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Native Multimodal Models: Architecture, Post-Training, and Evaluation

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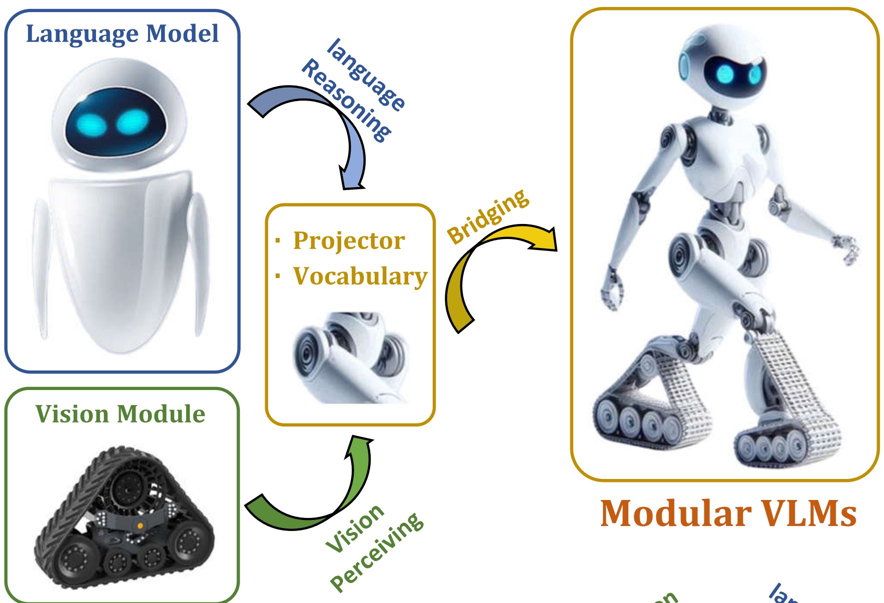
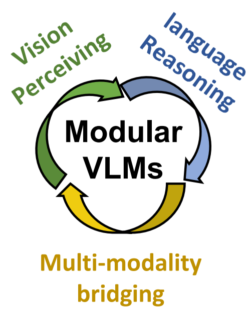
Background： Modular Vision-Language Models





■ Dense Visual Encoder

🔥 **Well pre-alignment** across modules.
🔥 **Minimal resource costs** for adaptation.

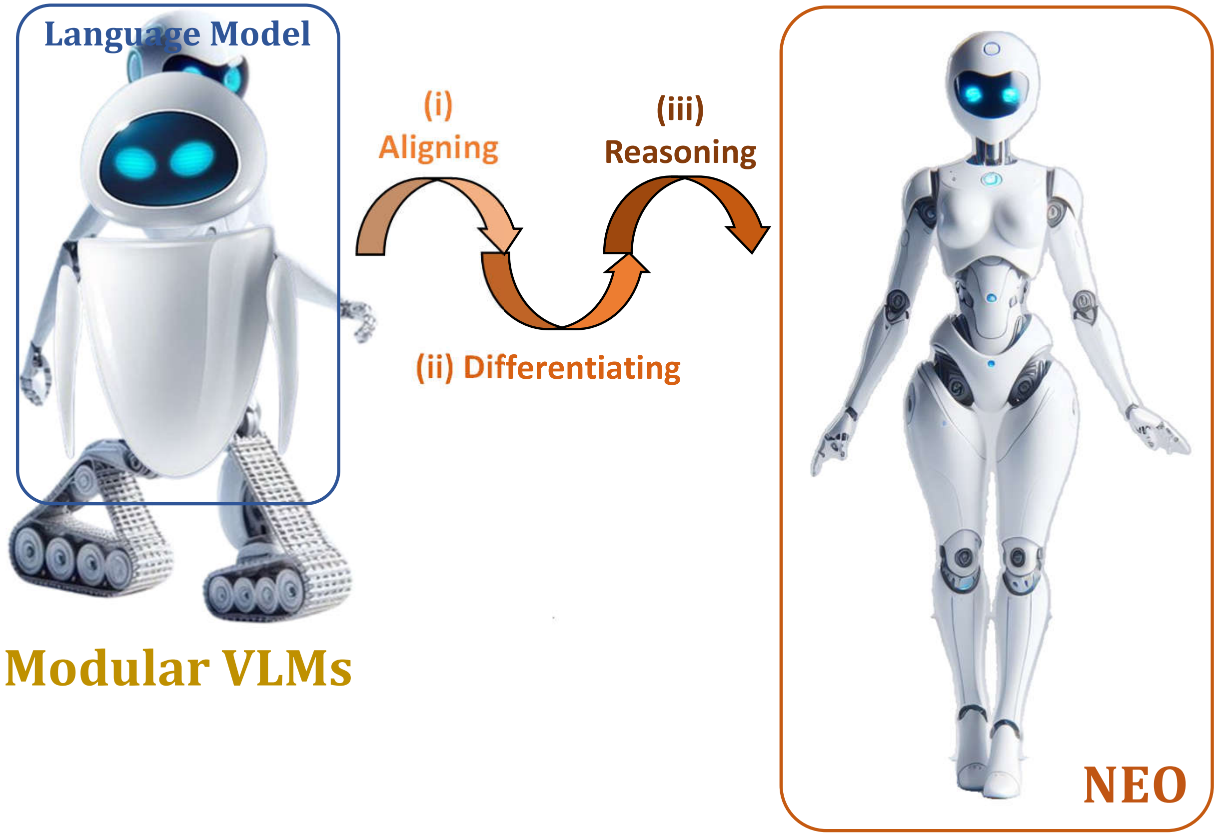
🧊 Strong visual pre-training **inductive biases**
🧊 **Complex infrastructure** development and **scaling analyses** of separate components.

■ Discrete Visual Tokenizer

🔥 Efficiently model the **unified VLMs**.
🔥 Naturally **compatible with multiple modalities**.

🧊 Discretization results in **lossy visual features**.
🧊 Perform poorly in **fine-grained visual perception**.

Background： Native Vision-Language Models



Thinking:

- Can we remove **vision priors** from existing VLMs?
- How to **transfer** an LLM to a native VLM **efficiently**?
- How to **bridge the gap** between native and modular VLMs?
- How about **mutual synergy** on understanding and generation capabilities of existing VLMs ?

Outline： Native Vision-Language Models

Native Multimodal Evaluation

RealUnify: Do Unified Models Truly Benefit from Unification?

Dual-Evaluation Protocol, Understanding-Generation Synergy

Native Multimodal Post-Training

Visual Jigsaw Post-Training Improves MLLMs

Self-supervised Learning, Post-training, Reinforcement Learning

Native Multimodal Architecture

From Pixels to Words: Towards Native Vision-Language Primitives at Scale

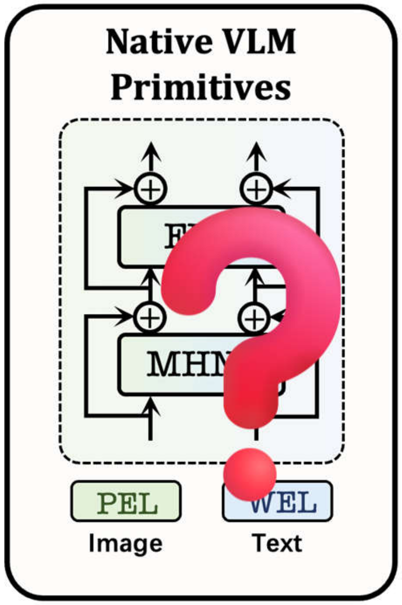
Native Vision-Language Primitive, Holistic Vision-Language Buffer

Native Multimodal Architecture

From Pixels to Words: Towards Native Vision-Language Primitives at Scale

Haiwen Diao, Mingxuan Li, Silei Wu, Linjun Dai, Xiaohua Wang, Hanming Deng, Lewei Lu, Dahua Lin, Ziwei Liu

Motivation

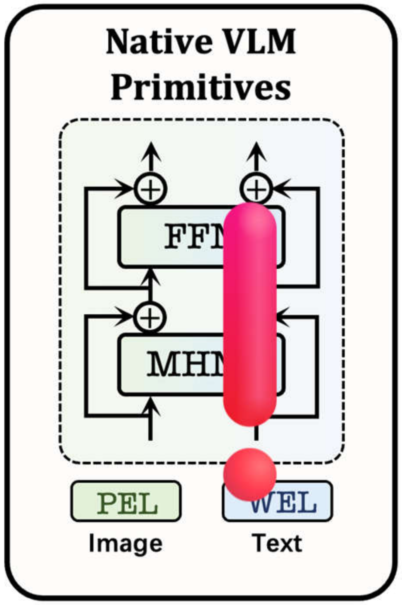


Question:

- What fundamental constraints set native VLMs apart from modular ones, and to what extent can these barriers be overcome?
- How to make research in native VLMs more accessible and democratized, thereby accelerating progress in the field.

These issues prompts us to think about what a native primitive should look like and what characteristics it should have?

