# MoAI: Mixture of All Intelligence for Large Language and Vision Models

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- Problem / objective
  - 최신 LLVM 들의 Vision 정보 활용 부족
     (연구들이 보통 downstream task 에 맞춰 Instruction tuning 및 모델 Scaling 에만 집중)
- Contribution / Key idea
  - Vision 정보 적극 활용하여 새로운 LLVM 인 MoAl 제안

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## 어떻게 적극 활용?

Out[MLLM]: 1) visual features, 2) language features

Out[외부 CV 모델들 -> MoAl-Compressor] : 3) auxiliary visual features

Out[MoAl-Mixer]: 6명의 전문가들이 위 3종류 feature 들을 잘 융합함으로서, 시각 인지 능력 크게 향상.

## 결과부터 보면

굉장히 좋아졌다!

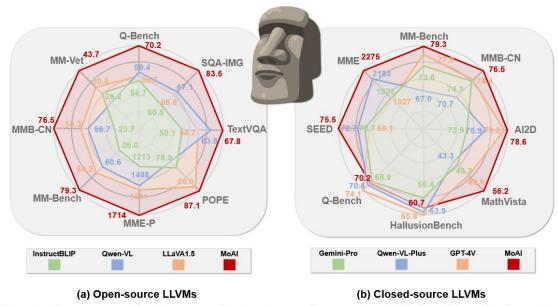
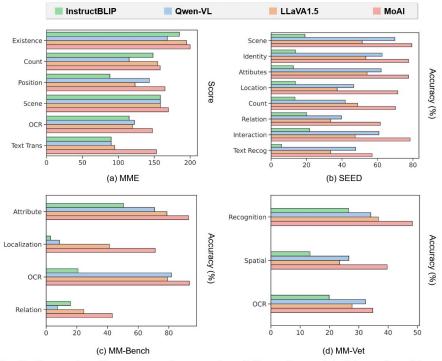


Fig. 1: Comparing the scores and accuracies of numerous VL benchmarks for various open-source and closed-source LLVMs with those for MoAI.

## 결과부터 보면

굉장히 좋아졌다!



**Fig. 2:** Comparing the scores and accuracies of dimensions related to real-world scene understanding in MME [28], SEED [55], MM-Bench [66], and MM-Vet [91] for validating capabilities of various LLVMs such as InstructBLIP [19], Qwen-VL [4], and LLaVA1.5 [63].

### Overview

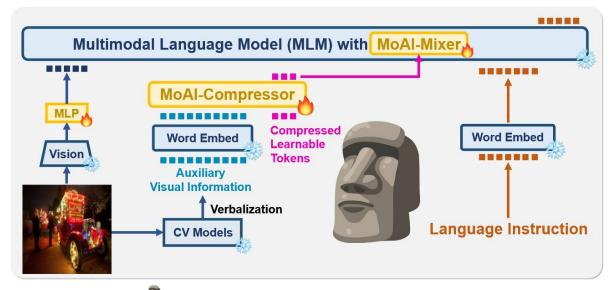


Fig. 3: Overview of MoAI architecture. Compressed learnable tokens, the parameters of MoAI-Compressor and MoAI-Mixer are learned. 'Vision' represents vision encoder to embed visual features and ice/fire symbols represent the modules to freeze or learn. Note that, 'Word Embed' represents the word embedding dictionary of MLM.

### **Architecture**

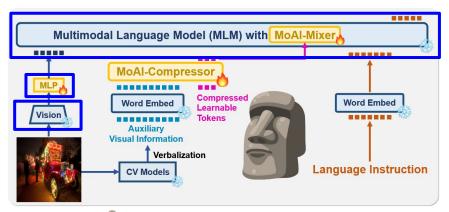


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- Vision encoder: CLIP-L/14
- Multimodal language model: InternLM2-7B
- MLP: 2 linear layers with GELU 활성 함수

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#### Verbalization

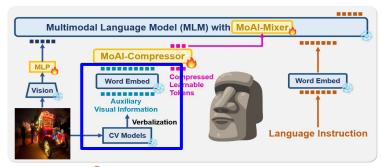


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- 외부 Vision 모델 4개 사용하여,
  - Panoptic Segmentation (PS)
  - Open-World Object Detection (OWOD)
  - Scene Graph Generation (SGG)
  - Optical Character Recognition (OCR)
- 4개의 보조 visual tokens 생성.

