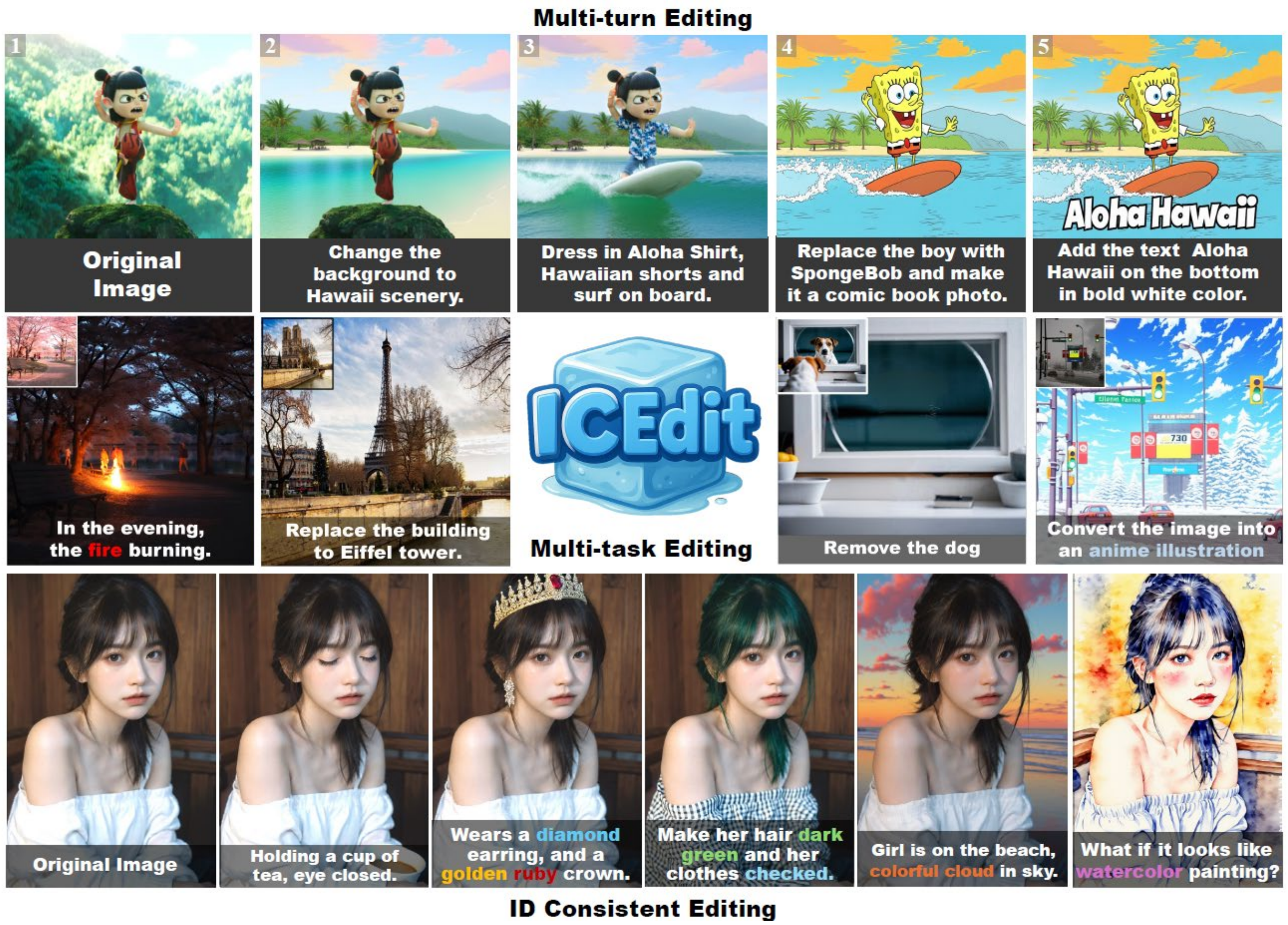
Enabling Instructional Image Editing with In-Context Generation in Large Scale Diffusion Transformer



Zechuan Zhang (张泽川)

I am currently a PhD student at Zhejiang University in Hangzhou, China. My PhD supervisor is Prof. Yi Yang. My research interests lie in the intersection of computer vision, machine learning. I am particularly interested in 3D vision, multi-modal, diffusion models and image generation and editing.

Prior to that, I obtained the B.Sc Degree in Geographical Information Science from Zhejiang University in 2023. I was also a member of Advanced Honor Class of Engineering Education (ACEE) at Chu Kochen Honors College (CKC) of Zhejiang University.

Email | CV | GitHub | Google Scholar | Twitter

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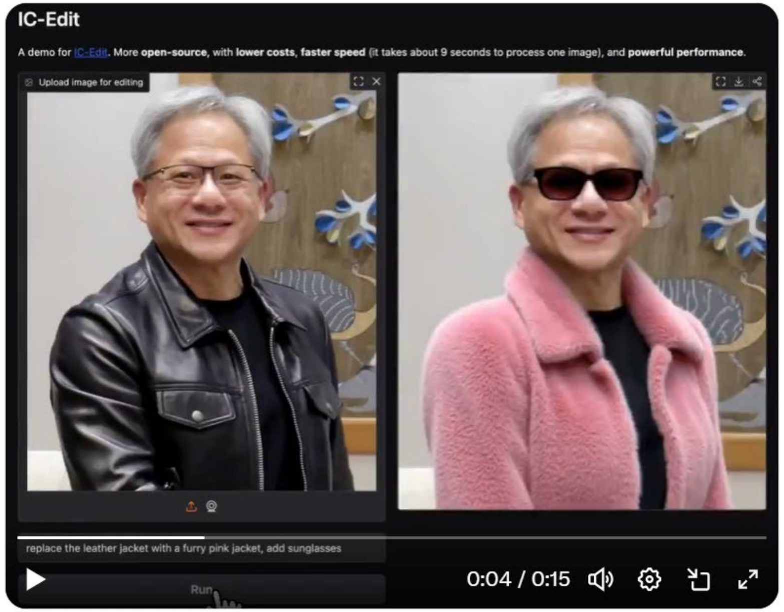
Image Editing via In-Context Generation

