SQuAI: Scientific Question-Answering with Multi-Agent Retrieval-Augmented Generation

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Abstract

We present SQuAI (https://squai.scads.ai/), a scalable and trustworthy multi-agent retrieval-augmented generation (RAG) framework for scientific question answering (QA) with large language models (LLMs). SQuAI addresses key limitations of existing RAG systems in the scholarly domain, where complex, open-domain questions demand accurate answers, explicit claims with citations, and retrieval across millions of scientific documents. Built on over 2.3 million full-text papers from arXiv.org, SQuAI employs four collaborative agents to decompose complex questions into sub-questions, retrieve targeted evidence via hybrid sparse-dense retrieval, and adaptively filter documents to improve contextual relevance. To ensure faithfulness and traceability, SQuAI integrates in-line citations for each generated claim and provides supporting sentences from the source documents. Our system improves faithfulness, answer relevance, and contextual relevance by up to +0.088 (12%) over a strong RAG baseline. We further release a benchmark of 1,000 scientific question-answer-evidence triplets to support reproducibility. With transparent reasoning, verifiable citations, and domain-wide scalability, SQuAI demonstrates how multi-agent RAG enables more trustworthy scientific QA with LLMs.

CCS Concepts

 $\bullet \ \, \textbf{Information systems} \rightarrow \textbf{Question answering;} \bullet \textbf{Computing methodologies} \rightarrow \textbf{Multi-agent systems}.$

Keywords

Retrieval-Augmented Generation, Scientific Question Answering, Attributed Text Generation, Large Language Model

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1 Introduction

Large Language Models (LLMs) have shown strong performance on tasks such as multi-step reasoning [34], summarization [37], and open-domain question answering (QA) [31]. Nonetheless, LLMs often generate hallucinations, i.e., factually incorrect or misleading information [13]. One approach to mitigating hallucinations is retrieval-augmented generation (RAG), which combines traditional information retrieval with LLMs [18]. In RAG, relevant documents are retrieved from external sources and used to ground the model's responses in curated, up-to-date information while reducing the likelihood of unsupported claims.

Scientific QA is a challenging setting, where hallucinations can have especially severe consequences. Unlike general-domain QA, it requires not only factually correct answers but also precise scientific terminology, long-form reasoning, and integration of evidence from multiple sources. Although RAG reduces hallucinations by grounding answers in retrieved documents, standard RAG methods treat questions monolithically and retrieve in a single step, often yielding incomplete or only marginally relevant evidence. Verifiability of LLM-generated answers is also crucial, and as proposed by Gao et al. [11], fine-grained in-line citations help users trace claims back to their sources and assess their reliability.

To overcome the limitations of standard RAG in scientific QA, we present *SQuAI*, a collaborative multi-agent RAG system. Our system is built on the newly released *unarXive 2024* dataset [5], which updates previous versions [28, 29] to provide large-scale, open-domain coverage of all publications from arXiv, enabling QA across a wide range of scientific topics. SQuAI provides an end-to-end QA user interface (UI) where users can select the LLM backend, configure retrieval systems such as sparse, dense, or hybrid, and examine intermediate reasoning steps during generation.

In contrast to existing systems like BioRAGent [2], PaperQA [21], and ScienceQA [20], SQuAI supports a wide range of scientific domains and offers adaptability to different use cases through configurable retrieval and generation settings. BioRAGent is restricted to biomedical QA, relies on static query expansion with snippet-level citation, and provides limited control over retrieval and answer generation. PaperQA retrieves information from full-text scientific papers but is designed primarily for offline use and lacks interactive, real-time capabilities. ScienceQA, while addressing scientific QA, does not generate in-line citations and is not based on a multi-agent architecture, limiting its traceability compared to SQuAI.

