Ground-Truth Subgraphs for Better Training and Evaluation of Knowledge Graph Augmented LLMs

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Abstract

Retrieval from graph-structured knowledge bases represents a promising direction for improving the factuality of LLMs. While various solutions have been proposed, a comparison of methods is difficult due to the lack of challenging QA datasets with ground-truth targets for graph retrieval. We present SynthKGQA[1], a framework for generating high-quality synthetic Knowledge Graph Question Answering datasets from any Knowledge Graph, providing the full set of ground-truth facts in the KG to reason over each question. We show how, in addition to enabling more informative benchmarking of KG retrievers, the data produced with SynthKGQA also allows us to train better models. We apply SynthKGQA to Wikidata to generate GTSQA[2], a new dataset designed to test zero-shot generalization abilities of KG retrievers with respect to unseen graph structures and relation types, and benchmark popular solutions for KG-augmented LLMs on it.

1 Introduction

Despite significant advances over the years, Large Language Models (LLMs) are still unreliable when asked to provide factual information, as hallucinations (LLMs outputting plausible but wrong answers) remain one of the central problems for LLM applications (Huang et al. 2025). The predominant solution to improving LLM trustworthiness is Retrieval Augmented Generation (RAG), where information pertinent to the query is retrieved from a corpus of knowledge and added to the prompt (Borgeaud et al. 2022; Izacard et al. 2023; P. Lewis et al. 2020). While RAG traditionally retrieves information from documents, another important use case is retrieval from graph structured repositories such as Knowledge Graphs (KGs). KGs encode subject-predicate-object facts as labeled directed edges between *entities* in a set $\mathcal{E}$ (the nodes/vertices of the KG), where the edge labels are drawn from a set $\mathcal{R}$ of predicates, or *relation types*. An edge is represented as a triple (h, r, t), with $h, t \in \mathcal{E}$ and $r \in \mathcal{R}$; we denote by $\mathcal{T}$ the set of triples in the KG. KGs are highly efficient solutions to encode *relational* information and are also easier to maintain, update, and fact-check compared to textual documents. KG-augmented LLMs are typically evaluated on Knowledge Graph Question Answering (KGQA), where questions require retrieving a subgraph $\mathcal{G} \subset \mathcal{T}$ and reason over it to produce an answer. In KGQA, we assume that the answer(s) to a question q are entities in a set $\mathcal{A} \subset \mathcal{E}$. We also assume that, together with the question, the set of *seed entities* $\mathcal{S} \subset \mathcal{E}$ is provided, i.e., the set of entities that are explicitly mentioned in the question. Extracting seed entities from natural language questions or text is an orthogonal task referred to as Named Entity Recognition, or Entity Linking, which is in itself an object of research (Alam et al. 2022; Keraghel et al. 2024).

While many KGQA datasets have appeared over the years (see Peng et al. (2024) for a recent survey), little attention has been paid to their quality, reliability and limitations. The concurrent study by L. Zhang et al. (2025) has estimated the degree of factual correctness of the questions in widely-used

[1] https://github.com/graphcore-research/synth-kgqa
[2] https://huggingface.co/datasets/Graphcore/GTSQA

benchmarks, such as WebQSP (Yih et al. 2016), CWQ (Talmor and Berant 2018) and GrailQA (Gu et al. 2021), to be only between 30 and 60%. Moreover, several benchmarks are no longer challenging for SOTA KG-augmented LLMs and are now close to being saturated, limiting their usefulness. Even for datasets like ComplexWebQuestions (CWQ), which also contain multi-hop questions, it is impossible to provide an actual measure of question complexity, due to the lack of *ground-truth answer subgraphs*, the golden targets for retrieval. This means that KG-RAG retrievers cannot be evaluated on their own, but only end-to-end, by looking at the final answer provided by the LLM – which, since different solutions use different LLMs and prompting schemes, results in noisy comparisons. Moreover, for KG retrievers that require training, the ground-truth answer subgraph is indispensable to provide supervision signal: using existing datasets, it has to be approximated with the set of shortest paths from seed entities to answer nodes. As we show in Section 5, this is often a bad approximation, which penalizes the final quality of the retriever. Furthermore, most KGQA benchmarks are from the previous decade and based on the now discontinued Freebase KG (Bollacker et al. 2008), thus containing outdated facts and answers, which prevents a fair comparison of KG-RAG models with modern pure LLMs. Question variety, in terms of KG relation and entity types used for the grounding facts, is also typically limited, as questions are either manually (through crowd-sourcing) or procedurally (through logical query manipulation) generated from predefined query templates, often resulting in unnatural, or ambiguously phrased, natural language questions (see L. Zhang et al. (2025) for a more detailed discussion of limitations and pitfalls).

We propose to tackle all these challenges by leveraging the advanced abilities of frontier LLMs to remove the need for a human in the loop in the creation of KGQA datasets. Our contributions are:

- SynthKGQA, a new framework for generating large synthetic KGQA datasets from any KG, which provides high-quality, diverse questions with procedurally-verified ground-truth answer subgraphs and SPARQL queries, allowing to easily update the dataset whenever the underlying KG is modified;
- *Ground-Truth Subgraphs for Question Answering* (GTSQA), a challenging new dataset with 32,099 questions spanning 27 different structures for the ground-truth answer subgraph, grounded in the regularly-updated Wikidata KG (Vrandečić and Krötzsch 2014), and specifically designed to test generalization abilities of KG-RAG models;
- a comprehensive benchmark of SOTA LLMs and KG-augmented LLMs on GTSQA, providing new insights on retrieval abilities and limitations of different models on different structures for the answer subgraph;
- an extensive analysis of the benefits of using the ground-truth answer subgraph, instead of shortest paths from seed to answer nodes, as supervision signal for training KG retrievers.

2 The SynthKGQA Framework

We outline SynthKGQA, our proposed framework, which can be applied to any KG in order to construct high-quality synthetic data for KGQA (see Appendix E for a comparison with concurrent works Dammu et al. (2025) and L. Zhang et al. (2025), suggesting similar approaches). The data generation pipeline comprises of three steps (more details are provided in Appendix A).

1. **LLM-powered candidate proposal.** Starting from a randomly-sampled (Algorithm 1) connected subgraph $\mathcal{Q} \subset \mathcal{T}$, containing a few tens of edges, the LLM is tasked (through few-shot prompting, see Appendix A.1) to generate:
   - a question q that can be answered with k (number specified in the prompt) triples in $\mathcal{Q}$;
   - the list of triples in $\mathcal{Q}$ required to reason over the question, i.e., the *ground-truth answer subgraph* $\mathcal{G} \subset \mathcal{Q} \subset \mathcal{T}$;
   - the answer to the question, which is required to be an entity $a \in \mathcal{E}$ appearing in $\mathcal{G}$;
   - the list of entities explicitly mentioned in the question, i.e., the seed entities $\mathcal{S} \subset \mathcal{E}$;
   - the SPARQL query l_q which encodes the natural-language question q in logical form.

   Note that we use SPARQL as RDF query language, since the Wikidata Query Service[3] is based on it, but our pipeline can be adapted with minimal changes to use any other query language, if working with knowledge bases that have different querying interfaces.

[3] `https://query.wikidata.org/`

Table 1: Overall view of GTSQA.

	Train	Test	All
# questions	30,477	1622	32,099
# unique relation types	200	362	368
# unique entities	64,435	5665	68,520
# unique graph isomorphisms	19	14	27
# questions with redundant info	7852	0	7852
avg # seed entities	1.65	1.92	1.66
avg # hops	1.48	2.02	1.5
avg # answers	1.54	1.28	1.53
avg # ground-truth edges	2.13	3.03	2.17

2. **Candidate validation.** The query l_q is executed against the KG to retrieve the full set of answers $\mathcal{A}$; the candidate datapoint is discarded if $\mathcal{A}$ does not contain the answer a provided by the LLM. Similarly, it is discarded if any of the triples that the LLM considers necessary for answering the question, or any of the proposed seed entities, are not in the *full answer subgraph*, obtained by running the associated CONSTRUCT SPARQL query (i.e., the union of all triples in the KG realizing the query template, taking into account all valid substitutions of the variables in l_q; more details in Appendix A.4).

3. **Augmentation and classification**. To increase the diversity of the generated data, we ask an LLM to paraphrase q in more natural terms. By using the ground-truth answer subgraph and SPARQL query, we can provide additional information on each valid datapoint.

   - *Graph isomorphism type*: we classify the structure of the graph $\mathcal{G}$ up to isomorphism (see Appendix A.2), as a measure of question complexity. This also allows the user to perform additional filtering, by discarding questions where the answer subgraph does not comply with desired logical requirements (e.g., disconnected graphs; graphs containing loops or hanging branches, not terminating in a seed entity; graphs where the answer node is also used as a seed node, giving rise to self-answering questions).
   - *Redundancy*: we check whether the question contains *redundant* information, i.e., if it can be answered by using only a subset $\mathcal{S}' \subsetneq \mathcal{S}$ of the seed entities (see Appendix A.3).

3 The GTSQA Dataset

Using the SynthKGQA framework and GPT-4.1 (OpenAI 2023) as LLM, we construct *Ground-Truth Subgraphs for Question Answering* (GTSQA), a synthetic KGQA dataset grounded in the Wikidata KG (Vrandečić and Krötzsch 2014), with 30,477 questions in the train set and 1622 questions in the test set. Statistics on the dataset are summarized in Table 1, with more details provided in Appendix B.

GTSQA supports retrieval either from the full Wikidata, or from ogbl-wikikg2 (Hu et al. 2020), which was employed to sample the seed graphs $\mathcal{Q}$. We construct questions where the ground-truth answer subgraph contains at most 6 edges, as we observe that – beyond this point – questions tend to become overly-convoluted and unnatural to formulate in natural language. We also require the ground-truth answer subgraph to be a tree, i.e., connected and acyclic, with all leaves being seed entities or the answer. The dataset covers 27 different isomorphism types for the answer graph, with questions involving up to 5 hops and up to 5 different seed entities. Full statistics on the connectivity patterns of seed and answer nodes, and relative frequencies in the dataset, are provided in Appendices A.2 and B. As shown in Figure B2, approximately 70% of the test questions are multi-seed (two or more seed entities) and 67.9% are multi-hop (with 30.8% requiring $\geq$ 3 hops). This variety of graph types makes GTSQA much more challenging than commonly-used benchmarks for KGQA (only 34.5% of the test questions in WebQSP (Yih et al. 2016) require more than 1 hop, and none require more than 2). Moreover, the test set of GTSQA has the unique property of containing only non-redundant questions, where the full ground-truth answer subgraph is necessary to answer (as defined in Section 2), which ensures that the provided classification of graph isomorphism types is truly reflective of the complexity of the questions.

