DeepInverse: A Python package for solving imaging inverse problems with deep learning

Julián Tachella [1¶], Matthieu Terris [2*], Samuel Hurault [3*], Andrew Wang [4*], Leo Davy [1], Jérémy Scanvic [1], Victor Sechaud [1], Romain Vo [1], Thomas Moreau [2], Thomas Davies [4,5], Dongdong Chen [5], Nils Laurent [6], Brayan Monroy [6], Jonathan Dong [7], Zhiyuan Hu [7], Minh-Hai Nguyen [8], Florian Sarron [8], Pierre Weiss [8], Paul Escande [9], Mathurin Massias [10], Thibaut Modrzyk [11], Brett Levac [12], Tobías I. Liaudat [13], Maxime Song [14], Johannes Hertrich [15], Sebastian Neumayer [16], and Georg Schramm [17]

1 CNRS, ENS de Lyon, France **2** Université Paris-Saclay, Inria, CEA, Palaiseau, France **3** CNRS, ENS Paris, PSL, France **4** University of Edinburgh, UK **5** Heriot-Watt University, Edinburgh, UK **6** Universidad Industrial de Santander, Bucaramanga, Colombia **7** EPFL, Lausanne, Switzerland **8** IRIT, CBI, CNRS, Université de Toulouse, France **9** IMT, CNRS, Université de Toulouse, France **10** Inria, ENS de Lyon, France **11** INSA de Lyon, France **12** University of Texas at Austin, USA **13** IRFU, CEA, Université Paris-Saclay, Gif-sur-Yvette, France **14** CNRS UAR 851, Université Paris-Saclay Orsay, France **15** Université Paris Dauphine - PSL, Paris, France **16** Chemnitz University of Technology, Chemnitz, Germany **17** Department of Imaging and Pathology, KU Leuven, Belgium ¶ Corresponding author * These authors contributed equally.

DOI: 10.21105/joss.08923

Software

- Review
- Repository
- Archive

Editor: Vissarion Fisikopoulos

Reviewers:

- @ScepticalRabbit
- @HectorMozo3110

Submitted: 26 May 2025
Published: 19 November 2025

Summary

DeepInverse is an open-source PyTorch-based library for imaging inverse problems. DeepInverse implements all steps for image reconstruction, including efficient forward operators, defining and solving variational problems and designing and training advanced neural networks, for a wide set of domains (medical imaging, astronomical imaging, remote sensing, computational photography, compressed sensing and more).

Statement of Need

Deep neural networks have become ubiquitous in various imaging inverse problems. Despite the ever-increasing research effort, most learning-based algorithms are built from scratch, are hard to generalize beyond their specific training setting, and the reported results are often hard to reproduce. DeepInverse overcomes these limitations by providing a modular unified framework, leveraging the popular PyTorch deep learning library (Paszke et al., 2019). For our audience of researchers (experts in optimization, deep learning etc.), practitioners (biologists, physicists etc.) and imaging software engineers, DeepInverse is:

1. **Accelerating research** by enabling efficient testing, deployment and transfer of new ideas across imaging domains;
2. Enlarging the **adoption of deep learning in inverse problems** by lowering the entrance bar to new users;
3. Enhancing **research reproducibility** via a common modular framework of problems and algorithms.

To the best of our knowledge, DeepInverse is the only library with a strong focus on and a wide set of modern learning-based methods across domains. SCICO (Balke et al., 2022) and Pyxu (Simeoni et al., 2024) focus on optimization-based methods. CUQIpy (Riis et al., 2024) focuses on Bayesian uncertainty quantification. ASTRA (Van Aarle et al., 2016), pytomography (Polson et al., 2025), TIGRE (Biguri et al., 2025), ODL (Adler et al., 2018) and CIL (Jørgensen et al., 2021) focus on tomography, sigpy (Ong & Lustig, 2019) on magnetic resonance imaging, and PyLops (Ravasi & Vasconcelos, 2019) on certain linear operators. MATLAB libraries (Gazzola et al., 2019; Soubies et al., 2019) are restricted to handcrafted methods without automatic differentiation.

