A Comprehensive Review of Classic and Modern Techniques for Ontology Matching

Rohan Shaan

June 4, 2023

A Comprehensive Review of Classic and Modern Techniques for Ontology Matching

Rohan Shaan

University of Hyderabad (India)

Abstract. Ontology matching facilitates interoperability and semantic integration across heterogeneous knowledge bases. Over the years, numerous techniques have been developed to effectively tackle the challenge of aligning ontologies. This paper provides a comprehensive review of classic and modern techniques for ontology matching. We present an overview of the fundamental concepts and principles underlying ontology matching, followed by an in-depth analysis of traditional methods, such as linguistic-based, structure-based, and instance-based approaches. Subsequently, we delve into the recent advancements in ontology matching, including machine learning-based techniques, deep learning-based strategies, and hybrid methods that combine multiple algorithms. We compare these techniques based on critical metrics, such as precision, recall, and F-measure, and discuss their strengths, limitations, and applicability in real-world scenarios. Additionally, we highlight the impact of ontological characteristics, such as size, complexity, and heterogeneity, on the performance of different matching techniques. Furthermore, we explore the challenges and open research directions in ontology matching, such as handling semantic drift, scalability, and incorporating contextual information. Therefore, this paper aims to provide researchers and practitioners with a comprehensive understanding of classic and modern ontology matching techniques, paving the way for further advancements and improvements in this critical area of semantic integration.

Keywords: Ontology alignment, Ontology mapping, Ontology matching

1 Introduction

In the increasing data complexity and heterogeneity era, achieving semantic interoperability has become crucial for enabling effective information integration and knowledge sharing across different systems and domains. Ontology matching aims to align and establish correspondences between ontologies and plays a fundamental role in bridging the semantic gaps among diverse knowledge representations [1]. Ontology matching supports various applications, including data integration, semantic search, and ontology merging By facilitating the seamless exchange of information [2,3]. Consequently, there has been a growing interest in developing robust and accurate techniques in academia and industry [4].

Figure 1 illustrates a simplified example of ontology matching between two ontologies. The ontologies are represented as circles, each representing a concept in the respective ontology. In this scenario, Ontology 1 consists of concepts: Concept 1a, 1b, and 1c. Ontology contains two concepts: Concept 2a and Concept 2b. The arrows connecting the concepts represent the matched entities between the ontologies. In this case, Concept 1a and 1b from Ontology 1 have been matched with Concept 2a from Ontology 2. Similarly, Concept 1c from Ontology 1 has been matched with Concept 2b from Ontology 2.

Ontology matching aims to establish correspondences or alignments between entities in different ontologies, enabling semantic integration and interoperability. Therefore, it can facilitate complex tasks such as knowledge sharing [5].

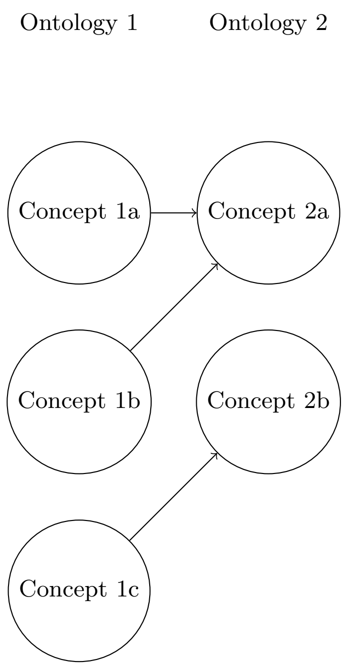

Fig. 1. Example of ontology matching

This paper aims to provide a review of classic and modern techniques for ontology matching. We aim to present an overview of the fundamental concepts and principles underlying ontology matching and delve into the strengths and limitations of different approaches. We evaluate and compare various techniques to show their performance and effectiveness under other ontological characteristics and scenarios. Furthermore, we discuss the recent advancements in ontology matching, including machine learning-based techniques, deep learning-based approaches, and hybrid methods. Furthermore, we seek to identify the gaps in the existing literature and suggest potential lines for future improvements.

The subsequent sections of this paper are organized as follows: Section 2 provides a background and fundamental understanding of ontology matching, including its definition, importance, and evaluation metrics. Section 3 presents a detailed analysis of classic techniques for ontology matching, encompassing linguistic-based, structure-based, and instance-based approaches. Section 4 delves into modern techniques, including machine learning-based, deep learning-based, and hybrid methods. Section 5 focuses on evaluating and comparing the performance of different techniques based on established metrics. In Section 6, we explore the impact of ontological characteristics, such as size, complexity, and heterogeneity, on the performance of ontology matching techniques. Section 7 discusses the challenges that ontology matching faces and highlights potential research directions. Finally, Section 8 concludes the paper by summarizing the techniques reviewed and highlighting key findings.

2 Background

Ontology matching refers to establishing correspondences between entities, relationships, and concepts in different ontologies [6]. An ontology represents a formal, explicit specification of a domain's concepts, attributes, and relationships. It serves as a shared vocabulary for knowledge representation and facilitates the integration and interoperability of information.