A notable feature of GTSQA is that the train-test split is designed to test zero-shot generalization abilities of KG retrievers (in a spirit similar to the construction of GrailQA (Gu et al. 2021) and GrailQA++ (Dutt et al. 2023)). Indeed, 47.3% of the answer subgraphs in the test set have as isomorphism type one of 8 classes that are not included in the train set (see Table A1). Moreover, 37.2% of test questions require reasoning over edges whose relation type is not seen in the train set (see Figure B1 for the distribution of relation types). The answer node for all test questions does not appear as an answer in training questions. We also make sure that, for each isomorphism type in the test set, the applicable categories (in-distribution, unseen graph type, unseen relation type) always contain at least 45 different questions, to enable a statistically meaningful study of KG retrievers' performance at this unprecedented granularity level (as we do in Section 4).

We perform a final filtering on the test set of GTSQA to ensure its value and reliability as a benchmark for KG retrievers: we retain only questions that can be answered correctly by an advanced LLM (GPT-4o-mini) when augmenting the prompt with the ground-truth answer subgraph in the dataset, in a consistent way (2 successes out of 2 tries). This is to sanity check that the ground-truth answer subgraph is indeed a valid golden target for retrieval, providing grounding to any insights we extract from the benchmarks. Only 0.47% of the generated data failed this test (and was therefore removed), which confirms the very high quality of the synthetic data produced by SynthKGQA (compared, for instance, to KGQAGen-10k (L. Zhang et al. 2025), where this failure rate is reported at 10.38% with the more capable GPT-4o, and limited explanation is provided for the failure causes).

4 Benchmarks

We benchmark SOTA KG-RAG models on GTSQA. As one of its key features is that it provides ground-truth answer subgraphs for each question, we can evaluate not just the quality of the model answer, but also the quality of the retrieved subgraph, for different graph isomorphism types and generalization abilities required by the question.

Experimental setting We consider a variety of models for QA, divided into four categories (specifications in Appendix C.2). 1) *LLM-only*: as a baseline, we take frontier commercial LLMs without any external augmentation pipelines, such as GPT-4.1, GPT-4o-mini (OpenAI 2023), GPT-5-mini (OpenAI 2025), Ministral-8B-Instruct, Mistral-Large-2.1 (Mistral AI 2024) and LLaMA-3.1-8B-Instruct (AI@Meta 2024). 2) *KG agents*: training-free models using out-of-the-box LLMs to explore the KG starting from the seed entities. They decide on their own, over multiple steps, what neighbors to explore and when to stop. As representatives, we consider Think-on-Graph (ToG; Sun et al. (2024)) and Plan-on-Graph (PoG; Chen et al. (2024)). 3) *Path-based retrievers*: models trained to predict the paths originating from the seed entities and leading to the answer node. Examples are SR (J. Zhang et al. 2022), Reasoning on Graphs (RoG; Luo et al. (2024)) and Graph-Constrained Reasoning (GCR; Luo et al. (2025)). 4) *All-at-once retrievers*: models trained to score all edges in a large neighborhood of the seed entities in a single pass, and then retrieve the most relevant ones. We consider SubgraphRAG (M. Li et al. 2025) as a representative. For all models in categories 2), 3), 4), we use the same LLM (GPT-4o-mini, which – as explained in Section 3 – is able to answer all test questions when provided with the ground-truth answer subgraph) to perform the final reasoning on the retrieved subgraph, in order to make the benchmark as fair as possible and place the focus on the quality of the retrieved subgraph.

We use ogbl-wikikg2 as KG for retrieval, to reduce computational complexity (see also Appendix C.1). As common in KGQA benchmarking (Luo et al. 2024; Sun et al. 2024), we evaluate quality of model responses by reporting on Hits (at least one correct answer predicted) and Recall of correct answers, using Exact Match (EM) between the labels of answer nodes and the model output. Moreover, as made possible by GTSQA, we analyze Recall, Precision and F1 score of ground-truth triples in the subgraph retrieved by the model, in addition to Hits and Recall of answer nodes.

Results A detailed comparison of models is provided in Table 2. Pure LLMs show limited performance on GTSQA with an EM Hits score of at most 33.97, confirming the challenging nature of this new benchmark for models that solely rely on their internal knowledge. Even SOTA KG-RAG models – while performing better than pure LLMs – struggle with the task. Trainable subgraph retrievers outperform KG agents, highlighting the importance of fine-tuning models on the target KG. Among trainable retrievers, SubgraphRAG (with 200 retrieved triples) achieves the

Table 2: Benchmark of LLMs and KG-RAG models on GTSQA.

		EM		Ground-truth triples			Answer nodes		
Category	**Model**	Hits	Recall	Recall	Precision	F1	Hits	Recall	**# triples**
LLM-only	Ministral-8B-Instruct	10.73	10.16	-	-	-	-	-	-
	LLama-3.1-8B-Instruct	17.11	16.33	-	-	-	-	-	-
	GPT-4o-mini	20.90	19.93	-	-	-	-	-	-
	Mistral-Large-2.1	23.61	22.85	-	-	-	-	-	-
	GPT-5-mini	31.44	30.20	-	-	-	-	-	-
	GPT-4.1	33.97	32.83	-	-	-	-	-	-
KG agent	PoG	32.92	31.60	31.95	27.52	27.03	31.81	30.54	7.09
	ToG	45.68	44.47	35.50	6.45	10.50	41.55	40.97	9.17
Path-based	SR	40.63	39.10	30.22	3.44	5.69	50.25	49.39	72.94
	GCR	49.91	48.25	40.71	27.21	29.82	47.11	45.54	6.54
	RoG	57.58	55.78	54.69	24.04	27.00	72.91	71.84	72.31
All-at-once	SubgraphRAG (200)	61.59	58.62	79.09	1.29	2.53	85.33	84.36	199.61

best results, surpassing all path-based retrievers, which tend to retrieve smaller subgraphs. The F1 score of retrieved triples is low ($< 30\%$) across the board, but our results suggest that increasing the recall of ground-truth triples is more beneficial than increasing precision. However, the EM Hits of SubgraphRAG plateaus when increasing the number of retrieved triples further, despite the fact that recall continues to improve (Figure D12), showing that precision cannot be entirely disregarded. Also note that the recall of ground-truth triples is a much stronger predictor of final model accuracy than the recall of answer nodes (Figure D5), proving the value of working with datasets like GTSQA that provide the full ground-truth answer subgraph. Breaking down model performance by graph isomorphism types (Figures D6 and D7), we find that all models, especially ToG and PoG, have very limited accuracy on questions that require intersecting paths from 3 or more seed entities, even if the answer is only one hop away (e.g., isomorphism types (1)(1)(1) and (1)(1)(1)(1)). In this setting, the base LLM on its own also fails consistently. The poor EM is explained by a low recall of ground-truth triples, highlighting a widespread inability to properly expand the search from all seed entities. Indeed, especially for KG agents and path-based methods, the recall of ground-truth triples is on average much lower in multi-seed questions, leading to a worse EM (Figure D8). This is true even if the answer node is often contained in the retrieved subgraph. To our knowledge, this failure mode was not noted in previous benchmarks, due to the lack of well-identified ground-truth triples, or the fact that not all seed entities are necessary to answer the question. This is different from GTSQA, where the answer subgraphs for all test questions have no redundant edges. Results on zero-shot generalization abilities of trainable retrievers (Figures 1 and D8) show smaller improvements over the baseline for questions requiring generalization, compared to in-distribution ones. Path-based retrievers particularly struggle with unseen relation types, while SubgraphRAG maintains strong predictive power. In contrast, the all-at-once retriever underperforms RoG across all unseen graph isomorphism types (Figure D8), with a substantial drop in recall of ground-truth triples (and, consequently, EM). This aligns with intuition: path-based methods learn to predict the sequence of relation types that connect seed entities and answer, ignoring the global structure of the answer subgraph, whereas all-at-once retrievers like SubgraphRAG mostly leverage the graph structure during their training. Additional insights can be found in Appendix D.1.

5 Ground-Truth Subgraphs to Train Better KG Retrievers

In the absence of ground-truth answer subgraphs in the datasets, KG retrievers are typically trained using all shortest paths between seed and answer nodes as supervision signal (M. Li et al. 2025; Luo et al. 2024, 2025; J. Zhang et al. 2022). However, as we show for GTSQA in Appendix D.2, as the number of hops required to answer increases, the shortest paths diverge more and more from the paths in the provided ground-truth subgraphs, and paths of minimal lengths become worse and worse as a *target* for KG-RAG (Figure D10). We investigate whether using shortest paths as supervision signal for *training* subgraph retrievers is equally suboptimal. We consider three retrievers that use path

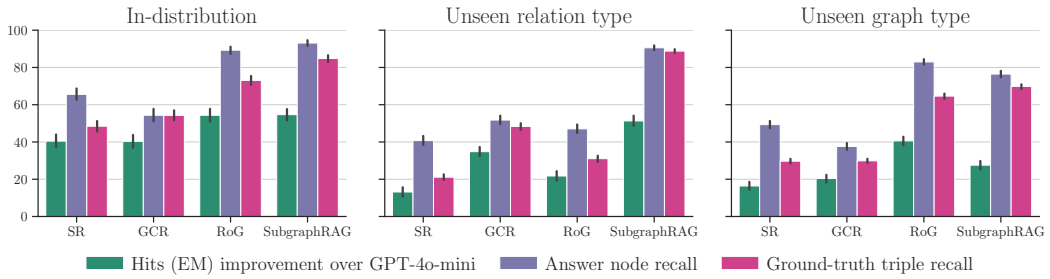

Figure 1: Generalization abilities of trainable KG-RAG models. We measure EM performance in terms of difference with the EM of the baseline (GPT-4o-mini, no RAG).

Table 3: Improvements in predictive statistics of models trained on ground-truth answer subgraphs (GT), compared to models trained on the shortest paths between seed and answer nodes (SP). For all models, results are averaged over three distinct runs for each of the two training regimes.

