

ACE: ALL-ROUND CREATOR AND EDITOR Following Instructions via Diffusion Transformer

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Contents

- 1. ACE: Making Editing as Simple as Generation
- 2. Unified Multi-Task Generation / Editing Framework
- 3. Data Structuring and Quality Tuning
- 4. Model Performance and Applications
- 5. Follow-up Work Related to ACE



ACE: Making Editing as Simple as Generation

ACE provides a more convenient and versatile way of editing with instructions

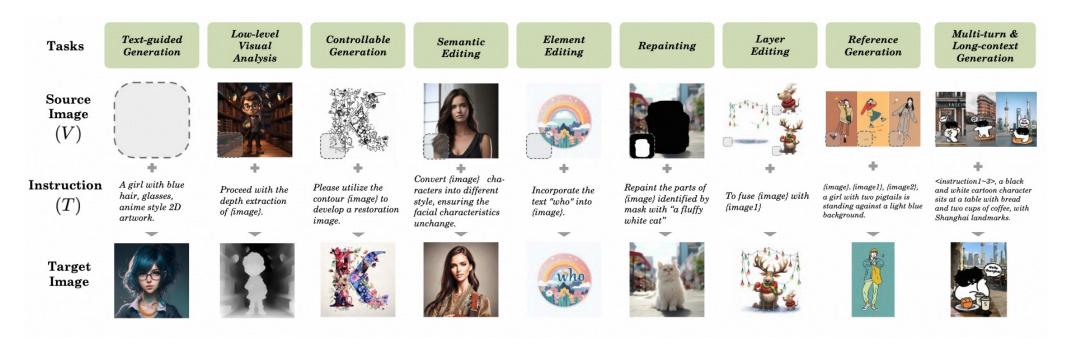






ACE: Making Editing as Simple as Generation

- √ Visual generation and editing can be categorized into 9 types.
- √ The various tasks can be defined through a unified format.



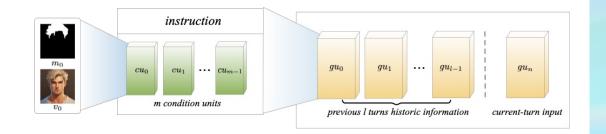


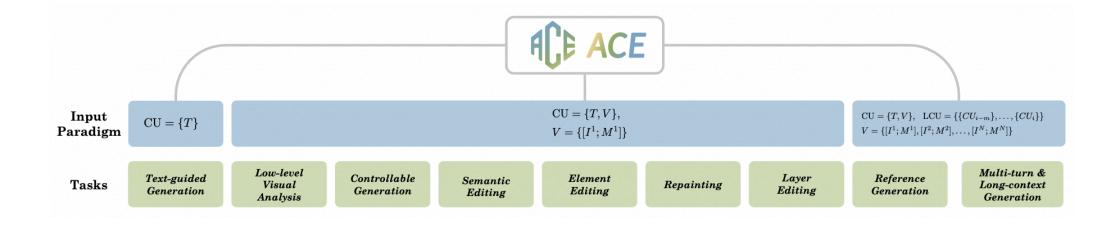
ACE: Making Editing as Simple as Generation

Unified Input Paradigm (LCU)

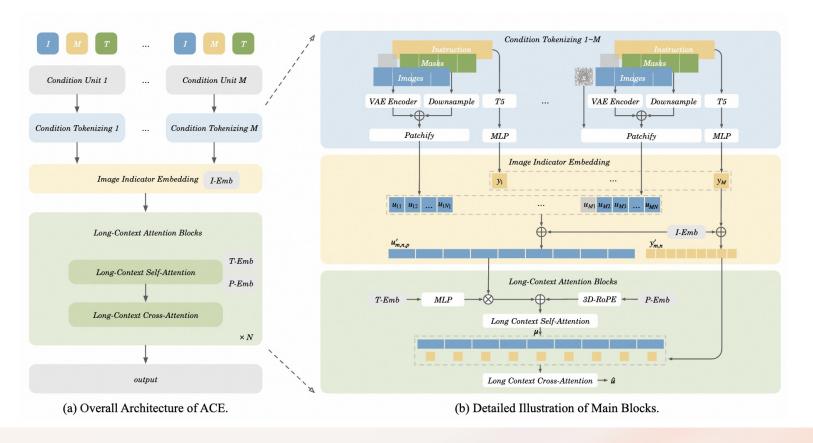
T: represents the instruction text,

V: represents the visual condition unit, consisting of the image I and the mask M





