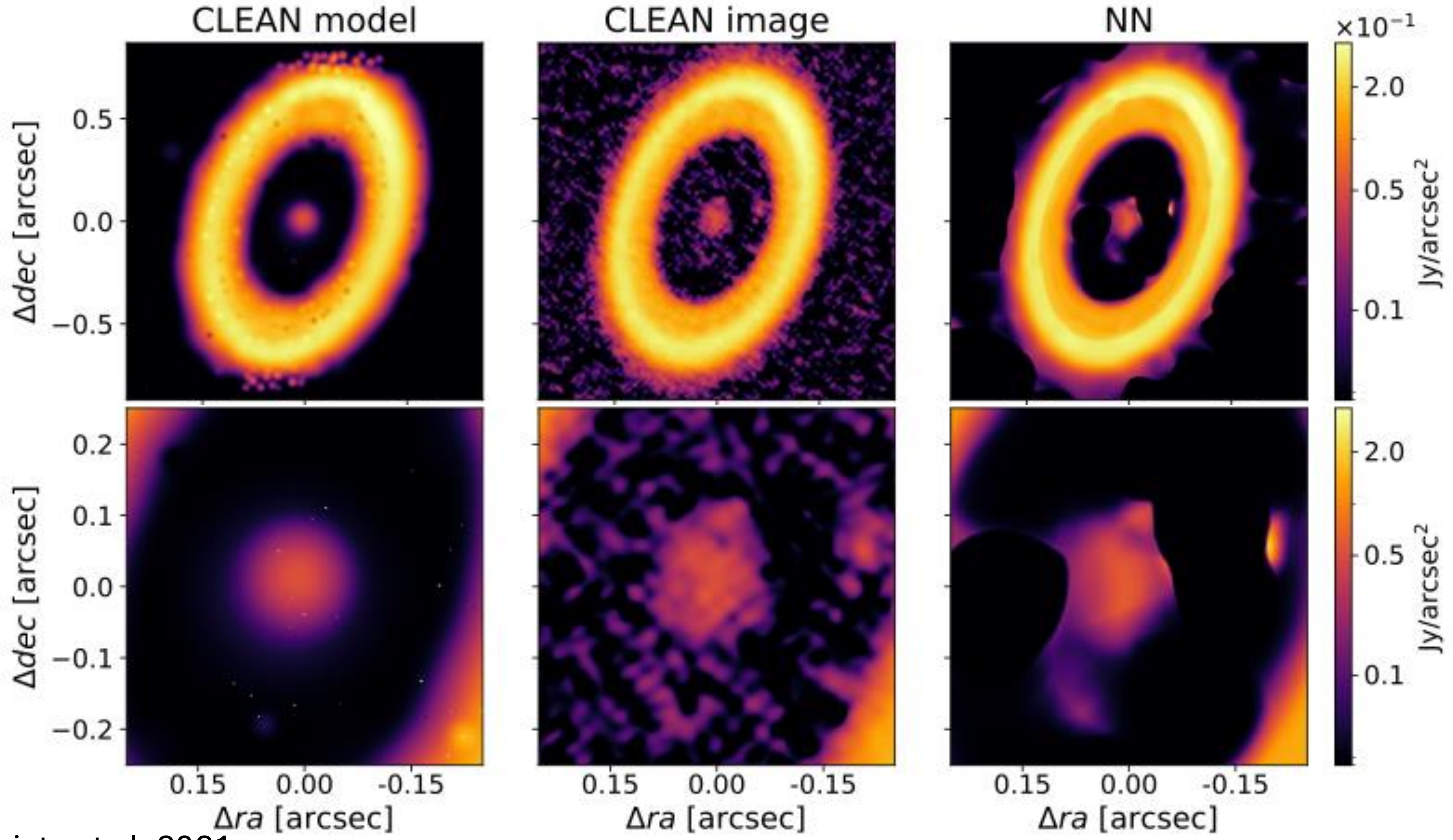
NN → Real Observation PDS70



Data from Benisty et al. 2021

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Summary

We developed a machine learning tool to reconstruct images from interferometric observations.

The tool

- learns directly from Fourier-domain data, without the need for pre-training or 'ground truth' priors,
- Is highly efficient, converging in just 5–10 minutes on a single NVIDIA A100 GPU for standard DSHARP-scale datasets.

