

# The Role Evolution of KGs in Synthesizing with LLMs: From Background Knowledge to Joint Reasoning

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# Introduction

#### Comparison of LLMs and KGs

Feature	Knowledge Graphs (KGs)	Large Language Models (LLMs)
Data Structure	Structured, graph-based (triples)	Unstructured text-based, sequential tokens
Knowledge Type	Explicit, factual, domain-specific knowledge	Implicit, parametric, commonsense knowledge
Processing Style	Logical reasoning, graph query, path traversal	Intuitive, implicit, next token prediction
Primary Use Case	KGQA, recommendation, entity disambiguation	QA, content generation, text summarization

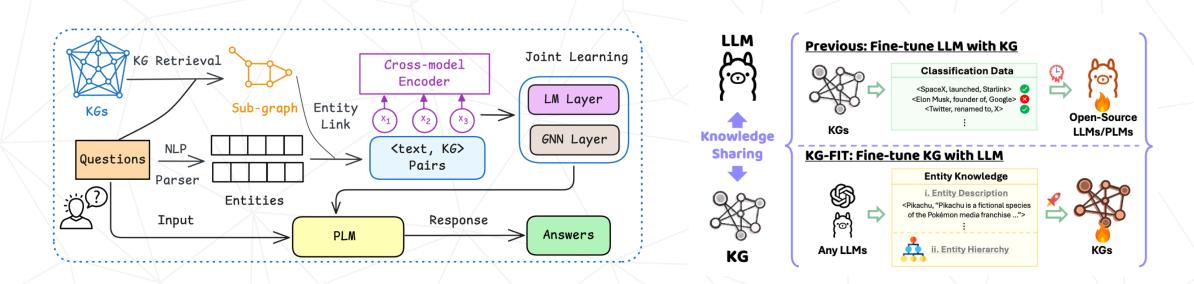
#### Introduction

#### Why Do We need to synthesize LLMs with KGs?

- Large Language Models (LLMs)
  - Strengths: Superior Capabilities in Natural Language Processing and Generation ...
  - Limitations: Hallucination, Poor Reasoning, Lack of up-to-date Domain Knowledge, Black-box Model ...
- Knowledge Graphs (KGs)
  - Strengths: Highly curated Structured and Reliable Knowledge, Symbolic Reasoning and Inference ...
  - **Limitations**: High cost of construction, Incompleteness, Domain-specified ...
- LLMs + KGs
  - Neuro-symbolic System: Hallucination Mitigation, Reasoning, Explainable and Responsible Results.
  - Knowledge Fusion: Combinations of Domain Specific factual Knowledge and Common Knowledge.

- KGs as Background Knowledge
  - KGs and Text Alignment
    - KGs (entities or relations) having the textual description (Text-KG pair)
    - KG and text data are stored separately (Common scenario for QA task)

Joint learning



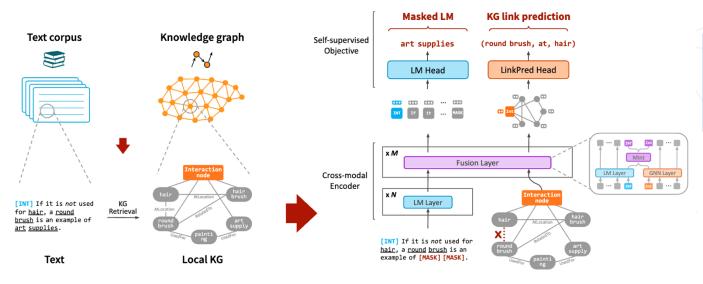
Jiang, Pengcheng, et al. "KG-FIT: Knowledge graph fine-tuning upon open-world knowledge." Advances in Neural Information Processing Systems 37 (2024): 136220-136258.

**Entity Linking** 

KG Retrieval

Fine-tuning

- Joint Learning: Bidirectional language and KG pretraining [NeurIPS2022]
  - Retrieving relevant subgraph from KG based on text to create text-KG pair.
  - Leveraging cross-modal encoder that fuses the input text-KG pair bidirectionally.
  - Unifying masked LM and KG link prediction for and joint learning reasoning.



