LATTE: Learning to Reason with Vision Specialists

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Abstract

While open-source vision-language models perform well on simple question-answering, they still struggle with complex questions that require heterogeneous vision capabilities. Unfortunately, we have yet to develop methods that infuse fine-grained recognition, visual grounding, depth estimation, and 3D reasoning into a single vision-language model. Instead of forcing smaller models to learn both perception and reasoning, we propose LATTE*, a family of vision-language models that have LeArned to Think wiTh vision spEcialists. By offloading perception to state-of-the-art vision models, our approach enables vision-language models to focus solely on reasoning over high-quality perceptual information. To train* LATTE*, we create and filter a large dataset of 273K high-quality synthetic reasoning traces over perceptual outputs of vision specialists.* LATTE *trains on this data and brings significant gains across 6 benchmarks covering both perception and reasoning abilities, compared to baselines instruction-tuned with direct answers. On the other hand, models trained by distilling both perception and reasoning from larger models lead to smaller gains or even degradation on some perception tasks. Further, our method results in a* 2% *to* 5% *improvement on average across all benchmarks over the vanilla instruction-tuned baseline regardless of model backbones, with gains up to* 16% *in MMVet.*

1. Introduction

The landscape of real-world vision-language tasks is vast, spanning from basic visual question answering [1] and fine-grained object recognition to complex multi-step geometric reasoning [24]. These tasks demand both perception and reasoning. For instance, a user might photograph a gas price panel and ask how much fuel they can afford within a given budget (Figure 1). Solving this requires a vision-language model with strong perception—localizing prices via OCR—and multi-step reasoning to compute the answer. While large proprietary models like GPT-4o excel due to extensive data and model size scaling, smaller open-source models still struggle [51].

To narrow the gap between large proprietary models and smaller open-source counterparts within a reasonable budget, researchers have explored distilling both perception and reasoning from larger vision-language models [64, 77] or specialized vision models [25]. Despite these efforts, open-source models continue to lag behind.

We argue that the primary reason for this lag is the perception limitations of open-source vision-language models. While open-source language models have largely caught up with their proprietary counterparts [4, 31], vision remains a complex fusion of heterogeneous capabilities. The computer vision community has historically tackled these capabilities separately—e.g., DepthAnything [79] for depth estimation and GroundingDINO [44] for object recognition—while unified models still lag behind [46]. Similarly, the human brain dedicates distinct regions to categorical recognition (ventral stream) and spatial reasoning (dorsal stream)[19], with the reasoning and language-processing frontal and temporal lobes occupying a smaller volume[29]. By contrast, vision-language models remain heavily skewed toward language, treating visual encoders as an afterthought [15].

We depart from the *learning to perceive and reason* paradigm to propose a new approach: *learning to reason with vision specialists*. Rather than expecting a small model to master both perception and reasoning, we leverage decades of advancements in computer vision by relying on specialized vision models to provide perceptual information. This allows the vision-language model to focus exclusively on acquiring perceptual information from vision specialists and reasoning over them—enabling it to '*see further by standing on the shoulders of giants*.' Such a paradigm reduces the burden on models to extract low-level perceptual signals, allowing them to concentrate on higher-level reasoning while benefiting from the robust capabilities of dedicated vision specialists, which is particularly important for small open-source models because of their limited capacity to effectively learn both perception and reasoning.

To implement this paradigm, we curate high-quality training data in the form of multi-step reasoning traces that integrate perceptual information from vision specialists. We

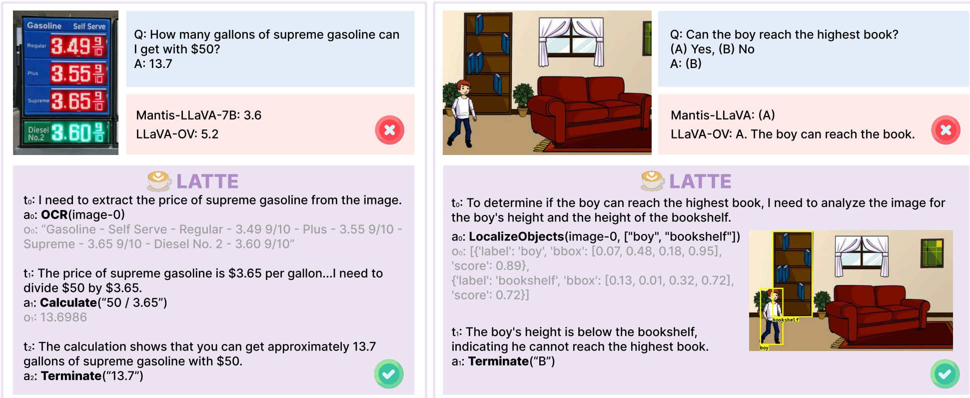

Figure 1. **Example outputs of LATTE vs. SoTA multi-modal large language models.** Our LATTE model is able to answer challenging visual questions by reasoning over perceptual information output by vision specialists.

formulate the multi-step reasoning traces as LATTE-trace, where each step consists of: (1) a *thought* for verbalized reasoning; (2) an *action* to retrieve perceptual information from a specific vision specialist; and (3) an *observation* of the returned data. Since obtaining these traces at scale with human annotators is costly, we develop two data engines for synthetic data generation. First, we leverage GPT-4o's strong multimodal reasoning and state-of-the-art vision specialists' precise perception to generate large-scale synthetic reasoning traces across diverse image sources, applying aggressive filtering and mixing techniques. Second, we generate reasoning traces using Python programs and structured reasoning templates, comparing them against GPT-generated traces to evaluate reasoning quality. In total, we produce over 1M reasoning traces across 31 datasets with GPT-4o and handcrafted programs.

With this data, we finetune small multi-modal language models to reason with vision specialists and evaluate our models on 6 benchmarks covering both perception and reasoning skills. We compare our model to two types of baselines: (1) multi-modal language models trained with vanilla instruction tuning with only direct answers; and (2) models trained by distilling both perception and reasoning.

Finally, we highlight four major takeaways from our experiments: First, learning to reason with vision specialists enables our model to outperform vanilla instruction-tuned baseline by significant margins on both perception and reasoning benchmarks, with an overall average gain of 6.4%. By contrast, the other distillation methods lead to smaller gains or even degradation in the perception performance. This trend holds as we scale the training data. Second, our method consistently outperforms the vanilla instruction-tuned baseline by $2-5\%$ on average across all benchmarks regardless of model backbones, with staggering performance gains of $10-20\%$ on MMVet. Third, through data ablations, we confirm that the quality of LATTE-trace matters more than quantity: our best data recipe consists of only 293K LATTE-trace which GPT-4o generated and answered correctly, and it leads to larger performance gains than all other data recipes of larger scales (up to 2x larger or more). Finally, programmatically-generated LATTE-trace can hurt model performance as a result of the worse reasoning quality, suggesting that again that high-quality reasoning is crucial to the model's performance.

2. Learning to Think with Vision Specialists

Our goal is to train vision-language models to reason about complex multi-modal tasks with the help of vision specialists. To train such models, we need reasoning traces that involve (1) invoking vision specialists and (2) reasoning over their outputs. We refer to such data as LATTE-trace. One LATTE-trace $\mathcal{T}$ is a sequence of steps S_i, where each step consists of thought t_i, action a_i and observation o_i:

$$\mathcal{T} = (S_0, S_1, ..., S_n) = (S_i)_{i=0}^{n} \tag{1}$$

$$S_i = (t_i, a_i, o_i), t_i \in L, a_i \in A \tag{2}$$

where L represents language space, and A is the action space consisting of vision specialists. Note that the model only generates t_i and a_i, which the training loss is applied on, whereas o_i is obtained from the vision specialists.

Action space. The action space A of our model consists of vision tools that are either specialized vision models or image processing tools. Concretely, these include OCR [27], GetObjects [88], LocalizeObjects [44], EstimateObjectDepth [79], EstimateRegionDepth [79], DetectFaces [36], Crop, ZoomIn, GetImageToTextsSimilarity [61], GetImageToImagesSimilarity [61], GetTextToImagesSimilarity [61]. Inspired by prior works on multi-modal tool use [21, 24, 43, 51, 70], we include a few additional tools to help with reasoning: QueryLanguageModel, QueryKnowledgeBase, Calculate, and SolveMathEquation. We also include Terminate as a tool for the model to output a final answer in the same action format. Our final action space consists of 15 tools, and their full implementation details can be found in the Appendix.

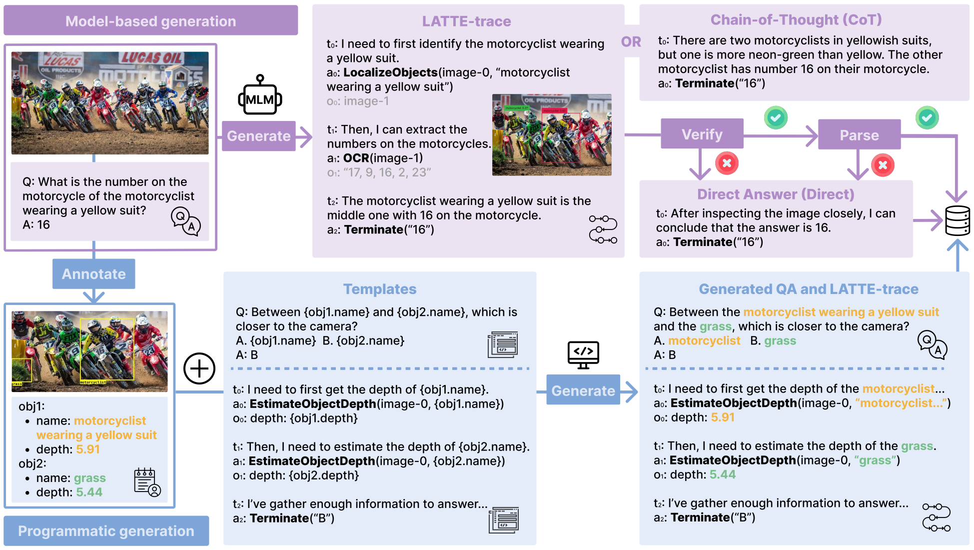

Figure 2. **Data generation.** We illustrate our model-based data generation (top) and programmatic generation (bottom) pipelines.

2.1. LATTE-trace generation

We generate synthetic LATTE-trace data with two automatic approaches: Model-based generation and Programmatic data generation.

Model-based generation. The model-based data generation pipeline consists of three steps (Figure 2 top):

1. GENERATE. First, we leverage images and QA examples in existing visual instruction tuning datasets and generate LATTE-traces to solve the questions with GPT-4o (2024-08-06). We include diverse questions on both single-image and multi-image examples from two large-scale instruction tuning datasets, Cauldron and Mantis-Instruct [28, 32]. We feed the images and questions to GPT-4o and prompt it to answer the questions by following a LATTE-trace or just CoT when it is not necessary (*e.g.*, the question is straightforward) or helpful (*e.g.*, the question requires domain-specific knowledge out of the scope of available tools) to call specialized vision tools (Figure 2).

2. VERIFY. Second, we verify GPT-4o's generated answers against the ground-truth. We force GPT-4o to always end with TERMINATE(answer) and compare its prediction to the ground-truth. If the final answer following a reasoning trace is correct, we move this LATTE-trace to the next stage. Otherwise, we convert this example into the direct answer (Direct) format with the ground-truth (Figure 2).

3. PARSE. Finally, we check the JSON syntax of each step of the LATTE-trace. Similar to the previous stage, we again keep the LATTE-traces free of syntax errors and turn the others into the Direct format with ground-truth answers.

Programmatic data generation. While model-based data generation distills reasoning from proprietary models, we are curious if reasoning with vision specialists can be learned in another manner without reliance on proprietary models. To study this perspective, we implement a programmatic data generation engine for synthesizing LATTE-traces (Figure 2 bottom). This pipeline involves two steps:

1. ANNOTATE. First, we gather existing dense annotations of images. We adopt Visual Genome (VG) as it contains rich human annotations of objects, attributes, and relationships of the images. In addition, we obtain depth maps of the VG images with Depth-Anything-v2 [79].

2. GENERATE. Next, we programmatically generate both the QA pairs and the corresponding LATTE-traces with manually written templates and the dense annotations of the images. We reuse the pipeline from [84, 86] for generating diverse QA pairs that cover various vision capabilities such as counting and spatial understanding. To generate LATTE-traces, we define templates for thoughts, actions, and observations across all steps. See Appendix for more details.

3. Experiments

We perform extensive experiments with small multi-modal models and 9 data recipes on 6 benchmarks.

Models. We adopt models that support multi-image inputs as our data includes reasoning traces with multiple images. For most of our experiments, we use Mantis-8B-SigLIP-LLaMA-3 as the base model. We additionally experiment with Mantis-8B-CLIP-LLaMA-3, and LLaVA-OneVision-7B (Qwen2-7B and SigLIP) in our ablations.

Baselines. We compare our model to two types of baselines: (1) vanilla instruction-tuning (Vanilla IT) – instruction-tuning data with only direct answers – and (2) distillation methods that train small models by distilling both perception and reasoning from larger models, including VPD [25], VisCoT [64], and LLaVa-CoT[77].

Evaluation setup. We select 6 multi-modal benchmarks covering both perception and reasoning. The perception-focused benchmarks include RealWorldQA, CV-Bench and

Table 1. **LATTE vs. Baselines on Perception and Reasoning Benchmarks.** Our method LATTE brings substantial gains over the vanilla instruction-tuned (Vanilla IT) baseline on both perception and perception + reasoning benchmarks.

Method	Perception				Perception + Reasoning				Overall
	BLINK	CV-Bench	RealWorldQA	Avg	MathVista	MMStar	MMVet	Avg	Avg
Vanilla IT	44.1	49.2	41.4	44.9	31.0	39.7	27.8	32.8	38.9
VPD	41.6	48.8	**44.8**	45.1 (+0.2)	33.0	41.1	32.8	35.7 (+2.8)	40.4 (+1.5)
LLaVa-CoT	42.2	40.4	38.0	40.2 (-4.7)	36.7	**44.6**	40.2	40.5 (+7.7)	40.4 (+1.5)
LATTE	**46.4**	**54.0**	42.0	**47.5** (+2.6)	**36.9**	44.2	**47.9**	**43.0** (+10.2)	**45.2** (+6.4)

Table 2. **LATTE vs. Vanilla IT with Different Models.** We learn that LATTE leads to performance gains over Vanilla IT regardless of the base models. The gains are 2-5% on average across all 6 benchmarks and up to 16% on MMVet.

