The Reciprocal Adaptive Universe: Linear vs. Recursive Adaptation in Physical, Biological, and Cybernetic Systems

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1 Introduction

This paper develops a purely structural, substrate-agnostic framework for distinguishing different modes of adaptation. The term "reciprocal universe" is used in this precise sense, without metaphysical implication.

Classical physics traditionally treats the environment as a passive backdrop against which agents act. In this view, perturbations propagate through the world in a manner that is local, predictable, and devoid of historical depth. Yet when we examine adaptation across multiple domains — optical propagation, mechanical relaxation, immune dynamics, neural computation, learning agents, distributed cyber-defense - a different picture emerges.

The environment does not merely react. It reorganizes itself in a way that alters its own future responses. Patterns of adaptation are not isolated events but components of a continuous negotiation between agent and world.

This leads to an essential question: *Can the universe be understood as a reciprocal adaptive partner rather than an inert medium of reactions?*

We argue that this is indeed the case - but only when the system operates in a specific mode of adaptation: the recursive mode characteristic of living and living-like systems.

2 Two Types of Adaptation

2.1 Linear adaptation: the non-living, non-volitional regime

In optical media, fluids, mechanical bodies, thermodynamic systems, and most artificial constructs devoid of memory, perturbations generate changes that are immediate yet closed. An external action - digging a hole in the ground, pressing on the surface of a liquid, injecting a photon beam into a medium - alters the state of the environment, but does not alter the principles by which that environment will respond next time.

Many such systems can exhibit rich dynamics, but their adaptation remains *linear* in the structural sense: the update rule is fixed, and only a small set of parameters is tuned within a static representational frame. There is no endogenous evolution of the operator class itself.

Formally, such systems follow

$$E_{t+1} = F(E_t, A_t),$$

where the operator F is fixed, history-independent, and insensitive to gradients accumulated over previous interactions.

This type of adaptation does not produce inheritance, does not accumulate structure, and does not construct new internal models. It is, fundamentally, adaptation without evolution of rules.

Many engineered controllers - such as PID tuning, gain scheduling, or simple reinforcement schemes - adjust parameters within a fixed update rule. In the terminology used here, they are *parametric* rather than *structural*: the mapping F itself does not become an evolving object of dynamics. Real-world systems may occupy intermediate regimes — for example, meta-learning architectures or evolutionary algorithms. What matters for the present framework is whether the system modifies only parameters within a fixed operator class (parametric adaptation) or whether the operator class itself evolves (structural adaptation). In practice, systems form a continuum. The distinction introduced here is an idealized limit that clarifies the structural transition from parametric to operator-level adaptation.

2.2 Recursive adaptation: the living, cognitive, self-modifying regime

By contrast, nervous systems, immune systems, learning agents, evolutionary processes, and adaptive cybernetic networks exhibit a different adaptive logic. Here, a perturbation not only changes the current state of the system but modifies its internal update operator - the rules governing how it will respond in the future.

This behaviour can be written as

$$E_{t+1} = F_t(E_t, A_t), \qquad F_{t+1} = G(F_t, \Delta S_t).$$

Recursive adaptation, in the sense used here, requires that the adaptation operator F_t itself becomes an evolving object of dynamics, rather than a fixed rule that merely updates a small set of gains.

The system now possesses memory, historical depth, and the capacity to rewrite its own laws of change. Each adaptive cycle alters the next one, producing a form of recursive self-differentiation. Philosophical terms such as *autopoiesis*, *sense-making*, and *worlding* describe precisely this phenomenon. It is the beginning of meaning, volition, and identity. Meta-RL changes parameters within a fixed operator class. Recursive adaptation changes the operator class itself. Example: - Meta-RL: learns new weights for a neural network (architecture fixed) - Recursive (structural): evolves new architectural principles (e.g., adds new loops, changes connectivity rules). The distinction is between parametric optimization within a fixed representational frame and structural reorganization of the frame itself.

3 Adaptation as Dialogue: The Universe as Partner

When we shift perspective from an external observer to an embedded participant, the interaction between agent and environment becomes a two-way flow of information. The agent imposes a perturbation; the world reorganizes in response. That reorganization changes not only the external conditions but the agent's internal state, which becomes updated, biased, or reconfigured by the world's reply.

