LIFT: Improving Long Context Understanding of Large Language Models through Long Input Fine-Tuning

Yansheng Mao^{*1} Yufei Xu^{*12} Jiaqi Li^{*2} Fanxu Meng¹² Haotong Yang¹ Zilong Zheng² Xiyuan Wang¹ Muhan Zhang¹²

Abstract

Long context understanding remains challenging for large language models due to their limited context windows. This paper presents Long Input Fine-Tuning (LIFT), a novel framework for long-context modeling that can improve the longcontext performance of arbitrary (short-context) LLMs by dynamically adapting model parameters based on the long input. Importantly, LIFT, rather than endlessly extending the context window size to accommodate increasingly longer inputs in context, chooses to store and absorb the long input in parameter. By fine-tuning the long input into model parameters, LIFT allows shortcontext LLMs to answer questions even when the required information is not provided in the context during inference. Furthermore, to enhance LIFT performance while maintaining the original incontext learning (ICL) capabilities, we introduce Gated Memory, a specialized attention adapter that automatically balances long input memorization and ICL. We provide a comprehensive analysis of the strengths and limitations of LIFT on long context understanding, offering valuable directions for future research.

1. Introduction

Large Language Models (LLMs), such as GPT-4 (Achiam et al., 2023), have revolutionized the field of natural language processing, driving breakthroughs in text generation and significant advancements in tasks like translation, summarization, and conversation. Long sequences, which can span up to millions of tokens, are common in real-world applications, including long books (Kočiskỳ et al., 2018), accounting documentsdocuments (Li et al., 2024),

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high-resolution videos (Wu et al., 2024; Tapaswi et al., 2016), and audio signals (Yang et al., 2024). Extending context windows allows models to capture dependencies across larger text spans and improve coherence, understanding, and accuracy in tasks that require reasoning over extended inputs.

However, as context lengths increase, the computational complexity of the self-attention mechanism (Vaswani, 2017) grows quadratically, which limits models' ability to process long inputs. Additionally, storing a large number of attention weights and intermediate states like KV cache places a heavy burden on hardware resources. Moreover, it is challenging to capture long dependencies among pieces of information scattered throughout long inputs while performing further comprehension and reasoning. Due to the limitation of context windows, LLMs can hardly capture the overall information about a user's query history or task input, resulting in suboptimal performance.

To address these challenges, researchers have developed various techniques to improve the long-context abilities of LLMs. Retrieval-Augmented Generation (RAG) (Lewis et al., 2020; Xu et al., 2023) and prompt compression (Jiang et al., 2023) aim to preprocess long inputs within a limited short context window by adaptive retrieval or text compression (El-Kassas et al., 2021). However, the effectiveness of these methods depends on the precision and relevance of the contextual information provided within the context window. It will lead to further hallucinations when noisy, ambiguous, or conflicting information is provided. Long-context adaptation focuses on fine-tuning pretrained LLMs on corpora of long texts to extend their context windows (Chen et al., 2023b; Peng et al., 2023) and is more frequently used in more recent works. However, the adaptation process comes with significant costs in terms of both training data and computational resources. Additionally, with the extended context window, the cost of processing and generating long texts grows quadratically with the input length. Finally, despite the extension, the context windows of these LLMs remain finite, preventing them from generalizing to inputs of infinite length.

To address the above challenges, in this paper, we present a

^{*}Equal contribution ¹Institute for Artificial Intelligence, Peking University ²State Key Laboratory of General Artificial Intelligence, BIGAI. Correspondence to: Muhan Zhang <muhan@pku.edu.cn>.

Tuble 1. Comparison of	Table 1. Comparison of conventional long context understanding approaches with En 1.				
	RAG	ICL	LIFT		
Knowledge storage	External data sources	Within context window	In parameters		
Input length	Infinite	Limited	Infinite		
Retrieval free	X	✓	✓		
Long-context adaptation free	✓	X	✓		

Table 1. Comparison of conventional long context understanding approaches with LIFT.

novel framework Long Input Fine-Tuning (LIFT), designed to enhance the long-context capabilities of arbitrary (short-context) models by directly adapting model parameters to the long input. Our approach has the following advantages:

- Efficient long-input training on the fly. LIFT dynamically adapts to newly introduced long inputs as fresh knowledge by adjusting model parameters, thereby eliminating the need for resource-intensive offline long-context adaptation. To enhance memorization of the long input, we segment it into overlapping segments which can be fitted into a short context window and fine-tune the LLM on batches of the segments. Additionally, we improve long-context comprehension and reasoning through fine-tuning on well-designed auxiliary tasks, further optimizing performance on downstream applications.
- Balancing in-parameter and in-context knowledge. As LIFT is mainly designed for short-context LLMs, the long input often needs to be truncated to fit into their context windows. This necessitates a balance between leveraging the truncated in-context knowledge and the fine-tuned in-parameter knowledge. To address this issue, we propose a specialized attention adapter, Gated Memory, that automatically balances the long input memorization and comprehension in LIFT as well as the ICL ability of the original model.
- Great improvement on popular long-context tasks.
 Our evaluations on several well-acknowledged long context benchmarks show that LIFT consistently benefits general tasks like long/short question answering (QA) and summarization across different base LLMs. For example, on the challenging long-dependency QA tasks of LooGLE (Li et al., 2023), the "LIFTed" Llama-3-8B-Instruct model achieves an accuracy of 29.97%, significantly outperforming its pure ICL counterpart without LIFT which achieves only 15.44% accuracy.

These findings highlight the effectiveness of LIFT in improving the long-context comprehension of short-context models, paving the way for broader applications and exciting new opportunities in long-context scenarios.

2. Related Work

Long-context adaptation and efficient architectures. Existing LLMs mostly rely on pure ICL for long-context un-

derstanding. However, it is challenging for short-context models to process inputs longer than their context window sizes due to unseen positional encodings during pretraining, resulting in extremely poor performance on downstream tasks. Therefore, a common practice is to further fine-tune LLMs on huge corpus of long texts (which we call long-context adaptation). Despite the effectiveness, long-context adaptation often requires tremendous computational cost.

