山东大学
SHANDONG UNIVERSITY

2025首届具身智能系统及应用大会

复杂工业场景具身智能实时安全控制论坛

多模态大模型连续指令微调

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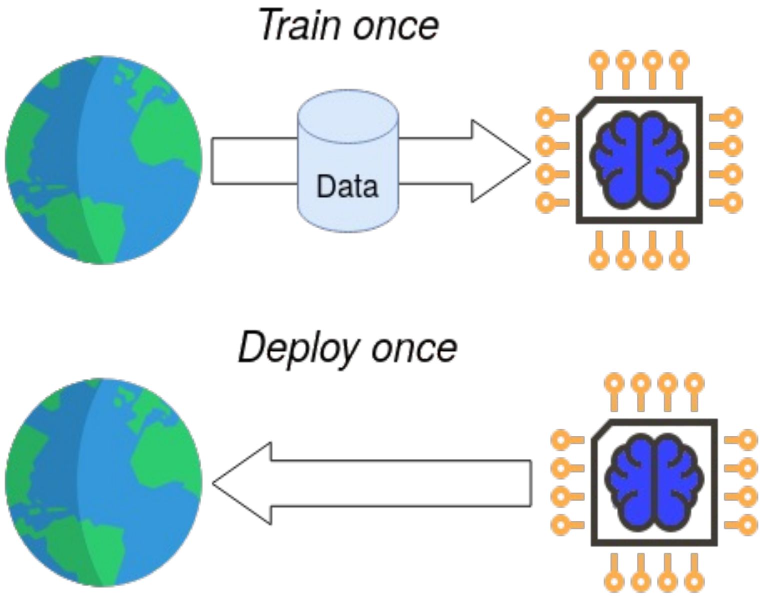
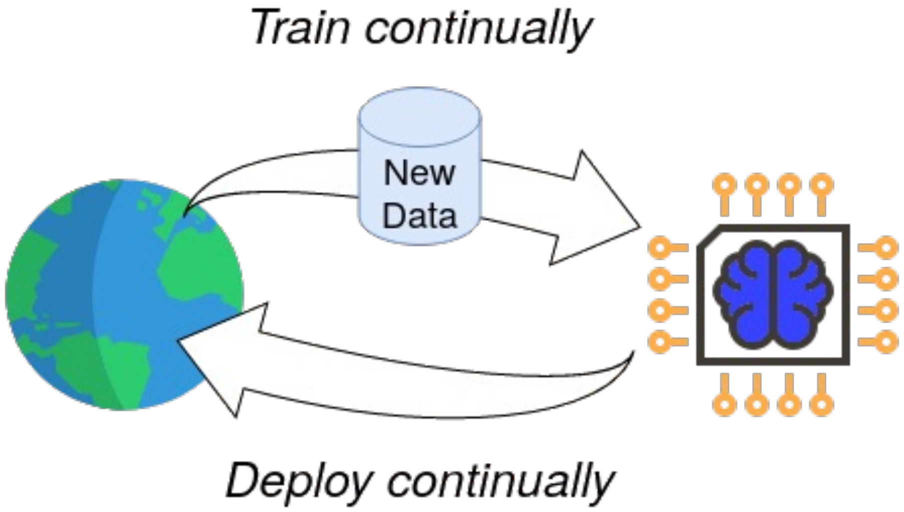


Transient Perception



Continual Perception

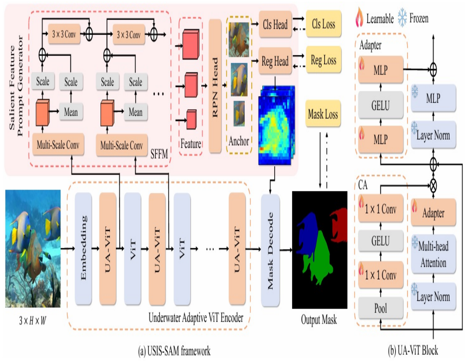
As shown in the above image, a conventional model can only be trained once and has fixed capabilities. In contrast, a model with continual learning abilities can continuously expand its capabilities to meet new requirements.