The importance of ontology matching lies in its ability to bridge the semantic gaps among diverse ontologies. As ontologies are often created independently and vary in terminology, structure, and conceptualizations, achieving a coherent and unified view of the underlying knowledge becomes challenging. Ontology matching enables the alignment of overlapping or related concepts, allowing for seamless data integration, information retrieval, and knowledge sharing. Establishing correspondences between ontologies makes it possible to infer implicit relationships, merge ontology, and support advanced inference mechanisms.

2.1 Ontology Representation and Structure

Ontologies typically represent using formal languages, such as the Web Ontology Language (OWL) or the Resource Description Framework (RDF). These languages provide a structured and machine-readable representation of concepts, attributes, and relationships, enabling automated processing and reasoning.

The structure of an ontology encompasses various components, including classes, properties, instances, and axioms. Classes define the concepts or categories in a domain, while properties represent relationships or attributes associated with classes. Instances represent individual entities or objects within a domain. Axioms, expressed in logical formalisms, specify additional constraints, rules, or logical relationships between the different components.

Ontologies can vary in size, complexity, and level of formalization. Some ontologies are domain-specific, focusing on particular areas such as biology [7], while others aim for a broader coverage across multiple domains [8]. The complexity of ontologies can range from simple taxonomies to more complex representations that involve inference rules, constraints, and logical expressions [9].

2.2 Evaluation Metrics for Ontology Matching

The evaluation of ontology matching requires the definition of metrics to assess the performance. Commonly used evaluation metrics include precision, recall, and F-measure. Precision measures the accuracy, indicating the proportion of correctly aligned entities Recall quantifies the completeness of the matching process by measuring the ratio of correctly aligned entities. F-measure combines precision and recall into a metric that provides a balanced evaluation.

Additional quality measures assess the alignment by considering various factors, such as semantic consistency, and expressiveness. These measures aim to capture the extent to which the alignment captures the intended semantics and the relationships between the ontologies being matched [10].

3 Classic Techniques for Ontology Matching

Classic techniques for ontology matching encompass a range of approaches developed over the years to address the challenge of aligning ontologies effectively [11,12]. These techniques primarily focus on leveraging linguistic, structural, and instance-based information.

The classical algorithm for simple ontology matching algorithm can be seen in Algorithm 1., and it is based on the following steps:

1. The algorithm takes two input ontologies, denoted as O_1 and O_2, and aims to find matching entities between them. The output is a set of matched entities, denoted as M.
2. The MatchOntologies function is the primary function that performs the ontology matching. It takes O_1 and O_2 as input and returns the set of matched entities M.
3. Initially, the set of matched entities M is initialized as an empty set.
4. The algorithm iterates over each entity e_1 in O_1.
5. For each entity e_1 in O_1, it initializes variables e_{best} and sim_{best} to keep track of the best matching entity and the corresponding similarity score.
6. It then enters a nested loop, iterating over each entity e_2 in O_2.
7. Within the nested loop, the algorithm computes the similarity score between the entities e_1 and e_2 using the function $\textsc{ComputeSimilarity}(e_1, e_2)$. The similarity score quantifies the semantic similarity between the entities.
8. If the computed similarity score sim is greater than the current best similarity sim_{best}, it updates the sim_{best} and e_{best} variables with the new values.

Algorithm 1 Ontology Matching

```
Require: O_1, O_2                                  ▷ Input ontologies
Ensure: M                                          ▷ Matched entities
function MatchOntologies(O_1, O_2)
    M ← {}                                         ▷ Initialize empty set of matched entities
    for e_1 in O_1 do
        e_best ← NULL                              ▷ Best matching entity
        sim_best ← 0                               ▷ Best similarity score
        for e_2 in O_2 do
            sim ← ComputeSimilarity(e_1, e_2)      ▷ Compute similarity
            if sim > sim_best then
                sim_best ← sim                     ▷ Update best similarity
                e_best ← e_2                       ▷ Update best matching entity
            end if
        end for
        if sim_best ≥ threshold then               ▷ Threshold for considering a match
            M ← M ∪ {(e_1, e_best)}                ▷ Add match to set
        end if
    end for
    return M                                       ▷ Return set of matched entities
end function
```

9. After iterating over all entities in O_2, it checks if the best similarity sim_{best} is greater than or equal to a specified threshold. If it is, it considers the entities as a match and adds the pair (e_1, e_{best}) to the set of matched entities M.
10. Finally, the function returns the set of matched entities M.

The algorithm compares each entity in O_1 with every entity in O_2, computes their similarity, and determines the best matches based on the similarity scores. It applies a threshold to filter out matches that do not meet a specific similarity criterion. The similarity computation function $\textsc{ComputeSimilarity}(e_1, e_2)$ is assumed to be defined separately.

3.1 Linguistic-based Approaches

Linguistic-based approaches exploit ontologies' lexical and semantic information to establish correspondences [13]. These techniques utilize lexical matching algorithms, such as string similarity measures (e.g., edit distance, Jaccard coefficient), to compare labels, names, or terms associated with ontology entities. Lexical matching is complemented by linguistic resources or domain-specific ontologies to effectively enrich the semantic information and handle synonyms, hyponyms, and hypernyms. Thesaurus-based techniques, such as those using thesauri, facilitate semantic matching by considering the hierarchical relationships and synonyms in these resources.

