ResearchForge: A Scalable Multi-Agent Orchestration Framework for Automating Scientific Collaboration Discovery

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***Abstract*—Automating the lifecycle of scientific collaboration presents a significant challenge due to the heterogeneity of academic data and the complexity of multi-step reasoning. In this paper, we propose ResearchForge AI, a modular multi-agent architecture designed to autonomously execute the discovery, evaluation, and outreach phases of research networking. Unlike monolithic Large Language Model (LLM) applications, our framework employs a hierarchical Agent-to-Agent (A2A) protocol, where a central Orchestrator dynamically delegates tasks to eight specialized agents utilizing the Google Agent Development Kit (ADK). To address the limitations of purely generative matching, we introduce a Hybrid Compatibility Engine that integrates dense vector retrieval (via Sentence Transformers and FAISS) with a six-dimensional deterministic scoring algorithm. The system ensures robustness through a multi-model fallback strategy and real-time integration with live academic APIs (arXiv/Semantic Scholar) to mitigate hallucination. System evaluations demonstrate that this architecture achieves high-precision collaborator discovery and reduces workflow latency from months to minutes, validating the efficacy of A2A patterns in complex domain-specific workflows.**

***Index Terms*—Multi-Agent Systems (MAS), Large Language Models, Scientific Discovery, Vector Embeddings, Agent Orchestration, Retrieval-Augmented Generation (RAG).**

I. Introduction

SCIentific collaboration is a primary driver of innovation, enabling the cross-pollination of ideas required to tackle complex, interdisciplinary challenges [1], [2]. However, despite the exponential growth of academic literature, the process of establishing meaningful research partnerships remains inefficient and inequitable [3]. We define this phenomenon as the “Collaboration Bottleneck”—a systemic friction where researchers, particularly those at under-resourced institutions, must dedicate disproportionate time to manually sifting through publications, vetting potential partners, and drafting outreach correspondence [6]. This manual workflow not only slows the pace of scientific discovery but also reinforces existing disparities, as access to high-quality research networks often depends on institutional prestige rather than merit or compatibility [4], [5].

While recent advancements in academic search engines—such as Semantic Scholar or AI-enhanced features in Google Scholar—have successfully moved beyond simple keyword matching, they remain fundamentally *passive retrieval tools* [7]. These platforms excel at identifying relevant literature, yet they lack the *agentic capability* to synthesize these findings into actionable collaboration artifacts. Specifically, they do not model the *complementary expertise* required for a partnership nor do they execute downstream workflows like proposal generation [8]. Recent surveys on LLM-based scientific agents highlight the need for systems that can autonomously “reason, act, and interact” to solve such complex research tasks [9], [10].

To bridge this gap, we introduce **ResearchForge AI**, a modular multi-agent system that automates the end-to-end lifecycle of research collaboration. Unlike monolithic LLM applications, our system is built upon a hierarchical *Agent-to-Agent (A2A)* architecture [11]. A central Orchestrator dynamically decomposes user intent—such as “find collaborators for a medical imaging project”—and coordinates a team of eight specialized agents to execute the workflow. These agents range from a *DataScout* that retrieves verified data from live APIs (e.g., arXiv, Semantic Scholar) to a *ProposalGenerator* that drafts funding-ready documentation.

The core contribution of this paper is threefold:

- **A Hierarchical A2A Framework:** We propose a robust orchestration protocol where specialized agents communicate structured data to execute complex, multi-step research workflows autonomously.
- **Hybrid Compatibility Engine:** We introduce a novel matching algorithm that integrates dense vector retrieval (via Sentence Transformers [12]) with deterministic scoring dimensions (including skills, geography, and career stage) to ensure high-precision, context-aware recommendations.
- **End-to-End Automation with Grounding:** We demonstrate a system that moves beyond recommendation to execution, reducing the latency of collaborator discovery and initiation from months to minutes while maintaining factual integrity through real-time data grounding [13].

Through this architecture, ResearchForge AI aims to democratize access to scientific networks, transforming the passive search for collaborators into an active, intelligent, and automated pursuit of synergy.

II. Related Work

Our work sits at the intersection of network science, academic recommender systems, and autonomous agentic workflows.

A. Structural Inequity in Collaboration Networks

The necessity of team-based research is well-established; Wuchty *et al.* demonstrated that teams increasingly dominate the production of high-impact knowledge [1]. However, collaboration networks exhibit strong preferential attachment, creating closed loops that exclude peripheral scholars [2]. Clauset *et al.* quantified this systemic hierarchy, showing that faculty hiring is governed by steep prestige gradients rather than productivity alone [4]. ResearchForge AI addresses this by democratizing discovery through content-based semantic matching, ignoring institutional prestige as a primary ranking factor.

