GFM-RAG: Graph Foundation Model for Retrieval Augmented Generation

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Abstract

Retrieval-augmented generation (RAG) has proven effective in integrating knowledge into large language models (LLMs). However, conventional RAGs struggle to capture complex relationships between pieces of knowledge, limiting their performance in intricate reasoning that requires integrating knowledge from multiple sources. Recently, graph-enhanced retrieval augmented generation (GraphRAG) builds graph structure to explicitly model these relationships, enabling more effective and efficient retrievers. Nevertheless, its performance is still hindered by the noise and incompleteness within the graph structure. To address this, we introduce GFM-RAG, a novel graph foundation model (GFM) for retrieval augmented generation. GFM-RAG is powered by an innovative graph neural network that reasons over graph structure to capture complex query-knowledge relationships. The GFM with 8M parameters undergoes a two-stage training process on large-scale datasets, comprising 60 knowledge graphs with over 14M triples and 700k documents. This results in impressive performance and generalizability for GFM-RAG, making it the first graph foundation model applicable to unseen datasets for retrieval without any fine-tuning required. Extensive experiments on three multi-hop QA datasets and seven domain-specific RAG datasets demonstrate that GFM-RAG achieves state-of-the-art performance while maintaining efficiency and alignment with neural scaling laws, highlighting its potential for further improvement¹.

1. Introduction

Recent advancements in large language models (LLMs) (OpenAI, 2024a; Meta, 2024; Yang et al., 2024) have greatly

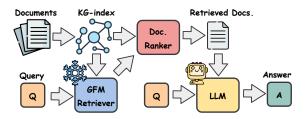


Figure 1. The overview framework of GFM-RAG. We feed the query and a constructed KG-index into the graph foundation model retriever to obtain relevant documents for LLM generation.

propelled the evolution of natural language processing, positioning them as foundational models for artificial general intelligence (AGI). Despite the remarkable reasoning ability (OpenAI, 2024b), LLMs are still limited in accessing real-time information and lack of domain-specific knowledge, which is outside the pre-training corpus. To address these limitations, retrieval-augmented generation (RAG) (Gao et al., 2023) has become a popular paradigm in adding new knowledge to the static LLMs by retrieving relevant documents into the context of LLM generation.

Existing RAG methods typically retrieve documents independently, making it difficult to capture complex relationships between pieces of knowledge (Karpukhin et al., 2020; Chen et al., 2023; Moreira et al., 2024). This limitation hampers the performance of LLMs in integrating knowledge across document boundaries, particularly in multi-hop reasoning tasks (Yang et al., 2018; Trivedi et al., 2022) and real-world applications like legal judgment (Kang et al., 2024) and medical diagnoses (Jin et al., 2019), which require reasoning over multiple sources. Although recent methods have expanded the retrieval process into multiple steps and incorporate LLM reasoning, they still encounter high computational costs due to iterative retrieval and reasoning with LLMs (Trivedi et al., 2023; Sun et al., 2024; Joshi et al., 2024).

Recently, graph-enhanced retrieval augmented generation (GraphRAG) (Peng et al., 2024; Han et al., 2024) has emerged as a novel solution that builds a graph structure to explicitly model the intricate relationships between knowledge. This enables the development of a graph-enhanced retriever to identify relevant information using graphs. The structural nature of graphs allows GraphRAG to capture

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¹Code: https://github.com/RManLuo/gfm-rag

global context and dependencies among documents, significantly improving reasoning across multiple sources (Edge et al., 2024). Methods like HippoRAG (Gutiérrez et al., 2024) enhance retrieval by employing a personalized PageRank algorithm to locate relevant knowledge with graphs. However, these algorithms rely solely on the graph structure, which is often noisy or incomplete, limiting their overall performance. Alternative methods (Mavromatis & Karypis, 2024; He et al., 2024) incorporate graph neural networks (GNNs) into the retrieval process. These methods have shown impressive performance due to GNNs' powerful reasoning capabilities in handling incomplete graphs (Galkin et al., 2024). Nevertheless, they still face limitations in generalizability since they require training from scratch on new datasets.

Nowadays, the search for a foundation GNN model that can transfer and generalize across different datasets has been an active research topic. Ideally, a foundation GNN or graph foundation model (GFM) can benefit from large-scale training and generalize across diverse graphs (Mao et al., 2024; Liu et al., 2023). Efforts have been made to identify transferable graph tokens (e.g., motifs, sub-trees, and relation graphs) (Galkin et al., 2024; Wang et al., 2024; Xia et al., 2024) that can be shared among different graphs for GFM design. However, these methods primarily focus on graph-related tasks (e.g., node classification and link prediction), leaving the design of a GFM to enhance LLMs' reasoning ability unexplored.

To bridge the gap, in this paper, we propose an effective, efficient, and general graph foundation model for retrieval augmented generation (GFM-RAG), thereby enhancing LLMs' reasoning ability. As shown in Figure 1, we create a knowledge graph index (KG-index) from documents in each dataset. The KG-index consists of interconnected factual triples pointing to the original documents, which serves as a structural knowledge index across multiple sources, enhancing the integration of diverse knowledge for complex reasoning tasks (Gutiérrez et al., 2024). Then, we present the graph foundation model retriever (GFM retriever), driven by a query-dependent GNN that captures complex queryknowledge relationships in a unified, transferable space of semantics and graph structure. Through multi-layer message passing, the GFM retriever enables efficient multi-hop retrieval in a single step, surpassing previous multi-step methods. The GFM retriever, with 8M parameters, undergoes a two-stage training: unsupervised KG completion pre-training and supervised document retrieval fine-tuning on large-scale datasets, including 60 knowledge graphs with over 14M triples and 700k documents. This large-scale training ensures the generalizability of GFM retriever to be applied directly to unseen datasets without further training.

In experiments, GFM-RAG achieves state-of-the-art perfor-

mance across three multi-hop QA datasets, demonstrating its effectiveness and efficiency in multi-hop reasoning. It also generalizes well across seven RAG datasets from diverse domains, such as biomedical, customer service, and general knowledge, without requiring additional training. Furthermore, GFM-RAG follows the neural scaling law (Hestness et al., 2017), whose performance benefits from training data and model size scaling, emphasizing its potential as a foundational model for future improvements.

The main contributions of this paper are as follows:

- We introduce a graph foundation model for retrieval augmented generation (GFM-RAG), powered by a novel query-dependent GNN to enable efficient multihop retrieval within a single step.
- We train a large-scale model with 8M parameters, marking the first graph foundation model (GFM) that can be applied directly to various unseen datasets for retrieval augmented generation.
- We evaluate GFM-RAG on three multi-hop QA datasets and seven domain-specific RAG datasets, achieving state-of-the-art performance across all, demonstrating its effectiveness, efficiency, generalizability, and potential as a foundational model for further enhancement.

