NEURAL NETWORKS: FROM IMAGING TO NANOPHOTONICS INVERSE DESIGN

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Introduction

Over the last decade, neural networks were brought into many physics workflows with great promise. However, after the first wave of excitement, their actual limitations began to surface. Now that the field is maturing, we aim to show their practical value in two specific areas: advanced imaging and inverse photonic design. In the area of imaging, specifically segmentation, ptychography and phase retrieval, we show that deep learning can significantly improve both the quality of the results and the elaboration speed, even when dealing with incomplete data. Beyond imaging, we look at their potential for inverse photonic design. Here we demonstrate how neural networks serve to improve and implement both direct and inverse design strategies. They can also act as direct optimizers by using automatic differentiation to find non-intuitive solutions that traditional methods might miss.

Phase Retrieval and Ptychography

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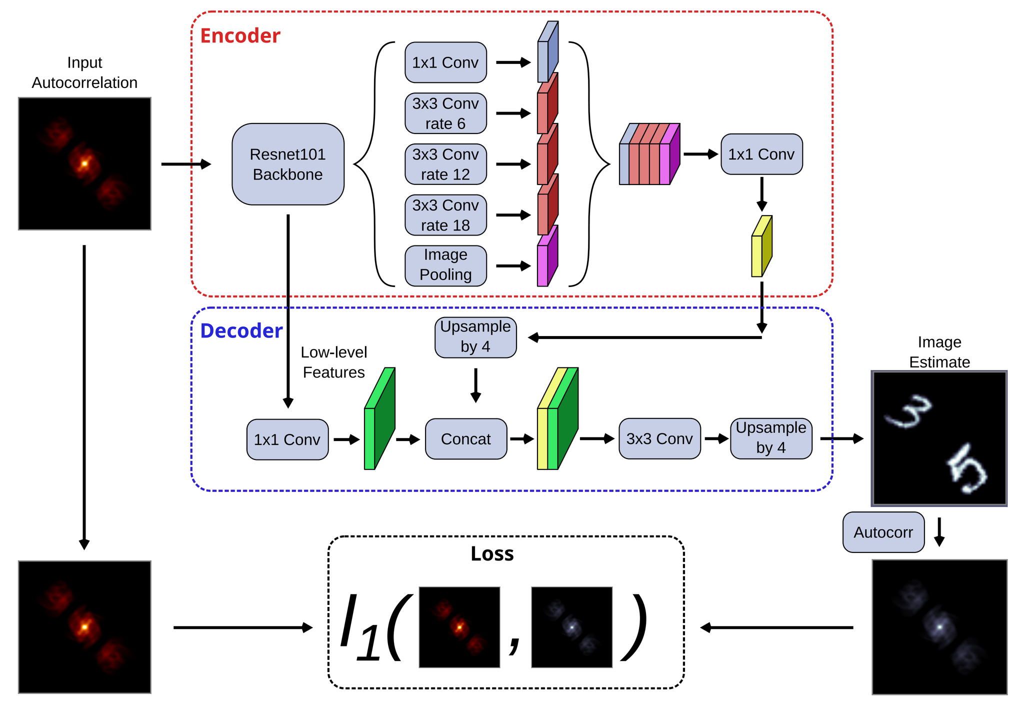
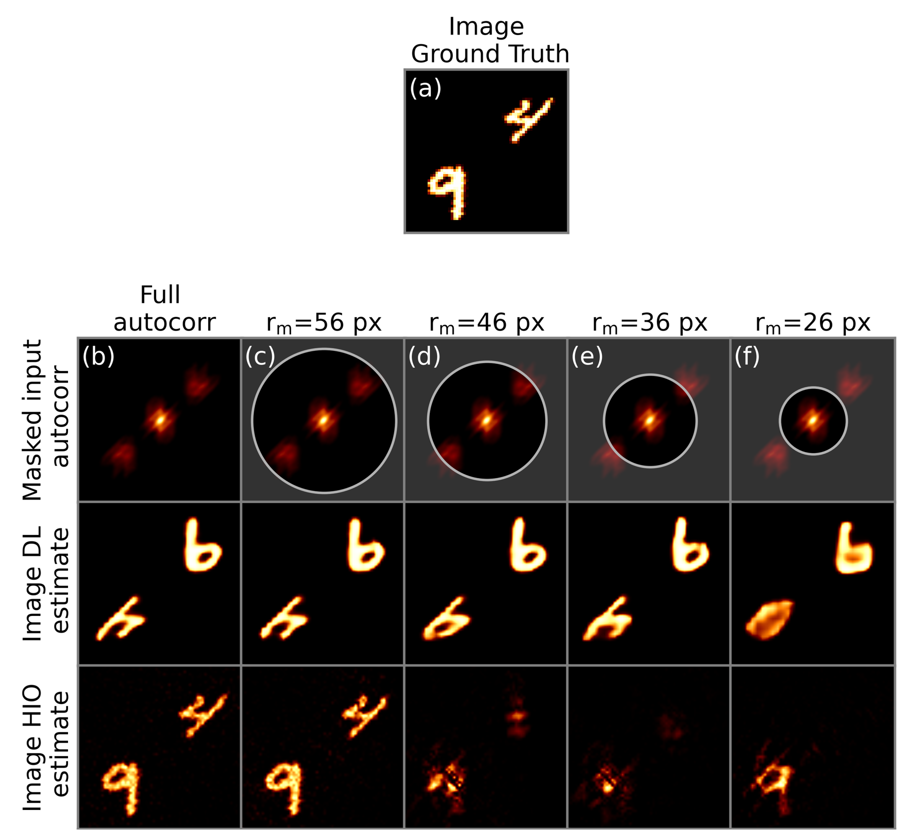
When dealing with computational microscopy or imaging in strongly scattering media, one often faces the so-called "phase retrieval problem". In these scenarios, only the amplitude of the Fourier transform of the original image is accessible, meaning the phase information is inherently lost. While traditional approaches rely on iterative methods we instead employ Physics-Informed Neural Networks. By embedding differentiable light propagation laws directly into the loss function, we enable the network to accurately retrieve the lost phase and achieve high-fidelity image reconstruction.

