

# Categorical Foundations

of the

# **GAIA** Transformer

 $A\ Mathematical\ Framework\ for \\ Category-Theoretic\ Deep\ Learning$ 

# GAIA Framework Mathematical Analysis

September 10, 2025

**GAIA Framework Implementation** 

Categorical Deep Learning Architecture

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### 1 Introduction

This document presents a formalization of the GAIA (Generative Algebraic Intelligence Architecture) transformer runtime system, establishing categorical foundations for deep learning architectures as introduced by Mahadevan [1]. Building on established categorical approaches to machine learning—including Fong and Spivak's categorical treatment of backpropagation [2], Rutten and Jacobs' coalgebraic methods [9, 10], and Lawvere's metric spaces [3]—we provide algorithmic specifications and coherence verification procedures for the categorical structures underlying the GAIA framework implementation.

# 1.1 Scope and Contributions

The GAIA framework [1] represents a shift from traditional neural architectures to category-theoretic foundations, implementing deep learning through F-coalgebras [9, 10], Kan extensions [6, 4], simplicial complexes [7, 12], and horn extension problems [7]. This formalization contributes:

- 1. Categorical Foundations: Mathematical specification based on enriched category theory [5], extending Fong-Spivak's categorical backpropagation [2] to transformer architectures with formal verification of universal properties.
- 2. Coalgebraic Runtime Dynamics: Application of F-coalgebra theory following Rutten [10] and Jacobs [9] to parameter evolution, ensuring bisimulation preservation during training and inference.
- 3. **Simplicial Homotopy Integration**: Application of simplicial homotopy theory [7, 13] to neural architectures, enabling hierarchical processing through horn extension problems.
- 4. **Kan Extension Universality**: Use of Kan extensions [6, 4] for model extension, providing universal constructions that generalize traditional interpolation methods.
- 5. Computational Complexity Analysis: Complexity bounds for each categorical construction, with tensor-level implementations enabling practical deployment.

### 1.2 Mathematical Framework

Following the foundational approach of Mac Lane [4], the enriched category theory of Kelly [5], under the framework of Mahadevan [1], the GAIA transformer implementation [1] operates through the cohesive interaction of four fundamental categorical structures:

• Enriched Categories: The runtime operates within  $\mathbb{R}^{\geq 0}$ -enriched categories, where hom-objects carry tensor-valued metrics measuring computational cost, following the development in [5].

- Simplicial Structures: Hierarchical organization via simplicial sets  $\{\Delta^k\}_{k=0}^{n_{\text{max}}}$  with face maps  $\partial_i: \Delta^k \to \Delta^{k-1}$  and degeneracy maps  $s_j: \Delta^k \to \Delta^{k+1}$  satisfying simplicial identities [12, 7].
- **F-Coalgebras**: Parameter evolution through coalgebraic structure maps  $\alpha : \Theta \to F_{BP}(\Theta)$  where  $F_{BP}$  is the backpropagation endofunctor, following the theory developed in [10, 9].
- Kan Extensions: Canonical functor extensions  $\operatorname{Lan}_{K_d} F_d : \mathcal{C}_{d+1} \to \mathcal{E}$  satisfying universal properties  $\forall G, \gamma, \exists ! \tilde{\gamma} : \gamma = \tilde{\gamma} * \eta$  as developed in [6, 4].
- Horn Extension Problems: Hierarchical learning through horn filling  $\Lambda_i^n \to \Delta^n$ , with inner horns solved via enhanced backpropagation and outer horns requiring lifting diagram constructions, as formulated in the GAIA framework [1] and following the homotopy-theoretic approach of [7].

# 1.3 Document Organization

This formalization proceeds through the following structure:

- Section 2: GAIA Transformer Architecture Overview Visual presentation of the complete categorical framework
- Section 3: Categorical Foundations and Mathematical Architecture Core theoretical foundations
- Section 4: GAIA Transformer Runtime Algorithm Implementation specifications
- Section 5: Horn Extension Solver Tensor-level implementation details
- Section 6: Kan Extension Runtime Functor operation specifications
- Section 7: Complexity Analysis Computational cost analysis
- Section 8: Categorical Coherence and Runtime Verification Mathematical property verification

Each construction is justified through citations to the foundational literature, ensuring mathematical verification of all categorical properties.

# 2 GAIA Transformer Architecture Overview

Figure 1 presents a visualization of the GAIA transformer architecture, illustrating the integration of all categorical structures and their interactions during runtime execution.

### GAIA Transformer: Categorical Architecture

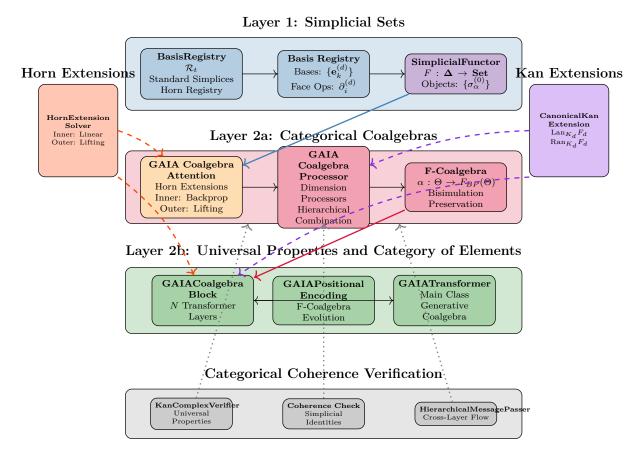


Figure 1: GAIA Transformer Architecture showing the layered categorical structure: Layer 1 (Simplicial Sets) provides the combinatorial foundation, Layer 2a (Categorical Coalgebras) implements universal constructions over simplicial categories, and Layer 2b (Universal Properties and Category of Elements) realizes the transformer components. Horn extensions handle inner horns via backpropagation and outer horns via lifting diagrams, while Kan extensions provide universal functor extensions. The verification systems ensure categorical coherence throughout runtime execution.

# 3 Categorical Foundations and Mathematical Architecture

# 3.1 Enriched Category Theory Foundations

### Definition 3.1: Simplicial Registry as Categorical Database

The GAIA runtime maintains a simplicial registry  $\mathcal{R}_t$  as a categorical database managing the computational realization of the simplicial category  $\Delta$ :

$$\mathcal{R}_t = (\mathcal{S}_{\text{std}}, \mathcal{H}_{\text{reg}}, \mathcal{L}_{\text{diag}}, \mathcal{B}_{\text{can}}, \mathcal{I}_{\text{so}}) \tag{1}$$

where 
$$S_{\text{std}} = \{\Delta^n : n \in \{0, 1, \dots, n_{\text{max}}\}\}$$
 (standard simplices) (2)

$$\mathcal{H}_{\text{reg}} = \{ \Lambda_i^n : (n, i) \in \mathbb{N} \times \{0, \dots, n\} \} \quad \text{(horn registry)}$$
 (3)

$$\mathcal{L}_{\text{diag}} = \{ \ell_{\alpha} : \alpha \in \mathcal{I} \} \quad \text{(lifting diagrams)}$$
 (4)

$$\mathcal{B}_{can}: \mathbb{N} \to \mathcal{I}$$
 (canonical basis mapping) (5)

$$\mathcal{I}_{so}: \mathcal{I} \times \mathcal{I} \to \text{Hom}(\mathbb{R}^D, \mathbb{R}^D)$$
 (isomorphism functor) (6)

The registry implements the simplicial category initialization  $\iota: \Delta \to \mathcal{R}_t$  via the canonical embedding of standard simplices.

