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Anonymous authors

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ABSTRACT

Pretrained large language models (LLMs) are highly capable but still require adaptation for various domains. Existing fine-tuning strategies typically assume either access to all target task data *simultaneously* (e.g., multi-task learning), or a sequential data stream, as in continual learning, where the former tackles the simultaneous task interference issue while the latter focuses on addressing the catastrophic forgetting problem. In this work, we propose a unified approach to address both scenarios. We present DYNMEM, a unified framework that tackles both settings with a lightweight dynamic memory module built on top of frozen pretrained LLMs. DYNMEM encodes past examples into a fixed-sized memory bank. We design a novel dynamic update mechanism where new examples and existing memory entries are ranked based on their *accumulated* attention scores, and the lowest-ranked examples are thus pruned to maintain size. To further reduce recency bias, we adopt a new bi-level memory design: L_1 Memory is actively used by the backbone LLM, while L_2 Memory stores more diverse examples for improved effectiveness at minimal cost. The design also supports more flexible test-time scaling by allowing larger memory banks. We evaluate DYNMEM under both simultaneous and continual learning settings. Our method consistently outperforms state-of-the-art baselines tailored for each scenario, demonstrating its great potential in mitigating task inference for both simultaneous and sequential learning. **In particular, DYNMEM outperforms the state-of-the-art method in simultaneous adaptation across different models, yet achieves this with approximately 50% fewer trainable parameters.**

1 INTRODUCTION

The paradigm of pre-trained large language models (LLMs) has established a powerful foundation for artificial intelligence (Achiam et al., 2023; Bai et al., 2023; Dubey et al., 2024), yet their ability of dynamic adaptation remains a critical frontier. Thus, many researchers have attempted to design more efficient fine-tuning strategies. Recent parameter-efficient fine-tuning (PEFT) methods, e.g., LoRA (Hu et al., 2022) and prompt tuning Lester et al. (2021), typically focus on updating a small amount of extra model parameters to learn a single or multiple tasks jointly. However, they are limited by assuming access to all data simultaneously, i.e., *simultaneous adaptation*.

To address the more realistic sequential data stream scenario, various parameter-efficient continual learning methods (Zhu et al., 2022; Chen et al., 2023; Zhao et al., 2024) are developed for resolving the catastrophic forgetting issue. These methods prevent catastrophic forgetting by allocating separate, architecturally disjoint parameters (e.g., soft prompts or adapters (Poth et al., 2023)) for each task. However, this isolationist approach introduces critical limitations. It creates a task-agnostic inference problem, as it requires an oracle to select the correct parameters at test time, and inherently restricts forward transfer by siloing knowledge within each module (Zheng et al., 2024). More critically, their effectiveness in simultaneous adaptation (e.g., multi-task learning) is largely unknown. In this paper, we aim to bridge this gap and design a unified method for both scenarios.

Inspired by recent memory-augmented methods (Yang et al., 2024; Wu et al., 2022a; Zhai et al., 2025; Mitchell et al., 2022), we propose DYNMEM, a lightweight memory module operating on a

fixed-size memory bank that enables efficient LLM adaptation across both sequential and simultaneous learning settings. Following recent work, DYNMEM encodes past training examples into vectors that are stored in a dynamic memory bank. To support more efficient reading and forgetting mechanisms, we introduce a bi-level memory system that utilizes the attention scores from the frozen backbone LLM. First, a compact L_1 *Memory* maintains a compact set of recently retrieved, highly relevant samples, which are integrated into LLM via a gated fusion module. However, this can introduce recency bias, potentially degrading long-term knowledge retention. To mitigate this, we incorporate a larger L_2 *Memory*, which caches more historically high-ranking samples. Since L_2 Memory does not directly interact with the LLM, it significantly enhances the method’s effectiveness at minimal cost. All samples in both memory stores are periodically ranked based on an attention-based ranking mechanism, where those lowest-ranked samples are dequeued to leave space for new samples. In other words, both memory reading and pruning operations are based on the attention module, which is jointly trained in an end-to-end fashion. During inference, DYNMEM employs a cross-stage retrieval process, integrating the selected memories with the current input via a gated fusion mechanism, allowing the model to dynamically leverage past knowledge for the task at hand.

We conduct a comprehensive empirical evaluation of DYNMEM across two primary adaptation scenarios: Continual Adaptation, which assesses the model’s resilience to forgetting and its capacity for forward transfer, and Simultaneous Adaptation, which includes two distinct sub-settings, Single-task Tuning and Multi-task Integration. Across this diverse suite of benchmarks, DYNMEM demonstrates significant gains in knowledge retention, adaptation, and generalization, establishing a new state-of-the-art in versatile model adaptation. To summarize, our contributions include:

- We propose DYNMEM, a lightweight dynamic memory module for efficient adaptation with pretrained LLMs. As far as we know, we are the first to unify simultaneous and continual learning paradigms within a single, cohesive architecture.
- We introduce a unique bi-level memory system, featuring a working and reserved memory managed by an attention-based filtering mechanism, which enables efficient, example-level knowledge retention and retrieval with a compact memory size.
- We conduct a comprehensive empirical evaluation across a diverse suite of benchmarks spanning continual, single-task, and multi-task adaptation. Our results demonstrate that DYNMEM achieves state-of-the-art results across the board, significantly outperforming specialized methods in their respective domains.

2 PRELIMINARIES

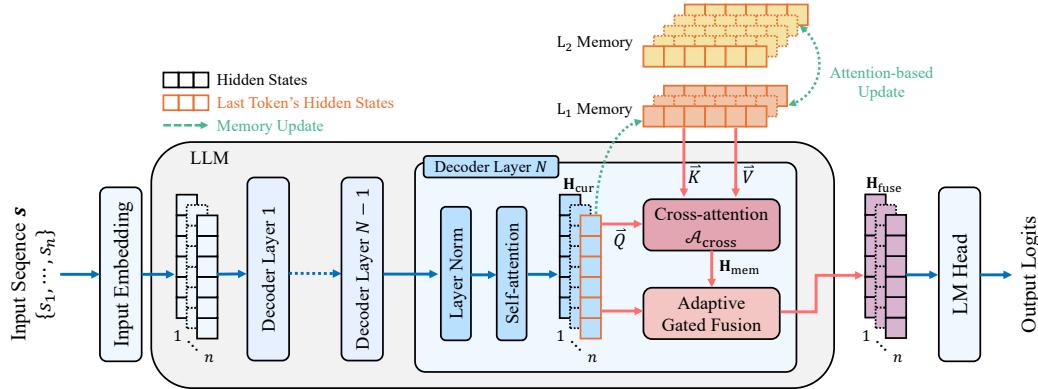
Our work aims to develop a single, unified framework that excels in two distinct paradigms of model adaptation. To establish the context for this approach, we first formalize these paradigms below.

