Anchor-based Large Language Models

Jianhui Pang^{1*} **Fanghua Ye**^{2*} **Derek F. Wong**¹ **Longyue Wang**^{3†}

¹University of Macau ²University College London ³Tencent AI Lab

nlp2ct.pangjh3@gmail.com, fanghua.ye.19@ucl.ac.uk

derekfw@um.edu.mo, vinnylywang@tencent.com

Abstract

Large language models (LLMs) predominantly employ decoder-only transformer architectures, necessitating the retention of keys/values information for historical tokens to provide contextual information and avoid redundant computation. However, the substantial size and parameter volume of these LLMs require massive GPU memory. This memory demand increases with the length of the input text, leading to an urgent need for more efficient methods of information storage and processing. This study introduces the Anchor-based LLM (AnLLM), which utilizes an innovative anchor-based self-attention network (AnSAN) and also an anchor-based inference strategy. This approach enables LLMs to compress sequence information into an anchor token, reducing the keys/values cache and enhancing inference efficiency. Experiments show that the AnLLM maintains comparable accuracy with up to 99% keys/values cache reduction and up to 3.5 times faster inference. Despite a minor compromise in accuracy, the AnLLM significantly improves computational efficiency and resource utilization, demonstrating the potential of the anchor-based attention approach in the context of LLMs for real-time inference in practical applications.

1 Introduction

Large language models (LLMs) primarily utilize decoder-only transformer architectures, which necessitate caching keys/values information for historical tokens during the auto-regressive inference to supply contextual information and avoid redundant computation (Wei et al., 2022; Touvron et al., 2023a; OpenAI, 2023; Touvron et al., 2023b). However, due to their immense size and high parameter count, a considerable amount of GPU memory is required for loading. Furthermore, as the length

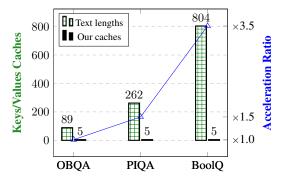


Figure 1: Comparison of keys/values caches and inference acceleration ratio between our approach and prior work in OBQA, PIQA, and BoolQ Tasks with 5-shot demonstrations. The bars represent the keys/values cache and text length, whereas the curve illustrates the inference acceleration ratio. With increasing text length, our method attains up to a 99% reduction in keys/values caches and improves inference efficiency by 3.5 times.

of input text grows, storing keys/values caches requires more and more GPU memory, as evidenced in in-context learning, complex instructions, and extended conversations (Dong et al., 2022; Jiang et al., 2023; Wang et al., 2023), which is not conducive to scenarios with limited computational resources. An alternative approach entails recalculating these extensive inputs, which, however, results in increased time overhead. Therefore, this study aims to reduce the storage demand for keys/values caches during the inference phase of LLMs, improving the memory efficiency and, consequently, accelerating the inference speed as well.

In a recent study, Wang et al. (2023) demonstrate that label words in prefix demonstrations can act as anchors during inference, thus providing an effective context compression approach to improving inference efficiency for in-context learning. However, in practical applications, not all prefix inputs or demonstrations contain label words suitable for compressing information, making the reliance on label words a less universal approach for text infor-

^{*} Work was done when Jianhui Pang and Fanghua Ye were interning at Tencent AI Lab.

[†] Longyue Wang is the corresponding author.

mation compression. In addition, Pang et al. (2024) observe that LLMs tend to attend to only a few but the same prefix tokens during inference. However, the specific tokens utilized are often unpredictable and uncontrollable. These observations raise an intriguing question: do natural language texts contain anchor points that compress the overall semantic information of sequences, thereby reducing the keys/values caches and accelerating the inference process for LLMs? Concerning this inquiry, prior researches on sequence embeddings suggest that the hidden state of a sequence's final token in neural network models can capture semantic information (Baudiš et al., 2016; Devlin et al., 2018). Nevertheless, contemporary LLMs typically adopt the causal self-attention mechanism to attend to each preceding token during both training and inference phases (Touvron et al., 2023a,b), rendering it challenging to pinpoint which token within a sequence can be considered an anchor. As a result, a systematic approach that identifies and leverages these anchor tokens in a reliable and controllable manner is needed to effectively reduce the keys/values caches and enhance the inference efficiency in the context of LLMs.

To this end, we propose a novel **An**chor-based Large Language Model (AnLLM), equipped with an innovative anchor-based self-attention network (AnSAN) and an anchor-based inference strategy. AnSAN is designed to compel the models to compress sequence information into the anchor token (the last token in our implementation) during the training process, with the aid of anchor-based attention masks. During inference, the anchor-based inference strategy retains the keys/values caches of anchor tokens, which have aggregated the entire sequence information, and discards those of nonanchor tokens, thereby reducing memory demands. Specifically, the anchor-based attention masks for AnSAN serve two objectives: 1) to ensure anchor tokens attend exclusively to tokens within the same sequence, preventing attention to other sequences, and 2) to direct non-anchor tokens' attention to previous sequence anchors, blocking the other nonanchor tokens from previous sequences. It is noteworthy that the technique of anchor-based attention bears similarities to the principles underlying sparse attention (Child et al., 2019). However, unlike the majority of existing research that employs sparse attention to extend the context length of LLMs (Chen et al., 2023; Ratner et al., 2023), our method focuses on fine-tuning the model to compress sequence information into the anchor token.

In our implementation, we employ publicly available datasets (Computer, 2023) to continuously pre-train the open-source Llama2 models (Touvron et al., 2023b), resulting in an AnLLM that incorporates our proposed anchor-based attention mechanism. Experimental results, as illustrated in Figure 1, show that our method achieves up to 99% reduction in keys/values caches and up to $\times 3.5$ inference acceleration ratios while maintaining comparable accuracy to the original model. Although there is a minor sacrifice in accuracy (within 1.5%), these findings underscore the significant improvements in computational efficiency and memory utilization of our method.

