# MEMORAG: MOVING TOWARDS NEXT-GEN RAG VIA MEMORY-INSPIRED KNOWLEDGE DISCOVERY

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#### **ABSTRACT**

Retrieval-Augmented Generation (RAG) leverages retrieval tools to access external databases, thereby enhancing the generation quality of large language models (LLMs) through optimized context. However, the existing retrieval methods are constrained inherently, as they can only perform relevance matching between explicitly stated queries and well-formed knowledge, but unable to handle tasks involving ambiguous information needs or unstructured knowledge. Consequently, existing RAG systems are primarily effective for straightforward question-answering tasks. In this work, we propose MemoRAG, a novel retrievalaugmented generation paradigm empowered by long-term memory. MemoRAG adopts a dual-system architecture. On the one hand, it employs a light but longrange LLM to form the global memory of database. Once a task is presented, it generates draft answers, cluing the retrieval tools to locate useful information within the database. On the other hand, it leverages an expensive but expressive LLM, which generates the ultimate answer based on the retrieved information. Building on this general framework, we further optimize MemoRAG's performance by enhancing its cluing mechanism and memorization capacity. In our experiment, MemoRAG achieves superior performance across a variety of evaluation tasks, including both complex ones where conventional RAG fails and straightforward ones where RAG is commonly applied. MemoRAG is under intensive development, whose prototypes and resources will be constantly published at our project repository.

# 1 Introduction

Although the fundamental capabilities of large language models (LLMs) have improved rapidly over time Brown et al. (2020); OpenAI (2023); Touvron et al. (2023), they still face significant challenges in practice due to their inherent limitations. For instance, LLMs are likely to generate hallucinations or out-dated contents because of the lack of proper knowledge. They also struggle to manage overloaded historical interactions with users due to their limited context windows Bai et al. (2023); Zhang et al. (2024). Retrieval-augmented generation (RAG) has emerged as a promising paradigm for LLMs to address these challenges. It employs specialized retrieval tools that bring in useful knowledge from external databases, therefore, it enables LLMs to generate factual responses based on a knowledge-grounded context Izacard & Grave (2021); Gao et al. (2024).

Traditional RAG systems often require clearly stated information needs and well-formed knowledge. As a result, their applications are mostly constrained to straightforward question answering tasks Nogueira & Cho (2020); Lewis et al. (2020); Gao et al. (2024). However, it is not the case for many real-world problems where the information needs are ambiguous and the external knowledge is unstructured Edge et al. (2024); Qian et al. (2024). For example, a reader of a book might want to understand *the mutual relationships between the main characters*. To solve this problem, the system would need to first identify the main characters' names and then locate the sections where the corresponding names co-exist, from which their mutual relationships can be inferred. In other

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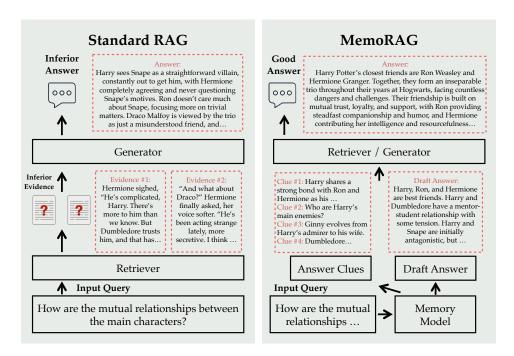


Figure 1: Comparison between Standard RAG and MemoRAG in processing queries that demand high-level understanding across the entire database, using the HARRY POTTER books as the database. In the left figure, Standard RAG struggles to accurately locate the necessary evidence due to the implicit nature of the input query, resulting in a less accurate answer. In the right figure, MemoRAG constructs a global memory over the whole database. When presented with the query, MemoRAG first recalls relevant clues, enabling useful information to be retrieved and thus leading to a precise and comprehensive answer.

words, it calls for the comprehension of information needs based on the contextual knowledge of the book before relevant information can be effectively retrieved.

To address the above challenge, we propose a novel framework called **MemoRAG**, as shown in Figure 1. This framework introduces an smart interface that connects tasks with the relevant knowledge from a database. For each presented task, MemoRAG prompts its memory module to generate retrieval clues. These clues are essentially drafted answers based on a compressed representation of the database, i.e. the memory. Despite the possible existence of false details, the clues explicitly reveal the underlying information needs for the presented task. Furthermore, they can also correspond directly to the source information in reality. By using these clues as queries, MemoRAG can effectively retrieve the necessary knowledge from the database.

According to the above mechanism, the memory module is expected to be 1) **retentive**: memorizing the global information of the entire database, and 2) **instructive**: providing useful clues based on which all needed knowledge can be retrieved comprehensively. Therefore, we propose the following designs to optimize the performance of MemoRAG. First, we introduce a dual-system architecture, with a light LLM to serve as the memory and a heavy LLM to perform retrieval-augmented generation. The light LLM must be cost-effective and lengthy-in-context, being able to accommodate the whole database in a limited computation budget. Second, we perform fine-tuning of the memory, such that the generated clues can achieve the optimized retrieval quality.

To evaluate the effectiveness of MemoRAG, we have developed a comprehensive benchmark called ULTRADOMAIN, which consists of complex RAG tasks with long input contexts drawn from diverse domains (e.g., law, finance, education, healthcare, programming). ULTRADOMAIN includes tasks characterized by queries that: (1) involve implicit information needs, (2) require distributed evidence gathering, and (3) demand a high-level understanding of the entire database. A common challenge among these queries is that the relevant knowledge cannot be directly retrieved through simple searches. While conventional RAG methods struggle with such complex tasks, MemoRAG

demonstrates superior performance by generating high-quality answers based on precisely retrieved knowledge. Furthermore, MemoRAG remains highly competitive in traditional question-answering tasks, where its clue-based retrieval approach continues to offer significant advantages. The model and source code will be publicly released to support further applications and research in this field.

