

TaskGalaxy: Scaling Multi-modal Instruction Fine-tuning

with Tens of Thousands Vision Task Types

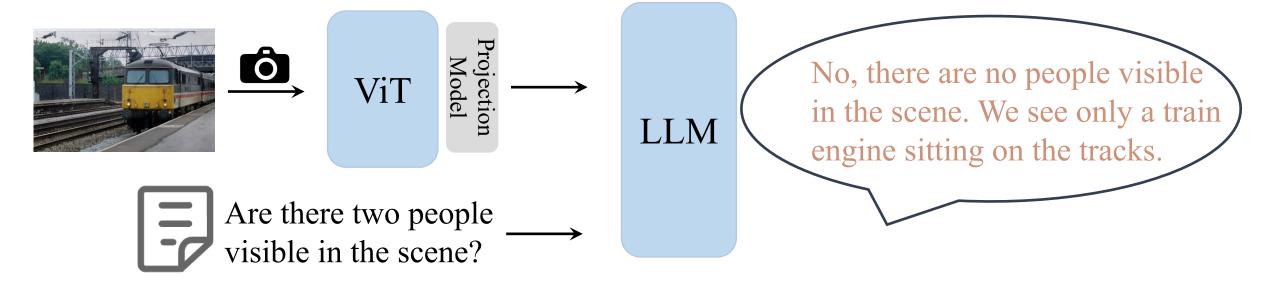


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YuanQi Team Introduction

■ Multi-modal Instruction Fine-tuning

> Task: Enable LLMs models to understand visual inputs and perform instruction-following outputs--dialogue capabilities based on visual data



> Format:

Predicted = MLLM(Input; θ), where Input = {<images>,<text>}

> Core Challenge: Poor task diversity limits the generalization ability of MLLMs, leading to biased outputs.

Motivation

■ Limitations of Existing Multi-modal Fine-tuning Datasets

> Insufficient Task-specific Data: Dataset The poor diversity of VQA tasks leads to MLLMs being exposed to out-of-distribution(OOD) situations. 😭

>Expensive, Time-consuming, Labor-intensive Annotations:

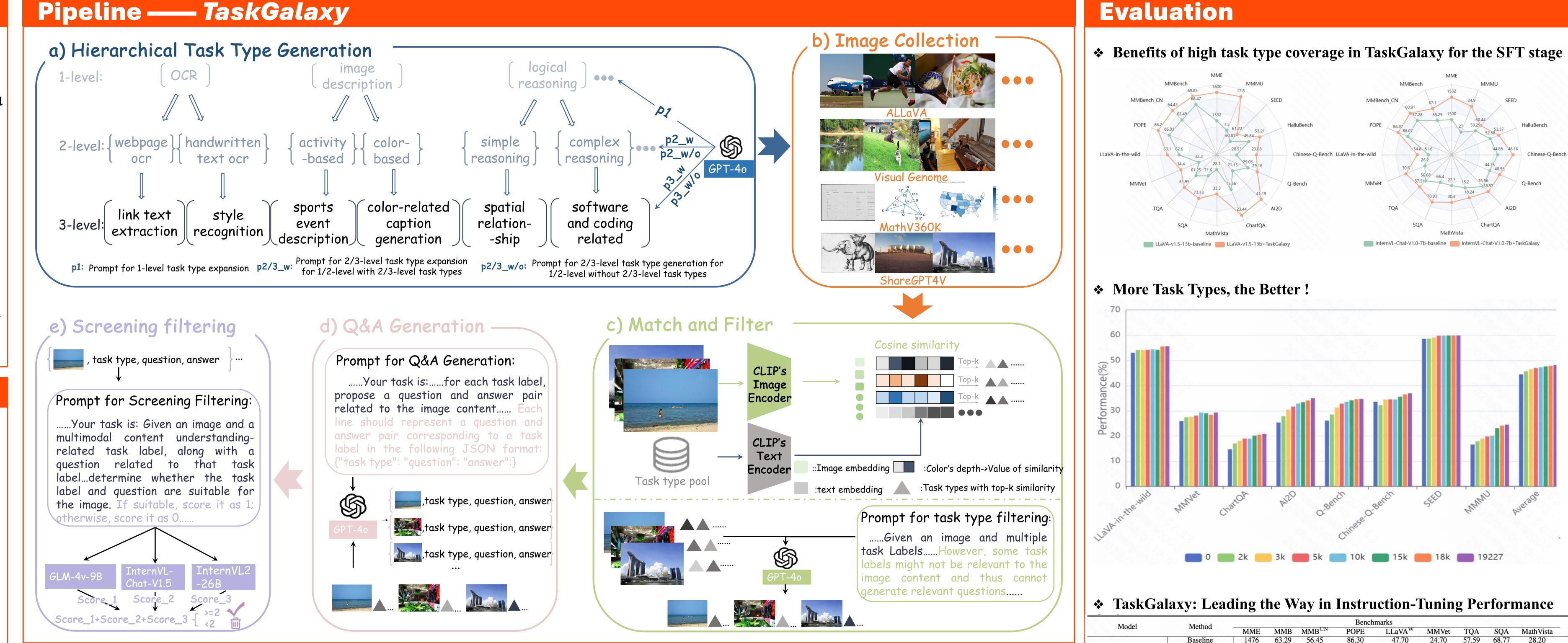
Source LLaVA Liu et al. (2024b) LAMM Yin et al. (2024) Unknown VL-Qwen Bai et al. (2023) M3IT Li et al. (2023d) mPlug-Owl Ye et al. (2023) Shikra Chen et al. (2023a) SVIT Zhao et al. (2023) MultiInstruct Xu et al. (2023) VISION-FLAN Xu et al. (2024) Public+Synthetic TaskGalaxy (Ours)

