

Improving LLM-based Ontology Matching with fine-tuning on synthetic data

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Abstract

Large Language Models (LLMs) are increasingly being integrated into various components of Ontology Matching pipelines. This paper investigates the capability of LLMs to perform ontology matching directly on ontology modules and generate the corresponding alignments. Furthermore, it is explored how a dedicated fine-tuning strategy can enhance the model's matching performance in a zero-shot setting. The proposed method incorporates a search space reduction technique to select relevant subsets from both source and target ontologies, which are then used to automatically construct prompts. Recognizing the scarcity of reference alignments for training, a novel LLM-based approach is introduced for generating a synthetic dataset. This process creates a corpus of ontology submodule pairs and their corresponding reference alignments, specifically designed to fine-tune an LLM for the ontology matching task. The proposed approach was evaluated on the Conference, Geolink, Enslaved, Taxon, and Hydrography datasets from the OAEI complex track. The results demonstrate that the LLM fine-tuned on the synthetically generated data exhibits superior performance compared to the non-fine-tuned base model. The key contribution is a strategy that combines automatic dataset generation with fine-tuning to effectively adapt LLMs for ontology matching tasks.

CCS Concepts

• **Computing methodologies** → *Ontology engineering*.

Keywords

Knowledge Graph, Complex Matching, Fine-tuning, LLM

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1 Introduction

Knowledge Graphs (KGs) are powerful structures for representing relational data, modeling how entities are interconnected within a specific domain. A key challenge in integrating and reusing these data structures arises from schema heterogeneity, where two KGs covering the same topic are modeled with different underlying schemas. These differences prevent direct integration and create the need for an alignment between the graphs. Heterogeneities can be linguistic (using different languages or synonyms for the same concept) or structural: representing the same idea with different levels of detail or composition. For example, a common structural heterogeneity is when the concept AcceptedPaper in one KG is equivalent to the combination of Paper and Acceptance in another. Without a formal alignment to bridge such gaps, seamlessly merging the two KGs is impossible.

Traditional matching methods, which rely on lexical comparisons or naive semantic similarity measures, are often insufficient to address the complex heterogeneities between ontologies. A significant advancement was achieved through the integration of embeddings—dense vector representations generated by Language Models or graph encoding techniques. These embeddings provide a more nuanced semantic similarity by capturing the contextual meaning of entities, effectively resolving issues like homonymy that purely lexical metrics cannot handle. Despite their power and practicality, relying solely on embedding similarity is inadequate for correctly matching complex entities, particularly those that map to a specific composition of multiple entities in the target ontology. A canonical example of this challenge is the correspondence between a FullName entity in a source ontology and the pair of FirstName and LastName in a target ontology. While embeddings can identify a high semantic similarity between FullName and the individual FirstName and LastName concepts, they are incapable of defining the structural transformation required to form an equivalence. In this scenario, the semantics of FullName can only be replicated by concatenating FirstName and LastName in a specific order. This compositional rule is rarely explicit in the ontology, requiring the matching system to infer and formalize this transformation during the matching process.

Large Language Models (LLMs) now dominate research in Knowledge Graph (KG) and ontology matching. Their ability to directly generate alignments from ontologies provided in a prompt offers remarkable flexibility. This allows matching systems to generalize across diverse domains and enables developers to instruct the model to perform various semantic tasks within the matching pipeline simply by modifying the prompt. Consequently, it is now feasible

to create adaptable matching frameworks where different LLMs can be interchanged, allowing for upgrades to more powerful or domain-specific models. While the application of LLMs for simple one-to-one entity matching is becoming widespread, their exploration for discovering complex alignments remains an emerging area of research.

However, directly applying LLMs to complex matching introduces significant challenges. First, complex entities are effectively subgraphs of their respective KGs, causing the search space for potential alignments to grow exponentially and requiring effective search space reduction strategies. Second, providing the entire source and target ontologies as input can be computationally prohibitive, consuming vast resources depending on the KG's size. Finally, a critical requirement is the ability to produce alignments in a standardized format, such as the Expressive and Declarative Ontology Alignment Language (EDOAL) [2], to facilitate automatic evaluation. Many LLMs lack familiarity with such formalisms, as their training data may not include examples of the EDOAL syntax, hindering their ability to generate verifiable and machine-readable output.

One of the initial works to explore LLMs in complex matching is the paper by [1], in which the GMO ontology was provided as context to ChatGPT to find corresponding modules in the GBO ontology. This pioneering study highlighted critical challenges: the prohibitive resource requirements for processing entire ontologies with locally hosted LLMs, and the generation of alignments in unstructured natural language, which requires a manual evaluation process. Building on this, the work by [12] addressed some of these limitations by proposing a search space reduction strategy coupled with few-shot prompting. This method successfully guided the model to produce alignments in the structured EDOAL format while reducing resource consumption. However, while effective in generating correct EDOAL syntax and identifying simple alignments, its performance on complex alignments still needs improvement.

In this work, it is proposed to enhance LLM performance on complex matching by applying instruction fine-tuning. As demonstrated in [14], fine-tuning can lead to superior performance and better task adaptation without relying on in-context examples. The proposed approach is rigorously evaluated on multiple datasets from the OAEI complex track.

The remainder of this paper is organized as follows. Section 2 provides an overview of related methods for complex matching and discusses their limitations. Section 3 introduces the proposed approach, which integrates fine-tuning with LLMs to enhance the understanding and performance of complex alignment tasks. Section 4 contains the experiment settings. Then, a series of experiments and case studies are presented in Section 5, highlighting both the strengths and weaknesses of this approach. Finally, Section 6 offers concluding remarks and outlines directions for future research, stressing the potential of fine-tuned LLMs in advancing the state of the art in complex semantic matching.

