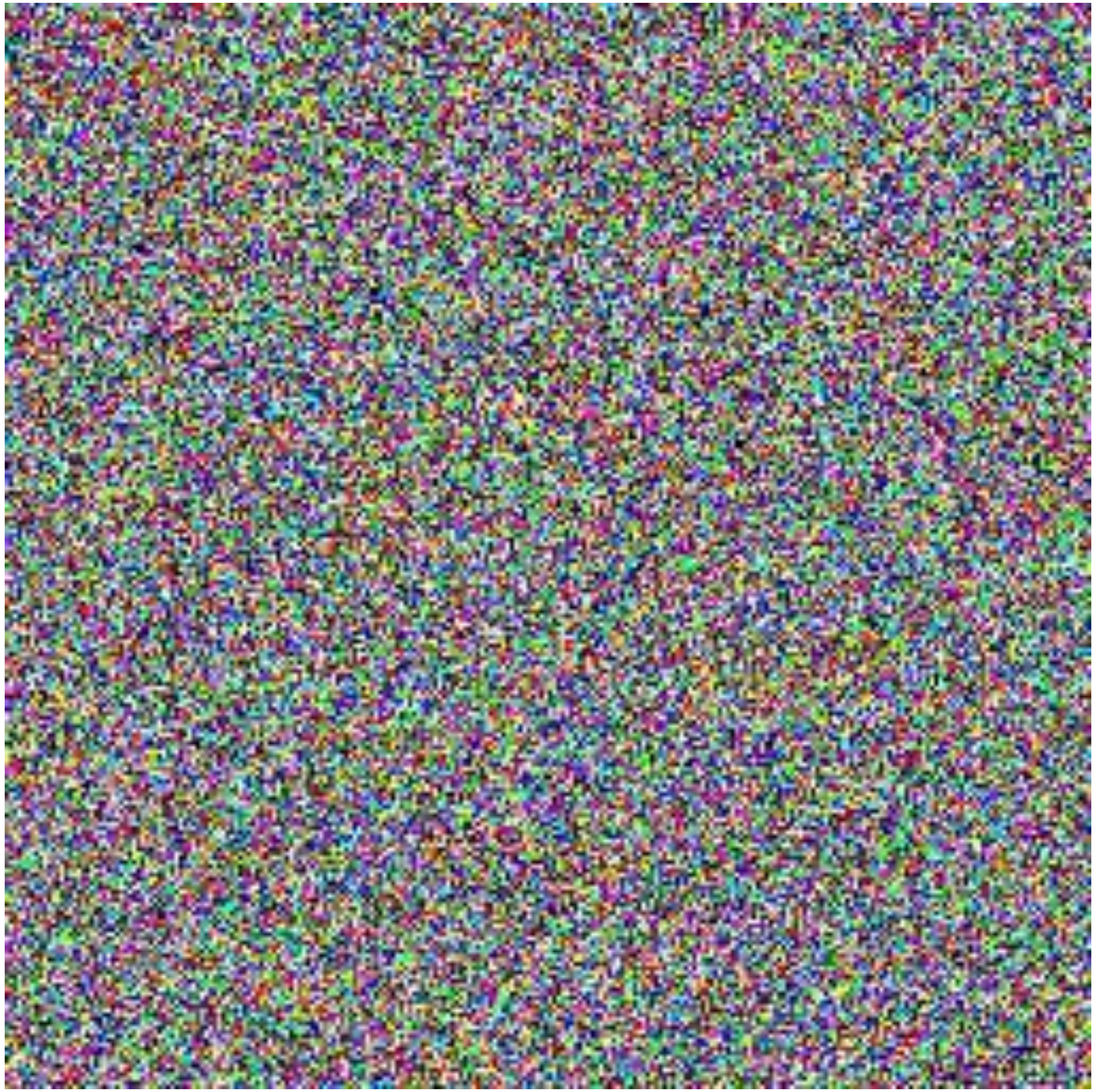
ETH zürich

RePaint: Inpainting using Denoising Diffusion Probabilistic Models

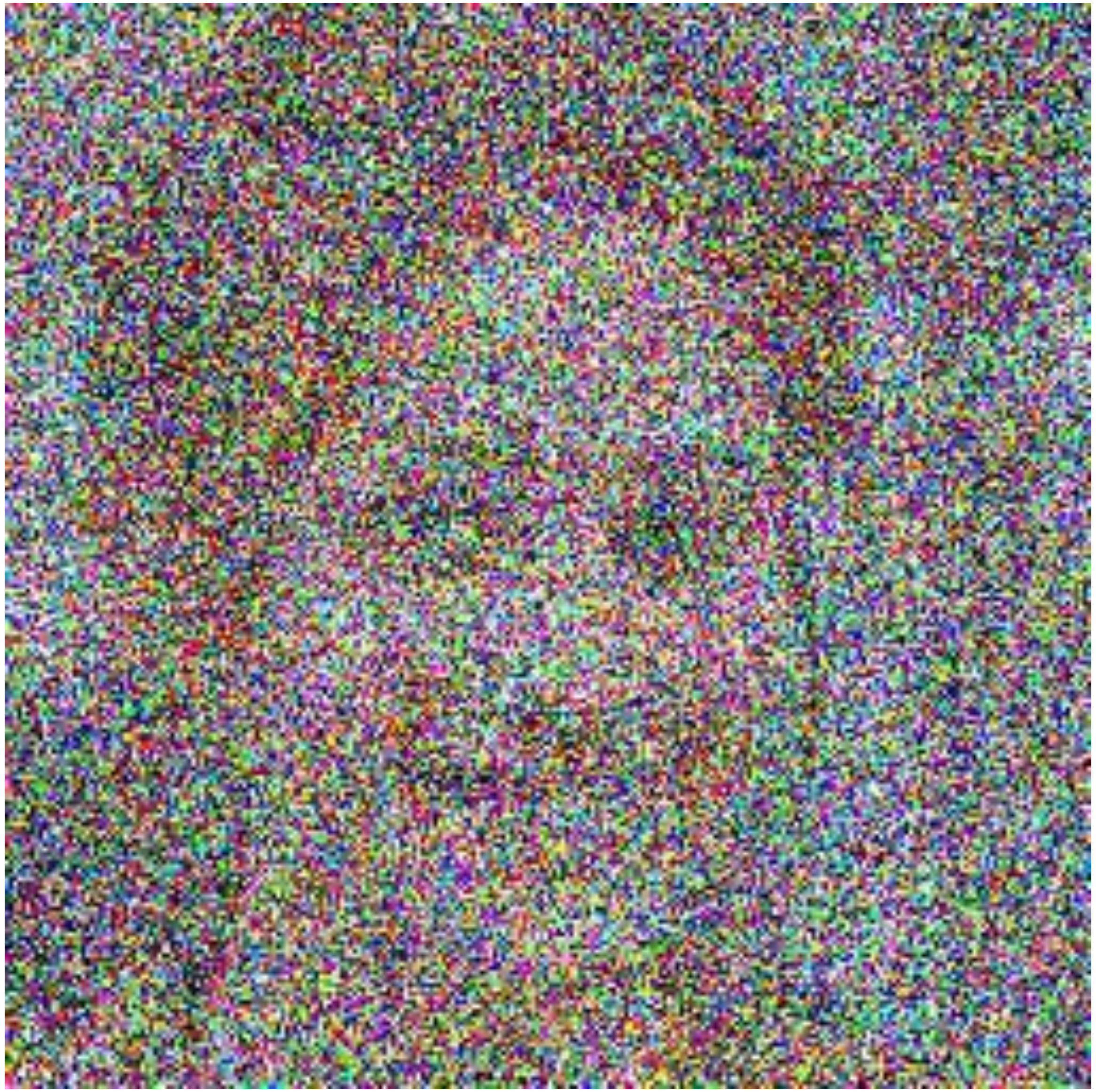
Andreas Lugmayr, Martin Danelljan, Andres Romero, Fisher Yu, Radu Timofte, Luc Van Gool

Input Image.

Remove this part.



Start with Noise.



Guide denoising
with known region.

Guide denoising with known region.

Guide denoising with known region.

Sample with different seed.

Sample with different seed.

Sample with different seed.

