AGENTIC ENVIRONMENTS FOR SCIENTIFIC REVIEW GENERATION

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ABSTRACT

This paper explores the application of agent-based systems to the task of automated scientific review generation over large document collections. This task requires handling long contexts, planning, and ensuring high factual accuracy - properties where agent-based methods have the greatest advantage. It is particularly relevant given the rapid growth of scientific publications, while existing solutions mostly focus on web search and question-answering scenarios. We investigate the applicability of architectures based on compact language-model agents equipped with specialized tools and provide an environment oriented toward subsequent reinforcement learning. Experimental results show that the proposed architecture achieves performance comparable to systems built on substantially larger models, and that the key factor for improving quality lies in the use of memory mechanisms.

1 Introduction

Due to improved reasoning structure and factual consistency, large language models (LLMs) have become a widespread tool in scientific workflows such as domain-specific QA, summarization, and review writing. The volume and diversity of scientific publications continue to grow, exceeding what individual researchers or small groups can regularly analyze, motivating the development of automated solutions. Producing high-quality reviews remains technically challenging for existing approaches: it requires effective information extraction, identification of key methods and results, citation-based attribution, and stable operation under extremely long contexts. This work investigates the effectiveness of agent-based approaches under these conditions.

Early approaches to multi-document summarization relied on generative transformer models; however, as corpus size and context length increased, they evolved toward RAG architectures, where retrieval of relevant fragments grounds generation on fixed sources and improves factual accuracy (Lewis et al. [2020]). In practice, RAG pipelines often involve complex multi-stage processes manually designed by researchers, heavily dependent on expert intuition to define retrieval, selection, and generation steps (Zhang et al. [2024]). In parallel, reinforcement learning (RL) has been applied to review generation, with varying designs of quality signals and preference aggregation (including training from human feedback and textual edits). RLHF has shown the best results, while RLAIF serves as a scalable alternative in low-annotation settings (Ouyang et al. [2022], Lee et al. [2023]). The ideas of step-by-step reasoning further evolved into ReAct and multi-agent pipelines with cooperating writer and critic models for long-context tasks (Yao et al. [2022], Shinn et al. [2023]). Compared to rigid RAG scripts, such systems enable more flexible role distribution and coordination of intermediate reasoning. Moreover, RL-trained agent systems have proven effective in web-search tasks, suggesting the potential of similar strategies for review generation (Qi et al. [2024]).

Despite significant progress, current solutions remain limited. RAG pipelines impose fixed sequential stages and poorly model inter-article relations, yielding fragmented and weakly structured reviews as the corpus grows. Agent-based methods have mostly targeted narrow domains (e.g., tables, long narratives) and were not explored as RL-trainable systems—although they naturally support policy learning for tool and memory interaction. In long-context tasks,

effective transfer and compression of working memory between iterations is critical, yet the most successful short-term memory methods have not been applied to review writing. RL approaches to summarization typically optimize proxy metrics and rarely integrate multi-agent coordination, limiting their applicability to scientific reviews. Finally, most existing systems focus on retrieval, while the main bottlenecks lie in information aggregation and verifiable attribution.

We developed an agent system tailored for scientific review generation. Its core consists of two interacting agents—a writer and a critic—coordinating text generation and verification. The writer drafts the review using specialized tools: semantic search over a fixed corpus, citation extraction, fragment rephrasing, and working memory management, which aggregates intermediate insights and maintains coherence across sections. The critic analyzes the writer's statements, verifies them against source documents, and identifies ungrounded claims using both working and episodic memory. We implemented an environment for further reinforcement learning that includes: tools for corpus interaction; a memory subsystem; a step-by-step interaction protocol with traceable actions and memory snapshots for reproducibility; multiple reward functions (evaluating coverage, factuality, and organizational coherence); and evaluation scenarios.

We introduce a new formulation of the review generation task that excludes the retrieval component, enabling isolated analysis of the agent's reasoning and aggregation abilities. We demonstrate that compact models operating in an agentic mode achieve quality comparable to much larger models on the same review tasks. The analysis of memory modules shows that their use is critical for this problem, significantly improving factual accuracy and textual coherence. Finally, we present a framework implementing the agent environment for review generation on fixed document corpora, supporting reproducible experimentation and further research.