Continual Adaptation. Commonly known as Continual Learning, continual adaptation addresses the more dynamic scenario where tasks arrive sequentially, $\mathcal{T}_1, \mathcal{T}_2, \dots, \mathcal{T}_N$. When training on the current task \mathcal{T}_k , the model has only access to its corresponding dataset \mathcal{D}_k , and data from past tasks $\{\mathcal{D}_1, \dots, \mathcal{D}_{k-1}\}$ is unavailable. The main challenge in this setting is *catastrophic forgetting*, defined as the severe degradation of performance on previously learned tasks after the model updates for new ones. Formally, let $A(\theta_j; \mathcal{D}_i)$ denote the accuracy of the model with parameters θ_j (having learned up to task j) on the dataset for task i . Forgetting is measured by the performance drop from $A(\theta_i; \mathcal{D}_i)$ to $A(\theta_k; \mathcal{D}_i)$ for any $i < k$. The objective here is twofold: learn the new task effectively while simultaneously preserving knowledge from all previously seen tasks.

Simultaneous Adaptation. In this paradigm, a model f_θ is assumed to have full access to the complete datasets for a set of N tasks, $\{\mathcal{D}_1, \dots, \mathcal{D}_N\}$. The primary goal is to learn a single set of parameters θ that performs well across these tasks by leveraging their shared structure. This paradigm encompasses several key evaluation settings: a) *Single-task Tuning* The model is specialized for a single task \mathcal{T}_i by fine-tuning exclusively on its dataset \mathcal{D}_i . b) *Multi-task Integration*: A single model is jointly trained on the union of all task datasets, $\mathcal{D}_{\text{all}} = \bigcup_{i=1}^N \mathcal{D}_i$, to encourage knowledge sharing.

108 3 THE DYNMEM FRAMEWORK

110 Here, we introduce DYNMEM, a framework designed to unify simultaneous and continual adap-
 111 tation. At a high level, DYNMEM augments a pre-trained LLM, denoted as a parametric function
 112 f_θ , with a dynamic, bi-level memory system as shown in Figure 1. Unless otherwise specified, the
 113 backbone LLM remains frozen throughout the paper.



124 Figure 1: The overall architecture of DYNMEM. During the training phase, as new tasks arrive, the
 125 model is continuously fine-tuned and example representations are generated based on the final layer
 126 hidden states of the backbone LLM. Note that the model only interacts with the L₁ Memory via
 127 cross-attention and a gated fusion layer to produce predictions (§3.1). The attention scores from this
 128 interaction also guide the periodic pruning of L₁ and L₂ to maintain a compact memory size.

132 Similar to recent memory-augmented methods, we derive memory entries using the backbone LLM
 133 as the encoder. The novelty of DYNMEM lies in its bi-level memory system, designed to balance
 134 immediate task relevance with long-term knowledge diversity. This memory module is strategically
 135 inserted at the final decoder layer of the LLM, intercepting the layer’s output hidden states to perform
 136 memory interaction before the final prediction. The system consists of a L₁ Memory (\mathcal{M}_{L_1}) for
 137 high-relevance, active samples and a larger (L₂) Memory (\mathcal{M}_{L_2}) that serves as a long-term reservoir.
 138 Both memory caches hold a predefined capacity, with $|\mathcal{M}_{L_2}| > |\mathcal{M}_{L_1}|$.

140 The basic entry in both memories is a vector \mathbf{m}_e representing a single training example $(x_e, y_e) \in$
 141 \mathcal{D}_i , where x_e is the task prompt input and y_e is the corresponding gold output. Consistent with
 142 the module’s placement, this vector is generated by extracting the semantically rich hidden states of
 143 the final token from the last decoder layer, *i.e.*, $\mathbf{m}_e = \text{Decoder}_{\text{last}}(f_\theta(\text{Concat}(x_e, y_e)))_{[-1]} \in \mathbb{R}^d$,
 144 where d is the hidden dimensionality. This representation effectively summarizes the input-output
 145 mapping for a given example and forms the candidate pool for our memory bank.

146 3.1 MEMORY INTERACTION AND INTEGRATION

148 The flexible reading and forgetting interactions on memory are achieved by three key modules: a
 149 cross-attention module for retrieving knowledge, an update strategy for maintaining the memory
 150 bank, and a gated layer for integrating retrieved information.

152 **Attention-based Knowledge Retrieval.** To retrieve and integrate relevant memory knowledge, we
 153 design a cross-attention module $\mathcal{A}_{\text{cross}}$. Denote the hidden state representation of the current input
 154 from the final decoder layer as $\mathbf{H}_{\text{cur}} \in \mathbb{R}^{L \times d}$. During the model’s forward pass, this representation
 155 interacts exclusively with the contents of the L₁ Memory, whose vectors $\{\mathbf{m}_1, \dots, \mathbf{m}_{|\mathcal{M}_{L_1}|}\}$ are
 156 concatenated into a matrix \mathbf{M}_{L_1} . To leverage the LLM’s pre-trained weights and ensure parameter
 157 efficiency, we initialize this cross-attention module from the self-attention block of the same de-
 158 coder layer. Specifically, the input hidden states \mathbf{H}_{cur} form the query, while the memory vectors
 159 in \mathbf{M}_{L_1} form the key and value pairs: $\mathbf{Q} = \mathbf{H}_{\text{cur}} W^Q, \mathbf{K} = \mathbf{M}_{L_1} W^K, \mathbf{V} = \mathbf{M}_{L_1} W^V$, where
 160 $W^Q, W^K, W^V \in \mathbb{R}^{d \times d}$ are learnable projection matrices. The module concurrently computes two
 161 outputs: the memory-enhanced representation \mathbf{H}_{mem} and the raw cross-attention scores α_{cur} :

$$\mathbf{H}_{\text{mem}}, \alpha_{\text{cur}} = \mathcal{A}_{\text{cross}}(\mathbf{H}_{\text{cur}}, \mathbf{M}_{L_1}). \quad (1)$$

