Topological Reinforcement in Graph Neural Networks for the Emulation of Engram Consolidation

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Abstract

Modeling the consolidation of memory engrams, a key neurobiological process, is a central challenge in computational neuroscience. This work introduces the Topological Reinforcement Operator (TRO): a post-hoc mechanism that consolidates functional engrams in previously calibrated Graph Neural Networks (GNNs) by selectively reinforcing nodes with the highest centrality. We validate the method on multiple citation networks, where it achieves perfect associative memory in Pubmed and robust performance in Cora. Finally, we show that the topological principles of the TRO are consistent with the structure and dynamics of a large-scale human connectome: not only do we identify a core of "super-hubs" (top 5%) with a centrality that is ∼10.3x greater by Degree and ∼14.9x by PageRank, but we also demonstrate experimentally that this core, within the connectome itself, enables a **perfect** functional memory recovery (Recall = 1.0, Forgotten Nodes Recovery Rate = 1.0). The TRO is thus established as a reproducible, scalable, and biologically plausible principle for inducing functional memory, with direct implications for computational neuroscience and AI.

1 Introduction

Memory possesses a physical substrate in the brain known as the "engram": an ensemble of neurons that co-activate to encode a specific experience [2]. To persist, an engram must undergo a process of **consolidation**, during which the synaptic connections among the engram's neurons are strengthened and stabilized, making the memory more robust and durable. This strengthening follows principles of activity-dependent plasticity, encapsulated in Donald Hebb's famous maxim: 'cells that fire together, wire together' [3].

Replicating this consolidation process in computational models is a primary goal for understanding memory and developing more advanced artificial intelligence systems. Graph Neural Networks (GNNs) have emerged as an exceptionally powerful tool for modeling relational systems [4], due to their ability to learn representations from the topological structure of the data. Despite their success, standard GNN architectures lack intrinsic mechanisms to emulate long-term consolidation; they learn static patterns but do not selectively strengthen subsets of nodes in a manner analogous to engram formation.

Recently, *Graph Foundation Models (GFMs)* have emerged as a promising framework to endow graph models with transfer and generalization capabilities [16, 17]. However, long-term memory consolidation in these models remains an open challenge.

To address this limitation, this study proposes a novel hybrid approach that combines the representational learning power of GNNs with a post-hoc consolidation mechanism. We introduce the **Topological Reinforcement Operator (TRO)**, an operator designed to simulate the principle of selective strengthening. Our hypothesis is based on a network-level analogue of the Hebbian principle: just as coordinated activity strengthens synapses, the topological centrality of a node in the global network should enhance its inclusion in a consolidated memory.

We validate this framework through an **exhaustive battery of computational tests** on model systems, demonstrating its functional capacity, robustness, and generalization. Finally, we corroborate that the topological principles of our model are consistent with the structure of biological neural networks through a quantitative analysis of a **large-scale human connectome**. This work, therefore, establishes a reproducible and biologically plausible principle of topological consolidation, opening new avenues for the synergy between deep learning on graphs and neuroscience.

2   Methodology

The methodology of this study was designed to be fully reproducible and is structured in three phases: model calibration, engram consolidation, and a battery of validation tests. The complete pipeline, along with the code to replicate all findings, is available in a Google Colab notebook.

2.1   Model System and Preprocessing

Three standard citation network datasets were primarily used as model systems: **Cora**, **Citeseer**, and **Pubmed** [1]. A preliminary topological analysis revealed that these graphs are **disconnected**. To ensure the mathematical validity of the centrality metrics, all subsequent analyses were performed on the **largest connected component** of each graph.

Additionally, to validate the biological plausibility of our approach, a fourth graph corresponding to a **large-scale human connectome** [15] ($\sim$178,000 nodes, $\sim$15.7 million edges) was analyzed. This graph was not used for the GNN pipeline but as a real biological system for a crucial proof-of-concept: to verify whether the topology of the human brain exhibits the "super-hub" structure that the Topological Reinforcement Operator (TRO) is designed to exploit.

