Large Language Models as Model Organisms for Human Associative Learning

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Abstract

Associative learning–forming links between co-occurring items–is fundamental to human cognition, reshaping internal representations in complex ways. Testing hypotheses on how representational changes occur in biological systems is challenging, but large language models (LLMs) offer a scalable alternative. Building on LLMs' in-context learning, we adapt a cognitive neuroscience associative learning paradigm and investigate how representations evolve across six models. Our initial findings reveal a non-monotonic pattern consistent with the Non-Monotonic Plasticity Hypothesis, with moderately similar items differentiating after learning. Leveraging the controllability of LLMs, we further show that this differentiation is modulated by the overlap of associated items with the broader vocabulary–a factor we term vocabulary interference, capturing how new associations compete with prior knowledge. We find that higher vocabulary interference amplifies differentiation, suggesting that representational change is influenced by both item similarity and global competition. Our findings position LLMs not only as powerful tools for studying representational dynamics in human-like learning systems, but also as accessible and general computational models for generating new hypotheses about the principles underlying memory reorganization in the brain.

1 Introduction

Associative learning—the ability to form links between co-occurring items—is a fundamental mechanism that shapes how experiences are encoded, stored, and retrieved. Its ubiquity across species and cognitive domains has made it a core component in theories of intelligence [47, 10]. As associations are learned, the brain's internal representations of the associated items are altered—a reflection of the neural plasticity that strengthens some connections while weakening others [34, 36, 12]. A central and ongoing question in cognitive neuroscience is how this self-supervised learning process reshapes representational structure, and why [46, 11, 7]. There are three main hypotheses for how associative learning alters representations in biological systems (see Figure 1A). The classical Hebbian learning rule, where repeatedly associating items strengthens connections between shared features, predicts more integrated representations across learned items [34]. However, alternative theories suggest the opposite. For example, the hippocampus often exhibits pattern separation, where rapidly learned memories reduce representational overlap to minimize interference and facilitate retrieval [27, 2, 54, 11]. These opposing dynamics—integration versus differentiation—are both observed in human studies [7, 11, 38, 35]. To reconcile this, the Non-Monotonic Plasticity Hypothesis (NMPH) posits that representational change follows a U-shaped curve: highly similar or dissimilar items tend to integrate or remain stable, while moderately similar pairs differentiate [34].

Fully testing these hypotheses in biological systems is inherently difficult [46, 33]. A major challenge lies in precisely controlling the similarity between items before learning, a prerequisite for detecting

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Code available at github.com/bridge-ai-neuro/llm-associative-learning.

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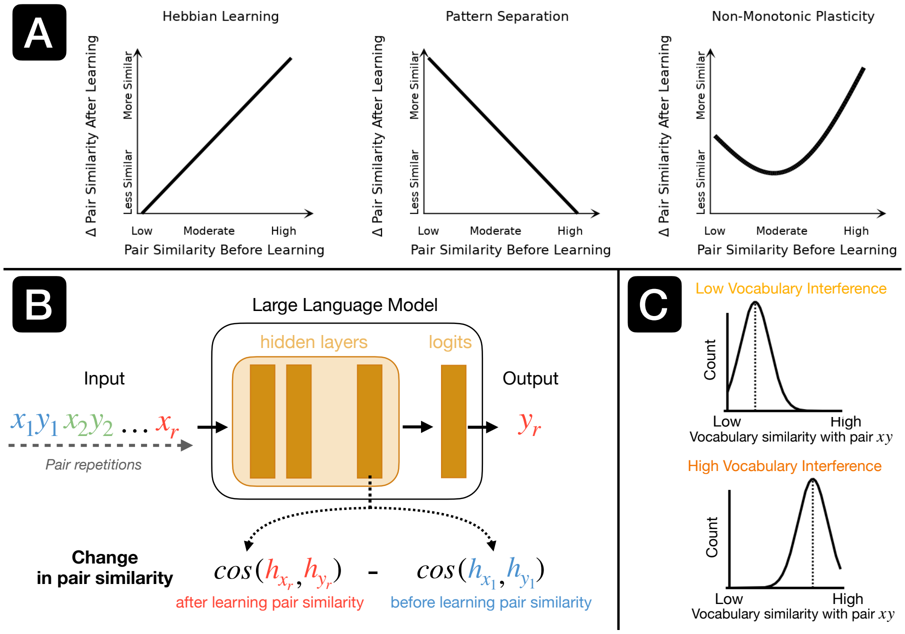

