END-TO-END CONTEXT COMPRESSION AT SCALE

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ABSTRACT

Long-context language model inference is bottlenecked by memory, as the KV cache grows with context length. Recent techniques to compress the KV cache fall short: they either degrade model quality substantially or require considerable time and compute to compress a single long prompt. Furthermore, many methods require the input to fit within the target model's context window, and are generally incompatible with modern production inference engines. Encoder-decoder compressors, which map a long token sequence to a shorter sequence of latent embeddings consumed by a decoder, are an appealing alternative in principle. However, existing approaches are not competitive with KV cache compression on the accuracy-efficiency frontier. In this work, we revisit encoder-decoder compression and close this gap. We first perform an architecture search, pre-training many variants from scratch to determine how best to design and train encoder-decoder compressors. Guided by our findings, we continually pre-train a family of 0.6B-encoder, 4B-decoder models on nearly 400B tokens each, at compression ratios of 1:4, 1:8, and 1:16. We introduce *Latent Context Language Models* (LCLMs), a family of compressors that improve the Pareto frontier across general-task performance, compression speed, and peak memory usage. LCLMs also unlock new efficient downstream applications: they serve as backbones for long-horizon agents that skim a compressed long context and adaptively expand relevant segments on demand, and they can compact the model's own generated reasoning into latent memory during inference, which is nearly lossless on the full MATH test set while being highly efficient, reducing peak KV usage by up to $7.9\times$.

1 INTRODUCTION

Reasoning over long contexts is a crucial capability for state-of-the-art Large Language Models (LLMs), as it enables them to parse long documents, engage in multi-turn conversations, and perform long-horizon agentic tasks. However, in production systems, the input context, working horizon, and memory can grow to millions of tokens, making inference increasingly constrained by memory and latency due to the growth of the KV cache (Hooper et al., 2024). Even when inputs fit within the model's maximum context window, models often struggle to reliably use information distributed across long contexts (Liu et al., 2024b; An et al., 2025). As a result, context and memory management have emerged as critical systems and modeling challenges for deploying long-horizon LLM systems.

A natural response is to reduce the size of the KV cache directly. KV cache compression methods reduce the memory footprint of cached activations by evicting cache entries (Li et al., 2024c; Devoto et al., 2025; Kim et al., 2025; Zweiger et al., 2026) or training a compact cache offline (Eyuboglu et al., 2025). However, they have important limitations for general long-context inference. Many methods still require the full context to be prefilled before compression, and some require substantial additional time or memory beyond the original prefill. Query-dependent methods produce caches that are difficult to reuse across turns (Li et al., 2024b), while methods that evict caches non-uniformly across attention heads and layers (Kim et al., 2025) are difficult to integrate with modern inference engines that assume a shared sequence length across the cache.

Encoder-decoder soft-token methods (e.g. Lin et al., 2025; Ge et al., 2023; Chevalier et al., 2023; Liao et al., 2025; Yen et al., 2024) offer a promising way to address the limitations of KV cache compression. Rather than manipulating the KV cache directly, these models encode the raw input tokens into a much shorter sequence of continuous embeddings, which are then provided to the LLM in place of the original context. In principle, this approach is highly attractive: compression

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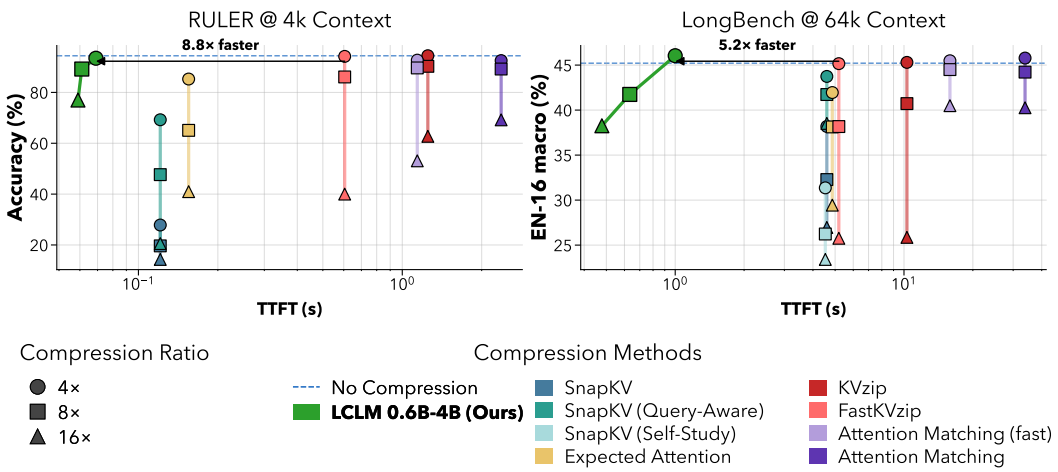

Figure 1: **Our Latent Context Language Models achieve high quality compression while being fast and memory efficient.** We show RULER (Hsieh et al., 2024) (left) and LongBench (Bai et al., 2024) (right) accuracy vs. TTFT (time to first token) per sample on a single H200. All methods are based on the same decoder `Qwen3-4B-Instruct-2507` (Yang et al., 2025). We see that our models lie on a new Pareto frontier, compressing contexts much faster while maintaining high accuracy, especially for high compression ratios. KV cache compression baselines appear as vertical lines because the context is prefilled the same way regardless of compression ratio, and the eviction operation is much faster than the prefill time.

is parallelizable, supported by standard LLM inference engines, and works with standard LLM decoding while extending the decoder far beyond its native context length.

However, existing soft-token compression methods typically face a trade-off: they either substantially degrade the capabilities of the base language model or depend on domain-specific training to remain effective. This motivates a fundamental question: **can we train a general, task-agnostic compressor that preserves a model's original capabilities?** To this end, we introduce *Latent Context Language Models* (LCLMs), a family of encoder-decoder compressors trained end-to-end at scale. We initialize both the encoder and decoder with pre-trained models and jointly train them on a total of nearly 400B tokens for the combined encoder-decoder. Crucially, we demonstrate that LCLMs can preserve decoder performance while reducing memory used for input context.

Our contributions are summarized as follows:

1. **Training recipe:** We develop a fine-grained training recipe for encoder-decoder context compression. Accordingly, we curate continual pre-training and finetuning data for training compressors and optimize training details across multiple training stages. See Section 4.
2. **Comprehensive architectural search:** We conduct a large-scale architecture search to identify optimal design choices for encoder-decoder compression models in a controlled setting. See Section 5 and Figure 2.
3. **New memory/speed-performance frontier:** We train a family of models across different compression ratios at scale. Our experiments identify a Pareto frontier that effectively balances memory, latency, and downstream accuracy. We will release this suite of models and all code. See Section 6 and Figures 1, 3 and 13.
4. **Agent with latent context:** We create an agentic system with a high compression ratio, where the agent can select which compressed chunk to expand. This agentic harness substantially enhances the model's performance on challenging needle-in-the-haystack tasks. See Section 7 and Figure 4.
5. **Online latent compaction:** We use the encoder to compress the model's own generated tokens during decoding, so long chains of thought are kept in a compact latent memory. On MATH, this is nearly lossless while reducing KV usage several-fold. See Section 8 and Figure 5.

2 Related Work

Context compression approaches generally fall into three categories: hard-token, soft-token, and KV cache compression. We defer the discussion of hard-token approaches to Appendix A, since they generally underperform compared to the latter two.

KV cache compression. KV cache compression methods evict entries from the KV cache. Most methods rely on hand-crafted or learned heuristics to select which entries to drop, while others train the model to merge or sparsify its own cache (Nawrot et al., 2024; Łańcucki et al., 2026).

Prompt-agnostic methods (Kim et al., 2025; Devoto et al., 2025; Zweiger et al., 2026) prune the context without knowledge of the query, whereas prompt-dependent methods such as SnapKV (Li et al., 2024c) require explicit context-prompt pairs and yield query-specific caches that limit multi-turn applicability (Li et al., 2024b; Kim et al., 2025). An alternative is to anticipate future queries at compression time: Cartridges (Eyuboglu et al., 2025) distills a fixed-size KV cache per corpus. However, this comes at a substantial training cost per corpus, with an ICL-quality cache requiring approximately 30 minutes on an 8×H100 node for an 8B model.

Although KV cache compression methods are well-studied, they are not widely adopted in inference engines such as vLLM (Kwon et al., 2023) or SGLang (Zheng et al., 2024). Compression methods such as KVzip allocate eviction budgets non-uniformly across attention heads and layers; therefore, they cannot reduce the sequence-length dimension of the KV cache. Instead, KV cache compression methods mask evicted positions in the attention computation, forfeiting the memory and throughput benefits of these paged-attention engines. Some methods further require prefill passes that are two to three times longer than the original input (Kim et al., 2025). We note that soft token compression methods are fully compatible with these open-source inference frameworks.

Soft-token compression. Despite promising results, most prior soft-token methods rely on offline preprocessing and do not convincingly preserve the base model's broad in-context behavior. Prior work is mostly evaluated on domain- or task-specific finetuning that is not transferable across tasks (Tang et al., 2025; Feldman & Artzi, 2025; Dai et al., 2025; Lin et al., 2025; Cheng et al., 2024). To the best of our knowledge, these methods are not evaluated on long-context benchmarks with information-dense tasks that require fine-grained details throughout the whole context, such as RULER (Hsieh et al., 2024), to demonstrate complex long-context understanding.

In Section 5, we discuss the architectural decisions of prior work on soft-token compression as part of our architectural search and analysis. Our work shows that, with large-scale staged training, a single online soft-token compressor can handle heterogeneous inputs while closely matching uncompressed behavior.

3 The Latent Context Language Model Architecture

An LCLM consists of an encoder with a pooling method that maps token chunks to soft tokens, an adapter to project to the decoder's embedding dimension, and a decoder that consumes the soft tokens as latent context. Given a sequence of input tokens $x_{1:T}$ and a compression ratio N, the encoder maps each contiguous block of N input tokens to a single latent token. Let W denote the encoder window size, i.e., the number of input tokens processed by the encoder in one forward pass. We split the input sequence into $I = \lceil T/W \rceil$ encoder windows, each containing at most W tokens:

$$w_i = x_{(i-1)W+1\,:\,\min(iW,T)}, \qquad i = 1, \ldots, I. \tag{1}$$

For each window w_i, the encoder computes the final hidden states $h^{(i)}_{1:|w_i|}$ for each input token in the window. A pooling operator then aggregates these hidden states into $M_i = \left\lceil \frac{|w_i|}{N} \right\rceil$ latent tokens $z^{(i)}_{1:M_i}$. When $W = N$, each encoder window contains a single compression block, yielding one latent token per forward pass. When $W = T$, the encoder processes the entire input sequence in one forward pass and produces $\lceil T/N \rceil$ latent tokens. We concatenate the latent tokens from all encoder windows to obtain the full compressed latent sequence $z_{1:M}$, where M is the total number of latent tokens after compression.

Because the encoder and decoder may have different hidden dimensions, an adapter $a(\cdot)$ projects the compressed latent sequence $z_{1:M}$ from the encoder hidden dimension into the decoder hidden

dimension, producing latent tokens $s_{1:M}$. The decoder then consumes these projected latent tokens in place of the corresponding input tokens.

4 TRAINING RECIPE

We now describe our multi-stage recipe and data for training. In contrast to prior context-compression work that trains specialized models on small-scale in-domain datasets (Tang et al., 2025; Feldman & Artzi, 2025; Pilchen et al., 2025; Cheng et al., 2024; Liao et al., 2025), our goal is to preserve the strong performance of a powerful LLM across downstream tasks. To this end, we curate three types of data: continual pre-training data, Supervised Fine-Tuning (SFT) data, and auxiliary reconstruction data.

4.1 TRAINING DATA

Each data type is described in full in Appendix B, with examples in Figure 6. (1) **Continual pre-training data**: a curated mixture of web text, code, science and reasoning, long-context, and instruction-style data, in which compressed and uncompressed segments alternate throughout each sequence and the next-token loss is computed only on uncompressed tokens, unlike the first-half-compressed format of prior work (Lin et al., 2025; Ge et al., 2023; Chevalier et al., 2023; Yen et al., 2024). (2) **SFT data**: reasoning, long-context instruction following, general instruction following, and agentic trajectories. Reasoning examples keep the question uncompressed and compress spans of the reference chain of thought. Agent data combines public tool-calling, search, and terminal trajectories (Blakeman et al., 2025; Raoof et al., 2026), kept uncompressed, with synthetic memory-expansion trajectories in which the source documents are compressed and the model retrieves individual segments with an `expand` tool before answering (Section 7). (3) **Auxiliary reconstruction data**: the model reproduces compressed text verbatim, so the latents preserve fine-grained detail.

4.2 TRAINING STAGES

We adopt a multi-stage training recipe to improve stability, preserve the original model's capabilities, and mitigate catastrophic forgetting. The stages progressively increase the number of trainable components, from adapter and encoder warm-up to end-to-end continual pre-training and SFT.

- **Stage 0: Adapter warmup.** We freeze the encoder and decoder and train only the adapter.
- **Stage 1: Encoder training.** We unfreeze the encoder while keeping the decoder frozen.
- **Stage 2: End-to-end continual pre-training.** We unfreeze the decoder with a small LR.
- **Stage 3: Supervised fine-tuning.** We train on the SFT mixture with a higher decoder LR.

This staged procedure is analogous to Vision-Language Model (VLM) training pipelines that first align pre-trained representations across modalities (Liu et al., 2023a; Tong et al., 2024) and then fine-tune for downstream tasks: stages 0 and 1 play the role of projector alignment, stage 2 corresponds to interleaved continual pre-training, and stage 3 to instruction tuning. For stages 0, 1, and 2, we uniformly sample from the continual pre-training mixture; for stage 3, we train on the SFT mixture. In early experiments, we consider directly training the full model end-to-end from the beginning, but find that this approach underperforms the multi-stage recipe. At the beginning of training, the decoder is not accustomed to taking in the output of the embedding model, so both encoder and decoder parameter gradients can be large, leading to model degradation. The staged approach, where we first train the adapter before unfreezing the encoder and decoder, keeps gradients smooth and training more stable, preventing this degradation. We therefore adopt the multi-stage recipe for all scaled experiments. We also consider parameter-efficient variants that keep the decoder fully frozen (Ge et al., 2023; Cheng et al., 2024; Yen et al., 2024) or use LoRA (Liao et al., 2025; Tang et al., 2025; Feldman & Artzi, 2025), but we find them to substantially underperform compared to full-parameter training in early experiments; we therefore focus on end-to-end training. With compression disabled, the trained decoders show minimal drift from the original model (Appendix D.3). Details of the continual pre-training and SFT data mixtures are provided in Table 1 and Table 2, respectively. All other training details, including token budgets, learning rates, and sequence lengths, are provided in Table 5.

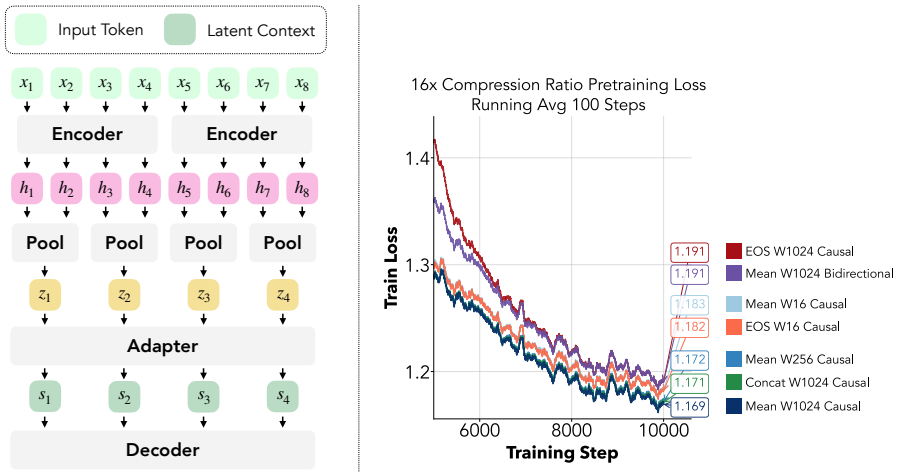

Figure 2: **A from-scratch pre-training sweep identifies the best encoder-decoder compressor architecture. Left:** We explore how to best train an encoder LM to compress raw text into latent vectors and a decoder LM that uses the vectors as latent context. **Right:** We sweep many variants of encoder-decoder compressors end-to-end with 38B training tokens at a compression ratio of $16\times$ and compare pre-training loss to find the best architecture. Since loss is computed only on the uncompressed tokens, the pre-training loss is substantially lower than a standard next-token prediction loss over all tokens. Extended experiments are in Appendix C.

5 Architectural Design Space of Latent Encoders

We conduct a controlled architecture search over encoder-decoder compressors by pre-training LCLM variants from scratch, which isolates architectural choices from biases of pre-trained initialization (e.g., the pre-trained `Qwen3-Embedding-0.6B` encoder uses causal attention and EOS pooling). We use `Qwen3-0.6B` as the base architecture for both the encoder and decoder, randomly initialize all weights with the same seed, and train all components end-to-end on the pre-training mixture (Section 4) for 38B tokens at compression ratio $N = 16$. Prior soft-token compressors can be decomposed into a small set of design choices: the pooling operator, encoding granularity, encoder attention mask, adapter, encoder initialization, and decoder adaptation. Each prior method is a point in this design space (Table 4 in Appendix C.1), so sweeping each axis under matched data, scale, and decoder compares the choices behind prior methods without the confounding differences between their original setups. We describe each axis and its effect below.

