LinkQ: An LLM-Assisted Visual Interface for Knowledge Graph Question-Answering

Harry Li*
MIT Lincoln Laboratory

Gabriel Appleby[†]
Tufts University

Ashley Suh[‡]
MIT Lincoln Laboratory

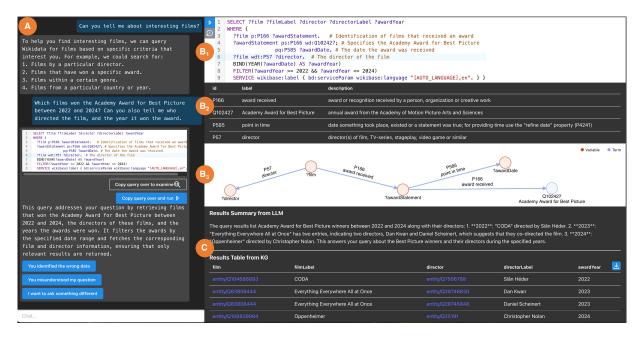


Figure 1: Exemplar workflow for LinkQ, a system leveraging an LLM for refining natural language questions into knowledge graph queries. The (A) *Chat Panel* lets users communicate with the LLM to ask specific or open-ended questions. The *Query Preview Panel* consists of three components: the (B1) *Query Editor*, which supports interactive editing; the (B2) *Entity-Relation Table*, which provides mapped data IDs from the KG, helping to assess the correctness of the LLM's generated query; and the (B3) *Query Graph*, which visualizes the structure of the query to illustrate the underlying schema of the KG. Finally, the (C) *Results Panel* provides a cleaned, exportable table as well as an LLM-generated summary based on the query results. Importantly, LinkQ ensures all data retrieved and summarized from the LLM comes from ground truth in the KG.

ABSTRACT

We present LinkQ, a system that leverages a large language model (LLM) to facilitate knowledge graph (KG) query construction through natural language question-answering. Traditional approaches often require detailed knowledge of complex graph querying languages, limiting the ability for users – even experts – to acquire valuable insights from KG data. LinkQ simplifies this process by first interpreting a user's question, then converting it into a well-formed KG query. By using the LLM to construct a query instead of directly answering the user's question, LinkQ guards against the LLM hallucinating or generating false, erroneous information. By integrating an LLM into LinkQ, users are able to conduct both exploratory and confirmatory data analysis, with the LLM helping to iteratively refine open-ended questions into precise ones. To demonstrate the efficacy of LinkQ, we conducted a qualitative study with five KG practitioners and distill their feedback. Our results indicate that practitioners find LinkQ effective for KG question-answering, and desire future LLM-assisted systems for the exploratory analysis of graph databases.

Index Terms: Knowledge graphs, large language models, query construction, question-answering, natural language interfaces.

1 Introduction

Knowledge graphs (KGs) have become an industry standard for representing complex relationships in data for various applications [2, 11] such as recommendation tasks [10] and visualization creation [17]. Despite their widespread use for managing data, a significant barrier to their effectiveness remains the retrieval of relevant data through querying [20, 19, 16]. This is partly because KG data retrieval can require a highly technical understanding of the KG itself or the KG's querying language [24], which typically differ across different graph databases [15]. When the user is a non-expert in querying, they must rely on KG query builders or traditional NL interfaces [6, 9, 35, 8], which tend to limit the expressivity of the user's data analysis questions due to their rule-based syntax [14]. Consequently, valuable insights contained in KGs are difficult to attain, limiting the accessibility of KGs in practice [16].

In this paper, we contribute LinkQ¹, a system that utilizes a large language model (LLM) conversational agent to assist users in

^{*}e-mail: harry.li@ll.mit.edu

[†]e-mail: gabriel.appleby@tufts.edu

[‡]e-mail: ashley.suh@ll.mit.edu

¹Open-source code: https://github.com/mit-ll/linkq

exploring and answering questions about KG data. Recent work has shown that LLMs are capable of interpreting analytic questions from natural language [1, 36] and writing code [29], including KG queries [29, 27]. LinkQ combines these ideas, implementing SPARQL-based confirmatory *and* exploratory question-answering with GPT-4 [25] for the WikiData [34] knowledge graph. When users ask open-ended questions about KG data, LinkQ guides the LLM in helping the user iteratively refine those questions until they can be translated into precise KG queries.

