Plug & Play imaging methods

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Plug-and-Play (PnP) methods constitute a class of iterative algorithms for imaging problems where regularization is performed by an off-the-shelf denoiser. Specifically, given an image dataset, optimizing a function (e.g. a neural network) to remove Gaussian noise is equivalent to approximating the gradient or the proximal operator of the log prior of the training dataset. Therefore, any off-the-shelf denoiser can be used as an implicit prior and inserted into an optimization scheme to restore images. After introducing the PnP and Regularization by Denoising frameworks, we will explore the different convergence analyses that have been proposed in the literature. From monotone operators theory to convex and non-convex analysis, we will propose various tools and deep denoisers that allow theoretical PnP convergence guarantees and state-of-the-art image restoration performance.

In the second part of this tutorial, we explore several extensions to the PnP framework for inverse problems in imaging. First, we explore the case of super-resolution and deblurring with spatially varying kernel. Previous PnP algorithms would be too computationally expensive in this case. This motivates the introduction of a PnP linearized ADMM algorithm with convergence guarantees and an unrolled version thereof, which produces competitive results with respect to state-of-the-art algorithms. Secondly, we study the problem of sampling the posterior distribution of an inverse problem based on an implicit PnP prior. We introduce PnP-ULA (Plug & Play unadjusted Langevin algorithm) for Monte Carlo sampling and minimum mean square error estimation, and we provide detailed convergence guarantees. Finally, we consider generative models like GANs, VAEs and Diffusion Models as an alternative to model the prior distribution, and we introduce algorithms for posterior maximization and sampling that use generative models as priors.