

# Compressed Convolutional Attention: Efficient Attention in a Compressed Latent Space

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**Abstract**—Multi-headed Attention’s (MHA) quadratic compute and linearly growing KV-cache make long-context transformers expensive to train and serve. Prior works such as Grouped Query Attention (GQA) and Multi-Latent Attention (MLA) shrink the cache, speeding decode, but leave compute, which determines prefill and training speed, largely unchanged. We introduce Compressed Convolutional Attention (CCA), a novel attention method which down-projects queries, keys, and values and performs the entire attention operation *inside the shared latent space*. This simple design dramatically cuts parameters, KV-cache, and FLOPs all at once by the desired compression factor. Because CCA is orthogonal to head-sharing, we combine the two to form Compressed Convolutional Grouped Query Attention (CCGQA), which further tightens the compute–bandwidth Pareto frontier so that users can tune compression toward either FLOP or memory limits without sacrificing quality. Experiments show that CCGQA consistently outperforms both GQA and MLA at equal KV-cache compression on dense and MoE models. Additionally, we show that CCGQA outperforms all other attention methods on MoE models with half the KV-cache of GQA and MLA, achieving an 8x KV-cache compression with no drop in performance compared to standard MHA. CCA and CCGQA also dramatically reduce the FLOP cost of attention which leads to substantially faster training and prefill than existing methods. On H100 GPUs, our fused CCA/CCGQA kernel reduces prefill latency by about 1.7× at a sequence length of 16k relative to MHA, and accelerates backward by about 1.3×.

## I. INTRODUCTION

Self-attention is the core sequence-mixing component of the ubiquitous transformer architecture (Vaswani et al., 2017; Brown et al., 2020; Kaplan et al., 2020). While self-attention is extremely expressive, enabling every token to attend to every other token, this expressivity comes at a high computational cost. Attention has quadratic complexity in both the model hidden dimension and sequence dimension. Moreover, during autoregressive generation the KV-cache grows linearly with sequence length and hidden size, incurring huge memory-bandwidth costs that cannot be amortized across batches. These issues become especially problematic with long contexts in “reasoning models” (Guo et al., 2025; Lambert et al., 2024), which produce extended chains of thought before responding. Serving models with KV-caches larger than a single GPU requires expensive context-parallelism approaches like Ring or Tree Attention (Liu et al., 2023; Shyam et al., 2024) and makes

autoregressive decoding memory-bandwidth bound, limiting hardware utilization.

A number of approaches in the literature have attempted to address this fundamental bottleneck. One popular approach is to create novel architectures such as state-space-models that eliminate the quadratic nature of self-attention entirely and instead utilize a constant size state rather than a linearly growing KV-cache (Gu et al., 2021; Gu & Dao, 2023; Katharopoulos et al., 2020; Yang et al., 2024a; Sun et al., 2023; Peng et al., 2023). However, these architectures tend to be less expressive than attention and often underperform on more complex tasks requiring sustained reasoning or in-context learning Jelassi et al. (2024); Park et al. (2024); Grazzi et al. (2024). This led to the proposal of hybrid architectures (Glorioso et al., 2024b,a; Lieber et al., 2024; Waleffe et al., 2024; Chu et al., 2024), which combine both SSMs and attention, and can achieve the best of both worlds. However, since hybrids still contain some attention, they do not ultimately eliminate the quadratic bottleneck either. Other approaches maintain the quadratic nature of self-attention but try to compress the KV-cache directly, usually in an offline fashion (Ge et al., 2023; Yang et al., 2024b; Kim et al., 2024; Liu et al., 2024). Such methods can achieve significant compression rates, but often come at a large cost to generation quality.

While these methods are more speculative and have not been ubiquitously adopted, fundamental improvements have also been made in the core self-attention operation. Multi-query attention (MQA) (Shazeer, 2019), and grouped query attention (GQA) (Ainslie et al., 2023) keep the core self-attention primitive and reduce the KV-cache requirements by parameter-sharing across K and V heads. GQA has seen significant recent adoption for language model pretraining being used in Jiang et al. (2023); Touvron et al. (2023); Abdin et al. (2024) and results in significant improvement in inference speed. Recently, another attention variant named Multi-Latent Attention (MLA) (DeepSeek-AI, 2025b) took a different approach by learning to directly compress the K and V projections needed for the KV-cache.

We consider GQA and MLA to each be instances of separate strategies for reducing the KV-cache. GQA uses parameter-sharing of the K and V heads. This reduces memory requirements, since the KV-cache effectively consists of many copies

of the same K and V heads, which can be merged. GQA does not reduce the FLOPs needed for training or prefill compared to MHA. However, for autoregressive generation, which is typically memory-bandwidth-bound, the savings in parameters that need to be loaded per token leads to a substantial increase in throughput.

MLA, by contrast, compresses the keys and values into a smaller, learnable, and shared subspace, which can then be used for generation. It uses this learnt subspace for storage of the KV-cache and up-projects back to the full dimension for the actual attention operation. This means that MLA does not offer compute savings in training or prefill over MHA or GQA and is in fact slightly more expensive in compute and parameters due to the up-projections. MLA also has additional complications due to RoPE (Su et al., 2023), which cannot operate directly on the compressed cache, so MLA must keep a separate key RoPE cache shared across heads. During decoding, however, MLA possesses an ‘MQA-mode’ which merges the up-projections for the shared-KV cache into the query up-projection and output projection. This significantly reduces the memory bandwidth-required during decoding.

Both GQA and MLA focus primarily on reducing the KV-cache, which is important for decoding speed, but do not meaningfully reduce the fundamental compute cost of attention which is the performance bottleneck in both training and inference prefill. Prefill performance is especially important during long-context workloads where the vast majority of tokens are inputs to the model rather than generated.

In this paper, we present Compressed Convolutional Attention (CCA), an elegant parameter- and compute- compression method, which removes the drawbacks of MLA and outperforms it in practice. Specifically, CCA performs the attention operation *entirely in the compressed latent space*, meaning that it can reduce the compute required for attention by a factor of the query compression rate, but also that it can seamlessly integrate RoPE without requiring separate heads and cache. By performing the full attention in the compressed space, CCA has substantial parameter savings at a fixed compression rate compared to MLA since it eschews the needs for QKV up-projection matrices.

While we found that naively performing attention on the compressed QKV latents incurs a significant performance penalty, we discovered that by performing additional convolutional sequence and channel mixing on the compressed Q and K latents, we can exceed the performance of MLA and even MHA. CCA outperforms all other methods, including both GQA and MLA at equal KV-cache compression rates in MoE settings with 4x less FLOPs.

Moreover, since parameter-compression and parameter-sharing approaches can be jointly utilized, we find it is productive to combine them in a method we call Compressed Convolutional Grouped Query Attention (CCGQA) which applies a GQA-style K and V head sharing within the already compressed latent space. This enables us to achieve an additional 2x KV cache reduction without performance penalty. (CCGQA also allows us to decouple the compression rates of

queries and keys, since we can replicate compressed keys to match less compressed queries). Additionally, we show that in a parameter-matched setting for MoEs, CCA can outperform MLA along both compute and KV-cache dimensions, thus creating a smooth Pareto frontier for CCA and CCGQA in which a trade-off can be made between compute-bound and memory-bandwidth-bound scenarios without sacrificing performance. Thus, CCA is a highly versatile method capable of improving performance in both single- or large-batch inference settings and can be flexibly adjusted to a wide variety of possible parallelism settings during pretraining.

In addition to the benefits in model quality at a fixed parameter budget and memory overhead, executing attention entirely in the compressed latent makes CCA—and its grouped variant CCGQA—substantially faster in practice. Because the  $S^2$  terms in  $QK^\top$  and Attn·V shrink by  $1/C$ , the speedup compared to MHA grows with sequence length. We implemented a fused kernel for CCGQA and found that on an H100 in BF16 with  $E=2048$ , CCA-4 $\times$  yields  $\approx 1.6-1.7\times$  lower prefill latency than MHA at  $S=16k$  across head dimensions  $d_h \in \{64, 128, 256\}$  ( $\sim 1.3-1.4\times$  vs. GQA-8 and  $\sim 1.3-1.5\times$  vs. MLA), while forward-causal shows  $\sim 1.6-1.9\times$  gains. Training backward is also faster by  $\approx 1.2-1.3\times$  at the same length. A decoupled CCA configuration with  $C_1=2$  for queries and  $C_2=8$  for keys/values retains strong efficiency, delivering  $\sim 1.3-1.4\times$  prefill speedup over MHA and  $\sim 1.1-1.3\times$  over GQA-8 at  $S=16k$ , while preserving the KV-cache savings and the theoretical  $1/C$  scaling.

TABLE I: Notation used throughout the paper.

| Symbol                                  | Definition / role   |
|---|---|
| $B$                                     | Batch size (number of sequences processed in parallel)    |
| $S$                                     | Sequence length (tokens per sequence)                     |
| $E$                                     | Model embedding / residual dimension                      |
| $n_h$                                   | Number of attention heads                                 |
| $d$                                     | Per-head dimension ( $d = E/n_h$ )                        |
| $G$                                     | Number of groups in GQA                                   |
| $C$                                     | Compression factor in CCA ( $C = E/\tilde{e}$ )           |
| $C_1, C_2$                              | Query-compression and KV-compression factors in CCGQA     |
| $c_q$                                   | Query compression factor in MLA                           |
| $c_{kv}$                                | Key/Value compression factor in MLA                       |
| $\tilde{e}$                             | Latent dimension after compression ( $\tilde{e} = E/C$ )  |
| $d_h$                                   | Latent per-head size ( $d_h = \tilde{e}/n_h$ )            |
| $x \in \mathbb{R}^{S \times E}$         | Input/residual token embeddings                           |
| $W_Q, W_K, W_V, W_O$                    | Standard projection matrices ( $E \times E$ )             |
| $\tilde{W}_Q, \tilde{W}_K, \tilde{W}_V$ | Down-projections to latent space ( $E \times \tilde{e}$ ) |
| $C_{KV}$                                | Shared compressed key-value cache                         |
| $C_Q$                                   | Compressed query latent                                   |
| $\tilde{q}, \tilde{k}, \tilde{v}$       | Compressed query, key, and value tensors                  |
| $o_h$                                   | Output of attention head $h$                              |
| $\beta$                                 | Learnable temperature scaling for keys                    |

## II. METHOD

### A. Preliminaries

#### 1) Multihead Attention (MHA)

Classical multi-head attention (MHA) (Vaswani et al., 2017) operates on the input embedding  $x \in \mathcal{R}^{S \times E}$  coming from the residual stream in a transformer, where  $S$  is the sequence length and  $E$  is the residual stream dimension (we omit the batch dimension to keep notation clearer), and produces the query  $q$ , key  $k$ , and value  $v$  matrices through separate linear projections of the embeddings:

$$\begin{aligned} q &= xW_Q \\ k &= xW_K \\ v &= xW_V \end{aligned} \quad (1)$$

The  $q, k, v$  projections are split into separate independent ‘heads’, such that  $q = [q_1, q_2 \dots q_{n_h}]$  where  $n_h$  is the number of heads. Each head has dimension  $d = E/n_h$ . The intuition behind this is that each head can be operated on independently and in parallel by attention, allowing them to specialize in attending to different aspects of the input.

