Randomized Probed Imaging through Deep K-learning

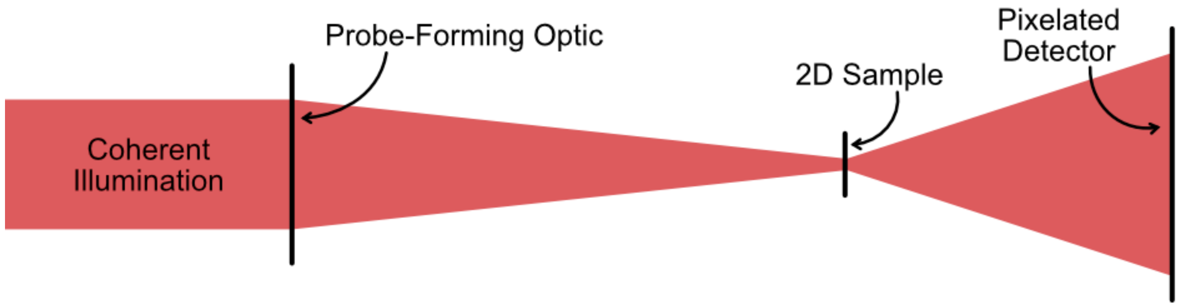
(Gradient Descent is All You Need)

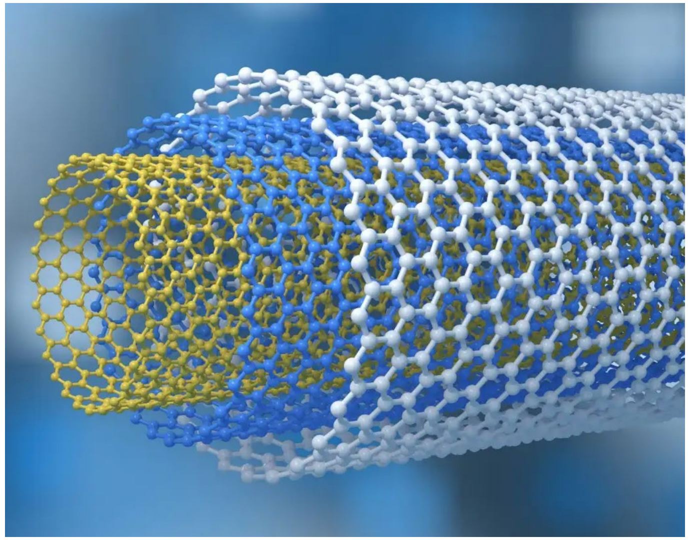
Zhen Guo

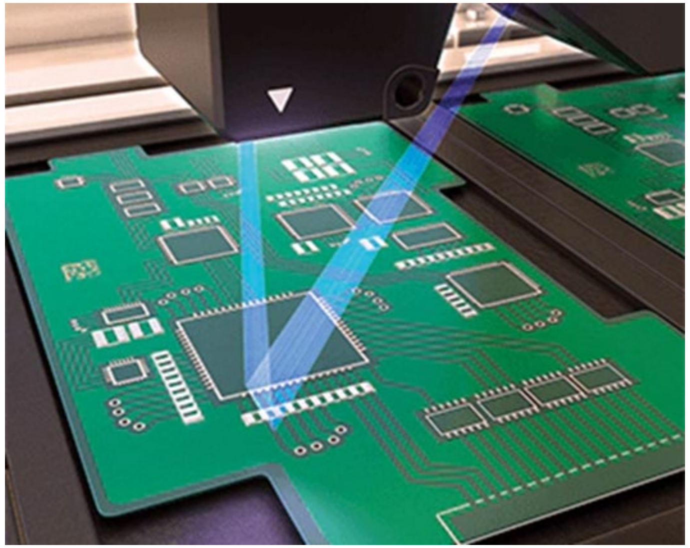
3D Optics at MIT

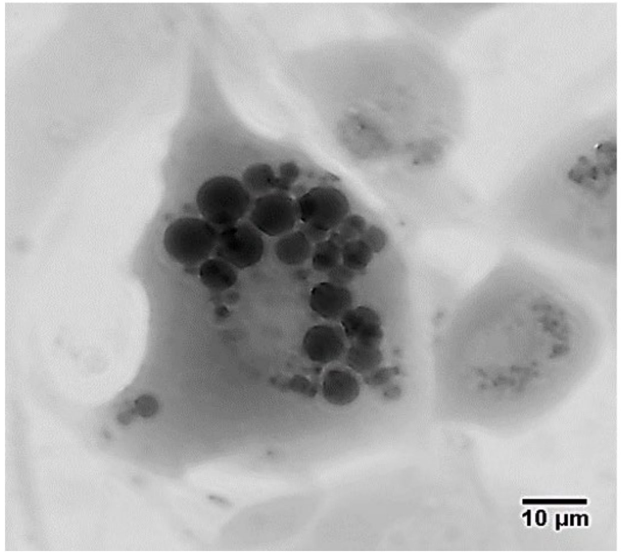
Massachusetts Institute of Technology

Coherent diffractive imaging









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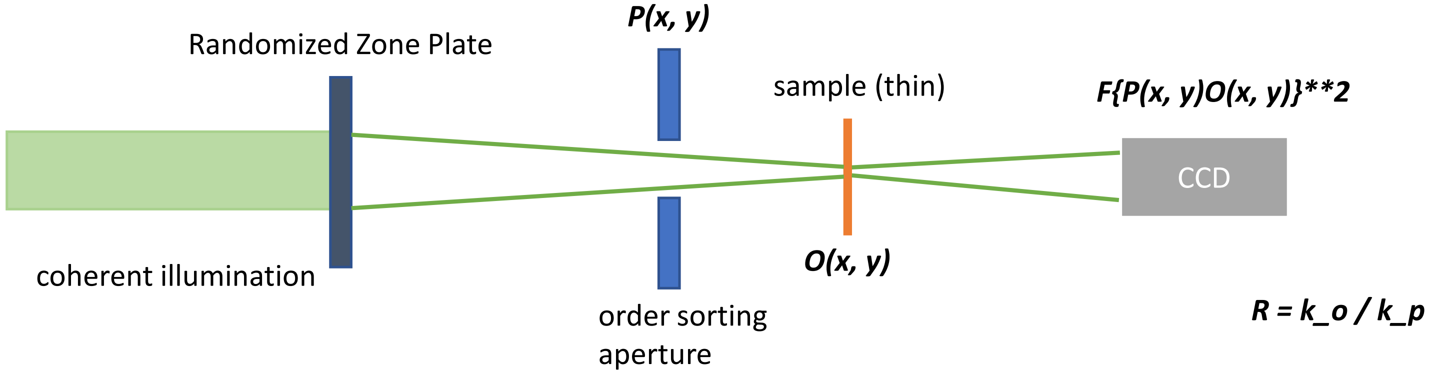
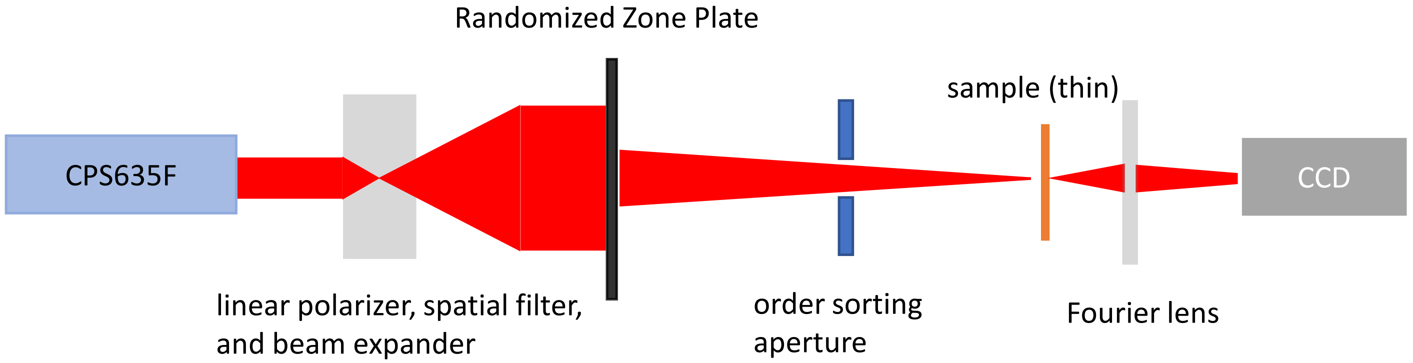
https://arstechnica.com/science/2018/05/forget-carbon-fiber-we-can-now-make-carbon-nanotube-fibers/
https://focalplane.biologists.com/2022/05/18/how-quantitative-phase-imaging-can-change-the-way-you-look-at-cells/

