GRAG: Graph Retrieval-Augmented Generation

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Abstract

While Retrieval-Augmented Generation (RAG) enhances the accuracy and relevance of responses by generative language models, it falls short in graph-based contexts where both textual and topological information are important. Naive RAG approaches inherently neglect the structural intricacies of textual graphs, resulting in a critical gap in the generation process. To address this challenge, we introduce Graph Retrieval-Augmented Generation (GRAG), which significantly enhances both the retrieval and generation processes by emphasizing the importance of subgraph structures. Unlike RAG approaches that focus solely on text-based entity retrieval, GRAG maintains an acute awareness of graph topology, which is crucial for generating contextually and factually coherent responses. Our GRAG approach consists of four main stages: indexing of k-hop ego-graphs, graph retrieval, soft pruning to mitigate the impact of irrelevant entities, and generation with pruned textual subgraphs, GRAG's core workflow—retrieving textual subgraphs followed by soft pruning—efficiently identifies relevant subgraph structures while avoiding the computational infeasibility typical of exhaustive subgraph searches, which are NP-hard. Moreover, we propose a novel prompting strategy that achieves lossless conversion from textual subgraphs to hierarchical text descriptions. Extensive experiments on graph multi-hop reasoning benchmarks demonstrate that in scenarios requiring multi-hop reasoning on textual graphs, our GRAG approach significantly outperforms current state-of-the-art RAG methods while effectively mitigating hallucinations.

1 Introduction

Large Language Models (LLMs) have demonstrated remarkable capabilities in a variety of reasoning tasks, including on graph-based data [Hu et al., 2023a, Chen et al., 2024, Fatemi et al., 2023]. However, LLMs themselves struggle with factual errors due to limitations in their training data and a lack of real-time knowledge [Mallen et al., 2023, Min et al., 2023]. Retrieval-Augmented Generation (RAG) [Lewis et al., 2020, Guu et al., 2020], which integrates external data retrieval into the generative process, has been widely used for its ability to help LLMs generate more relevant answers and reduce factual errors [Tang and Yang, 2024]. However, RAG-based retrievers focus solely on individual documents and retrieve relevant candidates based on text similarity. In many situations, we do have important correlations among documents, which are started to be heavily researched in recent years, called textual graphs such as scientific article networks, recommender systems, and knowledge graphs [He et al., 2023, Jin et al., 2023, Li et al., 2023]. For more complex and larger-scale reasoning tasks, we need to leverage the semantics inside and across documents [Yang et al., 2024, Tang and Yang, 2024]. For example, in Figure 1, we raise a question-answering (QA) task where the question is: How can AI's recent progress advance solar flare prediction? To answer this question, we need to locate the subgraph centering on the papers on existing AI techniques and their applications in solar flare prediction, then further traverse the citation graph through newer AI papers while considering their new advantages that can better tackle the hurdles in solar flare prediction. Such consideration of the rich semantic information correlating the documents cannot

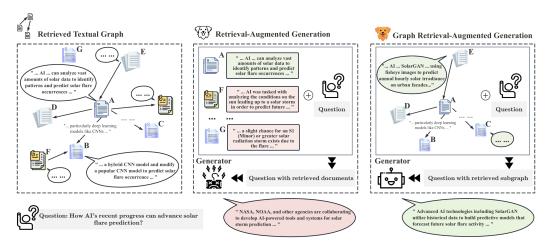


Figure 1: GRAG retrieves subgraphs relevant to the query rather than discrete documents like RAG to reduce the negative impact of semantically similar but irrelevant documents (in red) on the generation.

be handled by traditional RAG methods. To tackle this issue, this work formulates a new problem called **Graph Retrieval-Augmented Generation** (**GRAG**), which requires to first retrieve *query-relevant subgraphs* in textual graphs, and perform the LLM generation with joint text and topological information. Both of these two are nontrivial to be addressed. Specifically, first, the retrieval of relevant textual subgraphs on large-scale textual graphs is challenging due to the NP-hard nature of the problem [Johnson and Garey, 1979] and the need to balance efficiency and accuracy. Additionally, integrating both textual and topological information in the retrieved textual subgraphs into a coherent generative framework presents significant challenges.

This paper proposes a computational framework for GRAG. To address the challenge of efficient textual subgraph retrieval, we propose a divide-and-conquer strategy that indexes k-hop ego-graphs and employs a soft pruning mechanism to reduce the influence of irrelevant entities. To handle the challenge of integrating textual and topological information, we introduce a novel dual prompting method that divides prompts into two parts: hard prompts and soft prompts. Retrieved textual subgraphs are converted into hierarchical text descriptions and combined with the query to form the hard prompts, effectively preserving both semantic nuances and graph topology. Meanwhile, soft prompts retain the graph's topological information by encoding the graph into embeddings via graph encoders. More specifically, our GRAG approach involves four main stages. First, k-hop ego-graphs within the main textual graph are indexed and converted into graph embeddings using a pre-trained language model (PLM). Next, the system retrieves the top N textual subgraphs most relevant to the query. Third, a novel soft pruning approach reduces the influence of irrelevant entities within the retrieved textual subgraphs by learning scaling factors based on their relevance to the query. This provides an approximate solution to the most relevant textual subgraph structures, avoiding the NP-hard problem of exhaustively searching all subgraphs. Finally, the generation stage integrates both the pruned textual subgraphs and the original query, utilizing GNNs to aggregate information and then align the graph embedding with the LLM's text vectors. The generation by LLMs is controlled by both hard prompts and soft prompts.

