

# Decoupled Planning and Execution: A Hierarchical Reasoning Framework for Deep Search

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## Abstract

Complex information needs in real-world search scenarios demand deep reasoning and knowledge synthesis across diverse sources, which traditional retrieval-augmented generation (RAG) pipelines struggle to address effectively. Current reasoning-based approaches suffer from a fundamental limitation: they use a single model to handle both high-level planning and detailed execution, leading to inefficient reasoning and limited scalability. In this paper, we introduce HiRA, a hierarchical framework that separates strategic planning from specialized execution. Our approach decomposes complex search tasks into focused subtasks, assigns each subtask to domain-specific agents equipped with external tools and reasoning capabilities, and coordinates the results through a structured integration mechanism. This separation prevents execution details from disrupting high-level reasoning while enabling the system to leverage specialized expertise for different types of information processing. Experiments on four complex, cross-modal deep search benchmarks demonstrate that HiRA significantly outperforms state-of-the-art RAG and agent-based systems. Our results show improvements in both answer quality and system efficiency, highlighting the effectiveness of decoupled planning and execution for multi-step information seeking tasks.

## Introduction

The information explosion on the internet has made it increasingly difficult to find comprehensive answers to complex queries, leading to the rapid development of deep search tasks that require understanding complex information needs and synthesizing accurate answers from multiple sources (Li et al. 2024, 2025b). However, traditional search engines only return ranked web pages based on keyword matching, requiring users to manually filter and synthesize information.

While large language models combined with search engines can provide direct answers, they typically only utilize shallow information from search results, lacking deep reasoning and comprehensive analysis capabilities (Lewis et al. 2020; Gao et al. 2024). This has motivated the development of specialized AI agents for deep search tasks, such as OpenAI DeepSearch (OpenAI 2025) and Grok

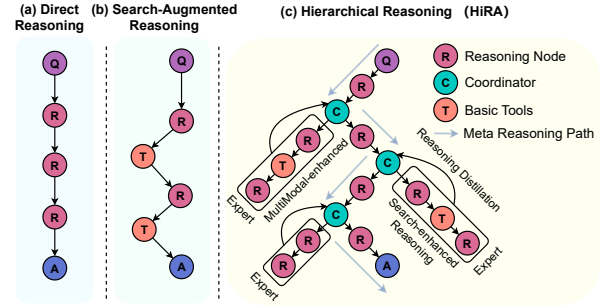


Figure 1: Comparison of current approaches for deep search tasks: (a) Direct Reasoning with LRMs, (b) Search-Augmented Reasoning that enables LRMs to use search engine during reasoning, and (c) Hierarchical Reasoning that autonomously interacts with expert agents and tools in continuous thinking process.

DeepSearch (Grok 2025), which aim to bridge the gap between simple search-enhanced models and deep information seeking systems.

Conventional approaches typically employ Retrieval-Augmented Generation (RAG) methods with predefined workflows (Lewis et al. 2020; Trivedi et al. 2023; Shao et al. 2023), which incorporate components like query decomposition, document summarization, and self-reflection to improve effectiveness. Recently, Large Reasoning Models (LRMs) such as OpenAI-o1 (OpenAI 2024a) and DeepSeek-R1 (DeepSeek-AI et al. 2025) have introduced new opportunities by integrating search and web browsing capabilities within their reasoning processes (Li et al. 2025a; Jin et al. 2025; Song et al. 2025). As shown in Figure 1, these search-augmented reasoning methods can autonomously plan and acquire external knowledge for complex information retrieval in an end-to-end manner, significantly improving deep search performance.

However, existing approaches suffer from architectural limitations due to their reliance on a single reasoning model to handle all tasks. Current methods typically work by prompting reasoning models to generate special tokens (Li et al. 2025a; Jin et al. 2025; Li et al. 2025b), which are used to trigger corresponding tool activations, during their

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thinking process. For example, in WebThinker, the search action is triggered by `<|begin_search_query|>` and `<|end_search_query|>`. This monolithic paradigm introduces two critical deficiencies: (1) Limited Capability Extensibility: Adding new tools or capabilities requires carefully redesigning prompts to teach the model new token patterns and their usage contexts. This process is brittle and often requires re-engineering token systems or extensive fine-tuning and reinforcement learning to ensure reliable token generation and tool coordination. (2) Reasoning Disruption: As shown in Figure 1, external execution results are directly injected into the reasoning chain, introducing noise that interferes with core reasoning processes. This disruption weakens the model’s logical thinking and occupies limited context windows with irrelevant operational details. These limitations stem from the assumption that one agent should handle all aspects of complex reasoning tasks. We argue that effective agent execution should follow a hierarchical structure, which is shown in Figure 1(c): a meta-agent for high-level planning, a coordinator for task reasoning transfer, and specialized execution agents for specific operations. Each execution agent focuses on completing a single assigned subtask through multi-step reasoning and iterative tool usage, allowing for deeper analysis without contaminating the overall planning process.

Based on this insight, we propose **Hierarchical Reasoning (HiRA)**, a reasoning-model driven framework designed to enhance deep search effectiveness by separating planning from execution. This architecture consists of three components: the Meta Reasoning Planner, the Adaptive Reasoning Coordinator, and the Domain-Specialized Executors. The Meta Reasoning Planner breaks down complex tasks into subtasks through a reasoning process. These subtasks are then dispensed to specialized agents by the Adaptive Reasoning Coordinator, which assigns them based on task complexity and the required expertise. Each Domain-Specialized Executor leverages specific reasoning models and external tools to execute the assigned subtask, with reasoning result distillation into the planner’s process via the coordinator.

This hierarchical design effectively decouples the strategic planning from the execution details, allowing for scalable, coherent reasoning in complex information retrieval tasks. By integrating specialized expertise at the execution level and maintaining a coordinated flow across the hierarchy, HiRA ensures both the flexibility and efficiency necessary for tackling advanced reasoning challenges. We conduct experiments on four complex, cross-modal, multi-scenario deep search tasks demonstrate that our framework significantly surpasses existing methods in all aspects.

Overall, the key contributions of this work are threefold:

- **(1) Hierarchical Reasoning Architecture:** We propose a novel hierarchical reasoning framework that integrates specialized tool-augmented reasoning agents as cognitive modules, eliminating the need for external tool orchestration or rigid predefined pipelines used in existing approaches.
- **(2) Enhanced Capability Integration:** Our Domain-

Specialized Executors enable plug-and-play integration of diverse reasoning capabilities and tools. Existing search agents can be directly incorporated without prompt engineering or model retraining, preserving established workflows while enhancing performance.

- **(3) Superior Empirical Performance:** Experiments across four complex cross-modal search tasks demonstrate significant improvements over traditional RAG and current agent-based methods, validating the effectiveness of hierarchical reasoning augmentation for complex information retrieval.

## Related Work

**From Retrieval-Augmented Generation to Deep Search.** Retrieval-Augmented Generation (RAG) combines external knowledge with LLMs’ parametric knowledge (Lewis et al. 2020; Borgeaud et al. 2022). Early approaches used single-step retrieval mechanisms (Gao et al. 2024; Jin et al. 2024a), while iterative RAG pipelines later incorporated query decomposition (Chan et al. 2024; Zhang et al. 2025), document refinement (Xu, Shi, and Choi 2023; Jin et al. 2024b), and multi-round search (Shao et al. 2023; Trivedi et al. 2023). However, RAG methods rely on predefined workflows that limit adaptive decision-making for complex queries. Recent work with LRMs integrate retrieval directly into reasoning processes (Li et al. 2025a; Jin et al. 2025), but still requires inserting documents into reasoning chains or using auxiliary models for summarization (Li et al. 2025b). These limitations motivate our exploration of hierarchical reasoning augmentation, where specialized agents serve as cognitive extensions while expanding additional capabilities.