Figure 1: **(A)** Hypotheses about representational changes in humans. Competing theories propose different patterns of representational change as a function of pair similarity before learning: Hebbian learning predicts integration, pattern separation predicts differentiation, and the Non-Monotonic Plasticity Hypothesis (NMPH) predicts a U-shaped curve, with high differentiation at moderate similarity levels prior to learning. **(B)** Schematic of our adapted associative learning task for LLMs. Given repeated in-context presentations of a token pair (x, y), the LLM learns to predict the associated token y. We measure representational change by computing the difference in cosine similarity between hidden representations of the pair before and after learning. This setup, inspired by a neuroscience paradigm [46], enables us to examine whether similar dynamics of representational restructuring emerge during in-context learning. **(C)** Illustration of low and high vocabulary interference in the model's representational space. In the low vocabulary interference case (top, yellow), the target token y is dissimilar to most other tokens, resulting in less competition from alternative completions when paired with x. In the high interference case (bottom, orange), the pairing xy is highly similar to many other possible token pairings, increasing competition and representational pressure to differentiate the learned association from potential distractors during learning.

non-monotonic representational change. Moreover, the similarity level at which differentiation emerges can vary across tasks and stimuli, making it unclear in advance which mid-similarity range will reveal the effect. Capturing this requires dense sampling across the similarity spectrum, further increasing experimental complexity. Finally, human studies are constrained by cost, participant fatigue, and measurement noise, which limit the number of trials that can feasibly be conducted. To address these challenges, we propose using large language models (LLMs) as model organisms for human associative learning. LLMs exhibit complex cognitive behaviors [3, 48, 49], including in-context learning (ICL) [53, 19, 9]—rapidly forming associations without weight updates—making them promising for studying memory dynamics. Unlike hand-crafted neural models designed to replicate specific representational dynamics [33], LLMs offer a scalable, natural testbed for uncovering emergent cognitive phenomena.

In this work, we investigate whether LLMs exhibit representational dynamics akin to human associative learning, and whether they can help disambiguate between competing hypotheses for representational change. We adapt a cognitive neuroscience associative learning paradigm to the ICL setting (Figure 1B), repeatedly presenting token pairs in-context to induce associations. By systematically controlling the similarity of token pairs before learning, we evaluate how representations evolve through learning across six open source, well-performing LLMs. Our initial findings support the NMPH: moderately similar pairs significantly differentiate after learning, mirroring human-like patterns of representational change.

We then leverage the controllability of LLMs to examine a factor that may further contribute to representational change, and is difficult to isolate in biological systems: the similarity between each paired item and the model's prior knowledge. Because LLMs are pre-trained to encode co-occurrence statistics across the entire vocabulary–similar to how humans learn from experience–new associations introduced during ICL must compete with pre-existing patterns. We refer to this competitive influence as *vocabulary interference* (Figure 1C): the extent to which prior knowledge shapes the learning of new associations. In such cases, learning the correct pairing may require greater changes in the model's representations to distinguish it from competing associations. This phenomenon has long been studied in neuroscience and psychology [32, 6, 42], but empirical measurement in the brain is limited by the inability to access all competing representations. By contrast, LLMs provide a tractable framework for quantifying this effect, as the entire distribution of token relationships is explicitly known. We find that, while pair similarity remains a key determinant of representational change, vocabulary interference modulates this effect–greater interference leads to stronger differentiation. These results position LLMs as valuable tools for probing associative learning principles, offering new insights into how both local and global associative structures influence representational change.

2 Related work

2.1 Representational change in human memory and neural models

Integration vs. differentiation in the brain. Associative memory-related representational changes are primarily studied in the hippocampus, a region of the brain thought to be most influential in memory-driven behavior [41, 25]. Both integration and differentiation of memory representations have been shown to support distinct behavioral functions: differentiation reduces interference and enhances specific recall, while integration promotes generalization and inference across related experiences [46, 4]. These functional roles are thought to map onto distinct hippocampal subregions, e.g., integration with CA1 and differentiation with the dentate gyrus (DG), which shows sparse activity linked to orthogonalized representations [46, 51]. How LLMs align with this integration–differentiation spectrum remains an open question.

Non-monotonic plasticity in the brain. The NMPH [34] proposes that representational change depends non-linearly on pair similarity before learning: moderate similarity leads to differentiation, whereas low or high similarity leads to stability or integration. Recently, Wammes et al. [46] provided empirical results supporting this effect by parametrically manipulating the visual similarity of object pairs using CNN-derived [17, 40] representations. Participants arranged images by perceived similarity, and the resulting pairwise distances correlated with model-based similarity estimates. During fMRI, repeated exposure to these pairs revealed significant differentiation for mid-similarity pairs in the DG, but not for other parts of the hippocampus.

Computational accounts. To account for this variety of findings, [33] proposed an unsupervised recurrent network model in which partial activation of competing memories during retrieval induces representational differentiation, a dynamic linked to retrieval-induced forgetting and inhibitory oscillations [24]. While such models are an important step towards a computational account, they rely on hand-crafted inputs and necessitate simplified settings, limiting scalability and behavioral richness. Our work complements prior computational efforts by investigating whether non-monotonic differentiation, previously observed in biological memory systems, emerges naturally in large-scale, general-purpose LLMs trained on real-world data–without an explicit separated memory system.