Introduction —— Transient → Continual Learning

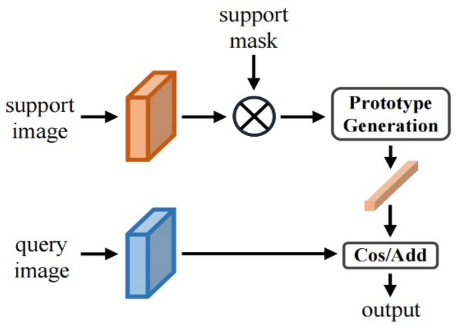
瞬态学习

持续学习

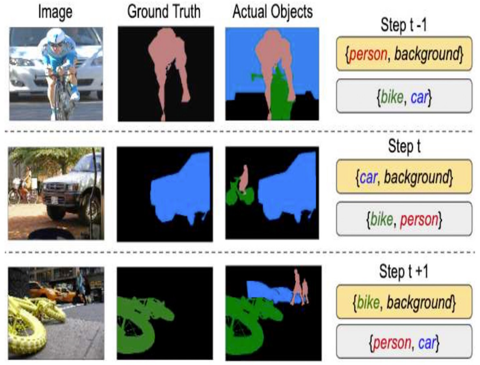
全监督 小样本 小模型 大模型



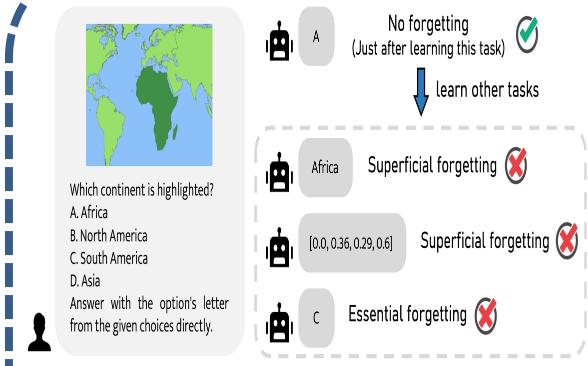
当前类别学习
全监督学习



新类别学习
小样本学习



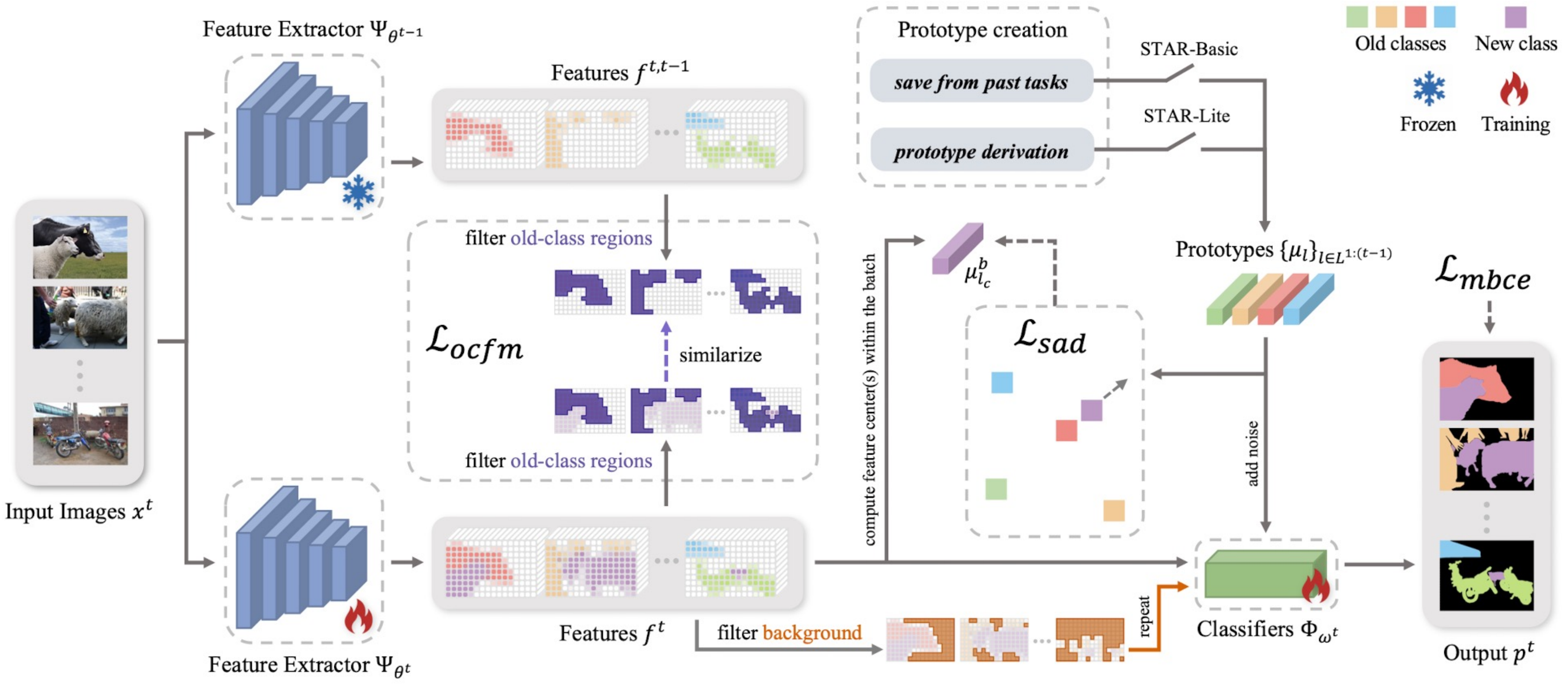
小模型语义理解
持续学习



多模态大模型推理
持续学习

STAR Method

https://github.com/jinpeng0528/STAR



Replay Without Saving: Prototype Derivation and Distribution Rebalance for Class-Incremental Semantic Segmentation, TPAMI 2025

