

# Paper Digest Meeting

## DreamSampler: Unifying Diffusion Sampling and Score Distillation for Image Manipulation

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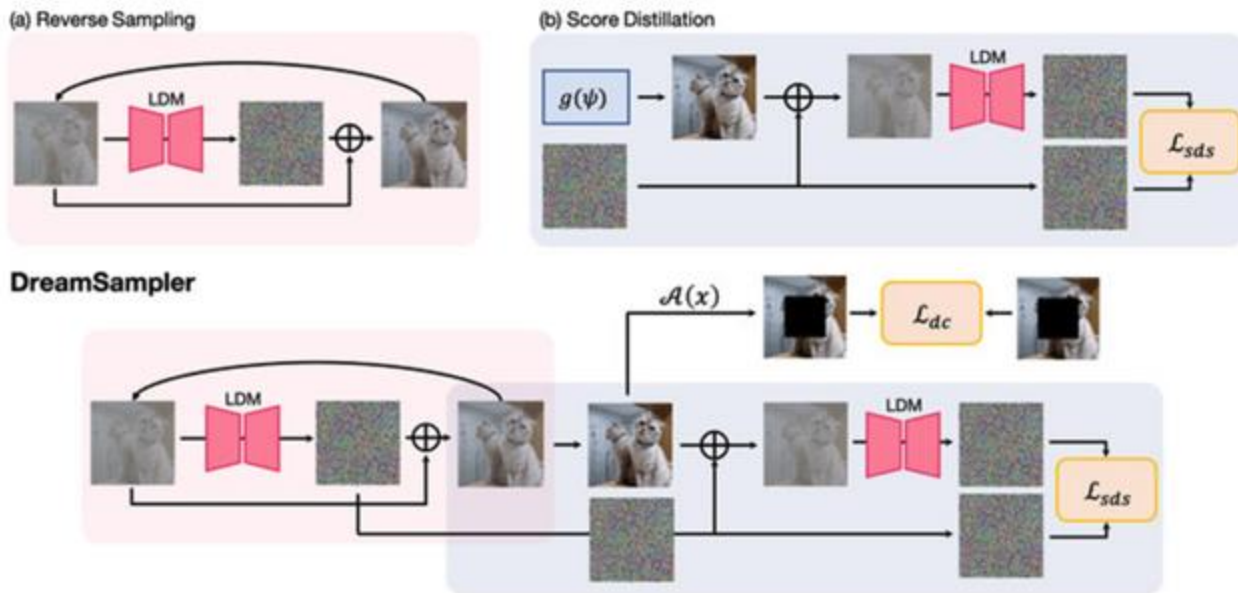
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# Problem Definition

Motivation: Reverse process sampling lacks flexibility, and SDS suffers from mode collapse.

Goal: Combine the benefits of the two sampling methods for flexible and high-quality generation.



# Key Ideas

DDIM Sampling from Optimization Perspective.

$$\mathbf{z}_{t-1} = \sqrt{\bar{\alpha}_{t-1}}\bar{\mathbf{z}} + \sqrt{1 - \bar{\alpha}_{t-1}}\tilde{\epsilon}, \quad \text{where} \quad \bar{\mathbf{z}} = \arg \min_{\mathbf{z}} \|\mathbf{z} - \hat{\mathbf{z}}_{0|t}\|^2$$

1. Connection to Score Distillation Sampling (SDS):

$$\begin{aligned} \|\mathbf{z} - \hat{\mathbf{z}}_{0|t}\|^2 &= \left\| \frac{\mathbf{z}_t - \sqrt{1 - \bar{\alpha}_t}\epsilon}{\sqrt{\bar{\alpha}_t}} - \frac{\mathbf{z}_t - \sqrt{1 - \bar{\alpha}_t}\epsilon_{\theta}(\mathbf{z}_t, t)}{\sqrt{\bar{\alpha}_t}} \right\|^2 \\ &= \frac{\sqrt{1 - \bar{\alpha}_t}}{\sqrt{\bar{\alpha}_t}} \|\epsilon - \epsilon_{\theta}(\mathbf{z}_t, t)\|^2, \end{aligned}$$

1. Add arbitrary regularization function:

$$\min_{\mathbf{z}} \|\mathbf{z} - \hat{\mathbf{z}}_{0|t}\|_2^2 + \lambda_{reg} \mathcal{R}(\mathbf{z})$$

# Method

DreamSampler Framework:

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**Algorithm 1** Score Distillation

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**Require:**  $T, \zeta, g, \psi, \mathcal{E}_\phi, \{\bar{\alpha}_t\}_{t=1}^T$

