Objective-Driven Modular and Hybrid Approach Combining Machine Learning and Ontology

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Abstract

Hybrid artificial intelligence is rapidly advancing, particularly in the domain of combining ontology and machine learning models. However, existing approaches in this field still encounter several limitations. Most current works tend to combine a single ontology model with a specific learning algorithm and often have a strong focus on specific application domains, which can complicate system adaptation and generalization.

To address these limitations, we introduce in this paper an objective-driven, hybrid, and modular approach that promotes the integration of multiple machine learning and ontology models. The approach consists of decomposing the studied application into several tasks, each of them using the most appropriate ontological and machine learning models applied to a subset of knowledge and data. Our approach enhances adaptability and flexibility by tailoring artificial intelligence models to specific goals and reasoning requirements, thereby promoting a more effective hybrid artificial intelligence system and enabling the abstraction and reuse of developed solutions in various application domains. The proposed approach is applied in the design of a hybrid artificial intelligence model for the development of a compact all-optical Arithmetic and Logic Unit.

1 Introduction

To acquire new knowledge, the human brain employs two main processes: **induction** and **deduction**. Induction enables the discovery of general laws by synthesizing specific facts, typically derived from observations and data. Deduction, conversely, allows for the decomposition and analysis of objects by starting from the general, as described by several propositions assumed to be true, and arriving at the particular in the form of a logical conclusion. These two approaches are naturally combined to create various methods for accessing and inferring specific knowledge.

In artificial intelligence, inductive reasoning is possible through using machine learning models, while deductive reasoning can be provided by using ontologies. By combining these two models, it becomes possible to build a hybrid reasoning model closer to the human cognitive process [1–3].

Hybrid artificial intelligence has emerged as a dynamic area of research and innovation. The approaches proposed in the literature promise to create artificial intelligence systems that are not only highly proficient in learning from data but also possess structured knowledge and inferential capabilities to make informed decisions. However, despite the significant progress made in this field, the proposed combined models still face limitations.

One of the main limitations is that existing methods often combine a specific machine learning algorithm, operating on all data, with a singular ontological model that integrates all available knowledge. This type of hybrid model can become unwieldy when dealing with diverse, multi-domain applications, leading to challenges such as scalability and maintenance complexities [4]. Moreover, relying on a single machine learning algorithm for all data types and tasks can lead to suboptimal performance, since different algorithms may be better suited to specific contexts [5].

To enhance the flexibility and adaptability of hybrid artificial models, it is essential to consider more modular and objective-aware concepts. In particular, the commonly used one-to-one strategy of standard hybrid systems could be significantly improved by synergetically involving multiple domain-specific models and machine learning algorithms.

In this paper, we present a modular and objective-driven hybrid concept that integrates several different machine learning and ontology models. We illustrate its application in the DALHAI[1] (Design of plasmonic ALU by Hybrid Artificial Intelligence) collaborative project, which aims at developing a compact all-optical Arithmetic and Logic Unit (ALU) using hybrid artificial intelligence guidance. Our objective is to design a flexible and adaptable hybrid architecture capable of orchestrating combinations of artificial intelligence models tailored to the specific goals and reasoning requirements of the sub-systems.

2 Combining Machine Learning and Ontologies

Several studies have explored the integration of both inductive reasoning, typically implemented using machine learning techniques, and deductive reasoning, often performed through the use of ontologies, within artificial intelligence systems. They can be gathered into three main categories of hybrid models: **Learning and Reasoning System**, **Semantic Data Mining** and **Learning-Enhanced Ontology**, as well as their main subcategories [6], as shown in Fig. 1.