3.2 Structure-based Approaches

Structure-based approaches exploit the structural organization of ontologies to establish correspondences. These techniques focus on aligning the hierarchical relationships, and the overall structure of ontologies. Structural similarity measures, such as graph-based algorithms or similarity metrics based on the depth and breadth of ontology entities, quantify the similarity between concepts and relationships [14]. Methods like the Tree Edit Distance leverage the structure of ontologies to determine the mapping between concepts.

3.3 Instance-based Approaches

Instance-based approaches utilize the instances or individual entities within ontologies to establish correspondences [15]. These techniques use instances' characteristics and properties, such as attribute values, object properties, or usage patterns, to infer semantic relationships between concepts. Instance-based matching can be performed using clustering algorithms, such as k-means or hierarchical clustering, to group instances based on their similarities. Alternatively, statistical methods, such as co-occurrence analysis or information content measures, can identify relationships between instances based on their usage patterns.

Classic ontology matching techniques often employ linguistic, structural, and instance-based approaches to achieve more accurate and comprehensive results. Hybrid strategies integrate multiple matching algorithms, leveraging each approach's strengths to overcome their limitations [16]. These techniques are often rule-based or heuristic-based, employing predefined rules or heuristics to guide the matching process based on the aligned ontologies' characteristics [17].

While classic techniques have provided valuable contributions to ontology matching, they face challenges in dealing with large-scale ontologies [18], handling heterogeneity [19], and capturing complex semantic relationships [20]. Recent advancements in ontology matching have introduced machine- and deep-learning-based techniques to overcome these limitations [21].

4 Modern Techniques for Ontology Matching

Modern techniques for ontology matching have witnessed significant advancements, leveraging the power of machine learning and deep learning to address the challenges posed by complex and large-scale ontologies [22]. These techniques go beyond traditional approaches and use data-driven methodologies to learn the matching patterns and capture intricate semantic relationships. We discuss three major categories of modern techniques: machine learning-based methods, deep learning-based techniques, and hybrid approaches.

4.1 Machine Learning-based Techniques

Machine learning-based techniques utilize algorithms and models that learn from labeled training data to predict correspondences between ontologies [23]. These techniques typically involve feature extraction, where relevant features are derived from ontology entities or their attributes, and a machine learning algorithm is trained to classify pairs of entities as matching or non-matching. Commonly used machine learning algorithms for ontology matching include decision trees [24], or support vector machines (SVM). Feature selection techniques, such as information gain or mutual information, are used to identify the most informative features for matching.

4.2 Deep Learning-based Techniques

Deep learning-based techniques leverage deep neural networks to learn complex representations and patterns from ontology data [25]. These techniques use architectures such as neural networks (RNN), or transformer-based models to capture the semantic relationships between entities [26]. Deep learning models can process various data types, including textual descriptions, structural information, or even graph representations [27]. The models are trained on large-scale datasets [28] and can learn hierarchical representations, encode contextual information, and capture latent semantic relationships, leading to improved matching accuracy.

4.3 Hybrid Approaches

Hybrid approaches combine the strengths of multiple techniques, including traditional methods, machine learning, and deep learning, to achieve more robust and accurate ontology matching [29,30]. These techniques integrate diverse matching algorithms, leveraging their complementary nature to overcome individual limitations [31,32,33]. For instance, a hybrid approach may use linguistic-based techniques for label matching, structure-based techniques for hierarchical alignment [34], and machine learning or deep learning models to capture more intricate semantic relationships. Hybrid approaches often require careful integration of different algorithms, parameter tuning, and selecting appropriate combination strategies to achieve optimal matching performance [35].

Modern techniques for ontology matching have demonstrated improved accuracy and flexibility in handling diverse characteristics, scalability, and complex semantic relationships [36]. However, these approaches may require large amounts of labeled training data, computational resources, and expertise in designing and training the models. Additionally, the selection of suitable features, handling of noisy or incomplete data, and interpretability of the models remain ongoing research challenges in the field [33].

5 Evaluation and Comparison of Techniques

The evaluation and comparison of ontology matching techniques are essential to assess their performance, effectiveness, and suitability for different scenarios. This section discusses the metrics, evaluation datasets, and considerations for evaluating and comparing these techniques.

5.1 Performance Metrics and Evaluation Datasets

Various metrics are employed to measure the performance of ontology matching techniques. Commonly used metrics include precision, recall, F-measure, and accuracy. Precision measures the proportion of correctly matched entities out of the total matched entities, while recall quantifies the proportion of correctly matched entities out of the existing correspondences. F-measure combines precision and recall into a metric that provides a balanced evaluation. Accuracy measures the overall correctness of the matching results, considering both true positives and negatives.

Researchers typically employ benchmark datasets to evaluate and compare techniques, consisting of pairs of ontologies with known correspondences. Prominent datasets used for evaluation include OAEI (Ontology Alignment Evaluation Initiative) datasets. These datasets cover various domains and represent diverse characteristics, allowing for a comprehensive assessment of techniques under different scenarios. Additionally, real-world ontologies and manually curated datasets can be used to evaluate techniques in specific application contexts.

5.2 Comparative Analysis of Techniques

Comparing ontology matching techniques involves analyzing their performance across multiple dimensions. Key aspects to consider include precision, recall, F-measure, and accuracy values achieved by each technique. Additionally, it is crucial to evaluate their scalability, robustness to noise or missing data, computational efficiency, and usability in practical scenarios. Comparisons may also include analyzing the impact of different ontological characteristics, such as ontology size, complexity, and heterogeneity, on the performance of the techniques.

