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Precision Learning Computed Tomography

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Precision Learning Concept [1]

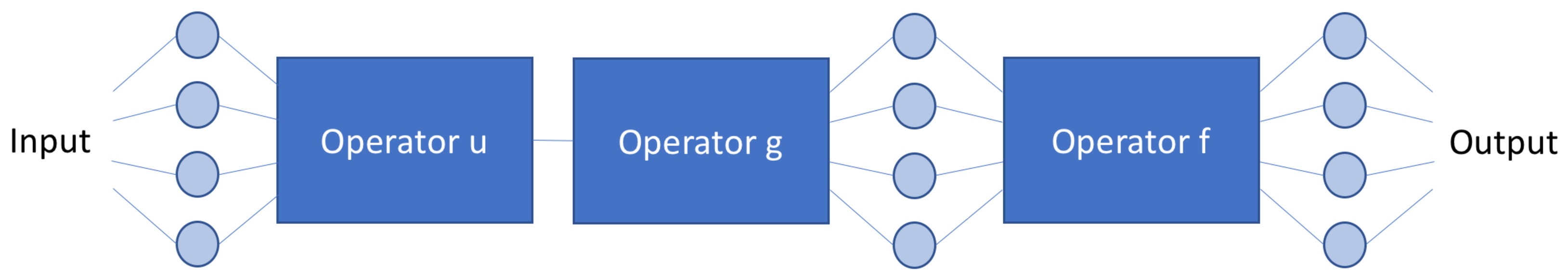


Figure 1: Known operators embedded in a neural network

Idea:
- Include known operators in learnable mappings
- Deduce network topologies using domain knowledge

Benefit:
- Faster convergence
- Domain knowledge restricts every block of the network

Precision Learning for Computed Tomography [2]

Most reconstruction algorithms are chains of operators. Architectures can be derived and initialized to be identical.