Empirical results on multi-hop graph reasoning tasks demonstrate that our GRAG approach significantly outperforms RAG-based retrievers and LLM baselines in graph reasoning scenarios. In particular, Frozen LLM with GRAG outperforms fine-tuned LLM on all tasks with much lower training cost.

The main contributions of this article are summarized below:

- We formulate the problem of Graph Retrieval-Augmented Generation (GRAG) and propose an efficient computational framework for GRAG, addressing the limitations of RAG methods in handling graph-based contexts.
- We provide an approximate solution for retrieving the most relevant textual subgraphs, efficiently avoiding the NP-hard problem of exhaustive subgraph searches. Furthermore, we introduce a novel prompting method to convert textual subgraphs into hierarchical text descriptions without losing both textual and topological information.

 Extensive experiments on graph multi-hop reasoning benchmarks demonstrate that GRAG significantly outperforms current state-of-the-art RAG methods in graph-related scenarios.

2 Related Work

2.1 LLMs in Graph Related Tasks

Large Language Models based on the Transformer architecture have shown promising capabilities in reasoning on graphs. On the one hand, the text embedding capability of LLMs helps encode textual node & edge attributes, which directly benefits the classification task [Hu et al., 2023a, Chen et al., 2023, 2024] and knowledge graph creation [Trajanoska et al., 2023, Yao et al., 2023]. On the other hand, the contextual reasoning capabilities of the LLM benefits the graph reasoning [Wang et al., 2024, Jiang et al., 2023, Luo et al., 2023] and graph answering in zero-shot scenarios [Baek et al., 2023, Hu et al., 2023b]. While training on large corpora of text data develops robust language understanding, it does not inherently equip LLMs to understand or reason about graph-structured data, as textual data lacks explicit topological information. Therefore, soft prompts that aggregate information from other modalities can be a powerful tool to help LLMs process and understand information in modalities beyond just text [Tian et al., 2024, He et al., 2024]. However, generating graph soft prompts that are suitable for LLMs remains an open problem. To address this problem, we propose a novel soft prompting strategy for graphs. Furthermore, we develop a novel hard prompting method to generate text descriptions of graphs while preserving topological information.

2.2 Retrieval Augmented Generation (RAG)

One limitation of LLMs is their dependence on the currency of their training data. RAG [Lewis et al., 2020] addresses this by enhancing LLMs with information retrieval systems, enabling the generation of more accurate and contextually relevant responses through the incorporation of the most current documents. Naive RAG approaches [Ram et al., 2023, Gao et al., 2023] achieve this by splitting text in documents into chunks and mapping these chunks into a vector space to calculate similarity to the query vector. However, for augmented generation that requires retrieval on graphs, while RAG can help by retrieving relevant entities within the graph, it does not account for critical non-textual elements such as the connectivity and topology of the graph.

Retrieve on Graphs. To address the challenge of losing topological information during text retrieval, Yasunaga et al. retrieve relevant nodes and create a joint graph that includes the QA context and the relevant nodes. Kang et al. and Kim et al. focus on retrieving triples rather than individual nodes and edges to capture more complex relational data. Particularly, some retrieval problems can be solved by reasoning chains, which can be simplified to retrieve the path between the question and the target entity [Lo and Lim, 2023, Choudhary and Reddy, 2023]. He et al. reconstruct the retrieved nodes and edges into a new graph and subsequently generate answers with the graph token and text tokens. However, none of these individual entity-based retrieval approaches could consider the topological information in the retrieval process. As shown in Figure 1, considering only text relevance without accounting for the graph topology during the retrieval process can result in retrieved entities that fail to enhance the generation of LLMs. Therefore, there is an emerging need to retrieve relevant subgraphs rather than individual entities. A few works propose new retrieval strategies for graph-related scenarios. For instance, Edge et al. leverage community detection algorithms to partition the graph into communities, then retrieve and aggregate relevant communities to generate the final answer to the query. Unlike our GRAG approach, none of these models directly retrieve at the graph level and prune irrelevant components to find the precise subgraph structure.

3 Problem Formalization

Textual Graphs are graphs consisting of text-attributed nodes and edges, which can be formally defined as $G(V, E, \{T_n\}_{n \in V}, \{T_e\}_{e \in E})$. V and E represent the node set and edge set. T_n and T_e represent the natural language attributes of the corresponding nodes and edges in the graph.

Textual Subgraphs are subgraph structures in a textual graph, e.g., G with finite node set V and edge set E, we have its subgraph set $\mathcal{S}(G) = \{g = (V', E', \{T_n\}_{n \in V'}, \{T_e\}_{e \in E'}) | V' \in \mathcal{P}(V), E' \in \mathcal{P}(E)\}$, where $\mathcal{P}(V)$ and $\mathcal{P}(E)$ represent the power set of V and E, respectively.