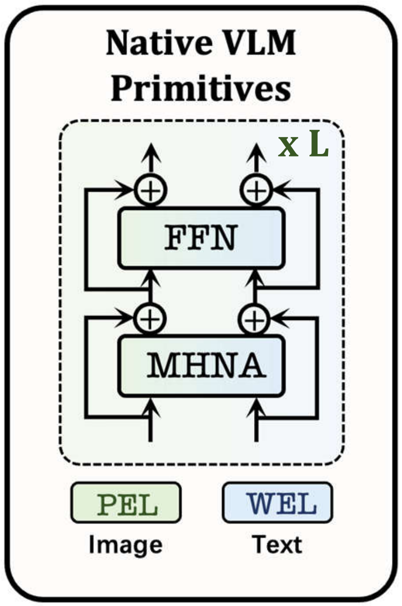
Motivation



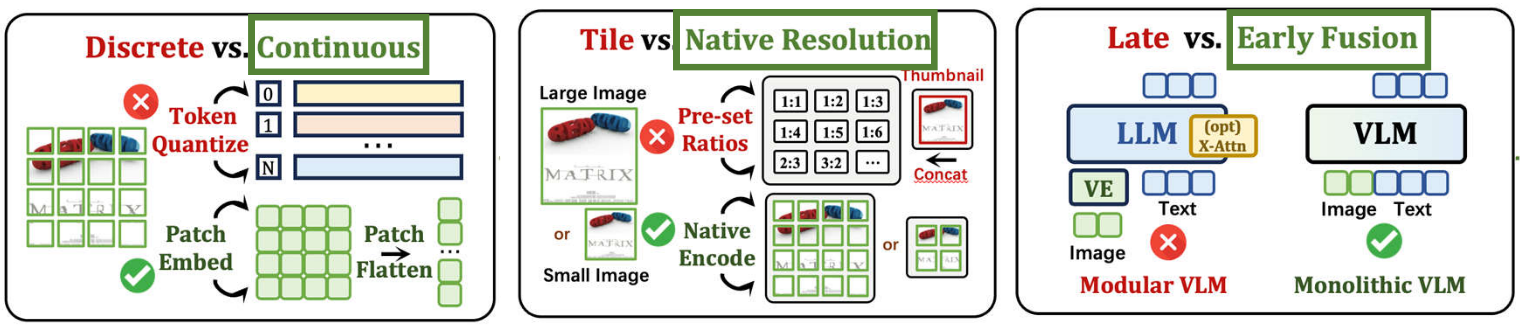
From first principles, one native VLM primitive should：

- effectively align pixel and word representations within a shared semantic space;
- seamlessly integrate the strengths of formerly separate vision and language modules;
- inherently embody various cross-modal properties that support unified vision-language encoding, aligning, and reasoning

Motivation

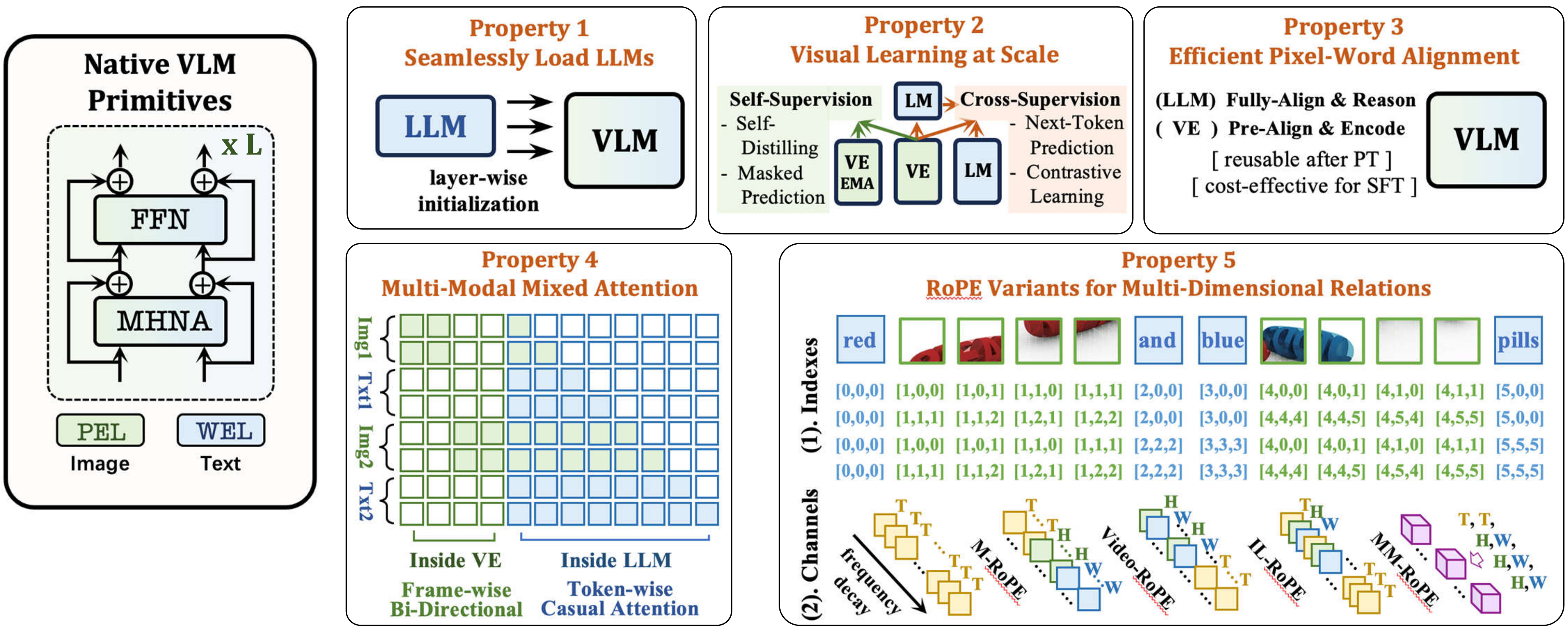


Build native VLMs from first principles ! ! !



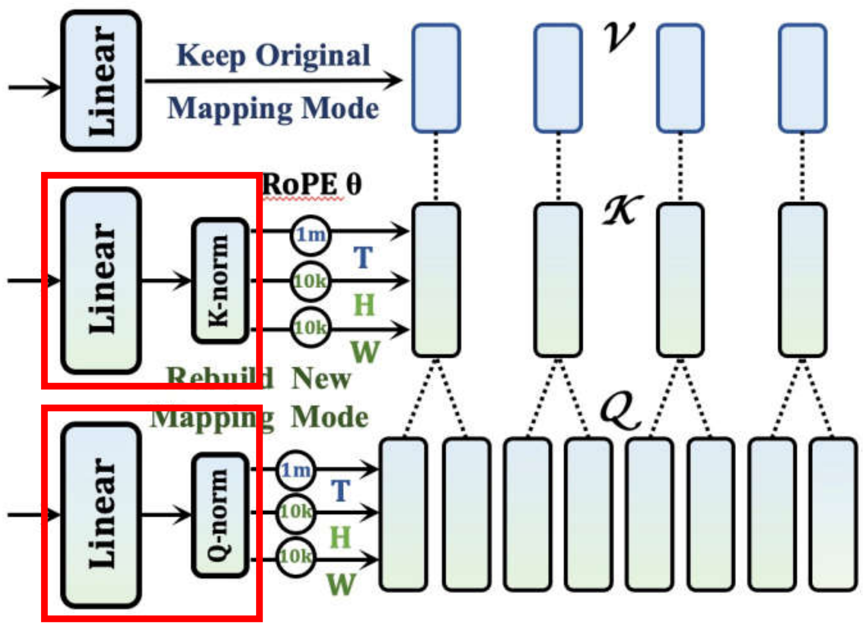
Motivation

Build native VLMs by leveraging the strengths of existing VLM designs ! ! !

