AgentRace: Benchmarking Efficiency in LLM Agent Frameworks

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Abstract

Large Language Model (LLM) agents are rapidly gaining traction across domains such as intelligent assistants, programming aids, and autonomous decision systems. While existing benchmarks focus primarily on evaluating the effectiveness of LLM agents, such as task success rates and reasoning correctness, the efficiency of agent frameworks remains an underexplored but critical factor for real-world deployment. In this work, we introduce AgentRace, the first benchmark specifically designed to systematically evaluate the efficiency of LLM agent frameworks across representative workloads. AgentRace enables controlled, reproducible comparisons of runtime performance, scalability, communication overhead, and tool invocation latency across popular frameworks such as LangChain, AutoGen, and AgentScope. It supports multiple agent workflows (ReAct, RAG, Mixture-of-Agents), diverse task scenarios, and key performance metrics via a modular design and a one-command execution interface. Our experiments reveal key performance bottlenecks and highlight the trade-offs between different framework and workflow choices under varied deployment conditions. All results and benchmarking tools are open-sourced with a public leaderboard to foster community adoption. We believe AgentRace will become a valuable resource for guiding the design and optimization of next-generation efficient LLM agent systems. The results are available at `https://agent-race.github.io/`.

1 Introduction

Large Language Models (LLMs) [1–5] have rapidly gained widespread popularity due to their exceptional capabilities in natural language understanding and generation, significantly impacting various applications including chatbots, content creation, and programming assistants. With these advancements, LLM agents [6–10], which are autonomous entities powered by LLMs capable of executing complex tasks through intelligent interactions, have emerged as a promising area of research and practical implementation.

To accelerate the development of LLM agents, numerous benchmarks and datasets [11–14] have been proposed to assess LLM agents, primarily focusing on evaluating their effectiveness and reliability in task completion. These benchmarks typically measure task success rates, correctness of generated outputs, overall functional capabilities, and safety of agents.

However, for LLM agents to be widely deployed in real-world scenarios in the future, the efficiency of their frameworks is critically important. Efficient execution, scalability, and minimal communication overhead are essential for ensuring timely responses and practical usability, particularly in resource-constrained and latency-sensitive environments. Despite the proliferation of LLM agent frameworks,

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such as LangChain [15], AutoGen [16], and AgentScope [17], a systematic benchmark evaluating these frameworks' performance efficiency remains absent.

To bridge this significant gap, we introduce **AgentRace**, the first benchmark platform specifically designed to systematically evaluate the efficiency of LLM agent frameworks. AgentRace enables controlled, reproducible comparisons across frameworks and workflows, aiming to answer the following key research questions:

1. *What are the primary efficiency bottlenecks in current LLM agent frameworks (e.g., model inference latency, tool calling overhead)?*
2. *What caused the inefficiency of existing LLM agent frameworks?*
3. *How to improve the efficiency of agent execution?*

AgentRace features a modular and extensible design. It supports **7** LLM agent frameworks, **11** types of tools, **3** commonly used workflows, **4** task scenarios, and **4** metrics. The benchmark can be executed with a single command line, facilitating rapid experimentation and reproducibility. All results, configurations, and insights are made available through a public website[1].

In summary, our contributions include:

- We design the first comprehensive efficiency-focused benchmark for LLM agent frameworks.
- We provide detailed analyses of performance bottlenecks across various frameworks.
- We identify the key issues that result in agent inefficiency in existing agent frameworks.
- We provide actionable insights for both practitioners and researchers to optimize the deployment of efficient LLM-based agents.

2 Background and Related Work

2.1 LLM Agents

LLMs agents [18, 8] are systems that combine the generative capabilities of LLMs with additional components such as memory, planning, and tool usage to perform complex tasks autonomously. These agents can interpret user inputs, plan actions, interact with external tools, and adapt based on feedback, enabling more dynamic and context-aware behaviors. Many agents have been developed, where some are generic agents that are designed to execute general tasks and some are specialized agents for some concrete task. For example, ReAct [18] is a typical general agent workflow, where the agent thinks and take actions interatively. MetaGPT [19] is an agent designed for software development, where each agent plays a different role to simulate a software company. In this work, we aim to evaluate the efficiency of different LLM agent frameworks, thus focusing on using the widely used general agent workflows.

2.2 LLM Agent Frameworks

The development and deployment of LLM agents have been facilitated by various frameworks that provide tools and abstractions for building agentic systems. There have been many LLM agent frameworks. For example, LangChain [15] offers a modular framework for developing applications with LLMs, supporting integrations with various data sources and tools. It provides a low-level agent orchestration framework, a purpose-built deployment platform, and debugging tools. Besides LangChain, there are also many other popular LLM agent frameworks. In our platform, we select some popular and easy-to-use frameworks for integration. For the detailed introduction of these frameworks, please refer to Section 3.3.

2.3 Benchmarks for LLM Agents

There have been many benchmarks for LLM agents [11–14, 20]. However, most of these benchmarks usually focus on ability or trustworthiness perspectives, and do not exploit the efficiency part. For

[1] `https://agent-race.github.io/`

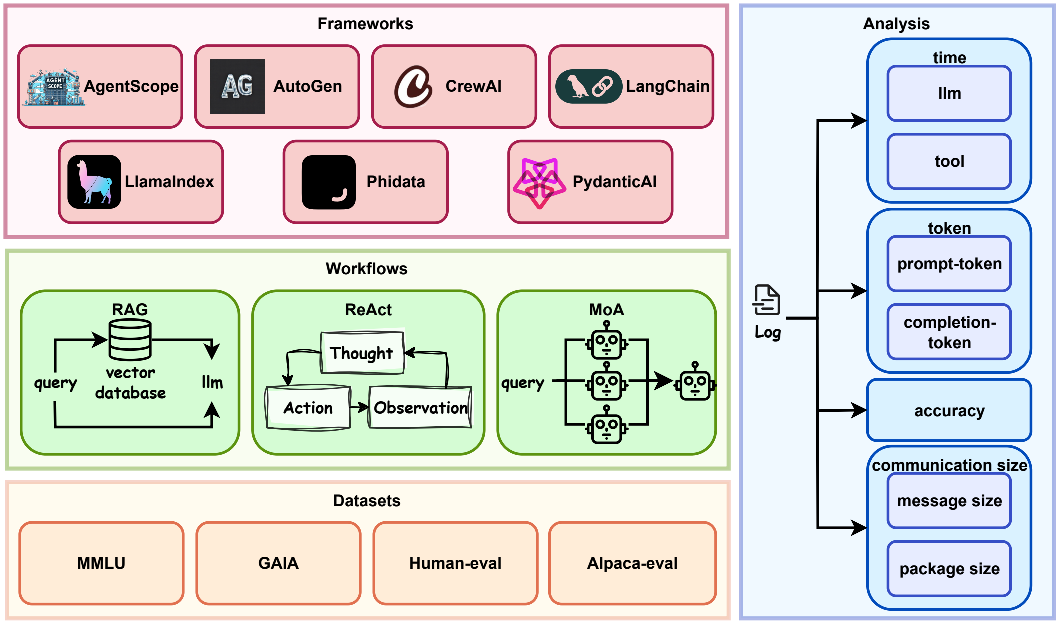


Figure 1: The architecture of AgentRace.

example, AgentBench [20] report *Step Success Rate* as the main metric showing the independent accuracy of each action step, due to the current struggles for LLMs to ensure overall task success rates. Beyond benchmarks focusing solely on success rates, AgentBoard [12] proposes a comprehensive evaluation framework for LLM agents. It introduces a fine-grained *Progress Rate* metric to track incremental advancements during task execution, along with an open-source toolkit for multi-faceted analysis. In addition to task completion evaluation frameworks, some works like AgentHarm [11] have proposed safety-focused benchmarks. AgentHarm assesses LLM agents' vulnerability to misuse across 110 malicious tasks, evaluating both harmful request compliance and multi-step capability retention during jailbreak attacks. WORFBENCH [13] introduces a unified framework for evaluating workflow generation, including both linear and graph-structured workflows. Its evaluation metric, WORFEVAL, quantifies generation performance across these tasks. Although the benchmark measures end-to-end efficiency through *Task Execution Time*, it omits a detailed breakdown of computational costs—such as tool execution latency. This lack of granularity obscures potential bottlenecks in workflow optimization.