Graph Retrieval Augmented Generation (GRAG) aims to enhance the trustworthiness and explainability of LLMs' generation in GraphQA. Given a specific question q over G, there must exist an

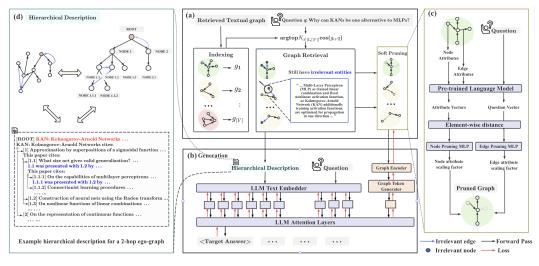


Figure 2: **Illustration of our GRAG approach.** Given a query and a related textual graph: (a) all k-hop ego-graphs (e.g., 1-hop here) are embedded into graph embeddings and compared with the query vector to retrieve the topN similar subgraphs. Irrelevant entities in the graph are partially masked using a soft pruning module. (b) For the final generation, pruned ego-graphs are encoded into a soft graph token, and textual information is encoded into text tokens. (c) Soft pruning module. (d) Generating text descriptions of ego-graphs preserving both textual and topological information.

optimal subgraph structure, i.e., $g \subseteq \mathcal{S}(G)$, leads the LLM to generate answers that meet expectations. The goal of GRAG is to find the subgraph g and integrate their information as tokens into LLM to enhance the generation. Formally, the probability distribution of the final output sequence is as:

$$p_{\theta}(Y|[X_q; X_g]) = \prod_{i=1}^{n} p_{\theta}(y_i|y_{< i}, [X_q; X_g])$$
(1)

where $y_{< i}$ represents the prefix tokens, X_q and X_g indicate the token sequence of the question and integrated graph information. $[\ ;\]$ represents the concatenation operator following a specified order.

In this paper, we investigate the following challenges of GRAG.

Challenge 1. Efficiency of retrieving relevant subgraph structures in large-scale textual graph scenarios. This problem is particularly difficult due to: (1) the high dimensionality of textual data within nodes and edges, which increases the complexity of the retrieval process; (2) the exponential growth of potential subgraphs with the size of the graph, necessitating efficient approximation methods; (3) and the need to ensure semantic relevance between the query and graph structures, which requires sophisticated algorithms to interpret and align both textual and structural information. These factors make exhaustive search methods impractical for large-scale textual graphs, highlighting the necessity for advanced techniques to manage the retrieval and generation processes effectively.

Challenge 2. Joint preservation of text and topological information in the retrieved textual subgraphs. Another critical challenge is the need to jointly preserve and leverage both textual and topological information in the retrieval and generation process. RAG methods primarily focus on text embeddings, often neglecting the structural aspects of graphs, which are crucial for accurate reasoning and context understanding in textual graph-related scenarios. Additionally, textual graphs often contain a vast amount of information, making it challenging to filter out irrelevant data while retaining useful graph context. Efficiently pruning irrelevant nodes and edges without losing critical information is essential for effective graph retrieval and generation.

4 Methodology

Overview. In this section, we introduce our GRAG approach for graph retrieval-augmented generation. As illustrated in Figure 2, GRAG comprises four main stages: indexing, graph retrieval, soft pruning, and generation. **To address the challenge in textual subgraph retrieval**, as shown in Figure 2(a), we search for the relevant subgraph structure by retrieving all *k*-hop ego-graphs and then learn and perform a soft pruning operation to reduce the impact of redundant entities and obtain an approximately optimal subgraph structure. Compared with entity retrieval on graphs (i.e.,

searching all entities in the graph whose total number is |V| + |E|, the retrieval efficiency of GRAG is guaranteed since only |V| k-hop ego-graphs need to be retrieved. To address the challenge of preserving both textual and topological information, as shown in Figure 2(b) & 2(d), we pursue two complementary views of textual graphs: 1) graph of text, using graph embedding as a soft prompt to preserve graph topology, and 2) text of graph, using structured textual documents as hard prompts to retain semantic nuances. Both methods are designed to preserve the textual and structural integrity of the graph, leveraging their complementary strengths: graph embedding excels in maintaining graph topology, while textual documents capture semantic nuances.

4.1 Textual Subgraph Retrieval

To search for the textual subgraph from the whole graph efficiently, we propose a new divide-andconquer strategy that exploits the trade-off between the number of candidates and computational intensity. More concretely, we first encode the neighborhood surrounding each node in an offline manner. During textual subgraph retrieval, we can quickly index a pool of promising candidates (textual subgraph indexing), from which we further rank and retain the top-ranked ones (textual subgraph ranking). This process is followed by a learnable pruner that carves the selected neighborhoods into subgraphs that are relevant to the query and most beneficial to the task (textual subgraph pruning).