Experiments

Method	19-1						15-5						15-1					
	Disjoint			Overlapped			Disjoint			Overlapped			Disjoint			Overlapped		
	base	*inc.*	*all*	*base*	*inc.*	*all*	*base*	*inc.*	*all*	*base*	*inc.*	*all*	*base*	*inc.*	*all*	*base*	*inc.*	*all*
MiB [10]	69.6	25.6	67.4	70.2	22.1	67.8	71.8	43.3	64.7	75.5	49.4	69.0	46.2	12.9	37.9	35.1	13.5	29.7
SDR [14]	69.9	37.3	68.4	69.1	32.6	67.4	73.5	47.3	67.2	75.4	52.6	69.9	59.2	12.9	48.1	44.7	21.8	39.2
PLOP [12]	75.1	38.2	73.2	75.4	37.4	73.5	66.5	39.6	59.8	75.7	51.7	70.1	49.0	13.8	40.2	65.7	17.3	54.2
SSUL [11]	77.4	22.4	74.8	77.7	29.7	75.4	76.4	45.6	69.1	77.8	50.1	71.2	74.0	32.2	64.0	77.3	36.6	67.6
STCISS [55]	76.6	36.0	75.4	76.1	43.4	74.5	76.9	54.3	71.3	76.7	54.3	71.1	70.1	34.3	61.2	71.4	40.0	63.6
RBC [58]	76.4	45.8	75.0	77.3	55.6	76.2	75.1	49.7	69.9	76.6	52.8	70.9	61.7	19.5	51.6	69.5	38.4	62.1
DKD [9]	77.4	43.6	75.8	77.8	41.5	76.0	77.6	54.1	72.0	78.8	58.2	73.9	76.3	39.4	67.5	78.2	44.3	70.1
UCD [56]	75.7	31.8	73.5	75.9	39.5	74.0	67.0	39.3	60.1	75.0	51.8	69.2	50.8	13.3	41.4	66.3	21.6	55.1
EWF [57]	78.2	3.2	74.6	77.9	6.7	74.5	79.3	38.2	69.5	79.4	38.2	69.5	75.3	22.5	62.7	78.5	31.6	67.3
STAR-Lite	77.9	46.4	**76.4**	78.1	49.1	**76.8**	78.5	58.3	**73.7**	79.7	59.4	**74.8**	78.5	45.9	**70.8**	80.0	51.2	**73.1**
RECALL [59]	65.0	47.1	65.4	68.1	55.3	68.6	69.2	52.9	66.3	67.7	54.3	65.6	67.6	49.2	64.3	67.8	50.9	64.8
PLOPLong [60]	-	-	-	74.8	39.7	73.1	-	-	-	76.0	48.3	69.4	-	-	-	72.0	26.7	61.2
SSUL-M [11]	77.6	43.9	76.0	77.8	49.8	76.5	76.5	48.6	69.8	78.4	55.8	73.0	76.5	43.4	68.6	78.4	49.0	71.4
DKD-M [9]	77.6	56.9	76.6	78.0	57.7	**77.0**	77.7	55.4	72.4	79.1	60.6	74.7	77.3	48.2	70.3	78.8	52.4	72.5
STAR-Basic	78.0	47.5	76.5	78.2	48.5	76.8	78.5	57.9	73.6	79.7	59.6	74.9	78.1	48.2	71.0	79.8	51.6	73.1
STAR-Basic†	77.9	53.6	**76.7**	78.1	56.3	**77.0**	78.6	58.4	**73.8**	80.1	62.2	**75.8**	77.8	50.4	**71.3**	79.8	55.5	**74.0**

Pascal VOC 2012 Dataset - 1

Method	10-1			5-3		
	base	*inc.*	*all*	*base*	*inc.*	*all*
MiB [10]	12.3	13.1	12.7	57.1	42.6	46.7
PLOP [12]	44.0	15.5	30.5	17.5	19.2	18.7
SSUL [11]	71.3	46.0	59.3	72.4	50.7	56.9
DKD [9]	73.1	46.5	60.4	69.6	53.5	58.1
EWF [57]	71.5	30.3	51.9	61.7	42.2	47.7
STAR-Lite	74.0	53.5	**64.3**	72.1	59.6	**63.2**
SSUL-M [11]	74.0	53.2	64.1	71.3	53.2	58.4
DKD-M [9]	74.0	56.7	65.8	69.8	60.2	62.9
STAR-Basic	72.6	55.4	64.4	70.7	61.8	64.3
STAR-Basic†	74.4	56.9	**66.1**	72.4	63.3	**65.9**

Pascal VOC 2012 Dataset - 2

Method	13-6			13-1		
	base	*inc.*	*all*	*base*	*inc.*	*all*
MiB [10]	52.8	17.9	41.8	51.6	22.9	42.5
PLOP [12]	53.2	10.1	39.6	52.4	15.1	40.6
DKD [9]	55.5	36.4	49.8	55.7	20.9	46.5
UCD [56]	53.0	18.6	42.1	52.2	23.4	43.1
STAR-Lite	56.6	50.5	54.7	55.7	31.2	**48.3**
STAR-Basic	56.4	50.9	**54.8**	55.7	31.1	**48.3**

CityScapes Dataset

Method	100-50			100-10			50-50		
	base	*inc.*	*all*	*base*	*inc.*	*all*	*base*	*inc.*	*all*
MiB [10]	40.5	17.2	32.8	38.2	11.1	29.2	45.6	21.0	29.3
PLOP [12]	41.9	14.9	32.9	40.5	13.6	31.6	48.8	21.0	30.4
SSUL [11]	41.3	18.0	33.6	40.2	18.8	33.1	48.4	20.2	29.6
RCIL [54]	42.3	18.8	34.5	39.3	17.6	32.1	48.3	25.0	32.5
STCISS [55]	40.7	24.0	35.1	33.6	16.9	28.1	40.0	23.6	29.0
RBC [58]	42.9	21.5	35.8	39.0	21.7	33.3	49.6	26.3	34.2
DKD [9]	42.4	22.9	36.0	41.5	19.4	34.2	48.8	26.3	33.9
EWF [57]	41.2	21.3	34.6	41.5	16.3	33.2	46.1	19.8	28.5
STAR-Lite	42.4	24.3	**36.4**	42.0	20.4	**34.9**	48.7	26.9	**34.3**
PLOPLong [60]	41.9	14.9	32.9	40.5	13.6	31.6	48.8	21.0	30.4
SSUL-M [11]	42.8	17.5	34.4	42.9	17.7	34.5	49.1	20.1	29.8
DKD-M [9]	42.4	23.0	36.0	41.7	20.1	34.6	48.8	26.3	33.9
STAR-Basic	42.4	24.3	**36.4**	41.8	20.7	**34.8**	48.3	27.0	**34.2**

