Symbolic Knowledge Injection in LLMs for Zero-Shot and Few-Shot Scenarios

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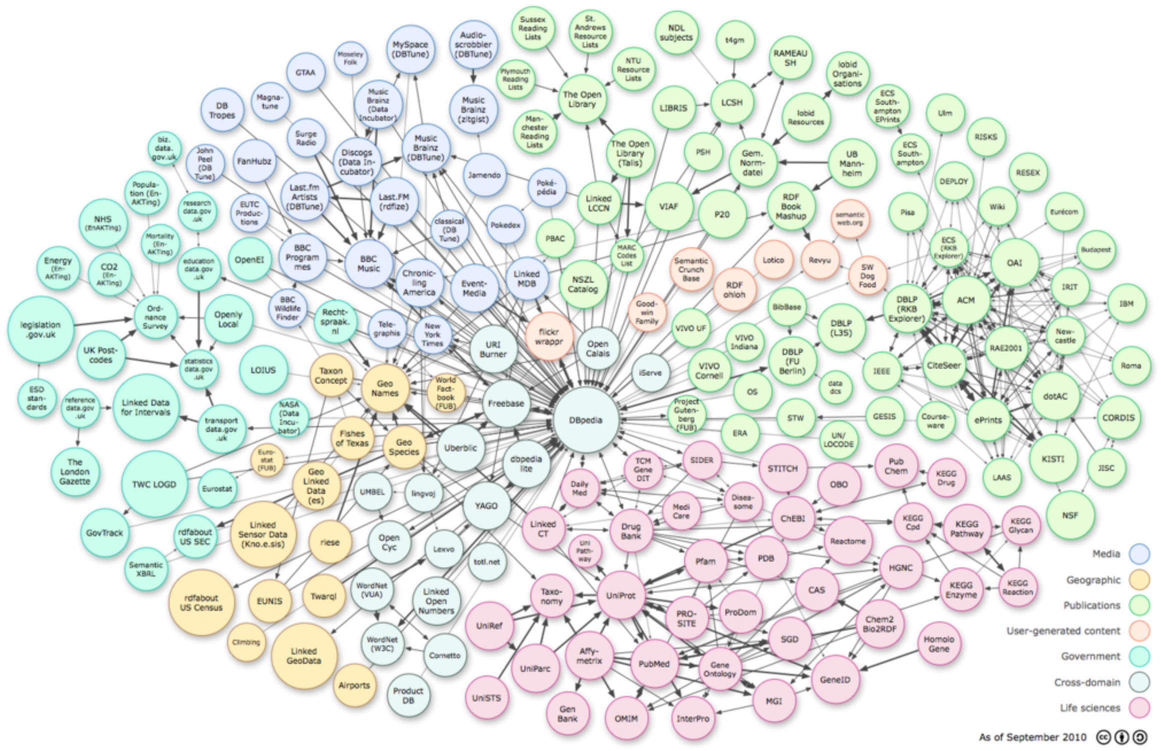
Research Subject

- LLMs can lack explicit understanding and reasoning capabilities

- For certain tasks, data can be rare (or absent): training becomes difficult or expensive…

  → Objective: use **knowledge graphs** and exploit richness of **structure** to improve reasoning capacity of LLMs + ground the model with facts

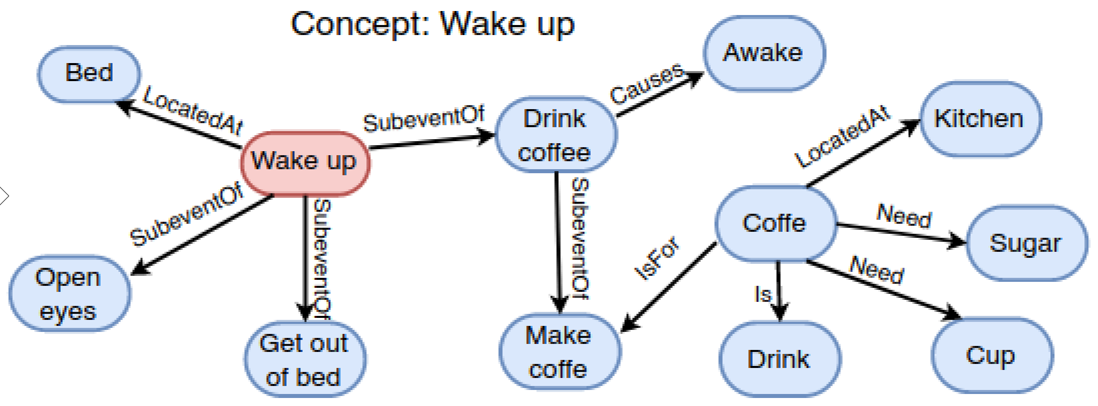


https://accidental-taxonomist.blogspot.com/2019/05/knowledge-graphs-and-ontologies.html

Knowledge Injection

What is a logical thing to do when waking up ?

Prompt



Pan et al. (2024)

You open your eyes and drink coffee

Output

→ Enable better **question understanding** + **reduce hallucinations**

→ Inject facts / implicit relationships (not mentioned in the prompt)

Knowledge Injection

Why using **knowledge graphs** ?

