



**MoAI: Mixture of All Intelligence
for Large Language and Vision Model**

Milano, Italy



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Introduction



Scene Perception: Detecting and Judging Objects Undergoing Relational Violations

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Scene Perception in the Human Brain

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Dense and Aligned Captions (DAC) Promote Compositional Reasoning in VL Models

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From Cognitive Science to Machine Learning,

Real-world scene understanding

- *Recognizing object presences*
- *Determining their positions*
- *Identifying their states*
- *Understanding their relationships*
- *Extracting spatial scene layouts*
- *Grasping non-object notions*

Compositional Reasoning



Real-world scene understanding

- *Recognizing object presences*
- *Determining their positions*
- *Identifying their states*
- *Understanding their relationships*
- *Extracting spatial scene layouts*
- *Grasping non-object notions*



From Rich CV Models

Segmentation/Detection

Segmentation/Detection

Scene Graph Generation

Scene Graph Generation

Segmentation/Detection/Scene Graph Generation

OCR



Proposed Method



External CV Models

- *Panoptic Segmentation (Mask2Former, CVPR 2022, Meta)* Swin-B/4 106M
 - *Open-World Object Detection (OWLv2, NeurIPS 2023, Google)* CLIP-B/16 154M (We use ADE20K-847+ImageNet)
 - *Scene Graph Generation (Panoptic SGG, ECCV 2022, Nanyang Tech)* ResNet-50 44M
 - *OCR (PaddleOCRv2, performant open-source OCR)* 14M (Chinese & English, Rotated Text O)
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What do we propose?

Compressor: *Compressing Auxiliary Visual Information from external CV models*

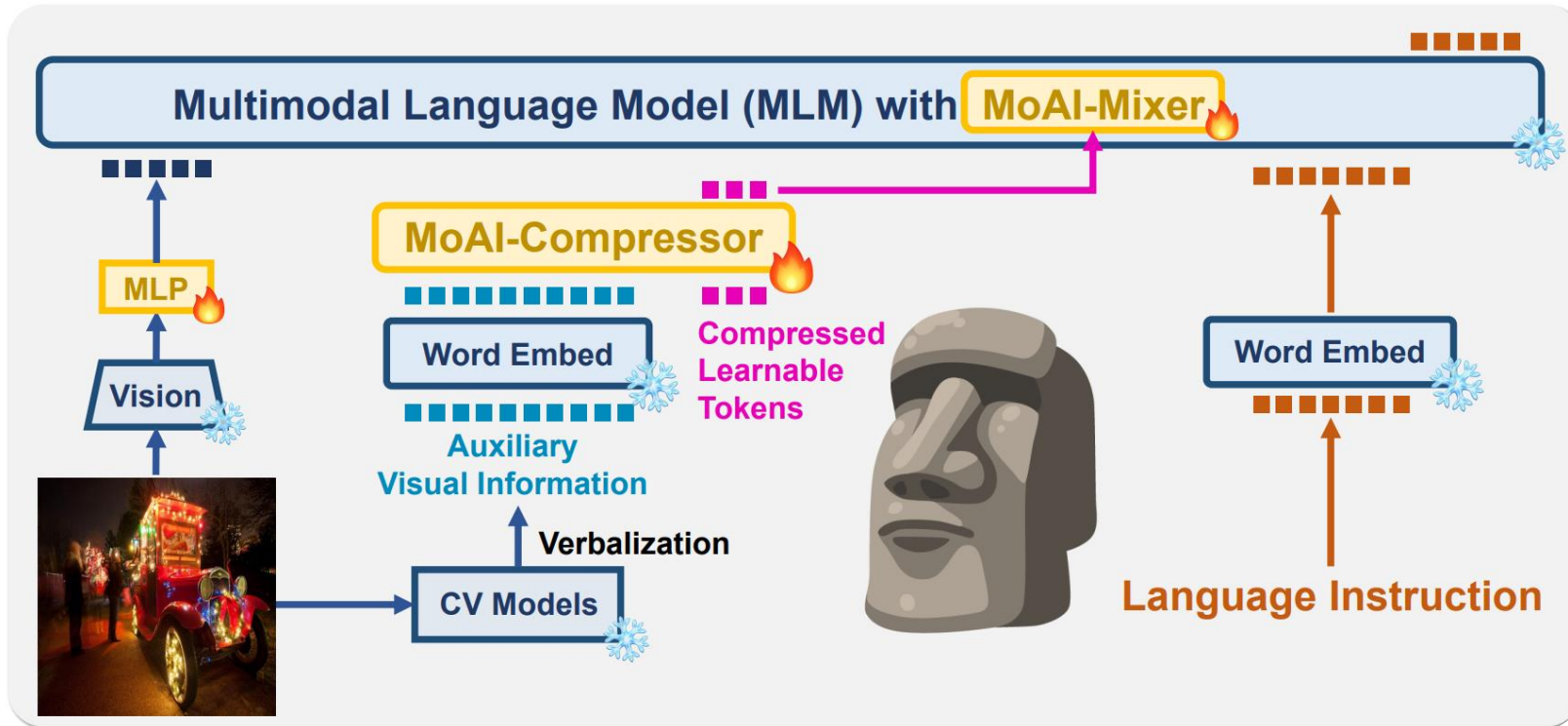
Mixer: *Blending Aux with Visual and Language Features in Multimodal LM (MLM)*