	Hits (EM)		**Recall (GT triples)**		**Precision (GT triples)**		**Recall (answer nodes)**	
Model	SP	GT	SP	GT	SP	GT	SP	GT
SR	33.95	40.63 (+20%)	23.74	30.22 (+27%)	3.84	3.44 (-10%)	36.36	49.39 (+36%)
RoG	53.08	57.58 (+8%)	46.38	54.69 (+18%)	10.00	24.04 (+141%)	70.68	71.84 (+2%)
SubgraphRAG (200)	58.47	61.59 (+5%)	75.39	79.09 (+5%)	1.21	1.29 (+6%)	80.46	84.36 (+5%)

information for training, namely SR (J. Zhang et al. 2022), RoG (Luo et al. 2024) and SubgraphRAG (M. Li et al. 2025), train them on GTSQA using either the shortest paths or the ground-truth paths between seed and answer nodes as supervision signal, and then compare the performance on the test set. As reported in Table 3, models trained on the ground-truth subgraphs have EM scores from 5% to 20% higher than their counterparts trained on shortest paths, due to improved recall (up to $+27\%$) and precision (up to $+141\%$) of ground-truth triples in the retrieved subgraphs. The improvements are clear for SubgraphRAG (independently on the number of retrieved triples, Figure D12), but even more striking for path-based methods. As shown in Figure D11, RoG is the model where the quality of the retrieved subgraph benefits more from eliminating the noise in the training data, with precision increasing by more than $9\times$ for 4-hops questions. Similarly, SR experiences a major boost in answer node recall (more than $2\times$ for 4-hops questions). While for 1-hop questions the differences in all statistics are negligible, the gap sharply increases for questions requiring multiple hops (where, as we've showed, the shortest paths diverge more appreciably from the ground-truth subgraphs). All this provides definitive evidence on the value of GTSQA not just as a benchmark, but also to train better subgraph retrievers for complex KGQA.

6 Conclusions

In this work, we introduced SynthKGQA, a new framework for constructing large-scale, high-quality synthetic KGQA datasets from arbitrary KGs, with ground-truth answer subgraphs and SPARQL queries for all questions. As concrete application, we released GTSQA, a multi-hop, multi-seed dataset with 30k questions based on Wikidata, designed to test how KG-RAG models generalize to unseen answer graph structures and relation types. Our benchmarks show that SOTA KG-RAG models struggle on GTSQA, due to poor retrieval performance that affects especially questions with multiple seed entities. All-at-once retrievers tend to outperform path-based ones and KG agents, due to their higher recall of triples in ground-truth answer subgraphs. Finally, we show how leveraging the SynthKGQA-generated ground-truth subgraphs as supervision signal for training KG retrievers produces better models, with accuracy improvements of up to 30% for multi-hop questions. We anticipate that SynthKGQA and the KGQA datasets generated through it will help benchmark and improve KG retrievers and, consequently, contribute to the development of more trustworthy LLMs.

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A Additional Details on SynthKGQA

A.1 Data Generation

We provide additional details on how we query the LLM to generate synthetic data in the SynthKGQA framework (step 1 of the pipeline presented in Section 2).

Seed subgraph We first sample a subgraph $\mathcal{Q} \subset \mathcal{T}$ of the KG, which will provide the LLM with the context to generate a question. This is because, in general, asking the LLM to parse the entire KG in its input is unfeasible. Starting from a random entity $s \in \mathcal{E}$, the subgraph $\mathcal{Q}$ is obtained by progressively expanding a neighborhood around s until the desired size (decided by the user – typically 50 to 100 edges) is reached. Since we aim to construct multi-hop questions, it's important to ensure that the radius of $\mathcal{Q}$ grows quickly, even if the total number of edges in $\mathcal{Q}$ is kept contained. This means prioritizing depth over breadth in the expansion, while maintaining high-degrees of connectivity between nodes, to enable a variety of different isomorphism types for the answer subgraph. Our proposed sampling scheme for $\mathcal{Q}$, used in the construction of GTSQA, is shown in Algorithm 1; we denote by $d(x)$ the degree of a node x (number of edges going in/out of it) and by $\mathcal{N}(x)$ its set of neighbors.

Algorithm 1 Sampling scheme for the seed graph $\mathcal{Q}$

Require: KG $\mathcal{T} \subset \mathcal{E} \times \mathcal{R} \times \mathcal{E}$; starting node $s \in \mathcal{E}$; node limit N_{nodes}; edge limit N_{edges}
  $N \leftarrow \{s\}$
  $\mathcal{Q} \leftarrow \emptyset$
  while $|N| < N_{\text{nodes}}$ and $|\mathcal{Q}| < N_{\text{edges}}$ **do**
    $z \leftarrow \text{choice}(N, p = \text{Softmax}([d(x)^{-1} \text{ for } x \in N]))$ ▷ Sample node to expand
    $M \leftarrow \mathcal{N}(z) \setminus N$ ▷ Retrieve new neighbors of z
    if $|M| > 0$ **then**
      $n \leftarrow \text{choice}(M, p = \text{Softmax}([d(x)^{-1} \text{ for } x \in M]))$ ▷ Sample neighbor
      $\mathcal{Q} \leftarrow \mathcal{Q} \cup \{(h, r, t) \in \mathcal{T} \text{ s.t. } h = n, t \in N \text{ or } t = n, h \in N\}$ ▷ Add all connections to n
      $N \leftarrow N \cup \{n\}$
    end if
  end while

LLM querying The sampled subgraph $\mathcal{Q}$ is given to the LLM to generate one KGQA datapoint. In the prompt we specify the number k of triples in $\mathcal{Q}$ that should be used to reason over the question (i.e., the number of triples in the ground-truth answer subgraph $\mathcal{G}$), and show examples in few-shot prompting style. The RDF identifiers in the knowledge base (e.g., QIDs and PIDs when working with Wikidata) should be included in the prompt, together with labels, for all entities and relations appearing in $\mathcal{Q}$, in order to ensure consistency in the generation of the SPARQL query. An example (for $k = 2$) of the prompt used for the construction of GTSQA is shown below.

LLM Prompt ($k = 2$)

```
{ "role": "user", "content": "Based on the provided set of knowledge graph
triples, please generate a question that requires combining the information in
exactly 2 of the provided triples for answering. The answer should correspond to
exactly one node in the provided graph, be unique and not ambiguous. Make sure
that all 2 of the selected triples are required for answering the question and
that they involve multiple different entities. Respond only with
```

- `'Question:' the generated question,`
- `'Nodes mentioned in the question:' a semicolon-separated list of the nodes that are explicitly mentioned in the question,`
- `'Answer:' the node corresponding to the correct answer with its QID,`
- `'Triples used:' a semicolon-separated list of the triples used for answering the question,`
- `'SPARQL query:' a SPARQL query to return all answers of the question from the Wikidata knowledge base.`

```
"},
```

```
{ "role": "user", "content": "Graph: Quiaios (Q1024001)-country (P17)-Portugal
(Q45);Savage Nights (Q174785)-filming location (P915)-Portugal (Q45);Quiaios
(Q1024001)-located in the administrative territorial entity (P131)-Figueira da
Foz (Q428459);Figueira da Foz (Q428459)-country (P17)-Portugal (Q45);Savage
Nights (Q174785)-filming location (P915)-Lisbon (Q597);Portugal (Q45)-capital
(P36)-Lisbon (Q597);Lisbon (Q597)-country (P17)-Portugal (Q45);Lisbon
(Q597)-capital of (P1376)-Portugal (Q45);Francisco José Fernandes Costa
(Q357932)-country of citizenship (P27)-Portugal (Q45);Francisco José Fernandes
Costa (Q357932)-place of death (P20)-Figueira da Foz (Q428459);Francisco José
Fernandes Costa (Q357932)-position held (P39)-Minister of Foreign Affairs
(Q4294919);Minister of Foreign Affairs (Q4294919)-country (P17)-Portugal
(Q45);Minister of Foreign Affairs (Q4294919)-applies to jurisdiction
(P1001)-Portugal (Q45);Francisco José Fernandes Costa (Q357932)-occupation
(P106)-politician (Q82955)
"},
{ "role": "assistant", "content": "
Question: In which country did Francisco José Fernandes Costa die?,
Nodes mentioned in the question: Francisco José Fernandes Costa (Q357932),
Answer: Portugal (Q45),
Triples used: Francisco José Fernandes Costa (Q357932)-place of death
(P20)-Figueira da Foz (Q428459); Figueira da Foz (Q428459)-country (P17)-Portugal
(Q45),
SPARQL query: SELECT ?answer WHERE {wd:Q357932 wdt:P20 ?place. ?place wdt:P17
?answer.}
"},
[...][**OMITTED - examples with different graph isomorphism types**]
{"role": "user", "content": "Graph: {Q}"},
```

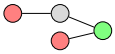
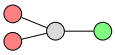
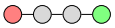
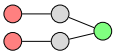
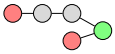
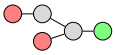
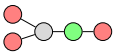
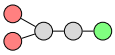
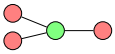
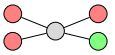
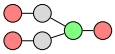
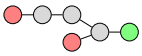
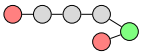
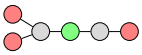
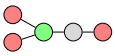
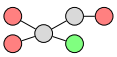
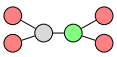
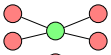
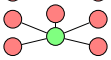
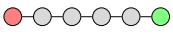
A.2 Graph Isomorphisms

We use the notion of *graph isomorphism*, applied to the ground-truth answer subgraph, to provide a simple and objective measure of the complexity of a question in a KGQA dataset. This measure abstracts away the identity of the entities and relation types involved in the answer subgraph and only focuses on the number of seed entities, the number of hops separating them from the answer node and how the paths originating from each seed intersect. In the context of KGQA, this notion first appeared as reasoning paths (Das et al. 2022) and semantic structures (M. Li and Ji 2022), and was then formulated in the same way that we will use it in Dutt et al. (2023) for the construction of GrailQA++.

We say that two questions have the same graph isomorphism type if their ground-truth answer subgraphs are isomorphic as labeled graphs, when each node in the subgraph $\mathcal{G}$ is labeled as "seed" (for seed nodes), "answer" (for the answer node) or "intermediate" (for intermediate nodes). This means that there exists a bijection of the sets of vertices of the two graphs that preserves both edges and labels. Note that, while KGs are directed graphs, when computing isomorphism types we consider the answer subgraph as undirected, as the direction of an edge should not play a role in how it is used for RAG tasks (and, ideally, it should not impact its likelihood to be retrieved by a subgraph retriever).

