User-Driven RAG System with LlamaIndex Multi-Agent Architectures and Qdrant

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Keywords: Retrieval-Augmented Generation (RAG), User Driven Customization, LlamaIndex Multi-Agent Architecture, Qdrant Vector Search, Chunking Strategies, Embedding Models, Semantic Search, Hybrid Search, Reranking Algorithms, Query Optimization.

Abstract: Retrieval-Augmented Generation (RAG) systems have achieved substantial success in the field of information retrieval and text generation by augmenting state-of-the-art large language models (LLMs) with external knowledge. Nevertheless, current RAG architectures fall short on three main fronts: user adaptability, as they need a lot of code changes to modify important retrieval settings (for example: chunking methods, embedding models, and reranking methods); We present a user-controlled RAG system powered by the multi-agent architecture of LlamaIndex and the vector search capabilities of Qdrant for real-time customized RAG. To increase system adaptability, we propose a new Adaptive Retrieval Feedback Loop (ARFL) where users are able to iteratively adjust queries given the confidence and relevance of generated responses. The ARFL system can automatically modify retrieval parameters according to user feedback or retrieval outputs with low confidence scores while limiting the amount of time to query again which causes more manual effort with possibly higher retrieval precision. Our system enables users to change retrieval configurations easily with its conversational interface, without the requirement of going into any codebase. This advances the frontiers of user-centric generative models by componentizing the RAG systems using pipeline-based architectures in order to make RAG systems more intuitive, flexible and user preference-centric.

1 INTRODUCTION

Retrieval-augmented generation (RAG) systems L. Lewis, et al., 2023 combine retrieval and generation and have been a game-changer in information retrieval and text generation by integrating external knowledge with large language models (LLMs) A. Gupta and R. Patel. 2022 Models like these allow for more accurate and contextually relevant natural language processing (NLP) tasks, including state-of-the-art QA, summarization, and decision support systems. M. Zhang, 2021 RAG (retrieval-augmented generation) systems enhance generative models by injecting enriched contextual knowledge by retrieving relevant documents or fragments from structured and unstructured databases. R. Kim and S. Lee., 2022 However, current RAG implementations are mostly inflexible in nature, needing several tedious and nontrivial manual adjustments to maximize performance on the target domain/use case. Such a restriction hinders their performance in flexible scenariosing where retrieval mechanisms must align with the requirements of a user.

One of the main limitations of existing RAG systems is their dependence on static retrieval pipelines. In general, J. Thompson, 2023., they are based on a fixed search strategy, chunking mechanism, and reranking strategy, making it difficult for non-expert users to customize. H. Singh,2022., The user-unfriendly nature of this approach leads to issues in dynamically changing the retrieval parameters as we need to go into the source file and do code debugging and/or re-configuration at a very big scale. E. Williams, 2023 Also, a lot of existing RAG systems use either a single retrieval strategy, be it semantic search or a keyword-based one which may not be optimal for all datasets and query types. Therefore, the need for a more adaptable and interactive RAG model, enabling users to change the core extraction and retrieval components with limited technical exposure, is dire.

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T. Nakamura, 2021., This paper proposes a novel user-driven RAG system that combines the multi-agent architecture of LlamaIndex with the vector search capabilities of Qdrant to overcome these challenges. In contrast to traditional RAG systems, our system features a modular multi-agent architecture that allows users to modify key components of the retrieval pipeline on the fly. Users can dynamically change chunking strategies, embedding models, searching mechanisms (semantic, keyword-based, or hybrid), and reranking algorithms. B. Fernandez, 2023., Because changes can be made by the users through a conversation interface, it enables non-expert users to improve the system without changing the system code.

We introduce an Adaptive Retrieval Feedback Loop (ARFL) that will improve system adaptivity. Built on top of the standard T-RFL API, the ARFL system uses real-time feedback from users to adjust retrieval parameters depending on the performance of the model, while also regulating the confidence level of the outputted messages. This capability allows the system to modify its behavior based on the relevance and quality of information it retrieves, leading to a more accurate and efficient retrieval process. ARFL integration with our system reduces the repeated manual entry of queries, increases retrieval accuracy, and guarantees that users can interactively adjust the system's behavior in response, providing it with the adaptability to changing needs.