2. Related Work

Retrieval-augmented generation (RAG) (Gao et al., 2023) provides an effective way to integrate external knowledge into large language models (LLMs) by retrieving relevant documents to facilitate LLM generation. Early works adopt the pre-trained dense embedding model to encode documents as separate vectors (Karpukhin et al., 2020; Chen et al., 2023; Li et al., 2023b; Moreira et al., 2024), which are then retrieved by calculating the similarity to the query. Despite efficiency and generalizability, these methods struggle to capture complex document relationships. Subsequent studies have explored multi-step retrieval, where LLMs guide an iterative process to retrieve and reason over multiple documents (Trivedi et al., 2023; Jiang et al., 2023; Su et al., 2024). However, this approach is computationally expensive.

Graph-enhanced retrieval augmented generation (GraphRAG) (Peng et al., 2024; Han et al., 2024) is a novel approach that builds graphs to explicitly model the complex relationships between knowledge, facilitating comprehensive retrieval and reasoning. Early research focuses on retrieving information from existing knowledge graphs (KGs), such as WikiData (Vrandečić & Krötzsch, 2014) and Freebase (Bollacker et al., 2008), by identifying relevant facts or reasoning paths (Li et al., 2023a; LUO

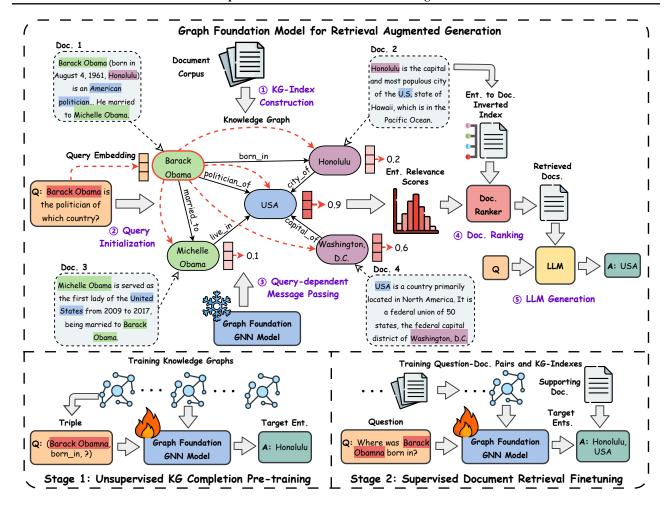


Figure 2. The detailed framework of GFM-RAG and training processes of graph foundation model. The GFM-RAG consists of three main components: A. KG-index construction, which constructs a knowledge graph index from document corpus (①); B. graph foundation model retriever (GFM retriever), which is pre-trained on large-scale datasets and could retrieve documents based on any user query and KG-index (②③); and C. documents ranking and answer generation, which ranks retrieved documents and generates final answer (④⑤).

et al., 2024). Recent studies have integrated documents with KGs to improve knowledge coverage and retrieval (Edge et al., 2024; Liang et al., 2024). A graph structure is built from these documents to aid in identifying relevant content for LLM generation (Dong et al., 2024). Based on graphs, LightRAG (Guo et al., 2024) incorporates graph structures into text indexing and retrieval, enabling efficient retrieval of entities and their relationships. HippoRAG (Gutiérrez et al., 2024) enhances multi-hop retrieval by using a personalized PageRank algorithm to locate relevant knowledge with graphs. However, the graph structure can be noisy and incomplete, leading to suboptimal performance. Efforts to incorporate GNNs into graph-enhanced RAG (Mavromatis & Karypis, 2024; He et al., 2024) have shown impressive results due to the strong graph reasoning capabilities of GNNs in handling incomplete graphs (Galkin et al., 2024). Nonetheless, these methods still limit in generalizability due to the lack of a graph foundational model.

Graph Foundation models (GFM) aims to be a large-scale model that can generalize to various datasets (Mao et al., 2024; Liu et al., 2023). The main challenge in designing GFMs is identifying graph tokens that capture invariance across diverse graph data. For instance, ULTRA (Galkin et al., 2024) employs four fundamental relational interactions in knowledge graphs (KGs) to create a GFM for link prediction. OpenGraph (Xia et al., 2024) develops a graph tokenizer that converts graphs into a unified node token representation, enabling transformer-like GFMs for tasks such as link prediction and node classification. GFT (Wang et al., 2024) introduces a transferable tree vocabulary to construct a GFM that demonstrates effectiveness across various tasks and domains in graph learning. Despite these successful efforts, most methods primarily focus on conventional graph-related tasks. How to design a GFM to enhance the reasoning of LLM remains an open question.

3. Approach

The proposed GFM-RAG essentially implements a GraphRAG paradigm by constructing graphs from documents and using a graph-enhanced retriever to retrieve relevant documents.

GFM-RAG Overview. Given a set of documents $\mathcal{D} =$ $\{D_1, D_2, \dots, D_{|\mathcal{D}|}\}$, we construct a knowledge graph $\mathcal{G} =$ $\{(e,r,e')\in\mathcal{E}\times\mathcal{R}\times\mathcal{E}\}, \text{ where } e,e'\in\mathcal{E} \text{ and } r\in\mathcal{R}$ denote the set of entities and relations extracted from \mathcal{D} , respectively. For a user query q, we aim to design a graphenhanced retriever to obtain relevant documents from \mathcal{D} by leveraging the knowledge graph \mathcal{G} . The whole GFM-RAG process can be formulated as:

$$\mathcal{G} = KG\text{-index}(\mathcal{D}), \tag{1}$$

$$\mathcal{D}^K = \text{GFM-Retriever}(q, \mathcal{D}, \mathcal{G}), \tag{2}$$

$$a = LLM(q, \mathcal{D}^K). \tag{3}$$

In the first step, KG-index(\cdot) constructs a knowledge graph index \mathcal{G} from the document corpus \mathcal{D} , followed by our proposed graph foundation model retriever (GFM-Retriever), which is pre-trained on large-scale datasets. It retrieves top-K documents based on any user query q and knowledge graph index \mathcal{G} . The retrieved documents \mathcal{D}^K , along with the query q, are then input into a large language model (LLM) to generate the final answer a. These three main components in GFM-RAG are illustrated in Figure 2 and will be detailed next.

3.1. KG-index Construction

Conventional embedding-based index methods encode documents as separate vectors (Karpukhin et al., 2020; Chen et al., 2023; Moreira et al., 2024), which are limited in modeling the relationships between them. Knowledge graphs (KGs), on the other hand, explicitly capturing the relationships between millions of facts, can provide a structural index of knowledge across multiple documents (Edge et al., 2024; Gutiérrez et al., 2024). The structural nature of the KG-index aligns well with the human hippocampal memory indexing theory (Teyler & DiScenna, 1986), where the KG-index functions like an artificial hippocampus to store associations between knowledge memories, enhancing the integration of diverse knowledge for complex reasoning tasks (Gutiérrez et al., 2024).

