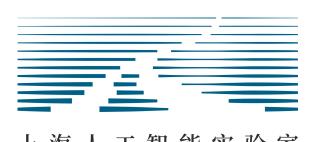


# OCTAVIUS: MITIGATING TASK INTERFERENCE IN MLLMS VIA MOE

Zeren Chen<sup>1,2\*</sup>, Ziqin Wang<sup>1,3\*</sup>, Zhen Wang<sup>2\*</sup>, Huayang Liu<sup>2</sup> Zhenfei Yin<sup>1,4</sup>, Si Liu<sup>3</sup>, Lu Sheng<sup>2</sup>, Wanli Ouyang<sup>1,4</sup>, Yu Qiao<sup>1</sup>, Jing Shao<sup>1</sup>
<sup>1</sup>Shanghai AI Laboratory, <sup>2</sup>School of Software, Beihang University
<sup>3</sup>Institute of Artificial Intelligence, Beihang University, <sup>4</sup>University of Sydney



上海人工智能实验室 Shanghai Artificial Intelligence Laboratory

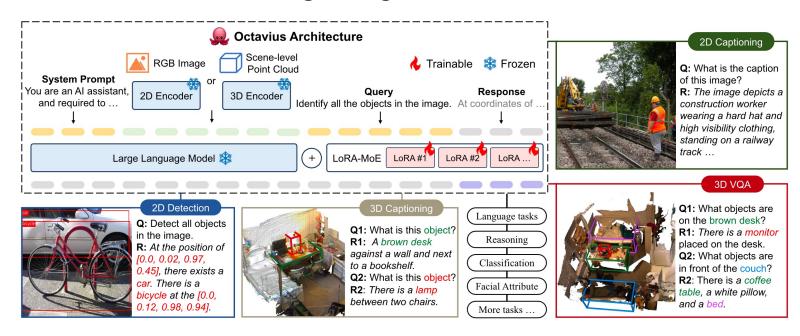




Homepage is available at <a href="https://openlamm.github.io/paper\_list/Octavius">https://openlamm.github.io/paper\_list/Octavius</a>

## Overview

- Propose a method called **LoRA-MoE**, which combine Mixture-of-Experts(MoE) with LoRA in Multimodal Large Language Models(MLLMs).
- We designed a point cloud encoder called **Object-As-Scene** to provide languagealigned scene-level representations. Additionally, we constructed the **Scan2Inst** dataset for 3D instruction tuning using ScanNet.

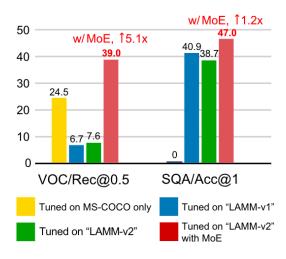


## Introduction & Motivation

- For MLLMs with LoRA, simultaneously learning different tasks may cause conflicts, and ultimately compromise the performance of each downstream task.
  - E.g. For the detection task alone, the performance on VOC is 24.5. However, when combined with the VQA task, the performance drops to around 7.
- Objective: Design a versatile and scalable MLLM framework that can effectively address diverse multimodal tasks, even when instruction-tuning data is limited.

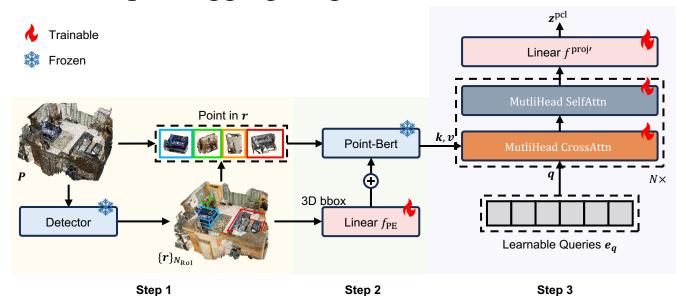
• We propose LoRA-MoE, a combination of MoE and LoRA, which has led to improved

performance on both VOC and SQA tasks.