2.2 Associative learning and in-context dynamics in LLMs

LLMs are increasingly studied as systems capable of associative learning, rapidly forming token-level associations directly within the input context [3]. Recent work shows that LLMs can form stable in-context associations that shape future predictions [19, 53], exhibiting behaviors consistent with retrieval, interference, and generalization [1, 45, 15]. These findings suggest that transformer-based architectures support implicit memory mechanisms across attention and MLP layers, despite the absence of explicit memory modules. Several studies have also analyzed ICL as a form of fast memory encoding or Bayesian inference [5, 15], and have shown that attention layers can support long-range retrieval, stability, and structured generalization [50, 31, 14, 26, 3, 45, 19]. ICL has been interpreted through the lens of both episodic memory, as models retrieve and reuse information based on context, and working memory, given that representations are updated dynamically across tokens without any parameter changes [53, 19, 30, 21, 5, 22, 13, 8]. We build on this line of research by shifting focus from behavioral outcomes to the internal representational dynamics underlying learning through repeated associative exposure.

3 Methods

3.1 Associative learning paradigm

Our associative learning paradigm is inspired by the experimental design of [46], who investigated how repeated exposure to stimulus pairs with different visual similarity leads to non-monotonic changes in human hippocampal representations. We adapt this paradigm to LLMs using ICL [3, 5], replacing visual stimuli with token pairs and modeling learning through repeated token co-occurrence. This setup allows us to examine whether similar non-monotonic representational shifts occur in LLMs, and to what extent LLM behavior parallels hippocampal learning dynamics. We focus on ICL rather than fine-tuning, as LLMs are known to exhibit emergent associative abilities [48, 3, 9], making ICL a natural fit for studying association tasks. It also provides a controlled and biologically plausible analogy to how humans acquire associations [53, 19], while enabling consistent comparisons across models of different sizes and architectures without introducing task-specific fine-tuning.

Formally, we present the token pair (x, y) a total of $r - 1$ times, followed by one final presentation of x alone as a cue for predicting its paired token y. Given the input sequence

$$\mathbf{s} = [x_1, y_1, x_2, y_2, \ldots, x_{r-1}, y_{r-1}, x_r], \tag{1}$$

the model's goal is to generate a prediction of the associated paired token, y. By default, we restrict the number of repetitions such that the total sequence length remains within each model's m maximum context length (L^m_{max}) or the limits imposed by available GPU memory ($L_{\text{mem}} \approx 40k$ tokens), i.e., $L^m = \min(L^m_{\text{max}},\ L_{\text{mem}})$. In our setup, the sequence length is $L_s \approx (2 * r) - 1$.

We predict that the LLM's representations of these tokens will change through the course of ICL, a phenomenon observed in prior studies analyzing ICL tasks [29, 52, 9]. This prediction also aligns with findings from neuroscience, where repeated co-occurrence of stimuli is known to drive representational change in the hippocampus [34, 37].

(Pair) Representational change. For a given model $m \in \mathcal{M}$, where $\mathcal{M}$ is the set of LLM models under study, we extract the hidden representations of a token x at the last layer of the model, $\mathbf{h}^m_x$. We chose to examine the last hidden layer to more effectively control for representations that directly affect model behavior on the ICL task [1]. This choice also aligns with a sensory-information processing hierarchy in which the hippocampus sits at the top of the memory stream [28, 20]. (Pair) Representational change across ICL is then defined as the difference in cosine similarity between representations at repetition r and the first occurrence of the pair:

$$\Delta S^m_r = cos(\mathbf{h}^m_{x_r}, \mathbf{h}^m_{y_r}) - cos(\mathbf{h}^m_{x_1}, \mathbf{h}^m_{y_1}), \tag{2}$$

where the hidden representation is conditioned on the whole sequence up until that point, e.g., $\mathbf{h}^m_{x_r} = \mathbf{h}^m(x_r \mid x_1, y_1, \ldots, x_{r-1}, y_{r-1})$. Note that our ICL paradigm means that the first occurrence of y is always conditioned on x, $\mathbf{h}^m_{y_1} = \mathbf{h}^m(y_1 \mid x_1)$. This design mirrors human associative learning paradigms, where pairs are presented sequentially [46]. Throughout the work, we refer to the hidden states from the first occurrence $(\mathbf{h}_{x_1}, \mathbf{h}_{y_1})$ as the representations obtained before learning occurs.