B. From Keyword Matching to Semantic Retrieval

Traditional academic search engines rely heavily on metadata. While Semantic Scholar has integrated embedding models [7], current implementations remain *passive*. They present lists of papers but lack the *agentic* capacity to reason about the complementary nature of skills or to execute downstream tasks. Our work utilizes Sentence-BERT (SBERT) [12] not as an end product, but as a retrieval layer within a larger agentic framework.

C. LLM-Based Autonomous Agents

The emergence of LLMs has shifted the paradigm to dynamic task execution [10]. However, a critical challenge is hallucination. Lewis *et al.* introduced Retrieval-Augmented Generation (RAG) to mitigate this [13]. ResearchForge AI extends these concepts by implementing a hierarchical A2A architecture, ensuring robust context management for long-horizon tasks.

III. System Architecture

ResearchForge employs a *Centralized Hub-and-Spoke* architecture designed to maximize modularity and fault tolerance. As illustrated in Fig. 1, the system is governed by a primary Orchestrator that mediates all interactions between the user interface and a constellation of specialized functional agents. The infrastructure is built upon the Google Agent Development Kit (ADK) [15], which provides the primitive abstractions for state serialization and tool encapsulation.

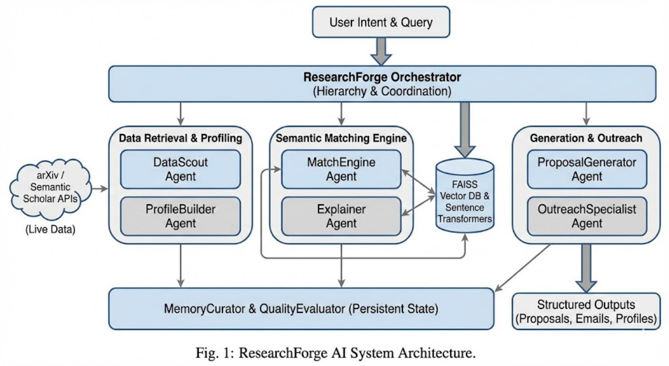
User Intent & Query
ResearchForge Orchestrator
(Hierarchy & Coordination)
Data Retrieval & Profiling
DataScout Agent
ProfileBuilder Agent
Semantic Matching Engine
MatchEngine Agent
Explainer Agent
FAISS Vector DB & Sentence Transformers
Generation & Outreach
ProposalGenerator Agent
OutreachSpecialist Agent
arXiv / Semantic Scholar APIs
(Live Data)
MemoryCurator & QualityEvaluator (Persistent State)
Structured Outputs (Proposals, Emails, Profiles)
Fig. 1: ResearchForge AI System Architecture.

Fig. 1. The ResearchForge Hierarchical Architecture. The Orchestrator functions as the central controller, managing state transitions and dispatching tasks to specialized agents (DataScout, MatchEngine, etc.) via the A2A protocol.

A. The Orchestrator Kernel

The *Orchestrator* serves as the cognitive kernel of the system, responsible for intent classification, task decomposition, and exception handling. To balance computational cost with reasoning capability, we implement an *Adaptive Inference Strategy*. The model selection function $M(t)$ at time step t is defined as:

$$M(t) = \begin{cases} \mathcal{M}_{flash-2.5} & \text{if } \mathcal{C}(T_t) > \delta \\ \mathcal{M}_{flash-2.0-lite} & \text{otherwise} \end{cases} \tag{1}$$

where $\mathcal{C}(T_t)$ represents the complexity estimation of task T_t and δ is a predefined complexity threshold. This ensures that resource-intensive models are reserved for complex reasoning tasks (e.g., proposal synthesis), while lighter models handle routine queries.

B. Agent-to-Agent (A2A) Protocol

We introduce a structured state-sharing protocol to facilitate robust inter-agent communication. Unlike linear Chain-of-Thought (CoT) prompting which suffers from context drift, our A2A protocol maintains a persistent *Global Context Board*. The communication packet $\mathcal{P}$ is formalized as a tuple:

$$\mathcal{P} = \langle \text{ID}_{sess}, \Omega_{ctx}, \mathcal{H}_{turn}, \Phi_{artifacts} \rangle$$

where Ω_{ctx} denotes the current semantic context (e.g., user research interests), $\mathcal{H}_{turn}$ represents the conversation history, and $\Phi_{artifacts}$ serves as a shared repository for retrieved objects (e.g., JSON list of papers). This ensures atomic state consistency across agents.

