Overcoming Limits in Nano-Optical Simulations, Design and Experiments Using Deep Learning

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Abstract

Subwavelength small particles can be tailored to fulfill manifold functionalities when interacting with light. During the past twenty years, tremendous research efforts have therefore been put into the field of nano-optics, leading to astonishing results and applications like flat optics, optical cloaking or negative index meta-materials. However, there are physical and/or methodological constraints which have proven hard to overcome. For instance, the optical diffraction limit is a difficult obstacle in many applications ranging from microscopy to optical information storage. In nano-optics modeling, inverse problems like the rational design of nano-structures are another example for a difficult tasks. We show how problems that were until recently considered very hard to solve, can be tackled efficiently using methods of artificial intelligence (AI) and specifically deep learning.

1. Introduction

Deep artificial neural networks (ANNs) have shown tremendous potential in solving problems that formerly were very hard or even impossible for "classical" algorithms. As a consequence, researchers from manifold areas including medicine, biology or physics started to increasingly use methods of AI [1, 2, 3]. ANNs can be very efficient in the analysis of large (scientific) datasets for instance from microscopy, tomography or spectroscopy [1, 4]. Trained on large datasets, neural networks can also learn to efficiently predict approximate solutions to notoriously hard inverse problems [5, 6] or to solve physical models *e.g.* in fluid mechanics or optics [7, 8, 9]. Furthermore, in several proof-of-principle studies ANNs have recently been used for the conception of on-demand photonic nanostructures and meta-materials [5, 8, 10, 11].

Here we give an example on how ANNs can be used to drastically accelerate simulations in nano-optics and give an outlook on how this can be used for generalized inverse design of photonic nanostructures. We also show how ANNs can help in the evaluation of experimental data in nano-optics and demonstrate at a specific example how the optical diffraction limit can be circumvented using an ANN, pushing the data density in optical information storage.

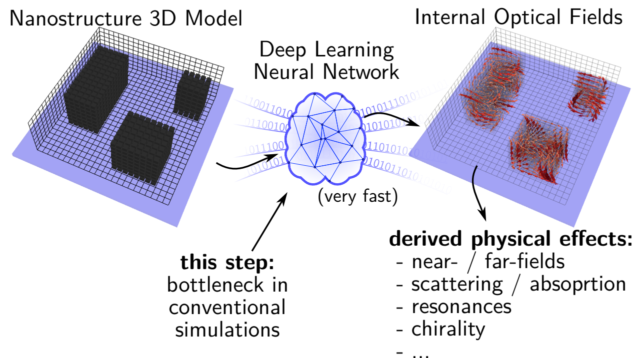

Figure 1: The internal optical fields of an arbitrary nanostructure upon plane wave illumination are predicted by an ANN and can then be used to derive various secondary quantities.

2. Generalized nano-optics predictor network

In most applications of deep learning in physics, ANNs are trained on very specific problems. If the problem changes, the time-consuming training procedure including costly data generation and testing needs to be re-done from scratch. We demonstrate here how to overcome this limitation by training an ANN on a very generalized description of light-matter interaction. To this end, we describe arbitrary nanostructures in a coupled dipole approximation (CDA) [12]. A 3D convolutional deep neural network is then trained on the prediction of the CDA-calculated internal fields in an arbitrary, volumne discretized nanostructure. As illustrated in figure 1 the input to the network is a volume model of the structure, and the output are the complex, time-harmonic fields at every mesh-cell. The predicted internal fields can then be used to derive manifold physical quantities in the near- and far-field region.

We show that a symmetric ANN model can be trained very efficiently on this problem and becomes capable to predict the optical response of individual nanostructures with an accuracy of around five percent [9]. We show how the approach can be extended to spectrally resolved predictions and multi-material scenarios and demonstrate how generalized inverse design can be achieved by an evolutionary optimization scheme [13], replacing the slow simulations routine by the very fast ANN model.

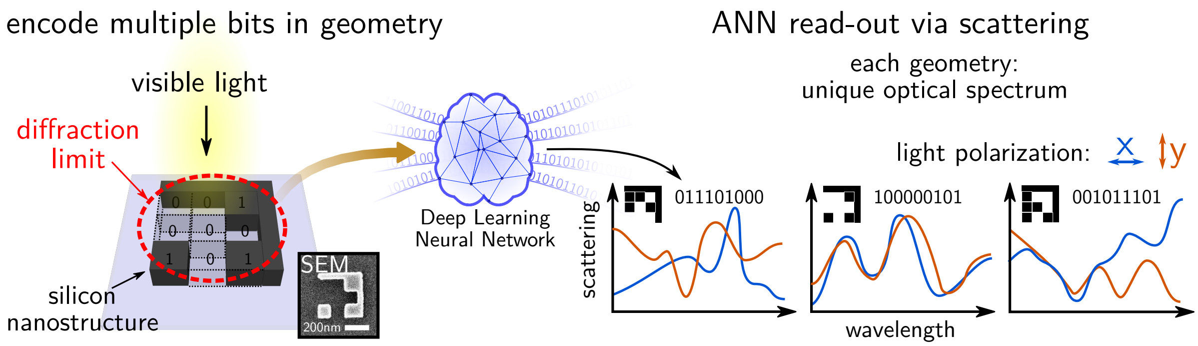

Figure 2: Up to 9 bits, encoded in a nanostructure of sub optical diffraction limit size, are decoded via their optical scattering spectrum, using an ANN for error free read-out, despite unavoidable fabrication imperfections and instrumental noise.

3. Deep learning for optical storage densities beyond the diffraction limit

Recently we developed a concept encoding multiple bits of information in the geometries of complex silicon nanostructures, each covering no more than a diffraction limited area (see left of Fig. 2). Via the optical scattering spectra we then read-out the sequences of binary data from a far-field measurement. This delicate task of data recovery through an optical measurement is however prone to instrumental noise and fabrication defects. We demonstrate how robust data read-out is possible based on an ANN, trained on the recognition of the optical scattering spectra of the topology-encoded nanostructures (right of Fig. 2). We experimentally achieve quasi-error-free readout of up to nine bits per diffraction limited area, effectively going beyond the Blu-ray data density. We show that an ANN can recover the information even using very limited spectral information like RGB color information, obtained from standard dark-field microscopy images [4]. The latter approach allows a massively parallel read-out of information encoded in many thousands of nanostructures simultaneously and together with the high bit-density is very promising for next-generation optical data storage solutions.

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