SHORT-PAPER

EDGE: A Conversational Interface driven by Large Language Models for Educational Knowledge Graphs Exploration

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Abstract

As education adopts digital platforms, the vast amount of information from various sources, such as learning management systems and learning object repositories, presents challenges in navigation and elaboration. Traditional interfaces involve a steep learning curve, limited user accessibility, and lack flexibility. Language models alone cannot address these issues as they do not have access to structured information specific to the educational organization. In this paper, we propose EDGE (EDucational knowledge Graph Explorer), a natural language interface that uses knowledge graphs to organize educational information. EDGE translates natural language requests into queries and converts the results back into natural language responses. We show EDGE's versatility using knowledge graphs built from public datasets, providing example interactions of different stakeholders. **Demo video**: https://u.garr.it/eYq63.

CCS Concepts

• **Information systems → Users and interactive retrieval**; • **Computing methodologies → Search methodologies**; **Knowledge representation and reasoning**.

Keywords

Learning Management, Information Retrieval, Conversational Interface, Graph Database, Knowledge Graph, Language Model.

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1 Introduction

With the adoption of digital tools and platforms, educational activities are introducing an abundance of information within organizations [11]. Navigating this wealth of information about both learning content and behavior presents a significant challenge for learners, educators, and managers [1, 6, 8, 10]. For instance, when the former visit the learning management system with a specific goal in mind [26], the interface often necessitates navigating through multiple menus and options. This process can be overwhelming and time-consuming, as it is constrained by the predefined functional paths [19]. Similarly, educators encounter difficulties in assessing student progress or accessing summarized course data, resorting to analyzing log tables or predefined dashboard plots [20, 25, 27]. Managers face similar challenges when extracting insights across courses, constrained by the limitations of graphic interfaces [5, 15]. As such, there is a need for more natural ways of interacting with the educational knowledge base of the organization.

Conversational interfaces have emerged as a promising solution to address the challenges faced in navigating educational information, offering a natural way of implementing personalization [16], tutoring [17], delivery [24], assessment [14], and support [3]. However, existing conversational interfaces often have a narrow focus and lack the capability to provide contextually-relevant and flexible access to the knowledge base of the organization [22]. While conversational interfaces driven by language models (LMs) have gained prominence in education [23], LMs still encounter difficulties in accessing organization-specific information and modeling it. Concurrently, knowledge graphs (KGs) have garnered attention as a method for modeling educational information [4, 29]. Their integration with conversational interfaces powered by LMs has been investigated in several fields [9, 12, 21] but remains unexplored in education, being a missed opportunity for exploring learning data in a more natural, accurate, and transparent manner. In contrast to conventional tools such as relational databases, which often necessitate manual and intricate querying based on string matching or basic operations, and vector search, which demands prior computation of the embeddings, the integration of LMs with KGs not only offers a more intuitive and sophisticated approach of retrieving information but also capitalizes on the inherent, nuanced semantic structure for modeling data that KGs provide. KGs represent knowledge through a semantic framework, which relates to natural language, an area in which contemporary LMs excel.

To bridge the gap between KGs and LMs and enable experimentation in the educational field, our contributions in this paper are:

- A *KG ontology mapping framework* able to turn educational datasets into a coherent semantic structure according to prior work, facilitating natural language exploration.
- A *LM-powered conversational interface*, named EDGE, which enables educational stakeholders to extract insights from educational KGs through natural language queries.
- A demonstration of EDGE's capabilities using knowledge graphs extracted through our framework from four existing public datasets across four different educational scenarios.

Our solution offers users a user-friendly natural language interface, allowing to seamlessly ask for information about the KG of the educational organization ecosystem. EDGE employs language models to interpret natural language requests, transforming them into queries that can be understood by the graph database. Then, it converts the query results into natural language responses for users. We qualitatively assess EDGE's capabilities via distinct scenarios, extracting and digesting knowledge graphs from four public educational datasets, and provide preliminary example interactions.

2 The EDGE Conversational Interface

EDGE follows a backend-frontend setup, with a three-tier layering including the *Presentation* layer in the frontend, and the *Application* and *Data* layers in the backend (Figure 1). The first layer provides a chat-based interface. The second layer handles natural language requests from the *Presentation* layer, converts them into queries for the *Data* layer's database, and generates natural language responses for the *Presentation* layer from query results. Lastly, the third layer stores educational KGs to be accessed by the *Application* layer.

Presentation Layer. EDGE implements a web-based conversational interface[1] using React[2], a framework renowned for responsive and interactive user interfaces. The *Presentation Manager* module is responsible for initializing the *Chat Container* component, which encompasses both the *Chat Messages* component to preserve the conversation history and the *Chat Input* component to allow sending natural language queries. Example natural language queries are provided to users to expedite their comprehension. Moreover, the integration of the React useWebSocket[3] library ensures a persistent connection with the *Application* layer. Using Tailwind CSS[4] within the *Style Manager* module enriches cross-device aesthetics.

