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ONTOLOGY MATCHING USING DEEP LEARNING

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ABSTRACT

Ontology matching is a critical task in knowledge representation and integration, with numerous applications in various domains. Deep learning methods have shown promising results in improving the accuracy and efficiency of ontology matching. However, there is a lack of comprehensive analysis and classification of these methods in the literature. In this paper, we conducted a systematic literature review of ontology matching using deep learning methods, covering articles published between 2005 and 2022. Our analysis includes a trend analysis of the articles, a framework for classifying them, and a detailed classification of the articles based on the deep learning method used.

Keywords: *Ontology Matching, Ontology Alignment, Literature Review, Deep Learning, Word Embedding*

1. INTRODUCTION

Ontology matching involves finding connections between concepts or entities in different ontologies. This process, also known as ontology alignment or mapping, is crucial in the semantic web field as it enables the integration of different ontologies and facilitates the exchange of data between them. Essentially, ontology matching aims to establish correspondences between concepts in different ontologies.

One approach to ontology matching is to use deep learning methods, which have been shown to be effective in a variety of natural language processing tasks. In particular, deep learning can be used to learn distributed representations of the concepts and entities in the ontologies, which can then be compared to identify correspondences.

A number of studies have investigated the use of deep learning for ontology matching and demonstrated its potential for improving the accuracy and efficiency of this task. For example, some studies have used Recursive Neural Networks (RvNNs) [1] or convolutional neural networks (CNNs) [2] to learn the semantic relationships between concepts in ontologies and have used these learned representations to identify correspondences. Other studies have employed attention mechanisms [3][4][5] to focus on relevant concepts and improve the performance of the ontology matching process.

Overall, the use of deep learning in ontology matching shows promise for improving the accuracy and efficiency of this important task in the semantic web. Further research is needed to continue to develop and refine these methods, and to explore their potential applications in a variety of domains.

In recent years, deep learning methods have been applied to ontology matching. Deep learning is a type of machine learning that uses artificial neural networks to learn from data. It has been used in many areas, such as natural language processing, computer vision, and speech recognition. In this paper, we review the literature on ontology matching using deep learning methods. We discuss existing approaches, algorithms, and tools for ontology matching. We also discuss the evaluation of ontology matching systems and the challenges that remain in this field, our study aims to address the following research questions:

1. What are the most used deep learning methods for ontology matching?

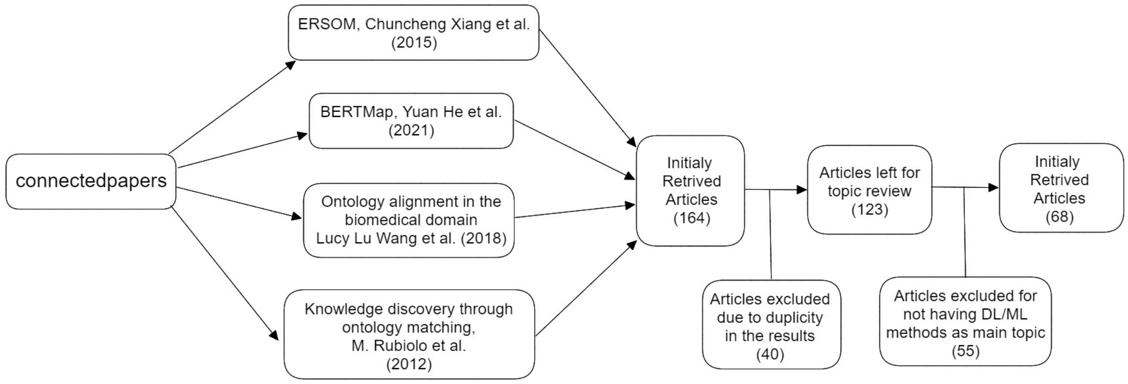

Figure 1 Methods for Identifying Relevant Articles for a Literature Review

2. What are the advantages and limitations of each deep learning method?
3. How has the use of deep learning methods for ontology matching evolved over time?
4. What are the gaps in the existing research and what opportunities exist for future research in the field?

While previous studies (Lorena OteroCerdeira et al. 2015 [6], P. Shvaiko et al. 2013, Inne Gartina Husein et al. 2016 [7], and Meriem Ali Khoudja et al. 2018 [8]) have addressed the ontology matching problem, they primarily focused on traditional machine learning methods and only covered articles until 2017 with little to low coverage on Deep learning methods. In contrast, our study is a comprehensive deep dive into deep learning methods for ontology matching tasks, covering articles published between 2005 and 2022. By conducting a systematic literature review and detailed classification, we aim to identify gaps in the existing research, highlight novel approaches and techniques, and provide insights for future research in the field. Our study's achievement lies in providing a framework for selecting the most suitable deep learning method for ontology matching tasks and serving as a foundation for further research in this area.

2. METHODOLOGY

To begin the process of conducting a literature review on ontology matching using deep learning, we used connectedpapers.com to search for articles that were similar to the following four articles:

- ERSOM: A Structural Ontology Matching Approach Using Automatically Learned Entity Representation [9]
- BERTMap: A BERT-based Ontology Alignment System [10]
- Ontology alignment in the biomedical domain using entity definitions and context [11]
- Knowledge discovery through ontology matching: An approach based on an Artificial Neural Network model [12]

In this paper, we provide a comprehensive review of the literature on ontology matching using deep learning methods. We discussed existing approaches, algorithms and tools for ontology matching. The focus of this paper is on the challenges that remain in this field and how they can be solved through deep learning techniques. The objective of this study is to focus mainly on journal articles and conference proceedings published within the last 17 years, as shown in figure 1. However, it is decided to exclude other publication forms and, focusing only on journal articles and conference proceedings, then we aimed to capture the majority of research papers published on the topic of ontology matching using deep learning.

Our initial search retrieved 164 articles, of which we selected four for further evaluation. We then excluded 40 articles from our review due to duplicity in the results, leaving us with 123 articles for topic review. This represented 75.6% of the initial number of articles. Of these, we further excluded 53 articles that did not have deep learning or machine learning methods as the main focus of their research. This left us with a total of 70 articles, representing 43.3% of the initial number of articles, for our literature review.

