The Future of Optimization for Imaging

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Abstract In this introductory talk to the session on "Large-scale Optimization for Computational imaging", we will first survey current optimization methods, also related to the subsequent presentations. We will then discuss fundamental limitations of optimization approaches, focusing in particular on the fact that current algorithms are predominantly run on digital hardware. As we will show, this can cause serious problems from a computability viewpoint, which can be provably resolved by using analogue hardware such as neuromorphic computing or quantum computing.

Efficient Lip-1 spline networks for convergent PnP image reconstruction

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Abstract Neural networks are constructed via the composition of simple modules: affine transformations (e.g. convolutions) and pointwise non-linearities. PnP schemes for image reconstruction make use of such convolutional neural networks for the so-called denoising step. The condition for convergence is that the denoising CNN should be non-expansive. It is achieved by imposing a tight Lipchitz-1 constraint on each module; for instance, by using ReLU non-linearities and by spectrally normalizing each linear layer. The downside of this simple normalization approach is that the resulting network generally loses expressivity. Concretely, this means that PnP with current Lip-1 CNN fall short of reaching the best possible (state-of-the-art) image quality, which is price to pay for the consistency and stability of the reconstruction. The approach that is investigated in this work is to replace the ReLU activations by more expressive trainable non-linearities, subject to the Lip-1 constraint. The foundation for our approach is a representer theorem for the design of deep neural networks with Lipchitz-constrained free-form activations subject to TV^2 regularization to favor "simple" neuronal responses. It states that the global optimum of this constrained functional optimization problem can be achieved with a configuration where each neuron is a linear spline with a small number of adaptive knots (break points). We then describe a B-spline framework for the efficient implementation and training of such Lip-1 spline networks. Finally, we apply our framework to the reconstruction of magnetic resonance images and show that it compares favorably with other existing Lip-1 neuronal architectures. Related work available on ArXiv (2210.16222, 1802.09210)

Optimization of deep neural networks under privacy constraints

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Abstract The utilization of deep neural networks in domains with sensitive data represents a challenging trade-off between data utilization and data protection. Modern privacy-enhancing technologies like differential privacy are able to bridge that gap and alleviate privacy concerns. However, they introduce undesirable privacy-utility trade-offs, both from a computational and an accuracy point-of-view. To tackle these trade-offs, innovative techniques for optimization must be developed. This talk will discuss such techniques by focusing on two distinct areas: On one hand, computational techniques which mitigate the decreased efficiency of private optimization. On the other hand, architecture design techniques which facilitate convergence in the presence of biased and noisy gradients necessary for differential privacy. Moreover, it will provide a concise introduction to the theory of differential privacy from a signal processing point of view. The works which will be discussed here are accessible at nature.com/articles/s41598-021-93030-0, and on ArXiv (2210.00053, 2209.04338, 2205.04095, 2203.00324).