In research, integrating LLMs with KGs has emerged as a promising direction for data management [7, 26]. KGs are largely used to help mitigate an LLM's *hallucinations* [21, 30, 22, 33], that is, the generation of false, erroneous data [28]. A recent survey paper details current techniques in this space [3]. KGs can also help an LLM access knowledge that it was not previously trained on, as KG data can be kept consistently up-to-date without incurring the expensive retraining process for LLMs [11, 34].

Building upon these ideas, we establish a protocol in LinkQ to ensure the LLM answers the user's questions by constructing and executing KG queries. Our protocol is designed to mitigate the LLM from hallucinating false data during query construction (Figure 2), in its outputs (Section 3), and allows users to retrieve recent data that may not be present in industry-standard LLMs. For example, in Figure 1, the LLM (GPT-4) uses ground-truth KG data to correctly show the 2024 Best Picture winning film, which (at the time of this writing) is data it has not be trained on [25]. LinkQ implements an interactive graph query visualization and an entity-relation table (Section 4), which are populated with ground-truth data from the KG. Both of these visualizations are included to facilitate users in assessing the accuracy of the LLM's query.

To demonstrate how LinkQ can be used for iterative KG query building from natural language (NL), we conducted a qualitative study with five data scientists who regularly work with KGs (Section 5). In this demonstration, we walked through several use cases for the system and allowed participants to ask their own questions for exploratory analysis. Participants found high value in the workflow of LinkQ, particularly the provided explanations from the LLM in its query generation process, the query graph for showcasing connections in the query, and the alleviated burden of constructing KG queries altogether. To conclude, we discuss the current limitations of LinkQ and future directions for designing LLM-driven visual data analysis tools for KGs (Section 6).

2 SYSTEM DESIGN GOALS

In the initial stages of designing LinkQ, we leveraged the learning outcomes from previous work in KG query builders [6, 9, 8], NL question-answering interfaces [4, 31, 32, 23, 12], as well as the feedback we received over a month-long collaboration with three data scientists who regularly use KGs in their work. Altogether, we arrived at the following design goals for our system:

- G1 Support back-and-forth conversation to refine natural language questions into precise queries. Users may have open-ended or targeted questions they want to ask about data in the KG. When the question is open-ended, an LLM should help users refine their search. Importantly, a well-structured, precise KG query should be generated while maintaining the semantic intent of the user's question.
- **G2** Mitigate the LLM's tendency to hallucinate false information. Using an LLM to generate KG queries may result in false data IDs or false query results. Precautions should be made to reduce the frequency of these occurrences.
- G3 Preview information about the LLM's generated query to assess its accuracy. KG queries can be computationally expensive to execute. A preview of the query, with relevant information, should be displayed to users to help assess the

```
Me Can you write a query about gold medal winners at the 2020 Summer Olympics?

LLM Here's a query to retrieve the winners of gold medals at the 2020 Summer Olympics:

SELECT ?athlete ?athleteLabel ?eventLabel ?countryLabel
WHERE {

"Athlete wdt:P31 wd:05;
" # Instance of: human
wdt:P26 ?country."
" # Award received: gold medal
" # Award r
```

Figure 2: Example of how an LLM can *hallucinate* [28] or misrepresent the data in a KG. Here, we ask ChatGPT [5] to write a query about gold medal winners from the 2020 Summer Olympics. In total, ChatGPT wrote three consecutive failing queries with incorrect IDs, while stating to us that it had corrected its previous mistakes.

accuracy of both the data and the query before its execution.

G4 Provide multimodal query results from both the LLM and the KG. Users perform question-answering with KGs for a multitude of purposes. Therefore, query results should be displayed in text form (for consumption) and tabular form (for further analysis). When possible, an LLM's summary of results should be grounded in KG data as often as possible.

3 LINKQ

LinkQ follows a state-machine workflow, shown in Figure 3. We provide details on the exact prompts and algorithmic workflow used for LinkQ in our supplemental material. The open-source code is available at https://github.com/mit-ll/linkq.

An important distinction to make in LinkQ is the difference in responsibilities for the **LLM**, **System**, and **User**. In this section, we discuss each as separate roles: The LLM is the language model that helps process and interpret text from the User and System; the backend System relays messages, prompts, and API calls between the LLM and KG; and the User converses with the LLM without having to directly interact with the KG or System.