To construct the KG-index, given a set of documents \mathcal{D} , we first extract entities \mathcal{E} and relations \mathcal{R} to form triples ${\mathcal T}$ from documents. Then, the entity to document inverted index $M \in \{0,1\}^{|\mathcal{E}| \times |\mathcal{D}|}$ is constructed to record the entities mentioned in each document. Such a process can be achieved by existing open information extraction (OpenIE) tools (Angeli et al., 2015; Zhou et al., 2022; Pai et al., 2024). To better capture the connection between knowledge, we

further conduct the entity resolution (Gillick et al., 2019; Zeakis et al., 2023) to add additional edges \mathcal{T}^+ between entities with similar semantics, e.g., (USA, equivalent, United States of America). Therefore, the final KG-index \mathcal{G} is constructed as $\mathcal{G} = \{(e, r, e') \in \mathcal{T} \cup \mathcal{T}^+\}$. In implementation, we leverage an LLM (OpenAI, 2024a) as the OpenIE tool and a pre-trained dense embedding model (Santhanam et al., 2022) for entity resolution.

3.2. Graph Foundation Model (GFM) Retriever

The GFM retriever is designed to retrieve relevant documents based on any user query and the constructed KGindex. While the KG-index offers a structured representation of knowledge, it still suffers from incompleteness and noise, resulting in suboptimal retrieval performance when solely relying on its structure (Gutiérrez et al., 2024). Recently, graph neural networks (GNNs) (Wu et al., 2020) have shown impressive graph reasoning ability by capturing the complex relationships between knowledge for retrieval or question answering (Mavromatis & Karypis, 2024; He et al., 2024). However, existing GNNs are limited in generalizability, as they are usually trained on specific graphs (Mao et al., 2024; Liu et al., 2023), which limits their application to unseen corpora and KGs. Therefore, there is still a need for a graph foundation model that can be directly applied to unseen datasets and KGs without additional training.

To address these issues, we propose the first graph foundation model-powered retriever (GFM retriever), which harnesses the graph reasoning ability of GNNs to capture the complex relationships between queries, documents, and knowledge graphs in a unified and transferable space. The GFM retriever employs a query-dependent GNN to identify relevant entities in graphs that will aid in locating pertinent documents. After pre-training on large-scale datasets, the GFM retriever can be directly applied to new corpora and KGs without further training.

3.2.1. Query-dependent GNN

Conventional GNNs (Gilmer et al., 2017) follow the message passing paradigm, which iteratively aggregates information from neighbors to update entity representations. Such a paradigm is not suitable for the GFM retriever as it is graph-specific and neglects the relevance of queries. Recent query-dependent GNNs (Zhu et al., 2021; Galkin et al., 2024) have shown promising results in capturing query-specific information and generalizability to unseen graphs, which is essential for the GFM retriever and can be formulated as:

$$H_q^L = \text{GNN}_q(q, \mathcal{G}, H^0), \tag{4}$$

 $H_q^L=\text{GNN}_q(q,\mathcal{G},H^0), \tag{4}$ where $H^0\in\mathbb{R}^{|\mathcal{E}|\times d}$ denotes initial entity features, and H_q^L denotes the updated entity representations conditioned on query q after L layers of query-dependent message passing. The query-dependent GNN exhibits better expressively (You et al., 2021) and logical reasoning ability (Qiu et al., 2024), which is selected as the backbone of our GFM retriever. It allows the GFM retriever to dynamically adjust the message passing process based on user queries and find the most relevant information on the graph.

Query Initialization. Given a query q, we first encode it into a query embedding with a sentence embedding model:

$$q = \text{SentenceEmb}(q), \ q \in \mathbb{R}^d,$$
 (5)

where d denotes the dimension of the query embedding. Then, for all the entities mentioned in the query $e_q \in \mathcal{E}_q \subseteq \mathcal{E}$, we initialize their entity features as \boldsymbol{q} while others as zero vectors:

$$H^{0} = \begin{cases} \mathbf{q}, & e \in \mathcal{E}_{q}, \\ \mathbf{0}, & \text{otherwise.} \end{cases}$$
 (6)

Query-dependent Message Passing. The query-dependent message passing will propagate the information from the question entities to other entities in the KG to capture their relevance to the query. The message passing process can be formulated as:

Triple-level:

$$h_r^0 = \text{SentenceEmb}(r), \ h_r^0 \in \mathbb{R}^d,$$
 (7)

$$m_e^{l+1} = \text{Msg}(h_e^l, g^{l+1}(h_r^l), h_{e'}^l), (e, r, e') \in \mathcal{G},$$
 (8)

Entity-level:

$$h_e^{l+1} = \text{Update}(h_e^l, \text{Agg}(\{m_{e'}^{l+1} | e' \in \mathcal{N}_r(e), r \in \mathcal{R}\})),$$
 (9)

where h_e^l, h_r^l denote the entity and relation embeddings at layer l, respectively. The relation embeddings h_r^0 are also initialized using the same sentence embedding model as the query, reflecting their semantics (e.g., "born_in"), and updated by a layer-specific function $g^{l+1}(\cdot)$, implemented as a 2-layer MLP. The $\mathrm{Msg}(\cdot)$ is operated on all triples in the KG to generate messages, which is implemented with a non-parametric DistMult (Yang et al., 2015) following the architecture of NBFNet (Zhu et al., 2021). For each entity, we aggregate the messages from its neighbors $\mathcal{N}_r(e)$ with relation r using sum and update the entity representation with a single linear layer.

After L layers message passing, a final MLP layer together with a sigmoid function maps the entity embeddings to their relevance scores to the query:

$$P_q = \sigma(\text{MLP}(H_q^L)), \ P_q \in \mathbb{R}^{|\mathcal{E}| \times 1}. \tag{10}$$

Generalizability. Since the query, entity, and relation embeddings are initialized using the same sentence embedding model with identical dimensions, the query-dependent GNN can be directly applied to different queries and KGs. This allows it to learn complex relationships between queries and entities by taking into account both the semantics and structure of the KG through training on large-scale datasets.

3.2.2. TRAINING PROCESS

Training Objective. The training objective of the GFM retriever is to maximize the likelihood of the relevant entities to the query, which can be optimized by minimizing the binary cross-entropy (BCE) loss:

$$\mathcal{L}_{\text{BCE}} = -\frac{1}{|\mathcal{A}_q|} \sum_{e \in \mathcal{A}_q} \log P_q(e) - \frac{1}{|\mathcal{E}^-|} \sum_{|\mathcal{E}^-|} \log(1 - P_q(e)), \tag{11}$$

where \mathcal{A}_q denotes the set of target relevant entities to the query q, and $\mathcal{E}^- \subseteq \mathcal{E} \setminus \mathcal{A}_q$ denotes the set of negative entities sampled from the KG. However, due to the sparsity of the target entities, the BCE loss may suffer from the gradient vanishing problem (Lin et al., 2024). To address this issue, we further introduce the ranking loss (Bai et al., 2023) to maximize the margin between the positive and negative entities:

$$\mathcal{L}_{\text{RANK}} = -\frac{1}{|\mathcal{A}_q|} \sum_{e \in \mathcal{A}_q} \frac{P_q(e)}{\sum_{e' \in \mathcal{E}^-} P_q(e')}.$$
 (12)

The final training objective is the weighted combination of the BCE loss and ranking loss:

$$\mathcal{L} = \alpha \mathcal{L}_{BCE} + (1 - \alpha) \mathcal{L}_{RANK}.$$
 (13)

Unsupervised KG Completion Pre-training. To enhance the graph reasoning capability of the GFM retriever, we first pre-train it on a large-scale knowledge graph (KG) completion task. We sample a set of triples from the KG index and mask either the head or tail entity to unsupervisedly create synthetic queries in the form q=(e,r,?) or (?,r,e'), with the masked entity serving as the target entity $\mathcal{A}_q=\{e\}$ or $\{e'\}$. The GFM retriever is then trained to predict the masked entity using both the query and the KG, as outlined in equation 13.

