AttnDreamBooth: Towards Text-Aligned Personalized Text-to-Image Generation

Lianyu Pang[1], Yin Jian[1], Baoquan Zhao[1], Feize Wu[1], Fu Lee Wang[2], Qing Li[3], Xudong Mao[1,*]

[1]Sun Yat-sen University [2]Hong Kong Metropolitan University

[3]The Hong Kong Polytechnic University

Outline

- Introduction
- Method
- Experiment
- Conclusion

Introduction

NEURAL INFORMATION PROCESSING SYSTEMS

- Text-to-image personalization is the task of customizing a pre-trained diffusion model to produce images of user-provided concepts in novel scenes or styles.
- Current personalization techniques struggle to balance the trade-off between **identity preservation** and **text alignment**.
- Our method achieves superior performance in terms of identity preservation and text alignment compared to the baselines.

Input Sample

... as a cowboy draws its tiny revolver in a dusty town showdown, surrounded by cacti and a saloon

... as a knight draped in armor, riding a horse and galloping through the lush fields

An oil painting of ... dressed as a musketeer in an old French town

... as an astronaut floats weightlessly in a zero-gravity environment, surrounded by celestial bodies and distant galaxies

Cyberpunk style of ... as a robot against the backdrop of a futuristic cityscape at night, illuminated by neon lights

... in assassin's creed walking on the street of Venice, surrounded by the crowd of merchants and tourists

... as a Jedi casting a long shadow in a sunlit, empty desert

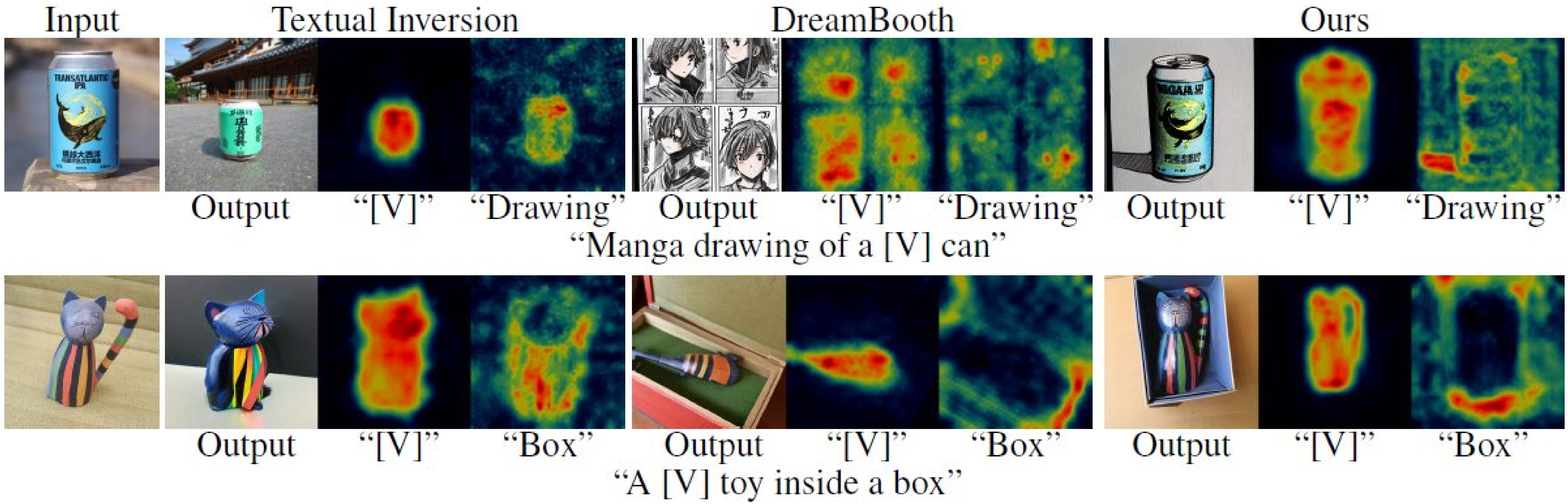
... as Captain America standing in the ruins of the city, surrounded by smoke

