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## Deep learning for tomographic reconstruction with limited data

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# Stellingen

Stellingen behorend bij het proefschrift getiteld “*Deep learning for tomographic reconstruction with limited data*”.

1. In practice, an X-ray tomography acquisition of just a single object can be sufficient to train a useful deep learning-based reconstruction method (Chapter 2).
2. Understanding the noise model at least qualitatively is essential for the self-supervised training of deep neural networks for denoising tasks (Chapter 3).
3. When measurement noise is the only obstacle to accurate tomographic reconstruction, then the presented self-supervised training techniques obviate the need for collecting low noise training data (Chapters 3 and 4).
4. The improvements in image quality that deep learning-based reconstruction algorithms can achieve on slightly improperly aligned tomographic data is dwarfed by the improvements that can be gained by proper geometric alignment (Chapters 2 and 5).
5. Self-supervised deep learning strategies benefit from the emergence of particle-counting detectors, because the counts can be separated into multiple uncorrelated measurements (Bepler et al, 2020, Nature Communications).
6. Standardized metrics calculation code, such as provided by the LoDoPaB-CT dataset (Leuschner et al, 2021, Scientific Data), can be further improved by calculating separate metrics for the foreground and background, exposing quality improvements that primarily affect empty regions of the reconstruction.
7. Signal processing techniques have the potential to improve the design of convolutional neural networks, restoring translation-equivariance by preventing aliasing (Zhang, 2019, ICML) and retaining high-frequency details using wavelet-based approaches (Han et al, 2018, IEEE TMI; Pan et al, 2018, CVPR).
8. Disregarding physical, mathematical, and computational considerations is unlikely to result in effective deep learning-based reconstruction algorithms (Zhu et al, 2018, Nature; Maier et al, 2019, Nature Machine Intelligence).
9. A powerful strategy to distract from tangible downsides of a proposal is by stressing another spurious disadvantage, especially when the latter implicitly suggests the successfulness of the proposal.
10. In deep learning research, the scientific method could be more stringently applied, specifically by changing exactly one factor at a time.

Allard A. Hendriksen,  
Leiden, Thursday March 3, 2022.