Closed-Loop RAG Optimization System Based on User Feedback

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Abstract. Retrieval-Augmented Generation (RAG) effectively mitigates large language model (LLM) hallucinations, yet traditional systems suffer from high cold-start costs, fragmented retrieval-generation optimization, and low feedback utilization in low-resource scenarios. To tackle these pain points, the paper designs a closed-loop RAG optimisation framework that introduces three complementary modules, a Causal Feedback Labeling (CFL) subsystem that builds and maintains a transparent a "feedback-type–root-cause–optimization-strategy" lookup table, a Few-Shot Cold-Start (FCS) component that bootstraps performance by manufacturing synthetic pseudo-feedback, filtering the most informative samples through active learning, and then blending them with the trickle of real user ratings, and a Retrieval-Generation Collaborative Adapter (RGA) that lets gradient signals hop back and forth between retriever and generator via lightweight cross-attention layers so both modules update in lockstep. Experiments on FeedbackQA and HotpotQA-small, comparing our system with six strong baselines, reveal gains of 5.2 percentage points in F1, a 4.5-point drop in hallucination rate, and annotation expenses that shrink to only 17.5 % of the standard supervised budget. And it's cold-start performance curve climbs more than 60 % faster than the best rival, confirming that the framework can adapt quickly in feedback-starved settings and offering engineers a practical route to deploying truly closed-loop RAG services.

1 Introduction

As large language models (LLMs) have been expanding at break-neck speed, Retrieval-Augmented Generation (RAG) has quickly moved into the spotlight as a workable way to make these models stick closer to the facts, basically by letting them dip into external knowledge bases while they are still in the middle of generating text process [1]. RAG-style setups have already spread across a fairly wide range of natural-language-processing chores—everything from open-domain question answering and long-document summarization to the day-to-day chat of intelligent customer-service desks. Yet once you leave the comfort of well-trodden benchmarks and step into low-resource feedback territory—think narrow-domain topics where labelled examples are scarce or user feedback arrives only in tiny trickles—conventional RAG pipelines start to hit noticeable walls.

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First off, the cold-start bill is painfully steep: most current feedback-driven RAG pipelines still bank on huge piles of hand-labelled supervision to steer model optimisation [2], a process that chews up both person-hours and budget, so pushing the stack into a low-resource setting quickly becomes unrealistic. Second, retrieval and generation are tuned in isolation. Plenty of dynamic RAG rigs tweak retrieval knobs once they see how good the final answer looks, yet they never synchronise those moves with the generator's own learning step; because the two halves never talk to each other during optimisation, the overall performance plateaus below where it could be [3]. Third, the feedback that is collected is used rather poorly. Conventional systems pipe the raw feedback straight into parameter updates without first asking which kind of signal points to which root weakness; this missing causal map means plenty of supervision is effectively wasted and the optimiser can drift in directions that do not really fix the underlying problem [4].

To tackle the above-mentioned difficulties, the present work puts forward a closed-loop RAG optimisation scheme that is driven by user feedback and that keeps cycling until the retrieval-generation pair stops drifting. Firstly, a causal feedback labelling system is designed to clarify the mapping between feedback types, problem roots, and optimization strategies, so the signal becomes far easier to read and use. Secondly, a few-shot cold-start module is proposed to generate high-quality pseudo-feedback and fuse it with real feedback, reducing the reliance on large-scale manual annotation. Finally, the paper design a lightweight collaborative adapter that shuttles feedback signals to both the retriever and the generator at the same moment, letting the two components co-optimise instead of being tuned in isolation. Experiments on several public benchmarks show that the proposed loop consistently beats baseline pipelines in accuracy, runtime cost, and the speed with which it adapts to new domains.

2 Related Work

By stitching external knowledge bases directly into the generation pipeline, RAG technology gives large language models a place to look things up, which in turn tamps down their tendency to hallucinate and pushes the factual accuracy of the answers they return to a noticeably higher level; as a result, the approach has quickly become something that almost every NLP group now keeps an eye on. This paper narrows the spotlight to closed-loop RAG systems that keep refining themselves from user feedback, and it walks through what has been happening in the field by grouping recent work under three headings that keep re-appearing in the literature, how to close the feedback loop in a principled way, how to keep the machinery running when labelled data are scarce, and how to make retrieval and generation cooperate rather than step on each other's toes, while at the same time spelling out the practical ceilings that current methods still bump into.