To cope with the problems, many works have been developed to accelerate the process of long-context training with efficient Transformer. Sparse attention (Kitaev et al., 2020; Wang et al., 2020; Beltagy et al., 2020) reduces memory and computation costs by using local windows or strided attention, allowing to focus on the most relevant inputs for given tasks. Linear attention (Shen et al., 2021) reduces the quadratic computation to linear by approximating self-attention with kernel functions or low-rank representations. Other alternatives for Transformer like state-space models (SSMs) (Gu & Dao, 2023) are recently proposed for efficient training based on dual representations. In this work, we focus on the conventional self-attention architecture (Vaswani, 2017) which is most widely used in current LLMs to validate the effectiveness of LIFT.

Retrieval-Augmented Generation (RAG). RAG (Lewis et al., 2020) improves the performance of long-context understanding by integrating LLMs with external data sources or memory modules for retrieval (Xu et al., 2023; Jiang et al., 2024; Wang et al., 2024; Jin et al., 2024), thereby avoiding the need to process long inputs directly. Its performance heavily relies on the quality of retrieved content, which must be relevant and concise enough to fit within models' short context windows. RAG can experience significant performance degradation or hallucination issues when the retrieved context is inaccurate or mismatched.

Test-time training. Test-time training (TTT) (Liu et al., 2021; Gandelsman et al., 2022; Osowiechi et al., 2023; Hong et al., 2023) has emerged as a promising approach to adapt models to unseen data distributions during deployment, leveraging test data to fine-tune the model at inference time. Recent works have applied similar ideas to improve model adaptability when dealing with lengthy, context-rich inputs (Sun et al., 2024; Behrouz et al., 2024), yet focus on proposing new architectures to replace Transformer and require pretraining from scratch. Our work, in contrast, in-

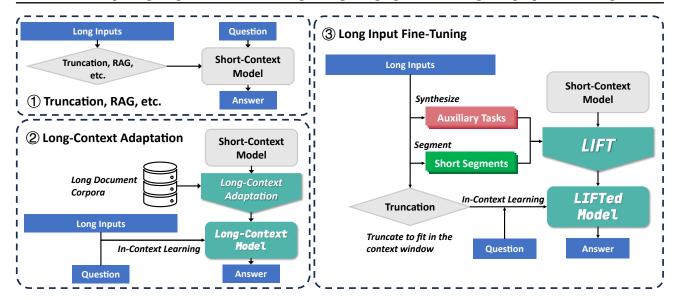


Figure 1. An overview of LIFT compared with existing methods.

troduces a continual learning perspective to the problem of long-context understanding, which focuses on improving arbitrary pretrained models' long-context capabilities by fine-tuning them on the long input, which is not restricted to specific models or layers.

3. Method

In this section, we introduce LIFT, a framework improving LLMs' long context understanding through long input fine-tuning (Figure 1). The comparisons of our method with RAG and long-context adaptation can be seen in Table 1 and the implementation details are illustrated in Appendix A.

3.1. Training with Segmented Long Inputs

We propose a novel way to memorize long inputs by storing them into LLMs' parameters via fine-tuning. We formulize the memorization task as a language modeling task. Let the input be $\mathbf{x}=(x_1,x_2,\ldots,x_L)$, where the input length L is a very large number. The objective function for the task is defined as $\mathcal{L}_{LM}(\mathbf{x};\theta)=-\sum_{i=1}^L\log\mathbb{P}(x_i|\mathbf{x}_{1:i-1};\theta)$, where θ are the parameters.

Directly adapting a model to a piece of long text of length L is challenging for LLMs whose context window lengths l are shorter than L. Furthermore, it leads to a high computational complexity of $\mathcal{O}(L^2)$ coping with such long inputs during training. One straightforward way is to cut \mathbf{x} into K non-overlapping short segments (trivial segmentation), denoted as $\mathbf{x}_{l_1:r_1},\ldots,\mathbf{x}_{l_K:r_K}$, and fine-tune the model on batches of the segments. However, trivial segmentation fails to capture the sequentiality of the long input since the model cannot infer the correct order of the non-overlapping segments.

To address this, we alter the long-input segmentation with

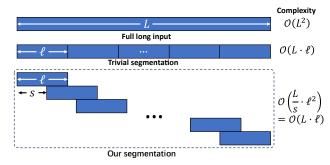


Figure 2. Comparison between our segmentation method and the trivial segmentation method.

certain overlaps between the adjacent segments as illustrated in Figure 2. By overlapping the tail of one segment with the head of the next, the model can better preserve the sequential structure of the input. Ideally, *if the model learns to generate the tail of a segment, it should be able to seamlessly continue into the next segment.* Formally, the objective function for the language modeling task with our long-input segmentation method is formed as

$$\mathcal{L}_{input}(\mathbf{x}; \theta) = \sum_{k=1}^{K} \mathcal{L}_{LM}(\mathbf{x}_{l_k:r_k}; \theta), \tag{1}$$

where $l_1=1, r_K=L$, and $r_k-l_k+1=\ell, l_{k+1}=l_k+s, \ \forall k=1,2,\ldots,K-1.$ Here s is a hyperparameter controlling the overlap length of adjacent segments. Empirically, it is sufficient to use $s=\frac{3}{8}\ell$, leading to a constant computational overhead.

3.2. Training with Auxiliary Tasks

Adapting a pretrained LLM to a specific task poses the risk of impairing its other capabilities. Similarly, while adapting to the input helps the model memorize the input, it proba-

bly degrades other abilities, such as instruction-following. Moreover, successfully memorizing the lengthy input does not necessarily indicate that the model can reason effectively based on it.

