Implicit Diffusion: Efficient Optimization through Stochastic Sampling

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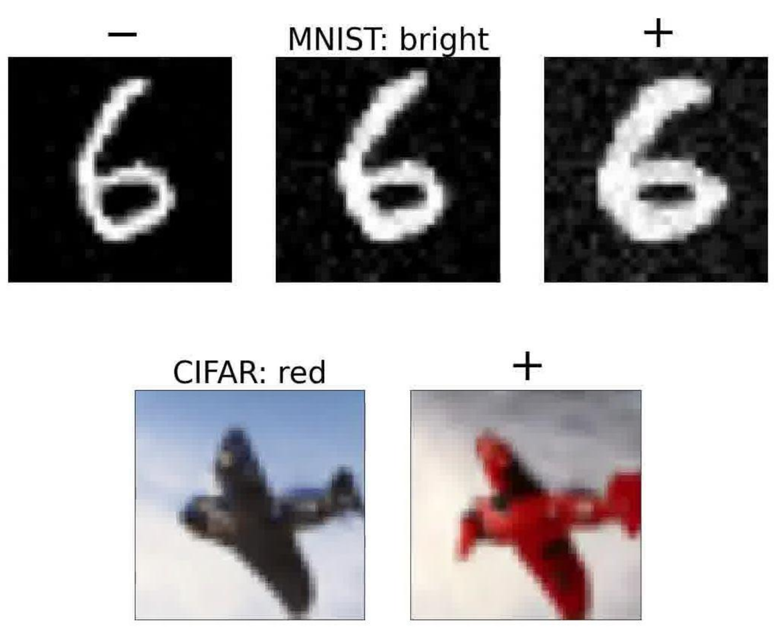
Introduction

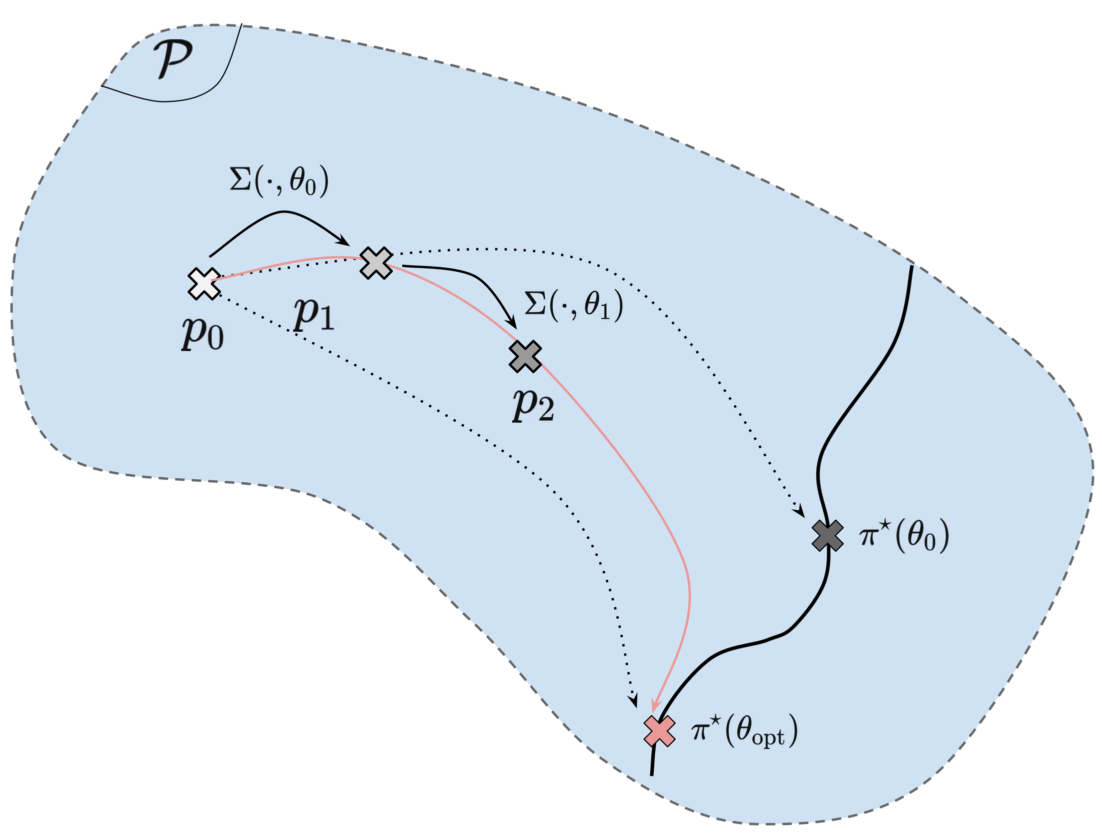
How can we optimize through sampling?:

Modify a sampling process to steer outcomes

Can be used to finetune generative models



Sampling / Optimization as bilevel optimization



Optimization - objective function defined on probabilities

$$\min_{\theta \in \mathbb{R}^p} \ell(\theta) := \mathcal{F}(\pi^\star(\theta))$$

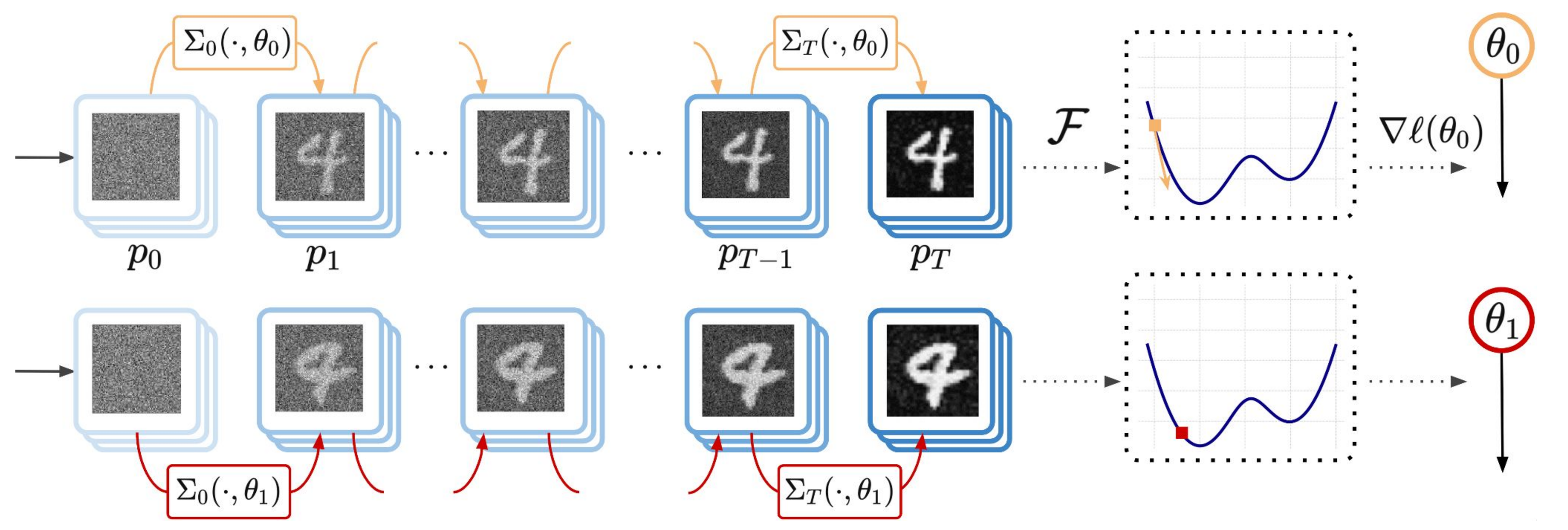
Example: regularized reward

$$\mathcal{F}(p) = -\lambda \mathbf{E}_{x\sim p}[R(x)] + \beta \mathrm{KL}(p \,||\, \pi^\star(\theta_0))$$