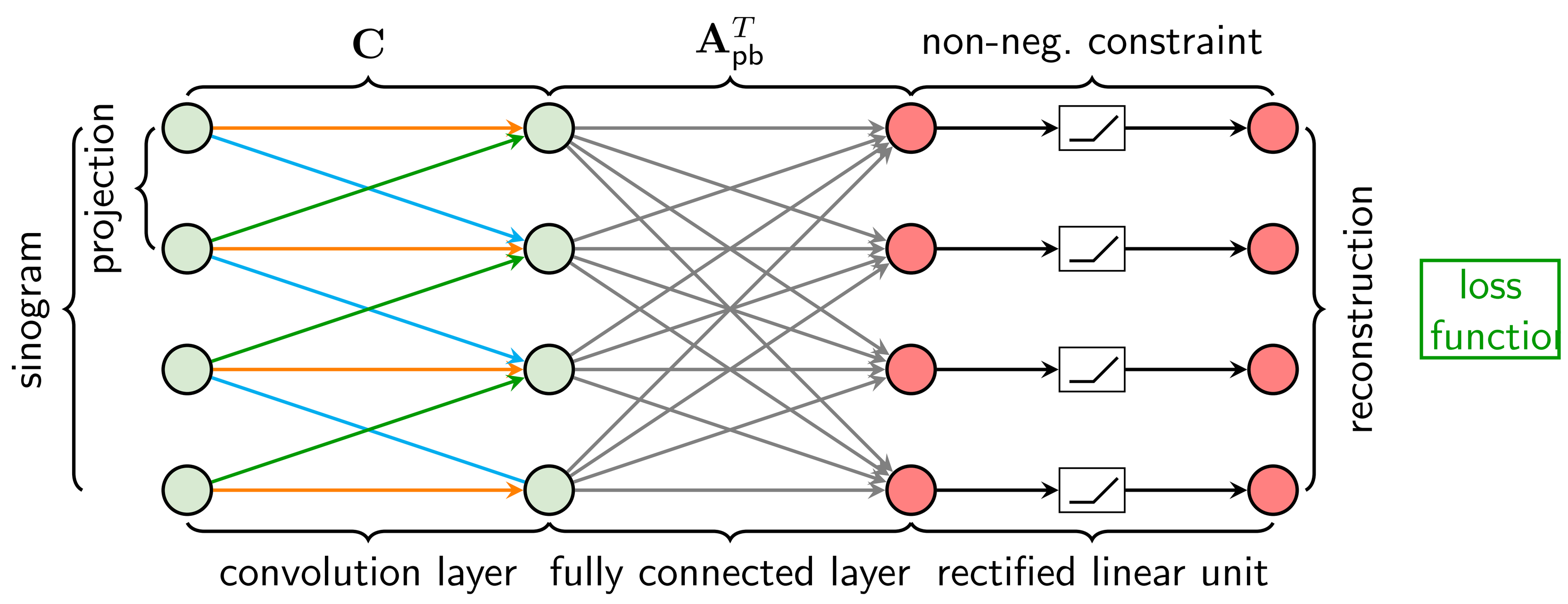
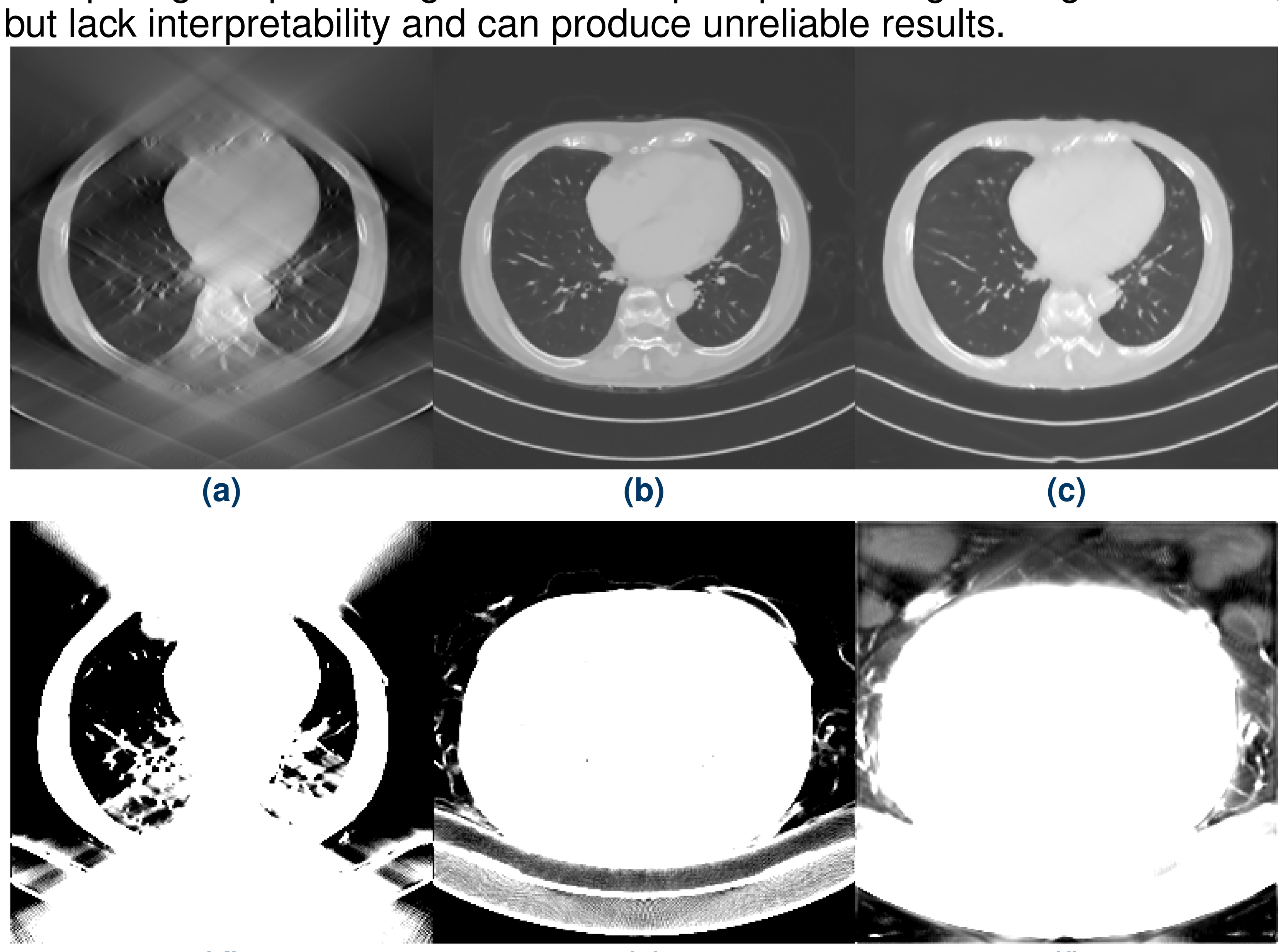


Figure 2: Neural network architecture equivalent to the filtered backprojection algorithm

An advantage is that weights can be adapted in a data-driven fashion.

Comparison to Deep-learning-based Reconstruction [3]

Competing deep learning networks as post-processing show great results, but lack interpretability and can produce unreliable results.



(a) (b) (c)

(d) (e) (f)

Figure 3: Fig. 3a: Limited-angle reconstruction; Fig. 3b: Corresponding groundtruth; Fig. 3c: U-net reconstruction; Figures 3d, 3e and 3f: Same images using different window

Application to Limited Angle Cone-beam CT [4]

Loss of mass in limited angle CT can be compensated using heuristic weig-hts. Using precision learning a data-optimal solution can be learned.

