The DPA Framework: A Structural Diagnostic for Resonant Propensity in Complex Systems

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Abstract

Across multiple complex systems, a recognizable pattern recurs: coherent, self-sustaining dynamics that persist within bounds, degrade predictably under stress, and resist simple cross-domain description. Despite this recurrence, no minimal structural language exists for diagnosing when such behavior is possible.

Such patterns can arise when three structural conditions are satisfied: dimensional freedom (D), proportional distribution (P), and alignment (A). Together these constitute a diagnostic for Resonant Propensity (R) – the conditional tendency for a system to develop and sustain bounded, self-reinforcing dynamics through internal feedback, not inherent to any architecture but emergent only when conditions are jointly satisfied.

The structural relationship $\mathbf{R} \propto \mathbf{D} \times \mathbf{P} \times \mathbf{A}$ indicates that resonant propensity depends on the simultaneous presence of D,P, and A, and collapses when any enabling condition fails.

The framework stratifies dynamical regimes from rigid order through chaotic instability to resonant propensity, and suggests structural analogues for the recurring failure modes observed across domains, including vanishing gradients in neural networks, trophic cascades in ecology, misaligned incentives in organizations, decoherence in quantum systems, and phase mismatch in physics.

DPA does not compete with domain-specific models, nor does it define resonance itself. Instead, it identifies the structural conditions enabling a system to enter and sustain resonant regimes, and provides a framework to diagnose systemic instability and the specific threshold for collapse.

Keywords: resonance, resonant propensity, complex systems, dimensional freedom, proportional distribution, feedback alignment, structural conditions, multiplicative dynamics, self-correction, dynamical systems, neural networks, cross-domain framework

1 Introduction

Resonant propensity — a conditional tendency for a system to sustain bounded, self-reinforcing dynamics through internal feedback — appears in a wide range of complex systems, from physical and biological to computational, organizational, economic, and quantum settings. Despite this recurrence, there is no simple, domain-independent diagnostic for when a system can exhibit such tendencies, nor a common structural language that spans these fields.

This paper proposes three structural conditions for resonant propensity: dimensional freedom (D), proportional distribution (P), and alignment (A). These conditions are formalized in a multiplicative relationship $R \propto D \times P \times A$ and are argued to stratify dynamical regimes from static order through chaotic complexity to resonant propensity, connecting classical work on deterministic chaos and synchronization [1, 2] with contemporary models in machine learning and ecology [3, 4].

The aim is not to replace domain-specific models, but to offer a unifying structural diagnostic that highlights shared failure modes and stability conditions across otherwise disparate systems.

2 Core Definitions

D (Dimensional Freedom) Sufficient dimensional accessibility: a continuous state space bounded by functional poles and constituted by the accessible range of intermediate states, enabling expressive variation without compression into rigid binaries.

P (Proportional Distribution) Proportionate distribution of energy, influence, or information among interacting components, shaped by variance limits that prevent overload or underutilization while matching the system's actual conditions.

A (Alignment) Constructive coupling among interacting elements: the degree to which phase/timing, directional, or incentive coherence are aligned and mutually reinforcing across the range of interacting agents, evaluated relative to preserving D and P.

R (Resonant Propensity) Conditional tendency for a system to sustain bounded, self-reinforcing dynamics through internal feedback. This propensity is not inherent to any architecture but can emerge when three structural conditions—dimensional freedom (D), proportional distribution (P), and alignment (A)—are simultaneously satisfied. The DPA formulation provides a structural diagnostic for whether these conditions are present, enabling domain-specific stability to become active (e.g., physical resonance, homeostasis, institutional coherence) and allowing the system to enter regimes of coherent amplification (with restorative forces, not mere self-reinforcing growth). The multiplicative relationship $R \propto D \times P \times A$ encodes the fragility of this propensity: degradation in any one factor reduces the likelihood that such regimes can emerge or persist. Thus, the framework predicts not the presence of resonance itself, but the structural readiness of a system to sustain it—and its collapse when any enabling condition fails.

3 Operationalization

To reduce the risk of post-hoc relabeling, treat D, P, and A as pre-scored indicators on a 0–1 scale, using a simple rubric that can be applied independently of any assessment of Resonant Propensity R. These indicators are intended as coarse structural diagnostics rather than precise measurements; their purpose is to capture whether each enabling condition is plausibly present within the system and time window under consideration.

3.1 D (Dimensional Freedom)

D estimates how many practically accessible states or strategies the system has, relative to its constraints, in a given regime.

- 0: System is effectively locked into one or two rigid states (e.g., binary control modes, near-frozen policy, monoculture).
- 0.5: Several distinct states exist, but transitions may be rare, costly, or tightly gated.
- 1: Rich, graded spectrum of states regularly occupied; explores many intermediate configurations.