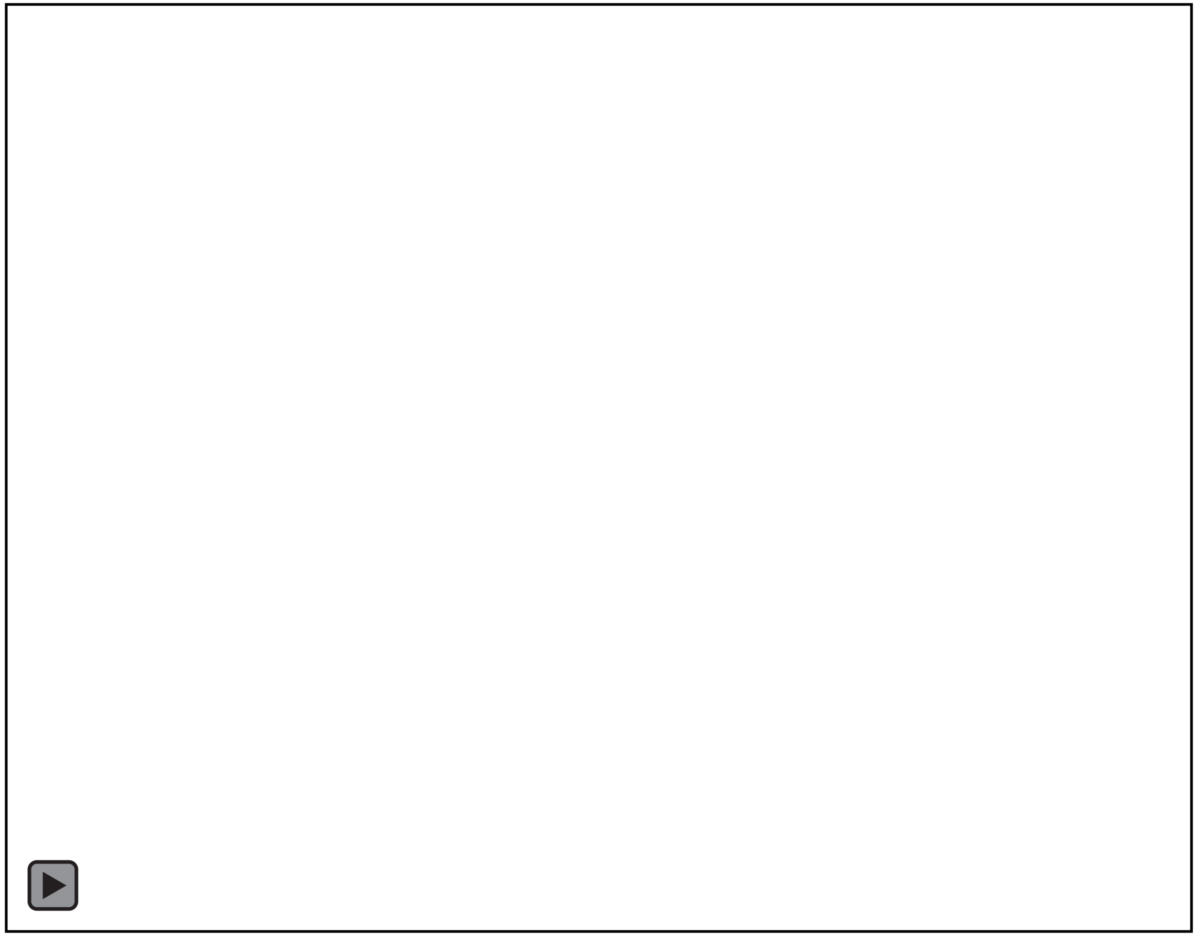
apolinario 🌐
@multimodalart

Whoa, I just tested the IC Edit @huggingface demo and it seems the new 🐐👑 of image editing for

It's an image editing LoRA for FLUX featuring:
🧑‍🎨 Identity preservation (beating GPT-4o)
✏️✏️ Does multiple edits
🐎 10s image editing
🌌 style support



5:05 PM · May 2, 2025 · **41.7K** Views



Impact on community

Gaining massive traction on Twitter, Reddit, and the ComfyUI community!

apolinario @multimodalart

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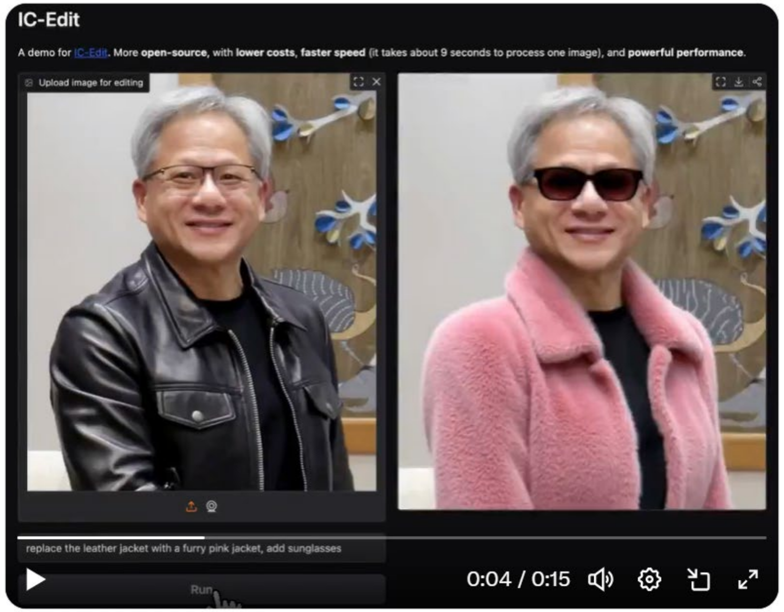

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r/StableDiffusion • 2 days ago
Some_Smile5927 Top 1% Poster

ICEdit, I think it is more consistent than GPT4-o.

Workflow Included

In-Context Edit, a novel approach that achieves state-of-the-art instruction-based editing **using just 0.5% of the training data and 1% of the parameters required by prior SOTA methods**.
https://river-zhang.github.io/ICEdit-gh-pages/

I tested the three functions of image deletion, addition, and attribute modification, and the results were all good.

317 · 77 · Share

Impact on community

- Attracted over **500,000 followers** across all platforms (first month)
- Gained more than **1,500 stars** on GitHub
- Remained ranked second on the Hugging Face trending list for a week.

