1. SFPM-10 — Semantic Futures Projection Model

1.1. Core idea

SFPM-10 does **not** predict future raw data.
It predicts how the **semantic state of attributes** will evolve over time:

- their **intensity**
- their **tier**
- their **influence**
- their **drift zone**
- their **risk of failure**

It sits on top of SIS-10, SIF-10, MCM-10, TIER-10, SICM-10, DIFS-10, QFIM-10, AMD-10.

1.2. State definition

For each attribute a_i, at time t, define a **semantic state vector**:

$$x_i(t) = \left(s_i(t),\ t_i(t),\ w_i(t),\ z_i(t),\ q_i(t) \right)$$

Where:

- $s_i(t)$: semantic intensity score (from SICM-10), $s_i(t) \in [0, 100]$
- $t_i(t)$: tier (from TIER-10), $t_i(t) \in T = \{\mathrm{E}, \mathrm{EC}, \mathrm{C}, \mathrm{CN}, \mathrm{N}\}$
- $w_i(t)$: influence weight (from SIF-10), $w_i(t) \in [0, 1]$, with $\sum_i w_i(t) = 1$
- $z_i(t)$: drift/fading subzone (from DIFS-10)
- $q_i(t)$: qualified interpretation level (from QFIM-10)

SFPM-10's job:
Given $x_i(t_0)$, and context evolution, estimate $x_i(t_0 + \Delta t)$.

1.3. Semantic evolution dynamics

SFPM-10 uses **semantic, not physical, dynamics**.

1. **Intensity evolution** (built on DIFS-10):

$$\frac{ds_i}{dt} = -\lambda_i \cdot s_i(t) + \beta_i(t)$$

- $\lambda_i \geq 0$: semantic drift coefficient (from DIFS-10)
- $\beta_i(t)$: context-driven reinforcement term (e.g., repeated confirmations)

Solution over $[t_0, t_0 + \Delta t]$ (assuming piecewise constant parameters):

$$s_i(t_0 + \Delta t) \approx s_i(t_0)e^{-\lambda_i \Delta t} + \int_{t_0}^{t_0 + \Delta t} \beta_i(\tau)e^{-\lambda_i(t_0 + \Delta t - \tau)}\, d\tau$$

2. **Tier evolution** (discrete Markov-like transitions):

Let T be the tier set and $P_i(t)$ be a tier transition matrix:

$$P_i(t) = \left[p_{jk}^{(i)}(t)\right], \quad p_{jk}^{(i)}(t) = \Pr\left(t_i(t + \Delta t) = k \mid t_i(t) = j \right)$$

Constrained by:

- Essential stability: transitions out of E are low probability
- Drift-based demotion: high drift can push tiers down

3. **Influence evolution**:

$$w_i(t + \Delta t) = f_{\text{inf}}\left(w_i(t), s_i(t + \Delta t), t_i(t + \Delta t), \text{context}(t, t + \Delta t) \right)$$

With normalization:

$$\sum_i w_i(t + \Delta t) = 1$$

4. **Qualified interpretation evolution**:

$$q_i(t + \Delta t) = QFIM\left(s_i(t + \Delta t), t_i(t + \Delta t), z_i(t + \Delta t) \right)$$

5. **Subzone evolution**:

$$z_i(t + \Delta t) = g_{\text{zone}}\left(s_i(t + \Delta t) \right)$$

(e.g., thresholds mapping score to DIFS-10 subzones.)

1.4. SFPM-10 operator

We define SFPM-10 as an evolution operator:

$$\mathrm{SFPM}_{\Delta t}: X(t) \to X(t+\Delta t)$$

Where:

$$X(t) = \{x_i(t)\}_{i=1}^{n}$$

So:

$$X(t+\Delta t) = \mathrm{SFPM}_{\Delta t}\Big(X(t), \mathrm{context}[t, t+\Delta t] \Big)$$

This is a **semantic futures projection**, not a physical forecast.

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2. Formal theorem: semantic prediction ≠ physical prediction

Now we formalize why **semantic prediction and physical prediction are fundamentally different classes of models**, even if both "predict the future".

2.1. Setup

Let:

- S = space of **semantic states** (e.g., all possible $X(t)$ from DAIS-10)
- P = space of **physical states** (e.g., positions, velocities, physical parameters)

A **physical prediction model** is a map:

$$F_{\mathrm{phys}}: P \times R^{+} \to P$$

A **semantic prediction model** (SFPM-10) is a map:

$$F_{\mathrm{sem}}: S \times R^{+} \to S$$

We want to show that, in general, there is **no isomorphism** that makes these two equivalent.

2.3. Proof (outline, standards-grade)

1. **Context dependence of semantics**
   Semantic state $X(t) \in S$ depends on **context** $C(t)$:

$$X(t) = G\Big(\text{data}(t), C(t), R\Big)$$

where R is a set of interpretation rules (SIS-10, MCM-10, TIER-10, etc.).

Physical state $P(t) \in P$ does **not** depend on context or rules. It is defined purely by physical quantities.

Thus, two identical physical states $P_1 = P_2$ can map to **different** semantic states if context differs:

$$C_1 \neq C_2 \implies X_1 \neq X_2$$

Therefore, any mapping $\phi: P \to S$ would have to be **context-dependent**, and thus not a function on P alone.

2. **Governance dependence of semantics**
   Semantic tiers, intensities, and qualifications depend on governance configurations (policies, thresholds, risk tolerance), which can change over time even if physical reality does not.
   Take a fixed physical state P. Change governance from G_1 to G_2. Then:

$$X_{G_1} \neq X_{G_2}$$

Again, ϕ cannot be defined purely on P; it would require governance parameters.

3. **Non-invertibility**
   Many different physical states can share the **same semantic interpretation** (e.g., many trajectories leading to the same risk classification). Therefore, any mapping from P to S is, in general, **many-to-one**, not bijective.
   So ϕ^{-1} does not exist as a function on S.

4. **Conclusion**
   Since:
   - ϕ cannot be defined on P alone (needs context + governance)
   - ϕ is many-to-one (not bijective)

   There is, in general, no bijection ϕ making:

$$F_{\text{sem}} = \phi \circ F_{\text{phys}} \circ \phi^{-1}$$

Hence, **semantic prediction and physical prediction are fundamentally non-equivalent model classes.**

□

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3. Compressed intuition

- Physical prediction:
  "Given where it is and the forces, where will it go?"
- Semantic prediction (SFPM-10):
  "Given what this means now, the context, and the rules, what will it *mean* later?"

One can inform the other; neither can **be** the other.