→ Density of information + rich structure

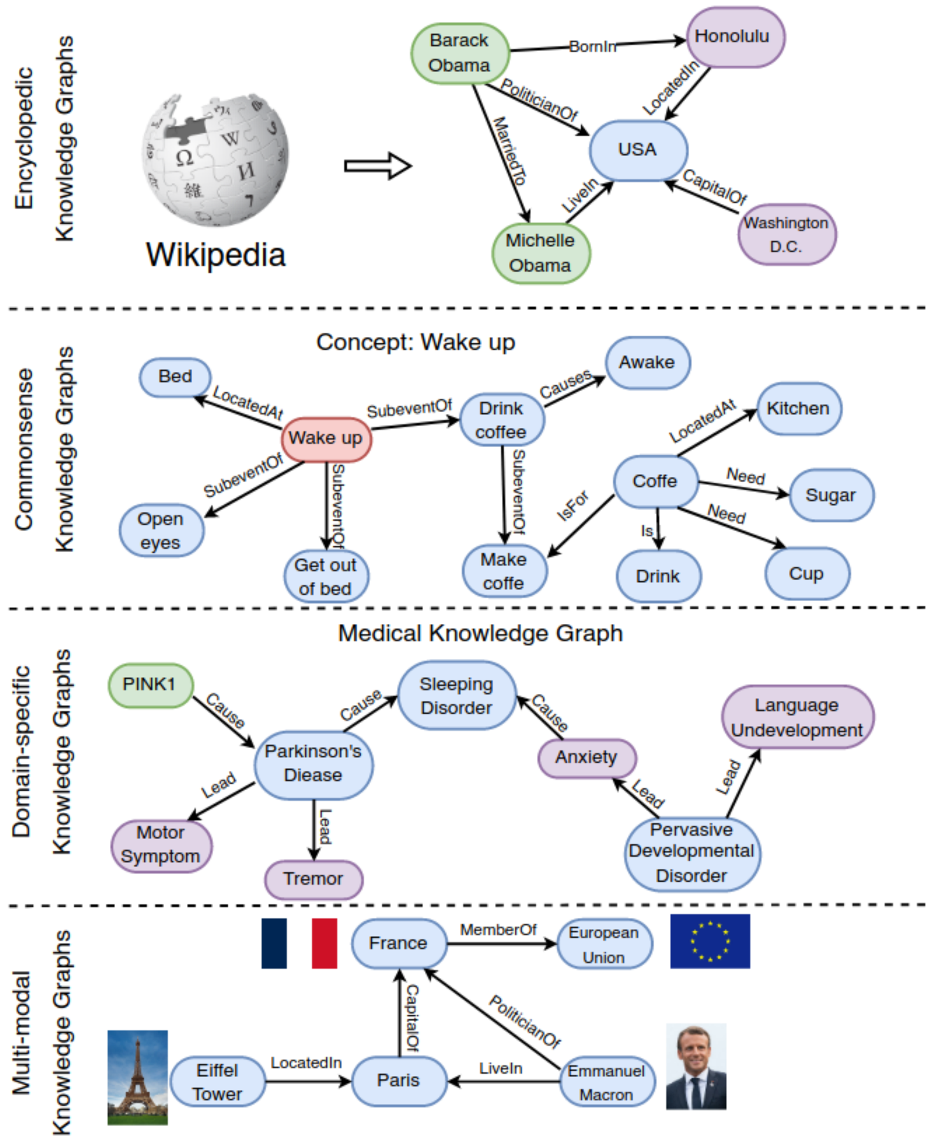
→ Traceability + results interpretation

→ Different graph types for different use cases

How to use them ?

