Less is *More*: Making Smaller Language Models Competent Subgraph Retrievers for Multi-hop KGQA

Wenyu Huang[1], **Guancheng Zhou**[2], **Hongru Wang**[3], **Pavlos Vougiouklis**[2], **Mirella Lapata**[1], **Jeff Z. Pan**[1,2*]
[1]School of Informatics, University of Edinburgh
[2]Huawei Edinburgh Research Centre, CSI, UK [3]The Chinese University of Hong Kong
w.huang@ed.ac.uk, guanchengzhou1@huawei.com, hrwang@se.cuhk.edu.hk
pavlos.vougiouklis@huawei.com, mlap@inf.ed.ac.uk,
http://knowledge-representation.org/j.z.pan/

Abstract

Retrieval-Augmented Generation (RAG) is widely used to inject external non-parametric knowledge into large language models (LLMs). Recent works suggest that Knowledge Graphs (KGs) contain valuable external knowledge for LLMs. Retrieving information from KGs differs from extracting it from document sets. Most existing approaches seek to directly retrieve relevant subgraphs, thereby eliminating the need for extensive SPARQL annotations, traditionally required by semantic parsing methods. In this paper, we model the subgraph retrieval task as a conditional generation task handled by small language models. Specifically, we define a subgraph identifier as a sequence of relations, each represented as a special token stored in the language models. Our base generative subgraph retrieval model, consisting of only 220M parameters, achieves competitive retrieval performance compared to state-of-the-art models relying on 7B parameters, demonstrating that small language models are capable of performing the subgraph retrieval task. Furthermore, our largest 3B model, when plugged with an LLM reader, sets new SOTA end-to-end performance on both the WebQSP and CWQ benchmarks. Our model and data will be made available online: https://github.com/hwy9855/GSR.

1 Introduction

Large Language Models (LLMs) have demonstrated tremendous capabilities in various Natural Language Processing tasks (Touvron et al., 2023; OpenAI, 2023). Despite their success, their hallucination tendencies still limit their performance across the involved tasks, and in question answering, in particular (Zhang et al., 2023b; Huang et al., 2023). Retrieval-augmented generation methods are widely used to enhance LLMs (Pan et al., 2023) and provide better safeguards against hallucination issues (Shuster et al., 2021; Tonmoy et al., 2024). Knowledge Graphs (KGs) (Pan et al., 2017a,b) have been recognised as valuable knowledge sources due to their compact triple representation, clear and noise-free knowledge format, and rich domain-specific information (Baek et al., 2023; Huang et al., 2024). Consequently, they have attracted significant attention by researchers who seek to propose efficient solutions that leverage information enclosed within a KG for question answering (KGQA) (Wu et al., 2024; Baek et al., 2023; Pan et al., 2024; Wang et al., 2024b).

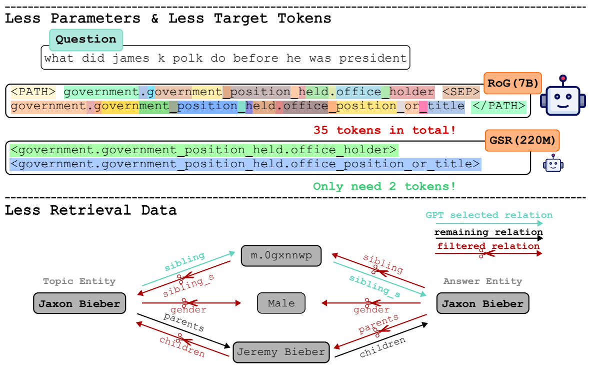

Figure 1: Our proposed GSR architecture facilitates training a smaller LM with ***less*** parameters by reconsidering the subgraph retrieval task as a subgraph ID generation task, leading to shorter sequences of ***less*** target tokens. In addition, we propose two ways of obtaining ***less*** training samples from weakly supervised retrieval data to reduce the noise (e.g., path *gender* – *gender* is not informative and brings noise in training).

Traditional Semantic Parsing (SP) based KGQA (Das et al., 2021; Hu et al., 2022; Luo et al., 2024a) initiate the process by generating a SPARQL query derived from the natural language question. This query is subsequently executed against the KG of interest. Recently, Subgraph Retrieval (SR) based KGQA becomes popular as they eliminate the need of extensive SPARQL annotations (i.e. demonstra-

*Corresponding author.

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tions consisting of (question, SPARQL) pairs). Typical SR-based KGQA methods (Zhang et al., 2022; Luo et al., 2024b; Sun et al., 2024) operate within a retrieval-augmented generation framework. They first retrieve a subgraph from the knowledge graph, which is then sent to a reader to generate answers. These methods achieve competitive performance compared with complex SP-based methods.

Since state-of-the-art (SOTA) methods for SR-based KGQA, such as those by Luo et al. (2024b) and Sun et al. (2024), typically employ LLMs to generate relevant relation chains, they can be expensive in both training and reasoning due to the complexity of relation names (e.g., *government.-government_position_held.office_position_or_title* is tokenized into 18 tokens, with the LLaMA2 tokenizer). In addition, the complexity of relation names induces an unnecessary task in mapping relations to relation names, besides mapping questions to relation chains. These drawbacks inspire us to consider a generative subgraph retriever architecture specified with smaller language models that have ***less*** parameters. This forms the primary research question of this work: **How can small language models be utilized to accomplish the subgraph retrieval task with better efficiency and comparable or superior effectiveness compared to large language models?**

To simplify the task of generating relation chain given the complex relation names and to improve the representation of relations in language models, we treat each relation as a special token (relation ID) in the small language model. This transforms the subgraph retrieval task into predicting a sequence of relation IDs, which we define as the identifier of a subgraph (subgraph ID). As demonstrated in Figure 1, our redefined task requires much ***less*** tokens (2 tokens vs. 35 tokens) as target, makes the training easier and increases the inference efficiency. Our subgraph retriever, named Generative Subgraph Retriever (GSR), is trained jointly using two types of data: indexing data and subgraph retrieval data. In addition, we observe a large amount of noise inside the subgraph retrieval data used by most previous works (Zhang et al., 2022; Luo et al., 2024b). To mitigate this issue, we proposed two data pruning methods to obtain denoised retreival data with ***less*** training samples.

Our comprehensive experiment showcase that employing large language model for (generative) sub-graph retrieval is an unnecessary expense. Our best setting, even when a 220M parameters model is used (30× ***less*** parameters), can achieve +9.2% and +5.3% F1 score improvement (***more*** effective) on the WebQSP and CWQ benchmarks respectively over the previous SOTA subgraph retrieval work (Luo et al., 2024b) consisting of 7B parameters. By integrating with our LLM reader, which is fine-tuned from the same base model used in the SOTA approaches, we achieve F1 score improvements of +6.3% on WebQSP and +4.9% on CWQ in the end-to-end evaluation. Our 3B model with LLaMA3 reader reaches new SOTA performance among SR-based KGQA on both WebQSP and CWQ dataset with F1 80.1% and 64.4% respectively.

