

GENERATIVE
RENAISSANCE

ASIA.SIGGRAPH.ORG/2025



SIGGRAPH 香港
ASIA 2025
HONG KONG 港

Conference 15 – 18 December 2025

Exhibition 16 – 18 December 2025

Venue Hong Kong Convention
and Exhibition Centre

B4M:
Breaking Low Rank Adapter
Making Content-Style
Customization

Sponsored by



Organized by





SIGGRAPH
ASIA 2025
HONG KONG 香港



Universität
Konstanz



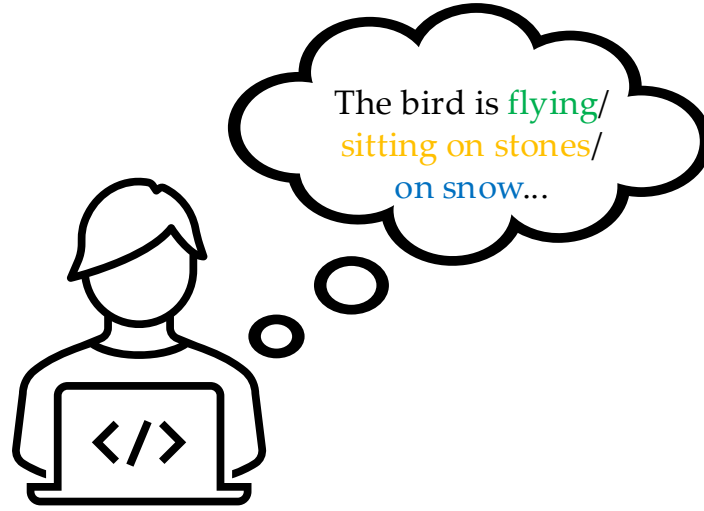
國立成功大學
National Cheng Kung University

B4M: Breaking Low-Rank Adapter for Making Content-Style Customization

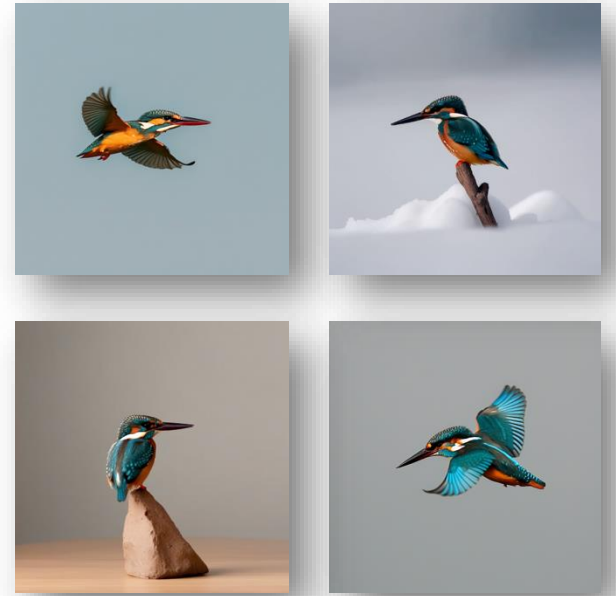
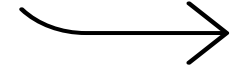
Yu Xu, Fan Tang, Juan Cao, Yuxin Zhang, Oliver Deussen,
Weiming Dong, Jintao Li, Tong-Yee Lee

Institutes of Computing Technology, Chinese Academy of Sciences
Institutes of Automation, Chinese Academy of Sciences
University of Konstanz
National ChengKung University

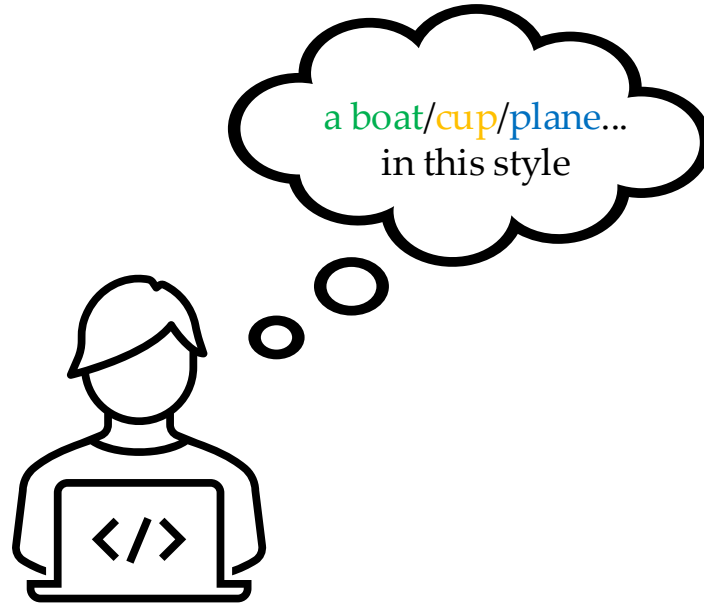
Content Reference



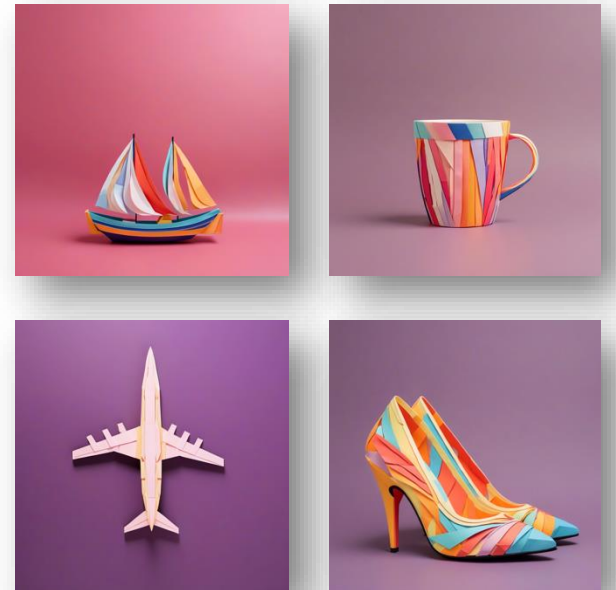
- LoRA
- Textual Inversion
- Dreambooth
- ...



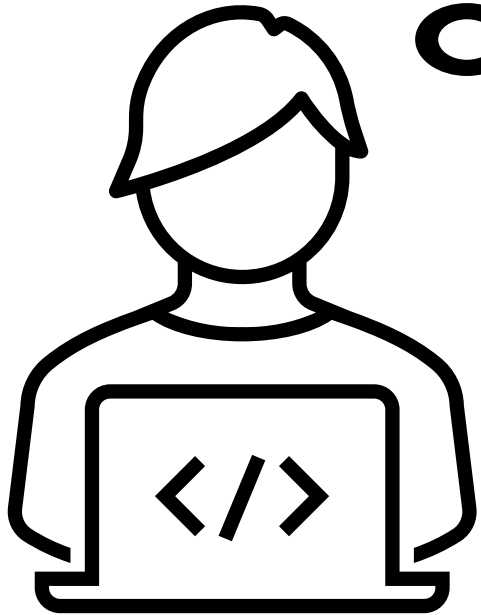
Style Reference



- LoRA
- Textual Inversion
- Dreambooth
- ...