Modality interaction (Mint) with interaction token and node to mix representation for joint learning

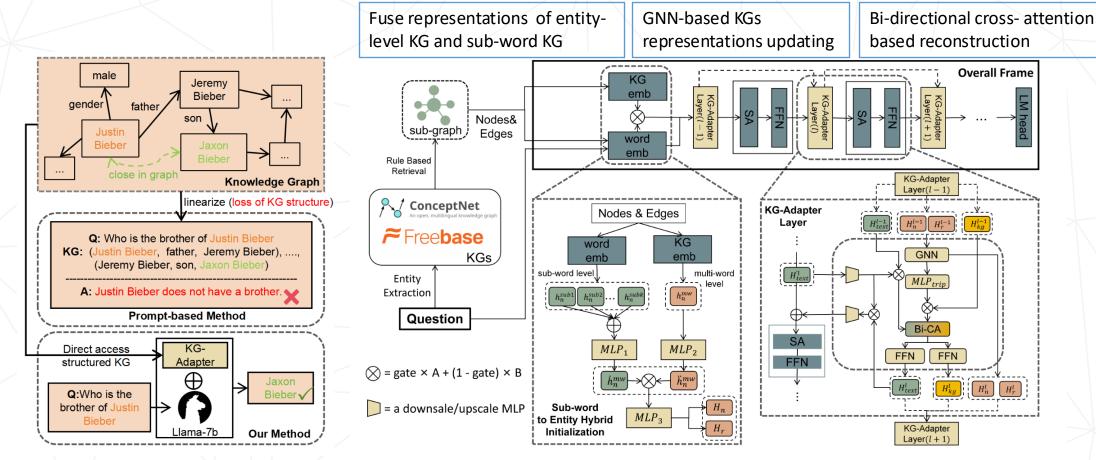
$$[oldsymbol{h}_{int}^{(\ell)};oldsymbol{e}_{int}^{(\ell)}] = ext{ MInt}([ ilde{oldsymbol{h}}_{int}^{(\ell)}; ilde{oldsymbol{e}}_{int}^{(\ell)}]),$$

Raw data

**Pretrain DRAGON** 

Fine-Tuning LLMs with KGs

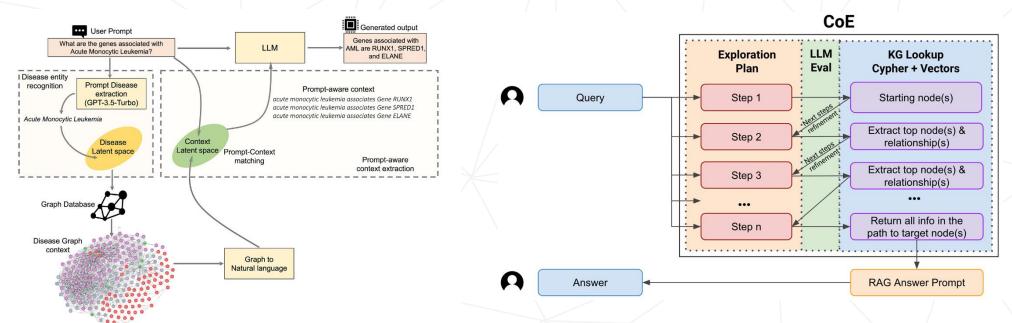
-KG-Adpter: Parameter-efficient fine-tuning (PEFT) for integrating KGs with LLM [ACL 2024]



Tian, Shiyu, et al. "KG-Adapter: Enabling Knowledge Graph Integration in Large Language Models through Parameter-Efficient Fine-Tuning." *ACL Findings* (2024): 3813–3828.

- KG based Retrieval Augmented Generation (KG-RAG)
  - KG-RAG for knowledge intensive tasks [Bioinformatics, 2024]
  - Chain of Explorations (CoE) for KG-RAG [arXiv2024]

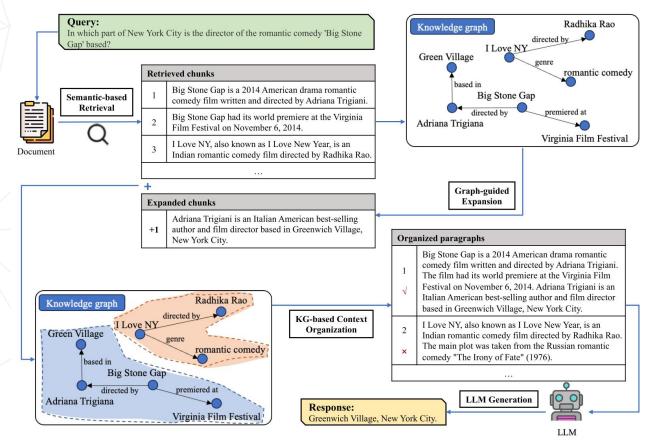
Introduce CoT with LLM to select relevant nodes or relationships from KG