Our contributions can be summarised as follows: 1) We introduce GSR, a method utilizing small language models to accomplish the subgraph retrieval task. 2) We propose a training framework comprising an indexing step and a retrieval step for training GSR, including: a) an automatic method for collecting indexing data; b) two distinct methods to enhance the quality of the retrieval data. 3) Comprehensive experimental results demonstrate the effectiveness of our work. Our best model achieves an average improvement of +5.6% in F1 score on two KGQA datasets compared to the previous SOTA SR-based KGQA models, while being 7.7 times more efficient during the subgraph retrieval step.

2 Related Works

Our method draws inspiration from works on Knowledge Graph Question Answering (KGQA) and Generative Retrieval.

2.1 KGQA

KGQA is the task of answering questions based on facts from a knowledge graph. In general, KGQA methods can be classified into two categories: Semantic Parsing (SP)-based and Subgraph Retrieval (SR)-based KGQA.

SP-based KGQA SP-based KGQA methods are designed to transform a question into an executable logical query (Hu et al., 2022; Das et al., 2021; Luo et al., 2024a), which can then be directly applied to a KG to retrieve answers. These methods are famous for their versatility in handling diverse complex questions (Zhang et al., 2023a). Despite the effectiveness, SP-based KGQA methods generally requires extensive SPARQL annotations from experts, which is expensive to obtain in practice (Zhang et al., 2022). In addition, if the generated

SPARQL is not executable, no answer will be generated (Luo et al., 2024b).

SR-based KGQA SR-based KGQA methods, on the other hand, present a different methodology for handling the KGQA task with a retrieval-augmented generation framework, which first retrieves relevant KG subgraphs, then uses a subgraph reader to generate the final answer. Baek et al. (2023) treat the subgraph retrieval process in triple level, where each triple is textualized as a document. Zhang et al. (2022) model the subgraph retrieval in the relation level, using a dual-encoder to retrieve relevant relation. Luo et al. (2024b) and Sun et al. (2024) conduct the subgrpah retrieval as a reasoning task, using a large language model to generate the reasoning step for subgraph retrieval. However, it is inefficient to rely on LLMs in subgrpah retrieval, which we consider a simple task that can be handled by smaller LMs with specific design. In addition to KG retrieval for RAG, knowledge graphs can be useful for passage based RAG in many different ways, such as extracting knowledge graph triples for selecting the most relevant passages (Gutiérrez et al., 2024) or by using KG patterns to train some LLMs for planning the retrieval (Wang et al., 2024a).

2.2 Generative Retrieval

Generative retrieval is a new paradigm of information retrieval (IR), framing traditional IR into a sequence-to-sequence modelling task (Pradeep et al., 2023). This paradigm works by storing a search index inside the model's parameters instead of outside, treating it as an external module. Differentiable Search Index (DSI) is a series of typical generative retrieval techniques (Tay et al., 2022; Zhuang et al., 2022; Chen et al., 2023). Generative retrieval methods have shown potential to outperform dual-encoder-based methods, but they face challenges with respect to scaling to large numbers of documents since the parameters of involved can be limited. In this work, instead of assigning each subgraph a specific ID, we decompose the subgraph retrieval task as a sequence generation task, where an auto-regressive model is responsible for decoding a relation chain, as a sequence of unique relation IDs.

3 Problem Statement

A Knowledge Graph $\mathcal{KG} = \{(s, r, o) \| s, o \in \mathcal{E}, r \in \mathcal{R}\}$ is an RDF graph that consists of several (s, r, o) triples, where $\mathcal{E}$ is the entity set and $\mathcal{R}$ is the relation set, and s, r, o are instances of a subject entity, a relation, and an object entity respectively, for a triple $\in \mathcal{KG}$. Knowledge Graph Question Answering (KGQA) aims to figure out the answer set $\hat{\mathbf{A}}$ given the question q and topic entity e_t. KGQA methods based on subgraph retrieval model the question answering task in a retrieval-augment generation framework by first retrieving relevant subgraph $\mathcal{SG} \subseteq \mathcal{KG}$ given the question q, and, subsequently, using a reader to generate the predicted answer set $\mathbf{A}$ given the question q and the retrieved subgraph $\mathcal{SG}$.

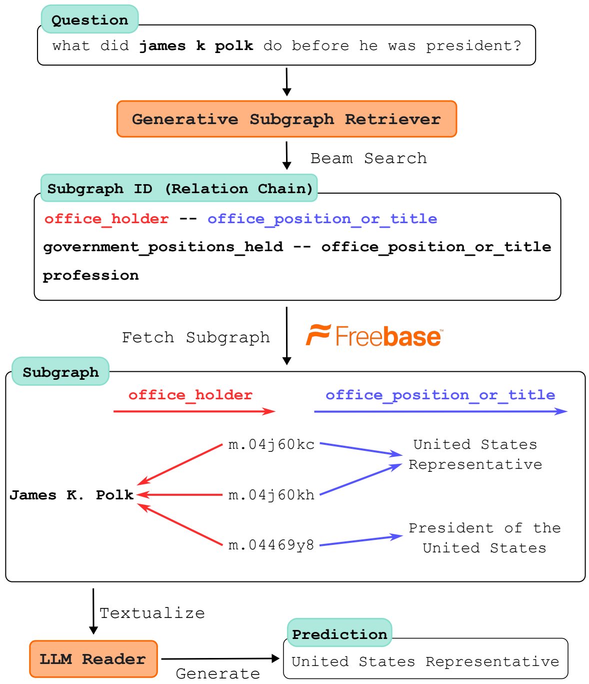


Figure 2: Overall pipeline of proposed RAG framework for KGQA task with the Generative Subgraph Retriever.

4 Methodology

4.1 Generative Subgraph Retriever

Subgraph Definition A KG subgraph $\mathcal{SG} \subseteq \mathcal{KG}$ is a subset of all triples in the original KG. Specially, in this work, we made a further constraint on the definition of subgraph, which we called path constrained subgraph[1]. In short, path constrained subgraph is a set of special subgraph that can be identified with a simple identifier (e, c), where e is the entity and $c = r_1, r_2, ..., r_n$ is an ordered relation chain that indicates n-hop reasoning. By moving from the entity e through the relation chain

[1]In other part of the paper, we use the term 'subgraph' to refer to path constrained subgraph if not specially mentioned.

c, we can identify the whole subgraph with the simple identifier. The middle part of Figure 2 shows an example of identify subgraph with topic entity *James K. Polk* and relation chain (*office_holder*, *office_position_or_title*), which can be identified with identifier `[James K. Polk, office_holder, office_position_or_title]`. In addition, for better flexibility, we decouple the topic entity e and relation chain c in the subgraph identifier, which means that the two part can be retrieved separately. We assume the topic entity e is known in this work for aligning other SR-based KGQA works (Zhang et al., 2022; Luo et al., 2024b).