2 Related Work

Recent advancements in ontology matching can be broadly categorized into two main streams of research: approaches based on entity and graph embeddings, and those ones based on LLMs.

2.1 Embedding-based

Embedding-based matchers primarily use vector representations to compute semantic similarity between ontology subgraphs. For example, the work in [10] extends the CANARD matcher [13] by incorporating LLM-generated embeddings to improve the matching of entities retrieved within the context of SPARQL queries. This enhanced method aggregates four main types of embeddings: label similarity, SPARQL query representations, subgraph embeddings, and instance embeddings. The objective of this aggregation is to address the challenges of representing complex entities and thereby achieve more accurate results. However, the CANARD architecture's reliance on fixed triple and path structures restricts its pattern-matching capabilities, as it cannot identify correspondences that require differently structured subgraphs.

Another matcher incorporating embeddings [9] proposes a novel approach to complex multi-ontology matching (CMOM), presenting a holistic matching solution for complex cases. This method combines lexical string similarity with geometric operations on a shared semantic space, derived from LLM embeddings, to discover complex mappings that involve multiple entities from different ontologies. The process involves several steps: preprocessing ontology vocabularies, generating candidate mappings through both lexical and LLM-based methods, and finally, aggregating and filtering these candidates to obtain the final alignment. A key limitation, however, is that this approach identifies corresponding target entities for a source entity without specifying how they logically combine to reconstruct its semantics. This results in a less general solution, as different logical constructors are often required to formally express the meaning of complex correspondences.

2.2 LLM-based

The emergence of LLMs has established a dominant paradigm in ontology matching research [5, 3]. A notable example of this trend is OntoAligner [4], a Python toolkit designed to integrate traditional methods with contemporary AI techniques, including Retrieval-Augmented Generation (RAG) and the direct application of LLMs. This toolkit provides a flexible and extensible framework for ontology matching, featuring a modular architecture that allows users to customize alignment algorithms, incorporate new datasets, and fine-tune pipelines for diverse use cases. However, a significant limitation is that the framework is primarily designed for simple alignments, focusing on the discovery of one-to-one (1:1) correspondences between source and target entities.

One of the earliest applications of LLMs to the complex matching task was presented in [1], who applied ChatGPT-4 to match the GMO and GBO ontologies from the Geolink dataset. Their work was among the first to propose loading entire ontologies directly into the prompt and instructing the LLM to generate the complete alignment. However, this strategy has significant limitations that hinder its general applicability. First, loading complete ontologies is computationally expensive and often infeasible due to the context length and memory constraints of modern LLMs. Second, the model was prompted to generate alignments in unstructured natural language, which precludes direct automatic evaluation. These factors severely compromise the approach's scalability and evaluability,

as the lack of a standardized output format needs manual post-processing. These issues were subsequently addressed in [12], who introduced a novel approach combining a search space reduction strategy with the generation of final alignments in a structured format. Their method tackles the challenge of processing large ontologies by selecting and integrating only the most relevant subsets from the source and target ontologies into the prompt. This reduction is achieved by automatically generating SPARQL queries based on entity PageRank scores. These queries, in conjunction with an embedding strategy, are used to retrieve semantically similar entities and their local graph structures. The resulting subsets are then presented to the LLM, which is prompted to generate complex alignments directly in the structured EDOAL format, rather than using natural language descriptions. This direct, standardized output simplifies the automatic evaluation and verification of the resulting alignments. While the approach is effective at reducing prompt size and enforcing a structured response, its performance in generating high-quality complex alignments still needs improvement.

3 Approach

This work extends a previous method proposed in the literature [12] by adding an instruction fine-tuning phase. Synthetically generated data is used to boost the performance of LLMs on the ontology matching task. The core idea is to make the problem manageable by breaking it down. The proposed method follows a clear pipeline: (i) **Decompose**: first, a space reduction strategy splits large ontologies into smaller, focused subontologies; (ii) **Query**: next, an LLM is prompt with these subontologies to generate partial alignments; and (iii) **Merge**: finally, the individual outputs are merged to create the final alignment. To measure the impact of these contributions, this strategy is applied and tested in both zero-shot and fine-tuned settings. The overall architecture is illustrated in Figure 1 and the proposed method for generating the synthetic data is described in the subsections below.

3.1 Space Reduction and Prompt Construction

The ontology alignment task requires comparing a vast search space of potential entity pairs, a process that is not only computationally expensive but also infeasible to handle within the context window of a single LLM prompt. To overcome this limitation, the proposed method employs a space reduction strategy. This strategy leverages both structural and semantic features to partition the ontologies into smaller, more relevant modules (i.e., subontologies), making the matching task tractable for an LLM.

The process unfolds in several stages. First, structurally significant entities are identified within the source ontology using centrality metrics such as PageRank. For each of these core source entities, embedding-based similarity is used to retrieve a candidate set of semantically related entities from the target ontology. Next, local modules are extracted around these corresponding source and target entity sets by including their neighboring classes and properties. Each of these paired modules forms a reduced subontology pair, which is then inserted into a predefined prompt template. This template instructs the LLM to find equivalent entities and return the partial alignment in EDOAL format. By iterating this process, multiple partial alignments are generated covering the most salient