Randomized Probed Imaging

Simulated Apparatus for Training



Experimental Apparatus for Testing



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Related Works

PtychoNet: Fast and High Quality Phase Retrieval for Ptychography

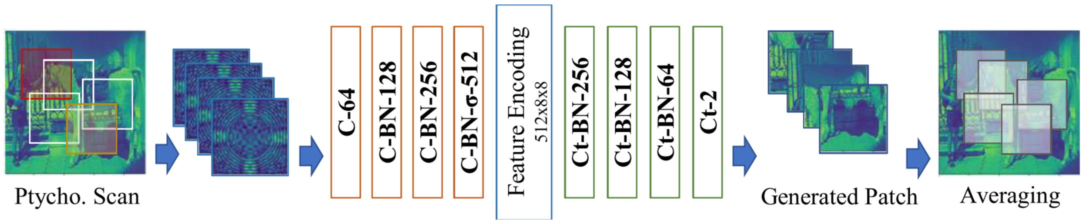

Figure 1: Architecture of PtychoNet. In the network: C - convolution, size 4x4, stride 2; Ct - convolution transpose, size 4x4, stride 2; BN - batch normalization; σ - sigmoid. Activation functions in the encoder is LeakyReLU, $\alpha = 0.2$; ReLU in the decoder.

ALGORITHM 1: Reconstruction using PtychoNet.

Input: Full scan $\mathbf{A} \in \mathbb{R}_+^{N\times h\times w}$, scan layout $\mathbf{M} \in \mathbb{Z}^{N\times 4}$.
Output: Object image $\mathbf{Y} \in \mathbb{R}^{2\times H\times W}$.

1 $\mathbf{Y} = \mathbf{K} = \mathbf{0}^{2\times H\times W}$;
2 **for** *each diffraction image* $\mathbf{A}_j$ *in parallel* **do**
3 Compute the corresponding object patch $\mathbf{Y}_j$ in real space with input $\mathbf{A}_j$;
4 $\mathbf{M}_j(\mathbf{Y}) = \mathbf{M}_j(\mathbf{Y}) + \mathbf{Y}_j$;
5 $\mathbf{M}_j(\mathbf{K}) = \mathbf{M}_j(\mathbf{K}) + \mathbf{1}$;
6 **end**
7 $\mathbf{Y} = \mathbf{Y} / \max(\mathbf{K}, \mathbf{1})$;

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Real-time sparse-sampled Ptychographic imaging through deep neural networks

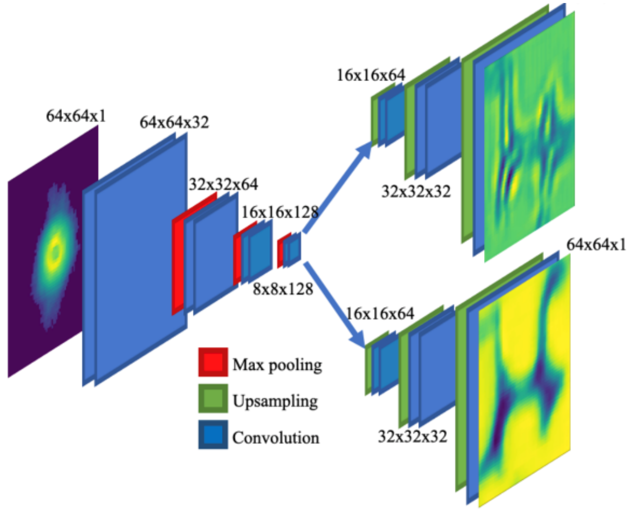


FIG. 1. Architecture of PtychoNN, a deep convolutional neural network that can predict real-space amplitude and phase from input diffraction data alone.

Deep neural networks in single-shot ptychography

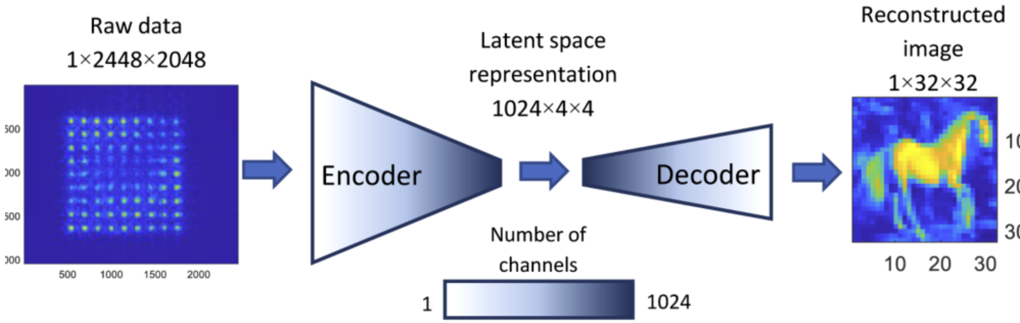
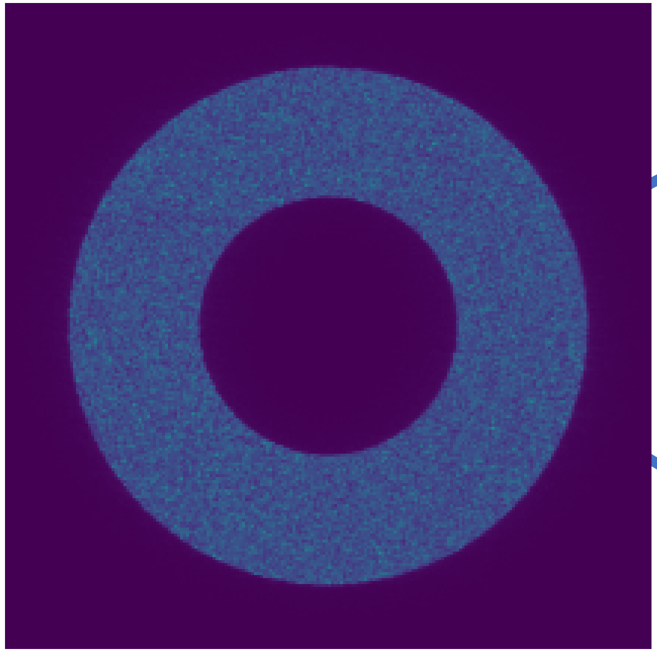


Fig. 2. A schematic of the proposed SspNet architecture. SspNet is comprised of an encoder network and a decoder network (a convolutional encoder-decoder) which are represented in this figure as trapezoids: the width of a trapezoid (parallel to the bases) indicates the spatial size of the tensors (not to scale) and the fill color indicates the number of channels where darker color means more channels.

Problems of Deep Learning in Far-field

global phase degeneracy prevent one-to-one correspondence



large domain transfer
Fourier to Real

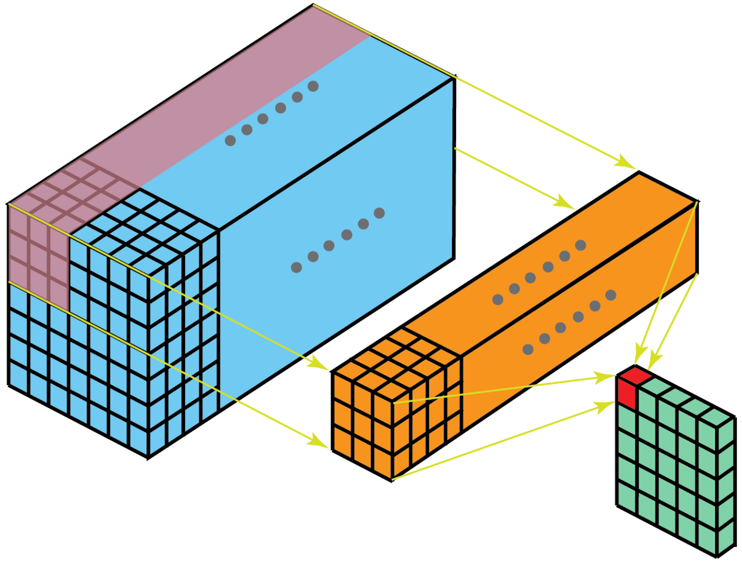
diffraction patterns

object phase

$$|\mathscr{F}\{P(x,y)O(x,y)\}|^2 = |\mathscr{F}\{P(k_x,k_y) * O(k_x,k_y)\}|^2,$$

