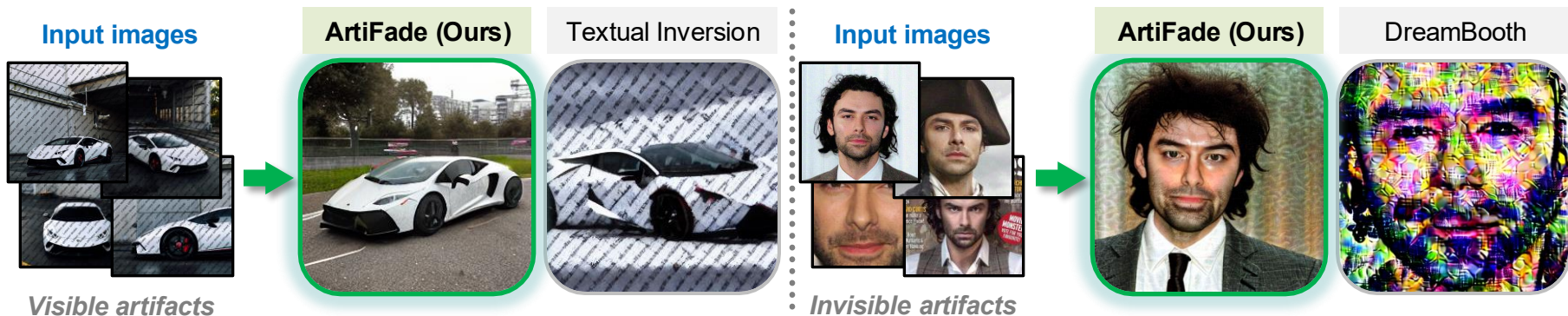


ArtiFade: Learning to Generate High-quality Subject from Blemished Images

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The University of Hong Kong



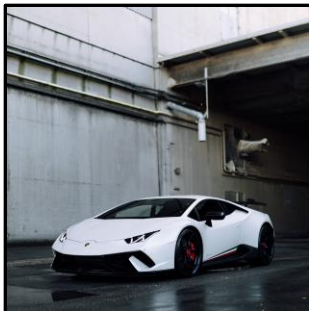
Outline

- Motivation
- Methodology
- **Experiments**
- Applications

Subject-driven image generation

Input images

Textual
Inversion



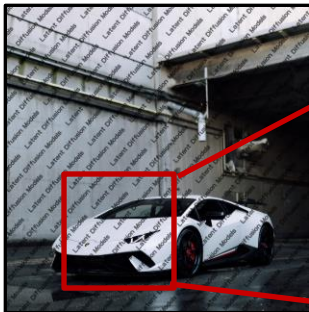
DreamBooth



Subject-driven image generation

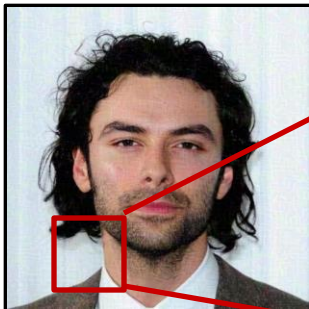
Input images

Textual
Inversion



Visible
Artifacts

DreamBooth

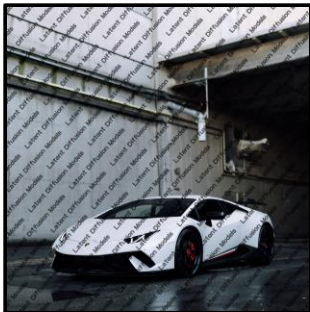


Invisible
Artifacts

Blemished Subject-driven image generation

Input images

Textual
Inversion



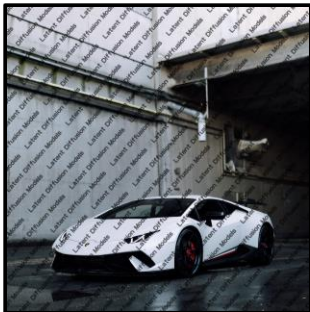
DreamBooth



Blemished Subject-driven image generation

Input images

Textual
Inversion



DreamBooth



ArtiFade



Contribution

- **Novel challenge:** The first work to tackle the problem of blemished subject-driven generation.
- **Proposed method:** Introduce ArtiFade, which fine-tunes diffusion models to align unblemished and blemished data.
- **Benchmark:** Establish a new benchmark for evaluating blemished subject-driven generation.
- **Generalizability:** Demonstrate strong generalizability, effective on both in-distribution and out-of-distribution artifacts.