Given the query, key, and value heads, we perform the softmax attention operation for each head independently then recombine the heads with the output projection  $W_o$ ,

$$\begin{aligned} o_h &= v_h \text{softmax} \left( \frac{q_h k_h^T}{\sqrt{d}} \right) \\ \text{out} &= W_o [o_1, o_2 \dots o_{n_h}] \end{aligned} \quad (2)$$

where  $h$  is the head index. Due to the  $q_h k_h^T$  term, attention computation scales quadratically in the sequence dimension. Since the  $W_q, W_k, W_v, W_o$  matrices are of dimension  $E \times E$ , it also scales quadratically in the channel dimension. For autoregressive generation, we typically store each  $k_h$  and  $v_h$  for each sequence element  $t$  in the KV-cache, which is thus of size  $2 \times S \times E$ .

#### 2) Grouped Query Attention (GQA)

GQA (Ainslie et al., 2023) is a method that aims to reduce the KV-cache size by sharing the parameters across K and V heads. Specifically, GQA splits the heads up into groups and sets the parameters of all the heads in a group to be equal. For example, for two groups of four heads, GQA asserts the following equality:  $k_{g1} = k_1 = k_2 = k_3 = k_4; k_{g2} = k_5 = k_6 = k_7 = k_8$ . Since all the heads within a group share the same parameters, they do not need to be stored separately within the KV-cache, allowing us to achieve  $n_h/G$  memory savings, where  $G$  is the number of groups. MQA (Shazeer, 2019) is the extremal version of GQA with  $G = 1$ , such that all pairs of key and value heads share the same parameters which reduces the KV-cache memory by a factor of  $n_h$ . However, this typically comes at a steep performance cost. GQA lets us interpolate between MHA and MQA to smoothly trade-off KV-cache size and model quality.

#### 3) Multi-Latent Attention (MLA)

MLA takes a different approach to reducing KV-cache size. Instead of sharing parameters, MLA projects the K and V parameters into a smaller shared latent space  $C_{KV} \in \mathcal{R}^{S \times \tilde{e}}$  from which the full K and V can then be (lossily) reconstructed. Here,  $\tilde{e}$  is the dimension of the compressed space. The compression is done with linear down-projections, such as  $\tilde{W}_{DKV} \in \mathcal{R}^{E \times \tilde{e}}$ ,

$$\begin{aligned} C_{KV} &= x\tilde{W}_{DKV} \\ C_Q &= x\tilde{W}_{DQ} \end{aligned} \quad (3)$$

In the KV-cache, we then only need to store the compressed representation  $C_{KV}$  which is  $\tilde{e}/E$  times smaller than the uncompresses MHA KV-cache. In MLA we typically compress queries by a smaller factor than the keys and values. Given the compressed cache, the K and V heads are generated using separate up-projection matrices of shape  $\tilde{e} \times E$ ,

$$\begin{aligned} [q_1, q_2 \dots q_{n_h}] &= \tilde{W}_{UQ} C_Q \\ [k_1, k_2 \dots k_{n_h}] &= \tilde{W}_{UK} C_{KV} \\ [v_1, v_2 \dots v_{n_h}] &= \tilde{W}_{UV} C_{KV} \end{aligned} \quad (4)$$

In the NoPE (Wang et al., 2024) setting, MLA is advantageous as one can amortize all up-projections at test time and transform into MQA using the following relation:

$$\begin{aligned} \text{softmax}(\underbrace{C_Q^\top W_{UQ}}_{q \in \mathbb{R}^{1 \times d_h}} \underbrace{W_{UK}^\top C_{kv}}_{k^\top \in \mathbb{R}^{d_h \times N}}) \underbrace{C_{kv}^\top W_{UV}}_{v \in \mathbb{R}^{N \times d_h}} W^o = \\ \text{softmax}(\underbrace{C_Q^\top W_{UQ} W_{UK}^\top}_{q' \in \mathbb{R}^{n_h \times d}} \underbrace{\underbrace{C_{kv}}_{k'^\top \in \mathbb{R}^{d \times N}}} \underbrace{\underbrace{C_{kv}^\top}_{v' \in \mathbb{R}^{N \times d}} W_{UV} W^o} \end{aligned} \quad (5)$$

The case of RoPE, however, is more complicated. We cannot apply the RoPE rotation matrix directly to the  $C_{KV}$  cache if we want to merge up- and down-projections perfectly at inference time. In MLA, the key RoPE head is shared across all heads. To handle this, we define special RoPE heads and RoPE cache,

$$\begin{aligned} q^r &= \text{RoPE}(W_{UQR} C_Q) \\ k^r &= \text{RoPE}(W_{KRx} x) \\ q &= [q_1, \dots q_{n_h}, q_1^r \dots q_{n_h}^r] \\ k &= [k_1, \dots k_{n_h}, k^r \dots k_{n_h}^r] \end{aligned} \quad (6)$$

With the concatenated RoPE and non-RoPE query and key heads, attention is then performed as in MHA. By compressing K and V into the shared latent  $C_{KV}$ , MLA can achieve significant reductions in KV-cache memory and attention parameters vs MHA. However, the up-projections add significant parameter overhead, and the shared key RoPE decreases expressivity of the positionally encoded information. In addition, since the q, k, v vectors are up-projected prior to attention, MLA uses approximately the same number of FLOPs in attention as MHA during training. During inference, MLA is advantageous due to the conversion of MHA to MQA via the amortized

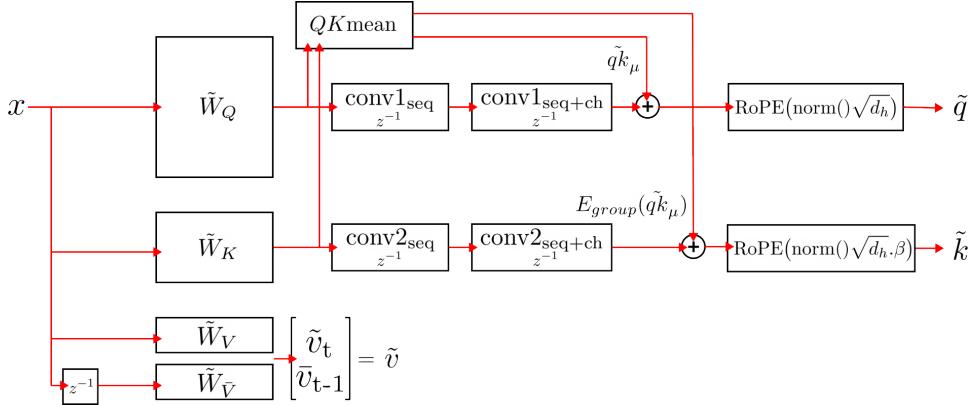


Fig. 1: Diagram of the operations involved in the CCA block. This diagram describes the computation of the compressed latent query, key, and value vectors prior to performing standard Flash Attention on the compressed latents. The input  $x$  is first down-projected using the  $\tilde{W}_Q, \tilde{W}_K, \tilde{W}_V$  matrices, then the two convolution operations are performed followed by the QK-mean operation, then normalization. For the V matrix, we do not apply any convolutions, but instead apply the v-shift operation.

| Attention | Parameters  | KV-cache                     | Forward FLOPs  | Decode FLOPs  |
|-----------|---|------------------------------|--|---|
| MHA       | $4E^2$  | $2BSE$                       | $8BSE^2 + 4BES^2$  | $8BE^2 + 4BES$  |
| GQA       | $2E^2 + 2\frac{E^2}{G}$                             | $2\frac{BSE}{G}$             | $(1 + \frac{1}{G})(4BSE^2) + 4BES^2$   | $(1 + \frac{1}{G})(4BE^2) + 4BES$   |
| MLA       | $E^2 + 3\frac{E^2}{c_{kv}} + 2\frac{E^2}{c_q}$      | $\frac{BSE}{c_{kv}} + BSE_r$ | $2BSE^2 + 4BS\frac{E^2}{c_q} + 6BS\frac{E^2}{c_{kv}} + 4BES^2$               | $(2BE^2 + 2BN_hE^2)(\frac{1}{c_{kv}}) + \frac{2BN_hE^2}{c_q c_{kv}} + \frac{2BE^2}{c_q} + \frac{4BESN_h}{c_{kv}}$ |
| CCA       | $4\frac{E^2}{C} + \text{Conv}$                      | $2\frac{BSE}{C}$             | $(\frac{2}{C})(4BSE^2) + \frac{4BES^2}{C} + \text{Conv}$                     | $(\frac{2}{C})(4BE^2) + \frac{4BES}{C} + \text{Conv}$   |
| CCGQA     | $2\frac{E^2}{C_1} + 2\frac{E^2}{C_2} + \text{Conv}$ | $2\frac{BSE}{C_2}$           | $(\frac{1}{C_1} + \frac{1}{C_2})(4BSE^2) + \frac{4BES^2}{C_1} + \text{Conv}$ | $(\frac{1}{C_1} + \frac{1}{C_2})(4BE^2) + \frac{4BES}{C_1} + \text{Conv}$   |

† Conv term. For CCA let  $\tilde{e} = E/C$ ,  $h$  be the number of heads. Conv-layer parameters =  $2\tilde{e} k_{\text{seq}} + \frac{\tilde{e}^2}{h} k_{\text{ch}}$ . Training FLOPs =  $2BS \left( 2\tilde{e} k_{\text{seq}} + \frac{\tilde{e}^2}{h} k_{\text{ch}} \right)$ ; decode FLOPs =  $= 2B \left( 2\tilde{e} k_{\text{seq}} + \frac{\tilde{e}^2}{h} k_{\text{ch}} \right)$ . For CCGQA replace  $\tilde{e}$  by  $\tilde{e} = \frac{E}{C_1} + \frac{E}{C_2}$  and  $h$  by  $h_q + h_k$ . Kernel sizes are  $k_{\text{seq}}$  (depth-wise causal) and  $k_{\text{ch}}$  (grouped).

TABLE II: Comparison of parameter count, KV-cache size, and computational complexity (FLOPs) for different attention mechanisms.  $E$  denotes the residual embedding dimension,  $B$  is the batch size,  $S$  is the sequence length,  $G$  is the group size in GQA and  $C$  denotes the compression factor in CCA. For MLA we use separate compression factors  $c_q, c_{kv}$  to denote the low rank dimensions for query (with RoPE) and the shared KV-cache (we omit the shared key-RoPE and query-RoPE inference projection for the FLOPs calculation. This means that MLA’s FLOPs are actually slightly higher than shown). For CCGQA we introduce two separate compression factors, one for queries and one for keys and values, denoted by  $C_1, C_2$ .  $E_r$  denotes the RoPE dimension in MLA. We observe that CCA has both significantly fewer parameters and smaller KV-cache requirements than alternative methods and also, unlike all other methods, reduces the ultimate attention FLOPs required. A full table of notation can be found in Table I

up-projections when memory-bandwidth bound (see Appendix B for a detailed discussion). While being parameter efficient, MQA is not entirely advantageous in multi-device inference in tensor-parallel settings, as each device would receive a copy of the shared KV latent before performing attention, which wastes potential expressivity.

