

# From Statistical Relational to Neuro-Symbolic Artificial Intelligence

Giuseppe Marra

KU Leuven, Department of Computer Science,  
Celestijnenlaan 200A, 3001 Leuven, Belgium  
giuseppe.marra@kuleuven.be

**Abstract.** The integration of learning and reasoning is one of the key challenges in artificial intelligence and machine learning today. The area of Neuro-Symbolic AI (NeSy) tackles this challenge by integrating symbolic reasoning with neural networks. In our recent work (De Raedt et al. 2020; Marra et al. 2024), we provided an introduction to NeSy by drawing several parallels to another field that has a rich tradition in integrating learning and reasoning, namely Statistical Relational Artificial Intelligence (StarAI).

**The seven dimensions of Neurosymbolic.** We identify seven dimensions that these fields have in common and that can be used to categorize both StarAI and NeSy approaches. These seven dimensions are concerned with:

1. *Logic Inference.* We distinguish two approaches to logical inference: model-based and the proof-based. According to the model-based perspective, logic rules are interpreted as a set of constraints on boolean variables. This perspective gives rise to NeSy methods where logic is turned into a regularization loss for neural networks. In the proof-theoretic perspective, logic rules are seen as inference rules and one performs a sequence of inference steps to obtain a proofs for a query. This perspective leads rise to NeSy methods where logic is a template for the architecture of a neural network.
2. *Logic syntax.* We categorize systems in terms of propositional, relational or first-order logic. Relational and first-order NeSy systems introduce logic variables in their logical statements, allowing a structured (i.e. templated) definition of their learning modules.
3. *Logic semantics.* In order to allow for gradient-based learning, the majority of NeSy systems introduce relaxation of the discrete boolean logic semantics. The most common choices are fuzzy and probabilistic logic.
4. *Learning.* NeSy systems are often concerned with learning the parameters of both the weighted logic theories or the weights of the neural networks. Some systems learn also the structure of the model, i.e. the shape of the logic rules or the architecture of the neural modules.
5. *Symbols vs sub-symbols.* We can contrast two main classes of representation for the elements a logic theory (e.g. constants or atoms), symbols versus sub-symbols (e.g. embeddings).
6. *Degree of integration.* We analyzed to which extent hybrid systems retain properties of the base paradigms, i.e. deep learning, computational logic and probability theory. It turns out that most of the system fails in recovering pure logic reasoning, as different degree of relaxations are often at the base of the NeSy integration. Systems that do retain pure logic reasoning capabilities are often computationally intractable.
7. *Tasks.* NeSy has been mainly applied on distant supervision settings, where logic is used to provide a weak supervision signal to the output of neural networks. Other common settings are collective classification, knowledge graph completion and knowledge induction.

**The NeSy recipe.** The definition of the seven dimensions serves to unify various NeSy systems under a common framework, akin to a standard "recipe." In particular, each system can be distilled into the same two fundamental choices:

- *Construction of a purely logical architecture.* Irrespective of whether a system is rooted in proof-based or model-based paradigms, both culminate in the generation of a "ground" theory. This theory can be represented in terms of an AND/OR tree.
- *Compilation of the logical architecture into a computational graph.* This phase involves the transformation of the aforementioned AND/OR tree into a continuous and differentiable architecture, akin to a computational graph. This transformation can often be described through the introduction of an algebraic structure. Here, AND and OR nodes are interpreted as continuous functions and leaves undergo substitution with neural network outputs. The resultant compiled structure is a hybrid deep computational graph.

## References

- De Raedt, L.; Dumančić, S.; Manhaeve, R.; and Marra, G. 2020. From statistical relational to neural-symbolic artificial intelligence. In *IJCAI*.
- Marra, G.; Dumančić, S.; Manhaeve, R.; and De Raedt, L. 2024. From Statistical Relational to Neurosymbolic Artificial Intelligence: a Survey. *Artificial Intelligence*, 104062.