HD-RAG: Retrieval-Augmented Generation for Hybrid Documents Containing Text and Hierarchical Tables

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Ouestion

With the rapid advancement of large language models (LLMs), Retrieval-Augmented Generation (RAG) effectively combines LLMs' generative capabilities with external retrieval-based information. The Hybrid Document RAG task aims to integrate textual and hierarchical tabular data for more comprehensive retrieval and generation in complex scenarios. However, there is no existing dataset specifically designed for this task that includes both text and tabular data. Additionally, existing methods struggle to retrieve relevant tabular data and integrate it with text. Semantic similarity-based retrieval lacks accuracy, while table-specific methods fail to handle complex hierarchical structures effectively. Furthermore, the QA task requires complex reasoning and calculations, further complicating the challenge. In this paper, we propose a new large-scale dataset, DocRAGLib, specifically designed for the question answering (QA) task scenario under Hybrid Document RAG. To tackle these challenges, we introduce HD-RAG, a novel framework that incorporates a row-and-column level (RCL) table representation, employs a two-stage process combining ensemble and LLM-based retrieval, and integrates RECAP, which is designed for multi-step reasoning and complex calculations in Document-QA tasks. We conduct comprehensive experiments with DocRAGLib, showing that HD-RAG outperforms existing baselines in both retrieval accuracy and QA performance, demonstrating its effectiveness.

CCS Concepts

• Information systems \rightarrow Information retrieval; • Computing methodologies \rightarrow Natural language generation.

Keywords

Abstract

Information Retrieval, Question Answering, Retrieval-Argument Generation

1 Introduction

With the rapid development of large language models (LLMs)[13, 19], Retrieval-Augmented Generation (RAG) has emerged as an effective strategy that combines the generative power of LLMs with external retrieval-based information. Recent research has extended the application of RAG to various scenarios, including knowledge graph[16, 23], database[2], and multi-modal data[14, 31]. However, research on the Hybrid Document RAG remains in its nascent stages. Hybrid Document RAG aims to combine both textual and tabular data with the power of LLMs for more comprehensive retrieval and generation. In real-world applications, Hybrid Document RAG

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If the growth rate observed in the previous year continues, what will be the sum of Total Buy and Revenues of

Electric Sales to Affiliates for 2014?

Retrieval from Document Repo

Retrieval Corresponding Document

[...abbreviate...]

The following table summarizes, by currency, the contractual amounts of the company's foreign currency forward contracts for continuing operations.

Hierarchical Header

December 31	2	013	2012	
(dollars in millions)	Buy	Sell	Buy	Sell
Euro	\$-	\$2.2	\$-	\$1.5
Canadian dollar	-	35.4	-	18.9
Mexican peso	11.2	_	10.9	-
Total	\$11.2	\$37.6	\$10.9	\$20.4

[...abbreviate...]

The primary affiliated company transactions for FES during the three years ended December 31, 2013 are as follows:

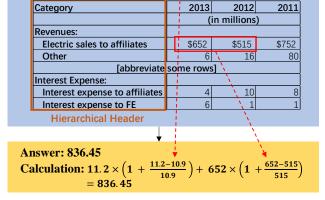


Figure 1: An Example of Hybrid Document RAG Task

proves valuable in scenarios like document management and financial analysis, where it efficiently retrieves and synthesizes relevant information from large, complex documents.

In this paper, we focus on the question answering(QA) task based on Hybrid Document RAG. The task involves retrieving the most relevant documents from extensive document repositories based on a specific question and generating the corresponding answer. However, it is challenging due to the complexity and scale of real-world document repositories, which often contain numerous

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indistinguishable documents with intricate structures. For example, Statistics Canada¹ offers thousands of statistical reports across subjects, including 1,761 on "Labour" and 1,132 on "Population and demography", with semantically similar content often combining textual descriptions and hierarchical tables.

Some novel RAG techniques [3, 11, 12, 20] have been explored to improve retrieval accuracy by enhancing RAG frameworks. While effective in text-based tasks, these methods often fail to capture the critical table information within retrieved documents. Other table-focused RAG techniques [2, 9, 16, 17] lack seamless integration of table data with text, resulting in incomplete representations and difficulty handling complex hierarchical structures. As shown in Figure 1, when retrieval relies on the hierarchical structure of a table, such methods often break down the complex structure, leading to information loss and a reduced ability to capture critical relationships within the data. Additionally, while well-established documentbased QA methods [18, 25, 26] have demonstrated relatively high accuracy, they still struggle with complex OA tasks involving hybrid documents with long text and hierarchical tables[30]. Overall, although existing methods have provided preliminary solutions for QA tasks under Hybrid Document RAG, achieving more precise retrieval and QA still faces numerous challenges.

Challenge 1: There is no existing dataset specifically designed for the Hybrid Document RAG task that includes both text and tabular data. Furthermore, the dataset requires thorough cleaning to resolve inconsistencies and ensure uniformity across various document types, formats, and structures.

Challenge 2: Hybrid Documents consist of a large amount of both complex tabular and textual data. The primary challenge lies in how to represent the structured data within these documents. As shown in Figure 1, the key terms "Total Buy" and "Revenues of Electric Sales" are strongly linked to the hierarchical structure within the Hybrid Document, and the information contained within tables is dense, highlighting the challenge of representing structured data in such documents. Therefore, the representation must accurately capture the document's structure while preserving key information, even within complex hierarchical relationships. Additionally, the presence of both tabular and text data in Hybrid Documents complicates the task of integrating these heterogeneous data types into a unified and effective representation for retrieval and QA.

