DAGR: Decomposition Augmented Graph Retrieval with LLMs

Anonymous ACL submission

Abstract

Large Language Models (LLMs) excel at many Natural Language Processing (NLP) tasks, but struggle with multi-hop reasoning and factual consistency, limiting their effectiveness on knowledge-intensive tasks like complex question answering (QA). Linking Knowledge Graphs (KG) and LLMs has shown promising results, but LLMs generally lack the ability to reason efficiently over graph-structured information. To address this challenge, we introduce DAGR, a retrieval method that leverages both complex questions and their decomposition in subquestions to extract relevant, linked textual subgraphs. DAGR first breaks down complex queries, retrieves subgraphs guided by a weighted similarity function over both the original and decomposed queries, and creates a question-specific knowledge graph to guide answer generation. The resulting Graph-RAG pipeline is suited to handle complex multi-hop questions and effectively reason over graph-structured data. We evaluate DAGR on standard multi-hop QA benchmarks and show that it achieves comparable or superior performance to competitive existing methods, using smaller models and fewer LLM calls. *Source code will be available upon acceptance.*

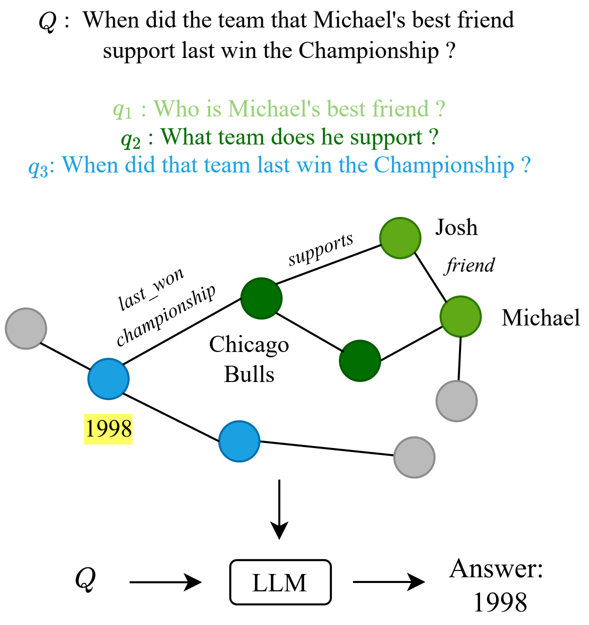

Q : When did the team that Michael's best friend support last win the Championship ?
q_1 : Who is Michael's best friend ?
q_2 : What team does he support ?
q_3: When did that team last win the Championship ?
Josh
supports
friend
Michael
last_won championship
Chicago Bulls
1998
Q
LLM
Answer: 1998

Figure 1: Illustration of DAGR, our novel decompositional retrieval method. We first decompose the complex question into sub-questions, perform iterative, context-aware retrieval conditioned on previous answers, and merges the resulting subgraphs. The resulting graph can then be used to ground the generation of an LLM.

1 Introduction

Large Language Models (LLMs) have demonstrated remarkable success across a wide range of natural language processing (NLP) tasks (Brown et al. (2020), Chowdhery et al. (2023), Touvron et al. (2023a), Ouyang et al. (2022)), including question answering (Kamalloo et al., 2023), summarization (Liu et al., 2024), and machine translation (Zhang et al., 2023). As LLMs have grown in size and have been trained on increasingly diverse and large datasets, their emergent ability to perform different types of reasoning (Wei et al. (2022a), Zhou et al. (2023)), ranging from arithmetic (Imani et al., 2023) and neurosymbolic reasoning (Fang et al., 2024) to commonsense inference (Zhao et al., 2023), has become a central focus of recent research. This has opened new possibilities for solving complex problems that traditionally required structured or symbolic approaches (Pan et al. (2023), He-Yueya et al. (2023)). However, despite their broad capabilities, LLMs still struggle with tasks requiring multi-hop reasoning (Yang et al., 2024), factual grounding, or explicit access to structured knowledge. These models are prone to hallucinations and logical inconsistencies, particularly when operating in knowledge-intensive domains (Ji et al. (2023b), Huang et al. (2025). This is partially due to the high reliance on implicit knowledge stored in parameters (Hu et al., 2024b), and the lack of explicit mechanisms for integrating or reasoning over structured information. Recent work on retrieval-augmented generation (Lewis et al., 2020), graph-augmented LLMs (Yasunaga et al., 2021), and neurosymbolic reasoning (Fang et al., 2024) has aimed to bridge this gap.

In this work, we propose DAGR, a retrieval method designed to improve structured knowledge access for LLMs through decompositional reasoning over textualized knowledge graphs. Given a complex question and a knowledge graph, DAGR decomposes it into sub-questions, retrieves relevant subgraphs using a hybrid similarity function informed by both the original and decomposed queries, and merges them into a coherent, question-specific textual graph. As seen on Figure 1, the resulting structured graphs can be plugged into Graph-RAG pipelines, enhancing their ability to guide LLMs toward more factual and interpretable answers. This novel retrieval method allows precise and coherent multi-step retrieval for complex questions, and removes the need of using very large models or fine-tuning the LLM on a specific graph. The hybrid similarity function fuses the richness of the generated subquestions as well as the anchoring of the initial complex question, helping to retrieve multiple coherent and linked subgraphs. We validate DAGR on the CWQ (Talmor and Berant, 2018) and WebQSP (Yih et al., 2016) multi-hop QA datasets, demonstrating that our decompositional retrieval method achieves state-of-the-art performance when paired with smaller, frozen LLMs, while requiring significantly fewer LLM calls.

- We propose DAGR, a retrieval method that augments the complex query with its decomposition to retrieve relevant linked subgraphs.
- We introduce a hybrid similarity function that integrates the full query and its decomposition to guide subgraph selection.
- We obtain state-of-the-art results on multi-hop QA benchmarks, without using large or fine-tuned LLMs.
- We achieve a 3×–5× reduction in LLM calls compared to baselines, highlighting the efficiency of our method.

2 Background

2.1 Can LLMs reason ?

LLMs such as GPT-3 (Brown et al., 2020), PaLM (Chowdhery et al., 2023), and LLaMA (Touvron et al., 2023a) have demonstrated strong performance across a wide range of language tasks, including reasoning-based benchmarks. Their ability to generalize in zero-shot (Kojima et al., 2022) and few-shot settings has led to the emergence of new prompting techniques, such as Chain-of-Thought (CoT) reasoning (Wei et al., 2022b), which improves multi-step reasoning by encouraging models to generate intermediate reasoning steps. Variants like self-consistency (Wang et al., 2023) further refines this by sampling multiple reasoning paths and aggregating answers for improved robustness. More recently, reinforcement learning has been used to entirely train new models (DeepSeek-AI et al., 2025) or improve model prompting (Pternea et al., 2024), showing great potential for the future.

Despite these advances, LLMs remain prone to hallucinations—generating fluent but factually incorrect or logically inconsistent outputs (Huang et al., 2025), (Srivastava et al., 2023), (Ji et al., 2023b). This is especially problematic in knowledge-intensive tasks requiring factual grounding, multi-hop reasoning, or domain-specific expertise (Ji et al. (2023a), Opsahl (2024)). These issues stem in part from the implicit nature of knowledge storage in model parameters, which limits their ability to verify facts or reason explicitly over external knowledge (Petroni et al. (2019), Bommasani et al. (2021)). Recent work has explored augmenting LLMs with tool use, such as code interpreters (Pi et al., 2022), equation solvers (He-Yueya et al., 2023) or symbolic solvers (Lam et al., 2024) (Pan et al., 2023), to externalize and validate parts of the reasoning process.

