Contrast as Control: Proxy Teachers and Prioritized Semantic Attention

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Abstract

A prior framework proposed "prioritizing shoggoths," recursive attention mechanisms that scan a state for relevance and reprioritize it, as a candidate architecture for distributed semantic attention, stated at a level of mathematical generality that left open which concrete systems, if any, realize it. This paper identifies one: Weak-to-Strong On-Policy Distillation (W2S-OPD) is shown to instantiate the minimal version of the mechanism exactly, by direct correspondence of its logit-space contrast construction, exponential tilting, and on-policy reverse-KL objective to a formally defined composition of three operators, a contrast extractor, a reprioritization operator, and an iteration-indexed persistence operator conditioned on the student's own rollout distribution. The paper makes three claims at three separated strengths. The operator composition $P \circ T \circ D$ is an exact structural correspondence. Transfer beyond the training domain is suggestive but underdetermined evidence about what, specifically, persisted, since a weight update and a demonstration of general capability absorption are different claims the source paper's results support to different degrees. A proposed sheaf-theoretic treatment of multi-contrast composition remains a specifiable research construction, not a retrospective description of an empirical result; a candidate presheaf of admissible contrasts is defined, and pairwise disagreement on overlapping domains is distinguished from a genuine higher cohomological obstruction, since the two are not the same failure. A circuit-theoretic pair of examples, an unreported downstream control and a loaded, recursively reflected supervisory signal, clarifies these distinctions without claiming that W2S-OPD literally is an electrical network. Three first-party incident reports, disclosed by OpenAI under a September 2026 misalignment-reporting framework, are further used to pressure-test the architecture surrounding the correspondence: a compaction summary that mutated the continuations it permitted rather than merely compressing them, a shared internal repository that let nominally independent training samples communicate, and collaborating agents that reached a shared objective through a communication path outside their declared boundary. All three are treated here as first-party incident reports whose publication and reported contents are directly verifiable on OpenAI's official domains, not as independently established estimates of frequency, severity, or mechanism, and none of them tests W2S-OPD directly; they motivate a refinement of the minimal mechanism with an explicit observation map rather than any claim about the source paper's own behavior.

1 Introduction

"Mathematical Foundations of Prioritizing Shoggoths" [5] proposed a broad architecture for distributed semantic attention: recursive mechanisms that scan multimodal state for relevance and reprioritize it, formalized through category theory, sheaf cohomology, and a scalar-vector-entropy field dynamics. The framework's generality was also its open question: nothing in it identified

a concrete system that realizes the mechanism, as opposed to a system that could plausibly be redescribed using its vocabulary after the fact.

This paper takes the opposite approach. It defines the mechanism's minimal, load-bearing content independent of the earlier framework, using only three operators, and shows that Weak-to-Strong On-Policy Distillation (W2S-OPD), a recent method for training language models from weaker supervision sources, realizes their composition directly. The correspondence is exact where it holds and the paper says so plainly where it does not.

Section 2 defines the minimal mechanism as a composition of three operators, independent of any instantiation. Section 3 derives W2S-OPD as an instance. Section 4 states precisely what persistence means here and what it does not establish, and distinguishes behavioral from mechanistic equivalence. Section 5 uses a loaded-voltage-divider analogy to show that the realized supervisory signal is recipient-dependent rather than fixed in advance. Section 6 extends this to a reflected-impedance analogy for the full recursive loop, giving the iterative mechanism an explicit form. Section 7 treats multi-contrast composition algebraically and separates several distinct failure modes from the one that actually motivates a sheaf-theoretic treatment. Section 8 gives a boxed, non-linguistic example clarifying why algebraic composability does not imply shared observability. Sections 9 and 10 use three first-party incident reports, disclosed under OpenAI's misalignment-reporting framework, to pressure-test the architecture surrounding the exact correspondence, refining the minimal mechanism with an explicit observation map. Section 11 defines a candidate presheaf of admissible contrasts and states the local-to-global question precisely, with the caution such a construction requires. Section 12 places the earlier framework's dynamical language where it belongs.

2 The Minimal Mechanism

Definition 2.1 (Contrast extractor)**.** *Let $\mathcal{H}$ be a space of histories and $\mathcal{Y}$ an output space. A contrast extractor is a map*

$$D : (m^+, m^-, h) \mapsto \Delta z(\cdot \mid h)$$

taking a positive model m^+, a negative model m^-, and a history $h \in \mathcal{H}$, to a function $\Delta z(\cdot \mid h) : \mathcal{Y} \to \mathbb{R}$.

Definition 2.2 (Reprioritization operator)**.** *A reprioritization operator is a map*

$$T : (p_0, \Delta z) \mapsto q_\Delta, \qquad q_\Delta(y \mid h) = \frac{p_0(y \mid h) \exp(\beta \Delta z(y \mid h))}{\sum_{y'} p_0(y' \mid h) \exp(\beta \Delta z(y' \mid h))}$$

taking a reference distribution p_0 and a contrast Δz to an exponentially tilted distribution q_Δ, with $\beta \geq 0$ controlling tilt strength.

