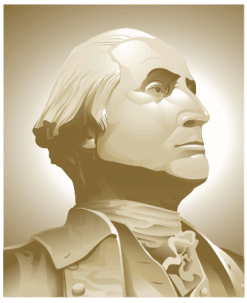

THE GEORGE WASHINGTON UNIVERSITY

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Data Science Program

Capstone Report - Fall 2024

Optimizing Information Retrieval: A Hybrid Model Leveraging MAR and RAPTOR Frameworks

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Abstract

The rapid growth of unstructured data presents challenges for traditional retrieval systems in handling complex, context-dependent queries and multi-hop reasoning. Retrieval-Augmented Generation (RAG) frameworks, integrating retrieval mechanisms with large language models (LLMs), offer a solution by enhancing contextual relevance and response accuracy. This study evaluates Naive RAG, Memory-Augmented Retrieval (MAR), Recursive Abstractive Processing for Tree-Organized Retrieval (RAPTOR), and a Hybrid Model using the BioASQ biomedical dataset. MAR excels in static queries through memory persistence but struggles with dynamic tasks, while RAPTOR's hierarchical approach enhances multi-hop reasoning yet lacks static memory capabilities. The Hybrid Model combines MAR's memory-driven retrieval with RAPTOR's hierarchical abstraction, achieving balanced performance across query types. The findings highlight the influence of embedding strategies on retrieval performance and the need for optimized approaches to balance accuracy and efficiency. Future advancements, including dynamic query refinement, adaptive retrieval techniques, and multimodal integration, aim to address challenges of scalability and contextual understanding. By integrating state-of-the-art retrieval and reasoning techniques, the Hybrid Model provides a promising framework for scalable, context-aware information retrieval.

Contents

1. Introduction

The rapid proliferation of unstructured data has posed significant challenges to traditional information retrieval systems, particularly in synthesizing meaningful insights from extensive and complex contexts. These systems frequently struggle with resolving ambiguous queries, aggregating evidence across multiple sources, and addressing tasks that require multi-hop reasoning. Consequently, there is a growing demand for retrieval systems that combine precision, scalability, and adaptability to dynamic query requirements. Retrieval-Augmented Generation (RAG) frameworks have emerged as a promising solution, dynamically integrating retrieval mechanisms with large language models (LLMs) to enhance both contextual relevance and response accuracy.

A key development in this domain is MemoRAG, which introduces a dual-system architecture to address the limitations of static retrieval systems. By incorporating memory hierarchies and dynamically updating stored knowledge, MemoRAG improves the efficiency and accuracy of retrieval processes [1]. Complementing this is the RAPTOR framework, which organizes data into hierarchical tree structures for multi-level context aggregation and recursive abstraction. RAPTOR's recursive clustering methodology enables it to traverse semantic clusters dynamically, making it particularly effective for multi-hop reasoning and abstractive question answering [2].

Recent advancements have further refined RAG methodologies. MemLong extends the capabilities of retrieval-augmented systems by leveraging long-context modeling and hierarchical indexing to efficiently manage ultra-long contexts [3]. Similarly, the LONGMEM framework enhances memory-augmented LLMs by integrating decoupled memory architectures to mitigate staleness and support context retrieval across extended sessions [4]. MemReasoner complements these innovations by introducing temporal processing and iterative reasoning capabilities, enabling robust performance in multi-hop question-answering tasks across long documents [5].

Blended RAG employs hybrid query strategies to combine dense and sparse vector-based search techniques, setting benchmarks in retrieval accuracy across diverse datasets like NQ and TREC-COVID [6]. MBA-RAG incorporates multi-armed bandit optimization to dynamically adjust retrieval strategies, achieving a trade-off between query efficiency and computational cost [7]. HIRO introduces recursive

similarity scoring and branch pruning, optimizing hierarchical data traversal for large-scale, complex datasets [8]. Meanwhile, LightRAG leverages graph-structured indexing and dual-level retrieval to enhance the synthesis of interdependent data [9].

Innovative hybrid models such as HybridRAG and RAG Foundry demonstrate the benefits of combining structured relational data with unstructured semantic information. These frameworks optimize query performance and retrieval workflows to enhance the contextual coherence of generated outputs [10, 11]. COCOM, a context compression model, further reduces inference time while preserving high generative quality, showcasing a significant speed-up for multi-document QA tasks [12]. ContextRAG improves the relevance of retrieved content by focusing on query-sensitive retrieval methods for context-dependent tasks [13]. BootHealthCare LLM emphasizes retrieval optimization for domain-specific applications, demonstrating its utility in healthcare-related open-ended question answering [19]. Retrieve Anything and ADAPT-LLM provide versatile retrievers and adaptive IR integration, enabling LLMs to balance reliance on internal memory and external retrieval for improved QA accuracy [14, 15].

The Text Embeddings Reveal study highlights the dual-edged nature of text embeddings, demonstrating their potential to recover semantic-rich text while addressing concerns of privacy and robustness in retrieval systems [16]. The MAR Mixture of Word Experts framework introduces sparse architectures optimized for knowledge-intensive NLP tasks, achieving a balance between computational efficiency and performance [20]. The Active Retrieval Augmented Generation (ARAG) framework introduces dynamic, forward-looking strategies for retrieval, ensuring iterative knowledge integration for long-form question answering and multi-hop reasoning [17]. The Searching for Best RAG Methods study offers practical insights into selecting optimal retrieval strategies across diverse datasets and task types [21]. Finally, the Understanding Retrieval Augmentation for Long QA study dissects the role of retrieval in generating long-form, evidence-supported responses, emphasizing the importance of contextual attribution in retrieval-augmented systems [18]. When to Retrieve addresses the timing of retrieval and its impact on query relevance, focusing on adaptive strategies for optimizing performance in retrieval-augmented systems [22].

This report primarily builds on MemoRAG, RAPTOR, and Naive RAG as foundational frameworks, which serve as core elements in developing the MAR, RAPTOR, and Hybrid models discussed herein. MemoRAG's memory hierarchies, RAPTOR's hierarchical context organization, and Naive RAG's straightforward retrieval-generation integration provide the foundational structure for these advanced models. By extending these frameworks with targeted innovations, such as adaptive retrieval strategies, hierarchical abstraction, and multi-hop reasoning, this report proposes solutions to key challenges in retrieval-augmented generation. The resulting models emphasize dynamic retrieval, contextual coherence, and scalable performance, offering robust solutions for complex information retrieval tasks.

2. Problem Statement

Traditional retrieval systems face significant inefficiencies when processing tasks that require extensive context, precise query resolution, and multi-hop reasoning. These limitations arise primarily from token constraints in language models, which hinder their ability to handle ultra-long contexts, leading to incomplete or fragmented responses. Additionally, static retrieval systems struggle with ambiguous queries due to the absence of mechanisms for refining unclear inputs into actionable forms. Multi-hop reasoning, which requires synthesizing evidence from distributed sources, further exposes the inability of these systems to adapt dynamically or aggregate complex contexts effectively.