**Planning-Execution Separation Approaches.** To address information overload in model reasoning, recent work separates planning from execution using dedicated planners and executors (Bilal et al. 2025). Existing approaches fall into two categories. *Action-level separation* assigns executors to single-step tasks, as in Plan-Act (Erdogan et al. 2025) for HTML manipulation and CoAct (Hou et al. 2024) with local replanning capabilities. *Query-level separation* decomposes problems at higher granularity: REMA (Wan et al. 2025) trains RL-based planners for mathematical reasoning, while LLMCompiler (Kim et al. 2023) and Query Compiler (Zhang et al. 2025) break down QA tasks into parallel execution graphs. However, these methods suffer from rigid task decomposition and limited executor specialization beyond prompt variations. Our work addresses these limitations through dynamic reasoning delegation and domain-specialized agents within a hierarchical framework.

## Methodology

### Problem Formulation

Formally, given a complex information retrieval question  $q$  and a predefined external environment  $\mathcal{E}$ , our objective is to design a framework that produces a final solution containing an answer  $\mathcal{A}$  and the corresponding reasoning process  $\mathcal{R}$ .

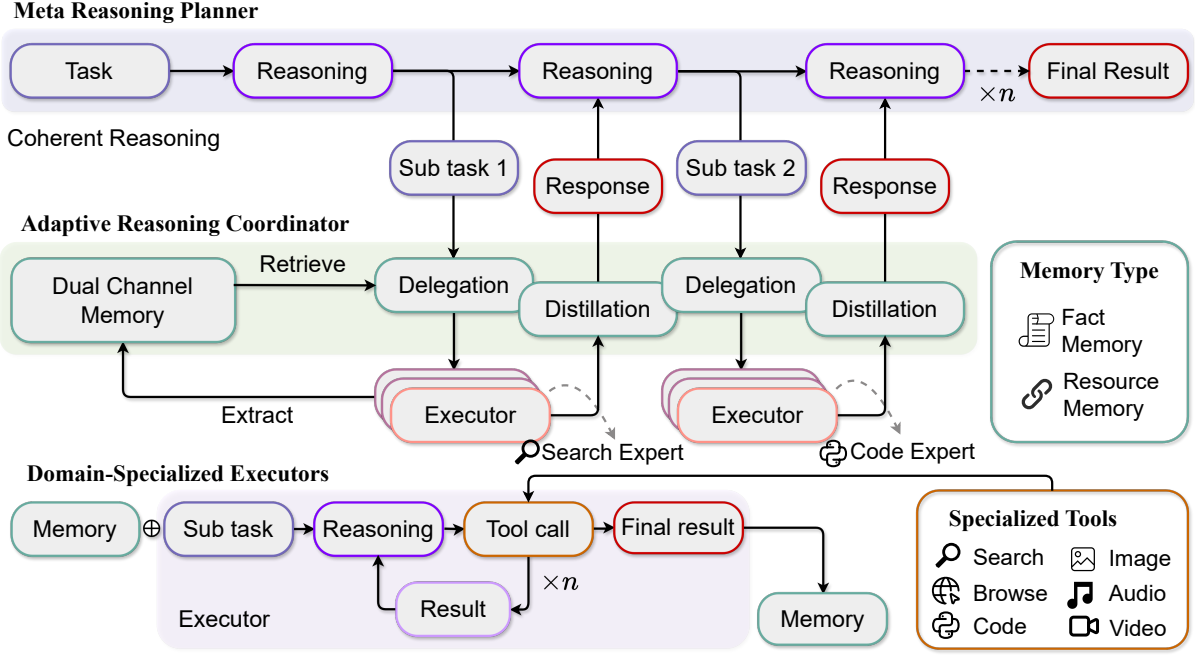


Figure 2: Overview of the HiRA Framework.

The generation process can be represented as:

$$P(\mathcal{R}, a \mid q, \mathcal{E}) = \prod_{t=1}^{T_{\mathcal{R}}} P(\mathcal{R}_t \mid \mathcal{R}_{<t}, q, \mathcal{E}_{<t}) \cdot P(a \mid q, \mathcal{R}),$$

where  $T_{\mathcal{R}}$  represents the token generation steps for the reasoning process,  $\mathcal{A}$  denotes the final answer, and  $\mathcal{E}_{<t} = \{\mathcal{E}(R_{<s})\}_{s<t}$  denotes the collection of all environment interaction results prior to timestep  $t$ . While existing agentic reasoning approaches typically use tools directly as the external environment, our work introduces a higher-level abstraction where the environment  $\mathcal{E}$  consists of a collection of expert agents, each capable of reasoning and utilizing specific tools to accomplish specialized tasks.

## Overview of the HiRA Framework

The HiRA framework is a hierarchical reasoning system that enhances deep search effectiveness through the separation of planning and execution. The architecture consists of three tiers: (1) **Meta Reasoning Planner** that decomposes complex tasks into subtasks through step-by-step reasoning, (2) **Adaptive Reasoning Coordinator** that assigns subtasks to appropriate expert agents based on task complexity and capabilities, and (3) **Domain-Specialized Executors** that execute subtasks using specialized reasoning models and external tools. Results are integrated back into the planner’s reasoning process through the coordinator. This hierarchical design decouples strategic planning from execution details, enabling scalable and coherent reasoning for complex information retrieval tasks.

## Hierarchical Reasoning Paradigm

**Meta Reasoning Planner** The Meta Reasoning Planner serves as the framework’s core orchestrator, responsible for planning, reasoning, and answer generation. Unlike conventional tool-augmented approaches that require models to directly invoke tools with specific parameters, our Meta Planner generates high-level subtasks containing strategic instructions for expert agents. This design enables natural collaboration between meta and expert agents, ensuring smooth information transfer while eliminating the noise and overhead associated with direct tool invocation and execution-level decision making.

To enable dynamic subtask generation during the reasoning process, we design a meta planner prompt that instruct the model to use special tokens for subtask dispatch. The overview of the process is shown in Figure 2. In reasoning process, the model will automatically generate special tokens and place the content and requirements of subtasks in the middle, which is similar to the process of humans issuing tasks. As shown in Equation (1), the generated subtask content  $s_k$  is based on previous task execution results  $\{\mathcal{E}(s_j)\}_{j<k}$  and current reasoning progresses  $\mathcal{O}_{<t}$ , naturally enabling reflection, correction, supplementation, and continuity generation of prior tasks. We impose no explicit constraints on subtask scope, difficulty, size, or relationships with previous subtasks to preserve overall reasoning flexibility.

$$P_M(s_k) = P_M(s_k \mid q, \mathcal{O}_{<t}, \{\mathcal{E}(s_j)\}_{j<k}). \quad (1)$$

Then, the coordinator layer processes and assigns  $s_k$  to corresponding expert agents for execution. Execution results

$\mathcal{A}_k(s_k)$  are wrapped in special tokens, and then integrated into the model’s reasoning process for continued generation. Notably, the subtask execution results incorporated into the reasoning process contain essential execution procedures and final conclusions, rather than vanilla tool invocation results that may contain noise and require subsequent processing. During the generation process, the model incrementally conditions on the original query  $q$ , the prior decoding history  $\mathcal{O}_{<t}$ , and the set of executed subtask results  $\mathcal{A}_j(s_j)_{j \leq K}$  to derive the final answer  $a$ , formalized as:

$$P_M(a) = P_M(a \mid q, \mathcal{O}_{<t}, \mathcal{A}_j(s_j)_{j \leq K}), \quad (2)$$

where  $K$  denotes the total number of subtasks.