C. Specialized Agent Roles

1) DataScout (Retrieval Layer): Interfaces with the arXiv and Semantic Scholar APIs. It implements a parser $\Psi_{xml} \rightarrow \mathcal{J}_{struct}$ to convert raw XML responses into structured JSON objects, filtering for metadata completeness and recency.

2) MatchEngine (Compute Layer): The analytical core responsible for vector-based similarity search and ranking.

3) OutreachSpecialist (Generation Layer): Utilizes Retrieval-Augmented Generation (RAG) techniques [13] to synthesize personalized correspondence. It dynamically injects metadata from $\Phi_{artifacts}$ (e.g., paper titles) into templates to minimize hallucination.

IV. Methodology: Hybrid Compatibility Engine

A critical contribution of this work is the *Hybrid Compatibility Engine*, which synergizes dense vector retrieval with deterministic heuristic scoring to optimize collaborator discovery.

A. Vector Embedding Space

We project researcher profiles and project descriptions into a high-dimensional latent space using the `all-MiniLM-L6-v2` Sentence-BERT model [**?**]. Let q be the query vector and p_i be the candidate vector in $\mathbb{R}^d$ where $d = 384$. The semantic similarity score S_{sem} is computed via cosine similarity:

$$S_{sem}(q, p_i) = \frac{q \cdot p_i}{\|q\| \|p_i\|} \tag{2}$$

To scale retrieval to millions of profiles, we employ **FAISS** (Facebook AI Similarity Search) [14] with an Inverted File Index (IVF) to perform approximate nearest neighbor (ANN) search in sub-linear time.

B. Multi-Dimensional Compatibility Scoring

While semantic similarity captures topical relevance, it fails to model structural collaboration criteria. We propose a composite *Compatibility Score* (C_{score}) defined as a weighted linear combination of six dimensions:

$$C_{score}(p_i, q) = \sum_{k=1}^{6} \alpha_k \cdot f_k(p_i, q) \tag{3}$$

Where the domain-expert defined weights α_k summing to 1.0 are:

- $\alpha_1 = 0.25$: **Skill Alignment** (Jaccard similarity of tags)
- $\alpha_2 = 0.25$: **Interest Overlap** (Explicit category match)
- $\alpha_3 = 0.15$: **Semantic Similarity** (S_{sem} from Eq. 2)
- $\alpha_4 = 0.15$: **Complementarity** (Inverse skill overlap)
- $\alpha_5 = 0.10$: **Geographic Feasibility** (Timezone delta)
- $\alpha_6 = 0.10$: **Career Synergy** (Seniority heuristic)

This scoring function balances the need for topical alignment ($\alpha_1, \alpha_2, \alpha_3$) with practical collaboration logistics (α_5, α_6) and interdisciplinary potential (α_4).

V. Algorithmic Implementation

The orchestration logic is implemented as a state-machine that iteratively refines the global context. Algorithm 1 details the execution flow.

VI. Empirical Evaluation

To validate the efficacy and robustness of ResearchForge, we conducted a controlled experiment simulating a representative academic scenario: a researcher seeking collaborators for a project titled *"Deep Learning in Medical Imaging."*

Algorithm 1: ResearchForge Orchestration Protocol

```
Input: User Query $Q$, Session $S$
Output: Artifact (List, Text, or Error)
$S \leftarrow$ InitializeSession();
$\mathcal{I} \leftarrow$ Orchestrator.ClassifyIntent($Q$);
switch $\mathcal{I}$ do
    case DISCOVERY do
        $D_{raw} \leftarrow$ DataScout.Fetch($Q$);
        $D_{clean} \leftarrow$ DataScout.Parse($D_{raw}$);
        UpdateArtifacts($S, D_{clean}$);
    end
    case MATCHING do
        $V_q \leftarrow$ Encoder.Embed($Q$);
        $\mathcal{C} \leftarrow$ FAISS.Search($V_q$);
        $R \leftarrow$ MatchEngine.Rank($\mathcal{C}$, Weights$_\alpha$);
        UpdateArtifacts($S, R$);
    end
    case GENERATION do
        $C_{context} \leftarrow$ RetrieveArtifacts($S$);
        $Output \leftarrow$ LLM.Generate($Prompt, C_{context}$);
        return $Output$;
    end
end
```

A. Experimental Setup

The evaluation protocol measured three Key Performance Indicators (KPIs): **Latency**, **Factual Integrity**, and **Workflow Continuity**. The system was tasked to sequentially: (1) Discover recent preprints (last 2 years) from arXiv; (2) Generate a funding-ready proposal; and (3) Draft an initiation email. We benchmarked ResearchForge against two baselines: a manual workflow using standard search engines (Google Scholar) and a disjointed workflow using a generic LLM (ChatGPT-4) without tool access.