Here "continuous" is interpreted in a loose, pragmatic sense: a high-D system need not have mathematically continuous state variables, only a non-trivial ladder of accessible intermediate states in its effective state space (e.g., a high-resolution finite state controller can count as high D if it makes use of that resolution in practice).[1]

3.2 P (Proportional Distribution)

P captures how proportionately energy, resources, and/or influence are distributed relative to component capacity and functional demand.

- 0: Extreme, persistent mismatch (e.g., a small subset of components is chronically overloaded while others are starved or idle).
- 0.5: Noticeable skew; some components are regularly under- or over-utilized, but the system remains functional.
- 1: No component is persistently overloaded or underused; allocation roughly tracks capacity and demand over the timescale of interest.

In practice, P can be approximated by simple inequality or mismatch measures (e.g., Gini-like indices for resource allocation [6], or comparison of observed loads to nominal capacities) rather than any single canonical metric.

3.3 A (Alignment)

A is a composite indicator capturing three forms of coherence:

1. Phase/timing coherence: Do key processes operate on compatible timescales and phases?
2. Directional coherence: Are actions and feedbacks broadly pushing in compatible directions in the system's state space?
3. Incentive coherence: Do local payoffs reinforce, rather than undermine, the emergent pattern?

Each facet can be scored on 0–1:

- 0: Strong, persistent conflict (e.g., chronically out-of-phase processes, systematically opposed incentives).
- 0.5: Mixed; some subsystems are aligned, others are not.
- 1: Predominantly mutually reinforcing across the relevant scales.

Define A as either the average or, in stricter applications, the minimum of these three facet scores, acknowledging that "alignment" is a structured bundle rather than a primitive scalar. The distinction between time and phase alignment in signal and systems engineering provides a concrete analogue for the first facet.

[1] State-space formulations in control and dynamical systems offer a natural formal backdrop for this notion of accessible dimensionality; see, for example, standard treatments of state-space representation in linear multivariable control.

4 Cross-Domain Application

Table 1: DPA conditions across domains (principle: expand beyond binaries, proportional energy, relational alignment).

Domain	Low Propensity	Transitional	High Propensity	Principle Fit
Neural Nets	Binary nets	Deep net	Transformer	Rich embeddings (D), balanced activations (P), gradient alignment (A)
Organizations	Siloed corp	Post-merger	Flywheel	Multi-strategy (D), equitable roles (P), mission coherence (A)
Ecology	Monocrop	Overfished	Coral reef	Trophic diversity (D), predation balance (P), co-evolution (A)
Physics	Mistuned osc.	Chaotic flow	Phase-locked	Continuous tuning (D), energy balance (P), phase sync (A)
Orbits	Crash orbit	Perturbed	Stable orbits	Elliptical paths (D), gravity proportion (P), vector alignment (A)
Economics	Zombie firms	Bubble	Bull market	Strategy spectrum (D), capital allocation (P), confidence (A)
Quantum	Decohered	GHZ state	BEC	Superposition (D), equal occupation (P), coherence (A)
Flocking	Foraging	—	Bait ball	Maneuvers (D), density balance (P), evasion sync (A)

5 Discussion

Complex systems can achieve resonant propensity when they expand beyond binary framing, distribute energy/influence proportionally among components, and maintain relational alignment among agents.

The multiplicative form $R \propto D \times P \times A$, used here as a first-order encoding, captures two intuitions: (i) each factor is individually necessary in the sense that if any one is at zero, R collapses, and (ii) R degrades continuously as any factor is weakened, without allowing unrealistically strong compensation by the others. This does not preclude alternative forms—such as $R \approx \min(D, P, A)$, explicit thresholds, or partially compensatory mixtures—which may better capture specific domains; distinguishing among these empirically is an open question.

For all three quantities, the emphasis is on pre-committing to a rubric and applying it to a system and time window *without* referencing its observed resonant propensity R. The framework is thus falsifiable in the following sense: if systems can be identified or engineered that, by the rubric above, (a) score high on D, P, and A but fail to exhibit resonant propensity, or (b) score low on one or more of D, P, and A yet clearly exhibit propensity, then the present formulation is either too coarse or wrongly targeted and would require revision or restriction of scope.

The DPA framework shares conceptual ground with Haken's synergetics [5], which similarly identifies structural conditions underlying self-organization. Whereas synergetics focuses on the emergence of ordered patterns through dynamical instabilities and order-parameter formation, DPA focuses on the structural readiness of systems to sustain coherent dynamical regimes - a diagnostic orientation rather than a generative one.

Future work could apply the DPA rubric quantitatively to time-series data from specific systems, e.g., activation histograms from neural nets, Gini coefficients from economic datasets.

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