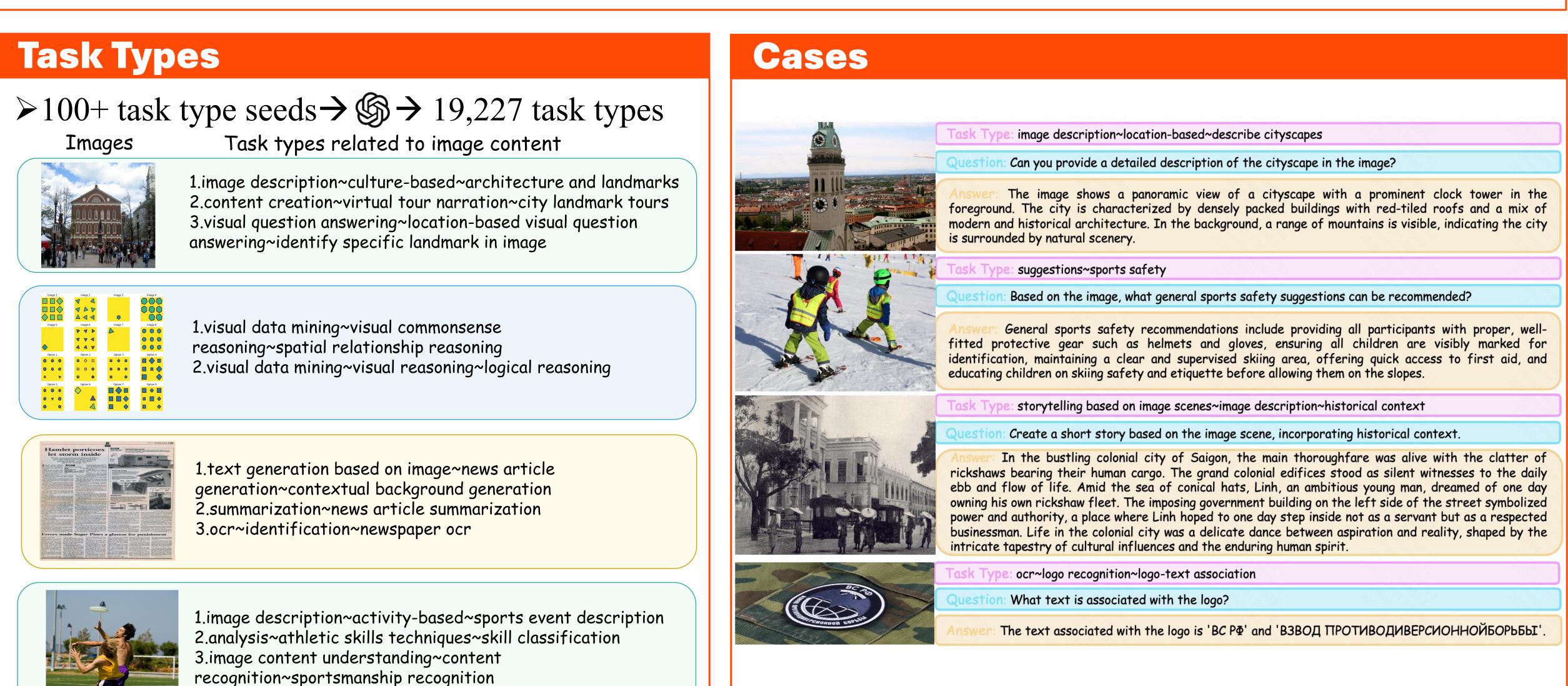
Involvement of a large number of specialized personnel, lack of automation. ■ Rich Knowledge and Strong Ability of MLLMs

