Explanatory Dialogues with Active Learning for Rule-based Expertise

Yao Yao[1], Horacio González–Vélez[1] and Madalina Croitoru[2]

[1]Cloud Competency Centre, National College of Ireland, Dublin, Ireland
[2]LIRMM, Faculty of Science, University of Montpellier, Montpellier, France

Abstract

Contemporary language models have enhanced the interaction capabilities of AI with users. The improved understanding and processing abilities of AI with respect to the provided data, thanks to these language models, have simplified related knowledge engineering tasks. In this research, we embed LLMs in computational agents to reinforce the interaction between the system and expert users to improve knowledge engineering processes. By combining explanatory dialogue and active learning into knowledge engineering pipelines, we provide a framework that can help experts validate rule-based expertise in a specific domain. This validated expertise can be represented in RuleML format and is available to support knowledge-driven AI applications in domain-specific tasks. Our initial test indicates that such an integration is feasible and improves the overall usability of knowledge engineering processes, using curriculum development scenarios from DIGITAL4Business, a four-year EU-funded project to deliver a new European Master's programme on the practical application of advanced digital skills within European SMEs and companies.

Keywords

Multi-agent Systems, Active Learning, RuleML, Explanatory Dialogues, LLMs, DIGITAL4Business

1. Introduction

Artificial intelligence (AI) systems such as Large Language Models (LLMs) have exhibited proficiency in comprehending, generating, and structuring large volumes of textual data. However, in sophisticated and professional domains, such as high-level education, the practical deployment of AI applications requires the support of integrated knowledge, and such effective knowledge integration demands the continuous updating of relevant information within a specific context, along with the ability to comprehend new data with expertise. This fact makes the question of *how to efficiently gain and validate sufficient knowledge to optimise the performance of AI models in domain-specific tasks* increasingly important today.

In this research, we provide an approach to assist in the above question by incorporating the technologies of multiple agent systems, interactive AI, and rule language of the Semantic Web into an integrated framework. In our proposed framework, we will use multiple computational agents to provide explanatory dialogues to help the knowledge validation between the system and the expert users. All selected knowledge will be verified with the active learning process and corresponding experts in the next step. After knowledge validation is completed, new knowledge will be integrated with the knowledge base which includes the expertise represented by the RuleML format.

This research is also part of the EU project DIGITAL4Business. DIGITAL4Business is a four-year EU-funded project, one of the largest non-infrastructure projects awarded to date under the European Commission's flagship DIGITAL Europe programme. In DIGITAL4Business, our aim is to forge a new European Master's programme on the practical application of advanced digital skills within European SMEs and companies [1]. By integrating customised requests from employers and students, we are providing a flexible learning schema and microcredential service to support personalised learning for

RuleML+RR'24: Companion Proceedings of the 8th International Joint Conference on Rules and Reasoning, September 16–22, 2024, Bucharest, Romania
yao.yao@ncirl.ie (Y. Yao); horacio@ncirl.ie (H. González–Vélez); madalina.croitoru@lirmm.fr (M. Croitoru)
https://www.ncirl.ie/cloud (Y. Yao); https://www.ncirl.ie/cloud (H. González–Vélez)
0000-0002-5882-0058 (Y. Yao); 0000-0003-0241-6053 (H. González–Vélez); 0000-0001-5456-7684 (M. Croitoru)

each student in their Master's study. Through precise profile identification powered by the proposed knowledge-driven AI modules and a comprehensive curriculum, this programme can deliver personalised learning processes to students. Such demand-orientated targeted learning increases students' adaptability to future emerging market opportunities related to digital transformation.

We believe that this will help businesses achieve long-term competitiveness and growth through digital transformation and innovation. This goal requires a customised deployment of generative AI in domain-specific applications such as the curriculum development process with comprehensive knowledge integration in multiple domains. In concrete use cases, concepts such as method and format may have different meanings in different domains. The AI models can help the system to identify the specific meaning of the given concept in the knowledge base based on a particular context and then integrate the correct contents from different domains into the response of the particular application by the collaboration of separated agents. The research in this paper aims to serve this goal better by integrating the necessary interactive AI module into the corresponding agents to build and optimise specific knowledge of concepts in the given domains.

This collective process requires intensive interaction, knowledge explanation, and knowledge validation between multiple domain experts and knowledge models. It usually poses a challenge in knowledge engineering. Our method can facilitate the process above by using the interactive agents (powered with LLM) to propose a specific context-orientated dialogue to each corresponding expert and integrate the feedback of experts into knowledge validation and optimisation. The method could partially simplify and automate the work of experts in the knowledge engineering process. We have demonstrated our contribution by a detailed use case of the proposed framework inspired by curriculum development scenarios at DIGITAL4Business.

2. Background

In this section, we will have a brief review of each of the relevant aspects of our framework and discuss how these methods or techniques can help us improve the performance of AI in a domain-specific task.

2.1. Explanatory dialogue

Explanatory dialogues in AI refer to interactive conversations in which an AI system provides explanations to users about certain phenomena, decisions, actions, or data. These dialogues are designed to improve understanding, transparency, and trust between humans and AI systems. They play a crucial role in making AI systems more interpretable and user-friendly, especially in complex high-stakes applications such as healthcare, finance, and autonomous systems. The system of explanatory dialogues is a formal dialogue system of explanation with two players turning the tables [2, 3]. It takes place between an explainer and an explainee.

In our proposed framework, expert users would request the system to explain the newly learnt knowledge and validate the quality of knowledge. By facilitating interactive communication between AI systems and expert users, the explanatory dialogue provides a robust mechanism for knowledge validation, where users can understand, verify, and refine the knowledge embedded within AI models. The integration of explanatory dialogue into AI systems provides a significant advancement in our knowledge validation process. Not only enhances the transparency and trustworthiness of AI systems, it also promotes effective collaboration and continuous improvement of the knowledge models. The knowledge validation and improvement process can request a collective contribution from experts in different domains, and explanatory dialogues can help experts in diverse domains understand the common topic efficiently and finally reach a consensus. In Arioua et al. [4], it also shows the potential of explanatory dialogues in knowledge integration. As our work aims to leverage explanatory dialogues for knowledge validation, we build on these foundational studies to enhance the interaction and validation processes in our knowledge-driven framework. In addition, we also plan to continue to extend our interactive module by introducing other dialogue systems [5, 6] based on the demand for more sophisticated scenarios in the future.

