Improving Reasoning on Large Ontologies via Ontology Modularity

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Introduction Oil platforms, classified as critical infrastructure, require intricate regulations and standards to ensure their safety. Constructing oil platforms involves various stakeholders, such as major oil companies like Equinor, Engineering, Procurement, and Construction (EPC) service providers like Aibel, and local governments. Consequently, a significant volume of documents is generated and exchanged among these parties to facilitate data and information transfer. However, ensuring data quality and managing operational costs, including time and human resources, prove challenging in project execution. To tackle these issues, Aibel has developed the Material Master Data (MMD) ontology, which serves as a standardized vocabulary for product classification and project description.

The MMD ontologies [1] are implemented in OWL 2 and provided in four different versions, all using Turtle syntax. Given the dynamic nature of the MMD ontology in real-world scenarios, regular classification is essential to ensure that any updates or modifications do not introduce errors in the ontology's modelling. However, reasoning on large OWL 2 ontologies, such as MMD, poses significant challenges. For instance, classifying the entire `mmd-reasoner` ontology using the HermiT reasoner takes approximately 30 minutes, which is not efficient for ontology engineers who frequently modify and debug ontologies. Therefore, finding a solution to improve reasoning performance on large ontologies becomes imperative, aiming to expedite the ontology classification process.

Another application of reasoning on the MMD ontology is in the selection of pipe components, which poses a challenge for pipe engineers due to the need to adhere to various regulations and standards. With millions of pipe components available for ordering, there is a risk of occasional mistakes that can result in significant financial losses. Fortunately, the introduction of the MMD ontologies has provided a solution. Pipe engineers can now utilize queries to identify and order the precise pipe components that comply with the required standards. This implementation has

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[1]https://github.com/Sirius-sfi/aibel-mmd-ontology

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brought substantial benefits, substantially decreasing project costs by reducing the procurement of incorrect pipe components. By leveraging the MMD ontologies, we could enhance the ability to ensure compliance, minimize errors, and optimize cost-efficiency in the pipe component ordering process. This development highlights the positive impact that reasoning on large ontologies can have on industrial operations and financial outcomes.

Solution In the aforementioned use cases, only a small portion of the ontology is typically involved. For instance, when modifying ontologies or querying the entire ontology, it is unnecessary to perform reasoning tasks on the entire ontology. Instead, a subset of the ontology can be extracted and reasoning can be conducted on this smaller set, yielding the same reasoning results. By reducing the size of the ontology, the reasoning tasks naturally become faster compared to reasoning on the entire ontology. This technique is called ontology modularity. An ontology module refers to a subset of the ontology that preserves the complete logical consequences relative to the given vocabulary, called a signature. Various module notions have been proposed, including locality-based modules, semantic modules, deductive modules, and more, tailored for different use cases. In our paper, we use locality-based modules due to their speed in module computation and ease of use. Although they may contain redundant axioms, these modules retain all the logical consequences of the original ontology. By leveraging ontology modularity, we can enhance reasoning efficiency by working with smaller subsets of ontology while preserving the necessary logical information.

Our framework comprises three key steps to enhance ontology reasoning efficiency:

1. Signature extraction: We identify a set of classes and properties crucial for ontology modelling and queries, which allows us to focus on the essential elements of the ontology.
2. Module extraction: Using the extracted signature, we generate a subset of the ontology called the locality-based module. This module includes all relevant axioms and logical consequences related to the specified signature. By reducing the ontology's size, we retain the necessary information for reasoning while significantly improving efficiency.
3. Reasoning on the modules: We perform reasoning tasks exclusively on the extracted module. This approach enables faster and more efficient reasoning compared to working with the entire ontology, while still producing the same high-quality results.

Evaluation and Further work We conducted a comprehensive evaluation of our framework using 916 queries and modifications provided by pipe engineers from Aibel. The results of our evaluation demonstrate the efficiency of our framework based on ontology modularity. The module extraction process ranged from approximately 2 seconds to 4.22 seconds. Additionally, the median classification time for the modules was 14 seconds, whereas classifying the entire ontology took 30 minutes. Moreover, performing query answering exclusively on the modules yielded identical results to querying the entire MMD ontology, showcasing a precision rate of 100%. These findings highlight the significant benefits of adopting an ontology modularity approach for enhancing reasoning performance in MMD ontologies. Moving forward, we aspire to explore alternative module concepts within MMD ontologies and investigate additional use cases that leverage semantic technologies. By doing so, we aim to further advance the application and effectiveness of our framework.