Can I generate **this bird** in **this style**?
with **diverse pose, scene...**



a [c] bird

+



[s] paper style

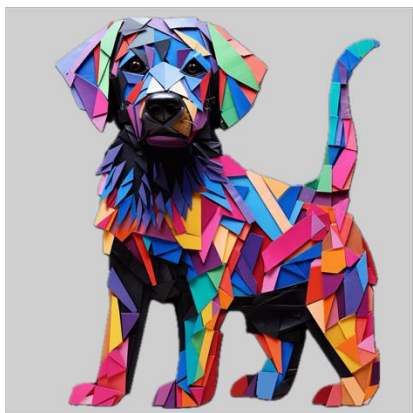
=



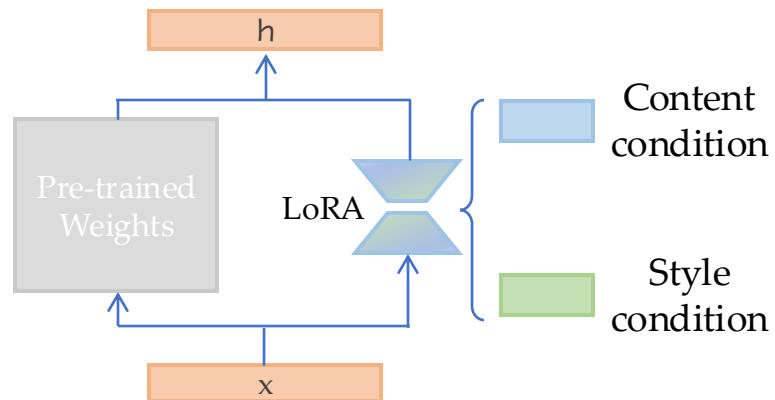
Content



Style

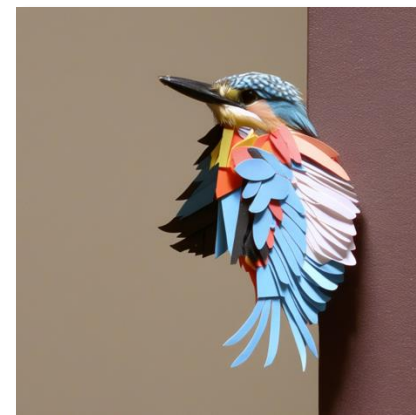
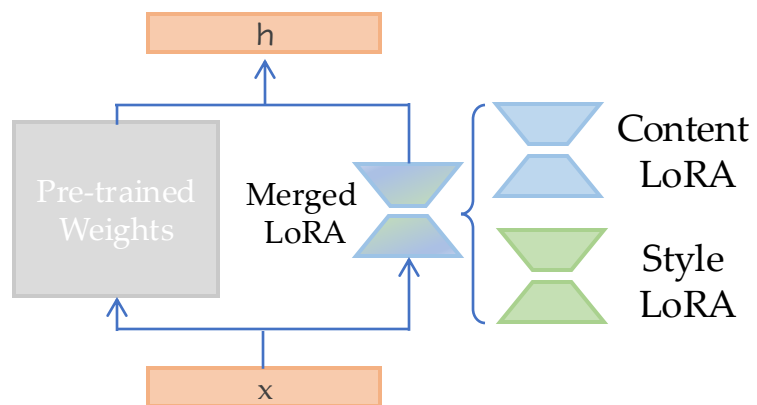


(a) LoRA Joint Training



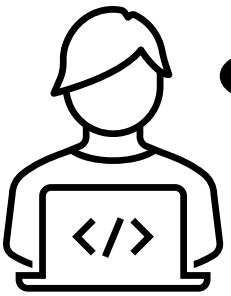
Mixed parameter space
Content and style entangled ❌

(b) LoRA Merging (ZipLoRA)

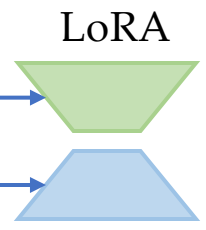
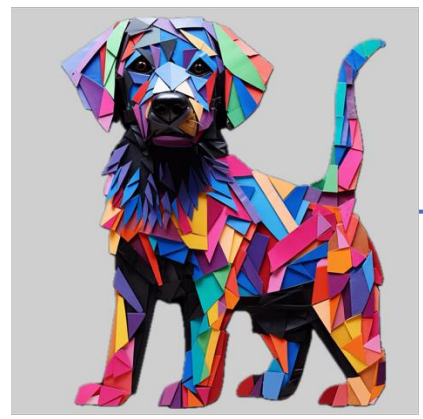


Conflict parameter space
Content and style unfaithful ❌

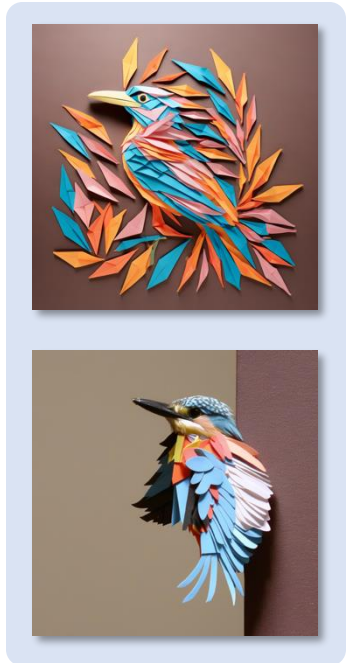
How to disentangle the content and style?



Separate parameter space for content and style



VS



Disentangled parameter space
Exactly what we want !!!

✓ Break LoRA for content and style separation

Content Reference



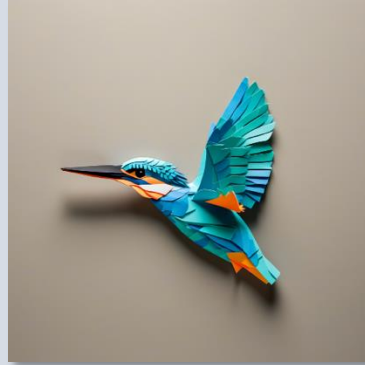
Style Reference



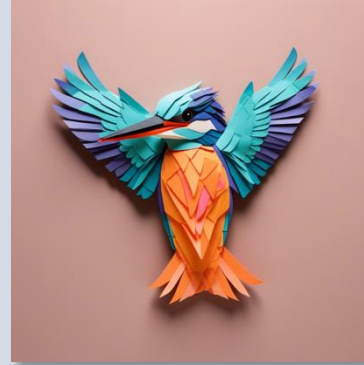
Content-style customization with diverse prompts



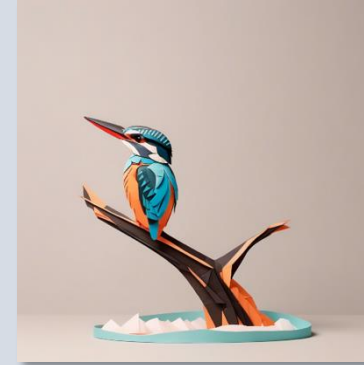
a [c] bird in [s] paper style



"flying"



"front view"



"on a branch"



"in nest"



"over water"



"singing"



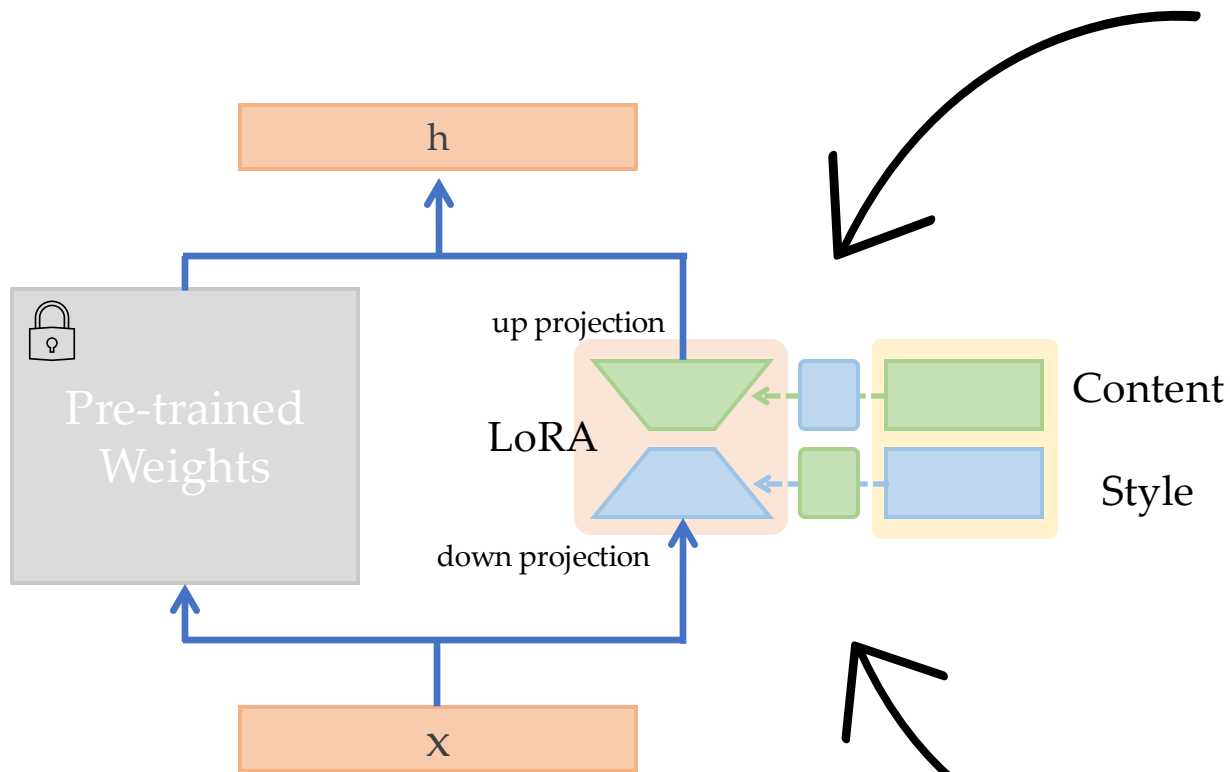
"wearing sunglasses"