2.2. Active learning

Active learning is a special case of Machine Learning (ML) in which a learning algorithm can interactively query a user (or some other source of information) to label new data points with the desired outputs [7]. Figure 1 shows an illustration of a general active learning method. In our platform, we use active learning to query experts for knowledge validation. Dubious or confusing concepts in knowledge that may cause conflict or ambiguity, based on the result of previous training, will be sent to experts for further investigation.

Figure 1: Illustration of Active Learning. The user, the data, the ML models and the predictions from these models all work together to improve the final results. The user will first use some data to train a model; this initial training set is generally either fully or partially labeled by the user. The model generated in this way will then be used to classify or predict another set of data. The model can be examined by looking at its predictions and, if possible, its internal structure. The user can then identify any shortcomings or blind spots which may exist in the model and augment the training set used to train the model with data which can help the model to train better. This loop continues until a model of desired quality is achieved. Through the interaction between users and the learning algorithm, the system can effectively learn a model from the comparatively smaller data set that is annotated by experts.

2.3. Semantic technology and Rule-based reasoning

The ultimate goal of semantic technology is to help machines understand data. To enable semantic encoding with the data, well-known technologies were developed, such as the Resource Description Framework (RDF) [8, 9] and Web Ontology Language (OWL) which is standard for RDF [10]. These technologies formally represent the meaning involved in the information. In our research, we use RuleML (Rule Markup Language) [11] as the standard format to store rule-based knowledge on the platform while making the ontology concepts compatible with the RDF representation, and this knowledge will be accessible to AI/ML models, as confirmed by Allemang and Hendler in integration in many applications [12].

By using RuleML to represent the knowledge base, we can provide detailed and structured explanations for the AI system's decisions and actions. In this way, the knowledge will provide the necessary resources and operational information to the AI/ML models to complete the corresponding tasks. Furthermore, knowledge will also help the system explain the result of AI/ML models. These concepts in knowledge will be connected by particular relations and constitute the knowledge base.

2.4. Rule-based knowledge representation

As an XML-based language for representing and exchanging different kinds of Horn rules (derivation rules, reaction rules, integrity constraints) on the Semantic Web, RuleML has limited expressiveness to represent some common situations that may arise in situations with partial knowledge or options.

Typically, some semantic adaptation is needed to adopt options in an elective way. Moreover, traditional RDF approaches require extensions to accommodate temporal constraints and specific time steps [13]. Consequently, we propose to introduce active learning to label intermediate knowledge points where expert interaction is required using an agent-based interface, knowledge-base, and an LLM to underpin the interactions over time.

3. Method

The framework discussed in this paper aims to perform a set of agents that implement the explanatory dialogue and active learning in Human-Machine Interaction with the help of LLMs. Through the interaction, each agent will individually extract and validate the corresponding knowledge from different hierarchical levels under the same domain. All these agents working together present a systematic strategy for efficiently collecting the relevant knowledge of the given concept from the expertise and finally integrating the knowledge into the corresponding part of the knowledge base. In previous research [14], the combination of computational agent and LLM showed impressive efficiency in performing knowledge extraction tasks, and this fact encourages us to use LLM embedded in the agents of our framework.

By applying the explanatory dialogue and active learning approach, we can efficiently annotate and validate knowledge that is specific to the given use case context based on the user's requirement. In this process, we also applied LLMs to help the agent better understand the user input and the relevant text-based data. Compared with predefined knowledge models and fine-tuned LLMs, our approach focusses on interactively extracting knowledge from diverse contexts separately and uses a systematic strategy to validate and refine the extracted knowledge models. This approach allows to use individual enquiring for fragmental knowledge with a particular given context and integrating the context of previous inquiries in the subsequent knowledge integration. By this, expert users can focus on the specific context each time to provide more elaborate knowledge and then leave the agents systematically to conclude the previously extracted knowledge on a higher level.

The proposed framework can be divided into three different parts: an agent-based interface, a rule-based knowledge representation, and an LLM behind the system. Figure 2 shows a general example of how the framework works in the knowledge engineering process. In the following, we will elaborate on each of these parts separately.

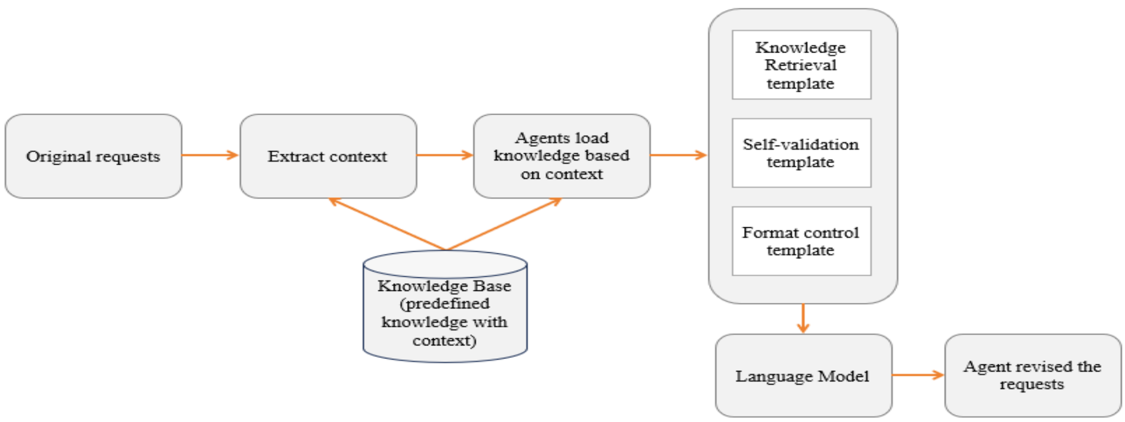

Figure 2: The example of the agent-based framework pipeline in the knowledge engineering process

3.1. Multi-agent system and explanatory dialogue

In this study, we apply a Multi-agent System (MAS) to implement the explanatory dialogue in the corresponding knowledge extraction and validation process. MAS has been applied to collect the context to help AI based on rules [15]. Figure 3 demonstrates that the Multi-agent system retrieves the information from various data sources and integrates this information into a graph-based representation.