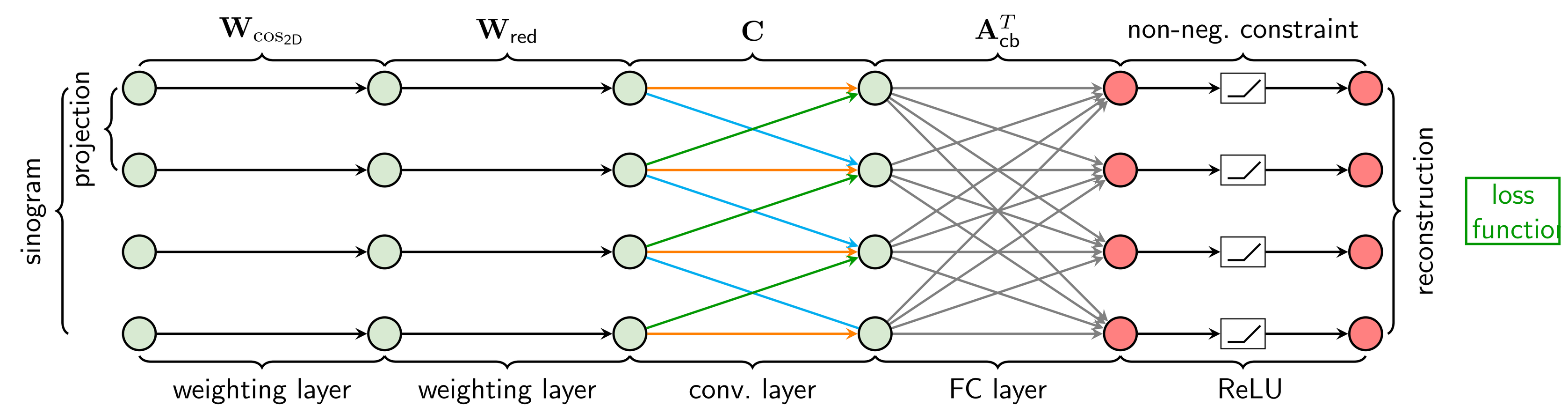
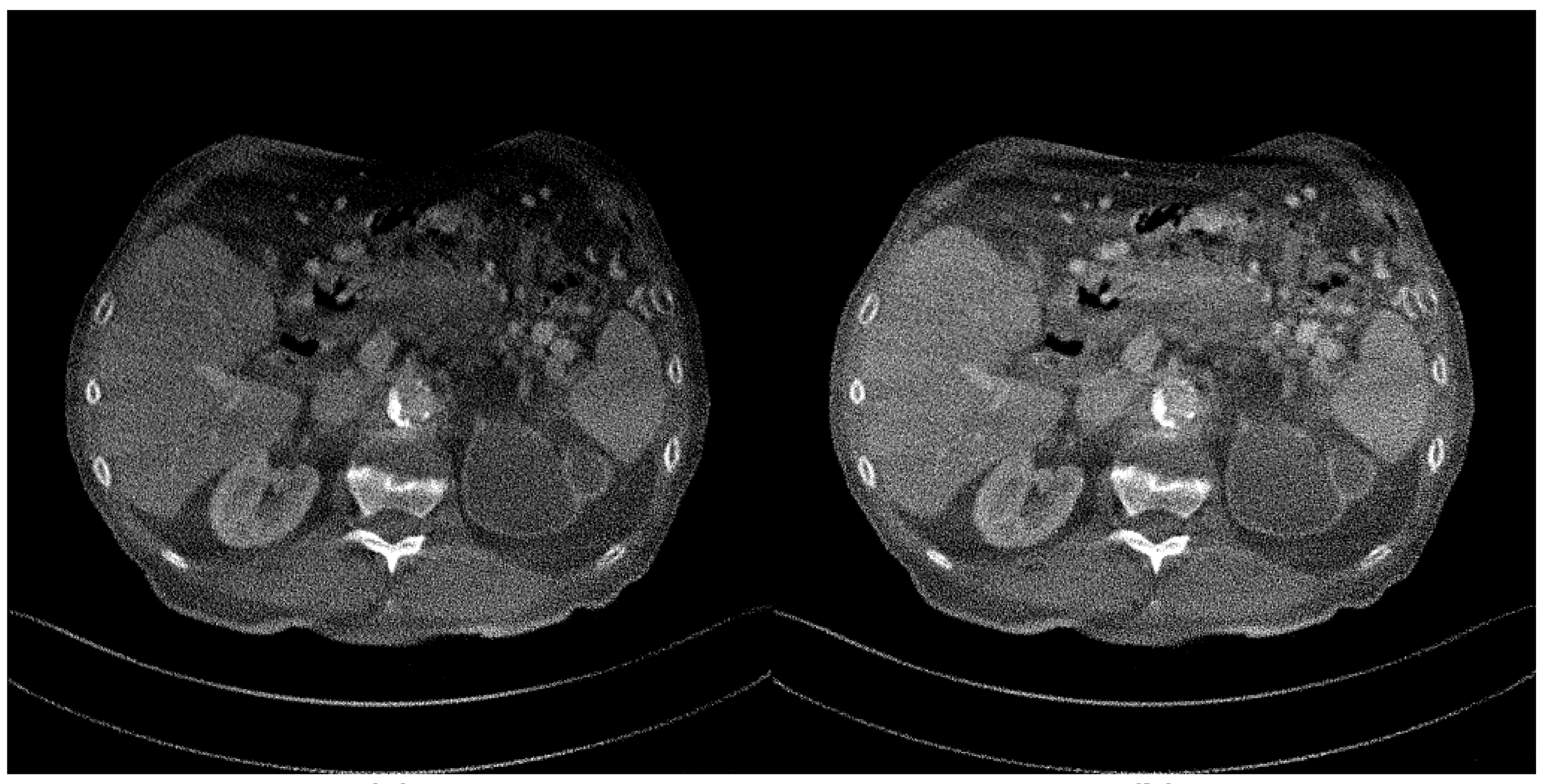


