Fundamental Interaction Language

Paolo Pignatelli

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Chapter 1

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 ρ 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:

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

$\hbar_s$ the *semantic Planck constant*, appearing in an uncertainty relation between discovery and invention operators:

$$\Delta D\,\Delta I \;\ge\; \tfrac{1}{2}\hbar_s. \tag{1.3}$$

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 **??** develops the geometric view (c_s as cone slope), Chapter **??** derives global limits from Eq. (**??**), Chapter **??** treats drift and masks, and Chapter **??** links the constants to physical information bounds.

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

Chapter 2

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 Δt.

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

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* $\mathcal{K}$ 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 [**?**](§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. (**??**) onto a Turing tape with physical delays τ, we recover the computational light-speed bound $c_s \approx 1/\tau$ [?]. 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 **??**).

2.5 Voronoi Tessellation and Knowledge Navigation

Traditional path-finding on a dense knowledge graph $G = (V, E)$ scales poorly with $|V|$. To achieve sub-logarithmic query time we partition V into *semantic Voronoi cells*:

Definition 2.1 (Semantic Voronoi Cell)**.** *For a seed node $s \in V$ the cell* Vor(s) *is*

$$\mathrm{Vor}(s) = \{v \in V \mid d_G(v, s) \leq d_G(v, s') \ \forall s' \neq s\}.$$

Cells tile the graph when seeds form a maximal ϵ-net. The navigation algorithm is then:

1. Locate the source and target cells via hashing of node signatures.
2. Traverse the cell adjacency graph (typically $O(\sqrt{|V|})$ cells).
3. Within the target cell, apply local Djikstra (size $\leq \epsilon$).

Curvature connection. Boundaries between cells coincide with geodesics of informational curvature κ (Section **??**). High κ regions produce finer tessellations, automatically allocating more seeds where semantic density is high.

Drift boundaries. In Chapter **??** drift masks align to cell faces; thus tessellation acts as a coarse pre-mask, reducing the dimensionality of drift correction.

Complexity. With uniform k-nearest-neighbour degree and n seeds the cell adjacency graph has $O(n)$ edges; navigation complexity becomes $O(\sqrt{n} + \epsilon)$, sub-logarithmic in $|V|$ for well-chosen $n \approx \sqrt{|V|}$.

Future work. Investigate hyperbolic Voronoi in negative-curvature regions and probabilistic tessellations where seed membership is fuzzy.

Chapter 3

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 $S \leq 2\pi kER/\hbar c$. In the FIL setting, tokens carry informational mass and the analogue becomes

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

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. finiteknowledgebounds2025 derive upper and lower compression bounds

$$\frac{|V|}{\log C_s} \;\leq\; H_P \;\leq\; |E|\, \log C_s. \tag{3.2}$$

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

accelleration2025 show that rapid semantic updates imply an *acceleration cost*

$$a_{\mathcal{L}} \;\equiv\; \frac{d^2 H}{dt^2} \;\leq\; c_s^2/\ell_{\min}, \tag{3.3}$$

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.

Chapter 4

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 SSR$_D raft3, wedefine \delta_k(n) \;=\; \frac{\|P_k^n - P_k^0\|}{\|P_k^0\|}$, (4.1) where P_k^n is the perturbation field of concept k at depth n. The *shadow depth* Δ_k^n is the first layer $m > n$ such that $\delta_k(m) < \varepsilon$. A rising sequence Δ_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:

$$T_1^n : \; M_k^1 \;\longmapsto\; M_k^n, \qquad T_1^n \;=\; T_{n-1}^n \circ \cdots \circ T_1^2. \tag{4.2}$$

The *error tensor*

$$E_k^n \;=\; M_k^n - T_1^n(M_k^1) \tag{4.3}$$

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 $\mathrm{GMM}(w_i, \mu_i, \Sigma_i)$. Overlap of components predicts hallucination regions. The mixture distance introduces a probabilistic refinement of the drift metric:

$$d_{\mathrm{GMM}}(p, q) \;=\; 1 - \sum_i \sqrt{w_i^{(p)}\, w_i^{(q)}}\; e^{-\frac{1}{2}\Delta\mu_i^{\intercal}\Sigma_i^{-1}\Delta\mu_i}. \tag{4.4}$$

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

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

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) $D_{t+1} \leftarrow D_t + \mathrm{NibblerStep}(D_t)$.
3. (Pattern) $P_{t+1} \leftarrow \mathrm{MetaPattern}(P_t, D_{t+1})$.
4. Repeat until ΔD and ΔP fall below thresholds.

The interface kernel

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

controls the discovery–pattern balance.

4.6 Integration with the UIL Framework

Integration$_UILextendthegraphmodeltoincludeconfidence$c$(\omega)$ and security $\lambda(\omega)$. The drift-aware propagation rule becomes

$$\Delta(v_i, v_{i+1}) \;=\; \min\Big(\text{info change} \mid \lambda(v_{i+1}) \geq \lambda_{\min},\; c(\omega) \geq c_{\min}\Big). \tag{4.7}$$

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 **??**.

Chapter 5

Physical and Computational Correspondence

5.1 Particles as Information Events

Each fundamental interaction instantiates new information[?]. Let $S(t) = \{p_i, E_{ij}\}$ denote the quantum state at time t. A collision $T : S(t) \to S(t+1)$ increases the descriptive complexity

$$\Delta I \;=\; I\big(S(t+1)\big) - I\big(S(t)\big) \;\leq\; kE. \tag{5.1}$$

This yields a conservation-of-information principle analogous to energy conservation in QFT.

5.2 Computational Relativity Analogy

5.2.1 Complexity *vs.* Time-Dilation

Landauer–Bremermann bounds suggest that executing N logical operations on mass m requires a minimum proper time $\Delta\tau \geq N\hbar/(mc^2)$. Interpreting complexity as curvature we obtain a metric on algorithmic spacetime:

$$ds^2 = -\Big(1 - \tfrac{2G\,C}{c^2 r}\Big)c^2 dt^2 + \Big(1 - \tfrac{2G\,C}{c^2 r}\Big)^{-1} dr^2 + r^2 d\Omega^2, \tag{5.2}$$

with C the local Kolmogorov-complexity density.

5.2.2 Physical Foundations of Computational Light-Speed

Chapter 3 of [?] derives a physical upper speed of algorithmic propagation that matches the semantic constant c_s from Chapter ??.

5.3 Computational Spacetime Geometry

Information flow defines a causal set $\mathcal{C}$ whose Hasse diagram embeds into the knowledge graph G. Curvature of $\mathcal{C}$ matches informational curvature κ of Section **??**, closing the semantic-physical loop.

5.4 Prime Path Encoding for Graph Compression

Path-encoding maps concept trajectories to unique prime products $\pi(P) = \prod p_i^{n_i}$. The path length satisfies

$$|P| \ \le \ O\big(\log \pi(P)\big), \tag{5.3}$$

providing asymptotically optimal storage[**?**].

5.5 Discussion and Future Work

Links between semantic and physical bounds suggest experimental tests:

1. Measure algorithmic time-dilation effects in high-complexity quantum circuits.
2. Investigate Hawking-like emission at semantic black-hole horizons where $\rho \to \infty$.
3. Extend computational-relativity metrics to non-commutative graph geometries.

Take-away. Physical interaction, algorithmic complexity, and semantic structure obey the same limiting principles, unifying FIL with foundational physics.