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Beyond the Hype: The Promise and Perils of Deep Learning

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Deep learning (DL) has emerged as a versatile numerical method in various fields of research. DL raises particularly high expectations for complicated problems where conventional techniques fail, for instance when tackling ill posed inverse problems such as design tasks [1, 2]. It is not exaggerated to call the current enthusiasm in the scientific community a veritable hype.

Illustrated by examples from nano-photonics, I will critically review deep learning in general and discuss its key strengths for scientific applications (Fig. 1): The differentiability of neural network models, the concept of the latent space, and the highly parallel, optimized performance [3,4].

In the second part I will discuss potentials and opportunities that arise as a side-effect from the huge global development efforts and monetary invest of Big Tech players in deep learning technology, that lead to the availability of powerful open source frameworks like tensorflow, jax or pytorch [6]. Beyond deep artificial neural networks, these highly optimized and GPU-ready automatic differentiation tools enable various further applications in physics.

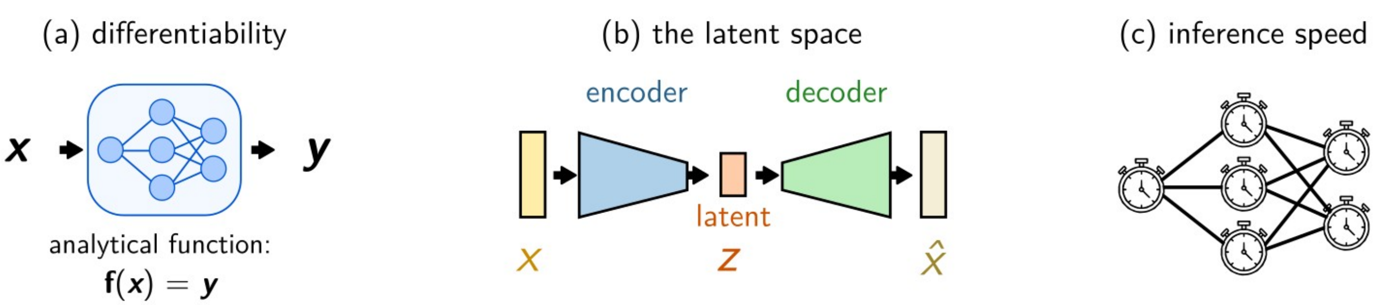

Figure 1: Deep learning key strengths [4].

References :
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[3] Khaireh-Walieh, A. et al. *A newcomer's guide to deep learning for inverse design in nano-photonics.* **Nanophotonics** 12, 4387–4414 (2023)
[4] Wiecha, P. R. *Deep learning for nano-photonic materials – The solution to everything!?* **COSSMS** 28, 101129 (2024)
[5] Unni, R. et al. *Advancing materials science through next-generation machine learning.* **COSSMS** 30, 101157 (2024)
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