SQuAI addresses key limitations of existing scientific QA systems through four core innovations. First, it achieves *high answer*

relevancy via a multi-agent architecture that decomposes user questions into sub-questions to enable more accurate evidence aggregation than standard RAG approaches. Second, it ensures contextual relevancy through adaptive document filtering, which prioritizes pertinent content for complex, multi-faceted queries, and through hybrid retrieval that combines sparse and dense approaches to improve literature coverage. Third, it improves faithfulness through traceability by providing fine-grained in-line citations along with citation context, i.e., the exact sentences supporting each claim, thus enabling transparent verification. Finally, SQuAI is designed to be scalable for real-world usage, operating on the full-text corpus of over 2.3 million scientific publications across multiple disciplines including computer science, mathematics, and physics. To our knowledge, SQuAI is the first publicly available system to integrate these capabilities in a unified platform for real-time, verifiable scientific QA at scale. SQuAI is accessible online,¹ and the accompanying code and datasets are available in our repository.²

Our contributions can be summarized as follows:

- We present SQuAI, a multi-agent RAG system for scientific QA over all arXiv publications up to 2024.
- We design a user-facing QA interface with modular configuration, transparent reasoning inspection, and fine-grained in-line citations with citation context for verification.
- We release a novel synthetic dataset with 1,000 scientific question-answer-evidence triplets tailored to unarXive 2024, supporting evaluation of scientific QA systems.
- We conduct an extensive evaluation, showing that SQuAI improves a combined score of Faithfulness and Answer / Contextual Relevancy by +0.088 (12%) over a RAG baseline.

2 Related Work

Multi-Agent Retrieval-Augmented Generation. Recent RAG research increasingly adopts multi-agent systems to enhance QA tasks. Zhao et al. [38] introduced *LongAgent*, where sub-tasked agents handle document segments under a coordinating leader. *IM-RAG* models an inner monologue between retriever, reasoner, and refiner agents to iteratively refine queries and results [36], with related work exploring agent specialization for planning or verification [14, 27]. Chang et al. [6] introduced *MAIN-RAG*, an architecture that improves evidence selection under noisy retrieval. Our work builds upon MAIN-RAG, further improving retrieval and refining answer generation through a fourth agent for query decomposition and through fine-grained in-line citations.

Attributed Text Generation. Also known as citation generation, this task aims to produce text with explicit links to source documents used for text generation, enhancing trust and verifiability. As discussed by Huang and Chang [12], Schreieder et al. [30], attribution approaches include parametric methods, which rely solely on internal model knowledge like Galactica [32], and non-parametric methods that access external sources. Non-parametric approaches are further divided into *post-generation*, where the model first generates an answer and then identifies supporting evidence [10, 24], and *post-retrieval*, which retrieve evidence before generation following the RAG framework [4, 9, 11]. Our work advances post-retrieval

approaches through a multi-agent architecture with query decomposition to retrieve more relevant evidence and generate a combined answer with fine-grained in-line citations and rich citation context.

Scientific Question Answering. Scientific QA tasks are typically categorized by input source and answer format. Input sources include *open-domain* settings, such as SciQA [3] and LitSearch [1], where answers are retrieved from corpora, and *document-grounded* settings, such as Qasper [7], where answers are derived from a provided document. Answer formats vary widely. Some tasks use multiple-choice or yes/no questions, such as ScienceQA [20], while others require short factoid or list-style responses, as in BioASQ-QA [17] and PubMedQA [15]. Some questions require long-form, free-text explanatory answers, as seen in SciQA [3]. While biomedical QA has advanced, *open-domain* long-form scientific QA remains underexplored. To help address this gap, we leverage questions from LitSearch [1], while using unarXive 2024 [5] as retrieval corpus due to its broad and diverse coverage of scientific literature.

3 System Overview

SQuAI is built on unarXive 2024 [5], a large-scale structured collection of all full-text arXiv papers from 1991 to 2024. Each paper includes rich metadata, annotated citations, section boundaries, LaTeX equations, and a detailed citation network. With substantial textual volume and dense technical content organized in deep section hierarchies, these papers provide a challenging benchmark for complex retrieval and citation tasks, enabling robust evaluation of RAG systems in realistic scientific QA settings.

