Journal of Information Technology and Computer Science

Journal Homepage:https://nicomarcinternationalpublishers.com/index.php/jitcs/index

JITCS

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| RESEARCH ARTICLE

Ontologies Alignment Towards A Hybrid Approach :A State of The Art

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| ABSTRACT

Ontologies are concepts that can represent forms of organization and intelligent control of knowledge. The diversity of ontologies poses a problem of heterogeneity, hence the need for the development of techniques and Tools aimed at promoting a certain interoperability of these ontologies and their union. Alignment between two ontologies (matching or mapping) consists of producing a set of matches between entities. These entities can be concepts, properties, or instances. As the evolution of these ontologies must be ensured, highly elaborate artificial intelligence techniques make it possible to ensure machine learning of the alignment process. This article presents a state-of-the-art of ontology alignment combined with artificial intelligence techniques that irreversibly improve the alignment process. The results known to date show several of several artificial intelligence tools implemented as part of the alignment and which have produced convincing results. In view of the limitations presented by the proposed approaches, we have opted to use genetic algorithms inspired by natural selection to optimize the results of the OWL ontology alignments.

| KEYWORDS

Ontology, alignment, interoperability, homogeneity, machine learnin

| ARTICLE INFORMATION

ACCEPTED: 26 March 2026 **PUBLISHED:** 23 April 2026

1.Introduction

Knowledge engineering has reached a level where knowledge is created from well-developed techniques and tools; we speak of ontologies. Ontologies are widely used in several fields and in particular in the representation of knowledge and the Semantic Web. In these two fields, a multitude of ontologies have been developed for knowledge modeling. In this context, knowledge and data need to be shared, so it is essential to establish semantic correspondences between the ontologies that describe them. The Semantic Web is an extension of the current Web with a well ened meaning of data and resources. It allows computers and users to cooperate and exchange information easily. The heterogeneity and evolution of the tools and techniques for designing, managing and sharing these ontologies poses a problem of interoperability today, hence the need to develop a unified procedure with the ability to learn automatically to guarantee the scalability of these ontologies. A lot of work has been done in the field of matching and matching associated with artificial intelligence, but these different solutions proposed for alignment are often tested on ontologies in a fairly dispersed way and encounter several difficulties such as the accuracy of the final alignment, the ability to process large ontologies, the ability to learn patterns and complex relationships, .

The majority of alignment tools [Aumuller and Do, 2005] and the ontology community [Zhdanova, 2005] relied on a classical presentation of the class hierarchy of two ontologies and some ways for the user to express alignment. These approaches assume that alignment is considered by an expert, which does not require a custom interface. However, several ontologies can include several forms of heterogeneity, namely: syntactic heterogeneity, terminological heterogeneity, conceptual heterogeneity and semiotic heterogeneity.

2.Related Works

Historically, ontology alignment has relied on manual or semi-automatic methods, often based on expert knowledge or predefined rules. These methods typically involve analyzing the structure, semantics, and context of ontologies to identify correspondences between entities. Techniques such as lexical matching, structural matching, and semantic similarity have been widely used in traditional ontology alignment approaches. The ontologies to be aligned have different structures and do not use the same vocabulary (i.e., different terms to describe the same concepts). In addition, the diversity of their heterogeneity: syntactic, terminological (or lexical) and structural, as well as their size and formats, make the task of ontology alignment very difficult. The techniques and methods used in the literature that address the problem of ontology alignment revolve around the search for similarity, dissimilarity or correspondence between two entities in general to identify the correspondence links between ontologies [KASSEL, G. 2002c]. In our context, the notion of semantic similarity is seen as that of topological similarity in mathematics, where it is associated with a function, called a similarity function. The diversity of these methods therefore leads to a diversity of approaches in the elaboration of ontology alignments.

2.1 *Asco3*

The asco3 algorithm proposes a similarity calculation model on two steps, partial similarity and final similarity. The partial similarity between two entities of the two ontologies is deduced between the components corresponding to the entities in question.

2.2 *Qom*

The qom (quick ontology matching) approach [ehrig et al., 2004]: is based on the nom (naive ontology matching) approach, which has shown that it is effective, but, we thought of optimizing it, which is what gave birth to the qom approach.

