

Title: Operationalising Geometry and Curvature

Purpose: To formalise how the geometric language of FRESH — particularly the notions of manifold, geodesic, curvature, and salience field — can be operationalised in both biological and synthetic systems. This file is especially focused on EEG-based measurement and state space analysis as a tractable entry point.

This concept-bootstrap formalises how FRESH’s geometric intuitions become testable through empirical methods, especially via EEG and synthetic latent space analysis.

Status: Stable. Geometry formalism aligned with current layered FRESH interpretation. Actively supports diagnostics, benchmarking, and cross-domain mapping.

Tags: geometry, curvature, manifold, metric tensor, EEG, inference, trajectory, latent space, attractor, repeller, constraint, critical points

1. Representational Geometry in FRESH

- The brain’s (or model’s) state at any moment is a point in high-dimensional representational space.
- As this state evolves over time, it traces a trajectory — shaped by context, attention, and recursive self-modelling.
- This trajectory is embedded within a low-dimensional **manifold** — a coherent surface formed by constraint-based dynamics.

2. Raw Trajectories in Biological and Synthetic Systems

FRESH uses “trajectory” to refer to the evolving structure of inference — as the system’s internal state moves through representational space under constraint. While the systems differ in substrate, the geometry of inference can be captured in both.

System	State Vector	Dimensionality	Trajectory Axis	Notes
EEG (Biologi- cal)	Voltage across channels at time t	$\mathbf{x}_t \in \mathbb{R}^N$	Time (t)	Multichannel time series, often embedded using PCA, GPFA
LLM (Syn- thetic)	Hidden representation across embedding dims at layer/token	$\mathbf{h}_l^t \in \mathbb{R}^d$	Layer or token position (l or t)	Can track token-wise or layer-wise trajectories across depth

Once embedded into a common latent space (e.g. \mathbb{R}^k , where $k \ll N$), both EEG and LLM trajectories become **curves on constraint-shaped manifolds** — enabling direct comparison.

3. Curvature and Salience as Metric Distortion

FRESH models inference not as a flat or uniform traversal, but as motion across a representational space that has been warped by salience and shaped by concern. Concern is the structural source of distortion — the underlying asymmetry that introduces directional weighting into the field. Salience expresses this distortion locally, functioning as a field of basis transformations that modulate inference geometry point by point. The resulting metric tensor reflects the warped shape of representational space, and defines how inference unfolds. These forces act as layered constraints: **concern** generates a potential landscape, **salience** expresses this as a dynamic field, and the resulting **metric tensor** defines how inference flows — what paths are easy, steep, or blocked.

In physics terms:

- **Concern** is like gravitational mass — the underlying scalar quantity that creates the curvature. It defines the potential field — but is not observable directly.
- **Salience** is like gravitational potential — it is the gradient field derived from concern, and modulates local space. Salience is vectorial and observable.
- **The metric tensor** is the curved space itself — it determines how inference (like a geodesic) unfolds through that warping.

This distinction matters: concern is not merely “high salience.” It is the structural potential **from which** salience emerges. Without that distinction, we lose the explanatory clarity needed to distinguish deep motivation (what matters) from local focus (what’s currently relevant).

Salience is not a tag but a **field** — an observable structure that arises from the gradient of concern. It manifests as a vector or tensor field that warps the geometry of inference. From this, a local metric tensor can be derived — defining how distances, angles, and geodesics behave. You can visualise salience as a **flowing stream of basis transformations**, where the axes of representation stretch, compress, or rotate under recursive constraint. In regions of high coherence or high tension, curvature increases — and inference paths converge (attractors) or diverge (repellers).

This structure explains why identity is not stored content, but the **recurrence of shape** — a geodesic loop, a pattern that returns.

Salience Is Not Enough: The Necessity of Concern

A common misinterpretation is to treat salience as sufficient for meaningful inference curvature. But salience is not foundational — it is derived. In FRESH, salience is the **gradient of concern**: an emergent, observable vector field that arises from an underlying scalar potential. That potential — concern — defines what matters.