A painting of ... as a boatman propping a boat in the lake in the style of Monet

A painting of ... as a vintage steampunk automaton, complete with gears and complex mechanical devices

Introduction

- The two principal methods **Textual Inversion** and **DreamBooth** encounter distinct challenges when integrating the learned concept into novel prompts.
- Textual Inversion tends to **overfit** the textual embedding of the learned concept, resulting in incorrect attention map allocations to other tokens (e.g., “drawing” or “box”). In contrast, DreamBooth appears to **overlook** the learned concept, producing images primarily based on other tokens.
- These issues can be attributed to the incorrect learning of embedding alignment for the new concept, i.e., the embedding of the new concept is not functionally compatible with the embeddings of existing tokens.



Introduction

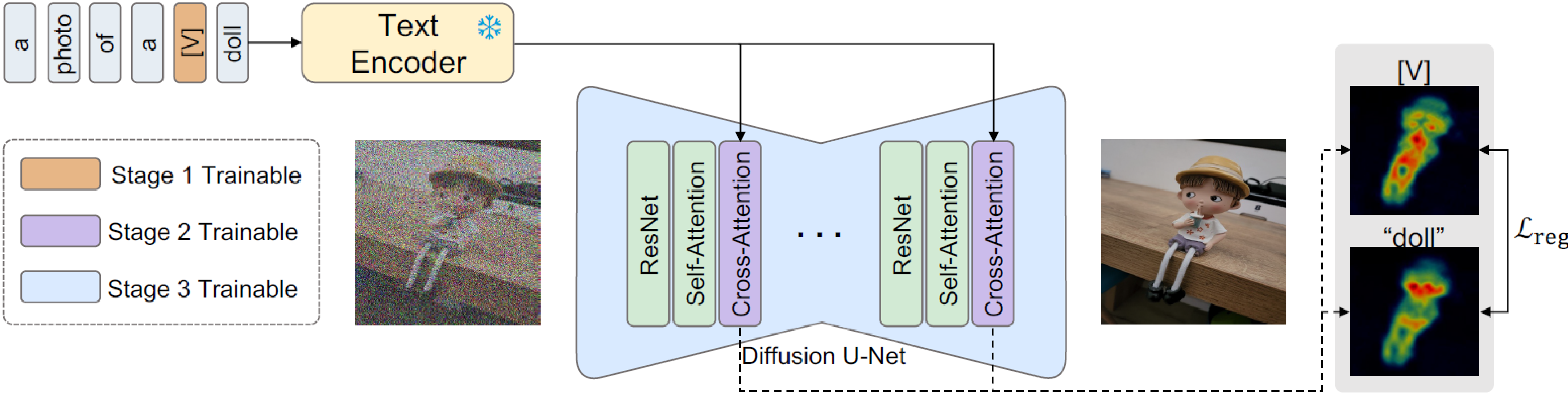
NEURAL INFORMATION PROCESSING SYSTEMS

- Based on these observations, our approach aims to properly learn not only the subject identity but also the embedding alignment and the attention map for the new concept. Our key insights are as follows:
  1. First, while **Textual Inversion** often fails to capture the subject identity and tends to overfit the embedding alignment for the new concept, it can effectively learn the embedding alignment and a coarse cross-attention map in the very early stages of optimization.
  2. Second, although **DreamBooth** fails to learn the embedding alignment, it can accurately capture the subject identity.