Sample with
different seed.

Denoising Diffusion Probabilistic Models

$$q(x_t|x_{t-1}) = \mathcal{N}(x_t; \sqrt{1-\beta_t}x_{t-1}, \beta_t\mathbf{I})$$

x_0

Denoising diffusion probabilistic models
Ho, J., Jain, A. and Abbeel

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Denoising Diffusion Probabilistic Models

$$p_\theta(x_{t-1}|x_t) = \mathcal{N}(x_{t-1}; \mu_\theta(x_t, t), \Sigma_\theta(x_t, t))$$

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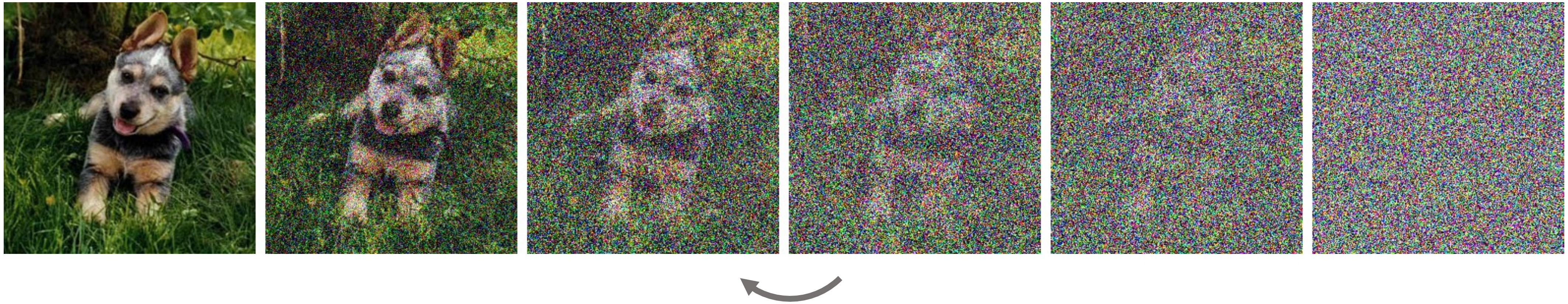