Compared with CLEAN:

- 4~10× smaller FWHM and higher resolution,
- higher overall image fidelity and structural similarity.

Ongoing and Future works

- Reconstructing continuous 3D flux distribution from multi-channel data
- Extending to
    - JWST NIRISS Aperture Masking Interferometry
    - ground-based optical/NIR interferometry
    - Event Horizon Telescope

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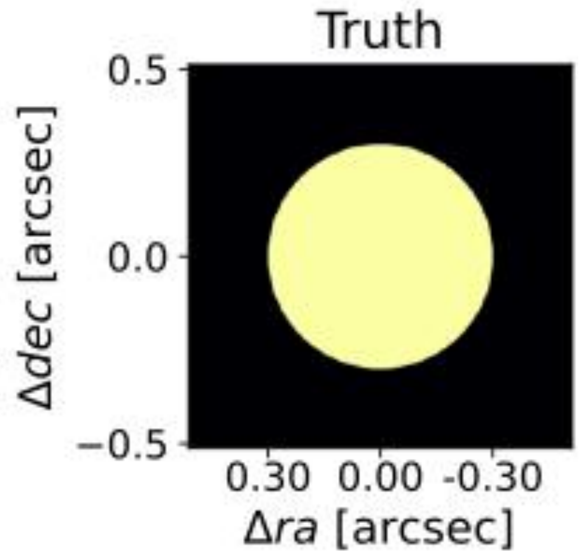
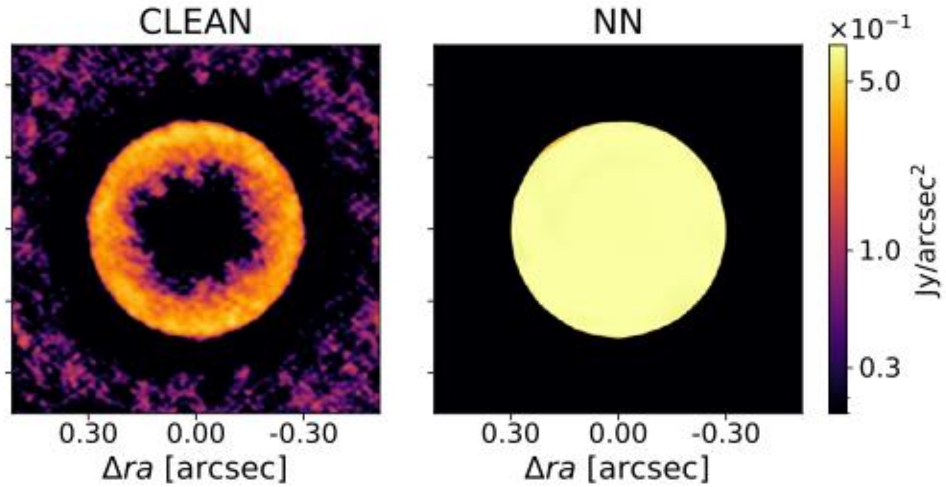
NN → Less Spatial Filtering