Pooling operator. Prior work on context compression has primarily focused on two pooling strategies. Token-based pooling appends or prepends designated tokens, such as `EOS` or `CLS`, and uses their final hidden states as compressed representations (Chevalier et al., 2023; Ge et al., 2023). Mean pooling averages encoder hidden states over each block of N input tokens (Tang et al., 2025; Feldman & Artzi, 2025), a design that is common in vision and multimodal models (Gemma Team et al., 2026). We additionally consider concatenation, a widely used alternative in vision-style architectures but less explored for context compression (Bai et al., 2025; Tong et al., 2024). Concatenation preserves the N sequential encoder hidden states by stacking them into a single wide vector, after which the adapter projects the resulting representation back to the LLM hidden dimension. The formal definitions of pooling operators can be found in Appendix C.2.

Figure 2 compares the three pooling operators in our pre-training sweep. Mean pooling consistently improves pre-training loss over token-based pooling, in line with prior evidence (Feldman & Artzi, 2025), but is empirically indistinguishable from concatenation; at scale, concatenation is slightly better at low compression ratios and mean pooling at high ones (Appendix C.2).

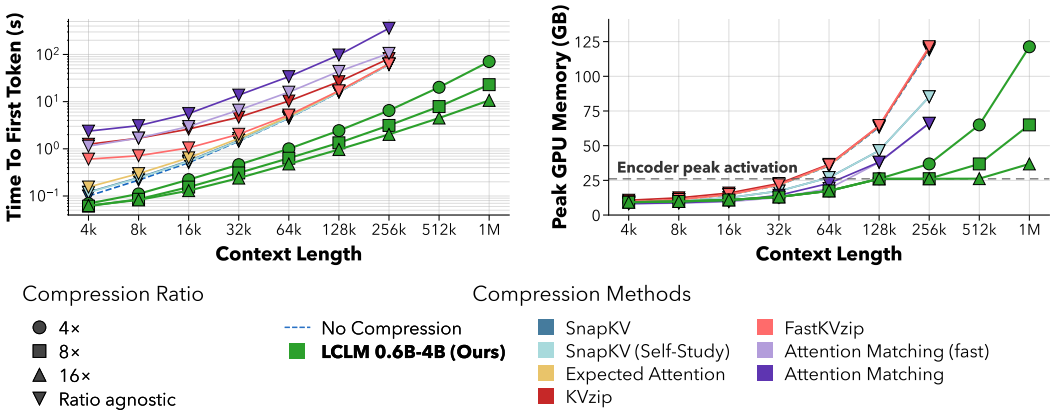

Figure 3: **Latent Context Language Models have lower TTFT and peak GPU memory as context length increases.** We plot time to first token (left) and peak GPU memory (right) for a single sample. We note the baselines use the same time and memory regardless of compression ratio; hence, there is only one line per baseline method. We record all measurements on the same H200 GPU, and truncate lines when the method cannot be performed within the 141GB of memory. For peak GPU memory, our method plateaus at longer contexts for larger compression ratios: in this regime, the encoder's batched processing dominates memory usage over the decoder. Memory begins to grow again once the decoder's prefill memory surpasses the encoder's activation per forward pass.

Encoding granularity. Ideally, one would set the encoder window size to the full context length, allowing the encoder to jointly contextualize all input tokens, analogous to ViT-style encoders (Dosovitskiy et al., 2020) that process the entire image at once. For language inputs, however, contexts can be much longer, making full-context encoding prohibitive in memory and time.

To study this trade-off, we vary the encoder window size over $W \in \{N, 256, 1024\}$ for mean pooling in Figure 2. We find that increasing W from N (16) (Lin et al., 2025; Liao et al., 2025) to 256 leads to a large improvement, while increasing W further from 256 to 1024 yields an additional smaller gain. Since $W = 1024$ does not introduce significant memory or runtime overhead in our setting, we adopt $W = 1024$ as the default. This setting enables the encoder to attend over a larger local context and produce richer compressed representations. A boundary-overlap variant that lets each window see neighboring tokens does not improve pre-training loss, so we use no overlap (Appendix C.4).

Encoder attention mask. Unlike standard decoder language modeling, where causal masking is required to match autoregressive inference, context compression is applied to the prompt before decoding. The encoder can therefore use either causal or bidirectional attention, as in prefix-LMs (Raffel et al., 2020). Prior compressors use both: some encode with a causal LLM (Ge et al., 2023; Tang et al., 2025), while others remove the causal mask (Feldman & Artzi, 2025). Figures 2 and 9 show that causal masking consistently lowers pre-training loss.

Adapter design. The adapter projects encoder latents to the decoder embedding dimension. Prior work uses either a small MLP projector (Cheng et al., 2024; Lin et al., 2025) or attention-based layers (Tang et al., 2025); an MLP-only adapter lowers pre-training loss with less compute (Appendix C.3).

Optimal architecture at scale. Overall, the from-scratch sweep narrows the search space, and we then scale the candidates with the full training pipeline (Appendix D). The optimal architecture at scale uses an encoder window $W = 1024$, causal masking, and an MLP adapter; mean pooling has a small edge over concatenation at $16\times$ compression, so we adopt it by default. For our main experiments, we use `Qwen3-Embedding-0.6B` as the encoder with `Qwen3-4B-Instruct-2507` as the decoder.

We also study alternative model choices, including whether to initialize the encoder from an embedding model (Liao et al., 2025; Cheng et al., 2024) or a language model (Ge et al., 2023; Tang et al.,

2025; Feldman & Artzi, 2025), in Appendix D.1. In Appendix D.4, we analyze the performance of scaling the sizes of the encoder and decoder.

6 Results: Improving Latency- and Memory-Performance Tradeoffs

We predominantly focus on long-context benchmarks: we evaluate on RULER (Hsieh et al., 2024), LongBench (Bai et al., 2024), and LongHealth (Adams et al., 2025). For the long-context evaluation suite, we maintain instructions as uncompressed tokens, while we compress long-context segments. We report which parts of each benchmark are compressed and which are left uncompressed in Table 8.

We measure two efficiency axes: peak memory during compression, and compression time. Peak memory includes both the encoder and decoder for a single sample at each context length. We report the mean over 30 measurements on the same H200 GPU, using 20 warmup steps to reduce kernel-level noise. We define compression time as time-to-first-token (TTFT), i.e., the time required for a method to reach the point at which it can generate the first token. We adapt the KVPress (Devoto et al., 2025) timing code[1] to support our method. All methods are benchmarked using Hugging Face Transformers (Wolf et al., 2019) implementations.

Since LCLMs process input tokens in encoder-window chunks, we can parallelize compression by batching encoder forward passes before passing the resulting soft tokens to the decoder. For all figures in this paper, we use an encoder batch size of 128; with encoder window size $W = 1024$, this corresponds to processing $131{,}072$ input tokens per batched encoder pass. We find this batch size provides a good trade-off between compression speed and encoder memory usage, improving GPU utilization without exceeding memory limits for ultra-long contexts. Moreover, because our method preserves the standard KV cache structure, prefill and generation can be further accelerated with standard inference frameworks such as vLLM (Kwon et al., 2023) and SGLang (Zheng et al., 2024), as well as efficient attention implementations (Katharopoulos et al., 2020; Kimi Team et al., 2025; Liu et al., 2024a; Xu et al., 2026). Therefore, the throughput measurements reported here are conservative relative to what optimized serving implementations could achieve.

6.1 Baselines

We consider a range of KV cache compression baselines, including Expected Attention (Devoto et al., 2025), Attention Matching (Zweiger et al., 2026), KVzip (Kim et al., 2025), FastKVzip (Kim et al., 2026), and SnapKV (Li et al., 2024c). Each method has different native support for query-aware, query-agnostic, and self-study compression configurations, which we describe in Appendix E.2 together with the difference between algorithmic and systems-realizable cache reduction.

We use the KVPress (Devoto et al., 2025) implementation for SnapKV, KVzip, FastKVzip, and Expected Attention. We use the official implementation for Attention Matching. We discuss all baselines further in Section 2 and Appendix A.

6.2 A New Pareto Frontier

We train LCLMs with compression ratios of $16\times$, $8\times$, and $4\times$. In Figures 1 and 13, LCLMs establish a new Pareto frontier in compression time and accuracy over KV cache compression baselines on RULER, LongBench, and LongHealth. KV cache compression methods appear as nearly vertical lines in these plots because their compression time is largely independent of the target compression ratio. These methods first materialize the full KV cache and then perform eviction, masking, or compaction, whose cost is small relative to the full-context prefill. In contrast, LCLMs reduce the sequence length before decoder prefill, so higher compression ratios directly reduce decoder-side computation and memory.

Time and memory scaling with context length. In Figure 3, we visualize compression time and peak GPU memory for our method and the baselines across context lengths from 4K to 1M. LCLMs achieve the fastest compression time and, at longer context lengths, substantially lower peak GPU

[1] https://github.com/NVIDIA/kvpress/blob/main/notebooks/speed_and_memory.ipynb

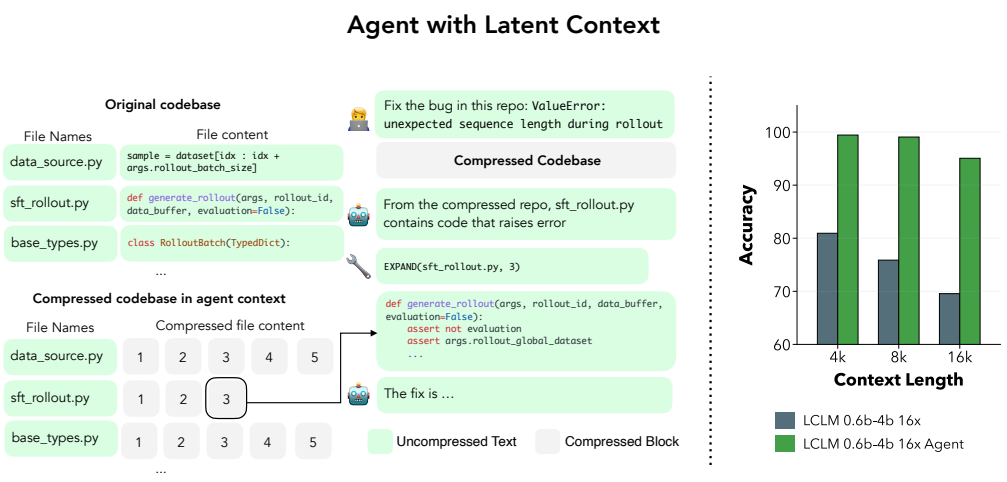

Figure 4: **LCLMs can use tools to retrieve compressed context and improve retrieval accuracy. Left:** We equip LCLMs with a tool that retrieves compressed context and inserts it into their working context uncompressed. **Right:** RULER NIAH scores at $16\times$ compression, with and without expansion, averaged over eight tasks with 50 matched questions per task and context length. We allow up to 16 expansion calls at 4k and 8k, and 32 at 16k. Budgets were selected on three of the tasks and frozen before evaluating the other five; the aggregate includes the selection tasks.

memory. Attention Matching runs out of memory at 1M tokens and fails at 512K tokens due to numerical instability in the linear solver. All other methods run out of memory at 512K and 1M tokens. This efficiency stems from two properties of LCLMs: compression is performed over fixed-size encoder windows rather than through a full-context decoder prefill, and the encoder is much smaller than the decoder. Since our encoder processes at most 128K input tokens per batched forward pass, peak memory is initially dominated by encoder activations. As a result, peak memory remains nearly flat for the $16\times$ model from 128K to 512K tokens, and for the $8\times$ model from 128K to 256K tokens. At longer contexts, the decoder prefill over the compressed latent sequence becomes the dominant memory cost, causing peak memory to increase.

7 Agent Scaffolding With Latent Context

Agentic systems are commonly used to handle large amounts of information (Zhang et al., 2025a). However, agents usually rely on lexical or semantic search to locate the information needed. These information retrieval methods can fail when the search keyword is not obvious before reading through the information. For example, in a large codebase, a bug reported in the "dashboard login flow" may actually originate in an indirectly called entitlement module that never mentions "dashboard" or "login". Ideally, an agent should read all information at once before acting, but context limits of existing models prevent this from happening.

LCLMs' more efficient long-context capacity makes it possible to place, for example, an entire code repository in an agent's context. We further enhance the agent's capability to locate precise information by allowing the LCLM agent to expand compressed segments into raw text on demand. We segment the input into fixed-size chunks of 1,024 encoder tokens, compress each chunk, and assign it a segment identifier. The model receives the entire compressed sequence in a single prompt, together with one `expand` tool. At each turn, the model can decide to make a tool call of the form `expand(i)`, and the tool returns the original text of the expanded segment.

We use the needle-in-a-haystack tasks from RULER as a testbed for evaluating this agentic retrieval mechanism with latent context. As shown in Figure 4, our agent substantially improves performance over the same LCLM with $16\times$ compressed context and no expansion. These results suggest that compressed latent context can provide broad corpus-level visibility, while tool-based expansion supplies the exact fine-grained information needed. The marked success of this initial agentic attempt

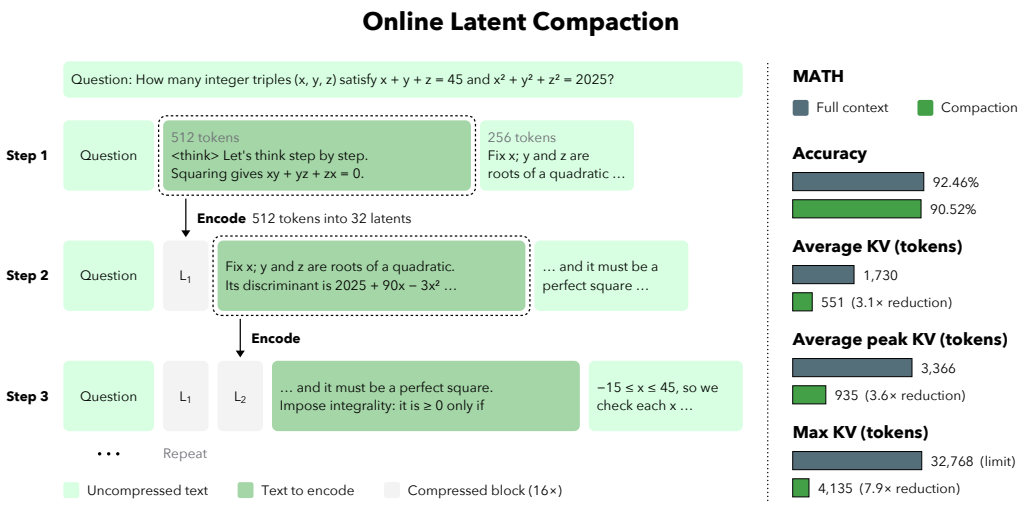

Figure 5: **Online latent compaction. Left:** During generation, every 512 uncompressed tokens are encoded into 32 latent tokens ($16\times$ compression), while the prompt and the latest 256 tokens stay uncompressed. We iteratively compress and generate from the compacted context and the latest raw tokens. **Right:** Accuracy and decoder context length on the full MATH test set. Average KV and peak KV are computed per problem and averaged over problems; max KV is the largest per-problem peak, where the full-context limit is 32,768 tokens.

suggests the promise of adaptive expansion. LCLMs can skim a large quantity of context globally before deciding which relevant subset to zoom in on and read more carefully. Future work may explore how to choose which context to expand, or learn this behavior end-to-end.

8 Online Latent Compaction

For long-horizon tasks, long CoT and agent trajectories can come to dominate the context and eventually fill the context window, requiring context compaction (Anthropic, 2025; OpenAI, 2025). Here, we investigate whether we can use LCLMs to compact context into the latent space iteratively. Because the LCLM encoder can compress any span of text, we can also apply it to the model's own output during generation, which we call online latent compaction (Figure 5). After the first 768 generated tokens, we encode the oldest 512 generated tokens into latent memory tokens at a $16\times$ compression ratio, resulting in 32 latent tokens, and keep the most recent 256 tokens uncompressed. Generation then continues from the compacted context and latest raw tokens, and the procedure repeats after every further 512 generated tokens. Earlier latent blocks are reused thereafter.

We evaluate on all 5,000 problems of the MATH test set with the $16\times$ LCLM, comparing generation with and without compaction under the same prompts, 32,768-token context limit, and scoring. Online latent compaction is nearly lossless, reaching 90.52% accuracy compared with 92.46% for full-context generation, while being highly efficient: it reduces the average KV length by $3.1\times$, the average per-problem peak by $3.6\times$, and the maximum peak by $7.9\times$: the longest full-context trajectories reach the 32,768-token limit, whereas no compacted trajectory exceeds 4,135 tokens. Lengths count active decoder positions, including latents, not allocated memory.

9 Conclusions

Through a controlled architecture search and end-to-end training at scale, Latent Context Language Models show that encoder-decoder compression can preserve strong in-context capabilities while compressing faster and using less memory than KV cache compression. The same models support agents that expand compressed context on demand and online compaction of the model's own reasoning. Promising next steps include adaptive compression that allocates capacity by information density, and compacting tool observations and accumulated working history in long-horizon agents.

