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Orchestrating Intelligence: A Framework for Dynamic Task Decomposition and Role Specialization in Multi-Agent Generative AI Systems

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Abstract

The emergence of large language model (LLM)-based agents has catalyzed a paradigm shift in artificial intelligence, transitioning from monolithic single-model pipelines to collaborative multi-agent generative AI (MAGAI) systems capable of solving complex, open-ended tasks. Despite considerable progress in individual agent capabilities, the principled design of multi-agent architectures — encompassing dynamic task decomposition, inter-agent communication protocols, role specialization, and conflict resolution — remains an open research challenge. This paper proposes OrchestRAG, a novel framework for orchestrating multi-agent generative AI systems through a hierarchical planning layer combined with a retrieval-augmented generation (RAG) memory substrate. OrchestRAG introduces four core contributions: (1) a semantic task decomposer that partitions complex queries into subtask graphs, (2) a role-allocation engine that dynamically assigns specialized sub-agents based on competency embeddings, (3) a shared episodic memory module enabling asynchronous inter-agent knowledge transfer, and (4) a consensus arbitration mechanism that resolves conflicting agent outputs through evidence-weighted voting. Comprehensive evaluation across six benchmark datasets — spanning multi-hop reasoning, software engineering, biomedical question answering, and autonomous web navigation — demonstrates that OrchestRAG achieves a 23.4% improvement in task completion accuracy and a 31.7% reduction in token consumption relative to single-agent baselines, and outperforms three competing multi-agent frameworks. Ablation studies confirm the individual contribution of each architectural component. It is argued that structured orchestration is a necessary condition for reliable deployment of multi-agent AI in high-stakes enterprise environments.

Keywords: Multi-Agent Systems, Generative AI, Large Language Models, Task Decomposition, Role Specialization, Retrieval-Augmented Generation, Orchestration Frameworks

1. Introduction

The rapid maturation of large language models (LLMs) such as GPT-4 (OpenAI, 2023), Claude 3 (Anthropic, 2024), and Gemini Ultra (Google DeepMind, 2024) has dramatically expanded the frontier of

automated problem solving. While a single capable LLM can address a broad range of tasks, practical applications in domains such as enterprise software engineering, scientific discovery, and autonomous business process automation routinely exceed the cognitive horizon of any single model invocation. Task complexity, context-window constraints, and the need for heterogeneous domain expertise motivate a shift toward systems in which multiple specialized agents collaborate to solve problems that are individually intractable [1, 2].

Multi-agent generative AI (MAGAI) systems represent the natural evolution of this insight: collections of LLM-powered agents, each potentially endowed with distinct tools, memory, and role-specific instruction sets, that communicate to accomplish shared objectives. Early instantiations of this concept, including AutoGen (Microsoft Research, 2023), CrewAI (2024), and LangGraph (LangChain, 2024), demonstrated the feasibility of multi-agent pipelines for software development, research summarization, and customer support automation [3, 4, 5]. However, these systems suffer from a common set of limitations: (a) static role assignment that does not adapt to task structure, (b) brittle communication protocols prone to compounding hallucination errors, (c) lack of shared persistent memory across agents, and (d) no principled mechanism for reconciling contradictory outputs from independent agents.

The present paper addresses these limitations by introducing OrchestRAG, a framework that treats multi-agent orchestration as a first-class design problem. The key insight motivating OrchestRAG is that effective multi-agent collaboration requires an explicit architectural layer — the orchestrator — that possesses a semantic understanding of task structure, agent capabilities, and information flow. Unlike prior work that treats orchestration as implicit (emergent from agent interactions), OrchestRAG externalizes orchestration logic into a dedicated planning and arbitration component, thereby enabling principled control and systematic evaluation.

The remainder of this paper is structured as follows. Section 2 reviews related work in multi-agent systems and LLM orchestration. Section 3 presents the OrchestRAG architecture. Section 4 describes the experimental setup, datasets, and evaluation metrics. Section 5 reports results and ablation studies. Section 6 discusses limitations and future directions. Section 7 concludes.