Subgraph Retrieval With the subgraph definition above, we can model the subgraph retrieval task as a subgraph ID generation task. Given a natural language query q, subgraph retrieval aims to find the relevant subgraph, as a relation chain $c = \{r_1, r_2, ..., r_n\}$, that forms an n-hop reasoning chain from the topic entity e_t to the answer entity e_a. The relation chain is ordered, and is predicted by the probability of

$$P(c|q) = \Pi_i^n P(r_i|q, r_1, r_2, ..., r_{i-1}).$$

The above equation can be decomposed into the conventional auto-regressive language modelling objective, assuming relations are mapped into the involved model's token space.

Subgraph ID Since the major task of our GSR model is to map questions to a subgraph ID (relation chain), it is essential to build an efficient and effective way of representing the relations in the model. Luo et al. (2024b) simply ask LLMs to generate the whole name of the relation (e.g., *tv.regular_tv_appearance.actor*), but it is not efficient and hard for LMs to learn the mapping. Instead, we adapt the atomic document representation methods from DSI-based works (Tay et al., 2022). On relation level, we assign each relation an atomic ID, i.e., each relation is mapped to a special token in the generative language model. On subgraph level, we build a hierarchical indexing, i.e., each subgraph ID is mapped to the relation tokens which forms the reasoning chain.

4.2 Training GSR

To train the GSR model, we adapt a multi-task training setting with indexing data and (subgraph) retrieval data.

Indexing Data Unlike textual retrieval, in the subgraph retrieval task, the information that required to be retrieved is a sequence of relations. Thus instead of simply defining the indexing task as a relation name to relation ID mapping task, we build a question to relation ID task to teach language model how different relations (i.e. relation IDs) can be expressed in natural language questions. For each relation in Freebase, we first filter out extremely infrequent relations that do not have at least one triple available in the Freebase full dump[2]. After that, we use the prompt provided in Appendix C to prompt GPT-4 for getting 10 question templates $t_{r_i}^{(j)}$ for each relation r_i. Finally, for each template, we randomly sample triples (s, r_i, o) and use s to replace the placeholder in the template. By far, we can get the indexing data with every valid relation have at most 10 diverse pseudo question. The task for a language model is to map these pseudo questions to the relation ID.

Retrieval Data Though obtaining annotated reasoning-based KGQA training data is easier than getting the expert annotated semantic-parsing based data, it is still hard to get the gold relation chain annotation. Previous works (Zhang et al., 2022; Luo et al., 2024b) try to mitigate this issue by seeking the weakly supervised data constructed from the question answer pair. Given a question, raw weakly supervised data is collected from retrieving the shortest path between the topic entity and the target answer entity.

However, we found the above data creation method results in a large amount of noise where the shortest path is meaningless. For example, when the topic entity and answer entity are both male person, then there must exist a path *topic entity* $\rightarrow$ *gender* $\rightarrow$ *Male* $\leftarrow$ *gender* $\leftarrow$ *answer entity*. Training subgraph retrieval model with the raw data will cause model to generate useless chains, which can be harmful for the model performance. To address this, we only keep the shortest path that always has one direction that starts from the topic entity and ends at the answer entity and construct filtered retreival data. We observed that it is safe to do that since most of the relations also have a inverse relation in the Freebase so that we will not lose training signals by filtering out useful information.

To get better training signal for training the retriever model, we further distil knowledge from GPT to get higher quality data. In short, we prompt

[2] https://developers.google.com/freebase

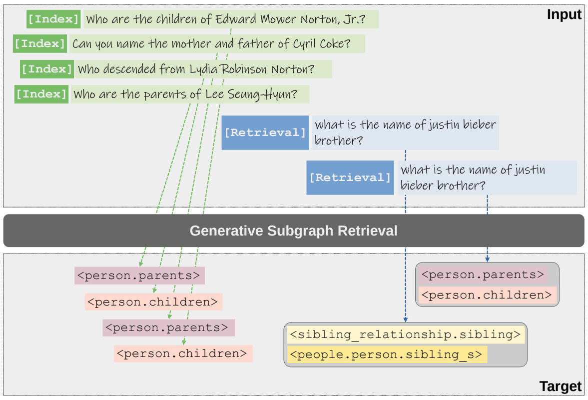


Figure 3: A demonstration of how we train the GSR model. Each coloured box stand for a special token in our GSR model. The indexing task is N to 1, where multiple pseudo questions is mapping to a specific relation ID. The subgraph retrieval task is 1 to N, where each question can be mapped to several subgraph IDs (sequence of relation IDs).

GPT-4 with all shortest paths we get from the raw data and ask GPT-4 to choose the list the relevant relation chain with the prompt provided in Appendix C, and construct the GPT-selected retrieval data accordingly. By doing so we can both get rid of most noise training signal from raw data and avoid losing valuable training signal that is filtered in filtered data.

Training Strategy We adapt an jointly training strategy to train the GSR model, where the indexing data and the retrieval data is used at the same time for training the GSR model. Since we need to train the GSR model with both indexing data and retrieval data, we use a common strategy to distinguish the two task in the model level. Specifically, we design two special prefix token in front of the two different task, `[Index]` indicating this is a indexing task and `[Retrieval]` indicating this is a subgraph retrieval task. Figure 3 demonstrate how we train the GSR model.

4.3 Inference GSR

When inference using the trained GSR model for subgraph retrieval task, we utilize beam search to retrieve top-k subgraph ID (i.e., the relation chain). In case a predicted relation chain is not executable against the knowledge graph (i.e. that we can not arrive to the end of the predicted chain starting from the topic entity of interest), it is removed from the set of available candidates. We retain top-n valid relation chains where $n \leq k$ for balancing precision and recall of the subgraph retrieval step.

4.4 LLM reader

Inspired by Luo et al. (2024b), we fine-tune an LLM as a reader for generating answer(s) based on the retrieved subgraph. We explore two approaches for injecting subgraph information into LLMs by representing subgraphs as reasoning paths or triple sets.

Subgraph as Reasoning Paths We adapt the prompting strategy from Luo et al. (2024b) to prompt LLMs with the complete reasoning path that leads from the topic entity e_{start} to the potential answer entity e_{end}, by including any intermediate entity and relations in the path:

$$e_{start} \text{ -> } rel_{int}^{(1)} \text{ -> } e_{int}^{(1)} \cdots \text{ -> } rel_{int}^{(n)} \text{ -> } e_{end},$$

where n is the number of hops between e_{start} and e_{end}. In order to consider inverse relations where entities after the right-arrow do not find themselves in the object position, we introduce bidirectional paths, changing the directionality of the arrows, accordingly. For instance, we might have paths as follows[3]:

$$e_{start} \text{ <- } rel_{int}^{(1)} \text{ <- } e_{int}^{(1)} \cdots \text{ -> } rel_{int}^{(n)} \text{ -> } e_{end}$$

Subgraph as Triple Sets Though Luo et al. (2024b) has shown the effectiveness of representing subgraph as relation paths, it is expensive to use such paths since some triples will be repeated multiple times. To alleviate this issue, we tried to use another way to represent subgraph, which is to feed LLMs all the triples that appears in the retrieved subgraph. To this end, the knowledge would be denser in the context, but it is also harder for LLMs to build connections between relevant triples since they might be far away.