Problems of Deep Learning in Far-field

Conv is translational invariant

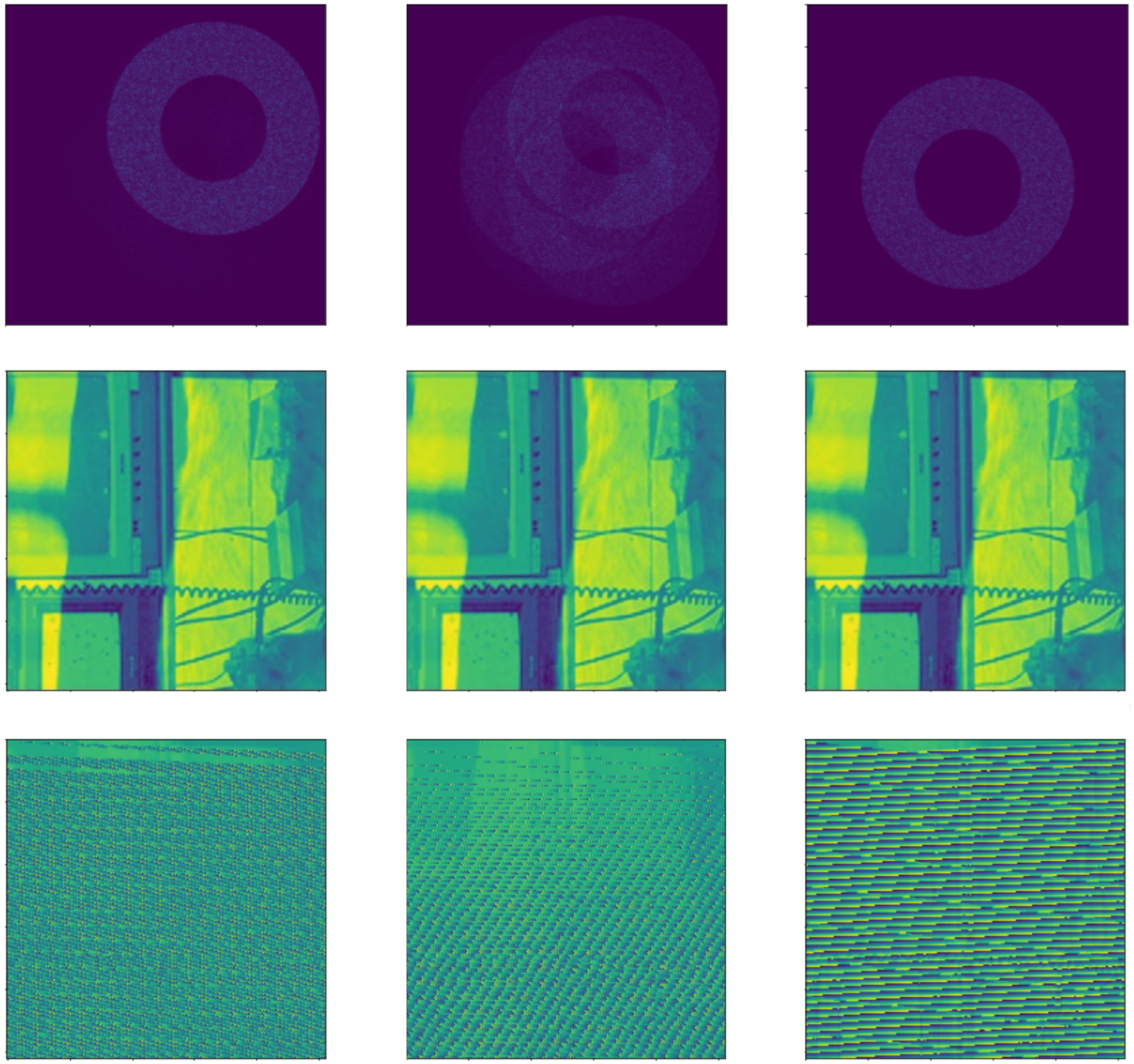


$$u_{ijm} = \sum_{k=0}^{K-1} \sum_{p=0}^{H-1} \sum_{q=0}^{H-1} z_{i+p,j+q,k}^{(l-1)} h_{pqkm} + b_{ijm}$$

simulated diffraction patterns

object amplitude

object phase



$$g_0(x+\delta x, y+\delta y) \neq |\mathscr{F}\{P(x,y)O(x+\delta x, y+\delta u)\}|^2.$$

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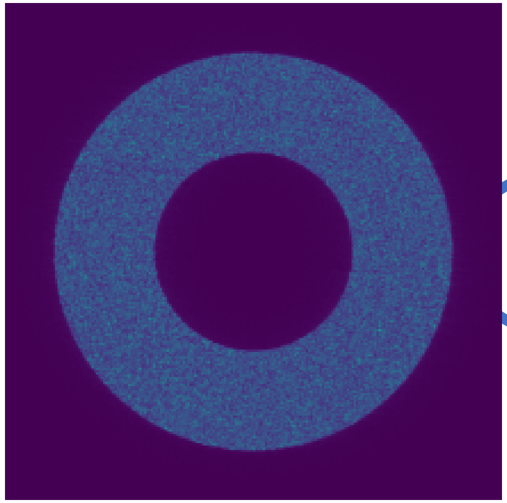
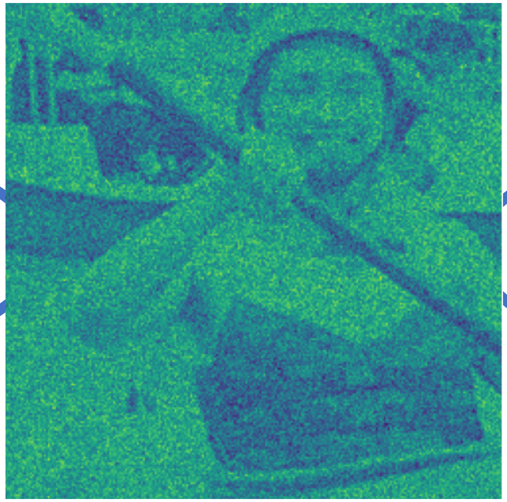
Solution? approximant prior + deep learning

- compute/memory efficient for training
- input to the convolutional network is in image domain
- ground phase state is produced (by tanh layer)