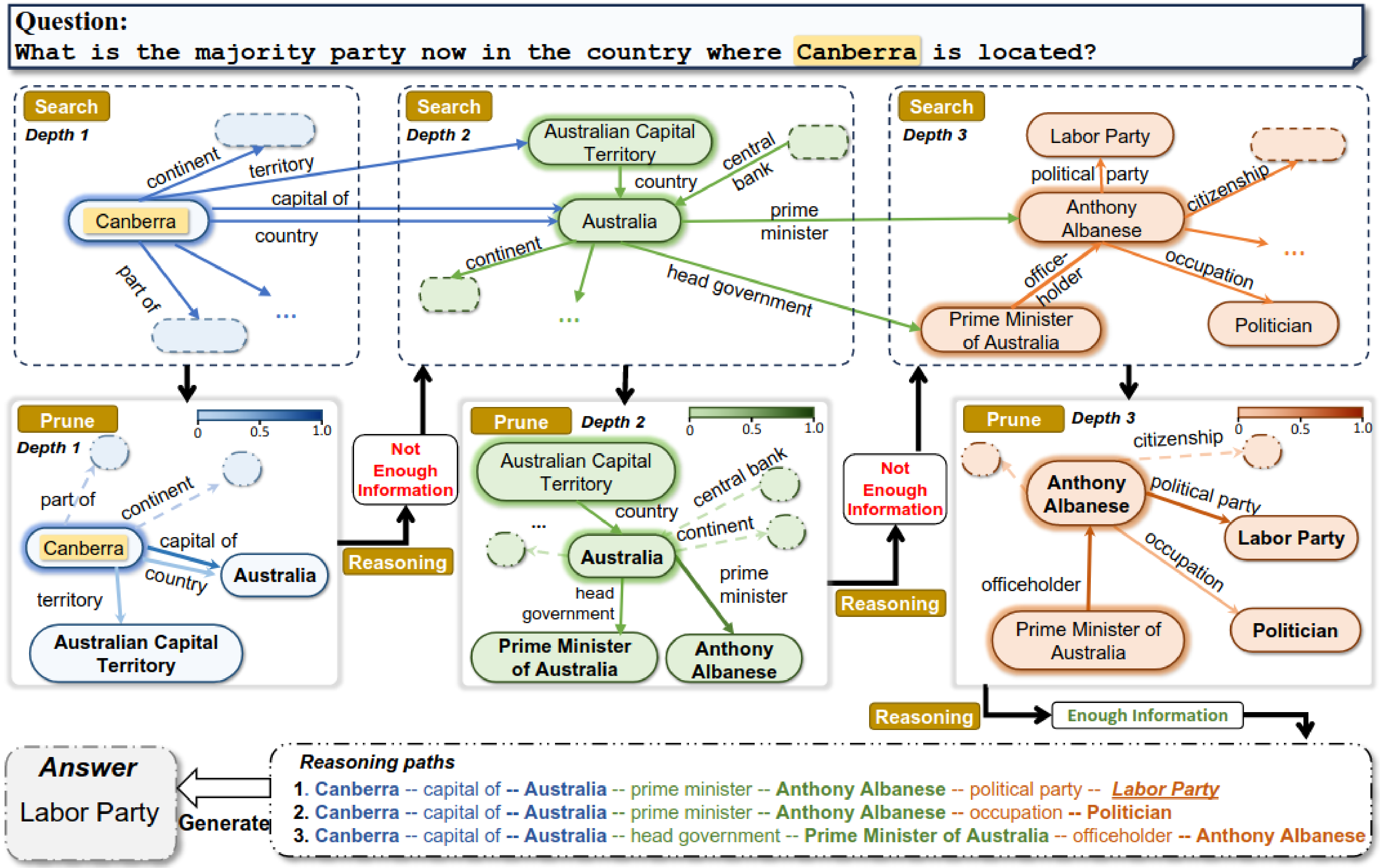
→ Triplets, reasoning paths, sub-graphs

→ Methods : GraphRAG, fine-tuning, pre-training



Pan et al. (2024)

How about reasoning ?



Sun et al.
(2024)

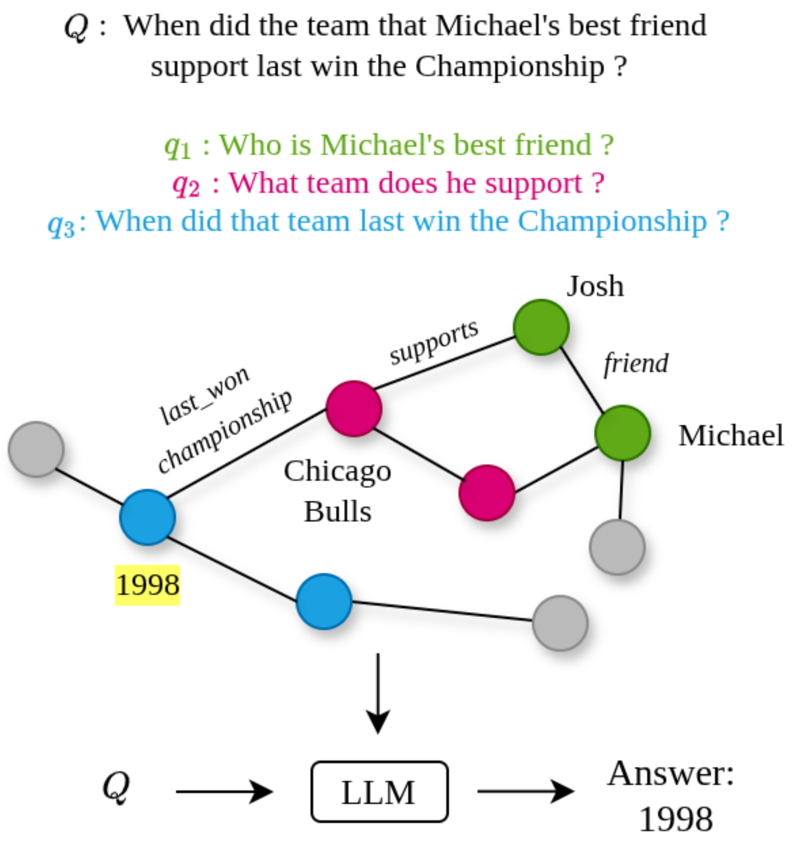
How to improve reasoning ?

Graph retrieval is a difficult task + expensive task for complex queries

Intuition :

- **Decomposing** complex questions in simple sub-questions and perform multiple retrievals
- Fully capture **all dimensions** of the complex question
- Use **reasoning** used within decomposition to improve graph retrieval

Using "G-Retriever" approach to handle textual graphs.


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

WebQSP vs. CWQ Benchmarks

- **WebQSP**: QA dataset, based on Freebase ; simple questions (2-hop max)