Proposed Method



MoAI: Mixture of All Intelligence for Large Language and Vision Model

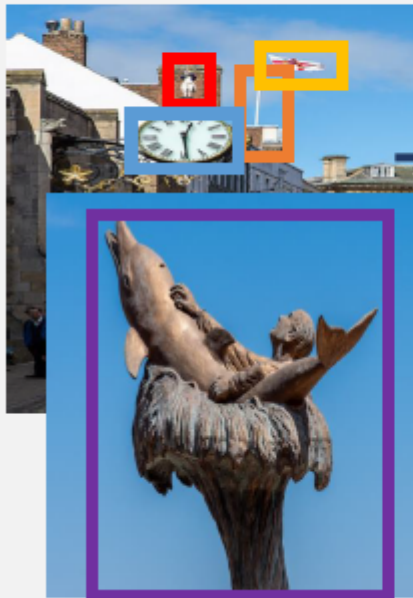




Proposed Method



• Open-World Object Detection (OWOD)



OWOD Result

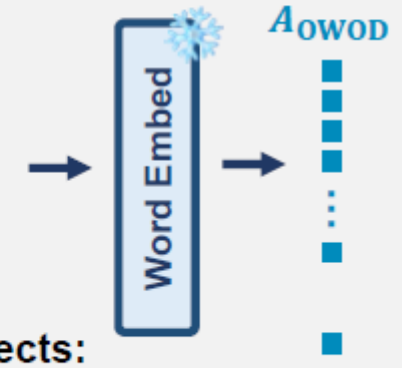
flag [0.64, 0.12, 0.78, 0.17]
flagpole [0.61, 0.11, 0.63, 0.30]
statue [0.42, 0.16, 0.46, 0.23]
clock [0.31, 0.26, 0.55, 0.39]

sculpture [0.14, 0.05, 0.82, 1.00]

