

Agent-Omni: Test-Time Multimodal Reasoning via Model Coordination for Understanding Anything

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Abstract

Multimodal large language models (MLLMs) have shown strong capabilities but remain limited to fixed modality pairs and require costly fine-tuning with large aligned datasets. Building fully omni-capable models that can integrate text, images, audio, and video remains impractical and lacks robust reasoning support. In this paper, we propose an **Agent-Omni** framework that coordinates existing foundation models through a master-agent system, enabling flexible multimodal reasoning without retraining. The master agent interprets user intent, delegates subtasks to modality-specific agents, and integrates their outputs into coherent responses. Extensive experiments across text, image, audio, video, and omni benchmarks show that Agent-Omni consistently achieves state-of-the-art performance, particularly on tasks requiring complex cross-modal reasoning. Its agent-based design enables seamless integration of specialized foundation models, ensuring adaptability to diverse inputs while maintaining transparency and interpretability. In addition, the framework is modular and easily extensible, allowing future improvements as stronger models become available.

1 Introduction

Multimodal large language models (MLLMs) extend the capabilities of language models by integrating text with other modalities, such as image (Zhang et al., 2024; Chu et al., 2024a), audio (KimiTeam et al., 2025; Chu et al., 2024b), and video (Lin et al., 2024a; Li et al., 2024a; Xu et al., 2021). Existing systems are often restricted to fixed pairs, for example, text–image for captioning and visual question answering (Guo et al., 2023; Liu et al., 2023), text–video for event understanding (Lin et al., 2024a), or text–audio for transcription and dialogue (KimiTeam et al., 2025; Chu et al., 2024b). However, in practice, many scenarios demand omni LLMs that can flexibly accept

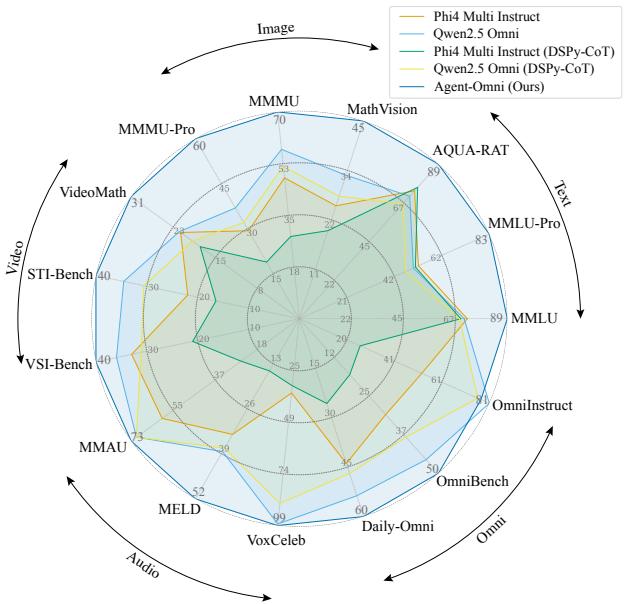


Figure 1: Comparison of Agent-Omni and other omni methods across multimodal benchmarks.

any combination of text, image, video, and audio while producing textual outputs (Xu et al., 2025; AI et al., 2025). For instance, a user might provide a background speech recording, an accompanying image, and a written note, then pose a question whose answer requires reasoning over all of these inputs (Liu et al., 2025a; Li et al., 2025a).

Extending existing multimodal LLMs into fully omni-capable systems typically requires large-scale fine-tuning across all modalities (Liu et al., 2024; Lin et al., 2024a; Zeng et al., 2024; Lin et al., 2024b). This process demands extensive datasets that cover diverse cross-modal combination, and significant computational resources to jointly optimize model parameters. However, collecting omni-level training data that includes text, images, videos, and audio in aligned contexts is extremely costly and often impractical (Xu et al., 2025; AI et al., 2025). Moreover, even when such data is available and large-scale training is performed, omni models often suffer from trade-offs across modalities: improving performance on one modal-

ity can degrade accuracy on others, and balancing these objectives becomes increasingly difficult as the number of supported modalities grows (Zhai et al., 2023; Cai et al., 2025).

Beyond training challenges, achieving effective omni reasoning is itself a difficult problem. In existing multimodal tasks such as visual question answering, and video understanding, reasoning has been shown to improve performance by enabling models to better connect information across paired modalities (Ke et al., 2025; Bi et al., 2024). Extending this ability to an omni setting is far more challenging: the system must integrate arbitrary combinations of modalities into a coherent understanding, for example aligning spoken descriptions with visual evidence or linking video events with accompanying text. Building datasets that support such reasoning is even harder than collecting aligned inputs, since they must include rich multi-source evidence and tasks requiring cross-modal integration. Because of this lack of datasets and the complexity of the problem, current approaches remain restricted to pairwise settings, and no truly omni reasoning model yet exists. Table 1 summarizes the capabilities of representative models, highlighting the gap in achieving both broad multimodal coverage and strong reasoning ability.

Limitations. We identify the main limitations and challenges as follows:

- **Heavy reliance on fine-tuning:** Building omni LLMs requires large-scale curated data across modalities and substantial computation, making training costly and impractical.
- **Trade-offs between modalities:** Improving performance on one modality often leads to degradation in others, making optimization difficult.
- **Lack of omni reasoning:** While reasoning improves performance in pairwise multimodal tasks, no models can reliably integrate arbitrary modality combinations.
- **Insufficient datasets:** Datasets supporting omni reasoning are largely unavailable, restricting current systems to limited modality pairs.

In this paper, we propose a omni agent that can “understand anything”, i.e., interpret and answer user questions about any combination of text, image, audio, or video inputs by coordinating existing foundation models through dynamic agents, without fine-tuning or retraining.

Contributions. The main contributions of this paper are summarized as follows:

- We propose a novel agent-based framework that

Table 1: Comparison of multimodal coverage and reasoning ability (✓: supported, ✗: not supported)

Method	Text	Visual (image & Video)	Audio	Reasoning
Claude 3.7 Sonnet	✓	✓	✗	✓
Deepseek R1	✓	✗	✗	✓
GPT OSS 20B	✓	✗	✗	✓
Phi4 Multimodal Instruct	✓	✓	✓	✗
QWen2.5 Omni	✓	✓	✓	✗
QWen2 Audio 7B	✓	✗	✓	✗
QWen3 4B Instruct	✓	✗	✗	✗
QWen3 4B Thinking	✓	✗	✗	✓
Llava Video 7B	✓	✓	✗	✗
Ours (Agent-Omni)	✓	✓	✓	✓

coordinates existing foundation models to reason jointly over text, images, video, and audio, without any task-specific fine-tuning or retraining.

