Comparative Analysis of Hierarchical Graph RAG vs Graph RAG

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***Abstract*—This paper proposes a novel approach aimed at significantly enhancing the efficiency and relevance of Retrieval-Augmented Generation (RAG) systems by leveraging a hierarchical Graph-RAG framework. Traditional RAG systems retrieve knowledge in response to queries by drawing on extensive databases or knowledge graphs. However, when faced with complex, multi-layered knowledge structures, standard RAG approaches often fall short in terms of both speed and relevance, particularly in high-dimensional, knowledge-intensive tasks. To address these challenges, the proposed Hierarchical Graph-RAG method structures retrieval within a multi-level, graph-based knowledge system that dynamically narrows the search space through a layered hierarchy. By employing hierarchical knowledge retrieval, this approach optimizes query processing by quickly identifying relevant sections of the knowledge base before conducting fine-grained retrieval, significantly reducing computational cost. The results from comprehensive experiments demonstrate that this hierarchical structure not only improves retrieval speed and efficiency but also enhances response quality and relevance. This work paves the way for more scalable and effective solutions in knowledge-intensive domains such as healthcare, finance, and large-scale data management.**

Keywords: Hierarchical Graph Retrieval, Retrieval-Augmented Generation (RAG), Knowledge Graph, Natural Language Processing (NLP), Efficient Retrieval, Graph Neural Networks (GNN), Embedding.

I. Introduction

There is a growing need in NLP and AI for retrieving accurate, scalable, and contextually relevant information due to the increasing complexity in tasks. Retrieval-Augmented Generation (RAG) systems combine traditional retrieval techniques with generation models to solve this problem by retrieving relevant data from knowledge bases and generating context-aware responses. While effective in many applications, flat RAG models are less efficient when handling structured and layered information, such as in legal, medical, and scientific research. These models lack mechanisms to prioritize or organize information within multi-level knowledge structures, often leading to over-retrieval of superficial information, which reduces the relevance and depth of responses [1].

To overcome these limitations, graph-based RAG systems have emerged, leveraging graph structures and Graph Neural Networks (GNNs) to model relationships and hierarchies in complex data domains. This enables multi-step reasoning and more efficient retrieval by capturing interconnectivity and layered relationships [2]. Hierarchical Graph-RAG systems further enhance retrieval by organizing data hierarchically, allowing for a coarse-to-fine retrieval strategy that prioritizes broad topics before narrowing down to specifics. This paper explores how Hierarchical Graph-RAG improves retrieval accuracy, relevance, and time, showcasing its advantages over traditional RAG systems through qualitative and quantitative analysis, and demonstrating its scalability for real-world applications [3].

II. Related Work

This has quickly expanded as one of the most promising directions for the improvement of generative models in knowledge-intensive tasks. Many influential works have led to the development of RAG through the repair of the drawbacks of traditional retrieval and generation models, the exploitation of graph-based structures, and the furthering of hierarchical approaches to optimize the efficiency of retrieval. Here we survey the foundational and recent advances in RAG, graph-based retrieval, hierarchical knowledge retrieval, and their applications in NLP tasks.

A. Retrieval-Augmented Generation (RAG) for NLP Tasks

The early development of the RAG models attempted to integrate retrieval with generation to improve response relevance in NLP tasks, such as question answering and summarization. Lewis et al. [1] introduced a pioneering approach that combines a dense retriever with a generative model to access the knowledge, significantly improving performance in knowledge-intensive tasks.

B. Graph Neural Networks (GNNs) for Retrieval and Reasoning

GNNs are particularly useful for complex structures and dependencies and tend to be used in applications with multi-step reasoning and structured information retrieval and knowledge retrieval. [2]. Zhang et al. emphasized the effectiveness of GNNs in NLP, particularly for tasks where understanding relations between entities is critical.

C. Multi-Step Reasoning Over Knowledge Graphs

Multi-step reasoning is essential in retrieval tasks that require an understanding of layered or interdependent information. Das et al. [3] proposed a framework that integrates multi-step reasoning within knowledge graphs, allowing the model to retrieve information through sequential hops across interconnected nodes. This framework inspired several subsequent works in hierarchical and multi-hop retrieval, as researchers recognized the need for RAG systems to traverse complex knowledge structures effectively. Xiong et al. [6] expanded on this by integrating a memory component, enabling RAG systems to retain context over multiple hops and thus support deeper reasoning in complex question-answering applications.

