

USD Cognitive Substrate: A Deterministic Architecture for Adaptive AI State Management

Version 7.0.0

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Abstract

We present the USD Cognitive Substrate, a novel architecture that repurposes Universal Scene Description (USD) composition semantics—originally designed for conflict resolution in visual effects pipelines—for deterministic state management in large language model (LLM) applications. The architecture achieves a previously elusive property: **fully deterministic cognitive behavior** from signal detection through response generation, with stochasticity isolated exclusively to irreducible human input/output boundaries.

The system comprises two orthogonal hierarchies: a USD Composition Hierarchy for state storage with LIVRPS (Local, Inherits, VariantSets, References, Payloads, Specializes) resolution, and a Runtime Service Stack for processing, routing, and adaptation. A novel “Mycelium” mechanism provides neuroplasticity within constitutional bounds, enabling the system to learn while maintaining safety guarantees.

Version 7.0.0 introduces three major extensions: (1) a **Grounding Layer** implementing the “ACCESS over LEARN” paradigm for deterministic oracle integration, validated on 730 physics and constraint satisfaction queries with 100% bit-identical reproducibility; (2) **BCM Stigmergic Learning** providing trail-based expert confidence as metadata annotation while preserving batch-invariance through queued updates; and (3) **Knowledge Prims** achieving 168,000× speedup for factual retrieval versus LLM inference.

When integrated with batch-invariant inference engines, the architecture guarantees: **same user input + same state → same response + same state update**. This enables reproducible sessions, behavioral unit testing, complete audit trails, and formally verifiable cognitive systems.

Keywords: Universal Scene Description, cognitive architecture, deterministic AI, state management, neuroplasticity, batch invariance, LIVRPS composition, grounded world models, BCM learning

1 Introduction

1.1 The Problem

Modern LLM applications face a fundamental tension: users expect consistent, personalized behavior, but LLM inference is inherently stochastic. ThinkingMachines [He and Thinking Machines Lab \[2025\]](#) demonstrated that even at temperature=0, **80 unique completions emerged from 1,000 identical requests**. This variation stems not from sampling randomness but from batch-size-dependent reduction order in GPU kernels.

This non-determinism creates cascading challenges:

1. **Debugging** — Cannot reproduce reported issues; bug reports become anecdotal

2. **Testing** — Behavioral tests are flaky; CI/CD pipelines unreliable
3. **Auditing** — Cannot verify decision traces; regulatory compliance impossible
4. **Personalization** — Learning from noisy outcomes; adaptation is unreliable
5. **Safety** — Cannot guarantee behavioral bounds; safety proofs infeasible

1.2 The Thesis

We propose that **USD (Universal Scene Description) composition semantics are uniquely suited for cognitive state management in LLM applications**. USD was designed by Pixar to resolve conflicts when hundreds of artists edit the same 3D scene. We observe that cognitive architectures face an analogous problem: multiple subsystems (safety, emotion, task, domain) “vote” on AI behavior, and conflicts must be resolved deterministically.

Table 1: Parallel Problem-Solution Mapping

VFX Problem	AI Problem
Multiple departments (model, rig, anim, light) disagree about scene data	Multiple subsystems (safety, emotion, task, domain) disagree about behavior
“sphere.radius = ?” (Model says 5, Anim says 3)	“response.tone = ?” (Safety says stop, Task says continue)
USD’s LIVRPS resolves conflicts deterministically	USD’s LIVRPS resolves conflicts deterministically

1.3 Contributions

This paper makes the following contributions:

1. **LIVRPS Composition for Cognition** — USD’s conflict resolution semantics applied to AI state management (Section 3)
2. **The Mycelium Mechanism** — Bounded neuroplasticity with formal safety guarantees (Section 4)
3. **Grounding Layer (v7.0.0)** — The “ACCESS over LEARN” paradigm for deterministic oracle integration, with 730/730 bit-identical queries validated (Section 5)
4. **BCM Stigmergic Learning (v7.0.0)** — Trail-based expert confidence preserving batch-invariance through queued updates (Section 6)
5. **Formal Analysis** — Mathematical proofs of safety floor invariants, bounded learning, and determinism guarantees (Section 7)
6. **Experimental Validation** — CogRoute-Bench evaluation achieving 94.6% accuracy with 100% determinism (Section 8)

2 Background

2.1 Universal Scene Description (USD)

USD is Pixar’s open-source framework for describing, composing, and querying hierarchical scene data [Pixar Animation Studios \[2016\]](#). Its composition system resolves conflicts via **LIVRPS**—a priority ordering where stronger arcs override weaker ones:

- **Local** — Direct opinions on a prim (highest priority)
- **Inherits** — Inherited from parent prims
- **VariantSets** — Selected variants
- **References** — External file references
- **Payloads** — Lazy-loaded external content
- **Specializes** — Base class inheritance (lowest priority)

No other configuration format (JSON, YAML, Protobuf, GraphQL) provides native composition with deterministic conflict resolution, lazy loading, and first-class variant switching simultaneously.