 $A_{\rm PS}$ ,  $A_{\rm OWOD}$ ,  $A_{\rm SGG}$ , and  $A_{\rm OCR}$ 

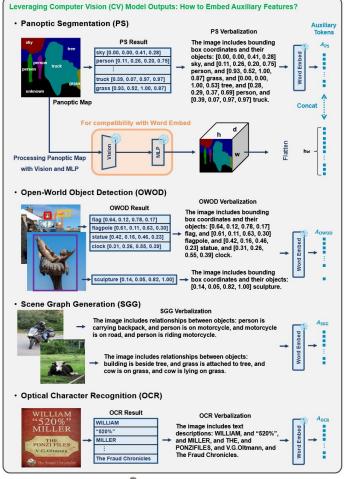


Fig. 4: Verbalization process of MoAI for external CV models: panoptic segmentation (PS), open-world object detection (OWOD), scene graph generation (SGG), and optical character recognition (OCR). Note that, 'd' denotes channel dimension of MLM, thus auxiliary tokens have equal channel dimension.

## **MoAl-Compressor**

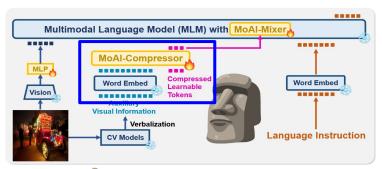


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- 구조 : Perceiver Resampler
- 인풋: 앞서 생성된 4개의 보조 토큰들 concat 한것 + 고정된 길이의 학습가능 토큰
- 아웃풋 : 똑같이 고정된 길이의 토큰

$$A = \text{MoAI-Compressor}(A_{PS}, A_{OWOD}, A_{SGG}, A_{OCR}), A_{input}).$$
 (1)  
 $A \in \mathbb{R}^{d \times 64}$  가변길이  $A \in \mathbb{R}^{d \times 64}$ 

#### **MoAl-Mixer**

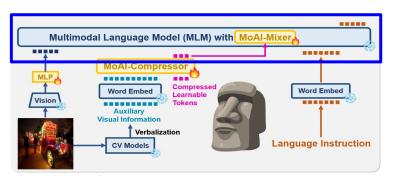
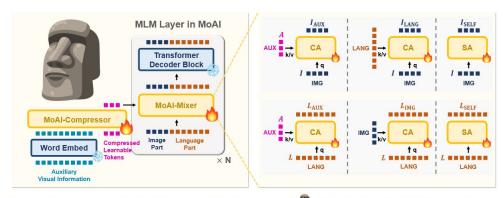


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**Fig. 5:** Illustrating MoAI-Mixer in MLM Layer of MoAI. In MoAI-Mixer, there are six expert modules to harmonize auxiliary features A and two original features (*i.e.*, visual I and language L features).

- MoAl-Mixer 는 MLM 에 임베딩되어있음.
- 인풋 : (MoAl-Compressor 의 아웃풋인) 보조 토큰들, Visual features, Language features

$$A \in \mathbb{R}^{d \times 64}$$
  $I^{(l)} \in \mathbb{R}^{d \times N_I} L^{(l)} \in \mathbb{R}^{d \times N_L}$ 

• I-th MLM layer with MoAI-Mixer : 
$$[\hat{I}^{(l)},\hat{L}^{(l)}] = \text{MoAI-Mixer}^{(l)}(A,I^{(l)},L^{(l)}),$$
 
$$[I^{(l+1)},L^{(l+1)}] = \text{TransDec}^{(l)}(\hat{I}^{(l)},\hat{L}^{(l)}),$$

*)* 전유2

#### **MoAl-Mixer**

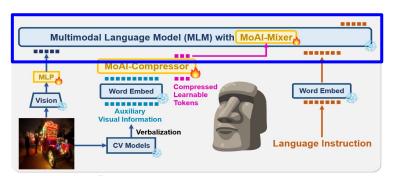
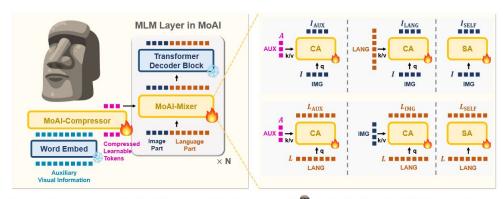


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**Fig. 5:** Illustrating MoAI-Mixer in MLM Layer of  $\P$  **MoAI.** In MoAI-Mixer, there are six expert modules to harmonize auxiliary features A and two original features (*i.e.*, visual I and language L features).