2.3 *Anchor-Prompt*

Anchor-PROMPT [Noy and Musen, 2001] constructs a directed labeled graph representing the ontology from the hierarchy of concepts (called classes in the algorithm) and the hierarchy of relations (called slots in the algorithm), where the nodes in the graph are concepts and the edges denote relationships between concepts (the labels of the edges are the names of the relations). This algorithm decides whether these concepts are semantically similar. [Yiling, L., 2003]

2.4 *Soda*

The new alignment method, SODA [Zghal et al., 2009]: (Structural Ontology OWL-DL Alignment), implements a new algorithm for aligning OWL-DL ontologies. The new alignment method is based on the calculation of similarity measures. The SODA method performs well on small and medium- sized ontologies and is not yet very well suited for large ontologies. [Cerqueus, T., 2012]

2.5 *Taxomap*

TaxoMap [Kasri, 2007]: is an alignment tool that aims to allow unified access via the Web to documents in the same field of application. It is suitable for the processing of taxonomies with heterogeneous and asymmetrical structures. The objective of TaxoMap is to map the concepts of the least structured taxonomy, the source taxonomy [Mizoguchi, R. et al., 2000].

2.6 *Asco3*

The asco3 algorithm [bach than et al, 2007]: represents ontologies in the form of a labeled, directed, cyclic graph, called an o-graph.

2.7 *Ola*

OLA [Djoufack et al., 2008]: for OWL-Lite Alignment is an algorithm for aligning ontologies represented in OWL. This algorithm uses the different similarity calculation methods to find the correspondences between the entities of two ontologies based on their characteristics and their relationships with other entities and to combine these similarity values calculated for each pair of entities it uses the weighted sum of the similarity values of each characteristic [Lynda DJAKHDJAKHA, 2014m].

2.8 *Falcon-Oa*

Falcon-AO [Hu et al., 2007]: is an alignment tool that was developed by Wei Hu to automatically discover correspondences between ontologies by exploiting the structure and language of these ontologies. It uses bipartite direct RDF graphs to represent ontologies. These graphs are derived from bipartite RDF graphs.

2.2 Table of systems of some traditional approaches

YEAR	TYPE	AUTOMATIC	SEMI-AUTOMATIC
2001	basic		
	Upgraded		**Anchor-prompt** (Upgraded version of SMART [28], Noy and Musen)
2002	basic		
	Upgraded		- **GLUE** (Ugraded of LSD [29], doan and al.) - COMA (combination of several matchers, Do and Rahm)
2003	basic	IF-Map (Kalfoglou and al.) S-Match (Giunchiglia and al.)	
	Upgraded		
2004	basic	NOM (Ehrig and al.) OLA (Euzde at and al.)	
	Upgraded	QOM (upgraded version of NOM, Ehrig and al.)	
2005	basic	ASCO1 (Bach)	

	Upgraded	ASCO2 (upgraded version of ASCO1, Bach)	
2006	Upgraded	ASCO3 (Upgraded version of ASCO2, Bach)	
	basic		
	Upgraded		
2007	basic	AROMA (jerôme David and al.)	FALCON-OA (Hu and al.) ASMOV (Hu and al.) TaxoMap (KASRI)
	Upgraded	ODOLA(ugraded versio, of OLA, Zghal and al.) SODA (Ugraded version of EDOLA, Zghal and al.) OLA2 (Ugraded version of OLA)	COMA++ (Ugraded version of COMA, Do and Rahm)
2008	basic		
	Ugraded	OLA3 (Upgraded version of OLA2, Djoufack and al.)	
2009	basic		

Table1: some proposed approches, compared according to several axes: date, author, automacity and type (basic or upgraded)

2006	Upgraded	ASCO3 (Upgraded version of ASCO2, Bach)	

	basic		
	Upgraded		
2007	basic	AROMA (jerôme David and al.)	FALCON-OA (Hu and al.) ASMOV (Hu and al.) TaxoMap (KASRI)
	Upgraded	ODOLA(ugraded versio, of OLA, Zghal and al.) SODA (Ugraded version of EDOLA, Zghal and al.) OLA2 (Ugraded version of OLA)	COMA++ (Ugraded version of COMA, Do and Rahm)
2008	basic		
	Ugraded	OLA3 (Upgraded version of OLA2, Djoufack and al.)	
2009	basic		