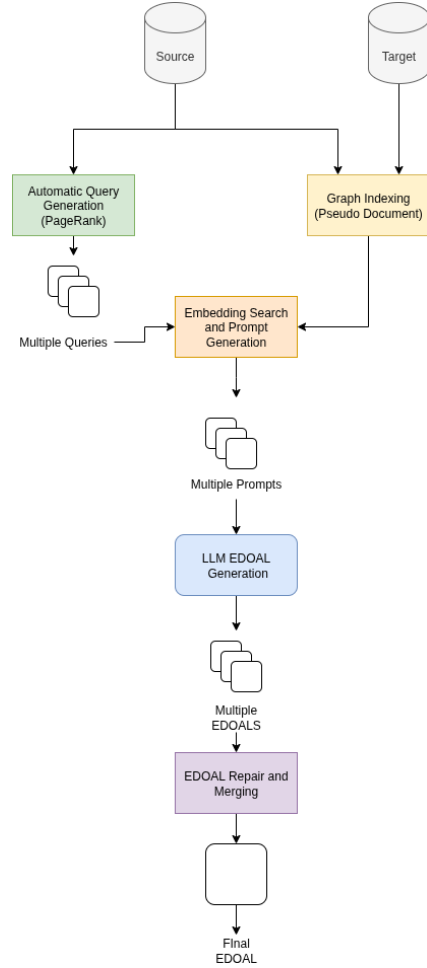


Figure 1: Overview of the proposed LLM-based ontology alignment pipeline. Starting from a source and target ontology, queries are automatically generated from the source ontology using a PageRank-based method. These queries are then used to select subontology parts to construct multiple prompts for direct LLM alignment, which generate multiple EDOAL alignments. These alignments are then post-processed through a repair and merging step to produce the final EDOAL alignment.

parts of the ontologies. These results are subsequently aggregated and post-processed to construct the final, comprehensive alignment for the entire ontology pair.

3.2 Alignment Aggregation

In this approach, the LLM is not just one component in a larger pipeline; it performs the entire matching process after the initial space reduction. In this process, each LLM call processes a pair of subontologies and generates a partial alignment in EDOAL. These partial outputs are then merged into a single alignment file after generation. To handle redundancy and potential conflicts across

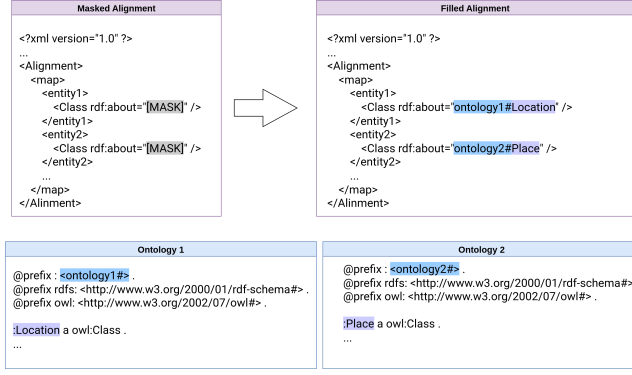


Figure 2: Alignment and ontology generation workflow. Starting from a seed alignment template, the LLM is prompted to fill in the masked placeholders with entities while preserving semantic equivalence. Once the alignment is completed, the LLM is then prompted to sequentially generate the ontologies that correspond to the proposed alignment.

prompts, a post-processing step is included to normalize, deduplicate, and validate the alignment. This step ensures that repeated mappings across different subontology pairs are not counted multiple times and that the final output conforms to the required format for evaluation.

3.3 Dataset Generation

To improve the LLM’s understanding of the ontology matching task, an instruction fine-tuning strategy is applied using an LLM-generated training dataset. The synthetic data generation method is based on the hypothesis that predicting the ontologies given the alignment between them is easier than finding the alignment between two ontologies, which is the objective task to solve. Since most of the models do not know the EDOAL structure, giving a seed EDOAL structure without the entities mitigates this problem, as the LLM just needs to fill in the blanks with plausible entity names in the EDOAL structure (not generate complex syntax from scratch), as illustrated in figure 2. Once the alignment template is filled, the LLM is prompted to generate the ontologies where the previous alignment was generated, trying to include entities not in common between the two ontologies. To provide contrast, a separate prompt instructs the LLM to generate ontology pairs without entities in common. This is a very important step for teaching the models to learn when they should not create an alignment, which helps them learn to avoid false positives. When building the dataset, there is no guarantee that the filled entities are semantically coherent and that equivalence holds between the generated entities. However, the hypothesis is that if fine-tuning on this noisy dataset still leads to improved performance on real-world benchmarks, it proves the model is learning valuable patterns for the ontology matching task.

The seed EDOAL structure is generated procedurally by deriving sentences [6] from the grammar present on the EDOAL webpage by randomly selecting a production rule from the grammar to build the template.¹ The code for this generator, along with all evaluations,

¹<http://ns.inria.org/edoal/1.0/>

is available on <https://anonymous.4open.science/r/llm-6E88/>. In addition to the synthetic data, the approach was evaluated using cross-validation with a dataset of manually created modules. For each fold, the model is fine-tuned on a set of subontology pairs and their corresponding ground-truth EDOAL alignments. This training data includes a mix of both simple and complex mappings to ensure broad coverage. The LLM’s core task is to learn how to generate the correct EDOAL mappings directly from any given pair of ontology fragments.

4 Experiment Settings

To evaluate the fine-tuning approach and compare it with the baselines, a series of experiments using pretrained LLMs was conducted. This section details the datasets, models, experimental configurations, and metrics used in this evaluation. The evaluation was performed on five datasets from the OAEI 2020 Complex Matching track:² **Conference**, **Geolink**, **Enslaved**, **Taxon**, and **Hydrography**. This specific year was chosen because it features the largest number of participating datasets and matching systems, providing a larger comparison. These datasets contain a variety of subjects, making them ideal for testing the limits of both baseline and fine-tuned models.

