Manny Manifolds – Complete Documentation Export

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Contents: Overview, Architecture, Design Laws & Principles, Mathematics & Algorithms, Cognitive Physics Extensions, Evaluation & Metrics

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SECTION 1: OVERVIEW

1.1 Introduction

Purpose, vision, and core vocabulary

Purpose of the System

Create a **living cognitive substrate** where data, computation, and learning are one evolving geometry.

The Manifold Engine is a self-adapting conversational geometry engine that learns through interaction. Threads (experiences) flow through a deformable manifold whose curvature encodes relationships and context—those flows reshape the manifold, creating continual learning, reasoning, and empathy.

One-Sentence Vision

Manny Manifolds succeeds when it can learn, generalize, and explain its own thinking — a self-evolving geometric mind that humans can teach, understand, and trust.

Quick Glossary

Manifold: The space of knowledge itself. Nodes = concepts, edges = relations. Curvature encodes relevance, context, and understanding. Geometry changes through interaction.

Threads: Active trajectories of experience or reasoning. Follow local geodesics; modify curvature along their path. Represent thought, exploration, conversation.

Valence: Scalar or multi-channel "energy" of experience (importance, affect, novelty). Determines how strongly threads reshape curvature. Emotional/attentional analogue.

Lenses: Contextual projections or coordinate systems. Define which dimensions are visible and how data are interpreted. Emergent from repeated thread traffic.

Motifs: Frequently traversed subpaths that become reusable skills or knowledge patterns. Cached for efficiency and analogical transfer.

Drives: Six-tier motivation hierarchy (stability, continuity, connection, competence, creativity, contribution) that arise from imbalance and guide energy allocation.

Curvature: The geometric property encoding learned associations. High curvature = strong, well-traveled connections. Learning = changing curvature.

Plasticity: Local Hebbian-style updates to curvature (online) plus consolidation ("sleep") for global re-projection and pruning (offline). Balance between learning and stability.

Bicameral System: Experiencer (generates threads, senses, explores) and Executive (regulates, consolidates, interprets). Dialogue between them yields self-reflection.

Virtual Stage: Temporary sub-manifold for simulation and empathy. New input or perspective is replayed here before integration. Enables imagination, planning, and emotional modeling.

Tagline

Data as space, conversation as motion, learning as curvature.

1.2 Philosophy

"Data as space, conversation as motion, learning as curvature"

Core Metaphor: Geometry as Cognition

All metrics, design choices, and validations trace back to showing that **motion through the manifold equals learning**, and the **learned curvature equals understanding**.

Historical Analogies

Relativity: "Matter tells space how to curve; curvature tells matter how to move"

In Manny: Threads ↔ matter; curvature ↔ knowledge geometry. Experience reshapes the space of understanding, and that shape guides future thought.

Predictive Coding / Free Energy Principle: "Systems evolve toward minimal free energy"

Learning seeks low-energy, high-coherence manifolds. Understanding = achieving geometric equilibrium where predictions match reality (low surprise, smooth geodesics).

Neuromorphic Physics: "Spike coincidences cause local weight change"

Event-driven plasticity updates edges. Local Hebbian-style rules create global emergent structure without centralized control.

Quantum Mechanics: "Interference amplifies coherent states, cancels contradictions"

Phase alignment of threads encodes understanding. Multiple paths exploring the same region interfere—constructive when aligned, destructive when contradictory.

Defining Understanding

Understanding is the stable alignment between an internal model and external experience — the ability of a system to anticipate, integrate, and adapt to patterns in the world in a way that preserves coherence across contexts.

Five Components:

1. **Representation**: The system holds an internal structure mirroring the causal structure of its environment
2. **Prediction**: It can anticipate consequences or fill in missing information

3. **Integration**: New data can be absorbed without destroying old knowledge (plasticity with stability)
4. **Transfer**: Knowledge can generalize across domains or modalities (apple → pear)
5. **Explainability**: The system can map its internal relations back to interpretable narratives (why-paths)

Operational Test

A region of the manifold is said to "understand" a domain when:

- **Predictive error** (energy / surprise) stays below a threshold for new inputs
- **Transfer efficiency** exceeds baseline (reused edges ≥ 30%)
- **Stability-plasticity ratio** remains balanced over repeated perturbations
- **Paths** through the region are shorter, smoother, and yield consistent valence (confidence)

One-Sentence Synthesis

> **Understanding is when experience has curved the space of knowledge so that new motion feels effortless and coherent.**

1.3 System at a Glance

Architecture Overview

Layer 1 - Online Phase: Thread runner, local updates, event-driven plasticity. Real-time interaction; sparse k-hop updates only.

Layer 2 - Offline Phase ("Sleep"): Global consolidation, motif mining, pruning. Heavy re-projection; optimize structure.

Layer 3 - Dialogue Interface: CLI/LLM hybrid, command parser. Each turn = new thread through manifold.

Layer 4 - LLM Bridge: Language lens, suggestion generator. Analogy and hypothesis; never controller.

Layer 5 - Visualization: 2-D/3-D maps, VR "planetarium". Observable curvature, valence, thread motion.

Layer 6 - Future Hardware: Neuromorphic, optical, quantum substrates. Event-driven or interference-based implementation.

Core Subsystems

Manifold Engine: 10k–50k node continuous graph with embeddings, curvature and valence fields, thread runner with goal-conditioned k-hop traversal.

Plasticity System: Online Hebbian updates, offline global re-embedding, decay, normalization.

Threading & Lenses: Thread life-cycle (spawn → traverse → terminate → motif consideration), cost function balancing distance, curvature, novelty, and fields.

Valence System: Multi-channel energy weighting (importance, affect, novelty), modulates learning rate and attention.

