Score-Guided Intermediate Layer Optimization: Fast Langevin Mixing for Inverse Problems

Giannis Daras (*) Yuval Dagan (*) Alexandros Dimakis Constantinos Daskalakis

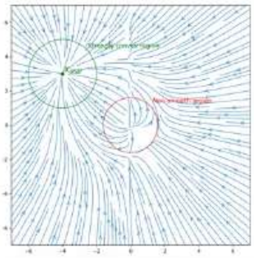



(*): equal contribution

Contributions of our work

▷ Solve inverse problems with extremely sparse measurements

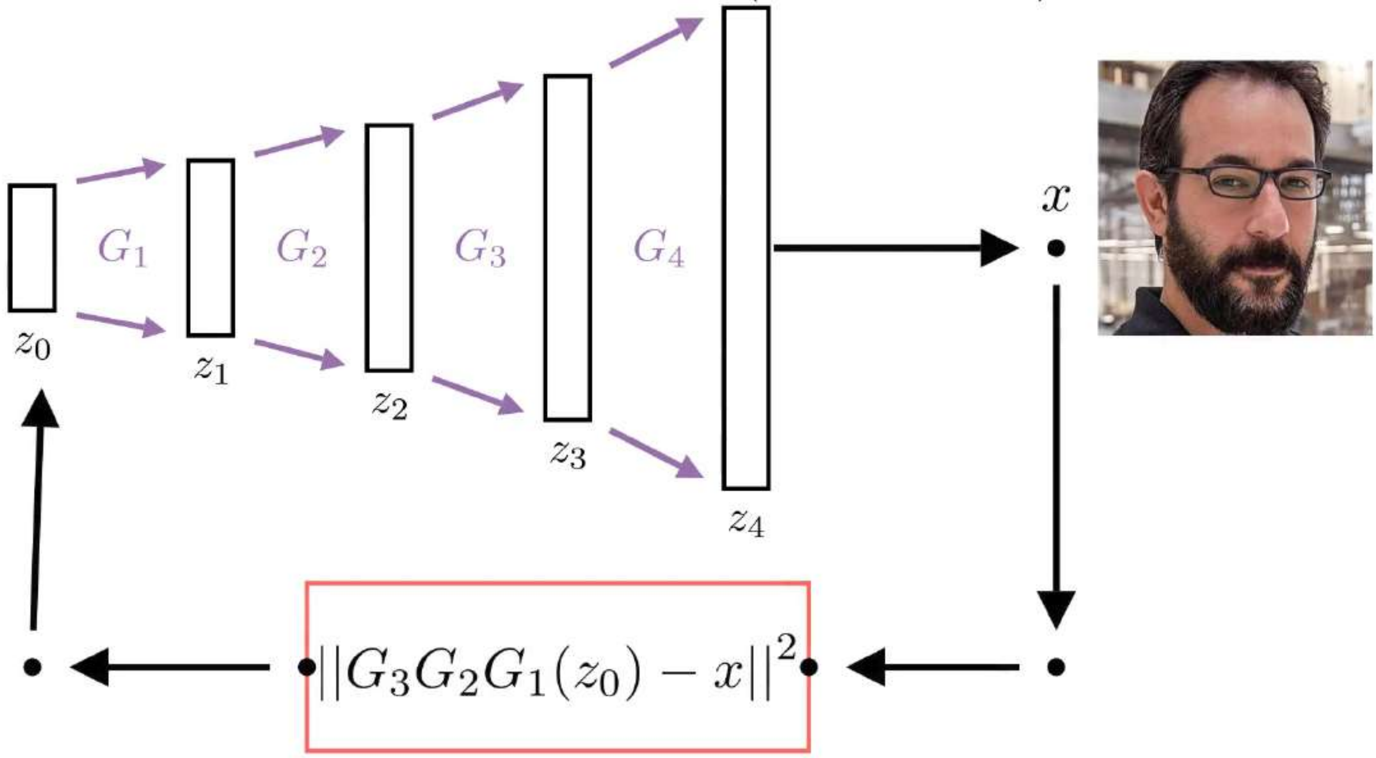
▷ Convergence of Langevin for Inverse Problems with generative models



▷ Posterior sampling with GANs

▷ GANs + Diffusion = ♡ for inverse problems

Prior work: CSGM (ICML 2017)



