# Fundamental Interaction Language

Paolo Pignatelli

June 16, 2025

# Foundations and Semantic Constants

# 1.1 The Information-Observation-Language (I-O-L) Triad

Modern knowledge systems reveal a recurring motif: comprehension requires only the *differences* between two bodies of knowledge, not their entirety. We formalise this with the **Information–Observation–Language triad** 

$$(\mathcal{I}, \mathcal{O}, \mathcal{L}) = (\mathcal{I}, \mathcal{O}, \mathcal{L}), \tag{1.1}$$

where  $\mathcal{I}$  denotes possible information states,  $\mathcal{O}$  the set of admissible observations, and  $\mathcal{L}$  the symbolic language capable of encoding both. Minimal "bridges" between domains are implemented by Local Language Constructors (LLCs), treated in Chapter ??.

#### 1.2 Foundational Postulates

**Postulate F1 (Semantic locality).** Any act of communication factors through a finite sub-language  $B \subseteq \mathcal{L}$  such that  $E \otimes B \cong \mathcal{L}$ , with E the receiver's existing language fragment.

Postulate F2 (Minimal bridges). Among all such B, natural communication selects one that minimises |B|.

Postulate F3 (Hierarchical union). Languages compose by hierarchical union and the semantic density  $\rho$  is non-decreasing under this union.

#### 1.3 Semantic Constants

We introduce two universal constants:

 $c_s$  the *semantic light-speed*, bounding information propagation in a knowledge graph:

$$d_G(v_1, v_2) \le c_s \Delta t. \tag{1.2}$$

 $\hbar_{\rm s}$  the *semantic Planck constant*, appearing in an uncertainty relation between discovery and invention operators:

$$\Delta D \, \Delta I \, \geq \, 12 \hbar_{\rm s}. \tag{1.3}$$

Convenient units set  $c_s = \hbar_s = 1$ ; deviations measure complexity.

#### 1.4 Road-map

This chapter establishes notation for the remainder of the book. Chapter  $\ref{cs}$  develops the geometric view ( $c_s$  as cone slope), Chapter  $\ref{cs}$  derives global limits from Eq. eq:sem-uncertainty, Chapter  $\ref{cs}$  treats drift and masks, and Chapter  $\ref{cs}$  links the constants to physical information bounds.

**Take-away.** The triad  $(\mathcal{I}, \mathcal{O}, \mathcal{L})$  and constants  $(c_s, h_s)$  provide an irreducible substrate on which all higher FIL structures are built.

# Semantic Geometry

#### 2.1 Semantic Light-Cones

In a knowledge graph G = (V, E) we define the semantic distance  $d_G(v_1, v_2)$  as the minimal edge-weighted path length between two concept vertices. Postulate F1 implies that information flow is bounded by the constant  $c_s$  introduced in Chapter ??:

$$d_G(v_1, v_2) \le c_s \Delta t. \tag{2.1}$$

Points satisfying equality trace **semantic light-cones**. They encode the frontier beyond which two agents cannot reach mutual comprehension within  $\Delta t$ .

**Propagation kernel.** Let  $K_t(v)$  denote the reachable set from v in time t. A discrete propagator is  $P_t = 1_{d_G \leq c_s t}$ .

#### 2.2 Informational Curvature

Light-cone slope alone does not capture *semantic gravitation*—the tendency of dense subgraphs to attract interpretive trajectories. We introduce an *informational curvature tensor* K via the deviation of geodesics in G:

$$\delta^2 d_G = -\mathcal{K}(\gamma, \dot{\gamma}) \, d\sigma^2. \tag{2.2}$$

Positive curvature corresponds to semantic "mass" and appears near high mutual-information clusters. See  $[?](\S 2)$  for the full derivation.

#### Example – category junction

Two dense languages  $L_1, L_2$  joined by a minimal LLC bridge B create negative curvature in the bridge (saddle) and positive curvature inside each language core.

#### 2.3 Computational Spacetime Correspondence

Mapping Eq. eq:semantic-cone onto a Turing tape with physical delays  $\tau$ , we recover the computational light-speed bound  $c_{\rm s} \approx 1/\tau$  [?]. Informational curvature then corresponds to non-uniform memory access latencies—regions of high semantic mass behave as RAM "black holes".

#### 2.4 Meta-Law and Quantisation

FL\_Field Meta-Law postulates a universal action principle in information space. Quantising small oscillations of  $d_G$  about a ground state yields a discrete spectrum analogous to normal modes in Riemannian geometry. This motivates the uncertainty relation derived in Eq. (??).

**Take-away.** The geometry of semantic light-cones and informational curvature generalises relativistic causality to knowledge systems, setting the stage for global bounds (Chapter ??) and dynamical drift analysis (Chapter ??).

# **Informational Bounds**

#### 3.1 Bekenstein-like Entropy Limit for Language

The classical Bekenstein bound [?] constrains the maximum entropy S of physical matter in a region of radius R and energy E by  $S \leq 2\pi k E R/\hbar c$ . In the FIL setting, tokens carry informational mass and the analogue becomes

$$H(\mathcal{L}) \leq 2\pi k_s E_{\mathcal{L}} R_{\mathcal{L}} / \hbar_s,$$
 (3.1)

where  $E_{\mathcal{L}}$  is the cumulative energetic cost of storing the language fragment and  $R_{\mathcal{L}}$  its semantic diameter.