[1]We leave solutions like **OpenWebUI** (https://docs.openwebui.com/) for future work.
[2]**React**: https://react.dev/
[3]**React useWebSocket**: https://www.npmjs.com/package/react-use-websocket
[4]**TailwindCSS**: https://tailwindcss.com/

Application Layer. We implemented the system's core logic using Python, structuring it into a series of steps as depicted in Figure 2. When a user submits a natural language query through the API from the *Presentation* layer, the query is forwarded to the LM through the *Text2Cypher* component[5]. The LM, in turn, generates a query in Cypher, the graph database language, tailored to the educational knowledge graph ontology. We experimented with both zero-shot and few-shot educational-specific techniques in order to tailor the approach to our target domain. Subsequently, this Cypher query is executed on the database stored in the *Data* layer, and the results are fetched using the *Graph Database Driver* component. Finally, the *Application Manager* component formulates a response to the user's query in natural language, arranging insights from the query results by means of the LM via the *Cypher2Text* component. In terms of implementation, we relied on the FastAPI[6] library to establish API endpoints, interfaced with OpenAI's GPT 3.5 Turbo LM (with 1000 as maximum tokens and 0.0 as the temperature) through the OpenAI[7] library within the *Language Model Driver*, and utilized the Neo4j[8] library for the *Graph Database Driver* to facilitate seamless communication with the graph database. Other open-sourced LMs and graph databases can be easily integrated.

Data Layer. The *Data* layer serves as the repository for pertinent organizational data, structured in the form of a knowledge graph. The latter is managed by the Neo4j[9] *Graph Database Management System* (DBMS) and stored within a Neo4j database. Neo4j was chosen for its robust scalability and optimized performance proven on graph-based data. Within this layer, the *KG Ingestor* facilitates the loading of a knowledge graph from a Turtle[10] file into a Neo4j database. This process involves several steps: initially, establishing a connection to Neo4j via API, then executing data import and translation queries. This ensures a seamless transition of data from the RDF[11] model to the property-graph model utilized by the Neo4j DBMS. By leveraging Neo4j's capabilities and the functionality provided by the *KG Ingestor* component, the *Data* layer ensures efficient management and utilization of the knowledge graphs.

3 Demonstration

The demonstration covers the core functionalities of EDGE through four example educational scenarios. To validate them, we conducted a preliminary qualitative analysis with local students and educators on response accuracy, completeness, and understandability[12].

3.1 Knowledge Graph Preparation and Upload

In a first step, we introduce attendees with the process of preparing knowledge graphs from conventional educational data and uploading them into EDGE through its *Data* layer components. To this end, we start by describing the educational ontology at the basis of the use cases considered during the demonstration. Coming from

[5]**NaLLM**: https://github.com/neo4j/NaLLM
[6]**FastAPI**: https://fastapi.tiangolo.com/
[7]**OpenAI Python**: https://github.com/openai/openai-python
[8]**Neo4j Python**: https://neo4j.com/docs/api/python-driver/current/
[9]**Neo4j**: https://neo4j.com/
[10]**Turtle**: https://www.w3.org/TR/turtle/
[11]**RDF**: https://www.w3.org/RDF/
[12]A more comprehensive evaluation is planned for future work. This demo aims to enable a pipeline for experimentation with different generation methods.

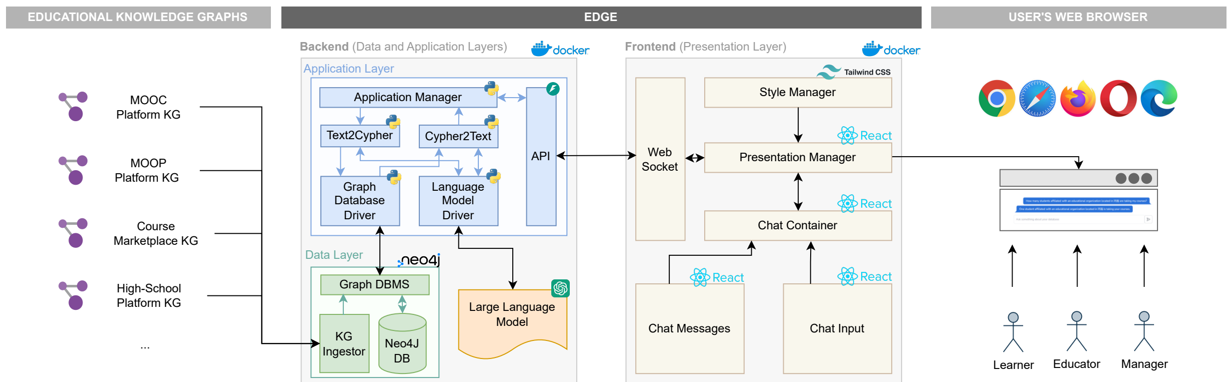


Figure 1: Architecture. EDGE leverages knowledge graphs of a given educational organization. It is based on a backend-frontend setup, with a three-tier layering including the presentation layer in the frontend, and application and data layers in the backend.

