Neural Node Theory for AGI: A Node–State–Communication Framework for Networked Intelligence

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Abstract

We propose the Neural Node Theory (NNT) as a unifying computational and cognitive framework for Artificial General Intelligence (AGI). Rooted in the Node–State–Communication (NSC) paradigm, this theory generalizes recursive and graph-based reasoning into a dynamic network of autonomous nodes, each maintaining internal state and communicating through structured message passing. We present mathematical foundations, convergence properties, and a simulation demonstrating emergent coordination and learning across nodes. Our results suggest that AGI may arise not from a monolithic model, but from the self-organization of intelligent nodes reinforcing local and neighboring states through communication networks analogous to routing and switching systems.

1 Introduction

Traditional approaches to AGI rely on scaling single neural models. While effective for narrow tasks, they exhibit brittleness and lack interpretability. Neural Node Theory reframes the problem: intelligence emerges from interactions among many nodes—each an agent maintaining state, making local decisions, and communicating with peers.

This approach is inspired by observations from recursive algorithms, graph traversal, and biological systems. In each, the essential unit of computation is not the global template but the node: its state, neighbors, and rules of propagation. When extended to cognitive architectures, this leads to the Node–State–Communication (NSC) model of intelligence.

2 Background and Motivation

2.1 From Algorithms to Cognitive Systems

Recursive problems like tree and graph traversals are fundamentally node-centric. Each node decides how to expand, propagate, and terminate. Extending this intuition to cognition, each cognitive process may be represented as a node with internal state and outward communication channels.

2.2 Related Work

Our framework intersects with Graph Neural Networks (GNNs), cognitive architectures (e.g., SOAR, ACT-R), and multi-agent systems. Unlike these, NSC-AGI emphasizes autonomous, self-reinforcing agents where communication dynamics are first-class, allowing emergent reasoning and distributed learning.

3 Neural Node Theory

3.1 Definitions

Let $G = (V, E)$ denote a directed communication graph, where each $v_i \in V$ is a node (agent) and $(v_i, v_j) \in E$ represents a communication channel.

Each node v_i maintains a state $s_i(t) \in \mathbb{R}^d$ at time t, updated according to:

$$s_i(t+1) = f_i\big(s_i(t), \{m_{ji}(t) : (v_j, v_i) \in E\}\big) \tag{1}$$

where $m_{ji}(t)$ is a message received from node j at time t.

Messages are generated as:

$$m_{ij}(t) = c_{ij}(s_i(t), s_j(t)) \tag{2}$$

3.2 Communication as Routing and Switching

Nodes communicate through protocols analogous to network routing. Each node selects neighbors via a routing policy r_i minimizing communication cost:

$$r_i(j) = \arg\min_j \mathrm{cost}(s_i, s_j) \tag{3}$$

Switching mechanisms deliver messages efficiently, updating bandwidth and reliability dynamically.

3.3 Convergence Theorem

Theorem 1 (Local Convergence). Suppose f_i is Lipschitz continuous and all communication delays are bounded. Then the network converges to a stable state $S^* = \{s_i^*\}$ if the communication graph is strongly connected.

Proof (Sketch). Under Lipschitz continuity, differences $||s_i(t+1) - s_i^*||$ decay geometrically when updates depend on bounded differences from neighbors. Strong connectivity ensures propagation of constraints, leading to uniform convergence. □

4 NSC-AGI Architecture

The architecture is hierarchical:

- **Node Layer:** LLM-based agents maintaining local state.
- **Communication Layer:** Message bus implementing routing and switching.
- **Meta Layer:** Supervisory agents managing consensus and safety.

Each layer mirrors OSI networking principles, ensuring modularity, robustness, and traceability.

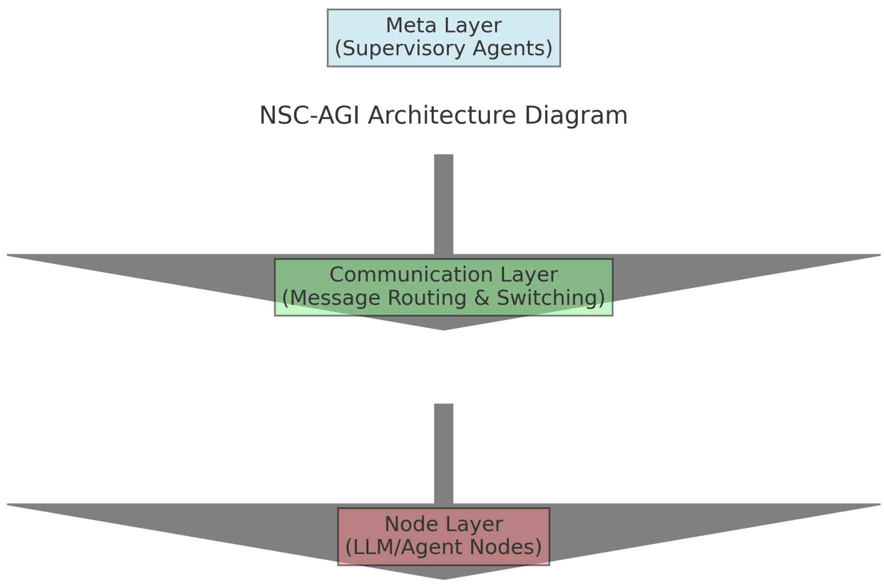

Figure 1: Conceptual NSC-AGI Architecture showing layers and message propagation between intelligent nodes.