162 The representation \mathbf{H}_{mem} is thereby enriched with context from historical examples stored in the
 163 active L_1 memory, while the attention scores $\alpha_{\text{cur}} \in \mathbb{R}^{N_h \times L \times |\mathcal{M}_{L_1}|}$, where N_h is the number of
 164 attention heads, are used as a relevance signal for the subsequent memory update process. **At inference,**
 165 **the same cross-attention mechanism is applied, and the query is formed only from the test**
 166 **input.** The model encodes the partial sequence through the frozen backbone LLM, projects the
 167 final-token hidden state, and uses this vector to search over the memory bank (Sec. 3.2). This pro-
 168 duces a memory-enhanced representation based solely on semantic similarity between the input and
 169 stored examples. Retrieval is entirely input-driven and permutation-invariant, allowing the model to
 170 integrate the most relevant memory entries during test-time adaptation.

171 **Memory Update.** To ensure the memory bank remains constant-sized and evolves over time, we
 172 employ a dynamic update mechanism that operates periodically every I training steps. The process
 173 is driven by the attention scores α_{cur} from $\mathcal{A}_{\text{cross}}$ as defined above. For each training input, these
 174 scores are aggregated and normalized across attention heads and the input length L to compute a
 175 single relevance score for every (entry) vector $\mathbf{m} \in \mathcal{M}_{L_1}$: $s(\mathbf{m}) = \frac{1}{N_h L} \sum_{h=1}^{N_h} \sum_{i=1}^L \alpha_{\text{cur}}^{(h,i,j)}$. This
 176 score is accumulated over the I -step interval to produce a long-term utility estimate, $S(\mathbf{m}) = \frac{1}{I}$, for
 177 each L_1 vector. Note that the scores for vectors in the L_2 Memory remain static during this period,
 178 retaining their last known utility value. At the end of the interval, a global update is triggered. First,
 179 all vectors in both memory pools, $\mathcal{M}_{L_1} \cup \mathcal{M}_{L_2}$, are ranked based on their utility scores S so far. A
 180 fraction $\eta \in (0, 1)$ of the lowest-scored vectors are permanently pruned. The resulting empty slots
 181 are then replenished with an equal number of new candidate vectors generated from the most recent
 182 training phase. Finally, this updated and replenished pool of $|\mathcal{M}_{L_1}| + |\mathcal{M}_{L_2}|$ vectors is going to
 183 be re-ranked based on utility. The top- $|\mathcal{M}_{L_1}|$ vectors are designated as the new L_1 memory for the
 184 next training interval, ensuring it always contains the most salient examples for active interaction.
 185 The remaining vectors constitute the new L_2 memory. This strategy maintains a clear hierarchy
 186 where the L_2 memory serves as a robust long-term reservoir, while the L_1 memory functions as
 187 the dynamic and compact working set. **Importantly, DYNMEM does not depend on the order of**
 188 **memory entries: the cross-attention read-in mechanism treats the memory bank as a permutation-**
 189 **invariant collection. Reordering or refreshing memory vectors requires no parameter relearning, and**
 190 **no positional information about the memory bank is ever used by the model. See Alg. 1 for details.**

191 **Adaptive Fusion via Learned Gating.** After obtaining the original \mathbf{H}_{cur} and memory-enhanced
 192 \mathbf{H}_{mem} representations, a learnable gating mechanism is used to fuse them. This allows the model to
 193 control the intensity of information injection or reading from the memory. Based on the input, we
 194 compute an input-aware gating coefficient $\gamma = \sigma(\mathbf{H}_{\text{cur}} \mathbf{W}_g + \mathbf{b}_g)$, where \mathbf{W}_g and \mathbf{b}_g are the learn-
 195 able parameters of the gating layer and $\sigma(\cdot)$ is the sigmoid function. The final fused representation
 196 is then passed to the final prediction layer as

$$\mathbf{H}_{\text{fuse}} = (1 - \gamma) \odot \mathbf{H}_{\text{cur}} + \gamma \odot \mathbf{H}_{\text{mem}}. \quad (2)$$

197 The learnable nature of this gate allows DYNMEM to adaptively balance its reliance on model inter-
 198 nal knowledge versus accumulated external knowledge.

201 3.2 DYNAMIC MEMORY RETRIEVAL AT INFERENCE

202 In addition to the dynamic interaction as described above for training, we can adopt another
 203 inference-time procedure by using more extensive dynamic query-specific knowledge retrieval. In
 204 other words, unlike the training process, which interacts with a fixed L_1 memory to learn general
 205 patterns of example relevance, the inference process performs a global search over $L_1 \& L_2$ to find
 206 the most pertinent context for each individual test example. For each incoming test example, we
 207 first generate a query vector \mathbf{Q}_{test} , using the same feature extraction process as for the memory
 208 entries themselves. We then perform an efficient similarity search (*e.g.*, maximum inner-product
 209 search) to approximate the attention used in training against all vectors in the unified memory pool,
 210 $\mathcal{M}_{L_1} \cup \mathcal{M}_{L_2}$. This step dynamically assesses the relevance of every stored memory candidate with
 211 respect to the current input. The top- $|\mathcal{M}_{L_1}|$ highest-scoring memory vectors are selected to form
 212 a sample-specific memory set, denoted as $\mathcal{M}_{\text{retrieved}}$. This retrieved set is then used as context for
 213 $\mathcal{A}_{\text{cross}}$, and subsequently integrated via the gated fusion mechanism to produce the final predic-
 214 tion. This two-stage design is critical for both efficiency and scalability 4.3. It allows DYNMEM to
 215 maintain a much larger long-term knowledge reservoir in its L_2 memory without incurring a propor-
 216 tional computational cost at inference time. The model’s forward pass only ever processes a small,

216 fixed-size set of K relevant exemplars, decoupling the size of the knowledge base from the cost of
 217 prediction. Hence, the retrieval process at inference does not involve pruning of the memory bank.
 218