Learning and Reasoning System refers to a computer system that uses machine learning and ontologies to solve complex problems and perform specific tasks in the same domain (e.g., a decision support system for the management

[1] `https://anr.fr/Project-ANR-20-CE24-0001`

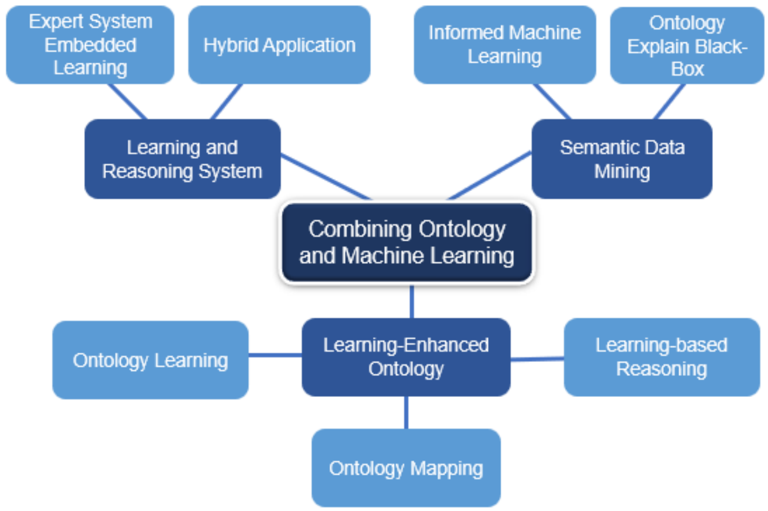

Figure 1: Main categories of approaches combining ontology and machine learning.

of cardiac pathology [7]). These complete systems correspond to two main subcategories: *Expert System Embedded Learning* and *Hybrid Application*.

The *Expert System Embedded Learning* subcategory represents ontology-based expert systems using machine learning to perform specific tasks, such as handling missing values [8]. An expert system is designed to simulate the reasoning and decision-making of a human expert in a particular domain. It comprises several modules including the knowledge base, the inference engine, and the interface [9]. In this subcategory, the machine learning component is considered as a subprogram of the system. It is used to analyze and learn from data in order to improve the overall system's performance.

The *Hybrid Application* subcategory includes all systems that integrate machine learning on raw data with ontological knowledge. The output of these systems results from the hybridization of the two techniques, where the result of one can be used to improve the functionality of the other. In this subcategory, some authors propose a pipeline that employs machine learning to classify data, populate the ontology with this data, and use a reasoning system to analyze, validate, and correct the result [10–13]. Other approaches complete the pipeline by transforming ontological entities into data that can be manipulated by machine learning algorithms, as well as the semantic relations of the ontology to create expert neural networks [14, 15].

Studies in **Semantic Data Mining** systematically integrate domain knowledge into the machine learning process in order to enhance its efficiency [16]. These approaches can be divided into two main subcategories: *Informed Machine Learning* and *Ontologies Explain Black-Box*.

In *Informed Machine Learning*, prior knowledge is incorporated into the machine learning process at various stages [17]. Prior knowledge is often represented by an ontology that can be used in the feature engineering phase for selection [18, 19], extraction [20–22], or augmentation [23, 24], in order to acquire more relevant features. They can also be used to facilitate the choice of the most suitable model structure [25] or be directly integrated into the machine learning algorithm [26–31].

Studies classified in the subcategory *Ontologies Explain Black-Box* aim to add a posteriori explainability to learning models using ontological knowledge. These explanations can be applied globally in decision-making [32], or locally for each individual [33]. This type of research work represents recent contributions in the field of explainable artificial intelligence, compared with LIME (Local Interpretable Model-agnostic Explanations) [34] and SHAP (SHapley Additive exPlanations) [35].

In **Learning-Enhanced Ontology**, the use of ontologies is improved through machine learning. This category can be divided into three main subcategories. The first subcategory considers that the creation and maintenance of ontologies can be (partially) automated using machine learning techniques. In this case, we refer to *Ontology Learning*, where ontologies can be “learned" from different resources [36–41]. The second subcategory, *Ontology Mapping*, groups studies that aim to improve ontology alignment through machine learning to ensure interoperability between the two models [42–46]. Finally, the subcategory *Learning-based Reasoning* covers approaches that seek to facilitate the deductive reasoning of an ontology using machine learning [47–51].