Analytics Hugging face

Last update: 3 hours ago · Next update: in 20 hours

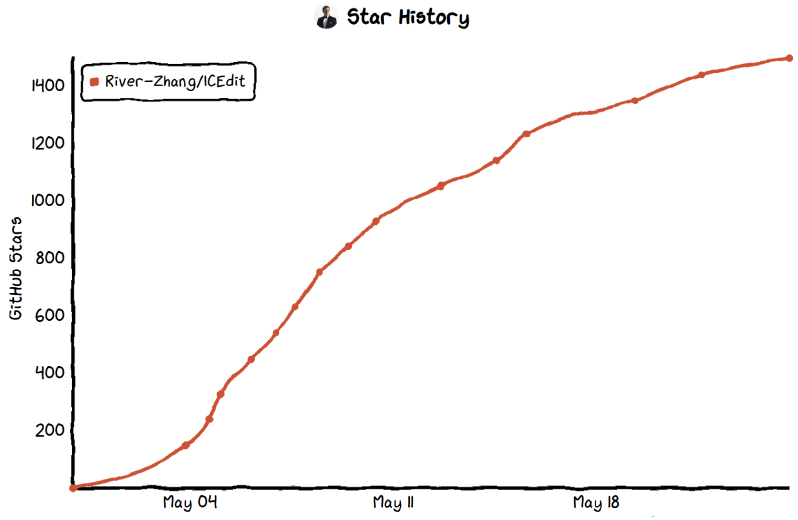
All time visits	Last month visits
352,268	352,268

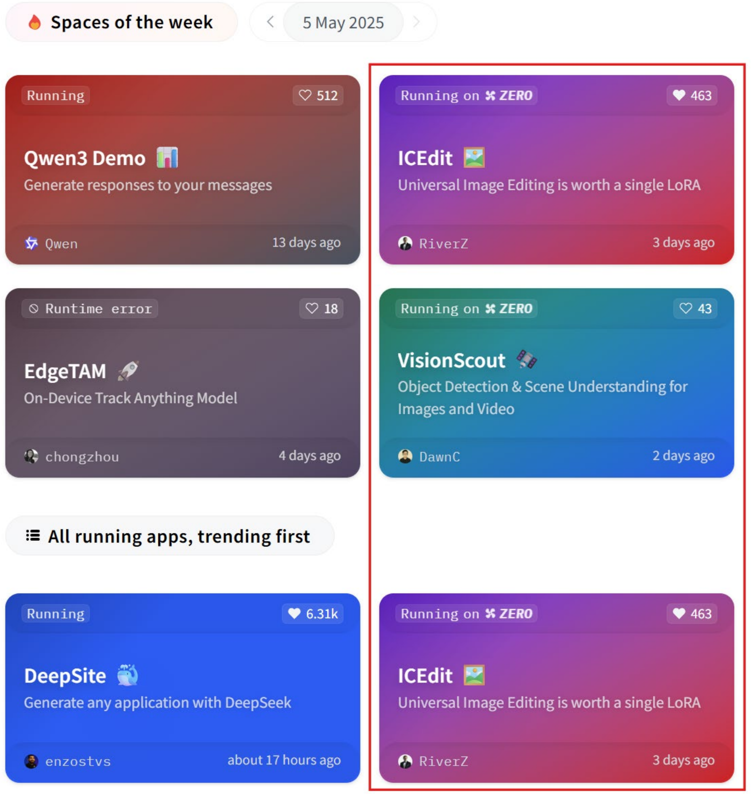
Project Page

River-Zhang/ICEdit

Image editing is worth a single LoRA! 0.1% training data for fantastic image editing! Training released! Surpasses GPT-4o in ID persistence! Official ComfyUI workflow release! Only 4GB VRAM is enou...

Python ★ 1.5k





https://github.com/River-Zhang/ICEdit

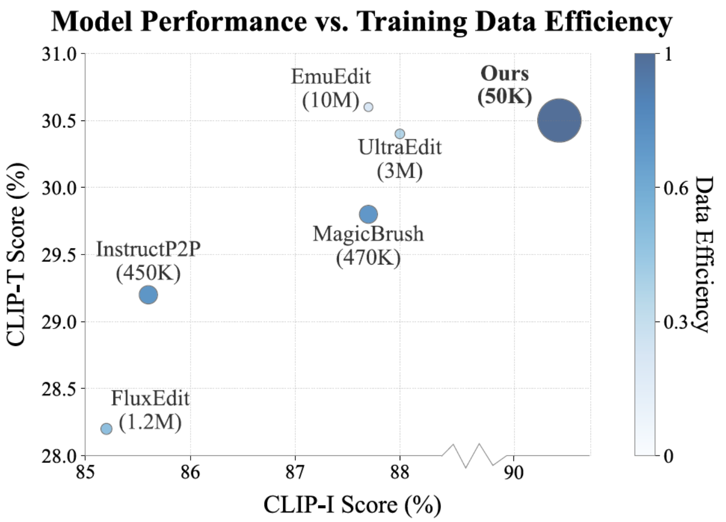
Introduction

Background:

- **Instruction-based image editing has garnered significant attention for its ability to transform and process images using natural language prompts。**

Challenge:

- Existing methods struggle to **balance precision and efficiency**.
- **Training-intensive approaches** achieve high-fidelity instruction execution but sacrifice efficiency, relying on: 10M+ training examples for instruction understanding; Large-scale model parameters (e.g., billions)
- **Training-free methods** save costs but suffer from poor editing precision.



- ➢ Our approach uses only **1% training parameters and 0.1% training data** for better performance.

- ➢ Training-free methods cannot directly understand instructional prompts and often fail to handle complex tasks

Motivation

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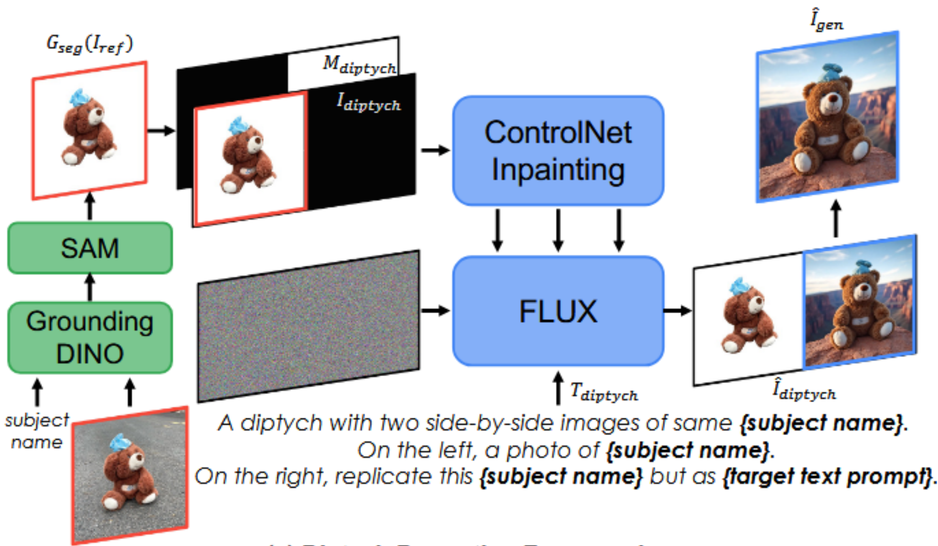
How to **balance precision and efficiency:** motivation from previous work based on Large Scale DIT

- ➢ No additional structure modification
- ➢ No fully tuning (e.g. LoRA)

Large-Scale Text-to-Image Model with Inpainting is a Zero-Shot Subject-Driven Image Generator

Chaehun Shin[1] Jooyoung Choi[1] Heeseung Kim[1] Sungroh Yoon[1,2,*]
[1]Data Science and AI Laboratory, ECE, Seoul National University
[2]AIIS, ASRI, INMC, ISRC, and Interdisciplinary Program in AI, Seoul National University



(a) Diptych Prompting Framework

OminiControl: Minimal and Universal Control for Diffusion Transformer

Zhenxiong Tan Songhua Liu Xingyi Yang Qiaochu Xue Xinchao Wang
National University of Singapore
{zhenxiong, songhua.liu, xyang, e1352520}@u.nus.edu xinchao@nus.edu.sg

求是創新 Can large scale DiT's generation capacity and contextual awareness directly address instruction-based image editing?