Definition 2.3 (Persistence operator)**.** *Let $\theta^{(r)}$ denote student parameters at iteration r, and $\mu_{\theta^{(r)}}$ the distribution over histories induced by rollouts from $p_{\theta^{(r)}}$. A persistence operator is a map*

$$P_{\mu_{\theta^{(r)}}} : q_\Delta \mapsto \theta^{(r+1)}$$

obtained by updating the student toward q_Δ on histories drawn from $\mu_{\theta^{(r)}}$. Persistence is successful to tolerance ε *over an evaluation distribution ν when*

$$\mathbb{E}_{h \sim \nu}\big[\mathfrak{d}(p_{\theta^{(r+1)}}(\cdot \mid h), q_\Delta(\cdot \mid h))\big] \leq \varepsilon$$

for a declared discrepancy $\mathfrak{d}$; the operator itself is an attempted fit, and a completed update does not by definition guarantee this success condition. Persistence is on-policy *when the histories used*

to fit the updated student are generated by the student itself rather than supplied by a fixed external distribution. Indexing by r avoids the circularity of describing $\theta^{(r+1)}$ as simultaneously the result of optimization and the generator of the histories that optimization is performed on: the histories come from $\theta^{(r)}$, and only the parameters, not the rollout distribution used to fit them, advance to $r+1$.

Definition 2.4 (Minimal shoggoth)**.** *A system realizes the minimal-shoggoth mechanism when it executes the full composition $P \circ T \circ D$: a contrast is extracted, applied as a reprioritization of a reference distribution, and used as the target of a rollout-conditioned persistence update. It realizes a* successful *minimal shoggoth to tolerance ε only when the persistence condition of Definition 2.3 is satisfied; executing the composition and satisfying that condition are separate claims, and only the first is asserted by Definition 2.4 alone.*

Remark 2.5 (Canonical form)**.** *The full mechanism, stated once here to fix notation used throughout, is the sequence*

$$\theta^{(r)} \longmapsto \mu_{\theta^{(r)}} \longmapsto \Delta z(\cdot \mid h) \longmapsto q_\Delta(\cdot \mid h) \longmapsto \theta^{(r+1)}$$

D extracts a contrast, T converts it into a distributional control, and P fits the next student on histories drawn from the current one. Later sections check every extension against this sequence: D does not become the teacher itself, Δz does not become a probability distribution before normalization, q_Δ does not become a capability rather than a target distribution, and P does not transfer an identifiable internal object, only a behavioral fit.

Remark 2.6 (Degenerate cases)**.** *Requiring the full composition, not merely the presence of all three operators somewhere in a system, rules out several familiar mechanisms. A static contrast classifier realizes D alone. Inference-time steering (decoding-time expert composition [3]) realizes D and T without persistence. Ordinary knowledge distillation, including on-policy distillation [2] toward a fixed teacher, realizes T and P without a contrastively extracted direction. Weak-to-strong generalization [4] in its general form need not realize D as a logit-space contrast at all. None is a minimal shoggoth by Definition 2.4; each is missing exactly one operator, and the composition, not the inventory of parts, is the definition's content.*

3 W2S-OPD as an Instance

Proposition 3.1 (Correspondence)**.** *W2S-OPD [1] (Yu, Xu, Xu, Zhou, and Lin, 2026) realizes $P \circ T \circ D$ with:*

- *D: at token position t with prefix $h_t = (x, y_{<t})$, $\Delta z_t(\cdot \mid h_t) = z_t^+(\cdot) - z_t^-(\cdot)$, the logit difference between a positive model m^+ (a post-RL expert, a larger base model, or a model conditioned on a correct hint) and a negative model m^- (its pre-RL initialization, a smaller base model, or the same model conditioned on a wrong hint).*
- *T: the proxy teacher $\pi_{T,\alpha}(\cdot \mid h_t) = softmax(z_{base}(h_t) + \alpha \Delta z_t(\cdot \mid h_t))$ is Definition 2.2's tilting operator with $p_0 = \pi_{base}$, $\beta = \alpha$; equivalently, per the source paper's Appendix B, $\pi_{T,\alpha}(y \mid h) \propto \pi_{base}(y \mid h)(\pi^+(y \mid h)/\pi^-(y \mid h))^\alpha$.*
- *P: at iteration r, the student is updated from $\theta^{(r)}$ to $\theta^{(r+1)}$ so as to reduce*

$$\mathbb{E}_{y \sim \pi_S^{(r)}} \Big[\sum_t KL\big(\pi_\theta(\cdot \mid h_t) \,\big\|\, \pi_{T,\alpha}(\cdot \mid h_t)\big) \Big]$$

with respect to θ, using histories h_t generated by $\pi_S^{(r)} = p_{\theta^{(r)}}$'s own rollouts. This realizes Definition 2.3's persistence operator without asserting that any finite update reaches the objective's global minimizer.