OWOD Verbalization

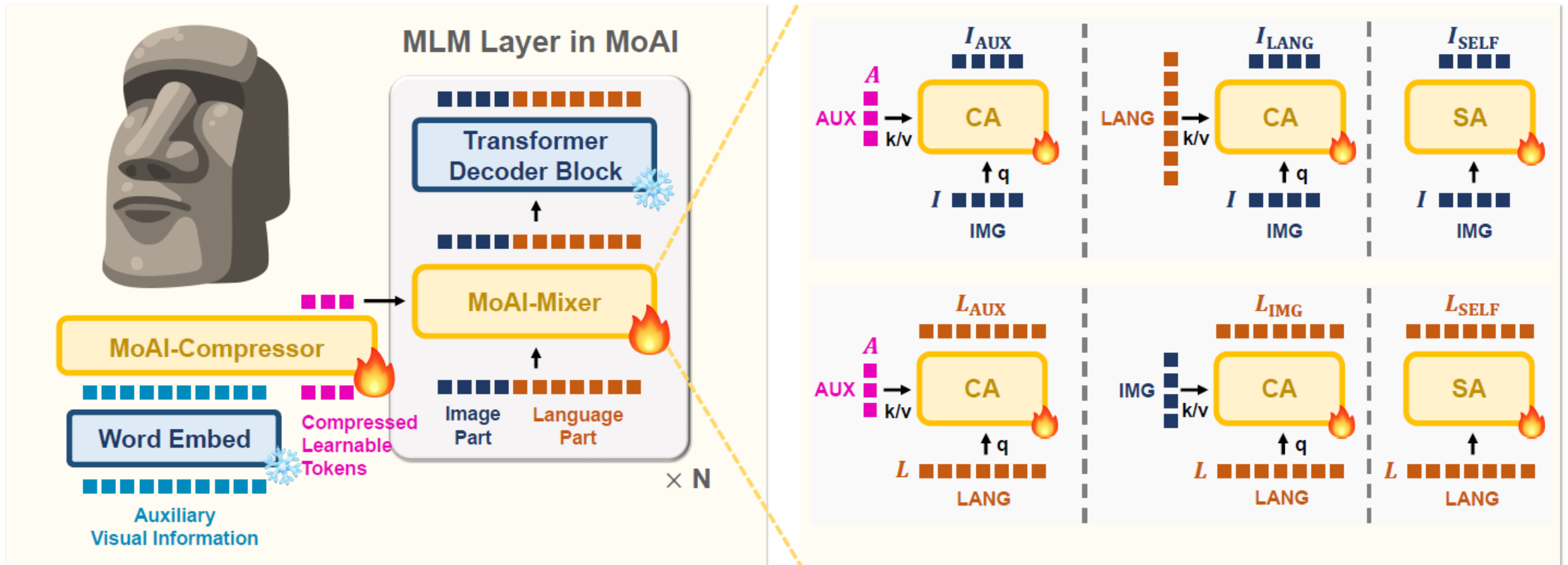
The image includes bounding box coordinates and their objects: [0.64, 0.12, 0.78, 0.17] flag, and [0.61, 0.11, 0.63, 0.30] flagpole, and [0.42, 0.16, 0.46, 0.23] statue, and [0.31, 0.26, 0.55, 0.39] clock.

The image includes bounding box coordinates and their objects: [0.14, 0.05, 0.82, 1.00] sculpture.