3. Machine Learning Approaches

Recent advances in machine learning have had a significant impact on the alignment of ontologies. Supervised, unsupervised, and semi-supervised learning techniques were applied to automate the alignment process [MAIZI Khawla, (2023)]. Supervised approaches use labeled training data to learn entity mappings, while unsupervised methods exploit the structure and inherent characteristics of ontologies to discover matches [DILEKH, Tahar (2019)]. Semi-supervised techniques combine labeled and unlabeled data to improve alignment accuracy [SAADI, I., [BORDJI, Z. (2024)]. Here are some existing approaches for aligning ontologies using machine learning.

3.1 Logmap

This approach uses machine learning to align ontologies using features such as lexical similarity and proximity in the ontology [Amin and al. (2015)].

3.2 *AOM*

This approach uses machine learning to align ontologies using features such as semantic similarity and proximity in the ontology [OAEI, 2016].

3.3 Ontoalign

uses machine learning to align ontologies using features such as lexical similarity and proximity in the ontology [Hong and al. (2010, May)].

3.4 *MLMA*

This approach uses machine learning to align ontologies using features such as semantic similarity and proximity in the ontology [Alasoud and al. (2007)].

3.5 Deeponto

This approach uses deep learning to align ontologies using features such as vector representations of concepts and relationships [He, Yuan, and al. (2024)].

3.6 Ontopilot

This approach uses machine learning to align ontologies using features such as lexical similarity and proximity in the ontology [Stucky, B., Luc, A. (2017)].

3.7 *SAMBO*

This approach uses machine learning to align ontologies using features such as semantic similarity and proximity in the ontology [Lambrix, and al. (2006)]. SAMBO is a system for aligning and merging develop and adapted for only biomedical ontologies. These approaches use different machine learning techniques, such as decision trees, random forests, support vector machines, neural networks, etc. It is important to note that these approaches can be combined and adapted to meet the specific needs of each ontology alignment problem.

3.8 System table of some machine learning alignment approaches

Years	Authors	Approaches	AI Algorithms	Observation
2004	Doan et al.	GLUE	Naive Bayes, SVM	Use classifiers to align concepts
2005	Noy et Musen	PROMPT	Naive Bayes, Decision Trees	Use classifiers to align concepts and relations
2007	Ehrig et al.	QOM	SVM, K-NN	Use classifiers to align concepts and instances
2009	Jean- Mary et al.	ASMOV	Naive Bayes, Decision Trees	Use classifiers to align concepts and relations (biomedical domain)
2010	Wang et al.	PARIS	SVM, Random Forest	Use classifiers to align concepts and instances based on probabilities
2012	Jim´enez- Ruiz et al.	LogMap	Naive Bayes, Decision Trees	Use classifiers to align concepts and relationships and improve accuracy

2017	Zhang et al.	DAN	Deep Learning (CNN)	Use Neural Networks to align concepts and instances
2018	Zhu et al.	OpenEA	Deep Learning (Attention based)	Use Neural Networks to align concepts and instances
2019	Hertling et al.	AML	Deep Learning (Graph- based)	Use Neural Networks to align concepts and instances

Table2 : Some proposed approaches, compared according to several axes: date, author, automaticity and type.

4. Limitations of Existing Approaches

Aligning ontologies using machine learning have some additional limitations. The lack of transparency in some machine learning models can be difficult to understand and explain the resultof the aligment. There are also hyper parameter dependence for some model performance that can be highly dependent on the hyper parameters chosen [[Michel Heon, (2014)].

The generalization of problems due to some models may not be a good outstanding to new ontologies or domains. There is also the Lack of annotated data for model training that can be scarce or expensive to obtain. The lack of context consideration in some models may not consider the context in which ontologies concepts are used.

Most of the models have less consideration of Temporality although ontologies can evolve over time, which requires taking into account temporality.

The granularity problem of ontologies can have different levels, which can make alignment more difficult. The limitations highlight the need to continue to improve ontology alignment approaches using machine learning to make them more efficient, accurate, and robust.

