AGENTIC ENVIRONMENTS FOR SCIENTIFIC REVIEW GENERATION

A PREPRINT

Gleb Dolgushev
faculty of Computational Mathematics
and Cybernetics
Moscow State University
Moscow, Russia
s02220087@gse.cs.msu.ru

Roman Ishenko
faculty of Computational Mathematics
and Cybernetics
Moscow State University
Moscow, Russia
stariate@ee.mount-sheikh.edu

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 $\{(\mathcal{D}_i, q_i, G_i)_{i=1}^N\}$, where $(\mathcal{D}_i = d_{i1}, \ldots, d_{im_i})$ is a closed set of source documents, G_i is written by experts gold overview and q_i is query that helps to clarify overview purpose. 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

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

producing a single sequence $\hat{S}_i$ (the review) that contains in-text citations referring to $\mathcal{D}_i$ and is relevant to q_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 $s_i \in \mathcal{S}$ contains the partial draft, tool outputs (closed-corpus retrieval over chunks of $\mathcal{D}_i$), and an agent memory m_i. The transition T advances the draft and memory given tool results. 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 $S = s_1, \ldots, s_N$, 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 $K = k_1, \ldots, k_M$ 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.

4 Proposed solution

We model our system as a triad of large-language-model policies $\mathcal{M} = (M_W, M_C, M_M)$. The **writer** M_W is a generative policy that drafts review text, the **critic** M_C is an evaluator that judges draft segments against evidence and produces textual feedback, the **memory manager** M_M maintains persistent memory. This architecture is a combination of the Reflection ideas and the MemGPT, created for working with long contexts.

4.1 Agent roles

Writer Conditioned on the current draft and memory, M_W alternates between reasoning and action. At each step, it either issues a **retrieve call** $T_{\text{DB}}(q, k)$ to collect the top-k document chunks most similar to a query q (using a dense embedding e and cosine similarity), or it calls **rewrite** current review $S_i \rightarrow S_{i+1}$. This ReAct-style interleaving of thought and retrieval enables the writer to plan and ground its output in evidence.

Critic After each segment, M_C queries the same evidence via T_{DB} and the memory manager T_{MEM} to verify the factuality of claims. It produces a natural-language critique, highlighting unsupported statements or missing sources. Unlike a scalar reward, this verbal feedback is appended to memory and used to bias subsequent actions, similar to the self-reflection model in Reflexion.

Memory manager We adopt and simplify MemGPT's hierarchical memory architecture. Memory is partitioned into a **main context** that fits into the LLM's window, and an **external context** that stores compressed long-term experiences. The memory manager provides two operations: MEMWRITE(s) adds summaries or critiques to the archive; MEMREAD(ℓ) returns the ℓ most relevant past entries.

4.2 Interaction protocol

The calling of agents occurs iteratively. On turn i, M_W forms a query, calls T_{DB} to fetch evidence and then writes overview changes S_{i+1}. Its output is assessed by M_C with respect to stored memory and database info; it then generates feedback pointing out errors, which is which is combined with the output of M_W and processed by M_M to expand external memory and form new input for M_W. This loop continues until a coherent, well-supported review is produced or maximum amount of steps achieved.

5 Experiments

5.1 Dataset

We evaluate our system on the SciReviewGen dataset, a large-scale benchmark for automated literature review generation built on the Semantic Scholar Open Research Corpus (S2ORC). It contains over 10,000 human-written literature reviews and roughly 690,000 cited papers across diverse scientific domains. For each review, SciReviewGen provides the abstracts of all cited papers, along with the review title and chapter titles, forming a query-focused multi-document summarization task. We use bibliographic metadata to build our database, define. Compared with earlier datasets such as Multi-XScience, SciReviewGen features much longer inputs and outputs and covers a broader range of topics, making it a more challenging benchmark.

5.2 Baselines

RAG Retrieval-Augmented Generation combines a neural retriever with a sequence-to-sequence generator to ground outputs in external documents. The retriever fetches the top-k passages relevant to a query, and the generator produces a summary conditioned on these retrieved passages. This architecture improves factual accuracy and enables explicit source citation, and it has been widely adopted across open-domain QA and summarization tasks. However, vanilla RAG employs a static single retrieval step and cannot iteratively refine retrieval; as a result, it may miss key documents or propagate hallucinations when the initial retrieval is imperfect.

Query-weighted Fusion-in-Decoder QFiD extends the Fusion-in-Decoder framework by weighting each cited paper according to its relevance to the query (the review title or chapter title). It encodes each paper with a BART encoder, computes a similarity weight between the paper's hidden state and the query using inner products, and then concatenates the weighted hidden states before feeding them to a BART decoder. This weighting mechanism allows the model to focus more on papers closely related to the chapter topic. We compare our solution with QFiD because it is designed for query-focused summarization and represent strong RAG-like baseline; but its static weighting cannot dynamically adjust when new information surfaces.

ChatCite It is an LLM-based solution designed for literature summarization with human workflow guidance. It first employs a Key Element Extractor to pull out research questions, methodologies, results, and other core elements from each reference paper. A Reflective Incremental Generator then iteratively produces comparative summaries, while a reflective evaluator votes on candidate summaries to select the best result. ChatCite emphasizes comparative analysis

and structural coherence, but it requires complex prompt engineering and multiple iterations; we include it as a strong baseline, which is a transition from RAG-like systems to agents.

5.3 Hypotheses

Our experiments test several hypotheses:

- **H1** (Metric sensitivity): Our multi-agent pipeline will achieve higher scores on FineSurE and G-Eval (reflecting factuality, coherence and integrity) but may underperform on BERTScore. If confirmed, this supports the argument that reference-based metrics alone (such as BERTScore) are insufficient for assessing scientific literature reviews.
- **H2** (Model efficiency): Smaller base models, when combined with our agentic pipeline and memory, can match or surpass larger RAG-based baselines in FineSurE and G-Eval, indicating that usage of tools, specialized on working with long contexts and modified feedback loops compensate for reduced model size.
- **H3** (Role of the critic): Introducing a critic module will reduce hallucinations and unsupported claims compared with single-agent baselines, leading to higher faithfulness scores in FineSurE.
- **H4** (Memory utility): Leveraging MemGPT's memory manager will improve integrity and comparative analisis by enabling long-range context tracking and reducing repetition, especially on longer reviews.

5.4 Headings: second level

5.4.1 Headings: third level

Paragraph

6 Examples of citations, figures, tables, references

6.1 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...

6.2 Figures

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6.3 Tables

See awesome Table 1.

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

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

[1] Sample of the first footnote.

Figure 1: Sample figure caption.

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

6.4 Lists

- Lorem ipsum dolor sit amet
- consectetur adipiscing elit.
- Aliquam dignissim blandit est, in dictum tortor gravida eget. In ac rutrum magna.

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