2.2 LLMs and graphs

Graphs offer a natural and interpretable way to represent real-world data through entities and their structured relationships. Integrating knowledge graphs with Large Language Models (LLMs) is a promising research direction that enables models to better handle real-life scenarios with structured data (Li et al., 2024) (Hu et al., 2024a). Knowledge graphs can enhance LLMs by providing explicit, grounded context, which

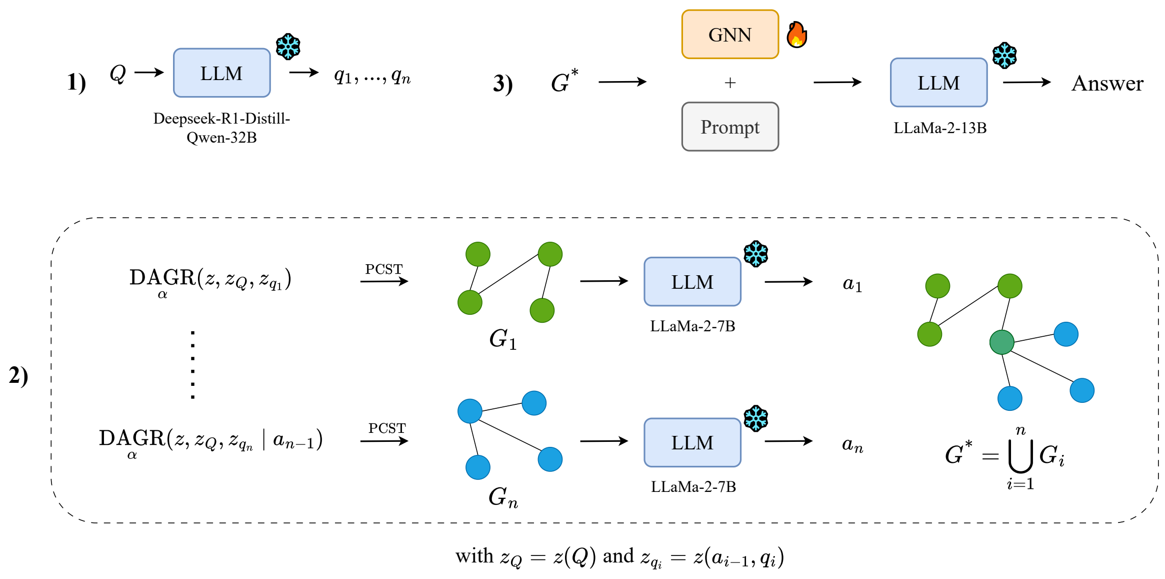

1)
Q
LLM
Deepseek-R1-Distill-Qwen-32B
$q_1, \ldots, q_n$
3)
G^*
GNN
+
Prompt
LLM
LLaMa-2-13B
Answer
2)
$\underset{\alpha}{\mathrm{DAGR}}(z, z_Q, z_{q_1})$
PCST
G_1
LLM
LLaMa-2-7B
a_1
$\underset{\alpha}{\mathrm{DAGR}}(z, z_Q, z_{q_n} \mid a_{n-1})$
PCST
G_n
LLM
LLaMa-2-7B
a_n
$G^* = \bigcup_{i=1}^{n} G_i$
with $z_Q = z(Q)$ and $z_{q_i} = z(a_{i-1}, q_i)$

Figure 2: Usage of our decompositional retrieval method: 1) The complex question is first decomposed into atomic subquestions ; 2) We conditionally perform retrieval and answer generation; once the retrieval is done for all subquestions, we merge the subgraphs ; 3) The resulting graph is given as a hard (textualized graph) and soft prompt (graph encoder output) to the model.

helps mitigate hallucinations (Li et al., 2024) (Agrawal et al., 2024), but also makes the model dependent on the noise or incompleteness of the graph (Dong et al., 2025). By grounding the generation process in a textualized or symbolic knowledge graph, LLMs can produce responses that are more accurate and aligned with real-world facts. This is especially useful in tasks such as question answering (Baek et al., 2023) (Yasunaga et al., 2021), logical reasoning (Choudhary and Reddy, 2024), or dialogue systems (Kang et al., 2023) where factual precision is crucial.

LLMs and graph neural networks (GNNs) can also be used together (Xu et al., 2024) (He et al., 2024a), each complementing the other. Graphs can be used to inject knowledge into LLMs via methods like structured prompting (Baek et al., 2023) (Zhang et al., 2024a) or retrieval-based augmentation (Lewis et al., 2020) (Peng et al., 2024). LLMs can support and enhance graph-centred tasks (Pan et al., 2024) by performing entity linking, relation extraction, or even link prediction (Shu et al., 2025), which largely improves the graph's coverage. LLMs have also been explored as generators of graph-structured outputs or as interpretable reasoning agents over graphs using intermediate symbolic steps. In such hybrid frameworks, LLMs benefit from the structure and factual reliability of graphs, while graphs gain from the generalization and language understanding ability of LLMs (Pan et al., 2024). Nonetheless, most existing methods remain heuristic and lack a principled understanding of how best to align symbolic and neural representations (Cheng et al., 2025).

3 Related Work

Several methods have demonstrated strong performance on Knowledge Graph Question Answering (KGQA) tasks by combining LLMs with structured information. He et al. (2024b) retrieves a single subgraph from a textual knowledge graph and directly feeds it into an LLM for answer generation. However, the lack of an explicit reasoning step limits its effectiveness on complex, multi-hop questions, where structured reasoning is essential. Other approaches incorporate reasoning more explicitly: for instance, Sun et al. (2024) introduces iterative entity and relation exploration guided by the LLM, while Chen et al. (2024) decomposes tasks and performs multiple reasoning cycles involving exploration, memory updates, and evaluation. While these iterative strategies improve reasoning quality, they rely on a high number of LLM calls and require large models (e.g., LLaMA-2-70B, GPT-3.5, or GPT-4) to plan and evaluate effectively, which increases the computational cost and inference time. Luo et al. (2024) instead predicts relation paths as intermediate plans, but requires training or distilling structured knowledge into the LLM so it can generate faithful and executable relation paths. In contrast, our method DAGR focuses on efficiently constructing question-specific subgraphs through decompositional retrieval, instead of relying on large models, dataset-specific fine-tuning, or LLM-guided exploration. DAGR breaks down complex questions into sub-questions and retrieves linked subgraphs using a hybrid similarity function, composing a targeted knowledge graph to support answer generation. This approach enables strong performance on complex QA tasks while using smaller, frozen LLMs, and reduces the number of LLM calls. Additionally, the lack of LLM fine-tuning makes our method DAGR adaptable to new datasets with minimal overhead.

4 Method

The overall generation pipeline that uses our method is presented in Figure 2. In order to tackle complex questions, we first decompose a complex question into a set of logically ordered subquestions. We then perform an iterative retrieval cycle by performing retrieval on the graph for each generated subquestion. The obtained subgraphs are then merged into a single knowledge graph. For the answer generation, the obtained graph is then fed to the LLM, following work done by He et al. (2024b).