This overview highlights the importance and evolving nature of hybrid artificial intelligence approaches that integrate machine learning and ontological reasoning to model systems combining data analysis and expert knowledge. Despite the advances in this field, this combination remains a significant scientific challenge, facing several methodological and practical difficulties. In addition to the complexity of combining these approaches, the main issue is that the proposed models often rely on a sequential pipeline using a global ontology and all available data at each stage. Existing methods frequently involve using a specific learning model applied to the entire dataset, combined with a single ontology covering all domain knowledge. This concept is often unsuitable for complex, multitasking applications. In fact, depending on the data type and the task to be performed, some machine learning models may be more suitable and efficient than others. Consolidating all knowledge into a single ontology also presents limitations. In practice, most reasoning processes are based on selecting knowledge relevant to the specific subject. Using all available knowledge can burden the reasoning process and make the task more complex. This can lead to problems with processing capacity and increase costs in terms of time and resources. Furthermore, the proposed solutions are often problem-specific and heavily dependent on the application domain and the addressed issue. This makes it challenging to reuse, evolve, or adapt these models for other types of applications.

3 Objective-Driven Hybrid and Modular Approach

To address the question of adaptability and flexibility in existing hybrid models, we propose a modular approach that supports the decomposition of the model into distinct modules based on specific data processing, reasoning requirements, and application objectives. This approach enables a seamless integration of machine learning and ontological reasoning, based on the needs of each stage in the application. This modular approach not only enhances the hybrid model's capacity to adapt to various types of applications but also enhances its scalability and ease of maintenance.

3.1 Presentation of the Approach

We propose a comprehensive, optimized, and adaptable hybrid model that encompasses various combinations of hybrid artificial intelligence models, depending on the system's objectives and reasoning requirements. Before defining the machine learning and logical reasoning models to be used, we decompose the application into simpler and autonomous modules, each focused on specific tasks to achieve a given objective. These individual modules can be developed and updated independently, and they can communicate and exchange results according to the application needs.

The modular approach creates hybrid and interoperable modules, each using a subset of data and knowledge, depending on the specific objective. Therefore, the development of goal-driven hybrid models is facilitated and results in enhanced adaptability and optimized performance compared to a global integrated system.

Among other assets, the modular concept increases model performance by using the most appropriate knowledge and learning techniques. Moreover, it improves reusability, parallel development, and cost reduction. The resulting models are more flexible, adaptable, and scalable, hence they can be integrated at several levels with other systems. An overview of our approach is presented in Fig. 2.

3.2 Application for the design of a photonic ALU

An ALU (Arithmetic and Logic Unit) is a key part of a computer processor. It is responsible for executing the arithmetic and logic operations required to process the data in a computer program. The ALU uses logic circuits to execute these operations, which are generally implemented using transistors and basic logic gates. Although transistors have been reduced to nanometric scales to increase device density, they still have physical and technical limitations that affect processor performance, particularly in terms of clock rate and power consumption.

The DALHAI project aims at developing a new generation of compact, interconnect-free, all-optical ALUs that use optical technology to process information faster, with reduced energy dissipation. In this approach, the operations are realized by a single resonant cavity object without resorting to an inter-device