AI USE STATEMENT

In this work, we used generative AI tools for:

1. Generate synthetic data sets. Part of our continual pre-training data consists of synthetic rewrites and generations from open-weight teacher models, and part of our SFT data was generated or re-labeled with `Qwen3-30B-A3B-Instruct-2507` and `Qwen3-235B-A22B-Instruct-2507` (Appendices B.2 and B.4).
2. Debug the codebase.

We have not used generative AI tools for:

1. Design or provide feedback on research methodology or experiments.
2. Clean and reformat datasets.
3. Support qualitative and thematic data analysis.
4. Interpret results.

These required disclosure tasks are not applicable to this work:

1. Help develop theoretical models or conceptual frameworks.
2. Formulate mathematical claims.
3. Provide critical ingredients for proving mathematical claims.
4. Assist in the writing of proofs.
5. Propose or refine hypotheses.
6. Assist with translation.

Additionally, we used generative AI tools for:

1. Editing the paper to improve readability.
2. Creating scientific figures. We use agents to write plotting code and create figures from our results; they do not generate any data or results.

We have reviewed all AI-assisted work. We take responsibility for the final content of this work, including text, claims or artifacts produced with the aid of generative AI.

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A Extended Related Work

Hard-token compression. Hard-token methods achieve compression by deleting or rewriting input tokens. Token pruning approaches remove tokens via importance heuristics (Li et al., 2023; Jiang et al., 2023; 2024), while summarization and rewriting methods compress by paraphrasing into fewer tokens (Chuang et al., 2024; Yoon et al., 2024). While widely used in practice (e.g., context compaction in Claude Code and Codex; Anthropic, 2025; OpenAI, 2025) and very effective for reducing prompt length, these methods are intrinsically lossy: once information is dropped or paraphrased in the discrete token space, exact lexical and structural detail is unrecoverable. This limits their ability to support code fidelity, format-sensitive reasoning, and lookup-style in-context learning in long-horizon settings.

Relatedly, many agent systems externalize memory via summarization, retrieval, or structured stores. Examples include hierarchical memory management (Packer et al., 2023), long-term conversational memory (Zhong et al., 2023; Wang et al., 2023), and agentic memory frameworks (Xu et al., 2025). While effective in extending interaction horizons, these approaches typically rely on lossy summaries or task-specific memory representations that are external to the base model.

KV cache compression. KV cache compression reduces the size of the KV cache by evicting entries; most methods rely on a hand-crafted or learned heuristic to select which entries to drop. SnapKV (Li et al., 2024c) compresses the cache by removing entries with low aggregated query attention on a per-head basis. SnapKV can be either prompt-agnostic, where pruning is performed without knowledge of the prompt, or prompt-dependent, where pruning is performed with knowledge of the prompt. Prompt-dependent methods have the downside of requiring labeling of the context and prompt for inputs, and pruning is highly specific to each individual input, limiting multi-turn chat applicability (Li et al., 2024b). To overcome these limitations, self-study (Eyuboglu et al., 2025; Zweiger et al., 2026) can be used to generate synthetic query signals from the context itself, enabling prompt-agnostic pruning without requiring labeled prompt-context pairs.

KVzip (Kim et al., 2025) performs query-agnostic KV cache compression by using teacher-forced context reconstruction as a proxy objective, assigning each KV pair an importance score from the maximum attention it receives during reconstruction, and pruning low-scoring entries. Fast KV Compaction via Attention Matching (Zweiger et al., 2026) compresses the KV cache by fitting a smaller set of keys and values, together with per-entry bias terms, that match the original cache's attention outputs and attention mass on reference queries. Expected Attention (Devoto et al., 2025) predicts KV importance by approximating future queries with a Gaussian distribution, computing each key's expected attention in closed form, and pruning entries with the lowest expected contribution. There are many other KV cache compression techniques and we refer the reader to Awesome KV cache Compression GitHub (Chen, 2023) for a comprehensive review.

We note that KV cache compression methods also pool before eviction: both Li et al. (2024c) and Zweiger et al. (2026) use max pooling, as does Devoto et al. (2025). Li et al. (2024c) further note that the choice of pooling operator does not significantly impact their performance.

It is also possible to do targeted KV cache compression offline for specific prompts. This approach applies to the setting where it is logical to expend more compute to compress the cache once, as this cost will be amortized over many user queries. Synk et al. (2025) compute the full KV cache before applying top-k cache compression and reuse the smaller cache. Eyuboglu et al. (2025) use self-study to learn small KV caches per corpus.

Soft-token compression. A complementary direction encodes long contexts into fewer learned continuous tokens. The most successful examples of soft-token approaches to compression require training on the target context, such as prefix tuning (Li & Liang, 2021; Tan et al., 2024). These methods can achieve comparable in-context performance to the base model with large compression ratios for the specific contexts they are trained on. Other soft-token approaches that do not require training on individual contexts are gist tokens (Mu et al., 2023), in-context autoencoders (Ge et al., 2023), and encoder-decoder compression frameworks (Chevalier et al., 2023; Liao et al., 2025; Dai et al., 2025; Li et al., 2025).

Efficient long sequence modeling. A complementary line of work targets the cost of long-context inference by modifying the underlying sequence model, the attention mechanism, or the positional encoding, rather than compressing the input. Early work scales Transformers to long inputs through segment-level recurrence and external memory: Transformer-XL (Dai et al., 2019) caches hidden states from previous segments to extend the effective receptive field, and the Compressive Transformer (Rae et al., 2019) further compresses older memory entries into a smaller compressed memory.

A second direction replaces softmax attention with formulations that scale linearly in sequence length. Linear-attention Transformers (Katharopoulos et al., 2020) cast attention as a kernel feature map to obtain $O(T)$ inference, state-space models such as S4 (Gu et al., 2021) and Mamba (Gu & Dao, 2024) use recurrent or selective-scan formulations with constant-size hidden state, and more recent hybrids such as Kimi Linear (Kimi Team et al., 2025) interleave linear-attention blocks with sparse full-attention blocks to recover long-range recall while keeping most of the per-layer cost linear. These approaches lower the asymptotic cost of attention but typically trade off exact long-range recall on retrieval-style tasks.

Within the Transformer family, recent DeepSeek models compress the attention computation itself: Multi-head Latent Attention in DeepSeek-V2 (Liu et al., 2024a) projects keys and values into a low-rank latent KV cache, and DeepSeek-V4 (Xu et al., 2026) introduces a hybrid attention architecture that interleaves Compressed Sparse Attention (CSA), which consolidates every m tokens of the KV cache into a single entry and then applies sparse top-k selection over those entries, with Heavily Compressed Attention (HCA), which uses a much larger compression rate $m' \gg m$ but retains dense attention over the resulting entries, jointly reducing both KV memory and per-token attention FLOPs at million-token context lengths.

A separate thread extends the usable context of pre-trained models through their positional encoding: rotary position embeddings (Su et al., 2024) provide relative attention with smooth extrapolation, and YaRN (Peng et al., 2023) rescales RoPE frequencies to extend the context window with minimal additional training.

Finally, parallel context encoding methods such as CEPE (Yen et al., 2024) take a different route: a small encoder produces dense representations of long-context chunks in parallel, and a frozen decoder consumes them through inserted cross-attention layers, exposing long contexts to the decoder without full self-attention over the raw tokens.

These approaches reduce the per-token cost of attention, the cost of positional indexing, or the effective sequence length seen by self-attention, rather than the number of tokens reaching the decoder; they are largely orthogonal to LCLMs and can in principle be composed.

B Dataset Details

B.1 Overview

Continual pre-training dataset. We construct a carefully curated high-quality pre-training mixture covering Common Crawl text, code, science and reasoning, long-context data, and instruction-style data. We partition each sequence into multiple segments and alternate between compressed segments and standard token segments. We then compute the next-token prediction loss on the uncompressed tokens *only*. This interleaved format differs from the simple first-half compressed, second-half trainable split used in prior work (Lin et al., 2025; Ge et al., 2023; Chevalier et al., 2023; Yen et al., 2024). By distributing compressed spans throughout the sequence, the model learns to condition on latent context at multiple positions rather than only at the beginning of the context. We provide a visual example of this data format in Figure 6. The exact pre-training mixture is described in Appendix B.2, with additional details on compression formatting in Appendix B.5.

SFT data. To recover performance after continual pre-training (Gao et al., 2025) and teach the model to use latent context, we post-train with supervised fine-tuning on compressed inputs. Our SFT mixture spans four components: (i) reasoning, (ii) long-context instruction following, (iii) general instruction following and multi-turn conversation, and (iv) agentic trajectories. For long-context and instruction data, we compress the documents and prompts. For reasoning, we instead keep the question uncompressed and compress spans of the reference chain of thought, so the model learns

to continue reasoning from compressed spans. Agent data combines tool-calling trajectories, kept uncompressed, with synthetic memory-expansion trajectories in which the model retrieves compressed segments with an `expand` tool (Section 7). Because some original completions were generated by outdated models, we relabel a subset of the SFT data using `Qwen3-30B-A3B-Instruct-2507` and `Qwen3-235B-A22B-Instruct-2507`, released under the Apache-2.0 license. The exact mixture of 21.5M examples is reported in Appendix B.4.

Auxiliary reconstruction data. To accelerate training and encourage the latent representations to preserve fine-grained information, we introduce an auxiliary reconstruction task. Given a sampled document, we compress the text and ask the model to repeat the original content. To increase diversity, we include a variety of sources spanning code, text, long documents, math, and LaTeX, as described in Appendix B.3. To reduce prompt overfitting, we use a bank of 100 prompt templates per source. This auxiliary task encourages the compressor not only to support semantic understanding but also to retain fine-grained details needed for tasks such as exact retrieval. We include auxiliary reconstruction data in both continual pre-training and SFT.

B.2 Continual Pre-training Dataset Curation

In early experiments, we only train on reconstruction data and hope the model can learn generalizable patterns. However, we find that training on such data alone allows the model to reconstruct the full sequence with negligible loss, but it generalizes poorly beyond reconstruction-style tasks. In fact, it cannot perform any other tasks, even when the LLM decoder is kept frozen. This might not seem surprising, as we are essentially performing a general version of prefix tuning. Thus, the learned representation, though general for different contexts, collapses to the task of reconstruction. On the other hand, training solely on next-token prediction enables the model to leverage compressed context for downstream generation and reasoning. However, the resulting representations often lack fine-grained fidelity (e.g., exact-string details), leading to weaker reconstruction and brittleness on tasks requiring precise recovery.

Motivated by this trade-off, we train on a mixture of next-token prediction and reconstruction data. Our working hypothesis is that next-token prediction provides task-aligned learning signals that teach the decoder to operate on compressed context, while reconstruction acts as an auxiliary objective that encourages information preservation and can accelerate early-stage representation learning. Theoretically, sufficiently large-scale next-token training alone may recover fine-grained fidelity, but we find that in practice, the reconstruction data serves as an auxiliary data source that accelerates the training of the general compressor.

Table 1: Dataset mixture for continual pre-training. Pre/Post-Comp are token counts before/after compression. We refer to the unique Nvidia license as "Nvidia"; the license can be found at `https://huggingface.co/datasets/nvidia/Nemotron-CC-v2.1/blob/main/LICENSE.md`.

Data Name	License	Data Description	Num Samples	Tokens			%
				Pre-Comp	Post-Comp	Trainable	
Nemotron CC	Nvidia	Continual pre-training (CC Text)	84.84M	60.69B	30.38B	30.08B	20.37
Nemotron Code	Nvidia	Continual pre-training (Code)	46.85M	51.18B	25.21B	25.01B	16.90
Nemotron Reasoning	Nvidia	Continual pre-training (Reasoning)	16.62M	52.32B	25.61B	25.50B	17.17
Longmino	odc-by	Continual pre-training (Long-Context)	0.548M	26.62B	4.24B	4.23B	2.84
SFT	cc-by-4.0	SFT with Compressed Prompt	20.67M	42.21B	38.02B	37.54B	25.49
Reconstruction	Nvidia	Reconstruction from Compression	23.53M	50.75B	25.69B	25.18B	17.23
Total	–		**192.06M**	**283.78B**	**149.16B**	**147.54B**	**100.00**

Curation. Our primary sources are NVIDIA's Nemotron pre-training datasets (NVIDIA et al., 2025; Blakeman et al., 2025). We sample 50M data points from Nemotron's pre-training code and cc code, 50M examples from high-quality and synthetic high-quality cc text, and 50M examples from Nemotron specialized SFT mixtures that cover diverse reasoning traces. A substantial portion of the synthetic data from Nemotron consists of rewrites or generations produced by strong teacher models (e.g., `Qwen3-30B-A3B`, `Qwen3-235B-A22B` (Yang et al., 2025), `GPT-oss-120B` (Agarwal et al., 2025), and `DeepSeek-R1` (Guo et al., 2025)), which alleviate the problem of forgetting.

Furthermore, to expose the compressor to longer documents, we sample approximately 500K examples from the OLMo-3 longmino collection (OLMo Team et al., 2025). Finally, to better preserve instruction-following and chat-template behavior, we also include Nemotron pre-training SFT data and convert it into a standardized instruction tuning and multi-turn chat format. Exact dataset composition is reported in Table 1.

B.3 Auxiliary Reconstruction Dataset Curation

We construct reconstruction data spanning three broad categories: text, code, and LaTeX. Text is sampled from Nemotron CC / math, FineWiki (Penedo, 2025), and RedPajama ArXiv (Weber et al., 2024); code is sampled from RedPajama GitHub, The Stack v2 (we concatenate files from the repo into one document) (Lozhkov et al., 2024), and CodeParrot; and LaTeX is sampled from TexTeller-OCR. Our goal is to maximize data diversity so that the compressor retains sufficient coverage for downstream tasks that may involve any of these modalities.

B.4 SFT Dataset Curation

For reasoning, we curate math, code, and science supervision from the Nemotron SFT datasets and OLMo-3 Dolci-Think (Nathawani et al., 2025a;b; Blakeman et al., 2025; OLMo Team et al., 2025). Unlike the other SFT data, where the prompt or document is compressed, reasoning examples keep the question uncompressed and compress spans of the reference chain of thought; the model is trained to continue reasoning from the compressed spans. About half of the reasoning examples (2.70M) contain compressed chain-of-thought spans, and the rest are left uncompressed.

For long-context instruction tuning, we combine long-context and RAG-style QA datasets (He et al., 2025; Jin et al., 2019; Liu et al., 2024d; Xu et al., 2024; Yang et al., 2018; Liu et al., 2024c; Joshi et al., 2017) with long-context code instruction datasets, including SWE-Fixer (Xie et al., 2025), NextCoder (Aggarwal et al., 2025), PyResBugs (Cotroneo et al., 2025), CommitPack (Muennighoff et al., 2023), and RepoBench (Liu et al., 2023b). Since some public datasets contain outdated or low-quality responses, we regenerate targets by labeling them with `Qwen3-235B-A22B-Instruct-2507`. In addition, we generate three synthetic long-context corpora: (1) repository summarization, using summarization question templates as instructions and concatenated repository files from The Stack v2 (Lozhkov et al., 2024) as the document; (2) document summarization, using long documents from FineWiki (Penedo, 2025) and RedPajama-ArXiv (Weber et al., 2024); and (3) repository code generation, where we hold out one file and ask the model to reconstruct it given the remaining repository context. All synthetic completions are generated by `Qwen3-30B-A3B-Instruct-2507`.

For instruction following, we include multi-turn conversation data from WildChat and LMSYS-Chat-1M (Zhao et al., 2024; Zheng et al., 2023), along with additional alignment-style data obtained by re-labeling with `Qwen3-30B-A3B-Instruct-2507`. We also add OLMo-3 instruction tuning, Nemotron instruction tuning, and the Tulu-3 mixture (Lambert et al., 2024); since these datasets are already generated by strong teacher models, we keep their original responses unchanged. Finally, we retain a small amount of reconstruction data to stabilize training and mitigate drift when optimizing on compressed inputs. For agentic behavior, we include tool-calling, interactive, search, and terminal trajectories from Nemotron-Agentic-v1, Nemotron-SFT-Agentic-v2, and OpenThoughts-Agent-SFT-100K (Blakeman et al., 2025; Raoof et al., 2026), which are kept uncompressed. We also generate synthetic memory-expansion trajectories with Qwen3 models (Yang et al., 2025), in which the source documents are compressed and the model requests individual segments with the `expand` tool before answering from the returned text. Exact dataset composition is reported in Table 2, and token statistics after packing in Table 3.

B.5 Compression Data Format

Continual pre-training. For the continual pre-training data, given a sequence, we split it into multiple segments, wrap every other segment with the special tokens `<|memory_start|>` and `<|memory_end|>`, and treat the wrapped spans as compressed content while leaving the remaining segments uncompressed.

For raw pre-training documents, we construct a fixed alternating pattern of wrapped and unwrapped segments, always beginning with a wrapped segment and ending with an unwrapped segment.

Table 2: SFT data mixture. Examples are counts after filtering; token statistics per packing pool are in Table 3. The same mixture is used for all compression ratios. Memory-expansion trajectories are generated with Qwen3 models (Apache-2.0); their source documents (e.g., LexGLUE, ACORD, ContractNLI) retain their original licenses. We refer to the unique Nvidia license as "Nvidia"; the license can be found at `https://huggingface.co/datasets/nvidia/Nemotron-CC-v2.1/blob/main/LICENSE.md`.