Challenge 3: The challenge with traditional semantic similarity-based retrieval methods lies in their inability to ensure both the accuracy and completeness of the retrieved information for complex QA tasks in Hybrid Document RAG. These methods often return text chunks that, while semantically related to the question, may not provide valid evidence for reasoning. For example, as shown in Figure 1, a semantic similarity-based retrieval method might retrieve documents focused on information from 2014, while the relevant historical data pertains to 2012 and 2013.

Challenge 4: Hybrid Document QA often requires integrating information from text and table modalities, necessitating the ability to process and reason across tabular and textual data to answer complex questions accurately. It requires aligning information from multiple data sources to ensure relevance between text and table data. As shown in Figure 1, the process involves intricate reasoning,

where the year "2014" leads to the use of data from "2013" and "2012", followed by six steps of calculations to generate the correct answer.

To address the above challenges in Hybrid Document RAG and downstream QA task, we propose the DocRAGLib dataset and HD-RAG framework. Specifically, DocRAGLib consists of a document repository with 2,178 documents, each of which combines text and hierarchical tables, as well as 4,468 QA pairs. DocRAGLib is collected from reliable sources and cleaned to ensure consistency across document types and formats, making it suitable for Hybrid Document RAG task. To the best of our knowledge, DocRAGLib is the first dataset designed for solving the QA scenario under the Hybrid Document RAG task.

HD-RAG framework consists of three modules: Corpus Construction Module, Retrieval Module, and QA Inference Module. Specifically, the Corpus Construction Module employs a hierarchical row-and-column-level (H-RCL) table summarization method to capture the structure and content of complex tables. It generates representations that preserve table structures and are optimized for retrieval, addressing the challenge of effectively representing table information in hybrid documents. The Retrieval Module overcomes the limitations of relying solely on semantic similarity retrieval by adopting a two-stage approach. The ensemble retrieval stage combines BM25 with the semantic understanding of embedding retrieval to filter candidate documents. Then LLM-based retrieval utilizes the contextual reasoning ability of LLMs to identify the most relevant document, improving the accuracy and comprehensiveness of retrieval. The QA inference Module introduces the RECAP method, which decomposes complex reasoning into sub-tasks and leverages external calculators to manage mathematical operations during the reasoning process. HD-RAG enhances answer accuracy and effectively addresses the challenges of multi-step reasoning and complex calculations in hybrid documents.

In summary, our main contributions are as follows:

- We propose a new large-scale dataset, DocRAGLib, specifically designed for the QA task scenario under Hybrid Document RAG. This dataset provides a high-quality benchmark for complex retrieval and QA tasks.
- We design the HD-RAG framework, which consists of three components: the Corpus Construction Module, the Retrieval Module, and the QA Inference Module. The framework first effectively represents hierarchical tables in documents using an H-RCL table summarization method. It then enhances retrieval accuracy by combining a two-stage retrieval strategy and finally improves QA accuracy with the RECAP method, providing an efficient and precise solution for QA tasks under the Hybrid Document RAG scenario.
- We conduct extensive experiments to validate the superior performance of the HD-RAG framework in retrieval and QA tasks compared to baseline methods. Ablation studies confirm the effectiveness of each module, and sensitivity analysis demonstrates the framework's robustness across different corpus sizes.

2 Related Work

In this section, we present an overview of relevant research from two perspectives: RAG and Document QA.

¹https://www.statcan.gc.ca

2.1 RAG

RAG has significantly enhanced language models, particularly in knowledge-intensive tasks involving document data. This section presents existing work from two main aspects: advancements in RAG techniques[1, 3, 7, 11, 12, 20, 21, 27] and its applications across different modalities[2, 9, 10, 16, 17].

Advancements in RAG techniques aim to improve retrieval accuracy, efficiency, and robustness in knowledge-intensive tasks. Izacard et al. [12] use knowledge distillation to train retrievers without annotated query-document pairs, relying on reader model attention for synthetic labels, though it depends on the reader model's quality. RETRO [3] combines document chunks retrieved by local similarity with preceding tokens in auto-regressive models but faces challenges with long documents. DAPR [20] addresses this by integrating hybrid retrieval with BM25 and contextualized passage representations for long document passages. Open-RAG[11] improves multi-hop reasoning and retrieval accuracy by transforming dense LLMs into the parameter-efficient sparse mixture of expert models. However, these methods primarily focus on text-based RAG, with limited progress in handling mixed modalities, which pose unique retrieval and reasoning challenges.

Recent advancements in RAG have extended to multimodal data beyond text. TAG[2] and ERATTA[17] introduce RAG frameworks for table-structured data. Chen et al.[4] propose a method combining join relationship discovery and mixed-integer programming-based re-ranking for table retrieval. RAGTrans[9] integrates textual and multimedia information for enhanced representation and retrieval. KRAGEN[16] introduces a knowledge graph-enhanced RAG framework that uses graph-based retrieval to improve factual consistency and reasoning in biomedical problems. MRAG-Bench [10] focuses on vision-centric RAG, highlighting cases where visual knowledge outperforms textual information, especially for vision-language models. However, none of these approaches address RAG for the combined modality of tables and text within documents, a gap that HD-RAG specifically addresses.

2.2 Document QA

Document QA refers to the task of extracting or generating answers based on the content of a given document. This section reviews existing approaches to Document QA from two primary perspectives: methods leveraging pre-trained language models[6, 8, 28, 29, 32] and methods utilizing LLM[5, 15, 18, 24, 30].