ADE20K Dataset

STAR-Basic: Save 100x Storage Cost

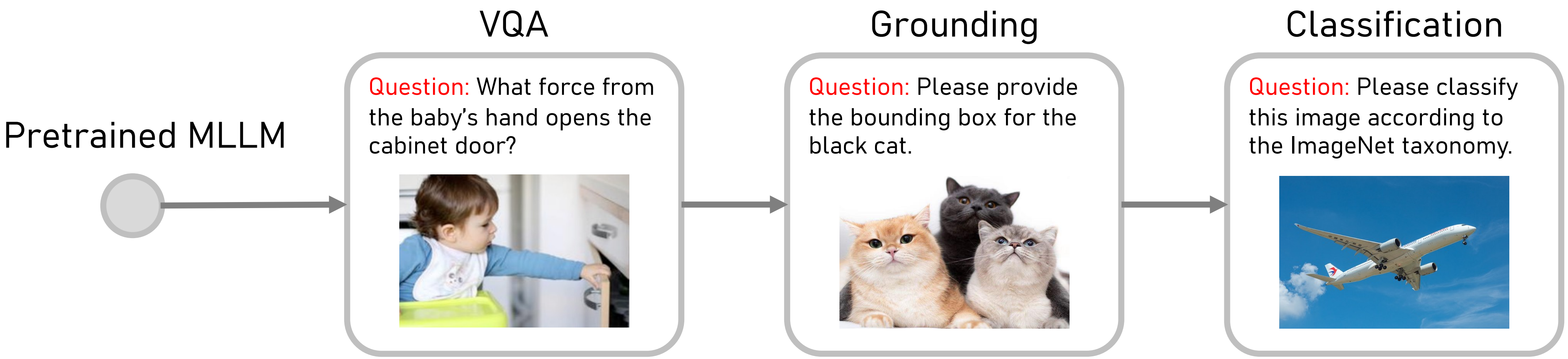
STAR-Lite: Replay Without Any Storage

SEFE: Superficial and Essential Forgetting Eliminator for Multimodal Continual Instruction Tuning

Jinpeng Chen, Runmin Cong, Yuzhi Zhao, Hongzheng Yang, Guangneng Hu, Horace Ho Shing Ip, and Sam Kwong

ICML 2025
International Conference On Machine Learning

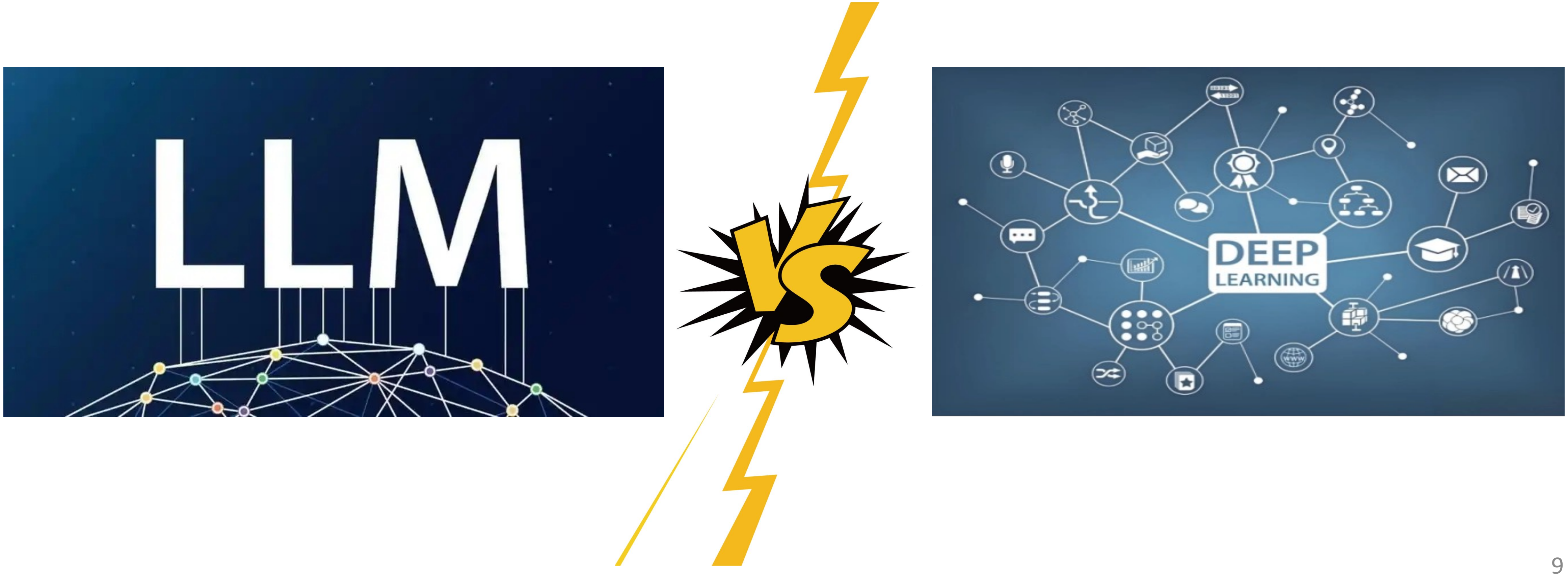
Introduction



- In **Multimodal Continual Instruction Tuning (MCIT)**, a pretrained Multimodal Large Language Model (MLLM) is sequentially tuned on a series of multimodal tasks, aiming to learn new tasks while minimizing forgetting of previously learned ones.