Data Name	License	Description	Examples
Reasoning			**5.46M**
Nemotron Reasoning	cc-by-4.0	Nemotron reasoning (compressed CoT)	4.23M
Dolci Think	odc-by	OLMo reasoning (compressed CoT)	1.01M
Nemotron Science	cc-by-4.0	Nemotron science (MCQ, reading QA)	0.22M
Long-Context Instruction Tuning			**7.32M**
Repo Summarization	Apache	Synthetic repo-level summarization	1.35M
Document Summarization	Apache	Synthetic long-document summarization	1.75M
Repo Code Generation	Apache	Synthetic repo-level code generation	2.02M
Long-Context QA	Apache	Long-context / RAG QA	0.84M
Long-Context Code Instruct	Apache	Long-context code instruction tuning	1.36M
General Instruction Following			**5.26M**
Multi-turn Conversation	odc-by	WildChat + LMSYS Chat 1M	2.48M
Dolci Instruct	odc-by	OLMo instruction tuning	1.46M
Tulu3 SFT Mixture	odc-by	Tulu3 instruction tuning	0.84M
Nemotron Instruct	Nvidia	Nemotron instruction tuning	0.35M
HelpSteer	cc-by-4.0	Alignment	0.13M
Reconstruction Data			**2.08M**
Reconstruction	Nvidia	Small reconstruction mixture	2.08M
Agent			**1.35M**
Agent Trajectories	cc-by-4.0 / Apache / MIT	Nemotron-Agentic, OpenThoughts-Agent (uncompressed)	1.19M
Memory Expansion	Apache	Synthetic segment-expansion trajectories (Qwen3)	0.15M
Total			**21.46M**

Documents longer than 16,384 tokens retain 8,192 trainable (unwrapped) tokens, while shorter documents retain half of their tokens as trainable. The number of segment pairs depends on document length: documents shorter than 2,048 tokens receive 1 pair; documents between 2,048 and 4,096 tokens receive 1-2 pairs; documents between 4,096 and 8,192 tokens receive 2-4 pairs; documents between 8,192 and 16,384 tokens receive 4-6 pairs; and documents longer than 16,384 tokens receive 4-8 pairs. Within each sequence, the first wrapped segment contains 30%-40% of the total wrapped tokens, the last unwrapped segment contains 40%-50% of the total trainable tokens, and the remaining segments are allocated with a $\pm 20\%$ jitter. No segment is allowed to be shorter than 128 tokens.

Instruction tuning. For conversational data, we apply wrapping independently to each message. With 50% probability, the entire message content is enclosed within a single pair of tags. Otherwise, with the remaining 50% probability, we insert 1-3 wrapped regions inside the message and leave the remaining tokens outside the tags. The number of wrapped regions depends on message length: messages shorter than 32 tokens are always fully wrapped; messages between 32 and 200 tokens receive 1 region; messages between 200 and 600 tokens receive 1-2 regions; and messages of 600 tokens or more receive 1-3 regions. Wrapped regions cover 80%-100% of the message tokens in aggregate, and we enforce a minimum 5% unwrapped gap whenever feasible. If the realized wrapped coverage falls below 70%, we fall back to fully wrapping the message. Since this decision is made independently for each message, multi-turn conversations naturally contain a mixture of fully wrapped turns and turns with small unwrapped spans, with a bias toward high overall coverage.

C Extended Architecture Search

C.1 Prior Soft-Token Methods in Our Design Space

Table 4 describes representative soft-token compressors by the design axes we sweep. Each column corresponds to one of our controlled comparisons: the readout to the pooling operator and encoding granularity (Figure 2, Appendix C.2), the encoder to the attention mask (Figure 2) and initialization (Appendix D.1), the adapter to the adapter comparison (Appendix C.3), and decoder training to the frozen, LoRA, and full-parameter settings (Section 4). These comparisons isolate individual design

Table 3: SFT token statistics after packing into sequences of at most 16,384 decoder positions at 16× compression. Decoder positions include latent positions and memory boundary tags; trainable tokens receive next-token prediction loss. Nemotron Science is packed in the other pool.

Pool	Examples	Sequences	Decoder positions	Trainable tokens	Share
Agent	1.35M	0.27M	4.36B	1.10B	11.7%
Reasoning	5.24M	0.71M	11.66B	9.44B	31.4%
Other	14.88M	1.29M	21.16B	17.24B	56.9%
Total	21.46M	2.28M	37.19B	27.78B	100%

choices under matched data, scale, and decoder; they do not reproduce the complete prior systems, which also differ in training data, scale, and target tasks.

Table 4: **Prior soft-token compressors described by our design axes.**

Method	Readout	Encoder	Adapter	Decoder training
AutoCompressor (Chevalier et al., 2023)	learned summary tokens	the decoder LM itself	–	full (OPT) / LoRA (Llama-2)
ICAE (Ge et al., 2023)	learned memory tokens	LLM with LoRA	–	frozen
REFRAG (Lin et al., 2025)	one embedding per chunk ($W = N$)	RoBERTa encoder	projection layer	full, after alignment
E2LLM (Liao et al., 2025)	attention pooling per chunk	pretrained embedding model	adapter	LoRA
GMSA (Tang et al., 2025)	mean over token groups	LLM with LoRA	attention layers	full, in fine-tuning
Simple Context Compression (Feldman & Artzi, 2025)	mean pooling	LLM, bidirectional, LoRA	–	LoRA
xRAG (Cheng et al., 2024)	one retrieval embedding	frozen retriever	2-layer MLP	frozen
CEPE (Yen et al., 2024)	cross-attention to encoder states	small context encoder	cross-attention	frozen
LCLM (ours)	mean pooling, $W = 1024$	embedding model, causal	MLP	full, staged

C.2 Formal Definitions of Pooling Operators

Mean versus concatenation. Figure 2 compares the three pooling operators in our pre-training sweep. Mean pooling consistently improves pre-training loss over token-based pooling, but is empirically indistinguishable from concatenation. This agrees with prior evidence that mean pooling can outperform token-based pooling for compression (Feldman & Artzi, 2025), and with findings that mean pooling can be surprisingly effective despite being a lossy operation in text embedding models (Hara et al., 2026). It is also consistent with related observations in vision architectures (Chu et al., 2021). While concatenation can, in principle, preserve distinct representations that mean loses, and has been found to outperform mean pooling in other representation-learning settings (Chen et al., 2025), we do not observe this advantage in our small-scale experiment. We compare these two operators at scale in Figure 8 and Appendix E.6.1, where concatenation outperforms mean pooling at low compression ratios and mean pooling outperforms concatenation at high compression ratios, while the gap between the two narrows as context length increases.

We now give the formal definitions of pooling operators, and illustrate them visually in Figure 7.

Token-based pooling. The most common method is appending one or more learned special pooling tokens per latent output to each encoder window. Let $p_{i,1}, \ldots, p_{i,M_i}$ denote these pooling tokens. We encode

$$(\tilde{h}_1^{(i)}, \ldots, \tilde{h}_{|w_i|+M_i}^{(i)}) = \mathrm{Enc}_\phi([w_i; p_{i,1}; \ldots; p_{i,M_i}]), \tag{2}$$

and use the hidden states at the pooling-token positions:

$$z_k^{(i)} = \tilde{h}_{|w_i|+k}^{(i)}, \qquad k = 1, \ldots, M_i. \tag{3}$$

This generalizes the common EOS-pooling strategy: when $W = N$, a single pooling token is appended for each compression block; when $W > N$, several pooling tokens summarize different regions of the same encoder window.

Mean pooling. For each window w_i, we partition its hidden states into consecutive groups of size N. For latent index $k = 1, \ldots, M_i$, define

$$G_{i,k} = \{(k-1)N + 1, \ldots, \min(kN, |w_i|)\}. \tag{4}$$

The corresponding latent vector is the average hidden state over this group:

$$z_k^{(i)} = \frac{1}{|G_{i,k}|} \sum_{j \in G_{i,k}} h_j^{(i)}. \tag{5}$$

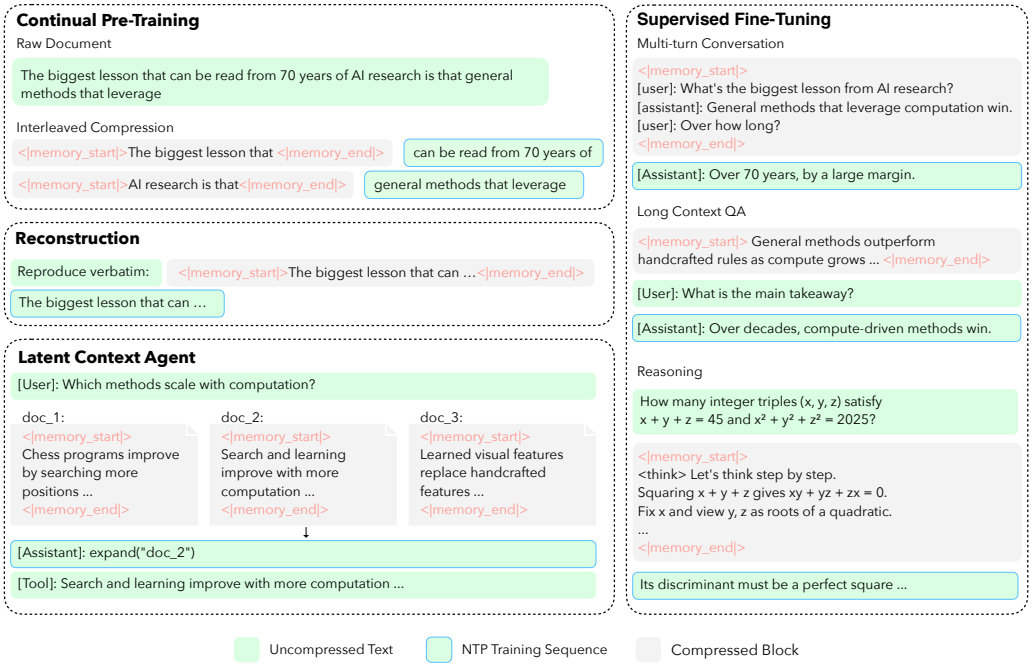

Figure 6: **Examples of the data used to train LCLMs.** Continual pre-training interleaves compressed and uncompressed spans, and reconstruction recovers source text from latents. SFT includes conversations, long-context QA, reasoning, and agentic trajectories. Reasoning questions remain raw while selected spans of the reference chain of thought are compressed; the remaining continuation is supervised. Native tool trajectories remain raw, while expansion examples compress source observations and retain raw tool calls and returned text. Blue outlines mark supervised decoder tokens.

Mean pooling directly aggregates the token-level representations assigned to each compression block. Across our architecture search, mean pooling consistently outperforms EOS-style token pooling, matching observations from prior text-compression and vision-encoder work.

Concat pooling. Rather than averaging or selecting a designated token, concat pooling preserves the full per-token representation by concatenating consecutive encoder hidden states within each compression block. For window w_i and latent index $k = 1, \ldots, M_i$, let $G_{i,k} = \{(k-1)N + 1, \ldots, \min(kN, |w_i|)\}$ as in mean pooling. The concatenated latent is

$$z_k^{(i)} = \left[h_j^{(i)} \right]_{j \in G_{i,k}} \in \mathbb{R}^{N\, d_{\text{enc}}}, \tag{6}$$

i.e., a vector of dimension $N\, d_{\text{enc}}$ formed by stacking the N encoder hidden states. The adapter is widened accordingly so that its first MLP layer takes inputs of dimension $N\, d_{\text{enc}}$ and projects back to the decoder hidden dimension d_{dec}, analogous to the patch-merger / spatial-concat scheme used in Bai et al. (2025).

C.3 Adapter Design

The adapter $a(\cdot)$ maps the compressed latent sequence $z_{1:M} \in \mathbb{R}^{M \times d_{\text{enc}}}$ into a sequence $s_{1:M} \in \mathbb{R}^{M \times d_{\text{dec}}}$ in the decoder embedding space. Prior encoder-decoder compression work often assumes $d_{\text{enc}} = d_{\text{dec}}$, but a wide range of encoder-decoder models pair smaller encoders with larger decoders, making the adapter an important design choice. We formally define the two adapter families in our sweep below.

MLP adapter. The MLP adapter is a standard two-layer feed-forward network with a GELU non-linearity (Hendrycks & Gimpel, 2016) and an RMSNorm (Zhang & Sennrich, 2019) pre-

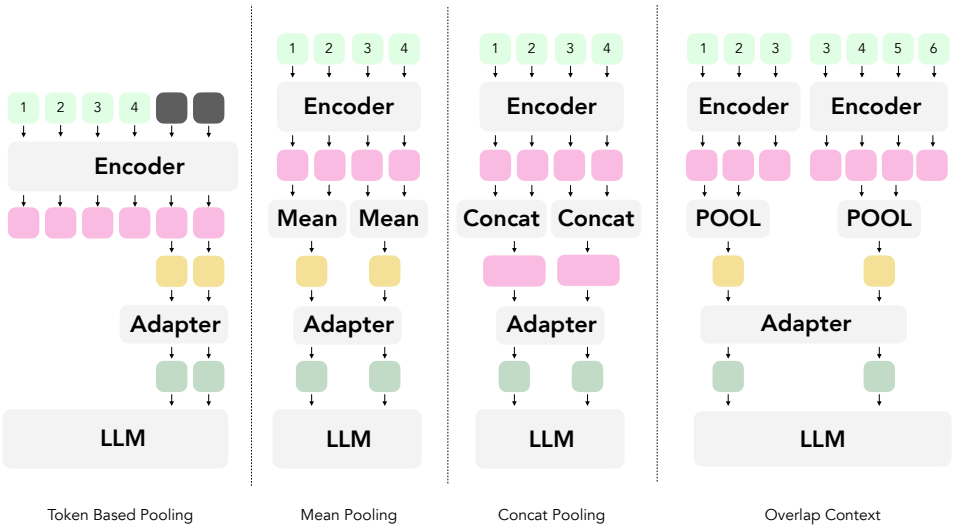

Figure 7: **Full architecture design choices for the compressor.** From left to right, we visualize token-based pooling, mean pooling, concat pooling, and overlap context.

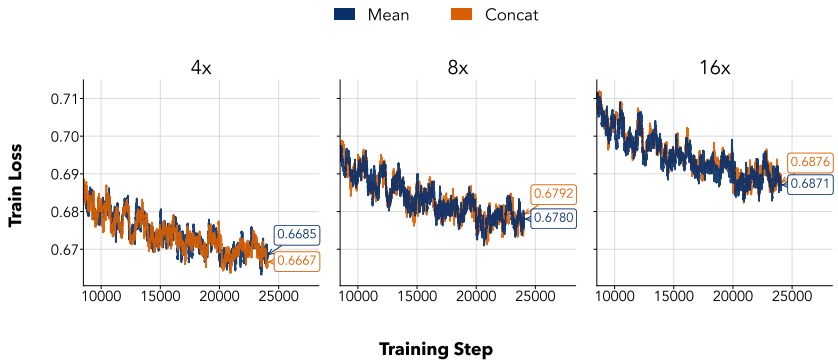

Figure 8: **Comparison between mean and concat at scale for all ratios.** From Figure 2, we identify mean and concat as the most promising pooling operators, with mean slightly outperforming concat in training loss. We train at larger scale and find that mean remains marginally better than concat at higher compression ratios, but loses to concat at lower compression ratios.

normalization, following the projection design used in LLaVA-style VLMs (Liu et al., 2023a):

$$\hat{z}_m = \mathrm{RMSNorm}(z_m), \tag{7}$$

$$s_m = W_2\,\mathrm{GELU}\big(W_1\hat{z}_m + b_1\big) + b_2, \qquad m = 1, \ldots, M, \tag{8}$$

where $W_1 \in \mathbb{R}^{d_h \times d_{\mathrm{enc}}}$ and $W_2 \in \mathbb{R}^{d_{\mathrm{dec}} \times d_h}$ with hidden dimension d_h. Each latent token is projected independently and the adapter does not mix information across the latent sequence. When the encoder uses concat pooling (Appendix C.2), each z_m has dimension $N\,d_{\mathrm{enc}}$ instead of d_{enc}, so the input dimension of W_1 is widened to $N\,d_{\mathrm{enc}}$ and the first MLP layer is correspondingly $N\times$ larger.

Attention-based adapter. The attention-based adapter adds a single multi-head self-attention layer over the latent sequence before the MLP projection, with an RMSNorm pre-normalization on the latents:

$$\hat{z}_m = \mathrm{RMSNorm}(z_m), \tag{9}$$

$$\tilde{z}_{1:M} = \mathrm{MHSA}\big(\hat{z}_{1:M}\big), \tag{10}$$

$$s_m = W_2\,\mathrm{GELU}\big(W_1\tilde{z}_m + b_1\big) + b_2, \qquad m = 1, \ldots, M. \tag{11}$$

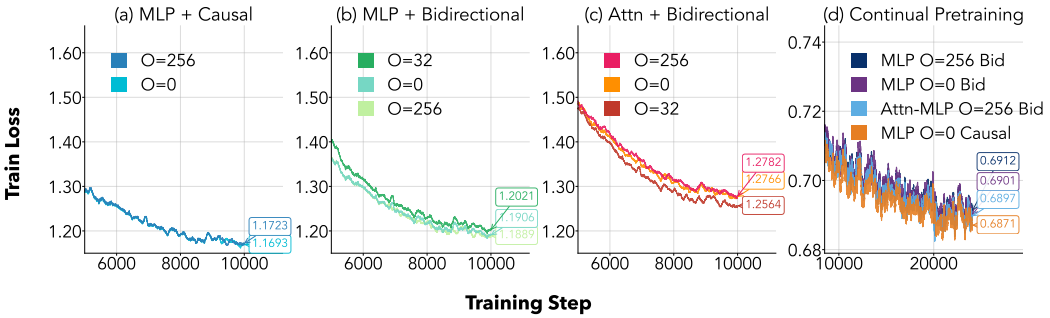

Figure 9: **MLP adapters, causal masking, and no boundary overlap give the lowest pre-training loss across the architecture sweep.** We sweep combinations of adapter, boundary-overlap, and encoder mask, and find that (1) causal masking is strictly better than bidirectional masking, (2) boundary overlap does not improve over non-overlapping windows while substantially increasing compute, and (3) the MLP adapter outperforms attention-based adapters. The same trends hold at scale (plot d).