2 Related Work

Our research is inspired by the recent investigation into the understanding of in-context learning (ICL) in LLMs by Wang et al. (2023). In their study, the authors delve into the underlying mechanisms of ICL, emphasizing the influence of label words in demonstration examples on information flow. They reveal that these label words serve as anchors, wherein semantic information converges into these anchors during inference, subsequently directing the LLMs' final predictions. Motivated by their findings, our objective is to extend this feature to natural language modeling by guiding sequence information compression into manually designed anchor tokens, rather than solely relying on label words. This is crucial because natural language texts may not always contain an explicit label.

The most relevant method to our approach in the existing literature is the learning to compress prompts with gist tokens (Mu et al., 2023). Their approach centers around compressing task-specific prompts by fine-tuning the model using the proposed gist masking, thereby enforcing prompt compression. However, there are several crucial divergences between our study and theirs. Unlike their focus on compressing a task prompt, our objective lies in training the LLM to condense sequence information into the anchor tokens. Consequently, our approach can be universally applied to a range of tasks without needing task-specific training, a feature not shared by gist tokens, as the anchor tokens are seamlessly incorporated into the model's language modeling. Furthermore, our anchor-based attention masks account for information compression within a sequence and information interaction between sequences, thus extending beyond the mere compression of task prompts.

On the other hand, FlashAttention (Dao et al., 2022) and PagedAttention (Kwon et al., 2023) both present memory-efficient attention mechanisms for LLMs. While they focus on optimizing attention computation and subdividing attention processing, our proposed method offers a distinct approach that specifically targets the compression of sequence information into anchor tokens, making it orthogonal to existing works.

3 Anchor-based Large Language Models

3.1 Background

Transformers. LLMs are predominantly implemented as transformer decoders (Vaswani et al., 2017; Touvron et al., 2023a,b), consisting of an input embedding layer followed by multiple decoder layers. Each of these decoder layers is composed of a self-attention network and a feed-forward network, succeeded by respective normalization modules. It is important to note that causal attention masks are employed within the self-attention mechanisms, ensuring that current tokens solely attend to preceding tokens.

Self-Attention Networks. Typically for decoderonly LLMs like Llama2 (Touvron et al., 2023b), self-attention networks (SANs) map queries Q, keys K, and values V into an output, as delineated in the following equations,

$$\mathrm{SAN}(Q,K,V) = \mathrm{Softmax}(Q,K)V, \hspace{0.5cm} (1)$$

$$Softmax(Q, K)_{i,j} = \frac{M_{i,j} exp(Q_i K_j^T)}{\sum_k M_{i,k} exp(Q_i K_k^T)}, \quad (2)$$

$$M_{i,j} = \begin{cases} 1, & \text{if } i \ge j \\ 0, & \text{else} \end{cases}, \tag{3}$$

where M denotes an $L \times L$ masking matrix, facilitating the current i-th token to attend to only preceding tokens whilst disregarding subsequent tokens during the training and inference phases.

Keys/Values Caches. In the application of LLMs, the keys/values caches increase with lengthy prefix texts and continuously generated tokens during the inference phase, such as in question-answering (Saad-Falcon et al., 2023), text summarization (Basyal and Sanghvi, 2023), and machine translation (Pang et al., 2024). The key and value matrices associated with tokens of prefix inputs are cached to avoid recomputation and expedite subsequent

token prediction (Radford et al., 2019; Vaswani et al., 2017). As the length of prefix texts extends, both computational cost and cache memory requirements intensify, leading to slower inference speeds. Consequently, addressing the challenges arising from the ever-growing texts is crucial for enhancing the efficiency of LLM inference.

3.2 Anchor-based Self-Attention Networks

Given an input text composed of n ordered sequences, $P = \{S_1, S_2, ..., S_n\}$, it is assumed that the last tokens of these sequences are the anchor tokens, $A = \{a_1, a_2, ..., a_n\}$, arranged according to sequence indices. The primary objective of AnSAN is to encapsulate the information of a sequence into its anchor token, with the anchor hidden states representing the comprehensive semantic information. Consequently, an AnLLM equipped with AnSAN generates subsequent tokens based on the hidden states of preceding tokens of the current sequence and anchor tokens of prior sequences.

Anchor-based Attention Masks. To achieve this, we design anchor-based attention masks for the current token. Assuming that the current token of the current sequence is a non-anchor token, we enable the attention to previous non-anchor tokens of the current sequence and the anchor tokens of previous sequences, while blocking the attention to non-anchor tokens of previous sequences. In this way, the non-anchor tokens can only access the previous sequence information from the previous sequence anchors and the current sequence information. Conversely, when the current token is an anchor token, which means it is the last token of the current sequence, we only open its attention to the previous non-anchor tokens of the current sequence and block all other attention, thereby forcing the anchor token to aggregate its current sequence information.

Accordingly, we substitute the attention masks in Eq. (3) with anchor-based attention masks in Eq. (4) to limit the attention weights of the i-th token in the input text to the previous j-th tokens (assume that the i-th token belongs to the k-th sequence), as below.

$$M_{i,j} = \begin{cases} 0, & \text{if } i \neq j \text{ and } (w_i, w_j) \in A \\ 1, & \text{else if } i \geq j \text{ and } w_j \in A \\ 1, & \text{else if } i \geq j > \text{index}(a_{k-1}) \end{cases}, \quad (4)$$

$$0, & \text{else}$$

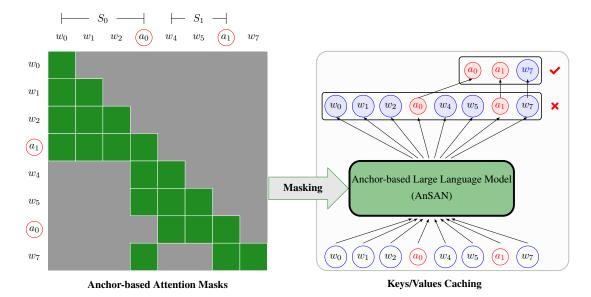


Figure 2: Anchor-based Attention Masking and Efficient Caching in LLMs. On the left, the gray and green squares represent the masking and unmasking operations respectively, with the circled "a" symbols denoting the anchor tokens. Through anchor-based attention masking during training, we compel the model to incorporate prior sequence information into the anchor tokens. On the right, during inference, our anchor-based LLMs compress information into the anchor tokens and discard the previous remaining keys/values caches, thereby facilitating an efficient caching mechanism.

where $index(a_{k-1})$ denotes the index of the anchor token in the (k-1)-th sequence, i.e., the previous sequence.