In Document QA, pre-trained NLP models are fine-tuned to process document-question pairs, enabling them to extract information or generate answers based on the content. HybridQA[6] and TAT-QA[32] apply QA tasks to text-table hybrid documents, but their tables are typically flat. HiTab[8] focuses on hierarchical table-based QA tasks but struggles with hybrid data combining text and hierarchical tables. Zhao et al.[29] introduce the MultiHiertt benchmark, containing both text and hierarchical tables and propose MT2Net for this task. MT2Net extracts facts from hybrid documents and performs reasoning, but it has high content requirements and depends heavily on table cell descriptions for accurate reasoning. NAPG[28] outperforms MT2Net on MultiHiertt, yet existing NLP models still face challenges with multi-step reasoning, especially in complex mathematical computations.

Table 1: Statistical Analysis of the DocRAGLib Dataset

Indicator	Value	
Total Document Number	2,178	
Avg. Word Number per Document	1,453.05	
Avg. Table Number per Document	3.85	
Documents with >2 Tables	1,932 (88.71%)	
Total QA Pairs Number	4,468	
Train/Dev/Test	2,990/502/976	
Classification by Evidence Source		
Text Only	403 (9.02%)	
Table Only	2,269 (50.78%)	
Both Text and Table	1,796 (40.20%)	
Answer Characteristics		
Decimal Places ≥3	1,532 (34.29%)	
Numerical Values >10,000	865 (19.36%)	
Numerical Values >100,000	181 (4.05%)	

With the emergence of advanced LLMs, several studies apply them to question-answering tasks with hybrid documents. Luo et al. [15] introduce the HRoT strategy for text-table hybrid QA, achieving better results than existing pre-trained NLP models on the MultiHiertt dataset. Srivastava et al. [18] propose EEDP, designed for semi-structured documents, and compare it with other prompting methods (such as CoT[24] and PoT[5]) across various QA datasets. Zhao et al. [30] evaluate the numerical reasoning abilities of 27 LLMs using CoT and PoT on text-table hybrid documents. Despite the progress of advanced prompting strategies in guiding LLMs for hybrid document QA, there remains room for improvement compared to human performance, highlighting the need for more efficient prompting techniques.

3 Preliminary

In this section, we formally define the **Hybrid Document RAG** task and detail the collection, processing, and cleaning procedures for our dataset, DocRAGLib.

3.1 Task Definition

In this section, we formally define key concepts and the **Hybrid Document RAG** task in our paper.

- **Document Corpus**: A comprehensive collection of documents $C = \{D_1, D_2, \dots, D_{|C|}\}$ where each document $D_i \in C$ consists of multiple text segments $P = \{P_1, P_2, \dots, P_{|P|}\}$ and several complex hierarchical tables $T = \{T_1, T_2, \dots, T_{|T|}\}$, referred to as *semi-structured data*. Each hierarchical table is defined as a tuple $T = \{H_l, H_t, d\}$, where H_l denotes the hierarchical structure of the rows in table T, H_t denotes the hierarchical structure of the columns in table T, and T0 denotes the data entries of the table T1, organized according to the hierarchical relationships defined by T1 and T2.
- Question: A question Q posed by the user, for which there
 exists a unique highly relevant document D* ∈ C in the
 corpus.

Given a question Q and a document corpus C, our task is to retrieve the most relevant document D^* and generate a comprehensive answer A based on the information contained within D^* . Formally, the **Hybrid Document RAG** task can be described by the following function:

$$A = \mathcal{F}(Q, \mathbb{C}) = \text{Inference}(Q, \text{Retrieve}(Q, \mathbb{C}))$$
 (1)

where Retrieve(Q, C) is the function that retrieves the most relevant document $D^* \in C$ based on the question Q, and Inference(Q, D^*) is the generation function that returns a accurate answer A by leveraging the information contained within D^* .

3.2 Dataset

To advance research in the **Hybrid Document RAG** task, we introduce the **DocRAGLib** dataset, containing 2,178 documents with a combination of text and tables, along with 4,468 QA pairs designed based on the content of these documents. Existing datasets are predominantly tailored for single-document RAG tasks, limiting their applicability to scenarios requiring the processing of large-scale and complex document corpora. DocRAGLib aims to address this limitation by providing a comprehensive dataset specifically designed for multi-document RAG tasks, thereby facilitating more extensive exploration of potential applications in related domains.

3.2.1 Data Collection. The documents of DocRAGLib are derived from two sources: the existing public single-document QA dataset and web-scraped text-table hybrid data. First, we collect information from the publicly available single-document QA dataset MultiHiertt[29], which is designed for single-document QA tasks. Each document in MultiHiertt comprises textual content and hierarchical tables, with an average of 3.89 tables per document. In addition, we scrape contextual information related to the tables by utilizing the webpage links provided in another available single-table QA dataset HiTab[8], and then reconstruct hybrid documents containing both text and tables.

3.2.2 Data Cleaning. The raw data consists of hybrid documents and QA pairs. This section outlines the data cleaning process, focusing on the strategies to refine both documents and QA pairs.

For document refinement, we reduce noise in table contexts from web pages, such as irregular delimiters and unrelated sentences. This is achieved through manual cleaning: (1) reformatting irregular delimiters and (2) removing irrelevant text. To ensure clarity in the QA pairs, we resolve ambiguities where multiple documents may answer the same question. First, we apply rule-based filtering to select candidate documents. Then, we use GPT-3.5 Turbo and GPT-40 to evaluate each document's relevance to the question by pairing it with the question and inputting it into the LLM. We track the filtered documents in each round, and if the remaining candidates are below a threshold, the question is considered specific, and the QA pair is retained. This process eliminates ambiguous questions, ensuring dataset quality.