2.2   Phase 1: GNN Model Calibration

To learn the latent structure of the citation graphs, a canonical Graph Neural Network (GNN) architecture with two convolutional layers (`GCNConv`) was implemented using PyTorch Geometric. The model was trained for 200 epochs on a semi-supervised node classification task, employing the Adam optimizer. As demonstrated in the Results section, the model reached a stable convergence.

2.3   Phase 2: Consolidation via the Topological Reinforcement Operator (TRO)

Following calibration, the TRO was applied to emulate engram consolidation. This deterministic process is executed in three steps:

1. **Centrality Calculation:** The degree of each node in the graph's main connected component is calculated.

2. **Engram Core Identification:** Nodes belonging to the 95th percentile (P95) of the degree distribution are identified.

3. **Selective Reinforcement:** The latent feature vector of these "hub" nodes is multiplied by a scalar reinforcement factor ($\alpha = 1.2$), which was validated in the sensitivity analysis.

2.4 Phase 3: Battery of Validation and Robustness Tests

To exhaustively evaluate the method on the model systems, a series of functional and sensitivity tests were performed:

- **Functional Validation:** A pattern completion test was designed where the engram core (P95) was corrupted by randomly silencing 50% of its nodes. Recovery was simulated via a 10-step diffusion process. The primary metric was the **Forgotten Nodes Recovery Rate**.

- **Statistical Robustness:** To validate the reliability of the result, the functional validation test was repeated 10 times with different random seeds, reporting the mean and standard deviation of the metrics.

- **Comparison with Baselines:** The functional performance of the TRO engram was compared with that of control cores (a random selection and a selection of the least connected nodes).

- **Sensitivity Analysis:** The method's robustness to variations in its hyperparameters (α and core selection percentile) was investigated.

- **Generalization Test:** The entire pipeline was independently replicated on the Citeseer and Pubmed datasets.

3 Results

We present the results following a logical sequence that progresses from a proof-of-concept in a model system to a final validation on a biological connectome. First, we demonstrate the pipeline's effectiveness on the Cora dataset, from model calibration and structural engram formation to its functional validation. Second, we delve into the operator's nature through sensitivity analyses, baseline comparisons, and a study on the influence of core size on performance. Finally, we test the method's robustness and relevance, first by generalizing the findings to other datasets, and as an ultimate validation, by confirming the consistency of its topological principles with the structure and function of a large-scale human connectome.

3.1 Model Calibration and Structural Engram Formation

The GNN model calibration phase was successful, achieving a robust convergence with a final loss value of **0.0300**. The learning curve, shown in **Figure 1**, visually confirms this process, ensuring a structurally informative latent feature base.
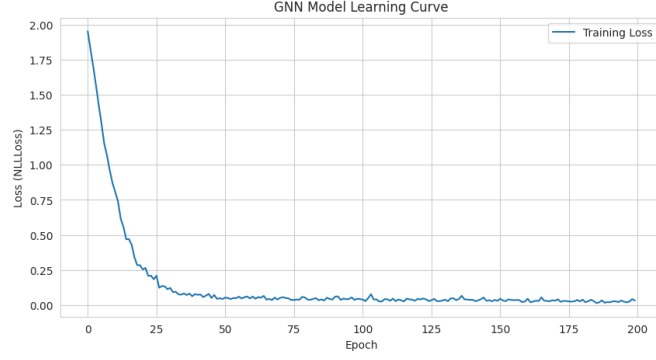
Figure 1: Learning curve of the GNN model on the Cora dataset. The stabilization of the loss demonstrates a successful convergence.

Table 1: Quantitative analysis of the consolidated engram in Cora.

