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

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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 (Soubies et al., 2019) (Gazzola et al., 2019) are restricted to handcrafted methods without automatic differentiation.

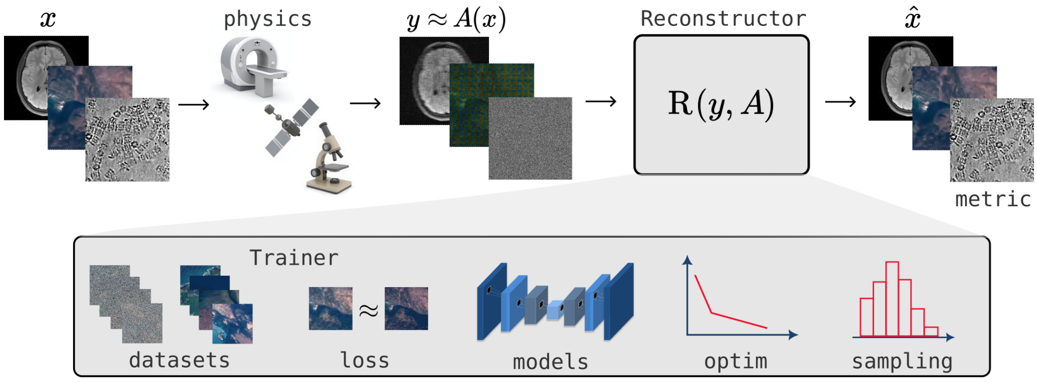

Figure 1: Schematic of the modular DeepInverse framework.

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 (Debarnot & Weiss, 2024) (Chung, Kim, Kim, et al., 2023), 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

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

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 (Zoran & Weiss, 2011) (Altekrüger et al., 2023);
- 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 (Bora et al., 2018) (Bendel et al., 2023) (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 (Yaman et al., 2020) (Wang & Davies, 2025);
- Network regularization losses (Pesquet et al., 2021);
- Adversarial losses (Bora et al., 2017) (Bora et al., 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 (Wang & Davies, 2024) (Tachella et al., 2025), plug-and-play methods (Terris et al., 2024) (Park et al., 2025), 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.

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