DeltaLLM: A Training-Free Framework Exploiting Temporal Sparsity for Efficient Edge LLM Inference

Jiawen Qio, Chang Gaoo, Zhaochun Reno, Qinyu Cheno

Abstract—Deploying Large Language Models (LLMs) on edge devices remains challenging due to their quadratically increasing computations with the sequence length. Existing studies for dynamic attention pruning are designed for hardware with massively parallel computation capabilities, such as GPUs or TPUs, and aim at long context lengths (e.g., 64K), making them unsuitable for edge scenarios. We present DeltaLLM, a trainingfree framework that exploits temporal sparsity in attention patterns to enable efficient LLM inference across both the prefilling and decoding stages, on resource-constrained edge devices. DeltaLLM introduces an accuracy- and memory-aware delta matrix construction strategy that introduces temporal sparsity, and a context-aware hybrid attention mechanism that combines full attention in a local context window with delta approximation outside it to increase accuracy. We evaluate our framework on the edge-device-friendly BitNet-b1.58-2B-4T model and Llama3.2-1B-Instruct model across diverse language tasks. The results show that on BitNet, our framework increases the attention sparsity from 0% to 60% during the prefilling stage with slight accuracy improvement on the WG task, and 0% to 57% across both the prefilling and decoding stages, with even higher F1 score from 29.63 to 30.97 on SOuAD-v2 task. On the Llama model, it can also achieve up to 60% sparsity during the prefilling stage and around 57% across both stages with negligible accuracy drop. These results demonstrate that *DeltaLLM* offers a promising solution for efficient edge deployment, requiring no fine-tuning and seamlessly integrating with existing inference pipelines.

I. Introduction

LLMs, such as GPT [1] and LLaMA [2], have demonstrated remarkable capabilities across a wide range of natural language processing tasks. While traditionally deployed in the cloud environments with high-end GPUs (e.g., NVIDIA H100) or NPUs (e.g., Google TPU v7) due to their high computational and memory demands, there is a growing interest in bringing LLMs to edge devices to enable offline applications, avoid communication latency, and preserve privacy. However, deploying LLMs on traditional edge devices introduces significant challenges, as they have much fewer computational resources than high-end devices, restricted memory bandwidth, and limited power budget. These bottlenecks necessitate novel techniques in model sparsification [3], quantization [4], and other efficient inference methods [5], [6] to make on-device LLM inference viable without severely compromising performance.

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This work is supported by LIACS Strategic Postdocs and PhD Research Program 2024.

Pruning is one of the key techniques to reduce the massive computation burden of LLMs, eliminating less important components during computation. Recently, different levels of pruning strategies have been investigated in both linear and attention layers. Within the linear layers, trivial weights or activations are pruned according to different rules, such as Wanda [7] and TEAL [3]. In the attention layer, a large intrinsic sparsity of the attention score has been found [8]. Based on this observation, various techniques are proposed to select essential tokens among all tokens from the queries and keys before calculating the attention score. StreamingLLM [9] and Minference [10] select the tokens based on pre-defined patterns. SnapKV [11] determines the important key tokens for decoding using the knowledge from the prefilling stage. InfLLM [12], FlexPrefill [13], and SpargeAttn [14] dynamically determine significant tokens by partitioning queries and keys into blocks and estimating the attention score of the blocks. However, each of these existing methods comes with certain limitations. SteamingLLM loses too much accuracy because of its simple fixed pruning pattern. Minference, FlexPrefill, and SnapKV only work on either the prefilling stage or decoding stage. InfLLM and SpargeAttn require additional matrix multiplications and pooling operations to determine important tokens. The computational overhead is large compared with the common tasks themselves in edge scenarios. Therefore, efficiently accelerating the attention computation through pruning on edge devices is still worth exploring.