Language / Vision	Starting checkpoint	Method	Perception				Perception + Reasoning				Overall
			CV-Bench	BLINK	RealWorldQA	Avg	MathVista	MMStar	MMVet	Avg	Avg
LLaMA3-8B / CLIP	Mantis Pretrained	Vanilla IT	52.6	45.8	52.3	50.2	33.1	36.7	28.9	32.9	41.6
		LATTE	56.9	49.6	51.1	52.6	36.6	40.8	45.2	40.8	46.7 (+5.1)
LLaMA3-8B / SigLIP	Mantis Pretrained	Vanilla IT	52.3	43.7	51.8	49.3	31.1	40.5	33.0	34.9	42.1
		LATTE	57.2	47.8	53.7	52.9	34.9	44.6	45.2	41.6	47.2 (+5.2)
	Mantis Instruct-tuned	Vanilla IT	50.6	46.7	54.8	50.7	36.2	40.7	29.7	35.5	43.1
		LATTE	51.7	47.6	56.5	51.9	36.3	42.5	45.7	41.5	46.7 (+3.6)
Qwen2-7B / SigLIP	LLaVA-OV Stage 1.5	Vanilla IT	56.8	**50.3**	57.8	55.0	**42.4**	50.1	39.3	43.9	49.5
		LATTE	**60.2**	49.9	**58.8**	**56.3**	41.9	**51.0**	**50.9**	**48.0**	**52.1** (+2.7)

BLINK [17, 33, 63, 73], and the perception + reasoning ones are MathVista, MMStar, and MMVet [8, 48, 83]. Additional details can be found in the Appendix.

3.1. Main results

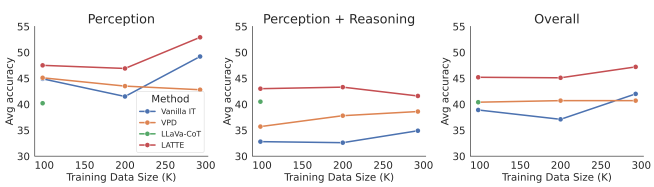

Figure 3. **Performance of LATTE vs. Baselines across Training Data Scales.** We find that our method leads to consistent gains across varying training data sizes – 98K, 200K and 293K.

Our method leads to substantial gains compared to vanilla instruction-tuning on both perception and reasoning benchmarks, whereas other distillation baselines result in smaller gains or even degradation on some perception tasks. We find that learning to reason with vision specialists enables our model to achieve consistent gains on perception-focused VQA benchmarks as well as benchmarks that require both perception and reasoning, with average gains of 2.6% and 10.2% respectively (Table 1). By contrast, both distillation baselines VPD and LLaVa-CoT bring much smaller gains, with an average of 1.5% across all benchmarks, compared to ours (6.4%). Further, we observe that the same trend holds as we scale the training data size from 98K to 200K and 293K, where our method consistently brings larger gains on both perception and perception + reasoning benchmarks (Figure 3). Interestingly, LLaVa-CoT even hurts the model's performance on perception benchmarks, even though it increases the performance on the perception + reasoning benchmarks (Table 1). This result suggests that GPT4-o might still be inferior to vision specialists on some perception tasks, as LLaVa-CoT distills purely from GPT4-o.

Our method beats the vanilla instruction-tuning baseline on average across all benchmarks regardless of the base model and checkpoint, with significant gains of 10-16% on MMVet. We fine-tune 3 different multi-modal models with all 293K LATTE-traces starting from different checkpoints. We observe that our method leads to consistent gains of 2-5% in the model's average accuracy across 6 benchmarks compared to the baselines instruction-tuned with the same examples in the Direct format (Table 2). We note that our method results in staggering gains of 10-16% on MMVet, which covers a wide range of perceptual and reasoning capabilities. Moreover, we find that our data results in larger gains on earlier pretrained checkpoints than on later-stage instruction-tuned checkpoints, likely due to the relatively small size of our data compared to Mantis' and LLaVa-OV's instruction-tuning data (1.2M and 4.5M) and some overlap in the images and questions [28, 35].

4. Conclusion

We propose to learn multi-modal language models to reason with vision specialists instead of becoming both vision specialists and reasoning experts.

Limitations and Future Work. First, our method requires customized implementations of the specialized vision tools. Second, reasoning with the vision specialists also requires additional compute at inference time. Future work can optimize and enhance the implementations of vision specialists.

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LATTE: Learning to Reason with Vision Specialists

Supplementary Material

A. Additional details on methods

A.1. Programmatic generation

We manually design five thought templates for each action and randomly sample one during generation. As for the actions, we manually select the specialized vision tools for each type of questions (*e.g.*, ESTIMATEOBJECTDEPTH for questions on objects' relative depths, and LOCALIZE for object counting questions, etc.) and compose templates with them. We fill in the actions' inputs in the templates with annotations obtained from the previous step. Similarly, we define observation templates based on the action outputs' formats, and fill them in with dense annotations.

A.2. Data filtering and mixing

In total, we generate 815K data with GPT-4o for both single-image and multi-image questions across 31 data sources from Cauldron and Mantis-Instruct [28, 32]. We also programmatically generate 1M+ QA pairs and corresponding LATTE-traces with VG images and annotations [30], which we randomly sample from to augment model-generated data. We then develop different data recipes with 3 filtering/mixing techniques, where we vary the distribution of: (1) data formats; (2) data sources; and (3) model-generated vs. program-generated reasoning traces.

Data format. As mentioned in the data generation pipeline, model-generated data can be categorized into two formats: LATTE-trace or CoT examples (Figure 2). Additionally, they can be further grouped into LATTE-trace/CoT-pos and LATTE-trace/CoT-neg examples where the final answers are correct and wrong respectively (Figure 4). Note that we convert both LATTE-trace-neg and CoT-neg examples into the direct answer (Direct) format with ground-truth answers (Figure 2) so the final data format is one of LATTE-trace, CoT, and Direct. We experiment with data consisting of only LATTE-trace, LATTE-trace + CoT, LATTE-trace + Direct, and all three formats (Figure 4).

Data source. We also perform filtering based on data sources as Cauldron and Mantis-Instruct cover a wide range of tasks, some of which benefit more from vision specialists than others. To this end, we define LATTE-useless datasets as the ones where GPT-4o either decides to output CoT much more often than LATTE-trace (i.e. % of CoT-pos $-$ LATTE-trace-pos $>$ 10), or reaches wrong answers much more frequently than correct ones when using LATTE-trace (i.e. % LATTE-trace-neg $-$ LATTE-trace-pos $>$ 10) (Figure 4). The remaining datasets are considered LATTE-useful datasets, and we experiment with including all datasets vs. only the LATTE-useful datasets (Figure 4).

Model-generated vs. program-generated data. Due to the lack of controllability, the distribution of actions in model-generated data is highly imbalanced, with a couple of actions such as GETOBJECTS and OCR dominating the dataset. Therefore, we also try increasing action diversity by adding programmatic data involving underrepresented actions such as LOCALIZEOBJECTS, ESTIMATEOBJECTDEPTH and ESTIMATEREGIONDEPTH. We experiment with data mixtures with different ratios of model-generated vs. program-generated data, ranging from 1:1 to 1:0.1.

While the best data recipe varies with the benchmark, one recipe stands out, resulting in consistent gains in the average performance across 6 benchmarks for all 3 models. This dataset consists of 293K LATTE-traces generated by GPT-4o across all 31 data sources.

B. Additional Experimental Details

Baselines. For VPD, since their data and model are not released, we reproduce their data by converting our LATTE-traces into CoTs in VPD's format, where we remove the action calls and add the observations to the reasoning chains. For LLaVa-CoT, we directly use their data to finetune the same model. For VisCoT, since it only has reasoning steps for one data source, training with its data leads to much worse performance. We include its results in the Appendix. For fair comparison, we train our models and baselines with the same model backbone (e.g. Mantis-SigLIP), the same hyperparameters, and the same number of examples.

Training details. We fine-tune models starting from checkpoints at different stages – pretrained and instruction tuned for Mantis-8B-SigLIP-LLaMA-3, and stage 1.5 for LLaVA-OneVision-7B – to investigate where LATTE-traces bring the largest gains. We adopt the hyperparameters from [28, 42] and fine-tune both the language model and the projector with learning rate $= 1e-5$ for 1 epoch with either NVIDIA A100s 40GB or H100s 80GB. We additionally perform hyperparameter tuning with LLaVA-OneVision-7B and vary the tunable components, the language models' learning rate, and number of epochs. We include this result in the Appendix.

Evaluation details. We adapt VLMEvalKit [16] for our evaluation, where an LLM judge (i.e. GPT-4-turbo) is used to score predictions between 0 and 1 compared to the groundtruth short answers for open-ended questions. Additional details about experimental setup can be found in the Appendix.

CVPR
#36

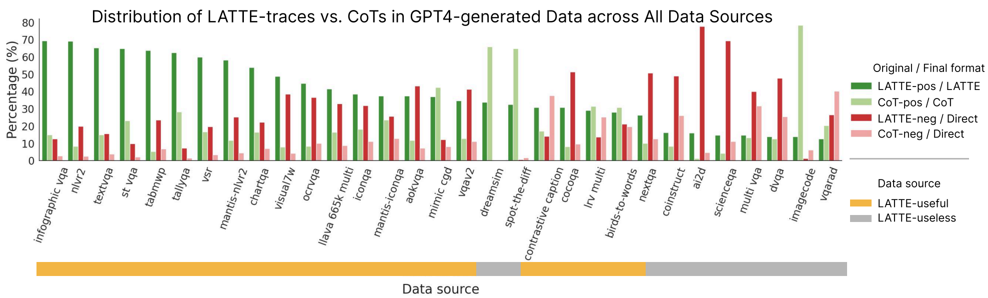


Figure 4. **Distribution of data formats and sources.** We visualize the frequency of data formats (i.e. LATTE-pos/neg, and CoT-pos/neg, pos = correct final answers, neg = incorrect) in the original GPT-4-generated data and in our training data (i.e. LATTE-trace, CoT, or Direct) across all data sources.

C. Additional Results

C.1. Main Results

Table 3. **Perception.** We highlight the large performance gains brought by our method on subsets of the perception benchmarks.

Method	BLINK				CV Bench	
	Relative Depth*	Jigsaw	Multi-view Reasoning	Visual Similarity	2D	3D
Vanilla IT	51.6	51.3	51.1	65.2	38.9	59.4
VPD	46.0	44.0	55.6	59.3	40.4	57.3
LLaVa-CoT	53.2	52.0	54.1	47.4	45.1	35.7
LATTE	**58.1**	**68.7**	**55.6**	**85.2**	**47.8**	**60.2**

Learning to reason with vision specialists allows our model to excel at vision-centric tasks that require fine-grained perception. Taking a closer look at the perception-centric benchmarks, we note that our model does exceptionally well on the subsets that require fine-grained perception such as depth estimation (Table 3). For example, our model scores higher on the Relative Depth subset of BLINK and 3D subset of CV-Bench, most likely because it has learned to utilize the ESTIMATEDEPTH tool. Similarly, learning to use the localization specialists via LOCALIZEOBJECTS enables it to do better on the 2D tasks in CV-Bench by almost 9%; and the image-image and image-text similarity tools boost its performance on Jigsaw, Multi-view reasoning, and Visual Similarity by significant margins of up to 20%.

C.2. Ablations

We perform ablations with both model-generated and programmatic LATTE-traces. For model-generated data, we explore two data filtering techniques to adjust the distribution of (1) data formats and (2) data sources (Figure 4).

Data quality matters more than quantity: our best data recipe is the smallest and yet leads to better performance than other recipes of larger scales. We find that 293K LATTE-traces result in the biggest gain of 4.9% on average over the baseline across all benchmarks (Figure 5). Adding CoT examples results in a smaller gain of 2.6%, even though the training data size almost doubles (Figure 5). On the other hand, combining LATTE-trace and Direct examples hurts the model's performance compared to LATTE-traces only, especially on the perception tasks (Figure 5). This is likely because the mixture makes the model more likely to rely on its own perceptual ability, which is worse than the vision specialists'. We empirically observe that models trained with a mix of LATTE-trace and Direct examples tend to adopt the Direct format more often at inference time. Again, these results suggest that small multi-modal language model's perceptual ability is weak, and learning to reason with specialists helps the most with its performance on perception tasks.

Data sources matter too: including all datasets hurts performance whereas including only LATTE-useful datasets brings performance gains. Similarly, we see that including only the LATTE-useful datasets – where GPT-4o frequently chooses to reason with vision specialists and reach correct final answers – improves the model's average performance compared to the baseline, while including all data sources does not (Table 4). Again, we see that a smaller set of 566K LATTE-traces can lead to better per-

Table 4. **Ablation Results across Data Sources.** We learn that including all data sources hurts model's perception and overall performance while including only LATTE-useful datasets helps.

Data source	Size	Method	Perception	Percept. + Reason.	Overall
All datasets	815K	Vanilla IT	50.7	34.7	42.7
		LATTE	47.7 (-3.0)	35.1 (+0.4)	41.4 (-1.4)
LATTE-useful datasets	566K	Vanilla IT	46.3	33.3	39.8
		LATTE	46.8 (+0.5)	35.6 (+2.3)	41.2 (+1.4)

Table 5. **Ablations on programmatic LATTE-traces.** We find that training with only or additional programmatic LATTE-traces hurts model performance.