Comparative analysis may involve conducting experiments using different techniques on the same datasets and reporting the results. Statistical significance tests, such as t-tests, can be employed to determine if the performance differences between techniques are statistically significant. Visualization techniques, such as precision-recall curves or ROC (Receiver Operating Characteristic) curves, can also provide a graphical representation of the comparative performance.

For example, Figure 2 depicts a precision-recall curve, which is a graphical representation of the performance of a binary classification model in ontology matching. The precision-recall curve illustrates the trade-off between precision (y-axis) and recall (x-axis) for different decision thresholds or retrieval cutoffs.

In the figure, the x-axis represents the recall, which is the proportion of relevant cases that are correctly retrieved. The y-axis represents the precision, which is the proportion of relevant retrieved cases.

The curve is formed by connecting several points on the graph. Each point represents a specific precision-recall pair the model achieves at a particular decision threshold or retrieval cutoff. The curve shows how precision changes as recall varies. In the example, the curve starts from the origin (0,0) and gradually rises towards the top-right corner. This indicates that as the recall increases, the precision initially rises and then stabilizes or may decrease. Along the curve, the

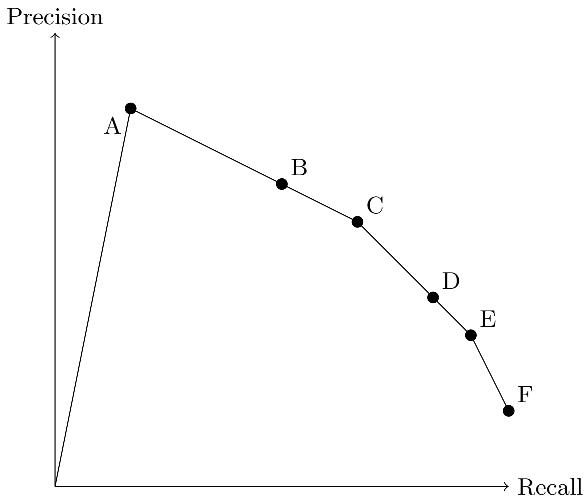

Fig. 2.

labeled points (A, B, C, D, E, and F) represent specific operating points. For example, point A represents a high precision achieved at a relatively low recall, while point F represents a relatively lower precision achieved at a high recall.

The precision-recall curve also helps evaluate and compare different classification or retrieval models. It provides insights into the model's performance across various decision thresholds, allowing one to select an appropriate operating point based on specific requirements. Typically, models that achieve higher precision at lower recall levels are preferred when precision is paramount. At the same time, models that maintain higher precision at higher recall levels are desired for tasks where recall is crucial. It is possible to assess the trade-off between precision and recall and make informed decisions about the model's performance and suitability for a given task by analyzing the precision-recall curve.

However, the choice of evaluation metrics and datasets should align with the ontology matching task's specific goals, requirements, and characteristics. The evaluation process should be transparent, reproducible and consider the limitations and assumptions of the compared techniques. Researchers and practitioners can gain insights into different approaches' strengths, weaknesses, and applicability by evaluating and comparing ontology matching techniques. This information can guide the selection and adaptation of techniques for specific use cases.

6 Impact of Ontological Characteristics

The characteristics of ontologies, such as their size, complexity, and heterogeneity, can significantly impact the performance and effectiveness of ontology matching techniques. Understanding and addressing the implications of these characteristics is crucial for selecting appropriate matching approaches and improving the overall matching results. This section discusses the impact of ontological aspects and the challenges they pose in ontology matching.

6.1 Size of Ontologies

The size of ontologies can vary significantly, ranging from small-scale ontologies with a few concepts to large-scale ontologies with thousands or even millions of entities [37]. The size of ontologies affects the scalability and efficiency of matching techniques. Matching large-scale ontologies can be computationally expensive and require specialized algorithms or optimization strategies to handle the complexity. Efficient and scalable methods are necessary to ensure practical usability.

6.2 Complexity of Ontologies

Ontologies can exhibit varying levels of complexity depending on the richness of their structure, the number of relationships, and the presence of logical axioms or constraints. Complex ontologies may include multiple inheritance hierarchies, qualified cardinality restrictions, or higher-order logic expressions. Matching complex ontologies requires handling intricate relationships, capturing logical constraints, and reasoning with expressive ontological languages. Developing techniques that effectively address complex ontologies is an ongoing research challenge [38].

6.3 Heterogeneity of Ontologies

Heterogeneity arises when ontologies originate from different sources or have been developed independently. Heterogeneous ontologies can differ in their terminology, conceptualizations, and modeling choices. Semantic mismatches, such as synonymy, polysemy, or differences in granularity, may occur, making the alignment task more challenging [39]. Matching techniques must be robust to handle heterogeneity and accommodate variations in representation and terminology across ontologies. Approaches that consider contextual information, or use adaptable similarity measures can effectively address the heterogeneity challenge.

6.4 Multilinguality and Multiculturalism

Ontologies may also exhibit multilingual or multicultural characteristics, expressing concepts and labels in different languages or cultural contexts [40]. Matching multilingual or multicultural ontologies requires techniques for handling cross-lingual or cross-cultural semantic relationships [41]. Language-aware matching techniques can address this challenge by leveraging machine translation, cross-lingual resources, or other kinds of background knowledge [42,**?**].