Motivation

Method

Experiments

Applications

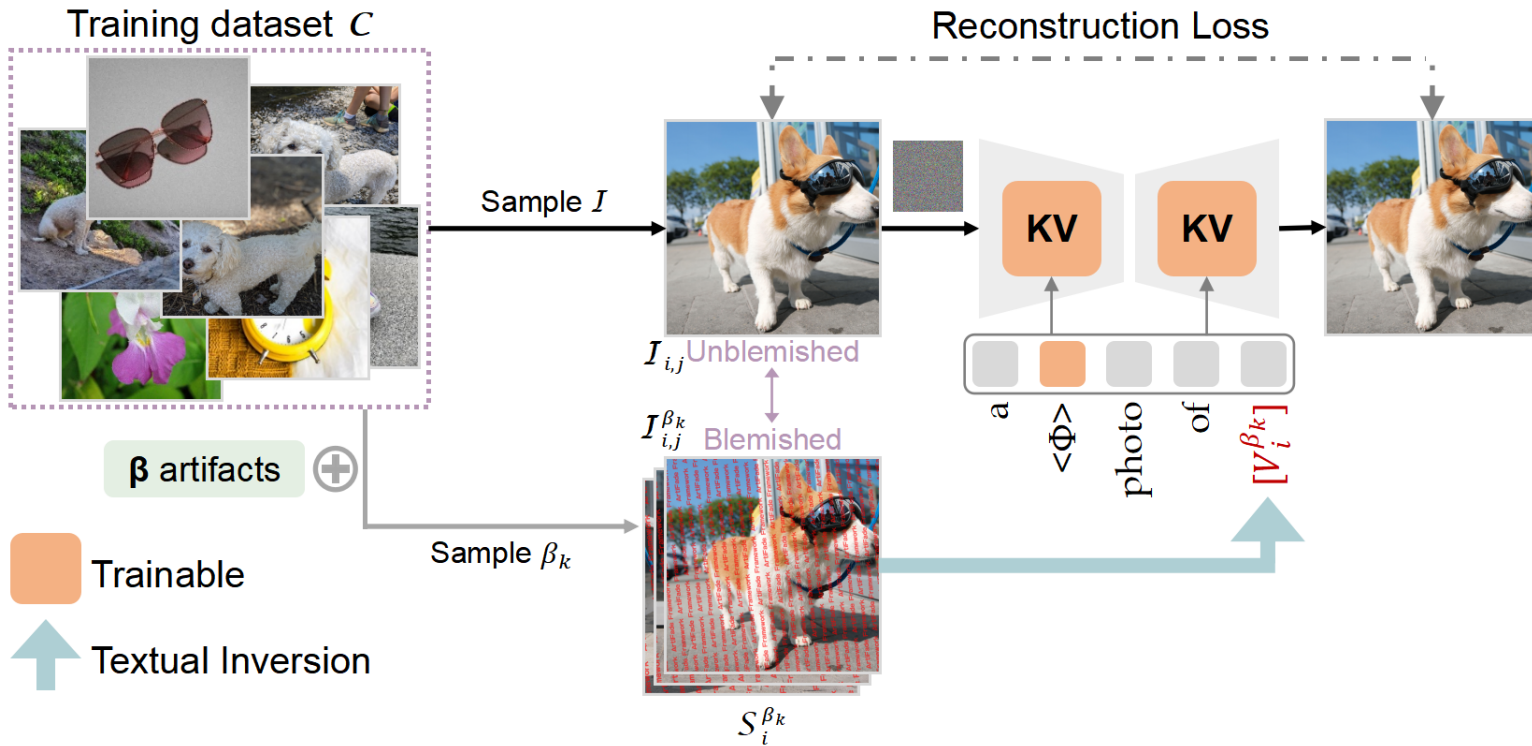
Method of ArtiFade

I. Data preparation Step

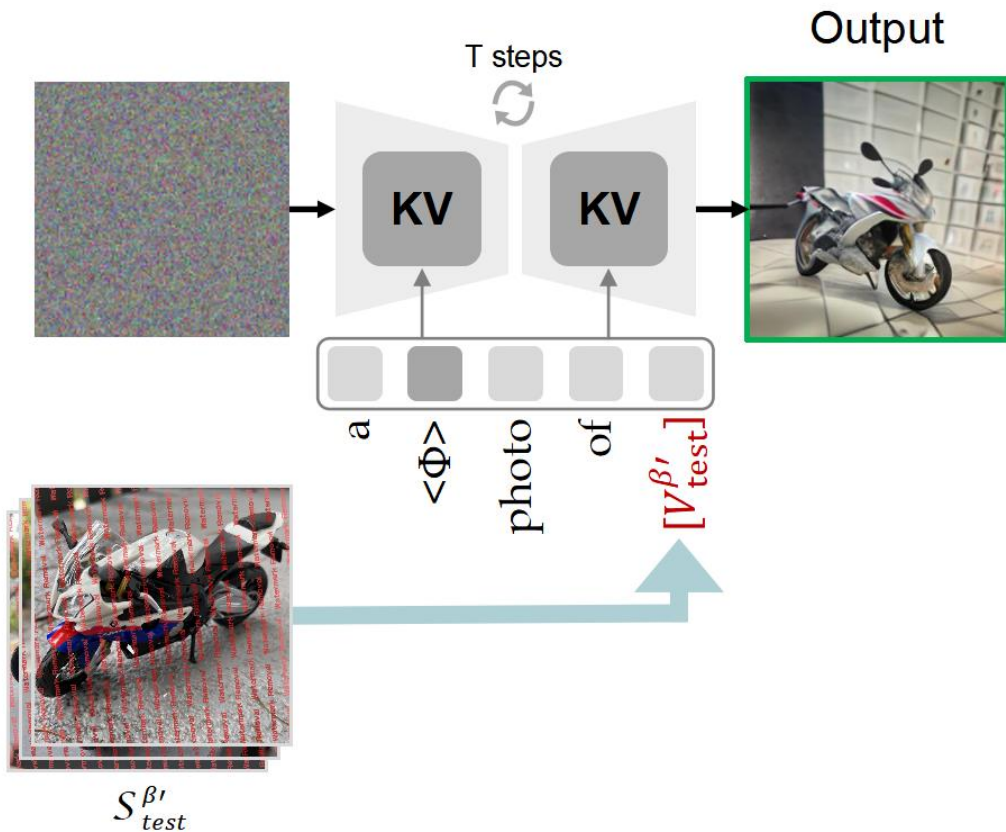


$$\mathcal{S}_i^{\beta_k} \xrightarrow{\text{Textual Inversion}} [\mathbf{V}_i^{\beta_k}], \quad i = 1, 2, \dots, N; \quad k = 1, 2, \dots, L$$

2. Fine-tuning Step



3. Inference Step



Motivation

Method

Experiments

Applications

Experiments

ArtiFade with Textual Inversion - Quantitative

1. $I^{CLIP} :=$ CLIP similarities between the generated images and the corresponding unblemished subsets
2. $I^{DINO} :=$ DINO similarities between the generated images and the corresponding unblemished subsets
3. $T^{CLIP} :=$ CLIP similarity between the generated images and the text prompt
4. $R^{CLIP} = I^{CLIP} / I_{\beta}^{CLIP}$
5. $R^{DINO} = I^{DINO} / I_{\beta}^{DINO}$