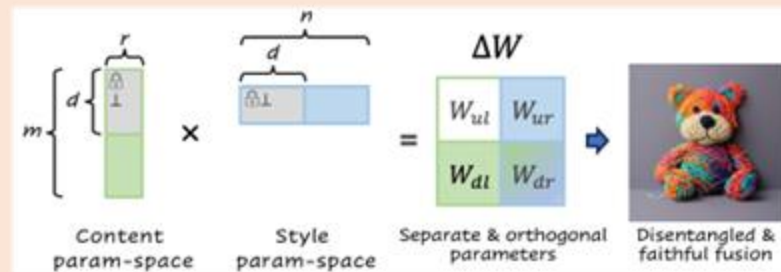
"with a hat"

Method

Overview



Partly Learnable Projection



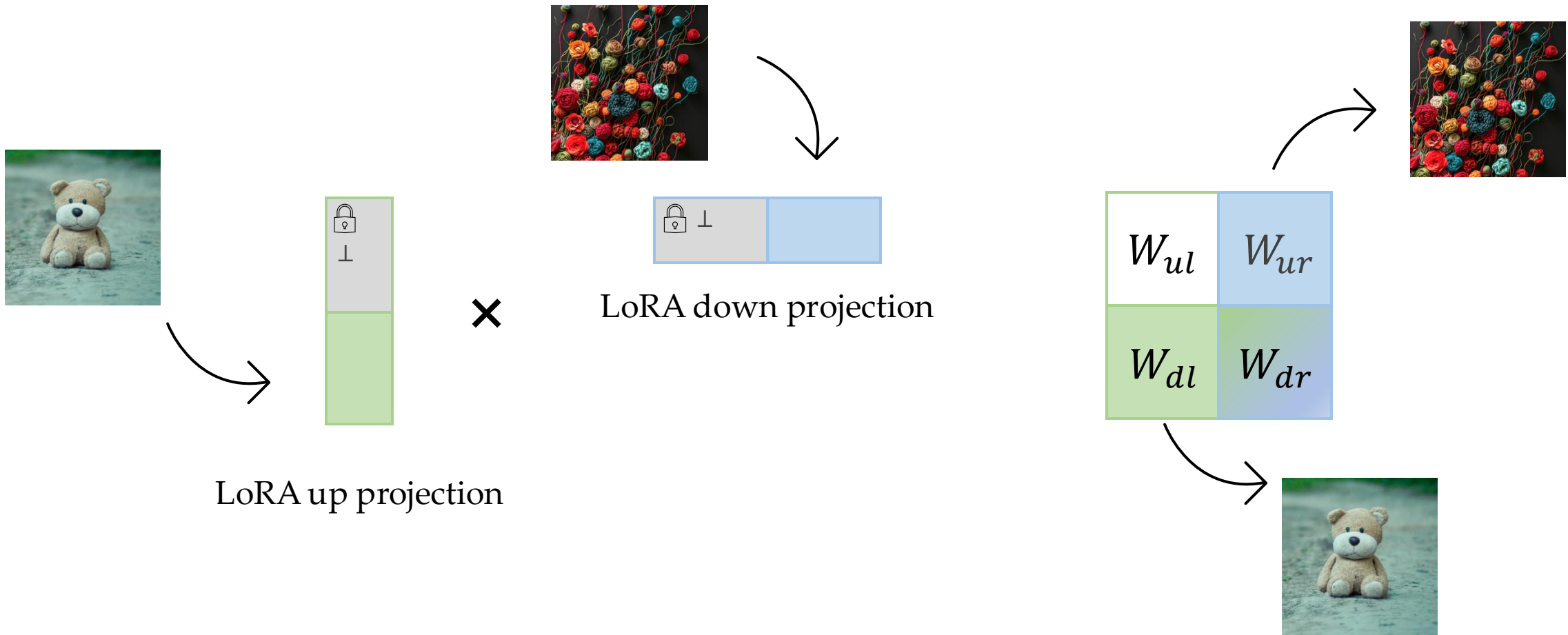
Multi-Correspondence Projection



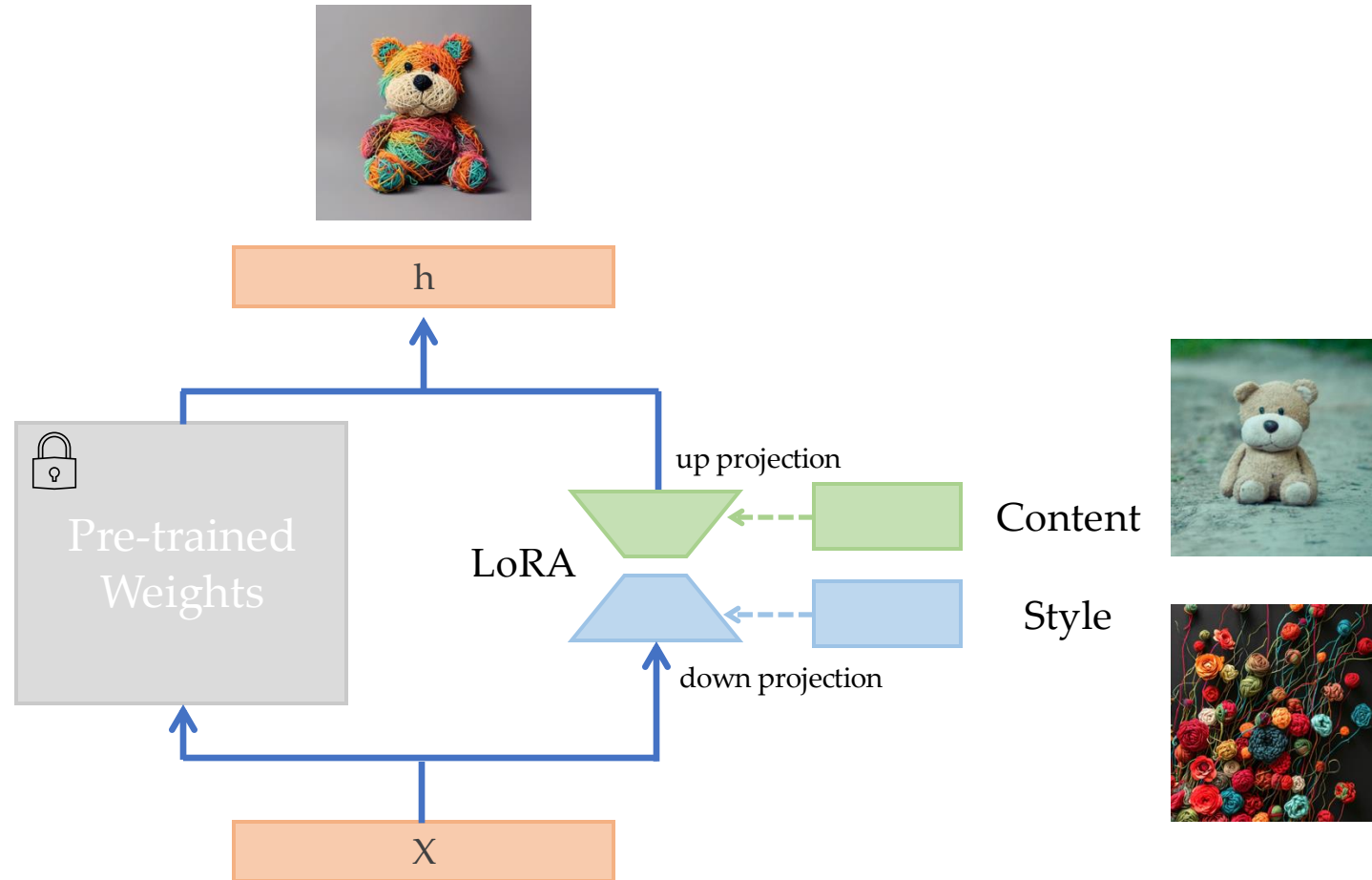
Riemannian Precondition

$$M_{t+1} = M_t - \alpha(N_t^T N_t)^{-1}(\nabla_{M_t} \mathcal{L}),$$
$$N_{t+1} = N_t - \alpha(\nabla_{N_t} \mathcal{L})(M_t M_t^T)^{-1},$$