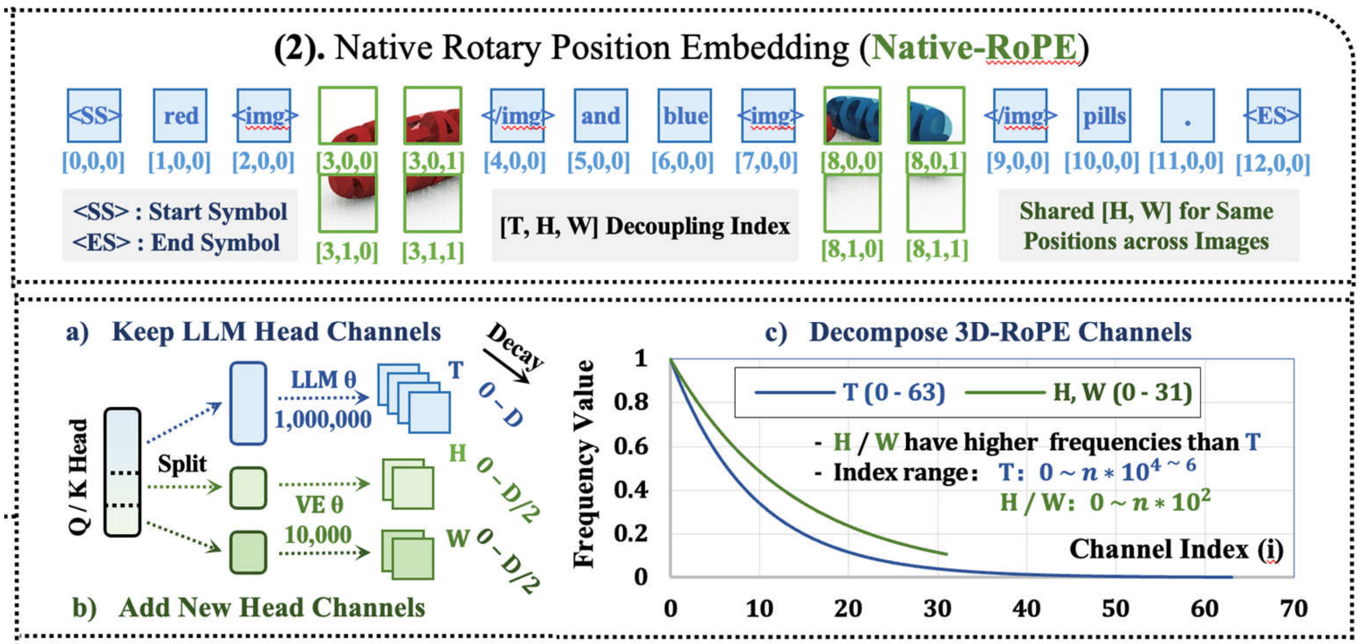


Methodology

(1). Introduce new FC/Norm into original Q, K for H, W



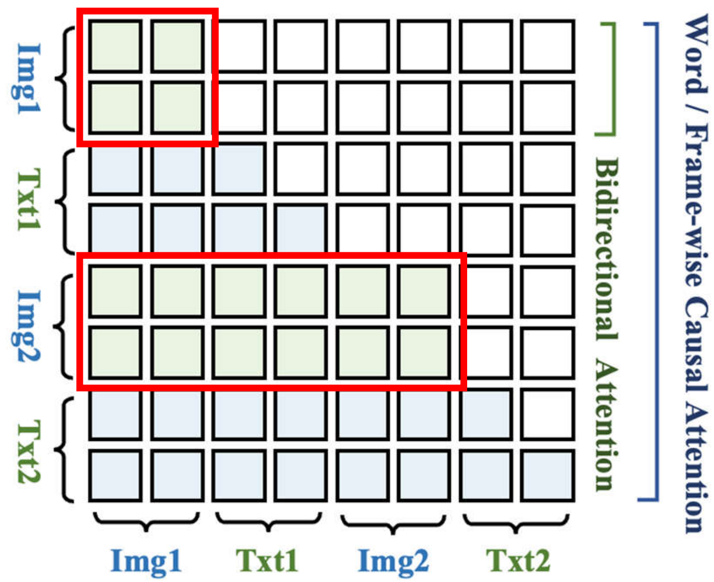
Methodology



- Native Rotary Position Embeddings (Native-RoPE) **eliminates index correlations** and **decouples channel allocation** between H / W and T;
- Native-RoPE with **modality-specific frequencies** captures **local dependencies** across H / W / T and **long-range relations** across T;

Methodology

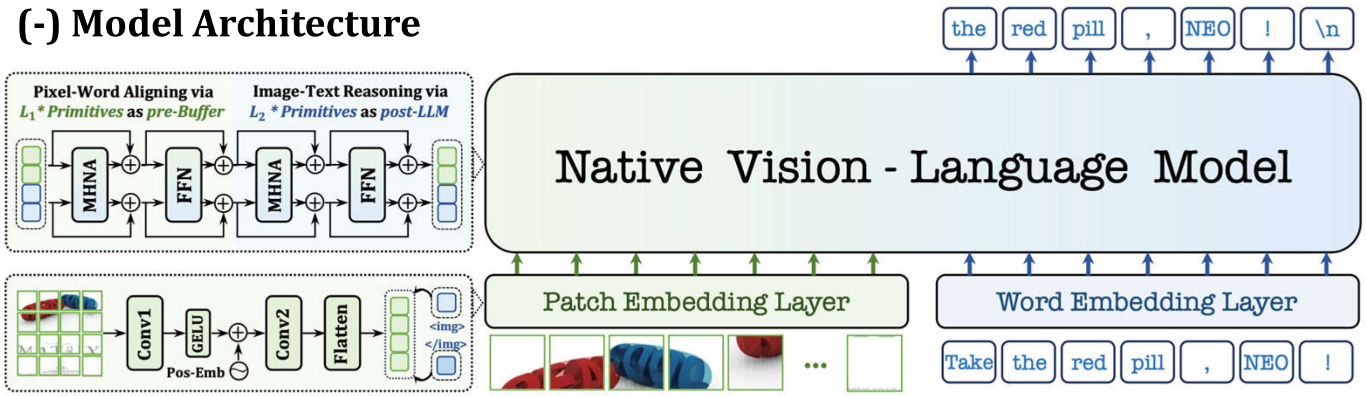
(3). Introduce **Frame-wise Native** Multi-Modal **Attention**



- Native Multi-Modal Attention captures **rich spatial correspondence within images** and **contextual vision-language dependencies**.

Methodology

(-) Model Architecture

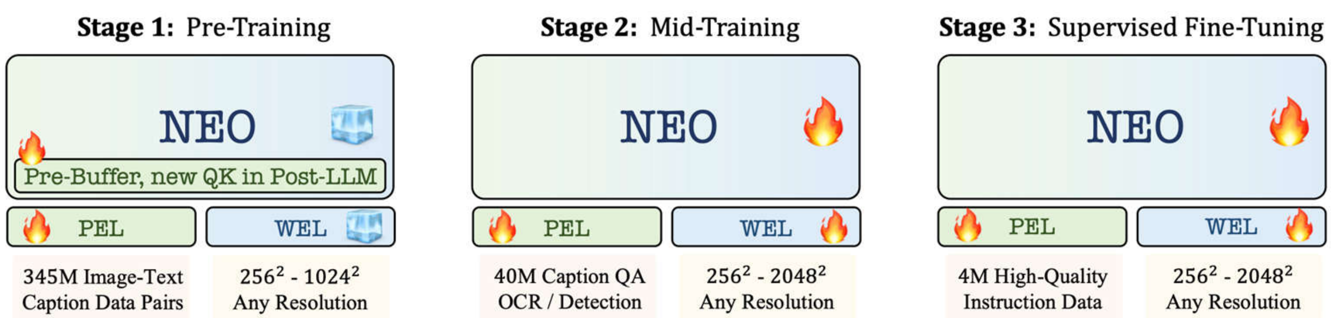


- Modality-shared pre-Buffer maps vision and language into a unified representation space.

Reusable for extensible ecosystem

- Post-LLM absorbs strong language proficiency and powerful reasoning capabilities of pre-trained LLMs.

(-) Training Recipe



- End-to-End Training Procedure
- Quite Efficient with Limited Data

With **390M** image-text samples, NEO efficiently **develops visual perception from scratch** while **mitigating vision-language conflicts inside one model.**

Main Results

(-) Evaluation Results on General Understanding

Model	LLM	# Data	MMMU	MMB	MMVet	MMStar	SEED-I	POPE	HallB
▼ *Modular Vision-Language Models (2B)*									
Qwen2-VL	Qwen2-1.5B	– / – / –	41.1	74.9	49.5	48.0	–	–	41.7
InternVL2.5	InternLM2.5-1.8B	>6B / 100M / 16M	43.6	74.7	60.8	53.7	–	**90.6**	42.6
Qwen2.5-VL†	Qwen2.5-1.5B	– / – / –	**51.2**	79.1	61.8	55.9	–	–	**46.3**
InternVL3†	Qwen2.5-1.5B	>6B / 100M / 22M	48.6	**81.1**	**62.2**	**60.7**	–	89.6	42.5
Encoder-Base	Qwen3-1.7B	>6B / 40M / 4M	47.1	75.8	37.4	52.7	**73.6**	87.0	44.4
▼ *Native Vision-Language Models (2B)*									
Mono-InternVL	InternLM2-1.8B	1.2B / 143M / 7M	33.7	65.5	40.1	–	67.4	–	34.8
Mono-InternVL-1.5	InternLM2-1.8B	400M / 150M / 7M	39.1	64.0	**54.0**	–	66.9	–	32.5
HoVLE	InternLM2-1.8B	550M / 50M / 7M	32.2	73.3	43.8	–	70.9	87.4	38.4
OneCAT	Qwen2.5-1.5B	436M / 70M / 13M	39.0	72.4	42.4	–	70.9	–	–
NEO	Qwen3-1.7B	345M / 40M / 4M	**48.6**	**76.0**	49.6	**54.2**	**74.2**	**87.5**	**43.1**
▼ *Modular Vision-Language Models (8B)*									
Qwen2-VL	Qwen2-7B	– / – / –	54.1	83	62.0	60.7	–	88.1	50.6
InternVL2.5	InternLM2.5-7B	>6B / 50M / 4M	56.0	**84.6**	62.8	64.4	–	90.6	50.1
Qwen2.5-VL†	Qwen2.5-7B	– / – / –	55.0	83.5	67.1	63.9	–	86.4	**52.9**
InternVL3†	Qwen2.5-7B	>6B / 100M / 22M	**62.7**	83.4	**81.3**	**68.2**	–	**91.1**	49.9
Encoder-Base	Qwen3-8B	>6B / 40M / 4M	54.1	84	60.0	63.5	**76.2**	87.8	51.4
▼ *Native Vision-Language Models (8B)*									
Fuyu	Persimmon-8B	– / – / –	27.9	10.7	21.4	–	59.3	84.0	–
Chameleon	from scratch	1.4B / 0M / 1.8M	25.4	31.1	8.3	–	30.6	19.4	17.1
EVE	Vicuna-7B	33M / 0M / 1.8M	32.6	52.3	25.7	–	64.6	85.0	26.4
SOLO	Mistral-7B	44M / 0M / 2M	–	67.7	30.4	–	64.4	78.6	–
Emu3	from scratch	– / – / –	31.6	58.5	37.2	–	68.2	85.2	–
EVEv2	Qwen2.5-7B	77M / 15M / 7M	39.3	66.3	45.0	–	71.4	87.6	–
BREEN	Qwen2.5-7B	13M / 0M / 4M	42.7	71.4	38.9	51.2	–	–	37.0
VoRA	Qwen2.5-7B	30M / 0M / 0.6M	32.0	61.3	33.7	–	68.9	85.5	–
SAIL	Mistral-7B	512M / 86M / 6M	–	70.1	46.3	53.1	72.9	85.8	**54.2**
NEO	Qwen3-8B	345M / 40M / 4M	**54.6**	**82.1**	**53.6**	**62.4**	**76.3**	**88.4**	46.4