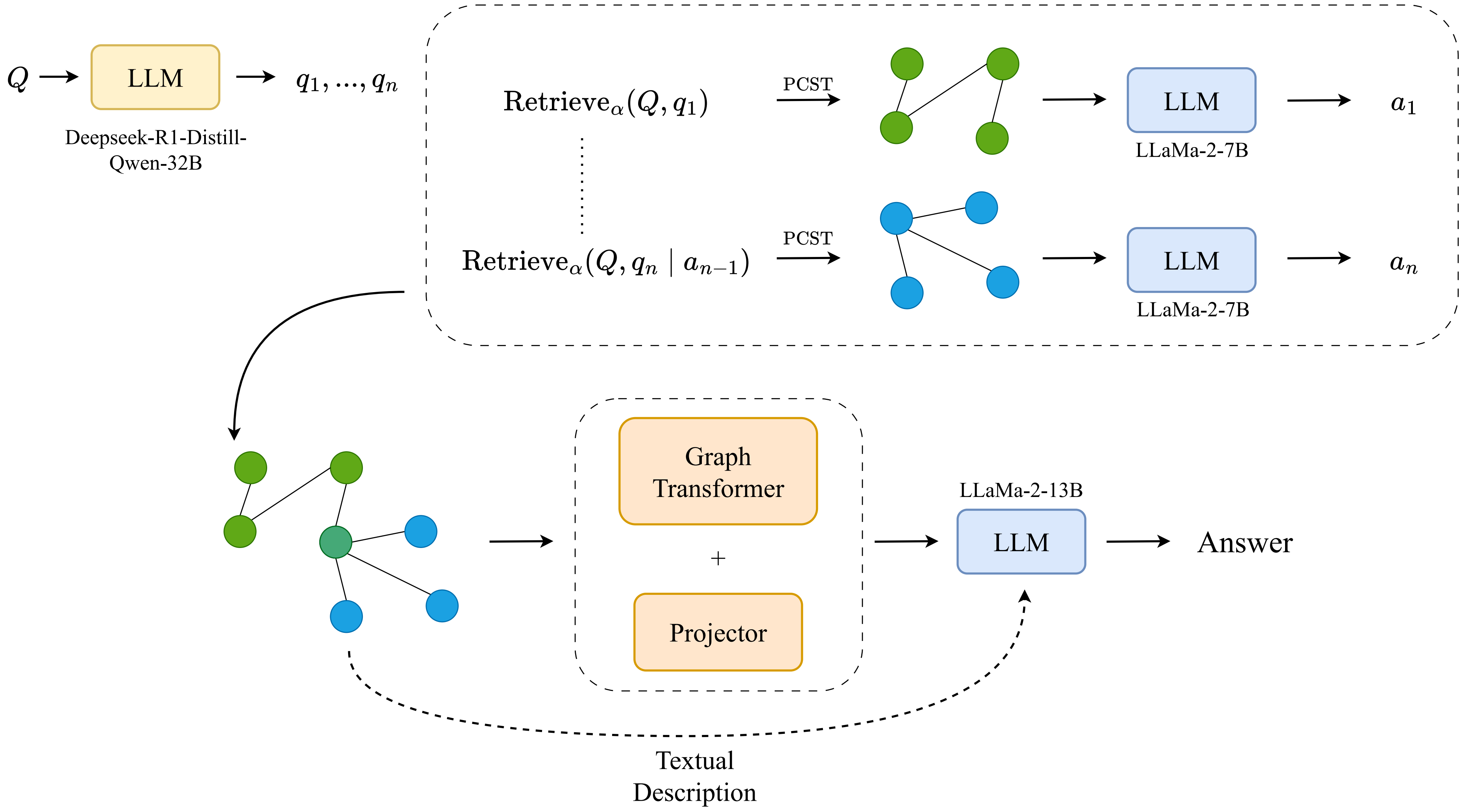
  → *used by G-Retriever*

- **CWQ** : also based on Freebase ; more complex questions (multi-hop)

  → *ignored by G-Retriever ; would probably struggle*

Objective: answer more complex questions that require multiple steps + reasoning

Overall Generation Pipeline


$Q \rightarrow$ LLM $\rightarrow q_1, \ldots, q_n$
Deepseek-R1-Distill-Qwen-32B
$\text{Retrieve}_\alpha(Q, q_1) \xrightarrow{\text{PCST}}$
LLM $\rightarrow a_1$
LLaMa-2-7B
$\text{Retrieve}_\alpha(Q, q_n \mid a_{n-1}) \xrightarrow{\text{PCST}}$
LLM $\rightarrow a_n$
LLaMa-2-7B
Graph Transformer
+
Projector
LLaMa-2-13B
LLM $\rightarrow$ Answer
Textual Description

Retrieval and Graph Construction

1) Knowledge retrieval for each sub-question

$$\left.\begin{aligned} V_k{}^i &= \underset{n \in V}{argtopk}\left[\alpha \cos\left(z_{q_i}, z_n\right) + \left(1-\alpha\right)\cos\left(z_q, z_n\right)\right] \\ E_k{}^i &= \underset{e \in E}{argtopk}\left[\alpha \cos\left(z_{q_i}, z_e\right) + \left(1-\alpha\right)\cos\left(z_q, z_e\right)\right] \end{aligned}\right\} \text{Construct sub-graph } G_i = \left(V_k{}^i, E_k{}^i\right)$$

Problem: sub-questions lack self-awareness ; not capturing the “global objective”

→ Retrieve the $\boldsymbol{k}$ most similar nodes + edges for each sub-question

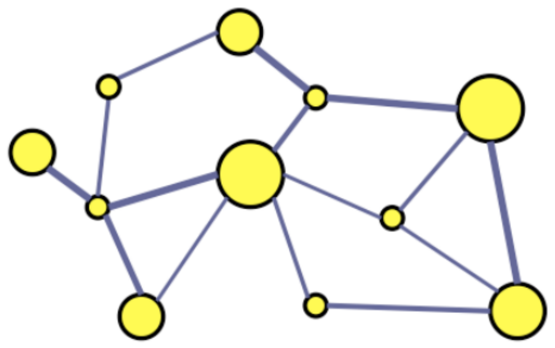
→ Using the initial question $\boldsymbol{Q}$ and current sub-question $\boldsymbol{q_i}$