Motivation

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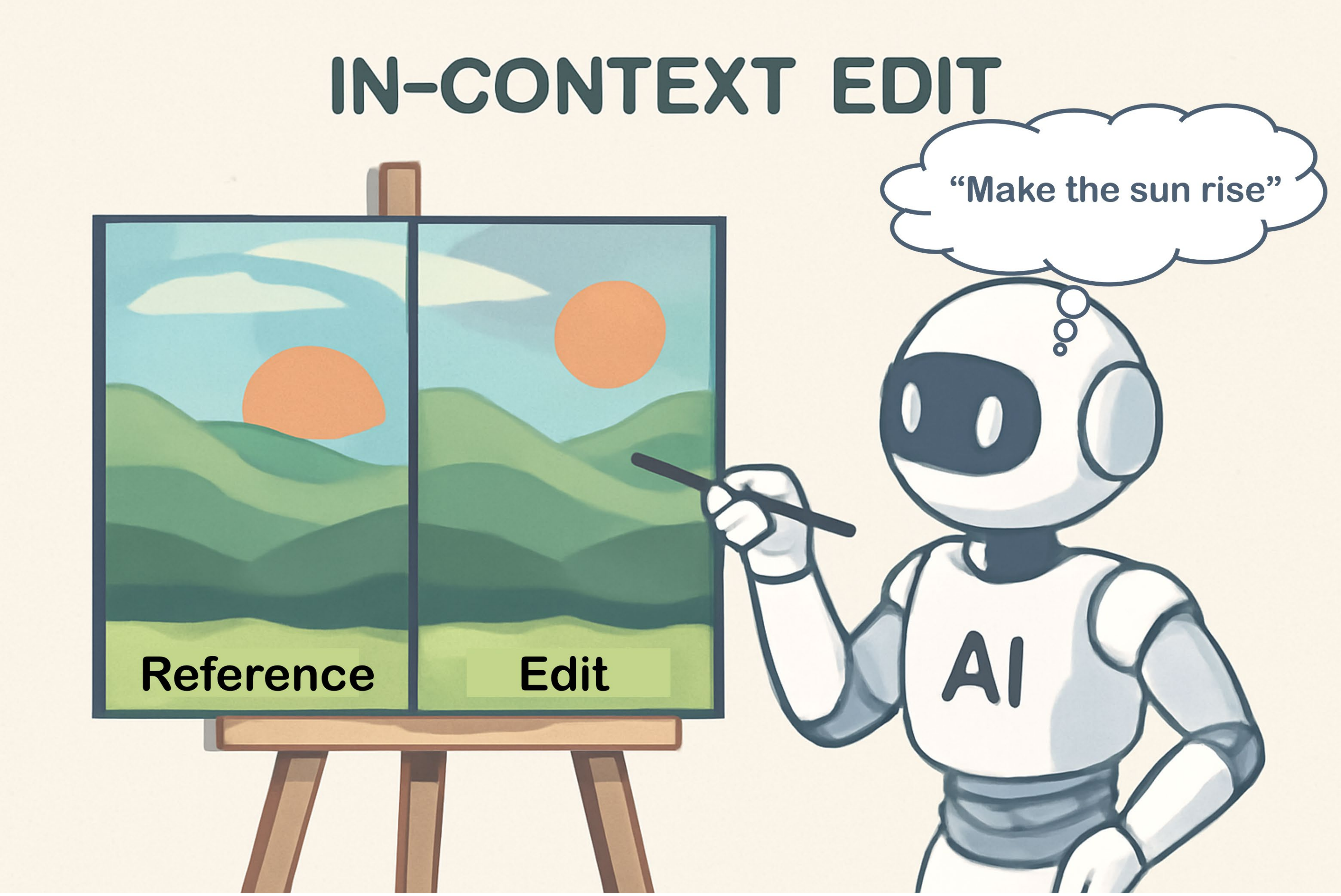
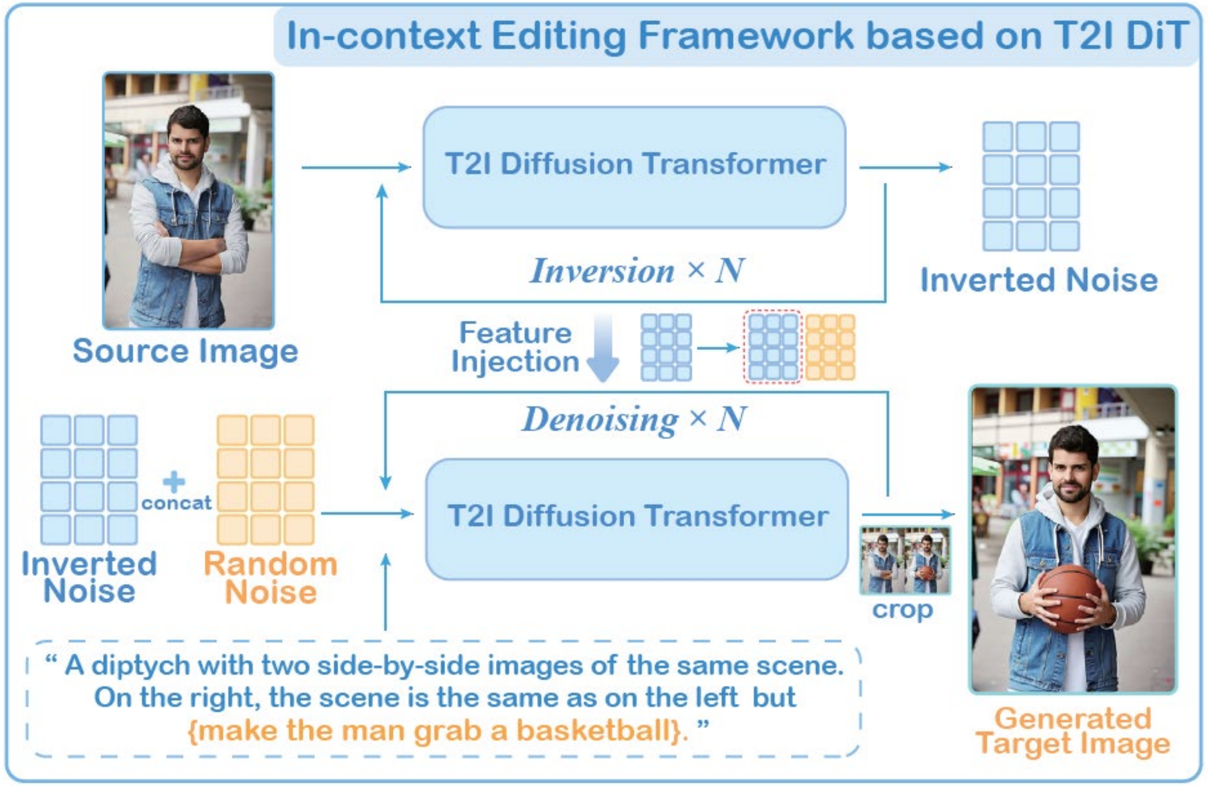
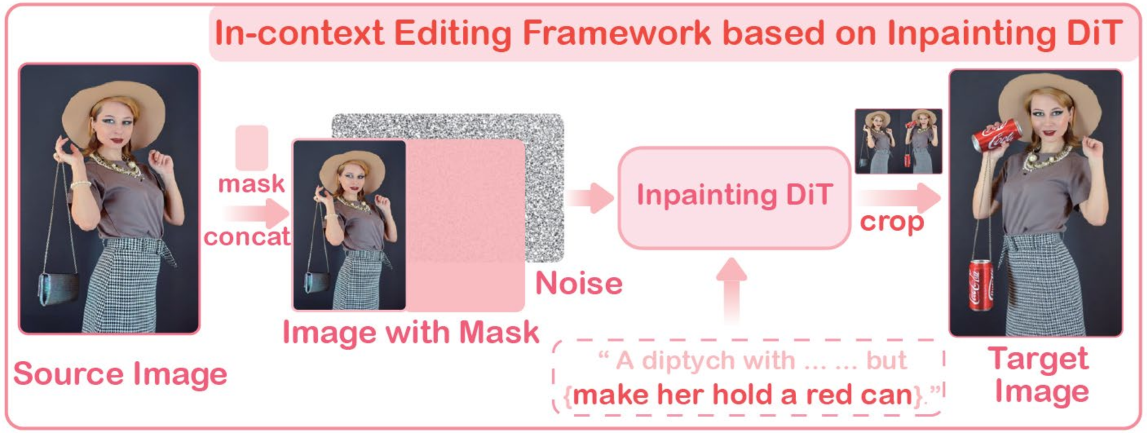