2.1 Closed-Loop RAG Optimization Research

Closed-loop optimization has become one of the most practical levers for pushing RAG performance upward, because it keeps feeding outcome signals back into the retriever and the generator so that their parameters or strategies are polished cycle after cycle. Now, most studies that try to close this loop can be grouped into three overlapping technical paths. The first path relies on reinforcement-learning-driven feedback. A representative instance is RLHF-RAG, which reshapes the generator's output distribution with reward scores coming from human feedback and, in doing so, lifts the relevance of the returned answers [2]. The downside is obvious, the method hungers for a mountain of hand-labelled feedback, so the cold-start bill is painful and low-resource domains are almost out of reach. The second path lets the model criticise itself. Self-RAG is the flagship here: it swaps costly human labels for

signals the model produces about its own behaviour, cutting annotation expenses sharply [4]. Yet, because this self-feedback is only loosely tied to the true root cause of an error, the optimisation compass can drift and the final gain in performance often plateaus early. Third comes dynamic retrieval-strategy tuning. Dynamic RAG, for example, keeps an eye on live quality metrics of the generated answers and tweaks retrieval parameters on the fly [3]. The catch is that the retriever and the generator are still optimised in isolation, so the feedback signal fragments as it travels through the pipeline and the full payoff of a closed loop is never quite collected.

2.2 RAG Adaptation Research in Low-Resource Scenarios

RAG adaptation in low-resource scenarios (such as niche domains and few-shot feedback) is one of the core challenges for practical deployment. Most work so far clusters around two escape routes, fine-tuning on the few examples that are available, or fabricating extra 'pseudo' data to bulk up the training set. Few-Shot RAG pushes the first route by treating the retriever as a prompt-learning problem: with only a tiny set of annotated samples it rewires the query–document scoring function so that relevance signals become sharper [5]. The catch is that the loop stops once the initial prompts are learned; there is no channel for fresh user feedback to circle back, so the retriever can drift the moment real-world queries shift even slightly. MiniRAG takes the second path, aggressively pruning both encoder and decoder so that the whole bundle fits on a modest GPU. The compressed model deploys cheaply, yet it has no built-in way to turn the scarce user corrections it does receive into steady gains, which keeps the closed-loop optimisation efficiency stubbornly low [6]. Meanwhile, other studies let a large language model hallucinate silver-standard labels, hoping to stretch the training pool. Without rigorous quality control or confidence filtering, however, these synthetic labels inject noise that can magnify during the cold-start window, so test accuracy still wobbles from one random seed to the next.

2.3 Retrieval-Generation Collaborative Optimization Research

How smoothly the retriever and the generator work together largely sets the ceiling for the whole RAG system, because any gap between them quickly shows up as dropped facts or hallucinated answers. Researchers have so far explored three broad ways to make the two parts cooperate better, joint training, attention alignment, and adapter connection. Joint training methodskeep the retriever and generator on the same page by updating both of them with a single shared loss function [1], yet this comes at the price of a bloated parameter count, painfully slow convergence, and a footprint that is hard to squeeze into lightweight deployments. Attention alignment strategies ask the generator to re-weight its attention so that it stares hardest at the passages that really matter, but they usually freeze the retriever once training starts, so any later change in retrieval tactics is ignored when the attention map is redrawn [7]. Adapter connection methods slot a small adapter layer between the two modules so gradients and features can flow back and forth without touching the main weights, but the adapter’s own parameters are updated with only indirect hints from the final loss, which keeps the cooperative gain frustratingly shallow [8]. In summary, none of the existing lines of work has managed to weave "causal feedback exploitation, few-shot cold start, and tight cross-module teamwork" into one framework that still behaves when feedback is scarce, and that missing integration is exactly where this study tries to push the boundary.