Determining linguistic and cultural variations is necessary to achieve culturally-sensitive ontology alignments.

Addressing the impact of ontological characteristics requires the development of techniques that are scalable, efficient, capable of handling complexity, robust to heterogeneity, and adaptable to linguistic and cultural variations. Additionally, the evaluation of ontology matching techniques should consider these characteristics to assess their performance in real-world scenarios.

7 Challenges and Open Research Directions

Ontology matching is a complex task that poses several challenges due to the diverse nature of ontologies, the evolving semantic landscape, and the increasing scale of data. Addressing these challenges is crucial for advancing the field and improving the accuracy and efficiency of ontology matching techniques [43]. This section highlights some key challenges and suggests open research directions for future exploration.

7.1 Semantic Heterogeneity and Interoperability

Semantic heterogeneity arises from the differences in terminology, conceptualizations, and domain-specific interpretations across ontologies. Developing techniques that effectively handle semantic heterogeneity and ensure interoperability between ontologies from different domains or communities is a significant challenge [44]. Future research should explore advanced semantic matching approaches that can capture nuanced relationships, accommodate varying levels of granularity, and handle complex linguistic variations.

7.2 Scalability and Efficiency

With the increasing size and complexity of ontologies, scalability and efficiency have become critical factors in ontology matching. Techniques capable of handling large-scale ontologies with millions of entities and complex relationships are needed. Research should focus on developing scalable algorithms, leveraging parallel and distributed computing [45], and employing indexing and compression techniques to improve the efficiency of matching processes.

7.3 Dynamic and Evolving Ontologies

Ontologies are dynamic entities that evolve due to updates, additions, or modifications. Keeping ontology alignments up to date in the face of evolving ontologies is challenging. Techniques that can adapt to ontological changes, efficiently update alignments, and detect and handle concept drift or concept evolution are required [46]. Research should explore incremental matching approaches that can incrementally update alignments based on changes in ontologies or leverage machine learning techniques to adapt to evolving ontologies.

7.4 Handling Big Data and Linked Data

The increasing volume and diversity of data present challenges for ontology matching. Big data environments, where large amounts of data need to be processed and matched, require efficient and scalable matching techniques. Additionally, where ontologies are interconnected through semantic links, linked data poses challenges in effectively capturing and utilizing these relationships [47]. Future research should focus on developing techniques that can handle big data environments, leverage distributed and parallel computing frameworks, and exploit the interconnectedness of linked data for improved matching results.

7.5 Explainability and Interpretability

As ontology matching techniques become more sophisticated, the need for explainability and interpretability becomes crucial [48]. Users must understand and trust the matching results, especially in critical domains. Research should develop techniques that provide transparent explanations of the matching process, enable users to interpret and validate the results, and support interactions to ensure trust and confidence in the matching outcomes [49].

7.6 Domain-specific Matching

Different domains may have specific requirements and characteristics for ontology matching. Research should explore domain-specific matching techniques that capture domain-specific semantics, leverage domain-specific resources, and address domain-specific challenges [50]. Customization of matching approaches to specific application domains can significantly improve the accuracy and relevance of the alignments.

Addressing these challenges and exploring these research directions will contribute to advancing ontology matching techniques and enable their effective utilization in real-world applications. Continued collaboration between researchers, practitioners, and domain experts is crucial to addressing these challenges.

8 Conclusion

We have provided an overview of classic and modern techniques for ontology matching. We have seen classic techniques, including linguistic-based, structure-based, and instance-based approaches, which leverage lexical, structural, and instance information for matching. We also explored modern techniques, such as machine learning-based and deep learning-based approaches, which harness the power of data-driven methodologies to capture complex relationships.

We have discussed the importance of evaluating and comparing ontology matching techniques, highlighting the metrics, evaluation datasets, and considerations involved in the evaluation process. Furthermore, we have emphasized the impact of characteristics such as the size, complexity, and heterogeneity of ontologies, on the performance of matching techniques.

We have also outlined the open challenges, including semantic heterogeneity, scalability, evolving ontologies, handling big data and linked data, and the need for explainability and interpretability. We have suggested open research directions that address these challenges, such as developing semantic interoperability and scalability techniques, handling evolving ontologies, and improving explainability and interpretability.

The field of ontology matching is constantly shifting and developing, and it is making steady progress thanks to the combination of diverse techniques. The development of ontology matching strategies that are more accurate, efficient, and domain-specific will be aided by combining traditional and modern methods, considering ontological traits, and addressing issues related to these factors.

