

# Diffusion Models for Image Generation and Inverse Problems

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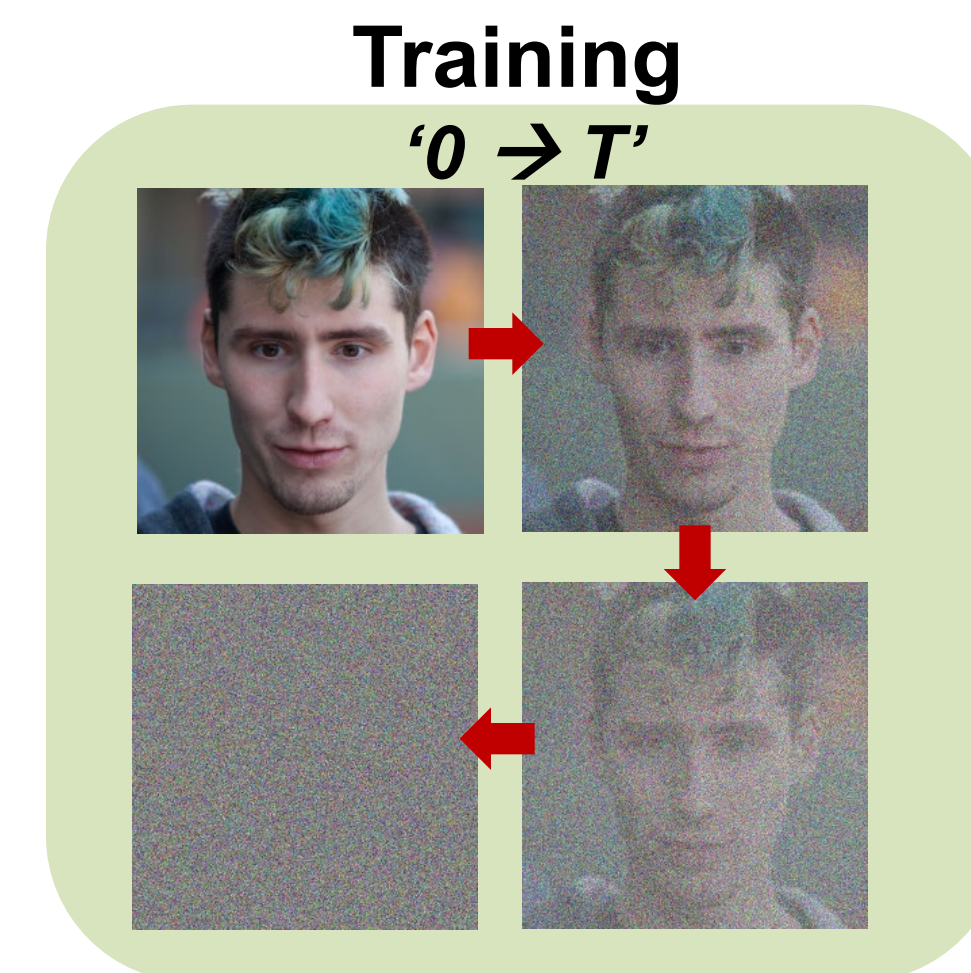
## Motivation