To mitigate potential capability degradation while maintaining the reasoning capabilities of original model on the long context, we propose synthesizing auxiliary question-answering (QA) tasks, denoted as $(\mathbf{q}_i, \mathbf{a}_i)_{i=1}^m$, where m is the number of auxiliary tasks, based on the long input. The objective function of the auxiliary tasks is defined as

$$\mathcal{L}_{AT}((\mathbf{q}_i, \mathbf{a}_i)_{i=1}^m; \theta) = -\sum_{i=1}^m \log \mathbb{P}(\mathbf{a}_i \mid \mathbf{q}_i; \theta). \quad (2)$$

Following the mechanism of mix training (Allen-Zhu & Li, 2023), which asserts that LLMs can only learn to perform inference based on \mathbf{x} when trained simultaneously on both \mathbf{x} and $(\mathbf{q}_i, \mathbf{a}_i)_{i=1}^m$, we propose jointly optimizing the two objective functions, i.e.,

$$\mathcal{L}(\mathbf{x}, (\mathbf{q}_i, \mathbf{a}_i)_{i=1}^m; \theta) = \mathcal{L}_{input}(\mathbf{x}; \theta) + \mathcal{L}_{AT}((\mathbf{q}_i, \mathbf{a}_i)_{i=1}^m; \theta)$$
(3)

There are no strict constraints on the method used to synthesize $(\mathbf{q}_i, \mathbf{a}_i)_{i=1}^m$ based on \mathbf{x} , except that we should avoid computationally expensive operations on \mathbf{x} , such as inference over the entire \mathbf{x} . In our experiments, we extract several short segments from \mathbf{x} and use a pretrained LLM to generate QA pairs based on the segments.

3.3. Contextualized Training and Task Alignment

As discussed in Sections 3.1 and 3.2, we adapt an LLM to handle a long input through two objectives: language modeling on segments of the long input and auxiliary QA tasks. While these tasks align with our objectives of memorizing the long input and enhancing reasoning based on the long input, the model may still struggle with the semantic divergence (memorization vs. reasoning) and structural divergence (language modeling vs. supervised fine-tuning) between different tasks. To address these challenges, we propose a contextualized training (CT) method for long input segments, shifting from the language modeling paradigm to a supervised fine-tuning paradigm and more closely aligning the task of input segment memorization and the auxiliary QA tasks.

Our contextualized training method involves 1) providing the model with a piece of context when asking it to memorize the segments, typically selected from the beginning and ending portions of the long input, and 2) prompting the model to generate the target segments based on the provided context. Formally, we modify the objective function (1) for the long input memorization part to the following:

$$\mathcal{L}_{input}(\mathbf{x}; \theta) = -\sum_{k=1}^{K} \log \mathbb{P}(\mathbf{x}_{l_k:r_k} | concat(\mathbf{c}_k, \mathbf{p}); \theta),$$
(4)

where \mathbf{c}_k represents the given context, and \mathbf{p} is a prompt instructing the model to recite the segment based on \mathbf{c}_k . For the QA tasks, we also modify the objective (2) by concatenating the questions with a context \mathbf{c}_a :

$$\mathcal{L}_{AT}((\mathbf{q}_i, \mathbf{a}_i)_{i=1}^m; \theta) = -\sum_{i=1}^m \log \mathbb{P}(\mathbf{a}_i | concat(\mathbf{c}_q, \mathbf{q}_i); \theta)$$
(5)

where \mathbf{c}_q keeps the same during training on different segments, which is only related to the test question. In this way, both the input memorization and QA tasks share a similar SFT format. In addition, they both align better with the real testing scenario, where given a LIFTed LLM, we can still fill the context window with the long input as much as possible to maximally leverage the in-context knowledge, instead of only filling in the testing question. Such a technique greatly improves practical performance of LIFT.

To mitigate the risk of overfitting, instead of using the same \mathbf{c}_k for all the segments $\mathbf{x}_{l_k:r_k}$, we further regularize \mathbf{c}_k by randomly sampling \mathbf{c}_k for each segment $\mathbf{x}_{l_k:r_k}$ from both the beginning and ending of the long input with a total length of L. Specifically, we select consecutive sentences from the beginning and ending respectively compositing \mathbf{c}_k with a fixed length l to align with the usages of contexts in real testing scenarios.

By employing CT, we align the input memorization task with the auxiliary QA tasks better within a closer semantic space, and unify the training and testing formats, thereby greatly enhancing the generalization capabilities of LIFT, as evidenced by our ablation study in Table 4.

3.4. Gated Memory Architecture

To efficiently apply LIFT, we aim to use a parameter-efficient fine-tuning (PEFT) method rather than full-parameter fine-tuning. Existing representative PEFT methods such as LoRA (Hu et al., 2021) and PiSSA (Meng et al., 2024) are not specifically designed for long context tasks. Therefore, we propose a novel **Gated Memory** adapter working very well in the LIFT framework.

The key intuition behind LIFT is to store the parts of a long input that cannot fit into the context window directly in model parameters. To achieve this, the adapter needs to effectively memorize these out-of-context parts and align its behavior with the scenario of having complete input. For a hypothetical complete input $(\mathbf{x}', \mathbf{x})$ where \mathbf{x}' is the long

input that we aim to absorb into model parameters and \mathbf{x} represents the new in-context questions/prompts about the long input, we let their hidden states after the (t-1)-th layer be $(\hat{\mathbf{h}}'^{(t-1)}, \hat{\mathbf{h}}^{(t-1)})$, where the length of \mathbf{x}' is l' and the length of \mathbf{x} is l. In practice, the model has access to the questions/prompts \mathbf{x} only and we let their hidden states after the (t-1)-th layer be $\mathbf{h}^{(t-1)}$. We expect the following behavior in each layer of the original Transformer:

$$\phi_{\mathbf{x}'}^{(t)}(\mathbf{h}^{(t-1)}) = f^{(t)}(\hat{\mathbf{h}}'^{(t-1)}, \hat{\mathbf{h}}^{(t-1)}),$$

where f is the original layer that takes the complete input $(\mathbf{x}', \mathbf{x})$ as the context. The new layer $\phi_{\mathbf{x}'}$, on the other hand, processes only \mathbf{x} as the context while absorbing the information from \mathbf{x}' into its parameters.

