

Concept Paper

Not peer-reviewed version

---

# The Geometry Theory of Intelligence Meets General Relativity

---

[Ketan Suhaas Saichandran](#) \*

Posted Date: 18 November 2024

doi: 10.20944/preprints202411.1242.v1

Keywords: Artificial Intelligence; Cognitive Science; Intelligence; Neuroscience; Differential Geometry; General Relativity



Preprints.org is a free multidisciplinary platform providing preprint service that is dedicated to making early versions of research outputs permanently available and citable. Preprints posted at Preprints.org appear in Web of Science, Crossref, Google Scholar, Scilit, Europe PMC.

Copyright: This open access article is published under a Creative Commons CC BY 4.0 license, which permit the free download, distribution, and reuse, provided that the author and preprint are cited in any reuse.

Concept Paper

# The Geometry Theory of Intelligence Meets General Relativity

Ketan Suhaas Saichandran

Boston University; ketanss@bu.edu

**Abstract:** Prior research has explored cognitive space-time primarily through the lens of how the brain represents and processes spatial and temporal information. This manuscript extends the geometry theory of intelligence from Riemannian to Lorentzian manifolds, introducing the concept of a different cognitive-spacetime. We unify Meng Lu's framework with ideas from general relativity, proposing a model where thought flows along geodesics in a cognitive-spacetime with time as an intrinsic dimension, influenced by cognitive masses and connected by cognitive wormholes. This approach provides a more comprehensive framework for understanding the dynamics of intelligence, memory, and cognitive processes.

**Keywords:** artificial intelligence; cognitive science; intelligence; neuroscience; differential geometry; general relativity

## 1. Introduction

In his manuscript [1], Meng Lu conceptualizes thought flow to navigate along geodesics on Riemannian manifolds across time, which have a positive definite metric. He introduces a perturbation that arises from external input and manifold adaptation, caused by evaluation errors between perception and prediction. Due to this complex phenomena of manifolds changing over time and motion along geodesics, combined with fixed points on a manifold in the Euclidean space, we propose modeling these dynamics on a Lorentzian manifold by incorporating time as another dimension. This approach enables us to model the geodesic movement intrinsically and incorporate changes to the manifold structure in a more meaningful manner, drawing inspiration from the principles of general relativity [2,3].

Meng Lu proposes that thought flow navigates along geodesics, which in the case of a Lorentzian manifold, is analogous to the natural path that a mass follows without any external forces acting on it—a *free fall*. The brain constantly tries to optimize energy consumption, resulting in thought flow moving towards lower-energy regions. In general relativity, any mass that exists curves the space-time around it. The larger the mass, the higher the curvature, and the slower the time near it. We extend this analogy to cognitive-spacetime, where cognitive masses (such as deeply held beliefs, emotional memories, or complex problem spaces) create curvature in the manifold.

Consider a force acting on the system which changes the manifold—this can be conceptualized as moving masses in cognitive-spacetime, which in turn reshapes the manifold's geometry, altering the relationships between points. Token embeddings serve as landmarks in this domain and remain relatively stable, as proposed by Meng Lu, with slight variability in their positions. What fundamentally occurs is that the relationships between these landmarks change with context. In Meng Lu's equations, the geometric tensor is affected by external forces, implying that the geometric tensor is time-variant. At a high level, the force changes the context vector which is ultimately responsible for the manifold's structure.

This leads us to propose that every context vector, or in other words, feature vectors formed by the input tokens, has its own associated Riemannian manifold, and as the context vector changes across time, it modifies the manifold's structure in the Riemannian space. This conceptualization provides a new framework for understanding memory and cognitive processes, building upon existing theories in cognitive science and neurobiology [4,5]. We aim to provide a more comprehensive model of cognitive dynamics.

Key contributions of our theory:

- Extension of Meng Lu's geometric framework from Riemannian to Lorentzian manifolds

- Introduction of cognitive masses and their effect on manifold curvature
- Mathematical formalization of thought transitions through cognitive wormholes
- Integration of multiple memory types into the context vector framework

This work builds upon fundamental concepts in differential geometry, particularly the Ricci flow [6,7], to describe the evolution of cognitive-spacetime and provide insights into the nature of intelligence and thought processes.

