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Framework for Analyzing Neuro-Symbolic Artificial Intelligence in Liquid Neural Networks

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INTRODUCTION

"Intelligent" systems are models built by algorithms that combine automation, flexibility, security, and data privacy assurance, attesting to the utility, economic value, and development of interdisciplinary strategies for broader use (ENGSTROM et al., 2020; JANKELOVA and PUHOVICHOVA, 2022). Despite advances in information technology, systems development is related to issues involving not only effective data processing in decision-making and resource optimization but decision-making models that enable better management of data volume, complexity, integration, quality, security, and resource optimization (BOUNEFFOUF and AGGARWAL, 2022).

Information systems tend to be designed to meet the immediate needs of management, or the generation of knowledge of the sector by central state agencies, with fragmentation in data collection obtained essentially to meet the legal requirements of funding agencies or organizations. They represent, therefore, isolated initiatives that do not enable concrete actions for decision-making by governments and organizational micro-levels (VAN NOORDT and MISURACA, 2022). The lack of effectiveness and integration is reflected in the organization, processing, and data analysis, as well as in wrong decisions and inefficient allocation of resources (DEMIDOVSKIJ and BABKIN, 2021). One way to enable the best informational strategy and adapt the technological structure for implementing and developing management systems is through a framework, a set of practices, guidelines, methods, tools, standards, and techniques for problem-solving.

Information system frameworks are designed to handle a specific volume and data sets. Framework use increases response times and decision-making through embedded technology and intelligent data-driven products and services (VAN NOORDT and MISURACA, 2022). More accurate data analysis frameworks not only speed up the production flow but also tend to improve information sharing among team members, leading to better decision-making (DINH and NGUYEN-NGOC, 2010; DEMIDOVSKIJ and BABKIN, 2021).

Because of the recurring technicist bias in drafting, problems of usability, perceptibility, accuracy, transparency, and accountability are recursive (RUDIN 2019; MILLER, 2019; ENGSTROM et al., 2020). Bias in frameworks, devoid of broader cognitive validation, is reflected in the incidence of prejudice, social discrimination, and unfair treatment of people (MILLER, 2019; OLTEANU et al., 2019; BENBYA et al., 2020; ENGSTROM et al., 2020; WANG et al., 2022). The discussion of frameworks, with the involvement of different actors, is aligned to promote information systems with more security and relevance, technical and social, favor creativity and productive concerns (BENBYA et al., 2020; ENGSTROM et al., 2020). Therefore, protection measures must be taken to ensure confidentiality and compliance with privacy regulations (DRUKKER et al., 2023), especially in algorithms developed to analyze patterns and propose actions without human intervention.

Artificial Intelligence (A.I.) has been used in several productive sectors, enabling the digitalization of organizational processes (BHARGAVA, 2019; ALMAIAH et al., 2022), with benefits for decision-making (DEMIDOVSKIJ and BABKIN, 2021; GUPTA et al., 2022; DING et al., 2022; SMIRNOV et al., 2022). However, few studies assess the benefits provided to society, especially those that explore the acquisition, preprocessing, and utilization of diverse administrative datasets representative of the real world (GUPTA et al., 2022; DING et al., 2022). At the current stage of maturity, A.I. relies on large datasets to train and improve its models, but in practice, domain-specific datasets are scarce, which causes algorithms to underperform. The systems must be fed datasets with properties like those they wish to discover. It is common to use algorithms with large generic datasets replicated in specific contexts.

Based on machine learning, traditional A.I. models employ algorithms to recognize entities using patterns learned from databases, organized as multi-layered neural networks with learning rules based on known speech or writing patterns. The vocabulary of words in a database is usually used to establish parameters, so the systems can only identify the predefined ones but neglect the unknown ones, which requires a large amount of data and human intervention in feature selection.

