DreamClean: Restoring Clean Image Using Deep Diffusion Prior

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Introduction

DNN-based Image Restoration Methods

☐ Supervised learning based IR methods

Collected Paired data + Effective Neural Network

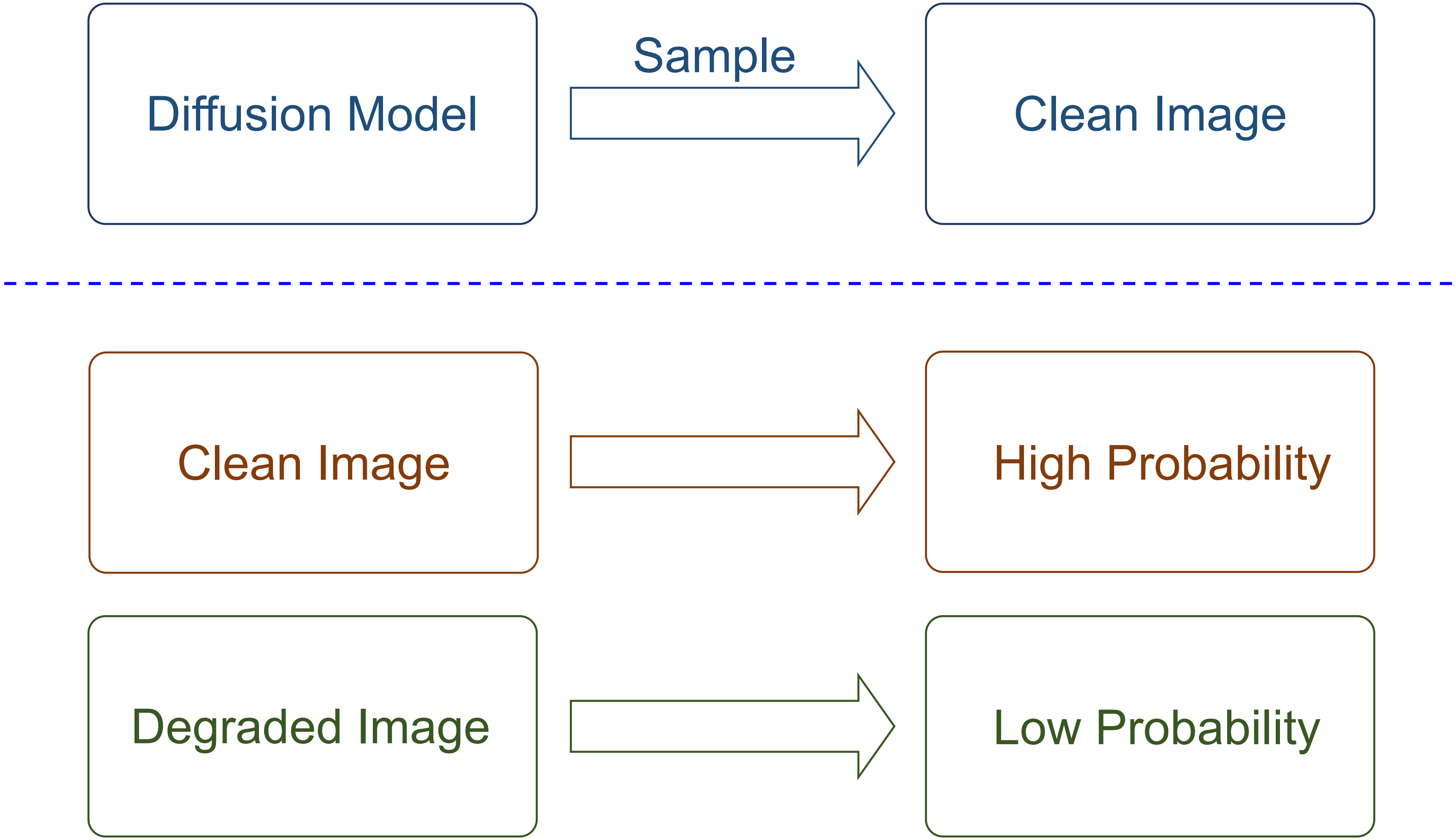
☐ Unsupervised learning based IR methods

