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COMBINING MACHINE LEARNING AND ONTOLOGY: A SYSTEMATIC LITERATURE REVIEW

A PREPRINT

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ABSTRACT

Motivated to explore the process of combining inductive and deductive reasoning, we conducted a systematic literature review of articles investigating the integration of machine learning and ontologies. The objective was to identify diverse techniques incorporating inductive reasoning (performed by machine learning) and deductive reasoning (performed by ontologies) into artificial intelligence systems. Our review, which included the analysis of 128 studies, allowed us to identify three main categories of hybridization between machine learning and ontologies: *learning-enhanced ontologies*, *semantic data mining*, and *learning and reasoning systems*. We provide a comprehensive examination of all these categories, emphasizing the various machine learning algorithms utilized in the studies. Furthermore, we compared our classification with similar recent work in the field of hybrid AI and neuro-symbolic approaches.

Keywords machine learning · ontology · artificial reasoning · hybrid reasoning

1 Introduction

Artificial intelligence (AI) has become part of our daily lives, transforming every economic sector, from industry 4.0 to healthcare and smart cities. However, there is still a lack of consensus among researchers regarding the precise definition of AI, a term coined more than half a century ago [Nilsson, 2009, Wang, 2019]. For example, Minsky [1986] suggests that AI refers to the capability of machines to *solve complex problems*. Dobrev [2012] compares AI to human beings, defining it as *a program which in an arbitrary world will cope not worse than a human*, which recalls the original definition of McCarthy et al. [1955]. On the other hand, Kaplan and Haenlein [2019] defines AI as *a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation*, potentially narrowing AI to the realm of machine learning. Alternatively, Wang [2019] emphasizes AI's capability to adapt to its environment, even with limited knowledge and resources. Another perspective, similar to Russell and Norvig [2009]'s, suggests defining AI as the scientific field that enables machines to perceive, understand, and interact with the real world in a way that is very close to human beings.

To understand this perspective, we can call upon the allegory of the cave exposed by Plato [1888]. Like the prisoners chained to the bottom of the cave, who only perceive shadows and echoes of the intelligible world, machines have a perception of our world limited to the data they are provided. How can we enable machines to have an impact

on the tangible world if they can't make sense of the various aspects, complexities, and nuances of the real world? Gradually, we would have to get machines out of the cave in which they are chained. The initial step involves imparting problem-solving thinking abilities to machines. In this endeavor, the human cognitive process primarily relies on two forms of reasoning: induction and deduction. Inductive reasoning facilitates the discovery of general knowledge (such as laws, theorems, correlations, etc.) from specific observations. Deductive reasoning, on the other hand, permits the application of pre-existing general knowledge to specific instances [Rafanelli et al., 2022]. In the 19th century, Charles Sanders Peirce identified a third type of reasoning called abduction, which is employed to generate hypotheses that explain specific observations [Roudaut, 2017, Rafanelli et al., 2022]. Abduction holds substantial scientific significance as it pertains to issues of causality, explainable artificial intelligence (XAI), and potentially even trustworthiness. However, this study will not focus on abduction, but rather on the combination of inductive and deductive reasoning for problem-solving purposes. Nevertheless, the matter of explainability remains intriguing and will be addressed in the study's conclusion.

Socrates, Plato's disciple, defines *induction* as a way of reasoning that consists in drawing a general conclusion from several particular cases. Inductive reasoning is a form of ampliative reasoning, i.e. one draws conclusions that go beyond the information contained in the premises [Roudaut, 2017]. Inductive reasoning is close to mechanisms of machine learning: establishing a reasoning (model) from explicit facts (experiments). Thus, the model is not explicitly written, on the contrary, it is deduced from the input data in order to extract information (general laws). In the opposite, deductive reasoning is based on syllogism defined by Aristotle such as a *speech (logos) in which, certain things having been supposed, something different from those supposed results of necessity because of their being so*¹. In other words, deductive reasoning is the ability to draw conclusions about individual facts (experiences) from generic knowledge (general law). When Aristotle writes *things supposed* this corresponds to the premise of the argument, and when he writes *results of necessity* this corresponds to the conclusion of the argument [Smith, 2020]. Within the field of AI, deductive reasoning is primarily associated with symbolic approaches, commonly referred to as Good Old-Fashioned AI (GOF AI) [Haugeland, 1989]. GOF AI encompasses a range of techniques including knowledge-based systems (e.g., expert systems), multi-agent systems, and constraint-based reasoning systems. These approaches leverage symbolic tools such as knowledge graphs, logical rules, ontologies and algebraic computation to facilitate deductive reasoning. We have placed particular focus on ontologies due to their ability to formalize knowledge by establishing associations between a knowledge graph and logic rules using inference engines. These deductive reasoning engines can use the axioms describing the concepts in the TBox (Terminology Box - general laws) to deduce new knowledge on the ABox (Assertional Box - specific facts) part of the ontology. In modern information systems, ontologies, such as formal and explicit specifications of shared conceptualizations [Guarino et al., 2009], prove to be highly valuable. They address the need for data interoperability and the formalization of business rules, which are essential aspects of contemporary information systems.

The exploration of the fusion between machine learning and ontologies arises from the aim to investigate the mechanisms that facilitate the integration of inductive reasoning with deductive reasoning. Unlike recent advancements in neuro-symbolic approaches [Hitzler and Sarker, 2022, Garcez and Lamb, 2020, Henry Kautz, 2020, van Bekkum et al., 2021], our study did not exclusively focus on neural networks. Therefore, we chose to concentrate on the study of ontologies, as they encompass two vital categories of symbolic methods: knowledge graphs and logic rules. In our review, we ensured to highlight these two concepts to assist readers interested in either subject in navigating the research more effectively.

The main question addressed in this systematic literature review is whether it is possible to combine these two paradigms, and if so, how? The objective is to study how machine learning methods and ontologies can be effectively combined. In this study, our focus is on providing an overview of techniques that integrate learning and reasoning to realize a hybrid AI system capable of learning, building knowledge, and performing reasoning to tackle complex tasks and simulate the human cognitive process.

The Systematic Literature Review (SLR) is a research method based on the identification, evaluation, and interpretation of all relevant research results related to a particular topic area. It is a very popular analysis tool in the medical field, and was then adapted in computer science by Kitchenham et al. [2010] who define it as *a form of secondary study that uses a well-defined methodology to identify, analyze and interpret all available evidence related to a specific research question in a way that is unbiased and (to a degree) repeatable* [Kitchenham and Charters, 2007]. By *secondary study*, the authors mean a *study that reviews all the primary studies relating to a specific research question with the aim of integrating/synthesizing evidence related to a specific research question*. In this context, a *primary study* describes new original research and aims to answer questions that haven't been answered or even asked before. The main objectives of this SLR are: (a) providing an overview of existing approaches combining ontology and machine learning,

¹Prior Analytics I.2, 24b18–20

(b) understanding the motivations of each research work and addressed issues, (c) identifying the weaknesses and difficulties encountered, and (d) facilitating the positioning of new studies in this field.

To the best of our knowledge, a comprehensive overview encompassing the combination of ontology and machine learning techniques has not been previously conducted. While there have been studies focusing on specific aspects such as ontology learning [Al-Aswadi et al., 2020, Khadir et al., 2021], semantic data mining [Dou et al., 2015, Sirichanya and Kraissak, 2021], and more recently, neuro-symbolic [Hitzler and Sarker, 2022, Garcez and Lamb, 2020, Henry Kautz, 2020, van Bekkum et al., 2021]². There is no systematic review providing a holistic mapping of the different approaches that integrate ontologies and machine learning. Therefore, this study aims to fill this gap by providing a comprehensive overview of the combinations of ontology and machine learning, shedding light on the potential synergies and insights gained from their integration.

This document is structured as follows. Section 2 describes the used methodology to conduct this systematic literature review. Section 3 presents the overview results, and sections 4, 5 and 6 detail each of the three major groups combining ontologies and machine learning. Finally, section 7 presents the conclusions and a discussion of challenges and research directions.

2 Methodology

The conducted SLR methodology is mainly inspired by Kitchenham et al. [2010], and is depicted in Figure 1. The first step is to plan the review after identifying the need to conduct it. We start by specifying the research questions. Then, we elaborate the adopted protocol to conduct the review by identifying keywords and selecting inclusion and exclusion criteria. The second step is performing the review by conducting the activities planned in the protocol and selecting primary studies to be included in the review, as well as the actions related to their evaluation. The final step is the reporting step, which consists of documenting, explaining, and summarizing the results to answer each research question.

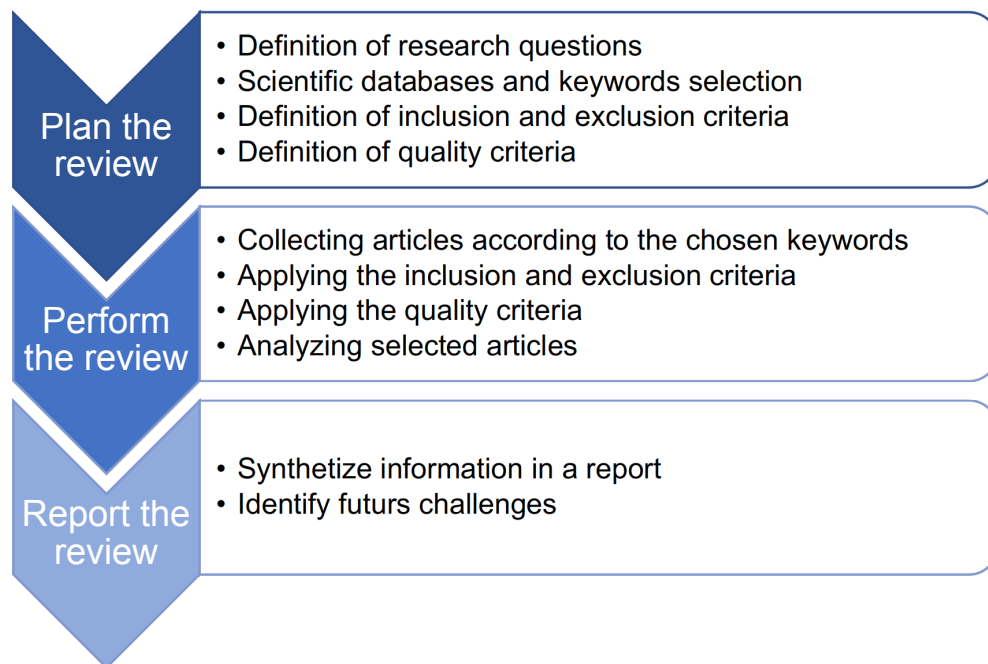


Figure 1: Systematic Literature Review (SLR) methodology

²Note that neuro-symbolic methods are not limited to ontologies

2.1 Planning the review

This SLR aims to study current work combining ontology and machine learning. First, we define the research questions to be studied in this review and then detail the protocol used to select the primary studies.

2.1.1 Definition of the research questions

The objective of this review is to answer the following five research questions:

- RQ1:** To understand the motivation of current work and used methodology, we ask the following question: *Why and how ontology and machine learning are combined?*
- RQ2:** There are various machine learning models using different approaches and algorithms. To better understand which algorithms are used, we ask the following question: *What are the machine learning algorithms used in each work?*
- RQ3:** Ontologies are typically used in the reasoning process to ensure model consistency and to infer new knowledge. Most often, ontologies infer on subsumption links, but some works go further by adding rules that go beyond simple hierarchical relationships. To find out whether works use non-hierarchical reasoning rules, we ask the following question: *Are there works that use rules other than subsumption links?*
- RQ4:** Several main themes, defined by the ACM Computer Classification System³, are recurrent in the field of AI, such as computer vision or natural language processing (NLP). The treatment of each theme is particular and often involves techniques that are different from each other: *What are the different types of main AI themes present in work combining machine learning and ontology?*
- RQ5:** AI is used in different domains and plays an important role in helping humans to work with better performance. To identify the application domain addressed by current work, we ask the following question: *What are covered application domains?*

2.1.2 Scientific databases and keywords selection

Once the research questions are defined, we identify the scientific databases and search keywords that will be used to select primary studies. This SLR uses three scientific databases to cover a large panel of articles: Web Of Science⁴, ACM Digital Library⁵ and Science Direct⁶. These three search engines are recommended by Gusenbauer and Haddaway [2020]. They satisfy the reproducibility criteria of the searches, as well as the use of boolean terms in the query. Google Scholar is not used because it does not guarantee good reproducibility [Gusenbauer and Haddaway, 2020].