References

1. J. Euzenat and P. Shvaiko, *Ontology matching.* Springer, 2007.
2. D. Aumueller, H. H. Do, S. Massmann, and E. Rahm, "Schema and ontology matching with COMA++," in *Proceedings of the ACM SIGMOD International Conference on Management of Data, Baltimore, Maryland, USA, June 14-16, 2005* (F. Özcan, ed.), pp. 906–908, ACM, 2005.
3. A. Gal, H. Roitman, and T. Sagi, "From diversity-based prediction to better ontology & schema matching," in *Proceedings of the 25th International Conference on World Wide Web, WWW 2016, Montreal, Canada, April 11 - 15, 2016* (J. Bourdeau, J. Hendler, R. Nkambou, I. Horrocks, and B. Y. Zhao, eds.), pp. 1145–1155, ACM, 2016.
4. L. Otero-Cerdeira, F. J. Rodríguez-Martínez, and A. Gómez-Rodríguez, "Ontology matching: A literature review," *Expert Syst. Appl.*, vol. 42, no. 2, pp. 949–971, 2015.
5. J. Martinez-Gil, "Automated knowledge base management: A survey," *Comput. Sci. Rev.*, vol. 18, pp. 1–9, 2015.
6. K. Kotis and M. Lanzenberger, "Ontology matching: Current status, dilemmas and future challenges," in *Second International Conference on Complex, Intelligent and Software Intensive Systems (CISIS-2008), March 4th-7th, 2008, Technical University of Catalonia, Barcelona, Spain* (F. Xhafa and L. Barolli, eds.), pp. 924–927, IEEE Computer Society, 2008.
7. I. F. Cruz, C. Stroe, C. Pesquita, F. M. Couto, and V. Cross, "Biomedical ontology matching using the agreementmaker system," in *Proceedings of the 2nd International Conference on Biomedical Ontology, Buffalo, NY, USA, July 26-30, 2011* (O. Bodenreider, M. E. Martone, and A. Ruttenberg, eds.), vol. 833 of *CEUR Workshop Proceedings*, CEUR-WS.org, 2011.
8. V. Mascardi, A. Locoro, and P. Rosso, "Automatic ontology matching via upper ontologies: A systematic evaluation," *IEEE Trans. Knowl. Data Eng.*, vol. 22, no. 5, pp. 609–623, 2010.
9. C. Meilicke and H. Stuckenschmidt, "Applying logical constraints to ontology matching," in *KI 2007: Advances in Artificial Intelligence, 30th Annual German Conference on AI, KI 2007, Osnabrück, Germany, September 10-13, 2007, Proceedings* (J. Hertzberg, M. Beetz, and R. Englert, eds.), vol. 4667 of *Lecture Notes in Computer Science*, pp. 99–113, Springer, 2007.
10. M. Niepert, C. Meilicke, and H. Stuckenschmidt, "A probabilistic-logical framework for ontology matching," in *Proceedings of the Twenty-Fourth AAAI Conference*

on Artificial Intelligence, AAAI 2010, Atlanta, Georgia, USA, July 11-15, 2010 (M. Fox and D. Poole, eds.), AAAI Press, 2010.
11. S. Zghal, S. B. Yahia, E. M. Nguifo, and Y. Slimani, "SODA: an OWL-DL based ontology matching system," in *Proceedings of the 2nd International Workshop on Ontology Matching (OM-2007) Collocated with the 6th International Semantic Web Conference (ISWC-2007) and the 2nd Asian Semantic Web Conference (ASWC-2007), Busan, Korea, November 11, 2007* (P. Shvaiko, J. Euzenat, F. Giunchiglia, and B. He, eds.), vol. 304 of *CEUR Workshop Proceedings*, CEUR-WS.org, 2007.
12. D. Faria, C. Pesquita, E. Santos, M. Palmonari, I. F. Cruz, and F. M. Couto, "The agreementmakerlight ontology matching system," in *On the Move to Meaningful Internet Systems: OTM 2013 Conferences - Confederated International Conferences: CoopIS, DOA-Trusted Cloud, and ODBASE 2013, Graz, Austria, September 9-13, 2013. Proceedings* (R. Meersman, H. Panetto, T. S. Dillon, J. Eder, Z. Bellahsene, N. Ritter, P. D. Leenheer, and D. Dou, eds.), vol. 8185 of *Lecture Notes in Computer Science*, pp. 527–541, Springer, 2013.
13. Q. Ji, W. Liu, G. Qi, and D. A. Bell, "LCS: A linguistic combination system for ontology matching," in *Knowledge Science, Engineering and Management, First International Conference, KSEM 2006, Guilin, China, August 5-8, 2006, Proceedings* (J. Lang, F. Lin, and J. Wang, eds.), vol. 4092 of *Lecture Notes in Computer Science*, pp. 176–189, Springer, 2006.
14. J. Martinez-Gil, I. Navas-Delgado, and J. F. Aldana-Montes, "Maf: An ontology matching framework," *J. Univers. Comput. Sci.*, vol. 18, no. 2, pp. 194–217, 2012.
15. W. Hu and Y. Qu, "Falcon-ao: A practical ontology matching system," *J. Web Semant.*, vol. 6, no. 3, pp. 237–239, 2008.
16. J. Martinez-Gil and J. F. Aldana-Montes, "Evaluation of two heuristic approaches to solve the ontology meta-matching problem," *Knowl. Inf. Syst.*, vol. 26, no. 2, pp. 225–247, 2011.
17. J. Martinez-Gil and J. F. Aldana-Montes, "An overview of current ontology meta-matching solutions," *Knowl. Eng. Rev.*, vol. 27, no. 4, pp. 393–412, 2012.
18. E. Jiménez-Ruiz and B. C. Grau, "Logmap: Logic-based and scalable ontology matching," in *The Semantic Web - ISWC 2011 - 10th International Semantic Web Conference, Bonn, Germany, October 23-27, 2011, Proceedings, Part I* (L. Aroyo, C. Welty, H. Alani, J. Taylor, A. Bernstein, L. Kagal, N. F. Noy, and E. Blomqvist, eds.), vol. 7031 of *Lecture Notes in Computer Science*, pp. 273–288, Springer, 2011.
19. P. J. Ochieng and S. Kyanda, "Large-scale ontology matching: State-of-the-art analysis," *ACM Comput. Surv.*, vol. 51, no. 4, pp. 75:1–75:35, 2018.
20. M. Mohammadi, W. Hofman, and Y. Tan, "SANOM-HOBBIT: simulated annealing-based ontology matching on HOBBIT platform," *Knowl. Eng. Rev.*, vol. 35, p. e13, 2020.
21. Y. Zhang, X. Wang, S. Lai, S. He, K. Liu, J. Zhao, and X. Lv, "Ontology matching with word embeddings," in *Chinese Computational Linguistics and Natural Language Processing Based on Naturally Annotated Big Data - 13th China National Conference, CCL 2014, and Second International Symposium, NLP-NABD 2014, Wuhan, China, October 18-19, 2014. Proceedings* (M. Sun, Y. Liu, and J. Zhao, eds.), vol. 8801 of *Lecture Notes in Computer Science*, pp. 34–45, Springer, 2014.
22. E. Jiménez-Ruiz, B. C. Grau, Y. Zhou, and I. Horrocks, "Large-scale interactive ontology matching: Algorithms and implementation," in *ECAI 2012 - 20th European Conference on Artificial Intelligence. Including Prestigious Applications of Artificial Intelligence (PAIS-2012) System Demonstrations Track, Montpellier, France, August 27-31 , 2012* (L. D. Raedt, C. Bessiere, D. Dubois, P. Doherty, P. Frasconi,