Next, we evaluated the relevance and significance of the identified papers to the topic of ontology matching using deep learning. This involved assessing the research methods and results of each paper, as well as their contributions to the field. We also noted any common themes or trends

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in the literature, as well as any gaps or areas for further research.

Once the relevant papers had been identified and evaluated, we organized and synthesized the findings into a coherent narrative. This involved summarizing the key findings of each paper and discussing their implications for the field of ontology matching using deep learning. We also provided our own analysis and interpretation of the literature, highlighting any key trends or themes, and making recommendations for future research.

Overall, the methodology for our literature review on ontology matching using deep learning involved using connectedpapers.com to identify relevant research papers, evaluating their relevance and significance, and synthesizing the findings into a coherent narrative. This provided a comprehensive overview of the current state of the field and identified areas for future research and development.

3. RESULT AND DISCUSSION

In this section, statistical information about a set of articles is presented and discussed. The articles were analyzed based on their publication year and the database from which they were obtained. Specifically, the number of articles published in each year and the percentage of the total number of articles that each year's articles represent are presented. The data is sorted by publication year, and a trend in the number of articles published over time can be observed.

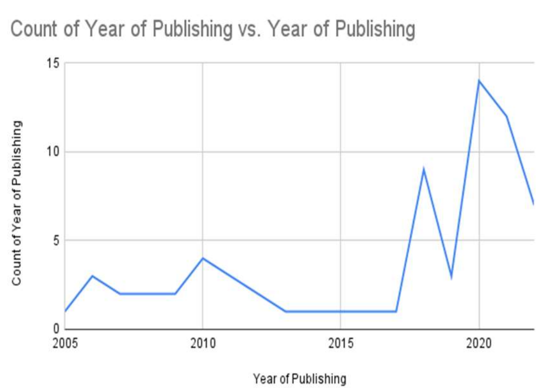

Figure 2 Articles Organized by year of publication

The graph in Figure 2 illustrates the trend of the number of articles over the years of their publication. The data for this trend is presented in Table 1. Based on the data provided in the table, it can be observed that the number of articles published in the field has fluctuated over the years. In the early years (2005-2012), the number of articles published was relatively low, with a sharp increase in the number of articles published in more recent years (2018-2022). The highest number of articles was published in 2020, with 14 articles, representing 20.59% of the total. The second highest number of articles was published in 2021, with 12 articles, representing 17.65% of the total.

The trend of increasing numbers of ontology matching articles based on deep learning methods in recent years (2018-2022) compared to the past (2005-2012) may be due to a number of factors. One possible reason is the increasing availability and accessibility of deep learning algorithms and tools, as well as the growing interest and investment in the field of artificial intelligence and machine learning. Another possible reason is the increased recognition of the effectiveness and efficiency of deep learning approaches in ontology matching tasks, which may have led to a shift in research focus and resources towards these methods. Additionally, the increasing volume and complexity of data being generated and shared across different domains may have also contributed to the growing interest in and demand for robust and scalable ontology matching solutions based on deep learning. Further research and analysis may be needed to fully understand and explain the trend observed in the data.

Overall, it appears that there has been a steady increase in the number of articles published in recent years, with a particularly pronounced increase in the number of articles published in 2018 and 2020. This increasing trend reflects the global interest of the research community in the field.

It's worth noting that the data provided only covers the years 2005–2022, and it is possible that the trend of increasing numbers of articles published may continue in the future.

Table 1 Distribution Of Articles By Year Of Publication

Year of Publishing	Count	Percentage
2005	1	1.47%
2006	3	4.41%
2007	2	2.94%
2008	2	2.94%
2009	2	2.94%
2010	4	5.88%
2011	3	4.41%
2012	2	2.94%
2013	1	1.47%

2014	1	1.47%
2015	1	1.47%
2017	1	1.47%
2018	9	13.24%
2019	3	4.41%
2020	14	20.59%
2021	12	17.65%
2022	7	10.29%
Grand Total	68	100%

4. CLASSIFICATION

Based on the analysis of the articles selected for the literature review, we have developed a framework for classifying them. This framework, depicted in figure 4, identifies 4 different types of methods the articles based on. The different categories we identified cover the most prominent deep learning-based techniques for ontology matching and include deep neural networks, Graph Representation methods, word embedding methods, and self-attention methods. This framework helps to organize and understand the articles in the literature review and provides a useful tool for further research in the field. In this research, we have classified the papers based on the following five categories:

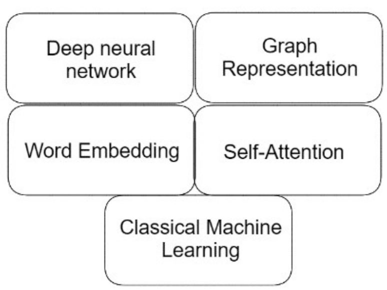

Figure 3 Classification System

- Deep neural networks (DNNs): Papers that focus on using deep neural networks, a type of machine learning model that consists of multiple layers of interconnected nodes, for ontology matching tasks.
- Graph Representation (GR): Papers that focus on using techniques to represent nodes in a graph in a continuous vector space for ontology matching tasks.
- Word embedding (WE): Papers that focus on using techniques to represent words or phrases in a continuous vector space for ontology matching tasks.
- Self-attention (SA): Papers that focus on using techniques that allow a machine learning model to attend to different parts of the input data at different times while processing it for ontology matching tasks.
- Classical machine learning (CML): Papers that focus on using traditional machine learning methods, such as decision trees, support vector machines, or logistic regression, for ontology matching tasks.

Table 2 and Figure 4 shows the distribution of articles in the dataset according to the deep learning method used. The most common approach is Deep Neural Networks, with 21 articles representing 30.88% of the total. The second most common approach is Word Embedding, with 15 articles representing 22.06% of the total. Self-Attention is the third most common approach, with 10 articles representing 14.71% of the total. Graph Representation is the fourth most common approach, with 13 articles representing 19.12% of the total. Finally, Classical Machine Learning is the fifth most common approach, with 9 articles representing 13.24% of the total.