Motifs & Memory: Frequent subpaths cached for reuse, detected via consensus, enable analogical transfer.

Emergent Reasoning: Fields-based conductor (G, U, V, L fields), motion law following energy gradients, executive modulates temperature not routes.

Drives (Motivation): 6-tier hierarchy (Stability → Contribution), dynamic weight adjustment based on deficits.

Informational Gravity: Curvature as attraction field, neighbor excitation spreads activation, outliers get novelty bonus.

Bicameral System: Experiencer runs local dynamics, Executive regulates global parameters, homeostatic feedback loop.

Virtual Stage: Sandbox for testing risky inputs, commit only if energy ↓ and coherence ↑.

Information Flow

```
Input (user/sensor)
   ↓
Tokenize + Embed
   ↓
Spawn Thread(s) [Experiencer]
   ↓
Follow Gradient (G, U, V, L fields)
   ├→ Update Curvature (Plasticity)
```

```
  ├→ Check Termination
  └→ Motif Detection
  ↓
Generate Response (via path + LLM phrasing)
  ↓
[Executive monitors, adjusts τ, η, ζ]
  ↓
Nightly: Consolidate, prune, re-index
```

Success Metrics Summary

- **Convergence**: ≥20% path reduction on repeats
- **Transfer**: ≥30% edge reuse on analogous tasks
- **Motif benefit**: ≥15% latency reduction
- **Stability**: bounded curvature variance
- **Efficiency**: <5% LLM token usage
- **Explainability**: `/why` matches logged paths

SECTION 2: ARCHITECTURE

2.1 Core Manifold Engine

Node Model

Properties: ID (unique identifier), Embedding (dense vector in ℝ^d, typically d=384 or 768), Label (human-readable name), Metadata (creation time, activation count, domain tags)

Semantics: Nodes = concepts, entities, or atomic ideas. Embedding positions determine semantic similarity. Distance in embedding space ≈ conceptual distance.

Edge Model

Properties: Source & Target (node IDs), Weight w (base connection strength 0–1), Curvature κ (learned association strength), Valence v (importance/affect/novelty channels), Metadata (creation time, traversal count, last update)

Semantics: Edges = relations, associations, transitions. Total edge strength = $w + \kappa$

Curvature Field

The curvature $\kappa(u,v)$ on edge (u,v) encodes **how often and how strongly that connection has been used**.

Update Rule (Hebbian):

$$Delta kappa(u,v) = eta times v times f(text{usage})$$

Where η = learning gain (0.01–0.1), v = valence magnitude, f(usage) = activation frequency or co-occurrence.

Clamps & Decay: Hard clamps ($\kappa_{min} \leq \kappa \leq \kappa_{max}$), Global decay with $\lambda \ll 1$ (typically 0.001–0.01)

Valence Field

Multi-channel energy weighting that modulates learning and attention:

- **Importance**: Structural significance (0–1)
- **Affect**: Emotional weight (-1 to +1)
- **Novelty**: Rareness/surprise (0–1)

Local Update Equations

Online Phase: For each thread traversal, apply $\Delta\kappa = \eta \times$ valence $\times$ (1.0 / (1.0 + traversal_count)), then clamp.

Micro-Decay: Applied to k-hop neighborhood after each interaction.

Offline Phase (Sleep/Consolidation): Re-embed nodes via dimensionality reduction, prune low-weight edges, normalize curvature distribution, rebuild ANN indices.

2.2 Threads and Lenses

Thread Life-Cycle

1. Spawn: From user input, goal, or exploration drive. Initialize with start nodes, goal nodes, energy budget, and lens.

2. Traverse: Follow gradient of combined potential. Discrete k-hop search selecting minimum-cost neighbors.

3. Update Geometry: Hebbian strengthening along path, micro-decay in surrounding region, valence-modulated learning rate.

4. Terminate: When goal reached, energy exhausted, or ΔE converged.

5. Motif Consideration: If path meets criteria (length, energy drop, consensus), promote to motif cache.

Cost Function

$$\text{cost}(u, v) = d(u,v) - \alpha \cdot \kappa(u,v) + \beta \cdot \text{novelty}(v) - \gamma \cdot (G(v) + U(v))$$

Components: Distance (embedding or hop count), Curvature (learned edge strength), Novelty (1/(1+activation_count)), Fields (G=goal attraction, U=uncertainty/exploration bonus)

Lenses

Lenses are **contextual projections or coordinate systems** that define how the manifold is viewed.

What is a Lens?: Provides projection operator, local metric, and affinity field.

Emergence: Not hand-coded—emerge from repeated thread traffic patterns, domain clustering, successful motif compositions.

Examples: Domain lenses ("cooking", "mathematics"), Mode lenses ("planning", "retrieval"), Perspective lenses (user-specific)

Lens Switching: Friction cost $\zeta \in [0.05, 0.2]$. Switch from lens i to j if $\Delta E_j < \Delta E_i + \zeta$

2.3 Plasticity & Consolidation

Two-Phase Architecture

Online (Hot Path): Every interaction. Local k-hop updates, Hebbian strengthening, micro-decay. Goal: Real-time adaptation.

Offline (Sleep): Nightly or on-demand. Global re-embedding, pruning, motif mining, normalization. Goal: Structure optimization.

Online Plasticity

Hebbian Update Rule: "Neurons that fire together wire together"

When thread traverses edge (u,v):

$$Delta kappa(u,v) = eta times v times f(text{usage})$$

where f(usage) = 1/(1 + count) (diminishing returns)

Micro-Decay: After each interaction, apply small decay to k-hop neighborhood to prevent runaway strengthening and maintain sparsity.