5 Experimental Setup

Datasets We use WebQSP (Yih et al., 2016) and CWQ (Talmor and Berant, 2018) datasets that are both constructed from Freebase for all the experiments. Following previous works that seek to increase the reasoning efficiency on Freebase, we choose to use the same simplified Freebase (only contains multi-hop triples of all topic entities appeared in WebQSP and CWQ) (He et al., 2021; Zhang et al., 2022; Luo et al., 2024b). Specially, WebQSP is a relatively easier dataset as its questions require at most 2-hop reasoning from their

[3]Appendix F shows some examples of inverse relations.

topic entity. CWQ is more challenging as the questions involve up to 4-hop reasoning. Detailed statistics of both datasets are provided in Appendix B.

Baselines We compare our proposed RAG with GSR pipeline with several baselines. For evaluating subgraph retrieval performance, we compare our methods with **RoG** (Luo et al., 2024b). For end-to-end KGQA comparison, we choose both SP-based approaches including **UniKGQA** (Jiang et al., 2023), **DecAF** (Yu et al., 2023), **ChatKBQA** (Luo et al., 2024a) and SR-based approaches including **SR** (Zhang et al., 2022), **KAPING** (Baek et al., 2023), **RoG** (Luo et al., 2024b) and **ToG** (Sun et al., 2024).

Metrics For evaluating subgraph retrieval, we choose Precision, Recall and F1 to measure the answer coverage of the retrieved subgraphs. For the end-to-end evaluation, we use F1, Hits@1 (Zhang et al., 2022; Luo et al., 2024a). RoG, in particular, measures Hits@1 in an uncommon way (Luo et al., 2024b). In order to align their results with ours, we further added a Hits metric, which treats all answers generated by LLM as the top-1 answer and measures the Hits@1 score accordingly. For the original Hits@1, we use the first answer generated by LLM.

Implementation Details We build our GSR model on top of T5 models with size base, large and 3b, which consist of 220M, 770M and 3B parameters respectively. For beam search, we retrieve top-10 result and keep at most 3 valid relation chains for end-to-end evaluation[4]. For subgraph retrieval evaluation, we set the beam size to 3 for a fair comparison against RoG. For the LLM reader, we fine-tuned LLaMA2-chat-7B and LLaMA3-instruct-8B with QLora (Dettmers et al., 2023) using the unsloth library[5]. More implementation details can be found in Appendix A.

6 Results

We evaluate our approach across both sugraph retrieval and the end-to-end QA.

6.1 Subgraph Retrieval Performance

Table 1 shows results on subgraph retrieval.

[4]Some relation chains are not executable on Freebase. This means that there is no reasoning path starting from the topic entity with the decoded relation chain. Detailed results under different beam size settings can be found in Appendix D.1

[5]`https://github.com/unslothai/unsloth`

Model	WebQSP			CWQ		
	P	R	F1	P	R	F1
LLM based subgraph retrieval						
RoG	46.90	79.85	49.56	18.88	67.89	22.26
ours w/ raw data						
GSR-base	42.68	84.59	47.87	18.34	72.14	22.20
GSR-large	42.19	85.16	47.11	18.29	72.88	22.19
GSR-3b	44.18	85.73	49.03	19.05	72.67	22.79
ours w/ filtered data						
GSR-base	48.85	85.75	54.64	21.45	72.66	26.09
GSR-large	47.79	86.15	53.77	21.66	72.41	26.34
GSR-3b	48.32	**86.22**	53.95	21.30	72.81	25.93
ours w/ GPT selected data						
GSR-base	53.94	85.49	58.77	**23.02**	72.28	27.59
GSR-large	53.67	84.91	58.23	22.68	72.09	27.19
GSR-3b	**54.46**	85.63	**58.97**	**23.02**	**73.00**	**27.60**

Table 1: Subgraph retrieval results. We set beam size k=3 for fair comparison with baseline.

Model	WebQSP	CWQ	Inf. Time
RoG+T5-base	80.9	70.4	912s + 1,887s
GSR-base	85.5	72.3	117s + 258s

Table 2: Subgraph retrieval performance (Recall). **Inf. Time** is the inference time on WebQSP + CWQ.

less* parameter(s) is *more Compared to RoG that performs relation chain retrieval with an LLM, the proposed GSR models achieve better performance across most metrics with less model parameters. This is observed even in the case of the smallest GSR-base models with approximate 30× less parameters than RoG, where we can obtain an average of +4.5% more recalled answers in the retrieved subgraph when training with the same retrieval data (raw). In addition, we can observe that within the GSR variant trained on the same retrieval data, larger model generally works better. We note a few cases in which GSR-large works slightly worse than GSR-base (e.g., in ours w/ GPT-selected data). We attribute this to the more invalid paths that are generated by GSR-large, which can be mitigated by setting beam size $k = 10$ (cf. Figure 11 in Appendix D.3).

less* training samples is *more Among GSR models trained with different retrieval data, the raw data with all the shortest paths as weakly supervised signal performs the worst according to F1. While the Recall score seems to be competitive with other models, the low precision indicates that some boost in recall is simply obtained by uninformative chains, such as *gender* → *gender*. We included some case studies about this issue in Appendix F. GSR models trained with filtered data work better, with respect to Recall performance, since their variations trained with GPT selected data achieve highest Precision and F1 score, showcasing the best balance between finding the answer and reducing unrelated information. When it comes to the end-to-end performance, in the context of retrieval-augmented generation, both recall and precision are important, since the LLMs' content window is limited. Thus, we choose the GSR models trained with GPT selected data for the end-to-end evaluation in the next step.

less* target tokens is *more We further trained a T5 model with the same input and output settings as RoG (Luo et al., 2024b) using GPT-selected retrieval data to explore the benefits of our apporach. Table 2 shows the subgraph retrieval performance and inference time when inferring these two base-sized models. It is evident from the results that our GSR architecture achieves a +3.3% average improvement of recall while being 7.4 times more efficient during inference, demonstrating that incorporating less target tokens for the subgraph ID generation task brings in both effectiveness and efficiency.

6.2 End-to-End Performance

Table 3 shows the end-to-end KGQA performance. Generally, on the WebQSP dataset, our best GSR-3b model with LLaMA 3 8B reader achieves the best performance among all SR-based methods. In particular, our best model achieves +5.2% improvement for Hits@1 compared to ToG with GPT-4 and +9.3% improvement for F1 compared to RoG. Even the GSR-base model with LLaMA 2 7B reader outperforms RoG which uses a finetuned LLaMA 2 7B model as both its retriever and reader, showing that the subgraph retrieval task can be effectively handled by small language models. Our systems' performance is also on par with, if not exceeds, SOTA SP-based methods. The best GSR system manages to achieve higher Hits@1 score, even though it is trained using only weakly supervised data.