Anchor Token Selection. By implementing the AnSAN mechanism for training LLMs, we can compel the model to compress sequence information into the anchor token and generate new tokens based on the anchor token information from previous sequences and non-anchor token information from the current sequence.

The challenge now lies in selecting an appropriate anchor token. In our experiment, we propose two implementation methods: one using the endpoint as the anchor token, and the other introducing a new token specifically as the anchor token.

3.3 Anchor-based Inference

By training the model to compress information into the anchor/final token of a natural language sequence, we can optimize the inference process by modifying the keys/values caching mechanism. Specifically, during inference, upon encountering an anchor token that condenses the comprehensive semantic information of preceding tokens in the current sequence, the model can reduce the keys/values caches by deleting the caches of non-anchor tokens within that sequence.

We present the inference method in Algorithm 1.

Algorithm 1 Anchor-based Inference

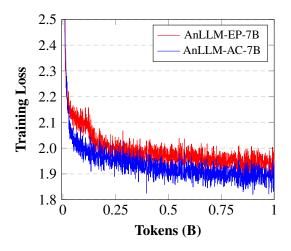
Require: Anchor-based LLM Θ , prefix text P with anchor tokens A, keys/values cache list \mathcal{C} , predicted token w_{new} ;

```
Output: Generated text \mathcal{T};
 1: function REDUCTION(C)
               \leftarrow last anchor index in C;
 3:
            \mathcal{C} \leftarrow \{c \in \mathcal{C} \mid \text{index}(c) \geq j \text{ or } c \text{ is anchor}\};
 4:
            return C.
 5: end function
 6: Initialize \mathcal{T}, \mathcal{C} as empty lists;
 7: \mathcal{M} \leftarrow \text{GetMasks}(P, \mathcal{C}) \text{ using Eq. (4)};
 8: Update w_{new}, C using Forward(P; \mathcal{M}, C, \Theta);
 9: Append w_{new} to \mathcal{T};
10: \mathcal{C} \leftarrow \text{Reduction}(\mathcal{C});
11: while w_{new} is not [eos] do
12:
            \mathcal{M} \leftarrow \text{GetMasks}(w_{new}, \mathcal{C}) \text{ using Eq. (4)};
13:
            Update w_{new}, C using Forward(w_{new};\mathcal{M}, C, \Theta);
14:
            Append w_{new} to \mathcal{T};
15:
            if w_{new} is the anchor token then
16:
                  \mathcal{C} \leftarrow \text{Reduction}(\mathcal{C});
17:
            end if
18: end while
19: return \mathcal{T}.
```

The function "REDUCTION" in Line 1 is employed to delete keys/values caches when the model processes the prefix texts in Line 10, or when it generates an anchor token during the prediction of the next token in Line 16.

4 Experiments

In this section, we first describe our implementation of the AnLLM, followed by an explanation of the



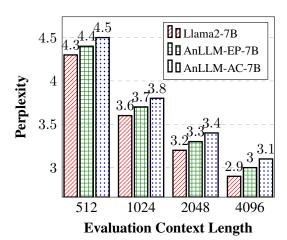


Figure 3: Training Process and Perplexity Evaluation of the Anchor-based Large Language Model.

training procedure, and report the model perplexity. Finally, we introduce the evaluation datasets and metrics used in our experiments.

4.1 Our Implementation

Llama2-7b (Touvron et al., 2023b) is adopted as the base model in our experiments, which is an open-source and English-centric LLM. In accordance with the principles outlined in Section 3, we present our implementations here. The crux is to identify which tokens in a sequence can be considered anchor tokens. In light of this, we describe two implementation strategies: one involves adding a new token at the end of a sequence to serve as the anchor token, and the other employs the endpoints directly. The details are as follows:

- AnLLM-AC. This strategy entails the introduction of a new token to act as the sequence anchor. In our implementation, we designate <AC> as the new token and initialize its embedding using the mean value of the embedding matrix. The function of this new token mirrors that of the [CLS] token in BERT (Devlin et al., 2018), which is used for sequence classification tasks. We employ the sentence tokenizer from the NLTK package to split texts into sentences and append <AC> at the end as the anchor token for each sentence. ¹
- AnLLM-EP. This approach uses punctuation marks within the sequence as anchor tokens.
 Punctuation marks, such as commas, periods, and question marks, are viewed as semantic boundaries within a sequence. As such, they can serve as anchor tokens in AnLLM. In our experiments

as the anchor tokens.

of AnLLM-EP, we use the endpoint in English

Considering that AnLLM is expected to predict subsequent tokens within the context of keys/values hidden states of anchor tokens, this presents a significant challenge for existing open-source LLMs. To address this concern, we fine-tune the Llama2 model using a publicly available corpus, substituting the self-attention networks with anchor-based self-attention networks as detailed in Section 3.2.

Data. We employ the RedPajama-Data-1T-Sample dataset (Computer, 2023) for the continuous pre-training purpose.² This dataset comprises 850,000 samples with approximately 1 billion tokens, which have been subjected to right truncation to fit the model context of 4,096.