- 1:  $\mathbf{z}_0 \leftarrow \mathcal{E}_\phi(\mathbf{x}_0)$
  - 2: **for**  $i = T$  **to** 1 **do**
  - 3:    $t \sim U[0, T]$
  - 4:    $\tilde{\epsilon} \sim \mathcal{N}(0, \mathbf{I})$
  - 5:    $\mathbf{z}_t \leftarrow \sqrt{\bar{\alpha}_t} \mathbf{z}_0 + \sqrt{1 - \bar{\alpha}_t} \tilde{\epsilon}$
  - 6:    $\hat{\epsilon}_\theta \leftarrow \epsilon_\theta^\omega(\mathbf{z}_t, t, c)$
  - 7:    $\nabla_\psi \mathcal{L}_{ds} \leftarrow \tilde{\epsilon} - \hat{\epsilon}_\theta$
  - 8:    $\psi \leftarrow \psi - \zeta \nabla_\psi \mathcal{L}_{ds}$
  - 9:    $\mathbf{z}_0 \leftarrow \mathcal{E}_\phi(g(\psi))$
  - 10: **end for**
  - 11: **return**  $\psi$
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**Algorithm 2** DreamSampler

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**Require:**  $T, \zeta, g, \psi, \mathcal{E}_\phi, \{\bar{\alpha}_t\}_{t=1}^T$

- 1:  $\mathbf{z}_0 \leftarrow \mathcal{E}_\phi(\mathbf{x}_0), \epsilon_\theta(\mathbf{z}_{T+1}) := \epsilon \sim \mathcal{N}(0, \mathbf{I})$
  - 2: **for**  $i = T$  **to** 1 **do**
  - 3:    $t \leftarrow i, \epsilon \sim \mathcal{N}(0, \mathbf{I})$
  - 4:    $\tilde{\epsilon} \leftarrow \frac{\sqrt{1 - \bar{\alpha}_{t-1} - \eta^2 \beta_t^2} \hat{\epsilon}_\theta + \eta \beta_t \epsilon}{\sqrt{1 - \bar{\alpha}_t}}$
  - 5:    $\mathbf{z}_t \leftarrow \sqrt{\bar{\alpha}_t} \mathbf{z}_0 + \sqrt{1 - \bar{\alpha}_t} \tilde{\epsilon}$
  - 6:    $\hat{\epsilon}_\theta \leftarrow \epsilon_\theta^\omega(\mathbf{z}_t, t, c)$
  - 7:    $\nabla_\psi \mathcal{L}_{ds} \leftarrow \tilde{\epsilon} - \hat{\epsilon}_\theta$
  - 8:    $\psi \leftarrow \psi - \zeta [\nabla_\psi \mathcal{L}_{ds} + \lambda_{reg} \nabla_\psi \mathcal{R}]$
  - 9:    $\mathbf{z}_0 \leftarrow \mathcal{E}_\phi(g(\psi))$
  - 10: **end for**
  - 11: **return**  $\psi$
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# Application

## Real Image Editing

$$\min_{\mathbf{z}} \|\mathbf{z} - \hat{\mathbf{z}}_{0|t}(c_\phi)\|^2 + \gamma R(\mathbf{z}), \quad \text{where} \quad R(\mathbf{z}) := \frac{\|\mathbf{z} - \hat{\mathbf{z}}_{0|t}(c_{tgt})\|^2}{(1 - \gamma)}$$

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**Algorithm 3** DreamSampler for Image Editing

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**Require:** source image  $\mathbf{x}$ , image encoder  $\mathcal{E}_\phi$ , latent diffusion model  $\epsilon_\theta$ , null-text embedding  $c_\phi$ , conditioning text embedding  $c_{tgt}$ .

$\mathbf{z}_0 \leftarrow \mathcal{E}_\phi(\mathbf{x})$

$\mathbf{z}_T \leftarrow \text{Inversion}(\mathbf{z}_0)$

**for**  $t \in [T, 0]$  **do**

$\hat{\epsilon}_\theta \leftarrow \epsilon_\theta(\mathbf{z}_t, t, c_\phi) + \gamma[\epsilon_\theta(\mathbf{z}_t, t, c_{tgt}) - \epsilon_\theta(\mathbf{z}_t, t, c_\phi)]$

$\tilde{\mathbf{z}} \leftarrow (\mathbf{z}_t - \sqrt{1 - \bar{\alpha}_t} \hat{\epsilon}_\theta) / \sqrt{\bar{\alpha}_t}$