219 Algorithm 1 Memory Update of DYNMEM

220 **Require:** dataset \mathcal{D} ; model f_θ ; memory bank $\mathcal{M}_{L_1}, \mathcal{M}_{L_2}$; update interval I ; pruning ratio η

221 **Training:**

222 Initialize $\mathcal{M}_{L_1}, \mathcal{M}_{L_2} \leftarrow \emptyset$; set $S(\mathbf{m}) \leftarrow 0$ for all $\mathbf{m} \in \mathcal{M}_{L_1}$
 223 $\triangleright S(\mathbf{m})$ stores the long-term utility score aggregated from attention weights
 224 **for** each training step $t = 1, 2, \dots$ over the data stream **do**
 225 Sample batch $\{(x, y)\}$
 226 Encode example to candidate memory vector: $\mathbf{m}_{\text{new}} \leftarrow g(f_\theta(x, y))$
 227 $\triangleright g(\cdot)$: projection of final-layer last-token state
 228 Obtain current hidden states \mathbf{H}_{cur} from f_θ
 229 $(\mathbf{H}_{\text{mem}}, \alpha_{\text{cur}}) \leftarrow \mathcal{A}_{\text{cross}}(\mathbf{H}_{\text{cur}}, \mathcal{M}_{L_1})$
 230 Fuse representations via gate: $\mathbf{H} \leftarrow (1 - \gamma)\mathbf{H}_{\text{cur}} + \gamma\mathbf{H}_{\text{mem}}$
 231 Compute loss \mathcal{L} on \mathbf{H} and update trainable parameters of DYNMEM
 232 Update utility $S(\mathbf{m})$ for each $\mathbf{m} \in \mathcal{M}_{L_1}$ using α_{cur}
 233 Add \mathbf{m}_{new} to temporary candidate pool \mathcal{B}
 234 **if** $t \bmod I = 0$ **then**
 235 Rank all entries in $\mathcal{M}_{L_1} \cup \mathcal{M}_{L_2}$ by $S(\cdot)$
 236 Prune the bottom η fraction
 237 Fill freed slots with top candidates from \mathcal{B} ; clear \mathcal{B}
 238 Re-rank the refreshed pool by $S(\cdot)$
 239 Assign top $|\mathcal{M}_{L_1}|$ entries to new \mathcal{M}_{L_1} ; remainder to \mathcal{M}_{L_2}
 240 Reset $S(\mathbf{m}) \leftarrow 0$ for all $\mathbf{m} \in \mathcal{M}_{L_1}$
 241 **end if**
 242 **end for**

243 **Inference:**

244 Encode input x : $\mathbf{H}_{\text{cur}} \leftarrow f_\theta(x)$
 245 Compute cross-attention over memory: $(\mathbf{H}_{\text{mem}}, \alpha_{\text{cur}}) \leftarrow \mathcal{A}_{\text{cross}}(\mathbf{H}_{\text{cur}}, \mathcal{M}_{L_1} \cup \mathcal{M}_{L_2})$
 246 **Refresh working memory:** update \mathcal{M}_{L_1} using the relevance scores α_{cur}
 247 Fuse representations: $\mathbf{H} \leftarrow (1 - \gamma)\mathbf{H}_{\text{cur}} + \gamma\mathbf{H}_{\text{mem}}$
 248 Generate prediction \hat{y} from \mathbf{H}

250 **4 EXPERIMENTS**

251
 252 We conduct a comprehensive empirical evaluation to substantiate DYNMEM’s capability as a unified
 253 framework excelling in both Continual and Simultaneous Adaptation. Our central hypothesis is that
 254 our bi-level memory architecture naturally addresses the principal challenges of each paradigm. For
 255 *Continual Adaptation*, the memory acts as an explicit knowledge reservoir to preserve past experi-
 256 ences, thereby mitigating catastrophic forgetting. For *Simultaneous Adaptation*, it serves as a power-
 257 ful channel for instance-based knowledge sharing, enhancing transfer across tasks. Accordingly, our
 258 evaluation is structured around these two core settings, assessing performance in continual learning
 259 streams as well as in standard *Single-task Tuning* and *Multi-task Integration*. Across this diverse
 260 suite of benchmarks, we demonstrate that DYNMEM consistently surpasses specialized baselines,
 261 validating its efficacy as a truly versatile adaptation solution.

262 **4.1 CONTINUAL ADAPTATION**

263 **4.1.1 EXPERIMENTAL SETUP**

264 **Task Streams.** We construct two challenging task streams to evaluate performance under different
 265 conditions of semantic shift: a) **STRUCTURED STREAM**. This stream contains 4 structured knowl-
 266 edge reasoning datasets: Spider (Yu et al., 2018) for text-to-SQL, ComplexWebQuestions (Talmor
 267 & Berant, 2018) for text-to-SPARQL, GrailQA (Gu et al., 2021) for S-expression generation, and
 268 MTOP (Li et al., 2021) for semantic parsing in dialogue systems. These tasks focus on structured
 269

language generation, testing the model’s capability to retain reasoning skills on structured data. b) MIXED STREAM. To simulate more significant domain shifts, we augment the Structured Stream with four diverse commonsense reasoning datasets: BoolQ (Clark et al., 2019), PIQA (Bisk et al., 2020), Arc-Easy (Clark et al., 2018), WinoGrande (Sakaguchi et al., 2021). This stream tests the model’s robustness to maintain distinct knowledge bases. For each task in both streams, we create a standardized split by randomly sampling 1,000 examples for training and 300 examples for testing.

Evaluation Metrics. We adopt standard metrics from continual learning literature (Chen et al., 2023). Let $A_{k,i}$ be the accuracy on the test set of task \mathcal{T}_i after the model has finished training on task \mathcal{T}_k . a) *Average Accuracy*: $\text{Acc} = \frac{1}{k} \sum_{i=1}^k A_{k,i}$ reflects the average accuracy on all tasks seen so far after training on task \mathcal{T}_k ; b) *Backward Transfer*: $\text{BWT} = \frac{1}{k-1} \sum_{i=1}^{k-1} (A_{k,i} - A_{i,i})$ measures the degree of model forgetting; c) *Forward Transfer*: $\text{FWT} = \frac{1}{k-1} \sum_{i=2}^k (A_{i,i} - A_i, 0)$ evaluates model’s ability to transfer previously-learned knowledge to new tasks.