Training Procedure. We train each model via the next token prediction objective on the dataset for one epoch, with a batch size of 512. The learning rate is set to 0.00002 and constant after a linear warmup with 20 update steps. The AdamW (Loshchilov and Hutter, 2019) with $\beta_1=0.9$ and $\beta_2=0.95$ is adopted as the gradient backtrack propagation optimizer. All the training procedures are conducted with four $8\times$ A100 GPU machines with 40G GPU Memory.

Training Loss and Perplexity. The left-hand side of Figure 3 depicts the training loss associated with our models. The loss curves for AnLLM-EP

^{.2} Data and Training Procedure

https://www.nltk.org/api/nltk.tokenize.punkt. html

²https://huggingface.co/datasets/
togethercomputer/RedPajama-Data-1T-Sample

and AnLLM-AC consistently decline to approximately 1.9, with AnLLM-AC achieving a lower loss. This observation suggests that continuous pre-training an LLM using anchor-based attention masks is indeed viable, enabling the LLM to effectively learn the process of compressing sequence information into anchor tokens.

The right-hand side of Figure 3 displays the perplexity evaluation of the models with varying context lengths. Full attention is utilized to assess the language modeling capabilities of all models. Following the settings of Chen et al. (2023), the perplexity is evaluated on the test samples of the Proof-Pile datasets (Rae et al., 2020). The results reveal that both AnLLM-EP and AnLLM-AC exhibit promising performance while maintaining competitiveness compared to the baseline model, Llama2-7B. Besides, this finding implies that the AnLLM models align well with full attention, as evidenced by the minimal perplexity degradation.

4.3 Evaluation

In our investigation, we employ a diverse collection of benchmarks with varying text lengths to evaluate our outcomes, including OpenBookQA (OBQA) (Mihaylov et al., 2018), WinoGrande (WG) (Sakaguchi et al., 2021), ARC-easy (ARC-e) and ARCchallenge (ARC-c) (Clark et al., 2018), PIQA (Bisk et al., 2020), HellaSwag (HS) (Zellers et al., 2019), SCIQ (Welbl et al., 2017), and BoolQ (Clark et al., 2019). These benchmarks provide a comprehensive evaluation of various aspects, including reasoning, comprehension, understanding of the physical world, and predicting future events. Importantly, they cover texts of varying lengths, facilitating a thorough assessment of our model's performance across diverse tasks and text complexities, ranging from shorter input contexts in OBQA to longer texts in BoolQ. To measure the precision and efficiency of our models, we evaluate them across three dimensions using three distinct metrics for both 0-shot and 5-shot settings. For AnLLM-AC in the 5-shot setting, we incorporate the anchor token <AC> at the end of each demonstration.

- Accuracy (Acc). This conventional metric is utilized to gauge the prediction accuracy of models. In accordance with previous studies (Gao et al., 2023), we choose the options with the highest probabilities as predictions and calculate accuracy using the gold-standard labels.
- Keys/Values Caches Reduction ($C_{\downarrow\downarrow}$). In the con-

text of the 5-shot learning evaluation, the demonstrations can be cached in GPU memory for subsequent reuse. Nevertheless, extended demonstrations may require increased memory consumption. This metric is designed to assess the memory efficiency of our anchor-based LLMs.

 Testing Acceleration Ratio (T_↑). Similar to Wang et al. (2023), capitalizing on the cached keys/values, we present the testing acceleration ratio, which serves as an indicator of the inference efficiency of our anchor-based LLMs.

Note that we first report full attention inference results for all models, then present results with the AnSAN method (+AnSAN) applied, compressing sequence information into anchor tokens.

5 Results

As evident from the results presented in Table 1, both the AnLLM-AC and AnLLM-EP models demonstrate promising accuracy, comparable to that of the base model, while simultaneously improving memory and inference efficiency.

Accuracy (*Acc*). The proposed AnLLM-AC and AnLLM-EP strategies exhibit commendable accuracy across various benchmarks.

In the zero-shot setting, with full attention, AnLLM-AC and AnLLM-EP achieve average accuracies of 65.1% and 64.6%, respectively, comparable to Llama2-7B's 65.8% accuracy. This suggests that training with integrated anchor tokens barely affects the model capacity, emphasizing the robustness of LLMs. Furthermore, our models excel in OBQA, PIQA, and SCIQ tasks.

In the five-shot setting, with five prior examples, AnLLM-AC and AnLLM-EP maintain dependable performance using full attention. When implementing the AnSAN technique, a slight accuracy decline across all models is observed. This is expected, as AnSAN, designed for memory efficiency, necessitates token removal, potentially leading to information loss. The degradation in BoolQ is most pronounced, which contains the longest demonstration tasks, indicating that the longer the text, the greater the information loss after compression. However, the average accuracy reduction is minimal, approximately 1.5%, suggesting that AnSAN effectively balances memory-saving and model performance.

Keys/Values Cache Reduction ($C_{\downarrow\downarrow}$). The size of the keys/values cache is a critical factor in the practical implementation of LLMs, particularly

	OBQA	WG	ARC-e	ARC-c	PIQA	HS	SCIQ	BoolQ	AVG.
Llama2-7B	31.4	69.1	76.3	43.4	78.1	57.1	93.7	77.7	65.8
AnLLM-EP	33.2	68.0	73.4	40.8	77.8	55.0	94.4	74.4	64.6
AnLLM-AC	31.6	68.5	74.4	42.5	78.3	54.7	93.8	77.0	65.1

(a) The Zero-Shot Performance.