Exploration



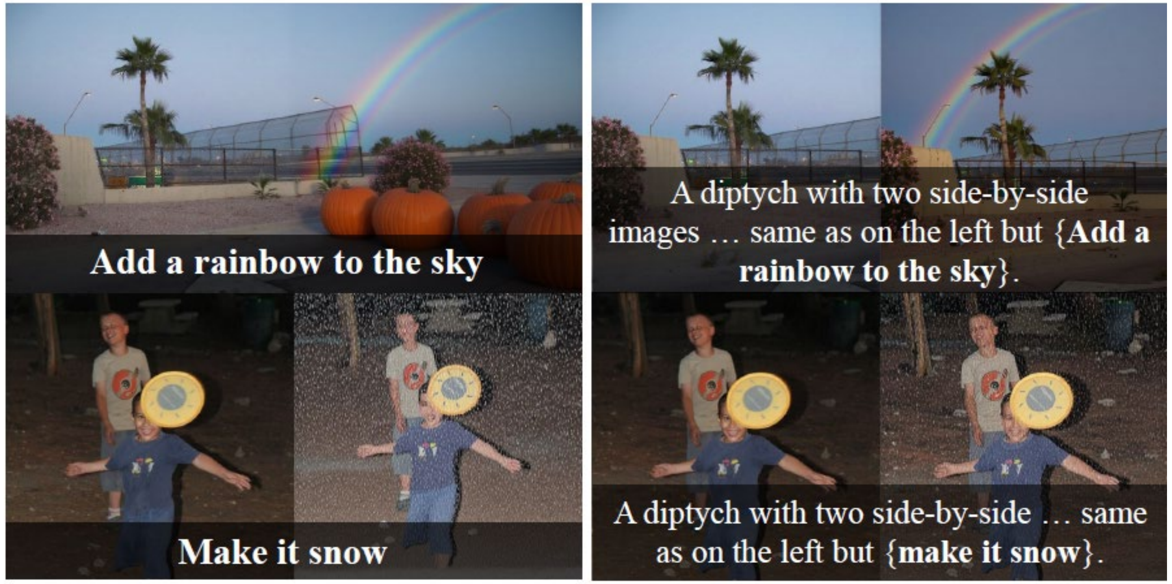
T2I model based framework



Inpainting model based framework

Exploration-Input Prompt Variants

- In-context Prompt – instructions embedded in structure "A diptych with... On the right, the same scene but {instruction}";
- Global Descriptive Prompt - uses full input/output captions ("On the left {input} On the right {output}").



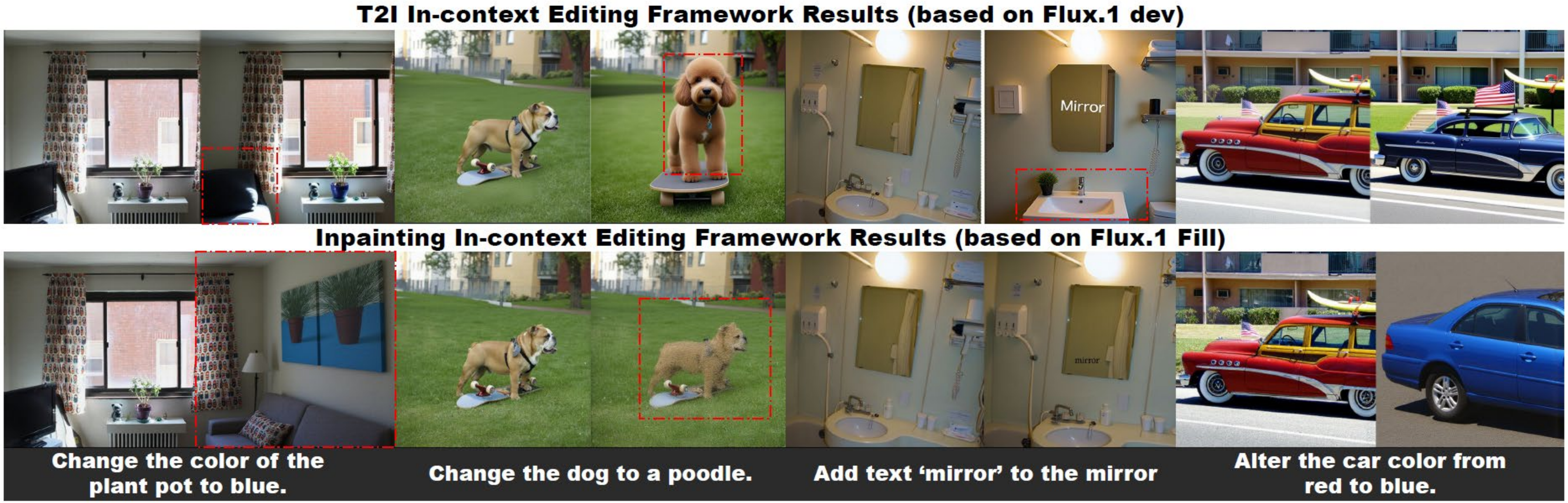
Direct Edit Instruction   In-Context Edit Prompt

Global Descriptive Prompt

Exploration

Training-Free Methods Show Limited Performance.