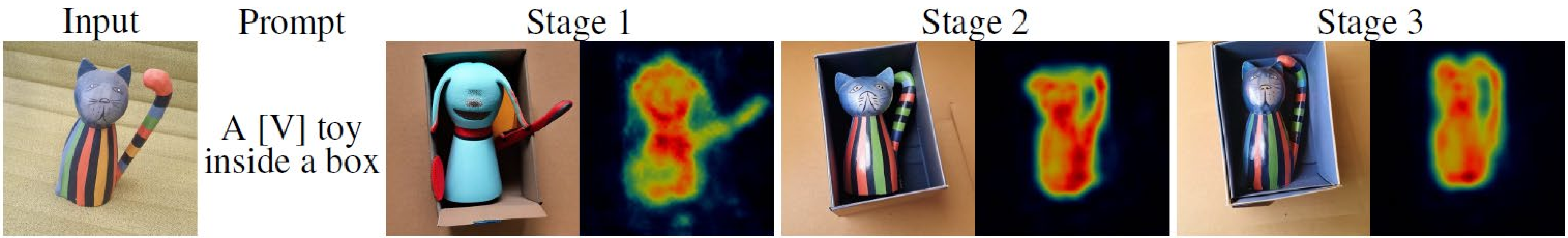
- We set the training prompt as “a photo of a [V] [super-category]”, and introduce a cross-attention map regularization term, which serves two purposes.
  1. First, since the new concept and its super-category belong to the same object category, the attention map of the super-category token can serve as a reference for the new concept.
  2. Second, since [V] and [super-category] are used together to describe the new concept when integrating it into new prompts, the attention maps of [V] and [super-category] should refer to the same region

Method

- We propose to decompose the personalization process into three training stages:
  1. Learning the embedding alignment
  2. Refining the attention map
  3. Acquiring the subject identity
- Furthermore, we introduce a cross-attention map regularization term to enhance the learning of the attention map



Method



- The generations along with the attention maps of “[V]” for each stage.
    1. In stage 1, the model properly aligns the embedding of [V] with other tokens, “inside a box”, but learns a very coarse attention map and subject identity.
    2. In stage 2, the model refines the attention map and subject identity.
    3. In stage 3, the model accurately captures the identity of the concept.

