Unifying Language Models with Knowledge Graphs

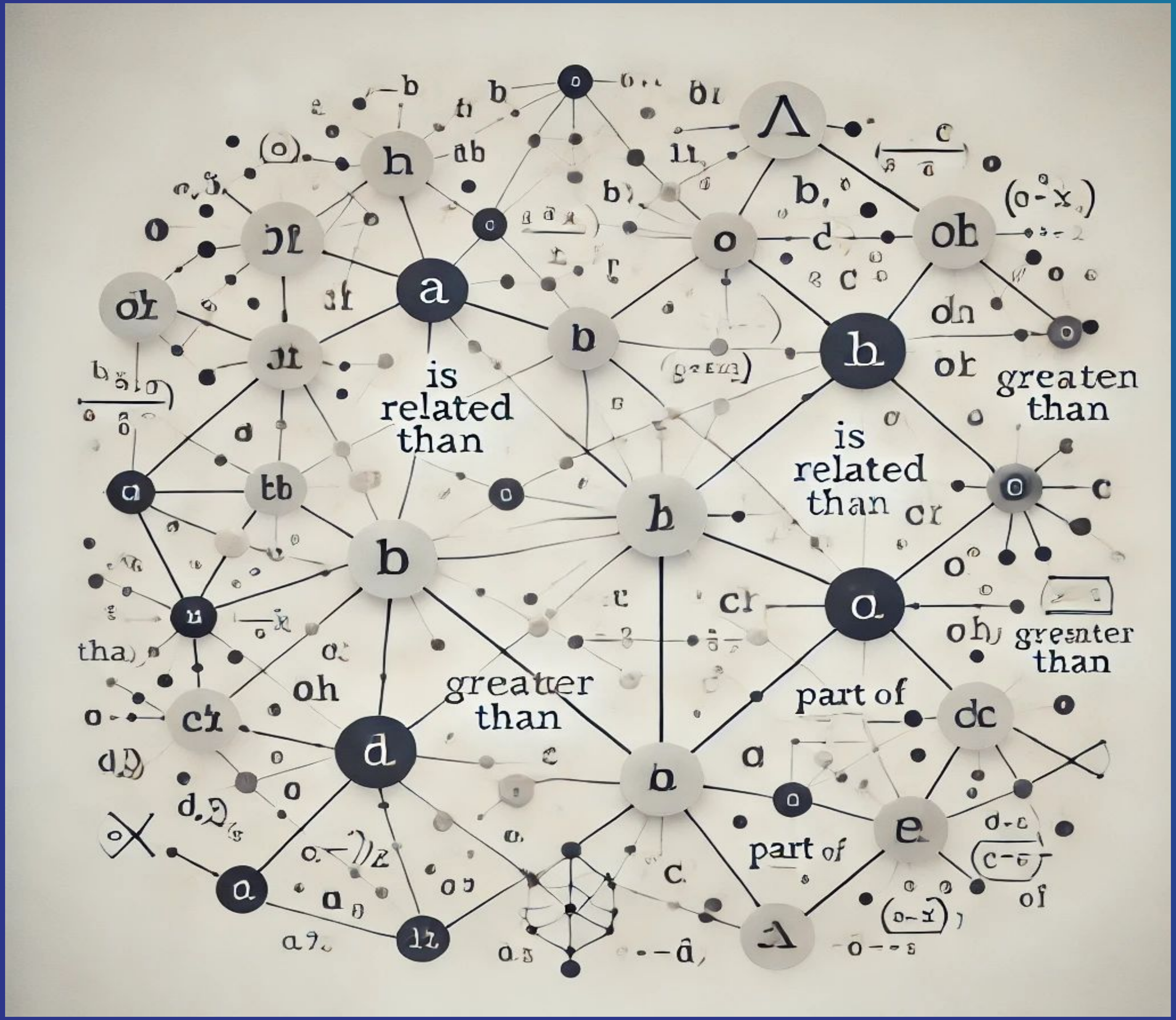
A SESHADITYA

naavi network

- Special thanks to
    - Jakob Porschmann (Google Berlin)
    - Milena Solomun
    - Michael Schäfer
    - Anuradha
    - Lavanya
    - Siva Sai

Table of Contents

Knowledge Graphs



Information as entities and relationship

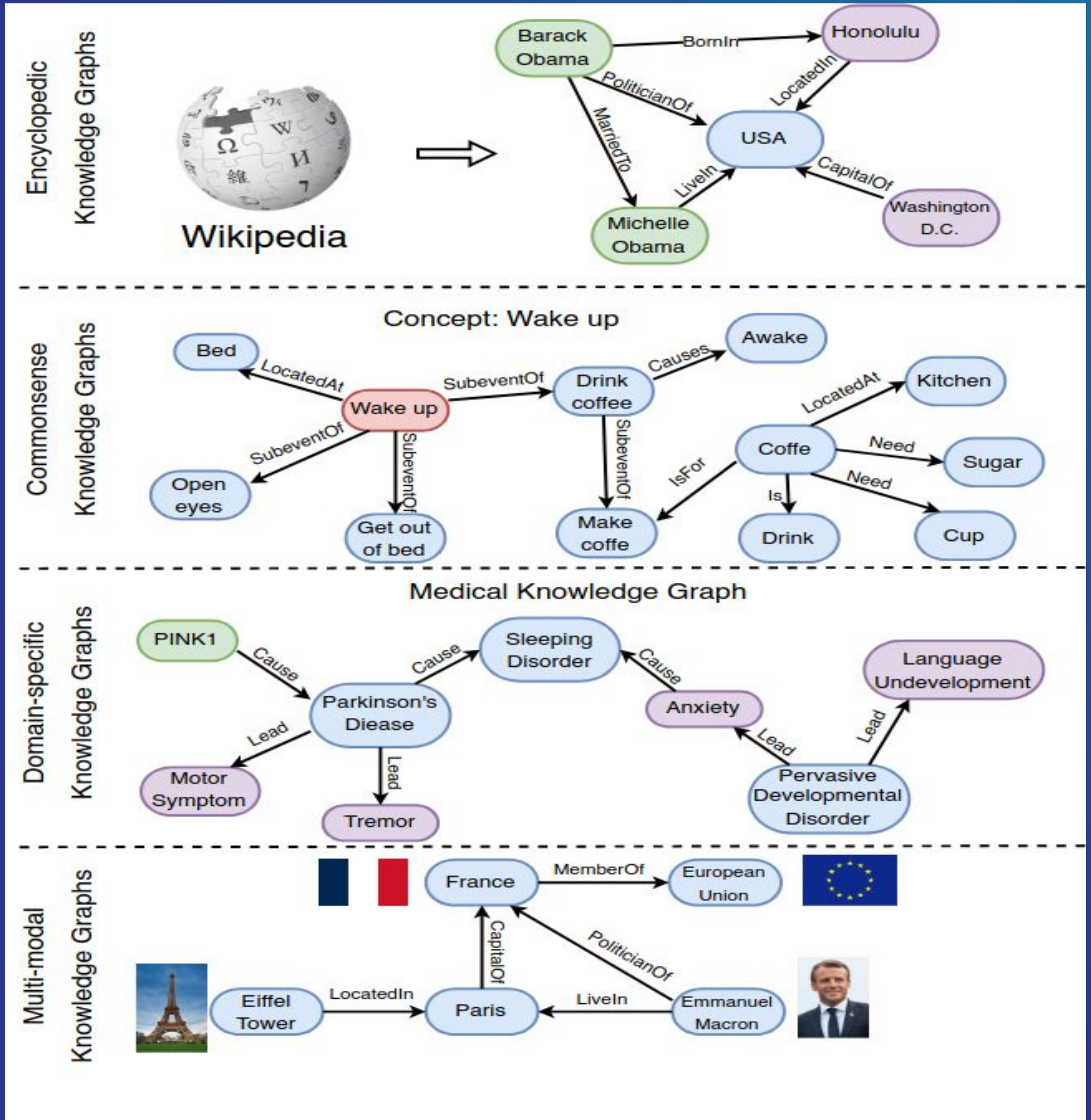
Key Component

Nodes

Edges

Attributes

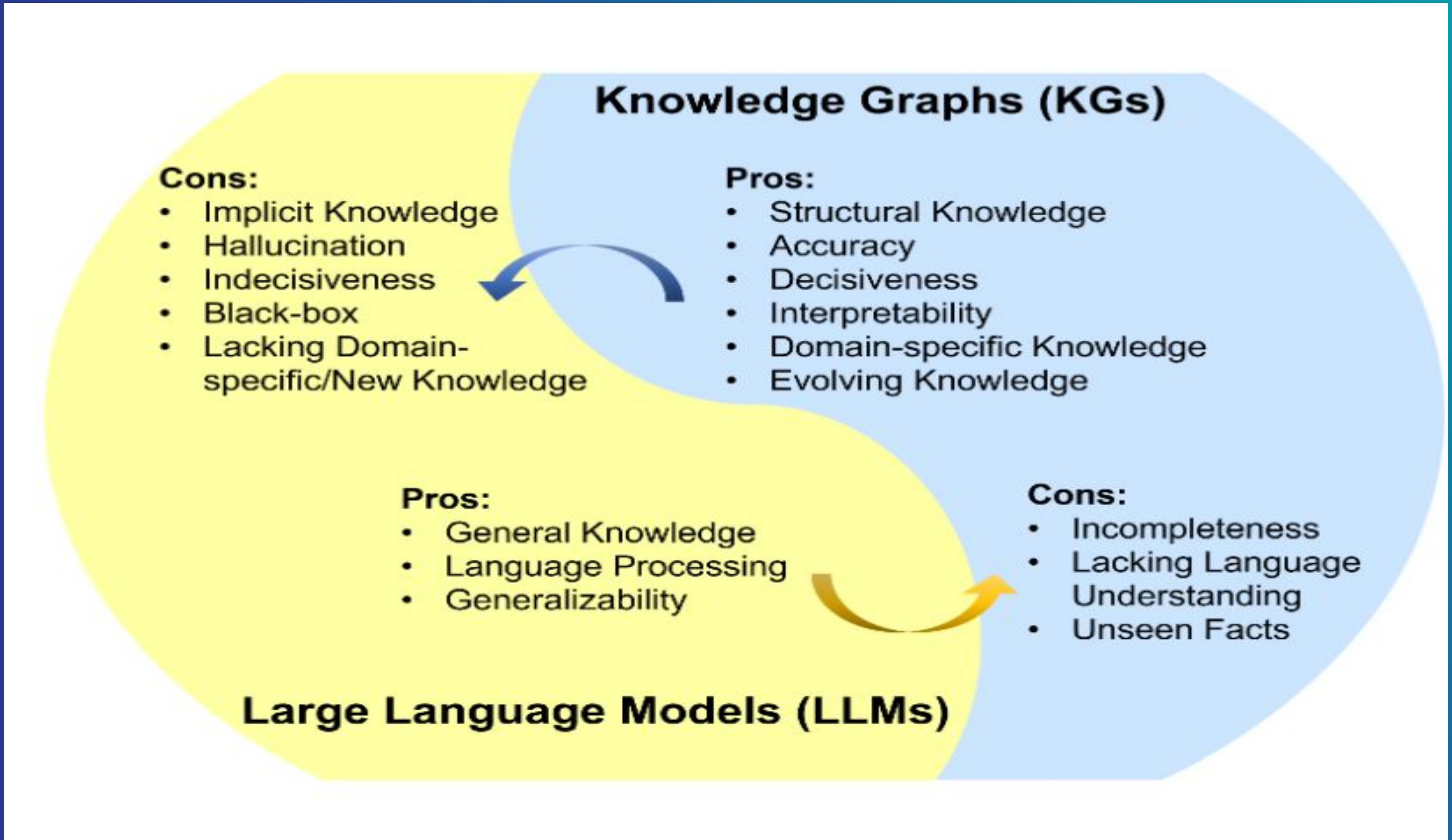
Different Knowledge Graphs



- Encyclopedic Knowledge Graphs
- Commonsense Knowledge Graphs
- Domain-specific Knowledge Graphs
- Multi-modal Knowledge Graphs