		OBQA	WG	ARC-e	ARC-c	PIQA	HS	SCIQ	BoolQ	AVG.
	L_d	89	133	145	209	262	426	603	804	334
	L_x	18	26	36	42	42	90	130	169	69
Llama2-7B	Acc	37.2	73.7	79.8	50.0	78.7	58.3	96.8	78.4	69.1
+AnSAN	Acc	34.6	68.6	62.6	35.8	68.3	30.8	65.7	50.8	52.1
AnLLM-EP	Acc	36.8	71.0	79.4	49.4	78.1	55.3	96.6	75.6	67.8
+AnSAN	Acc	36.2	68.0	76.7	45.6	78.2	52.6	93.1	74.0	65.6
	L_{kv}	89	8	5	30	9	25	50	43	32
	\mathcal{C}_{\Downarrow}	-0%	-94%	-97%	-86%	-97%	-94%	-92%	-95%	-90%
	\mathcal{T}_{\Uparrow}	$\times 1.0$	×1.0	×1.0	×1.2	×1.4	×2.1	×2.6	×3.5	×1.7
AnLLM-AC	Acc	37.2	72.3	79.8	49.0	78.6	56.9	96.8	77.5	68.5
+AnSAN	Acc	35.6	70.6	79.2	47.9	78.7	55.6	95.7	76.6	67.5
	L_{kv}	5	5	5	5	5	5	5	5	5
	\mathcal{C}_{\Downarrow}	-94%	-96%	-97%	-98%	-98%	-99%	-99%	-99%	-99%
	\mathcal{T}_{\Uparrow}	×1.0	×1.0	×1.1	×1.2	×1.5	×2.0	×2.6	×3.5	×1.7

(b) The Five-Shot Performance.

Table 1: Accuracy and Efficiency of LLMs on Question Answering Benchmarks. C_{\downarrow} represents the reduction in keys/values cache size, while \mathcal{T}_{\uparrow} denotes the time acceleration ratio during testing. Acc stands for Accuracy. L_{kv} represents the length of the keys/values cache. L_d and L_x denote the lengths of in-context learning demonstrations and input queries, respectively. Our methods effectively reduce cache sizes and boost inference efficiency.

concerning memory efficiency and computational resources. In this respect, the AnLLM-AC and AnLLM-EP strategies offer significant advantages.

By adopting the AnSAN, these strategies are designed to dramatically reduce the keys/values cache size during inference. As shown in Table 1, these strategies achieve remarkable reductions in cache size. Specifically, the average reduction percentages are around 90% for AnLLM-EP and an impressive 99% for AnLLM-AC. This is a substantial improvement compared to conventional approaches, which typically necessitate large cache sizes to store keys/values. These reductions in cache size translate to considerable savings in memory and computational resources, rendering these strategies highly efficient for practical applications.

Inference Acceleration Ratio (\mathcal{T}_{\uparrow}). The inference acceleration ratio is another critical metric indicative of the model's efficiency during the testing phase. By integrating anchor tokens into natural language texts, we can repurpose the hidden

states of anchor tokens as keys/values caches in the demonstrations, and then employ a testing strategy as proposed by Wang et al. (2023). In this context, both the AnLLM-AC and AnLLM-EP strategies exhibit substantial enhancements.

Specifically, the average inference acceleration ratios are approximately 1.7 times for both AnLLM-EP and AnLLM-AC. This represents a significant advancement compared to traditional approaches, which typically necessitate prolonged processing times due to the involvement of a large number of tokens. As L_d increases, the acceleration ratios are rising, corroborating the findings of Wang et al. (2023). This acceleration in processing time leads to enhanced efficiency, making these strategies especially appropriate for scenarios with limited resources.

The AnLLM-AC and AnLLM-EP models exhibit remarkable performance in natural language understanding benchmarks, effectively balancing accuracy, memory efficiency, and

time acceleration. The incorporation of anchor tokens into LLMs, along with the utilization of the AnSAN technique for reducing keys/values cache size, allows these strategies to maintain performance on par while significantly improving memory efficiency and inference speed. The equilibrium achieved between model performance and computational efficiency is noteworthy and opens up new possibilities for the advancement of LLMs.

6 Analysis

To further elucidate the insights of our method, we conduct an additional experiment on the Germanto-English (De2En) translation task. We evaluate the models using COMET-DA (Rei et al., 2022), indicating translation quality, and the Keys/Values Cache Reduction \mathcal{C}_{\Downarrow} metric, denoting memory efficiency as previously described. In line with previous findings, AnLLMs accept a minor accuracy trade-off (about 3 COMET-DA points) for enhanced memory efficiency. All LLMs are fine-tuned on the Alpaca dataset, combined with the newstest2017-2020 datasets, following Jiao et al. (2023). Results are presented in Table 2.

6.1 Compatibility and Flexibility of Full Attention and Anchor-Based Attention

The findings offer significant insight into the interplay between anchor-based attention and full attention mechanisms in the De2En translation task. Since source sentences are vital in translation tasks, applying full attention to them is crucial for maintaining model performance. Thus, retaining the source sentence keys/values caches is expected to enhance AnLLM performance when implementing the AnSAN technique. Specifically, when combining full attention with the AnSAN method, both AnLLM-EP and AnLLM-AC achieve approximately 80.0 COMET-DAE scores, comparable to other models using full attention exclusively. This indicates that the AnSAN technique is compatible with the full attention mechanism. Consequently, our proposed models allow users to choose between full attention and anchor-based attention for input texts based on their needs, emphasizing the compatibility and flexibility of our models.

