

Jena NA Summer School 2025

Tensors and numerical multilinear algebra

Some references for further reading (highly incomplete)

Overview articles

- Bachmayr, M. (2023). “Low-rank tensor methods for partial differential equations”. In: *Acta Numer.* 32, pp. 1–121.
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Low-rank matrix optimization (lecture 1)

- Baldi, P. and K. Hornik (1989). “Neural networks and principal component analysis: Learning from examples without local minima”. In: *Neural Networks* 2.1, pp. 53–58.
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Tensors and basic approximation algorithms (lectures 2 & 3)

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Tree tensor networks and TT format (lectures 4 & 5)

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