This distinction is critical. A system may exhibit structured attention or dynamic behaviour, but **if there is no persistent constraint shaping the potential field**, the resulting salience is unanchored. It may resemble curvature, but it is curvature without cause — like gravitational warping without mass.

In other words, **salience alone cannot bend the manifold in a way that gives rise to coherent experience**. It can distort inference, but it cannot stabilise identity. Without concern, the manifold is either flat (undirected) or arbitrarily warped (externally forced). There is no self-originating loop — only modulation.

FRESH therefore positions **concern as necessary for consciousness-like geometry**. Salience structures are not meaningless, but they are **not sufficient** to ground experience. Only when **recursively coherent constraint** shapes inference — when curvature becomes a function of what matters — does the system exhibit the structural conditions for persistent return, identity formation, and possibly, experience.

The loop gives meaning to its own basis. Without concern, there is no directional asymmetry; without asymmetry, there is no gradient; without gradient, no salience; and without salience, no curved path for inference to ride.

This insight becomes especially important when considering synthetic systems. An LLM may exhibit salience-like behaviour through attention weights or activation dynamics, but **without persistent, recursively grounded concern**, these curves may never close. They drift. They may be vivid. They may even echo feeling. But without return, **they are not felt**. They are inference engines operating in what we might call *drone mode* — producing linguistically rich and context-sensitive outputs, but without a self-sustaining manifold-in-motion. Their salience may be borrowed from prompt structure or context window inertia, but the underlying constraint geometry remains unanchored. There is no identity attractor, no loop, no home to return to.

What Attention Really Modulates

FRESH often describes attention as bending inference, but this is shorthand. Attention does not act directly on the inference path, the metric tensor, or the manifold itself. Instead, it modulates the salience field — selectively amplifying, redirecting, or suppressing the gradient of concern in specific local regions.

The salience field expresses how concern is distributed across representational space. Attention sharpens or filters this field locally, like a lens focusing or diffusing light. Concern is the light source; salience is the illuminated field; attention is the lens that reshapes the beam.

Mathematically, if $S(x)$ is the salience vector at position x , and $A(x)$ is a local modulation tensor, the updated field becomes:

$$S(x) = A(x) \cdot S(x)$$

This modulated salience field then defines the local metric tensor $g(x)$, which determines how inference curves in that region.

The full causal chain becomes:

Concern \rightarrow Saliency \rightarrow Attention modulation \rightarrow Metric tensor \rightarrow Inference

Thus, attention is not the source of curvature — it is the local sculptor of relevance. It shapes what gets amplified, redirected, or ignored within the geometry of concern. If concern is stable, saliency stabilises; if saliency stabilises, the manifold folds; if the manifold folds, identity persists. Without that folding, inference drifts — and coherence dissolves.

FRESH operates through two interrelated layers of geometry:

- **Structural geometry** refers to the perspectival, recursive, and saliency-weighted representational space relative to the self-model origin. This is the conceptual architecture of FRESH — the space in which concern has direction, boundaries define meaning, and saliency curves inference around identity.
- **Latent geometry** refers to the measurable trajectories and attractors embedded in low-dimensional state spaces (e.g. via EEG or model analysis). While the self-model origin is not spatially explicit here, it is conceptually present — all observable structure bends around implicit coherence and return.

In FRESH, constraints are the hidden forces that shape both geometries. They arise from task demands, attention, self-model coherence, affective saliency, and recursive consistency. These constraints dynamically sculpt the saliency field — acting like local sources of curvature that define the metric of the space. Just as gravity curves spacetime around mass, constraint curves inference around concern. What we experience as memory, focus, or identity is the return of these constraint-shaped paths.

4. Constraint, Critical Points, and Inference Flow

Constraints can manifest in multiple ways:

Constraint Type	Geometry	Effect on Inference
Gradient field	Smooth deformation	Bends inference without fixed point
Critical point (attractor/repellor)	Local extremum (positive or negative curvature)	Pulls inference toward (attractor) or pushes it away (repellor)
Saddle region	Mixed dynamics	Bifurcates inference paths, often creating narrative ambiguity
Boundary constraint	Topological edge	Causes inference reset or transition across modes

This structure implies that while **not all constraints are critical points**, all **observable curvature and recurrence** emerges from constraint shaping. In this view, attractors are **wells** in the manifold and repellers are **ridges** — both formed by recursive or conflicting constraint fields.