Overall, the data suggests that Deep Neural Networks and Word Embedding are the most popular approaches for ontology matching using deep learning methods. This is likely due to the effectiveness and versatility of these approaches in various tasks, as well as the availability of resources and tools for implementing them. The relatively lower usage of Self-Attention, Graph Representation may be due to the specific requirements and limitations of these approaches, such as the need for more computing power and scalability issues. Additionally, the availability of alternative solutions that may be more suitable for certain ontology matching tasks may also be a factor. Further research and analysis may be needed to understand the factors influencing the adoption and usage of different deep learning approaches in ontology matching.

Table 2 Articles organized by deep learning method

Approach	Count of Paper	Percentage
Deep Neural Network	21	30.88%
Word Embedding	15	22.06%
Self-Attention	10	14.71%
Graph Representation	13	19.12%
Classical Machine learning	9	13.24%
Grand Total	68	100%

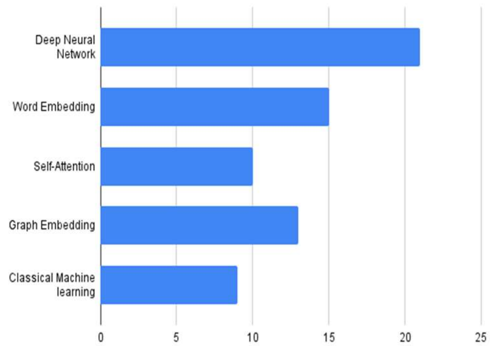

Figure 4 Number of Articles per deep learning method

Table 3 presents the classification results for the articles in the dataset, sorted by year of publication. It includes the number of articles that fall into each category and the percentage of total articles published in that year. The data is also depicted visually in Figure 5, which allows for easier identification of trends and patterns over time.

Table 3 Results of the Classification

Year	DNN	WE	GR	SA	CML	Total	Prc.
2005	1	-	-	-	-	1	1.47
2006	1	-	-	-	2	3	4.41
2007	2	-	-	-	-	2	2.94
2008	1	-	-	-	1	2	2.94
2009	1	-	-	-	1	2	2.94
2010	3	-	-	-	1	4	5.88
2011	1	-	-	-	2	3	4.41
2012	2	-	-	-	-	2	2.94
2013	1	-	-	-	-	1	1.47
2014	-	1	-	-	-	1	1.47
2015	1	-	-	-	-	1	1.47
2017	1	-	-	-	-	1	1.47
2018	1	7	1	-	-	9	13.2
2019	1	2	-	-	-	3	4.41
2020	2	3	5	3	1	14	20.5
2021	2	1	4	5	-	12	17.6
2022	-	1	3	4	1	7	10.2
Total	21	15	13	10	9	68	100

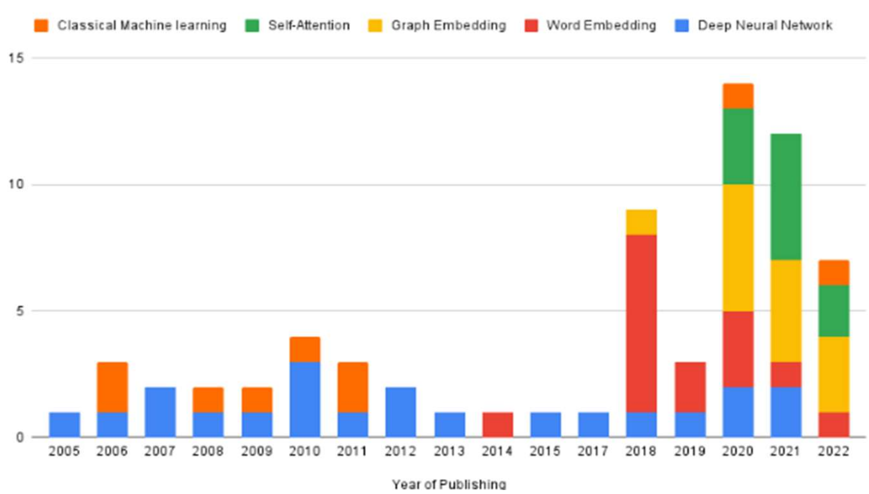

Figure 5 Progress of different categories per year

In the first five years of the table (2005-2010), the number of papers published in the categories of deep neural networks and classical machine learning remained relatively low, with only a few papers published in each category each year. This is in contrast to the category of word embeddings, which saw a steady increase in the number of papers published over this period, reaching a peak of 7 papers in 2018.

The number of papers published in each category reached its peak in the following years: self-attention in 2021 with 5 papers, Graph Representation in 2020 with 5 papers, and classical

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machine learning with a decrease of papers published in the following years.

The trend for each category shows some variation. The number of papers published in the deep neural networks category remained relatively steady from 2005 to 2022, with a slight increase in 2010. This was followed by a decrease in the number of papers published until 2018, after which there was an increase again. The trend for the word embeddings category was a steady increase from 2006 to 2018, with a peak in 2018 and a decrease in the following years. The self-attention category saw a steady increase in the number of papers published from 2018 to 2021, with a peak in 2021. The Graph Representation category had a relatively low number of papers published from 2005 to 2019, followed by a sudden increase in 2020 and a slight decrease in 2021. Finally, the classical machine learning category also saw a low number of papers published from 2005 to 2019, followed by a sudden increase in 2020 and a slight decrease in 2021.

In the following sections, we will delve deeper into the analysis of each of the categories, providing a more detailed description of the papers within each category, with inner classifications for each one of these general categories.

Ontology matching using deep learning techniques propose different approaches for the matching that are implemented in ontology matching algorithms. When building an ontology matching system, different algorithms are usually used, exploiting therefore different ontology matching techniques. In this category two different types of articles have been identified. Some articles are devoted to describing new trained deep learning models, while others make use of such pre-trained deep learning models. In total there are 85 articles in this category, where 32.35% (22 articles) belong to the first group of papers that used a pre-trained deep learning model and 67.64% (46 articles) belong to complex matching techniques. The different matching techniques have been the subject of study in recent years. For the purpose of this review, to sort the matching techniques we proposed the following classification.