ground truth



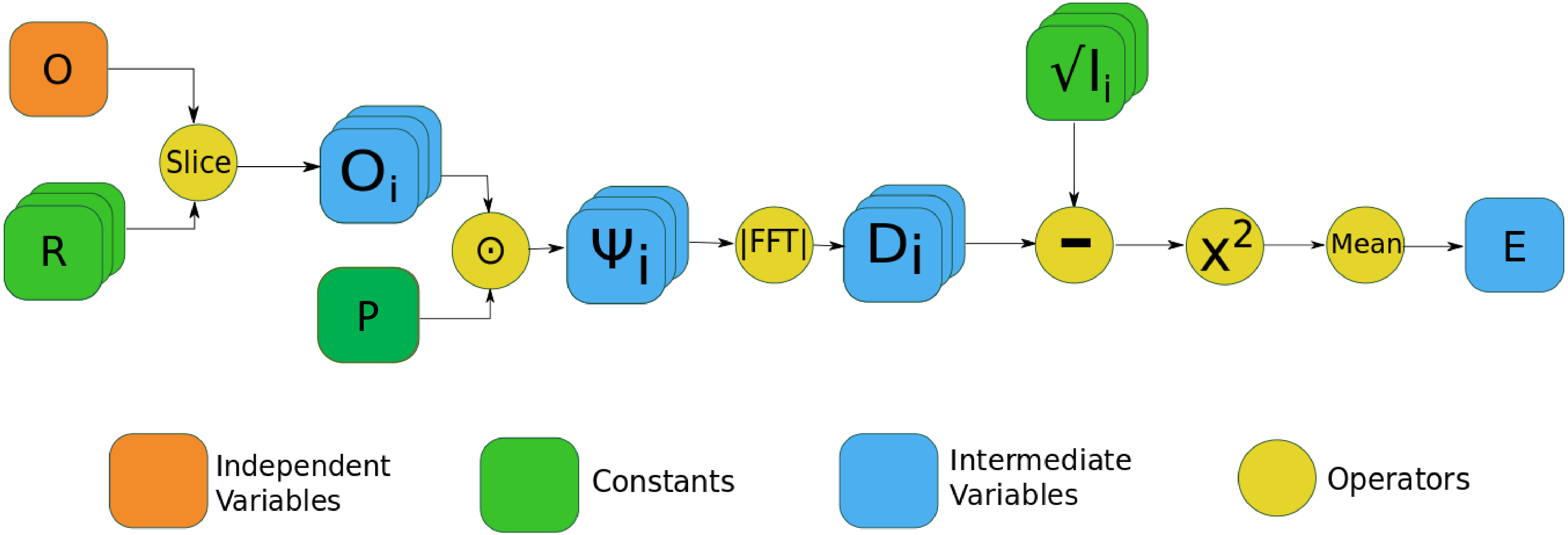
diffraction patterns



approximant phase

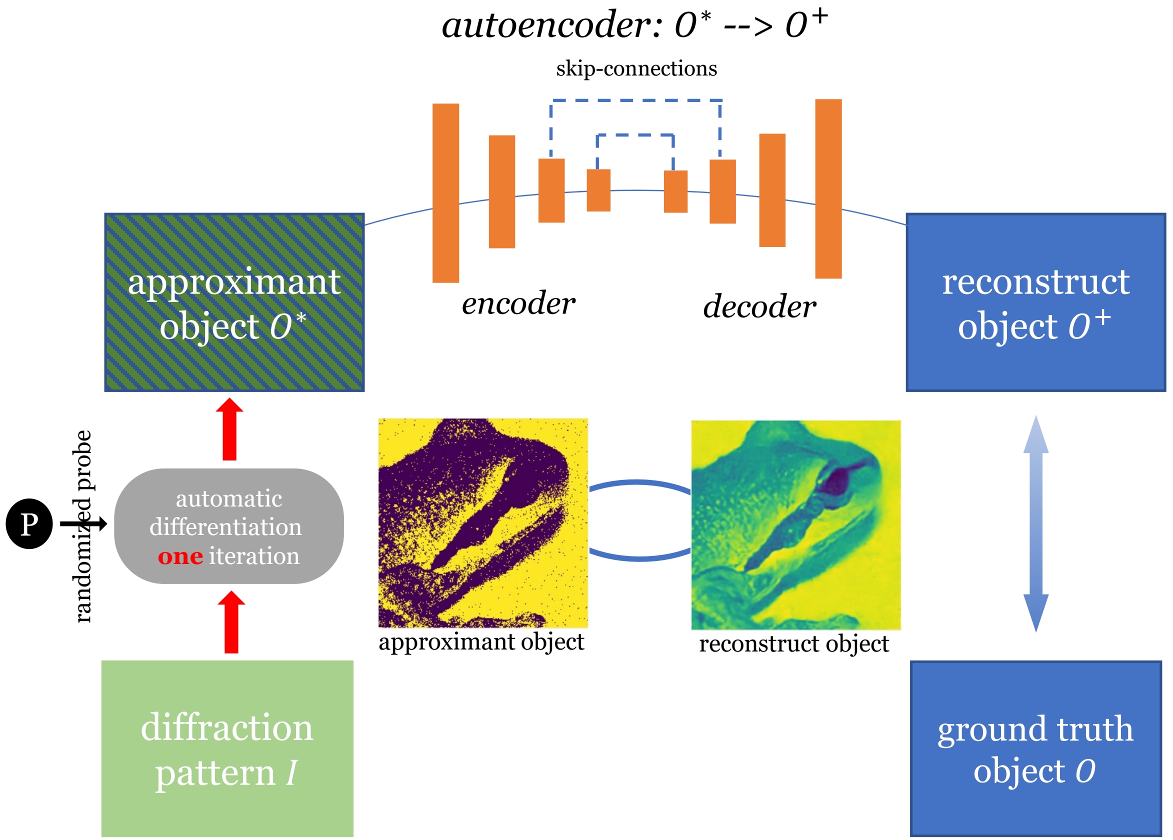
ML reconstructed phase

Generating approximant via automatic differentiation with one iteration



Ghosh, Sushobhan, et al. "ADP: Automatic differentiation ptychography." *2018 IEEE International Conference on Computational Photography (ICCP)*. IEEE, 2018

Network Architecture



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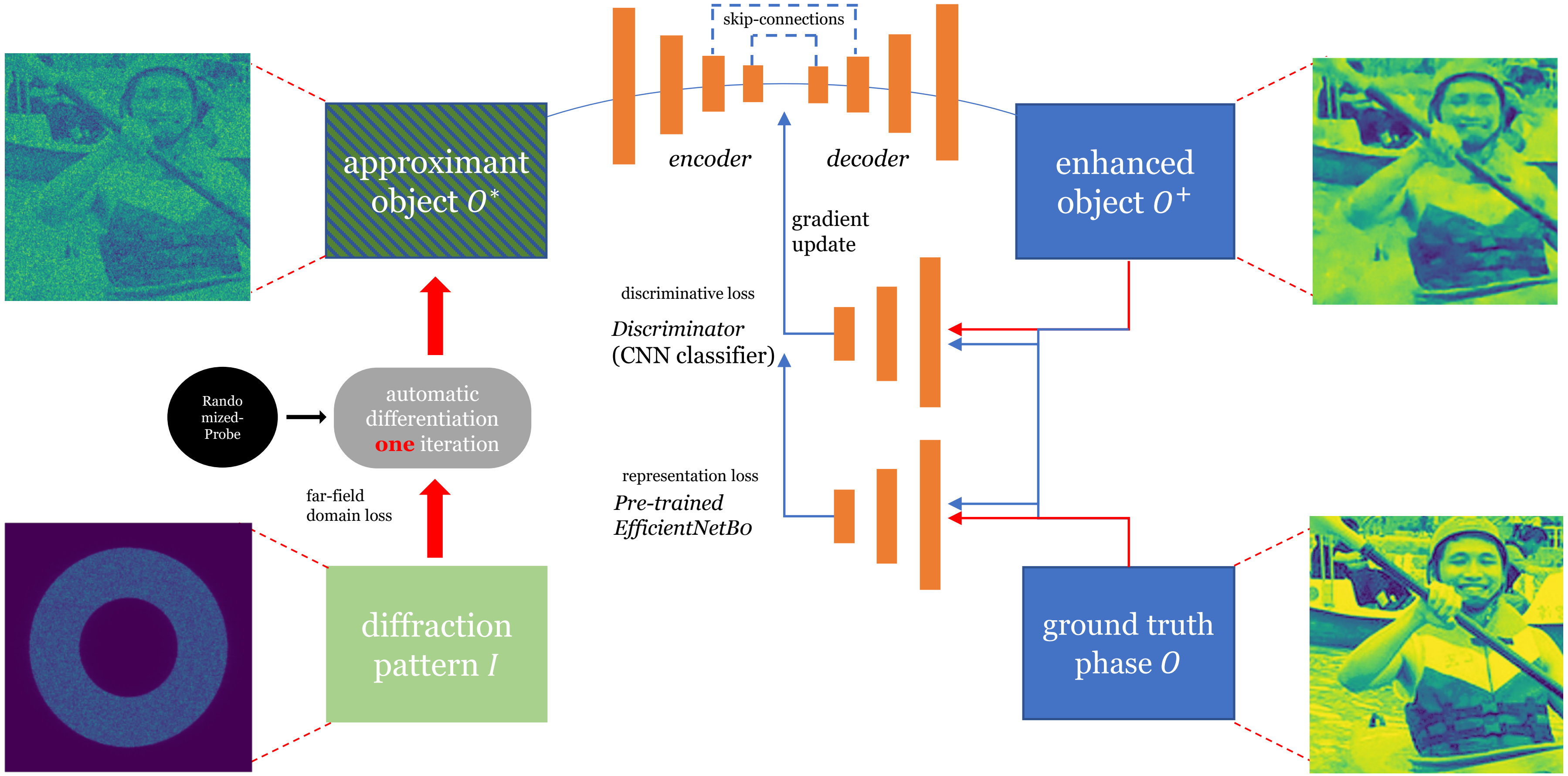
Network Architecture



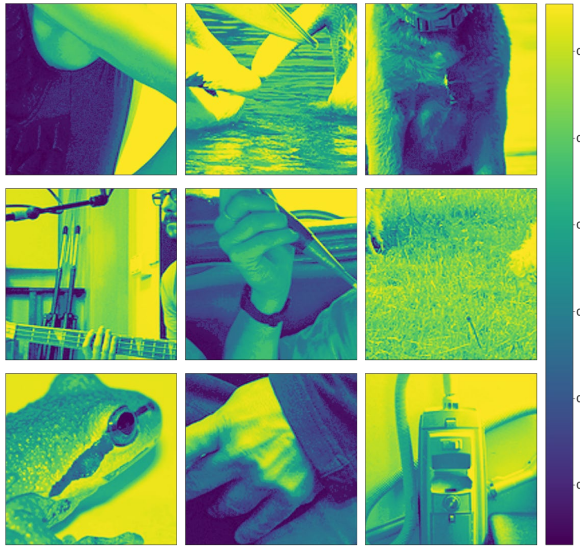
$$\mathcal{L}_{\text{npcc}}(G_{\mathbf{w}}) = \mathbb{E}_{O,O^*}[-r_{O,G_{\mathbf{w}}(O^*)}]$$

$$\mathcal{L}_{\text{mae}}(G_{\mathbf{w}}) = \mathbb{E}_{O,O^*}[\|H(O) - H(G_{\mathbf{w}}(O^*))\|_1]$$

$$\mathcal{L}_{\text{adv}}(G_{\mathbf{w}}, D'_{\mathbf{w}}) = \left(\mathbb{E}_{\mathbf{o}\sim\mathbf{p_o(o)}}\left[\log D_{\mathbf{w}'}(\mathbf{o})\right] + \mathbb{E}_{\mathbf{o}^*\sim\mathbf{p}_{\mathbf{o}^*}(\mathbf{o}^*)}\left[\log(1 - D_{\mathbf{w}'}(G_{\mathbf{w}}(\mathbf{o}^*)))\right]\right)$$