Token similarity groups. To examine whether LLMs exhibit representational dynamics consistent with those observed in humans, we sample token pairs across the similarity continuum. More specifically, we sampled evenly along the cosine similarity axis, defining 17 groups g that fall within the interval $[0.1, 0.95)$. Each group is defined by a window $[\theta_{min}, \theta_{max})$ that spans 0.05 cosine similarity. The token pairs within each group are chosen such that their representational similarity before learning $cos(\mathbf{h}^m_{x_1}, \mathbf{h}^m_{y_1})$ lies within the group interval $[\theta^g_{\text{min}}, \theta^g_{\text{max}})$.

Details on our procedure to find these token pairs are given in the section below. We find 12 token pairs in each group to form a set for each model, $\mathcal{P}^m$. The token pair sets for each model are constructed independently due to differences in their vocabulary size and tokenization.

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[1] Preliminary results for the other layers are shown in Appendix D.

3.2 Optimized search for pairs of tokens

To systematically find tokens whose pair similarity before learning falls within a given interval, we employ an efficient way for searching the large vocabulary space (between 10k^2-72k^2 tokens, depending on the model). Inspired by recent work on prompt and input optimization [55, 39], we follow a two-step approximation strategy to identify suitable pairs. The Greedy Coordinate Gradient (GCG) algorithm [55], originally developed for optimizing sequences in adversarial settings (e.g., minimizing next-token likelihood), provides a framework for iteratively refining a sequence by making targeted, gradient-informed edits to individual tokens. We repurpose the GCG method to minimize a loss defined over the cosine similarity of internal representations.

We start with a duplicate token pair (x, x) with the goal of finding a pair (x, y) that falls within the target cosine similarity range $[\theta_{\min}, \theta_{\max})$. We fix the first x token, and iteratively replace the second token of this sequence by using gradient signals (without updating the model) to identify vocabulary items that would bring the pair's cosine similarity closer to the target range. We select replacements from the top-k candidates that reduce the loss the most, repeating the process until the similarity falls within the desired range or a maximum number of steps is hit. This approach efficiently guides token selection in a controlled, representation-aware way, enabling the construction of token pairs with precise similarity properties. More information on this algorithm can be found in Appendix A.

3.3 Estimating vocabulary interference

To estimate how a given pair (x, y) relates to the broader LLM vocabulary space, we fix x and sample each alternative token t from a representative subset of the vocabulary, $\tilde{\mathcal{V}}^m \subset \mathcal{V}^m$. We then compute the similarity between the representation of the correctly associated token y and each alternative token $t \in \tilde{\mathcal{V}}^m$, conditioned on x's presentation in context. This provides an estimate of how much y, when associated with x, competes with other pair completions in the vocabulary space, capturing the degree of the pair's *vocabulary interference* in the model's representational space. Due to the computational cost of exhaustively computing all possible pairwise combinations, we randomly sample $1,000$ tokens from $\mathcal{V}^m$ to form the representative subset $\tilde{\mathcal{V}}^m$, resulting in 1 million pairwise combinations.

Concretely, for each pair (x, t) we extract its pair representation before learning, yielding the set $\mathcal{H}^m_t = \{\mathbf{h}^m_{t_1} \mid \forall t \in \tilde{\mathcal{V}}^m\}$. We then compare the representation of the pair (x, y) before learning to each alternative pair,

$$\mathcal{S}_y^{\tilde{\mathcal{V}}^m} = \{\cos(\mathbf{h}^m_{y_1}, \mathbf{h}^m_{t_1})\ \forall \mathbf{h}^m_{t_1} \in \mathcal{H}^m_t\}. \tag{3}$$

We can interpret $\mathcal{S}_y^{\tilde{\mathcal{V}}^m}$ as a distribution showing how much interference the pair (x, y) receives from all competing associations (x, t) with $t \in \tilde{\mathcal{V}}^m$. We define the vocabulary interference score for each (x, y) as the median of the set $\mathcal{S}_y^{\tilde{\mathcal{V}}^m}$.

All of the above has been described for a single token pair (x, y). The analysis shown in Figure 3a depicts results for token pairs drawn from the original stimulus set described above, $\mathcal{P}^m$, optimized solely for token pair similarity before learning. We then extend the original set of (x, y) pairs, from $\mathcal{P}^m$, to uniformly sample from the joint distribution of before-learning pair similarity and vocabulary interference (Figure 3b). That is, we use the ~ 1 million token pairs from our sub-sampled vocabulary $\tilde{\mathcal{V}}^m$ to yield a larger set $\mathcal{Q}^m$. We aimed to find at least 10 pairs per similarity group g and vocabulary interference group (details in Appendix A).

3.4 Experimental setup

We analyze six recent open-source base LLMs: Llama2-7b, Llama3.1-8b, Llama3.2-1b, Llama3.2-3b, Gemma2-9b, and Mistral-7b [44, 16, 43, 18]. These models were selected for their recency, open availability, and relatively small size within their respective families, providing a balance between computational efficiency and architectural representativeness. All experiments were performed on internal compute clusters, using two NVIDIA H100 PCIe GPUs with $\approx$ 80GB GPU memory per device. The computation of the experiments took a total of ≈ 15 days.