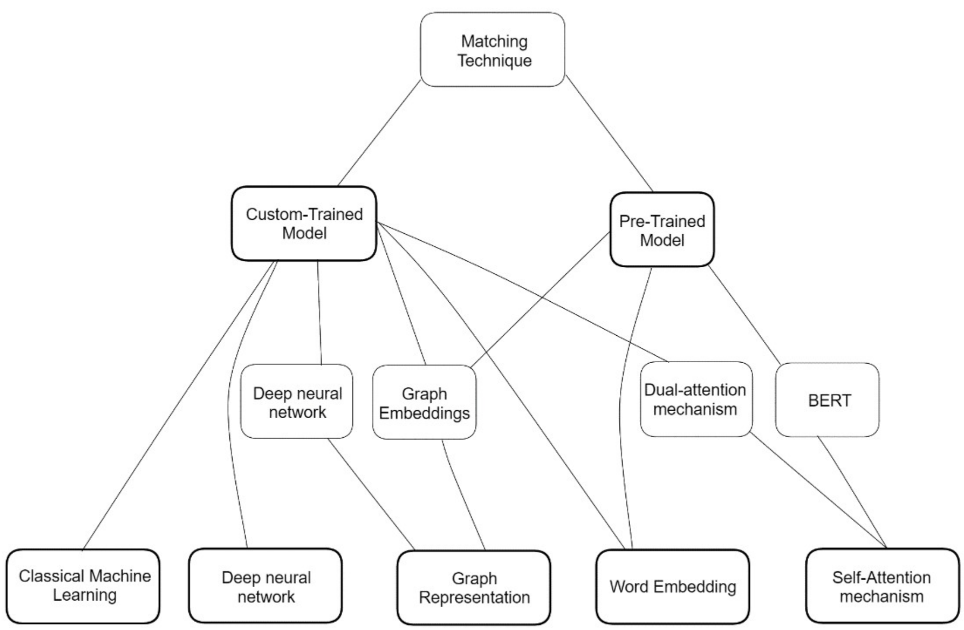

Figure 6 Classification of deep learning matching techniques

4.1 Sections and Subsections

Classical machine learning methods can be used for ontology matching by training a model on a dataset of aligned ontologies and using the trained model to identify correspondences in new ontologies. This can be done using a variety of machine learning algorithms, such as decision trees, support vector machines, or k-nearest neighbors. The trained model can then be used to automatically align new ontologies, improving the interoperability and integration of distributed data sources on the Semantic Web.

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- Combining Ontology Alignment Metrics Using the Data Mining Techniques (Babak Bagheri Hariri et al., 2006) [13]: This paper presents a method for selecting more effective metrics for recognizing relationships between elements of two ontologies using data mining techniques.
- A new Structural Similarity Measure for Ontology Alignment (Babak Bagheri Hariri et al., 2006) [14]: This paper presents a new method for computing structural similarity between ontologies based on the notion of information content. The method is evaluated using precision, recall, and sensitivity analysis from data mining.
- Ontology Mapping: As a Binary Classification Problem (Ming Mao et al., 2008) [15]: This paper proposes a non-instance learning-based approach that transforms the ontology mapping problem to a binary classification problem and utilizes machine learning techniques as a solution. The features proposed in this approach are generic and do not rely on the existence and sufficiency of instances, making it a more general solution that can be applied to different domains without extra training efforts. The approach is evaluated using two experiments, and the results show that it performs well on most OAEI benchmark tests when training and testing on the same mapping task, and the results vary according to the likelihood of training data and testing data when training and testing on different mapping tasks.
- Advancing ontology alignment: new methods for biomedical ontology alignment using non equivalence relations (J. Kalita et al., 2009) [16]: This research aims to advance the state of the art in automated ontology alignment by extending the information that can be derived in ontology alignment, using semantics in conjunction with upper ontologies and other linguistic resources to enhance the alignment process, and investigating scalability issues in aligning large-scale ontologies.
- Recovering uncertain mappings through structural validation and aggregation with the MoTo system (F. Esposito et al., 2010) [17]: An automated ontology matching methodology, supported by various machine learning techniques, as implemented in the system MoTo.
- Composite ontology matching with uncertain mappings recovery (N. Fanizzi et al., 2011) [18]: This paper presents an automated ontology matching methodology, called MoTo, supported by various machine learning techniques. The methodology uses a meta-learner to elicit certain mappings and a validation process to recover uncertain mappings, which are then aggregated through linguistic quantifiers. The methodology is tested on benchmark ontologies and found to be effective.
- A Dynamic Multistrategy Ontology Alignment Framework Based on Semantic Relationship using WordNet (N. V. Shende et al., 2011) [19]: This paper presents a dynamic multistrategy ontology alignment framework that uses WordNet and semantic relationships to improve the accuracy and efficiency of ontology alignment. The framework was evaluated on a variety of ontologies and demonstrated good performance in terms of precision, recall, and efficiency.
- Tool Support for Ontology Design and Quality Assurance (I. Horrocks et al., 2020) [20]: This paper describes the use of machine learning and large-scale knowledge resources to support ontology design and quality assurance, including identifying errors in the FoodOn ontology.
- Machine Learning-Friendly Biomedical Datasets for Equivalence and Subsumption Ontology Matching (Yuan He et al., 2022) [21]: This paper introduces five new biomedical ontology matching tasks and a comprehensive evaluation framework for both machine learning-based and non machine learning-based systems. The tasks involve ontologies extracted from Mondo and UMLS and include both equivalence and subsumption matching. The quality of the reference mappings is ensured through human curation and ontology pruning.

4.2 Graph Representation

The nodes of a graph may be represented as continuous, low-dimensional vectors in a mathematical space using a technique called Graph Representation. These vectors, often referred to as embeddings, record the connections among the graph's nodes and may be used to a number of subsequent tasks, including visualization, link prediction, and node categorization. Graph Representations may be learnt using a variety of

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methods, including matrix factorization, approaches based on random walks, and neural network-based methods. Two subclasses within the Graph Representation class were identified:

4.2.1 Graph Neural Networks

Graph neural networks (GNNs) are a type of neural network that operates on graphs and uses graph embeddings as inputs. GNNs can learn to perform various tasks such as node classification and link prediction by learning to manipulate the graph embeddings through multiple layers of computation.