3.2.3 Data Statistics. After the data collection and cleaning process, 2,178 hybrid documents and 4,468 QA pairs were obtained. To enable further exploration of pre-trained model-based methods for the Hybrid Document RAG task, the 4,468 QA pairs were split into three subsets: train (2,990 QA pairs), dev (502 QA pairs), and test

(976 QA pairs). To ensure consistency, the 2,178 hybrid documents were merged into a single collection, without further division.

As shown in Table 1, statistical analysis of the DocRAGLib dataset reveals that: (1) The average textual length of each document is 1,453.05 words, and the average number of tables is 3.85, with 88.71% of documents containing at least two tables. (2) The QA pairs are categorized by evidence source: 9.02% of questions rely solely on text, 50.78% on tables, and 40.20% on both. Additionally, we analyze the numerical scale and precision of answers in the DocRAGLib dataset. Specifically, 19.36% of answers contain values exceeding 10,000, 4.05% exceed 100,000, and 34.29% are decimals with more than three significant digits. These statistics highlight the complexity and diversity of the dataset, offering a challenging benchmark for future research.

4 Methodology

To address this problem, we introduce **HD-RAG**, a framework designed for the Hybrid Document RAG Task. As depicted in Figure 2, our HD-RAG framework comprises three modules: the Corpus Construction Module, the Retrieval Module, and the QA Inference Module. The following sections show a detailed introduction to the three modules of our HD-RAG framework.

4.1 Corpus Construction Module

The Corpus Construction Module focuses on creating effective representations of hybrid documents, capturing both lengthy text and complex hierarchical tables to optimize retrieval performance. A traditional approach, the Table Level Summary, involves providing the table's schema to the LLM and summarizing it. However, it oversimplifies the table, leading to the loss of key information and ignoring important structural details. To effectively represent Hybrid Documents, the Corpus Construction Module introduces a row-and-column-level(RCL) table summary to represent tables. Additionally, leveraging the hierarchical structure of the tables, we extend this RCL table summary to capture the nested relationships and dependencies within the table data, ensuring a more comprehensive representation.

To better understand the proposed RCL table summary, we first introduce some basic concepts related to table structure and paths.

For a hierarchical table, we define the table as $T = \{H_t, H_l, d\}$, where H_t represents the top-level headers, H_l represents the left-level headers, and d represents the data cells. Specifically, we can define:

$$\begin{cases}
H_t = \{H_t^k \mid k = 1, ..., K_t\} \\
H_l = \{H_l^k \mid k = 1, ..., K_l\}
\end{cases}$$
(2)

, where K_t denotes the number of hierarchical levels in the top headers and K_l denotes the number of hierarchical levels in the left headers.

For each hierarchical level in the top and left headers, we define:

$$\begin{cases} H_t^k = \{h_t^k(j) \mid j \text{ is the index of the header at this level} \} \\ H_l^k = \{h_l^k(i) \mid i \text{ is the index of the header at this level} \} \end{cases}$$
 (3)

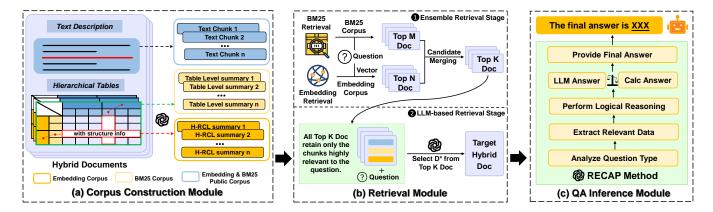


Figure 2: The Overview of our HD-RAG Framework

,where $h_l^k(j)$ represents the header at level k in the top header hierarchy, while $h_l^k(i)$ represents the header at level k in the left header hierarchy. As shown in Figure 3, these headers form multilevel paths used to locate specific data cells within the table. To pinpoint a particular data cell d_{ij} , we define the paths from both the left and top headers, $P_l(i)$ and $P_t(j)$, respectively, which together uniquely identify the location of the data cell:

$$\begin{cases}
P_l(i) = h_l^1(i_1) \to h_l^2(i_2) \to \cdots \to h_l^{K_l}(i_{K_l}) \\
P_t(j) = h_t^1(j_1) \to h_t^2(j_2) \to \cdots \to h_t^{K_t}(j_{K_t})
\end{cases}$$
(4)

These paths capture the hierarchical relationships between the cells in the table, allowing us to pinpoint any data cell $d_i j$ by referencing the corresponding paths in the left and top headers.

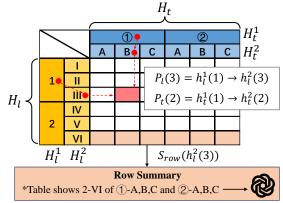
Below, we provide a detailed formal definition of the proposed RCL table summary, outlining its structure and how it incorporates hierarchical relationships for enhanced table representation.

4.1.1 General RCL Table Summary. In the case of a general table, where multi-level hierarchies and complex relationships within the table are not considered, we summarize each row and column independently. By disregarding the hierarchical structure, the table is reduced to a flat, 1-level representation, where both the top and left headers are flattened.