### B. Compressed Convolutional Attention (CCA)

Our proposed CCA method follows MLA and GQA in compressing the KV-cache, but performs attention purely in the compressed latent space. This enables RoPE to be seamlessly integrated without the need of special RoPE heads and projections, reduces the training parameter cost by more than  $2\times$  compared to MLA since we no longer require up-projection matrices, and reduces attention FLOPs by the compression factor  $E/\tilde{e}$ , which can be substantial even if it

does not directly address the quadratic compute bottleneck. For instance, CCA with a  $16\times$  compression enables  $\sqrt{16} = 4\times$  longer sequences to be processed for the same FLOP budget. Like MLA, CCA performs a linear down-projection of the queries, keys, and values into a compressed latent space. However, to maintain and enhance performance, CCA then performs three key innovations: convolutional mixing across both sequence and channel dimensions, q-k-mean, and value-shift prior to performing standard attention on the adjusted q, k, v.

The first step of CCA is projecting  $q$  and  $k$  into the compressed latent space with matrices  $\tilde{W}_Q, \tilde{W}_K \in \mathcal{R}^{E \times \tilde{e}}$ :

$$\begin{aligned} \tilde{q} &= [\tilde{q}_1, \tilde{q}_2, \dots, \tilde{q}_{n_h}] = \tilde{W}_Q x \\ \tilde{k} &= [\tilde{k}_1, \tilde{k}_2, \dots, \tilde{k}_{n_h}] = \tilde{W}_K x \end{aligned} \quad (7)$$

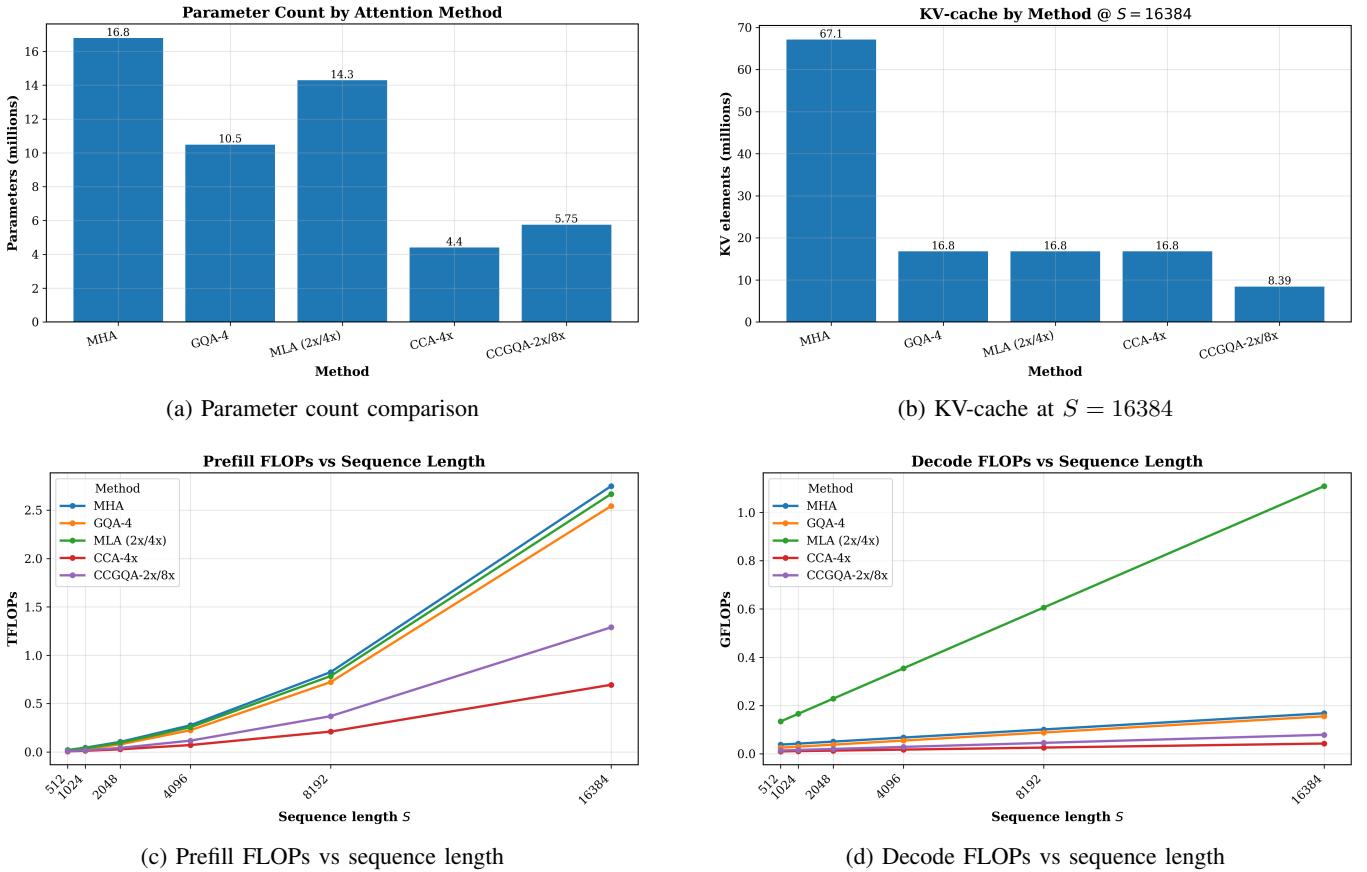


Fig. 2: Theoretical computational and memory complexity analysis across attention mechanisms with  $E = 2048$ . (a) Parameter counts show compression methods reduce model size. (b) KV-cache memory at long context demonstrates substantial savings. (c) Prefill and (d) decode FLOPs exhibit quadratic and linear scaling with sequence length respectively. Note that these are theoretical FLOP counts. See empirical latency measurements in Figures 10-18. Our kernel implementation will be further improved through better operator fusion and memory access patterns. See Appendix V for more details on MLA inference considerations.

Unlike MLA, since we are performing the full attention in the compressed latent space, we compress the queries by the same factor as keys and values. In the CCGQA case, where we are repeating key and value heads, we can compress queries less, up to a multiple of the number of groups.

We find that performing convolutional mixing across both the sequence and channel dimensions (within a head) for  $q$  and  $k$  can substantially improve the resulting performance of CCA. Our intuition is that these convolutions give additional expressivity to the transforms learned in the latent space, and that this additional smoothing allows better information transfer and preservation through attention, similar to how the causal convolution prior to the SSM in Mamba (Gu & Dao, 2023) improves sequence mixing performance. In a similar vein, recently-proposed “canon layers” are convolutional mixing layers applied across MLP and attention layers (Allen-Zhu, 2025). Unlike canon layers, we only apply convolutions to  $q$  and  $k$  operations within the attention blocks, and use a sequence of two convolution layers instead of one. We find that mixing both across channels within a head (ch) and across the

sequence (seq) is helpful.

$$\begin{aligned}\tilde{q} &= \text{conv2}_{\text{seq+ch}}(\text{conv1}_{\text{seq}}(\tilde{q})) \\ \tilde{k} &= \text{conv2}_{\text{seq+ch}}(\text{conv1}_{\text{seq}}(\tilde{k}))\end{aligned}\quad (8)$$

Next, we perform the q-k-mean operation, which adds the mean of the values of  $q$  and  $k$  pre and post convolution to the convolved values. Intuitively, this helps share information between  $q$  and  $k$ , and also allows the model to interpolate the strength of the convolution by providing a skip connection. Geometrically, this increases the sparsity of the attention diagonal when combined with QK-norm. We compute this as follows:

$$\begin{aligned}\tilde{qk}_\mu &= \frac{1}{2}(\tilde{q}_{\text{pre}} + B_{\text{group}}(\tilde{k}_{\text{pre}})) \\ \tilde{q} &= \tilde{q} + \tilde{qk}_\mu \\ \tilde{k} &= \tilde{k} + E_{\text{group}}(\tilde{qk}_\mu)\end{aligned}\quad (9)$$

Where  $\tilde{q}_{\text{pre}}$  and  $\tilde{k}_{\text{pre}}$  are the  $q$  and  $k$  latent priors to the convolution. Operation  $B_{\text{group}}(\cdot)$  is performing broadcast among the heads for the queries that have the same key assigned.

| Model | Loss  | HellaSwag | ARC Easy | ARC HARD | Piqa | Winogrande | Avg  |
|-------|-------|-----------|----------|----------|------|------------|------|
| MHA   | 2.297 | 58.9      | 63.4     | 37.2     | 74.5 | 56.8       | 58.2 |
| MLA   | 2.321 | 57.8      | 63.3     | 35.4     | 74.6 | 57.6       | 58.2 |
| GQA   | 2.297 | 58.6      | 62.3     | 34.7     | 73.5 | 56.9       | 57.2 |
| CCA   | 2.307 | 57.4      | 62.4     | 34.7     | 74.0 | 56.7       | 57.0 |
| CCGQA | 2.286 | 59.6      | 62.6     | 36.0     | 75.0 | 59.7       | 58.6 |

TABLE III: Table of loss and evaluation scores for CCA, MHA, and related attention methods for a dense 1B parameter model trained for 300B tokens on the Zyda2 dataset.

Operation  $E_{\text{group}}(\cdot)$  is just performing the mean across the heads that are combined into a single one for the keys. Both  $B_{\text{group}}$  and  $E_{\text{group}}$  are used in our GQA version of CCA, in which keys and values are shared in a group.

Finally, for the value projection, we introduce an operation referred to as *value-shift*. Here, each attention head receives two distinct types of value vectors: one derived from the current input embedding, and another generated from the previous embedding in the sequence. These two value types are produced through independent transformations, each with its own set of parameters. Each one of these will generate the values needed for half of the heads.

$$\begin{aligned} \tilde{v}_t &= \tilde{W}_V x_t \\ \bar{v}_{t-1} &= \tilde{W}_{\bar{V}} x_{t-1} \\ \tilde{v} &= [\tilde{v}_t, \bar{v}_{t-1}] \end{aligned} \quad (10)$$

Given the compressed latent vectors  $\tilde{q}, \tilde{k}, \tilde{v}$ , we then perform Q, K L2 normalization and scale by the square-root of the head dimension, multiply the key by a learnable temperature parameter  $\beta$  and apply RoPE before performing standard attention,

$$\begin{aligned} \tilde{q} &= \text{RoPE}(\text{norm}(\tilde{q}) \sqrt{d_h}) \\ \tilde{k} &= \text{RoPE}(\text{norm}(\tilde{k}) \sqrt{d_h} \cdot \beta) \\ \tilde{o}_h &= \tilde{v}_h \text{softmax}\left(\frac{1}{\sqrt{d}} \tilde{q}_h \tilde{k}_h^T\right) \\ \text{out} &= \tilde{W}_O [\tilde{o}_1, \tilde{o}_2 \dots \tilde{o}_{n_h}] \end{aligned} \quad (11)$$

Where  $\tilde{W}_O \in \mathcal{R}^{\tilde{e} \times E}$  performs the up-projection back to the dimension of the residual stream. While CCA may look somewhat complicated, the additional operations of the convolutions, q-k-mean-adjustment and value-shift require very few additional parameters and FLOPs while giving substantial improvements in perplexity and stability, which make performing the attention in the fully compressed latent space viable.