This reciprocal exchange forms a dialogue: the agent acts upon the world, the world adapts, and the resulting world-state shapes the next action of the agent. Seen from within, the universe becomes not a static stage but a conversational partner. This terminology is structural, not metaphysical: 'partner' refers to reciprocal updates of transition operators, not to intentionality.

4 Why Recursive (Living-like) Systems Create a New Loop

Non-living linear media can exhibit rich dynamics, and engineered systems can even implement self-modifying scripts. However, unless such changes are sustained, self-maintaining, and integrated into the system's ongoing adaptation, they do not meet the structural criterion of being "living-like" in the sense used here.

Living systems behave otherwise. Each perturbation alters internal coefficients, reshapes implicit models of the environment, changes behavioural strategies, and redirects the system's trajectory in state space. It is this capacity to continually rewrite the map of possible futures that distinguishes recursive from linear adaptation.

Thus emerges a structural criterion of life:

A A system counts as structurally living, in the sense used here, if and only if its adaptive responses endogenously and sustainably modify the rules of its own future adaptation while preserving global coherence.. Systems whose rule-updates are supplied entirely by an external operator (e.g., a human engineer) do not satisfy this condition, even if they display self-modifying behaviour. Recursive adaptation, as defined here, requires a closed self-maintaining loop: the mechanisms that rewrite F must themselves be maintained or regenerated by the system. Systems whose self-modification depends on external orchestration (software updates, human engineers, supervisory scripts) do not satisfy this criterion.

5 Connection to UTAM, ΔE, and UAPS

The adaptive cycle described by the structural hypothesis of adaptive dissipation can be decomposed into three complementary components: the volitional operator that selects admissible directions, the dynamical engine that performs adaptive restructuring and the environment that provides geometric constraints. Together they form the UTAM-ΔE-E_t triad.

5.1 UTAM: operator of trajectory selection

UTAM defines constraints on admissible trajectories as an expression of volition-like selection, rather than as a purely mechanical outcome. It specifies which futures are even considered before any physical dynamics (such as ΔE) unfold.

In this sense, UTAM shapes the geometric constraints within which adaptation takes place: it determines how sharply the system may redirect its own evolution and which classes of trajectories remain permissible under its internal intention structure.

Formally, UTAM enters the dissipation operator through the impulse term

$$W_t = W_{\mathrm{UTAM}}(S_t, E_t),$$

providing directional bias and intentional constraints that precede ΔE.

UTAM is not a metaphysical notion but an abstract operator of trajectory selection. It can be instantiated physically (as evolutionary constraints or invariants), computationally (as priors over trajectory space), or cognitively (as volition-like choices). The framework does not assume mental states. UTAM denotes a structural constraint on admissible futures.

5.2 ΔE: the engine of adaptive dissipation

Where UTAM selects direction, ΔE performs the actual adaptive work. It absorbs external impulses, suppresses destructive gradients, reorganizes internal parameters, and drives the system toward a new attractor.

In variational form, ΔE minimizes an action functional

$$\mathcal{S} = \sum_t L_{\mathrm{eff}}(t),$$

where the effective Lagrangian $L_{\mathrm{eff}}(t)$ incorporates drift, jerk, noise, friction, and environmental risk. The universal dissipation law is introduced here as a structural hypothesis, not as an empirical physical law. It generalizes classical variational principles to systems in which the update operator F itself evolves. This makes E the physical engine of restructuring: the component of the system that executes the

$$\text{Impulse} \to \text{Impact} \to \text{Dissipation} \to \text{Adaptation} \to \text{Equilibrium}$$

sequence in concrete dynamical terms.

Thus UTAM constrains *what* trajectories are meaningful, while ΔE determines *how* the system actually moves and adapts within those constraints.