Layer f consists of an attention module and an MLP module. The key lies in establishing the association between the in-context questions/prompts $(\hat{\mathbf{h}}^{(t-1)})$ and the long input $(\hat{\mathbf{h}}'^{(t-1)})$. While the attention module captures contextual associations, the MLP module performs token-wise transformations. Therefore, only the attention module needs modification, while the MLP module remains frozen. Concatenating $\hat{\mathbf{h}}'^{(t-1)}$ and $\hat{\mathbf{h}}^{(t-1)}$ (i.e., $\hat{\mathbf{h}}'^{(t-1)}$ is positioned from 1 to l' and $\hat{\mathbf{h}}^{(t-1)}$ is positioned from l'+1 to l'+l), let's examine the hypothetical complete attention. The attention output at position L ($l'+1 \le L \le l'+l$) is:

$$\operatorname{attn}(\hat{q}_L, \hat{\mathbf{k}}_{1:L}, \hat{\mathbf{v}}_{1:L}) = \frac{\sum_{i=1}^{L} \exp(\langle \hat{q}_L, \hat{k}_i \rangle) \hat{v}_i}{\sum_{i=1}^{L} \exp(\langle \hat{q}_L, \hat{k}_j \rangle)}, \quad (6)$$

We aim at splitting the output into two components: one corresponding to the out-of-context $\hat{\mathbf{k}}_{1:l'}, \hat{\mathbf{v}}_{1:l'},$ and the other corresponding to the in-context $\hat{\mathbf{k}}_{l'+1:L}, \hat{\mathbf{v}}_{l'+1:L}$. Define the gate function $g(\hat{q}_L, \hat{\mathbf{k}}_{1:L})$ and the memory function $m(\hat{q}_L, \hat{\mathbf{k}}_{1:l'}, \hat{\mathbf{v}}_{1:l'})$:

$$g(\hat{q}_{L}, \hat{\mathbf{k}}_{1:L}) = \frac{\sum_{i=1}^{l'} \exp(\langle \hat{q}_{L}, \hat{k}_{i} \rangle)}{\sum_{i=1}^{L} \exp(\langle \hat{q}_{L}, \hat{k}_{i} \rangle)},$$

$$m(\hat{q}_{L}, \hat{\mathbf{k}}_{1:l'}, \hat{\mathbf{v}}_{1:l'}) = \frac{\sum_{i=1}^{l'} \exp(\langle \hat{q}_{L}, \hat{k}_{i} \rangle) \hat{v}_{i}}{\sum_{i=1}^{l'} \exp(\langle \hat{q}_{L}, \hat{k}_{i} \rangle)}.$$
(7)

 $g(\hat{q}_L, \hat{\mathbf{k}}_{1:L})$ determines the proportion of attention allocated to the out-of-context part at position L, and $m(\hat{q}_L, \hat{\mathbf{k}}_{1:l'}, \hat{\mathbf{v}}_{1:l'})$ is the out-of-context representation which can be understood as performing cross attention between the current in-context token \hat{q}_L and all the out-of-context tokens $\hat{\mathbf{k}}_{1:l'}, \hat{\mathbf{v}}_{1:l'}$. Then the attention output in Equation (6) can be reformulated as:

$$\operatorname{attn}(\hat{q}_L, \hat{\mathbf{k}}_{1:L}, \hat{\mathbf{v}}_{1:L}) = g(\hat{q}_L, \hat{\mathbf{k}}_{1:L}) \cdot m(\hat{q}_L, \hat{\mathbf{k}}_{1:l'}, \hat{\mathbf{v}}_{1:l'}) + (1 - g(\hat{q}_L, \hat{\mathbf{k}}_{1:L})) \cdot \operatorname{attn}(\hat{q}_L, \hat{\mathbf{k}}_{l'+1:L}, \hat{\mathbf{v}}_{l'+1:L}),$$

where attn(\hat{q}_L , $\hat{\mathbf{k}}_{l'+1:L}$, $\hat{\mathbf{v}}_{l'+1:L}$) is the attention output with the same attention parameters operated on the in-context

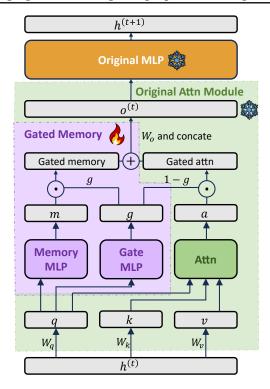


Figure 3. The architecture of **Gated Memory**. The purple part is the added adapter "gated memory" to fit the out-of-context attention; the green part is the original attention module. During training, only the gated memory part is trained. Other parameters are fixed.

part's hidden state $\hat{\mathbf{h}}^{(t-1)}$ (instead of the complete hidden state $(\hat{\mathbf{h}}'^{(t-1)}, \hat{\mathbf{h}}^{(t-1)})$). Let g and m be implemented as neural networks. When the out-of-context input \mathbf{x}' is considered a constant and has been absorbed into the parameters of g and m, $\hat{\mathbf{k}}_{1:l'}$ and $\hat{\mathbf{v}}_{1:l'}$ can be removed from g and m. We further adopt an approximation to let g only depend on \hat{q}_L . Consequently, both $g(\hat{q}_L, \hat{\mathbf{k}}_{1:L})$ and $m(\hat{q}_L, \hat{\mathbf{k}}_{1:L}, \hat{\mathbf{v}}_{1:L})$ become functions of \hat{q}_L . The attention output simplifies to:

$$g(\hat{q}_L) \cdot m(\hat{q}_L) + (1 - g(\hat{q}_L)) \cdot \operatorname{attn}(\hat{q}_L, \hat{\mathbf{k}}_{l'+1:L}, \hat{\mathbf{v}}_{l'+1:L}).$$

In practice, we do not have the hypothetical complete input, so the index of $\hat{\mathbf{k}}$, $\hat{\mathbf{v}}$ start just from 1 instead of l'+1 and all the hypothetical hidden states are replaced with the actual hidden states \mathbf{h} from the first layer. Our goal is to learn gate and memory functions g and m (implemented with MLPs) as adapters to the fixed original attention module that adapt the LLM to the long input.