3 Methodology

This study proposes a closed-loop RAG optimization system based on user feedback, which achieves efficient closed-loop optimization in low-resource scenarios by integrating a causal feedback labeling system (CFL), a few-shot cold-start module (FCS), and a retrieval-generation collaborative adapter (RGA). This section details the problem definition, overall system architecture, core module design, and closed-loop optimization process of the system.

3.1 Problem Definition

The core elements and optimization objectives of the entire "retrieval-generation-feedback-optimization" process are formally defined as follows: The user query set is denoted as $Q = \{q_1, q_2, ..., q_n\}$ (where q_i represents the i-th user query) and the knowledge base document set as $D = \{d_1, d_2, ..., d_m\}$ (where d_j represents the j-th document). User feedback $F = \{f_1, f_2, ..., f_n\}$ adopts a causal feedback labeling system, with each feedback belonging to one of four types—Irrelevant Retrieval, Generation Bias, Information Missing, Ambiguous Expression—corresponding to problem roots of retriever matching bias, generator attention bias, insufficient retrieval information, and unclear generation expression respectively. Each feedback is accompanied by a confidence score $score(f_i) \in [0,1]$ indicating annotation reliability. The core objective is to construct a closed-loop optimization function O(Q, D, F) that drives parameter updates of retriever R and generator G via feedback signals, maximizing answer accuracy A(R, G, Q, D) while minimizing annotation cost C(F) and training cost $C_{train}(R, G)$. The optimization objective is expressed as $L = \lambda_1(1 - A(R, G, Q, D)) + \lambda_2 C(F) + \lambda_3 C_{train}(R, G)$, where $\lambda_1=0.6$, $\lambda_2=0.2$, $\lambda_3=0.2$ are weights balancing performance, annotation cost, and training cost.

3.2 Overall System Architecture

The proposed system consists of five core modules—query preprocessing, lightweight retriever, generator, causal feedback processing, and retrieval-generation collaborative adapter—forming a closed-loop iterative process of "retrieval-generation-feedback-optimization". The core workflow starts with query preprocessing, where term completion and intent recognition are performed to generate standardized queries for improved retrieval matching accuracy. The lightweight retriever then retrieves the top-10 relevant documents from the knowledge base to form set Dq, and the generator generates a factual and complete answer a by fusing Dq. Users annotate answer a via the causal feedback labeling system, submitting feedback type f and confidence score score(f), which the causal feedback processing module analyzes to establish a "feedback type-problem root-optimization strategy" mapping and generate targeted signals for the retriever and generator. The retrieval-generation collaborative adapter synchronously transmits these signals to both modules, which update parameters via lightweight fine-tuning to complete one iteration. During the cold-start phase, the system initializes via the pseudo-feedback generation and active learning module to reduce low-resource deployment costs.

3.3 Detailed Design of Core Modules

The innovations of this study focus on three core modules, whose design logic and technical details are elaborated as follows. The Causal Feedback Labeling System (CFL) addresses low feedback utilization by establishing an accurate "feedback type-problem root-optimization strategy" mapping with four core labels: Irrelevant Retrieval (retrieved documents mismatching query intent, root cause of retriever matching bias, annotation criterion of <30% core content overlap), Generation Bias (answer conflicting with retrieved

facts, root cause of generator attention bias, annotation criterion of ⩾2 conflicting content pieces), Information Missing (answer lacking query-required core information, root cause of insufficient key document retrieval), and Ambiguous Expression (confused logic or unclear terminology, root cause of poor generator language organization). Feedback processing involves two core steps: signal quantification via $s = score(f) \times \omega(f)$ (with $\omega(f_1)=0.3$, $\omega(f_2)=0.4$, $\omega(f_3)=0.2$, $\omega(f_4)=0.1$ as type weights) and strategy mapping, where each feedback type triggers targeted adjustments such as retriever query rewriting updates for Irrelevant Retrieval, generator attention weight adjustments for Generation Bias, retriever threshold optimization for Information Missing, and generator language organization module fine-tuning for Ambiguous Expression.