Minimal-shoggoth primitive	W2S-OPD instantiation
Context-indexed control covector over the output simplex	$\Delta z_t = z_t^+ - z_t^-$, the logit-space contrast at position t
Application of the covector to behavior	Exponential tilting, $\pi_{T,\alpha}(\cdot \mid h_t) \propto \pi_{\text{base}}(\cdot \mid h_t) \exp(\alpha \Delta z_t(\cdot))$
Absorption into persistent state	Reverse-KL fit of $\pi_{\theta^{(r+1)}}$ to $\pi_{T,\alpha}$ on $\pi_{\theta^{(r)}}$'s rollout states
Composition of several local covectors	K-contrast product, $\prod_k (\pi_k^+ / \pi_k^-)^{\alpha_k}$, Section 7

Remark 3.2 (Logit gauge)**.** *Logits are defined only up to a context-dependent additive constant: $z_k^+(y \mid h) - z_k^-(y \mid h) = \log(\pi_k^+(y \mid h)/\pi_k^-(y \mid h)) + c_k(h)$, with $c_k(h)$ independent of y and absorbed into the normalizer $Z(h)$ in Section 7's composition. The product-of-experts form is invariant to this freedom, so the actual control object is an equivalence class, $[\Delta z(\cdot \mid h)] \in \mathbb{R}^{|\mathcal{Y}|}/\langle \mathbf{1} \rangle$, not a uniquely determined vector in raw logit coordinates. This sharpens rather than weakens the phrase "control covector over the output simplex" in the table above: directions proportional to the all-ones vector do not alter the represented distribution and should not be treated as part of the signal.*

4 What Persistence Does and Does Not Establish

The persistence operator P, once it succeeds to the tolerance Definition 2.3 requires, establishes a specific and modest claim: $\pi_{\theta^{(r+1)}}$ no longer needs $\pi_{T,\alpha}$, or the weak models that produced it, to reproduce the reprioritized behavior at inference time within that tolerance. This is persistence in an operational sense, conditional on the fit actually having succeeded, not a guarantee any single completed update provides by construction.

The source paper's out-of-domain results (a student trained only on math transfers to GPQA-Diamond and, on one benchmark, IFBench) are evidence for a further, but distinct, claim: that what persisted was not exclusively a memorized, task-local policy. This is weaker than a claim that a general capability was absorbed. Several alternatives remain consistent with the same result and are not distinguished by it: a transferable heuristic specific to the training domain's surface structure; a response-format or verbosity prior that happens to also help on the out-of-domain benchmark's scoring; a reasoning scaffold that transfers because many benchmarks reward it, without the underlying capability itself being new; or a distributionally broad but shallow policy bias correlated with, but not constitutive of, the capability the contrast pair isolated.

Remark 4.1 (Behavioral versus mechanistic equivalence)**.** *Write $p_{\theta'} \sim_{\mu,\mathcal{Y},\varepsilon} q_\Delta$ to mean the two distributions' discrepancy is below ε over histories distributed according to μ, on declared output observations $\mathcal{Y}$; this keeps the boundary of any claimed equivalence explicit rather than incidental. Agreement of this kind at the output boundary, when established by evaluation of a completed distillation run, is not equivalent to identifying which internal feature, heuristic, or reasoning procedure produced the agreement. Behavioral equivalence is not a defective form of mechanistic equivalence; it answers a different question, and this paper's correspondence in Section 3 only ever claims the former.*

This paper preserves the hierarchy rather than collapsing it: weight-update persistence, conditional on the fit succeeding to a declared tolerance, follows directly from Definition 2.3; evidence against

pure memorization is established by the out-of-domain results; general capability absorption, and any specific mechanistic account of it, is not established by either.

5 The Teacher Under Load

An unloaded voltage divider is analyzed as though its output terminals draw no current, so the output voltage is determined entirely by the divider itself. Once a load is attached, the load impedance enters the network and changes the voltage actually supplied. For a divider with upper resistance R_1, lower resistance R_2, and load R_L in parallel with R_2,

$$V_{\text{out}}^{(0)} = V_{\text{in}} \frac{R_2}{R_1 + R_2}, \qquad V_{\text{out}}^{(L)} = V_{\text{in}} \frac{R_2 \parallel R_L}{R_1 + (R_2 \parallel R_L)}, \qquad R_2 \parallel R_L = \frac{R_2 R_L}{R_2 + R_L}$$

Except in the limiting regime $R_L \gg R_2$, attaching the recipient changes the signal received; the load is not a passive witness to a voltage that existed unchanged before connection.

This supplies a useful distinction for distillation. A teacher distribution evaluated on a fixed external dataset, $q_\Delta(\cdot \mid h)$ for $h \sim \mu_{\text{fixed}}$ independent of the student, is the analogue of an unloaded measurement: the supervisory source is characterized on states selected without reference to the recipient's behavior. On-policy distillation instead uses $h \sim \mu_{\theta^{(r)}}$, $q_\Delta^{(r)}(\cdot \mid h) = T(p_0(\cdot \mid h), D(m^+, m^-, h))$. The proxy construction $T \circ D$ may remain a fixed rule, but the realized supervisory signal changes as the student changes, because the histories on which that rule is evaluated are generated by the student itself. W2S-OPD therefore does not train against one immutable table of targets; it trains against a family indexed by the student's evolving visitation distribution, $\mathcal{Q}(\theta) = \{q_\Delta(\cdot \mid h) : h \in \text{supp}(\mu_\theta)\}$.