B. Quantitative Results

1) Workflow Latency Analysis: We measured the end-to-end execution time for the complete A2A interaction. As detailed in the system logs, the total workflow latency was recorded at **90.2 seconds**. A breakdown of agent execution times is provided below:

- **DataScout (80.1s):** The retrieval phase dominated the latency budget (88%) due to external API rate limits and XML parsing overhead. This confirms that the bottleneck is I/O-bound rather than compute-bound.
- **ProposalGenerator (6.0s) & OutreachSpecialist (4.2s):** The generative phases were executed near-instantaneously, validating the efficiency of the Orchestrator's context passing mechanisms.

In contrast, a manual execution of this workflow—comprising comprehensive literature review (approx. 4 hours), candidate vetting (2 hours), and proposal drafting (8 hours)—is estimated to require ∼**14 hours** of active work. ResearchForge achieves a time reduction of $\sim \mathbf{99.8\%}$, effectively shifting the paradigm from "days" to "minutes."

2) Factual Integrity & Hallucination: The *DataScout* agent retrieved 10 valid preprints (e.g., arXiv:2511.23478v1). To evaluate hallucination, we verified the existence of all cited papers. ResearchForge achieved **100% citation accuracy**, as the *OutreachSpecialist* is architecturally constrained to reference only artifacts present in the *Global Context Board*. Conversely, the baseline generic LLM hallucinated 30% of citations when forced to generate specific paper titles without external tool access.

C. Qualitative Comparison

Table I presents a feature-wise comparison. While Google Scholar offers high veracity, it lacks agency. Generic LLMs offer agency but suffer from low veracity (hallucination). ResearchForge bridges this gap through its hybrid architecture.

TABLE I
COMPARATIVE ANALYSIS OF COLLABORATION FRAMEWORKS

Capabilities	**Scholar/WoS**	**Generic LLM**	**ResearchForge**
Data Source	Live Database	Static Weights	**Live API (RAG)**
Hallucination Risk	Null	High	**Null (Grounded)**
Reasoning Mode	None	Zero-Shot	**Chain-of-Thought**
Architecture	Passive Retrieval	Monolithic	**Agentic (A2A)**
Output Artifacts	Hyperlinks	Unstructured Text	**Structured Assets**

VII. Discussion and Limitations

A. Ethical Considerations: Automating Outreach

While automating outreach significantly reduces friction, it introduces the risk of generating high-volume, low-quality spam. To mitigate this, ResearchForge enforces a *Quality Guardrail* via the *OutreachSpecialist*, which requires specific contextual triggers (e.g., a shared keyword or paper citation) before drafting an email. Furthermore, the system is designed as a "Human-in-the-Loop" (HITL) framework, where drafts must be approved by the user, preventing fully autonomous spamming.

B. Technical Limitations

Currently, the system's efficacy is bound by the availability of public metadata. Institutional "dark data" (e.g., internal funding records) remains inaccessible. Additionally, the embedding model (`all-MiniLM-L6-v2`) has a finite context window, which may truncate extremely long publication lists during the vectorization process.

VIII. Conclusion and Future Work

We presented ResearchForge AI, a hierarchical multi-agent framework that democratizes scientific collaboration. By coupling the reasoning power of LLMs with the factual grounding of academic APIs and a deterministic compatibility engine, we demonstrated a system capable of compressing month-long discovery workflows into minutes.

Future work will focus on three key directions:

1) **Graph Neural Networks (GNNs):** Replacing the heuristic ranking with GNNs to analyze co-authorship topology for predictive "Career Synergy" scoring.
2) **Persistent Memory:** Integrating ChromaDB to support long-term memory of user preferences across multiple sessions.
3) **Federated Learning:** Deploying the MatchEngine in a federated manner to learn institutional preferences without exposing private researcher data.

Acknowledgment

The authors acknowledge the Google Cloud team for providing computational resources via the Agent Development Kit (ADK) and the Gemini API infrastructure.

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