Frugal Dictionary Learning for Imaging

Supervision :

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Context Dictionary learning is crucial in addressing inverse problems in imaging, such as denoising, deblurring, and compressive sensing. In these tasks, the objective is to represent data using a sparse combination of learned dictionary elements, known as atoms, which encapsulate the underlying structure of the signal. Traditionally, this process involves iterative optimization methods ; however, recent advancements have introduced neural network-inspired approaches that unroll these iterative algorithms into fixed-depth networks. Noteworthy examples, such as DRUNet [1], demonstrate state-of-the-art performance by training deep neural networks to function as plug-and-play (PnP) priors [5]. Unrolling frameworks replicating iterative optimization over fixed layers provides competitive accuracy while significantly reducing computational overhead [2]. As illustrated in [4], even shallow unrolling—using just a few layers—can surpass DRUNet in both accuracy and computational efficiency for specific imaging problems. This underscores the potential of sparse and interpretable methods to achieve efficiency and robustness.

Despite these advancements, several critical challenges remain in unrolled dictionary learning for imaging. First, tuning hyperparameters, such as regularization strength and step size, is essential for ensuring robustness to noise, but this process largely remains empirical. Second, identifying the optimal number of dictionary atoms poses an open question that directly affects memory usage, computational cost, and model accuracy.

Methods The theoretical framework of adaptive layer selection and convergence analysis presented in [6] offers a promising approach to optimizing dictionary size within the unrolling paradigm. This project aims to tackle these challenges by building on these principles and developing a robust, efficient dictionary-learning framework for inverse problems.

The primary objective of this project is to integrate theoretical insights from sparse coding and adaptive optimization in order to design noise-resilient dictionaries. This involves exploring task-driven approaches that dynamically adjust the dictionary size during training. Additionally, the project will tailor the regularization strategy for noise-aware learning, ensuring that the learned dictionary generalizes well under varying conditions during inference. These enhancements aim to improve the robustness of unrolled dictionary learning methods compared to traditional deep learning models.

A secondary focus will be on the energy efficiency of dictionary learning in comparison to deep networks, such as DRUNet. While architectures like DRUNet require substantial computational resources, dictionary learning offers a more interpretable and lightweight alternative. The project will analyze the energy consumption involved in both the learning and inference phases, comparing these profiles to those of state-of-the-art neural networks. Metrics such as floating-point operations (FLOPs), power consumption, and inference latency will be used to quantify the advantages of more efficient learning approaches.

Environment The internship will take place at the Laboratoire Interdsciplinaire des Sciences du Numérique (LISN), in the Inria Tau team.

The internship may lead to a Ph.D. position.

Requirements

— Strong mathematical background. Knowledge in numerical optimization is a plus.
— Good programming skills in Python.

Références

[1] Zhang, K., Li, Y., Zuo, W., Zhang, L., Van Gool, L., & Timofte, R. (2021). Plug-and-play image restoration with deep denoiser prior. IEEE Transactions on Pattern Analysis and Machine Intelligence, 44(10), 6360-6376.

[2] Gregor, K., & LeCun, Y. (2010). Learning fast approximations of sparse coding. In Proceedings of the 27th International Conference on Machine Learning (ICML).

[3] Malézieux, B., Moreau, T., & Kowalski, M. (2022). Understanding approximate and unrolled dictionary learning for pattern recovery. In International Conference on Learning Representations.

[4] Kowalski, M., Malézieux, B., Moreau, T., & Repetti, A. (2024). Analysis and Synthesis Denoisers for Forward-Backward Plug-and-Play Algorithms. https ://hal.science/hal-04786802

[5] Venkatakrishnan, S. V., Bouman, C. A., & Wohlberg, B. (2013). Plug-and-play priors for model-based inversion. In Proceedings of the IEEE Global Conference on Signal and Information Processing (GlobalSIP).

[6] Verbockhaven, M., Rudkiewicz, T., Chevallier, S., & Charpiat, G. (2024). Growing Tiny Networks : Spotting Expressivity Bottlenecks and Fixing Them Optimally. Transactions on Machine Learning Research (2024).