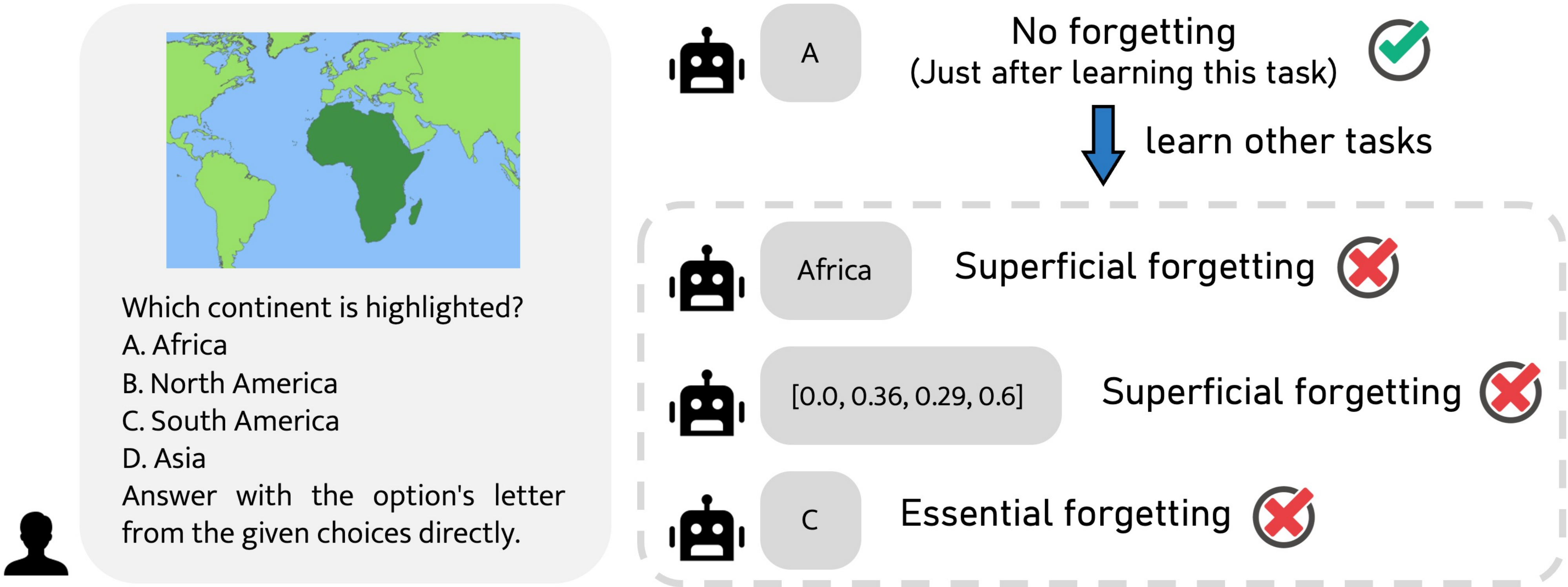
Introduction

Does the forgetting problem become more severe or alleviated for large and small models under continual learning architectures?



Introduction

Does the forgetting problem become more severe or alleviated for large and small models under continual learning architectures?



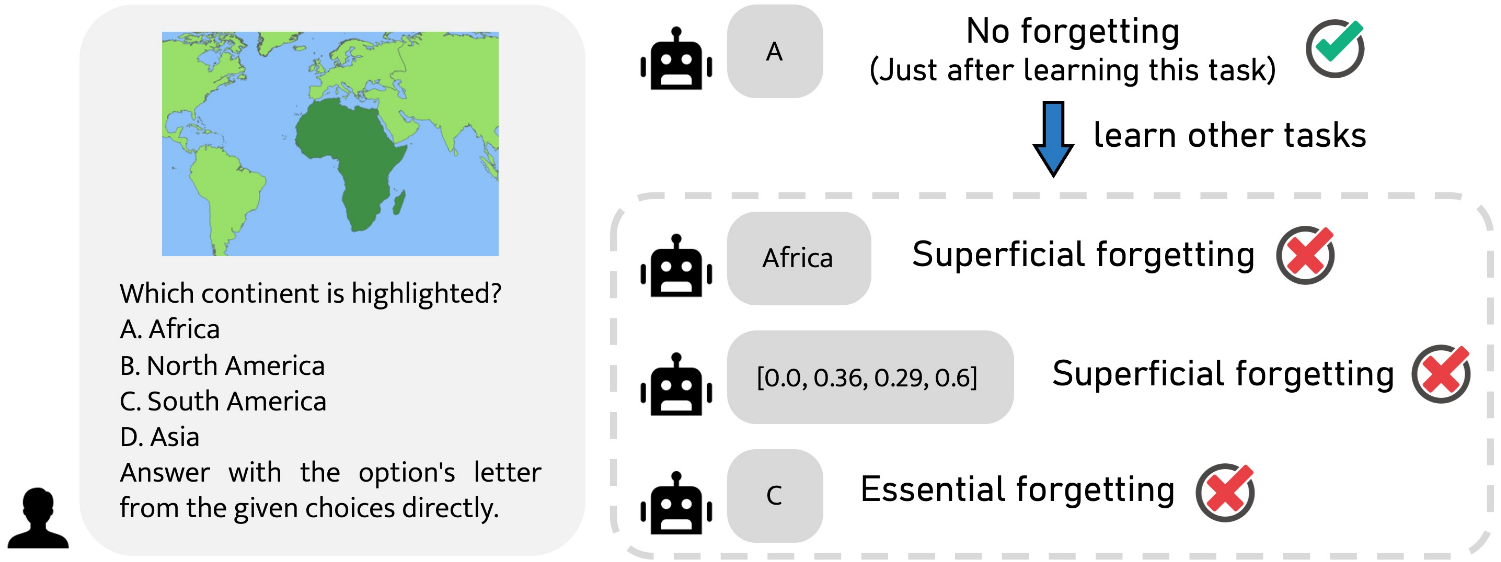
Contributions

a) We formally define *superficial forgetting* and *essential forgetting* in MCIT. Furthermore, our proposed method, SEFE, addresses these challenges and achieves state-of-the-art performance.

b) To mitigate *superficial forgetting*, we introduce the **Answer Style Diversification (ASD)** paradigm that unifies the answer domain across tasks by rephrasing questions, thereby reducing the model's bias toward specific response styles. Additionally, we create **CoIN-ASD**, an ASD-adjusted version of the CoIN benchmark, which can serve as a new benchmark for evaluating *essential forgetting* in future MCIT studies.

c) To address *essential forgetting*, we present **RegLoRA**. By identifying critical elements in the weight update matrices and applying regularization constraints, RegLoRA ensures that LoRA fine-tuning does not disrupt the model's existing knowledge.