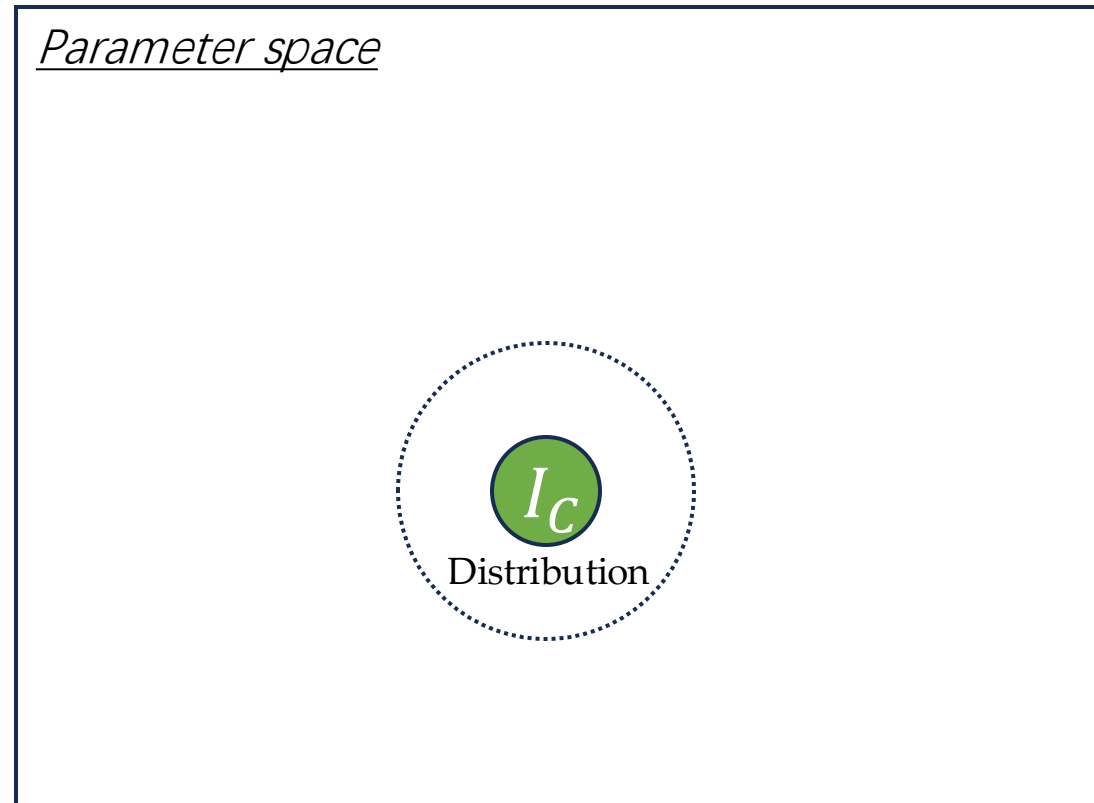
Partly Learnable Projection (PLP)



Low rank adaptation training with PLP

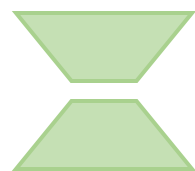


Multi-Correspondence Projection

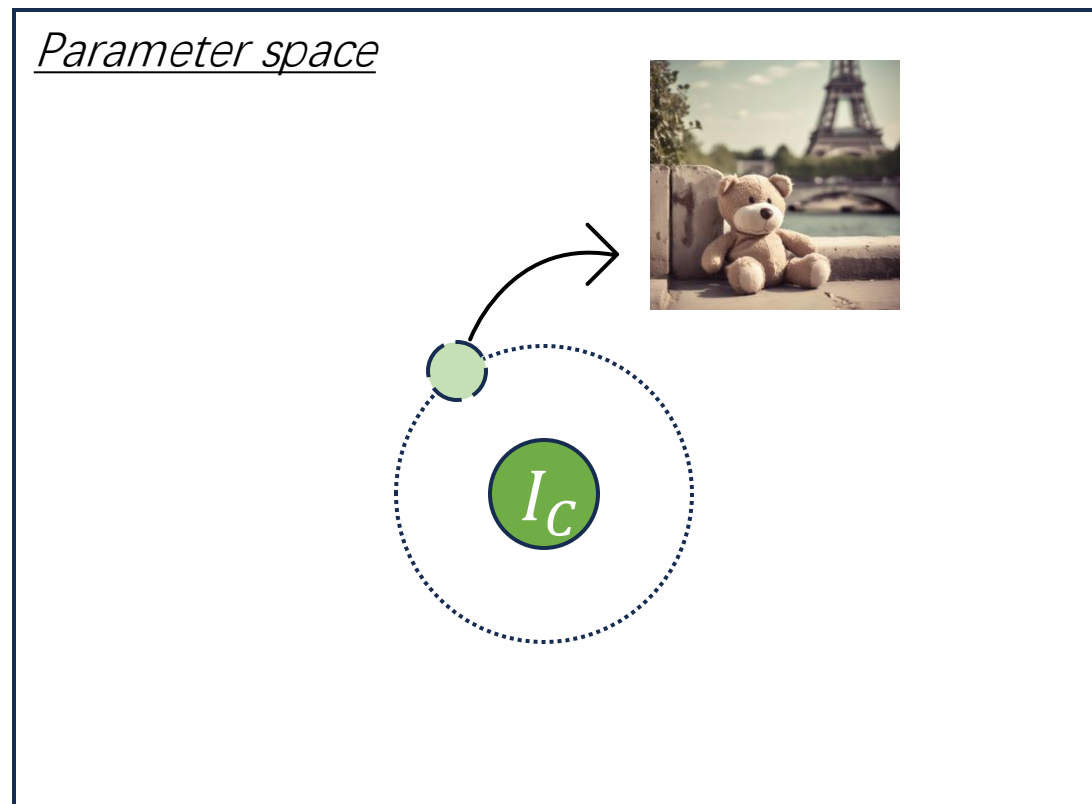


I_C

Multi-Correspondence Projection



Content LoRA



I_C

Distribution of a customized content I_C

A sample within the I_C distribution

Multi-Correspondence Projection



I_C

(content reference)



I_S^1

(style reference)



Multi-Correspondence Projection

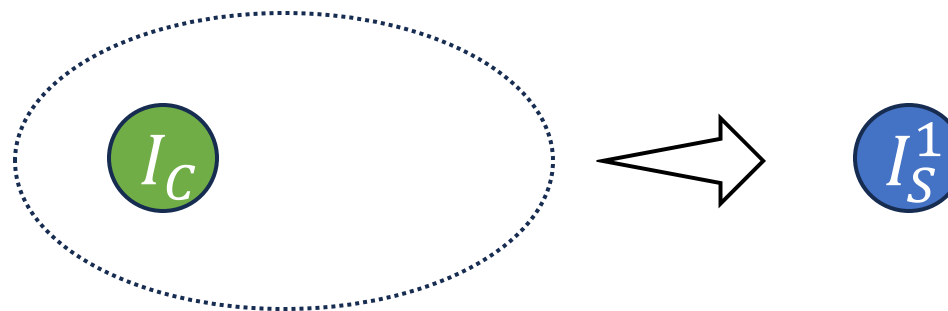


I_C



I_S^1

(style reference)



Distribution of I_C W/o “Multi-Correspondence Projection”