Method

First-order optimization on sampling

Example: Diffusion denoising with brightness reward



Challenges

No closed forms for outcome distributions

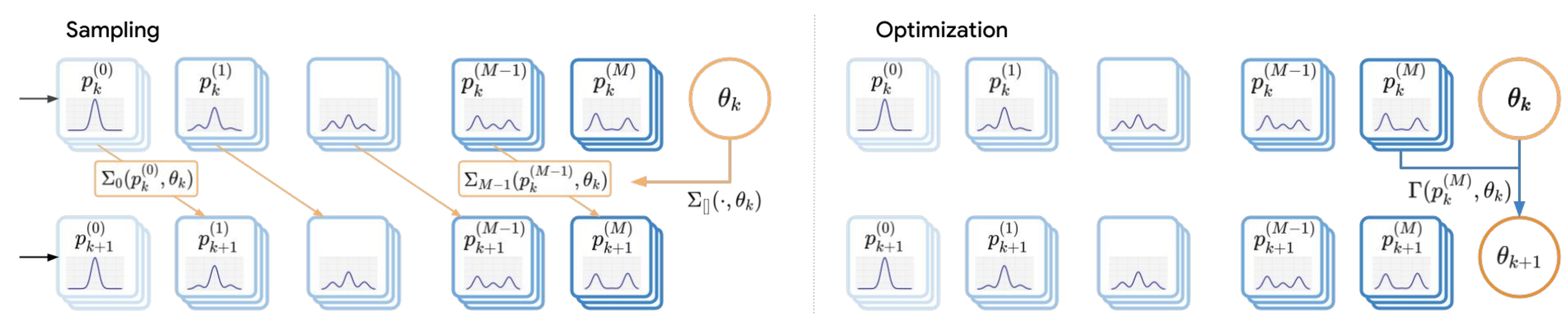
Methodology problem: how can we evaluate gradients?

Loss / Gradient evaluation require iterative sampling (nested loops)

Implicit Diffusion

Single loop algorithm - based on implicit differentiation

Inspired by literature on bilevel optimization



Algorithm 2 Implicit Diff. optimization, infinite time

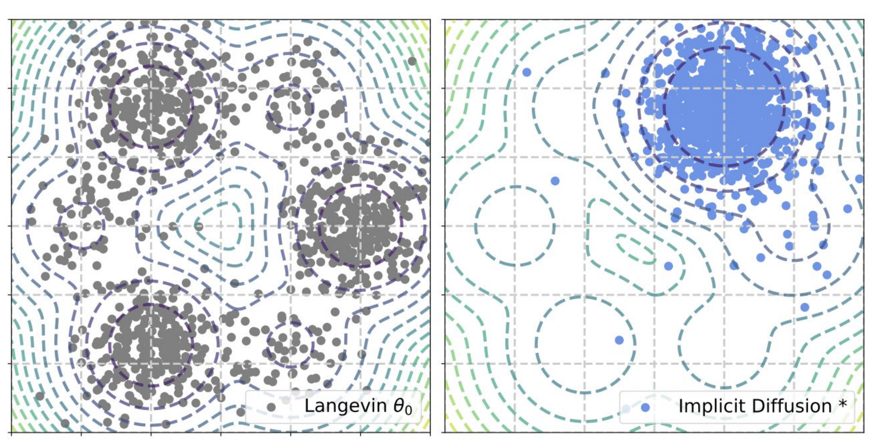
input $\theta_0 \in \mathbb{R}^p, p_0 \in \mathcal{P}$
for $k \in \{0, \dots, K-1\}$ (joint single loop) **do**
$p_{k+1} \leftarrow \Sigma_k(p_k, \theta_k)$
$\theta_{k+1} \leftarrow \theta_k - \eta \Gamma(p_k, \theta_k)$ (or another optimizer)
output θ_K