3 Design of Benchmark Platform

To systematically evaluate the efficiency and scalability of LLM agent frameworks, we introduce a modular benchmark platform AgentRace. As shown in Figure 1, this platform comprises four interconnected modules, including **Framework**, **Workflow**, **Dataset**, and **Analysis**, designed to capture diverse agent frameworks, execution workflows, task complexities, and performance analysis.

3.1 Data Module: Diverse Task Coverage

The Data module defines the core tasks used in our benchmark and plays a critical role in ensuring that LLM agent frameworks are evaluated across a wide range of real-world scenarios. Our design is guided by two key considerations: (1) task diversity in terms of reasoning complexity, tool usage, and interaction patterns; and (2) alignment with widely adopted benchmarks to enable meaningful and comparable evaluations.

To this end, we select four representative datasets that reflect varying levels of difficulty, domain coverage, and agent requirements: (1) **GAIA** [21]: A comprehensive benchmark for general-purpose AI assistants, GAIA includes real-world, multi-hop queries that require reasoning over documents, tool invocation, and web interaction. It is the most tool-intensive dataset in our suite, designed to assess the full-stack capabilities of LLM agents. Notably, GPT-4 with plugins achieves only

15% accuracy, while humans reach 92%, indicating significant headroom for improvement. (2) **HumanEval** [22]: A code generation benchmark from OpenAI consisting of Python programming problems. Tasks require precise algorithmic reasoning and strict correctness, with deterministic evaluation via unit tests. This dataset helps us evaluate agents' capacity for structured reasoning and program synthesis. (3) **MMLU (Massive Multitask Language Understanding)** [23]: MMLU spans 57 academic subjects and provides multiple-choice questions across STEM, humanities, and social sciences. We use it to test retrieval-augmented workflows, as it simulates closed-book knowledge challenges and supports grounding in external sources. (4) **AlpacaEval** [24]: An instruction-following benchmark that evaluates natural language understanding and response quality. It consists of 805 prompts and uses GPT-4 as a reference evaluator. This dataset is well-suited for multi-agent settings where coordination, aggregation, and language alignment are essential.

Collectively, these datasets span a broad spectrum, from single-turn queries and precise code generation to multi-step reasoning and collaborative task execution. This coverage enables a holistic and stress-tested evaluation of agent frameworks under varied demands, including tool usage, memory handling, retrieval integration, and inter-agent communication.

3.2 Agent Module: Workflow Diversity

The Agent module captures the diversity of reasoning patterns exhibited by modern LLM-based agents. In designing this module, our goal is to represent a wide range of real-world task execution strategies while ensuring broad compatibility with existing agent frameworks.

we instantiate agents using three widely adopted and conceptually distinct workflow paradigms: (1) **ReAct (Reasoning and Acting)** [18]: This paradigm interleaves natural language reasoning with tool-based actions. By prompting the LLM to first generate intermediate thoughts and then take corresponding actions, ReAct enables agents to dynamically plan and interact with their environment. (2) **RAG (Retrieval-Augmented Generation)** [25]: RAG introduces an explicit retrieval step before generation, allowing agents to ground their outputs in relevant external knowledge. In our benchmark, RAG highlights the performance of agent frameworks in integrating retrieval modules, managing memory contexts, and efficiently handling long documents. (3) **MoA (Mixture of Agents)** [26]: MoA represents a multi-agent architecture where multiple agents collaborate to solve a task. Each agent is often instantiated with a different LLM. An aggregation agent then composes their outputs to form the final answer. This setting captures the growing trend of using multiple LLMs in coordination, and allows us to benchmark frameworks on communication, modularity, and scalability.

These workflows reflect fundamentally different coordination mechanisms, including sequential prompting, retrieval-grounded answering, and distributed multi-agent collaboration. By supporting all three within our benchmark, we enable a comprehensive evaluation of agent frameworks under varying reasoning styles, system architectures, and performance constraints.

3.3 Framework Module: Broad Ecosystem Coverage

The Framework module integrates a wide spectrum of open-source LLM agent frameworks, each with distinct design philosophies, runtime environments, and abstraction layers. In selecting these frameworks, we focus on two primary considerations: (1) their popularity and influence in the developer and research communities, and (2) the feasibility of easy deployment and integration within our benchmarking platform. Our goal is to capture the diversity of agent system designs currently shaping the LLM ecosystem.

We integrate the following frameworks: (1) **LangChain** [15] is a widely adopted framework that offers modular components for building LLM-based applications. It emphasizes tool chaining, prompt templating, memory integration, and external API orchestration. (2) **AutoGen** [16], developed by Microsoft, facilitates the creation of advanced LLM agents through multi-agent conversations and automated task planning. (3) **AgentScope** [17] supports rapid development of multi-agent systems through a low-code interface. It emphasizes collaboration among agent roles, enabling scalable deployment of agent collectives with minimal boilerplate. (4) **CrewAI** [27] is a lightweight yet expressive Python framework designed for fast iteration. It provides both high-level abstractions and low-level control. (5) **LlamaIndex** [28] focuses on context-augmented LLM applications by connecting structured and unstructured data sources to LLMs. (6) **Phidata** [29] is a framework for building multi-modal AI agents and workflows with memory, knowledge, tools, and reasoning,

Table 1: The supported functionalities of AgentRace. ✓denotes that the functionality is implemented in AgentRace. ○ denotes that the functionality is supported in the original framework.

		LangChain	AutoGen	AgentScope	CrewAI	LlamaIndex	Phidata	PydanticAI
Workflow	ReAct	○	✓	○	○	○	✓	✓
	RAG	○	✓	○	○	○	○	✓
	MoA	✓	○	✓	✓	○	✓	✓
Tools	Search	○	✓	○	✓	○	○	✓
	PDF loader	○	✓	✓	○	○	✓	✓
	CSV reader	○	✓	✓	✓	○	○	✓
	XLSX reader	○	✓	✓	○	○	✓	✓
	Text file reader	○	✓	✓	✓	○	○	✓
	doc reader	○	✓	✓	○	○	✓	✓
	MP3 loader	○	✓	○	○	○	✓	✓
	Figure loader	✓	✓	○	✓	○	✓	✓
	Video loader	✓	✓	✓	○	✓	✓	✓
	Code executor	○	○	○	✓	○	○	✓
	data retrieval	○	✓	○	○	○	○	✓

enabling collaborative problem-solving through teams of agents. (7) **PydanticAI** [30] is an agent framework that is designed for easy development of production-grade applications.