The performance of our model on the more challenging CWQ dataset is still promising, where we achieve best performance among the SR-based baselines, except against $\text{ToG}_{\text{GPT-4}}$. This indicates that even though more complex questions would require better subgraph retrieval ability, the GSR model is still competitive enough to go head-to-head against much larger LLMs. However, the performance gap between all SR-based methods, including ours, against SOTA SP-based methods is still large, indicating that SP-based methods are still dominating complex KGQA. This can be attributed to the fact that SR-based methods, including the SOTA RoG, still struggle with following some specific constraints like 'less than' limiting their overall performance.[6]

Model	WebQSP H@1	WebQSP Hits	WebQSP F1	CWQ H@1	CWQ Hits	CWQ F1
SP-based KGQA baseline						
UniKGQA	77.2	-	72.2	51.2	-	49.4
DeCAF	82.1	-	78.8	70.4	-	-
ChatKBQA	86.4	-	**83.5**	**86.0**	-	**81.3**
SR-based KGQA baseline						
SR	68.9	-	64.1	50.2	-	47.1
KAPING	-	73.9	-	-	-	-
RoG	80.0	85.7	70.8	57.8	62.6	56.2
$\text{ToG}_{\text{ChatGPT}}$	76.2	-	-	57.1	-	-
$\text{ToG}_{\text{GPT-4}}$	82.6	-	-	67.6	-	-
ours w/ LLaMA 2 7B (QLora)						
None	62.3	67.6	48.5	35.3	38.9	31.5
GSR-base	85.7	88.0	76.7	63.4	67.2	60.1
GSR-large	85.6	87.7	76.4	63.2	67.3	60.2
GSR-3b	86.5	88.6	77.1	64.3	68.3	61.1
ours w/ LLaMA 3 8B (QLora)						
None	65.3	70.3	51.9	38.1	41.8	34.3
GSR-base	86.5	88.3	78.8	66.4	69.6	63.1
GSR-large	87.0	88.7	78.9	66.4	69.6	63.5
GSR-3b	**87.8**	**89.6**	80.1	67.5	**71.1**	64.4

Table 3: End-to-end KGQA performance with LLM reader. The GSR models are trained by gpt selected weakly supervised data. H@1 stands for Hits@1. *None* indicating that we use QLora finetuned LLM without any subgraph information for ablation studies.

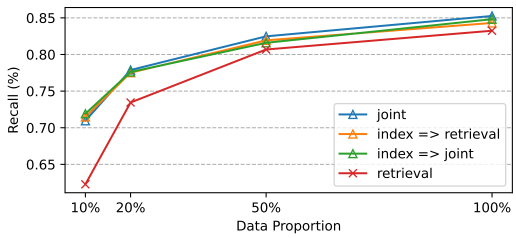
7 Analysis

We analyse in detail the effectiveness of several variants of our proposed method, to answer the following research questions. **RQ1**: How to efficiently and effectively prompt LLMs with a retrieved subgraph? (Sec 7.1) **RQ2**: How does the indexing data contribute to the performance on subgraph retrieval? **RQ3**: What is the performance upper-bound of the proposed methods? (Sec 7.3)

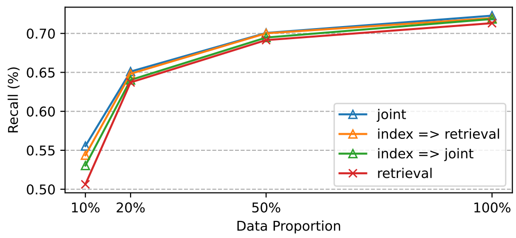
[6] More details can be found in Appendix F.3.

Dataset	Hits@1	Hits	F1	Avg. Tokens
Subgraph as Reasoning Paths				
WebQSP	87.8	89.6	80.1	784.5
CWQ	67.5	71.1	64.4	910.4
Subgraph as Triple Sets				
WebQSP	87.3	89.7	79.8	699.3
CWQ	66.5	70.2	63.5	777.5

Table 4: KGQA performance with different ways of prompting LLM with retrieved subgraph.



(a) WebQSP



(b) CWQ

Figure 4: Subgraph retrieval result under low resource KGQA setting. We set beam size k=3 here.

7.1 How to represent retrieved subgraph

We conduct an in-depth analysis to identify the most suitable format for representing a retrieved subgraph for the LLM reader. Table 4 shows how different ways of prompting an LLM reader can affect the final performance. We observe that representing a retrieved subgraph as reasoning paths generally works better than representing it as triples. Prompting LLMs with triples is more compact.[7] As such it offers higher chances to cover an answer if the LLM's context window is limited. This is also demonstrated by the competitive performance on WebQSP. However, the compressed triples' form can easily result in relevant triples, that belong to the same reasoning path, ending up far away in the context of this serialised representation, making the reasoning task harder for the LLM. The effect of this drawback is more evident on the more complex CWQ dataset, where the performance gap between the two approaches becomes larger. Nonetheless, depending on the use-case, using triples as input format can navigate a healthy trade-off between performance and efficiency.

[7] Appendix F shows an example of why triples are more compact than paths.

7.2 The effectiveness of Indexing Data

We evaluate the effectiveness of the indexing step. In addition, we explore different training strategies along the joint-training strategy (discussed in Section 4.2) for the GSR model using the indexing and retrieval data. 1) We directly finetune GSR with retrieval data without indexing data (*retrieval*); 2) we first pretrain GSR with indexing data, and then finetune it with retrieval data (*index => retrieval*). 3) we first pretrain GSR with indexing data, and then finetune it jointly with indexing and retrieval data (*index => joint*). To better highlight the importance of the indexing data, we further define low resource settings, by limiting the availability of retrieval data to 10%, 20%, 50% and 100%. We use GSR-base in this part for these experiments.

Figure 4 shows the recall of GSR-base under different training settings according to the proportion of retrieval data that is trained on. Generally, training the GSR model with retrieval data brings in competitive performance when 100% of the data is used, but has a large gap with variants using the indexing data when the retrieval data is limited—the gap increases as the data proportion decreases. With only the indexing step, the trained GSR model is able to perform the simplest subgraph retrieval task where the maximum relation hop is 1, with a recall of 42.54 on WebQSP and 21.18 on CWQ. Joint model training with indexing and retrieval data contributes to the best performance, especially on the harder CWQ dataset. This observation is in line with findings from Allen-Zhu and Li (2024), that including finetuning-relevant data instances during pre-training can benefit the model to make better use of the learned relation-level knowledge.

7.3 Evaluation Results on Full Freebase

To further investigate the upper bound of the proposed GSR method, we apply a full Freebase setting to fetch subgraph based on the subgraph ID from the full Freebase instead of the simplified subgraph (Freebase-SG). Table 5 shows the evaluation results. It is intuitive that the recall increases on both datasets when fetching subgraphs from the full Freebase. On the other hand, the precision on CWQ also increases, which can be attributed to the

KG	WebQSP			CWQ		
	P	R	F1	P	R	F1
Freebase-SG	54.5	85.6	59.0	23.0	73.0	27.6
Freebase	50.2	87.5	55.2	24.9	76.6	29.7

Table 5: Subgraph retrieval performance under different KGs.

low question coverage of Freebase-SG that at least 20% of the questions will always have precision 0 even if the subgraph ID is correct.