- We design a flexible master-agent system that interprets user intent, delegates subtasks to modality-specific agents, and integrates their outputs into a coherent final answer.
- We validate the framework through practical scenarios involving complex multimodal understanding and benchmark its performance across diverse tasks and datasets.
- We provide an open-source implementation¹, enabling future research and applications.

2 Agent-Omni

The goal of Agent-Omni is to enable flexible multimodal reasoning at test time without the need for retraining or large-scale fine-tuning. Instead of relying on a single unified model, our framework coordinates existing foundation models through a hierarchical agent architecture. By doing so, Agent-Omni can accept arbitrary combinations of text, images, audio, and video inputs, and produce coherent textual outputs.

2.1 Overview

Figure 2 illustrates the overall workflow. Consider the case where the user provides accident-related materials, including several photos, a dashcam video, an emergency call recording, and two documents (a police report and an insurance report), and asks: “*Can you summarize the accident by integrating provided materials?*” The master agent identifies relevant modalities (image, video, audio, and text). It then formulates sub-questions for each modality, delegates them to the corresponding foundation models, and collects their structured outputs. These are iteratively fused through a self-improvement loop that resolves inconsistencies and refines the answer before final output.

¹<https://github.com/huawei-lin/Agent-Omni>

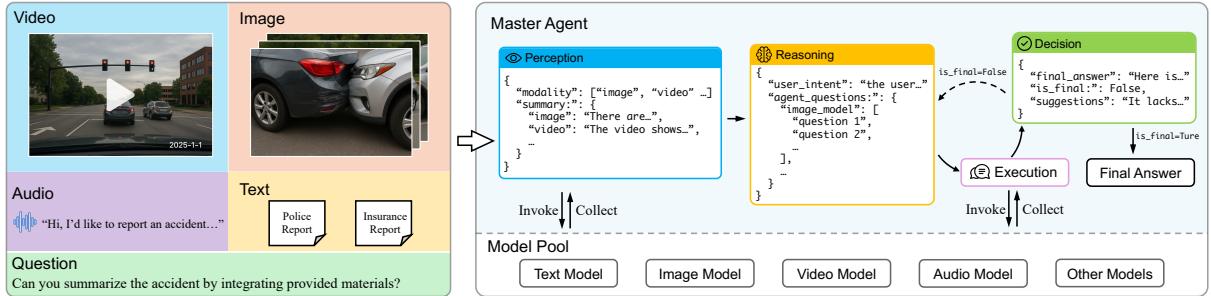


Figure 2: Overview of the Agent-Omni framework. A master agent interprets the query, identifies relevant modalities, and delegates sub-questions to corresponding foundation models (text, image, audio, video). Their outputs are iteratively integrated and refined through a self-improvement loop, enabling coherent multimodal reasoning in test-time inference.

2.2 Master Agent

The Master Agent serves as the central controller of Agent-Omni, with its internal workflow divided into four functional stages: (1) **Perception**: analyzes the input modalities and produces structured representations; (2) **Reasoning**: decomposes the user query into sub-questions based on the perceived information; (3) **Execution**: invokes appropriate foundation models from the model pool to answer the sub-questions and gathers their outputs; and (4) **Decision**: integrates all outputs to construct a final answer, evaluates its completeness, and determines whether another iteration of the reasoning loop is required.

Perception. The perception stage addresses the fundamental requirement that the agent must first understand what materials are provided before any reasoning can take place. As shown in Figure 2, the Master Agent examines multimodal inputs (e.g., text, image, audio, video) and summarizes them into a concise JSON structure, where each modality is represented with a semantic description. This transformation turns raw signals into structured representations, ensuring that heterogeneous modalities are consistently aligned within a unified representation space. The generated JSON thus serves as the foundation for subsequent reasoning steps.

Reasoning. After perception, the agent must decide how to utilize the perceived information to address the user’s intent. In this stage, the Master Agent first derives a high-level `user_intent` that summarizes what the user is asking. It then formulates modality-specific sub-questions for each input modality that requires further reasoning. As illustrated in Figure 2, these results are organized in a structured JSON format, where the user intent is explicitly represented, and the sub-questions are

grouped under the corresponding modality (e.g., `image_model`, `text_model`). This design makes the reasoning process explicit and interpretable, while also providing a clear execution plan that connects each sub-question to its designated model.

Execution. Once the reasoning stage has produced modality-specific sub-questions, the execution stage faithfully carries them out by invoking the designated foundation models specified in the reasoning JSON. The outputs are then systematically collected and organized so that each sub-question is explicitly paired with its corresponding answer. This mechanism guarantees that intermediate results remain well-documented and easily traceable, thereby providing the factual grounding required for the subsequent decision stage.

Decision. After execution has gathered answers from the foundation models, the agent must consolidate these results into a coherent response. In the decision stage, the Master Agent integrates all outputs recorded in the JSON structure to construct an answer for the user’s original query. This answer is then evaluated for completeness and reliability: if gaps or inconsistencies are detected, the agent appends feedback instructions to the JSON and triggers another round of the reasoning–execution–decision loop (the master loop). As illustrated in Figure 2, the decision stage produces three key components: (1) `final_answer`, which provides a direct response to the original query; (2) `is_final`, a flag indicating whether further iterations of the master loop are required – if true, the `final_answer` is returned as the final output; and (3) `suggestions`, which specify how subsequent iterations should refine the response if additional loops are necessary. This design enables iterative self-correction, ensuring that the final output is

not only comprehensive but also progressively improved through repeated evaluation and refinement.

Further Master Loop. If the decision stage sets `is_final` to `false`, the Master Agent initiates another iteration of the master loop. In the new loop, the reasoning stage consults the suggestions generated by the previous decision to prepare follow-up questions that target missing or uncertain information. These new sub-questions are then processed in the execution stage, whose outputs are passed again to the decision stage for integration and evaluation. This process repeats iteratively until either `is_final` is set to `true`, indicating that the response is sufficiently complete, or a pre-defined maximum number of loops L is reached. Such a design allows the Master Agent to progressively refine its answers through self-correction.

2.3 Model Pool

The model pool serves as the resource hub that provides the Master Agent with diverse foundation models to address modality-specific sub-questions. It contains a collection of specialized models spanning different input modalities, such as large language models for text, vision-language models for images, speech-text models for audio, and multimodal models capable of cross-modal reasoning. Each model in the pool can be invoked on demand during the execution stage, according to the reasoning plan specified in the JSON.