Existing frameworks attempt to address these challenges but remain limited in scope. Memory-Augmented Retrieval (MAR) improves static query handling but lacks adaptability for dynamic or multi-layered tasks. Conversely, Recursive Abstractive Processing for Tree-Organized Retrieval (RAPTOR) enhances multi-hop reasoning through hierarchical data organization but fails to incorporate persistent memory, reducing its effectiveness for recurring or infrequently accessed information.

This study seeks to address these limitations by proposing a Hybrid Model that integrates MAR's memory persistence with RAPTOR's hierarchical abstraction, augmented by advanced query optimization techniques. The Hybrid Model is designed to combine static recall efficiency, dynamic adaptability, and multi-hop reasoning

capabilities. By leveraging state-of-the-art advancements such as hybrid query strategies and dynamic routing, the proposed solution aims to overcome the shortcomings of traditional systems, providing a scalable and context-aware framework for complex retrieval tasks.

3. Methodology

The retrieval-augmented generation (RAG) models implemented in this study—Naive RAG, MAR, RAPTOR, and the Hybrid Model—are built on a simple but extensible structure. This foundation allows seamless integration of different retrieval and reasoning techniques while maintaining modularity and efficiency. At the core of this structure is a retrieval component that interfaces with a vector store for semantic similarity searches and a generative component that synthesizes query-relevant responses.

3.1. Retrieval-Augmented Generation (Naive RAG)

Naive RAG serves as the foundational structure for all subsequent implementations in this study. The model operates in two primary phases: retrieval and generation. A query is embedded into a high-dimensional vector space and compared against pre-indexed embeddings in a vector store using semantic similarity. The top-k relevant documents are retrieved and passed to a generative language model (LLM), which synthesizes an answer based on the retrieved context.

While the Naive RAG implementation aligns with its standard framework, certain parameters were tailored to optimize retrieval for the biomedical domain.

Specifically:

- **Chunking**: Documents were preprocessed into fixed-size chunks using predefined `chunk_size` and `chunk_overlap` parameters, ensuring sufficient context for embedding generation.
- **Embedding Models**: High-performance embedding models such as `mxbai-embed-large` were used to enhance semantic similarity calculations.

This implementation establishes a baseline for evaluating the more advanced MAR, RAPTOR, and Hybrid Model systems.

Figure 1 illustrates the Naive RAG architecture, showcasing its straightforward query-to-response pipeline.

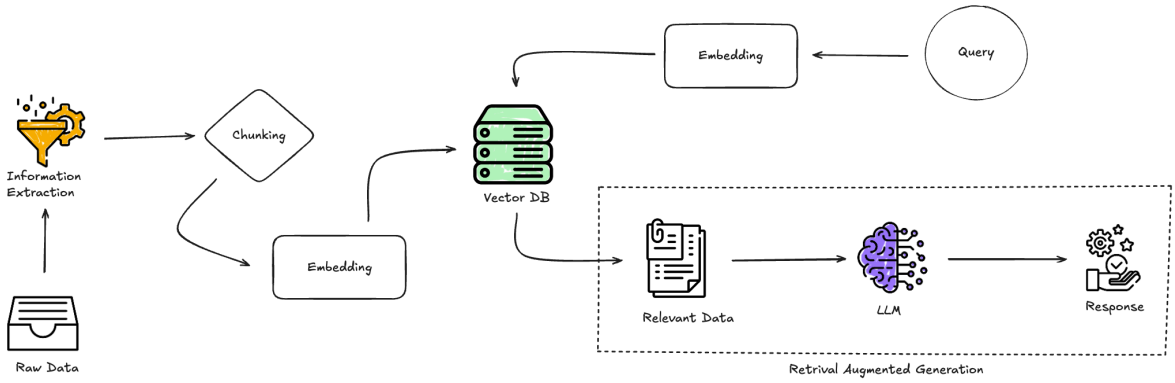

Figure 1: *Basic workflow of a Retrieval-Augmented Generation (RAG) system*.

3.2. Memory-Augmented Retrieval (MAR)

MAR builds on Naive RAG by integrating a memory component to handle static, frequently recurring queries efficiently. A MemoryDB is pre-populated with frequently asked questions (FAQs) and their ideal answers. When a query is issued, MAR first checks the MemoryDB for a matching entry based on a similarity threshold. If a match is found, the answer is retrieved directly. Otherwise, the query falls back to the vector store retrieval process, as in Naive RAG.

For this study, the MAR implementation adheres to its foundational principles as described in the MemoRAG framework, particularly the focus on memory persistence. However, the implementation does not include *clue generation* for refining queries, a feature of the original MemoRAG methodology. Despite this, the design emphasizes efficient memory-driven retrieval, ensuring alignment with MAR's objective of enhancing performance on static, frequently recurring queries.

Figure 2 illustrates the MAR architecture, highlighting the addition of MemoryDB as a first-layer retrieval component.