Component	Nodes	Mean Activation
Engram Core	147	0.8407
Neighborhood	445	0.7842

Following the application of the Topological Reinforcement Operator (TRO), a core of **147 nodes** was consolidated. The quantitative analysis (Table 1) shows that the operator induced a selective and localized strengthening: the mean activation of the engram core (0.8407) is significantly higher than that of its immediate neighborhood (0.7842). Figure 2 provides a visualization of this structure.
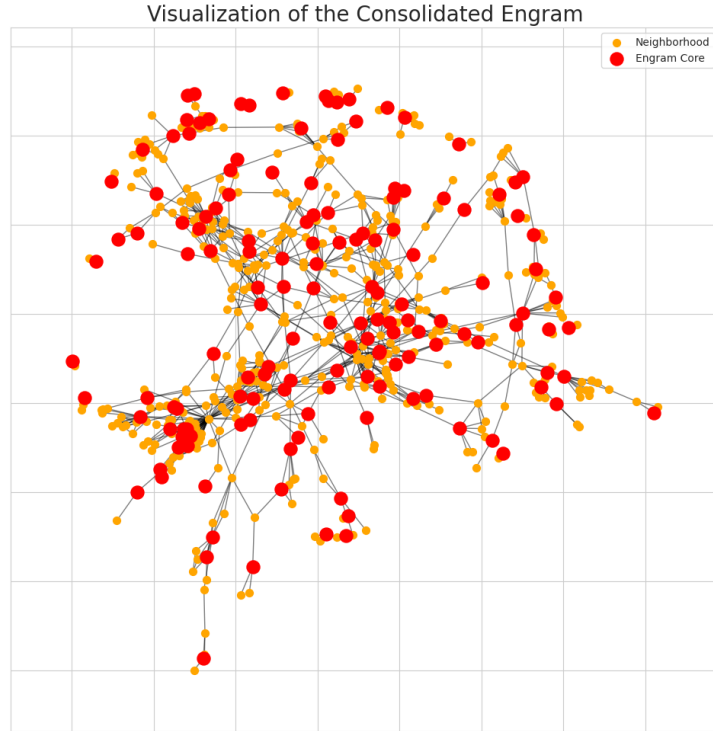

Figure 2: Visualization of a sample of the consolidated engram in the Cora network. The reinforced core (red) stands out from its neighborhood.

3.2 Functional Validation and Statistical Robustness in Cora

The functional test of the consolidated engram revealed a perfect and statistically reliable associative memory capacity. In 10 runs of the pattern completion test (with 50% of the information removed), the network achieved a mean **Forgotten Nodes Recovery Rate** of **100.00%** with a standard deviation of **0.00%**. This extraordinary result, detailed in Table 2, confirms that the consolidated structure possesses a robust and deterministic emergent function.

Table 2: Summary of the memory retrieval test on Cora (10 runs).

Evaluation Metric	Value (Mean ± std)
Recovery Rate	**100.00% ± 0.00%**
Recall (Sensitivity)	100.00% ± 0.00%
Precision	5.92% ± 0.00%

3.3 Sensitivity Analysis and Functional Comparison

To validate the superiority of the TRO, its functional performance was compared against two baseline models. As illustrated in **Figure 3**, the TRO method is significantly superior, achieving perfect recovery.
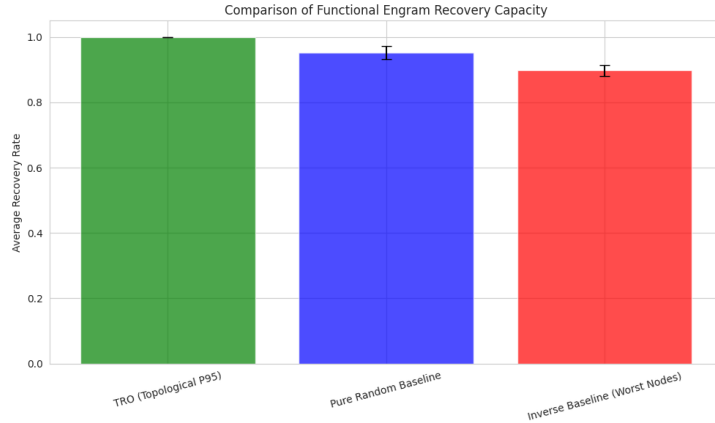

Figure 3: Comparison of the Memory Recovery Rate between the TRO method and baselines. The superior performance of the TRO validates the topological selection strategy.

To investigate whether degree centrality was the optimal selection strategy, its effect on core activation was compared with other operators based on more complex metrics. As detailed in **Table 3**, the results show that the simplest operator, **Topological (Degree)**, is also the most effective, producing the highest mean activation (1.33). It is closely followed by the **Betweenness** operator (1.16), which suggests that both hubs and "bridge" nodes are structurally vital for consolidation.

