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A Hybrid Cognitive Architecture for AGI: Bridging Symbolic and Subsymbolic AI

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Abstract
This paper presents a novel hybrid cognitive architecture designed to advance Artificial General Intelligence (AGI) by integrating symbolic and subsymbolic AI approaches using graph neural networks (GNN). The architecture comprises several key components: a perception module using neural networks to process raw sensory data, a symbol grounding module to map subsymbolic features to symbolic representations, a symbolic knowledge base for storing facts and rules, a reasoning engine for logical deductions, and a learning module for updating the system based on experience. The GNN serves as an integration layer, connecting symbolic concepts and subsymbolic features to facilitate bidirectional communication, enhancing the system's ability to reason and generalize. This hybrid approach aims to combine the strengths of symbolic AI (logical reasoning) and subsymbolic AI (pattern recognition), offering a promising pathway toward achieving general intelligence, with potential applications in robotics, natural language processing, and visual reasoning.

1. Introduction
Artificial General Intelligence (AGI) aims to create AI systems capable of performing any intellectual task a human can do, requiring both reasoning and learning abilities. Current AI systems often fall into two categories: symbolic AI, which excels at logical reasoning but struggles with learning from data, and subsymbolic AI (like neural networks), which is great at pattern recognition but lacks transparency in reasoning. Combining these approaches in a hybrid cognitive architecture could bridge these gaps, offering a promising path toward AGI. This paper proposes a novel architecture using graph neural networks to integrate symbolic and subsymbolic AI, potentially revolutionizing AGI development.
Survey Note: A Comprehensive Exploration of Hybrid Cognitive Architectures for AGI

2. Background and Motivation
Artificial General Intelligence (AGI) seeks to develop AI systems with human-like general intelligence, capable of performing any intellectual task across diverse domains. The field has historically been divided between symbolic AI, which relies on explicit rules and logic for reasoning, and subsymbolic AI, primarily neural networks, which excel at learning from data but lack explainability. Symbolic AI, rooted in early expert systems like XCON at DEC (Symbolic artificial intelligence - Wikipedia), is adept at handling structured knowledge but struggles with uncertainty and learning from raw data. Conversely, subsymbolic AI, driven by deep learning advancements since the 2010s, has shown remarkable success in tasks like image recognition and natural language processing but often fails in reasoning and generalization beyond trained data (Neuro-symbolic AI - Wikipedia).

The limitations of these standalone approaches have led to a growing interest in hybrid cognitive architectures that combine both paradigms. Research suggests that integrating symbolic reasoning with subsymbolic learning could address AGI's requirements for both
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structured knowledge manipulation and adaptive learning from experience. This survey explores the integration of these approaches, focusing on a novel architecture using graph neural networks (GNNs) as an integration layer, aiming to bridge the gap and enhance AGI capabilities.

3. Review of Existing Hybrid Approaches

Several cognitive architectures have been proposed for AGI, with some incorporating hybrid elements. For instance, SOAR, developed in the 1980s, is primarily symbolic but includes subsymbolic mechanisms for decision-making (Soar (cognitive architecture) - Wikipedia). ACT-R (Adaptive Control of Thought-Rational) also combines symbolic and subsymbolic components, modeling human cognition through procedural and declarative memories (Theoretical Foundations of AGI: A Comprehensive Overview - Omnidigital Content). Recent research, such as "Combining neural networks and symbolic inference in a hybrid cognitive architecture" (Combining neural networks and symbolic inference in a hybrid cognitive architecture - ScienceDirect), proposes using neural networks for generating solutions and symbolic inference for verification, enhancing trustworthiness.

Neuro-symbolic AI, a broader term for hybrid approaches, has gained traction, with frameworks like Logic Tensor Networks and DeepProbLog combining neural and symbolic methods (Neuro-symbolic AI - Wikipedia). These systems often use knowledge graphs for symbolic representation, with GNNs applied in domains like combinatorial optimization and relational reasoning (Graph Neural Networks Meet Neural-Symbolic Computing: A Survey and Perspective - arXiv). However, existing architectures face challenges in seamless integration, scalability, and handling complex knowledge representations, necessitating novel solutions.