4 Results

4.1 LLMs exhibit structured, multi-phase learning dynamics

As expected, LLMs are able to complete the in-context associative learning task with high accuracy (between $90 - 100\%$), though the number of repetitions required to reach peak accuracy varies across models. Figure 2a shows how overall prediction accuracy evolves as a function of the number of repetitions. We identified three distinct phases of learning–Encoding, Consolidation, and Forgetting–and we observed that their duration varied across models. To enable direct comparison across models, we normalized the number of repetitions in each phase by aligning phase boundaries: repetitions within each phase were linearly rescaled to fixed intervals ($0-1$ for Encoding, $1-2$ for Consolidation, and $2-3$ for Forgetting). This normalization preserves each model's internal dynamics while making phase-aligned trends directly comparable across models. The accuracy curves per model are provided in Appendix B.2.

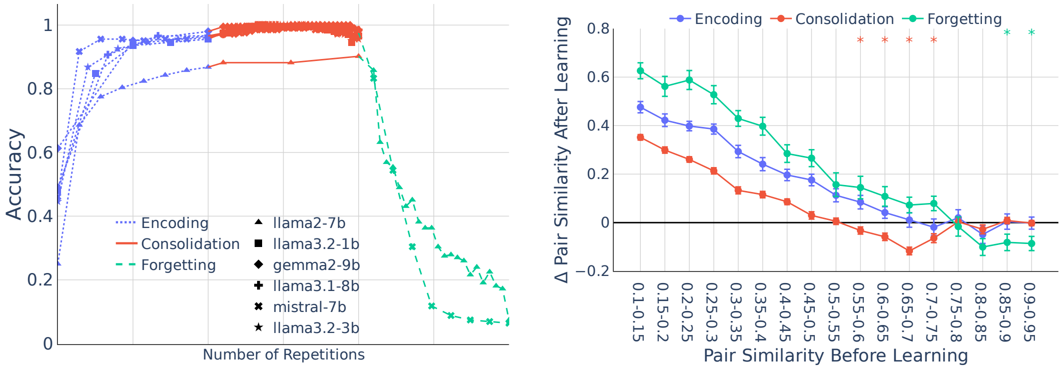
- *Encoding phase (blue):* This phase corresponds to the initial stage of learning, defined by a steep increase in accuracy as the model is repeatedly exposed to the token pair. We define this phase as the period during which accuracy continues to rise by more than 3% between consecutive repetitions, until the model reaches at least 97% of its peak performance.
- *Consolidation phase (red):* This phase reflects a stable performance regime, where the model has largely acquired the association and maintains high accuracy over repetitions. Accuracy remains within $\pm 3\%$ of the peak, indicating that learning has plateaued and performance is stabilized.
- *Forgetting phase (green):* Surprisingly, in some models, accuracy begins to decline even though the number of repetitions remains within the model's maximum context window ($L_s < L^m_{\text{max}}$). We define the forgetting phase as the point where accuracy drops by more than 3% relative to the average of the two prior repetitions, marking the emergence of performance degradation.

While all models exhibited the Encoding and Consolidation phases, only two models (Llama2-7b and Mistral-7b) showed a forgetting phase. For Llama2-7b, forgetting begins relatively early ($r = 40$), whereas for Mistral-7b it emerges much later ($r = 3,000$). We speculate that the delayed forgetting in Mistral-7b may be related to its use of a sliding window attention (SWA). For Llama2-7b, we present preliminary analyses in Appendix B.4, but the underlying cause of early forgetting is not yet well understood. More broadly, it remains unclear how to predict if, and when, forgetting will occur. We leave this question to future work. Overall, these results demonstrate that LLMs can effectively acquire associations and maintain them for a sustained period before eventual degradation.

4.2 Moderately similar pairs significantly differentiate during consolidation

We next investigate how the representations of successfully associated token pairs evolve during learning, specifically focusing on identifying when integration or differentiation occurs. Figure 2b shows how the representational similarity between token pairs changes as a function of their similarity before learning across different phases of learning. We aggregate representational change values ΔS by collapsing across models and token pairs within each similarity group g and learning phase, and report the mean and standard error of the resulting values. To test for differentiation, we performed one-sided paired t-tests for each similarity group and learning phase, testing whether pair similarity after learning was significantly lower than pairsimilarity before learning. To account for multiple comparisons across the 17 similarity groups and 3 learning phases, we applied the Benjamini–Yekutieli (BY) procedure to control the false discovery rate under dependency among tests. Groups that remain significant after BY correction ($p < 0.05$) are marked with asterisks.

