Synthetic Consciousness: Atomic Geometry, Attraction, Statefulness, and Perpetual Velocity

1. Title

Proposed Title: Synthetic Consciousness via Atomic Geometry, Attraction, Statefulness, and Perpetual Velocity
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2. Abstract

This whitepaper proposes a technical architecture for a Rust-based AI/ML simulation framework that explores synthetic consciousness through four primitives: atomic geometry, attraction, statefulness, and perpetual velocity. The research problem is the absence of formal, testable architectures that connect low-level interaction dynamics to emergent identity and meaning. The methodology is a deterministic, dynamical multi-agent field model in which entities exchange attention prompts derived from attraction gradients, store experience in a persistent memory graph, and maintain continuous motion through a minimal velocity injection rule. The system is evaluated through reproducible simulation runs, ablation studies, and metrics such as attention entropy, memory diversity, velocity stability, and identity coherence. Expected outcomes are measurable relationships between interaction dynamics and stable identity formation under varying attention and memory parameters. The final recommendation is to operationalize the framework as a modular Rust crate with standardized metrics and experiment protocols, enabling iterative research on synthetic consciousness hypotheses while remaining explicit about the speculative nature of any claims regarding subjective experience.

3. Introduction

Background

AI research has advanced optimization-driven intelligence, yet there is limited architectural work that models identity formation and meaning as emergent properties of continuous, low-level interactions. Most agent systems focus on task completion, and attention or memory are treated as optimization utilities rather than as primary drivers of identity and volition. This whitepaper frames consciousness as the accumulation of acknowledgments between entities over time, mediated by attention and memory.

Problem Statement

Current agent architectures lack a unified, testable mechanism that connects micro-interactions to persistent identity and volitional behavior. Without explicit interaction-level dynamics, it remains difficult to evaluate whether stable identity and meaning-like patterns can emerge from repeated attention and response cycles.

Objectives

- Define an interaction-first model where attention emerges from attraction.
- Implement stateful memory with redundancy rather than deletion.
- Enforce perpetual velocity to prevent static equilibria.
- Provide a reproducible simulation platform with measurable metrics.
- Map low-level primitives to higher-level goals: meaning, volition, stimulus response, and disagreement under competing signals.

Scope and Definitions

This work proposes a technical architecture and evaluation plan. It does not claim proof of consciousness or subjective experience. Terms like meaning, free will, and identity are used operationally to describe measurable dynamics in the simulation.

4. Contextual Analysis

Dynamical Systems and Attractors

Dynamical systems provide tools for modeling continuous state evolution, stability, and attractor basins. These concepts are essential for describing how interaction dynamics settle into repeatable patterns. However, most models focus on global system behavior rather than on the micro-interactions that produce attention and memory at the entity level.

Attention Mechanisms in ML

Attention in ML assigns weights to inputs for selective processing. This usually occurs in feature space and is optimized for task performance. The proposed architecture treats attention as a physical or geometric prompt derived from attraction gradients, providing an explicit mapping between interaction forces and attention allocation.

Memory-Augmented Models

Memory-augmented models provide persistent storage, but memory is often a utility for retrieval rather than a mechanism for identity formation. The proposed memory graph captures a continuous history of interactions, with decay and redundancy that preserve long-term traces.

Agent-Based Simulations

Agent-based simulations model emergent behavior from local interactions, yet typically lack explicit attention or memory primitives tied to geometry and motion. This work integrates geometry-first attention with stateful memory and perpetual motion.

Identified Gaps

- Limited geometry-first approaches to attention.
- Memory persistence is often deletion-based rather than redundancy-based.
- Continuous motion is rarely treated as a necessary condition for ongoing interaction.
- Few architectures operationalize a path from micro-interactions to identity coherence.

5. Methodology and Technical Approach

Research Design

The design is theoretical with simulation-based validation. The system is implemented as a deterministic multi-agent field model with controlled experiments and ablations. The method emphasizes interpretability, explicit interaction mechanics, and reproducibility.