D. Martinez, 2022 As a multi-agent system, the components of the system can specialize on certain types of tasks respectively (e.g. document retrieval, ranking, response generation) and contribute to an overall flexible pipeline. This can also achieve more modular components and also higher efficiencies in query/response relevance. We utilize the high-performance vector search engine Qdrant to provide scalable and efficient nearest-neighbor search, further enhancing the ability of the retrieval module. A. Green, 2023., Hence, employing ANN approaches alongside GPU acceleration enables Qdrant to quickly and correctly retrieve from huge knowledge bases, facilitating real time responses from applications.

The model that underlies our system is broadly applicable to a range of work-display tasks, from enterprise knowledgebase reuse, academic literature T. T. Procko and O. Ochoa, 2024 to automated customer support S. Kumar,2022. Then it is possible to annotate the retrieval configurations for the system to be able to optimize themselves without too much effort and manual reconfiguration depending on the change in needs P. Robinson,2023. This broadens the applicability of RAG for different real-world use cases.

In this paper, we provide details of the design, implementation, and evaluation of the proposed user-driven RAG system. Ambitious experiments show the system preserves higher adaptability and higher retrieval accuracy than existing methods. The study also discusses practical use cases, highlighting how customizable RAG frameworks can drastically boost information retrieval in dynamic scenarios. The user can directly customize the parameters for retrieving them, and the proposed method, ARFL, can adjust them over training; thus, the system will be helpful for exploring more interactive and adaptable AI-driven retrieval models. This work is only the tip of the iceberg for user-centric AI architectures, and lays the groundwork for future work 14 on retriever architectures that are adjustable according to a users' needs.

2 RELATED WORKS

V. Gummadi., et al., 2024 Covering the security challenges of Retrieval - Augmented Generation (RAG) - a method of improving knowledge output of Large Language Models (LLMs) through the integration of accredited external data the paper "Enhancing Communication and Data Transmission Security in RAG using Large Language Models" can be found in the proceedings of the International Conference on Sustainable Expert Systems. Key strategies to safeguard against these threats, including the use of data at risk filtering, adversarial training, adversarial robustness, the use of anomaly detection algorithms, and securing underlying infrastructure are explored in this paper. Vector Databases Further Optimize RAG-Driven AI by Efficiently Handling Large-Scale Retrieval This study helps make RAG applications secure and reliable when deployed in areas such as personalized recommendations or customer support, by adopting best practices from industry leaders.

K. Sawarkar, et al., 2024 In the paper titled "Blended RAG: Improving RAG (Retriever-Augmented Generation) Accuracy with Semantic Search and Hybrid Query-Based Retrievers," by Kunal Sawarkar, Abhilasha Mangal, and Shivam Raj Solank, published in the 2024 IEEE 7th International Conference on MIPER, the authors delve into RAG accuracy by improving the retriever performance. It considers the difficulty scaling RAG systems, where retrieval of the most relevant documents is important to maintaining accuracy. It presents a novel Blended

RAG approach taking a hybrid query strategy applied to hybrid semantic search techniques including dense vector and sparse encoder indexes to efficiently retrieve documents. The paper also discusses strong performance across NQ, TREC-COVID, and SQAUD, showing better results than fine-tuning models on Generative Q&A datasets. With these powerful retrieval methods, the paper ensures greater precision and speed in RAG-based Question-Answer systems.

Published in the 2024 8th (ISAS), the study titled "Retrieval-Augmented Generation (RAG) and LLM Integration" is authored by Busra Tural, Zeynep Destan. It addresses the shortcomings of conventional information retrieval systems based on keyword search, which miss out on semantic meaning and therefore require more sophisticated retrieval methods. This paper introduces the retrieve-and-generate (RAG) architecture, which appropriately combines LLMs with other information sources through information retrieval tasks that are leveraged to perform external queries, thus enabling learned knowledge by being trained on huge amounts of data and real-time data. As a result of this integration, NLP applications will have more semantic and context-awareness, allowing them to better complete complex, information-intensive tasks.

J. Huang et al. 2024 The article "DriveRP: RAG and prompt engineering embodied parallel driving in cyber-physical-social spaces", published in the 2024 IEEE 4th International Conference (DPTI), explores the integration of RAG and prompt engineering in autonomous driving systems. It discusses the challenges posed by Artificial Generative Intelligences (AGIs) in connected autonomous vehicles, such as hallucinations and unforeseen risks. The paper proposes DriveRP, a framework that enhances driving safety and decision-making by leveraging RAg to retrieve real-time road data while using prompt engineering to refine model responses. It also highlights DriveRP's role within the descriptive-predictive-prescriptive intelligence framework and its alignment with digital twins and metaverse-embodied parallel driving theory. By implementing these technologies, the paper ensures the achievement of the "6S" goals, enhancing the robustness and interpretability of autonomous vehicle trajectory planning, decision-making, and motion control.