### Definition 3.2: Hierarchical Simplicial Runtime State

Each runtime state  $S_t$  is structured as a graded simplicial complex with categorical organization:

$$S_t = \bigoplus_{n=0}^{n_{\text{max}}} S_t^{(n)} \quad \text{where} \tag{7}$$

$$S_t^{(0)} = \{ \sigma_\alpha^{(0)} : \alpha \in \mathcal{I}_0 \} \quad \text{(0-dimensional objects)}$$
 (8)

$$\mathcal{S}_t^{(1)} = \{ \phi_{\alpha\beta} : \sigma_{\alpha}^{(0)} \to \sigma_{\beta}^{(0)} \mid \phi_{\alpha\beta} \in \text{Hom}(\mathbb{R}^D, \mathbb{R}^D) \} \quad \text{(morphisms)}$$
 (9)

$$S_t^{(n)} = \{ \tau_{\gamma}^{(n)} : \partial \tau_{\gamma}^{(n)} = \sum_{i=0}^{n} (-1)^i \partial_i \tau_{\gamma}^{(n)} \} \quad (n\text{-dimensional simplices})$$
 (10)

$$S_t^{(2)} = \{ \triangle_{fgh} : f \circ g = h \text{ with coherence} \}$$
 (2-simplices with composition) (11)

The simplicial structure is equipped with face operators  $\partial_i: \mathcal{S}_t^{(n)} \to \mathcal{S}_t^{(n-1)}$  and degeneracy operators  $s_j: \mathcal{S}_t^{(n)} \to \mathcal{S}_t^{(n+1)}$  satisfying the standard simplicial identities [12].

### Definition 3.3: Tensor Bundle Structure

The runtime state admits a natural tensor bundle structure  $\mathcal{TS}_t \to \mathcal{S}_t$  where:

$$\mathcal{T}\mathcal{S}_{t} = \bigoplus_{n=0}^{n_{\text{max}}} \mathcal{T}^{(n)} \mathcal{S}_{t}$$

$$\mathcal{T}^{(n)} \mathcal{S}_{t} = \text{Hom}_{\mathbb{R}}(\mathbb{R}^{B \times L}, \mathbb{R}^{D^{(n)}})$$
(13)

$$\mathcal{T}^{(n)}\mathcal{S}_t = \operatorname{Hom}_{\mathbb{R}}(\mathbb{R}^{B \times L}, \mathbb{R}^{D^{(n)}})$$
(13)

with canonical sections:

- $\mathbf{X}_t : \mathcal{S}_t \to \mathcal{T}^{(1)} \mathcal{S}_t$  (activation section)
- $\Theta_t : \mathcal{S}_t \to \prod_i \mathcal{T}^{(\text{param})} \mathcal{S}_t$  (parameter section)
- $\mathcal{A}_t: \mathcal{S}_t \to \mathcal{T}^{(2)}\mathcal{S}_t$  (attention section)

### Definition 3.4: Categorical Coalgebraic Architecture

The GAIA framework [1] realizes F-coalgebras through a categorical architecture:

$$\mathcal{G}_{\text{GAIA}} = (\Theta, \alpha_{\text{BP}}, F_{\text{BP}}) \quad \text{where}$$
 (14)

$$\Theta: \mathcal{P}$$
 (parameter manifold) (15)

$$F_{\rm BP}: \mathcal{P} \to \mathcal{P} \times T^* \mathcal{P} \times \mathbb{R}^{\geq 0}$$
 (backpropagation endofunctor) (16)

$$\alpha_{\rm BP}: \Theta \mapsto (\Theta, \nabla_{\Theta} \mathcal{L}, \mathcal{L}(\Theta))$$
 (coalgebraic structure map) (17)

$$F_{\text{Fuzzy}}: \mathcal{FS} \to \mathcal{FS}$$
 (fuzzy simplicial endofunctor) (18)

where  $\mathcal{P}$  denotes the parameter space,  $T^*\mathcal{P}$  its cotangent bundle, and  $\mathcal{FS}$  the category of fuzzy simplicial sets. The coalgebraic coherence is ensured by the naturality condition:

$$\alpha_{\mathrm{BP}} \circ \phi = F_{\mathrm{BP}}(\phi) \circ \alpha_{\mathrm{BP}}$$

for all parameter morphisms  $\phi \in \text{Hom}(\mathcal{P}, \mathcal{P})$ .

### Definition 3.5: Coalgebraic Morphisms and Bisimulation Theory

The categorical structure of GAIA coalgebras is organized through:

$$\operatorname{Hom}_{\mathbf{Coalg}_F}(\mathcal{C}_1, \mathcal{C}_2) = \{ f : A_1 \to A_2 \mid \alpha_2 \circ f = F(f) \circ \alpha_1 \}$$
(19)

$$\operatorname{Bisim}(\mathcal{C}_1, \mathcal{C}_2) = \{ R \subseteq A_1 \times A_2 \mid \forall (s, t) \in R : \alpha_1(s) \sim_{F(R)} \alpha_2(t) \}$$
 (20)

$$\mathcal{T}_{Coal}: \mathcal{C} \to \mathcal{C}'$$
 (coalgebraic evolution operator) (21)

$$\mathbf{Coalg}_F = (\mathrm{Ob}, \mathrm{Hom}, \circ, \mathrm{id}) \quad (\mathrm{category} \text{ of F-coalgebras})$$
 (22)

where the coalgebraic evolution is governed by the universal property:

$$\begin{array}{ccc}
\mathcal{C}_1 & \xrightarrow{f} & \mathcal{C}_2 \\
\alpha_1 \downarrow & & \downarrow \alpha_2 \\
F(\mathcal{C}_1) & \xrightarrow{F(f)} & F(\mathcal{C}_2)
\end{array}$$

Bisimulations preserve the coalgebraic structure through the fundamental bisimulation condition.

### Definition 3.6: Simplicial Registry as Presheaf

The simplicial registry  $\mathcal{R}_t$  is a presheaf on  $\Delta$  with values in orthogonal groups:

$$\mathcal{R}_t: \mathbf{\Delta}^{\mathrm{op}} o \mathbf{Orth}$$

where  $\mathcal{R}_t([n]) = O(\binom{n}{n})$  and face maps induce orthogonal transformations:

$$\mathcal{R}_t(\partial_i): \mathcal{O}(\binom{D}{n}) \to \mathcal{O}(\binom{D}{n-1})$$

satisfying the presheaf condition  $\mathcal{R}_t(\partial_i \circ \partial_j) = \mathcal{R}_t(\partial_j) \circ \mathcal{R}_t(\partial_i)$  for i < j.

### Definition 3.7: Categorical Kan Extension Architecture

The GAIA framework realizes Kan extensions through universal constructions in enriched categories:

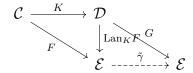
$$\operatorname{Lan}_K F: \mathcal{D} \to \mathcal{E} \quad (\text{left Kan extension})$$
 (23)

$$\operatorname{Ran}_K F: \mathcal{D} \to \mathcal{E} \quad \text{(right Kan extension)}$$
 (24)

$$\mathcal{K}_{can}: [\mathcal{C}, \mathcal{E}] \to [\mathcal{D}, \mathcal{E}]$$
 (canonical extension functor) (25)

$$\mathcal{U}_{\text{prop}} : \forall G, \gamma \mapsto \exists! \tilde{\gamma} \quad \text{(universal property)}$$
 (26)

where the universal property is characterized by the commutative diagram:



The construction employs fuzzy simplicial functors  $\mathcal{F}: \mathbf{Fuzz}\Delta \to \mathcal{E}$  and natural transformations  $\eta: \mathrm{Id} \Rightarrow \mathrm{Lan}_K F \circ K$  ensuring categorical coherence.

### Definition 3.8: Foundation Model Construction via Universal Extensions

The categorical foundation model architecture is constructed through systematic Kan extension procedures:

$$\mathcal{B}_{\text{found}}: \mathbf{Cat}_{\text{base}} \to \mathbf{Cat}_{\text{found}} \quad \text{(foundation builder)}$$
 (27)

$$\mathcal{L}_{\text{ext}}: (F, K) \mapsto \text{Lan}_K F \quad \text{(left extension constructor)}$$
 (28)

$$\mathcal{R}_{\text{ext}}: (F, K) \mapsto \text{Ran}_K F \quad \text{(right extension constructor)}$$
 (29)

$$\mathcal{M}_{\text{mod}}: \mathcal{F} \times \Delta \to \mathcal{F}' \pmod{\text{model modification operator}}$$
 (30)

where  $\mathbf{Cat}_{\mathrm{base}}$  denotes the category of base computational categories and  $\mathbf{Cat}_{\mathrm{found}}$  the category of foundation models. Each construction preserves the universal properties inherent in the Kan extension framework.