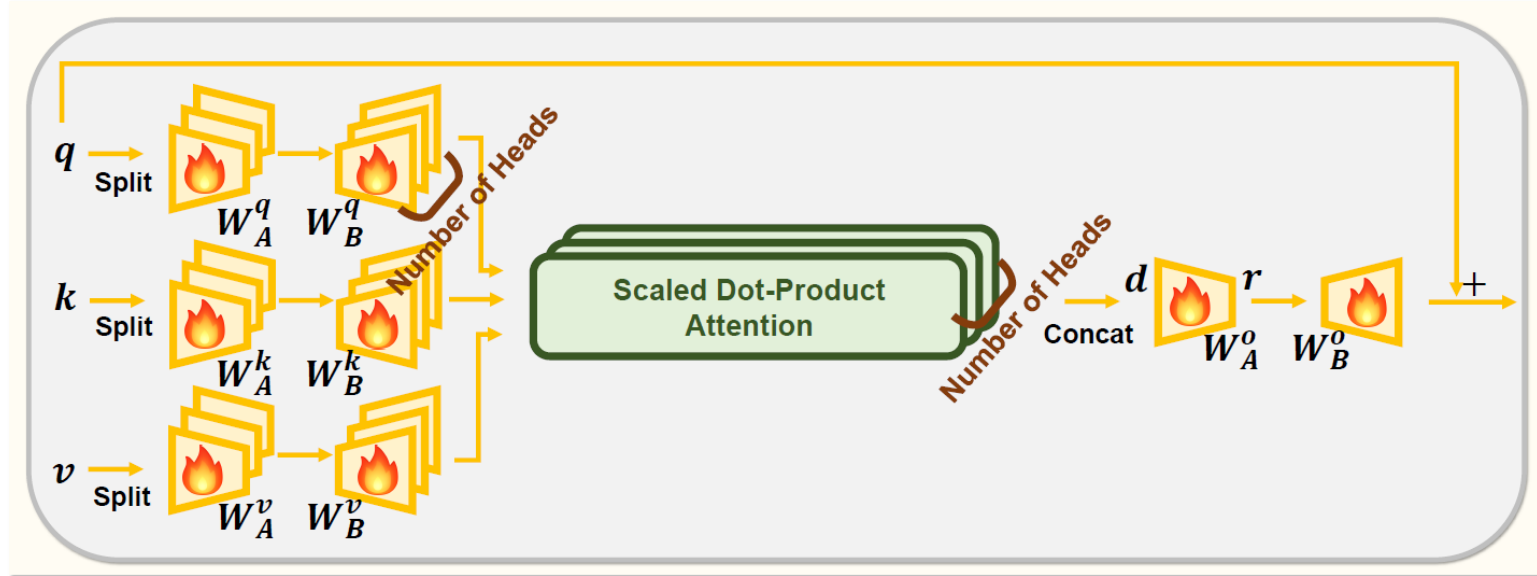


Proposed Method

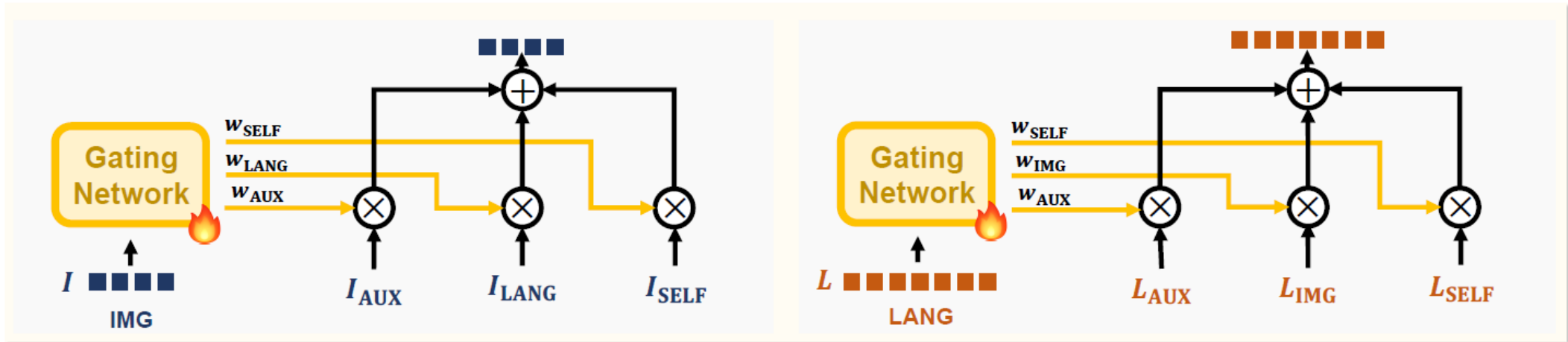




Proposed Method



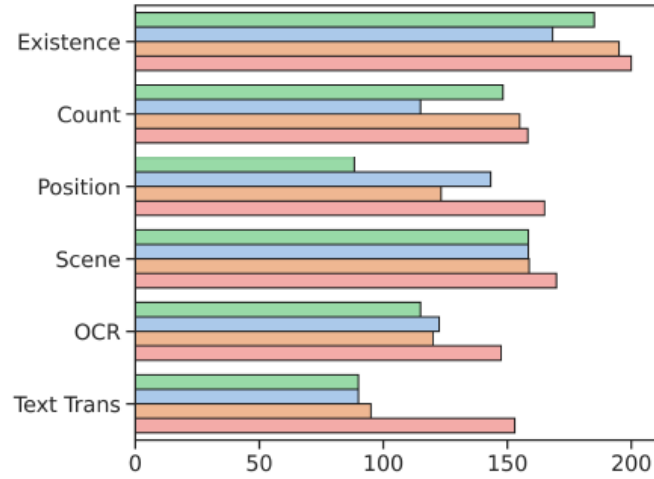
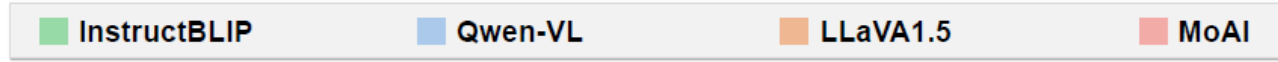
(a) CA/SA with Low Rank Adaptation (LoRA) for Expert Modules