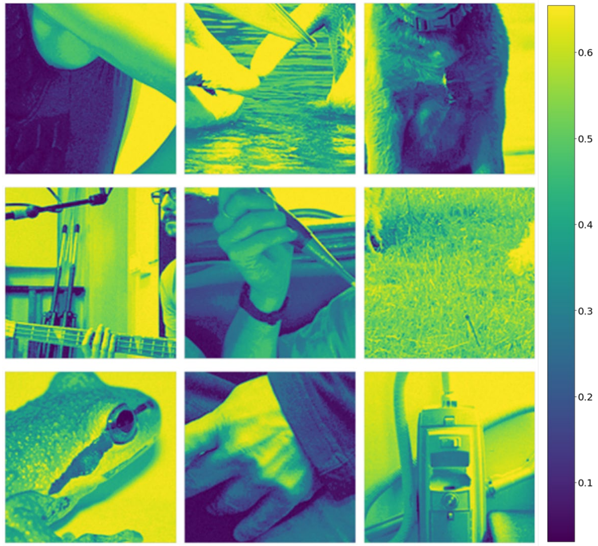
$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{npcc}}(G_{\mathbf{w}}) + \alpha \times \mathcal{L}_{\text{mae}}(G_{\mathbf{w}}) + \beta \times \arg\min_{G_{\mathbf{w}}}\max_{D_{\mathbf{w}'}} \mathcal{L}_{\text{adv}}(G_{\mathbf{w}}, D'_{\mathbf{w}})$$

Numerical Results (R = 0.5 with 10^4 photons per pixel)