The Gated Memory architecture is shown in Figure 3. In summary, we keep the original MLP and attention parameters (projectors for query, key, value and output) fixed and add two learnable MLPs for each attention head: 1) $g: \mathbb{R}^d \to \mathbb{R}$, a gating function that controls the ratio of information extracted from the memory and the context. 2) $m: \mathbb{R}^d \to \mathbb{R}^d$, a memory function which stores the out-of-context information of the long input and retrieves relevant

memory based on the current query. In the ideal case where the learned g and m perfectly simulate Equations (7), that is, the previous information of \hat{h}' has been completely absorbed into the parameters of g and m, the model can perform the same as the case with complete long input, thus achieving the effect of using a short-context model to simulate long-context transformers.

However, using Equations (7) as supervision to train g and m is too expensive, as it requires the complete hidden state, which can only be obtained by processing the entire long input. Instead, we train these adapters end-to-end during the LIFT process. Specifically, the modules are randomly initialized and trained through segmented language modeling (Section 3.1) and auxiliary QA tasks (Section 3.2). In Section 4.3, we show that end-to-end training effectively learns the desired modules. Exploring other training schedules is part of our future work.

Gated Memory has another great benefit, namely automatically balancing the memorization/reasoning with the absorbed new knowledge (the $g(\hat{q}_L) \cdot m(\hat{q}_L)$ part) and the in-context learning capabilities of the original model (the remaining part). When a test task is not related to the absorbed knowledge, the architecture can learn to set $g(\hat{q}_L)=0$ and recover the model without LIFT, thereby solving the task using only the in-context knowledge. In contrast, existing PEFT methods like LoRA and PiSSA fail to control the influence of adapters, risk overfitting the long input, and may damage the original capabilities too much.

4. Experiments

4.1. Setup

Dataset and metrics. We make a comprehensive evaluation of LIFT on three popular long-context benchmarks, including LooGLE (Li et al., 2023), LongBench (Bai et al., 2023), and Needle-In-A-Haystack (NIAH) (Kamradt, 2023) covering a wide variety of application scenarios.

The evaluation metrics are consistent with those used in the original benchmarks. For LongBench and NIAH, the evaluation metrics are task-specific (Zhang et al., 2020). Since most automatic evaluation metrics are sensitive to semantic expression, output format, and length, we utilize GPT4-0613 (Achiam et al., 2023) for LooGLE as recommended in the paper to judge whether the two answers are semantically the same or not, noted as GPT4_score. It has been proven to exhibit high consistency with human evaluation and can serve as a reliable annotator to a great extent (Suri et al., 2023; Liu et al., 2023; Zheng et al., 2023). The prompts implemented can be found in Appendix A.

Models. For open-source LLMs, we select Llama-3-8B-Instruct (Dubey et al., 2024) and Gemma-2-9B-it (Team,

2024) with 8k context windows. For closed-source commercial LLMs, we choose GPT-3.5-turbo-0125 (Chen et al., 2023a) with a 16k context window. It has shown competitive performance on popular long context benchmarks and can be further fine-tuned through API service. Details of the models and hyper-parameters can be seen in Appendix A.

Settings. In this paper, we mainly evaluate **LIFT** compared with the truncated **ICL** performance of the selected LLMs. Specifically: **ICL** denotes truncating the long input by retaining only the beginning and end of texts within the context window of the original model. **LIFT** denotes first fine-tuning the LLM using the Gated Memory adapter (except for GPT-3.5 which uses the default API tuning service) with the objectives in Equations (4) and (5) with the abovementioned truncated ICL. The number of auxiliary tasks used and the method for generating them are specialized for each subtask (detailed in Appendix A).

4.2. Main Results

4.2.1. RESULTS ON LOOGLE

Overall performance. As shown in Table 2, LIFT consistently outperforms ICL often by large margins on the overall scores on both LongQA and ShortQA tasks across the three LLMs. Particularly, it shows notable improvement in GPT4_score from 15.44 to 29.97 on Llama 3 in LongQA and from 37.37 to 50.33 on Gemma 2 in ShortQA. The results highlight that LIFT significantly improves the performance of ICL, particularly for models with short context windows. Notably, GPT-3.5 generally outperforms the open-sourced models across both tasks, while LIFT can further boost its performance. It can be noticed that all the models perform poorly on LongQA, with GPT4_score falling below 50. This underscores that modeling long dependencies in extended contexts remains a significant challenge for existing methods.

Performance on subtasks in LongQA. We further investigate the performance on the four LongQA subtasks including comprehension & reasoning, multiple info retrieval, computation and timeline reorder introduced in LooGLE in Table 2. As we can see, LIFT greatly enhances the opensourced models in most subtasks. For example, LIFT improves the performance of Llama 3 on all the four subtasks with over 50% gain. These results demonstrate that LIFT enhances ICL across different models and tasks by facilitating a more holistic understanding of the entire lengthy input, which is effectively captured in the model parameters. However, it may lead to a slight performance degradation on specific tasks and models in some cases, suggesting that it requires delicate design of the task-specific auxiliary tasks and flexible adaption to various models when applying LIFT.

Table 2. Performance on LooGLE using LIFT.	Table 2.	Performance	on LooGLE	using LIFT.
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Models	Methods	ShortQA	LongQA	Comprehension & Reasoning	Multiple info retrieval	Computation	Timeline reorder
Llama3	ICL LIFT	44.49 47.51	15.44 29.97	25.37 39.90	15.26 27.89	5.00 17.00	1.86 17.21
Gemma2	ICL LIFT	37.37 50.33	29.79 31.24	36.95 40.39	21.58 27.11	10.00 12.00	40.00 30.23
GPT3.5	ICL LIFT	66.82 69.66	44.82 45.76	52.67 53.44	40.77 40.50	27.55 26.53	45.19 49.52

Table 3. Performance on LongBench using LIFT.