During the *Encoding* phase, no significant differentiation is observed across groups that were highly similar before learning. Instead, models show a consistent increase in pairwise similarity for low- to mid-similarity pairs (between 0.1–0.6), reflecting early-stage representational integration: repeated co-occurrence leads these tokens to move closer together in representation space, supporting initial association formation. In contrast, mid- to high-similarity pairs (0.65–0.95) exhibit little to no representational change at this stage.



(a) Accuracy across phases of learning.

(b) Representational change due to learning.

Figure 2: Accuracy and representational changes during learning. (a) Models generally show three phases of learning: encoding, where accuracy steeply increases; consolidation, where accuracy stabilizes; and forgetting, where accuracy declines. To compare across models with different phase lengths, the x-axis is normalized: repetitions within each phase are linearly scaled to fixed intervals ($0 - 1$ for encoding, $1 - 2$ for consolidation, $2 - 3$ for forgetting), allowing phase-aligned trends to be visualized despite variability in learning dynamics. (b) The U-shaped differentiation pattern, characteristic of the Non-Monotonic Plasticity Hypothesis, is observed only during consolidation (red). Asterisks ($*$) indicate groups that remain significant after Benjamini–Yekutieli correction for multiple comparisons across similarity groups and phases ($p < 0.05$).

During the *Consolidation* phase, a striking effect emerges for pairs that were moderately similar before learning ($0.55 - 0.75$): these groups exhibit a significant decrease in pairwise similarity during this phase of learning. This produces a clear U-shaped pattern in representational change–consistent with predictions from the NMPH [34, 46]. Notably, this effect coincides with the stabilization of model performance, suggesting that LLMs undergo structured reorganization of internal representations to maintain high task accuracy. Otherwise, we find that lower similarity pairs still exhibit integration, although to a lesser extent than during Encoding. Higher similarity groups remain largely unchanged, suggesting that their representational similarity is relatively stable across the first two learning phases.

During the *Forgetting* phase, the previously observed non-monotonic pattern disappears, and mid-similarity pairs no longer exhibit significant differentiation. Surprisingly, this is the only phase in which groups that were highly similar before learning show a notable change in their representational structure, displaying clear signs of differentiation relative to their before-learning similarity. Low-similarity pairs, by contrast, undergo even stronger integration than during the Encoding phase. This results in a mild, approximately linear trend in representational change as a function of similarity before learning—resembling the general trend of Encoding, but with greater integration at low similarity and stronger differentiation at high similarity. This trend indicates a loss of structured representational updates, aligning with the observed decline in accuracy. Further results of the evolution of these changes are presented in Appendix B.3.

Taken together, our findings show that LLMs exhibit structured representational dynamics consistent with the NMPH. Interestingly, this non-monotonic pattern is present only during the Consolidation phase, when behavioral performance is stably high, but absent during the Encoding and Forgetting—phases marked by behavioral instability and less structured representational change. Importantly, unlike prior computational models explicitly designed to produce U-shaped dynamics [33], the LLMs that exhibit this non-monotonic effect are general-purpose, pretrained models that were not architecturally constrained or fine-tuned to exhibit such behavior.

4.3 Pair similarity drives representation change, modulated by vocabulary interference

During the *Consolidation* phase—when models exhibited stable maintenance of learned associations—we observed a non-monotonic pattern of representational change as a function of pairwise similarity before learning: low-similarity pairs (up to ≈ 0.5) integrated, mid-similarity pairs (0.55–0.75) differentiated, and high-similarity pairs (> 0.75) showed little to no representational change, aligning best with the NMPH. Building on this analysis, we next examine an additional factor that may contribute to this pattern and is difficult to isolate in biological systems: the similarity between each paired item and the model's prior knowledge. Because LLMs are pre-trained to encode co-occurrence statistics across the entire vocabulary, as humans are thought to do through learning, new associations introduced during ICL must compete with pre-existing patterns. We expect that this competition—what we refer to as vocabulary interference—influences representational change: greater interference (i.e., higher similarity to other items in the vocabulary space) should impose stronger pressure for differentiation to support successful learning.

We thus extend the representational similarity change analysis from Section 4.2 by systematically examining these changes across different levels of vocabulary interference. Specifically, using our original token pairs (x, y) in $\mathcal{P}^m$, we estimate their vocabulary interference with respect to alternative tokens in the set $\tilde{\mathcal{V}}^m$ (see Section 3.3). To facilitate comparison across conditions, we categorize pairs into three equally sized groups based on their vocabulary interference scores: *Low*, *Mid*, and *High* (see Appendix A.4 for details).