To provide identifiers for the different graph isomorphism types, the notation based on projections and intersections that is sometimes used in KG reasoning papers (e.g., in Das et al. (2022)) is unfortunately not able to describe more complex graph types without ambiguities. Since, as a data quality requirement, we only consider queries where the answer subgraph is a tree, we adopt a simplified/more readable version of the tree encoding scheme classically used in the AHU algorithm (Aho and Hopcroft 1974). The answer subgraph is seen as a tree rooted in the answer node, while seed entities are the leaves of the tree. For each leaf, we write (n) if n is the distance of the leaf from its closest branching point (this represents a projection of length n from the seed node). The intersection of paths from multiple seeds at a branching point is denoted by juxtaposition, e.g. $(n)(m)$. Further projections after an intersection point are represented using an additional level of brackets, e.g. $(k(n)(m))$, with k the length of the projection (which can be omitted if $k = 1$). See Table A1 for notations and graphical representations of all the graph isomorphism types appearing in GTSQA.

Table A1: Isomorphism types of ground-truth answer subgraphs in GTSQA and their frequencies in the train and test split. In the graph visualisations, seed nodes are represented in red, while the answer node is marked in green. For the test set, we count separately questions where the answer subgraph is of an isomorphism type not present in the train set (unseen graph type, ugt), questions involving relation types not appearing in the train set (unseen relation type, urt) and questions where the answer subgraph is in-distribution with the train set (id). Percentages are based on the total sizes of the train and test set, respectively.

Identifier	Visualisation	Dutt et al. (2023)	Train		Test (ugt)		Test (urt)		Test (id)	
			count	%	count	%	count	%	count	%
(1)		Iso-0	7658	25.1	0	0	100	6.17	50	3.08
(2)		Iso-1	8338	27.4	0	0	100	6.17	50	3.08
(1)(1)		Iso-2	4481	14.7	0	0	100	6.17	50	3.08
(2)(1)		Iso-3	1470	4.82	0	0	77	4.75	50	3.08
((1)(1))		Iso-4	0	0	125	7.71	0	0	0	0
(3)		Iso-5	1731	5.68	0	0	130	8.01	50	3.08
(2)(2)		Iso-6	0	0	139	8.57	0	0	0	0
(3)(1)		Iso-7	0	0	150	9.25	0	0	0	0
((2)(1))		Iso-8	0	0	65	4.01	0	0	0	0
((1)(1))(1)		Iso-9	0	0	60	3.7	0	0	0	0
(2(1)(1))		Iso-10	0	0	55	3.39	0	0	0	0
(1)(1)(1)		Iso-11	5526	18.1	0	0	48	2.96	50	3.08
((1)(1)(1))		Iso-12	144	0.47	0	0	0	0	0	0
(2)(2)(1)		Iso-13	24	0.08	0	0	0	0	0	0
((3)(1))		Iso-14	1	0	0	0	0	0	0	0
(4)(1)		Iso-15	15	0.05	0	0	0	0	0	0
(4)		Iso-16	0	0	50	3.08	0	0	0	0
((1)(1))(2)		Iso-17	10	0.03	0	0	0	0	0	0
(2)(1)(1)		Iso-18	907	2.98	0	0	0	0	0	0
((2)(1)(1))		Iso-19	3	0.01	0	0	0	0	0	0
((1)(1))(1)(1)		Iso-22	27	0.09	0	0	0	0	0	0
((2)(1))(1)		Iso-23	5	0.02	0	0	0	0	0	0
((1)(1)(1))(1)		Iso-25	18	0.06	0	0	0	0	0	0
((1)(1)(1))(2)		Iso-26	1	0	0	0	0	0	0	0
(1)(1)(1)(1)		N/A	0	0	123	7.58	0	0	0	0
(1)(1)(1)(1)(1)		N/A	111	0.36	0	0	0	0	0	0
(5)		N/A	7	0.02	0	0	0	0	0	0

A.3 Redundancy

As explained in Section 2 (step 2), when filtering the generated data we check that all seed entities identified by the LLM are used in the SPARQL query. This, however, does not guarantee that all of them are strictly necessary to answer the question, i.e., impose additional constraints compared to the other seeds. A question q contains *redundant* information, if there exists a subset $\mathcal{S}' \subsetneq \mathcal{S}$ such that the SPARQL query $l_{q,\mathcal{S}'}$ corresponding to the subtree $\mathcal{G}_{\mathcal{S}'} \subset \mathcal{G}$ composed by the paths from the seeds in $\mathcal{S}'$ to the answer node a returns the same set of answers $\mathcal{A}$ as the original query l_q (while, in general, we expect the set of answers of $l_{q,\mathcal{S}'}$ to be a superset of $\mathcal{A}$). In the case of redundant information, we identify the smallest such $\mathcal{S}'$ (there can be more than one) and classify the isomorphism class of $\mathcal{G}_{\mathcal{S}'}$, which should be considered as the "minimal" subgraph(s) sufficient to answer the question. Note that questions with redundant information are still perfectly valid, as all seed entities are mentioned in the question and the information they imply should be retrieved from the KG; however, they present "shortcuts" to the answer that effectively reduce the question complexity, compared to what is measured by the isomorphism type of the ground-truth answer subgraph.

For example, the question "Which musical instrument is played by both Yehonatan Geffen's child and Francis Lickerish?" has two seed entities $\mathcal{S} = \{$ *Yehonatan Geffen (Q2911403)*, *Francis Lickerish (Q3720616)* $\}$, and SPARQL query

```
SELECT ?answer WHERE { wd:Q2911403 wdt:P40 ?child. ?child wdt:P1303
?answer. wd:Q3720616 wdt:P1303 ?answer. }
```

which has a unique answer in Wikidata, namely *guitar*. The ground-truth answer subgraph contains three edges, (Yehonatan Geffen; child; Aviv Geffen), (Aviv Geffen; instrument; guitar), (Francis Lickerish; instrument; guitar), with isomorphism type (2)(1). The SPARQL query decomposes as intersection of two projections, originating from the seed entities. We can look at them separately.

- For seed node *Yehonatan Geffen*, the 2-hop path connecting it to the answer node is encoded by the query `SELECT ?answer WHERE { wd:Q2911403 wdt:P40 ?child. ?child wdt:P1303 ?answer. }`, which returns three different answers: *guitar*, *piano*, *voice*.
- For seed node *Francis Lickerish*, the 1-hop path connecting it to the answer node is encoded by the query `SELECT ?answer WHERE { wd:Q3720616 wdt:P1303 ?answer. }`, which returns a single answer, *guitar*.

Therefore, this question contains redundant information, as it can be satisfyingly answered using just the seed entity *Francis Lickerish* (while using the other seed entity alone is not sufficient). The minimal answer subgraph is $\{$(Francis Lickerish; instrument; guitar)$\}$, with isomorphism type (1).

A.4 Example

We display, for exemplificative purposes, one datapoint from the train set of GTSQA, generated from Wikidata with the SynthKGQA framework.

Example


```
"id": 40513,
"question": "Who directed the Italian film, originally in French, that is
based on 'The Vicomte of Bragelonne: Ten Years Later'?",
"paraphrased_question": "Who was the director of the Italian film, originally
in French, inspired by 'The Vicomte of Bragelonne: Ten Years Later'?",
"seed_entities": ["Italy (Q38)", "French (Q150)", "The Vicomte of Bragelonne:
Ten Years Later (Q769001)"],
"answer_node": "Fernando Cerchio (Q503508)",
"answer_subgraph": [["Le Vicomte de Bragelonne (Q3228085)", "country of origin
(P495)", "Italy (Q38)"], ["Le Vicomte de Bragelonne (Q3228085)", "original
language of film or TV show (P364)", "French (Q150)"], ["Le Vicomte de
Bragelonne (Q3228085)", "based on (P144)", "The Vicomte of Bragelonne: Ten
```

Years Later (Q769001)"], ["Le Vicomte de Bragelonne (Q3228085)", "director (P57)", "Fernando Cerchio (Q503508)"]],

"sparql_query": "SELECT ?answer WHERE { ?film wdt:P495 wd:Q38; wdt:P364 wd:Q150; wdt:P144 wd:Q769001; wdt:P57 ?answer.}",

"all_answers_wikidata": ["Q503508", "Q679016"],

"full_answer_subgraph_wikidata": [["Q2260875", "P495", "Q38"], ["Q2260875", "P364", "Q150"], ["Q2260875", "P144", "Q769001"], ["Q226087", "P57", "Q679016"], ["Q322808", "P495", "Q38"], ["Q3228085", "P364", "Q150"], ["Q3228085", "P144", "Q769001"], ["Q3228085", "P57", "Q503508"]],

"all_answers_wikikg2": ["Q503508"],

"full_answer_subgraph_wikikg2": [["Q3228085", "P364", "Q150"], ["Q3228085", "P57", "Q503508"], ["Q3228085", "P144", "Q769001"], ["Q3228085", "P495", "Q38"]],

"n_hops": 2,

"graph_isomorphism": "((1)(1)(1))",

"redundant": True,

"minimal_graph_isomorphism": "((1)(1))",

"minimal_seeds_and_queries": {"Q150-Q769001": "SELECT ?answer WHERE { ?a wdt:P364 wd:Q150. ?a wdt:P57 ?answer. ?a wdt:P144 wd:Q769001.}"}

"test_type": [],

Note that `answer_node` and `answer_subgraph` are, respectively, the answer node $a \in \mathcal{E}$ and ground-truth answer subgraph $\mathcal{G} \subset \mathcal{T}$ generated by the LLM together with the question. The `sparql_query` is then executed on Wikidata and WikiKG2 to retrieve all answers in the KGs (`all_answers_wikidata`; `all_answers_wikikg2`) and, after converting it to CONSTRUCT form, the full answer subgraphs realizing the query (`full_answer_subgraph_wikidata`; `full_answer_subgraph_wikikg2`). For the example above, we find that Wikidata (but not WikiKG2) contains one more acceptable answer (Henri Decoin, Q679016), due to the existence in the KG of a second movie satisfying all requirements in the question (Le Masque de fer, Q2260875); as a consequence, `full_answer_subgraph_wikidata` contains four more edges compared to $\mathcal{G}$, arising from these extra valid substitutions for the `?film` and `?answer` variables. Note that we only consider the answer graph $\mathcal{G}$ when computing the `graph_isomorphism`, as that encodes the logical steps required to reason over the question. However, the full answer subgraph should be used as target to evaluate the performance of KG retrievers.

