Verification for Neuro-Symbolic Artificial Intelligence

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Abstract. This Verification for Neuro-Symbolic Artificial Intelligence (VNSAI) track explores the intersection of neural networks and symbolic reasoning in artificial intelligence, combining the strengths of both approaches to enable learning, generalization, and explainability in complex systems. This track invites researchers to share their work on developing rigorous methodologies for analyzing and reasoning about neuro-symbolic AI systems, including formal verification, automated analysis, and symbolic explanation generation. Building on last year's track dedicated to the Safety Verification of Deep Neural Network (SVDNN), it also seeks contributions to benchmarking and standardization efforts in neural network verification, including submissions to the International Verification of Neural Networks Competition (VNN-COMP), the Applied Verification for Continuous and Hybrid Systems Competition (ARCH-COMP), and Verification of Neural Networks standard (VNN-LIB) initiatives. The track's overall goal is to foster collaboration across disciplines and advance the state-of-the-art in neuro-symbolic AI verification and explainability.

Keywords: Neuro-symbolic reasoning · Verification · Deep neural networks · Benchmarking.

1 Overview

Neuro-Symbolic artificial intelligence (AI) is a burgeoning area of artificial intelligence that combines the strengths of neuro-computational and symbolic models. Neural networks, inspired by the brain's structure and function, are used for learning and processing complex patterns in data. In contrast, symbolic reasoning, which uses logical rules and representations, is used for generalization, reasoning, and explanation. This integration allows Neuro-Symbolic AI systems to learn from large amounts of data, reason about abstract concepts, and provide explainable solutions to complex problems.

This track focuses on developing rigorous methodologies for analyzing and reasoning about neuro-symbolic AI systems, including their formal verification.

We aim to foster collaboration among researchers across various related areas, including neural control of continuous systems, neural ordinary and partial differential equations (ODEs/PDEs), automated analysis of neuro-symbolic AI, and neuro-symbolic verification. Another topic of interest is the generation of symbolic explanations for neural networks and other AI systems.

Building upon our efforts from last year's iteration of the related Safety Verification of Deep Neural Networks (SVDNN) track [4] that focused more on neural systems, we also seek to collect benchmarks for future iterations of the International Verification of Neural Networks Competition (VNN-COMP) [1] and the International Competition on Verifying Continuous and Hybrid Systems (ARCH-COMP) category on Artificial Intelligence and Neural Network Control Systems (AINNCS) [3], as well as input for the Verification of Neural Networks standard (VNN-LIB) [2]. We welcome the submission of benchmark systems, networks, and specifications to support developing and evaluating novel verification techniques for neural networks, neuro-symbolic AI, and related systems.

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