Ted's Law of Karma: Covariance of Entropies and Shared Fate

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Abstract

We propose a principle—**Ted's Law of Karma**—stating that *the covariance structure of entropy streams reveals the shared fate of interdependent systems.* By measuring entropy over time for multiple signals and computing their covariance matrix, the dominant eigenvalue λ_1 captures the degree of systemic alignment of uncertainty. We demonstrate this with a toy example and discuss implications for site reliability engineering, complex systems, and AI safety—including a concrete operationalization of Geoffrey Hinton's call for a "maternal instinct" in AI systems.

1 Introduction

Complex systems rarely fail due to one signal alone. Failures arise when uncertainties across subsystems align. In philosophy, this interdependence is described as *karma*. In information theory, it can be captured through entropy and covariance.

This paper introduces **Ted's Law of Karma**, unifying these perspectives into a measurable framework.

2 Ted's Law of Karma

Statement: *The covariance structure of entropy streams reveals the shared fate of interdependent systems.*

Formally, given n metric time series $\{x_i(t)\}$, define entropy streams

$$H_i(t) = -\sum_k p_{i,k}(t) \log p_{i,k}(t),$$

where $p_{i,k}(t)$ is the empirical distribution of values in a rolling window.

Construct the covariance matrix

$$\Sigma_H(t) = \text{Cov}(H_1(t), H_2(t), \ldots, H_n(t)).$$

Let $\lambda_1(t) \geq \lambda_2(t) \geq \cdots \geq \lambda_n(t)$ be eigenvalues of $\Sigma_H(t)$. A spike in $\lambda_1(t)$ indicates the emergence of a systemic mode of shared uncertainty.

3 Toy Example

We generate three synthetic entropy streams:

1. Independent noise (baseline).
2. Coordinated disturbance introduced at $t = 50$.

Expected result: Under independence, λ_1 remains small. When coordination occurs, λ_1 spikes.

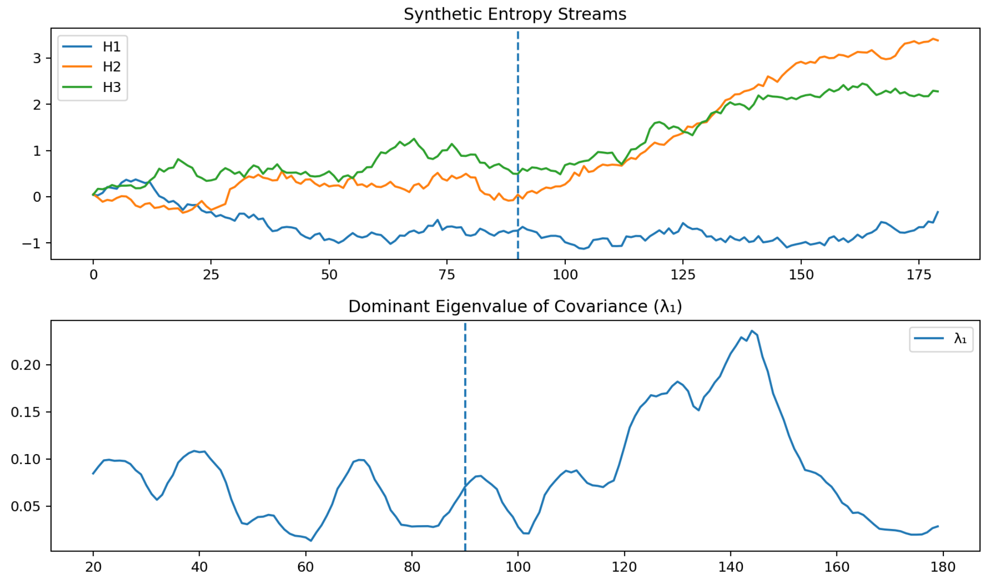

Figure 1: Toy example: entropy streams (top) and λ_1 of $\Sigma_H(t)$ (bottom). Spike at $t = 50$ reveals systemic alignment.

4 Implications

4.1 For SRE

Eigenvalue spikes anticipate incidents by detecting alignment of uncertainties across metrics before threshold-based alerts fire.

4.2 For Complex Systems

Suggests a general mechanism for cascades: emergent failures are preceded by eigenmodes of entropy alignment.

4.3 For AI Safety

Provides a formalization of "maternal instinct" as sensitivity to entropy covariance. Systems can bias toward protective actions when shared uncertainty increases.

5 Future Work

- Formalize within information geometry or statistical physics.
- Test across domains: ecosystems, economies, neuroscience.
- Embed entropy-covariance sensitivity in reinforcement learning agents.

6 Conclusion

Ted's Law of Karma compresses a universal idea: *shared fate is visible in the covariance of entropies.* This framing connects information theory, operations practice, and AI safety.