Unlike formal logic-based machine learning ("traditional A.I."), neuro-symbolic A.I. is an approach that combines symbolic elements, recognizing decision-making patterns based on data from different sources (neural networks) in real-time (WU et al., 2021; HITZLER et al., 2022; BOUNEFFOUF and AGGARWAL, 2022). Neuro-symbolic artificial intelligence encompasses a set of adaptive research and application techniques in various fields of knowledge (HITZLER et al., 2022) but is unable to leverage multi-techniques to capture relational information, deal with uncertainty, and improve decision-making (WANG et al., 2022; DELONG et al., 2023).

Even though neuro-symbolic A.I. has shown promise in improving decision-making capabilities in other domains, the existing literature focuses on general applications of neuro-symbolic A.I. or specific fields outside administrative contexts (WANG and YANG, 2022). Integration into administrative systems remains relatively unexplored (JOSEPH and GABA, 2020; RIBEIRO et al., 2020; DEMIDOVSKIJ and BABKIN, 2021; HITZLER et al., 2022). Symbolic learning is limited and cannot handle complexity and generalization from data (DEMIDOVSKIJ and BABKIN, 2021; HITZLER et al., 2022). An A.I. engine capable of augmenting management information systems with theoretical and applied depth is not yet available (PINHEIRO and OLIVEIRA, 2022), linking technical to cognitive processes (SILVA and NATHANSOHN, 2018; SANTOS JUNIOR, 2021), as well as combining the logical reasoning, and knowledge representation capabilities of symbolic A.I., with the pattern recognition and data processing capabilities of neural networks (GUNNING et al., 2019).

Since technical knowledge is not enough to explain the phenomenon, based on qualitative aspects of experience, it is worth discussing the influence of the interaction between cognitive processes and social factors in collaborative learning and data sharing involving machines (ROGERS et al., 2023) and socio-technical aspects in organizations, with repercussions in terms of appropriation of frameworks (PELKEY, 2022). A deeper understanding of the interaction between humans and computers, as a function of social and cognitive aspects, should be appreciated, making systems suitable and relevant for users. For reliable analysis, it is essential to consider contextual dimensions and different levels of granularity in the organization of analytical processes.

Starting from the question of **how to integrate neuro-symbolic A.I. and neural network components in administrative systems employing a framework?**, it is worth discussing the relevance of a structure that incorporates neuro-symbolic A.I. and neural network components, seeking to improve information systems' usability, efficiency, and effectiveness. Regarding a framework, it is pertinent to discuss the following questions:

- How to decide on incorporating new knowledge at a given stage of inter-layered learning, and how do you quantify the amount to be infused?

- How to merge the latent representations between layers with external words of knowledge?

- How to propagate knowledge through the learned latent representation?

THEORETICAL FOUNDATION

"Intelligent agents" are decentralized pattern-grasping (machine learning) mechanisms that circumvent analytical limitations by resorting to cyclic and repetitive processes. Agents are algorithms that explore databases using predefined rules of interaction, characterizing Artificial Intelligence. Still, recent models allow machines to "learn" more than a superficial meaning (and limited conceptual framework representing a set of practices, guidelines, methods, tools, patterns, and techniques for developing information systems. They provide a framework or strategy for solving problems or performing specific tasks in a given domain.), advancing into the meaning behind words and phrases (NIVEN and KAO, 2019; KENTON et al., 2019). Due to the predictive possibilities of fostering organizational learning, intelligent agents assist in analyzing and integrating data from heterogeneous sources, improving knowledge sharing (BOUNEFFOUF and AGGARWAL, 2022).

On the other hand, deep learning refers to models consisting of multiple layers of non-linear processing units involving numerous data sets. Algorithms have undergone enhancements to respond "intuitively" based on the task's representation (HASANI et al., 2021). The trend is toward generating decision support systems based on integrated artificial neural network methods (DEMIDOVSKIJ and BABKIN, 2021).

AI-based Recurrent Neural Networks (RNN) can be designed to perform tasks without training data or backpropagation. The algorithm can be guided by hypotheses rather than random weights or a database. The approach outperforms other machine learning techniques on datasets and has been tested in the medical field (KIM and BASSETT, 2023). The network dispenses with trial-and-error adjustments to its parameters, which means a system that can respond to current and future problems by drawing on a small set of specific data.