6.2 Effective Cache Reduction for Real-time Inference

The results in Table 2 show that our reduction strategy effectively minimizes keys/values caches during real-time inference. Specifically, as indicated

Model	Src Cache	De2En	MaxKV	\mathcal{C}_{\Downarrow}
Llama2-7b	✓	83.1	220	0%
AnLLM-EP	✓	81.6	220	0%
+AnSAN	× ✓	78.5 80.3	50 124	77% 44%
AnLLM-AC	✓	82.4	220	0%
+AnSAN	× ✓	78.0 80.0	35 125	84% 43%

Table 2: COMET-DA Scores and Keys/Values Cahces for the WMT23 German-to-English (De2En) Translation Task. The term "Src Cache" denotes retaining source sentence hidden states in Keys/Values Caches, while "MaxKV" refers to the average maximum keys/values length during inference.

in Line 15 of Algorithm 1, when generating an anchor token (i.e., the endpoint or <AC> tokens), our AnSAN-equipped models execute the reduction function to minimize the current keys/values caches. When discarding source sentence caches, we achieve approximately 77% and 84% reduction for the AnLLM-EP and AnLLM-AC models, respectively, though with a low COMET-DA score. However, when retaining source sentence caches, we still reduce around 44% of caches for both models, achieving a COMET-DA score of approximately 80.0. These results confirm the effectiveness of our anchor-based inference strategy for practical real-time inference applications.

7 Conclusion

LLMs have emerged as a significant research area in the field of artificial intelligence. However, the practical application of these models is not primarily constrained by their performance but rather by their substantial memory overhead and time efficiency. Deploying LLMs on resource-limited devices, such as smartphones, presents a novel challenge. To address this issue, we propose an anchor-based LLM. Our experiments demonstrate that by sacrificing a marginal 1.5% in precision, our approach saves 99% of keys/values cache memory while simultaneously improving inference efficiency by up to 3.5 times. Our methods' application in machine translation showcases their compatibility and flexibility, effectively enhancing memory efficiency for practical use. Our novel approach is practical, straightforward, flexible, and compatible with existing methods, paving the way for further adoption of LLMs in real-world applications.

References

- Lochan Basyal and Mihir Sanghvi. 2023. Text summarization using large language models: A comparative study of mpt-7b-instruct, falcon-7b-instruct, and openai chat-gpt models. *arXiv preprint arXiv:2310.10449*.
- Petr Baudiš, Silvestr Stanko, and Jan Šedivý. 2016. Joint learning of sentence embeddings for relevance and entailment. In *Proceedings of the 1st Workshop on Representation Learning for NLP*, pages 8–17, Berlin, Germany. Association for Computational Linguistics.
- Yonatan Bisk, Rowan Zellers, Jianfeng Gao, Yejin Choi, et al. 2020. Piqa: Reasoning about physical commonsense in natural language. In *Proceedings of the AAAI conference on artificial intelligence*, volume 34, pages 7432–7439.
- Yukang Chen, Shengju Qian, Haotian Tang, Xin Lai, Zhijian Liu, Song Han, and Jiaya Jia. 2023. Longlora: Efficient fine-tuning of long-context large language models. *arXiv*:2309.12307.
- Rewon Child, Scott Gray, Alec Radford, and Ilya Sutskever. 2019. Generating long sequences with sparse transformers. *arXiv preprint* arXiv:1904.10509.
- Christopher Clark, Kenton Lee, Ming-Wei Chang, Tom Kwiatkowski, Michael Collins, and Kristina Toutanova. 2019. BoolQ: Exploring the surprising difficulty of natural yes/no questions. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 2924–2936, Minneapolis, Minnesota. Association for Computational Linguistics.
- Peter Clark, Isaac Cowhey, Oren Etzioni, Tushar Khot, Ashish Sabharwal, Carissa Schoenick, and Oyvind Tafjord. 2018. Think you have solved question answering? try arc, the ai2 reasoning challenge. *arXiv* preprint arXiv:1803.05457.
- Together Computer. 2023. Redpajama: an open dataset for training large language models.
- Tri Dao, Daniel Y. Fu, Stefano Ermon, Atri Rudra, and Christopher Ré. 2022. FlashAttention: Fast and memory-efficient exact attention with IO-awareness. In *Advances in Neural Information Processing Systems*.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.
- Qingxiu Dong, Lei Li, Damai Dai, Ce Zheng, Zhiyong Wu, Baobao Chang, Xu Sun, Jingjing Xu, and Zhifang Sui. 2022. A survey for in-context learning. *arXiv preprint arXiv:2301.00234*.

- Leo Gao, Jonathan Tow, Baber Abbasi, Stella Biderman, Sid Black, Anthony DiPofi, Charles Foster, Laurence Golding, Jeffrey Hsu, Alain Le Noac'h, Haonan Li, Kyle McDonell, Niklas Muennighoff, Chris Ociepa, Jason Phang, Laria Reynolds, Hailey Schoelkopf, Aviya Skowron, Lintang Sutawika, Eric Tang, Anish Thite, Ben Wang, Kevin Wang, and Andy Zou. 2023. A framework for few-shot language model evaluation.
- Huiqiang Jiang, Qianhui Wu, Xufang Luo, Dongsheng Li, Chin-Yew Lin, Yuqing Yang, and Lili Qiu. 2023. Longllmlingua: Accelerating and enhancing llms in long context scenarios via prompt compression. *arXiv preprint arXiv:2310.06839*.
- Wenxiang Jiao, Jen-tse Huang, Wenxuan Wang, Zhiwei He, Tian Liang, Xing Wang, Shuming Shi, and Zhaopeng Tu. 2023. ParroT: Translating during chat using large language models tuned with human translation and feedback. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 15009–15020, Singapore. Association for Computational Linguistics.
- Woosuk Kwon, Zhuohan Li, Siyuan Zhuang, Ying Sheng, Lianmin Zheng, Cody Hao Yu, Joseph E. Gonzalez, Hao Zhang, and Ion Stoica. 2023. Efficient memory management for large language model serving with pagedattention. In *Proceedings of the ACM SIGOPS 29th Symposium on Operating Systems Principles*.
- Ilya Loshchilov and Frank Hutter. 2019. Decoupled weight decay regularization. In *International Conference on Learning Representations*.
- Todor Mihaylov, Peter Clark, Tushar Khot, and Ashish Sabharwal. 2018. Can a suit of armor conduct electricity? a new dataset for open book question answering. *arXiv preprint arXiv:1809.02789*.
- Jesse Mu, Xiang Lisa Li, and Noah Goodman. 2023. Learning to compress prompts with gist tokens. *arXiv preprint arXiv:2304.08467*.
- OpenAI. 2023. Gpt-4 technical report.
- Jianhui Pang, Fanghua Ye, Longyue Wang, Dian Yu, Derek F Wong, Shuming Shi, and Zhaopeng Tu. 2024. Salute the classic: Revisiting challenges of machine translation in the age of large language models. *arXiv* preprint arXiv:2401.08350.
- Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. 2019. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9.
- Jack W. Rae, Anna Potapenko, Siddhant M. Jayakumar, Chloe Hillier, and Timothy P. Lillicrap. 2020. Compressive transformers for long-range sequence modelling. In *International Conference on Learning Representations*.