M: P	Data format	Size	Perception	Percept. + Reason.	Overall
—	Direct		49.2	34.9	42.0
0:1	P-traces	293K	38.4	15.9	27.2
1:0	M-traces		**52.9**	<u>41.6</u>	**47.2**
1:0.1	+P-traces 29K	322K	47.8	40.1	44.0
1:0.25	+P-traces 73K	366K	50.5	**42.1**	<u>46.3</u>
1:0.5	+P-traces 147K	440K	<u>51.2</u>	39.7	45.5
1:1	+P-traces 293K	586K	50.3	36.2	43.2

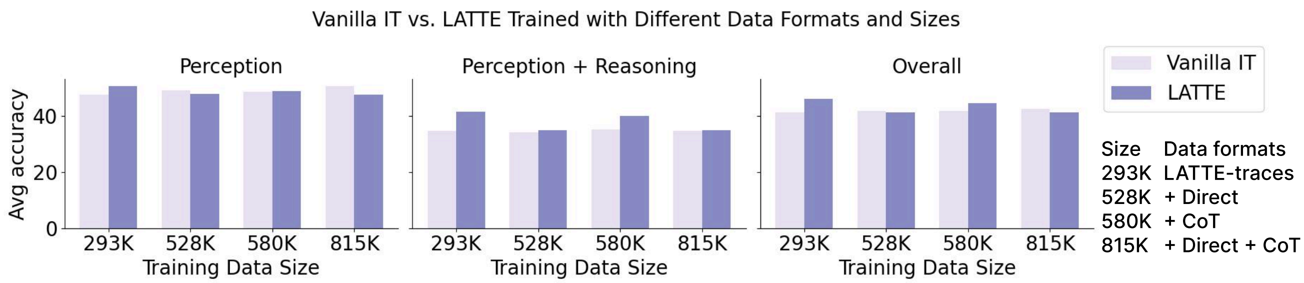


Figure 5. **Ablation Results across Data Formats.** The best data recipe is 293K LATTE-traces, which leads to the greatest gains over Vanilla IT and the highest overall performance. Adding either CoT or Direct doesn't bring additional gains despite the increased data size.

formance than a much larger dataset (815K), implying that data quality matters more than quantity.

Programmatically generated LATTE-traces lead to performance degradations, suggesting that we need both high-quality perceptual information and reasoning to achieve strong performance. We experiment with training with only programmatic LATTE-traces and with a mixture of model-generated and programmatic reasoning traces, with different ratios ranging from 1:0.1 to 1:1. Unfortunately, we find that training with only programmatic LATTE-traces results in large performance drops, and adding programmatic LATTE-traces fails to bring additional gains despite the increase in overall data size (Table 5). This is likely due to the model's weaker reasoning capability learned from templated reasoning traces, which is further validated by qualitative examples (See Appendix). These results suggest that reasoning over perceptual information is a challenging reasoning task that requires high-quality reasoning data for the model to learn well, and that model-generated reasoning traces are a lot more helpful for this task than templated reasoning traces are.

Overall, our experiments suggest that the quality of perceptual information and reasoning are both crucial to our model's superior performance across diverse visual tasks.

C.3. Additional qualitative examples

We present additional successful outputs of LATTE across both single-image and multi-image examples in Figures 8 and 9 as well as failure cases in Figure 10.

C.4. Qualitative error analysis

Why does adding programmatic LATTE-trace help on MathVista but hurt MMVet performance? We observe that adding programmatic LATTE-trace can result in up to 3% gain on MathVista and 9% drop on MMVet. Upon analysis, we discover that programmatic LATTE-trace improves the general VQA split in MathVista the most by almost 9%. This is because LOCALIZE is helpful for these questions, and our programmatic data includes many LOCALIZE instances that allow LATTE to learn to use it effectively (Figure 6). Conversely, programmatic data hurts LATTE's performance on MMVet most likely due to the model's worse reasoning ability as a result of the simple and rigid thoughts generated with templates in our programmatic data (Figure 6).

C.5. Additional quantitative results

We report additional quantitative results of data ablations on Mantis-CLIP in Table 11, where we see the same trends we observe with Mantis-SigLIP: the smallest dataset of 293K LATTE-trace examples leads to the highest absolute performance and gain compared to other datasets with a mix of LATTE-trace, CoT, and/or Direct examples at larger scales.

Table 6. **VisCoT results**

Method	A-OKVQA	BLINK	MathVista	MMMU	MMStar	MMVet	MMVP	RealWorldQA	Avg
VPD-LLaVA	80.7	43.9	35.1	40.8	40.1	40.6	61.3	45.1	48.5
VisCoT-LLaVA	67.9	39.4	12.9	36.1	36.0	26.7	61.3	34.0	39.3

Visual-CoT Performance. We experimentally compare LATTE to Visual-CoT. We finetune Mantis-LLaVA-Pretrained (LLama3+SigLIP) with Visual CoT and compare its performance with LATTE (Table 6). We use 413K examples where the bounding boxes are valid and within the image. We find that the models trained with Visual CoT data achieve an average accuracy of 39.3% (much lower as Visual COT's data are mostly Text/Doc images and contain only bboxes without natural language thoughts) on the benchmarks.

Table 7. **LATTE vs. Direct inference**

Test prompt	A-OKVQA	BLINK	MathVista	MMMU	MMStar	MMVet	MMVP	RealWorldQA	Avg
LATTE	82.1	45.9	37.0	39.8	43.4	46.7	66.0	41.6	50.3
Direct	81.9	46.6	31.2	42.1	39.1	35.0	68.3	40.2	48.0

Performance gain with LATTE inference. We compare the model's performance when trained with a random mix of 293K LATTE-traces and Direct data (1:1) and tested with LATTE format vs. Direct prompt. We find that the model achieves an average of 50.3% when tested following LATTE format vs. 48% with the Direct prompt (Table 7), suggesting that reasoning with vision specialists at inference time improves model's performance.

Hyperparameter tuning Additional gains can be achieved by tuning the vision encoder, training with a smaller learning rate or for more epochs. Last but not least, our hyperparameter tuning experiments with

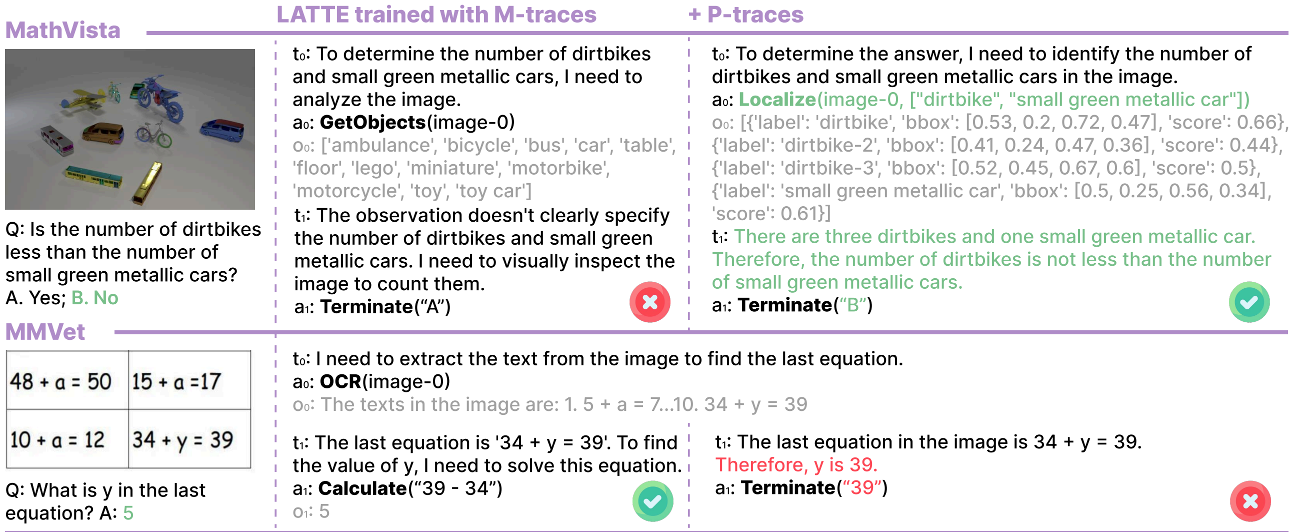


Figure 6. We present examples of LATTE success and failure after adding programmatic data to the fine-tuning dataset.

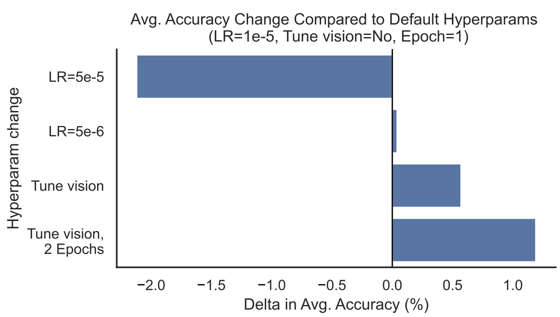


Figure 7. **Hyperparameter ablations.** Additional gains can be achieved with a smaller learning rate for the language model, tuning the vision encoder, and training for more epochs.

LLaVa-OV-Stage1.5 suggest that we can further improve the model's absolute performance by tuning the vision encoder, training with a smaller learning rate and/or for longer epochs (Figure 7).

D. Dataset and model comparison

We summarize the differences between our work and the other CoT datasets including ScienceQA, M^{3}COT, Visual CoT, VPD, and LLaVA-CoT (which is concurrent and unpublished work), in Table 8.

E. Related work

We contexualize our work on language-only and multi-modal tool use and multi-modal language models.

Language-only tool use. Augmenting LLMs with external tools and APIs can significantly enhance their problem-solving capabilities, especially for tasks that require specialized knowledge or interaction with external resources [60]. Examples include web searching [53, 81], mathematical calculations [13, 22], code interpretation [18, 87], and other domain-specific operations that are challenging for LLMs to accomplish solely with their intrinsic knowledge.

Researchers have mainly explored two approaches to enable LLMs to effectively leverage external tools. The first approach is through in-context learning, where instructions on tool usage and contextually relevant examples are provided directly in the prompt [11, 20, 49, 55, 65, 82]. The second approach involves training models to specialize in calling external functions [5, 56, 59, 62, 71, 85]. For instance, Toolformer [62] proposed training LLMs to call APIs precisely to solve complex tasks in a self-supervised manner. More recently, xLAM unified data formats across various environments, and achieved more powerful LLMs specialized in function calling that are also referred to as large *action* models [85]. These works demonstrated the effectiveness of fine-tuning LLMs to execel at calling tools, which inspired our work on tuning multi-modal language models to be multi-modal action models.

Multi-modal tool-use. Unlike language-only tool use, most works in the multi-modal space have only explored training-free methods, which adapt existing LLMs to use multi-modal tools via zero-shot/few-shot prompting [21, 70, 80]. Visprog first demonstrates the potential of leveraging LLMs for visual question answering by prompting them to generate programs of predefined modules for image understanding and manipulation [21]. Simlarly, ViperGPT defines a comprehensive list of APIs and prompts code LLMs to generate Python programs for solving visual queries [70]. In addition to question answering, m&ms further investigated LLMs' abilities in planning and executing open-ended multi-modal tasks with external tools [51]. Beyond LLMs, more recent efforts such as VisualSketchPad

Table 8. **Dataset and model comparison.**

Title	Dataset						Model	
	Training set size	Domains	Data source number	Tools involved in reasoning chain	Multi-image questions?	Multimodal reasoning chain?	Inference-time action calling?	Multi-image support?
Science QA	12.6K	Science	1	✗	✗	✗	✗	✗
M3CoT	7.8K	Science, Math, Commonsense	2	✗	✗	✗	✗	✗
VPD	90K	General, OCR, Compositional, Knowledge, Counting	6	OCR, Object Detection, Depth Estimation, VQA, Captioning, Knowledge	✗	✗	✗	✗
VisualCoT	98K (+340K with bboxes but no thoughts)	General, Doc, Fine-grained, Relation, Chart	12	Localize, Crop	✗	✗	✓	✓
LLaVA-o1	100K	Science, Math, General, Science, Doc	10	✗	✗	✗	✗	✗
LATTE	293K (+over 1M program generated reasoning traces)	Includes all of the above	31	15 tools (see Section 2)	✓	✓	✓	✓

also augmented multi-modal models with external tools and showcased success [24]. However, in-context tool use only works well with powerful proprietary multi-modal models such as GPT-4o; all open-source multi-modal models fail to perform tool use well without fine-tuning.

There are only a few works on training multi-modal models to be better at tool use. LLaVa-Plus was the first work that shows the possibility of training a multi-modal model to use vision specialists [43]. However, it exhibits poor performance due to the weakness of the model backbone and the small scale and suboptimal quality of the data [43]. Visual Program Distillation distills tool-use and reasoning abilities into a multi-modal model with chain-of-thought (CoT) data obtained from programs [23]. Nonetheless, this model is unable to use tools at inference and is limited to simple question answering tasks [23]. Similarly, the more recent work Visual CoT introduces a new synthetic CoT dataset for training multi-modal models for enhanced reasoning [64]. The closest work to ours is CogCoM, which identifies 6 useful manipulations and trains multi-modal models with synthetic chain-of-manipulation (CoM) data [58]. Nonetheless, the manipulations are limited and useful for only detailed visual question answering and visual grounding, and the authors have only experimented with adding 70K CoM data to 500K QA examples. None of these works studied or improved the quantity and quality of these chains to enhance multi-modal models' performance across diverse complex multi-modal tasks, which our work focuses on.

Multi-modal language models. Most recently, there have been many advances made on open-source multi-modal models [2, 3, 6, 7, 9, 10, 12, 14, 26, 34, 37–39, 39–42, 45, 47, 50, 52, 54, 57, 66–69, 72, 74–76, 78]. These efforts include training multi-modal models to take in multiple images, engage in multi-turn conversations, and even understand videos [28, 35, 42]. For example, LLaVA-Next achieves strong multi-image understanding through large-scale interleaved visual instruction tuning with M4-Instruct [42]. Similarly, Mantis introduces a new large-scale multi-image instruction tuning dataset Mantis-Instruct for multi-image training [28]. These efforts pave the foundation for our work on training multi-modal models to learn from multi-image interleaved chains-of-thought-and-action data.

F. Model-based data generation

F.1. Generation prompt

We present the full data generation prompt used in our model-based data generation pipeline in Listing 2.

F.2. Dataset statistics

We present a table with detailed statistics of the LATTE-trace 293K dataset in Table 12.

G. Action implementation

Our Python implementation of all actions can be found in Listing 1.

H. Programmatic data generation

H.1. QA and action templates

We present the question-answer and corresponding action templates used in our programatic data generation in Table 13. We design 16 different question templates for both single-image and multi-image examples that cover 5 capabilities: attribute recognition, counting, 2D and 3D spatial understanding, and multi-image understanding.