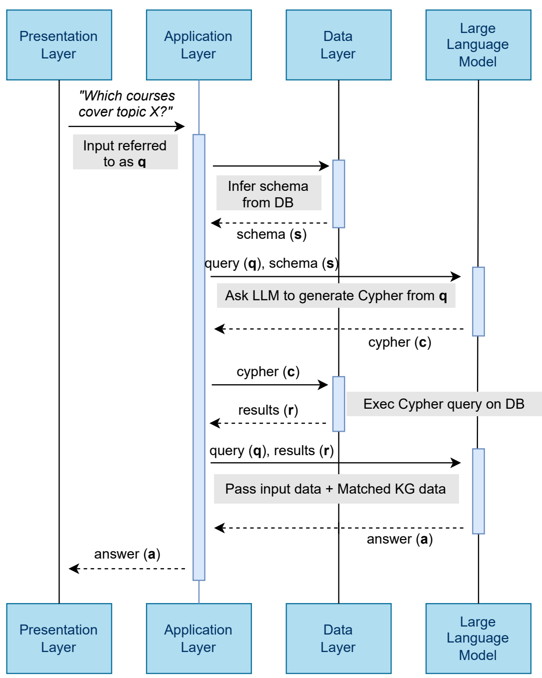


Figure 2: Workflow. The user submits natural language. The LM converts it into a Cypher query based on the educational ontology. This query is run on the graph database. The LM generates a natural language response from the query result.

extensive validation conducted by [2], the ontology[13] was created through a collaborative approach of conceptualization, development, and validation, by engaging learners, educators, and learning analytics researchers. Subsequently, we delineate the four representative educational environments under consideration, along with their corresponding knowledge graphs, namely a Massive Open Online Course (MOOC) platform [28], a Massive Open Online Practice (MOOP) platform [18], a course marketplace [7], and a high-school platform [13]. We emphasize the distinctive entities and relationships each of the environments enables in the considered ontology. We finally showcase how the encoded files can be transformed into the format supported by Neo4j, and the steps to perform into the Neo4J DBMS to upload the converted knowledge graph.

3.2 Use Case #1: MOOC Platform (MOOCCube)

In a subsequent step, we delve into XuetangX[14], an online learning platform spearheaded by Tsinghua University, with a mission to provide learners with the high quality courses from elite Chinese universities. In this case, we demonstrate EDGE's capabilities by leveraging a knowledge graph created from the Xuetang-collected MOOCCube dataset [28]. As an icebreaker, we suggest a series of example queries to the attendees. For instance, a learner seeking to discover a course might submit the query "Which courses cover the subject forecasting model?". Traditionally, this would involve performing textual searches, applying filtering parameters, browsing through paginated results, and possibly navigating between different pages. With EDGE, the learner can send the request through the interface and receive the result shown in Figure 3a. As another example, an educator curious about the diversity of educational backgrounds might inquiry "Which subjects are preferred the most among learners enrolled in my courses?". Without EDGE, the educator would need to manually analyze enrollment curricula. With EDGE, they input the query and receive a breakdown detailing the most frequent subjects. Similarly, managers might need to identify the courses with the least amount of learners enrolled. They might submit the query "Are there any courses with no learners enrolled? If so, please provide a list of course IDs". Without EDGE, the manager might need to go through all the course enrollments lists or ask to do this to the platform admin. With EDGE, the response might be "Yes, there are X courses with no learners enrolled, including ...".

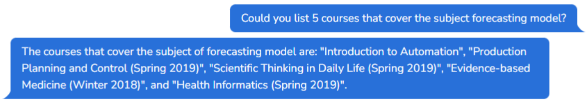
3.3 Use Case #2: MOOP Platform (MOOPer)

In a third step, we introduce the attendees with Educoder[15], a platform for computer science subjects in China that provides students with a practice-oriented approach to subjects. A knowledge

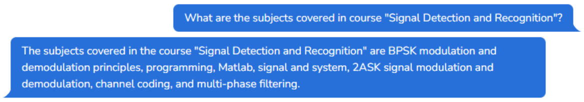
[13]**KG Ontology**: https://u.garr.it/ATBgW

[14]**XuetangX**: https://www.xuetangx.com/global/

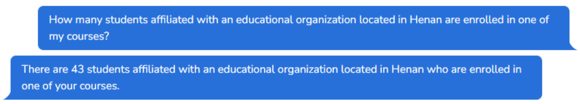
[15]**Educoder**: https://www.educoder.net/



(a) Courses by topic retrieval on top of MOOCCube's KG.