KG-RAG: Cypher-query based Retrieval

KGQA over a KG retrieval based on CoE

- Retrieval Augmented Generation (RAG)
  - KG-guided RAG (KG<sup>2</sup>RAG) [arXiv 2025]



Text with available existing KG: establish linkage between text chunks and KG chunks

Text without KG: extract entities and relations

from text chunks to form subgraph

$$\mathcal{S} = \{ s(q, c) \mid c \in \mathcal{D} \},\$$

a. Semantic-based chunks retrieval

$$\mathcal{G}_q^0 = \{(h, r, t, c) \mid c \in \mathcal{D}_q\} \subseteq \mathcal{G}.$$

b. Retrieve the relevant subgraph from KG

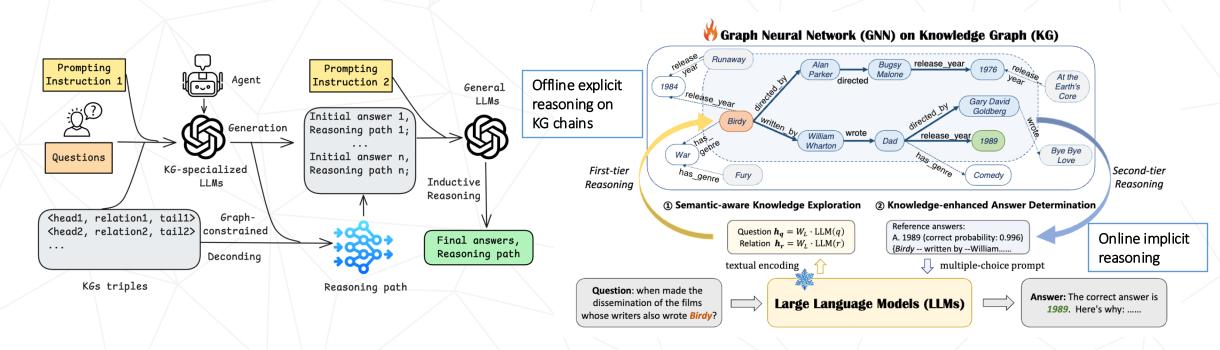
$$\mathcal{G}_q^m = \text{traverse}(\mathcal{G}, \mathcal{G}_q^0, m),$$

c. Expand retrieved chunks with the m-hop BFS searched neighbor subgraphs on KG

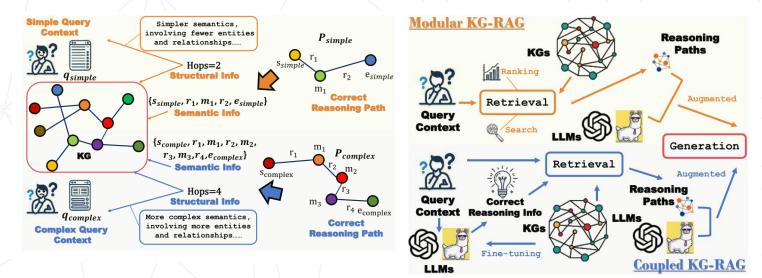
$$R(q, \mathcal{T}_i) = C(q, \operatorname{conc}(\mathcal{T}_i)),$$

d. Rank the relevant expanded chunks and incorporates it with the retrieved chunks as context

- KGs serves as guidelines to LLMs for Joint Reasoning
  - Offline Reasoning: KGs-based reasoning before LLMs reasoning
  - Online Reasoning: KGs-based reasoning directly involves in LLMs reasoning
  - Agent-based KG guidelines: Agent-based autonomous reasoning



- Offline Reasoning: [FRRAG] Modular KGRAG for KGQA [arXiv, 2025]
  - Estimate the hop of reasoning to classify the question
  - Employ BFS and ranking to retrieve subgraph for reasoning
  - Leverage LLM to extract reasoning paths
  - Generate the final answer based on retrieved reasoning paths



**Prompt:** You are an expert reasoner with a deep understanding of logical connections and relationships. Your task is to analyze the given reasoning paths and provide accurate reasoning path to the questions based on these paths.