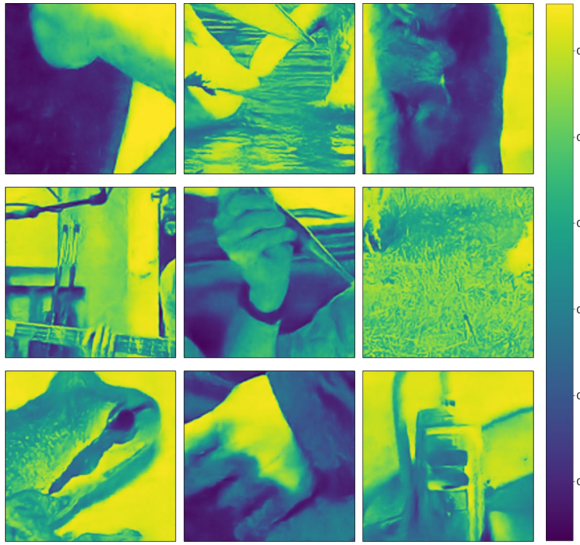


Ground truth

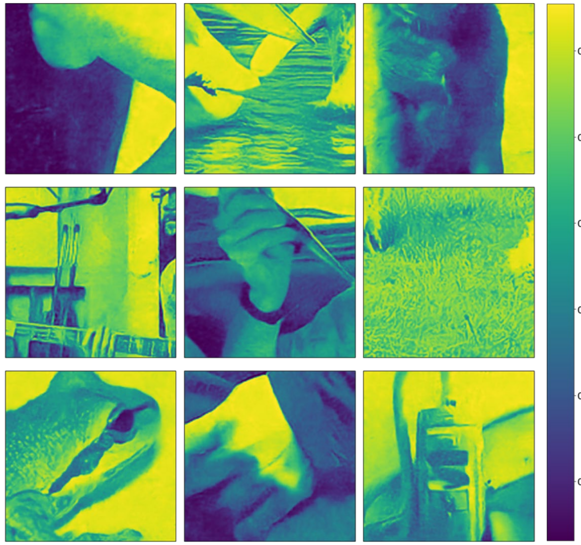
One iteration Approx



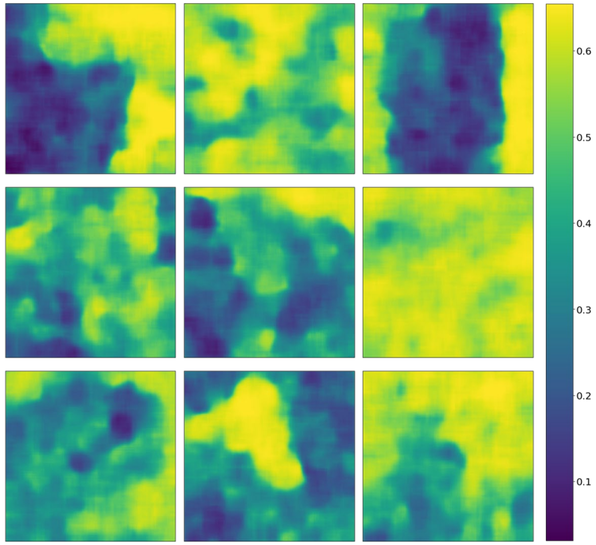
100 iterations



Non-generative

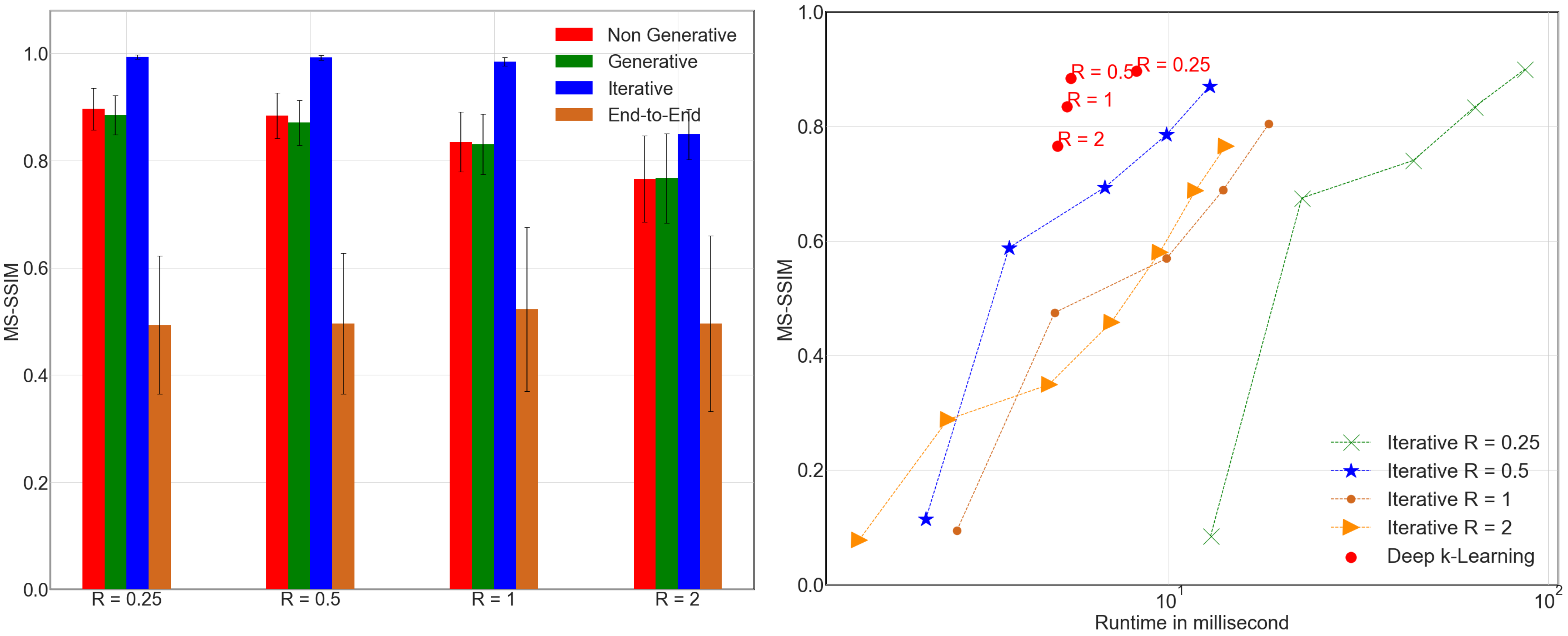


Generative



End-to-End

Numerical Results



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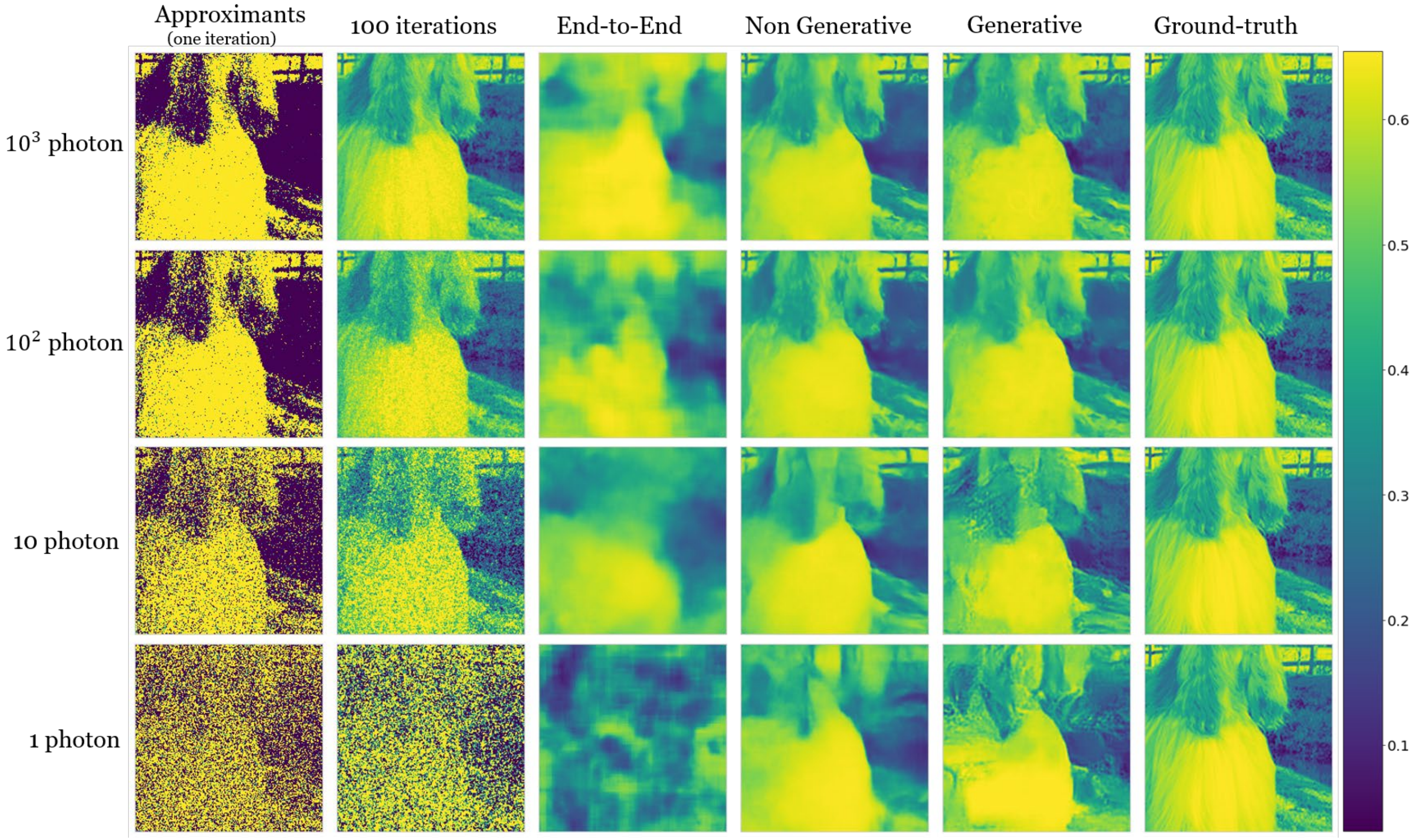
Numerical Results (R=0.5)



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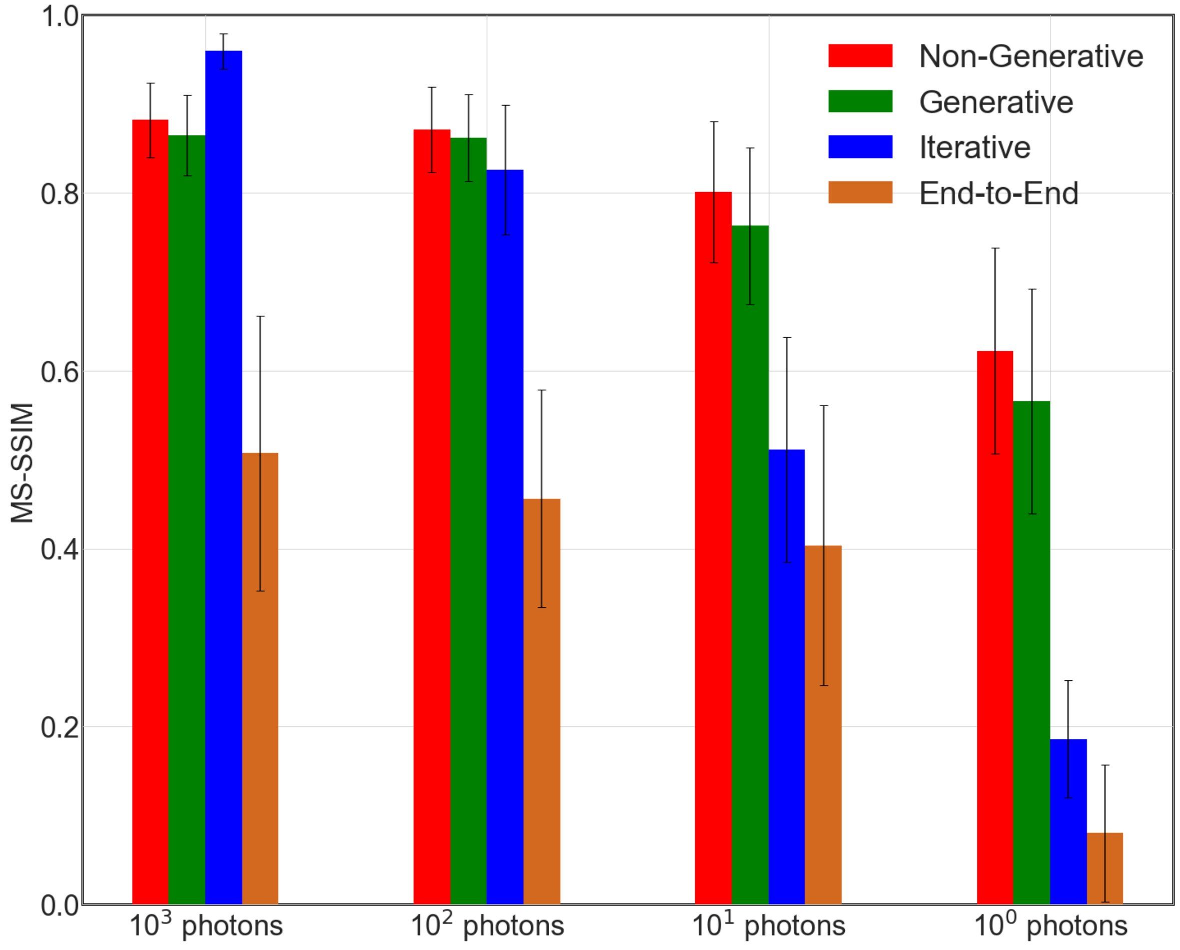
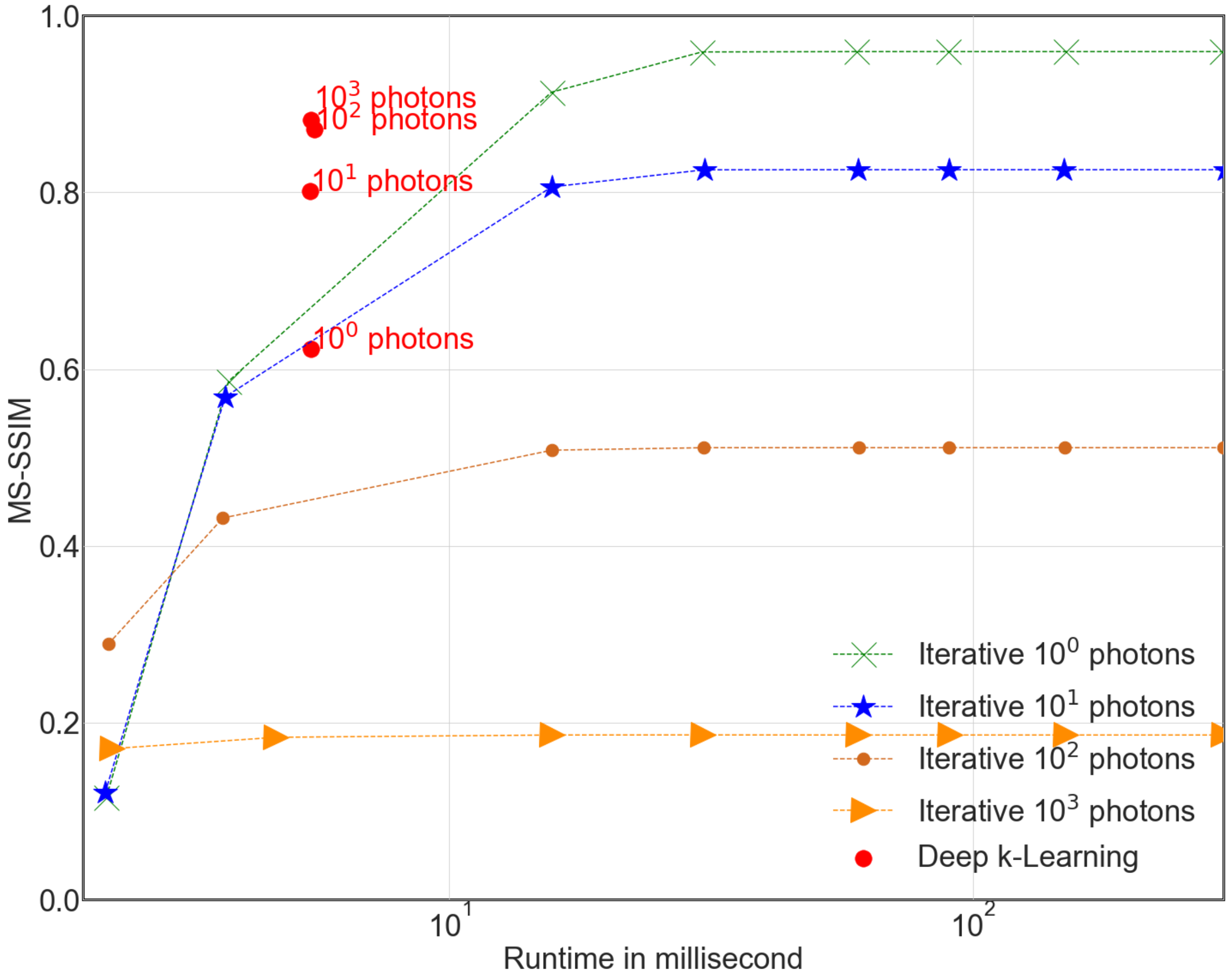
Numerical Results