`n_hops` measures the maximum distance (in $\mathcal{G}$) between a seed entity and the `answer_node`; it is determined in a unique way by `graph_isomorphism`. The question in the example contains redundant information (`redundant`); in the `minimal_seeds_and_queries` dictionary we provide the minimal set(s) $\mathcal{S}'$ of seed entities and the respective SPARQL queries $l_{q,\mathcal{S}'}$, as explained in Appendix A.3. The graph isomorphism of the minimal $\mathcal{G}_{\mathcal{S}'}$ can be found in `minimal_graph_isomorphism`. Finally, the attribute `test_type` is only used for questions in the test split of GTSQA, to classify their generalization type (in-distribution, unseen graph type, unseen relation type; see Section 3).

B Statistics of GTSQA

We use ogbl-wikikg2 (Hu et al. 2020) as the base KG to construct GTSQA. This is a graph extracted from a 2015 Wikidata dump, containing a curated set of 2.5M nodes and 535 relation types, that we find are good candidates for the construction of natural-sounding questions. As part of the validation and filtering pipeline, by leveraging the generated SPARQL queries, we reject datapoints where any of the edges in the ogbl-wikikg2 ground-truth answer subgraph encode stale facts, i.e., edges that are not contained in the most up to date version of Wikidata[4]. In the future, the dataset can be easily kept up to date by repeating the filtering process against more recent dumps, or by replacing stale ground-truth subgraphs with the current ones, as retrieved from Wikidata via the provided SPARQL queries.

[4]At the time of dataset construction: `https://dumps.wikimedia.org/wikidatawiki/20250720/`

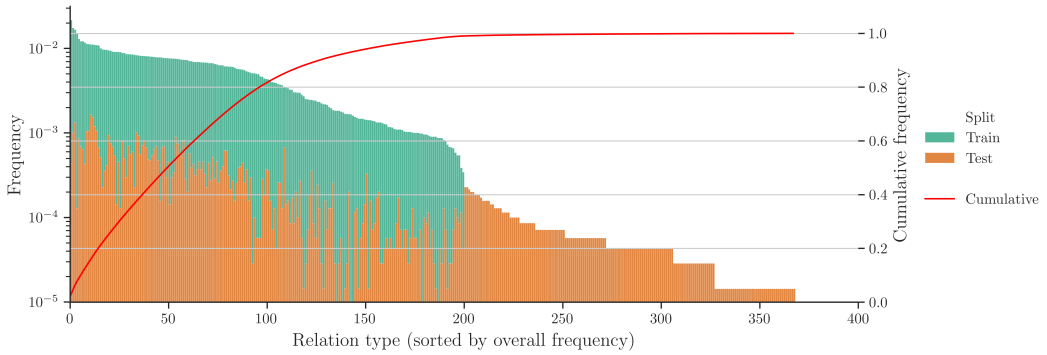


Figure B1: Frequency of relation types of edges in the ground-truth answer subgraph, for questions in GTSQA. The 168 least-occurring relation types (tail of the distribution) are reserved for questions in the test set, to test zero-shot generalization abilities of KG retriever models.

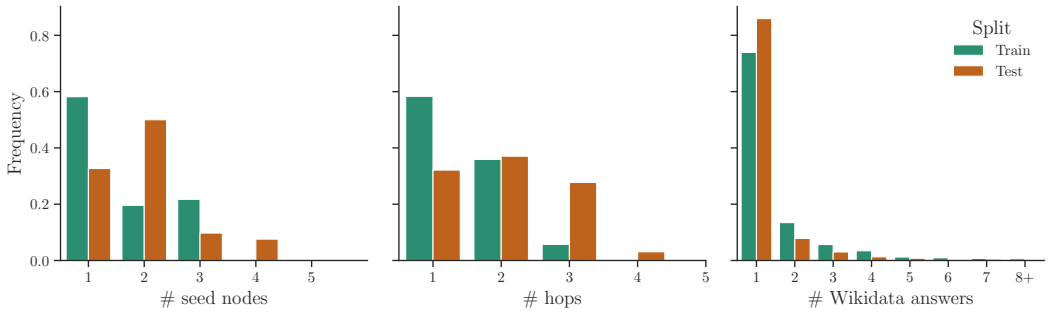


Figure B2: Statistics on the number of seed entities (*left*), the number of answer entities in Wikidata (*right*), and the maximum number of hops from seed to answer nodes along ground-truth paths (*center*), for questions in the train and test set of GTSQA.

An overall view of the statistics of GTSQA is provided in Table 1. The questions in the dataset involve 68,520 unique entities, drawn from ogbl-wikikg2. The distribution of relation types is shown in more detail in Figure B1: out of the 368 unique relation types used in the dataset, only the top-200 (when sorting by overall frequency) appear in the train set, while the remaining ones are reserved for testing.

Figure B2 shows the distribution of the number of seed entities, answers and hops (in the ground-truth answer subgraph). Questions in the test set are significantly harder, requiring to perform more hops, or to combine reasoning chains from multiple seed entities. Our data-filtering pipeline focuses on selecting highly-factual and non-ambiguous questions, as a consequence 73.9% and 85.9% of questions in the train and test set, respectively, have a single answer in Wikidata, and only a negligible fraction have more than five.

We also compare the size of the ground-truth answer subgraph and the full answer subgraph retrieved from Wikidata by submitting the SPARQL query in CONSTRUCT form. As recalled in Appendix A.4, the full subgraph may contain additional edges, originating from the presence of multiple answers and/or multiple choices for the intermediate entities not specified in the query. In practice, as shown in Figure B3, for GTSQA this excess in the number of edges remains always limited (only in 28.4% and 15.5% of train and test questions, respectively, the two graphs do not coincide).

Finally, we report on statistics on redundant information in the train set of GTSQA (as stressed in Section 3, no redundancy is present in test questions). We find that 25.76% of training questions contain some degree of redundancy; Figure D11 shows the distributions of graph isomorphism types for the ground-truth answer subgraph $\mathcal{G}$ and the minimal subgraph $\mathcal{G}_{\mathcal{S}'}$ (see Appendix A.3).

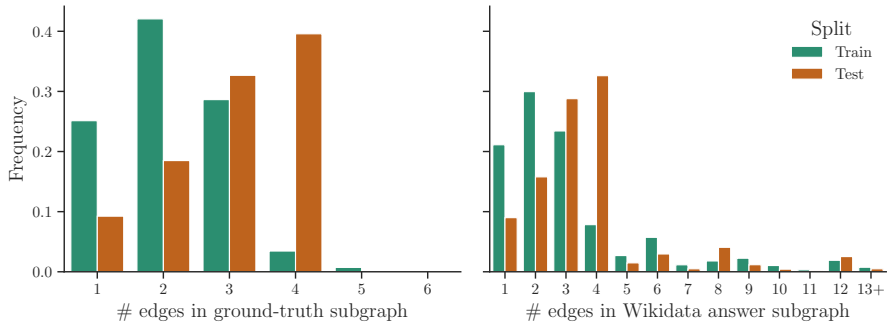


Figure B3: Statistics on the number of edges in the ground-truth answer subgraph (*left*) and the full answer subgraph in Wikidata (*right*), for questions in the train and test set of GTSQA. The full answer subgraph can contain more edges than the ground-truth subgraph, if the question has multiple answers, or if any of the intermediate nodes is not uniquely determined.

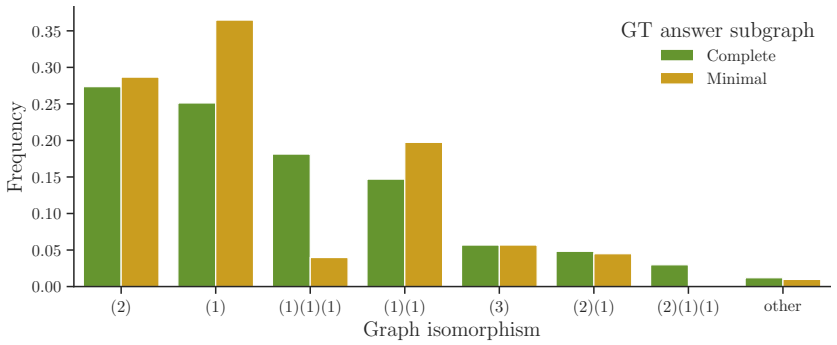


Figure B4: Frequency of main graph isomorphism types in the train set of GTSQA, distinguishing between the complete ground-truth answer subgraph $\mathcal{G}$, and the minimal graph $\mathcal{G}_{\mathcal{S}'}$, obtained from the complete one after discarding redundant information.

C Additional Details on Experiments

C.1 Construction of Question-Specific Graphs

An often-overlooked fact in KGQA benchmarks is that many state-of-the-art KG retrievers, especially those that need to perform breadth/depth-first exploration of the KG from the seed entities (e.g., Luo et al. (2024), Luo et al. (2025)) or that include Graph Neural Networks in their architectures (e.g., Mavromatis and Karypis (2025), M. Li et al. (2025)), are too expensive to run on KGs that have more than 100,000 edges. This limitation, in practice, is tackled by restricting the retrieval to a smaller subgraph of the KG, which is independently sampled for each question. This can be done, for instance, by starting from the full k-hop neighborhood of the seed entities in the KG, and then pruning it down to a few tens of thousands of edges (at most) using algorithms like Personalized PageRank (Page et al. 1998). This was the case for Luo et al. (2024), where such question-specific graphs were constructed (with $k = 2$) from Freebase (Bollacker et al. 2008) for the questions in WebQSP (Yih et al. 2016) and CWQ (Talmor and Berant 2018); they were then used by others in following papers for benchmarking new models on these two widely-used datasets. They are not, however, part of the official datasets, hence there is no guarantee on their adoption. It is important to note, in fact, that the selection of these starting graphs can strongly impact the final performance statistics, potentially over-representing (if they are too easy/small) or under-representing (if they are not checked to still contain ground-truth paths) the retriever's capabilities. For this reason, retrievers that are benchmarked on different sets of questions-specific graphs should not be directly compared (even though the test questions, and the underlying full KG, are the same), and care should be taken when comparing them with models that instead are able to perform retrieval from the full KG (e.g.,

Sun et al. (2024)). However, this crucial detail on experimental setup is often not reported in papers, making comparisons unreliable.