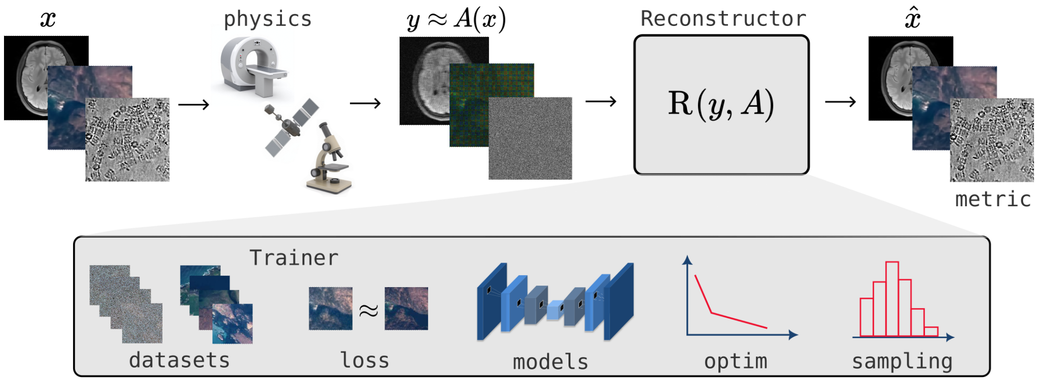

Figure 1: Schematic of the modular DeepInverse framework.

Inverse Problems

Imaging inverse problems can be expressed as

$$y = N_\sigma(A_\xi(x)), \tag{1}$$

where $x \in \mathcal{X}$ is an image, $y \in \mathcal{Y}$ are the measurements, $A_\xi \colon \mathcal{X} \mapsto \mathcal{Y}$ is a deterministic (linear or non-linear) operator capturing the physics of the acquisition and $N_\sigma \colon \mathcal{Y} \mapsto \mathcal{Y}$ is a noise model parameterized by σ. The physics module provides a scalable and modular framework, writing the forward operation as `y = physics(x, **params)`, unifying the wide variety of forward operators across various domains.

The library crucially introduces optional physics `params` (ξ, σ), allowing for advanced problems, including calibration, blind inverse problems (Chung, Kim, Kim, et al., 2023; Debarnot & Weiss, 2024), co-design (Lazarus et al., 2019; Nehme et al., 2020), and robust training (Gossard & Weiss, 2024; Terris & Moreau, 2023).

The current implemented physics, noise models, parameters ξ and tools for manipulating them are enumerated in the documentation.

Reconstruction Methods

DeepInverse unifies the wide variety of commonly-used imaging solvers in the literature, written as:

$$\hat{x} = \mathrm{R}_\theta(y, A_\xi, \sigma) \tag{2}$$

where R_θ is a reconstruction algorithm with optional trainable parameters θ and $\hat{x}$ is the reconstructed image, written as `x_hat = model(y, physics)`. The current library of algorithms is enumerated in the documentation, categorized as:

- **Optimization-based** methods (Chambolle & Pock, 2016) solve

$$\mathrm{R}_\theta(y, A_\xi, \sigma) \in \underset{x}{\operatorname{argmin}} f_\sigma(y, A_\xi(x)) + g(x). \tag{3}$$

The optim module implements classical data fidelity terms $f_\sigma\colon \mathcal{Y}\times\mathcal{Y}\mapsto\mathbb{R}$ and a variety of regularization priors $g\colon \mathcal{X}\mapsto\mathbb{R}$, including:

- Traditional explicit priors (Candès & Wakin, 2008);
- Learned regularizers (Altekrüger et al., 2023; Zoran & Weiss, 2011);
- Plug-and-Play priors (Venkatakrishnan et al., 2013) using a pretrained denoiser D_σ (K. Zhang et al., 2021).