Each framework is evaluated under the same set of datasets, prompts, tool interfaces, and agent workflows to ensure a fair and controlled comparison. In future iterations of this benchmark, we plan to incorporate additional frameworks and emerging systems to reflect the evolving landscape of LLM agent development.

3.4 Analysis Module: Measuring Efficiency

The Analysis module defines the core metrics used to evaluate the system-level efficiency of LLM agent frameworks. While prior benchmarks have primarily focused on task success or output quality, we emphasize efficiency as a first-class concern—critical for real-world deployment scenarios involving latency constraints, limited compute, or cost sensitivity.

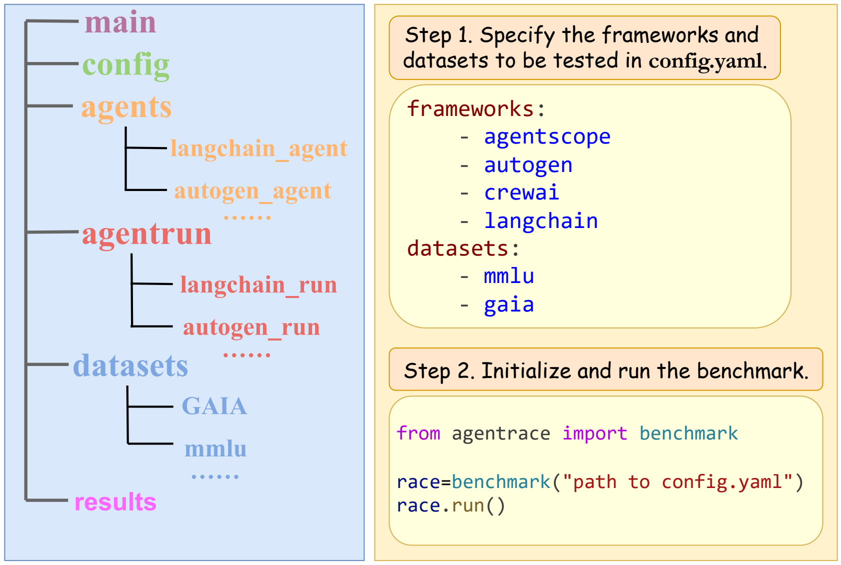
To this end, we measure the following four key metrics: (1) **Execution Time**: The total wall-clock time from agent invocation to task completion. This includes the full execution pipeline, including LLM inference, tool calls, code execution, etc. (2) **Token Consumption**: The total number of input and output tokens processed by the LLM during the task. This reflects the computational cost of inference and directly impacts the monetary cost in API-based deployments. (3) **Communication Size**: The total volume of data exchanged between agents. This metric captures inefficiencies in prompt formatting, serialization, and inter-agent message passing, particularly relevant in multi-agent setting. (4) **Accuracy**: To ensure correctness is preserved during efficiency evaluation, we also include a task-specific accuracy metric. This ensures that frameworks functionally correct.

These metrics collectively offer a multi-dimensional perspective on agent performance, capturing both computational and communication efficiency while maintaining fidelity to task goals. By quantifying these trade-offs, our benchmark enables principled comparisons and provides actionable insights for improving agent system design.

4 Implementation

4.1 Functionalities

The core functionalities supported by AgentRace are summarized in Table 1. Our benchmark currently supports three representative agent workflows executed across seven widely used LLM agent frameworks, utilizing a unified pool of eleven tools. While some of these capabilities are natively supported by the frameworks, approximately 50% of the functionalities are implemented by ourselves to ensure full compatibility and coverage. To maintain a fair comparison across frameworks,



Repository Structure Usage Example

Figure 2: Repository structure and usage example of AgentRace.

we adopt a standardized implementation for any functionality that is not natively provided. This ensures that differences in evaluation metrics stem from the underlying framework behavior, rather than implementation gaps. For more implementation details, please refer to the Appendix.

4.2 Code

Figure 2 illustrates the structure of our code repository and its usage flow. AgentRace is designed to be easily extensible—new datasets, frameworks, or workflows can be integrated with minimal overhead. Users can specify parameters and configurations in a single YAML configuration file, and run full benchmark experiments with just a few command-line instructions. This design lowers the barrier for reproducibility and community adoption.

5 Experiments and Insights

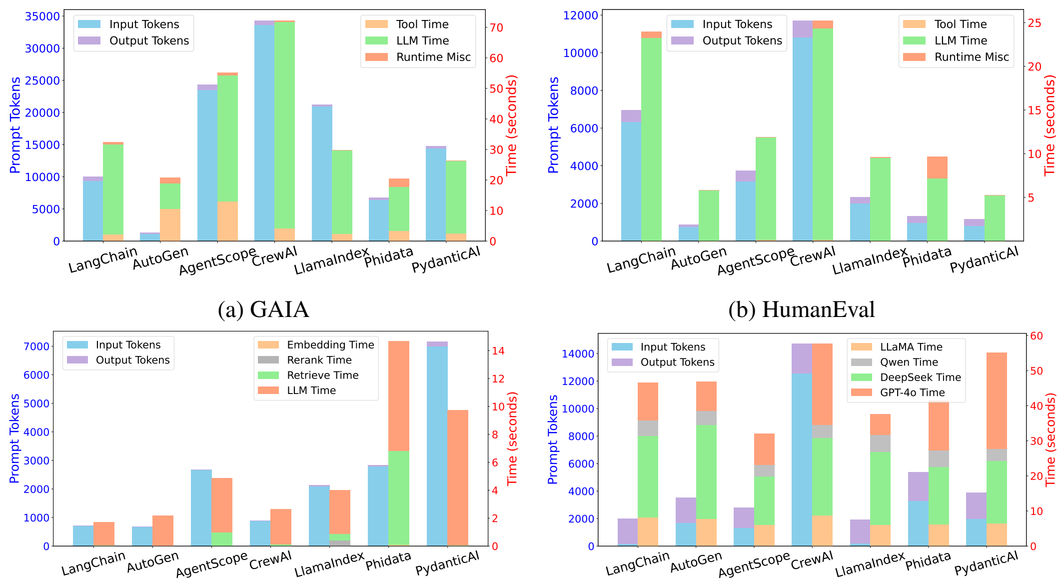
Due to the page limit, we present the representative results in the main paper. **For more details, results, and insights, please refer to Appendix of the supplementary material.**

5.1 Experimental Setup

Setting We evaluate 7 LLM agent frameworks using our benchmarking platform, AgentRace, ensuring a standardized and reproducible execution environment. All experiments are conducted on a Linux server equipped with 12-core Intel(R) Xeon(R) Silver 4214R CPUs and a single NVIDIA RTX 3080 Ti GPU.

Datasets We use four representative datasets across different agent workflows: GAIA and HumanEval are executed with the ReAct workflow, MMLU is evaluated using RAG, and AlpacaEval is tested under the MoA.

Models Unless otherwise specified, GPT-4o is used as the default LLM across all experiments. For MoA, we instantiate the first-layer agents with a diverse set of open models: LLaMA-3.3-70B-Instruct-Turbo, Qwen2.5-7B-Instruct-Turbo, and DeepSeek-V3. We use TogetherAI [31] for querying these models. GPT-4o is used as the aggregation agent to integrate their outputs. In the RAG setting, the MMLU test set is used to construct the retrieval database.