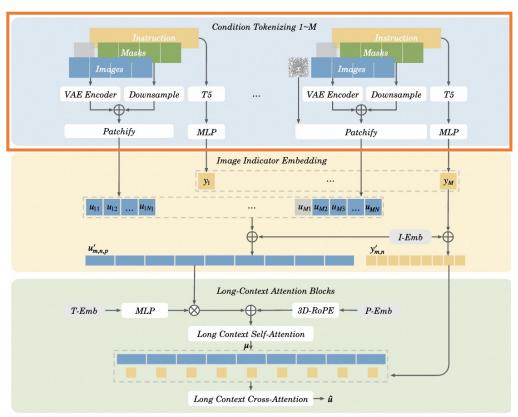
✓ Multimodal Editing and Generation Framework Based on Dit(0.6B)





✓ Multimodal Editing and Generation Framework Based on Dit

Condition Tokenizing





✓ Multimodal Editing and Generation Framework Based on Dit

Condition Tokenizing

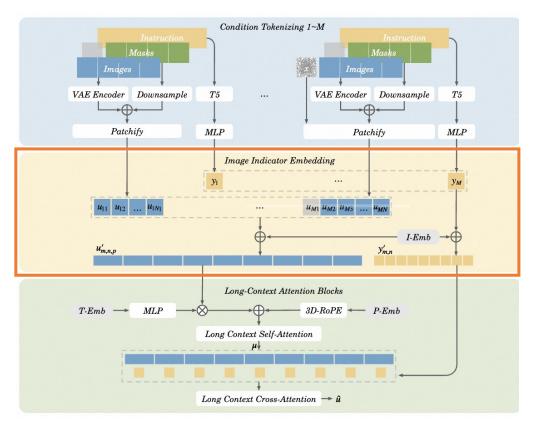
$$y'_{m,n} = y_m + I\text{-Emb}_{m,n},$$

$$u'_{m,n,p} = u_{m,n,p} + I$$
-Emb _{m,n} .

Image Indicator Embedding









✓ Multimodal Editing and Generation Framework Based on Dit

Condition Tokenizing

$$y'_{m,n} = y_m + I\text{-Emb}_{m,n},$$

$$u'_{m,n,p} = u_{m,n,p} + I$$
-Emb_{m,n}.

Image Indicator Embedding

$$\hat{u}_{m,n} = Attn(\mu_{m,n}, y'_{m,n}).$$

Long-Context Attention Blocks





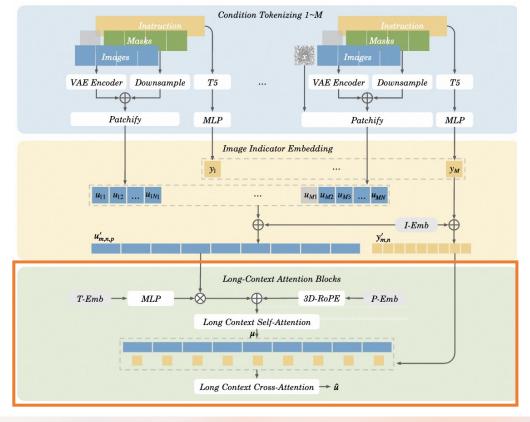














Data Structuring and Quality Tuning

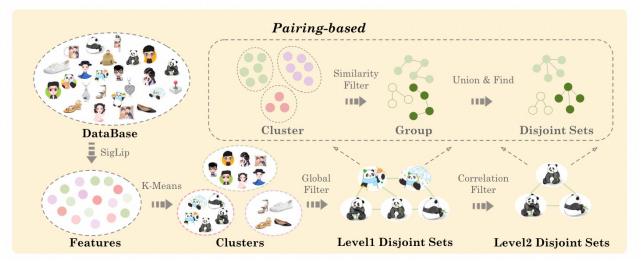
Scaling Data Construction and Annotation Process

- ✓ Generate corresponding editing task data pairs based on existing generative models.
- ✓ Construct data pairs with similar attributes based on feature clustering, typically referencing image-related tasks.