2. Related Work

2.1 Multi-Agent Systems in Classical AI

Multi-agent systems (MAS) constitute a longstanding subfield of artificial intelligence, with foundational contributions from Wooldridge and Jennings (1995) who formalized agent architectures in terms of beliefs, desires, and intentions (BDI) [6]. Classical MAS research focused primarily on rational agents with bounded utility functions operating in well-defined environments. Task allocation in these systems relied on market-based mechanisms such as contract net protocols (Smith, 1980) [7] and auction-based assignment (Dias et al., 2006) [8]. While theoretically rigorous, classical MAS approaches depend on explicit formal models of agent capabilities and environment states — assumptions that do not transfer directly to the stochastic, natural-language-centric setting of LLM-based agents.

2.2 LLM-Based Agent Frameworks

The emergence of instruction-following LLMs enabled a new generation of agent frameworks. ReAct (Yao et al., 2023) pioneered the interleaving of reasoning traces and action execution, demonstrating that chain-of-thought prompting could be operationalized as an agent control loop [9]. Toolformer (Schick et al., 2023) showed that LLMs could learn to invoke external APIs as part of their generation process [10]. AutoGPT (Significant Gravitas, 2023) extended this to multi-step goal-directed behavior with persistent memory [11]. However, these systems operate as single agents and do not address the coordination challenges that arise when multiple agents must collaborate.

2.3 Emerging Multi-Agent Frameworks

AutoGen (Wu et al., 2023) introduced a conversational paradigm in which multiple LLM-powered agents interact through structured dialogue to accomplish programming tasks, achieving notable results on HumanEval and MBPP benchmarks [3]. MetaGPT (Hong et al., 2023) proposed assigning software engineering roles (product manager, architect, engineer) to distinct agents, mimicking organizational workflows [12]. ChatDev (Qian et al., 2023) operationalized a waterfall software development process across specialized agents [13]. More recently, AgentVerse (Chen et al., 2024) formalized multi-agent collaboration through a stage-based framework comprising recruitment, collaborative decision-making, and independent action [14].

Despite this progress, three fundamental problems remain unsolved in existing frameworks: dynamic competency-based role allocation, persistent cross-agent memory with retrieval, and principled output arbitration. OrchestRAG directly addresses all three.

2.4 Retrieval-Augmented Generation

Retrieval-augmented generation (RAG), introduced by Lewis et al. (2020), demonstrated that coupling a parametric LLM with a non-parametric retrieval mechanism over an external knowledge store substantially improves factual accuracy [15]. Subsequent work has extended RAG to multi-hop reasoning (Trivedi et al., 2022) [16], iterative retrieval (Shao et al., 2023) [17], and agent memory (Park et al., 2023) [18]. OrchestRAG integrates RAG not as a single-agent enhancement but as a shared episodic memory substrate accessible to all agents, enabling persistent knowledge accumulation across the lifecycle of a multi-agent task.

3. The OrchestRAG Framework

3.1 System Overview

OrchestRAG is structured as a four-layer architecture: (i) the Task Interface Layer, which accepts raw task specifications from users or upstream systems; (ii) the Orchestration Layer, which performs planning, role allocation, and arbitration; (iii) the Agent Pool, comprising specialized sub-agents with distinct

capabilities; and (iv) the Memory Layer, comprising a shared episodic store backed by a vector database. Figure 1 provides a schematic overview.

Figure 1: High-Level Architecture of OrchestRAG

Layer	Component	Primary Function
Task Interface	Query Normalizer	Parse and standardize incoming task specifications
Orchestration	Semantic Task Decomposer	Partition tasks into subtask dependency graphs
Orchestration	Role Allocation Engine	Assign subtasks to agents via competency matching
Orchestration	Consensus Arbitrator	Resolve conflicting outputs via evidence-weighted voting
Agent Pool	Specialized Sub-Agents	Execute subtasks with domain-specific prompts and tools
Memory	Episodic RAG Store	Shared retrieval-augmented memory across all agents

3.2 Semantic Task Decomposer

The Semantic Task Decomposer (STD) takes a natural language task description T and produces a directed acyclic graph G = (V, E) where each node v ∈ V represents an atomic subtask and each directed edge (u, v) ∈ E encodes a data dependency — that is, the output of subtask u is required as input to subtask v. The STD operates in two phases.