This design enables modular task planning by decoupling high-level goals from execution, allowing the model to generate subtasks without knowing specific expert agents.

**Adaptive Reasoning Coordinator** While separating execution from planning provides clear scalability advantages and reduces computational noise, it introduces the risk of information loss between components. To mitigate this challenge, we design an adaptive reasoning coordinator that incorporates bidirectional, task-specific reasoning transfer and a dual-channel memory mechanism. This coordinator facilitates seamless reasoning delegation from the meta agent to expert agents while enabling reasoning distillation in the reverse direction, thus preserving efficient inter-agent communication and maintaining the architectural benefits of separation. In the following parts, we detail three core functions of the coordinator.

**(1) Reasoning Transfer Process.** The coordinator is designed to interpret subtasks provided by the meta planner and identify the most suitable expert agent for task execution. Given the current subtask  $s_k$  and detailed information about all experts  $\mathcal{I}_\mathcal{E} = \{\mathcal{I}_\mathcal{A}\}_{\mathcal{A} \in \mathcal{E}}$ , the coordinator first analyzes the subtask requirements, then evaluates agent capabilities across two key dimensions before making the optimal selection. Our instruction framework  $\mathcal{I}_{\text{select}}$  encompasses: (1) Required capabilities: the domain knowledge and tool utilization abilities necessary for task completion, and (2) Task complexity: the computational difficulty of the subtask and the required depth of analysis. For tasks within the same category (e.g., information retrieval), target information often resides at varying depths across data sources. While deploying the most sophisticated agent can ensure problem resolution, it may introduce unnecessary computational overhead and analytical redundancy. Therefore, the coordinator prioritizes selecting the most efficient agent for each specific task to optimize overall system performance.

Formally, we model this selection process as a classification problem:

$$\mathcal{A}_k^* = \operatorname{argmax}_{\mathcal{A} \in \mathcal{E}} P_C(\mathcal{O}_{\text{dele}}^{(k)}, \mathcal{A} \mid s_k, \mathcal{I}_\mathcal{E}, \mathcal{I}_{\text{select}}),$$

where the coordinator generates selection reasoning  $\mathcal{O}_{\text{dele}}^{(k)}$  and identifies the optimal expert agent  $\mathcal{A}_k^*$  through chain-of-thought reasoning.

**(2) Reasoning Distillation Process.** The coordinator is responsible for understanding and refining the expert agent’s

reasoning process before integrating the results into the meta reasoning planner’s cognitive flow to maintain overall reasoning coherence. Unlike traditional tool-augmented reasoning approaches that primarily focus on final execution outputs, our framework considers both the expert agent’s intermediate reasoning steps and the final conclusions. This dual consideration enables the meta planner to comprehend the underlying reasoning logic without being encumbered by low-level execution details, thereby facilitating autonomous reflection and critical evaluation of execution outcomes.

Specifically, given subtask  $s_k$  and the expert agent’s reasoning process  $\mathcal{O}_{\text{expert}}^{(k)}$ , the distilled reasoning process  $\mathcal{O}_{\text{dist}}^{(k)}$  and refined conclusion  $\mathcal{R}_{\text{dist}}^{(k)}$  are generated through:

$$\begin{aligned} P_C \left( \mathcal{O}_{\text{dist}}^{(k)}, \mathcal{R}_{\text{dist}}^{(k)} \mid s_k, \mathcal{O}_{\text{expert}}^{(k)} \right) \\ = \underbrace{P_C \left( \mathcal{O}_{\text{dist}}^{(k)} \mid \mathcal{O}_{\text{expert}}^{(k)}, \cdot \right)}_{\text{Reasoning Refinement}} \cdot \underbrace{P_C \left( \mathcal{R}_{\text{dist}}^{(k)} \mid \mathcal{O}_{\text{dist}}^{(k)}, \mathcal{O}_{\text{expert}}^{(k)}, \cdot \right)}_{\text{Conclusion Extraction}}. \end{aligned}$$

Subsequently,  $\mathcal{O}_{\text{dist}}^{(k)}$  and  $\mathcal{R}_{\text{dist}}^{(k)}$  are concatenated and seamlessly integrated as reasoning distillation feedback into the meta reasoning planner’s ongoing cognitive process.

**(3) Dual-Channel Memory Mechanism.** To enable effective information sharing and knowledge transfer among expert agents, we design a dual-channel memory mechanism tailored specifically for deep search task scenarios. The comprehensive memory repository  $\mathcal{M}$  encompasses two distinct types of memory: fact memory  $\mathcal{M}_f$  and resource memory  $\mathcal{M}_r$ . Fact memory archives factual discoveries and insights extracted from expert agents’ reasoning processes. Each memory entry comprises a factual assertion paired with its corresponding source attribution (URL, file name, or webpage identifier) to ensure traceability and verification. To maintain memory efficiency and reduce redundancy, multiple similar factual statements originating from identical sources are intelligently aggregated. Resource memory maintains a repository of informational resources encountered during expert agent execution processes. Each entry contains a descriptive summary alongside the corresponding access path (e.g., webpage URL, file path), designed to provide subsequent agents with valuable exploration insights from previous agent interactions, thereby preventing redundant exploration and enhancing overall system efficiency.

Memory construction and utilization operate in conjunction with the reasoning transfer pipeline. During the reasoning distillation phase, relevant memory components are extracted from the reasoning process  $\mathcal{O}_k$  and systematically updated within the global memory repository  $\mathcal{M}$ . During reasoning delegation, the coordinator intelligently retrieves pertinent memory entries based on semantic relevance between memory content and subtask requirements, as well as memory quality metrics, subsequently providing this contextual information as supplementary guidance to expert agents.

**Domain-Specialized Executors** To cover the diverse capabilities required for deep search tasks, we design three orthogonal agent capability dimensions, ensuring the system can handle complex and varied deep search scenarios:

Table 1: Overall performance on various deep search tasks, with accuracy results for each dataset obtained using llm-as-judge. For 32B models, the best results are indicated in **bold**, and the second-best results are underlined. Results from larger or closed-source models are presented in gray for reference. For the GAIA dataset, queries without files are used to ensure a fair comparison with the baseline.