Synthesizing-based

**The control of the control of

Pair Data





Data Structuring and Quality Tuning

Instruction Labeling With Template-based and MLLM-based Methods

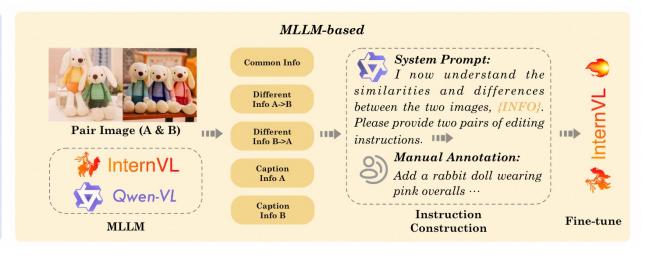
- ✓ Template-based method constructs instruction templates for specific vision tasks by leveraging human knowledge priors.
- ✓ The Instruction Captioner finetuned with curated instructions datasets to generate unique instructions for each given editing pair.

Template-based

Referring to depth map {image}, please restore the specific areas highlighted by the mask, as detailed in the text description {caption}.

System Prompt: I need your help with instructions on image editing from a given {image}, {caption}, and mask. For the definition of instructions I want to describe more clearly, accurately, diverse, sentence structure and expression can be richer.

[Instruction-1] (Instruction-2) ··· (Instruction-N)





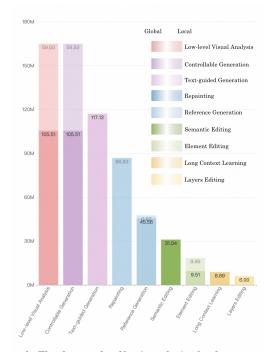
Data Structuring and Benchmark

ACE Dataset Distribution

✓ Covers 37 subtasks under 8 fundamental tasks.



a. The distribution of all tasks in the dataset



b. The data scale of basic tasks in the dataset

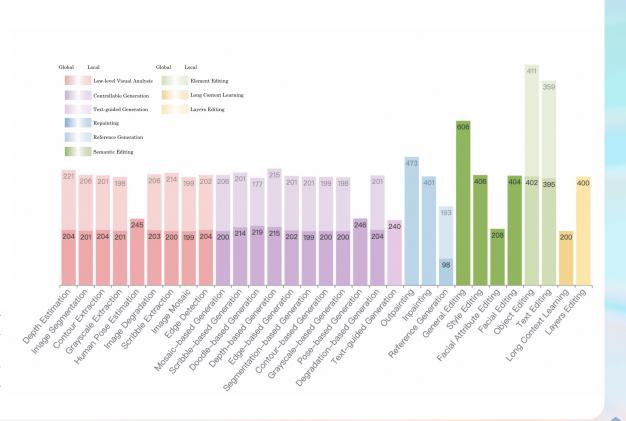


Data Structuring and Benchmark

ACE Benchmark Distribution

- (1) Total 12k: includes 6k real images and 6k generated images.
- (2) Evaluation for tasks such as local and global editing, reference generation, multi-round editing, and composite generation.
- (3) Total 31 subtasks: it is currently the largest benchmark in the field with the most comprehensive coverage of tasks.

Benchmark	Real Image?	Generated Image?	Multi-turn?	Regional?	Tasks	Data Scale
MagicBrush Emu Edit	Y Y	N N	Y N	Y N	8	1588 3589
ACE	Y	Y	Y	Y	31	12000