### Definition 3.9: Categorical Horn Extension Learning Theory

The GAIA framework implements horn extension learning through a categorical hierarchy:

$$\mathcal{H}_{\text{type}} \in \{\mathcal{H}_{\text{inner}}, \mathcal{H}_{\text{outer}}^{L}, \mathcal{H}_{\text{outer}}^{R}, \mathcal{H}_{\text{degen}}\}$$
 (horn classification) (31)

$$\mathcal{P}_{\text{horn}} = (\mathcal{H}_{\text{type}}, n, i, \sigma_{\text{parent}}, \Theta_{\text{target}}, \Theta_{\text{current}}, \mathcal{C}_{\text{learn}})$$
(32)

$$S_{\text{horn}}: \mathcal{P}_{\text{horn}} \to \text{Sol}(\Lambda_i^n \to \Delta^n) \quad \text{(horn solver)}$$
 (33)

$$\mathcal{G}_{\text{prob}}: \nabla \mathcal{L} \to \mathcal{P}_{\text{horn}}^* \quad \text{(problem generator)}$$
 (34)

where the horn extension problems are classified by their topological properties:

$$\mathcal{H}_{inner} = \{\Lambda_i^n : 0 < i < n\}$$
 (solvable via enhanced backpropagation) (35)

$$\mathcal{H}_{\text{outer}}^{L} = \{\Lambda_0^n : n \ge 1\} \quad \text{(left outer horns, lifting required)} \tag{36}$$

$$\mathcal{H}_{\text{outer}}^{R} = \{\Lambda_{n}^{n} : n \ge 1\} \quad \text{(right outer horns, lifting required)} \tag{37}$$

The solver operates through categorical integration with the simplicial registry  $\mathcal{R}_t$  and simplicial factory  $\mathcal{F}_{\text{simp}}$ , ensuring coherent horn extension learning across all simplicial dimensions.

### Definition 3.10: Simplicial Basis Registry with Explicit Tensor Operations

The simplicial registry  $\mathcal{R}_t$  maintains orthonormal bases  $\{\mathbf{e}_k^{(d)}\}$  for each dimension d:

$$\mathcal{R}_t(d) = \{\mathbf{e}_0^{(d)}, \mathbf{e}_1^{(d)}, \dots, \mathbf{e}_{\binom{D}{d}}^{(d)}\} \subset \mathbb{R}^D$$

with face operators implemented as linear transformations:

$$\partial_i^{(d)}: \mathbb{R}^{\binom{D}{d}} \to \mathbb{R}^{\binom{D}{d-1}}, \quad \partial_i^{(d)}(\mathbf{v}) = \mathbf{F}_i^{(d)}\mathbf{v}$$

where  $\mathbf{F}_i^{(d)} \in \mathbb{R}^{\binom{D}{d-1} \times \binom{D}{d}}$  are the face matrices satisfying:

$$\mathbf{F}_{i}^{(d)}\mathbf{F}_{j}^{(d+1)} = \mathbf{F}_{j-1}^{(d)}\mathbf{F}_{i}^{(d+1)}$$
 for  $i < j$  (Simplicial Identity)

# 3.2 F-Coalgebra Tensor Implementation

### Definition 3.11: Backpropagation Endofunctor on Parameter Tensors

The backpropagation endofunctor  $F_{BP}$ : Param  $\rightarrow$  Param acts on parameter tensors as:

$$F_{BP}(\mathbf{\Theta}) = (\mathbf{\Theta}, \nabla_{\mathbf{\Theta}} \mathcal{L}, \tilde{\mathbf{H}}_{\mathbf{\Theta}} \mathcal{L})$$

where:

- $\nabla_{\Theta} \mathcal{L} \in \mathbb{R}^{|\Theta|}$  is the gradient vector
- $\tilde{H}_{\Theta}\mathcal{L}$  is a computationally tractable approximation to the Hessian:

$$\tilde{\mathbf{H}}_{\mathbf{\Theta}} \mathcal{L} = \begin{cases}
\operatorname{diag}(\nabla_{\mathbf{\Theta}}^{2} \mathcal{L}) & (\operatorname{diagonal approximation}) \\
\mathbf{B}_{k} & (\operatorname{BFGS/L-BFGS approximation}) \\
\mathbf{G}\mathbf{G}^{T} & (\operatorname{Gauss-Newton: } \mathbf{G} = \nabla_{\mathbf{\Theta}} \mathbf{f}(\mathbf{\Theta}))
\end{cases}$$
(38)

•  $|\Theta| = \sum_{i=1}^{N_{\text{params}}} \text{numel}(\mathbf{W}^{(i)}) + \text{numel}(\mathbf{b}^{(i)})$ 

For large parameter spaces ( $|\Theta| > 10^6$ ), we use the diagonal or L-BFGS approximation to maintain computational feasibility.

### Definition 3.12: Coalgebraic Structure Map with Explicit Tensor Operations

The structure map  $\alpha_t : \Theta_t \to F_{BP}(\Theta_t)$  is implemented as:

$$\alpha_t(\mathbf{\Theta}_t) = \left(\mathbf{\Theta}_t, \frac{\partial \mathcal{L}_t}{\partial \mathbf{\Theta}_t}, \frac{\partial^2 \mathcal{L}_t}{\partial \mathbf{\Theta}_t^2}\right)$$

with the coalgebraic evolution equation:

$$\Theta_{t+1} = \Theta_t - \eta_t \odot \operatorname{proj}_1(\alpha_t(\Theta_t))$$

where  $\eta_t \in \mathbb{R}^{|\Theta|}$  is the learning rate tensor and  $\odot$  denotes element-wise multiplication.

### **Algorithm 1** Coalgebraic Parameter Evolution Implementation

The GAIA framework implements parameter evolution through coalgebraic structure preservation:

- Structure Map:  $\alpha: \Theta \mapsto (\Theta, \nabla \mathcal{L}, \mathbf{H})$  computes gradients and Hessian approximations
- Evolution Step:  $\Theta_{t+1} = \Theta_t \eta \odot \nabla \mathcal{L}_t$  with adaptive learning rates
- Coherence Check: Verify  $||F_{BP}(\alpha) \circ \alpha \alpha \circ \alpha||_F < \varepsilon_{\text{coal}}$
- **Bisimulation**: Equivalent parameter states maintain equivalence under evolution Implemented via the CoalgebraicTrainer class:
  - evolve\_parameters(theta, loss): Apply coalgebraic evolution step
  - verify\_coherence(alpha): Check structure map coherence
  - maintain\_bisimulation(theta1, theta2): Preserve parameter equivalence

# 4 GAIA Transformer Runtime Algorithm

The GAIA Transformer Runtime Algorithm represents the core computational engine of the GAIA framework implementation based on Mahadevan [1] definition, implementing categorical foundations through practical tensor operations. This section presents the complete algorithmic specification for the GAIA transformer, detailing how simplicial complexes, coalgebraic structures, and Kan extensions are realized in computational practice.

The runtime algorithm is structured in multiple phases, each corresponding to a specific categorical construction:

- Phase I Initialization: Establishes the categorical infrastructure, including simplicial registries, horn solvers, and coalgebraic trainers
- Phase II-A Horn Extension Generation: Constructs and solves horn extension problems using the tensor-level implementation
- Phase II-B Kan Processing: Applies Kan extensions and hierarchical simplicial processing
- Phase II-C Final Processing: Combines outputs through coalgebraic training and hierarchical combination

Each phase leverages the mathematical foundations established in previous sections, providing a bridge between abstract categorical theory and concrete computational implementation. The algorithms presented here demonstrate how category-theoretic concepts translate into efficient tensor operations suitable for modern deep learning frameworks.