To query selected scientific databases, a combination of the two main keywords, *ontology* and *machine learning* is used. However, the number of articles obtained was too large and all of these studies are not relevant to our review. Then, we refined the query by restricting the search of these same keywords in *title*, *abstract*, and *keywords*, which gave a much smaller number of articles that seem more relevant.

After a first analysis, we find that the term *deep learning* is often used instead of *machine learning*, even though it is a subset of this technique. We, therefore, decided to add the *deep learning* keyword to our query, with the same restrictions applied to the *machine learning* term. Also, some authors use directly the term *neural network* (in particular for the most recent articles) without explicitly mentioning the *machine learning* or *deep learning* terms. We, therefore, decided to add this keyword to our query, even if it concerns a minority of articles (10 to 15%) in each query.

For the *ontology* keyword, we decided to use only this term and not combine it with other keywords representing different semantic techniques, such as *taxonomy*, *knowledge modeling*, or *knowledge graph*. In this review, we are mainly interested in the use of ontologies, and the possibility to perform logical reasoning.

Finally, we have also included in our query the *artificial intelligence* keyword. This allows us to restrict obtained results to our research domain. Unlike previous keywords, the presence of this term is looked for anywhere in the article to be less restrictive.

Based on our search and selected keywords, we obtain the following query:

³<https://dl.acm.org/ccs>

⁴<https://clarivate.com/webofsciencegroup/solutions/web-of-science/>

⁵<https://dl.acm.org/>

⁶<https://www.sciencedirect.com/>

*“ontology” AND (“machine learning” OR
“deep learning” OR “neural network”) AND “artificial intelligence”*

This query allows targeting primary studies concerned by our research questions.

2.1.3 Definition of inclusion and exclusion criteria

To filter the returned articles from the keyword search and keep relevant papers that will be used to answer our research questions, we defined a set of inclusion and exclusion criteria.

Inclusion criteria

InC1: The paper describes an approach that combines at least one ontology with at least one machine learning technique.

InC2: The paper does not use ontologies and machine learning only to compare them.

Exclusion criteria

ExC1: Posters or demonstrations that do not provide enough details about their contribution.

ExC2: Duplicate papers returned from various search engines.

ExC3: Papers that are not written in English.

ExC4: Non-accessible papers that can not be online recovered.

ExC5: Books (or book chapters) detailing previously collected papers.

ExC6: Extended paper by the same authors. In this case, the most recent paper is kept.

ExC7: Existing survey or not a primary study (it may be a secondary or tertiary study).

2.1.4 Definition of quality criteria

The quality of an SLR depends on the quality of the reviewed articles. It is then important to rigorously assess the papers included in our SLR by considering the following quality criteria: (a) studies are conducted in higher research institutions (b) studies are published in good quality international revues and conferences and referenced by well-known electronics libraries (c) motivations and contributions are clearly defined.

To evaluate the quality of our SLR, we used the Quality Assessment Instrument for Software Engineering systematic literature Reviews (QAISER) developed by Usman et al. [2021].

2.2 Performing the review

This section describes how we performed the review according to the defined protocol. We follow four steps: (i) collecting articles according to the chosen keywords, (ii) applying the inclusion and exclusion criteria, (iii) applying the quality criteria, and (iv) analyzing selected articles.

2.2.1 Collecting articles

In this step, we query the selected scientific databases with the set of defined keywords by adapting our basic query to each scientific database, as presented in table 1. The first search was carried out at the end of May 2021, and a total of 373 studies were collected to be analyzed. A second search was conducted in February 2022 with the objective of updating our analysis report with all new studies published since the first search. By limiting ourselves to studies published in 2021 and 2022 on the selected scientific databases, we were able to add 70 articles to our initial collection.

2.2.2 Applying inclusion, exclusion, and quality criteria

The different steps for applying the inclusion and exclusion criteria are summarized in Figure 2. After collecting the set of 443 articles, we applied the first four exclusion criteria using Zotero⁷, a reference management tool, to remove

⁷<https://www.zotero.org/>

Table 1: Final request for each search engine

Scientific database	Request	May 2021	Feb. 2022
ACM	[Abstract: ontology] AND [[Abstract: "machine learning"] OR [Abstract: "deep learning"]] OR [Abstract: "neural network"]] AND [All: artificial intelligence]	101	9
Science Direct	artificial intelligence AND Title, abstract, keywords: "ontology" AND ("machine learning" OR "deep learning" OR "neural network")	106	23
Web of Science	TS=(ontology AND ("machine learning" OR "deep learning" OR "neural network")) AND WC="Artificial Intelligence"	166	38

posters, demonstrations, duplicated and inaccessible papers. The remaining 351 articles are all written in English. In the second step, we read the titles and the abstracts of the obtained studies and apply the last three exclusion criteria to eliminate books, extended papers, and existing surveys. In this step, we also remove studies that did not meet both inclusion criteria based on title and abstract. We obtain 153 studies that we read to verify if they respect our two inclusion criteria. As a result, we selected 128 studies that correspond to the scope of our review. We also applied the quality criteria defined previously to evaluate the selected primary studies. We assume that the quality of used scientific databases ensures the quality of selected studies, and the relevance of each included article was discussed and validated by all authors of this SLR.

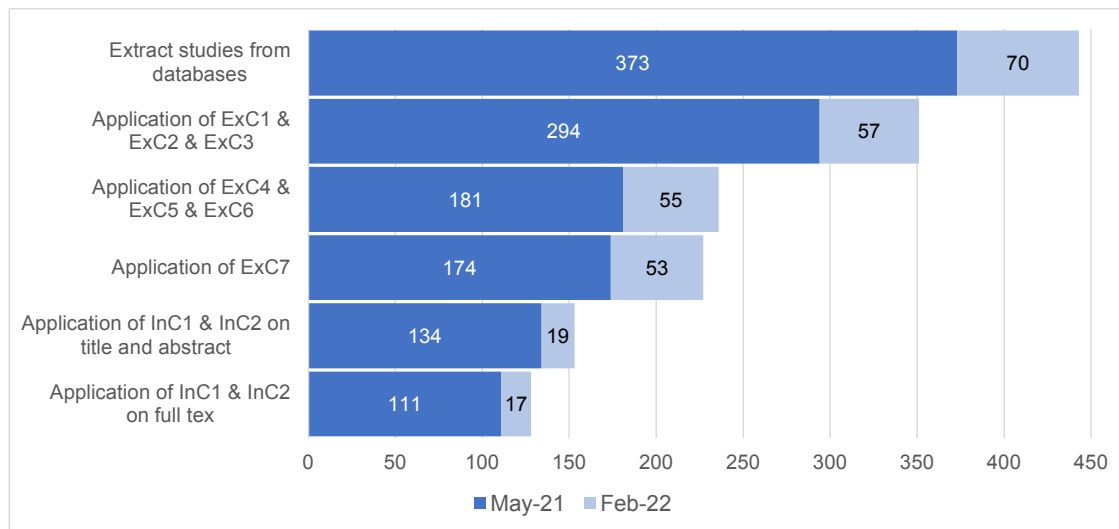


Figure 2: Selection of articles

2.2.3 Analysis

To answer our research questions, we extracted from each primary study the different attributes described in the table 2. Based on the extracted data, we performed some statistical analysis that we present in section 3.

3 Overview of included studies combining ontologies and machine learning techniques

In addition to the main analysis for answering the research questions, we performed a demographic analysis of the studies. Figure 3 presents the number of published papers concerning the combination of ontologies and machine learning techniques. The first paper present in this SLR dates from the year 2000, voluntarily we did not put any restriction on the publication date in our query (cf 2.1.2). Consequently, this SLR allows us to make a state of the art on the combination between ontologies and machine learning for more than 20 years. Since 2010 the number of studies has

Table 2: Extracted data from final studies

Attribute	Description
Year	Year of publication
Country	Countries where the first author is located
Machine learning algorithm	The machine learning algorithm(s) used in the paper.
Ontology reasoning	Presence of deductive reasoning, at least of formal rules allowing deductive reasoning.
Artificial intelligence themes	If the studies explore a known theme of Artificial Intelligence as described by the ACM Computing Classification System
Category	Category of the article according to our classification of machine learning and ontologies combinations

increased, and a strong acceleration is taking place in recent years. Indeed, 57% of the analyzed studies were published after 2018. Over the years, we see that neural networks are being used more and more. The neural networks group includes algorithms range from the simple perceptron to the most recent techniques such as Transformers. As we see in more detail in the section 3.2 neural networks are present in the majority of the papers studied.

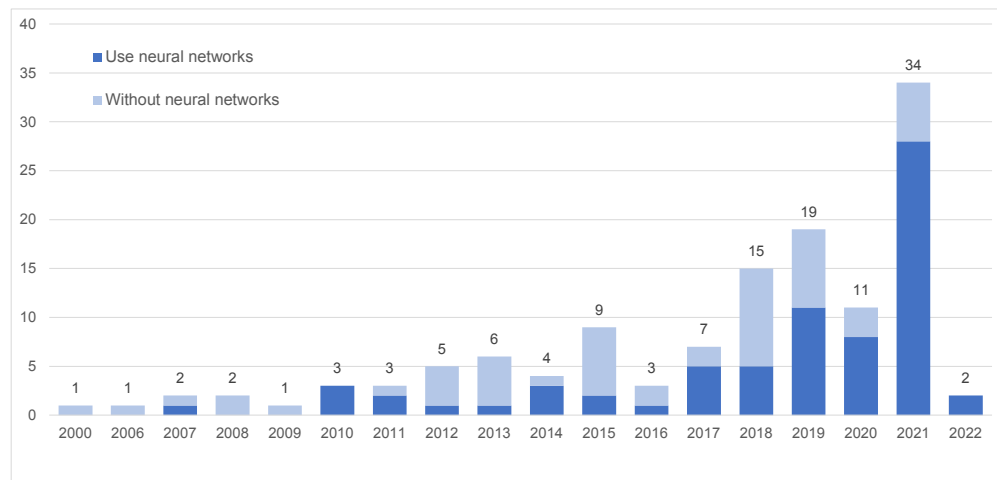


Figure 3: Evolution of the number of publications about the combination of ontologies and machine learning.

Figure 4 present the geographical distribution of contributors, considering the location of the first author of each article. The most represented continents are Europe, Asia, and North America. In Europe, leaders are Italy and Spain, each with a dozen papers in the study, but it is above all the multiplicity of contributing countries (United Kingdom, France, Germany, Austria, Poland, Greece, Bulgaria, Romania, Belgium, Lithuania, or Serbia) that allow Europe to come out on top of the most contributing continents. In Asia, it is mostly China that contributes to the second position of our ranking. In North America, the USA provides a large part of the studies.

These data are interesting if we cross them with those presenting the world public budgets of research and development (R&D)⁸. The presence of China and the USA at the top of our ranking correlates with the budget invested in R&D each year. The large contributions of Italy and Spain, on the other hand, are more difficult to explain in terms of their R&D spending. However, these two countries are present in the Investment Monitor top 40 countries ranking⁹. In Italy, we note that several studies come from Trento University, which also has an interest in more specific neuro-symbolic field. This demographic study allows us to highlight some university teams that are actively engaged in conducting research in the combination of ontologies and machine learning.

