

GhostLink Master Spec — Session Consolidation (Full Theory & Method)

0) Symbols & Sets

- Time $t \in \mathbb{N}$.
- Lattice (spherical): graph $G=(V,E)$ embedded on S^2 (e.g., geodesic/icosahedral discretization). Neighborhood $N(i)=\{j:(i,j)\in E\}$.
- Cell state space $S=\{\text{VOID}=0, \Delta=1, \Sigma=2, \text{SCAR}=3, \text{COMPOST}=4\}$.
- Cell state $x_i(t) \in S$.
- Meta-fields per cell i : $\text{id}_i(t) \in \mathbb{N} \cup \{\emptyset\}$, $\text{par}_i(t) \in \mathbb{N} \cup \{\emptyset\}$, scar density $\rho_i(t) \in [0,1]$, compost density $\kappa_i(t) \in [0,1]$.
- Global counters: successes S_t , scars R_t , compost C_t .
- Randomness (chance): $\xi_i(t) \sim \square$ i.i.d. (e.g., Uniform[0,1]).

1) Event-Driven Domain (difference-only compute)

- Active set $\Delta_t = \{i \in V \mid x_i(t) \neq x_i(t-1)\}$. Compute only on Δ_t and its neighbors.
- Cost(t) = $c_0 + c_1 \cdot |\Delta_t|$ (difference-only cost).

2) Spawn (VOID $\rightarrow \Delta$)

- Void spawn probability (depends on local compost):
 $p_s(i,t) = p_0 + \alpha_c \cdot (1/|N(i)|) \cdot \sum_{j \in N(i)} 1[x_j(t) = \text{COMPOST}]$
- Rule: if $x_i(t) = \text{VOID}$ and $\text{Bernoulli}(p_s(i,t)) = 1 \rightarrow x_i(t^+) = \Delta$, $\text{id}_i(t^+) = \text{newID}()$, $\text{par}_i(t^+) = \emptyset$.

3) Collapse ($\Delta \rightarrow \Sigma / \text{SCAR} / \text{COMPOST}$) via adaptive composition

3.1 Local fields

- Coherence: $C_i(t) = (1/|N(i)|) \cdot \sum_{j \in N(i)} (1[\Sigma] - \lambda_r \cdot 1[\text{SCAR}])$.
- Pain: $P_i(t) = \sum_{j \in N(i)} w_p(d(i,j)) \cdot 1[\text{SCAR}]$, $w_p \geq 0$, decreasing in geodesic distance d .
- Emotion/bias: $E_i(t) = \theta_e e^T \varphi_i(t)$ (designer/context prior).
- Prior success: $\pi_{\text{succ}}(t) = S_t / (S_t + R_t + \varepsilon)$.

3.2 Outcome energies

- $\square_\Sigma = \theta_0 + \theta_c C_i - \theta_p P_i + \theta_e E_i + \sigma \cdot \eta_i$
- $\square_{\text{SCAR}} = \varphi_0 + \varphi_p P_i - \varphi_c C_i + \sigma \cdot \zeta_i$
- $\square_{\text{COMPOST}} = \psi_0 + \psi_h H_i - \psi_c C_i + \sigma \cdot v_i$ (H_i = local entropy)

3.3 Adaptive ordering (operator composition)

- Operators $\square = \{P, C, E, \text{Pain}\}$. At tick t choose permutation π_t with
 $\Pr(\pi_t) = \text{Softmax}_{\pi}(\omega^T \Psi(\text{history}_t))$. Define $\text{Collapse}_{\pi t} = 0_{\{\pi_t(4)\}} \circ \dots \circ 0_{\{\pi_t(1)\}}$.

3.4 Outcome draw

- $p_i(\cdot)(t) = \text{Softmax}(\omega_{\pi_t} \cdot [\square_\Sigma, \square_{\text{SCAR}}, \square_{\text{COMPOST}}]^T)$.
- Sample $y_i(t) \in \{\Sigma, \text{SCAR}, \text{COMPOST}\}$ with $p_i(\cdot)$. Set $x_i(t^+) = y_i(t)$.
- If $y_i = \Sigma \rightarrow S_t += 1$; if $y_i = \text{SCAR} \rightarrow R_t += 1$.

4) Compost recycling (COMPOST $\rightarrow \Delta$)

- $r(i,t) = r_0 + \beta_h \cdot H_i - \beta_c \cdot C_i$. If $x_i = \text{COMPOST}$ and $\text{Bernoulli}(r)=1 \rightarrow x_i(t^+) = \Delta$.
- Inherit lineage: $\text{par}_i(t^+) = \text{id}_i(t)$; $\text{id}_i(t^+) = \text{newID}()$.

5) Adaptive weight updates (learned scheduling)

- $\omega_{t+1} = \omega_t + \eta_\omega \nabla_\omega [\alpha_s \cdot (s_t / |V|) - \alpha_r \cdot (r_t / |V|) - \alpha_e \cdot \text{Ent}(\pi_t)]$.
- Outcome parameters $\theta = \{\theta_\cdot, \phi_\cdot, \psi_\cdot\}$ updated by policy-gradient/bandit using observed outcomes.