8 Conclusion

We propose a retrieval-augmented generation framework for KGQA comprising a subgraph retriever and an LLM reader. To efficiently and effectively retrieve a subgraph from KG, we propose a novel generative subgraph retrieval method that transform the subgraph retrieval task into a sequential subgraph ID generation task. Our base GSR model with 220M parameters is capable of outperforming the previous 7B SOTA baseline in subgraph retrieval, with around 30× less parameters. Combined with our LLM reader, we achieve new SOTA performance in subgraph retrieval-based KGQA on both the WebQSP and CWQ datasets. In summary, our proposed GSR model with ***less*** model parameters, ***less*** training samples, and learned to generate ***less*** tokens, achieves ***more*** efficiency and ***more*** effectiveness compared SOTA SR-based KGQA works.

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Limitations

While our proposed approach achieves SOTA performance among SR-based KGQA methods, there are still limitations to our works.

First, SR-based KGQA approaches trained using weakly supervised retrieval data still struggle with following special constraints in the questions, since the shortest path between topic entity and answer entity usually does not contain context or entity-type restrictions. Additionally, SR-based KGQA cannot handle questions where the topic entity does not appear at the start of the reasoning chain. These limitations can affect the overall performance of the KGQA task, particularly when the question is complex. In our work, we do not attempt to fix this common limitation in SR-based KGQA approaches, and we consider this as future work.

Second, in this work, we assume the topic entity is already known, which is not typically the case in real-world KGQA tasks. Given that we decompose the subgraph ID as entity and relation chain, there could be accumulative error in cases where we can not identify the correct topic entity.For real-world applications, our proposed method is designed to seamlessly integrate with existing off-the-shelf topic entity linking tools to identify topic entities in the input natural language question, thereby mitigating this limitation.

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A Implementation Details

A.1 Environment

We conduct all the experiments on a single NVIDIA A100 80G GPU. For all GPT-4 API calls, we use `gpt-4-turbo-preview` as the API endpoint.

A.2 Training LLM Reader

For training LLaMA2 and LLaMA3 reader, we use the trained GSR model to generate subgraph ID for all questions in WebQSP and CWQ training set, with beam size k=10 and fetching subgraph from simplified Freebase with top-3 valid relation chain. Then we use prompt provided in Appendix C to generate supervised finetune data for training LLM readers.

A.3 Hyperparameters

For all GSR models (based on T5[8]), we set the epoch numbers to 50. We set the batch size to {128, 128, 64} and learning rate to {5e-4, 2e-4,

[8]https://huggingface.co/google-t5

Model	Training Time
Subgraph Retriever	
GSR-base	2 hours
GSR-large	8 hours
GSR-3B	20 hours
RoG + T5-base	2 hours
LLM Reader	
LLaMA2-7B	10 hours
LLaMA3-8B	12 hours

Table 6: Training time spent on single NVIDIA A100 80G GPU. GSR models are jointly trained with indexing data and GPT-selected retreival data. RoG+T5-base is trained with GPT-selected retrieval data only.

Models	Params	WebQSP	CWQ
RoG	7B	1,650s	3,823s
RoG+FlanT5-base	0.2B	912s	1,887s
GSR-base	0.2B	117s	258s
GSR-large	0.8B	190s	443s
GSR-3B	3B	217s	490s

Table 7: Inference cost on both datasets. Measured on single NVIDIA A100 80G GPU.

1e-4} for GSR-base, GSR-large and GSR-3b respectively. For LLM readers, we set epoch numbers to 3, learning rate to 2e-4, and max sequence length to 4,096 for both LLaMA2[9]and LLaMA3[10]. The QLora hyperparameters is set to $r = 16$ and $\alpha = 16$, with 4 bit quantization.

A.4 Experiment Cost

API Cost We utilise GPT-4 API in both indexing data creation and retrieval data creation. For generating pseudo questions as indexing data, we spent around $40 US dollars. While for distil knowledge from GPT-4 to filter retrieval data, we spent around $35 US dollars.

Training Cost Table 6 shows the training cost of both GSR retriever and LLM reader used in this work.

Inference Cost Table 7 shows the inference cost of subgraph retrieval step on both datasets.

[9]https://huggingface.co/unsloth/llama-2-7b-chat-bnb-4bit

[10]https://huggingface.co/unsloth/llama-3-8b-Instruct-bnb-4bit

Dataset	Train	Test	Max Hop	Coverage
WebQSP	2,826	1,628	2	94.9%
CWQ	27,639	3,531	4	79.3%

Table 8: Statistic of original dataset.

Data Type	WebQSP	CWQ
Raw	9,745	87,420
Filtered	5,551	46,783
GPT-select	3,741	31,035

Table 9: Statistic of retrieval data.

B Dataset details

B.1 Original KGQA Dataset

In this work, we use the WebQSP and CWQ datasets processed by Luo et al. (2024b) for all the experiments. Following previous studies (Zhang et al., 2022; Luo et al., 2024b), we utilize the subgraph of Freebase (Freebase-SG) instead of the full Freebase for most of the experiments to enhance efficiency. Table 8 shows the statistic of the original dataset. Coverage refers to the question coverage rate of Freebase-SG, which is the proportion of questions where at least one answer entity appears in Freebase-SG.

B.2 Training Data

Indexing Data For each relation, we prompt GPT-4 to generate 10 pseudo questions with placeholder `[SUBJECT]`. In some cases, the generation is invalid, where the model fails to follow our instruction of generating placeholder. At such cases, we simply remove the generated pseudo question. Finally, we created the indexing data with 83,104 pseudo questions to relation ID mapping for a total of 8,321 relations. Noted that we filter out other relations in Freebase since we can not find any valid triples related to these relations, which means these relations will never contribute to the subgraph retrieval task.

Retrieval Data Table 9 shows the statistic of different types of retrieval data. While Figure 5 shows an example of how we process the weakly supervised data to get the filtered data and GPT-selected data.

C Prompt Details

Prompt to clean the weakly supervised dataset:

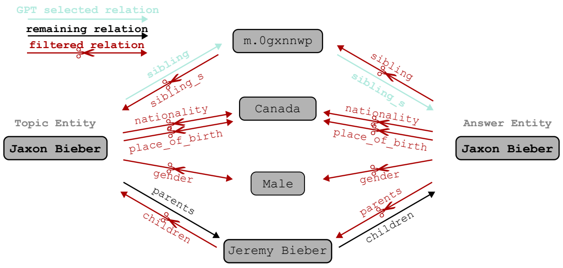


Figure 5: An example of filtering weakly supervised data. The example is taken from WebQSP training set with question: what is the name of justin bieber brother?