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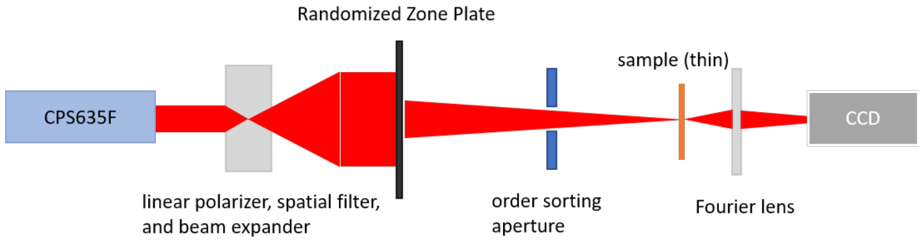
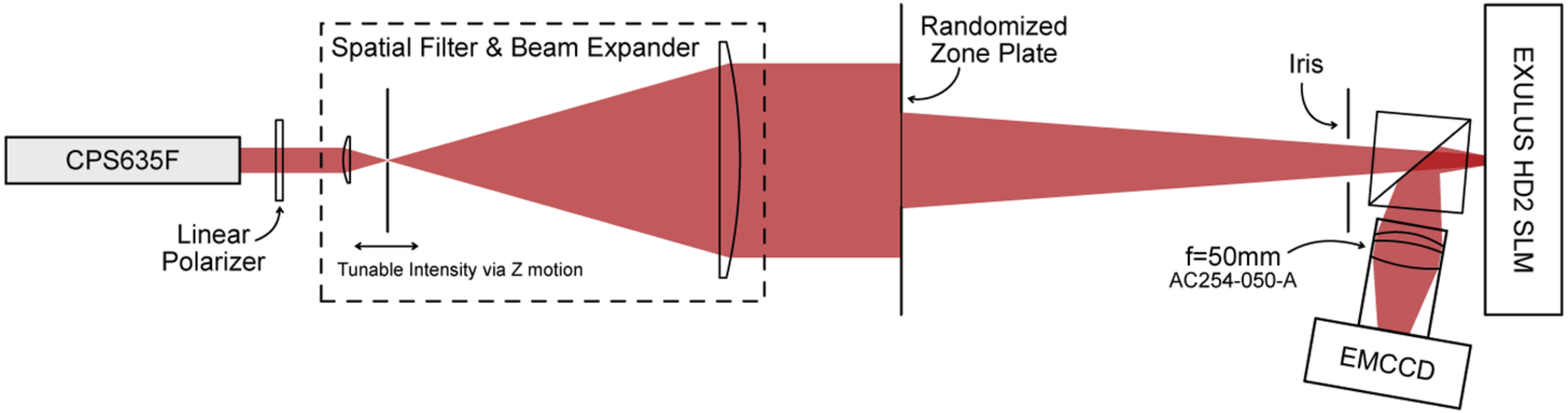
Experimental study



Apparatus for SLM produced dataset



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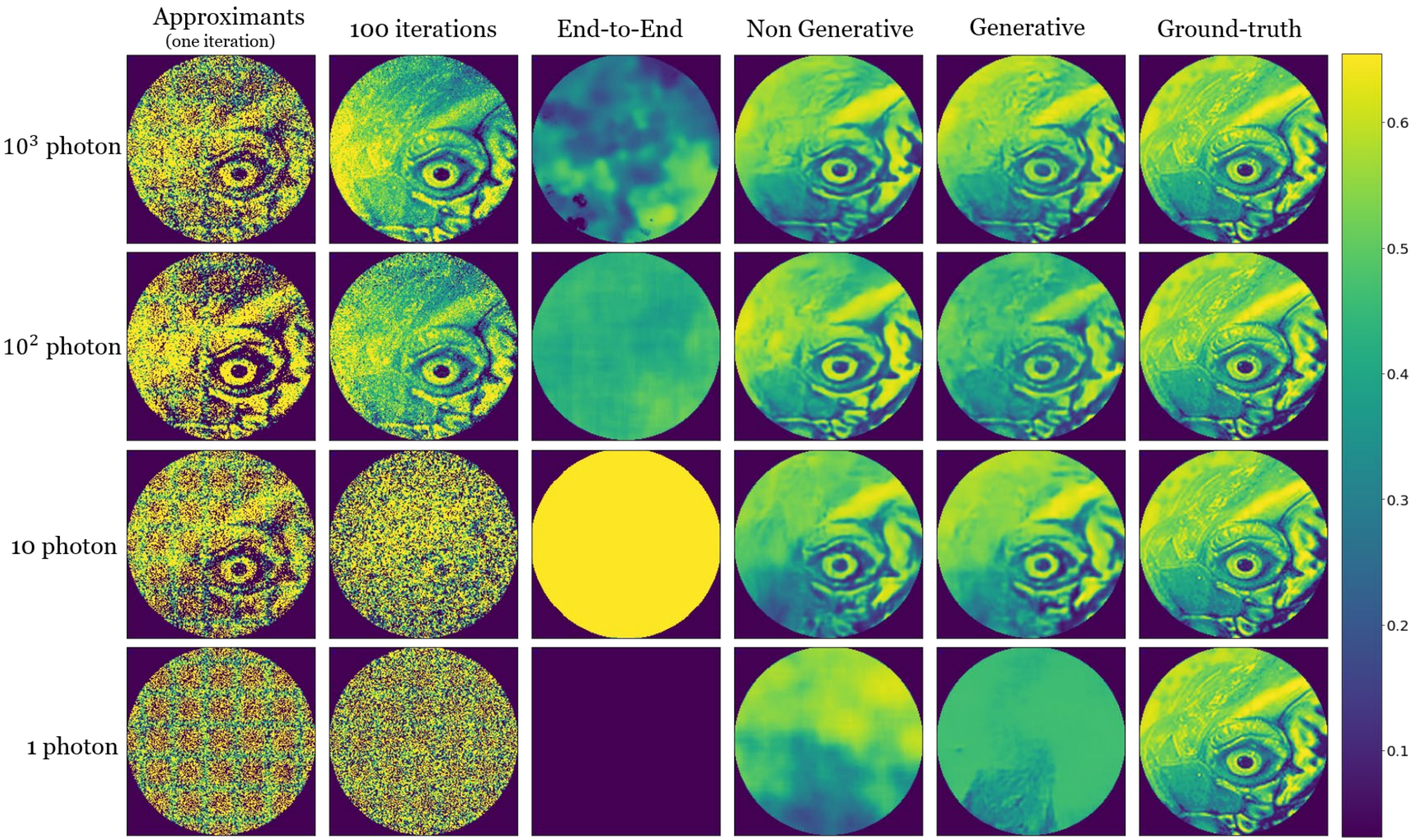
Experimental Results (R=0.5)