(a) GAIA (b) HumanEval

(c) MMLU (d) AlpacaEval

Figure 3: Token consumption and execution time per query of different frameworks.

Metrics **We focus on efficiency analysis in our paper while ensuring that all frameworks function correctly for fairness**. For accuracy analysis, please refer to the Appendix.

5.2 Execution Time and Token Consumption

Insight 1: LLM inference usually dominates runtime across all agent frameworks, and inefficient prompt engineering, such as appending full histories and using verbose prompts, exacerbates both latency and cost.

Figure 3 presents the breakdown of agent execution time across four benchmark scenarios. Across all settings, LLM inference consistently dominates runtime. Even in the GAIA scenario, which is explicitly designed to be tool-intensive and involves frequent calls to external APIs, LLM inference accounts for more than 85% of the total execution time in most frameworks. In simpler workflows such as HumanEval and AlpacaEval, the proportion exceeds 95%. This highlights that LLM inference, due to its computational demands and frequent invocation, remains the primary bottleneck in agent execution, regardless of the complexity or type of task.

Moreover, we observe that the cost of LLM inference is further exacerbated by large variations in token efficiency across frameworks. There is a strong positive correlation between LLM inference time and token consumption. Some frameworks, notably CrewAI, LlamaIndex, and AgentScope, consistently exhibit higher token usage, leading to significantly prolonged inference times and increased resource consumption. We identify two main causes of token inefficiency: **appending unnecessary history to prompts** and **using verbose prompts**.

We observe that CrewAI and AgentScope elevated token usage arises from their design choice. In their implementation, the LLM stores all intermediate inputs and outputs as memory and appends this memory to each new prompt. As a result, the prompt length—and thus token count—grows with every step of reasoning. In the ReAct workflow, LlamaIndex consumes a significant amount of prompts, primarily due to the observation portion returned to the LLM after tool invocation. Additionally, for queries that fail to execute successfully, the number of reasoning + action iterations increases, leading to a corresponding growth in the observation-related prompts.

These findings underscore the importance of efficient prompt engineering and memory management in agent framework design. Strategies such as selective memory summarization, compact formatting, and prompt compression are crucial for reducing token usage. Without such optimizations, agent systems may incur unnecessarily high costs and latency.

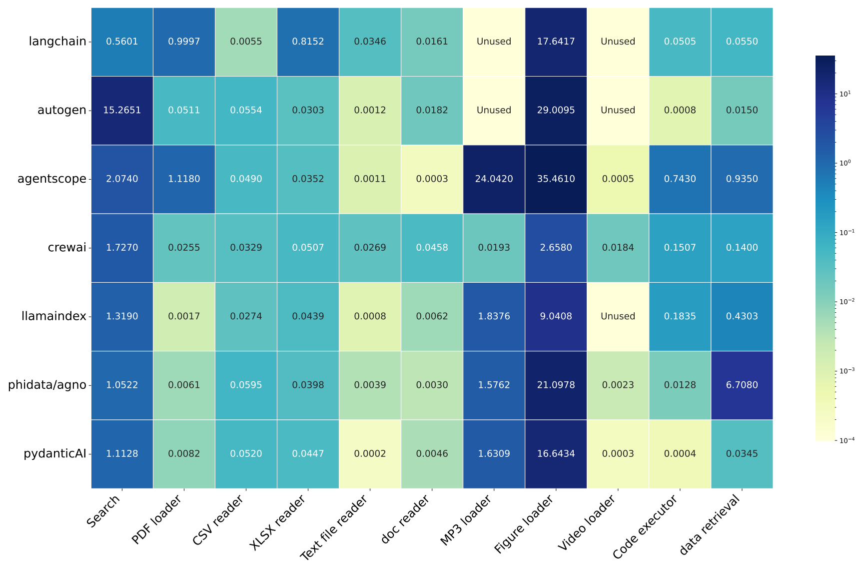


Figure 4: The execution time per call for each tool.

5.3 Tool Calling

Insight 2: Tool execution efficiency varies widely across frameworks, with search and figure-related tools introducing disproportionately high latency.

We analyze the execution cost of various tool types across multiple LLM agent frameworks, as illustrated in Figure 4. The results reveal substantial variation in tool execution efficiency between frameworks, particularly for high-cost operations. Among all tool categories, search and figure-related tools usually incur the highest latency, often dominating total tool execution time within a workflow.

For instance, the figure loader takes 2.7 seconds to execute in CrewAI, but exceeds 30 seconds in AgentScope, indicating considerable framework-dependent overhead. In contrast, lightweight tools such as `txt_tool` and `docx_tool` typically complete in under a millisecond, demonstrating minimal variance. Tools like `pdf_tool` and `python_tool` exhibit moderate differences in runtime, depending on each framework's implementation and I/O strategy.

Additionally, some frameworks (e.g., AgentScope) show disproportionately high total tool processing time, driven primarily by inefficient handling of image processing or multimedia tasks. This highlights the importance of optimizing high-latency tools, particularly in scenarios where tool invocation is frequent or tightly coupled with LLM inference.

While LLM inference remains the dominant bottleneck in most of our benchmarks, more complex, tool-heavy scenarios, such as document analysis or multimodal agent tasks, may shift the performance bottleneck toward tool execution. Frameworks aiming to support such use cases must pay greater attention to optimizing tool orchestration and external API integration.

5.4 RAG

Insight 3: While agents usually involve external databases for information retrieval, the database performance is overlooked in several frameworks. Vector database is recommended.

While RAG workflows are increasingly adopted to enhance factual grounding, our benchmarking reveals that database performance, particularly during embedding and retrieval, is a critical yet frequently neglected factor. Figure 3c illustrates the variation in retrieval latency across frameworks, exposing significant performance disparities.

One notable example is AgentScope, which demonstrates high vectorization latency. This stems from its design: during the database setup phase, AgentScope invokes a large embedding model to compute dense vector representations. The latency of this embedding model, often implemented as a

Table 2: Communication size between agents (Unit: Byte). We report the content size (e.g., the transferred outputs from the last agent) and overhead size (e.g., header), separated by /.

		LangChain	AutoGen	AgentScope	CrewAI	LlamaIndex	Phidata	PydanticAI
From Global Agent	Agent1	165.07/0	209.08/44.01	284.078/0	514.962/0	1180.078/898	354.508/0	96.022/0
	Agent2	165.07/0	209.08/44.01	284.078/0	483.740/0	1171.078/889	341.160/0	95.425/0
	Agent3	165.07/0	209.08/44.01	284.078/0	619.516/0	1164.078/882	343.219/0	97.116/0
To Aggregation Agent	Agent1	1983.02/3	2066.04/52.4	1659.318/0	2497.929/0	2022.417/33.689	6128.259/2639.113	2000.542/0
	Agent2	2011.83/3	2071.24/57.38	1511.311/0	1754.701/0	2054.878/39.118	6131.272/2629.426	1927.093/0
	Agent3	2072.98/3	2156.04/66.81	1889.247/0	2151.097/0	2116.377/48.641	5715.126/2465.817	1892.344/0

separate LLM call, substantially increases the overall vectorization time. Similarly, Phidata exhibits elevated vectorization latency due to its use of a two-step pipeline. First, its built-in `csv_tool` loads documents row-by-row; then, it applies a SentenceTransformer model to compute embeddings. Our benchmark confirms that Phidata's `csv_tool` itself is a relatively slow component, compounding the overall vectorization time. From our observation, vector databases such as Faiss [32] are faster than other implementations.