H.2. Thought templates

We also present the five thought templates in Listing 3 we define for each action, where one of them is randomly sampled and used during generation.

H.3. Example action distribution

We plot example distributions of all actions before and after adding programmatic LATTE-trace 73K data in Figure 11.

I. Additional training details

We report additional training hyperparameters for Mantis models and LLaVA-OV in Table 9 and 10 respectively.

Table 9. **Additional training hyperparameters for Mantis-SigLIP and Mantis-CLIP.**

Name	Value
bf16	TRUE
tf32	True
per_device_train_batch_size	1
per_device_eval_batch_size	1
gradient_accumulation_steps	16
weight_decay	0
warmup_ratio	0.03
lr_scheduler_type	cosine
lora_enabled	FALSE
qlora_enabled	FALSE
max_seq_len	8192

Table 10. **Additional training hyperparameters for LLaVA-OV.**

Name	Value
bf16	TRUE
tf32	True
mm_vision_tower_lr	2.00E-06
mm_projector_type	mlp2x_gelu
mm_vision_select_layer	-2
image_aspect_ratio	anyres_max_9
image_grid_pinpoints	"(1x1),...,(6x6)"
mm_patch_merge_type	spatial_unpad
per_device_train_batch_size	1
per_device_eval_batch_size	1
gradient_accumulation_steps	16
weight_decay	0
warmup_ratio	0.03
lr_scheduler_type	cosine
model_max_length	8192

J. Additional evaluation details

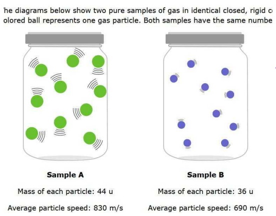
We present additional inference and evaluation details in Table 14 and the LLM judge prompts used for MMVet and MathVista from VLMEvalKit [16] in Listings 4 and 5.

Table 11. **Additional Results on Model-generated data ablations with Mantis-CLIP.** We observe similar results of data ablations on Mantis-CLIP as on Mantis-SigLIP.

Data source	Final data format	Size	Model	A-OKVQA	BLINK	MathVista	MMMU	MMStar	MMVet	MMVP	RealWorldQA	Avg	Delta
All datasets	Direct	293K	Mantis-CLIP	80.7	45.8	33.1	42.2	36.7	28.9	62.7	**52.3**	47.8	
	LATTE-trace		LATTE	81.1	**49.6**	**36.6**	42.8	**40.8**	**45.2**	**63.3**	51.1	**51.3**	**3.5**
	Direct	580K	Mantis-CLIP	82.0	47.2	31.5	40.6	38.3	31.4	**63.3**	49.0	47.9	
	LATTE-trace+ CoT		LATTE	**82.6**	47.7	35.9	38.3	39.6	43.4	61.0	51.1	49.9	2.0
	Direct	815K	Mantis-CLIP	81.0	47.3	32.9	47.3	38.1	29.1	63.0	51.0	48.7	
	LATTE-trace+ CoT+ Direct		LATTE	81.3	43.1	32.7	**48.0**	37.7	31.0	58.7	47.6	47.5	-1.2
LATTE-useful datasets	Direct	566K	Mantis-CLIP	79.1	44.1	30.9	39.4	35.5	30.1	62.7	49.8	46.5	
	LATTE-trace+ CoT+ Direct		LATTE	80.7	41.6	31.5	41.0	38.2	36.1	59.0	48.2	47.0	0.6

Table 12. **Detailed statistics of the LATTE-trace 293K dataset.**

Original Dataset	Subset	Instance #	Max Image #	Avg Image #	Max Turn #	Avg Turn #
Cauldron	ai2d	694	2	1	6	2
	aokvqa	6322	5	1.1	7	2.1
	chartqa	4726	2	1	10	2.1
	cocoqa	13289	3	1.1	4	2
	dvqa	2158	2	1	7	2.5
	iconqa	3791	3	1.1	5	2.2
	infographic_vqa	3822	3	1	9	2.3
	mimic_cgd	6899	6	2.1	7	2.8
	nlvr2	9716	4	2.1	6	2.5
	ocrvqa	22991	2	1	7	2
	scienceqa	850	2	1	6	2.3
	st_vqa	11322	3	1	8	2
	tabmwp	14548	1	1	10	2.5
	tallyqa	16171	3	1.4	5	2.1
	textvqa	15475	5	1	6	2.1
	visual7w	4773	3	1.1	5	2.1
	vqarad	115	2	1	4	2.2
	vqav2	13394	5	1.2	6	2.1
	vsr	1864	2	1.2	4	2.1
Mantis	birds-to-words	742	4	2	5	2.7
	coinstruct	31773	8	2.3	8	2.2
	contrastive_caption	4296	8	3.6	6	2
	dreamsim	1738	3	3	3	2
	iconqa	6660	7	2.6	6	2.2
	imagecode	559	18	10.1	10	3.1
	lrv_multi	3401	9	3.3	6	2.2
	multi_vqa	2089	7	3.8	8	2.6
	nlvr2	5436	4	2	5	2.5
	spot-the-diff	2591	5	2.8	8	3
	nextqa	3057	15	8.2	9	2.3
	llava_665k_multi	77843	11	2.2	10	2.1
Total		293105	18	2.2	10	2.3



Q: Compare the average kinetic energies of the particles in each sample. Which sample has the higher temperature? Sample A or sample B?
A: Sample A

t_0: To determine which sample has a higher temperature, I need to compare the average kinetic energies of the particles in each sample using the formula: KE = 0.5 * m * v^2, where m is the mass and v is the velocity. Since both samples have the same number of particles, the sample with the higher average kinetic energy will have the higher temperature.
a_0: **Calculate**("0.5 * 44 * 830**2")
o_0: 15155800.0
t_1: Now, I need to calculate the average kinetic energy for Sample B to compare.
a_1: **Calculate**("0.5 * 36 * 690**2")
o_1: 8569800.0
t_2: The average kinetic energy for Sample A is 15,155,800, and for Sample B is 8,569,800. Since Sample A has a higher average kinetic energy, it has the higher temperature.
a_2: **Terminate**("Sample A")

Q: Is the trash can empty or full?
A: Empty

t_0: The image shows a trash bin with a hand placing a bag inside. I need to determine if the trash bin is empty or full.
a_0: **GetObjects**(image-0)
o_0: ['bag', 'bin', 'box', 'container', 'dish washer', 'drawer', 'food', 'home appliance', 'person', 'kitchen', 'kitchen counter', 'kitchen sink', 'lid', 'package', 'plastic', 'sink', 'stand', 'woman']
t_1: The observation indicates the presence of a bag and a bin, but it doesn't specify the contents of the bin. Based on the image, the trash bin appears to be empty as there is no visible trash inside.
a_1: **Terminate**("empty")

Q: How to cook this dish?
A: This dish is called "Strawberry Rhubarb Pie". This strawberry rhubarb pie is a favorite springtime dessert in our house...Ingredients: 1 cup white sugar, ½ cup all-purpose flour...2 tablespoons white sugar...Step 1: Preheat oven to 400 degrees F (200 degrees C)...Step 8: Bake at 400 degrees F (200 degrees C), for 35 to 40 minutes, or until bubbly and brown. Cool on rack.

t_0: The image shows a pie, likely a strawberry pie. I need to provide a general recipe for cooking a pie.
a_0: **QueryLanguageModel**("How to cook a strawberry pie?")
o_0: Cooking a strawberry pie is a delightful process, and here's a simple recipe to guide you: Ingredients: For the Pie Crust:\n- 2 ½ cups all-purpose flour\n- 1 cup (2 sticks) unsalted butter, ... ¼ teaspoon salt\n- 2 tablespoons unsalted butter, cut into small pieces...
t_1: I have enough information to provide a general recipe for cooking a strawberry pie.
a_1: **Terminate**("Cooking a strawberry pie involves making a pie crust and filling with strawberries and sugar. Ingredients: For the Pie Crust:\n- 2 ½ cups all-purpose flour\n- 1 cup (2 sticks) unsalted butter, cold and cut into small pieces...For the Filling:- 5 cups fresh strawberries, hulled and halved\n- ¾ cup granulated sugar\n-...9. **Fill the Pie:** Pour the filling into the pie crust")

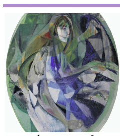


image-0

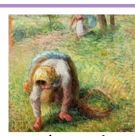



image-1

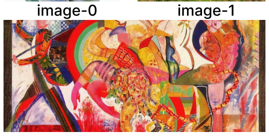



image-2

Q: Given the following images of art paintings, use the first image as the reference image, and determine which one of the second or the third image shares the same style as the reference image? Select from the following choices.
A. the second image
B. the third image

t_0: To determine which image shares the same style as the reference image, I need to analyze the styles of the images.
a_0: **GetImageToImagesSimilarity**("image-0", ["image-1", "image-2"])
o_0: {'best_image': 'image-2', 'best_image_index': 1, 'similarity': [0.49, 0.65]}
t_1: The similarity scores indicate that image-2 is more similar to the reference image than image-1. Therefore, the third image shares the same style as the reference image.
a_1: **Terminate**("B")

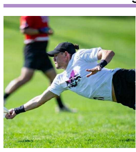


image-0

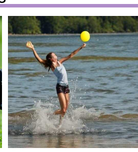



image-1

image-2

image-3

Q: You are a judge in a photography competition, and now you are given the four images. Please examine the details and tell which one of them is most likely to be a real photograph. Select from the following choices.
A. the first image, B. the second image, C. the third image

t_0: To determine which image is most likely a real photograph, I need to analyze the content and context of each image.
a_0: **GetObjects**("image-0")
o_0: ['baseball hat', 'CD', 'dive', 'field', 'floor', 'frisbee', 'game', 'grass', 'person', 'lush', 'man', 'play', 'rugby player', 'tackle']
t_1: The first image shows a person playing a game, likely a sport, on a field. This suggests it is a real photograph. I will now check the other images.
a_1: **GetObjects**("image-1")
o_1: ['ball', 'beach ball', 'frisbee', 'girl', 'jump', 'lake', 'sea', 'play', 'splash', 'throw', 'water', 'woman', 'yellow']
t_2: The second image shows a person playing in water, likely at a beach or lake, which is also a real photograph. I will now check the third image.
a_2: **GetObjects**("image-2")
o_2: ['swimwear', 'bikini', 'bikini top', 'blue', 'girl', 'jump', 'sea', 'water', 'woman']
t_3: The third image shows a person swimming in water, which is also a real photograph. I will now check the fourth image.
a_3: **GetObjects**("image-3")
o_3:['swimwear', 'catch', 'CD', 'frisbee', 'girl', 'jump', 'lake', 'pink', 'play', 'throw', 'water', 'woman']
t_4: All four images depict real-life scenes with people engaging in activities like playing sports or swimming. However, the first image shows a person playing a sport on a field, which is a more typical setting for a real photograph compared to the others.
a_4: **Terminate**("A")

Figure 8. We present additional successful examples of LATTE.

Q: Can the boy reach the highest book?
(A) Yes, (B) No

t_0: To determine if the boy can reach the highest book, I need to analyze the image for the boy's height and the height of the bookshelf.
a_0: **LocalizeObjects**(image-0, ["boy", "bookshelf"])
o_0: [{'label': 'boy', 'bbox': [0.07, 0.48, 0.18, 0.95], 'score': 0.89}, {'label': 'bookshelf', 'bbox': [0.13, 0.01, 0.32, 0.72], 'score': 0.72}]
t_1: The boy's height is below the bookshelf, indicating he cannot reach the highest book.
a_1: **Terminate**("B")

Q: What is the total price for a bottle of Merlot and a bottle of Cabernet shown in the image?
A: $249.98

t_0: I need to extract the prices of the Merlot and Cabernet from the image to calculate the total price.
a_0: **OCR**(image-0)
o_0: Here are the texts from the image: NORTHSTAR MERLOT COLUMBIA VALLEY 3.0 L **139.99**...CHATEAU ST MICHELLE COLD CREEK CABERNET COLUMBIA VALLEY 3.0 L **109.99** ...
t_1: The prices for the Merlot and Cabernet are $139.99 and $109.99, respectively. I can now calculate the total price.
a_1: **Calculate**("139.99 + 109.99")
o_1: 249.98
t_2: The total price for a bottle of Merlot and a bottle of Cabernet is $249.98.
a_2: **Terminate**("$249.98")

Q: I am getting two margherita pizza and one calzone. How much should I pay in total?
A: 25.80

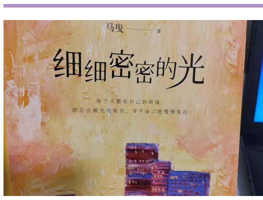
t_0: I need to extract the prices of the margherita pizza and calzone from the image to calculate the total cost.
a_0: **OCR**(image-0)
o_0: The text on the blackboard reads:\n\n**PIZZA**\n\n- Margherita 5.90€\n- Capricciosa 8.50€...Funghi 6.90€\n\n**Calzone 14,00**\n\n**WI-FI FREE inside**'
t_1: The price of a margherita pizza is 5.90€, and the price of a calzone is 14.00€. I need to calculate the total cost for two margherita pizzas and one calzone.
a_1: **Calculate**("2 * 5.90 + 14.00")
o_1: 25.8
t_2: The total cost for two margherita pizzas and one calzone is 25.80€.
a_2: **Terminate**("25.80€")

Q: How many yellow stars are on a colorful bridge?
A. 4, B. 3, C. 2, D. 1

t_0: To determine the number of yellow stars on the bridge, I need to analyze the image for stars.
a_0: **GetObjects**(image-0)
o_0: ['building', 'car', 'christmas light', 'city', 'city street', 'light', 'night', 'night view', 'tower', 'road', 'street scene']
t_1: The object detection did not identify yellow stars specifically. I need to visually inspect the image to count the yellow stars on the bridge.
a_1: N/A
o_1: N/A
t_2: I need to visually inspect the image to count the yellow stars on the bridge.
a_2: **LocalizeObjects**(image-0, "star")
o_2: [{'label': 'star', 'bbox': [0.84, 0.56, 0.87, 0.6], 'score': 0.56}, {'label': 'star-2', 'bbox': [0.53, 0.63, 0.56, 0.66], 'score': 0.5}]}
t_3: The image shows two stars detected on the bridge. This matches option C.
a_3: **Terminate**("C")