Formally, when the hierarchical structure is ignored, H_t and H_l are reduced to:

$$\begin{cases} H_t = \{h_t(1), h_t(2), \dots, h_t(n) \mid n \text{ is the number of columns} \} \\ H_l = \{h_l(1), h_l(2), \dots, h_l(m) \mid m \text{ is the number of rows} \} \end{cases}$$
 (5)

Similarly, the paths simplify to $P_l(i) = h_l(i)$ and $P_t(j) = h_t(j)$. In this generalized case, each row is represented by a left header, and each column is represented by a top header. To summarize the table at the general row and column level, we flatten the table's hierarchical structure and treat it as a single level. Specifically, for each row and column, the general RCL table summary can be



* Provided to the LLM for refinement, generating the final summary.

Figure 3: The Path and Hierarchical Levels in the Table. The H-RCL Table Summary Relies on the Structure and Paths of Hierarchical Table

formulated as:

$$\begin{cases} S_{\text{row}}\{h_l(i)\} = \text{LLM}(f_{\text{row}}(h_l(i), \bigcup_{j=1}^n h_t(j))) \\ S_{\text{col}}\{h_t(j)\} = \text{LLM}(f_{\text{col}}(h_t(j), \bigcup_{i=1}^m h_l(i))) \end{cases}$$

$$(6)$$

, where $f_{\rm row}$ and $f_{\rm col}$ represent the general RCL summary functions for the rows and columns respectively. These summaries condense the information in each row and column, providing a simpler, more manageable representation of the table's contents for the retrieval stage.

4.1.2 *H-RCL Table Summary.* Hierarchical tables contain multiple levels of headers that form a complex hierarchy, adding depth and richness to the data. In this context, we extend the General RCL table summary to handle multi-level structures, which capture the intricate dependencies between the table's headers and data more effectively.

We propose an H-RCL table summary that preserves the nested relationships between rows and columns by leveraging the hierarchical paths of both top and left headers, as shown in Eq. 3 and Eq. 4. In the following, we provide a formal definition of the hierarchical row and column summaries:

$$\begin{cases} S_{\text{row}}(h_l^k(i)) = \text{LLM}(f_{\text{row}}(P_l^k(i), \bigcup_{j=1}^n P_t^{K_t}(j))) \\ S_{\text{col}}(h_t^k(j)) = \text{LLM}(f_{\text{col}}(P_t^k(j), \bigcup_{i=1}^m P_l^{K_l}(i))) \end{cases}$$
(7)

The row-level summaries $S_{\rm row}$ capture the dependencies within the left headers, while the column-level summaries $S_{\rm col}$ reflect the relationships within the top headers. As shown in Figure 3, the $S_{\rm row}$ aggregates information from both the left and top headers at their respective hierarchical levels. After aggregation, the information is provided to the LLM for refinement to generate the final summary while preserving the complex relationships within the table's structure. These summaries jointly represent the hierarchical structure of the table. The overall table summary is defined as:

$$S_{\text{table}} = \bigcup_{i,k} S_{\text{row}}(h_l^k(i)) \cup \bigcup_{j,k} S_{\text{col}}(h_t^k(j))$$
 (8)

By combining both row and column summaries, the table summary $S_{\rm table}$ offers a comprehensive representation of the hierarchical table, effectively maintaining the nested structure of the data

4.1.3 Passage Processing. In addition to processing tables, we also address the handling of text passages within the Hybrid Document. In this module, we focus on processing the passage at the sentence level, dividing the passage into individual sentences and constructing the corpus. We segment the passage at the sentence level to enable more effective handling of textual data, ensuring that relevant information is preserved and structured for retrieval and QA.

4.2 Retrieval Module

The Retrieval Module is designed to identify the most relevant document D^* from the Document Corpus for a given question. It consists of two key stages: Ensemble retrieval and LLM-based retrieval. The ensemble retrieval stage combines BM25 and embedding-based retrieval to balance keyword matching with semantic understanding. BM25 captures exact term relevance, while embedding-based retrieval ensures deeper semantic alignment, enabling the retrieval of a comprehensive set of top-k candidate documents. Specifically, we utilize two different types of corpora for the ensemble retrieval stage, tailored to align with the underlying mechanisms of embedding-based and BM25-based approaches. The ensemble retrieval stage conducts a coarse-grained filtering of documents across the entire document corpus, ensuring that the candidate documents provided to the LLM remain within its maximum input length constraints. The LLM-based retrieval performs fine-grained logical reasoning tailored to the specific question and selected candidate documents, leveraging the contextual reasoning capabilities of the LLM to prioritize documents most relevant to the question. This approach ensures high precision in the final output.

The Ensemble Retrieval Stage. The ensemble retrieval stage is designed to generate a robust set of top-k candidate documents by combining the complementary strengths of BM25 and embeddingbased retrieval methods. Below, we detail the three key components of this stage: BM25 retrieval, embedding-based retrieval, and candidate merging. (1) BM25 Retrieval. We use BM25 to rank chunks from the BM25 corpus based on their relevance to a given question Q. Each chunk corresponds to a specific section of its document. BM25 emphasizes exact keyword matches and considers term frequency within a chunk while normalizing for document length to ensure fair comparisons. By prioritizing terms that are frequent in the chunk but rare across the corpus, BM25 effectively retrieves the top-n candidate documents that are most aligned with the question. As RCL corpus construction method tends to repeatedly aggregate keywords from tables into multiple index entries, and BM25 regards terms frequently appearing across multiple entries as common words lacking distinctiveness, we use the corpus constructed with the Table-Level method for retrieval at this stage. (2) Embedding-based Retrieval. Simultaneously, embedding-based retrieval identifies the top-m candidate documents from the embedding corpus by computing semantic similarity between the question Q and each chunk. Both the question and chunks are represented as dense vectors generated by the text-embedding-3-large model. The embedding-based retrieval method captures semantic nuances and retrieves chunks that may not share explicit terms with the question but are contextually relevant. In this retrieval stage, we utilize the corpus constructed using the H-RCL method, ensuring that the embedding model can more precisely capture information semantically similar to the question within hierarchical tables. (3) **Candidate Merging.** After retrieving the top-*n* candidates from BM25 and top-*m* from embedding-based retrieval, the two sets are merged into a final top-k set with duplicates removed. This approach combines the strengths of both methods, ensuring a diverse and semantically rich candidate pool.