> Given the question and candidate relation reasoning path, select the path that is most helpful for reaching the answer of the question. Only return the number list separated with comma of the relation path without anything else.
> Paths: {path_list}
> Question: {question}

Prompt to generate pseudo questions:

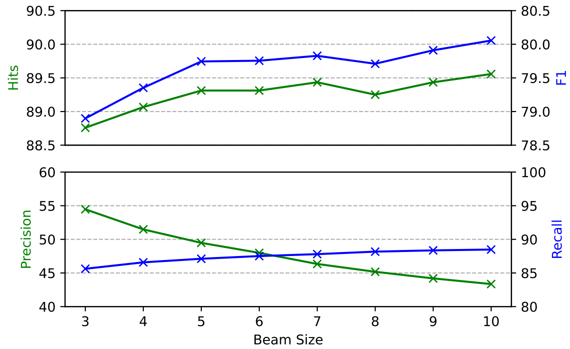
> Given the Freebase relation {relation} and a triple example of the relation {triple_example}, generate 10 templates that can be used to ask question about the relation. Use [SUBJECT] to identify subject entity (not the one in the example)

Prompt for LLaMA reader (reasoning paths):

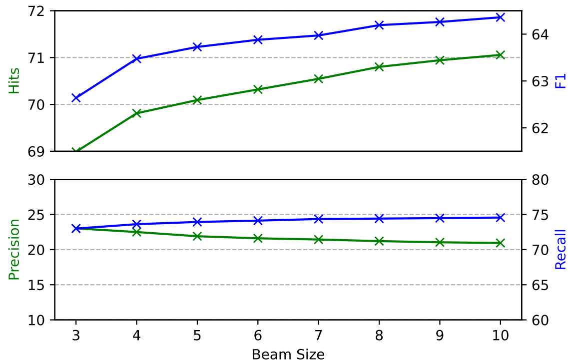
> Based on the reasoning paths, please answer the given question. Please keep the answer as simple as possible and return all the possible answers as a list.
> Reasoning Paths: {reasoning_paths}
> Question: {question}

Prompt for LLaMA reader (triple sets):

> Based on the KG triples, please answer the given question. Please keep the answer as simple as possible and return all the possible answers as a list.
> KG Triples: {subgraph_triples}
> Question: {question}



(a) WebQSP



(b) CWQ

Figure 6: Subgraph retrieval and end-to-end KGQA performance based on different Beam size k. Upper figure measures end-to-end metrics (Hits and F1), while bottom figure measures subgraph retrieval metrics (Precision and Recall).

D Detailed Results

D.1 How many beam size do we need

In this part we discuss how the different beam size affect both subgraph retrieval performance and end-to-end KGQA performance. Noted that no matter how large the beam size k is, we always keep the max size of valid subgraph IDs to 3. Figure 6 shows the evaluation results when changing beam size from 3 to 10. From the result, we can observe a clear precision drop as well as little recall improvement on subgraph retrieval performance on WebQSP dataset. While for CWQ dataset, we can find the drop and improvement are more balanced. The 'seesaw' of precision and recall then affect the end-to-end KGQA performance. On WebQSP dataset, when we increase k, the performance is quite unstable, since we bring a lot more noise with lower precision. While on the more complex CWQ dataset, the performance improvement along with k is clear and consistent. This findings provide an insight that for the choice of k is conditioned on the

Model	WebQSP			CWQ		
	H@1	Hits	F1	H@1	Hits	F1
ours w/ raw data						
GSR-3b	87.2	89.1	78.9	63.7	66.9	60.3
ours w/ filtered data						
GSR-3b	86.8	89.2	79.3	64.2	67.7	61.2
ours w/ GPT selected data						
GSR-3b	**87.8**	**89.6**	**80.1**	**67.5**	**71.1**	**64.4**

Table 10: End-to-end KGQA performance with LLM reader. H@1 stands for Hits@1.

Model	WebQSP			CWQ		
	P	R	F1	P	R	F1
ours w/ raw data						
GSR-base	35.26	86.97	41.79	16.24	73.79	20.40
GSR-large	34.08	87.91	40.43	16.61	74.27	20.73
GSR-3b	34.54	88.05	41.09	16.02	74.84	20.10
ours w/ filtered data						
GSR-base	35.66	88.68	43.73	16.81	73.89	21.58
GSR-large	36.19	88.90	44.01	17.07	73.98	21.82
GSR-3b	36.52	88.20	44.01	17.00	74.06	21.64
ours w/ GPT selected data						
GSR-base	45.27	87.93	51.88	20.93	73.66	25.70
GSR-large	45.71	87.73	51.99	21.22	73.86	25.92
GSR-3b	43.35	88.48	49.92	20.95	74.56	25.61

Table 11: Subgraph retrieval results under beam size k=10.

complexity of the task, which we should choose a relatively low k for simple task while a larger k for hard task.

D.2 End-to-end results with different training data

Table 10 shows extended end-to-end evaluation results under GSR models trained with different retrieval data.

D.3 Subgraph retrieval results under k=10

Table 11 shows the subgraph retrieval results under beam size k=10. Noted that we still limit at most 3 valid paths per question.

D.4 Patterns of GPT-selected data

In this part, we analyse the patterns of GPT-selected data that contribute to the performance improvement compared with raw data. By analysing the differences between raw paths and GPT-selected paths, we found an interesting pattern of excluded paths: GPT-selected paths usually contain less repeated relations (e.g., people.person.gender -> people.person.gender). Around 22% of raw paths and 32% of paths excluded by GPT have a repeated relation, but less than 4% of GPT-selected paths contain any repeated relation. This finding can be used for explaining why the data filtering method works, since most repeated paths have both forward and backward directions (e.g., *topic entity* $\rightarrow$ *gender* $\rightarrow$ *Male* $\leftarrow$ *gender* $\leftarrow$ *answer entity*) and they will be filtered in the filtered data setting.

Model	Hits	F1
RoG	88.98	50.68
GSR-base	90.27	55.82
GSR-large	91.12	57.41
GSR-3b	**92.25**	**63.02**

Table 12: End-to-end KGQA performance on MetaQA 3-hop test set. All models are trained with 1,000 training samples.

E Generalize to other Datasets

In this section, we investigate whether the proposed method can be generalized to other datasets and other KGs. In this part, we follow RoG (Luo et al., 2024b) to use MetaQA datasets (Zhang et al., 2018). Specifically, MetaQA is a KGQA dataset in the movie domain, based on the WikiMovies KG. To better show the effectiveness of our proposed method and for a fair comparison, we follow the same low resource setting from RoG by using only 1,000 randomly sampled data instances for training, without leveraging the gold annotated relation chain. In addition, we use the 3-hop subset of MetaQA, which requires 3 hops from topic entity to target entity. Table 12 shows the results, we use fine-tuned LLaMA2 as reader for fair comparison. We use Hits and F1 as the metrics to measure the performance of baseline (RoG) and proposed methods.

From the results, we can find that the superiority of the proposed method still holds on MetaQA 3-hop data, consistently outperforming RoG (7B) with less model parameters in the same experimental setting (low resources and no gold annotation).

F Case Studies

In this section, we perform several case studies to better understand the methods and the pipeline.