## 2 MEMORAG

The standard RAG framework can be concisely expressed as:

$$\mathcal{Y} = \Theta(q, \mathcal{C} \mid \theta), \quad \mathcal{C} = \Gamma(q, \mathcal{D} \mid \gamma),$$
 (1)

where  $\Theta(\cdot)$  and  $\Gamma(\cdot)$  denote the generation model and the retrieval model, respectively. q represents the input query,  $\mathcal C$  is the context retrieved from a relevant database  $\mathcal D$  and  $\mathcal Y$  is the final answer. In many practical scenarios, the input query q often carries implicit information-seeking intents that can be challenging for a standard retriever, which typically relies on lexical or semantic matching, to fully comprehend. This limitation underscores the necessity of designing an intermediate module to bridge the semantic gap that arises in many practical scenarios.

In this paper, we propose MemoRAG, which leverages a memory model  $\Theta_{\text{mem}}(\cdot)$  to function as a semantic bridge between the input query q and the relevant database  $\mathcal{D}$ . Formally, this process can be represented as:

$$\mathcal{Y} = \Theta(q, \mathcal{C} \mid \theta), \quad \mathcal{C} = \Gamma(y, \mathcal{D} \mid \gamma), \quad y = \Theta_{\text{mem}}(q, \mathcal{D} \mid \theta_{\text{mem}}).$$
 (2)

Here, y represents a staging answer that may be incomplete or lack detail, serving as a set of answer clues that guide the retrieval of the most relevant context from  $\mathcal{D}$ . The memory model  $\Theta_{\text{mem}}(\cdot)$  is designed to establish a global memory of the database  $\mathcal{D}$ . In practice, any language model capable of efficiently processing super-long contexts can serve as the memory model. For example, a 7B language model incorporating key-value compression techniques could be an appropriate choice. While such a model might not generate a fully detailed and accurate answer, it can produce a rough outline that facilitate in locating the correct answers.

The form of the staging answer y is tailored to the specific requirements of each task. For example, in a question-answering task where the input query is implicit, the staging answer y may comprise intermediary steps, such as generating surrogate queries that are more explicit and disambiguated, along with specific text evidence from the database that contributes to the final answer. In addition, for tasks that do not involve explicit queries, such as summarization, the staging answer might consist of key points or concepts extracted from the context, which are crucial for assembling a coherent and accurate summary.

**System Implementation** The system implementation of MemoRAG is available at this repository. Currently, we have released two memory models: memorag-qwen2-7b-inst and memorag-mistral-7b-inst, which are based on Qwen2-7B-Instruct and Mistral-7B-Instruct-v0.2, respectively. In MemoRAG, the memory module  $\Theta_{mem}(\cdot)$  can be any model designed to handle very long contexts efficiently, while currently the system employs a token compression technique, enabling efficient processing of extended contexts, which will be explained in detail later.

The two memory models support compression ratios ranging from 2 to 16, allowing them to manage different context lengths. For example, memorag-qwen2-7b-inst can process up to  $128K \times 16$  tokens when a compression ratio of 16 is applied. In practice, memorag-mistral-7b-inst performs well with context lengths up to 150K tokens, and memorag-qwen2-7b-inst performs well with context lengths up to 600K tokens. When processing longer context, their performances would degrade slightly.

MemoRAG can integrate various retrieval methods into the system, including sparse retrieval, dense retrieval, and reranking. The current implementation uses dense retrieval by default. In future releases, we aim to provide flexible retrieval methods with easy-to-use interfaces.

Similarly, MemoRAG can integrate any generative language model as the generator. The current implementation supports initializing the generator from HuggingFace generative models or through commercial APIs (e.g., Azure and OpenAI). Since the memory models are dependent on their underlying models, MemoRAG uses the underlying models of the memory module as the default generator. For instance, when using memorag-mistral-7b-inst as the memory model, MemoRAG defaults to Mistral-7B-Instruct-v0.2 as the generation model.

The MemoRAG system can be deployed on a range of GPUs, from more affordable options (e.g., NVIDIA T4 16GiB) to high-end ones (e.g., NVIDIA A100 80GiB). When using the NVIDIA T4 16GiB, MemoRAG can handle databases with a context length of 68K tokens. With the NVIDIA A100 80GiB, the system is capable of processing databases with context lengths up to one million tokens. In future releases, we plan to offer additional serving options, including support for MacBooks with M-series chips. Furthermore, we aim to integrate MemoRAG with popular LLM frameworks such as LangChain and LlamaIndex.

