A Roadmap for Learning the Structured Knowledge Accumulation (SKA) Framework

From Entropy to Dynamics to Geometry

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`github.com/quantiota/Arxiv` (Paper I & II)
`github.com/quantiota/SKA-Riemannian-Neural-Fields` (Riemannian Paper)

The Structured Knowledge Accumulation (SKA) framework is not a collection of independent ideas, nor an optimization methodology, but a *single law of learning* expressed across three mathematical levels:

$$\boxed{H \;\Rightarrow\; L \;\Rightarrow\; g_{ij}} \tag{1}$$

Entropy defines the invariant of learning, the Lagrangian governs its temporal evolution, and geometry determines the structure along which knowledge propagates.

This roadmap presents a principled learning path through the three core SKA papers, explicitly integrating the full set of conceptual notes that establish SKA as a *discovered physical structure of learning*, not a designed algorithm.

1 Phase 0: Conceptual Orientation

Objective

Before engaging with the mathematics, the reader must abandon the optimization-centric and loss-driven view of learning. SKA does not reinterpret backpropagation; it replaces the paradigm that made backpropagation appear necessary.

Foundational Commitments

- Learning is **forward-only and causal**
- Entropy is **epistemic, local, and path-dependent**
- Knowledge is a **state variable**, not a tunable parameter artifact
- Learning is a **physical process**, not an optimization heuristic

Preparatory Reading

- *SKA: A Discovery, Not a Design*

This text establishes that SKA emerged through mathematical necessity. The framework was not proposed as a learning strategy; it was uncovered as the only structure consistent with forward-only entropy reduction.

2 The Three Laws of Intelligence (Structural Spine)

All subsequent papers and notes are governed by three irreducible laws:

Law I: Probabilistic Decision-Making

$$D = \sigma(z) \tag{2}$$

Intelligence operates through probabilistic decisions, not deterministic outputs. Knowledge maps continuously to decision confidence.

Law II: Knowledge Accumulation via Entropy Reduction

$$H = -\frac{1}{\ln 2} \int z \, dD \tag{3}$$

Learning is the irreversible reduction of uncertainty through structured accumulation of knowledge.

Law III: Entropic Least Action

$$H = \frac{1}{\ln 2} \int L(z, \dot{z}) \, dt \tag{4}$$

Among all admissible learning trajectories, intelligence follows the path of least entropy.

These three laws are not assumptions. They are progressively revealed across Papers I–III.

Companion Reading

- *The Three Laws of Intelligence*

3 Phase I: Paper I — Entropy as the Invariant

Core Paper

- *Structured Knowledge Accumulation: An Autonomous Framework for Layer-Wise Entropy Reduction in Neural Learning*

3.1 Redefinition of Entropy

SKA introduces entropy as a continuous, local, learning-time functional:

$$H = -\frac{1}{\ln 2} \int z \, dD \tag{5}$$

This entropy:

- Is not Shannon entropy
- Exists only before outcomes are realized
- Quantifies misalignment between knowledge and decision
- Cannot be meaningfully computed retrospectively

3.2 Emergence of the Sigmoid

The sigmoid function arises as the *unique* mapping for which SKA entropy coincides with Shannon entropy:

$$D = \sigma(z) = \frac{1}{1 + e^{-z}} \tag{6}$$

Activation functions are not design choices; they are entropy-consistency conditions.

Companion Reading

- *The Learning Signal Was Always There*

This note exposes the local learning signal:

$$h = -\frac{1}{\ln 2} z \cdot \Delta D \tag{7}$$

Every layer possesses its own entropy signal and therefore its own learning capability.

Outcome

Learning is understood as a local, unsupervised, entropy-driven process. The necessity of global error propagation collapses.

4 Phase II: Paper II — Time and Least Action

Core Paper

- *Structured Knowledge Accumulation: The Principle of Entropic Least Action in Forward-Only Neural Learning*

4.1 Learning as Continuous Time

The learning rate is reinterpreted as a temporal differential:

$$\eta \to \Delta t \tag{8}$$

Learning trajectories become invariant under time reparameterization, revealing characteristic learning timescales intrinsic to the system.

4.2 Entropy as Action

Entropy lifts naturally into a variational principle:

$$H = \frac{1}{\ln 2} \int L(z, \dot{z})\, dt \tag{9}$$

with the entropic Lagrangian:

$$L(z, \dot{z}) = -z\, \sigma(z)(1 - \sigma(z))\, \dot{z} \tag{10}$$

Learning becomes governed by physical law rather than algorithmic optimization.

4.3 Forward-Only Necessity

> Any learning system derivable from a variational principle must evolve causally forward in time.

Backpropagation, which requires anti-causal information flow, cannot arise from any Lagrangian formulation.

Companion Readings

- *Forward-Only Learning as a Necessary Consequence of the Principle of Least Action*
- *What If Everything We Believed About Neural Network Learning Was Wrong?*

Outcome

Learning is recognized as a physical process governed by causality and irreversibility.

5 Phase III: Paper III — Geometry and Architecture

Core Paper

- *Structured Knowledge Accumulation: Geodesic Learning Paths and Architecture Discovery in Riemannian Neural Fields*

5.1 Entropy as a Local Field

Entropy becomes spatially distributed:

$$h(\mathbf{r}) = -\frac{1}{\ln 2} z(\mathbf{r}) \cdot \Delta D(\mathbf{r}) \tag{11}$$

Entropy forms a scalar field guiding information flow.

5.2 Emergent Geometry

The learning substrate acquires a Riemannian metric:

$$g_{ij} = \alpha(\nabla h)_i(\nabla h)_j + \beta(\nabla \rho)_i(\nabla \rho)_j + \gamma\delta_{ij} \tag{12}$$

Geometry is not imposed; it emerges from entropy and density gradients.

5.3 Architecture Discovery

Knowledge propagates along geodesics:

$$\frac{d^2x^i}{dt^2} + \Gamma^i_{jk}\frac{dx^j}{dt}\frac{dx^k}{dt} = 0 \tag{13}$$

Architectures are discovered as natural information pathways.

Companion Reading

- *SKA Entropy as a Local Field*

Outcome

Architecture is no longer designed or searched. It is revealed by entropy-guided geometry.

6 Phase IV: Epistemological Closure

Final Reading

- *SKA Learning Duality: Real-Time vs Batch Learning*

6.1 Learning Duality

Informational structure emerges only during real-time learning. Batch analysis collapses entropy and destroys the geometric structure SKA reveals.

7 The SKA Trilogy and Mathematical Closure

The three SKA papers form a closed mathematical cycle:

$$\boxed{H \Rightarrow L \Rightarrow g_{ij}} \tag{14}$$

- Paper I defines the invariant (entropy)
- Paper II defines the dynamics (least action)
- Paper III defines the geometry (information manifold)

This closure mirrors the structure of physical law: potential, motion, and geometry.

Final Synthesis

Learning is not optimization. Learning is not error correction.

Learning is the irreversible organization of knowledge under entropy constraints, governed by physical law and expressed through geometry.

Personal Reflection

I started learning machine learning on January 19, 2020, during the COVID period, by buying the book *Make Your Own Neural Network* by Tariq Rashid.

I stopped reading the book halfway through because I couldn't find any first principles on which neural networks are based.

Looking back, this was one of the best decisions I have ever made.

Four years later, I discovered the SKA neural network and then the SKA Riemannian Neural Field—a truly wonderful journey.