Image Prior + Degradation Model

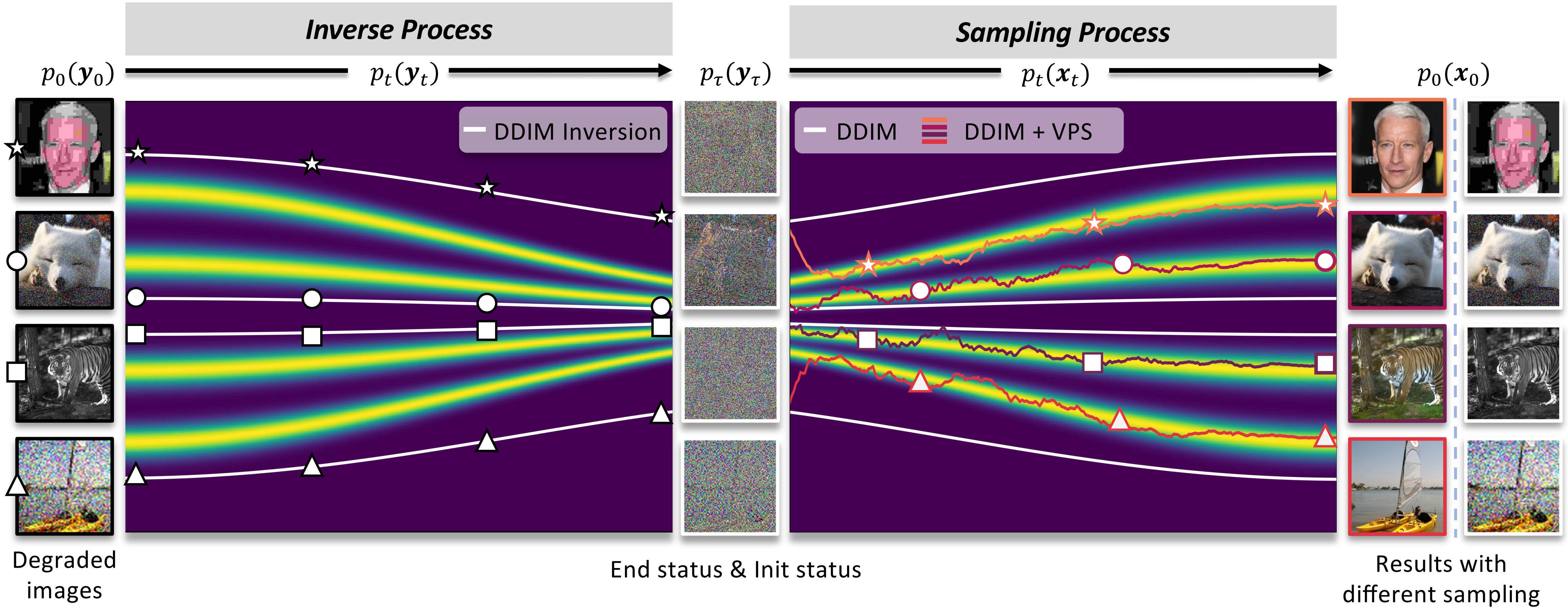
DreamClean can restore images without explicit or implicit assumptions about the specific degradation model.

Method

Motivation


Diffusion Model
Sample
Clean Image
Clean Image
High Probability
Degraded Image
Low Probability

Overview


Inverse Process
Sampling Process
$p_0(\boldsymbol{y}_0)$
$p_t(\boldsymbol{y}_t)$
$p_\tau(\boldsymbol{y}_\tau)$
$p_t(\boldsymbol{x}_t)$
$p_0(\boldsymbol{x}_0)$
DDIM Inversion
DDIM
DDIM + VPS
Degraded images
End status & Init status
Results with different sampling

Method

DDIM Inversion

Inversion

$$y_{t+1} = \sqrt{\alpha_{t+1}}\left(\frac{y_t - \sqrt{1-\alpha_t}\epsilon_\theta^t(y_t,t)}{\sqrt{\alpha_t}}\right) + \sqrt{1-\alpha_{t+1}}\epsilon_\theta^t(y_t,t)$$

Variance Preservation Sampling

Sampling

$$y_t^m = y_t^{m-1} + \eta_l \nabla \log p_t(y_t^{m-1}) + \eta_g \epsilon_g^m, \quad m = 1,2\ldots, M, \mathrm{y}_\mathrm{t}^0 = \mathrm{y}_\mathrm{t},$$

where $\eta_l = \gamma(1-\alpha_t), \eta_g = \sqrt{\gamma(2-\gamma)}\sqrt{1-\alpha_t}, \nabla \log p_t(y_t^{m-1}) = -\frac{\epsilon_\theta(y_t^{m-1},t)}{\sqrt{1-\alpha_t}}$

Denoising Sampling

$$y_{t-1} = \sqrt{\alpha_{t-1}}\left(\frac{y_t - \sqrt{1-\alpha_t}\epsilon_\theta^t(y_t,t)}{\sqrt{\alpha_t}}\right) + \sqrt{1-\alpha_{t-1}}\epsilon_\theta^t(y_t,t)$$

Experiment

Quantitative Results

Table 1: Quantitative results of 4×SR with Gaussian noise $\sigma = 0.05$ on CelebA.