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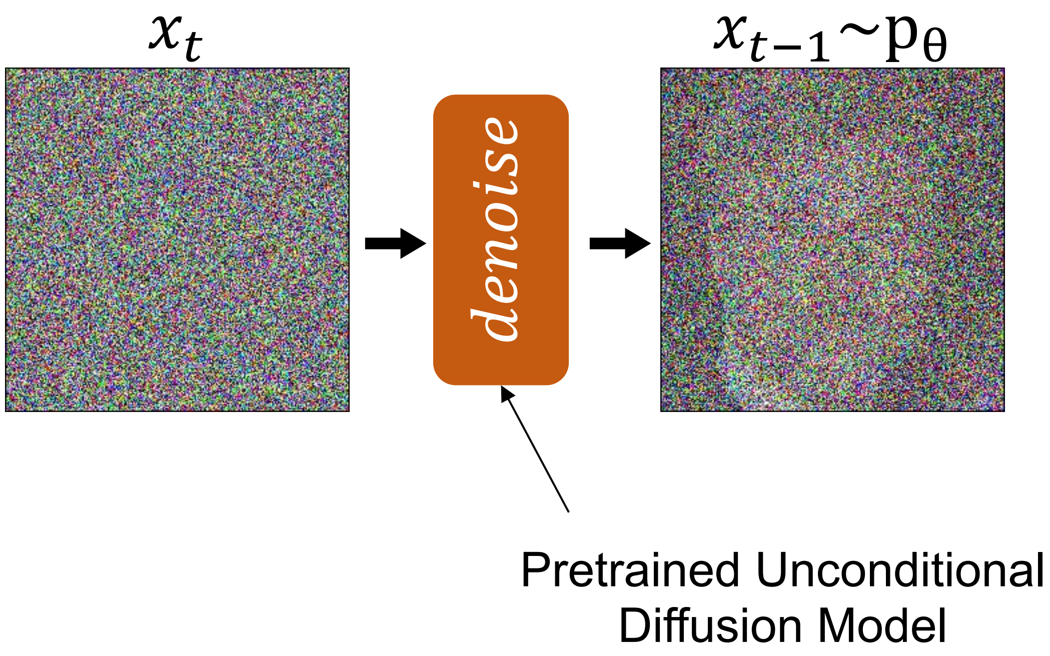
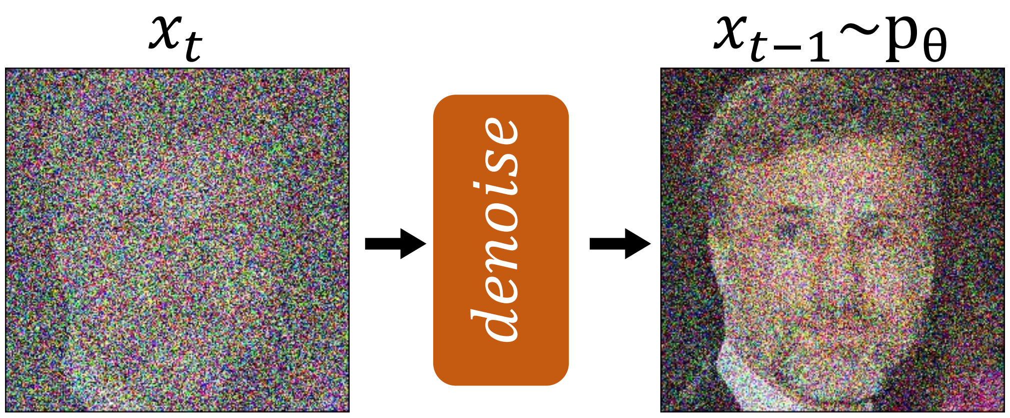


x_t
denoise
$x_{t-1} \sim p_\theta$
Pretrained Unconditional
Diffusion Model



x_t
denoise
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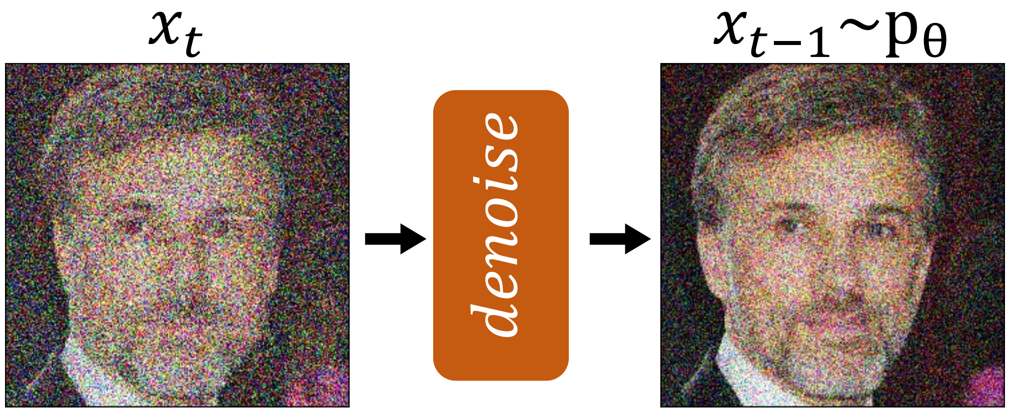

x_t
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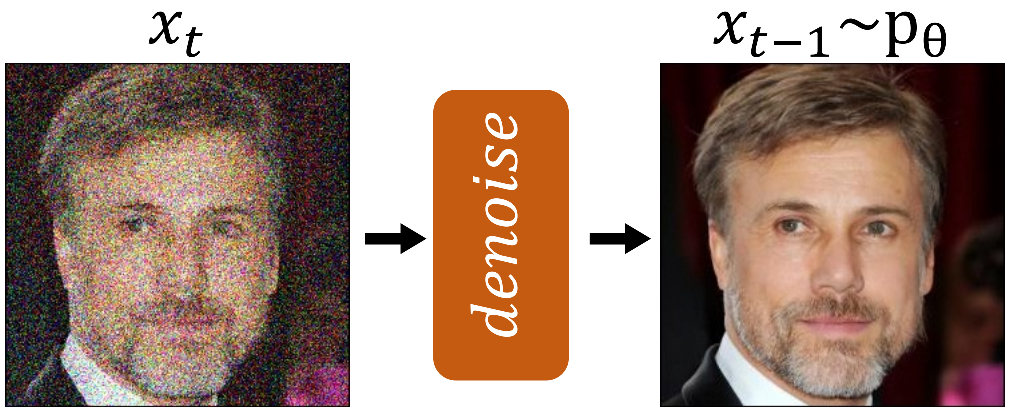
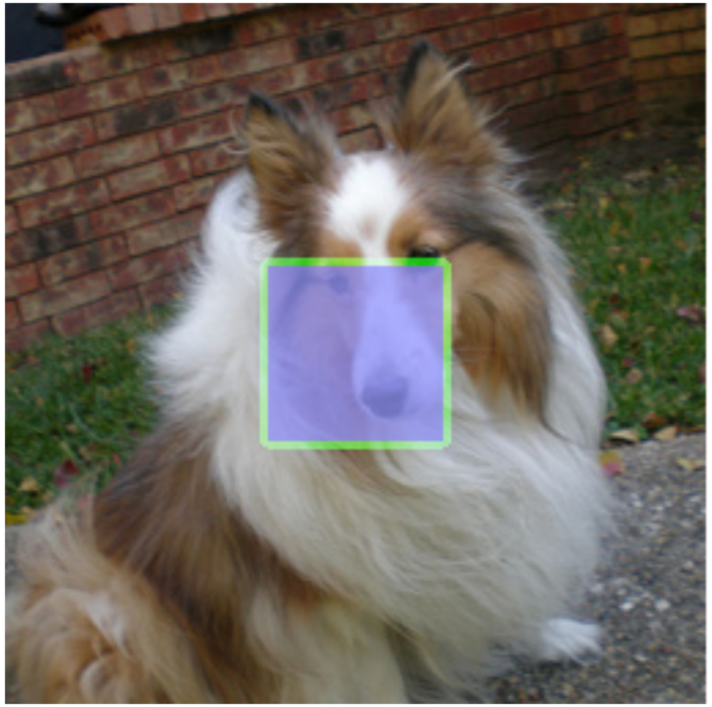