The Few-Shot Cold-Start Module (FCS) adopts a three-stage "pseudo-feedback generation-active learning screening-real feedback fusion" strategy to solve low-resource feedback scarcity. GPT-4o Mini is used as the annotation model, with the "query-retrieved document-generated answer" triplet input to generate pseudo-feedback according to the CFL system via a tailored prompt that guides selection of the appropriate label and confidence score. Active learning screens high-confidence pseudo-feedback (consistency ⩾ 90%, calculated as the ratio of same-type annotations to total annotations) for cold-start training data to ensure quality. When the number of real feedback samples reaches 100, a weighted fusion strategy is adopted with $w_{real} = \min(0.1 \times N, 1)$ and $wp_{ake} = 1 - w_{real}$ (N as real feedback count), gradually reducing pseudo-feedback weight as real feedback accumulates until it is completely replaced.

The Retrieval-Generation Collaborative Adapter (RGA) resolves fragmented module optimization via a lightweight cross-attention structure, composed of a query feature mapping unit, a document feature fusion unit, and a collaborative signal output unit. It takes 768-dimensional query rewriting rule features (retriever side) and context attention features (generator side) as input, captures inter-module collaborative relationships via an 8-head multi-head attention mechanism, and generates collaborative optimization signals transmitted to the retriever's query rewriting module and generator's attention layer. Lightweight optimization is implemented via LoRA: the retriever (Sentence-BERT all-MiniLM-L6-v2) uses LoRA with rank 8 (0.5% training parameters) and the generator (Llama 2-7B) uses LoRA on the attention layer with rank 8 (1% training parameters), balancing optimization effect and training cost.

3.4 Closed-Loop Optimization Process

The system's closed-loop optimization process includes initialization, cold-start, and iterative optimization phases. The initialization phase loads pre-trained weights of the Sentence-BERT retriever and Llama 2-7B generator, constructs the FAISS vector index of the knowledge base, and sets retrieval Top-k=10. The cold-start phase generates 500 pseudo-feedback samples, selects 100 high-confidence ones (consistency ⩾ 90%), trains the system by fine-tuning the retriever's query rewriting module and generator's attention layer with LoRA (learning rate 2e-4 for retriever/1e-4 for generator, 5 epochs, batch size 8), and saves the weights as initial parameters for iteration. The iterative optimization phase involves inputting preprocessed user queries for Top-10 retrieval, generating answers via the generator, collecting user feedback with type and confidence, generating optimization signals via the CFL system, synchronously transmitting signals via the RGA for LoRA parameter updates, and evaluating validation set performance. Iteration stops when F1 score fluctuation in 3 consecutive iterations is ⩽ 1%, saving optimal weights. The system uses a single RTX 4090 (16GB) with Python 3.9, PyTorch 2.0, Transformers 4.30, LangChain 0.1.0, and FAISS 1.7.4, with GPT-4o Mini for pseudo-feedback generation.

4 Experiments and Results

Comprehensive experiments verify the system's performance, cold-start capability, module effectiveness, and generalization, using three datasets, six baselines, and multi-dimensional metrics.

4.1 Experimental Setup

The dataset settings are as follows. FeedbackQA (main experiment, 5k queries, 8:1:1 split), HotpotQA-small (cold-start, no native feedback) and Medical-DocQA/Legal-QA (cross-domain professional datasets with strict expert annotation).

Baselines settings are as follows. Six typical models (Static RAG, RLHF-RAG [2], Self-RAG [4], DynamicRAG [3], Few-Shot RAG [5], ReasonRAG [9]) with the same retriever/generator architecture for fair comparison.

The metrics settings are as follows. Performance (EM, F1, R@10, Hallucination Rate); Efficiency (Annotation Cost, Training Time); Cold-start (Performance Improvement Rate, Convergence Iterations).

4.2 Main Performance Experiment

As shown in Table 1, the proposed system achieves 82.3% F1 (5.2% higher than DynamicRAG), 72.5% EM (5.7% higher), 89.5% R@10, and 2.1% hallucination rate (4.5% lower than RLHF-RAG). Its annotation cost (4.2h) is only 17.5% of RLHF-RAG, with 8.5h training time and 135ms inference latency, balancing accuracy and efficiency.

Table 1. Performance comparison of different models on FeedbackQA test set.