Distinct LLMs were employed for different stages of this experiment. For the Dataset Generation step, Microsoft/Phi-4³ was used. For the baseline experiment (b0), the models are Meta/LLaMA-3.2-3B-Instruct (3B), Meta/LLaMA-3.1-8B-Instruct (8B), microsoft/Phi-4-mini-instruct (4B), microsoft/phi-4 (14B), Qwen/Qwen3-14B (14B), a reasoning model, and mistralai/Mistral-7B-Instruct-v0.3 (7B). All the models were downloaded from HuggingFace⁴ and run locally. For the fine-tuning experiments, the performance of two setups was compared using the model the models Meta/LLaMA-3.2-3B-Instruct (3B) due to resource constraints:

Cross-Validation Fine-Tuning (b1): In this "leave-one-out" approach, the model is fine-tuned on data from four of the datasets and then evaluated on the remaining one; **Synthetic Data Fine-Tuning (b2):** In this setup, the model is fine-tuned on the synthetically generated dataset.

For all variants, the LLM was prompted using a multi-turn format. The system role established the task, and the user provided the module pair for matching. The modules were generated manually with the procedure described in the next section to compare only the LLM performance without the effect of the space reduction module. Performance was measured using the metrics proposed in [11]. These metrics adapt the standard precision, recall, and F-measure to effectively evaluate complex alignments while also applying to simple (1:1) correspondences. The generated alignments from each model were compared against the gold standard reference alignments to compute the final scores.

5 Results and Discussion

To improve the capacity of the matcher in producing complex alignments, the point of higher increase in performance is in the LLM module in the architecture. To verify the impact of the model on

²<https://oaei.ontologymatching.org/2020/results/complex/index.html>

³<https://huggingface.co/microsoft/phi-4>

⁴<https://huggingface.co/models>

the architecture performance, it needs to be evaluated in isolation from the other modules, as the reduction of space can remove or insert irrelevant entities that can change the results. To this, a set of modules was manually created for all 5 ontologies, and then, for all entities in all correspondence, the modules were merged to form the input ontology. The number of modules for all ontologies is present in Table 1. Furthermore, all correspondences with overlapping modules are joined in a single alignment. With this procedure is ensured that all entities in the correspondences are included in the input ontologies.

Ontology	Modules
cmt	12
ekaw	15
edas	24
confOf	13
conference	22
enslaved	18
wikidata	19
gbo	24
gmo	31
cree	13
swo	22
hydrOntology	35
hydro3	7
taxon	4
agrovoc	2
taxref	4
dbpedia	2

Table 1: Ontology modules count

The procedure of creation of the modules is the following: for all entities in the module, if the entity has no `rdf:type` and is from a standard vocabulary from <http://www.w3.org> or <http://ns.inria.org/edoal/> it is filtered. Then the entity is added to the new ontology, with descriptions and labels added. For simplicity, properties with `BNode` as objects are filtered, and 5 superclasses are added, and then the final modules are rendered in turtle. This procedure was used to keep the maximum prompt size within a manageable range. With this approach, the maximum prompt size is 6336 tokens from the hydrography dataset in the pair `hydrOntology-swo`, and most of the prompts lie in the range between 0 and 1000 tokens. Estimating the prompt sizes by just concatenating the two ontologies, arrives in the distribution present in figure 3. With those modules, it is possible to experiment with fine-tuning in the LLM, isolating it from the impact on the automatic module generation performance.

A preliminary experiment was done with the LLMs Meta/LLaMA-3.1-8B-Instruct (8B) and microsoft/phi-4 (14B) to see how the models behave if given the manually produced modules. This experiment was conducted by using the baseline approach and another prompt template that uses complex correspondence templates described in [8]. The results of this preliminary evaluation are presented in Table 2. It is possible to see in the results that both approaches have better results in the simple case when compared to the complex case. Considering the LLMs, the phi-4 that has more parameters

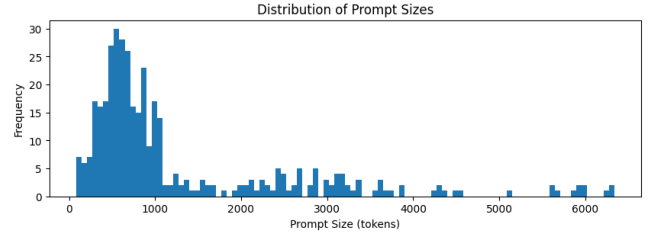


Figure 3: Distribution of prompt tokens .

performed better on average in the simple case, while having comparable results in the complex case. The correspondence patterns in the prompt result in slightly lower performance in both simple and complex cases when compared with the base approach.

Type	Dataset	A prec.	B prec.	A rec.	B rec.	A f1	B f1
Simple	Conference	0.25	0.42	0.54	0.58	0.28	0.43
	Enslaved	0.16	0.14	0.20	0.18	0.16	0.14
	Geolink	0.20	0.22	0.19	0.18	0.17	0.18
	Hydrography	0.21	0.24	0.33	0.37	0.16	0.21
	Taxon	0.06	0.15	0.08	0.00	0.03	0.00
Complex	Conference	0.01	0.04	0.11	0.08	0.00	0.01
	Enslaved	0.01	0.00	0.06	0.08	0.01	0.00
	Geolink	0.05	0.03	0.17	0.14	0.05	0.02
	Hydrography	0.00	0.01	0.21	0.21	0.00	0.01
	Taxon	0.02	0.00	0.18	0.14	0.03	0.00
Simple (Patterns)	Conference	0.15	0.36	0.39	0.50	0.18	0.38
	Enslaved	0.07	0.16	0.12	0.15	0.08	0.14
	Geolink	0.13	0.20	0.16	0.19	0.12	0.15
	Hydrography	0.11	0.22	0.20	0.31	0.09	0.19
	Taxon	0.13	0.25	0.13	0.10	0.09	0.09
Complex (Patterns)	Conference	0.06	0.02	0.07	0.06	0.02	0.01
	Enslaved	0.01	0.00	0.05	0.09	0.01	0.00
	Geolink	0.03	0.01	0.12	0.11	0.03	0.01
	Hydrography	0.05	0.01	0.11	0.15	0.02	0.00
	Taxon	0.00	0.01	0.07	0.16	0.01	0.01

Table 2: Comparison of A (Llama 3.1) and B (Phi 4) on Simple and Complex datasets with and without patterns.

