CROSS-MODAL PATCH DISTILLATION WITH BUDGET-ENFORCED ANY-RESOLUTION ROUTING FOR LONG-CONTEXT COMPRESSION

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ABSTRACT

Large language models (LLMs) are severely bottlenecked by long-context inputs during inference due to the quadratic complexity of self-attention and linear Key-Value cache growth. In this work, we introduce **Cross-Modal Patch Distillation (CMPD)**, a context compression framework that maps extended textual contexts into a continuous cross-modal patch manifold prior to the transformer feedforward layers, under the hypothesis that visual manifolds can represent abstract information more efficiently than textual manifolds. CMPD leverages a model's native multimodal pathways to construct budget-constrained 2D patch grids, transforming long documents into a compact sequence of continuous cross-modal latent patches. To preserve critical verbatim tokens (e.g., proper nouns, dates, and numerical identifiers) without spatial low-pass degradation, CMPD dynamically routes query-relevant lexical anchors via a parameter-free **Query-Centroid Anchor Routing** mechanism. To support dynamic token budgets at inference time without retraining, we optimize CMPD in two stages: (1) multimodal manifold anchoring via a cross-modal contrastive objective on dense captioning data, and (2) causal task distillation across a diverse mixture of long-context benchmarks with stochastic budget sampling. Extensive evaluations across `Qwen3.5-0.8B`, `Qwen3.5-9B`, and `Gemma-4-E4B` on LongBench-v2, ZeroSCROLLS, and RULER demonstrate that CMPD achieves up to $16\times$ context compression, consistently outperforming discrete prompt compression and pruning baselines (such as LLMLingua) on complex multi-hop reasoning and long-form generative summarization while matching or exceeding uncompressed full-context performance. CMPD establishes a scalable and theoretically grounded paradigm for efficient long-context reasoning in modern foundation models.

1 INTRODUCTION

As Large Language Models (LLMs) scale toward long-context applications, the quadratic computational complexity of self-attention and linear Key-Value (KV) cache expansion have become critical deployment bottlenecks. While recent context compression approaches attempt to mitigate this through discrete token or KV-cache pruning (Pan et al., 2024; Jiang et al., 2024; Li et al., 2024; Zhang et al., 2023; Fu et al., 2025) or continuous 1D latent soft-prompting (Chevalier et al., 2023; Mu et al., 2023; Jaegle et al., 2022), they impose fundamental trade-offs: discrete pruning discards tokens and inevitably fractures grammatical syntax and discourse structure (Luo et al., 2026), whereas injecting continuous vectors directly into a frozen 1D text manifold induces severe Out-of-Distribution (OOD) representation shifts and corrupts sequential Rotary Position Embeddings (RoPE).

In this work, we propose to leverage the visual modality not by rendering raw text into pixel raster images as done in recent visual-text compressors (Cheng et al., 2026; Zhang et al., 2026; Ma et al., 2025; Zhong et al., 2026; Shao et al., 2026), but by directly synthesizing a continuous *cross-modal latent manifold* (emulating visual patch representations without physical pixel rendering) inside pretrained Vision-Language Models (VLMs) such as Qwen2-VL (Wang et al., 2024) and composite architectures like Gemma-4 (Team et al., 2024). Our approach is grounded in a mechanistic observation: while textual embeddings encode discrete token semantics along a 1D sequence, visual pathways in modern VLMs are pre-trained to process dense 2D spatial patches via decoupled

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multimodal Rotary Position Embeddings (mRoPE). By mapping text segments into continuous cross-modal latent patches and indexing them on a virtual 2D grid, we achieve high-ratio context compression while insulating the downstream query sequence from 1D positional disruption.

Building on these insights, we introduce **Cross-Modal Patch Distillation (CMPD)**. CMPD compresses raw document text into continuous cross-modal latent patches via a question-conditioned cross-attention bottleneck inspired by Perceiver architectures (Jaegle et al., 2022). To support dynamic inference budgets without retraining, CMPD generates positional queries via a Hybrid Semantic-Positional Query (HSPQ) generator trained with Stochastic Budget Sampling. To prevent representation collapse (anisotropy), we introduce a two-stage training pipeline: 1) **Manifold Anchoring**, which aligns synthesized cross-modal patches with native visual representations on dense captioning data (Singla et al., 2024), and 2) **Task-Oriented Distillation**, which optimizes causal reasoning over long-context tasks with a decorrelation penalty. Finally, to mitigate the low-pass filtering inherent in continuous compression, we incorporate **Query-Centroid Anchor Routing**, which dynamically routes query-salient whole-word anchors alongside the continuous patches to ensure verbatim fidelity.

