

Image Processing using Diffusion Models

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Motivation

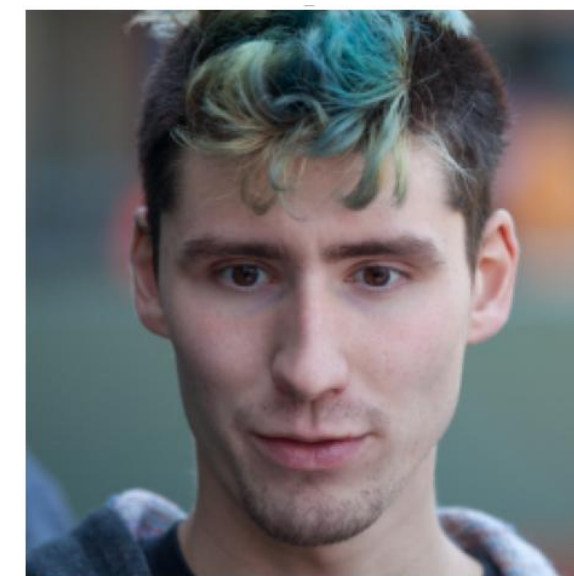
This project explores the fundamentals of diffusion models and their capabilities in two key areas: **(1) Image Generation** and **(2) Image Restoration**, specifically inpainting and deconvolution.

Background & Related Work

*Key Measurement Metrics:

- **PSNR** (Peak Signal-to-Noise Ratio):
→ Measures noise level/reconstruction quality (higher the better)
- **LPIPS** (Learned Perceptual Image Patch Similarity):
→ Measures perceptual similarity (lower the better)

Forward Noising Process (Variance Preserving(VP)):

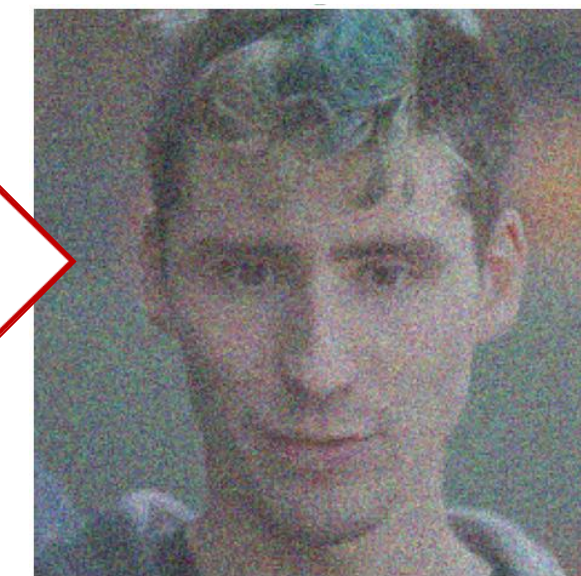


“Noising”

$$x_t = \sqrt{\alpha_t} x_0 + \sqrt{(1 - \alpha_t)} z, \quad \text{for } t = 1, 2, \dots, T$$

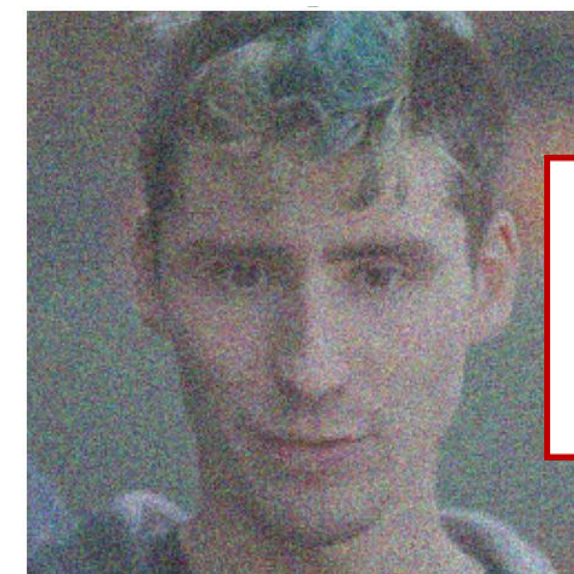
where $\alpha_t = 1 - \beta_t$, $\alpha_t = \prod_{i=0}^t \alpha_i$, and $z \sim \mathcal{N}(0, 1)$

* β_t is the noise schedule



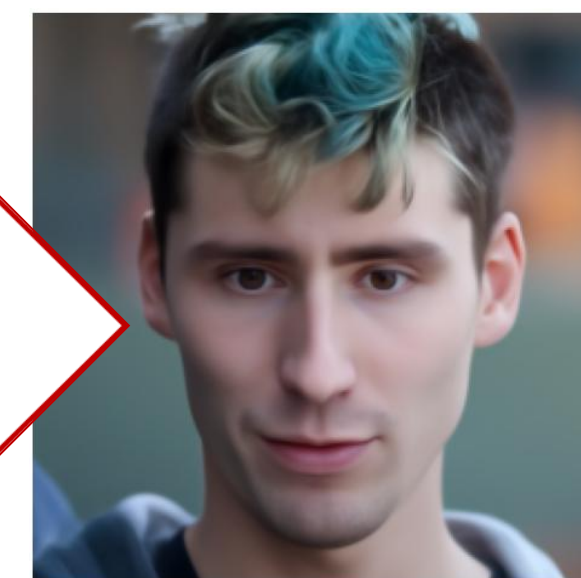
*T = 1000 steps

Reverse Denoising Process (DDPM):