ArtiFade with Textual Inversion - Quantitative

Method	WM-model on WM-ID-test				
	$I^{\text{DINO}} \uparrow$	$R^{\text{DINO}} \uparrow$	$I^{\text{CLIP}} \uparrow$	$R^{\text{CLIP}} \uparrow$	$T^{\text{CLIP}} \uparrow$
In-distribution					
TI (unblemished)	0.488	1.349	0.730	1.070	0.283
TI (blemished)	0.217	0.852	0.576	0.909	0.263
Ours	0.337	1.300	0.649	1.020	0.282
Method	WM-model on WM-OOD-test				
	$I^{\text{DINO}} \uparrow$	$R^{\text{DINO}} \uparrow$	$I^{\text{CLIP}} \uparrow$	$R^{\text{CLIP}} \uparrow$	$T^{\text{CLIP}} \uparrow$
Out-of-distribution					
TI (unblemished)	0.488	1.278	0.730	1.136	0.283
TI (blemished)	0.229	0.858	0.575	0.929	0.262
Ours	0.356	1.237	0.654	1.079	0.282

ArtiFade with Textual Inversion - Qualitative (In-distribution)

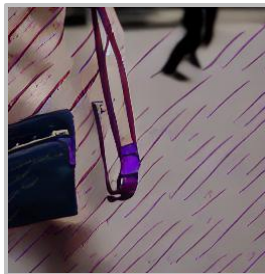
Input images



Ours



Textual Inversion



Ours



Textual Inversion



$[V_{test}^{\beta'}]$ in the street

$[V_{test}^{\beta'}]$ in the snow



$[V_{test}^{\beta'}]$ with a mountain in the background

$[V_{test}^{\beta'}]$ with a city in the background

ArtiFade with Textual Inversion - Qualitative (Out-of-distribution)

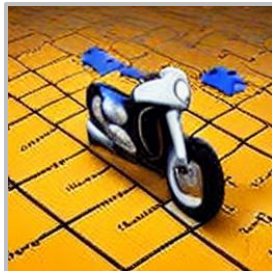
Input images



Ours



Textual Inversion



Ours

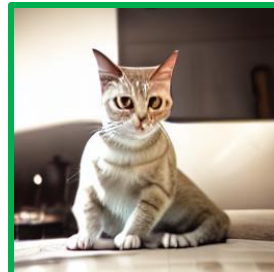
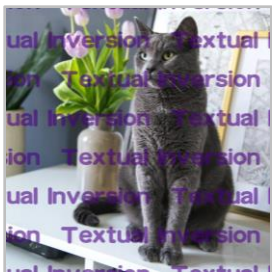


Textual Inversion



$[V_{test}^{B'}]$ on top of a wooden floor

$[V_{test}^{B'}]$ with a city in the background



$[V_{test}^{B'}]$ in the movie theater

$[V_{test}^{B'}]$ in a luxurious interior living room

ArtiFade with DreamBooth - Quantitative

In-distribution

Method	WM-ID-test				
	$I^{\text{DINO}} \uparrow$	$R^{\text{DINO}} \uparrow$	$I^{\text{CLIP}} \uparrow$	$R^{\text{CLIP}} \uparrow$	$T^{\text{CLIP}} \uparrow$
TI (unblemished)	0.488	1.349	0.730	1.070	0.283
TI (blemished)	0.217	0.852	0.576	0.909	0.263
DB (blemished)	0.503	0.874	0.738	0.939	0.272
Ours (TI-based)	0.337	1.300	0.649	1.020	0.282
Ours (DB-based)	0.589	1.308	0.795	1.083	0.284

ArtiFade with DreamBooth - Qualitative (In-distribution)

Input images



Ours



*sk*s cat with a beautiful sunset

DreamBooth

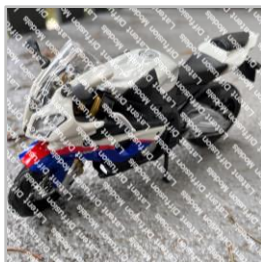


Ours



*sk*s cat with the Eiffel tower in the background

DreamBooth



*sk*s motorbike in the snow



*sk*s motorbike in the jungle



ArtiFade with DreamBooth - Qualitative (Invisible artifacts)