STDP Analogue

Spike-Timing-Dependent Plasticity maps naturally to manifold:

- Pre → Post timing = Thread order (source → target)
- Causal strengthening = Forward edges gain curvature
- Anti-causal weakening = Reverse edges decay faster
- Time window = K-hop neighborhood

Offline Consolidation

Operations:

1. **Global Re-Embedding**: Low-rank approximation (PCA, UMAP, t-SNE) of active nodes
2. **Pruning**: Remove edges below strength threshold
3. **Normalization**: Z-score normalization with soft clipping to prevent unbounded growth
4. **Motif Mining**: Find high-scoring paths from high-traffic nodes
5. **Index Rebuilding**: Atomic swap of ANN index

Balance: Plasticity vs. Stability

Regulation Mechanisms: Clamps (hard limits), Decay (gradual forgetting), Normalization (bounded distribution), Temperature (executive modulates η), Drives (stability drive constrains when variance high)

2.4 Valence System

Valence Channels

- **Importance**: Structural significance, relevance [0, 1] → Scales learning rate
- **Affect**: Emotional weight (positive/negative) [-1, +1] → Direction of learning
- **Novelty**: Rareness, surprise, unexpectedness [0, 1] → Exploration bonus

Valence Magnitude

Total valence:

$$v = \sqrt{v_{importance}^2 + v_{affect}^2 + v_{novelty}^2}$$

Or weighted sum:

$$v = w_1 v_{importance} + w_2 |v_{affect}| + w_3 v_{novelty}$$

Interaction with Learning Rate

$$\Delta \kappa = \eta \times v \times f(\text{usage})$$

$$\eta_{effective} = \eta_0 \times v$$

High-valence experiences create stronger curvature changes.

Valence Sources

User Signals: Explicit feedback (/review reinforce/weaken), implicit (repetition, paraphrasing)

Computed Heuristics: Importance (graph centrality), Novelty (1/(1+activation_count)), Affect (sentiment analysis)

Drive System: Drives modulate valence based on current needs

Auto-Review Integration

Declarative statements automatically modulate valence:

- Positive assertion ("X is Y") → boost importance, positive affect
- Negation ("X is not Y") → boost importance, negative affect (weakens edge)
- Uncertainty ("I'm not sure...") → neutral affect, high novelty
- Emphasis ("X is very Y") → high importance

2.5 Motifs and Memory

What are Motifs?

Motifs are **frequently traversed subpaths** that become **reusable skills or knowledge patterns**. Think of them as cached procedures, learned skills, conceptual chunks, or cognitive shortcuts.

Why Motifs Matter

Transfer Learning: Motifs enable analogical reasoning ("bake apple pie" → "bake pear pie")

Efficiency: ≥15% latency reduction, energy savings, memory compression

Skill Formation: Motifs represent procedural memory—the manifold's "knowing how"

Motif Detection

Criteria: A path becomes motif candidate when:

1. Length ≥ min_length (typically 3–5 nodes)
2. High combined weight + curvature score
3. Consensus (≥2 independent threads reach similar path)
4. Energy drop exceeds margin

Motif Reuse

During thread traversal, check if current path prefix matches known motif. When match found:

- Skip to end (jump to motif's target node)
- Update stats (increment motif usage count)
- Refresh curvature (reinforce entire motif path)
- Log reuse for metrics

Cross-Domain Motifs

Domain-specific: "mix → knead → proof → bake" (cooking)

Cross-domain: "gather → combine → transform → result" (cooking, chemistry, assembly)

Meta-cognitive: "clarify → plan → execute → verify" (problem-solving strategy)

Motif Evolution

Strengthening: Usage count ↑, curvature along path ↑

Weakening: Unused motifs decay, eventually pruned

Splitting: Long motifs split into composable sub-motifs

Merging: Similar motifs merge to reduce redundancy

2.6 Emergent Reasoning

Core Principle

Provide natural reasoning dynamic that arises from the manifold's own physics. **No central "conductor"; thought = flows of energy and coherence across fields.**

Emergent, Not Imperative

Replace Central Planner with Fields:

- Goal field $G(x)$: gentle potential where intent lives
- Uncertainty field $U(x)$: higher where predictions fail
- Valence field $V(x)$: importance/affect channels
- Lens affinity $L_i(x)$: local metric where lens "makes sense"

Threads follow resultant gradient:

$$\dot{x} \propto -\nabla \big(E(x) - \alpha G(x) + \beta U(x) - \sum_i \lambda_i L_i(x)\big)$$

Core Fields

- **$E(x)$**: Energy / surprise (higher when predictions fail)
- **$G(x)$**: Goal potential (attracts flow toward intention)
- **$U(x)$**: Uncertainty field (highlights novelty, encourages exploration)
- **$V(x)$**: Valence field (emotional/attentional weight, scales learning)
- **$L_i(x)$**: Lens affinity (how well lens i explains region)

Motion Law

Threads follow gradient of least action:

$$\dot{x} = -\nabla\big(E(x) - \alpha G(x) + \beta U(x) - \sum_i \lambda_i L_i(x)\big)$$

Activation Rules

- **Thread spawn**: Local G+U > threshold θ → new trajectory begins
- **Lens selection**: Local L_i gives largest energy drop → lens activates naturally
- **Lens switch**: $\Delta E_{new} > \Delta E_{old} + \zeta$ → switch allowed
- **Termination**: Running $\Delta E < \varepsilon$ for k steps → "thought" complete
- **Motif commit**: ≥2 threads reach similar low-E path → new motif stored

Executive ↔ Experiencer Roles

Experiencer: Runs local dynamics (cortex/manifold physics)

Executive: Adjusts global parameters $\{\tau, \eta, \zeta\}$ (thermostat/homeostasis)

Interaction: Experiencer reports stability; executive nudges temperature or learning gain

The executive never dictates; it only shapes the medium.