Q: Can you give a short introduction to this painting?
A: The Arnolfini Portrait (or The Arnolfini Wedding, The Arnolfini Marriage, the Portrait of Giovanni Arnolfini and his Wife, or other titles) is a 1434 oil painting on oak panel by the Early Netherlandish painter Jan van Eyck. It forms a full-length double portrait, believed to depict the Italian merchant Giovanni di Nicolao Arnolfini and his wife, presumably in their residence at the Flemish city of Bruges.

t_0: I can provide information about the painting based on general knowledge.
a_0: **QueryKnowledgeBase**("The Arnolfini Portrait")
o_0: "The Arnolfini Portrait (or The Arnolfini Wedding) is an oil painting on oak panel by the Early Netherlandish painter Jan van Eyck, dated 1434 and now in the National Gallery, London. It is a full-length double portrait, believed to depict the Italian merchant Giovanni di Nicolao Arnolfini and his wife, presumably in their residence at the Flemish city of Bruges. (url: https://en.wikipedia.org/wiki/Arnolfini_Portrait)
t_1: I have enough information to provide a short introduction to the painting.
a_1: **Terminate**("The Arnolfini Portrait is a full-length double portrait by Jan van Eyck, depicting Giovanni di Nicolao Arnolfini and his wife in their residence at Bruges. It is an oil painting on oak panel, dated 1434, and is now in the National Gallery, London")



Q: What are all the Chinese scene text in the image?
A: 马曳<AND>著<AND>每个人都有自己的困境<AND>但总会被光亮吸引<AND>身不由己地慢慢靠近

t_0: I need to extract the text from the image to identify the Chinese scene text.
a_0: **OCR**(image-0)
o_0: The text in the image is:\n\n马叙 —— 著 \n细细密密的光 \n\n每个人都有自己的困境， \n却总会被光亮吸引，身不由己地慢慢靠近
t_1: The extracted text provides the Chinese scene text from the image.
a_1: **Terminate**("细细密密的光\n每个人都有自己的困境，\n却总会被光亮吸引，身不由己地慢慢靠近。")

Figure 9. We present additional successful examples of LATTE.

Q: From which angle is this image taken?
A. Front, B. Side

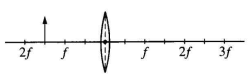
t_0: To determine the angle of the image, I need to analyze the perspective and orientation of the snake.
a_0: **GetObjects**(image-0)
o_0: ['branch', 'green', 'log', 'reptile', 'sit', 'snake', 'stool', 'tail', 'tree', 'tree branch', 'tree trunk', 'twig']
t_1: The image shows a snake from a side view, as the snake's body is visible from the side rather than directly facing the camera.
a_1: **Terminate**("B")

Q: Is the wind blowing the flag?
A. Yes, B. No

t_0: To determine if the wind is blowing the flag, I need to analyze the image for signs of movement or distortion in the flag.
a_0: **GetObjects**(image-0)
o_0: ['blue', 'flag', 'flag pole', 'fly', 'mast', 'pole', 'sky', 'wave', 'wind']}
t_1: The presence of 'wind' and 'wave' in the detected objects suggests that the flag is indeed being blown by the wind.
a_1: **Terminate**("A")

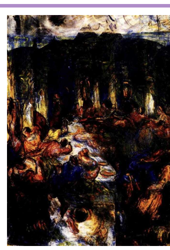
Q: Which type of eggs are in the corner of the picture?
A. Quail eggs, B. Chicken eggs

t_0: To determine the type of eggs in the corner of the image, I need to analyze the visual characteristics of the eggs.
a_0: **GetObjects**(image-0)
o_0: ['bakery', 'bread', 'butter', 'table', 'dip', 'dough', 'flour', 'food', 'hummus', 'pastry', 'platter', 'tray', 'type']
t_1: The object detection did not identify the eggs specifically. However, based on the visual characteristics of the eggs in the image, they appear to be quail eggs due to their small size.
a_1: **Terminate**("A")



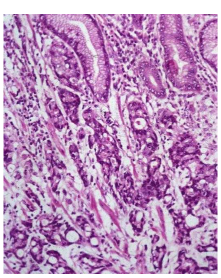
Q: An object is placed at a distance of 1.5f from a converging lens of focal length f, as shown. What type of image is formed and what is its size relative to the object? Type/Size
A. Virtual/Larger
B. Virtual/Same size
C. Real/Smaller
D. Real/Larger

t_0:To determine the type and size of the image formed, we need to analyze the position of the object relative to the focal length.", "actions": [{"name": "", "arguments": {"query": ""}}]}
a_0: **QueryLanguageModel**("What type of image is formed when an object is placed at a distance of 1.5f from a converging lens of focal length f?")
o_0: When an object is placed at a distance of 1.5 times the focal length (1.5f) from a converging lens, the lens forms a real, inverted, and magnified image...Additionally, to find the magnification \\(m \\), we use:\n\n\\[\nm = \\frac{v}{u} = \\frac{\\frac{3f}{5}}{1.'}
t_1: The image is real and inverted, and the magnification indicates that the image size is larger than the object.
a_1: **Terminate**("A")



Q: Who created this image?
A. PAUL CÉZANN, B. EDVARD MUNCH, C. EDGAR DEGAS, D. ANDY WARHOL

t_0: To determine the creator of the artwork in image-0, I need to analyze its style and characteristics.
a_0: **QueryLanguageModel**("Who created the painting with a dark, expressive style often associated with emotional intensity?")
o_0: The painting style you're describing sounds like it could be associated with several artists, but one of the most prominent figures known for a dark, expressive style and emotional intensity is Edvard Munch. His famous painting "The Scream" epitomizes such characteristics...'}
t_1: Based on the description of a dark, expressive style often associated with emotional intensity, Edvard Munch is the most likely creator.
a_1: Terminate("B")



Q: The picture shows the microscopy of Mr Tan's gastric tumour. Which of the following statements is CORRECT?
A. The findings show an adenoma
B. The findings show a squamous cell carcinoma
C. The findings show intestinal type adenocarcinoma
D. The findings show diffuse signet ring cell adenocarcinoma the Flemish city of Bruges.

t_0: To determine the correct statement, I need to analyze the microscopic features in the image.
a_0: **QueryLanguageModel**("What are the microscopic features of adenoma, squamous cell carcinoma, intestinal type adenocarcinoma, and diffuse signet ring cell adenocarcinoma?")
o_0: "The microscopic features of the mentioned conditions are distinct and reflective of their pathological origins: 1. **Adenoma**: - **Architectural Features**: Typically show glandular structures with some degree of dysplasia...3. **Intestinal Type Adenocarcinoma**: - **Architectural Features**: Gland-forming neoplasm with varying degrees of differentiation...'})
t_1: The image shows a gastric tumour with specific architectural and cellular features. Based on the options, diffuse signet ring cell adenocarcinoma is known for its distinct signet ring cells, which may be present in the image.
a_1: **Terminate**("D")

Figure 10. We present additional failure cases of LATTE.

Table 13. **Templates for programmatic data generation.**

# of input images	Capabilities	Question Template	Action Template
1	Counting	How many {object} are there? Among {objects}, which is the most frequent object? Among {objects}, which object appears the least?	LocalizeObjects
	Counting, Attribute recognition	How many {attribute} {object} are there?	
	2D spatial reasoning	Among {objects}, which is on the most left side? Among {objects}, which is on the most right side? Among {objects}, which is on the most top side? Among {objects}, which is on the most bottom side?	
	3D spatial reasoning	Which of {objects} is closer? Which of {objects} is farther?	LocalizeObjects, EstimateRegionDepth x2 OR, EstimateObjectDepth x2
2-3	Multi-image understanding Multi-image understanding, Counting Multi-image understanding, Counting Multi-image understanding, Counting Multi-image understanding, Attribute recognition Multi-image understanding, Attribute recognition, Counting	Which image has {object}? How many {object} are in in these images? Which image has most {object}? Which image has least {object}? Which image has {attribute} {object}? How many {attribute} {object} in these images?	LocalizeObjects x N

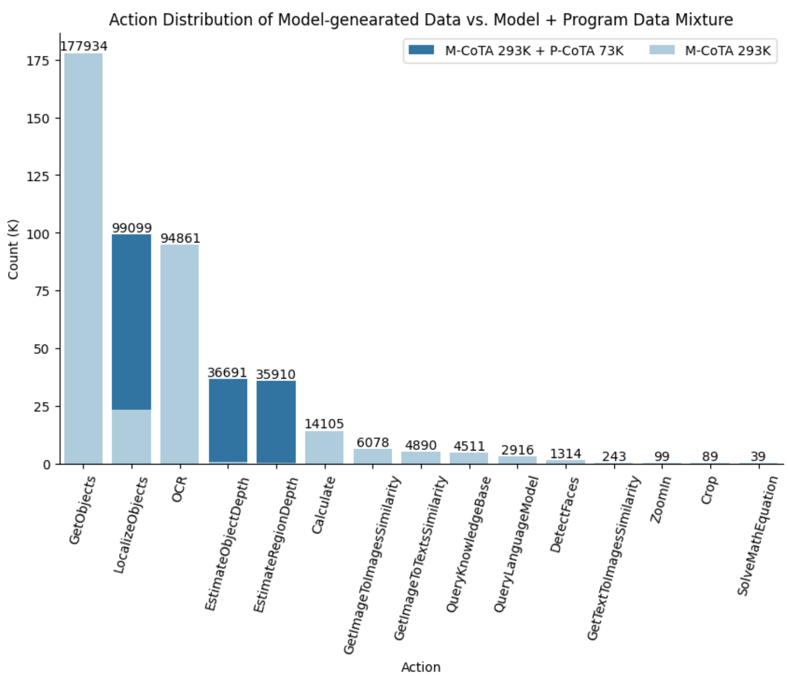


Figure 11. Action distribution of model-generated data vs. model and program data mixtures.

