GPR: Empowering Generation with Graph-Pretrained Retriever

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Abstract

Graph retrieval-augmented generation (GRAG) places high demands on graph-specific retrievers. However, existing retrievers often rely on language models pretrained on plain text, limiting their effectiveness due to *domain misalignment* and *structure ignorance*. To address these challenges, we propose GPR, a graph-based retriever pretrained directly on knowledge graphs. GPR aligns natural language questions with relevant subgraphs through LLM-guided graph augmentation and employs a structure-aware objective to learn fine-grained retrieval strategies. Experiments on **two** datasets, **three** LLM backbones, and **five** baselines show that GPR consistently improves both retrieval quality and downstream generation, demonstrating its effectiveness as a robust retrieval solution for GRAG.

1 Introduction

Graph Retrieval-Augmented Generation (GRAG) has emerged as an effective paradigm for enhancing the capabilities of large language models (LLMs) (Min et al., 2019). By retrieving structured and high-quality knowledge from graphs, these models are able to acquire comprehensive context regarding questions and generate more accurate and grounded responses (Zhang et al., 2025).

The effectiveness of GRAG hinges on the quality of the retrieved graph components, placing high demands on the retriever. To meet this challenge, retrievers based on pretrained language models (PLMs) (Karpukhin et al., 2020) have emerged as a promising solution. These retrievers operate directly on natural language queries without relying on handcrafted rules (Mavromatis and Karypis, 2024) or task-specific features (Luo et al., 2023), offering greater flexibility and generalizability compared to traditional approaches such as non-parametric or graph neural network-based retrievers (Peng et al., 2024; Li et al., 2023). However, despite these advantages, existing PLM-based retrievers exhibit the following shortcomings:

S1: Domain Misalignment. Most of the current PLM-based retrievers are built on models pretrained solely on plain text (He et al., 2024; Li et al., 2023). These models are proficient in understanding natural language queries, but struggle to interpret graph-structured data, which are composed of semi-structured triplets with irregular formats. The misalignment between query representations in text and the structured nature of graph data leads to suboptimal retrieval, constraining the overall effectiveness of GRAG systems.

S2: Structure Ignorance. In addition, many approaches directly apply language models to retrieve individual nodes (He et al., 2024), triplets (Li et al., 2023), or subgraphs (Li et al., 2024; Hu et al., 2024), mirroring strategies used in traditional text-based retrieval-augmented generation (Karpukhin et al., 2020). However, this overlooks the fundamental property of knowledge graphs: connectivity. Encoding graph elements as isolated units fails to capture the relational structure essential for effective graph retrieval.

To address these limitations, we propose **G**raph **P**retrained **R**etriever (GPR), a simple yet effective retriever pretrained directly on knowledge graphs. To resolve **S1**, GPR leverages LLM-guided graph augmentation to align natural language questions with relevant subgraphs, without relying on additional supervision or schema-specific features. To tackle **S2**, GPR employs a structure-aware pretraining objective that distinguishes triplets based on their relevance with questions, encouraging the model to selectively capture comprehensive context that could boost the LLMs.

We evaluate GPR on **two** benchmark datasets using **three** backbone LLMs and **five** baselines. Results show that GPR consistently retrieves more relevant knowledge from graph and enhances downstream generation. These findings establish GPR

as a generalizable and effective solution for graph-based retrieval, advancing the development of knowledge-grounded language models.

2 Related Work

Retrieval-augmented generation (RAG) (Gao et al., 2023; Guo et al., 2023; Ma et al., 2023) has emerged as a promising approach to mitigate intrinsic limitations of large language models, such as hallucinations (Zhang et al., 2023; Tonmoy et al., 2024). Its specialized variant, Graph RAG (GRAG) (Min et al., 2019), extends this paradigm by retrieving high-quality knowledge from structured knowledge graphs, demonstrating strong potential in knowledge-intensive tasks (Zhang et al., 2025). Pretrained Language Model (PLM)-based retrievers (Karpukhin et al., 2020) have been widely adopted in GRAG systems, enabling knowledge retrieval at various granularities, including nodes (He et al., 2024), triplets (Li et al., 2023), and subgraphs (Li et al., 2024; Hu et al., 2024). In these approaches, knowledge is encoded using language models pretrained on general plain text, and the retrieved results are either directly fed into the large language models for reasoning or processed by additional adaptation modules to enhance the model's ability to interpret the retrieved content. While most methods simply leverage pretrained language models, some prior work (Dong et al., 2023) has explored pretraining these models on knowledge graphs using conventional objectives such as InfoNCE (Oord et al., 2018) and Masked Language Modeling (Devlin et al., 2019). Nevertheless, these efforts overlook the alignment between the textual query modality and the graph-structured knowledge, often degrading retrieval effectiveness.