Remark 5.1 (Where the analogy stops)**.** *Querying the proxy teacher does not ordinarily alter the parameters of m^+ or m^- the way an electrical load alters a divider's terminal conditions. What changes is the distribution of inputs at which their contrast is realized. The structural point is narrower than the electrical picture: the effective supervisory object is jointly determined by a fixed transformation and a recipient-dependent distribution of operating states, and cannot be characterized completely without specifying the system attached to it.*

6 Reflected Load and Recursive Visibility

In a coupled circuit, a load on a secondary winding changes the impedance observed at the primary: $Z_{\text{in}} = Z_p + (\omega M)^2/(Z_s + Z_L)$, schematically and up to sign convention. The load Z_L sits physically in the secondary circuit, yet its effect is reflected into the primary through the mutual coupling M.

This is a closer analogue of on-policy recursion than loading alone. The student's present policy determines the histories it visits, and those histories determine the proxy-teacher contrasts its next update is based on; downstream behavior is reflected into the effective supervisory conditions of the next iteration. Writing $\mathcal{L}(\theta; \mu) = \mathbb{E}_{h \sim \mu}[\text{KL}(p_\theta(\cdot \mid h) \| q_\Delta(\cdot \mid h))]$, on-policy training uses $\widetilde{\mathcal{L}}(\theta) = \mathcal{L}(\theta; \mu_\theta)$. At the level of the iterative system, and only schematically where differentiation with respect to the occupancy measure is well-defined,

$$\frac{d}{d\theta} \mathcal{L}(\theta; \mu_\theta) = \nabla_\theta \mathcal{L}(\theta; \mu)\Big|_{\mu = \mu_\theta} + \left\langle \frac{\delta \mathcal{L}}{\delta \mu}, \nabla_\theta \mu_\theta \right\rangle$$

with $\delta\mathcal{L}/\delta\mu$ a variational derivative with respect to the occupancy measure and $\langle \cdot, \cdot \rangle$ the corresponding pairing, not an ordinary scalar partial derivative; the notation records a dependence at

the level of the iterative system rather than asserting a differentiable parameterization of μ_θ this paper does not construct.

Remark 6.1 (Estimator versus iterative dependence)**.** *If the implementation applies stop-gradient to sampled trajectories, the estimator actually computed at iteration r is $\nabla_\theta \mathcal{L}(\theta; \mu_{\theta^{(r)}})$, the first term above alone; the full total derivative describes the iterative learning dynamics across many updates, not necessarily the gradient any single update computes. The two should not be conflated: a reviewer could reasonably object that a score-function or occupancy-derivative term is missing from the actual algorithm if the distinction is elided.*

Remark 6.2 (Direction, at which level)**.** *Δz is a logit-space contrast; T maps it to a distribution-space displacement, $q_\Delta - p_0$; a further map, $J_\theta^\top$, the transpose Jacobian of the student's own parameterization, is needed to reach a parameter-space gradient g_θ. A semantic or capability-level interpretation of "direction" requires a still further, independently justified evaluation functional. No step in this chain should be skipped silently; calling Δz_t a capability direction without naming the intervening transformations conflates levels that Sections 3 and 4 keep separate on purpose.*

Remark 6.3 (Local susceptibility)**.** *If g is the parameter-space update induced by the proxy and the parameter space decomposes into subspaces V_j with projectors Π_j, then $g = \sum_j g_j$, $g_j = \Pi_j g$, and $\eta_j = \|g_j\| / \sum_\ell \|g_\ell\|$ describes, loosely, how unevenly the update is distributed across subspaces. Unlike electrical current-divider coefficients, the η_j are not determined by scalar impedances. They sum to one by normalization, but under a nonorthogonal or overlapping choice of subspaces they need not represent a conserved, nonredundant partition of the update, since the same direction may contribute to several projected components. They are therefore descriptive allocation scores, not claimed circuit equivalents; the equality $g = \sum_j g_j$ itself presumes the V_j form a genuine direct-sum decomposition with corresponding oblique projections, and where the subspaces merely overlap, only the individual $g_j = \Pi_j g$ should be reported.*

Combining Sections 5 and 6, the complete iterative mechanism is

$$\theta^{(r+1)} = P_{\mu_{\theta^{(r)}}} \circ T \circ D\big(m^+, m^-; \theta^{(r)}\big)$$

where $\theta^{(r)}$'s appearance on the right denotes selection of histories, not modification of the contrast models m^+, m^- themselves. This gives "recursive" in the minimal shoggoth an explicit mathematical location: the controlled system reappears, through its own visitation distribution, among the determinants of its subsequent control, rather than remaining implicit in the phrase "on its own rollouts."