Quantitative Analysis

Settings	Methods	L1↓	L2↓	CLIP-I↑	DINO↑	CLIP-T1							
	Global Description-guided												
_	SD-SDEdit (Meng et al., 202)	0.1014	0.0278	0.8526	0.7726	0.2777							
	Null Text Inversion (Mokady et al., 2022)	0.0749	0.0197	0.8827	0.8206	0.2737							
	GLIDE (Nichol et al., 2022)	3.4973	115.8347	0.9487	0.9206	0.2249							
5	Blended Diffusion (Avrahami et al., 2021)	3.5631	119.2813	0.9291	0.8644	0.2622							
le-t	ACE (Ours)	0.0505	0.0160	0.9436	<u>0.9184</u>	0.2833							
Single-turn	Instruction-guided												
••	HIVE (Zhang et al., 2024)	0.1092	0.0380	0.8519	0.7500	-							
	InstructPix2Pix (Brooks et al., 2023)	0.1122	0.0371	0.8524	0.7428	0.2764							
	MagicBrush (Zhang et al., 2023a)	0.0625	0.0203	0.9332	0.8987	0.2781							
	UltraEdit (Zhao et al., 2024)	0.0575	0.0172	0.9307	0.8982	-							
	ACE (Ours)	0.0507	0.0165	0.9453	0.9215	0.2841							
	Global Description-guided												
	SD-SDEdit (Meng et al., 202)	0.1616	0.0602	0.7933	0.6212	0.2694							
	Null Text Inversion (Mokady et al., 2022)	0.1057	0.0335	0.8468	0.7529	0.2710							
	GLIDE (Nichol et al., 2022)	11.7487	1079.5997	0.9094	0.8494	0.2252							
	Blended Diffusion (Avrahami et al., 2021)	14.5439	1510.2271	0.8782	0.7690	0.2619							
	ACE (Ours)	0.0778	0.0290	0.9124	0.8611	0.2843							
Ē	ACE (Ours w/ LC)	0.0768	0.0285	0.9136	0.8635	0.2819							
Multi-turn	Instruction-guided												
Μ	HIVE (Zhang et al., 2024)	0.1521	0.0557	0.8004	0.6463	0.2673							
-	InstructPix2Pix (Brooks et al., 2023)	0.1584	0.0598	0.7924	0.6177	0.2726							
	MagicBrush (Zhang et al., 2023a)	0.0964	0.0353	0.8924	0.8273	0.2754							
	UltraEdit (<mark>Zhao et al</mark> ., <mark>2024</mark>)	0.0745	0.0236	0.9045	0.8505	-							
	ACE (Ours)	0.0773	0.0293	0.9128	0.8661	0.2855							
	ACE (Ours w/ LC)	0.0761	0.0284	0.9140	0.8668	0.2809							

Comparison on the MagicBrush Benchmark

Method	CLIPdir↑	CLIPout [↑]	L1↓	CLIPimg↑	DINO↑
InstructPix2Pix (Brooks et al., 2023) MagicBrush (Zhang et al., 2023a) Emu Edit (Sheynin et al., 2024) UltraEdit (Zhao et al., 2024) CosXL (StabilityA., 2024)	0.0739 0.0831 0.1073 0.0888 0.0901	0.2681 0.2701 0.2791 <u>0.2783</u> 0.2775	0.1240 0.0995 0.0893 0.0532 0.0940	0.8508 0.8664 0.8743 <u>0.8814</u> 0.8686	0.7647 0.7927 0.8398 <u>0.8524</u> 0.8340
ACE (Ours)	0.0855	0.2746	0.0761	0.8952	0.8620

Comparison on the EmuEdit Benchmark

Method	Face Similarity	Effective Score
InstantID [†] Wang et al. (2024b)	84.08	0.96
CosXL StabilityA (2024)	66.49	0.37
UltraEdit Zhao et al. (2024)	62.91	0.16
IP-Adapter Ye et al. (2023)	<u>66.51</u>	0.31
FaceChain Liu et al. (2023b)	65.46	0.42
ACE (Ours)	70.07	0.67

Quantitative Evaluation of Portrait Preservation

Method	Edit Distance	Sentence Accuracy
UDiffText (Zhao & Liar, 2024) AnyText (Tuo et al., 2023)	0.6827 0.6035	<u>0.4110</u> 0.3313
ACE (Ours)	0.8211	0.5767