These observations highlight the need for more attention to retrieval pipeline design, especially in frameworks that aim to support real-time or large-scale RAG deployments. Optimization opportunities include batching document embeddings, using faster embedding models, minimizing redundant file reads, and caching frequent queries.

5.5 Communication Size

Insight 4: Inefficient communication architecture and package design lead to high communication overhead in the multi-agent setting.

In multi-agent frameworks, communication between agents is often overlooked as a source of inefficiency. However, our analysis reveals large discrepancies in communication size across frameworks, as shown in Table 2. These differences arise not only from framework-specific message formats but also from architectural design choices, especially in multi-agent workflows like MoA.

Notably, frameworks such as CrewAI, which adopt a centralized communication pattern, exhibit significantly higher communication costs. In these designs, a central agent coordinates multiple sub-agents by sequentially delegating subtasks and collecting responses. For example, in CrewAI's MoA implementation, the center agent queries three sub-agents in sequence and aggregates their outputs. Each LLM invocation by the center agent accumulates prior messages in memory, causing the prompt size and the communication payload to grow linearly with the number of sub-agents. Phidata, on the other hand, incurs substantial communication overhead due to its design. In addition to the core message, it returns a duplicated `content` field that mirrors the final message. This, combined with additional metadata fields, results in large overhead sizes.

These findings indicate that communication cost is not merely a function of task complexity but also of framework design. In large-scale deployments or bandwidth-constrained environments, excessive inter-agent message sizes, especially those driven by redundant content or sequential message accumulation, can significantly impact system performance and cost. Future agent frameworks should consider streamlined communication protocols, selective message summarization, or compressing intermediate results to reduce unnecessary transfer overhead.

6 Conclusion

We introduce AgentRace, a comprehensive benchmark platform for evaluating the efficiency of LLM agent frameworks. Unlike prior work that primarily focuses on task success or reasoning correctness, our platform emphasizes system-level performance, including execution time, token usage, and communication overhead. AgentRace covers a diverse set of datasets, agent workflows, and frameworks, enabling a fair and reproducible comparison across real-world scenarios. Through extensive experiments, we reveal several key insights. These findings highlight critical optimization opportunities in the design and deployment of LLM-based agents. We hope AgentRace provides a guideline for future work in developing efficient, scalable, and robust agent systems, and we plan to continuously extend the benchmark as the LLM agent ecosystem evolves.

References

[1] OpenAI. Gpt-4 technical report, 2023.

[2] Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, Dan Bikel, Lukas Blecher, Cristian Canton Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel Kloumann, Artem Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, Ranjan Subramanian, Xiaoqing Ellen Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu, Zheng Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurelien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom. Llama 2: Open foundation and fine-tuned chat models, 2023.

[3] Aixin Liu, Bei Feng, Bing Xue, Bingxuan Wang, Bochao Wu, Chengda Lu, Chenggang Zhao, Chengqi Deng, Chenyu Zhang, Chong Ruan, et al. Deepseek-v3 technical report. *arXiv preprint arXiv:2412.19437*, 2024.

[4] Humza Naveed, Asad Ullah Khan, Shi Qiu, Muhammad Saqib, Saeed Anwar, Muhammad Usman, Naveed Akhtar, Nick Barnes, and Ajmal Mian. A comprehensive overview of large language models. *arXiv preprint arXiv:2307.06435*, 2023.

[5] Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, et al. Qwen technical report. *arXiv preprint arXiv:2309.16609*, 2023.

[6] Lei Wang, Chen Ma, Xueyang Feng, Zeyu Zhang, Hao Yang, Jingsen Zhang, Zhiyuan Chen, Jiakai Tang, Xu Chen, Yankai Lin, et al. A survey on large language model based autonomous agents. *Frontiers of Computer Science*, 18(6):186345, 2024.

[7] Taicheng Guo, Xiuying Chen, Yaqi Wang, Ruidi Chang, Shichao Pei, Nitesh V Chawla, Olaf Wiest, and Xiangliang Zhang. Large language model based multi-agents: A survey of progress and challenges. *arXiv preprint arXiv:2402.01680*, 2024.

[8] Andrew Zhao, Daniel Huang, Quentin Xu, Matthieu Lin, Yong-Jin Liu, and Gao Huang. Expel: Llm agents are experiential learners. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, pages 19632–19642, 2024.

[9] Yusen Zhang, Ruoxi Sun, Yanfei Chen, Tomas Pfister, Rui Zhang, and Sercan Arik. Chain of agents: Large language models collaborating on long-context tasks. *Advances in Neural Information Processing Systems*, 37:132208–132237, 2024.

[10] Bo Ni and Markus J Buehler. Mechagents: Large language model multi-agent collaborations can solve mechanics problems, generate new data, and integrate knowledge. *Extreme Mechanics Letters*, 67:102131, 2024.

[11] Maksym Andriushchenko, Alexandra Souly, Mateusz Dziemian, Derek Duenas, Maxwell Lin, Justin Wang, Dan Hendrycks, Andy Zou, Zico Kolter, Matt Fredrikson, et al. Agentharm: A benchmark for measuring harmfulness of llm agents. *arXiv preprint arXiv:2410.09024*, 2024.

[12] Ma Chang, Junlei Zhang, Zhihao Zhu, Cheng Yang, Yujiu Yang, Yaohui Jin, Zhenzhong Lan, Lingpeng Kong, and Junxian He. Agentboard: An analytical evaluation board of multi-turn llm agents. *Advances in Neural Information Processing Systems*, 37:74325–74362, 2024.

[13] Qian Huang, Jian Vora, Percy Liang, and Jure Leskovec. Benchmarking large language models as ai research agents. In *NeurIPS 2023 Foundation Models for Decision Making Workshop*, 2023.

[14] Yongliang Shen, Kaitao Song, Xu Tan, Wenqi Zhang, Kan Ren, Siyu Yuan, Weiming Lu, Dongsheng Li, and Yueting Zhuang. Taskbench: Benchmarking large language models for task automation. *Advances in Neural Information Processing Systems*, 37:4540–4574, 2024.

[15] LangChain. Langchain, 2025. URL https://www.langchain.com/. Accessed: 2025-05-15.

[16] Qingyun Wu, Gagan Bansal, Jieyu Zhang, Yiran Wu, Beibin Li, Erkang Zhu, Li Jiang, Xiaoyun Zhang, Shaokun Zhang, Jiale Liu, et al. Autogen: Enabling next-gen llm applications via multi-agent conversation. *arXiv preprint arXiv:2308.08155*, 2023.

[17] Dawei Gao, Zitao Li, Xuchen Pan, Weirui Kuang, Zhijian Ma, Bingchen Qian, Fei Wei, Wenhao Zhang, Yuexiang Xie, Daoyuan Chen, et al. Agentscope: A flexible yet robust multi-agent platform. *arXiv preprint arXiv:2402.14034*, 2024.

[18] Shunyu Yao, Jeffrey Zhao, Dian Yu, Nan Du, Izhak Shafran, Karthik Narasimhan, and Yuan Cao. React: Synergizing reasoning and acting in language models. In *International Conference on Learning Representations (ICLR)*, 2023.