Another possibility of improvement is testing how fine-tuning can improve the LLM capacity of complex alignments and if it can generalize. To test this, the first experiment was to fine-tune the model Meta/LLaMA-3.2-3B-Instruct (3B) in the modules dataset with different proportions of train and test, and compare with the LLMs Meta/LLaMA-3.1-8B-Instruct (8B) and microsoft/phi-4 (14B) without training. The test was performed with 90% train with a total reference size of 382 EDOAL files, 798 correspondences. With this split, 343 pairs are in train and 39 are in test. The model was trained for 100 epochs. The results of this test are present in Figure 4. It is possible to see that the fine-tuning improved the performance of the model, leading it to have better results in both simple and complex cases, even with the model being smaller. Those results show the potential of fine-tuning in improving the capacity of the models given high-quality training data. While having improvements, the performance is still low (below 0.5). One of the hypotheses of this limited improvement lies in the low amount of specific alignment data for training. To investigate this path, a synthetic data generation strategy described in the next section was performed.

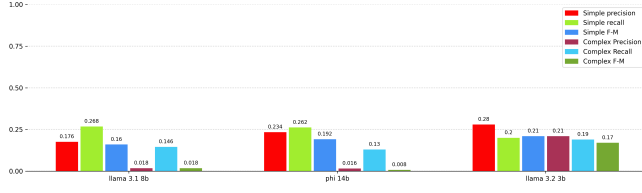


Figure 4: Performance of the models compared with the smaller but fine-tuned model.

5.1 Dataset Generation and Performance across Prompting Strategies

This section presents the results of the synthetic dataset generation process, followed by an analysis of the LLM’s performance. The dataset generation process yielded a total of 6,650 alignment pairs: 4,650 pairs contained one or more correspondences, while the remaining 2,000 were empty alignments with no correspondences.

Parsing the raw textual output from the LLM revealed that a subset of the generated files contained syntactical errors. These issues primarily included:

- Missing prefix declarations
- Missing ontology tags
- Entities without a prefix
- Invalid literal
- EOS tokens

To address these issues, an automated script has been implemented to repair such errors by adding missing prefix declarations and correcting ontology tags. After applying these corrections, 4,407 of the 4,650 alignments (95%) were successfully validated, leaving 243 (5%) as invalid. Similarly, 1,892 of the 2,000 empty alignment pairs (95%) were rendered valid. Cumulatively, the combined generation and repair pipeline demonstrated a high degree of reliability, producing syntactically valid data in 95% of all cases.

matcher	s-p	s-r	s-f	c-p	c-r	c-f
Conference						
AMLC	0.00	0.01	0.00	0.13	0.20	0.15
AROA	0.00	0.00	0.00	0.00	0.00	0.00
CANARD	0.00	0.00	0.00	0.00	0.00	0.00
b0 (Llama-3-1-8B)	0.03	0.19	0.05	0.06	0.10	0.05
b0 (Llama-3-2-3B)	0.25	0.12	0.14	0.09	0.03	0.03
b0 (Phi-4-mini)	0.00	0.00	0.00	0.00	0.00	0.00
b0 (Qwen3-14B)	0.53	0.66	0.55	0.24	0.37	0.24
b0 (Mistral-7B)	0.14	0.12	0.11	0.08	0.05	0.05
b0 (phi-4)	0.62	0.47	0.48	0.23	0.19	0.13
b1	0.05	0.11	0.07	0.02	0.03	0.02
b2	0.50	0.25	0.33	0.00	0.15	0.00

Table 3: Performance comparison of the proposed approach against other matchers on the Conference dataset. The table displays precision (p), recall (r), and F-measure (f) for both simple (s-p, s-r, s-f) and complex (c-p, c-r, c-f) correspondences.

matcher	s-p	s-r	s-f	c-p	c-r	c-f
Enslaved						
AMLC	0.45	0.93	0.60	0.32	0.06	0.11
AROA	0.00	0.00	0.00	0.00	0.00	0.00
CANARD	0.54	0.68	0.60	0.18	0.06	0.09
b0 (Llama-3-1-8B)	0.04	0.18	0.07	0.00	0.05	0.00
b0 (Llama-3-2-3B)	0.00	0.00	0.00	0.00	0.00	0.00
b0 (Phi-4-mini)	0.00	0.00	0.00	0.00	0.00	0.00
b0 (Qwen3-14B)	0.12	0.32	0.18	0.21	0.08	0.12
b0 (Mistral-7B)	0.00	0.00	0.00	0.00	0.00	0.00
b0 (phi-4)	0.00	0.00	0.00	0.00	0.00	0.00
b1	0.13	0.04	0.06	0.09	0.00	0.01
b2	0.09	0.18	0.12	0.00	0.01	0.00

Table 4: Performance comparison of the proposed approach against other matchers on the Enslaved dataset. The table displays precision (p), recall (r), and F-measure (f) for both simple (s-p, s-r, s-f) and complex (c-p, c-r, c-f) correspondences.

