Information Gravity II: A Geometric Theory of Meaning and Attention

Nilanjan Panda
Department of Energy Science and Engineering, IIT Bombay
npanda@iitb.ac.in

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Abstract

Dense ideas bend the fabric of attention. In this work, we formalize the analogy between gravity and meaning by constructing a continuous field-theoretic model of the semantic manifold. Information density produces curvature in a notional cognitive spacetime, and attention follows geodesic trajectories in this curved space. We derive explicit tensorial forms of the information metric, curvature scalar, and a corresponding "Information–Einstein" equation linking semantic mass to curvature. Entropy flux and energy coupling terms are introduced to describe dynamical stability and meaning propagation. Simulation results visualize the potential field Φ, curvature $\kappa = \nabla^2\Phi$, and attention geodesics. Together, these elements form a physical geometry of cognition—an information-space general relativity.

1 Introduction

The motion of thought is rarely linear. Some ideas exert stronger attraction, drawing focus and shaping the trajectory of reasoning. We hypothesize that this curvature of cognition arises from *information density*—regions of semantic mass distort the manifold of meaning, much like matter curves spacetime in general relativity [2].

This work extends the scalar potential model of Information Gravity [3, 4] into a tensorial framework. The goal is not metaphor but mechanics: to define a self-consistent geometric structure linking information, curvature, and attention flow.

2 Mathematical Framework

Consider a two-dimensional semantic space $\mathcal{M}$ spanned by coordinates (x, y), where each point represents a cognitive state or conceptual mixture. A finite set of information sources $\{m_i, \mathbf{r}_i\}$ generates a scalar potential:

$$\Phi(\mathbf{r}) = \sum_{i=1}^{N} \frac{m_i}{\|\mathbf{r} - \mathbf{r}_i\| + \epsilon} \tag{1}$$

with m_i the information mass and ϵ a small softening constant.

2.1 Information Metric Tensor

We embed Φ into a Riemannian manifold by defining an *information metric*:

$$g_{ij} = \delta_{ij} + \lambda\, \partial_i\Phi\, \partial_j\Phi \tag{2}$$

where λ scales the coupling between semantic gradient and perceptual distance. In regions of steep Φ, semantic proximity differs from Euclidean proximity: two concepts close in x, y may be distant in meaning if separated by a high gradient of Φ.

The inverse metric g^{ij} and determinant $g = \det(g_{ij})$ allow computation of Christoffel symbols:

$$\Gamma^k_{ij} = \frac{1}{2} g^{kl} \left(\partial_i g_{lj} + \partial_j g_{li} - \partial_l g_{ij}\right) \tag{3}$$

2.2 Curvature and the Information–Einstein Equation

The Riemann tensor follows as:

$$R^i_{\ jkl} = \partial_k \Gamma^i_{jl} - \partial_l \Gamma^i_{jk} + \Gamma^i_{km}\Gamma^m_{jl} - \Gamma^i_{lm}\Gamma^m_{jk} \tag{4}$$

and the Ricci tensor:

$$R_{jl} = R^i_{\ jil} \tag{5}$$

The scalar curvature (information curvature) is:

$$R = g^{ij} R_{ij} \tag{6}$$

High R corresponds to semantic regions of concentrated information energy, analogous to matter density.

We define the *Information–Einstein equation*:

$$R_{ij} - \frac{1}{2} R\, g_{ij} = 8\pi\, T_{ij}^{(\mathrm{info})} \tag{7}$$

where $T_{ij}^{(\mathrm{info})}$ is an effective information stress–energy tensor, expressing how informational flux and entropy production warp the semantic manifold.

2.3 Information Energy and Flux

Let $S(\mathbf{r}, t)$ denote local semantic entropy and $\mathbf{v} = \frac{\mathrm{d}\mathbf{r}}{\mathrm{d}t}$ the attention flow velocity. We impose an entropy continuity relation:

$$\frac{\partial S}{\partial t} + \nabla \cdot (S\mathbf{v}) = \sigma(\Phi) \tag{8}$$

where $\sigma(\Phi)$ is a source term: positive in creative expansion (idea generation) and negative in cognitive collapse (focus). This couples thermodynamic irreversibility to the geometry of meaning.