## Modality Encoder

- For image encoder, we use the pre-trained CLIP visual encoder ViT-L/14.
- For point cloud encoder, we propose a structure called Object-As-Scene.
  - Step 1: Locating regional RoIs as candidates.
  - Step 2: Extracting RoI features aligned with language and image.
  - Step 3: Aggregating RoI features as scene features.



$$egin{aligned} \{m{h}^{ ext{pcl}}\}_{N_{ ext{RoI}}} &= f^{ ext{Point-Bert}}(m{P},\{m{r}\}_{N_{ ext{RoI}}}) \ m{h}^{ ext{pcl}}_q &= ext{MHCA}(m{q} = m{e}_q, m{k}m{v} = \{m{h}^{ ext{pcl}} + f_{ ext{PE}}(m{r})\}_{N_{ ext{RoI}}}) \ m{z}^{ ext{pcl}} &= f^{ ext{proj}'}(m{h}^{ ext{pcl}}_q) \end{aligned}$$

### 3D Dataset Construction

• We employed GPT to enrich the question and answer in ScanQA.

#### **Original question**

What is over the chair beneath the blackboard?

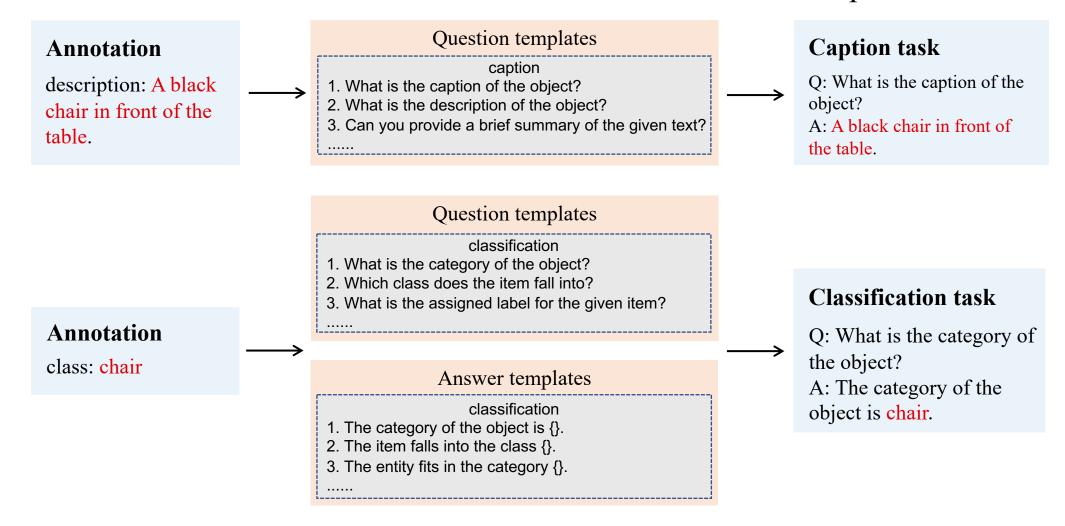


#### **Enriched questions**

- Can you please describe the objects or items that are positioned on the chair beneath the blackboard?
- Are there any specific colors, patterns, or designs on the item placed over the chair beneath the blackboard?
- Could you provide information about the purpose or function of the object that is currently resting on the chair beneath the blackboard?

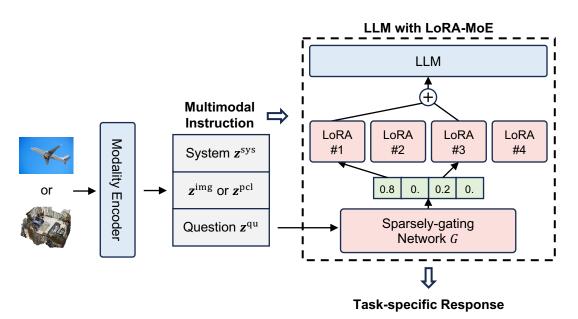
## 3D Dataset Construction

• We utilized annotations from ScanNet to construct data use templates.



## Multimodal Decoder

- We propose a unified **LoRA-MoE** decoder based on an **instance-based gate** routing strategy.
  - Instance-based gate take the questions as input to predict routing scores for each expert.
  - We select sparsely-activated experts based on routing scores for each individual instance.