Textual Subgraph Indexing. We index k-hop ego-graphs in G and convert them to graph embeddings. All embeddings are stored for further retrieval process. Since graph embeddings will calculate similarity with the question embedding in the retrieval stage from the perspective of semantic meaning, graph embeddings need to be semantically meaningful. Therefore, we leverage a pretrained language model (PLM) to convert text attributes of nodes and edges to embeddings. Then, we perform a mean pooling operation on these embeddings to obtain a graph embedding, e.g., $z_q \in \mathbb{R}^d$ for each subgraph $g \in \mathcal{S}(G)$, where d represents the dimension of the graph embedding:

$$z_g = \text{POOL}(\text{PLM}(\{T_n\}_{n \in V_q}, \{T_e\}_{e \in E_q}))$$
(2)

where V_g and E_g represent the node set and edge set of the subgraph g.

Textual Subgraph Ranking. During the retrieval phase, the same PLM as encoder is used to obtain the question embeddings:

$$z_q = \text{PLM}(q) \in \mathbb{R}^d \tag{3}$$

where z_q has the same dimension as graph embeddings. Then, we calculate the similarity between the question and each k-hop ego-graph then find the top-N relevant subgraphs as:

$$S(G)_N = \operatorname{argtop} N_{q \in S(G)} \cos(z_q, z_g) \tag{4}$$

where $\cos(\cdot, \cdot)$ represents the cosine similarity function. $\mathcal{S}(G)_N \subseteq \mathcal{S}(G)$ containing N subgraphs with the highest similarity to the question is retrieved for subsequent generation.

Textual Subgraph Pruning. We use graph embedding to retrieve subgraphs, resulting in some redundant irrelevant nodes and edges still in the subgraph, and these irrelevant entities will not contribute to the final generation. Therefore, we propose a soft pruning approach to reduce the negative impact of these irrelevant entities. To be specific, we calculate the distance between the question and node & edge texts, and then use the distance to scale the node & edge attributes:

$$z_n = \operatorname{PLM}(T_n) \in \mathbb{R}^d, n \in V_g, \qquad z_e = \operatorname{PLM}(T_e) \in \mathbb{R}^d, e \in E_g$$

$$\alpha_n = \operatorname{MLP}_{\phi_1}(z_n \ominus z_q), \qquad \alpha_e = \operatorname{MLP}_{\phi_2}(z_e \ominus z_q)$$
(5)

$$\alpha_n = \mathsf{MLP}_{\phi_1} \ (z_n \ominus z_q), \qquad \qquad \alpha_e = \mathsf{MLP}_{\phi_2} \ (z_e \ominus z_q) \tag{6}$$

where \ominus represents the operator to measure the element-wise distance, i.e., euclidean distance where $z_n \ominus z_q = \sqrt{\sum_{i=1}^d (z_n[i] - z_q[i])^2}$. α_n and α_e are scalars measuring the correlation via a same MLP. In this way, if information provided by some nodes & edges has a negative impact on the final generation during the training process, they will be given a small scaling factor to reduce their impact.

Textual Graph Augmented Generation

The generation by LLMs is controlled by both retrieved ego-graphs and the question. That is, the prompts to LLMs consist of questions and information about the retrieved textual subgraphs. Prompts are divided into two parts: soft prompts, which capture the graph's topological information through

¹In this work, SentenceBert [Reimers and Gurevych, 2019] is used to encode the question and text attributes.

graph embeddings, and hard prompts, which preserve semantic nuances by representing the graph's textual data and the query text.

Hard Prompts. Recent advancements demonstrate that LLMs exhibit strong reasoning capabilities on graphs [Fatemi et al., 2023]. In particular, their proficiency in contextual reasoning allows LLMs to effectively understand structured textual documents [Saad-Falcon et al., 2023]. During training, LLMs are often exposed to structured documents with inherent or annotated hierarchical structures, such as Wikipedia pages. This exposure enables LLMs to learn the rules and patterns of textual graph representations, facilitating reasoning on hierarchical data. Therefore, representing retrieved textual subgraphs in a hierarchical structure can preserve topological information for LLMs.

Despite the promise of using structured textual document to represent textual graph information, how to achieve such transformation automatically is an open problem. Here we propose a novel algorithm to achieve this based on graph and tree traversals. The gap between k-order ego-graph and tree is that there are additional edges between nodes in addition to the edges between levels. To overcome this challenge, we design a prompt template that describes the text graph as a tree-like structure while retaining textual and topological information. As shown in Figure 2(d), we split each retrieved k-order ego-graph into two parts, denoted by $g = \mathcal{T}_g \cup \mathcal{E}_g$ where \mathcal{T}_g indicates a partially ordered set that forms a tree rooted at the ego node and \mathcal{E}_g is an edge set consisting of edges not included in the tree. We leverage Breadth-First Search (BFS) on each ego-graph to find its \mathcal{T}_g , and then \mathcal{E}_g can be easily obtained. Afterwards, we perform pre-order traversal on \mathcal{T}_g and append the texts of visited node & edge with a relation description template such as {head} is connected to {tail} via {relation} . For edges in \mathcal{E}_g , we insert textual descriptions of these edges into their head nodes, following the same relationship description template. The final description, denoted by D_g , retains all textual information and topological information with a hierarchical structure, enabling lossless conversion between the k-hop ego-graphs and text descriptions. Then, we generate text embeddings of the hard prompt with LLM's text embedder, which is the first layer of a pretrained and frozen LLM:

$$\mathbf{h}_q = \text{TextEmbedder}(q) \in \mathbb{R}^{L_q \times d_{\text{LLM}}}$$
(7)

$$\mathbf{h}_{T} = \text{TextEmbedder}(\text{Concat}(\{D_g\}_{g \in S(G)_N})) \in \mathbb{R}^{L_T \times d_{\text{LLM}}}$$
(8)

where L_q and L_T represent the number of tokens converted from the question and graph descriptions.