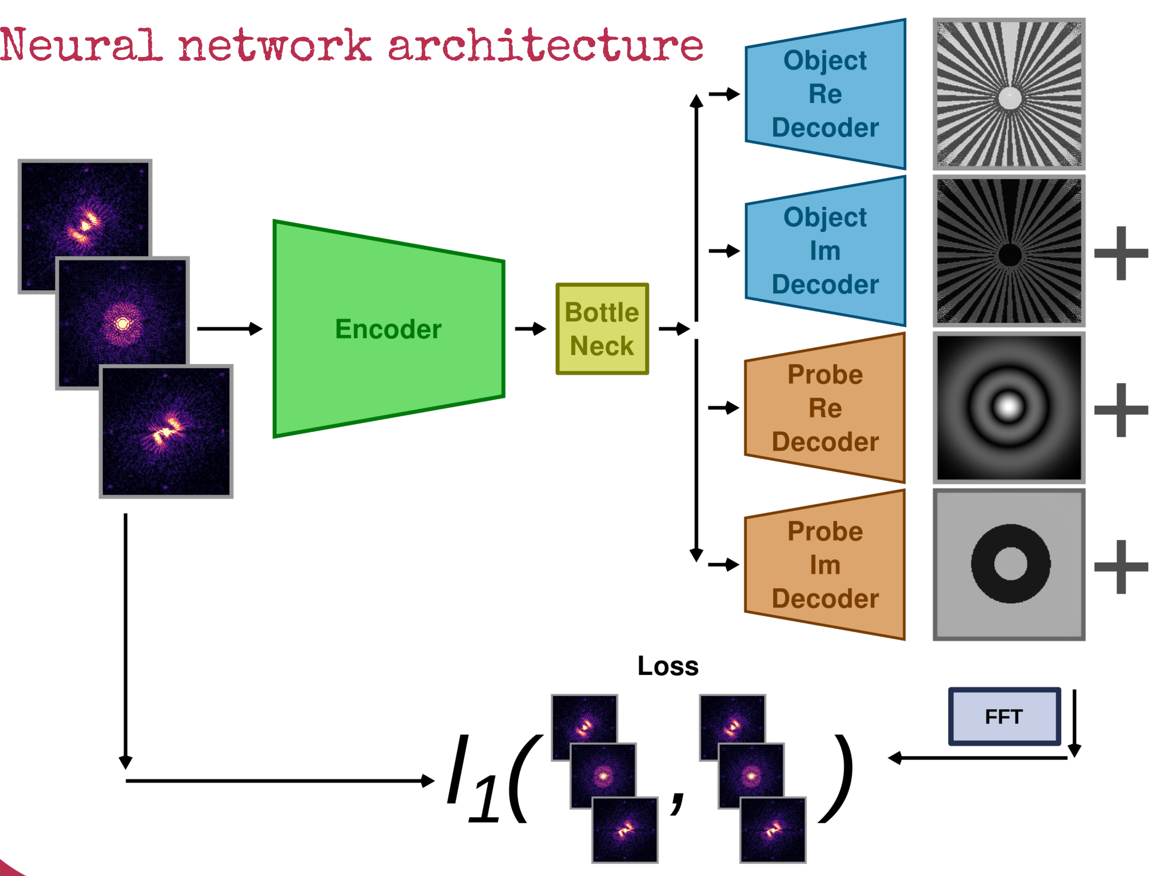
Neural network architecture



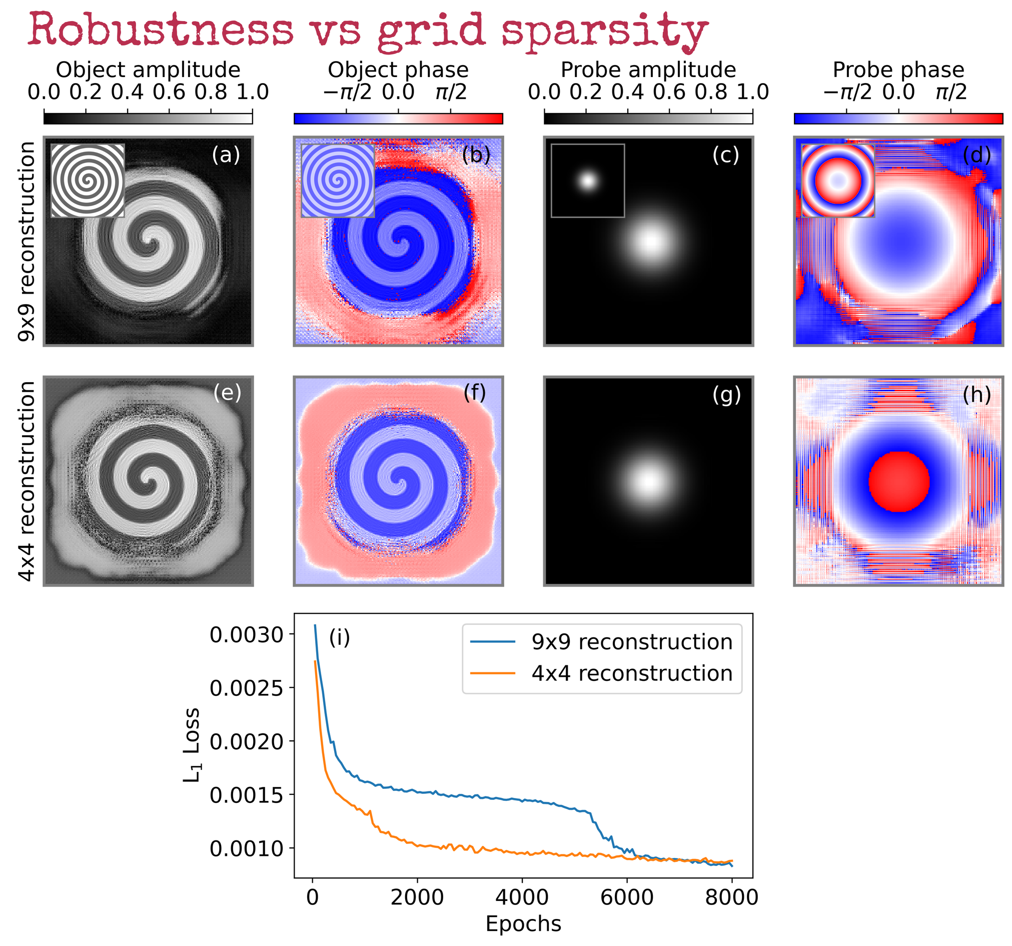
Neural network VS iterative



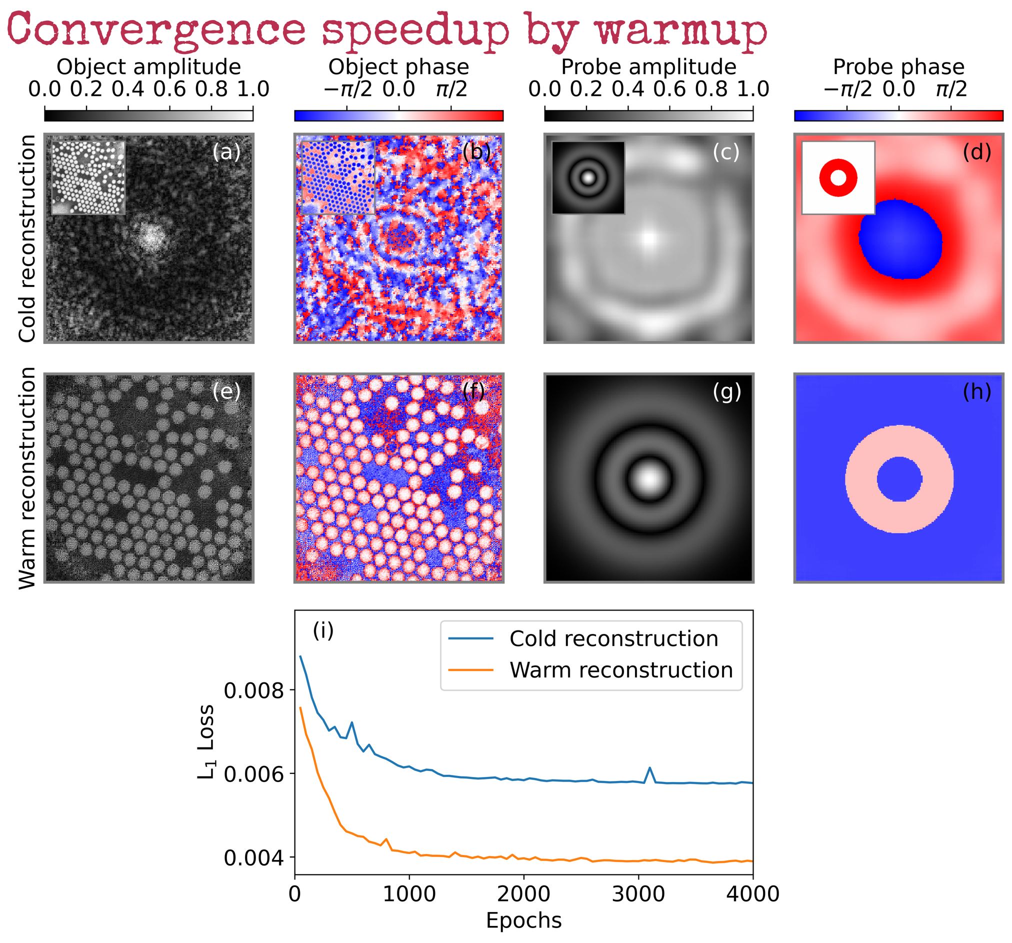
Neural network architecture



Robustness vs grid sparsity



Convergence speedup by warmup

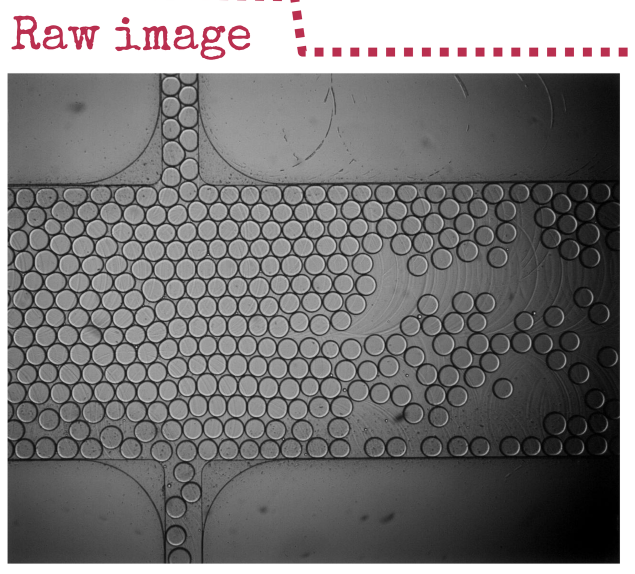


Bubble Tracking