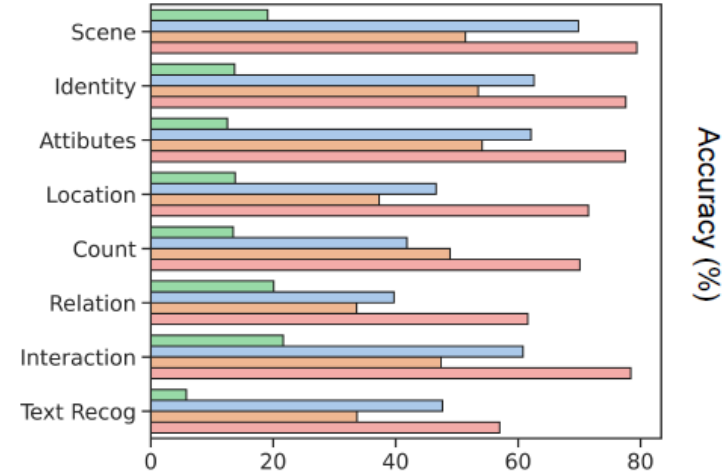
(b) Gating Networks for MoAI-Mixer



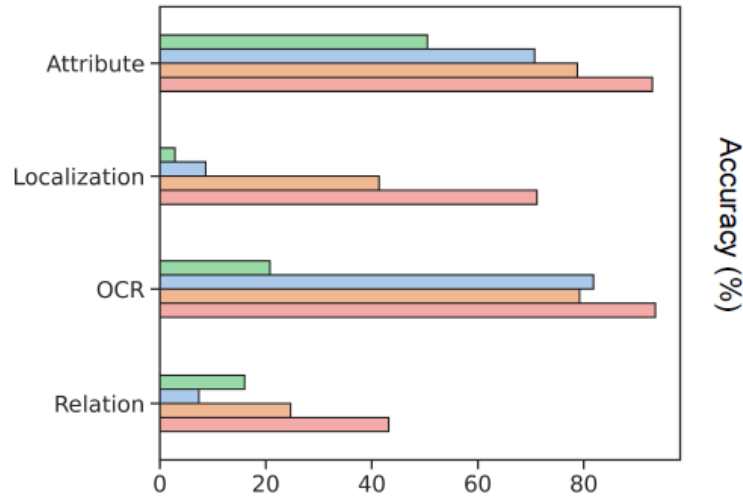
Experiments



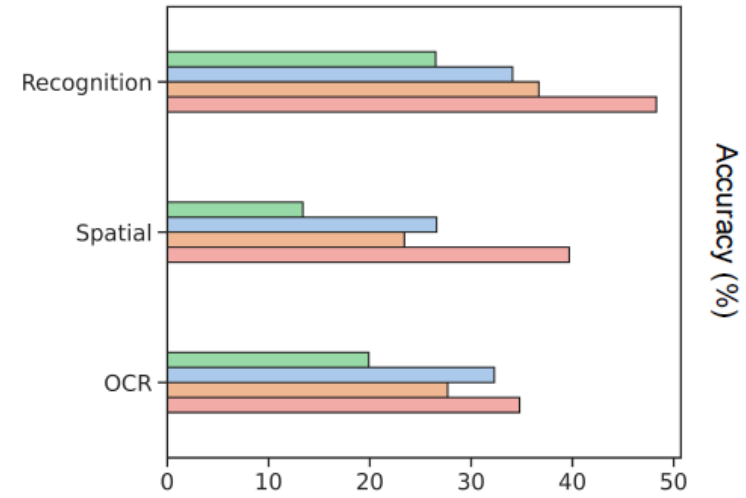
(a) MME



(b) SEED



(c) MM-Bench



(d) MM-Vet



Experiments



VLMs	Q-Bench	SQA-IMG	TextVQA	POPE	MME-P	MME-C	MM-Bench	MMB-CN	MM-Vet
BLIP2-13B [42]	-	61.0	42.5	85.3	1294	290	-	-	22.4
InstructBLIP-7B [16]	56.7	60.5	50.1	-	-	-	36.0	23.7	26.2
InstructBLIP-13B [16]	-	63.1	50.7	78.9	1213	-	-	-	25.6
Shikra-13B [9]	54.7	-	-	-	-	-	58.8	-	-
IDEFICS-9B [38]	-	-	25.9	-	-	-	48.2	25.2	-
IDEFICS-80B [38]	-	-	30.9	-	-	-	54.5	38.1	-
Qwen-VL-7B [4]	59.4	67.1	63.8	-	-	-	38.2	7.4	-
Qwen-VL-Chat-7B [4]	-	68.2	61.5	-	1488	361	60.6	56.7	-
MiniGPT-4-7B [83]	-	-	-	-	582	-	23.0	-	22.1
Otter-7B [40]	47.2	-	-	-	1292	-	48.3	-	24.6
LLaVA-7B [50]	-	38.5	-	-	807	248	34.1	14.1	26.7
MiniGPT-v2-7B [8]	-	-	-	-	-	-	-	-	-
MiniGPT-v2-Chat-7B [8]	-	-	-	-	-	-	-	-	-
LLaVA1.5-7B [48]	58.7	66.8	58.2	85.9	1511	294	64.3	58.3	30.5
LLaVA1.5-13B [48]	62.1	71.6	61.3	85.9	1531	295	67.7	63.6	35.4
mPLUG-Owl-7B [75]	58.9	-	-	-	967	-	46.6	-	-
mPLUG-Owl2-7B [76]	62.9	68.7	58.2	-	1450	-	64.5	-	36.2
ShareGPT4V-7B [10]	63.4	68.4	-	-	1567	376	68.8	62.2	37.6
CogVLM-17B [71]	-	68.7	58.2	-	-	-	65.8	55.9	54.5
LLaVA-XTuner-20B [15]	-	-	-	-	-	-	75.1	73.7	37.2
Intern-XC-7B [78]	64.4	-	-	-	1528	391	74.4	72.4	35.2
MoAI-7B	70.2	83.5	67.8	87.1	1714	561	79.3	76.5	43.7