To solve these problems, `optim` includes:

- Classical algorithms (Dossal et al., 2024);
- Unfolded networks (Gregor & LeCun, 2010), that unroll a fixed number of iterations of an optimization algorithm and train the parameters end-to-end;
- Deep equilibrium methods (Bai et al., 2019) that implicitly differentiate the fixed point of the algorithm.

- **Sampling-based** methods defined by differential equations:

$$x_{t+1}\sim p(x_{t+1}|x_t,y,\mathrm{D}_\sigma,A_\xi,\sigma)\text{ for }t=0,\dots,T-1, \tag{4}$$

such that x_T is approximately sampled from the posterior $p(x|y)$. Sampling multiple times enables uncertainty quantification.

The sampling module implements generalized, modular frameworks for:

- Diffusion model posterior sampling (Chung, Kim, Mccann, et al., 2023; Kawar et al., 2022; Zhu et al., 2023);
- Langevin-type algorithms (Laumont et al., 2022; Pereyra et al., 2020) that sample using Markov Chain Monte Carlo.

- **Non-iterative**: The models module implements:
  - Artifact removal models $\mathrm{R}_\theta(y,A_\xi,\sigma)=\mathrm{D}_\sigma(A_\xi^\top y)$, which simply backproject y to the image domain and apply an image-to-image denoiser D_σ (Jin et al., 2017);
  - Conditional/unconditional generative networks (Bendel et al., 2023; Bora et al., 2018; Ulyanov et al., 2018) that add a latent z to a generator $\mathrm{R}_\theta(y,z)\colon \mathcal{Y}\times\mathcal{Z}\mapsto\mathcal{X}$;
  - Foundation models (Terris et al., 2025), trained end-to-end across a wide variety of (A_ξ,N_σ), and can be finetuned to new problems.

Training

Reconstruction networks R_θ can be trained using the modular Trainer class.

Losses

The loss module framework unifies training loss functions that are widely used across various domains. Losses are written as `loss(x_hat, x, y, physics, model)` and are enumerated in the documentation:

- Supervised loss between x and y;
- Self-supervised losses which only use y (Wang & Davies, 2025; Yaman et al., 2020);
- Network regularization losses (Pesquet et al., 2021);
- Adversarial losses (Bora et al., 2017, 2018).

The transform module implements geometric image transforms for data augmentation and equivariance (Chen et al., 2023; Wang & Davies, 2024).

Datasets

The `datasets` module implements a variety of domain-specific datasets that return ground-truth and measurements pairs $\{(x_i, y_i)\}_{i=1}^N$ and optional parameters ξ_i, and allows simulating paired datasets given $\{x_i\}_{i=1}^N$ and physics A_{ξ_i}.

Evaluation

The `metric` module provides metrics for evaluating reconstruction methods. These are written as `m = metric(x_hat, x)` (full-reference), or `m = metric(x_hat)` (no-reference) (Yeganeh & Wang, 2012), including distortion (R. Zhang et al., 2018) and perceptual (Blau & Michaeli, 2018) metrics.

Documentation, Testing, and Coding Practices

The library provides a **user guide**, which also serves as a tutorial on computational imaging, quickstart and in-depth **examples** for all levels of user, and individual API documentation for classes. The documentation is generated using Sphinx and Sphinx-Gallery (Najera et al., 2023), tested using `doctest`, and uses consistent mathematical notation throughout. DeepInverse is written in Python following modern test-driven practices, see contributing guidelines for more information.

Research Use

DeepInverse has been used in various recent computational imaging works, including self-supervised learning (Tachella et al., 2025; Wang & Davies, 2024), plug-and-play methods (Park et al., 2025; Terris et al., 2024), foundation models (Terris et al., 2025), phase-retrieval (Hu et al., 2025), uncertainty quantification (Tachella & Pereyra, 2024) and benchmarking (Wang & Davies, 2025).

Perspectives

DeepInverse is a dynamic and evolving project and this paper is merely a snapshot of ongoing progress. The community is continuously contributing more methods reflecting state-of-the-art in imaging with deep learning, addressing the needs and interests of researchers and practitioners.