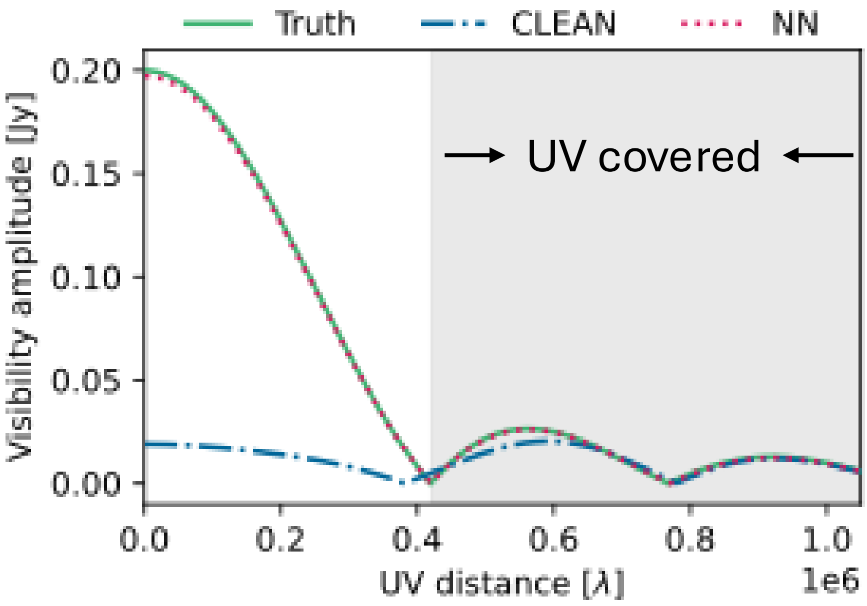


synthetic visibility

simobserve

with **long baseline (C-9) only**





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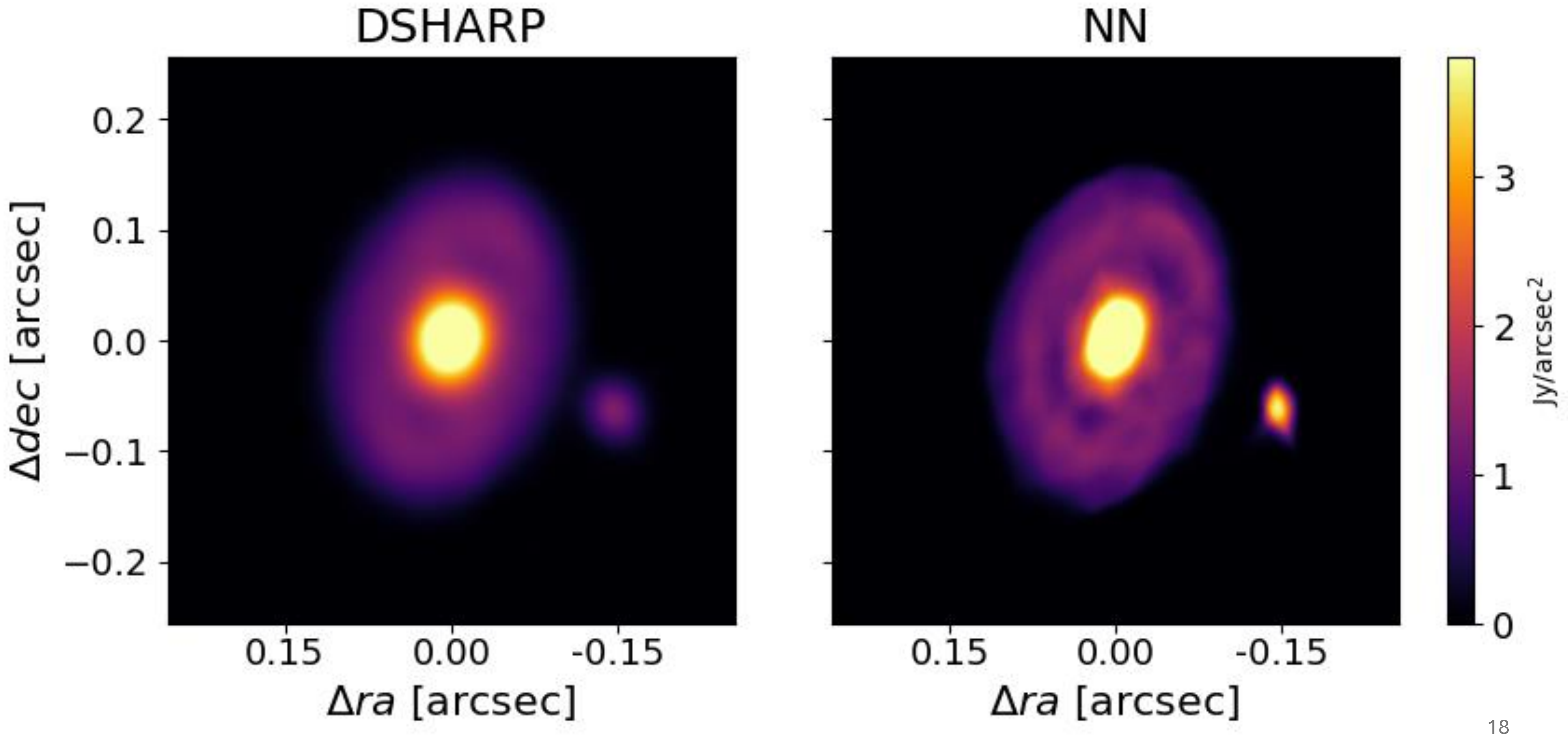
NN → HTLup Substructure



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Resolution