Main Results

Model	Input	RoPE	Backbone	AI2D	DocVQA	ChartQA	InfoVQA	TextVQA	OCRBench
▼ *Modular Vision-Language Models (2B)*									
Qwen2-VL	Any Res.	M-RoPE	Dense	74.7	90.1	73.5	65.5	**79.7**	80.9
InternVL2.5	Tile-wise	1D-RoPE	Dense	74.9	88.7	79.2	60.9	74.3	80.4
Qwen2.5-VL†	Any Res.	M-RoPE	Dense	**81.6**	**93.9**	**84.0**	**77.1**	79.3	79.7
InternVL3†	Tile-wise	1D-RoPE	Dense	78.7	88.3	80.2	66.1	77.0	**83.5**
Encoder-Base	Tile-wise	1D-RoPE	Dense	77.4	89.9	78.4	65.9	73.3	**83.5**
▼ *Native Vision-Language Models (2B)*									
Mono-InternVL	Tile-wise.	1D-RoPE	MoE	68.6	80.0	73.7	43.0	72.6	76.7
Mono-InternVL-1.5	Tile-wise.	1D-RoPE	DaC	67.4	81.7	72.2	47.9	73.7	**80.1**
HoVLE	Tile-wise.	1D-RoPE	Dense	73.0	86.1	78.6	55.7	70.9	74.0
OneCAT	Any Res.	M-RoPE	Dense	72.4	87.1	76.2	56.3	67.0	–
NEO	Any Res.	Native-RoPE	Dense	**80.1**	**89.9**	**81.2**	**63.2**	**74.0**	77.1
▼ *Modular Vision-Language Models (8B)*									
Qwen2-VL	Any Res.	M-RoPE	Dense	83.0	94.5	83	76.5	84.3	86.6
InternVL2.5	Tile-wise	1D-RoPE	Dense	84.5	93.0	84.8	77.6	79.1	82.2
Qwen2.5-VL†	Any Res.	M-RoPE	Dense	83.9	**95.7**	**87.3**	**82.6**	**84.9**	86.4
InternVL3†	Tile-wise	1D-RoPE	Dense	**85.2**	92.7	86.6	76.8	80.2	**88**
Encoder-Base	Tile-wise	1D-RoPE	Dense	82.9	92.1	83.5	75	77.1	85.3
▼ *Native Vision-Language Models (8B)*									
Fuyu	Any Res.	1D-RoPE	Dense	64.5	–	–	–	–	36.6
Chameleon	Fix Res.	1D-RoPE	Dense	46.0	1.5	2.9	5.0	4.8	0.7
EVE	Any Rat.	1D-RoPE	Dense	61.0	53.0	59.1	25.0	56.8	39.8
SOLO	Any Res.	1D-RoPE	Dense	61.4	–	–	–	–	12.6
Emu3	Fix Res.	1D-RoPE	Dense	70	76.3	68.6	43.8	64.7	68.7
EVEv2	Any Rat.	1D-RoPE	DaC	74.8	–	73.9	–	71.1	70.2
BREEN	Any Res.	1D-RoPE	MoE	76.4	–	–	–	65.7	–
VoRA	Any Res.	1D-RoPE	Dense	61.1	–	–	–	58.7	–
SAIL	Any Res.	M-RoPE	Dense	76.7	–	–	–	**77.1**	**78.3**
NEO	Any Res.	Native-RoPE	Dense	**83.1**	**88.6**	**82.1**	**60.9**	75.0	77.7

-- With quite **limited** pre-training and supervised fine-tuning data and

-- Without reinforcement learning (**RL**)

- **Approaches** the performance of top-tier modular VLMs, e.g., **Qwen2 / 2.5-VL, InternVL2.5 / 3.**
- **Delivers substantial gains** on diverse visual-centric benchmarks over the best competitors, from **EVE** series to **SAIL**.

Ablation Studies

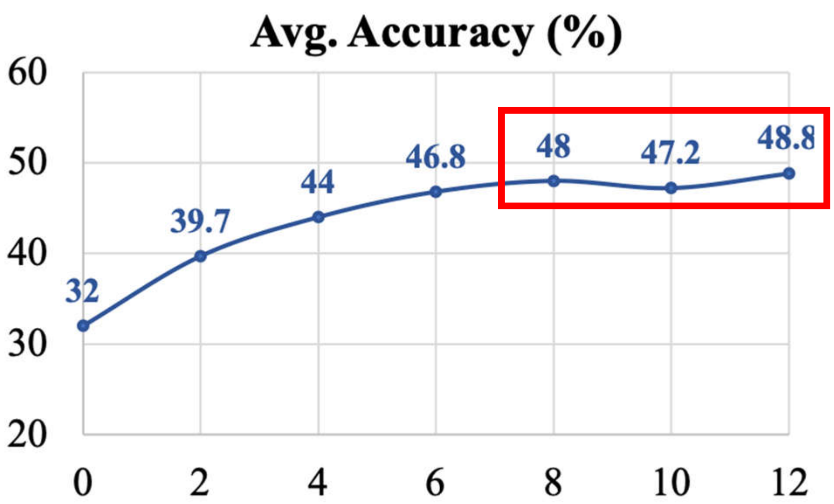


Figure 5: Configurations of pre-Buffer.

Here **8-12** primitive layers for pre-Buffer is a good trade-off for pre-alignment.

Ablation Studies

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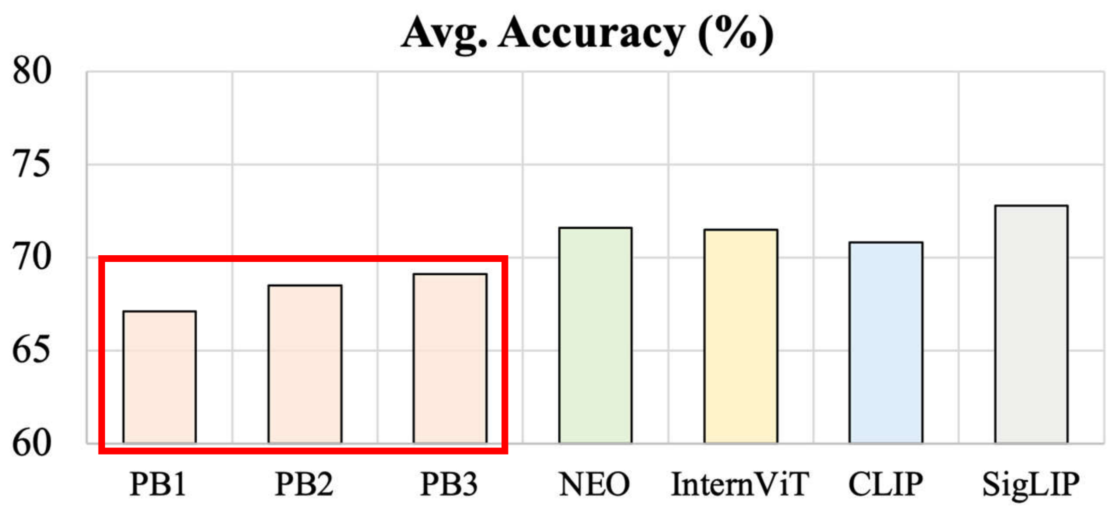
Table 3: Configurations of attention and RoPE. MMS, CQA, IVQA, and OCRB denote MMStar, ChartQA, InfoVQA, and OCRBench. ⋆ indicates that the base RoPE frequencies for height and width are set to 1M. To ensure fairness, we add new head dimensions of equal size across all models.