5. Proposed Approach

The hybrid approach we propose uses directed data graphs [Mariem Mahfoudh; 2015] to capture the semantic structure of input ontologies. Next, a GNN network is applied for learning representations (embeddings). Genetic algorithms are used to optimize the selection of final matches. The main advantage of this method is that, it threats alignment as a multidimensional problem. Where a classic algorithm might fail due to different terminology, the neural network finds the semantic link. If the neural network proposes too many candidates, the genetic algorithm filters out structural inconsistencies based on the graph's topology.

The approach we propose consists of two main steps:

Steps +	Components	Main Fonction	Contribution to alignment

Steps +	Components	Main Fonction	Contribution to alignment
Step 1	**Directed graphs**	Modeling	Taxanomy structure conservation
Step 2	**Neural networks**	Feature extraction	Discovery of complex semantic similarities
	Genetic Algorithms	Search of optimum	Avoid local optima and manage large search areas

Table 3 : A resume of the approach

5.1- Architecture of the approach

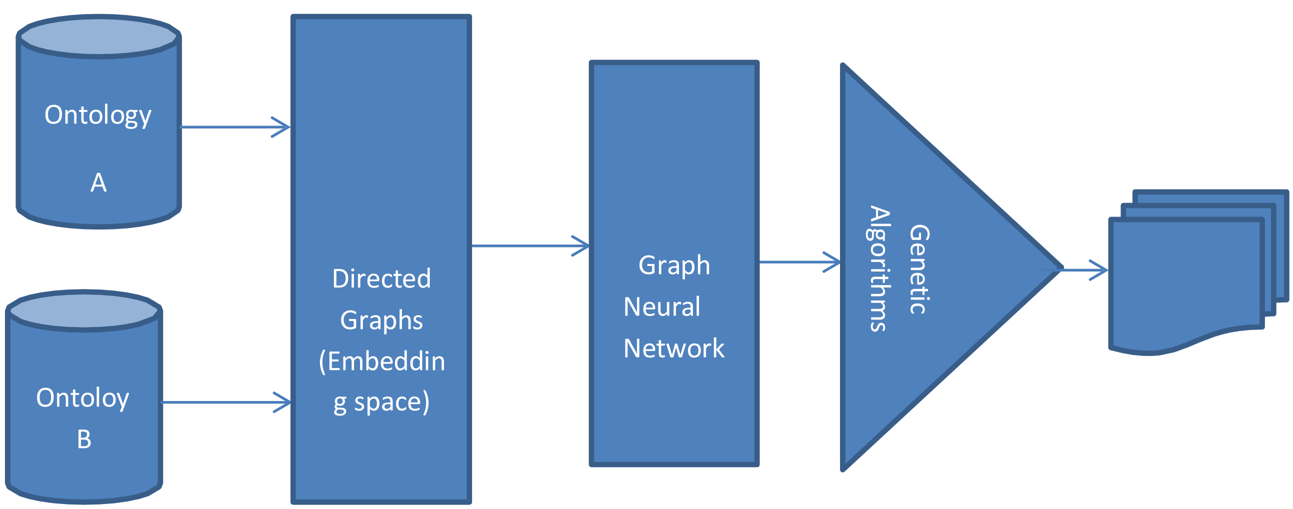

Figure1: Workflow of the approach

The process unfolds in 3 majors phases:

5.1.1. Directed graph Modeling.

Unlike flat approaches, we model each ontology as a directed graph where**:**

- The nodes represent the concepts and properties.
- The arcs represent semantic hierarchical (is-a) relationships.
- The orientation helps to preserve the hierarchy of subsumption, crucial for avoiding false positives.

5.1.2. Representational learning through neural networks

We use Graph Neural networks (GNN) to transform each node into a digital vector (embeddings) [Li, N. and al., (2024)].

- **Mechanism**: Each node aggregates information from its immediate neighbors.
- **Objective**: to capture not only the entity's name, but also its structural context.
- **Result**: Two entities are initially judged to be similar if their velocities in latent space are close (cosinus similarity) [Euzenat, J., Bach and al., (2006)].

5.1.3 Optimization by Genetic Algorithms

The final step consists of extracting the best subset of matches (Mapping) [Amir Laadhar, (2019)]. This is a complex combinatorial optimization problem. The input layer is **the population** in wish, each individual is a potential alignment (a set of pairs) and then **the fitness function** used to maximize overall similarity while minimizing structural conflicts (e.g., a class cannot be aligned with two incompatible classes).

