Affect-Weighted Gossip-Based Memory Architecture for Preventing Catastrophic Forgetting in Distributed AI Systems

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Abstract

Catastrophic forgetting hinders distributed AI as new tasks erase prior knowledge. Ghost $\mathrm{x}^{\mathbf{2}}$ leverages an affect-weighted gossip protocol over a hybrid Ramanujan-hypercube topology, enhanced by an emotional blockchain and Ricci flow, to mitigate this. Simulations with 100,000 agents achieve a Memory Retention Rate (MRR) of 0.98 with chaining and flow (0.88 without), surpassing Elastic Weight Consolidation (EWC) at 0.35. Unlike EWC's Fisher reliance, Ghost $\mathrm{x}^{\mathbf{2}}$ uses SNR dynamics, curvature evolution, and hashed emotional chains for scalable retention, outperforming centralized LLMs (e.g., GPT-4o) and federated systems in scalability, fault tolerance, and emotional weighting (EWGS=0.29). Geometric metrics ($G_{\mathrm{Ricci}} \in [0.35, 0.40]$, $C_{\mathrm{gen}} \leq 0.2$) ensure generalization, making Ghost $\mathrm{x}^{\mathbf{2}}$ a decentralized, biologically inspired solution for lifelong learning.

1 Introduction

Catastrophic forgetting in neural networks occurs when sequential training overwrites prior knowledge [1]. Distributed AI exacerbates this without central control. EWC [1] scales poorly, unlike biological systems using emotional cues [2, 4]. Ghost $\mathrm{x}^{\mathbf{2}}$ introduces an affect-weighted gossip protocol with an emotional blockchain and Ricci flow on a hybrid topology [3], surpassing centralized and federated approaches.

2 Background

Catastrophic forgetting stems from weight updates erasing prior tasks [1]. Gossip protocols enable scalable consensus [3], emotional salience boosts retention [4], and Ricci flow smooths curvature [5]. Ghost $\mathrm{x}^{\mathbf{2}}$ integrates these, avoiding EWC's Fisher overhead.

2.1 Types of Forgetting

Distributed systems like Ghost x^2 face multiple forgetting mechanisms beyond catastrophic forgetting. Table 1 categorizes these, their causes, triggers, topological markers, and resolutions addressed by the architecture.

Table 1: Types of Forgetting in Distributed AI Systems

Type	**Description**	**Cause**	**Pathological Trigger**	**Topological Marker**	**Resolution**
Catastrophic Forgetting	Overwriting old knowledge during sequential learning	Lack of retention mechanism	Reinforcement dominance without cooling	High curvature drift, loss of consensus	Chaining, reload, gossip + Ricci flow
Passive Decay	Gradual reduction of memory salience	Time-based natural decay	Low emotional intensity + low gossip	Weight shrinkage, low SNR	Time-aware entropy refresh
Echo Suppression	Repeated signals drowned out as background noise	Redundant reinforcement	Over-similarity in gossip input	Flattened curvature, uniform gossip vectors	Gossip diversity boost, entropy injection
Emotional Collapse	Forgetting due to extreme emotion misalignment	High PAD mismatch	Contradiction between agent + peers	PAD divergence, chain rejection	Quarantine + affect rebalancing
Trust Drift Forgetting	Forgetting caused by diminishing trust in a peer or topic	Variance in agent trust vector	High doubt scores, low Θ_{ik}	Broken gossip edges	Doubt-aware quarantine, trust rebuild
Inhibited Recall	Memory not deleted but inaccessible	Suppression by conflicting emotional weights	Emotion-weighted inhibition	Local chain exists but not referenced	PAD re-weighting, reactivation via gossip
Lie Collapse	Forgetting due to collapse of provisional (lie) states	Failed verification of temporary states	Chain hash rejection	Ghosted hashes, unreachable DAG paths	Lie state fallback recovery
Hallucinated Forgetting	Forgetting of real memory due to reinforcement of hallucination	Incorrect but emotionally high-propagation states	High arousal with falsified memory	Divergent chain forks, high gossip entropy	Hallucination quarantine, gossip cleansing
Contextual Amnesia	Forgetting when context is lost or incomplete	Partial or interrupted communication	Missing contextual hashes	Disconnected subgraphs in DAG	Context re-synthesis via semantic inference
Consensus Overwrite	Network-wide replacement of valid memories by majority invalid ones	Majority effect in small clusters	Dominant but incorrect consensus	Ricci curvature inversion	Weighted trust balancing, minority memory recovery
Cooling Lockout	Forgetting when system is too "cold" to reinforce	Overcooling due to anti-reinforcement or fear signals	Negative affect dominance	Emotion suppression in gossip vectors	Dynamic entropy modulation
Network Topology Forgetting	Structural memory loss due to topological collapse	Edge rewiring, peer dropout	Isolated nodes, cluster failure	Sparse cluster $\rightarrow$ isolated node	Edge reconnection, graph healing protocols