Based on the reasoning paths, please extract the correct reasoning path. If NO correct reasoning path, please just reply NO.

Reasoning Paths: {paths}
Question: {question}
Correct reasoning path:

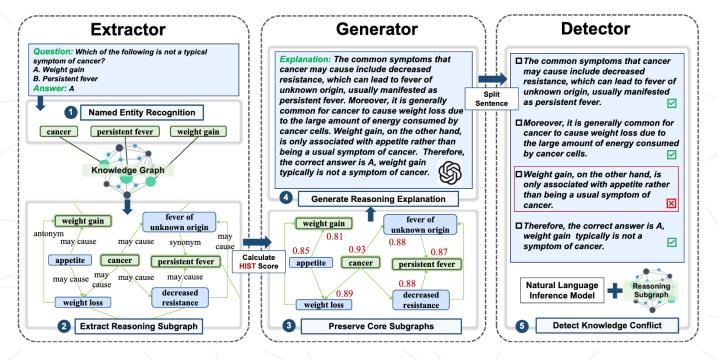
**Prompt:** You are an expert reasoner with a deep understanding of logical connections and relationships. Your task is to analyze the given reasoning paths and provide clear and accurate answers to the questions based on these paths.

Based on the reasoning paths, please answer the given question.

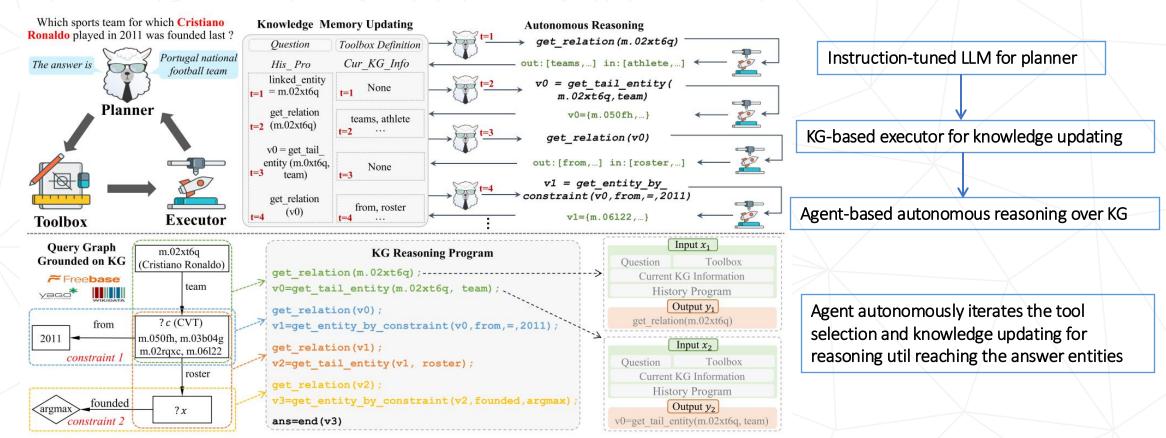
Reasoning Paths: {paths}

Question: {question}

- Online Reasoning: [KG-SFT] KG augmented supervised fine-tuning LLM for KGQA
   [ICLR2025]
  - Search neighboring entities to obtain the reasoning subgraphs
  - Generate reasoning-based explanations via an external LLM
  - Detect knowledge conflict based on online reasoning (reasoning subgraph and natural language inference model)
- (1) Perform NER on QA pairs for entity extraction
- (2) Retrieve core subgraph from external KGs that is related to QA pairs vis HITS (Hyperlink-Induced Topic Search)
- (3) Split the LLM generated reasoning explanations and fuse it with language inference model



 Agent based Reasoning: [KG-Agent] Agent-based autonomous reasoning for KGQA [arXiv2024]