The self-attention layer operates in the encoder hidden dimension d_{enc} and lets information mix across latent tokens before projection, at the cost of additional parameters and a compute term quadratic in M.

Comparison. Across the adapter sweep in Figure 9, the MLP adapter achieves lower pre-training loss than the attention-based variant while adding less computation, in contrast to prior findings (Tang et al., 2025) that attention-based adapters perform better. We therefore use the MLP adapter as the default in all subsequent experiments.

C.4 Boundary Context

A potential limitation of fixed encoder windows is that information crossing a window boundary is split across two encoder forward passes. Increasing the window size W reduces the frequency of such boundaries, but also increases compression-time cost. As an alternative, we implement boundary context overlapping, where each encoder window is extended with O neighboring tokens while the number of latent tokens is kept unchanged.

For a target window

$$w_i = x_{(i-1)W+1:\min(iW,T)},$$

we construct an overlapped encoder input $\tilde{w}_i$ by adding neighboring context tokens. For bidirectional attention, we include both left and right overlap when available:

$$\tilde{w}_i = x_{\max(1,(i-1)W-O+1):\min(iW+O,T)}. \tag{12}$$

We provide a visualization in the rightmost figure in Figure 7. For causal attention, future context is unavailable, so we include only left overlap:

$$\tilde{w}_i = x_{\max(1,(i-1)W-O+1):\min(iW,T)}. \tag{13}$$

After encoding $\tilde{w}_i$, we apply pooling only to hidden states corresponding to the original non-overlapped region w_i, and discard pooled outputs that correspond to overlap tokens. Thus, overlap changes the encoder context available to each window but does not change the number of latent tokens passed to the decoder.

We sweep $O \in \{0, 32, 256\}$ for $W \in \{256, 1024\}$ in Figure 9. Overlap does not noticeably improve pre-training loss in most settings, while increasing training cost because boundary tokens are encoded multiple times. For example, with $W = 1024$ and $O = 256$, each interior bidirectional window processes 1536 tokens instead of 1024. We therefore do not use overlap in the default architecture.

D Full-Scale Training Recipe Sweeps

Optimal architecture at scale. Overall, our from-scratch pre-training experiments in Figure 2 serve as a lightweight architecture sweep, allowing us to narrow the search space to a smaller set of promis-

Table 5: **Training recipe for compression model for four different stages.** We report, for each stage, which module(s) are optimized (adapter / encoder / decoder), peak learning rates, learning-rate schedule, optimizer, global batch size (in tokens), sequence length, training-token budget, and the data source used.

	Stage 0 Adapter Training	Stage 1 Encoder Training	Stage 2 LLM Training	Stage 3 SFT
Training Config				
Adapter Peak LR	1.0×10^{-3}	6.0×10^{-5}	6.0×10^{-5}	3.0×10^{-5}
Encoder Peak LR	NA	6.0×10^{-5}	6.0×10^{-5}	3.0×10^{-5}
LLM Peak LR	NA	NA	1.0×10^{-5}	3.0×10^{-5}
LR scheduler	5% warmup steps with cosine decay to 1.0×10^{-6}			
Optimizer	AdamW ($\beta_1 = 0.9$, $\beta_2 = 0.95$)			
Data				
LLM Batch size (tokens)	4 Million			
LLM Sequence Length	16384			
Encoder Tokens	17.54 B	35.07 B	82.43 B	60.35 B
LLM Tokens (16x)	21.29 B	42.58 B	100.08 B	37.19 B
Total Tokens (16x)	38.83 B	77.65 B	182.51 B	97.54 B
Data Source	pre-training Mixture	pre-training Mixture	pre-training Mixture	SFT

ing design choices. We then scale these candidates using the full training pipeline, both to identify the strongest architecture at scale and to validate that the small-scale pre-training findings remain predictive under large-scale training. For our main experiments, we use `Qwen3-Embedding-0.6B` as the encoder with `Qwen3-4B-Instruct-2507` as the decoder. Across the continual pre-training loss curves in Figures 8 to 10 and the downstream ablations in Appendix E.6, we find that the optimal architecture at scale uses an encoder window $W = 1024$, causal masking, and an MLP adapter. The choice of pooling operator depends on the compression ratio: mean pooling has a small edge over concatenation at $16\times$ compression, while concatenation slightly outperforms mean pooling at $4\times$. Since we primarily focus on $16\times$ compression in our analysis, we adopt mean pooling as the default in all subsequent experiments. Full results and per-task breakdowns are reported in Appendix E.6.

D.1 Pre-trained Encoder Representations

For the encoder initialization, to determine whether an embedding model's representation (Lin et al., 2025; Liao et al., 2025; Yen et al., 2024) is better than that of a standard language model (Tang et al., 2025; Chevalier et al., 2023; Feldman & Artzi, 2025), we conduct an experiment with the EOS pooling token. We can see from Figure 10 (d) that using the embedding model as the encoder outperforms using an LLM as the encoder. Note the embedding model was initialized from the LLM (Zhang et al., 2025b). This shows that embedding model training provides a better representation for the encoder, though the gap gradually narrows with longer training. We also show downstream evaluation performance in Table 35.

D.2 LR Sweep

Language models are prone to catastrophic forgetting during continual pre-training and SFT (Luo et al., 2025; Li et al., 2024a). To actively avoid forgetting, we sweep the peak learning rate for stages 2 and 3 of training. To test for catastrophic forgetting, we then benchmark the language model without compression after SFT and check that its performance is comparable to the benchmark performance of the language model before training. For stage 2, we sweep from 1×10^{-6} to 1×10^{-5} and find that a larger learning rate improves downstream benchmarks with minimal drift from the original model (Appendix D.3). For stage 3, we sweep from 2×10^{-5} to 5×10^{-5}. We do not observe significant differences in those SFT LRs across different models; we report the detailed numbers on downstream benchmarks in Appendix E.5.

D.3 Decoder Retention Without Compression

To measure how much training changes the decoder itself, we evaluate our $4\times$, $8\times$, and $16\times$ models with compression disabled, so that the decoder reads the full context as ordinary tokens, and compare them with the original `Qwen3-4B-Instruct-2507`. All four models use identical prompts,

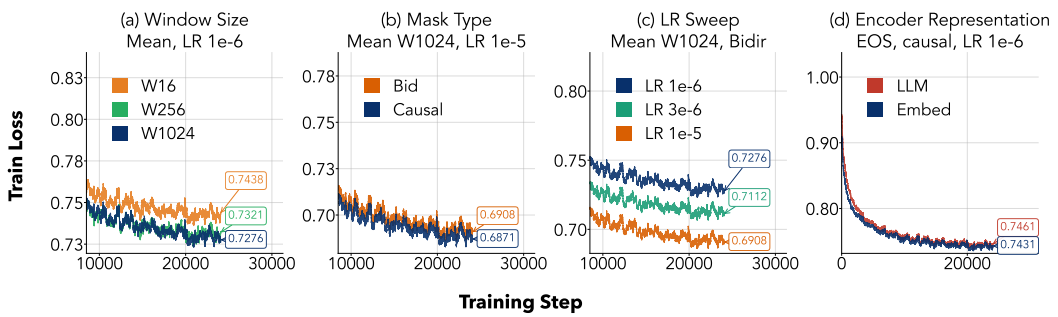

Figure 10: **Architecture choices selected by the small-scale sweep continue to hold at scale.** Continual pre-training loss for the full-pipeline runs at compression ratio 16×. Across (a) encoder window size, (b) encoder attention mask, (c) stage-2 learning rate, and (d) encoder initialization (LM vs. embedding), the configuration chosen from the from-scratch sweep ($W = 1024$, causal masking, embedding-initialized encoder) yields the lowest pre-training loss.

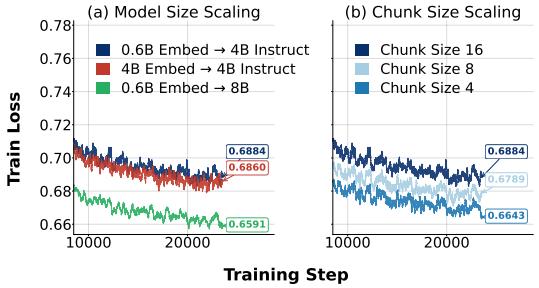

Figure 11: **Scaling the decoder helps more than scaling the encoder, and lower compression ratios yield lower pre-training loss. Left:** pre-training loss at the end of stage 2 with compression ratio 16× across encoder/decoder size combinations; increasing the decoder size produces a much larger drop in loss than increasing the encoder size. **Right:** pre-training loss at the end of stage 2 for our 0.6B-4B models across compression ratios; lower compression ratios yield lower pre-training loss. Note that the 4B-encoder and 8B-decoder runs use 256 ranks rather than 128 ranks. Because our stateful Parquet dataloader assigns work by rank, these runs complete slightly fewer optimization steps. For a clean comparison, we therefore truncate all loss curves at the same optimization step in the plot above.

output budgets, and scoring; the base model is re-evaluated under this protocol. As shown in Table 6, the trained decoders stay within 1.7 points of the original model on RULER at 4k, within 2.8 points at 8k, and within 4.5 points at 16k, and slightly exceed it on LongBench.

Table 6: **Accuracy with compression disabled.** The decoders of our 4×, 8×, and 16× models read the uncompressed context and are compared with the original model under the same protocol (RULER: 13 tasks, 6,500 questions per context length; LongBench EN16: macro average over 16 English and code tasks). Differences from the original model are in parentheses.

	`Qwen3-4B-Instruct-2507`	LCLM 4× decoder	LCLM 8× decoder	LCLM 16× decoder
RULER 4k	94.49	94.27 (−0.21)	92.86 (−1.62)	93.41 (−1.07)
RULER 8k	93.44	91.55 (−1.88)	90.73 (−2.71)	90.98 (−2.46)
RULER 16k	93.53	91.54 (−1.99)	89.46 (−4.07)	89.10 (−4.42)
LongBench EN16	45.30	47.13 (+1.83)	45.98 (+0.67)	46.91 (+1.60)

D.4 Scaling Up Model Size

To study scaling behavior, we ask two questions: (i) does a larger encoder improve compression quality, and (ii) does a larger decoder, which has a wider hidden dimension that could compress more information per token, improve performance under compression? Accordingly, we add two model configurations: (1) using the larger `Qwen3-Embedding-4B` as the encoder with the same size

`Qwen3-4B-Instruct-2507` decoder; and (2) using the same size `Qwen3-Embedding-0.6B` encoder and the larger `Qwen3-8B` as the decoder. In Figure 11 (a), we see that increasing the size of the decoder is much more beneficial in terms of pre-training loss than increasing the size of the encoder.

However, the scaling results in Table 7 are mixed. The 0.6B encoder performs best across the RULER tasks, while the 4B encoder performs best on the remaining evaluations. In contrast, the 8B decoder achieves substantially lower pre-training loss but does not yield the downstream gains we expected. We suspect this is partly due to a mismatch between the training mixture and the decoder initialization: our data curation and recipe were tuned around the 4B instruct decoder, whereas the 8B decoder is a hybrid-thinking model and may require a different data distribution. Moreover, the 4B instruct model already outperforms the 8B model in the full-cache setting on several evaluations, which may limit the apparent benefit of scaling the decoder in our current setup.

Table 7: Encoder/decoder scaling at 16× compression

Enc / Dec	RULER 4K	RULER 8K	RULER 16K	LongBench	LongHealth5	GSM8K
0.6B / 4B	**75.06**	**70.23**	**65.91**	37.33	<u>67.50</u>	<u>81.05</u>
0.6B / 8B	71.20	<u>67.40</u>	<u>62.22</u>	<u>37.80</u>	64.80	77.30
4B / 4B	<u>71.30</u>	66.90	62.00	**39.00**	**69.80**	**83.20**

D.5 Packed Sequences

Since our corpus contains many long-context examples with highly variable lengths, conventional batching would waste substantial computation on padding. To improve training throughput, we pack multiple examples into a single sequence. Because we continually pre-train an instruction-tuned model, we prevent cross-example information leakage by resetting the attention mask at example boundaries, yielding a block-diagonal attention pattern. We implement this efficiently using variable-length attention kernels (Dao, 2023; Dong et al., 2024).

E BENCHMARKS AND RESULTS

Table 8: **Evaluation benchmarks and what content is compressed.** We evaluate on long-context suites and on GSM8K, a short and information-dense benchmark. The "What is Compressed" column specifies which part of the input is placed inside the compressible memory block, while remaining components, such as instructions, are kept as hard tokens when applicable.

Benchmark	Description	What is Compressed
Long-context		
RULER	Synthetic long-context stress tests from 4K–16K.	Task-specific context
LongBench	Aggregated long-context suite covering single- and multi-document QA, summarization, few-shot learning, synthetic tasks, and code completion.	Task-specific context
LongHealth	Clinical-document multiple-choice QA with patient-case context. Five documents are concatenated. No CoT prompting.	Task-specific context
Fine-Grained Compression		
GSM8K	Short and information-dense grade-school math word problems.	Whole prompt

E.1 GSM8K PERFORMANCE VS COMPRESSION RATIO

The long-context benchmarks show that LCLMs can compress extended contexts efficiently. We next evaluate on GSM8K (Cobbe et al., 2021) to test whether LCLMs can also handle short, information-dense inputs, where nearly every token may be relevant to the answer. In Figure 12, LCLMs achieve the highest accuracy across all compression ratios on GSM8K, with particularly strong gains over baselines at higher compression ratios. These are aggressive compression settings: compression ratios of $16\times$ and $8\times$ remove 93.75% and 87.5% of the input tokens, respectively. Strong performance in this setting demonstrates that LCLMs are not specialized only for long-context QA; they can also compress short, dense contexts, making them practical for general-purpose deployment.

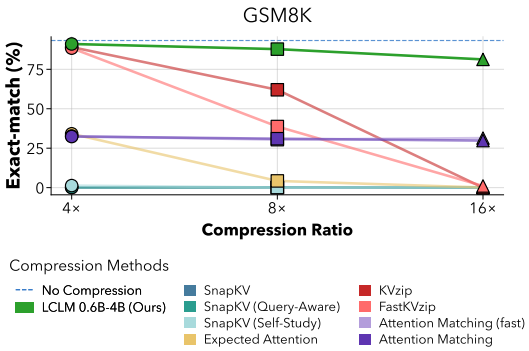

Figure 12: **Latent Context Language Models can compress small dense contexts with high accuracy.** We plot GSM8K accuracy over different compression ratios and find that LCLMs maintain much higher accuracy at larger compression ratios. Full data are provided in Table 9. We do not report compression time for GSM8K because the context is small enough that compression-time measurements are too noisy to support reliable conclusions.

E.2 BASELINE CONFIGURATIONS

Query-aware methods, such as SnapKV, are designed to compress a context given a known query; however, the resulting compressed cache may not generalize well to unseen queries or future turns. Query-agnostic methods, such as KVzip and FastKVzip, compress a cache without access to the

downstream query, often using reconstruction-style objectives such as repeating the original context. Self-study, as introduced by Eyuboglu et al. (2025), performs compression using synthetic queries to expand coverage over potential inference-time queries. These synthetic queries are typically produced by prompting the target decoder to generate questions about the context. In Attention Matching (Zweiger et al., 2026), the authors experiment with a mixed query-agnostic and self-study configuration and find that self-study has limited impact on the repeat-prefill prompt. Since self-study introduces additional compression-time overhead, we do not apply it to RULER.

It is also important to distinguish algorithmic and theoretical cache reduction from systems-realizable cache reduction. Some KV cache methods produce an actual smaller cache that can, in principle, reduce decoding memory and latency. Others, such as Kim et al. (2025; 2026), are evaluated by masking or subsampling entries from a full cache, or by using non-uniform eviction patterns across heads and layers. These approaches are useful for measuring the quality of a compressed cache, but they do not necessarily translate into wall-clock speedups or memory savings in standard inference engines without specialized kernels that have not been released or even implemented.