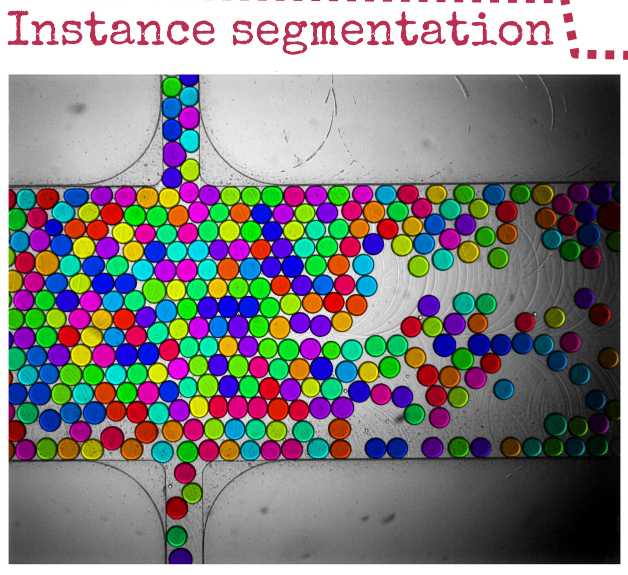
(Collab with Lafsi @ UniPd)

Microfluidic bubble ensembles serve as mesoscopic models for mimicking the mechanical properties of atomic systems at more accessible temporal and spatial scales. To extract quantitative morphological data, including average size and aspect ratio, or to characterize dynamics such as the velocity field, we must automatically track every individual bubble within the imaging field. We utilize Meta's foundational Segment Anything Model (SAM) to automate the extraction of geometrical and dynamical information, achieving robust tracking across the entire field of view with negligible error rates.

