Large Language Model Assisted Multi-Agent Dialogue for Ontology Alignment

Extended Abstract

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ABSTRACT

Ontology alignment is critical in cross-domain integration; however, it typically necessitates the involvement of a human domain-expert, which can make the task costly. Although a variety of machine-learning approaches have been proposed that can simplify this task by learning the patterns from experts, such techniques are still susceptible to domain knowledge updates that could potentially change the patterns and lead to extra expert involvement. The use of Large Language Models (LLMs) has demonstrated a general cognitive ability, which has the potential to assist ontology alignment from the cognition level, thus obviating the need for costly expert involvement. However, the process by which the output of LLMs is generated can be opaque and thus the reliability and interpretability of such models is not always predictable. This paper proposes a dialogue model, in which multiple agents negotiate the correspondence between two knowledge sets with the support from an LLM. We demonstrate that this approach not only reduces the need for the involvement of a domain expert for ontology alignment, but that the results are interpretable despite the use of LLMs.

KEYWORDS

Ontology Alignment; Large Language Model; Multi-Agent System; Dialogue; Negotiation

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1 INTRODUCTION

Ontology alignment, whereby entities in one ontology are mapped to the corresponding entities in the second [2], has become a critical task in ensuring knowledge integration across different domains. The use of dialogues has been used as a rational means for agents to negotiate over candidates correspondence based on their private preferences and background knowledge, through argumentation [4, 8] or knowledge refinement [3]. Knowledge-based solutions have been proposed that have subsequently been widely exploited, although most of these necessitate the involvement of a human domain-expert to develop *gold-standard* alignments between pairs of ontologies. This intensive approach can be costly, both in terms of time and resource, and can even result in the generation of inconsistent alignments [7].

Recent Large Language models such as GPT-4 have demonstrated a close-to-human-level performance in various domains and tasks [1], suggesting that they could be used to replace the role that some experts have for zero-shot ontology alignment. However, such models can be opaque (i.e. they exhibit the properties of a black-box), and it can be difficult for such approaches to be accountable for any alignments generated between different ontologies. Furthermore, LLM usually can only take a limited number of tokens, which is not enough for large ontology alignment tasks.

Unlike other studies in this area, this study explores how the LLM could investigate the implicit knowledge from different ontologies by means of a dialogue process. Instead of simply using the LLM to generate alignments directly, we assume each LLM only has incomplete knowledge and choose a candidate correspondence between entities in the different sub-graphs of the ontologies based on its cognition. The cognitive environment is based on the ontology structure, and thus, the extracted knowledge is dependent on the ontology itself. This study not only proposes a new paradigm for LLM-assisted dialogue-based ontology alignment, but also presents insights on how the complete knowledge in the ontology can be expressed to support generative AI models.

2 LLMA DIALOGUE MODEL

The *LLMA Dialogue Model* presented here is based on the *Correspondence Inclusion Dialogue* [6], and utilises an LLM to select each correspondence possessed by one of the agents. This correspondence is then proposed as part of the dialogue to the other agent with the aim of collaboratively finding a set of correspondences (i.e. an *alignment*) between the two ontologies. Through this approach, the cognitive capability of LLMs can be regarded as

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a special function executor of each agent, where each agent has incomplete knowledge about the entire ontological space. Although a simplistic approach would be to rely on the LLM's selection of individual correspondences (in which only a single subject entity appears), this kind of approach ignores the semantic scope difference across domains; e.g., the same natural language description from different ontologies having different scopes. Thus, agents will need to provide entities which have similar semantic meanings to the LLM for selection with this context awareness.

The dialogue involves two agents x and $\hat{x}$ to determine an alignment $\mathcal{AL}^{<O^x, O^{\hat{x}}>}$ between ontologies of each agent O^x and $O^{\hat{x}}$. The alignment is a set of correspondences that denotes the relation between two classes, one of which from O^x, and the other from $O^{\hat{x}}$. The process to determine an alignment is the process to find correspondences within the complete knowledge $\mathcal{K} = (O^x \cup O^{\hat{x}}) \cup C$, where C is the universal set of correspondences, and $\mathcal{AL}^{<O^x, O^{\hat{x}}>} \in C$. To achieve the result, the dialogue is conducted by rounds of negotiations, each of which results to a correspondence $c = <e^x, e^{\hat{x}}>$ where e^x and $e^{\hat{x}}$ are entities of O^x and $O^{\hat{x}}$ respectively, and $c \in C$. During each round of negotiation, each agent handles incomplete knowledge $\mathcal{K}^x \in \mathcal{K}$ due to the semantic scope difference, and $|\mathcal{K}^x| + n < m$, where n is the token length of prompt template and m is the maximum token that LLM can accept. To track the negotiation process, each agent manages a private set of classes that have been negotiated, denoted as $\mathcal{N}$, such that $\forall e \in \mathcal{N}, e \in O$.