Table 2: Illustrating the effectiveness of external computer vision (CV) models compared by the perception scores in MME [25] and MM-Bench [51]. ‘TT’ denotes text translation task that requires OCR as a priority.

PS+OWOD	SGG	OCR	MME				MM-Bench				
			Existence	Position	Scene	OCR	TT	Recognition	Localization	Spatial	OCR
\times	\checkmark	\checkmark	187	154	161	145	138	77.6	54.0	32.6	84.6
\checkmark	\times	\checkmark	198	145	164	147	150	89.7	65.3	35.8	90.9
\checkmark	\checkmark	\times	199	163	166	120	95	91.8	69.2	42.8	80.1
\checkmark	\checkmark	\checkmark	200	165	170	148	153	92.9	71.1	43.2	93.5

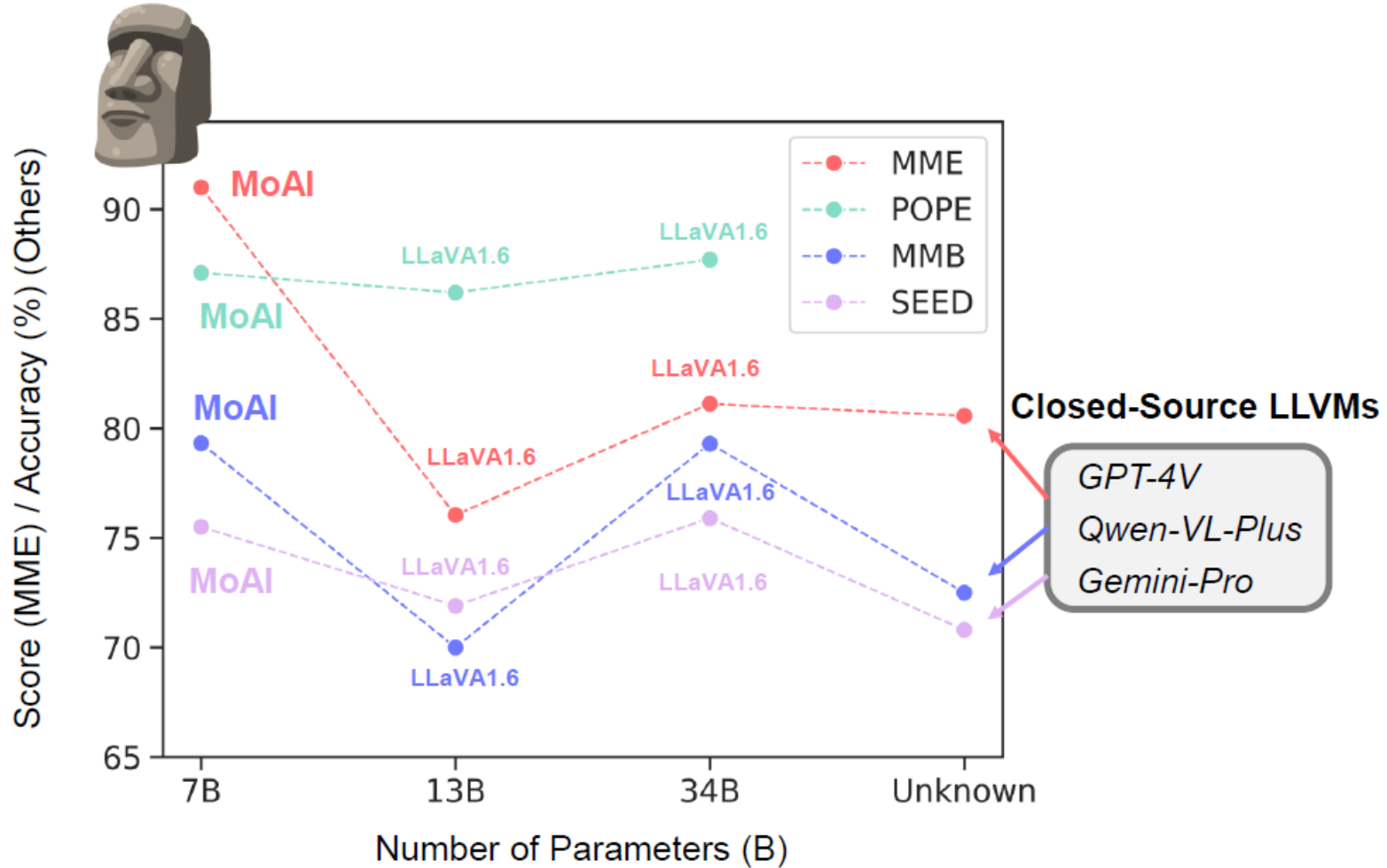


Table 3: Ablation study for training step choice, selecting top- k expert modules in MoAI-Mixer, and the type of weights for gating network.

(a) Training step choice			(b) Selecting Top- k Experts			(c) Gating network weights		
Step	MME-P	MME-C	k	MME-P	MME-C	Gating	MME-P	MME-C
First	1542	369	1	1588	387	Random	1520	348
Second	1654	511	2	1638	451	Uniform	1617	485
Combined	1714	561	3	1714	561	Trained	1714	561



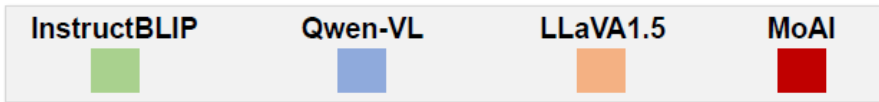
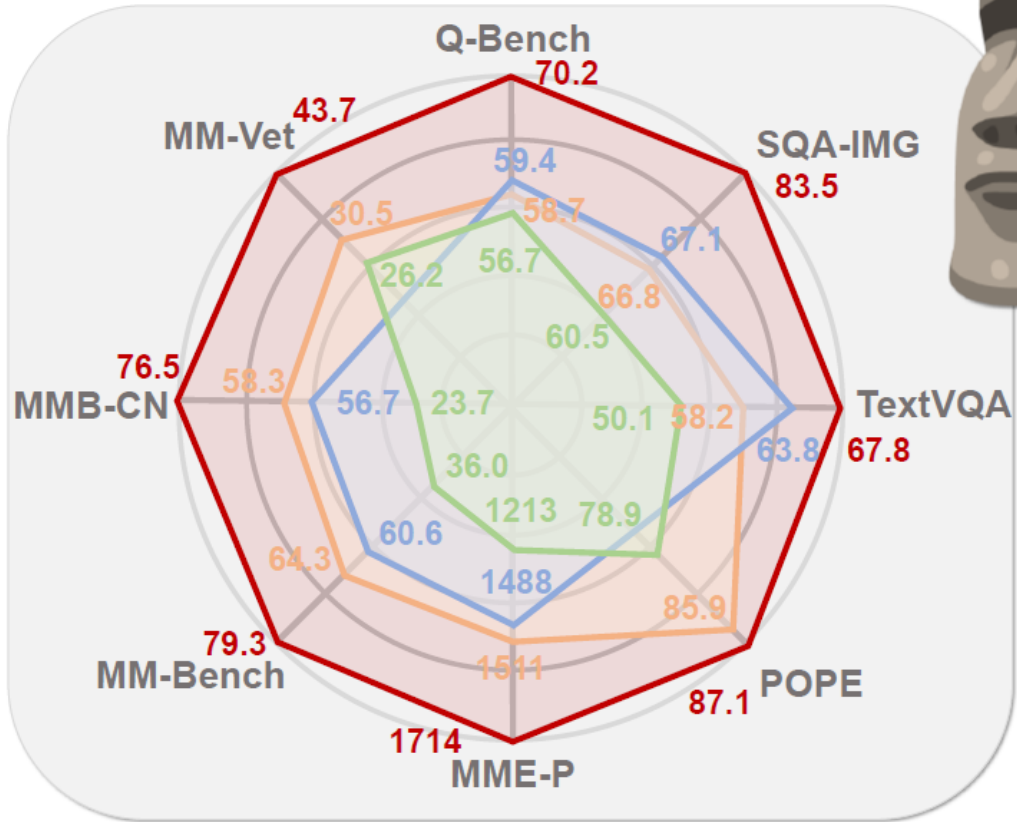
Experiments