- Operators: Crossover and mutation help explore the solution space to avoid local optima

5.2. Experimental Methodology

PARAMETER	DESCRIPTION
Input	OWL/RDF files transformed into graphs
GNN	Use of the GraphSAGE architecture for scalability.
Genetic Algorithm	Population size: 100, Generations: 500.

Table4: Description and parameters of the approach

The evaluation metrics to get the performance of the alignment is measured by:

1. Precision wish is a proportion of correct matches found.
2. Recall use to calculate the ability to find all existing matches.

F-Score an harmonic mean of the previous two

LAYER	RECOMMENDED TOOL	USE

Parsing	Owlready2	Seamless OWL -> Python

LAYER	RECOMMENDED TOOL	USE
Embeddings	PyTorch Geometric	State-of-the-art for neural networks on graphs..
NLP Processing.	Sentence-Transformers	Fast calculation of semantic similarity between labels
Optimization	PyGAD	Ease of implementing the fitness function.
Storage	GraphDB	To persist and visualize the final alignments.

Table5: Technological Summary (Recommended Stack)

To validate this approach, we use the OAEI (Ontology Alignment Evaluation Initiative) reference dataset, [OAEI, (2024)]. The growing number of methods available for schema or ontology matching necessitates a consensus for evaluating these methods. The Ontology Alignment Evaluation Initiative is an international coordinated effort aimed at establishing this consensus.

6. **Discussion and Advantages**

The originality of this approach lies in its robustness:

- The GNN handles the semantic and textual aspects smoothly [Li, N., Bailleux, T., Bouraoui, Z., Schockaert, S. (2024)]..
- The Directed Graph maintains the logical integrity of the ontology.
- The Genetic Algorithm resolves alignment conflicts that greedy methods cannot address. The main advantage of this method is that it treats alignment as a multidimensional problem.

Where a conventional algorithm might fail due to different terminology, the neural network finds the semantic connection. If the neural network proposes too many candidates, the genetic algorithm filters structural inconsistencies based on the graph's topology.

7. Challenges and Future Directions

Despite significant progress, ontology alignment still faces several challenges, including scalability, Heterogeneity and ontology dynamics. Future research directions could focus on the development of hybrid approaches [Amir Laadhar, and al., (2019)] that combine the strengths of traditional methods, machine learning, and Semantic Web technologies. In addition, addressing the interpretability and explain ability of alignment results will be crucial to improve the reliability and usability of automated alignment systems.

Here we list some potential research areas for ontology alignment and machine learning:

- Improved machine learning algorithms for ontology alignment [Euzenat, J. et Shvaiko, P. (2007)].
- Development of new ontology representation techniques to improve alignment [DILEKH, Tahar (2019)].
- Integration of domain knowledge to improve alignment accuracy [Stuckenschmidt, and al., (2004)].
- Management of uncertainty and ambiguity in ontologies.

- Scalability of alignment approaches for large ontologies.
- Interpretability of machine learning models for ontology alignment [RAMDANE Ahmed Merouane (2019)].
- Development of evaluation methods for the alignment of ontologies [Kaladzavi et al., (2018)].
- Application of ontology alignment to specific domains (health, finance, etc.) [Lambrix, P., Tan, H. (2006)]..
- Integration of ontology alignment with other artificial intelligence techniques (automatic reasoning, etc.) [Abdoulaye Diallo and al., (2021)].
- Development of platforms and tools to facilitate ontology alignment. Item Search for new data sources for training machine learning models [SAADI, I., BORDJI, Z. (2024)].
- Study of the robustness of machine learning models in the face of noisy or incomplete data.
- Development of methods for updating machine learning models to keep up with ontologies [Stucky, B., Luc, A. (2017).].

Research into new dimensionality reduction techniques to improve alignment [Li, N., Bailleux, T., Bouraoui, Z., Schockaert, S. (2024)].