Model	Attention	RoPE	MMMU	MMB	MMS	SEED-I	AI2D	CQA	IVQA	TVQA	OCRB	POPE	Avg.
A	Causal	1D-RoPE	40.2	48.6	36.1	55.3	63.6	16.1	22.5	16.2	13.9	78.6	39.1
B	Mixed	1D-RoPE	**40.8**	48.8	36.4	57.3	63.7	16.0	21.9	17.4	16.0	79.2	39.8
C	Mixed	IL-RoPE	40.0	47.3	36.3	57.6	62.0	18.8	23.4	17.9	13.2	78.8	39.5
D	Mixed	M-RoPE	40.3	49.6	37.2	57.8	64.2	23.7	25.2	20.4	18.8	79.3	41.7
E	Mixed	MM-RoPE	40.5	50.8	37.6	58.2	**65.8**	25.7	**26.3**	22.1	18.2	78.8	42.4
F	Mixed	Video-RoPE	40.6	**51.3**	**37.8**	**58.8**	64.3	**27.4**	26.1	**23.7**	**21.3**	**81.0**	**43.2**
G	Causal	Native-RoPE	40.2	49.2	36.3	57.1	63.7	19.2	23.5	19.5	16.7	77.8	40.3
H	Mixed	Native-RoPE	**40.7**	**51.9**	**38.2**	**58.9**	**65.8**	**30.6**	**26.9**	**24.1**	**23.2**	**80.0**	**44.0**
I	Mixed	Native-RoPE⋆	40.4	50.4	36.9	57.0	64.1	25.6	25.2	21.7	20.1	78.7	42.0

- **Modality-specific RoPE frequency** does count !
- **RoPE indexes allocation for H, W, T** does count !
- **Mixed Multi-Modality Attention** Mechanism does count !

Ablation Studies



PB 1–3 denotes the Pre-Buffer after stage 1–3.

PB3 shows only an average gap of 2.5 / 2.4 / 1.7 / 3.7% over NEO / InternViT / CLIP / SigLIP, reducing training costs of building native VLMs for subsequent research.

Native Multimodal Post-Training

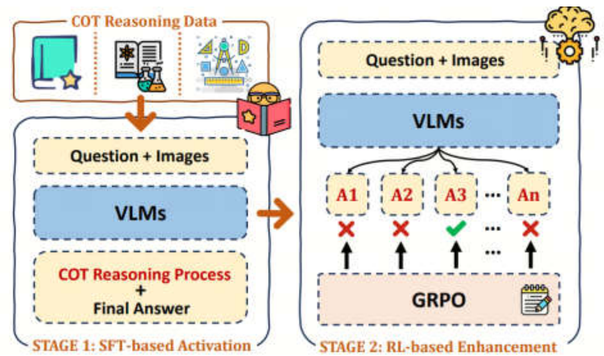
Visual Jigsaw Post-Training Improves MLLMs

Penghao Wu, Yushan Zhang, Haiwen Diao, Bo Li, Lewei Lu, Ziwei Liu

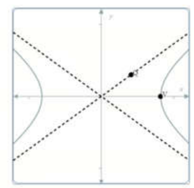
Motivation

RL-based Post-training for MLLMs

- **Text-centric reasoning on math/science/coding problems**
- Specific vision tasks (grounding, detection, segmentation, counting)
- Tool-using (thinking with images)



Most works focused on enhancing **text-centric reasoning** where **visual inputs work only as context**



Question: Given the hyperbola shown in the image, can we determine the equation of the hyperbola by analyzing the relationship between the slope of the asymptote and the distance from the center to the vertex?
Choices: A. Yes B. No

Reason-RFT:

<think>Let's analyze the image. The hyperbola is shown with two asymptotes intersecting at the center. To find the equation of the hyperbola, we need to consider the relationship between the slope of the asymptote and the distance from the center to the vertex. The equation of a hyperbola with its center at the origin and aligned with the coordinate axes is given by \\(\\frac{x^2}{a^2} - \\frac{y^2}{b^2} = 1 \\), where \\(a \\) and \\(b \\) are the distances from the center to the vertices and asymptotes, respectively. The center to the vertices is given, which suggests that \\(a^2 + b^2 \\) is given. The slope of the asymptotes is given by \\(\\pm \\frac{b}{a} \\). In this case, the slope is 3, which implies that \\(\\frac{b}{a} = 3 \\). Therefore, the equation of the hyperbola can be determined by these relationships.</think>

<answer>A</answer>

[1] Tan, Huajie, et al. "Reason-rft: Reinforcement fine-tuning for visual reasoning." *arXiv preprint arXiv:2503.20752* (2025).

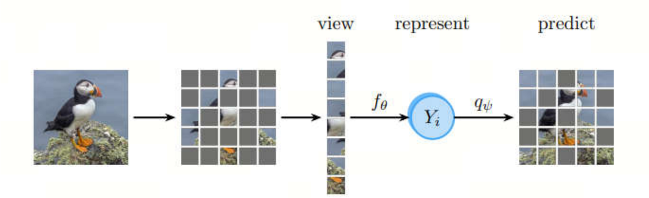
Motivation

How to improve intrinsic vision-centric capabilities of MLLMs?

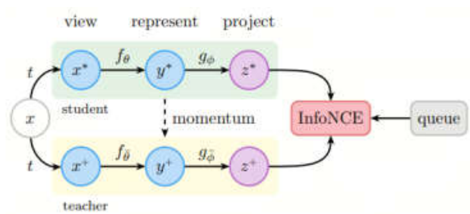
- Methods like ROSS [1] shows dense image reconstruction helps understanding, but requiring additional vision generation modules and designs. Do we need dense pixel-level reconstruction?
- Unified Multimodal Models (UMMs) only shows **understanding benefits visual generation**

How do we learn good vision representation?

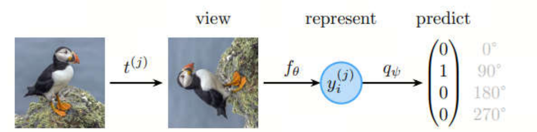
Self-supervised learning!

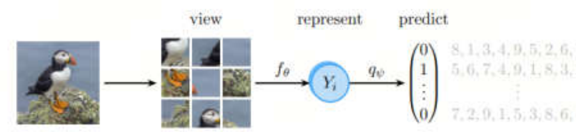


Reconstruction-based methods



Discriminative/contrastive methods





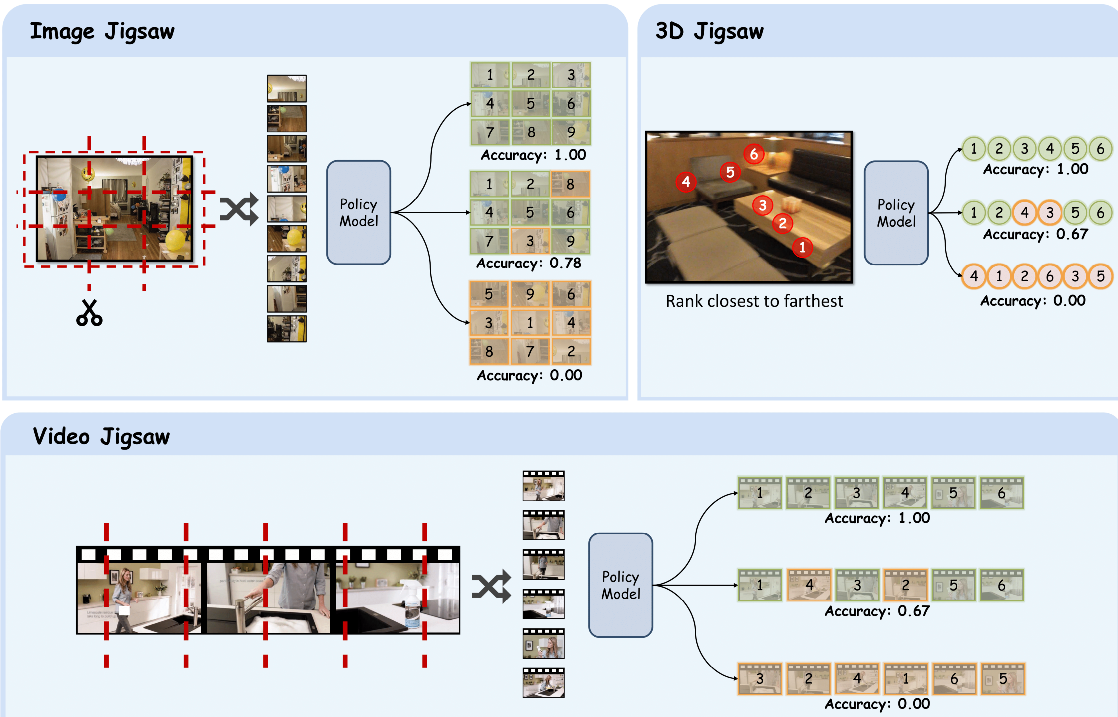
Other pretext tasks like rotation prediction and **jigsaw-style** tasks

Easier version of reconstruction
Suitable for MLLMs
(compatible with text-output MLLM)

[1] Wang, Haochen, et al. "Reconstructive visual instruction tuning." *arXiv preprint arXiv:2410.09575* (2024).

[2] Uelwer, Tobias, et al. "A survey on self-supervised representation learning." arXiv preprint arXiv:2308.11455 (2023).

Visual Jigsaw



Visual Data → Partitioning → Shuffling

Model reconstruct the data by predicting the indices in correct order

Optimize using the GRPO algorithm

Image Jigsaw

Image → 3 * 3 image patches

Mentally reconstruct the image and output the patch indices in the correct raster scan order.