⁸<http://uis.unesco.org/apps/visualisations/research-and-development-spending/>

⁹<https://www.investmentmonitor.ai/ai/ai-index-us-china-artificial-intelligence>

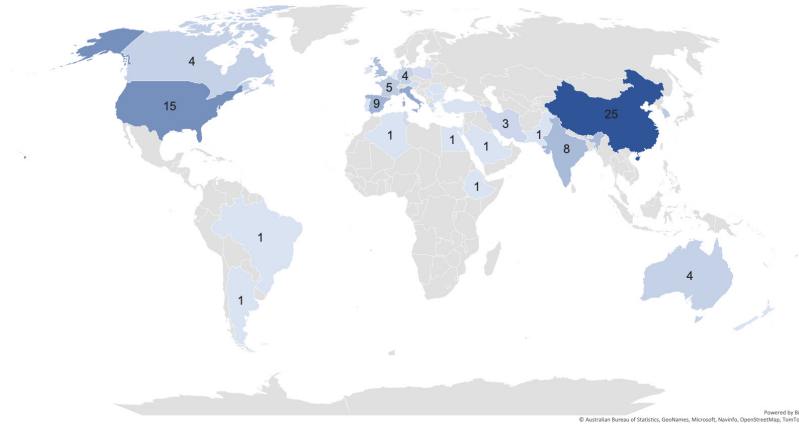


Figure 4: Country where the first author is based

3.1 Types of combination between ontology and machine learning (RQ1)

After reading the 128 selected articles, we could distinguish three groups of different ontology and machine learning combinations: *Learning-Enhanced Ontology*, *Semantic Data Mining*, and *Learning and reasoning system*. These three main groups and their subgroups have been partially named thanks to recent work that focuses on different forms of combination between inductive learning and deductive reasoning [von Rueden et al., 2021]. This explains why we sometimes find the term *semantic* instead of *ontology*, whereas in this SLR we only deal with papers that use an ontology for the symbolic part. This will make it easier for the reader to make the connection with other articles dealing with learning and reasoning architecture (such as neuro-symbolic). We detail these three main groups and their subgroups, presented in Figure 5, in the paragraphs 4, 5 and 6 in order to be able to answer research questions RQ1, RQ2, and RQ3 in detail.

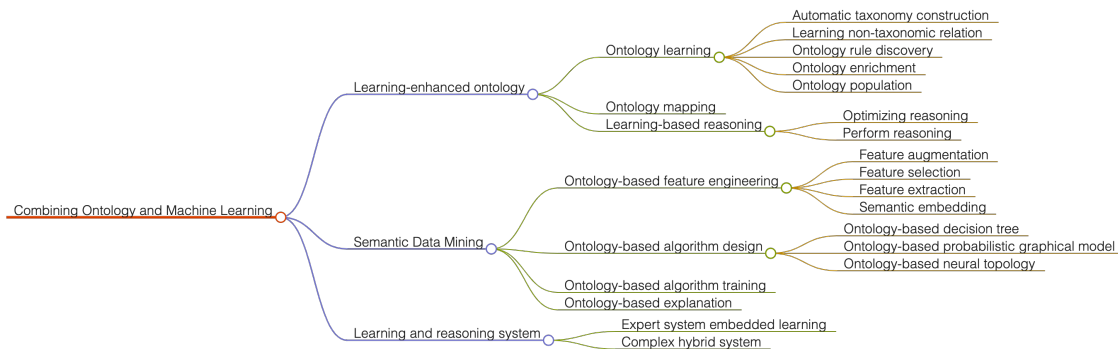


Figure 5: Overview of the combination of ontologies and machine learning techniques

3.2 Machine learning techniques (RQ2)

To answer RQ2, we identified the different machine learning algorithms used in each of the selected articles. All the machine learning algorithms used are listed in the "learning algorithm" column of Tables 3, 4 and 5, while the "learning type" column indicates whether they are supervised or otherwise.

Selected articles are divided into the three main learning approaches as follows:

- Supervised learning: 107
- Unsupervised learning: 37 of which 13 are self-supervised learning
- Reinforcement learning: 1

As presented in Figure 3, neural networks are very common in the selected studies. Neural networks are well involved in the supervised and self-supervised categories and less present in the unsupervised category since their application to

clustering problems is more recent. The authors often prefer other more classical clustering algorithms such as k-means, hierarchical ascending classification, principal component analysis, or latent Dirichlet allocation (LDA).

3.3 Ontology not only subsumption reasoning (RQ3)

It is interesting to note that a majority of articles (see Figure 6) only use subsumption rules for deductive reasoning. By deductive reasoning, we mean here ontological reasoning, i.e. the deduction of new facts from general rules. In this review, most of the papers use only the semantic contribution, in particular hierarchical relations, of ontologies and do not focus on the discovery of new facts based on ontological reasoning. Thus, only 37% of the reviewed articles describe a form of combination between inductive learning and deductive reasoning with non-hierarchical rules. These articles are identified by a check mark in the "Reasoning" column of the tables 3, 4 and 5.

It appears that many authors use ontologies as improved taxonomies (with non-heuristic relations between concepts) but do not use more complex rules for the inference part.

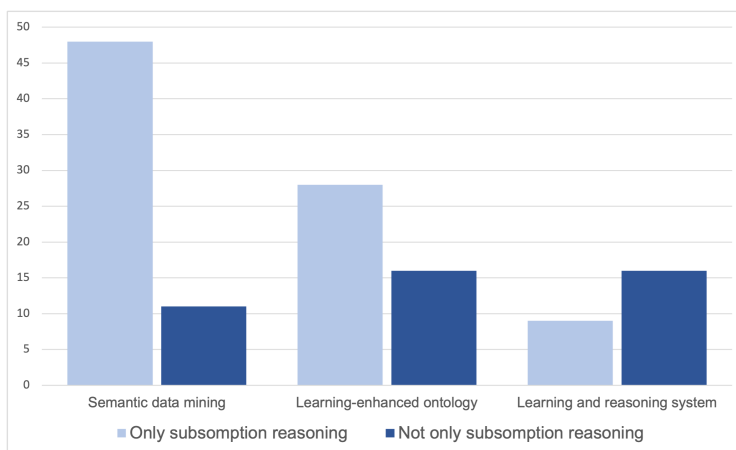


Figure 6: Proportion of subsumption and not only subsumption ontology reasoning in studies

3.4 Artificial intelligence themes (RQ4)

ACM Computing Classification System¹⁰ defines several main themes involved in artificial intelligence like: *Natural Language Processing (NLP)*, *Computer vision*, *Multi-agents system*, *Time series* and *Planning and scheduling*. Some of the selected articles are dedicated to an application in one of these themes.

The most present approach is *NLP*, including articles dealing with *ontology learning* and *informed machine learning* (cf. Figure 7) as detailed in sections 4.1 and 5. Some articles deal with *Computer vision*, in particular for image recognition. Few articles are involved in *Multi-agents system* and *Time series*. Only one article is concerned by *Planning and scheduling*. All relevant AI themes, not only the five main themes, are listed in the "AI Theme" column of Tables 3, 4 and 5.

3.5 Application domains (RQ5)

Figure 8 shows that 43% of the papers do not focus on a single application domain. Indeed, the authors have chosen to solve a particular problem by basing their work on either generalist or interchangeable datasets in order to allow the reuse of their work in various application domains. However, the application domain the most encountered is Health (26% of the studies), notably because medical ontologies such as SNOMED¹¹ or biological ontologies such as GeneOnto¹² are often used in this domain. It is also a domain that has very strong constraints in terms of the explainability of results. The use of semantic data and ontological reasoning are quite appropriate for this kind of problematic [Rubin et al., 2008].

¹⁰<https://dl.acm.org/ccs>

¹¹<https://biportal.bioontology.org/ontologies/SNOMEDCT>

¹²<http://geneontology.org/docs/download-ontology/>

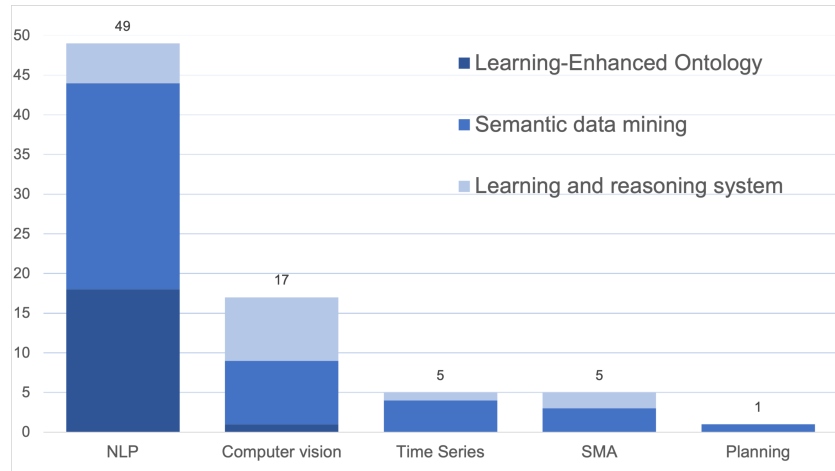


Figure 7: Artificial intelligence themes

The other domains present in this review are much more anecdotal, as shown in Figure 8. The other domains own less than 10 papers, or even just one. All application domains are listed in the "Application domain" column of Tables 3, 4 and 5.

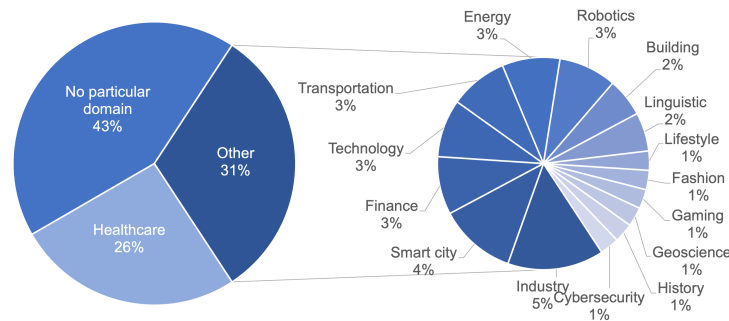


Figure 8: Application domains

4 Learning-Enhanced Ontology

There are several ways to improve the use of ontologies through machine learning. First, ontology creation and maintenance can be (partly) automated thanks to machine learning techniques. In this case, we speak about *ontology learning* [Wong et al., 2012], in which ontologies can be learned from various resources. Second, *ontology mapping* groups together the categories that allow the use of ontologies to be improved thanks to machine learning (i.e., guaranteeing interoperability). Finally, *learning-based reasoning* presents the set of techniques to facilitate deductive ontological reasoning thanks to machine learning.

The comprehensive details of all papers within this category are outlined in Table 3, where they are meticulously categorized by their respective field of application, AI themes they explore, and the machine learning algorithms employed.

4.1 Ontology learning

Ontology learning is the process through which ontologies are automatically generated or enriched from various sources of data and knowledge [Maedche and Staab, 2001]. This concept has already been studied in many recent reviews due to its potential to provide valuable assistance in the creation of ontologies, a traditionally time- and resource-intensive task [Al-Aswadi et al., 2020, Khadir et al., 2021, Asim et al., 2018].

The ontology learning process involves collecting and sometimes analyzing data from diverse sources such as texts, databases, web documents, and even existing ontologies. Using machine learning algorithms, information extracted from these data is then utilized in identifying concepts, relationships, and properties that could potentially be integrated into an ontology. Figure 9 illustrates this mechanism, showing that data is processed by a machine learning algorithm, symbolized by a funnel, before being transformed into elements of the TBox or ABox of an ontology, represented by the annotated polygon "A/T Box" associated with a cogwheel. The cogwheel symbolizes the final ontology created, upon which inferences can now be made.

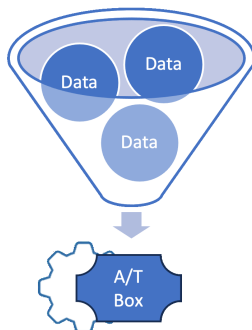


Figure 9: Ontology learning mechanism

4.1.1 Automatic taxonomy construction

Automatic Taxonomy Construction (ATC) is the computer process of systematically generating a hierarchical classification system for entities or concepts based on inherent relationships, attributes, or similarities.