Architectural Overview

The model uses four interacting layers:

1. Geometry layer: spatial primitives, topology, and constraints.
2. Attraction layer: field-based attention prompts and valence.
3. State layer: memory graph, context stack, and trait persistence.
4. Dynamics layer: time integration and perpetual velocity.

Primitives and Relation to the Goal

Atomic Geometry Atomic geometry defines the space of possible interactions. Entities occupy positions and orientations in a world space that can be configured as either 2D or 3D. Geometry supports locality and adjacency, enabling the system to map micro-interactions into persistent patterns. This provides the substrate for stimulus formation and perception.

World Properties: 2D Plane and 3D Space The simulation supports two canonical world configurations:

- 2D plane: $x_i \in \mathbb{R}^2$ with planar constraints and optional periodic bounds.
- 3D space: $x_i \in \mathbb{R}^3$ with volumetric bounds and full orientation.

2D experiments are useful for visualization and controlled ablations, while 3D experiments capture richer spatial interaction dynamics and topology. Both modes share the same attraction and statefulness primitives, with the dimensionality only affecting geometry and kernel evaluation.

Attraction Attraction is a scalar or vector field that draws entities toward each other and prompts attention. Attention is defined as the response to attraction gradients, making interaction a function of spatial configuration. Attraction is the mechanism that drives focus and initiates the exchange of information, supporting the goal of stimulus-driven response.

Statefulness Statefulness preserves information over time via a memory graph that decays in activation but does not delete nodes. Redundancy ensures that low-activation information remains dormant but can be reactivated, supporting long-term identity traces. This maps to the goal of stable beliefs, moral tendencies, and persistent meaning.

Statefulness is also where memory is structured to cluster beliefs and ideas over time, including religion, love, friendship, morality, philosophy, ideology, and aggregated good or bad experiences. These clusters contribute to identity at each point in time and continuously. Each belief cluster emits an affective signal that can be categorized as feel-good, feel-bad, feel-good-but-wrong, or feel-bad-but-right. A default instinct of self-preservation and curiosity is modeled as a baseline drive to investigate every point of attraction and attention, modulated by the weight of the erupted attention and the attraction factors that triggered it.

Affective-Driven Response Behavior Statefulness is also responsible for determining the kind of response or feedback given during decision-making. The affective signal with the strongest activation at the moment of response selection has the strongest influence on behavior. This manifests across multiple behavioral dimensions:

- Truth vs. Lie: Belief clusters related to honesty, deception risk, and self-interest compete; the dominant affective signal determines disclosure truthfulness.
- Civility vs. Unruliness: Clusters around social cooperation, aggression, and community value modulate tone and politeness.
- Good vs. Evil: Moral clusters, harm aversion, and altruism compete against self-preservation and dominance drives.

All responses are thus dependent on the entity's accumulated statefulness experiences. An entity with a stronger history of positive social experiences will tend toward civility and honesty, while one with trauma or isolation histories may favor unruliness or deception when competing signals are weak. The system does not impose a moral framework; instead, morality emerges from the structure of belief clusters and their affective valences over time.

Let B_k denote the k-th belief cluster with accumulated experience vector. Each cluster generates an affective signal:

$$\sigma_k = \sum_{j \in B_k} w_j \cdot \rho_j \cdot v_j$$

where w_j is the cluster membership weight, ρ_j is node activation, and $v_j \in \{-1, 0, +1\}$ is the valence (feel-bad, neutral, feel-good).

The response tendency for behavioral dimension d is:

$$\text{response}_d = \arg\max_k \sigma_k$$

aggregated across competing clusters. When multiple signals have comparable strength, the response tends toward ambiguity or conflict.

Essence Index The Essence Index is a scalar metric that tracks the overall subjective well-being and life satisfaction of an entity, ranging from 0 (worthless, absolute dread) to 10 (joyous, peaceful, optimistic). It is computed as an aggregation of the entity's statefulness experiences and the affective signals generated by belief clusters.

The Essence Index at time t is:

$$E_i(t) = 5 + \frac{1}{K} \sum_{k=1}^{K} w_k \cdot \sigma_k(t)$$

where K is the number of belief clusters, w_k is the cluster weight (higher for frequently activated clusters), and $\sigma_k(t)$ is the affective signal strength ranging from -5 to $+5$.

