

Difficulty-Aware Agent Orchestration in LLM-Powered Workflows

Jinwei Su, Yinghui Xia, Qizhen Lan, Xinyuan Song
 ChenChen, Yang Jingsong, Lewei He, Tianyu Shi

Abstract

Large Language Model (LLM)-based agentic systems have shown strong capabilities across various tasks. However, existing multi-agent frameworks often rely on static or task-level workflows, which either over-process simple queries or underperform on complex ones, while also neglecting the efficiency-performance trade-offs across heterogeneous LLMs. To address these limitations, we propose **Difficulty-Aware Agentic Orchestration (DAAO)**, a dynamic framework that adapts workflow depth, operator selection, and LLM assignment based on the difficulty of each input query. DAAO comprises three interdependent modules: a variational autoencoder (VAE) for difficulty estimation, a modular operator allocator, and a cost- and performance-aware LLM router. By leveraging heterogeneous LLMs and dynamically tailoring workflows, DAAO enables fine-grained, query-specific reasoning strategies. DAAO outperforms prior multi-agent systems in both accuracy and inference efficiency across six benchmarks. We will release our code and implementation details upon publication.

Introduction

Large Language Model (LLM)-based agents (Richards et al. 2023; Nakajima 2023; Reworkd 2023) have exhibited remarkable capabilities across a wide spectrum of tasks, including question answering (Zhu et al. 2024), data analysis (Hong et al. 2024; Li et al. 2024), decision-making (Song et al. 2023), code generation (Shinn, Labash, and Gopinath 2023) and web navigation (Deng et al. 2024). Building upon the success of single agents, recent advancements reveal that organizing multiple LLM-based agents into structured agentic workflows can significantly enhance task performance. In such workflows, agents can interact either cooperatively (Zhuge et al. 2024) or competitively (Zhao et al. 2023) depending on the task context. These multi-agent systems can overcome the cognitive and functional limitations of individual models (Du et al. 2023; Liang et al. 2023; Wang et al. 2023b; Jiang, Ren, and Lin 2023; Wu et al. 2023; Zhang et al. 2024a), thereby exhibiting collective intelligence similar to human collaboration in a society of agents.

In recent years, the research community has focused on automating multi-agent system design. For instance,

DsPy (Khattab et al. 2023) and EvoPrompting (Guo et al. 2023) automate prompt optimization, GPTSwarm (Zhuge et al. 2024) optimizing inter-agent communication, and EvoAgent (Yuan et al. 2024) self-evolving agent profiling. However, these systems are often constrained by limited search spaces and rigid representation paradigms, resulting in marginal performance gains and limited adaptability to diverse task requirements. Subsequently, ADAS (Hu, Lu, and Clune 2024) and AFlow (Zhang et al. 2024b) employ code as representation for workflow, facilitating robust and flexible workflow searches through different paradigms, with ADAS utilizing heuristic search and AFlow adopting Monte Carlo tree search. MaAS (Zhang et al. 2025) proposes an agentic supernet to generate a query-specific multi-agent system for each user query.

Despite their success, existing automation pipelines often lack complex adaptivity and LLM heterogeneity. Task-level workflows (Hu, Lu, and Clune 2024; Zhang et al. 2024b) are typically built as uniform multi-agent systems for entire task categories, achieving strong metrics like accuracy and pass@k but relying on heavy pipelines with excessive LLM calls and tool usage. This design over-processes simple queries, wasting resources and overlooking factors like token cost and latency. Query-level workflows (Zhang et al. 2025) introduce input-specific adaptation, but their granularity is often insufficient, leading to suboptimal or oversimplified workflows for difficult inputs. These limitations motivate a difficulty-adaptive framework that dynamically balances complexity and cost. Furthermore, most workflows (Hu, Lu, and Clune 2024; Zhang et al. 2024b, 2025) rely on a single large LLM (e.g., GPT-4o (OpenAI 2024)), ignoring recent findings (Ye et al. 2025; Chen, Zaharia, and Zou 2023; Hu et al. 2024) that different LLMs exhibit complementary capabilities. Smaller models can outperform larger ones on specific tasks while significantly reducing cost. Thus, there is increasing support for agentic workflows that integrate diverse LLMs of varying sizes, leveraging their specialization to improve performance and efficiency.

To address the challenges of adapting reasoning strategies to queries with varying difficulty and domain characteristics, we propose **Difficulty-Aware Agentic Orchestration (DAAO)**. DAAO is a dynamic framework that estimates the difficulty of each incoming query and composes optimized workflows by selecting suitable agentic operators—such as

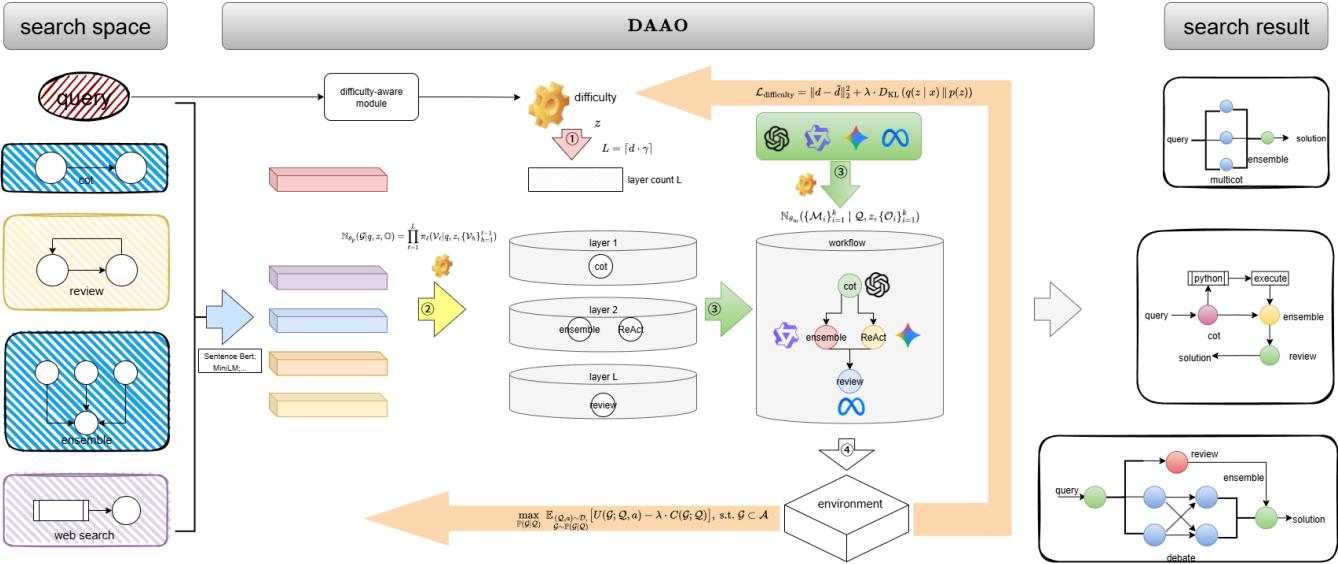


Figure 1: The overall framework of our proposed DAAO.