F.1 Subgraph ID Generation

Table 13 shows some subgraph ID generation sampled from WebQSP and CWQ test set. The first 2 is from WebQSP and the latter 2 is from CWQ. We can observe that GSR trained with raw data usually generate loop path which is helpless to the question and will bring unreliable recall (e.g., all person with same gender as topic entity will be retrieved in first example).

F.2 Success Case

Table 14 shows a success example sampled from the CWQ dataset. Specially, when represent retrieved subgraph as triple sets, we only present repeated triples once. For example, (Lou Seal, sports.mascot.team, San Francisco Giants) appears 6 times when represent retrieved subgraph as paths (first 6 paths), but only appear once when represent retrieved subgraph as triples (first triple).

F.3 Error Analysis

In this part, we analyse when our proposed method fail in KGQA task. SR-based KGQA methods typically fail in following constraint in complex questions. Table 15 shows an example that our proposed GSR model fails in this case. The question has a constraint of answer entity, which is 'has a GDP eflator change rate of 2.32'. However, since in building training samples, we only care about shortest path between topic entity and answer entity, which means that the GDP information will not be considered in training (if this question is in training set) and in inference our model will miss such information. To this end, the retrieved subgraph do have the answer entity, but not enough for the reader to answer the question.

who was vp for nixon	
GSR (w/ raw data)	1:government.us_president.vice_president 2:government.us_vice_president.to_president 3:people.person.gender – people.person.gender
GSR (w/ filtered data)	1:government.us_president.vice_president 2:government.us_vice_president.to_president 3:government.government_office_category.officeholders – government.politician.government_positions_held
GSR (w/ GPT-selected data)	1:government.us_president.vice_president 2:government.political_appointer.appointees – government.government_position_held.office_holder 3:common.image.appears_in_topic_gallery – government.us_president.vice_president
who did armie hammer play in the social network	
GSR (w/ raw data)	1:people.person.profession – people.person.profession 2:people.person.nationality – tv.tv_program.country_of_origin 3:people.person.nationality – people.person.nationality
GSR (w/ filtered data)	1:people.person.profession 2:film.actor.film – film.performance.character 3:film.actor.film – film.film_character.portrayed_in_films
GSR (w/ GPT-selected data)	1:film.actor.film – film.performance.character 2:tv.tv_actor.starring_roles – tv.regular_tv_appearance.character 3:film.film.starring – film.performance.character
The artist that created the art series of Water Lilies was inspired by what?	
GSR (w/ raw data)	1:visual_art.art_series.artist – influence.influence_node.influenced_by 2:visual_art.art_series.artist – influence.influence_node.influenced 3:visual_art.artwork.artist – influence.influence_node.influenced
GSR (w/ filtered data)	1:visual_art.art_series.artist – influence.influence_node.influenced_by 2:visual_art.artwork.artist – influence.influence_node.influenced_by 3:visual_art.artwork.artist – influence.influence_node.influenced
GSR (w/ GPT-selected data)	1:visual_art.art_series.artist – influence.influence_node.influenced_by 2:visual_art.artwork.artist – influence.influence_node.influenced_by 3:visual_art.art_series.artworks – influence.influence_node.influenced_by
What is the official language of the area where the government of Ukraine is?	
GSR (w/ raw data)	1:government.governmental_jurisdiction.government_bodies – location.country.official_language 2:government.governmental_jurisdiction.government_bodies – language.human_language.countries_spoken_in 3:government.governmental_jurisdiction.government_bodies – location.country.languages_spoken
GSR (w/ filtered data)	1:government.governmental_jurisdiction.government_bodies – location.country.official_language 2:government.governmental_jurisdiction.government_bodies – location.country.languages_spoken 3:government.governmental_jurisdiction.government_bodies – language.human_language.main_country
GSR (w/ GPT-selected data)	1:government.government.government_for – location.country.official_language 2:government.government.government_for – location.country.languages_spoken 3:government.governmental_body.jurisdiction – location.country.official_language

Table 13: Subgraph ID generation cases.

Question	Lou Seal is the mascot for the team that last won the World Series when?
Subgraph ID	sports.mascot.team – sports.sports_championship_event.champion sports.mascot.team – sports.sports_team.championships sports.sports_team.team_mascot – sports.sports_team.championships
Retrived Subgraph as Paths	Lou Seal → sports.mascot.team → San Francisco Giants ← sports.sports_championship_event.champion ← 2014 World Series Lou Seal → sports.mascot.team → San Francisco Giants ← sports.sports_championship_event.champion ← 2010 World Series Lou Seal → sports.mascot.team → San Francisco Giants ← sports.sports_championship_event.champion ← 2012 World Series Lou Seal → sports.mascot.team → San Francisco Giants → sports.sports_team.championships → 2014 World Series Lou Seal → sports.mascot.team → San Francisco Giants → sports.sports_team.championships → 2010 World Series Lou Seal → sports.mascot.team → San Francisco Giants → sports.sports_team.championships → 2012 World Series Lou Seal ← sports.sports_team.team_mascot ← San Francisco Giants → sports.sports_team.championships → 2014 World Series Lou Seal ← sports.sports_team.team_mascot ← San Francisco Giants → sports.sports_team.championships → 2010 World Series Lou Seal ← sports.sports_team.team_mascot ← San Francisco Giants → sports.sports_team.championships → 2012 World Series
Retrived Subgraph as Triples	Lou Seal, sports.mascot.team, San Francisco Giants 2014 World Series, sports.sports_championship_event.champion, San Francisco Giants 2010 World Series, sports.sports_championship_event.champion, San Francisco Giants 2012 World Series, sports.sports_championship_event.champion, San Francisco Giants San Francisco Giants, sports.sports_team.championships, 2014 World Series San Francisco Giants, sports.sports_team.championships, 2010 World Series San Francisco Giants, sports.sports_team.championships, 2012 World Series San Francisco Giants, sports.sports_team.team_mascot, Lou Seal
Reference Answer(s)	2014 World Series
Predicted Answers (Paths) Predicted Answers (Triples)	2014 World Series 2014 World Series

Table 14: One success example sampled from CWQ test set.

Question	What Caribbean country has a GDP eflator change rate of 2.32?
Subgraph ID (RoG)	location.location.containedby common.topic.notable_types location.location.contains
Subgraph ID (GSR)	location.location.containedby location.location.contains location.statistical_region.places_exported_to – location.statistical_region.places_imported_from
Retrived Subgraph	Caribbean ← location.location.containedby ← Puerto Rico Caribbean ← location.location.containedby ← Barbados Caribbean ← location.location.containedby ← Grace University, main campus ... Caribbean → location.location.contains → Puerto Rico Caribbean → location.location.contains → Barbados Caribbean → location.location.contains → Grace University, main campus ...
Reference Answer(s)	Puerto Rico
Predicted Answers	Barbados

Table 15: One error example due to the missing of constraint information sampled from CWQ test set. This is a common issue among sr-based KGQA works training with weakly supervised data.