2 Related Work

From Retrieval-Augmented Generation to Agent Systems   Early works addressing similar problems used RAG (Lewis et al. [2020]), suffering from efficient aggregation mechanism. To cope with this disadvantage, solutions with modified pipelines were built (Zhang et al. [2024]). But they were mostly based on researcher intuition, static, lacking adaptive, iterative control. Agent-based approaches enable more flexible alternation. ReAct demonstrated that interleaving reasoning and action reduces hallucinations and improves QA performance (Yao et al. [2022]). Reflexion extends this idea: agents store prior decisions and verbal experiences, analyze mistakes, and adjust future actions (Shinn et al. [2023]). For long-context tasks, LongAgent and MA-RAG employ multiple worker agents and managers reading text in parts and synthesizing answers (Zhao et al. [2024], Nguyen et al. [2025]), scaling LLMs to longer inputs. However, the success of agent systems is highly known in QA tasks, not in overview generation.

Memory Mechanisms in Agent Systems   Simplest agent architectures pass all information between iterations directly through the model context, leading to input growth and poor scalability in deep reasoning tasks. Scientific review writing requires many iterations of information gathering and processing under large contexts. A straightforward solution is adding a separate aggregation model (Shinn et al. [2023], Yu et al. [2025], Li et al. [2025]). More advanced solutions employ specialized memory architectures that index accumulated insights, context, and interaction history, accessible later via dedicated tools (Packer et al. [2023], Xu et al. [2025]). Recent studies introduce graph-based modifications that reduce token processing costs and improve generalization in long dialogues (Chhikara et al. [2025], Zhou et al. [2025]). In our task, interest in memory mechanisms stems from their absence in prior work on automated review generation.

Reinforcement Learning for Summarization   RL has been used to mitigate exposure bias and align generation with target metrics. Paulus et al. combined MLE and policy gradient, reducing repetitions and improving readability [18]. Later, new reward functions were proposed: DSR employs semantic embeddings instead of ROUGE to encourage diversity and fluency [42]; RewardsOfSum introduces RISK-based rewards for stricter alignment [21]; Topic-guided RL rewards topical consistency in MDS [22]. Inverse RL learns reward functions from examples, avoiding manual task weighting [43]. Other studies use BERTScore as reward to improve quality and reduce redundancy [23], apply RL with AI feedback (RLAIF) to replace costly RLHF (Lee et al. [2023]), and demonstrate summary generation without reference data [24]. However, RL complexity, the need for many rollouts, and the lack of standardized rewards still limit practical adoption.

Evaluation of Scientific Review Quality   Assessing review quality remains difficult due to the scarcity of datasets containing reference reviews, as producing them requires substantial human effort. Until recently, the only relevant dataset was Multi-XScience, which included only Related Work sections or abstracts (Lu et al. [2020]). Only in the past year several works have addressed this via automatic and manual filtering of the S2ORC dataset (Lo et al. [2020]) (Bao et al. [2025], Su et al. [2025]). Many open challenges concern abstractive summarization evaluation. Classical metrics such as ROUGE (Lin [2004]) fail to capture semantic similarity, leading to LLM-based alternatives (Zhang et al.

[2019]). For evaluating individual aspects of generated reviews without references, metrics such as FineSure (Song et al. [2024]) and G-eval (Liu et al. [2023]) were introduced, both showing high correlation with human judgments.

3 Problem statement

Data   Let the dataset be $\{(\mathcal{D}_i, G_i)_{i=1}^N\}$, where $(\mathcal{D}_i = d_{i1}, \dots, d_{im_i})$ is a closed set of source documents and G_i is written by experts gold overview. By construction, G_i cites only items from $\mathcal{D}_i$, no external data is used, G_i can contain claims based on info in $\mathcal{D}_i$ but not directly mentioned in it.

Task mapping   The model implements a mapping

$$f_\theta : \ \mathcal{P}(\mathcal{D}_i) \ \longrightarrow \ \hat{S}_i \in \Sigma^*,$$

producing a single sequence $\hat{S}_i$ (the review) that contains in-text citations referring to $\mathcal{D}_i$. We do not hard-constrain attribution.

Agent formulation   We formalize the generator as an **MDP** $(\mathcal{S}, \mathcal{A}, T, R, \gamma)$. A state $s_t \in \mathcal{S}$ contains the partial draft, tool outputs (closed-corpus retrieval over chunks of $\mathcal{D}_i$), and an agent memory m_t. Actions $a_t \in \mathcal{A}$ include RETRIEVE(q, k), WRITE(Δ), CITE(r), MEMUPDATE$(\cdot)$, and STOP. The transition T advances the draft and memory given tool results; $\gamma \in [0, 1]$. In this work, we do **zero-shot** generation and evaluate only terminal outputs (no policy learning), while the same MDP supports future RL by defining episodic rewards from the external metrics below. Also, we can easily formalize all RAG-like pipelines as similar iterative interactions with the environment.