x_t
denoise
$x_{t-1} \sim p_\theta$

Resampling



Input

n = 1

Resampling Schedule

Generation Step

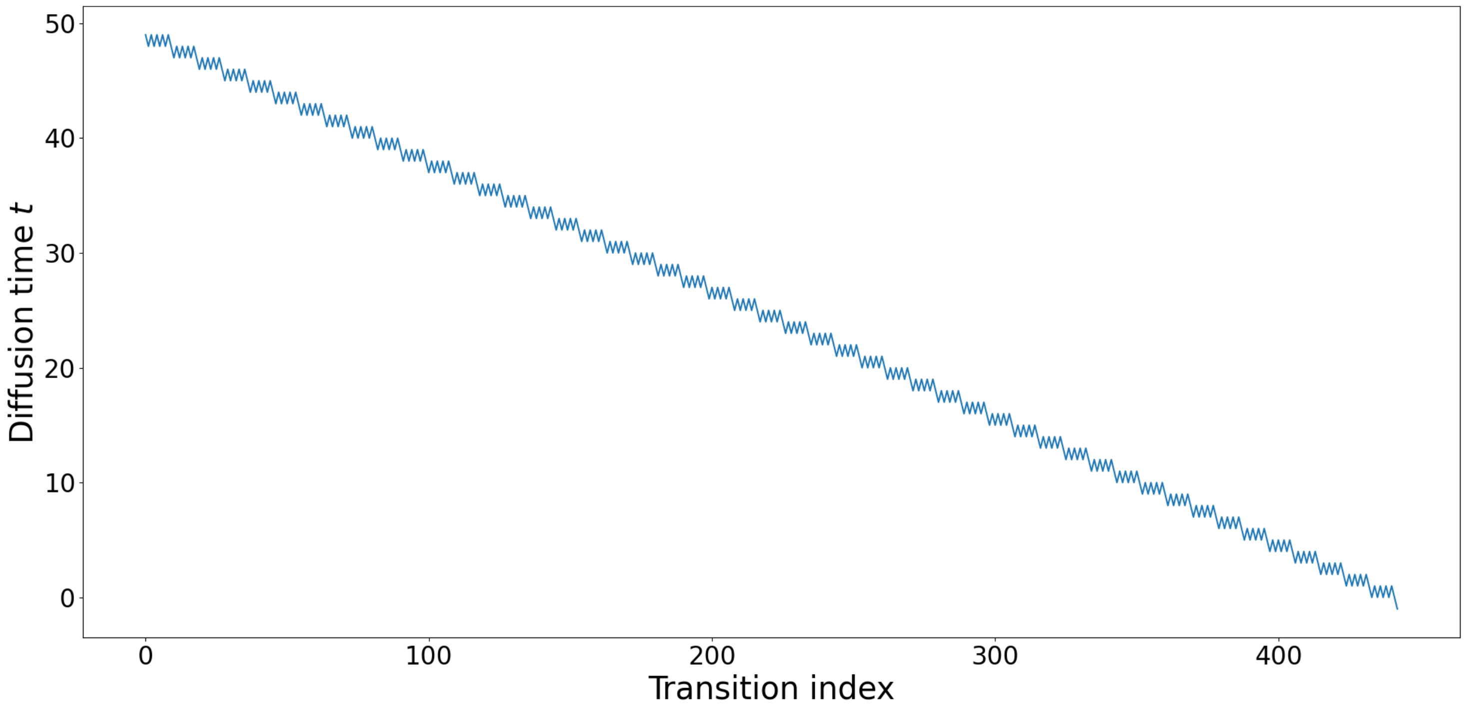
$$x_{t-1}^{\text{known}} \sim \mathcal{N}(\sqrt{\bar{\alpha}_t}x_0, (1-\bar{\alpha}_t)\mathbf{I})$$

$$x_{t-1}^{\text{unknown}} \sim \mathcal{N}(\mu_\theta(x_t, t), \Sigma_\theta(x_t, t))$$