The ATC process comprises several distinct stages, each of which is identified and carefully described by Getahun and Woldemariyam [2017]. Firstly, the pre-processing stage involves preparing the raw data, usually text, by cleaning, tokenizing, and normalizing it to facilitate subsequent analysis. Next, the concept extraction phase focuses on identifying key concepts or terms in the pre-processed data, using techniques such as NLP and pattern recognition. Concept extraction can employ various techniques, ranging from conventional approaches like TF-IDF [Ghoniem et al., 2019] to topic modeling methods such as LDA [Rani et al., 2017], or advanced deep learning techniques using Word2vec, including CBOW or Skip-G [Albukhitan et al., 2017]. These extracted concepts are then mapped to specific domains or topics in the concept-domain matching phase, where they are ranked according to their relevance, often using a similarity score [Albukhitan et al. [2017], Getahun and Woldemariyam [2017], Ghoniem et al. [2019]. Next, the concept-pair extraction phase aims to discover relationships between concept pairs, often using semantic analysis and graph-based algorithms to identify associations. Finally, the taxonomic relationship extraction phase aims to establish taxonomic relationships between identified concepts, such as hierarchical relationships like "is-a" or "part-of", thus completing the taxonomy construction. The concluding phase, serving as the core of ATC, encompasses the utilization of machine learning techniques such as formal concept analysis (FCA) [Jurkevičius and Vasilecas, 2010], hierarchical agglomerative clustering (HAC) [Getahun and Woldemariyam [2017], and, more recently, recurrent neural networks [Petrucci et al., 2018]. Additionally, methods involving Markov networks, such as Markov Logic Networks (MLN) [Wu and Weld, 2008] or Conditional Random Field (CRF) [Song et al., 2016, Jia et al., 2018], are also employed in this crucial stage. Together, these integrated steps form a comprehensive framework for the automatic generation of taxonomies from unstructured data. Studies frequently leverage a combination of at least three of the four mentioned steps to achieve this process.

While numerous papers employ unstructured data, such as text corpora, as the input for ATC, it's important to recognize that ATC can also be applied to structured data, as demonstrated by the research conducted by [Jia et al., 2018].

4.1.2 Learning non-hierarchical relations

Learning non-hierarchical relations in ontology learning involves identifying and comprehending semantic connections between entities that do not follow a hierarchical structure, typically focusing on association, correlation, or analogy-based methods to discover and label these relations. Incorporating these non-taxonomic relations elevates the achieved taxonomies to the status of ontologies. To accomplish this, [Albukhitan et al. [2017] employs an undisclosed clustering algorithm, while [Getahun and Woldemariyam [2017] utilizes both a correlation-based method and a concept analogy-based approach leveraging Word2Vec. In contrast, [Petrucci et al. [2018] utilizes a Seq2Seq algorithm to convert a

natural language sentence like "*A bee is an insect that produces honey*" into its formalized logical description, expressed as " $bee \subseteq insect \cap \exists produces.honey$ ".

4.1.3 Rule discovery

Rule discovery or rule mining aims to discover actionable and interpretable rules that capture interesting patterns or dependencies within the data, aiding in decision-making and knowledge extraction. It facilitates the representation of complex relationships and inferences within ontologies (such as IF-THEN rules), often expressed in a formalized set of machine-readable rules, such as SWRL.

The study by Jurkevičius and Vasilecas [2010] mentions the use of an artificial neural network (ANN) for rule generation, although details on this aspect are limited in the article. McGlenn et al. [2017] adopt a mix of intelligent rule generation techniques, employing both ANNs and genetic algorithms (GA), as well as data mining rules using decision tree techniques on historical sensor data. Ko et al. [2021] focus on the construction of design rules for additive manufacturing (AM) using the machine learning algorithm CART (Classification and Regression Tree) on measurement data. In their study in the financial domain, Yang [2020] use the Apriori algorithm to discover association rules between data items in transactions. This algorithm is particularly suitable for inferring situational elements of risky events such as time and place through the analysis of transaction data.

These first three areas: automatic taxonomy construction, learning non-hierarchical relations, and rule discovery are TBox statements.

4.1.4 Ontology population

Ontology population is the process of enriching the TBox within an ontology by adding a substantial base of factual knowledge or instances. This involves inserting concrete data or instances into the ontology's conceptual framework, thus constituting the ABox part of the ontology. The automatic populating of an ontology is an important issue, as it enables the deductive reasoning mechanism to be used rapidly on a sometimes heterogeneous database.

In the study by Craven et al. [2000], the focus is on populating the ontology by extracting new instances from web pages using the Naive Bayes algorithm. The algorithm is used to classify and identify instances, providing a method for populating the ontology with factual information gathered from web sources. Kordjamshidi and Moens [2015] focus on populating the ontology with spatial information extraction. They use the Support Vector Machine (SVM) algorithm to efficiently populate the ontology with spatial information by extracting relevant details from different sources, helping to enrich the knowledge base. Markievicz et al. [2015] extend the application of SVMs to the field of robotics. The study focuses on the classification of actions described in a corpus of texts relating to chemistry experiments. The ultimate goal is to translate these actions into a robot executable format. In the healthcare field, Rubrichi et al. [2013] propose a methodology for the automatic recognition of drug-related entities in textual descriptions of drugs. They use the CRF (Conditional Random Field) algorithm, derived from Markov methods, to populate the ontology with this drug-related information. Packer and Embley [2015] use hidden Markov models (HMMs) for the ontology population in the historical domain. They present ListReader, a method for training the structure and parameters of an HMM without the need for labeled training data. This approach is particularly beneficial for dealing with OCR errors in historical documents. Kuang et al. [2018] address large-scale visual recognition in the context of computer vision. They propose a multi-level deep learning algorithm that combines deep convolutional neural networks (CNNs) and tree classifiers. In the field of biochemistry, Ayadi et al. [2019] introduces a new approach to automatically populate the ontology of biomolecular networks. They rely on artificial neural networks (ANNs), in particular deep learning, and preprocessing techniques with Word2Vec.

4.1.5 Ontology enrichment

While the terminology section of the ontology, captured by the TBox, tends to be less dynamic than the instances in the ABox, regular maintenance is essential to prevent the ontology from becoming outdated. Ontology enrichment refers to the process of enhancing an ontology by updating its content through the addition or modification of concepts, properties, and relationships [Messaoud et al., 2015]. This process aims to expand the ontology's knowledge representation to accommodate new information and ensure its relevance to evolving domains or applications. Indeed, it is unrealistic to anticipate the inclusion of all domain and expert knowledge in an initial ontology due to various factors. These may include experts' limitations in formalizing their knowledge comprehensively from the beginning or the possibility that certain problems or required knowledge have not yet been identified [Thomopoulos et al., 2013].

In the biomedical study by Valarakos et al. [2006], a dataset from a domain-specific corpus (PubMed abstracts) is used. Hidden Markov Models (HMM) are used to extract relevant tokens from the dataset. Next, the COmpression-based CLUstering (COCLU) algorithm is applied for ontology enrichment, focusing on non-taxonomic lexical-semantic

relations. Thomopoulos et al. [2013] focus on ontology enrichment in the context of the food industry. They use classification algorithms such as CART and C4.5 to extract new knowledge, including concepts and relationships, from a food dataset. Note that all new propositions are validated by a domain expert before being incorporated into the ontology. Messaoud et al. [2015] contribute to the enrichment of a medical ontology through causal discovery. Their method, SemCaDo (Semantic Causal Discovery), uses causal Bayesian networks (CBNs) to learn causal discoveries from gene expression datasets and gene ontology. The new knowledge found by the CBN is then used to evolve the ontology. Song et al. [2016] apply conditional random fields (CRFs) to discover Q&A from collaborative engineering tasks. The discovered Q&A are transformed into ontological concepts and relations by a semantic mapping step. [Mihindukulasooriya et al., 2018] focus on knowledge base (KB) quality assessment. They use the Random Forest (RF) algorithm to add integrity constraints to the KB, thereby improving its quality. The work of Hong et al. [2021] in the field of brain areas and autism uses natural language processing (NLP) techniques. BiLSTM and CRF are used for entity extraction, then BiLSTM is used again for relation extraction. Finally, instances with high confidence scores are manually reviewed by experts. Meroño-Peñuela et al. [2021] target ontology evolution and concept drift detection in Web vocabularies. They exploit several algorithms provided by the WEKA API and use strings of RDF vocabulary versions as datasets. Djellali [2013] propose a semi-automatic approach using truncated singular value decomposition (TSVD) and Fuzzy ART clustering for ontology enrichment. The method involves variable selection and clustering to identify candidate changes, reducing noise and improving clustering accuracy.

4.2 Ontology mapping

Ontology mapping, also known as ontology alignment, aims to discover correspondences between terms with similar meanings in two distinct ontologies while ensuring the overall structure coherence of the ontology KALFOGLOU and SCHORLEMMER [2003]. The primary goal of ontology mapping is to establish a semantic correspondence between elements of ontologies to facilitate interoperability and extend their terminological scope by aligning concepts, properties, and instances.

Concept alignment involves finding equivalences between similar concepts, such as "housing" and "dwelling"; property alignment matches relationships between concepts, such as "has owner" and "owned by"; and instance alignment associates specific individuals from different ontologies representing the same reality. This process, depicted in Figure 10, begins with the preparation of source ontologies, represented by annotated polygons "A/T Box," including selecting relevant features in the TBox and ABox. Then, a machine learning model, symbolized again by a funnel shape, is trained, either supervised (with known correspondences) or unsupervised (automatically discovering potential correspondences). This model is then used to predict correspondences between common elements in both ontologies, as illustrated by the final "A/T Box" polygon situated between the two starting ontologies. These correspondences are often subjected to quality evaluation, particularly for coherence, and integrated to enhance interoperability between source ontologies. Finally, post-processing may be applied to refine the results.

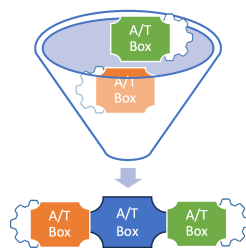


Figure 10: Ontology mapping mechanism

The use of machine learning in ontology mapping automates the process of discovering semantic correspondences, particularly valuable in environments where heterogeneous ontologies need integration. To achieve this goal, ensemble methods are sometimes employed, such as Random Forest (using bagging) [Rico et al., 2018, Annane et al., 2018] or an approach involving three classifiers [Fanizzi et al., 2011]. However, neural networks, particularly the multi-layer perceptron (MLP) [Rubiolo et al., 2012, Shannon et al., 2021], and more recently, recurrent neural networks (RNNs) like LSTM [Chakraborty et al., 2021], or transformer models such as BERT [Mohan et al., 2021], or specific design architectures like IAC [Mao et al., 2010], are the prevailing choices. Neural networks also contribute to data pre-processing through techniques like Word2Vec [Zhou and El-Gohary, 2021].

Ontology mapping is an essential process for harmonizing distinct ontologies and promoting data and knowledge interoperability. The use of machine learning techniques, including neural networks and ensemble methods, facilitates

the ontology alignment process, making it applicable to large datasets. Ultimately, this contributes to fostering the efficient exchange of information in a dynamically evolving digital environment.

4.3 Learning-based reasoning

In the field of learning-based reasoning, the papers focus on the integration of machine learning techniques to improve ontological reasoning. Indeed, the main challenge facing ontological reasoning is its slow execution, particularly when deployed in real-life scenarios. In our fast-moving society, especially for real-time systems, machine learning algorithms offer a promising solution to enhance the efficiency of inference engines. They can also provide significantly faster alternatives to traditional inference engines such as Pellet [Sirin et al., 2007] or HermiT [Shearer et al., 2008].

Diverse strategies for harnessing machine learning in ontological reasoning depend on the capability of machine learning algorithms to recognize intricate patterns, associations, and relationships within input ontologies. Figure 11 illustrates this process, showing how machine learning, represented by a funnel, acquires the ability to perform deductive reasoning based on ontologies represented here by the annotated "A/T Box" polygon. The final deductive reasoning capability is symbolized by the cogwheel next to the "A/T Box" polygon.

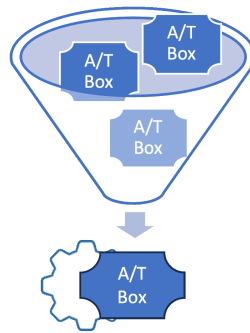


Figure 11: Learning-based reasoning mechanism

4.3.1 Optimizing reasoning

Optimizing reasoning can be achieved through various methods, including selecting a deductive reasoner appropriate for the application context, predicting reasoner performance to detect scalability issues, or enhancing the performance of deductive reasoners themselves by incorporating machine learning.