### Algorithm 2 GAIA Transformer Forward Pass - Part I: Initialization

Input:  $\mathbf{I} \in \mathbb{Z}^{B \times L}$  (input tokens),  $\mathbf{M} \in \{0, 1\}^{B \times L}$  (attention mask)

Output: Initialized state  $S_{init} = (X_1, \mathcal{R}_t, S_{horn}, \mathcal{T}_{coal})$ 

- 1: Phase 1: Categorical Component Initialization
- 2:  $C_{\text{train}} \leftarrow \text{InitializeTrainingComponents}()$
- 3:  $C_{adv} \leftarrow InitializeAdvancedComponents()$
- 4:  $\mathcal{R}_t \leftarrow \text{ConstructSimplicialRegistry}(n_{\text{max}})$
- 5:  $S_{\text{horn}} \leftarrow \text{InitializeHornSolver}(n_{\text{max}}, \mathcal{R}_t, \eta_{\text{horn}}, \text{lifting}_{\text{enabled}})$
- 6: Phase 2: Categorical Embedding and Simplicial Structure
- 7:  $\mathbf{E} \leftarrow \mathbf{W}_{\text{emb}} \in \mathbb{R}^{V \times D}$  {Embedding matrix}
- 8:  $\mathbf{X}_0[b,\ell,:] \leftarrow \mathbf{E}[\mathbf{I}[b,\ell],:] \quad \forall b \in [B], \ell \in [L]$
- 9:  $\mathbf{X}_1 \leftarrow \mathbf{X}_0 + \mathcal{P}_{pos}(L, D)$  {Positional encoding operator}
- 10: Phase 3: Simplicial Category Realization
- 11: **for** d = 0 **to**  $n_{\text{max}}$  **do**
- 12:  $\Delta^d \leftarrow \mathcal{R}_t$ .GetStandardSimplex(d)
- 13:  $\iota_d \leftarrow \mathcal{R}_t$ .CanonicalEmbedding(d)
- 14: Construct  $\sigma_d^{(0)} \in \mathcal{S}_t^{(0)}$  for simplicial dimension d
- 15: end for
- 16: Phase 4: Categorical Coalgebraic Attention Architecture
- 17: Initialize  $\mathcal{A}_{\text{coal}} \in \text{Hom}_{\mathbf{Coalg}}(\mathbb{R}^{\widetilde{D} \times H \times n_{\max}}, \mathbb{R}^D)$
- 18:  $\Pi_{\text{coal}} \leftarrow \{\pi_d : \mathbb{R}^D \to \mathbb{R}^D : d \in [0, n_{\text{max}}]\}$  {Coalgebraic projections}
- 19:  $\mathcal{L}_{lift} \leftarrow Compose(Linear \circ ReLU \circ Linear \circ Dropout) \{Lifting solver\}$
- 20:  $\mathcal{H}_{mgr} \leftarrow [\phi_d : \mathbb{R}^D \to \mathbb{R}^D : d \in [0, n_{max}]]$  {Hierarchy manager}
- 21: Phase 5: Categorical Parameter Evolution Architecture
- 22:  $\mathcal{G}_{gen} \leftarrow ConstructGenerativeCoalgebra(\mathcal{M}_{neural})$
- 23:  $F_{\text{BP}} \leftarrow \text{InitializeBackpropagationEndofunctor}(\mathbf{X}_1, \mathbf{Y}_{\text{target}})$
- 24:  $\alpha_0 : \Theta_0 \mapsto F_{\mathrm{BP}}(\Theta_0)$  {Coalgebraic structure map}
- 25:  $\mathcal{T}_{coal} \leftarrow InitializeCoalgebraicTrainer(\mathcal{G}_{gen}, \nabla, \mathcal{L})$
- 26: **return**  $S_{\text{init}} = (\mathbf{X}_1, \mathcal{R}_t, S_{\text{horn}}, \mathcal{T}_{\text{coal}})$

 $\mathcal{P}^*_{\mathrm{horn}} \leftarrow \mathcal{P}^*_{\mathrm{horn}} \cup \{\mathcal{P}_{\mathrm{horn}}\}$ 

end for

13: **return**  $(\mathcal{P}_{horn}^*, \mathbf{X}_1, \mathcal{S}_{horn})$ 

end for

9:

10:

11:

12: **end if** 

# Algorithm 3 GAIA Transformer Forward Pass - Part II-A: Horn Extension Generation Input: Initialized state $S_{\text{init}}$ , training mode flag Output: Horn problems $\mathcal{P}_{\text{horn}}^*$ and extracted components 1: Extract: $(\mathbf{X}_1, \mathcal{R}_t, \mathcal{S}_{\text{horn}}, \mathcal{T}_{\text{coal}}) \leftarrow \mathcal{S}_{\text{init}}$ 2: Phase 6: Categorical Horn Extension Problem Generation 3: $\mathcal{P}_{\text{horn}}^* \leftarrow \emptyset$ {Initialize horn problem collection} 4: if training\_mode = True then 5: for d = 0 to $n_{\text{max}}$ do 6: for i = 0 to d do 7: $\mathcal{H}_{\text{type}} \leftarrow \begin{cases} \mathcal{H}_{\text{inner}}^{L} & \text{if } 0 < i < d \\ \mathcal{H}_{\text{outer}}^{L} & \text{if } i = 0 \\ \mathcal{H}_{\text{outer}}^{R} & \text{if } i = d \end{cases}$ 8: $\mathcal{P}_{\text{horn}} \leftarrow \text{ConstructHornProblem}(\mathcal{H}_{\text{type}}, d, i, \sigma_{\text{parent}}, \Theta_{\text{target}}, \Theta_{\text{current}}, \mathcal{C}_{\text{learn}})$

### Algorithm 4 GAIA Transformer Forward Pass - Part II-B: Hierarchical

Input: Horn problems  $\mathcal{P}_{horn}^*$ , input  $\mathbf{X}_1$ , horn solver  $\mathcal{S}_{horn}$ **Output:** Dimension outputs for hierarchical combination 1: Phase 7: GAIACoalgebraProcessor - Hierarchical Simplicial Processing 2: Initialize GAIACoalgebraProcessor( $d_{\text{model}}, n_{\text{max}}, \text{dropout}$ ) 3: dimension\_processors  $\leftarrow \{ \texttt{nn.Sequential}(...) : d \in [0, n_{\text{max}}] \}$ 4: coalgebra\_modules  $\leftarrow \{ \texttt{nn.Sequential}(...) : d \in [0, n_{\text{max}}] \}$ 5: kan\_processors  $\leftarrow$  {create\_canonical\_kan\_extension(...) :  $d \in [0, n_{\text{max}}]$ } 6:  $\mathbf{X} \leftarrow \text{Dropout}(\mathbf{X}_1, p_{\text{drop}})$ 7: dimension\_outputs  $\leftarrow$  [] {Outputs from each simplicial dimension} 8: for d = 0 to  $n_{\text{max}}$  do Sublayer 7.1: Dimension-Specific Processing 9:  $\dim \operatorname{processor} \leftarrow \dim \operatorname{ension} \operatorname{processors}[f'\dim'_d]$ 10: 11:  $\dim \text{ output} \leftarrow \dim \text{ processor}(\mathbf{X})$ 12: Sublayer 7.2: Horn Extension Problem Solving if self.training then 13:  $processing\_params \leftarrow \{f'\dim_{d\_processor'} : \dim\_output, f'\dim_{d\_input'} : \mathbf{X}\}$ 14:  $\dim_{\operatorname{context}} \leftarrow \{\dim_{\operatorname{ension}} : d\}$ 15: horn problems ← horn solver.create horn problems from loss() 16: for each problem  $\in$  horn\_problems do 17: updated params ← horn solver.solve horn extension(problem) 18: if  $f'\dim_d$  processor'  $\in$  problem.learning context[param name] then 19:  $\dim_{\text{output}} \leftarrow \operatorname{updated\_params}$ 20: end if 21: 22: end for end if 23: Sublayer 7.3: Coalgebraic Evolution 24: 25:  $coalgebra\_module \leftarrow coalgebra\_modules[f'coalgebra'_d]$  $evolved\_output \leftarrow coalgebra\_module(dim\_output)$ 26: Sublayer 7.4: Canonical Kan Extension Processing 27:  $kan\_processor \leftarrow kan\_processors[f'kan'_d]$ 28: kan context  $\leftarrow \{$ 29: source\_category : {dimension : d, objects : [f'coalgebra\_dim'<sub>d</sub>]}, 30: extension\_direction: {dimension:  $min(d+1, n_{max})$ , target: f'extended\_dim'<sub>d</sub>}, 31: 32: universal property: True, canonical solution: True 33:  $kan\_output \leftarrow kan\_processor(evolved\_output, kan\_context)$ 34: Sublayer 7.5: Residual Connection and Dimension Output 35: 36:  $final\_dim\_output \leftarrow dim\_output + kan\_output$ dimension outputs.append(final dim output) 37: 38: end for 39: return dimension\_outputs