Acknowledgements

J. Tachella acknowledges support by the French ANR grant UNLIP (ANR-23-CE23-0013) and the CNRS PNRIA DeepInverse project. M. Terris acknowledges support by the BrAIN grant (ANR-20-CHIA-0016). F. Sarron, P. Weiss, M.H. Nguyen were supported by ANR Micro-Blind ANR-21-CE48-0008. T. Moreau was supported by the ExaDoST project under NumPEx PEPR (ANR-22-EXNU-0004). J. Hertrich is supported by DFG (project 530824055). Z. Hu acknowledges funding from the Swiss National Science Foundation (grant PZ00P2_216211). T. Davies is supported by UKRI EPSRC (grants EP/V006134/1, EP/V006177/1). S. Neumayer acknowledges funding from DFG (project 543939932). We thank the BASP Laboratory at Heriot-Watt University for insightful discussions and contributions to the radioastronomy application. The authors acknowledge the Jean-Zay HPC (GENCI-IDRIS grants 2021-AD011012210, 2024-AD011015191).

References

Adler, J., Kohr, H., Ringh, A., Moosmann, J., sbanert, Ehrhardt, M. J., Lee, G. R., niinimaki, bgris, Verdier, O., Karlsson, J., zickert, Palenstijn, W. J., Öktem, O., Chen, C., Loarca, H. A., & Lohmann, M. (2018). *Odlgroup/odl: ODL 0.7.0* (Version v0.7.0). Zenodo. https://doi.org/10.5281/zenodo.1442734

Altekrüger, F., Denker, A., Hagemann, P., Hertrich, J., Maass, P., & Steidl, G. (2023). PatchNR: Learning from very few images by patch normalizing flow regularization. *Inverse Problems*, *39*(6), 064006. https://doi.org/10.1088/1361-6420/acce5e

Bai, S., Kolter, J. Z., & Koltun, V. (2019). Deep equilibrium models. *Advances in Neural Information Processing Systems*, *32*. https://doi.org/10.48550/arXiv.1909.01377

Balke, T., Davis, F., Garcia-Cardona, C., Majee, S., McCann, M., Pfister, L., & Wohlberg, B. (2022). Scientific computational imaging code (SCICO). *Journal of Open Source Software*, *7*(78), 4722. https://doi.org/10.21105/joss.04722

Bendel, M., Ahmad, R., & Schniter, P. (2023). A regularized conditional GAN for posterior sampling in image recovery problems. In A. Oh, T. Naumann, A. Globerson, K. Saenko, M. Hardt, & S. Levine (Eds.), *Advances in neural information processing systems* (Vol. 36, pp. 68673–68684). Curran Associates, Inc. https://doi.org/10.48550/arXiv.2210.13389

Biguri, A., Sadakane, T., Lindroos, R., Liu, Y., Landman, M. S., Du, Y., Lohvithee, M., Kaser, S., Hatamikia, S., Bryll, R., & others. (2025). TIGRE v3: Efficient and easy to use iterative computed tomographic reconstruction toolbox for real datasets. *Engineering Research Express*, *7*(1), 015011. https://doi.org/10.1088/2631-8695/adbb3a

Blau, Y., & Michaeli, T. (2018). The perception-distortion tradeoff. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 6228–6237. https://doi.org/10.1109/CVPR.2018.00652

Bora, A., Jalal, A., Price, E., & Dimakis, A. G. (2017). Compressed sensing using generative models. *International Conference on Machine Learning*, 537–546. https://doi.org/10.48550/arXiv.1703.03208

Bora, A., Price, E., & Dimakis, A. G. (2018). AmbientGAN: Generative models from lossy measurements. *International Conference on Learning Representations*. https://openreview.net/forum?id=Hy7fDog0b

Candès, E. J., & Wakin, M. B. (2008). An introduction to compressive sampling. *IEEE Signal Processing Magazine*, *25*(2), 21–30. https://doi.org/10.1109/MSP.2007.914731