matcher	s-p	s-r	s-f	c-p	c-r	c-f
Geolink						
AMLC	0.00	0.00	0.00	0.07	0.00	0.01
AROA	0.94	0.82	0.87	0.56	0.15	0.24
CANARD	0.00	0.00	0.00	0.00	0.00	0.00
b0 (Llama-3-1-8B)	0.02	0.05	0.03	0.00	0.02	0.00
b0 (Llama-3-2-3B)	0.00	0.00	0.00	0.00	0.00	0.00
b0 (Phi-4-mini)	0.04	0.00	0.00	0.00	0.00	0.00
b0 (Qwen3-14B)	0.18	0.79	0.30	0.26	0.26	0.26
b0 (Mistral-7B)	0.16	0.59	0.25	0.18	0.05	0.07
b0 (phi-4)	0.27	0.14	0.18	0.29	0.02	0.04
b1	0.51	0.16	0.24	0.08	0.01	0.01
b2	0.51	0.61	0.55	0.00	0.02	0.00

Table 5: Performance comparison of the proposed approach against other matchers on the Geolink dataset. The table displays precision (p), recall (r), and F-measure (f) for both simple (s-p, s-r, s-f) and complex (c-p, c-r, c-f) correspondences.

The full evaluation results are presented in Table 3 for Conference, Table 4 for Enslaved, Table 5 for GeoLink, Table 6 for Hydrography, and Table 7 for Taxon, where a score of zero indicates that a matcher failed to produce any alignments for a given dataset. A breakdown of the top performers shows that in the Conference dataset, the proposed setting variant b0 with Qwen3-14B led in simple matching with an F-measure of 0.55 and also in complex matching with a F-measure of 0.24, but the variant b0 with phi-4 has the highest precision in simple matching with 0.62. For the Enslaved dataset, AMLC [7] and CANARD tied for the lead in simple matching with an F-measure of 0.60, and AMLC also topped the complex alignments precision with 0.32, and the top complex F-measure is the variant b0 Qwen-14B with 0.12. AROA [15] dominated the Geolink dataset in simple with 0.87 f-measure and highest precision in complex with 0.56, but in complex f-measure, the b0

matcher	s-p	s-r	s-f	c-p	c-r	c-f
Hydrography						
AMLC	0.02	0.00	0.00	0.02	0.02	0.02
AROA	0.00	0.00	0.00	0.00	0.00	0.00
CANARD	0.00	0.00	0.00	0.00	0.00	0.00
b0 (Llama-3-1-8B)	0.30	0.13	0.15	0.08	0.14	0.06
b0 (Llama-3-2-3B)	0.04	0.00	0.01	0.00	0.00	0.00
b0 (Phi-4-mini)	0.00	0.00	0.00	0.00	0.00	0.00
b0 (Qwen3-14B)	0.41	0.46	0.41	0.39	0.24	0.28
b0 (Mistral-7B)	0.41	0.10	0.13	0.18	0.11	0.04
b0 (phi-4)	0.36	0.35	0.32	0.27	0.24	0.16
b1	0.27	0.04	0.07	0.43	0.04	0.07
b2	0.37	0.18	0.24	0.00	0.16	0.00

Table 6: Performance comparison of the proposed approach against other matchers on the Hydrography dataset. The table displays precision (p), recall (r), and F-measure (f) for both simple (s-p, s-r, s-f) and complex (c-p, c-r, c-f) correspondences.

matcher	s-p	s-r	s-f	c-p	c-r	c-f
Taxon						
AMLC	0.00	0.00	0.00	0.00	0.00	0.00
AROA	0.00	0.00	0.00	0.00	0.00	0.00
CANARD	0.35	0.02	0.03	0.38	0.34	0.34
b0 (Llama-3-1-8B)	0.04	0.02	0.01	0.26	0.10	0.14
b0 (Llama-3-2-3B)	0.00	0.00	0.00	0.00	0.00	0.00
b0 (Phi-4-mini)	0.00	0.00	0.00	0.00	0.00	0.00
b0 (Qwen3-14B)	0.19	0.09	0.12	0.05	0.17	0.07
b0 (Mistral-7B)	0.05	0.00	0.00	0.00	0.02	0.00
b0 (phi-4)	0.21	0.00	0.00	0.00	0.14	0.00
b1	0.06	0.00	0.00	0.27	0.03	0.06
b2	0.19	0.02	0.03	0.00	0.02	0.00

Table 7: Performance comparison of the proposed approach against other matchers on the Taxon dataset. The table displays precision (p), recall (r), and F-measure (f) for both simple (s-p, s-r, s-f) and complex (c-p, c-r, c-f) correspondences.

with Qwen3-14B has the highest value with 0.26. In the Hydrography dataset, the b0 variation with Qwen3-14B dominates in both simple and complex f-measures with 0.41 and 0.28, respectively. Finally, the b0 variant with Qwen3-14B has the highest f-measure in the simple case with 0.09, but in the complex case, CANARD has the highest results with 0.34 f-measure. These results reveal several trends. First, different systems tend to excel on different datasets, showing a high degree of matcher specialization with no single best performer across all datasets. Second, as expected, performance on complex matching is still lower than on simple matching for all systems. Finally, generalization remains a significant challenge, as many matchers do not produce results for all datasets. A clear example is CANARD, which requires instances to run and therefore fails on the instance-free Conference and Geolink datasets, resulting in a zero score.