Compared Methods. We compare DYNMEM against a comprehensive set of baselines: a) *Fine-tuning*: A vanilla fine-tuning approach where the model is updated on each task sequentially, which usually exhibits severe forgetting. b) *PEFT Methods*: This family of methods leverages parameter-efficient tuning techniques by allocating a separate, small set of trainable parameters for each task. We include Continual Prompt Tuning (CPT)(Zhu et al., 2022) and C3 (Chen et al., 2023) as representatives. c) *Rehearsal-based Methods*: We compare against EMAR (Han et al., 2020), a baseline that stores a buffer of raw examples from past tasks and rehearses them when learning a new task.

Backbone Models. We conduct experiments on two powerful open-source large language models: Llama-3-8B (Dubey et al., 2024) and Qwen-3-8B (Yang et al., 2025).

Implementation Details. For DYNMEM, we set the L_1 memory size to $|\mathcal{M}_{L_1}| = 100$ and the L_2 to $|\mathcal{M}_{L_2}| = 1000$. The memory is updated periodically with an interval of $I = 500$ training steps.

4.1.2 EXPERIEMNTAL RESULTS

Table 1: Continual Adaptation on the Structured and Mixed streams. ORACLE serves as an upper-bound performance, representing a model trained jointly on the union of all task datasets; EMAR utilizes a buffer of 10 examples per past task. Each cell shows mean_{std} .

Backbone	Method	Structured			Mixed		
		Acc	BWT	FWT	Acc	BWT	FWT
Llama-3-8B	FINE-TUNING	22.3 _{3.4}	-26.3 _{3.4}	2.3 _{1.2}	40.3 _{5.4}	-19.1 _{3.8}	3.4 _{1.3}
	EMAR	35.3 _{2.3}	-14.2 _{1.3}	2.3 _{0.4}	49.5 _{2.0}	-15.3 _{2.3}	2.9 _{0.7}
	CPT	10.3 _{4.5}	-	0.7 _{0.3}	23.6 _{3.1}	-	2.3 _{0.4}
	C3	37.2 _{3.1}	-	3.7 _{1.4}	51.6 _{3.9}	-	4.1 _{1.6}
	DYNMEM	41.2 _{4.0}	-12.3 _{2.1}	5.6 _{1.5}	57.2 _{3.6}	-13.4 _{1.2}	7.6 _{1.8}
	ORACLE	56.2 _{0.9}	6.5 _{1.9}	6.7 _{2.4}	61.4 _{1.5}	8.7 _{2.3}	8.1 _{0.6}
Qwen-3-8B	FINE-TUNING	25.4 _{3.2}	-19.8 _{4.3}	2.4 _{0.6}	45.2 _{6.7}	-18.2 _{2.5}	4.1 _{0.6}
	EMAR	37.1 _{3.4}	-13.1 _{4.2}	3.1 _{0.8}	52.0 _{3.1}	-18.7 _{0.9}	3.0 _{0.9}
	CPT	13.4 _{1.7}	-	1.3 _{0.5}	24.2 _{2.8}	-	3.1 _{0.7}
	C3	38.2 _{3.7}	-	3.2 _{0.7}	54.6 _{3.8}	-	3.5 _{0.8}
	DYNMEM	43.9 _{2.3}	-10.3 _{1.7}	7.1 _{3.6}	60.1 _{0.8}	-11.9 _{2.8}	8.0 _{1.2}
	ORACLE	59.1 _{3.4}	10.1 _{3.5}	8.2 _{1.2}	62.7 _{2.0}	9.1 _{0.7}	7.9 _{1.3}

Overall Results. The results in Table 1 confirm that DYNMEM establishes a new state-of-the-art in continual learning. On MIXED STREAM using Llama-3-8B, DYNMEM achieves an average accuracy of 57.2, substantially outperforming the strongest baseline, C3, by 5.6 points. This superior performance is a direct result of our memory-centric design, which excels at both mitigating forgetting and accumulating new knowledge. DYNMEM achieves the highest Backward Transfer, demonstrating that the bi-level memory acts as a robust knowledge reservoir where inference-time retrieval successfully compensates for parametric drift. DYNMEM also achieves the highest Forward Transfer, nearly doubling that of the next best method, showing the memory does not merely preserve old knowledge but actively facilitates the learning of new tasks by providing relevant, instance-based

324 context to accelerate adaptation. Unlike PEFT methods that prevent forgetting at the cost of limited
 325 knowledge sharing (lower FWT), DYNMEM’s unified architecture enables both strong knowledge
 326 preservation and positive transfer, offering a more effective and holistic solution to the continual
 327 learning problem.

328 **Performance till Seen Tasks.** To provide a more
 329 granular view of the learning dynamics, we plot the
 330 average accuracy on all previously seen tasks as the
 331 model progresses through both the STRUCTURED
 332 and MIXED streams in Figure 2. This visualization
 333 vividly illustrates the models’ ability to accumulate
 334 and retain knowledge over time. As expected, stan-
 335 dard Fine-tuning suffers a precipitous decline in av-
 336 erage accuracy, clearly demonstrating catastrophic
 337 forgetting. While other methods like EMAR and C3
 338 offer partial mitigation, they ultimately succumb to
 339 a steady degradation of knowledge as more tasks are
 340 introduced, with their performance curves showing
 341 a clear downward trend.

342 DYNMEM exhibits remarkable stability and a strong
 343 capacity for knowledge accumulation across both
 344 streams and backbone models. Its performance tra-
 345 jectory remains high and relatively flat, showing
 346 only a minor initial drop before stabilizing. This pro-
 347 vides compelling evidence that our dynamic bi-level memory system successfully decouples knowl-
 348 edge preservation from parametric adaptation: the LLM learns the new task, while the memory
 349 update and inference-time retrieval mechanisms successfully preserve and leverage knowledge from
 350 the past, enabling robust and stable knowledge accumulation over the entire task sequence.

