# Data-driven regularisation for solving inverse problems

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Most inverse problems of interest are ill-posed and require appropriate mathematical treatment for recovering meaningful solutions. Regularization is one of the main mechanisms to turn inverse problems into well-posed ones by adding prior information about the unknown quantity to the problem, often in the form of assumed regularity of solutions. Classically, such regularization approaches are handcrafted. Examples include Tikhonov regularization, the total variation and several sparsity-promoting regularizers such as the L1 norm of Wavelet coefficients of the solution. While such handcrafted approaches deliver mathematically and computationally robust solutions to inverse problems, providing a universal approach to their solution, they are also limited by our ability to model solution properties and to realise these regularization approaches computationally. Recently, a new paradigm has been introduced to the regularization of inverse problems, which derives regularization approaches for inverse problems in a data driven way. Here, regularization is not mathematically modelled in the classical sense, but modelled by highly over-parametrised models, typically deep neural networks, that are adapted to the inverse problems at hand by appropriately selected (and usually plenty of) training data. In this talk, I will review some machine learning based regularization techniques, present some work on unsupervised and deeply learned convex regularisers and their application to image reconstruction from tomographic and blurred measurements, and finish by discussing some open mathematical problems.