LLMs, Frameworks, and KGs Used: We tested variations of GPT [5], Code Llama [29], and Mistral [13] during the design of LinkQ, ultimately deciding on GPT-4. We found the performance of GPT-4 to be the most consistent, but any LLM (either off-the-shelf or fine-tuned) could be used in its place. Since KGs vary widely in their structure and quality [11], we use the Wikidata KG as it is well-maintained, generalizable, and has a robust API service. LinkQ is implemented using TypeScript and React.

3.1 Natural Language Question Interpretation

To start, the System instructs the LLM that: (1) it is responsible for generating KG queries from a User's natural language questions; (2) it must help the user refine a vague, subjective, or openended question into a well-defined one; and (3) during refinement, it should only suggest data that it would expect to be in the KG.

Open-ended versus Targeted Question: The User might have an open-ended question, such as "what are some interesting things about cats?" When the User's question is subjective or exploratory in nature, the LLM will follow up with suggested properties or relationships from the KG that could possibly be used in place of vague qualifiers like "interesting." This back-and-forth ensures a well-formed KG query can be written (G1).

Extracting Entities, Relations, and Properties: After the User asks a precise question, the LLM lets the System know that it is ready to begin building a query. The System then instructs the LLM to extract the names of all entities, relations, and properties in the question. We leverage the text-processing capabilities of LLMs to identify these concepts for KG search traversal.

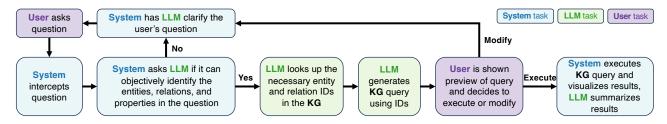


Figure 3: Illustrative state machine of LinkQ's system architecture, as described in Section 3. In our pipeline, the **LLM**, **System**, and **User** have distinct roles, responsible for communicating with one another to complete different tasks across different states.

3.2 Mapping Data to the Knowledge Graph

LLMs are known to state plausible but erroneous information to users [28]. We observed this phenomenon during our initial work with various LLMs to generate KG queries – entity and relation IDs were often incorrect. An example is illustrated in Figure 2.

That said, it is computationally impractical to fine-tune an LLM to memorize all possible entity, relation, and property IDs in a KG. For example, the Wikidata KG has more than a hundred million entities [34]. Even if the KG were small in size, any maintenance updates to IDs could result in having to retrain the LLM.

We implemented a scalable protocol to address this, such that the LLM interfaces with the KG to identify the ground truth IDs of data extracted by name from the User's original question (G2).

Fuzzy Searching for Entities by Name and Context: Our protocol leverages fuzzy search so the LLM does not have to rely on *exact* entity names to identify IDs, and instead focuses on identifying IDs from entities based on semantic similarity. The System instructs the LLM to select the entity ID that most closely matches the context of the User's question, this approach helps with duplicate and ambiguous entities – a common KG data quality and querying obstacle [19]. For example, if the User asks a question about the *box office total* for *The Godfather*, the LLM should select the entity ID matching the film, rather than the book series.

Given an Entity, Find its Relations and Properties: In the second step, the LLM follows a similar approach in which it semantically searches for all properties and relations that closely match the User's original question. Importantly, this search ensures that the properties and relationships actually belong to that entity in the KG. For example, if the User asks about the *box office total* for *The Godfather*, the LLM would look for any properties or relations belonging to *The Godfather* that are named similarly to *box office*.

Traverse the Graph for Multi-Hop Relationships: In the last step, the LLM traverses the KG from one head entity to a tail entity to identify multi-hop data. This is necessary for building successful queries, since KG data is maintained as a series of triplets connecting one another. For example, when mapping data from the question "Who are the Founders of Google, and what are their birthdates," the LLM would have to hop from the Google entity to its Founder entities to identify their birthdate properties.

3.3 Writing, Explaining, and Executing KG Queries

After all necessary IDs have been identified from the KG, the System instructs the LLM to create a query that will answer the original question using the fetched IDs. Since LinkQ uses the Wikidata KG, which is based on the RDF framework, the LLM is responsible for writing SPARQL queries.

The KG query is then previewed, along with an LLM-generated explanation, to the User in the interface (discussed in Section 4). To produce this explanation, the System instructs the LLM to summarize why the generated query addresses the User's original question, e.g., which components of the query have been mapped from the question. LinkQ takes roughly 10-15 seconds to complete the

protocol of converting the User's natural language question to an LLM-generated KG query and query explanation.