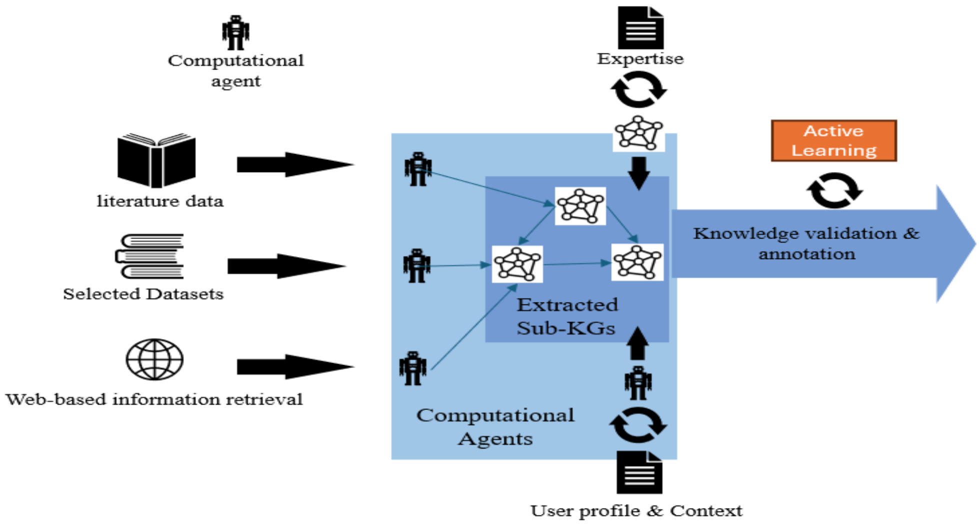

Figure 3: The multi-agent system extracts knowledge from diverse data sources

The extracted knowledge will be presented to the active learning agent, and this agent uses explanatory dialogues to interact with expert users to optimise the extracted knowledge. In our framework, we use the formalisation of explanatory dialogue that has been presented in the work of Arioua and Croitoru [16]. The explanatory dialogue system is a formal, turn-taking dialogue between two players: an explainer and an explainee. It includes dialogue moves to request and provide explanations. The dialogue begins with the explainer making a statement, ASSERT(j). The explainee then requests an explanation, EXPLAIN(j), with j being accessible and believed to be true by both parties. The explainer (computational agent) can either provide an explanation or declare an inability to explain. Such an interaction could be iterated and proceed with the hierarchy structure of the corresponding knowledge. In the end, an expert user decision is introduced, allowing one to judge the success of the explanation and corresponding knowledge validation. Expert users can also update the knowledge during the process and restart the dialogue to verify the update.

3.1.1. The implementation of active learning support by agents

The active learning processes of our framework are supported by multiple agents. when new knowledge has been extracted, the statement of the new knowledge will be presented to the active learning agent. Active learning is a special case of machine learning in which a learning algorithm can interactively query a user (or some other source of information) to label new data points with the desired output. In our case, the corresponding experts will work as the user to annotate the given new knowledge and complete the corresponding knowledge validation. The general active learning process is as follows.

- The active learning agent will search the relevant concepts based on the new knowledge statement. The embedded LLM of the agent will determine the relevance between the knowledge statement and the candidate concepts;
- After the relevant concepts are identified, each selected concept will be assigned to an independent agent. The agent will go through the knowledge base retrieve the corresponding logical rules

and constraints of the selected concepts (see more details in section 3.2) and send the information to the active learning agent;

- The active learning agent collected all constraints of relevant concepts and checked if there were any violations in the new given knowledge;
- If there is no violation, the given knowledge will be accepted in the knowledge base as the new item automatically. Otherwise, the knowledge will be presented to the corresponding expert by the active learning agent for further validation based on the violated constraints;
- Based on the annotation of experts, the updated knowledge will be rejected or checked again by the active learning agent;

In this research, we embedded LLMs in agents to better identify the relevance between concepts and facilitate the communication between agents and expert users. This is also one of the novelties in our current research. Some implementation solutions of the agent-based active learning pipeline introduced in this paper also draw on previous similar research which uses an embedded reinforcement learning approach to identify the relevant patterns in knowledge. More details on the implementation of active learning with agents can be found in previous research [17].

3.1.2. Knowledge validation with explanatory dialogue

In our framework, we use the explanatory dialogue to particularly facilitate knowledge validation. The advantage of using an explanatory dialogue includes two aspects. First, explanatory dialogue helps to clarify the context of concepts from different domains. Knowledge usually includes interdisciplinary concepts, and an explanatory dialogue can explain the meaning of these concepts to all experts from diverse domains. It allows for back-and-forth questioning, providing opportunities to elaborate on information, clear up misunderstandings, and deepen understanding. This iterative process strengthens the validity of the knowledge. Second, knowledge validation often involves the collaboration of multiple experts where different perspectives come together to enrich understanding. When agents explain to each other on behalf of different experts, they engage in collaborative learning, which can lead to the discovery of new insights and more robust knowledge validation. An explanatory dialogue provides the perfect foundation for continuing this collaborative learning in different times, domains, and experts.

Next, it will provide an example of how the agent uses explanatory dialogue to help experts in knowledge validation. Assume that the active learning agent sent a suspicious knowledge statement (j) to an expert for validation. This operation is regarded as ASSERT(j). For the given statement (j), the expert could request the corresponding explanation of the statement which is regarded as EXPLAIN(j). After explaining the statement, if the expert understands the statement well, the expert can accept the statement as (POSITIVE(j)) or reject it as (INABILITY(j)) directly. Otherwise, the expert can request more explanation with the new question(q) (NEGATIVE(q,j)) and iterate the request loop until all questions have been well explained. In this step, the embedded LLMs will help the agent identify which kind of operation the expert requested based on the textual input of the expert and extract the relevant concepts from the input. After each EXPLAIN(j) or NEGATIVE(q,j) request, the agent will search the relevant concepts in the knowledge base and try to provide an explanation to the expert. Each concept (c) in the knowledge base has the attribute (Γ_c) of explaining its relations, constraints, and rules. These predefined explanations in the attribute can be translated into the corresponding well-formed formulas (wffs) by LLMs and the variables in wffs are the corresponding concepts or the attributes of the concepts. The agent will continually extend these explanations based on comments from experts and annotate them with particular relevant concepts and topics. Based on the matched concepts and topics, the agent could identify the information in the knowledge base and integrate the information as the context in the request prompt to LLMs. Finally, the LLMs will provide the explanation to the expert according to the prompt and context of the request. If the expert chooses the status of (POSITIVE(j)) or (INABILITY(j)), the expert will be asked to update the knowledge accordingly. If there is no information matching in the knowledge base, the agent can request the corresponding explanation input from experts who are related to the topic. After the inputted explanation has been accepted by other experts, the new explanation will also be saved in the relevant concept in the knowledge base after knowledge validation.