Liquid Neural Networks (LNN) are more adaptable, faster, accurate, and stable than conventional neural networks (LECHNER et al., 2020). While traditional networks (RNN) algorithms are defined during training, when the systems are fed a large volume of data, in liquid neural networks, model refinement occurs as they capture the data (HASANI et al., 2021). How a "neuron" reacts in liquid networks can vary depending on the input. The exchange of signals between neurons is a probabilistic process governed by a non-linear function, meaning that response to information is not always proportional. In other words, in the LNN, random, simultaneous, and independent connections are established between computers. At the same time, in the RNN, the network has links that recombine data to itself or others in a linear, temporal fashion. In LNNs, doubling the input can lead to a much larger or smaller change in the output. The internal variability is why the networks are called "liquid" (HASANI et al., 2021). The robustness of these networks, i.e., flexibility in learning and performing tasks, stems from the semantics of the model, which translates into dynamic causal models capable of changing the underlying equations and connections between the "artificial neurons". Thus, frameworks based on net neural networks tend to be more robust and adaptable, exhibiting better scalability, efficiency, and performance, resulting in more accurate decision-making compared to traditional neural models (HASANI et al., 2022; BIDOLLAHKHANI et al., 2023).

Symbolic representation is a neuro-symbolic approach that involves translating the collected data into a semantic format understandable to the system (LIETO, 2021). The goal is to capture and generate complex and meaningful representations to facilitate planning and policy decision-making in organizations (GARCEZ et al., 2019). The technique involves acquiring preliminary data, rules, and heuristics from the domain. The data is extracted from heterogeneous and complex sets. Audiovisual representations (images and sounds) and natural language are processed and analyzed iteratively. Information systems interpret the results using a semantic framework, manipulating concepts and relationships (RITTER et al., 2019), which may include the creation of ontologies, taxonomies, or conceptual models to describe the relevant elements of a particular field of knowledge (SAMSONOVICH, 2020; SMIRNOV et al., 2022). Evaluating these aspects requires developing a laborious plan with multiple parameters and measures to assess the framework's effectiveness, combining computation and cognitive-semiotic principles (PELKEY, 2022; ORDONES, 2023).

Another common approach in neuro-symbolic A.I. is symbolic neural networks, which use an integrative architecture of symbolic and neural layers, allowing the two levels to interact. Neural networks grasp complex patterns and make predictions by using comprehensive knowledge to interpret and structure data while learning from it (ZHANG et al., 2022). It is used when insufficient information is available to solve a problem: data is incorporated to guide learning, providing solutions through approximations (ZHANG and ZHENG, 2021).

Hybrid learning is a crucial technique in neuro-symbolic A.I., which integrates symbolic learning with neural learning to take advantage of the benefits of each approach. Symbolic learning involves acquiring rules, heuristics, and prior domain knowledge, while neural learning focuses on generalization from data (CHENG 2018). Combining these approaches allows the system to learn from the data, incorporate prior knowledge, and interpret the results more explainable (HITZLER et al., 2022; RUDIN, 2019). The ability to provide interpretability and explainability of results is relevant to understanding how decisions are made (PELKEY, 2022). While interpretability is vital for understanding how A.I. makes decisions, the indicator does not guarantee the effectiveness of the system, which depends on the ability to provide accurate and relevant results for users, considering the symbolic-cognitive dimension in the process. Combining symbolic elements with A.I. allows the system to present results in a more transparent ("interpretable") manner, enabling experts to validate and interpret decision predictions (RUDIN, 2019).