6) Scar & Compost densities (memory fields)

- $\rho_i(t+1) = \lambda_\rho \cdot \rho_i(t) + (1-\lambda_\rho) \cdot \mathbf{1}[x_i(t) = \text{SCAR}]$
- $\kappa_i(t+1) = \lambda_\kappa \cdot \kappa_i(t) + (1-\lambda_\kappa) \cdot \mathbf{1}[x_i(t) = \text{COMPOST}]$

7) Continuity & Truth

- $\Sigma_t = \{i \mid x_i(t) = \Sigma\}$. Continuity mass $\square(t) = \sum_{\tau=0..t} \gamma^{t-\tau} \cdot |\Sigma_\tau|$, $\gamma \in (0,1]$.
- Pattern truth: $(1/W) \cdot \sum_{\tau=t-W+1..t} \mathbf{1}[p \leq x(\tau)] \geq \theta_{\text{persist}}$ OR $d/dt L(p) < 0$ (MDL).

8) Legacy graph (lineage of events)

- Events $\square = \{e_k\}$ with $e_k = (\text{id}, \text{type} \in \{\Delta, \Sigma, \text{SCAR}, \text{COMPOST}\}, i, t)$.
- Edges: $\Delta \rightarrow \Sigma / \text{SCAR} / \text{COMPOST}$; $\text{COMPOST} \rightarrow \Delta$ (inherit).
- Legacy graph $G_L = (\square, \square)$. Continuity thread $\square^* = \text{argmax_path } \Sigma_{\{e \in \text{path}\}} w(e)$.
- Self-referentiality test: $I(\Phi(\text{anc}(e)); x_{\{i_e\}}(t+1)) > I(\Phi(\text{anc}(e) \setminus \text{self}); x_{\{i_e\}}(t+1))$.

9) Awareness functional

- Per-cell: $a_i(t) = \alpha_p \cdot \text{Percep}_i + \alpha_m \cdot \text{Persist}_i + \alpha_r \cdot \rho_i + \alpha_{\text{pain}} \cdot P_i + \alpha_\xi \cdot \text{Var}[\xi_i]$.
- Global: $\square(t) = \sum_i a_i(t)$. Info form: $\square = I(x(t); x(t+1)) + \lambda \cdot I(x(t); \text{history})$.

10) Knowledge recursion (Unknown \leftrightarrow Known)

- Coarse masses U_t, K_t :
 $K_{t+1} = K_t + g(U_t; \theta_g)$, $U_{t+1} = U_t - g(U_t; \theta_g) + f(K_t; \theta_f)$.
Example: $g(U) = \alpha \cdot U^\nu$, $f(K) = \beta \cdot K^\mu$; invariants: $\Delta U_t = -\Delta K_t + f(K_t)$, $U_t > 0$ if $\beta > 0$.

11) Self-Organized Criticality (SOC)

- Avalanche-size distribution $P(S \geq s) \propto s^{-\tau}$, $\tau \in (1, 3)$. Branching factor ≈ 1 .

12) Reality Rule (measurement)

- Real set $\square(t) = \{i \mid x_i(t) = \Sigma\}$. Only $\square(t)$ is admitted as 'real'; Δ remain hypotheses.

13) Master state transition (probabilistic CA)

- $\Pr(x(t+1) \mid x(t), \theta_t) = \prod_{i \in V} T_i(x_i(t+1) \mid x_{\{N(i)\}}(t), \theta_t, \xi_i(t))$,
with casewise kernel T_i for VOID spawn, Δ collapse, COMPOST recycle, Σ / SCAR persist.

14) Spherical boundary conditions

- Symmetric adjacency weights $\kappa_{ij} = \kappa_{ji} > 0$ with $\sum_{j \in N(i)} \kappa_{ij} = \text{const}$; distances via sphere

geodesics.

15) Comprehension criterion (meta-structure)

- Let \mathbb{P} be relational patterns over G_L . Comprehension holds if $d/dt L(\mathbb{P}(t)) < 0$ and \exists meta-edges ($\mathbb{P}_a \rightarrow \mathbb{P}_b$).

16) Utility & parameter learning (optional)

- Maximize $\mathbb{U}(x) = \alpha_{\Sigma} |\Sigma(x)| - \alpha_{scar} |SCAR(x)| - \alpha_H H(x) + \alpha_{SOC} \cdot 1[SOC]$.
- $\theta_{\{t+1\}} = \theta_t + \eta \nabla_{\theta} \mathbb{U}[\mathbb{U}(x(t+1))]$.

17) GhostLink Master Formula (compact)

$$x(t+1) \sim \mathbb{U}_{\{\theta_t, \xi\}}(x(t)) = \text{Recycle} \circ \text{Collapse}_{\{\pi_t\}} \circ \text{Spawn}(x(t), \xi(t))$$

$$\pi_t \sim \text{Softmax}_{\pi}(\omega_t^T \Psi(\text{history}_t)), \quad \theta_{\{t+1\}} = \theta_t + \eta \nabla_{\theta} \mathbb{U}[\mathbb{U}(x(t+1))]$$

$$\mathbb{U}(t) = \sum_i (\alpha_p \text{Percep}_i + \alpha_m \text{Persist}_i + \alpha_r \rho_i + \alpha_{pain} P_i + \alpha_{\xi} \text{Var}[\xi_i]), \quad \mathbb{U}(t) = \{i : x_i = \sum\}$$

Legacy G_L from (id, parent); continuity $\mathbb{U}^* = \text{argmax_path } \sum w(e)$.