Langevin - EBM

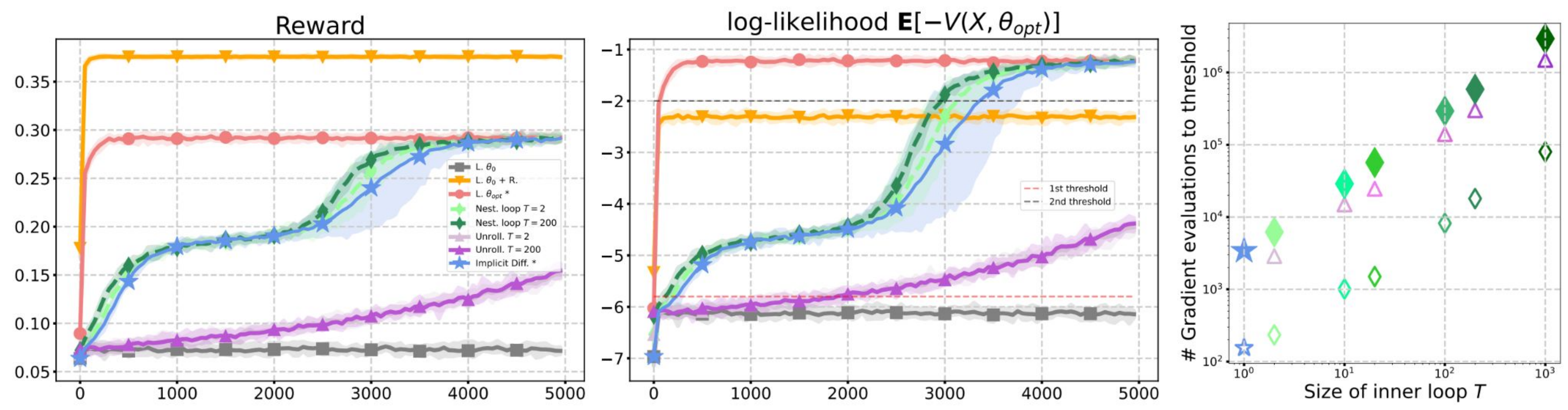
Energy-based models

Sampling with a Langevin diffusion

$\pi^\star(\theta) \propto \exp(-V(x, \theta))$



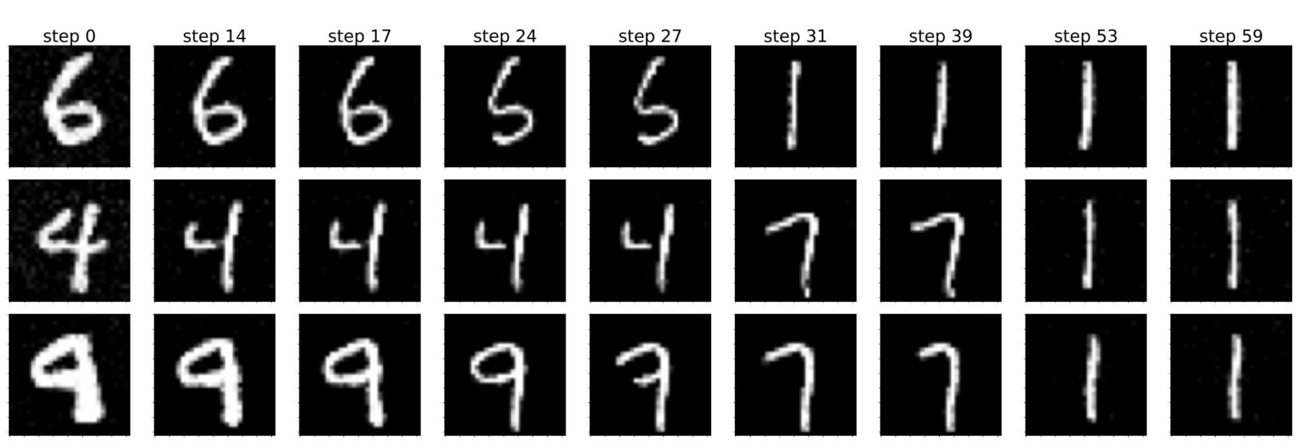
Comparison: Strong advantage of single-loop methods.

