# PHYSICS INFORMED MACHINE LEARNING IN MICROMAGNETISM

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## ABSTRACT

*Physics-Informed Neural Networks* (PINNs) [1] can be used to find solutions to a wide variety of problem settings, including parameter-dependent PDEs and inverse problems, while still respecting physical constraints. PINNs can solve high dimensional PDEs that are often intractable using traditional numerical methods. We are particularly interested to approximate solutions to the inherently nonlocal stray field problem in micromagnetism, where the computation of the nonlocal interactions is very time-consuming. Therefore, we demonstrate how to use neural networks and recent advances in numerical optimization to solve nonlinear PDEs, inverse problems or perform energy minimization. Since PINNs can easily be parameterized, we can compute whole families of solutions at once with a single PINN [2], such as for varying source term or geometrical constraints. We further talk about numerical aspects of optimization related to stiffness in the gradient flow dynamics, which involves adaptive weights and neural tangent kernel adjustment [3] during stochastic gradient descent.

## References

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[2] A. Kovacs, L. Exl, A. Kornell, J. Fischbacher, et al. *Conditional physics informed neural networks.* Communications in Nonlinear Science and Numerical Simulation 104 (2022), p. 106041.

[3] S. Wang, X. Yu, and P. Perdikaris, *When and why PINNs fail to train: A neural tangent kernel perspective.* Journal of Computational Physics 449 (2022): 110768.

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