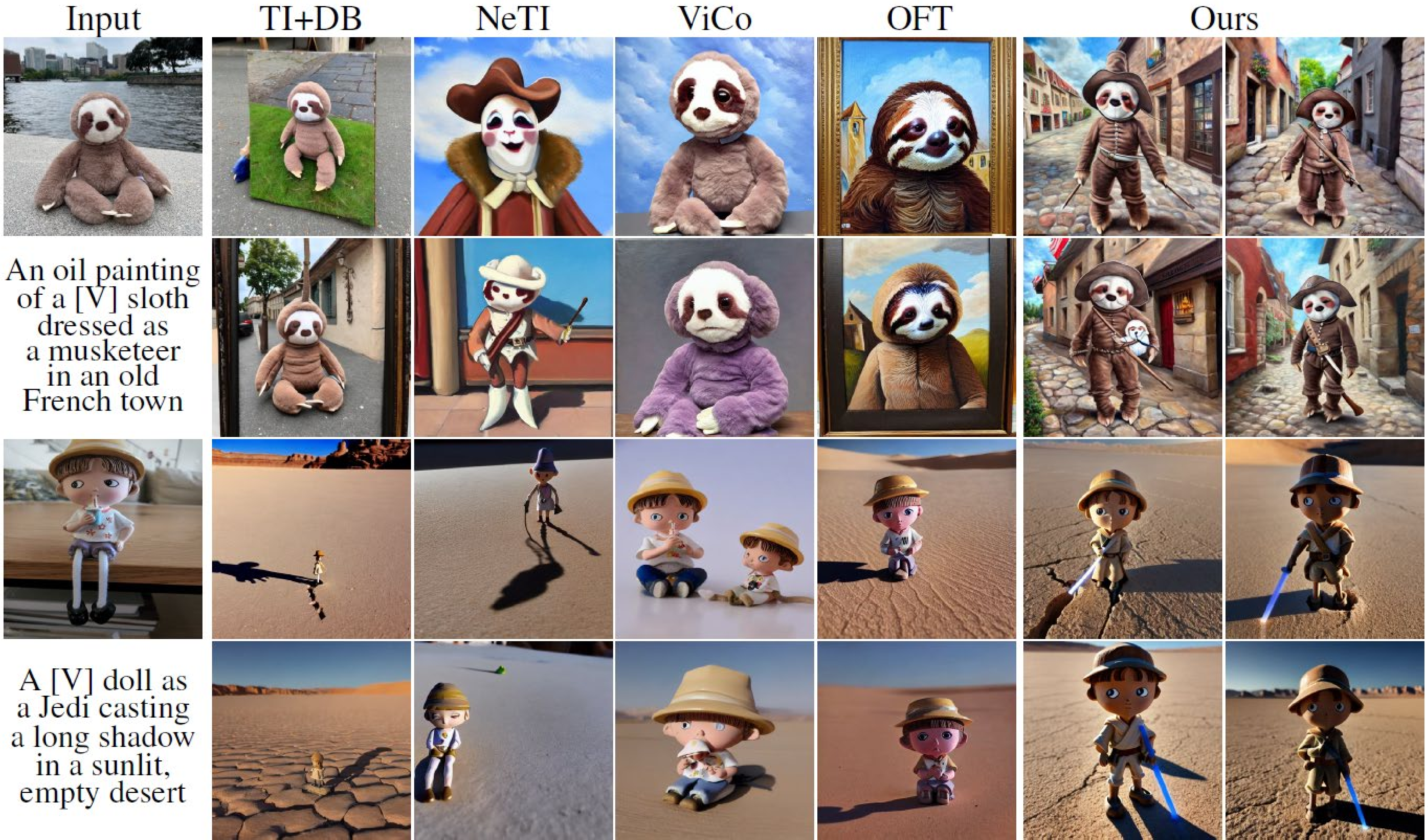
Experiment

- **Dataset**
  - We collect 22 concepts from **Textual Inversion** and **DreamBooth**.
  - We use a set of 24 text prompts for the quantitative evaluation.
- **Metric**
  - **Identity preservation:** measured by the cosine similarity between the CLIP embeddings of generated and real images