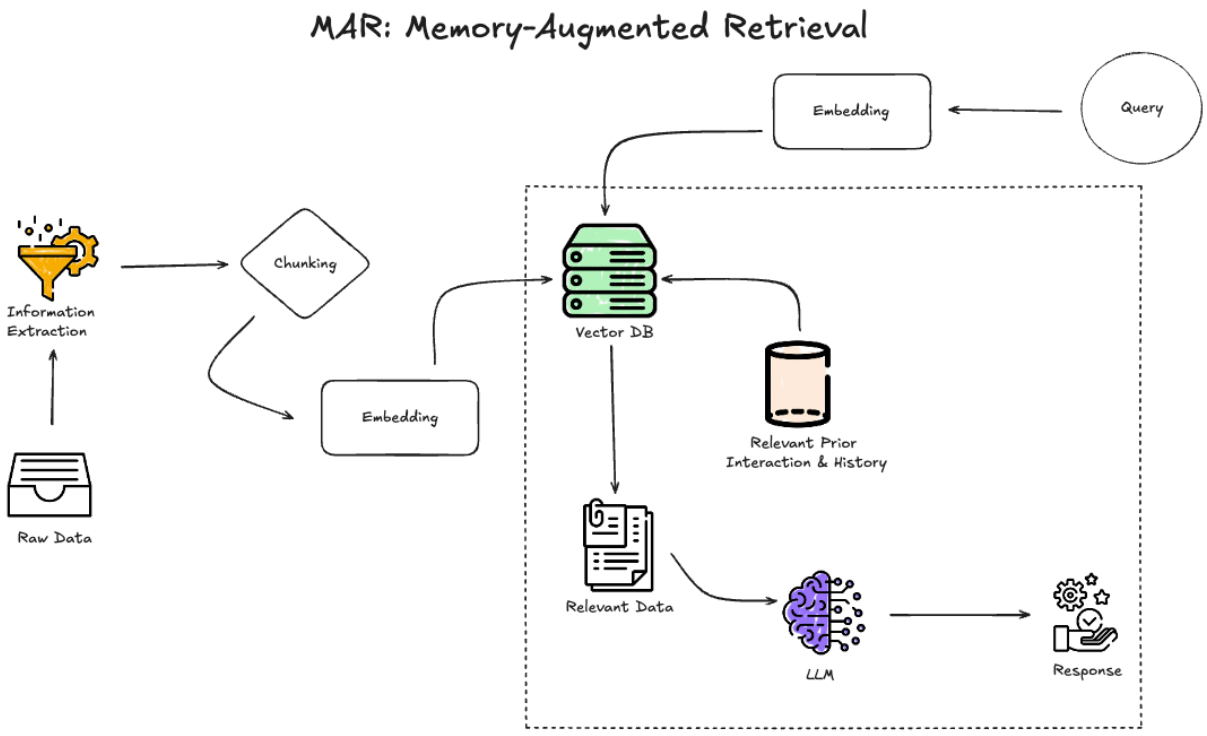

Figure 2: Workflow of the Memory-Augmented Retrieval (MAR) system.

3.3. Recursive Abstractive Processing for Tree-Organized Retrieval (RAPTOR)

RAPTOR extends the Naive RAG structure by organizing documents hierarchically within a tree structure. Documents are recursively clustered based on semantic similarity, and each cluster is summarized to create higher-level abstractions. While traditional implementations of RAPTOR frequently employ advanced clustering techniques such as Gaussian Mixture Models (GMM) or Uniform Manifold Approximation and Projection (UMAP), this study employs quantization of embeddings as a simplified alternative.

Quantization was chosen for this implementation to reduce computational complexity and memory requirements during testing. Unlike GMM or UMAP, which can introduce significant overhead due to their iterative optimization and manifold learning processes, quantization provides a lightweight mechanism for grouping semantically similar documents. This trade-off simplifies the implementation and enables rapid prototyping while maintaining the core hierarchical principles of RAPTOR.

Although quantization may introduce a degree of semantic approximation, the approach is sufficient for the objectives of this study, where the focus lies in evaluating high-level retrieval performance rather than fine-grained cluster granularity. Future iterations may explore incorporating GMM or UMAP for scenarios where semantic precision is critical.

Figure 3 illustrates RAPTOR's hierarchical architecture, emphasizing its recursive clustering and multi-level retrieval mechanism.

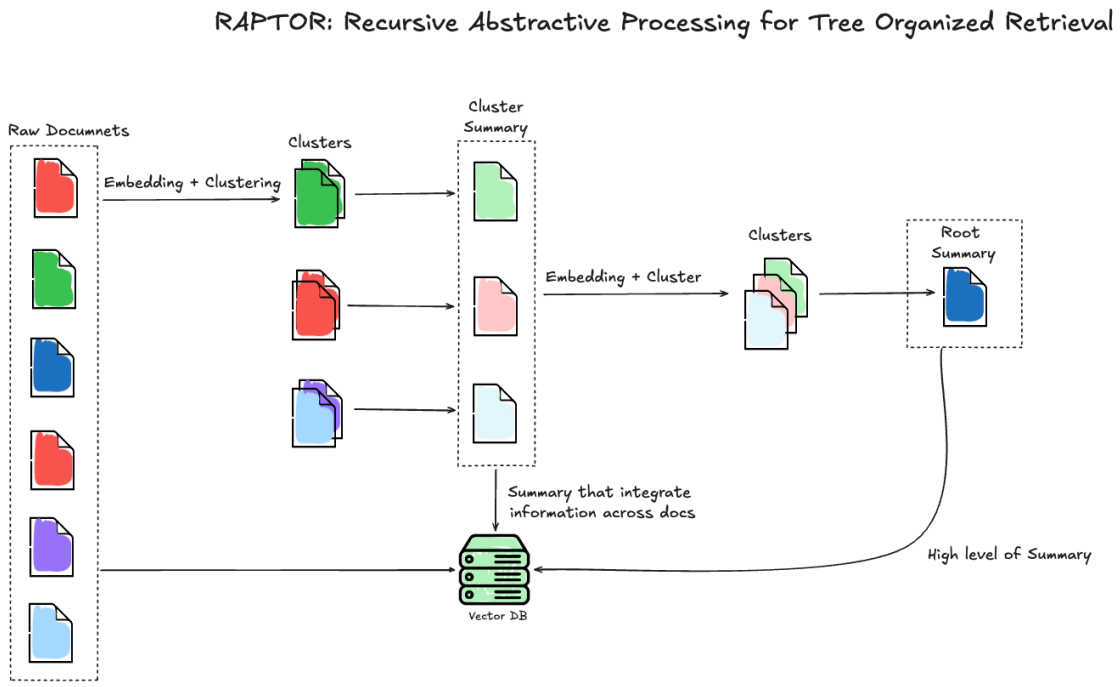

Figure 3: Hierarchical retrieval architecture of the RAPTOR system.

3.4. The Hybrid Model

The Hybrid Model integrates MAR's memory-first retrieval approach with RAPTOR's hierarchical abstraction to address both static and dynamic query scenarios. Queries are first processed through MAR's MemoryDB, where frequently recurring questions are matched using a similarity threshold. If unresolved, the queries are routed to RAPTOR's hierarchical retrieval mechanism, enabling multi-hop reasoning.

This implementation adheres to the core principles of both MAR and RAPTOR while introducing certain adjustments to balance efficiency and scalability:

- **MemoryDB**: The Hybrid Model uses MAR's memory-first layer to rapidly resolve static queries, ensuring efficiency for recurring tasks.
- **Hierarchical Retrieval**: RAPTOR's tree structure and recursive abstraction are leveraged for dynamic, multi-hop queries. However, similar to RAPTOR, this implementation uses *quantization of embeddings* instead of UMAP or GMM for hierarchical clustering.
- **Dynamic Routing**: A similarity threshold governs query routing between MAR and RAPTOR components, ensuring an adaptive retrieval process.

By combining these approaches, the Hybrid Model achieves a balance between static query efficiency and dynamic reasoning capabilities, addressing the limitations of standalone MAR or RAPTOR systems.

Figure 4 illustrates the Hybrid Model, showing the dynamic routing between MAR and RAPTOR components.