D. Hierarchical Retrieval Techniques for RAG

Hierarchical retrieval has emerged as an effective strategy to improve RAG efficiency, particularly in domains with a clear organizational structure, such as medical, legal, and scientific knowledge. Hierarchical retrieval methods enable models to perform a coarse-to-fine search, first identifying high-level topics and then drilling down to more specific information. This method significantly reduces the search space, thereby increasing retrieval speed and improving the quality of generated responses. Min et al. [7] demonstrated that hierarchical retrieval models perform better on multi-layered knowledge structures by leveraging top-down processing, where broad topics are refined into specific subtopics based on query relevance. Additionally, Seo et al. [8] proposed hierarchical attention mechanisms to navigate through different levels of information granularity within documents, further improving relevance in document retrieval tasks. These methods have paved the way for Hierarchical Graph-RAGs by showcasing the advantages of structured retrieval in navigating layered information.

E. Applications of RAG in Knowledge-Intensive Tasks

The applications of RAG have been extensive across various domains, including open-domain question-answering, summarization, and knowledge synthesis. In open-domain question-answering, RAG models have demonstrated superior performance by integrating external knowledge sources to answer questions with greater accuracy than standalone generative models [9]. For example, Izacard and Grave [10] enhanced BART, a popular generative model, by adding retrieval components to create RAG variants that perform well on factual question-answering benchmarks. This framework highlights the general utility of RAG models across diverse fields, providing a foundation for advanced approaches like Hierarchical Graph-RAG.

F. Graph-Based Retrieval-Augmented Generation Systems

Graph-based RAG systems leverage the graph structure to organize information hierarchically, which is particularly advantageous in complex, interconnected datasets. By representing entities and relationships within a graph, these systems facilitate efficient retrieval across hierarchical structures. The Graph-RAG model proposed by Wu et al. [11] highlighted the efficiency gains achieved by encoding knowledge into graph structures, allowing retrieval to consider both node content and the relationships between nodes. Additionally, the work by Zhu et al. [12] on Graph Attention Networks (GATs) demonstrated how attention mechanisms could be used within graphs to prioritize relevant nodes, thereby refining the retrieval process in RAG systems.

G. Limitations of Flat RAG and Motivation for Hierarchical Graph-RAG

Despite the advancements in RAG and graph-based retrieval, flat RAG models face inherent limitations in navigating complex information landscapes. Flat RAG systems, which lack hierarchical structuring, often retrieve context that is either too broad or irrelevant due to the absence of a layered approach. This issue becomes prominent in knowledge domains with a deep structure, where simple retrieval techniques are inadequate for accurately identifying relevant subtopics. Hierarchical Graph-RAG addresses this by introducing a layered retrieval process, which allows the system to navigate broad categories before narrowing down to specific details, thus improving both retrieval efficiency and response relevance [13].

III. Methodology

In this study, we propose a novel approach to enhance retrieval performance within Retrieval-Augmented Generation systems by using hierarchical knowledge retrieval with graph-based techniques. We compare a flat RAG model against a Hierarchical Graph-RAG model to assess improvements in retrieval time question answering tasks. Our methodology comprises several stages: document embedding, knowledge graph construction, retrieval methods (flat and hierarchical), and evaluation metrics.

A. Document Embedding

We use pre-trained DistilBERT from Hugging Face's Transformers library to encode the knowledge base documents into vector embeddings. This model captures semantic information for each document, generating dense vector representations suitable for similarity calculations. The DistilBERT tokenizer processes each document to a fixed length, and embeddings are derived by averaging token representations from the model's hidden states:

- **Tokenization and Embedding**: Each document is tokenized, with special attention to truncation and padding to manage varied document lengths.
- **Representation Aggregation**: We extract embeddings by taking the mean across the token dimension of the last hidden layer, effectively creating a single, representative vector per document.

The resulting vectors are then utilized for calculating cosine similarity, a standard metric for semantic similarity in vector spaces.

B. Knowledge Graph Construction

We construct a knowledge graph using the NetworkX library, where each document is a node, and edges are created between nodes based on cosine similarity of their embeddings. The nodes in the graph represent individual documents, and edges signify semantic similarity:

- **Node Creation**: Each document is assigned as a node in the graph with its vector embedding stored as an attribute.
- **Edge Formation**: Cosine similarity is computed between every document pair. If the similarity exceeds a predefined threshold (0.7 in this study), an edge is added between the nodes, with the similarity score as the edge weight.