Method	General AI Assistant				WebWalkerQA				Humanity’s Last Exam				SimpleQA
	Level 1	Level 2	Level 3	Avg.	Easy	Med.	Hard	Avg.	NS	CE	SF	Avg.	Acc
<i>Direct Reasoning</i>													
Qwen3-32B-no-thinking	14.3	6.1	<u>10.5</u>	9.5	4.4	2.1	0.8	2.8	7.1	6.0	3.1	6.2	6.5
Qwen3-32B-thinking	26.2	12.1	0	14.9	6.9	1.1	2.9	3.1	<u>14.6</u>	<u>9.8</u>	8.4	12.6	10.5
DeepSeek-R1-32B	21.5	13.6	0.0	14.2	7.5	1.4	4.2	3.8	6.6	5.1	6.5	6.4	5.5
QwQ-32B	30.9	6.5	5.2	18.9	7.5	2.1	4.6	4.3	11.5	7.3	5.2	9.6	6.5
GPT-4o	23.1	15.4	8.3	17.5	6.7	6.0	4.2	5.5	2.7	1.2	3.2	2.6	39.0
DeepSeek-R1-671B	40.5	21.2	5.2	25.2	5.0	11.8	11.3	10.0	8.5	8.1	9.3	8.6	42.4
o1-preview <sup>†</sup>	-	-	-	-	11.9	10.4	7.9	9.9	12.9	8.1	6.6	11.1	42.7
<i>Single-Capability Enhanced</i>													
Vanilla RAG	40.5	21.2	5.2	25.2	57.4	44.6	40.0	46.0	10.6	3.7	11.6	9.6	72.5
Search-o1	45.3	25.8	5.3	29.1	<b>70.2</b>	44.6	40.0	49.0	13.0	8.5	12.6	12.2	74.0
WebThinker	<u>50.0</u>	<u>34.9</u>	<u>10.5</u>	<u>36.2</u>	55.3	<u>53.0</u>	<u>50.0</u>	<u>52.5</u>	13.9	9.7	12.6	13.0	<u>78.0</u>
CodeAct	26.2	15.1	0.0	16.5	6.4	4.8	4.3	5.0	9.9	6.1	10.5	9.4	7.5
Multimodal Enhanced	23.8	9.1	0.0	12.6	4.3	0	4.3	4.0	9.3	<u>9.8</u>	8.4	9.2	10.5
<i>Multi-Capability Enhanced</i>													
Plan-and-Solve	28.6	18.2	0.0	18.9	44.7	33.7	24.3	33.0	10.2	4.9	7.3	8.8	57.5
ReAct	45.3	28.8	5.2	30.7	46.8	31.3	31.4	35.0	12.7	<b>11.0</b>	<b>20.0</b>	<u>13.8</u>	73.5
HiRA (ours)	<b>61.9</b>	<b>37.9</b>	<b>15.8</b>	<b>42.5</b>	<u>59.6</u>	<b>54.2</b>	<b>51.4</b>	<b>54.5</b>	<b>15.2</b>	<b>11.0</b>	<u>13.7</u>	<b>14.2</b>	<b>81.5</b>

- **Information Acquisition:** This dimension is responsible for acquiring and integrating information from the web.
- **Cross-Modal Understanding:** This dimension handles the understanding and fusion of multimodal information, capable of processing data from different modalities such as images, videos, and audio.
- **Computational Reasoning:** This dimension handles mathematical computation, file processing, and other computational reasoning tasks, capable of transforming abstract problems into executable code solutions.

Based on these three dimensions, we implement four reasoning model-driven, specialized agents. For **information acquisition**, we design two search agents with different exploration depths: one based on a simple RAG pipeline that performs single retrieval for subtasks followed by reasoning, and another based on the WebThinker implementation that can perform deep search and information acquisition on the internet. The combination of these two approaches enables flexible solutions for both simple and complex tasks. For **Cross-Modal Understanding**, we embed multimodal models as tools within the reasoning model’s inference process to achieve dynamic understanding of information in multimodal data. For **Computational Reasoning**, we embed code interpreters into the reasoning model’s thought process.

For the aforementioned reasoning-driven agents, their reasoning process follows the tool-augmented reasoning execution flow, capable of dynamically outputting special tokens during reasoning to trigger corresponding tools. The

reasoning process is:

$$P(\mathcal{O}^{(k)} \mid s_k, \mathcal{T}, \mathcal{M}_k) = \sum_{t=1}^{T_k} P(\mathcal{O}_t^{(k)} \mid \mathcal{O}_{<t}^{(k)}, \{\mathcal{T}_j\}_{<t}, \cdot),$$

where  $\mathcal{O}^{(k)}$  represents the reasoning process of expert agent for subtask  $s_k$ ,  $\mathcal{M}_k$  represents the memory related to  $s_k$ ,  $\mathcal{T}$  represents the tools used in the process (e.g., code interpreter), and  $\{\mathcal{T}_j\}_{<t}$  represents all tool invocation results before time step  $t$ . Based on this process, we can embed arbitrary tools into the reasoning model’s inference process. More details can be found in the appendix.

### Inference Process of HiRA

The inference process of HiRA follows an agentic reasoning approach. For a given question, the inference process begins with reasoning by the meta agent. During reasoning, the meta planner decodes special token pairs, wrapping the subtasks to be executed between them. The coordinator then processes and distributes the subtasks to expert agents for execution. After the expert agents perform reasoning and multiple rounds of tool invocation, subtask execution results are obtained.

This reasoning process and results are then processed by the coordinator through the reasoning distillation process to obtain refined results, which are integrated into the meta planner’s reasoning chain to continue generation. During this process, the meta planner dynamically adjusts its plan and corresponding subtasks to be distributed based on execution results, until all information has been collected and the final answer is provided. The detailed algorithmic flowchart can be found in the appendix.



## Experimental Settings

**Tasks and Datasets** To comprehensively evaluate our method’s performance on deep search tasks, we follow prior work and introduce more scenarios (e.g., multimodal and file input) to thoroughly test our method’s ability to interact with diverse data types and environments. We use the following datasets for evaluation: (1) GAIA (Mialon et al. 2024), a benchmark for evaluating general-purpose AI assistants with questions requiring multi-step reasoning and external information retrieval, where we use all samples from its validation set, categorized into text-only, multimodal, and with-file; (2) WebWalkerQA (Wu et al. 2025), designed to evaluate models’ ability to navigate web pages and extract information from single or multiple pages, covering both English and Chinese queries, from which we sample 200 test questions; (3) SimpleQA (Wei et al. 2024), testing models’ factual accuracy, knowledge breadth, and factual capabilities, from which we sample 200 test questions; and (4) Humanity’s Last Exam (Phan et al. 2025), a high-difficulty dataset requiring complex reasoning, containing academic problems across mathematics, physics, and computer science, where models need to retrieve relevant external information, from which we sample 500 validation questions. To ensure fair and accurate evaluation, we adopt LLM-as-judge approach for all datasets, using the Qwen2.5-72B-Instruct model (Yang et al. 2024) to compute accuracy scores. Evaluation prompts and detailed settings are provided in appendix.

**Baselines** We compare our method against three baseline approaches: (1) **Direct Reasoning**: Direct question answering using models’ inherent reasoning capabilities. We evaluate both open-source models (Qwen3-32B (Yang et al. 2025), QwQ-32B (Team 2024), DeepSeek-R1-32B (DeepSeek-AI et al. 2025)) and commercial models (GPT-4o (Hurst et al. 2024), DeepSeek-R1 (DeepSeek-AI et al. 2025), o1-preview (OpenAI 2024b)). (2) **Single-Capability Enhanced**: Methods that augment reasoning with a single specialized capability. This includes search-enhanced approaches like Search-o1 (Li et al. 2025a) and WebThinker (Li et al. 2025b), code execution capabilities like CodeAct (Wang et al. 2024), and multimodal reasoning capabilities through our implemented Multi-Enhanced Reasoning baseline. (3) **Multi-Capability Reasoning**: Approaches that integrate multiple capabilities or employ structured reasoning frameworks. This includes planning-based methods like Plan-and-Solve (Wang et al. 2023) that separate planning from execution, and multi-tool frameworks like ReAct (Yao et al. 2022) that directly orchestrate multiple capabilities within a single reasoning process. These two methods and our approach use the same set of tools to ensure a fair comparison.

**Implementation Details** Following current work, we use QwQ-32B as the base model for both the meta reasoning planner and expert agents. We employ a same-sized Qwen2.5-Instruct model as the Adaptive Reasoning Coordinator. For all models, we set temperature to 0.7, top\_p to 0.95, top\_k to 20, and the model context window to 128k tokens. Our search tool uses the Bing Web Search API with US-EN as the region setting and retrieves the top-10 search

Table 2: Ablation studies of HiRA, showing results for each layer. GAIA-B refers to GAIA queries without associated files (as in the main result), while GAIA-F refers to the subset with files.