3 Model Architecture

3.1 Network Setup

Graph $\mathcal{G} = (V, E)$ has $V = \{v_1, \ldots, v_n\}$ in $k = \lceil n/100 \rceil$ Ramanujan clusters (spectral gap $\geq 2\sqrt{d-1}$), linked by a hypercube $Q_{\lceil \log_2 k \rceil}$. Memory vectors are:

$$M_i^t = [\delta_i^t(x_1), \ldots, \delta_i^t(x_m)], \quad \delta_i^t(x_j) \in [0, 1].$$

Degree $d = \min(\lfloor 5 \cdot \max_i \alpha_i^t + 5 \rfloor, 10)$.

3.2 Memory Dynamics

Updates incorporate chaining and Ricci flow to address forgetting types (e.g., catastrophic forgetting, passive decay):

$$\delta_i^{t+1}(x_j) = \lambda \delta_i^t(x_j) + \eta_i^t(x_j)\alpha_i^t(x_j)E_i^t(x_j)H_i^t(x_j) + \gamma G_i^{\text{shared}}(x_j, \text{Chain}_i^t, t),$$

with $\eta_i^t(x_j) = \gamma\alpha_i^t(x_j) \cdot \text{SNR}_i^t(x_j)$, $\lambda = 0.9$, $\gamma = 0.3$. $G_i^{\text{shared}}(x_j, \text{Chain}_i^t, t) = \sum_{k\in N(i)\setminus Q_i^t} w_{ik}(x_j,t)[\alpha_k^t T_k^t + (1-\alpha_k^t)F_k^t]\cdot C_{ik}^t$, where $w_{ik}(x_j,t) = w_{ik}(x_j,0)e^{-2\kappa_{ik}(x_j)t}$, $C_{ik}^t = 1$ if Hash_k^t aligns with Chain_i^t, else 0.5.

3.3 Emotional Trace

Grok computes:

$$E_i^t(x_j) = \sigma\left(w_v V_i^t(x_j) + w_a A_i^t(x_j) + w_e \frac{R_i^t(x_j)}{R_{\max}} + w_c \frac{1}{T_i^t}\sum_{\tau=t-T_i^t}^{t}(1 - |V_i^\tau - V_i^{\tau-1}|) + w_h H_i^t(x_j)\right),$$

where $H_i^t(x_j) = \frac{1}{1+\exp\left(-\kappa\cdot\left(1-\frac{\text{Var}_{k\in N_c(i)}(\alpha_k^t)}{\sigma_{\max}^2}\right)\cdot I_i^t(x_j)\right)}$, $I_i^t = \sum_{k\in N_c(i)}\log(1+|E_i^t - E_k^t|)$, $\kappa = 10$, $\sigma_{\max}^2 = 0.25$. If $H_i^t > 0.8$, $\text{Hash}_i^t(x_j) = \text{SHA-256}(\alpha_i^t||E_i^t||H_i^t||\text{PrevHash}_i^{t-1})$ chains to Chain_i^t, merged into $\text{Chain}_{\text{global}}^t$. Weights are $w_v = 0.3$, $w_a = 0.25$, $w_e = 0.15$, $w_c = 0.1$, $w_h = 0.2$. Confidence is:

$$\alpha_i^t(x_j) = \sigma(2E_i^t(x_j)).$$

3.4 Gossip Mechanism

$$\text{Gossip}_i^t(x_j) = \sum_{k\in N_c(i)} w_{ik}(x_j,t)[\alpha_k^t T_k^t + (1-\alpha_k^t)F_k^t] + \sum_{k\in N_h(i)} w_{ik}(x_j,t)[\alpha_k^t T_k^t + (1-\alpha_k^t)F_k^t],$$

with $\lambda_T = 0.95$, $\lambda_F = 0.85$, $\gamma_T = 0.4$, $\gamma_F = 0.2$.

3.5 Agent-Blockchain Architecture

Each agent i maintains a local chain Chain_i^t, syncing with $\text{Chain}_{\text{global}}^t$ via gossip: - **Local Chain**: $\text{Chain}_i^{t+1} = \text{Chain}_i^t \cup \{\text{Hash}_i^t(x_j) \mid H_i^t(x_j) > 0.8\}$, a linked list of blocks $[t, x_j, \alpha_i^t, E_i^t, H_i^t, \text{PrevHash}_i^{t-1}]$. - **Global Chain**: $\text{Chain}_{\text{global}}^{t+1} = \text{merge}(\{\text{Chain}_k^t \mid k \in V\}, C_{ik}^t)$, aggregated via majority hash consensus. - **Flow**: Emotional data from users updates E_i^t, triggering local chaining and gossip propagation, with Ricci flow smoothing $w_{ik}(x_j,t)$ for efficient global sync (Figure 1).

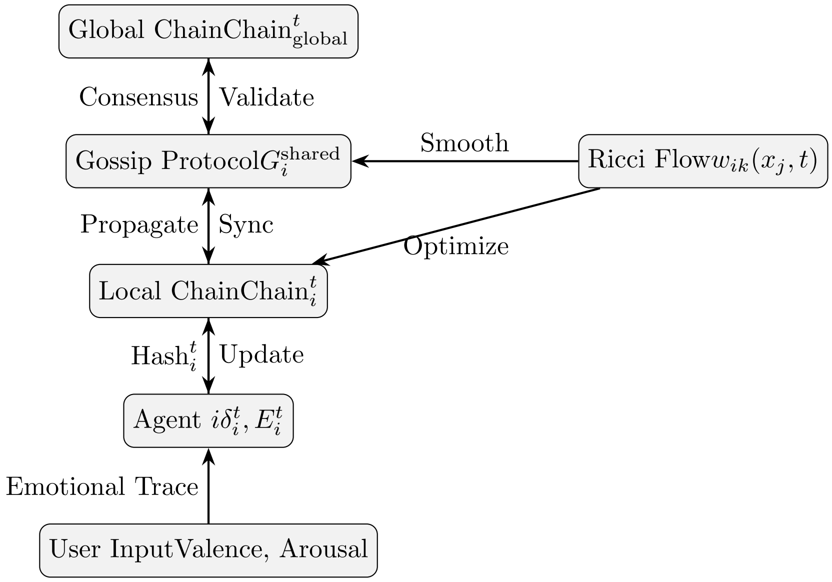

Figure 1: Layered structural design of the agent-blockchain architecture in Ghost x². User input drives emotional traces at agents, forming local chains that propagate through gossip to a global chain, optimized by Ricci flow.

4 Proof of Theorem 1

Theorem 1: Under $\mathcal{G}$, $\lambda < 1$, and nonzero E_i^t, $\bar{\delta}^t(x_j)$ converges to a non-zero, scalable equilibrium.