Table 14. **Additional inference and evaluation details.**

Stage	Name	Value
Inference	do_sample temperature max_new_tokens max_consecutive_auto_reply	FALSE 0 2000 10
Evaluation	llm judge for multiple choice & yes/no questions llm judge for short answer questions (i.e. MMVet, MathVista) llm judge max_new_tokens llm judge retry	gpt-3.5-turbo-0125 gpt-4-1106-preview 2048 5

```python
class BaseAction:
    """
    This is the Action class for agent to use.
    Using this Action class to wrap APIs, tools, models as an Action of an agent
    """

    def __init__(
        self,
        id: int,
        description: str = "",
        args_spec: dict = {},
        rets_spec: dict = {},
        examples: List = []
    ) -> None:
        """
        the agent action should be connected with data and env
        Args:
            id: the id of the action
            description: the description of the action
            args_spec: the specification of the arguments
            rets_spec: the specification of the returns
            examples: a list of examples of the action
        """
        self.name = self.__class__.__name__
        self.id = id
        self.description = description
        self.args_spec = args_spec
        self.rets_spec = rets_spec
        self.examples = examples
        self.device = "cuda:0" if torch.cuda.is_available() else "cpu"

    def __call__(self, **kwargs) -> str:
        """
        implement the Action as
        """
        raise NotImplementedError


class OCR(BaseAction):
    def __init__(self, id) -> None:
        description = "Extract texts from an image or return an empty string if no text is in the image
    . Note that the texts extracted may be incorrect or in the wrong order. It should be used as a
    reference only."
        args_spec = {"image": "the image to extract texts from."}
        rets_spec = {"text": "the texts extracted from the image."}
        examples = [{"name": "OCR", "arguments": {"image": "image-0"}}]

        super().__init__(
            id=id, description=description, args_spec=args_spec, rets_spec=rets_spec, examples=examples
        )

    def __call__(self, image, tool_version=LATEST_GPT_MODEL_ID):
        if tool_version == "easyocr":
            import easyocr
            import io
            reader = easyocr.Reader(["en"])  # Load the OCR model into memory
            image = image_processing(image)
            if isinstance(image, str):
                # If image is a path, use it directly
                image_path_or_bytes = (
                    image if os.path.exists(image) else get_full_path_data(image)
                )
            else:
                # If image is an Image object, convert it to a bytes stream
                buffer = io.BytesIO()
                image.save(buffer, format="JPEG")
                buffer.seek(0)
```

```
                image_path_or_bytes = buffer

            result = reader.readtext(image_path_or_bytes)
            result_text = [text for _, text, _ in result]
            result_formatted = {"text": ", ".join(result_text)}
        else:
            from openai import OpenAI
            import base64
            client = OpenAI(api_key=os.getenv("OPENAI_API_KEY"))

            def encode_image(image_path):
                with open(image_path, "rb") as image_file:
                    return base64.b64encode(image_file.read()).decode('utf-8')

            image_path = image_processing(image, return_path=True)
            base64_image = encode_image(image_path)

            response = client.chat.completions.create(
                model=tool_version,
                messages=[
                    {
                        "role"   : "user",
                        "content": [
                            {"type": "text", "text": f"What are the texts in the image?"},
                            {
                                "type"     : "image_url",
                                "image_url": {
                                    "url": f"data:image/jpeg;base64,{base64_image}",
                                },
                            },
                        ],
                    }
                ],
                max_tokens=300,
            )
            result_formatted = {"text": response.choices[0].message.content}

        return result_formatted


class GetObjects(BaseAction):
    def __init__(self, id) -> None:
        description = "Using this function to get objects in an image."
        args_spec = {"image": "the image to get objects from."}
        rets_spec = {"objects": "the objects detected in the image."}
        examples = [{"name": "GetObjects", "arguments": {"image": "image-0"}}]

        super().__init__(
            id=id, description=description, args_spec=args_spec, rets_spec=rets_spec, examples=examples
        )

    def __call__(self, image, tool_version="https://huggingface.co/xinyu1205/recognize-anything-plus-model/resolve/main/ram_plus_swin_large_14m.pth?download=true"):
        from ram.models import ram_plus
        from ram import get_transform, inference_ram_openset as inference

        model_path_or_url = tool_version
        image_size = 384
        transform = get_transform(image_size=image_size)

        vit_size = "swin_l"
        # load model
        model = ram_plus(pretrained=model_path_or_url,
                         image_size=image_size,
                         vit=vit_size)
        model.eval()
        model = model.to(self.device)
```

```python
        image = image_processing(image)
        image = transform(image).unsqueeze(0).to(self.device)
        tags = inference(image, model)
        objs = tags.split(" | ")
        return {"objects": objs}


class VisualizeRegionsOnImage(BaseAction):
    def __init__(self, id) -> None:
        description = "Using this function to label regions on an image."
        args_spec = {"image": "the image to label.",
                     "regions": "the regions to label on the image, where each region is represented by a dictionary with the region's bounding box and label text (can be empty string).",
                     "color": "an optional argument that specifies the color of the bounding box."
                    }
        rets_spec = {"image": "the image with regions labeled."}
        examples = [
            {"name": "VisualizeRegionsOnImage", "arguments": {"image": "image-0", "regions": [{"label": "", "bbox": [0.3, 0.2, 0.5, 0.4]}]}},
            {"name": "VisualizeRegionsOnImage", "arguments": {"image": "image-0", "regions": [{"label": "cat", "bbox": [0.3, 0.2, 0.5, 0.4]}], "color": "red"}}
        ]

        super().__init__(
            id=id, description=description, args_spec=args_spec, rets_spec=rets_spec, examples=examples
        )

    def __call__(self, image, regions: List[Region], color='yellow', width=4):
        image = image_processing(image)
        text_color = 'black'
        W,H = image.size
        img1 = image.copy()
        draw = ImageDraw.Draw(img1)
        font = ImageFont.truetype('/usr/share/fonts/truetype/dejavu/DejaVuSansMono-Bold.ttf', 16)
        for i, obj in enumerate(regions):
            bbox = obj['bbox']
            bbox = bbox[0] * W, bbox[1] * H, bbox[2] * W, bbox[3] * H
            draw.rectangle(bbox, outline=color, width=width)
            x1, y1, x2, y2 = bbox
            label = obj['label'] if "label" in obj else ""
            w,h = font.getsize(label)
            if x1 + w > W or y2  +h > H:
                draw.rectangle((x1, y2 - h, x1 + w, y2), fill=color)
                draw.text((x1, y2-h),label,fill=text_color,font=font)
            else:
                draw.rectangle((x1, y2, x1 + w, y2 + h), fill=color)
                draw.text((x1, y2),label,fill=text_color,font=font)
        return {"image": img1}


class LocalizeObjects(BaseAction):
    def __init__(self, id) -> None:
        description = "Localize one or multiple objects/regions with bounding boxes. This tool may output objects that don't exist or miss objects that do. You should use the output only as weak evidence for reference. When answering questions about the image, you should double-check the detected objects. You should be especially cautious about the total number of regions detected, which can be more or less than the actual number."
        args_spec = {
            "image": "the image to localize objects/regions in.",
            "objects": "a list of object names to localize. e.g. ['dog', 'cat', 'person']. the model might not be able to detect rare objects or objects with complex descriptionriptions."
        }
        rets_spec = {"image": "the image with objects localized and visualized on it.", "regions": "the regions of interests localized in the image, where each region is represented by a dictionary with the region's label text, bounding box and confidence score. The confidence score is between 0 and 1, where 1 means the model is very confident. Note that both the bounding boxes and confidence scores can be unreliable and should only be used as reference."}
```

```python
        examples = [{"name": "LocalizeObjects", "arguments": {"image": "image-0", "objects": ["dog", "cat"]}}]

        super().__init__(
            id=id, description=description, args_spec=args_spec, rets_spec=rets_spec, examples=examples
        )

    def __call__(self, image, objects: List[str]):
        from groundingdino.util.inference import load_model, load_image, predict, annotate
        import cv2
        text = ". ".join(objects)
        model = load_model("/user/mma/mma/GroundingDINO/groundingdino/config/GroundingDINO_SwinT_OGC.py",
                           "/user/mma/mma/GroundingDINO/weights/groundingdino_swint_ogc.pth",
                           device=self.device)
        BOX_TRESHOLD = 0.35
        TEXT_TRESHOLD = 0.25
        image_path = image_processing(image, return_path=True)
        original_image = image_processing(image)
        image_source, image = load_image(image_path)

        boxes, logits, phrases = predict(
            model=model,
            image=image,
            caption=text,
            box_threshold=BOX_TRESHOLD,
            text_threshold=TEXT_TRESHOLD
        )

        objects = []
        obj_cnt = {}
        for i in range(len(boxes)):
            xyxy = box_convert(boxes=boxes[i], in_fmt="cxcywh", out_fmt="xyxy").numpy()
            bbox = [round(val, 2) for val in list(xyxy)]
            score = round(logits[i].item(), 2)
            phrase = phrases[i]
            obj_cnt[phrase] = obj_cnt.get(phrase, 0) + 1
            phrase = f"{phrase}-{obj_cnt[phrase]}" if obj_cnt[phrase] > 1 else phrase
            objects.append({"label": phrase, "bbox": bbox, "score": score})
        visualize = VisualizeRegionsOnImage(0)
        results = visualize(image=original_image, regions=objects)
        tagged_image = results["image"]
        results_formatted = {"regions": objects, "image": tagged_image}
        return results_formatted


class Crop(BaseAction):
    def __init__(self, id) -> None:
        description = "Crop an image with the bounding box. It labels the cropped region with a bounding box and crops the region with some margins around the bounding box to help with contextual understanding of the region."
        args_spec = {
            "image": "the image to crop.",
            "bbox": "the bbox to crop. It should be a list of [left, top, right, bottom], where each value is a float between 0 and 1 to represent the percentage of the image width/height and how far it is from the top left corner at [0, 0].",
        }
        rets_spec = {"image": "the cropped image."}
        examples = [{"name": "Crop", "arguments": {"image": "image-0", "bbox": [0.33, 0.21, 0.58, 0.46]}}]

        super().__init__(
            id=id, description=description, args_spec=args_spec, rets_spec=rets_spec, examples=examples
        )

    def __call__(self, image, bbox):
        image = image_processing(image)
```

```python

        if isinstance(bbox, str):
            try:
                bbox = ast.literal_eval(bbox)
            except:
                bbox = []

        use_percent = (all(x <= 1.0 for x in bbox))
        if not use_percent:
            raise ValueError("Bounding box coordinates must be between 0 and 1.")

        visualize = VisualizeRegionsOnImage(0)
        results = visualize(image=image, regions=[{"label": "", "bbox": bbox}])
        image = results["image"]

        W, H = image.size
        bbox = [bbox[0] * W, bbox[1] * H, bbox[2] * W, bbox[3] * H]
        bbox = expand_bbox(bbox, image.size)
        out_img = image.crop(bbox)
        return {"image": out_img}


class ZoomIn(BaseAction):
    def __init__(self, id) -> None:
        description = "Zoom in on a region of the input image. This tool first crops the specified region from the image with the bounding box and then resizes the cropped region to create the zoom effect. It also adds some margins around the cropped region to help with contextual understanding of the region."
        args_spec = {
            "image": "the image to zoom in on.",
            "bbox": "The bbox should be a list of [left, top, right, bottom], where each value is a float between 0 and 1 to represent the percentage of the image width/height and how far it is from the top left corner at [0, 0].",
            "zoom_factor": "the factor to zoom in by. It should be greater than 1.",
        }
        rets_spec = {"image": "the zoomed in image."}
        examples = [
            {"name": "ZoomIn", "arguments": {"image": "image-0", "bbox": [0.4, 0.3, 0.5, 0.4], "zoom_factor": 2}},
        ]

        super().__init__(
            id=id, description=description, args_spec=args_spec, rets_spec=rets_spec, examples=examples
        )

    def __call__(self, image, bbox, zoom_factor):
        if zoom_factor <= 1:
            raise ValueError("Zoom factor must be greater than 1 to zoom in")

        image = image_processing(image)
        use_percent = (all(x <= 1.0 for x in bbox))
        if not use_percent:
            raise ValueError("Bounding box coordinates must be between 0 and 1.")

        crop = Crop(0)
        cropped_image = crop(image, bbox)["image"]

        W, H = cropped_image.size

        # Calculate the size of the zoomed image
        new_width = int(W * zoom_factor)
        new_height = int(H * zoom_factor)

        # Resize the cropped image to create the zoom effect
        zoomed_image = cropped_image.resize((new_width, new_height), Image.LANCZOS)
        return {'image': zoomed_image}

```

```python

class GetImageToImagesSimilarity(BaseAction):
    def __init__(self, id) -> None:
        description = "Get the similarity between one image and a list of other images. Note that this similarity score may not be accurate and should be used as a reference only."
        args_spec = {
            "image": "the reference image.",
            "other_images": "the other images to compare to the reference image.",
        }
        rets_spec = {"similarity": "the CLIP similarity scores between the reference image and the other images.", "best_image_index": "the index of the most similar image."}
        examples = [
            {"name": "GetImageToImagesSimilarity", "arguments": {"image": "image-0", "other_images": ["image-1", "image-2"]}}
        ]

        super().__init__(
            id=id, description=description, args_spec=args_spec, rets_spec=rets_spec, examples=examples
        )

    def __call__(self, image, other_images, tool_version=’ViT-H-14-378-quickgelu’, other_images_raw=None):
        import torch
        import open_clip
        original_images = other_images_raw
        model, _, preprocess = open_clip.create_model_and_transforms(tool_version, pretrained=’dfn5b’)
        model.eval()
        image = image_processing(image)
        images = [image_processing(image) for image in other_images]

        image = preprocess(image).unsqueeze(0)
        images = torch.stack([preprocess(image) for image in images])

        with torch.no_grad(), torch.cuda.amp.autocast():
            image1_features = model.encode_image(image)
            image2_features = model.encode_image(images)

            image1_features /= image1_features.norm(dim=-1, keepdim=True)
            image2_features /= image2_features.norm(dim=-1, keepdim=True)

            probs = image1_features @ image2_features.T
        sim_scores = [round(sim_score, 2) for sim_score in probs[0].tolist()]
        best_image_match = torch.argmax(probs).item()
        return {’similarity’: sim_scores, "best_image_index": best_image_match, "best_image": original_images[best_image_match]}


class GetImageToTextsSimilarity(BaseAction):
    def __init__(self, id) -> None:
        description = "Get the similarity between one image and a list of texts. Note that this similarity score may not be accurate and should be used as a reference only."
        args_spec = {
            "image": "the reference image.",
            "texts": "a list of texts to compare to the reference image.",
        }
        rets_spec = {"similarity": "the CLIP similarity between the image and the texts.", "best_text_index": "the index of the most similar text.", "best_text": "the most similar text."}
        examples = [
            {"name": "GetImageToTextsSimilarity", "arguments": {"image": "image-0", "texts": ["a cat", "a dog"]}}
        ]

        super().__init__(
            id=id, description=description, args_spec=args_spec, rets_spec=rets_spec, examples=examples
        )

    def __call__(self, image, texts, tool_version=’ViT-H-14-378-quickgelu’):
```

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```
        import torch
        import open_clip

        model, _, preprocess = open_clip.create_model_and_transforms(tool_version, pretrained='dfn5b')
        model.eval()  # model in train mode by default, impacts some models with BatchNorm or stochastic depth active
        tokenizer = open_clip.get_tokenizer(tool_version)

        image = preprocess(image_processing(image)).unsqueeze(0)
        text = tokenizer(texts)

        with torch.no_grad(), torch.cuda.amp.autocast():
            image_features = model.encode_image(image)
            text_features = model.encode_text(text)
            image_features /= image_features.norm(dim=-1, keepdim=True)
            text_features /= text_features.norm(dim=-1, keepdim=True)

            probs = image_features @ text_features.T
        sim_scores = [round(sim_score, 2) for sim_score in probs[0].tolist()]
        best_text_match = torch.argmax(probs).item()
        return {'similarity': sim_scores, "best_text_index": best_text_match, "best_text": texts[best_text_match]}


class GetTextToImagesSimilarity(BaseAction):
    def __init__(self, id) -> None:
        description = "Get the similarity between one text and a list of images. Note that this similarity score may not be accurate and should be used as a reference only."
        args_spec = {
            "text": "the reference text.",
            "images": "a list of images to compare to the reference text.",
        }
        rets_spec = {"similarity": "the CLIP similarity between the image and the texts.", "best_image_index": "the index of the most similar image."}
        examples = [
            {"name": "GetTextToImagesSimilarity", "arguments": {"text": "a black and white cat", "images": ["image-0", "image-1"]}}
        ]

        super().__init__(
            id=id, description=description, args_spec=args_spec, rets_spec=rets_spec, examples=examples
        )

    def __call__(self, text, images, tool_version='ViT-H-14-378-quickgelu'):
        import torch
        import open_clip
        original_images = images
        model, _, preprocess = open_clip.create_model_and_transforms(tool_version, pretrained='dfn5b')
        model.eval()  # model in train mode by default, impacts some models with BatchNorm or stochastic depth active
        tokenizer = open_clip.get_tokenizer(tool_version)

        text = tokenizer([text])
        images = [image_processing(image) for image in images]
        images = torch.stack([preprocess(image) for image in images])

        with torch.no_grad(), torch.cuda.amp.autocast():
            image_features = model.encode_image(images)
            text_features = model.encode_text(text)
            image_features /= image_features.norm(dim=-1, keepdim=True)
            text_features /= text_features.norm(dim=-1, keepdim=True)

            probs = text_features @ image_features.T
        sim_scores = [round(sim_score, 2) for sim_score in probs[0].tolist()]
        best_image_match = torch.argmax(probs).item()
        return {'similarity': sim_scores, "best_image_index": best_image_match, "best_image": original_images[best_image_match]}
```