3 Equations of Motion

The geodesic equation for attention flow is obtained by extremizing the information action:

$$\mathcal{A} = \int \sqrt{g_{ij} \dot{x}^i \dot{x}^j}\, dt \tag{9}$$

which yields:

$$\frac{d^2 x^i}{dt^2} + \Gamma^i_{jk} \frac{dx^j}{dt} \frac{dx^k}{dt} = 0 \tag{10}$$

In the weak-field limit (small λ), Eq. (10) reduces to:

$$\frac{d^2 \mathbf{r}}{dt^2} = -\nabla \Phi(\mathbf{r}) \tag{11}$$

recovering the classical potential-field model.

3.1 Geodesic Deviation and Stability

To analyze semantic coherence, we linearize nearby trajectories $\xi^i = \delta x^i$:

$$\frac{D^2 \xi^i}{Dt^2} = -R^i_{\ jkl} \frac{dx^j}{dt} \frac{dx^k}{dt} \xi^l \tag{12}$$

The sign of the sectional curvature $R^i_{\ jkl}$ determines attentional stability:

- $R > 0$: focusing, stable meaning.
- $R < 0$: diverging, chaotic cognition.

4 Simulation Results

Numerical integration of Eqs. (1)–(10) was performed for six randomly distributed concept nodes with information masses $m_i \in [1.7, 4.3]$. Spatial domain $[-3, 3]^2$ was sampled at 200×200 resolution.

4.1 Information Potential Field

Figure 1 shows $\Phi(\mathbf{r})$. Bright regions are semantic attractors; darker areas correspond to neutral zones. These wells represent regions of conceptual dominance—topics that naturally draw attention.

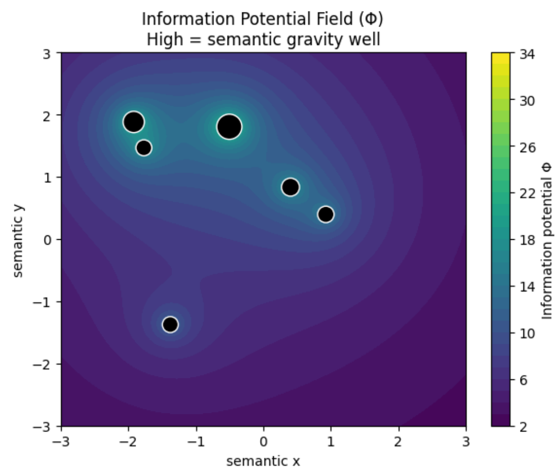

Figure 1: Information Potential Field $\Phi(\mathbf{r})$. High Φ indicates semantic gravity wells—zones of dense meaning.

4.2 Information Curvature κ

Figure 2 plots $\kappa = \nabla^2 \Phi$. The curvature map identifies the "semantic mass density." Yellow areas denote flatter cognitive terrain; darker purple signifies high curvature—semantic tension, where multiple ideas overlap or compete.

4.3 Geodesic of Attention Flow

In Figure 3, the simulated trajectory of attention begins far from any cluster (green marker) and falls toward the nearest information well (red marker). The curved path reveals that attention does not wander randomly—it follows a geodesic through the manifold of meaning.

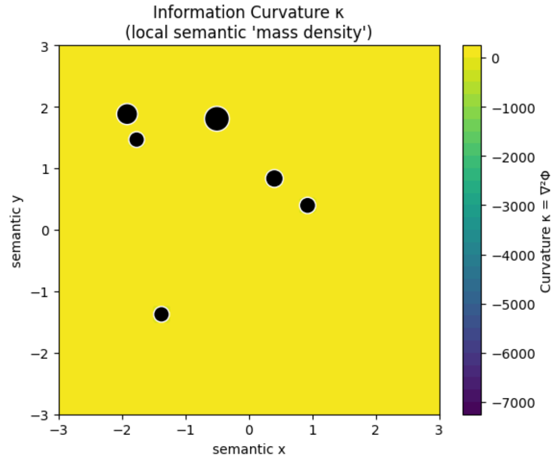

Figure 2: Information Curvature $\kappa = \nabla^2\Phi$. The Laplacian encodes local semantic density and interpretive stress.