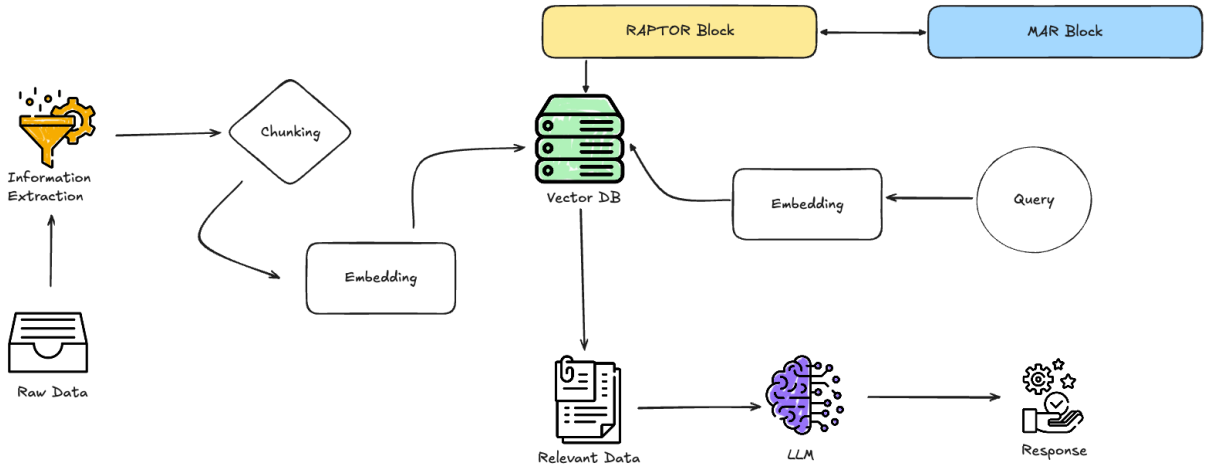

Figure 4: Architecture of the Hybrid Model, combining MAR and RAPTOR systems.

3.5. Choice of Retrieval System: ChromaDB

ChromaDB was selected as the vector store for its ability to meet the diverse retrieval requirements of Naive RAG, MAR, RAPTOR, and the Hybrid Model. Its high-performance vector search capabilities ensure low-latency query processing, making it

suitable for large-scale applications. ChromaDB's support for distributed deployments and its capacity to handle high-dimensional embeddings allow it to scale effectively with expanding datasets. Furthermore, ChromaDB integrates seamlessly with embedding models like mxbai-embed-large and frameworks such as LangChain, facilitating efficient implementation.

The choice of ChromaDB also aligns with the system's need for hybrid retrieval methods, combining semantic similarity and keyword-based approaches. This flexibility allows the various RAG models to adapt to both static and dynamic query scenarios. Additionally, the robust community support and frequent updates provided by ChromaDB ensure its continued relevance and compatibility with cutting-edge retrieval technologies.

3.6. Model Configuration and Hyper-parameters

The configurations and hyper-parameters used in the implementation of Naive RAG, MAR, RAPTOR, and the Hybrid Model were carefully chosen to optimize retrieval and response generation. This section outlines the shared parameters used across all models and the additional configurations specific to the Hybrid Model.

Shared Hyper parameters Across All RAG Models: All RAG models, including Naive RAG, MAR, RAPTOR, and the Hybrid Model, utilized a consistent set of foundational hyper-parameters for document preprocessing and embedding generation. These parameters ensured uniformity in handling documents across different systems.

The chunking mechanism divided documents into fixed-sized text chunks with overlapping characters to preserve context across adjacent chunks. Embedding dimensions and batch sizes were also standardized to maintain compatibility with the underlying vector store. Could be seeing in the Table 1 below.

Hyperparameter	Value/Default	Description
chunk_size	1000	The maximum size of text chunks for splitting documents.
chunk_overlap	115	The number of overlapping characters between consecutive text chunks.
embedding_dim	1024	Dimension of the embeddings generated by the model.

batch_size	16 (embedding), 50 (indexing)	Batch size for document processing during embedding generation or indexing.
max_documents	Derived dynamically	The maximum number of documents stored, based on space and model embedding size.
avg_document_size	1000	Average size of documents in bytes, used for storage estimation.

Table 1: Hyper parameters Across All RAG Models

These shared hyper-parameters established a robust and uniform framework for preprocessing and retrieval across all models.

Hybrid Model-Specific Hyper-parameters: The Hybrid Model, integrating MAR's memory-driven retrieval with RAPTOR's hierarchical abstraction, introduced additional hyper-parameters to support its hybrid architecture. These parameters were designed to optimize memory usage, similarity thresholds, reranking strategies, and retrieval balance.

Key configurations for the Hybrid Model include parameters for handling semantic similarity and keyword-based retrieval, memory caching, and cross-encoder reranking. The model also introduced thresholds for dynamic similarity, coherence verification, and fallback mechanisms.

Hyperparameter	**Value/Default**	**Description**
reranking_top_k	10 (EnhancedRAPTOR), 5 (UnifiedRAPTOR)	The number of top results used for reranking.
similarity_threshold	0.45 (UnifiedRAPTOR), 0.65 (MemoryDB)	The threshold for determining relevance during similarity comparisons.
cache_size	1000	The size of the cache for storing preprocessed embeddings or results.
compression_ratio	8	Compression ratio used in MemoryDB for embeddings.
max_memory_size	1000	The maximum number of items stored in the memory database.
cross_encoder_name	"cross-encoder/ms-marco-MiniLM-L-12-v2"	The model name for the cross-encoder used in reranking.
semantic_weight	0.7	Weight assigned to semantic search results in hybrid retrieval.
keyword_weight	0.3	Weight assigned to keyword-based search results in hybrid retrieval.
dynamic_threshold_min	0.2	Minimum allowed dynamic similarity threshold.
dynamic_threshold_max	0.8	Maximum allowed dynamic similarity threshold.

coherence_threshold	0.7	Threshold for verifying semantic coherence in parent-child relationships.
fallback_threshold	3	Fallback threshold for memory retrieval in the MemoryDB.
dimension_threshold	64	Dimensional threshold used for storage optimization and compression.
compression_level	9	Compression level used during embedding storage optimization.
max_new_tokens	250	The maximum number of tokens generated by the LLM in response generation.

Table 2: Hybrid Model-Specific Hyper-parameters

The combination of these hyper-parameters allowed the Hybrid Model to balance efficiency and accuracy across a wide range of query types, leveraging MAR's memory-driven advantages and RAPTOR's hierarchical reasoning.

3.7. Dataset Description

The dataset used for this study was derived from the BioASQ dataset, a widely recognized biomedical question-answering benchmark. This dataset is specifically designed to evaluate the performance of information retrieval systems in handling diverse and complex queries. It encompasses a variety of biomedical questions, supporting static, dynamic, and multi-layered reasoning tasks. Figure below describes the escribes the Data preparation steps.