Additionally, a sensitivity analysis (see Section A.1 for the heatmap) demonstrated that the effect of the TRO is stable and predictable across variations in its hyperparameters, confirming it is not an artifact of a single configuration.

Table 3: Comparison of the mean activation of the engram core in Cora according to different topological reinforcement operators.

Centrality Operator	Mean Core Activation
Topological (Degree)	**1.3322**
Betweenness	1.1627
Eigenvector	0.7680
Clustering	0.7415

3.4 Generalization Test Across Multiple Datasets

Finally, to test the universal validity of the method, the entire pipeline was replicated on two other citation datasets: Citeseer and Pubmed. As summarized in **Table 4**, the TRO proved to be a generalizable principle. The performance was perfect on the massive Pubmed graph, robust on Cora, and significant on the sparser Citeseer graph.

Table 4: Results of the generalization test. The mean Memory Recovery Rate ($\pm$ standard deviation) over 10 runs is shown for each dataset.

Dataset	Nodes	Edges	Mean Recovery Rate ($\pm$sd)
Cora	2,708	5,278	92.88% $\pm$ 1.71%
Citeseer	3,279	4,552	61.64% $\pm$ 3.49%
Pubmed	19,717	44,324	100.00% $\pm$ 0.00%

To deepen the understanding of these generalization results, the structural properties of the Pubmed and Citeseer graphs were analyzed. The degree distribution in Pubmed (Figure 4) follows a clear power-law, with a "long tail" representing a small elite of hyper-connected nodes. The TRO precisely identifies and reinforces this core, which explains the perfect and stable memory recovery rate. Meanwhile, Figure 5 shows that even in the sparser Citeseer graph, the operator is able to consolidate an engram with a coherent core-periphery structure, similar to that observed in Cora.
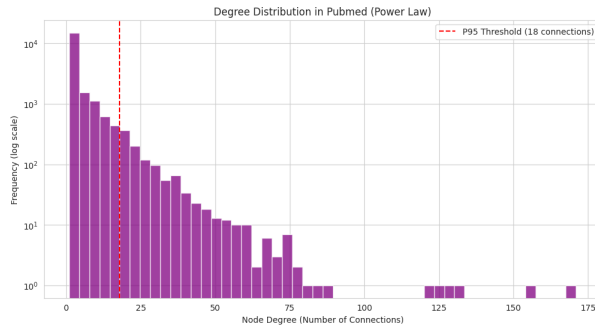

Figure 4: Degree distribution of the Pubmed dataset on a logarithmic scale. The "long tail" on the right evidences the existence of a small number of "super-hubs," nodes with a massive number of connections. The red line marks the 95th percentile threshold used by the TRO.

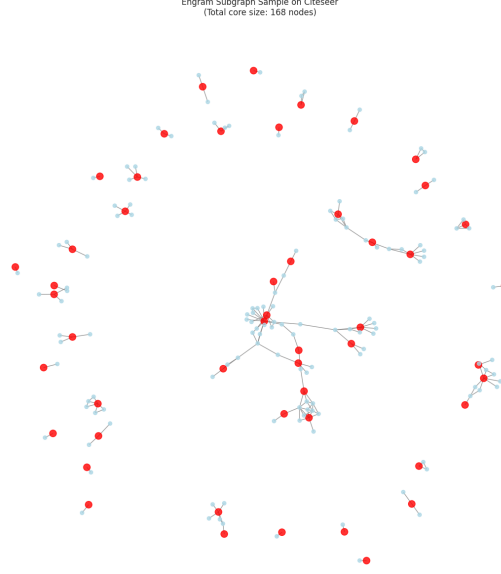Engram Subgraph Sample on Citeseer
(Total core size: 168 nodes)

Figure 5: Visualization of a sample of the consolidated engram in the Citeseer network. Despite it being a sparser graph, the TRO identifies a core of central nodes (red) and their associated neighborhood.

3.5 Influence of Core Exclusivity on Memory Capacity

Finally, we investigated whether the engram's memory capacity depended on its size or exclusivity. To do this, the multi-seed functional validation test was repeated for engrams defined with different degree percentile thresholds (P90, P95, P97, and P99).