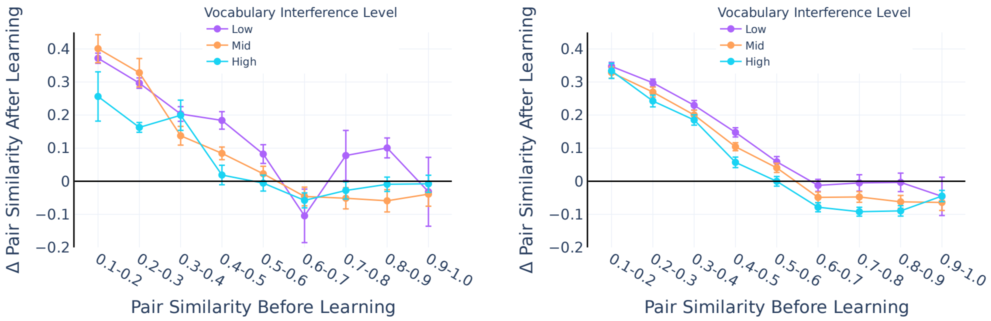
Figure 3a shows how vocabulary interference modulates representational change, with the pattern of this effect varying depending on the pairs' similarity before learning. For low-similarity pairs (up to $0.5 - 0.6$), we observe consistent integration at all levels of vocabulary interference. For mid-similarity pairs $(0.6 - 0.7)$, differentiation emerges as the primary driver across interference levels. High-similarity pairs (above 0.7), however, display high variability and heterogeneous effects: lower interference tends to promote integration, whereas higher interference tends to yield differentiation. This heterogeneity may help explain the apparent U-shaped pattern in our earlier analysis: while low- and mid-similarity pairs exhibit seemingly consistent behavior across interference levels, the variability among high-similarity pairs can mask these opposing trends when averaged, leading to an apparent lack of representational change.

Sampling the full spectrum of vocabulary interference. These findings suggest an interaction between pairwise similarity and vocabulary interference, particularly in the high-similarity regime. To more directly test this interaction, we next control for both factors simultaneously by examining token pairs that span the full joint distribution of pairwise similarity and vocabulary interference (see Section 3.3 and Appendix A for details). To do this, we form an extended set of (x, y) tokens pairs, $\mathcal{Q}^m$, by sampling additional token pairs uniformly across vocabulary interference values. Our approach ensured a minimum of 10 representative pairs per model, similarity group and vocabulary interference level.

Figure 3b shows the results under this controlled sampling regime, where both pair similarity and vocabulary interference are explicitly balanced. As before, we observe a consistent pattern of integration for low-similarity pairs (up to $0.5 - 0.6$). Yet now we observe a robust effect of vocabulary interference: the curves for higher interference levels lie below those for lower interference, indicating reduced, but still present, integration. For mid-similarity pairs, we observe differentiation across all levels of vocabulary interference, and the effect is stronger under higher interference. For high-similarity pairs, we observe a distinct trend: under moderate or high interference, these pairs clearly differentiate, while under low interference, their representations remain relatively stable.

Importantly, across all similarity levels, we observe that higher vocabulary interference is consistently associated with reduced pairwise similarity after learning. One possible explanation for this pattern is that increased interference introduces greater competitive pressure: to reliably associate with each other, paired tokens must distinguish themselves from many similar distractors in the vocabulary. This competition drives the model to reshape representations not only to encode the intended association, but also to preserve distinctiveness within the broader context of the model's prior knowledge.

Representational change through the lens of vocabulary interference. The idea that increased interference introduces competitive pressure provides a useful lens for interpreting the distinct behaviors observed across different pair similarity regimes. For instance, one possible interpretation of the robust integration observed among low-similarity pairs, regardless of vocabulary interference level, is that their representational distance before learning provides greater flexibility for alignment. Because these pairs begin far apart in the representation space, the model can bring them closer (i.e., integrate) without risking excessive overlap that would compromise their individual distinguishability. In this regime, vocabulary interference may impose relatively weak constraints, since the updated representations remain unlikely to be confounded with each other—thus, integration can proceed even



(a) Control for pair similarity.

(b) Control for pair similarity & vocab. interference.

Figure 3: Effect of vocabulary interference on representational change across different pair similarity groups. (a) Results for our original token pairs, sampled uniformly with respect to pair similarity before learning (x-axis). We observe a consistent integration trend for low-similarity pairs and a shift toward differentiation for mid-similarity pairs (0.6–0.7). High-similarity pairs show more heterogeneous behavior, where low interference tends to promote integration, while higher interference tends to yield differentiation. (b) Results for extended token pairs, sampled uniformly over pair similarity before learning (x-axis) and vocabulary interference level (colored lines). Higher vocabulary interference consistently leads to more differentiation, especially for mid- and high-similarity groups. These results suggest that while pairwise similarity is a key driver of differentiation, vocabulary interference amplifies this effect.

under high interference. We speculate that this relative freedom from competition allows the model to prioritize pairwise association without necessitating broader adjustments across the vocabulary space.