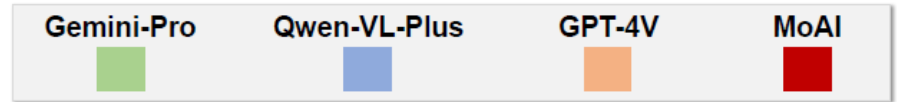
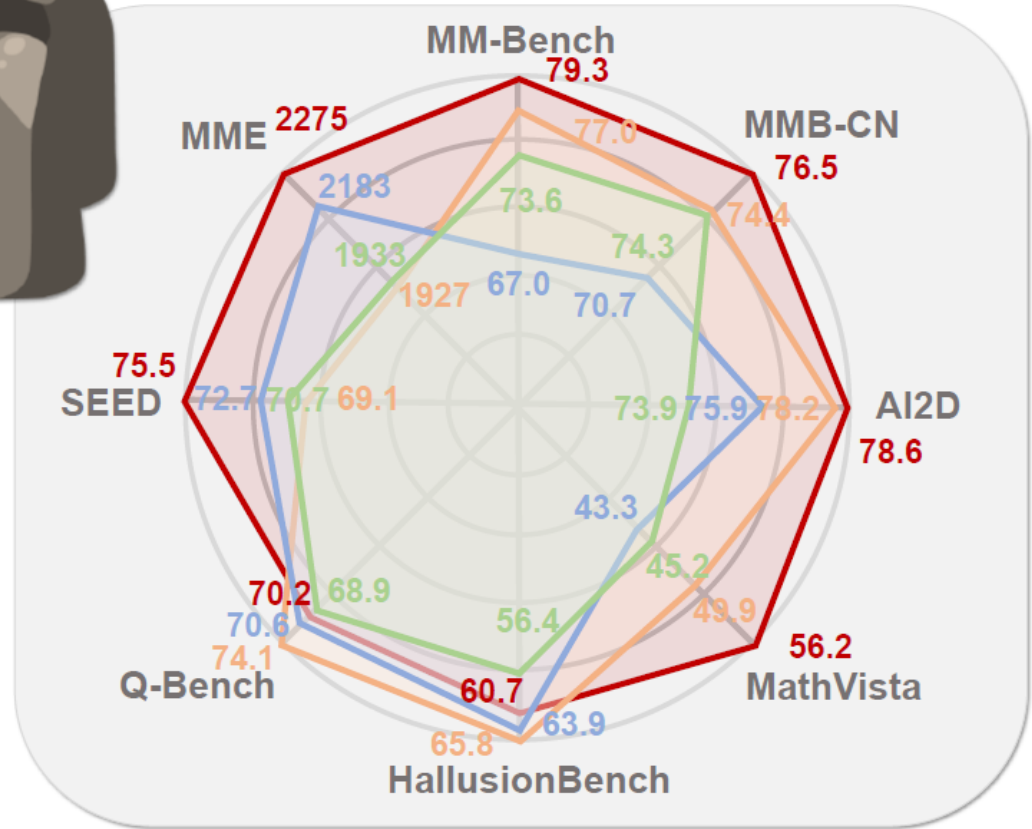
(a) MME/POPE/MMB/SEED by Scale



Experiments



(a) Open-source LLMs



(b) Closed-source LLMs





Discussion and Limitation



Discussion and Limitation. From the results, we can gain insight that prioritizing perception capabilities is more crucial than relying on extra curation of visual instruction datasets or scaling up model size. As illustrated in Fig. 7(a), MoAI-7B surpasses the zero-shot performances despite being relatively small compared to the considerably larger open-source and closed-source models. Notably, Fig. 7(b) also indicates that MoAI performs well even in hallucination zero-shot datasets: POPE [44] and HallusionBench [47]. This suggests that recognizing objects and their relationships accurately can help prevent LLMs from doing mistakes. Looking ahead, as MoAI is tailored for real-world scene understanding, we will incorporate more external CV models to provide LLMs with diverse capabilities for low-level vision understanding, common-sense knowledge, non-object notions beyond text descriptions such as charts, diagrams, signs, and symbols, and solving advanced math problems.