Method	PSNR ↑	SSIM ↑	LPIPS ↓	NFEs ↓
Baseline	23.64	0.51	0.64	0
DGP	18.40	0.40	0.70	1500
SNIPS	26.38	0.74	0.20	1000
DPS	24.42	0.70	0.17	1000
DDRM	29.21	0.83	0.09	100
DDNM	29.17	0.82	0.09	100
GDP	24.38	0.71	0.15	1000
Ours	27.23	0.77	0.12	90
Ours*	**30.19**	**0.84**	**0.08**	60

Table 2: Quantitative results of 4×SR with Gaussian noise $\sigma = 0.05$ on ImageNet.

Method	PSNR ↑	SSIM ↑	LPIPS ↓	NFEs ↓
Baseline	21.85	0.47	0.58	0
DGP	9.50	0.12	0.93	1500
RED	22.90	0.49	NA	100
DPS	24.42	0.70	0.36	1000
DDRM	25.67	0.73	0.30	100
DDNM	25.56	0.72	0.30	100
GDP	24.33	0.67	0.39	1000
Ours	24.31	0.67	0.40	90
Ours*	**25.84**	**0.74**	**0.23**	60

Table 3: Quantitative results of JPEG compression artifacts correction on CelebA.

Method	PSNR ↑	SSIM ↑	LPIPS ↓	NFEs ↓
Baseline	24.79	0.69	0.41	0
QGAC	24.28	0.68	0.32	1
FBCNN	26.37	0.77	0.24	1
DDNM	24.40	0.66	0.31	100
DDRM-JPEG	26.41	0.77	**0.20**	100
Ours	**27.58**	**0.82**	**0.20**	90

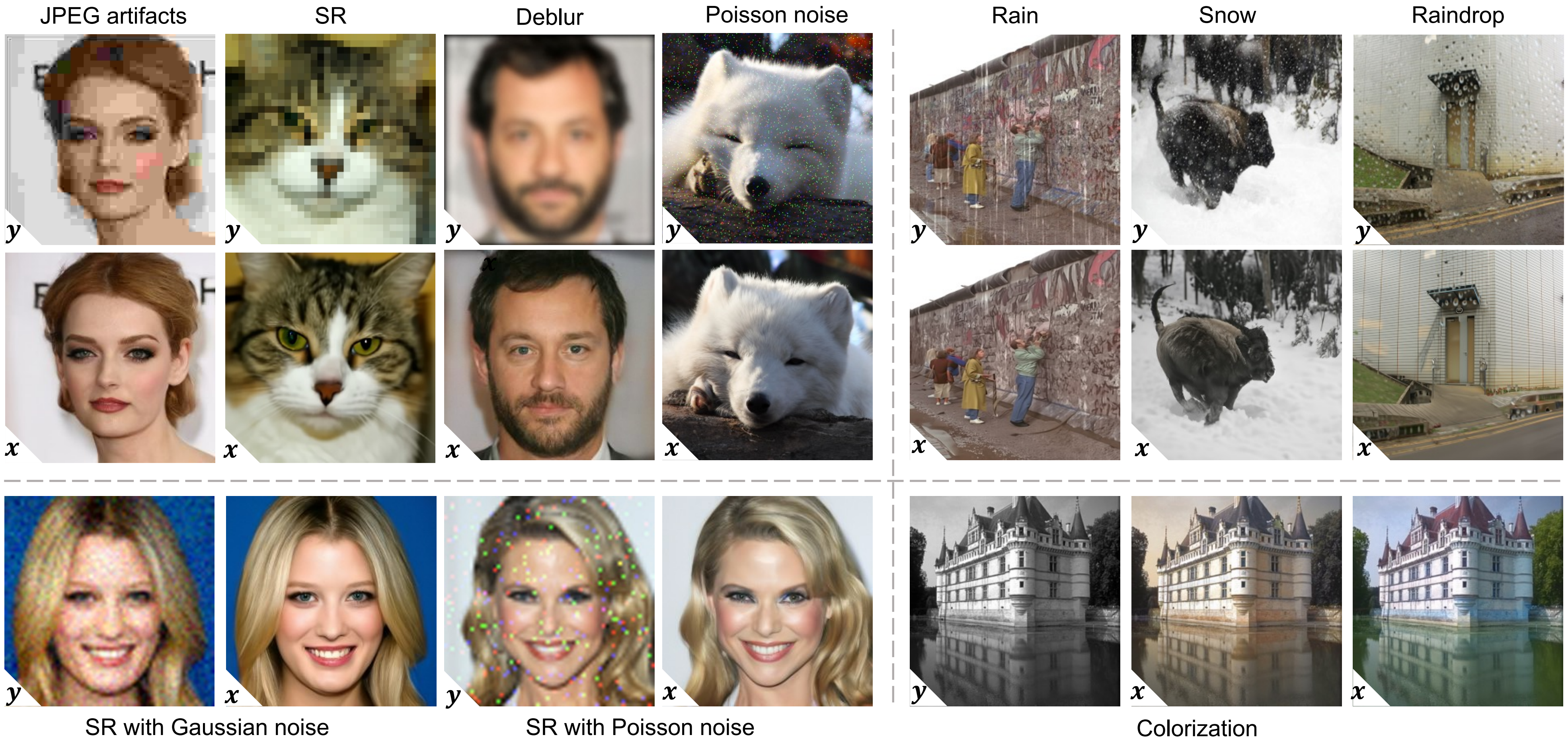
Table 4: Quantitative results of JPEG compression artifacts correction on LSUN bedroom.