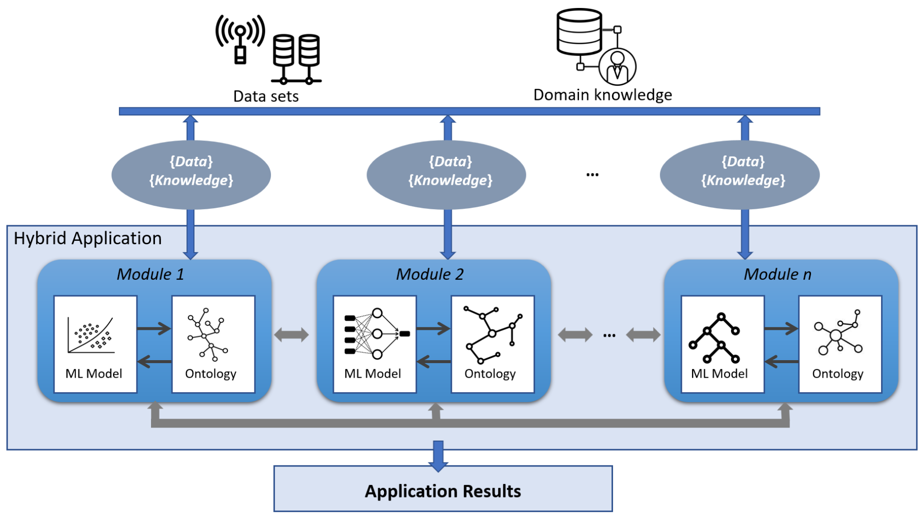

Figure 2: Global view of the objective-driven hybrid and modular approach

cascade. The classical challenge of circuit design is replaced by elaborating the appropriate cavity shape that can perform the desired processing logic functions. To achieve this objective, it is necessary to find the ALU device shape and excitation parameters for operating the holistic logic gate devices. The first successful experimental results were obtained using a double-hexagon (DH) structure for a set of logic gates [52]. However, the discovery of more complex ALU configurations may be limited by the choice of structure and simulation parameters, often defined based on domain experts' intuitive assumptions. To address this limitation, we propose to use a modular and hybrid artificial intelligence approach to facilitate the exploration of new shapes and excitation parameters for solving the inverse design of complex and reconfigurable ALUs.

To identify the learning and reasoning models to be implemented in the DALHAI project, we have conducted a knowledge acquisition process based on the cooperative knowledge elicitation approach [53] to collect domain constraints and expert knowledge. According to the knowledge elicitation results and the application requirements, the developed model must achieve three main objectives: finding an optimal shape of the device (objective 1) by optimizing the excitation parameters (objective 2) to support various logic gates (objective 3).

This presents a multi-objective optimization problem, requiring precise modeling and evaluation of proposed solutions. Solving this type of question in artificial intelligence involves using optimization methods and machine learning techniques to find possible solutions and evaluate them according to specific performance criteria. To attain this goal, we propose a modular, hybrid architecture combining machine learning models to generate optimal solutions, and ontological reasoning models to verify whether the selected solution is feasible according to the knowledge and physical constraints defined by domain experts. In this context, the machine learning part can be seen as a generator part proposing different solutions, while the ontological part can be assimilated to a discriminator part evaluating the solution's viability and, if required, proposing adjustments to the learning model.

Fig. 3 shows a global view of the proposed architecture for the DALHAI project. First, we use a genetic evolutionary algorithm [54–56] to create and optimize the shape and excitation parameters (Part 1 in Fig. 3). Evolutionary algorithms are suitable for addressing multi-objective optimization problems. These algorithms are inspired by the principles of natural selection and evolution to iteratively improve potential solutions over generations. When dealing with multi-objective optimization, where multiple conflicting objectives need to be considered simultaneously, evolutionary algorithms allow the exploration of solution spaces and the identification of trade-offs among these objectives.

Depending on the targeted logic gates, the evolutionary algorithm generates a shape on which a numerical simulation of the laser field propagation is calculated using the PyGDM tool[2] [57]. This first algorithm includes a second evolutionary algorithm dedicated to optimizing the excitation parameters (laser position, polarization, and phase) for a particular shape (Part 2 in Fig. 3).

Each solution produced by the genetic algorithm must respect the physics constraints defined by the domain experts in order to ensure the feasibility and reproducibility of the results in experimentation. We have identified three main types of knowledge required to define: (1) the shape, (2) the excitation parameters, and (3) the detection parameters of the logic gates.

This has led to the definition of three ontologies. The first, *Shape Ontology*, gathers knowledge and constraints related to the description of the device shape according to constraints imposed by the experimental implementation. In the context of this project, we are targeting polygon-type shapes (a closed planar figure made up of connected segments) with specific constraints linked to the physical realization of the shape in experimentation, such as the minimum and maximum size of a segment, the minimum value of an angle, the minimum and maximum surface area of the shape, etc. This ontology takes as input the shape generated by the learning part, and determines whether it is valid and respects all the specified constraints.

The second ontology, *Excitation parameter ontology*, concerns excitation parameters (laser characteristics, input/output port locations, etc.). It corresponds to physical knowledge related to the concrete feasibility of the experiment, such as the location of the two laser spots, which must respect a certain distance from each other or the difference between two polarizations enabling the unambiguous encoding of the logic input values. The third ontology, *Logic gate ontology*, is used to capture knowledge about logic gates and their connection. Its objective is to verify the correct assembly between input and output points and ensure that the result corresponds to the desired logic gate. The reasoning result of the three ontologies can also be used to make adjustments to the learning model