3 Graph Pretrained Retriever (GPR)

Problem Formulation. We consider the graph retrieval-augmented generation (RAG) setting, where a large language model (LLM) generates answers based on a question q and a retrieved knowledge subgraph $\mathcal{S}_q$. The model takes the pair $(q, \mathcal{S}_q)$ as input, where $\mathcal{S}_q$ is retrieved from a knowledge graph $\mathcal{G}$ conditioned on q, i.e., $\mathcal{S}_q = \mathbb{Q}(q, \mathcal{G})$, and $\mathbb{Q}$ denotes the retriever. We define $\mathcal{S}_q$ as the union of triplets $\tau = (h, r, t)$, where each $\tau \in \mathcal{G}$ represents a factual statement relevant to the question.

Following prior work (Li et al., 2024), we reduce subgraph retrieval to a triplet ranking task, where the goal is to learn a retriever $\mathbb{Q}$ that assigns higher scores to relevant triplets τ given the question q. The retriever is optimized to improve downstream generation quality by supplying more informative context to the LLM.

Establishing Question-triplet Alignment via Graph Augmentation. In typical retrieval training, the retriever $\mathbb{Q}$ is optimized to align questions with their corresponding documents. In our formulation, this translates to learning a mapping between a natural language question q and a relevant set of knowledge triplets $\mathcal{T}_q \subseteq \mathcal{G}$. However, under the general RAG framework, only question-answer pairs are available, with no explicit supervision for question-triplet alignment (Peng et al., 2024). This motivates us to establish the question-triplet alignment by augmenting the knowledge graph. Specifically, we generate synthetic natural language questions from triplets by performing masked triplet prompting. For each triplet $\tau = (h, r, t) \in \mathcal{G}$, we mask one entity to construct masked triplet $\tau' \in \{([MASK], r, t), (h, r, [MASK])\}$, and prompt LLaMA-3.1-8B-Instruct (Grattafiori et al., 2024) with instructions to generate a synthetic question in natural language q_τ, corresponding to the original triplet τ.

Each synthetic question q_τ aligns with its original triplet τ, as well as neighboring triplets τ_{nb} that share at least one entity with τ. We treat both types as positive signals: the original triplet τ is directly relevant to the question q_τ, while its neighbors provide contextual support for better understanding. Formally, we construct the positive set:

$$\mathcal{D}_{\text{pos}} = \{(q_\tau, \tau),\ (q_\tau, \tau_{\text{nb}})\}, \tau_{\text{nb}} \in \mathcal{G},\ \tau_{\text{nb}} \cap \tau \neq \emptyset. \tag{1}$$

We further introduce negative set $\mathcal{D}_{neg}$ by randomly sampling triplets from $\mathcal{G}$ such that they do not overlap with τ, serving as irrelevant distractors τ_{neg}:

$$\mathcal{D}_{\text{neg}} = \{(q_\tau, \tau_{\text{neg}})\}, \tau_{\text{neg}} \cap \tau = \emptyset. \tag{2}$$

By integrating these sets, we construct the final pretraining dataset that captures varying levels of alignment between queries and knowledge triplets:

$$\mathcal{D} = \{(q_\tau, \tau, \tau_{\text{nb}}, \tau_{\text{neg}})\}. \tag{3}$$

Examples of the graph augmentation procedure are available in Appendix A.

Mining Question-triplet Alignment with Pretraining. To model the varying level of alignment constructed in dataset $\mathcal{D}$ with our retriever $\mathbb{Q}$, we

Table 1: Question answering results (%) on WebQSP and CWQ datasets. The best-performing results are highlighted in **bold**.