$\tilde{\epsilon} \leftarrow (\sqrt{1 - \bar{\alpha}_{t-1}} - \eta^2 \beta_t^2 \hat{\epsilon}_\theta + \eta \beta_t \epsilon) / \sqrt{1 - \bar{\alpha}_{t-1}}$

$\mathbf{z}_t \leftarrow \sqrt{\bar{\alpha}_{t-1}} \tilde{\mathbf{z}} + \sqrt{1 - \bar{\alpha}_{t-1}} \tilde{\epsilon}$

**end for**

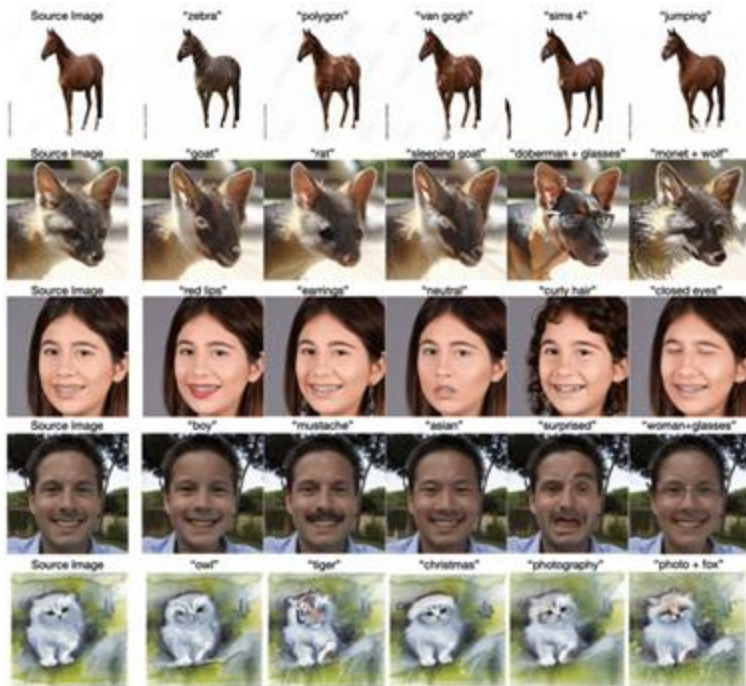
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## Inverse Problems

$$\min_{\psi} (1 - \gamma) \lambda_{SDS} \|\mathcal{E}(g(\psi)) - \hat{\mathbf{z}}_{0|t}(c_{\mathbf{y}})\|^2 + \gamma \lambda_{DC} \|\mathbf{y} - \mathcal{A}g(\psi)\|^2,$$

# Experiments

Identity Renderer ( $g$ )



Real Image Editing

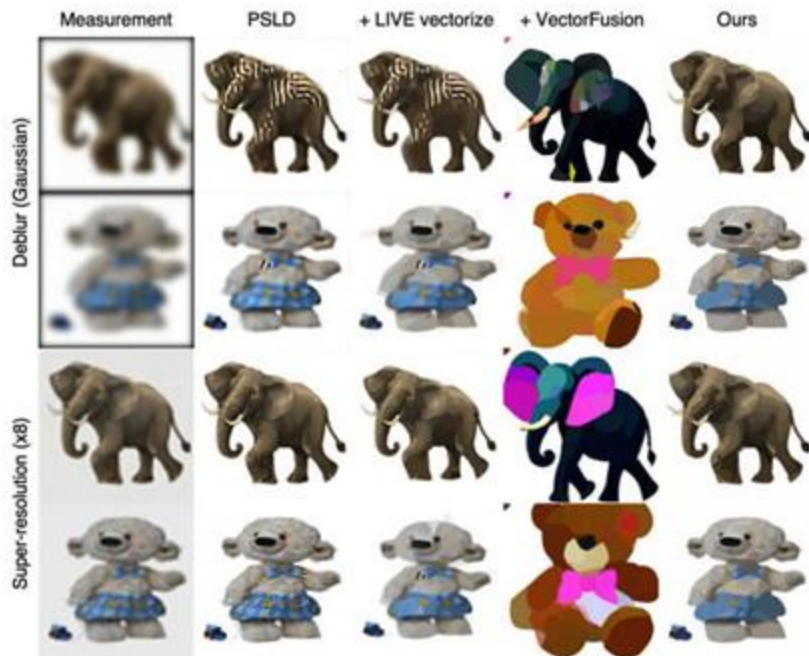


Image Inpainting



# Experiments

## Non-Identity Renderer ( $g$ )



SVG Inverse Problem



Novel View Synthesis from Blurry Inputs