- DAEOM: A Deep Attentional Embedding Approach for Biomedical Ontology Matching (J. Wu et al., 2020) [22]: This paper presents a deep learning approach for ontology matching that encodes both terminological descriptions and network structure. It also introduces an automatic method for adjusting the final alignment threshold.
- MEDTO: Medical Data to Ontology Matching Using Hybrid Graph Neural Networks (Junheng Hao et al., 2021) [23]: The paper proposes a novel framework for data to ontology matching in the medical domain. The framework, called MEDTO, consists of three innovative techniques: a method for creating a semantically rich ontology from a given medical database, a hyperbolic graph convolution layer that encodes hierarchical concepts in the hyperbolic space, and a heterogeneous graph layer that encodes both local and global context information of a concept. The authors evaluate MEDTO on two real-world medical datasets and a benchmark from the Ontology Alignment Evaluation Initiative, and show significant improvements compared to state-of-the-art methods.
- Ontology Matching Using Neural Networks: Evaluation for OAEI Tracks (Meriem Ali Khoudja et al., 2020) [24]: In this paper, the authors present an ontology matching approach that uses neural networks and evaluate it on six test cases from four different tracks of the Ontology Alignment Evaluation Initiative (OAEI) campaigns. They use a cross-validation procedure and standard evaluation measures to show that their approach achieves a high level of accuracy in ontology matching. The results show that the proposed approach outperforms other OAEI matching systems on all the selected campaigns, according to the evaluation metrics used. The authors conclude that the approach can effectively improve the performance of ontology matching tasks.
- Matching Biomedical Ontologies via a Hybrid Graph Attention Network (P. Wang et al., 2022) [25]: This study proposes an alternative biomedical ontology-matching framework called BioHAN via a hybrid graph attention network, which consists of three techniques: an ontology-enriching method, hyperbolic graph attention layers, and a graph attention network. BioHAN is demonstrated to be competitive with state-of-the-art ontology matching methods on real-world biomedical ontologies.

4.2.2 Graph Embeddings

Graph embeddings are continuous, low-dimensional vectors that represent the nodes in a graph and capture their relationships. They can be used for various tasks such as node classification and link prediction. graph embeddings are fixed, pre-computed representations of the graph.

- ALOD2Vec matcher (J. Portisch et al., 2018) [26]: This paper introduces the ALOD2Vec Matcher, an ontology matching tool that uses a large data set as an external knowledge source.
- Matching Biomedical Knowledge Graphs with Neural Embeddings (R. Neves et al., 2020) [27]: This paper presents two novel knowledge graph matching approaches using neural embeddings, one based on plain embedding similarity and the other one using a more complex word-based model. These approaches are integrated into the matching process using the AgreementMakerLight system, and are evaluated on three biomedical ontology matching test cases. The results show that the proposed approaches outperform other systems that do not use external ontologies, and also surpass some that do benefit from them.
- Ontology Matching by Jointly Encoding Terminological Description and Network Structure (J. Wu et al., 2020) [28]: This paper proposes an ontology matching framework that models the matching process by embedding techniques with jointly encoding ontology terminological description and network structure. The

approach is evaluated and compared with state-of-the-art ontology matching systems on four Ontology Alignment Evaluation Initiative (OAEI) datasets.

- OWL2Vec*: Embedding of OWL Ontologies (J. Chen et al., 2020) [29]: This paper presents a method for encoding the semantics of an OWL (Web Ontology Language) ontology by taking into account its graph structure, lexical information, and logical constructors. It uses a random walk and word embedding approach to create ontology embeddings.
- ONTOCONNECT: Domain-Agnostic Ontology Alignment using Graph Embedding with Negative Sampling (J. Chakraborty et al., 2021) [30]: An ontology alignment approach using graph embedding with negative sampling.
- OTMapOnto: optimal transport-based ontology matching (Y. An et al., 2021) [31]: This paper describes a system that uses optimal transport techniques to match terms across different ontologies. It converts ontology elements into embedding vectors and applies optimal transport to move masses from the source to the target embedding space. The solution to the optimal transport problem gives rise to a set of candidate matchings that can be refined.
- Towards Neural Schema Alignment for OpenStreetMap and Knowledge Graphs (A. Dsouza et al., 2021) [32]: This paper proposes a neural architecture that aligns tag-to-class in OSM and knowledge graphs, resulting in new semantic annotations for over 10 million OSM entities worldwide.
- Box Embeddings for the Description Logic EL++ (B. Xiong et al., 2022) [33]: This paper presents BoxEL, a geometric KB embedding approach that models concepts as axis-parallel boxes, entities as points inside boxes, and relations as affine transformations. It demonstrates theoretical guarantees and superior performance on subsumption reasoning and a protein-protein prediction task.
- Context-Enriched Learning Models for Aligning Biomedical Vocabularies at Scale in the UMLS Metathesaurus (N. D. Q. Bui et al., 2022) [34]: This paper investigates the role of multiple types of contextual information for the UMLS vocabulary alignment problem. It develops context-enriched learning models by adding contextual information to a lexical-based learning model. The models are evaluated using UVA generalization test datasets and show improvement over the lexical-based model.

4.3 Self-Attention mechanism

kinds of neural networks use self-attention as a method to let the model concentrate on certain input components while processing them. Each input piece is given a weight to represent its relative relevance to the whole input, which is how it operates. When processing the input, the model may utilize these weights to choose give certain items more attention while giving others less. The papers in the sel-attention class were divided into two subclasses:

4.3.1 Dual-attention mechanism

A dual-attention mechanism is a type of deep learning model that uses two attention mechanisms to weight the importance of different input tokens or contexts in generating output predictions.

- Biomedical Ontology Matching Through Attention-Based Bidirectional Long Short-Term Memory Network (Xingsi Xue et al., 2021) [3]: This paper presents an attention-based bidirectional long short-term memory network (At-BLSTM) for determining mappings between heterogeneous biomedical entities in different ontologies. The At-BLSTM model is able to capture the semantic and contextual features of biomedical entities and outperformed state-of-the-art approaches in experiments.
- VeeAlign: Multifaceted Context Representation Using Dual Attention for Ontology Alignment (Vivek Iyer et al., 2020) [4]: This paper proposes a deep learning-based model for ontology alignment that uses a dual-attention mechanism to compute contextualized representations of concepts. The model is evaluated on four different datasets from various domains and languages, and is shown to be superior to other approaches through detailed ablation studies.
- VeeAlign: a supervised deep learning approach to ontology alignment (Vivek Iyer et al., 2020) [5]: In this paper, the authors propose a dual-attention based approach using a multi-faceted context representation to compute contextualized

representations of concepts to discover semantically equivalent concepts in ontology alignment. The approach aims to mitigate some of the limitations of deep learning approaches in ontology alignment, including poor context modeling, overfitting, and dataset sparsity.