One way to increase the sparsity of the tokens is to convert dense vectors into temporally sparse vectors. The Delta Network [15] is a dynamic pruning method inspired by biological principles that neurons in the human brain illustrate sparse transmission activities. It transforms dense vectors into sparse delta vectors by computing differences between vectors that are consecutive in time and zeroing out small changes based on a delta threshold. It has been proven to successfully work on different types of deep learning models such as GRU [15], LSTM [16] and CNN [17]-[19] with additional fine-tuning. The corresponding customized hardware accelerators [20]-[22] exploiting this temporal sparsity are reported to gain up to 10× better energy efficiency. While the delta algorithm is applied on a small transformer-based model [23] with only around 5 M parameters for a simple classification task, it has not been investigated on LLMs with millions or billions of parameters.

This work proposes *DeltaLLM*, a training-free framework to exploit the attention sparsity in LLMs while still fitting the state-of-the-art inference paradigm for resource-constrained

edge devices. It is also easy to integrate into existing inference pipelines. Our work makes the following contributions:

- We propose an accuracy-aware and memory-aware delta matrix construction strategy, which determines how to build the delta matrix by introducing temporal sparsity. This strategy supports both prefilling and decoding stages, while preserving accuracy and minimizing memory overhead.
- We introduce a context-aware hybrid attention strategy that dynamically mixes full attention within a local context window and delta approximate attention outside the window to increase accuracy.
- We evaluate *DeltaLLM* on the edge-device-friendly BitNet-b1.58-2B-4T model and the LLaMA3.2-1B-Instruct model. On BitNet, our method increases attention sparsity from 0% to 60% during the prefilling stage, with a slight accuracy improvement on the WG task. When applied to both the prefilling and decoding stages, it achieves up to 57% sparsity and improves the F1 score on SQuAD-v2 from 29.63 to 30.97. For the LLaMA model, the framework similarly achieves up to 60% sparsity in the prefilling stage and around 57% across both stages, with negligible accuracy degradation. These results demonstrate the potential of our *DeltaLLM* framework to enable efficient on-device LLM inference by exploiting delta sparsity.

II. BACKGROUND AND RELATED WORK

A. Attention Mechanism and Inference Stages

Attention is the core operation that enables LLMs to condition every token on every other token in the same sequence to dynamically determine important information in the context. Concretely, for an input sequence $X \in \mathbb{R}^{n \times d}$, where n is the number of tokens in the current sequence and d is the embedding length of each token, it is linearly projected into queries Q, keys K, and values V (each in $\mathbb{R}^{n \times d_{head}}$). The process of the attention operation is described in Eq. (1). Firstly, QK^{\top} produces the attention score by the scaled dot product of tokens from queries and keys. Then the attention score is converted to a probability distribution through the rowwise softmax operation. Finally, the probability weighted sum with V blends information from the whole sequence into each token's new embedding.

Attention
$$(Q, K, V) = \operatorname{softmax}\left(\frac{QK^{\top}}{\sqrt{d_{head}}}\right)V$$
 (1)

The attention score requires $\Theta(n^2d)$ floating-point operations, where the operations keep increasing as the sequence length grows longer during the inference process. For LLMs to be deployed on edge devices, the quadratic term from attention computation dominates inference budgets when input sequences reach hundreds of tokens. This problem motivates the wide application of Key-Value (KV) caching to trade memory consumption for computations.

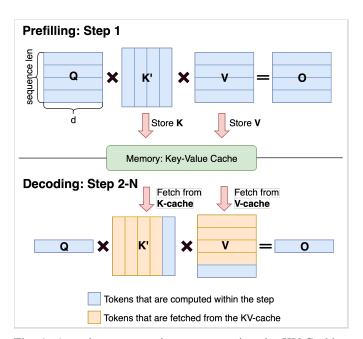


Fig. 1: Attention computation process using the KV-Caching technique.

As shown in Fig. 1, the inference process is divided into two stages: prefilling and decoding. During the prefilling stage, all input tokens are processed to generate the first new token. The corresponding key and value tokens generated during the prefilling stage are stored in memory. Then, during the decoding stage, the remaining tokens are computed autoregressively until the end of the sentence is reached. At each step, the model uses the previously generated token together with the stored keys and values to compute the new query, key, and value for the next prediction. By storing the keys and values, KV-caching reduces the computation complexity from $\Theta(n^2d)$ to $\Theta(nd)$. However, for edge devices with limited computation resources and restricted requirements on energy efficiency, it is of interest to reduce the computation further during both prefilling and decoding stages.