(b) Topics per course retrieval on top of MOOPer's KG.



(c) Student statistics on courses on top of MOOPer's KG.

Figure 3: Example Responses. Users initiate queries in natural language, and the system responds based on the retrieved data. Each response includes a toggle (available in the demo video) with the generated Cypher query, for interpretability.

graph created from the Educoder-collected MOOPer dataset [18] is adopted to demonstrate EDGE's capabilities. As an example, a learner seeking information about the subjects of a course can query EDGE with a request like "What subjects does course *X* cover?", bypassing the need to navigate via multiple pages (Figure 3b). Similarly, an educator's inquiry about the number of learners enrolled in their course from a given geographic area can be addressed via EDGE, with no need to manipulate enrollment files (Figure 3c). Lastly, the manager's need to identify courses requiring improvements can be met by querying EDGE with "Which course has received the lowest review score on average?", as an example.

3.4 Use Case #3: Course Marketplace (COCO)

We then move to a course marketplace scenario. Udemy[16] is a prominent online learning platform that hosts thousands of courses. We demonstrated EDGE's capabilities under this environment by leveraging a knowledge graph extracted from the COCO dataset [7]. Learners seeking courses covering specific topics and languages can leverage EDGE to streamline their search process. Traditionally, they would need to manually check course descriptions or consult academic advisor. Search functions might be sometimes available but do not allow to perform semantically-complex searches. With EDGE, a query like "Are there any courses covering math and science and delivered in Japanese?" yields a list of relevant courses. Educators also benefit from EDGE's capabilities, e.g., in computing course statistics. By inputting queries like "On average, how many resources are included in a course? Separate them by type", educators get breakdowns for course preparation reasoning. Managers can find EDGE valuable, such as for identifying learners with heavy course workloads. Queries like "Which learners are enrolled in more than *X* courses?" are supported to streamline monitoring.

[16]**Udemy**: https://www.udemy.com/

3.5 Use Case #4: High-School Platform (EduKG)

Finally, we cover the high-school scenario, specifically focusing on the transition to the university. To this end, we leverage the EduKG [13] knowledge graph created from survey answers given by learners from French high schools and universities. As an example, high-school learners exploring university opportunities can utilize EDGE to inquire about Engineering Technological Bachelor's courses, asking, "Could you give me a list of Engineering Technological Bachelor's courses?" In response, EDGE can provide a list of relevant courses such as Energy, Industrial Logistics, Physics, Electrical Engineering, Mechanical Engineering, Civil Engineering, Industrial Engineering, Materials Engineering, Packaging, and so on. Meanwhile, educators in a graduate program seeking insights into learner engagement with specific topics can query EDGE with, "How many learners enrolled in 'Bachelor's Degree - Psychology' have dealt with the subject 'digital skills'?" In this scenario, EDGE can reports that 37 learners enrolled in 'Bachelor's Degree - Psychology' have engaged with the subject 'digital skills'. Additionally, managers interested in tracking enrollment in dual bachelor's degree programs can input the query "How many learners are enrolled in Dual Bachelor's programs?" to receive the response indicating that there are 47 learners who interacted with this type of course.

4 Conclusion and Future Work

In this paper, we presented EDGE, a system that leverages the natural language processing capabilities of large language models and the structural advantages of knowledge graphs to provide support within the educational domain. Additionally, we developed a pipeline for mapping general datasets into an educational knowledge graph ontology, enabling their integration into EDGE through the user interface. Through tailored demonstrations, we illustrated how EDGE can streamline time-consuming tasks, simplify interactions, and provide access to information otherwise hard to obtain.

Future research will be directed towards automating knowledge extraction and ingestion, and enabling multi-channel delivery (e.g., via Moodle and Telegram) and multi-language support (beyond English). We plan to define and implement an evaluation strategy to measure the effectiveness of various natural language modeling techniques, leveraging open-source language models and retrieval-augmented generation methods originally applied to domains other than education as baselines. Following this, we will develop and test improved generation methods to enhance the performance of the underlying approach. We will explore extending capabilities beyond text generation, to include outputs such as figures, and integrating other intelligent systems, such as recommendation models. Lastly, we will test the prototype with university students for a large-scale validation, evaluating aspects such as accuracy and reliability.

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