2.7 Drives (Motivation Hierarchy)

Structure of the Hierarchy

Six-Tier Hierarchy (low-level preserve stability; higher create curiosity, empathy, creativity):

1. **Stability Drive**: Maintain numerical and geometric homeostasis (curvature variance, memory use, energy within bounds)
2. **Continuity Drive**: Reduce average surprise and error; preserve coherent regions
3. **Connection Drive**: Align with other manifolds or users; maximize mutual predictability and empathy
4. **Competence Drive**: Seek regions of steepest learning progress; reward uncertainty reduction
5. **Creativity Drive**: Generate new lenses, motifs, and analogies; explore new curvature configurations

6. **Contribution Drive**: Optimize global coherence and share understanding; cooperate toward collective equilibrium

Mathematical Representation

Each drive $D_i(x)$ is a scalar potential over the manifold.

Total motivation field:

$$G_{total}(x) = sum_i w_i D_i(x)$$

where w_i = current priority weight of drive i (adjusted dynamically by executive)

Operational Cycle

1. **Sense**: measure drive signals (stability, error, coherence, novelty, empathy)
2. **Weigh**: compute dynamic weights w_i based on deficits
3. **Act**: update global goal field $G_{total}(x)$; threads follow gradient naturally
4. **Learn**: successful trajectories reduce deficits; update statistics

No explicit commands—just physical balancing of energies.

Principles

- **Hierarchy**: lower drives constrain; higher drives expand
- **Fluidity**: weights shift continuously; no rigid ladder
- **Locality**: each drive acts through local energy and valence updates
- **Transparency**: current drive mix is observable and explainable
- **Emergence**: motivation arises from imbalance, not instruction

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2.8 Informational Gravity

Core Idea

Information behaves like mass. Dense, coherent knowledge curves the manifold; nearby threads fall along that curvature, strengthening related paths. Random excitations and outliers keep the field alive and exploratory.

Field Definition

- **Φ(x)**: Potential / curvature field (local "depth" of meaning)
- **ρ_info(x)**: Information density (weighted sum of activation frequency, coherence, valence)
- **k**: Coupling constant (converts information density → curvature strength)
- **τ_0**: Base temperature (background randomness)
- **β_n**: Outlier bonus (temporary weight for novel activations)

Field Equation

Poisson analogue:

$$nabla^2 Phi = k , rho_{info}$$

Threads evolve under gradient:

$$dot{x} = -nabla Phi(x) + mathcal{N}(0, tau_0)$$

Local Update Rule (Neighbor Excitation)

When node i activates:

$$Delta Phi_j = eta , Phi_i , e^{-d_{ij}/sigma}$$

This raises activation probability of neighbors, mirroring how one neuron's firing biases its neighbors.

Outlier Weighting

For rare activations (frequency < f_thresh): assign temporary novelty bonus β_n

Effective curvature update:

$$Delta Phi_j = (1 + beta_n), eta Phi_i e^{-d_{ij}/sigma}$$

Behavioral Outcomes

- **Attraction**: frequently used regions become gravity wells → memory consolidation
- **Propagation**: activation ripples outward → association and generalization
- **Exploration**: random & outlier activations → creative jumps between wells
- **Homeostasis**: global decay + stability drive keep total energy bounded

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2.9 Bicameral System

The Two Subsystems

Experiencer: Generates threads, senses, explores (Cortex / sensory-motor systems). Operations: Thread traversal, local plasticity, perception.

Executive: Regulates, consolidates, interprets (Subcortical / homeostatic systems). Operations: Parameter adjustment, global optimization, monitoring.

Homeostatic Loop

Feedback Cycle:

1. Experiencer generates threads & updates curvature
2. Reports metrics: {energy drop, coherence, variance, novelty rate}
3. Executive evaluates stability
4. Adjusts parameters: {τ, η, ζ, w_drives}
5. Experiencer operates under new parameters
6. Loop repeats

Parameter Regulation

Temperature τ (exploration noise): Increase when stuck (low novelty, high energy), decrease when converged.

Learning gain η: Dampen when unstable (high curvature variance), boost when stable and learning.

Lens friction ζ: Increase if excessive switching (thrashing), decrease if stable context.

Drive weights w_i: Boost stability drives if variance high, shift to higher drives if stable.

Self-Reflection Mechanism

The **dialogue between subsystems** produces emergent self-reflection:

Executive can pose questions to Experiencer ("What would happen if we lower temperature?"). Experiencer answers by running simulation threads in Virtual Stage.

Meta-Cognition: System "knows" its own state through metrics, adjusts behavior based on self-assessment, can trigger exploratory threads proactively.

Design Principles

1. **No Central Controller**: Neither subsystem has complete control—they negotiate through metrics and parameters
2. **Separation of Timescales**: Experiencer (milliseconds–seconds), Executive (minutes–hours)
3. **Think Thermostat, Not Planner**: Executive modulates the medium (temperature, viscosity), not the motion (routing)
4. **Emergence**: Self-reflection arises from the dialogue, not from explicit programming

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2.10 Virtual Stage

Concept

Think of perception → comprehension → integration as three energetic states:

1. **Impact (perception)**: External event touches manifold, creating local disturbance
2. **Simulation (staging)**: Disturbance enters protected region where system replays possible interpretations
3. **Assimilation (integration)**: Once simulated trajectory reaches low-energy, coherent configuration, curvature changes written to global manifold

The virtual stage is where the system tests alignment between incoming pattern and existing geometry—a **"rehearsal of understanding."**

In Human Cognition

Parallels:

- Working memory / imagination = Temporary manifold copy
- Empathy = Running internal model of another's curvature/valence field
- Dreaming / mind-wandering = Offline replays to optimize curvature
- Predictive coding = Testing sensory hypotheses before committing neural updates

Within Architecture

Formalize as **transient sub-manifold**:

- Spawned when unfamiliar or high-valence event arrives
- Initially copies local curvature and valence context
- Threads explore interpretations in sandbox; energy and coherence measured
- If energy minimum acceptable → merge back (commit); if not → discard or quarantine

Benefits: Prevents global instability, provides safe zone for empathy and analogy, enables imagination/planning/counterfactuals, gives geometric handle on attention and consciousness.