Methods	WebQSP				CWQ			
	Accuracy	Precision	Recall	F1	Accuracy	Precision	Recall	F1
ChatGPT	46.62	65.97	39.48	49.40	37.88	42.19	35.63	38.63
+ G-Retriever	42.70	63.32	36.44	46.26	33.51	39.42	31.84	34.99
+ G-RAG	39.40	57.55	33.63	42.45	31.87	36.44	30.55	33.21
+ Hybrid	50.38	64.25	37.52	47.37	39.55	44.52	37.06	40.47
+ SKP	44.80	62.10	36.98	46.36	33.43	38.71	31.71	34.83
+ Two Tower	39.14	57.30	34.30	42.67	30.85	36.34	29.60	32.64
+ GPR	**62.40**	**73.46**	**46.31**	**56.79**	**43.25**	**47.59**	**39.59**	**43.22**
LLaMA2-Chat-7B	40.16	59.82	34.85	43.76	28.23	9.99	28.23	14.70
+ G-Retriever	44.00	66.22	37.68	47.84	30.77	36.51	29.32	32.52
+ G-RAG	20.81	36.43	19.29	25.26	9.53	11.81	9.21	10.31
+ Hybrid	53.40	71.44	42.08	52.79	35.12	**40.70**	33.25	**36.61**
+ SKP	43.93	63.02	37.11	46.61	28.54	33.48	27.04	29.86
+ Two Tower	38.51	58.23	33.54	42.44	27.38	32.57	26.12	29.01
+ GPR	**61.90**	**77.57**	**47.44**	**58.76**	**44.27**	15.41	**44.27**	**22.93**
Flan-T5-xl	10.86	19.16	10.40	13.41	12.22	16.94	12.22	14.21
+ G-Retriever	21.41	39.37	20.49	26.91	17.97	22.51	17.62	19.76
+ G-RAG	19.72	35.20	18.86	24.32	16.89	20.31	16.40	18.17
+ Hybrid	31.37	49.82	27.67	35.54	25.14	29.94	24.24	26.77
+ SKP	21.29	37.04	20.53	26.45	18.82	22.66	18.32	20.26
+ Two Tower	18.00	33.05	17.58	22.83	16.23	20.22	15.90	17.81
+ GPR	**39.48**	**56.94**	**35.23**	**43.51**	**28.20**	**38.54**	**28.20**	**32.47**

firstly encode query and triplets with retriever $\mathbb{Q}$, then optimize the retriever with a structure-aware objective function.

Encoding. We adopt a two-tower architecture (Karpukhin et al., 2020), commonly used in information retrieval, as the basis for our retriever. It consists of separate encoders for natural language queries and knowledge triplets, denoted by E_q and E_τ, respectively, i.e., $\mathbb{Q} = \{E_q, E_\tau\}$. For question q_τ and triplets τ, τ_{nb}, τ_{neg}, their embeddings are computed as $z_q = E_q(q_\tau)$, $z_\tau = E_\tau(\tau)$, $z_{nb} = E_\tau(\tau_{nb})$, and $z_{neg} = E_\tau(\tau_{neg})$, serving as a prerequisite for subsequent structure-aware optimization.

Optimization. To effectively answer knowledge-intensive questions, the retriever should prioritize facts that are directly relevant to the query. In addition, supporting knowledge that addresses secondary aspects of the queried fact can provide helpful context and improve answer quality. On the other hand, retrieving irrelevant knowledge offers little benefit and may introduce noise, reducing overall performance. Based on this motivation, we optimize the retriever using a customized variant of triplet loss (Schroff et al., 2015), which is designed to learn from varying levels of preference. Given a query q, a more preferred triplet p, and a less preferred triplet n, the basic triplet loss is defined as:

$$\mathcal{M}(p, n, q, \gamma) = \max(0, \gamma + \cos(n, q) - \cos(p, q)), \tag{4}$$

where $\cos(\cdot, \cdot)$ denotes cosine similarity, and γ is the margin hyperparameter. This formulation encourages the model to assign higher similarity to preferred triplets relative to less preferred ones.

We apply and customize this loss by enforcing a soft preference ordering among triplets conditioned on the question q_τ: the exact matching triplet τ is preferred over its neighbors q_{nb}, which in turn are preferred over irrelevant triplets q_{neg}. The final pretraining loss is represented as:

$$\mathcal{L} = \mathcal{M}(z_\tau, z_{nb}, z_q, \gamma_1) + \mathcal{M}(z_{nb}, z_{neg}, z_q, \gamma_2), \tag{5}$$

with separate margins γ_1 and γ_2 for each preference level.

Leveraging Question-triplet Alignment during Inference. At inference time, the pretrained

Figure 1: Top-ranked triplets retrieved by pretraining-free two tower retriever and GPR, given the query *"What does Jamaican people speak?"*.