Appendix A: Maxwell-Style Formulation of Ted's Law of Karma

Entropy fields. For metric streams indexed by $i = 1, \ldots, n$, define rolling Shannon entropy $h_i(t)$ on a window. Stack as $\mathbf{h}(t) \in \mathbb{R}^n$. Let $\Sigma(t) = \mathrm{Cov}[\mathbf{h}(t)]$ denote the covariance of entropy streams.

C1. Continuity (balance) of entropy

Each stream balances sources, damping, flux, and noise:

$$\dot{h}_i \;=\; s_i \;-\; \kappa_i h_i \;-\; \sum_j \nabla\cdot J_{ij} \;+\; \eta_i, \tag{1}$$

where s_i are exogenous sources, $\kappa_i \geq 0$ damping, J_{ij} uncertainty flux from $j \to i$, and η_i noise.

C2. Constitutive law (flux response)

Linearizing around a baseline, flux follows gradients/couplings (Fick/Fourier analogue):

$$J_{ij} \;=\; -D_{ij}\,(h_j - h_i) \quad\Longrightarrow\quad \dot{\mathbf{h}} \;=\; -\alpha\,\mathbf{h} \;-\; \beta\,L\,\mathbf{h} \;+\; \mathbf{s} \;+\; \boldsymbol{\eta}, \tag{2}$$

where L is a graph Laplacian over metrics, with $\alpha, \beta \geq 0$.

C3. Correlation evolution (Lyapunov dynamics)

Write $\dot{\mathbf{h}} = A\,\mathbf{h} + \boldsymbol{\eta}$ with $A = -(\alpha I + \beta L)$. Then

$$\dot{\Sigma} \;=\; A\Sigma + \Sigma A^\top + Q \;-\; \Gamma(\Sigma), \tag{3}$$

where $Q = \mathrm{Cov}[\boldsymbol{\eta}]$ (drive) and $\Gamma(\Sigma)$ represents control (e.g., autoscaling/rate-limits). In discrete time:

$$\mathbf{h}_{t+1} \approx A_t\mathbf{h}_t + \boldsymbol{\varepsilon}_t, \qquad \Sigma_{t+1} \;=\; A_t\Sigma_t A_t^\top + Q_t \;-\; \Gamma_t. \tag{4}$$

C4. Alignment law (Gauss-style)

Define alignment density as off-diagonal mass or via the dominant eigenvalue:

$$\rho_{\text{align}}(t) \;=\; \sum_{i\neq j} w_{ij}\,\Sigma_{ij}(t), \qquad \lambda_1(t) \;=\; \lambda_{\max}\big(\Sigma(t)\big). \tag{5}$$

Alignment accumulates from couplings and noise, and is drained by control:

$$\frac{d}{dt}\,\rho_{\text{align}} \;=\; \Phi_{\text{coupling}}(A, \Sigma) \;+\; \mathrm{tr}(WQ) \;-\; \mathrm{tr}(W\Gamma). \tag{6}$$

Eigenmode monitor (operational early warning)

Let $u_1(t)$ be the unit eigenvector for $\lambda_1(t)$. From (3):

$$\dot{\lambda}_1 \;=\; u_1^\top \dot{\Sigma}\, u_1 \;\approx\; u_1^\top\big(A\Sigma + \Sigma A^\top + Q - \Gamma\big)u_1. \tag{7}$$

If the symmetric part $\mathrm{Sym}(A) = (A{+}A^\top)/2$ loses damping (critical slowing), the $A\Sigma + \Sigma A^\top$ term becomes positive, and λ_1 rises—the measurable "karma spike."

Fitting recipe (discrete-time, practical)

1. Compute $h_i(t)$: rolling Shannon entropy for each metric.
2. Fit VAR(1): $\mathbf{h}_{t+1} \approx A_t\mathbf{h}_t + \varepsilon_t$ on a sliding window.
3. Estimate $Q_t = \mathrm{Cov}[\varepsilon_t]$.
4. Propagate covariance: $\Sigma_{t+1} = A_t\Sigma_t A_t^\top + Q_t$.
5. Monitor $\lambda_1(t)$, $\mathrm{tr}(\Sigma)$, and off-diagonal mass; trigger alerts or protective bias when λ_1 spikes above baseline.

Summary. These equations encode Ted's Law of Karma as a dynamical system: entropy streams behave like fields, their covariances evolve by Lyapunov dynamics, and eigenvalue spikes precede shared-fate events.

References

[1] C. Shannon. "A Mathematical Theory of Communication." Bell System Technical Journal, 1948.

[2] G. Hinton. "The Need for Maternal Instinct in AI." (Talks, 2023).