

Learning Like Nature

Notes Toward a Physics of Learning

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*What do a river, a neural network, and a living cell have in common?
They all learn by exporting disorder.*

Preamble

All my research has revolved around a single question: how to build the most faithful digital twin possible?

I explored many paths. Apache Spark for processing massive geospatial datasets [1]. Large language models for their ability to compress and reconstruct the world. Blockchain for traceability and audit. Each approach solved part of the puzzle. But after years of work, I found myself facing what felt like an impasse: the more sophisticated the tools became, the more energy they consumed; the more accurate the models, the faster they drifted from reality.

Then I started paying attention to different systems. A human brain consumes 20 watts – less than a light bulb – for capabilities no data center can match. A river finds its way to the sea without GPS. A cell maintains its organization without storing anything. These systems know something we have not yet learned to formalize.

These observations made me rethink the problem entirely. Not “how to store more” but “how to stay synchronized with less.”

This document is not a finished theory. It is a direction of inquiry – an invitation to rethink AI as a science of continuous observation and learning, much like Darwin who, by patiently observing the world, wove connections to understand the environment in which he lived.

First Observation: Two Ways of Learning

There are, broadly speaking, two ways to build a system that learns.

The first consists of collecting large amounts of data, storing it, then optimizing an objective function over this frozen set. This is the dominant paradigm in artificial intelligence. It works remarkably well. It also has interesting characteristics: energy cost grows with desired precision, the model gradually diverges from the reality it represents, and auditing becomes difficult beyond a certain scale.

The second is the one nature has employed for a few billion years. A river does not store data about the terrain – it *becomes* the most efficient path to the sea. Its bed is crystallized knowledge. A cell does not memorize its environment – it stays synchronized with it by continuously exporting disorder.

The difference is not one of degree but of kind.

The Framework: Bayesian Dissipative Structures

Prigogine showed in 1977 that certain structures maintain their order not *despite* the energy flux passing through them, but *because of* it [3]. He called them dissipative structures.

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graph LR
    A["Incoming flux  
(water, light,  
data...)"] --> B["Structure  
[Crystallized]  
knowledge"]
    B --> C["Exported entropy  
(heat, waste,  
disorder)"]

```

I propose to formalize these systems as Bayesian agents: they maintain beliefs (probability distributions) that naturally degrade over time, and they use incoming flux to restore their precision [4].

I call this framework **BEDS** – Bayesian Emergent Dissipative Structures [2].

A Simple Result

Within this framework, one can derive a relationship between energy expenditure and maintained precision.

To maintain precision τ against dissipation γ requires minimum power:

$$P \geq \frac{\gamma k_B T}{2}$$

In other words: maintaining information against thermal noise costs energy. This is not surprising – it follows from Landauer’s principle [5]. What may be less obvious is that the relationship is *continuous*: more precision = more power, with no discontinuity.

Practical corollary: halving uncertainty requires quadrupling power.

An Interesting Recursion

When one level crystallizes sufficiently stable knowledge, that structure becomes the *prior* for the next level:

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Level 0:  Flux → [Structure0] → Entropy
           ↓ (becomes prior)
Level 1:      Flux → [Structure1] → Entropy
           ↓ (becomes prior)
Level 2:      Flux → [Structure2] → ...

```

This may be how levels of organization emerge: atoms, molecules, cells, organisms, societies. Each level inherits the regularities crystallized by the level below and no longer needs to relearn them.

Three Problem Classes

The formalism suggests a taxonomy:

Class	Definition	Example
BEDS-attainable	A finite flux suffices to reach target precision	Calibrating an instrument
BEDS-maintainable	A continuous flux maintains precision indefinitely	Homeostasis, thermostat
BEDS-crystallizable	The structure becomes self-sustaining	Formation of a concept, a crystal

These classes appear orthogonal to classical complexity classes. An NP-complete problem can be BEDS-maintainable. A polynomial problem can be BEDS-unattainable if the flux is insufficient.

There is probably something interesting to explore here, in the direction of energy landscapes and phase transitions [6].

What This Suggests

If this framework captures something real, a few directions open up:

For artificial systems – One could design architectures that *drift with* reality rather than diverge from it. Systems where precision adjusts to available flux. Where forgetting is a feature.

For understanding life – The brain may not be a computer that stores, but a flame that sustains itself [7]. Thought as thermodynamic process rather than symbol manipulation.

For mathematics – There may be a link between the limits of continuous inference (thermodynamics) and the limits of formal systems [8]. Both involve a form of incompleteness tied to self-reference. This is speculative, but intriguing.

By Way of Conclusion

Nature has been learning for a long time. It does so with an elegance and economy we are only beginning to understand.

This document does not claim to have found *the* answer. It proposes a direction of inquiry: treating learning as a physical phenomenon, with its laws, its constraints, its possibilities.

The next twenty years of research could explore this territory. Or not. Time will tell whether this path leads somewhere interesting.

References

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