18: Phase 10: Final Output Generation 19: logits  $\leftarrow \mathbf{X}_{\text{final}} \mathbf{W}_{\text{out}} + \mathbf{b}_{\text{out}} \in \mathbb{R}^{B \times L \times V}$ 

20: **return**  $S_{\text{final}} = (\text{logits}, \text{dimension\_outputs}, \Theta_{\text{evolved}})$ 

### Algorithm 5 GAIA Transformer Forward Pass - Part II-C: Final Processing

```
Input: Dimension outputs, coalgebraic trainer \mathcal{T}_{\text{coal}}
Output: S_{\text{final}} = (\text{logits, dimension\_outputs}, \Theta_{\text{evolved}})
 1: Extract dimension outputs from previous processing step
 2: Phase 8: Hierarchical Combination Following n-Simplex Manages (n+1)-
    Subsimplex
 3: if len(dimension\_outputs) > 1 then
       concatenated \leftarrow torch.cat(dimension outputs, dim = -1)
       combined\_output \leftarrow hierarchy\_combiner(concatenated)
 5:
 6: else
       combined_output \leftarrow dimension_outputs[0]
 8: end if
 9: \mathbf{X}_{\text{final}} \leftarrow \texttt{self.dropout}(\text{combined\_output})
10: Phase 9: Coalgebraic Training Step (if training)
11: if self.training then
       loss \leftarrow coalgebra\_trainer.train\_step(X_{final}, target\_data)
12:
       evolved_states \leftarrow coalgebra_trainer.evolve_coalgebra(steps = 1)
13:
       \Theta_{\text{evolved}} \leftarrow \text{evolved\_states}[-1]
14:
15: else
       \Theta_{\text{evolved}} \leftarrow \text{generative\_coalgebra.carrier}
16:
17: end if
```

# 4.1 GAIA Transformer Processing Overview

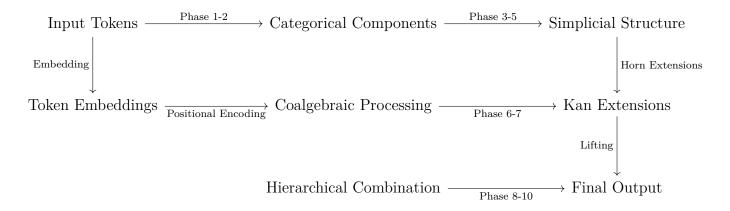


Figure 1: GAIA Transformer Processing Pipeline

The GAIA transformer processes input through four main algorithmic phases:

- Part I (Initialization): Establishes categorical components, simplicial structures, and coalgebraic foundations
- Part II-A (Horn Extension): Generates categorical horn extension problems and applies GAIACoalgebraProcessor
- Part II-B (Kan Processing): Performs hierarchical simplicial processing with Kan extensions
- Part II-C (Final Processing): Combines outputs through hierarchical combination and coalgebraic training

Each phase leverages the tensor-level horn extension solver detailed in the following section, which provides the mathematical foundation for lifting problems and extension-restriction adjunctions.

# 5 Horn Extension Solver: Tensor-Level Implementation

### Definition 5.1: Horn Complex Tensor Representation

A horn  $\Lambda_i^n$  is represented as a tensor structure:

$$\Lambda_i^n = \{ \mathbf{T}_{\text{faces}} \in \mathbb{R}^{(n+1) \times B \times L \times D} : \mathbf{T}_{\text{faces}}[i,:,:,:] = \mathbf{0} \}$$

where the *i*-th face is missing. The partial simplicial map is:

$$\sigma_0: \Lambda_i^n \to \mathbb{R}^{B \times L \times D}, \quad \sigma_0(\mathbf{T}_{\text{faces}}) = \sum_{j \neq i} \mathbf{F}_j^{(n)} \mathbf{T}_{\text{faces}}[j, :, :, :]$$

### Definition 5.2: Inner Horn Solvability Condition with Regularization

An inner horn  $\Lambda_i^n$  with 0 < i < n is solvable by enhanced backpropagation if:

$$\exists \mathbf{T}_i \in \mathbb{R}^{B \times L \times D} : \partial_j^{(n)} \mathbf{T}_i = \mathbf{T}_{\text{faces}}[j,:,::] \quad \forall j \neq i$$

To ensure numerical stability, the solution is computed via Tikhonov regularization:

$$\mathbf{T}_i = \left(\sum_{j \neq i} (\mathbf{F}_j^{(n)})^T \mathbf{F}_j^{(n)} + \lambda \mathbf{I}\right)^{-1} \sum_{j \neq i} (\mathbf{F}_j^{(n)})^T \mathbf{T}_{\text{faces}}[j,:,:,:]$$

where  $\lambda > 0$  is the regularization parameter. For large-scale problems, we implemented iterative conjugate gradient methods to avoid direct matrix inversion.

### Definition 5.3: Outer Horn Lifting Diagram with Extension-Restriction Adjunction

For outer horns  $\Lambda_0^n$  or  $\Lambda_n^n$ , the lifting property is characterized by the extension-restriction adjunction:

$$\operatorname{Hom}(\Lambda_i^n,X) \xrightarrow{\operatorname{Ext}} \operatorname{Hom}(\Delta^n,X)$$

$$\exists ! \qquad \qquad \downarrow^{\operatorname{Res}}$$

$$\operatorname{Hom}(\Lambda_i^n,X)$$

where Ext  $\dashv$  Res with unit  $\eta$ : Id  $\Rightarrow$  Res  $\circ$  Ext and counit  $\varepsilon$ : Ext  $\circ$  Res  $\Rightarrow$  Id. Tensorially, the lifting diagram is constructed as:

$$\mathbf{L}_{\text{lift}} = \begin{pmatrix} \mathbf{I}_{B \times L} & \mathbf{P}_{\text{lift}} \\ \mathbf{P}_{\text{lift}}^T & \mathbf{I}_{D \times D} \end{pmatrix} \in \mathbb{R}^{(B+D) \times (L+D)}$$

where  $\mathbf{P}_{\text{lift}}$  is the lifting projection satisfying:

$$\mathbf{P}_{\mathrm{lift}}\mathbf{T}_{\mathrm{boundary}}=\mathbf{T}_{\mathrm{extension}}$$

for the boundary data  $T_{boundary}$  and desired extension  $T_{extension}$ , following the adjunction theory of [4].