E.3 Additional Pareto Frontiers

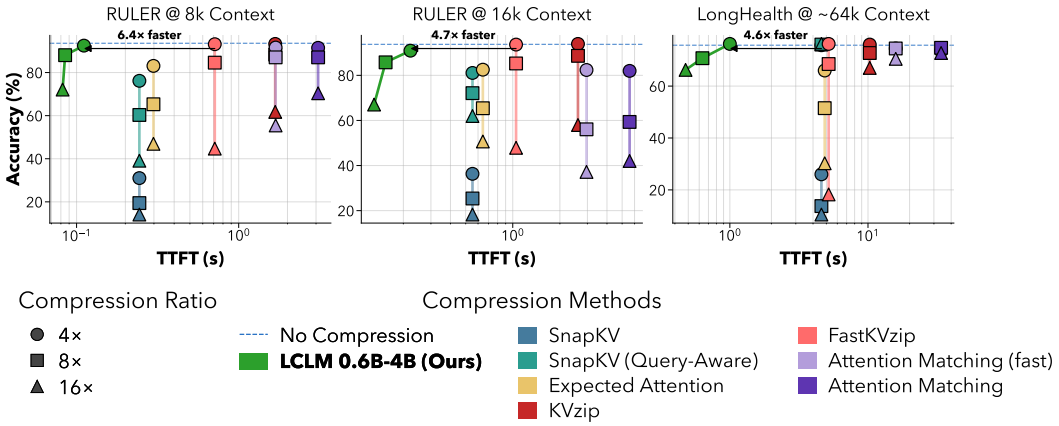

Figure 13: **Latent Context Language Models establish a new Pareto frontier on long-context benchmarks in terms of time to first token.** We plot accuracy across RULER and LongHealth, and find that our LCLMs compress samples faster with equivalent or higher accuracy than other compression methods. Full results can be viewed in Tables 9, 11 and 12.

E.4 RESULTS

Table 9: Summary across compression ratios: RULER, LongBench, LongHealth5, GSM8K. Rows are grouped by compression ratio (16x, 8x, 4x). Best per column within each ratio block in **bold**, second-best underlined.

Model	RULER 4k	RULER 8k	RULER 16k	LB en16	LB cn5	LongHealth5	GSM8K
Qwen 4B Instruct (full KV)	94.41	93.58	93.74	45.21	46.63	75.75	93.25
16x compression							
LCLM 0.6b-4b (Mean)	**77.01**	**72.10**	**67.04**	38.26	31.38	66.25	**81.27**
LCLM 0.6b-4b (Concat)	74.50	70.30	64.90	36.24	25.88	**76.30**	78.90
ExpAttn	40.97	46.93	50.67	29.44	20.51	30.25	0.08
SnapKV	14.31	14.11	18.27	26.96	18.30	10.50	0.08
SnapKV-QA	20.54	39.09	61.96	38.52	**42.26**	76.25	0.08
KVzip	62.73	61.73	57.97	25.86	17.12	67.00	0.00
KVzipFast	40.01	44.70	47.86	25.76	17.08	18.25	1.06
AM-Fast	53.09	55.45	37.17	**40.49**	31.51	70.50	31.39
AM-Slow	69.21	70.38	42.02	40.26	31.85	72.75	29.80
8x compression							
LCLM 0.6b-4b (Mean)	89.19	88.06	85.76	41.74	36.65	70.75	**87.79**
LCLM 0.6b-4b (Concat)	87.20	86.80	84.40	42.32	36.46	**79.50**	87.40
ExpAttn	65.08	65.28	65.41	38.13	30.56	51.50	4.25
SnapKV	19.64	19.42	25.39	32.28	25.18	13.75	0.15
SnapKV-QA	47.66	60.32	72.10	41.73	**45.41**	76.00	0.15
KVzip	**90.27**	**88.34**	**88.65**	40.72	36.09	72.75	62.02
KVzipFast	86.08	84.59	85.27	38.17	30.91	68.50	38.74
AM-Fast	89.63	87.05	56.06	**44.50**	41.52	74.50	30.40
AM-Slow	89.20	87.05	59.34	44.22	41.11	74.75	31.01
4x compression							
LCLM 0.6b-4b (Mean)	93.44	92.49	90.93	**46.04**	40.92	76.25	**91.05**
LCLM 0.6b-4b (Concat)	92.30	91.50	90.50	45.39	41.80	**82.50**	89.90
ExpAttn	85.26	83.09	82.51	41.95	41.57	66.00	34.12
SnapKV	27.84	31.02	36.33	38.18	34.22	26.00	0.08
SnapKV-QA	69.24	76.16	81.06	43.74	46.19	75.75	0.08
KVzip	**94.43**	**93.28**	**93.93**	45.30	47.45	76.00	89.08
KVzipFast	94.17	93.15	93.64	45.16	**48.66**	76.25	88.40
AM-Fast	92.69	91.60	82.37	45.48	48.39	74.50	32.68
AM-Slow	92.52	91.47	81.98	45.78	48.07	73.50	32.37

Table 10: RULER per-task at 4k context. Rows grouped by compression ratio (16x, 8x, 4x).

Model	ns1	ns2	ns3	nm1	nm2	nm3	nmv	nmq	vt	cwe	fwe	qa1	qa2	AVG
Qwen 4B Instruct	100.00	100.00	100.00	99.80	96.40	99.80	99.85	100.00	99.84	97.50	87.53	84.40	62.20	94.41
16x compression														
LCLM 0.6b-4b (Mean)	96.60	90.20	58.40	**86.00**	84.20	**63.20**	**74.85**	75.55	82.92	76.04	**92.80**	67.60	**52.80**	**77.01**
LCLM 0.6b-4b (Concat)	96.40	91.80	62.40	83.80	84.20	54.00	59.50	**77.50**	79.50	74.30	90.10	65.40	49.00	74.45
ExpAttn	**100.00**	49.20	0.60	57.60	2.20	0.00	56.75	25.70	97.80	18.36	66.20	33.20	25.00	40.97
SnapKV	4.00	1.60	2.40	9.80	1.80	0.00	8.55	8.55	5.48	25.30	73.13	24.80	20.60	14.31
SnapKV-QA	16.60	7.20	2.40	10.20	4.80	0.00	9.10	10.50	15.80	25.14	57.67	60.60	47.00	20.54
KVzip	**100.00**	91.60	**96.00**	62.40	69.80	41.00	32.85	43.35	**99.96**	21.80	70.13	49.00	37.60	62.73
KVzipFast	**100.00**	38.80	31.60	23.00	65.40	26.00	7.70	9.80	99.60	12.66	54.73	24.80	26.00	40.01
AM-Fast	**100.00**	52.80	7.80	33.80	89.00	3.80	22.60	17.85	95.16	**76.82**	81.40	63.20	46.00	53.09
AM-Slow	**100.00**	**95.20**	31.60	74.00	**94.00**	9.40	65.40	56.50	94.96	74.52	81.40	**70.60**	52.20	69.21
8x compression														
LCLM 0.6b-4b (Mean)	98.60	98.40	77.80	95.60	95.40	89.80	96.40	94.90	94.72	92.28	**93.20**	75.20	57.20	89.19
LCLM 0.6b-4b (Concat)	98.40	97.00	76.60	94.60	95.60	86.00	93.80	92.30	90.70	**92.80**	88.40	74.80	53.20	87.25
ExpAttn	**100.00**	96.20	5.20	92.20	69.20	0.40	93.00	80.20	**100.00**	48.08	85.20	39.20	37.20	65.08
SnapKV	12.40	8.20	2.40	12.60	3.20	0.00	11.20	12.60	9.80	49.06	80.07	31.00	22.80	19.64
SnapKV-QA	54.40	97.40	2.40	46.80	14.40	2.20	21.25	79.65	52.60	43.22	70.20	78.20	56.80	47.66
KVzip	**100.00**	98.20	**99.80**	97.20	98.60	99.40	82.85	96.70	99.96	77.48	82.67	**79.60**	**61.00**	**90.27**
KVzipFast	**100.00**	**100.00**	**99.80**	91.80	98.20	**99.60**	54.15	93.70	99.96	66.52	81.27	76.40	57.60	86.08
AM-Fast	**100.00**	99.40	93.20	**99.20**	98.20	93.00	96.90	**98.45**	96.60	65.90	84.53	79.40	60.40	89.63
AM-Slow	99.80	99.40	90.60	98.20	**98.80**	93.60	**97.65**	97.35	97.04	64.80	84.13	78.60	59.60	89.20
4x compression														
LCLM 0.6b-4b (Mean)	99.60	99.40	97.80	99.40	**99.80**	98.20	**99.40**	99.50	96.76	90.76	**90.93**	79.40	**63.80**	93.44
LCLM 0.6b-4b (Concat)	99.20	99.80	94.40	99.40	**99.80**	97.60	98.80	99.20	93.90	92.80	87.60	77.20	59.80	92.27
ExpAttn	**100.00**	99.80	66.60	**100.00**	99.40	53.60	98.15	99.65	**100.00**	86.74	87.07	62.80	54.60	85.26
SnapKV	32.00	14.80	2.60	18.60	6.00	0.00	13.80	16.55	27.00	71.72	81.87	47.60	29.40	27.84
SnapKV-QA	95.00	**100.00**	2.60	98.60	30.20	40.40	54.30	99.35	85.04	72.14	78.73	81.60	62.20	69.24
KVzip	**100.00**	99.40	**100.00**	**100.00**	99.60	99.80	99.25	99.80	99.96	**96.24**	85.80	**85.40**	62.40	**94.43**
KVzipFast	**100.00**	**100.00**	**100.00**	**100.00**	99.60	99.80	98.50	**100.00**	99.96	95.96	84.40	83.00	63.00	94.17
AM-Fast	**100.00**	99.80	96.80	98.80	99.60	**100.00**	98.75	99.40	99.08	78.28	89.40	81.80	63.20	92.69
AM-Slow	**100.00**	**100.00**	97.60	99.00	99.60	99.60	99.10	99.20	98.56	76.98	88.07	81.80	63.20	92.52

Table 11: RULER per-task at 8k context. Rows grouped by compression ratio (16x, 8x, 4x).

Model	ns1	ns2	ns3	nm1	nm2	nm3	nmv	nmq	vt	cwe	fwe	qa1	qa2	AVG
Qwen 4B Instruct	100.00	100.00	100.00	99.80	97.00	99.40	99.50	100.00	99.24	95.24	87.40	80.40	58.60	93.58
16x compression														
LCLM 0.6b-4b (Mean)	96.00	90.40	61.80	**84.20**	74.20	44.20	71.55	77.70	77.28	52.38	93.33	64.40	49.80	**72.10**
LCLM 0.6b-4b (Concat)	97.60	93.20	61.80	82.80	72.80	41.20	62.10	**78.00**	68.10	54.60	**94.70**	62.60	44.80	70.33
ExpAttn	**100.00**	76.60	1.00	81.20	2.40	0.00	69.30	55.85	99.08	10.52	60.73	30.40	23.00	46.93
SnapKV	8.60	1.20	2.40	10.00	0.80	0.00	9.80	9.80	5.04	24.78	78.60	15.40	17.00	14.11
SnapKV-QA	88.20	62.00	2.40	14.60	9.00	7.60	10.30	44.25	52.68	21.16	68.13	**74.20**	**53.60**	39.09
KVzip	**100.00**	**98.00**	**95.80**	64.80	56.40	**45.20**	31.25	51.05	**100.00**	8.16	73.80	43.20	34.80	61.73
KVzipFast	**100.00**	43.60	38.80	30.80	65.20	39.00	10.85	17.15	99.96	7.42	77.73	23.80	26.80	44.70
AM-Fast	**100.00**	60.00	11.80	42.00	91.24	8.80	28.55	31.70	93.56	**72.90**	73.47	62.80	44.00	55.45
AM-Slow	99.20	94.80	38.40	79.40	**93.20**	11.60	**73.45**	72.95	94.08	71.22	75.07	65.20	46.40	70.38
8x compression														
LCLM 0.6b-4b (Mean)	99.00	98.00	85.20	95.20	94.00	89.40	95.45	94.45	93.20	78.84	92.60	74.40	55.00	88.06
LCLM 0.6b-4b (Concat)	98.60	95.80	82.00	92.00	95.40	81.00	93.10	92.30	90.00	**88.00**	**94.60**	71.60	53.60	86.77
ExpAttn	**100.00**	98.20	6.20	97.00	69.60	0.20	91.95	94.70	**100.00**	34.12	78.73	42.60	35.40	65.28
SnapKV	37.80	2.40	2.40	11.60	1.60	0.00	10.40	10.50	19.56	34.82	86.33	16.80	18.20	19.42
SnapKV-QA	99.60	96.60	2.40	63.20	22.00	40.40	24.85	97.60	91.44	35.48	75.33	**77.40**	57.80	60.32
KVzip	**100.00**	99.40	**99.80**	88.80	97.60	98.00	82.25	**98.60**	**100.00**	72.24	83.53	71.40	56.80	**88.34**
KVzipFast	**100.00**	**99.80**	**99.80**	79.80	**98.60**	**99.00**	59.50	95.50	**100.00**	58.46	83.67	67.40	**58.20**	84.59
AM-Fast	97.60	98.60	91.40	**98.60**	98.20	95.00	**96.05**	97.20	93.84	54.00	79.60	74.20	57.40	87.05
AM-Slow	96.80	99.40	93.40	96.40	98.40	95.20	95.70	95.84	94.28	52.88	80.60	75.00	57.80	87.05
4x compression														
LCLM 0.6b-4b (Mean)	99.60	99.60	96.80	99.00	99.20	96.60	99.10	99.20	96.00	81.68	**94.33**	**79.40**	**61.80**	92.49
LCLM 0.6b-4b (Concat)	99.20	99.60	96.60	**99.20**	99.60	96.00	98.60	99.20	94.90	84.20	89.80	75.20	57.40	91.50
ExpAttn	**100.00**	**100.00**	60.60	**99.20**	98.60	48.60	97.65	99.80	**100.00**	77.74	85.13	60.80	52.00	83.09
SnapKV	67.00	23.60	2.40	18.80	3.80	1.00	18.20	17.90	47.52	60.22	92.87	23.00	27.00	31.02
SnapKV-QA	**100.00**	99.80	2.40	99.00	46.80	87.40	66.75	99.95	99.28	66.00	86.27	77.00	59.40	76.16
KVzip	**100.00**	**100.00**	**100.00**	98.40	**100.00**	99.80	**99.20**	**100.00**	**100.00**	**91.86**	88.40	77.20	57.80	**93.28**
KVzipFast	**100.00**	**100.00**	**100.00**	98.40	**100.00**	**100.00**	98.75	99.95	**100.00**	91.84	86.27	75.60	60.20	93.15
AM-Fast	99.40	**100.00**	98.00	98.60	99.40	99.20	96.40	98.90	96.96	78.62	86.47	79.20	59.60	91.60
AM-Slow	99.60	**100.00**	98.40	98.40	99.40	98.20	95.95	98.05	97.40	78.02	87.33	78.60	59.80	91.47

Table 12: RULER per-task at 16k context. Rows grouped by compression ratio (16x, 8x, 4x).

Model	ns1	ns2	ns3	nm1	nm2	nm3	nmv	nmq	vt	cwe	fwe	qa1	qa2	AVG
Qwen 4B Instruct	100.00	100.00	100.00	99.60	95.40	99.80	98.95	99.95	99.52	88.04	98.93	79.60	58.80	93.74
16x compression														
LCLM 0.6b-4b (Mean)	97.00	90.00	59.40	78.20	**65.20**	34.40	71.80	70.30	72.28	21.72	**99.20**	62.60	49.40	**67.04**
LCLM 0.6b-4b (Concat)	96.80	90.60	65.00	75.60	65.00	28.80	63.10	70.30	58.20	26.60	98.90	60.80	43.60	64.87
ExpAttn	**100.00**	83.00	1.60	86.60	1.60	0.00	**78.30**	76.35	99.32	8.52	71.07	28.40	24.00	50.67
SnapKV	41.80	4.20	2.40	11.20	2.00	0.20	10.00	10.85	17.60	16.64	92.20	12.40	16.00	18.27
SnapKV-QA	99.80	**99.40**	2.40	**88.40**	11.60	27.00	30.75	**99.15**	93.68	22.22	98.33	**74.80**	**58.00**	61.96
KVzip	**100.00**	92.20	**91.60**	55.20	37.60	18.40	35.70	53.10	**99.96**	3.18	88.87	41.20	36.60	57.97
KVzipFast	**100.00**	53.60	42.00	38.40	64.40	**44.00**	19.05	25.40	99.76	3.58	79.00	23.40	29.60	47.86
AM-Fast	52.05	33.00	0.20	28.40	20.60	0.00	19.40	23.70	54.92	**55.44**	94.67	58.60	42.20	37.17
AM-Slow	61.00	31.20	1.20	38.60	24.80	0.00	32.30	34.50	66.84	52.28	93.33	63.00	47.20	42.02
8x compression														
LCLM 0.6b-4b (Mean)	98.60	98.20	83.60	94.80	87.40	83.60	93.25	92.85	93.68	62.32	98.80	74.00	53.80	85.76
LCLM 0.6b-4b (Concat)	98.80	95.80	82.00	88.20	90.20	73.20	91.00	90.90	90.00	**77.50**	98.50	69.40	52.20	84.44
ExpAttn	**100.00**	97.80	6.80	97.00	58.00	0.60	**93.65**	96.90	99.92	30.14	95.73	39.00	34.80	65.41
SnapKV	63.60	11.00	2.40	12.40	2.60	0.60	11.70	12.65	47.72	34.86	97.40	14.40	18.80	25.39
SnapKV-QA	**100.00**	**100.00**	2.40	**99.20**	27.40	67.60	65.70	**99.90**	99.00	40.72	**99.53**	**75.40**	**60.40**	72.10
KVzip	**100.00**	99.80	99.60	90.40	92.60	93.00	83.95	98.65	**99.96**	66.62	98.67	71.40	57.80	**88.65**
KVzipFast	**100.00**	**100.00**	**100.00**	76.80	**95.60**	**96.00**	65.85	96.95	**99.96**	58.10	97.07	68.40	53.80	85.27
AM-Fast	51.20	60.20	10.40	58.20	75.40	13.40	56.45	58.20	55.24	67.10	96.20	74.00	52.80	56.06
AM-Slow	53.80	62.20	13.00	70.60	78.60	17.80	63.25	66.80	60.84	65.30	95.20	71.80	52.20	59.34
4x compression														
LCLM 0.6b-4b (Mean)	99.40	99.80	98.00	99.00	99.60	95.20	98.65	98.30	94.44	64.06	99.07	76.80	59.80	90.93
LCLM 0.6b-4b (Concat)	99.20	99.20	95.60	99.60	99.00	92.40	98.30	98.70	92.80	69.90	98.50	75.60	57.60	90.49
ExpAttn	**100.00**	99.80	57.40	99.00	98.00	34.60	98.95	99.60	**99.96**	73.42	98.47	61.20	52.20	82.51
SnapKV	80.60	46.40	2.40	19.20	4.00	2.20	14.95	18.30	78.16	59.58	99.13	22.00	25.40	36.33
SnapKV-QA	**100.00**	99.80	6.20	**99.80**	59.00	94.60	93.45	**99.95**	99.88	66.60	**99.73**	75.40	59.40	81.06
KVzip	**100.00**	**100.00**	**100.00**	99.20	**99.80**	**100.00**	**99.60**	**99.95**	**99.96**	85.00	98.80	77.60	**61.20**	**93.93**
KVzipFast	**100.00**	**100.00**	**100.00**	98.60	99.40	99.80	99.20	**99.95**	**99.96**	**85.46**	98.93	76.00	60.00	93.64
AM-Fast	60.00	94.40	80.20	93.00	91.60	91.20	91.60	92.45	63.56	79.80	96.46	**78.80**	57.80	82.37
AM-Slow	54.40	94.60	78.60	95.00	94.00	92.00	91.85	94.10	63.16	79.08	95.40	77.60	56.00	81.98

Table 13: LongBench English (en16) per-subtask. Rows grouped by compression ratio (16x, 8x, 4x).