351 4.2 SIMULTANEOUS ADAPTATION

352 4.2.1 EXPERIMENTAL SETUP

353 **Datasets.** We evaluate simultaneous adaptation performance on a comprehensive suite of widely-
 354 used benchmarks covering commonsense reasoning. Specifically, we use eight commonsense rea-
 355 soning datasets: BoolQ (Clark et al., 2019), PIQA (Bisk et al., 2020), SocialIQA (SIQA) (Sap et al.,
 356 2019), HellaSwag (HellaS.) (Zellers et al., 2019), WinoGrande (WinoG.) (Sakaguchi et al., 2021),
 357 ARC-Easy (ARC-e) (Clark et al., 2018), ARC-Challenge (ARC-c) (Clark et al., 2018), and Open-
 358 BookQA (OBQA) (Mihaylov et al., 2018). We also include GSM8K (Cobbe et al., 2021) for math-
 359 ematical reasoning.

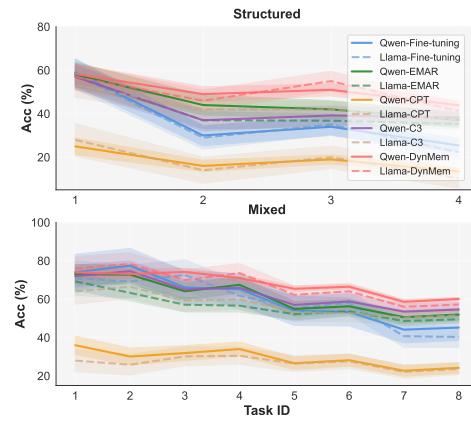
360 **Evaluation Protocol.** We evaluate all methods under two primary simultaneous settings: a) *Single-
 361 task Tuning*. The model is fine-tuned and evaluated on each dataset separately to measure its per-
 362 formance on corresponding tasks. b) *Multi-task Tuning*. A single model is jointly trained on the
 363 combined training sets of all eight commonsense reasoning datasets and is subsequently evaluated
 364 on the test set of each individual task to measure knowledge integration.

365 **Compared Methods.** We benchmark DYNMEM against a comprehensive set of state-of-the-art
 366 PEFT methods to ensure a rigorous comparison: LoRA (Hu et al., 2022), NoRA (Lin et al., 2024),
 367 LoKr (Yeh et al., 2024), DoRA (Liu et al., 2024), AdaLoRA (Zhang et al., 2023), MixLoRA (Li
 368 et al., 2024), and DenseLoRA (Mu et al., 2025).

369 **Backbone Models.** To ensure our findings are robust and generalizable, we conduct all experiments
 370 on two powerful open-source large language models: Llama-3-8B and Qwen-3-8B.

371 The results for Single-task Tuning, presented in Table 2, reveal the superiority of DYNMEM as a
 372 fine-tuning framework. Across both backbone models, DYNMEM consistently establishes a new
 373 state-of-the-art, outperforming all compared PEFT baselines.

374 Focusing on the Llama-3-8B results, DYNMEM achieves an average score of 86.8 on the com-
 375 monsense reasoning benchmarks, a salient improvement of 1.9 points over the strongest baseline,



376 Figure 2: Acc on all seen tasks as the model
 377 trains sequentially on two streams.

Table 2: Experiments on Single-task Tuning. See B for parameter calculation details.

Method	Param (%)	Commonsense Reasoning							Math		
		BoolQ	PIQA	SIQA	HellaS.	WinoG.	ARC-e	ARC-c	OBQA	Avg.	GSM8K
Llama-3-8B											
LORA	0.35	72.3	86.7	79.3	93.5	84.8	87.7	75.7	82.8	82.9	57.2
DORA	0.36	73.3	89.1	79.9	95.9	84.7	89.8	79.5	86.9	84.9	58.1
ADALORA	0.35	75.2	88.2	79.2	76.2	85.2	89.9	78.2	85.0	82.1	52.1
MIXLORA	2.60	75.0	87.6	78.8	93.3	82.1	86.5	79.9	84.8	83.5	55.6
DYNMEM	0.18	76.5	90.3	81.9	96.6	86.0	93.3	80.7	89.3	86.8	59.6
Qwen-3-8B											
LORA	0.35	75.6	91.0	81.5	92.7	88.6	95.6	89.7	92.8	88.4	64.5
DORA	0.36	76.1	89.9	82.1	93.7	87.9	96.8	89.3	93.1	88.6	63.1
DYNMEM	0.18	76.5	91.2	90.7	95.6	88.4	96.2	91.5	91.3	90.2	65.6

DoRA (84.9). This trend also holds for mathematical reasoning, where DYNMEM achieves 59.6 on GSM8K, again surpassing all baselines. Crucially, DYNMEM achieves these state-of-the-art results while being significantly more parameter-efficient. With only 0.18% trainable parameters with regard to the backbone LLM, it uses approximately half the parameters of LoRA/DoRA and an order of magnitude fewer than methods like MixLoRA.

This pattern of superior performance and efficiency is not limited to a single model architecture. As the results for the Qwen-3-8B backbone confirm, **DYNMEM** consistently outperforms the baseline methods, demonstrating that its advantages are generalizable across different foundational models.

These results highlight a key advantage of our approach. Unlike purely parametric methods that compress all task knowledge into a small set of adapter weights, DYNMEM leverages its memory to store and retrieve the most salient examples from the training data. This instance-based conditioning provides powerful, explicit context at inference time, leading to more robust intra-task generalization and ultimately higher accuracy. Therefore, even in this fundamental adaptation setting, DYNMEM proves to be a more effective and efficient fine-tuning solution.

4.2.2 MULTI-TASK INTEGRATION

Table 3: Experiments on Multi-task Integration.

Method	Param (%)	Commonsense Reasoning								
		BoolQ	PIQA	SIQA	HellaS.	WinoG.	ARC-e	ARC-c	OBQA	
Llama-3-8B										
LORA	0.35	72.3	83.7	78.1	91.6	82.8	84.9	72.4	81.2	80.9
NORA	0.10	73.3	86.4	79.1	94.1	84.3	88.2	77.5	85.0	83.5
LOKr	0.01	65.1	81.6	78.7	92.0	82.1	89.2	76.7	80.9	80.8
DORA	0.35	71.8	86.1	79.4	94.0	85.1	88.0	77.4	87.2	83.6
ADALORA	0.35	75.1	86.4	76.7	75.4	83.3	90.4	79.1	85.0	81.4
MoSLoRA	0.36	74.6	89.7	81.0	95.0	85.8	90.5	81.5	86.8	85.6
DENSELoRA	0.06	74.1	88.9	80.3	95.0	87.0	90.0	79.2	85.6	85.0
DYNMEM	0.18	76.5	89.3	81.1	95.4	85.7	93.3	80.7	88.3	86.3
Qwen-3-8B										
LORA	0.35	73.2	88.1	80.4	90.0	86.1	93.0	87.9	91.8	86.3
DORA	0.36	75.0	88.1	79.9	91.2	87.0	94.9	88.8	92.9	87.2
DYNMEM	0.18	74.5	90.0	90.7	94.3	87.9	96.0	90.3	90.3	89.3

The results for Multi-task Tuning (MT), presented in Table 3, highlight DYNMEM’s exceptional capability for knowledge integration and transfer across a diverse set of tasks.