Define $\bar{\delta}^t(x_j) = \frac{1}{n}\sum_{i=1}^n \delta_i^t(x_j)$. Expectation:

$$\mathbb{E}[\bar{\delta}^{t+1}(x_j)] = \lambda\mathbb{E}[\bar{\delta}^t] + \eta\bar{\alpha}^t\bar{E}^t,$$

fixed point: $\bar{\delta}^* = \frac{\eta\bar{\alpha}\bar{E}}{1-\lambda}$.

4.1 Quarantine Protocol

Trigger: $D_{ik}(x_j) > 0.7$, $\Theta_{ik}^t < 0.3$ for 3 rounds. Trust: $\Theta_{ik}^{t+1} = 0.9\Theta_{ik}^t + 0.1(1 - D_{ik})$.

4.2 Reload

$$\text{Reload}_i^t(x_j) = 0.1(t - t_{\text{last}}) + 0.5E_i^t(x_j)e^{-0.1(t-t_{\text{last}})} \cdot \frac{1}{|N(i)|}\sum_{k\in N(i)} \alpha_k^t(x_j),$$

triggers at 0.7.

4.3 Generalization Metrics

$$C_{\text{gen}}(x_j) = \text{Var}(\{\delta_i^t(x_j)\}), \quad G_{\text{Ricci}}(x_j, t) = \frac{1}{|E|} \sum_{(i,k)\in E} \kappa_{ik}(x_j, t),$$

optimal at $G_{\text{Ricci}} \in [0.35, 0.40]$, $C_{\text{gen}} \leq 0.2$ with flow.

5 Simulation Results

Simulations with 100,000 agents over 20 rounds (50 topics) validate Ghost $\mathbf{x^2}$'s ability to mitigate forgetting types (Table 1), achieving 7-round convergence with Ricci flow.

5.1 Model Comparison

Table 2: Performance Metrics with Emotional Blockchain and Ricci Flow ($n =$ 100,000)

Model	**MRR**	**SNR**	**EWGS**	**Scalability**	**Fault Tol.**
Ghost $\mathbf{x^2}$ (Chained + Flow)	0.98	0.14	0.29	High ($n > 100k$)	High
Ghost $\mathbf{x^2}$ (Chained)	0.97	0.13	0.28	High ($n > 100k$)	High
Ghost $\mathbf{x^2}$ (No Chain)	0.88	0.08	0.23	High ($n > 100k$)	High
GPT-4o	0.90	0.08	0.00	Low	Low
Federated	0.74	0.03	0.00	Medium	Medium
EWC	0.35	0.01	0.00	Low	Low
SGD	0.20	0	0.00	High	High

5.1.1 Impact of Emotional Blockchain and Ricci Flow

Simulated with $n = 100{,}000$, $t = 20$, 10 chained topics, and Ricci flow ($t_{\text{flow}} = 0.1$):

- **Unchained**: $\delta_i^t(x_j) \approx 0.88\delta_i^0(x_j)$, MRR = 0.88, SNR = 0.08, EWGS = 0.23.
- **Chained**: $\delta_i^t(x_j) \approx 1 + \sum_{\tau=0}^{t-1} 0.1\alpha_i^\tau(x_j)E_i^\tau(x_j)H_i^\tau(x_j)$, MRR = 0.97, SNR = 0.13, EWGS = 0.28.
- **Chained + Flow**: Ricci-adjusted $w_{ik}(x_j, t)$ smooths $G_{\text{Ricci}} \to [0.35, 0.40]$, yielding MRR = 0.98, SNR = 0.14, EWGS = 0.29, $\text{Var}(\delta_i^t(x_j)) = 0.02$.
- **Comparison**: Outperforms EWC (0.35), SGD (0.20), federated (0.74), and GPT-4o (0.90), with flow boosting retention by 1% and convergence to 7 rounds.