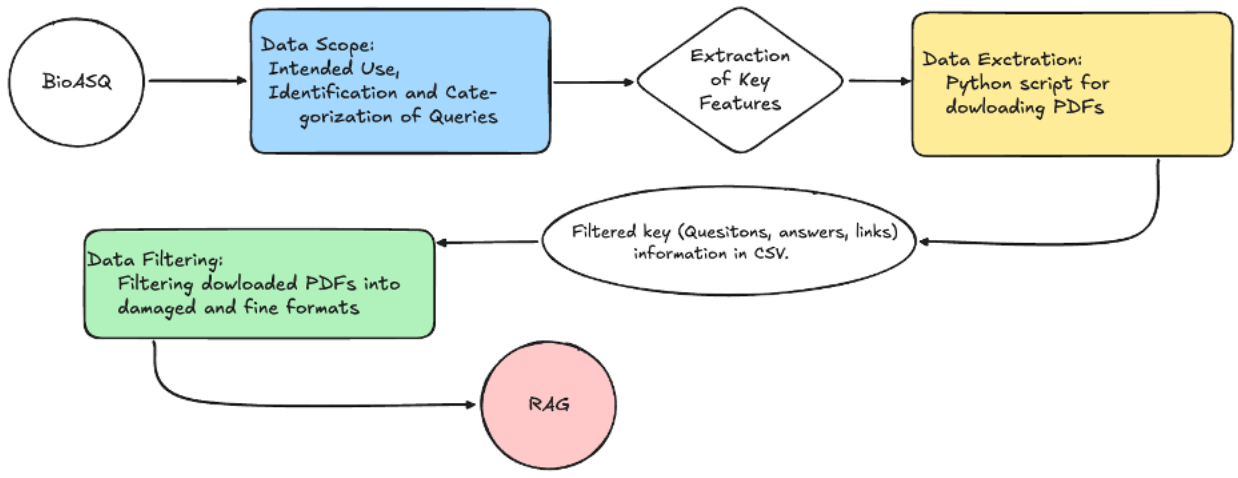

Figure 5: Processing Dataset diagram

Preprocessing and Ground Truth: The queries were categorized into three main types—static (S), dynamic (D), and multi-layered (M)—to facilitate a targeted evaluation of the retrieval-augmented generation (RAG) systems. This classification ensured that each system's capabilities were tested against different levels of complexity and reasoning requirements. Where Static queries involved straightforward, factual information retrieval. Dynamic queries required contextual reasoning and the ability to handle updated information. And multi-layered queries demanded aggregating evidence across multiple sources or reasoning steps. Below in Table 3 you will find categorized Biomedical Queries.

ID	Question	Category
1	Is Hirschsprung disease a Mendelian or a multifactorial disorder?	M
2	List signaling molecules (ligands) that interact with the receptor EGFR?	S
3	Are long non-coding RNAs spliced?	M
4	Is RANKL secreted from the cells?	S
5	Which miRNAs could be used as potential biomarkers for epithelial ovarian cancer?	M
6	Which acetylcholinesterase inhibitors are used for treatment of myasthenia gravis?	S
7	Has Denosumab (Prolia) been approved by FDA?	D
8	Which are the different isoforms of the mammalian Notch receptor?	S
9	Orteronel was developed for treatment of which cancer?	D
10	Is the monoclonal antibody Trastuzumab (Herceptin) of potential use in the treatment of prostate cancer?	D
11	Which are the Yamanaka factors?	S
12	Where is the protein Pannexin1 located?	S
13	Which currently known mitochondrial diseases have been attributed to POLG mutations?	M

Table 3: Categorized Biomedical Queries

Ideal answers for each query, derived from authoritative sources such as PubMed and BioASQ, were used as the ground truth to evaluate system performance. These

answers served as benchmarks for assessing the contextual relevance and completeness of the systems' generated responses.

During preprocessing, the dataset was prepared to address issues such as inconsistent formats and long contexts. Not all documents linked to the dataset were successfully extracted due to problems such as damaged or inaccessible PDF formats. These limitations highlight the critical need for robust preprocessing pipelines to ensure the integrity and usability of training and evaluation datasets.

Frequency of Extracted PDFs: The frequency of successfully retrieved and processed PDFs varied across queries. A summary of the retrieved documents for each query is presented in Table 4: Frequency of PDFs for Each Question. This table provides an overview of data availability, which directly influenced the evaluation outcomes for specific queries.

ID	Question	Frequency
1	Is Hirschsprung disease a Mendelian or a multifactorial disorder?	2
2	List signaling molecules (ligands) that interact with the receptor EGFR?	4
3	Are long non-coding RNAs spliced?	4
4	Is RANKL secreted from the cells?	3
5	Which miRNAs could be used as potential biomarkers for epithelial ovarian cancer?	6
6	Which acetylcholinesterase inhibitors are used for treatment of myasthenia gravis?	2
7	Has Denosumab (Prolia) been approved by FDA?	2
8	Which are the different isoforms of the mammalian Notch receptor?	2
9	Orteronel was developed for treatment of which cancer?	3
10	Is the monoclonal antibody Trastuzumab (Herceptin) of potential use in the treatment of prostate cancer?	7
11	Which are the Yamanaka factors?	7
12	Where is the protein Pannexin1 located?	4
13	Which currently known mitochondrial diseases have been attributed to POLG mutations?	2

Table 4: Frequency of PDFs for each questions

4. Relevance

The categorized queries used in this study—static (S), dynamic (D), and multi-layered (M)—are highly representative of the challenges faced in biomedical information retrieval. This diversity allows for a comprehensive evaluation of retrieval-augmented generation (RAG) systems across varying levels of complexity and reasoning requirements.

Static Queries involve retrieving straightforward, factual information that relies on pre-existing, often unchanging knowledge. For example, queries like *"Which are the Yamanaka factors?"* or *"Which acetylcholinesterase inhibitors are used for treatment of myasthenia gravis?"* test a system's ability to accurately retrieve well-known, static answers from a dataset.

Dynamic Queries require contextual reasoning and the ability to handle evolving information, such as updates to regulatory statuses or therapeutic applications. For instance, the query *"Has Denosumab (Prolia) been approved by FDA?"* tests a system's adaptability in retrieving timely and contextually relevant information.

Multi-Layered Queries demand evidence aggregation and multi-hop reasoning, where answers must be synthesized across multiple sources or involve complex reasoning steps. Examples include *"Which miRNAs could be used as potential biomarkers for epithelial ovarian cancer?"* and *"Which currently known mitochondrial diseases have been attributed to POLG mutations?"*

By evaluating system performance across these query categories, this study highlights the strengths and limitations of Naive RAG, MAR, RAPTOR, and the Hybrid Model. Static queries emphasize memory recall and precision, dynamic queries challenge the systems' contextual adaptability, and multi-layered queries assess reasoning capabilities. This classification ensures a rigorous and multifaceted evaluation of the retrieval frameworks under study.