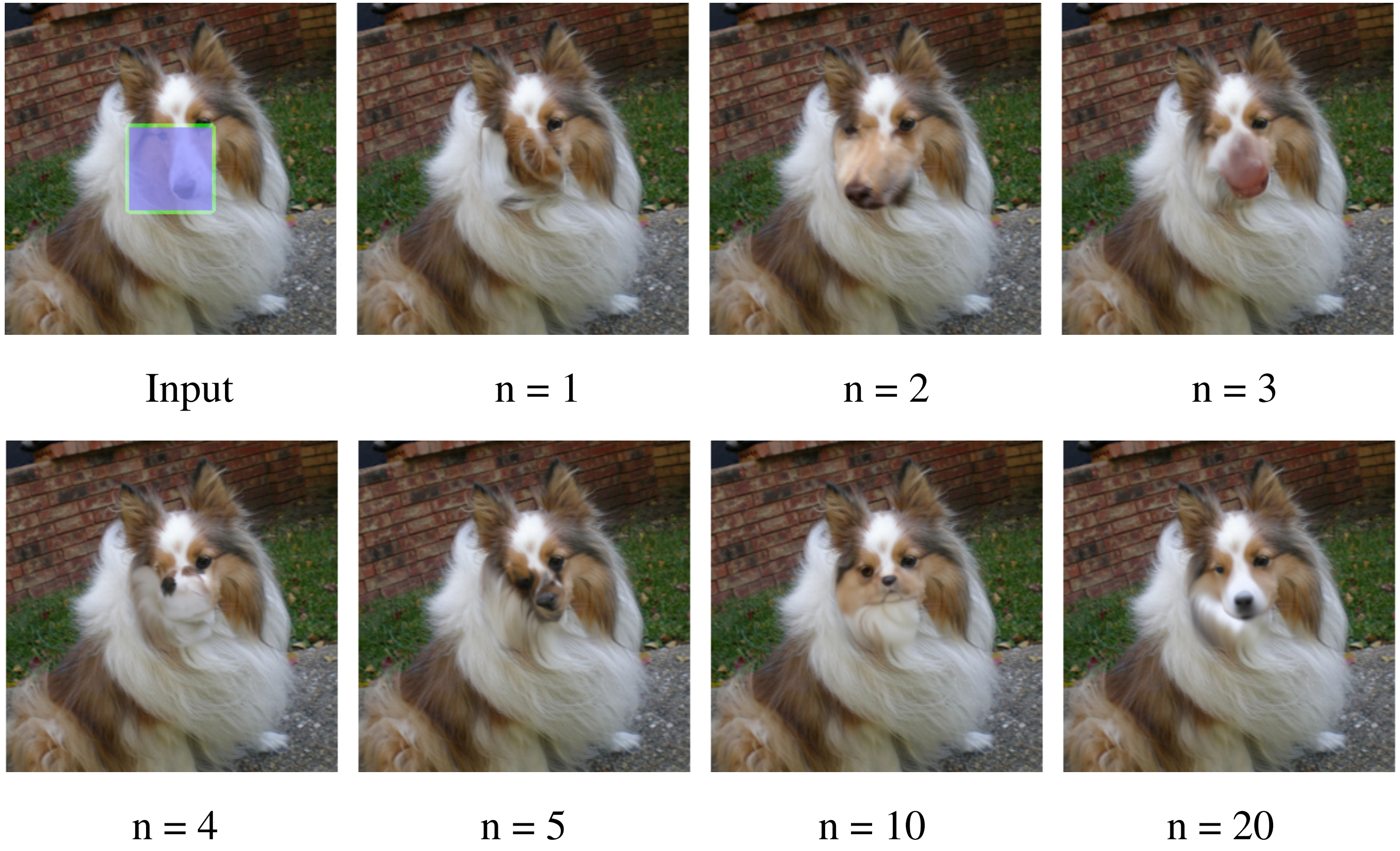
$$x_{t-1} = m \odot x_{t-1}^{\text{known}} + (1-m) \odot x_{t-1}^{\text{unknown}}$$

Undo Step

$$q(x_t|x_{t-1}) = \mathcal{N}(x_t; \sqrt{1-\beta_t}x_{t-1}, \beta_t\mathbf{I})$$