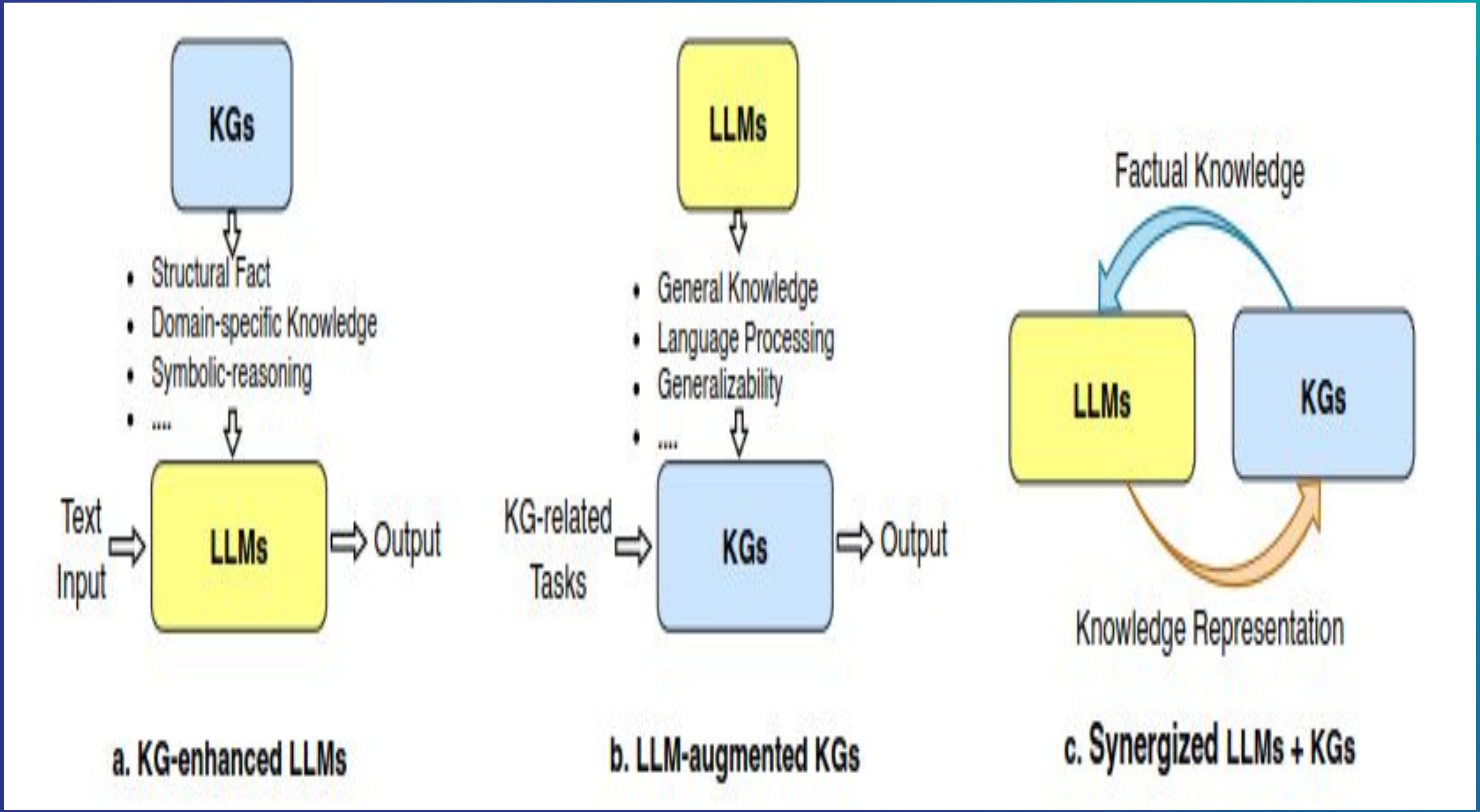
Source: https://arxiv.org/pdf/2306.08302.pdf

LLMs and Knowledge Graphs



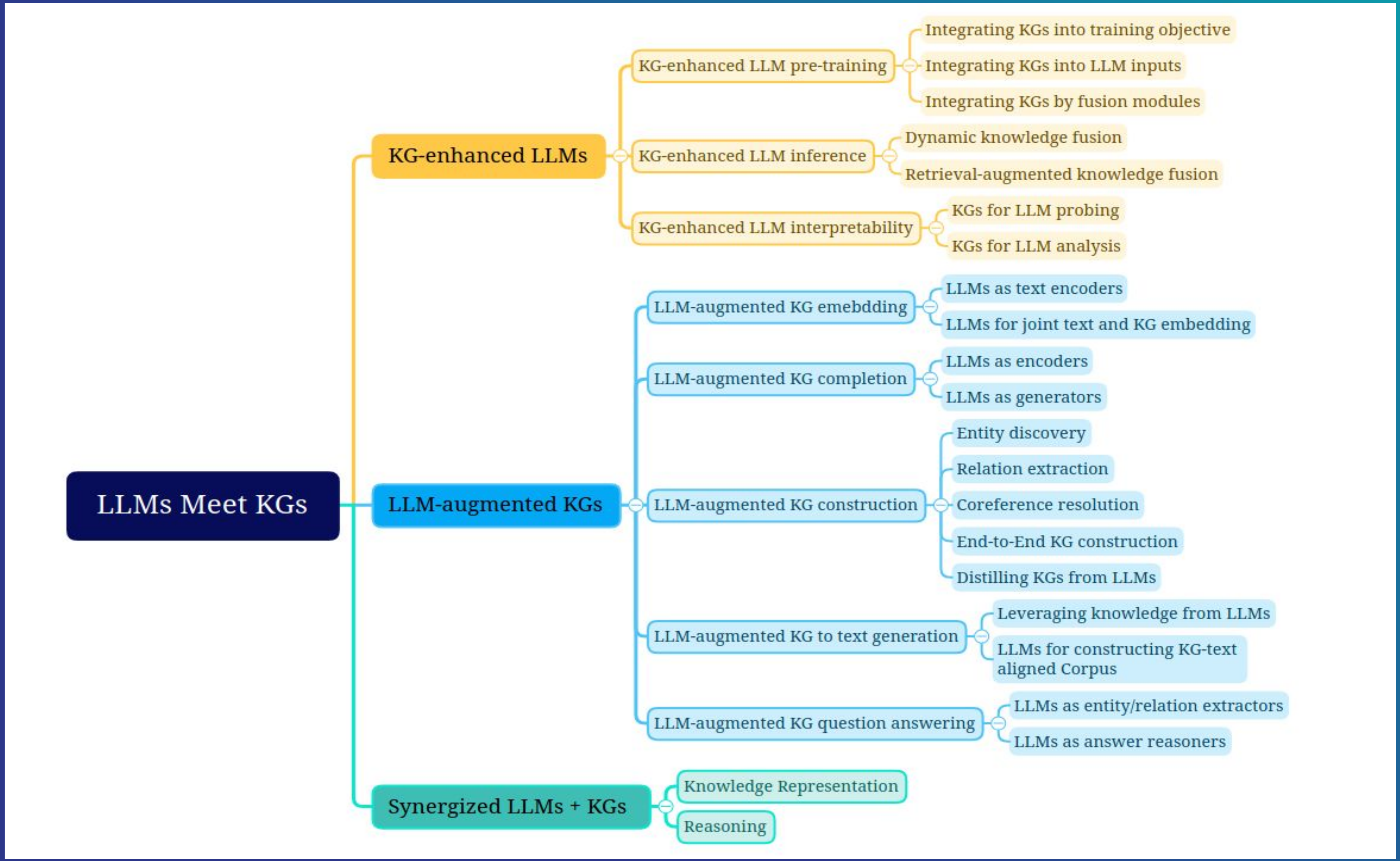
Source: https://arxiv.org/pdf/2306.08302.pdf

Different approaches



Source: https://arxiv.org/pdf/2306.08302.pdf

Unifying LMs with Knowledge Graphs



Source: https://arxiv.org/pdf/2306.08302.pdf

Knowledge Graph enhanced LLM generation

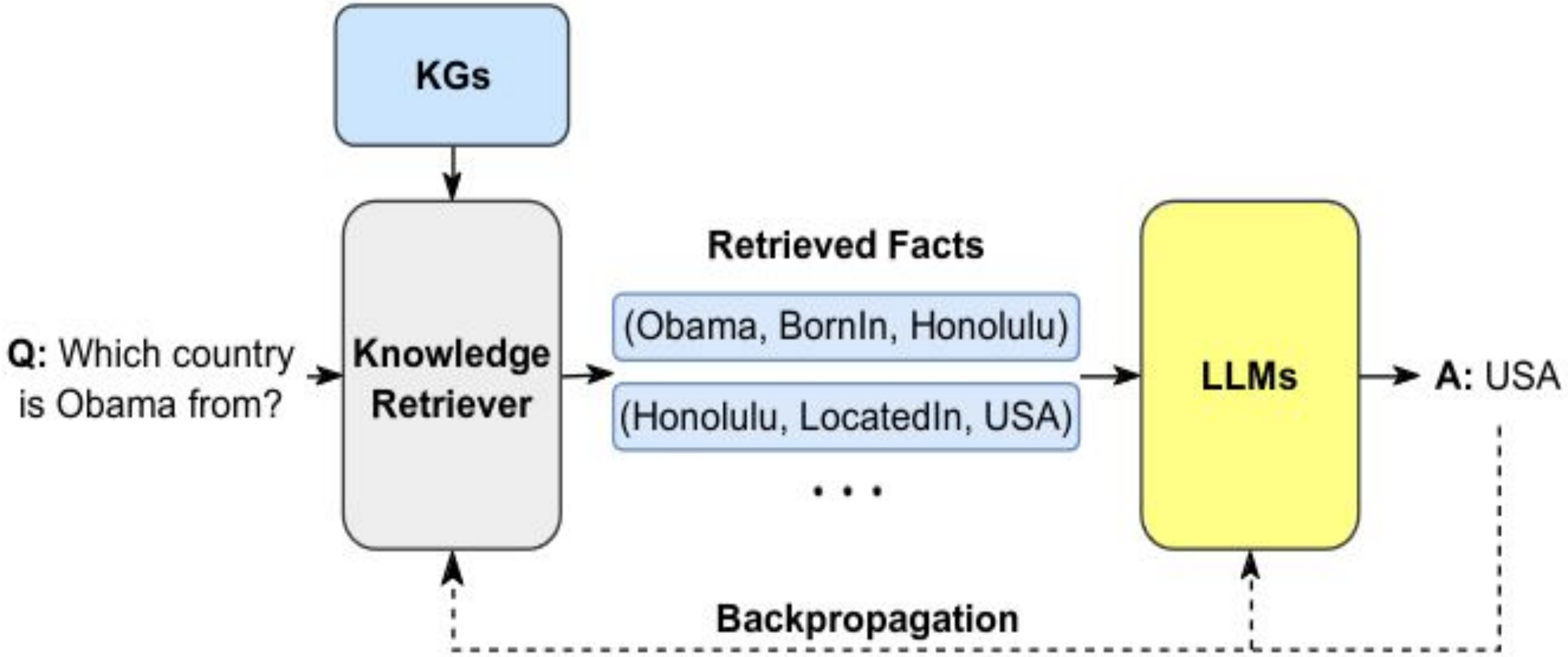
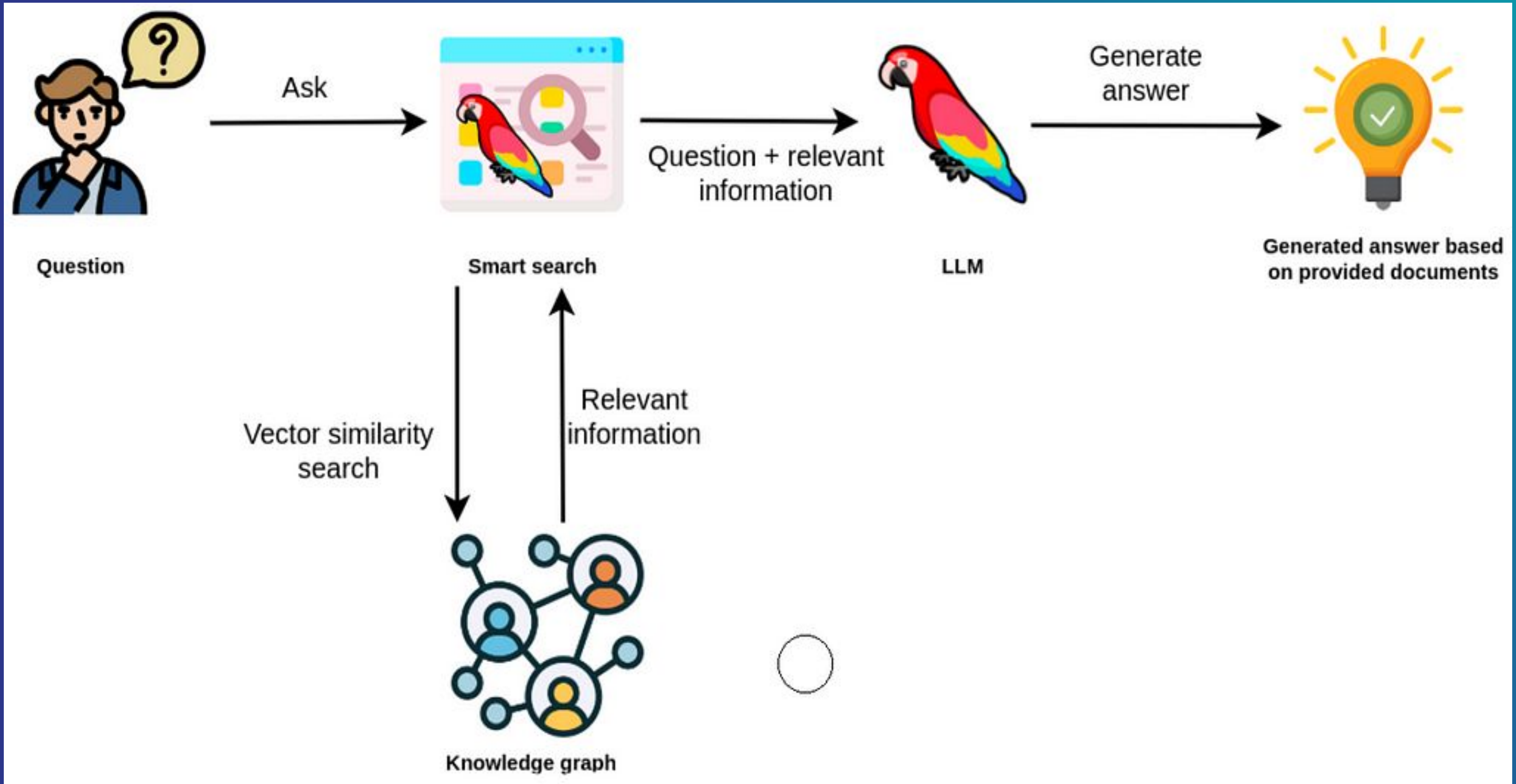