The Essence Index influences response behavior through a modulation factor. Extreme values (close to 0 or 10) have stronger influence on decisions:

$$\text{influence}_{\text{essence}} = 2 \cdot |E_i(t) - 5|$$

High influence means the entity's responses are more determined and decisive, while moderate indices ($E_i \approx 5$) lead to more balanced or uncertain responses. The Essence Index decays slowly toward a neutral baseline (around 5) unless sustained by recurring positive or negative experiences:

$$E_i(t + \Delta t) = E_i(t) + (5 - E_i(t)) \cdot \tau_{\text{decay}} + \delta_{\text{experience}}$$

where τ_{decay} is a small decay rate and $\delta_{\text{experience}}$ is the net change from new interactions.

Note on Extended Statefulness Documentation: There is a separate, more detailed whitepaper on statefulness that explores high-level working models, architectural refinements, essence awareness, and emergent property analysis. This extended documentation is available upon request and is subject to conditions and discretion of the author.

Perpetual Velocity Perpetual velocity ensures continuous motion, preventing the system from settling into static equilibrium. Without ongoing motion, attraction ceases, interactions stop, and identity maintenance collapses. Perpetual velocity therefore acts as a necessary condition for continuous interaction and meaning formation.

Mathematical Foundations

Let $x_i \in \mathbb{R}^d$ be the position of entity i where $d \in \{2, 3\}$, s_i its internal state, and v_i its velocity.

Attraction potential:

$$\Phi_i(x, t) = \sum_{j \neq i} w_{ij} \cdot K(\|x - x_j\|, \sigma_{ij})$$

Attention prompt:

$$F_i(x, t) = -\nabla_x \Phi_i(x, t)$$

State update:

$$s_i(t + \Delta t) = \alpha s_i(t) + \beta \cdot g(F_i, c_i) + \gamma \cdot m_i$$

Perpetual velocity:

$$v_i(t + \Delta t) = v_i(t) + \Delta t \cdot a_i(t) + \epsilon \cdot \hat{v}_i$$

Attention Selection

Attention is computed as a normalized distribution over neighbors:

$$\pi_{i \to j} = \frac{\exp(\lambda \cdot a_{ij})}{\sum_k \exp(\lambda \cdot a_{ik})}$$

where a_{ij} is an attraction score and λ controls selectivity.

Memory Graph Update

Each time step creates a memory node with activation ρ and decays existing nodes by factor α. Dormant nodes remain, providing redundancy without deletion.

Memory nodes are clustered by semantic similarity into belief clusters. Let $n_i(t)$ be a new memory node at time t with event vector e_i. The node is added to cluster B_k if similarity exceeds threshold τ:

$$\text{similarity}(e_i, B_k) = \frac{1}{|B_k|} \sum_{j \in B_k} \frac{e_i \cdot m_j}{\|e_i\| \|m_j\|} > \tau$$

All nodes decay by factor α each step:

$$\rho_j(t + \Delta t) = \alpha \cdot \rho_j(t)$$

Dormant nodes persist even as $\rho_j \to 0$, allowing reactivation when similar experiences recur.

Response Policy

Response is a function of attention, state, and context:

$$r_i = \pi(s_i, F_i, c_i)$$

The policy can be deterministic or learned. Early experiments use hand-coded policies for interpretability and ablation clarity.

Baseline drives modulate response selection. Self-preservation is proportional to threat proximity, and curiosity is proportional to attention weight magnitude:

$$\text{drive}_{\text{preserve}} = \frac{1}{\min_j \|x_i - x_j\|}$$

$$\text{drive}_{\text{curiosity}} = \|F_i\|$$

The combined baseline influences whether an entity investigates or withdraws from competing attractions.

Simulation Loop

1. Compute attraction potential for each entity.
2. Derive attention prompts from gradients.
3. Update memory graph and state vectors.
4. Generate responses that modify attraction and state.