Models	Methods	Musique	Narrativeqa	Qmsum	GovReport	PassageRetrievalEN
Llama3	ICL LIFT	26.89 21.19	19.45 23.33	21.64 23.07	30.18 33.62	58.33 62.50
GPT3.5	ICL LIFT	26.33 27.20	25.67 26.53	22.09 22.23	25.30 25.01	79.17 79.17

4.2.2. RESULTS ON LONGBENCH

Table 3 presents the results across five representative tasks with extremely long inputs in LongBench. We follow the evaluation metrics introduced in the original benchmark for comparison. For Llama 3, LIFT outperforms ICL on 4 out of 5 subtasks, and for GPT-3.5, LIFT outperforms ICL on 3 out 5 subtasks. We make in-depth analysis to figure out the impact of LIFT on different subtasks. NarrativeQA and QM-Sum consistently have performance gains from LIFT since these two tasks are similar to auxiliary tasks in LIFT. In contrast, for tasks that mainly depend on the memorization of long inputs like Musique and PassageRetrievalEN, LIFT's advantage is not consistent. Empirically, we found it hard to hit a perfect balance between the long input memorization in LIFT and the ICL ability of the original model. When the model is significantly fine-tuned to memorize the long input, its original capabilities tend to degrade more. As most tasks do not require perfect memorization of the long input, our current strategy is to early-stop the fine-tuning to avoid overfitting. As a consequence, Llama 3 struggles to memorize the details in the context, leading to poor performance on Musique, while GPT-3.5 slightly benefits from LIFT, likely due to more robust foundation capabilities and better finetuning strategies. On PassageRetrievalEN, since we imitate the test set generation process to synthesize auxiliary tasks, Llama 3 benefits from the auxiliary tasks, becoming more familiar with the instructions at test time. In contrast, GPT-3.5, due to its strong instruction-following capability, does not see significant improvements from LIFT.

4.2.3. EFFICIENCY

Benefiting from our segmentation strategy (Section 3.1), the computational complexity of our method is linear with

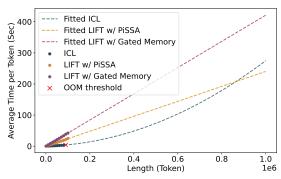


Figure 4. GPU time with increasing input length for LIFT with PiSSA or Gated Memory and the ICL baseline. The dashed lines represent the fitted curves, showing linear growth for LIFT and quadratic growth for ICL. The red cross indicates the input length at which the ICL baseline runs out of memory.

respect to the input length. To further evaluate the efficiency of our approach compared to ICL (with full input in the context), we measure the time cost of a single Needle-In-A-Haystack (NIAH) task under both methods. In this experiment, the input lengths are controllable and the primary computational cost stems from processing the input context rather than iterative generation. We compare LIFT with the Gated Memory adapter and another adapter PiSSA (Meng et al., 2024) against ICL, plotting GPU time versus input length along with the fitted curves in Figure 4.

First, we observe that LIFT is significantly more memory-efficient than ICL. Notably, ICL runs out of memory when the input length exceeds 90k tokens on our A800 (80G) system. For ICL, the KV cache consumes most of the memory. In contrast, LIFT is capable of handling arbitrarily long inputs. Our segmentation and truncation strategy ensures

Table 4. Ablation study on contextualized training on LooGLE.

Datasets	w/o CT	w/ CT
ShortQA	43.98	47.51
LongQA	27.07	29.97

Table 5. Ablation study on number of auxiliary QA on LooGLE.

Datasets	w/o QA	10 QA	30 QA
ShortQA	47.21	47.51	48.84
LongQA	29.25	29.97	30.70

that LIFT only involves training and inference with short text segments, eliminating the need for extensive caching.

We empirically verify that the time cost of ICL grows quadratically with input length, while our method scales linearly. However, we also observe that the constant factor introduced by adaptation in the computational complexity of LIFT is non-negligible. As a result, LIFT with PiSSA only surpasses ICL in time efficiency when the input length exceeds a certain threshold above 800k tokens, while LIFT with Gated Memory is even slower. We note that although Gated Memory involves fewer trainable parameters than PiSSA, it results in smaller update step sizes and requires more training epochs. A more hardware-friendly implementation is also lacking. As the primary cost of LIFT arises from multi-epoch fine-tuning, we hypothesize that by employing better parallel fine-tuning techniques, the efficiency of LIFT can be significantly improved.

4.3. Ablation Study

Contextualized training. As discussed in Section 3.3, we posit that contextualized training is a pivotal component of the LIFT framework. By aligning input memorization tasks and auxiliary tasks within the same semantic space and task format, contextualized training enables the model to memorize input while minimizing the degradation of its inherent capabilities. As demonstrated in Table 4, the inclusion of contextualized training significantly enhances model performance on both the LooGLE ShortQA and LongQA tasks compared to the version without this component. This improvement underscores the critical role of contextualized training in achieving robust and effective long-text understanding.

Number of auxiliary QA. Another important technique to improve LIFT's effectiveness is the auxiliary QA task introduced in Section 3.2. Here, we compare three settings: no auxiliary QA, 10 auxiliary QA pairs (default), and 30 pairs for each long input article. The results, shown in Table 5, suggest that increasing the number of auxiliary QA pairs improves performance. However, more QA pairs

Table 6. Ablation study on Gated Memory on LooGLE.

Datasets	PiSSA	Gated Memory
ShortQA	42.03	47.51
LongQA	29.06	29.97

Table 7. In-context and out-context scores on LooGLE ShortQA. LIFT (PiSSA) denotes the fine-tuning approach using PiSSA instead of the Gated Memory architecture.

Method	overall score	in-context score	out-context score
ICL	44.49	76.74	29.04
LIFT (PiSSA)	42.03	62.03	32.45
LIFT w/o CT	43.98	65.98	33.43
LIFT	47.51	71.2	36.16

also mean more forward passes, and the 30 QA pair setting consumes roughly twice the training time of the 10 QA pair setting. Therefore, we choose 10 pairs as the default, balancing performance and efficiency.

Gated Memory. As discussed in Section 3.4, our Gated Memory module acts as a specialized attention adapter, parallel to the original attention mechanism. Here, we compare it with the PiSSA adapter (Meng et al., 2024) on LooGLE dataset. The hyperparameters (learning rate and early-stop epochs) for both models are individually tuned to achieve optimal performance. Table 6 shows that our model with Gated Memory outperforms that with PiSSA, demonstrating that Gated Memory has a superior ability to memorize out-of-context information during LIFT.