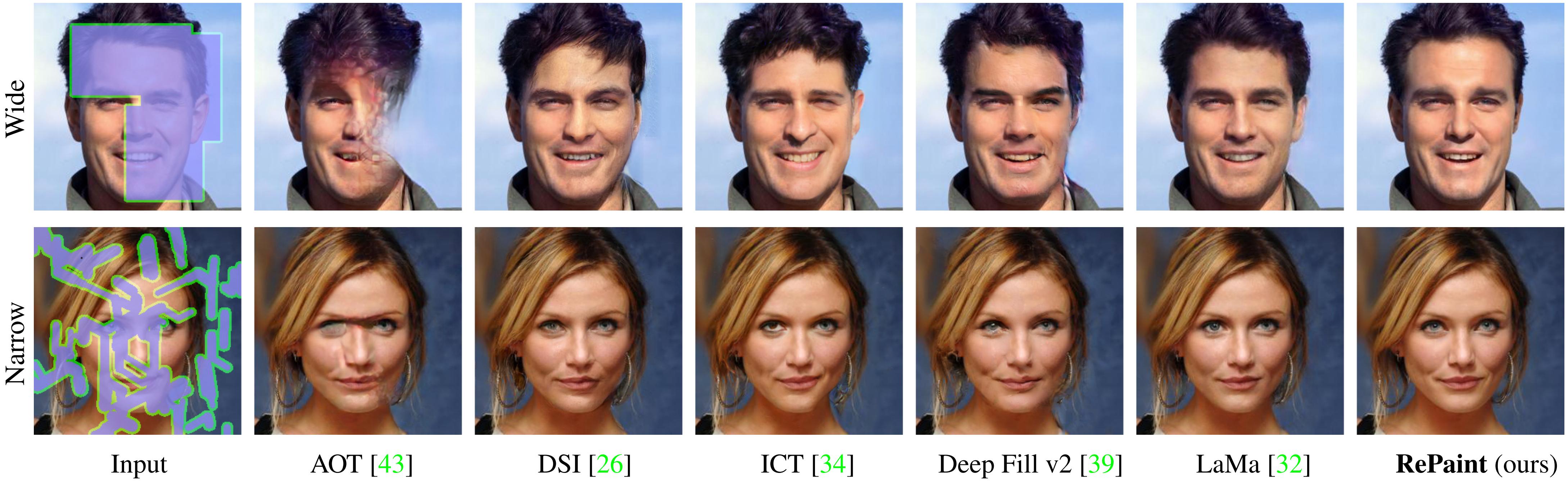
Resampling



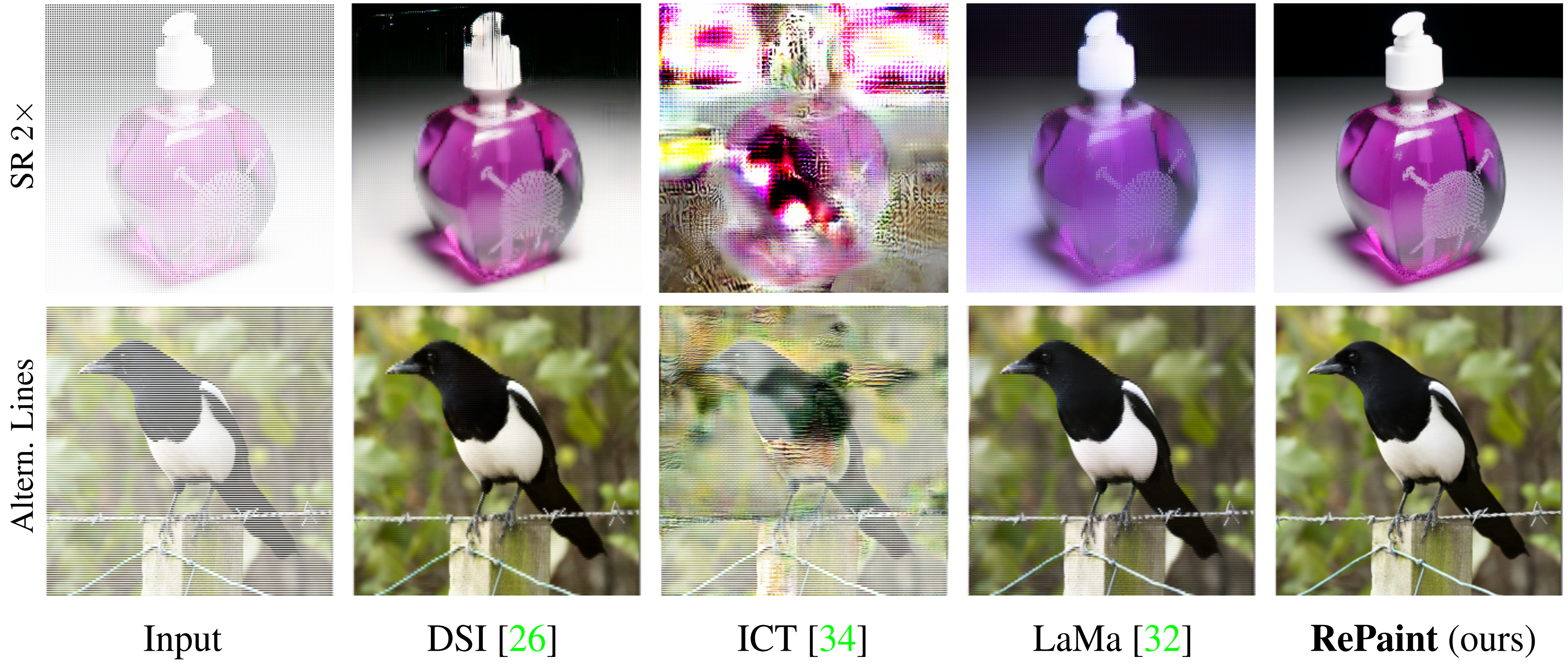
Resampling Jumps

- With increasing resampling
  - The semantic consistency improves
  - The image becomes blurrier
- When increasing the transition step length
  - Semantic consistency is not influenced
  - Images are less blurry