4.3.2 BERT

BERT (Bidirectional Encoder Representations from Transformers) is a deep learning model that uses an attention mechanism and transformer architecture to generate contextualized word embeddings.

- A Pre-Training Technique to Localize Medical BERT and to Enhance Biomedical BERT (Shoya Wada et al., 2020) [35]: This paper introduces a method to train a BERT model using a small medical corpus in English and Japanese. The method involves simultaneous pre-training on the small medical corpus and amplified vocabulary to suit the small corpus using byte-pair encoding. The performance of the BERT models is evaluated on tasks such as medical document classification and biomedical language understanding. The results show that the Japanese medical BERT outperforms baselines on the medical-document classification task, and the English BERT performs well on the biomedical language understanding evaluation benchmark.
- BERTMap: A BERT-based Ontology Alignment System (Yuan He et al., 2021) [10]: This paper presents a novel ontology alignment system, called BERTMap, which uses the contextual embedding model BERT to support both unsupervised and semi-supervised settings. Mappings are first predicted using a classifier based on fine-tuning BERT on text semantics corpora extracted from ontologies, and then refined through extension and repair using the ontology structure and logic. The system is evaluated on three alignment tasks with biomedical ontologies, and is shown to often outperform the leading systems LogMap and AML.
- KERMIT - A Transformer-Based Approach for Knowledge Graph Matching (S. Hertling et al., 2022) [36]: An approach for ontology alignment using transformer-based language models, with a two-step process using bi-encoders and fine-tuned transformer cross-encoders
- Biomedical ontology alignment with BERT (Yuan He et al., 2021) [37]: An ontology alignment system using the contextual embedding model BERT, which outperforms leading systems using only the to-be-aligned classes as input.
- The quest for better clinical word vectors: Ontology based and lexical vector augmentation versus clinical contextual embeddings (N. Nath et al., 2021) [38]: This paper compares the performance of clinically adapted word2vec vectors and Bio + Clinical BERT vectors at encapsulating concepts of lexical and clinical synonymy and antonymy, and at NER. The results show that the clinically adapted word2vec vectors are successful at encapsulating synonymy and antonymy, but Bio + Clinical BERT vectors perform better at NER and avoid out-of-vocabulary words.
- Towards Automatic Ontology Alignment using BERT (Sophie Neutel et al., 2021) [39]: This paper examines the automatic alignment of two occupation ontologies using BERT and compares the performance of five alignment systems. It concludes that a hybrid approach combining automatic and manual techniques is needed to improve coverage and eliminate errors.
- Contextual Semantic Embeddings for Ontology Subsumption Prediction (Jiaoyan Chen et al., 2022) [40]: This paper presents a new subsumption prediction method called BERTSubs that uses the pre-trained language model BERT to compute contextual embeddings of a class in an OWL ontology. Customized templates are used to incorporate the class context and logical existential restrictions. BERTSubs is able to predict multiple kinds of subsumers and was shown to outperform baselines using knowledge graph embeddings, non-contextual word embeddings, and state-of-the-art OWL ontology embeddings in evaluations on five real-world ontologies.

4.4 Word Embedding

Word embeddings are continuous, low-dimensional vectors that represent words in a mathematical space. They capture the relationships between words and can be used for various natural language processing tasks such as language modeling, text classification and in our case ontology matching.

4.4.1 Custom-trained word embeddings

Custom-trained word embedding models are models that are trained specifically for ontology matching tasks. They may be trained from scratch or fine-tuned on top of a pre-trained model.

- Ontology Matching with Word Embeddings (Yuanzhe Zhang et al., 2014) [41]: This paper presents a method for ontology matching using word embeddings and evaluates its performance in element-level matching.
- Breaking-down the Ontology Alignment Task with a Lexical Index and Neural Embeddings (Ernesto Jiménez-Ruiz et al., 2018) [42]: This paper presents an approach for aligning large ontologies by combining a lexical index, a neural embedding model, and locality modules. The approach is designed to divide the ontology alignment task into smaller, more tractable sub-tasks. The method was evaluated using datasets from the Ontology Alignment Evaluation Initiative and showed promising results.
- DOME results for OAEI 2018 (S. Hertling et al., 2018) [43]: DOME (Deep Ontology MatchEr) is a scalable matcher that relies on large texts describing ontological concepts to train a fixed-length vector representation of the concepts. Mappings are generated if two concepts are close to each other in the resulting vector space. If no large texts are available, DOME falls back to a string-based matching technique. The results of DOME in the OAEI 2018 competition are discussed in this paper.
- Ontology Alignment Based on Word Embedding and Random Forest Classification (I. Nkisi-Orji et al., 2018) [44]: This work introduces a random forest classifier approach for ontology alignment which relies on word embedding for determining a variety of semantic similarity features between concepts and combines string-based and semantic similarity measures to form feature vectors that are used by the classifier model to determine when concepts align.
- We divide, you conquer: from large-scale ontology alignment to manageable subtasks with a lexical index and neural embeddings (Ernesto Jiménez-Ruiz et al., 2018) [45]: This paper presents an approach for dividing a large ontology matching task into smaller, more tractable sub-tasks using a lexical index, a neural embedding model, and locality modules. The method is evaluated on datasets from the Ontology Alignment Evaluation Initiative, with encouraging results.
- Multi-view Embedding for Biomedical Ontology Matching (Weizhuo Li et al., 2019) [46]: This paper proposes an alternative ontology matching framework called MultiOM, which models the matching process using embedding techniques from multiple views. The framework is evaluated on real-world biomedical ontologies and found to be competitive with other top-ranked systems in terms of F1-measure.
- Dividing the Ontology Alignment Task with Semantic Embeddings and Logic-based Modules (Ernesto Jiménez-Ruiz et al., 2020) [47]: This paper presents an approach that combines a neural embedding model and logic-based modules to accurately divide an input ontology matching task into smaller and more tractable matching tasks. The method is evaluated using the datasets of the Ontology Alignment Evaluation Initiative and is shown to be effective in practice.
- Improving Biomedical Ontology Matching Using Domain-specific Word Embeddings (Guoxuan Li et al., 2020) [48]: A method for improving the performance of biomedical ontology matching by combining representation learning with traditional feature engineering methods

4.4.2 Pre-trained word embeddings

Pre-trained word embedding models are models that have been trained on a large dataset and can be used as a starting point for learning other tasks. Examples include Word2Vec and GloVe.