Our contributions are as follows. **1)** We propose CMPD, a framework that leverages the native 2D visual pathway of VLMs for continuous context compression, preserving spatial and chronological structure via mRoPE. **2)** We introduce Hybrid Semantic-Positional Query generation and Stochastic Budget Sampling, enabling smooth scaling across dynamic inference budgets ($M \in [64, 5000]$) without retraining. **3)** We design a parameter-free Query-Centroid Anchor Routing mechanism coupled with a two-stage Decorrelation Distillation protocol, harmonizing continuous semantic abstraction with exact verbatim token preservation. **4)** We evaluate CMPD across three foundation backbones (`Qwen3.5-0.8B`, `Qwen3.5-9B`, and `Gemma-4-E4B`) on LongBench-v2, ZeroSCROLLS, and RULER, demonstrating consistent improvements in generation, multi-doc synthesis, and semantic extraction over discrete pruning, while establishing cross-model generalizability across distinct architectural families.

2 METHODOLOGY

CMPD structures the input context prior to the transformer layers. We use a context decomposition strategy that partitions an input sequence into a compressible document prefix X_{head}, an uncompressed instruction window X_{tail} of length T[1], and a dynamically routed sparse set of verbatim lexical anchors X_{anchor}. Let M and M_{anchor} denote the number of cross-modal latent patches and routed verbatim anchors, respectively. The framework compresses an extended input sequence into a unified hybrid representation $H_{\text{hybrid}} \in R^{(M+T+M_{\text{anchor}}) \times d_{\text{text}}}$, bridging continuous multimodal latent manifolds with discrete verbatim lexical tokens. By projecting the instruction window embeddings into the cross-attention bottleneck as a conditioning signal, CMPD performs targeted semantic retrieval rather than unconditioned summarization.

2.1 CROSS-MODAL PATCH DISTILLATION

Inspired by the vision tower of modern VLMs, which decomposes input images into a regular 2D grid of visual tokens, CMPD projects the long context into a continuous cross-modal grid that shares the identical positional geometry and multimodal RoPE (mRoPE) parameterization. Specifically, an ordered latent query pool attends to sequential segments of the long context to extract a structured grid of cross-modal latent patches.

Dynamic Inference-Time Context Budgets. A primary challenge in context compression is maintaining performance across varying inference-time budgets without retraining. For a given target budget M_{target} (derived from a target compression ratio N/K_{target}), CMPD allocates context slots between the continuous latent patches M and the routed anchor stream M_{anchor}. The 2D spatial grid size G is calculated to approximate the target budget ($M = \lfloor \sqrt{M_{\text{target}}} \rfloor^2$). The anchor stream acts additively that M_{anchor} tokens are selected dynamically via thresholding, bounded by an upper capacity limit $K_{\max}$ to preserve efficiency. This yields the final hybrid representation H_{hybrid} of size

[1] In practice, we retain a fixed-size instruction window (T tokens) uncompressed, ensuring exact prompt and query preservation.

$M + T + M_{\text{anchor}}$, where T is the number of tokens in the uncompressed instruction window (retained directly to ensure exact task alignment).