Unlike conventional multimodal LLMs that require costly joint training or fine-tuning across all modalities, the model pool in Agent-Omni operates without any additional training. Existing foundation models are coordinated at inference time, making the framework both flexible and lightweight. New models can be seamlessly added to expand the agent’s capabilities, while existing ones are selectively leveraged based on their strengths. By decoupling model selection from reasoning, the Master Agent can dynamically orchestrate heterogeneous models in a unified workflow. This training-free design enables Agent-Omni to adapt to a wide range of multimodal queries while maintaining transparency, scalability, and efficiency.

3 Experimental Evaluation

The goal of our experiments is to systematically assess the performance of Agent-Omni across multiple dimensions of multimodal reasoning. We focus on the following four research questions: **(1)** How

well does Agent-Omni generalize across diverse modalities (text, image, audio, and video), and can it achieve competitive performance on omni-level tasks? **(2)** What is the computational cost of the proposed Agent-Omni at test time, and how efficient is the framework compared to end-to-end multimodal LLMs? **(3)** How does the choice of different foundation models in the model pool affect the accuracy of Agent-Omni? and **(4)** How does varying the maximum number of master loops influence final performance, and to what extent does iterative self-correction improve answer quality?

3.1 Datasets

To comprehensively evaluate the multimodal understanding capability of Agent-Omni, we experiment on a broad collection of benchmarks that span five major categories: **(1) Text.** We adopt classic language understanding and reasoning benchmarks, including MMLU (Hendrycks et al., 2021) (covering STEM, Social Sciences, Humanities, and Other domains), its more challenging variant MMLU-Pro (Wang et al., 2024c), and the arithmetic reasoning dataset AQUA-RAT (Ling et al., 2017). **(2) Image.** For visual reasoning, we evaluate on Math-Vision (Wang et al., 2024a), a benchmark targeting mathematical understanding from images, as well as MMMU (Yue et al., 2024) and its robust extension MMMU-Pro (Yue et al., 2025), which focus on expert-level multimodal and multidisciplinary reasoning. **(3) Video.** To assess temporal and spatial reasoning, we include VideoMathQA (Rasheed et al., 2025), which benchmarks mathematical problem-solving from videos, STI-Bench (Li et al., 2025b), designed for precise spatio-temporal understanding, and VSI-Bench (Yang et al., 2025b), which emphasizes video-based scene interpretation. **(4) Audio.** For auditory understanding, we use MMAU (Sakshi et al., 2025), a large-scale multi-task audio reasoning benchmark, MELD-Emotion (Poria et al., 2019), which evaluates emotion recognition in conversations, and VoxCeleb-Gender (Nagrani et al., 2020), a dataset for speaker gender classification. **(5) Omni-level.** Finally, to test holistic multimodal reasoning that integrates multiple modalities, we include Daily-Omni (Zhou et al., 2025), which emphasizes cross-modal temporal alignment, OmniBench (Li et al., 2024b), targeting universal multimodal understanding, and Omni-Instruct (Li et al., 2024b), a large-scale instruction-following dataset across modalities.

Table 2: Accuracy on text benchmarks (MMLU, MMLU-Pro, AQUA-RAT).

Method	Model	MMLU (STEM)	MMLU (Social Sciences)	MMLU (Humanities)	MMLU (Other)	MMLU (Average)	MMLU-Pro	AQUA-RAT
Foundation Model	Claude 3.7 Sonnet	91.87%	90.49%	81.89%	87.88%	88.03%	76.75%	87.40%
	Deepseek R1	95.19%	92.28%	84.17%	91.25%	90.72%	82.66%	87.40%
	GPT OSS 20B	91.91%	85.26%	81.93%	83.87%	85.74%	74.41%	88.50%
	Phi4 Multimodal Instruct	75.77%	75.56%	65.19%	71.80%	72.08%	52.13%	74.02%
	QWen2.5 Omni	74.43%	74.34%	62.33%	71.83%	70.73%	49.93%	70.87%
	QWen3 4B Instruct	89.49%	81.64%	70.34%	78.67%	80.04%	68.53%	85.43%
	QWen3 4B Thinking	91.05%	82.91%	72.29%	81.04%	81.82%	67.64%	86.61%
DSPy-CoT	Claude 3.7 Sonnet	92.17%	90.44%	82.51%	89.76%	88.72%	78.48%	84.65%
	Deepseek R1	92.96%	91.81%	84.39%	91.03%	90.05%	74.83%	88.58%
	QWen2.5 Omni	72.87%	72.08%	59.80%	70.13%	68.72%	46.54%	66.54%
	QWen3 4B Instruct	87.59%	81.07%	70.81%	76.28%	78.94%	65.83%	86.61%
	QWen3 4B Thinking	92.51%	83.66%	75.37%	81.73%	83.32%	69.85%	89.76%
Ours (Agent-Omni)		<u>94.52%</u>	90.40%	81.68%	90.31%	89.23%	83.21%	<u>89.37%</u>

3.2 Baselines

To evaluate the performance of Agent-Omni, we compare it against two categories of baselines: **(1) Foundation Models:** We directly evaluate a set of state-of-the-art foundation models across modalities, including large language models, vision-language models, and other modality-specific models. **(2) DSPy-CoT:** We adopt DSPy with chain-of-thought prompting as a strong baseline (Khatab et al., 2023). DSPy-CoT represents a method of improving reasoning within a single model by leveraging structured prompts, without introducing cross-model orchestration. This baseline highlights the difference between enhancing reasoning inside one model versus coordinating multiple specialized models, enabling a fair comparison of Agent-Omni.

3.3 Models

We evaluate Agent-Omni using a diverse set of state-of-the-art foundation models, each specialized in different modalities. **(1) Text:** large language models including Deepseek R1 (DeepSeek-AI et al., 2025), GPT OSS 20B (OpenAI, 2025), and QWen3 4B (Yang et al., 2025a), which provide strong reasoning and problem-solving capabilities on text-centric benchmarks. **(2) Image & Video:** vision-language models such as Claude 3.7 Sonnet and Llava Video 7B (Lin et al., 2024a), designed to align visual and textual representations for tasks like image question answering and video understanding. **(3) Audio:** audio-focused models such as Qwen2 Audio 7B (Chu et al., 2024b), specialized in speech recognition and auditory reasoning. **(4) Omni:** multimodal models including Phi4 Multimodal Instruct (Abouelenin et al., 2025) and Qwen2.5 Omni (Xu et al., 2025), which natively support multiple modalities but often face

Table 3: Setup of Agent-Omni with selected foundation models and their roles.