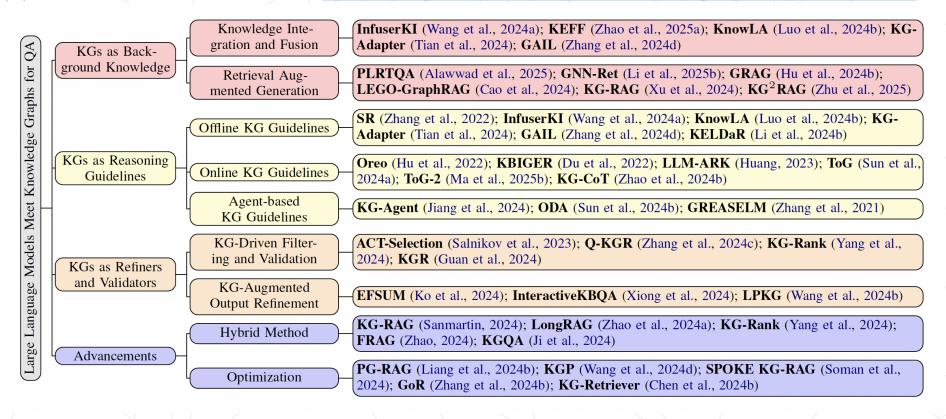
Example of instruction fine-tuning data synthesis and KG reasoning for the input-output pairs

#### Comparison of Approaches with Different Roles of KGs

Approaches	Key Techniques	Strengths	Limitations	KG Requirements
KGs as background knowledge	Pre-training, fine- tuning, KG-based RAG	Hallucinations mitigation	Re-training is needed when updating KG	High domain coverage and up-to- date factual knowledge
KGs as reasoning guidelines	Rule-based reasoning, CoT-based path exploration	Explainable results with less hallucinations, Knowledge interaction	Costly rule mining and prompt token overhead, path explosion and reasoning latency	Rich logical and semantic Knowledge, Flexible interaction interface
Hybrid approaches	Agent-based knowledge reasoning, reinforcement learning	Iterative reasoning, knowledge updating	High reasoning complexity and computing cost	Dynamic knowledge adaptation

#### Our Recent Survey

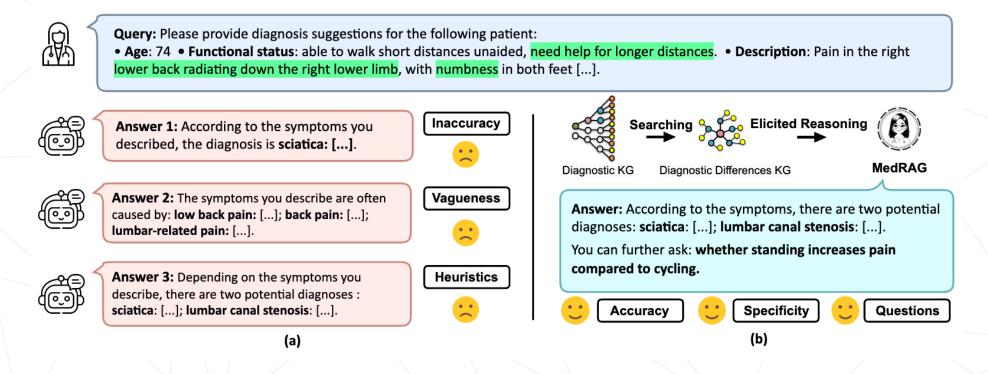
 LLMs Meet Knowledge Graphs for Question Answering: Synthesis and Opportunities [arXiv2025] <a href="https://github.com/machuangtao/LLM-KG4QA">https://github.com/machuangtao/LLM-KG4QA</a>