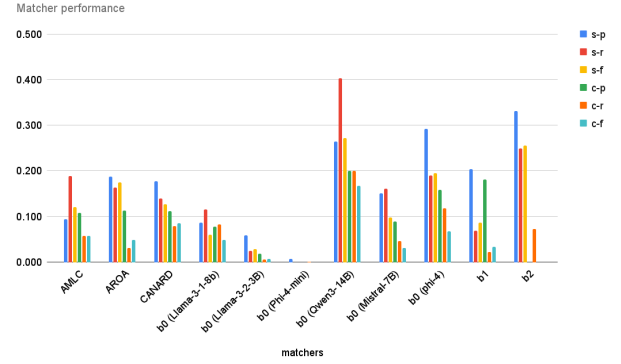


Figure 5: Average performance of the proposed approaches across all evaluated datasets. The table shows precision (p), recall (r), and F-measure (f) for both simple (s-p, s-r, s-f) and complex (c-p, c-r, c-f) correspondences.

To assess the generalization capabilities of the matchers, their average performance across all datasets is presented in Figure 5. On average, the proposed method with the b0 variation with Qwen3-14B achieved the highest scores for the simple alignments and for the complex alignments of the complex track. The results confirm that the LLM is capable of doing direct matching if the right modularization is found. Moreover, fine-tuning provides a performance boost over the base model for these types of correspondences. However, this approach, in the way it was implemented, comes with clear trade-offs. The b2 model, for example, was limited to generating only 1:1 correspondences, which decreased its performance on complex matching tasks. In contrast, the cross-validation variant successfully increased the model's precision, but this gain came at the cost of a lower recall.

5.2 Discussion and Implications

These results confirm the significant potential of leveraging LLMs for ontology matching. With proper training and carefully designed prompts, these models can achieve strong generalization and performance, even when applied in a zero-shot setting. However, key challenges remain. The limited recall and consistently low performance on complex n:m correspondences indicate that further research is required to produce the high-quality, robust alignments needed for real-world scenarios.

The approach proposed in this paper, instruction fine-tuning on domain-specific data, is a direct step toward bridging this performance gap. By providing a robust method for generating subontology training pairs, the proposed method can be configured to address specific challenges. In particular, this adaptability opens future avenues for creating training data that explicitly targets n:m alignments and even multilingual contexts, paving the way for more powerful and versatile LLM-based ontology matchers.

6 Conclusion

These results confirm the significant potential of leveraging LLMs for ontology matching. It is possible to see that the size of the LLM

impacts the matching performance, also with the usage of reasoning models. With proper training and carefully designed prompts, these models can achieve strong generalization and performance, even when applied in a zero-shot setting. However, key challenges remain. The limited recall and consistently low performance on fine-tuning for complex alignments indicate that further research is required to produce the high-quality, robust alignments needed for real-world scenarios. In addition, improving the quality of the space reduction module is required to achieve the highest results as found in this experiment.

The evaluation across five datasets from the OAEI Complex Track demonstrated that fine-tuning on the generated data (b2) significantly improved performance for simple 1:1 alignments, while cross-validation fine-tuning (b1) increased precision for complex alignments. These results highlight that synthetic training data can enhance the adaptability of LLMs for ontology matching, even when manually aligned examples from the target domain are unavailable.

Nevertheless, the experiments also revealed that performance on complex alignments remains limited, especially for n:m correspondences. While the fine-tuned models achieved higher precision and recall on some datasets, generalization across all benchmarks remains a significant challenge. This suggests that further advances are needed in two key areas: the generation of training data that better captures complex alignment structures and the design of prompts and model architectures tailored for structured semantic reasoning.

Future work will focus on several key directions. It is possible to expand the synthetic data generation process to include the verification of the integrity and semantic equivalence of correspondences. It is also possible to extend its coverage to a broader variety of logical constructors and multilingual scenarios. Furthermore, more improvements can come from integrating explicit reasoning mechanisms into the LLM pipeline and exploring hybrid approaches that combine LLM-based generation with traditional ontology matching techniques. Through these efforts, it is expected to bridge the current performance gap in complex alignment quality and advance towards more robust, scalable, and generalizable ontology matching solutions powered by LLMs.