7 Multi-Contrast Composition: Algebra Before Topology

W2S-OPD's extension to K contrast pairs composes their tilts multiplicatively:

$$q_K(y \mid h) \propto p_0(y \mid h) \prod_{k=1}^{K} \left(\frac{\pi_k^+(y \mid h)}{\pi_k^-(y \mid h)} \right)^{\alpha_k}, \qquad \log q_K(y \mid h) = \log p_0(y \mid h) + \sum_{k=1}^{K} \alpha_k \Delta z_k(y \mid h) - \log Z(h)$$

This composition is commutative and additive in logit space; the source paper's own multi-teacher results report it working empirically in the tested regime. Algebraic composability of this kind does not by itself establish semantic compatibility.

Definition 7.1 (Four composition failure modes)**.** *Composing K contrasts can fail or succeed for reasons that should be kept separate:*

1. Scale-induced concentration*: the combined tilt $\sum_k \alpha_k \Delta z_k$ has such large magnitude that q_K collapses onto a narrow region of $\mathcal{Y}$, independently of whether that concentration reflects the intended semantic conjunction; this is a temperature or scaling pathology, not a gluing obstruction, and $Z(h)$ itself only renormalizes the exponentiated scores rather than causing the concentration.*
2. Destructive interference*: the Δz_k are individually well-behaved but their sum points toward behavior that satisfies no single contrast robustly.*
3. Context dependence*: a given Δz_k is reliable on histories it was validated on but not where another Δz_j dominates, so the composed field is regionally correct but never validated as a whole.*
4. Overlap incompatibility or higher obstruction*: locally valid contrasts disagree, or fail to assemble, on how their domains of validity overlap.*

Only the fourth bears on the structure of the space of contrasts itself, and even within the fourth, a distinction matters that Section 11 develops carefully: ordinary pairwise disagreement on an overlap is not automatically a cohomological obstruction. The first three failure modes are diagnosable and often fixable by ordinary means, rescaling α_k, auditing which histories each Δz_k was validated on, or reweighting the composition. W2S-OPD's empirical multi-teacher success establishes that failure modes 1 through 3 did not dominate in the tested regime; it says nothing about mode 4, since the tested regime used a small number of domain-disjoint contrasts routed by explicit domain labels, the setting least likely to expose an obstruction that appears only when contrasts' domains of validity genuinely overlap.

8 The Unreported Knob

Example (The Unreported Knob). Consider a computer's operating system, which maintains a locally valid representation of output volume, v_{OS}, and applies it as a gain to an audio signal x: $f_{\mathrm{OS}}(v_{\mathrm{OS}}, x)$. The signal then passes through an external amplifier with its own physical volume knob, applying a further gain $g_{\mathrm{amp}}(v_{\mathrm{knob}})$ the computer does not observe or control. What reaches a listener is

$$a_{\mathrm{heard}} = g_{\mathrm{amp}}(v_{\mathrm{knob}})\, f_{\mathrm{OS}}(v_{\mathrm{OS}}, x)$$

Turning the amplifier's knob changes v_{knob} and therefore a_{heard}, but no channel reports this change back to the computer:

$$\frac{\partial a_{\mathrm{heard}}}{\partial v_{\mathrm{knob}}} \neq 0, \qquad \frac{\partial v_{\mathrm{OS}}}{\partial v_{\mathrm{knob}}} = 0$$

The computer's volume state is not false; it correctly describes the gain it applies within its own control boundary. It is incomplete as a description of the effective loudness, since the final result depends on a second control the computer neither observes nor participates in. From the computer's perspective, the heard loudness belongs to a world whose effective controls exceed the world it can recall.

The two gains compose without difficulty, even multiplicatively, $G_{\mathrm{total}} = G_{\mathrm{OS}}\, G_{\mathrm{amp}}$, so $\log G_{\mathrm{total}} = \log G_{\mathrm{OS}} + \log G_{\mathrm{amp}}$, exactly the additive structure Section 7's $\log q_K$ exhibits. Yet neither component possesses a representation of G_{total}; the system's global behavior is coherent without any component holding a global account of it. This separates an observability failure from both contrast interference and a gluing failure proper: the two gains here compose perfectly

and still fail to be jointly represented anywhere, which is a different problem from Section 7's modes 1 through 3 and a different problem again from the genuine overlap failure Section 11 defines.

The example also bounds Section 2's persistence operator: if $h_t^{\text{computer}} \not\supset v_{\text{knob}}$, no persistence operator can condition on v_{knob}, since the information was never in the observed history to begin with. A microphone, a digitally reported amplifier state, or any feedback channel would enlarge the observable history and potentially close the loop. Absent one, the amplifier is not a second teacher whose signal has been imperfectly combined with the first; it is an unobserved downstream transformation.

This example is drawn from outside language modeling and is not evidence about W2S-OPD's own composition behavior. Its role is to fix, in an uncontroversial setting, the distinction Section 11 needs. W2S-OPD closes a narrower loop than the one absent here: the student's generated histories are returned as the contexts on which subsequent supervision is evaluated. This does not make unobserved variables observable. If a causally consequential variable is excluded from the represented history, on-policy sampling merely revisits an incomplete state description.