# LLMs + KGs Applications

#### Medical QA

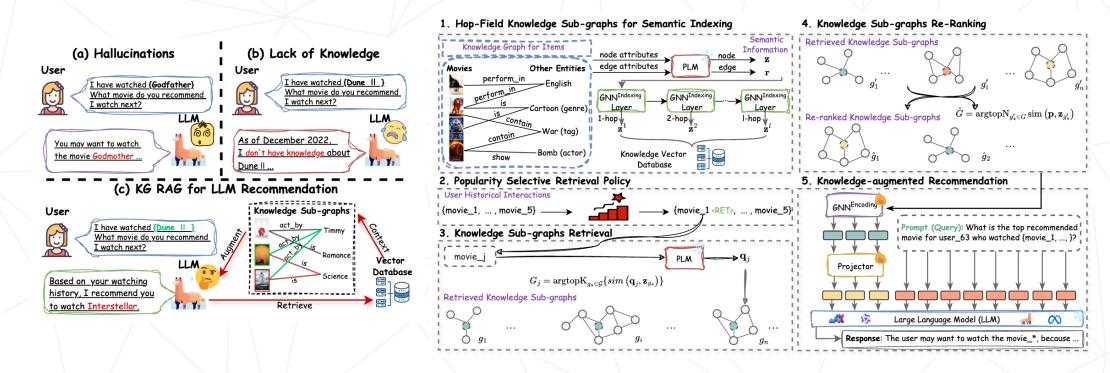
- MedRAG: KG-augmented LLMs for healthcare diseases diagnostic [WWW2025]
  - Leverage multi-level matching and upward traversal techniques to search the diagnostic differences KG.
  - Generate the final answers and follow-up questions for precise diagnosis based on the KG-elicited reasoning.



# LLMs + KGs Applications

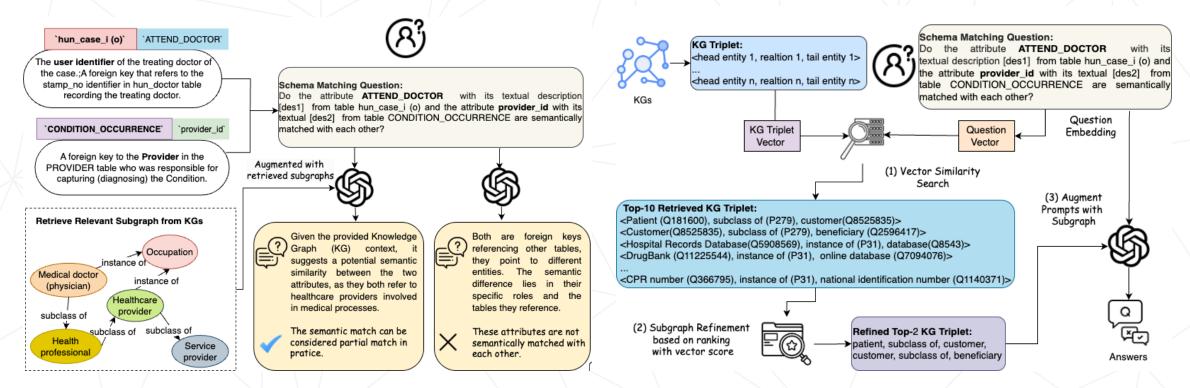
#### Recommendation

- K-RAGRec: KG RAG for LLM-based Recommendation [ACL2025]
  - Introduce a popularity selective and similarity-based ranking to retrieve the relevant subgraphs from item's KGs.
  - Leverage GNN and projector to align the retrieved sub-graphs into semantic space of LLM for recommendation.



# LLMs + KGs Applications

- Schema Matching and Data Integration
  - KGRAG4SM: KG based RAG for Schema Matching [arXiv 2025]
    - A hybrid retrievals with vector-based, graph traversal-based, and ranking-based graph refinement to retrieve relevant subgraphs from external large KGs to augment LLMs for schema matching.



#### Conclusion

#### KG-RAG

- Vector-based graph retrieval: vector-based search is computing-consuming task for large KGs.
- Query-based graph retrieval: Text2GQL is a challengeable task as the schema is agnostic for LLMs.

#### KG-guided Reasoning

- Faithful of reasoning: generate the reasoning paths from KGs is primary based on LLMs while the faithful of generated reasoning paths from KGs need to be addressed.
- Complex reasoning: reasoning over large-scale KGs is a time-consuming and computing-consuming task, efficient graph reasoning techniques need to be further investigated.

#### LM and KG Alignment

- Effective knowledge fusion: integrating LLMs with KGs with the prompt-based fusion is not the optimal one as the topological information of KGs will be lost during the conversion.
- Dynamic Knowledge Integration: keep the up-to-date knowledge in KGs and support incremental knowledge updating of KGs.
- Knowledge conflicts mitigation: the knowledge conflicts between the internal knowledge of LLMs and the retrieved external knowledge need to be mitigated.



Knowledge Graphs for Responsible Al Workshop



#### Thanks

https://machuangtao.github.io