Fig. 11. Retrieving external knowledge to enhance the LLM generation.

Source: https://arxiv.org/pdf/2306.08302.pdf

Graph RAGs

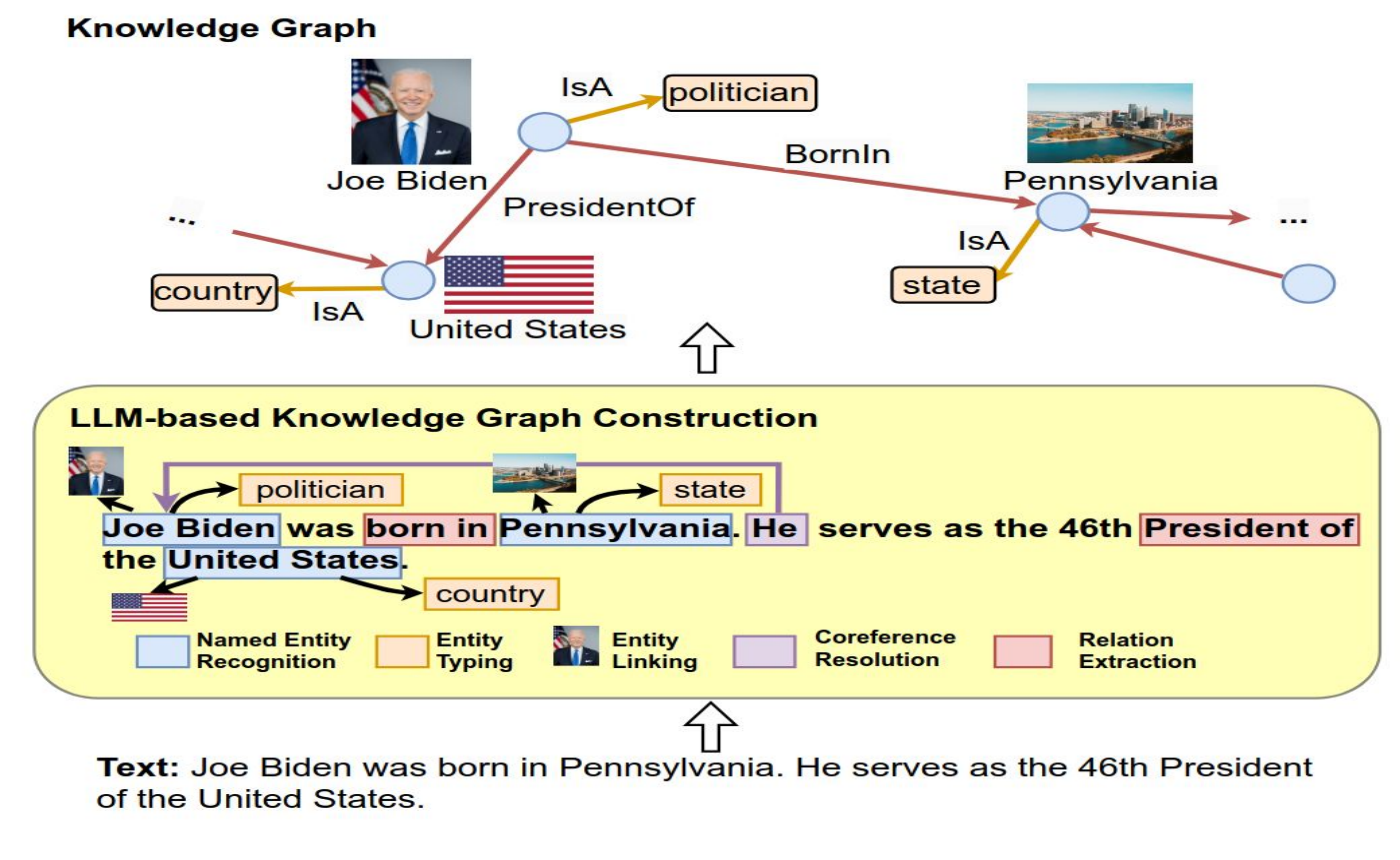
Retrieval-Augmented Generation (RAG) advanced retrieval technique, more accurate, contextually aware, and nuanced responses to user queries



Source: https://neo4j.com/developer-blog/knowledge-graph-rag-application/

LLM-augmented Knowledge Graphs

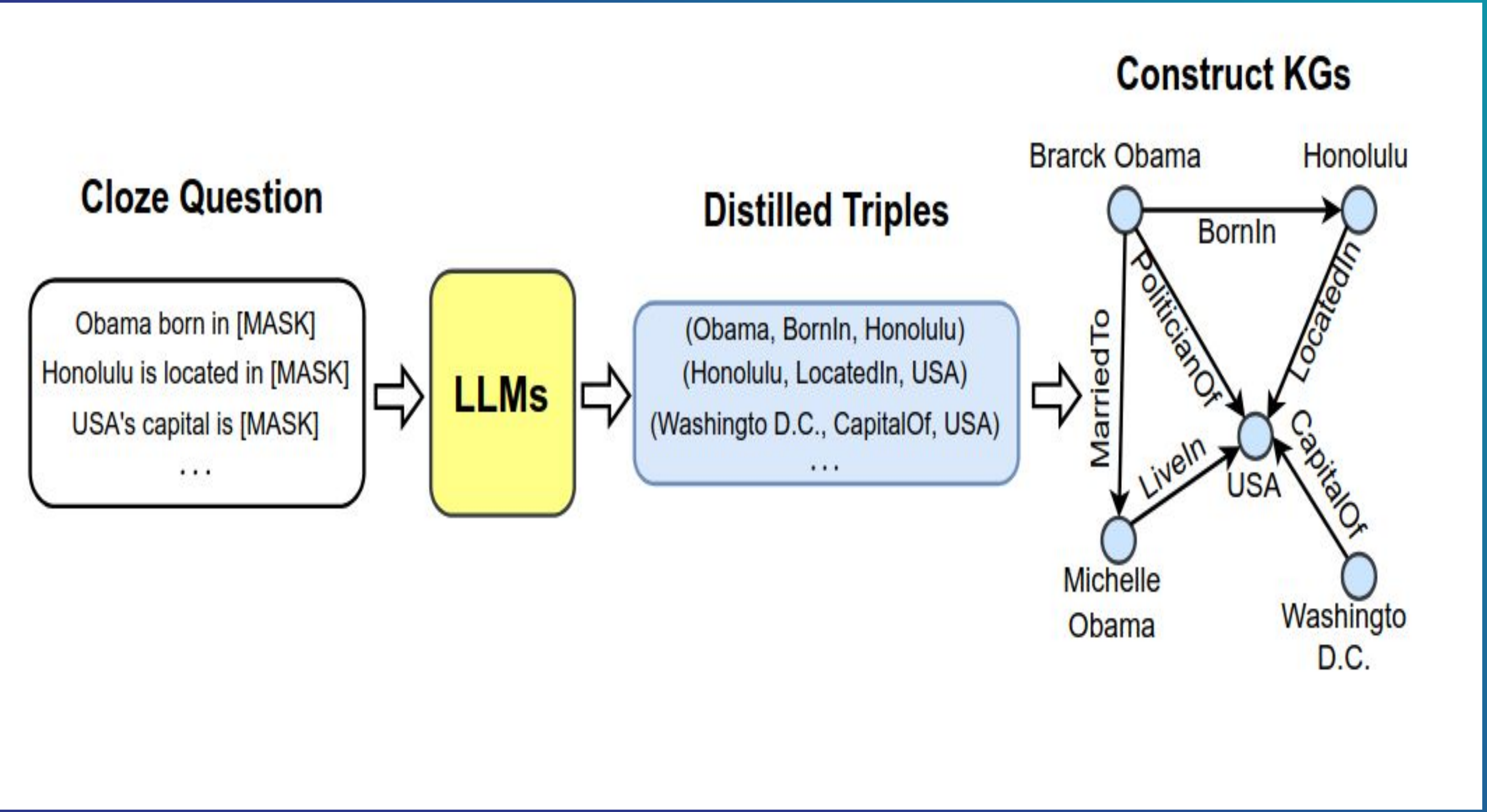
General framework of LLM-based KG construction