Soft Prompts. To aggregate topological information of graphs while minimizing the impact of irrelevant entities on the generation, we propose a novel soft prompting strategy that controls the message passing of GNNs via learnable relevance scaling factors. Subsequently, we use an MLP to align the graph embeddings and LLM tokens. This approach allows for controlled message passing in GNNs based on the relevance between nodes, edges, and the query as,

$$m_u^{(l)} = \text{MSG}^{(l)}\left(\alpha_u \cdot h_u^{(l-1)}, \alpha_{uv} \cdot e_{uv}\right), u \in \{\mathcal{N}(v) \cup v\}$$

$$\tag{9}$$

where $h_u^{(0)}=z_n$ and $e_{uv}=z_{uv}$, $\mathcal{N}(v)$ represents the set of neighboring nodes of v, $h_u^{(l-1)}$ are the node features from the previous layer, e_{uv} denotes the attributes of the edge connecting nodes u and v, α_u and α_{uv} are coefficients by Eq. (6) applied to the node & edge features. We leverage Graph Attention Network (GAT) [Veličković et al., 2018] as the graph encoder to aggregate all information in subgraphs. Since multiple subgraphs are retrieved and there is still a gap between graph encoder and LLMs' text encoder, we average the graph embedding of the retrieved subgraphs then use an MLP to align its dimension and that of the LLMs' text vectors to obtain the graph token as,

$$\mathbf{h}_{G} = \mathrm{MLP}_{\phi_{3}} \left(\frac{1}{N} \sum_{g \in \mathcal{S}(G)_{N}} \mathrm{POOL}(\mathrm{GNN}_{\Phi}(g)) \right) \in \mathbb{R}^{d_{\mathrm{LLM}}}$$
 (10)

where $d_{\rm LLM}$ indicates the dimension of the LLMs' text vector. ${\bf h}_G$ is used as a soft prompt, aggregating information from the most relevant subgraph structures and allowing the LLM to be aware of topological textual information during the generation stage. The final stage involves generating the answer Y using both the graph tokens and text tokens. The generation of LLM is controlled by graph soft prompts and text hard prompts as:

$$p_{\theta,\phi_1,\phi_2,\phi_3,\Phi}(Y|G,q) = \prod_{i=1}^{r} p_{\theta,\phi_1,\phi_2,\phi_3,\Phi}(y_i|y_{< i},[\mathbf{h}_G;\mathbf{h}_T;\mathbf{h}_q]), \tag{11}$$

where LLM's parameters θ are frozen. $[\mathbf{h}_G; \mathbf{h}_T; \mathbf{h}_q]$ concatenates the graph token and all text tokens.

5 Experiments

5.1 Experiment Setup

Tasks and Datasets. We conduct experiments on the GraphQA benchmark [He et al., 2024], where each question is asked to explore specific elements or relationships in a textual graph. Table 1 records the statistics of the dataset. WebQSP [Yih et al., 2016, Luo et al., 2023] is a large-scale multi-hop knowledge graph QA dataset consisting of 4,737 questions. ExplaGraphs [Saha et al., 2021] is a dataset about commonsense reasoning consisting of 2,766 questions focused on predicting positions in debates. Multi-hop reasoning is required to answer these questions accurately.

Table 1: Dataset statistics (average).

Dataset	WebQSP	ExplaGraphs		
# Graphs	4,700	2,766		
# Nodes	1370.89	5.17		
# Edges	4252.37	4.25		
# Tokens	100,627	1,396		

Evaluation Metrics. For the large-scale dataset WebQSP, we utilize the F_1 Score, Hit@1, and Recall metrics to comprehensively evaluate performance of models. For ExplaGraphs which focuses on common-sense reasoning, we employ Accuracy (Acc) as the primary metric.

Comparison Methods. To demonstrate the effectiveness of GRAG, we compare its performance to widely used retrievers on graph multi-hop reasoning tasks. We compare GRAG with the following models: **BM25** [Robertson et al., 2009], which is a statistical model, scores documents based on term frequency, inverse document frequency, and document length, using probabilistic principles to estimate the relevance of documents to a query; MiniLM-L12-v2, which is a SentenceTransformer model [Reimers and Gurevych, 2019] widely used in clustering and semantic search; LaBSE [Feng et al., 2022], a BERT-based model that performs retrieval by using a dual-encoder framework to learn cross-lingual sentence embeddings; mContriever [Izacard et al., 2021], which utilizes a contrastive learning approach with a bi-encoder architecture to independently encode documents and queries; E5 [Wang et al., 2022], that employs a contrastive pre-training strategy using a bi-encoder architecture, optimizing similarity between relevant pairs while distinguishing from irrelevant ones using in-batch negatives; G-Retriever [He et al., 2024], which retrieves relevant nodes and edges, and then constructs a relevant subgraph using a Prize-Collecting Steiner Tree method. Additionally, we establish two LLM baselines: (1) directly utilizing the LLM to answer questions, and (2) fine-tuning the LLM using LoRA [Hu et al., 2021] for question answering, where questions and textual graphs without any retrieval operations are used in both settings. The default LLM in experiments is Llama2-7b model [Touvron et al., 2023]. Detailed experimental settings are provided in Appendix A.1.