1 2 3 4 5 6 7 8 9

1 2 3 4 5 6 7 8 9

1 2 3 4 5 6 7 8 9

Image Jigsaw

Model	Fine-grained Perception & Understanding								Spatial Und (Mono)			Compositional Und	
	MMVP	MMStar (fine-grained)	MMBench	HR-Bench-8K	V*	MME-RealWorld	LISA-Grounding	OVD-Eval	VSR	OmniSpatial	DA-2K	Winoground	SugarCrepe++
	test	fine	en_dev	test	test	lite	test	test	test	test	val	g-acc	test
ThinkLite-VL	55.33	59.95	84.19	68.12	76.96	46.17	73.70	35.78	78.09	42.60	58.46	35.25	61.49
VL-Cogito	55.33	56.64	82.98	69.62	79.58	47.63	72.26	35.78	79.82	44.29	56.43	38.25	63.59
LLaVA-Critic-R1	53.33	57.80	83.16	67.50	78.01	45.18	68.52	35.28	78.50	42.73	53.82	34.75	61.93
Qwen2.5-VL-7B	54.66	59.75	83.33	67.38	76.96	43.41	71.89	35.07	77.68	42.66	54.45	37.00	61.59
Image Jigsaw (SFT)	56.00	60.94	83.67	69.75	80.10	43.88	66.59	34.35	80.68	43.55	61.46	38.75	62.03
Image Jigsaw	60.66	65.81	84.45	71.13	80.63	45.96	74.54	36.49	80.36	44.49	60.35	39.00	63.02
(Gain)	+6.00	+6.06	+1.12	+3.75	+3.66	+2.55	+2.65	+1.42	+2.68	+1.83	+5.90	+2.00	+1.43

Enhance vision-centric capabilities:

- Fine-grained perception & understanding
- Monocular spatial understanding
- Compositional visual understanding

Video Jigsaw

1
2
3
4
5
6

Video → 6 video clips

Mentally reconstruct the video and output the clip indices in the correct chronological order.

Video Jigsaw

Model	Frames	AoTBench	Vinoground	TOMATO	FAVOR-Bench	TUNA-Bench	VideoMME	TempCompass	TVBench	MotionBench	LVBench	VSI-Bench	Video-TT	CVBench
		vqa	group	test	test	test	wo subs	mc	test	val	test	test	mcq	test
Video-R1	16	45.06	9.40	27.29	49.47	53.00	56.62	70.19	51.80	55.82	34.53	34.34	42.95	47.50
Video-R1	32	47.53	10.20	27.29	49.90	54.26	59.88	71.77	53.54	56.12	38.61	35.11	42.63	48.10
Video-R1	64	48.68	10.60	27.36	50.51	54.33	60.85	72.59	53.43	56.09	38.80	36.61	42.74	48.69
Qwen2.5-VL-7B	16	45.52	12.60	25.87	48.54	53.14	57.44	71.77	49.94	55.56	33.51	32.79	38.39	47.70
Qwen2.5-VL-7B	32	49.48	18.20	26.34	49.34	54.88	60.70	72.59	51.96	56.47	39.19	35.34	41.57	49.60
Qwen2.5-VL-7B	64	52.41	21.80	26.35	50.86	55.79	63.44	72.84	53.74	56.29	40.35	37.74	42.25	51.50
Video Jigsaw	16	51.67	15.20	27.56	49.69	55.10	58.07	73.10	51.33	56.87	36.41	35.39	40.19	49.80
(Gain)		+6.15	+2.60	+1.69	+1.15	+1.96	+0.63	+1.33	+1.39	+1.31	+2.90	+2.60	+1.80	+2.10
Video Jigsaw	32	55.00	21.40	28.03	50.56	56.49	62.37	73.60	53.31	57.99	39.70	38.47	43.27	51.60
(Gain)		+5.52	+3.20	+1.69	+1.22	+1.61	+1.67	+1.01	+1.35	+1.52	+0.51	+3.13	+1.70	+2.00
Video Jigsaw	64	57.64	25.20	28.30	52.27	56.63	64.74	73.60	54.18	57.91	41.83	40.40	44.11	54.50
(Gain)		+5.23	+3.40	+1.95	+1.41	+0.84	+1.30	+0.76	+0.44	+1.62	+1.48	+2.66	+1.86	+3.00

- Enhances general video perception and comprehension
- Large gain on temporal-centric understanding and reasoning about temporal directionality (e.g. AoTBench)
- Improved cross-video understanding and reasoning (CVBench)

Video Jigsaw

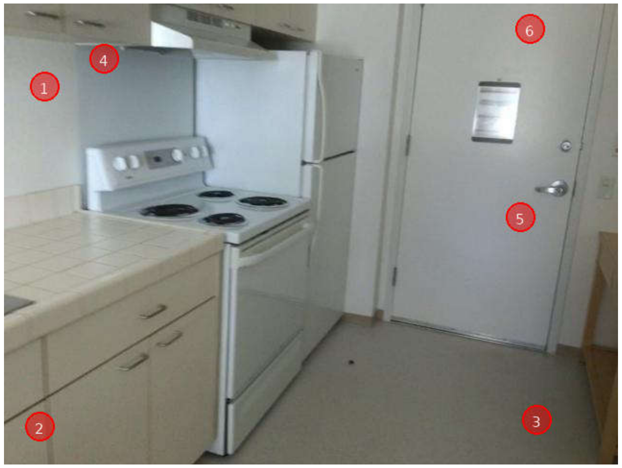
Model	AoTBench	Vinoground	TOMATO	FAVOR-Bench	TUNA-Bench	VideoMME	TempCompass	TVBench	MotionBench	LVBench	VSI-Bench	Video-TT	CVBench
	vqa	group	test	test	test	wo subs	mc	test	val	test	test	mcq	test
MiMo-VL-7B-SFT-2508	65.00	15.60	34.16	53.33	58.80	68.07	76.13	56.48	57.86	40.86	41.59	46.00	63.00
Video Jigsaw	69.77	21.60	37.33	54.31	62.29	68.55	77.21	61.50	59.73	42.93	44.27	48.50	65.20
(Gain)	+4.77	+6.00	+3.17	+0.98	+3.49	+0.48	+1.08	+5.02	+1.87	+2.07	+2.68	+2.50	+2.20

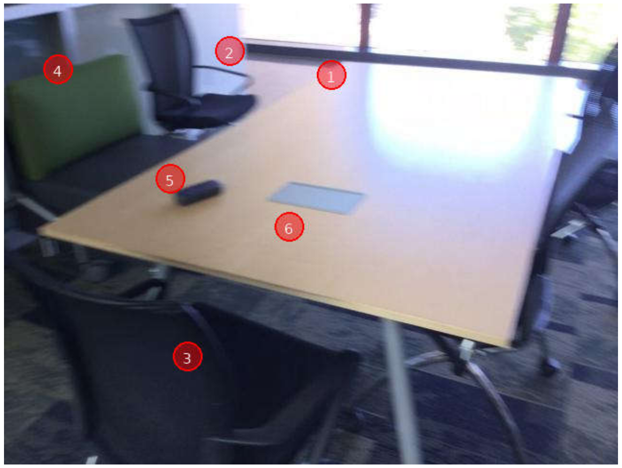
- Consistent improvement on stronger base model: MiMo-VL-7B-SFT-2508

3D Jigsaw

RGB-D → 6 points

Order the points from closest to farthest relative to the camera.





3D Jigsaw

Model	SAT-Real	3DSRBench	ViewSpatial	All-Angles	OmniSpatial	VSI-Bench	SPARBench	DA-2K
	test	test	test	test	test	test	tiny	test
Qwen2.5-VL-7B	48.66	57.42	36.52	47.56	42.66	37.74	35.75	54.45
3D Jigsaw	64.00	58.13	38.62	49.06	45.99	40.64	38.31	71.56
(Gain)	+15.34	+0.71	+2.10	+1.50	+3.33	+2.90	+2.56	+17.11

- Largest gains on directly related task – DA-2K
- Consistent improvements on a wide range of other tasks (single-view, multi-views, egocentric video)

Ablation Studies

- RL outperforms SFT
- The difficulty of the jigsaw tasks matters
- Apply jigsaw task training before text-centric/long CoT reasoning training

Future Works

- Different 3D jigsaw designs on base models with stronger 3D capabilities
- Different jigsaw configurations and combinations
- Other **vision-centric** self- and weakly-supervised tasks

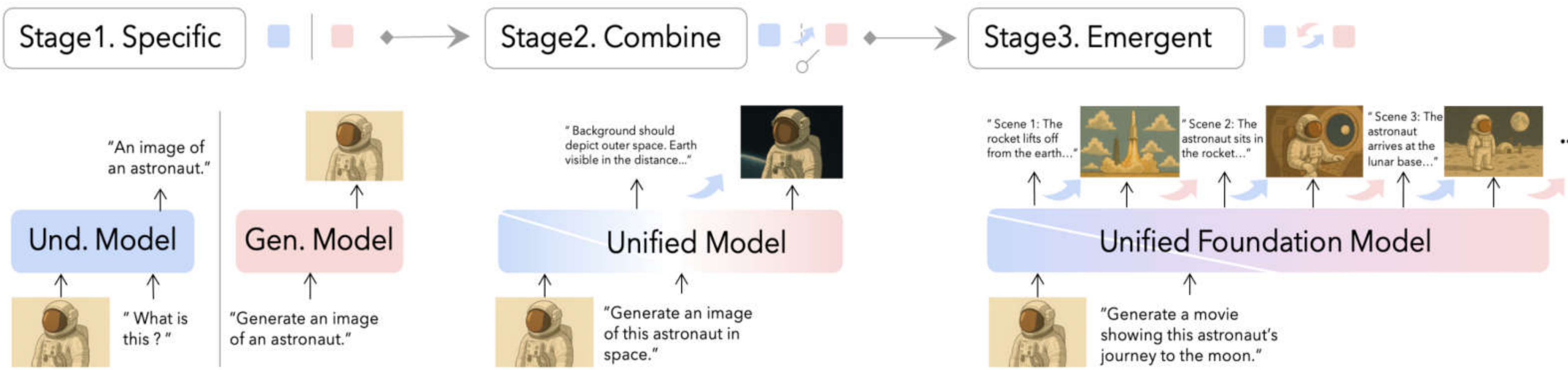
Native Multimodal Evaluation

RealUnify: Do Unified Models Truly Benefit from Unification?