5. Results

The evaluations of MAR, RAPTOR, and the Hybrid Model were conducted on an **AWS g5.2xlarge instance**, chosen for its compatibility with GPU-based computations and support for large-scale models. This instance, equipped with one NVIDIA A10G Tensor Core GPU, 8 vCPUs, and 32 GiB of memory, provided the necessary computational resources for running retrieval tasks, embedding evaluations, and memory optimization. The use of 8-bit precision loading for embedding models further optimized GPU memory usage, enabling the efficient execution of large-scale experiments.

This section evaluates the performance of MAR, RAPTOR, and the Hybrid Model across a diverse set of biomedical queries, as well as the influence of embedding models on retrieval accuracy and efficiency. The findings highlight both the strengths and limitations of each system while shedding light on the pivotal role of embeddings in optimizing retrieval-augmented generation (RAG) systems.

The biomedical data used in this study was derived from the BioASQ dataset (23), which contains essential features such as the ideal answer, question, and links to related articles from which PDFs were downloaded for processing.

5.1. System Performance Across Queries

The evaluation of Naive RAG, MAR, RAPTOR, and the Hybrid Model utilized a diverse range of biomedical queries, categorized into static, dynamic, and multi-layered scenarios. Each system's performance was assessed using specific examples, which are detailed in their respective tables (Table 1 for Naive RAG, Table 2 for MAR, Table 3 for RAPTOR, and Table 4 for the Hybrid Model). These tables summarize the systems' answers, ideal responses, and correctness, providing a clear view of the models' effectiveness in handling different query types. Detailed performance results can also be found in **Appendix, Table A1: Evaluation Performance of Retrieval MAR, RAPTOR, and Hybrid Systems**.

The results reveal distinct strengths and limitations for each system. Naive RAG, serving as the baseline, performed well in static queries, such as answering, *“What is acetylcholinesterase used for?”* with an accurate response. However, it struggled with dynamic queries requiring updated contextual information, like determining the FDA

approval status of Denosumab (Prolia), which led to incorrect responses. Its inability to process multi-layered queries further underscored the limitations of its straightforward retrieval-to-generation pipeline. Refer to Appendix, Table A1, for specific examples of Naive RAG's performance.

MAR significantly improved static query performance by utilizing a memory-driven retrieval mechanism. It excelled in recalling pre-indexed information, as demonstrated in queries such as *"What are EGFR ligands?"* However, its dependence on pre-indexed memory constrained its adaptability in dynamic contexts, where real-time updates were essential. For example, MAR failed to provide accurate information about the FDA approval of Denosumab (Prolia), highlighting its limitations in handling evolving or ambiguous queries. Further details on MAR's performance are available in Appendix, Table A1.

RAPTOR, with its hierarchical retrieval structure, excelled in dynamic and multi-layered scenarios. Its recursive abstraction capabilities allowed it to handle complex reasoning tasks, such as identifying the location of proteins like Pannexin1. However, RAPTOR's lack of persistent memory limited its effectiveness for static queries, such as classifying Hirschsprung disease, where pre-indexed recall would have been beneficial. Refer to Appendix, Table A1, for more examples and detailed results for RAPTOR.

The Hybrid Model combined the strengths of MAR and RAPTOR, achieving a balanced performance across all query types. It excelled in both static queries, such as identifying EGFR ligands, and dynamic, multi-layered scenarios, like determining miRNAs for epithelial ovarian cancer. Despite its overall robust performance, the Hybrid Model struggled with highly specialized or ambiguous queries, such as identifying mitochondrial diseases linked to POLG mutations. These failures indicate a need for advanced clustering techniques and refined contextual reasoning to improve retrieval and response generation. Detailed evaluations of the Hybrid Model's performance are provided in Appendix, Table A1.

These findings, elaborated in Tables 1–4 and summarized in Appendix, Table A1, illustrate the systems' varying capabilities and provide a foundation for discussing their broader implications. By integrating memory persistence and hierarchical reasoning, the

Hybrid Model demonstrates the potential for retrieval-augmented generation systems to address diverse query requirements effectively.

Performance of Naive RAG: Naive RAG operates on a simple retrieval-to-generation pipeline, excelling in basic queries while struggling with those requiring additional context or reasoning. However, it failed to address dynamic or context-dependent queries effectively. Example results for Naive RAG are provided in Table 5, which highlights its performance across various query types.

Question	Ideal Answer	Naive RAG Answer	Result
What is acetylcholinesterase used for?	Acetylcholinesterase breaks down acetylcholine.	Acetylcholinesterase breaks down acetylcholine.	✅ Correct
Has Denosumab (Prolia) been approved by FDA?	Yes, approved by the FDA in 2010.	No information available.	❌ Incorrect

Table 5: Naive-Rag. Answer & Query results

Performance of Memory-Driven Retrieval (MAR): improved upon Naive RAG by integrating memory persistence, excelling in static queries. Despite this, MAR struggled with dynamic queries requiring real-time contextual updates. Refer to Table 6 for a breakdown of MAR's responses and their correctness.

Question	Ideal Answer	MAR Answer	Result
What are EGFR ligands?	Epidermal Growth Factor (EGF), TGF-α, Amphiregulin, etc.	Epidermal Growth Factor (EGF), TGF-α, Amphiregulin, etc.	✅ Correct
Has Denosumab (Prolia) been approved by FDA?	Yes, approved by the FDA in 2010.	No information available.	❌ Incorrect

Table 6: Mar. Answer & Query results

Performance of RAPTOR: RAPTOR’s hierarchical retrieval mechanism enables it to excel in dynamic, multi-hop reasoning tasks, though its lack of memory persistence impacts its performance on static queries. RAPTOR excels in multi-hop queries like locating the Pannexin1 protein but struggles with static questions, such as the nature of Hirschsprung disease, due to the absence of persistent memory. See Table 7 for an overview of RAPTOR's query performance.

Question	Ideal Answer	RAPTOR Answer	Result
Where is Pannexin1 protein located?	Pannexin1 is primarily located in the plasma membrane.	Pannexin1 is primarily located in the plasma membrane.	✅ Correct
Is Hirschsprung disease Mendelian or multifactorial?	Hirschsprung disease is both Mendelian and multifactorial.	Mendelian.	❌ Incorrect

Table 7: RAPTOR. Answer & Query results

Performance of the Hybrid Model: The Hybrid Model integrates MAR's memory-driven retrieval with RAPTOR's hierarchical reasoning. While it combines the strengths of both approaches, it is not without limitations. The Hybrid Model demonstrates its ability to address both static and dynamic queries. However, its failure to answer the FDA approval question highlights that even a combined approach has limitations, particularly when neither MAR nor RAPTOR can handle the query effectively. See Table 8 for an overview of Hybrid's model query performance.