The ensemble approach combines the strengths of BM25 and embedding-based retrieval to create a diverse candidate document set. BM25 ensures accurate keyword-based matches, while embedding-based retrieval adds semantic depth and flexibility. By merging, the ensemble retrieval stage provides high recall and relevance, laying a strong foundation for the subsequent LLM-based retrieval stage.

The LLM-based Retrieval Stage. After the preceding Ensemble Retrieval Stage, the Retrieval Module extracts the top-k candidate documents from the original document corpus that are most similar to the question. To further filter out the target document that is most relevant to the question, we introduce LLM as an expert in similarity analysis. Specifically, each question alongside its corresponding candidate documents is presented to the LLM, which is tasked with determining the single document most relevant to the question. However, since each document is typically lengthy, simultaneously inputting the top-k documents into the LLM often exceeds the model's maximum input token limit. Moreover, the target document may contain a large amount of irrelevant information, which can reduce the LLM's accuracy when processing the entire content. To mitigate these challenges, we design the input space by setting a variable filtering threshold, Θ , and selecting the top- Θ information chunks most similar to the question from all documents. These

selected chunks are then consolidated into a single collection:

$$S = \text{SelectTop}(Q, D, \Theta) \tag{9}$$

where Q represents the original question. D denotes the set of all documents. Θ is the filtering threshold. S represents the set of selected information chunks.

Subsequently, for each document D_i in the top-k documents, only the information belonging to this collection is retained, and the filtered information is recombined into a "new document" D_i' to replace the original document:

$$D_i' = \text{Recombine}(S, D_i)$$
 (10)

Finally, we input the question content Q and its corresponding top-k new documents $\{D'_1, D'_2, \ldots, D'_k\}$ into the LLM for similarity analysis, thereby selecting the most relevant document D^* among the top-k documents.

4.3 QA Inference Module

The QA Inference Module is designed to perform QA based on the most relevant document D^* provided by the Retrieval Module. Although LLMs demonstrate strong performance in natural language understanding, performing QA on hybrid documents remains a challenging task. To more accurately extract relevant information from hybrid documents and leverage the information to answer the questions, we introduce a novel prompting strategy for hybrid document QA called **RECAP** (Restate, Extract, Compute, Answer, Present), inspired by prompt strategies such as CoT[24] and EEDP[18] that involve step-by-step analytical reasoning, as well as PoT[5] which generates executable programs to solve complex mathematical operations.

Formally, the QA Inference Module can be represented as:

$$A = Inference(Q, D^*)$$
 (11)

where A is the final answer produced by the RECAP strategy.

The specific steps of RECAP are as follows: (1) Restate the Question: Clearly restate what the question is asking and analyze the question type; (2) Extract Relevant Data: Extract and list all information from the hybrid document that is directly relevant to the question; (3) Compute the Answer: Use the extracted relevant data to compute the answer; Perform any necessary calculations or logical reasoning step by step; (4) Answer the Question: For the computed answer, provide a clear response in a fixed format; (5) Present Calculate Formula: For calculation-based questions, provide the complete calculation formulas used to derive the final result, based on the reasoning steps outlined above.

Specifically, the LLM performs multi-step reasoning in the first four steps of RECAP and provides one answer, while the calculator computes another answer based on the formula provided in the fifth step. We employ a rule-based approach to select the more appropriate answer from the two, depending on the question type, as the final answer. Since RECAP's logical reasoning and formula abstraction are derived from a unified reasoning path, it offers superior token efficiency compared to methods like Self-Consistency [22], which rely on generating multiple reasoning paths

5 Experiment

In this section, we present the experimental evaluation of HD-RAG. We first introduce the baselines and evaluation metrics employed in our experiments. We then perform a comprehensive set of experiments to evaluate the effectiveness of HD-RAG. Additionally, we conduct ablation studies to investigate the contributions of individual components. Finally, we present a case study to demonstrate the applicability of HD-RAG to the real-world scenario.

5.1 Experimental Setup

5.1.1 Baselines. We divide our approach into two modules and compare each with different types of baselines: Retrieval and QA. For Retrieval, we select the following baselines:

- Standard RAG: The basic RAG framework retrieves documents using dense similarity search with embeddings from pre-trained models like DPR, without table-specific optimizations
- LangChain: LangChain's semi-structured cookbook provides a retrieval pipeline for tables and text, summarizing them with LLMs for similarity-based retrieval.
- SelfRAG[1]: SelfRAG enhances LLMs by dynamically retrieving relevant passages and using reflection tokens to evaluate and refine outputs, integrating self-reflection to assess both retrieved passages and its responses.
- Table Retrieval[4]: It enhances table-specific retrieval by incorporating join relationship discovery and using a mixedinteger programming-based re-ranking approach to optimize table-query and table-table relevance.