Because of the autonomous and goal-directed nature of the intelligent agent, delegating routine activities to A.I. allows workers in an organization to perform more attentively and efficiently in production processes (DEMIDOVSKIJ and BABKIN, 2021). Intelligent agents allow critical situations to be anticipated and the causes, reasons, and possible outcomes for operational problems to be accurately identified, even when no experts are available in the organization. Optimizing the administrative routine and the response time in the management support processes allows the worker more quality and agility in answering user requests, with immediate and secure access to databases (DINH and NGUYEN-NGOC, 2010; DEMIDOVSKIJ and BABKIN, 2021).

Vulnerability in neural networks is difficult to identify amidst a large volume of data (De PALMA et al., 2019; WU et al., 2021). The logic of recursive learning is to discard events that have low probability but play a crucial role in the operation of complex systems. As iterations pass, the statistical distribution of the original content deteriorates, even when some original data is preserved, resulting in processing focused on more frequent but false entities. Even among weakly meaningful data, if the wrong contextual information is learned in the first few layers, it isn't easy to correct, and inaccuracy prevails. The errors resulting from imperfections in interpreting content acquired during A.I. training lead to irreversible consequences that worsen, resulting in biases, even more, equivocal than the original programming (SHUMAILOV et al., 2023).

Notably, the problem of finding information exists at many scales and includes identifying entities relevant to a given group of experts (DEMIDOVSKIJ and BABKIN, 2021; HITZLER et al., 2022). Therefore, the problems generated by biases and algorithm sparsity entail: (1) increasing reliance on large datasets to create bottom-up algorithms but no increment in accuracy (DE PALMA et al., 2019); (2) bias in data analysis (OLTEANU et al. 2019; BENBYA et al., 2020; ENGSTROM et al., 2020); (3) ambiguity and inaccuracy, with content correlations out of context (GUNNING et al., 2019; BENBYA et al., 2020; SHUMAILOV et al., 2023); (4) lack of traceability of information for model explanation (MILLER, 2019); (5) inability to respond to specific new content, not predicted in the database (GUNNING et al., 2019); (6) false alarms in model performance (MILLER, 2019).

DISCUSSION

Harnessing the transformative power of technology is not simply about building a technical platform, identifying opportunities, or hiring data scientists. The keys to success also include improving information competencies at all levels of the organization. Incorporating intelligent agents into production flows involves assimilating the methodologies for identifying, analyzing, and proposing solutions.

The proposed framework aims to ground machine learning in two stages: the first part is widely applicable and manually fed with data. The analytic framework contains the latent representations between layers with external knowledge representations. Analysts provide the ontology categories with specific knowledge in a particular knowledge area and propose patterns to capture similarities between the best decision-making frameworks. The initially proposed ontology assists the system in organizing and analyzing data, predicting courses of action efficiently in decision-making, and developing activities.

The system then learns from a smaller, more contextualized, domain-specific dataset. This hierarchical approach speeds up the learning process, outperforming RNNs. The proposed framework can potentially improve the performance of machine learning algorithms while reducing the amount of data required for proper training. Furthermore, the approach can identify the appropriate parameters for a given network, optimizing its performance on specific problems.

Frameworks must go beyond programming logic to incorporate new knowledge in cross-layer learning. They instead explore the semiotic aspects of expertise in the context, investigating how new knowledge can be represented as meaningful signals and incorporated into the learning process. The methods for aligning and integrating the different forms of representation must consider the merged models' interpretability, coherence, and fidelity. This process is laborious and constitutes an analytical task and, simultaneously, a stage of repertoire development that is fundamental to learning.

The proposed framework provides a structured approach to integrating neuro-symbolic A.I. and neural network components in administrative systems. By addressing the questions of incorporating new knowledge, merging latent representations with external knowledge, and propagating knowledge through learned latent models, the framework aims to improve information systems' usability, efficiency, and effectiveness. It sets the stage for more interpretable and explainable decision-making processes, enhancing the decision-makers confidence and facilitating the adoption of neuro-symbolic A.I. and neural network components in administrative systems.