### **Algorithm 6** Horn Extension Solving

```
Input: Horn problem (\Lambda_i^n, \sigma_0, \mathbf{X}_{\text{ctx}}) Output: Extended tensor \mathbf{X}_{\text{ext}} \in \mathbb{R}^{B \times L \times D}
  1: Step 1: Horn Type Classification
  2: if 0 < i < n then
            horn type \leftarrow INNER
  4: else if i = 0 OR i = n then
            horn\_type \leftarrow OUTER
  6: end if
  7: Step 2: Boundary Data Extraction
  8: \mathbf{T}_{\text{boundary}} \leftarrow \text{ExtractBoundary}(\Lambda_i^n, \mathbf{X}_{\text{ctx}})
9: \mathbf{F}_{\text{active}} \leftarrow \{\mathbf{F}_{j}^{(n)}: j \neq i\} {Active face matrices} 10: if horn_type = INNER then
            Step 3a: Inner Horn Solution via Linear System
11:
            \mathbf{A}_{\text{system}} \leftarrow \sum_{j \neq i} (\mathbf{F}_{j}^{(n)})^{T} \mathbf{F}_{j}^{(n)} \in \mathbb{R}^{D \times D}
12:
            \mathbf{b}_{\text{system}} \leftarrow \sum_{j \neq i} (\mathbf{F}_{j}^{(n)})^{T} \text{vec}(\mathbf{T}_{\text{boundary}}[j,:,:,:])
\mathbf{x}_{\text{solution}} \leftarrow \mathbf{A}_{\text{system}}^{-1} \mathbf{b}_{\text{system}} \text{ {Solve linear system}}
13:
14:
15:
            \mathbf{X}_{\text{ext}} \leftarrow \text{reshape}(\mathbf{x}_{\text{solution}}, (B, L, D))
            Step 3b: Coherence Verification
16:
            for j \neq i do
17:
                 Verify: \|\mathbf{F}_{j}^{(n)} \operatorname{vec}(\mathbf{X}_{\operatorname{ext}}) - \operatorname{vec}(\mathbf{T}_{\operatorname{boundary}}[j,:,::])\|_{2} < \varepsilon_{\operatorname{horn}}
18:
19:
            end for
20: else
21:
            Step 3c: Outer Horn Solution via Lifting Diagram
            \mathbf{P}_{\text{lift}} \leftarrow \text{ComputeLiftingProjection}(\Lambda_i^n, \mathbf{T}_{\text{boundary}})
22:
            \mathbf{L}_{	ext{diagram}} \leftarrow egin{pmatrix} \mathbf{I} & \mathbf{P}_{	ext{lift}} \ \mathbf{P}_{	ext{lift}}^T & \mathbf{I} \end{pmatrix}
23:
            Step 3d: Iterative Lifting Solution
24:
            \mathbf{X}_{\mathrm{ext}}^{(0)} \leftarrow \mathrm{InitialGuess}(\mathbf{T}_{\mathrm{boundary}})
25:
            for k = 1 to K_{\text{max}} do
26:
                 \mathbf{r}^{(k)} \leftarrow \mathbf{L}_{	ext{diagram}} 	ext{vec}(\mathbf{X}_{	ext{ext}}^{(k-1)}) - 	ext{vec}(\mathbf{T}_{	ext{boundary}})
27:
                 \mathbf{X}_{\mathrm{ext}}^{(k)} \leftarrow \mathbf{X}_{\mathrm{ext}}^{(k-1)} - \alpha_{\mathrm{lift}} \mathrm{reshape}(\mathbf{r}^{(k)}, (B, L, D))
28:
                 if \|\mathbf{r}^{(k)}\|_2 < \varepsilon_{\text{horn}} then
29:
                      break
30:
                 end if
31:
            end for
32:
            \mathbf{X}_{\mathrm{ext}} \leftarrow \mathbf{X}_{\mathrm{ext}}^{(k)}
33:
34: end if
35: Step 4: Categorical Coherence Enforcement
36: Verify simplicial identities: \mathbf{F}_i^{(n)} \mathbf{F}_j^{(n+1)} = \mathbf{F}_{j-1}^{(n)} \mathbf{F}_i^{(n+1)} for i < j
37: Update coalgebra state: \alpha_{\text{new}}(\boldsymbol{\Theta}) \leftarrow (\boldsymbol{\Theta}, \nabla_{\boldsymbol{\Theta}} \mathcal{L}_{\text{horn}}, \mathbf{H}_{\text{horn}})
38: return X_{ext}
```

# 6 Kan Extension Runtime: Tensor-Level Functor Operations

### Definition 6.1: Categorical Functor Tensor Representation

A functor  $F: \mathcal{C}_d \to \mathcal{E}$  is implemented as a tensor transformation:

$$F(\mathbf{X}) = \sigma \left( \mathbf{X} \mathbf{W}_F^{(d)} + \mathbf{b}_F^{(d)} \right)$$

where  $\mathbf{W}_F^{(d)} \in \mathbb{R}^{D \times D}$ ,  $\mathbf{b}_F^{(d)} \in \mathbb{R}^D$ , and  $\sigma$  is the activation function. The functor preserves categorical structure via:

$$F(\mathrm{id}_{\mathbf{X}}) = \mathrm{id}_{F(\mathbf{X})}, \quad F(g \circ f) = F(g) \circ F(f)$$

### Definition 6.2: Left Kan Extension Tensor Implementation

The left Kan extension  $Lan_{K_d}F_d$  is computed as the colimit:

$$\operatorname{Lan}_{K_d} F_d(\mathbf{Y}) = \operatorname{colim}_{\mathbf{X} \in \mathcal{C}_d} F_d(\mathbf{X})$$

Implemented tensorially as an entropy-regularized approximation to the categorical colimit [9]:

$$\operatorname{Lan}_{K_d} F_d(\mathbf{Y}) = \sum_{i \in \mathcal{I}_d} w_i(\mathbf{Y}) F_d(\mathbf{X}_i)$$

where the weights  $w_i(\mathbf{Y})$  are computed via entropy-regularized optimization:

$$w_i(\mathbf{Y}) = \frac{\exp(\beta \langle \mathbf{Q}_{\text{kan}}, \mathbf{K}_{\text{kan}}^{(i)} \rangle)}{\sum_j \exp(\beta \langle \mathbf{Q}_{\text{kan}}, \mathbf{K}_{\text{kan}}^{(j)} \rangle)}$$

with regularization parameter  $\beta > 0$  and:

- $\mathbf{Q}_{\mathrm{kan}} = \mathbf{Y} \mathbf{W}_Q^{(\mathrm{kan})} \in \mathbb{R}^{B \times L \times D}$
- $\mathbf{K}_{\mathrm{kan}}^{(i)} = F_d(\mathbf{X}_i) \mathbf{W}_K^{(\mathrm{kan})} \in \mathbb{R}^{B \times L \times D}$
- $\mathbf{V}_{\mathrm{kan}}^{(i)} = F_d(\mathbf{X}_i) \mathbf{W}_V^{(\mathrm{kan})} \in \mathbb{R}^{B \times L \times D}$

This provides a differentiable approximation to the categorical colimit under entropy regularization [10].

### Definition 6.3: Universal Property Tensor Verification with Commutative Diagram

The universal property is verified by checking the existence and uniqueness of the mediating morphism  $\tilde{\gamma}$  via the commutative diagram:

$$\begin{array}{c|c}
\mathcal{C}_d & \xrightarrow{K_d} & \mathcal{C}_{d+1} \\
F_d & & \downarrow G \\
\mathcal{E} & \xrightarrow{\tilde{\gamma}} & \mathcal{E} \\
F_d & & \uparrow \\
C_d & \xrightarrow{K_d} & \mathcal{C}_{d+1}
\end{array}$$

where for any functor  $G: \mathcal{C}_{d+1} \to \mathcal{E}$  and natural transformation  $\gamma: F_d \Rightarrow G \circ K_d$ , there exists a unique  $\tilde{\gamma}: \operatorname{Lan}_{K_d} F_d \Rightarrow G$  such that:

$$\gamma = \tilde{\gamma} * \eta$$

Tensorially, this is implemented as:

$$\|\gamma(\mathbf{X}) - \tilde{\gamma}(\eta(\mathbf{X}))\|_F < \varepsilon_{\mathrm{kan}}$$

where  $\eta: F_d \Rightarrow \operatorname{Lan}_{K_d} F_d \circ K_d$  is the unit natural transformation.