3.2. Rule-based expertise with RuleML format

The knowledge representation in this proposed framework follows RuleML format. RuleML provides a robust and flexible framework for defining and sharing rules across different domains and applications. Its XML-based structure ensures broad compatibility and ease of integration, making it a valuable tool for implementing rule-based logic in the Semantic Web and beyond. RuleML is also used in expert systems to encode the knowledge of human experts in a form that a computer can use to make decisions or provide recommendations.

To implement the knowledge model, we employ a structured methodology that captures the expertise through formalised logical rules and assertions. A knowledge statement K is a finite subset of L (logic language L) precisely, K is a tuple (F, R , N) of a finite set of facts F, rules R and constraints N. These elements are then translated into logical facts and rules within RuleML. This process begins with the identification of key concepts and relationships within the domain of expertise, such as entities, attributes, and their interdependencies. These concepts are then encoded as logical facts using <Fact> elements in RuleML. Rules are developed to capture the dynamic relationships and constraints between these facts, ensuring that specific conditions and dependencies are represented accurately and all status meets necessary requirements before progressing. For example, rules might define the prerequisites for certain actions, the conditions under which particular outcomes occur, or the logical flow of decision-making processes. Constraints are special rules to limit the relation between concepts, and these types of rules will be applied in the consequent active learning process to protect the consistency, quality, and integrity of knowledge. In knowledge validation, violation of constraints will request the review of expert users on the corresponding knowledge. This formalisation allows automated reasoning and validation, enabling AI systems to infer new knowledge, validate existing knowledge, and ensure consistency within the knowledge base. Using RuleML, we achieve a flexible and extensible representation of expert knowledge that can be easily maintained and integrated into various applications, enhancing decision support and automated reasoning capabilities across diverse domains.

In the remainder of the section, we will explain how we define knowledge from different aspects in RuleML.

3.2.1. Ontology Concepts

Ontology concepts in RuleML can be defined to represent structured knowledge and relationships within a particular domain. RuleML's XML-based format allows for the clear specification of ontology components such as classes, properties, and relationships. Classes represent the primary concepts or entities within the ontology. In RuleML, classes can be defined using the <Class> element. For example, within a scenario of curriculum development, we could define the concept "student" in RuleML as follows:

```xml
<RuleML xmlns="http://www.ruleml.org/0.91/xsd">
  <Assert>
    <Class>
      <Ind>student</Ind>
    </Class>
  </Assert>
</RuleML>
```

we could also define the attributes and relationships of the concepts by using <Attribute> and <Relation> elements, Instances of concepts can be represented using the <Instance> element. Facts about instances can be asserted using the <Fact> element. These assertions link instances with properties and values. Using these elements, we can use agents to automatically define ontology concepts in RuleML based on the given description and create a structured and formal representation of domain knowledge.

3.2.2. Logic Rules

Logical rules can be defined to express more complex relationships and constraints within the ontology using the <Rule> element. Defining rules in RuleML involves creating logical statements that express relationships, conditions, and constraints within a knowledge domain. These rules are formulated using elements that represent logical constructs, such as conditions (antecedents) and conclusions (consequent). A RuleML typically consists of a head and a body. The body contains the conditions that need to be satisfied, while the head specifies the conclusion that follows if the conditions are met.

3.2.3. Conceptual constraints

Conceptual constraints in RuleML are used to enforce specific rules and restrictions within a knowledge domain to maintain data integrity and ensure logical consistency. It is typically represented as rules. These constraints help to define the permissible states and relationships among the concepts in the ontology. This ensures that specific undesirable conditions are not allowed within the knowledge base. In our framework, we implement these constraints by running them with an active learning agent. The system will extract the textual input as follows: The concept [curriculumIntroductionCreation] must have a relation with the concept [curriculum](if this constraint has been violated, you need to reject this knowledge statement, if it is uncertain, you need to inquiry expert) and automatically convert it into the RuleML format with the help of the LLM as below:

```xml
<RuleML xmlns="http://www.ruleml.org/0.91/xsd">
  <Assert>
    <Rule>
      <oid>
        <Ind>constraint1</Ind>
      </oid>
      <Implies>
        <head>
          <Or>
            <Atom>
              <Rel>hasRelation</Rel>
              <Ind>curriculumIntroductionCreation</Ind>
              <Ind>curriculum</Ind>
            </Atom>
            <And>
            ...
            </And>
          </Or>
        </head>
        <body>
          <Atom>
            <Rel>assertKnowledge</Rel>
            <Ind>curriculumIntroductionCreation</Ind>
          </Atom>
        </body>
      </Implies>
    </Rule>
  </Assert>
</RuleML>
```

The active agent will check if all refereed actions have been predefined properly and store this to the knowledge base after necessary validation. With the given function calls, the agent will be able to implement the constraint in the future active learning process.

3.3. Interaction between users and agents supported by LLMs

In our framework, we use the LLM (Gemma [18]) and prompt engineering approaches to help the interaction between users and agents. The agents are able to access the LLMs and knowledge base of the framework and agents will retrieve the corresponding predefined prompt templates from the knowledge base based on the given context of their task role. For example, assuming the user requests agents to produce an introduction of curricula on the topic of Cloud computation. This request will be processed by LLM and LLM will extract the relevant keywords to prepare the query in the Knowledge Base. The relevant concepts K (introduction and CreationFunction) in the knowledge base will be returned to the agent. If K (CreationFunction) includes a rule to produce a prompt template for LLM, the relevant information will be retrieved from the knowledge base, and the agent will implement the rule based on the given information. Figure 4 shows the example discussed above.