CCA can also be combined with a GQA-style parameter sharing approach. Specifically, we can apply GQA directly to the compressed heads in the latent space. We apply GQA directly to the compressed key and value heads of CCA e.g. we share  $\tilde{k}_{g1} = \tilde{k}_1 = \tilde{k}_2 = \tilde{k}_3 = \tilde{k}_4$  in the case where the group size is 4. We call this method Compressed Convolutional Group Query Attention (CCGQA). We find that this approach can again obtain the best-of-both-worlds of parameter sharing and compression, enabling us to achieve higher compression ratios for the same performance. Example

pytorch code implementing CCA and CCGQA is provided in Appendix A.

### C. Methodology

For our experiments, we do not do FLOPs/byte matched ablations. We instead opt for parameter-matched (total and active parameters) and KV-cache-size-matched experiments. The reason to do this is to give decode-focused methods such as MLA and GQA a fair chance. When we cannot perfectly match, we deliberately give the advantage for the non-CCA method. For instance, when comparing to MHA, we match parameters but ignore CCA’s KV-cache compression rate. For MLA, GQA, we match parameters and compression rate, but not FLOPs since GQA and especially MLA utilize many more FLOPs than CCA.

In all ablations, the models were trained on a randomly selected subset of the Zyda2 (Yury Tokpanov et al., 2024) dataset. We trained standard Llama3-style 1B dense transformer models for 300B tokens and a 300M-active/1.5B-total parameter models using our MoE architecture. We tested both dense and MoE to determine if there were differences in trends between architectures.

For CCGQA on our MoE architecture, we do a single experiment with  $8\times$  compression to illustrate the Pareto frontier of increasing high arithmetic intensity with respect to performance (see fig 4). For different economic constraints one might opt for less arithmetic intensity, but a more computationally efficient variant.

## III. RESULTS

### A. Dense Model Experiments

For CCA on dense models, we show results for a configuration with 4 query heads and 4 kv heads. For CCGQA, we use 16 query heads and 4 kv heads, repeated 4 times. We also illustrate the compute tradeoff in the parameter-matched setting through a comparison between MLA, MHA, and GQA with CCA and CCGQA. Furthermore, for MLA, GQA, CCA and CCGQA, the KV-cache compression was matched at 1/4 of MHA. We observe that for dense models, in the parameter-matched setting, CCA outperforms MLA in loss while achieving a significant reduction in training and inference FLOPs. CCGQA outperforms MHA despite matching in parameters and with substantial KV-cache compression and reduced FLOPs.

| Settings |         |         | Evaluation Scores |          |          |      |            |      | Loss  |
|----------|---------|---------|-------------------|----------|----------|------|------------|------|-------|
| Convs    | QK-Mean | V-Shift | HellaSwag         | ARC Easy | ARC HARD | Piqa | Winogrande | Avg  |       |
| 0        | X       | X       | 56.8              | 59.7     | 34.0     | 73.9 | 56.0       | 56.1 | 2.330 |
| 1        | X       | X       | 57.1              | 58.8     | 33.5     | 72.9 | 54.8       | 55.4 | 2.327 |
| 2        | X       | X       | 58.2              | 60.4     | 33.9     | 74.3 | 56.3       | 56.6 | 2.319 |
| 2        | X       | ✓       | 58.0              | 59.3     | 33.4     | 73.7 | 56.1       | 56.1 | 2.317 |
| 2        | ✓       | ✓       | 57.4              | 62.4     | 34.7     | 74.0 | 56.7       | 57.0 | 2.315 |

TABLE IV: Ablation study of CCA in 1B parameter models. We test CCA with zero, one, or two conv layers, with and without qk-mean residual, and with and without the v-shift operation. Each version is trained on  $\sim 300$  billion tokens of Zyda2 dataset, on which we show the validation cross-entropy loss and several benchmarks.

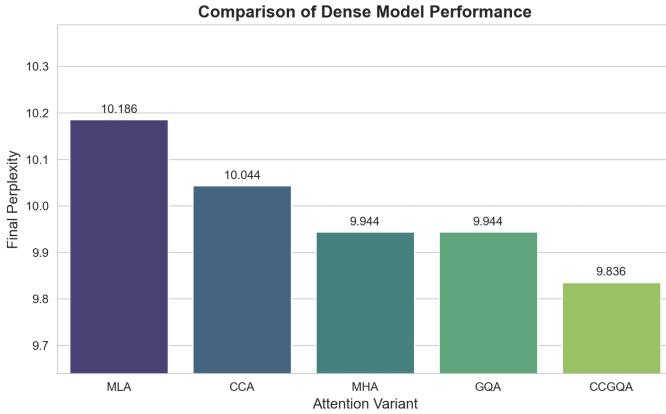


Fig. 3: Comparison of perplexity on the Zyda2 dataset for 1B parameter dense transformer models trained for 300B tokens with different attention mechanisms. CCA beats MLA in the parameter-matched setting with less FLOPs. When matching CCA FLOPs to GQA and MHA via CCGQA, we see a substantial improvement in perplexity.

### B. MoE Model Experiments

For CCA on our MoE architecture, we use CCGQA with 2 kv heads ( $8\times$  compression) and 8 query heads ( $2\times$  compression) and CCA with 4 q, kv heads ( $4\times$  compression). These comparisons are all parameter-matched and KV-cache-matched with the exception of MHA, which has  $4\times$  the KV-cache. We provide these results to further illustrate that parameter-efficient attention types, including MLA, are more useful in the MoE setting, since when parameter matching the forward and total parameters, reducing the parameters allocated to attention allows more to be assigned to the experts. This enables each expert to grow in size, which in turn reduces the total number of experts required for a fixed total parameter budget. Under our MoE architecture, we have found this reallocation to be beneficial. Additionally, shifting parameters from attention to the experts reduces the number of fixed parameters in the forward pass, making the model more expressive without increasing the total or forward parameter count.

For MLA, we match total parameters and forward parameters for training. In order to show that CCA’s operations are universal across attention methods we additionally provide results for CCMLA in Appendix C. CCMLA utilizes the same query and KV-cache compression ratios as CCGQA, and

crucially does not share key and value heads, as sequence convolutions on values prior to attention was empirically poor. We instead simply apply up-projections and 50% rope to CCGQA to illustrate the tradeoff between additional expressivity in the up-projections versus decreased expressivity in the shared key rope across heads.

We show that CCA is capable of beating MLA with significantly less parameters and less FLOPs. We show here that when matching KV-cache and decreasing compute with CCA, we beat MLA, and we can match MLA when halving KV-cache and matching compute with CCGQA, in the parameter-matched setting for MoEs. Depending on training versus inference cost, there exists a smooth Pareto frontier for which a CCGQA configuration is optimal.

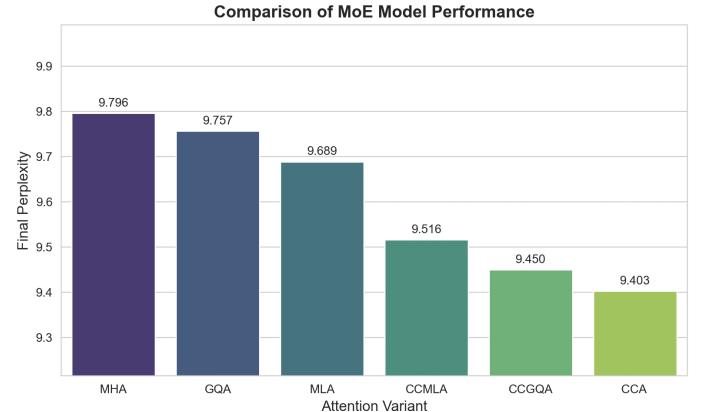


Fig. 4: Comparison of perplexity on 50B tokens of the Zyda2 dataset for 350M/1.5B parameter proprietary MoE models with different attention mechanisms. Our proposed methods, CCA and CCGQA, achieve lower loss than GQA and MLA at equivalent parameter counts with less compute cost, and less training parameters in the case of MLA.

### C. CCA Ablations

To illustrate the relative importance of each component in CCA, we show ablations on the 4 query, 4 key, 4 value variant of CCA on a 1B dense model and our proprietary 350M/1.5B ablation sized MoE. The majority of performance increase in CCA comes from the sequential convolutions. The auxiliary modifications of qk-mean and value-shift together provide a small, but noticeable decrease in perplexity and boost in evaluations. In our MoE, we see more significant jumps due

to the auxiliary modifications, which can be illustrated here by perplexity shown in Table 4.

#### IV. KERNEL PERFORMANCE

Compressed Convolutional Attention (CCA) executes the entire attention operation in a compressed latent space, which significantly reduces both the arithmetic intensity and the data-movement requirements relative to competing methods such as MHA, GQA, and MLA. From Table II, we expect the  $S^2$  terms from  $QK^\top$  and  $\text{Attn} \cdot V$  to scale by  $1/C$  once  $Q$ ,  $K$ , and  $V$  live in a latent of width  $\tilde{E} = E/C$ . We have designed an H100 GPU kernel to fuse the convolution with an online softmax in the style of the flash attention series of kernels (Dao, 2023).

Our FLOP complexity model roughly aligns with the implementation results. Discounting the small convolutional terms called out in Table II, the  $S^2$  components of both matrix multiplications shrink by  $1/C$ , and the projection terms shrink proportionally as well. As a result, we expect latency gains that grow with sequence length, since fixed overheads amortize at the larger sequence lengths.

A key difference from methods that only rebalance bandwidth in decode is that CCA reduces both prefill and decode compute and shrinks the KV cache simultaneously. CCGQA inherits GQA’s KV reuse benefits in the latent while preserving CCA’s  $1/C$  scaling of the matmuls. KV cache results will be included in a follow-up work, since the focus of this initial work is on pretraining.

| Ablation Settings |         |         | Loss  |
|-------------------|---------|---------|-------|
| Convs             | QK-Mean | V-Shift |       |
| 0                 | ✗       | ✗       | 2.280 |
| 1                 | ✗       | ✗       | 2.264 |
| 2                 | ✗       | ✗       | 2.252 |
| 2                 | ✗       | ✓       | 2.248 |
| 2                 | ✓       | ✓       | 2.241 |

TABLE V: Ablation study of CCA in our 350M/1.5B MoE models. We test CCA with zero, one, or two conv layers, with and without qk-mean residual, and with and without the v-shift operation. Each version is trained on 50 billion tokens of Zyda2 dataset, on which we show the validation cross-entropy loss.