Multi-Correspondence Projection

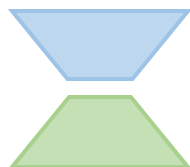


I_C

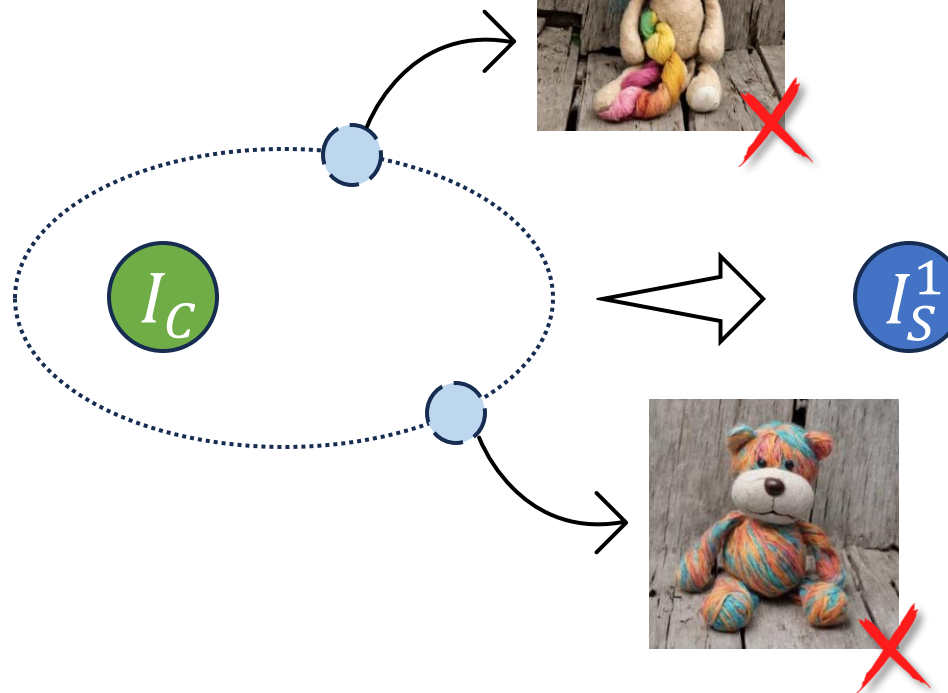


I_S^1

(style reference)



Single style reference
content PLP



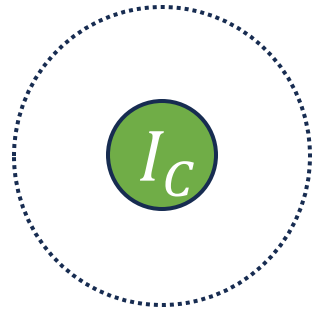
Distribution of I_C W/o “Multi-Correspondence Projection”

Samples are overfitting to specific style

Multi-Correspondence Projection



I_C



Multi-Correspondence Projection



I_C



I_S^1



I_S^2



I_S^3



I_S^4



Multi-Correspondence Projection



I_C



I_S^1



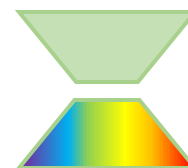
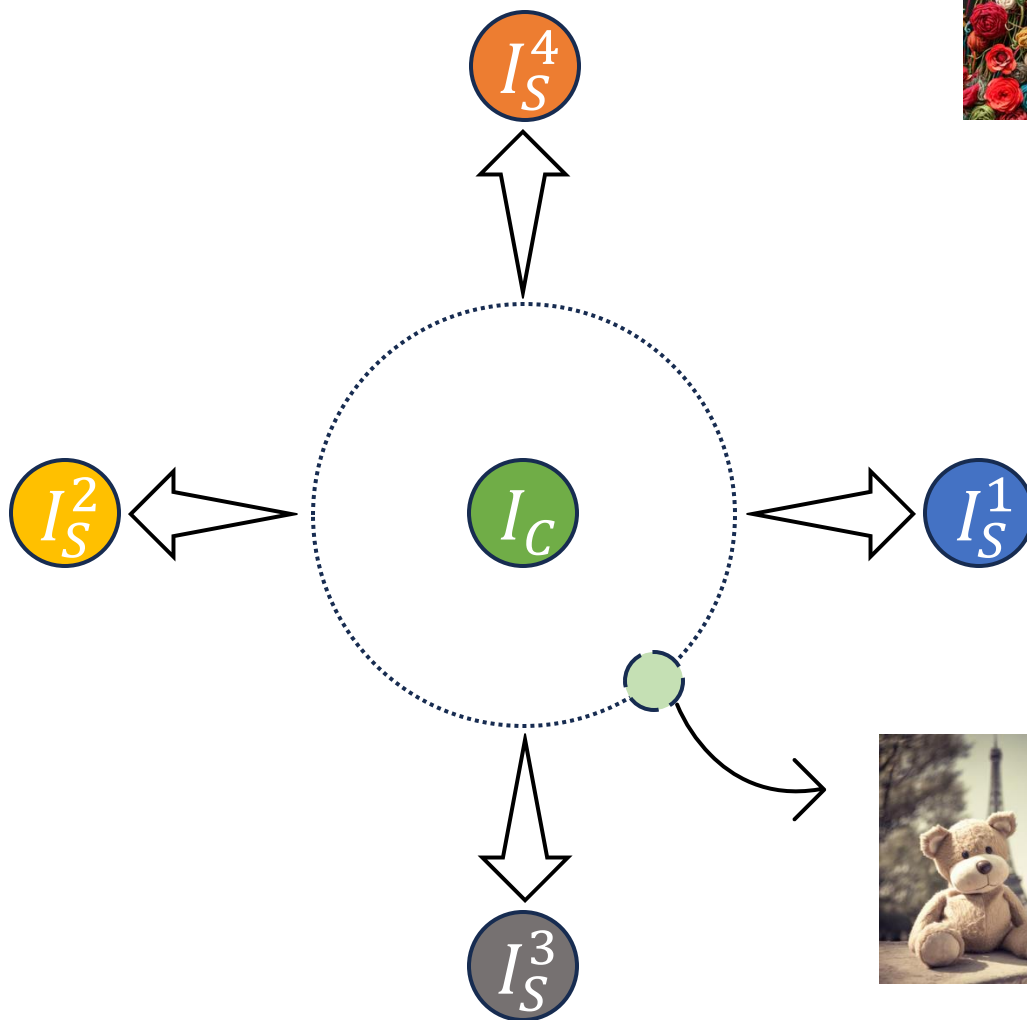
I_S^2