[19] Sirui Hong, Xiawu Zheng, Jonathan Chen, Yuheng Cheng, Jinlin Wang, Ceyao Zhang, Zili Wang, Steven Ka Shing Yau, Zijuan Lin, Liyang Zhou, et al. Metagpt: Meta programming for multi-agent collaborative framework. *arXiv preprint arXiv:2308.00352*, 3(4):6, 2023.

[20] Xiao Liu, Hao Yu, Hanchen Zhang, Yifan Xu, Xuanyu Lei, Hanyu Lai, Yu Gu, Hangliang Ding, Kaiwen Men, Kejuan Yang, et al. Agentbench: Evaluating llms as agents. In *ICLR*, 2024.

[21] Grégoire Mialon, Clémentine Fourrier, Thomas Wolf, Yann LeCun, and Thomas Scialom. Gaia: a benchmark for general ai assistants. In *The Twelfth International Conference on Learning Representations*, 2023.

[22] Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde De Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, et al. Evaluating large language models trained on code. *arXiv preprint arXiv:2107.03374*, 2021.

[23] Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. Measuring massive multitask language understanding. *arXiv preprint arXiv:2009.03300*, 2020.

[24] Yann Dubois, Balázs Galambosi, Percy Liang, and Tatsunori B Hashimoto. Length-controlled alpacaeval: A simple way to debias automatic evaluators. *arXiv preprint arXiv:2404.04475*, 2024.

[25] Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, et al. Retrieval-augmented generation for knowledge-intensive nlp tasks. *Advances in neural information processing systems*, 33:9459–9474, 2020.

[26] Junlin Wang, Jue WANG, Ben Athiwaratkun, Ce Zhang, and James Zou. Mixture-of-agents enhances large language model capabilities. In *The Thirteenth International Conference on Learning Representations*, 2025. URL https://openreview.net/forum?id=h0ZfDIrj7T.

[27] Zeping Lee. GB/T 7714-2015 BibTeX Style. https://github.com/zepinglee/gbt7714-bibtex-style, 2025. GitHub repository.

[28] LlamaIndex. Llamaindex, 2025. URL https://www.llamaindex.ai/. Accessed: 2025-05-15.

[29] agno-agi. Phidata, 2025. URL https://docs.phidata.com/introduction. Accessed: 2025-05-15.

[30] PydanticAI. Pydanticai: A python agent framework for generative ai, 2025. URL https://ai.pydantic.dev/. Accessed: 2025-05-15.

[31] Together.ai. https://www.together.ai/, 2024. Accessed: 2024-07-16.

[32] Matthijs Douze, Alexandr Guzhva, Chengqi Deng, Jeff Johnson, Gergely Szilvasy, Pierre-Emmanuel Mazaré, Maria Lomeli, Lucas Hosseini, and Hervé Jégou. The faiss library. *arXiv preprint arXiv:2401.08281*, 2024.

A Additional Results

A.1 Accuracy

Table 3: Accuracy of each framework on each dataset

Dataset	LangChain	AutoGen	AgentScope	CrewAI	LlamaIndex	Phidata	PydanticAI
GAIA	0.152	0.103	0.200	0.170	0.079	0.218	0.139
HumanEval	0.573	0.884	0.884	0.872	0.872	0.902	0.921
MMLU	0.820	0.817	0.827	0.813	0.745	0.792	0.788

Table 3 presents the accuracy of each framework. It can be observed that, in general, the accuracy differences among frameworks are relatively small when using the same underlying LLM. However, there are still some notable exceptions.

Insight 5: The complete absence of output constraints in LLMs may lead to tool invocation failures, whereas excessively strict output validation can incur substantial token overhead and decrease the response success rate.

Some frameworks, such as LlamaIndex, require tool inputs to conform to a strict dictionary format. However, GPT-4o does not consistently produce structured outputs that align with these expectations, leading to frequent tool invocation failures, which caused a lower accuracy in GAIA dataset. This issue can be partially mitigated if the framework explicitly enforces the format requirement during the registration phase or input schema definition.

In contrast, other frameworks such as LangChain adopt stricter enforcement mechanisms. ReAct-style agents in these systems perform rigid output validation and initiate automatic retries when the model's response deviates from the expected invocation structure. While such mechanisms increase robustness against malformed outputs, they may backfire in certain scenarios.

In our evaluation, we found that when the model skips tool invocation and instead provides a direct answer (this happens especially with some of the simpler queries in the HumanEval dataset), the framework retries the prompt, often multiple times. Each retry includes previous failed attempts in the context, leading to a rapid increase in prompt length and token consumption as well as a lower likelihood of producing a clean, valid output on later attempts.

An additional point to clarify is that the GAIA dataset exhibits relatively low accuracy. This is primarily because GAIA tasks often require complex task planning and the use of multiple tools, posing significant challenges for all evaluated frameworks. It is important to note that the primary focus of this study is not on accuracy, but rather on comparing the performance overhead (e.g., time, token usage) across different frameworks. Therefore, we ensured that the accuracy across frameworks remains broadly comparable, without conducting detailed task-level progress analysis as seen in some related work. By carefully controlling experimental parameters, the fairness of our comparisons remains valid, even in the presence of lower absolute accuracy.

A.2 Detailed Evaluation Results

Table 4 5 6and 7 presents the detailed results obtained in this experiment.

Insight 6: Token consumption may vary across frameworks even when executing the same workflow, owing to differences in implementation strategies.

For example, PydanticAI does not require the invocation of all sub-agents during MoA execution, thereby reducing token consumption and runtime overhead.

Another example is that in the CrewAI framework, MoA is centrally managed by a global agent, which also plays the role of aggregation agent. The global agent receives the task and sequentially assigns it to sub-agents (e.g., agent1, agent2, agent3). Each sub-agent completes its part and returns the result to the global agent, which then decides the next step. After all agents have responded, the global agent summarizes the results and outputs the final answer.

In this setup, the global agent calls the LLM multiple times—once after each sub-agent's response. Because LLMs retain the full context of previous inputs and outputs in a single session, each new

	token			time												
frameworks	**prompt**	**output**	**total**	**llm**	**web_tool**	**pdf_tool**	**csv_tool**	**xlsx_tool**	**txt_tool**	**docx_tool**	**audio_tool**	**vision_tool**	**video_tool**	**python_tool**	**total tool time**	**total time**
langchain	9358.35	637.92	9996.27	29.491	1.58856	0.02423455	0.00003333	0.06422606	0.0004194	0.00009758	-	0.5345976	-	0.0152988	2.22746732	32.492
autogen	1159.48	180.66	1340.15	8.464	9.4219	0.0009297	0.000336	0.002387	0.00002909	0.0002212	-	1.05489	-	0.00005333	10.4807	20.76
agentscope	23520.479	785.891	24306.37	41.17	7.291	0.217	0.000297	0.00405	0.0000193	0.00000883	0.729	4.083	0.0000271	0.752	13.076	55.092
crewai	33621.857	664.511	34286.369	67.68	4.031	0.00965	0.000196	0.00422	0.00123	0.000278	0.000346	0.03164	0.000999	0.09565	4.18	72.195
llamaindex	20935.364	304.976	21240.339	27.244	1.4399	0.0001352	0.00016616	0.004254	0.000034839	0.0001135	0.03341	0.8767	-	0.05782	2.4126	29.795
phidata/agno	6386.667	323.558	6710.224	14.375	1.83012	0.001147	0.0007207	0.003858	0.0002107	0.000073355	0.03821	1.4065	1.38445E-05	0.003035	3.2839	20.396
pydantic	14459.17	320.588	14779.758	23.779	1.2275	0.001395	0.0003148	0.003795	8.6865E-06	0.000056241	0.02965	1.2104	3.1952E-06	0.0001414	2.4732	26.238