#### V. DISCUSSION

In this paper, we have presented CCA and CCGQA, a novel method for performing parameter compression in self-attention. CCA and CCGQA enable significant compression factors to be achieved while also improving performance relative to MHA, making significantly longer context lengths more feasible. CCA also outperforms existing methods such as GQA and MLA in model quality for fixed compression rate, allowing either greater compression rates to be used with acceptable loss or models to be improved at the same compression rate. Specifically, we find that in dense models we significantly outperform all other prominent attention types when matching training parameters to MHA and GQA (CCGQA, 16 query heads, 4 kv heads), and we beat MLA

with  $16\times$  less decoding FLOPs (CCA, 4 query heads, 4 kv heads), and with  $8\times$  less FLOPs in the case of CCGQA.

Our work is also the first to note and theoretically clarify that parameter-sharing methods such as GQA and parameter-compression methods such as MLA and CCA are orthogonal to one another and can be effectively combined. This implies that there is a Pareto-front which allows one to trade-off the degree of parameter sharing vs parameter compression to achieve the same compression rate. Notably, CCA is the first method that performs attention *entirely within a compressed latent space*, for both training and inference, thus demonstrating that there exists significant redundancy of parameters and activations in classic attention methods. This approach allows us to elegantly and seamlessly integrate RoPE (or indeed any position embedding) into CCA, unlike MLA, and also lets us save substantial compute for both prefill and decoding. Although CCA does not address the fundamental quadratic complexity of attention, by reducing the compute required by a factor of the compression rate, CCA can enable substantially longer sequences to be processed for a given compute and memory budget.

Since it does not address the quadratic all-to-all nature of attention, CCA is thus orthogonal to methods that try to apply sequence compression like NSA (Yuan et al., 2025), MoBA (Lu et al., 2025), and DSA (DeepSeek-AI, 2025a) and future work can explore to what extent we can apply both channel/cache compression and sequence compression and selectivity to continue to reduce the cost of attention while maintaining core sequence mixing performance. Future work could also investigate how well the compressed KV-cache of CCA interacts with offline KV-cache compression methods.

The architectural innovations used in CCA to boost performance – sequence and channel mixing convolutions, qk-mean-adaptation, and value-shift, are not necessarily specific to CCA and could be used to improve sequence mixers in general. The value-shift adds a strong inductive bias that half the heads cannot see the present, which seems generally useful. RWKV (Peng et al., 2023) use a similar approach (which they call token-shift); which they find improves performance of their RNN-based sequence mixer. This provides some circumstantial evidence towards the general utility of this bias. The qk-mean effectively adds a bias towards strengthening the diagonal of the attention scores matrix and also, when combined with normalization, slightly sparsifies the key and query vectors.

More generally, we expect that performing carefully chosen additional operations, including additional nonlinearity, on the compressed latent query, key, and value vectors is a promising direction to further increase the expressivity of attention and make up for the loss of expressivity from the dimensional compression. At high compression rates, such operations are relatively cheap in terms of FLOPs and parameters and, indeed in CCA, the convolutions and other operations have negligible overhead, since the vast majority of parameters exist in the downprojection matrices. However, despite being theoretically negligible in FLOPs, in practice these operations do often

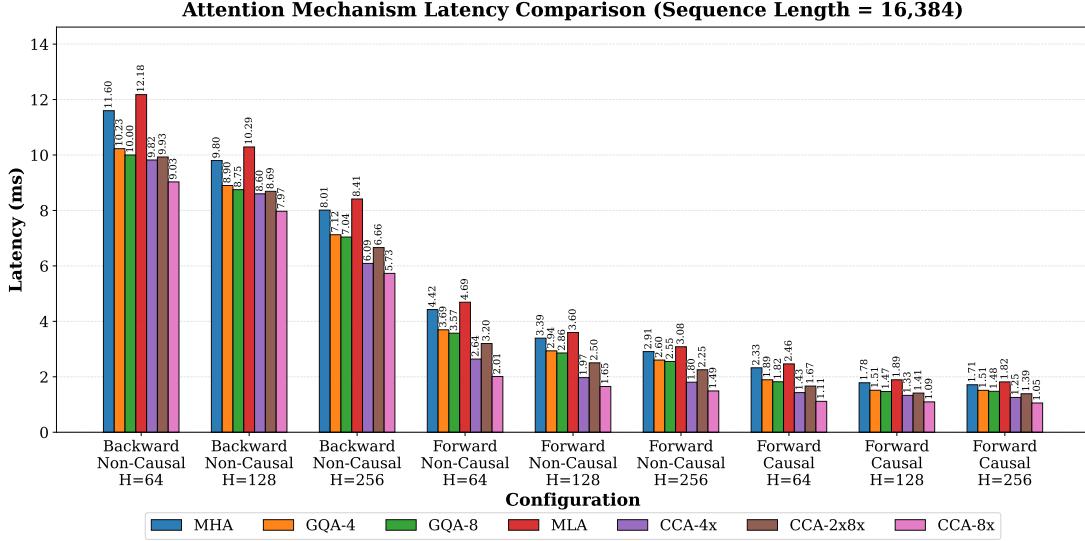


Fig. 5: Performance of CCA versus competing attention methods with hidden dimension 2048 and BFLOAT16 on an H100 GPU

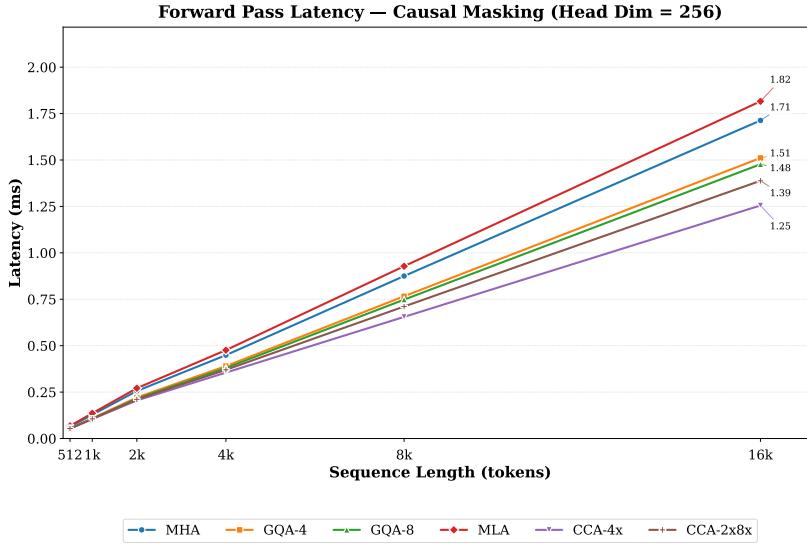


Fig. 6: Prefill forward (causal) attention latencies: Head dimension 256

cause overhead in a naive pytorch implementation. A fused kernel for CCA is required to obtain the full speedup that is theoretically possible. One note for concern, however, is that compared to MLA/GQA, which like MHA, only do linear projections of q,k,v, CCA does more involved operations on the compressed latents. This induces a measure of inductive bias into CCA which is less present in MLA and GQA and may mean that CCA outperforms at small scales while the benefits lessen at larger scales. Testing how CCA performs and compares with alternatives on larger scales would be important to verify or falsify this hypothesis.

Due to CCGQA’s versatility, it is also more amenable to support existing parallelism schemes, unlike MLA. For instance, sharding CCA’s latent representation with TP incurs only the same cost as GQA and is relatively cheap as long as

the TP rank is the same as the number of groups. Context-parallellism is also simple to implement, since one can simply communicate the smaller latent width  $E/C$  instead of the standard full width  $E$  within a ring or tree. Unlike MLA, CCA applies RoPE directly in the latent and only needs a constant-size latent halo for the causal convolutions and one-token value-shift, so no extra collectives or re-materialized up-projections are required.

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## A.1: PYTORCH CODE FOR CCA

```

1 class CCA(nn.Module):
2     def forward(self, hidden_states):
3         # Note: for simplicity this code is split up; many operations can be fused.
4         # hidden_states.shape: seq_len, batch_size, hidden_dim
5
6         # Initial low-rank combined down projection for query and key
7         qk_packed0 = self.linear_qk(hidden_states)[0]
8         qk_packed1 = qk_packed0.permute(1, 2, 0)
9
10        # Padding for causal convolutions
11        qk_packed2 = F.pad(qk_packed1, (self.total_padding, 0))
12
13        # Sequence convolution
14        qk_packed3 = self.conv_qk0(qk_packed2)
15
16        # Head-wise grouped sequence convolution
17        qk_packed3 = self.conv_qk1(qk_packed3).permute(2, 0, 1)
18
19        # Calculation of query and key mean for biasing
20        key_pre = qk_packed0[..., self.latent_q_dim:(self.latent_k_dim + self.latent_q_dim)]
21        key_pre = key_pre.view(*key_pre.shape[:2], self.num_k_heads, self.head_dim).unsqueeze
22        (-2).repeat(1, 1, 1, self.gqa_groups, 1)
23        key_pre = key_pre.view(*key_pre.shape[:2], self.num_q_heads, self.head_dim)
24        query_pre = qk_packed0[..., 0:self.latent_q_dim]
25        query_pre = query_pre.view(*query_pre.shape[:2], self.num_q_heads, self.head_dim)
26        qk_mean_q = (query_pre + key_pre) / 2
27        qk_mean_k = qk_mean_q.view(*qk_mean_q.shape[:2], self.num_k_heads, self.gqa_groups, -1)
28        .mean(dim=-2)
29        query = qk_packed3[..., 0:self.latent_q_dim].reshape(* qk_packed3.shape[:2], self.
30        num_q_heads, -1) + qk_mean_q
31        key = qk_packed3[..., self.latent_q_dim:(self.latent_k_dim + self.latent_q_dim)].
32        reshape(* qk_packed3.shape[:2], self.num_k_heads, -1) + qk_mean_k
33
34        # Padding for value_shift
35        hidden_states_d = F.pad(hidden_states[:-1], pad=(0, 0, 0, 0, 1, 0))
36
37        # Value_shift
38        value1, _ = self.val_proj1(hidden_states)
39        value2, _ = self.val_proj2(hidden_states_d)
40        value = torch.cat([value1, value2], dim=-1).reshape(* hidden_states.shape[:2], self.
41        num_k_heads, -1)
42
43        # Query and key normalization with temperature and scaling
44        query_norm = query.norm(p=2, dim=-1, keepdim=True)
45        key_norm = key.norm(p=2, dim=-1, keepdim=True)
46        key = (key * self.sqrt_head_dim / key_norm) * torch.exp(self.temp[None, None].unsqueeze
47        (-1))
48        query = (query * self.sqrt_head_dim / query_norm)
49
50        # Can now pass to flash attention with requisite settings
51        return query.contiguous(), key.contiguous(), value.contiguous()

```

Listing 1: PyTorch implementation of Compressed Convolutional Attention (CCA).