Chain-of-Thought (CoT) (Wei et al. 2022), Multi-Agent Debate (Du et al. 2023), and ReAct (Yao et al. 2023)—and assigning them to appropriate LLMs. By tailoring both workflow depth and model assignment based on query characteristics, DAAO balances reasoning effectiveness and computational cost. Furthermore, the system refines its predictions over time through feedback, enabling continual adaptation.

Technically, DAAO decomposes the orchestration process into three interdependent modules. It begins with a **query difficulty estimator**, implemented as a variational autoencoder (VAE) (Kingma and Welling 2014), which encodes each input query into a latent representation reflecting its difficulty. This difficulty signal then guides the **agentic operator allocator**, which determines the depth of the workflow and selects suitable reasoning operators based on both the query and its inferred complexity. Finally, the **LLM router** assigns each selected operator to a language model that best fits its role, enabling heterogeneous and cost-effective reasoning. Together, these modules form a cohesive and adaptive orchestration framework that supports flexible, query-specific agentic workflows.

We conduct comprehensive evaluations on six widely adopted benchmarks. Empirical results reveal that our DAAO achieves both state-of-the-art performance and remarkable cost-reduction. For instance, our DAAO surpasses state-of-the-art automated multi-agent systems by 11.21% in accuracy, while requiring only 64% of their inference costs, owing to its difficulty-aware routing and adaptive workflow construction.

Our key contributions are as follows:

- **Query-Level Difficulty Estimation for Workflow Adaptation:** We propose a difficulty-aware orchestration framework that estimates the complexity of each input query using a variational autoencoder (VAE). This latent difficulty signal informs both the depth and structure of the workflow, enabling fine-grained, query-specific adap-

tation beyond static or task-level designs.

- **Modular Agentic Workflow Construction with Heterogeneous Operators and LLMs:** We develop a modular pipeline that selects agentic operators based on query difficulty and context, and assigns each to the most suitable LLM. This fine-grained routing leverages the complementary strengths of diverse models to enhance reasoning performance while reducing cost.
- **Efficient and Scalable Execution with Empirical Gains:** Our method achieves state-of-the-art performance on six benchmarks, outperforming prior multi-agent systems by up to 11.21% in accuracy while using only 64% of the inference cost. The effectiveness of difficulty-guided orchestration is further validated through comprehensive ablation and cost-efficiency analysis.

Related Work

Automated Agentic Workflows. The development of agentic workflows has evolved from manual configurations to automated systems, with the latter offering improved adaptability and task performance. Early approaches to automation focus on optimizing prompt structures and inter-agent communication protocols (Khattab et al. 2023; Guo et al. 2023; Zhuge et al. 2024; Yuan et al. 2024), thereby enhancing the robustness of workflows across a variety of tasks. More recent systems, such as ADAS (Hu, Lu, and Clune 2024) and AFlow (Zhang et al. 2024b), leverage code-based representations to enable real-time structural adaptation and communication strategy refinement based on environmental feedback. MaAS (Zhang et al. 2025) further introduces query-specific multi-agent composition using a supernet-like architecture. Despite these advances, most existing workflows remain LLM-homogeneous, typically instantiating all agents with a single high-capacity model (e.g.,

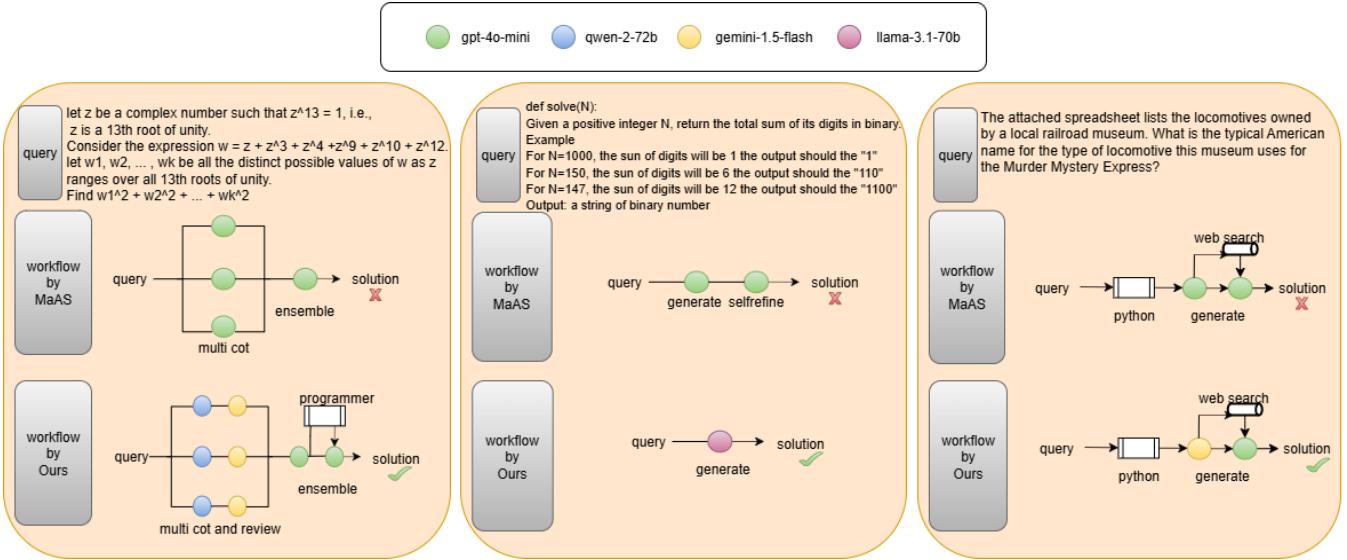


Figure 2: Case study and visualization for MaAS (Zhang et al. 2025) and Ours. Queries are from MATH, HumanEval and GAIA benchmarks. Left: our method solves the query while MaAS fails. Middle: our workflow is simpler for easy queries. Right: our method leverages heterogeneous LLMs within the same workflow structure.

GPT-4o (OpenAI 2024)), which limits both efficiency and the ability to specialize across sub-tasks. Additionally, the adaptivity of these systems is often coarse-grained, leading to under- or over-processing depending on query complexity.

LLM Heterogeneity and Difficulty-Aware Reasoning. Emerging research increasingly highlights the complementary strengths of LLMs with different capacities. Works such as X-MAST (Ye et al. 2025), FrugalGPT (Chen, Zaharia, and Zou 2023), and RouterBench (Hu et al. 2024) demonstrate that smaller LLMs can outperform larger models in specific domains while incurring lower inference costs. These findings suggest that heterogeneous model ensembles, if properly orchestrated, can achieve better cost-performance trade-offs than homogeneous systems (Gong et al. 2023). Concurrently, there is growing interest in difficulty-aware reasoning, where model behavior is conditioned on the estimated hardness of each query (Li et al. 2023; Zhang et al. 2023). However, most existing systems do not incorporate fine-grained difficulty estimation into workflow generation (Lin et al. 2023). Our work builds upon these insights by introducing a unified framework that integrates both difficulty-aware reasoning and LLM heterogeneity for efficient and adaptive agentic workflow construction.