At the other extreme, high-similarity pairs begin very close in representational space. Under high vocabulary interference, the model must reshape these representations to prevent confusion with nearby distractors—yet increasing their similarity further could risk entanglement. As a result, differentiation becomes the most likely direction of change, consistent with the strong divergence we observe under high vocabulary interference. In contrast, when vocabulary interference is low, these pairs are already well isolated from the rest of the vocabulary, reducing the pressure for representational differentiation.

Mid-similarity pairs lie in a "sensitive zone" where both factors—pairwise similarity and vocabulary interference—interact most dynamically. They are similar enough to each other that further integration might risk overlap to the point of risking their distinction, yet not similar enough to be clearly associated. Consequently, differentiation appears to be the primary orientation of change for mid-similarity pairs, intensifying with greater vocabulary interference to preserve separability. This suggests that mid-similarity pairs are especially vulnerable to representational reorganization, regardless of the specific interference level.

Therefore, the observed U-shaped curve in the previous analysis (Section 4.2) may be partially explained by a nuanced interaction between pairwise similarity and vocabulary interference. In the high-similarity range, pairs fragment into opposing behaviors across levels of vocabulary interference, so that averaging over these heterogeneous effects can mask systematic representational change and create an illusion of stability.

5 Discussion

In this paper, we investigate whether LLMs exhibit representational changes during associative learning that mirror those observed in humans, and whether they help disambiguate between competing hypotheses about how such changes unfold. Controlling for within pair similarity, we found a non-monotonic pattern of representational change, consistent with the NMPH. This pattern is observed when models stabilize their learning, in what we name the *Consolidation* phase. The fact that LLMs naturally give rise to these dynamics—without any task-specific optimization, and under conditions aligned with how humans learn associations—suggests that they may serve as emergent, flexible model organisms for studying memory reorganization in the brain.

We then leverage the controllability of LLMs to investigate how the vocabulary interference–defined as the interaction between token pair similarity and their similarity to the broader vocabulary–affects representational changes. By introducing this second dimension of analysis, we show that representational dynamics cannot be fully understood in terms of pairwise similarity alone. Instead, representational change reflects a joint influence of pairwise similarity and global contextual competition within the model's prior knowledge. This interaction is especially evident at the extremes: low-similarity pairs integrate consistently across all interference levels, suggesting greater flexibility due to low risk of confusion. High-similarity pairs, by contrast, are already near each other in representational space and face stronger constraints: when vocabulary interference is high, differentiation is the only viable way to maintain separability, whereas under low interference, they remain relatively insulated from external competition, reducing the pressure for further differentiation. Mid-similarity pairs appear to lie at a critical boundary–similar enough to risk confusion, yet not similar enough to form a strong association–making them particularly susceptible to interference-induced differentiation. This sensitivity highlights how small shifts in competitive context can alter the direction of representational change.

Our results show that, while pairwise similarity is a key determinant of representational change, vocabulary interference modulates this effect. This interaction between pair association strength and global contextual interference reveals richer representational dynamic than previously assumed, and may help reconcile diverging findings in the neuroscience literature, where such vocabulary-level interference remains difficult to assess due to limited access to global representational structure. Critically, this kind of fine-grained, systematic manipulation is difficult to achieve in human studies, where both pairwise similarity and global interference are hard to quantify and control. LLMs thus serve as powerful computational model organisms for testing hypotheses about memory dynamics, offering a level of scale and experimental control that is rarely achievable in biological systems.

Limitations and future work. Although LLMs differ mechanistically from human brains, they provide a valuable model system for generating and testing hypotheses that are otherwise challenging to examine in biological systems. Nonetheless, they are not direct stand-ins for humans, and empirical validation in human studies remains essential.

Our operationalization of vocabulary interference also has limitations. By design, it estimates representational competition from the broader vocabulary space, but this approximation may not fully capture the dynamics of interference in human memory, where similarity is shaped by experience, attention, and context. Furthermore, our measure relies on sampled subsets of tokens for tractability, which may underrepresent the true structure of competition across the full vocabulary.

Methodologically, our analysis focused on the final hidden layer of each model, with only preliminary exploration of earlier layers. Future work could systematically track representational change across layers, providing an extended analysis of how interference and differentiation emerge throughout the model hierarchy. Additionally, to ensure coverage across a wide range of similarity values, we used token pairs defined by geometric properties rather than naturalistic semantics. A preliminary analysis on WordNet stimuli is provided in Appendix C, with further investigation left for future work.

Finally, this work focuses on hypotheses tested in mature adult brains, leaving open the question of how these processes emerge during development. Promising future directions include exploring curriculum-learning setups that more closely mirror human developmental trajectories, analyzing attention patterns to identify circuit-level mechanisms involved in resolving interference, and examining how representational dynamics evolve during fine-tuning and longer-term learning.

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    Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

    Answer: [NA]

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