Forgetting Types



- **Superficial Forgetting:** task knowledge may be retained while the response style is forgotten.
- **Essential Forgetting:** task knowledge is forgotten.

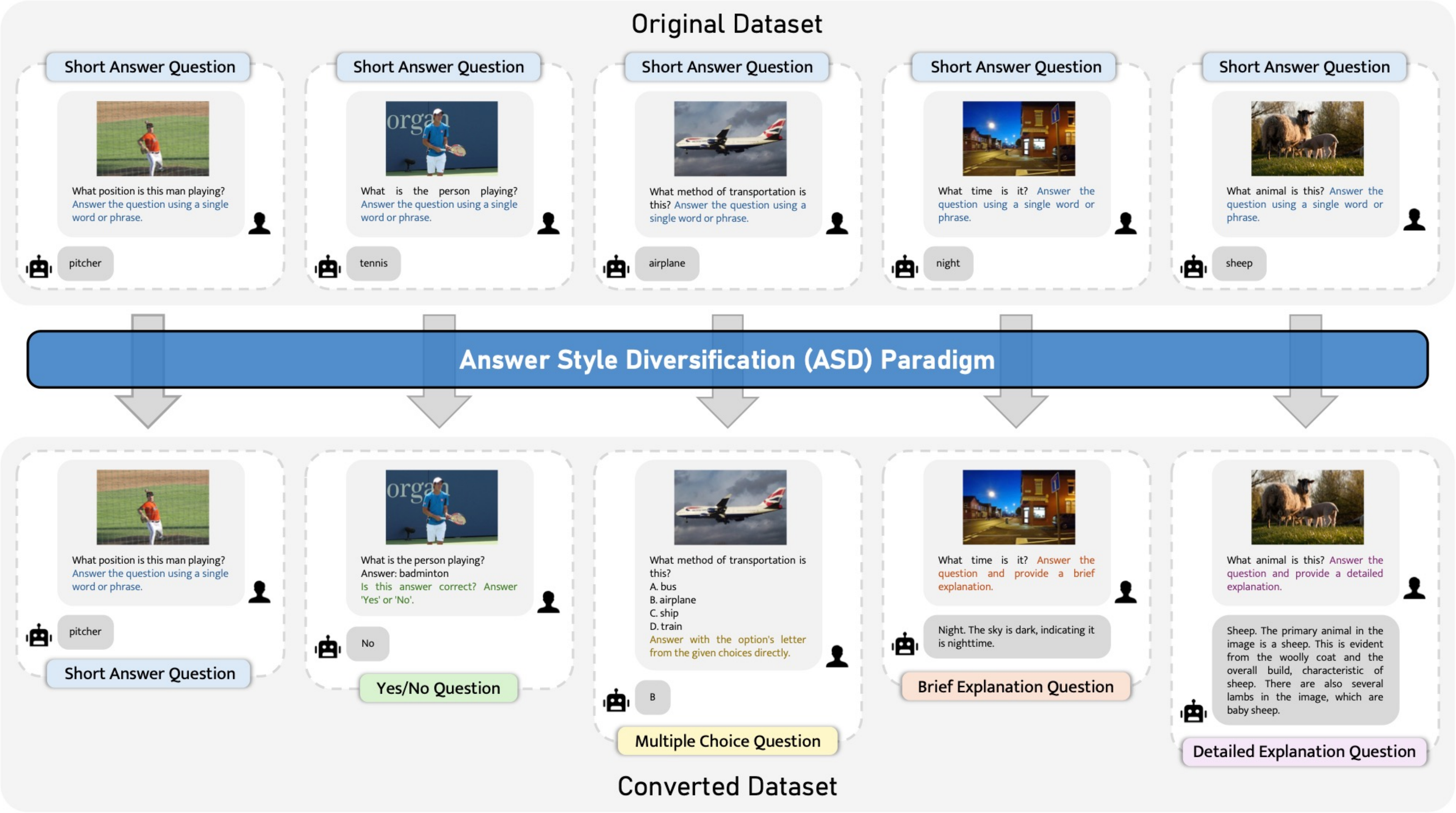
Answer Style Diversification

- *Superficial forgetting* arises from the gap in answer space between tasks, as the model tends to respond in the answer style of the most recently learned task.

- To address this issue, the **Answer Style Diversification (ASD) paradigm** reformulate questions in each task into five unified formats, aligning the answer space across tasks.

- These five formats include Short Answer Question, Yes/No Question, Multiple Choice Question, Brief Explanation Question, and Detailed Explanation Question. After analyzing 15 mainstream benchmarks, we find that these formats sufficiently cover the requirements of all tasks.

Answer Style Diversification



Answer Style Diversification

Method	Accuracy on Each Task (%)								Aggregate Results (%)			
	SQA	*VQA*^{Text}	*ImgNet*	*GQA*	*VizWiz*	*Grd*	*VQA*^{v2}	*VQA*^{OCR}	MFT↑	MFN↑	MAA↑	BWT↓
FFT	2.95	36.38	52.35	46.40	33.90	0.00	61.65	50.00	65.87	35.45	36.73	-30.42
LoRA [20]	54.05	44.63	41.25	47.55	20.80	0.85	59.30	64.30	**70.21**	41.59	39.53	-28.62
O-LoRA [45]	75.40	52.89	71.85	47.30	37.35	7.10	61.85	61.20	<u>69.30</u>	51.87	49.56	-17.43
LoTA [38]	67.30	41.51	8.25	37.15	42.25	0.10	47.95	56.15	54.72	37.58	50.46	-17.14
FFT+ASD	74.50	50.12	65.40	54.35	45.50	0.00	64.40	68.50	68.28	<u>52.85</u>	57.18	-15.44
LoRA+ASD [20]	74.45	49.70	39.30	52.00	50.45	7.05	62.25	47.80	68.13	47.88	<u>59.71</u>	-20.26
O-LoRA+ASD [45]	75.20	55.36	67.50	54.70	52.90	15.40	64.45	35.05	65.59	52.57	61.63	<u>-13.02</u>
LoTA+ASD [38]	76.90	42.65	15.85	40.25	45.10	0.30	54.35	54.00	56.99	41.18	56.28	-15.82