Adopting the multi-agent filtering approach from the MAIN-RAG framework [6], we introduce a substantially enhanced multi-agent architecture for scientific QA. We introduce a novel query decomposition and generate precise in-line citations. In Figure 1, we detail our agents' roles: Agent-1 decomposes the input query into sub-questions. For each sub-question, a hybrid retriever selects top-k documents, Agent-2 generates initial answers, Agent-3 filters question-answer-evidence (Q-A-E) triplets. Finally, Agent-4 generates the final answer with in-line citations and citation context.

3.1 Multi-Agent System Design

The overall architecture comprises five main components:

3.1.1 Agent-1: Decomposer. Agent-1 serves as the initial stage of the QA pipeline, tasked with decomposing complex user queries into simpler, semantically distinct sub-questions. For example, the query "What is quantum computing and how is it used in cryptography?" can be decomposed into two sub-questions:

"What is quantum computing?" and "How is quantum computing used in cryptography?"

This decomposition enables more precise retrieval for each aspect of the original query, enhancing SQuAI's evidence aggregation. Complex or multi-faceted queries are common in real-world information-seeking tasks, particularly in scientific and technical domains [16, 23]. Prior work has emphasized the benefits of handling these cases via decomposition to improve both retrieval and downstream answer quality [35]. Our system handles complex queries by decomposing them into sub-questions, enabling targeted retrieval and reducing ambiguity across large scientific corpora.

¹https://squai.scads.ai/

²https://github.com/faerber-lab/SQuAI

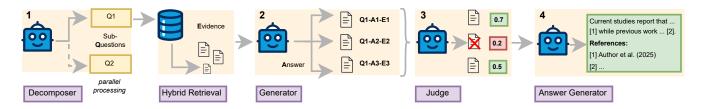


Figure 1: An overview of the SQuAI framework including four agents and hybrid retrieval for scientific QA.

Subsequently, each sub-question is processed independently and in parallel by **Hybrid Retrieval**, (2) **Generator**, and (3) **Judge**.

3.1.2 Hybrid Retrieval. Our system combines sparse and dense retrieval models to maximize both lexical and semantic coverage. Motivated by prior work [22], this hybrid approach aims to improve retrieval performance, particularly for complex scientific texts. For sparse retrieval, we use BM25, a well-established exact term matching model [25, 26], while dense retrieval relies on intfloat/e5-base-v2 embeddings [33]. We primarily use paper abstracts for indexing, supported by findings from the LitSearch paper [1] that full-text retrieval offers only marginal gains. Limiting retrieval scope is crucial for scalability across millions of long-scale documents without sacrificing performance. The final document scores are computed by interpolating both retrieval scores.

$$S_{\text{hybrid}}(d) = \alpha \cdot S_{\text{sparse}}(d) + (1 - \alpha) \cdot S_{\text{dense}}(d)$$
 (1)

Following the findings of Mosquera et al. [22], we set $\alpha=0.35$ to slightly favor dense retrieval while preserving complementary signals from sparse retrieval.

3.1.3 Agent-2: Generator. After document retrieval, we select up to top_k candidate papers per sub-query, where top_k is adjustable between 3 and 10 to balance the number of documents retrieved with processing efficiency. Agent-2 processes each document individually within its sub-query context to generate Q-A-E triplets, which serve as structured input for Agent 3. More than just creating Q-A pairs, this agent isolates potentially relevant content from each document, enabling a more fine-grained evaluation and selection of information in the next stage.