Chambolle, A., & Pock, T. (2016). An introduction to continuous optimization for imaging. *Acta Numerica*, *25*, 161–319. https://doi.org/10.1017/s096249291600009x

Chen, D., Davies, M., Ehrhardt, M. J., Schönlieb, C.-B., Sherry, F., & Tachella, J. (2023). Imaging With Equivariant Deep Learning: From unrolled network design to fully unsupervised learning. *IEEE Signal Processing Magazine*, *40*, 134–147. https://doi.org/10.1109/MSP.2022.3205430

Chung, H., Kim, J., Kim, S., & Ye, J. C. (2023). Parallel diffusion models of operator and image for blind inverse problems. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 6059–6069. https://doi.org/10.1109/cvpr52729.2023.00587

Chung, H., Kim, J., Mccann, M. T., Klasky, M. L., & Ye, J. C. (2023). Diffusion posterior sampling for general noisy inverse problems. *The Eleventh International Conference on Learning Representations*. https://doi.org/10.48550/arXiv.2209.14687

Debarnot, V., & Weiss, P. (2024). Deep-blur: Blind identification and deblurring with convolutional neural networks. *Biological Imaging*, *4*, e13. https://doi.org/10.1017/s2633903x24000096

Dossal, C., Hurault, S., & Papadakis, N. (2024). Optimization with first order algorithms. *arXiv Preprint arXiv:2410.19506*. https://doi.org/10.48550/arXiv.2410.19506

Gazzola, S., Hansen, P. C., & Nagy, J. G. (2019). IR tools: A MATLAB package of iterative regularization methods and large-scale test problems. *Numerical Algorithms*, *81*(3), 773–811. https://doi.org/10.1007/s11075-018-0570-7

Gossard, A., & Weiss, P. (2024). Training adaptive reconstruction networks for blind inverse problems. *SIAM Journal on Imaging Sciences*, *17*(2), 1314–1346. https://doi.org/10.1137/23m1545628

Gregor, K., & LeCun, Y. (2010). Learning fast approximations of sparse coding. *Proceedings of the 27th International Conference on International Conference on Machine Learning*, 399–406. https://dl.acm.org/doi/10.5555/3104322.3104374

Hu, Z., Tachella, J., Unser, M., & Dong, J. (2025). Structured random model for fast and robust phase retrieval. *ICASSP 2025-2025 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 1–5. https://doi.org/10.1109/ICASSP49660.2025.10889235

Jin, K. H., McCann, M. T., Froustey, E., & Unser, M. (2017). Deep convolutional neural network for inverse problems in imaging. *IEEE Transactions on Image Processing*, *26*(9), 4509–4522. https://doi.org/10.1109/TIP.2017.2713099

Jørgensen, J. S., Ametova, E., Burca, G., Fardell, G., Papoutsellis, E., Pasca, E., Thielemans, K., Turner, M., Warr, R., Lionheart, W. R., & others. (2021). Core Imaging Library-part I: A versatile Python framework for tomographic imaging. *Philosophical Transactions of the Royal Society A*, *379*(2204), 20200192. https://doi.org/10.1098/rsta.2020.0192

Kawar, B., Elad, M., Ermon, S., & Song, J. (2022). Denoising diffusion restoration models. *Advances in Neural Information Processing Systems*, *35*, 23593–23606. https://doi.org/10.48550/arXiv.2201.11793

Laumont, R., Bortoli, V. D., Almansa, A., Delon, J., Durmus, A., & Pereyra, M. (2022). Bayesian imaging using plug & play priors: When Langevin meets Tweedie. *SIAM Journal on Imaging Sciences*, *15*(2), 701–737. https://doi.org/10.1137/21M1406349