- Biomedical ontology alignment: an approach based on representation learning (Prodromos Kolyvakis et al., 2018) [49]: In this work, the authors present a novel representation learning approach for aligning biomedical ontologies based on embedding ontological terms in a high-dimensional Euclidean space using a phrase retrofitting strategy that leverages terminological embeddings to capture semantic similarity.
- DeepAlignment: Unsupervised Ontology Matching with Refined Word Vectors (Prodromos Kolyvakis et al., 2018) [50]: This paper presents an unsupervised entity alignment method called DeepAlignment, which refines pre-trained word vectors to

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derive ontological entity descriptions specifically tailored for the ontology matching task.

- Ontology alignment in the biomedical domain using entity definitions and context (Lucy Lu Wang et al., 2018) [11]: This paper proposes a method for enriching entities in an ontology with external definition and context information, and uses this additional information for ontology alignment. A neural architecture is developed to encode the additional information when available, and the method is evaluated on the Ontology Alignment Evaluation Initiative (OAEI) largebio SNOMED-NCI subtask, achieving an F1-score of 0.69.
- HARE: a Flexible Highlighting Annotator for Ranking and Exploration (Denis Newman-Griffis et al., 2019) [51]: An exploratory study that investigates the use of Wasserstein distance, a continuous space distance measure, for measuring similarity between ontologies and discovering and refining matchings between individual elements.
- DeepFCA: Matching Biomedical Ontologies Using Formal Concept Analysis Embedding Techniques (Guoxuan Li et al., 2020) [52]: This paper proposes a biomedical ontology matching method called DeepFCA that combines FCA and word2vec techniques to enhance performance. Experiments on real-world biomedical ontologies show that DeepFCA improves recall and F1-measure compared to traditional FCA methods and achieves competitive performance compared to state-of-the-art systems.
- Biomedical Vocabulary Alignment at Scale in the UMLS Metathesaurus (Vinh Phu Nguyen et al., 2021) [53]: This paper presents a supervised learning approach for suggesting synonymous pairs in the construction of the UMLS Metathesaurus terminology integration system. The approach uses deep learning and negative pairs with various degrees of lexical similarity during training, and is evaluated against a rule-based approach that approximates the current UMLS construction process. The deep learning approach is shown to have strong performance in terms of recall, precision, and F1 score, and largely outperforms the rule-based approach.
- Exploring Wasserstein Distance across Concept Embeddings for Ontology Matching (Yuan An et al., 2022) [54]: An exploratory study that investigates the use of Wasserstein distance, a continuous space distance measure, for measuring similarity between ontologies and discovering and refining matchings between individual elements.

4.5 Deep Neural Networks

Deep Neural Networks (DNNs) are multi-layered artificial neural networks that learn complex patterns in data. They are highly effective for applications such as image recognition, speech recognition, and predictive analytics. DNNs are trained with labeled data and optimization algorithms to adjust the connections between neurons and minimize error.

- Learning Ontology Alignments Using Recursive Neural Networks (A. Chortaras et al., 2005) [1]: This work proposes an automatic ontology alignment method based on the recursive neural network model that uses ontology instances to learn similarities between ontology concepts.
- A Neural-Networks-Based Approach for Ontology Alignment (Babak Bagheri Hariri et al., 2006) [55]: This paper describes a method for creating a compound metric for ontology alignment using a supervised learning approach in data mining. The method involves training a neural network model on a training set and performing sensitivity analysis on the model to select appropriate metrics. The resulting compound metric is then used to align ontologies. Empirical results of applying the method to a set of ontologies are also presented.
- X-SOM: A Flexible Ontology Mapper (C. Curino et al., 2007) [56]: This paper presents X-SOM, an ontology mapping and integration tool with a modular and extensible architecture that automatically combines several matching techniques using a neural network. The tool also performs ontology debugging to avoid inconsistencies and has been tested with promising results against the OAEI 2006 benchmark.
- ANN-Agent for Distributed Knowledge Source Discovery (G. Stegmayer et al., 2007) [57]: This work presents a reference

architecture for a distributed knowledge source discovery system using an ontology-matching model based on artificial neural networks (ANN).