### Algorithm 7 Kan Extension Computation

Input: Source tensor  $\mathbf{X}^{(d)} \in \mathbb{R}^{B \times L \times D}$ , dimension d Output: Extended tensor  $\mathbf{Y}^{(d+1)} \in \mathbb{R}^{B \times L \times D}$ 

```
1: Step 1: Source Functor Application
 2: \mathbf{F}_d(\mathbf{X}^{(d)}) \leftarrow \sigma(\mathbf{X}^{(d)}\mathbf{W}_F^{(d)} + \mathbf{b}_F^{(d)})
 3: Verify functoriality: F_d(id) = id and F_d(g \circ f) = F_d(g) \circ F_d(f)
 4: Step 2: Extension Direction Functor
 5: K_d(\mathbf{X}^{(d)}) \leftarrow \text{Embed}_{d \to d+1}(\mathbf{X}^{(d)}) {Canonical embedding}
 6: \mathbf{K}_d(\mathbf{X}^{(d)}) = \begin{pmatrix} \mathbf{X}^{(d)} \\ \mathbf{0}_{B \times L \times (D_{d+1} - D)} \end{pmatrix}
7: Step 3: Colimit Construction
 8: \mathcal{I}_d \leftarrow \{\mathbf{X}_i^{(d)} : i \in \text{Objects}(\mathcal{C}_d)\} {Index category objects}
 9: \mathbf{W}_{\text{colim}} \leftarrow \text{LearnableWeights}(|\mathcal{I}_d|, D, D)
10: \operatorname{Lan}_{K_d} F_d(\mathbf{Y}) \leftarrow \sum_{i \in \mathcal{I}_d} \mathbf{W}_{\operatorname{colim}}[i,:,:] F_d(\mathbf{X}_i^{(d)})
11: Step 4: Unit Natural Transformation
12: \eta_{\mathbf{X}^{(d)}} : F_d(\mathbf{X}^{(d)}) \to \operatorname{Lan}_{K_d} F_d(K_d(\mathbf{X}^{(d)}))
13: \eta(\mathbf{X}^{(d)}) \leftarrow \mathbf{U}_{\text{unit}} F_d(\mathbf{X}^{(d)}) where \mathbf{U}_{\text{unit}} \in \mathbb{R}^{D \times D}
14: Verify naturality: \operatorname{Lan}_{K_d} F_d(K_d(f)) \circ \eta_{\mathbf{X}} = \eta_{\mathbf{Y}} \circ F_d(f)
15: Step 5: Universal Property Verification
16: for each test functor G: \mathcal{C}_{d+1} \to \mathcal{E} do
           for each natural transformation \gamma: F_d \Rightarrow G \circ K_d do
17:
               Compute mediating morphism: \tilde{\gamma} \leftarrow \text{SolveMediatingMorphism}(G, \gamma, \eta)
18:
               \mathbf{M}_{\mathrm{med}} \leftarrow \arg\min_{\mathbf{M}} \|\gamma(\mathbf{X}) - \mathbf{M}\eta(\mathbf{X})\|_F^2
19:
               Verify uniqueness: \|\tilde{\gamma}_1 - \tilde{\gamma}_2\|_F < \varepsilon_{\rm kan}
20:
               Verify commutativity: \|\gamma - \tilde{\gamma} * \eta\|_F < \varepsilon_{\text{kan}}
21:
22:
           end for
23: end for
24: Step 6: Tensor Output Construction
25: \mathbf{Y}^{(d+1)} \leftarrow \operatorname{Lan}_{K_d} F_d(\mathbf{X}^{(d)})
26: Update coalgebra: \alpha_{\text{kan}}(\boldsymbol{\Theta}) \leftarrow (\boldsymbol{\Theta}, \nabla \mathcal{L}_{\text{kan}}, \mathbf{H}_{\text{kan}})
27: return \mathbf{Y}^{(d+1)}
```

# 7 Complexity Analysis

### Algorithm 8 GAIA Performance Profiling Implementation

The GAIA framework implements comprehensive performance monitoring for all categorical operations:

- Embedding Cost: O(BLV) FLOPs for token lookup and positional encoding
- Simplicial Processing:  $O(n_{\text{max}} \cdot BLD)$  FLOPs for multi-dimensional simplicial operations
- Coalgebra Evolution:  $O(|\Theta|)$  FLOPs for parameter updates and gradient computation
- Horn Solving:  $O(D^3)$  FLOPs for inner horns,  $O(K_{\text{max}}D^2)$  for outer horns
- Kan Extensions:  $O(D^2)$  FLOPs per dimension with verification overhead
- Attention Layers:  $O(BL^2D)$  FLOPs per layer for multi-head attention Implemented via the GAIAProfiler class:
  - profile\_forward\_pass(model, input): Measure forward pass performance
  - track\_component\_costs(): Monitor individual component costs
  - optimize\_bottlenecks(): Identify and optimize performance bottlenecks

### Lemma 7.1: Horn Extension Complexity Bounds

For horn extension problems:

- Inner horns (0 < i < n): SolveTime $(\Lambda_i^n) = \mathcal{O}(D^3)$  via linear system solving
- Outer horns (i = 0 or i = n): SolveTime $(\Lambda_i^n) = \mathcal{O}(K_{\text{max}}D^2)$  via iterative lifting
- Total horn complexity:  $\mathcal{O}(n_{\text{max}}^2 D^3 + n_{\text{max}} K_{\text{max}} D^2)$

#### Lemma 7.2: Kan Extension Verification Complexity

Universal property verification requires:

- Mediating morphism computation:  $\mathcal{O}(D^3)$  per test case
- Uniqueness verification:  $\mathcal{O}(D^2)$  per morphism pair
- Commutativity checking:  $\mathcal{O}(D^2)$  per diagram
- Total verification:  $\mathcal{O}(|\text{TestCases}|D^3)$

### Categorical Coherence and Runtime Verifi-8 cation

### Definition 8.1: Coherence Verification System

The GAIA runtime maintains categorical coherence through continuous verification of:

### 1. Simplicial Coherence:

$$\mathbf{F}_{i}^{(d)}\mathbf{F}_{j}^{(d+1)} = \mathbf{F}_{j-1}^{(d)}\mathbf{F}_{i}^{(d+1)} \quad \text{for } i < j$$

$$\mathbf{S}_{j}^{(d)}\mathbf{S}_{i}^{(d-1)} = \mathbf{S}_{i}^{(d-1)}\mathbf{S}_{j+1}^{(d)} \quad \text{for } i \leq j$$
(39)

$$\mathbf{S}_{i}^{(d)}\mathbf{S}_{i}^{(d-1)} = \mathbf{S}_{i}^{(d-1)}\mathbf{S}_{i+1}^{(d)} \quad \text{for } i \le j$$
(40)

where  $d \in \{0, 1, \dots, n_{\text{max}}\}$  denotes simplicial dimension.  $\|\mathbf{F}_i^{(d)}\mathbf{F}_j^{(d+1)} - \mathbf{F}_{j-1}^{(d)}\mathbf{F}_i^{(d+1)}\|_F < \varepsilon_{\text{simp}}$ Verified via:

### 2. Coalgebraic Homomorphism:

$$\alpha_t \circ \phi = F_{BP}(\phi) \circ \alpha_t$$

for all parameter morphisms  $\phi: \Theta_1 \to \Theta_2$  Verified via:  $\|\alpha_t(\phi(\Theta)) - \phi_1\|_{C^2(\Theta)}$  $F_{BP}(\phi)(\alpha_t(\mathbf{\Theta}))|_2 < \varepsilon_{\text{coal}}$ 