Preliminary

In this section, we formally define the search space of **DAAO** and its associated optimization objective.

Search Space. We define the basic unit of DAAO’s search space, referred to as an **agentic operator**. An agentic operator \mathcal{O} is a composite module consisting of a language model

and an associated collaborative protocol:

$$\mathcal{O}_j^i = \{\mathcal{M}, \mathcal{P}\}, \quad \mathcal{M} \in \mathbb{M}, \quad \mathcal{P} \in \mathbb{P}, \quad (1)$$

where \mathcal{M} denotes a selected LLM backbone from the set of available models \mathbb{M} , and \mathcal{P} specifies a collaboration protocol from the protocol set \mathbb{P} . For example, $\mathcal{O}_{\text{CoT}}^q = \{\text{Qwen2-70B, Chain-of-Thought}\}$ denotes using Qwen2-70B with a step-by-step reasoning strategy, whereas $\mathcal{O}_{\text{debate}}^g = \{\text{GPT-4o-mini, Multi-agent debate}\}$ configures multiple GPT-4o-mini instances to engage in turn-based argumentation. The set of feasible operators is denoted by \mathbb{O} .

We define an **agentic workflow** as a directed acyclic graph (DAG):

$$\mathcal{G} = \{\mathcal{V}, \mathcal{E}\}, \quad \mathcal{V} \subset \mathbb{O}, \quad \mathcal{E} \subset \mathcal{V} \times \mathcal{V}, \quad (2)$$

where \mathcal{V} denotes the set of selected operators and \mathcal{E} encodes their directed connectivity. The DAG structure enforces hierarchical operator execution.

Definition of DAAO. DAAO is denoted as $\mathcal{A} = \{\pi, \mathbb{O}\} = \{\{\pi_\ell(\mathcal{O})\}_{\mathcal{O} \in \mathbb{O}}\}_{\ell=1}^L$, where

$$\begin{aligned} \pi_\ell(\mathcal{O}) &= p(\mathcal{O} | \mathcal{A}_{1:\ell-1}), \quad \mathcal{O} \in \mathbb{O}, \\ \mathcal{A}_{1:\ell-1} &= \{\{\pi_k(\mathcal{O})\}_{\mathcal{O} \in \mathbb{O}}\}_{k=1}^{\ell-1}, \end{aligned} \quad (3)$$

and $\pi_\ell(\mathcal{O})$ denotes the probability of selecting operator \mathcal{O} at layer ℓ , conditioned on the prior layers $\mathcal{A}_{1:\ell-1}$. This defines a sequential decision process for operator selection.

The induced supernet defines a joint distribution over all multi-layer agentic workflow configurations:

$$p(\mathcal{G}) = \prod_{\ell=1}^L \prod_{\mathcal{O} \in \mathbb{O}} \pi_\ell(\mathcal{O})^{\mathbb{I}_{\mathcal{O} \in \mathcal{V}_\ell}}, \quad (4)$$

where $\mathbb{I}_{\mathcal{O} \in \mathcal{V}_\ell}$ is an indicator function denoting the inclusion of operator \mathcal{O} at layer ℓ of the workflow.

Optimization Objective. Given a benchmark dataset \mathcal{D} containing queries \mathcal{Q} and their corresponding oracle answers a , the objective of **DAAO** is to learn a query-conditioned policy that balances task utility and inference cost. The objective is formally defined as:

$$\max_{\mathbb{P}(\mathcal{G}|\mathcal{Q})} \mathbb{E}_{(\mathcal{Q}, a) \sim \mathcal{D}} [U(\mathcal{G}; \mathcal{Q}, a) - \lambda \cdot C(\mathcal{G}; \mathcal{Q})], \quad \text{s.t. } \mathcal{G} \subset \mathcal{A}, \quad (5)$$

where $\mathbb{P}(\mathcal{G} | \mathcal{Q})$ is a distribution over query-specific workflows, $U(\cdot)$ and $C(\cdot)$ denote the utility (e.g., accuracy) and cost (e.g., token usage, latency) of executing workflow \mathcal{G} on query \mathcal{Q} , respectively, and λ is a trade-off coefficient that balances performance and efficiency.

Methodology

We first provide a roadmap of our method, then elaborate on each component in detail. Figure 1 presents the overall architecture of **DAAO**, which dynamically generates agentic workflows for input queries from various domains and difficulty levels. A controller network (Zoph and Le 2017) analyzes each query’s complexity and domain features, and dispatches it to three key modules: a query difficulty estimator ($\mathbb{N}\theta_d$), an agentic operator allocator ($\mathbb{N}\theta_p$), and an LLM router ($\mathbb{N}\theta_m$). The estimator, based on a variational autoencoder (VAE) (Kingma and Welling 2014), encodes the query into a latent difficulty representation, guiding workflow depth and operator choice. The allocator selects suitable agentic operators using this representation and context, while the LLM router assigns appropriate language models by balancing reasoning needs and computational cost. This process yields a customized, multi-stage workflow for each query. After execution, output quality is evaluated, and feedback is used to jointly update the controller and modules, enabling continual improvement over time.

Difficulty-Aware Agent Orchestration

Given a query \mathcal{Q} , DAAO aims to dynamically construct a customized agentic workflow by analyzing the query’s complexity and domain characteristics, with the objective of generating a high-quality response:

$$p(a|\mathcal{Q}) = \int e(a|\mathcal{G}) \mathbb{N}_\theta(\mathcal{G}|\mathcal{Q}) d\mathcal{G}, \quad (6)$$

where \mathbb{N}_θ denotes the controller network parameterized by θ , which takes \mathcal{Q} as input. The function $e(\cdot|\cdot)$ denotes the conditional likelihood of obtaining the response a by executing the workflow \mathcal{G} . The controller network \mathbb{N}_θ is composed of three sequential modules:

$$\mathbb{N}_\theta = \mathbb{N}_{\theta_d} \circ \mathbb{N}_{\theta_p} \circ \mathbb{N}_{\theta_m}, \quad (7)$$

where $\mathbb{N}_{\theta_d} : \mathcal{Q} \rightarrow z$ is the query difficulty estimator, $\mathbb{N}_{\theta_p} : (\mathcal{Q}, \mathbb{O}, z) \rightarrow \{\mathcal{V}_i\}_{i=1}^L$ is the agentic operator allocator, and $\mathbb{N}_{\theta_m} : (\mathcal{Q}, z, \{\mathcal{V}_i\}_{i=1}^L) \rightarrow \{\mathcal{V}_j\}_{j=1}^L$ is the LLM router, which assigns specific language models to each selected operator. Here, the operator \circ denotes function composition, applied in order from right to left.