F. Heintz, and P. J. F. Lucas, eds.), vol. 242 of *Frontiers in Artificial Intelligence and Applications*, pp. 444–449, IOS Press, 2012.
23. A. Doan, J. Madhavan, P. M. Domingos, and A. Y. Halevy, "Ontology matching: A machine learning approach," in *Handbook on Ontologies* (S. Staab and R. Studer, eds.), International Handbooks on Information Systems, pp. 385–404, Springer, 2004.
24. S. Amrouch, S. Mostefai, and M. Fahad, "Decision trees in automatic ontology matching," *Int. J. Metadata Semant. Ontologies*, vol. 11, no. 3, pp. 180–190, 2016.
25. M. Rubiolo, M. L. Caliusco, G. Stegmayer, M. Coronel, and M. G. Fabrizi, "Knowledge discovery through ontology matching: An approach based on an artificial neural network model," *Inf. Sci.*, vol. 194, pp. 107–119, 2012.
26. X. Xue, C. Jiang, J. Zhang, and C. Hu, "Biomedical ontology matching through attention-based bidirectional long short-term memory network," *J. Database Manag.*, vol. 32, no. 4, pp. 14–27, 2021.
27. M. A. Khoudja, M. Fareh, and H. Bouarfa, "Deep embedding learning with autoencoder for large-scale ontology matching," *Int. J. Semantic Web Inf. Syst.*, vol. 18, no. 1, pp. 1–18, 2022.
28. F. Giunchiglia, M. Yatskevich, P. Avesani, and P. Shvaiko, "A large dataset for the evaluation of ontology matching," *Knowl. Eng. Rev.*, vol. 24, no. 2, pp. 137–157, 2009.
29. K. Eckert, C. Meilicke, and H. Stuckenschmidt, "Improving ontology matching using meta-level learning," in *The Semantic Web: Research and Applications, 6th European Semantic Web Conference, ESWC 2009, Heraklion, Crete, Greece, May 31-June 4, 2009, Proceedings* (L. Aroyo, P. Traverso, F. Ciravegna, P. Cimiano, T. Heath, E. Hyvönen, R. Mizoguchi, E. Oren, M. Sabou, and E. P. B. Simperl, eds.), vol. 5554 of *Lecture Notes in Computer Science*, pp. 158–172, Springer, 2009.
30. L. Zhao and R. Ichise, "Aggregation of similarity measures in ontology matching," in *Proceedings of the 5th International Workshop on Ontology Matching (OM-2010), Shanghai, China, November 7, 2010* (P. Shvaiko, J. Euzenat, F. Giunchiglia, H. Stuckenschmidt, M. Mao, and I. F. Cruz, eds.), vol. 689 of *CEUR Workshop Proceedings*, CEUR-WS.org, 2010.
31. J. Wang, Z. Ding, and C. Jiang, "GAOM: genetic algorithm based ontology matching," in *Proceedings of The 1st IEEE Asia-Pacific Services Computing Conference, APSCC 2006, December 12-15, 2006, Guangzhou, China*, pp. 617–620, IEEE Computer Society, 2006.
32. J. Martinez-Gil, E. Alba, and J. F. Aldana-Montes, "Optimizing ontology alignments by using genetic algorithms," in *Proceedings of the First International Workshop on Nature Inspired Reasoning for the Semantic Web, Karlsruhe, Germany, October 27, 2008* (C. Guéret, P. Hitzler, and S. Schlobach, eds.), vol. 419 of *CEUR Workshop Proceedings*, CEUR-WS.org, 2008.
33. J. Martinez-Gil and J. M. Chaves-Gonzalez, "Interpretable ontology meta-matching in the biomedical domain using mamdani fuzzy inference," *Expert Syst. Appl.*, vol. 188, p. 116025, 2022.
34. D. Ngo and Z. Bellahsene, "YAM++ : A multi-strategy based approach for ontology matching task," in *Knowledge Engineering and Knowledge Management - 18th International Conference, EKAW 2012, Galway City, Ireland, October 8-12, 2012. Proceedings* (A. ten Teije, J. Völker, S. Handschuh, H. Stuckenschmidt, M. d'Aquin, A. Nikolov, N. Aussenac-Gilles, and N. Hernandez, eds.), vol. 7603 of *Lecture Notes in Computer Science*, pp. 421–425, Springer, 2012.
35. Z. Lv and R. Peng, "A novel meta-matching approach for ontology alignment using grasshopper optimization," *Knowl. Based Syst.*, vol. 201-202, p. 106050, 2020.