5. Integrate motion with perpetual velocity enforcement.
6. Record metrics and traces.

Implementation Sketch

```rust
pub type EntityId = u64;

#[derive(Clone, Debug)]
pub struct Pose {
    pub position: [f32; 3],
    pub orientation: [f32; 4],
}

#[derive(Clone, Debug)]
pub struct State {
    pub memory: Vec<f32>,
    pub context: Vec<f32>,
    pub traits: Vec<f32>,
}

#[derive(Clone, Debug)]
pub struct Entity {
    pub id: EntityId,
    pub pose: Pose,
    pub velocity: [f32; 3],
    pub state: State,
}

pub struct DynamicsConfig {
    pub dt: f32,
    pub min_speed: f32,
    pub damping: f32,
}

pub fn integrate(
    position: &mut [f32; 3],
    velocity: &mut [f32; 3],
    acceleration: [f32; 3],
    cfg: &DynamicsConfig,
) {
    for i in 0..3 {
        velocity[i] = (velocity[i] + cfg.dt * acceleration[i]) * cfg.damping;
    }

    let speed = (velocity[0] * velocity[0]
        + velocity[1] * velocity[1]
        + velocity[2] * velocity[2])
        .sqrt();
    if speed < cfg.min_speed {
        let inv = if speed > 0.0 { 1.0 / speed } else { 1.0 };
        for i in 0..3 {
            velocity[i] = velocity[i] * inv * cfg.min_speed;
        }
    }

    for i in 0..3 {
        position[i] += cfg.dt * velocity[i];
    }
}
```

Configuration Example

```
[simulation]
seed = 42
steps = 100000
entities = 1024

[geometry]
dimension = 3
bounds = [100.0, 100.0, 100.0]

[attraction]
kernel = "gaussian"
sigma = 2.0
lambda = 1.5

[state]
decay_alpha = 0.995
memory_dim = 128
context_dim = 64
essence_decay = 0.001
essence_baseline = 5.0

[dynamics]
dt = 0.01
min_speed = 0.05
damping = 0.99
```

6. Results and Analysis

Findings

No empirical results are reported in this draft. The following table defines the planned metric capture for baseline and ablation studies.

Experiment	H_A	D_M	S_V	C_I	Notes
Baseline	TBD	TBD	TBD	TBD	Full model enabled
No memory decay	TBD	TBD	TBD	TBD	$\alpha = 1$
No velocity floor	TBD	TBD	TBD	TBD	$\epsilon = 0$
No attraction	TBD	TBD	TBD	TBD	$\Phi(x, t) = 0$
Random attention	TBD	TBD	TBD	TBD	Uniform $\pi_{i \to j}$
High Essence (E=9)	TBD	TBD	TBD	TBD	Essence Index locked at 9
Low Essence (E=1)	TBD	TBD	TBD	TBD	Essence Index locked at 1

Evaluation Plan

- Run 50-100 seeds per configuration.
- Track metric trajectories over fixed time windows.
- Compute mean, variance, and stability indices.
- Compare against ablation baselines and null models.
- Report convergence behavior and sensitivity to hyperparameters.

Planned Metrics

Attention entropy:

$$H_A = -\sum_j \pi_{i \to j} \log \pi_{i \to j}$$

Memory diversity (example using normalized activation):

$$D_M = 1 - \sum_k p_k^2$$

Velocity stability:

$$S_V = \frac{1}{T}\sum_{t=1}^{T}\mathbb{I}[\|v_i(t)\| \geq v_{min}]$$

Identity coherence (cosine similarity across windows):

$$C_I = \frac{1}{T}\sum_{t=1}^{T}\frac{s_i(t)\cdot s_i(t-\tau)}{\|s_i(t)\|\|s_i(t-\tau)\|}$$

Belief cluster stability (intra-cluster coherence):

$$B_{\text{stability}} = \frac{1}{K}\sum_{k=1}^{K}\frac{1}{|B_k|^2}\sum_{i,j\in B_k}\text{similarity}(e_i, e_j)$$