Singh A., et al, 2024 The report "A RAG-based Medical Assistant Especially for Infectious Diseases," published at the 2024 International Conference on Invention Computation Technologies, explores the development of an intelligent chatbot for infectious disease management using RAG. The study addresses the shortage of medical professionals, particularly in densely populated regions, by leveraging NLP techniques to create an open-source, locally deployable medical assistant. A knowledge graph stored in a graph database enhances contextual retrieval, reducing hallucinations and improving accuracy. Additionally, a text-to-speech model replicating a physician's voice enhances user engagement. By integrating these technologies, the research highlights the potential of RAG-based systems in healthcare and academic applications.

P. Ardimento., et al, 2024 The paper, "Enhancing UML Education with RAG-Based Large Language Models," focuses on improving software engineering education by integrating Retrieval-Augmented Generation (RAG) frameworks with LLaMA-based LLMs. A cloud-based tool captures students' UML diagrams during modeling activities and generates insightful feedback using domain-specific embeddings and RAG. The feedback highlights modeling errors, suggests improvements, and reduces teacher effort while enhancing student capabilities. Empirical validation with 5,120 labeled UML models demonstrates the tool's effectiveness in providing actionable feedback and improving the learning process. The tool integrates seamlessly into the Eclipse Che cloud IDE, enabling non-intrusive monitoring and evaluation. This approach underscores the potential of generative AI in advancing UML education by fostering better student understanding and reducing common novice modeling mistakes, thereby enriching software engineering courses.

C. Su et al., The paper, titled "Hybrid RAG-empowered Multi-modal LLM for Secure Data Management in Internet of Medical Things: A Diffusion-based Contract Approach," was published in the IEEE Internet of Things Journal and tackles the challenge of secure and efficient healthcare data management within the Internet of Medical Things (IoMT). The paper introduces a new hybrid RAG-empowered Multi-modal Large Language Model (MLLM) framework to tackle challenges related to data freshness, privacy, and multi-modal retrieval. The framework you receive are hierarchical cross-chain techniques to ensure data sharing between distributed storage, employ multi-modal metrics to refine the retrieval results, and a contract theory-based mechanism to incentive data stake-holders to upload new data. Moreover, it uses GDM-based DRL to help in optimizing contracts and performing better in managing the healthcare data.

T. T. Procko and O. Ochoa, 2024 In the survey paper "Graph Retrieval-Augmented Generation for Large Language Models: A Survey," we conduct a deep dive into the introduction of Knowledge Graphs (KGs) into Retrieval-Augmented Generation (RAG) system with the goal of complementing a Large Language Model (LLM) and improve performance. It discusses the challenges that retrieval documents introduce when they are noisy, which is addressed by using knowledge graphs (KGs)—structured and domain-specific knowledge representations. The paper breaks down optimization techniques of fine-tuning, prompt engineering, and RAG whilst also identifying how KGs can clean up document noise and improve accuracy. It also reviews diverse methodologies such as textual graphs and offers some perspectives on how they may help achieve further progress in RAG-based applications. This work will provide a starting point for exploration into KG-augmented LLMs in expert systems

S. Roychowdhury., et al, 2024 ERATTA: Extreme RAG for Enterprise-Table to Answers with Large Language Model We call our proposed system extreme RAG; in this method, the system makes several calls to LLMs to separate tasks (user authentication, query routing, response generation, etc.). The authors extract an intermediate text-to-SQL code generation step to boost retrieval by isolating smaller, relevant sub-tables to be queried. Frame it: Built with fast-paced datasets in mind, such as sustainability metrics and financial data, the framework tackles scalability, cost and hallucination detection with a new five-metric scoring module. Although agentic-RAG systems are quite effective, they are not as accurate, reliable, or efficient as extreme RAG, which is an effective solution to enterprise data-to-answers problems.