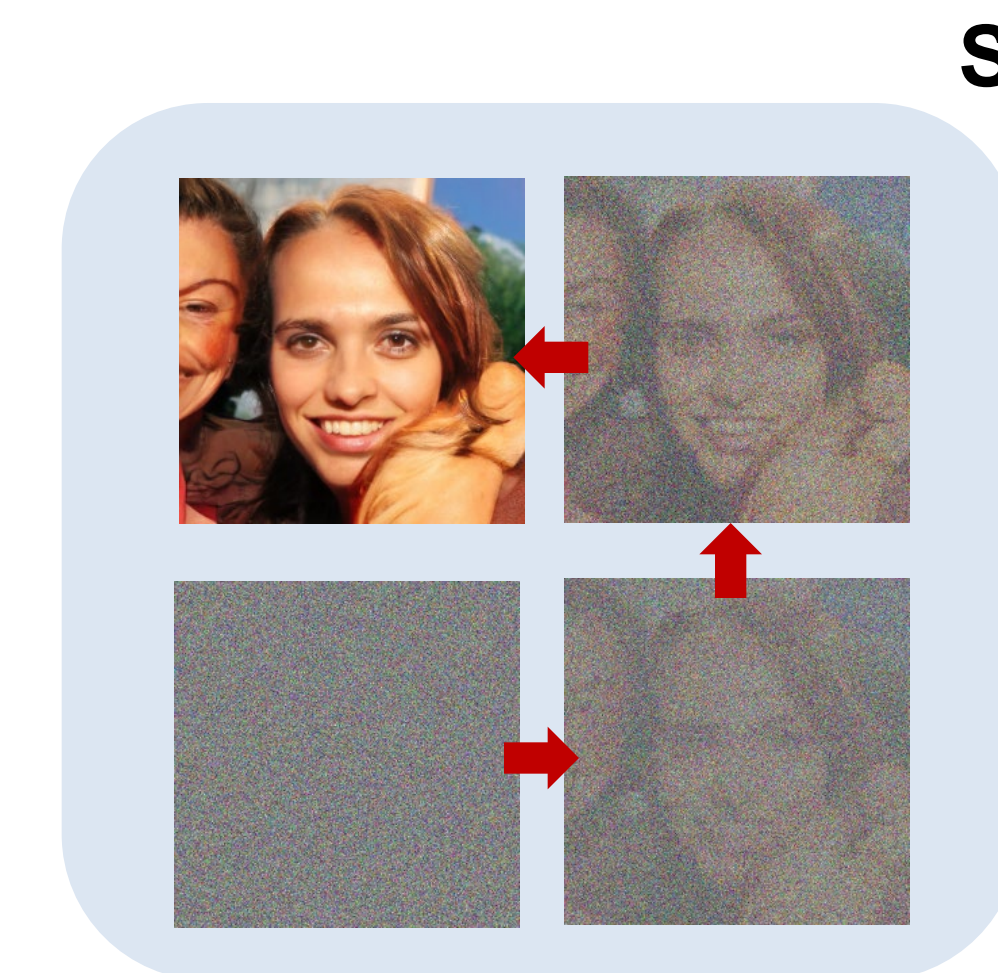
### Diffusion model for image restoration and generation

- The straightforward structure and efficient training process of diffusion models have made them a popular choice for generative modeling.
- In this work, we implemented several diffusion model approaches utilizing a pre-trained score predictor for image denoising, unconditional image generation, and tackling inverse problems, including inpainting and deconvolution.