5.2 Main Results

Table 2 reports the overall results across datasets (i.e., WebQSP and ExplaGraphs) and compare the performance of GRAG with all the retrievers and baselines introduced in Section 5.1. More details can be found in Appendix A.2.

Key Observations. Our GRAG approach surpasses all compared retrievers and LLM baselines. Notably, GRAG significantly outperforms the fine-tuned LLM in all metrics across both datasets by generating soft tokens of retrieved textual subgraphs without fine-tuning the LLM. Fine-tuning offers only marginal performance gains when GRAG is employed, as evidenced by the limited improvement on the WebQSP dataset, with the Hit@1 metric increasing from 0.7236 to 0.7275. This suggests that GRAG is a more effective strategy for enhancing the graph reasoning capabilities of LLMs than mere fine-tuning. This can further reduce the cost of training LLMs for graph-related tasks.

When all textual information from graphs is integrated into the prompt, LLMs exhibit suboptimal performance, even on the <code>ExplaGraphs</code> dataset, which features smaller graph sizes. This underscores the critical need to implement retrieval operations to mitigate the negative impact of redundant information in graphs. Notably, fine-tuning yields significant improvements in the performance of the LLM when reasoning on small graphs, with a notable increase from 33.94% to 89.27% accuracy on <code>ExplaGraphs</code>. However, the benefits of fine-tuning diminish with larger graph sizes, with <code>Hit@1</code> on <code>WebQSP</code> only increasing from 0.4148 to 0.6186.

GRAG demonstrates the potential to transfer learned textual graph encoding capabilities across datasets. Table 4 reports the performance of GRAG on cross-dataset evaluations. When trained on a large dataset, GRAG can enhance generation on a smaller dataset using the trained model. Notably,

Table 2: Performance comparison across WebQSP and ExplaGraphs datasets. **Bold** numbers indicate the best performance among all models. Highlight numbers demonstrate the performance improvement achieved by our GRAG approach compared to the LLM baselines.

Model	$\Phi(\mathbf{g})$	Fine-tuning		ExplaGraphs			
			F_1 Score	Hit@1	Recall	Acc	
Baselines							
LLM only	X	X	0.2555	0.2555 0.4148		0.3394	
\mathbf{LLM}_{LoRA}	X	✓	0.4295	0.6186	0.4193	0.8927	
Compared Retrievers							
BM25	Х	X	0.2999	0.4287	0.2879	0.6011	
MiniLM-L12-v2	X	X	0.3485	0.4730	0.3289	0.6011	
LaBSE	X	X	0.3280	0.4496	0.3126	0.6011	
mContriever-Base	X	X	0.3172	0.4453	0.3047	0.5866	
E5-Base	X	X	0.3421	0.4705	0.3254	0.6011	
G-Retriever	✓	X	0.4674 0.6808		0.4579	0.8825	
G -Retriever $_{LoRA}$	✓	✓	0.5023	0.7016	0.5002	0.9042	
Our Retrieval Approach							
GRAG	√	Х	0.5022	0.5022 0.7236 0.5099		0.9223	
Δ_{LLM}			↑ 96.56%	↑ 74.45%	↑ 74.62%	↑ 171.74%	
$GRAG_{LoRA}$	✓	√	0.5041	0.7275	0.5112	0.9274	
Δ_{LoRA}			↑ 17.37%	† 17.60%	↑21.92%	↑ 3.89%	

performance on ExplaGraphs surpasses that of the naive LLM when the model is trained on WebQSP, with an accuracy improvement of 33.77%.

Larger LLMs may underperform relative to their smaller counterparts in graph-related tasks, suggesting that merely increasing the number of parameters does not inherently enhance LLMs' graph reasoning capabilities. Without leveraging retrieval approaches, using larger LLMs does not yield better performance in graph reasoning tasks. This is illustrated by the performance of llama2-7b-chat-hf and llama2-13b-chat-hf on both datasets. The former achieves an accuracy of 33.94% on the commonsense reasoning task in the ExplaGraphs dataset, whereas the latter records a slightly lower accuracy of 33.57%. A similar pattern is observed on the WebQSP dataset, where the 13B model's Hit@1 score of 0.4112 falls below the 0.4148 achieved by the smaller 7B model.