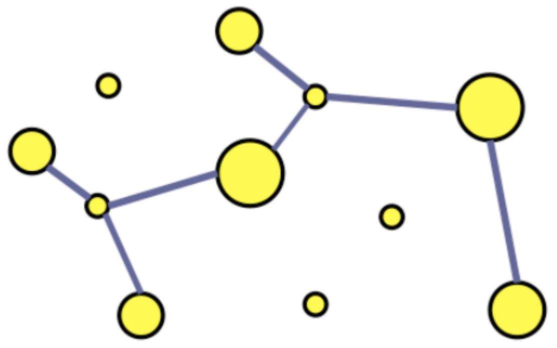
Parameter $\boldsymbol{\alpha}$ to control grounding ; “double cosine similarity”

Retrieval and Graph Construction

2) Graph transformation for each sub-question

→ Prize-Collecting Steiner Tree Algorithm (*TL;DR : most useful graph with minimal size)*





$$G_i = \left(V_k^{\,i}, E_k^{\,i}\right) \longrightarrow G_i^{\,*} = PCST\left(V_k^{\,i}, E_k^{\,i}\right)$$

Retrieved Graph

Filtered + Connected Graph

Akhmedov et al. (2018)

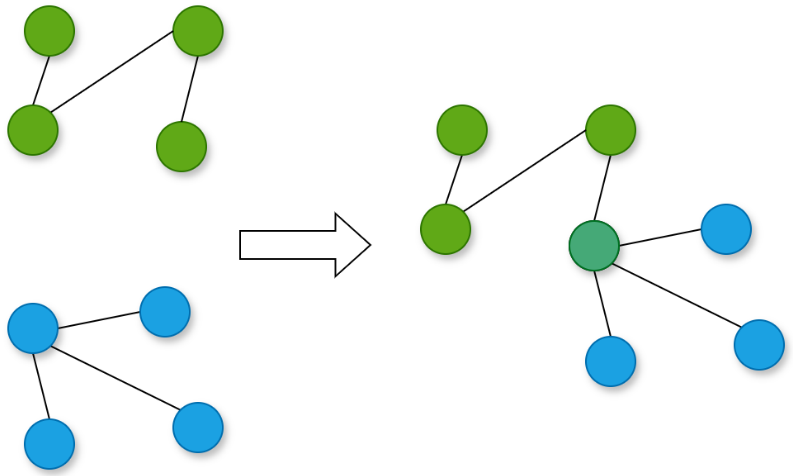
Retrieval and Graph Construction

3) Graphs merging

$$\boxed{G_i^* = PCST\left(V_k^{\,i}, E_k^{\,i}\right)} \longrightarrow \boxed{G^* = \coprod_i^n \left(G_1^*, \ldots, G_n^*\right)}$$

Obtaining connected sub-graphs

Merging



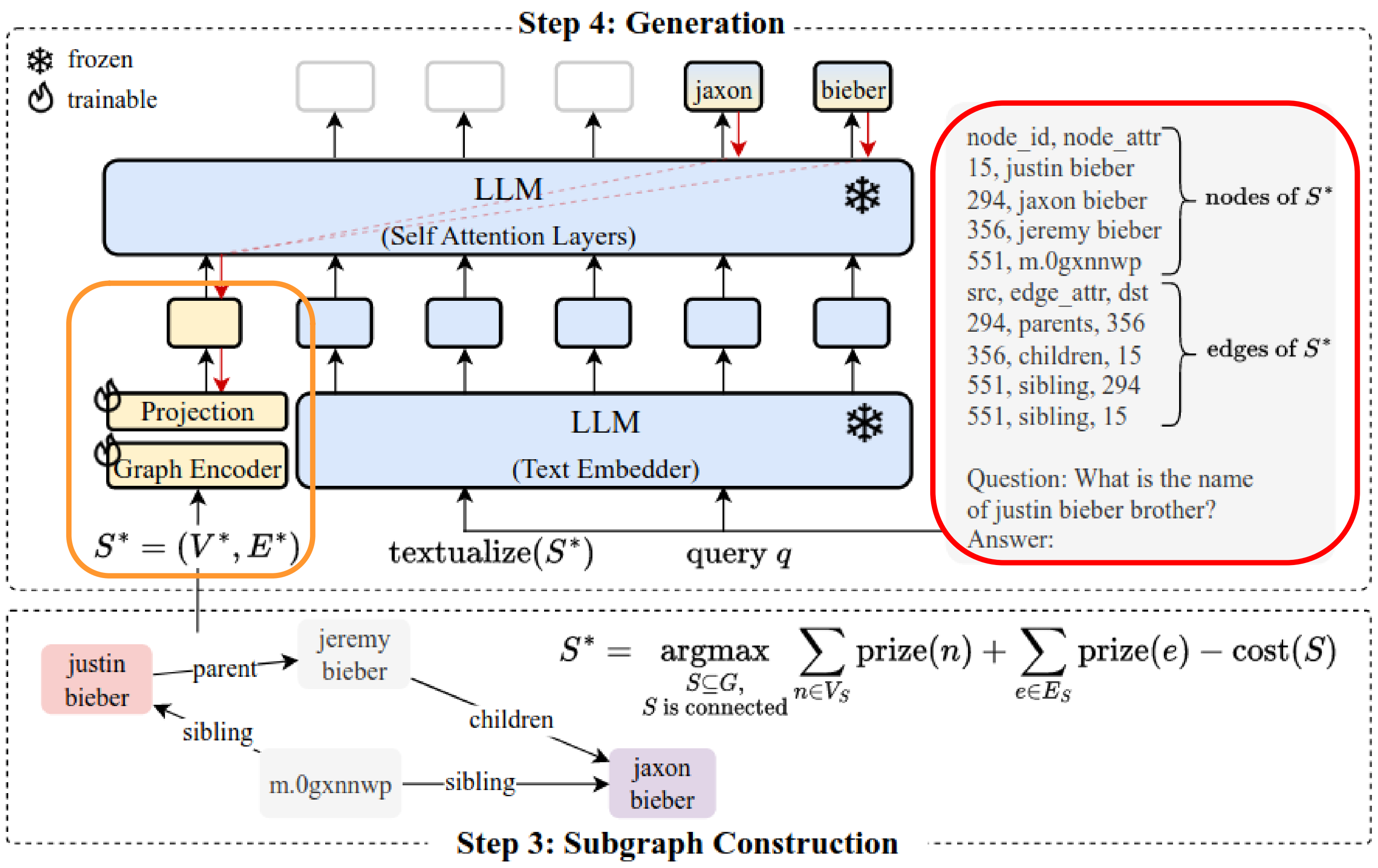
→ For each question, we **merge** the sub-graphs corresponding to the sub-questions