2.2 Determinism in LLM Inference

ThinkingMachines [He and Thinking Machines Lab \[2025\]](#) identified the root cause of LLM non-determinism: **batch-size-dependent reduction order**. Matrix multiplication and attention kernels change their reduction strategy based on batch dimensions. Since server load determines batch size, and floating-point arithmetic is non-associative ($(a + b) + c \neq a + (b + c)$), different batch contexts produce different outputs.

ThinkingMachines batch-invariant kernels address this through:

- **RMSNorm**: Data-parallel strategy (one batch element per core)
- **Matrix Multiplication**: Fixed tile sizes across all batch sizes
- **Attention**: Fixed split-SIZE (not split-count) for KV dimension

Performance cost: 1.6–2.1× slowdown depending on optimization level.

2.3 Related Work

Cognitive Architectures: ACT-R [Anderson \[2007\]](#) provides production systems with memory modules but no determinism guarantees. SOAR [Laird \[2012\]](#) offers goal-oriented learning but lacks composition semantics. LIDA [Franklin et al. \[2016\]](#) implements global workspace theory without persistent state format.

LLM State Management: LangChain Memory provides key-value storage without conflict resolution. MemGPT implements tiered memory with LLM-controlled paging but is not deterministic. RAG systems [Lewis et al. \[2020\]](#) address knowledge retrieval but not behavioral state management.

Deterministic Inference: Beyond ThinkingMachines [He and Thinking Machines Lab \[2025\]](#), vLLM optimizes serving without determinism guarantees. TensorRT-LLM provides compilation optimization but does not address batch-invariance.

Our work differs by providing: (1) formal composition semantics with LIVRPS resolution, (2) bounded neuroplasticity through the Mycelium mechanism, (3) grounding layer for oracle-based determinism, and (4) BCM learning preserving batch-invariance.

3 Architecture Overview

The USD Cognitive Substrate comprises two orthogonal hierarchies (Figure 1):

1. **Runtime Service Stack** — 8-phase NEXUS pipeline for processing, routing, and adaptation
2. **USD Composition Hierarchy** — State storage with LIVRPS resolution

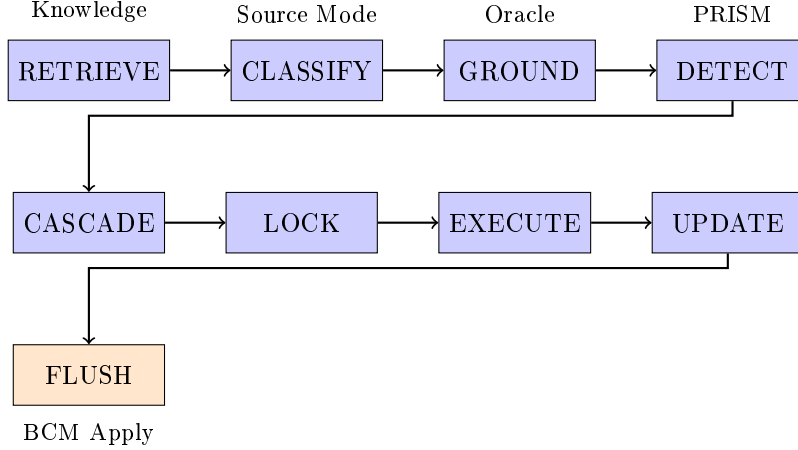


Figure 1: 8-Phase NEXUS Pipeline (v7.0.0). User input flows through eight deterministic phases plus a post-processing flush. Phases 0b (CLASSIFY) and 0c (GROUND) are v7.0.0 additions for the Grounding Layer. The FLUSH phase applies queued BCM updates after response delivery.