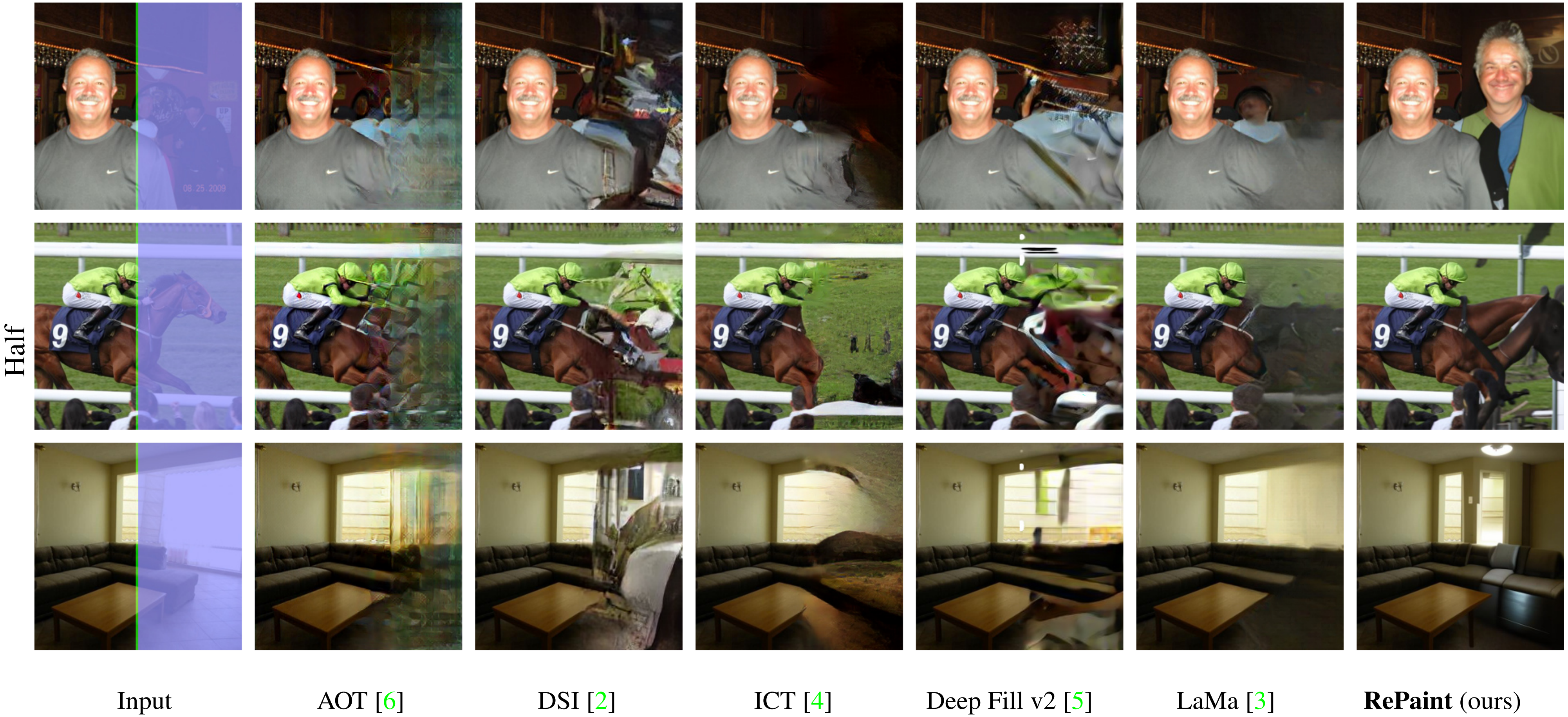
SOTA Comparison CelebA-HQ



SOTA Comparison ImageNet



SOTA Comparison Places2



SOTA Comparison

CelebA-HQ	Wide		Narrow		Super-Resolve 2×		Altern. Lines		Half		Expand	
Methods	LPIPS↓	Votes [%]	LPIPS↓	Votes [%]	LPIPS↓	Votes [%]	LPIPS↓	Votes [%]	LPIPS↓	Votes [%]	LPIPS↓	Votes [%]
AOT [43]	0.104	11.6 ± 2.0	0.047	12.8 ± 2.1	0.714	1.1 ± 0.6	0.667	2.4 ± 1.0	0.287	9.0 ± 1.8	0.604	8.3 ± 1.7
DSI [26]	0.067	16.0 ± 2.3	0.038	22.3 ± 2.6	0.128	5.5 ± 1.4	0.049	5.1 ± 1.4	0.211	4.5 ± 1.3	0.487	4.7 ± 1.3
ICT [34]	0.063	27.6 ± 2.8	0.036	30.9 ± 2.9	0.483	4.2 ± 1.2	0.353	0.7 ± 0.5	0.166	12.7 ± 2.1	0.432	8.8 ± 1.8
DeepFillv2 [39]	0.066	23.9 ± 2.6	0.049	21.0 ± 2.5	0.119	9.8 ± 1.8	0.049	10.6 ± 1.9	0.209	4.1 ± 1.2	0.467	13.1 ± 2.1
LaMa [32]	0.045	41.8 ± 3.1	0.028	33.8 ± 3.0	0.177	5.5 ± 1.4	0.083	20.6 ± 2.5	0.138	35.6 ± 3.0	0.342	24.7 ± 2.7
RePaint	0.059	*Reference*	0.028	*Reference*	0.029	*Reference*	0.009	*Reference*	0.165	*Reference*	0.435	*Reference*

ImageNet	Wide		Narrow		Super-Resolve 2×		Altern. Lines		Half		Expand	
Methods	LPIPS↓	Votes [%]	LPIPS↓	Votes [%]	LPIPS↓	Votes [%]	LPIPS↓	Votes [%]	LPIPS↓	Votes [%]	LPIPS↓	Votes [%]
DSI [26]	0.117	31.7 ± 2.9	0.072	28.6 ± 2.8	0.153	26.9 ± 2.8	0.069	23.6 ± 2.6	0.283	31.4 ± 2.9	0.583	9.2 ± 1.8
ICT [34]	0.107	42.9 ± 3.1	0.073	33.0 ± 2.9	0.708	1.1 ± 0.6	0.620	6.6 ± 1.5	0.255	51.5 ± 3.1	0.544	25.6 ± 2.7
LaMa [32]	0.105	42.4 ± 3.1	0.061	33.6 ± 2.9	0.272	13.0 ± 2.1	0.121	9.6 ± 1.8	0.254	41.1 ± 3.1	0.534	20.3 ± 2.5
RePaint	0.134	*Reference*	0.064	*Reference*	0.183	*Reference*	0.089	*Reference*	0.304	*Reference*	0.629	*Reference*

Class Guided Inpainting

- Use of Diffusion Models that were trained class conditionally
- RePaint creates meaningful images for different classes