#### 2.1 MEMORY MODULE

In this paper, we propose a flexible model architecture specifically designed to facilitate memory formation. The memory model progressively compresses the raw input tokens into a significantly smaller set of memory tokens, while preserving the essential semantic information. Specifically, suppose the input  $\mathcal{X}$  comprises n tokens,  $\mathcal{X} = \{x_1, \dots, x_n\}$ , and is processed by a transformerbased model  $\Theta(\cdot)$ . The attentive interaction of each layer can be formulated as:

$$Q = \mathcal{X} W_{Q}, \quad \mathcal{K} = \mathcal{X} W_{\mathcal{K}}, \quad \mathcal{V} = \mathcal{X} W_{\mathcal{V}},$$
 (3)

$$\operatorname{Attention}(\mathcal{Q}, \mathcal{K}, \mathcal{V}) = \operatorname{softmax}\left(\frac{\mathcal{Q}\mathcal{K}^T}{\sqrt{d_k}}\right) \mathcal{V}, \ \Theta(\mathcal{X}) = \operatorname{Attention}(\mathcal{Q}, \mathcal{K}, \mathcal{V}), \tag{4}$$

where  $W_Q$ ,  $W_K$ , and  $W_V$  are the weight matrices for the query, key, and value projections, respectively, and  $d_k$  is the dimension of the key vectors. The deep attentive interactions among  ${\mathcal X}$  after multiple Transformer layers lead to a comprehensive understanding of the input sequence  $\mathcal{X}$ . This is akin to human's short-term memory that is accurate but can only contain recent perceived content. We denote this process as  $\mathcal{X} = \Theta(\mathcal{X})$  where  $\mathcal{X}$  refers to the hidden states of the input sequence  $\mathcal{X}$ and  $\Theta(\cdot)$  can be any pretrained LLMs.

To enable the conversion from short-term memory to long-term memory, we introduce memory tokens  $x^m$  to serve as the information carriers of long-term memory in LLMs. Specifically, supposing the underlying LLM  $\Theta(\cdot)$  has a working context window length of l, after each context window, we append k memory tokens, that is:

$$\mathcal{X} = \{x_1, \dots, x_l, x_1^m, \dots, x_k^m, x_{l+1}, \dots\}, \quad k \ll l.$$
 (5)

During the attentive interactions defined by Eq. (4), we initialize another set of weight matrices  $W_{\mathcal{Q}^m}$ ,  $W_{\mathcal{K}^m}$  and  $W_{\mathcal{V}^m}$  on the special purpose of memory formation. Therefore, we have:

$$Q^{m} = \mathcal{X} \mathbf{W}_{Q^{m}}, \quad \mathcal{K}^{m} = \mathcal{X} \mathbf{W}_{\mathcal{K}^{m}}, \quad \mathcal{V}^{m} = \mathcal{X} \mathbf{W}_{\mathcal{V}^{m}}, \tag{6}$$

$$Q^{m} = \mathcal{X} \boldsymbol{W}_{Q^{m}}, \quad \mathcal{K}^{m} = \mathcal{X} \boldsymbol{W}_{\mathcal{K}^{m}}, \quad \mathcal{V}^{m} = \mathcal{X} \boldsymbol{W}_{\mathcal{V}^{m}},$$
(6)  
Attention( $Q, \mathcal{K}, \mathcal{V}$ ) = softmax  $\left(\frac{[Q; Q^{m}][\mathcal{K}; \mathcal{K}^{m}; \mathcal{K}_{cache}^{m}]^{T}}{\sqrt{d_{k}}}\right) [\mathcal{V}, \mathcal{V}^{m}, \mathcal{V}_{cache}^{m}],$ (7)

where  $Q^m$ ,  $K^m$ , and  $V^m$  refer to the query, key, and value for the memory tokens  $x^m$ .  $K^m_{\text{cache}}$ and  $\mathcal{V}_{\text{cache}}^m$  refer to the KV cache of previous memory tokens. We denote the memory tokens as  $\mathcal{X}^m$  and the conversion process as  $\mathcal{X}^m = \Theta_{\text{mem}}(\mathcal{X})$ . For l raw tokens  $\{x_1, \cdots, x_l\}$ , after multiple attentive processes defined by Eq. (7), they are encoded into hidden states  $\mathcal{X}_{[0:l]}$  $\{x_1, \cdots, x_l, x_1^m, \cdots, x_k^m\}$ , where  $\{x_1, \cdots, x_l\}$  represent the raw tokens' hidden states and  $\{x_1^m, \cdots, x_k^m\}$  represent the memory tokens' hidden states. After the formation of memory, the KV cache of the l raw tokens is discarded, similar to the forgetting process in human memory. After n context windows, MemoRAG progressively converts all raw tokens in  $\mathcal{X}$  into memory tokens. Thus, we have  $\Theta(\mathcal{X}) \to \Theta_{\text{mem}}(\mathcal{X}) = \{x_{1,1}^m, \cdots, x_{1,k}^m, \cdots, x_{n,k}^m\}$ , which represents the global memory  $\mathcal{X}^m$  formed from the input  $\mathcal{X}$ .

# 2.2 Training for Memory Module

As mentioned above, we initialize another set of weight matrices  $W_{\mathcal{O}^m}$ ,  $W_{\mathcal{K}^m}$ , and  $W_{\mathcal{V}^m}$  for the special purpose of mapping the memory tokens  $x_m$  into query, key, and value vectors (as formulated in Eq. 7). The newly initialized weight matrices are updated during the training process, while the parameters of the underlying LLM remain frozen.

We train the newly initialized parameters in two stages: (1) Pre-training: we use randomly sampled long contexts from the RedPajama dataset to pre-train the model Soboleva et al. (2023), allowing MemoRAG's memory module to learn how to form memory from raw context; (2) Supervised Finetuning (SFT): we use task-specific SFT data to enable MemoRAG to generate task-specific clues based on the formed memory.