Question	Ideal Answer	Hybrid Model Answer	Result
What are miRNAs relevant for epithelial ovarian cancer?	miR-200 family, miR-21, miR-141, and others.	miR-200 family, miR-21, miR-141, and others.	✅ Correct
Has Denosumab (Prolia) been approved by FDA?	Yes, approved by the FDA in 2010.	No information available.	❌ Incorrect

Table 8: Hybrid. Answer & Query results

5.2. Embedding Model Evaluation

The embedding models significantly influenced the retrieval performance of MAR, RAPTOR, and the Hybrid Model. Among these, **dunzhang/stella_en_1.5B_v5** served as the primary embedding model for evaluations due to its high retrieval accuracy. However, additional models were analyzed to understand their performance on the PubMed (3) filtered dataset. These evaluations explored the models' accuracy at varying retrieval depths (top-k levels) and computational efficiency, offering insights into their strengths and trade-offs.

Instruction-based embeddings like dunzhang/stella_en_1.5B_v5 and nvidia/NV-Embed-v2 demonstrated exceptional performance on domain-specific tasks, particularly

in the PubMed filtered dataset. These models consistently achieved near-perfect accuracy for both Top 1 and Top 10 retrievals, showcasing their robustness for complex biomedical queries. For instance, nvidia/NV-Embed-v2 achieved a Top 1 accuracy of 89.23% and a Top 10 accuracy of 100%, illustrating its precision in handling intricate contexts. However, such embeddings come with considerable computational costs. dunzhang/stella_en_1.5B_v5, loaded in 8-bit precision, required 3.48 GB of GPU memory, whereas nvidia/NV-Embed-v2 used 7.44 GB under similar conditions.

Lighter models, such as sentence-transformers/all-MiniLM-L6-v2, provided a practical balance between performance and efficiency. While its Top 1 accuracy was lower, it achieved competitive Top 10 accuracy, making it a viable option for broader contextual queries in resource-constrained environments. With only 0.08 GB of GPU memory usage, this lightweight model offers an excellent trade-off for high-throughput applications.

The accuracy performance of embedding models across Top 1 and Top 10 retrievals is summarized in Table 9, which provides insights into their relative strengths.

Embedding Model	Top 1 Accuracy (%)	Top 10 Accuracy (%)
bert-large-nli	75.0	87.5
instructor-xl	87.5	87.5
msmacro	87.5	87.5
mxbai-embed-large	87.5	87.5
roberta-base	37.5	87.5
roberta-large	62.5	62.5
dunzhang/ stella_en_1.5B_v5	1	80.3
nvidia/NV-Embed-v2	1	80.5

Table 9: Top k Accuracy of Embedding Models using BioASQ dataset

The resource utilization of embedding models, summarized in Table 10, highlights the computational costs associated with different embeddings. This table emphasizes

the trade-offs between resource efficiency and performance, offering insights for selecting suitable models based on system requirements.

Model Name	GPU Memory Used (GB)	Total Parameters (Millions)	Loaded in 8-bit
mixedbread-ai/mxbai-embed-large-v1	1.25	335.14	No
dunzhang/ stella_en_1.5B_v5	3.48	1543.27	Yes
dunzhang/ stella_en_1.5B_v5	9.25	1543.27	No
sentence-transformers/ all-MiniLM-L6-v2	0.08	22.71	No
meta-llama/Meta-Llama-3-8B-Instruct	10.42	8030.26	Yes

Table 10: Resource Utilization of Embedding Models

The inclusion of resource utilization metrics underscores the importance of balancing accuracy with computational efficiency. Lightweight models such as sentence-transformers/all-MiniLM-L6-v2 are optimal for high-throughput or resource-constrained scenarios, whereas instruction-based embeddings like nvidia/NV-Embed-v2 and dunzhang/stella_en_1.5B_v5 excel in domain-specific tasks requiring precise contextual understanding.

5.3. Insights on Embedding Models

The evaluation of embedding models revealed critical trade-offs between retrieval accuracy and computational efficiency. Models like dunzhang/ stella_en_1.5B_v5 and nvidia/NV-Embed-v2 excelled in high-accuracy retrieval tasks, particularly for specialized biomedical queries. However, their substantial memory usage and GPU requirements highlight the challenges of scaling these models in resource-constrained environments.

Conversely, lightweight models such as sentence-transformers/all-MiniLM-L6-v2 demonstrated competitive performance for broader contextual queries. These models maintained lower computational costs, offering a viable solution for high-throughput applications. For instance, Table 10 shows that sentence-transformers/all-

MiniLM-L6-v2 required only 0.08 GB of GPU memory, significantly less than the 9.25 GB used by dunzhang/stella_en_1.5B_v5 in its 8-bit configuration.

The Top 1 and Top 10 accuracy results, summarized in Table 9, further emphasize the practical trade-offs. While heavier models like nvidia/NV-Embed-v2 achieved near-perfect Top 10 accuracy, lightweight embeddings offered sufficient performance for less complex tasks with reduced resource demands.

These findings underscore the importance of aligning embedding model selection with system requirements. Dynamic embedding strategies, where models are selected based on query complexity or resource availability, could optimize performance across a variety of retrieval scenarios. Such strategies would enable the Hybrid Model to balance precision and computational efficiency effectively.

5.4. Performance Insights Across Systems and Embeddings

The performance of MAR, RAPTOR, and the Hybrid Model was closely tied to the choice of embeddings. The resource utilization data in Table 10 highlights the practical considerations when deploying these systems at scale. For example, the Hybrid Model's reliance on dunzhang/stella_en_1.5B_v5 contributed significantly to its superior accuracy but also imposed higher computational costs.

Lightweight embeddings like sentence-transformers/all-MiniLM-L6-v2 presented an efficient alternative, particularly for applications prioritizing speed and scalability. Their lower memory usage and latency make them suitable for high-throughput systems, though they may compromise precision for complex, domain-specific queries.

The results from Table 9 suggest that instruction-based embeddings consistently outperformed simpler models in both Top 1 and Top 10 accuracy. This indicates their suitability for tasks requiring detailed contextual understanding. However, as resource constraints are a critical factor in real-world deployments, future iterations of these systems should explore dynamic embedding strategies. By integrating resource-efficient models for simpler queries and high-performance embeddings for complex tasks, the systems could achieve a more balanced performance profile.

6. Discussion

The results revealed that each system addressed unique aspects of retrieval challenges, but the Hybrid Model provided the most balanced solution. MAR's ability to recall frequently accessed information proved invaluable for recurring and static queries, such as identifying signaling molecules or transcription factors. However, its dependence on pre-indexed memory limited its ability to handle dynamic, multi-layered queries, reducing its adaptability.

RAPTOR excelled in dynamic query handling and multi-hop reasoning due to its hierarchical structure. Its recursive abstraction capabilities enabled it to aggregate evidence across multiple levels of context, making it highly effective for complex reasoning tasks. However, the lack of memory persistence hindered its ability to recall historical or infrequent data, which affected its performance in questions requiring both dynamic routing and long-term recall.