I_S^3

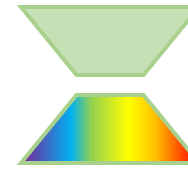


I_S^4

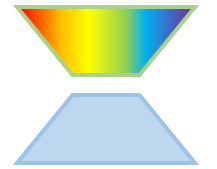


Multi style reference content PLP

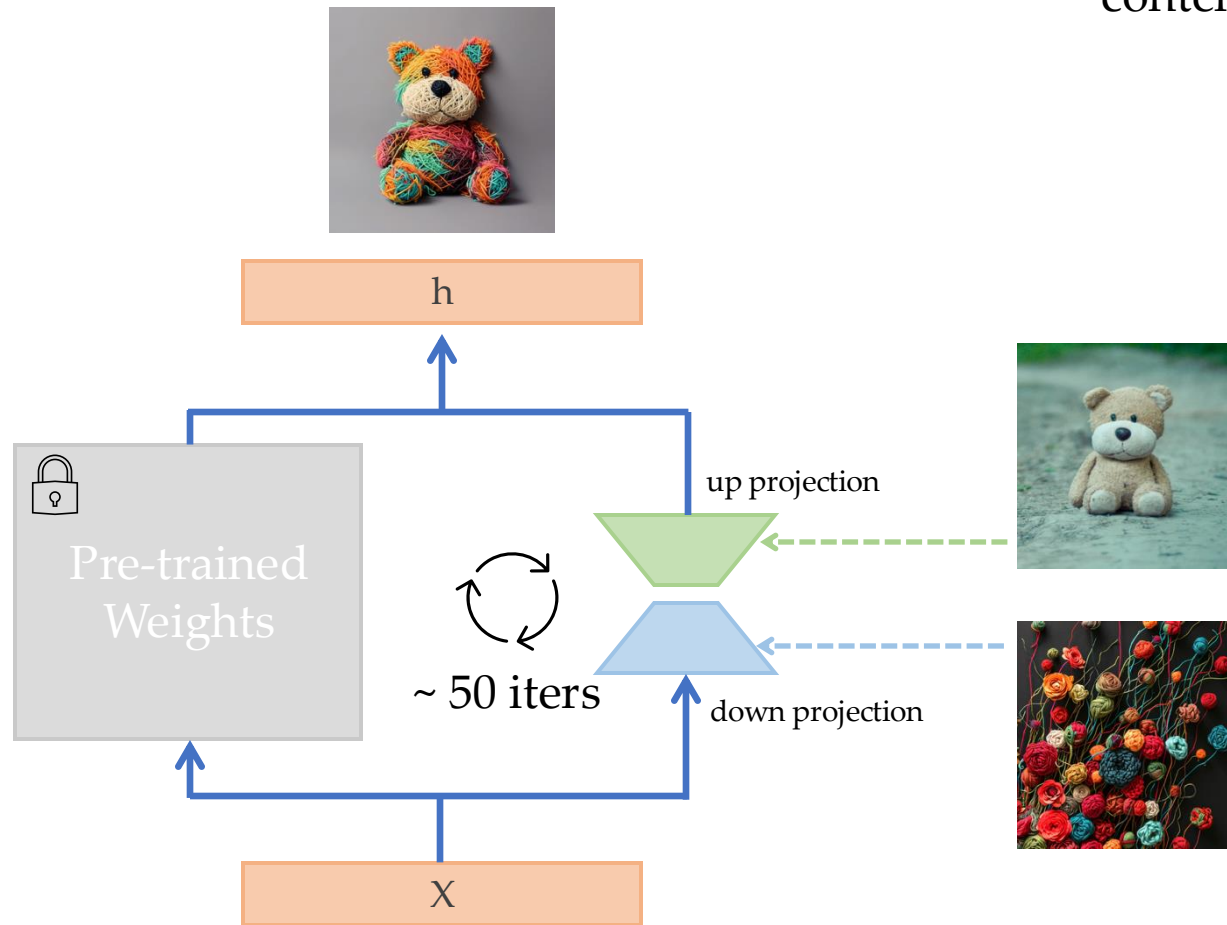
Distribution of I_C With "Multi-Correspondence Projection"



Multi style reference
content PLP



Multi content reference
Style PLP



Riemannian Precondition

Training progress



Content



step 0

step 500

step 1000



Style



step 0

step 500

step 1000

Training progress



Content

Just right !