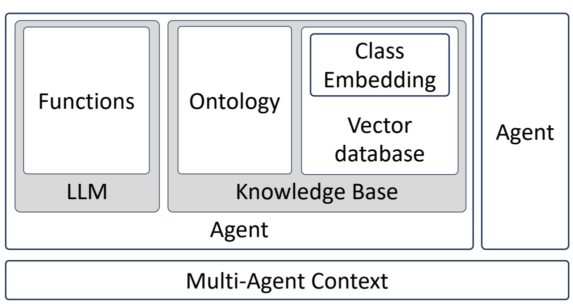

Figure 1: LLMA Dialogue Model Architecture

The alignment architecture (illustrated in **Figure 1**) is situated within a multi-agent context that provides multi-threading and message exchange support. Each agent has access to one instance of an LLM (which is associated with multiple functions enabled by prompt templates), and one Knowledge Base (that manages the agent's ontology and embedded class vectors).

The dialogue used is designed to ensure that each agent only reasons using its own ontology and knowledge that is shared between the two agents, and that this is used to determine what is subsequently shared. Each agent will only conduct the following three moves in each round of negotiation (**Figure 2**): (a) *pick* an entity $e \in O, e \notin \mathcal{N}$; (b) *propose* a recommended entity for correspondence e' and a set of entities $\mathcal{E}^x$ for alternative correspondences, selected by LLM, from a set of relevant entities $\mathcal{E} = \{e_i | relevance(e, e_i) > \epsilon, e_i \in O, e_i \notin \mathcal{N}\}$, where $relevance(e, e_i)$ is the cosine similarity of the embedding vectors of entities, ϵ is the similarity threshold; (c) *decide* the correspondence c by using LLM to select two entities, one of which from entities $<e', \mathcal{E}^{\hat{x}}>$ proposed by the other agent, and the other from its own ontology $<e, \mathcal{E}'>$ where $\mathcal{E}' = \{e_i | relevance(e^{\hat{x}}, e_i) > \epsilon, e_i \in O, e_i \notin \mathcal{N}, e^{\hat{x}} \in <e', \mathcal{E}^{\hat{x}}>\}$.

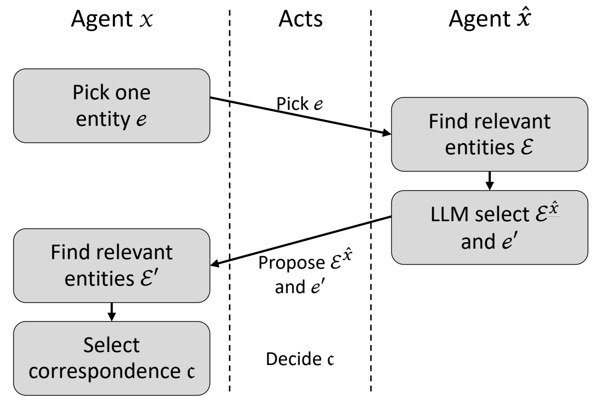

Figure 2: Agents Negotiation Flow

3 EXPERIMENT AND DISCUSSION

Our source code to implement the LLMA Dialogue Model has been published online[1]. The empirical evaluation uses the OAEI Anatomy dataset [5] with all non-anonymous entities. The LLMA Dialogue Model achieved 54.4% in precision, 59.9% in recall, and 66.6% in F-measure. The evaluation took 1 hour 56 minutes 26 seconds to align two ontologies, with a total 6048 entities from both ontologies and conducted 3.77k calls of GPT's API.

The proposed LLMA Dialogue Model has its advantages in ontology alignment, including generalization and interpretability. It does not need domain-specific expert involvement or particular training to achieve the ontology alignment tasks, and therefore, it can be easily used in general cross-domain scenarios. For interpretability concerns, the behaviours of the LLM are integrated into the agent dialogue processes, and thus, we can transparently evaluate how the ontology alignment is achieved step by step.

4 CONCLUSION

In this paper, we have proposed the *LLMA Dialogue Model*, which enables LLM-assisted agents to negotiate knowledge in regard to correspondences between ontological entities through a dialogical game where no pre-training or fine-tuning is required. We have empirically evaluated the proposed model with the OAEI Anatomy dataset. The proposed model has its advantages in generalization and interpretability, and it is suitable for some scenarios when the stakeholders do not want to share all of their own ontology information or do not totally trust the LLM-generated results.

ACKNOWLEDGMENTS

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[1]https://github.com/JadeGreened/AI-Semantic-Alignment

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