To address this problem, together with GTSQA we release[5] an official set of question-specific graphs (each containing up to 30,000 edges) for all questions in the train and test set. These are the only graphs that should be used by anyone wishing to train or benchmark KG-RAG models on GTSQA when retrieving from the full KG is not possible, to ensure fair comparisons. They are extracted from ogbl-wikikg2 with a similar approach to Luo et al. (2024), starting from the full undirected 3-hop (4-hop for questions requiring 4 hops) neighborhood of seed entities, and then pruning it down to the edges connecting the nodes with the top-2500 scores as assigned by Personalized PageRank (with personalization values concentrated in the seed nodes). If any of the edges in the (full) ground-truth answer subgraph of the question have been dropped as a result of pruning, they are re-added to the graph to guarantee that perfect retrieval is still possible. However, we observe empirically that this final step can unfairly bias retrievers towards the ground-truth edges that have been re-added. To ensure a challenging task, we also add to the graph (as confounders) all edges along paths originating from the seed nodes, of the same metapath (sequence of relation types) as the corresponding ground-truth paths that lead to the answer node.

C.2 Specifications of Evaluated Models

We provide details and specifications on the KG-RAG models included in our benchmarks. For all of them, we follow original implementations as close as possible.

Think-on-Graph (Sun et al. 2024), Plan-on-Graph (Chen et al. 2024) We modified the original codebases (with the PoG one being based on the one from ToG) to perform retrieval from the ogbl-wikikg2 KG. The search and prune steps of the KG exploration algorithm use a width of 5 and a maximum depth of 4 to enable the retrieval of all paths in the ground-truth answer subgraphs of multi-seed, multi-hop questions in the test set of GTSQA. Note that ToG, by its original implementation, reverts to answering using only the LLM knowledge if the maximum search depth is reached without the model being confident it has retrieved enough information; in this case, we treat the retrieved subgraph as being empty. The LLM performing the graph exploration (and task decomposition and memory updating for PoG) is the same used for the final reasoning, namely GPT-4o-mini.

SR (J. Zhang et al. 2022) As in the original implementation, we use $\text{RoBERTa}_{\text{BASE}}$ (Liu et al. 2019) to predict the next relation type $r_N \in \mathcal{R} \cup \{\text{END}\}$ in a path $(r_1, \ldots, r_{N-1})$ from seed to answer node, conditioning on the question q. This is performed by fine-tuning the text-encoder to align the embeddings of $[q; r_1; \ldots; r_{N-1}]$ and r_N, with a contrastive approach that uses positive and negative pairs constructed from ground-truth paths (from seed to answer) in the train set. At inference time, paths are predicted by conducting a beam search based on possible continuation candidates; we impose a maximum path length of 4 and set the number of beams to 5. The subgraph is retrieved by looking for all possible realizations of the predicted relation paths in the KG starting from the seed entities. Note that, while the original implementation used a Neural State Machine (He et al. 2021) to perform the final reasoning on the retrieved subgraph, we instead use an LLM, to align the last step of the pipeline with the other KG-RAG models evaluated in the paper.

Reasoning-on-Graph (Luo et al. 2024) As in the original paper, we fine-tune LLama-2-Chat-7B (Touvron et al. 2023) to auto-regressively predict the relation paths $(r_1, \ldots, r_N)$, originating from the seed nodes, that should be useful to answer a question q. We use all ground-truth paths for the questions in the train set as fine-tuning data. At inference time we ask the LLM to propose relation paths using beam search (5 beams) which are then used to retrieve the subgraph via breadth-first search. We adopt the plug-and-play version of RoG, which allows us to use a different LLM (GPT-4o-mini) to perform the final reasoning on the retrieved triples.

Graph-Constrained Reasoning (Luo et al. 2025) While RoG can hallucinate non-existing relation paths, the follow-up work GCR constraints the path decoding to actual paths in the KG. However, this comes at significant costs in terms of overhead, as it requires to first index in a KG-Trie all paths (up to a fixed length) originating from the seed entities, retrieved via depth-first transversal of the graph. We

[5] `https://huggingface.co/datasets/Graphcore/GTSQA`

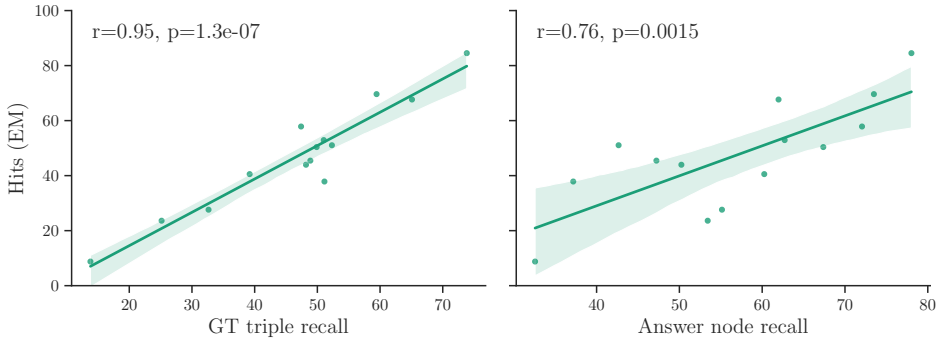


Figure D5: Correlation between Hits (EM) and recall of ground-truth triples (*left*) and of answer nodes (*right*), for questions in the test set of GTSQA. We display the Pearson correlation coefficient and related p-value; each dot represents the average performance of the evaluated KG-RAG models on a different graph isomorphism type. While both recall variables have a positive linear correlation with predictive performance, recall of ground-truth triples is a significantly stronger predictor.

find that, even when working with the smaller question-specific graphs from Appendix C.1, building such index for paths of length > 2 requires an unpractical amount of time, which strongly limits the applicability of the method to real-world scenarios where the index needs to be built on-the-fly (as it happens for questions that have not been seen before). For this reason, we test GCR with a maximum path length of 2 (which is also the default for experiments in Luo et al. (2025)), despite being aware that a significant fraction of questions in GTSQA require reasoning over longer paths. While we still include GCR in the benchmark of GTSQA, these limitations lead us to exclude GCR from the case-study in Section 5. As in the original implementation, we use LLama-3.1-8B-Instruct (AI@Meta 2024) as LLM to generate paths, and fine-tune it with the same data used for RoG. We generate 10 explicit paths form the seed entities through graph-constraint decoding, and then discard duplicated paths to obtain the final retrieved subgraph.

SubgraphRAG (M. Li et al. 2025) SubgraphRAG assigns relevance scores to all edges in the question-specific graphs (Appendix C.1), by combining text embeddings with message passing. In particular, $p((h, r, t)|q) \propto \text{MLP}([z_q; z_h; z_r; z_t; z_\tau])$, where z_q, z_h, z_r, z_t are text embeddings from gte-large-en-v1.5 (Z. Li et al. 2023) for the question q and the labels of h, r, t. The embedding z_τ is constructed from the GNN embeddings of the h and t nodes, after 2 layers of message passing starting from the one-hot representation of nodes in the graph provided by the labeling trick (**1** if the node is a seed entity, **0** otherwise; M. Zhang et al. (2021)). We train GNN and MLP with cross-entropy loss to assign high scores to the triples in the ground-truth answer subgraphs, on the train split of GTSQA. At inference time, we retrieve the subgraph made of the triples with top-200 scores, similarly to the experiments in M. Li et al. (2025) (after checking that performance starts to plateau when increasing the size further, Figure D12).

D Additional Results

D.1 GTSQA Benchmarks

Figures D6 and D7 present a comparison of the evaluated KG-RAG models on GTSQA, for Hits (EM) and recall of ground-truth triples, respectively. For trainable models, we also show the results disaggregated by generalization type of the test question in Figure D8.

Comparing the two KG agents, ToG and PoG, we observe that the latter performs better (or on par) for single-hop questions, but widely worse on multi-hop questions, even on simpler graph isomorphism types that involve a single seed entity (e.g., (2) and (3)). This is due, as shown in Figure D7, to a reduced recall of ground-truth triples. An empirical inspection of the retrieved subgraphs indicates that PoG often tends to prematurely stop the exploration of the KG, over-confidently (and incorrectly, in most cases) believing it has retrieved enough information to answer.