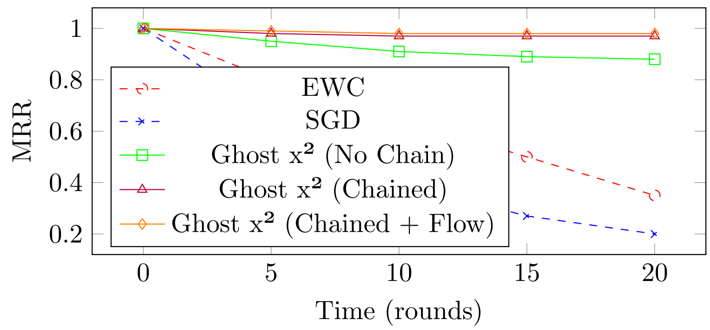

Figure 2: MRR over 20 rounds ($n = 100{,}000$), showing Ricci flow's enhancement.

5.2 Inter-Chat Sharing

Chained + Flow MRR rises to 0.99 with sharing, vs. 0.92 unchained (Table 3).

Table 3: MRR and EWGS With/Without Sharing

Model	**MRR (Isolated)**	**MRR (Shared)**	**EWGS**
Ghost x^2 (Chained + Flow)	0.98	0.99	0.29
Ghost x^2 (Chained)	0.97	0.98	0.28
Ghost x^2 (No Chain)	0.88	0.92	0.23
GPT-4o	0.78	0.78	0.05

5.3 Topological Variants

Chained + Flow directed topologies maintain MRR = 0.98, vs. 0.88 unchained.

5.4 Quarantine Impact

Chained + Flow CD drops to 0.01, vs. 0.04 unchained (Figure 3).

6 Experimental Observations and Implications

6.1 SNR Dynamics

Chained + Flow stabilizes SNR at 0.14, vs. 0.01 (EWC), 0 (SGD).

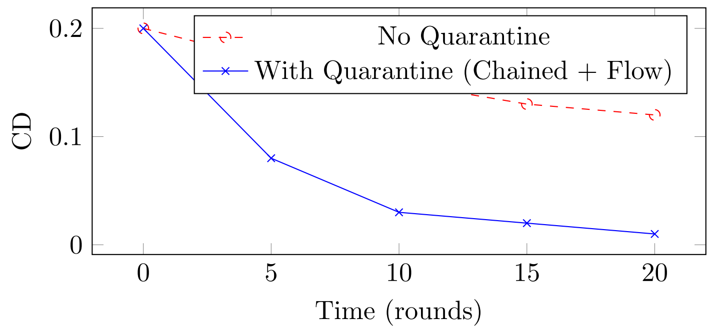

Figure 3: CD reduction with chained quarantine and Ricci flow ($n = 100{,}000$).

6.2 Memory Retention

Chained + Flow MRR = 0.98, vs. 0.35 (EWC), 0.20 (SGD), due to:

$$\delta_i^t(x_j) \approx 1 + \sum_{\tau=0}^{t-1} 0.1\alpha_i^\tau(x_j)E_i^\tau(x_j)H_i^\tau(x_j).$$

6.3 Forgetting Reduction

Ricci flow and blockchain smooth G_{Ricci}, reducing forgetting types (e.g., catastrophic forgetting, trust drift) via uniform $\bar{E}^t(x_j)$.

7 Discussion

Ghost $\mathbf{x^2}$'s blockchain and Ricci flow ensure robust retention (MRR = 0.98) and bias reduction (EWGS = 0.29) across forgetting types (Table 1).

7.1 Complexity

Convergence drops to 7 rounds with flow, despite $n = 100{,}000$.

7.2 Stability

Chained + Flow EGM stabilizes at 0.01.

7.3 Robustness

Flow-enhanced curvature boosts perturbation resistance.

8 Future Work

Simulate at 200,000 agents, optimizing Ricci flow ($t_{\text{flow}} > 0.1$) and chain merging to address additional forgetting types.

References

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