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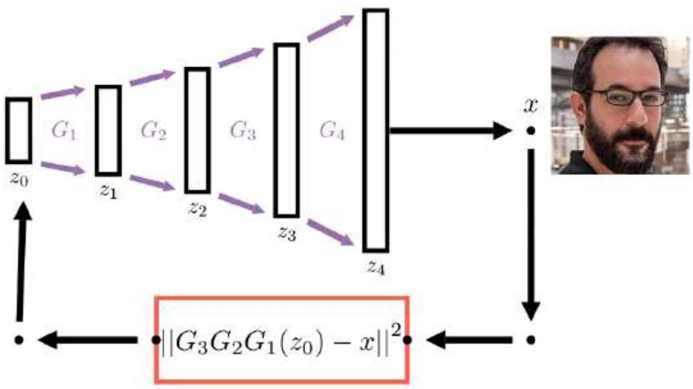
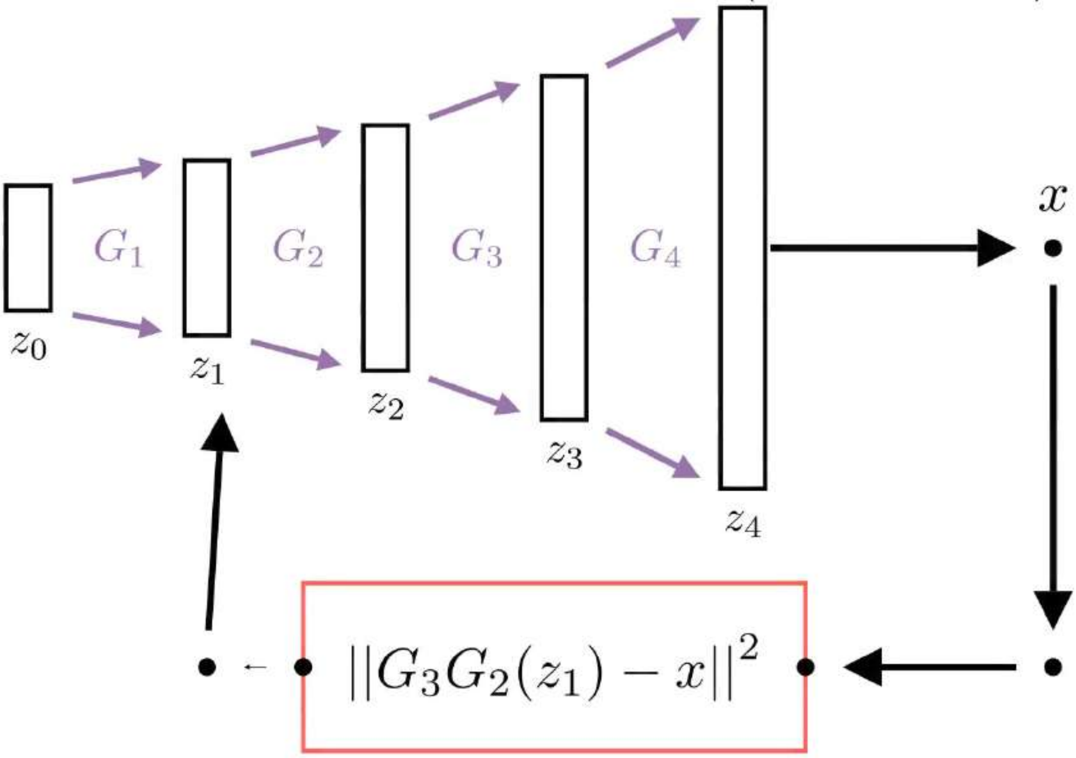


$G(z_0*)$

Prior work: CSGM (ICML 2017)



