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Precision Learning – A new Concept to unite Computational Imaging and Deep Learning

C. Syben and A. Maier

Friedrich-Alexander-University Erlangen-Nuremberg, Germany
Andreas.Maier@fau.de

In recent years, the methods of deep learning have revolutionized large fields in pattern recognition from speech processing to computer vision [4]. Lately, these techniques became also popular in image reconstruction and for the efficient solution of inverse problems [10, 12, 9]. We propose to blend black-box deep learning with prior knowledge in order to restrict the solution space to physically and algorithmically plausible solutions. We coined this known operator approach *precision learning*. In [3], we demonstrated that this approach reduces maximal error bounds of the training problem and has several other guarantees that black-box deep learning is not able to give. In our framework, any operation that allows computation of a sub-gradient towards its input variables can be employed.

In [8, 9], we demonstrate that the well-known Feldkamp-Davis-Kress (FDK) Algorithm can be mapped mathematically identically onto a three-layer neural network that consists of a multiplicative, a convolutional, and a fully connected layer. Doing so, one does not even require training, as the multiplication is initialized using Cosine and Parker weights, the convolutional layer uses the Ramp Filter, and the fully connected layer implements back-projection. In this constellation, we demonstrated that we are able to train the weights of the multiplicative layer to limited angle problems, even though the actual back-projection matrix does not fit into a computer's main memory. We use – similar to iterative reconstruction – efficient implementation of projection and back-projection on GPUs. This way the limited angle reconstruction is solved efficiently in a single forward-pass at run-time. Learned weights resemble heuristic configuration that were found by other researchers [5, 6]. Remaining streaks can be efficiently further reduced using the variational networks approach by Hammernik et al. [1]. This way, we remain with an interpretable neural network that is analytically equivalent to FDK reconstruction followed by iterative image-domain de-streaking.

Recently, so-called adversarial attacks have demonstrated to mislead neural networks towards false classifications [11]. So far, this concept was only applied to classification or segmentation tasks. In [2], we demonstrated that similar concepts also apply to reconstruction networks. In particular, we found that U-nets with their non-local receptive field can be misled in such a way that lesions disappear from CT slice images. Hence, general black-box deep learning reconstruction networks like the ones presented in [12] are to be handled with caution.

Given the concept of precision learning and the mathematical equivalence of neural network and reconstruction algorithm, we can also approach other problems in medical imaging. In [7], we investigate whether it is possible to re-bin a parallel MRI acquisition to fan-beam geometry using a filtering-based approach. We demonstrate that we can reformulate the problem using an algebraic approach. Doing so, we solve for the unknown fan-beam projections and postulate that the inverse that is required during this computation is a circulant matrix. As a result, we derive an algorithm that is known up-to-the circulant operator that is conveniently initialized as the Ramp filter. Using 50 synthetic phantoms, we demonstrate that we are able to estimate an appropriate filter kernel that also generalizes to real data. As such we employ deep learning merely as a tool to efficiently minimize our optimization problem. Still, we hope that such use of the back-propagation algorithm will futher facilitate the blend of math, physics, and computer science.

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