Deep learning concepts are presently intruding almost all fields of science and engineering. Such concepts produce astonishing experimental results and seem to bypass easily well established and well researched classical approaches in particular for applications in data analysis and image processing. However, this is not the case for inverse problems where applying deep neural networks as a generic toolbox fails.

The classical approach to inverse problems starts with an analytical description $F : X \to Y$ of the forward operator in some function spaces $X; Y$. The field of inverse problems addresses the task of reconstructing an unknown $x$ from noisy data $y \sim F(x)$ with the further complication that the inverse of $F$ or any type of generalized inverse is unbounded.

This inherent and unavoidable instability, which cannot be remedied by preconditioning or any other type of data preprocessing, is reflected by the failure of naively transferring deep learning concepts from image processing directly to inverse problems in tomography, non-destructive testing or monitoring physical-technical processes in general.

In this talk we will discuss specific deep learning concepts for inverse problems, which allow an interpretation in terms of the classical analytical regularization theory. These results so far only apply to comparatively small network designs. In addition we demonstrate the potential for large scale problems in the field of magnetic particle imaging.