B. Pruning for Attention Score Computation

Pruning is one of the key techniques to further reduce the number of computations of the attention score (QK^{\top}) . For the decoding stage, StreamingLLM [9] is a static pruning method selecting tokens in the query and key matrix to partially compute the attention score following a fixed Λ -shape pattern. It is based on the observation that most attention scores in the attention score matrix are located within the attention sink (the first few columns in the attention score matrix) and the context window (elements close to the diagonal of the matrix), as shown in Fig. 2a. Although static methods are simple to compute, they often suffer from large accuracy degradation due to abandoning too many important tokens outside the fixed pattern, which is the case in Fig. 2b. In terms of the prefilling stage, Minference [10] predefined two more fixed patterns for different attention heads, but they require a pre-run of the

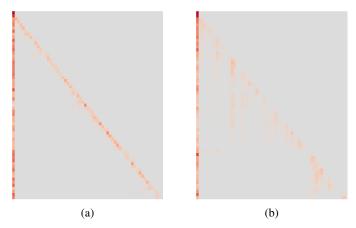


Fig. 2: Heatmap of attention scores in two different layers of LLaMA3.2 model during prefilling stage.

model to determine suitable parameters for different inputs. SpargeAttn [14] brings out the idea of generating a dynamic mask to help determine important tokens more accurately in the query and key before computing the similarity matrix. It improves the accuracy in long context scenarios while keeping a reasonable sparsity of around 50%. However, this method introduces large computation overhead, such as mean pooling and multiplication operations, making it inefficient for edge deployment. Therefore, it is of interest to design dedicated algorithms that enable efficient attention computation with little overhead on edge devices.

C. Delta Network Algorithm

The Delta Network algorithm is a biologically inspired algorithm to increase the sparsity of matrix multiplication, which converts regular dense matrix multiplication to temporally sparse matrix multiplication. Given two regular (dense) matrices A and B, the result of the dot product R is computed by two steps: generating the sparse delta matrix $\Delta A(t)$ and performing regular-delta matrix multiplication. Specifically, step (i): convert rows/columns a_0, a_1, \ldots, a_n from regular matrix A into a sequence of input vectors $a(0), a(1), \ldots, a(t)$. Then construct the delta matrix ΔA by sequentially computing a series of delta vectors $\Delta a(1), \Delta a(2), \dots, \Delta a(t)$ and stacking the basis vector a(0) with these delta vectors. These delta vectors are obtained by comparing the difference between the current input vector a(t) and the previous reference vector $\hat{a}(t-1)$ to a threshold value θ :

$$\Delta a(t) = \begin{cases} a(t) - \hat{a}(t-1), & |a(t) - \hat{a}(t-1)| > \theta \\ 0, & |a(t) - \hat{a}(t-1)| \le \theta \end{cases}$$

$$\hat{a}(t) = \begin{cases} a(t), & |a(t) - \hat{a}(t-1)| > \theta \\ \hat{a}(t-1), & |a(t) - \hat{a}(t-1)| \le \theta \end{cases}$$
(3)

$$\hat{a}(t) = \begin{cases} a(t), & |a(t) - \hat{a}(t-1)| > \theta \\ \hat{a}(t-1), & |a(t) - \hat{a}(t-1)| \le \theta \end{cases}$$
(3)

where $\hat{a}(0)$ is initialized to **0**. Step (ii): compute R(0) as the basis vector and calculate output vectors $R(1), \ldots, R(t)$