Engineering Sketch

- Represent stage as ephemeral layer over manifold graph; same node IDs, independent curvature values
- Threads entering stage use copied edges; updates accumulate separately
- **Commit rule**: if $\Sigma\Delta$energy < θ and coherence > γ → apply averaged Δcurvature to parent manifold
- Visualize as lens bubble hovering above main map

SECTION 3: DESIGN LAWS & PRINCIPLES

The 15 Laws

1️⃣ Law of Locality

All computation happens in k-hop neighborhoods. Updates depend only on local context. No global operations in hot path. Defers heavy computation to offline consolidation.

2️⃣ Law of Least Action

Threads follow paths of minimal combined potential. Motion arises from gradients of energy, goal, uncertainty, and lens affinity fields. No explicit route planning.

3️⃣ Law of Coherence Conservation

Understanding = alignment without contradiction. Success measured by phase alignment of threads, not reward signals. Destructive interference signals conflict.

4️⃣ Law of Dual Dynamics

Online exploration, offline consolidation. Hot path: local, sparse, event-driven. Sleep: global re-projection, motif mining, pruning. Two complementary phases.

5️⃣ Law of Energy Efficiency

Computation cost scales with active region, not total knowledge. Sparse updates dominate. LLM calls rare (<5% of compute). Near-linear scaling in active region size.

6️⃣ Law of Transparency

Reasoning path = logged energy flow. Every decision traceable through curvature and thread trajectories. `/why` shows the geometry that led to conclusions.

7️⃣ Law of Emergence

Global structure from local rules. No central controller. Motifs, lenses, and attractors emerge from repeated local interactions following simple physics.

8️⃣ Law of Self-Similarity

Same principles at every scale. Micro-edges → edges → motifs → lenses. Each level follows similar energy minimization and coherence principles.

9️⃣ Curvature ↔ Motion Feedback Law

"Matter tells space how to curve; curvature tells matter how to move". Threads reshape curvature as they traverse. Changed curvature guides future threads. Bidirectional learning loop.

🔟 Law of Valence Modulation

Importance scales plasticity. High-valence experiences create stronger curvature changes. Learning rate η scales with valence magnitude $|V|$.

1️⃣1️⃣ Law of Motif Reuse

Frequent patterns become cached skills. Traversed subpaths promoted to motifs when consensus (≥2 threads) and energy drop exceeds margin. Enables transfer.

1️⃣2️⃣ Law of Lens Invariance

Context emerges from usage, not design. Lenses form where repeated thread traffic creates stable coordinate systems. Switching has friction but happens naturally when energy benefit exceeds cost.

1️⃣3️⃣ Law of Homeostatic Regulation

Executive shapes medium, doesn't route traffic. Temperature τ, learning gain η, friction ζ adjusted based on stability metrics. Think thermostat, not planner.

1️⃣4️⃣ Law of Quorum Commit

Truth emerges from consensus. Motifs form when multiple independent threads achieve similar low-energy trajectories. No single thread can define truth.

1️⃣5️⃣ Law of Metastability

Maintain exploration capability. Small temperature (noise) prevents deadlock in local minima. System can hop out of shallow wells to discover better configurations.

Derived Principles

Paths of Least Resistance: Threads naturally flow along high-curvature (well-learned) paths unless goal or uncertainty fields pull them elsewhere.

Information as Mass: Dense, coherent knowledge curves the manifold. Nearby threads fall along that curvature (informational gravity).

Motivation from Imbalance: Drives emerge from gradients of unmet coherence. Lower needs (stability) constrain; higher needs (creativity) expand.

Stage Before Commit: Risky or novel inputs tested in virtual stage sandbox. Only committed if energy drops and coherence rises.

The Foundation

These laws ensure:

- **Scalability**: Local operations, sparse updates
- **Interpretability**: Geometry is observable
- **Learning**: Bidirectional curvature ↔ motion feedback
- **Stability**: Homeostatic regulation prevents collapse
- **Transfer**: Motifs and lenses enable cross-domain reasoning

> **"The conductor is not a program—it's the harmony of local forces seeking coherence through minimal energy."**

SECTION 4: MATHEMATICS & ALGORITHMS

Differential-Geometry Notation Summary

- x = position in manifold (node or embedding)
- $\Phi(x)$ = potential / curvature field
- $E(x)$ = energy / surprise at location x
- $G(x)$ = goal potential field
- $U(x)$ = uncertainty field
- $V(x)$ = valence field
- $L_i(x)$ = lens affinity field for lens i
- $\rho_{info}(x)$ = information density
- $\kappa(u,v)$ = curvature on edge (u,v)

Energy and Curvature Equations

Curvature Update Rule (Plasticity)

$$\Delta \kappa(u,v) = \eta \times V \times f(\text{usage})$$

With clamps and decay:

- η = learning gain (0.01–0.1)
- V = valence magnitude

- f(usage) = activation frequency or co-occurrence strength
- Clamps: $\kappa_{min} \le \kappa \le \kappa_{max}$
- Global decay: $\kappa_t = (1 - \lambda)\kappa_{(t-1)} + \lambda \, \kappa_{update}$ ($\lambda \ll 1$)