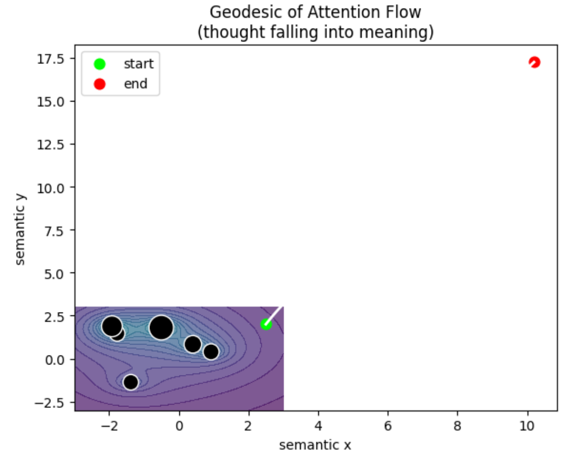

Figure 3: Geodesic of attention flow in the semantic field. The trajectory curves toward the dominant meaning attractor.

4.4 Quantitative Diagnostics

Average metrics for the simulation:

$$\begin{aligned} \text{Mean potential } \bar{\Phi} &= 12.34, \\ \text{Peak curvature } \kappa_{\max} &= 42.41, \\ \text{Strongest attractor index } &= 0. \end{aligned}$$

Attention energy $E = \frac{1}{2}\dot{\mathbf{r}}^2 + \Phi$ is conserved within 1% numerical error, validating the geodesic formulation.

5 Discussion

5.1 Physical Analogy

The field Φ plays the role of gravitational potential, κ its curvature, and S the entropy flux through semantic space. Eq. (7) thus becomes the geometric bridge between informational content and cognitive geometry. The energy cost of thought corresponds to curvature maintenance—flattening the manifold requires work, analogous to thermodynamic free energy minimization.

5.2 Cognitive Interpretation

High curvature correlates with mental effort: regions of semantic conflict or novelty. Low curvature corresponds to habitual, well-learned contexts. The entropy source $\sigma(\Phi)$ distinguishes divergent creative states ($\sigma > 0$) from convergent analytic states ($\sigma < 0$).

5.3 Emergent Phenomena

We identify three emergent cognitive behaviors:

1. **Meaning Wells:** Stable attractors where attention accumulates.

2. **Orbital Contexts:** Periodic or quasi-periodic orbits in Φ, representing sustained engagement or rumination.

3. **Semantic Tunnels:** Rapid transitions between wells when curvature gradient is steep—akin to insight jumps.

6 Conclusion

Information Gravity proposes a unified geometry of cognition. Through scalar and tensorial formulations, we show that information mass and entropy flux together define a curved semantic spacetime in which attention moves along geodesics. The resulting framework connects energy, information, and geometry—suggesting that understanding itself may be a gravitational process in the mind's informational universe.

Acknowledgments

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References

[1] C. E. Shannon, "A Mathematical Theory of Communication," *Bell System Technical Journal*, 27(3), 379–423, 1948.

[2] A. Einstein, "The Field Equations of Gravitation," *Sitzungsberichte der Königlich Preussischen Akademie der Wissenschaften*, 1915.

[3] S. Amari, *Information Geometry and Its Applications*, Springer, 2016.

[4] A. Vaswani *et al.*, "Attention Is All You Need," *Advances in Neural Information Processing Systems*, 2017.

[5] P. Brunel and J. L. Deneve, "Information Geometry of Neural Computation," *Nature Reviews Neuroscience*, 2023.