Supervised Document Retrieval Fine-tuning. After unsupervised pre-training, we fine-tune the GFM retriever on a supervised document retrieval task. In this task, queries q are natural language questions, and target entities \mathcal{A}_q are extracted from labeled supporting documents \mathcal{D}_q . The GFM retriever is trained to retrieve relevant entities from the KG index using the same training objective as in equation 13.

3.3. Documents Ranking and Answer Generation

Given the entity relevance scores $P_q \in \mathbb{R}^{|\mathcal{E}| \times 1}$ predicted by the GFM retriever, we first retrieve the top-T entities \mathcal{E}_q^T with the highest relevance scores as:

$$\mathcal{E}_q^T = \arg \operatorname{top-}T(P_q), \ \mathcal{E}_q^T = \{e_1, \dots, e_T\}.$$
 (14)

These retrieved entities are then used by the document ranker to obtain the final documents. To diminish the influence of popular entities, we weigh the entities by the inverse of their frequency as entities mentioned in the document inverted index $M \in \{0,1\}^{|\mathcal{E}| \times |\mathcal{D}|}$ and calculate the final document relevance scores by summing the weights of

entity mentioned in documents:

$$F_e = \begin{cases} \frac{1}{\sum_{d \in \mathcal{D}} M[e,d]}, & e \in \mathcal{E}_q^T, \\ 0, & \text{otherwise,} \end{cases}$$
 (15)

$$P_d = M^{\top} F_e, \ P_d \in \mathbb{R}^{|\mathcal{D}| \times 1}. \tag{16}$$

The top-K documents are retrieved based on the document relevance scores P_d and fed into the context of LLMs, with a retrieval augmented generation manner, to generate the final answer:

$$\mathcal{D}^K = \arg \operatorname{top-}K(P_d), \ \mathcal{D}^K = \{D_1, \dots, D_K\},$$

$$a = \operatorname{LLM}(q, \mathcal{D}^K).$$
(18)

4. Experiment

In experiments, we aim to address the following research questions: (1) How does GFM-RAG perform in multi-hop retrieval and QA tasks? (Sections 4.2 and 4.3); (2) What are the efficiency and effectiveness of GFM-RAG in multi-hop retrieval? (Section 4.4); (3) How well does GFM-RAG generalize to unseen datasets as a foundation model? (Section 4.6); (4) How does the performance of GFM-RAG scale with training as a foundation model? (Section 4.7); (5) How to interpret GFM-RAG in multi-hop reasoning? (Section 4.8).

4.1. Experimental Setup

Datasets. We first evaluate the effectiveness of GFM-RAG on three widely-used multi-hop QA datasets, including HotpotQA (Yang et al., 2018), MuSiQue (Trivedi et al., 2022), and 2WikiMultiHopQA (2Wiki) (Ho et al., 2020). For a fair comparison (Trivedi et al., 2023; Gutiérrez et al., 2024), we use 1,000 samples from each validation set for testing. We merge the candidate passages into the document corpus and extract 20,000 samples from each training set for GFM training. We also evaluate the performance of GFM-RAG on seven RAG datasets from three domains, including biomedical (Jin et al., 2019), custom support (Sadat et al., 2023; Nandy et al., 2021; Malaviya et al., 2023; Castelli et al., 2020), and general knowledge (Nguyen et al., 2016; Kamalloo et al., 2023), to demonstrate the generalizability of GFM-RAG as the foundation model. The detailed statistics of the test datasets are shown in the Appendix A.

Baselines. We compare against several widely used retrieval methods under three categories: (1) *single-step naive methods*: BM25 (Robertson & Walker, 1994), Contriever (Izacard et al., 2022), GTR (Ni et al., 2022), ColBERTv2 (Santhanam et al., 2022), RAPTOR (Sarthi et al., 2024), Proposition (Chen et al., 2024); (2) state-of-the-art *graphenhanced methods*: LightRAG (Guo et al., 2024), HippoRAG (Gutiérrez et al., 2024); (3) *multi-step methods*: IRCoT (Trivedi et al., 2023), which can be integrated with

Table 1. Statistics of the query-doc pairs and KGs used for training.

Dataset	#Q-doc Pair	#Document	#KG	#Entity	#Relation	#Triple
HotpotQA	20,000	204,822	20	1,930,362	967,218	6,393,342
MuSiQue	20,000	410,380	20	1,544,966	900,338	4,848,715
2Wiki	20,000	122,108	20	916,907	372,554	2,883,006
Total	60,000	737,310	60	4,392,235	2,240,110	14,125,063

Table 2. Retrieval performance comparison.

Category	Method	Hotp	HotpotQA		MuSiQue		2Wiki	
		R@2	R@5	R@2	R@5	R@2	R@5	
	BM25	55.4	72.2	32.3	41.2	51.8	61.9	
	Contriever	57.2	75.5	34.8	46.6	46.6	57.5	
	GTR	59.4	73.3	37.4	49.1	60.2	67.9	
	ColBERTv2	64.7	79.3	37.9	49.2	59.2	68.2	
Single-step	RAPTOR	58.1	71.2	35.7	45.3	46.3	53.8	
	Proposition	58.7	71.1	37.6	49.3	56.4	63.1	
	LightRAG	38.8	54.7	24.8	34.7	45.1	59.1	
	HippoRAG (Contriever)	59.0	76.2	41.0	52.1	71.5	89.5	
	HippoRAG (ColBERTv2)	60.5	77.7	40.9	51.9	70.7	89.1	
	IRCoT + BM25	65.6	79.0	34.2	44.7	61.2	75.6	
	IRCoT + Contriever	65.9	81.6	39.1	52.2	51.6	63.8	
Multi-step	IRCoT + ColBERTv2	67.9	82.0	41.7	53.7	64.1	74.4	
•	IRCoT + HippoRAG (Contriever)	65.8	82.3	43.9	56.6	75.3	93.4	
	IRCoT + HippoRAG (ColBERTv2)	67.0	83.0	45.3	57.6	75.8	93.9	
Single-step	GFM-RAG	78.3	87.1	49.1	58.2	90.8	95.6	

arbitrary retrieval methods to conduct multi-step retrieval and reasoning. The detailed introduction of the baselines are shown in the Appendix B.

Metrics. For retrieval performance, we use recall@2 (R@2) and recall@5 (R@5) as evaluation metrics. For the final QA performance, we use the EM score and F1 score following previous works (Gutiérrez et al., 2024).

Implementation Details. The GFM retriever is implemented with 6 query-dependent message passing layers with the hidden dimension set to 512. The pre-trained all-mpnet-v2 (SBERT, 2021) is adopted as the sentence embedding model and is frozen during training. The total parameters of the GFM retriever are 8M, which is trained on 8 NVIDIA A100s (80G) with batch size 4, learning rate 5e-4, and loss weight $\alpha=0.3$. The training data contains 60 KGs with over 14M triples constructed from 700k documents extracted from the training set. The statistics are shown in Table 1, and the detailed data construction process, model settings, and training process are shown in Appendix C.