Two Tower

```
Kemar Bailey-Cole | languages | English Language
The problem of freedom | subjects | Jamaica
The Blue Lagoon | language | English Language
Hansle Parchment | nationality | Jamaica
```

GPR

```
Jamaican English | countries_spoken_in | Jamaica
Jamaican Creole English | countries_spoken_in | Jamaica
Jamaica | languages_spoken | Jamaican English
Jamaica | languages_spoken | Jamaican Creole English
```

retriever $\mathbb{Q}$, optimized with augmented question-triplet alignment with structure-awareness (Eq. 5), is used to query the knowledge graph $\mathcal{G}$ and retrieve top-K triplets to construct the subgraph $\mathcal{S}_q$. This subgraph provides knowledge-rich context to enhance the LLM's performance, without requiring any additional fine-tuning on the question answering task.

4 Experiments

Experiment Settings. All experiments settings are available in Appendix B.

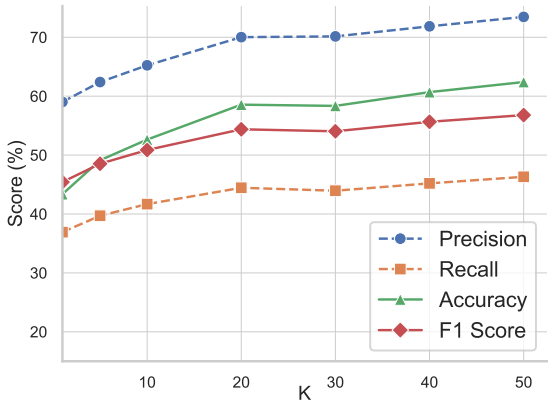
Evaluation Results. The experiment results are available in Table 1. Key insights we obtain through the analysis include:

Pretrained language models struggle to perform effective retrieval over structured graph data. Using language models pretrained on plain text as retrievers often results in limited and inconsistent gains. While effective for natural language understanding, they lack the structural alignment and graph-specific inductive biases necessary for reasoning over knowledge graphs. Notably, the two tower retriever, which shares the same architecture as GPR but omits graph pretraining, performs poorly, highlighting the limitations of relying solely on plain-text pretrained models for graph-based retrieval tasks.

GPR *advances graph retrieval by bridging text and graph with structure-awareness.* Across all evaluated settings, GPR consistently outperforms retrievers without targeted pretraining, effectively aligning textual queries with relevant subgraphs. Its improvements on downstream question answering tasks reflect the quality of retrieved subgraphs in providing accurate and contextually relevant information. Given that the pretraining-free two tower variant performs poorly, the strong performance of GPR stems not from its structure alone but from its carefully designed pretraining strategy. This highlights the effectiveness of our question-triplet alignment objective and our success in modeling structural relations between text and graph through pretraining.

Qualitative Analysis. We conduct a case study to qualitatively analyze the retrieved facts of GPR, with results shown in Figure 1. Intuitively, methods relying on language models pretrained on general text struggle to bridge the gap between natural language queries and knowledge graph content, retrieving low-relevance and noisy results. In contrast, GPR benefits from knowledge graph-based pretraining with a discriminative optimization objective, resulting in retrieved facts that are more relevant and coherent with the input query.

Figure 2: Performance vs K in the selection of top-ranked triplets.



Quantitative Analysis. We further conduct a quantitative analysis by varying the top-K value used during triplet retrieval, as shown in Figure 2. All metrics exhibit a consistent upward trend as K increases. These results highlight that GPR consistently benefits from an increasing amount of retrieved content, demonstrating its ability to capture broader context while maintaining robustness to potential noise introduced by retrieval.

5 Conclusion

We introduced GPR, a simple yet effective retriever pretrained on knowledge graphs to support retrieval-augmented generation over knowledge graphs. Through LLM-guided graph augmentation and structure-aware pretraining, GPR learns to align questions with informative subgraphs in a flexible and data-agnostic manner. Comprehensive experiments show that GPR consistently enhances both retrieval quality and downstream generation performance.

Limitations

While GPR demonstrates strong performance in graph retrieval, it still has two limitations. First, our pretraining currently considers only 1-hop neighbors due to computational constraints, which may limit the model's effectiveness in capturing larger contextual subgraphs or longer reasoning paths. Extending the method to incorporate multi-hop structures remains feasible and is worth exploring. Second, although the pretraining strategy is broadly applicable, we adopt a basic two-tower retriever for implementation due to limited bandwidth. Investigating more expressive retriever architectures presents a promising direction for future work.