4.1 Subquestions Generation

Given a complex question Q, we want to obtain a set of subquestions $\{q_1, ..., q_n\}$. The subquestions must be logically ordered (answering q_1 is necessary to answer q_2, etc.), atomic (can not be split into smaller subquestions), and cover all aspects of the complex question. Therefore, answering all subquestions in the given order should be equivalent to answering the complex question. In our work, we generate the subquestions using an LLM, leveraging its semantic understanding and its implicit knowledge capabilities. Using an LLM provides a flexible framework for decomposing complex questions, independent of the domain or the question type. To fulfill all the mentioned conditions above, we prompt the model with specific instructions about subquestions; we also provide some manually generated examples of decomposition to guide the model's behavior (see Appendix B for details about prompting).

4.2 Hybrid Entity Retrieval

For each generated subquestion q, we want to obtain a subgraph G_q. Performing a retrieval step for each subquestion helps to exploit the richness of the decomposition, using all implicit reasoning steps to answer the complex question Q. But treating each subquestion independently might lead to very distant subgraphs; moreover, the subquestions can lack sufficient contextual information on their own to retrieve all the relevant nodes and edges from the knowledge graph. To address this issue, we introduce a hybrid similarity function (Figure 3) that combines both the subquestion and the original complex question, allowing the model to benefit from the specificity of q and retain the broader context provided by the latter Q. In our hybrid similarity function, the influence of both components is controlled by a parameter α.

$$\underset{\alpha}{\mathrm{DAGR}}(z, z_q, z_Q) = \alpha\ \cos(z, z_q) + (1-\alpha)\ \cos(z, z_Q)$$

$$V_k{}^q = \underset{n \in V}{\mathrm{argtopk}}\, \underset{\alpha}{\mathrm{DAGR}}(z_n, z_q, z_Q)$$

$$E_k{}^q = \underset{e \in E}{\mathrm{argtopk}}\, \underset{\alpha}{\mathrm{DAGR}}(z_e, z_q, z_Q)$$

Figure 3: Hybrid graph-based retrieval using our proposed similarity function (with parameter α), which combines subquestion-level and global question-level semantics. The sets $V_k{}^q$ and $E_k{}^q$ represent the top-k nodes and edges in the graph $G = (V, E)$, retrieved based on their similarity to subquestion embedding z_q and the original question embedding z_Q.

Before retrieval, we embedded our different components (complex question, the subquestions, and the textual attributes of the nodes/edges in the graph) using a Sentence Transformer embedding model (see Appendix B for details). When performing retrieval on the graph for the subquestion q_i, we keep track of the answer a_{i-1} to the previous subquestion q_{i-1}. This is crucial, as the answer to q_i usually depends on the answer to q_{i-1}. Therefore, we combine the subquestion q_i and the previous answer a_{i-1} in a single embedding $z_q = z(a_{i-1}, q_i)$. For simplicity, we choose to concatenate the previous answer element and the next subquestion, allowing context sharing from the previous step. After having retrieved all necessary nodes and edges, we build a connected subgraph from these elements, ensuring that a subgraph represents a single component with linked graph entities. The connectivity of the graph is enforced by the Prize-Collecting Steiner Tree (PCST) algorithm (Bienstock et al., 1993), which optimizes the selection of a subgraph of maximum value based on node/edge weights and query similarity, under a size constraint. This method also allows us to control the size of the retrieved subgraph, as a large subgraph might not always fit in the context size of the model. Impact of the chosen maximal size of a subgraph is studied in later analysis.

4.3 Subgraphs Merging

After retrieving subgraphs corresponding to each subquestion, we proceed to merge them in order to link relevant information and remove redundancy. To form the final graph, we take the union of all distinct nodes and edges across all subgraphs, removing duplicate entities: $G^* = \bigcup_{i=1}^{n} G_i$. A crucial observation is that the resulting merged graph is almost always connected, thanks to the anchoring used in the similarity function at each step, by using the initial complex question Q. This allows us to bypass enforcing connectivity by introducing virtual edges, which could potentially compromise the semantic integrity of the graph or resort to computationally expensive graph expansion methods.

4.4 Answer Generation

Once we obtain the merged graph G^* from the different subgraphs, we pass it to the LLM, following the generation process described in He et al. (2024b): we provide a textualized version of the graph in the prompt, and also pass the graph through a trained graph encoder (Shi et al., 2021) followed by a linear projection layer. Providing the encoded graph as a soft prompt guides the LLM's response by feeding a trained embedding vector to the self-attention layers of the language model. When answering the complex question, we chose not to include the answers to the subquestions in the final prompt, as a single prior error can force the model to give a wrong answer. Instead, the prompt only contains Q and merged graph.

5 Experiments

5.1 Benchmarks

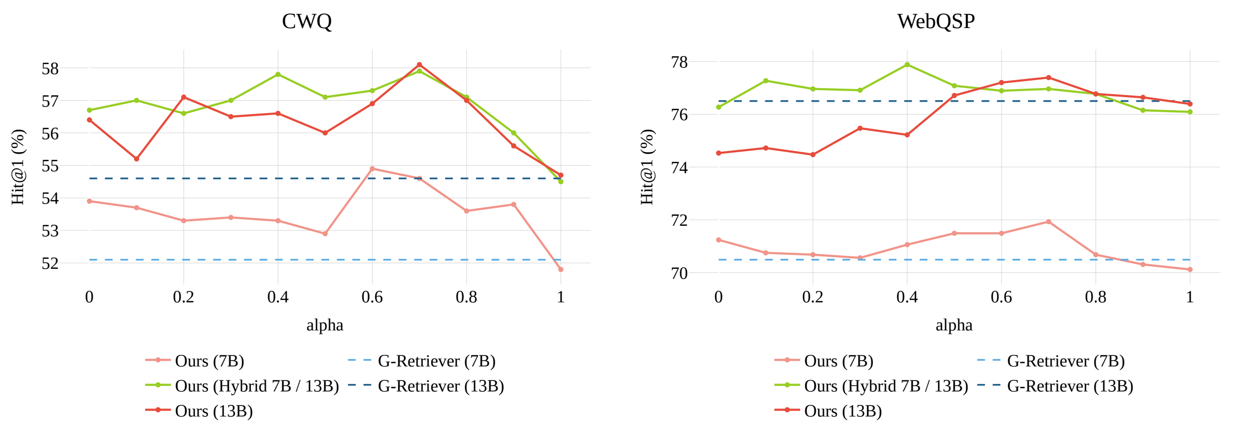
We evaluate our method on two different Question-Answering (QA) benchmarks to assess the quality of our results: CWQ (ComplexWebQuestions) (Yih et al., 2016) and WebQSP (WebQuestionsSemanticParses) (Talmor and Berant, 2018), which are both based on the Freebase (Bollacker et al., 2008a) knowledge base. CWQ is a complex QA benchmark that focuses on multi-hop questions. As it needs the integration of multiple facts, it benefits from compositional reasoning, making it a suitable benchmark for our approach. WebQSP, on the other hand, contains a wide range of simple and factual questions. It also includes SPARQL annotations that we do not use in this work. This benchmark is used to evaluate the performance of our method on simpler questions, that may not always require decomposition. We use the preprocessed version of the dataset provided in Luo et al. (2024).

5.2 Evaluation Metrics

We use the standard QA evaluation metrics found in related work. We report performance using accuracy and F1 scores. Accuracy measures exact matches, while F1 allows a more nuanced evaluation, especially when predictions are partially correct. In line with previous studies (Chen et al. (2024), Sun et al. (2024), Luo et al. (2024)), we use Hit@1 as our primary accuracy metric. Hit@1 determines whether the top prediction matches the ground truth and is widely used in QA evaluation. We report both Hit@1 and F1, enabling direct comparison with prior work.