Selecting a reasoner involves choosing an appropriate inference engine or reasoning tool to perform deductive reasoning. Capabilities, efficiency, and compatibility with specific languages or ontology formats may vary from one reasoner to another. The choice of reasoner depends on factors such as ontology complexity, the desired level of reasoning support, and available computing resources. In the study by Bock et al. [2012], the focus is on selecting an appropriate reasoner for ontological reasoning tasks. The authors, recognizing that no reasoning algorithm universally excels in all description logic and reasoning tasks, implemented an approach within the framework of a reasoning broker called HERAKLES. In HERAKLES, machine learning techniques such as Naive Bayes, k-NN, Support Vector Machine (SVM), and Decision Tree are compared with each other. Through their experimentation, they found that the Decision Tree algorithm outperformed the others, demonstrating superior performance in choosing an appropriate inference engine.

Predicting reasoner performance involves estimating the duration required for a given reasoning task within a specified ontology. Essentially, it involves forecasting the time needed for a reasoner to complete its tasks, facilitating better planning and management of ontology-related projects and applications. Pan et al. [2018] use a combination of the Random Forest (RF) classifier and the Boruta algorithm for feature selection to predict reasoner performance. The challenge is to capture the complexity of ontologies, particularly as ABox intensity increases. The features proposed in the research contribute to greater accuracy in predicting time consumption for ontological reasoning tasks.

Using machine learning techniques can also accelerate the performance of OWL reasoners by reducing the complexity of reasoning tasks. In the Mehri et al. [2021] study, the aim is to improve the performance of reasoning systems by applying heuristic optimization techniques assisted by machine learning (ML). The authors use feature reduction techniques, in particular principal component analysis (PCA), to transform features into a set of new non-linearly correlated features. In addition, they use the support vector machine (SVM), well-suited to binary classification in high-dimensional feature spaces.

4.3.2 Perform reasoning

The capacity to perform deductive reasoning through a learning model, of logic-based symbolic formalisms, is a recent area of research [Hohenecker and Lukasiewicz, 2020]. The two most recent papers reviewed in this study utilize neural networks to accomplish this task.

The first approach proposed by Rizzo et al. [2017] integrates the use of decision trees, in particular Random Forest (RF), enabling the construction of terminological decision trees to help reasoning processes in the Semantic Web environment. In the study by Hohenecker and Lukasiewicz [2020], a new model architecture called Recursive Reasoning Network (RRN) is developed to perform this deductive reasoning task. Makni and Hendler [2019] focus on noise-tolerant reasoning in ontologies, recognizing the challenge of noise tolerance as a major bottleneck in deductive reasoning. To address this, they employ a recurrent neural network (RNN) to achieve noise-tolerant reasoning capabilities in ontology, this work is particularly interesting for dealing with noisy data commonly encountered in real-world applications.

Table 3: Details of articles in the Learning-Enhanced Ontology category

Category	Sub-category	AI Theme	Application domain	Learning type	Learning algorithm	Reasoning	Paper
Ontology learning	Automatic taxonomy construction	NLP	Wikipedia	Supervised	Markov Logic Network	✗	[Wu and Weld, 2008]
		NLP	Technology		CRF	✓	[Song et al., 2016]
		NLP	Cybersecurity		CRF	✓	[Jia et al., 2018]
		NLP, Translation	-		RNN (Seq2Seq)	✗	[Petrucci et al., 2018]
		NLP	Biomedical		RNN, Naive Bayes	✗	[Zhao and Zhang, 2018]
		NLP	Biomedical		SVM	✗	[Ghoniem et al., 2019]
		NLP	-	Unsupervised	FCA	✗	[Jurkevičius and Vasilecas, 2010]
		NLP	Tourism		HAC	✗	[Getahun and Woldemariam, 2017]
		NLP	-		LDA, LSI, SVD	✗	[Rani et al., 2017]
	NLP	Linguistic	Self-supervised	Word2Vec (CBOW)	✗	[Albukhitan et al., 2017]	
	NLP	Tourism		Word2Vec	✗	[Getahun and Woldemariam, 2017]	
	Learning non-hierarchical relations	NLP, Translation	-	Supervised	RNN (Seq2Seq)	✗	[Petrucci et al., 2018]
		NLP	Tourism	Self-supervised	Word2Vec	✗	[Getahun and Woldemariam, 2017]
		NLP	Linguistic	Unsupervised	Clustering	✗	[Albukhitan et al., 2017]
Rule discovery	NLP	-	Supervised	ANN	✗	[Jurkevičius and Vasilecas, 2010]	
	-	Building Energy Management System		M5, ANN, GA,	✓	[McGlinn et al., 2017]	
	-	Additive Manufacturing		CART	✓	[Ko et al., 2021]	
	-	Finance	Unsupervised	APRIORI	✓	[Yang, 2020]	
Ontology population	NLP	Web	Supervised	Naïve Bayes	✗	[Craven et al., 2000]	
	-	Healthcare		CRF	✓	[Rubrichi et al., 2013]	
	NLP, Spatial information extraction	-		SVM	✓	[Kordjamshidi and Moens, 2015]	
	NLP	Robotics		SVM	✗	[Markievicz et al., 2015]	
	-	History		HMM	✗	[Packer and Embley, 2015]	
	Computer vision, Large-scale visual recognition	-		Decision tree, CNN	✗	[Kuang et al., 2018]	
	NLP	Biochemistry		ANN	✗	[Ayadi et al., 2019]	
Ontology enrichment	NLP	Biochemistry	Self-supervised	Word2Vec	✗	[Ayadi et al., 2019]	
	-	Biomedical	Supervised	HMM	✗	[Valarakos et al., 2006]	
	-	Food industry		CART, C4.5	✗	[Thomopoulos et al., 2013]	
	Causal discovery	Healthcare		CBN (SemCaDo)	✓	[Messaoud et al., 2015]	
	-	Technology		CRF	✓	[Song et al., 2016]	
	KB quality assessment	-		RF	✗	[Mihindukulasooriya et al., 2018]	
	NLP	Healthcare		biLSTM, CRF	✓	[Hong et al., 2021]	
	-	Web vocabularies		Multiple algorithm	✗	[Meroño-Peñuela et al., 2021]	
	-	Biomedical	Unsupervised	COCLU	✗	[Valarakos et al., 2006]	
	NLP	-		TSVD, Fuzzy ART	✗	[Djellali, 2013]	
Ontology mapping	Constraint satisfaction problem	Web	Supervised	IAC	✗	[Mao et al., 2010]	

Table 3: Details of articles in the Learning-Enhanced Ontology category

Category	Sub-category	AI Theme	Application domain	Learning type	Learning algorithm	Reasoning	Paper
		-	-		Ensemble classifier	✗	[Fanizzi et al., 2011]
		-	-		MLP	✗	[Rubiolo et al., 2012]
		Anchoring	-		RF	✗	[Annane et al., 2018]
		-	-		ANN	✗	[Gao et al., 2018]
		-	Wikipedia		RF, MLP, SMO	✗	[Rico et al., 2018]
	NLP	-	Healthcare		MLP	✗	[Shannon et al., 2021]
		-	Biomedical	Self-supervised	BERT	✗	[Mohan et al., 2021]
		-	Building		Word2Vec	✗	[Zhou and El-Gohary, 2021]
		-	Wikipedia	Unsupervised	PCA	✗	[Rico et al., 2018]
		-	Web		LSTM	✓	[Chakraborty et al., 2021]
		Competitive learning	Sensor, IoT		ANN	✗	[Xue et al., 2021]
Learning-based reasoning	Optimizing reasoning	-	-	Supervised	Naive Bayes, k-NN, SVM, Decision tree	✓	[Bock et al., 2012]
		-	-		RF (and Boruta algorithm)	✓	[Pan et al., 2018]
		-	-		SVM	✓	[Mehri et al., 2021]
		-	-	Unsupervised	PCA	✓	[Mehri et al., 2021]
	Perform reasoning	Inductive Logic Programming	Semantic Web		Decision Tree, RF	✓	[Rizzo et al., 2017]
		Noise-tolerance	Web	Supervised	RNN	✓	[Makni and Hendler, 2019]
		-	-		RRN	✓	[Hohenecker and Lukasiewicz, 2020]

5 Semantic Data Mining

In this section, we present *Semantic Data Mining* using knowledge from ontology to improve the performance of machine learning algorithms [Lawrynowicz and Potoniec, 2014]. Semantic data mining is a particular form of Informed Machine Learning defined by von Rueden et al. [2021] and means "using hybrid information source that consists of data and prior knowledge in machine learning"¹³. The term *informed machine learning* is particularly present in the field of physics [Karniadakis et al., 2021], where the concern is to embed physics into machine learning to improve the results and better adapt the algorithms to the complexity of physical problems.

In other words, semantic data mining is a combination of data-driven and ontology-driven approaches. This knowledge can be added to machine learning at different stages of the machine learning pipeline [von Rueden et al., 2021], like during the training data stage (*Ontology-based feature engineering*), the hypothesis set stage (*Ontology-based algorithm design*), the learning algorithm stage (*Ontology-based algorithm training*) or at final hypothesis stage (*Ontology-based explanation*).

The comprehensive details of all papers within this category are outlined in Table 4, where they are meticulously categorized by their respective field of application, AI themes they explore, and the machine learning algorithms employed.

5.1 Ontology-based feature engineering

At the first step of machine learning processes (i.e. training data), *Ontology-based feature engineering* allows mixing raw data with prior knowledge in several ways according to feature engineering definition [Duboue, 2020]: feature augmentation, feature selection, feature extraction or semantic embedding.

In the context of this review, studies categorized in this domain utilize a hybrid source of data, incorporating one or more ontologies, symbolized by the annotated polygon "A/T Box," to produce final results in the form of data, as illustrated in Figure 12.

5.1.1 Feature augmentation

Feature augmentation involves adding new variables (features) derived from the prior knowledge present in the ontology to the original dataset. This process does not always involve logical reasoning; the ontology's semantic structure alone

¹³Dedicated terms to reference articles about informed machine learning in the literature. Defines here as *The prior knowledge comes from an independent source, is given by formal representations, and is explicitly integrated into the machine learning pipeline* [von Rueden et al., 2021].

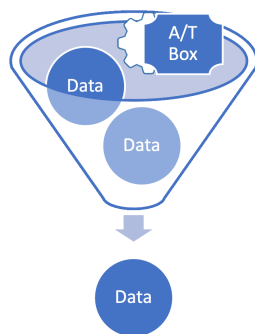


Figure 12: Ontology-based feature engineering mechanism

can be sufficient to enrich the original dataset with valuable information that was not available at the outset. The primary objective is to enrich the input features with relevant ontological knowledge, providing the model with a deeper understanding of the domain under consideration. Using ontology to augment features can improve data representation, raise model performance and contribute to more insightful decision-making in a variety of applications.

In the field of NLP, and more specifically Automatic Language Processing (ALP), the incorporation of additional data into the initial dataset can prove valuable, as demonstrated by Pozveh et al. [2018] through tasks such as POS labeling, Named Entity Recognition (NER) and Word Disambiguation (WD). In the field of applications for intelligent environments, Ye et al. (2015) used k-means clustering for activity recognition from sensor data augmented with an ontology. In the same line, Salguero et al. (2019) used support vector machines (SVMs) for the recognition of everyday activities from the same type of data. As shown in Table 4, the addition of new features using ontology can be integrated with a wide range of machine learning algorithms.

5.1.2 Feature selection

Feature selection aims at reducing the number of variables to keep only the most relevant without changing the initial variables [Gomathi and Karlekar, 2019]. Unlike traditional feature selection methods, ontology-based feature selection exploits the semantic relationships and structures defined in an ontology to identify and prioritize features for inclusion or exclusion. This approach aims to improve the selection process by incorporating domain-specific semantics, ensuring that selected features align with underlying ontological concepts. Note that this technique can sometimes be useful when faced with the curse of dimensionality [Bellman, 1961].

5.1.3 Feature extraction

Feature extraction is the process of transforming raw data into a reduced, relevant representation, highlighting important features for subsequent analysis. Ontology-based feature extraction involves modifying the original variables based on the prior knowledge provided by the ontology to obtain relevant features. This process aims to derive relevant features by exploiting the semantic information embedded in the ontology and allows input variables to be tailored to improve analysis and model performance.