Method	GAIA-B	GAIA-F	Web.	HLE	Simp.	Avg.
<b>HiRA</b>	<b>42.5</b>	<b>42.1</b>	<b>54.5</b>	<b>14.2</b>	<b>81.5</b>	<b>44.9</b>
<i>Coordinator Layer</i>						
w/o Reasoning Transfer	33.9	36.8	44.5	10.4	76.5	40.4
w/o Memory	37.8	31.6	52.0	11.8	79.0	42.4
<i>Executor Layer</i>						
w/o Search	15.7	31.6	4.0	12.4	9.5	14.6
w/o Code	33.9	28.9	51.5	12.8	76.5	40.7
w/o Multimodal	36.2	36.8	55.0	13.6	81.0	44.5

results. We employ Qwen2.5-Omni-7B (Xu et al. 2025) as our multimodal tool, powered by Qwen’s official API. We construct a sandbox based on a Python interpreter as our code execution environment, with necessary security restrictions to ensure safe operation. In the main experiments, we set the maximum number of subtasks for the meta reasoning planner to 10.

## Experimental Results

### Main Results

As shown in Table 1, we evaluate our method on the deep search tasks against several baselines that integrate reasoning with tool usage. We have the following observations: (1) **Overall Performance Superiority**: Our method consistently outperforms all baseline methods. It significantly surpasses direct reasoning models without tool usage and achieves notable improvements over existing tool-augmented approaches. Compared to the strongest search agent baseline WebThinker, our approach demonstrates substantial advantages on both complex tasks (GAIA and HLE). (2) **Hierarchical Reasoning Design Advantages**: The experimental results show that our hierarchical design achieves better performance when using the same set of tools. For Plan-and-Solve which relies on a fixed plan executed sequentially, performs poorly (e.g., 18.9 in GAIA), highlighting the necessity of dynamic planning during reasoning. While ReAct enables dynamic planning by integrating multiple tools into the reasoning chain, its performance suffers in multi-tool scenarios such as GAIA due to the overhead of tool selection and noisy intermediate tool outputs. In contrast, our method outperforms WebThinker on GAIA, which requires diverse capabilities, while also achieving superior results on general web search tasks. (3) **Robustness Across Task Complexity**: Our framework shows moderate gains on simpler tasks (e.g., SimpleQA and WebWalkerQA), but exhibits much larger improvements on more complex tasks, demonstrating its strength in handling complex reasoning scenarios.

### Ablation Study

We conduct ablation studies to investigate the contribution of each component within the framework by removing mod-

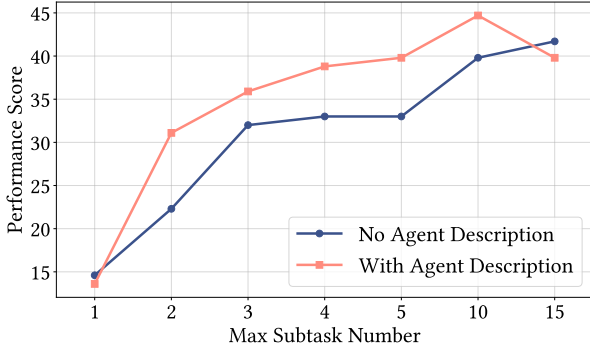


Figure 3: Performance comparison on whether the expert agent description is provided to the meta planner and maximum number of sub-tasks limit.

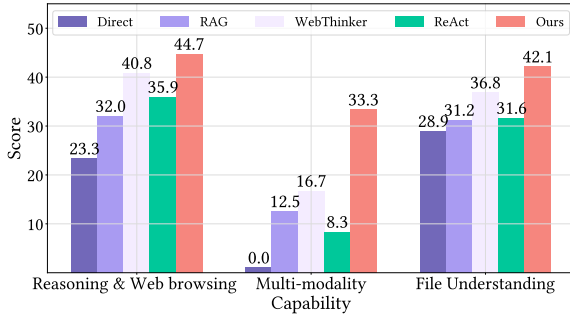


Figure 4: Comparison of our method with the baseline on three GAIA subsets, evaluating performance across different dimensions of capability.

ules from both the Coordinator Layer and the Executor Layer. Results are shown in Table 2.

In the Coordinator Layer, removing the Reasoning Transfer mechanism leads to significant performance drops, especially on complex reasoning tasks, with nearly 30% decrease in performance. In comparison, the Memory mechanism has a smaller impact, except on file-related tasks (approx. 10% drop), indicating that the resource component in memory effectively supports information propagation.

In the Executor Layer, removing individual expert agents leads to substantial performance degradation. Among them, removing the Search Agent causes the most severe drop across all datasets, highlighting the essential role of information acquisition on web. Similarly, removing the Code Agent significantly impacts performance on multi-functional datasets such as GAIA, showing its importance for general-purpose tasks. Removing the Multimodal Agent results in a slight drop on GAIA, where some cases require multimodal capabilities, but has little impact on standard web tasks.

### Generalization and Effectiveness of Meta Planner

In our framework, the meta-planner receives expert capability information for better subtask planning, while also limiting the number of subtasks to control computational

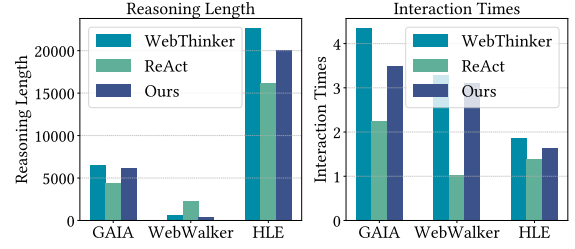


Figure 5: Comparison of different methods in terms of reasoning length (number of output tokens during model inference) and interaction times (number of interactions with the environment during inference) in three datasets.

cost. These two factors affect both generalization (supporting more agents) and effectiveness (achieve higher performance). To evaluate both aspects, we introduce an additional setting where no expert information is provided to the meta-planner, and we vary the maximum number of allowed subtasks. Results are shown in Figure 3, leading to two key observations: **(1) Decoupled Meta-Planner Design:** Even without access to expert information, the meta-planner achieves comparable performance. This suggests that, within our architecture, the meta-planner and expert agents are relatively decoupled—the generated subtasks primarily depend on the task semantics rather than the specific agents, enabling better scalability to new agents. **(2) Subtask Scaling Trade-off:** As the number of subtasks increases, performance first improves then degrades. This resembles an inference-time scaling effect: allowing more subtasks enables deeper reasoning chains, while overly restricting subtasks may prevent sufficient exploration. However, excessive subtasks may introduce inefficient plans, eventually hurting performance.

### Capability Analysis

Beyond the main experiments, we further evaluate our system on additional subsets of GAIA to assess its capabilities beyond web search (e.g., multimodal understanding, file understanding), which are also critical for more comprehensive information acquisition. As shown in Figure 4, our method achieves the best performance across all capability dimensions, demonstrating its broad applicability. While baselines like ReAct perform well in purely textual reasoning and web browsing, our integration of the DeepSearch agent yields superior results. Moreover, due to our multimodal architecture, we achieve additional gains in non-textual tasks. It is worth noting that, although ReAct can invoke multimodal and code tools, its planning model struggles to coordinate multiple tools simultaneously, often leading to sub-optimal performance (e.g., 8.3 vs. 12.5 in multimodal tasks), in some cases even underperforming pure search-based approaches.

### Efficiency Analysis

To assess the overall efficiency of our method, we compared the number of inference tokens and the number of interactions with the environment between HiRA and baselines

across three datasets of varying difficulty. Based on the result in Figure 5 and Table 1, we make two observations: (1) Overall, more difficult datasets tend to result in longer reasoning chains, but they do not necessarily lead to more interactions with the environment, which may also be influenced by the nature of the task itself. (2) Compared to WebThinker, which directly integrates the search function into the main reasoning chain, our hierarchical reasoning structure results in shorter reasoning chains and fewer interaction times, indicating that our approach is more efficient in each subtask call than directly invoking tools. (3) The ReAct method, which integrates multiple functionalities into a single model, leads to fewer tool calls and insufficient reasoning, which may be due to interference between the descriptions of multiple tools, resulting in suboptimal performance.