3.1.4 Agent-3: Judge. This agent evaluates each Q-A-E triplet to determine whether the document is relevant and supportive for answering the query. For each triplet, Agent-3 generates a binary assessment ("Yes" or "No") in response to the question: "Is this document relevant for answering the query?" To enable adaptive filtering beyond binary decisions, we compute a relevance confidence score (RelScore) based on the model's output probabilities:

RelScore =
$$\log p(\text{"Yes"}) - \log p(\text{"No"})$$

This scoring method allows us to distinguish strong vs. weak affirmatives and to dynamically adjust filtering sensitivity based on query difficulty. Instead of a fixed threshold for filtering retrieved documents by relevance scores, we compute a query-specific threshold using the mean score (τ_q) and standard deviation (σ) of all candidate documents. The system retains a document if:

RelScore
$$\geq \tau_q - n \cdot \sigma$$

where n is a hyperparameter that controls filtering stringency. Based on empirical results from the MAIN-RAG study, n = 0.5 yields the best trade-off between precision and recall [6].

3.1.5 Agent-4: Answer Generator. Following document filtering, Agent-4 synthesizes a final, coherent answer for all sub-queries by combining the full-text from the relevant documents retained by Agent-3. Crucially, this step also requires precise citation placement: Each factual assertion must be followed by a citation in the standardized [X] format, linking to the associated arXiv entry.

The model must identify discrete factual claims within the answer, determine which documents support each claim (which may vary in style or coverage), and insert the correct citation(s) immediately after. This includes handling multiple sources for a single claim (e.g., [1][2]) and integrating complementary or conflicting evidence across documents. To guide the model, we use a structured few-shot prompt with three carefully crafted exemplars illustrating correct and incorrect citation practices. This lightweight alignment encourages the model to generalize proper citation behavior without fine-tuning. The model is instructed that every factual sentence must include at least one citation and should reference diverse sources rather than relying heavily on a single document. The Answer Generator must balance informativeness with traceability by citing appropriate evidence or rephrasing/removing unsupported claims. This ensures the output is grounded in retrieved papers and meets academic standards of transparency and attribution. In addition Agent-4 is prompted to extract the citation context.

Below is an example of an appropriate answer generated in response to the previous question: Quantum computing uses qubits to perform computations based on quantum mechanics [1]. It has potential applications in cryptography, particularly for breaking classical encryption schemes (...)[2].

3.2 User Interface

SQuAI is implemented as a web application using the Streamlit framework for a clean and responsive UI, and FastAPI for the backend. We offer several key features designed for transparency and flexibility. Users can enter a question via a dedicated input field and initiate retrieval with a search button. For added interpretability, the UI displays the decomposed sub-queries generated by SQuAI. Answers are shown in text boxes with in-line citations, accompanied by a list of reference snippets, each including direct, clickable links to the corresponding arXiv papers. Users can configure parameters that balance different retrieval methods and control strictness of document filtering. The UI also allows the selection of a retrieval model, such as hybrid, sparse, or dense, based on the task.

LitSearch unarXive Simple unarXive Expert Approach Ans. Con. Fai. Avg. Ans. Con. Fai. Avg. Ans. Con. Fai. Avg. Standard RAG 0.897 0.513 0.983 0.798 0.750 0.562 0.965 0.759 0.762 0.643 0.984 0.796

0.748

0.883

Table 1: Evaluation of SQuAI on LitSearch, unarXive Simple, and Expert with metrics Answer Relevance (Ans.), Contextual Relevance (Con.), Faithfulness (Fai.), and their mean (Avg.). We compare standard RAG with SQuAI using abstracts and full-texts.

4 Evaluation

To evaluate SQuAI's performance, we employ *DeepEval* [8], an open-source LLM-as-a-judge framework that offers prompt-based metrics delivering continuous scores along with detailed supporting rationales. These evaluation metrics are implemented using chain-of-thought prompting inspired by G-Eval [19]. We report results across three benchmarks, providing a thorough comparison of SQuAI's performance against a state-of-the-art RAG baseline.