Quantitative Evaluation of Text Editing

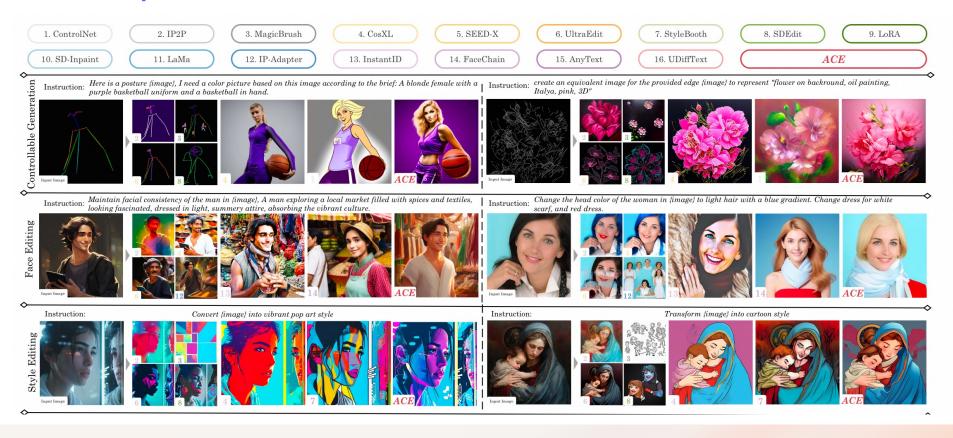


Human Study

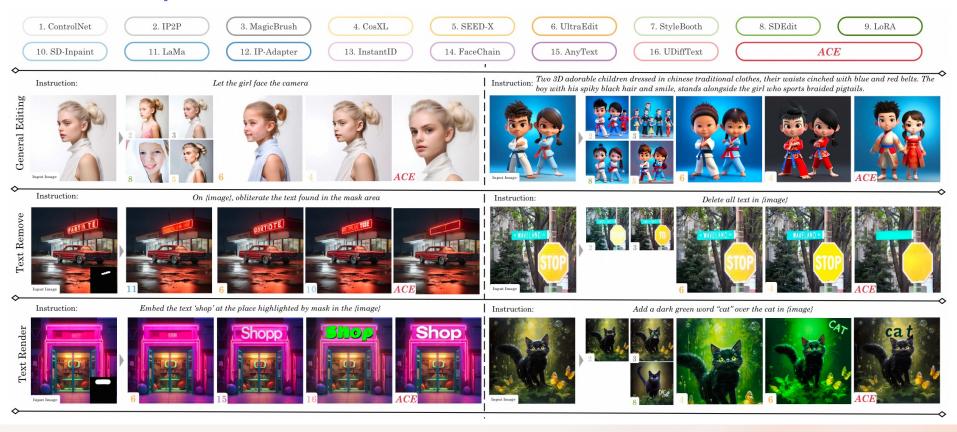
- (1) Results generated by different methods are ranked manually.
- (2) Five designers serve as annotat ors, ensuring that each sample is e valuated by at least three individuals.
- (3) Among the 21 benchmarkable t asks, a win rate of 15 out of 21 has been achieved.

	Txt2img		Contr	ollable		S	emant	ic		Eler	nent		Repai	nting
	• Txt2img	• Canny	 Depth 	 Scribble 	• Pose	• Face	• Style	General	Add Text	• Rm Text	• Add Obj.	• Rm Obj.	• Inpaint	 Outpaint
Global Editing														
SD1.5 (AI, 2022a) 3.3/2.2 -											_			
SDXL (StabilityAI, 2021)	4.1/2.8	-	_	_	-	-	_	_	-	_	_	-	_	_
CtrlNet (Zhang et al., 2023b)	-	2.5/2.0	3.8/2.4	1.9/2.0	2.9/1.9	-	_	_	_	_	_	_	_	_
StyleBooth (Han et al., 2024)	_	-	_	_	_	-	3.3/2.6	-	-	-	_	-	_	_
IP-Adapter (Ye et al., 2023)	_	-	-	_	_	2.0/2.2	-	1.7/2.5	_	_	-	-	_	_
InstantID (Wang et al., 2024b)	-	-	-	-	-	2.5/2.7	-	-	-	-	-	-	-	-
FaceChain (Liu et al., 2023b)	-	-	-	-	-	2.0/3.0	-	-	-	-	-		-	-
SDEdit (Meng et al., 2021)	-	1.4/1.9	1.3/1.8	1.1/1.6	1.2/1.4	1.3/2.1	1.1/1.7	1.5/2.1	1.1/2.2	1.1/1.7	1.5/2.1	1.1/2.0	-	-
IP2P (Brooks et al., 2023)	-			1.5/2.3									-	-
MB (Zhang et al., 2023a)	-	1.3/1.8	1.3/1.7	1.3/1.9	1.1/1.3	2.4/2.3	1.4/2.0	2.2/2.3	1.5/2.4	<u>2.2</u> /2.5	3.1 /2.2	2.1/2.4	-	-
SEED-X (Ge et al., 2024b)	-	1.6/2.1	1.7/2.0	1.7/2.2	1.5/1.5	2.0/2.7	2.2/2.5	2.1/2.7	1.3/2.6	2.1/2.6	1.9/ 2.6	<u>2.5</u> /2.4	-	-
CosXL (StabilityA , 2024)	-			<u>2.6/2.9</u>									-	-
UltraEdit (Zhao et al., 2024)	-			1.3/2.3										-
ACE (Ours)	<u>3.7/2.5</u>	4.6 / <u>2.7</u>	4.5/2.8	4.8/2.9	4.1/2.3	<u>2.8</u> /2.8	2.4/2.6	2.1/2.5	2.8/2.7	4.4/2.9	2.6/2.4	3.9 /2.5	-	-
				L	ocal Ea	liting								
LaMa (Suvorov et al., 2022)	-	-	_	_	-	-	_	_	l -	3.6/2.8	-	4.5/2.8	1.6/2.3	3.0/2.4
SDInpaint (AI, 2022b)	-	_	_	_	_	-	_	_	_			2.2/2.5		
CtrlNet (Zhang et al., 2023b)	-	-	_	_	_	_	_	_	_			$2.6/\overline{2.2}$		
AnyText (Tuo et al., 2021)	-	-	_	-	_	-	_	_	3.5/2.7	-	-	-	-	
UDiffText (Zhao & Lian, 2024)	-	-	_	_	_	-	_	_	3.6/2.7	_	-	-	_	_
UltraEdit (Zhao et al., 2024)	-	1.4/1.9	1.2/1.8	1.2/2.0	_	-	_	_	1.1/2.8	1.2/2.9	2.9/2.5	1.4/2.5	1.1/1.7	1.1/2.1
ACE (Ours)	-	4.8/2.6	4.3/2.5	4.8/2.6	-	-	-	-	4.5/2.9	4.5/2.9	3.7/ <u>2.5</u>	<u>4.3/2.5</u>	4.4/2.7	4.6/2.8