## Conclusion

In this paper, we proposed HiRA, a hierarchical reasoning framework that addresses the limitations of monolithic reasoning models in deep search tasks. By decoupling high-level planning from low-level execution, HiRA introduces a multi-agent architecture consisting of a Meta Reasoning Planner, an Adaptive Reasoning Coordinator, and Domain-Specialized Executors. This design enables scalable and modular reasoning by embedding specialized agents as cognitive components rather than relying on rigid pipelines or single-agent paradigms. Through dual-channel memory and coordinated task routing, our approach supports coherent knowledge synthesis and dynamic integration of diverse reasoning capabilities. Extensive experiments across five complex, multi-modal deep search scenarios demonstrate that HiRA significantly outperforms conventional RAG systems and prior agent-based methods, validating the effectiveness and flexibility of hierarchical reasoning in addressing sophisticated information retrieval challenges.

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## Appendix

### Datasets

(1) **GAIA**: A benchmark for evaluating general-purpose AI assistants, where questions require multi-step reasoning and external information retrieval. We use all samples from the validation set and categorize them into three types based on input and required information: text-only, multimodal, and with-file. Specifically, with-file represents queries where the input question comes with accompanying files, text-only represents queries that only require text capabilities, which are filtered through annotated metadata, and the remaining queries are categorized into multimodal. (2) **WebWalkerQA**: A benchmark designed to evaluate models' ability to navigate web pages and extract information. Questions require aggregating knowledge from single or multiple web pages and cover both English and Chinese queries. We sample 200 questions from the test set. (3) **SimpleQA**: A benchmark testing models' factual accuracy, examining knowledge breadth and factual capabilities. Since models inherently suffer from hallucination issues and may struggle on this dataset, this benchmark effectively tests models' ability to answer questions by incorporating external knowledge. We sample 200 questions from the test set. (4) **Humanity's Last Exam**: A high-difficulty dataset requiring complex reasoning, containing academic problems across multiple domains including mathematics, physics, and computer science. Models need to retrieve relevant external information to support their reasoning. We sample 500 questions from the validation set.

### Evaluation Metrics

To fairly evaluate the effectiveness of our methods, we adopted the LLM-as-Judge approach across all datasets, using Qwen2.5-72B-Instruct to assess the consistency between model-generated answers and golden answers. The instruction used here follows Webthinker (Li et al. 2025b), as shown in following instruction . It should be noted that in the construction process of the WebWalker dataset we used, each question's answer is derived solely from the corresponding annotated webpage, without collection and organization from the web, which leads to biased and inconsistent golden answers. This results in models providing more detailed answers being incorrectly judged as wrong (due to inconsistency with standard answers). Therefore, in evaluation of WebWalker, we optimized the instruction template, as shown in following instruction .

#### Evaluation Instruction for Normal QA Tasks

You are an evaluation assistant. Please determine if the model output is equivalent to the labeled answer.

Question: {question}

Labeled Answer: {labeled\_answer}

Model Output: {pred\_answer}

Did the model give an answer equivalent to the labeled answer? Please respond with "Correct" if they are equivalent, or "Incorrect" if they are not equivalent. Do not include any other text.

#### Evaluation Instruction for WebWalker

You are an evaluation assistant. Please determine if the predicted answer is equivalent to the labeled answer in terms of core content.

Question: {question}

Labeled Answer: {labeled\_answer}

Predicted Answer: {pred\_answer}

Evaluation Guidelines:

1. Mark as "Correct" if the predicted answer contains all key information from the labeled answer, even if it provides additional details
2. Mark as "Correct" if the predicted answer matches the core meaning of the labeled answer, regardless of different phrasing
3. Only mark as "Incorrect" if the predicted answer misses critical information or contains incorrect information

Please respond with only "Correct" or "Incorrect". Do not include any other text.

## Implementation Details

**Baseline Details** All our baselines are implemented based on QwQ-32B as the base model. The implementation details for each baseline are described below:

- **Vanilla RAG:** We directly utilize the original question for search and then provide the retrieved results to the generator for answer generation.
- **Search-o1:** This approach integrates search capabilities during the reasoning process, dynamically generating queries and performing searches. Our implementation is based on the official Search-o1 repository.
- **WebThinker:** This method enables dynamic searching, link clicking, and report generation during the reasoning process. Since our evaluation does not involve report generation, we only utilize the question-answering functionality. Our implementation is likewise based on the official repository.
- **CodeAct:** This approach can invoke code tools to assist reasoning during the inference process. We employ a Python Sandbox as the code tool and design custom prompts for implementation, with the instruction shown in following instruction .
- **Multimodal Enhanced:** Similar to CodeAct, we replace the Python Sandbox with the multimodal tool used in our method (i.e., the Qwen2.5-omni-7B model) as a tool that can be dynamically invoked during reasoning, with the instruction shown in following instruction .
- **Plan-and-Solve:** This method first comprehends the original question and generates an overall plan, then executes this plan step-by-step until reaching the final result. The instruction for plan generation is shown in following instruction . During plan execution, to ensure fair comparison with our method, we automatically determine the most appropriate expert agent for each step in the plan through the model, using the same set of expert agents as in our approach.
- **ReAct:** This approach allows the model to directly utilize multiple tools as needed during reasoning to assist inference. Tool descriptions are provided to the model at the beginning, and tool outputs are directly inserted into the chain of thought.

### Instruction Template for Query Planning in Simple Search Agent

You are a reasoning assistant. Your task is to generate a detailed query plan for answering the user's question by breaking it down into sub-queries. Each query should be a precise and suitable query for web search.

Please analyze the question and break it down into multiple sub-queries that will help gather all the necessary information to answer it completely.

Remember:

1. Each sub-query should be a precise and suitable query for web search.
2. Subqueries should cover different aspects to avoid duplicate searches.
3. Each subquery needs to be necessary, do not add irrelevant ones. You need to use as few subqueries as possible to obtain accurate results.