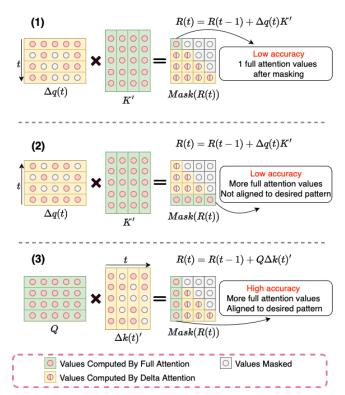


Fig. 3: Comparison of attention score accuracy under different delta matrix construction methods. Strategy (3) achieves the highest accuracy by aligning the preserved scores with the desired attention pattern.

recursively:

$$R(t) = \begin{cases} \Delta a(0)B, & t = 0\\ \Delta a(t)B + R(t-1), & t > 0 \end{cases}$$
 (4)

The output matrix is therefore the stack of R(t)

III. DELTALLM FRAMEWORK

In this section, we present *DeltaLLM*, a training-free framework that leverages temporal sparsity to accelerate attention computation in LLMs. We first describe our accuracy-aware and memory-aware strategy for constructing delta matrices (Section III-A), followed by our context-aware hybrid attention mechanism (Section III-B). Finally, we detail the complete workflow (Section III-C).

A. Accuracy-Aware and Memory-Aware Delta Matrix Construction Strategy

Standard attention mechanisms exhibit characteristic sparsity patterns where attention scores concentrate near the diagonal and in initial columns (the attention sink), as illustrated in Fig. 2. Preserving these salient regions is crucial for maintaining model performance. Additionally, the attention mask in the prefilling stage restricts active scores to the lower triangle of the attention map, which should be considered when constructing delta matrices.

Naive application of the Delta Network to both query and key matrices would introduce approximation errors uniformly across all attention scores, resulting in significant accuracy degradation. To address this challenge, we develop a strategic approach for delta matrix construction that preserves critical attention patterns while maximizing sparsity.

Prefilling Stage Analysis. In the prefilling stage, we observe that the choice of which matrix to transform (query or key) and which row is used as the basis (i.e., the order of computation) significantly impacts accuracy due to the masking and the presence of the attention sink. We empirically analyze three delta matrix construction strategies, illustrated in Fig. 3:

- (1) **Top-down query deltas:** Generate $\Delta q(t)$ starting from the top row of the query matrix while keeping keys unchanged. This produces a dense first row in the delta matrix, yielding exact computation for the first attention row. However, after masking, only the top-left attention score remains accurate, resulting in poor performance.
- (2) Bottom-up query deltas: Generate $\Delta q(t)$ starting from the bottom row of the query matrix. This improves upon strategy (1) by preserving all accurate scores after masking, as the dense row aligns with the unmasked region.
- (3) **Top-down key deltas:** Generate $\Delta k(t)$ starting from the top row of the key matrix while keeping queries unchanged. This strategy achieves optimal accuracy by preserving the entire first column of attention scores, which precisely aligns with the attention sink pattern critical for model performance.

Based on this analysis, we adopt strategy (3), using the key matrix as the source for delta computation with the first key vector as the basis.

Decoding Stage Considerations. Without attention masking in the decoding stage, the choice between query and key matrices for delta construction would theoretically yield similar accuracy. However, memory efficiency becomes the primary consideration. Selecting queries would require storing both previous queries q(t-1) and attention scores R(t-1) across all layers and heads. In contrast, using keys leverages the existing KV-cache infrastructure without additional memory overhead, as previous keys are already cached and attention scores need not persist between decoding steps.

Therefore, we consistently use the key matrix as the delta source during both stages for preserving the accuracy and memory efficiency. Additionally, we store delta vectors $\Delta k(t-1)$ rather than original keys k(t-1) in the KV-cache, eliminating redundant delta computations in subsequent steps.

B. Context-Aware Hybrid Attention Strategy

To improve accuracy while preserving sparsity, *DeltaLLM* incorporates a hybrid attention mechanism that applies full attention within a context window and delta-based approximate attention elsewhere.

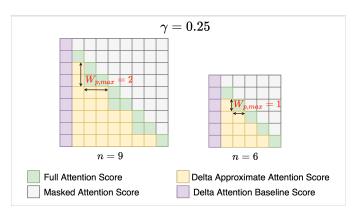


Fig. 4: Example of the full attention and delta approximate attention pattern at different input sequence lengths.