Efficiency and Accuracy Trade-off. The retrieval efficiency of our method is ensured because only |V| ego-graphs need to be retrieved. However, retrieving more k-hop ego-graphs with larger sizes requires encoding additional information during the generation process, leading to longer training and inference times. Figure 3 shows the performance of GRAG on WebQSP as the number of 1-hop and 2-hop ego-graphs changes. With the same number of ego-graphs, using 2-hop ego-graphs consistently outperform using 1-hop ego-graphs. However, increasing the number of retrieved subgraphs does not necessarily improve performance due to the introduction of redundant information. A drop in the generation quality can be observed when the number of ego graphs increases from 15 to 20 on WebQSP. Moreover, using a larger number of subgraphs results in more robust generation, as indicated

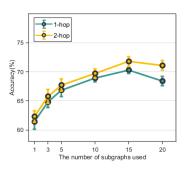


Figure 3: Performance on WebQSP.

by a smaller standard deviation. For scenarios where optimal generation results are not required, more low-hop ego-graphs can be used to achieve similar effects to higher-hop ones. Using ten 1-hop subgraphs achieves the same generation quality as using fifteen 2-hop subgraphs on WebQSP, while reducing training time by three times.

Human Evaluation on Hallucinations. We conduct small human evaluations on GRAG outputs to evaluate hallucinations. In particular, we randomly select and manually review 100 samples from WebQSP and ExplaGraphs results. Following Menick et al. and He et al., human annotators evaluate whether the model output is reasonable and supported, i.e., in graph-related scenarios, verifying whether nodes and edges referenced in the output exist in the actual graph. To be specific, we count the valid entities, i.e., the fraction of total valid nodes & edges. The output of GRAG references 79% of the valid entities in the graph compared to MiniLM-L12-v2 and G-Retriever, where the output of MiniLM-L12-v2 and G-Retriever reference 62% and 71% of the valid entities.

Thorough Comparisons with Different Retrievers and Baselines. Overall, the LLM can generate better responses with retrieved entities by all tested retrievers. However, even if advanced retrievers use more data for training and increase the embedding dimension to obtain better embeddings, their focus remains exclusively on the text domain, creating a performance bottleneck as no topological information is retrieved. As shown in Table 2, when graph tokens are not considered, there is only a slight difference in the enhancement generated by various retrievers. This phenomenon is further discussed in Appendix A.2. G-Retriever, which aggregates topological information as soft prompts, outperforms other retrievers, but it also fails to consider topology during the retrieval process. Our GRAG approach addresses this limitation by directly retrieving subgraphs instead of discrete entities within graphs, thereby achieving optimal performance on both datasets.

5.3 Ablation Study

We conducted a series of ablations to our GRAG framework to identify which components play a key role. We evaluate four model variants trained differently, where fine-tuning is used and 2-hop ego-graphs are retrieved in all settings: *No Retrieval* trains the LLM with question-answer pairs with fine-tuning; *No Graph Encoder* trains the LLM using the text on the retrieved textual subgraphs, but does not generate graph tokens; *No Soft Pruning* indicates that irrelevant entities are not pruned when retrieved subgraphs are encoded to the graph tokens; *No Graph Description* trains the LLM without the hierarchical text descriptions of retrieved textual subgraphs. As shown in Table 3, GRAG's performance drops when any of these components are removed. Our main findings are as follows:

Setting	Hit@1	Δ_{GRAG}
w/o Retrieval	0.6093	↓ 16.25%
w/o Graph Encoder	0.5835	↓ 19.79%
w/o Soft Pruning	0.5671	↓ 22.05%
w/o Graph Descriptions	0.4496	↓ 38.20%

Dataset	Acc	Δ_{LLM}
WebQSP \rightarrow ExplaGraphs	0.4540	↑ 33.77%
ExplaGraphs $ ightarrow$ WebQSP	0.4237	↑ 2.15%

Table 3: Ablation study on WebQSP.

Table 4: Transfer learning performance.

Importance of Soft Prompting. When no graph token is concentrated to the prompt, LLM's generation quality is not improved (even worse than the *No Retrieval* variant) even texts on the retrieved subgraph are used. This suggests that the soft pruning also affects the hard prompts.

Impact of Pruning. When irrelevant entities in retrieved textual subgraphs are not pruned (*No Soft Pruning*), the performance on WebQSP is worse compared to the *No Retrieval* and *No Graph Encoder* variant. This suggests that pruning is crucial, especially in dense graphs, to improve the quality of graph tokens and avoid negative impacts from irrelevant entities.

Importance of Text Attributes. When text attributes of retrieved textual subgraphs are not used, the graph token does not benefit the generation process. The performance of this variant is worse than the *No Retrieval* variant, with a Hit@1 score dropping to 0.4496, a 38.2% decrease. This indicates that the textual attributes of nodes and edges are essential for generation. Although GNNs aggregate attributes, the inclusion of text attributes is still important for the generation of the LLM.