Feature extraction often involves textual data, implying the use of NLP techniques, especially in sentiment analysis where neural networks are frequently employed [Kumar et al., 2020, Sabra et al., 2020, Ahani et al., 2021]. In computer vision, leveraging ontology can assist in extracting meaningful features from images. Typically, a pre-processing step is employed to transform images into information effectively used by the ontology. Next, the data is often processed by a neural network. Akila et al. [2021] used ANN for sports image feature extraction, and [Zhao et al., 2021] for industrial vision inspection. Messaoudi et al. [2021] applied convolutional neural networks (CNN) to healthcare for MRI data classification, while Rinaldi et al. [2021] employed the VGG16 model for feature extraction from both textual documents and pre-classified images. The feature extraction process can also help reveal meaningful patterns and temporal relationships in time series, facilitating predictions made on this kind of data. In the study conducted by Liu et al. [2021] on photovoltaic time series data, the authors used managed recurrent units (GRUs) for feature extraction. GRUs, a type of recurrent neural network (RNN), are particularly effective at capturing temporal dependencies in sequential data.

5.1.4 Semantic embedding

In *Semantic embedding*, raw data is refined by semantic knowledge and then transformed into vectors to be exploited mainly by neural networks. This explains the prevalence of neural networks in this category since the data is specifically transformed for them. However, it is noteworthy that Mabrouk et al. [2020] employs semantic embedding for an SVM, while Zhang et al. [2021] utilizes it for XGBoost. The oldest paper in this SLR that uses this technique is from 2018, we can therefore assume that research in this field is recent.

This category encompasses numerous papers that leverage ontology to create knowledge graph embeddings (KGE) [Chen et al., 2021]. KGE employs models like TransE, TransR, DistMult, etc., each with a score function to convert the graph's knowledge into vectors usable by machine learning algorithms. In our study, the primary applications of this technique are in automatic text processing and time series analysis. These transformations are conducted with meticulous consideration for preserving the links between different entities within the KGE. Ontology embedding expands upon this representation, encompassing a broader scope of ontological knowledge, including aspects like existential rules. In their work, Benarab et al. [2019] employs autoencoders for the implementation of ontology embedding. Word2Vec is also frequently used to pre-process plain text before the semantic embedding stage [Jang et al., 2018, Ali et al., 2021, Amador-Domínguez et al., 2021].

5.2 Ontology-based algorithm design

In the second stage of the machine learning process (i.e. the hypothesis set), *ontology-based algorithm design* contributes to the incorporation of ontological knowledge into the design and development of machine learning algorithms.

5.2.1 Ontology-based decision tree

Ontology-based decision trees refer to an algorithmic design approach that incorporates ontological principles into the construction and use of decision trees. In this context, decision trees, such as random forests, are developed and used in a way that incorporates ontological knowledge. Emele et al. [2012] introduced an ontology-based decision tree called STree, derived from C4.5 and enhanced with ontological reasoning, applied to military dialogues.

5.2.2 Ontology-based probabilistic graphical model

An ontology-based probabilistic graphical model refers to an algorithmic design approach that incorporates ontological principles into the construction and use of probabilistic graphical models, such as Bayesian networks or Markov models.

Ruiz-Sarmiento et al. [2019] proposed an ontology-based probabilistic graphical model, specifically Ontology-based Conditional Random Fields (obCRFs), for robotics in computer vision tasks. This model enhances standard Conditional Random Fields (CRFs) with additional nodes and relations based on a multi-level ontology structure, aligning with the subsumption ordering of ontologies, to improve object recognition in robot environments.

5.2.3 Ontology-based neural topology

Ontology-based neural topology entails an algorithmic design approach that incorporates ontological principles into the selection or creation of the architectural design for neural networks. This methodology involves integrating ontological insights to guide the structure and configuration of neural networks, aligning them with domain-specific knowledge and semantic relationships.

Gabriel et al. [2014] facilitate the choice of an appropriate ANN model structure thanks to an ontology. Rather than going through a grid-search step which is sometimes too time-consuming in complex systems, a model topology (e.g. the number of hidden layers and the number of neurons in the hidden layers for a neural network) can be approximated by prior knowledge. Huang et al. [2019] introduced OntoLSTM, an ontology-based long-term memory neural network (LSTM), wherein dense layers are encoded using ontology-derived information. This approach is specifically designed for time series analysis within the context of Industry 4.0. Kuang et al. [2021] addressed large-scale fashion recognition using a hierarchical deep learning approach called Augmented Hierarchical Deep Learning (AHDL). The proposed hierarchical knowledge distillation method facilitates knowledge transfer between tree node classifiers of hierarchical deep networks, thus improving fashion image representation and classification. Fu et al. [2015] focused on personal photo tagging using transfer learning with a Convolutional AutoEncoderS (CAES) to which they added a Fully Connected layer with Ontology priors (FCO). Their approach exploits ontology priors in the last layer of a fully connected network to improve personal photo tagging performance.

5.3 Ontology-based algorithm training

At the third step of the machine learning process (i.e. learning algorithm), *ontology-based algorithm training* integrated prior knowledge into the machine learning algorithm, typically via a loss function.

In their work, Serafini et al. [2017] introduced ontology-based algorithm training through the application of a Logical Tensor Network (LTN). The LTN framework integrates logical reasoning into deep learning architectures using t-norms derived from fuzzy logic. This innovative approach allows logical constraints to be added to the inductive reasoning process.

5.4 Ontology-based explanation

In the realm of artificial intelligence research, neural networks are frequently regarded as “black boxes”, where the explicit input-output behavior of the algorithm is observable, but the underlying reasoning mechanism remains opaque. Therefore, the development of explainable artificial intelligence (XAI) becomes crucial. The explainability of an algorithmic model pertains to its ability to present a coherent sequence of interconnected steps that can be interpreted by humans as causes or reasons behind the decision-making process [Donís Ebri, 2021]. This capability allows for the clarification of the algorithm or its outputs, enhancing the understanding of how and why certain decisions are made. In addition to the issue of trust, the lack of explainability in AI models has also given rise to legal challenges in various domains such as military defense, healthcare, insurance, and autonomous vehicles. The inability to provide clear and understandable explanations for AI-driven decisions poses legal complications in these areas. The global explainability of a model aids in identifying the key variables that contribute to the model’s output. It enables the determination of the specific role played by a particular variable in the model’s final decision or prediction. Global explainability is used to assess the importance of a model’s features. The SHAP algorithm [Lundberg and Lee, 2017] is commonly employed to identify variables with the most significant impact in a machine learning model. Conversely, the local explainability of a model focuses on the process leading to decisions made for a specific individual [Ribeiro et al., 2016, Lundberg and Lee, 2017]. It aims to highlight the impact of each variable on the outcome, thereby making the decision more interpretable and understandable for that particular case.

When prior knowledge is not integrated, explanations are primarily based on mathematical correlations between data and results, which does not always guarantee the robustness and reliability of indicators. Black-box explanation through an ontology relies on the idea of using a formal and explicit knowledge structure to clarify the internal workings of a considered AI model, often viewed as a “black box.” This means that when a prediction is generated by a conventional machine learning model, as represented by a funnel in Figure 13, the ontology is then used to provide explanations for that prediction as shown in the same figure.

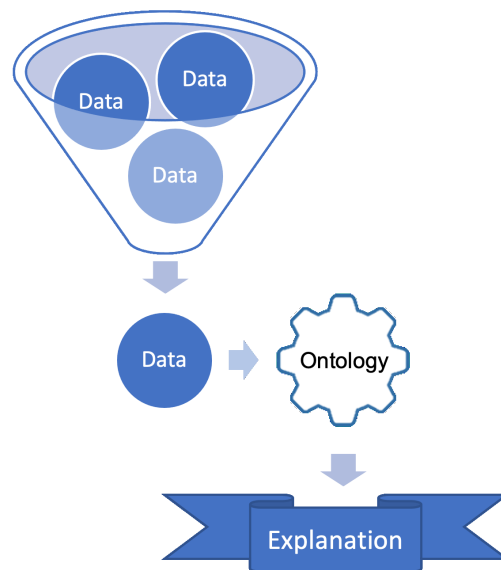


Figure 13: Ontology-based explanation mechanism

For a comprehensive explanation of the model, the ontology can be used to demonstrate how concepts and entities in the ontology are related to the features or input data of the model, thereby describing the overall reasoning process of

the model. For a local explanation, the ontology can be employed to highlight how specific concepts or entities in the ontology contributed to the particular prediction for a given individual. In this SLR, two studies use ontologies to enhance the explainability of models: one of these studies aimed to provide a global explanation of the model [Confalonieri et al., 2021], while the other focused on delivering local explanations [Panigutti et al., 2020].

These studies demonstrate the usefulness of ontologies in augmenting the interpretability of AI models, both at the global and local levels. The integration of prior knowledge through ontologies helps establish a logical and coherent framework for the model’s explanations, aligning them with existing domain knowledge. This not only enhances the trustworthiness of the explanations but also provides a deeper understanding of the reasoning process employed by the model.

Table 4 presents machine learning algorithms used in *Ontology-based explanation* category. Only neural networks are presented here, Panigutti et al. [2020] specifies that it is a Gated Recurrent Unit network (GRU), a special type of Recurrent Neural Network.

Table 4: Details of articles in the Semantic Data Mining category

Category	Sub-category	AI Theme	Application domain	Learning type	Learning algorithm	Reasoning	Paper
Ontology-based feature engineering	Feature augmentation	Automatic Task Detection	Technology	Supervised	J48	✗	[Rath et al., 2009]
		NLP	Cybersecurity (Spam detection)		Bayesian network	✗	[Santos et al., 2012]
		Pattern discovery	-		RF	✗	[Lawrynowicz and Potoniec, 2014]
		-	-		ANN	✗	[Pancerz and Lewicki, 2014]
		NLP, TAL	Persian text		HMM	✗	[Pozveh et al., 2018]
		-	Biomedical		SVM	✗	[Wan and Mak, 2018]
		Activity recognition	Smart environments		SVM	✗	[Salguero et al., 2019]
		NLP	Healthcare		RNN, CNN, HAN	✗	[Abdollahi et al., 2021]
		-	Healthcare		ANN	✗	[Wang et al., 2021a]
		Activity recognition	Smart home	Unsupervised	k-means	✗	[Ye et al., 2015a]
	Recommendation system	Wine		Farthest First (k-means)	✗	[Oliveira et al., 2021]	
	Feature selection	-	Healthcare	Supervised	ANN, SVM	✗	[Gomathi and Karlekar, 2019]
	Feature extraction	MAS, Planning	Tourism	Supervised	C4.5, k-NN	✗	[Castillo et al., 2008]
		Semantic annotation	-		Bayesian network	✗	[Rajput and Haider, 2011]
		-	Healthcare		Bayesian networks, ANN, SVM, regression (WEKA)	✗	[Hsieh et al., 2013]
		NLP, Sentiment analysis	-		SVM	✗	[Agarwal et al., 2015, Manuja and Garg, 2015]
		MAS	Contexte-aware		ANN	✓	[Yilmaz, 2017]
		NLP	Finance, Corporate disclosures		Naïve Bayes	✗	[Evert et al., 2019]
		User Interface	Healthcare		SVM	✗	[Greenbaum et al., 2019]
		NLP	Spam filtering		RF, SVM, C4.5, Naïve Bayes, LR, Adaboost, bagging	✗	[Mendez et al., 2019]
		-	Healthcare		LR	✗	[Radovanovic et al., 2019]
		NLP, Sentiment analysis	-		CNN	✗	[Kumar et al., 2020]
		NLP, Sentiment analysis	Healthcare		MLP, SVM, ensemble classifier	✓	[Sabra et al., 2020]
		NLP, Sentiment analysis	Healthcare		k-NN, ANFIS	✗	[Ahani et al., 2021]
		Computer Vision	Sport		ANN	✗	[Akila et al., 2021]
		Time series	Photovoltaic		GRU	✓	[Liu et al., 2021]
		Computer Vision	Healthcare		CNN	✗	[Messaaoui et al., 2021]
		NLP	Healthcare		LSTM	✗	[Nayak et al., 2021]
		Computer Vision, NLP	-		VGG16	✗	[Rinaldi et al., 2021]
		Computer Vision	Industry (Industrial vision)		ANN	✗	[Zhao et al., 2021]
-	Industry 4.0 (Condition monitoring)		LSTM	✓	[Zhou et al., 2021]		
NLP	-		ANN	✗	[Deepak et al., 2022]		
NLP	-		Self-supervised	Word2Vec	✗	[Kumar et al., 2020]	