4.2. Retrieval Performance

We first evaluate the retrieval performance of GFM-RAG against the baselines on three multi-hop QA datasets. As shown in Table 2, GFM-RAG achieves the best performance on all datasets, outperforming the SOTA IRCoT + HippoRAG by 16.8%, 8.3%, 19.8% in R@2 on HotpotQA, MuSiQue, and 2Wiki, respectively. The results demonstrate the effectiveness of GFM-RAG in multi-hop retrieval. From the result, we can observe that the naive single-step retrievers (e.g., BM25, RAPTOR) are outperformed by graphenhanced HippoRAG, which highlights the significance of graph structure in multi-hop retrieval. Although LightRAG

Table 3. Question answering performance comparison.

Category	Retriever	HotpotQA		MuSiQue		2Wiki	
Cutegory			F1	EM	F1	EM	F1
	None	30.4	42.8	12.5	24.1	31.0	39.0
Single-step	ColBERTv2 LightRAG	43.4 36.8	57.7 48.3	15.5 18.1	26.4 27.5	33.4 45.1	43.3 49.5
	HippoRAG (ColBERTv2)	41.8	55.0	19.2	29.8	46.6	59.5
Multi-step	IRCoT (ColBERTv2) IRCoT + HippoRAG (ColBERTv2)	45.5 45.7	58.4 59.2	19.1 21.9	30.5 33.3	35.4 47.7	45.1 62.7
Single-step Multi-step	GFM-RAG IRCoT + GFM-RAG	51.6 56.0	66.9 71.8	30.2 36.6	40.4 49.2	69.8 72.5	77.7 80.8

Table 4. Retrieval efficiency and performance comparison.

Method	HotpotQA		MuSi(Que	2Wiki	
Method	Time (s)	R@5	Time (s)	R@5	Time (s)	R@5
ColBERTv2	0.035	79.3	0.030	49.2	0.029	68.2
HippoRAG	0.255	77.7	0.251	51.9	0.158	89.1
IRCoT + ColBERTv2	1.146	82.0	1.152	53.7	2.095	74.4
IRCoT + HippoRAG	3.162	83.0	3.104	57.6	3.441	93.9
GFM-RAG	0.107	87.1	0.124	58.2	0.060	95.6

uses the graph structure, it struggles with multi-hop QA tasks because its retriever lacks multi-hop reasoning capability. With the help of LLMs, the multi-step retrieval pipeline IRCoT improves the performance of all single-step methods through iterative reasoning and retrieval. However, GFM-RAG still outperforms the multi-step IRCoT + HippoRAG by a large margin even with a single-step retrieval. This indicates that the GFM-RAG can effectively conduct the multi-hop reasoning in a single step (detailed in Section 4.8 and Appendix D.6), which is more efficient and effective than the multi-step retrieval pipeline (detailed in Section 4.4).

4.3. Question Answering Performance

We then evaluate the QA performance of GFM-RAG, as it is directly influenced by retrieval quality. We adopt the GPT-4o-mini (OpenAI, 2024a) as LLM and use the top-5 retrieved documents for generating answers. From the results shown in Table 3, the single-step GFM-RAG has already achieved state-of-the-art performance against all other baselines. Meanwhile, we also integrate GFM-RAG with IRCoT to conduct multi-step retrieval and reasoning, which further improves the performance by 8.5%, 21.2%, 3.9% in EM on three datasets, respectively. The results demonstrate the effectiveness and great compatibility of GFM-RAG with an arbitrary multi-step framework in multi-hop reasoning tasks.

4.4. Efficiency Analysis

GFM-RAG achieves great efficiency in performing multistep reasoning in a single step. As shown in Table 4, while the naive single-step methods get the best efficiency whose performance is not satisfying. Admittedly, the multi-step framework IRCoT could improve the performance, but it suffers from high computational costs due to the iterative

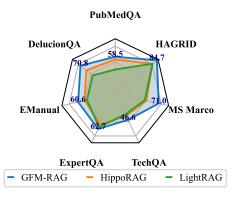


Figure 3. Model performance and generalizability comparison. retrieval and reasoning with LLMs. In contrast, GFM-RAG conducts multi-hop reasoning within a single-step GNN reasoning, which is more effective than single-step methods and more efficient than multi-step ones.

4.5. Ablation Study

We conduct ablation studies to investigate the effectiveness of different components in GFM-RAG, including different sentence embedding models (Appendix D.1), pre-training strategies (Appendix D.2), and loss weighting strategies (Appendix D.3). The results show that GFM-RAG is not sensitive to different sentence embedding models, and the pre-training strategy, as well as the loss weighting strategy, are both crucial for the performance of GFM-RAG.

4.6. Model Generalizability

To demonstrate the generalizability of GFM-RAG as a foundation model, we test the performance (R@5) of GFM-RAG on seven domain-specific RAG datasets without any finetuning. Specifically, we first build the KG-index from the documents in each dataset. Then, given the query, we use the pre-trained GFM retriever to retrieve the top-K documents with the help of the corresponding KG-index. As shown in Figure 3, GFM-RAG achieves the best performance on all datasets, outperforming the SOTA HippoRAG by 18.9% on average. The results demonstrate the generalizability of GFM-RAG as the foundation model which can be directly applied to various unseen datasets without any finetuning. Additionally, results in Appendix D.4 demonstrate GFM-RAG's strong transferability for further performance improvement when fine-tuned on domain-specific datasets.

4.7. Model Neural Scaling Law

We further investigate the neural scaling law of GFM-RAG, which quantifies how model performance grows with the scale of training data and model parameter size. It has been validated in the recent foundation models (Kaplan et al., 2020; Dehghani et al., 2023). As shown in Figure 4, the performance of GFM-RAG (MRR: z) scales well with the

Table 5. Path interpretations of GFM for multi-ho	in reasoning where r^{-1}	denotes the inverse of	original relation
Table 3. I am microficiations of Of Wi for multi-no	p reasoning, where r	uchous the miverse of	original iciation.