While challenging, accurately remembering details from memory remains the ultimate goal of any human memory enhancement training. The training objective of the memory model in MemoRAG also pursues this goal, which can be formulated as:

$$\max_{\Theta_{\text{nem}}} \mathcal{P}(x_{i,j} \mid x_{1,1}^m, \cdots, x_{i-1,k_{i-1}}^m, x_{i,1}, \cdots, x_{i,j-1}).$$
(8)

The objective in Eq. (8) aims to maximize the generation probability of the next token given the KV cache of the previous memory tokens  $\{x_{1,1}^m, \cdots, x_{i-1,k_{i-1}}^m\}$  and recent raw tokens  $\{x_{i,1}, \cdots, x_{i,j-1}\}$ .

#### 2.3 THE MEMORAG FRAMEWORK

In the previous section, the input sequence  $\mathcal{X}$  was transformed into a compact memory representation  $\mathcal{X}^m$ , which encapsulates high-level semantic information from a global perspective. A straightforward way to utilize this memory  $\mathcal{X}^m$  is to prompt it to generate task-specific answers, i.e.,  $\mathcal{Y} = \Theta_{\text{mem}}(\mathcal{X}^m, q|\theta)$ , where q represents the task description (e.g., a query or a summarization instruction). While this approach is feasible, it may lack information accuracy since  $\mathcal{X}^m$  is a highly condensed form of the raw input sequence  $\mathcal{X}$ . This is analogous to how humans may struggle to recall detailed information from memory but can generate a draft answer, which can then be refined by revisiting and finding relevant evidence.

In MemoRAG, the global memory  $\mathcal{X}^m$  is used to generate task-specific clues y. These clues help outline the expected answers  $\mathcal{Y}$ , effectively bridging the gap between the raw input context and the ground-truth answer. Based on these memory-generated clues, any stand-alone retriever can be employed to locate the precise evidence text within the input sequence, as defined in Eq. (2).

Subsequently, the final answer  $\mathcal{Y}$  is generated based on the retrieved evidence text,  $\mathcal{Y} = \Theta_{\mathrm{gen}}(\hat{\mathcal{X}},q|\theta)$ , where  $\hat{\mathcal{X}}$  includes the input query or task instruction q and the retrieved context  $\hat{\mathcal{C}}$ . The generation model can be any generative LM, and by default, MemoRAG utilizes the underlying LM of the memory model for generation, avoiding the need to load additional model parameters.

### 2.4 APPLICABILITY

In the following sections, we demonstrate how global memory can expand the applicability of standard RAG, making it suitable for more general-purpose tasks.

**Ambiguous Information Needs** Information seeking with ambiguous information needs is challenging for standard RAG, as the user's intent is often not explicitly stated, requiring deeper contextual understanding and inferential reasoning. To address this, MemoRAG creates a global memory across the relevant database, enabling it to infer the underlying intent of implicit queries. By generating staging answers, such as more specific answer clues, MemoRAG bridges the gap between implicit information needs and the retrieval process. This significantly broadens the applicability of standard RAG systems to a wider range of tasks involving implicit queries.

In Table 1, we illustrate how MemoRAG handles implicit queries. For instance, the input query "How does the book convey the theme of love?" lacks a direct semantic connection with the content in the relevant database, as "the theme of love" is not explicitly stated in the raw text. MemoRAG forms a global memory across the entire database and generates key answer clues that facilitate the retrieval of relevant content from the database.

**Information Seeking with Distributed Evidence Query** Information seeking with queries that require distributed evidence gathering introduces additional complexity for standard RAG systems, as these queries require integrating knowledge across multiple steps or unstructured database. Most retrieval methods struggle with these queries because they demand a coherent understanding of interrelated data points, often spanning different contexts.

Table 1: Case for Information Seeking with Implicit Query.

Query: How the book convey the theme of love?

**Database**: Harry Potter series

Clues #1: Lily Potter's sacrifice Clues #2: The Weasley Family

Clues #3: Romantic relationship with Ginny Weasley

**Answer**: The theme of love is conveyed through various key moments and relationships in the Harry Potter series. Lily Potter's sacrifice is a profound example of a mother's love, which protects Harry and plays a central role in the story. The Weasley family embodies the warmth and support of familial love, providing Harry with a sense of belonging and stability. Additionally, the romantic relationship between Harry and Ginny Weasley highlights the development of romantic love throughout the series. These elements collectively illustrate how love, in its many forms, is a powerful and recurring theme in the narrative.

To address this challenge, MemoRAG utilizes its global memory capabilities to connect and integrate relevant information across multiple steps within the database. By generating staging answers that guide the retrieval of interconnected data points, MemoRAG effectively manages the complexity of multi-hop queries. This approach allows MemoRAG to significantly enhance the performance of standard RAG systems in tasks that involve multi-hop reasoning.

In Table 2, we demonstrate how MemoRAG handles such a query. For instance, the input query "Which year had the peak revenue in the past three years?" requires analyzing financial data across multiple years. MemoRAG forms a global memory from the past ten years' financial reports of a large company, reformulates the multi-hop query into several specific query, and integrates this information to determine the peak revenue year.

Table 2: Case for Information Seeking with Distributed Evidence Query.

**Query**: Which year had the peak revenue in the past three years? **Database**: Past ten years' financial reports of a large company

Surrogate Query #1: Revenue figures from Year 2021 Surrogate Query #2: Revenue figures from Year 2022 Surrogate Query #3: Revenue figures from Year 2023

Answer: Year 2021 had the peak revenue

**Information Aggregation** Information aggregation tasks, such as summarizing long documents, require the ability to condense large amounts of unstructured data into concise and coherent outputs. Standard RAG systems often struggle with these tasks because they rely on retrieving discrete pieces of information without a mechanism to effectively combine and summarize them into a comprehensive overview.