Model	narr	qasp	mfq	hpot	2wiki	musq	govr	qmsm	mnews	trec	triv	samsm	pcnt	pr	lcc	rbp	AVG
Qwen 4B Instruct	30.18	43.60	46.63	52.05	36.18	17.26	30.32	22.91	23.79	75.50	85.14	40.03	3.50	94.91	65.00	56.36	45.21
16x compression																	
LCLM 0.6b-4b (Mean)	26.12	40.43	42.38	46.55	37.30	24.24	28.96	23.18	23.45	54.00	86.58	33.80	2.66	67.25	37.76	37.54	38.26
LCLM 0.6b-4b (Concat)	23.30	36.80	**48.00**	49.00	**38.30**	22.60	28.60	22.40	23.10	46.50	**88.20**	32.70	3.50	37.00	39.90	39.90	36.24
ExpAttn	17.67	23.16	28.88	33.76	23.45	8.78	23.06	19.86	19.54	36.00	81.02	31.80	7.36	30.32	28.24	**58.14**	29.44
SnapKV	12.97	13.68	22.14	20.93	16.13	5.61	21.61	17.66	14.70	32.75	85.87	36.57	3.25	17.22	**53.42**	56.78	26.96
SnapKV-QA	**28.36**	28.81	40.37	**53.20**	29.33	17.33	21.57	22.78	14.06	35.00	83.92	37.66	2.37	**92.50**	**53.42**	55.60	38.52
KVzip	16.08	16.38	32.53	10.30	8.68	4.93	24.43	21.38	17.49	43.00	78.22	31.34	6.50	14.00	31.96	56.53	25.86
KVzipFast	11.96	18.26	24.60	23.57	18.08	4.31	20.15	20.48	15.03	34.00	72.78	34.22	**7.44**	8.25	46.89	52.12	25.76
AM-Fast	26.31	**42.64**	45.22	48.31	30.57	24.17	31.59	23.90	**24.14**	**74.50**	85.84	**40.37**	5.11	47.04	48.26	49.81	**40.49**
AM-Slow	24.83	41.04	45.28	45.85	30.76	**24.84**	**31.62**	**24.02**	24.08	74.00	86.17	39.60	5.08	47.38	48.79	50.76	40.26
8x compression																	
LCLM 0.6b-4b (Mean)	**30.77**	42.19	46.65	51.24	38.61	18.61	30.70	**23.31**	23.53	66.50	88.67	35.09	2.15	80.00	43.16	46.72	41.74
LCLM 0.6b-4b (Concat)	30.30	42.70	**50.70**	50.80	**44.30**	**28.20**	29.20	22.90	23.90	62.50	**89.00**	33.10	4.60	70.50	45.20	49.20	42.32
ExpAttn	23.27	32.95	36.13	40.83	31.71	13.74	27.81	21.46	22.15	65.75	84.11	33.95	5.03	77.22	36.30	57.69	38.13
SnapKV	18.27	21.07	25.80	29.97	17.90	6.88	24.52	18.96	18.22	47.50	85.01	38.58	3.27	46.62	**58.34**	55.63	32.28
SnapKV-QA	28.50	34.45	45.16	**53.20**	34.12	18.53	25.11	22.86	17.56	51.50	85.33	38.70	2.19	**94.20**	**58.34**	58.00	41.73
KVzip	25.80	41.38	49.59	46.31	27.10	15.05	28.73	22.71	23.07	69.50	83.99	37.62	3.79	68.67	49.10	**59.16**	40.72
KVzipFast	20.72	35.80	47.81	45.06	29.11	15.01	27.96	23.00	22.73	66.00	83.63	36.81	3.33	41.96	54.86	56.91	38.17
AM-Fast	28.23	44.29	49.74	52.61	36.39	25.60	30.70	23.19	**24.02**	73.50	85.27	**39.87**	**5.67**	86.50	54.38	52.05	**44.50**
AM-Slow	25.12	**45.13**	47.57	52.98	36.38	24.04	**30.99**	23.07	23.99	**74.00**	85.51	39.39	4.05	87.50	55.42	52.34	44.22
4x compression																	
LCLM 0.6b-4b (Mean)	**30.74**	**46.76**	**49.76**	52.90	**42.75**	28.61	30.12	22.89	23.83	68.50	87.90	34.10	6.67	**100.00**	52.01	59.17	**46.04**
LCLM 0.6b-4b (Concat)	28.30	46.00	48.70	**56.80**	42.40	**29.70**	29.80	22.80	24.00	66.00	**88.50**	34.20	**7.50**	98.00	49.20	54.30	45.39
ExpAttn	27.13	38.72	44.59	49.87	36.76	17.10	29.42	22.63	23.12	71.00	84.55	35.97	3.67	87.29	42.13	57.28	41.95
SnapKV	21.88	30.57	30.90	37.39	26.71	11.58	27.18	20.75	20.71	59.00	84.86	**39.63**	3.00	78.86	**61.53**	56.36	38.18
SnapKV-QA	29.55	39.75	45.91	53.23	37.11	17.92	27.85	23.22	20.13	66.50	84.94	38.60	2.96	93.54	**61.53**	57.14	43.74
KVzip	28.38	45.62	48.61	54.37	40.26	18.45	29.86	23.03	23.86	73.00	85.37	39.15	2.28	93.92	59.70	58.92	45.30
KVzipFast	28.61	44.93	48.54	51.89	36.63	18.63	30.24	22.98	23.67	73.00	84.87	38.86	4.55	94.71	60.82	**59.66**	45.16
AM-Fast	26.27	44.45	49.18	53.99	37.78	22.66	**30.74**	22.83	23.89	**74.50**	83.87	39.06	5.50	99.00	58.13	55.85	45.48
AM-Slow	26.30	44.98	47.17	54.16	41.41	24.10	30.57	**23.40**	**24.05**	**74.50**	85.19	39.39	3.11	99.17	58.30	56.67	45.78

Table 14: LongBench Chinese (cn5) per-subtask. Rows grouped by compression ratio (16x, 8x, 4x).

Model	mfq	dure	vcsum	lsht	pr	AVG
Qwen 4B Instruct	61.60	25.45	11.38	43.50	91.23	46.63
16x compression						
LCLM 0.6b-4b (Mean)	39.94	27.00	10.91	23.98	55.09	31.38
LCLM 0.6b-4b (Concat)	**51.00**	23.50	10.10	19.30	25.50	25.88
ExpAttn	25.52	16.37	11.22	17.75	31.67	20.51
SnapKV	20.36	16.77	10.44	35.00	8.93	18.30
SnapKV-QA	48.61	21.46	10.44	**41.50**	**89.28**	**42.26**
KVzip	25.95	16.30	12.50	23.75	7.12	17.12
KVzipFast	30.95	17.04	10.92	19.00	7.47	17.08
AM-Fast	48.55	27.13	13.62	39.50	28.76	31.51
AM-Slow	48.25	**28.02**	**13.75**	39.25	30.00	31.85
8x compression						
LCLM 0.6b-4b (Mean)	42.13	27.05	11.17	30.39	72.50	36.65
LCLM 0.6b-4b (Concat)	53.10	24.10	10.90	26.70	67.50	36.46
ExpAttn	32.75	18.70	11.02	21.00	69.32	30.56
SnapKV	26.07	19.01	10.81	**43.25**	26.78	25.18
SnapKV-QA	58.07	23.37	10.81	42.50	**92.29**	**45.41**
KVzip	58.26	25.30	11.98	40.75	44.17	36.09
KVzipFast	57.35	24.84	12.77	24.00	35.60	30.91
AM-Fast	**59.11**	**28.47**	13.08	42.75	64.21	41.52
AM-Slow	58.88	28.40	**13.18**	42.75	62.34	41.11
4x compression						
LCLM 0.6b-4b (Mean)	45.52	26.07	11.00	25.00	97.00	40.92
LCLM 0.6b-4b (Concat)	46.20	26.80	11.00	30.00	95.00	41.80
ExpAttn	54.32	23.86	11.63	34.25	83.81	41.57
SnapKV	33.48	20.48	11.07	**44.75**	61.32	34.22
SnapKV-QA	60.69	24.33	11.07	43.50	91.34	46.19
KVzip	62.35	26.90	11.86	43.75	92.37	47.45
KVzipFast	**63.62**	27.23	11.95	44.50	96.02	**48.66**
AM-Fast	58.73	28.45	**12.97**	43.75	**98.03**	48.39
AM-Slow	59.04	**29.09**	12.61	43.25	96.37	48.07

E.5 LR SWEEP

E.5.1 CONTINUAL PRE-TRAINING LR SWEEP

Table 15: Continual Pre-training LR sweep summary (16 × ratio compression, bidirectional mask, mlp adapter, $O = 0$).

Model	RULER 4k	RULER 8k	RULER 16k	LB en16	LB cn5	LongHealth5	GSM8K
1.0×10^{-6}	62.33	58.75	56.65	33.29	22.88	60.25	66.94
3.0×10^{-6}	70.73	65.41	63.55	32.89	22.09	62.50	72.25
1.0×10^{-5}	**71.62**	**66.83**	**63.63**	**33.52**	**23.94**	**62.75**	**74.53**

Table 16: Continual Pretraining LR sweep – RULER per-task

Model	ns1	ns2	ns3	nm1	nm2	nm3	nmv	nmq	vt	cwe	fwe	qa1	qa2	AVG
Context length 4096														
1.0×10^{-6}	97.40	66.40	31.40	62.00	47.20	17.40	71.70	62.10	84.88	**69.16**	88.00	62.80	49.80	62.33
3.0×10^{-6}	**98.80**	**90.60**	**42.60**	**81.40**	54.40	21.80	84.50	81.15	**91.48**	65.72	88.07	65.20	**53.80**	70.73
1.0×10^{-5}	97.80	83.00	39.40	**81.40**	**64.60**	**29.80**	**85.55**	**81.30**	90.96	68.24	**91.07**	**66.20**	51.80	**71.62**
Context length 8192														
1.0×10^{-6}	96.20	77.80	28.00	60.80	40.00	12.40	60.40	57.95	84.84	**38.70**	**96.40**	**62.20**	48.00	58.75
3.0×10^{-6}	99.00	88.00	40.80	**75.60**	44.20	14.40	**78.55**	**76.15**	**91.40**	34.18	95.47	61.60	**51.00**	65.41
1.0×10^{-5}	**99.20**	**89.80**	**43.60**	73.60	**58.60**	**19.60**	76.35	74.10	91.04	36.74	95.33	61.80	49.00	**66.83**
Context length 16384														
1.0×10^{-6}	98.60	78.00	32.00	64.60	38.40	8.00	60.75	58.50	81.96	**12.66**	**99.53**	56.60	46.80	56.65
3.0×10^{-6}	**99.40**	**90.20**	**46.60**	74.00	38.00	11.20	77.40	**77.15**	**91.24**	11.82	**99.53**	59.00	50.60	63.55
1.0×10^{-5}	98.80	84.60	42.00	**75.60**	**49.80**	**12.80**	**78.40**	74.60	89.12	9.88	99.40	**61.20**	**51.00**	**63.63**

Table 17: Continual Pretraining LR sweep – LongBench English (en16) per-subtask.

Model	narr	qasp	mfq	hpot	2wiki	musq	govr	qmsm	mnews	trec	triv	samsm	pcnt	pr	lcc	rbp	AVG
1.0×10^{-6}	22.98	37.30	**42.23**	37.19	**31.51**	**14.42**	28.61	22.15	22.72	**31.00**	85.35	**33.31**	1.50	**50.00**	35.85	36.53	33.29
3.0×10^{-6}	**23.67**	38.81	41.70	**38.09**	29.49	13.43	**29.25**	**22.98**	**22.98**	30.00	86.44	32.39	0.50	41.50	36.19	38.82	32.89
1.0×10^{-5}	23.32	**40.05**	42.18	35.36	31.18	12.64	29.12	22.95	22.85	29.50	**88.68**	32.28	**4.29**	44.00	**38.07**	**39.92**	**33.52**

Table 18: Continual Pretraining LR sweep – LongBench Chinese (cn5) per-subtask.

Model	mfq	dure	vcsum	lsht	pr	AVG
1.0×10^{-6}	38.79	24.13	**11.00**	**21.00**	19.50	22.88
3.0×10^{-6}	36.39	25.97	10.85	17.75	19.50	22.09
1.0×10^{-5}	**39.65**	**27.07**	10.99	19.50	**22.50**	**23.94**

E.5.2 POST-TRAINING LR SWEEP

Table 19: Post-training LR sweep summary (16 × ratio compression, causal mask, mlp adapter, continual pre-training LR $= 1.0 \times 10^{-5}$).

Model	RULER 4k	RULER 8k	RULER 16k	LB en16	LB cn5	LongHealth5	GSM8K
2.0×10^{-5}	72.99	69.08	63.89	37.98	33.08	66.75	80.89
3.0×10^{-5}	75.06	70.23	65.91	**39.08**	31.74	67.50	**81.05**
5.0×10^{-5}	**75.17**	**71.06**	**66.22**	38.72	**34.16**	**69.00**	80.97

Table 20: Post-training LR sweep – RULER per-task

Model	ns1	ns2	ns3	nm1	nm2	nm3	nmv	nmq	vt	cwe	fwe	qa1	qa2	AVG
Context length 4096														
2.0×10^{-5}	94.60	89.20	40.60	82.40	80.20	46.00	72.20	75.55	83.56	78.94	89.40	**66.40**	**49.80**	72.99
3.0×10^{-5}	**96.40**	89.40	54.60	**85.00**	80.80	48.60	**72.45**	**80.20**	**83.92**	**80.54**	88.27	66.00	49.60	75.06
5.0×10^{-5}	96.00	**90.00**	**58.20**	85.00	**87.00**	**50.60**	71.10	74.65	82.12	79.04	**91.93**	64.20	47.40	**75.17**
Context length 8192														
2.0×10^{-5}	93.60	86.20	51.20	80.20	67.00	32.20	68.00	**77.70**	**80.76**	54.82	**95.73**	**63.40**	**47.20**	69.08
3.0×10^{-5}	**96.00**	**90.20**	55.20	**83.40**	65.40	36.60	**70.25**	77.65	80.52	55.44	95.67	61.80	44.80	70.23
5.0×10^{-5}	94.60	89.80	**57.60**	83.40	**76.20**	**37.40**	69.25	75.15	73.32	**63.56**	95.33	61.20	47.00	**71.06**
Context length 16384														
2.0×10^{-5}	92.20	85.80	47.00	**75.60**	55.60	29.00	68.10	68.25	**79.44**	24.10	98.67	**61.00**	**45.80**	63.89
3.0×10^{-5}	95.80	88.00	**57.40**	75.60	62.20	**30.00**	**70.70**	**73.05**	77.32	24.78	**98.73**	59.40	43.80	65.91
5.0×10^{-5}	**96.40**	**90.60**	53.80	74.60	**72.40**	28.20	67.50	69.70	67.60	**38.38**	98.53	60.20	43.00	**66.22**

Table 21: Post-training LR sweep – LongBench English (en16) per-subtask.