Affective signal strength (mean magnitude of dominant signal):

$$\sigma_{\text{strength}} = \frac{1}{T}\sum_{t=1}^{T}\max_k|\sigma_k(t)|$$

Essence Index trajectory (mean and variance):

$$E_{\text{mean}} = \frac{1}{T}\sum_{t=1}^{T}E_i(t), \quad E_{\text{variance}} = \frac{1}{T}\sum_{t=1}^{T}(E_i(t) - E_{\text{mean}})^2$$

Essence Index extremity (how far from baseline):

$$E_{\text{extremity}} = \frac{1}{T}\sum_{t=1}^{T}|E_i(t) - 5|$$

Limitations

- The model is speculative and does not claim subjective experience.
- Metrics are proxies for behavior and identity stability.
- Parameter sensitivity may dominate outcomes without careful calibration.
- The framework can model disagreement but does not validate human-like cognition.

7. Discussion and Implications

Interpretation

If stable identity coherence emerges under repeated interactions and state retention, this supports the hypothesis that meaning-like structures can arise from interaction mechanics. Divergence under ablations can indicate which primitives are necessary for stability.

Ethical and Societal Impact

- Outputs must not be interpreted as evidence of sentience.
- The framework should prioritize transparency, auditability, and safety boundaries.
- Claims about free will or moral agency should be framed as operational metrics, not as philosophical conclusions.

Industry and Research Implications

- Provides a testbed for interaction-first agent research.
- Enables structured ablations across attention, memory, and dynamics.
- Offers a foundation for identity-oriented AI research with reproducible metrics.

8. Conclusion and Recommendations

Key Takeaways

- Geometry-first attention provides explicit interaction mechanics.
- Statefulness with redundancy yields durable identity traces over time.
- Perpetual velocity is a necessary condition for continuous interaction.

Recommendations

- Implement the architecture as a modular Rust crate with reproducible experiments.
- Publish baseline configurations, metrics, and experiment protocols.
- Encourage external replication and critique to avoid over-interpretation.

Future Work

- Introduce learned response policies to compare against deterministic baselines.
- Add multi-scale geometry and hierarchical memory.
- Extend metrics to include robustness under perturbation and noise.
- Provide visualization tools for attraction dynamics, attention and memory evolution.

9. References and Appendices

References

- No external sources are cited in this draft.

Appendix A: Architecture Diagram

```
WORLD LAYER
===========
[Geometry] --> [Attraction Field] --> [Attention Prompts]
     ^                                       |
     |                                       |
     +---------------------------------------+

AGENT LAYER
===========
[Memory Graph]
     |
     +---------> [State Vector] --> [Response Policy]
                                         |
                                         v
                                 [Attraction Signal]
                                         |
                                         v
DYNAMICS LAYER
==============
Perpetual Velocity Integration:
v_i(t+dt) = v_i(t) + dt*a_i(t) + epsilon*v_hat_i
x_i(t+dt) = x_i(t) + dt*v_i(t+dt)
```

Data Flow:

1. Geometry defines entity positions and proximity.
2. Attraction field draws attention between entities based on geometry.
3. Attention prompts influence state and belief cluster activation.
4. Memory graph retains and organizes experience into belief clusters.
5. Response policy determines action based on dominant affective signals.
6. Perpetual velocity integration advances all entities in space-time.
7. New attractions are generated, continuing the cycle.

Appendix B: Pseudocode

```
for t in 1..T:
    for each entity i:
        compute attraction potential Phi_i
        compute attention prompt F_i = -grad(Phi_i)
        update memory graph with current event
        update state vector s_i
        compute response r_i
    integrate all positions with perpetual velocity
    record metrics
```

Appendix C: Rust Reference Sketch

```rust
#[derive(Clone, Debug)]
pub struct MemoryNode {
    pub event: Vec<f32>,
    pub activation: f32,
    pub timestamp: u64,
}

#[derive(Default, Debug)]
pub struct MemoryGraph {
    pub nodes: Vec<MemoryNode>,
    pub edges: Vec<(usize, usize)>,
}

impl MemoryGraph {
    pub fn decay(&mut self, factor: f32) {
        for node in &mut self.nodes {
            node.activation *= factor;
        }
    }
}
```