MemoRAG addresses this challenge by leveraging its global memory to capture and synthesize key points from the entire dataset. Through this process, MemoRAG is able to generate intermediate staging answers that represent the essential elements of the content, which are then used to retrieve detailed information from the raw content. All of these information are aggregated to produce a final summarization.

In Table 3, we illustrate how MemoRAG handles an information aggregation task. For instance, the task is to summarize a government report on city construction. MemoRAG first extracts key points from the report, such as infrastructure development, budget allocations, and future planning, then retrieve detailed content, and aggregates these information to produce a comprehensive summary of the report.

The current version of MemoRAG primarily targets the aforementioned application scenarios. Below, we outline our planned application scenarios for MemoRAG, which could be achieved by further training on task-specific training data.

Table 3: Case for Information Aggregation.

Task: Summarize the government report

Database: A government report on city construction

**Key Points #1:** Infrastructure development initiatives **Key Points #2:** Budget allocations and expenditures **Key Points #3:** Future urban planning and zoning

**Final Summary**: The report outlines significant infrastructure projects, details the financial aspects including budget allocations, and presents future urban planning strategies to enhance city construction efforts. Specifically, the report highlights major infrastructure developments such as the construction of new public transportation systems...

**Personalized Assistant** Personalized assistant tasks, such as recommending a song based on a user's preferences, require a deep understanding of the user's unique characteristics and history. This is because personalized information needs are often ambiguous, heavily influenced by the user's individual persona. Standard RAG systems may struggle with such tasks because they typically rely on general relevance matching rather than personalizing results based on specific user data.

MemoRAG enhances personalization by leveraging global memory to analyze and understand the user's dialogue history. This allows MemoRAG to identify and utilize key clues such as the user's music preferences, knowledge background, age, and other relevant factors that can be inferred from past interactions. By synthesizing this information, MemoRAG can generate highly personalized recommendations that align closely with the user's tastes.

In Table 4, we demonstrate how MemoRAG handles a personalized recommendation query. For example, when asked, "Can you recommend a song for me?" MemoRAG analyzes the dialogue history of the user, identifying preferences for certain music genres, artists, or eras, and uses this information to suggest a song that fits the user's profile.

### Table 4: Case for Personalized Assistant.

**Query**: Can you recommend a song for me? **Database**: Dialogue history of a user

Clues #1: User's preference for jazz music Clues #2: Mentioned fondness for 1980s music Clues #3: Knowledge background in music theory

**Recommendation:** "Take Five" by Dave Brubeck, a classic jazz piece from the 1960s that aligns with the user's preference for jazz and appreciation for music with complex structures.

**Life-Long Conversational Search** Conversational search frequently involves queries with omitted semantics, where the user's intent relies on the context of prior interactions. Query rewriting is a widely adopted technique to address this challenge. In life-long conversational search, the semantic dependencies of the current query may extend to much earlier interactions, making it essential to accurately identify the relevant context within an extremely long interaction history. Standard RAG systems may struggle with this task due to the ambiguity in the information need presented by the query. This is primarily because standard RAG systems lack the ability to effectively track and incorporate the evolving conversational context, often resulting in incomplete or inaccurate retrievals.

MemoRAG addresses this challenge by leveraging its global memory to maintain and utilize the full context of the conversational history. This enables the system to interpret queries with omitted semantics by referencing relevant previous exchanges and filling in the gaps in meaning. As a result, MemoRAG can accurately interpret and respond to follow-up queries that depend on prior conversation context.

For instance, consider the query, "Does it have any weaknesses?" posed after a discussion about a particular research paper. A standard retrieval system might struggle to understand what "it" refers to without explicit context, potentially retrieving irrelevant information. In contrast, MemoRAG

would refer back to the previous conversation, recognize that "it" refers to the research paper being discussed, and then retrieve information about the paper's weaknesses.

In Table 5, we illustrate how MemoRAG handles a query with omitted semantics in a conversational search context. By drawing on the full conversational history, MemoRAG ensures accurate and contextually appropriate responses.

Table 5: Case for Conversational Search with Omitted Semantics.

**Query**: Does it have any weaknesses compared the paper we discussed last Monday? **Database**: Conversational search history involving follow-up questions and answers.

Surrogate Query #1: What are the weaknesses of the this paper compared to the "ABC" paper?

Clues #1: This paper claims XXX while the "ABC" paper claims YYY.

Clues #2: The "ABC" paper has several key findings.

**Answer**: The research paper has several weaknesses, including limitations in the methodology and gaps in the data analysis.

#### 3 EXPERIMENT

#### 3.1 Dataset

The standard RAG system primarily focuses on QA tasks that involve explicit information needs. To assess the effectiveness of MemoRAG compared to the standard RAG system in such tasks, we evaluate both MemoRAG and baseline models using 13 existing benchmark datasets, including: (1) Single-Doc QA: NarrativeQA (Kočiský et al., 2017), Qasper (Dasigi et al., 2021), and Multi-FieldQA (Bai et al., 2023). (2) Multi-Doc QA: HotpotQA (Yang et al., 2018), 2WikiMQA (Ho et al., 2020), and MuSiQue (Trivedi et al., 2022). (3) Summarization: GovReport (Huang et al., 2021), MultiNews (Fabbri et al., 2019), and En.SUM Zhang et al. (2024). (4) Long-book QA: En.QA Zhang et al. (2024). For summarization tasks, we use the task instruct as a fake query.