4 USER INTERFACE DESIGN

LinkQ is divided into three user interface panels, shown in Figure 1: the Chat Panel, the Query Preview Panel, and the Query Results Panel.

4.1 Chat Panel

The Chat Panel (Figure 1-A) enables user communication with the LLM. Under the hood, this panel maintains a record of the conversation and, optionally, displays the output generated by the LLM's message passing with the System. This panel includes features to help simplify query refinement (G1). For example, once a query is generated, two buttons are provided to the user: one to copy the query to the editor and another to copy and run the query immediately. This design prevents unintended overwriting of in-progress queries, although a query history is available for reference (see Section 4.2). Additional buttons are designed to insert verified prompts into the chat, helping users correct or redirect the LLM as needed.

4.2 Query Preview Panel

The Query Preview Panel comprises the Query Editor, Entity-Relation Table, and the Query Graph visualization. These three pieces work in tandem to preview the potentially computationally expensive query before it is run, and ensure the accuracy of Wikidata entity identifiers (G3).

Query Editor The Query Editor (Figure 1-B1) is a standard SPARQL code interface with keyword highlighting, helping users assess the syntax of the query (G3). The editor also features a query history, allowing users to quickly retrieve past queries.

Entity-Relation Table The Entity-Relation Table (Figure 1-B2) shows contextual information (e.g., a human-readable label and short description) about the entities and properties found in the query (**G3**). This table is intended to help users assess whether the LLM has identified the correct data for the generated query.

Query Graph The Query Graph (Figure 1-B3) shows a visual preview (G3) of a syntactically valid query. This graphic allows the user to understand the relationships within their queries better, regardless of whether the queries are constructed by the LLM or themselves. Specifically, the query is parsed for basic graph patterns (BGP), and the triples contained within the BGPs are plotted within the graph. All items and data values are represented as nodes, and all properties are represented as edges. The nodes and edges are labeled by their corresponding text from the query, as well as labels retrieved from the KG. Known Wikidata entities are colored blue, and unresolved variables are colored orange.

4.3 Query Results Panel

The Query Result Panel (Figure 1-C) provides the results of the query in formats best for both consumption and analysis (G4).

Use Case	Natural Language Question to Translate
Films	(Q1) Which directors won the <i>Academy Award for Best Director</i> between 2014 and 2024, and for which films?
	(Q2) Which film genres most commonly win the Academy Award for Best Picture?
Cybersecurity	(Q3) What are some different types of cyberattacks?
	(Q4) What are examples of cyberattacks that have occurred in history?
Geography	(Q5) What is the official language for each country in Europe?
	(Q6) What are the top 10 tallest mountains in the world, and what country do they belong to?

Table 1: Questions we walked through with participants during the demonstration of LinkQ. More details in Section 5.

Exportable Results Table Query results are automatically parsed from JSON to a cleaned CSV format, removing unnecessary metadata retrieved from the KG, then visualized as a table. Users can choose to export the results for downstream analysis (G4).

LLM Results Summary The LLM also provides a succinct paragraph to summarize the query results for the user (**G4**). When the query results are empty, LinkQ instructs the LLM to provide a best guess for what could have gone wrong with the query.

5 DEMONSTRATION

To gather feedback on our system, we demonstrated its questionanswering capabilities with a team of five data scientists (two we previously collaborated with, see Section 2) who work with KGs. Our goal was to determine whether LinkQ satisfies its design goals, and to identify features that could be improved in the future.

We demoed three use cases with participants, all questions from the demonstration are provided in Table 1. Participants were also asked to input their own questions to LinkQ. Our supplemental provides complete details on our protocol, our participants' experience levels, and the correct answers to each of the questions asked.

5.1 Question-Answering Results

Participants observed two inaccuracies. First, the LLM mistakenly used the ID for 'Best Director' instead of for 'Best Picture,' which participants identified using the Entity-Relation table (G3). This mistake was corrected after participants iterated with the LLM. In Q6, the query was syntactically correct but incorrectly resulted in U.S. mountains, likely due to a unit conversion error between feet and meters, as cautioned by the LLM's Summary Panel.

During the free-form Q&A, participants intentionally asked questions they thought LinkQ would fail in translating. To their surprise, in 2/3 cases our system successfully resulted in syntactically correct SPARQL queries and correct IDs. Failures were due to missing data in Wikidata or incorrect unit specifications in queries.