Prefilling Stage. Given an input sequence of length n which is known, we define a dynamic context window of maximum length $W_{p,max}$ along the attention matrix diagonal:

$$W_{p,max} = \min(|\gamma \cdot n|, W_{max}) \tag{5}$$

where $\gamma \in (0,1)$ is a predefined scaling factor that controls the length of the context window dynamically according to the input length, and W_{max} is an upper bound to avoid the context window from being too large.

Fig. 4 shows an example of the full attention and delta approximate attention pattern for different input lengths when $\gamma=0.25$. The initial pattern of the full attention score is a series of squares with length $W_{p,max}$ along the diagonal of the attention map. The characteristic "jigsaw" pattern emerges from the interaction with masking. Within this block, attention scores are computed using full attention to ensure accuracy in the most relevant regions. Outside the block, delta attention is applied to maintain sparsity. The reason to use a dynamic window size is to maintain the sparsity for various lengths of inputs.

Decoding Stage. Since the final sequence length is unknown during autoregressive generation, we employ a fixed context window W_d . The most recent W_d tokens receive full attention computation, while historical tokens beyond this window use delta approximation. This design ensures accurate modeling of immediate dependencies while efficiently processing the growing context.

The effective computational sparsity S_c achieved by our hybrid approach is:

$$S_c = \begin{cases} S_m \cdot (1 - W_{p,max}/n), & \text{prefilling} \\ S_m \cdot (1 - W_d/n), & \text{decoding} \end{cases}$$
 (6)

where S_m denotes the sparsity of the underlying delta matrix.

C. DeltaLLM Workflow

Fig. 5 illustrates the complete *DeltaLLM* workflow, seamlessly integrating our delta construction and hybrid attention strategies across both inference stages.

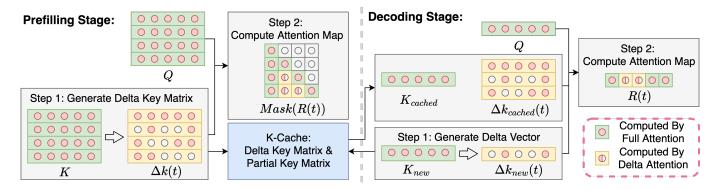


Fig. 5: Workflow of DeltaLLM.

During the prefilling stage, the process begins by constructing the delta key matrix ΔK from the input sequence. Using a small context window (e.g., $W_p=1$ in the illustration), we compute the attention map through our hybrid mechanism: full attention within the diagonal window and delta approximation elsewhere. To prepare for subsequent decoding, we cache both the complete delta matrix ΔK and the final W_d original key vectors (e.g., $W_d=2$ in the example).

During the decoding stage, for each new token generation, we compute its key vector k_{new} and corresponding delta Δk_{new} . The attention computation leverages the cached keys: recent tokens within the window W_d use original keys with full attention, while historical tokens use cached deltas for approximate attention. The K-cache is incrementally updated by Δk_{new} and k_{new} to compute the next token.

IV. EXPERIMENTS

We conduct comprehensive experiments to evaluate the effectiveness of *DeltaLLM* across different models and inference scenarios. This section presents our experimental methodology, followed by detailed results and analysis.

A. Experiment Setup

We evaluate our *DeltaLLM* framework on two representative models suitable for edge deployment: the LLaMA3.2-1B-Instruct model [24] and BitNet-b1.58-2B-4T [25]. The latter is a ternary quantized model with weights in -1,0,1, specifically optimized for resource-constrained and low-power scenarios. To test the effect of *DeltaLLM* in the prefilling and decoding stage, we measure the accuracy and sparsity introduced by the delta matrix under two different scenarios:

- Prefilling-only optimization: Apply DeltaLLM exclusively during the prefilling stage while maintaining standard attention in decoding. This scenario isolates the framework's effectiveness in handling initial context processing.
- End-to-end optimization: Apply DeltaLLM across both prefilling and decoding stages. This scenario evaluates the framework's full potential in complete inference pipelines.