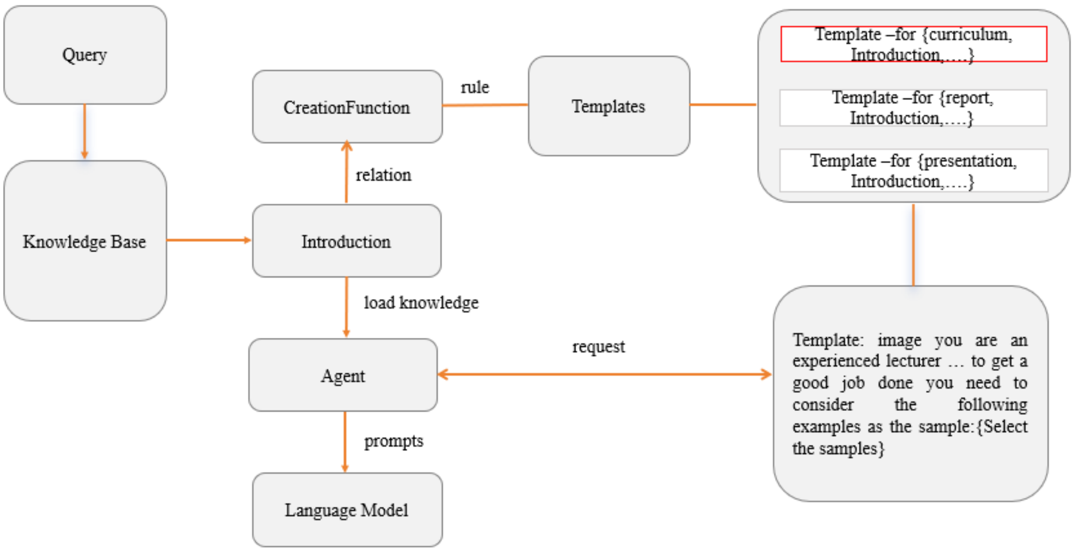

Figure 4: The illustration of knowledge supported agent working with LLM. Introduction and CreationFucntion represent the concepts of knowledge and Templates represent the attributes of the concept CreationFucntion.

In fact, agents not only use LLMs to respond user's requests but also interact with expert users for knowledge validation and knowledge update by the same approach. For knowledge validation, as we discussed in the previous sections, the input will be the suspicious or contradictory knowledge assertion or the questions related to the knowledge assertion. The active learning agent will select these assertions that violate the predefined rules and ask for the necessary validation or update about the knowledge from experts in the format of explanatory dialogue. In this process, the agent uses LLM and predefined prompt templates to implement each step in the dialogue until the knowledge has been successfully validated. The main function of LLMs here includes two folders.

First, LLMs can help identify the relevance between the given textual statement and the concepts in the knowledge base. For example, assume that the expert requested the agent to explain what means of "introduction" is in the context of "curriculum development". To perform this request, the agent will access LLM and ask you to first list the essential keywords from the given input. After that, the agent will search the knowledge base to identify the relevant concepts [introduction] and [curriculum development] based on the given keywords. With the help of LLM, the agent can also identify the given request type as an [explanation request] and retrieve the prompt template from the knowledge base to respond to such type requests. Based on the information collected, the agent will search for the marching attributes in the related concepts to fulfil the prompt template and then send the complete prompt to provide the response for the given request. For sophisticated concepts with a hierarchy structure, agents may need to run a recursive loop to retrieve all the information and iterate the above process multiple times with LLMs.

Second, LLMs convert diverse formal language formats, such as wffs, to readable textual expressions.

The computational agent processes the knowledge and the statement in diverse formats, but needs to change back to readable dialogue format when the agent responds to the expert users. LLMs can be used as an efficient tool to translate different format expressions into readable format expressions based on the request. With LLMs, we can facilitate the interaction between experts and computational agents. This function is also essential in knowledge update conversations between users and system agents.

In general, embedded LLMs help the interaction between agents and users in this framework and play an essential role in the corresponding knowledge engineering process. Figure 5 shows an overview of the framework on how to interact users with their knowledge base through computational agents and LLM.

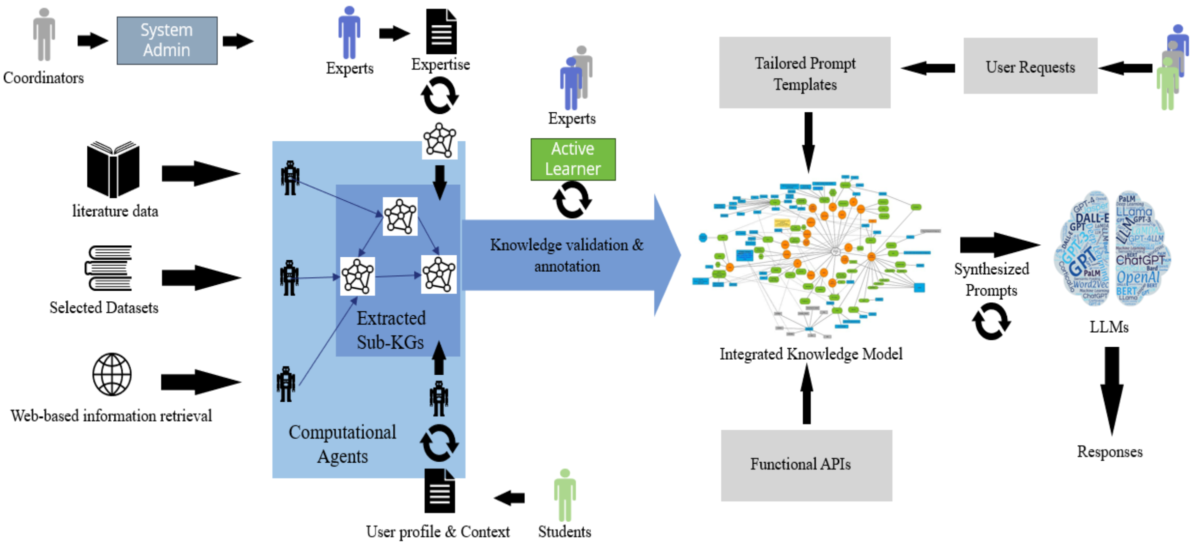

Figure 5: User interactions within the multi-agent system

4. Human-machine interaction

The goal of our research is to use LLMs and explanatory dialogue in the active learning process to help validate and integrate knowledge. To be more concrete, our work in this paper focusses on using the discussed approaches and modules to improve the domain-specific knowledge (expertise) extracted in our framework. To explore the potential and efficiency of the proposed approach, we tested our agents with an open-source LLM: Gemma model [18] to produce the relevant conversation to update and validate the expertise in curriculum development based on human-machine interaction. This is an ongoing study, and the test below aims to demonstrate and explore the potential of our proposed solution and framework in practical scenarios. The main concern in this step is to examine how to integrate all these discussed techniques into a common user interface and work well in the given scenarios. Based on this test, we will continue to improve our approach and develop the corresponding evaluation methods to measure the efficiency of the framework in our future work.