5.3 Choice of language models

Our method requires the usage of two language models, each having a different focus. First, strong decompositional reasoning is needed to break down the complex question into logically ordered, comprehensive, and atomic subquestions. We use a Qwen-32B model distilled from Deepseek-R1 (DeepSeek-AI et al., 2025) for its advanced reasoning abilities. We test different model sizes at the decomposition step (7B, 14B and 32B) and we evaluate the quality of the generated subquestions (see Table 4 and Table 5 in Appendix A), and we show that the 32B model produces superior decomposition compared to other models. We do not consider larger models, as the model size would become a strong usage limitation. Second, we need an efficient model to iteratively answer the subquestions and generate the final answer. For this, we experiment both with LLaMA-2-7B and LLaMA-2-13B (Touvron et al., 2023b). We also propose a "Hybrid 7B/13B" setting in which the 7B model answers the subquestions, while the 13B model handles the final complex question. The rationale is that atomic



(a) CWQ benchmark (b) WebQSP benchmark

Figure 4: Model Accuracy (Hit@1) against the value of the α parameter for both CWQ and WebQSP datasets.

subquestions are simple and can be handled by a smaller model, while the final answer, requiring the integration of the full merged graph, benefits from the greater capacity of a larger model. This setting leverages model efficiency by allocating larger capacity only where necessary. We evaluate both uniform and hybrid settings in Section 6.

5.4 Balancing the Hybrid Retrieval

Using the subquestion alone for retrieval can lead to ineffective results, as it lacks the broader context of the original question. To address this, we balance the influence of the complex question and the current subquestion in the retrieval query. The α parameter (Section 4.2) controls this trade-off via a weighted average of their respective query embeddings. As shown in Figure 3, α determines the contribution of each: lower values emphasize the subquestion, while higher values shift focus toward the original complex question. When $\alpha = 1$, retrieval is based solely on the complex question, without any decompositional reasoning, as in He et al. (2024b). We experiment with different values of α to decide on the importance that both elements should have during the retrieval process.

6 Results

6.1 Influence of α parameter

During retrieval, we use both the complex question and the corresponding subquestions, with the α parameter controlling their relative importance in the query (Figure 3). We vary α and report model accuracy in Figure 4.

The first observation is that the value of α has a strong impact on the resulting graph topology, affecting the connectivity and density of the resulting merged graph. Experiments show that higher α leads to more connected and denser graphs (Figures 5, 9), while lower values produce more distinct subgraphs and a sparser, occasionally disconnected graph. The topology of the graphs is highly important for the LLM that will use the retrieved graph: we show (Appendix A) that connected graphs empirically yield better performance, although disconnected graphs remain rare in proportion, as seen on Figure 5. We also discuss the statistical significance of these results in Appendix A.

The second observation is that the α parameter influences the precision (Matching and Exact Matching) of the retrieved entities. Exact Matching score is defined as the percentage of graphs containing a node that exactly matches the answer label (or how often a graph contains the answer to the question asked. We define Matching as the percentage of retrieved graphs that contain a semantically close node to the answer label (using standard cosine similarity between embeddings, and a similarity threshold of 0.9). This metric is more flexible and helps checking the presence of highly related nodes in the retrieved graph. Here, we report the Exact Matching score for different α values, and we observe in Figure 6 that focusing on the subquestions leads to a higher Exact Matching score. Naturally, by setting $\alpha = 1$, we obtain similar metrics to He et al. (2024b). We observe similar results for the Additional similar results for Matching and Exact Matching (using different graph size) can be found in Appendix A.

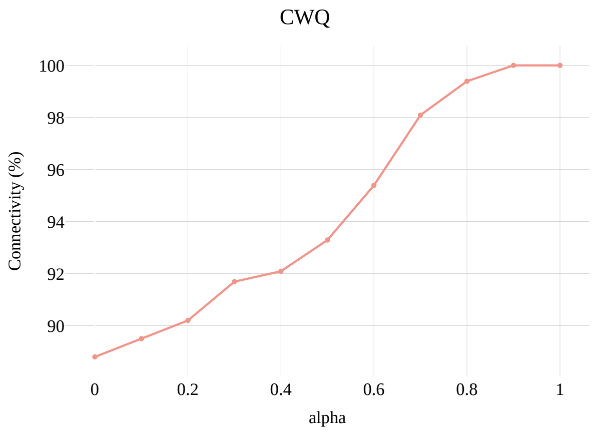


Figure 5: Graph connectivity against the value of the α parameter, for the CWQ benchmark.

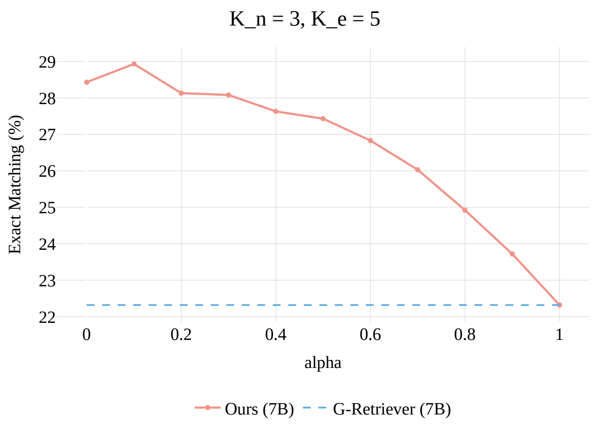


Figure 6: Exact Matching against the value of the α parameter, for the CWQ benchmark.

In the end, we observe that using a larger model (13B) in the final answer stage (7B/13B and 13B setups) significantly outperforms the 7B-only setup ; however, using the 13-B model for iterative subquestions answering offers no clear benefit. We observe indeed that the hybrid 7B/13B and 13B-only setups yield similar results. Across all setups, extreme α values (near 0 or 1) underperform, and intermediate values (0.4 to 0.8) work best ; choosing an intermediate value for α helps to make a compromise between a clean graph topology and retrieving relevant graph entities. This supports the intuition of balancing the focus between subquestions and the main question during retrieval. In the rest of the paper and all following results, we use $\alpha = 0.7$.

6.2 Graph size

According to Figure 3, we can control the size of the retrieved nodes (noted as K_n) and edges

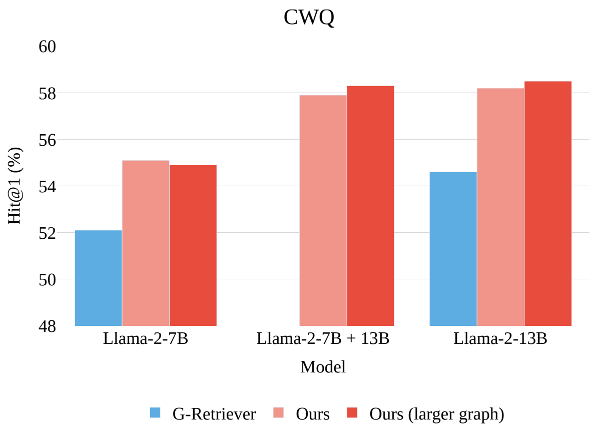


Figure 7: Model Accuracy (Hit@1) for different model sizes, for the CWQ benchmark. In default setting, we use $K_n = 3$, $K_e = 5$; for "larger graphs", we use $K_n = 5$, $K_e = 7$.