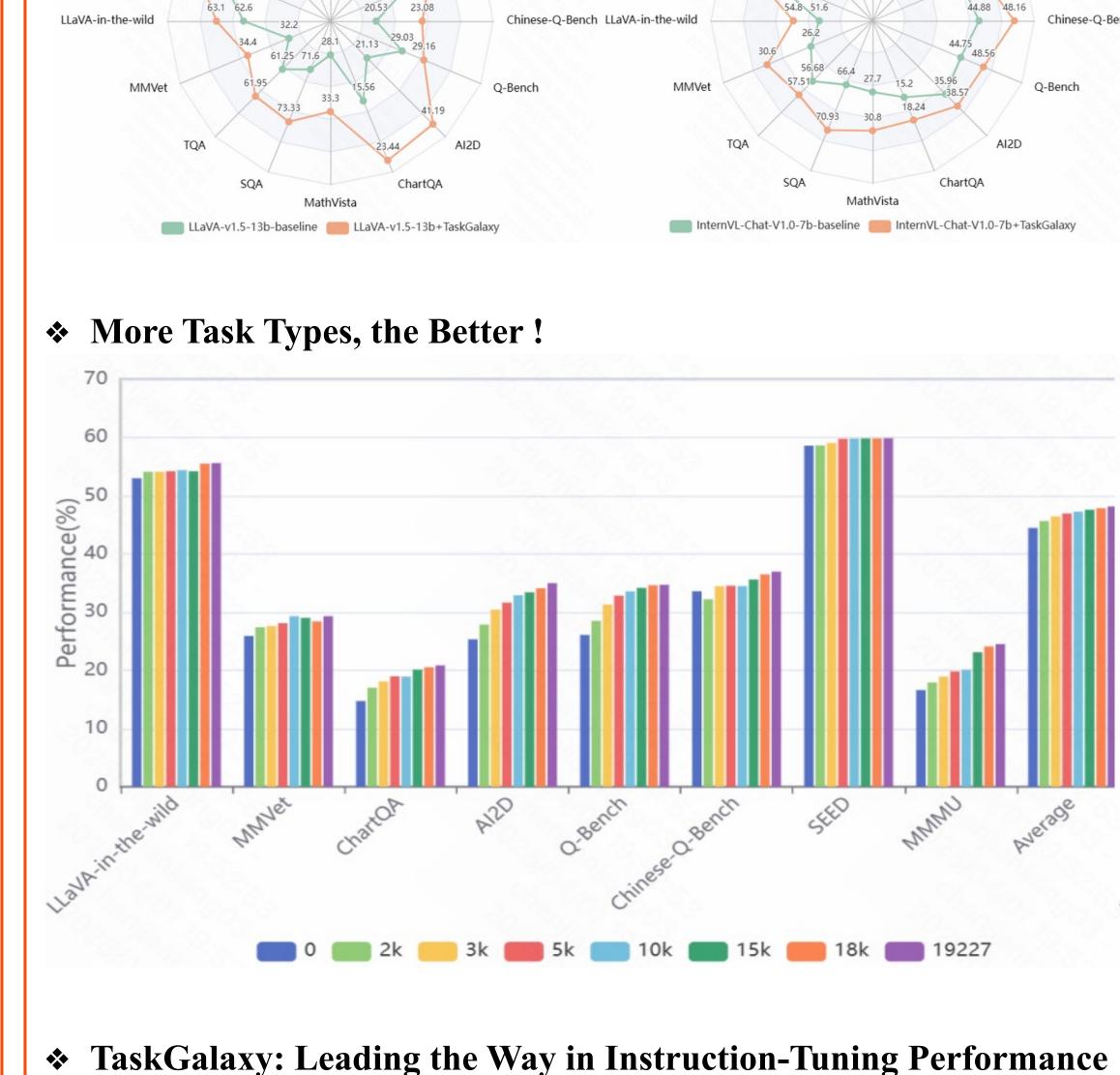
- > GPT-40: Powerful text understanding, visual-text understanding, reasoning abilities
- > CLIP: Robust text-to-image alignment capabilities
- > GLM-4v, InternVL-Chat, InternVL2: Strong visual understanding and question answering ability, skilled at solving multimodal tasks