Query Difficulty Estimator. The module $\mathbb{N}_{\theta_d} : \mathcal{Q} \rightarrow z$ maps the input query \mathcal{Q} to a latent difficulty representation $z \in \mathbb{R}^k$ using a variational autoencoder (VAE). Given a query embedding $x \in \mathbb{R}^d$, the encoder network parameterized by θ_d outputs the mean and log-variance of a Gaussian posterior:

$$\mu, \log \sigma^2 = f_{\text{enc}}(x), \quad z \sim \mathcal{N}(\mu, \sigma^2), \quad (8)$$

where f_{enc} denotes the encoder. The latent variable z is then decoded into a scalar difficulty score:

$$d = f_{\text{dec}}(z), \quad d \in [0, 1]. \quad (9)$$

To train the VAE, we employ a difficulty-guided objective that encourages alignment between the predicted difficulty d and the observed task outcome $y \in \{0, 1\}$. The training loss is defined as:

$$\mathcal{L}_{\text{difficulty}} = \|d - \tilde{d}\|_2^2 + \lambda \cdot D_{\text{KL}}(q(z|x)\|p(z)), \quad (10)$$

where \tilde{d} is a pseudo-target adjusted based on the outcome:

$$\tilde{d} = \text{clamp}(d + \gamma(1 - 2y), 0, 1). \quad (11)$$

Here, γ controls the adjustment magnitude, and λ balances the prediction loss and KL regularization. This enables \mathbb{N}_{θ_d} to learn a meaningful prior over query difficulty, guiding downstream operator selection and model routing. In the KL term, $q(z|x) = \mathcal{N}(z; \mu, \sigma^2)$ denotes the approximate posterior from the encoder, and $p(z) = \mathcal{N}(0, I)$ is the standard Gaussian prior. The KL divergence encourages $q(z|x)$ to stay close to $p(z)$, promoting regularity in the latent space.

Agentic Operator Allocator. Before assigning agentic operators, we first determine the number of layers L in the resulting workflow based on the predicted difficulty of the input query. Specifically, L is computed as

$$L = \lceil d \cdot \ell \rceil,$$

where ℓ is a hyperparameter denoting the maximum allowed number of layers, and $d \in [0, 1]$ is the predicted difficulty score from the previous module. This formulation allows the workflow complexity to be adaptively scaled with query difficulty.

We implement \mathbb{N}_{θ_p} as a sequential operator selection process:

$$\mathbb{N}_{\theta_p}(\mathcal{G} | q, z, \mathbb{O}) = \prod_{\ell=1}^L \pi_\ell(\mathcal{V}_\ell | q, z, \{\mathcal{V}_h\}_{h=1}^{\ell-1}), \quad (12)$$

where \mathcal{V}_h denotes the set of operators selected at layer h . The operator selection at layer ℓ is conditioned on the query q , latent difficulty z , and operator sets from preceding layers.

We implement the policy π_ℓ using a Mixture-of-Experts (MoE) architecture (Shazeer et al. 2017; Huang et al. 2024). For each layer ℓ , the model selects a subset of operators $\mathcal{V}_\ell = \{\mathcal{O}_{\ell 1}, \mathcal{O}_{\ell 2}, \dots, \mathcal{O}_{\ell t}\}$ based on the current query and difficulty embedding:

$$\pi_\ell : (q, z) \rightarrow \mathcal{V}_\ell. \quad (13)$$

The number of selected operators t is determined by thresholding the sorted activation scores:

$$t = \arg \min_{k \in \{1, \dots, |\mathcal{O}|\}} \sum_{j < k} \mathbf{S}_j^\downarrow > P, \quad (14)$$

where $\mathbf{S} \in \mathbb{R}^{|\mathcal{O}|} = [S_1, \dots, S_{|\mathcal{O}|}]$ contains the activation scores of all candidate operators, and \mathbf{S}^\downarrow denotes the same scores sorted in descending order. Operators are included sequentially until the accumulated score exceeds a predefined threshold P .

Each activation score S_i is computed using a feed-forward network:

$$S_i = \text{FFN} \left(z \|\mathbf{v}(q)\| \sum_{\mathcal{O} \in \mathcal{V}_1} \mathbf{v}(\mathcal{O}) \| \cdots \| \sum_{\mathcal{O} \in \mathcal{V}_{\ell-1}} \mathbf{v}(\mathcal{O}) \right), \quad (15)$$

where $\mathbf{v}(\cdot)$ is an embedding function implemented using lightweight models such as MiniLM (Wang et al. 2020) or Sentence-BERT (Reimers 2019), and $\|$ denotes vector concatenation.

LLM Router. Inspired by (Ye et al. 2025; Barandoni et al. 2024), we recognize that different large language models (LLMs) offer varying strengths and limitations. Effective routing should exploit this heterogeneity rather than enforce uniformity. In workflows where all operators share the same LLM, even when enhanced with techniques such as chain-of-thought (CoT) or debate frameworks, the resulting reasoning process remains homogeneous. This often limits performance gains and increases computational cost. To address this, we adopt a heterogeneous workflow design where each operator is paired with the LLM best suited to its function. This approach preserves model diversity, improves efficiency, and enhances task performance through specialization.

We model the assignment of an LLM \mathcal{M}_i to each selected operator \mathcal{O}_i , conditioned on the input query \mathcal{Q} and its latent difficulty z . The overall routing objective is defined as:

$$\mathbb{N}_{\theta_m}(\{\mathcal{M}_i\}_{i=1}^k \mid \mathcal{Q}, z, \{\mathcal{O}_i\}_{i=1}^k) = \prod_{i=1}^k \pi_m(\mathcal{M}_i \mid \mathcal{Q}, z, \mathcal{O}_i), \quad (16)$$

where $\pi_m(\mathcal{M}_i \mid \mathcal{Q}, z, \mathcal{O}_i)$ denotes the probability of assigning LLM \mathcal{M}_i to operator \mathcal{O}_i .

Each selection probability is modeled using a temperature-scaled softmax over projected embeddings:

$$\pi_m(\mathcal{M}_i \mid \mathcal{Q}, z, \mathcal{O}_i) = \frac{\exp\left(\frac{\langle H_i^{\text{comb}}, e_{\mathcal{M}_i} \rangle}{\tau}\right)}{\sum_{j=1}^{N_m} \exp\left(\frac{\langle H_i^{\text{comb}}, e_{\mathcal{M}_j} \rangle}{\tau}\right)}, \quad (17)$$

where $H_i^{\text{comb}} = \text{FFN}_{\text{comb}}([\text{FFN}_q([\mathcal{Q}; W_z z]); \text{FFN}_o(\mathcal{O}_i)]) \in \mathbb{R}^d$ is the combined contextual embedding of the query, difficulty, and operator. The term $e_{\mathcal{M}_j} = \text{FFN}_m(\mathcal{M}_j) \in \mathbb{R}^d$ is the projected embedding of candidate LLM \mathcal{M}_j , and τ is a temperature parameter controlling the sharpness of the distribution. The dot product $\langle \cdot, \cdot \rangle$ measures cosine similarity after the embeddings are normalized.

The routing module is trained to maximize the likelihood of selecting the ground-truth LLMs:

$$\mathcal{L}_{\text{llm}} = \sum_{i=1}^k \log \pi_m(\mathcal{M}_i \mid \mathcal{Q}, z, \mathcal{O}_i). \quad (18)$$

This formulation enables the system to route operators to diverse LLMs based on query difficulty and operator context, promoting specialized and adaptive reasoning across the workflow.