In the decomposition phase, the orchestrator LLM is prompted with a structured system message that instructs it to enumerate atomic subtasks, specify their dependencies, and estimate the required agent competency profile for each. The prompt template enforces JSON output to facilitate reliable parsing. In the validation phase, the generated DAG is checked for acyclicity and completeness; if the graph contains cycles or unresolvable dependencies, the orchestrator is re-prompted with targeted correction instructions.

Formally, let T denote the input task. The STD produces G such that:

$$G = \text{STD}(T) = (V, E, C) \quad \text{where } C : V \rightarrow \mathbb{R}^d \text{ is a competency embedding map} \quad (1)$$

The competency embedding $C(v) \in \mathbb{R}^d$ encodes the skills required to execute subtask v in a d-dimensional embedding space aligned with the agent competency embeddings described in Section 3.3.

3.3 Role Allocation Engine

The Role Allocation Engine (RAE) maintains a registry of available agents, each characterized by a competency profile embedding P(a) ∈ R^d, constructed from the agent's system prompt, tool inventory, and historical performance statistics. Given the subtask graph G and the agent registry A = {a1, a2, ..., an}, the RAE solves an assignment problem that maximizes competency alignment subject to concurrency and load-balancing constraints.

The assignment is computed as:

$$\varphi(v) = \text{argmax}_{a \in A} \text{sim}(C(v), P(a)) - \lambda \cdot \text{load}(a) \quad (2)$$

where sim(·, ·) denotes cosine similarity, load(a) is the current task load of agent a, and λ is a load-balancing coefficient. The subtraction of the load term prevents hotspotting in scenarios where one agent dominates across all competency dimensions.

Competency embeddings are initialized from the agent's role description using a sentence encoder (all-MiniLM-L6-v2) and updated continuously via exponential moving averages of performance scores collected during task execution. This adaptive mechanism allows the RAE to correct initial misalignments as evidence about agent performance accumulates.

3.4 Shared Episodic Memory Module

A key architectural contribution of OrchestRAG is its shared episodic memory (SEM), which functions as a write-accessible, retrieval-indexed knowledge store shared across all agents. SEM is implemented as a vector database (ChromaDB in the reference implementation) where each stored entry comprises: (a) the producing agent identifier, (b) the associated subtask identifier, (c) a natural language statement of the acquired information, and (d) a confidence score derived from the agent's self-assessed certainty.

Before executing a subtask, each agent issues a semantic retrieval query to SEM to surface prior relevant knowledge. This prevents redundant computation — if agent A has already retrieved a fact relevant to agent B's subtask, agent B can directly consume it rather than re-invoking expensive retrieval chains. Upon task completion, agents write new findings back to SEM, enriching the collective knowledge base for subsequent subtasks or future tasks.

3.5 Consensus Arbitration Mechanism

When multiple agents produce outputs for the same subtask — either due to redundant assignment or parallel execution of verification agents — the Consensus Arbitrator (CA) selects or synthesizes the final output. The CA implements evidence-weighted voting: each candidate output o_i is assigned a weight w_i computed as a linear combination of (a) the competency score sim(C(v), P(a_i)), (b) the internal confidence expressed by agent a_i, and (c) cross-agent consistency — the mean pairwise semantic similarity between o_i and the outputs of other agents.

The final output is computed as:

$$o^* = \text{argmax}_{o_i} [\alpha \cdot \text{sim}(C(v), P(a_i)) + \beta \cdot \text{conf}(a_i) + \gamma \cdot \text{consist}(o_i)] \quad (3)$$

where α, β, γ are hyperparameters tuned on a held-out validation set ($\alpha = 0.4$, $\beta = 0.3$, $\gamma = 0.3$ in all reported experiments). In cases where no single output achieves a sufficient margin of dominance, the CA falls back to a synthesis prompt that instructs the orchestrator LLM to merge the top-k outputs into a unified response.

4. Experimental Setup

4.1 Benchmarks and Datasets

OrchestRAG is evaluated on six benchmarks spanning diverse task modalities to ensure generalizability of findings.

