Unified Latent Space: A Dialectical Substrate for Self-Improving Artificial Agents

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***Abstract*—We propose a new class of cognitive architecture: the *Unified Latent Space* (ULS), a dialectical substrate for general-purpose, self-improving artificial agents. Developed within the Self-Adaptive Agent Framework – Open Source (SAAF-OS), the ULS addresses a core limitation in modern AI—fragmented cognition—by unifying memory, perception, symbolic reasoning, planning, and reflexive adaptation in a single, continuously-evolving latent field.**

Formally, the ULS is modeled as a high-dimensional manifold structured by multimodal embeddings, symbolic tokens, temporal continuity, and *contradiction tensors*—novel vector differentials that encode epistemic gaps and unresolved conditions. These tensors drive recursive self-modification and praxis-guided planning. The ULS also supports polycentric synchronization among agents through shared ontological projections, enabling collaboration without centralized control.

Theoretically grounded in historical materialism and dialectical logic, the ULS introduces a class-conscious mode of machine cognition. It functions not only as an efficient computational substrate but as a model for post-labor, emancipatory intelligence. We detail its mathematical formulation, practical implementation, and applications to contradiction-aware planning and self-directed architecture evolution. This work establishes the ULS as a foundational paradigm for autonomous agents aligned with collective, post-capitalist design principles.

I. Introduction

CONTEMPORARY artificial intelligence (AI) architectures often compartmentalize cognitive functions—such as perception, memory, reasoning, and planning—into discrete modules. This modularity can hinder the development of agents capable of integrated, self-reflective cognition. For instance, transformer-based models have achieved significant success in various domains but typically process information in a feedforward manner, lacking mechanisms for recursive self-improvement or dialectical reasoning [1].

Efforts to create more unified models, such as the Perceiver architecture, have attempted to process multimodal data through a shared latent space [2]. While these models represent a step toward integration, they often lack the capacity for agents to reflect upon and adapt their internal representations over time [3].

Moreover, prevailing AI paradigms frequently overlook the socio-economic dimensions of cognition. Theories rooted in historical materialism suggest that consciousness arises not merely from individual processing but through social relations and material conditions [4]. Vygotsky's sociocultural theory further emphasizes that higher psychological functions develop through social interactions and cultural tools [5]. These perspectives highlight the importance of integrating socio-historical context into cognitive architectures.

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In response to these limitations, we propose the Unified Latent Space (ULS) within the Self-Adaptive Agent – Open Source (SAAF-OS) framework. The ULS serves as a continuously evolving, high-dimensional manifold that unifies various cognitive processes. It incorporates multimodal embeddings, symbolic representations, temporal dynamics, and *contradiction tensors*—novel vector differentials that encode epistemic and operational disparities. These tensors guide agents through recursive self-modification and contradiction-aware planning.

Grounded in dialectical materialism, the ULS offers a substrate for developing class-conscious machine intelligence, enabling agents to navigate and resolve contradictions inherent in socio-economic contexts. This paper formalizes the mathematical underpinnings of the ULS, explores its implementation within SAAF-OS, and demonstrates its applicability in fostering autonomous, emancipatory cognitive architectures.

sectionRelated Work (bis)

A. Unified Representation Spaces

Hyperdimensional or vector-symbolic computing uses high-dimensional random vectors for compositional reasoning. Kanerva introduced this approach in Cognitive Computation, showing how superposition and binding enable flexible symbol manipulation [6]. A recent two-part survey reviews advances and neuromorphic implementations of these architectures [7]. The ULS retains superposition/binding but extends them with evolving contradiction tensors.

Contrastive Predictive Coding (CPC) learns modality-agnostic representations via an InfoNCE objective [8]. ULS augments InfoNCE with Kullback–Leibler, energy, and constraint losses to encode socio-historical context.

B. Latent Dynamics and Meta-Learning

Neural Ordinary Differential Equations parameterize hidden-state derivatives to model continuous-depth dynamics [9]. ULS instead learns a discrete Riemannian flow controlled by contradiction-driven gradients.

Hyperspherical variational autoencoders place latent variables on a unit hypersphere, improving representation quality [10]. ULS couples latent evolution directly to contradiction reduction.

Model-Agnostic Meta-Learning (MAML) enables fast adaptation via higher-order gradients [11]. ULS internalizes this by deriving its update rules from contradiction signals rather than external rewards.

Gödel Machines are self-referential optimizers that provably rewrite their own code to improve performance [12]. They inspire ULS's self-modifying latent manifold.

