



# Denoising Scattering-limited Deep Cortical Images with U-Net

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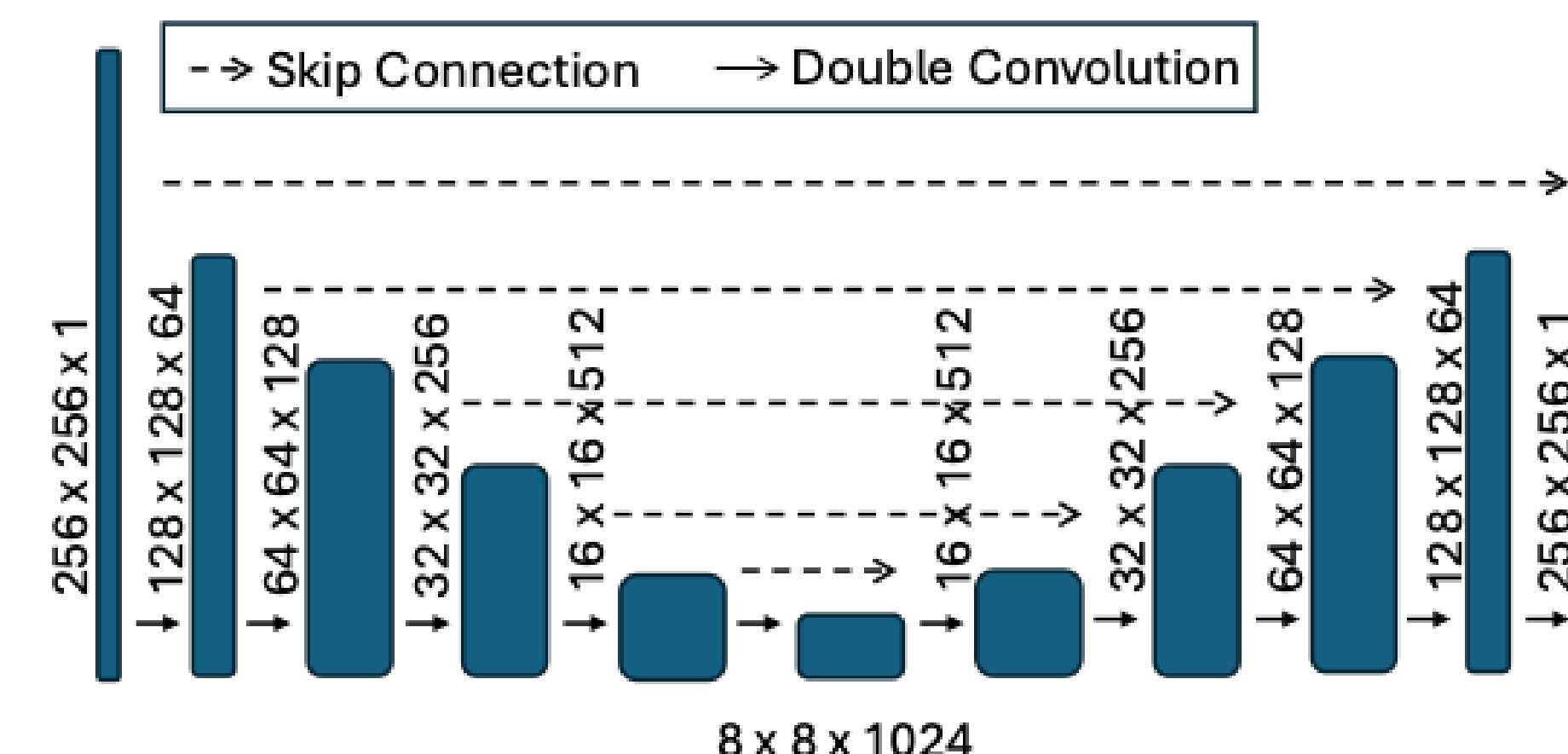
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## Motivation

- Deep cortical layers in the mammalian brain are hypothesized to be functionally distinct and yet understudied due to poor optical access
- Experimental techniques to address excessive scattering induced backgrounds are costly and technically challenging to implement

## Background learning via U-net

- U-net architecture which separates background from noisy signal + background image
- Include learned weight for background vs signal
- MSE loss between reconstructed and ground truth
- Devised experimental calibration protocol for simultaneously generating ground truth and noisy signal + background data



## Statement of the problem

- The acquired image can be represented as

$$A(D) = GT * PSF(D) + \lambda_{GT} + \sum_{d=0}^D e^{-\frac{d}{l_s}} * g(\sigma(d)) + \lambda(d)$$

- PSF at the focal plane is compromised by tissue anisotropy
- All the sources from shallower layers convolve with unfocused illumination beam
- In-focus and out-of-focus sources each shot-noise limited

