



HAL
open science

Hybridization of Machine Learning and Numerical Linear Algebra Techniques for Scientific Computing: Learned Minimum Residual Solvers for the Helmholtz Equations

Yanfei Xiang, Luc Giraud, Paul Mycek, Carola Kruse

► **To cite this version:**

Yanfei Xiang, Luc Giraud, Paul Mycek, Carola Kruse. Hybridization of Machine Learning and Numerical Linear Algebra Techniques for Scientific Computing: Learned Minimum Residual Solvers for the Helmholtz Equations. CSE 2023 - SIAM Conference on Computational Science and Engineering, Feb 2023, Amsterdam, Netherlands. 2023. hal-04398087

HAL Id: hal-04398087

<https://inria.hal.science/hal-04398087>

Submitted on 16 Jan 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution 4.0 International License

2023 SIAM Conference on Computational Science and Engineering(SIAM CSE23). Part of MS0: Advances in Large-Scale Solvers in Computational Science and Engineering: Hybridization of machine learning and numerical linear algebra techniques for scientific computing

Yanfei Xiang*

Inria, Cerfacs, Concace joint Inria team with Airbus C R& T and Cerfacs, France

yanfei.xiang@inria.fr

Luc Giraud

Inria, Concace joint Inria team with Airbus C R& T and Cerfacs, France

luc.giraud@inria.fr

Paul Mycek

Cerfacs, Concace joint Inria team with Airbus C R& T and Cerfacs, France

mycek@cerfacs.fr

Carola Kruse

Cerfacs, Concace joint Inria team with Airbus C R& T and Cerfacs, France

carola.kruse@cerfacs.fr

*Speaker

Abstract

In the recent years, research on scientific machine learning based on deep learning solvers has been increasingly applied to scientific computing and computational engineering. However, even though these newly data-driven deep learning solvers could be very effective as soon as they have been properly trained, they can (in general) provide us with a solution of limited accuracy. Furthermore, the computational cost in the training phase can be extremely expensive. In this talk, we presents some ways of hybridizing the newly emerging deep learning solvers and the more traditional numerical linear algebra techniques to let them benefit from each other. In the context of solving a heterogeneous Helmholtz equation, we first focus on introducing some mathematical ingredients from classical iterative solver into the training phase of a recently proposed deep neural network solver. The main benefit is a significant improvement in the training phase that is more robust and faster, which turns out to be applicable to the testing process as well. Furthermore, once the network solvers have been properly trained, their inferences can be applied as a nonlinear preconditioner in the traditional flexible GMRES and flexible FOM methods. This part demonstrates

that these hybrid variants have clear advantages over both the newly emerging deep neural network approach and the classical iterative Krylov solver in terms of both computational cost and accuracy of the computed solution.