- Both T2I and inpainting DiT frameworks (based on Flux) yield suboptimal results.
- Despite these shortcomings, both demonstrate potential in following instructions and modifying edited regions



Exploration

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Discussion of the two training-free framework

- While both frameworks demonstrate some editing capability, their zero-shot performance is unsatisfactory
- We attribute this to the lack of learned image-to-image editing priors. This limitation could be mitigated through lightweight adjustments, such as finetuning or test-time scaling.
- Given that the T2I DiT framework requires time-consuming image inversion, we favor the inpainting-based framework for its straightforward operation, which facilitates further finetuning.

(a) **Ablation study on model structure (§4.2).**

Settings	Params	CLIP-I ↑	CLIP-T ↑	GPT ↑
Training-free w/o IC prompt	-	0.681	0.258	0.14
Training-free w/ IC prompt	-	0.794	0.273	0.24
Only MoE module	130M	**0.929**	0.300	0.51
LoRA (r=64) w/ IC prompt	240M	<u>0.911</u>	<u>0.301</u>	0.60
Ours w/o IC prompt	214M	0.896	0.300	<u>0.62</u>
Ours	214M	0.907	**0.305**	**0.68**

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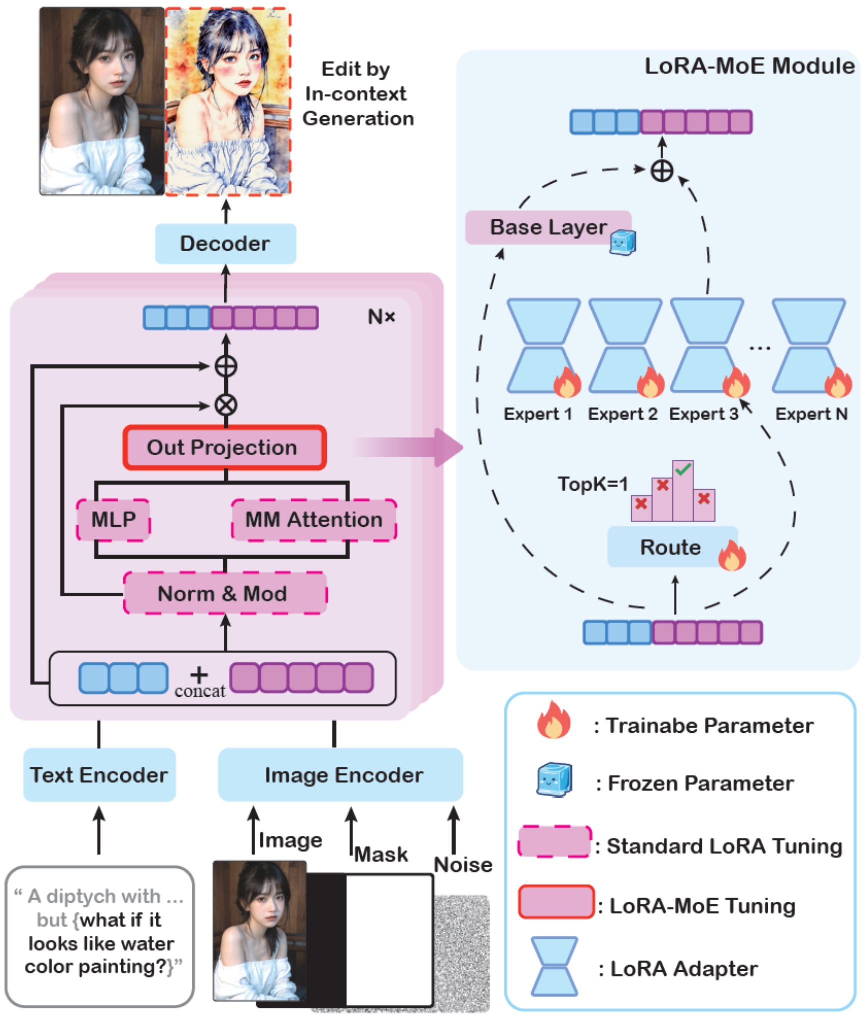
Finetuning



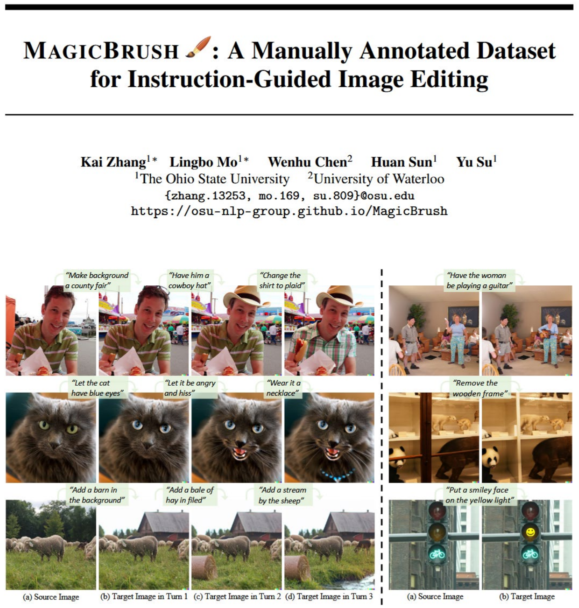
(b) Finetuning Strategy for ICEdit

Training Data (Randomly Selected)

Table 1: Dataset Statistics by Task Type

Task Type	Removal	Addition	Swap	Attribute Mod.	Style	Total
Count	13,272	11,938	5,823	11,484	10,530	53,047

OmniEdit



Magicbrush

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Experiment

Test results in paper

Table 1: **Quantitative results on Emu Test set (§4.1).** Following [4, 3], we compute CLIP-I and DINO scores between the source and edited image, while CLIP-out measures the distance between output caption and edited image. We also employ GPT-4o to evaluate the edited results. The Train. Pa. means parameters finetuned for the editing task. * indicates methods that rely on output captions.