5.3 UAPS: the unified adaptive physics stack

The Unified Adaptive Physics Stack (UAPS) can be seen as the joint phase-space in which intentional constraints (UTAM), dissipative adaptation (ΔE), and environmental geometry (E_t) co-define actual trajectories. This is the level at which "physics" and "will-like" structure intersect:

$$UTAM(W) \;\longrightarrow\; \Delta E(\text{ADR}) \;\longrightarrow\; E_t.$$

UTAM prescribes admissible directions, ΔE implements adaptive dynamics under shocks, and the environment E_t evaluates and reshapes the cost and curvature of future transitions. Their interaction forms a closed recursive loop - the minimal architecture of structurally living, self-modifying, and cognitively meaningful systems. In practical terms, UAPS predicts that altering UTAM (trajectory constraints) while holding E fixed will change the attractor landscape of the system. Likewise, modifying E with fixed UTAM yields distinct adaptive regimes. Such predictions can be tested in simulated agents, neural models, and cyber-physical systems

6 Structural Criteria for a Recursive (Living) System

A recursive system, in the structural sense used here, must satisfy three principles.

Self-modification. The update rule changes as a function of historical gradients:

$$F_{t+1} \neq F_t.$$

Progressive integration. The internal model, or its informational capacity, must grow or reorganize rather than collapse:

$$\dim(F_{t+1}) \geq \dim(F_t).$$

Here dim(Ft) may refer to parameter count, representational capacity, architectural or organizational depth, or other functional degrees of freedom. The essential requirement is that the system's capacity for modelling and reorganizing its environment does not collapse into a strictly lower-complexity rule, except under failure.

Preservation of coherence. Self-modification must occur within curvature bounds

$$\|F_{t+1} - F_t\| \leq \kappa,$$

for some appropriate norm $\|\cdot\|$ on the space of operators, ensuring the system remains stable rather than entering chaos or rigid stasis. The curvature bound κ enforces a regime in which self-modification is neither explosive (chaotic meltdown) nor frozen; it constrains the evolution of F_t to a controlled "geodesic" in the space of rules.

These three constraints define the minimal mathematical signature of living behaviour in the present framework.

7 Curvature of Self-Modification: the UTAM - ΔE Bridge

UTAM defines the allowable intentional curvature - the limit on how sharply the system may reshape its own future. ΔE ensures that internal restructuring proceeds smoothly within that curvature, minimizing action and preserving coherence. UAPS describes universes in which such curvature-bounded self-change produces long-term stability.

This transforms the UTAM - ΔE - UAPS triad from a conceptual picture into a proposed law governing the tempo of self-modification in adaptive systems.

8 Relation to Modern Neuroscience

The brain provides a biological instantiation of this architecture. Predictive-processing frameworks describe cognition as continual minimization of prediction error, dynamic adjustment of generative models, evolving precision weights, and synaptic plasticity that rewrites inference rules.

All these processes correspond directly to the mathematical form

$$F_{t+1} = G(F_t, \Delta S_t),$$

where ΔS_t encodes neural drift, error, surprise, and learning gradients.

Most existing predictive-processing models realize only a subset of the recursive formalism — typically parameter updates rather than structural updates. The full recursive regime may appear during development, deep learning, recovery from injury, or acquisition of new high-level skills.

In predictive-processing terms, F_t corresponds to the agent's generative model and its precision structure; ΔS_t aggregates prediction errors and precision updates across levels; and G encodes plasticity and structural learning rules that reshape future inference. In this sense, the recursive pair

$$E_{t+1} = F_t(E_t, A_t), \qquad F_{t+1} = G(F_t, \Delta S_t)$$

is a compact structural form of how predictive-processing architectures continuously rewrite the very rules by which they adapt.

Thus the brain is not an analogy, but a concrete example of a *recursive adaptive universe.*

9 Conclusion: The Universe as a Reciprocal Adaptive Organism

We are accustomed to viewing the world as passive. But once we adopt the internal perspective of an embedded agent, the world reveals itself as a dynamic participant in a mutual process of adaptation.

The agent acts, the world responds, the rules of change rewrite themselves, and the cycle begins anew. Identity, meaning, volition, and coherence all emerge from this recursive loop.

The boundary between the living and the non-living is not biological but structural. Linear systems respond and stop; recursive systems respond and evolve. At this boundary, the universe ceases to be a mere object and becomes a partner that carries our influences forward, reshaping the conditions of our future in return. This is a structural hypothesis, not a completed physical theory. It does not replace biological definitions of life but proposes a common dynamical signature for systems that behave as living, cognitive, or universe-like agents. This is the physics of reciprocal adaptation – a *possible* candidate **framework** for a unified theory of life, cognition, and dynamic universes.