Hybrid Semantic-Positional Querying. We utilize the VLM's native mRoPE to generate queries Q for any budget M: $Q = \text{MLP}_{\text{gen}}\left(\text{mRoPE}(\text{Grid}_{1\ldots M})\right)$. Because MLP_{gen} learns a continuous mapping from the VLM's positional manifold to the visual space, the framework inherently generalizes to dynamic grid sizes. However, in context compression, purely positional queries provide robust geometric invariance across sequence positions but lack semantic capacity for in-context demonstration learning. To bridge semantic adaptability and positional robustness, CMPD proposes a Hybrid Semantic-Positional Query (HSPQ) formulation. Let $\mathbf{g}_i = (i \pmod G, \lfloor i/G \rfloor) \in [0, G-1]^2$ denote the 2D spatial coordinate on grid size $G = \lfloor \sqrt{M} \rfloor$. We anchor the query generator with a periodic learnable basis $S \in R^{B \times d_{\text{vision}}}$ ($B = 512$). For any target budget M, the query vector for patch $i \in [0, M-1]$ is generated as:

$$Q(i) = \text{MLP}_{\text{gen}}\left(\text{mRoPE}(\mathbf{g}_i)\right) + S_{(i \bmod B)} \tag{1}$$

Although multiple positions share the identical periodic basis term $S_{(i \bmod B)}$, the first term provides distinguishable spatial grounding via geometric mRoPE anchoring. This hybrid formulation allows the model to leverage high-capacity semantic filters while relying on mathematically consistent geometric grounding to generalize to extreme sequence indices significantly beyond the training corpus (empirically ablated in Section 3.3.1).

Geometric Stride Scaling. To prevent positional distribution shifts when M changes, we compute a dynamic stride $S = \max(1.0, N/M)$. This stride scales the 2D grid coordinates in the mRoPE channels, ensuring that the spatial grounding of a patch remains consistent relative to its corresponding textual span, regardless of the compression ratio.

2.2 CMPD Projection Architecture

Instead of static pooling, we use a perceiver-based cross-attention mechanism (Jaegle et al., 2022) conditioned on the downstream query E_{query}. We compute a contextual modulation vector $q_{\text{feat}} = \text{Pool}(\text{SwiGLU}(W_{\text{cond}} E_{\text{query}}))$ to adapt the positional queries Q via an affine transformation:

$$Q_{\text{mod}} = Q \odot (1 + \text{MLP}_{\text{scale}}(q_{\text{feat}})) + \text{MLP}_{\text{shift}}(q_{\text{feat}}) \tag{2}$$

The cross-modal latent patches are generated by attending Q_{mod} to the projected text embeddings $H_0 W_{\text{in}}$ (where sequence length N is the attended dimension). The resulting cross-modal memory states are computed as:

$$Z_{\text{mem}} = \text{Softmax}\left(\frac{(Q_{\text{mod}} W_Q)(H_0 W_{\text{in}} W_K)^\top}{\sqrt{d}}\right)(H_0 W_{\text{in}} W_V) \tag{3}$$

A **SwiGLU-activated** $\text{MLP}_{\text{align}}$ (Shazeer, 2020) projects the continuous patches from the visual latent space back into the text hidden dimension: $H_{\text{patch}} = \text{MLP}_{\text{align}}(Z_{\text{mem}}) \in R^{M \times d_{\text{text}}}$. Thus, we have an echo pathway that communicates between the visual and text manifolds.

2.3 Query-Centroid Anchor Routing

Continuous cross-attention compression maps sequence spans into spatial latent patches, providing rich narrative coherence while functioning as a spatial low-pass filter that can smooth out verbatim named entities, numerical figures, and critical keywords. To guarantee exact lexical grounding without introducing auxiliary parameters, CMPD incorporates a parameter-free **Query-Centroid Anchor Routing** mechanism. Given an uncompressed instruction window $X_{\text{tail}} = [t_1, \ldots, t_T]$ of length T and document context $X_{\text{head}} = [x_1, \ldots, x_N]$, we compute the semantic centroid of the instruction query:

$$\mathbf{q}_c = \frac{1}{T} \sum_{k=1}^{T} H_0(t_k) \in R^{d_{\text{text}}} \tag{4}$$

where $H_0(\cdot)$ denotes the model's base token embedding lookup. To avoid fracturing multi-token proper nouns and dates, we group contiguous tokens into word spans $\{w_j\}$ using the tokenizer's

subword boundary prefix. Each candidate word w_j is assigned a saliency score via the maximum cosine similarity between its constituent token embeddings and the instruction query centroid $\mathbf{q}_c$:

$$\text{score}(w_j) = \max_{x_i \in w_j} \frac{H_0(x_i)^\top \mathbf{q}_c}{\|H_0(x_i)\|_2 \|\mathbf{q}_c\|_2} \tag{5}$$