step 0

step 500

step 1000



Style

Underfitting



step 0

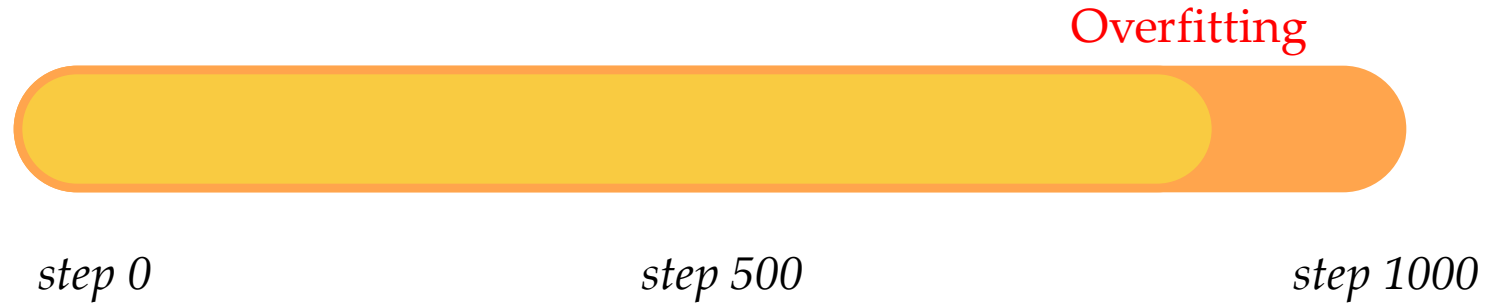
step 500

step 1000

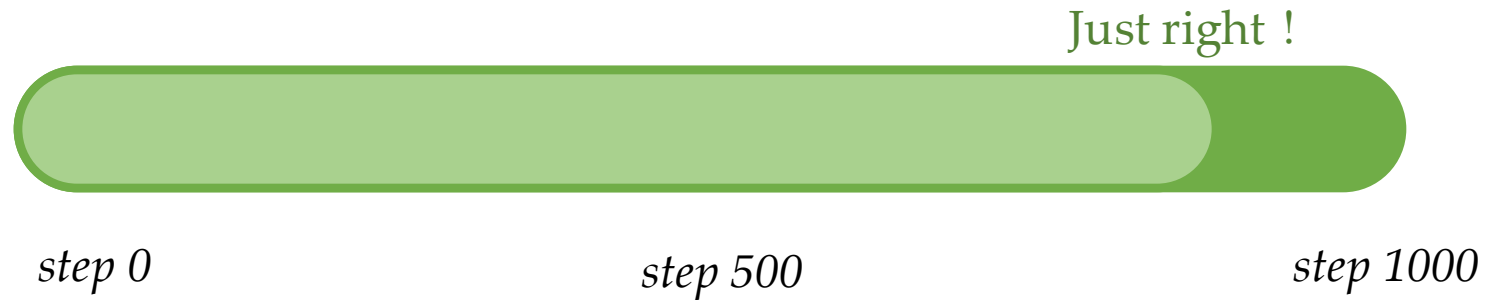
Training progress



Content



Style



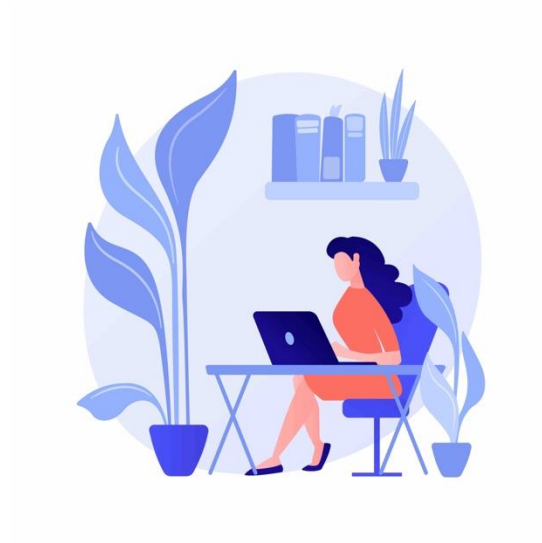
Overfitting to references



skateboarding



Content



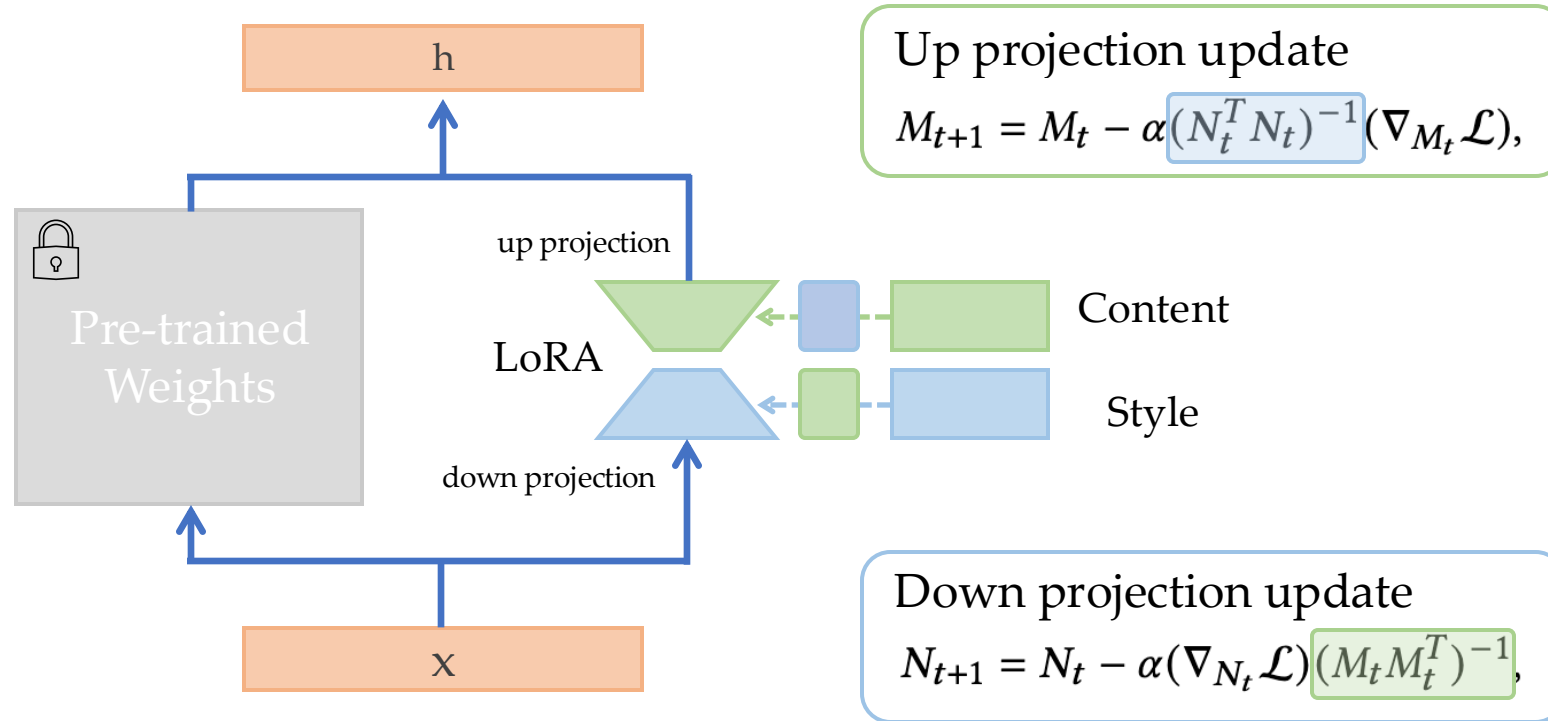
Style



with a hat

Riemannian Precondition

for balance training



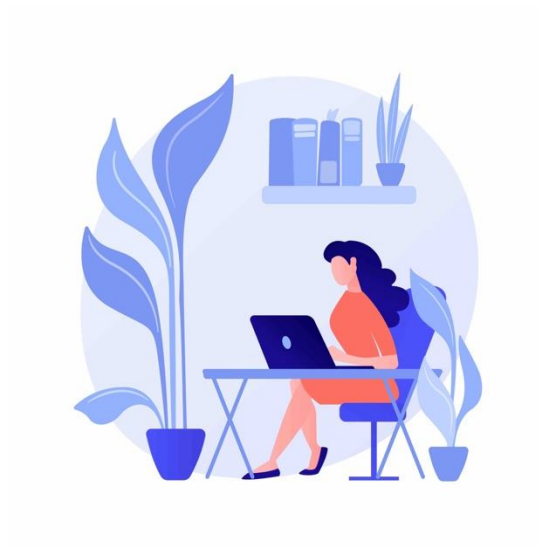
Without Riemannian Precondition



skateboarding



Content



Style



with a hat

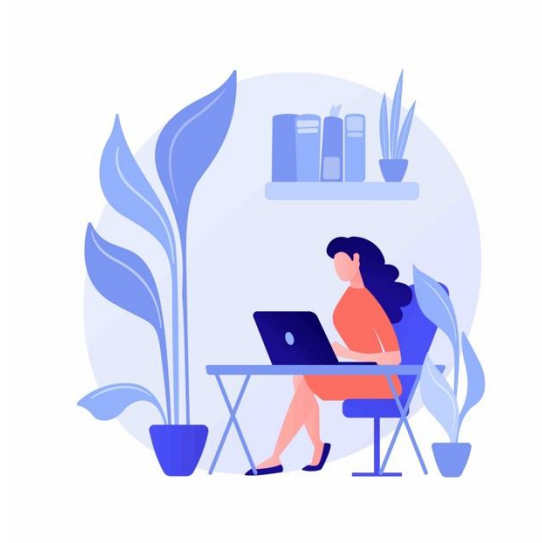
With Riemannian Precondition



skateboarding



Content



Style



with a hat

Comparison with related works

Qualitative comparison

Content reference



Style reference



Ours



- ✓ Content
- ✓ Style

Joint training



- ✓ Content
- ✗ Style

Textual Inversion



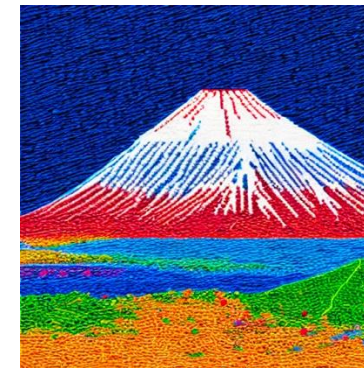
- ✗ Content
- ✓ Style

ProSpect



- ✗ Content
- ✗ Style

Custom Diffusion



- ✗ Content
- ✗ Style

ZipLoRA



- ✓ Content
- ✗ Style

Qualitative comparison

Content reference



Style reference

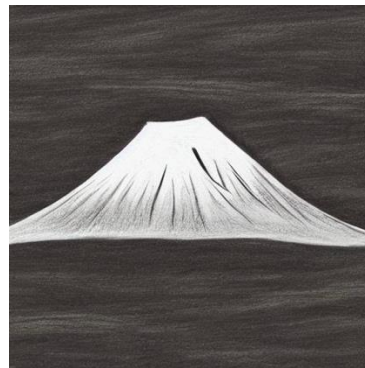


Ours



✓ Content
✓ Style

Joint training



✓ Content
✗ Style

Textual Inversion



✗ Content
✓ Style

ProSpect



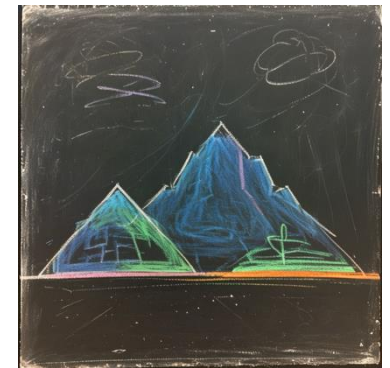
✗ Content
✓ Style

Custom Diffusion



✗ Content
✓ Style

ZipLoRA



✗ Content
✓ Style

Qualitative comparison

Content reference



Style reference



Ours



✓ Content
✓ Style

Joint training



✓ Content
✗ Style

Textual Inversion



✗ Content
✗ Style

ProSpect



✗ Content
✗ Style

Custom Diffusion



✓ Content
✗ Style

ZipLoRA



✓ Content
✗ Style

Qualitative comparison

Content reference



Style reference



Ours



✓ Content
✓ Style

Joint training



✓ Content
✗ Style

Textual Inversion



✗ Content
✗ Style

ProSpect



✗ Content
✗ Style

Custom Diffusion



✓ Content
✗ Style

ZipLoRA



✓ Content
✗ Style

Quantitative comparison

Methods	JTtrain	TI	ProSpect	CD	ZipLoRA	Ours
Content alignment (\uparrow)	0.5221	0.4942	0.4816	0.5181	0.5319	0.5288
Style-alignment (\uparrow)	0.5438	0.6092	0.6165	0.6345	0.6403	0.6754
Prompt-alignment (\uparrow)	0.3038	0.2836	0.3156	0.2778	0.3319	0.4107
Average (\uparrow)	0.4566	0.4623	0.4712	0.4768	0.5014	0.5383



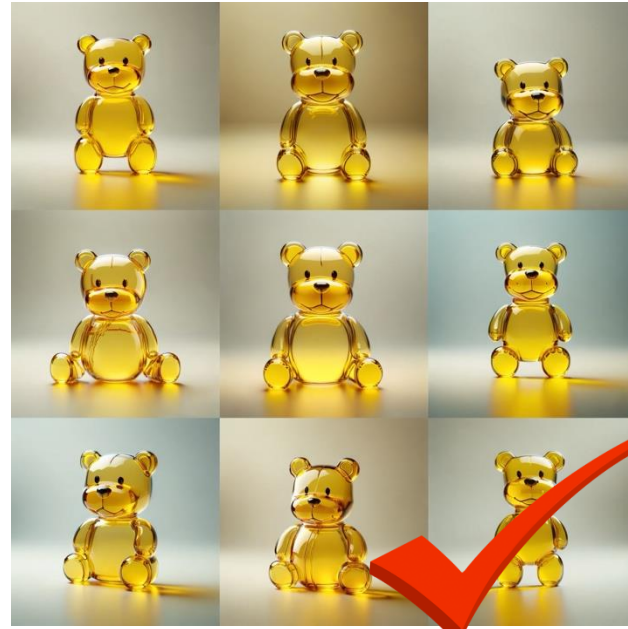
+ 7.36 %

We leverage DINOv2 [Oquab et al. 2023] to evaluate content and style alignment, and CLIP [Ilharco et al. 2021] to evaluate prompt alignment.