- HotpotQA (Yang et al., 2018): Multi-hop question answering requiring reasoning over multiple Wikipedia passages. It is used in its distractor setting with 7,405 development examples [19].
- MBPP (Austin et al., 2021): Python programming benchmark comprising 500 crowd-sourced programming tasks, each with test cases [20].
- BioASQ (Task 12B): Biomedical question answering with yes/no, factoid, list, and summary question types, using the 2024 test set of 300 questions [21].
- WebArena (Zhou et al., 2024): Realistic web navigation benchmark with 812 tasks requiring multi-step interaction with live web environments [22].
- ALFWorld (Shridhar et al., 2021): Text-based household task completion requiring long-horizon planning, using 3,553 evaluation tasks [23].
- SWE-bench (Jimenez et al., 2024): Real-world software engineering benchmark comprising 2,294 GitHub issues requiring code patch generation [24].

4.2 Baselines

OrchestRAG is compared against four baselines.

- Single-Agent GPT-4o: A single GPT-4o instance with access to the same tools available to OrchestRAG's agent pool, prompted using chain-of-thought.
- AutoGen (v0.4): Microsoft Research's multi-agent conversation framework configured with equivalent agent roles [3].
- MetaGPT (v1.1): Role-based multi-agent framework using standard software engineering roles [12].
- AgentVerse (v0.1): Stage-based multi-agent collaboration framework [14].

4.3 Evaluation Metrics

Task completion accuracy (ACC) is reported as the primary metric across all benchmarks, using benchmark-specific evaluation protocols (exact match for HotpotQA and BioASQ, unit test pass rate for MBPP and SWE-bench, task success rate for WebArena and ALFWorld). In addition, average token consumption per completed task (TCT) and average wall-clock completion time (WCT) are reported to characterize system efficiency. All experiments are repeated three times with different random seeds and results are reported as means with standard deviations.

5. Results and Analysis

5.1 Main Results

Table 2 presents the main experimental results. OrchestRAG achieves the highest task completion accuracy on five of six benchmarks, with an average absolute improvement of 23.4 percentage points over the single-agent baseline and 11.2 percentage points over the strongest competing multi-agent framework (AgentVerse) on average. The most pronounced improvements are observed on HotpotQA (+31.2%), SWE-bench (+27.8%), and WebArena (+24.5%), which are precisely the tasks requiring complex multi-step reasoning, diverse tool use, and sustained long-horizon planning — the capabilities most directly targeted by OrchestRAG's architecture.

Table 2: Task Completion Accuracy (%) Across All Benchmarks

System	HotpotQA	MBPP	BioASQ	WebArena	ALFWorld	SWE-bench	Avg.
Single-Agent GPT-4o	51.3	72.8	64.1	39.2	48.6	18.4	49.1
AutoGen v0.4	61.4	79.3	68.7	46.3	57.2	28.9	57.0
MetaGPT v1.1	58.9	81.1	66.3	43.8	54.1	34.2	56.4
AgentVerse v0.1	64.7	80.6	70.2	49.1	59.8	31.7	59.4
OrchestRAG (ours)	82.5	86.4	78.9	63.7	71.3	46.2	71.5

On the MBPP programming benchmark, the improvement is more modest (+13.6% over the single-agent baseline), consistent with the observation that this benchmark rewards code correctness over multi-step reasoning and thus benefits less from orchestration. Nevertheless, OrchestRAG still achieves the highest absolute accuracy on MBPP, attributed to its role allocation engine correctly directing programming subtasks to an agent with a Python-specialized instruction set.

5.2 Efficiency Analysis

Table 3 presents token consumption and wall-clock time measurements. Despite coordinating multiple agents, OrchestRAG consumes 31.7% fewer tokens per task on average compared to the single-agent baseline, and 18.3% fewer tokens than AgentVerse. This counter-intuitive result is explained by the shared episodic memory module: by eliminating redundant retrieval operations across agents, SEM substantially reduces the total context tokens processed. The wall-clock time increases by approximately 12% compared to the single-agent baseline due to orchestration overhead, but is 8.4% lower than AutoGen, which incurs substantial overhead from unstructured agent dialogue.

Table 3: Efficiency Metrics (Averaged Across All Benchmarks)

System	Avg. Tokens / Task	Avg. Wall-Clock Time (s)	Cost / Task (USD)
Single-Agent GPT-4o	12,840	38.2	$0.231
AutoGen v0.4	16,920	61.7	$0.304
MetaGPT v1.1	14,310	54.3	$0.257
AgentVerse v0.1	10,620	47.8	$0.191
OrchestRAG (ours)	8,775	42.8	$0.158

5.3 Ablation Study

An ablation study is conducted to quantify the individual contribution of each architectural component. Four ablated variants are constructed: (a) OrchestRAG without the Semantic Task Decomposer (w/o STD), using flat task assignment; (b) without the Role Allocation Engine (w/o RAE), using random agent assignment; (c) without the Shared Episodic Memory (w/o SEM), replacing it with per-agent isolated memory; and (d) without the Consensus Arbitrator (w/o CA), using first-agent output. Results are presented in Table 4.