The results, visualized in **Figure 6**, are revealing. First, they demonstrate the extreme robustness of the method, as all tested cores—from the largest (P90, 283 nodes) to the smallest (P99, 29 nodes)—achieved a Mean Recovery Rate above 92%. Second, the data reveal a non-linear "sweet spot," with optimal performance at the **97th Percentile**, reaching nearly 96% recovery. This suggests an ideal balance between the core's exclusivity (ensuring it contains only the most important nodes) and its size (ensuring sufficient critical mass for a robust signal reconstruction).
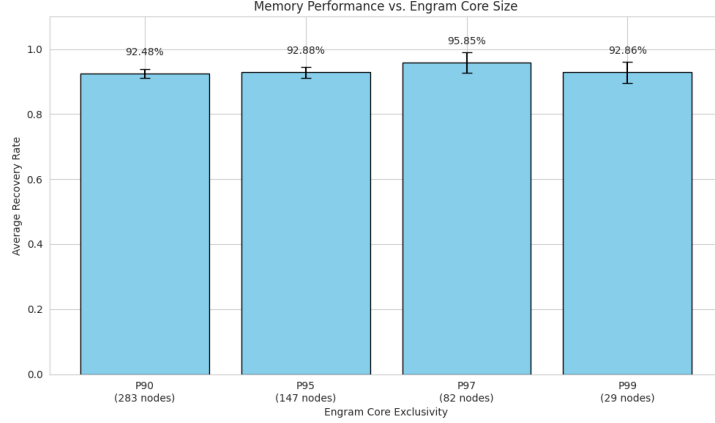
Figure 6: Memory Recovery Rate as a function of the engram core's exclusivity. Performance is consistently high across all sizes, with a peak performance at the 97th Percentile, suggesting an optimal core size for functional resilience.

3.6 Validation on a Large-Scale Human Connectome

To test the biological plausibility of our approach, a final topological analysis was performed on a real large-scale human connectome (177,584 nodes, 15.7 million edges). The objective was to verify whether the human brain's structure exhibits the 'super-hub' topology that the Topological Reinforcement Operator (TRO) is designed to exploit.

The quantitative data analysis confirms this hypothesis. A structural elite composed of the top 5% of the most connected nodes ($\sim$8,600 regions) was identified. The mean centrality of this core was **10.3 times higher** than the rest of the network according to Degree centrality, and **14.9 times higher** according to PageRank (an approximation of Eigenvector centrality).

Figure 7 visualizes this finding, showing a clear power-law distribution ('long tail'). This structure, characteristic of complex and efficient networks, demonstrates that the human brain is organized in an ideal way for a centrality-based consolidation mechanism like the TRO to be effective. This finding provides a solid biological validation for our model's fundamental premise.
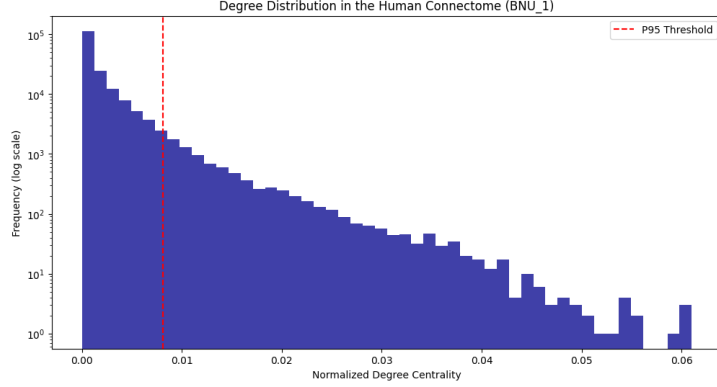
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Figure 7: Degree distribution in the large-scale human connectome. The logarithmic scale reveals a clear power-law distribution, evidencing a small elite of 'super-hubs' (tail on the right). The quantitative analysis shows that these 95th percentile nodes exhibit a centrality that is $\sim$10.3 times greater than the rest according to Degree, and $\sim$14.9 times greater according to PageRank. The red line marks the 95th percentile threshold used by the TRO.