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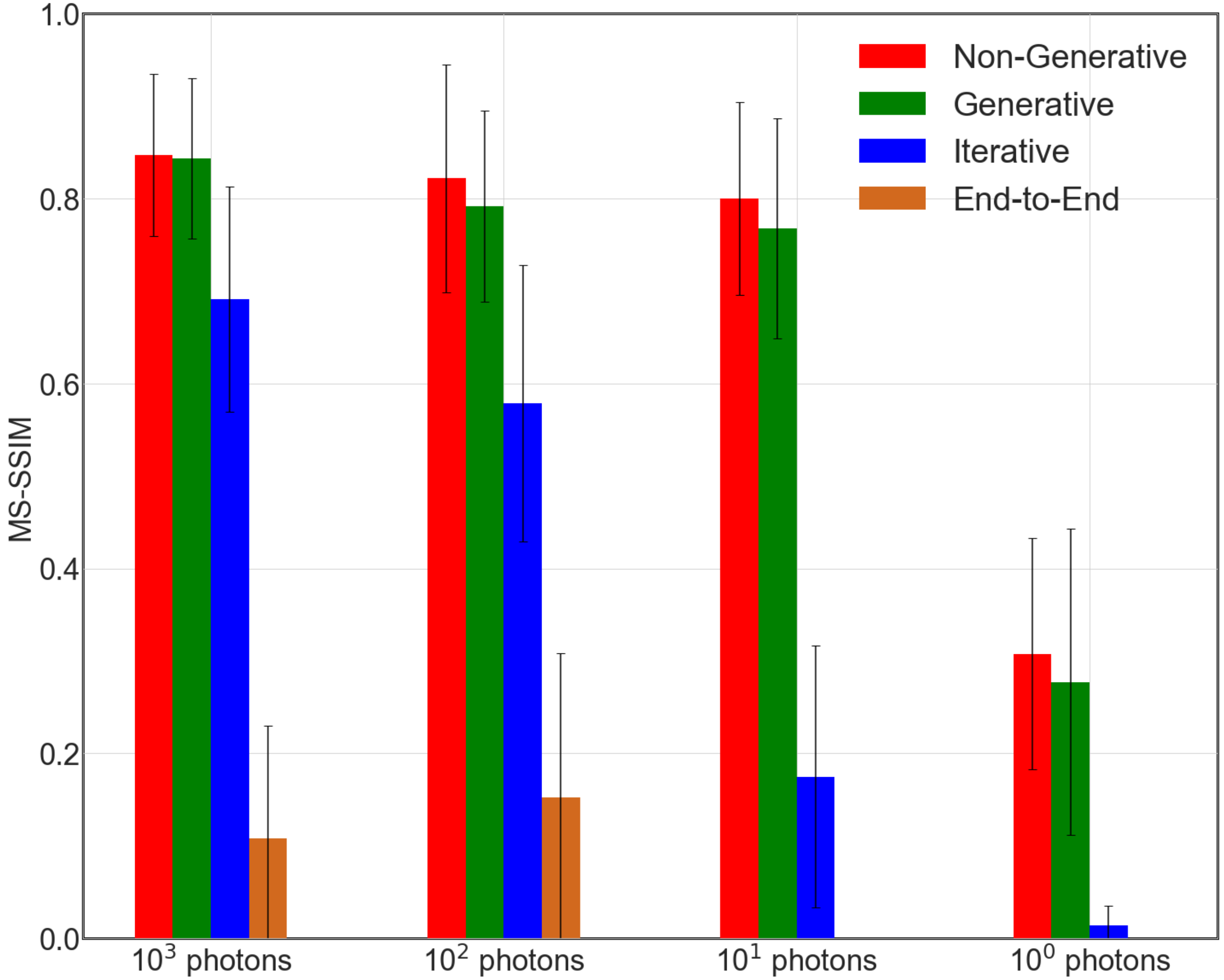
Experimental Results



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Thanks the TEAM!

Abraham Levitan

George Barbastathis

Riccardo Comin

Mo Deng

I A R P A
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MIT EECS

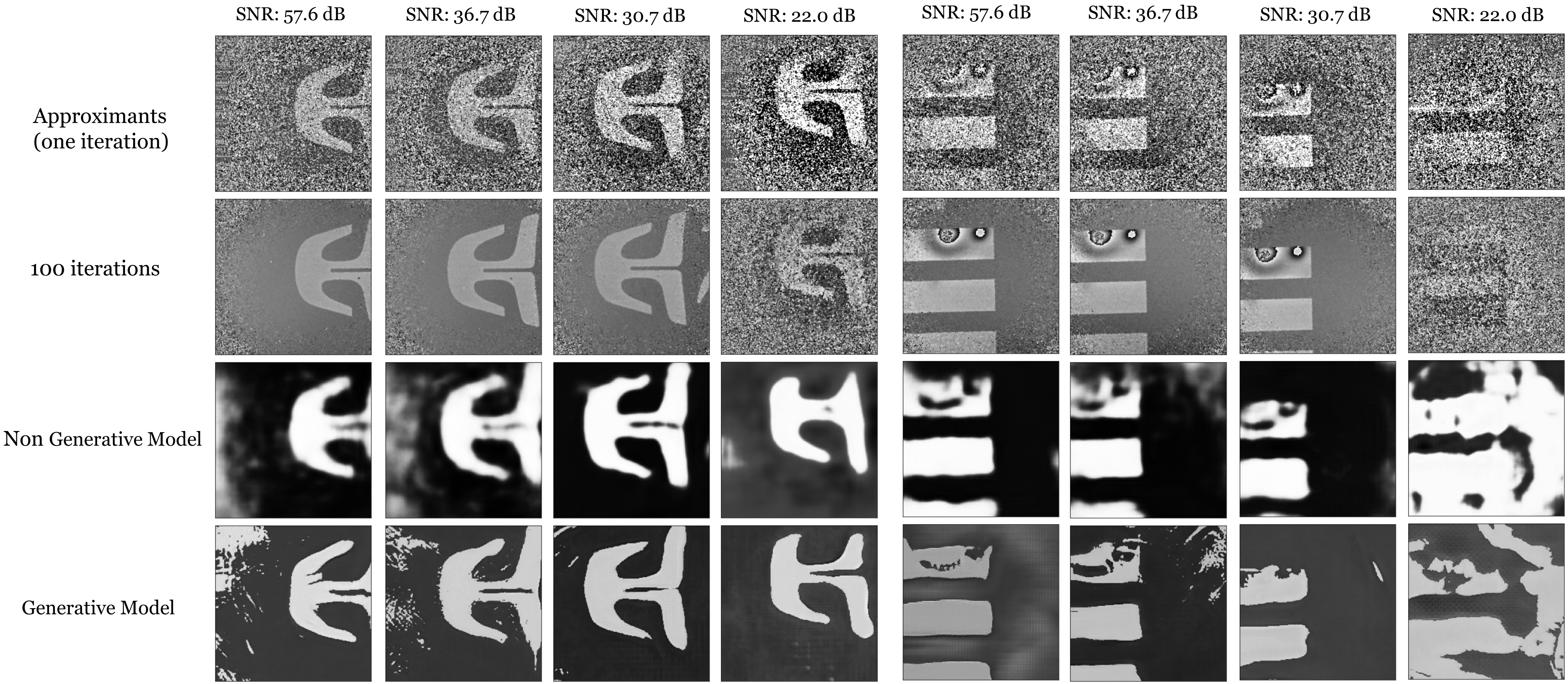
MIT Physics

MITMECHE

Ptychography Probe retrieval

RPI reconstruction (100 photon)

Experimental Results



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