## B.1: MLA INFERENCE COMPUTE CONSIDERATIONS

MLA inference is somewhat underdiscussed in the literature, but it is a prominent attention used in modern frontier models (DeepSeek-AI, 2025b; Team et al., 2025).

The logic behind MLA is as follows: for decoding, the optimal attention architecture is MQA due to being memory

bandwidth bound, and for training/prefill the optimal attention architecture is MHA so as to maximize expressivity. The two modes of MLA enable switching between these settings as desired – in the decode setting, the MQA variant can be used while in prefill, or training settings, the standard MHA-style MLA can be used. The full MHA-style MLA is slightly less

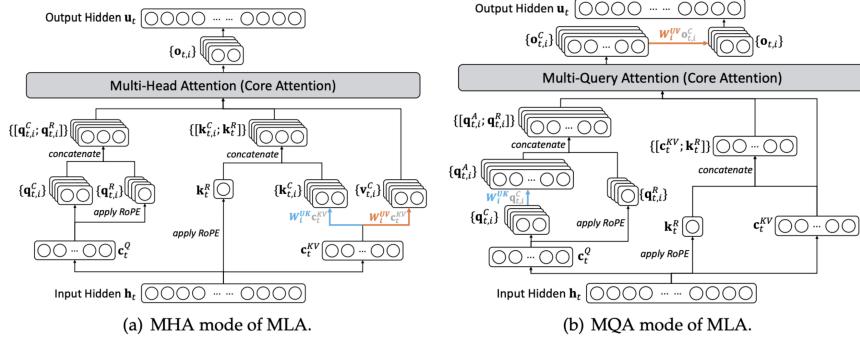


Fig. 7: Depiction of MLA in both MHA and MQA modes from [DeepSeek-AI \(2025a\)](#)

expensive than regular MHA in terms of both FLOPs and parameters, due to low rank projections, but MLA still retains the traditional self-attention compute cost.

Another way to think about this is that MQA maximizes the utilization of memory bandwidth by performing repeated computation over the shared key-value heads, while MHA maximizes unique computations for expressivity but at the cost of massive memory bandwidth requirements. MLA has a shared key-value MQA in the decoding mode that leverages high arithmetic intensity proportional to the number of heads. This falls short in cases where speculative decoding is utilized such that the arithmetic intensity passes the roofline; MLA additionally fails in cases where tensor parallel (TP) is used in inference, as MQA is no longer advantageous due to the necessity of repeating the shared KV-cache across devices. The optimal inference attention with tensor parallel is a latent GQA with number of key-value heads being equivalent to TP size, while having as many groups as possible to maximize arithmetic intensity. CCGQA is thus extremely well-suited for tensor-parallelism compared with MLA.

MLA has an arithmetic intensity of  $2n_{heads}$  at inference time, which is very large, and targets the ridge of the roofline plot on a H100 for a single query. For speculative decoding, the excess use of FLOPs for relatively little increase in performance is not necessarily optimal. The arithmetic intensity required to breach the ridge of the roofline for an Nvidia H100 under bfloat16 is 295 FLOPs per byte ([NVIDIA, 2022](#)). Deepseek seemingly chose their number of heads for the DeepseekV3 model to accordingly saturate the roofline to approach compute bound inference at batch size 1. GQA has a limited arithmetic intensity of  $n_{groups}$ , but is far more versatile under a number of conditions. Recall MLA at inference time:

$$\text{softmax}(\underbrace{\mathbf{q}_{lr}^\top \mathbf{W}^q \mathbf{W}_k^\top}_{q' \in \mathbb{R}^{n_h \times d_c}} \underbrace{\mathbf{k}^\top}_{k' \in \mathbb{R}^{d_c \times N}} \mathbf{v}^\top) \underbrace{\mathbf{k}^\top}_{v' \in \mathbb{R}^{N \times d_c}} \mathbf{W}^v \mathbf{W}^o \quad (12)$$

This is equivalent to MQA with the head size being the shared KV latent. This is optimal when setting number of heads exactly to the ridge of the roofline plot. In most cases, using MQA mode is a large increase in FLOP count, but these FLOPS are computed by streaming multiprocessors (SMs) that would otherwise go unused or idle on decoding. With an

approximate arithmetic intensity of  $2n_{heads}$ , Deepseek selects their number of heads to almost exactly reach the ridge of the roofline plot. Considering Deepseek are under constraints of H800 devices, using MQA mode makes sense, since tensor parallel is heavily penalized. Specifically, under tensor parallel (TP) conditions. E.g. under TP=8, with an MQA model with 1 kv head and 16 query heads, the model must copy the shared kv head across devices according to the TP rank. The optimal attention has as many unique kv heads as TP shards, as to maximize kv reuse within devices and minimize kv reuse across devices. During the creation of CCA and CCGQA, this was heavily considered. This also appears to be why models which use MLA tend towards heavy expert-parallelism and ultimately pipeline parallelism instead of tensor parallelism.

An additional point is that while MLA is capable of better compute utilization on decode, the increase in FLOPs that would otherwise go unused does not automatically result in victory. Model quality and latency, not SM utilization, is the end goal. The primary tradeoff to mode-switch between MQA and MHA in traditional GQA attentions is whether maximizing of unique computations in training mode (MHA) is worth the decrease in expressivity from shared key rope and sharing keys and values. In order to show that this decreased expressivity imposes a steep penalty in practice, we test a CCMLA variant with up-projections on the latent key and value, and with shared key rope, as shown in figure 4. These results illustrate that it may not be necessarily optimal to utilize MLA's architecture under many conditions and that CCGQA is both more flexible and more expressive.

We designed CCA to be versatile and agnostic to all future model parallelism strategies and speculative decoding strategies, with arithmetic intensity of  $n_{groups}$ . Since CCA is capable of much larger KV-cache compression with the same performance, this enables a larger arithmetic intensity compared to GQA if desired.

### C.1 LOSS PLOTS

Here, we present our full loss plots for CCA under both MoE and dense conditions. For all of our MoE ablations we use a 350M active/1.5B total parameter model with 28 layers. Our 1B parameter dense model was trained with 24 layers for 300B tokens, while our small MoE was trained for 50B

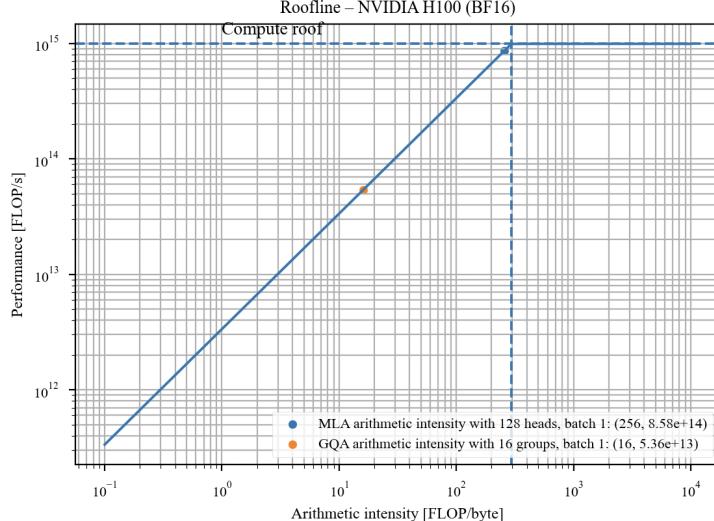


Fig. 8: Dense BF16 roofline of an Nvidia Hopper H100 SXM GPU, with the theoretical arithmetic intensity for both GQA with 16 groups, and MLA with 128 heads. Note CCGQA has the same arithmetic intensity as GQA.

tokens. Both models were trained on a subset of the Zyda2 dataset. We parameter match all comparisons across both total parameters and active parameters for inference. This ensures a fair comparison between attentions with drastically different higher arithmetic intensity.

Notice that training was stable in all cases and that the differences in loss appear stable across many steps. Once they emerge they do not appear to converge again or cross one-another, meaning that some methods have long-term advantages over others in loss, averaged across samples. Per sample, the losses track each other very closely but at a roughly fixed offset.

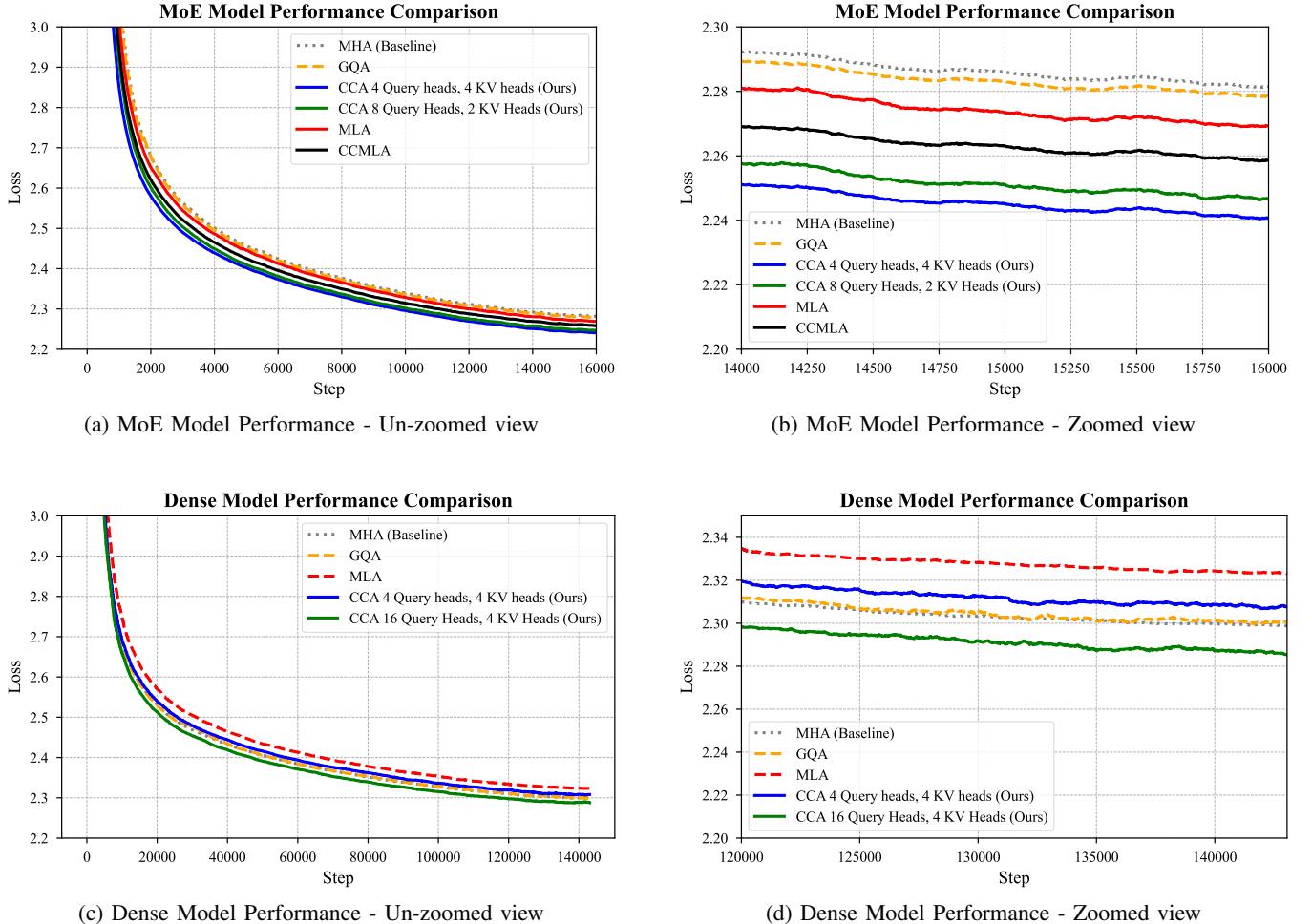


Fig. 9: Comparison of loss on the Zyda2 dataset for both MoE (top row) and dense (bottom row) models. For MoE: 350M/1.5B parameter models with different attention mechanisms. Our proposed methods, CCA and CCGQA, achieve lower loss than existing efficient attention variants like GQA and MLA at equivalent parameter counts. For Dense: 1B parameter models where all attention methods are restricted to equal KV-cache size (4x compression) except MHA. CCGQA has 8x KV-cache compression, while MLA, CCA and GQA have 4x compression relative to MHA.