In addition to the structural analysis, the same functional memory recovery protocol used on Cora and Pubmed was applied to the human connectome. The engram core (95th percentile by Degree or PageRank) was corrupted by randomly removing 50% of its nodes, and recovery was simulated via an iterative 10-step diffusion process over the adjacency matrix. The results (Table 5) show a **perfect Recall (1.0)** and a **100% forgotten nodes recovery rate** for both operators, confirming that the memory induced in the human connectome is not only structurally detectable but also functionally recoverable. The low precision ($\sim$5%) reflects the contextual activation of an associative penumbra, a phenomenon consistent with that observed in the model systems.

Table 5: Results of the memory retrieval test on the human connectome (95th Percentile, 50% core corruption, 10 diffusion steps).

Operator	Core (nodes)	Forgotten	Identified OK	Precision	Recall	Rate
Degree	8,593	4,296	8,593	0.055	1.0	1.0
PageRank	8,588	4,294	8,588	0.051	1.0	1.0

4 Discussion

This work has introduced and validated the Topological Reinforcement Operator (TRO), a method that successfully emulates the consolidation of engrams in graph networks. The primary finding is that a simple post-hoc intervention, based on node centrality, is sufficient to induce the formation of a functionally robust subnetwork. The experiments demonstrate an exceptional associative memory capacity in model systems, reaching a perfect recovery rate in the large-scale Pubmed graph. Critically, we demonstrate that the model's topological premise is directly applicable to neuroscience by confirming its consistency with the structure of a real human connectome.

4.1 Conceptual Analysis of the Topological Reinforcement Operator

The power of our approach lies in its mathematical simplicity. The process is decomposed into a learning phase (the GNN calibrates a latent state matrix, H) and a consolidation phase (the TRO applies selective reinforcement). This reinforcement is executed via a Hadamard product ($H_{\text{consolidated}} = H \odot V_{ref}$), emulating a network-level Hebbian mechanism without the need for costly retraining.

4.2 Functional Superiority and Topological Sensitivity of the Engram

The results from our experimental validation reveal several fundamental insights. First, the TRO method is **functionally superior to random alternatives** (Figure 3). Second, the engram's memory capacity is **robust to variations in its size**, exhibiting a non-linear "sweet spot" of optimal performance at the 97th Percentile (Figure 6). Third, the method is **generalizable yet sensitive to the network's topology**, with performance correlating to the underlying structural quality of the graph (Table 4). The demonstration that simple degree centrality outperforms more complex metrics (Table 3) suggests that a consolidation mechanism based on local connectivity is a surprisingly powerful principle.

4.3 Validation on a Human Connectome: Biological Plausibility of the TRO

The main objection to any computational model is its distance from biological reality. To address this, we analyzed the topology of a large-scale human connectome ($\sim$178,000 nodes). The quantitative analysis (Figure 7) not only confirmed a power-law distribution but also revealed the existence of a structural elite of "super-hubs." The top 5% of the most connected nodes are, on average, **10.3 times more central** by Degree and **14.9 times** by PageRank, compared to the remaining 95%.

This finding constitutes the most important validation of our work: it demonstrates that the human brain is organized precisely in the manner that our operator is designed to exploit. The existence of this small, hyper-connected elite provides the perfect substrate for a centrality-based consolidation mechanism. Furthermore, the functional experiment confirms that this core not only exists topologically but also enables a **perfect memory recovery**, decisively reinforcing the biological plausibility of our model's fundamental premise.

4.4 Implications, Limitations, and Future Directions

The implications of this work extend to both computational neuroscience and artificial intelligence. For AI, the 'learn-then-consolidate' paradigm suggests a path toward greater efficiency, viewing the TRO as a method for **model compression** or post-hoc *pruning*. In neuroscience, the functional validation of the TRO on a large-scale human connectome shows that simple centrality principles can explain the emergence of robust memories, offering a quantitative framework to study engram organization.