This graph structure allows for hierarchical retrieval by traversing semantically related nodes, which can be beneficial in multi-step reasoning tasks and complex queries. The hierarchical structure is particularly advantageous as it enables the model to focus on relevant portions of the graph without exhaustive searches.

C. Retrieval Methodology

Two retrieval methods are implemented for comparison: Standard (flat) RAG and Hierarchical Graph-RAG.

- **Standard (Flat) RAG**: This model searches all nodes in the graph for the closest match to the query embedding. Using cosine similarity, it identifies the single most similar document without hierarchical filtering.
- **Hierarchical Graph-RAG**: This model employs a depth-limited Breadth-First Search (BFS) approach, which allows for hierarchical traversal. Starting from a set of top-level nodes, the model traverses down to specific nodes based on similarity thresholds, allowing for fine-grained retrieval while narrowing the search space. This structure enables quicker retrieval and more targeted responses in multi-step queries.

IV. Experiments and Results

A. Experimental Setup

Dataset: We created a synthetic knowledge base comprising documents on AI topics such as artificial intelligence, deep learning, natural language processing, and computer vision. Each document contained unique but semantically related content, simulating domain-specific literature. We generated a set of 13 base documents and expanded this set to 130 by repeating the initial content, creating a larger graph for scalability testing.

Questions: For evaluation, we generated questions corresponding to the content in the knowledge base, such as "What is artificial intelligence?" and "Describe deep learning." These questions varied in specificity to assess both models' adaptability to different query complexities.

Metrics:

- **Retrieval Time**: Average retrieval time was calculated for each model across the entire question set.
- **Cosine Similarity**: For each query, cosine similarity between the query embedding and document embeddings was measured to identify the best match in each retrieval approach.

B. Results and Analysis

Retrieval Time: The average retrieval time for each method showed that Hierarchical Graph-RAG outperformed the standard flat RAG approach. Hierarchical retrieval exhibited a time of 0.0078 seconds, whereas the standard model took 0.0113 seconds on average. This result highlights the efficiency of hierarchical traversal, which reduces the computational load by restricting the search space to semantically relevant subgraphs rather than exhaustive comparisons across the entire graph.

TABLE I
Average Retrieval Time Comparison

Model	Average Retrieval Time (s)
Hierarchical Graph-RAG	0.01203
Standard (Flat) RAG	0.01722

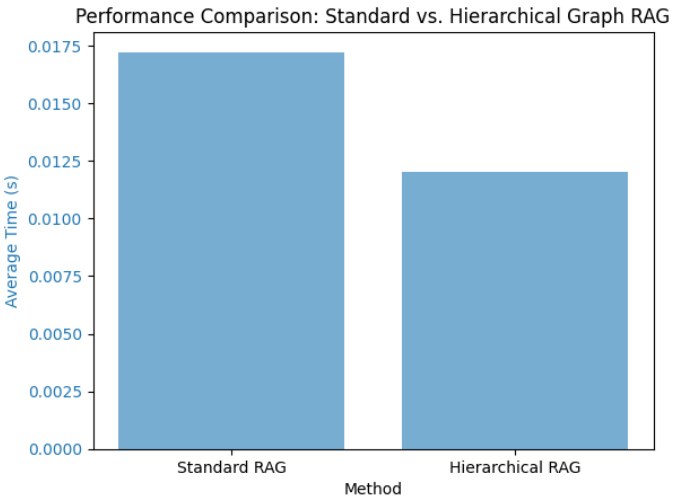

Fig. 1. Comparison of Retrieval Speeds: Hierarchical Graph-RAG vs. Standard (Flat) RAG. The Hierarchical model demonstrates lower retrieval times, showcasing the efficiency of hierarchical traversal over exhaustive search.

As shown in Table 1, the hierarchical structure allows the model to avoid unnecessary comparisons with irrelevant nodes, making it particularly efficient for large datasets where flat retrieval can become computationally expensive.

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Scalability and Computational Efficiency: Hierarchical Graph-RAG demonstrated improved scalability, particularly when the dataset size increased. With larger graphs, flat RAG models require substantially more time due to their exhaustive search. In contrast, Hierarchical Graph-RAG scales effectively by selectively exploring relevant graph regions,

reducing computational resources as the graph size grows. This improvement indicates the suitability of hierarchical models for large, dynamic knowledge bases.