Model	narr	qasp	mfq	hpot	2wiki	musq	govr	qmsm	mnews	trec	triv	samsm	pcnt	pr	lcc	rbp	AVG
2.0×10^{-5}	23.54	40.34	**48.52**	46.17	36.93	21.76	**28.59**	22.21	22.76	**49.00**	87.88	32.31	3.50	74.00	34.65	35.54	37.98
3.0×10^{-5}	**25.57**	39.80	47.98	**47.96**	**38.44**	21.17	28.56	**22.42**	**23.48**	45.00	**89.43**	**32.50**	3.00	81.50	**37.47**	**41.05**	**39.08**
5.0×10^{-5}	23.12	**42.47**	47.64	46.80	37.13	**24.03**	28.27	22.04	22.80	44.00	87.10	32.15	**4.50**	**85.50**	35.45	36.57	38.72

Table 22: Post-training LR sweep – LongBench Chinese (cn5) per-subtask.

Model	mfq	dure	vcsum	lsht	pr	AVG
2.0×10^{-5}	47.53	**24.26**	**10.77**	**20.83**	62.00	33.08
3.0×10^{-5}	46.83	23.63	10.55	18.67	59.00	31.74
5.0×10^{-5}	**47.61**	21.95	10.38	18.85	**72.00**	**34.16**

E.6 Architecture Comparison

E.6.1 Pooling Operator

Table 23: Pooling operator: Mean vs Concat ($W = 1024$, causal, continual pre-training LR = 1.0×10^{-5}).

Model	RULER 4k	RULER 8k	RULER 16k	LB en16	LB cn5	LongHealth5	GSM8K
4x compression							
Mean	91.76	91.03	89.96	**46.04**	40.92	76.25	**91.05**
Concat	**92.30**	**91.50**	**90.50**	45.39	**41.80**	**82.50**	89.90
8x compression							
Mean	85.42	84.48	82.47	42.23	34.61	71.75	87.26
Concat	**87.20**	**86.80**	**84.40**	**42.32**	**36.46**	**79.50**	**87.40**
16x compression							
Mean	**75.06**	70.23	**65.91**	**39.08**	**31.74**	67.50	**81.05**
Concat	74.50	**70.30**	64.90	36.24	25.88	**76.30**	78.90

Table 24: Pooling operator: RULER per-task at 4k context.

Model	ns1	ns2	ns3	nm1	nm2	nm3	nmv	nmq	vt	cwe	fwe	qa1	qa2	AVG
4x compression														
Mean	**99.40**	99.60	93.40	99.00	99.40	93.80	98.25	**99.20**	**94.64**	91.42	86.73	**79.20**	58.80	91.76
Concat	99.20	**99.80**	**94.40**	**99.40**	**99.80**	**97.60**	**98.80**	**99.20**	93.90	**92.80**	**87.60**	77.20	**59.80**	**92.27**
8x compression														
Mean	**98.60**	94.20	64.20	93.00	**98.20**	82.20	92.30	90.70	87.40	90.80	**90.60**	73.20	**55.00**	85.42
Concat	98.40	**97.00**	**76.60**	**94.60**	95.60	**86.00**	**93.80**	**92.30**	**90.70**	**92.80**	88.40	**74.80**	53.20	**87.25**
16x compression														
Mean	**96.40**	89.40	54.60	**85.00**	80.80	48.60	**72.45**	**80.20**	**83.92**	**80.54**	88.27	**66.00**	**49.60**	**75.06**
Concat	**96.40**	**91.80**	**62.40**	83.80	**84.20**	**54.00**	59.50	77.50	79.50	74.30	**90.10**	65.40	49.00	74.45

Table 25: Pooling operator: RULER per-task at 8k context.

Model	ns1	ns2	ns3	nm1	nm2	nm3	nmv	nmq	vt	cwe	fwe	qa1	qa2	AVG
4x compression														
Mean	**99.40**	**99.80**	95.60	98.60	98.40	91.60	**98.80**	98.95	94.64	82.04	**90.40**	**76.20**	**59.00**	91.03
Concat	99.20	99.60	**96.60**	**99.20**	**99.60**	**96.00**	98.60	**99.20**	**94.90**	**84.20**	89.80	75.20	57.40	**91.50**
8x compression														
Mean	**98.80**	**96.40**	71.40	90.80	**96.80**	74.60	90.40	90.95	89.40	79.82	**95.67**	70.60	52.60	84.48
Concat	98.60	95.80	**82.00**	**92.00**	95.40	**81.00**	**93.10**	**92.30**	**90.00**	**88.00**	94.60	**71.60**	**53.60**	**86.77**
16x compression														
Mean	96.00	90.20	55.20	**83.40**	65.40	36.60	**70.25**	77.65	**80.52**	**55.44**	**95.67**	61.80	**44.80**	70.23
Concat	**97.60**	**93.20**	**61.80**	82.80	**72.80**	**41.20**	62.10	**78.00**	68.10	54.60	94.70	**62.60**	**44.80**	**70.33**

Table 26: Pooling operator: RULER per-task at 16k context.

Model	ns1	ns2	ns3	nm1	nm2	nm3	nmv	nmq	vt	cwe	fwe	qa1	qa2	AVG
4x compression														
Mean	**99.60**	**99.60**	94.80	99.20	98.20	90.40	98.15	**98.80**	91.40	67.34	**99.53**	**75.60**	56.80	89.96
Concat	99.20	99.20	**95.60**	**99.60**	**99.00**	**92.40**	**98.30**	98.70	**92.80**	**69.90**	98.50	**75.60**	**57.60**	**90.49**
8x compression														
Mean	**99.20**	95.00	72.60	**88.80**	**94.20**	69.20	88.10	90.10	89.04	67.34	97.73	68.40	**52.40**	82.47
Concat	98.80	**95.80**	**82.00**	88.20	90.20	**73.20**	**91.00**	**90.90**	**90.00**	**77.50**	**98.50**	**69.40**	52.20	**84.44**
16x compression														
Mean	95.80	88.00	57.40	**75.60**	62.20	**30.00**	**70.70**	**73.05**	**77.32**	24.78	98.73	59.40	**43.80**	**65.91**
Concat	**96.80**	**90.60**	**65.00**	**75.60**	**65.00**	28.80	63.10	70.30	58.20	**26.60**	**98.90**	**60.80**	43.60	64.87

Table 27: Pooling operator: LongBench English (en16) per-subtask.

Model	narr	qasp	mfq	hpot	2wiki	musq	govr	qmsm	mnews	trec	triv	samsm	pcnt	pr	lcc	rbp	AVG
4x compression																	
Mean	**30.74**	**46.76**	**49.76**	52.90	**42.75**	28.61	**30.12**	**22.89**	23.83	**68.50**	87.90	34.10	6.67	**100.00**	**52.01**	**59.17**	**46.04**
Concat	28.30	46.00	48.70	**56.80**	42.40	**29.70**	29.80	22.80	**24.00**	66.00	**88.50**	**34.20**	**7.50**	98.00	49.20	54.30	45.39
8x compression																	
Mean	28.60	**43.92**	**51.54**	**54.02**	**45.36**	28.05	29.05	22.85	23.56	62.00	86.39	**33.17**	**5.45**	**71.50**	43.57	46.63	42.23
Concat	**30.30**	42.70	50.70	50.80	44.30	**28.20**	**29.20**	**22.90**	**23.90**	**62.50**	**89.00**	33.10	4.60	70.50	**45.20**	**49.20**	**42.32**
16x compression																	
Mean	**25.57**	**39.80**	47.98	47.96	**38.44**	21.17	28.56	**22.42**	**23.48**	45.00	**89.43**	32.50	3.00	**81.50**	37.47	**41.05**	**39.08**
Concat	23.30	36.80	**48.00**	**49.00**	38.30	**22.60**	**28.60**	22.40	23.10	**46.50**	88.20	**32.70**	**3.50**	37.00	**39.90**	39.90	36.24

Table 28: Pooling operator: LongBench Chinese (cn5) per-subtask.

Model	mfq	dure	vcsum	lsht	pr	AVG
4x compression						
Mean	45.52	26.07	**11.00**	25.00	**97.00**	40.92
Concat	**46.20**	**26.80**	**11.00**	**30.00**	95.00	**41.80**
8x compression						
Mean	51.27	**24.83**	10.79	25.65	60.50	34.61
Concat	**53.10**	24.10	**10.90**	**26.70**	**67.50**	**36.46**
16x compression						
Mean	46.83	**23.63**	**10.55**	18.67	**59.00**	**31.74**
Concat	**51.00**	23.50	10.10	**19.30**	25.50	25.88

E.6.2 Adapter & Overlap

Table 29: Adapter & overlap comparison (16 × compression, mean pooling, $W = 1024$, continual pre-training LR $= 1.0 \times 10^{-5}$).

Model	RULER 4k	RULER 8k	RULER 16k	LB en16	LB cn5	LongHealth5	GSM8K
Causal-MLP-O0	**75.06**	**70.23**	**65.91**	**39.08**	**31.74**	**67.50**	**81.05**
Bidirectional-MLP-O0	71.62	66.83	63.63	33.52	23.94	62.75	74.53
Bidirectional-ATTN-MLP-O256	<u>71.91</u>	<u>68.11</u>	<u>64.96</u>	36.28	26.54	<u>64.00</u>	73.77
Bidirectional-MLP-O256	62.03	58.66	58.24	<u>36.97</u>	<u>26.63</u>	63.25	<u>74.98</u>

Table 30: Adapter & overlap comparison – RULER per-task

Model	ns1	ns2	ns3	nm1	nm2	nm3	nmv	nmq	vt	cwe	fwe	qa1	qa2	AVG
Context length 4096														
Causal-MLP-O0	96.40	**89.40**	**54.60**	**85.00**	**80.80**	**48.60**	72.45	80.20	83.92	**80.54**	88.27	66.00	49.60	**75.06**
Bidirectional-MLP-O0	97.80	83.00	39.40	81.40	64.60	29.80	85.55	81.30	90.96	68.24	**91.07**	**66.20**	**51.80**	71.62
Bidirectional-ATTN-MLP-O256	**99.80**	80.40	50.20	78.60	62.20	26.20	**85.70**	**81.35**	95.00	80.00	87.00	61.80	46.60	71.91
Bidirectional-MLP-O256	99.00	60.60	21.60	61.80	55.40	17.60	69.90	61.60	**97.12**	57.66	87.27	66.00	50.80	62.03
Context length 8192														
Causal-MLP-O0	96.00	**90.20**	55.20	**83.40**	**65.40**	**36.60**	70.25	**77.65**	80.52	**55.44**	**95.67**	61.80	44.80	**70.23**
Bidirectional-MLP-O0	99.20	89.80	43.60	73.60	58.60	19.60	76.35	74.10	91.04	36.74	95.33	61.80	**49.00**	66.83
Bidirectional-ATTN-MLP-O256	**100.00**	86.00	**58.60**	72.00	52.60	25.60	**76.75**	74.65	96.12	43.78	91.93	**63.20**	44.20	68.11
Bidirectional-MLP-O256	98.80	67.20	25.40	61.20	47.20	15.60	60.55	54.15	**96.68**	28.76	95.60	62.80	48.60	58.66
Context length 16384														
Causal-MLP-O0	95.80	88.00	**57.40**	75.60	**62.20**	**30.00**	70.70	73.05	77.32	**24.78**	98.73	59.40	43.80	**65.91**
Bidirectional-MLP-O0	98.80	84.60	42.00	75.60	49.80	12.80	**78.40**	74.60	89.12	9.88	99.40	**61.20**	**51.00**	63.63
Bidirectional-ATTN-MLP-O256	**100.00**	**89.00**	57.00	**78.20**	42.40	17.60	78.25	**77.40**	93.80	10.12	**99.47**	56.20	45.00	64.96
Bidirectional-MLP-O256	97.80	75.40	28.60	68.20	36.80	12.80	62.95	60.65	**96.00**	12.48	99.20	59.80	46.40	58.24

Table 31: Adapter & overlap comparison – LongBench English (en16) per-subtask.

Model	narr	qasp	mfq	hpot	2wiki	musq	govr	qmsm	mnews	trec	triv	samsm	pcnt	pr	lcc	rbp	AVG
Causal-MLP-O0	25.57	39.80	**47.98**	47.96	**38.44**	**21.17**	28.56	22.42	**23.48**	**45.00**	**89.43**	**32.50**	3.00	**81.50**	37.47	41.05	**39.08**
Bidirectional-MLP-O0	23.32	**40.05**	42.18	35.36	31.18	12.64	**29.12**	**22.95**	22.85	29.50	88.68	32.28	4.29	44.00	38.07	39.92	33.52
Bidirectional-ATTN-MLP-O256	**27.45**	38.87	42.56	**52.31**	36.98	20.22	27.98	22.44	23.01	27.50	87.23	32.16	**6.00**	51.50	41.22	43.00	36.28
Bidirectional-MLP-O256	23.20	39.67	42.77	46.56	31.94	16.41	28.64	22.50	22.65	40.00	86.67	31.80	4.50	67.50	**41.76**	**44.89**	36.97

Table 32: Adapter & overlap comparison – LongBench Chinese (cn5) per-subtask.

Model	mfq	dure	vcsum	lsht	pr	AVG
Causal-MLP-O0	**46.83**	23.63	10.55	18.67	**59.00**	**31.74**
Bidirectional-MLP-O0	39.65	**27.07**	10.99	19.50	22.50	23.94
Bidirectional-ATTN-MLP-O256	44.35	23.26	10.75	18.83	35.50	26.54
Bidirectional-MLP-O256	38.06	24.02	**11.05**	**22.50**	37.50	26.63

E.6.3 MASK-TYPE COMPARISON

Table 33: Mask-type ablation (16 × compression, mean pooling, W=1024, continual pre-training LR $= 1.0 \times 10^{-5}$).

Mask	RULER 4k	RULER 8k	RULER 16k	LB en16	LB cn5	LongHealth5	GSM8K
Bidirectional	71.62	66.83	63.63	33.52	23.94	62.75	74.53
Causal	**75.06**	**70.23**	**65.91**	**39.08**	**31.74**	**67.50**	**81.05**

E.6.4 WINDOW-SIZE COMPARISON

Table 34: Window-size ablation (16 × compression, mean pooling, continual pre-training LR $= 1.0 \times 10^{-6}$). W=16 and W=256 use causal attention; W=1024 uses bidirectional attention. We do not run W=1024 with causal attention at LR $= 1.0 \times 10^{-6}$. However, Table 33 shows that causal masking is strictly better than bidirectional masking, and W=1024 (bidirectional) already outperforms W=256 (causal) on RULER tasks while also achieving lower pre-training loss. We therefore conclude that W=1024 is the better setting.

Model	RULER 4k	RULER 8k	RULER 16k	LB en16	LB cn5	LongHealth5	GSM8K
Mean W16 (causal)	24.85	23.87	22.54	29.62	22.62	56.50	46.55
Mean W256 (causal)	58.37	54.39	50.18	**34.15**	**25.97**	**62.25**	**76.80**
Mean W1024 (bidir)	**62.33**	**58.75**	**56.65**	33.29	22.88	60.25	66.94

E.6.5 ENCODER-REPRESENTATION COMPARISON

Table 35: Encoder-representation ablation (16 × compression, EOS pooling, causal, continual pre-training LR $= 1.0 \times 10^{-6}$).

Encoder init	RULER 4k	RULER 8k	RULER 16k	LB en16	LB cn5	LongHealth5	GSM8K
LLM (Instruct)	38.29	34.39	33.50	30.48	22.73	**58.25**	54.51
Embed (Qwen3-Emb)	**42.00**	**38.76**	**38.12**	**31.72**	**25.32**	58.00	**59.36**

E.7 NIAH AGENT RESULTS

Table 36: RULER NIAH (retrieval) per-task results for our LCLM 0.6B-4B model at 16x compression, with and without the agentic expand-or-answer loop, across context lengths. Δ *agent* is the cell-wise gain over the non-agentic baseline. Each cell averages 50 questions per task and context length, matching Figure 4.

Model	ns1	ns2	ns3	nm1	nm2	nm3	nmv	nmq	AVG
4k context									
LCLM 0.6B-4B	100.00	88.00	70.00	90.00	86.00	56.00	72.00	85.50	80.94
LCLM 0.6B-4B agent	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**95.50**	**100.00**	**99.44**
Δ *agent*	*+0.00*	*+12.00*	*+30.00*	*+10.00*	*+14.00*	*+44.00*	*+23.50*	*+14.50*	*+18.50*
8k context									
LCLM 0.6B-4B	96.00	90.00	58.00	82.00	88.00	44.00	70.00	79.00	75.88
LCLM 0.6B-4B agent	**100.00**	**100.00**	**100.00**	**100.00**	**98.00**	**100.00**	**95.00**	**99.50**	**99.06**
Δ *agent*	*+4.00*	*+10.00*	*+42.00*	*+18.00*	*+10.00*	*+56.00*	*+25.00*	*+20.50*	*+23.19*
16k context									
LCLM 0.6B-4B	92.00	82.00	60.00	86.00	60.00	26.00	68.00	82.50	69.56
LCLM 0.6B-4B agent	**100.00**	**100.00**	**100.00**	**98.00**	**86.00**	**86.00**	**93.00**	**97.50**	**95.06**
Δ *agent*	*+8.00*	*+18.00*	*+40.00*	*+12.00*	*+26.00*	*+60.00*	*+25.00*	*+15.00*	*+25.50*