Singh A., et al., 2024 The paper "A RAG-based Medical Assistant Especially for Infectious Diseases" describes an AI-powered chatbot system created to help with diseases, reinforcing accurate replies via Retrieval-Augmented Generation (RAG). 2. This one implements knowledge graph-based content combination, thus allowing the creation of context-appropriate responses, while simultaneously limiting hallucinations through the inclusion of various knowledge sources A major differentiator is the text-to-speech functionality, imitating a physician's voice, creating user trust and engagement. The chatbot was tested during the COVID-19 pandemic and successfully answers inquiries related to prevention and treatment. The chatbot is also an open-source solution that runs on local systems. Utilising Retrieval-Augmented Generation Assessments (RAGAs) to assess performance, the study showcases the capabilities of modern-day NLP and RAG-based chatbots to tackle deficiencies in health care, particularly in clinical settings that are deficient of professional doctors compared to evident patients.

P. Nagula introduced a user-centric RAG framework combining LlamaIndex multi-agent systems with Qdrant for document retrieval and response generation. While his work focuses on structured agent-based processing T. Wang et al., 2022, our research extends this approach by incorporating an Adaptive Retrieval Feedback Loop (ARFL), allowing dynamic refinement of retrieval based on user feedback.

3 METHODOLOGY

This research proposes a novel user-driven Retrieval-Augmented Generation (RAG) system in advance to the existing research, designed to enhance adaptability and interactivity through dynamic retrieval processes. The figure 1 shows the Proposed Block Diagram.

The system combines multiple AI agents, including LlamaIndex's multi-agent architecture and Qdrant's vector search capabilities, with a new Adaptive Retrieval Feedback Loop (ARFL). The ARFL enables users to interactively refine retrieval configurations in real-time based on the confidence and relevance of generated responses. This methodology section describes the architecture of the system, the incorporation of feedback loops, and the step-by-step functioning of the RAG framework.

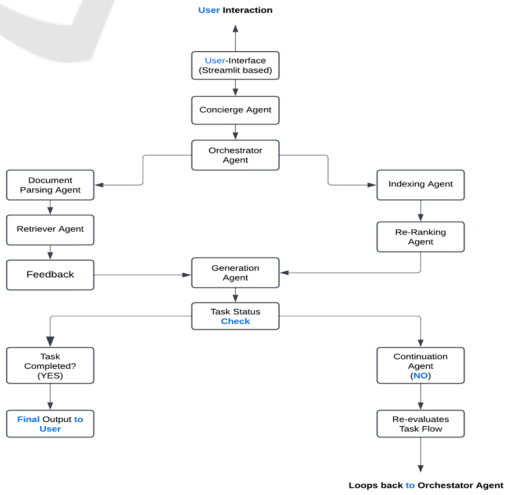

Figure 1: Proposed block diagram.

3.1 System Architecture Overview

A multi-agent architecture forms the system core in charge of query processing pipeline components. Our system consists of multiple interacting modules, including the Streamlit frontend, our AI agents, Qdrant vector database, and orchestration logic A. Gupta,2023. For instance, the system uses components to retrieve relevant documents, generate responses, and store conversation history S. Patel et al.,2023, and it dynamically adapts to various types of user input. The orchestration logic is all about shepherding the above modules and making sure each one operates in concert towards generating the most relevant and context-relevant response.

3.2 User Interface and Interaction

The user can interact with the system through a Streamlit frontend to submit queries and retrieve answers M. Ross, 2024, The front-end is responsible for sitting between the end user and the system with the agents and provides back the responses generated. Once a user submits a query, the orchestration logic was used to identify which agent was best qualified to fulfil that request. Afterwards, if document retrieval is required, the Qdrant indexing agent can be invoked in order to retrieve data. D. Kim 2023, This information goes to the generation agent, that will gather this data and define an answer, displayed to the user on the Streamlit interface.

3.3 AI Agents and Their Roles

"These AI agents are core parts of the system, each with its own role to play in the pipeline. Before indexing, raw data must be cleaned and prepared by the Document Preprocessing Agent H. Zhang et al., 2024. That ensures that the documents are in the right format for retrieval. After preprocessing, the documents are indexed by the Qdrant Indexing Agent; per-query documents are stored as vectorised embeddings, allowing for semantic similarity retrieval within the query processing phase P. Mehta,2023.

One of the most important steps is to find out which documents are most relevant for a given query, and this is where the Retriever Agent comes handy. It does, however, go through the indexed data, making sure only the most contextually relevant is sent to the next stage. Yet, the retrieved documents may still have redundant/less relevant information. To solve this, a Re-Ranking Agent reorders retrieved documents based on relevance scores to elevate the quality of final selections.