(noted as K_e) for each subgraph. At the retrieval step, we set the values of K_n and K_e to extract a certain number of relevant entities in the original graph (Figure 3). Choosing higher values of K_n and K_e leads to a higher quantity of retrieved information, which improves the probability of retrieving relevant nodes and edges, but also increases the noise in the subgraph that we are building. We show that higher values of K_n and K_e produces significantly larger graphs (Figure 11 in Appendix A), which is harder to handle for the LLM. We show (Appendix A for detailed findings) that setting K_n and K_e too low will not allow retrieving enough relevant information, while setting them to high introduces noise in the final subgraph. For larger models (Figure 7), using larger graphs ($K_n = 5$, $K_e = 7$) offers marginal gains over smaller graphs ($K_n = 3$, $K_e = 5$), further indicating noise in larger subgraphs. We use $K_n = 3$ and $K_e = 5$ as default values for evaluation.

6.3 Main Results

For our main evaluation, we consider various baselines and model configurations. In particular, we highlight our "Hybrid 7B/13B" setting, where a 7B model answers each subquestion and a 13B model handles final answer generation (as described in Section 5.3).

Across both CWQ and WebQSP benchmarks (Table 1), DAGR achieves strong performance compared to approaches using similar model sizes

Method	**CWQ**		**WebQSP**	
	Hit@1	F1	Hit@1	F1
IO prompt (ChatGPT)	37.6	-	63.3	-
CoT (ChatGPT)	38.8	-	62.2	-
StructGPT (ChatGPT)	54.3	-	72.6	-
ToG (LLaMa-2-70B)	53.6	-	63.7	-
ToG (ChatGPT)	57.1	-	76.2	-
RoG (LLaMa-2-7B + FT)	<u>62.6</u>	56.2	**85.7**	70.8
PoG (GPT-3.5)	**63.2**	-	<u>82</u>	-
G-R (LLaMa-2-7B)	52.1	44.8	70.5	51.7
DAGR (LLaMa-2-7B)	54.9	46	71.9	52.4
G-R (LLaMa-2-13B)	54.6	46.9	76.5	<u>57.2</u>
DAGR (Hybrid 7B/13B)	<u>57.9</u>	<u>50.3</u>	**77.9**	**58.2**
DAGR (LLaMa-2-13B)	**58.1**	**50.8**	<u>77.4</u>	56.4

Table 1: Performance comparison on the CWQ and WebQSP benchmarks. Bold indicates best results; underlined values indicate second-best. Results are sourced from the original papers: Brown et al. (2020), Wei et al. (2022b), Jiang et al. (2023), Sun et al. (2024), Luo et al. (2024), Chen et al. (2024), He et al. (2024b).

and no fine-tuning. On CWQ, which features multi-hop questions, we observe a significant improvement over prior non-finetuned baselines, including those using larger models like Sun et al. (2024) (70B) and He et al. (2024b) (13B). On WebQSP, a simpler QA dataset, our method still equals most related methods, although decomposition might be less helpful for single-hop questions. In both cases, only methods relying on dataset-specific fine-tuning or very large models (e.g., GPT-3.5 in (Chen et al., 2024)) achieve better scores, highlighting the value of simple decompositional reasoning at the retrieval stage. A key observation is that our "Hybrid 7B/13B" retrieval setup performs similarly to a full 13B pipeline, suggesting that most of the benefits come from decompositional retrieval, not simply model scale. Figure 7 highlights this efficiency: we maintain competitive performance while using fewer resources, by relying on a lightweight model for subquestions and a larger one only for the final answer.

Method	**CWQ**	**WebQSP**
ToG	22.6	15.9
PoG	13.3	9.0
Ours	**4.8**	**4.3**

Table 2: Average number of LLM calls per question on the CWQ and WebQSP datasets

Finally, Table 2 compares the average number of LLM-calls for our method and compares it with baselines that made this data available (Sun et al. (2024), Chen et al. (2024)). These methods use iterative cycles to answer the complex question, which does not give any upper-bound for the number of calls to the model. In our case, the number of calls to the model directly depends on the number of generated subquestions, which can ultimately be controlled via prompting at the decomposition step. While achieving state-of-the-art accuracy, we also notably reduce LLM usage for both datasets, showing the efficiency of our decompositional retrieval method. Since we only use a single LLM call for both decomposition and final answer generation, we can deduce the average number of subquestions generated. Without setting a limit on the number of subquestions, we obtained an average of 2.8 subquestions for CWQ and 2.3 for WebQSP, which shows that more complex questions will be decomposed in more subquestions.

7 Conclusion

We propose DAGR, a graph retrieval method using decompositional reasoning with LLMs, combining textual knowledge graphs and hybrid retrieval to improve multi-hop QA. Our approach achieves state-of-the-art accuracy on standard benchmarks without increasing model size, highlighting the value of structured knowledge and explicit reasoning in knowledge-intensive tasks.

Limitations

Although our method demonstrated state-of-the-art results with smaller LLMs, we can mention some limitations of the approach. Our method is mostly adapted to complex QA datasets, as the decomposition works best on difficult and multi-hop questions that can be transformed into a set of simple and atomic questions. The decomposition is not systematic, and we prompt the LLM to not decompose a question if it is considered to be simple enough; this approach can work on simple QA datasets (shown in Table 1 for the WebQSP dataset), but there is no guaranty that the model will not force the decomposition of simple questions.

We decompose complex questions using an LLM with a specific prompting technique shown in Appendix B. This method is advantageous for preprocessing an entire dataset, but it requires the use of a large enough LLM (we use Deepseek-R1-Distill-Qwen-32B, which is still relatively small compared to other baselines used for direct reasoning). Also, it is hard to control the quality of the decomposition; manual evaluation has been conducted to control the quality of the decomposition. It has been observed that some generated subquestions were redundant or irrelevant to the final goal, which can act as noise when providing them to the model. Potential future work might focus on implementing a error detection mechanism to control the quality of generated subquestions ; a path to explore would be to use a "LLM-as-a-judge" technique, where a larger model could be used to judge the quality of the generated subquestions.

Ethical Considerations

This work improves the reasoning abilities of large language models by using structured knowledge from textual graphs. While this improves the model's ability to make consistent and transparent predictions, it does not eliminate risks such as the propagation of biases present in the training data or the underlying knowledge graphs. We do not train new language models or use user-generated content. Our experiments are conducted using publicly available datasets. No personal or sensitive data is used. Nevertheless, caution should be exercised when deploying such systems in high-stakes or real-world applications, as flawed reasoning over structured data can result in factually inaccurate outputs.

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A Experimental Results

The value of the α parameter, which controls the hybrid retrieval mechanism, can cause the retrieved graphs to be more or less connected. We saw (Figure 5) that with a lower value of α, we sometimes produce disconnected graphs; at a higher value of α, most (if not all) graphs become naturally connected. Figure 8 suggests that the model better handles the connected graphs, as they lead to better results, but the low number of disconnected graphs questions the statistical significance of this hypothesis. We observe that for some alpha values, the p-value is less than 0.05. We also use a Beta law to estimate the posterior distribution of p, the parameter for the Binomial law that represents the accuracy of our predictions. Over the different alpha values, we obtain $P(connected > disconnected) = 0.919$, which indicates the plausibility of our claim.

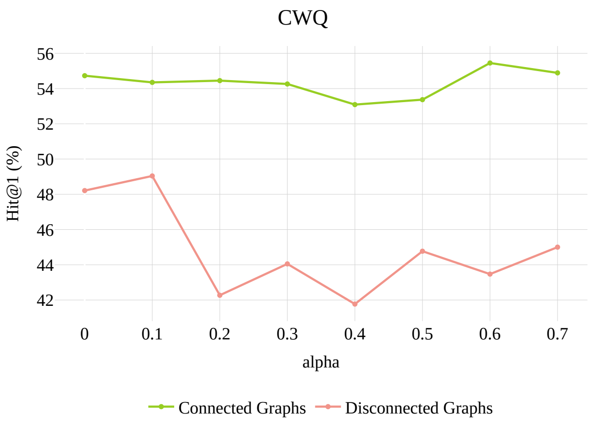

Figure 8: Model Accuracy (Hit@1) for connected and disconnected graphs against the value of the α parameter for the CWQ dataset.