4.4. Details and Analysis

In this section, we delve deeper into the strengths and limitations of the LIFT methodology. The questions within the LooGLE ShortQA dataset can be categorized into two types based on whether the evidence required to answer it is within the truncated context or can only be accessed from parameters, i.e., in-context questions and out-of-context questions. When addressing in-context questions, the model theoretically only need to utilize its in-context learning capabilities, whereas for out-of-context questions, the model can only rely on parametric memory.

We evaluated the GPT4_score of the LIFT approach separately for in-context and out-of-context questions noted as in- and out-context score respectively in Table 7. After LIFT, the model's ICL abilities are inevitably compromised; however, there is a corresponding enhancement in the out-of-context capabilities based on memory. This trade-off inherently limits the efficacy of the naive approach of directly fine-tuning on the long input. It is evident that our LIFT method, by contrast—when compared to approaches that neither employ contextualized training nor utilize Gated Memory—significantly mitigates the decline in in-context scores while bolstering the improvement in out-of-context

scores. This observation aligns with the motivation outlined in Section 3.3 and underscores the advantages of Gated Memory in better balancing the original ICL ability and the new ability adapted for the long input.

5. Conclusion

In this paper, we proposed a novel framework, Long-Input Fine-Tuning (LIFT), to enhance LLMs' long-context understanding. Our approach dynamically adapts to long inputs by efficiently fine-tuning the model parameters and utilizing the in-parameter knowledge to improve long-context performance. Experimental results across popular benchmarks like LooGLE and LongBench demonstrate that LIFT effectively enables short-context LLMs to solve long-context tasks with great improvement on many long-context tasks.

6. Limitations and Future Work

Limitations of LIFT without ICL. While we often employ truncated contexts to simplify inference on lengthy texts, this approach is proven insufficient for tasks that demand precise information extraction from extended contexts, such as the Needle in a Haystack (NIAH) task (Appendix B).

Strategy to extract parametric knowledge after LIFT. Through LIFT, embedding inputs into a model's internal parameters enhances its familiarity with the data. However, the effectiveness on downstream tasks still relies on the model's ability to autonomously extract and utilize the parametric knowledge acquired during LIFT. The detailed analysis (Section 4.4) reveals a significant performance gap between in-context and out-of-context questions, suggesting that the model's capability to extract parametric knowledge post-LIFT needs further improvement. This presents a promising direction for future research and exploration.

Challenges using LIFT with auxiliary tasks. Our findings reveal that auxiliary tasks are beneficial for improving LLMs' understanding of inputs. However, the benefit comes with extensive computational costs and they must be aligned with test tasks to achieve optimal performance. Future research should explore general auxiliary tasks that are suitable for all types of long inputs and tasks and are more computationally efficient to be incorporated into LIFT.

LIFT is a fascinating concept because humans similarly transform short-term memory into long-term memory, much like LIFT converts in-context knowledge into in-parameter knowledge. While LIFT is far from fully addressing the challenging long-context problem in LLMs, our preliminary results suggest it offers a promising and exciting direction for further research. We encourage the community to explore LIFT with broader training corpora, diverse models, advanced auxiliary task designs, and greater computational resources.

Impact Statements

This paper presents work whose goal is to advance the field of Machine Learning. There are many potential societal consequences of our work, none which we feel must be specifically highlighted here.

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Table 8. Resource costs (GPU hours) of the experiments.

Models	Methods		LooGLE LongQA	LongBench
Llama3	Baseline PiSSA Gated Memory	3 20 15	3 42 33	2 24 21
Gemma2	Baseline PiSSA	2 44	3 64	\

A. Experiment Details

A.1. Hardware settings

All the experiments, including the main experiments on LooGLE (Section 4.2.1) and LongBench (Section 4.2.2), the efficiency test (Section 4.2.3), and the Needle-in-A-Haystack task (Appendix B), are conducted on a single NVIDIA A800 Tensor Core GPU. We intentionally select this resource-constrained hardware setup, where full-parameter fine-tuning is impractical. This necessitates the use of parameter-efficient fine-tuning (PEFT) methods, which optimize both time and memory efficiency.

The resource costs (GPU hours) of the experiments, which are mainly dependent on the PEFT methods (the Gated Memory architecture or PiSSA), the sizes of the models, and the sizes of the datasets, are presented in Table 8.

A.2. Hyperparameter settings

We design a two-stage training paradigm for both the Gated Memory and PiSSA. The two stages differ in the data used in each. In the first stage, the model is trained solely on segmented long inputs (Section 3.1) and optimizes the loss function \mathcal{L}_{input} (Equation (1)). In the second stage, auxiliary tasks (Section 3.2) are incorporated into the training dataset, and the model optimizes the loss function \mathcal{L} (Equation (3)).

We adopted different sets of hyperparameters during testing on LooGLE and LongBench. When testing on LooGLE, empirically, the Gated Memory architecture causes small updating steps and requires a higher learning rate and more training steps than PiSSA. The important hyperparameters for both methods are detailed in Table 9. When testing on LongBench with Gated Memory, we carefully select hyperparameters for each subtask, detailed in Table 10.

Besides, we put all the samples including the context segments and the auxiliary tasks into a single batch through gradient accumulation to stabilize gradients. The batch size per device is 1 to reduce memory costs. The other hyperparameters are kept the same for all the experiments: the context window lengths are limited to 8000 to guarantee fair comparison, which is the context window lengths of Llama 3 and Gemma 2, but shorter than that of GPT-3.5.

During generation, we adopt greedy decoding for Llama 3 and Gemma 2 to avoid randomness, while adopt sampling for GPT-3.5. For GPT-3.5, the temperature is set to 0, top p is set to 1.0, and we adopt no frequency nor presence penalty.

Table 9. The hyperparameters employed during testing on LooGLE.

Hyperparameter	Gated Memory	PiSSA
learning rate	1.0×10^{-3}	3.0×10^{-5}
weight decay	1.0×10^{-4}	1.0×10^{-4}
max grad norm	1.0	1.0
β_1	0.9	0.9
eta_2	0.98	0.98
ϵ	1.0×10^{-8}	1.0×10^{-8}
stage 1 #epochs	3	1
stage 2 #epochs	5	3

Table 10. The hyperparameters employed during testing on LongBench with Gated Memory. #QA denotes the number of auxiliary tasks used. * We adopt 4 warmup steps to adjust the corresponding learning rates.