→ Detailed merging process:

- Extract sets of unique nodes + edges
- Create merged graph

Note: there is no guaranty that the final graph is connected, but most likely it will be

Answer Generation



He et al. (2024)

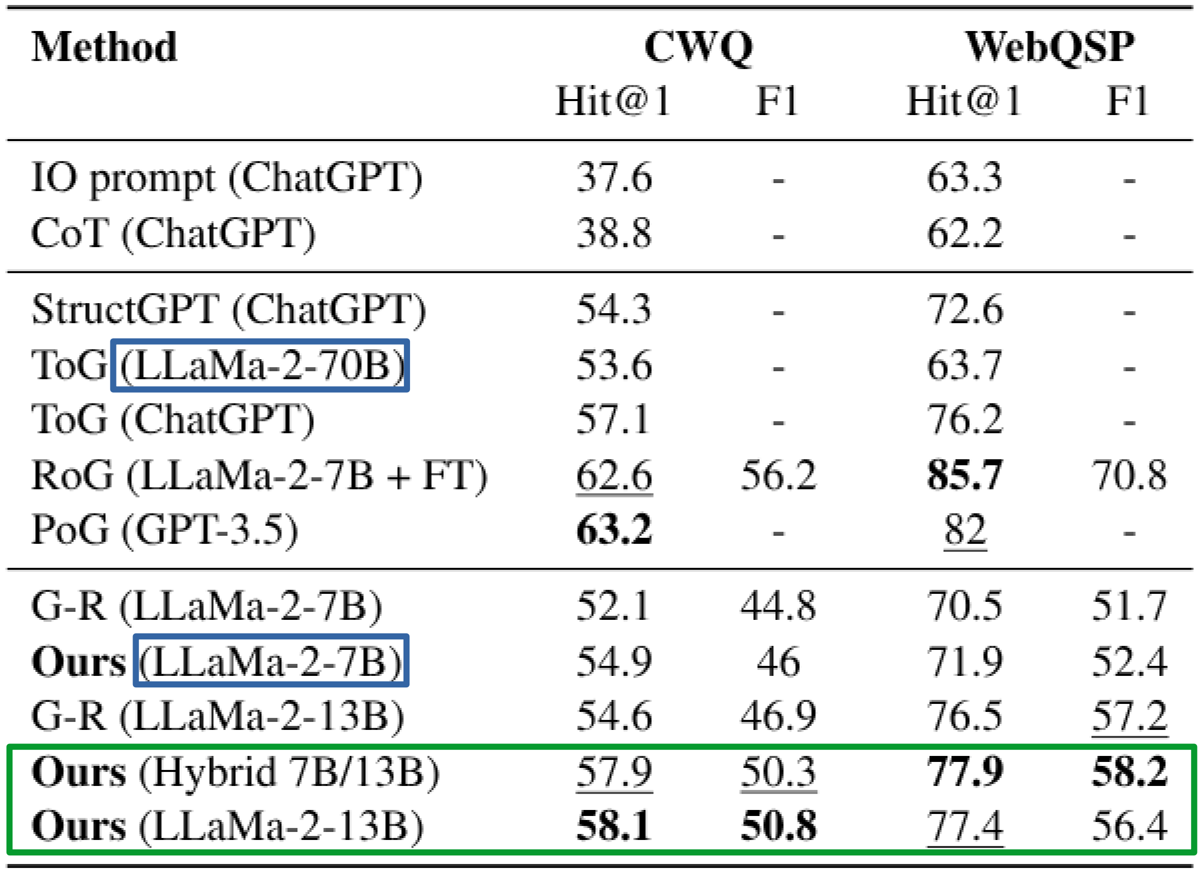
Generation:

Hard prompt + Soft prompt

Reconstruction:

Connected sub-graph from retrieved elements

Results



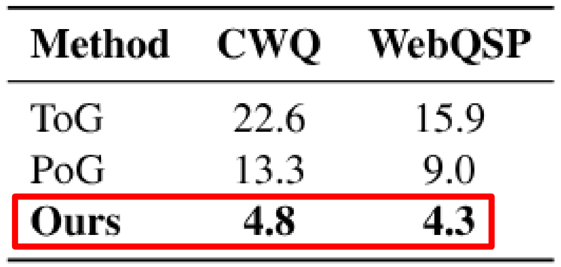
Method	CWQ Hit@1	CWQ F1	WebQSP Hit@1	WebQSP F1
IO prompt (ChatGPT)	37.6	-	63.3	-
CoT (ChatGPT)	38.8	-	62.2	-
StructGPT (ChatGPT)	54.3	-	72.6	-
ToG (LLaMa-2-70B)	53.6	-	63.7	-
ToG (ChatGPT)	57.1	-	76.2	-
RoG (LLaMa-2-7B + FT)	62.6	56.2	**85.7**	70.8
PoG (GPT-3.5)	**63.2**	-	82	-
G-R (LLaMa-2-7B)	52.1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