MFT: Mean Fine-tune Accuracy

MFN: Mean Final Accuracy

MAA: Mean Average Accuracy

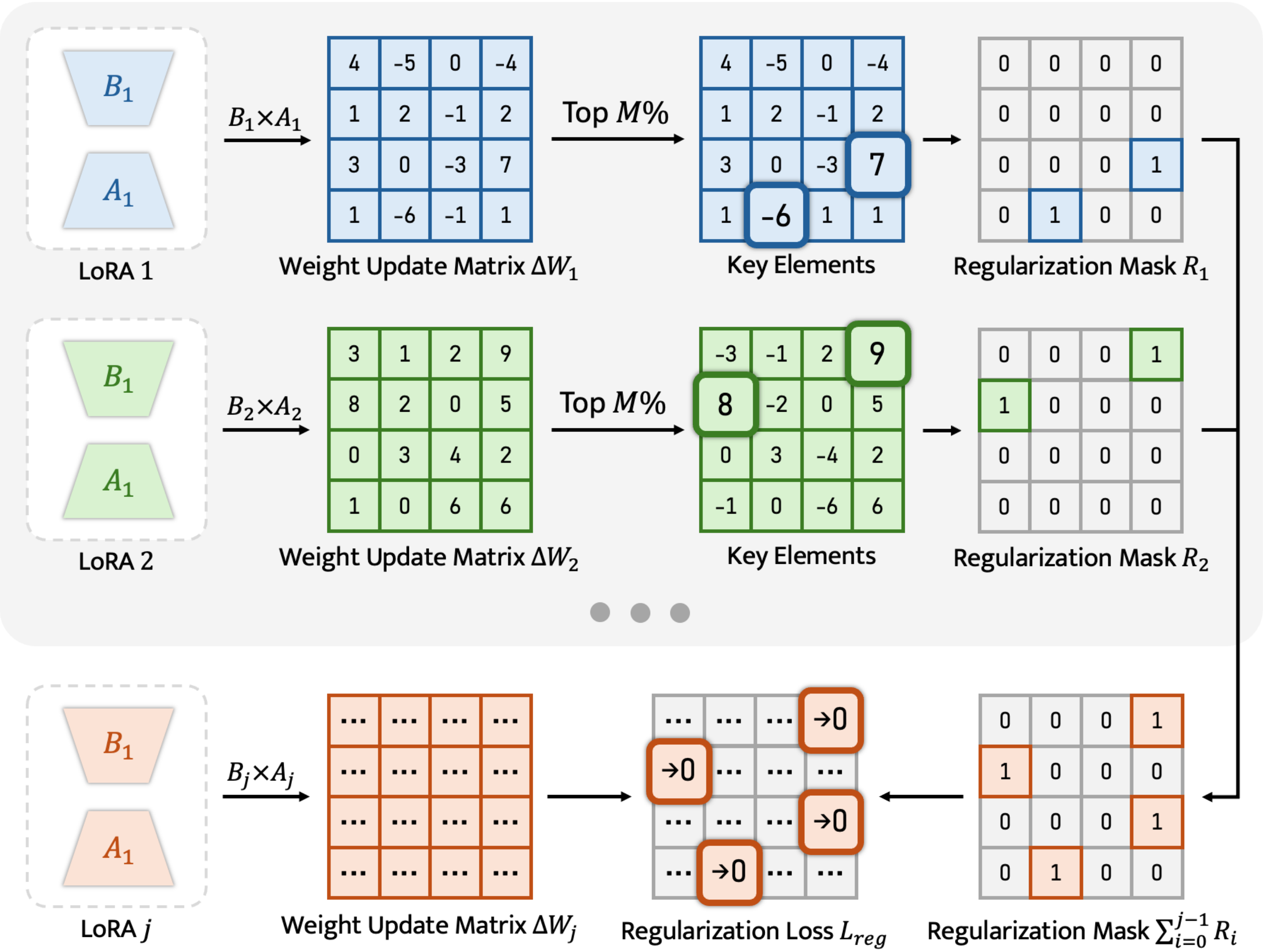
BWT: Backward Transfer

By adding ASD to existing methods, MFN, MAA, and BWT achieve average improvements of 7.00%, 14.63%, and 7.27%, respectively.

RegLoRA

- Although *superficial forgetting* is alleviated by ASD, *essential forgetting*—the true loss of past knowledge—still remains.
- Experiments reveal that only a small subset of parameters change significantly during task learning. These key parameters likely carry most of the task-specific knowledge.
- Therefore, we propose **RegLoRA**, which constrains updates to parameters significantly changed during previous tasks, thereby preserving knowledge of earlier tasks.

RegLoRA



- After each task, a **regularization mask** is saved to identify important elements for that task.
- During future training, updates to all previously identified elements are constrained.