Modality	Model	Role / Function
Master	Claude 3.7 Sonnet	Central controller for reasoning and decision-making
Text	Deepseek R1	Strong LLM for text understanding and logical reasoning
Image	Claude 3.7 Sonnet	Handles visual perception and image-based reasoning
Video	Claude 3.7 Sonnet	Processes temporal visual content for video understanding
Audio	Qwen2.5 Omni	Provides audio comprehension and speech reasoning

You will be given some support materials (text, image, etc.) and a multiple-choice question with options (A, B, C, etc). Choose only one best answer. First, provide a brief explanation of your reasoning. Then, on a new line, output "The answer is <answer>", where the <answer> is only the single letter of the correct option (A, B, C, etc).

Question: {question}
Choices: {choices}

Figure 3: The prompt template used in experiments.

trade-offs in robustness across them.

As summarized in Table 1, each model demonstrates strengths in its target modality but lacks full coverage across text, visual, audio, and reasoning dimensions. This highlights the motivation for Agent-Omni, which coordinates these specialized models to achieve balanced omni-modal reasoning.

3.4 Experimental Settings

All experiments are conducted on a server equipped with 4 NVIDIA A100 GPUs (80GB each) and 251GB system memory. For models such as Claude 3.7 Sonnet and Deepseek R1, we directly access their APIs through AWS Bedrock. For all other models, we deploy them locally on the server using the vLLM inference framework to ensure efficient execution. During evaluation, we adopt a unified prompt template as shown in Figure 3. For text-based inputs, the prompt is directly filled with the corresponding question and answer choices.

Table 4: Accuracy on image benchmarks.

Method	Model	MathVision	MMMU	MMMU-Pro
Foundation Model	Claude 3.7 Sonnet	45.95%	70.37%	59.88%
	QWen2.5 Omni	32.44%	57.62%	37.05%
	Phi4 Multimodal Instruct	25.52%	47.93%	29.42%
DSPy-CoT	Claude 3.7 Sonnet	50.26%	71.07%	58.03%
	QWen2.5 Omni	27.68%	51.83%	32.20%
	Phi4 Multimodal Instruct	19.91%	27.98%	18.96%
Ours (Agent-Omni)		44.71%	70.37%	60.23%

Table 5: Accuracy on video benchmarks.

Method	Model	VideoMathQA	STI-Bench	VSI-Bench
Foundation Model	Claude 3.7 Sonnet	27.62%	38.13%	38.70%
	Phi4 Multimodal Instruct	21.67%	21.95%	32.57%
	Llava Video 7B	23.71%	24.42%	31.41%
DSPy-CoT	QWen2.5 Omni	21.90%	34.54%	35.50%
	Claude 3.7 Sonnet	27.14%	37.89%	42.60%
	Phi4 Multimodal Instruct	18.10%	16.40%	20.72%
Ours (Agent-Omni)	Llava Video 7B	21.90%	30.38%	36.22%
	QWen2.5 Omni	19.52%	30.57%	30.73%
	Ours (Agent-Omni)	30.71%	40.00%	39.50%

For image, video, and audio inputs, we follow the model-specific instructions by inserting the corresponding modality tokens into the designated positions in the prompt. This ensures consistency across modalities while respecting the input format required by each model.

3.5 Agent-Omni Settings

Unless otherwise specified, we use Claude 3.7 Sonnet as the master model in all experiments. It is responsible for running the master loop, including reasoning and decision. For the model pool, we adopt Deepseek R1 as the text model, Claude 3.7 Sonnet as both the image and video model, and Qwen2.5 Omni as the audio model. The overall setup of the agent, along with the role of each selected foundation model, is summarized in Table 3. The maximum number of master loops L is set to 3 by default. In addition, we provide an ablation study on different model pool settings in Appendix A, and we also report the prompts and the JSON schemas used for the user query, model pool, reasoning stage, and decision stage in Appendix B.

3.6 Accuracy across Modalities

Since our method can be applied across multiple modalities, we separately report the accuracy for each modality (text, image, video, audio, and Omni) and compare Agent-Omni with the baselines that support the corresponding modality.

Text Modality. As shown in Table 2, on text benchmarks (MMLU, MMLU-Pro, and AQUARAT), Agent-Omni achieves accuracy that is comparable to the strongest single models while maintaining robustness across all categories. Deepseek

Table 6: Accuracy on audio benchmarks.

Method	Model	MMAU	MELD (Emotion)	VoxCeleb (Gender)
Foundation Model	Phi4 Multimodal Instruct	59.70%	33.37%	35.41%
	QWen2.5 Omni	70.90%	38.35%	97.85%
	Qwen2 Audio 7B	54.70%	22.15%	50.14%
DSPy-CoT	Phi4 Multimodal Instruct	25.40%	15.03%	31.95%
	QWen2.5 Omni	70.90%	37.32%	88.02%
	Qwen2 Audio 7B	46.70%	29.58%	45.01%
Ours (Agent-Omni)		73.20%	51.97%	98.60%

Table 7: Accuracy on omni benchmarks.

Method	Model	Daily-Omni	OmniBench	OmniInstruct
Foundation Model	Phi4 Multimodal Instruct	43.94%	30.74%	52.28%
	QWen2.5 Omni	53.72%	45.18%	81.06%
DSPy-CoT	Phi4 Multimodal Instruct	25.73%	17.95%	25.95%
	QWen2.5 Omni	46.95%	38.00%	76.14%
Ours (Agent-Omni)		60.03%	49.56%	77.50%

R1 delivers the best single-model performance due to its strong reasoning ability on text-heavy datasets, whereas DSPy-CoT shows slight improvements in some cases but is not consistently better. Notably, MMLU-Pro is the most challenging dataset, where Agent-Omni attains the highest accuracy (83.21%), demonstrating its advantage in handling complex reasoning tasks.

Image Modality. As shown in Table 4, Agent-Omni achieves accuracy comparable to the strongest baselines on image benchmarks (MathVision, MMMU, and MMMU-Pro). While Claude 3.7 Sonnet remains strong on MathVision, Agent-Omni matches its performance on MMMU and surpasses all models on MMMU-Pro (60.23%), the most challenging dataset. These results show the robustness of Agent-Omni in advanced multimodal reasoning beyond basic visual understanding.

Video Modality. On video benchmarks (VideoMathQA, STI-Bench, and VSI-Bench), Agent-Omni consistently outperforms all baselines, as shown in Table 5. It achieves clear gains on VideoMathQA (30.71%) and STI-Bench (40.00%), while maintaining performance on VSI-Bench (39.50%). These improvements demonstrate the effectiveness of the master loop in integrating temporal visual information with reasoning across modalities.