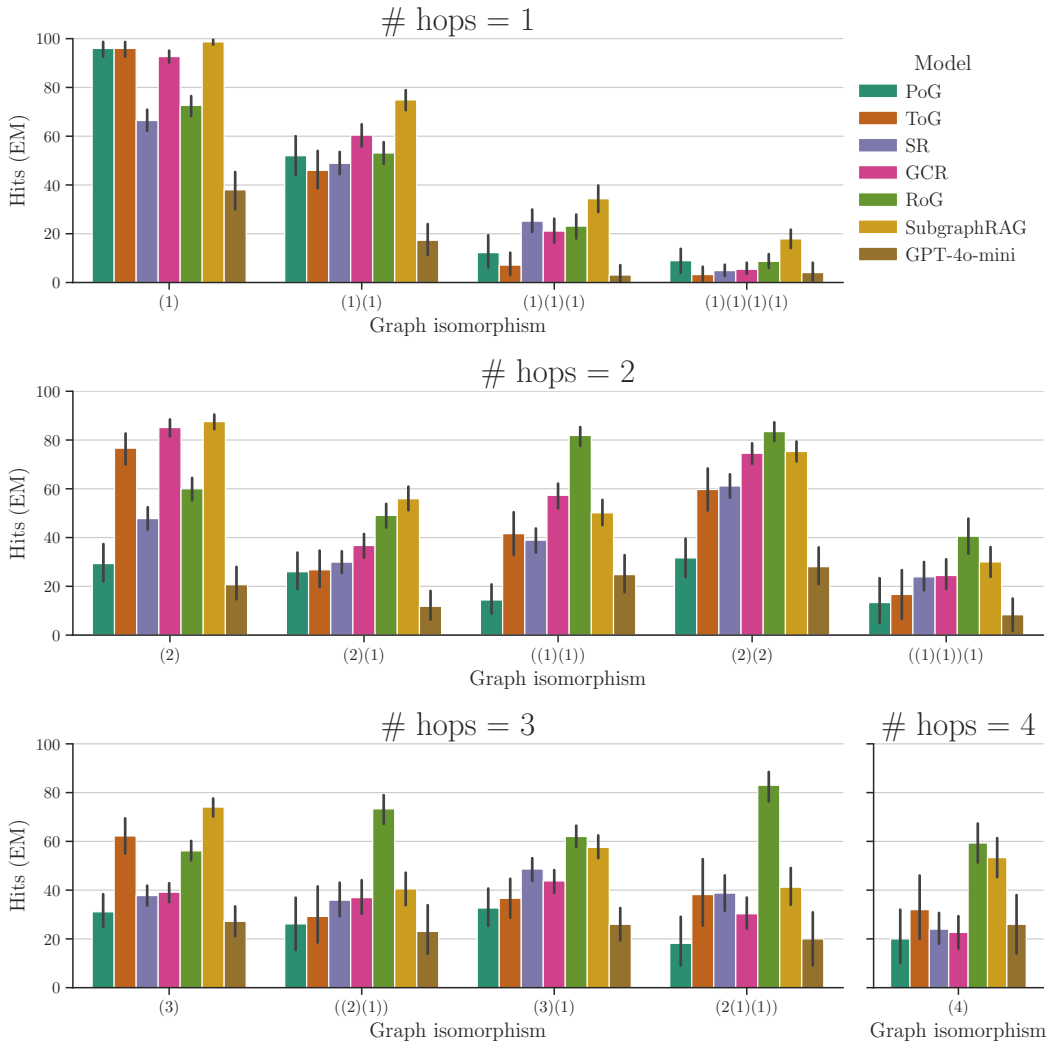


Figure D6: Hits (EM) of KG-RAG models on different graph isomorphism types, compared to the baseline (GPT-4o-mini, no RAG). Isomorphism types are grouped by the maximum number of hops; inside each subplot, moving from left to right corresponds to an increase in the total number of edges in the ground-truth answer subgraph.

We point out the limited performance of GCR (compared, in particular, to its predecessor RoG) across all graph isomorphism types requiring more than 2 hops from the seed entities, which should mostly be attributed to the implementation restrictions and choices explained in Appendix C.2. Indeed, for these questions we observe the peculiar property that answer node recall drops much more than ground-truth triple recall (Figure D8), because only partial paths from the seed entities (up to 2 hops) can be retrieved. However, it is interesting to observe how GCR also performs worse than RoG on some questions with only 2 hops required, e.g., isomorphism types ((1)(1)) and (2)(1). On the other hand, GCR appears much more robust than RoG when generalizing to unseen relation types, as its path predictions are grounded in the KG and hence less dependent on the relation types seen during training.

D.2 Shortest Paths vs Ground-Truth Paths

Path overlap There is no guarantee that the paths of minimal length connecting seed nodes to answer nodes are the correct paths required to answer the question. For example, the question "What

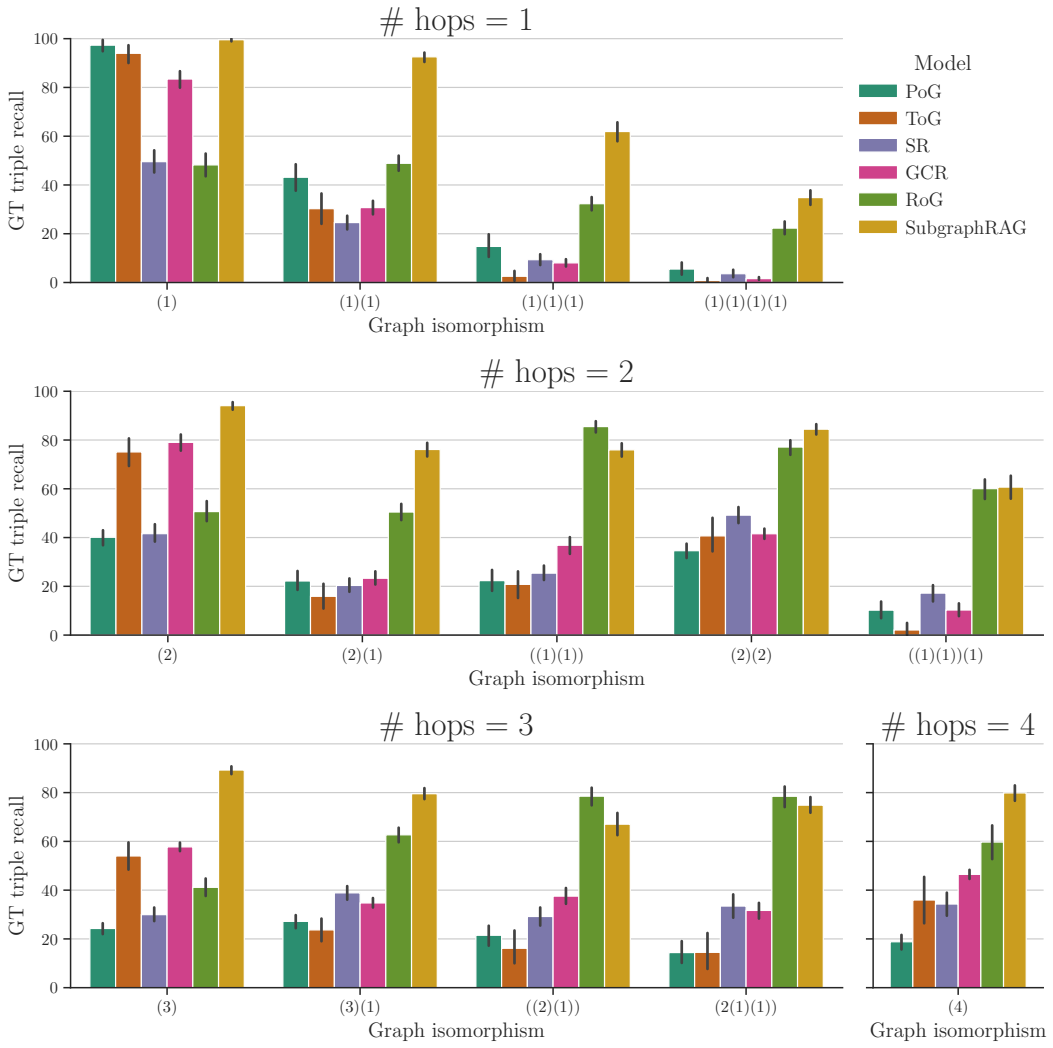


Figure D7: Recall of triples in ground-truth answer subgraph, for KG-RAG models on different graph isomorphism types.

is the canonization status of Gregory the Illuminator's grandchild?" requires retrieving the 3-hop path *Gregory the Illuminator* → *child* → *St. Vrtanes I* → *child* → *St. Husik I* → *canonization status* → *saint*. However, in Wikidata, the shortest path connecting the seed node (*Gregory the Illuminator*) to the answer node (*saint*) consists of a single edge: *Gregory the Illuminator* → *canonization status* → *saint*, which does not provide the correct reasoning. We refer to similar cases, where the minimal length of paths between seed and answer node is strictly smaller than the length of the ground-truth path, as *shortcuts*. A second source of problems arises from *parallel* (shortest) *paths*: as the distance between the seed and answer node increases, the number of distinct paths of minimal length connecting them is expected to grow exponentially, but only one of them (or none, if there are shortcuts) is a ground-truth path. We provide statistics on the occurrence of shortcuts and parallel paths in GTSQA in Figure D9; their combined effect, as documented in Table D2, strongly reduces the overlap between ground-truth and shortest paths for questions requiring multiple hops (for 4-hop questions, on average, only 13% of the triples along shortest paths are contained in the ground-truth answer subgraph and more than 72% of the ground-truth triples do not lie on paths of minimal length).

RAG with shortest paths Following shortcuts or parallel paths, rather than the ground-truth path that we provide in the dataset, not always has to lead to a degradation in the quality of the final

Figure D8: Detailed analysis of generalization abilities of trainable KG-RAG models, on different graph isomorphism types. We measure EM performance in terms of difference with the EM of the baseline (GPT-4o-mini, no RAG).

Table D2: Overlap of triples in ground-truth (GT) answer subgraph and triples on shortest paths (SP) between seed nodes and answer nodes. Questions are grouped by the maximum number of hops in the ground-truth subgraph (# hops); the other columns report the average metric values.

# hops	% GT triples in SP	% SP triples in GT	# GT triples	# SP triples
1	100.0	91.0	2.37	2.67
2	89.8	52.7	3.08	19.6
3	54.7	29.6	3.6	46.3
4	27.5	13.3	4	100.4

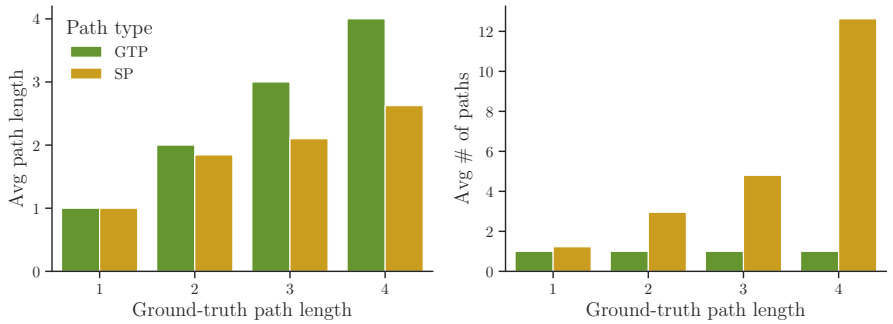


Figure D9: Comparison of ground-truth paths (GTP) and shortest paths (SP) connecting a question seed node to the answer node, in the train split of GTSQA. *Left:* for questions where the ground-truth paths require multiple hops, the distance from the seed node to the answer node along the shortest path increases sub-linearly (shortcuts). *Right:* as the distance between seed and answer node increases, the number of parallel paths of minimal length between them grows exponentially.