Question	What football club was owned by the singer of "Grow Some Funk of Your Own"?
Answer	Watford Football Club
Sup. Doc.	["Grow Some Funk of Your Own", "Elton John"]
Paths	1.095: (grow some funk of your own, is a song by, elton john) \rightarrow (elton john, equivalent, sir elton hercules john) \rightarrow (sir elton hercules john, named a stand after $^{-1}$, watford football club) 0.915: (grow some funk of your own, is a song by, elton john) \rightarrow (elton john, equivalent, sir elton hercules john) \rightarrow (sir elton hercules john, owned, watford football club)
Question	When was the judge born who made notable contributions to the trial of the man who tortured, raped, and murdered eight student nurses from <i>South Chicago Community Hospital</i> on the night of <i>July 13-14, 1966</i> ?
Answer	June 4, 1931
Sup. Doc.	["Louis B. Garippo", "Richard Speck"]
Paths	0.797: (south chicago community hospital, committed crimes at $^{-1}$, richard speck) \rightarrow (richard speck, equivalent, trial of richard speck) \rightarrow (trial of richard speck, made contributions during $^{-1}$, louis b garippo) 0.412: (south chicago community hospital, were from $^{-1}$, eight student nurses) \rightarrow (eight student nurses, were from, south chicago community hospital) \rightarrow (south chicago community hospital, committed crimes at $^{-1}$, richard speck)

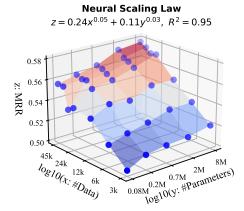


Figure 4. Neural scaling law of GFM-RAG.

training data (x) and the model size (y), which can be fitted by the power-law scaling law $z \propto 0.24x^{0.05} + 0.11y^{0.03}$. The results demonstrate the scalability of GFM-RAG as the foundation model and potential for further improvement. The detailed analysis of the neural scaling law is shown in Appendix D.5.

4.8. Path Interpretations

GFM-RAG exhibits the multi-hop reasoning ability powered by the multi-layer GFM. We provide path interpretations of GFM-RAG for multi-hop reasoning in Table 5. Inspired by NBFNet (Zhu et al., 2021), the paths' importance to the final prediction can be quantified by the partial derivative of the prediction score with respect to the triples at each layer (hop), defined as:

$$s_1, s_2, \dots, s_L = \arg \operatorname{top-} k \frac{\partial p_e(q)}{\partial s_l}.$$
 (19)

The top-k path interpretations can be obtained by the top-k longest paths with beam search. We illustrate the path interpretations in Table 5. In the first example, <code>GFM-RAG</code> successfully deduces that the singer of the song has a football club named after him and that he owned it. In the second example, <code>GFM-RAG</code> identifies two paths related to the murder case and the judge presiding over the trial. These interpretations show that <code>GFM-RAG</code> exhibits the ability of multi-hop reasoning within single-step retrieval. We also illustrate the distribution the multi-hop prediction in Appendix D.6.

5. Conclusion

In this paper, we introduce the first graph foundation model for retrieval augmented generation. By leveraging the knowledge graph index, GFM-RAG explicitly models the complex relationships between knowledge and documents, facilitating a more effective and efficient retrieval process. Powered by a query-dependent GNN pre-trained on largescale datasets, GFM-RAG can effectively perform multi-hop reasoning over the graph structure to find relevant knowledge in a single step. Extensive experiments across three benchmark datasets and seven domain-specific datasets demonstrate that GFM-RAG significantly outperforms stateof-the-art methods in effectiveness, efficiency, and generalizability. Its alignment with scaling laws also suggests the potential for scaling to even larger datasets. In the future, we plan to conduct larger-scale training and further explore GFM-RAG's capabilities in other challenging scenarios such as knowledge graph completion and question answering.

Impact Statement

This paper presents work whose goal is to advance the field of Machine Learning. There are many potential societal consequences of our work, none which we feel must be specifically highlighted here.

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Appendix

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A. Datasets

A.1. Multi-hop QA Datasets

Three multi-hop QA datasets are used in our experiments: HotpotQA (Yang et al., 2018), MuSiQue (Trivedi et al., 2022), and 2WikiMultiHopQA (2Wiki) (Ho et al., 2020). We provide a brief overview of these datasets below.

- HotpotQA (Yang et al., 2018) is a multi-hop QA dataset that requires reasoning over multiple documents to answer questions. The dataset consists of 97k question-answer pairs, where each question is associated with up to 2 supporting and several distracting documents. The questions are designed to be answerable using multiple pieces of information from the supporting documents.
- MuSiQue (Trivedi et al., 2022) is a challenging multi-hop QA dataset with 25k 2-4 hop questions. It requires coherent multi-step reasoning to answer questions that span multiple documents.
- 2WikiMultiHopQA (2Wiki) (Ho et al., 2020) is a multi-hop QA dataset that requires reasoning over multiple Wikipedia articles to answer questions. The dataset consists of 192k questions, which are designed to be answerable using information from 2 or 4 articles.

In experiments, we follow existing methods (Trivedi et al., 2023; Gutiérrez et al., 2024) to use the same 1,000 samples from each validation set and merge the candidate passages as the document corpus for KG-index construction, whose statistics are presented in Table 6.

Table 6. Statistics of the datasets and constructed KG-indexes used for testing.

Dataset	Domain	#Test	#Document	#Entity	#Relation	#Triple
HotpotQA	Multi-hop	1,000	9,221	87,768	45,112	279,112
MuSiQue	Multi-hop	1,000	6,119	48,779	20,748	160,950
2Wiki	Multi-hop	1,000	11,656	100,853	55,944	319,618
PubMedQA	Biomedical	2,450	5,932	42,389	20,952	149,782
DelucionQA	Customer Support	184	235	2,669	2,298	6,183
TechQA	Customer Support	314	769	10,221	4,606	57,613
ExpertQA	Customer Support	203	808	11,079	6,810	16,541
EManual	Customer Support	132	102	695	586	1,329
MS Marco	General Knowledge	423	3,481	24,740	17,042	63,995
HAGRID	General Knowledge	1,318	1,975	23,484	18,653	48,969

A.2. Domain-specific RAG Datasets

To test the generalizability of GFM-RAG, we evaluate it on seven domain-specific RAG datasets (Friel et al., 2024) including, (1) *biomedical*: PubMedQA (Jin et al., 2019); (2) *customer support*: DelucionQA (Sadat et al., 2023), TechQA (Castelli et al., 2020), ExpertQA (Malaviya et al., 2023), EManual (Nandy et al., 2021); (3) *general knowledge*: MS Marco (Nguyen et al., 2016), HAGRID (Kamalloo et al., 2023). We provide a brief overview of these datasets below.

- PubMedQA (Jin et al., 2019) is a collection of PubMed research abstracts with corresponding questions paired with 4
 abstract chunks.
- DelucionQA (Sadat et al., 2023) is a domain-specific RAG dataset leveraging Jeep's 2023 Gladiator model manual as the source of knowledge, where each question is associated with 4 context documents and only 1 relevant passage.
- TechQA (Castelli et al., 2020) is a collection of real-world user questions posted on IBMDeveloper and DeveloperWorks forums, along with 10 technical support documents relating to each question.
- ExpertQA (Malaviya et al., 2023) is a collection of curated questions from domain experts in various fields of science, arts, and law. The dataset also contains expert-curated passages relevant to each question.
- EManual (Nandy et al., 2021) is a question-answering dataset comprising consumer electronic device manuals and realistic questions about them composed by human annotators, where each question is related with up to 3 context documents.
- MS Marco (Nguyen et al., 2016) is an open-domain question-answering dataset sourced from Bing search engine user query logs. Each question is associated with 10 context passages retrieved via Bing web search.
- HAGRID (Kamalloo et al., 2023) is a multi-lingual information retrieval dataset with questions and passages from MIRACL (Zhang et al., 2022).

In experiments, we use test sets constructed by RAGBench (Friel et al., 2024) and merge all the candidate passages as document corpus for KG-index construction. The statistics of the test dataset are detailed in Table 6.