User study

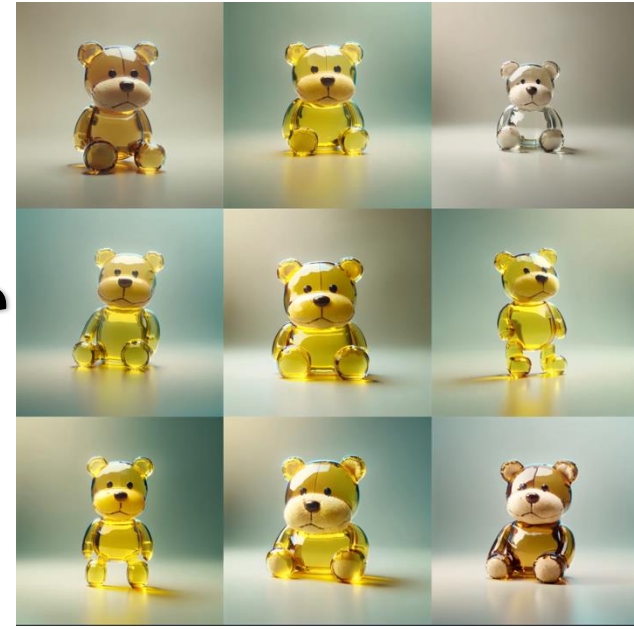


References



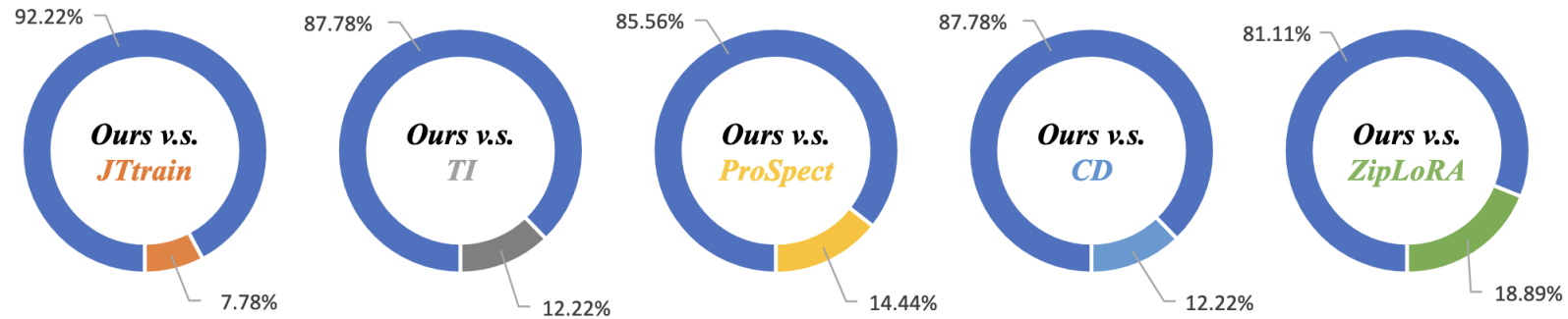
Ours

VS



ZipLoRA (A/B testing)

Our method demonstrates strong generation stability.



Stability preference comparison in user study.
Our results have better preference than other baselines.

More results of ours

Customize your style with diverse content



A [c1] teddybear



A [c2] character



A [c3] bird



A [c4] mountain



A [c5] building



A [c6] sculpture



A dog
in [s] paper style



A [c1] teddybear
in [s] paper style



A [c2] character
in [s] paper style



A [c3] bird
in [s] paper style



A [c4] mountain
in [s] paper style



A [c5] building
in [s] paper style



A [c6] sculpture
in [s] paper style

Customize your content with diverse style



A dog in
[s1] paper style



Flowers in
[s2] yarn style



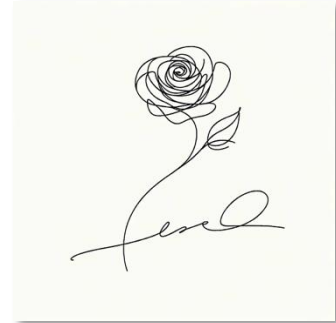
A tree in
[s3] sticker style



A woman in
[s4] cartoon style



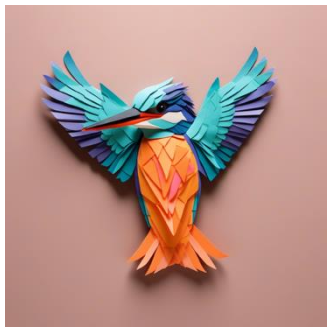
A cat in
[s5] painting style



A rose in
[s6] painting style



A [c] bird



A [c] bird in
[s1] paper style



A [c] bird in
[s2] yarn style



A [c] bird in
[s3] sticker style



A [c] bird in
[s4] cartoon style



A [c] bird in
[s5] painting style



A [c] bird in
[s6] painting style

Re-textualization



A [c] dog



...running.



...on mountain.



...reading books.



A tree
in [s] sticker style



...sleeping.



...practicing karate.



...as a chef.

Re-textualization



A [c] teapot



...floating on river.



...on grass.



...turquoise.



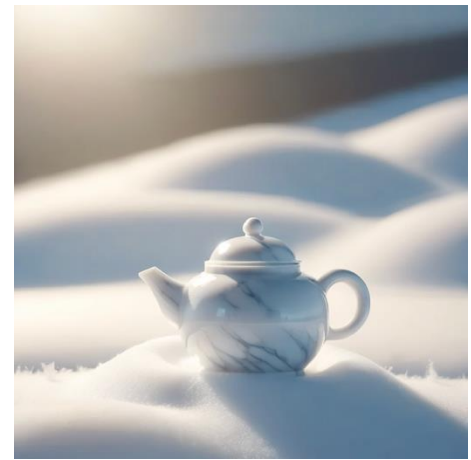
Cup
in [s] marble style



...by window.



...on a picnic table.

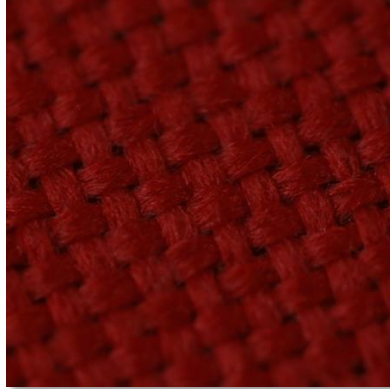


...on top of snow.

Application—Texture

Style

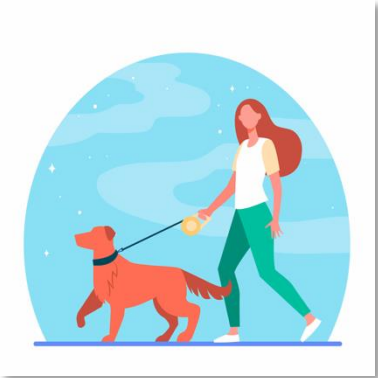
Content



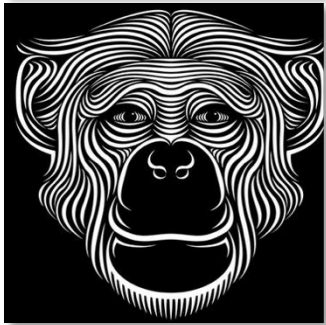
Application—Portrait

Portrait

Style



Application—Modern Art



Hypnotic line art



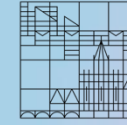
Portrait map art



SIGGRAPH
ASIA 2025
HONG KONG 香港



Universität
Konstanz



國立成功大學
National Cheng Kung University

Thanks.

B4M: Breaking Low-Rank Adapter for Making Content-Style Customization

Project page: <https://yuci-gpt.github.io/B4M/>

Code: <https://github.com/ICTMCG/Break-for-make>



GENERATIVE

RENAISSANCE



SIGGRAPH 香港
ASIA 2025
HONG KONG 港