3.1 External metrics

For the most comprehensive and comprehensive assessment, the following metrics were selected.

BERTScore   Determine semantic similarity to G_i. With contextual token embeddings, recall and precision are

$$R_{\text{BERT}} = \frac{1}{|x|} \sum_{x_i \in x} \max_{\hat{x}_j \in \hat{x}} x_i^\top \hat{x}_j, \quad P_{\text{BERT}} = \frac{1}{|\hat{x}|} \sum_{\hat{x}_j \in \hat{x}} \max_{x_i \in x} x_i^\top \hat{x}_j, \quad F_{\text{BERT}} = \frac{2 P_{\text{BERT}} R_{\text{BERT}}}{P_{\text{BERT}} + R_{\text{BERT}}}$$

FineSurE   FineSurE is a fine-grained LLM-based evaluator for summarization along faithfulness, completeness, and conciseness. Given source documents D and a generated summary $S = s_1, \dots, s_N$, sentence-level fact checking yields $S_{\text{fact}} \subseteq S$ (sentences with no factual error), and

$$\text{Faithfulness}(D, S) = \frac{|S_{\text{fact}}|}{|S|}.$$

With a key-fact list $K = k_1, \dots, k_M$ build a bipartite alignment $E = (k, s) : k \to s$ between key-facts and summary sentences; then

$$\text{Completeness}(K, S) = \frac{|\{k : (k, s) \in E\}|}{|K|}, \qquad \text{Conciseness}(K, S) = \frac{|\{s : (k, s) \in E\}|}{|S|}.$$

For sentence-level meta-evaluation it reports balanced accuracy

$$bACC = \tfrac{1}{2}(TPR + TNR).$$

G-Eval   G-Eval is a rubric-based, reference-free evaluator that uses an LLM with chain-of-thought and a form-filling template. A prompt provides task introduction and evaluation criteria; the LLM generates evaluation steps and returns a discrete rating $s_i \in S$. The final continuous score is the probability-weighted expectation:

$$\text{Score} = \sum_{i=1}^{n} p(s_i), s_i.$$

Where $p(s_i)$ is probability of s_i token calculated in the last layer of the generative model.

3.2 Headings: second level

3.2.1 Headings: third level

Paragraph

../figures/log_reg_cs_exp-eps-converted-to.pdf

Figure 1: Sample figure caption.

4   Examples of citations, figures, tables, references

4.1   Citations

Citations use `natbib`. The documentation may be found at

http://mirrors.ctan.org/macros/latex/contrib/natbib/natnotes.pdf

Here is an example usage of the two main commands (`citet` and `citep`): Some people thought a thing [**??**] but other people thought something else [**?**]. Many people have speculated that if we knew exactly why **?** thought this...

4.2   Figures

Suspendisse vitae elit. Aliquam arcu neque, ornare in, ullamcorper quis, commodo eu, libero. Fusce sagittis erat at erat tristique mollis. Maecenas sapien libero, molestie et, lobortis in, sodales eget, dui. Morbi ultrices rutrum lorem. Nam elementum ullamcorper leo. Morbi dui. Aliquam sagittis. Nunc placerat. Pellentesque tristique sodales est. Maecenas imperdiet lacinia velit. Cras non urna. Morbi eros pede, suscipit ac, varius vel, egestas non, eros. Praesent malesuada, diam id pretium elementum, eros sem dictum tortor, vel consectetuer odio sem sed wisi. See Figure 1. Here is how you add footnotes. [1] Sed feugiat. Cum sociis natoque penatibus et magnis dis parturient montes, nascetur ridiculus mus. Ut pellentesque augue sed urna. Vestibulum diam eros, fringilla et, consectetuer eu, nonummy id, sapien. Nullam at lectus. In sagittis ultrices mauris. Curabitur malesuada erat sit amet massa. Fusce blandit. Aliquam erat volutpat. Aliquam euismod. Aenean vel lectus. Nunc imperdiet justo nec dolor.

4.3   Tables

See awesome Table 1.

The documentation for `booktabs` ('Publication quality tables in LaTeX') is available from:

https://www.ctan.org/pkg/booktabs

4.4   Lists

  • Lorem ipsum dolor sit amet

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[1]Sample of the first footnote.

Table 1: Sample table title

	Part	
Name	Description	Size (μm)
Dendrite	Input terminal	$\sim$100
Axon	Output terminal	$\sim$10
Soma	Cell body	up to 10^6

- consectetur adipiscing elit.
- Aliquam dignissim blandit est, in dictum tortor gravida eget. In ac rutrum magna.

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