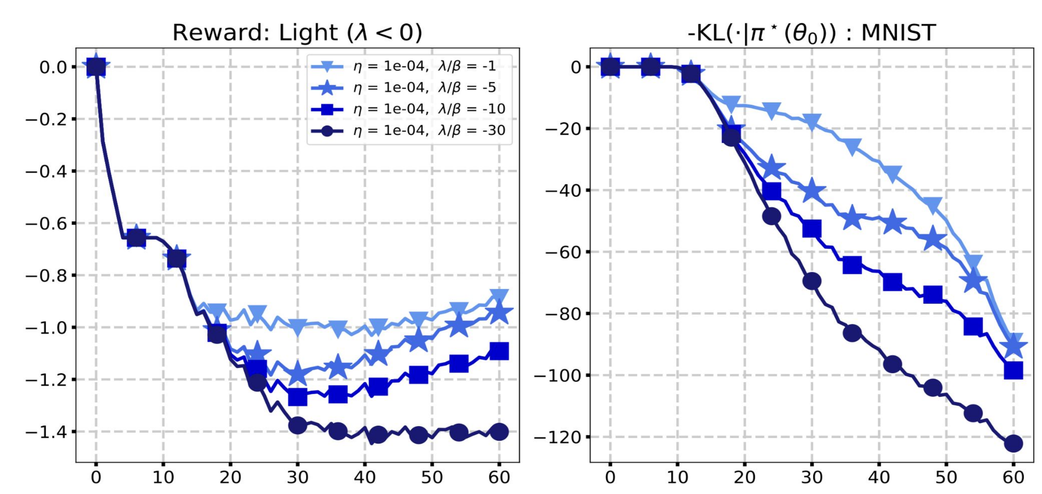


Diffusions

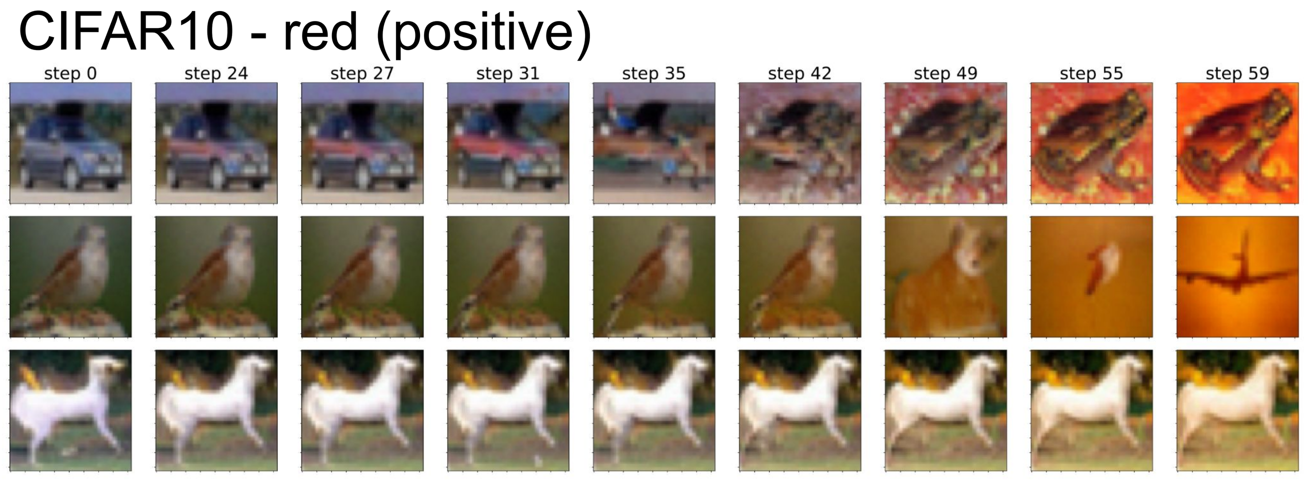
Diffusion denoising finetuning

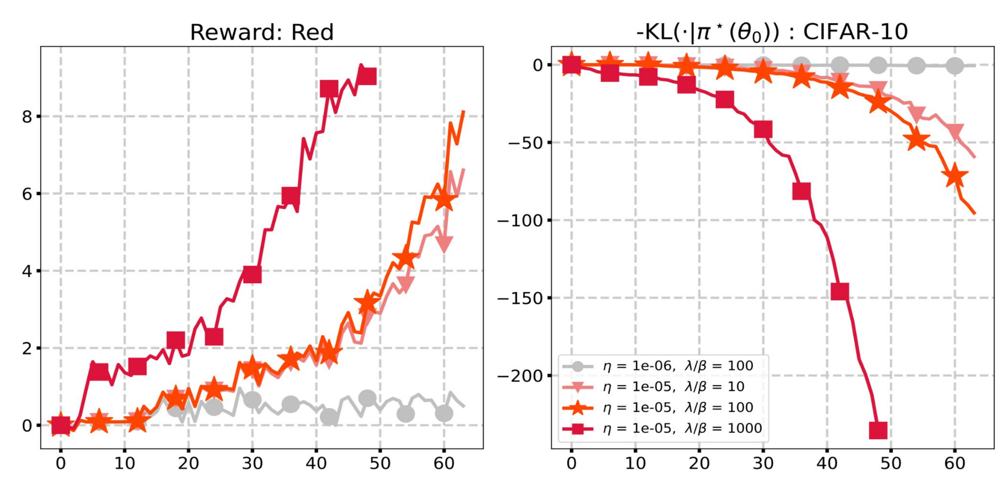
MNIST - brightness (negative)





CIFAR10 - red (positive)





Paper

Code