Residual Learning for Astronomical Images: A PSF-Blind Approach to Deconvolution

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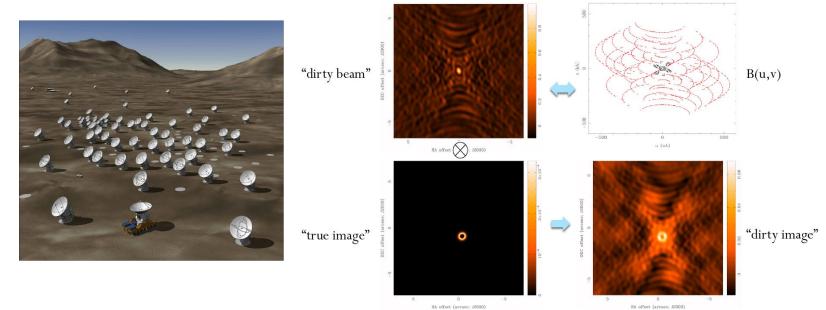
Data generated from simulation

and convolved with given PSF.

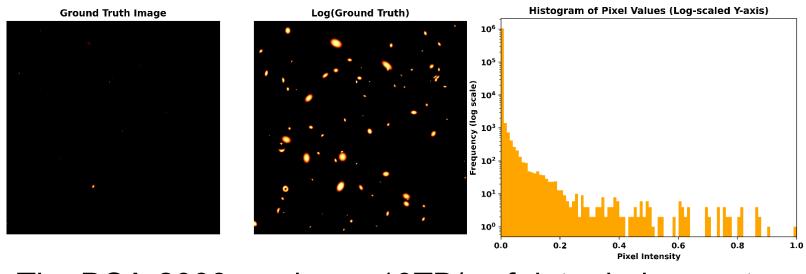
 $I_d = (I_s + \eta) \circledast k = I_s + R^*$

Background & Motivation

Images are captured in by connected telescopes forming baselines to sparsely capture the frequency domain of the sky leading to noisy and blurry images.



The captured sky can have very high dynamic range.



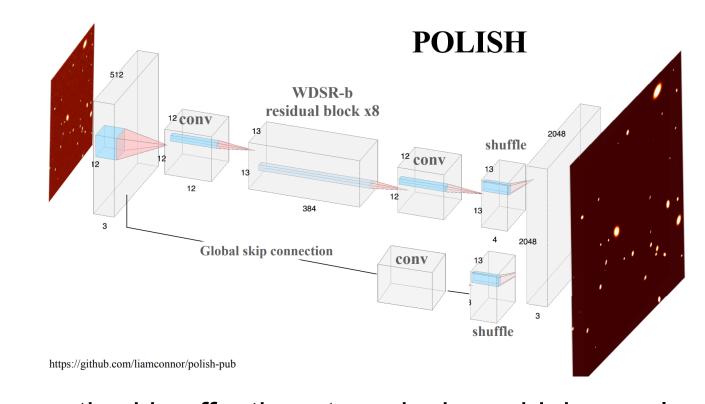
The DSA-2000 produces 10TB/s of data during capture thus it is impractical store all the raw measurements to post-process. Which motivates a **feed-forward method** for real-time processing.

Having more accurate observations of galaxies can help us:

- Improve understanding of galaxy formation and evolution through morphological analysis.
- Study star formation and stellar populations from accurate measurements of brightness and luminosity.
- Precise mass mapping of lensing structures, accurate reconstruction of background sources, and improved cosmological parameter estimation from gravitational lensing effects.

Related Work

Connor et al. introduced POLISH [1], a deep learning method based on WDSR [2] architecture for deconvolution and super-resolution of DSA-2000 measurements.



The method is effective at producing a high angular resolution reconstruction of the input dirty image by utilizing a PSF distribution as a physics-informed guide to the WDSR block. But this relies on pre-existing calibrated PSF profile.

Denoising CNNs (DnCNN) have shown success by using residual learning to learn the noise map [3, 4, 5], however they have yet to examine the efficiency on images with noise convolved with an unknown PSF kernel.