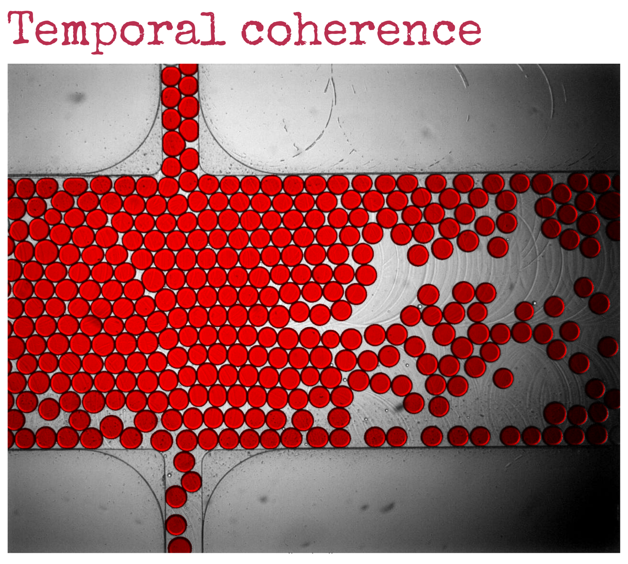
Raw image



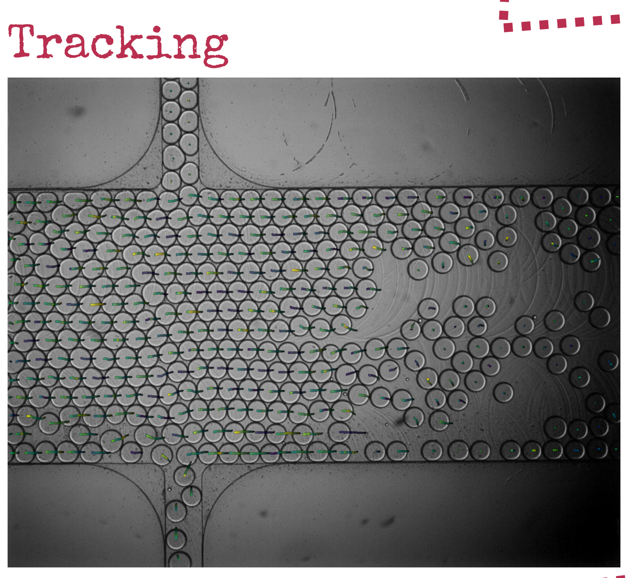
Instance segmentation



Temporal coherence

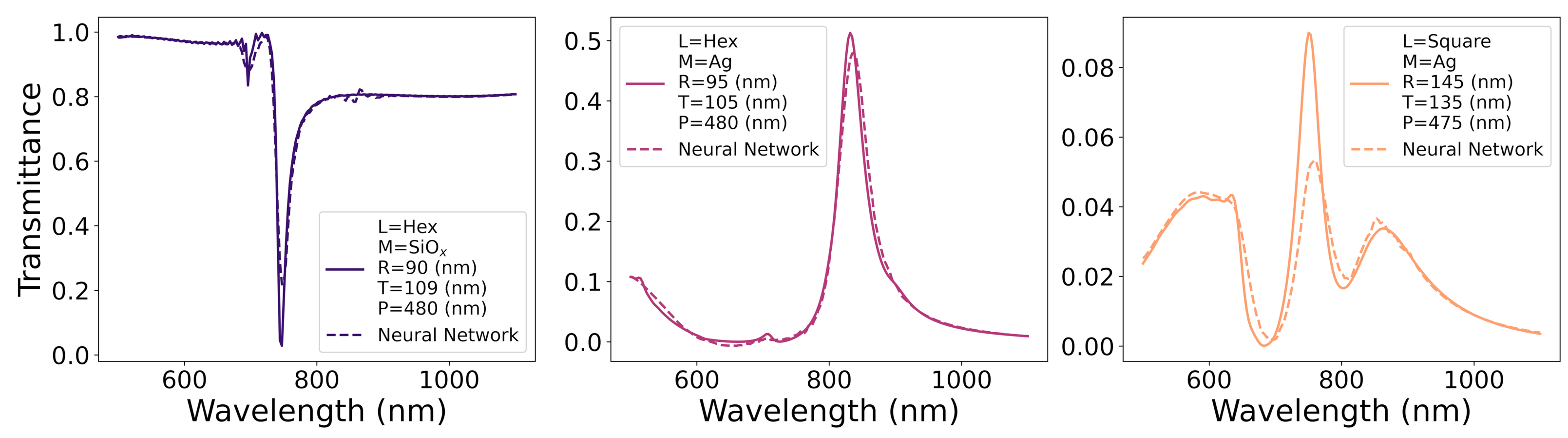


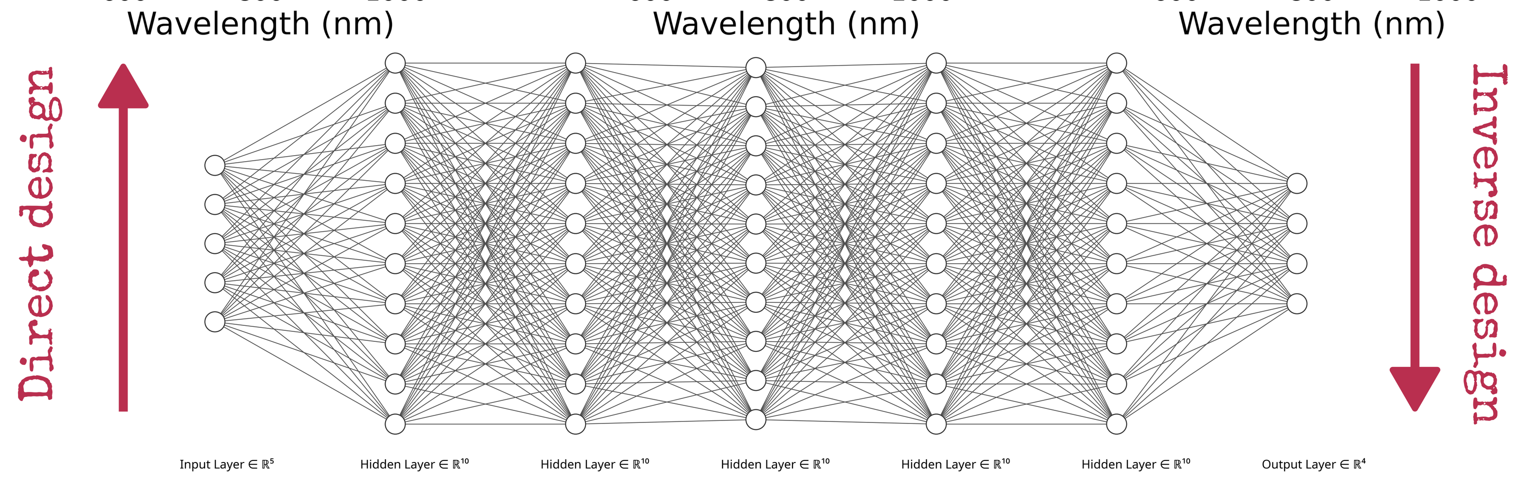
Tracking

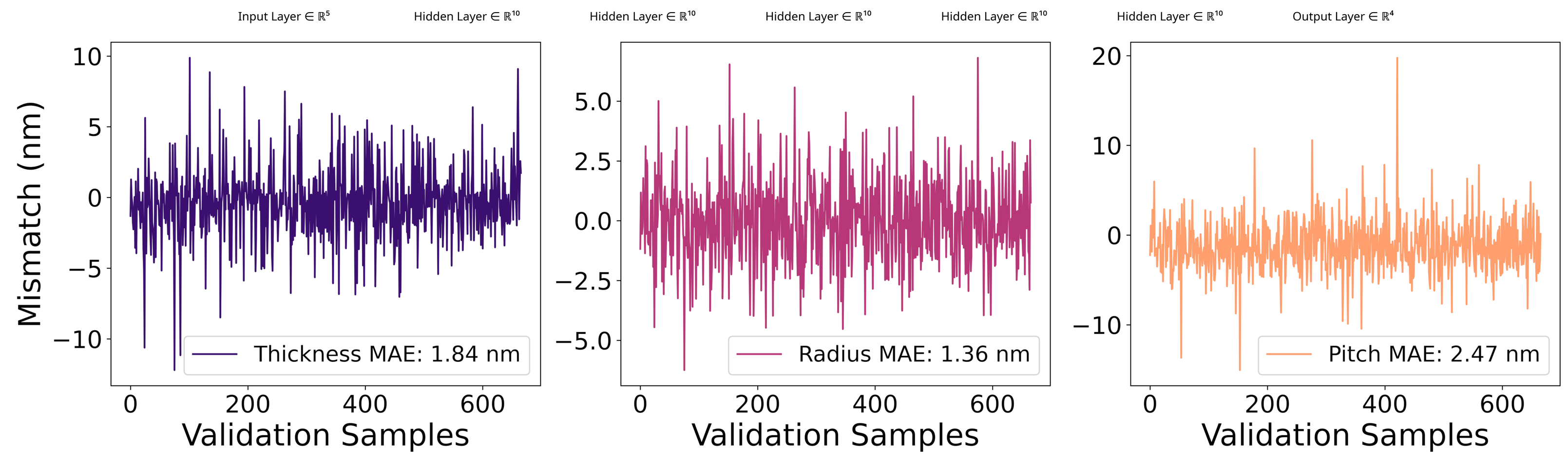


Inverse Design (of a simple metasurface)

Neural networks provide efficient solutions for both the direct and inverse design of nanophotonic systems. In direct design, they function as surrogate models that substantially accelerate simulations once training is complete. Inverse design strategies range from single forward pass mappings of optical properties to geometric features, to gradient based techniques where neural network frameworks enable the computation of gradients with respect to geometric parameters. Advanced architectures further integrate these networks with differentiable physical models to enable parameter updates beyond simple gradient descent.







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