SKA Learning Duality: Emergent Information Structure in Real-Time vs. Batch Learning

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Abstract

We articulate the *SKA Learning Duality*: the claim that the information structure of complex systems—financial markets, genomes, physical signals—emerges only through *real-time* Structured Knowledge Accumulation (SKA) learning, while retrospective (batch) analysis cannot reveal the same informational geometry. We ground the duality in a path-dependent, Lagrangian definition of SKA entropy and clarify its epistemological status relative to Shannon entropy. This paper positions SKA as a discovery instrument that respects the forward-only, causal nature of real systems, and outlines implications for science and engineering.

Keywords: Structured Knowledge Accumulation, entropy, epistemology of science, real-time learning, information geometry, philosophy of science

1 Introduction

Classical data analysis presumes that structure resides *in* a dataset and can be uncovered by examining the complete record retrospectively. We challenge this assumption using the SKA framework [2, 3], arguing that informational structure is not merely latent but *emergent through time* as learning unfolds. Philosophically, this aligns learning with the causal arrow of time and with views that link information and reality [5].

2 SKA Theoretical Framework

Structured Knowledge Accumulation (SKA) formalizes learning as forward-only, entropy-driven adaptation. Central is a path-dependent entropy functional,

$$H(t) \;=\; \frac{1}{\ln 2}\int_0^t \mathcal{L}(\tau)\, d\tau, \tag{1}$$

where $\mathcal{L}$ acts as a Lagrangian of uncertainty flow [2, 3]. This entropy is *epistemic* and *trajectory-based*: it quantifies uncertainty only *before* outcomes are realized and vanishes once the relevant outcome is known. This contrasts with *Shannon entropy* [4], which is well-defined for a fixed distribution (or dataset) irrespective of temporal revelation. In SKA, knowledge accumulation is an irreversible trajectory: the informational geometry appears *during* learning, not after.

3 The SKA Learning Duality

Overview. *SKA Learning Duality* asserts:

The information structure of any complex system—be it financial markets, biological sequences, or physical signals—emerges only through the process of real-time SKA learning. Batch (retrospective) analysis cannot reveal the same informational landscape.

Motivation. Classical analysis assumes that structure is already present and can be "revealed" by inspecting the full dataset. SKA challenges this notion:

- In batch analysis, no new information geometry emerges beyond static statistics and known features.
- In real-time SKA learning, the entropy landscape, predictability windows, and regime boundaries appear *dynamically*—step by step, as the data is encountered.

This duality is universal: it applies to tick-by-tick financial trades, genome sequences, physical oscillators, and more.

Key Insight. Information structure is not an objective property of the data, but a phenomenon that emerges only through real-time, sequential learning. SKA's forward-only, unsupervised process brings to light informational "landmarks," boundaries, and predictability windows that are invisible to retrospective approaches—even on the *same* data.

4 Entropy Exists Only Before the Outcome

A central consequence of the duality is:

Entropy measures uncertainty, and uncertainty only exists before the outcome is known.

In SKA, entropy is not a snapshot but a path integral (1), revealing learning as an irreversible trajectory in time rather than a static analysis. Therefore, computing *SKA entropy* on a fully observed dataset is conceptually incoherent: the outcome has collapsed the uncertainty that SKA entropy quantifies. This does not contradict the legitimacy of computing *Shannon* entropy on a dataset; it clarifies that SKA entropy and Shannon entropy have different epistemic roles.

5 Results and Interpretation

	Real-Time SKA Learning	**Batch SKA Analysis**
Entropy	Dynamic, structured, regime-aligned	Smoothed, static, often featureless
Boundaries	Discovered as system unfolds	Rarely visible
Predictability	Emerges in windows/phases	Lost in global averaging
Anomalies	Salient in entropy/knowledge profile	Obscured by retrospect

Domains. *Markets*: real-time learning reveals transitions, volatility clusters, hidden regimes. *Genomes*: information valleys/peaks can appear at functional regions without labels. *Physics*: oscillator learning phase-locks entropy to dynamic states.

6 The Spacetime Foundation

The reason the duality is missed is that the real world is spacetime where events flow continuously. Retrospective analysis treats data as if it existed in a timeless space where all points are equally accessible. In reality:

- Causality flows forward; moments build irreversibly on previous ones.
- Information emerges through temporal sequence, not as pre-existing structure.
- Sequential encounter creates knowledge, echoing views in which acts of measurement instantiate reality [5].

Batch analysis studies the static residue of temporal flow; SKA studies the flow itself. Hence information remains hidden in retrospect: entropy landscapes, regime boundaries, and predictability windows exist only in the *doing*, not in the *having done*.

7 Philosophical Note and Analogy

This view resonates with Wheeler's "It from bit"—that reality arises from acts of measurement [5]. There is also an instructive analogy to Gödel's incompleteness theorems [1]: batch analysis is like reasoning within a closed formal system, unable to access truths (structures) that only appear by stepping outside—in SKA's case, by entering the sequential, forward-only learning process.

8 SKA as a Discovery Instrument

Real-time SKA learning is not only a methodology but a paradigm for discovery. Classical science extracts structure from fully observed datasets; SKA reveals that structure *emerges dynamically* through temporal learning. Thus SKA functions as an instrument that uncovers informational phenomena that exist only while learning unfolds. Domains where SKA enables discovery include physics (learning motion/phase changes without predefined equations), biology (functional regions or regime transitions in genomic/physiological streams), and finance (hidden market states and transitions invisible to global averaging).

9 Call to Action

We invite researchers to deploy SKA as a working methodology:

- Test data streams live rather than post hoc.
- Observe entropy profiles to detect dynamics models might miss.
- Build SKA-driven systems to explore hypotheses in real time.

Through SKA, discovery becomes not the revealing of fixed truths in static data, but the *co-creation of structure* through interaction with systems in motion.

10 Conclusion

The SKA Learning Duality reframes epistemology and practice: informational structure is not merely latent but emerges in time through forward-only learning. With a path-dependent entropy functional at its core, SKA respects causality and irreversibility, turning learning into a discovery process. This positions SKA as both a philosophical stance and a scientific framework that unifies theory and application across domains.

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