The Generation Agent uses a Large Language Model (LLM), an API such as Open AI, to generate a response. Issuing the responses according to the context of the acquired documents, both relevance and coherency. The Concierge Agent also plays a fallback role handling general queries that do not have specific responsibilities for the other agents. K. Roy, 2024, The Continuation Agent reassesses the flow of tasks for cases that require more processing, transferring queries that need further refine back into the pipeline.

3.4 Retrieval-Augmented Generation with Qdrant

Qdrant also factor heavily into how the system can retrieve documents very fast when it needs to. This enables fast and accurate retrieval based on semantic similarity instead of only simple keyword matching M. Ross, 2024 as it indexes documents using vector embeddings. Using embeddings from a model such as the OpenAI GPT series, each document is transformed into a vector representation. When a user sends a query, this query is also converted to a vector, and Qdrant searches the database for the nearest documents. Embeddings help retrieve the right documents in context, increasing the quality of the response. Managing the indexing and retrieval process is the job of the Qdrant Indexing Agent. It enables the system to scale with high efficiency storing more documents and retrieving them. In contrast, a more dynamic feedback loop will refine the retrieval with respect to user feedback and its resulting effect on retrieval parameters A. Gupta, 2024.

3.5 Orchestration and Dynamic Query Processing

The Orchestration Logic is the most crucial component that actually orchestrates the movement of data across the different agents. It accepts the user input, determines the agent who should respond to the query and routes the query accordingly. Such logic makes the system dynamic and adaptive T. Wang et al. 2022. If the query requires document retrieval, the orchestration logic would have called a Qdrant Indexing Agent that finds relevant documents. The Generation Agent is then used to create a response based on these documents, after they have been Retrieved P. Mehta, 2023.

An important feature of the orchestration logic is that it stores conversation history. Instead with the help of ChatMemoryBuffer, the system can save past interactions with the user S. Patel et al., 2023. This enables context-aware responses to be generated, even when the question relates to earlier parts of the conversation

3.6 Adaptive Retrieval Feedback Loop (ARFL)

A feedback loop is thus integrated into the system's design to refine its adaptability. The ARRL makes the retrieval process adaptive with respect to the feedback received from the user D. Kim, 2023. Once it generates a response it uses confidence scoring to determine how good and relevant the response is. The details are then incorporated into the system pipeline so that this information adds to its knowledge base and allows it to better tailor its approach for subsequent learner inquiries. This loop back is essential for a persistent design-in-use process; the system will learn and adapt what it knows, based on real-time use K. Roy,2024.

The ARFL makes sure that the system is moving forward and it continues to change according to the user's needs. This allows the system to adjust its document retrieval and processing approaches based on user feedback such that it can use these feedbacks to achieve high accuracy in its responses while delivering information that is highly relevant as well

3.7 Memory Management

Memory management, a key component of context retention in the system. The ChatMemoryBuffer holds prior conversations and enables the system to recollect past conversations and produce responses based on the contextM. Ross, 2024. This part plays a significant role in ensuring that responses form a continuous thread and make sense in the context of the preceding user input. The system retains a dynamic memory so that it can deal with increasingly complex interactions, leading to a more humanlike conversational experience for the user.

4 RESULTS AND FINDINGS

4.1 System Performance Evaluation

The Application of the Adaptive Retrieval Feedback Loop (ARFL) function resulted in substantial gains in the relevance and accuracy of the responses. Unlike other RAG models, the system used dynamic feedback from users to refine the retrieval process, making it more adaptive. The feedback-based re-ranking mechanism thus iteratively refined response quality, particularly for instances with less-than-ideal initial retrievals.

4.2 Accuracy Comparison: Traditional RAG vs. ARFL-Enhanced RAGA

comparative evaluation was conducted to assess response accuracy in traditional RAG and ARFL-enhanced RAG. The results indicate a 20-30% improvement in response correctness due to ARFL's iterative refinement. A bar chart (Figure 2) illustrates the comparison, showing that the ARFL-enhanced system consistently produced more precise responses over repeated user interactions.