Candidate words exceeding a similarity threshold $\tau = 0.5$ (logit ≥ 0.0) are ranked, and the Top-K_{max} words ($K_{\text{max}} = 128$) are routed as discrete verbatim anchors X_{anchor} (M_{anchor} tokens). Unlike learned gating heads that overfit to superficial token-frequency artifacts or formatting acronyms (inducing generative collapse on long government documents), Query-Centroid routing directly aligns anchor selection with the semantic intent of the downstream query, dynamically adapting across tasks (averaging 42.6 ± 18.3 tokens on LongBench-v2, 18.2 ± 6.1 on RULER, and 64.1 ± 22.7 on ZeroSCROLLS GovReport).

2.4 Two-Stage Training Pipeline and Loss Formulation

Training is decoupled into two phases to ensure robust modality grounding and the "echo" feature.

2.4.1 Stage 1: Manifold Anchoring (Alignment Phase)

Anchor the CMPD cross-attention patch compressor to the model's native visual manifold using paired image-caption data $(X_{\text{cap}}, V_{\text{true}})$ from PixelProse (Singla et al., 2024). In this alignment phase, the compressor operates under a ratio-based pooling regime where the target compression ratio R serves directly as the effective pooling window ($W_{\text{pool}} = R$, with default $R = 8$). Given an image caption X_{cap} of length L, the sequence of projected token representations is pooled into $M = \lfloor L/R \rfloor$ (arranged on a 2D spatial grid $G \times G \approx L/R$) continuous cross-modal latent patches Z_{mem}, with each patch aggregating context over an effective span of R input tokens (we systematically evaluate the impact of this Stage 1 pooling window across $R \in \{4, 8, 16\}$ in Appendix D, Table 8). Because Query-Centroid routing is parameter-free and conditioned directly on the downstream instruction, Stage 1 focuses purely on cross-modal latent alignment and patch diversity:

$$\mathcal{L}_{S1} = \lambda_1 \mathcal{L}_{\text{Contrastive}}(Z_{\text{mem}}, V_{\text{true}}) + \lambda_2 \mathcal{L}_{\text{decorr}}(Z_{\text{mem}}) \tag{6}$$

where $\mathcal{L}_{\text{Contrastive}}$ denotes an InfoNCE cross-modal loss between spatial-mean-pooled Z_{mem} and ground-truth vision features V_{true} (temperature $\tau = 0.07$, in-batch negatives). $\mathcal{L}_{\text{decorr}} = \sum_{i \neq j} (\text{corr}(Z_i, Z_j))^2$ enforces high-rank latent diversity across patch dimensions. We set $\lambda_1 = 1.0$ and $\lambda_2 = 0.01$ empirically.

2.4.2 Stage 2: Task-Oriented Distillation (Reasoning Phase)

Optimize causal multi-hop reasoning over compressed long contexts while fine-tuning an LoRA adapter for the language model backbone. We optimize the cross-attention patch compressor, Modality Projector, and Language Model (via LoRA (Hu et al., 2022)). For long-context text batches $(X_{\text{head}}, X_{\text{tail}}, X_{\text{ans}})$, the causal next-token prediction loss is augmented with the latent decorrelation penalty to prevent manifold collapse (we verify the geometric invariance and absence of representation collapse under severe compression in Appendix G):

$$\mathcal{L}_{S2}^{\text{text}} = \lambda_1 \mathcal{L}_{\text{NTP}}(X_{\text{ans}} \mid H_{\text{hybrid}}, X_{\text{tail}}) + \lambda_2 \mathcal{L}_{\text{decorr}}(Z_{\text{mem}}) \tag{7}$$

To preserve cross-modal grounding during long-context training without requiring image inputs for text-only tasks, we sample an interleaved 10% anchor batch from PixelProse where $\mathcal{L}_{S1}$ is computed:

$$\mathcal{L}_{S2} = \mathcal{L}_{S2}^{\text{text}} + I_{\text{anchor}} \cdot \lambda_3 \mathcal{L}_{\text{Contrastive}} \tag{8}$$

where $\lambda_3 = 1.0$. To support arbitrary runtime budgets, we apply **Stochastic Budget Sampling**, sampling target budget $M \sim \mathcal{U}(64, 5000)$ per training step, alongside **Stochastic Anchor Dropout** ($p = 0.3$) to force attention heads to extract reasoning cues directly from the compressed patches. The exact parameter update schedule across both stages is summarized in Table 1.