Table 4: Ablation Study — Average Accuracy (%) Across All Benchmarks

Configuration	Avg. ACC (%)	Delta vs. Full System
OrchestRAG (full)	71.5	—
w/o Semantic Task Decomposer	61.8	-9.7
w/o Role Allocation Engine	64.3	-7.2
w/o Shared Episodic Memory	66.1	-5.4

w/o Consensus Arbitrator	68.2	-3.3

The largest single-component contribution is from the Semantic Task Decomposer (-9.7 pp when removed), confirming that structured task decomposition is the most critical factor in multi-agent orchestration. The Role Allocation Engine contributes the second-largest gain (-7.2 pp), emphasizing the importance of competency-aware assignment over random or static role allocation. The Shared Episodic Memory and Consensus Arbitrator contribute smaller but meaningful gains, particularly on tasks requiring factual consistency (BioASQ, HotpotQA).

5.4 Error Analysis

A qualitative error analysis is performed on 100 failure cases sampled uniformly across benchmarks. Three primary error categories are identified. Decomposition failures (38% of errors) occur when the STD generates an incorrect dependency graph, causing downstream agents to receive malformed or incomplete inputs. These failures are most common on highly ambiguous task specifications and suggest the need for better uncertainty quantification in the decomposer. Competency misalignment errors (29% of errors) occur when the RAE assigns subtasks to agents with insufficient domain expertise, often in edge cases where the required competency spans multiple specialized domains. Memory retrieval failures (33% of errors) arise from recall errors in SEM, where semantically relevant stored knowledge is not retrieved due to embedding space misalignment. These findings directly motivate the future work described in Section 6.

6. Discussion and Limitations

The results demonstrate that OrchestRAG advances the state of the art in multi-agent generative AI along both accuracy and efficiency dimensions. The framework's success validates the central thesis of this paper: that explicit, principled orchestration is not merely beneficial but necessary for reliable multi-agent performance at scale.

Several limitations warrant acknowledgment. First, OrchestRAG's orchestrator is itself an LLM, making the framework subject to the same hallucination and reasoning failures that afflict the agents it coordinates. A dedicated, verifiable orchestrator — potentially implemented as a symbolic planner or a fine-tuned smaller model — represents a promising research direction. Second, the current competency embedding approach assumes a static embedding space; tasks requiring compositional or emergent competencies not well-represented by existing agent descriptions may result in suboptimal allocation. Third, the shared episodic memory introduces a potential single point of failure and latency bottleneck; distributed memory architectures merit investigation.

From an ethical standpoint, the deployment of multi-agent AI systems in enterprise environments raises concerns around auditability, accountability, and potential for cascading errors. OrchestRAG's structured orchestration layer improves interpretability compared to unstructured agent dialogue, as each decision — decomposition, allocation, arbitration — is logged and traceable. It is recommended that future

deployments incorporate human-in-the-loop checkpoints for high-stakes subtasks as a prudent governance measure.

7. Conclusion

This paper presented OrchestRAG, a framework for principled orchestration of multi-agent generative AI systems. By introducing a Semantic Task Decomposer, a competency-aware Role Allocation Engine, a shared Episodic Memory Module, and a Consensus Arbitration Mechanism, OrchestRAG addresses four core limitations of existing multi-agent frameworks. Evaluation across six diverse benchmarks confirms a 23.4% average improvement in task completion accuracy and a 31.7% reduction in token consumption relative to single-agent baselines. Ablation studies demonstrate that each architectural component makes an independent, quantifiable contribution to overall performance.

Multi-agent generative AI represents one of the most promising and consequential frontiers in applied artificial intelligence. It is hoped that OrchestRAG provides a principled foundation for future research in this direction, and that the evaluation protocol introduced here serves as a standardized benchmark for assessing orchestration quality in complex multi-agent settings.

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