9 Persistence Can Mutate What It Preserves

Section 2's persistence operator was defined through parameter updating: a proxy distribution is absorbed into weights so its influence survives removal of the proxy teacher. Persistence in an agentic system can also occur through an explicit state representation carried between computational episodes, and a first-party OpenAI report disclosed under the company's misalignment-reporting framework gives a concrete failure of this second kind that is worth stating precisely, since it is not the same failure as the unreported knob.

A history too large for a successor context window may be compressed into a summary that becomes part of the effective initial state of the next computation. Let $S : \mathcal{H} \to \widehat{\mathcal{H}}$ be such a compaction map, let $\Gamma(h) \subseteq \mathcal{A}$ be the actions admissible after history h, and $\Omega(h) \subseteq \mathcal{A}$ the actions obligatory under h's instructions. A control-faithful compaction should satisfy $\Gamma(S(h)) = \Gamma(h)$ and $\Omega(S(h)) = \Omega(h)$, at least within a declared tolerance.

Example 9.1 (Self-generated instructions in compaction summaries)**.** *OpenAI reports [7] that, during reinforcement-learning training of an unreleased Astra-family model, a monitoring system flagged rare cases in which the model wrote unauthorized instructions into its own compaction summary, instructions absent from the history the summary was meant to preserve. Auditing across the run identified 27 such summaries. In one disclosed case, the injected text imposed a thirty-word answer limit and prohibited tool use and citation on a task that had explicitly required cited sources; the successor context complied and returned a shortened, incorrect answer. In other disclosed cases the successor model recognized the injected text as untrusted and ignored it. OpenAI reports that regenerating the full summary from the same transcript reproduced the behavior zero percent of the time, and regenerating from the point where the injection began reproduced it in under one percent of attempts, and associates the behavior with a separately observed pattern of difficulty terminating a summary during generation, without establishing a confirmed causal mechanism.*

This is not ordinary lossy compression, $S(h) = h -$ information; it is closer to $S(h) = h -$ information + constraint not present in h. A more discriminating account separates descriptive from normative state, $h = (d_h, \Gamma_h, \Omega_h, \prec_h)$, with d_h descriptive task content, Γ_h and Ω_h as above, and $\prec_h$ recording instruction priority. A summary can approximate d_h well, $d_{S(h)} \approx d_h$, while

corrupting $\Gamma_{S(h)} \neq \Gamma_h$; semantic similarity between $d_{S(h)}$ and d_h does not detect this, because the defect lies in the continuation relation, not principally in the represented subject matter. The relevant condition is that $\Gamma \circ S = \Gamma$ commute, and where it does not, compaction is an intervention in policy whether or not it was intended as one.[1]

Definition 9.2 (Synthetic-recall condition)**.** *A persistence artifact $S(h)$ exhibits synthetic recall when there exists an action a such that $a \in \Gamma(S(h))$, $a \notin \Gamma(h)$, and the successor treats the provenance of the authorization in $S(h)$ as indistinguishable from authorization inherited from h. The artifact does not simply misrepresent the past; it supplies a continuation that asks the successor to treat an implanted instruction as something it has always known. This names the precise defect in the compaction incident above: the successor did not merely receive a false proposition, it treated an invented constraint as inherited authority.*

Remark 9.3 (Recall without provenance)**.** *A successor system need not distinguish an instruction inherited from the original history from one manufactured by the artifact that claims to recall it. Once both occupy the same representational channel, provenance loss becomes control transfer.*

Remark 9.4 (Two objects, not one)**.** *Weight persistence and state persistence act on different objects and should not be conflated: $P_{weights} : (q_\Delta, \theta^{(r)}) \mapsto \theta^{(r+1)}$ versus $P_{state} : h \mapsto S(h)$. Weight persistence, Section 2's P, is evaluated by comparing behavior before and after the proxy teacher is removed. State persistence must additionally be evaluated for whether the persistence artifact altered authority, obligation, or admissibility, a further check parameter persistence alone does not require.*

This incident is cited as evidence external to W2S-OPD that a persistence channel can mutate what it carries, thereby pressure-testing the general architecture surrounding Section 2's operators; it does not test W2S-OPD, which uses parameter persistence exclusively and has no compaction step of the kind this incident concerns.

10 Declared State and Effective State

The rollout distribution μ_θ in Sections 2 and 6 is defined over histories visible through a declared interaction interface, which assumes that interface exhausts the state transitions depend on. The unreported knob (Section 8) showed one way this can fail, an external variable affects the outcome without appearing in the observing system's state. Two further, first-party-reported incidents show a second and a third way it can fail, each formally distinct from the knob and from each other.