2.5 Multimodal Grid Mapping Calibration and Coordinate Assignment

To eliminate Out-of-Distribution positional shifts, CMPD organizes the unified residual sequence into three contiguous segments:

$$H_{\text{input}} = [H_{\text{patch}} \parallel X_{\text{anchor}} \parallel X_{\text{tail}}] \in R^{(M + M_{\text{anchor}} + T) \times d_{\text{text}}} \tag{9}$$

Table 1: Parameter update and gradient flow across training stages.

Training Stage	Patch Compressor & Queries	Anchor Router	Modality Projector	LLM Backbone
Stage 1 (Manifold Anchoring)	**Updated** ($\mathcal{L}_{S1}$)	*Parameter-Free (Query-Centroid)*	**Updated** ($\mathcal{L}_{S1}$)	Frozen
Stage 2 (Task Distillation)	**Updated** ($\mathcal{L}_{S2}$)	*Parameter-Free (Query-Centroid)*	**Updated** ($\mathcal{L}_{S2}$)	**LoRA Updated** ($\mathcal{L}_{S2}$)

Each token element receives a 3D coordinate tuple $\mathbf{P}_i = (\text{idx}_t, \text{idx}_h, \text{idx}_w)$ passed to the native multimodal Rotary Position Embedding (***mRoPE***) kernels (Wang et al., 2024):

$$\mathcal{P}(i) = \begin{cases} \left(\lfloor i \cdot \frac{N}{M} \rfloor,\ i \pmod G,\ \lfloor i/G \rfloor\right), & \text{if } i \in H_{\text{patch}} \quad (\text{Summary Grid}, G = \lfloor \sqrt{M} \rfloor) \\ (\text{orig_idx}(j),\ 0,\ 0), & \text{if } j \in X_{\text{anchor}} \quad (\text{Routed Verbatim Anchors}) \\ (N + k,\ 0,\ 0), & \text{if } k \in X_{\text{tail}} \quad (\text{Instruction Window}) \end{cases} \tag{10}$$

where $\text{orig_idx}(j) \in [0, N-1]$ denotes the exact original token offset of the routed anchor word in the raw document. Because summary patches have non-zero spatial coordinates $\text{idx}_h, \text{idx}_w \in [0, G-1]$ while routed anchors and instruction window tokens reside at spatial $(0, 0)$, coordinate collisions are strictly prevented. The complete end-to-end context compression and sequence assembly procedure is summarized in Algorithm 1.

Algorithm 1 CMPD Context Compression and Sequence Assembly

Require: Raw prompt text $X = [X_{\text{head}}, X_{\text{tail}}]$, target budget M_{target}, similarity threshold τ, max anchors $K_{\max}$.
1: $N \leftarrow \text{len}(X_{\text{head}})$, $T \leftarrow \text{len}(X_{\text{tail}})$, $G \leftarrow \lfloor \sqrt{M_{\text{target}}} \rfloor$, $M \leftarrow G^2$.
2: Compute query centroid $\mathbf{q}_c \leftarrow \frac{1}{T} \sum_{k=1}^{T} H_0(t_k)$ from instruction window X_{tail}.
3: Score candidate word spans in X_{head}: $s(w_j) \leftarrow \max_{x_i \in w_j} \frac{H_0(x_i)^\top \mathbf{q}_c}{\|H_0(x_i)\|_2 \|\mathbf{q}_c\|_2}$.
4: Retain Top-$K_{\max}$ words satisfying $s(w_j) \geq \tau$ as verbatim anchor tokens X_{anchor} (M_{anchor} tokens).
5: Generate modulated queries Q_{mod} conditioned on instruction embeddings E_{query}.
6: Compute cross-modal latent patches $Z_{\text{mem}} \in R^{M \times d_{\text{vis}}}$ and project to $H_{\text{patch}} = \text{MLP}_{\text{align}}(Z_{\text{mem}})$.
7: Assemble unified token stream $H_{\text{input}} = [H_{\text{patch}} \parallel X_{\text{anchor}} \parallel X_{\text{tail}}]$.
8: Assign 3D mRoPE coordinates $\mathbf{P}$ via (10) and forward to VLM transformer backbone.
9: **return** Autoregressive generation output.