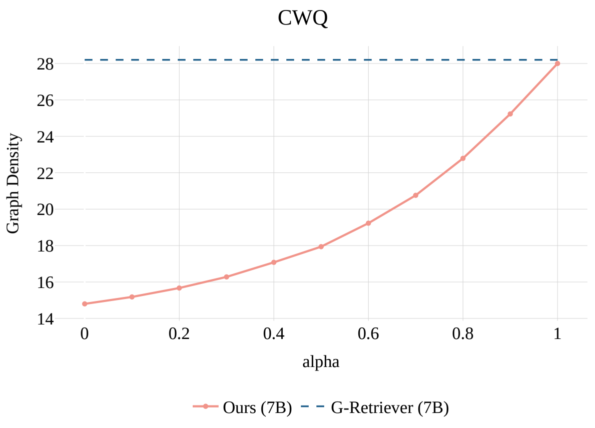

Figure 9: Graph density against the value of the α parameter, for the CWQ benchmark.

We make a similar observation with graph density; as shown in Figure 9, a lower α produces less dense graphs, but the retrieved graphs will be denser as the value of the parameter increases towards 1. Evidently, $\alpha = 1$ produces identical results to He et al. (2024b), as we only use the complex question. The density of a graph $G = (V, E)$ is given by Figure 10 :

$$D(G) = \frac{2 \cdot |E|}{|V| \cdot (|V| - 1)}$$

Figure 10: Graph density formula (undirected graph). $|V|$ and $|E|$ denote the number of nodes and edges in the graph $G = (V, E)$. Density quantifies how many edges exist compared to the maximum possible number of edges in the graph.

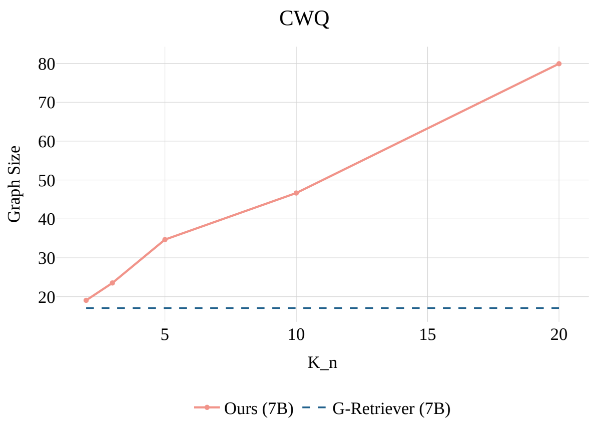

Figure 11: Graph size against the value of the K_n parameter (retrieved nodes), for the CWQ benchmark.

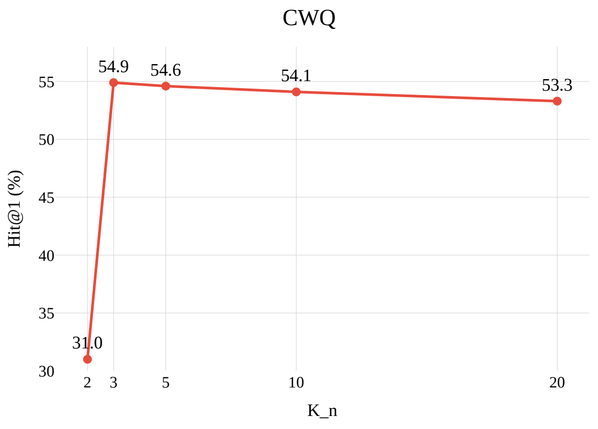

Figure 12: Accuracy (Hit@1) against the value of the K_n parameter (retrieved nodes), for the CWQ benchmark. Those results were obtained for our 7B model.

Figure 11 shows how changing K_n (similar effects with K_e) acts on the size of the final merged graph. As we perform retrieval for each subquestion (multiple times for each complex question), a small increase in the value of K_n will result in a much larger merged graph (each subgraph is larger). This effect will naturally have an impact on the performance of our method, as the model needs to process larger graphs.

Figure 12 highlights the importance of choosing the right values for K_n at retrieval. Increasing K_n or K_e beyond certain values does not improve performance, which is consistent with findings from He et al. (2024b) on other datasets. Setting K_n too low (e.g., $K_n = 2$) limits knowledge retrieval, while higher values (e.g., $K_n > 5$) introduce noise from irrelevant nodes, degrading answer quality.

The Exact Matching score is a metric that describes how often the exact answer to the complex question is found within the retrieved graph. We test the performance of our retrieval method with different models and retrieval settings (K_n and K_e), controlling the size of retrieved graphs. Overall, we observe that the α parameter has a high influence on the metric, which shows that our method improves the presence of target entities in the retrieved graphs. Also, regardless of the value of α, all experiments show that we obtain higher Exact Matching than by simply using the complex question.

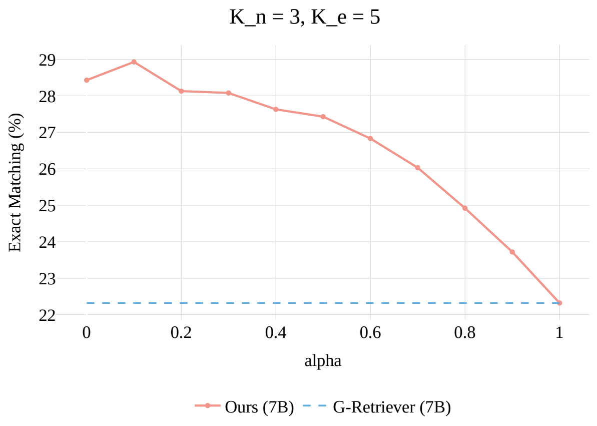

Figure 13: Exact matching (%) as a function of the α parameter on the CWQ benchmark for the 7B model with $K_n = 3$ and $K_e = 5$

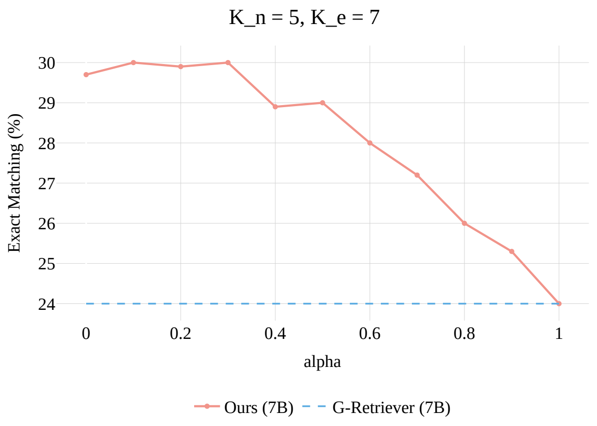

Figure 14: Exact matching (%) as a function of the α parameter on the CWQ benchmark for the 7B model with $K_n = 5$ and $K_e = 7$