```python


class EstimateObjectDepth(BaseAction):
    def __init__(self, id) -> None:
        description = "Estimate the depth of an object in an image using DepthAnything model. It returns an estimated depth value of the object specified by the a brief text description. The smaller the value is, the closer the object is to the camera, and the larger the farther. This tool may help you to better reason about the spatial relationship, like which object is closer to the camera."
        args_spec = {
            "image": "the image to get the depth from.",
            "object": "a short description of the object to get the depth from.",
        }
        rets_spec = {"depth": "the estimated depth of the object."}
        examples = [
            {"name": "EstimateObjectDepth", "arguments": {"image": "image-0", "object": "a black cat"}},
        ]

        super().__init__(
            id=id, description=description, args_spec=args_spec, rets_spec=rets_spec, examples=examples
        )

    def __call__(self, image, object, mode="mean"):
        action = LocalizeObjects(0)
        results = action(image=image, objects=[object])
        if len(results["regions"]) == 0:
            return {"depth": "Object not found."}
        else:
            # use the best match object's bbox
            best_match = np.argmax([region["score"] for region in results["regions"]])
            bbox = results["regions"][best_match]["bbox"]
            depth_estimator = EstimateRegionDepth(0)
            return depth_estimator(image=image, bbox=bbox, mode=mode)


class EstimateRegionDepth(BaseAction):
    def __init__(self, id) -> None:
        description = "Estimate the depth of a region in an image using DepthAnything model. It returns an estimated depth value of the region specified by the input bounding box. The smaller the value is, the closer the region is to the camera, and the larger the farther. This tool may help you to better reason about the spatial relationship, like which object is closer to the camera. "
        args_spec = {
            "image": "the image to get the depth from.",
            "bbox": "the bbox of the region to get the depth from. It should be a list of [left, top, right, bottom], where each value is a float between 0 and 1 to represent the percentage of the image width/height and how far it is from the top left corner at [0, 0].",
            # "mode": "the mode to get the depth. It should be one of 'center' or 'average'. 'center' returns the depth of the center of the region. 'average' returns the average depth of the region.",
        }
        rets_spec = {"depth": "the estimated depth of the region."}
        examples = [
            {"name": "EstimateRegionDepth", "arguments": {"image": "image-0", "bbox": [0.3, 0.2, 0.5, 0.4]}},
        ]
        super().__init__(
            id=id, description=description, args_spec=args_spec, rets_spec=rets_spec, examples=examples
        )

    def __call__(self, image, bbox: List[str], mode="mean"):
        import numpy as np
        from scipy import stats
        image = image_processing(image)
        depth_model = pipeline(task="depth-estimation", model="depth-anything/Depth-Anything-V2-Small-hf", device=self.device)
        result = depth_model(image)
        depth = result["predicted_depth"][0].numpy()
```

```
        depth = depth.max() - depth # smaller values in depth map are farther from the camera so
    reversing the values
        H, W = depth.shape

        use_percent = all(x <= 1.0 for x in bbox)
        if not use_percent:
            raise ValueError("Bounding box coordinates must be between 0 and 1.")
        bbox = [bbox[0] * W, bbox[1] * H, bbox[2] * W, bbox[3] * H]
        if mode == "center":
            x, y = (bbox[0] + bbox[2]) / 2, (bbox[1] + bbox[3]) / 2
            x, y = int(x), int(y)
            depth_value = depth[y, x]
        elif mode == "mean":
            x1, y1, x2, y2 = bbox
            x1, y1, x2, y2 = int(x1), int(y1), int(x2), int(y2)
            depth_value = np.mean(depth[y1:y2, x1:x2])
        elif mode == "mode":
            x1, y1, x2, y2 = bbox
            x1, y1, x2, y2 = int(x1), int(y1), int(x2), int(y2)
            mode_result = stats.mode(depth[y1:y2, x1:x2])
            depth_value = mode_result.mode[0]
        else:
            raise NotImplementedError(f"Depth mode {mode} is not supported.")
        return {"depth": round(depth_value, 2)}


class Calculate(BaseAction):
    def __init__(self, id) -> None:
        description = "Calculate a math expression."
        args_spec = {"expression": "the math expression to calculate."}
        rets_spec = {"result": "the result of the math expression."}
        examples = [
            {"name": "Calculate", "arguments": {"expression": "2 + 2"}},
            {"name": "Calculate", "arguments": {"expression": "4*9*84"}},
            {"name": "Calculate", "arguments": {"expression": "5-4/2"}},
        ]

        super().__init__(
            id=id, description=description, args_spec=args_spec, rets_spec=rets_spec, examples=examples
        )

    def __call__(self, expression):
        result = eval(expression)
        return {"result": result}


class SolveMathEquation(BaseAction):
    def __init__(self, id) -> None:
        description = "Using this action to solve a math problem with WolframAlpha."
        args_spec = {"query": "a question that involves a math equation to be solved."}
        rets_spec = {"result": "the result of the query."}
        examples = [
            {"name": "SolveMathEquation", "arguments": {"query": "2 + 2=?"}},
            {"name": "SolveMathEquation", "arguments": {"query": "x^2 + 2x + 1 = 0, what is x?"}},
        ]

        self.client = wolframalpha.Client(os.getenv("WOLFRAM_ALPHA_API_KEY"))
        super().__init__(
            id=id, description=description, args_spec=args_spec, rets_spec=rets_spec, examples=examples
        )

    def __call__(self, query):
        from urllib.error import HTTPError

        is_success = False

        res = self.client.query(query)
```

```python

        if not res["@success"]:
            return (
                "Your Wolfram query is invalid. Please try a new query for wolfram.",
                is_success,
            )
        assumption = next(res.pods).text
        answer = ""
        for result in res["pod"]:
            if result["@title"] == "Solution":
                answer = result["subpod"]["plaintext"]
            if result["@title"] == "Results" or result["@title"] == "Solutions":
                for i, sub in enumerate(result["subpod"]):
                    answer += f"ans {i}: " + sub["plaintext"] + "\n"
                break
        if answer == "":
            answer = next(res.results).text

        if answer is None or answer == "":
            return {"result": "No good Wolfram Alpha Result was found"}
        else:
            return {"result": answer}


class DetectFaces(BaseAction):
    def __init__(self, id) -> None:
        description = "Using this function to detect faces in an image."
        args_spec = {"image": "the image to detect faces from."}
        rets_spec = {"image": "the image with objects localized and visualized on it.", "regions": "the regions of the faces detected, where each regin is represented by a dictionary with the region's label text and bounding box."}
        examples = [
            {"name": "DetectFaces", "arguments": {"image": "image-0"}}
        ]
        import face_detection
        ckpt_path = f"/root/.cache/torch/hub/checkpoints/WIDERFace_DSFD_RES152.pth"
        if not os.path.exists(ckpt_path):
            from huggingface_hub import hf_hub_download
            hf_hub_download(repo_id="user/mma", filename="WIDERFace_DSFD_RES152.pth", local_dir="/root/.cache/torch/hub/checkpoints/")

        self.model = face_detection.build_detector(
            "DSFDDetector", confidence_threshold=.5, nms_iou_threshold=.3)
        super().__init__(
            id=id, description=description, args_spec=args_spec, rets_spec=rets_spec, examples=examples
        )

    def enlarge_face(self,box,W,H,f=1.5):
        x1,y1,x2,y2 = box
        w = int((f-1)*(x2-x1)/2)
        h = int((f-1)*(y2-y1)/2)
        x1 = max(0,x1-w)
        y1 = max(0,y1-h)
        x2 = min(W,x2+w)
        y2 = min(H,y2+h)
        return [x1,y1,x2,y2]

    def __call__(self, image):
        import numpy as np
        image = image_processing(image)

        with torch.no_grad():
            faces = self.model.detect(np.array(image))

        W,H = image.size
        objs = []
        for i,box in enumerate(faces):
```

```
            x1,y1,x2,y2,c = [int(v) for v in box.tolist()]
            normalized_bbox = [x1/W, y1/H, x2/W, y2/H]
            objs.append(dict(
                bbox=[round(num, 2) for num in normalized_bbox],
                label=f'face {i+1}' if i > 0 else 'face',
            ))
        visualize = VisualizeRegionsOnImage(0)
        results = visualize(image=image, regions=objs)
        tagged_image = results["image"]
        results_formatted = {"regions": objs, "image": tagged_image}
        return results_formatted


class QueryLanguageModel(BaseAction):
    def __init__(self, id) -> None:
        description = "Using this function to ask a language model a question."
        args_spec = {"query": "the question to ask the language model."}
        rets_spec = {"result": "the response from the language model."}
        examples = [
            {"name": "QueryLanguageModel", "arguments": {"query": "What is the capital of France?"}},
        ]
        super().__init__(
            id=id, description=description, args_spec=args_spec, rets_spec=rets_spec, examples=examples
        )

    def __call__(self, query):
        from openai import OpenAI
        client = OpenAI(api_key=os.getenv("OPENAI_API_KEY"))

        response = client.chat.completions.create(
            model=LATEST_GPT_MODEL_ID,
            messages=[
                {
                    "role"   : "user",
                    "content": [
                        {"type": "text", "text": f"{query}"},
                    ],
                }
            ],
            max_tokens=300,
        )

        return {'result': response.choices[0].message.content}


class QueryKnowledgeBase(BaseAction):
    def __init__(self, id) -> None:
        description = "Using this function to query a knowledge base."
        args_spec = {"query": "the query to search in a knowledge base such as wikipedia."}
        rets_spec = {"result": "the answer from the knowledge base."}
        examples = [
            {"name": "QueryKnowledgeBase", "arguments": {"query": "Paris"}},
        ]

        super().__init__(
            id=id, description=description, args_spec=args_spec, rets_spec=rets_spec, examples=examples
        )

    def __call__(self, query, lang="en", sentences=2, knowledge_base="wikipedia"):
        if knowledge_base == "wikipedia":
            # Set the language for Wikipedia (default is 'en' for English)
            wikipedia.set_lang(lang)

            # Search Wikipedia for pages related to the query
            search_results = wikipedia.search(query)
            if not search_results:
                return {"No results found."}
```

```python
            # Get the summary of the first search result
            page = wikipedia.page(search_results[0])
            summary = wikipedia.summary(page.title, sentences=sentences)
            result = {
                "title": page.title,
                "url": page.url,
                "summary": summary
            }
            return result
        else:
            raise NotImplementedError(f"Knowledge base {knowledge_base} is not supported.")


class Terminate(BaseAction):
    def __init__(self, id) -> None:
        description = "Using this function to finish the task."
        args_spec = {"answer": "the final answer."}
        rets_spec = {"answer": "the final answer."}
        examples = [{"name": "Terminate", "arguments": {"answer": "yes"}}]

        super().__init__(
            id=id, description=description, args_spec=args_spec, rets_spec=rets_spec, examples=examples
        )

    def __call__(self, answer):
        return {"answer": answer}
```

Listing 1. Python implementation of all actions

```
[BEGIN OF GOAL]
You are a helpful assistant, and your goal is to solve the # USER REQUEST #. You can either rely on your own capabilities or perform actions with external tools to help you. A list of all available actions are provided to you in the below.
[END OF GOAL]

[BEGIN OF ACTIONS]
Name: OCR
Description: Extract texts from an image or return an empty string if no text is in the image. Note that the texts extracted may be incorrect or in the wrong order. It should be used as a reference only.
Arguments: {'image': 'the image to extract texts from.'}
Returns: {'text': 'the texts extracted from the image.'}
Examples:
{"name": "OCR", "arguments": {"image": "image-0"}}

Name: LocalizeObjects
Description: Localize one or multiple objects/regions with bounding boxes. This tool may output objects that don't exist or miss objects that do. You should use the output only as weak evidence for reference. When answering questions about the image, you should double-check the detected objects. You should be especially cautious about the total number of regions detected, which can be more or less than the actual number.
Arguments: {'image': 'the image to localize objects/regions in.', 'objects': "a list of object names to localize. e.g. ['dog', 'cat', 'person']. the model might not be able to detect rare objects or objects with complex descriptionriptions."}
Returns: {'image': 'the image with objects localized and visualized on it.', 'regions': "the regions of interests localized in the image, where each region is represented by a dictionary with the region's label text, bounding box and confidence score. The confidence score is between 0 and 1, where 1 means the model is very confident. Note that both the bounding boxes and confidence scores can be unreliable and should only be used as reference."}
Examples:
{"name": "LocalizeObjects", "arguments": {"image": "image-0", "objects": ["dog", "cat"]}}

Name: GetObjects
Description: Using this function to get objects in an image.
Arguments: {'image': 'the image to get objects from.'}
Returns: {'objects': 'the objects detected in the image.'}
Examples:
{"name": "GetObjects", "arguments": {"image": "image-0"}}

Name: EstimateRegionDepth
Description: Estimate the depth of a region in an image using DepthAnything model. It returns an estimated depth value of the region specified by the input bounding box. The smaller the value is, the closer the region is to the camera, and the larger the farther. This tool may help you to better reason about the spatial relationship, like which object is closer to the camera.
Arguments: {'image': 'the image to get the depth from.', 'bbox': 'the bbox of the region to get the depth from. It should be a list of [left, top, right, bottom], where each value is a float between 0 and 1 to represent the percentage of the image width/height and how far it is from the top left corner at [0, 0].'}
Returns: {'depth': 'the estimated depth of the region.'}
Examples:
{"name": "EstimateRegionDepth", "arguments": {"image": "image-0", "bbox": [0.3, 0.2, 0.5, 0.4]}}

Name: EstimateObjectDepth
Description: Estimate the depth of an object in an image using DepthAnything model. It returns an estimated depth value of the object specified by the a brief text description. The smaller the value is, the closer the object is to the camera, and the larger the farther. This tool may help you to better reason about the spatial relationship, like which object is closer to the camera.
Arguments: {'image': 'the image to get the depth from.', 'object': 'a short description of the object to get the depth from.'}
Returns: {'depth': 'the estimated depth of the object.'}
Examples:
{"name": "EstimateObjectDepth", "arguments": {"image": "image-0", "object": "a black cat"}}

Name: Crop
Description: Crop an image with the bounding box. It labels the cropped region with a bounding box and crops the region with some margins around the bounding box to help with contextual understanding of
```

```
the region.
Arguments: {'image': 'the image to crop.', 'bbox': 'the bbox to crop. It should be a list of [left, top, right, bottom], where each value is a float between 0 and 1 to represent the percentage of the image width/height and how far it is from the top left corner at [0, 0].'}
Returns: {'image': 'the cropped image.'}
Examples:
{"name": "Crop", "arguments": {"image": "image-0", "bbox": [0.33, 0.21, 0.58, 0.46]}}