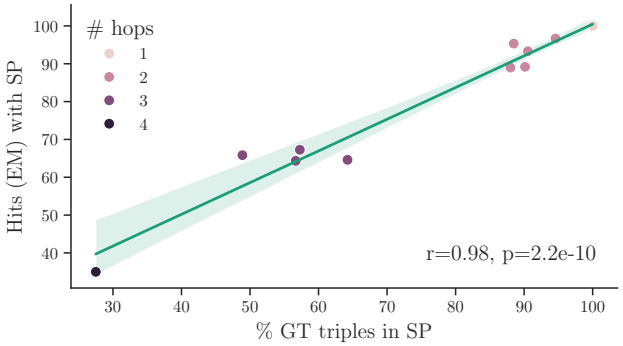


Figure D10: Correlation between the percentage of ground-truth (GT) triples contained in the set of shortest paths (SP) from seed to answer nodes, and EM Hits of GPT-4o-mini when augmented with all SP triples. Each dot represents a different isomorphism type of ground-truth answer subgraph in the test set of GTSQA: they are clearly clustered based on the (maximum) number of hops. Note that we already adjust for any spurious effects of the number of hops on EM, since GPT-4o-mini is able to answer all questions correctly when augmented with GT triples.

answer of the LLM. For instance the question "Which country is home to the administrative region that includes Nieuw-Weerdinge?", which comes with the 2-hop ground-truth path *Nieuw-Weerdinge* $\rightarrow$ *located in the administrative territorial entity* $\rightarrow$ *Emmen* $\rightarrow$ *country* $\rightarrow$ *Netherlands*, can be answered equally well with the shortcut *Nieuw-Weerdinge* $\rightarrow$ *country* $\rightarrow$ *Netherlands*. Similarly, Wikidata contains pairs of inverse relation types (e.g., *child* and *father*) that can give rise to parallel (undirected) paths encoding the same semantical information. We therefore look at the performance of GPT-4o-mini on the test set of GTSQA, when augmenting the prompt with all KG triples on the shortest paths between seed and answer nodes (recall that this LLM is always able to answer correctly when instead we augment the prompt with the triples in the ground-truth answer subgraph). As shown in Figure D10, there is a strong positive correlation between Hits (EM) and the fraction of ground-truth triples that are contained in the set of shortest path triples. Both metrics harshly degrade as the distance between seed and answer node increases. This confirms that shortest paths (even though they end at the correct answer node) often fail to capture the information required to reason over multi-hop questions, and should therefore not be used as an approximation of ground-truth paths.

E Comparison with Concurrent Works

With the latest advancements in LLM reasoning abilities, strong interest has arisen in using generative AI to create synthetic datasets for a variety of applications (Long et al. 2024). To our knowledge, two

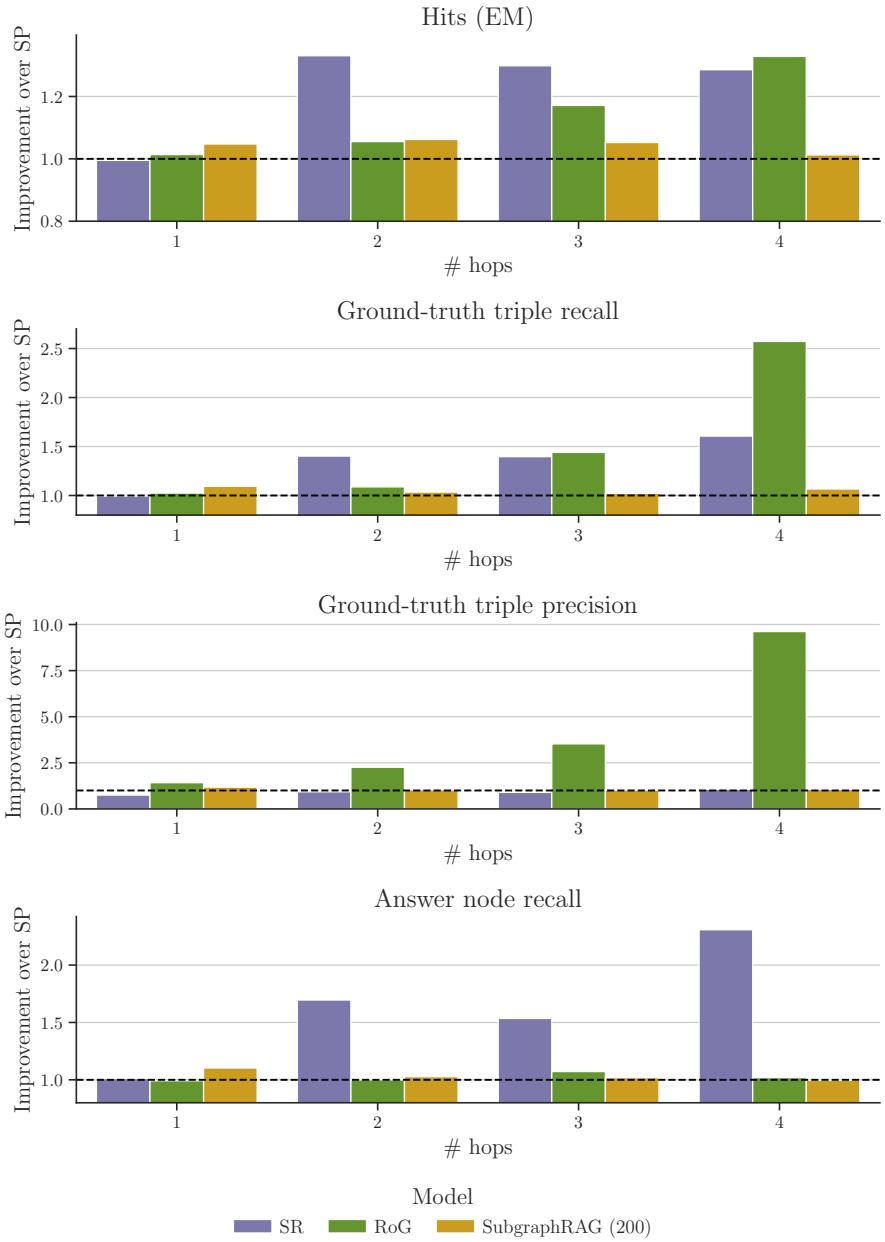


Figure D11: Comparison of predictive statistics when training models on ground-truth (GT) answer subgraphs compared to training on shortest paths (SP), for questions requiring different number of hops. The y-axis measures the GT/SP ratio of the averages of the statistic on the test set (over three distinct training runs); if the ratio is above the dashed line, training on the ground-truth subgraph is better.

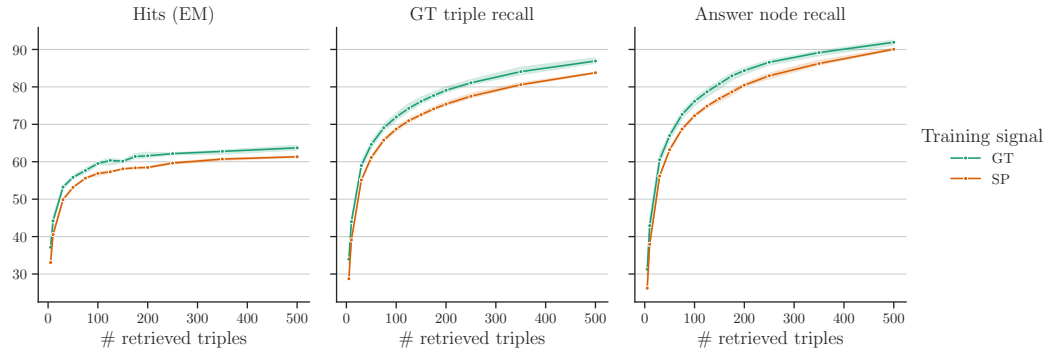


Figure D12: Performance of SubgraphRAG on the test set of GTSQA, as we increase the size of the retrieved subgraph. While recall for both ground-truth triples and answer nodes steadily increases, the final predictive accuracy (EM) eventually plateaus, as too much irrelevant information is added to the LLM prompt. Across all subgraph sizes, training on the ground-truth answer subgraphs (GT) outperforms training on shortest path triples (SP).

concurrent works (Dammu et al. 2025; L. Zhang et al. 2025) have proposed similar pipelines to the one outlined in Section 2 to create synthetic datasets for KGQA. We briefly discuss differences and reciprocal advantages.

- Dynamic-KGQA (Dammu et al. 2025) is designed to build (question, answer subgraph) pairs on the fly using LLMs, starting from compact seed subgraphs in YAGO 4.5 (Suchanek et al. 2024) that group triples around a common theme. However, as observed in L. Zhang et al. (2025), the generation pipeline is still prone to hallucinations, with factual correctness of questions estimated to be not better than previous benchmarks. Moreover, no logical query is executed on the KG: the LLM is tasked to judge whether the proposed answer subgraph captures the correct reasoning paths from seed to answer nodes, resulting in higher likelihood of incorrect data, compared to our validation approach based on SPARQL queries.
- KGQAGen (L. Zhang et al. 2025) proposes a more cost-efficient validation pipeline, based on SPARQL query execution and iterative revisions of incorrect queries (while we directly discard datapoints where the SPARQL query does not execute, or returns incompatible results with the LLM-generated ones). However, it does not keep track of all the seed entities mentioned in the natural-language question, only providing the node from which the seed graph is constructed (equivalent to our entity s in Algorithm 1), which limits the usefulness for benchmarking KG-RAG models that use multiple seed entities at once. The datasets presented in the paper, KGQAGen-10k, contains 10,787 questions with a random 80/10/10 train/validation/test split (while we carefully curate the split of GTSQA to test zero-shot generalization abilities of models), constructed from Wikidata, with seed entities from a set of 16,000 Wikipedia's Vital Articles[6].

While both Dynamic-KGQA and KGQAGen are presented as multi-hop datasets, neither paper includes statistics on the distribution of structures for their respective ground-truth answer subgraphs, making hard to actually evaluate the degree of question complexity in these datasets. On the other hand, our framework makes this very simple, using the metrics provided by the classification of graph isomorphism (Appendix A.2). Similarly, while Dynamic-KGQA uses an LLM as-a-judge to assess the presence of redundant information in the question, our approach based on decomposition of SPARQL queries and identification of minimal subsets of seed entities sufficient to answer (Appendix A.3) uniquely provides an exact measure of redundancy. Finally, GTSQA ensures better reliability as a benchmark for KG-augmented LLMs by verifying that the ground-truth subgraphs provided can indeed be utilized by an LLM to answer test questions correctly.

[6] `https://en.wikipedia.org/wiki/Wikipedia:Vital_articles`