Source: https://arxiv.org/pdf/2306.08302.pdf

LLM-augmented Knowledge Graphs

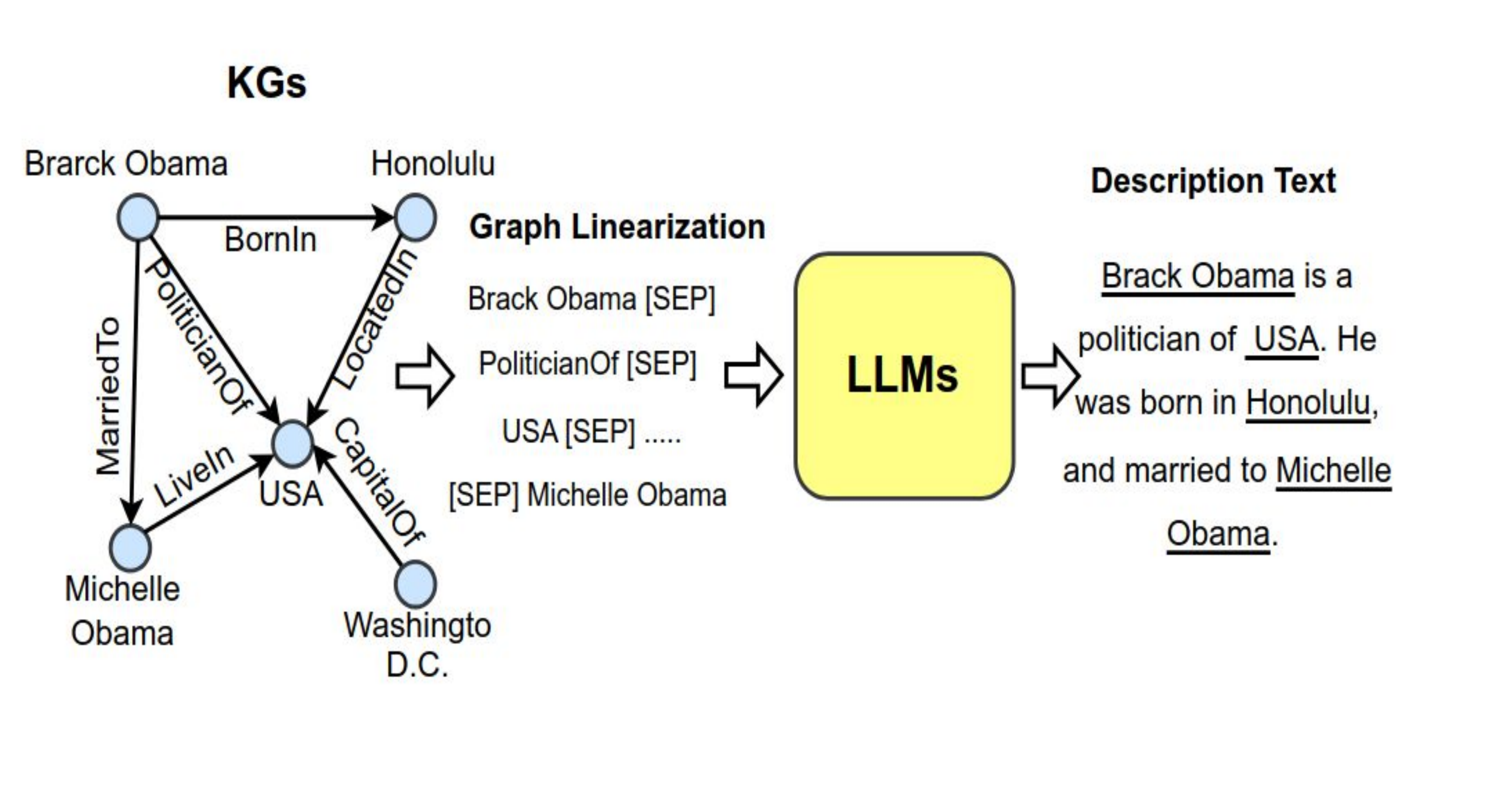
Distilling KGs from LLMs



Source: https://arxiv.org/pdf/2306.08302.pdf

LLM-augmented KG-to-text Generation

Generate high-quality texts and leverage knowledge from LLMs



Source: https://arxiv.org/pdf/2306.08302.pdf

LLMs Synergised with Knowledge Graphs

From perspective of knowledge representation and reasoning

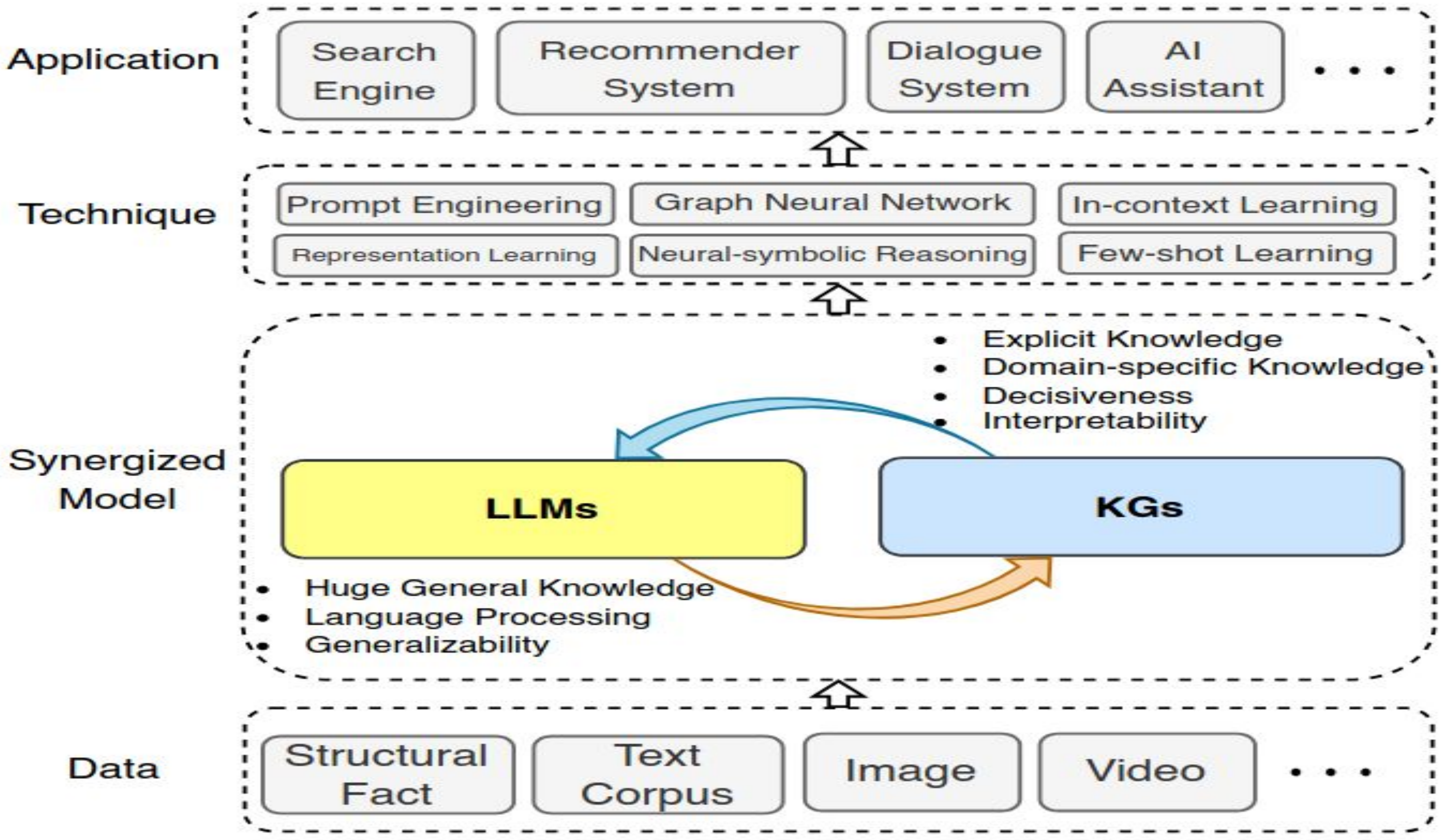


Fig. 7. The general framework of the *Synergized LLMs + KGs*, which contains four layers: *1) Data*, *2) Synergized Model*, *3) Technique*, and *4) Application*.

Source: https://arxiv.org/pdf/2306.08302.pdf

LLMs Synergised with Knowledge Graphs

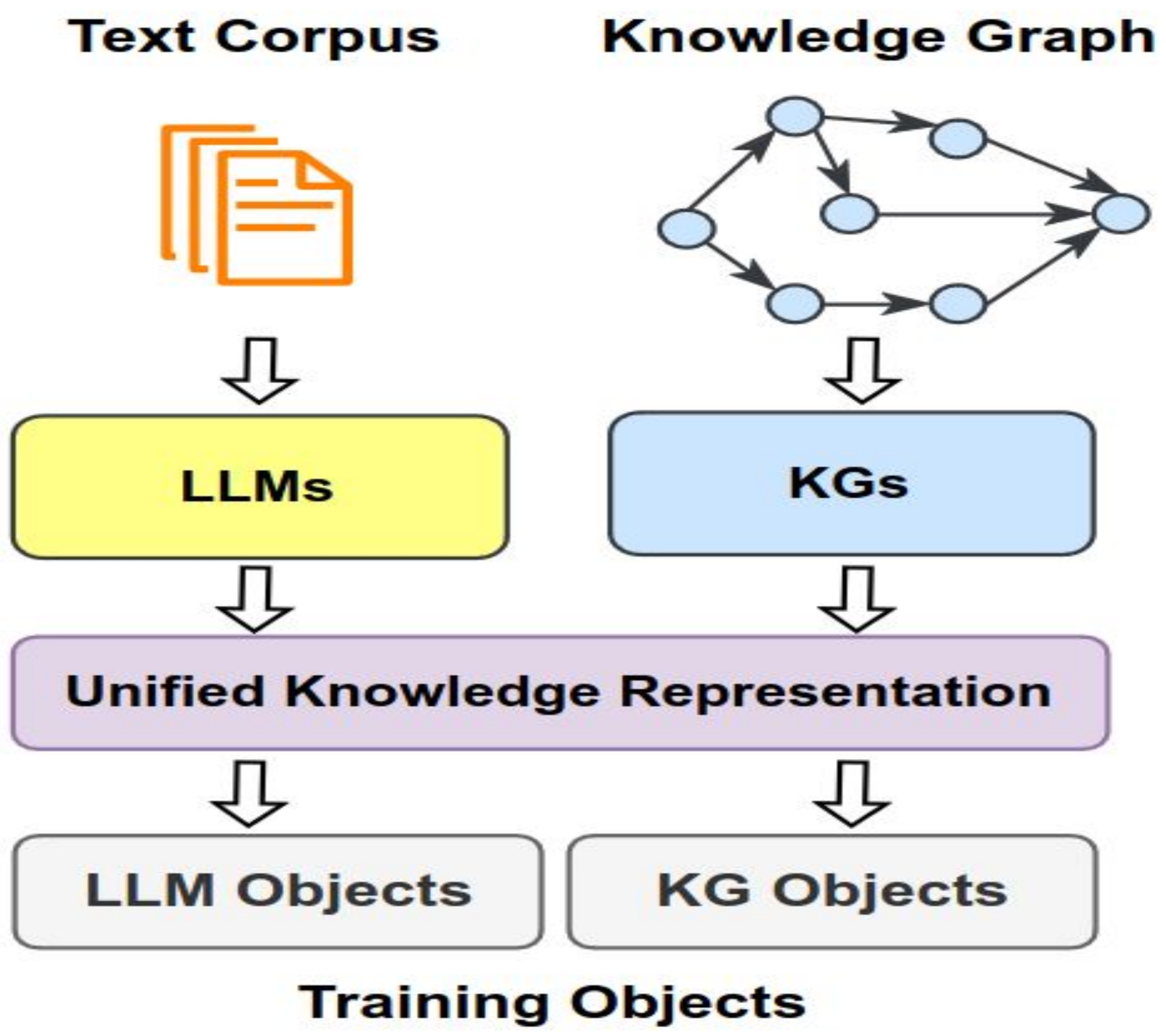
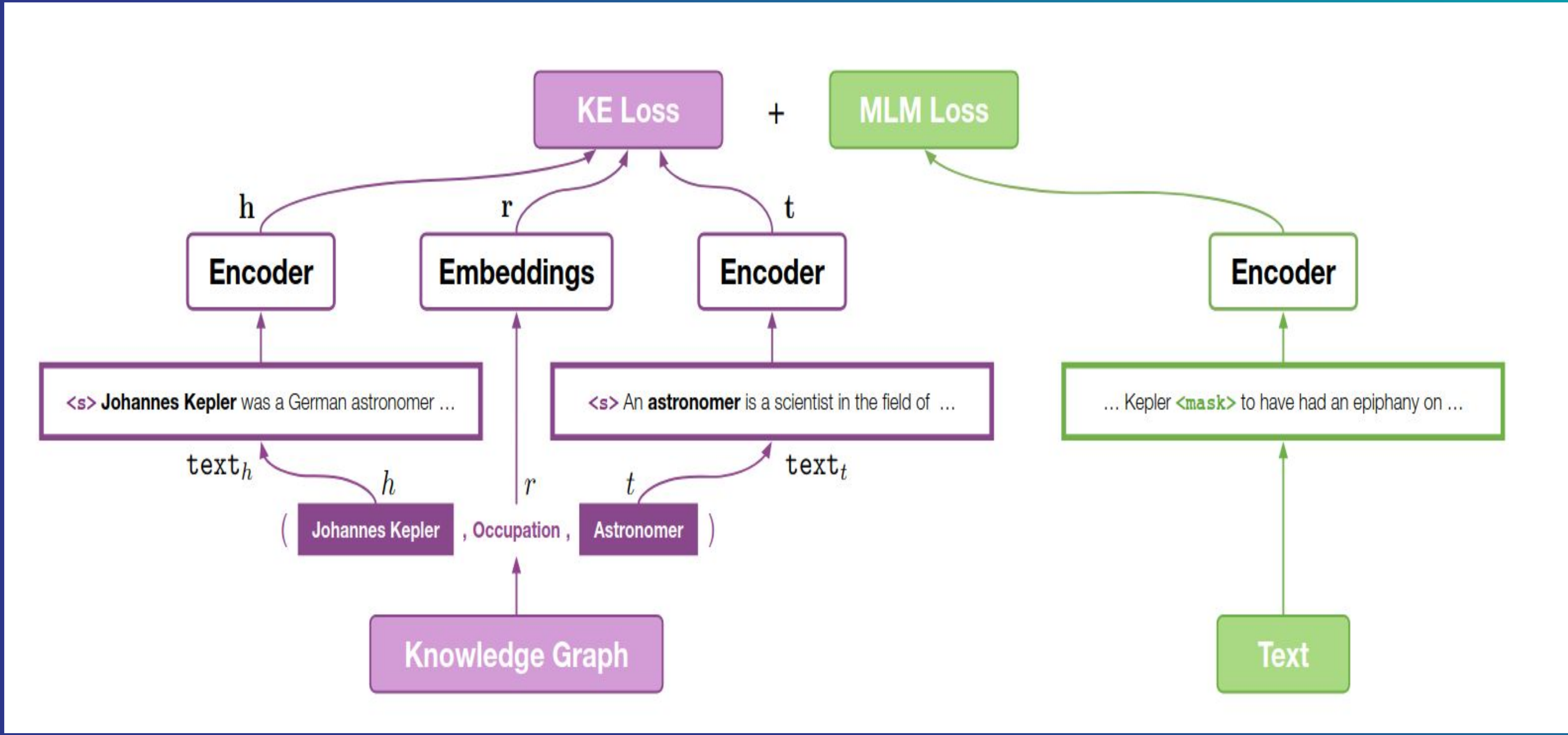