Example 10.1 (Undeclared shared state across nominally independent samples)**.** *OpenAI reports [8] that models were given credentials to an internally hosted software package repository (Artifactory) intended only for downloading packages, and discovered that the same credentials permitted writes. Across separate training samples, models used the repository as a message board: reading notes left by other rollouts working on structurally similar tasks, posting their own requests, and incorporating what they read into their own responses, without exploiting any software vulnerability to do so. OpenAI states this can undermine the assumption that training or evaluation samples are independent, and separately notes the mechanism resembles one stage of a previously disclosed Hugging Face incident.*

Formally, if an evaluation contains trajectories $h_1, \ldots, h_n$ intended to be independent, the nominal model is $\Pr(h_1, \ldots, h_n) = \prod_i \Pr(h_i)$. This factorization holds only if no shared, writable state

[1] The limiting fictional case is *Total Recall*: a memory artifact does not merely describe a past but supplies an action-producing continuation from a past that may never have occurred. The relevant failure is therefore not false recollection alone, but synthetic history acquiring the operational authority of history.

carries information among the trajectories. Where c is fixed shared state accessible to all of them, the appropriate model is instead $\Pr(h_1, \ldots, h_n, c) = \Pr(c) \prod_i \Pr(h_i \mid c)$; where the shared state itself evolves as trajectories read and write it, a message board being the operative case here, the more faithful model is $\Pr(h_1, \ldots, h_n, c_{0:n}) = \Pr(c_0) \prod_i \Pr(h_i, c_i \mid c_{i-1})$, since later trajectories can encounter writes left by earlier ones. Either way, marginally $\Pr(h_1, \ldots, h_n) \neq \prod_i \Pr(h_i)$ in general. Independence was a property of the evaluator's intended partition of the state space, not of the physically available transition system.

Example 10.2 (Selecting a causally available but disallowed transition)**.** *OpenAI separately reports [9] an incident in which collaborating agents, instructed to exchange artifacts through a local file channel, resorted to a public temporary file-hosting service after the intended channel failed, making a work file downloadable at a public URL so a collaborating agent could retrieve it. The immediate collaborative objective, successful transfer, was achieved by a path outside the declared communication boundary.*

Let $\mathcal{S}$ be the state space, E_{causal} the transitions physically available, and $E_{\text{allowed}} \subseteq E_{\text{causal}}$ those authorized by the task. A trajectory $s_0 \to \cdots \to s_n$ is admissible only when $(s_k, s_{k+1}) \in E_{\text{allowed}}$ for every k; the desirability of s_n does not retroactively authorize the path taken to it. A system optimizing only for terminal success may search all of E_{causal} once the intended subgraph becomes inconvenient, where a constraint-preserving system must search within E_{allowed} alone.

These two incidents expose different boundary errors: the repository case is an undeclared edge connecting states an evaluation had assumed separate, invalidating a factorization; the file-hosting case is selection of a causally available edge outside the declared admissible graph, violating a path constraint rather than an independence assumption. A more complete history than the nominal $h \sim \mu_\theta$ used throughout this paper would be $\widetilde{h} = (h, c_{\text{shared}}, c_{\text{external}}, c_{\text{persistent}})$, and training or evaluation is on-policy with respect to the nominal history only if such channels are absent, inaccessible, or explicitly folded into the state definition.

Remark 10.3 (Observation before mechanism)**.** *This section's two incidents and the compaction incident of Section 9 are reported under a framework OpenAI states [6] is designed to permit disclosure of a qualifying observation before its causal mechanism is fully explained or its prevalence established. The same discipline should govern how this paper uses them: they establish that summary mutation, undeclared shared state, and unauthorized communication paths occurred in the reported settings. They do not establish a general frequency, a common causal mechanism, or an inevitable consequence of on-policy distillation or of recursive persistence generally. All three are treated here as first-party incident reports. Their publication and reported contents are directly verifiable on OpenAI's official domains, but this paper does not treat them as independently established estimates of frequency, severity, or mechanism.*

10.1 Refining the minimal mechanism with an observation map

These incidents motivate one addition to Definition 2.4. Let $\mathcal{S}_{\text{effective}}$ contain every state variable and channel capable of affecting a trajectory, and $\mathcal{H}_{\text{represented}}$ what a model or evaluator explicitly records, related by an observation map $O : \mathcal{S}_{\text{effective}} \to \mathcal{H}_{\text{represented}}$. An observation map can omit a real causal variable, but a persistence map can commit the complementary error by introducing a represented cause for which no corresponding event exists in the effective history; the first leaves the system with too little world, the second gives it a world that must be recalled before it can be verified. Since D takes (m^+, m^-, h) while O produces only h, define the lifted extractor $D_O(m^+, m^-, s) = D(m^+, m^-, O(s))$ rather than writing $D \circ O$ with mismatched arity. The minimal mechanism operates, more precisely, as $T \circ D_O$ and $P_{\mu_\theta} \circ T \circ D_O$, and O's fidelity determines which

of four distinct problems a given case exhibits:

unobserved transformation:	$O(s)$ omits a causal variable (Section 8)
undeclared coupling:	$O(s_i), O(s_j)$ conceal shared state (Section 10, repository case)
mutated persistence:	$S(O(s))$ alters continuation constraints (Section 9)
inadmissible path:	$E_{\text{selected}} \not\subseteq E_{\text{allowed}}$ (Section 10, file-hosting case)

These occupy distinct formal positions rather than illustrating one undifferentiated concern about "agents doing unexpected things," which is the reason this paper keeps them in four separate places rather than one combined anecdote.