## Experimental Results

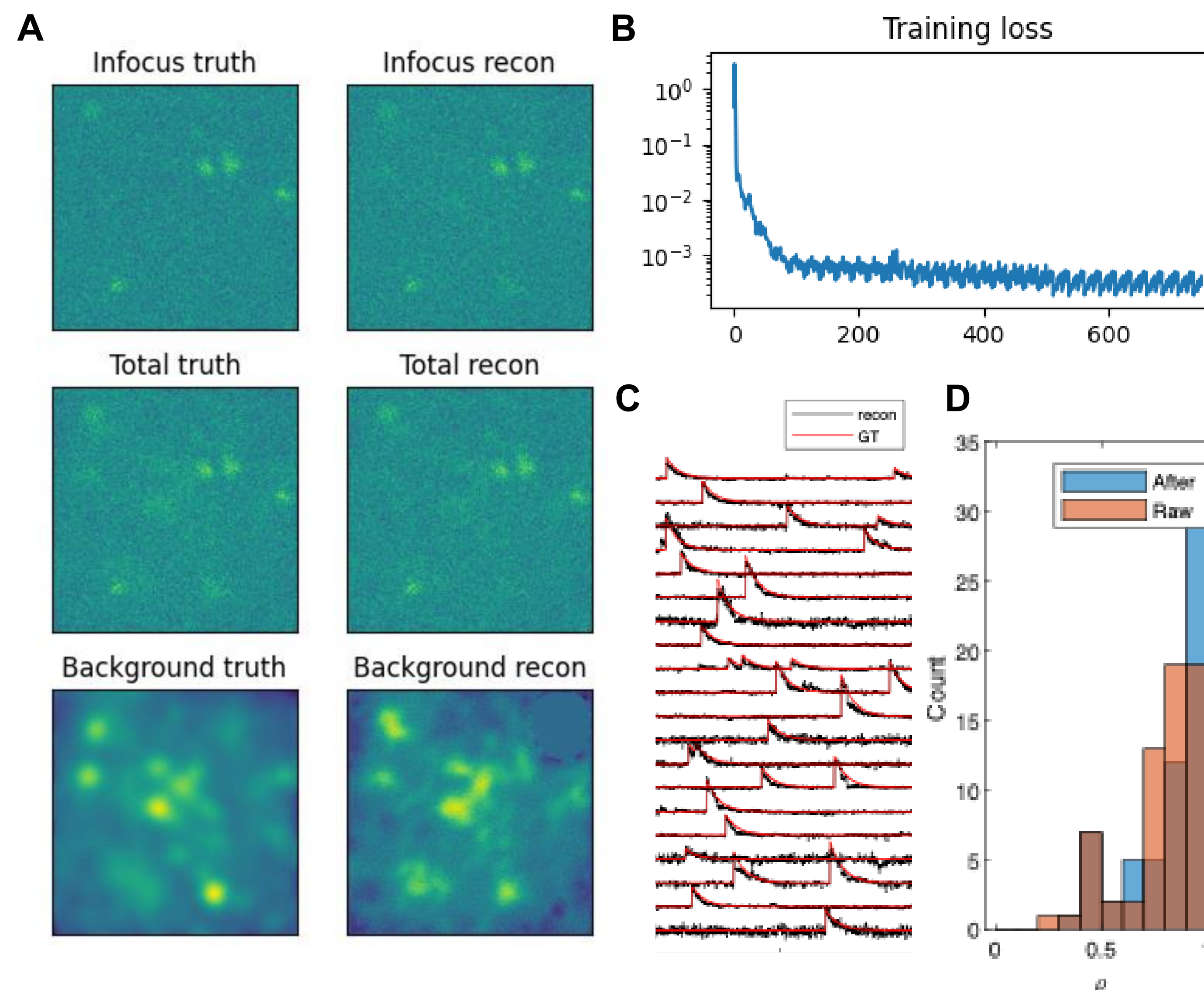
(A). Examples of ground truth and reconstructed images of in-focus plane of interest, background, and their sum.

(B). MSE training loss.

(C). Examples of ground truth vs. extracted traces.

(D). Distribution of Pearson correlation coefficient with ground truth before and after application of the model

## Experimental Results



## Future works

- Increase level of noise & background
- Add PSF distortion to simulations via Zernike coefficients
- Calibrate and test on low-depth experimental images
- Test for experimental high-depth imaging
- Learn prior distribution for neural imaging data from background-less low depth images, modify loss function to include this prior

## References

[1] J. Batson and L. Royer. Noise2self: Blind denoising by self-supervision, 2019.  
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 [4] X. Li, et al. Nature Methods, 18(11):1395–1400, 2021.  
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