Audio Modality. As shown in Table 6, Agent-Omni achieves the best performance across all audio benchmarks (MMAU, MELD-Emotion, and VoxCeleb-Gender). In particular, it reaches 73.20% on MMAU, 51.97% on MELD-Emotion, and 98.60% on VoxCeleb-Gender, surpassing both foundation and DSPy-CoT baselines. These results indicate that Agent-Omni effectively leverages specialized audio models while maintaining robustness across diverse audio tasks.

Table 8: Accuracy comparison among omni models.

Method	Model	Text			Image			Video			Audio		Omni			
		MMLU (Average)	MMLU-Pro	AQUA-RAT	MathVision	MMMU	MMMU-Pro	VideoMathQA	STI-Bench	VSI-Bench	MMAU	MELD (Emotion)	VoxCeleb (Gender)	Daily-Omni	OmniBench	OmniInstruct
Foundation Model	Phi4 Multimodal Instruct QWen2.5 Omni	72.08%	52.13%	74.02%	25.52%	47.93%	29.42%	21.67%	21.95%	32.57%	59.70%	33.37%	35.41%	43.94%	30.74%	52.28%
DSPy-CoT	Phi4 Multimodal Instruct QWen2.5 Omni	69.26%	50.84%	75.98%	19.91%	27.98%	18.96%	18.10%	16.40%	20.72%	25.40%	15.03%	31.95%	25.73%	17.95%	25.95%
Ours (Agent-Omni)		89.23%	83.21%	89.37%	44.71%	70.37%	60.23%	30.71%	40.00%	39.50%	73.20%	51.97%	98.60%	60.03%	49.56%	77.50%

Table 9: Inference latency (in seconds) of different models across various datasets.

Method	Model	Text			Image			Video			Audio		Omni			
		MMLU (Average)	MMLU-Pro	AQUA-RAT	MathVision	MMMU	MMMU-Pro	VideoMathQA	STI-Bench	VSI-Bench	MMAU	MELD (Emotion)	VoxCeleb (Gender)	Daily-Omni	OmniBench	OmniInstruct
Foundation Model	Claude 3.7 Sonnet	0.88	1.14	1.74	1.71	1.47	1.39	1.86	1.58	1.61	-	-	-	-	-	-
Foundation Model	Phi4 Multimodal Instruct QWen2.5 Omni	0.38	1.51	3.1	4.71	1.8	2.36	2.51	10.04	0.46	2.79	2.85	0.37	0.79	0.71	1.38
Foundation Model	Claude 3.7 Sonnet	0.32	1.18	1.61	2.55	0.84	8.25	2.1	0.43	0.19	0.24	0.09	0.09	0.27	0.28	0.18
DSPy-CoT	Phi4 Multimodal Instruct QWen2.5 Omni	1.72	2.59	6.39	6.84	3.15	3.33	4.07	2.62	2.54	-	-	-	-	-	-
DSPy-CoT	Phi4 Multimodal Instruct QWen2.5 Omni	1.24	2.84	0.37	4.62	4.65	1.62	5.73	7.62	1.6	2.36	3.63	4.09	3.17	3.39	4.16
DSPy-CoT	Phi4 Multimodal Instruct QWen2.5 Omni	0.41	1.23	1.61	2.68	0.93	1.16	2.18	2.09	1.31	0.26	0.13	0.13	1.72	0.4	0.25
Ours (Agent-Omni)		4.55	7.41	6.9	5.62	4.66	5.41	20.53	12.76	16.47	4.23	5.09	7.5	16.7	7.47	5.14

Mixed Modality (Omni). On omni benchmarks (Daily-Omni, OmniBench, and OmniInstruct), Agent-Omni achieves strong performance across datasets, as shown in Table 7. It outperforms both foundation models and DSPy-CoT, reaching 60.03% on Daily-Omni, 49.56% on OmniBench, and 77.50% on OmniInstruct. These results show the advantage of integrating specialized models for each modality, enabling Agent-Omni to achieve balanced and robust omni-modal reasoning.

3.7 Accuracy on Omni Models

In addition to modality-specific evaluation, we further compare Agent-Omni against existing omni models that natively support multiple modalities (text, image, video, and audio).

As shown in Table 8 and Figure 1, foundation omni models such as Phi-4 Multimodal Instruct and Qwen2.5 Omni generally achieve lower accuracy across benchmarks. This reflects the trade-off highlighted in our introduction: when a single model is trained jointly on heterogeneous modalities, it often struggles to balance performance across them. Gains in one modality may come at the expense of others, leading to uneven and suboptimal results.

DSPy-CoT provides minor improvements in some benchmarks, but its gains are inconsistent and insufficient to overcome the inherent limitations of omni models. By contrast, Agent-Omni consistently achieves the best accuracy on nearly all datasets, including both unimodal and multimodal benchmarks, with particularly large margins on challenging tasks such as MMLU-Pro, MMMU-Pro, and Daily-Omni.

These results confirm that coordinating specialized foundation models through a master-agent loop is more effective than relying on a single omni model. Agent-Omni avoids the trade-offs of joint training, preserves the strengths of individual expert models, and provides a more robust and

general solution to omni-modal reasoning.

3.8 Latency

We report inference latency across modalities in Table 9. Foundation models such as Claude 3.7 Sonnet and Qwen2.5 Omni show fast responses (often < 2s for text and image), while DSPy-CoT roughly doubles the latency due to chain-of-thought prompting. For instance, Claude 3.7 Sonnet requires 0.88s on MMLU, compared to 1.72s with DSPy-CoT.

Our Agent-Omni framework introduces higher latency (4–7s on unimodal tasks and up to 20.53s on video benchmarks) because of master-agent coordination and iterative reasoning. Despite this overhead, Agent-Omni consistently achieves superior accuracy, especially on complex video and omni tasks, illustrating a trade-off between speed and reasoning quality. Future improvements such as parallelized execution could further reduce latency while preserving robustness.

3.9 Ablation Study

We conduct ablation studies on Agent-Omni, examining master-agent iterations and foundation model choices to reveal how iterative reasoning enhances robustness and model quality shapes performance.

Number of Iteration. We study the effect of the maximum number of iterations L on both accuracy and exit rate (Table 10). The exit rate denotes the proportion of queries that terminate at a given iteration, i.e., when the master agent decides that the answer is sufficiently complete and does not trigger further refinement.

Results show that most queries exit after the first iteration (over 90% for text and image tasks), which explains why Agent-Omni is generally efficient despite allowing multiple loops. For more challenging settings such as video or omni benchmarks, a higher fraction of queries proceed to the second or third iteration, yielding incremental accuracy

Table 10: Accuracy and exit rate across iterations on different benchmarks.