8. Conclusion

In conclusion, ontology alignment is a dynamic and evolving field that plays a fundamental role in knowledge representation and artificial intelligence. Traditional methods, machine learning approaches, and semantic web technologies have all contributed to advancing the state of the art. The integration of directed graphs, neural networks and genetic algorithms is a key step to an accuracy appraoch and a real interoperability. Transforming datas into a unify knowledge, this model could propbably become usefull in biomedical domain. Ontology alignment By addressing key challenges and adopting emerging trends, researchers can further improve the efficiency and applicability of ontology alignment techniques in real-world scenarios.

References

[1] Abdoulaye, D., & Thiam, M. (2021). *Etat de l'art sur l'alignement des ontologies*. hal03330388.
[2] Achichi, M., et al. (2016). Results of the ontology alignment evaluation initiative 2016. *OM: Ontology Matching* (No. 1766).
[3] Alasoud, A., Haarslev, V., & Shiri, N. (2007). A multi-level matching algorithm for combining similarity measures in ontology integration. In *ODBIS 2005/2006 Revised Papers* (pp. 1–17). Springer.
[4] Amin, M. B., Khan, W. A., Lee, S., & Kang, B. H. (2015). Performance-based ontology matching. *Applied Intelligence, 43*, 356–385.
[5] Berners-Lee, T. (2001). The semantic web. *Scientific American, 284*(5), 35–43.
[6] Corcho, O., Fernandez-Lopez, M., & Gomez-Perez, A. (2003). Methodologies, tools and languages for building ontologies. *Data & Knowledge Engineering, 46*(1), 41–64.
[7] Diallo, A., & Thiam, M. (2021). *Etat de l'art sur l'alignement des ontologies*.
[8] Dilekh, T. (2019). *Un modele semantique pour la recherche d'information en langue arabe* (Doctoral dissertation).
[9] Djoufak-Kengue, J.-F., Euzenat, J., & Valtchev, P. (2008). Alignement d'ontologies dirigé par la structure. In *Actes LMO* (pp. 43–57).
[10] Euzenat, J. (2001). Towards a principled approach to semantic interoperability. In *IJCAI Workshop* (pp. 19–25).
[11] Euzenat, J., & Shvaiko, P. (2007). *Ontology matching*. Springer.
[12] He, Y., et al. (2024). Deep-Onto. *Semantic Web, 15*(5), 1991–2004.
[13] Hong, J. L., Siew, E. G., & Egerton, S. (2010). Aligning data records using WordNet. In *ICCRD* (pp. 56–60). IEEE.
[14] Jaro, M. A. (1995). Probabilistic linkage of large public health data files. *Statistics in Medicine, 14*, 491–498.
[15] Kaladzavi, et al. (2018). Assessing similarity value between two ontologies.
[16] Khiat, A. (2017). *Developpement d'un environnement pour l'alignement des ontologies*.
[17] Laadhar, A. (2019). *Local matching learning of large scale biomedical ontologies* (Doctoral dissertation).
[18] Lambrix, P., & Tan, H. (2006). SAMBO. *Journal of Web Semantics, 4*(3), 196–206.
[19] Li, N., et al. (2024). Ontology completion. *arXiv preprint arXiv:2403.17216*.
[20] Mahfoudh, M. (2015). *Adaptation d'ontologies...* (Doctoral dissertation).
[21] Noy, N., Fergerson, R. W., & Musen, M. A. (2000). The knowledge model of Protege2000. In *EKAW*.
[22] PRO. (2002). *Protege2000 Ontology Editor*. http://protege.stanford.edu/
[23] Ramdane, A. M. (2019). *Alignement d'ontologies de domaine*.
[24] Ring, J. (2009). *Evolving an autonomous test and evaluation enterprise*.
[25] Roussey, C., et al. (2015). *Les ontologies en agriculture*.
[26] Saadi, I., & Bordji, Z. (2024). *Revue systematique...* (Doctoral dissertation).
[27] Shvaiko, P., & Euzenat, J. (2007). A survey of schema-based matching. *Journal on Data Semantics*.
[28] Stuckenschmidt, H., et al. (2004). *State of the art on ontology alignment*.
[29] Stucky, B., & Luc, A. (2017). OntoPilot. *Biodiversity Information Science and Standards*.
[30] Yassine, N., et al. (2016). *Alignement d'ontologies du web semantique*.