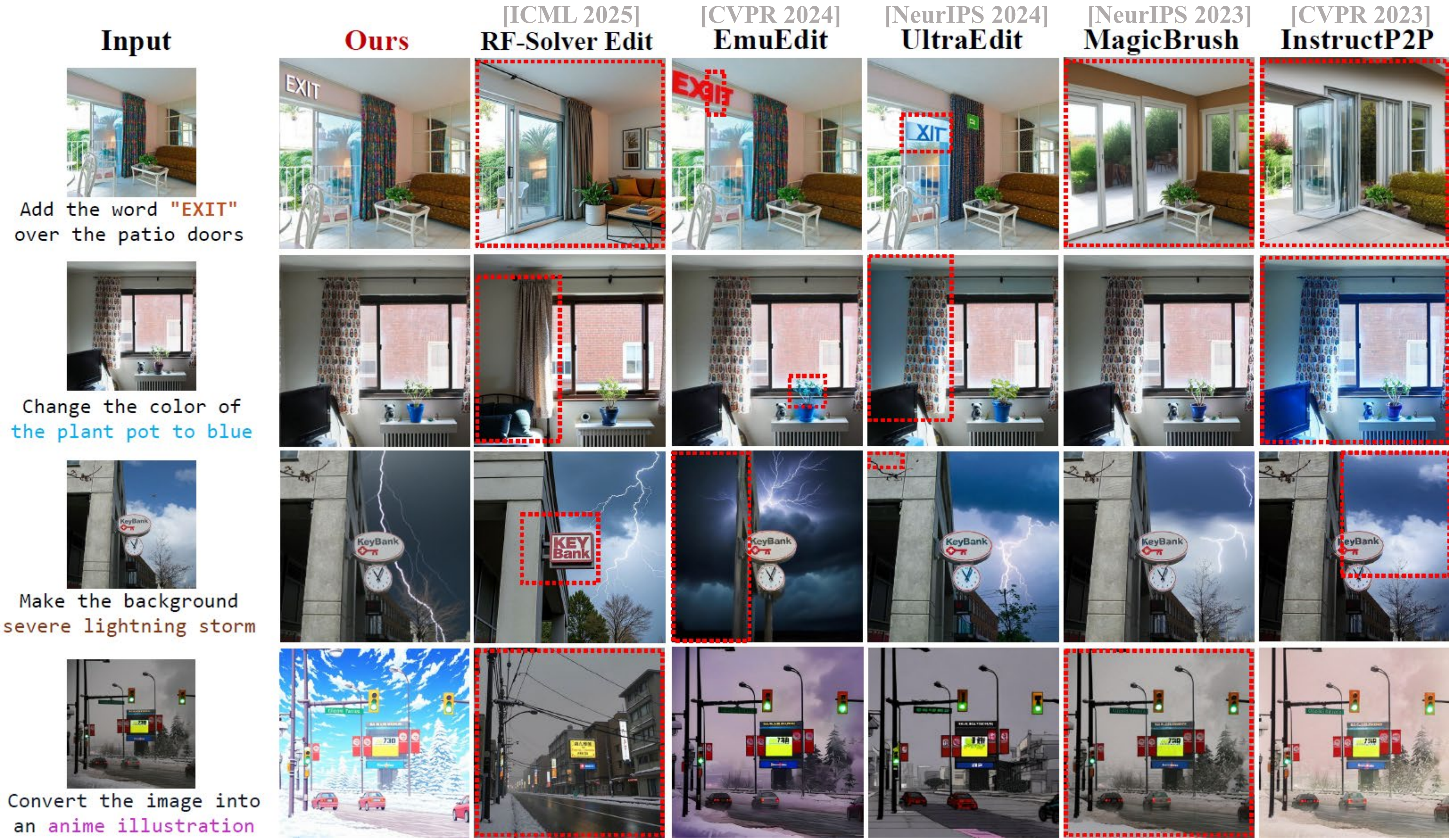
Methods	Base Model	Train. Pa.	Data Usage	CLIP-I ↑	CLIP-Out ↑	DINO ↑	GPT ↑
InstructP2P [CVPR23]	SD 1.5	0.9B	0.45M	0.856	0.292	0.773	0.36
MagicBrush [NeurIPS23]	SD 1.5	0.9B	0.47M	0.877	0.298	0.807	0.48
EmuEdit [CVPR24]	Close Source	2.8B	10M	0.877	0.306	0.844	**0.72**
UltraEdit [NeurIPS24]	SD 3	2.5B	3M	0.880	0.304	0.847	0.54
FluxEdit [huggingface]	Flux.1 dev	12B	1.2M	0.852	0.282	0.760	0.22
FLUX.1 Fill [huggingface]	Flux.1 Fill	-	-	0.794	0.273	0.659	0.24
RF-Solver Edit* [ICML25]	Flux.1 dev	-	-	0.797	**0.309**	0.683	0.32
ACE++ [arXiv25]	Flux.1 Fill	12B	54M	0.791	0.280	0.687	0.24
ICEdit (ours)	Flux.1 Fill	0.2B	0.05M	**0.907**	0.305	**0.866**	0.68

Table 2: **Quantitative results on MagicBrush test set.** Following [4], all metrics are calculated between the edited image and GT edited image provided by MagicBrush [2].

Methods	$L1$ ↓	CLIP-I ↑	DINO ↑
InstructP2P	0.114	0.851	0.744
MagicBrush	0.074	0.908	0.847
UltraEdit	0.066	0.904	0.852
FluxEdit	0.114	0.779	0.663
FLUX.1 Fill	0.192	0.795	0.669
RF-Solver Edit*	0.112	0.766	0.675
ACE++	0.195	0.741	0.591
ICEdit (ours)	**0.060**	**0.928**	**0.853**

Results

Our method achieves higher editing accuracy and better preservation of non-editing regions compared to existing approaches.



Test time scaling

- During inference, we find that initial noise significantly shapes editing outcomes, with some inputs producing results better aligned with human preferences.