## Methods

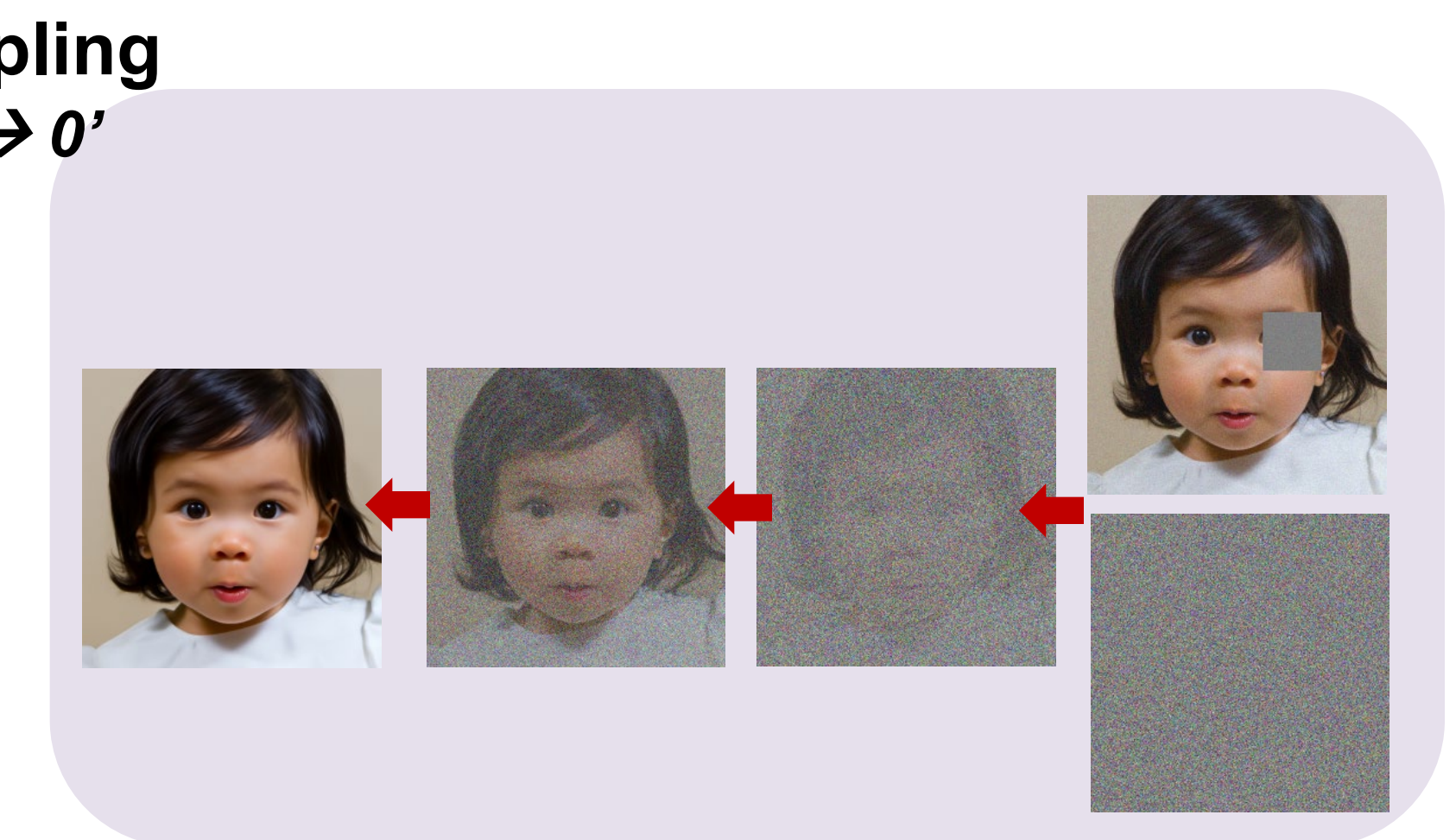


Pre-trained score  
( $s_\theta(x_t, t)$ ) predictor



Reverse Diffusion: DDPM

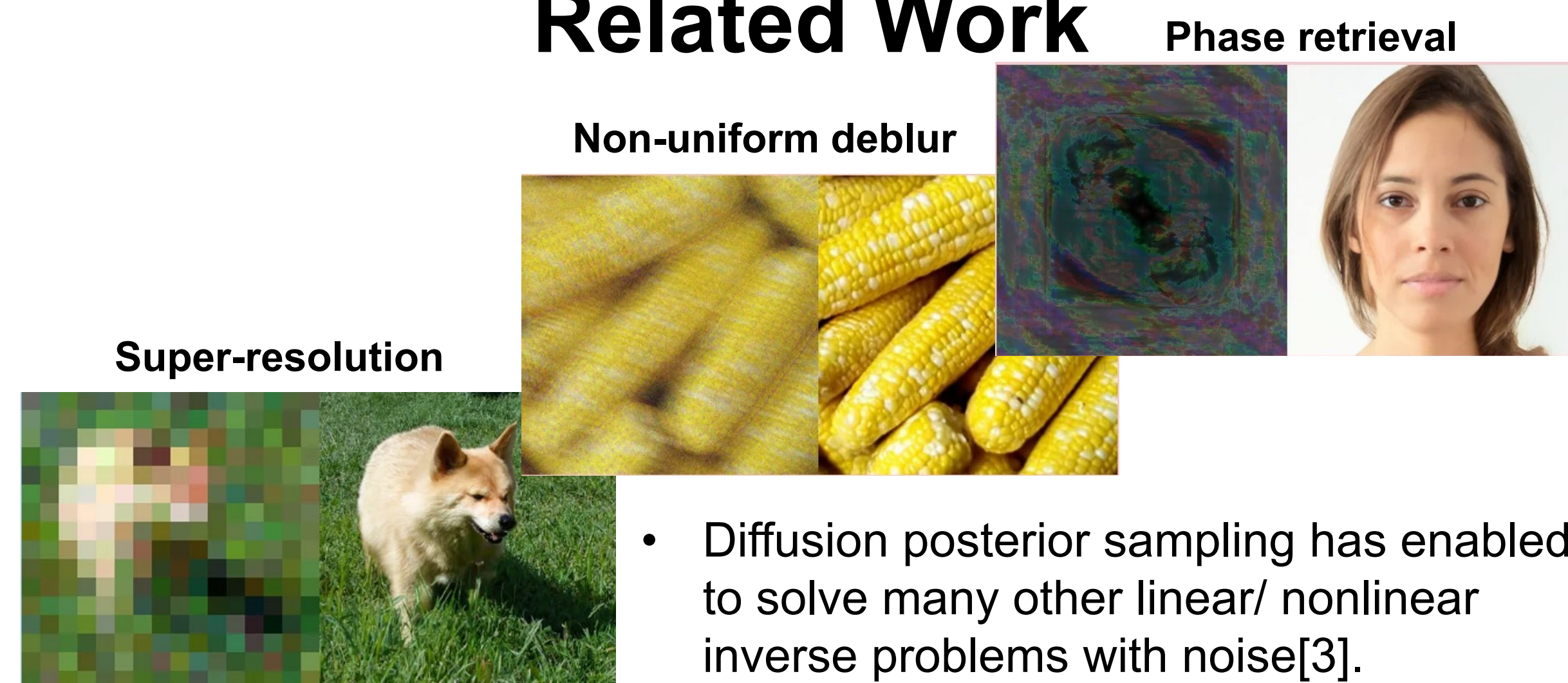
$$\hat{x}_0 = \frac{1}{\sqrt{\bar{\alpha}_t}} (x_t + (1 - \bar{\alpha}_t) s_\theta(x_t, t))$$
$$x_{t-1} = \frac{\sqrt{\bar{\alpha}_t(1-\bar{\alpha}_{t-1})}}{1-\bar{\alpha}_t} x_t + \frac{\sqrt{\bar{\alpha}_{t-1}(1-\alpha_t)}}{1-\bar{\alpha}_t} \hat{x}_0 + \sqrt{1-\alpha_t} z$$



Posterior Sampling: ScoreALD, DPS

$$\hat{x}_0 = \frac{1}{\sqrt{\bar{\alpha}_t}} (x_t + (1 - \bar{\alpha}_t) s_\theta(x_t, t))$$
$$x_{t-1}' = \frac{\sqrt{\bar{\alpha}_t(1-\bar{\alpha}_{t-1})}}{1-\bar{\alpha}_t} x_t + \frac{\sqrt{\bar{\alpha}_{t-1}(1-\alpha_t)}}{1-\bar{\alpha}_t} \hat{x}_0 + \sqrt{1-\alpha_t} z$$
$$x_{t-1} = x_{t-1}' - \frac{1}{\sigma^2 + \gamma_t^2} \nabla_{x_t} \|\mathcal{A}(x_t) - y\|^2$$