• For LoRA #k when generating i-th token:

$$Gate_k = G(oldsymbol{z}^{ ext{qu}})_k \ Emb_k = E_k^{ ext{LoRA}}( ext{tok}_{0...i-1})$$

Generate i-th token use sparsely-activated experts:

$$N = \{k; LoRA_k \ is \ activated \}$$
 
$$tok_i = f^{\mathrm{LLM}}( tok_{0...i-1}) + \sum_k^N G(\boldsymbol{z}^{\mathrm{qu}})_k E_k^{\mathrm{LoRA}}( tok_{0...i-1})$$

## Experiments

### • Comparison on image modalities

Models	MoE	FT. Dataset	Det. (IoU=0.5)		VQA	Cap.	Cls.	Facial Attr		Δνα
Models	MOE	r I. Dalasel	Recall	Prec	Acc@1	CIDEr	Acc@1	Hair Acc@1	Smile Acc@1	- Avg.
LAMM	<b>√</b>	LAMM v2	7.61 <b>39.04</b>	5.95 <b>35.21</b>	40.31 <b>46.95</b>	0.21 <b>5.66</b>	<b>73.50</b> 65.40	58.04 <b>60.93</b>	50.15 <b>59.82</b>	20.89% ↑
LLaVA-LoRA	✓	LLaVA	- -	- -	52.35 <b>55.58</b>	<b>30.75</b> 23.08	2.89 <b>41.00</b>	<b>12.50</b> 3.93	50.23 <b>52.17</b>	_ 18.36% ↑

### • Comparison on point cloud modalities

			FT. Res	ults		ZS. Results				
Models	Cap. (Scan2Cap)		VQA (ScanQA)		Cls. (ScanNet)	Cls. (ShapeNet)	Cap. (Nr3d)		ZS. Avg.	
	BLEU-1	CIDEr	BLEU-1	CIDEr	Acc@1	Acc@1	BLEU-1	CIDEr	25.11.6.	
3D-LLM (Flamingo)	36.10 <sup>†</sup>	-	30.30	59.20	=	_	-	_	-	
Ours Ours w/ MoE	33.58 <b>35.94</b>	35.11 <b>39.38</b>	43.21 <b>44.24</b>	<b>168.21</b> 167.31	47.40 <b>48.80</b>	19.75 <b>24.85</b>	20.02 <b>21.16</b>	16.19 <b>17.22</b>	_ 17.06% ↑	

## Experiments

### • Comparison on image & point cloud modalities

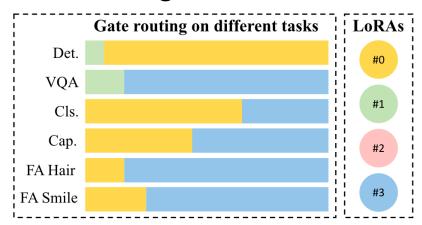
	MoE	2D Results (ZS.)						3D Results (FT.)			3D Results (ZS.)		
FT. Dataset		Det.	VQA	Cap.	Cls.	Fa	cial	Cap.	VQA	Cls.	Cls.	Cap.	Avg.
		Rec@0.5	Acc	CIDEr	Acc	Hair	Smile	CIDEr	CIDEr	Acc	Acc	CIDEr	
LAMM v2		7.61	40.31	13.28	73.50	58.04	50.15	_	_	_	_	_	_
Li divilvi v2	$\checkmark$	39.04	46.95	26.71	65.40	60.93	59.82	_		_	_	_	
Scan2Inst		_	_	_	_	_	_	39.56	162.14	47.60	19.75	16.19	_
Scanzinst	✓	_	_	_	_	_	_	CIDEr CIDEr Acc  39.56 162.14 47.60 1 39.38 167.31 43.40 2  19.76 <b>182.00</b> 38.80 1	24.85	17.22	_		
LAMM v2+Scan2Inst		2.64	39.71	0.04	71.66	42.47	50.66	19.76	182.00	38.80	14.85	8.26	_
LAWINI VZ+SCallZIIISt	✓	34.30	35.80	10.06	56.86	51.52	54.22	33.29	VQA         Cls.         Cl           CIDEr         Acc         Acc           -         -         -           162.14         47.60         19.16           167.31         43.40         24.16           182.00         38.80         14.16	21.10	17.22	$21.40\% \uparrow$	

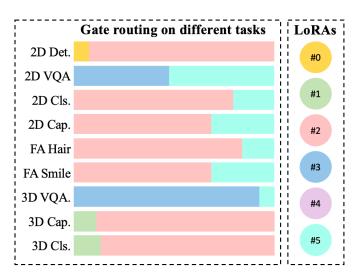
#### • Ablation studies of MoE on 2D tasks