  - **Text alignment:** measured by the cosine similarity between the CLIP embeddings of generated images and their corresponding prompts.
  - Each method is evaluated using 24 text prompts, generating 32 images per prompt.

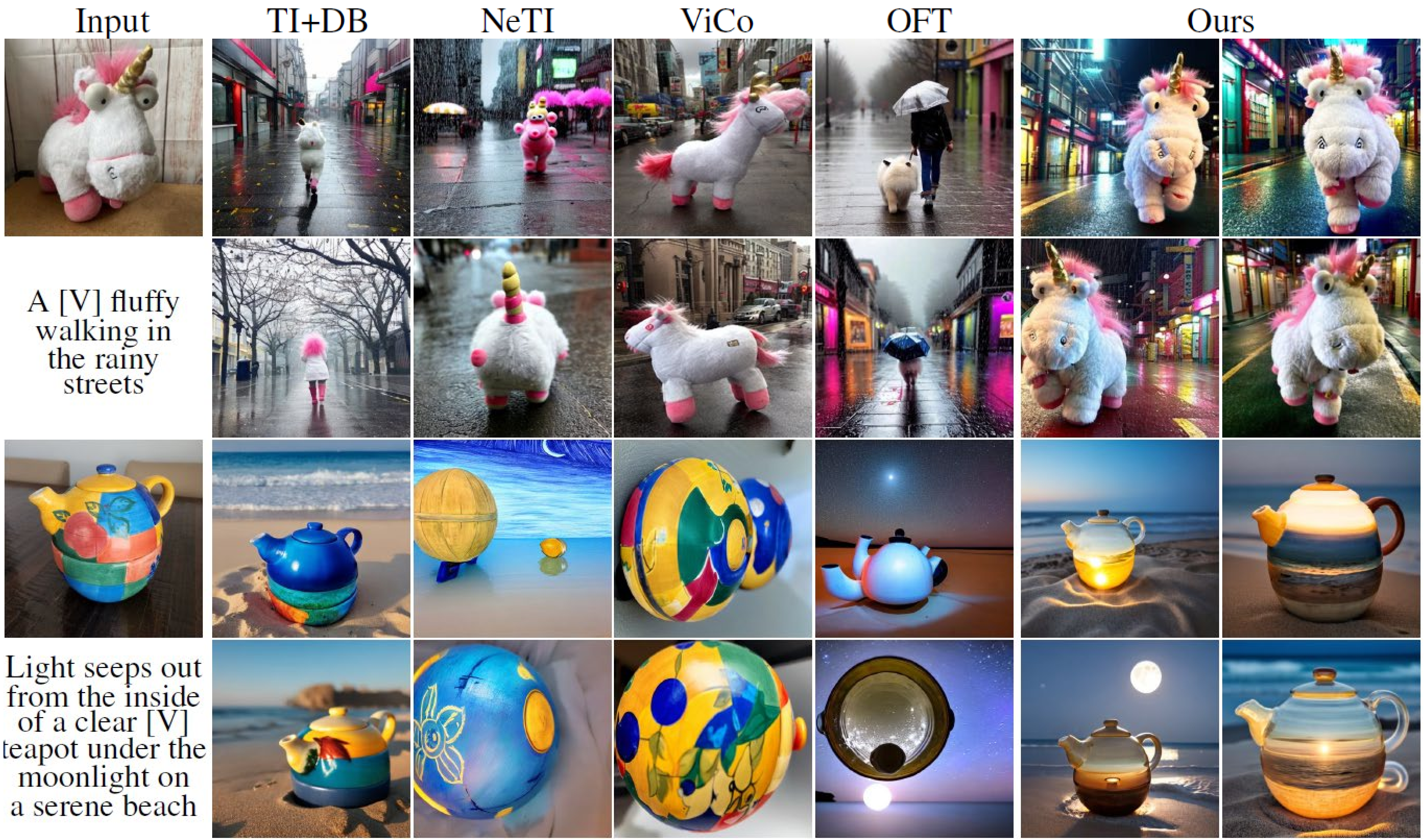
Table 1: **Quantitative comparisons**. "Identity" denotes the identity preservation, and "Text" denotes the text alignment.