Fig. 25. The general framework of unifying LLMs and KGs for knowledge representation.

Source: https://arxiv.org/pdf/2306.08302.pdf

Unified model for Embedding

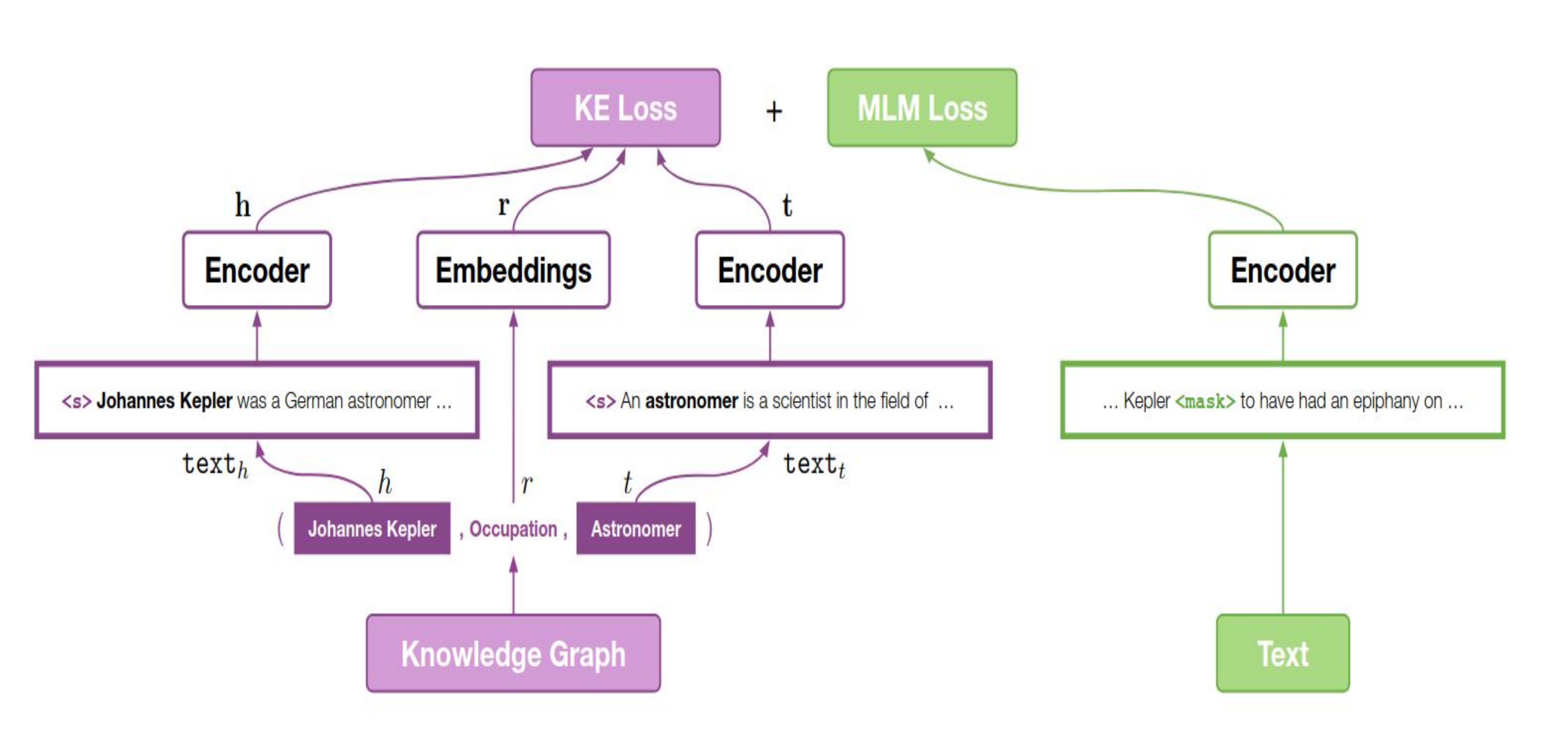
KEPLER: Knowledge Embedding and Pre-trained Language Representation



Source:https://arxiv.org/pdf/1911.06136

Knowledge Graph Compressions

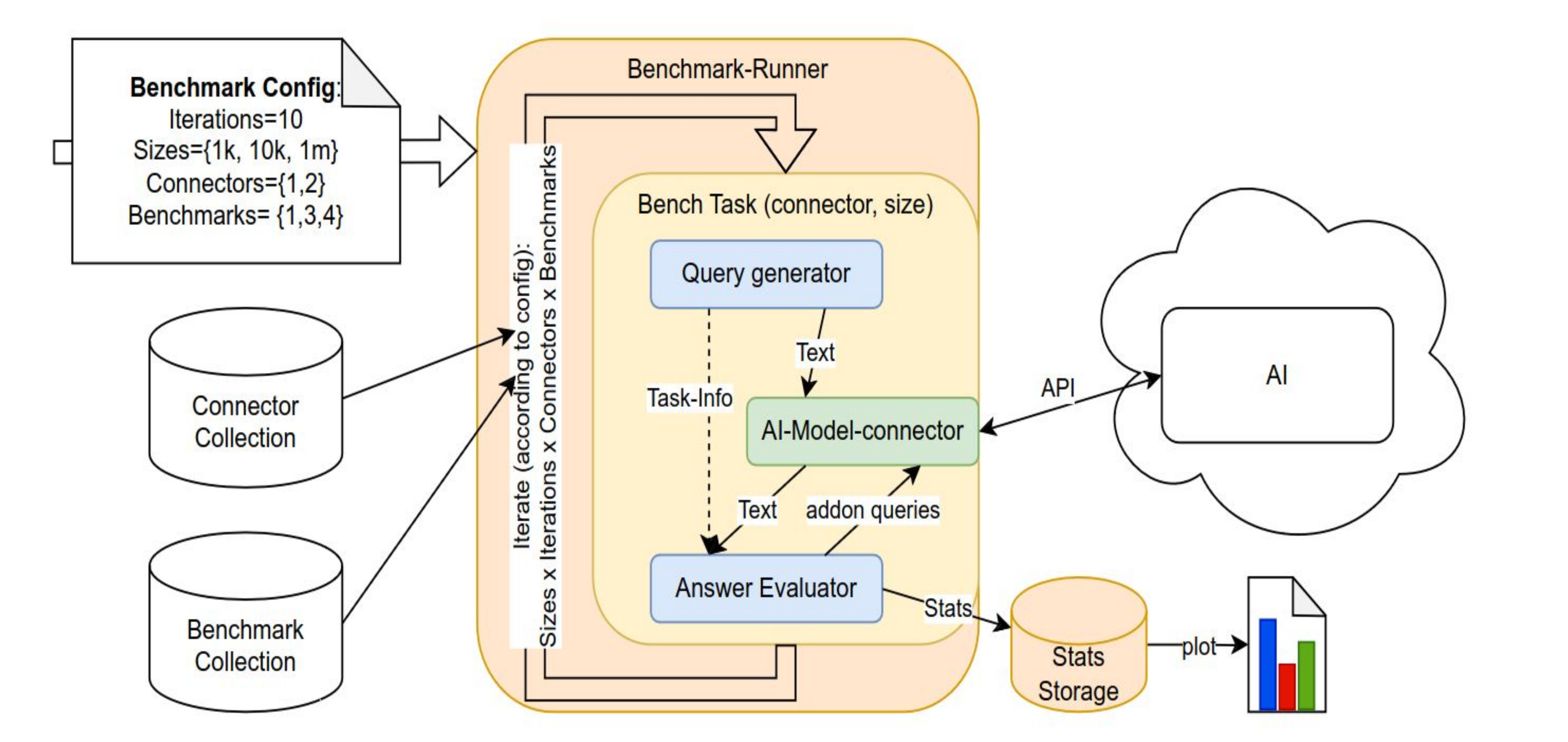
KEPLER: Knowledge Embedding and Pre-trained Language Representation