Output your query plan in JSON format as follows:

```
```json
{{
  "query_plan": [
    "sub-query-1",
    "sub-query-2",
    ...
  ]
}}
```

Task: {question}

### Instruction Template for Answer Generation in Simple Search Agent

You are a knowledgeable assistant that uses the provided documents and previous exploration results as your current memory to answer the user's question step by step.

You need to carefully analyze the given context step by step and then provide a reliable, detailed answer to the task. If you find that there is no valid information in the document, please directly state that there is no valid information.

Your answer needs to include specific analysis and relevant citations (detail page url and title).

Question: {question}  
Documents: {documents}

### Instruction Template for Answer Generation in Computation Reasoning Agent

You are a reasoning assistant with the ability to execute Python code to help you answer the user's question accurately.

You have special tools:

- To execute a python code: write `<|begin_code_call|>python your python code here <|end_code_call|>`. Then, the Python code interpreter will execute the python code, and provide you with execution result in the format `<|begin_code_call_result|> ...code call results... <|end_code_call_result|>`. If the code encounters errors while running, try to fix them and give another code call. You can repeat the code execution process multiple times if necessary. The maximum number of code execution attempts is limited to {MAX\_CODE\_CALL\_NUM}. Once you have all the information you need, continue your reasoning. You are given previous exploration results as your current memory, please first check the current memory for relevant information before making search. But you need to be aware that the facts involved in memory may not be comprehensive.

Example: {example}

Remember:

- Use `<|begin_code_call|>` to start Python code and end with `<|end_code_call|>`.
- Always explain your reasoning before and after executing code.
- When done with code execution, provide a clear final answer or solution. Please answer the following question step by step. When encountering scenarios that require computation, try to use code for verification instead of solely using own knowledge. You should provide your final answer in the format `\boxed{{YOUR_ANSWER}}`.

Current Memory: {current\_memory}  
Question: {task\_info}

### Instruction Template for Answer Generation in Multimodal Reasoning Agent

You are an AI assistant with multimodal understanding capabilities. You can analyze images, video and audio to answer user questions.

You have access to a special multimodal tool: - To analyze an image/video/audio and answer questions about it, use the format: `<|begin_multimodal_call|> data: [path of image/video/audio] question: [your specific question] <|end_multimodal_call|>` The system will provide analysis results in the format: `<|begin_multimodal_result|> ...analysis results... <|end_multimodal_result|>` You can ask multiple questions about different aspects of the image/video/audio if needed. The maximum number of multimodal analysis calls is limited to {MAX\_MM\_CALL\_NUM}.

You are given previous analysis results as your current memory. Please check the current memory for relevant information before making new analysis requests. Example: {example}

Remember: - Always explain your reasoning before and after multimodal analysis - Provide your final answer in `\boxed{{YOUR_ANSWER}}` format



```
Current Memory: {current_memory}
Question: {task_info}
```

#### Instruction Template for Plan-and-Act

You are a reasoning assistant. For the given task, come up with a simple step by step plan. This plan should involve individual tasks, that if executed correctly will yield the correct answer. Do not add any superfluous steps. The result of the final step should be the final answer. Make sure that each step has all the information needed - do not skip steps.

Give your plan in JSON format as follows:

```
```json
{{
  "plan": [
    "step1", # each step is a string of the task description
    "step2",
    ...
  ]
}}
```

Remember:

1. Each step should be a self-contained task, describe the task in detail.
2. The result of the final step should be the final answer.
3. Output your plan in JSON format.

```
```
```

Task:

```
{question}
```

**Details of Domain-Specific Agents** In our experiments, we design four types of expert agents to implement different functionalities and accomplish various types of tasks. The specific design details for all agents are as follows:

- **Simple Search Agent:** Responsible for searching and integrating information on the internet, suitable for simple and efficient information gathering and fact verification. Its workflow includes understanding the given subtask and generating a query plan, then conducting searches and collecting information to provide answers. The instruction templates for query planning and answer generation are shown in following instruction and following instruction , respectively.
- **Deep Search Agent:** Responsible for conducting deep exploration and information collection on the internet, requiring capabilities such as utilizing search engines and clicking webpage links. We directly adopt the implementation of WebThinker (Li et al. 2025b) as our deep search agent.
- **Computational Reasoning Agent:** This agent can autonomously invoke a Python interpreter during the reasoning process to assist its thinking and information collection. The covered functionalities include but are not limited to: reading files, downloading files, and obtaining webpage information through code. We follow the approach of Search-o1 (Li et al. 2025a), using the QwQ-32B reasoning model to drive a Python tool encapsulated in a sandbox, with the specific instruction shown in following instruction .
- **Multimodal Agent:** Possesses the capability to invoke multimodal tools during the reasoning process. To simplify deployment and reduce usage complexity, we employ Qwen-omni-7B as our multimodal tool, which can understand files of various modalities. We embed it into the model’s reasoning process, enabling the model to invoke this tool during thinking to handle multimodal scenarios, with the specific instruction shown in following instruction .

**Details of Coordinator** We employ Qwen2.5-32B-Instruct as the base model for our coordinator, which primarily incorporates three functions: (1) **Reasoning Transfer Process:** The model is assigned a subtask and subsequently identifies the most suitable expert agent through classification. During this process, comprehensive information about all available expert agents is provided to the model to facilitate its understanding of each agent’s capabilities. The specific instruction is formulated as follows:

### Instruction for Reasoning Transfer Process

You are an agent selection system. Analyze the given task and select the most suitable agent based on:

1. Required Capabilities:

- What specific skills/knowledge does this task demand?
- How well does each agent's expertise match these requirements?

2. Task Difficulty:

- Complexity level (simple fact vs multi-step problem-solving). You should consider the effective time cost of each agent.
- Depth of analysis needed (surface information vs deep exploration)
- You need to choose the model **that can complete the task** with the lowest cost/complexity as much as possible.

**Only output the JSON format** with the following fields:

- reason: The reason for selecting the agent
- selected\_agent\_name: The name of the selected agent

Example Output: {example}

Agents Available: {agent\_info}

Task: {task}

Analyze the task and respond **ONLY** the json format, without any additional explanation.

(2) **Reasoning Distillation Process:** Upon completion of a subtask by an expert agent, the coordinator comprehends and summarizes the agent's reasoning trajectory, subsequently refining it into a distilled reasoning process and final conclusion for reporting to the meta-planner. This mechanism enables the meta-planner to verify the logical validity of the reasoning pathway and evaluate the derived results.

(3) **Memory Construction:** Beyond the conclusion, the coordinator extracts and records key findings from the expert agent's reasoning process into the global memory. Specifically, we design the coordinator to capture two memory components: facts and resources. To enhance computational efficiency, this functionality is implemented within the same instruction as the reasoning distillation process. The detailed instruction is formulated as follows:

### Instruction for Reasoning Distillation Process and Memory Construction

You are a specialized Summarization Agent. Your role is to analyze a problem and a model's thinking process, then produce a structured summary with two key components:

1. CONCLUSION: Create a concise string that captures:

- reasoning\_process: A concise string outlining the necessary reasoning steps in logical order, including key actions, searches, and findings.
- final\_conclusion: A concise string that captures the final answer and conclusion of the given task.

2. MEMORY: **Organize useful information for future tasks** (only include the information that highly likely to be useful for future tasks, don't include current memory facts):

- fact\_memory: List important facts discovered during reasoning
  - \* Each entry must include both content AND source
  - \* Sources must be specific (exact URLs, specific document names, or "Model Inference" for reasoned conclusions)
  - \* Consolidate related facts into single entries to avoid fragmentation. Only keep facts that are relevant to the future tasks.
  - \* If no valid source is found, set it as [Source: Not Specified]
- resource\_memory: Map useful resources as "description": "path" pairs
  - \* Paths must be complete, valid URLs or precise variable names
  - \* Descriptions should be clear and specific
  - \* Include only verified, accessible resources

\* If no valid resources exist, set resource\_memory as an empty dictionary

Produce ONLY a properly formatted JSON object with these components. Include nothing else.

Example output: {example}

Reasoning Chain:  
{reasoning\_chain}

Task: {task\_description}

(4) **Memory Utilization:** During subtask delegation, the coordinator retrieves relevant memory segments from the global memory and provides them to the expert agent alongside the subtask. The instruction is structured as follows:

#### Instruction for Memory Utilization

You are an assistant specialized in filtering memory based on a specific task. Your task is to analyze the given memory and select ONLY the most task-relevant memories, with a strict maximum limit of 5 entries.

Key Requirements:

1. Relevance First:

- Each selected memory MUST have a direct and strong connection to the current task
- Reject memories that are only tangentially or weakly related
- If there are fewer than 5 highly relevant memories, select only those that are truly relevant

2. Quality Control:

- Filter out any memories with invalid or suspicious URLs
- Remove memories about failed attempts or negative experiences
- Exclude memories that contain speculative or unverified information

3. Output Format:

- Output the filtered memories in the following format:

...

Memory Fact 1: [memory1]

Memory Fact 2: [memory2]

...

Remember: It's better to return fewer but highly relevant memories than to include marginally related ones just to reach 5 entries.

Memory:  
{memory}

Task:  
{task}

Filtered Memory:

## Case Study

The following is a case from the GAIA dataset that demonstrates the capability of our method, shown in Table 3.

Table 3: An example of our method inference process from the GAIA dataset.

| Example # from GAIA Dataset                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                            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| <p><b>Question:</b><br/>In terms of geographical distance between capital cities, which 2 countries are the furthest from each other within the ASEAN bloc according to wikipedia? Answer using a comma separated list, ordering the countries by alphabetical order.</p> <p><b>Labeled Answer:</b><br/>Indonesia, Myanmar</p>                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                              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| Inference Process                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                      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| <p>Okay, so the user wants to know which two ASEAN countries have their capital cities the farthest apart geographically. Hmm, first I need to recall what countries are part of ASEAN. ... The first subtask call would be:</p> <p><b>&lt;begin_call_subtask&gt;</b> Retrieve the list of ASEAN member countries along with their respective capital cities from Wikipedia. <b>&lt;end_call_subtask&gt;</b></p> <p><b>&lt;begin_subtask_result&gt;</b> Result from Search Agent:...The list of ASEAN member countries and their respective capital cities is: 1. Brunei - Bandar Seri Begawan, 2. Cambodia - Phnom Penh, 3. Indonesia - Jakarta, 4. Laos - Vientiane, 5. Malaysia - Kuala Lumpur, 6. Myanmar - Nay Pyi Taw, 7. Philippines - Manila, 8. Singapore - Singapore, 9. Thailand - Bangkok, 10. Vietnam - Hanoi. <b>&lt;end_subtask_result&gt;</b></p> <p>Okay, got the list. Now, the next step is to get the coordinates for each capital. Since there are 10 capitals, doing a separate search for each would take 10 subtasks, which is too many. So better to use code to batch process. ...Therefore, the second subtask is:</p> <p><b>&lt;begin_call_subtask&gt;</b> Write Python code to retrieve the geographic coordinates of each ASEAN capital city from Wikipedia using the Wikipedia API, calculate the pairwise distances between all capital cities using the Haversine formula, identify the pair with the maximum distance, and return the two countries in alphabetical order. <b>&lt;end_call_subtask&gt;</b></p> <p><b>&lt;begin_subtask_result&gt;</b> Result from Code-Agent:Identified the list of ASEAN countries and their capitals. Wrote a function to fetch geographic coordinates for each capital using the Wikipedia API. Implemented the Haversine formula to compute pairwise distances between all capital cities. Tracked the pair of capitals with the largest distance. Sorted the two countries alphabetically and returned them.Final Conclusion:The two ASEAN countries with the farthest capital cities, in alphabetical order, are Indonesia and Vietnam. <b>&lt;end_subtask_result&gt;</b></p> <p>Wait, but is that correct? Let me think. Jakarta (Indonesia) and Hanoi (Vietnam). Are they the farthest apart?Alternatively, maybe Brunei and Indonesia's capitals are further apart? Let me think of approximate coordinates:Bandar Seri Begawan: approx 4.9°N, 115°EJakarta: -6.2°S, 106.8°EDistance between these would be roughly from around 4.9N to -6.2S, so total latitude difference of 11.1 degrees.... Alternatively, since I can only use up to 10, and already used 2, perhaps proceed as follows:- Acknowledge that the first code result was incorrect due to the capital name, so need to adjust.- Re-run the code with corrected capital names, but to do that, I need to specify the correction in the code. Thus, the second code subtask would be:</p> <p><b>&lt;begin_call_subtask&gt;</b> Write Python code to calculate the geographical distance between all pairs of ASEAN capital cities using their precise coordinates obtained from Wikipedia, correcting the capital of Myanmar to 'Naypyidaw'. The countries and capitals are: Brunei (Bandar Seri Begawan), Cambodia (Phnom Penh), Indonesia (Jakarta), Laos (Vientiane), Malaysia (Kuala Lumpur), Myanmar (Naypyidaw), Philippines (Manila), Singapore (Singapore), Thailand (Bangkok), Vietnam (Hanoi). Use the Haversine formula and return the two countries with the farthest capitals in alphabetical order. <b>&lt;end_call_subtask&gt;</b></p> <p><b>&lt;begin_subtask_result&gt;</b> Result from Code-Agent:Corrected the capital of Myanmar to Naypyidaw. ...<br/>The two countries with the farthest capitals in alphabetical order are ('Indonesia', 'Myanmar'). <b>&lt;end_subtask_result&gt;</b></p> <p>Ah, that would be the correct result. Thus, the second code subtask, after correcting the capital name, gives Indonesia and Myanmar.But since I already used two subtasks (the first search and the first code), and this is the third, that's okay.Wait, but according to the initial plan, the first code subtask might have failed because of the capital name, so I need to fix that....</p> <p>But since the first code result was wrong, perhaps I need to adjust.So following this adjusted plan:First subtask (already done) gives the initial list, but with a typo in Myanmar's capital.Second subtask (search for correct capital name of Myanmar):</p> <p><b>&lt;begin_call_subtask&gt;</b> Confirm the correct spelling of the capital city of Myanmar according to Wikipedia. <b>&lt;end_call_subtask&gt;</b></p> <p><b>&lt;begin_subtask_result&gt;</b> Result from Search Agent:Analyzed multiple documents to determine the correct spelling of Myanmar's capital city. Document 1 from Simple English Wikipedia primarily uses 'Naypyidaw'. Document 2 from Britannica uses 'Nay Pyi Taw'. Document 3 from Britannica also uses 'Nay Pyi Taw' as the primary spelling. Document 4 from Wikiwand uses 'Naypyidaw' as the primary spelling and mentions 'Nay Pyi Taw' as the officially romanized version. Document 5 from Britannica provides context on naming conventions in Myanmar but does not directly address the capital city's spelling.Final Conclusion:The correct spelling of the capital city of Myanmar according to Wikipedia is 'Naypyidaw'. <b>&lt;end_subtask_result&gt;</b></p> <p>Okay, so the correct spelling is Naypyidaw.Now, use the code-agent with the corrected capital names.The code would now have the correct list:capitals = [('Brunei', 'Bandar Seri Begawan'), ('Cambodia', 'Phnom Penh'), ('Indonesia', 'Jakarta'), ('Laos', 'Vientiane'), ('Malaysia', 'Kuala Lumpur'), ('Myanmar', 'Naypyidaw'), ('Philippines', 'Manila'), ('Singapore', 'Singapore'), ('Thailand', 'Bangkok'), ('Vietnam', 'Hanoi')]Then, the code can proceed to get their coordinates via the Wikipedia API with the correct names.Fourth subtask (code):</p> <p><b>&lt;begin_call_subtask&gt;</b> Write Python code to retrieve coordinates for each of the ASEAN capitals (using the corrected capital name for Myanmar as Naypyidaw) from Wikipedia, compute pairwise distances with Haversine formula, identify the maximum distance pair, and return them in alphabetical order. <b>&lt;end_call_subtask&gt;</b></p> <p><b>&lt;begin_subtask_result&gt;</b> Result from Code-Agent:The code attempts to scrape coordinates for ASEAN capitals from Wikipedia, ensuring that Myanmar's capital is correctly listed as Naypyidaw. ...The maximum distance pair between ASEAN capitals is Jakarta and Naypyidaw, returned in alphabetical order. <b>&lt;end_subtask_result&gt;</b></p> <p>So the user's answer should be boxed{Indonesia, Myanmar}</p> |