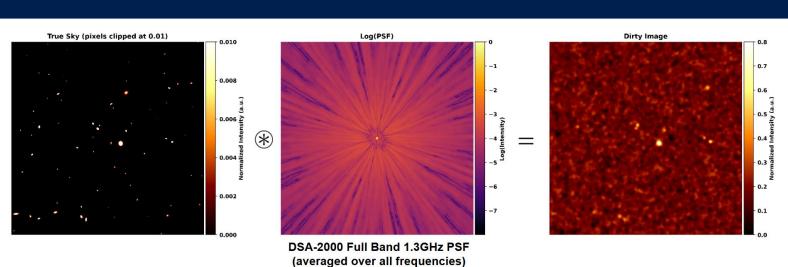
References



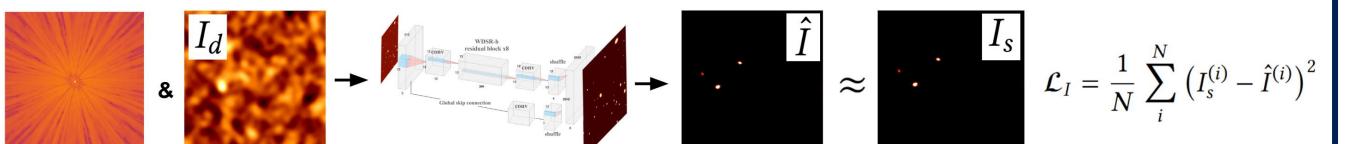
Acknowledgement

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the project scope and direction!

Our Modification to POLISH

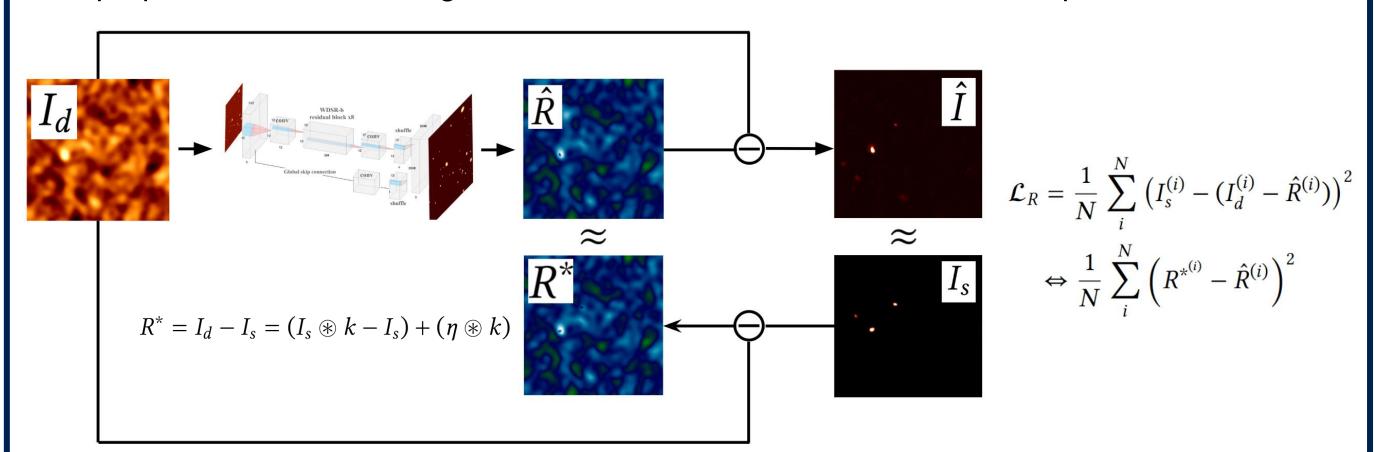


POLISH uses the given PSF and the dirty image to learn the true sky:



Inspiration: DnCNN (Denoising CNN) for convolved noise and blur. **Our research question:** How well will the model learning a representation of the true sky via optimizing the residual map?

We propose to direct learning to the residual, without the need of a PSF prior:



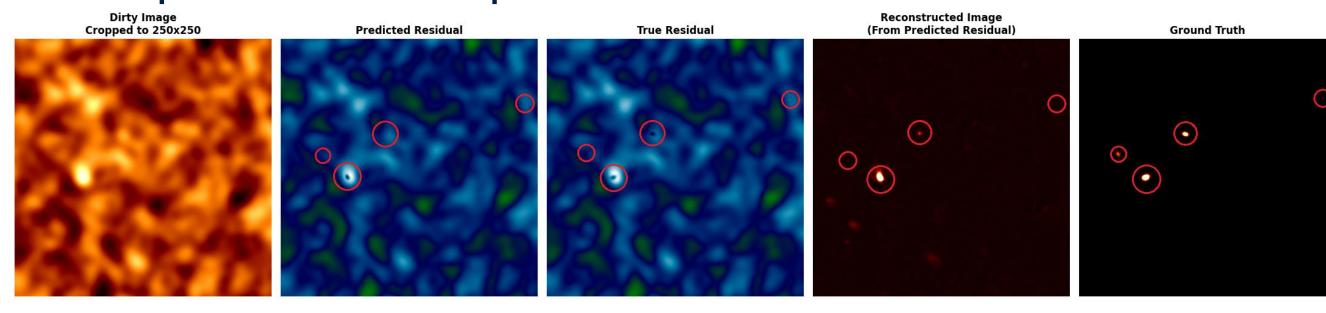
Experimental Results

POLISH-Torch provides an option to train without the PSF prior and without upsampling. We trained both method on a set of 800 samples with no PSF and validated on a set of 100 validation samples using 3 quantitative metrics used in the POLISH paper. Both model a trained for the same amount of time (8 hours/150 epochs) on the same hardware.

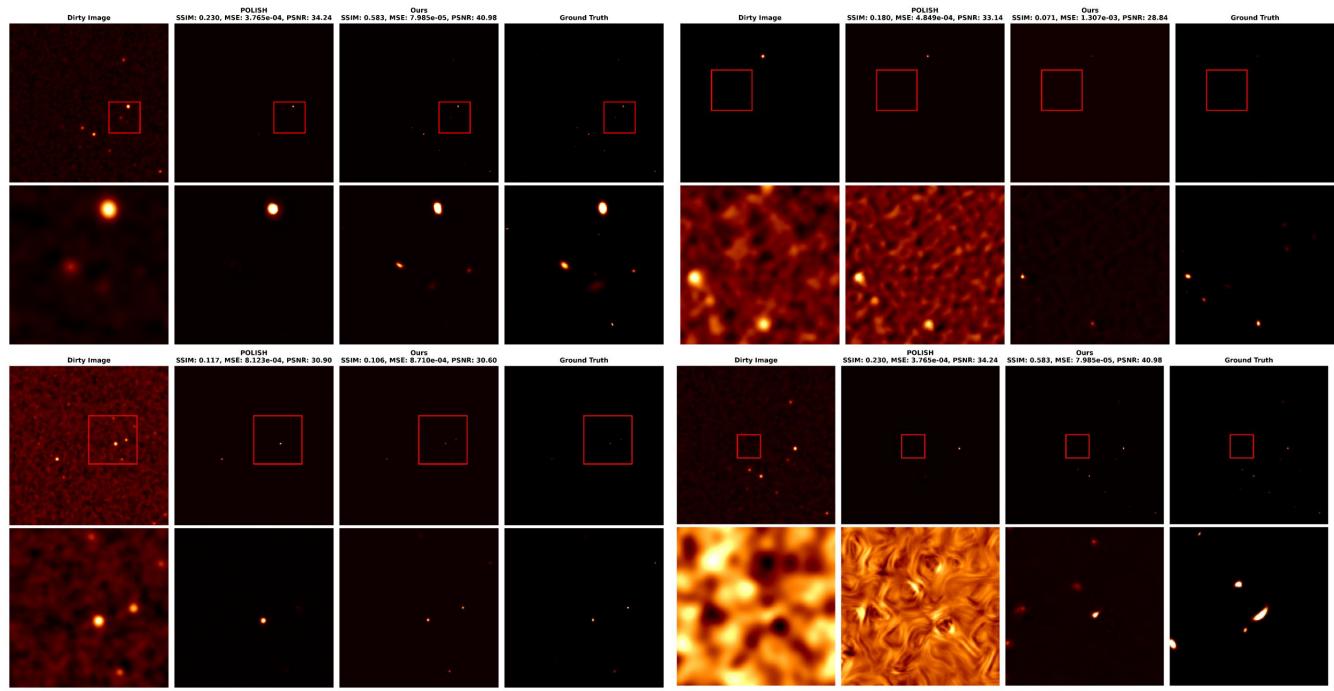
Metric	POLISH	Ours
SSIM	0.2444 ± 0.2144	0.4558 ± 0.2507
MSE	0.00216 ± 0.00411	0.00027 ± 0.00039
PSNR	32.294 ± 7.13	387228 ± 541

The metrics are imperfect: pixel-wise with high bias towards the dominant feature (noise). However, when averaged over a large sample count can still give a rough approximation of reconstruction quality.

An example of our model's output:



Comparison with POLISH:



Our method performs better than POLISH for faint signals given the same training time and configuration, without upsampling and knowledge of the PSF distribution. Comparison against POLISH with provided PSF-prior is desired for more thorough analyses. *Figures can also be viewed via the QR code:*