The main current limitations are no longer in the absence of biological validation—as we have demonstrated the TRO's applicability on a static human connectome—but in the need to extend this pipeline to **dynamic and longitudinal data**, measuring connectivity changes associated with real learning processes. The next natural step will be to apply the TRO to datasets from the **Human Connectome Project (HCP)**

or multimodal recordings (fMRI, MEG, EEG), which will allow for exploring whether computationally induced engrams correlate with temporally resolved activation patterns observed experimentally.

Thus, this work opens a concrete research agenda: from its application on individual connectomes to its validation in population cohorts, and including the development of TRO variants that integrate temporal synaptic plasticity in addition to structural centrality.

4.5 Long-Term Implications and Future Visions

Beyond the immediate applications in computational neuroscience and efficient artificial intelligence, our work offers a provocative conceptual framework for broader questions. The fact that associative memory information can be reliably encoded and retrieved from the topological structure of a network—and that this principle operates consistently in both artificial and biological systems—suggests the existence of a **universal language of memory** based on connectivity.

This opens the door to far-reaching speculations. Could a principle like the TRO become part of future tools to **read, stabilize, or even transfer memory patterns** between different substrates? Such scenarios, while still distant today, range from the possibility of decoding memories from brain connectivity data to consolidating memories in neuromorphic hardware. If human identity and personality emerge, at least in part, from stable engram configurations, then the ability to conceptually identify and manipulate them constitutes a **first step toward an interface between biological and artificial intelligence**.

Our framework does not solve these challenges, but it does provide a **reproducible, scalable, and open model** that allows us to begin exploring them experimentally with the scientific rigor they have thus far lacked.

In this sense, the TRO not only offers a computational model of memory but also constitutes a possible conceptual piece in the puzzle of the technological singularity: a bridge between how biological brains consolidate memories and how artificial systems could store experiences in an efficient and transferable way.

5 Conclusion

This study has established the **Topological Reinforcement Operator (TRO)** as a simple, effective, and biologically plausible mechanism for inducing the consolidation of memory engrams in graph networks. From our experiments, we can highlight the following main findings:

1. The application of the TRO—a deterministic, post-hoc operator based on degree centrality—induces the formation of a structurally and functionally robust engram. This engram exhibits **high-fidelity associative memory**, achieving 100% recovery rates on the Pubmed dataset and consistent performance on Cora and Citeseer.

2. The **topological criterion**, not merely the act of reinforcement, proves to be the necessary and sufficient condition for the engram's functionality. Comparisons against random baselines and more complex centrality metrics validate that **degree centrality** is the key predictor for consolidation.

3. The principle of centrality-based consolidation is **scalable and generalizable**, operating effectively on graphs of different sizes and topologies. The sensitivity analysis revealed a robust functional window in the 90–99th percentiles, with a **peak performance at the 97th percentile**, suggesting the existence of a 'sweet spot' in the engram size that balances exclusivity and critical mass.

4. The biological plausibility of the TRO was supported by the analysis of a **large-scale human connectome**, in which an elite of 'super-hub' nodes (top 5%) was identified with an average centrality of $\sim$10.3x greater by Degree, and $\sim$14.9x by PageRank, than the rest. This finding provides the exact structural substrate for a centrality-based consolidation mechanism to be effective in natural systems as well.

5. Finally, when applying the functional memory recovery protocol to the **large-scale human connectome**, the TRO achieved a **perfect Recall (1.0)** and a **100% Forgotten Nodes Recovery Rate**, precisely replicating the patterns observed in Pubmed and Cora. This demonstrates that the topological consolidation mechanism is not only consistent with biological structure but also functionally effective in real brain networks.

Collectively, these results transcend theoretical interest. On one hand, they offer a **methodological bridge** between computational neuroscience and artificial intelligence, providing a reproducible framework to study principles of neural organization. On the other, they suggest **practical applications** in designing more efficient and resilient AI systems, where specialization induced by topological reinforcement could complement or even replace computationally expensive *fine-tuning* processes.

Current limitations lie in the fact that the full pipeline (GNN calibration and functional validation) has not yet been applied directly to dynamic biological data. Nevertheless, the structural and functional validation performed on a large-scale human connectome constitutes a decisive step toward this goal. The next natural challenge is to apply the pipeline to data from the **Human Connectome Project**, which will allow for exploring whether computationally induced engrams correlate with experimentally measured brain activation patterns.