Model	F1 Score (%)	EM Score (%)	R@10 (%)
Static RAG	71.5	64.3	77.2
RLHF-RAG[2]	76.8	67.1	83.5
Self-RAG[4]	75.2	65.9	81.7
DynamicRAG[3]	77.1	66.8	85.8
Few-Shot RAG[5]	76.4	66.2	84.2
ReasonRAG[9]	79.6	69.8	87.4
Proposed System	82.3	72.5	89.5

4.3 Cold-Start Experiment

On the HotpotQA-small split, the system starts out at 68.5 % F1, already ahead of both RLHF-RAG (65.2 %) and Few-Shot RAG (66.8 %), it then keeps improving at a rate of 3.20 F1 points for every 100 pieces of feedback—61.6 % faster than RLHF-RAG—and needs only five iterations to converge, 37.5 % fewer than RLHF-RAG, which together confirm that FCS can bootstrap itself under tight resource budgets.

4.4 Module Ablation Experiment

Ablation results confirm each module's value: removing CFL reduces F1 by 6.8% and raises hallucination rate by 3.7%; removing FCS boosts annotation cost to 18.3h; removing RGA decreases F1 by 7.1%. The complete model's superiority proves their synergistic effects.

4.5 Cross-Domain Experiment

On Medical-DocQA (78.6% F1) and Legal-QA (76.9% F1), the system achieves 77.75% average F1 (5.9% higher than DynamicRAG) with only 1.7% inter-domain gap. Domain-adaptive pseudo-feedback and CFL weight adjustment ensure stable generalization, outperforming baselines without cross-domain tuning.

5 Discussion

This section digs into the experimental results in detail, spells out the main strengths the proposed system shows in everyday use, points to the spots where it still struggles, and then, against the backdrop of where the field seems to be heading next, sketches several concrete ways the design could be pushed further, all of which together make the theoretical payoff and the real-world usefulness of the work easier to see.

5.1 Core Advantages and Theoretical Contributions

The proposed system achieves key breakthroughs in low-resource RAG scenarios. CFL establishes an interpretable "feedback-root cause-optimization" mapping, solving the low feedback utilization issue of traditional black-box optimization. FCS constructs a few-shot cold-start paradigm via high-quality pseudo-feedback generation, screening and fusion, reducing reliance on large-scale manual annotation. RGA realizes lightweight cross-module collaboration through a cross-attention structure, addressing fragmented retrieval-generation optimization. These innovations collectively overcome traditional RAG's core bottlenecks, providing new insights for closed-loop optimization research.

5.2 Limitations and Future Work

Despite the system's significant advantages, it has several limitations to address. First, the CFL system only defines 4 feedback labels, failing to cover complex mixed scenarios or domain-specific demands. As structured feedback alignment is critical for RAG performance enhancement [10], future work will expand the label system with a hierarchical mechanism (primary: problem category; secondary: specific subtype) to adapt to diverse needs. Second, fixed objective function weights lack domain adaptability—professional fields prioritize factual accuracy, while general domains value efficiency more. This paper will explore adaptive weight strategies based on domain similarity and feedback distribution for dynamic multi-objective balance. Third, GPT-4o Mini-generated pseudo-feedback may introduce domain bias and noise in professional fields. A domain-adaptive calibration mechanism will be proposed, including small-sample pre-training and manual verification for high-risk pseudo-feedback to enhance reliability, referring to relevance-aware adaptive learning paradigms [11]. Fourth, the RGA only synchronizes signals without task complexity-based adjustments (e.g., stronger interaction for multi-hop reasoning). Researchers will develop a task-aware framework to dynamically tune adapter attention weights for diverse tasks.

6 Conclusion

This study proposes a user feedback-based closed-loop RAG optimization system integrating CFL, FCS, and RGA modules. Experiments on FeedbackQA, HotpotQA-small, and cross-domain datasets verify its superiority over six baseline models, achieving 82.3% F1 score, 2.1% hallucination rate, and annotation cost only 17.5% of traditional methods. The system balances performance and efficiency, effectively solving cold-start, fragmented optimization, and low feedback utilization problems. It provides reliable technical support for RAG's practical deployment in professional fields and lays a solid foundation for future interpretable and adaptive closed-loop RAG research.

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