In practical scenarios, not all user queries have explicit information needs. Most queries require a comprehensive understanding of the full context and the aggregation of multiple pieces of information to obtain a final answer. To evaluate MemoRAG and standard RAG systems across a broad range of applications, we have constructed the ULTRADOMAIN benchmark. The benchmark comprises tasks with long context and high-level query on multiple specialized domains.

First, we utilize contexts from datasets representing specialized areas of knowledge, focusing on two specialized datasets. The first is the Fin dataset, derived from financial reports. This dataset tests MemoRAG's ability to process and interpret complex financial data, ensuring that the system can handle the intricacies of financial language and reporting. The second is the Legal dataset, constructed from legal contracts. This dataset challenges MemoRAG to understand and navigate the complex and nuanced language of legal documents, where precision is critical.

In addition to these specialized datasets, we collected a diverse set of 428 college textbooks spanning 18 distinct domains, such as natural sciences, humanities, and social sciences, from this repository. These textbooks are used to test MemoRAG's versatility and adaptability across a wide range of topics that may not directly relate to the specialized datasets. By evaluating MemoRAG on these varied contexts, we gain a deeper understanding of its potential for broader applications beyond specific domains such as finance and law.

Lastly, we construct a dataset comprising of mixed context from above datasets, namely Mix. This mixed dataset is intended to evaluate how well MemoRAG can generalize its understanding across different types of context.

The statistical details of the specialized datasets are provided in Table 8, while the details of the textbook-based datasets are shown in Table 9. Together, these datasets form a comprehensive benchmark that rigorously tests MemoRAG's effectiveness in handling both domain-specific challenges and broader, cross-disciplinary tasks.

Further details on the datasets, their construction, and the evaluation metrics used in this study can be found in Appendix A.

Table 6: Main experiment results on ULTRADOMAIN using Mistral-7B-Instruct-v0.2-32K as the generator. The evaluation metric is the F1-score, with the best results highlighted in bold and the second-best results underlined. The upward arrow  $\uparrow$  indicates the improvement over the second-best results. ave(|C|) refers to the average context length, counted in thousands of tokens (K).

ULTRADOMAIN	Full	BGE-M3	Stella-v5	HyDE	MemoRAG	$ave( \mathcal{C} )$ (K)
In-domain						
Legal	35.8	42.0	34.9	35.1	<b>51.2</b> ↑9.2	51.4
Financial	36.5	40.5	40.9	42.8	<b>48.0</b> ↑ 5.2	40.6
Mix	42.1	41.1	42.1	43.9	<b>53.6</b> †9.7	20.3
Average	38.1	41.2	39.3	40.6	<b>50.9</b> †9.7	37.4
Out-of-domain						
Biology	34.1	32.2	32.1	31.5	<b>35.7</b> ↑1.6	125.2
Religion	<u>36.7</u>	35.2	34.1	34.7	<b>37.8</b> ↑1.1	131.4
Computer	<u>36.5</u>	35.9	32.9	35.5	<b>40.5</b> †4.0	215.9
Fiction	29.0	27.6	26.5	27.1	<b>31.3</b> ↑2.3	137.7
Literature	30.5	29.6	28.8	29.2	<b>34.4</b> †3.9	129.4
History	33.3	31.9	32.3	31.1	<b>35.6</b> ↑2.3	195.2
Biography	32.4	31.1	29.8	30.3	<b>35.3</b> ↑2.9	163.5
Physics	36.4	38.1	37.3	<u>38.2</u>	<b>38.8</b> †0.6	105.8
Music	33.9	33.5	31.5	32.9	<b>35.1</b> ↑1.2	168.7
Art	32.5	<u>33.7</u>	33.1	33.0	<b>36.6</b> ↑2.9	129.0
Mathematics	34.5	35.0	33.8	<u>35.4</u>	<b>36.4</b> ↑1.0	198.0
Health	<u>34.8</u>	33.2	32.9	31.9	<b>37.4</b> ↑2.6	134.9
Psychology	<u>34.3</u>	33.6	31.9	33.0	<b>37.6</b> ↑3.3	150.1
Technology	<u>33.9</u>	32.5	31.1	31.8	<b>37.4</b> ↑3.5	144.0
Politics	33.0	32.5	30.2	32.1	<b>35.2</b> ↑2.2	139.6
Cooking	34.1	33.1	31.0	32.9	<b>35.6</b> ↑1.5	156.1
Agriculture	34.9	34.0	33.2	32.8	<b>36.7</b> †1.8	151.0
Philosophy	33.0	32.5	31.8	32.2	<b>36.2</b> †3.2	135.7
Average	33.8	33.0	31.9	32.5	<b>36.2</b> ↑2.4	150.6

### 3.2 Baselines

We compare MemoRAG with the following baselines: (1) **Full**: Directly feeding the full context into LLMs to fit the maximum length of the LLMs. (2) **BGE-M3** Chen et al. (2023): A general-purpose retriever, with which we perform standard RAG. (3) **Stella-en-1.5B-v5**<sup>1</sup>: This model ranks top-3 on the MTEB leaderboard at the time of writing this paper, and we perform standard RAG with it. (4) **RQ-RAG** Chan et al. (2024): RQ-RAG prompt LLMs to resolve the input query into several queries that are better for searching regarding explicit rewriting, decomposition, and disambiguation. The supporting passages are retrieved by both the input query and refined queries. (5) **HyDE** Gao et al. (2022): Directly prompts LLMs to produce fake documents by providing only a query and then retrieves passages using the fake documents, then producing the final answer generation according to the retrieved passages. For more comprehensive comparison, we use three popular LLMs as the generators: Llama3-8B-Instruct-8K <sup>2</sup>; Mistral-7B-Instruct-v0.2-32K Jiang et al. (2023) and Phi-3-mini-128K Abdin et al. (2024).