0.903

0.937

0.739

0.677

0.966

0.984

0.869

0.866

4.1 Benchmarks & Metrics

SQuAI (Abstract)

SQuAI (Full Text)

We evaluate the system performance across three QA benchmarks focused on long-form scientific QA. All benchmarks are based on arXiv publications and designed to test different aspects of RAG across varying complexity levels.

LitSearch. This retrieval benchmark consists of literature-search questions derived from computer science papers [1]. The questions originate from both GPT-4-generated prompts and author-written queries. We use a subset of 478 questions that include at least one arXiv ID as ground truth, ensuring compatibility with unarXive.

unarXive Simple. This benchmark consists of 500 long-form, open-domain questions synthetically generated using DeepEval and LLaMa 3.3 70B Instruct. The questions are derived from individual papers and are designed to be less complex and more general, making them suitable for a broad, non-specialist audience.

unarXive Expert. Similar to unarXive Simple, this benchmark contains 500 questions generated using DeepEval and LLaMa 3.3 70B Instruct. The questions are more specific and technical, requiring detailed evidence from the source paper to answer.

We assess answer quality using three key DeepEval metrics. Each metric uses the LLaMA 3.3 70B Instruct model and structured reasoning steps modeled on G-Eval's chain-of-thought methodology. For each Q-A-E triplet, the model outputs three scalar scores in [0, 1], each with an intermediate rationale. We avoid evaluating against synthetic reference answers to prevent circularity, as both system and baseline outputs are LLM-generated. Instead, we focus on verifiability by judging answers directly against the evidence they cite, ensuring a traceable and source-grounded evaluation.

Answer Relevancy. This metric evaluates how well the answer addresses the given question, focusing on semantic alignment between the question and the generated response.

Contextual Relevancy. This metric measures how effectively the answer incorporates the provided evidence passages, assessing whether cited content is meaningfully used.

Faithfulness. This metric assesses whether the answer remains accurate with respect to evidence, penalizing unsupported claims.

4.2 Results

0.954

0.988

0.828

0.847

0.808

0.948

0.653

0.649

0.974

0.995

0.812

0.864

0.782

0.670

We compare SQuAI against standard RAG, which follows a conventional setup without multi-agent orchestration or query decomposition. The model is guided by a single prompt including task instructions and the retrieved papers to generate an answer. Table 1 shows that SQuAI, using hybrid retrieval, consistently improves upon the baseline across all benchmarks. While both settings yield gains, the abstract-only variant shows larger and more consistent improvements (+0.068 to +0.088) than the full-text setting (+0.016 to +0.071). Answer Relevance is higher for SQuAI (Full-Text), while Contextual Relevance is higher for SQuAI (Abstract), reflecting a trade-off where more context better addresses the question but can overwhelm the LLM with excessive information. These results highlight that abstract-based generation provides strong performance benefits with lower computational overhead, making it a more efficient choice for scientific QA in certain scenarios. Notably, SQuAI achieves large improvements over standard RAG in Answer Relevance and Contextual Relevance, while Faithfulness remains reliably high with scores exceeding 0.95 across all configurations.

5 Conclusion

With SQuAI we introduced a multi-agent RAG framework to enhance trustworthiness in scientific QA. SQuAI outperforms a state-of-the-art RAG baseline by up to +0.088 (12%) for faithfulness, answer relevance, and contextual relevance. These gains arise from four key innovations. First, to improve answer relevance, we decompose complex questions into sub-questions for more accurate evidence aggregation. Second, to enhance contextual relevance, we apply adaptive document filtering and hybrid retrieval for broad and relevant literature coverage. Third, to strengthen faithfulness, we provide fine-grained in-line citations and context for transparent verification. Finally, we ensure SQuAI scales to real-world use, operating over 2.3 million scientific papers across diverse domains.

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GenAI Usage Disclosure

The authors utilized GPT-40 for grammar and spelling checks, minor rewording, and structural editing support. The AI tools did not contribute to the intellectual content or scientific conclusions. All content was subsequently reviewed and edited by the authors, who assume full responsibility for the publication.

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