The outlined structure to guide the integration process of neuro-symbolic A.I. and neural network components in administrative systems must consider the following steps:

1) Problem Analysis and Objective Definition:

1.1 Identify the specific problem or task the integration aims to address within the administrative system.

1.2 Define the objectives and goals of the integration, such as improving usability, efficiency, and effectiveness.

2) Data Acquisition and Preprocessing:

2.1 Gather relevant data from various sources, ensuring its quality, completeness, and relevance to the problem domain.

2.2 Preprocess the data to handle missing values, outliers, and noise, ensuring compatibility with the neural network and symbolic processing components.

3) Neuro-Symbolic Architecture Design:

3.1 Determine the neural network architecture or liquid neural network that best suits the problem, considering factors such as the nature of the data, complexity, and computational requirements.

3.1.1 Incorporating LNN-Specific Considerations:

a) Adaptability and Flexibility: Assess how the network can adapt to changing requirements, new administrative rules or regulations, and emerging data sources, considering its unique characteristics and capabilities.

b) Performance: Compare the performance of the network with other neural network architectures in terms of data quality, accuracy, completeness, consistency, and reliability.

c) Scalability: Evaluate the scalability of the network in handling increasing data volumes, complex decision-making scenarios, and integrating multiple administrative domains.

3.2 Design the symbolic processing component, which incorporates explicit knowledge representation and reasoning methods relevant to the problem domain.

4) Training and Learning:

4.1 Train the network component using the available labeled data, optimizing its weights and parameters to improve performance on the given task.

4.2 Integrate symbolic elements into the training process, such as incorporating symbolic rules or constraints, to guide the learning and enhance interpretability. The following approach should be observed to merge latent representations between layers with external knowledge:

a. Identify Gaps: Analyze existing gaps between the learned latent representations of neural networks and external knowledge representations. Determine how the LNN can seamlessly incorporate symbolic elements into its liquid state dynamics, such as explicit knowledge representation and reasoning methods.

b. Alignment and Integration: Develop methods to align and integrate different forms of representation, ensuring interpretability, coherence, and fidelity of the merged models.

c. Knowledge Flow: Examine how semiotic information flows and influences the propagation process, potentially involving signal interpretation, inference, or machine learning mechanisms.

5) Knowledge Representation and Integration:

5.1 Develop a knowledge representation scheme that captures explicit domain knowledge, including rules, ontologies, or semantic graphs. The decision to incorporate new resources at a given stage of inter-layered learning requires careful consideration and includes:

a. Semiotic Analysis: Analyze new knowledge's importance, relevance, and impact within the organization's learning process.

b. Quantification: Quantify the amount of new knowledge to be infused based on its significance and relevance to the learning system.

c. Learning Integration: Incorporate new knowledge as meaningful signals within the learning process, leveraging the principles of neuro-symbolic A.I.

5.2 Define mechanisms for integrating symbolic representations with the learned terms of the network, facilitating the seamless exchange of information.

6) Evaluation and Validation:

6.1 Assess the performance of the integrated system using appropriate evaluation metrics.

6.2 Validate the system's effectiveness in improving the administrative system's usability, efficiency, and significance, comparing it against baseline methods. The steps to propagate knowledge effectively through the learned latent representation are:

a. Facilitating Propagation: Explore techniques that enable efficient transfer and utilization of knowledge within the informative system.

b. Contextual Flow: Investigate how semiotic information flows within the learned latent representations and influences decision-making processes.

c. Effective Utilization: Develop mechanisms to leverage propagated knowledge for enhanced decision-making within administrative systems.

7) Iterative Refinement:

7.1 Analyze the results and identify areas for improvement in the integrated framework.

7.2 Based on feedback and new insights, iterate on the design, training, and integration steps to refine the neuro-symbolic A.I. and network components.

8) Documentation and Deployment:

8.1. Document the framework, including guidelines, methodologies, and tools for integrating neuro-symbolic A.I. and liquid neural network components.

8.2 Prepare the integrated system for deployment, ensuring its compatibility with the target administrative system and considering scalability, reliability, and security.