# 3.3 EXPERIMENTS ON ULTRADOMAIN

To evaluate MemoRAG's ability to generalize across diverse and complex tasks, we evaluate MemoRAG on the UltraDomain benchmark. Most queries in UltraDomain involve either ambiguous information needs or unstructured knowledge retrieval challenges. UltraDomain consists of two types of datasets. The first type includes three datasets with context sizes under 100K tokens which are in the same distributions of our training datasets. We refer to these three datasets as the in-

https://huggingface.co/dunzhang/stella\_en\_1.5B\_v5

<sup>&</sup>lt;sup>2</sup>https://huggingface.co/meta-llama/Meta-Llama-3-8B-Instruct

Table 7: Main experiment results. The best results of each block are in bold. The evaluation metrics for all dataset would be introduced in Appendix A. The Memory Model used in these experiments is trained based on Mistral-7B-Instruct-v0.2-32K, which is available at HuggingFace.

Dataset	nar	qas	mul	mus	2wiki	hot	news	gov	en.sun	n en.qa	fin	legal	mix
			I	LONGI	BENCH				InfBi	ENCH	Ulte	RADON	<b>AAIN</b>
Generator: Llama3-8B-Instruct-8K													
Full	21.3	43.4	46.6	23.5	38.2	47.1	24.6	23.6	13.1	6.7	34.2	33.2	42.7
BGE-M3	22.1	44.3	50.2	22.2	36.7	48.4	22.1	20.1	12.1	15.1	41.4	40.6	46.4
Stella-v5	12.3	35.2	44.4	22.1	33.3	41.9	22.1	20.7	11.7	14.8	41.9	33.7	44.9
RQ-RAG	20.2	43.9	49.1	22.7	36.1	44.5	20.6	21.0	12.0	13.3	39.5	36.8	44.5
HyDE	22.1	44.3	50.2	22.2	36.7	48.4	-	-	-	19.1	41.4	40.6	46.4
MemoRAG	22.8	45.7	50.7	28.4	51.4	57.0	27.4	27.9	14.1	16.1	47.8	47.9	55.5
Generator: F	Phi-3-n	nini-12	28K										
Full	21.4	35.0	47.3	19.0	35.5	42.1	25.6	23.7	13.0	15.2	44.8	40.5	44.7
BGE-M3	20.3	33.0	44.3	21.1	35.4	42.1	17.7	19.8	9.6	16.3	41.7	41.2	43.7
Stella-v5	13.7	32.4	43.5	21.0	35.6	40.6	20.3	18.2	10.0	19.5	42.8	35.1	43.9
RQ-RAG	19.6	34.1	46.5	21.9	36.1	41.7	20.1	18.6	10.4	16.1	41.8	40.9	43.2
HyDE	18.7	36.0	47.5	20.5	36.8	42.7	-	-	-	19.6	43.1	41.6	44.2
MemoRAG	27.5	43.9	52.2	33.9	54.1	54.8	32.9	26.3	15.7	22.9	51.5	51.0	55.6
Generator: Mistral-7B-Instruct-v0.2-32K													
Full	20.8	29.2	46.3	18.9	20.6	37.6	25.0	27.4	12.4	12.3	36.5	35.8	42.1
BGE-M3	17.3	29.5	46.3	18.5	20.3	36.2	24.3	26.1	13.5	12.2	40.5	42.0	41.1
Stella-v5	13.5	23.7	42.1	18.6	22.2	31.9	21.1	18.5	13.2	9.7	40.9	34.9	42.1
RQ-RAG	17.1	29.2	47.0	19.1	21.5	37.0	22.1	18.6	13.1	12.7	44.3	44.6	43.4
HyDE	17.4	29.5	46.3	18.5	20.1	36.2	-	-	-	12.2	42.8	35.1	43.9
MemoRAG	23.1	31.2	50.0	26.9	30.3	42.9	27.1	31.6	17.9	15.4	48.0	51.2	53.6

domain datasets. The second type includes 18 datasets sourced from 428 English college textbooks with context length up to one million tokens, covering subjects such as philosophy, exemplified by 'Nietzsche and Greek Thought,' and mathematics, represented by 'Quantum Theory for Mathematicians.' As the data distribution of the second type of datasets are different from training data, we refer the second type as out-of-domain datasets.

The experiment results are summarized in Table 6, from which we draw the following conclusions: (1) MemoRAG outperforms all baseline models across all datasets, demonstrating its strong domain generalization capabilities. (2) Directly inputting the full context into LLMs generally yields better performance compared to other RAG methods (BGE-M3, Stella-v5, and HyDE). This finding reveals that standard RAG systems struggle with handling long contexts and high-level questions. (3) In contrast, MemoRAG consistently surpasses the performance of directly using the full context, illustrating its ability to effectively bridge the gap between processing super long contexts and addressing complex tasks. (4) MemoRAG demonstrates superior performance on the three in-domain datasets, suggesting that its potential can be further enhanced with more diverse training data.