Figure 4: Compensation weights can be learned to compensate for missing data. Benefits are the increased robustness and interpretability by design.

Precision learning methods are less prone to disturbances like noise or different object appearance when compared to deep learning methods.



(a) (b)

Figure 5: Fig. 5a: Limited-angle reconstruction with simulated noise; Fig. 5b: Reconstruction using the learned compensation weights

Deriving an Architecture for Rebinning [5]

We can also hypothesize whole algorithms and learn unknown elements.

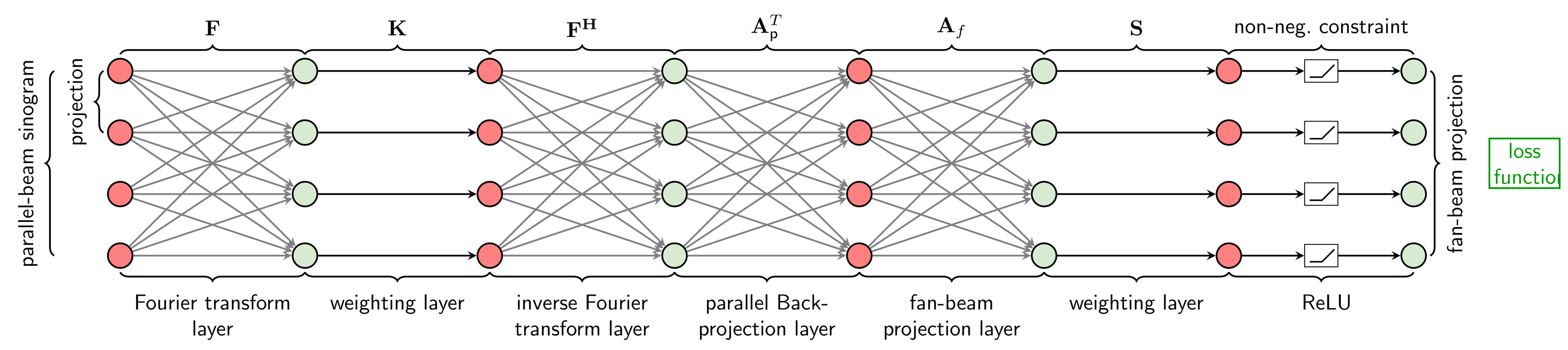


Figure 6: Parallel-beam to fan-beam projection rebinning can be formulated as an efficient convolution-based solution, with a filter learned in a data-driven manner

Learned filters produce sharper images faster than classical algorithms.

References

[1] A. Maier, F. Schebesch, C. Syben, T. Würfl, S. Steidl, J.-H. Choi, and R. Fahrig, "Precision Learning: Towards Use of Known Operators in Neural Networks,"

[2] T. Würfl, F. C. Ghesu, V. Christlein, and A. Maier, "Deep learning computed tomography,"

[3] Y. Huang, T. Würfl, K. Breininger, L. Liu, G. Lauritsch, and A. Maier, "Some investigations on robustness of deep learning in limited angle tomography,"

[4] T. Würfl, M. Hoffmann, V. Christlein, K. Breininger, Y. Huang, M. Unberath, and A. K. Maier, "Deep learning computed tomography: Learning projection-domain weights from image domain in limited angle problems," *IEEE transactions on medical imaging.*

[5] C. Syben, B. Stimpel, J. Lommen, T. Würfl, A. Dörfler, and A. Maier, "Deriving neural network architectures using precision learning: Parallel-to-fan beam conversion,"

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