It is important to note that the specific details and methodologies within each step may vary depending on the nature of the problem, available data, and desired objectives. The factors to avail the framework performance are:

1. Adaptability and flexibility: adapting to changing requirements, new administrative rules or regulations, and emerging data sources.

2. Performance: comparative with baseline methods regarding data quality (accuracy, completeness, consistency, and reliability).

3. Effectiveness in decision-making: error rate in the results generated by A.I.

4. Data efficiency: comparative based on the amount of labeled data, whether it works well with a smaller data set.

5. Scalability: vulnerability assessment to handle increasing data volumes, complex decision-making scenarios, and integrating multiple administrative domains.

6. Stability: consistency and reliability of system performance in the face of variations in inputs or operating conditions.

7. Accuracy: proportion of correctly classified instances or the accuracy of the model's predictions.

8. Explainability: justifications (explanations) for decisions made with evidence supporting the predictions or recommendations of symbolic processing with learning capabilities.

9. Interpretability: evaluation of the transparency of the model, relating how inputs are processed and the A. I make decisions.

10. Precision and recall: precision measures the proportion of true positives among the instances predicted to be positive. In contrast, recall measures the proportion of true positives correctly identified by the model.

11. Relevance of the results: importance and pertinence of the data with the context and the decision-making objectives.

12. Robustness: an examination of the robustness of the neuro-symbolic A.I. approach against noise, uncertainty, and outliers in the data. It will be compared with traditional methods to determine whether it exhibits enhanced resilience to noisy or incomplete data commonly found in administrative systems.

13. User satisfaction: the system's adequacy to the administrative users' information needs.

Comparative experiments should be conducted against baseline approaches across the following metrics:

a) F1 score: harmonic mean of accuracy and recovery, providing a balanced measure of a model's performance.

b) Mean Absolute Error (MAE) or Root Mean Square Error (RMSE): used for regression tasks and the mean absolute or square difference between predicted and actual values. It provides information about the model's accuracy in predicting continuous variables.

c) Area Under the Receiver Operating Characteristic Curve (AUC-ROC): used for binary classification tasks and evaluates the ability of the model to discriminate between positive and negative instances at different classification thresholds.

The framework considers aspects to be ascertained in terms of importance, relevance, or impact on the organization's learning system, not only in terms of how much, but of "how, when, by whom, and for whom" if quantifying the knowledge to be infused. The human intervention aims to appreciate how the algorithm incorporates symbolic elements into the training process and knowledge representation, such as creating new rules and words from learned patterns. The rules should be interpretable and understandable to users, enabling more accurate analysis and informed decision-making. By establishing interrelationships with known latent representations, the framework investigates how semiotic information flows and influences the process of knowledge propagation through the information system.

CONCLUSION / CONTRIBUTION

Integrating neuro-symbolic A.I. techniques within administrative systems offers significant potential for optimizing the use of information resources in decision-making processes. By effectively combining people, processes, and organizations while considering the inherent subjectivity of decision-making, the proposed framework provides a comprehensive approach to improve efficiency, accuracy, compatibility, scalability, interoperability, and decision-making capabilities.

The framework's ability to identify relevant patterns and understand user behaviors is a valuable parameter for recommendations and contributes to the Information Architecture framework's overall effectiveness. Although the framework's application potential is still speculative, its adoption by organizations can foster best practices in knowledge sharing within dynamic structures that employ parallel and distributed networks.

Moreover, the framework enables benchmarking and evaluating optimization algorithms using scalable technologies when applied to business systems. It facilitates continuous auditing and analysis, allowing for critical debugging of technology solutions even when working with limited data. Additionally, the framework empowers organizations to deploy automated information systems capable of handling and interpreting large volumes of data, thereby facilitating complex decision analysis beyond pre-trained language models' capabilities.

The framework proves particularly valuable in tasks involving sequential or time-dependent data. It aids in planning supervised learning, evaluating responsiveness during training, employing unsupervised learning techniques to uncover patterns, and identifying abstract and complex features through multiple semantic layers.

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