## Related Work

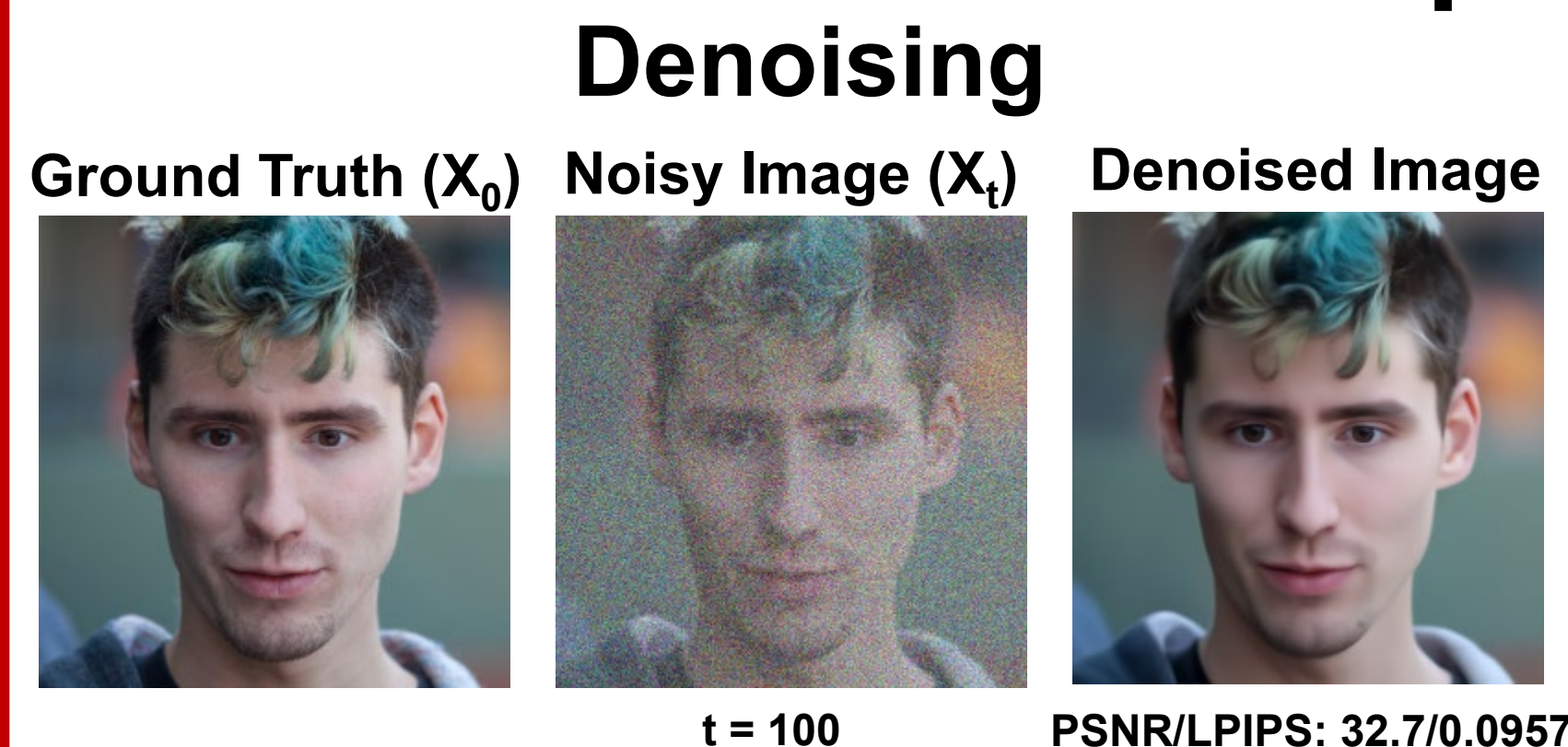


- Diffusion posterior sampling has enabled to solve many other linear/ nonlinear inverse problems with noise[3].

## References

- [1] C. Meng, Y. He, Y. Song, J. Song, J. Wu, J.Y. Zhu, S. Ermon, "SDEdit: Guided Image Synthesis and Editing with Stochastic Differential Equations", ICLR 2022
- [2] J. Ho, et al, "Denoising Diffusion Probabilistic Models", NeurIPS 2020
- [3] H.Chung, et al, "Diffusion posterior sampling for general noisy inverse problems", ICLR 2023

## Experimental Results



### Unconditional Image Generation