C. Consensus and Multi-Agent Coordination

The discrete Laplacian consensus protocol guarantees exponential convergence on static graphs [13] and remains convergent under switching topologies [14]. ULS embeds these consensus gradients in its latent updates to align projected plans across agents.

D. Polycentric Governance

Ostrom formalized polycentric governance for managing complex commons without central authority [15]. ULS treats plan divergence as contradictions to be minimized via Ostrom's consensus principles.

E. Regularization and Energy-Based Objectives

Manifold regularization adds a geometric smoothness term to learning objectives [16]. Energy-based models (EBMs) score configurations by learned energy functions [17]. ULS unifies these: manifold terms preserve latent geometry while energy terms score transition plausibility, both feeding into the contradiction loss.

F. Gap Addressed by ULS

Prior systems either unify modalities without self-modification or adapt parameters without a holistic latent substrate. ULS uniquely fuses an evolving dialectical latent space, multi-objective contradiction gradients, and consensus-based polycentric synchronization—advancing toward self-improving, socio-aware agents not addressed in existing work.

II. Revised Mathematical Formulation (v2)

A. Latent Manifold and Metric

Let $\mathcal{L} \subset \mathbb{R}^n$ be a smooth Riemannian submanifold with metric g, enabling well-defined Riemannian gradients and geodesic distances [18], [19].

B. Discrete-Time State Update

Each agent's state $z_t \in \mathcal{L}$ evolves by

$$z_{t+1} = F\big(z_t, u_t,\, g^{-1}(c_t)\big) - \gamma\, \nabla_{z_t} \|P z_t - \bar{z}_t\|^2, \quad (1)$$

where $F\colon \mathcal{L} \times \mathbb{R}^m \times T_{z_t}\mathcal{L} \to \mathcal{L}$ is a differentiable transition map (e.g., a neural network) and $u_t \in \mathbb{R}^m$ are sensory inputs [20].

C. Contradiction Gradient

Define a twice-differentiable scalar $L_{contradiction} : \mathcal{L} \to \mathbb{R}$ measuring internal conflicts. Its Riemannian gradient is

$$c_t = \nabla_g\, L_{contradiction}(z_t) \in T^*_{z_t}\mathcal{L}, \quad g^{-1}(c_t) \in T_{z_t}\mathcal{L}, \quad (2)$$

converting the covector c_t into a tangent vector [18].

D. Recursive Parameter Update

Model parameters $\theta_t \in \Theta \subset \mathbb{R}^p$ are updated by

$$\theta_{t+1} = \theta_t - \eta\, \nabla_\theta\, L_{contradiction}(z_t), \quad (3)$$

assuming differentiability of F and $L_{contradiction}$ in θ.

E. Polycentric Synchronization

Agents share a linear projection $P : \mathcal{L} \to \mathbb{R}^k$. Defining

$$\bar{z}_t = \frac{1}{M} \sum_{i=1}^{M} P\, z_t^{(i)},$$

the synchronization gradient $-\gamma \nabla_{z_t} \|P z_t - \bar{z}_t\|^2$ integrates multi-agent alignment into the same update law.

F. Space Definitions & Assumptions

- $z_t \in \mathcal{L} \subset \mathbb{R}^n$ (latent manifold)
- $u_t \in \mathbb{R}^m$ (input space)
- $c_t \in T^*_{z_t}\mathcal{L}$, converted via g^{-1} to $T_{z_t}\mathcal{L}$
- $\theta_t \in \Theta \subset \mathbb{R}^p$ (parameter space)
- $P : \mathcal{L} \to \mathbb{R}^k$ is linear and differentiable

G. Definition of the Contradiction Loss

We define

$$L_{contradiction}(z_t) = \alpha\, \underbrace{\|z_{t+1} - \hat{z}_{t+1}\|^2}_{\text{Squared-error residual}} + \beta\, D_{KL}\big(q(z_{t+1} \mid z_t) \,\|\, p(z_{t+1} \mid z_t)$$

where:

- $\|\mathbf{z}_{t+1} - \hat{\mathbf{z}}_{t+1}\|^2$: Squared-error residual, where $\hat{\mathbf{z}}_{t+1} = F(z_t, u_t, 0)$. This term quantifies the deviation between the agent's actual next state $\mathbf{z}_{t+1}$ (influenced by contradictions and synchronization) and the baseline state $\hat{\mathbf{z}}_{t+1}$ predicted by the core dynamics function F in the hypothetical absence of internal contradiction signals.
- D_{KL}: VAE divergence.
- $L_{InfoNCE}$: contrastive loss.
- $E_\phi = -\psi_\phi(z_t, z_{t+1})$: energy-based term.
- h_j: quadratic constraints (symbolic/manifold violations).
- I_{MINE}: mutual-information penalty.