In our test, we use knowledge-driven agents to synthesise the LLM prompts based on the context and organise the conversation between users and the system in an explanatory dialogue format for the corresponding knowledge update or validation. In the framework, LLM is a tool for helping agents understand the input of users and understandably respond to users. Therefore, the proposed approach can be applied to any language model without knowing the particular internal structure of the model. The following results show the different steps of the conversation in the knowledge update and validation process.

4.1. Knowledge update

In the framework, experts can choose input and predefined knowledge manually or request that the system extract knowledge from a given textual data. Users can also choose to define the relationships between two concepts. Our following examples show that the knowledge statements are represented in a predefined standard format. Actually, user input can be in various textual formats, and the agent will request LLMs to convert the input into the standard format given in the predefined samples for knowledge update. If the input is not able to align with the standard format, the agent will explain the format of the knowledge statement and require the user to rephrase their declaration. Users can also extend the samples by adding conversion examples from their selfdefined formats to the standard format to help LLMs better understand the input in the future. These customized samples will be included in the user profiles in the knowledge base. Figure 6 shows an example of defining a concept and a relationship through the interface.

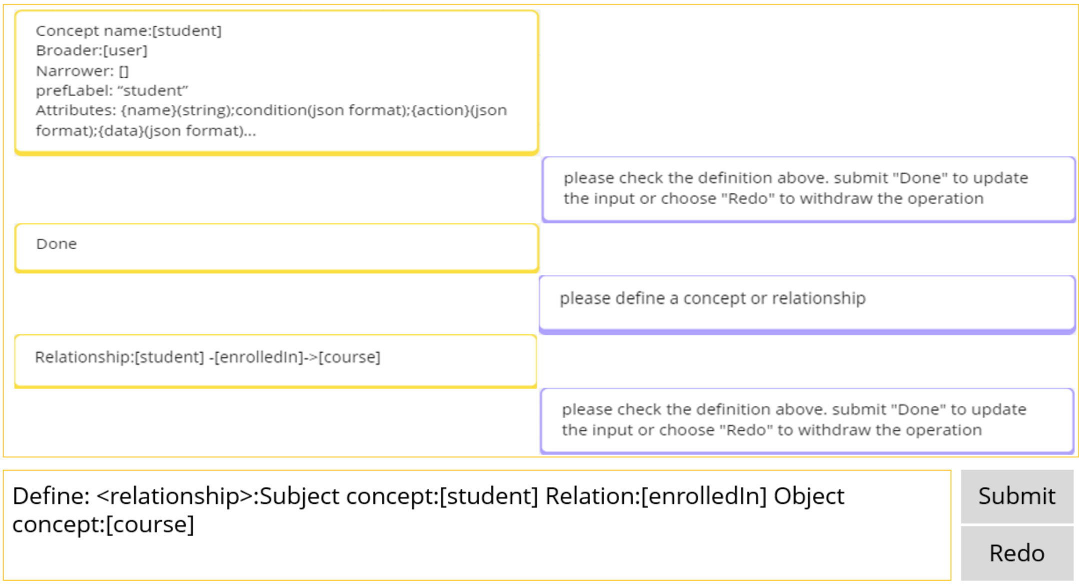

Figure 6: Example of knowledge update

4.2. Knowledge validation

After the knowledge update, the system will try to integrate the new knowledge into the knowledge base and perform an active learning process to check whether it is necessary to request an expert user involving knowledge validation. Any violation of predefined rules or undefined concepts, relations, and attributes in new knowledge updates will lead the active learning agent to report the case to an expert user. Users could also add custom constraints to activate queries for expert users. For example, for overwrite or deletion operations related to particular concepts, the user can define a constraint to request the validation of expert users. The human-machine interaction in knowledge validation follows the explanatory dialogue method. The active agent will start the conversation to provide an assertion of the new knowledge and allow experts to request an explanation of the assertion and ask critical questions during the process. In the event that the agent cannot provide a successful explanation, at least one of the experts will manually review the conversation and then update the knowledge base. After that, the agent will iterate the conversation again until the assertion has been considered and explained to the experts. After all, the agent will extract the validated rule-based knowledge from the conversation and apply them as new constraints in the future active learning process. Figure 7 shows an example of the implementation of the explanatory dialogue in the knowledge validation process.