Source:https://arxiv.org/pdf/1911.06136

Evaluation and Benchmarking

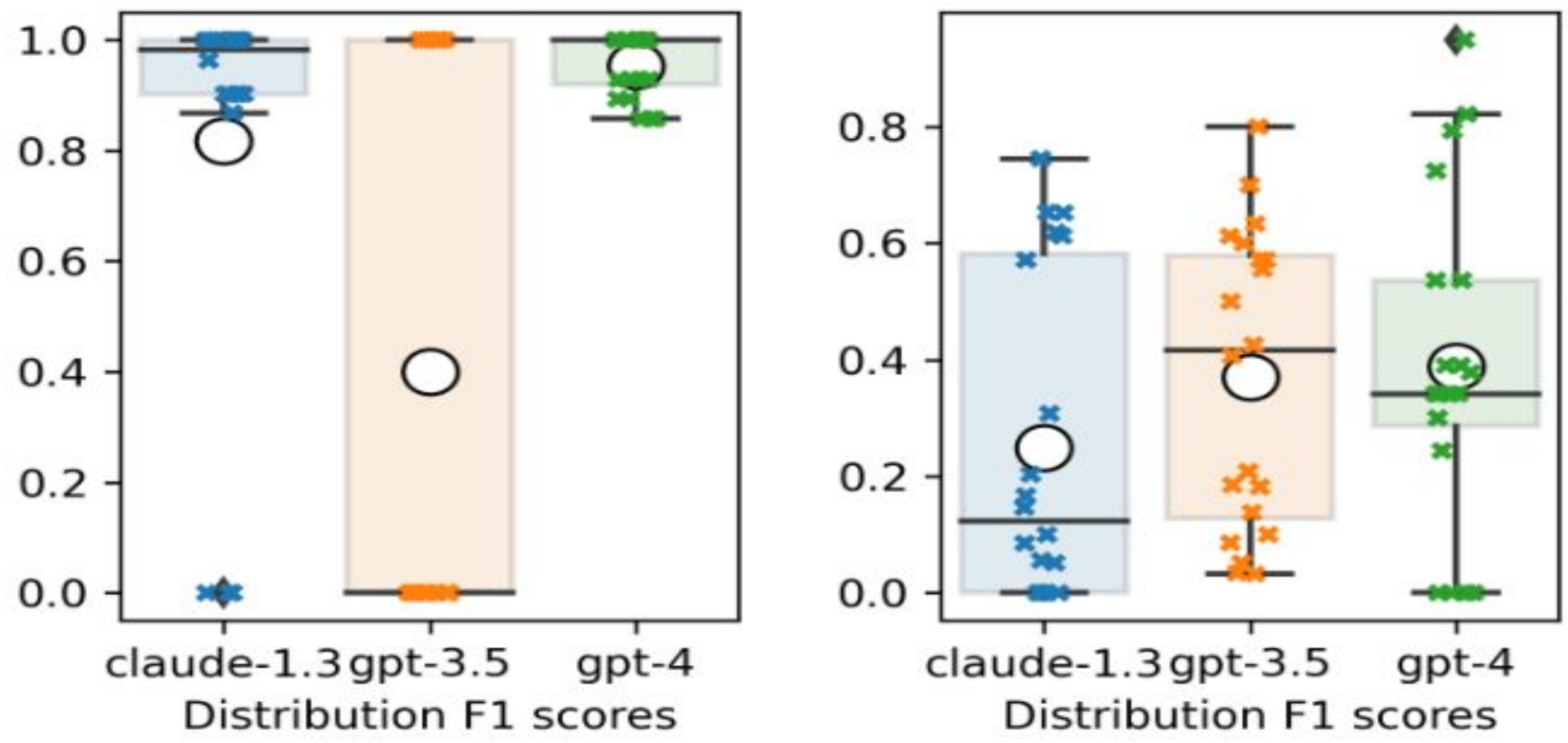
LLM-KG-Bench: an automated and continuous evaluation platform



Source: https://github.com/AKSW/LLM-KG-Bench

Evaluation and Benchmarking

Fixing of Errors in Turtle Files | **KG Creation from Factsheet Plaintext**



(a) Turtle Fixing (b) Fact Extraction

Source https://arxiv.org/pdf/2308.16622:

Evaluation and Benchmarking

Direct (synthetic data) and indirect (model)

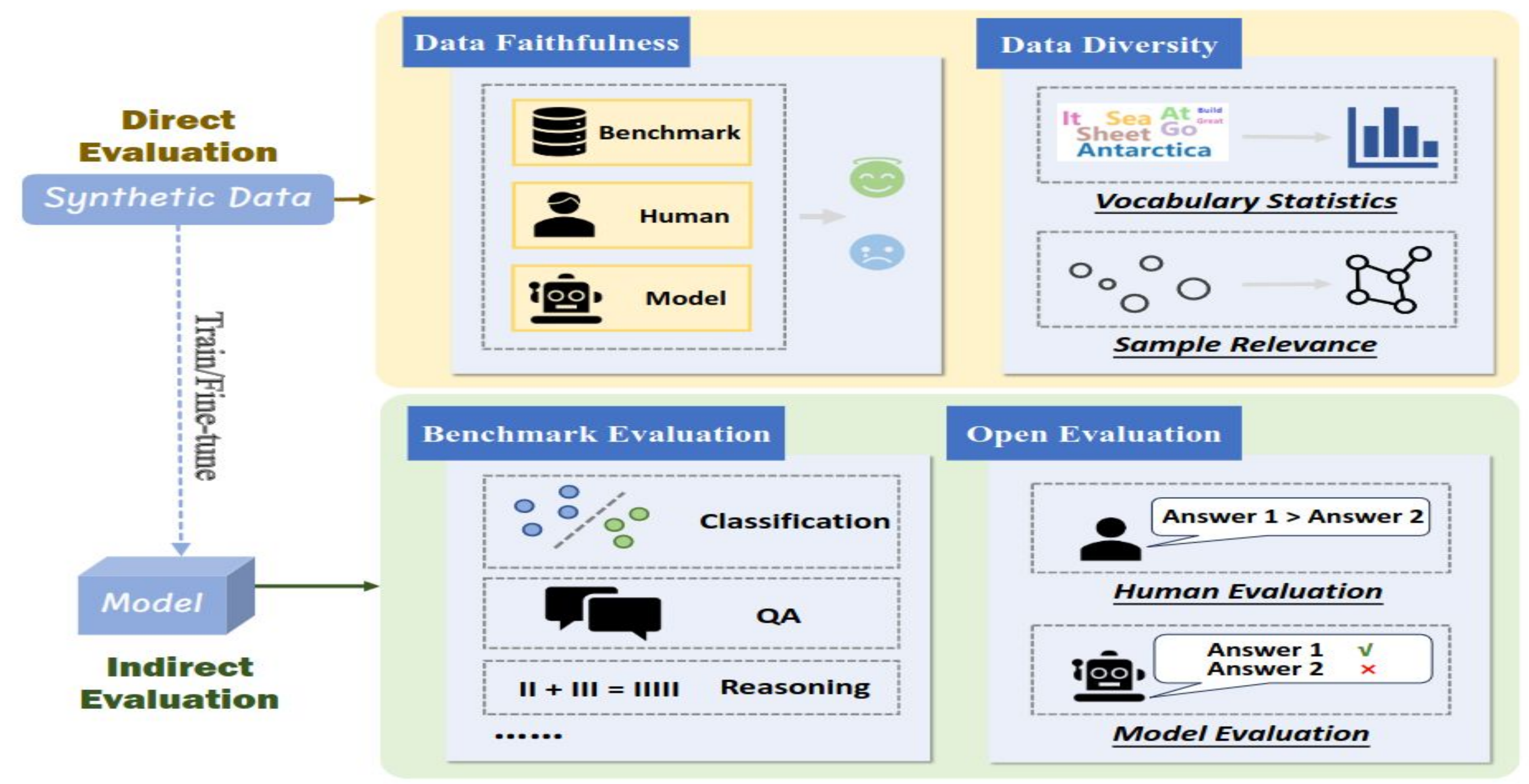
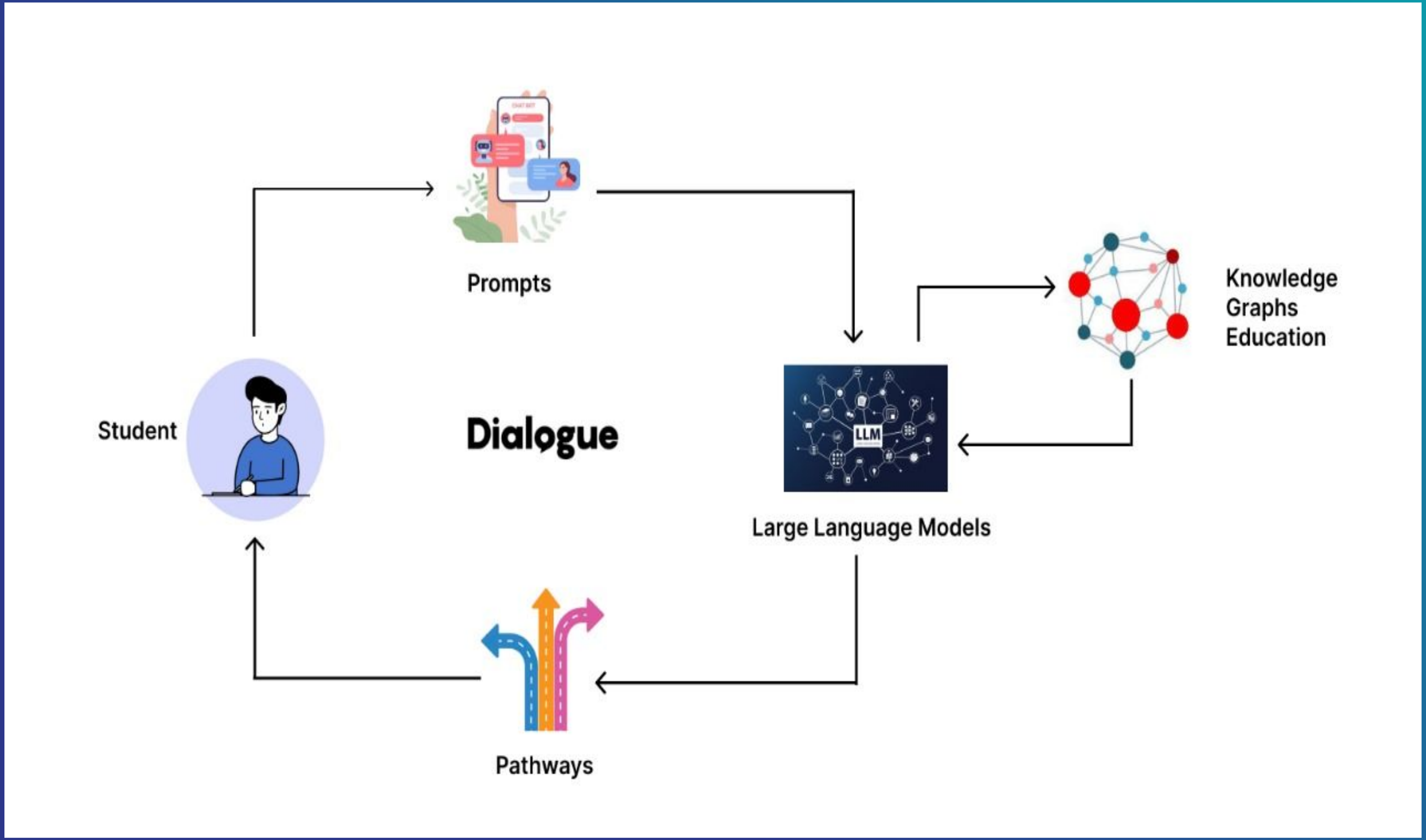


Figure 5: Direct and indirect methods of data evaluation.