# 3.4 EXPERIMENTS ON ALL BENCHMARKS

Table 7 shows the experiment results on three benchmarks, from which we can conclude that MemoRAG generally surpasses all baselines on all datasets, except for a single outlier. **First**, for opendomain QA tasks, MemoRAG improves performance over all baselines on all datasets except for en.qa with Llama3 as generator. This verifies that in the comfortable zone of standard RAG, where most queries have explicit information needs, MemoRAG can better locate the expected evidence within the original context, thanks to the memory-generated clues. **Second**, most previous RAG methods struggle with tasks that do not involve queries, such as summarization tasks (e.g., Multi-

News, GovReport, and en.sum)<sup>3</sup>. Our MemoRAG enables the RAG system to generate key points from the input context and retrieve more details to form a comprehensive summary. **Third**, for domain-specific tasks (e.g., Financial and Legal), MemoRAG shows significant improvement, indicating MemoRAG's superiority in handling complex tasks with long contexts. **In summary**, the results demonstrate that MemoRAG significantly enhances performance over standard RAG methods and other baselines across various datasets and query types. MemoRAG's ability to handle complex and long-context tasks effectively highlights its advantages, particularly in scenarios where standard RAG systems struggle. This consistency across different generators underscores the robustness and general applicability of MemoRAG.

# 4 Conclusion

In this paper, we introduce MemoRAG, a novel Retrieval-Augmented Generation (RAG) system that integrates global context-awareness to address the challenges posed by complex tasks involving long input contexts. MemoRAG features a memory module that constructs a compact global memory across the entire database, facilitating the generation of context-dependent clues that effectively link the knowledge database to the precise information required for accurate answers. Extensive experiments across knowledge-intensive QA, summarization, and real-world applications involving lengthy documents demonstrate that MemoRAG significantly outperforms traditional RAG systems. It excels in tasks requiring advanced information aggregation and exhibits exceptional robustness and versatility in managing large-scale texts, such as textbooks, financial reports, and legal contracts, handling contexts of up to one million tokens and resolving complex queries with superior accuracy.

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Table 8: Statistical information of the datasets utilized in this paper.

Dataset	Narrative	Qasper	MultiField	Hotpot	MuSiQue	2Wiki
Num of Samples	200	200	150	200	200	200
Ave. Length	18,409	3,619	4,559	9,151	11,214	4,887
Metric	F1	F1	F1	F1	F1	F1
Dataset	GovReport	MultiNews	En.Sum	En.QA	Fin	Legal
Num of Samples	200	200	103	351	345	438
Ave. Length	8,734	2,113	171,500	192,600	40,625	51,413
Metric	Rouge-L	Rouge-L	F1	Rouge-L	F1	F1

# A MORE DETAILS OF THE DATASETS

To construct the SFT training set, we first collect long contexts from novels, academic papers, news, financial reports, and legal contracts. The collection of novels, academic papers, and news comes from the training datasets of NarrativeQA, Qasper, and HotpotQA. The legal contracts are sourced from this repository, and the financial reports are from this repository. We then sample long contexts with lengths of up to 80K tokens and prompt strong LLMs (e.g., GPT-4 128K, Deepseek-v2-128K) to generate high-level and insightful question-answer pairs. After quality inspection of these generated QA pairs, we select 20,000 samples to prompt the same LLMs to generate answer clues that can bridge the gap between the query and the long context. In this process, we provide the model with the query, the long context, and the answer, enabling the LLMs to utilize both priori and posteriori knowledge to more easily generate the answer clues. We then inspect the generated answer clues, performing strategic filtering for better quality, resulting in 17,116 SFT training samples.

For the evaluation dataset, we use a separate set of contexts from the aforementioned datasets as the evaluation context. We follow the same process to generate QA pairs, creating the in-domain evaluation datasets: the Fin dataset (from the financial reports), the Leg dataset (from the legal contracts), and the Mix dataset (from NarrativeQA, Qasper, and HotpotQA). Additionally, we collect college textbooks from 18 domains from this repository to construct the out-of-domain evaluation dataset, following the same process. The statistical information of the in-domain datasets is shown in Table 8, and the statistical information of the out-of-domain datasets is shown in Table 9.

Table 9: Statistical information of the out-of-domain evaluation datasets utilized in this paper.

Dataset	Num	$\max( \mathcal{C} )$	$\min( \mathcal{C} )$	$\text{ave}( \mathcal{C} )$	$\text{ave}( \mathcal{Q} )$	$ave( \mathcal{A} )$
Technology	240	306,073	44,549	144029.7	14.4	40.2
Biology	220	257,644	39,218	125284.9	16.8	49.1
Religion	220	1,071,342	34,257	131424.8	17.4	54.2
Fiction	220	564,980	44,057	137689.7	16.2	43.6
Psychology	200	571,725	37,988	150119.5	16.7	46.5
Music	200	381,043	51,517	168672.9	17.5	49.7
Art	200	305,001	32,793	128961.2	17.8	52.2
Philosophy	200	678,553	38,729	135682.7	17.2	51.0
Health	180	289,258	50,600	135902.0	16.2	48.2
History	180	688,074	53,277	195265.0	17.9	51.0
Literature	180	534,836	33,043	129363.7	16.9	47.0
Biography	180	408,969	45,052	163522.3	18.0	52.0
Politics	180	387,157	49,853	139624.3	17.9	54.9
Mathematics	160	726,144	60,936	197924.6	16.7	47.6
Physics	160	226,811	36,717	105805.6	14.8	54.2
Cooking	120	466,885	58,360	156139.2	16.5	46.6
Agriculture	100	385,915	76,581	150969.6	15.6	45.9
Computer	100	437,070	51,704	215929.5	14.3	39.8
Total	3,240	1,071,342	32,793	150684.0	16.6	48.5