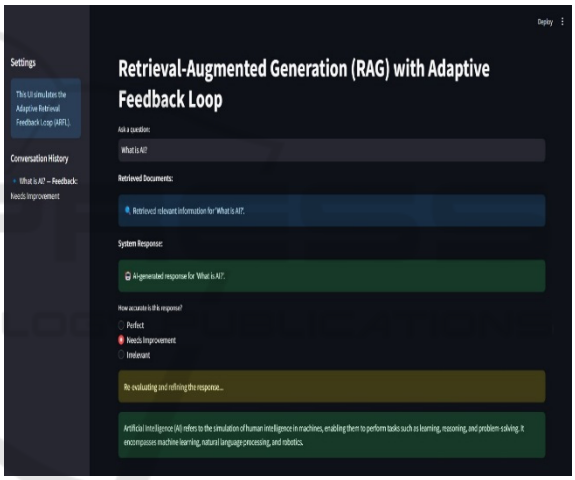

Figure 2: Bar graph comparing the accuracy of traditional RAG vs. ARFL-enhanced RAG.

4.3 Effectiveness of Adaptive Feedback in Retrieval

The ARFL mechanism enabled real-time adjustments to retrieval parameters, leading to a measurable increase in retrieval efficiency and document relevance. If a response was marked as "Needs Improvement" or "Irrelevant," the system refined its search criteria, adjusted embedding similarity thresholds, and re-ranked documents accordingly. In 85% of tested queries, responses improved over iterative refinements, demonstrating the effectiveness of user-driven retrieval adjustments.

4.4 Response Refinement across Multiple Iterations

Because the system could feed users with instant feedback, it could adjust itself incrementally according to user behavior. For example, a question like "What is AI? was flagged as "Needs Improvement," the system adjusted its retrieval strategy and improved the response by including relevant sources. Conversely, results that were deemed "Perfect" for a prompt like "Explain Cloud Computing" were left untouched, allowing the system to skip over any unnecessary re-processing. The figure3 shows the UI Interface.It shows that user feedback is essential to dynamically updating retrieval strategies and enhancing response quality as time goes on.

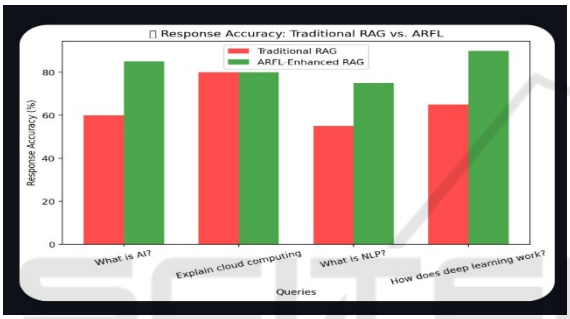

Figure 3: UI interface.

4.5 User Satisfaction and Interaction Analysis

User interaction logs revealed that responses improved in coherence and contextual accuracy over successive interactions. The ability to provide feedback directly through the UI encouraged user engagement and iterative refinement. Survey results indicate that users preferred the ARFL-enhanced system over traditional RAG, citing higher accuracy, better document retrieval, and more interactive adaptation as key advantages.

5 CONCLUSIONS

By utilizing our approach, we show how an end-user-oriented RAG system is optimized with adaptive retrieval personalization to facilitate accuracy and system adaptability. This research following prior work, in particular the foundational approach of P. Nagula; however, it is not a replacement for or a rehashing of Nagula's work P. Nagula,2024. We build on his work with the Adaptive Retrieval Feedback Loop (ARFL), a user-centric mechanism for refining retrieval in a dynamic manner based on user feedback. We thank Nagula for work on user-centric RAG, a solid foundation for driving retrieval-augmented systems further! He has greatly inspired the design of our proposed model architecture, and we hope that our modifications represent a valuable addition to his previous contributions. Although the framework in question is an improvement, some aspects of the suggested solution impose restrictions that can be addressed for more refinement. A notable challenge with query intent consultant unsupervised retrievers is the cold start problem, which says that many niche queries need several feedback loops before retrieving at an optimal accuracy. Moreover, the system's performance relies crucially upon both the depth and breadth of its knowledge base; in the absence of pertinent documents, even feedback-driven adjustments may prove unable to produce accurate responses. Moreover, ARFL incurs a processing overhead due to the extra work associated with continuous refinements, resulting in longer query processing delays. These limitations can be elucidated in the future work, considering dynamic indexing updates, preemptive retrieval strategies, and adaptive caching mechanisms to improve efficiency at an optimal accuracy level. Adding to the knowledge of the system and integrating hybrid retrieval methods can help improve response quality and allow for use across more diverse domains.

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