(3)

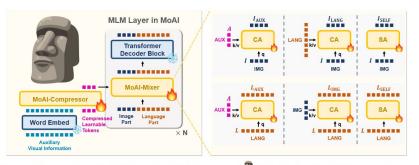
- MoAl-Mixer 에는 6개의 전문가 모듈 존재
  - o 구조 : Cross-attention, Self-attention
  - 인풋 : I / L (Visual features / Language features)
  - o 아웃풋 : IAUX, ILANG, and ISELF / LAUX, LIMG, and LSELF

$$I_{\{\text{AUX or LANG}\}}^{(l)} = \text{CA}^{(l)}(q = I^{(l)}, k = \{A \text{ or } L^{(l)}\}, v = k),$$

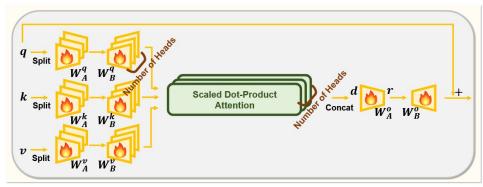
$$L_{\{\text{AUX or IMG}\}}^{(l)} = \text{CA}^{(l)}(q = L^{(l)}, k = \{A \text{ or } I^{(l)}\}, v = k).$$

전유진

#### **MoAl-Mixer**



**Fig. 5:** Illustrating MoAI-Mixer in MLM Layer of  $\P$  **MoAI.** In MoAI-Mixer, there are six expert modules to harmonize auxiliary features A and two original features (*i.e.*, visual I and language L features).



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

- MoAl-Mixer 에는 6개의 전문가 모듈 존재
  - o 구조 : Cross-attention, Self-attention
    - Projection matrix W 를 LoRA 기반 decompose 해서 연산량 줄임.
    - Residual addition 통해 트랜스포머 디코더 최적화 과정 안정화시킴.

## First Training Step - 즉, 전문가 친구들 독립적으로 학습

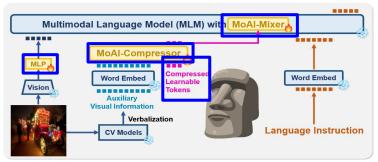


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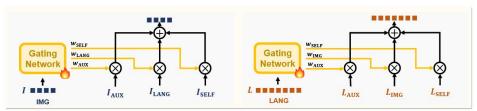
- Visual instruction tuning 데이터셋으로 MLP connector, Ainput, MoAl-Compressor, and MoAl-Mixer 4개 학습.
- MoAl-Mixer 내 6명의 전문가의 아웃풋인, 각각 3개의 visual/language features 중 각각 1개 랜덤 샘플링해서 학습.

$$\hat{I}^{(l)} = \text{Sample}(I_{\text{AUX}}^{(l)}, I_{\text{LANG}}^{(l)}, I_{\text{SELF}}^{(l)}), \quad \hat{L}^{(l)} = \text{Sample}(L_{\text{AUX}}^{(l)}, L_{\text{IMG}}^{(l)}, L_{\text{SELF}}^{(l)}). \quad (4)$$

$$\text{TransDec}_{I}(\hat{I}^{(l)}, \hat{L}^{(l)})$$

전유진

## Second Training Step - 이번엔, 학습된 전문가들 조합할 수 있도록 Gating Networks 학습



(b) Gating Networks for MoAl-Mixer

• 2개의 gating networks 존재 (Visual features 용도의 single layer, Language features 용도의 single layer)

(5)

$$W_{\text{Gating}_I}$$
 and  $W_{\text{Gating}_I} \in \mathbb{R}^{d \times 3}$ 

원래의 feature 와 MoAl-Mixer 가 생성한 3개의 features 간 weight 구해서 적용

$$[w_{\text{AUX}}, w_{\text{LANG}}, w_{\text{SELF}}] \leftarrow \text{Softmax}(I^{(l)^{\mathsf{T}}} W_{\text{Gating}_{I}}, \text{dim}=1),$$

$$\hat{I}^{(l)} = w_{\text{AUX}} \odot I_{\text{AUX}}^{(l)} + w_{\text{LANG}} \odot I_{\text{LANG}}^{(l)} + w_{\text{SELF}} \odot I_{\text{SELF}}^{(l)}$$

$$[w_{\text{AUX}}, w_{\text{IMG}}, w_{\text{SELF}}] \leftarrow \text{Softmax}({L^{(l)}}^\mathsf{T} W_{\text{Gating}_L}, \text{dim}{=}1),$$

$$\hat{L}^{(l)} = w_{\text{AUX}} \odot L_{\text{AUX}}^{(l)} + w_{\text{IMG}} \odot L_{\text{IMG}}^{(l)} + w_{\text{SELF}} \odot L_{\text{SELF}}^{(l)},$$

# **Experiments**

- External CV models
  - o panoptic segmentation : Mask2Former w/ Swin-B/4
  - open-world object detection : OWLv2 w/ CLIP-B/16
  - scene graph generation : panoptic SGG w/ ResNet-50
  - o ocr : PaddleOCRv2
  - -> 위의 파라미터 다 합치면 332 M 개로 괜춘.