6 Conclusion

In this paper, we introduced Graph Retrieval-Augmented Generation (GRAG), a novel approach addressing the limitations of traditional Retrieval-Augmented Generation (RAG) methods in graph-based contexts. GRAG enhances the generation capabilities of Large Language Models (LLMs) by retrieving query-relevant textual subgraphs, preserving both textual and topological information essential for accurate reasoning. Our framework employs a divide-and-conquer strategy for efficient subgraph retrieval, using k-hop ego-graphs and a soft pruning mechanism to mitigate irrelevant entities, and introduces dual prompting with hard and soft prompts to maintain semantic nuances and graph topology. Empirical results on multi-hop graph reasoning tasks demonstrate that GRAG significantly outperforms state-of-the-art RAG methods and LLM baselines, particularly in scenarios requiring detailed, multi-hop reasoning on textual graphs. This approach not only addresses the NP-hard problem of exhaustive subgraph searches but also shows that a frozen LLM with GRAG can outperform fine-tuned LLMs with lower training costs, representing a significant advancement in integrating graph-based information retrieval and generation.

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A Appendix

A.1 Implementation

All experiments are performed on a Linux-based server with 4 NVIDIA A10G GPUs. We use SentenceBert [Reimers and Gurevych, 2019] to encode the question and text attributes to obtain vectors for the retrieval process. The graph encoder, i.e. GAT [Veličković et al., 2018], has 4 layers with 4 heads per layer and a hidden dimension size of 1024.

The LLM backbone is Llama-2-7b-hf, while the model used is in the setting of LLM only is Llama-2-7b-chat-hf. We employ Low-rank Adaptation (LoRA) [Hu et al., 2021] for fine-tuning, configuring the LoRA parameters as follows: the dimension of the low-rank matrices is set to 8; the scaling factor is 16; and the dropout rate is 0.05. For the optimization, AdamW optimizer [Loshchilov and Hutter, 2018] is used. The initial learning rate is set to 1e-5 and the weight decay is 0.05. Each experiment runs for up to 10 epochs, and the batch size is 2. For compared retrievers, each experiment on ExplaGraphs is replicated three times, utilizing different retrieval settings for each run, i.e., top-3, top-5 and top-10; Each experiment on WebQSP is replicated five times, utilizing different retrieval settings for each run, i.e., top-3, top-5, top-10, top-15 and top-20, where top-k indicates how many relevant entities are retrieved and used for the generation. In our GRAG approach, since the graphs in ExplaGraphs are constructed from several triples, each graph is actually a chain consisting of only a few nodes. Therefore, we feed the entire graph into the LLM without retrieval.

A.2 Experiment

Evaluation Metrics. Hit@1 assesses whether the top retrieved result is correct. It is particularly useful for understanding the accuracy of the first retrieval hit in graph-based question answering tasks. F_1 **Score** is the harmonic mean of precision and recall, providing a single metric that balances both false positives and false negatives. **Recall** measures the proportion of relevant entities that are successfully retrieved. High recall indicates that the retrieval system captures most of the relevant information. **Accuracy (Acc)** measures the proportion of correctly answered questions. It is particularly useful for tasks like ExplaGraphs, where the focus is on commonsense reasoning.

Table 5: Performance of RAG-based retrievers: Hit@1 on WebQSP and Acc on ExplaGraphs.

Model	WebQSP				ExplaGraphs			
	top-3	top-5	top-10	top-15	top-20	top-3	top-5	top-10
BM25	0.3722	0.3821	0.4109	0.4165	0.4287	0.5704	0.5921	0.6011
MiniLM-L12-v2	0.4251	0.4251	0.4539	0.4625	0.4730	0.5848	0.5939	0.6011
LaBSE	0.4091	0.4171	0.4294	0.4527	0.4496	0.6011	0.6011	0.6011
mContriever-Base	0.4183	0.4158	0.4349	0.4459	0.4453	0.5866	0.5866	0.5866
E5-Base	0.4404	0.4558	0.4662	0.4650	0.4705	0.5921	0.5939	0.6011

Effects of the Number of Retrieved Entities. Top-kindicates k nodes and k edges are retrieved. The performance of various RAG retrievers on the WebQSP and ExplaGraphs datasets, with different numbers of retrieved entities, is summarized in Table 5. GRAG in Figure 4 indicates that the hard prompts of the text descriptions are replaced by texts of retrieved entities, while the soft prompt is the token generated by the retrieved k-hop ego-graphs. As observed, increasing the number of retrieved entities generally improves performance up to a point. For instance, BM25's Hit@1 score on WebQSP increases from 0.3722 with top-3 retrievals to 0.4287 with top-20 retrievals. Similarly, MiniLM-L12-v2 shows improvement from 0.4251 to 0.4730 over the same range. However, this trend does not continue indefinitely; for some models, performance plateaus or even slightly decreases beyond a certain number of en-

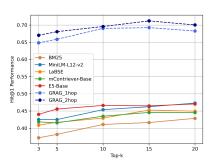


Figure 4: Effects of the number of retrieved entities on the WebQSP dataset.

tities. For example, LaBSE's performance peaks at top-15 and then slightly drops at top-20 on WebQSP. This indicates that retrieving too many entities can introduce irrelevant information, which may negatively impact the final generation. On the ExplaGraphs dataset, the trend is less pro-

nounced due to the smaller graph sizes, with most models showing minimal performance changes beyond top-5 retrievals. When the graph size is small, indicating that limited information is available, all RAG-based retrievers encounter a performance bottleneck. In contrast, our GRAG approach can leverage topological information, effectively breaking through this performance limitation.