## D.1 BENCHMARKING SETUP AND KERNEL NOTES

All measurements are single-GPU latencies on an H100 with BF16 precision, using  $E=2048$ ,  $\text{head\_dim} \in \{64, 128, 256\}$ , and sequence lengths from 512 to 16,384. The latency of the forward is reported in both non-causal and causal forms; backward results are reported for non-causal. CCA and CCGQA execute attention entirely in the latent space of width  $\tilde{e} = E/C$ , using RoPE position embeddings, L2 normalization for the queries and keys with key temperature scaling, qk-mean coupling, and value-shift as fused prologues/epilogues with online softmax for the causal case.

The alignment between the theoretical FLOP predictions and latencies is clearest at large  $S$ , where the  $S^2/C$  terms dominate. At shorter sequences, constant overheads from kernel launches, reductions, and the fixed parts of prologue/epilogue keep the realized speedups below the ideal factor  $C$ , but the ordering across methods remains stable. MLA’s decode-time amortization strategy and GQA’s KV sharing primarily reconfigure bandwidth usage; neither reduces the core  $S^2$  arithmetic during prefill or training, which is why their curves sit closer to MHA than CCA in the forward plots.

While most prior works comparing attention implementations use TFLOPs, we chose latency. This is because, while TFLOPs are useful to compare an implementation’s achieved efficiency compared to the maximum throughput of the accelerator for a given operation, it is misleading to compare TFLOPs between different attention methods entirely, since the actual FLOP costs of the methods are different. CCA is expected to have slightly lower throughput on large accelerators than MHA due to the reduced compute needs, but this reduction in compute itself leads to significant end-to-end speedup and better performance in terms of loss. In general, efficiently using a lot of flops is only useful if the FLOPs buy you something. Using substantially less FLOPs, slightly less efficiently, can often be useful in practice. We will also note that another benefit of performing attention on a smaller latent space, reduction in KV-cache size, is not demonstrated in these results but will result in significant decoding speed improvements.