Method	PSNR ↑	SSIM ↑	LPIPS ↓	NFEs ↓
Baseline	23.39	0.68	0.34	0
QGAC	23.41	0.69	0.34	1
FBCNN	24.10	0.73	**0.31**	1
DDNM	22.73	0.66	0.33	100
DDRM-JPEG	24.06	0.73	0.32	100
Ours	**24.35**	**0.74**	**0.31**	90

Visual Results

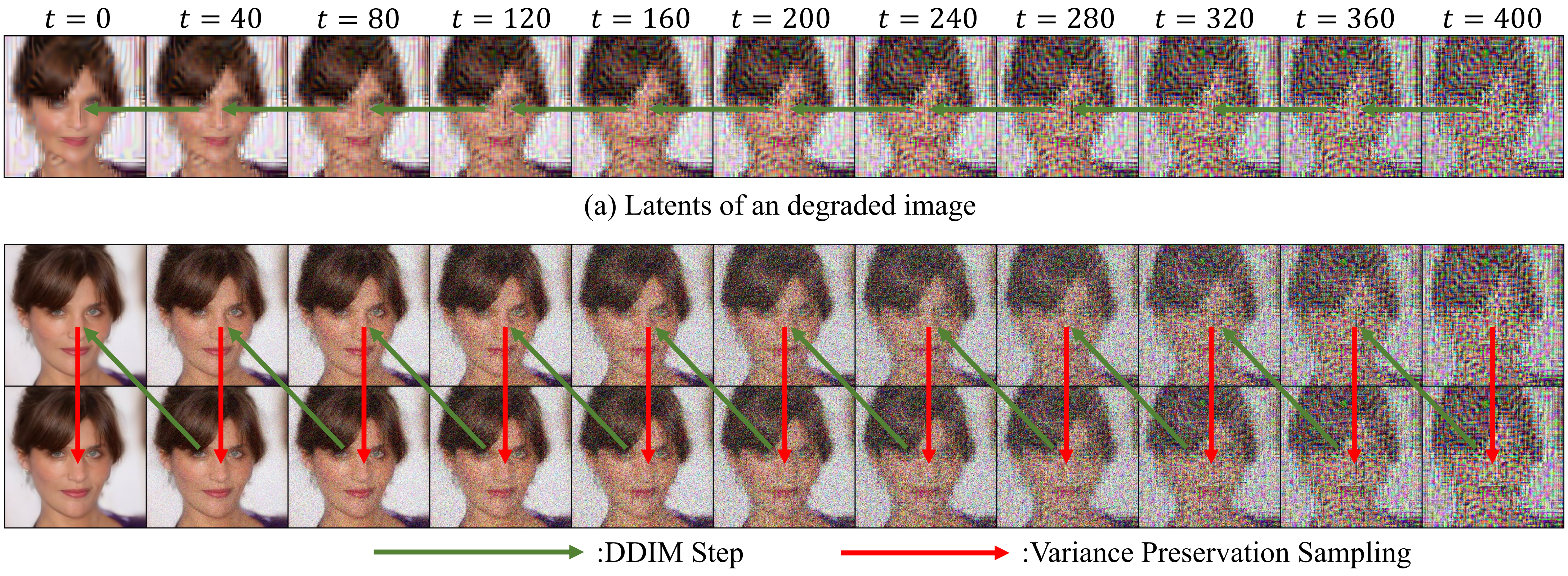
Results of JPEG artifacts correction. DreamClean is blind to the degradation model. DreamClean can still recover a 1024x1024 high-quality image given the extremely destroyed image based on the advanced Stable Diffusion XL.

Visual Results



DreamClean can resort to the inherent prior of diffusion models to tackle with linear degradation, noisy linear degradation, non-linear degradation and complex bad weather degradation. $\boldsymbol{y}$: the degraded image, $\boldsymbol{x}$: our result.

Analysis



(b) Visualization of latents of DreamClean

Visualization of latents of DDIM and VPS. VPS translates original degraded artifacts to Gaussian-like noise and DDIM step is responsible for progressively reducing the amount of Gaussian noise contained in latents.

Conclusion

Conclusion

- Unsupervised IR method
- without assuming degraded model explicitly or implicitly
- harness the advanced generative models such as Stable diffusion

Thanks !