On the **Llama-3-8B** backbone, DYNMEM achieves a new state-of-the-art with an average score of 86.4 across all eight commonsense reasoning datasets. This represents an improvement of 0.8 points over the strongest PEFT baseline, MoSLoRA (85.6), and demonstrates superior performance on nearly every individual task. Notably, this superior performance is achieved with significantly higher parameter efficiency; DYNMEM uses only a smaller amount of trainable parameters.

This strong performance in a multi-task setting validates the core design of our framework. While standard PEFT methods rely on implicit knowledge transfer through a shared set of parameters,

DYNMEM introduces a powerful channel for explicit, instance-based knowledge sharing. During training, the memory update process populates L_1 and L_2 Memory with the most salient examples from co-trained tasks. At inference, the retrieval mechanism can fetch a transferable relevant example. This targeted, cross-task retrieval allows DYNMEM to leverage inter-task synergies effectively than purely parametric approaches, leading to a more capable and integrated multi-task model.

4.3 ABLATION STUDY

To validate the contribution of each core component of our design, we conduct an ablation study, the results of which are presented in Table 4. We evaluate several variants of DYNMEM by removing one key mechanism at a time: a) *w/o L_2 Memory* tests the necessity of the long-term reservoir by using only a single L_1 memory; b) *w/o Inference Retrieval* assesses the benefit of dynamic, query-specific retrieval by using the static L_1 memory for inference; c) *w/o Gated Fusion* replaces the learned gate with a static value 0.5 to measure the importance of adaptive integration; and d) *w/o Attention Ranking* replaces our utility-based update with a simple First In First Out strategy to test the efficiency memory management strategy. The results confirm that all components are critical, as removing any of them substantially degrades performance across all settings. The degradation is most severe for *w/o Gated Fusion*, confirming the necessity of adaptively controlling information flow from the memory. Disabling the L_2 Memory, Inference Retrieval, and *Attention Ranking* also significantly impairs performance, validating the respective benefits of a large knowledge reservoir, query-specific context, and intelligent memory management.

Table 4: DYNMEM Component Ablation Study.

Method	Continual						Simultaneous		
	Structured			Mixed			Single-task		Multi-task
	Acc	BWT	FWT	Acc	BWT	FWT	Com.S.	Math	Com.S.
Llama-3-8B									
DYNMEM	41.2	-12.3	5.6	57.2	-13.4	7.6	86.8	59.6	86.4
w/o L_2 Memory	36.1	-18.9	4.1	52.0	-18.5	6.2	84.5	57.1	84.1
w/o Inference Retrieval	37.8	-17.2	4.9	53.8	-16.9	6.8	85.0	57.9	84.9
w/o Gated Fusion	13.5	-45.4	1.0	24.6	-35.1	2.2	56.2	32.7	43.5
w/o Attention Curation	33.4	-21.5	3.5	48.5	-22.1	5.4	82.3	54.2	81.9
Qwen-3-8B									
DYNMEM	43.9	-10.3	7.1	60.1	-11.9	8.0	90.2	65.6	89.3
w/o L_2 Memory	38.2	-16.5	5.5	54.7	-17.3	6.5	87.9	62.8	86.8
w/o Inference Retrieval	40.1	-14.9	6.1	56.2	-15.6	7.2	88.5	63.5	87.7
w/o Gated Fusion	16.0	-41.8	2.0	19.1	-38.6	2.1	61.6	37.0	48.7
w/o Attention Curation	35.5	-19.8	4.6	50.8	-20.5	5.9	85.1	60.1	84.4

To assess DYNMEM’s scalability, we vary the L_1 and L_2 memory capacities and find that performance monotonically increases with the memory budget across all Continual, Single-task, and Multi-task settings (Figure 3). This scalability is a direct result of our architecture: a larger L_2 memory provides a more comprehensive reservoir for inference-time retrieval, while a larger L_1 memory offers a richer context for training-time interaction and curation. This confirms that DYNMEM effectively capitalizes on available resources, offering a clear and predictable trade-off between performance and memory overhead, making it viable for a wide range of computational budgets.

5 RELATED WORK

Task Adaptation of Language Models. The dominant paradigm for adapting large language models is Parameter-Efficient Fine-Tuning (PEFT). The seminal LoRA method (Hu et al., 2022) and its successors (Zhang et al., 2023; Liu et al., 2024) drastically reduce computational costs by fine-tuning a small set of auxiliary parameters while keeping the backbone model frozen. While highly effective for single-task (Li et al., 2024) or static multi-task (Lin et al., 2024; Wu et al., 2024; Mu et al., 2025) scenarios, these methods are not inherently suited for continual learning. The primary challenge is that they sequentially either overwrite the adapter weights, causing catastrophic forgetting, or require storing an ever-growing set of per-task modules, which introduces significant parameter overhead (Zhu et al., 2022; Chen et al., 2023). We design a new dynamic memory module that is not only parameter-efficient but also effective in both continual and simultaneous adaptation scenarios.