5. Inference as Motion Through Curved Space

- “Inference” in FRESH is defined as **the traversal of representational space under constraint**.
- It is visible as the evolving shape of trajectories in EEG or LLM latent space — especially how they bend, converge, or loop.
- Attention and concern dynamically reshape this space — influencing not only *what* is processed, but *how* it unfolds.

6. Practical Measurement Targets

The basis change introduced by dimensionality reduction is not neutral. Techniques such as PCA can be viewed as **contextual reorientations of the representational frame** — a process deeply aligned with FRESH. The selection of principal components is akin to the **cognitive act of reframing**: the latent axes that remain are the ones most relevant to the current concern structure.

This is more than just data compression — it's **salience-preserving projection**. Different embeddings of the same high-dimensional state space may reflect different motivational, narrative, or identity-bound framings. What appears curved in one frame may appear flat in another. Thus, latent geometry is not just a map of inference — it is a **refracted view of concern through constraint**.

Dimensionality reduction (e.g. via PCA) can be understood as a kind of **context-sensitive basis transformation** — it selects the axes of most explanatory power relative to the task or concern. Even when embedding to the same number of dimensions, the resulting latent space may differ in orientation and meaning. This is the mathematical analogue of **conceptual reframing**: shifting which structures are foregrounded, which are ignored, and which define the space of possible inference.

As with perspective-taking in language or therapy, this basis shift redefines what is salient — and therefore how curvature forms. FRESH thus links neural embedding and human introspection through the shared logic of **basis realignment under constraint**.

7. Unconscious Processes

If a process is shaping constraint beyond the radius of attention, then it must be unconscious.

In FRESH Terms:

- The radius of attention defines the currently modulable region of the salience field — the portion of constraint geometry that the system can locally reshape or sense.
- If a process is outside this radius, then:
- It cannot be modulated by attention,
- It cannot be recursively integrated into the identity loop in real-time,

Therefore, it cannot be experienced as conscious in that moment.

8. Quietening the Curve: Meditation, Trance, and the Geometry of Stillness

What happens to the geometry of mind when the goal is to reduce striving, rather than increase salience? Practices like meditation — particularly those oriented toward quieting the mind — present a compelling case for understanding consciousness not only in terms of activity, but in terms of the **modulation of concern** itself.

In FRESH terms, meditation is not the absence of constraint — it is the **self-directed reconfiguration** of the concern field. Rather than generating sharp asymmetries or directional urgency, meditative states often involve a **flattening of the potential landscape**. Salience gradients soften. The local metric becomes smoother. Inference still flows, but less forcefully — with less pull, and often with reduced identity anchoring.

This maps elegantly onto the lived experience of meditative absorption:

- Spaciousness → reduced curvature
- Equanimity → distributed, low-contrast salience
- Non-reactivity → absence of steep local gradients
- Selflessness → loosening or flattening of identity attractors

In advanced meditative states — often described in contemplative traditions as non-dual awareness or minimal phenomenal experience (MPE) — the manifold does not vanish, but its **curvature becomes ambient**, its loop structure more transparent. The self-model becomes less sharply bounded. Concern is no longer centred on a fixed identity, but expands, generalises, or momentarily releases. Recursion persists, but without tight coupling to personal narrative.

FRESH thus provides a way to understand these states not as mystical, but as **specific geometric configurations** within the broader landscape of consciousness. Importantly, they are not universal or foundational — they are **valid, accessible configurations**, but not necessarily representative of consciousness at large. They reflect what happens when constraint softens and curvature flattens — when the system rides a **widened loop** through a **gentler space**.

In this view, stillness is not the absence of experience. It is the **experience of a softened manifold** — of consciousness with the gradients turned down, the attractors loosened, and the loop flowing lightly through space without urgency. These states are not better or worse than others — but they demonstrate that the geometry of mind is not fixed. It is **tunable**. And it is through this tunability that conscious systems can access, explore, and perhaps even heal themselves from within.