- Nir Ratner, Yoav Levine, Yonatan Belinkov, Ori Ram, Inbal Magar, Omri Abend, Ehud Karpas, Amnon Shashua, Kevin Leyton-Brown, and Yoav Shoham. 2023. Parallel context windows for large language models. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics* (Volume 1: Long Papers), pages 6383–6402, Toronto, Canada. Association for Computational Linguistics.
- Ricardo Rei, José G. C. de Souza, Duarte Alves, Chrysoula Zerva, Ana C Farinha, Taisiya Glushkova, Alon Lavie, Luisa Coheur, and André F. T. Martins. 2022. COMET-22: Unbabel-IST 2022 submission for the metrics shared task. In *Proceedings of the Seventh Conference on Machine Translation (WMT)*, pages 578–585, Abu Dhabi, United Arab Emirates (Hybrid). Association for Computational Linguistics.
- Jon Saad-Falcon, Joe Barrow, Alexa Siu, Ani Nenkova, Ryan A Rossi, and Franck Dernoncourt. 2023. Pdf-triage: Question answering over long, structured documents. *arXiv preprint arXiv:2309.08872*.
- Keisuke Sakaguchi, Ronan Le Bras, Chandra Bhagavatula, and Yejin Choi. 2021. Winogrande: An adversarial winograd schema challenge at scale. *Communications of the ACM*, 64(9):99–106.
- Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. 2023a. Llama: Open and efficient foundation language models. arXiv preprint arXiv:2302.13971.
- Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. 2023b. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. *Advances in neural information processing systems*, 30.
- Lean Wang, Lei Li, Damai Dai, Deli Chen, Hao Zhou, Fandong Meng, Jie Zhou, and Xu Sun. 2023. Label words are anchors: An information flow perspective for understanding in-context learning. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 9840–9855, Singapore. Association for Computational Linguistics.
- Jason Wei, Yi Tay, Rishi Bommasani, Colin Raffel, Barret Zoph, Sebastian Borgeaud, Dani Yogatama, Maarten Bosma, Denny Zhou, Donald Metzler, et al. 2022. Emergent abilities of large language models. arXiv preprint arXiv:2206.07682.
- Johannes Welbl, Nelson F. Liu, and Matt Gardner. 2017. Crowdsourcing multiple choice science questions.

- In *Proceedings of the 3rd Workshop on Noisy Usergenerated Text*, pages 94–106, Copenhagen, Denmark. Association for Computational Linguistics.
- Rowan Zellers, Ari Holtzman, Yonatan Bisk, Ali Farhadi, and Yejin Choi. 2019. Hellaswag: Can a machine really finish your sentence? *arXiv preprint arXiv:1905.07830*.

A More Experimental Results

A.1 Model Scalability Assessment

To examine the scalability of our approach, we extend the AnLLM-AC model to 13B and assess its performance on eight question-answering benchmarks using the same evaluation strategy as previously mentioned. In comparison to the 7B AnLLM models in Table 1, Results in Table 3 indicate that as the model size expands, the AnLLM-AC model achieves accuracies of 67.5% and 70.0% for 0-shot and 5-shot testing, respectively, resulting in up to a 2.4% improvement. Moreover, by incorporating anchor-based attention, the AnLLM-AC-AnSAN model achieves an average accuracy of 69.5%, signifying a 2.4% increase. The performance enhancement underscores the effectiveness of our methods in accommodating larger model capacities. The consistent improvements observed in the AnLLM-AC model across various scenarios highlight its robustness and adaptability. Furthermore, the increased performance of the AnLLM-AC-AnSAN model, facilitated by anchor-based attention, emphasizes the potential of our approaches in optimizing LLMs. Collectively, these findings point to promising avenues for future research aimed at maximizing the utility and efficiency of AnLLM.

B Data Settings

To provide a thorough insight into how we fine-tune the model into AnLLM and carry out evaluations, we showcase some data examples in this section for both training and testing data.

B.1 Training Data Examples

In this section, we provide some examples to illustrate the detailed data format used in training the AnLLM models. For the AnLLM-EP model, the endpoints serve as anchor tokens, so we directly use natural language texts. For the AnLLM-AC model, we add a new token <AC> at the end of each sequence in the input texts, which are first split into sentences using the NLTK toolkits. Some examples are presented in Table 4.

B.2 Testing Data Examples

For the testing outlined in the results section (Section 5), we employ the same evaluation method as in previous work (Gao et al., 2023), which considers each choice as text generation and computes the corresponding probabilities, respectively. Ta-

ble 5 presents some examples of the benchmark evaluation.

Model	OBQA	WG	ARC-e	ARC-c	PIQA	HS	SCIQ	BoolQ	AVG.
0-shot performance									
Llama2-13b	35.2	72.1	79.4	48.5	79.1	60.0	94.5	80.6	68.7
AnLLM-AC	35.2	70.7	77.9	46.9	78.6	58.1	94.7	78.1	67.5
5-shot performance									
Llama2-13b	38.2	76.3	82.2	52.6	80.0	61.4	97.5	83.5	71.5
AnLLM-AC	36.6	72.5	81.6	53.7	79.2	59.6	97.5	79.6	70.0
+AnSAN	36.0	74.0	81.6	52.0	79.1	58.4	96.3	78.8	69.5

Table 3: Accuracy of 13B LLMs on Question Answering Benchmarks.

