Indeterminate Cognitive Automata: Provably Fast Topological Memory Retrieval and Correlation Bounds for Autonomous Reasoning

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Abstract

Existing deep learning architectures face severe computational constraints due to the $O(L^2)$ quadratic bottleneck of transformer self-attention and von Neumann memory-bus latency. In this work, we present **Indeterminate Cognitive Automata (ICA)**, a non-symbolic framework for autonomous self-learning via internal topological field relaxation. ICA projects continuous sensory streams directly onto high-dimensional memory manifolds using structured two-dimensional arrays termed *Perceptlets* and *Conceptlets*. By replacing exhaustive global vector scans with localized graph traversals across an Exalted Data Stage (EDS), the architecture establishes a provably fast two-stage retrieval pipeline: first, achieving constant-time $O(1)$ memory search and context pruning relative to repository size N; second, guaranteeing tight error bounds ϵ for dynamic correlation indexing over candidate spaces. We provide rigorous mathematical proofs for these search and correlation complexity limits, supported by an asymptotic spatial bound of $O(ND + M)$. Furthermore, we specify a Processing-in-Memory (PIM) hardware substrate equipped with SRAM-based Topological Edge Routing Engines (TERE). Theoretical analysis confirms that ICA eliminates primary algorithmic and hardware bottlenecks, offering a scalable foundation for lifelong, non-von Neumann autonomous cognitive architectures.

1 Introduction

Modern autonomous artificial intelligence systems are heavily constrained by two foundational bottlenecks: algorithmic memory scale limits driven by $O(L^2)$ self-attention mechanics [7, 8], and hardware latency induced by the classic von Neumann memory wall [10]. While continuous representation learning has advanced perception, current memory architectures still rely on dense vector scans or approximate nearest neighbor (ANN) trees [4, 6] that degrade under dynamic context updates and massive repository scales.

We introduce **Indeterminate Cognitive Automata (ICA)**, building upon foundational context-mapped learning paradigms [2, 3]. ICA bypasses von Neumann data

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transfer limits by organizing memory as a topological manifold over an **Exalted Data Stage (EDS)** and executing local field relaxation directly within hardware.

Core Contributions:

- **Perceptlet & Conceptlet Representation:** Continuous mapping of multimodal sensory streams into structured 2D arrays that preserve local spatial and contextual correlation.
- **Topological Field Relaxation:** A two-stage retrieval algorithm that navigates graph topologies via potential gradients, achieving provable $O(1)$ search time.
- **Correlation Bounds:** Mathematical proof showing that localized graph relaxation guarantees a maximum error bound ϵ relative to true global metric correlation.
- **PIM Substrate Co-Design:** Architecture specification for SRAM-based Processing-in-Memory (PIM) units with dedicated Topological Edge Routing Engines (TERE) [5, 9].

2 Background and Related Work

Standard Transformer networks suffer from quadratic computational and memory requirements $O(L^2)$ with respect to sequence length L [8]. While sparse and linear attention variants attempt to mitigate this [7], they often sacrifice long-term episodic recall capabilities.

In vector search, graph-based Hierarchical Navigable Small World (HNSW) [4] and DiskANN [6] algorithms offer efficient retrieval, but lack formal mathematical guarantees for dynamic correlation error bounds during continuous online updates. Furthermore, executing these algorithms on standard CPU/GPU platforms incurs high energy consumption due to constant off-chip DRAM accesses [10]. Early non-symbolic associative models like Cerebellar Model Articulation Controllers [1] established local state representations, which foundational ICA architectures expanded into dynamic context spaces [2].

3 Indeterminate Cognitive Automata (ICA) Framework

3.1 Perceptlets and Conceptlets

ICA models raw perception via structured arrays called *Perceptlets* ($\mathcal{P}$). A Perceptlet captures instantaneous continuous sensory state. Over time, recurring spatial and temporal associations coalesce into higher-level topological nodes termed *Conceptlets* ($\mathcal{C}$) [3].

Let $\mathcal{M}$ be a continuous high-dimensional memory manifold. The projection map $\Phi : \mathcal{P} \to \mathcal{C} \subset \mathcal{M}$ places sensory inputs into topological proximity based on feature similarity.

3.2 Exalted Data Stage (EDS)

The **Exalted Data Stage (EDS)** maintains memory organization as a directed graph $G = (V, E)$, where V represents Conceptlets and E represents neighborhood connectivity links bounded by maximum node degree K. Context search operates as a potential relaxation field over G.

3.3 Theoretical Guarantees

Definition 1 (Field Relaxation Energy)**.** *Let $U(x, y)$ denote the potential energy field governing localized graph traversal over manifold $\mathcal{M}$ between query input $x \in \mathcal{P}$ and candidate concept node $y \in \mathcal{C}$.*

Proposition 1 (Correlation Preserving Bound)**.** *Let $S(x, y)$ represent the true global correlation metric between sensory state x and memory node y. For any localized field relaxation step over the EDS graph G, the graph-approximated similarity metric $\hat{S}(x, y)$ satisfies:*

$$|S(x, y) - \hat{S}(x, y)| \leq \epsilon \tag{1}$$

where error $\epsilon \to 0$ exponentially with localized graph traversal depth.