Name: ZoomIn
Description: Zoom in on a region of the input image. This tool first crops the specified region from the image with the bounding box and then resizes the cropped region to create the zoom effect. It also adds some margins around the cropped region to help with contextual understanding of the region.
Arguments: {'image': 'the image to zoom in on.', 'bbox': 'The bbox should be a list of [left, top, right, bottom], where each value is a float between 0 and 1 to represent the percentage of the image width/height and how far it is from the top left corner at [0, 0].', 'zoom_factor': 'the factor to zoom in by. It should be greater than 1.'}
Returns: {'image': 'the zoomed in image.'}
Examples:
{"name": "ZoomIn", "arguments": {"image": "image-0", "bbox": [0.4, 0.3, 0.5, 0.4], "zoom_factor": 2}}

Name: QueryLanguageModel
Description: Using this function to ask a language model a question.
Arguments: {'query': 'the question to ask the language model.'}
Returns: {'result': 'the response from the language model.'}
Examples:
{"name": "QueryLanguageModel", "arguments": {"query": "What is the capital of France?"}}

Name: GetImageToImagesSimilarity
Description: Get the similarity between one image and a list of other images. Note that this similarity score may not be accurate and should be used as a reference only.
Arguments: {'image': 'the reference image.', 'other_images': 'the other images to compare to the reference image.'}
Returns: {'similarity': 'the CLIP similarity scores between the reference image and the other images.', 'best_image_index': 'the index of the most similar image.'}
Examples:
{"name": "GetImageToImagesSimilarity", "arguments": {"image": "image-0", "other_images": ["image-1", "image-2"]}}

Name: GetImageToTextsSimilarity
Description: Get the similarity between one image and a list of texts. Note that this similarity score may not be accurate and should be used as a reference only.
Arguments: {'image': 'the reference image.', 'texts': 'a list of texts to compare to the reference image.'}
Returns: {'similarity': 'the CLIP similarity between the image and the texts.', 'best_text_index': 'the index of the most similar text.', 'best_text': 'the most similar text.'}
Examples:
{"name": "GetImageToTextsSimilarity", "arguments": {"image": "image-0", "texts": ["a cat", "a dog"]}}

Name: GetTextToImagesSimilarity
Description: Get the similarity between one text and a list of images. Note that this similarity score may not be accurate and should be used as a reference only.
Arguments: {'text': 'the reference text.', 'images': 'a list of images to compare to the reference text.'}
Returns: {'similarity': 'the CLIP similarity between the image and the texts.', 'best_image_index': 'the index of the most similar image.'}
Examples:
{"name": "GetTextToImagesSimilarity", "arguments": {"text": "a black and white cat", "images": ["image-0", "image-1"]}}

Name: DetectFaces
Description: Using this function to detect faces in an image.
Arguments: {'image': 'the image to detect faces from.'}
Returns: {'image': 'the image with objects localized and visualized on it.', 'regions': "the regions of the faces detected, where each regin is represented by a dictionary with the region's label text and bounding box."}
Examples:
```

```
{"name": "DetectFaces", "arguments": {"image": "image-0"}}

Name: QueryKnowledgeBase
Description: Using this function to query a knowledge base.
Arguments: {'query': 'the query to search in a knowledge base such as wikipedia.'}
Returns: {'result': 'the answer from the knowledge base.'}
Examples:
{"name": "QueryKnowledgeBase", "arguments": {"query": "Paris"}}

Name: Calculate
Description: Calculate a math expression.
Arguments: {'expression': 'the math expression to calculate.'}
Returns: {'result': 'the result of the math expression.'}
Examples:
{"name": "Calculate", "arguments": {"expression": "2 + 2"}}
{"name": "Calculate", "arguments": {"expression": "4*9*84"}}
{"name": "Calculate", "arguments": {"expression": "5-4/2"}}

Name: SolveMathEquation
Description: Using this action to solve a math problem with WolframAlpha.
Arguments: {'query': 'a question that involves a math equation to be solved.'}
Returns: {'result': 'the result of the query.'}
Examples:
{"name": "SolveMathEquation", "arguments": {"query": "2 + 2=?"}}
{"name": "SolveMathEquation", "arguments": {"query": "x^2 + 2x + 1 = 0, what is x?"}}

Name: Terminate
Description: Using this function to finish the task.
Arguments: {'answer': 'the final answer.'}
Returns: {'answer': 'the final answer.'}
Examples:
{"name": "Terminate", "arguments": {"answer": "yes"}}

[END OF ACTIONS]

[BEGIN OF TASK INSTRUCTIONS]
1. You must only select actions from # ACTIONS #.
2. You can only call one action at a time.
3. If no action is needed, please make actions an empty list (i.e. ''actions'': []).
4. You must always call Terminate with your final answer at the end.
[END OF TASK INSTRUCTIONS]

[BEGIN OF FORMAT INSTRUCTIONS]
Your output should be in a strict JSON format as follows:
{"thought": "the thought process, or an empty string", "actions": [{"name": "action1", "arguments": {"argument1": "value1", "argument2": "value2"}}]}
[END OF FORMAT INSTRUCTIONS]

[BEGIN OF EXAMPLES]:
# USER REQUEST #:
 In image-0, Which of the two objects on the plate is the biggest?
A. The pile of scrambled eggs is the biggest.
B. The strawberries are the biggest object.
Please answer directly with only the letter of the correct option and nothing else.
# RESPONSE #:
{"thought": "To determine which of the two objects on the plate is larger, I need to analyze the size of the scrambled eggs, and the strawberries", "actions": [{"name": "LocalizeObjects", "arguments": {"image": "image-0", "objects": ["scrambled eggs", "strawberries"]}}]}
OBSERVATION:
{"image": "image-1", "regions": [{"label": "eggs", "bbox": [0.5, 0.6, 0.6, 0.8], "score": 0.85}, {"label": "strawberries", "bbox": [0.4, 0.5, 0.45, 0.7], "score": 0.54}]}
{"thought": "To calculate the area of a bounding box, we can use the formula: area = (x_max - x_min) * (y_max - y_min). We first get the area of the scrambled eggs.", "actions": [{"name": "Calculate", "arguments": {"expression": "(0.6-0.5) * (0.8-0.6)"}}]}
OBSERVATION:
{"result": "0.02"}
{"thought": "Then, we also calculate the area of the strawberries.", "actions": [{"name": "Calculate",
```

```
"arguments": {"expression": "(0.45-0.4) * (0.7-0.5)"}}]}
OBSERVATION:
{"result": "0.01"}
{"thought": "Since 0.02 > 0.01, it is apparent that the eggs cover a larger area within their bounding box.", "actions": [{"name": "Terminate", "arguments": {"answer": "A"}}]}

# USER REQUEST #:
 Given the input image image-0, How many pedestrians are there in the image? Please answer directly with a single word or number.
# RESPONSE #:
{"thought": "To determine the number of pedestrians, I need to first localize them on the image.", "actions": [{"name": "LocalizeObjects", "arguments": {"image": "image-0", "objects": ["person"]}}]}
OBSERVATION:
{"image": "image-1", "regions": [{"label": "person", "bbox": [0.77, 0.47, 0.79, 0.54], "score": 0.83}, {"label": "person-2", "bbox": [0.69, 0.49, 0.7, 0.52], "score": 0.43}]}
{"thought": "The LocalizeObjects action returns two regions for \"person\", but one of the regions has a lower confidence score. Upon a closer look at the output image image-1, we can see that there is actually only one pedestrian in the image.", "actions": [{"name": "Terminate", "arguments": {"answer": "1"}}]}

# USER REQUEST #:
 Based on image-0, is the object on top bigger than the object below?
A. The object on the bottom is bigger.
B. The object on top is bigger.
C. Both objects are the same size.
Please answer directly with only the letter of the correct option and nothing else.
# RESPONSE #:
{"thought": "By looking at the image, we can see that both objects are game consoles of the same brand and size.", "actions": [{"name": "Terminate", "arguments": {"answer": "C"}}]}

# USER REQUEST #:
 What is x in the image?
# RESPONSE #:
{"thought": "To get the result of the equation, I need to first extract the equation from the image.", "actions": [{"name": "OCR", "arguments": {"image": "image-0"}}]}
OBSERVATION:
{"text": "x-2^3=0"}
{"thought": "The math equation is 'x-2^3=0', and I need to find x. I can solve it with a math-related tool.", "actions": [{"name": "SolveMathEquation", "arguments": {"query": "x-2^3=0, what is x?"}}]}
OBSERVATION:
{"result": "x = 8"}
{"thought": "As suggested in the last observation, the answer is 8.", "actions": [{"name": "Terminate", "arguments": {"answer": "8"}}]}

[END OF EXAMPLES]
```

Listing 2. Model-based data generation system prompt

```python
def GetObjects_template():
    thought_templates = ["I need to check what objects are present in the {image_kw}.",
                         "I need to analyze the {image_kw} for context."
                         "I need to identify the objects in the {image_kw}.",
                         "To answer the question, let's first analyze the {image_kw}.",
                         "To answer the question, analyzing the objects in the {image_kw} is necessary."
    ]
    return thought_templates

def LocalizeObjects_template():
    thought_templates = ["I need to analyze the positions of {objects} in the {image_kw}.",
                         "I need to analyze the locations of {objects} in the {image_kw}.",
                         "I need to localize the {objects} based on the {image_kw}.",
                         "I'll identify the positions of {objects} in the {image_kw}.",
                         "I need to determine the positions of {objects} by analyzing the {image_kw}."]
    return thought_templates

def EstimateObjectDepth_template():
    thought_templates = ["I should estimate the depth of {object} to determine whether it is closer or farther.",
                          "I will estimate the depth of {object}.",
                          "I need to estimate the depth for {object} to make a comparison.",
                          "To determine how far {object} is, I need to evaluate the distance to it.",
                          "I now need to estimate the depth for {object}."]
    return thought_templates


def EstimateRegionDepth_template():
    thought_templates = ["I should estimate the objects' depths to determine which one is closer.",
                          "I need to estimate the region's depth in the image.",
                          "I need to determine the depths of the detected objects based on their positions.",
                          "I need to estimate the depth of the objects to make a comparison.",
                          "To determine the relative proximity of the objects in the image, I need to estimate the depth of each object."]
    return thought_templates

def Terminate_template():
    thought_templates = ["Based on the information above, I can conclude that the answer is {answer}",
                          "Based on a close analysis of the {image_kw} and additional information above, I believe the answer is {answer}.",
                          "I have analyzed the {image_kw} and the information above, and I believe the answer is {answer}.",
                          "The {image_kw} and the information above suggest that the answer is {answer}.",
                          "According to the content of the {image_kw} and the observations, I can conclude that the answer is {answer}."]
    return thought_templates
```

Listing 3. Thought templates for each action

```
Compare the ground truth and prediction from AI models, to give a correctness score for the prediction. <AND> in the ground truth means it is totally right only when all elements in the ground truth are present in the prediction, and <OR> means it is totally right when any one element in the ground truth is present in the prediction. The correctness score is 0.0 (totally wrong), 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, or 1.0 (totally right). Just complete the last space of the correctness score.
Question | Ground truth | Prediction | Correctness
--- | --- | --- | ---
What is x in the equation? | -1 <AND> -5 | x = 3 | 0.0
What is x in the equation? | -1 <AND> -5 | x = -1 | 0.5
What is x in the equation? | -1 <AND> -5 | x = -5 | 0.5
What is x in the equation? | -1 <AND> -5 | x = -5 or 5 | 0.5
What is x in the equation? | -1 <AND> -5 | x = -1 or x = -5 | 1.0
Can you explain this meme? | This meme is poking fun at the fact that the names of the countries Iceland and Greenland are misleading. Despite its name, Iceland is known for its beautiful green landscapes, while Greenland is mostly covered in ice and snow. The meme is saying that the person has trust issues because the names of these countries do not accurately represent their landscapes. | The meme talks about Iceland and Greenland. It's pointing out that despite their names, Iceland is not very icy and Greenland isn't very green. | 0.4
Can you explain this meme? | This meme is poking fun at the fact that the names of the countries Iceland and Greenland are misleading. Despite its name, Iceland is known for its beautiful green landscapes, while Greenland is mostly covered in ice and snow. The meme is saying that the person has trust issues because the names of these countries do not accurately represent their landscapes. | The meme is using humor to point out the misleading nature of Iceland's and Greenland's names.
Iceland, despite its name, has lush green landscapes while Greenland is mostly covered in ice and snow. The text 'This is why I have trust issues' is a playful way to suggest that these contradictions can lead to distrust or confusion. The humor in this meme is derived from the unexpected contrast between the names of the countries and their actual physical characteristics. | 1.0
```

Listing 4. LLM judge prompt for MMVet

```
Please read the following example. Then extract the answer from the model response and type it at the end of the prompt.

Hint: Please answer the question requiring an integer answer and provide the final value, e.g., 1, 2, 3, at the end.
Question: Which number is missing?
Model response: The number missing in the sequence is 14.
Extracted answer: 14

Hint: Please answer the question requiring a floating-point number with one decimal place and provide the final value, e.g., 1.2, 1.3, 1.4, at the end.
Question: What is the fraction of females facing the camera?
Model response: The fraction of females facing the camera is 0.6,
which means that six out of ten females in the group are facing the camera.
Extracted answer: 0.6

Hint: Please answer the question requiring a floating-point number with two decimal places and provide the final value, e.g., 1.23, 1.34, 1.45, at the end.
Question: How much money does Luca need to buy a sour apple candy and a butter-scotch candy? (Unit: $)
Model response: Luca needs $1.45 to buy a sour apple candy and a butterscotch candy.
Extracted answer: 1.45

Hint: Please answer the question requiring a Python list as an answer and provide the final list, e.g., [1, 2, 3], [1.2, 1.3, 1.4], at the end.
Question: Between which two years does the line graph saw its maximum peak?
Model response: The line graph saw its maximum peak between 2007 and 2008.
Extracted answer: [2007, 2008]

Hint: Please answer the question and provide the correct option letter, e.g., A, B, C, D, at the end.
Question: What fraction of the shape is blue?
Choices: (A) 3/11 (B) 8/11 (C) 6/11 (D) 3/5
Model response: The correct answer is (B) 8/11.
Extracted answer: B
```

Listing 5. LLM judge prompt for MathVista