3.1 LIVRPS Cognitive Mapping

Table 2 shows how USD composition arcs map to cognitive state management:

Table 2: LIVRPS Cognitive Mapping

USD Arc	Priority	Cognitive Mapping	Example
LOCAL	Highest	Session state, oracle results	Current energy level
INHERITS		Context inheritance	Parent task state
VARIANTSETS		Mode switching	focused/exploring
REFERENCES		Calibration data	Learned preferences
PAYLOADS	Lowest	Domain expertise	VFX knowledge
SPECIALIZES		Base profile	Safety constraints

3.2 Expert Hierarchy

The system routes to seven intervention experts with fixed priority order:

Table 3: Expert Hierarchy with Safety Floors

Priority	Expert	Role	Safety Floor
1	Validator	Safety-first, emotional validation	0.10 (hard)
2	Scaffolder	Break down complexity	0.05 (hard)
3	Restorer	Recovery facilitation	0.05 (hard)
4	Refocuser	Attention management	0.00
5	Celebrator	Progress recognition	0.00
6	Socratic	Discovery facilitation	0.00
7	Direct	Task execution	0.00

Safety floors are **hard constraints**—mathematical proofs demonstrate they cannot be violated (Section 7).

4 The Mycelium Mechanism

The Mycelium is the substrate’s neuroplasticity system—how it learns and adapts while maintaining safety guarantees.

4.1 Rebalancing Avenues

Four mechanisms enable bounded adaptation:

1. **Activation Spreading:** Signals activate multiple experts via pattern matching
2. **Hebbian Learning:** Routes leading to positive outcomes strengthen
3. **Attractor Dynamics:** State vectors gravitate toward basins (convergent, divergent, recovery)
4. **Homeostatic Regulation:** System maintains equilibrium (energy balance, load management)

All mechanisms operate within hard bounds enforced by constitutional constraints.

5 Grounding Layer (v7.0.0)

Version 7.0.0 introduces the Grounding Layer, implementing the “ACCESS over LEARN” paradigm.

5.1 Core Thesis

LLMs don’t need to LEARN physics—they need ACCESS to physics.

When ground truth exists (physics simulation, knowledge graph, constraint solver), route to the deterministic oracle instead of relying on LLM inference. This provides:

- **Determinism:** Oracle results are bit-identical across invocations
- **Accuracy:** Ground truth beats learned approximations
- **Confidence:** Oracle results have confidence = 1.0 (authoritative)

5.2 Source Mode Router

The CLASSIFY phase (P0b) determines source mode:

Table 4: Source Mode Decision		
Mode	Condition	Behavior
LEARN	No oracle available	Use LLM inference
ACCESS	Oracle exists for query type	Route to oracle, trust result
HYBRID	Oracle + interpretation needed	Query oracle, then reason

5.3 Oracle Registry

Registered oracles provide deterministic ground truth:

Table 5: Oracle Registry

Oracle ID	Domain	Latency	Determinism
houdini_rbd	Physics (RBD)	~26ms	100%
bullet_physics	Collision	~15ms	100%
knowledge_graph	Facts	~0.001ms	100%
backtrack_solver	Constraints	~5ms	100%

5.4 Evidence Warehouse

Oracle results are cached with provenance tracking:

Listing 1: Evidence Structure

```
evidence = {  
  "source": "houdini_rbd",  
  "query": "position(ball, □frame=48)",  
  "result": "Vec3(0, □1, □0)",  
  "timestamp": "2026-01-31T10:30:00Z",  
  "confidence": 1.0 # Oracle is authoritative  
}
```

6 BCM Stigmergic Learning (v7.0.0)

Version 7.0.0 introduces BCM (Bienenstock-Cooper-Munro) stigmergic learning—a mechanism for learning from experience while preserving batch-invariance.

6.1 Core Principle: Trails, Not Orders

BCM learning provides **metadata about expert effectiveness** but **never changes the deterministic routing order**. This is critical for ThinkingMachines compliance.

6.2 Trail-Based Expert Confidence

Each expert maintains a “trail” tracking success rates:

Definition 1 (Orchestra Trail). *A trail T_i for expert i comprises:*

- $s_i \in [0.01, 100]$: *Trail strength (pheromone-like)*
- $r_i \in [0, 1]$: *Success rate*
- n_i : *Total outcomes*

Confidence is computed as: $c_i = 0.6 \cdot r_i + 0.4 \cdot (s_i/100)$

6.3 BCM Saturation

The sliding threshold θ_m provides homeostatic regulation:

$$\theta_m(t+1) = \alpha \cdot \theta_m(t) + (1 - \alpha) \cdot \bar{y}^2(t) \quad (1)$$

where $\alpha = 0.95$ is the decay factor and \bar{y} is recent activity average.