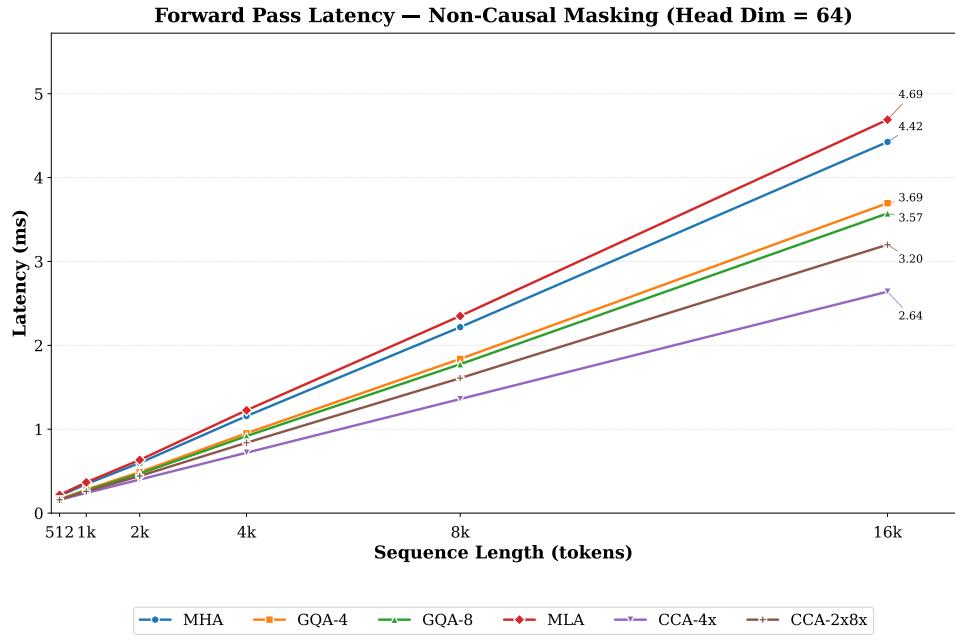


Fig. 10: Prefill forward (non-causal) attention latencies: Head dimension 64

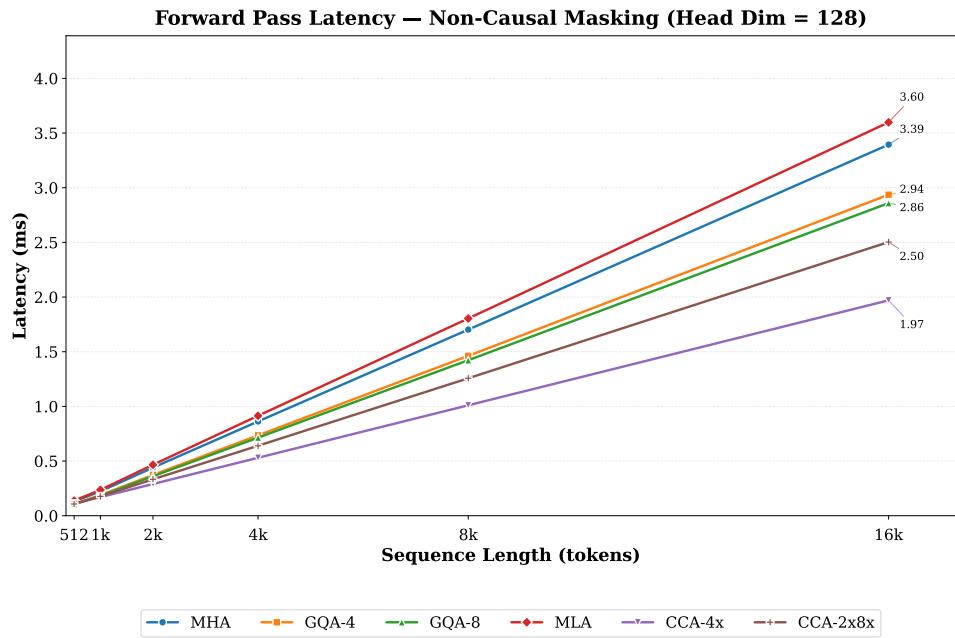


Fig. 11: Prefill forward (non-causal) attention latencies: Head dimension 128

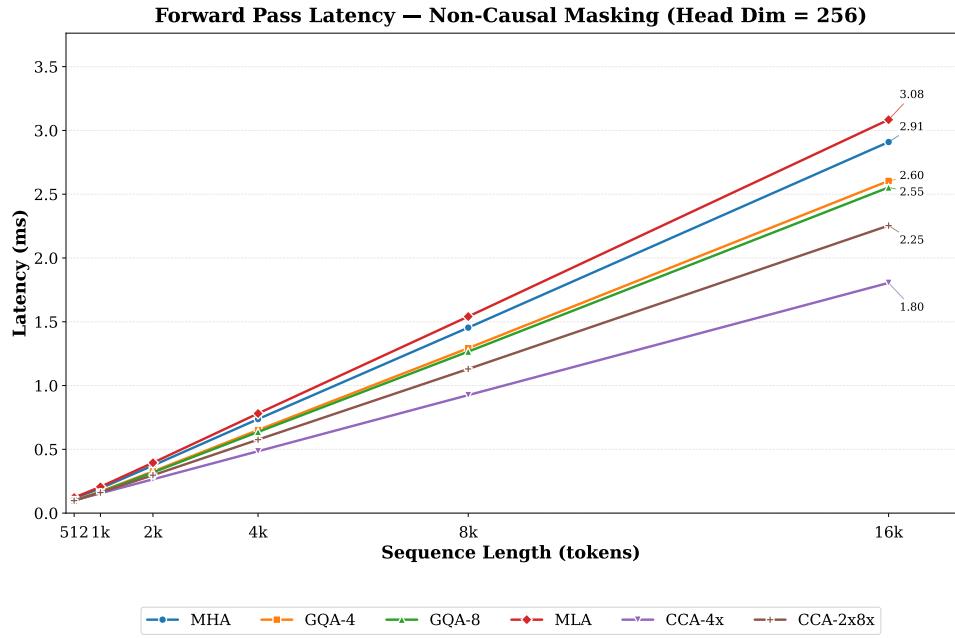


Fig. 12: Prefill forward (non-causal) attention latencies: Head dimension 256

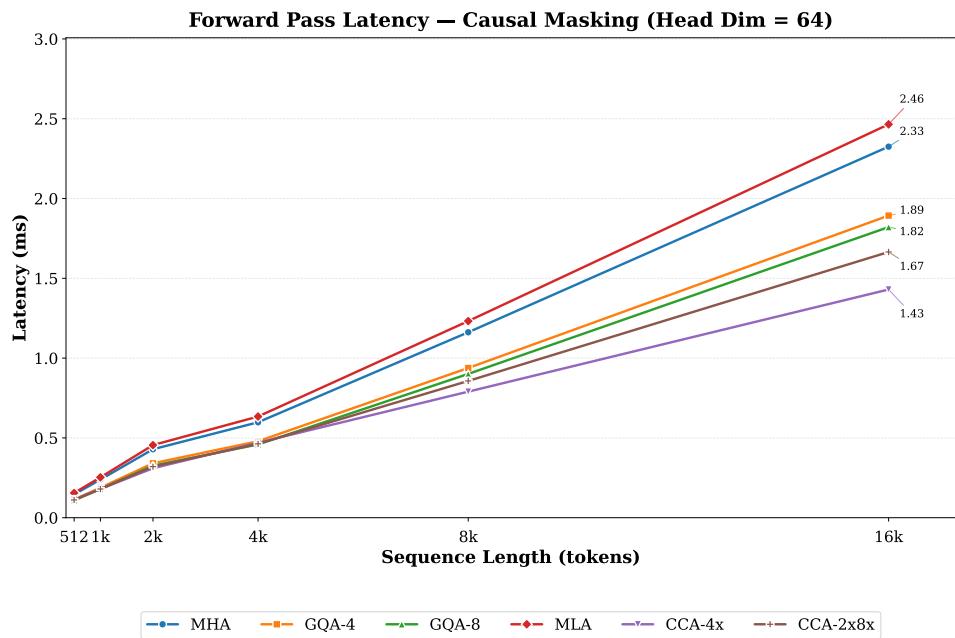


Fig. 13: Prefill forward (causal) attention latencies: Head dimension 64

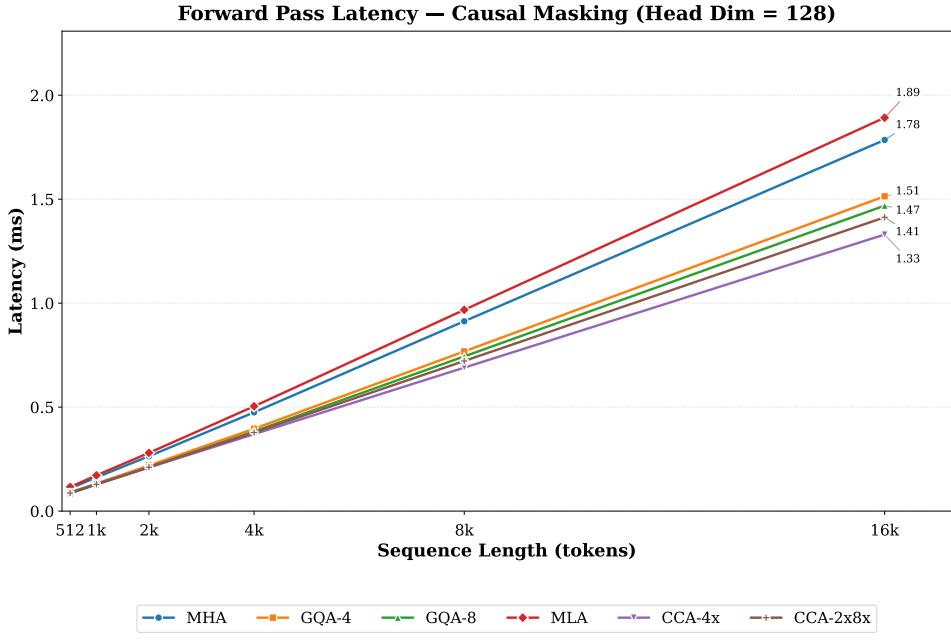


Fig. 14: Prefill forward (causal) attention latencies: Head dimension 128

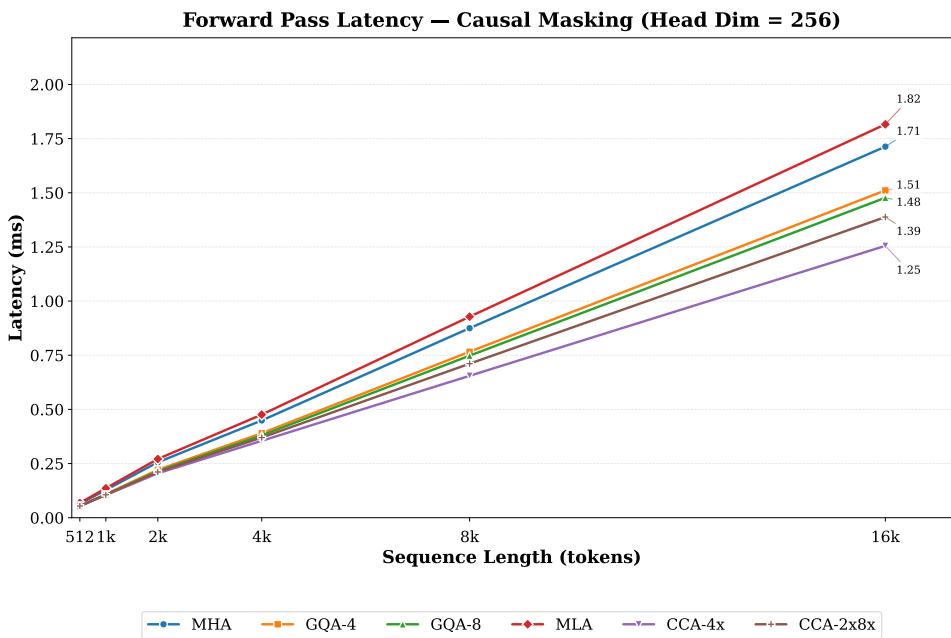


Fig. 15: Prefill forward (causal) attention latencies: Head dimension 256

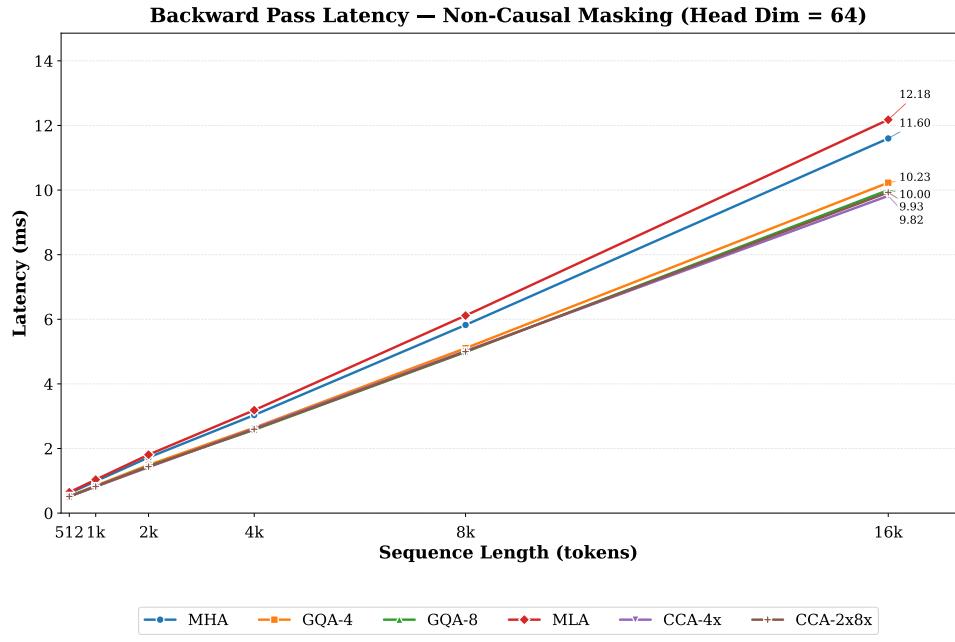


Fig. 16: Backward attention latencies: Head dimension 64

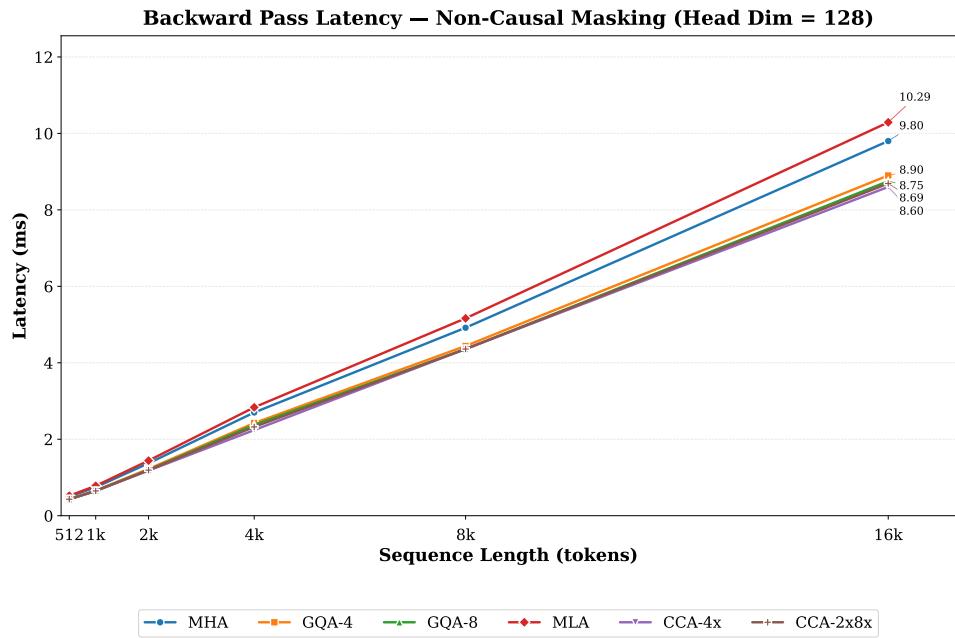


Fig. 17: Backward attention latencies: Head dimension 128

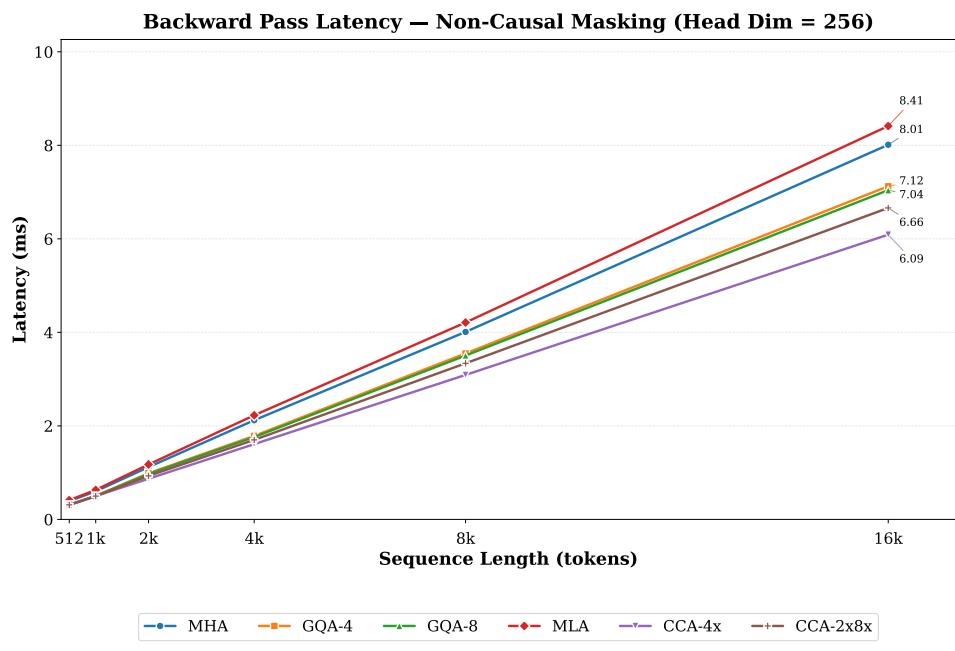


Fig. 18: Backward attention latencies: Head dimension 256