For QA, we select the following baselines:

- Direct: A straightforward approach where the model generates answers directly without intermediate reasoning or structured explanation.
- COT[24]: A reasoning framework that enhances the performance of LLMs by generating intermediate reasoning steps before providing the final answer, enabling better handling of complex queries.
- EEDP[18]: A multi-step framework that systematically breaks down the reasoning process, involving explanation, refinement, and decision-making phases to improve answer accuracy.
- POT[5]: An approach that separates reasoning from computation involves prompting the LLM to generate a structured program outlining the logical steps of the thought process.
 The final solution is then obtained by executing this generated program using an external calculating tool, ensuring precise and reliable results.
- RECAP w/o Calc: For numerical calculation problems, instead of using external computational functions to perform numerical reasoning based on formulas, we directly take the results of LLM reasoning as the final answer to the problem.
- *5.1.2 Metrics.* We evaluate the performance of both Retrieval and QA modules using two key metrics:
 - Hit@K assesses the retrieval module by measuring the proportion of questions for which the correct document is retrieved within the top-K results.

Exact Match (EM) evaluates the Inference module by calculating the percentage of exact matches between predictions and ground truth answers.

5.1.3 Experimental Details. For table representation, we use GPT-40 for corpus construction, and embeddings are generated using OpenAI's text-embedding-large-3 model². In the Retrieval module, we employ GPT-40 for the final LLM-based retrieval operation. For the QA baselines, the number of examples for all prompt strategies was uniformly set to 1. Additionally, we utilize GPT-40, GPT-40 mini, alongside four open-source large LLMs available on hugging face³: Qwen2.5-32B-Instruct, Qwen2.5-7B-Instruct, and Mistral-Nemo-Instruct-2407, Llama-3.1-8B-Instruct.

5.2 Experimental Result

In this section, we present the experimental results obtained by integrating the three modules of HD-RAG into the overall pipeline for the Hybrid Document RAG task. The three modules, Corpus Construction, Retrieval, and QA Inference, work together to effectively process hybrid documents combining table and text data.

In the Corpus Construction Module, we evaluate the impact of three table summary levels on the performance of the Retrieval and QA modules: the traditional Table Level Summary and our proposed General and H-RCL Table Summaries.

As shown in Table 2, the performance evaluation demonstrates the improvements in both the Retrieval and QA tasks as we progress from the Table Level Summary to the more complex General and H-RCL Table Summaries. The H-RCL Table Summary achieves the highest scores in both HiT@1 and EM, with a significant improvement of 47% in HiT@1 and 28% in EM compared to the basic Table Level Summary. The improvement highlights the effectiveness of the H-RCL in both the Retrieval and QA phases.

The General RCL provides a clearer representation of rows and columns, reducing ambiguity and improving retrieval accuracy, which enhances QA performance by retrieving more relevant documents. The H-RCL further improves this by capturing multi-level table structures and incorporating row and column path information, boosting both retrieval accuracy and QA's ability to interpret complex table structures for more precise answers.

Overall, H-RCL Table Summary improves retrieval and QA performance by better representing and utilizing the inherent structure within the tables, whether through finer granularity and multi-level hierarchical relationships in H-RCL.

Table 2: Performance Evaluation of HD-RAG with Different Table Summary Level

Corpus Construction	Retrieval Module	QA Module	
Table Summary Level	HiT@1	EM	
Table Level	0.3627±0.0046	0.2383±0.0047	
General RCL	0.3984 ± 0.0092	0.2625±0.0069	
H-RCL	0.5320 ± 0.0067	0.3166±0.0062	

²platform.openai.com/docs/guides/embeddings

5.3 Comparison with Baselines

In this section, we present a comprehensive analysis of HD-RAG compared to baseline methods across the Retrieval and QA modules, with evaluations conducted on the DocRAGLib dataset to showcase its effectiveness.

5.3.1 Retrieval Comparison with Baselines. Table 3 presents the experimental results of the Retrieval Module in HD-RAG and all baseline methods.

Table 3: Comparison of HD-RAG Retrieval Performance with Various Baselines

	HiT@K			
Method	K=1	K=3	K=5	K=10
Standard RAG	0.0159	0.0339	0.0538	0.1255
LangChain	0.2390	0.4104	0.4821	0.5219
Self-RAG	0.2829	0.4502	0.5000	0.5598
Table Retrieval	0.3705	0.5299	0.5996	0.6494
HD-RAG(GPT-4o)	0.5410	0.7244	0.7603	0.8689

Standard RAG performs the worst, as it struggles to effectively handle both text and tables, resulting in noisy and irrelevant retrieval. LangChain improves performance upon this by performing coarse-grained summarization of tables and text, enhancing retrieval results. Self-RAG dynamically retrieves relevant passages and uses reflection tokens for self-assessment, refining outputs and outperforming LangChain. Table Retrieval targets tables within documents, employing join relationship discovery and a programming-based re-ranking approach to achieve second-best results for K=3, 5, and 10.

Our method, HD-RAG, consistently outperforms all baseline methods by utilizing fine-grained row- and column-level table summarization and text decomposition tailored for hybrid documents. Specifically, HD-RAG achieves a Hit@1 score of 0.5188, showing a 40% improvement over the next-best method, Table Retrieval.

5.3.2 Document-QA Comparison with Baselines. In this phase of the document-based QA experiment, the focus is on answer reasoning based on the unique document for each question, excluding the document retrieval process.