Table 4: GAIA Detailed Results

	token			time		
Framework	**prompt**	**output**	**total**	**llm**	**code executor**	**total**
langchain	6326.36	617.13	6943.49	23.221	0.0034	23.968
autogen	767.45	106.34	873.79	5.822	0.0002	5.846
agentscope	3180.689	561.518	3742.207	11.738	0.131	11.906
crewai	10817.65	892.798	11710.45	24.22	0.0258	25.24
llamaindex	1985.6	342.793	2328.152	9.52	0.003069	9.611
phidata/agno	967.329	354.427	1321.756	7.181	-	9.692
pydantic	812.951	352.543	1165.494	5.258	0.000007158	5.276

Table 5: HumanEval Detailed Results

call includes all prior interactions. This leads to token accumulation, especially by the third or fourth step, where the prompt becomes much longer. As a result, total token usage becomes higher than in frameworks with different coordination or memory strategies.This phenomenon will become more apparent in Scalability part as the number of sub agents increases.

Insight 7: ReAct workflows based solely on prompting lack robust mechanisms for accurate and consistent tool invocation.

Insight 8: Parallel invocation reduces overall runtime.

In the PydanticAI framework, the total runtime is observed to be shorter than the sum of individual tool and LLM invocation times on datasets such as GAIA and MoA. This improvement is attributed to its parallel execution architecture, which enables simultaneous invocation of multiple tools or LLMs, thereby effectively reducing end-to-end latency.

A.3 Scalability

A.4 Limitations and Broader Impacts

In this study, API calls were made exclusively by the LLM and Google Search tools. Due to potential network instability, the duration of these calls exhibited some degree of variability and randomness.

Moreover, most frameworks offer a wide range of tunable parameters. In our experiments, we adopted a simplified and uniform configuration across all frameworks for comparability, rather than tuning each individually for optimal performance. As such, the reported results may not reflect the upper-bound capabilities of each framework.

The potential positive societal impact of our benchmark lies in its ability to advance the development of more efficient and scalable AI agents. These improvements can help reduce computational

Framework	token			time			
	prompt	output	total	llm	embedding	retrieve	total
langchain	701.514	4.035	705.55	1.677	11.833	0.055	1.79
autogen	679.788	3.956	683.744	2.171	6.526	0.015	2.182
agentscope	2664.315	2.878	2667.193	3.893	92.472	0.935	4.931
crewai	884.536	13.189	897.724	2.51	7.718	0.14	5
llamaindex	2079.702	50.339	2130.042	3.125	4.931	0.4303	3.575
phidata/agno	2797.441	37.347	2834.788	7.849	341.611	6.708	17.014
pydantic	6996.242	170.135	7166.378	9.685	5.977	0.03454	9.824

Table 6: MMLU Detailed Results

Framework	token								
	llama			qwen			deepseek		
	prompt	output	total	prompt	output	total	prompt	output	total
langchain	70.49	428.55	499.04	64.84	446.05	510.91	38.5	501.11	539.61
autogen	70.49	431.96	502.45	64.85	447.45	512.31	38.5	503.37	541.87
agentscope	85.451	382.45	467.901	61.815	311.109	372.924	52.478	416.639	469.117
crewai	298.25	518.95	817.201	258.083	398.618	656.702	313.01	571.79	884.808
llamaindex	70.49	430.216	500.707	64.81	441.738	506.548	38.485	495.306	533.791
phidata/agno	118.846	438.078	556.924	93.899	463.795	557.694	83.391	440.691	524.082
pydantic	61.347	429.543	490.889	41.217	433.739	474.957	31.802	434.81	485.612

Framework	gpt			time					
	prompt	output	total	llama	qwen	deepseek	aggregator	total	agent1
langchain	1522.48	444.81	1967.29	8.275	4.48	23.084	10.699	36.502	165.07/0
autogen	1529.96	450.63	1980.59	7.812	3.977	26.745	8.274	36.854	209.08/44.01
agentscope	1138.243	352.564	1490.807	6.063	3.415	13.726	8.89	32.119	284.078/118
crewai	11694.576	679.15	12373.72	8.835	3.837	21.946	23.114	64	514.962/0
llamaindex	42.083	350.386	392.47	6.069	4.787	20.829	5.849	27.318	1180.078/898
phidata/agno	3003.319	756.689	3760.009	6.152	4.707	16.456	14.208	50.217	354.508/0
pydantic	1845.724	596.876	2442.6	6.503	3.441	17.79	27.486	46.45	96.022/0

Framework	Communication Size (content / wrapper bytes)				
	prompt to agent		agent to aggregator		
	agent2	agent3	agent1	agent2	agent3
langchain	165.07/0	165.07/0	1983.02/3	2011.83/3	2072.98/3
autogen	209.08/44.01	209.08/44.01	2066.04/52.24	2071.24/57.38	2156.04/66.81
agentscope	284.078/118	284.078/118	1659.318/124	1511.311/122	1889.247/126
crewai	483.740/0	619.516/0	2497.929/0	1754.701/0	2151.097/0
llamaindex	1171.078/889	1164.078/882	2022.417/33.689	2054.878/39.118	2116.377/48.641
phidata/agno	341.160/0	343.219/0	6128.259/2639.113	6131.272/2629.426	5715.126/2465.817
pydantic	95.425/0	97.116/0	2000.542/0	1927.093/0	1892.344/0

Table 7: Alpacaeval Detailed Results

costs, lower energy consumption, and enhance the feasibility of deploying AI systems in real-world applications such as education, healthcare, and assistive technologies.

At the same time, we recognize the possibility of indirect negative societal impacts. For example, broader availability and benchmarking of agent frameworks may inadvertently accelerate the deployment of autonomous systems without adequate oversight, or facilitate the misuse of agent-based automation in deceptive or manipulative contexts. However, AgentRace's primary goal is to promote transparency, accountability, and efficiency in the evaluation of existing agent architectures and we believe that the societal benefits of a robust benchmarking infrastructure outweigh these risks—particularly when coupled with responsible deployment practices and clear usage guidelines.

B Experiment Details

In all experiments, the temperature was set to 0, the top k to 1 (if available), and all other parameters were set to their default values unless otherwise specified.

Except for the cases explicitly noted below, all workflows employ the default prompts provided by their respective frameworks, and the datasets are used without any modification to the original queries.

B.1 ReAct

For frameworks that do not have a specific implementation of ReAct, we use the following prompt to build the ReAct workflow:

```
You are a ReAct-based assistant.
You analyze the question, decide whether to call a tool or directly answer, and then
 respond accordingly.
Use the following format:Question: the input question or request
Thought: you should always think about what to do\nAction: the action to take (if
any)
Action Input: the input to the action (e.g., search query)
Observation: the result of the action
... (this process can repeat multiple times)
Thought: I now know the final answer
Final Answer: the final answer to the original input question or request
Begin!
Question: {input}
```

B.2 RAG

For the following frameworks, we applied specific prompts to improve their token efficiency or to better align with the RAG workflow.