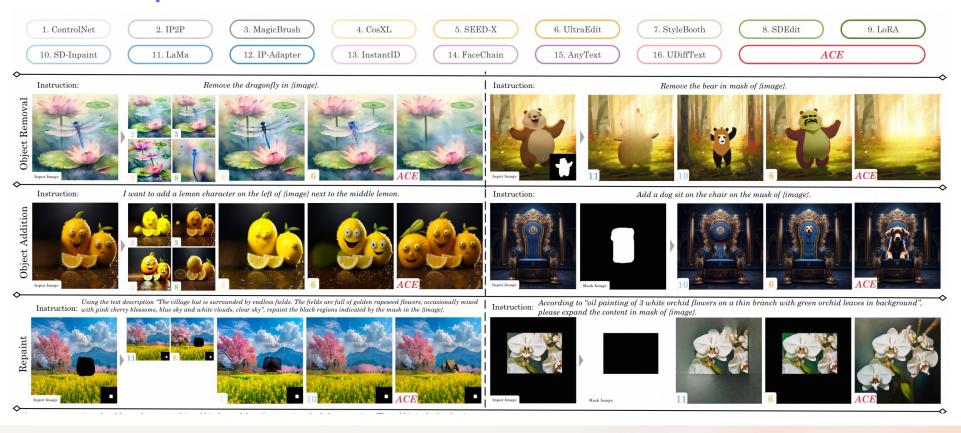














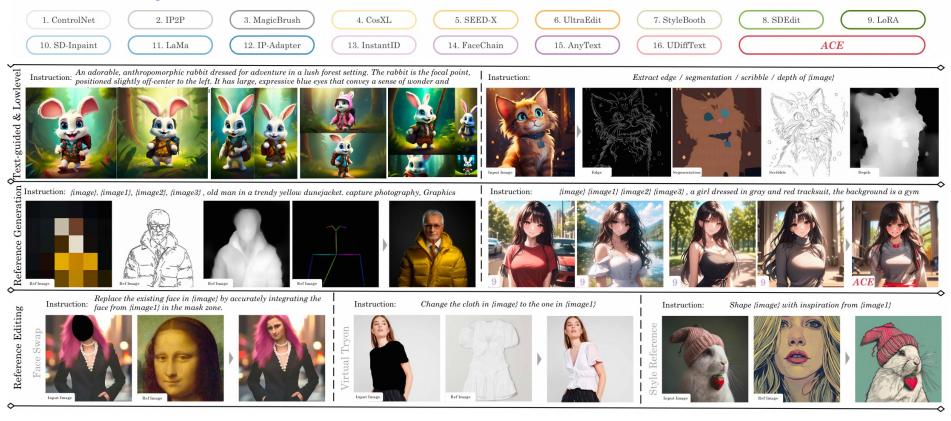
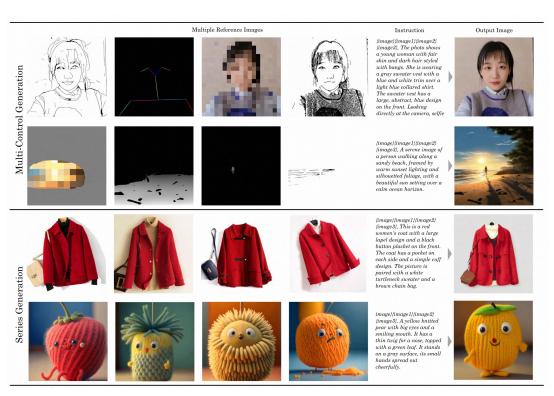