Diffusion models beat gans on image synthesis
Dhariwal, P. and Nichol

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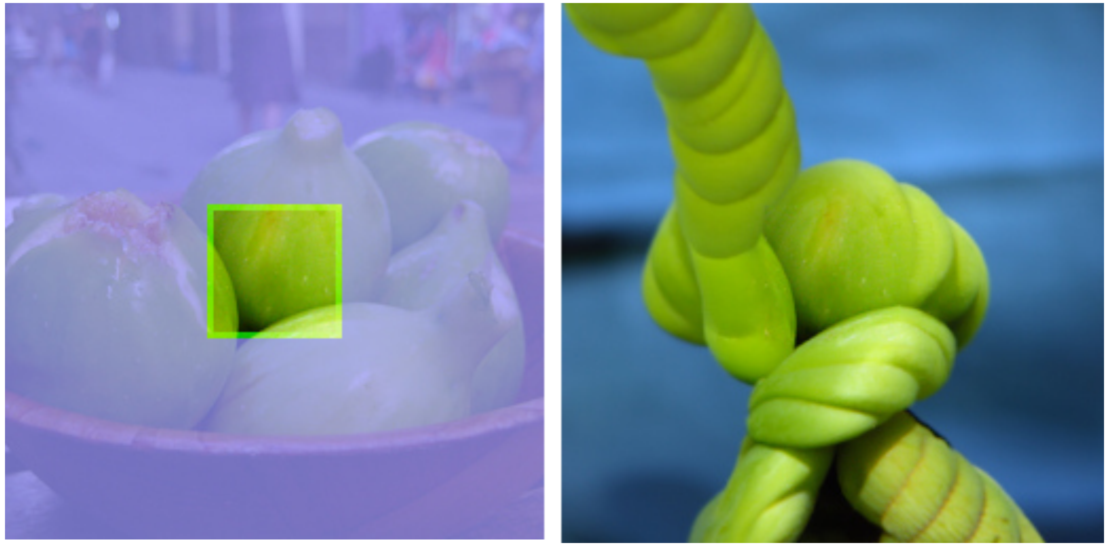

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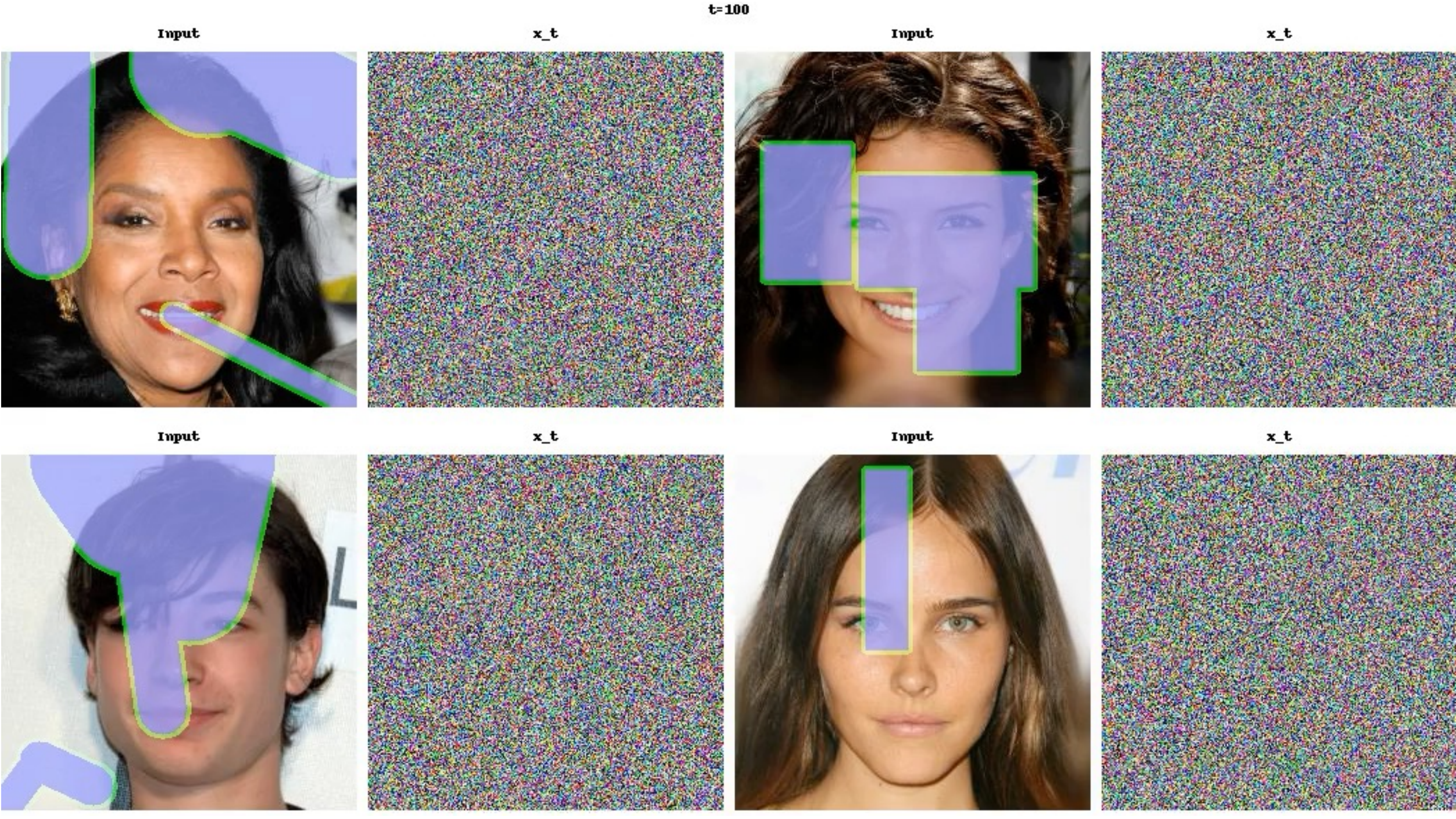
t=100
Input
x_t
Input
x_t
Input
x_t
Input
x_t

git.io/RePaint