Experiments

Experiment Setup

Benchmarks. We evaluate **DAAO** on six public benchmarks covering three domains: (1) math reasoning, **GSM8K** (Cobbe et al. 2021) and **MATH** (Hendrycks et al. 2021b); (2) code generation, **HumanEval** (Chen et al. 2021) and **MBPP** (Austin et al. 2021)); tool use, **GAIA** (Mialon et al. 2023). Additionally, we include **MMLU** (Hendrycks et al. 2021a), a benchmark covering 57 academic subjects, to assess general knowledge and multitask language understanding. For the **MATH** benchmark, we follow (Hong et al. 2024) in selecting a harder subset (617 problems).

Baselines. We compare **DAAO** with three of agentic baselines: (1) single-agent approaches, including **CoT** (Wei et al. 2022), **ComplexCoT** (Fu et al. 2022), **Self-Consistency** (Wang et al. 2023a); (2) autonomous agentic workflows, including **ADAS** (Hu, Lu, and Clune 2024), **AFlow** (Zhang et al. 2024b) and **MaAS** (Zhang et al. 2025). (3) LLM routers, **PromptLLM** (Feng, Shen, and You 2024), **RouteLLM** (Ong et al. 2024) and **MasRouter** (Yue et al. 2025).

LLM Backbones. We select LLM Pool with varying sizes and capacities, including **gpt-4o-mini-0718** (OpenAI 2024), **gemini-1.5-flash** (Team et al. 2024), **llama-3.1-70b** (Dubey et al. 2024), **Qwen-2-72b** (Yang et al. 2024). LLMs are accessed via APIs, with the temperature set to 1.

Implementation Details. Building upon established methodologies in workflow automation (Saad-Falcon et al. 2024; Hu, Lu, and Clune 2024; Zhang et al. 2024b), we divide each dataset into training and test sets using a TRAIN:TEST ratio of 1:4. We initialize the feasible space of operator nodes with the following operators: CoT, LLM-Debate, Review, Ensemble, ReAct, Self-Consistency, Testing. We set the max number of layers as $L = 5$, the cost penalty coefficient λ as $\lambda \in \{1e-3, 5e-3, 1e-2\}$.

Performance Analysis

High-performing. The experimental results in Table 1 demonstrate that DAAO effectively constructs high-performing agentic workflows. Compared to existing automated orchestration methods, DAAO achieves an average accuracy improvement of 2.83% \sim 11.21%, and outperforms recent LLM routing methods by 2.60% \sim 7.76%. On the **MATH** benchmark, DAAO attains a best-in-class score of 55.37%, surpassing the second-best method, MasRouter,

Method	LLM	MMLU	GSM8K	MATH	HumanEval	MBPP	Avg.
Vanilla	gpt-4o-mini	77.81	87.45	46.29	85.71	72.20	73.89
	qwen-2-72b	80.22	85.40	46.10	64.65	73.90	70.05
	gemini-1.5-flash	80.04	86.76	48.00	82.61	73.00	74.08
	llama-3.1-70b	79.08	86.68	45.37	80.75	68.20	72.01
CoT (Wei et al. 2022)	gpt-4o-mini	78.43	87.10	46.40	86.69	69.60	73.64
	gemini-1.5-flash	81.35	86.47	48.00	81.37	73.00	74.04
ComplexCoT (Fu et al. 2022)	gpt-4o-mini	81.05	86.89	46.53	87.58	75.80	75.57
	gemini-1.5-flash	80.74	86.01	48.28	80.12	71.80	73.39
SC(CoT) (Wang et al. 2023a)	gpt-4o-mini	81.05	87.57	47.91	87.58	73.00	75.42
	gemini-1.5-flash	81.66	87.50	48.73	80.75	72.00	74.13
ADAS (Hu, Lu, and Clune 2024)	gpt-4o-mini	79.54	86.12	43.18	84.19	68.13	72.23
	gemini-1.5-flash	79.68	86.00	45.89	80.69	68.00	72.05
AFlow (Zhang et al. 2024b)	gpt-4o-mini	83.10	91.16	51.82	90.93	81.67	79.73
	gemini-1.5-flash	82.35	90.43	52.00	85.69	76.00	77.29
MaAS (Zhang et al. 2025)	gpt-4o-mini	83.01	92.30	51.82	92.85	82.17	80.43
	gemini-1.5-flash	83.42	92.00	52.25	90.55	82.69	80.18
PromptLLM (Feng, Shen, and You 2024)	LLM Pool	78.43	88.68	52.30	86.33	73.60	75.86
RouteLLM (Ong et al. 2024)	LLM Pool	81.04	89.00	51.00	83.85	72.60	75.50
MasRouter (Yue et al. 2025)	LLM Pool	84.25	92.00	52.42	90.62	84.00	80.66
Ours	LLM Pool	84.90	94.40	55.37	94.65	86.95	83.26

Table 1: Performance comparison across baseline prompting strategies, single-agent methods, autonomous agentic workflows, and LLM routing approaches. Bold numbers indicate the best performance, while underlined numbers denote the second-best. The LLM pool comprises both lightweight and high-capacity models to support diverse routing strategies.

by 2.95%. Across five datasets, DAAO consistently outperforms all baselines, highlighting its versatility and robustness.

Table 2 further compares DAAO with existing automated systems on the GAIA benchmark—a challenging, high-complexity evaluation suite for multi-agent systems in realistic, multimodal, and tool-augmented settings. Unlike traditional benchmarks focused on static question answering or single-step reasoning, GAIA tasks require multi-step planning, cross-modal understanding, and tool interaction (e.g., web browsing, file system access). While AFlow uses a fixed workflow and MaAS does not fully exploit LLM specialization, DAAO dynamically generates query-specific workflows and allocates tasks to LLMs based on domain expertise. As a result, DAAO outperforms AFlow and MaAS by 17.97% and 8.33%, respectively, demonstrating its effectiveness in complex, real-world scenarios.

Method	Level 1	Level 2	Level 3	Avg.
GPT-4o-mini	7.53	4.40	0	4.65
ADAS	13.98	4.40	0	6.69
AFlow	10.75	8.81	4.08	8.00
MaAS	20.45	18.61	6.25	17.64
Ours	30.42	24.00	8.50	25.97

Table 2: Performance comparison on the GAIA benchmark. Results are reported across three difficulty levels, with average scores shown in the last column. The best results are highlighted in bold.

Method	Training	inference	overall	Acc.
AFlow	22.50	1.66	24.16	51.82
MaAS	3.38	0.42	3.80	51.82
MasRouter	3.56	0.65	4.21	52.42
Ours	2.34	0.27	2.61	55.37

Table 3: Training, inference, and overall cost (in USD) on the MATH benchmark, along with corresponding accuracy. Our method achieves the lowest cost and highest accuracy. AFlow and MaAS use GPT-4o-mini, while other methods utilize an LLM pool.

