Provably convergent deep learning-based methods for imaging inverse problems

Carola-Bibiane Schönlieb
Department of Applied Mathematics and Theoretical Physics, University of Cambridge
cbs31@cam.ac.uk

Deep learning had remarkable empirical success in recent years in solving a variety of inverse problems in imaging, including image denoising, deblurring, tomographic image reconstruction, and image inpainting, just to name a few. This has catalyzed an ongoing quest for precise characterization of correctness and reliability of such data-driven methods in critical use-cases, e.g., those arising in medical imaging.

Notwithstanding the excellent empirical performance of data-driven methods for image reconstruction, concerns have been raised regarding their stability, or lack thereof, with serious practical implications. In applications where imaging is used for discovering new scientific phenomena, it is important to have mathematical guarantees to ensure the correctness and reliability of the reconstructed images.

In this talk, we will introduce different notions of convergence pertaining to image reconstruction problems and provide a broad overview of recent data-driven techniques that satisfy some of those convergence properties. In particular, the talk will focus on data-driven regularization methods through explicit functionals parametrized by neural networks [1–5] and via plug-and-play deeply-learned denoisers [6, 7]. We will highlight the requisite properties that such a regularization functional or a denoiser must satisfy to establish convergence guarantees of different types.

Joint work with: Martin Burger, Marcello Carioni, Sören Dittmer, Sebastian Lunz, Subhadip Mukherjee, Ozan Öktem and Zakhar Shumaylov

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