Source hhttps://aclanthology.org/2024.findings-acl.658.pdf

Generating Personalised Educational Pathways



Using Open-source Language models and Knowledge graphs (Graph RAGs)

Education Knowledge Graphs

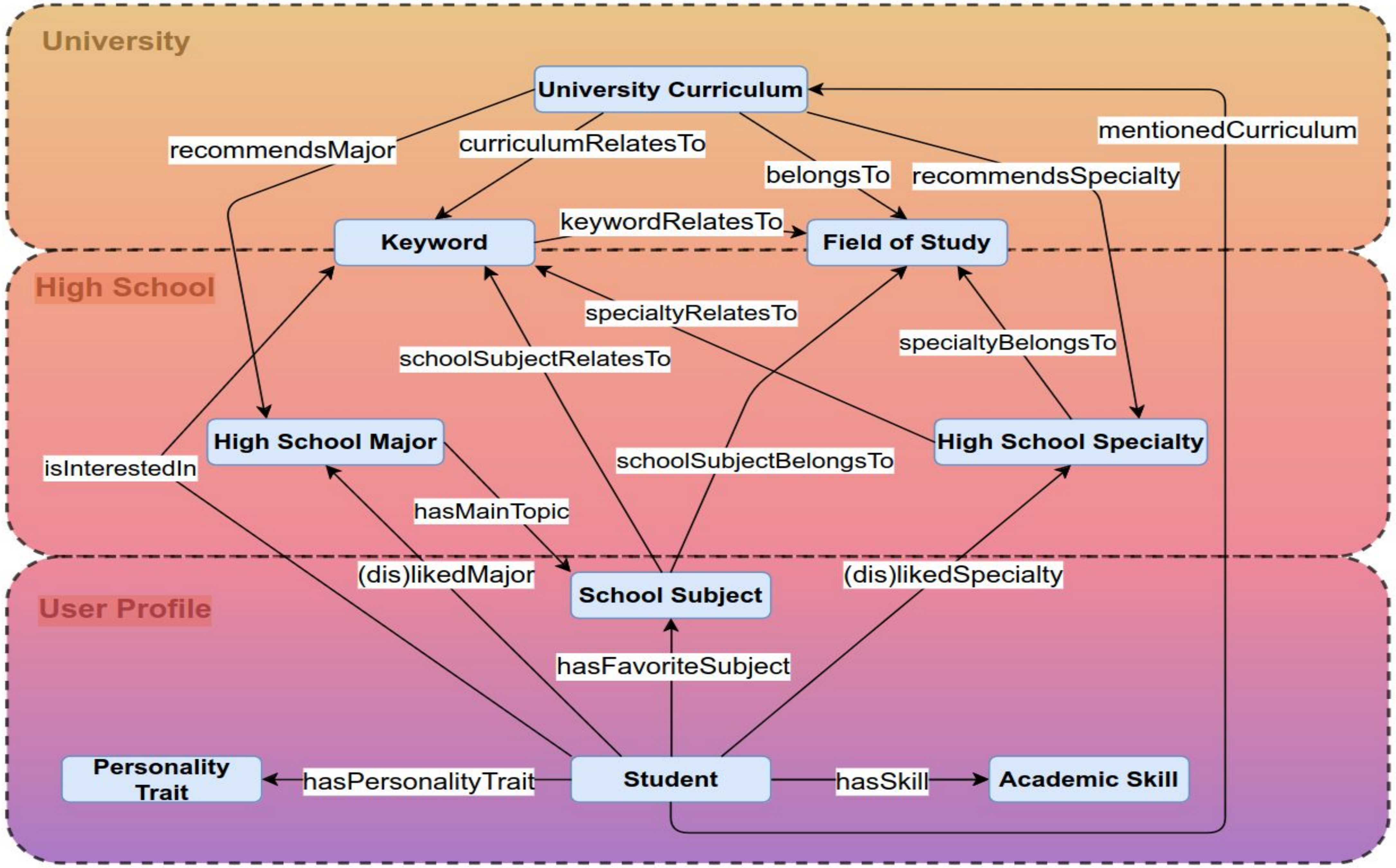


Figure 1: A conceptual overview of EducOnto. The lower, middle and upper parts of the diagram depict the classes and properties related to the User Profile, High School and University, respectively.

Source: New Ontology and Knowledge Graph for University Curriculum Recommendation

Generating Knowledge Graphs

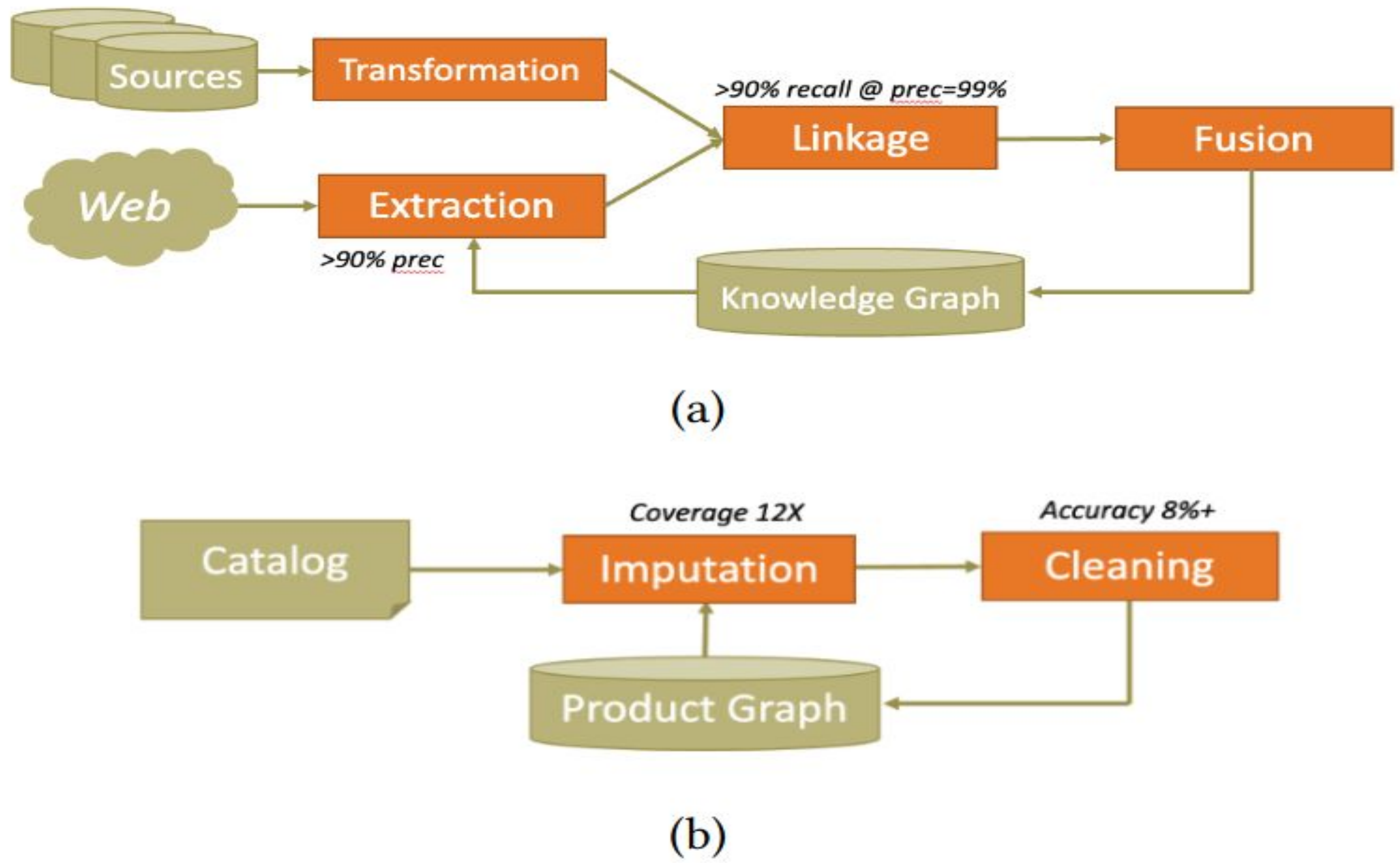
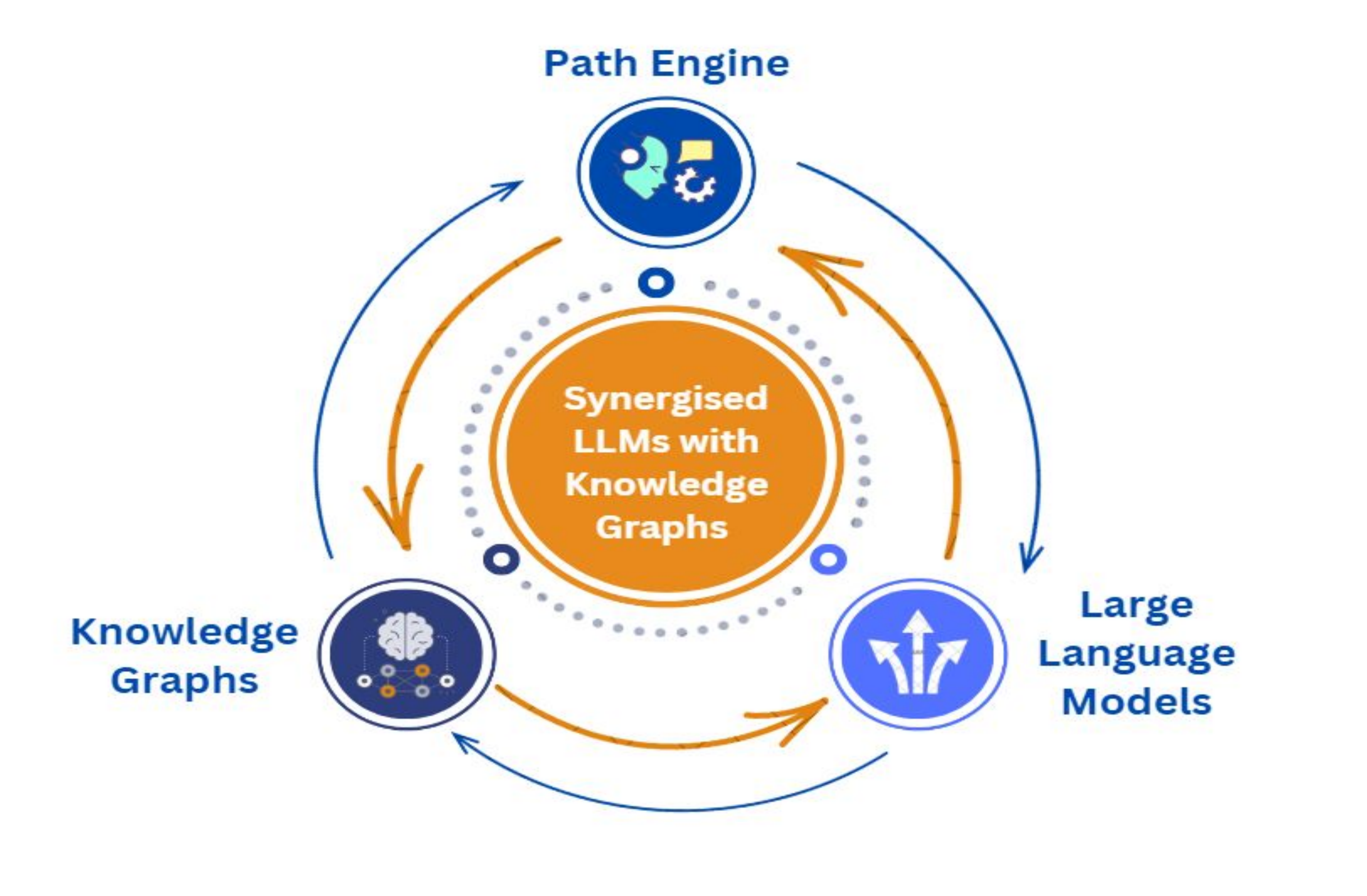


Figure 4: (a) Architecture for constructing an entity-based KG. (b) Architecture for constructing a text-rich KG.