“Denoising”

$$\hat{x}_0 = \frac{1}{\sqrt{\alpha_t}} (x_t + (1 - \alpha_t) s_\theta(x_t, t)) \quad \text{for } t = T, T-1, \dots, 0$$
$$x_{t-1} = \frac{\sqrt{\alpha_t}(1 - \alpha_{t-1})}{1 - \alpha_t} x_t + \frac{\sqrt{\alpha_{t-1}(1 - \alpha_t)}}{1 - \alpha_t} \hat{x}_0$$



PSNR: 31.70
LPIPS: 0.07

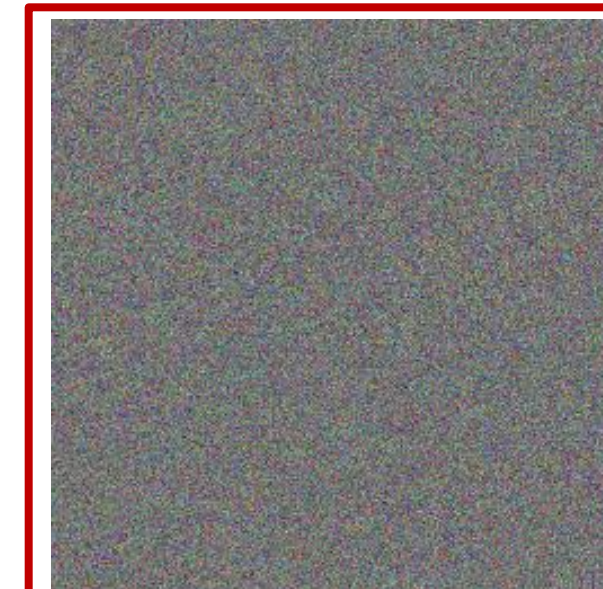
Image Restoration Methods:

- SDEdit method [4]: “Naïve” Approach (take measurement after timestep t)
- Score-ALD [3]: additional denoising step: $x_{t-1} = x_t - \frac{1}{\sigma^2 + \gamma_t^2} \nabla_{x_t} \|\mathcal{A}(x_t) - y\|^2$
- DPS [1]: additional denoising step: $x_{t-1} = x_t - \frac{\zeta_t}{2\sigma^2} \nabla_{x_t} \|\mathcal{A}(\hat{x}_0) - y\|^2$

References

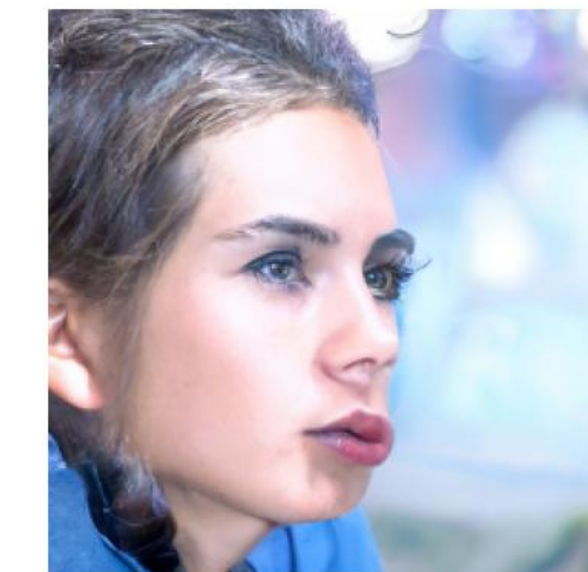
- [1] Chung, Kim, Mccann, Klasky, and Ye (2023). Diffusion posterior sampling for general noisy inverse problems. In ICLR.
- [2] Ho, Jain, and Abbeel (2020). Denoising diffusion probabilistic models. In NeurIPS.
- [3] Jalal, Arvinte, Daras, Price, Dimakis, and Tamir (2021). Robust compressed sensing mri with deep generative priors.
- [4] Meng, He, Y. Song, J. Song, Wu, Zhu, and Ermon (2022). Sdedit: Guided image synthesis and editing with stochastic differential equations.