For scenario (1), we evaluate the zero-shot performance on a range of language tasks: ARC-Easy [26], ARC-Challenge [26], BoolQ [27], Hellaswag [28], OpenbookQA [29], PIQA [30], Winogrande [31]. For scenario (2), the framework is evaluated on SQuAD-v2 [32]. All the experiments, including the baselines, are conducted by the unified evaluation framework: Im-evaluation-harness [33] with default settings on a single NVIDIA A100 GPU (40GB GPU memory). Importantly, no fine-tuning is performed—DeltaLLM operates as a purely inference-time optimization.

B. Experiment Results

Scenario (1) is designed to evaluate the impact of applying DeltaLLM during the prefilling stage only. We examine the impact of two hyperparameters: The delta threshold θ , which controls the sparsity of the constructed delta matrix, and the prefilling context window scaling factor γ , which determines the size of the full attention region.

Table I shows the results of the accuracy and sparsity by varying θ while fixing γ to 0.05. From the results, we observe that the model performance, both in terms of accuracy and sparsity, is affected by the choice of θ . Different models exhibit different sensitivities to θ : the LLaMA3.2-1B-Instruct model shows a clearer degradation in accuracy as θ increases, indicating a higher sensitivity to this hyperparameter. In contrast, the BitNet-b1.58-2B-4T model demonstrates a relatively stable accuracy across different θ values, suggesting it is more robust to threshold variations. BitNet maintains high accuracy across all evaluated tasks, for instance, on PQ when θ is increased to 1.2, sparsity is increased to 54.5% with even 0.1% accuracy improvement.

Table II presents the complementary analysis where the scaling factor γ is varied while keeping the threshold θ fixed (at 0.6 for LLaMA and 1.0 for BitNet). While changing γ also influences model performance, the extent of variation is generally smaller than that caused by θ . Slight accuracy improvements can be observed at intermediate γ values. For example, setting $\gamma=0.1$ leads to accuracy gains in LLaMA on the ARCc and OQ, and in BitNet on ARCc, OQ, and PQ.

In scenario (2), we further apply *DeltaLLM* to both the prefilling and decoding stages and evaluate the performance

	ARCe		ARCc		BQ		HS		OQ		PQ		WG	
	Acc_n	S_c	Acc_n	S_c	Acc	S_c	Acc_n	S_c	Acc_n	S_c	Acc_n	S_c	Acc	S_c
LLaMA (baseline)	63.25	0.00	37.88	0.00	69.11	0.00	60.80	0.00	34.40	0.00	74.04	0.00	59.90	0.00
LLaMA ($\theta = 0.6$)	62.84	36.78	37.46	36.85	68.84	42.83	60.33	40.18	34.00	31.86	72.75	36.75	57.70	39.87
LLaMA ($\theta = 0.8$)	61.62	45.42	36.10	46.45	68.32	52.62	59.68	49.56	33.80	39.92	73.51	45.65	58.33	48.85
LLaMA ($\theta = 1.0$)	61.03	52.88	36.10	54.70	67.34	60.68	58.49	57.45	35.20	46.51	72.64	52.55	55.96	56.04
BitNet (baseline)	75.00	0.00	49.65	0.00	80.48	0.00	68.45	0.00	41.80	0.00	76.98	0.00	72.45	0.00
BitNet ($\theta = 1.0$)	74.54	46.83	49.23	48.98	79.63	58.63	68.02	53.31	42.00	46.34	76.83	47.41	71.59	56.33
BitNet ($\theta = 1.2$)	74.11	53.01	50.17	56.06	79.64	65.40	67.65	60.10	40.80	52.04	77.10	54.49	71.43	62.98
BitNet $(\theta = 1.4)$	74.54	57.82	49.06	61.49	79.33	70.59	67.25	65.38	40.60	56.28	76.44	60.31	70.56	68.00

TABLE I: *DeltaLLM* on the prefilling stage. Various θ , $\gamma = 0.05$.