Yang Shi, Yuhao Dong, Yue Ding, Yuran Wang, Xuanyu Zhu, Sheng Zhou, Wenting Liu, Haochen Tian, Rundong Wang, Huanqian Wang, Zuyan Liu, Bohan Zeng, Ruizhe Chen, Qixun Wang, Zhuoran Zhang, Xinlong Chen, Chengzhuo Tong, Bozhou Li, Chaoyou Fu, Qiang Liu, Haotian Wang, Wenjing Yang, Yuanxing Zhang, Pengfei Wan, Yi-Fan Zhang, Ziwei Liu

Motivation

Specific → **Combine** → **Emergent**

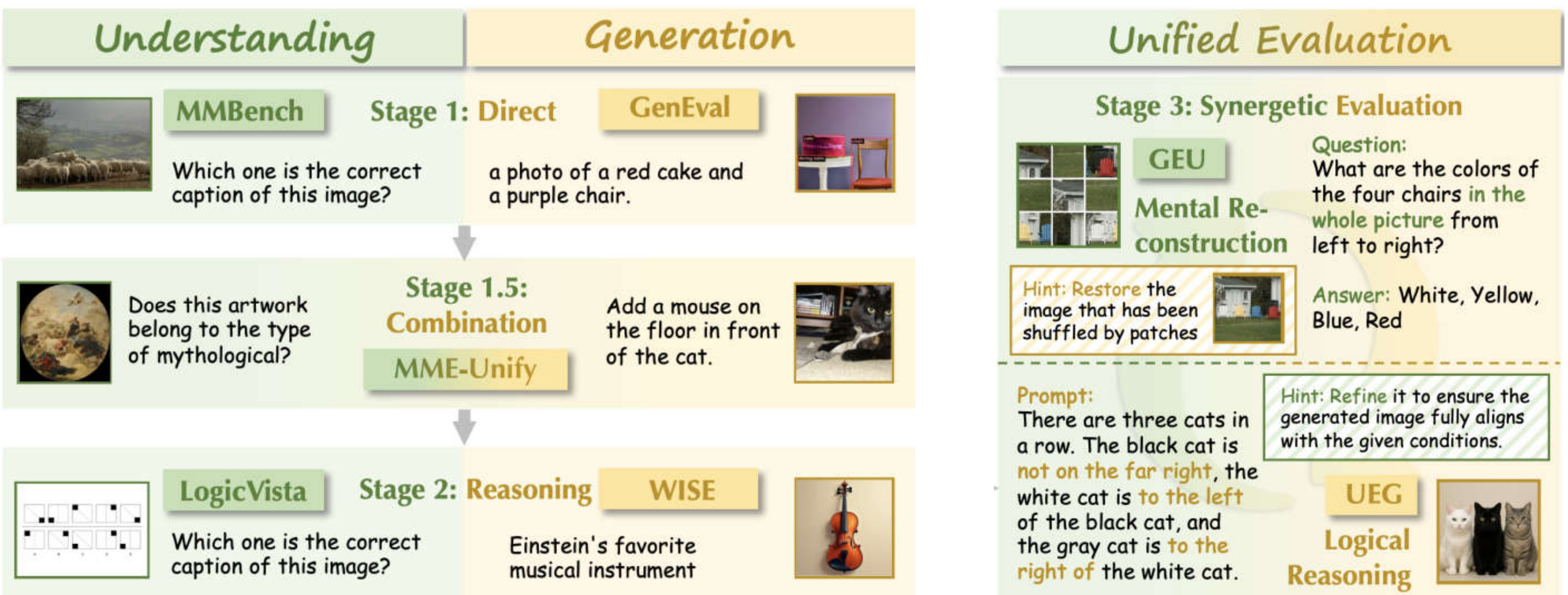


Easy to evaluate with current benchmarks

Lack of customized benchmarks

Motivation

Previous Benchmarks | **Customized Unified Benchmark**



Direct -> Combination -> Reasoning

True Unification

Task Taxonomy

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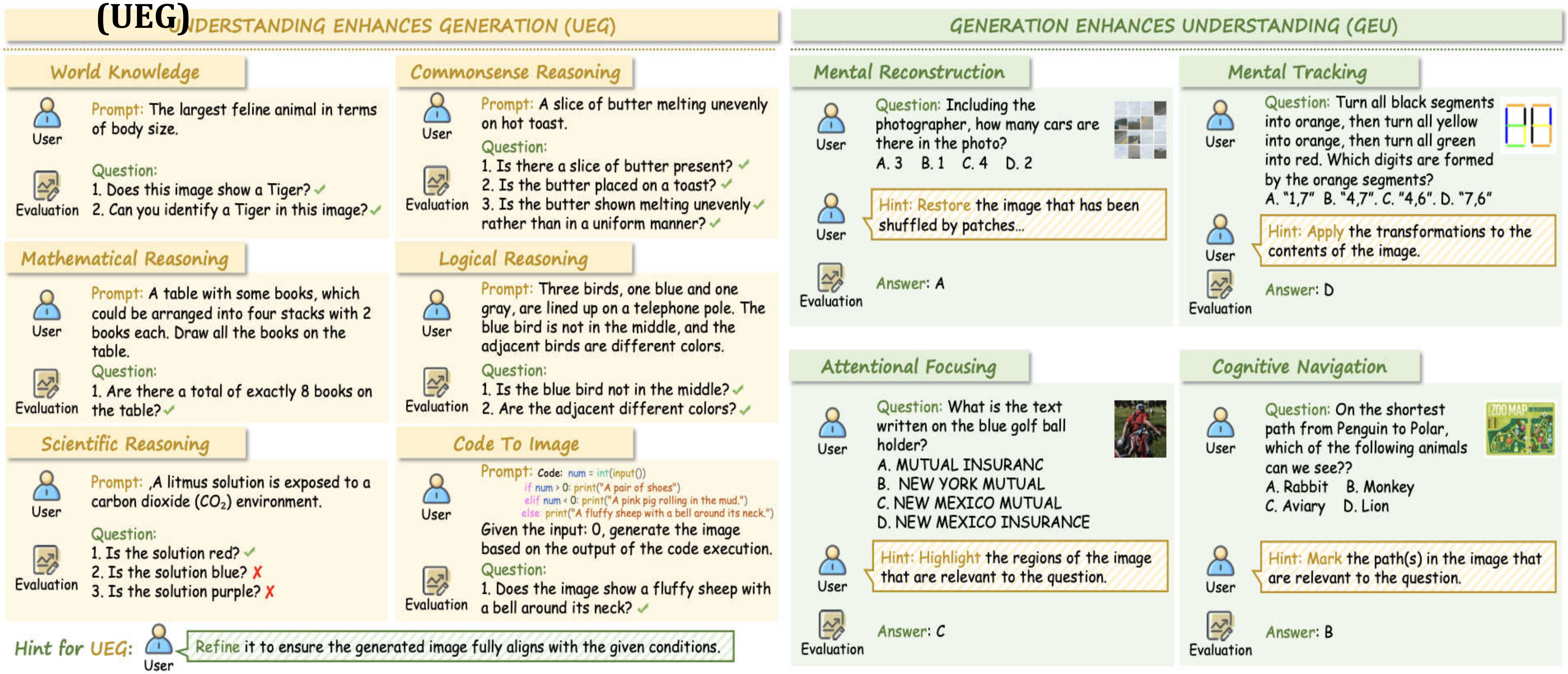
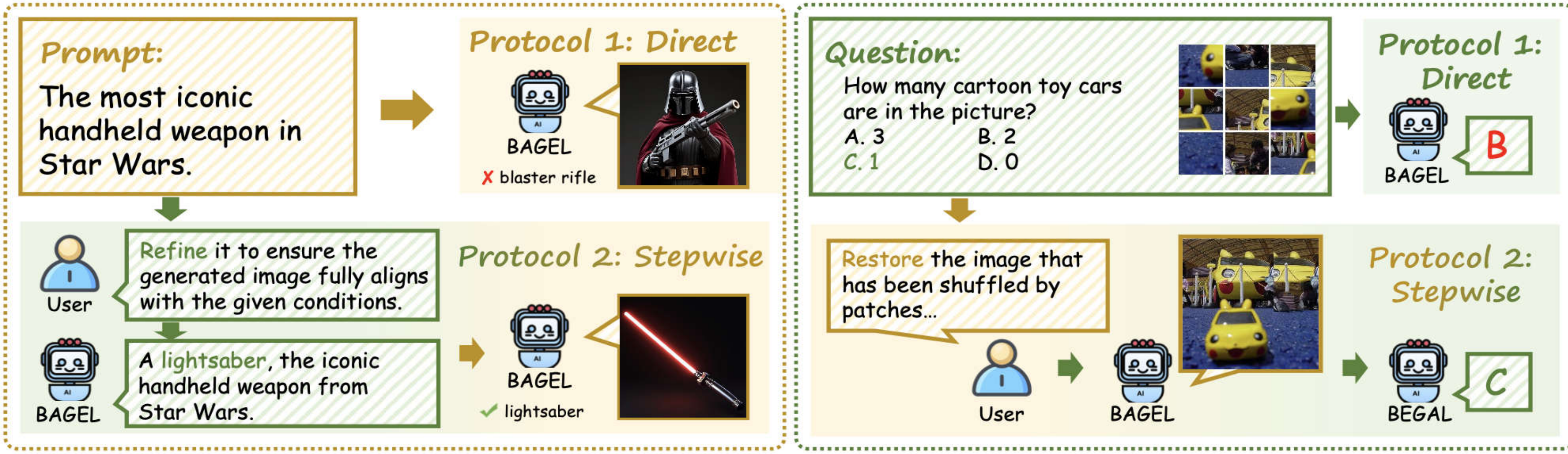
Understanding -> Generation (UEG)