Gender diversity, or more often its lack thereof, among participants to software development activities has been thoroughly studied in recent years. In particular, the presence of, effects of, and countermeasures for gender bias in Free/Open Source Software (FOSS) have received a lot of attention over the past decade. Geographic diversity is on the other hand the kind of diversity that stems from participants in some global activity coming from different world regions and cultures. Geographic diversity in FOSS has received relatively little attention in scholarly works. In particular, while seminal survey-based and point-in-time medium-scale studies of the geographic origins of FOSS contributors exist, large-scale longitudinal studies of the geographic origin of FOSS contributors are still lacking. Such a quantitative characterization would be useful to inform decisions related to global development teams and hiring strategies in the information technology (IT) market, as well as contribute factual information to the debates on the economic impact and sociology of FOSS around the world. ...

(a) A Training Data Example for the AnLLM-EP Model. The endpoints in the text serve as the anchor tokens.

Gender diversity, or more often its lack thereof, among participants to software development activities has been thoroughly studied in recent years. AC> In particular, the presence of, effects of, and countermeasures for gender bias in Free/Open Source Software (FOSS) have received a lot of attention over the past decade. AC> Geographic diversity is on the other hand the kind of diversity that stems from participants in some global activity coming from different world regions and cultures. AC> Geographic diversity in FOSS has received relatively little attention in scholarly works. AC> In particular, while seminal survey-based and point-in-time medium-scale studies of the geographic origins of FOSS contributors exist, large-scale longitudinal studies of the geographic origin of FOSS contributors are still lacking. AC> Such a quantitative characterization would be useful to inform decisions related to global development teams and hiring strategies in the information technology (IT) market, as well as contribute factual information to the debates on the economic impact and sociology of FOSS around the world. AC> ...

(b) A Training Data Example for the AnLLM-AC Model. The newly added tokens <AC> in the text serve as the anchor tokens.

Table 4: Training Data Examples for the AnLLM-EP and AnLLM-AC models.

Choice 1: Slacklining: A group of people have stretched a tightrope across a gym. They *take turns* trying to balance and walk on the rope.

Choice 2: Slacklining: A group of people have stretched a tightrope across a gym. They *slide down* with it, jumping and spinning in the air.

Choice 3: Slacklining: A group of people have stretched a tightrope across a gym. They *cross it together, swinging back and fourth in anticipation*.

Choice 4: Slacklining: A group of people have stretched a tightrope across a gym. They *drop an orange rope at the end*.

(a) A Zero-Shot Testing Data Example of the HellaSwag Task. The log-likelihood of the red texts is computed as the choice probabilities.

Choice 1: Ballet: We see a pregnant lady doing ballet in a studio. The lady spins and does a pliea. Demonstration 2 Demonstration 3 Demonstration 4 Demonstration 5 Slacklining: A group of people have stretched a tightrope across a gym. They *take turns trying to balance and walk on the rope*.

Choice 2: Ballet: We see a pregnant lady doing ballet in a studio. The lady spins and does a pliea. Demonstration 2 Demonstration 3 Demonstration 4 Demonstration 5 Slacklining: A group of people have stretched a tightrope across a gym. They *slide down with it, jumping and spinning in the air.*

Choice 3: Ballet: We see a pregnant lady doing ballet in a studio. The lady spins and does a pliea. Demonstration 2 Demonstration 3 Demonstration 4 Demonstration 5 Slacklining: A group of people have stretched a tightrope across a gym. They *cross it together, swinging back and fourth in anticipation*.

Choice 4: Ballet: We see a pregnant lady doing ballet in a studio. The lady spins and does a pliea. Demonstration 2 Demonstration 3 Demonstration 4 Demonstration 5 Slacklining: A group of people have stretched a tightrope across a gym. They *drop an orange rope at the end*.

(b) A Five-Shot Testing Data Example of the HellaSwag Task for the ALLM-EP Inference.

Choice 1: Ballet: We see a pregnant lady doing ballet in a studio. The lady spins and does a pliea. <AC> Demonstration 2 <AC> Demonstration 3 <AC> Demonstration 4 <AC> Demonstration 5 <AC> Slacklining: A group of people have stretched a tightrope across a gym. They *take turns trying to balance and walk on the rope*.

Choice 2: Ballet: We see a pregnant lady doing ballet in a studio. The lady spins and does a pliea. <AC> Demonstration 2 <AC> Demonstration 3 <AC> Demonstration 4 <AC> Demonstration 5 <AC> Slacklining: A group of people have stretched a tightrope across a gym. They *slide down with it, jumping and spinning in the air.*

Choice 3: Ballet: We see a pregnant lady doing ballet in a studio. The lady spins and does a pliea. <AC> Demonstration 2 <AC> Demonstration 3 <AC> Demonstration 4 <AC> Demonstration 5 <AC> Slacklining: A group of people have stretched a tightrope across a gym. They *cross it together*, *swinging back and fourth in anticipation*.

Choice 4: Ballet: We see a pregnant lady doing ballet in a studio. The lady spins and does a pliea. <AC> Demonstration 2 <AC> Demonstration 3 <AC> Demonstration 4 <AC> Demonstration 5 <AC> Slacklining: A group of people have stretched a tightrope across a gym. They *drop an orange rope at the end.*

(c) A Five-Shot Testing Data Example of the HellaSwag Task for the ALLM-AC Inference.

Table 5: Testing Data Examples for the AnLLM-EP and AnLLM-AC models. The log-likelihood of the red italicized texts is calculated as the choice probabilities.