Gate Type	Gate 1	Input	#Evm outs	LaDA Danis	Det. (VOC, IoU=0.5)		VQA	#Trainable Param.	
	Question	System	#Experts	LoRA-Rank	Recall	Prec.	Acc@1	#1ramable Param.	
- (Baseline)			1	32	7.61	5.95	40.31	0.4%	
Sparse Top-2	$\checkmark$		4	32	39.04	35.21	46.95	1.6%	
Sparse Top-2	<b>√</b>	<b>√</b>	4	32	34.23	30.78	40.25	1.6%	
Dense	$\checkmark$		4	32	9.78	5.33	44.71	1.6%	
Sparse Top-2	✓		4	16	32.81	24.46	39.11	0.8%	
Sparse Top-2	$\checkmark$		4	8	25.44	21.87	37.65	0.4%	

## Experiments

• Gate routing on different tasks



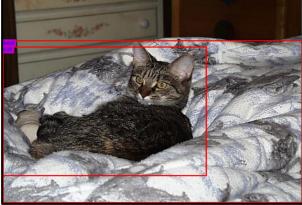


• Ablation studies on load balancing in MoE

#Experts	LB	Token	De	VQA	
			Recall	Prec.	Acc@1
4			39.04	35.21	46.95
4	$\checkmark$		33.21	26.80	45.26
8			22.30	11.01	39.91
8	$\checkmark$		21.52	12.10	37.53
4		✓		Fail	
4	✓	✓		Fail	

### Visualization on 2D tasks



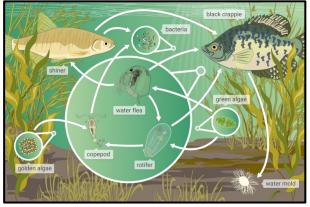


**Question**: Identify all objects in the image and provide their positions. **Answer**: Positioned at [0.0, 0.24, 0.68, 0.86] within the image is an object that can be classified as belonging to the **cat** category, characterized by its unique texture and distinctive silhouette that differentiates it from other elements in the scene. This cat appears to be the focal point of the image, drawing the viewer's attention with its relaxed posture. At the [0.0, 0.21, 1.0, 0.99] position of the image, there is an object categorized as **bed**. The cat seems to be lying on the bed, adding a sense of tranquility and homeliness to the image.

**Question**: What is the caption of the image? **Answer**: The image shows a man and woman holding hands in a river.



**Question**: What is the caption of the image? **Answer**: The image depicts a scene where a group of people are gathered near a tower with a clock face.



**Question**: Which of the following organisms is the primary consumer in this food web?

**Context**: Below is a food web from Little Rock Lake, a freshwater lake ecosystem in Wisconsin. A food web models how the matter eaten by organisms moves through an ecosystem. The arrows in a food web represent how matter moves between organisms in an ecosystem.

Choice: (A) copepod (B) black crappie (C) bacteria

**Answer**: After examining the picture closely, it can be concluded that copepod is the answer to this question.



**Question**: Which of these states is farthest west?

Context: N/A

**Choice**: (A) Missouri (B) Florida (C) Montana (D) Oregon **Answer**: After a thorough examination of the picture, it becomes apparent that the correct answer is (D) Oregon.

### Visualization on 3D tasks



Question: What is the caption of the

point cloud?

Answer: This is a trash can. it sets in

the corner.

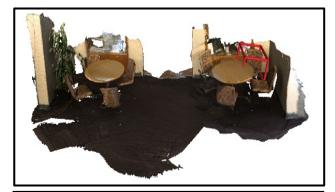


**Question**: Which side of the monitor is

the shelf positioned on?

**Answer**: The shelf is on the right side

of the monitor.

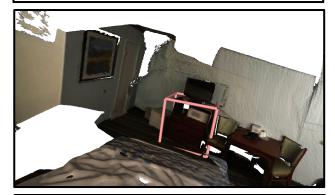


Question: What is located to the left of

the display case?

Answer: A brown chair can be found in

that position.



**Question**: What is the shape of the object that is in contact with a wall surface?

**Answer**: The object in the scene is rectangular in shape.

Question: What is the caption of the

point cloud?

Answer: This is a black coffee table. it is

in front of the couch.



Question: What is the color of the door

located in the corner?

**Answer**: The door situated in the corner

is brown in color.

Thanks for your watching!