Bridging Complexity in Ontology Meta-Matching Through Interpretability

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Abstract

Ontology meta-matching is essential for semantic web applications, as it helps align different ontologies, thereby ensuring interoperability and the seamless integration of knowledge. Yet, the opaqueness of numerous meta-matching algorithms has sparked issues around their transparency, leading to difficulties in trusting and utilizing their outcomes effectively. This research delves into the interpretability of ontology meta-matching, seeking to illuminate this crucial facet in the field of knowledge engineering.

Keywords: Ontology alignment, Ontology meta-matching, Semantic Similarity Measurement

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1. Introduction

This invited talk is about effectively mapping heterogeneous ontologies, i.e., ontology meta-matching. This challenge has gained prominence in the ever-expanding landscape of knowledge representation. Ontology meta-matching is necessary for integrating and aligning knowledge from different data sources. In this context, its application is vital to integrating diverse sources and facilitating data exchange and reasoning. However, as ontologies grow in complexity and diversity, the need for interpretability in the meta-matching process becomes increasingly evident. The reason is that while ontologies serve as fundamental knowledge structures in various domains, their alignment processes often need more clarity and insight for decision-makers, domain experts, and practitioners to understand, validate, and trust the results [4].

The confluence of ontology meta-matching and interpretability represents an area of research that addresses the complex challenge of improving transparency during the process [12]. This work involves the development of methodologies, algorithms, and tools capable of processing the ins and outs, unveiling the logic underlying alignment decisions, and providing meaningful insight into the underlying processes [13]. The goal is two-fold: to help stakeholders understand and evaluate the results and to build confidence in the results generated automatically.

This presentation thoroughly explores the intersection between transparency, interpretability, and meta-matching. We will see the theoretical foundations, methodological advances, and practical implications of bringing interpretability into the meta-matching process. We will discuss the various dimensions of transparency, the technical aspects of algorithmic transparency, the cognitive aspects of human-computer interaction, and domain-specific interpretability requirements. Additionally, we will examine the implications of this research in various domains, from healthcare to finance.

Throughout this presentation, we will examine several fundamental concepts, methodological frameworks, and emerging trends that define the landscape of interpretability. The goal is to illuminate the path toward a more understandable, accountable, and reliable alignment process, fostering advances in knowledge integration, semantic interoperability, and informed decision-making.

2. Related Works

Semantic similarity measurement [8] is pivotal by quantitatively assessing the similarity or relatedness between entities (concepts or terms) within different ontologies. This measurement serves as a fundamental building block in the process of aligning and integrating ontologies, and its significance can be summarized in several vital aspects [3, 5]

Ontology meta-matching typically refers to a process in the field of ontology alignment or ontology matching. Ontology matching is finding correspondences between concepts or entities in different ontologies, formal representations of knowledge or data [7, 15] Therefore, the expression ontology meta-matching in this context implies a higher-level process where various ontology matching techniques are compared, evaluated, or combined to improve the quality of ontology alignment [6].

3. Contribution

Ontology meta-matching refers to matching ontologies from different sources, often in the context of semantic web applications. The goal is to find correspondences between entities in other ontologies. In this context, the goal is to implement a matching algorithm using several semantic similarity measures [9] to find correspondences between entities in different ontologies. This could involve techniques like graph-based matching, instance-based matching, or machine learning-based approaches such as [2, 11, 14].

It is necessary to remark that ontology meta-matching is pivotal in knowledge integration and semantic interoperability across various domains. The opacity of matching algorithms can hinder their adoption, highlighting the importance of interpretability in this field [1].

To consider interpretability concerning an existing method, it is necessary to consider techniques such as:

- Explanation Generation: Explain why two entities were (or not) matched.
- Confidence Scores: Assign confidence scores to indicate the level of certainty.
- Visualizations: Create visualizations to help users understand the alignments.

A deep exploration of interpretability within the context of ontology meta-matching reveals its critical role in improving the effectiveness and trustworthiness of the integration processes [10]. At its core, meta-matching involves the alignment of ontologies from different sources, making it a fundamental task in semantic interoperability. Interpretability mechanisms within this framework facilitate a deeper understanding of the alignment results, allowing stakeholders to understand the rationale behind specific matches or mappings.

These mechanisms can include visualization techniques, explanation algorithms, and transparent models that shed light on the decision-making process, enabling domain experts to verify and refine alignment outcomes. Ultimately, by investigating the complexities of interpretability, researchers and practitioners can facilitate knowledge integration systems with transparency and accountability, enabling greater confidence in the alignment results and facilitating the exchange of information across diverse semantic repositories.

4. Conclusion

This talk will explore the interpretability techniques in ontology meta-matching to enhance transparency and insight into the matching processes. Our findings should lead to several interesting conclusions. Our investigation into transparency and insight in ontology meta-matching should demonstrate that interpretability techniques can bridge the gap between automated matching algorithms and human understanding. The idea behind carefully selecting and applying these techniques can pave the way for more trustworthy, accountable, and widely adopted ontology alignment systems.

We will also review future lines of research. The reason is that the field of ontology meta-matching continues to evolve, and future research should focus on developing more advanced interpretability methods tailored to the unique characteristics of ontologies. Additionally, interdisciplinary collaborations between computer science, ontology engineering, and domain experts will be instrumental in advancing the field.

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