Accuracy results compared to SOTA

Smaller models

Larger models ≠ better performance

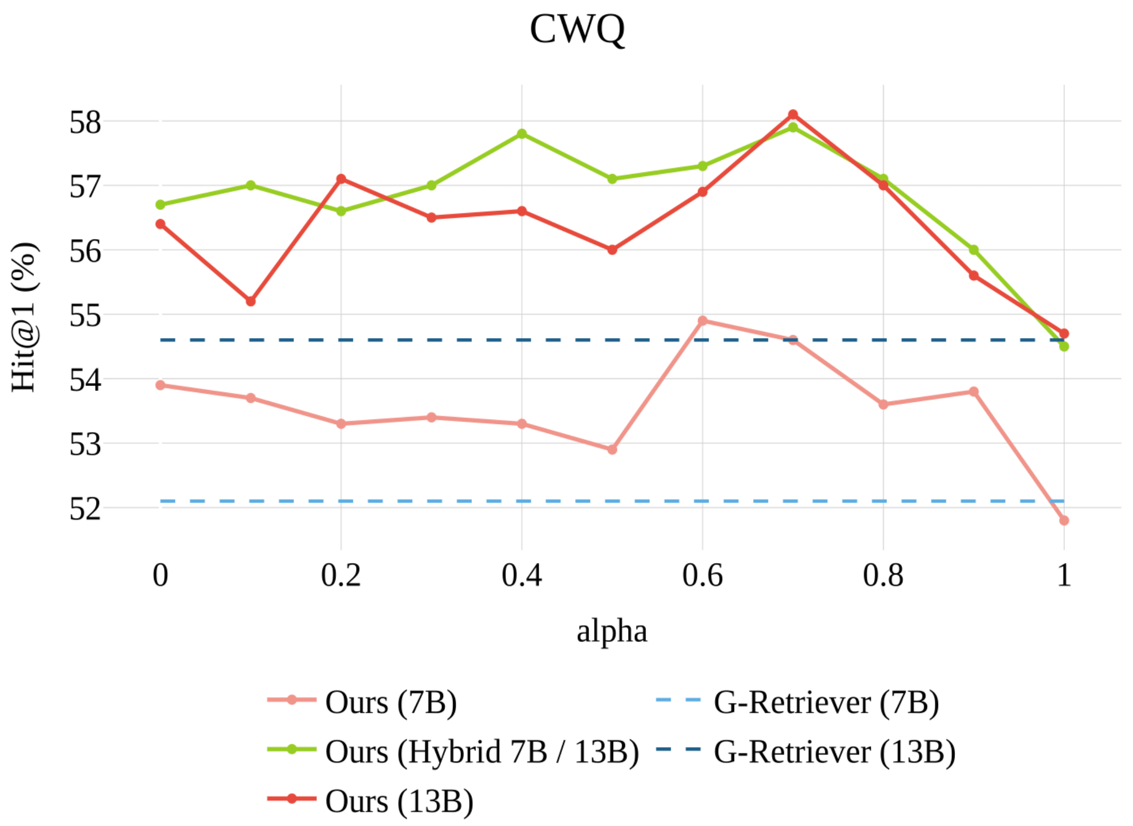
Fewer LLM calls

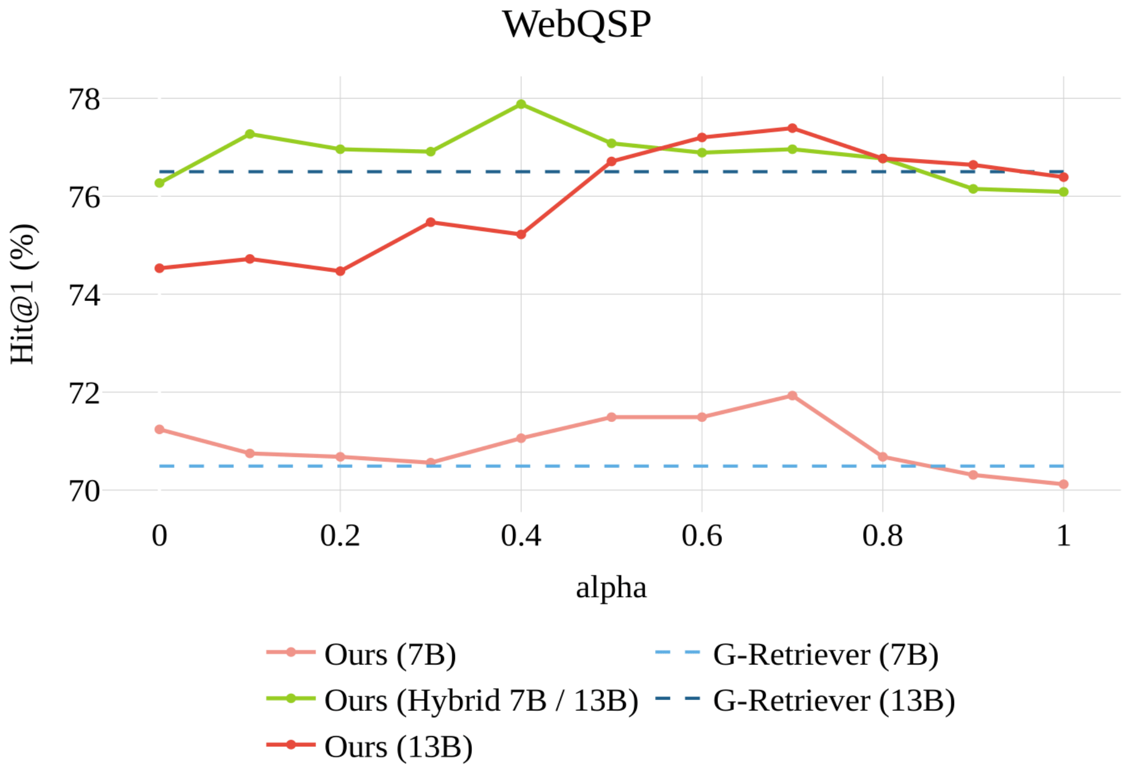


Method	CWQ	WebQSP
ToG	22.6	15.9
PoG	13.3	9.0
Ours	**4.8**	**4.3**

Number of LLM calls

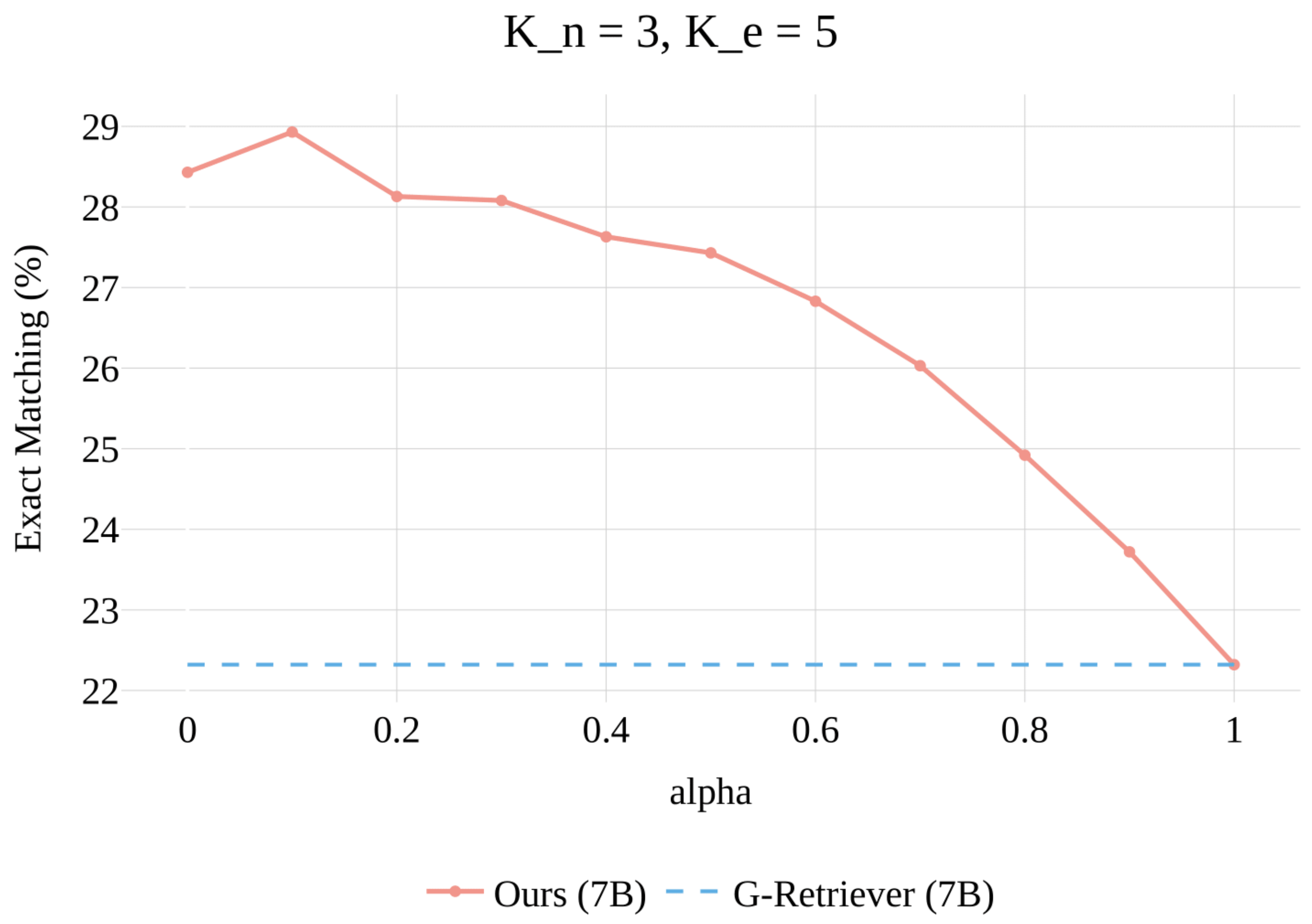
Results





Our retrieval methods improves the performance of G-Retriever for different model sizes. We introduce an hybrid approach where we alternate between 7B and 13B models; this approach achieves similar performances to the 13B model for the entire pipeline.

Results



In this context, Exact Matching corresponds to the percentage of retrieved graphs that contain the ground truth answer.

Focusing on the sub-questions gives better EM, at the cost of having disconnected and less dense graphs…

References

« Unifying Large Language Models and Knowledge Graphs: A Roadmap » (Pan et. al)

« Think-on-Graph: Deep and Responsible Reasoning of Large Language Model on Knowledge Graph » (Sun et al.)

« G-Retriever: Retrieval-Augmented Generation for Textual Graph Understanding and Question Answering » (He et al.)