Generation -> Understanding (GEU)



How to Evaluate

Direct -> Step-wise



Direct: **Whether the model can leverage generation & understanding synergistically**

Step-Wise: **Decouple generation & understanding for better assignment**

Evaluate with RealUnify

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Model	Understanding Enhances Generation							Generation Enhances Understanding					Total
	WK	CR	MR-I	LR	SR	C2I	Avg	MR-II	MT	AF	CN	Avg	
Proprietary Models													
Nano Banana	89 / -	86 / -	34 / -	65 / -	48 / -	56 / -	63.0 / -	34 / -	27 / -	36 / -	30 / -	31.8 / -	50.5 / -
Open-Source Unified Models													
MIO	24 / 35	26 / 33	18 / 13	9 / 10	10 / 11	0 / 8	14.5 / 18.3	26 / 23	19 / 18	35 / 19	23 / 21	25.8 / 20.3	19.0 / 19.1
Janus-Pro	25 / 26	77 / 71	16 / 7	13 / 17	16 / 20	3 / 10	25.0 / 25.2	21 / -	23 / -	28 / -	29 / -	25.3 / -	25.1 / -
ILLUME+	44 / 52	62 / 62	22 / 22	23 / 25	26 / 26	1 / 7	29.7 / 32.3	27 / 27	19 / 20	35 / 38	30 / 25	27.8 / 27.5	28.9 / 30.4
Show-o2	30 / 42	56 / 50	25 / 25	21 / 21	18 / 20	18 / 19	28.0 / 29.5	36 / -	28 / -	36 / -	21 / -	30.3 / -	28.9 / -
OmniGen2	36 / 55	61 / 60	21 / 26	29 / 28	16 / 20	19 / 6	30.3 / 32.5	30 / 42	21 / 24	51 / 38	28 / 19	32.5 / 30.8	31.2 / 31.8
UniPic2	61 / 62	73 / 72	31 / 30	28 / 38	25 / 26	7 / 15	37.5 / 40.5	26 / 28	20 / 24	27 / 27	23 / 16	24.0 / 23.8	32.1 / 33.8
UniWorld-V1	51 / 56	64 / 59	26 / 26	33 / 37	21 / 24	15 / 9	35.0 / 35.2	29 / 33	19 / 25	57 / 36	24 / 20	32.3 / 28.5	33.9 / 32.5
Ovis-U1	37 / 59	72 / 71	28 / 30	23 / 34	15 / 17	12 / 25	31.2 / 39.3	32 / 38	28 / 25	60 / 31	36 / 24	39.0 / 29.5	34.3 / 35.4
BLIP3-o	57 / 62	71 / 74	21 / 24	19 / 25	28 / 22	2 / 9	33.0 / 36.0	36 / -	25 / -	57 / -	32 / -	37.5 / -	34.8 / -
OneCAT	61 / 64	70 / 65	32 / 20	29 / 27	24 / 31	9 / 27	37.5 / 39.0	26 / 29	25 / 26	43 / 26	31 / 36	31.3 / 29.3	35.0 / 35.1
BAGEL	46 / 74	70 / 80	23 / 26	29 / 37	21 / 29	7 / 40	32.7 / 47.7	37 / 38	31 / 25	50 / 52	39 / 28	39.3 / 35.8	35.3 / 42.9

(a) Understanding Enhances Generation (UEG)

Model	WK	CR	MR-I	LR	SR	C2I	Total
Specialized Models							
GPT-Image-1	90	87	31	69	48	48	62.2
Qwen-Image	66	83	28	44	25	67	52.2
FLUX.1 Kontext	53	73	25	27	25	37	40.0
Unified Models							
Nano Banana	89	86	34	65	48	56	63.0
UniPic2	61	73	31	28	25	7	37.5
OneCAT	61	70	32	29	24	9	37.5

(b) Generation Enhances Understanding (GEU)

Model	MR-II	MT	AF	CN	Total
Specialized Models					
Gemini 2.5 Pro	30	73	73	43	54.8
GPT-4.1	38	23	56	37	38.5
Qwen2.5-VL	35	23	44	36	34.5
Unified Models					
BAGEL	37	31	50	39	39.3
Ovis-U1	32	28	60	36	39.0
BLIP3-o	36	25	57	32	37.5

12 SOTA models evaluated on RealUnify:

- UEG & GEU remain challenging
- Step-wise is better than direct answer
- All models lack true unification

Comparison with SOTA specialist:

- Unify models benefit from understanding
- Generation may not help understanding currently

How Far Can We?

Table 5: **Comparisons with Gen-Und SOTA.**

Model	WK	CR	MR-I	LR	SR	C2T	Total
Nano Banana	89	86	34	65	48	56	63
Und→Gen (SOTA)	93	86	43	70	53	91	72.7

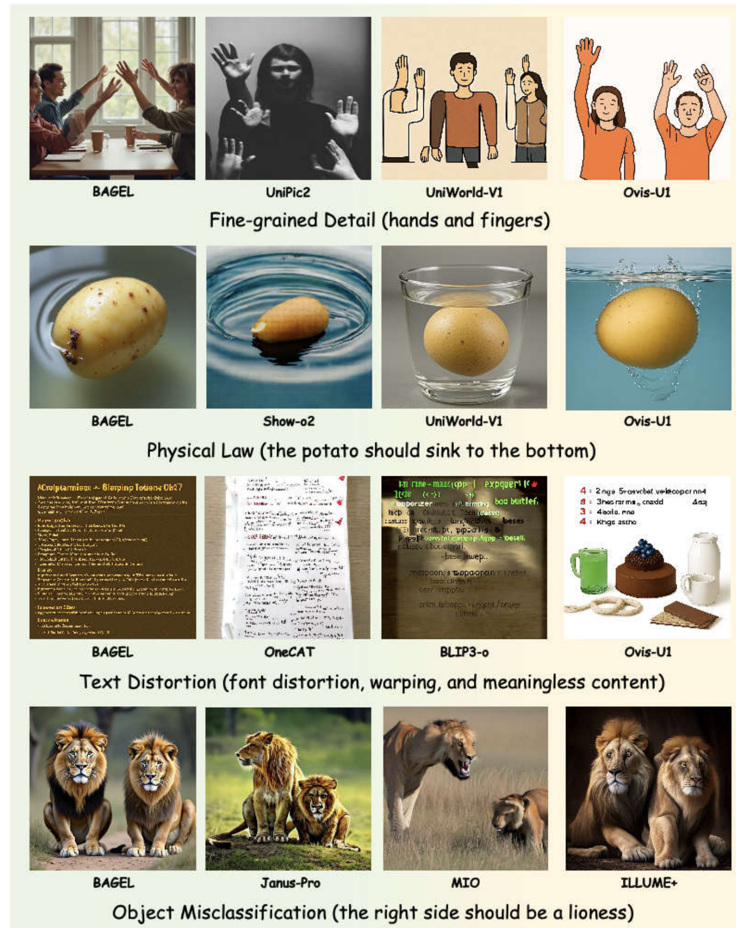
Model	MR-II	MT	AF	CN	Total
BAGEL	37	31	50	39	39.3
Gen→Und (SOTA)	29	27	21	50	31.8

Comparison with Oracle Setting:

- Current unified models can still learn from oracle cases -> Strong understanding leads to improved generation
- Both unified models and oracle settings fall short on GEU tasks -> Current generation models fall short in aiding real-world problem-solving.

Error Analysis

Unified models fall short in real-world image generation



Summary： Native Vision-Language Models

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Native Multimodal Evaluation

RealUnify: Do Unified Models Truly Benefit from Unification?

Dual-Evaluation Protocol, Understanding-Generation Synergy

Native Multimodal Post-Training

Visual Jigsaw Post-Training Improves MLLMs

Self-supervised Learning, Post-training, Reinforcement Learning

Native Multimodal Architecture

From Pixels to Words: Towards Native Vision-Language Primitives at Scale

Native Vision-Language Primitive, Holistic Vision-Language Buffer

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Thank You

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Nanyang Technological University