- In instruction-based editing, we observe that **success in instruction alignment often become evident in few inference steps,** we can evaluate edit success with only a few steps

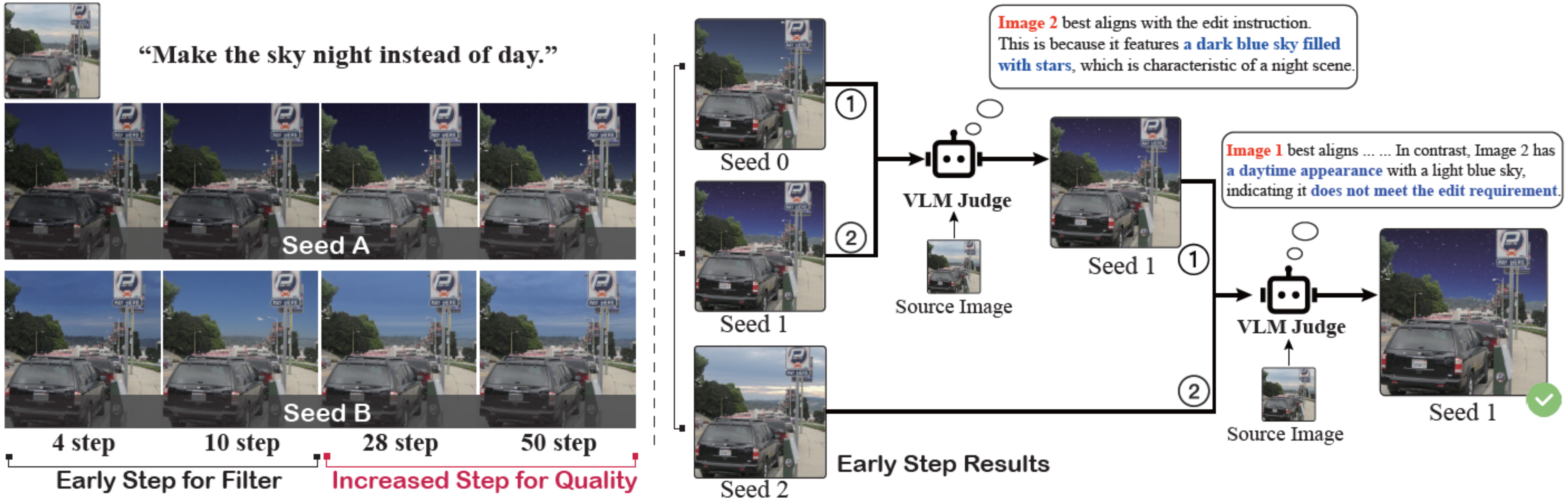


Figure 6: **Illustration of Inference-Time Scaling Strategy (§3.3).** The upper rows demonstrate that edit success can be assessed within a few initial steps. These early results are used to filter the optimal initial noise with VLM judges.

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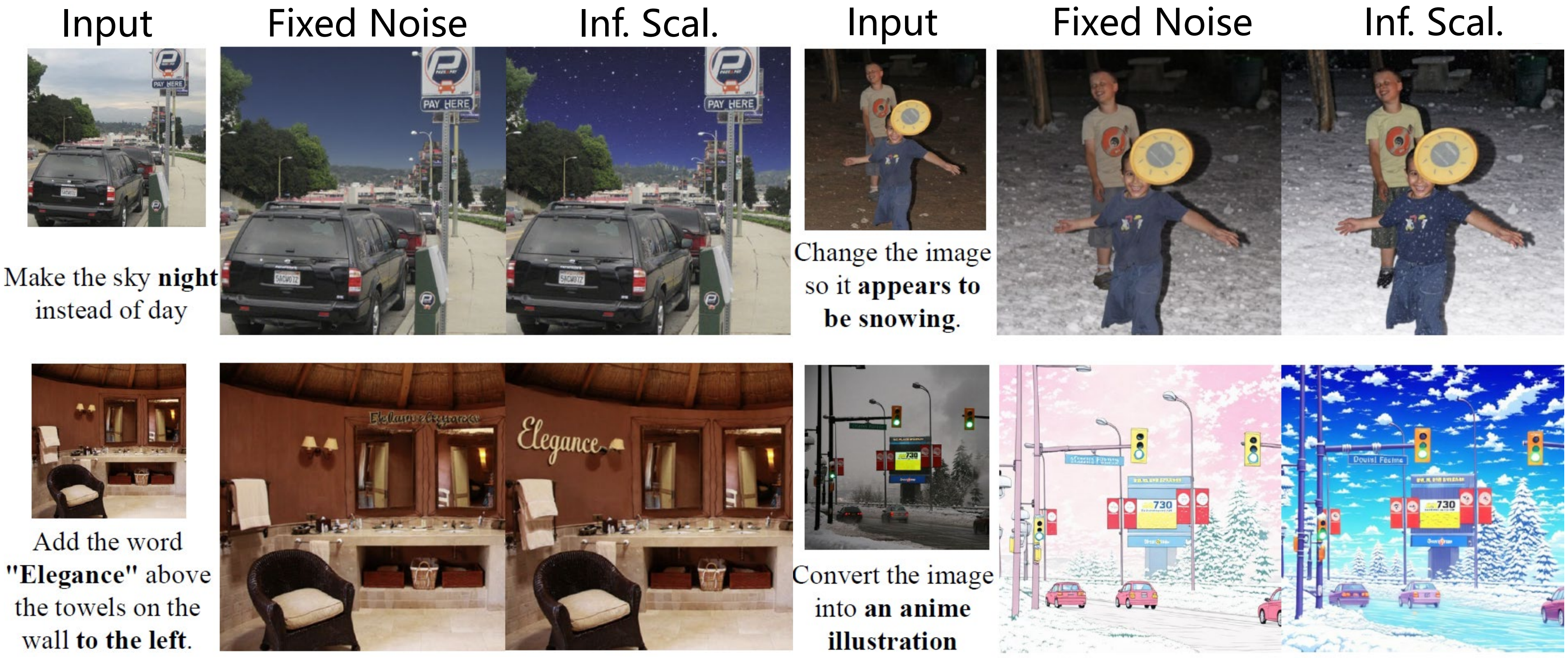
Results

The proposed inference-time scaling strategy can quickly filter the best editing candidates at the inference stage, improving editing quality and stability.



Results

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More harmonious editing results

Commercial
SeedEdit(Doubao)

Ours

Results

Multi-task and ID consistent editing

In the evening, the **fire** burning.

Replace the building to **Eiffel tower**.

Remove the **dog**.

Original Image

Holding a cup of tea, eye **closed**.

Wears a **diamond** earring, and a **golden ruby** crown.

Make her hair **dark green** and her clothes **checked**.

Girl is on the beach, **colorful cloud** in the sky.

What if it looks like **watercolor** painting?

Results

Multi-turn edits

Original Image | Change the background to **Hawaii scenery**. | Dress in **Aloha Shirt, Hawaiian shorts** and **surf on board**. | Replace the boy with **SpongeBob** and make it **a comic book photo**. | Add the **text "ICCV2025"** on the bottom in **bold white color**.

Image-to-image translation

input

output

Some Limitations

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➢ Object Movement: Instructions requiring spatial relocation (e.g., "move the chair to the corner") may fail due to insufficient exposure to motion oriented data in general editing datasets.

➢ Semantic Understanding Limitations: While T5 demonstrates strong text encoding capabilities, its semantic understanding remains constrained, particularly in resolving polysemous terms

Figure 7: Some failure cases of our methods, such as object movement, semantic ambiguity.

Thanks!