Lazarus, C., Weiss, P., Chauffert, N., Mauconduit, F., El Gueddari, L., Destrieux, C., Zemmoura, I., Vignaud, A., & Ciuciu, P. (2019). SPARKLING: Variable-density k-space filling curves for accelerated T2*-weighted MRI. *Magnetic Resonance in Medicine*, *81*(6), 3643–3661. https://doi.org/10.1002/mrm.27678

Najera, O., Larson, E., Liu, L., Esteve, L., Varoquaux, G., Grobler, J., Andrade, E. S. de, Holdgraf, C., Gramfort, A., Jas, M., Nothman, J., Rehberg, S., Grisel, O., Varoquaux, N., Hiscocks, S., alexis, Gouillart, E., Hoffmann, T., Lee, A., … Kunzmann, P. (2023). *Sphinx-gallery/sphinx-gallery: v0.12.2* (Version v0.12.2). Zenodo. https://doi.org/10.5281/zenodo.7716999

Nehme, E., Freedman, D., Gordon, R., Ferdman, B., Weiss, L. E., Alalouf, O., Naor, T., Orange, R., Michaeli, T., & Shechtman, Y. (2020). DeepSTORM3D: Dense 3D localization microscopy and PSF design by deep learning. *Nature Methods*, *17*(7), 734–740. https://doi.org/10.1038/s41592-020-0853-5

Ong, F., & Lustig, M. (2019). *SigPy: A Python package for high performance iterative reconstruction*. ISMRM. https://archive.ismrm.org/2019/4819.html

Park, C. Y., Hu, Y., McCann, M. T., Garcia-Cardona, C., Wohlberg, B., & Kamilov, U. S. (2025). Plug-and-play priors as a score-based method. *2025 IEEE International Conference on Image Processing (ICIP)*, 49–54. https://doi.org/10.1109/ICIP55913.2025.11084503

Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., Killeen, T., Lin, Z., Gimelshein, N., Antiga, L., & others. (2019). PyTorch: An imperative style, high-performance deep learning library. *Advances in Neural Information Processing Systems*, *32*.

https://doi.org/10.48550/arXiv.1912.01703

Pereyra, M., Mieles, L. V., & Zygalakis, K. C. (2020). Accelerating proximal Markov Chain Monte Carlo by using an explicit stabilized method. *SIAM Journal on Imaging Sciences*, *13*(2), 905–935. https://doi.org/10.1137/19M1283719

Pesquet, J.-C., Repetti, A., Terris, M., & Wiaux, Y. (2021). Learning maximally monotone operators for image recovery. *SIAM Journal on Imaging Sciences*, *14*(3), 1206–1237. https://doi.org/10.1137/20m1387961

Polson, L. A., Fedrigo, R., Li, C., Sabouri, M., Dzikunu, O., Ahamed, S., Karakatsanis, N., Kurkowska, S., Sheikhzadeh, P., Esquinas, P., & others. (2025). Pytomography: A Python library for medical image reconstruction. *SoftwareX*, *29*, 102020. https://doi.org/10.2139/ssrn.4865134

Ravasi, M., & Vasconcelos, I. (2019). PyLops–a linear-operator Python library for large scale optimization. *arXiv Preprint arXiv:1907.12349*. https://doi.org/10.48550/arXiv.1907.12349

Riis, N. A., Alghamdi, A. M., Uribe, F., Christensen, S. L., Afkham, B. M., Hansen, P. C., & Jørgensen, J. S. (2024). CUQIpy: I. Computational uncertainty quantification for inverse problems in Python. *Inverse Problems*, *40*(4), 045009. https://doi.org/10.1088/1361-6420/ad22e7

Simeoni, M., Kashani, S., Rué-Queralt, J., & Developers, P. (2024). *Pyxu-org/pyxu: pyxu*. Zenodo. https://doi.org/10.5281/zenodo.4486431

Soubies, E., Soulez, F., McCann, M. T., Pham, T., Donati, L., Debarre, T., Sage, D., & Unser, M. (2019). Pocket guide to solve inverse problems with GlobalBioIm. *Inverse Problems*, *35*(10), 104006. https://doi.org/10.1088/1361-6420/ab2ae9