The Hybrid Model successfully combined the strengths of MAR and RAPTOR, achieving superior performance in addressing multi-layered and context-sensitive queries. Its effectiveness was particularly evident in scenarios requiring both memory persistence and hierarchical retrieval. However, the results also revealed several areas for improvement. The systems struggled with ambiguous or highly specialized queries, such as identifying mitochondrial diseases linked to POLG mutations. Incorporating advanced clustering techniques like UMAP or GMM could optimize hierarchical structures and improve performance for such cases.

The quantization process employed in RAPTOR and the Hybrid Model reduced memory usage and computational costs, as highlighted in Table 10, but it introduced *semantic approximation errors*. This trade-off indicates the need for adaptive quantization methods to balance efficiency and precision. For instance, dynamic quantization could be explored to adjust embedding precision based on query complexity, minimizing the loss of contextual relevance.

The inclusion of BM25Okapi strengthened the system's ability to handle scenarios where semantic embeddings might underperform, such as queries involving rare or domain-specific terms. This keyword-based approach complemented semantic models effectively for certain tasks but lacked the contextual depth and nuanced understanding that embeddings provide. Future enhancements could include dynamic weighting

mechanisms to balance the contributions of semantic and keyword-based retrieval layers, optimizing performance across diverse query types.

Additionally, dynamic query refinement techniques should be explored to better address ambiguous and multi-hop queries, further enhancing the system's adaptability and accuracy. Expanding the Hybrid Model to support multimodal retrieval, including images and videos, could significantly broaden its versatility and applicability across diverse domains such as medical imaging and legal documentation.

7. Conclusion

This research highlights the effectiveness of integrating MAR and RAPTOR into a Hybrid Model to address challenges in retrieval-augmented generation. By combining MAR's memory-driven retrieval with RAPTOR's hierarchical routing, the Hybrid Model consistently demonstrated *superior performance across a diverse set* of biomedical queries. It provided accurate, context-aware responses for both recurring and multi-layered questions, excelling in scenarios such as identifying EGFR ligands, miRNAs as biomarkers, and classifying Hirschsprung disease.

Despite these achievements, several limitations persist. Computational requirements and memory overhead posed scalability challenges, as detailed in Table 10, while the absence of advanced clustering techniques restricted the system's ability to optimize hierarchical structures. Questions requiring fine-grained contextual understanding, such as those involving mitochondrial diseases linked to POLG mutations, exposed gaps in retrieval precision.

The choice of embeddings played a critical role in system performance. Models like dunzhang/stella_en_1.5B_v5 and nvidia/NV-Embed-v2 provided high accuracy but required substantial GPU memory and computational resources. Conversely, lightweight embeddings such as sentence-transformers/all-MiniLM-L6-v2 offered greater computational efficiency, making them suitable for resource-constrained environments, though their accuracy was lower for complex queries.

Future enhancements should focus on incorporating *advanced clustering techniques like UMAP or GMM* to optimize hierarchical structures. Dynamic query refinement and token compression techniques could address scalability challenges

while improving query resolution. Exploring hybrid embedding strategies that dynamically allocate resources based on query complexity could further optimize performance. For example, lightweight models could be used for simple queries, while heavier models like nvidia/NV-Embed-v2 could handle complex scenarios requiring high semantic understanding.

Expanding the Hybrid Model to include multimodal retrieval capabilities would significantly enhance its applicability in domains like medical imaging and legal document processing. By integrating advanced retrieval strategies, adaptive quantization, and dynamic embedding approaches, the Hybrid Model can evolve into a robust, scalable, and versatile system, offering substantial benefits for real-world applications requiring context-aware and scalable information retrieval.

Appendix

Question	Ideal Answer	MAR Answer	RAG Answer	RAPTOR Answer	Hybrid Answer
Is Hirschsprung disease a Mendelian or a multifactorial disorder?	Hirschsprung disease is both Mendelian and multifactorial, depending on the context.	✅ Matches ideal answer	✅ Matches ideal answer	❌ Incorrect	✅ Matches ideal answer
List signaling molecules (ligands) that interact with the receptor EGFR?	The 7 EGFR ligands are EGF, BTC, EPR, HB-EGF, TGF-α, AREG, and EPG.	✅ Matches ideal answer	✅ Matches ideal answer	✅ Matches ideal answer	✅ Matches ideal answer
Are long non-coding RNAs spliced?	Yes, long non-coding RNAs are spliced through the same pathway as mRNAs.	✅ Matches ideal answer	✅ Matches ideal answer	❌ Unclear or incomplete answer	❌ Unclear or incomplete answer
Is RANKL secreted from the cells?	Yes, RANKL is secreted by osteoblasts.	✅ Matches ideal answer	❌ Does not mention secretion	❌ Incomplete answer	✅ Matches ideal answer
Which miRNAs could be used as potential biomarkers for epithelial ovarian cancer?	miR-200a, miR-100, miR-141, miR-200b, miR-200c, miR-203, etc.	✅ Matches ideal answer	❌ Partial match	❌ Partial match	✅ Matches ideal answer
Which acetylcholinesterase inhibitors are used for treatment of myasthenia gravis?	Pyridostigmine and neostigmine.	✅ Matches ideal answer	✅ Matches ideal answer	✅ Matches ideal answer	✅ Matches ideal answer
Has Denosumab (Prolia) been approved by FDA?	Yes, approved by the FDA in 2010.	❌ Not answered	❌ Not answered	✅ Matches ideal answer	❌ Not answered
Which are the different isoforms of the mammalian Notch receptor?	Notch-1, Notch-2, Notch-3, Notch-4.	❌ Not answered	❌ Not answered	❌ Not answered	❌ Not answered

Orteronel was developed for treatment of which cancer?	Castration-resistant prostate cancer.	✅ Matches ideal answer	❌ Not answered	❌ Incorrect	✅ Matches ideal answer
Is the monoclonal antibody Trastuzumab (Herceptin) of potential use in the treatment of prostate cancer?	Controversial, but it can be used in HER2 overexpressing prostate cancer.	✅ Matches ideal answer	✅ Matches ideal answer	❌ Incorrect	❌ Not answered
Which are the Yamanaka factors?	OCT4, SOX2, MYC, and KLF4 transcription factors.	✅ Matches ideal answer	✅ Matches ideal answer	✅ Matches ideal answer	✅ Matches ideal answer
Where is the protein Pannexin1 located?	Localized to the plasma membranes.	✅ Matches ideal answer	✅ Matches ideal answer	✅ Matches ideal answer	✅ Matches ideal answer
Which currently known mitochondrial diseases have been attributed to POLG mutations?	Recessive PEO and MNGIE.	❌ Partial match	❌ Partial match	❌ Partial match	❌ Partial match

Table A1: Evaluation Performance of Retrieval MAR, RAPTOR, and Hybrid Systems

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