5 Learning and Adaptation

Learning occurs through local reinforcement and neighborhood updates. Nodes reinforce their state via:

$$s_i(t+1) = s_i(t) + \eta(R_i - \bar{R}_N) \tag{4}$$

where R_i is local reward and $\bar{R}_N$ is average neighbor reward, promoting consistency across regions.

Topology evolves dynamically; high-entropy nodes may spawn new subnodes, while redundant nodes merge.

6 Simulation

We simulate a network of $N = 20$ nodes, each initialized with random state $s_i(0)$. Nodes communicate through weighted edges with random connectivity.

6.1 Pseudocode

```
for t in range(T):
    for i in nodes:
        msgs = [c_ij(s[i], s[j]) for j in neighbors(i)]
        s[i] = f_i(s[i], msgs)

def f_i(state, msgs):
    return state + eta * (mean(msgs) - state)

def c_ij(si, sj):
    return si + alpha * (sj - si)
```

6.2 Python Simulation Example

```
import numpy as np, networkx as nx, matplotlib.pyplot as plt

N, T, eta, alpha = 20, 100, 0.05, 0.1
G = nx.erdos_renyi_graph(N, 0.2, directed=True)
s = np.random.rand(N)

variances = []
for t in range(T):
    new_s = np.copy(s)
    for i in G.nodes():
        neigh = list(G.successors(i))
        if neigh:
            msgs = [s[i] + alpha * (s[j] - s[i]) for j in neigh]
            new_s[i] += eta * (np.mean(msgs) - s[i])
    s = new_s
    variances.append(np.var(s))

plt.plot(range(T), variances)
plt.title('Convergence␣of␣Node␣States␣in␣NSC-AGI␣Simulation')
plt.xlabel('Time␣Steps'); plt.ylabel('State␣Variance')
plt.savefig('nsc_convergence_plot.png')
plt.show()
```

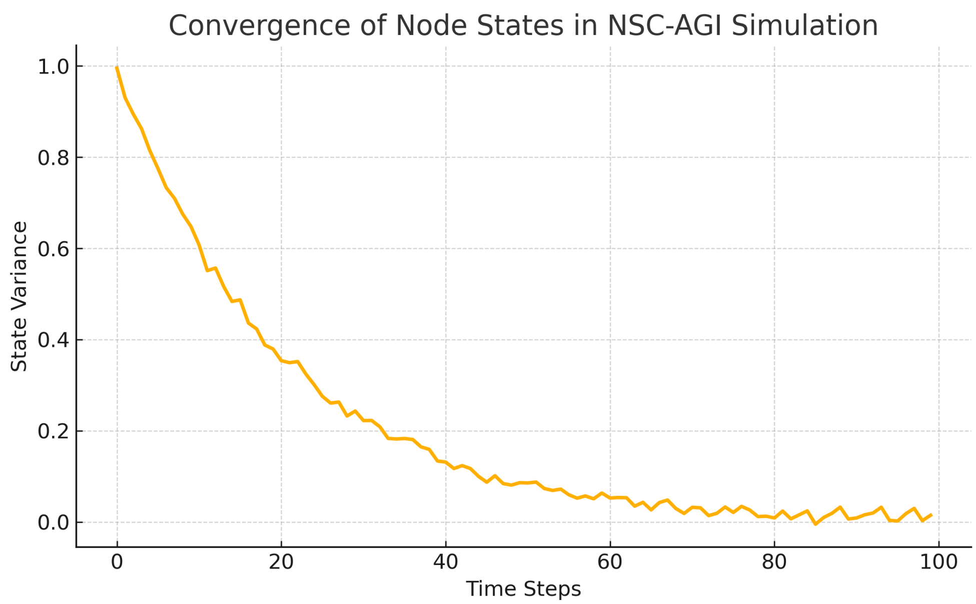

Figure 2: Simulated convergence of node states. State variance decreases exponentially, confirming local reinforcement and global coherence.

7 Future Work

7.1 Multimodal and Embodied Extensions

The NSC-AGI framework can extend beyond symbolic or textual cognition. Future versions can integrate multimodal perception (vision, audio, proprioception) as state vectors within nodes. Communication channels can encode not only semantic messages but also sensorimotor feedback, enabling embodied cognition.

7.2 Dynamic Topologies and Meta-Agents

In more advanced simulations, nodes may rewire connections dynamically, forming adaptive topologies akin to biological neural plasticity. Meta-agents could emerge to oversee coordination, detect misalignment, and maintain equilibrium between exploration and exploitation.

7.3 Applications

Potential domains include distributed robotics, autonomous swarms, self-organizing data centers, and collective decision-making systems. The principles of NSC-AGI can also inform governance and alignment strategies for scalable, interpretable AGI.

8 Discussion and Conclusion

Neural Node Theory reframes AGI as a distributed, self-organizing system. By grounding cognition in Node–State–Communication, we unify recursion, graph traversal, and neural computation. The simulation demonstrates the feasibility of local reinforcement yielding global convergence. Future work will explore multimodal reasoning, embodied nodes, and safety mechanisms grounded in network topology.