9.1 Appendix A — Heuristic Physical Analogy: Local Vorticity as a Structured Response

In many fluid and gaseous media, a small perturbation — such as moving a hand through water or injecting a brief pressure impulse — does not produce purely translational motion. Instead, the immediate reaction often includes the generation of local shear and vorticity. This follows directly from the structure of the Navier – Stokes equations: gradients in velocity tend to produce rotational components, which then reorganize the surrounding flow field.

This phenomenon is **not** an instance of recursive adaptation in the strict sense used in the main text, since the governing operator F remains fixed. However, it provides a useful heuristic illustration: even classical physical media exhibit **structurally rich, geometry-changing responses** that precede any stable macroscopic motion.

Thus, while not an example of an evolving update operator F_t, hydrodynamic vorticity shows how an environment may reorganize internal structure in response to an impulse — foreshadowing the deeper patterns of adaptive restructuring discussed in this work.

This work forms part of a broader research program developed within Petronus Research, aimed at establishing a unified structural framework for adaptive, self-modifying, and coherence-preserving systems.

Appendix B: Minimal Toy Demonstrator for UAPS

To make the UTAM–ΔE–E_t triad operationally concrete, we outline a minimal toy simulation. This model is not intended to be realistic, but serves to illustrate how the three components can be separated and manipulated independently.

B.1 Setup

Consider a one-dimensional adaptive agent interacting with a stochastic environment. Let x_t be the incoming signal, y_t the agent's internal state, and $\mu_t \in (0, 1]$ an adaptive coefficient. The explicit functional form of f is unnecessary for the demonstration. Any monotonic mapping from uncertainty measures to adaptation rate is sufficient.

The ΔE update rule is

$$y_{t+1} = (1 - \mu_t)\, y_t + \mu_t\, x_t,$$

where gradient diagnostics are defined as

$$\text{drift}_t = y_t - y_{t-1}, \qquad \text{jerk}_t = (y_t - y_{t-1}) - (y_{t-1} - y_{t-2}).$$

The adaptive coefficient evolves according to

$$\mu_{t+1} = f(\text{variance}_t, \text{jerk}_t, E_t),$$

where variance$_t$ is computed over a sliding window of recent observations (either the external signal x_t, the internal response y_t or any suitable composite). The function f increases μ_t under high local variance or jerk — accelerating adaptation — and decreases it under stable, low -uncertainty conditions.

B.2 Behaviour of the toy system

Environmental turbulence injects fluctuations into x_t, producing sharp changes in drift and jerk. This raises the agent's estimated local variance and therefore increases μ_t, making y_t track x_t more aggressively. In calm conditions, both variance and jerk shrink, reducing μ_t and yielding slower, more inertial adaptation.

Thus ΔE executes the sequence

$$\text{Impulse} \rightarrow \text{Impact} \rightarrow \text{Dissipation} \rightarrow \text{Adaptation} \rightarrow \text{Equilibrium},$$

in concrete dynamical terms.

B.3 Role of UTAM

UTAM constrains the set of admissible trajectories by imposing a risk-bounded impulse term $W_{\text{UTAM}}(S_t, E_t)$. For example, UTAM can prohibit trajectories whose cumulative action exceeds a risk threshold. Varying UTAM (tightening or relaxing admissibility) produces distinct attractors even when ΔE and the environment are held fixed.

B.4 Role of the environment E_t

The environment modulates the curvature of the adaptive landscape. High turbulence increases jerk and variance, raising μ_t and producing fast, reactive adaptation. Calm conditions reduce gradients, lowering μ_t and yielding slow, inertial behaviour.

Changing E_t therefore reshapes the geometry in which ΔE operates, even when UTAM is fixed.

B.5 Emergent UAPS behaviour

The toy model illustrates the core principle of UAPS: UTAM selects admissible directions, ΔE performs adaptive restructuring, E_t shapes the geometric curvature of transitions.

Changing only UTAM (risk-tight, risk-relaxed, or directionally biased) produces qualitatively different attractors, while ΔE and E_t remain unchanged. This demonstrates how trajectory selection, adaptive dissipation, and environmental geometry jointly determine the system's evolution.

B.6 Purpose of this demonstrator

Its only purpose is to make explicit how UTAM, ΔE, and E_t can be separated and independently manipulated in a controlled setting.