
LEARNING PRIORS FOR INVERSE PROBLEM RESOLUTION THROUGH DEEP-LEARNING



PARIETAL



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Context The resolution of inverse problems is a major challenge in many fields, from astrophysics to bio-imaging. These problems occur naturally when trying to study the source of an observed signal, knowing the physics of the observation of this signal. This is typically the case for source localization in MEG signals. These problems are usually ill-posed and it is rare that we have a ground truth to evaluate them. The most classic resolution approach is to formulate them as optimization problems integrating a prior on the structure of the solutions, and to perform minimization by iterative methods. Computational efficiency and the quality of the solutions depends strongly on the prior choice.

With the success of deep neural networks for supervised learning, particularly on classification and regression tasks, the question of their use to solve inverse problems has arisen. Recent studies have shown that deep neural networks can be designed based on iterative thresholding algorithms used to solve inverse problems. Their use speeds up and improves inference compared to original solvers [2, 3]. While the first empirical approaches have shown the potential of these methods, particularly in terms of reducing computation time and performance on synthetic data, the results are regularly confronted with the problem of overfitting and the evaluation of their quality remains an open question. Returning to the point of view of an iterative algorithm, it is possible to study these models with the tools of convex optimization, compressed acquisition and parsimonious coding. Our recent works [1, 4] take this point of view to show some properties of networks based on iterative thresholding.

However, rather than learning how to speed up the resolution of the inverse problem for a given prior, it seems more relevant to use deep learning to learn directly an adapted prior using a parametric model on a class of signals. This would allow us to exploit both the advantages traditional analytical methods and those of learning methods. The prior learning for inverse problems is often done by learning a dictionary to break down the signals and exploits parsimony. This approach reveals two opposite problems which can also be solved using deep neural networks such as ISTA-Net [5]. It seems to be therefore relevant to study the question of how to effectively learn to solve an inverse problem using deep learning? Should we learn the reverse operator as suggested above? or a prior based on a learnable dictionary that exploits parsimony?

Methods In order to answer these questions, we propose to study these methods by considering the networks of deep neurons for inverse problems as a way of doing prior learning. The idea of this internship is to see the different way of using such methods, using the analysis and/or synthesis perspectives. The performance of product algorithms will be able to benefit from the computational ecosystem for deep learning and including GPU implementations for these models. This empirical development will be conducted in parallel with study of the convergence of the algorithms learned towards a fixed point as part of dictionary learning. Doing so, it should be possible to better evaluate the quality of the proposed solution. The links with classical K-SVD approaches can then be explored, allowing to benefit from various approaches that could reduce the computational complexity of these methods.

Environment The internship will take place in Inria Saclay, in the [Parietal team](#). This is a large team working focused on mathematical methods for statistical modeling of brain function using neuroimaging data (fMRI, MEG, EEG). Particular topics of interest include machine learning techniques, numerical and parallel optimization, applications to human cognitive neuroscience, and scientific software development.

Requirements

- Strong mathematical background. Knowledge in numerical optimization is a plus.
- Good programming skills in Python. Knowledge of a deep-learning library is a plus.

References

- [1] Pierre Ablin, Thomas Moreau, Mathurin Massias, and Alexandre Gramfort. Learning step sizes for unfolded sparse coding. *preprint ArXiv*, 1905.11071, 2019.
- [2] Karol Gregor and Yann Le Cun. Learning Fast Approximations of Sparse Coding. In *International Conference on Machine Learning (ICML)*, pages 399–406, 2010.
- [3] Jialin Liu, Xiaohan Chen, Zhangyang Wang, and Wotao Yin. ALISTA: Analytic Weights are as good as Learned weights in LISTA. In *International Conference on Learning Representation (ICLR)*, pages 1113–1117, New-Orlean, LA, USA, 2019.
- [4] Thomas Moreau and Joan Bruna. Understanding Neural Sparse Coding with Matrix Factorization. In *International Conference on Learning Representation (ICLR)*, Toulon, France, 2017.
- [5] Jian Zhang and Bernard Ghanem. ISTA-Net: Interpretable Optimization-Inspired Deep Network for Image Compressive Sensing. In *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pages 1828–1837, Salt Lake City, UT, USA, 2018.