References

- [1] Reihaneh Amini, Sanaz Saki Norouzi, Pascal Hitzler, and Reza Amini. 2024. Towards complex ontology alignment using large language models. In *Knowledge Graphs and Semantic Web - 6th International Conference, KGSWC 2024, Paris, France, December 11–13, 2024, Proceedings* (Lecture Notes in Computer Science). Sanju Tiwari, Boris Villazón-Terrazas, Fernando Ortiz-Rodríguez, and Soror Sahri, (Eds.) Vol. 15459. Springer, 17–31. doi:10.1007/978-3-031-81221-7_2.
- [2] Jérôme David, Jérôme Euzenat, François Scharffe, and Cássia Trojahn dos Santos. 2011. The alignment API 4.0. *Semantic Web*, 2, 1, 3–10. doi:10.3233/SW-2011-0028.
- [3] Hamed Babaei Giglou, Jennifer D'Souza, Felix Engel, and Sören Auer. 2024. Llm4om: matching ontologies with large language models. In *The Semantic Web: ESWC 2024 Satellite Events - Hersonissos, Crete, Greece, May 26–30, 2024, Proceedings, Part I* (Lecture Notes in Computer Science). Albert Meroño-Peñuela et al., (Eds.) Vol. 15344. Springer, 25–35. doi:10.1007/978-3-031-78952-6_3.
- [4] Hamed Babaei Giglou, Jennifer D'Souza, Oliver Karras, and Sören Auer. 2025. Ontoaligner: A comprehensive modular and robust python toolkit for ontology alignment. In *The Semantic Web - 22nd European Semantic Web Conference, ESWC 2025, Portoroz, Slovenia, June 1–5, 2025, Proceedings, Part II* (Lecture Notes in Computer Science). Edward Curry, Maribel Acosta, María Poveda-Villalón, Marieke van Erp, Adegboyega K. Ojo, Katja Hose, Cogan Shimizu, and Pasquale Lisena, (Eds.) Vol. 15719. Springer, 174–191. doi:10.1007/978-3-031-94578-6_10.
- [5] Sven Hertling and Heiko Paulheim. 2023. Olala: ontology matching with large language models. In *Proceedings of the 12th Knowledge Capture Conference 2023, K-CAP 2023, Pensacola, FL, USA, December 5–7, 2023*. Kristen Brent Venable, Daniel Garijo, and Brian Jalaian, (Eds.) ACM, 131–139. doi:10.1145/3587259.3627571.
- [6] Daniel Jurafsky and James H. Martin. 2025. *Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition with Language Models*. (3rd ed.). Online manuscript released January 12, 2025. <https://web.stanford.edu/~jurafsky/slp3/>.
- [7] Beatriz Lima, Daniel Faria, Francisco M. Couto, Isabel F. Cruz, and Catia Pesquita. 2020. OAEI 2020 results for AML and AMLC. In *Proceedings of the 15th International Workshop on Ontology Matching co-located with the 19th International Semantic Web Conference (ISWC 2020), Virtual conference (originally planned to be in Athens, Greece), November 2, 2020* (CEUR Workshop Proceedings). Pavel Shvaiko, Jérôme Euzenat, Ernesto Jiménez-Ruiz, Oktie Hassanzadeh, and Cássia Trojahn, (Eds.) Vol. 2788. CEUR-WS.org, 154–160. https://ceur-ws.org/Vol-2788/oeai20%5C_paper3.pdf.
- [8] François Scharffe. 2009. *Correspondence patterns representation*. PhD thesis. University of Innsbruck.
- [9] Marta Contreiras Silva, Daniel Faria, and Catia Pesquita. 2024. Complex multi-ontology alignment through geometric operations on language embeddings. In *ECAI 2024 - 27th European Conference on Artificial Intelligence, 19–24 October 2024, Santiago de Compostela, Spain - Including 13th Conference on Prestigious Applications of Intelligent Systems (PAIS 2024)* (Frontiers in Artificial Intelligence and Applications). Ulle Endriss, Francisco S. Melo, Kerstin Bach, Alberto José Bugarín Diz, Jose Maria Alonso-Moral, Senén Barro, and Fredrik Heintz, (Eds.) Vol. 392. IOS Press, 1333–1340. doi:10.3233/FAIA240632.
- [10] Guilherme Sousa, Rinaldo Lima, and Cássia Trojahn. 2025. Complex ontology matching with large language model embeddings. *CoRR*, abs/2502.13619. arXiv: 2502.13619. doi:10.48550/ARXIV.2502.13619.
- [11] Guilherme Henrique Santos Sousa, Rinaldo Lima, and Cássia Trojahn dos Santos. 2025. On evaluation metrics for complex matching based on reference alignments. In *The Semantic Web - 22nd European Semantic Web Conference, ESWC 2025, Portoroz, Slovenia, June 1–5, 2025, Proceedings, Part I* (Lecture Notes in Computer Science). Edward Curry, Maribel Acosta, María Poveda-Villalón, Marieke van Erp, Adegboyega K. Ojo, Katja Hose, Cogan Shimizu, and Pasquale Lisena, (Eds.) Vol. 15718. Springer, 77–93. doi:10.1007/978-3-031-94575-5_5.
- [12] Guilherme Henrique Santos Sousa, Rinaldo Lima, and Cássia Trojahn. 2024. Towards generating complex alignments with large language models via prompt engineering. In *Proceedings of the 19th International Workshop on Ontology Matching co-located with the 23rd International Semantic Web Conference (ISWC 2024), Baltimore, USA, November 11, 2024* (CEUR Workshop Proceedings). Ernesto Jiménez-Ruiz, Oktie Hassanzadeh, Cássia Trojahn, Sven Hertling, Huanyu Li, Pavel Shvaiko, and Jérôme Euzenat, (Eds.) Vol. 3897. CEUR-WS.org, 43–56. https://ceur-ws.org/Vol-3897/om2024%5C_LTpaper4.pdf.
- [13] Élodie Thiéblin, Guilherme Sousa, Ollivier Haemmerlé, and Cássia Trojahn. 2024. CANARD: an approach for generating expressive correspondences based on competency questions for alignment. *Semantic Web*, 15, 3, 897–929. doi:10.3233/SW-233521.
- [14] Jason Wei, Maarten Bosma, Vincent Y. Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M. Dai, and Quoc V. Le. 2022. Finetuned language models are zero-shot learners. In *The Tenth International Conference on Learning Representations, ICLR 2022, Virtual Event, April 25–29, 2022*. OpenReview.net. <https://openreview.net/forum?id=gEZrGCzqdR>.
- [15] Lu Zhou and Pascal Hitzler. 2020. AROA results for OAEI 2020. In *Proceedings of the 15th International Workshop on Ontology Matching co-located with the 19th International Semantic Web Conference (ISWC 2020), Virtual conference (originally planned to be in Athens, Greece), November 2, 2020* (CEUR Workshop Proceedings). Pavel Shvaiko, Jérôme Euzenat, Ernesto Jiménez-Ruiz, Oktie Hassanzadeh, and Cássia Trojahn, (Eds.) Vol. 2788. CEUR-WS.org, 161–167. https://ceur-ws.org/Vol-2788/oeai20%5C_paper4.pdf.