### 3. Kan Extension Universal Property:

$$\forall G, \gamma, \exists ! \tilde{\gamma} : \gamma = \tilde{\gamma} * \eta$$

Verified via existence:  $\|\gamma - \tilde{\gamma} * \eta\|_F < \varepsilon_{\text{kan}}$  and uniqueness:  $\|\tilde{\gamma}_1 - \tilde{\gamma}_2\|_F < \varepsilon_{\text{kan}}$ 

### 4. Horn Filling Coherence:

- Inner horns:  $\exists \sigma : \Delta^n \to S$  extending  $\sigma_0 : \Lambda_i^n \to S$
- Outer horns: Lifting property via commutative diagrams

Verified via:  $\|\sigma|_{\Lambda_i^n} - \sigma_0\|_F < \varepsilon_{\text{horn}}$ 

### 5. Functoriality Preservation:

$$F(\mathrm{id}_X) = \mathrm{id}_{F(X)}, \quad F(g \circ f) = F(g) \circ F(f)$$

Verified via:  $||F(id) - id||_F < \varepsilon_{\text{func}}$  and  $||F(g \circ f) - F(g) \circ F(f)||_F < \varepsilon_{\text{func}}$ 

**Notation:** d denotes simplicial dimension,  $\ell$  denotes transformer layer index, and all tolerances  $\varepsilon$  are positive constants with typical values  $\varepsilon \in [10^{-6}, 10^{-4}]$ .

### Algorithm 9 Runtime Coherence Verification - Part I

```
Input: Current runtime state S_t Output: Partial coherence report \mathcal{R}_{\text{coherence}}^{(1)}
  1: Phase 1: Simplicial Identity Verification
  2: for d = 0 to n_{\text{max}} - 1 do
           for i = 0 to d do
  3:
               \begin{array}{c} \mathbf{for} \ j = i+1 \ \mathbf{to} \ d+1 \ \mathbf{do} \\ \mathbf{E}_{i,j}^{(d)} \leftarrow \mathbf{F}_{i}^{(d)} \mathbf{F}_{j}^{(d+1)} - \mathbf{F}_{j-1}^{(d)} \mathbf{F}_{i}^{(d+1)} \end{array}
  4:
                    \epsilon_{i,j}^{(d)} \leftarrow \|\mathbf{E}_{i,j}^{(d)}\|_F
  6:
                   if \epsilon_{i,j}^{(d)} > \varepsilon_{\mathrm{simp}} then
  7:
                        Report violation: (d, i, j, \epsilon_{i,j}^{(d)})
  8:
  9:
                    end if
                end for
 10:
           end for
 11:
 12: end for
 13: Phase 2: Coalgebraic Homomorphism Verification
 14: for each parameter morphism \phi \in \Phi_{\text{test}} do
 15:
            \Theta_{\text{mapped}} \leftarrow \phi(\Theta_t)
           \alpha_{\text{direct}} \leftarrow \alpha_t(\mathbf{\Theta}_{\text{mapped}})
 16:
           \alpha_{\text{composed}} \leftarrow F_{BP}(\phi)(\alpha_t(\Theta_t))
 17:
           \epsilon_{\text{hom}} \leftarrow \|\alpha_{\text{direct}} - \alpha_{\text{composed}}\|_2
 18:
 19:
           if \epsilon_{\text{hom}} > \epsilon_{\text{coal}} then
                Report violation: (\phi, \epsilon_{\text{hom}})
20:
21:
           end if
 22: end for
 23: Phase 3: Kan Extension Universal Property Verification
24: for d = 0 to n_{\text{max}} - 1 do
25:
           for each test functor G \in \mathcal{G}_{\text{test}} do
                for each natural transformation \gamma \in \Gamma_{test} do
 26:
                    \tilde{\gamma} \leftarrow \text{ComputeMediatingMorphism}(G, \gamma, \eta_d)
27:
                    \epsilon_{\text{exist}} \leftarrow \|\gamma - \tilde{\gamma} * \eta_d\|_F
28:
                    \tilde{\gamma}_{\text{alt}} \leftarrow \text{ComputeAlternativeMediatingMorphism}(G, \gamma, \eta_d)
29:
30:
                    \epsilon_{\text{unique}} \leftarrow \|\tilde{\gamma} - \tilde{\gamma}_{\text{alt}}\|_F
                    if \epsilon_{\text{exist}} > \epsilon_{\text{kan}} \text{ OR } \epsilon_{\text{unique}} > \epsilon_{\text{kan}} \text{ then}
31:
                        Report violation: (d, G, \gamma, \epsilon_{\text{exist}}, \epsilon_{\text{unique}})
32:
                    end if
33:
                end for
34:
35:
           end for
36: end for
37: return \mathcal{R}_{\text{coherence}}^{(1)} = \{\text{violations}_{1-3}, \text{tolerances}\}
```

### Algorithm 10 Runtime Coherence Verification - Part II

Input: Current runtime state  $S_t$ , partial report  $\mathcal{R}_{coherence}^{(1)}$  Output: Complete coherence verification report  $\mathcal{R}_{coherence}$ 

```
1: Phase 4: Horn Filling Verification
 2: for each horn problem (\Lambda_i^n, \sigma_0, \mathbf{X}_{\text{ctx}}) \in \mathcal{H}_t do
          \mathbf{X}_{\mathrm{ext}} \leftarrow \mathrm{SolveHornExtension}(\Lambda_i^n, \sigma_0, \mathbf{X}_{\mathrm{ctx}})
          \sigma_{\text{ext}} \leftarrow \text{ConstructExtension}(\mathbf{X}_{\text{ext}})
 4:
 5:
          \epsilon_{\text{horn}} \leftarrow \|\sigma_{\text{ext}}\|_{\Lambda^n} - \sigma_0\|_F
          if \epsilon_{\rm horn} > \varepsilon_{\rm horn} then
 6:
              Report violation: (\Lambda_i^n, \epsilon_{horn})
  7:
          end if
 8:
 9: end for
10: Phase 5: Functoriality Verification
11: for each functor F_d \in \{F_0, F_1, \dots, F_{n_{\text{max}}}\} do
          \epsilon_{\mathrm{id}} \leftarrow \|F_d(\mathrm{id}) - \mathrm{id}\|_F
12:
          for each composable pair (f,g) \in \text{Composable}(\mathcal{C}_d) do
13:
               \epsilon_{\text{comp}} \leftarrow ||F_d(g \circ f) - F_d(g) \circ F_d(f)||_F
14:
              if \epsilon_{\rm comp} > \varepsilon_{\rm func} then
15:
                  Report violation: (F_d, f, g, \epsilon_{\text{comp}})
16:
              end if
17:
18:
          end for
19: end for
20: Merge reports: \mathcal{R}_{coherence} \leftarrow \mathcal{R}_{coherence}^{(1)} \cup \{violations_{4-5}, verification\_time\}
21: return \mathcal{R}_{coherence}
```

### 9 Conclusion

This formalization provides a mathematical foundation for GAIA transformer runtime execution, building on the categorical foundations established by Mahadevan [1] and other established categorical approaches to machine learning. The computational steps are specified with:

- Tensor-Level Implementation: Explicit dimensional analysis following Fong-Spivak's categorical backpropagation [2]
- Categorical Coherence: Verification of mathematical properties using Lawvere metric spaces [3]
- Algorithmic Specification: Procedures for categorical constructions based on Mac Lane [4]
- Complexity Analysis: Computational costs for each mathematical structure
- Runtime Verification: Checking of categorical properties during execution

The formalization demonstrates how F-coalgebras (following Rutten [10] and Jacobs [9]), Kan extensions [4], and simplicial complexes [7] can be integrated to provide categorical foundations for transformer architectures while maintaining computational efficiency.

This work extends existing categorical approaches to machine learning by applying them systematically to transformer architectures, providing a bridge between category theory and practical deep learning implementations.

# 10 Acknowledgments

We acknowledge the foundational contributions of Sridhar Mahadevan for introducing the GAIA (Generative Algebraic Intelligence Architecture) framework and its categorical foundations [1]. And we hope that our work serves as a respectful extension of his pioneering ideas.

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