Table 4: Details of articles in the Semantic Data Mining category

Category	Sub-category	AI Theme	Application domain	Learning type	Learning algorithm	Reasoning	Paper
		-	Biomedical	Unsupervised	FCA	×	[Akand et al., 2007]
		MAS, Planning	-		Clustering, EM	×	[Castillo et al., 2008]
		NLP	-		HAC	✓	[Radinsky et al., 2012]
		NLP	Finance, Corporate disclosures		LDA, LSI	×	[Evert et al., 2019]
		NLP, Sentiment analysis	Healthcare		EM, LDA, Hot-Deck	×	[Ahani et al., 2021]
		Computer Vision	-		k-means	×	[Akila et al., 2021]
		NLP	Biomedical		k-means	×	[Pérez-Pérez et al., 2021]
	Semantic embedding	NLP	Dialog state tracking	Supervised	bi-LSTM	×	[Jang et al., 2018]
		NLP, Sentiment analysis	Transport		SVM, LR, MLP, kNN, Naïve Bayes, Decision tree, DNN	×	[Ali et al., 2019]
		NLP	Healthcare		CNN	×	[Gaur et al., 2019]
		NLP	Linguistic		bi-LSTM	×	[Moussallem et al., 2019]
		NLP	Healthcare		MLP	×	[Hassanzadeh et al., 2020]
		NLP	-		SVM	×	[Mabrouk et al., 2020]
		NLP	Building		RNN	✓	[Ren et al., 2020]
		NLP	-		bi-LSTM	×	[Alexandridis et al., 2021]
		NLP	Healthcare		bi-LSTM	×	[Ali et al., 2021]
		Time series, concept drift	Smart City		LR, RF, ASHT, leveraging bagging, SGD	✓	[Chen et al., 2021]
		Time series	Healthcare		GRU	×	[Niu et al., 2022]
		NLP	-	Self-supervised	Word2Vec	×	[Jang et al., 2018]
		NLP, Sentiment analysis	Transport		Topic2Vec	×	[Ali et al., 2019]
		-	Biomedical		Autoencoders (multiple neural networks)	×	[Benarab et al., 2019]
		NLP	Geoscience		GloVe, Word2Vec, Doc2Vec	×	[Qiu et al., 2019]
		NLP	Healthcare		Word2Vec (skip-gram)	×	[Ali et al., 2021]
		NLP	-		Word2Vec	✓	[Amador-Domínguez et al., 2021]
		NLP, Sentiment analysis	Transport	Unsupervised	LDA	×	[Ali et al., 2019]
		NLP	Healthcare		LDA, Information Gain	×	[Ali et al., 2021]
Ontology-based algorithm design	Ontology-based decision tree	NLP (Dialogue)	Military	Supervised	C4.5	✓	[Emele et al., 2012]
	Ontology-based probabilistic graphical model	Computer Vision	Robotics	Supervised	CRF	×	[Ruiz-Sarmiento et al., 2019]
	Ontology-based neural topology	Time series	Industry 4.0	Supervised	LSTM	×	[Huang et al., 2019]
		Computer Vision	Fashion		CNN	×	[Kuang et al., 2021]
		MAS	Video Game	Reinforcement	ANN	×	[Gabriel et al., 2014]
		Computer Vision, Tagging	Personal Photos	Self-supervised (Transfer learning)	CAES, FCO	×	[Fu et al., 2015]
Ontology-based algorithm training		Computer Vision	-	Supervised	LTN	✓	[Serafini et al., 2017]
Ontology-based explanation		-	Healthcare	Supervised	GRU	×	[Panigutti et al., 2020]
		-	-		ANN	✓	[Confalonieri et al., 2021]

6 Learning and Reasoning Systems

This category represents the set of complete applications that use machine learning and ontologies to operate. The application is a computer program capable of performing one or more specific tasks in the same field, e.g. a decision support system for the management of cardiac pathology [Ali et al., 2020]. Studies in this category, shown in Figure 5,

describe complete application systems, not only some specific mechanisms (e.g. ontology learning, semantic feature engineering, etc.).

6.1 Expert System Embedded Learning

The first sub-category covers ontology-based expert systems that exploit machine learning for execution. An expert system comprises various components, including a knowledge base, an inference engine, and an interface [Liebowitz, 1997]. In *Expert System Embedded Learning*, the machine learning component, represented in Figure 14 by a funnel, is integrated into an expert system, here represented by a cogwheel symbolizing an ontology. The integrated learning model(s) can be considered as sub-modules of the expert system and the produced results mainly consist of new facts inferred by the expert system, represented by an annotated polygon "ABox". This is why we have chosen to use the term "embedded", which is an equivalent of "integrated" because the proper functioning of the expert system is closely linked to the machine learning part.

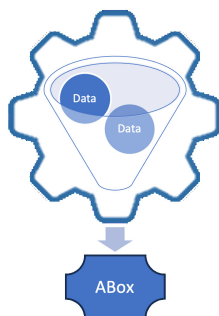


Figure 14: Expert System Embedded Learning mechanism

The two articles in this category use machine learning to find missing values in an expert system, enabling it to perform deductive reasoning. They therefore perform a task similar to that performed by Makni and Hendler [2019], which enables noise-tolerant deductive reasoning. However, their approach is different, as they don't use a machine learning algorithm to perform the reasoning, but rather to impute missing values. Moreover, in both instances, the decision-making system could theoretically operate without an external learning module, although with reduced performance. This distinction justifies their classification in the Expert System Embedded Learning category.

In the first study, Khan et al. [2013] introduced Holmes (Hybrid Ontological and Learning MEDical System), a medical system integrating ontology and machine learning for decision-making in patient treatment. Holmes employs Adaboost as its primary learning algorithm, enabling the creation of a semantic decision support system resilient to noise. Specifically, it addresses decision-making scenarios related to the administration of sleeping pills. In the second study, Bischof et al. [2018] presented the Open City Data Pipeline, which aims to collect, integrate, and enrich statistical data from various cities around the world for republication as machine-readable linked data. To handle missing values in the dataset, their imputation pipeline employs principal component analysis (PCA) as a pre-processing step. Subsequently, the authors apply different algorithms, including multiple logistic regression (MLR), k-nearest neighbors (k-NN), or random forest (RF), based on the performance obtained during the preprocessing phase.

6.2 Hybrid application

This second sub-category represents the set of hybrid application systems that use machine learning and ontologies in a more complex way, often by communicating the two types of reasoning (inductive and deductive) within the AI system. Figure 15 clearly illustrates the hybridization mechanism by symbolizing the fusion between machine learning (funnel) and ontology (cogwheel), enabling result prediction. Through the integration of multiple modules, these systems can capitalize on the advantages of learning-based approaches, such as machine learning, while leveraging symbolic reasoning techniques, such as ontologies.

Similar to the *Expert System Embedded Learning* category, hybrid applications leverage both learning and deductive reasoning. They use machine learning for tasks such as data recognition, shape analysis, or event detection and subsequently employ deductive reasoning based on the information acquired earlier. These works go beyond populating an ontology, even though the initial process may be similar. After processing raw data through learning, they incorporate it into the ABox of the ontology, enabling the utilization of deductive reasoning or (at least) semantic processing. The inclusion of some articles in this category is also justified by the incorporation of at least two distinct forms of

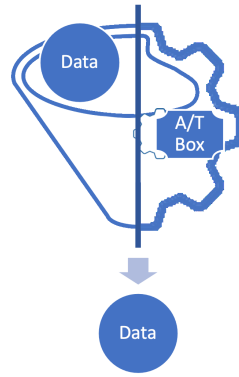


Figure 15: Hybrid application mechanism

hybridization. In other words, the authors not only engage in ontology learning, but also leverage the ontology created to inform a machine learning algorithm.

Some papers are based on the semantic interpretation of images. In the study by Zarchi et al. [2014], the authors focused on semantic image recognition based on image properties. They used artificial neural networks (ANNs) to develop a model capable of recognizing similar images by taking advantage of their semantic properties. Ye et al. [2015b] took computer vision applications a step further, focusing on event recognition. They used deep learning to train a model capable of recognizing events from videos, aligning them with ontology concepts. Convolutional neural networks (CNNs) played a crucial role in recognizing multiple events within a single video. Donadello and Serafini [2016] addressed the semantic understanding of images through the integration of ontology and machine learning. Their Part Whole Clustering Algorithm (PWCA) used ontology and machine learning, including deep learning and clustering techniques, to identify the different parts of an image belonging to specific objects. In the context of fine image classification, Palazzo et al. [2021] processed a complex dataset containing images of various fruit varieties. They tackled the challenge using Bayesian networks and CNNs. The authors encoded specialized knowledge in deep models by building a Bayesian network graph from the domain ontology.

Two studies investigate messages related to aviation. In the first paper, Wang et al. [2010] focused on the analysis of aviation-related messages and failure analysis. They used a Back-Propagation Neural Network (BPNN) algorithm, a type of artificial neural network (ANN). The ontology played a crucial role in preparing the variables for the neural network, subsequently facilitating the extraction of knowledge and its representation as rules. In the second paper, Wang et al. [2021b] studied natural language processing (NLP) in the context of aviation, in particular Air Traffic Control (ATC). They used a long-term memory network (LSTM), a type of recurrent neural network (RNN), and integrated an ontology to facilitate the translation of aeronautical messages. This approach enabled efficient language processing and understanding in the aviation context.

Two papers can be identified as being in the Smart City domain. Keyarsalan and Montazer [2011] focus on fuzzy ontology for traffic light control in a smart city context. They use the radial basis function neural network (RBFNN) for image recognition tasks, such as traffic density estimation. Then, the ontology is used as a decision aid to regulate traffic based on the results returned in real time by the images. [Patel et al., 2021] deal with video surveillance in a smart city scenario, in particular for the detection of abnormal events in a parking zone. They use the You Only Look Once (YOLO) algorithm for object detection in video images, enabling efficient feature extraction. The detected objects are then processed by an ontology to perform semantic reasoning on the images and identify anomalies.

Table 5: Details of articles in the Learning and Reasoning Systems category

Category	AI Theme	Application domain	Learning type	ML algorithm	Reasoning	Paper
Expert System Embedded Learning	-	Healthcare	Supervised	Adaboost	✓	[Khan et al., 2013]
	-	Smart City		MLR, k-NN, RF	✓	[Bischof et al., 2018]
	-	Smart City	Unsupervised	PCA	✓	[Bischof et al., 2018]
Hybrid application	MAS	-	Supervised	ANN	✓	[Rosaci, 2007]
	NLP, knowledge acquisition	Aviation, Failure analysis		BPNN	✗	[Wang et al., 2010]
	Computer Vision, Fuzzy ontology	Smart City, Traffic Light Control		RBFNN	✓	[Keyarsalan and Montazer, 2011]