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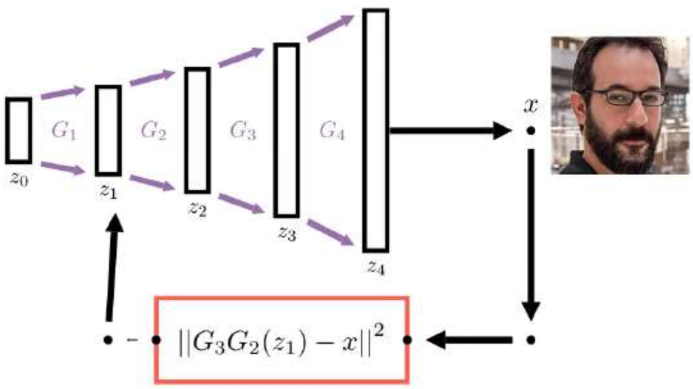
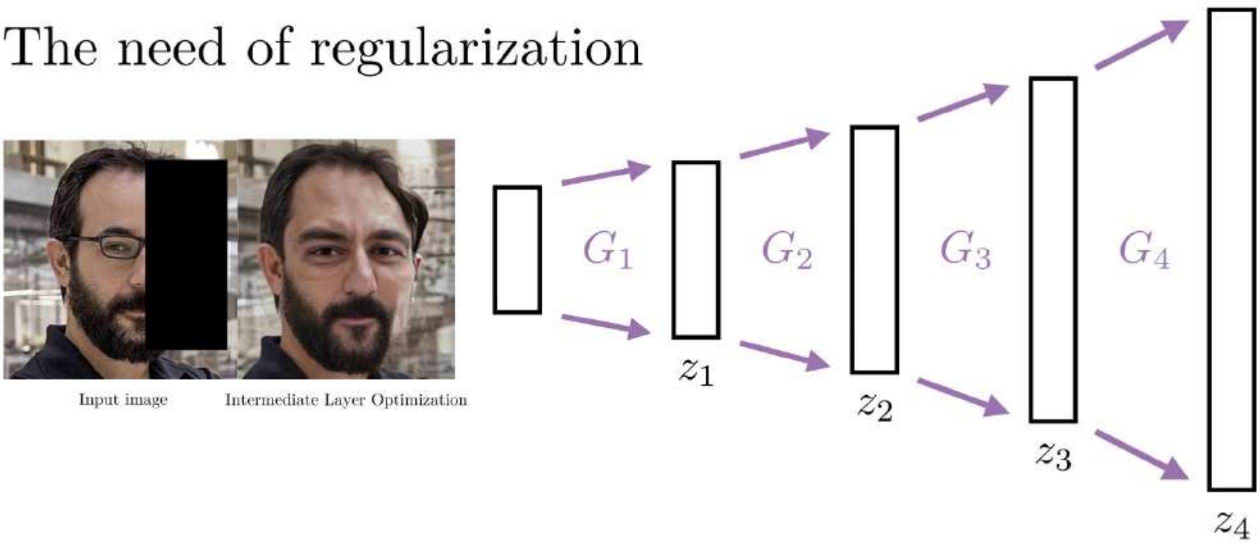


$G_3G_2(z_1*)$

The need of regularization

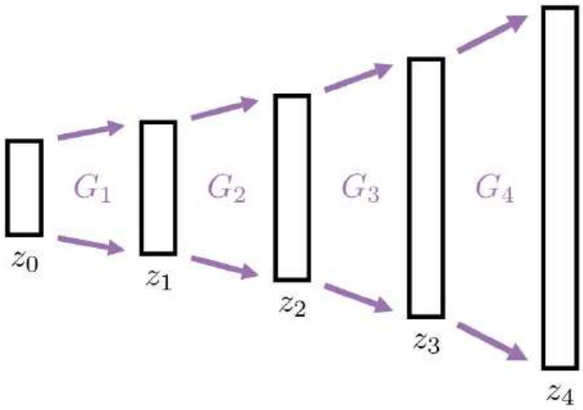
Input image Intermediate Layer Optimization

The need of regularization



$$\min_{z_1} ||G_3 G_2(z_1) - x||^2 + \underbrace{R(z_1)}_{\text{regularization}}$$

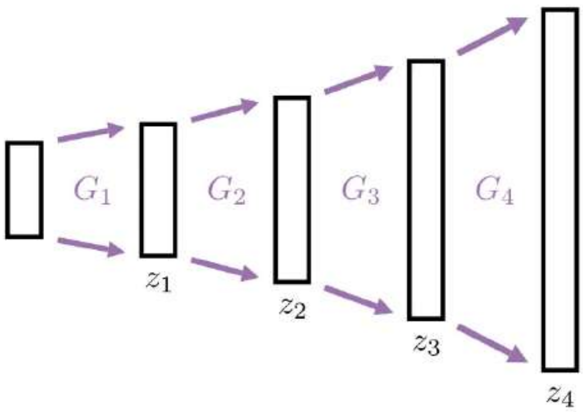
Prior work: Intermediate Layer Optimization (ICML 2021)



$\min_{z_1} ||G_3 G_2(z_1) - x||^2 + R(z_1)$

$R(z_1)$: close to the range of the previous layer.

Score-Guided Intermediate Layer Optimization (SGILO)



$$\text{ILO} : \min_{z_1} ||G_3 G_2(z_1) - x||^2 + \lambda \cdot D(\text{range}(G_1))$$