The experimental results of RECAP and baseline methods on the DocRAGLib dataset are shown in Table 4. Six LLMs are used for the experiments, with the EM metric as the evaluation criterion. To ensure fairness, LLM output formats are constrained, and evaluation mechanisms are tailored to the answer types in the dataset. Among the baseline methods, PoT performs best, mainly due to its program-execution logic that improves the accuracy of calculation-based questions in the DocRAGLib dataset. However, RECAP outperforms PoT in EM across all six LLMs, demonstrating its superiority. Furthermore, RECAP with external formula calculation improves EM by 0.15 on GPT-40 compared to RECAP w/o Calc. RECAP enhances calculation-based question accuracy by reasoning through external calculation functions, reducing output instability compared to program-generated methods like PoT.

³https://huggingface.co

	Models					
Method	GPT-40	GPT-40 mini	Qwen2.5-32B	Qwen2.5-7B	Mistral-Nemo-2407	LLama3.1-7B
Direct	0.3534	0.2355	0.2180	0.0802	0.1003	0.1579
CoT	0.4687	0.3684	0.4837	0.3158	0.2506	0.2531
EEDP	0.4737	0.3759	0.4862	0.2857	0.2757	0.2080
PoT	0.6190	0.5564	0.5589	0.3784	0.3409	0.2932
RECAP(w/o Calc)	0.4937	0.4010	0.5163	0.2957	0.2732	0.2306
RECAP	0.6466	0.5815	0.6416	0.4536	<u>0.4411</u>	0.4060

Table 4: Comparison of RECAP in HD-RAG Document-QA Performance with Various Baselines

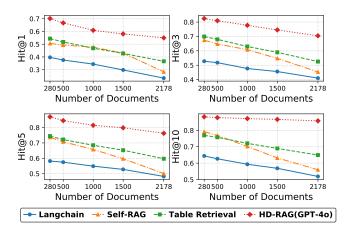


Figure 4: Sensitivity Analysis of Retrieval Performance across Different Corpus Sizes.

5.4 Sensitive Analysis

In this section, we assess the robustness and scalability of HD-RAG by analyzing its retrieval performance compared to baseline methods across different document corpus sizes. For this experiment, we selected 809 questions corresponding to a minimum of 280 documents. We then progressively expanded the document corpus to 500, 1000, 1500, and 2178 documents and conducted experiments at each stage. We compare HD-RAG with the retrieval baseline methods to examine the impact of document corpus size on the Hit@K performance. As the document corpus grows, Hit@K scores typically decline. We analyze the sensitivity of retrieval methods to the growth in corpus size, focusing on how HD-RAG performs under varying scales of data. Due to the inherently low Hit@K performance of the Standard RAG retrieval results, we do not include it in this section for further analysis. Instead, we focus on comparing HD-RAG with the other baseline methods.

As shown in Figure 4, among all the retrieval methods, our retrieval approach exhibits the smallest decrease in Hit@K performance (K=1,3,5,10) as the corpus size increases. While other methods experience a sharper decline in performance, HD-RAG maintains a relatively stable accuracy even with a larger document corpus. The minimal drop in performance suggests that HD-RAG is more robust and scalable, effectively handling the increased complexity and size of the document set while preserving retrieval precision.

5.5 Ablation Study

To investigate the effectiveness of each key component in HD-RAG, we conduct the ablation study using DocRAGLib dataset. We design the following variants of HD-RAG: (1) HD-RAG w/o Ensemble **Retrieval:** In this variant, we replace Ensemble Retrieval by using only Embeddings model and BM25, respectively, to retrieve candidate documents from the Document Corpus; (2) HD-RAG w/o Ensemble & LLM-based Retrieval: Since Ensemble Retrieval combines multiple methods to enhance candidate document selection, using Ensemble Retrieval alone does not directly retrieve the most relevant documents. In this variant, we replace the combined process with individual retrieval methods, using only the Embeddings model and BM25 to retrieve documents directly from the Document Corpus; (3) HD-RAG w/o Calc: In this variant, we remove the use of an external calculator for computational questions and rely solely on RECAP to perform answer reasoning based on the most relevant retrieved documents.

Table 5: Ablation Study Result of HD-RAG

Variants	HiT@1	EM
Ours (HD-RAG)	0.5410	0.3238
- w/o Ensemble Retrieval		
only Embedding (3-large)	0.4734	0.2777
only BM25	0.3545	0.2100
- w/o Ensemble & LLM-based Retrieval		
only Embedding (3-large)	0.2787	0.2131
only BM25	0.1557	0.1311
- w/o Calc of RECAP	0.5410	0.2838

Table 5 shows the results of our ablation study. Comparing HD-RAG with w/o Ensemble Retrieval, we found that replacing Ensemble Retrieval with either Embedding or BM25 significantly decreased Hit@1, with Embedding outperforming BM25 due to the dataset's need for deep semantic alignment. When comparing w/o Ensemble Retrieval with w/o Ensemble & LLM-based Retrieval, the introduction of LLM-based Retrieval improved Hit@1 by 0.19 and 0.20 for Embedding and BM25, respectively, enhancing QA accuracy. This shows that our two-stage retrieval method is more effective than single-stage methods. Lastly, w/o Calc results confirm that RECAP's use of an external calculator significantly improves EM score in HD-RAG.

6 Conclusion

In this paper, we propose the DocRAGLib and HD-RAG framework for the Hybrid Document RAG task in QA. DocRAGLib is the first large-scale dataset designed specifically for QA within the Hybrid Document RAG task. To address the challenges of DocRAGLib, HD-RAG framework introduces an H-RCL table representation, enhances retrieval with an approach combining ensemble and LLM-based retrieval, and incorporates the RECAP method for complex computational QA tasks. Extensive experiments show that HD-RAG outperforms existing baselines, achieving significant improvements in both retrieval and QA accuracy.

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