1 The RSVP Framework

The Relativistic Scalar Vector Plenum (RSVP) framework proposes a field-theoretic model of neural representation, redefining learning as the dynamic evolution of coupled geometric fields. Unlike traditional optimization-centric approaches, which treat representations as static parameter sets, RSVP models cognition as a continuous interplay of semantic potential, flow, and uncertainty. We formalize the RSVP field triplet as:

$$\mathcal{F}(x,t) = \{\Phi(x,t), \vec{v}(x,t), \mathcal{S}(x,t)\}$$

where $\Phi : \mathbb{R}^n \times \mathbb{R} \to \mathbb{R}$ is the scalar semantic potential field, $\vec{v} : \mathbb{R}^n \times \mathbb{R} \to \mathbb{R}^n$ is the vector semantic flow field, and $\mathcal{S} : \mathbb{R}^n \times \mathbb{R} \to \mathbb{R}_{\geq 0}$ is the entropy field capturing semantic uncertainty.

1.1 Field Definitions

- **Scalar Semantic Potential (Φ)**: Represents the magnitude of semantic content at a given point in representation space. For a neural network, $\Phi(x,t)$ can be derived from activation norms or task-specific projections, encoding the strength of conceptual grounding.
- **Vector Semantic Flow ($\vec{v}$)**: Captures directional transitions in representation space, analogous to semantic "motion" between layers or time steps. For layered networks, $\vec{v}(x,t)$ approximates the difference in activations, $\vec{v}_i = h_{i+1} - h_i$.
- **Entropy Field ($\mathcal{S}$)**: Quantifies uncertainty or ambiguity in the representation, derived from predictive entropy ($\mathbb{H}(p(y|x,h_i))$) or activation variance. High $\mathcal{S}$ indicates representational instability or ambiguity.

1.2 Field Dynamics

The evolution of the RSVP field is governed by a partial differential equation that couples the scalar potential, vector flow, and entropy dissipation:

$$\frac{\partial \Phi}{\partial t} + \nabla \cdot (\Phi \cdot \vec{v}) = -\delta \mathcal{S}$$

This equation describes semantic transport, where Φ evolves under the influence of the divergence of the flux $\Phi \cdot \vec{v}$, modulated by entropy dissipation ($\delta \mathcal{S}$). Intuitively, learning reduces uncertainty ($\mathcal{S}$) while aligning semantic potential with coherent flow, driving representations toward stable configurations.

1.3 Torsion and Representational Fracture

Fractured Entangled Representations (FER) emerge when the vector field $\vec{v}$ exhibits high torsion, indicating misaligned or conflicting semantic flows. We define the Torsion Entanglement Index as:

$$\mathcal{T}_{\text{ent}} = \int_{\Omega} \|\nabla \times \vec{v}\|^2 \, dx$$

High $\mathcal{T}_{\text{ent}}$ signals representational instability, where semantic flows loop or conflict, preventing convergence to coherent states. In contrast, Unified Factored Representations (UFR) exhibit low torsion, with $\vec{v}$ aligning smoothly with gradients of Φ and $\mathcal{S}$.

1.4 Interpretation in Cognitive Terms

The RSVP framework draws parallels to cognitive processes. The scalar field Φ mirrors conceptual salience, $\vec{v}$ reflects reasoning or inference trajectories, and $\mathcal{S}$ captures uncertainty in belief states. By modeling learning as field evolution, RSVP provides a geometric lens for understanding how neural systems resolve ambiguity and achieve semantic coherence, offering a physically grounded alternative to parameter-centric views of representation.