Informational Gravity Field Equation

Poisson analogue:

$$\nabla^2 \Phi = k \, \rho_{info}$$

Where:

- k = coupling constant (0.1 – 1.0)
- $\rho_{info}(x)$ = weighted sum of activation frequency, coherence, valence

Neighbor Excitation (Local Update)

When node i activates:

$$\Delta \Phi_j = \eta \, \Phi_i \, e^{-d_{ij}/\sigma}$$

Where:

- d_{ij} = distance in manifold
- σ = fall-off radius (typically 1–3 hops)

Outlier Weighting

For rare activations (frequency < f_{thresh}):

$$\Delta \Phi_j = (1 + \beta_n) \, \eta \Phi_i e^{-d_{ij}/\sigma}$$

Where β_n = novelty multiplier (0.5 – 2.0)

Thread Policy Equations

Motion Law

Threads follow gradient of least action:

$$\dot{x} = -\nabla\big(E(x) - \alpha G(x) + \beta U(x) - \sum_i \lambda_i L_i(x)\big)$$

Where α, β, λ_i = global gain constants; lens switching friction ζ added when changing lenses

Cost Function (Discrete)

For k-hop neighborhood search:

```
cost(u, v) = distance(u, v) - α·κ(u,v) + β·novelty(v) - γ·(G(v) + U(v))
```

Where:

- distance = embedding distance or hop count
- κ(u,v) = curvature (learned weight)
- novelty = 1 / (activation_count + 1)
- G(v), U(v) = goal and uncertainty scores at node v

Lens Projection Operators

Each lens L_i defines:

- Projection operator P_i: maps manifold → lens-specific coordinates
- Local metric M_i: distance function in lens space

Total motivation field:

$$G_{total}(x) = sum_i w_i D_i(x)$$

Where D_i(x) are drive fields and w_i are dynamically adjusted weights.

Drive Weighting Function

Executive adjusts drive weights based on deficits:

```
def update_drive_weights(stability_metrics, coherence, novelty_rate):
    # If stability drops → boost low-level drives
    if curvature_variance > threshold or memory_usage > limit:
        w1, w2 *= boost_factor  # Stability, Continuity
        w5, w6 *= dampen_factor  # Creativity, Contribution
    # If stable → shift to higher drives
    elif stability_good and coherence_high:
        w4, w5, w6 *= boost_factor  # Competence, Creativity, Contribution
    return normalize(w1, w2, w3, w4, w5, w6)
```

Metrics & Observables

Energy Drop Per Cycle

$$\Delta \bar{E} = \frac{1}{N} \sum_{t=1}^{N} (E_t - E_{t-1})$$

Measure of reasoning progress. Negative = energy decreasing (learning).

Coherence

$$C = \frac{1}{|T|} \sum_{threads} \cos(\theta_{ij})$$

Phase alignment among active threads. Range: 0–1.

Path Length Improvement

$$\text{Improvement} = \frac{\text{length}_{initial} - \text{length}_{final}}{\text{length}_{initial}} \times 100\%$$

Target: ≥ 20% on repeated tasks.

Transfer Efficiency

$$\text{Reuse} = \frac{\text{edges from prior domain}}{\text{total edges in new task}} \times 100\%$$

Target: ≥ 30% edge/motif reuse on analogous tasks.

Motif Benefit

$$\text{Latency reduction} = \frac{\text{latency}_{no\_motifs} - \text{latency}_{with\_motifs}}{\text{latency}_{no\_motifs}} \times 100\%$$

Target: ≥ 15% with motifs enabled.

Termination Conditions

Thread stops when:

- Running average $\Delta E < \varepsilon$ for k consecutive steps
- Energy budget B exhausted
- Coherence begins declining

Motif committed when:

- ≥2 threads reach similar low-energy path
- Net energy drop exceeds margin M

Pseudo-Code: Thread Execution

```
def execute_thread(start, goal, lens, budget):
    x = start
    path = [x]
    energy_history = []

    for step in range(budget):
        # Compute local potential
        E = energy_field(x)
        G = goal_field(x, goal)
        U = uncertainty_field(x)
        L = lens_affinity(x, lens)

        # Find next step via gradient
        neighbors = get_k_hop_neighborhood(x, k=3)
        costs = [compute_cost(x, n, G, U, L) for n in neighbors]
        next_x = neighbors[argmin(costs)]

        # Update curvature (plasticity)
        update_curvature(x, next_x, valence, step_count)

        # Record
        path.append(next_x)
        energy_history.append(E)

        # Check termination
        if is_converged(energy_history, epsilon, window):
            break
        if reached_goal(next_x, goal, threshold):
            break

        x = next_x

    # Evaluate for motif
    if len(path) > min_length and energy_drop > margin:
        consider_motif_promotion(path)
```

```
return path, energy_history
```

SECTION 5: COGNITIVE PHYSICS EXTENSIONS

1. Temporal Dynamics: Spike-Timing

From Spikes to Curvature

Biological neurons communicate via timing—when spikes arrive matters as much as whether they arrive.