## 2. Meng Lu's Geometric Framework of Intelligence

### 2.1. Thought Flow as Geodesic Motion

Meng Lu's framework conceptualizes intelligence through the lens of differential geometry, where thought flow follows geodesics on Riemannian manifolds. The fundamental geodesic equation describing this motion is:

$$\frac{d^2x^i}{dt^2} + \Gamma_{jk}^i \frac{dx^j}{dt} \frac{dx^k}{dt} = 0 \quad (1)$$

Where  $\Gamma_{jk}^i$  are the Christoffel symbols that encode the manifold's local geometry. This equation represents the path of least action in the manifold, analogous to how thought naturally flows along paths of least cognitive effort.

### 2.2. Geodesic Equation with Feedback

A crucial extension in Meng Lu's work is the incorporation of consciousness (self-awareness) through a feedback mechanism. This feedback modulates the trajectory of thought flow based on prediction errors, leading to the perturbed geodesic equation:

$$\frac{d^2\gamma^\mu(t)}{dt^2} + \Gamma_{\nu\lambda}^\mu \frac{d\gamma^\nu(t)}{dt} \frac{d\gamma^\lambda(t)}{dt} = \kappa \cdot \frac{d^2\psi(\Delta^\mu(t))}{dt^2} \quad (2)$$

This equation describes a path that:

1. Is determined by the geometry of the curved manifolds formed by token embeddings
2. Minimizes the distance (or energy) in the manifold formed by the token embeddings

The right-hand side term  $\kappa \cdot \frac{d^2\psi(\Delta^\mu(t))}{dt^2}$  represents the feedback mechanism, where:

- $\gamma(t)$  represents the state of intelligence at time  $t$
- $\Delta^\mu(t)$  represents the prediction error
- $\psi$  is a feedback function that processes this error
- $\kappa$  is a coupling constant determining the strength of the feedback

### 2.3. Curvature and Connection

The geometric structure is further characterized by the Riemann curvature tensor:

$$R_{jkl}^i = \partial_k \Gamma_{jl}^i - \partial_l \Gamma_{jk}^i + \Gamma_{km}^i \Gamma_{jl}^m - \Gamma_{lm}^i \Gamma_{jk}^m \quad (3)$$

This tensor quantifies how parallel transport of vectors around closed loops fails to return to their initial configuration, effectively measuring the manifold's intrinsic curvature.

The Christoffel symbols themselves are derived from the metric:

$$\Gamma_{jk}^i = \frac{1}{2} g^{im} (\partial_j g_{mk} + \partial_k g_{mj} - \partial_m g_{jk}) \quad (4)$$

These equations form the mathematical foundation of Meng Lu's framework, describing how thought flows along geodesics while the underlying manifold evolves in response to learning and external inputs. This framework provides the basis for our extension to Lorentzian manifolds in the following sections.

### 3. Cognitive-Spacetime Theory

#### 3.1. Manifold Evolution

The Equation (5) presented describes the evolution of the geometry of a manifold over time. It combines principles from differential geometry, specifically the Ricci flow, with the idea of incorporating external forces or context changes that affect the manifold's structure. This evolution equation is commonly used in contexts such as metric learning or geometrically-driven optimization processes, where the goal is to adapt the manifold's geometry based on both its intrinsic curvature and external influences. The geometry of the manifold itself evolves over time according to:

$$\frac{\partial g_{ij}}{\partial t} = -2\alpha R_{ij} + \nabla_i \zeta_j + \nabla_j \zeta_i \quad (5)$$

Where:

- $g_{ij}$  is the metric tensor
- $R_{ij}$  is the Ricci tensor describing the manifold's curvature
- $\alpha$  is a learning rate
- $\zeta_i$  represents external forces or context vector changes

This evolution equation captures how the manifold's structure adapts based on both internal geometric properties ( $R_{ij}$ ) and external influences ( $\zeta_i$ ).

#### 3.2. Memory and Context in Cognitive-Spacetime

In Meng Lu's framework a perturbation in the feature vector, or in other words, the context vector formed by input tokens, influences the curvature of the space. We propose that the context vector is a function of not just short-term memory, but also working, sensory, and long-term memories which exist as cognitive masses in the cognitive-spacetime. This multi-faceted context vector influences the curvature of cognitive-spacetime:

$$\zeta_i = f(M_{ST}, M_W, M_{SR}, M_{LT}) \quad (6)$$

Where  $M_{ST}$ ,  $M_W$ ,  $M_{SR}$ , and  $M_{LT}$  represent short-term, working, sensory, and long-term memories respectively.