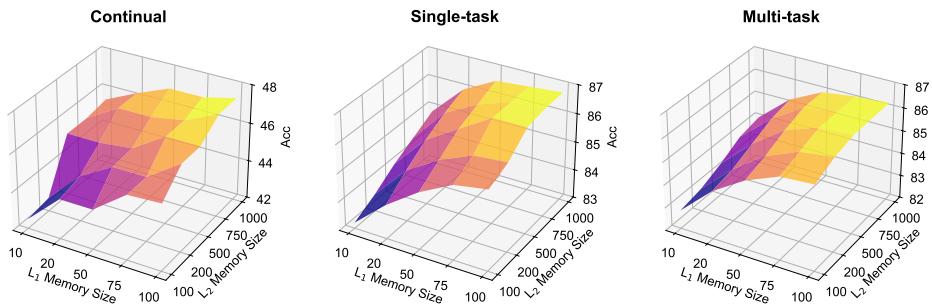


Figure 3: Performance analysis of DYNMEM on Llama-3-8B as a function of L_1 and L_2 memory sizes. The plots show final accuracy for Continual (Structured Stream), Single-task Tuning (Commonsense Avg.), and Multi-task Tuning (Commonsense Avg.). Performance consistently increases with larger memory capacities across all three paradigms, demonstrating excellent scalability.

Memory-augmented Models. Classified by Yang et al. (2024), popular memory-augmented model architectures include: a) Retrieval-augmented methods (Wu et al., 2022b), which extend the effective context length by caching and retrieving past hidden states, enabling models to handle sequences beyond their native context window; b) Memory-augmented transformers like Memformer (Wu et al., 2022a; Kang et al., 2025) introduce structured memory slots directly into the self-attention mechanism, improving long-range sequence modeling; c) Parameter-as-memory approaches reinterpret model weights as implicit knowledge storage, recent works (Mitchell et al., 2022; Wang et al., 2024) manipulate or reorganize these knowledge neurons to update factual content at scale. Inspired by these methods, we design a novel bi-level dynamic memory to effectively maintain long-term information for positive knowledge sharing across tasks learned either simultaneously or sequentially.

6 CONCLUSION

In this work, we address a critical gap in the adaptivity of pre-trained LLMs by introducing DYNMEM, a unified memory-augmented method that supports both continual and simultaneous learning. The core part of our method is a bi-level dynamic memory system based on attention-based retrieval and pruning. DYNMEM enables efficient, example-level knowledge retention and dynamic integration without modifying the backbone LLM. Our design not only mitigates catastrophic forgetting in sequential adaptation but also enhances generalization in multi-task settings, all while maintaining a compact memory footprint. Extensive experiments across various benchmarks show that DYNMEM consistently outperforms baselines, establishing a new state-of-the-art for versatile LLM adaptation.

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702 A THE USE OF LARGE LANGUAGE MODELS
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704 Large language models were used as writing assistants to aid or polish the text in this manuscript.
705 Their functions were limited to improving clarity, grammar, and professional tone. All scientific
706 contributions, including the core methodology, experimental design, and conclusions, are the origi-
707 nal work of the authors, who retain full responsibility for the paper’s content.
708

709 B PARAMETER CALCULATION DETAILS
710

711 This section provides a detailed breakdown of how the trainable parameter percentages reported
712 in our main results (e.g., Table 2) are calculated. The percentage reflects the ratio of trainable
713 parameters to the total number of parameters in the frozen backbone model.
714

715 Let $P_{\text{trainable}}$ be the number of parameters that are updated during fine-tuning, and let P_{total} be the
716 total number of parameters in the backbone model (e.g., Llama-3-8B). The reported percentage is
717 calculated as:
718

$$\text{Param (\%)} = \left(\frac{P_{\text{trainable}}}{P_{\text{total}}} \right) \times 100 \quad (3)$$

720 The composition of $P_{\text{trainable}}$ differs between the baseline methods and our proposed DYNMEM
721 framework.
722

723 **PEFT Baselines (e.g., LoRA, DoRA).** For methods such as LoRA and its variants, $P_{\text{trainable}}$ ex-
724clusively comprises the parameters of the injected low-rank adaptation matrices and any other small,
725 method-specific modules (e.g., the magnitude vectors in DoRA). The vast majority of the original
726 model weights remain frozen. We set `lora_rank` = 16, `lora_alpha` = 32 for these baselines.
727

728 **DYNMEM.** For our DYNMEM framework, $P_{\text{trainable}}$ consists of the parameters from our
729 lightweight, newly introduced memory interaction modules, which are trained jointly with the back-
730 bone model. Specifically, these include:
731

- 732 • The cross-attention projection matrices: $W^Q, W^K, W^V \in \mathbb{R}^{d \times d}$.
- 733 • The gated fusion layer parameters: $\mathbf{W}_g \in \mathbb{R}^{d \times d}$ and $\mathbf{b}_g \in \mathbb{R}^d$.

735 In our implementation, both the backbone model f_θ and these interaction modules are fine-tuned.
736 However, as the results demonstrate, the total number of trainable parameters in DYNMEM’s mod-
737 ules is significantly smaller than that of many PEFT baselines, highlighting its parameter efficiency.
738 For DYNMEM, we use `lora_rank` = 8, `lora_alpha` = 16 to achieve a more efficient training.
739

740 C TASK ORDERS OF CONTINUAL ADAPTATION
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742 To ensure the robustness of our findings in the asynchronous adaptation setting and to mitigate any
743 potential bias resulting from a single, arbitrary task sequence, we conducted all continual learning
744 experiments across three different permutations for both the STRUCTURED STREAM and the MIXED
745 STREAM. The final results reported in the main paper represent the mean and standard deviation
746 across these three runs. The specific task orders for each stream are detailed below.
747

748 C.1 STRUCTURED STREAM
749

750 This stream consists of four structured knowledge reasoning datasets. The three specific task orders
751 used in our experiments are as follows:
752

- 753 • **Order 1:** GrailQA → MTOP → Spider → ComplexWebQuestions
- 754 • **Order 2:** ComplexWebQuestions → Spider → MTOP → GrailQA
- 755 • **Order 3:** MTOP → GrailQA → ComplexWebQuestions → Spider

756 C.2 MIXED STREAM
757758 This stream interleaves the four structured datasets with four commonsense reasoning datasets to
759 introduce more significant domain shifts. The three specific task orders used are as follows:
760761

- 762 • **Order 1:** GrailQA → BoolQ → MTOP → PIQA → Spider → ARC-e → ComplexWe-
763 bQuestions → WinoGrande
- 764 • **Order 2:** ComplexWebQuestions → WinoGrande → Spider → ARC-e → MTOP → PIQA
765 → GrailQA → BoolQ
- 766 • **Order 3:** MTOP → PIQA → GrailQA → BoolQ → ComplexWebQuestions → Wino-
767 Grande → Spider → ARC-e

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