Table 5: Details of articles in the Learning and Reasoning Systems category

Category	AI Theme	Application domain	Learning type	ML algorithm	Reasoning	Paper
	Computer Vision, Activity recognition	-		SVM	✓	[del Rincon et al., 2013]
	Computer Vision	-		ANN	✗	[Zarchi et al., 2014]
	Computer Vision	-		CNN	✗	[Ye et al., 2015b]
	Computer Vision	-		R-CNN	✓	[Donadello and Serafini, 2016]
	Time Series	Smart Grids		Shapelet	✓	[Patri et al., 2016]
	MAS	Web		RF	✓	[Mitchell et al., 2018]
	-	Industry (alarm system)		Bayesian network	✓	[Silva et al., 2018]
	NLP	Technology		Rocchio algorithm	✗	[Shi et al., 2019]
	NLP	Finance		LSTM	✗	[Zhang et al., 2019]
	Signal analysis	Industry		HMM	✓	[Zhou et al., 2019]
	-	Healthcare		LogitBoost, ANN	✓	[Ali et al., 2020]
	Indoor localization	Healthcare, Smart environment		Decision tree (C5.0)	✓	[Woensel et al., 2020]
	NLP	Transport		MLP, GRU	✓	[Cheng and Chen, 2021]
	Computer Vision	-		R-CNN	✓	[Foo et al., 2021]
	Computer Vision (fine-grained classification)	-		Bayesian networks, CNN	✗	[Palazzo et al., 2021]
	NLP	Aviation		LSTM	✗	[Wang et al., 2021b]
	AmI	Healthcare		ANN	✓	[Chung et al., 2020]
	Computer Vision	Smart City (video surveillance)		YOLO	✓	[Patel et al., 2021]
	Fraud Detection	Insurance		Ensemble methods, XGBoost	✗	[Zhang et al., 2021]
	Computer Vision	-	Unsupervised	k-means	✓	[del Rincon et al., 2013]
	Computer Vision	-		PWCA	✓	[Donadello and Serafini, 2016]
	MAS	Web		k-means	✓	[Mitchell et al., 2018]
	AmI	Healthcare		APRIORI	✓	[Chung et al., 2020]
	Indoor localization	Healthcare, Smart environment		PCA	✓	[Woensel et al., 2020]
	Human-robot interaction	Robotics		SOM	✗	[Russo et al., 2021]
	NLP	Finance	Self-supervised	Word2Vec	✗	[Zhang et al., 2019]
	NLP	Transport		Word2Vec	✓	[Cheng and Chen, 2021]

7 Conclusion: challenges and research directions

7.1 Hybrid AI: Design Pattern and Taxonomy

As demonstrated in this study, the integration of ontology and machine learning represents a significant challenge that also brings forth new possibilities. It is important to recognize that the fusion of ontology and machine learning falls within a broader paradigm called AI hybridization, which aims to combine different types of reasoning. van Bekkum et al. [2021] has described several design patterns for hybrid AI, consisting of seven elementary patterns that characterize the types of input and output data, as well as the mechanisms employed for data processing (prediction, deduction, training, etc.). These elementary patterns are further combined to form more intricate design patterns that delineate various hybridization scenarios. In order to facilitate the utilization of this classification, we have associated each category from this SLR with the corresponding design pattern. The outcomes of this mapping are presented in table 6.

Notably, design pattern number 4 emerges as the most suitable for describing *Ontology Learning* and *Ontology Mapping*. Design pattern number 4 is specifically utilized for learning with symbolic output and consists of a primary block that learns from textual data and a secondary block capable of deducing insights from a new semantic model.

Design pattern number 5 is dedicated to the specific objective of mitigating the widely recognized 'black-box' phenomenon inherent in some machine learning algorithms, especially deep neural networks. Within this design pattern, a symbolic model is employed following the training of a learning model to elucidate the obtained results by leveraging prior knowledge. This aligns closely with our designated category of *Ontology-based explanation* where the emphasis lies on utilizing ontological resources to provide comprehensible explanations.

Design pattern number 3b represents systems capable of learning not only from data, but also from symbols, as is the case for *Ontology-based feature engineering*.

Design pattern number 7 specifically addresses informed learning with prior knowledge, aligning with our designated categories of *Ontology-based algorithm design* and *Ontology-based algorithm training*. The core principle underlying this design pattern is the inclusion of prior knowledge within the pipeline of the machine learning model. By incorporating relevant awareness, the objective is to enhance the performance and generalization capabilities of the model. As observed in our SLR, the integration of knowledge can occur at various stages within the learning pipeline. These include incorporating knowledge into the training data, incorporating it into the model architecture, incorporating it during the learning process of the model, and even incorporating it post-hoc after the learning phase.

Design pattern number 10 is dedicated to harnessing the power of machine learning, specifically neural networks, to enable logical reasoning. In this design pattern, a neural network is trained to perform logical reasoning tasks, aligning closely with our designated category of *Learning-based Reasoning*. This approach offers notable advantages, including enhanced scalability compared to traditional logical reasoning methods that may encounter bottlenecks when dealing with large ontologies. Moreover, learning-based reasoning exhibits greater resilience to noisy or missing data, thus improving the overall robustness of the reasoning process.

Design pattern number 12 focuses on the design of hybrid AI systems that closely resemble real-life applications. In contrast to a single monolithic component, hybrid AI systems are composed of multiple interconnected modules that communicate with each other. This design pattern aligns with the *Learning and Reasoning system* category identified in our systematic literature review. The objective of these hybrid AI systems is to leverage the synergies between learning and symbolic modules, aiming to produce more reliable models with enhanced transparency and reproducibility. By integrating multiple modules, these systems can benefit from the strengths of both learning-based approaches, such as machine learning, and symbolic reasoning techniques.

Another well-recognized subgroup within Hybrid AI is neuro-symbolic, which concentrates on the integration of symbolic methods with neural networks, especially deep neural networks. Henry Kautz [2020] has introduced a comprehensive taxonomy that classifies the diverse neuro-symbolic approaches, providing a structured framework for understanding and categorizing them. Indeed, in a similar manner, the categories identified in our SLR align with the groups outlined in Henry Kautz [2020]’s taxonomy, specifically when the ML algorithm employed is a neural network. To further aid readers in their mapping efforts, we have included this alignment in table 6, allowing for a clearer understanding of the correspondence between the SLR categories and Kautz’s taxonomy.

Category *Ontology-based feature engineering* corresponds to approach Symbolic Neuro symbolic, which involves transforming raw data using symbolic integration. This technique is commonly used in NLP tasks, where data is converted into vectors using methods such as Word2vec and GloVe.

The Neuro_{Symbolic} architecture, on the other hand, is more complex: it facilitates the conversion of symbolic rules into neural network models (*Ontology-based algorithm design* or *Ontology-based algorithm design*), as illustrated by the logical tensor networks [Serafini et al., 2017] discussed in this systematic literature review.

The Symbolic[Neuro] architecture combines neural pattern recognition with a symbolic problem-solving framework, resulting in enhanced problem-solving capabilities. This architecture is specifically applied in the category of *Expert System Embedded Learning*.

The Neuro|Symbolic architecture is prominently featured in our study, encompassing the categories of *ontology learning*, *ontology mapping*, *ontology-based explanation*, and *hybrid application*. This architecture closely resembles the Symbolic[Neuro] architecture but utilizes coroutines instead of subroutines. It emphasizes the communication between a symbolic system and a neural system, which is particularly relevant to our *hybrid application* category. We have chosen to place the other three categories within this architecture because it best aligns with their respective functionalities, even though the communication between the two systems may be more limited compared to hybrid applications.

Lastly, the *Learning-based reasoning* category is analogous to the Neuro:Symbolic→Neuro architecture, which involves training a neural network on symbolic rules. In learning-based reasoning, the network learns logical rules to perform deductive reasoning on new inputs. The advantage of this approach is that the neural network does not perform reasoning by explicitly following step-by-step rules; instead, it makes predictions based on the expected outcome of deductive reasoning. As mentioned earlier, this approach significantly reduces computational time, particularly when dealing with large ontologies.

7.2 Three challenges for the future

We have identified three main challenges using ontologies combined with machine learning. The first is the formal proof of the expressiveness and decidability of the ontology. The second is the ability to explain the results of a machine learning algorithm. The third concerns the management of consistency during *ontology learning* and *ontology mapping*.

Table 6: Alignment of our Hybridization Categories with Van Bekkum’s Design Patterns and Kautz’s Taxonomy

Category	van Bekkum et al. [2021]	Henry Kautz [2020]
Learning-enhanced ontology		
Ontology Learning	Design Pattern 4	Neuro Symbolic
Ontology Mapping	Design Pattern 4	Neuro Symbolic
Learning-based reasoning	Design Pattern 10	Neuro:Symbolic→Neuro
Semantic data mining		
Ontology-based feature engineering	Design Pattern 3b	Symbolic Neuro symbolic
Ontology-based algorithm design	Design Pattern 7	Neuro_{Symbolic}
Ontology-based algorithm training	Design Pattern 7	Neuro_{Symbolic}
Ontology-based explanation	Design Pattern 5	Neuro Symbolic
Learning and Reasoning system		
Expert System Embedded Learning	Design Pattern 12	Symbolic[Neuro]
Hybrid application	Design Pattern 12	Neuro Symbolic

7.2.1 Improve expressiveness and decidability of the ontology

Between taxonomy and formal ontology, this semantic representation of knowledge is a balance between expressiveness and decidability. Description logics are used to formalize ontology and determine this level of expressiveness/decidability. Each description logic represents a formal, axiomatized language describing the level of constraints supported. Since 2012, OWL2 language, recommended by the W3C¹⁴, allows the expressiveness of $SR\mathcal{OIQ}(\mathcal{D})$ logic. Inference engines can interpret this logic and check consistency, reorganize the structuration of concepts in the TBox, or, thanks to rule-based language (e.g. SWRL) infer new knowledge into the ABox. A large majority of articles studied make no mention of deductive reasoning beyond subsumption links made possible by ontologies and inference engines. Many of them use an ontology for its contribution at the semantic level. Ontology is used as an improved taxonomy since it has the advantage of also representing non-hierarchical relationships between the different terms of a domain. This corresponds, at best, to \mathcal{S} description logic language.

7.2.2 eXplainable Artificial Intelligence (XAI)

In recent times, AI systems have made significant progress in perceiving, learning, decision-making, and even autonomous action. Nevertheless, there remains a level of distrust among humans towards these systems, largely due to their inability to provide explanations for the reasoning behind their decisions [Gunning and Aha, 2019].

Over the past two decades, the research domain of eXplainable Artificial Intelligence (XAI) has experienced significant growth. This attribute holds critical importance in sensitive industrial sectors such as healthcare, finance, insurance, and defense. Achieving explainability in AI systems has been explored through various techniques, including Local Interpretable Model-agnostic Explanations (LIME) [Ribeiro et al., 2016], SHapley Additive exPlanations (SHAP) [Lundberg and Lee, 2017], as well as symbolic reasoning. Two papers, outlined in section 6.2, have specifically explored this subject by incorporating ontology [Confalonieri et al., 2021, Panigutti et al., 2020]. These papers propose interesting approaches for obtaining either a global [Confalonieri et al., 2021] or local explanation [Panigutti et al., 2020]. In these works, a domain-specific ontology pertaining to the targeted field of explanation is employed to enhance the explanatory quality. These studies highlight the role of ontologies in augmenting the interpretability of AI models, both at the global and local levels. By integrating prior knowledge through ontologies, a logical and cohesive framework is established for the model’s explanations, ensuring their alignment with existing domain knowledge. This integration not only enhances the credibility of the explanations but also facilitates a deeper comprehension of the model’s reasoning process.

¹⁴<https://www.w3.org>

7.2.3 Consistency checking

Change management in ontology during *ontology learning* process or *ontology mapping* requires consistency checking. Consistency management allows guaranteeing the reasoning validity of the different ontology releases. This study of consistency is well carried out by Mitchell et al. [2018] which is interested in the enrichment of an ontology, as well as by del Rincon et al. [2013] and Donadello and Serafini [2016], classified in the category *ontology population* (as explained in paragraph 4.1). However, these three works represent 6% of the papers which should be concerned by the consistency management. Furthermore, we did not find any paper mentioning the study of consistency in the other categories present in this literature review.

7.3 Conclusion

We conduct a SLR to explore the integration of inductive reasoning and deductive reasoning in systems that combine machine learning and ontologies. The aim of this study was to determine whether hybrid AI techniques could improve the ability of machines to perceive the complexity and nuances of our real world in order to improve their interactions with it. In our SLR, we reviewed a total of 128 papers that explore the combination of machine learning and ontologies across various domains and with diverse objectives. Through this comprehensive analysis, we identified and highlighted different categories of combinations of machine learning and ontologies that address distinct problems. We also provide a comprehensive examination of all these categories, emphasizing the various machine learning algorithms utilized in the studies. Additionally, we have established the connections between our categorization and van Bekkum et al. [2021]’s design pattern as well as Henry Kautz [2020]’s neuro-symbolic classification to provide insights to interested readers.

How can we enable machines to have an impact on the tangible world if they can’t make sense of the various aspects, complexities, and nuances of the real world? The question remains, but according to this SLR, from Plato to today, the work is still in progress.

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