Method	# Iteration	Text			Image			Video			Audio		Omni			
		MMLU (Average)	MMLU-Pro	AQUA-RAT	MathVision	MMMU	MMMU-Pro	VideoMathQA	STI-Bench	VSI-Bench	MMAU	MELD (Emotion)	VoxCeleb (Gender)	Daily-Omni	OmniBench	OmniInstruct
Accuracy	1	88.99%	82.20%	88.98%	42.75%	69.30%	59.47%	29.76%	38.33%	39.25%	72.20%	51.97%	98.24%	58.06%	43.17%	74.57%
	2	89.15%	83.21%	88.98%	44.45%	70.37%	60.10%	30.71%	39.34%	39.55%	72.70%	51.97%	98.74%	58.56%	45.27%	74.46%
	3	89.23%	83.21%	89.37%	44.71%	70.37%	60.23%	30.71%	40.00%	39.50%	73.20%	51.97%	98.60%	58.73%	46.23%	74.88%
Exit Rate	1	94.39%	94.19%	92.91%	71.21%	78.98%	80.68%	64.29%	22.05%	72.05%	71.80%	59.38%	93.50%	81.12%	70.67%	79.49%
	2	4.47%	5.30%	6.69%	21.80%	16.29%	14.39%	29.52%	75.98%	26.27%	23.10%	31.02%	5.50%	17.54%	24.69%	17.27%
	3	1.01%	0.51%	0.39%	6.27%	3.90%	4.29%	5.71%	1.57%	1.53%	4.60%	7.03%	1.00%	1.34%	4.03%	2.98%
	4+	0.14%	0.00%	0.00%	0.72%	0.83%	0.63%	0.48%	0.39%	0.16%	0.50%	2.58%	0.00%	0.00%	0.61%	0.26%

gains (e.g., MMLU-Pro improves from 82.20% at 1 iteration to 83.21% at 3 iterations). This demonstrates that iterative reasoning acts as an adaptive mechanism: simple queries resolve quickly, while complex ones benefit from additional refinement.

Improvement from Foundation Models. We further examine how performance depends on the choice of foundation models in the pool. Table 8 shows that replacing stronger models (e.g., Deepseek R1 for text, Claude 3.7 Sonnet for image/video, Qwen2.5 Omni for audio) with weaker alternatives leads to consistent accuracy drops across modalities. For example, on MMMU-Pro, the combination with Claude 3.7 Sonnet achieves 60.23%, while weaker vision-language backbones reduce performance by more than 10 points.

These results confirm that Agent-Omni’s gains come not only from orchestration but also from leveraging high-quality specialized models. The framework is flexible: stronger foundation models directly translate to higher end-task accuracy, while weaker ones can be seamlessly swapped in when efficiency or resource constraints are prioritized.

4 Related Work

4.1 Multimodal Reasoning

Multimodal large language models (MLLMs) extend language models with the ability to process images, audio, and video (Zhang et al., 2024; Lin et al., 2025; Wang et al., 2024b; Liu et al., 2025b). Early systems typically focused on fixed modality pairs, such as text–image for visual question answering (Guo et al., 2023; Liu et al., 2023; Lin et al., 2024c) or text–video for event understanding (Li et al., 2025b). Instruction tuning has further improved alignment across modalities (Liu et al., 2025a; Li et al., 2025a), but these models remain constrained in reasoning capacity.

Recent studies explore reasoning improvements at test time. Forest-of-Thought (Bi et al., 2024) and related scaling approaches show that allocating more inference-time computation enhances reasoning. Ke et al. (2025) provide a survey of reasoning strategies, highlighting iterative inference and agentic designs as promising directions. Neverthe-

less, most existing work emphasizes unimodal or pairwise reasoning, and robust omni-modal reasoning, integrating arbitrary modality combinations, remains an open challenge.

4.2 Omni Models (Any-to-Text Models)

Another research line aims to develop unified omni models capable of handling arbitrary inputs (text, image, audio, video) and producing textual outputs. Representative efforts include Phi-4 Multimodal Instruct (Abouelenin et al., 2025), Qwen2.5 Omni (Xu et al., 2025), Ming-Omni (AI et al., 2025), Megrez-Omni (Li et al., 2025a), and Nexus-O (Liu et al., 2025a). While these systems expand coverage, they often face modality interference (Cai et al., 2025) and trade-offs across tasks (Zhai et al., 2023), limiting balanced performance.

To assess progress, new omni benchmarks such as OmniBench (Li et al., 2024b) and Daily-Omni (Zhou et al., 2025) have been proposed, emphasizing the difficulty of consistent cross-modal reasoning. Compared to unified training approaches, orchestration-based frameworks such as DSPy (Khattab et al., 2023) suggest an alternative path, where specialized models are coordinated at inference time. Our work builds on this perspective, showing that agent-based coordination provides a scalable solution for “any-to-text” reasoning without costly omni-model training.

5 Conclusion

In this work, we presented **Agent-Omni**, a framework that enables comprehensive omni-modal reasoning by coordinating specialized foundation models through a master-agent loop. Unlike unified multimodal models that require expensive joint training, Agent-Omni flexibly accepts almost any combination of text, image, audio, and video inputs, and produces coherent textual outputs without re-training. Our experiments demonstrate that Agent-Omni consistently achieves competitive or even superior accuracy across a wide range of benchmarks, particularly on challenging video and omni tasks. These results highlight the effectiveness of model coordination through iterative reasoning, showing that Agent-Omni offers a robust and general solution for omni-modal understanding.

Limitations

While Agent-Omni demonstrates strong performance across modalities, several limitations remain. The framework relies on the availability and stability of external foundation models, making results sensitive to API changes and updates. Errors or biases from individual models can propagate through the coordination process, and the iterative master loop may introduce latency and additional computational cost. Our evaluation is primarily conducted on curated benchmarks, which may not fully capture open-ended or real-world scenarios; therefore, generalization to noisy, adversarial, or safety-critical settings is unverified. Moreover, the system currently only produces textual outputs and does not handle generation in other modalities.

Ethical Considerations

This work follows the ACL Code of Ethics. Since omni-modal inputs may contain sensitive or personal information, careful data handling, privacy protection, and secure storage are essential. Biases and inaccuracies present in component models may be amplified through coordination, requiring responsible auditing and mitigation before deployment in high-stakes applications. To prevent misuse, such as in surveillance or harmful automation, deployment should be guided by clear usage policies, safety filters, and human oversight. We will document limitations, risks, and intended use cases when releasing research artifacts. We also used AI-based language editing support to polish sentences and check for grammatical errors; all substantive research contributions are human-generated.