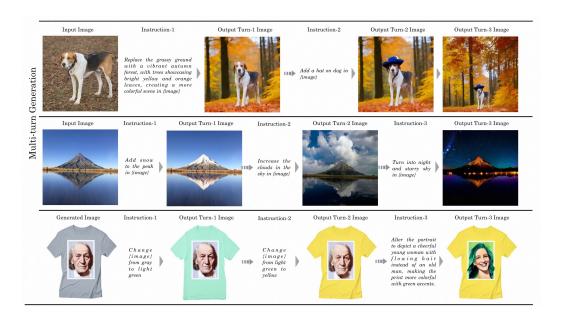
Image Layering Capability and Image Fusion Capability



Composite Generation and Reference Generation Capability



Visual Comparison



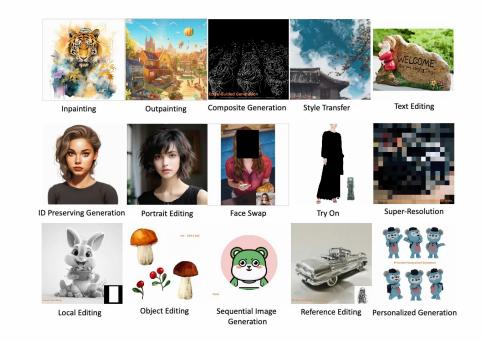


Multi-Round Editing and Identity Preservation Generation



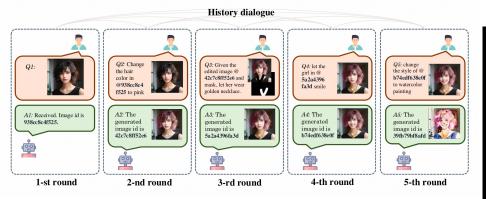
Applications: Basic Editing and Generation Tasks

- ✓ It can be used for 15 common image generation and editing tasks.
- ✓ Interactive generation and editing through instructions can significantly reduce deployment and usage costs.





Applications: Conversational Editing and Generation.



✓ In conversational mode, multiround editing of images can be achieved through chat.





ACE Usage

Project Page: https://ali-vilab.github.io/ace-page/



https://huggingface.co/spaces/scepter-studio/ACE-Chat







ACE++: Instruction-Based Image Creation and Editing via Context-Aware Content Filling

✓ ACE++ is an upgrade Version based on post-training using FLUX-Dev.

Project Page: https://ali-vilab.github.io/ACE_plus_page/

- https://github.com/ali-vilab/ACE_plus?tab=readme-ov-file
- https://huggingface.co/spaces/scepter-studio/ACE-Plus
- https://www.modelscope.cn/studios/iic/ACE-Plus



Wan2.1:

✓ The text data from ACE is used to train the Chinese and English text rendering capabilities of Wan 2.1.

Project Page: https://wanxai.com/



https://github.com/Wan-Video

https://huggingface.co/Wan-Al

https://www.modelscope.cn/models/Wan-AI/



ICEBench: A Unified and Comprehensive Benchmark for Image Creating and Editing

✓ ICEBench is a more refined definition and collection of ACEBench.

Project Page: https://ali-vilab.github.io/ICE-Bench-Page/



VideoACE: All-in-One Video Creation and Editing

✓ VideoACE is the adaptation of ACE for video tasks.

Project Page: https://ali-vilab.github.io/VACE-Page/



https://github.com/ali-vilab/VACE





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