Cost-effective. We emphasize the cost-efficiency of our agentic automation framework across two key dimensions: training expenditure and inference overhead. We compare against AFlow and MaAS, where AFlow represents the state-of-the-art (SOTA) among task-level frameworks, and MaAS is the SOTA among query-level frameworks. As shown in Table 3, AFlow incurs a substantial training cost of \$22.50 and inference cost of \$1.66, totaling \$24.16. In contrast, our method significantly reduces these costs to \$2.34 for training and \$0.27 for inference—only 10.4% and 16.3% of AFlow’s respective costs.

This cost-efficiency is attributed to our adaptive model selection strategy, which dynamically leverages more affordable models such as LLaMA-3.1 or Qwen-2-72B when sufficient, rather than defaulting to high-cost models like GPT-4o-mini. Notably, our method not only reduces cost but also achieves the highest accuracy of 55.37%, outperforming

both AFlow and MaAS.

MasRouter adopts a collaborative paradigm, assigning multiple LLMs to role-play in handling a query. However, it suffers from two drawbacks: (1) redundant participation of LLMs in each collaborative step, and (2) lack of adaptation for easy queries, leading to excessive cost without proportional performance gains.

Case Study

Figure 2 presents visual comparisons of workflows produced by our framework and MaAS on MATH, HumanEval, and GAIA. For easy queries (middle), our method simplifies the workflow without compromising accuracy, thereby reducing cost. In contrast, for difficult queries (left), MaAS generates oversimplified workflows that fail to solve the problem, while our framework assembles a more complex, heterogeneous workflow that effectively combines different models’ strengths—achieving higher performance with controlled cost (\$0.0035 vs. \$0.0028 for MaAS).

Furthermore, under the same workflow structure, our method achieves comparable accuracy to MaAS while incurring lower cost, highlighting the effectiveness of our query-aware complexity adaptation and fine-grained cost–performance control.

Figure 3 shows the distribution of LLMs selected by DAAO on the MMLU and MATH benchmarks. Our framework selects LLMs based on both domain and difficulty, effectively exploiting the specialized capabilities of each model.

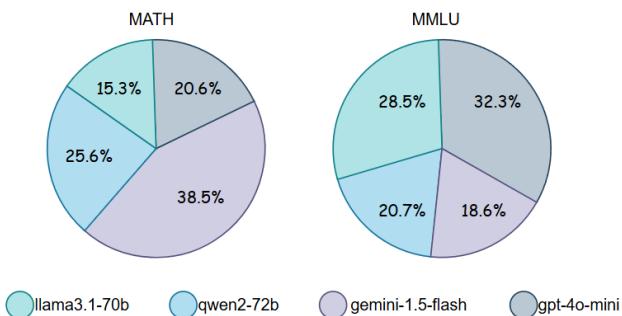


Figure 3: Distribution of LLM selections made by DAAO on the MATH and MMLU benchmarks. The results reflect how the framework dynamically routes queries to different LLMs based on domain and difficulty.

Ablation Study

We conduct an ablation study on two key components of our DAAO framework: (1) w/o **DA**, removing the difficulty-aware module; and (2) w/o **LS**, removing the LLM selector and routing all subtasks to a fixed LLM; (3) w/o $C(\cdot)$, eliminating the cost constraint in Equation (5). As shown in Table 4, removing the difficulty-aware module leads to the largest drop in both accuracy and efficiency, especially on the MATH dataset. This highlights the importance of adaptive reasoning control based on estimated query difficulty

Dataset	HumanEval		MATH		
	Metric	Pass@1 (%)	Cost ($10^{-3}\$$)	Accuracy (%)	Cost ($10^{-3}\$$)
Vanilla		93.37	1.23	55.37	0.55
w/o DA		90.21	1.34	50.18	0.67
w/o LS		92.69	1.60	53.42	0.89
w/o $C(\cdot)$		93.21	1.58	55.40	1.00

Table 4: Ablation study of **DAAO** on HumanEval and MATH. We report performance (Pass@1 or Accuracy) and corresponding inference cost. w/o **DA** removes the difficulty-aware module; w/o **LS** disables LLM selection; w/o $C(\cdot)$ omits the cost-awareness component.

(e.g., dynamically adjusting the number of reasoning layers instead of using a fixed number).

Removing the LLM router slightly affects accuracy, but leads to a notable increase in inference cost, as it prevents the system from using lightweight models when appropriate. Removing $C(\cdot)$ does not significantly impact the performance, but it disrupts the adaptive capability of DAAO to query difficulty. Overall, the results demonstrate that both components are crucial for balancing performance and cost in multi-step reasoning tasks.

Conclusion

In this work, we presented **DAAO**, a difficulty-aware agentic orchestration framework that dynamically adapts reasoning workflows to the complexity and domain characteristics of each query. By combining query-level difficulty estimation, modular operator allocation, and heterogeneous LLM routing, DAAO constructs flexible and cost-efficient agentic workflows. Our approach moves beyond static, one-size-fits-all designs by leveraging the complementary strengths of diverse LLMs and adapting workflow depth on a per-query basis. Extensive experiments across six benchmarks demonstrate that DAAO consistently outperforms existing multi-agent and LLM routing systems in both accuracy and efficiency, achieving up to 11.21% higher accuracy while reducing inference cost by up to 36%. These results validate the importance of difficulty-guided, modular orchestration in building scalable and performant LLM-based agents. Future work includes extending DAAO to handle multimodal queries and incorporating real-time feedback for online adaptation.

References

- Austin, J.; Odena, A.; Nye, M.; Bosma, M.; Michalewski, H.; Dohan, D.; Jiang, E.; Cai, C.; Terry, M.; Le, Q.; et al. 2021. Program synthesis with large language models. *arXiv preprint arXiv:2108.07732*.
- Barandoni, S.; Chiarello, F.; Cascone, L.; Marrale, E.; and Puccio, S. 2024. Automating Customer Needs Analysis: A