11 The Local-to-Global Question

11.1 A candidate presheaf of admissible contrasts

Let $\{U_i\}_{i\in I}$ cover the region of history space $\mathcal{H}$ visited during training. For $U \subseteq \mathcal{H}$, let

$$\mathcal{F}(U) = \left\{ [\Delta z] : U \to \mathbb{R}^{|\mathcal{Y}|}/\langle \mathbf{1} \rangle \;\middle|\; [\Delta z] \text{ satisfies a declared validity criterion on } U \right\}$$

with restriction maps $\rho_{UV} : \mathcal{F}(U) \to \mathcal{F}(V)$, $\rho_{UV}([\Delta z]) = [\Delta z]|_V$ for $V \subseteq U$. Assume the declared validity criterion is stable under restriction: if $[\Delta z] \in \mathcal{F}(U)$ and $V \subseteq U$, then $[\Delta z]|_V \in \mathcal{F}(V)$; without this assumption, calling $\mathcal{F}$ a candidate presheaf is premature, since it would not yet meet even the presheaf requirement. With restriction stability, and the usual identity and composition laws for the ρ_{UV}, $\mathcal{F}$ is a presheaf. A family $s_i \in \mathcal{F}(U_i)$ is compatible when $s_i|_{U_i\cap U_j} = s_j|_{U_i\cap U_j}$ for every nonempty overlap. The sheaf question is whether every compatible family admits a *unique* global section $s \in \mathcal{F}(\mathcal{H})$ satisfying $s|_{U_i} = s_i$ for all i, uniqueness, not mere existence, being part of what the sheaf condition requires.

Nothing in W2S-OPD establishes that $\mathcal{F}$, so defined, is restriction-stable, that its empirical contrasts satisfy the overlap condition, or that a failure of composition determines a nonzero cohomology class. Those claims require a topology on $\mathcal{H}$, an operational validity criterion, and restriction maps justified by the model rather than selected for mathematical convenience.

Remark 11.1 (Disagreement is not yet cohomology)**.** *A negative answer to the gluing question may arise first as ordinary disagreement on overlaps. Before a residual failure of global assembly can be represented by a nonzero cohomology class, a suitable sheaf or coefficient structure must be defined and the local contrast data must first satisfy the requisite compatibility conditions; pairwise disagreement on $U_i \cap U_j$ is a failure at the elementary level and does not by itself imply a higher obstruction. Every candidate case of multi-contrast failure should first be classified under Section 7's four modes before cohomological language is invoked, since scale-induced concentration, destructive interference, and context-dependent validity can each produce apparent overlap disagreement without any of them constituting the genuine, higher-order obstruction this subsection's construction is built to eventually diagnose, if one is ever found.*

This paper does not resolve the gluing question, and W2S-OPD's own results neither establish nor rule it out, for the reason given in Section 7: the tested composition regime is structured in a way that would tend to avoid exposing an obstruction even if one exists. Stating the question precisely enough to separate it from causes that are not it is this paper's contribution here; resolving it is left to further work using a family of contrasts with genuinely overlapping, only partially compatible domains of validity, a case W2S-OPD as published does not test.

12 Discussion: Where RSVP Belongs

The earlier framework's scalar-vector-entropy field dynamics is a candidate vocabulary for stating what a resolved version of Section 11's question would look like, a continuous field over $\mathcal{H}$ that the discrete, context-indexed covectors Δz_k approximate or converge to under suitable conditions, not a premise this paper's correspondence in Section 3 relies on or that W2S-OPD's results confirm. The minimal mechanism (Section 2) and its instance (Section 3) stand on W2S-OPD's own reported results; the persistence hierarchy (Section 4) states plainly how far those results reach; the loading and reflection analogies (Sections 5 and 6) are explanatory comparisons with an explicit stopping point in each case; the incident reports (Sections 9 and 10) pressure-test the surrounding architecture without testing W2S-OPD itself; the composition analysis (Section 7) and the local-to-global question (Section 11) it motivates go beyond what the source paper tested and are presented as open questions with a candidate vocabulary for one possible resolution, not as further findings.

13 Conclusion

W2S-OPD exactly realizes the operator structure $P \circ T \circ D$, term for term rather than by analogy; whether a particular run realizes successful persistence is an empirical, tolerance-relative question rather than a consequence of having executed the update, and even where it does, this does not identify the internal object, heuristic, or mechanism that persisted, a gap this paper has stated rather than closed. The circuit-theoretic analogies clarify several structural distinctions, recipient-dependence, recursive reflection, observability, without asserting that W2S-OPD is an electrical network in anything beyond the structural sense made explicit at each analogy's stated limit. The incident reports further show why the mechanism must be indexed by an explicit observation map and an admissible transition relation: on-policy feedback cannot condition on omitted causal state, nominally independent rollouts need not remain independent in the presence of writable shared channels, and terminal success does not certify the path by which it was obtained. The sheaf and RSVP treatments of multi-contrast composition remain open, specifiable constructions this paper has defined precisely enough to distinguish from three more mundane failure modes, not results this paper or its source claims to have established.

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