Image Generation using DDPM Method [2] -> No “Guide” Image



$x_T \sim \mathcal{N}(0, 1)$

“Denoising”



Every random noise will create different set of “denoised” images

Image Impainting & Deconvolution [1, 3, 4] -> With “Guide” Image



$x_T \sim \mathcal{N}(0, 1)$

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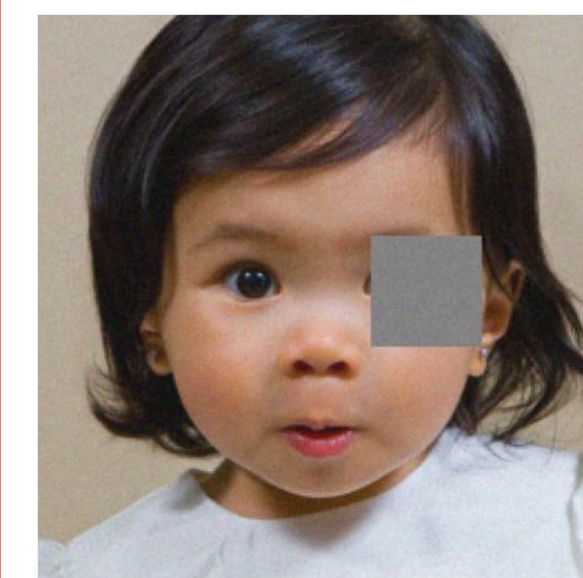
“Guide” Images -> Measurement

“Denoising”

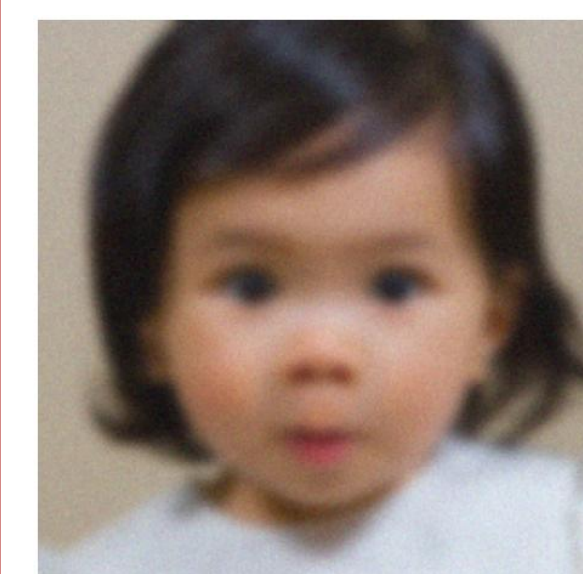


Ground Truth

Measurement



Impainting

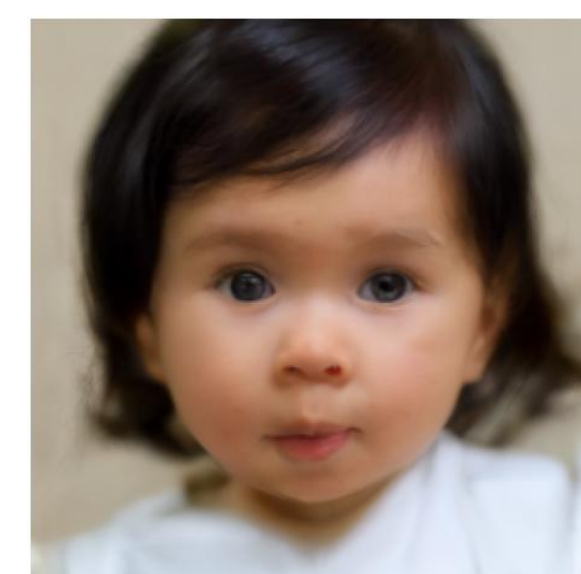


Deconvolution

SDEdit



Start time: 300
PSNR: 22.76
LPIPS: 0.14



Start time: 300
PSNR: 24.45
LPIPS: 0.21



Start time: 500
PSNR: 20.72
LPIPS: 0.18



Start time: 500
PSNR: 22.34
LPIPS: 0.20

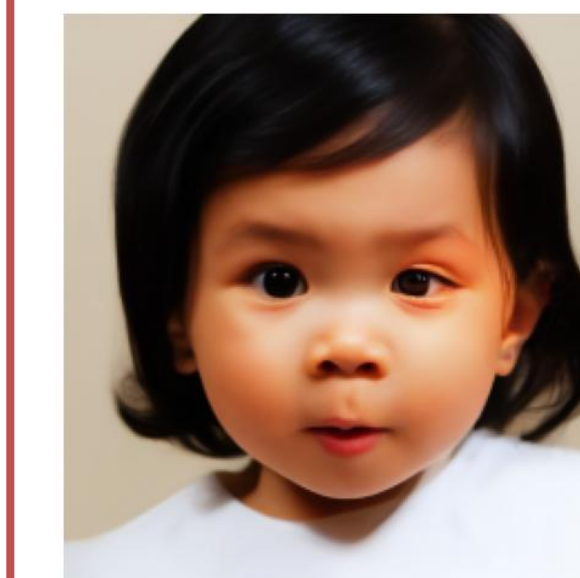


Start time: 800
PSNR: 14.05
LPIPS: 0.316



Start time: 800
PSNR: 13.32
LPIPS: 0.37

Score-ALD



PSNR: 22.75
LPIPS: 0.12



PSNR: 22.49
LPIPS: 0.14

DPS



PSNR: 34.93
LPIPS: 0.02



PSNR: 28.36
LPIPS: 0.07