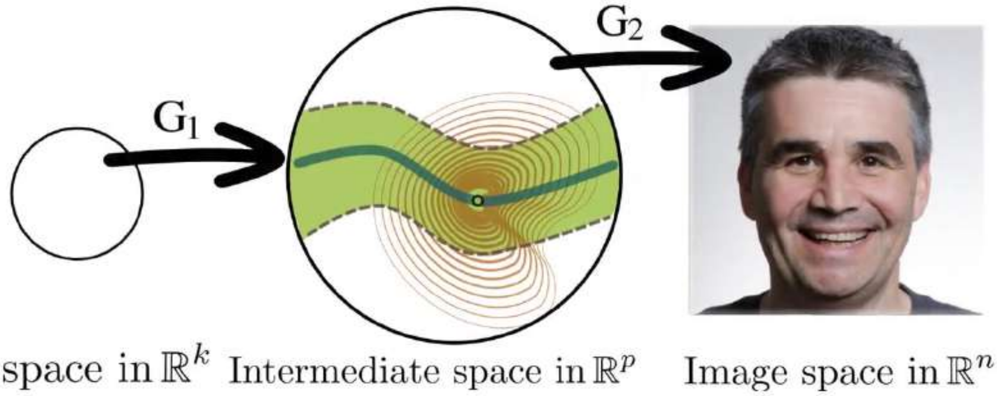
$$\text{SGILO} : \log p(z_1|x) \propto ||G_3 G_2(z_1) - x||^2 - \lambda \log p(z_1)$$

Changes:

1) From optimization to posterior sampling

2) Learned prior on latent space

Score-Guided Intermediate Layer Optimization (SGILO)



Changes:

1) From optimization to posterior sampling

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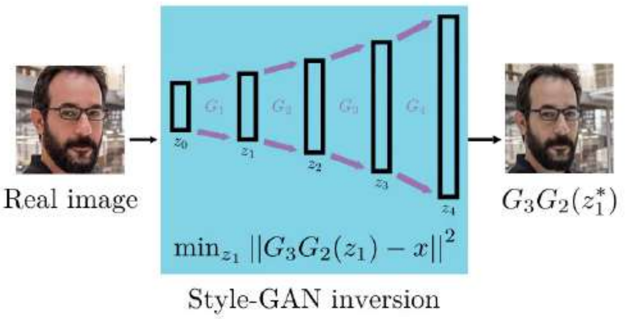
Method: Training Phase



Dataset : $\{z_1^{*,(1)}, z_1^{*,(2)}, ...\}$

We train a diffusion model to learn the distribution of StyleGAN-2 intermediate latents

Method: Sampling Phase

We want to:

1) match the measurements 2) Find a realistic latent 3) Be stochastic

Real image: x

Input image: Ax

$$z_1(t+1) = z_1(t) - \eta \left(\nabla_{z_1(t)} ||AG_3G_2(z_1(t)) - Ax||^2 - \lambda s_\theta(z_1(t)) \right) + \sqrt{2\eta\beta^{-1}} u$$

As $t \to \infty$, we will be sampling from

$$\exp(-\beta \left(||AG_3G_2(z_1(t)) - Ax||^2 - \lambda \log p_\theta(z_1) \right)$$

Convergence of Langevin Dynamics for random generators

▷ Hand and Voroniski (2018): GD (wht no prior) converges fast to the optimum **point** for solving inverse problems with random generators

▷ SGLD (with no prior) converges fast to the stationary **distribution** for solving inverse problems with random generators

Overview of the proof

▷ 0) Loss concentration.

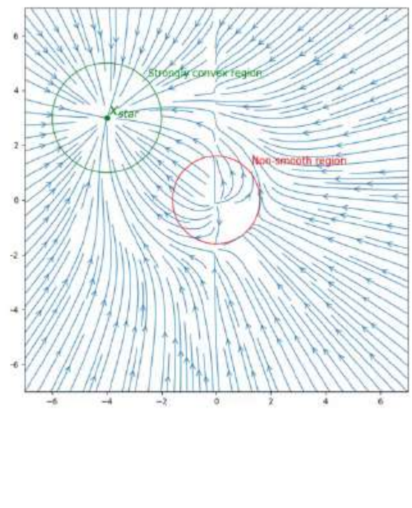
▷ 1) Closed expression for expected loss.

▷ 2) Analyze vector field of expected loss.

▷ 3) W.h.p. we avoid the bad region and we enter the strongly convex region.

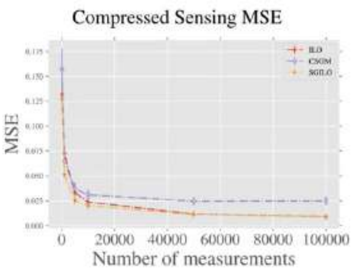
▷ 4) W.h.p. we don't escape the strongly convex region.

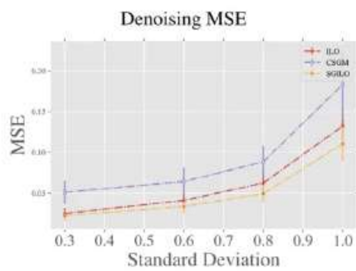
▷ 5) Discrete and continuous dynamics are close for strongly convex functions.



Results

▷ Superior performance to inverse problems, compared to ILO and CSGM





▷ Diverse reconstructions using posterior sampling

▷ Fast and flexible image prior