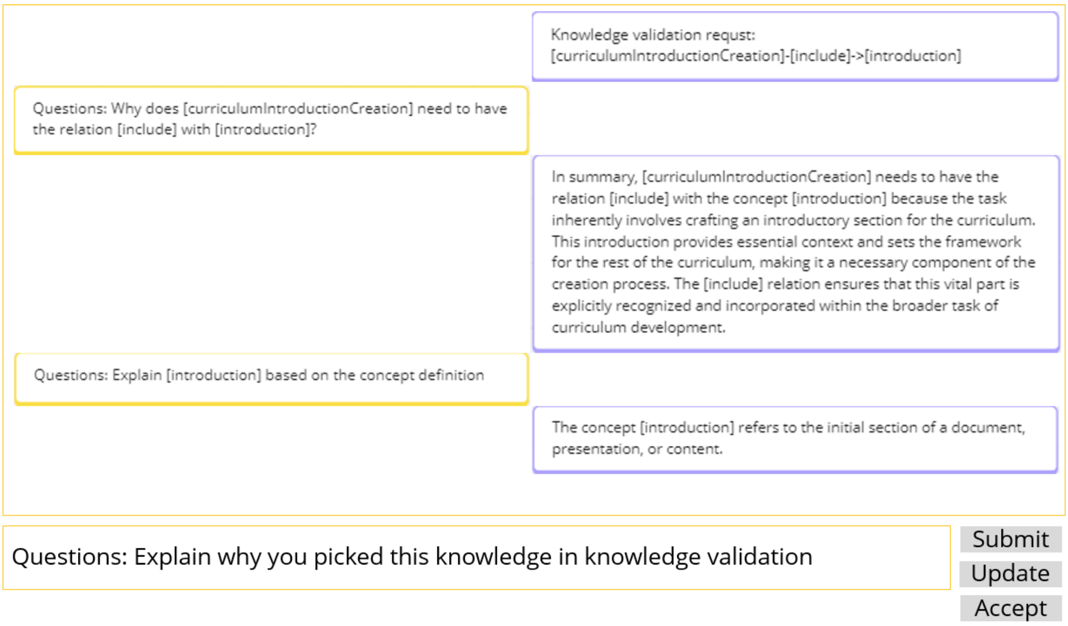

Figure 7: Knowledge validation with explanatory dialogue

4.3. Review knowledge and define constraints for the active learning agent

Expert users can select concepts, relations, attributes, and rules from the knowledge base and review them as necessary. Based on the feedback of a particular task, a user can trace the related knowledge that has been applied to support the AI model in the task. For knowledge validation, expert users can also request the agent to implement customised constraints through the interface. Figure 8 shows an example of reviewing a concept related to the introduction creation task. After the review, the user added a custom constraint on this concept.

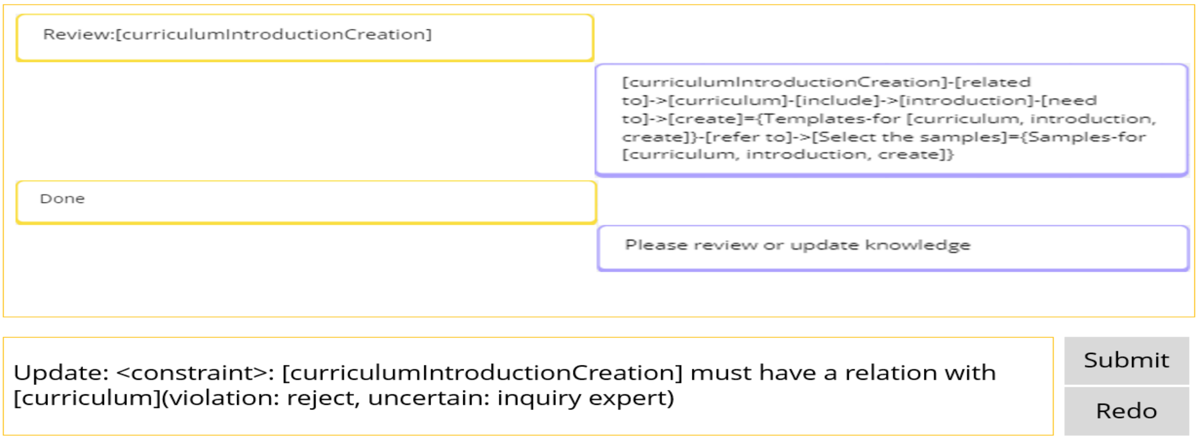

Figure 8: Review and defining constraints

5. Conclusion

In this research, we proposed a novel approach using LLM and explanatory dialogues to improve the active learning process within knowledge validation. Through the discussed use case of curriculum development, we tested the potential of this approach and identified the steps of essential dialogues in this approach. The importance of relevant domain-specific knowledge and the necessity of expert participation is critical to the performance of AI models, and our proposed framework could facilitate the construction of a knowledge base underpinned by an efficient human-machine interaction. Despite the surprising ability of LLMs in semantic processing and inference, many limitations and problems revealed in practical scenarios tell us that LLMs still need input from human experts to construct sophisticated models for practical tasks in the given domain. Building and validating such competent knowledge models is a challenge because the knowledge is difficult to predefine by certain experts at once. One reason is because of the necessary comprehensiveness and context awareness for these models. Certain experts have difficulty covering all aspects of knowledge in all possible contexts in knowledge engineering, especially for tasks requiring interdisciplinary knowledge.

Another reason is the extendability and compatibility of the knowledge models. For implementing practical tasks, the required knowledge may need to be continually updated. Knowledge integration and new knowledge validation are necessary, but implementation processes are difficult to pre-defined in advance. Due to the reasons above, we believe that a constant and collective collaboration between experts and the system would be a promising solution to cope with this challenge. Our current research aims to provide a framework that constantly requires dynamic updates and optimisation based on the feedback of experts to maintain competent knowledge models for domain-specific tasks.

There is a rational and practical concern about whether the system can have sufficient and adequate input from experts to build the expected knowledge models. In our solution, we tried to use LLM-powered agents and explanatory dialogue to mitigate this problem. With the help of LLMs, agents can automatically extract knowledge statements from designated datasets and present them to the system, reducing the need for manual inputs for knowledge updates. For uncertain or contradictory knowledge statements, the agent will use explanatory dialogue to explain them to multiple related experts and facilitate the corresponding knowledge integration and knowledge validation. Following the accumulation of knowledge in active learning, the demand for expert knowledge validation will quickly decrease. Experts only need to participate in the validation when an unknown case emerges. To ensure the understanding of experts in the given topic during knowledge validation, we can provide customised conversation samples as context into the prompts for corresponding experts to make the response of LLM easy to understand for the corresponding experts.

Moreover, the explanatory dialogue can involve multiple experts and each expert will be consulted with familiar topics based on the profile of the expert. The agent will explain the context of the given topic based on validated knowledge so that it can minimise the knowledge requirement of experts on other topics. We tested the idea with simple examples in our initial tests. Improving and enriching the corresponding prompt templates and samples for this purpose is one of the important parts of our future work. Through the initial tests that have been done, we realise that the development of the necessary knowledge models in a practical task is complicated and challenging, and it requires more effort to improve the current pipeline. Fortunately, previous tests have shown that, with proper dialogues and prompt engineering templates, LLMs can help simplify the entire process, from knowledge validation and integration to the deployment of knowledge models in specific tasks.