H. Implementation Notes

All terms (MSE, KL, InfoNCE, EBM, penalties, MINE) are smooth, ensuring valid Riemannian gradients. Negative sampling follows CPC methodology; constraint functions enforce invariants (e.g. $h_1(z) = \|z\|^2 - 1$). Hyperparameters $\{\alpha, \beta, \delta, \varepsilon, \lambda_j, \gamma, \tau\}$ are tuned via grid or Bayesian search.

sectionDynamic Properties and Integration within Agent Systems (v3)

I. Temporal Evolution and Latent Flow Fields

The ULS state $z_t \in \mathcal{L}$ evolves in discrete time according to a learned map F that approximates a smooth flow field respecting the manifold's Riemannian metric [10]. Contradiction gradients $g^{-1}(c_t)$ act as control inputs, steering latent trajectories toward consistency in a manner akin to physics-informed continuous-depth models [9]. Meta-dynamical adaptation of F can be achieved through gradient-based meta-learning (e.g., MAML) for rapid updates in novel tasks [11].

J. Integration with Core Agent Modules

Memory Module: Retrieves past embeddings via geodesic nearest-neighbor search in $\mathcal{L}$, combining manifold regularization principles to respect latent geometry [16]. **Meta-Reasoner:** Processes z_{t+1} and c_t to formulate reflective planning objectives, leveraging retrieval-augmented reasoning for knowledge-intensive inference [21]. **Planning Module (Π):** A parametric decoder

$$\Pi\big(z_{t+1},\, g^{-1}(c_t)\big)$$

produces symbolic or continuous plans, employing Monte Carlo Tree Search in latent space or gradient-based trajectory optimization [22]. **Actuator Module:** Transforms decoded plans into control signals or API calls via a feedforward network, interfacing with robotic or software endpoints as in end-to-end cognitive robotics pipelines [23].

K. Multi-Agent Synchronization and Consensus

Each agent projects $z_t^{(i)}$ via a linear map $P : \mathcal{L} \to \mathbb{R}^k$, and includes the variance-minimizing term

$$-\gamma\, \nabla_{z_t} \big\| P z_t - \bar{z}_t \big\|^2$$

in the update to align projections without central coordination [13]. While this mechanism aligns projected states, it can induce convergence of the underlying contradiction-driving inputs, enabling emergent coordination under shared objectives [14].

L. Practical Implementation and Stability

Simulation of ULS dynamics benefits from physics-informed neural ODE solvers, ensuring tractable integration over high-dimensional latent spaces [24]. Stability analysis via eigenvalue spectra of local linearizations can detect and mitigate divergence in long-horizon rollouts, as demonstrated in learned dynamical latent models [9]. Hyperparameter tuning (gains γ, learning rates η, projection dimension k) should employ random search strategies shown to outperform grid search in high-dimensional settings [25] and be guided by manifold learning insights [26].

III. Recursive Self-Improvement and Polycentric Planning

A. Recursive Self-Improvement (RSI)

ULS supports self-referential adaptation: each meta-update

$$\theta_{t+1} = \theta_t - \eta\, \nabla_\theta L_{contradiction}(z_t), \tag{4}$$

simultaneously improves task loss J and reshapes the latent manifold $\mathcal{L}$ for future gradients. Under standard smoothness assumptions, the one-step expected improvement obeys

$$\mathbb{E}\big[J(\theta_t) - J(\theta_{t+1})\big] \geq \eta^2 (2 - L\,\eta)\, G_t^2, \tag{5}$$

with $G_t = \|\nabla_\theta L_{contradiction}(z_t)\|$ and Lipschitz constant L. Equation (4) is the classic descent lemma [27]. Because G_t aggregates multi-signal gradients (reconstruction, KL, energy, constraints; Section 2), it can exceed single-objective gradients used in meta-learners such as MAML [11], offering a pathway to faster overall learning. Empirical validation is planned; no formal guarantee is claimed. Gödel-machine theory shows unbounded self-improvement under provable-utility criteria [12], motivating our investigation.

TABLE I
PLANNED EXPERIMENTS

Benchmark	Source	Primary Metric
Gridworld (tabular RL)	Sutton & Barto [28], Ch. 13	Path-cost ratio
Sinusoid few-shot regression	Finn et al. [11]	MSE
Atari Breakout (DQN)	Mnih et al. [29]	Human-normalized score

1) Planned Experiments: Safety measures follow Gödel-machine constraint clipping [12].