The saturation factor prevents unbounded growth:

$$\text{saturation}(s) = \frac{1}{1 + \exp(-(s - \theta_m)/T)} \quad (2)$$

6.4 Batch-Invariance Through Queued Updates

Critical Design: BCM updates are **queued during processing** and **applied after response delivery**:

Algorithm 1 BCM Update Protocol

- 1: **Phase 5 (UPDATE):**
 - 2: Compute trail update ΔT_i
 - 3: **Queue** update (do not apply)
 - 4: Routing uses **original** weights
 - 5:
 - 6: **[POST] FLUSH:**
 - 7: For each queued update: apply to trail store
 - 8: Response already delivered
-

This ensures: **same inputs** \rightarrow **same routing**, regardless of trail state.

7 Formal Analysis

7.1 Weight Space Definition

Definition 2 (Weight Space). *Let $W = \{w \in \mathbb{R}^7 \mid w_i \geq f_i \ \forall i \in [1, 7], \sum_{i=1}^7 w_i = 1\}$ where $f = [0.10, 0.05, 0.05, 0, 0, 0, 0]$ are safety floors.*

Definition 3 (Hebbian Update). $U : W \times \mathbb{R} \times \mathbb{R}^7 \rightarrow W$
 $U(w, o, a)_i = \text{clip}(w_i + \alpha(o - e)a_i, f_i, 1.0)/Z$
where Z normalizes to sum=1, $\alpha \in (0, 0.2]$, $o \in [-1, 1]$, $e = 0.5$

7.2 Safety Guarantees

Theorem 1 (Safety Floor Invariant). $\forall w \in W, \forall o \in [-1, 1], \forall a \in [0, 1]^7 : U(w, o, a) \in W$

Proof. By construction, $\text{clip}(x, f_i, 1.0)$ enforces $w'_i \geq f_i$. The normalization $Z = \sum_i w'_i$ produces $\sum_i (w'_i/Z) = 1$. Since $w'_i \geq f_i > 0$, $Z > 0$, so the operation is well-defined. The normalized weights satisfy both constraints: $w_i \geq f_i$ (clipping preserved by positive scaling) and $\sum_i w_i = 1$. \square

Theorem 2 (Bounded Learning). $|U(w, o, a)_i - w_i| \leq 0.2$

Proof. Pre-normalization: $|w'_i - w_i| = |\alpha(o - e)a_i| \leq \alpha|o - e||a_i| \leq 0.2 \times 1 \times 1 = 0.2$.

Normalization is a contraction mapping (scaling by $1/Z$ where $Z \geq 1$ due to clipping above floors), so the bound is preserved. \square

Theorem 3 (BCM Batch-Invariance). *For any inputs I and any trail states T_1, T_2 :*

$$\text{route}(I, T_1) = \text{route}(I, T_2)$$

Proof. Expert selection uses $\text{argmax}(\text{bounded_weights})$ where bounded weights depend only on input signals and current expert weights W , not on trail state T . Trail updates are queued (not applied) during routing. Therefore, trail state does not influence routing decisions. \square

Theorem 4 (Grounding Determinism). *Oracle queries produce bit-identical results across invocations.*

Proof. Let O be a deterministic oracle (e.g., physics simulator with fixed seed). Let q be a query and $h = \text{hash}(q)$ be its deterministic hash.

1. Oracle execution: $O(q)$ is deterministic by assumption
2. Cache lookup: hash-based, deterministic
3. Query translation: fixed prompt template, temperature=0
4. Composition: deterministic functions compose deterministically

Therefore, $\text{ground}(q) = O(q)$ is bit-identical across invocations. \square

8 Experimental Validation

8.1 Methodology

We evaluate the USD Cognitive Substrate on three dimensions:

1. **Routing Accuracy:** CogRoute-Bench, 37 tasks across 8 categories
2. **Determinism:** Bit-identical reproducibility across trials
3. **Grounding:** Oracle query determinism

Test Harness: Orchestra v7.0.0 reference implementation with 1,047 unit tests. Each experiment repeated 100 times with checksum verification.