36. É. Thiéblin, O. Haemmerlé, N. Hernandez, and C. Trojahn, "Survey on complex ontology matching," *Semantic Web*, vol. 11, no. 4, pp. 689–727, 2020.
37. Z. Wang, Y. Wang, S. Zhang, G. Shen, and T. Du, "Matching large scale ontology effectively," in *The Semantic Web - ASWC 2006, First Asian Semantic Web Conference, Beijing, China, September 3-7, 2006, Proceedings* (R. Mizoguchi, Z. Shi, and F. Giunchiglia, eds.), vol. 4185 of *Lecture Notes in Computer Science*, pp. 99–105, Springer, 2006.
38. M. Sabou, M. d'Aquin, and E. Motta, "Exploring the semantic web as background knowledge for ontology matching," *J. Data Semant.*, vol. 11, pp. 156–190, 2008.
39. G. Diallo, "An effective method of large scale ontology matching," *J. Biomed. Semant.*, vol. 5, p. 44, 2014.
40. M. A. Helou and M. Palmonari, "Multi-user feedback for large-scale cross-lingual ontology matching," in *Proceedings of the 9th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management - (Volume 2), Funchal, Madeira, Portugal, November 1-3, 2017* (D. Aveiro, J. L. G. Dietz, and J. Filipe, eds.), pp. 57–66, SciTePress, 2017.
41. J. Chen, X. Xue, Y. Huang, and X. Zhang, "Interactive cross-lingual ontology matching," *IEEE Access*, vol. 7, pp. 79095–79102, 2019.
42. A. N. Tigrine, Z. Bellahsene, and K. Todorov, "Selecting optimal background knowledge sources for the ontology matching task," in *Knowledge Engineering and Knowledge Management - 20th International Conference, EKAW 2016, Bologna, Italy, November 19-23, 2016, Proceedings* (E. Blomqvist, P. Ciancarini, F. Poggi, and F. Vitali, eds.), vol. 10024 of *Lecture Notes in Computer Science*, pp. 651–665, 2016.
43. P. Shvaiko and J. Euzenat, "Ontology matching: State of the art and future challenges," *IEEE Trans. Knowl. Data Eng.*, vol. 25, no. 1, pp. 158–176, 2013.
44. X. Xue, H. Yang, J. Zhang, J. Zhang, and D. Chen, "An automatic biomedical ontology meta-matching technique," *J. Netw. Intell.*, vol. 4, no. 3, pp. 109–113, 2019.
45. M. Gulic, B. Vrdoljak, and M. Pticek, "Automatically specifying a parallel composition of matchers in ontology matching process by using genetic algorithm," *Inf.*, vol. 9, no. 6, p. 138, 2018.
46. J. Martinez-Gil and J. F. Aldana-Montes, "Reverse ontology matching," *SIGMOD Rec.*, vol. 39, no. 4, pp. 5–11, 2010.
47. F. Scharffe and J. Euzenat, "Linked data meets ontology matching - enhancing data linking through ontology alignments," in *KEOD 2011 - Proceedings of the International Conference on Knowledge Engineering and Ontology Development, Paris, France, 26-29 October, 2011* (J. Filipe and J. L. G. Dietz, eds.), pp. 279–284, SciTePress, 2011.
48. J. Martinez-Gil and J. M. Chaves-Gonzalez, "A novel method based on symbolic regression for interpretable semantic similarity measurement," *Expert Syst. Appl.*, vol. 160, p. 113663, 2020.
49. W. Hu and Y. Qu, "Falcon-ao: A practical ontology matching system," *Journal of web semantics*, vol. 6, no. 3, pp. 237–239, 2008.
50. I. F. Cruz, A. Fabiani, F. Caimi, C. Stroe, and M. Palmonari, "Automatic configuration selection using ontology matching task profiling," in *The Semantic Web: Research and Applications - 9th Extended Semantic Web Conference, ESWC 2012, Heraklion, Crete, Greece, May 27-31, 2012. Proceedings* (E. Simperl, P. Cimiano, A. Polleres, Ó. Corcho, and V. Presutti, eds.), vol. 7295 of *Lecture Notes in Computer Science*, pp. 179–194, Springer, 2012.