[2] `https://homepages.laas.fr/pwiecha/pygdm_doc/`

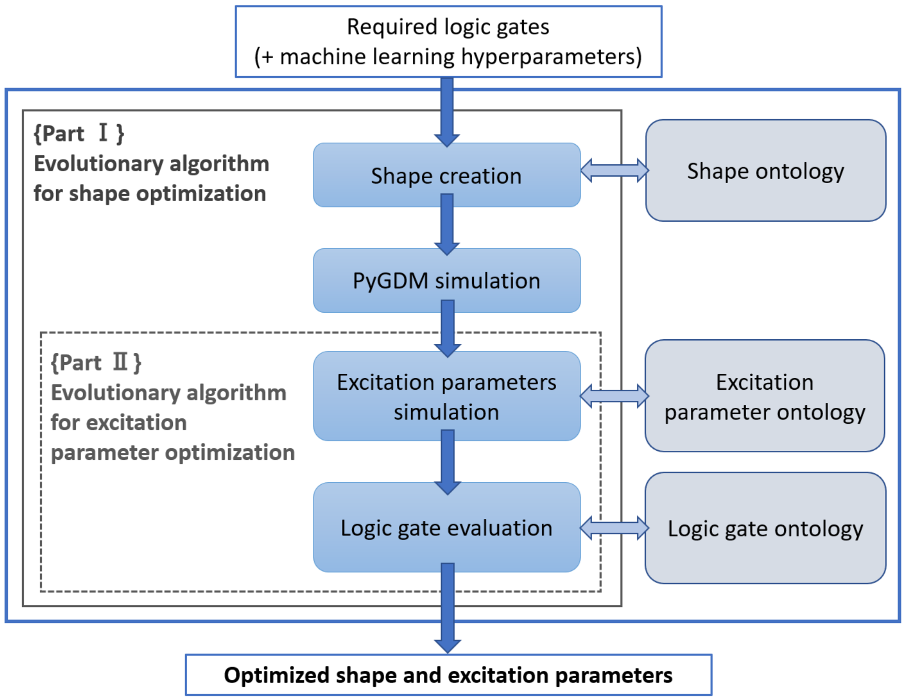

Figure 3: Objective-driven hybrid and modular approach applied to the DALHAI project

parameters, resulting in a powerful, efficient, and faster hybrid and modular reasoning model.

4 Conclusion

Human reasoning involves several cognitive processes for problem-solving and decision-making. Because of this complexity, the real-life systems that we need to implement are also often complex and multifaceted. These systems can be difficult to solve satisfactorily using only deductive or inductive reasoning methods. Hybrid artificial reasoning is therefore essential for simulating and digitalizing a cognitive process closer to human reasoning. It combines the advantages of both reasoning methods and overcomes their respective limitations. Moreover, reasoning models are often based on data and knowledge from different, heterogeneous, and sometimes contradictory sources. Hybrid reasoning aims to facilitate the processing of this data and knowledge, using methods adapted to their nature, source, and use, in order to obtain more robust and reliable results.

In recent years, the hybridization of reasoning combining ontological models and machine learning algorithms has been widely developed, but the proposed approaches face a number of limitations. After studying existing approaches, we identified a particular challenge related to the complexity and lack of adaptability of existing models. Indeed, the approaches presented in the literature are often based on a sequential pipeline that uses a global ontology and all the data in each of its operating stages. All logical knowledge is grouped together in a single ontology, which can quickly become complex and difficult to maintain, resulting in high costs in terms of time and resources. Moreover, these models are often constrained by a specific machine learning model on all the data and are built according to the specific needs of the studied application in a particular domain. This makes them difficult to update and adapt to other types of applications.

To address this issue, this article proposes a hybrid, modular, and objective-driven approach. The idea is to decompose the problem to be solved into several tasks according to the objectives to be achieved. Each of these tasks uses the most appropriate ontological and machine learning models on a subset of knowledge and data in order to achieve more flexible, adaptable, and easily scalable systems. On the one hand, this approach allows modules to evolve separately, and on the other, it encourages the abstraction and reuse of modules in other types of applications.

We have successfully applied our approach in the DALHAI collaborative project aimed to develop a hybrid artificial intelligence model for constructing a photonic ALU. The resulting model allowed independent development and maintenance of the various modules and facilitated the use of the data and knowledge required for each stage, demonstrating our approach's application in a real project.

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