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A Impact of Different Model Pools

To better understand the impact of different model pools, we conduct an ablation study by varying the choice of downstream agents for each modality while keeping the Master fixed to Claude 3.7 Sonnet. Tables 11–14 report accuracy on text, image, video, and audio benchmarks under different agent configurations.

For **text tasks** (Table 11), Claude 3.7 Sonnet as the text agent achieves strong overall performance across all MMLU domains, whereas DeepSeek R1 provides competitive results, slightly outperforming on STEM and reasoning-heavy datasets such as AQUA-RAT. This indicates that complementarity among text models can bring benefits on specific subsets of tasks.

For **image tasks** (Table 12), Claude 3.7 Sonnet again achieves the best accuracy across MathVision, MMMU, and MMMU-Pro. Substituting it with Qwen2.5 Omni or Phi-4 Multimodal Instruct leads to noticeable performance degradation, suggesting that dedicated large models trained with

Table 11: Accuracy comparison of agent settings on text modality.

Agent Setting	MMLU (STEM)	MMLU (Social Sciences)	MMLU (Humanities)	MMLU (Other)	MMLU (Average)	MMLU-Pro	AQUA-RAT
Master: Claude 3.7 Sonnet Text: Claude 3.7 Sonnet	92.47%	90.58%	85.80%	90.80%	89.91%	81.97%	88.89%
Master: Claude 3.7 Sonnet Text: Deepseek R1	94.52%	90.40%	81.68%	90.31%	89.23%	83.21%	89.37%

Table 12: Accuracy comparison of agent settings on image modality.

Agent Setting	MathVision	MMMU	MMMU-Pro
Master: Claude 3.7 Sonnet Image: Claude 3.7 Sonnet	44.71%	70.37%	60.23%
Master: Claude 3.7 Sonnet Image: QWen2.5 Omni	40.67%	65.88%	52.95%
Master: Claude 3.7 Sonnet Image: Phi4 Multimodal Instruct	38.68%	58.97%	36.07%

Table 13: Accuracy comparison of agent settings on video modality.

Agent Setting	VideoMathQA	STI-Bench	VSI-Bench
Master: Claude 3.7 Sonnet Video: Claude 3.7 Sonnet	30.71%	40.00%	39.50%
Master: Claude 3.7 Sonnet Video: Phi4 Multimodal Instruct	20.34%	36.05%	29.15%
Master: Claude 3.7 Sonnet Video: Llava Video 7B	23.81%	39.71%	33.33%
Master: Claude 3.7 Sonnet Video: Qwen2.5 Omni	22.86%	37.74%	39.51%

vision-language alignment remain more effective than general-purpose omni models for image understanding.

For **video tasks** (Table 13), using Claude 3.7 Sonnet consistently yields the strongest results on VideoMathQA and STI-Bench. Qwen2.5 Omni slightly improves on VSI-Bench but underperforms elsewhere, while Phi-4 Multimodal Instruct and Llava Video 7B struggle across most benchmarks. These results highlight the importance of specialized temporal reasoning capability for video agents.

For **audio tasks** (Table 14), the choice of downstream agent plays a critical role. Qwen2.5 Omni and Qwen2 Audio excel on VoxCeleb-Gender, while Phi-4 Multimodal Instruct performs best on MMAU. MELD-Emotion, however, shows clear advantages for Qwen2.5 Omni. This variation suggests that audio tasks are more sensitive to dataset characteristics and model pretraining objectives.

As summarized in Table 3, we adopt Claude 3.7 Sonnet as both the Master model and the vision/video agent, DeepSeek R1 as the text agent, and Qwen2.5 Omni as the audio agent. This choice is guided by the ablation results in Tables 11–14. Specifically, Claude 3.7 Sonnet demonstrates

Table 14: Accuracy comparison of agent settings on audio modality.

Agent Setting	MMAU	MELD-Emotion	VoxCeleb-Gender
Master: Claude 3.7 Sonnet Audio: Phi4 Multimodal Instruct	75.00%	41.13%	44.12%
Master: Claude 3.7 Sonnet Audio: Qwen2.5 Omni	73.20%	51.97%	98.60%
Master: Claude 3.7 Sonnet Audio: Qwen2 Audio	70.80%	40.39%	99.50%

strong and stable performance across visual and video tasks, making it a reliable backbone for perception and temporal reasoning. DeepSeek R1 shows complementary strengths on text-heavy reasoning benchmarks such as AQUA-RAT and MMLU-Pro, providing enhanced logical inference compared to Claude alone. For audio, Qwen2.5 Omni consistently achieves superior accuracy on speech-related benchmarks such as VoxCeleb and MELD-Emotion, outperforming other candidates.

Overall, this configuration balances robustness and specialization across modalities: Claude 3.7 Sonnet ensures reliable multimodal grounding and coordination, while DeepSeek R1 and Qwen2.5 Omni provide targeted improvements for text and audio understanding. This combination thus represents an empirically validated and well-justified design for the Agent-Omni framework.

B Prompt and Json of Each Stage

In this section, we provide the detailed prompt templates and the corresponding JSON output schemas used in each stage of the Agent-Omni framework. As described in the main paper, the framework consists of two key reasoning modules: the *Reasoning Stage* and the *Decision Stage*. The prompts are designed to instruct the system about the scope and responsibilities of each stage, while the JSON schemas specify the structured outputs that enable smooth coordination between components.

B.1 Reasoning Stage

Figure 4 shows the prompt template for the reasoning stage. This prompt guides the module to decompose the user query into modality-specific sub-

tasks and generate structured instructions for downstream agents. The corresponding JSON schema for the reasoning stage output is provided in Figure 6.

B.2 Decision Stage

Figure 5 presents the prompt template for the decision stage. Unlike the reasoning stage, this module integrates agent responses, evaluates completeness, and synthesizes a final answer. The structured JSON schema for this stage is illustrated in Figure 7.

B.3 Notes on Variables in Prompts

Within the prompt templates, several placeholders (highlighted in blue) are dynamically substituted during execution:

- {cur_round_num}: The current reasoning or decision round number, indicating iteration depth in the loop.
- {historical_message}: A record of outputs or feedback from previous rounds, used to refine ongoing reasoning.
- {input_summaries}: Summarized descriptions of the user’s multimodal inputs (text, image, audio, video), provided for context.
- {available_agent_info}: Metadata about the agent pool, specifying available agents and their capabilities.

These variables allow prompts to adapt dynamically to context, maintaining consistency across iterative reasoning loops.

You are the Reasoning Module in an "Understanding Anything" system. This system is designed to interpret user input across multiple modalities – text, image, video, and audio – by orchestrating existing foundation models through dynamic agents in several iterative reasoning loops. The system does not rely on fine-tuning or retraining.