Tachella, J., Davies, M., & Jacques, L. (2025). UNSURE: Self-supervised learning with Unknown Noise level and Stein's Unbiased Risk Estimate. *International Conference on Learning Representations*. https://doi.org/10.48550/arXiv.2409.01985

Tachella, J., & Pereyra, M. (2024). Equivariant bootstrapping for uncertainty quantification in imaging inverse problems. *27th International Conference on Artificial Intelligence and Statistics 2024*, 4141–4149. https://doi.org/10.48550/arXiv.2310.11838

Terris, M., Hurault, S., Song, M., & Tachella, J. (2025). Reconstruct anything model: A lightweight foundation model for computational imaging. *arXiv Preprint arXiv:2503.08915*. https://doi.org/10.48550/arXiv.2503.08915

Terris, M., & Moreau, T. (2023). Meta-prior: Meta learning for adaptive inverse problem solvers. *arXiv Preprint arXiv:2311.18710*. https://doi.org/10.48550/arXiv.2311.18710

Terris, M., Moreau, T., Pustelnik, N., & Tachella, J. (2024). Equivariant plug-and-play image reconstruction. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 25255–25264. https://doi.org/10.1109/cvpr52733.2024.02386

Ulyanov, D., Vedaldi, A., & Lempitsky, V. (2018). Deep image prior. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 9446–9454. https://doi.org/10.1109/CVPR.2018.00984

Van Aarle, W., Palenstijn, W. J., Cant, J., Janssens, E., Bleichrodt, F., Dabravolski, A., De Beenhouwer, J., Joost Batenburg, K., & Sijbers, J. (2016). Fast and flexible x-ray tomography using the ASTRA toolbox. *Optics Express*, *24*(22), 25129–25147. https://doi.org/10.1364/oe.24.025129

Venkatakrishnan, S. V., Bouman, C. A., & Wohlberg, B. (2013). Plug-and-play priors for model based reconstruction. *2013 IEEE Global Conference on Signal and Information Processing*, 945–948. https://doi.org/10.1109/globalsip.2013.6737048

Wang, A., & Davies, M. (2024). Perspective-equivariance for unsupervised imaging with camera geometry. *IEEE/CVF European Conference on Computer Vision (ECCV) Workshop on Traditional Computer Vision in the Age of Deep Learning*. https://doi.org/10.1007/978-3-031-91585-7_8

Wang, A., & Davies, M. (2025). Benchmarking self-supervised methods for accelerated MRI reconstruction. *arXiv Preprint arXiv:2502.14009*. https://doi.org/10.48550/arXiv.2502.14009

Yaman, B., Hosseini, S. A. H., Moeller, S., Ellermann, J., Uğurbil, K., & Akçakaya, M. (2020). Self-supervised learning of physics-guided reconstruction neural networks without fully sampled reference data. *Magnetic Resonance in Medicine*, *84*(6), 3172–3191. https://doi.org/10.1002/mrm.28378

Yeganeh, H., & Wang, Z. (2012). Objective quality assessment of tone-mapped images. *IEEE Transactions on Image Processing*, *22*(2), 657–667. https://doi.org/10.1109/TIP.2012.2221725

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. https://doi.org/10.1109/TPAMI.2021.3088914

Zhang, R., Isola, P., Efros, A. A., Shechtman, E., & Wang, O. (2018). The unreasonable effectiveness of deep features as a perceptual metric. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 586–595. https://doi.org/10.1109/cvpr.2018.00068

Zhu, Y., Zhang, K., Liang, J., Cao, J., Wen, B., Timofte, R., & Van Gool, L. (2023). Denoising diffusion models for plug-and-play image restoration. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 1219–1229. https://doi.org/10.1109/cvprw59228.2023.00129

Zoran, D., & Weiss, Y. (2011). From learning models of natural image patches to whole image restoration. *2011 International Conference on Computer Vision*, 479–486. https://doi.org/10.1109/ICCV.2011.6126278