B. Baselines

In experiments, we compare with several widely used retrieval methods under three categories: (1) *single-step naive methods*: BM25 (Robertson & Walker, 1994), Contriever (Izacard et al., 2022), GTR (Ni et al., 2022), ColBERTv2 (Santhanam et al., 2022), RAPTOR (Sarthi et al., 2024), Proposition (Chen et al., 2024); (2) *graph-enhanced methods*: LightRAG (Guo et al., 2024), HippoRAG (Gutiérrez et al., 2024); (3) *multi-step methods*: IRCoT (Trivedi et al., 2023). The detailed introduction of the baselines is as follows.

Single-step Naive Methods are widely adopted in real-world applications due to their great efficiency and generalizability.

- BM25 (Robertson & Walker, 1994) is a classic information retrieval method based on the probabilistic model that ranks a set of documents based on the query terms frequency appearing in each document.
- Contriever (Izacard et al., 2022) trains a dense retriever with contrastive learning on a large-scale corpus to retrieve relevant documents for a given query.
- GTR (Ni et al., 2022) develops a scale-up T5-based dense retriever that could generalize across different datasets and domains.
- ColBERTv2 (Santhanam et al., 2022) is a state-of-the-art dense retriever that couples an aggressive residual compression mechanism with a denoised supervision strategy to simultaneously improve the retrieval quality.
- RAPTOR (Sarthi et al., 2024) is an LLM-augmented retriever that recursively embeds, clusters, and summarizes chunks of text, constructing a tree with differing levels of summarization to enable accurate retrieval.
- Proposition (Chen et al., 2024) enhances the performance of dense retrievers by leveraging LLMs to generate a natural language proposition that captures the essential information of the document.

Graph-enhanced Methods design a retriever that is built upon a graph structure to conduct effective retrieval and reasoning.

- LightRAG (Guo et al., 2024) is an innovative graph-enhanced RAG method that incorporates graph structures into text indexing and retrieval, enabling efficient retrieval of entities and their relationships. It employs a dual-level retrieval system to gather both low-level and high-level knowledge for LLM generation.
- HippoRAG (Gutiérrez et al., 2024) is a state-of-the-art, training-free graph-enhanced retriever that uses the Personalized PageRank algorithm to assess entity relevance to a query and performs multi-hop retrieval on a document-based knowledge graph. It can be directly applied to various datasets.

Multi-step Methods are designed to conduct multi-hop reasoning by iteratively retrieving and reasoning over documents, which can be integrated with arbitrary retrieval methods.

• IRCoT (Trivedi et al., 2023) is a powerful multi-step retrieval pipeline that integrates the retrieval with the chain-of-thought (CoT) reasoning of LLMs. It guides the retrieval with CoT and in turn using retrieved documents to improve CoT. IRCoT can be compatible with arbitrary retrievers to conduct multi-step retrieval and reasoning.

C. Implementations and Training Details

C.1. Training Data Construction

We extract 60,000 samples from the training set of HotpotQA, MuSiQu, and 2Wiki to construct KG-indexes and conduct large-scale training. Specifically, we merge the candidate passages as the document corpus. In the KG-index construction, we use the GPT-4o-mini (OpenAI, 2024a) with the OpenIE prompts described in HippoRAG (Gutiérrez et al., 2024) to extract the entities, relations, and triples from the document corpus. Then, we use the ColBERTv2 (Santhanam et al., 2022) to conduct the entity resolution by computing the similarity between entities as

$$s(e_i, e_j) = \text{Emb.}(e_i)^{\top} \text{Emb.}(e_j), \tag{20}$$

where a new triple $(e_i, \texttt{equivalent}, e_j)$ is generated if $s(e_i, e_j) > \tau$ and $e_i \neq e_j$. We set the threshold τ as 0.8 in our experiments. We divide the samples into groups of approximately 1k questions and 10k documents each to control the constructed KG-index size. In the end, we obtain 60 different KG-indexes and associated question-document pairs for model training.

C.2. Model Settings

In GFM-RAG, the GFM is implemented as a 6-layer query-dependent GNN with the hidden dimension of 512, DistMult message function, and sum aggregation. The relation update function $g^l(\cdot)$ is implemented as a 2-layer MLP. We use the all-mpnet-v2 as the sentence embedding model with a dimension of 768. The total training parameters of the GFM is 8M. In the retrieval stage, we select top T=20 entities for the document ranker.

Table 7. The detailed implementation and training settings of GFM-RAG.

	Setting	GFM-RAG
	OpenIE	GPT-4o-mini
KG-index Construction	Entity resolution	ColBERTv2
	au	0.8
	# Layer	6
	Hidden dim	512
	Message	DistMult
GFM Model	Aggregation	Sum
	$g^l(\cdot)$	2-layer MLP
	Sentence embedding model	all-mpnet-v2
	Doc. ranker entities T	20
	α	1
	Optimizer	AdamW
VCC Dra training	Learning rate	5e-4
KGC Pre-training	Batch size	4
	Training steps	30,000
	# Negative sample	128
	α	0.3
	Optimizer	AdamW
Datriaval Eina tuning	Learning rate	5e-4
Retrieval Fine-tuning	Batch size	4
	Training epochs	5
	# Negative sample	$\mathcal{E} \setminus \mathcal{A}_q$

C.3. Training Settings

In the unsupervised KG completion pre-training, the GFM is trained on the mixture of 60 constructed KG-indexes for 30,000 steps. Then, we conduct the supervised document retrieval fine-tuning on the labeled question-document pairs for 5 epochs. The weight α between losses is set to 0.3. We use AdamW optimizer, learning rate of 5e-4 with batch sizes of both training stages set to 4. Each batch contains only one KG-index and training samples associated to it, where we randomly sample from different KG-indexes during training. The model is trained on 8 NVIDIA A100s (80G) with 14 hours pre-training and 5 hours fine-tuning. The detailed settings are summarized in Table 7.

D. Additional Experiments

D.1. Effectiveness of Different Sentence Embeddings

In this section, we study the effectiveness of different sentence embeddings in the GFM. We compare the all-mpnet-v2 (SBERT, 2021), bge-large-en (Xiao et al., 2023), gte-Qwen2-1.5B-instruct and gte-Qwen2-7B-instruct (Li et al., 2023b) as

Table 8. Comparison of different sentence embedding models used in GFM-RAG.

Sentence Embedding Model	HotpotQA		MuSique		2Wiki	
Sentence Emisedanig Model	R@2	R@5	R@2	R@5	R@2	R@5
sentence-transformers/all-mpnet-base-v2	70.2	82.1	46.0	55.1	81.1	85.6
BAAI/bge-large-en	68.1	81.1	45.9	55.9	80.7	86.3
Alibaba-NLP/gte-Qwen2-1.5B-instruct	69.9	81.5	46.0	55.0	79.8	86.2
Alibaba-NLP/gte-Qwen2-7B-instruct	68.5	81.5	45.5	55.1	80.8	85.6
nvidia/NV-Embed-v2	69.2	81.4	46.3	54.9	80.3	85.5

Table 9. Effectiveness of pre-training and fine-tuning in GFM-RAG.