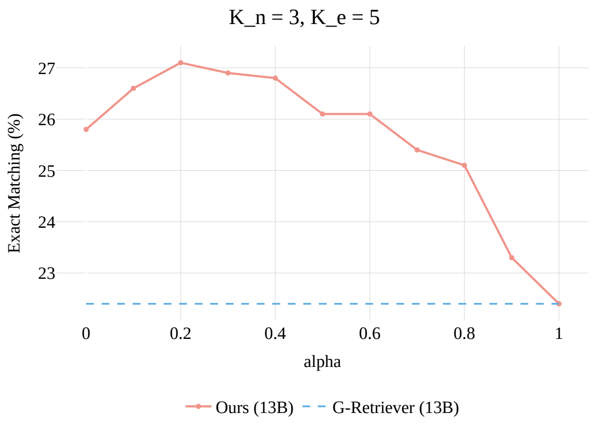

Figure 15: Exact matching (%) as a function of the α parameter on the CWQ benchmark for the 13B model with $K_n = 3$ and $K_e = 5$

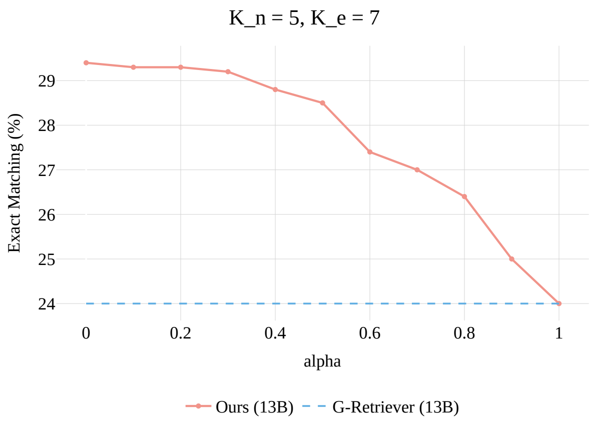

Figure 16: Exact matching (%) as a function of the α parameter on the CWQ benchmark for the 13B model with $K_n = 5$ and $K_e = 7$

Another useful metric to asses the quality of our retrieval method is the Matching metric. Compared to the Exact Matching, this metric allows for more flexibility and can evaluate the

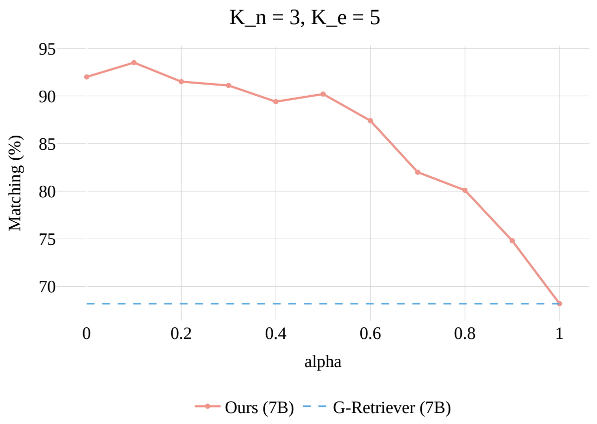

Figure 17: Matching (%) as a function of the α parameter on the CWQ benchmark for the 7B model with $K_n = 3$ and $K_e = 5$

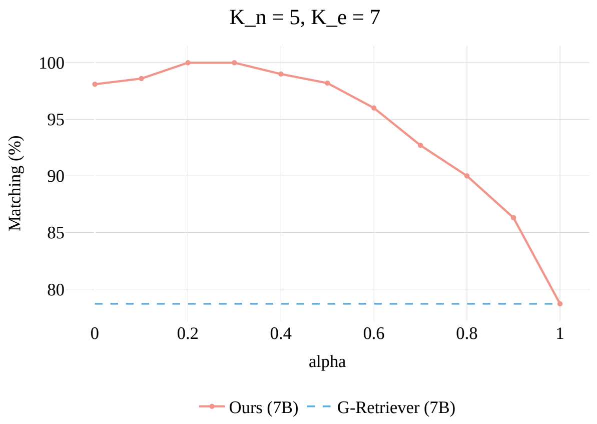

Figure 18: Matching (%) as a function of the α parameter on the CWQ benchmark for the 7B model with $K_n = 5$ and $K_e = 7$

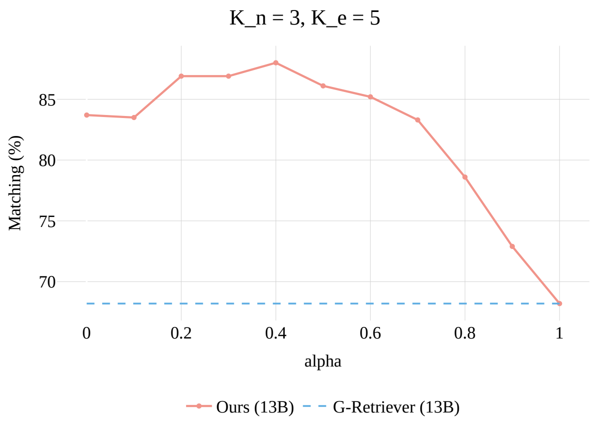

Figure 19: Matching (%) as a function of the α parameter on the CWQ benchmark for the 13B model with $K_n = 3$ and $K_e = 5$

presence of highly similar entities (compared to the ground-truth answer) within the retrieved graph. We run experiments using a similarity threshold of 0.95 with the cosine similarity function. We make

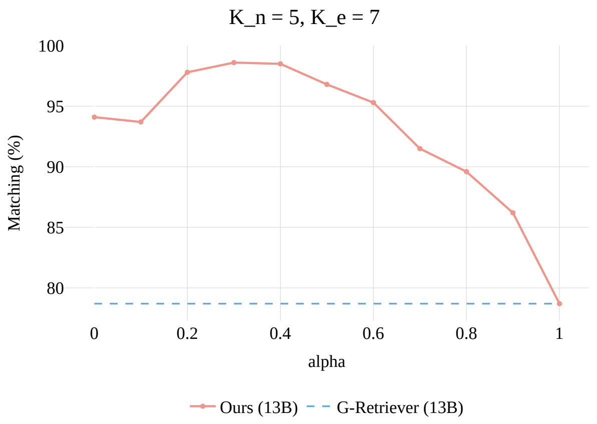

Figure 20: Matching (%) as a function of the α parameter on the CWQ benchmark for the 13B model with $K_n = 5$ and $K_e = 7$

similar observations as for the Exact Matching metric, and we empirically show that our method achieves better Matching than previous methods.

Configuration	Hit@1	Impact
Full Pipeline	54.9	-
w/o Graph Encoding	42.8	-12.1
w/o Textual Graph	35.8	-9.1
w/o SQs Dependency	36.3	-18.6
w/o Graph Connectivity	43.7	-10.2

Table 3: Ablation study showing the impact of various components from the pipeline. The results provided were obtained on CWQ using LLaMa-2-7B.

We ablate key components of our pipeline on CWQ using LLaMa-2-7B (see Figure 3). Removing the graph encoder or textual representation leads to substantial drops in Hit@1 (-12.1, -9.1 points respectively), confirming the importance of both structured and textual graph information for accurate generation. At the graph retrieval stage, we measure the impact of treating the subquestions dependency or connecting subgraphs. Removing the dependency between subquestions is equivalent to the case where subquestions don't have access to previous subquestions and answers. Again, we observe the importance of both steps at the retrieval stage for the QA pipeline on complex questions.

We test evaluate the quality of generated subquestions ; in that end, we perform a manual evaluation for a random sample of 200 complex questions. We classify each instance in one of four classes ; the results of the evaluation are presented in Table 4:

Quality	**7B**	**14B**	**32B**
++ (Excellent)	27	34	69.5
+ (Good)	11	11	12.5
- (Weak)	27	24.5	11.5
- - (Poor)	35	30.5	7.5

Table 4: Evaluation of question decomposition quality across four levels: Excellent (++), Good (+), Weak (–), and Poor (– –). Evaluation was perfomed a random sample of 200 questions. Results are expressed in percentages.