	ARCe		ARCc		BQ		HS		OQ		PQ		WG	
	Acc_n	S_c	Acc_n	S_c	Acc	S_c	Acc_n	S_c	Acc_n	S_c	Acc_n	S_c	Acc	S_c
LLaMA (baseline) LLaMA ($\gamma = 0.1$) LLaMA ($\gamma = 0.05$)	63.25 62.97 62.84	0.00 36.78 37.78	37.88 38.57 37.46	0.00 33.00 36.85	69.11 68.87 68.84	0.00 40.32 42.83	60.80 60.51 60.33	0.00 37.47 40.18	34.40 35.00 34.00	0.00 31.86 31.86	74.04 72.58 72.75	0.00 32.25 36.75	59.90 58.57 57.70	0.00 36.79 39.87
$LLaMA (\gamma = 0.02)$	62.25	40.35	37.38	36.85	68.11	44.20	60.03	42.67	34.80	31.86	72.42	36.75	57.62	42.60
BitNet (baseline) BitNet ($\gamma = 0.1$)	75.00 74.74	0.00 46.82	49.65 49.92	0.00 43.86	80.48 79.82	0.00 55.10	68.45 68.06	0.00 49.61	41.80 42.40	0.00 46.33	76.98 77.04	0.00 41.37	72.45	0.00 52.27
BitNet ($\gamma = 0.05$) BitNet ($\gamma = 0.02$)	74.54 74.50	46.83 51.40	49.23 49.75	48.97 48.98	79.63 79.73	58.63 70.59	68.02 68.03	53.31 60.48	42.00 41.40	46.34 46.34	76.83 76.88	47.41 47.41	71.59 72.54	56.33 60.20

TABLE II: DeltaLLM on the prefilling stage. Various γ , $\theta = 0.6$ for the Llama3.2-1B-Instruct model and $\theta = 1.0$ for BitNet-b1.58-2B-4T model.

on SQuAD-v2. For each model, we adopt the hyperparameter settings that achieved the best average performance in scenario (1), and set the $W_d=4$. As illustrated in Table III, this configuration enables BitNet to achieve approximately 57% while even improving the F1 score from 29.63 to 30.97 on BitNet.

	HasAns: F1	S_c
LLaMA (baseline) LLaMA ($\theta=0.6, \gamma=0.1, W_d=4$)	53.65 52.31	0.00 56.85
$\label{eq:bitNet} \hline \\ \text{BitNet (baseline)} \\ \text{BitNet } (\theta=1.0, \gamma=0.1, W_d=4) \\ \hline$	29.63 30.97	0.00 57.24

TABLE III: DeltaLLM on both stages on SQuAD-v2.

Overall, the proposed DeltaLLM framework defines a flexible design space characterized by tunable hyperparameters. By appropriately selecting these parameters, one can navigate the trade-off between accuracy and computational sparsity. Experimental results across multiple benchmarks demonstrate that, in certain configurations, *DeltaLLM* even improves accuracy while reducing computation. This makes the framework particularly promising for deployment on efficient hardware, as it enables dynamic sparsity control tailored to both task requirements and resource constraints.

V. CONCLUSION

In this paper, we propose *DeltaLLM*, a training-free framework that enables efficient LLMs inference on resource-constrained edge devices by exploiting temporal sparsity in attention computation to reduce the heavy computation load. Unlike existing methods designed for high-end hardware or

long-context scenarios, DeltaLLM introduces two key innovations tailored for edge deployment: (1) an accuracy- and memory-aware delta matrix construction strategy that selectively prunes key vectors, and (2) a context-aware hybrid attention mechanism that combines full and approximate attention, across varying sequence lengths. The results show that *DeltaLLM* can increase sparsity while even improving the accuracy on some tasks such as SQuAD-v2. Our *DeltaLLM* framework can be seamlessly integrated into existing inference pipelines and combined with other compression techniques such as quantization to boost the inference speed of LLMs on edge devices.

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