- Comparative Study of Large Language Models in the Travel Industry. *arXiv:2404.17975*.
- Chen, L.; Zaharia, M.; and Zou, J. 2023. Frugalgpt: How to use large language models while reducing cost and improving performance. *arXiv preprint arXiv:2305.05176*.
- Chen, M.; Tworek, J.; Jun, H.; Yuan, Q.; Ponde de Oliveira Pinto, H.; Kaplan, J.; Edwards, H.; Burda, Y.; Joseph, N.; Brockman, G.; Ray, A.; Puri, R.; Krueger, G.; Petrov, M.; Khlaaf, H.; Sastry, G.; Mishkin, P.; Chan, B.; Gray, S.; Ryder, N.; Pavlov, M.; Power, A.; Kaiser, L.; Bavarian, M.; Winter, C.; Tillet, P.; Petroski Such, F.; Cummings, D.; Plappert, M.; Chantzis, F.; Barnes, E.; Herbert-Voss, A.; Hebbgen Guss, W.; Nichol, A.; Paino, A.; Tezak, N.; Tang, J.; Babuschkin, I.; Balaji, S.; Jain, S.; Saunders, W.; Hesse, C.; Carr, A. N.; Leike, J.; Achiam, J.; Misra, V.; Morikawa, E.; Radford, A.; Knight, M.; Brundage, M.; Murati, M.; Mayer, K.; Welinder, P.; McGrew, B.; Amodei, D.; McCandlish, S.; Sutskever, I.; and Zaremba, W. 2021. Evaluating Large Language Models Trained on Code.
- Cobbe, K.; Kosaraju, V.; Bavarian, M.; Chen, M.; Jun, H.; Kaiser, L.; Plappert, M.; Tworek, J.; Hilton, J.; Nakano, R.; Hesse, C.; and Schulman, J. 2021. Training Verifiers to Solve Math Word Problems. *arXiv preprint, abs/2110.14168*.
- Deng, X.; Gu, Y.; Zheng, B.; Chen, S.; Stevens, S.; Wang, B.; Sun, H.; and Su, Y. 2024. Mind2web: Towards a generalist agent for the web. *Advances in Neural Information Processing Systems*, 36.
- Du, Y.; Li, S.; Torralba, A.; Tenenbaum, J. B.; and Mordatch, I. 2023. Improving Factuality and Reasoning in Language Models through Multiagent Debate. *CoRR*, abs/2305.14325.
- Dubey, A.; Jauhri, A.; Pandey, A.; Kadian, A.; Al-Dahle, A.; Letman, A.; Mathur, A.; Schelten, A.; Yang, A.; Fan, A.; et al. 2024. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783*.
- Feng, T.; Shen, Y.; and You, J. 2024. GraphRouter: A Graph-based Router for LLM Selections. *arXiv:2410.03834*.
- Fu, Y.; Peng, H.; Sabharwal, A.; Clark, P.; and Khot, T. 2022. Complexity-based prompting for multi-step reasoning. In *The Eleventh International Conference on Learning Representations*.
- Gong, Y.; Zhao, M.; Bai, Y.; Gao, Y.; Yang, X.; and Zhang, W. 2023. EfficientAgent: Curriculum-Driven Model Selection for Efficient Multi-Agent Collaboration. *arXiv preprint arXiv:2312.05611*.
- Guo, Q.; Wang, R.; Guo, J.; Li, B.; Song, K.; Tan, X.; Liu, G.; Bian, J.; and Yang, Y. 2023. Connecting large language models with evolutionary algorithms yields powerful prompt optimizers. *arXiv preprint arXiv:2309.08532*.
- Hendrycks, D.; Burns, C.; Basart, S.; Zou, A.; Mazeika, M.; Song, D.; and Steinhardt, J. 2021a. Measuring Massive Multitask Language Understanding. *Proceedings of the International Conference on Learning Representations (ICLR)*.
- Hendrycks, D.; Burns, C.; Kadavath, S.; Arora, A.; Basart, S.; Tang, E.; Song, D.; and Steinhardt, J. 2021b. Measuring Mathematical Problem Solving With the MATH Dataset. *NeurIPS*.
- Hong, S.; Lin, Y.; Liu, B.; Liu, B.; Wu, B.; Zhang, C.; Wei, C.; Li, D.; Chen, J.; Zhang, J.; et al. 2024. Data interpreter: An llm agent for data science. *arXiv preprint arXiv:2402.18679*.
- Hu, Q. J.; Bieker, J.; Li, X.; Jiang, N.; Keigwin, B.; Ranganath, G.; Keutzer, K.; and Upadhyay, S. K. 2024. ROUTERBENCH: A Benchmark for Multi-LLM Routing System. *arXiv preprint arXiv:2403.12031*.
- Hu, S.; Lu, C.; and Clune, J. 2024. Automated design of agentic systems. *arXiv preprint arXiv:2408.08435*.
- Huang, Q.; An, Z.; Zhuang, N.; Tao, M.; Zhang, C.; Jin, Y.; Xu, K.; Chen, L.; Huang, S.; and Feng, Y. 2024. Harder Tasks Need More Experts: Dynamic Routing in MoE Models. *arXiv preprint arXiv:2403.07652*.
- Jiang, D.; Ren, X.; and Lin, B. Y. 2023. LLM-Blender: Ensembling Large Language Models with Pairwise Ranking and Generative Fusion. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 14165–14178. Toronto, Canada: Association for Computational Linguistics.
- Khattab, O.; Singhvi, A.; Maheshwari, P.; Zhang, Z.; Santhanam, K.; Vardhamanan, S.; Haq, S.; Sharma, A.; Joshi, T. T.; Moazam, H.; et al. 2023. Dspy: Compiling declarative language model calls into self-improving pipelines. *arXiv preprint arXiv:2310.03714*.
- Kingma, D. P.; and Welling, M. 2014. Auto-Encoding Variational Bayes. *arXiv preprint arXiv:1312.6114*.
- Li, X.; Mao, Y.; Wang, X.; Shi, Z.; Li, J.; Zhou, S.; Sun, H.; Zhou, J.; and Zhou, Z. 2023. LLM Routing: Cost-Efficient Inference for Large Language Models. *arXiv preprint arXiv:2309.15661*.
- Li, Z.; Zang, Q.; Ma, D.; Guo, J.; Zheng, T.; Liu, M.; Niu, X.; Wang, Y.; Yang, J.; Liu, J.; et al. 2024. AutoKaggle: A Multi-Agent Framework for Autonomous Data Science Competitions. *arXiv preprint arXiv:2410.20424*.
- Liang, T.; He, Z.; Jiao, W.; Wang, X.; Wang, Y.; Wang, R.; Yang, Y.; Tu, Z.; and Shi, S. 2023. Encouraging Divergent Thinking in Large Language Models through Multi-Agent Debate. *CoRR*, abs/2305.19118.
- Lin, Z.; Wang, J.; Zhang, K.; Yang, B.; and Yang, Q. 2023. TaskMoE: Task-Aware Mixture-of-Experts for Cost-Efficient Inference. *arXiv preprint arXiv:2310.02225*.
- Mialon, G.; Fourrier, C.; Swift, C.; Wolf, T.; LeCun, Y.; and Scialom, T. 2023. Gaia: a benchmark for general ai assistants. *arXiv preprint arXiv:2311.12983*.
- Nakajima, Y. 2023. BabyAGI. <https://github.com/yoheinakajima/babyagi>.
- Ong, I.; Almahairi, A.; Wu, V.; Chiang, W.-L.; Wu, T.; Gonzalez, J. E.; Kadous, M. W.; and Stoica, I. 2024. RouteLLM: Learning to Route LLMs with Preference Data. *arXiv:2406.18665*.
- OpenAI. 2024. GPT-4O Mini: Advancing cost-efficient intelligence.
- Reimers, N. 2019. Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks. *arXiv preprint arXiv:1908.10084*.