Our evaluation is made in the following way: an excellent decomposition (++) corresponds to a human-level decomposition ; a good decomposition (+) corresponds to a satisfying decomposition that a human subject would slightly change ; a weak decomposition (-) represents cases where some subquestions repeat or are not useful, which can cause disturbance, but will likely not break the reasoning chain ; finally, a poor decomposition (- -) corresponds to a false or non-existing decomposition. We observe that the "smaller" models produce a decomposition which is much less qualitative. There is a large gap between the 14B and 32B models, highlighting the emerging capabilities of LLMs with a larger number of parameters.

Decomposition Model	**7B**	**14B**	**32B**
Accuracy (Hit@1)	49.2	49.9	54.9

Table 5: We measure the accuracy (Hit@1) obtained using different model sizes at the decomposition step ; for the inference pipeline, we use LLaMa-2-7B. Results show the importance in the quality of the decomposition.

We can analyze how the noise in the subquestions propagates through the inference pipeline and the consequences on the overall performance: in Table 5, we observe that that the performance of the overall pipeline decreases when using a smaller model at decomposition. This statement confirms the manual evaluation that was done previously, where we observed a lower quality in the generated subquestions when using 7B and 14B models. In the manual evaluation, we saw that the 7B and 14B models produced subquestions of similar quality, while the 32B model outperformed them quite clearly ; in terms of accuracy, wa find similar results, as the 7B and 14B models lead to similar accuracy, and the 32B model outperforms them by more than 5%.

B Experimental Setup

Prompt for Subquestion Generation

You are an expert at decomposing complex questions into smaller, atomic subquestions. If the question can't be decomposed into smaller questions, leave it as it is. Decompose the following question into a list of simpler subquestions that:

- Are atomic (addressing only one piece of information at a time)
- Are logically ordered
- Have access to answers from previous subquestions
- Cover all necessary aspects of the original question
- Can be answered with a single entity
- Lead to the answer in the last subquestion

You must strictly format your answer as a valid JSON array; do NOT include explanations or reasoning.

Now decompose the following question in JSON format.

Complex Question:
"Which city is the birthplace of the author of the novel "1984"?"
Subquestions:
1. Who is the author of the novel "1984"?
2. Where was this author born?

Figure 21: Example of decomposition prompt for a complex question.

At the retrieval step, we encode all nodes and edges using Sentence-BERT model; we use a ver-

Few-shot Prompting

Examples:

Input: What is the capital of the country that exports the most honey ?
Output: ["Which country exports the most honey ?", "What is the capital of that country ?"]

Input: What sports team does Michael's best friend support ?
Output: ["Who is Michael's best friend ?", "What sports team does he support ?"]

Input: What fruits grow in the hottest countries from the largest continent in the world ?
Output: ["What is the largest continent in the world ?", "What countries are hottest on this continent ?", "What fruits grow in those countries ?"]

Input: How old is Obama ?
Output: ["How old is Obama ?"]

Now decompose the following question in JSON format.

Figure 22: Example of possible few-shot prompting

sion based on the roberta-large model [1]. For the language models, we use Deepseek-R1-Distill-Qwen-32B [2] (DeepSeek-AI et al., 2025) for preprocessing (complex questions decomposition); for inference, we use both LLaMa-2-7B and LLaMa-2-13B (Touvron et al., 2023b). At all steps (question decomposition and answer generation), we use the models in a greedy setting (setting the temperature parameter to 0). For the generation pipeline and the choice of hyperparameters, we follow work done in He et al. (2024b) [3]. We set the maximum input text length of the model to 512 tokens and the maximum output size to 32 tokens. For prompt tuning, we set the number of virtual tokens to 10. The setup of the language models, along with the deterministic nature of the hybrid retrieval process, allows for reproducible results for identical runs. All reported results for our method correspond to a single run, and not a mean of different runs. For the graph encoder, we follow Shi et al. (2021) (4 layers, 4 attention heads per layer, hidden dimension of 1024); the following projection layer is a simple feedfoward neural network (2 linear layers, 1 activation layer), where the output size needs to match the hidden representation dimension for the LLM which is being used. For training the graph encoder, we use the AdamW optimizer (Loshchilov and Hutter, 2017); we train the graph encoder with a batch size of 4 for 10 epochs (with early stopping). The initial learning rate is set to 10^{-5}, with a weight decay of 0.05. At the retrieval step, when creating a connected graph using PCST, we choose to use the default values of $K_n = 3$ and $K_e = 5$.

For the datasets, we work with the preprocessed versions of CWQ [4] and WebQSP [5] obtained by Luo et al. (2024). For the dataset split, we use the default train and test sets proposed in the indicated versions.

We propose an example of a prompt used for decomposing a complex question into multiple atomic and logically ordered subquestions. See Figure 21 for an illustration. Additionally, we provide examples of decomposition to the model to clarify the task and the expected output format. Figure 22 presents some decomposition examples on made-up complex questions; we also choose to add simple questions to show that decomposition is not always necessary.

C Compute Resources and Energy Consumption

We compute the total energy consumption for both CWQ and WebQSP datasets. For each model used, we use a single A100 40GB GPU. The LLaMa-2-13B model consumes more energy and also takes longer to run compared to LLaMa-2-7B. Our hybrid setup is a combination of both models, where we use LLaMa-2-7B for the subquestions, and LLaMa-2-13B only for the final question answering. We showed that we obtain similar accuracy results for the Hybrid 7B/13B model and for LLaMa-2-13B; but Table 6 shows that the hybrid option is much more economical, as we are able to reduce energy consumption by

[1]https://huggingface.co/sentence-transformers/all-roberta-large-v1

[2]https://huggingface.co/deepseek-ai/DeepSeek-R1-Distill-Qwen-32B

[3]code used is under MIT license

[4]https://huggingface.co/datasets/rmanluo/RoG-cwq

[5]https://huggingface.co/datasets/rmanluo/RoG-webqsp

17%. Compared to the LLaMa-2-7B model, the hybrid option only consumes 6% more energy, all experiments considered.

Model	GPU	Energy (kWh)
LLaMa-2-7B	A100 40GB	4.62
LLaMa-2-13B	A100 40GB	5.94
Hybrid 7B/13B	A100 40GB	4.95

Table 6: Energy consumption for test-set experiments across model configurations.

Model	Dataset	GPU	Energy (kWh)
R1-Q-32B	CWQ	H100 96GB	3.15
R1-Q-32B	WebQSP	H100 96GB	0.72

Table 7: Energy consumption for question decomposition (entire dataset preprocessing).

Task	CO_2 Emissions ($kgCO_2e$)
Preprocessing	2.27
Inference	6.2

Table 8: CO_2 Emissions (kg) for dataset preprocessing and model inference.

We also compute the total energy consumption for dataset preprocessing, which mainly consists of decomposing all questions in the dataset as a set of subquestions. For this task, we use a larger model (DeepSeek-R1-Distill-Qwen-32B), and we report the total energy consumption for each dataset in Table 7. Since the CWQ dataset is much larger than the WebQSP dataset, we observe a large difference in the energy needed in both cases.

Having given the energy consumption for our experiments, we compute the corresponding CO_2 emissions (Mass of CO_2 equivalent, $kgCO_2e$) for the different compute tasks (Table 8).