**Interpretation.** If H exceeds this limit, further compression (via LLC bridges) or hierarchical segmentation is required.

#### 3.2 Finite Knowledge Bounds

Let G = (V, E) be a directed knowledge graph with path entropy  $H_P$  and symbol complexity  $C_s$ . finiteknowledgebounds 2025 derive upper and lower compression bounds

$$\frac{|V|}{\log C_s} \le H_P \le |E| \log C_s. \tag{3.2}$$

We adopt the lower bound as the *finite knowledge bound* (FKB) for any segment.

#### 3.2.1 Prime-Encoding Lower Bound

Prime-encoding of edge labels achieves the lower bound asymptotically; see Appendix ??.

#### 3.2.2 Voronoi Capacity Upper Bound

Semantic Voronoi cells give a geometric ceiling; we revisit this in Chapter ?? when studying drift fields.

#### 3.3 Acceleration Constraint

accelleration 2025 show that rapid semantic updates imply an acceleration cost

$$a_{\mathcal{L}} \equiv \frac{d^2 H}{dt^2} \le c_{\rm s}^2 / \ell_{\rm min},$$
 (3.3)

with  $\ell_{\min}$  the minimum edge length. This links light-cone slope  $(c_s)$  to second-order dynamics.

#### 3.4 Big Bang as Information Phase Transition

The cosmological Big Bang is recast as a phase transition where  $H \to 0$  while  $dH/dt \to \infty$ . Under FKB this corresponds to the creation of the minimal language fragment required for any subsequent evolution.

#### 3.5 Road-map

Informational limits set the stage for Chapter ??, where drift and masks operate within these bounds, and Chapter ??, which ties them to particle-level information exchange.

# Dynamics, Drift, and Mask-Based Stabilisation

#### 4.1 Diagnosing Semantic Drift

Let  $\delta_k(n)$  denote the drift magnitude of concept k after n network layers. Following  $\mathrm{SSR}_D raft3$ ,  $we define \delta_k(n) = \frac{\|P_k^n - P_k^0\|}{\|P_k^0\|}$ , (4.1) where  $P_k^n$  is the perturbation field of concept k at depth n. The shadow depth  $\Delta_k^n$  is the first layer m > n such that  $\delta_k(m) < \varepsilon$ . A rising sequence  $\Delta_k^n$  indicates unstable semantics.

#### 4.2 Mask Evolution Operator

Dynamic masks  $M_k^n$  are injected at layer n to probe drift. The **Mask Evolution** Operator (MEO) propagates masks across depth:

$$T_1^n: M_k^1 \longmapsto M_k^n, \qquad T_1^n = T_{n-1}^n \circ \dots \circ T_1^2.$$
 (4.2)

The error tensor

$$E_k^n = M_k^n - T_1^n(M_k^1) (4.3)$$

serves as a drift-diagnostic:  $||E_k^n|| \to 0$  implies layer stability.

#### 4.3 Gaussian-Mixture View of Observation

Observation tokens are embedded as weighted Gaussian mixtures  $GMM(w_i, \mu_i, \Sigma_i)$ . Overlap of components predicts hallucination regions. The mixture distance introduces a probabilistic refinement of the drift metric:

$$d_{GMM}(p,q) = 1 - \sum_{i} \sqrt{w_i^{(p)} w_i^{(q)}} e^{-12\Delta \mu_i^{\mathsf{T}} \Sigma_i^{-1} \Delta \mu_i}. \tag{4.4}$$

#### 4.4 Perturbation Cellular Automata

Discrete propagation of truth-wavefronts may be simulated by a perturbation cellular automaton (PCA) on the concept graph G=(V,E). Each cell updates via

$$s_{t+1}(v) = f(s_t(v), (s_t(u))_{u \in N(v)}),$$
 (4.5)

where f conserves a local semantic energy to satisfy the bound  $d_G \leq c_s \Delta t$ .

#### 4.5 The Nibbler Algorithm

- 1. Initialise discovery state  $D_0$  and pattern set  $P_0$ .
- 2. (Discovery)  $D_{t+1} \leftarrow D_t + NibblerStep(D_t)$ .
- 3. (Pattern)  $P_{t+1} \leftarrow MetaPattern(P_t, D_{t+1})$ .
- 4. Repeat until  $\Delta D$  and  $\Delta P$  fall below thresholds.

The interface kernel

$$k_{NI}(x,y) = \alpha k_D(x,y) + (1-\alpha)k_P(x,y)$$
 (4.6)

controls the discovery–pattern balance.

#### 4.6 Integration with the UIL Framework

Integration  $UILext end the graph model to include confidence c(\omega)$  and security  $\lambda(\omega)$ . The drift-aware propagation rule becomes

$$\Delta(v_i, v_{i+1}) = \min \Big( infochange \mid \lambda(v_{i+1}) \ge \lambda_{\min}, \ c(\omega) \ge c_{\min} \Big). \tag{4.7}$$

#### 4.7 Outlook

This chapter introduced dynamical machinery that preserves the semantic constants while allowing adaptive evolution. Chapter ?? maps these operators to physical processes—e.g. interferometric stabilisation in the InterferoShell.

**Take-away.** Mask evolution, GMM observation, and Nibbler search conspire to keep drift bounded without violating the informational limits of Chapter ??.