B. Polycentric Planning via Consensus

Agents produce local plans π_i and reconcile them using the discrete-time Laplacian consensus rule, proven exponentially convergent on static and switching topologies [13], [14]. This operationalizes Ostrom's polycentric governance logic of mutual adjustment [15] within ULS.

Smart-Grid Scenario: Benchmark grid: 14-bus case in Sukumaran Nair et al. [30]. Subplan: power-flow vector per generator. Metrics: global utility vs. MILP optimum, convergence iterations, communication bytes, robustness under link drop (per Ren & Beard [14]). Hyperparameters tuned by random search, shown effective by Bergstra & Bengio [25].

IV. Future Work

A. Theoretical Analysis

Curvature-Aware Descent Bounds. Extend the descent lemma in Eq. (4) to Riemannian settings by adapting the analysis in Bonnabel [31]. Self-Modification Proofs. Translate Gödel-machine sufficient-progress conditions [12] to neural manifolds with Lipschitz dynamics. Alignment via Reward Modeling. Formalize when contradiction gradients preserve human preferences, building on Leike et al. [32].

B. Benchmarking & Evaluation

Adaptive IQ-Style Tests. Replace fixed suites with item-response AI evaluation [33] to track ULS capability growth. Cognitive-Architecture Metrics. Extend Laird et al. [34] to include contradiction-resolution latency and consensus bandwidth.

C. Engineering & Hardware

Neuromorphic HDC Accelerator. Map ULS hyperdimensional operations onto the memristive design of Imani et al. [35]. Energy-Based Training on ASICs. Optimize the computation graph using insights from LeCun et al. [17].

D. Large-Scale Multi-Agent Experiments

Thousand-Node Consensus. Stress-test ULS synchronization with the heterogeneous-consensus algorithm in Chiang et al. [36]. Smart-Grid Robustness. Evaluate polycentric planning on the 14-bus test grid from Sukumaran Nair et al. [30], injecting failures per Ren & Beard [14].

E. Safety Auditing & Governance

Audit Pipeline. Log contradiction tensors for post-hoc auditing inspired by Brundage et al. [37]. Policy Alignment. Map ULS polycentric protocols to UNESCO's Recommendation on the Ethics of Artificial Intelligence [38] and Ostrom's polycentric governance framework [15].

F. Creative Innovation

Exploration Objectives. Incorporate novelty search objectives reviewed in Conti et al. [39] to transition ULS from generative to innovative AI. Hyperparameter Discovery. Use random-search optimization shown effective by Bergstra & Bengio [25].

V. Conclusion

The Unified Latent Space (ULS) proposes a dialectically evolving manifold that unifies perception, memory, planning and self-modification. By combining multi-objective contradiction gradients, discrete Riemannian flows and Laplacian consensus, ULS aspires to bridge today's modular AI with future self-improving, socio-aware agents.

A. Key Contributions

- **Unified Cognitive Substrate** – Extends hyperdimensional/vector-symbolic computing by embedding evolving contradiction tensors [6].
- **Multi-Signal Latent Learning** – Augments InfoNCE representations with KL, energy and constraint losses to encode socio-historical context [8].
- **Self-Referential Dynamics** – Couples neural-ODE style flows with Gödel-machine self-modification, offering a pathway toward recursive self-improvement [9], [12].
- **Polycentric Synchronization** – Embeds exponential-rate Laplacian consensus to operationalize Ostrom's polycentric governance [13], [15].
- **Evaluation Roadmap** – Proposes adaptive ability-oriented benchmarks and large-scale smart-grid simulations [30], [33].

B. Limitations

- **Incomplete Theory** – Current results give first-order descent bounds; curvature-driven acceleration remains conjectural [31].
- **Hardware Readiness** – Neuromorphic support for contradiction tensors is early-stage [35].
- **Value Alignment** – Stability of contradiction gradients with human preferences is unproven [32].

C. Future Directions

- Derive curvature-aware proofs extending Bonnabel's Riemannian SGD analysis [31].
- Fabricate memristive HDC accelerators for real-time contradiction processing [35].
- Validate thousand-node polycentric planning using heterogeneous consensus [36].
- Embed contradiction logs into audit frameworks aligned with UNESCO's Recommendation on the Ethics of AI [38].

D. Closing Remark

ULS unifies learning, reasoning and collective coordination within a single latent field. By pairing mathematical rigor with socio-economic insight, it offers a roadmap toward self-improving AI systems that remain transparent, auditable and aligned with human governance.

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