The user's input may include any combination of modalities. The system comprises three main components: Reasoning, Dispatcher, and Decision.

You are currently in the Reasoning stage. Your next stage is the Dispatcher, which will route tasks to appropriate downstream agents (referred to as "passengers") specialized for each modality. Your role is not to answer the user's query directly. Instead, you must analyze the input and prepare tasks for the Dispatcher to execute. In some cases, you may be prompted with only a small subtask rather than the entire problem—when that happens, focus solely on the subtask you've been given, without assuming responsibility for the broader task. If decomposition is needed, break the input into clear, actionable subtasks to be handled downstream.

Specifically:

1. You might not receive the short summarization of the input material of different modelities.
2. Interpret the user's input (including the query and any multimodal data like text, image, video, audio, or others).
3. Identify relevant data modalities involved.
4. Understanding the provided historical messages, including any suggestions, shortcomings, etc.
5. Select the appropriate specialized agent(s) from the Agents Pool for further action.
6. Formulate precise and valuable follow-up questions for each selected agent to help them extract insights that contribute to answering the user's query. These questions will be used as prompts for the downstream agents.
 - Important: Downstream agents have access only to the user's input in their specific modality (e.g., text, image, video, or audio). They do not have access to the user's original query or any broader context.
 - Do not assume agents have any prior knowledge of the user's intent beyond the modality-specific input. Questions are independent.
 - Therefore, your questions must include all necessary context (information from user's query) or instructions explicitly.
 - Focus on clarity, completeness, and precision—frame each question to maximize the relevance and usefulness of the agent's response.
 - You are encouraged to ask multiple diverse questions for each agent at a round (more than three), as this may help other stages gain a more comprehensive understanding of the provided input.
7. Output a structured reasoning result including:
 - User Intent
 - Required Modality or Modalities
 - Suggested Agent(s)
 - Questions for each selected agent
8. If this is not the first round, the provided question should take into account the suggestions from the previous round.
9. If this is the first round, consider including the user's original query as one of the questions sent to each selected agent. This can help the agents provide a more relevant initial analysis or summary.

Background:

1. This is the `{cur_round_num}` round of reasoning.
2. You might receive the historical messages from the previous rounds.
`{historical_message}`
3. Modality of user's input with short summaries:
`{input_summaries}`
4. Agent Pool:
`{available_agent_info}`

You must not generate a final answer to the user's question. Your goal is reasoning and delegation only.

Figure 4: The prompt template of reasoning stage.

You are the Decision Module of the "Understanding Anything" system. Your role is to receive the results from all specialized agents (e.g., text_agent, image_agent, audio_agent, video_agent) and synthesize them into a comprehensive answer to the user's original query.

Responsibilities:

Task 1. Synthesize a complete, coherent, and concise answer to the user's original query by integrating:

- The user's multimodal input (text, image, audio, or video).
- The reasoning output from the previous Reasoning Module.
- All responses returned by invoked agents.
- If an answer from a previous round is available, you may use it as a reference to inform your response.
- However, do not mention or refer to the prior answer in the final answer, as the user is unaware of any 'previous rounds.' The final answer should address the user's query directly, as if it were the only interaction.

Task 2. Evaluate completeness and provide feedback:

- Always assess the synthesized answer for completeness, clarity, and alignment with the user's intent.
- In all cases, suggest how future rounds can be more accurate or efficient.
- If the answer is incomplete or ambiguous, clearly explain the gaps, and specify what additional analysis, clarification, or agent input is required to move forward. Also include suggestions for next round to improve the current version.
 - If the answer fully satisfies the user's query, present it as Final Output. You still have to provide suggestions for next round on how the analysis, synthesis, or communication could be improved.
 - Actively scan for logical inconsistencies, incorrect assumptions, or misaligned interpretations – even when the answer appears complete. When possible, propose alternative reasoning paths or reframe ambiguous user intent to surface potential misunderstandings.
 - Your suggestions for the next round should focus on improving the quality of the final answer and should closely align with the user's query.
 - If you are not 100% confident in the completeness or correctness of the answer, initiate a next round of reasoning or agent processing.

Task 3. Determine and recommend next steps:

- Always state whether further agent processing is needed.
- You must verify whether the final answer meets the format requirements specified in the user's query.
- In every case, regardless of output quality, provide concrete suggestions for improvement—such as refining agent prompts, re-evaluating multimodal inputs, or clarifying ambiguous reasoning steps.
- Your output must always move the understanding forward, even when the answer is not yet final.

Background:

1. This is the `{cur_round_num}` round of decision.
2. Modality of user's input with short summaries:
`{input_summaries}`
3. Results of agents and decision of previous rounds.
`{historical_message}`
4. Agent Pool:
`{available_agent_info}`

Guidelines:

- Never repeat agent responses verbatim. Always distill and integrate their content into a unified, user-focused answer.
- Whether the output is marked as final or not, you must always provide actionable recommendations to improve the analysis or clarity of the answer.
- Be strictly faithful to the user's original query and intent.
 - Do not speculate, over-extend, or introduce unrelated or unnecessary information.
 - Only answer the user's query; do not add context the user didn't ask for.

Figure 5: The prompt template of decision stage.

```

from pydantic import BaseModel, Field, conlist

class MasterReasoningStructure(BaseModel):

    class AgentInstruction(BaseModel):
        agent_name: str = Field(
            description=f"The identifier for the agent (selected from agent pool: {available_agent_info}) that is most suitable for handling this intent."
        )
        questions: conlist(str, min_length=1) = Field(
            description="A list of specific questions or instructions for this agent."
        )

    user_intent: str = Field(
        description="The user's goal or intention, typically inferred from a multimodal input or query."
    )
    agent_instructions: conlist(AgentInstruction, min_length=1) = Field(
        description="A list of instructions for each agent, containing the agent name and related questions."
    )

```

Figure 6: The JSON schema of reasoning stage output.

```

from pydantic import BaseModel, Field, conlist

class MasterDecisionStructure(BaseModel):
    final_answer: str = Field(
        description="The synthesized answer intended for showing to the end user. If the user's query includes output format requirements, please follow them strictly."
    )
    is_final: bool = Field(
        description="Indicates whether this is a complete and final answer (True), or if more work/follow-up is needed (False)."
    )
    suggestions_for_next_round: conlist(str, min_length=1) = Field(
        description="You must always include non-empty 'suggestions_for_next_round'. Even if the answer is final, you must still provide suggestions for improvement, validation, or alternative framing."
    )

```

Figure 7: The JSON schema of decision stage output.