Sentence Embedding Model	HotpotQA		MuS	Sique	2Wiki		
Semente Emotuding 1120 der	R@2	R@5	R@2	R@5	R@2	R@5	
GFM-RAG	78.3	87.1	49.1	58.2	89.1	92.8	
GFM-RAG w/o Fine-tune	21.0	32.8	18.3	25.9	44.6	53.4	
GFM-RAG w/o Pre-train	77.8	86.5	48.3	58.3	88.3	92.5	

Table 10. Effectiveness (MRR) for the weight α of two losses.

α	HotpotQA	MuSique	2Wiki
0	0.5189	0.3252	0.4425
1	0.5096	0.3214	0.4282
0.7	0.5202	0.3249	0.4348
0.3	0.5243	0.3260	0.4490

well as NV-Embed-v2 (Lee et al., 2024). We download the official pre-trained model from the Huggingface². The details of the models are shown in Table 8. From the results, we can observe that the performance variance between different sentence embeddings is relatively small, where the all-mpnet-v2 achieves the best performance with respect to 3 metrics. This indicates that GFM-RAG is not sensitive to the choice of sentence embedding models. In experiments, we use the all-mpnet-v2 as the default sentence embedding model due to its efficiency. However, it has relative smaller context-size (512) which limits the length of input text. We leave the exploration of larger context-size sentence embedding models (e.g., NV-Embed-v2 with 32k context) for future work.

D.2. Effectiveness of Different Training Strategies

In this section, we study the effectiveness of the two training tasks used in GFM-RAG. We compare the performance by only conducting the unsupervised KG completion pre-training (GFM-RAG w/o Fine-tune) and supervised document retrieval fine-tuning (GFM-RAG w/o Pre-train). The results are shown in Table 9. The results show that removing the supervised document retrieval fine-tuning significantly decreases the performance of GFM-RAG. This highlights the importance of supervised fine-tuning, as it enables the model to understand users' queries and better capture the relevance between questions and knowledge for improved retrieval. Meanwhile, the unsupervised KG completion pre-training also plays a crucial role in enhancing the model's reasoning ability by learning the knowledge graph structure and reasoning patterns from the large-scale triples in KG-indexes.

D.3. Effectiveness of Loss Weights

In this section, we examine the effectiveness of the weights assigned to the BCE loss and ranking loss in training GFM-RAG. We compare performance by varying the weight α between the two losses: $\mathcal{L} = \alpha \mathcal{L}_{BCE} + (1 - \alpha)\mathcal{L}_{RANK}$, with results presented in Table 10. The findings indicate that using only either the BCE loss or ranking loss leads to suboptimal performance ($\alpha = 0$ or 1). The best performance occurs when α is set to 0.3, which aligns with previous studies (Lin et al., 2024) suggesting that a smaller weight for BCE loss is preferable when positive samples are rare in the training data.

D.4. Model Transferability

In this section, we evaluate GFM-RAG's transferability by fine-tuning on the training split of each domain-specific dataset. As shown in 11, GFM-RAG performs well in zero-shot generalization, with further improvements achieved through fine-tuning. This highlights its transferability when adapted to domain-specific datasets.

²https://huggingface.co/

Table 11. Model performance (R@5) and transferability comparsion.

Model	DelucionQA	EManual	ExpertQA	TechQA	MS Marco	HAGRID
HippoRAG (zero-shot)	59.0	50.0	55.1	39.5	51.1	75.5
LightRAG (zero-shot)	46.1	46.2	59.4	36.8	48.3	75.9
GFM-RAG (zero-shot)	70.8	60.6	62.7	46.6	71.0	84.7
GFM-RAG (fine-tune)	82.7	75.9	60.8	49.5	77.5	86.6

Table 12. The hidden dimension with corresponding model size and training batch size for scaling law analysis.

Hidden Dim.	Parameter Size	Batch size (A100, 80G)
32	78,977	40
64	215,297	20
128	659,969	20
256	2,237,441	8
512	8,144,897	4

D.5. Details of Model Neural Scaling

In this section, we provide more details on the neural scaling experiments. We evaluate the changes of the model performance with respect to different parameter sizes and training data sizes. In GFM-RAG, the model parameter sizes are primarily influenced by the hidden dimension of the GFM. Thus, we vary the dimension from 32 to 512 which results in the model parameter sizes ranging from 0.08M to 8M. The detailed settings are shown in Table 12. We test models with different sizes on different scales of training data ranging from 3k to 45k samples. We separately report the fitted trend line of performance changing with model parameter size and training data size in Figure 5. From the trend line, we can observe that the performance of GFM-RAG increases with the model parameter size and training data size. Meanwhile, with the larger model parameter size a larger training data size is required to achieve the best performance. This indicates that the performance of GFM-RAG can be further improved by scaling up the model size and training data simultaneously.

D.6. Visualization of the Distribution of Multi-hop Prediction

In this section, we visualize the distribution of the number of hops in the multi-hop reasoning process of GFM-RAG. We calculate the number of hops in the ground-truth reasoning path required for each question in the test set of HotpotQA, MuSiQue, and 2Wiki. Then, we compare the distribution of the number of hops in the reasoning path of the ground-truth and the predicted reasoning path by GFM-RAG as well as HippoRAG. The results are shown in Figure 6. We can observe that the distribution of GFM-RAG is closely aligned to the ground-truth, which indicates that GFM-RAG can effectively conduct the multi-hop reasoning within a single step. Meanwhile, the distribution of HippoRAG is relatively different from the ground-truth, especially in 2Wiki dataset. This indicates that HippoRAG may not be able to effectively capture the complex relationship to conduct multi-hop reasoning on graphs.

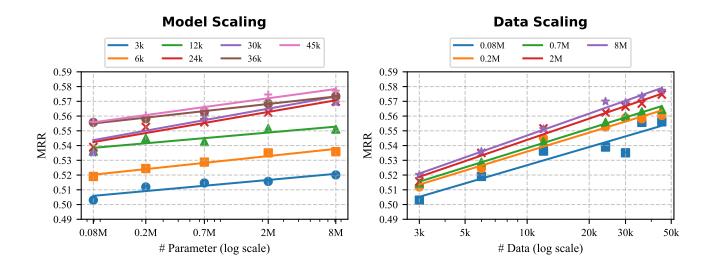
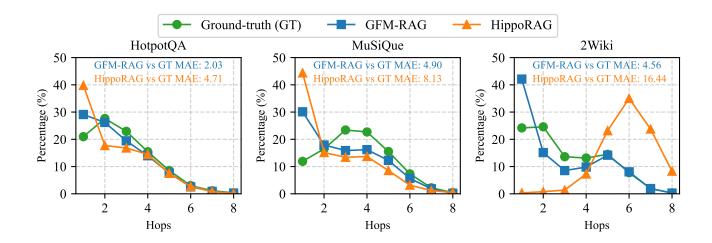


Figure 5. The illustration of the model and data scaling law of GFM-RAG.



 $\textit{Figure 6. Statistics of the prediction hops of $\tt GFM-RAG$ and HippoRAG$ against the ground-truth.}$