Intermediate Layer Optimization for Inverse Problems using Deep Generative Models

ICML 2021

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Introduction

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Motivation and Contributions

The central question that we want to address in this work is how to optimally use pre-trained generative models to solve inverse problems.

Contributions:

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- We theoretically analyze our framework by establishing sample complexity and error bounds.

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- We propose a novel optimization method, **Intermediate Layer Optimization** (**ILO**), for solving general inverse problems.
- We theoretically analyze our framework by establishing sample complexity and error bounds.
- We show experimentally significant improvements over previous state-of-the-art methods for solving inverse problems with pre-trained generators.

Problem Setup and Prior Work

Goal: Recover an unknown image x by observing some noisy measurements $\mathcal{A}(x) + \eta$. Prior work:

- CSGM [1]. Assume access to a pre-trained generator $G(z) : \mathbb{R}^k \to \mathbb{R}^n$. Use Gradient Descent to solve the following problem:

$$z^* = \min_{z \in \mathbb{R}^k} ||\mathcal{A}(G(z)) - \mathcal{A}(x)||. \tag{1}$$

- PULSE [2]. Improves upon CSGM by refining the latent space optimization and using the StyleGAN [3, 4] pretrained model. Excellent results for super-resolution.

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- Generations are constrained to a low-dimensional manifold of the output space.
- Pre-trained generators reflect or amplify dataset biases.
- Existing algorithms fail to achieve reconstruction of images that are outside of the training distribution.
- Previous state-of-the-art methods address each inverse problem separately, instead of providing a unified framework to solve all of them.

ILO (Algorithm)

We propose Intermediate Layer Optimization (ILO), a novel optimization algorithm that expands the range of the generator to solve general inverse problems. Our algorithm has the following key ideas:

- We split the generator G into multiple parts, i.e. $G = G_l \circ G_{l-1} \circ ... \circ G_2 \circ G_1$.

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- We optimize over the input space of G_1, we find a z^*, and we use $G_1(z^*)$ as an initialization for a new optimization problem in the input space of G_2.

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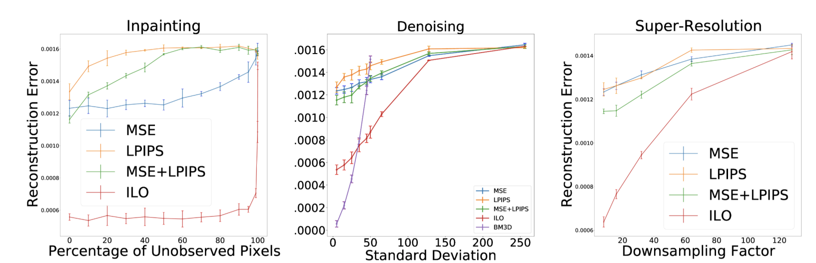
- We follow this idea to optimize over the input space of deeper layers, effectively expanding the range of the generator.
- To avoid overfitting to the measurements, we constrain the solutions of the optimization problem to an l_1 ball around the range of the previous layer.

Experiments (Visual Results)

Experiments (Qualitative Results)



Experiments (Out of distribution generation)

ILO (Theory)

Theorem

Let $G = G_2 \circ G_1$ with $G_1 : \mathbb{R}^k \to \mathbb{R}^p$ be an L_1-Lipschitz function and $G_2 : \mathbb{R}^p \to \mathbb{R}^n$ be an L_2-Lipschitz function. Let $A \in R^{m \times n}$ be the measurements matrix with $A_{ij} \sim \mathcal{N}(0, 1/m)$ i.i.d. entries.

Let K be a parameter of our choice where $K \leq \sqrt{p}$, and $r_2 = \frac{K\delta}{L_2}$. Consider the true optimum in the extended range

$$\bar{z}^p = \mathrm{argmin}_{z^p \in G_1(B_2^k(r_1)) \oplus B_1^p(r_2)} ||x - G_2(z^p)||, \tag{2}$$

and the measurements optimum in the extended range

$$\tilde{z}^p = \mathrm{argmin}_{z^p \in G_1(B_2^k(r_1)) \oplus B_1^p(r_2)} ||Ax - AG_2(z^p)||. \tag{3}$$

Then, if the number of measurements is sufficiently large:

$$m = \frac{1}{(1-\gamma)^2} \Omega \left(k \log \frac{L_1 L_2 r_1}{\delta} + K^2 \log p \right), \tag{4}$$

then with probability at least $1 - e^{-\Omega((1-\gamma)^2 \cdot m)}$, we have the following error bound:

$$||x - G_2(\tilde{z}^p)|| \leq \left(1 + \frac{4}{\gamma}\right) ||x - G_2(\bar{z}^p)|| + \delta \cdot \frac{\log(4K)}{\gamma} \cdot \frac{\sqrt{p}}{K} \log \frac{\sqrt{p}}{K}. \tag{5}$$

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