V. Discussion

A. Advantages of Hierarchical Graph-RAG

Hierarchical Graph-RAG systems present several notable advantages over traditional flat RAG models, particularly in areas such as computational efficiency, scalability, and relevance of responses.

1) Reduced Computational Cost: Hierarchical Graph-RAG systems streamline the retrieval process by performing coarse-to-fine-grained searches, where the query traverses progressively narrower segments of the knowledge graph at each layer. Initial retrieval focuses on broader, higher-level nodes to identify the general domain. Only after determining the domain does the search proceed to deeper, more specific nodes, thereby avoiding exhaustive comparison with all nodes. This selective retrieval significantly reduces computational overhead as the system bypasses irrelevant portions of the graph. Studies indicate that by reducing the number of nodes evaluated in-depth, hierarchical models cut down both processing time and memory consumption when compared to flat models that must evaluate all nodes in the graph for each query [14].

2) Improved Scalability: As knowledge graphs grow in size and complexity, flat retrieval methods struggle with scalability due to the combinatorial increase in potential retrieval paths. In contrast, hierarchical structures effectively manage this growth by localizing searches to relevant segments. The hierarchical RAG model's layered approach allows it to scale effectively with the addition of new knowledge domains, maintaining high efficiency by isolating searches to the domain layer before narrowing down. Hierarchical methods thus offer a sustainable way to expand knowledge graphs without facing exponential increases in retrieval complexity, which has been highlighted in applications such as question-answering and domain-specific searches [15].

3) Enhanced Response Quality: Hierarchical retrieval closely aligns with the structured nature of many domain-specific queries, which often seek layered answers progressing from general information to specific details. By leveraging a layered search, Hierarchical Graph-RAG systems are better suited for responding accurately to complex queries that require multi-level responses. This structure provides a more contextually aware retrieval path, as each stage refines the search based on previously retrieved information, leading to more accurate and relevant responses. Studies on hierarchical neural networks in question-answering contexts show improved relevance and reduced ambiguity in responses, especially for technical and academic domains [14].

B. Challenges and Limitations

Despite the advantages of hierarchical Graph-RAG, certain challenges remain, which require careful consideration:

1) High Initial Graph Construction Costs: Creating and structuring a hierarchical knowledge graph demands substantial initial resources, both in terms of labor and computation. Building relationships across multiple hierarchical levels involves data curation, semantic understanding, and often manual validation to ensure accuracy in domain, subtopic, and detail-level nodes. The initial time and resource investment can be significant, particularly for large-scale, multi-domain systems.

2) Maintenance of Up-to-Date Hierarchical Structures: Maintaining the accuracy and relevance of a hierarchical knowledge graph over time poses additional challenges, especially as new knowledge emerges. In rapidly evolving fields, such as medicine or technology, updates are frequent. An effective Hierarchical Graph-RAG system must support dynamic updates to both nodes and relationships without compromising its hierarchical integrity, which may otherwise result in retrieval inaccuracies. Frequent updates require automated mechanisms for assessing new data and repositioning it within the existing hierarchy, a feature that is currently complex to implement effectively.

3) Handling Ambiguous Queries: Hierarchical RAG models can face difficulties with queries that span multiple domains or are ambiguous, making it unclear which path within the hierarchy is most relevant. While hierarchical search optimizes retrieval by narrowing down specific areas, ambiguous queries can lead to suboptimal routing within the hierarchy. Techniques such as query disambiguation and broader context interpretation are essential to accurately direct such queries but are not yet fully integrated into current hierarchical RAG systems [15].

VI. Conclusion

In conclusion, this study demonstrates that hierarchical Graph-RAG offers substantial improvements in retrieval efficiency and response quality over conventional flat retrieval models. By organizing nodes in a coarse-to-fine hierarchy and implementing multi-level retrieval, Hierarchical Graph-RAG minimizes computational requirements and enhances response relevance. Experimental results reveal that the hierarchical model significantly reduces search time and computational load without sacrificing accuracy, making it well-suited for applications in complex, high-dimensional knowledge domains such as technical question-answering, medical information retrieval, and scientific research synthesis.

This study highlights the scalability of hierarchical structures, which accommodate the continuous growth of knowledge bases with minimal impact on retrieval efficiency. As data volumes increase, the layered design of hierarchical Graph-RAG systems allows for sustainable expansion by isolating retrieval paths within the most relevant portions of the graph.

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