Overall, participants praised LinkQ's ability to preserve their semantic intent during question-answering (G1), and told us that – even when the LLM's query failed, our Query Graph gave them the insight to update the query correctly themselves.

5.2 Participants' Feedback on LinkQ

After the demonstration, we performed a semi-structured interview with participants to discuss the system features that seemed most helpful in answering questions, as well as which features could be added to improve usability. We highlight interesting observations and takeaways from participants to help inform this design space.

With enough guidance, LLMs can alleviate the burden of manual data retrieval: Without hesitation, the immediate feedback we received was, "What I like about this is that I don't have to write SPARQL queries anymore!" Participants suggested it would be extremely beneficial to data scientists if our system could also retrieve data from multiple enterprise Wikis and databases simultaneously.

The KG-generated Entity-Relation table and Graph Query increase trust in the LLM's outputs: All participants told us that knowing the table and query graph were extracted from the KG gave them confidence in the LLM's queries (G2). The two participants who work most closely with KGs praised the graph query visualization: "You see edge connections that you wouldn't otherwise see from just the entity-relation table." Participants less familiar with KGs preferred the table, particularly the data descriptions.

The LLM Summary Panel can inform what went wrong with the query, or the query results: Participants told us, "The LLM summary is helpful and informative...it gives us information on what could've gone wrong in the query. It captured the intention of my query, which was unexpected." This feedback suggests that there are benefits to using LLMs over traditional NLP approaches for query building. Of course, the quality of an LLM's insights depends on its own knowledge of the data domain.

Question-answering with ground truth data is seen as a novel task for LLMs: One participant told us, "This is one of the cooler applications I've seen of LLMs. It's retrieving actual, ground truth information. Usually LLMs are just text generators." Participants stressed again that research should continue to examine how LLMs can be used to improve search and data retrieval tasks for data scientists, as manual keyword search is both tedious and flawed.

Make visual distinctions between LLM output and KG output: One participant told us that he sometimes forgot which outputs came from the LLM versus the KG, and suggested that a visual distinction (e.g., different colored background panels) should be added. All participants agreed that both the LLM summary and KG results table seem equally important, just categorically different.

Additional visualizations seemed unnecessary: We asked participants if they wanted or expected to see additional visualizations after receiving query results. Surprisingly, not a single participant said yes, and instead told us the LLM's text summary and KG results table were ideal (G4). Two participants told us that it depends on the data and task, e.g., an organizational data domain could benefit from hierarchical-based charts.

6 LIMITATIONS AND FUTURE WORK

The positive feedback we received from participants suggests that systems like LinkQ can be successfully used for question-answering over knowledge graphs. That said, it is important to note that we observed a great deal of necessary hand-holding in implementing an LLM for successful KG query writing. Of course, this makes sense, as off-the-shelf LLMs are typically performant on text-based tasks like summarization [36].

In future work, we would like to evaluate the effectiveness of LinkQ against traditional NLP and emergent RAG [18] approaches. We can quantitatively compare the goodness of generated queries, as well as users' subjective views on how well an LLM captures their semantic intent during question-answering. Future evaluations could also include the testing of different visual encodings or designs for increasing trust in LLMs, as participants strongly favored the use of ground truth from KGs for LLM outputs.

Future work can also investigate optimizing our approach discussed in Section 3. Could embeddings be used more effectively for fetching entity IDs? Are there other architectural designs we could implement to manage poor-quality KG data? These directions can help us better understand how systems like LinkQ can aid data scientists in conducting visual data analysis with KGs.

7 CONCLUSION

We presented LinkQ, a system that implements an LLM for KG question-answering without the expertise of a KG querying language. LinkQ supports users in asking natural language questions, either open-ended or targeted, which are iteratively refined with an LLM until they can be translated into well-formed KG queries. LinkQ implements a scalable protocol to reduce the frequency of LLMs hallucinating data from the KG, requiring no fine-tuning of the LLM. Our interface provides two types of query visualizations, an entity-relation table and query graph structure, to help users both ascertain the accuracy of the LLM's generated query, and to inform them of how a query could be incorrect or improved upon. From a demonstration with five data scientists, we found that LinkQ exceeded expectations on converting NL questions to SPARQL queries, which participants stressed is a huge improvement to the burden of manually writing and assessing KG queries.

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