- Reworkd. 2023. AgentGPT. <https://github.com/reworkd/AgentGPT>.
- Richards, T. B.; and et al. 2023. Auto-GPT: An Autonomous GPT-4 Experiment. <https://github.com/Significant-Gravitas/Auto-GPT>.
- Saad-Falcon, J.; Lafuente, A. G.; Natarajan, S.; Maru, N.; Todorov, H.; Guha, E.; Buchanan, E. K.; Chen, M.; Guha, N.; Ré, C.; et al. 2024. Archon: An architecture search framework for inference-time techniques. *arXiv preprint arXiv:2409.15254*.
- Shazeer, N.; Mirhoseini, A.; Maziarz, K.; Davis, A.; Le, Q.; Hinton, G.; and Dean, J. 2017. Outrageously large neural networks: The sparsely-gated mixture-of-experts layer. *arXiv preprint arXiv:1701.06538*.
- Shinn, N.; Labash, B.; and Gopinath, A. 2023. Reflexion: an autonomous agent with dynamic memory and self-reflection. *arXiv preprint abs/2303.11366*.
- Song, C. H.; Wu, J.; Washington, C.; Sadler, B. M.; Chao, W.-L.; and Su, Y. 2023. Llm-planner: Few-shot grounded planning for embodied agents with large language models. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 2998–3009.
- Team, G.; Georgiev, P.; Lei, V. I.; Burnell, R.; Bai, L.; Guagliati, A.; Tanzer, G.; Vincent, D.; Pan, Z.; Wang, S.; et al. 2024. Gemini 1.5: Unlocking multimodal understanding across millions of tokens of context. *arXiv:2403.05530*.
- Wang, W.; Wei, F.; Dong, L.; Bao, H.; Yang, N.; and Zhou, M. 2020. Minilm: Deep self-attention distillation for task-agnostic compression of pre-trained transformers. *Advances in Neural Information Processing Systems*, 33: 5776–5788.
- Wang, X.; Wei, J.; Schuurmans, D.; Le, Q. V.; Chi, E. H.; Narang, S.; Chowdhery, A.; and Zhou, D. 2023a. Self-Consistency Improves Chain of Thought Reasoning in Language Models. In *The Eleventh International Conference on Learning Representations*.
- Wang, Z.; Mao, S.; Wu, W.; Ge, T.; Wei, F.; and Ji, H. 2023b. Unleashing Cognitive Synergy in Large Language Models: A Task-Solving Agent through Multi-Persona Self-Collaboration. Work in progress.
- Wei, J.; Wang, X.; Schuurmans, D.; Bosma, M.; Ichter, B.; Xia, F.; Chi, E.; Le, Q.; and Zhou, D. 2022. Chain-of-Thought Prompting Elicits Reasoning in Large Language Models.
- Wu, Q.; Bansal, G.; Zhang, J.; Wu, Y.; Zhang, S.; Zhu, E.; Li, B.; Jiang, L.; Zhang, X.; and Wang, C. 2023. AutoGen: Enabling Next-Gen LLM Applications via Multi-Agent Conversation Framework.
- Yang, A.; Yang, B.; Hui, B.; Zheng, B.; Yu, B.; Zhou, C.; Li, C.; Li, C.; Liu, D.; Huang, F.; Dong, G.; Wei, H.; Lin, H.; Tang, J.; Wang, J.; Yang, J.; Tu, J.; Zhang, J.; Ma, J.; Xu, J.; Zhou, J.; Bai, J.; He, J.; Lin, J.; Dang, K.; Lu, K.; Chen, K.-Y.; Yang, K.; Li, M.; Xue, M.; Ni, N.; Zhang, P.; Wang, P.; Peng, R.; Men, R.; Gao, R.; Lin, R.; Wang, S.; Bai, S.; Tan, S.; Zhu, T.; Li, T.; Liu, T.; Ge, W.; Deng, X.; Zhou, X.; Ren, X.; Zhang, X.; Wei, X.; Ren, X.; Fan, Y.; Yao, Y.; Zhang, Y.; Wan, Y.; Chu, Y.; Cui, Z.; Zhang, Z.; and Fan, Z.-W. 2024. Qwen2 Technical Report. *ArXiv*, abs/2407.10671.
- Yao, S.; Zhao, J.; Yu, D.; Du, N.; Shafran, I.; Narasimhan, K. R.; and Cao, Y. 2023. ReAct: Synergizing Reasoning and Acting in Language Models. In *The Eleventh International Conference on Learning Representations*.
- Ye, R.; Liu, X.; Wu, Q.; Pang, X.; Yin, Z.; Bai, L.; and Chen, S. 2025. X-MAS: Towards Building Multi-Agent Systems with Heterogeneous LLMs. *ArXiv*, abs/2505.16997.
- Yuan, S.; Song, K.; Chen, J.; Tan, X.; Li, D.; and Yang, D. 2024. EvoAgent: Towards Automatic Multi-Agent Generation via Evolutionary Algorithms. *arXiv preprint arXiv:2406.14228*.
- Yue, Y.; Zhang, G.-M.; Liu, B.; Wan, G.; Wang, K.; Cheng, D.; and Qi, Y. 2025. MasRouter: Learning to Route LLMs for Multi-Agent Systems. *ArXiv*, abs/2502.11133.
- Zhang, G.; Yue, Y.; Li, Z.; Yun, S.; Wan, G.; Wang, K.; Cheng, D.; Yu, J. X.; and Chen, T. 2024a. Cut the Crap: An Economical Communication Pipeline for LLM-based Multi-Agent Systems. *arXiv preprint arXiv:2410.02506*.
- Zhang, G.-M.; Niu, L.; Fang, J.; Wang, K.; Bai, L.; and Wang, X. 2025. Multi-agent Architecture Search via Agenetic Supernet. *ArXiv*, abs/2502.04180.
- Zhang, J.; Xiang, J.; Yu, Z.; Teng, F.; Chen, X.; Chen, J.; Zhuge, M.; Cheng, X.; Hong, S.; Wang, J.; et al. 2024b. Aflow: Automating agentic workflow generation. *arXiv preprint arXiv:2410.10762*.
- Zhang, M.; Chen, Y.; Xie, Y.; and Li, Y. 2023. AdaptiveAgent: Curriculum-Aware Multi-Agent Collaboration via Difficulty Modeling. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing (EMNLP)*.
- Zhao, Q.; Wang, J.; Zhang, Y.; Jin, Y.; Zhu, K.; Chen, H.; and Xie, X. 2023. Competeai: Understanding the competition behaviors in large language model-based agents. *arXiv preprint arXiv:2310.17512*.
- Zhu, J.-P.; Cai, P.; Xu, K.; Li, L.; Sun, Y.; Zhou, S.; Su, H.; Tang, L.; and Liu, Q. 2024. AutoTQA: Towards Autonomous Tabular Question Answering through Multi-Agent Large Language Models. *Proceedings of the VLDB Endowment*, 17(12): 3920–3933.
- Zhuge, M.; Wang, W.; Kirsch, L.; Faccio, F.; Khizbulin, D.; and Schmidhuber, J. 2024. GPTSwarm: Language Agents as Optimizable Graphs. In *Forty-first International Conference on Machine Learning*.
- Zoph, B.; and Le, Q. V. 2017. Neural Architecture Search with Reinforcement Learning. In *Proceedings of the International Conference on Learning Representations (ICLR)*.