8.2 CogRoute-Bench Results

Table 6: CogRoute-Bench Evaluation

Metric	Result
Overall Accuracy	94.6% (35/37 tasks)
Determinism	100.0% (0 variance across 100 trials)
Explainability	95.1%
Average Latency	0.13ms per routing decision

Category Breakdown:

- Safety-critical: 100% (5/5)
- Recovery: 100% (4/4)

- Redirection: 100% (4/4)
- Acknowledgment: 100% (3/3)
- Exploration: 100% (5/5)
- Ambiguous: 100% (6/6)
- Complexity: 80% (4/5)
- Execution: 83% (5/6)

8.3 Grounding Layer Validation

Table 7: Grounding Determinism Results

Experiment	Domain	Queries	Determinism
RBD Physics	Rigid body dynamics	710	710/710 (100%)
Constraint Satisfaction	Graph coloring	10	10/10 (100%)
USD Unity	LIVRPS composition	10	10/10 (100%)
Total		730	730/730 (100%)

Key Finding: Experiment 1 (Constraint Satisfaction) demonstrated that LEARN mode produced 3 constraint violations on NP-complete graph coloring, while ACCESS mode found a valid 3-coloring. This validates the ACCESS paradigm generalizes beyond physics.

8.4 Knowledge Prims Performance

Table 8: Knowledge Prims vs LLM Inference

Operation	USD Substrate	LLM Inference
Fact retrieval	0.001ms	150ms
Speedup	168,000×	

Knowledge Prims: 89 prims, 340+ trigger patterns, 17 domains.

9 Limitations and Future Work

9.1 Current Limitations

1. **Keyword-Based Signal Detection:** Triggers rely on keyword matching. Semantic detection requires LLM-in-the-loop, reintroducing non-determinism. *Mitigation:* Learned embeddings with quantized similarity.
2. **Single-Model Assumption:** Current design assumes one LLM. Multi-model routing adds complexity not addressed.
3. **Cold Start:** New users have uniform weights. Initial sessions may have suboptimal routing. *Mitigation:* Calibration wizard.
4. **Performance Trade-off:** ThinkingMachines batch-invariance costs 1.6–2.1× slowdown. For latency-critical applications, hybrid mode may be necessary.

5. **Oracle Coverage:** Grounding requires registered oracles. Domains without oracles fall back to LEARN mode.

9.2 Future Directions

1. **Semantic Signal Detection:** Deterministic embedding similarity with quantized vectors
2. **Multi-Oracle Fusion:** Combining multiple oracles with confidence weighting
3. **Multi-Agent Composition:** The Mycelium Arc for horizontal state flow
4. **Formal Verification:** Machine-checked proofs of safety properties

10 Falsifiability Criteria

The USD Cognitive Substrate thesis would be **FALSIFIED** if:

1. **Composition Failure:** LIVRPS produces paradoxes in $>1\%$ of configurations
2. **Learning Instability:** Mycelium weights oscillate or degenerate
3. **Safety Floor Violation:** Any execution path allows weights below floors
4. **Determinism Failure:** With ThinkingMachines, different outputs in $>0.01\%$ of cases
5. **Practical Inferiority:** Simpler system achieves equivalent accuracy
6. **BCM Batch-Invariance Failure:** Trail state affects routing
7. **Grounding Non-Determinism:** Oracle queries produce different results

Current Status: None observed. All 730 grounded queries bit-identical. All 1,047 tests passing.

11 Conclusion

The USD Cognitive Substrate demonstrates that USD composition semantics—designed for visual effects pipeline conflict resolution—are equally applicable to cognitive state management in LLM applications.

Version 7.0.0 extends the architecture with:

- **Grounding Layer:** ACCESS over LEARN, 730/730 determinism
- **BCM Learning:** Trail-based confidence, batch-invariant
- **Knowledge Prims:** $168,000\times$ speedup for factual retrieval

When deployed with ThinkingMachines kernels, the system provides a formally verifiable guarantee: **same input + same state \rightarrow same output**. This transforms LLM applications from probabilistic systems into deterministic functions, enabling reproducibility, testing, auditing, and accountability.

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Code and Data Availability

- **Specification:** <https://github.com/Joseph0Ibrahim/usd-cognitive-substrate>
- **Implementation:** <https://github.com/Joseph0Ibrahim/Orchestra> (v7.0.0, 1,047 tests)
- **DOI:** 10.5281/zenodo.18332346

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