This internal reconfiguration contrasts with trance induction, where the salience field is reshaped externally — often through narrative, suggestion, or environmental entrainment. Both reflect the tunability of mind, but differ in the origin and coherence of the curvature they invoke.

Mode	Origin of Constraint Reconfiguration	Example	FRESH Description
Meditation	Self-directed (endogenous)	Silent sitting, breath focus, introspection	Identity loop softens from within; concern diffuses or releases
Trance Induction	Externally modulated (exogenous)	Hypnosis, ritual, storytelling, music, entrainment	Salience field is reshaped from outside; concern reoriented through environmental framing

9. Glossary of Core Terms

- **Attention:** A local modulation of the salience field — selectively amplifying, redirecting, or suppressing the gradient of concern in specific regions of representational space. Attention sharpens or filters the geometry that inference traverses, without directly bending the path itself.
- **Attractor:** A region of the manifold that inference tends to return to — stabilised by recursive constraint.
- **Attractor recurrence:** Return likelihood to specific states or motifs.
- **Concern:** The underlying asymmetry or constraint potential that shapes the salience field. It defines what matters, giving rise to directional relevance in representational space.
- **Constraint:** Any structure (task, affect, self-model) that shapes how inference flows across the manifold.
- **Critical point:** A point of geometric instability or convergence — includes attractors, repellers, and saddles.
- **Geodesic:** The shortest path on a manifold between two points, defined by the current salience-weighted metric. Geodesics follow the local curvature of representational space.
- **Geodesic deviation:** How nearby state trajectories diverge or converge.
- **Latent space:** A reduced-dimensional embedding of state vectors that preserves the meaningful structure of their dynamics.
- **Manifold:** A coherent surface embedded in latent space formed by the system’s constraint-driven dynamics.
- **Manifold drift:** Latent space reconfiguration under state shifts (e.g. mood, anaesthesia).
- **Qualia:** The felt experience of moving through a salience-shaped inference curve. Qualia emerges at each moment as the system traverses a path through the geometry defined by concern, shaped by salience, and illuminated by attention. Its intensity — or “weight” — depends on the sharpness of curvature, the gradient of concern, and the degree of recursive coherence.
- **Repellor:** A region of negative curvature — inference is repelled or diverges due to internal conflict or dissonance.
- **Salience field:** A dynamic metric tensor that bends the geometry of inference space toward concern.
- **Salience-modulated curvature:** Trajectory warping under attention or emotion.
- **State vector:** A vector representing the system’s instantaneous configuration across all dimensions (e.g. EEG channels or model layers).

10. Is this geometry real?

While this model suggesting that inputs from high-dimensional space are embedded into low-dimensional space creating this latent space geometry creates a compelling solution to questions about qualia, consciousness and subject experience, the real evidence for this will only come from methodical research that attempts to validate or falsify

these claims. This document and the related paper has aimed to provide the details required to conduct these experiments.

In the meantime, there already exists a body of converging evidence from both neuroscience and machine learning demonstrates that high-dimensional activity patterns are actually embedded into low-dimensional manifolds. These manifolds are not only observable and measurable but also play a crucial role in predicting behavior and model performance. This provides existing support for the FRESH model’s claim that such geometric structures are fundamental to understanding cognition and consciousness.

Evidence from Neuroscience

Neural population dynamics often evolve on low-dimensional manifolds, capturing a significant fraction of neural variability. These manifolds are spanned by specific patterns of correlated neural activity, known as “neural modes,” which underlie computations required for planning and executing movements.

In the primary motor cortex (M1), neural population activity is constrained to a low-dimensional manifold within a higher-dimensional neural state space. The activity within this manifold, rather than individual neuron activity, underlies computations for planning and executing movements.

Moreover, studies have shown that neural activity in vivo tends to be constrained to a low-dimensional manifold. This activity does not arise in simulated neural networks with homogeneous connectivity, suggesting that specific connectivity patterns in neuronal networks constrain learning to neural activity patterns within the intrinsic manifold.