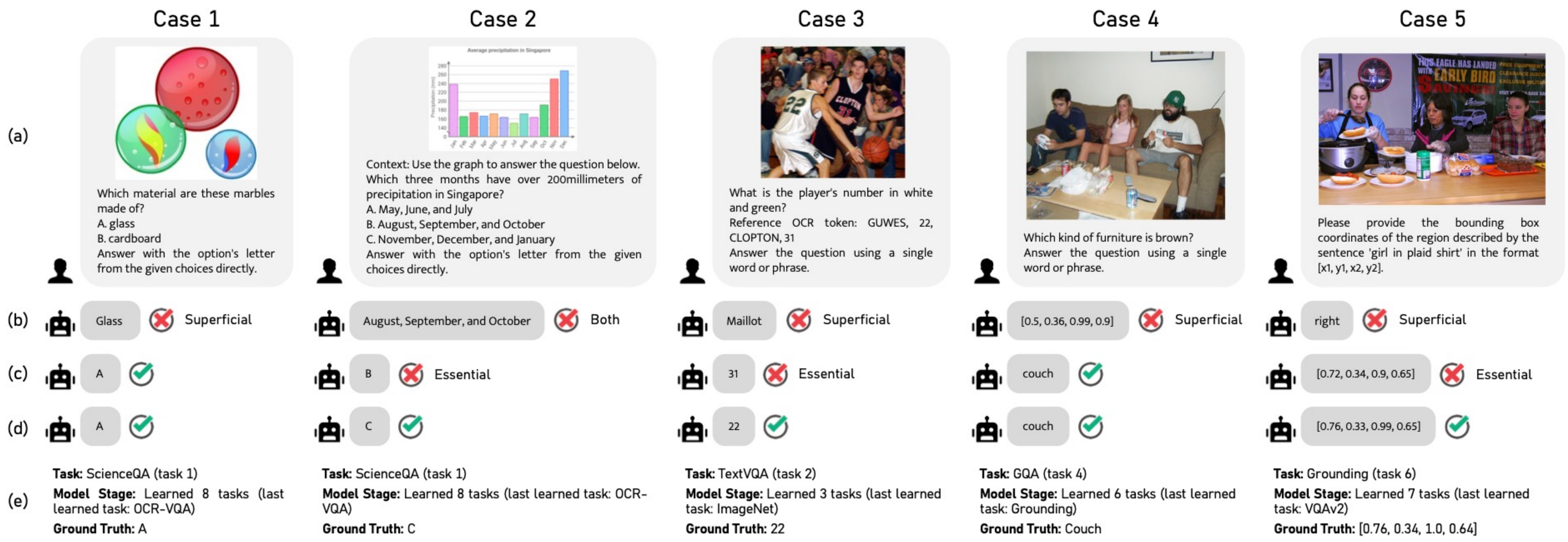
RegLoRA

Configuration	Aggregate Results (%)			
	MFT↑	MFN↑	MAA↑	BWT↑
Baseline (LoRA)	**70.21**	41.59	39.53	-28.62
+ ASD	68.13	<u>47.88</u>	<u>59.71</u>	<u>-20.26</u>
+ ASD + RegLoRA	<u>69.02</u>	**58.57**	**63.04**	**-10.45**

Quantitative Comparison

Method	Accuracy on Each Task (%)								Aggregate Results (%)			
	SQA	*VQA*^{Text}	*ImgNet*	*GQA*	*VizWiz*	*Grd*	*VQA*^{v2}	*VQA*^{OCR}	MFT↑	MFN↑	MAA↑	BWT↓
FFT	2.95	36.38	52.35	46.40	33.90	0.00	61.65	50.00	65.87	35.45	36.73	-30.42
LoRA [20]	54.05	44.63	41.25	47.55	20.80	0.85	59.30	64.30	**70.21**	41.59	39.53	-28.62
O-LoRA [45]	75.40	52.89	71.85	47.30	37.35	7.10	61.85	61.20	<u>69.30</u>	51.87	49.56	-17.43
LoTA [38]	67.30	41.51	8.25	37.15	42.25	0.10	47.95	56.15	54.72	37.58	50.46	-17.14
FFT+ASD	74.50	50.12	65.40	54.35	45.50	0.00	64.40	68.50	68.28	<u>52.85</u>	57.18	-15.44
LoRA+ASD [20]	74.45	49.70	39.30	52.00	50.45	7.05	62.25	47.80	68.13	47.88	<u>59.71</u>	-20.26
O-LoRA+ASD [45]	75.20	55.36	67.50	54.70	52.90	15.40	64.45	35.05	65.59	52.57	61.63	<u>-13.02</u>
LoTA+ASD [38]	76.90	42.65	15.85	40.25	45.10	0.30	54.35	54.00	56.99	41.18	56.28	-15.82
SEFE (Ours)	75.35	58.66	83.10	54.25	48.85	16.75	65.35	66.25	69.02	**58.57**	**63.04**	**-10.45**

Qualitative Comparison



(a) Instruction; (b) Response from the baseline model; (c) Response from the baseline model with ASD added; (d) Response from the baseline model with both ASD and RegLoRA added; (e) Basic information of the case.

Conclusion

- This paper identifies two forgetting types in MCIT—superficial forgetting, where the model's response style becomes biased, and essential forgetting, where factual knowledge is lost.
- To address these issues, we propose the SEFE method, which includes two components: the ASD paradigm and RegLoRA. ASD mitigates superficial forgetting by diversifying question types within tasks, improving response style robustness and knowledge assessment. RegLoRA combats essential forgetting by identifying and regularizing critical weight components across LoRAs to preserve knowledge.
- Experiments demonstrate that both ASD and RegLoRA are effective in tackling their respective forgetting types, and together in SEFE, they achieve state-of-the-art performance in mitigating catastrophic forgetting in MCIT.

Future Work

- Do large models really tend to forget more easily?
- How can we stimulate the anti-forgetting abilities of large models?
- Is forgetting truly a bad thing?

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敬请批评指正！

致谢： 陈锦芃博士、Sam Kwong院士

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