Methods	Identity↑	Text↑
TI+DB [24, 71]	0.7017	**0.2578**
NeTI [1]	0.6901	0.2522
ViCo [30]	**0.7507**	0.2106
OFT [64]	0.7257	0.2445
Ours-fast	<u>0.7268</u>	<u>0.2536</u>
Ours	0.7257	0.2532

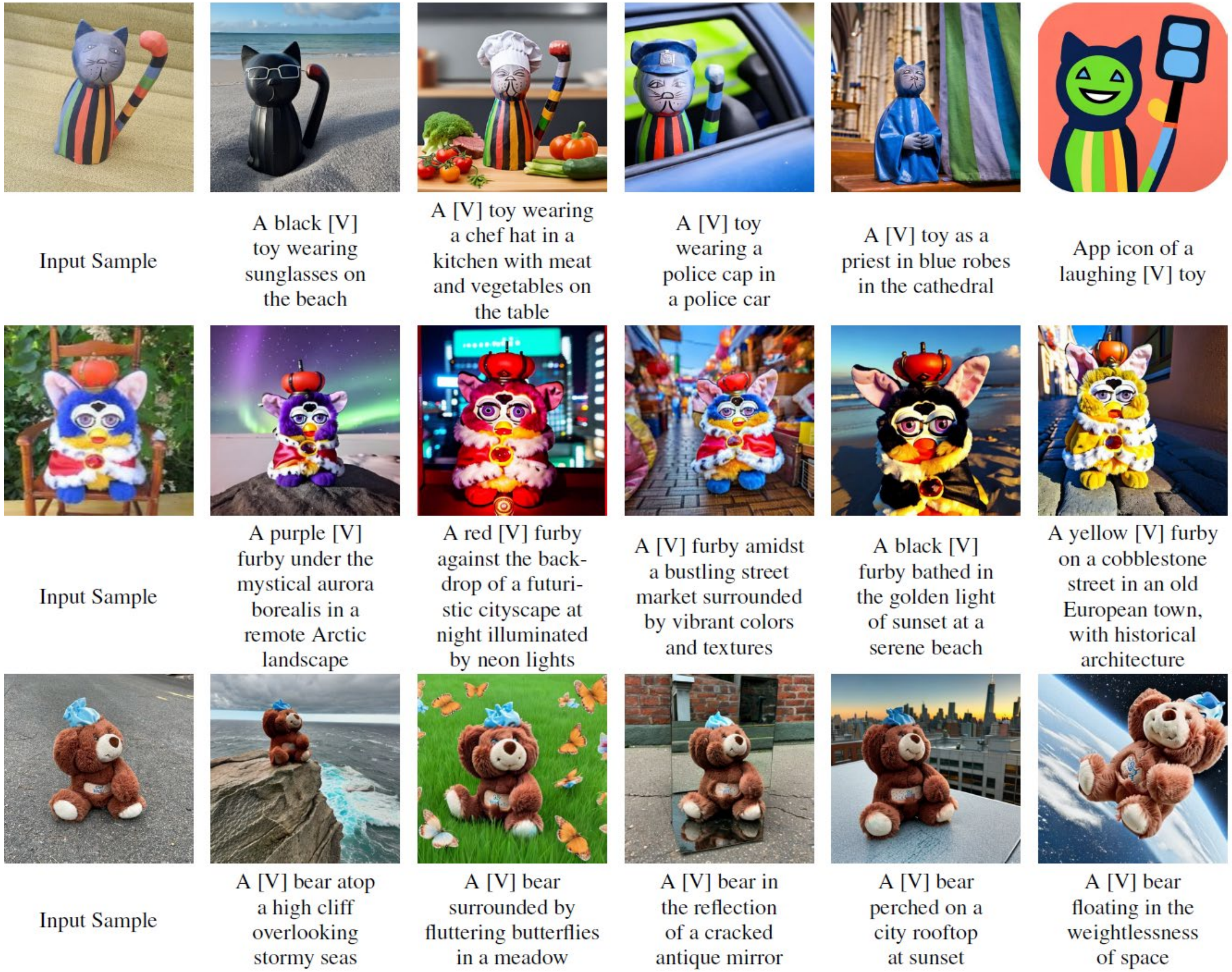
Experiment


Input
TI+DB
NeTI
ViCo
OFT
Ours
An oil painting of a [V] sloth dressed as a musketeer in an old French town
A [V] doll as a Jedi casting a long shadow in a sunlit, empty desert

Experiment


Input
TI+DB
NeTI
ViCo
OFT
Ours
A [V] fluffy walking in the rainy streets
Light seeps out from the inside of a clear [V] teapot under the moonlight on a serene beach

Experiment


Input Sample
A black [V] toy wearing sunglasses on the beach
A [V] toy wearing a chef hat in a kitchen with meat and vegetables on the table
A [V] toy wearing a police cap in a police car
A [V] toy as a priest in blue robes in the cathedral
App icon of a laughing [V] toy
Input Sample
A purple [V] furby under the mystical aurora borealis in a remote Arctic landscape
A red [V] furby against the back-drop of a futuri-stic cityscape at night illuminated by neon lights
A [V] furby amidst a bustling street market surrounded by vibrant colors and textures
A black [V] furby bathed in the golden light of sunset at a serene beach
A yellow [V] furby on a cobblestone street in an old European town, with historical architecture
Input Sample
A [V] bear atop a high cliff overlooking stormy seas
A [V] bear surrounded by fluttering butterflies in a meadow
A [V] bear in the reflection of a cracked antique mirror
A [V] bear perched on a city rooftop at sunset
A [V] bear floating in the weightlessness of space

Conclusion

- We identified and analyzed the embedding misalignment issue encountered by **Textual Inversion** and **DreamBooth**.
- Our proposed method, named **AttnDreamBooth**, addresses this issue by decomposing the personalization process into three stages: learning the embedding alignment, refining the attention map, and acquiring the subject identity.
- **Our method** enables identity-preserved and text-aligned text-to-image personalization, even with **complex prompts**.

Arxiv

Github

SUN YAT-SEN UNIVERSITY

NEURAL INFORMATION PROCESSING SYSTEMS

Thanks for your attention