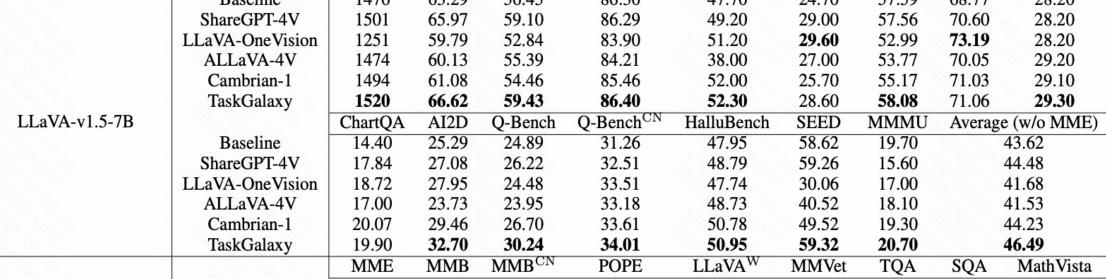
Contribution

- > A novel multi-modal instruction fine-tuning dataset, *TaskGalaxy*, which contains tens of thousands of vision task types and approximately 413k samples, addressing the limitation of task diversity in existing datasets
- > An almost fully automated pipeline for creating a comprehensive finetuning dataset of diverse task types was designed, which can be flexibly expanded by incorporating high-quality images, task types, and questionanswer samples
- Incorporating TaskGalaxy into the fine-tuning of LLaVA-v1.5 and InternVL-Chat-v1.0 resulted in improvements across all 16 benchmarks compared to fine-tuning with the original data, proving expanding the diversity of visual task types and high-quality question-answer pairs associated with these tasks significantly enhances the generalization capabilities of multimodal models









ShareGPT-4V

❖ The Benefits of Chain-of-Thought

Model	Method	Benchmarks								
		MME	MMB	LLaVAW	MathVista	ChartQA	Q-Bench	MMMU	Average(w/o MME)	
LLaVA-v1.5-7B	Baseline	1506	64.69	53.0	26.7	14.72	26.08	16.6	44.46	
	Baseline+max_5	1506	65.80	53.4	27.3	20.20	36.48	17.4	46.61	
	Baseline+max_5 (CoT)	1523	66.72	64.7	27.9	20.96	43.27	19.3	47.92	

* TaskGalaxy remains strong on advanced architecture.

Model	Method	Benchmarks								
Wiodei		MME	MMB	MMB^{CN}	POPE	LLaVA ^W	MMVet	TQA	SQA	MathVista
InternVL-Chat-V2.0-8B	Baseline	1536	68.52	66.46	86.30	63.20	46.17	66.24	90.58	50.10
	TaskGalaxy	1565	73.88	70.79	86.90	62.85	48.86	70.49	92.71	52.31
	7 05 0	ChartQA	AI2D	Q-Bench	Q-Bench ^{CN}	HalluBench	SEED	MMMU	Average (w/o MME	
	Baseline	76.64	75.88	57.79	56.98	57.51	62.72	40.50	65.86	
	TaskGalaxy	76.56	76.75	59.65	57.12	58.99	64.25	41.22	67.81	