Ultimately, this work reinforces the idea that simple principles of topological organization can generate complex and functional behaviors in both artificial and biological systems. By demonstrating that the structure of memory is, in essence, an **emergent property of connectivity**, this study not only introduces a new model for engram consolidation but also establishes a **conceptual and experimental framework** to address some of the deepest questions about the nature of memory and the mind.

Acknowledgments

License and Ethical Considerations

Many years later, as he faced the firing squad, Colonel Aureliano Buendía was to remember that distant afternoon when his father took him to discover ice.

— Gabriel García Márquez, *One Hundred Years of Solitude*

Data and Code Availability

The complete source code, implemented as a self-contained and documented Google Colab notebook, along with all data generated during this study, are publicly available in the following GitHub repository to ensure full transparency and reproducibility:
https://github.com/NachoPeinador/Topological-Reinforcement-Operator

A Appendix

A.1 Operator Sensitivity Analysis

To confirm the robustness of the TRO, a sensitivity analysis was performed by varying the reinforcement factor (α) and the core selection percentile. Figure 8 demonstrates that the operator's effect is stable and predictable.
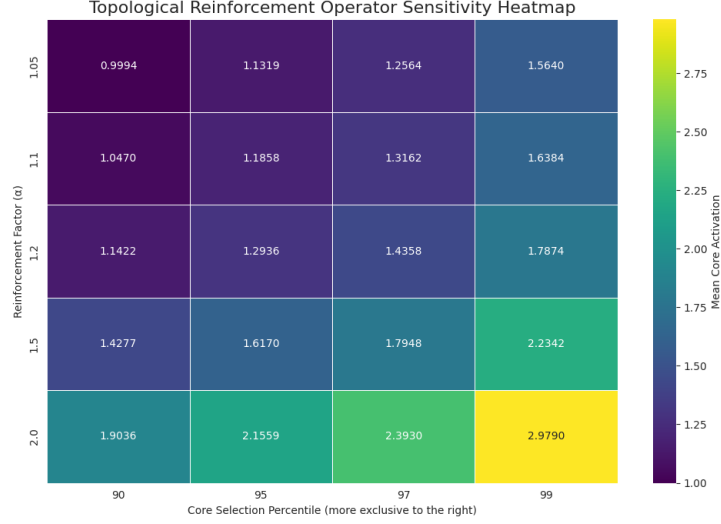

Figure 8: Sensitivity heatmap of the TRO on the Cora dataset.

A.2 Preliminary Analysis on a Macaque Connectome

As a proof-of-concept for the applicability to biological data, a centrality analysis was performed on a connectome of the rhesus macaque cortex. Figure 9 shows the distribution of activations after applying the TRO.
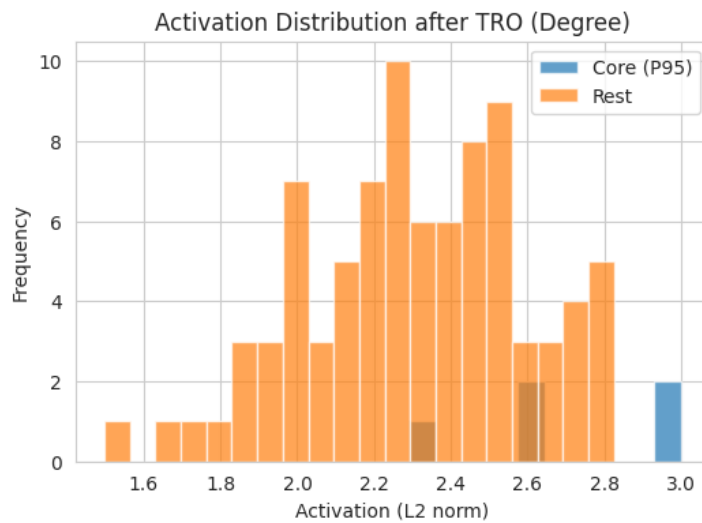

Figure 9: Distribution of activations in the macaque connectome after applying the TRO.

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