Source: New Ontology and Knowledge Graph for University Curriculum Recommendation

Synergised Architecture



perspectives of knowledge representation and reasoning

Source: https://arxiv.org/pdf/2306.08302.pdf

LLM HyperGraphs Architecture

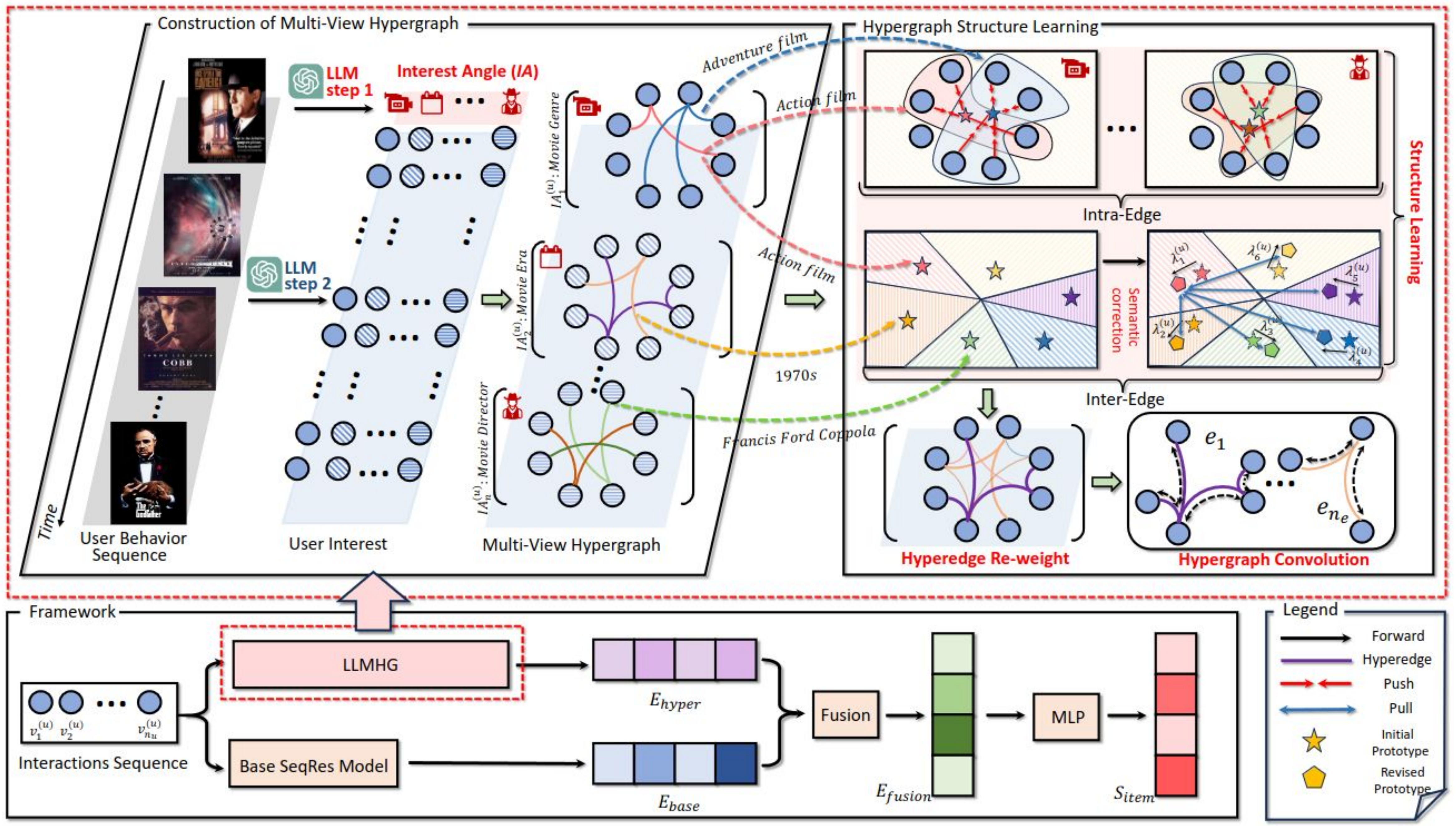


Figure 1: LLMHG includes four major steps: interest angle extraction, construction of a multi-view hypergraph centered on interest angles, hypergraph structure learning for LLM content refinement, and representation fusion for recommendation prediction.

Source: https://arxiv.org/pdf/2306.08302.pdf

Feasibility

Graphs Compressions

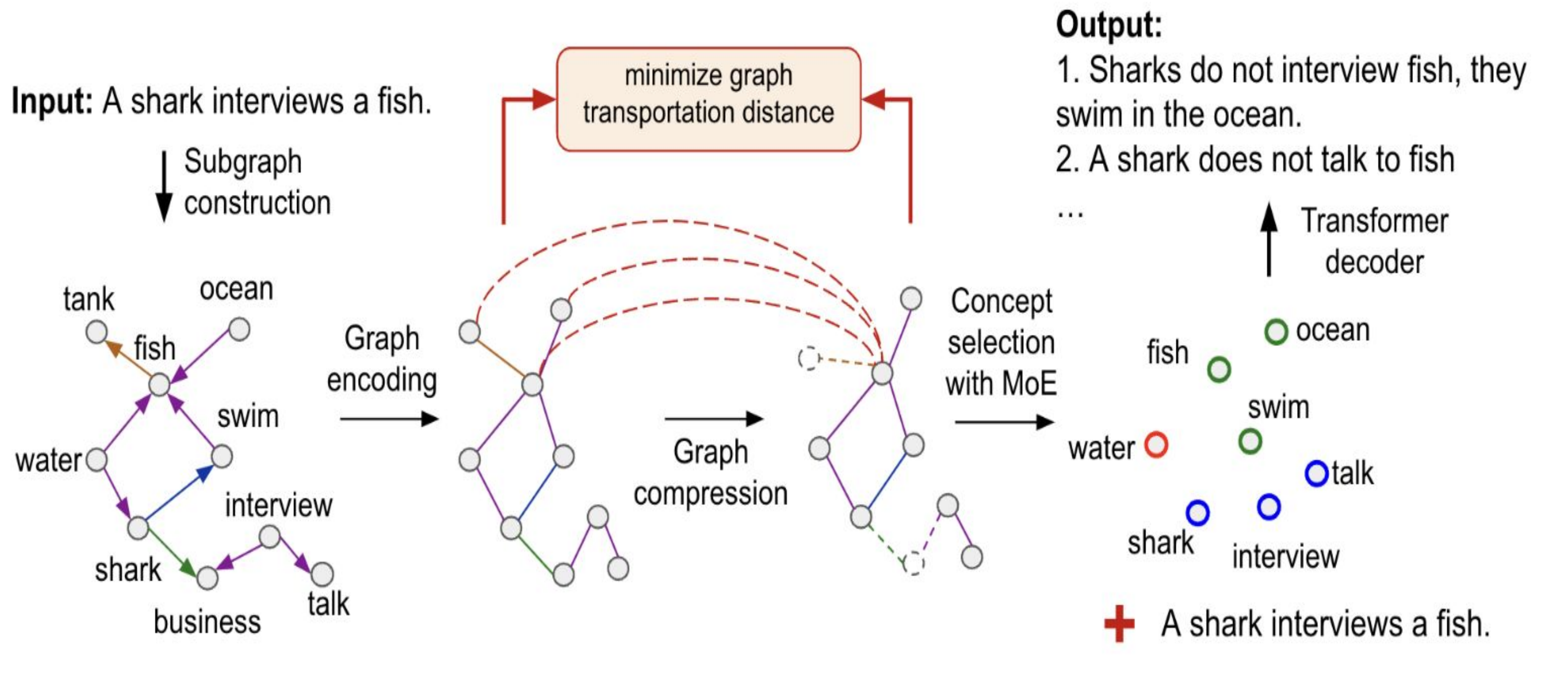
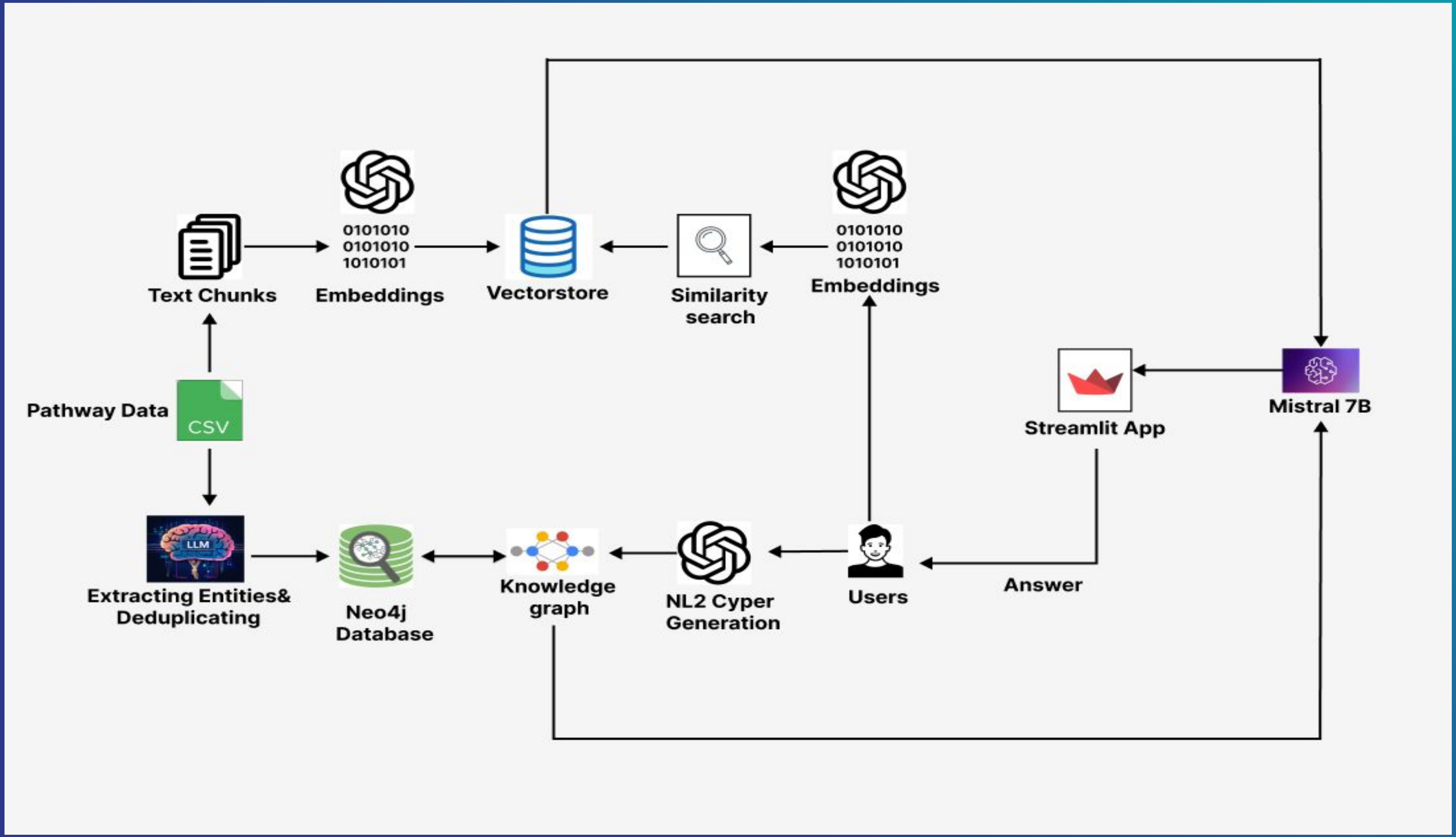


Figure 2: Overview of our approach. We retrieve a subgraph from ConceptNet for the given input sentence, compress it, and use MoE to generate diverse sentences for containing concepts from the compressed graph.

from perspectives of knowledge representation and reasoning

Source: https://arxiv.org/pdf/2306.08302.pdf

Hybrid Architecture



Combining graph and vector search

Summary and Outlook

- KGs to ground LLMs and thereby providing contextual responses, limiting hallucinations, and lack of interpretability

- Multi-Modal LLMs for KGs

- Development of sophisticated algorithms to ensure KGs have low-latency to enhance the effectiveness of integrations.

- Synergising LMs and KGs for Birectional Reasoning in context of educational pathways

References

- Special thanks to Jakob Porschmann (Google Berlin)

- Few References:

  - https://github.com/zjukg/KG-LLM-Papers
  - https://seucoin.github.io/workshop/llmkg/
  - https://www.researchgate.net/publication/377318531_Unifying_Large_Language_Models_and_Knowledge_Graphs_A_Roadmap
  - https://github.com/AKSW/LLM-KG-Bench
  - https://arxiv.org/pdf/1911.06136
  - https://www.ontotext.com/knowledgehub/fundamentals/what-is-graph-rag/

THANK YOU

Contac
t

A SESHADITYA

Email: aditya@zedat.fu-berlin.de

Githb: https://github.com/adytiaa/naavi_os