4. Proposed Hybrid Cognitive Architecture

To address these gaps, we propose a novel hybrid cognitive architecture for AGI, detailed as follows:
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- **Perception Module**: Utilizes neural networks, such as convolutional neural networks for visual data or recurrent neural networks for sequential data, to process raw sensory inputs and extract features. This aligns with subsymbolic AI's strength in pattern recognition, enabling the system to handle diverse data types like images, audio, and text.
- **Symbol Grounding Module**: Maps subsymbolic features to symbolic representations, a critical step for bridging the gap between data-driven outputs and structured knowledge. For example, it might map visual features of a rectangular object with wheels to the symbol "car." This process draws on research like "A symbolic/subsymbolic interface protocol for cognitive modeling" (A symbolic/subsymbolic interface protocol for cognitive modeling - PMC), emphasizing the need for effective mapping mechanisms.
- **Symbolic Knowledge Base**: Stores symbolic knowledge, including facts (e.g., "cars are vehicles"), rules (e.g., "vehicles must follow traffic laws"), and relationships (e.g., "cars can carry people"). This component supports reasoning and is inspired by traditional AI systems like knowledge graphs (What is Neuro-Symbolic AI? - AllegroGraph).

- **Reasoning Engine**: Performs logical deductions, planning, and decision-making using the symbolic knowledge base. For instance, it might infer that a car on a road should stop at a red light based on traffic rules, leveraging symbolic AI's strength in structured reasoning.
- **Learning Module**: Enables the system to learn from experience, updating both neural networks and the symbolic knowledge base. This could involve reinforcement learning for adapting to new environments or symbolic learning for acquiring new rules, aligning with research on "Neuro-symbolic Learning Yielding Logical Constraints" (Neuro-symbolic Learning Yielding Logical Constraints - ResearchGate).
- **Integration Layer**: The novel aspect is the use of a graph neural network (GNN) as the integration layer, representing both symbolic concepts and subsymbolic features as nodes in a graph, with edges indicating mappings or relationships. For example, nodes might include "car" (symbolic) and "rectangular shape, wheels" (subsymbolic), with edges connecting them based on feature relevance. The GNN learns to propagate information, allowing symbolic knowledge to influence neural learning and vice versa, enhancing the system's ability to reason and generalize.

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This approach builds on "Graph Neural Networks Meet Neural-Symbolic Computing: A Survey and Perspective" (Graph Neural Networks Meet Neural-Symbolic Computing: A Survey and Perspective - arXiv), extending GNN applications to cognitive architectures for AGI.

5. Implementation and Use Case

Implementation involves training each module and ensuring seamless interaction through the GNN integration layer. For instance, the perception module processes an image, the symbol grounding module maps detected objects to symbols, and the reasoning engine uses the knowledge base to infer relationships. The GNN layer facilitates bidirectional communication, such as updating symbolic rules based on learned patterns or guiding neural network predictions with symbolic constraints.

A practical use case is a robotic navigation system. The robot uses the perception module to detect objects (e.g., cars, pedestrians, roads) from camera inputs, maps these to symbols, and reasons about safe paths using the knowledge base (e.g., "avoid pedestrians"). The learning module adapts to new environments, and the GNN integration layer ensures that symbolic plans (e.g., "turn left at the intersection") are informed by subsymbolic data (e.g., traffic density from sensor readings), improving adaptability and safety.

6. Potential Applications and Benefits

This architecture is applicable to various AGI tasks, including natural language understanding, visual reasoning, and planning. For example, in natural language processing, it could parse sentences symbolically while using neural networks for context understanding, enhancing tasks like question answering. In visual reasoning, it could identify objects and reason about their interactions, such as determining if a person is likely a driver or pedestrian based on image features and symbolic rules. The hybrid approach promises improved generalization, explainability, and adaptability, addressing AGI's need for human-like intelligence across diverse domains.

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7. Challenges and Future Directions

Challenges include scalability, as large graphs may require significant computational resources, and interpretability, given GNN's complexity. Training the integrated system efficiently, especially aligning symbolic and subsymbolic representations, is another hurdle. Future research could explore different GNN architectures (e.g., Graph Convolutional Networks, Graph Attention Networks) for the integration layer, develop methods for lifelong learning, and integrate advanced symbolic reasoning techniques like probabilistic logic. Additionally, evaluating the architecture on benchmark AGI tasks could validate its effectiveness and guide further improvements.

8. Conclusion

This survey presents a novel hybrid cognitive architecture for AGI, leveraging graph neural networks to integrate symbolic and subsymbolic AI. By combining the strengths of both paradigms, the architecture offers a promising pathway toward achieving general intelligence, with potential applications in robotics, language processing, and beyond. While challenges remain, the approach opens new avenues for research, aiming to bridge the gap between data-driven learning and structured reasoning in the quest for AGI.

9. Key Citations

1. Symbolic artificial intelligence - Wikipedia
2. Neuro-symbolic AI - Wikipedia
3. Soar (cognitive architecture) - Wikipedia
4. Theoretical Foundations of AGI: A Comprehensive Overview - Omnidigital Content
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6. Combining neural networks and symbolic inference in a hybrid cognitive architecture - ScienceDirect
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8. What is Neuro-Symbolic AI? - AllegroGraph
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