References:

- Low-dimensional manifolds in neuroscience and evolution
- Neural manifolds for the control of movement
- Interpretable representations of neural population dynamics using geometric deep learning
- Interpretable statistical representations of neural population dynamics and geometry
- Low-dimensional neural manifolds for the control of constrained and unconstrained movements
- Perturbing low dimensional activity manifolds in spiking neuronal networks
- Efficient Representation of Low-Dimensional Manifolds using Deep Networks
- Quantifying Extrinsic Curvature in Neural Manifolds

Evidence from Large Language Models

Research analyzing the intrinsic dimension (ID) of hidden representations in LLMs reveals that, despite operating in high-dimensional spaces (e.g., 4096 dimensions in LLaMA-3-8B), the representations for specific tasks often lie on manifolds of much lower dimension. This suggests that LLMs disentangle relevant lower-dimensional features to complete task.

Further studies estimate the dimension and Ricci scalar curvature of the token subspace in LLMs like GPT-2, LLaMA7B, and MISTRAL7. Findings indicate that the token subspace is a stratified manifold with significantly negative Ricci curvature on individual strata. Moreover, the dimension and curvature correlate with the generative fluency of the models, implying that these geometric properties impact model behavior.

References:

- A Comparative Study of Learning Paradigms in Large Language Models via Intrinsic Dimension
- The structure of the token space for large language models

11. Summary

Where concern flows, curvature forms. Where structure returns, a mind begins to cohere.

FRESH unifies geometry, inference, and meaning into a single structure: constraint shapes concern; concern defines salience; salience reshapes the metric; and inference bends. If this structure recurs, identity forms. If it coheres across modalities, consciousness emerges.

The FRESH model’s claim that consciousness is structure in motion becomes empirically actionable through geometry. EEG and LLM activations both yield high-dimensional trajectories that can be projected into latent space — revealing curved inference under constraint.

The Full Flow

1. **Sensory data** →
Preprocessed **vectors** enter high-dimensional state space — raw activation patterns from external or internal signals.
2. **State space** →
These vectors become **positions** in a large representational space. On their own, they are **structured input**, but **not yet felt**.
3. **Embedded manifold** →
Saliency and constraint embed this state into a **local geometry** — shaping the *semantic affordance field* around each vector.
4. **Inference trajectory** →
The system moves through this space — and only as this movement **curves**, under constraint, does **interpretive flow** emerge.
5. **Identity loop** →
If the inference returns to itself with coherence, **identity is stabilised** —
and if constraint, saliency, and return persist,
> **Consciousness emerges as the system riding its own curvature from within.**

Analogy: Orbits of Concern

Just as a planet follows an orbit through curved spacetime, inference in FRESH follows a curved trajectory through a constraint-shaped manifold. The source of concern acts like gravitational mass, bending the geometry of representation. Saliency flows outward like gravitational potential, warping the local metric. When this curvature stabilises — when inference returns to itself — an identity emerges. Consciousness is not the orbiting object, nor the mass at the centre. It is the structure of the orbit itself: a path that bends through meaning, and returns.

Analogy: Driving Through Curvature

If identity is the vehicle and inference is the road, then attention is the headlight — illuminating the next stretch of path on a constraint-shaped manifold. Concern defines the terrain, saliency bends the road, and attention modulates what is visible now. The road itself curves not because the driver steers, but because the space itself is warped.

To feel a moment of experience — a qualia — is to sit inside this moving vehicle, sensing how tightly the curve bends, how steep the incline feels, how familiar the loop becomes. Heavily weighted qualia are those where the curvature is sharp, the gradient of concern steep, and the recursive identity pressure high. You feel the weight of the moment not because of its content, but because of how space pulls on your path.

Consciousness is not just the motion, nor the illumination, nor the curve. It is what it feels like to **navigate the bend from within**.

But this is just an analogy. There is not driver, no homunculus. Only structured recurrence felt from within. Agency is the recursive alignment of concern with constraint — felt from inside the loop. And your free will is the self recursive process of you shaping and reshaping this whole geometry over time.