most of the problems of two-step approaches, they are usually computationally costy because they are iterative in nature and the relative similarity of absorption coefficients often leads to poor convergence. We present a method that combines preconditioning in the sinogram domain and an efficient numerical method for the nonlinear problem with a simple and thus fast iteration for the linear part of the problem. Our hybrid method does not suffer from systematic problems like beam hardening or difficulties with not perfectly aligned images for different energy bins. It is iterative but convergence is fast and the computational cost of each iteration is modest.

## Learning Sparsifying Regularisers

MS24 2
Thu Sep 7
4:00 pm
4:30 pm
VG1.101

**S. Neumayer**

Solving inverse problems is possible, for example, by using variational models. First, we discuss a convex regularizer based on a one-hidden-layer neural network with (almost) free-form activation functions. Our numerical experiments have shown that this simple architecture already achieves state-of-the-art performance in the convex regime. This is very different from the non-convex case, where more complex models usually result in better performance. Inspired by this observation, we discuss an extension of our approach within the convex non-convex framework. Here, the regularizer can be non-convex, but the overall objective has to remain convex. This maintains the nice optimization properties while allowing to significantly boost the performance. Our numerical results show that this convex-energy-based approach is indeed able to outperform the popular BM3D denoiser on the BSD68 test set for various noise scales.

## Deep Learning Methods for Partial Differential Equations and Related Parameter Identification Problems

MS51 1
Thu Sep 7
1:30 pm
2:00 pm
VG1.108

**D. Nganyu Tanyu, J. Ning, T. Freudenberg, N. Heilenkötter, A. Rademacher, U. Iben, P. Maass**

Recent years have witnessed a growth in mathematics for deep learning–which seeks a deeper understanding of the concepts of deep learning with mathematics, and explores how to make it more robust–and deep learning for mathematics, where deep learning algorithms are used to solve problems in mathematics. The latter has popularised the field of scientific machine learning where deep learning is applied to problems in scientific computing. Specifically, more and more neural network architectures have been developed to solve specific classes of partial differential equations (PDEs). Such methods exploit properties that are inherent to PDEs and thus solve the PDEs better than classical feed-forward neural networks, recurrent neural networks, and convolutional neural networks. This has had a great impact in the area of mathematical modeling where parametric PDEs are widely used to model most natural and physical processes arising in science and engineering, In this work, we review such methods and extend them for parametric studies as well as for solving the related inverse problems. We equally proceed to show their relevance in some industrial applications