Leveraging LLMs in Semantic Mapping for Knowledge Graph-based Automated Enterprise Model Generation

Benedikt Reitemeyer [1] and Hans-Georg Fill [1]

Abstract: Automated enterprise model generation applies artificial intelligence and other machine-processable approaches to improve decision making and adoption in complex and changing environments. The emergence of Large Language Models (LLMs) opens a new playing field for machine-processability in enterprise modeling, especially when it comes to processing natural language contextual knowledge. In this extended abstract, we show the use of LLMs in semantic mapping tasks for real-world and modeling language concepts based on an ArchiMate and National Information Exchange Model (NIEM) example. The results indicate that LLMs are useful in automated enterprise modeling tasks.

Keywords: Enterprise Modeling, Large Language Models, Semantic Mapping

Extended Abstract

Machine-based, automated generation of enterprise models leads to better decision making and adaptation to complex and changing environments [Re20]. Existing approaches rely on Artificial Intelligence (AI) and further machine-processable approaches using formal semantics, e.g. [Dr23; PGM23]. With the emergence of Large Language Models (LLMs) a new playing field for the application of AI in enterprise modeling can be explored and first results in using LLMs in this context were impressive [FFK23].
So far, LLMs have been used mainly in generating XML-based models from pre-defined use cases. But beneath generating complete models with LLM-support, more specialized use cases in automated modeling need to be investigated. Historically, knowledge graph-based approaches have been used for making the former human-focused tasks of enterprise modeling and semantic mapping machine-processable. Typically, pre-defined mapping rules from real-world concepts to modeling language concepts were necessary and defined with human help. Now, the use of LLMs in those semantic mapping tasks may be helpful, especially when it comes to integrating technological knowledge and business and strategic knowledge, for example in service descriptions. Therefore, we investigated how LLMs can be utilized in semantic mapping between real-world concepts and modeling language concepts, generate rankings in a structured order with concrete measures, and which terms the LLMs use for those activities.

1 University of Fribourg, Digitalization and Information Systems Group, Fribourg, Switzerland,
benedikt.reitemeyer@unifr.ch, https://orcid.org/0009-0001-4131-1716;
hans-georg.fill@unifr.ch, https://orcid.org/0000-0001-5076-5341
 https://doi.org/10.18420/modellierung2024-ws-006

In experiments with ChatGPT 3.5, we developed a prompt that combined the task of semantic mapping between a National Information Exchange Message (NIEM) [NIEM24] service description and the ArchiMate strategy layer [OG24] elements' capability, resource, action, and value stream, and the task of ranking the strategy layer elements on a five-value scale from 'very high' to 'very low'. The prompt now includes a description of Electronic Court Filing and a contextual description of NIEM. The specification texts for each ArchiMate element were taken from the ArchiMate 3.2 standard. The inputs were extracted from dedicated NIEM and ArchiMate Knowledge Graphs to ensure a trustworthy information base. The mapping and ranking process was tested 20 times to establish its effectiveness. The results show that LLMs are able to perform semantic mapping and ranking of real-world and modeling language concepts in a consistent manner. When ChatGPT is asked for mapping-relevant terms, it returns terms from the input prompt and refers to both, real-world and modeling context.
While the experiments showed the general feasibility, further evaluation is essential for future research to gain more concrete insights into advantages and limitations of the approach. For example, the quality of results in comparison between human modelers or domain experts and LLMs. Since the state-of-the-art for semantic mapping is graph-based approaches, the performance in comparison to LLM-based semantic mapping should be investigated. Third, experiments with other LLMs, especially open source LLMs, should be conducted to gain more control over the results and to reduce dependencies. Finally, an end-to-end use case that demonstrates the technical feasibility of automated enterprise model generation should be implemented, demonstrating the possible automation level in modeling and its limitations considering necessary real world human interactions in the modeling process.

References

[Dr23] Drieschner, C.; Sensoy, M.; Weking, J.; Krcmar, H.: Business Capability Mining - Opportunities and Challenges. In: 31st European Conference on Information Systems. 2023, URL: https://aisel.aisnet.org/ecis2023%5C_rp/388.

[FFK23] Fill, H.-G.; Fettke, P.; Köpke, J.: Conceptual modeling and large language models: impressions from first experiments with ChatGPT. Enterprise Modelling and Information Systems Architectures (EMISAJ) 18/, pp. 1–15, 2023.

[NIEM24] NIEMOpen, 2024, URL: https://www.niem.gov/about-niem/message-exchange-package-mep-registry-repository, visited on: 01/02/2024.

[OG24] The Open Group, 2024, URL: https://pubs.opengroup.org/architecture/archimate3-doc/ch-Strategy-Layer.html, visited on: 01/02/2024.

[PGM23] Pinheiro, C.; Guerreiro, S.; Mamede, H. S.: A Survey on Association Rule Mining for Enterprise Architecture Model Discovery. Business Information Systems Engineering/, 2023, ISSN: 1867-0202, URL: https://doi.org/10.1007/s12599-023-00844-5.

[Re20] Reitemeyer, B.: Automatic Generation of Conceptual Enterprise Models. In: 2020 IEEE 24th International Enterprise Distributed Object Computing Workshop (EDOCW). Pp. 74–79, 2020.