- Neural Network based Constraint Satisfaction in Ontology Mapping (A. Lancia et al., 2008) [58]: This work presents a neural network based approach for ontology mapping that integrates both structural and semantic information. The approach is evaluated on a real-world dataset and found to be effective.
- Knowledge Source Discovery: An Experience Using Ontologies, WordNet and Artificial Neural Networks (M. Rubiolo et al., 2009) [59]: This paper documents research on discovering distributed knowledge sources from a user query using an artificial neural network model combined with WordNet.
- An adaptive ontology mapping approach with neural network based constraint satisfaction (Ming Mao et al., 2010) [60]: This paper proposes a new generic and adaptive ontology mapping approach, called the PRIOR+, based on propagation theory, information retrieval techniques and artificial intelligence, which shows that harmony is a good estimator of f-measure and the harmony based adaptive aggregation outperforms other aggregation methods.
- Semantic Web Technologies and Artificial Neural Networks for Intelligent Web Knowledge Source Discovery (M. L. Caliusco et al., 2010) [61]: This chapter discusses the use of agent-based technologies and artificial neural networks for intelligent web knowledge source discovery in the Semantic Web.
- Ontology Mapping Neural Network: An Approach to Learning and Inferring Correspondences among Ontologies (Yefei Peng et al., 2010) [62]: An ontology mapping neural network (OMNN) is proposed in order to learn and infer correspondences among ontologies. It extends the Identical Elements Neural Network (IENN)'s ability to represent and map complex relationships. The learning dynamics of simultaneous (interlaced) training of similar tasks interact at the shared connections of the networks. The output of one network in response to a stimulus to another network can be interpreted as an analogical mapping. In a similar fashion, the networks can be explicitly trained to map specific items in one domain to specific items in another domain. Representation layer helps the network learn relationship mapping with direct training method. OMNN is applied to several OAEI benchmark test cases to test its performance on ontology mapping. Results show that OMNN approach is competitive to the top performing systems that participated in OAEI 2009.
- Ontology matching with CIDER: evaluation report for OAEI 2011 (Pablo N. Mendes et al., 2011) [63]: CIDER is a schema-based ontology alignment system. This paper describes CIDER and its results at the Ontology Alignment Evaluation Initiative 2011 campaign (OAEI'11).
- Introducing Artificial Neural Network in Ontologies Alignement Process (W. Djeddi et al., 2012) [64]: An artificial neural network approach is taken to learn and adjust weights of different similarity measures of different categories such as string, linguistic, and structural based similarity measures, with the purpose of avoiding some disadvantages in both rule-based and learning-based aligning algorithms.
- Knowledge discovery through ontology matching: An approach based on an Artificial Neural Network model (M. Rubiolo et al., 2012) [12]: This work presents an Artificial Neural Network (ANN) based ontology matching model for knowledge source discovery on the Semantic Web and shows that the model provides satisfactory responses.
- Ontology alignment using artificial neural network for large-scale ontologies (W. Djeddi et al., 2013) [65]: A machine learning-based method using Artificial Neural Network to combine multiple similarity measures into a single aggregated metric to improve ontology alignment quality
- ERSOM: A Structural Ontology Matching Approach Using Automatically Learned Entity Representation (Chuncheng Xiang et al., 2015) [9]: This paper presents an ontology matching approach called ERSOM, which uses deep neural networks to learn the general representation of entities and an iterative similarity

propagation method that utilizes the structure of the ontology to discover more mappings. The approach is evaluated on datasets from the Ontology Alignment Evaluation Initiative (OAEI) and shows competitive performance compared to state-of-the-art ontology matching systems.

- Knowledge entity learning and representation for ontology matching based on deep neural networks (L. Qiu et al., 2017) [66]: A representation learning method based on deep neural networks that aims to learn high level abstract representations of input entities to better measure similarity.
- A New Supervised Learning Based Ontology Matching Approach Using Neural Networks (Meriem Ali Khoudja et al., 2018) [67]: This paper proposes a new ontology matching approach based on supervised learning and neural networks, which combines the top ranked matching systems using a single layer perceptron to define a matching function that leads to a better set of alignments between ontologies.
- Semantic Mediation Model to Promote Improved Data Sharing Using Representation Learning in Heterogeneous Healthcare Service Environments (Ali et al., 2019) [68]: A semantic mediation model for interoperability in heterogeneous healthcare service environments using Web of Objects framework, deep representation learning, and standard vocabulary and data modeling.
- Ontology Matching Using Convolutional Neural Networks (Alexandre Bento et al., 2020) [2]: In this paper, the authors present a methodology to align ontologies using machine learning techniques, specifically convolutional neural networks to perform string matching between class labels using character embeddings. The authors report state-of-the-art performance on ontologies from the Ontology Alignment Evaluation Initiative (OAEI) and good performance on a different domain.
- Sentence-Embedding and Similarity via Hybrid Bidirectional-LSTM and CNN Utilizing Weighted-Pooling Attention (Degen Huang et al., 2020) [69]: This paper presents a neural network model for measuring sentence similarity that incorporates a weighted-pooling attention layer to retain the most important semantic information in an input. The model, which combines a Siamese structure based on bidirectional long short-term memory and a convolutional neural network, is evaluated on datasets for semantic relatedness and paraphrase identification and found to outperform state-of-the-art approaches.
- Augmenting Ontology Alignment by Semantic Embedding and Distant Supervision (Jiaoyan Chen et al., 2021) [70]: A machine learning based extension to traditional ontology alignment systems that uses distant supervision, ontology embedding, and Siamese Neural Networks to incorporate richer semantics and improve accuracy.
- Matching Biomedical Ontologies: Construction of Matching Clues and Systematic Evaluation of Different Combinations of Matchers (Peng Wang et al., 2021) [71]: This paper presents a spectrum of matchers with different combination strategies to investigate the effectiveness of matching clues and composite match approaches, and empirically studies their influence on matching biomedical ontologies. Atomic and composite matching clues are constructed in 4 dimensions: terminology, structure, external knowledge, and representation learning. Results show that distinguishing clues have significant implications for matching biomedical ontologies and that matchers combining multiple clues exhibit more stable and accurate performance. In addition, the approach based on extended reduction anchors performs well for large ontology matching tasks, demonstrating an effective solution for the problem.

5. Conclusion

This study provides a comprehensive analysis of ontology matching using deep learning techniques. The scope of the search strategy was limited to articles published between 2005 and 2022, which is a potential limitation of the study. Nevertheless, our findings show that Deep Neural Networks and Word Embedding are the most popular approaches for ontology matching using deep learning, while Self-Attention, Graph Representation, and Classical Machine Learning are also used to a lesser extent. We also critically assessed the limitations of our study, such as the possibility of bias in article selection, and highlighted the need for further research to fully understand the factors influencing the adoption and usage of different deep learning approaches in ontology matching.

The scientific contribution of this work lies in the synthesis and analysis of a large body of literature and the development of a framework for classification that can be used as a tool for future research. By providing an updated overview and classification of ontology matching techniques based on deep learning, this study identifies gaps and opportunities for further research in the field.

In summary, our study contributes significantly to the existing literature on ontology matching using deep learning techniques by presenting an updated overview of the field, highlighting emerging trends and techniques, and identifying opportunities for future research. This work provides a foundation for researchers and practitioners to select suitable deep learning methods for ontology matching tasks and develop new techniques to improve the accuracy and efficiency of the matching process.

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