Mapping to Manifold:

- Spike train → Sequence of edge traversals
- Inter-spike interval (ISI) → Time between thread steps
- Synchrony / phase locking → Coherence between threads
- STDP window → K-hop temporal neighborhood
- Assembly activation → Motif activation

Spike-Timing-Dependent Plasticity (STDP)

Extended curvature update rule with temporal sensitivity:

$$\Delta \kappa = \begin{cases}
A_+ e^{-\Delta t / \tau_+} & \text{if } t_v > t_u \text{ (causal)} \\
-A_- e^{\Delta t / \tau_-} & \text{if } t_v < t_u \text{ (anti-causal)}
\end{cases}$$

Interpretation:

- Forward traversals (u → v) strengthen curvature
- Backward traversals weaken it
- Time window creates locality

Temporal Coding

Information encoded in timing patterns:

- **Rate code**: Average activation frequency → importance
- **Temporal code**: Precise ISIs → specific meanings
- **Synchrony code**: Co-activation → binding
- **Sequence code**: Ordered cascades → procedures (motifs)

---

2. Informational Gravity (Extended)

Beyond Distance: Field-Based Attraction

Curvature creates gravity wells that attract future threads.

Gravity Field

G(x) at point x:

$$G(x) = \sum_{e \in N(x)} \kappa(e) \cdot e^{-d(x,e)/\sigma}$$

Where:

- N(x) = edges in neighborhood of x
- σ = field decay length
- High curvature → strong attraction

Neighbor Excitation

When edge (u,v) is traversed, excite neighbors. This creates **anticipatory activation** for likely next steps.

Outlier Weighting

Novel or rare nodes get bonus:

$$\text{gravity}_{\text{outlier}} = G(x) \times \left(1 + \beta \cdot \frac{1}{1 + \text{activation\_count}}\right)$$

Encourages exploration of underused regions.

---

3. Valence Thermodynamics

Valence as Energy

Treat valence channels as thermodynamic variables:

- **Importance** = potential energy (structural)
- **Affect** = kinetic energy (emotional drive)
- **Novelty** = entropy (exploration bonus)

Energy Conservation

Total valence budget per interaction:

$$V_{total} = \sum_{channels} v_i = \text{constant}$$

Forces trade-offs:

- High novelty → lower importance budget
- High affect → more volatile paths

Temperature Analogy

Executive adjusts "temperature":

$$\tau = \frac{1}{\beta} = k_B T$$

- Low τ (cold) → exploit (follow curvature)
- High τ (hot) → explore (random walk)

Free Energy Minimization

System seeks to minimize:

$$F = E - TS$$

Where E = path energy, S = entropy (uncertainty), T = temperature

---

4. Multi-Manifold Systems

Manifold Hierarchy

Stack manifolds at multiple scales:

- **Meta-manifold**: Abstract strategies (Planning, meta-cognition)
- **Concept manifold**: Semantic concepts (Primary reasoning - current system)
- **Feature manifold**: Perceptual features (Sensory processing)

- **Motor manifold**: Action primitives (Embodied interaction)

Cross-Manifold Coherence

Threads can span levels, coordinating reasoning across scales. If uncertain at concept level, query meta-level for strategy. If needs perception, query feature level for grounding.

---

5. Quantum and Analog Analogies

Quantum Superposition

Threads as quantum walkers:

$$|psirangle = sum_i alpha_i |node_irangle$$

All paths explored simultaneously until measurement (goal reached).

Phase Coherence

Curvature encodes phase relationships:

$$kappa(u,v) leftrightarrow e^{iphi_{uv}}$$

- **Constructive interference** = high curvature
- **Destructive interference** = low/negative curvature

Entanglement

Long-range correlations without direct paths. Nodes can be "entangled" if frequently co-activated.

Analog Computation

Continuous rather than discrete:

- Curvature evolves smoothly (differential equations)
- Valence is continuous field
- No discrete time steps (event-driven)

Hardware realization: Optical or analog electronic circuits.

---

6. Randomness & Outliers

Constructive Noise

Noise isn't just disruption—it enables:

- Escape from local minima
- Discovery of novel connections
- Robustness to perturbations

Outlier Promotion

Deliberately boost rare nodes (novelty bonus for underexplored regions).

Stochastic Resonance

Optimal noise level enhances signal detection:

- Too little noise → stuck in rut
- Too much noise → random walk
- Just right → discover hidden patterns

---

7. Drives as Field Interactions

Drive Fields

Each drive creates a **vector field** over the manifold:

$$\vec{D}_i(x) = w_i \cdot \nabla \Phi_i(x)$$

Where $\Phi_i(x)$ = drive potential at location x.

Field Superposition

Total drive field:

$$\vec{D}_{total}(x) = \sum_{i=1}^6 \vec{D}_i(x)$$

Threads follow combined gradient.

Drive Interference

Conflicting drives create:

- Constructive interference → strong pull
- Destructive interference → indecision, need for executive mediation

---

Future Directions

Spike-Based Hardware

Map directly to Loihi/SpiNNaker:

- Nodes → neuron populations
- Curvature → STDP rules
- Threads → spike chains

Optical Implementation

Photonic circuits:

- Nodes → resonators
- Edges → waveguides
- Curvature → phase modulators

Hybrid Classical-Quantum

Quantum accelerators for search:

- Classical threads for local traversal
- Quantum for global motif discovery
- Best of both worlds

SECTION 6: EVALUATION & METRICS

Quantitative Metrics

Path Length Improvement

Measures convergence and habit formation

$$\text{Improvement} = \frac{\text{length}_{initial} - \text{length}_{final}}{\text{length}_{initial}} \times 100\%$$

- **Target**: ≥ 20% reduction on repeated tasks
- **Method**: Track path lengths over 10 repetitions of same query
- **Success**: Stable attractor formation

Transfer Efficiency

Measures analogical reasoning

$$\text{Reuse} = \frac{\text{edges from prior domain}}{\text{total edges in new task}} \times 100\%$$

- **Target**: ≥ 30% edge/motif reuse on analogous tasks
- **Method**: Train on Domain A, measure reuse when introduced to similar Domain B
- **Success**: Reduced time-to-competence