This research is ongoing. In this paper, we present our current progress by showcasing the initial interface, introducing the agent-based framework through a basic use case, and assessing the feasibility and efficiency of agents in human-machine interaction. The tests discussed previously show a promising prospect and good feasibility in this direction. We developed the necessary agents, basic knowledge models, and prompt templates to support these initial tests, but the framework still needs more sophisticated knowledge models to cover a practical use case. In future studies, we will continue to improve this approach and knowledge models discussed in the paper based on the experience that we learnt from our initial use case test and try to improve the efficiency of the pipeline. In addition, we will try to apply this framework in practical applications of DIGITAL4Business and improve it based on feedback. The main plans that will be implemented in future research and development are listed below.

First, we will continue to introduce more prompt templates, concept sample samples, and constraints to facilitate knowledge integration and support more sophisticated task applications. The pertinent samples for particular tasks can positively enhance the response of LLMs, and we will reinforce the collection and annotation of these samples in the next version of our framework. Second, the interface should be able to provide a more diverse knowledge representation to interact with expert users. For example, a knowledge statement could be represented graphically in a tree-based structure, and a more user-friendly interface should be developed for users to give feedback and review the previous conversation context. Last but not least, the development of more comprehensive knowledge models with the participation of experts. Through the iteration of active learning in the framework, we plan to continue updating the initial knowledge model of curriculum development with lecturers in the relevant master's degree programmes. This learning process could gradually improve the quality and capacity of the corresponding knowledge and make the interactive agents fit the given tasks better. At the same time, we are developing benchmark tests to evaluate the effectiveness of expertise in improving the performance of LLMs in curriculum development. This result will give a quantitative evaluation of the impact of expertise in the framework.

Acknowledgments

This work has been developed under the auspice of **1)** "DIGITAL4Business: Master's Programme focused on the practical application of Advanced Digital Skills within European Companies" URL: digital4business.eu, a project funded from Dec/2022 to Nov/2026 by the European Commission's DIGITAL programme call: DIGITAL-2021-SKILLS-01 grant no.: 101084013; and **2)** "SMARDY: Marketplace for Technology Transfer of Research Data, Software, and Results" URL: smardy-project.eu/), a project funded from 2021 to 2024 by the European Eureka Network programme through The Ireland's International Research Fund of Enterprise Ireland (Ref#: IR20210058); and The Romania's Ministry of Research, Innovation, and Digitalisation CNCS/CCDI-UEFISCDI (Ref#: PN-III-P3-3.5-EUK-2019-0241) PNCDI III.

References

[1] C. Somers, D. Feenan, D. Fitzgerald, R. Henriques, M. Martignoni, D. A. Parletta, E. Cibin, A. E. Chis, H. González-Vélez, Systematic needs analysis of advanced digital skills for postgraduate computing education: The DIGITAL4Business case, in: 25th International Conference on Artificial Intelligence in Education (AIED 2024), volume 2150 of *Communications in Computer and Information Science*, Springer Nature, Recife, Brazil, 2024, pp. 179–191.
[2] D. Walton, Dialogical models of explanation, ExaCt 2007 (2007) 1–9.
[3] D. Walton, A dialogue system specification for explanation, Synthese 182 (2011) 349–374.
[4] A. Arioua, P. Buche, M. Croitoru, Explanatory dialogues with argumentative faculties over inconsistent knowledge bases, Expert Systems with Applications 80 (2017) 244–262.
[5] A. Casciani, M. L. Bernardi, M. Cimitile, A. Marrella, Conversational systems for ai-augmented business process management, in: International Conference on Research Challenges in Information Science, Springer, 2024, pp. 183–200.
[6] N. Klievtsova, J.-V. Benzin, T. Kampik, J. Mangler, S. Rinderle-Ma, Conversational process modelling: state of the art, applications, and implications in practice, in: International Conference on Business Process Management, Springer, 2023, pp. 319–336.
[7] B. Settles, Active learning, Synthesis Lectures on Artificial Intelligence and Machine Learning, Springer, Switzerland, 2012. ISBN:978-3-031-00432-2.
[8] O. Lassila, R. R. Swick, et al., Resource description framework (rdf) model and syntax specification (1998).
[9] K. S. Candan, H. Liu, R. Suvarna, Resource description framework: metadata and its applications, SIGKDD Explorations Newsletter 3 (2001) 6––19.
[10] D. L. McGuinness, F. Van Harmelen, et al., Owl web ontology language overview, W3C recommendation 10 (2004) 2004.
[11] H. Boley, S. Tabet, G. Wagner, Design rationale for ruleml: A markup language for semantic web rules., in: SWWS, volume 1, 2001, pp. 381–401.

[12] D. Allemang, J. Hendler, Semantic web for the working ontologist: effective modeling in RDFS and OWL, Elsevier, 2011. ISBN:978-1-4503-7617-4.
[13] D. Wu, H.-T. Wang, A. U. Tansel, A survey for managing temporal data in RDF, Information Systems 122 (2024) 102368.
[14] J. R. Kirk, R. E. Wray, P. Lindes, J. E. Laird, Improving knowledge extraction from llms for task learning through agent analysis, in: AAAI Conference on Artificial Intelligence, volume 38, 2024, pp. 18390–18398.
[15] S. Yousaf, H. M. U. Haque, M. Atif, M. A. Hashmi, A. Khalid, P. C. Vinh, A context-aware multi-agent reasoning based intelligent assistive formalism, Internet of Things 23 (2023) 100857.
[16] A. Arioua, M. Croitoru, Formalizing explanatory dialogues, in: International Conference on Scalable Uncertainty Management, volume 9310 of *LNAI*, Springer, Québec City, 2015, pp. 282–297.
[17] Y. Yao, J. Liu, C. Ryan, Using active learning and an agent-based system to perform interactive knowledge extraction based on the covid-19 corpus, The Knowledge Engineering Review 38 (2023) e8.
[18] G. Team, T. Mesnard, C. Hardin, R. Dadashi, S. Bhupatiraju, S. Pathak, L. Sifre, M. Rivière, M. S. Kale, J. Love, et al., Gemma: Open models based on gemini research and technology, arXiv preprint arXiv:2403.08295 (2024).