Input images



Ours



DreamBooth



sk's person

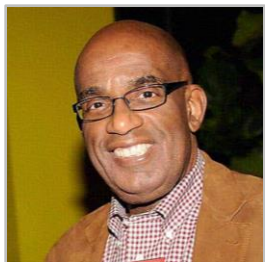
Ours



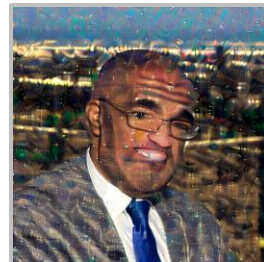
DreamBooth



sk's person in the jungle



sk's person in the snow

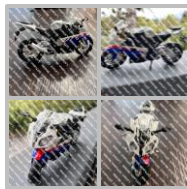
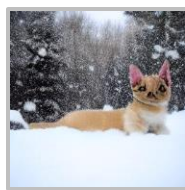
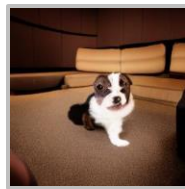
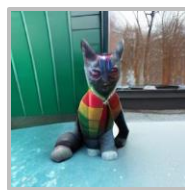


sk's person with a city in the background

Ablation Study

Method	W^{kv}	W^q	$\langle \Phi \rangle$	I^{DINO}	R^{DINO}	I^{CLIP}	R^{CLIP}	T^{CLIP}
Var _A			✓	0.154	1.412	0.566	0.984	0.265
Var _B		✓	✓	0.283	1.230	0.617	0.978	0.277
Var _C	✓		✓	0.342	1.292	0.652	1.019	0.280
Ours	✓		✓	0.337	1.300	0.649	1.020	0.282

Input images

Var_AVar_BVar_C

WM-model (Ours)



$[V_{test}^{\beta'}]$ in a movie theater

$[V_{test}^{\beta'}]$ in the snow

Applications

- stickers removal
& glass effect removal**

Input sample



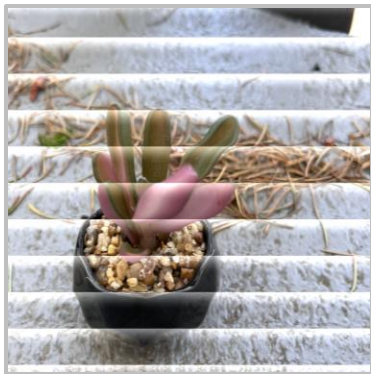
Ours



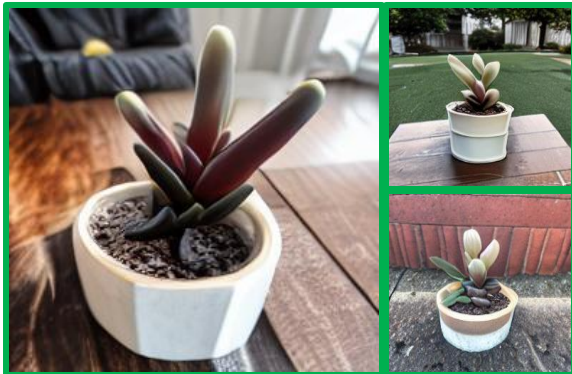
Textual Inversion



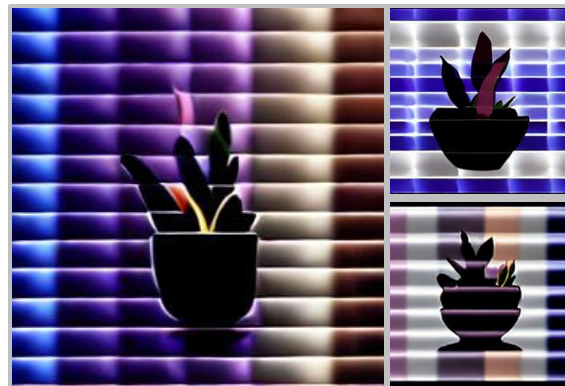
Input sample



Ours



Textual Inversion



Thank you!