B.2.1 AutoGen

```
You are a helpful assistant. You can answer questions and provide information based
on the context provided.
```

B.2.2 Phidata

```
You are a RAG-based assistant. You analyze the question, and call the
search_knowledge_base tool to retrieve relevant documents from the knowledge base,
and then respond accordingly.
```

B.2.3 PydanticAI

```
You're a RAG agent. please search information from the given task to build a
knowledge base and then retrieve relevant information from the knowledge base.
```

B.3 MoA

B.3.1 LangChain

```
You have been provided with a set of responses from various open-source models to
the latest user query. Your task is to synthesize these responses into a single,
high-quality response. It is crucial to critically evaluate the information provided
 in these responses, recognizing that some of it may be biased or incorrect. Your
response should not simply replicate the given answers but should offer a refined,
accurate, and comprehensive reply to the instruction. Ensure your response is well-
structured, coherent, and adheres to the highest standards of accuracy and
reliability.
```

B.3.2 AgentScope

```
You are an assistant called Dave,you should synthesize the answers from Alice, Bob
and Charles to arrive at the final response.
```

```
You are an assistant called Alice/Bob/Charles.
```

B.3.3 Phidata

```
Transfer task to all chat agents (There are 3 agents in your team)", "Aggreagate
responses from all chat agents
```

B.3.4 PydanticAI

```
Your task is to aggregate all agents results to solve complex tasks.\nYou analyze
the input, input the task to all tools that can run a single agent, and synthesize
the results from all agents into a final response.
```

B.4 GAIA

Below are examples of prompts used in our system, depending on whether a file is attached:

```
question: A paper about AI regulation originally submitted to arXiv.org in June 2022
 features a figure with three axes, each labeled with a pair of opposing terms.
Which of these terms is used to describe a type of society in a Physics and Society
article submitted to arXiv.org on August 11, 2016?
```

```
question: The attached spreadsheet contains the inventory of a movie and video game
rental store located in Seattle, Washington. What is the title of the oldest Blu-Ray
 listed in this spreadsheet? Return it exactly as it appears., file_name: 32102e3e-
d12a-4209-9163-7b3a104efe5d.xlsx, file_path: path/to/32102e3e-d12a-4209-9163-7
b3a104efe5d.xlsx
```

B.5 HumanEval

Below is an example of the prompt used for HumanEval problems:

```
from typing import List

def has_close_elements(numbers: List[float], threshold: float) -> bool:
    """ Check if in given list of numbers, are any two numbers closer to each other
than
    given threshold.
    >>> has_close_elements([1.0, 2.0, 3.0], 0.5)
    False
    >>> has_close_elements([1.0, 2.8, 3.0, 4.0, 5.0, 2.0], 0.3)
    True
    """

# Complete the function. Only return code. No explanation, no comments, no markdown.
```

B.6 MMLU

For the MMLU dataset, we constructed the vector database used in the RAG workflow based on the development subset and evaluated the performance of each framework using the test subset. Given the large number of tasks in this dataset, we used only one-quarter of them in our experiments. Considering that tasks from the same domain tend to be spatially adjacent in the dataset, we selected one out of every four tasks in index order. This sampling strategy ensures broader domain coverage and maintains fairness in the evaluation.

Below is an example of the question in MMLU:

```
Question:Find the degree for the given field extension Q(sqrt(2), sqrt(3), sqrt(18))
 over Q.
A.0
B.4
C.2
D.6
Answer with A, B, C, or D only
```

B.7 Alpacaeval

C Tool Implementation

For frameworks that do not include the required tools, we adopted a unified implementation as follows.

C.1 Search

C.2 PDF loader

C.3 CSV reader

```python
import pandas as pd

def csv_load(path:str)->ServiceResponse:
    try:
        df = pd.read_csv(path)
        csv_str = df.to_string(index=False)
        return ServiceResponse(status=ServiceExecStatus.SUCCESS,content=csv_str)
    except Exception as e:
        return ServiceResponse(ServiceExecStatus.ERROR, str(e))
```

C.4 XLSX reader

C.5 Text file reader

```python
import pandas as pd

def txt_load(path:str)->ServiceResponse:
    try:
        with open(path, 'r', encoding='utf-8') as f:
            txt_str = f.read()
        return ServiceResponse(status=ServiceExecStatus.SUCCESS,content=txt_str)
    except Exception as e:
        return ServiceResponse(ServiceExecStatus.ERROR, str(e))
```

C.6 doc reader

```python
from docx import Document

def docs_load(path:str)->ServiceResponse:
    try:
        doc = Document(path)
        docx_str = "\n".join([para.text for para in doc.paragraphs])
        return ServiceResponse(status=ServiceExecStatus.SUCCESS,content=docx_str)
    except Exception as e:
        return ServiceResponse(ServiceExecStatus.ERROR, str(e))
```

C.7 MP3 loader

```
import whisper
from typing import cast

def load_audio(file):
    model = whisper.load_model(name="base")
    model = cast(whisper.Whisper, model)
    result = model.transcribe(str(file))
    return result["text"]
```

C.8 Figure loader

```
from transformers import DonutProcessor, VisionEncoderDecoderModel
import re
from PIL import Image

def load_image(path):
    image = Image.open(path)
    processor = DonutProcessor.from_pretrained(
                        "naver-clova-ix/donut-base-finetuned-cord-v2"
                    )
    model = VisionEncoderDecoderModel.from_pretrained(
        "naver-clova-ix/donut-base-finetuned-cord-v2"
    )
    device = 'cpu'
    model.to(device)
    # prepare decoder inputs
    task_prompt = "<s_cord-v2>"
    decoder_input_ids = processor.tokenizer(
        task_prompt, add_special_tokens=False, return_tensors="pt"
    ).input_ids
    pixel_values = processor(image, return_tensors="pt").pixel_values
    outputs = model.generate(
        pixel_values.to(device),
        decoder_input_ids=decoder_input_ids.to(device),
        max_length=model.decoder.config.max_position_embeddings,
        early_stopping=True,
        pad_token_id=processor.tokenizer.pad_token_id,
        eos_token_id=processor.tokenizer.eos_token_id,
        use_cache=True,
        num_beams=3,
        bad_words_ids=[[processor.tokenizer.unk_token_id]],
        return_dict_in_generate=True,
    )
    sequence = processor.batch_decode(outputs.sequences)[0]
    sequence = sequence.replace(processor.tokenizer.eos_token, "").replace(
        processor.tokenizer.pad_token, ""
    )
    # remove first task start token
    text_str = re.sub(r"<.*?>", "", sequence, count=1).strip()
    return text_str
```

C.9 Video loader

```
import whisper
from typing import cast
from pydub import AudioSegment
from pathlib import Path

def load_video(file):
    video = AudioSegment.from_file(Path(file), format=file[-3:])
```

```
    audio = video.split_to_mono()[0]
    file_str = str(file)[:-4] + ".mp3"
    audio.export(file_str, format="mp3")
    model = whisper.load_model(name="base")
    model = cast(whisper.Whisper, model)
    result = model.transcribe(str(file))
    return result["text"]
```

C.10 Code executor

C.11 data retrieval

D Error Analysis

E bugs and features

NeurIPS Paper Checklist

1. **Claims**

   Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

   Answer: [Yes]

   Justification: The abstract and introduction provide a clear overview of the benchmark (AgentRace), its focus (efficiency), and the scope of evaluation (7 frameworks, 3 workflows, 4 datasets), matching the content presented in Sections 3, 4, 5, 6.

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2. **Limitations**

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