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A Example of Graph Augmentation

Table 2 presents examples in Freebase (Bollacker et al., 2008) that appear in our augmented dataset, demonstrating how the graph augmentation process operates.

B Experiment Details

Datasets. Following previous studies(Luo et al., 2023), we adopt two prevalent datasets for experiments, i.e., WebQSP (Yih et al., 2016), under the CC BY 4.0 License, and CWQ (Talmor and Berant, 2018), under the Apache-2.0 License. The WebQSP test set used for inference contains 1.628 question–answer pairs, while the CWQ test set comprises 3.531 pairs.

Implementation. We implement our two-tower retriever with two distilbert-base-uncased (Sanh et al., 2019) encoders. We choose the same text encoder for all retrievers for the fair comparison. For methods requiring pretraining (SKP and GPR), we perform pretraining on a subset of Freebase (Bollacker et al., 2008) that includes entities related to the WebQSP and CWQ datasets, which are independent of the question answering task, eliminating any data leakage concern. Pretraining is conducted for 5 epochs using AdamW (Loshchilov and Hutter, 2017), with a batch size of 512 and a learning rate of 2e-5. Margins γ_1 and γ_2 in Eq. 5 are both set to 0.5. The retrievers are further evaluated in the zero-shot setting.

Backbones. Retrieval strategies are evaluated with LLM backbones pretrained in general domains, including ChatGPT-3.5 Turbo (Achiam et al., 2023), LLaMA2-7B (Touvron et al., 2023), and Flan-T5-XL (Chung et al., 2024), covering large language models of varying sizes and both open- and closed-source types. The usage of these artifacts aligns with their intended use for research purposes.

Computational Devices. All experiments were conducted on four NVIDIA A6000 GPUs with CUDA version 12.0, running on an Ubuntu 20.04.6 LTS server.

Baselines. We include the following graph-retrieval baselines for comparison:

G-Retriever (He et al., 2024) is a retrieval-augmented generation framework designed for question answering over textual graphs. It retrieves relevant nodes and edges based on semantic similarity and constructs subgraphs using the Prize-Collecting Steiner Tree (PCST) algorithm to form

Original Triplet τ	(Attention deficit hyperactivity disorder, treatments, Modafinil)
Generated Questions q_τ	*What is a treatment for Attention deficit hyperactivity disorder?* *What is Modafinil used to treat?*
Neighbor Triplets τ_{nb}	(Attention deficit hyperactivity disorder, treatments, Zooey Deschanel) (Cephalon, product, Modafinil)
Negative Triplets τ_{neg}	(Prednisone, active_moiety_of_formulation, Prednisone 10 tablet) (Welcome To The Jungle, written_by, Jonathan Hensleigh)

Table 2: Example of graph augmentation.

concise, query-relevant subgraphs for generation .

G-RAG (Hu et al., 2024) is a graph retrieval-augmented generation method that enhances LLMs by retrieving and integrating textual subgraphs. It represents subgraphs as pooled embeddings of k-hop ego-graphs and retrieves them to incorporate both textual and topological information through dual prompting, improving performance on multi-hop reasoning tasks .

Hybrid (Li et al., 2023) is a hybrid retrieval model that combines sparse retrieval (BM25) and dense retrieval (DPR) for coarse retrieval, followed by reranking with a cross-encoder to improve retrieval performance.

SKP (Dong et al., 2023) leverages traditional approaches like contrastive learning and masked language prediction on graphs to obtain a more graph-concentrated encoder for retrieval, enhancing the model's ability to represent complex subgraphs.

Two-tower (Karpukhin et al., 2020) is a dense passage retrieval approach for open-domain question answering. Utilizing a dual-encoder framework, it learns dense representations from question-passage pairs, outperforming traditional sparse retrieval methods like BM25 in top-20 passage retrieval accuracy.

All the baselines are required to retrieve knowledge without prior information about entities in question or answer of the question. For approaches containing multiple stages such as GNN-tuning (He et al., 2024; Hu et al., 2024) or parameter-efficient fine-tuning (Hu et al., 2024), we just take their PLM-based graph-retrieval module for fair comparison.

C Potential Risk

Although GPR demonstrates strong performance, it is still possible for the retrieved results to reflect biases. Blind reliance on these results—treating them as factual without contextual verification—may raise societal concerns. Users of GPR are encouraged to critically assess the retrieved content within the specific application context to mitigate potential ethical risks.