DEADiff: An Efficient Stylization Diffusion Model with Disentangled Representations

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Outline

1 Background







BLIP-Diffusion: Pre-trained Subject Representation for Controllable Text-to-Image Generation and Editing

Dongxu Li[†], Junnan Li[†], Steven C.H. Hoi[†] Salesforce AI Research

[†]Corresponding authors: {li.d,junnan.li,shoi}@salesforce.com https://github.com/salesforce/LAVIS/tree/main/projects/blip-diffusion

Two stage pre-training



BLIP2 Representation Learning Objectives



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Background BLIP2 Representation Learning Objectives



[text prompt], the [subject text] is [subject prompt]"



Generating training image pair





- Subject-specific Fine-tuning and Inference
- Structure-controlled Generation with ControlNet
- Subject-driven Editing with Attention Control



zero-sort subject-driven generation



wearing top hat





as plushie







painting by Van Gogh painted green



on a red rug at Palace of Versailles seen from back made of lego at grand canyon



on the beach





decorated on cup wearing glasses







few-step fine-tuned subject-driven generation Background



silver scuplture bronze sculpture

paper sculpture

as perfume atomizer as teapot



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structure controled subject-driven generation



subject-driven image editing with attention control



- context-appearence entanglement
- failing to address the text prompt
- wrong spatial composition



Subject images

A backpack on top of a **purple rug** in a forest.

Subject images

A **cube-shaped** bear plushie.

Subject images

A sneaker **on top of** a mirror.

Outline





4 Experiments

Author

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1999-2002 Tianjin University, PhD, Signal and Information Processing 2002-2017 Researcher, Institute of Computing Technology, Chinese Academy of Sciences Professor at the University of Science and Technology of China from 2017 to present

Research directions include multimedia content analysis, cybersecurity, and computational imaging.

Results preview



Reference

(a) T2I-Adapter

(b) DEADiff

Contributions

Disentangle style and semantic representation of the reference image

Injecting image style/semantic representation to different crossattention layers



Disentangle style and semantic representation of the reference image



Injecting image style/semantic representation to different



Injecting image style/semantic representation to different crossattention layers



Injecting image style/semantic representation to different crossattention layers



Establishing paired datasets

Text prompt combination

Image generation and collection

Paired images selection

Outline









- Evaluation
 - Style Similarity (SS)
 - Text Alignment capability (TA)
 - Image Quality (IQ)
 - Subjective Preference (SP)



Quantitative Comparisons

Method	SS↑	IQ↑	TA↑	SP↑
InST [37]	0.215	5.148	0.237	6.3
CAST [36]	0.224	4.922	0.282	8.7
StyTr ² [3]	0.214	5.037	0.282	13.1
T2I-Adapter [17]	0.241	5.500	0.224	2.7
IP-Adapter [34]	0.274	<u>5.598</u>	0.155	-
DEADiff	0.229	5.840	0.284	69.0

Ablations

Method	Style Similarity [↑]	Text Alignment↑
Baseline	0.274	0.148
+ DCM	0.259	0.224
+ STRE	0.222	0.286
+ SERE	0.221	0.287
DEADiff	0.224	0.289

"A dog in a bucket."

























Reference Baseline +DCM

+STRE

+SERE

DEADiff

Applications



Ablations



"A robot"

Ablations

"A cat wearing a hat."



Reference SD v1.5 Realistic Vison V5.1 DreamShaper V8

Thanks!

BLIP2 pre-training