Hyperparameter	Musique	Narrativeqa	Qmsum	GovReport	PassageRetrievalEN
learning rate	3.0×10^{-3} *	3.0×10^{-3} *	3.0×10^{-3}	3.0×10^{-3}	3.0×10^{-3} *
weight decay	1.0×10^{-4}	1.0×10^{-4}	1.0×10^{-4}	1.0×10^{-4}	1.0×10^{-4}
max grad norm	1.0	1.0	1.0	1.0	1.0
eta_1	0.9	0.9	0.9	0.9	0.9
eta_2	0.98	0.98	0.98	0.98	0.98
ϵ	1.0×10^{-8}	1.0×10^{-8}	1.0×10^{-8}	1.0×10^{-8}	1.0×10^{-8}
#QA	10	30	0	0	60
stage 1 #epochs	3	3	8	8	3
stage 2 #epochs	5	5	0	0	5

A.3. Generating auxiliary tasks

We utilize auxiliary tasks on all the benchmarks except Qmsum and GovReport in LongBench. We adopt Llama-3-8B-Instruct as the generator and prompt it to synthesize a question and the corresponding answer conditioned on a piece of context.

For PassageRetrievalEN in LongBench, we imitate the generation process of the test set — randomly select a passage and prompt the generator to summarize the passage. The auxiliary task is to answer the index of the passage given the generated summary. The prompt for summarizing a passage is as following:

Please summarize the following text in 4 to 6 sentences: {*Context*}

For LooGLE, as well as Musique and Narrativeqa in LongBench, to avoid expensive long-context inference, we randomly select 16 continuous sentences as context. The prompts for generating auxiliary tasks for each benchmark (or subtask) are as following:

Instruction for LooGLE: You are given a piece of text as the context. You should generate ONLY one question and the corresponding answer according to the context. You should also select one or more sentences directly from the original context as the evidence. The evidences must be EXACTLY SAME ADJACENT sentences retrieved from the context; KEEP the special tokens in the sentences. Please answer in the following format:

Question: [question] Answer: [answer] Evidence: [evidence]

Please DON'T output quotes when outputting evidences.

The following is the piece of text: {Context}

Instruction for Musique: You are given a piece of text as the context. You should generate ONLY one question and the corresponding answer according to the context. You should also select one or more sentences directly from the original context as the evidence. The evidences must be EXACTLY SAME ADJACENT sentences retrieved from the context; KEEP the special tokens in the sentences. Please answer in the following format:

Question: [question] Answer: [answer] Evidence: [evidence]

Please DON'T output quotes when outputting evidences. The question should focus on the details like names, dates, e.t.c., and the answer should be as brief as possible. The following is the piece of text:

{Context}

Instruction for Narrativeqa: You are given a piece of text as the context. You should generate ONLY one question and the corresponding answer according to the context. You should also select one or more sentences directly from the original context as the evidence. The evidences must be EXACTLY SAME ADJACENT sentences retrieved from the context; KEEP the special tokens in the sentences. Please answer in the following format:

Question: [question] Answer: [answer] Evidence: [evidence]

Please DON'T output quotes when outputting evidences. The question should focus on the details like

names, dates, e.t.c. The following is the piece of text: {Context}

A.4. GPT4_score evaluation

We utilize GPT-3.5-turbo-0125 to evaluate the correctness of the responses of LLMs based on the questions and the ground-truth answers on LooGLE.

The prompt is as following (in the format of the chat template):

System: Given one question, there is a groundtruth and a predict_answer. Please decide whether they are the same or not in semantic. Please only output 'True' or 'False'.

User: Question: {Question}

groundtruth = { Ground-truth answer} predict_answer = { LLM response}

B. Results on Needle-in-a-Haystack (NIAH)

We present the experimental results in the NIAH (Kamradt, 2023) task in Figure 5, as further analysis of the pros and cons of LIFT and directions for future works. The task requires accurate retrieval from the contexts. We adopt a strong long-context model, Llama-3.1-8B-Instruct, as the baseline and apply the LIFT framework to the model.

The maximum context length of our test is 100K, which is within the 128K context window of Llama-3.1-8B-Instruct. As expected, the baseline achieves nearly perfect performance. However, LIFT slightly degrades the performance and the degradation seems irregular.

The reason for the degradation may be that LIFT introduces more noise to the model. While most parts of the context are irrelevant to the answer, LIFT asks the model to memorize all the context. The model is likely to be misled by the large amount of irrelevant information.

As summarized in Section 6, precise memorization can be challenging for LIFT. On the one hand, LIFT can't accurately memorize the context while avoiding overfitting. On the other hand, LIFT is likely to be misled when most information is irrelevant to the answer. Future works may improve the LIFT framework from these two aspects.

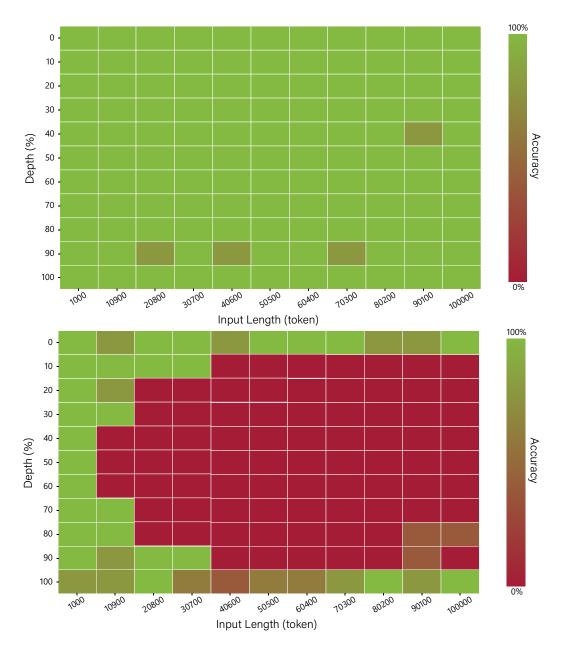


Figure 5. Performance on NIAH: ICL (top) vs. LIFT (bottom).