The evolution of the metric tensor can then be expressed as:

$$\frac{\partial g_{ij}}{\partial t} = -2\alpha R_{ij} + \nabla_i f(M_{ST}, M_W, M_{SR}, M_{LT})_j + \nabla_j f(M_{ST}, M_W, M_{SR}, M_{LT})_i \quad (7)$$

This formulation allows for a more comprehensive representation of cognitive processes, going beyond the capabilities of current Large Language Models (LLMs) by incorporating various types of memory and their interactions in shaping the cognitive landscape.

#### 3.3. Cognitive Masses: Regions of High Curvature and Thought Lingering

In the framework of cognitive-spacetime, curvature is influenced by the existence of cognitive masses. Regions of high cognitive mass correspond to areas of high curvature. These regions, similar to the gravitational wells found around massive objects in physical spacetime, create a strong "pull" on thought flow. When thought flow encounters these areas, it tends to linger or "orbit," continuously revisiting central concepts, memories, or ideas.

This phenomenon mirrors the behavior of objects or particles that experience intense gravitational forces in physical spacetime, where they remain trapped in the well or follow complex, looping paths. In cognitive-spacetime, high cognitive mass regions represent concepts, thoughts, or memories that are cognitively significant or emotionally charged, resulting in increased cognitive attention or prolonged engagement with these elements. This mechanism is akin to "mental gravity," where certain

ideas or memories exert a strong influence on the flow of cognition, causing an individual to revisit them repeatedly.

Thus, cognitive masses can help explain phenomena such as the persistence of certain thoughts, the tendency to focus on emotionally significant memories, or the difficulty in moving away from specific concepts or problems.

#### 3.4. Cognitive Wormholes: Abrupt Thought Jumps

To account for sudden, seemingly discontinuous transitions in thought or memory recall, we introduce the concept of cognitive wormholes. These are analogous to Einstein-Rosen bridges in physical spacetime, which are theoretical shortcuts or tunnels that connect distant regions of spacetime. In cognitive-spacetime, cognitive wormholes represent abrupt changes in the curvature of the cognitive landscape, facilitating rapid transitions between disparate thought contexts or memory states.

Cognitive wormholes provide a model for understanding how individuals might experience sudden "jumps" in thought, where an idea, memory, or concept previously distant from the current focus suddenly becomes relevant. These transitions can occur due to strong associative links, emotional resonance, or external stimuli that trigger deep connections between disparate ideas. Just as physical wormholes allow objects to traverse vast distances in spacetime in a short time, cognitive wormholes allow thoughts to transition between different mental states almost instantaneously, bypassing intermediary cognitive structures.

In this context, cognitive wormholes help explain phenomena such as sudden insights, unexpected recollections, or creative leaps, where connections are made that might not have been apparent through a gradual process of thought progression. These moments of cognitive "jumping" reflect the non-linear, dynamic nature of memory and thought, where large-scale shifts in the mental landscape can happen with little apparent warning, driven by hidden associations or external influences.

## 4. Conclusion

By extending Meng Lu's framework to Lorentzian manifolds, we have developed a richer model of cognitive dynamics that incorporates the effects of cognitive masses, memory, and abrupt transitions in thought. This model, based on the concept of cognitive-spacetime, offers a more nuanced understanding of intelligence, memory, and the processes of thought. The idea of cognitive wormholes provides a novel perspective on how the brain navigates complex cognitive landscapes, making sudden jumps in thought that reflect the dynamic and evolving nature of human cognition.

## References

1. Lu, M. A mathematical framework of intelligence and consciousness based on Riemannian Geometry, 2024, [arXiv:2407.11024].
2. Misner, C.W.; Thorne, K.S.; Wheeler, J.A. *Gravitation*; W. H. Freeman and Company, 1973.
3. Wald, R.M. *General Relativity*; University of Chicago Press, 1984.
4. Baddeley, A. Working memory: theories, models, and controversies. *Annual Review of Psychology* **2012**, *63*, 1–29.
5. Squire, L.R. Memory systems of the brain: a brief history and current perspective. *Neurobiology of Learning and Memory* **2004**, *82*, 171–177.
6. Hamilton, R.S. Three-manifolds with positive Ricci curvature. *Journal of Differential Geometry* **1982**, *17*, 255–306.
7. Perelman, G. The entropy formula for the Ricci flow and its geometric applications. *arXiv preprint math/0211159* **2002**.

**Disclaimer/Publisher's Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.