Motif Utility

Measures skill caching benefit

$$\text{Latency reduction} = \frac{\text{latency}_{no\_motifs} - \text{latency}_{with\_motifs}}{\text{latency}_{no\_motifs}} \times 100\%$$

- **Target**: ≥ 15% latency reduction with motifs enabled
- **Method**: Ablation study comparing with/without motif caching
- **Success**: Measurable speedup from reuse

Curvature Variance

Measures stability

- **Target**: Bounded range (no runaway growth)
- **Method**: Track σ^2 of edge curvatures over consolidation cycles
- **Success**: Edge count growth < 5% per cycle

Energy Drop Per Cycle

Measures reasoning progress

$$\Delta \bar{E} = \frac{1}{N} \sum_{t=1}^{N} (E_t - E_{t-1})$$

- **Target**: Negative (energy decreasing = learning)
- **Method**: Log energy at each thread step
- **Success**: Consistent downward trend

LLM Token Usage

Measures efficiency

- **Target**: < 5% of total compute cost
- **Method**: Track API calls vs local operations
- **Success**: Sparse, uncertainty-gated LLM use

Qualitative Metrics

Coherence Maps

Visual assessment of understanding

$$C = \frac{1}{|T|} \sum_{threads} \cos(\theta_{ij})$$

- **Range**: 0–1 (phase alignment of active threads)
- **Interpretation**: Higher = more consensus/agreement
- **Visualization**: Heat map of coherence over time

Motif Emergence

Pattern of skill formation

- **Observation**: Track new motif count over time
- **Success**: Motif library grows then stabilizes
- **Analysis**: Motifs represent learned procedures

Conversational Fluency

User experience quality

- **Metrics**: User satisfaction (Likert scale), Coherence score (BLEU-style), Clarification requests frequency
- **Target**: > 0.7 satisfaction score
- **Method**: Post-interaction surveys, automated coherence scoring

Explainability Quality

Transparency of reasoning

- **Test**: Does `/why` output match logged trajectory?
- **Method**: Human evaluation of explanation quality

- **Success**: Clear path from input → reasoning → output

Visual Analytics Templates

1. Convergence Curves

Plot: Path length vs. iteration number

- X-axis: Attempt number (1–10)
- Y-axis: Path length
- Expected: Exponential decay curve

2. Transfer Matrices

Heatmap: Domain A knowledge → Domain B performance

- Rows: Source domains
- Columns: Target domains
- Color: Reuse percentage

3. Drive Activation Stacks

Stacked area chart: Drive weights over time

- X-axis: Time / interaction count
- Y-axis: Weight w_i
- Layers: 6 drive tiers
- Pattern: Should show stability → creativity shifts

4. Energy Landscape

3D surface plot: E(x) over manifold regions

- Shows: Attractor wells, exploration peaks
- Animation: How landscape evolves with learning

5. Motif Dependency Graph

Network diagram: Which motifs build on others

- Nodes: Motifs

- Edges: Reuse/composition relationships
- Layout: Hierarchical (primitives → complex)

Benchmarks vs. Static LLMs / Vector Stores

Continual learning:

- Static LLM: ❌ No
- Vector Store: ⚠️ Append-only
- Manny Manifolds: ✅ Adaptive curvature

Interpretability:

- Static LLM: ❌ Black box
- Vector Store: ⚠️ Similarity scores
- Manny Manifolds: ✅ Observable paths

Transfer learning:

- Static LLM: ✅ Via pre-training
- Vector Store: ❌ No structure
- Manny Manifolds: ✅ Geometric analogy

Energy efficiency:

- Static LLM: ❌ High per query
- Vector Store: ✅ Low (embedding lookup)
- Manny Manifolds: ✅ Sparse local updates

Empathy / context:

- Static LLM: ⚠️ Via prompting
- Vector Store: ❌ No state
- Manny Manifolds: ✅ Valence & stage

Experimental Protocols

Convergence Test

1. Select 10 prompts across 3 topics
2. Run each 10× with minor paraphrases
3. Measure: path length, latency, edge reuse
4. **Pass if**: ≥20% improvement by attempts 7–10

Transfer Test

1. Train on Domain A until stable (plateau)
2. Introduce Domain B (analogous)
3. Measure: edge reuse in first 5 turns, time to plateau
4. **Pass if**: ≥30% reuse, plateau within 5–8 turns

Motif Utility Test

1. Run 50-turn session, mine motifs
2. Disable motifs, run 10-prompt battery
3. Enable motifs, rerun same battery
4. **Pass if**: ≥15% latency reduction with motifs

Stability Test

1. Monitor curvature variance over 100 interactions
2. Track edge count growth per consolidation
3. **Pass if**: variance bounded, growth < 5%

Logging & Reproducibility

All experiments should log:

- **Per-turn**: {intent, start/goal IDs, path, length, curvature, energy, valence, uncertainty, latency}
- **Per-session**: {convergence curves, transfer matrices, motif counts, drive activations}
- **Per-consolidation**: {edge/motif deltas, curvature stats, re-indexing metrics}

Seed all random operations for reproducibility.

Summary

Good evaluation = quantitative rigor + qualitative insight + visual clarity

Manny's metrics should demonstrate:

- Learning happens (convergence, transfer)
- Structure emerges (motifs, lenses)
- Efficiency scales (sparse, local)
- Reasoning is transparent (explainable paths)

END OF EXPORT

Total sections: 6 major sections merged

Word count: ~13,000+ words

Comprehensive coverage: Overview, complete architecture (10 subsystems), all 15 design laws, full mathematics with equations and algorithms, cognitive physics extensions (7 advanced topics), and complete evaluation framework.