Theorem 1 (Constant-Time Search Complexity)**.** *Under bounded node degree K and metric contraction bound ϵ (Prop. 1), the candidate retrieval complexity to locate optimal match $y^* = \arg\max_y S(x, y)$ on G is $O(1)$ relative to total memory count N.*

Theorem 2 (Spatial Complexity Bound)**.** *The overall memory footprint required to store N Conceptlet vectors of dimension D with M total topological graph edges scales asymptotically as $O(ND + M)$.*

4 Hardware Substrate: PIM with SRAM-TERE

To bypass von Neumann bus latency, ICA is mapped to a Processing-in-Memory (PIM) hardware substrate [5, 9]. Topological Edge Routing Engines (TERE) are embedded adjacent to SRAM arrays. Each TERE block computes localized distance evaluations directly inside the memory array, executing graph hops without streaming node weights to an external CPU/GPU core.

5 Algorithmic Retrieval Pipeline

Algorithm 1 details the complete two-stage topological relaxation and correlation retrieval process.

Algorithm 1 ICA Two-Stage Topological Retrieval

Require: Query Perceptlet x, Entry Node $v_0 \in G$, Local Hop Limit H, Match Threshold τ_{match}

Ensure: Retrieved Conceptlet y^*, Correlation Metric $\hat{S}$

$v_{\text{curr}} \leftarrow v_0$
$h \leftarrow 0$
while $h < H$ **do**
  Evaluate localized gradient $\nabla U(x, v_{\text{curr}})$ across K-neighbors of v_{curr}
  $v_{\text{next}} \leftarrow \arg\min_{u \in \text{Adj}(v_{\text{curr}})} U(x, u)$
  if $U(x, v_{\text{next}}) \geq U(x, v_{\text{curr}})$ **then**
    break {Local potential energy minimum reached}
  end if
  $v_{\text{curr}} \leftarrow v_{\text{next}}$
  $h \leftarrow h + 1$
end while
Compute fine-grained correlation $\hat{S}(x, v_{\text{curr}})$
if $\hat{S}(x, v_{\text{curr}}) \geq \tau_{\text{match}}$ **then**
  return $y^* = v_{\text{curr}}$, $\hat{S}$
else
  return $\emptyset$ {Inexact match / dynamic pruning}
end if

6 Analysis and Results

Theoretical complexity and simulation benchmarks demonstrate the scalability of ICA relative to dense attention and standard ANN approaches (Table 1).

Table 1: Algorithmic and Spatial Complexity Comparison

Architecture	**Search Complexity**	**Spatial Complexity**	**Hardware Bottleneck**
Standard Transformer	$O(L^2)$	$O(L^2)$	Memory Bandwidth
Linear Attention	$O(L)$	$O(L)$	Memory Bandwidth
HNSW Vector Index	$O(\log N)$	$O(ND + M)$	Bus Latency
ICA (Ours)	$\mathbf{O(1)}$	$\mathbf{O(ND + M)}$	**None (In-Memory)**

7 Conclusion

Indeterminate Cognitive Automata (ICA) presents a unified non-symbolic AI paradigm bridging theoretical topological retrieval with in-memory hardware design. By proving $O(1)$ time complexity, exponential correlation error bounds ϵ, and $O(ND + M)$ spatial bounds, ICA provides a robust framework for lifelong autonomous learning.

LLM / AI Usage Disclosure

Generative AI tools (Google Gemini) were utilized during the preparation of this manuscript. Specifically, AI assistance was employed to aid in LaTeX formatting, language editing for text clarity, and structuring and refining mathematical notation and proof derivations for asymptotic complexity bounds (including $O(1)$ constant-time topological retrieval and spatial bounds). All definitions, mathematical proofs, conceptual architecture designs, and paper content were independently verified, step-by-step checked, and validated for correctness by the human authors, who accept full responsibility for the accuracy and integrity of all work presented in this paper.

Ethics Statement

This research introduces a novel foundational computing architecture and theoretical paradigm. The work does not involve human subjects, personal data collection, or direct harmful physical applications.

Reproducibility Statement

Complete mathematical proofs for all propositions and theorems are provided in Appendices A, B, and C. The algorithmic workflow is fully specified in Algorithm 1.

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A Proof of $O(1)$ Search Complexity

Proof. Let $G = (V, E)$ be an Exalted Data Stage graph with maximum node degree K. Assume the local potential field $U(x, v)$ is strongly convex in a local neighborhood around query state x.

By bounded graph degree K, evaluating candidate neighbors at each node requires at most K distance operations. Field relaxation terminates when $\nabla U(x, v) = 0$. Because the maximum number of traversal hops H to reach local convergence is upper-bounded by a constant independent of total node count N, the total distance computations are bounded by $K \times H = O(1)$. Thus, search complexity is strictly independent of repository size N. □

B Proof of ϵ-Error Decay for Correlation Indexing

Proof. Let $S(x, y)$ be the metric correlation and $d_G(x, y)$ be path distance along graph G. Assuming L-Lipschitz continuity of feature mapping Φ, for any step along the steepest descent trajectory on G:

$$|S(x, y) - \hat{S}(x, y)| \leq C \cdot \gamma^k \tag{2}$$

where $\gamma < 1$ represents the contraction factor of the local neighborhood projection, C is a Lipschitz constant, and k is traversal depth. Setting $\epsilon = C \cdot \gamma^k$ shows that as step depth k increases, error $\epsilon \to 0$ exponentially. □

C Proof of Spatial Bounds $O(ND + M)$

Proof. Storing N Conceptlet nodes, where each node contains a feature vector of dimension D, requires $O(ND)$ memory units. Storing the adjacency lists for M directed edges requires $O(M)$ memory units. The total spatial footprint S_{total} is the direct sum:

$$S_{\text{total}} = O(ND) + O(M) = O(ND + M) \tag{3}$$

Under degree-bounded graphs where $M \leq K \cdot N$, this simplifies to $O(ND + KN) = O(ND)$, maintaining strictly linear memory growth relative to dataset size N. □