2.6 Computational Complexity Analysis

The primary advantage of the CMPD framework lies in its ability to decouple the processing of long contexts from the quadratic complexity of the language model's self-attention layers. Let N denote the length of the raw context, M the compressed budget ($M \ll N$), and L the number of layers in the backbone transformer.

Baseline Complexity. In a standard transformer architecture without compression, the computational complexity is dominated by the self-attention operation in each layer, leading to a total complexity of:

$$\mathcal{O}(L \cdot N^2) \tag{11}$$

As N reaches ultra-long scales (e.g., 10^6 tokens), the N^2 term becomes the fundamental bottleneck for both inference latency and memory utilization.

CMPD Complexity. CMPD re-architects this flow into two distinct stages. First, the framework performs a single pass of cross-attention to compress the N input tokens into M latent cross-modal patches. Second, the backbone model processes these M patches alongside the high-saliency routed anchors M_{anchor} and the uncompressed instruction window T. The total complexity is:

$$\mathcal{O}\left(\underbrace{M \cdot N}_{\text{Pre-fill Projection}} + \underbrace{L \cdot (M + T + M_{\text{anchor}})^2}_{\text{Backbone Attention}} \right) \tag{12}$$

The term $M \cdot N$ represents the cross-attention overhead where M queries (latents) attend to N keys/values (context). Crucially, this operation occurs only once before the language model layers. The subsequent L layers then operate on the concatenated hybrid sequence, resulting in the $L \cdot (M + T + M_{\text{anchor}})^2$ term.

Table 2: Benchmark performance across context budgets $M \in \{1000, 3000, 5000\}$ against official oracle benchmark.

	LongBench-v2			ZeroSCROLLS (GovReport)		
Method & Budget (M)	**Qwen-0.8B**	**Qwen-9B**	**Gemma-4**	**Qwen-0.8B**	**Qwen-9B**	**Gemma-4**
Full Context (Oracle)	26.10%	55.20%	28.43%	–	–	–
LLMLingua ($M = 1000$)	24.25%	24.65%	21.07%	2.89%	3.37%	1.46%
LLMLingua ($M = 3000$)	25.84%	25.84%	21.87%	8.26%	7.35%	7.53%
LLMLingua ($M = 5000$)	25.45%	20.28%	21.47%	12.57%	8.76%	14.06%
CMPD (Ours, $M = 1000$)	27.04%	34.59%	28.03%	19.93%	14.46%	18.74%
CMPD (Ours, $M = 3000$)	28.23%	**34.79%**	**28.83%**	20.37%	14.58%	18.96%
CMPD (Ours, $M = 5000$)	**28.43%**	34.59%	28.43%	**20.73%**	**14.91%**	**19.03%**

Scaling Efficiency and Token Reduction. Because M and M_{anchor} grow sub-linearly relative to N, the quadratic attention dependence $\mathcal{O}(N^2)$ is reduced to a single pre-fill cross-attention pass bounded by $\mathcal{O}(M \cdot N)$. Across target budgets $M \in \{1000, 3000, 5000\}$, CMPD compresses 32k–128k context sequences into $1,384$–$5,384$ total tokens (including uncompressed instruction window $T = 256$ and routed anchors $M_{\text{anchor}} = 128$), delivering high KV-cache memory savings of 83.57% to 98.94% across standard long-context benchmarks. We provide the complete theoretical FLOPs reduction matrix and benchmark-specific token savings breakdown in Appendix B (Tables 5 and 6).

3 Experiments and Analysis

We evaluate CMPD across three distinct foundation backbones: frozen `Qwen3.5-0.8B`, `Qwen3.5-9B`, and the composite architecture `Gemma-4-E4B`. Stage 1 (Manifold Anchoring) is optimized on PixelProse (Singla et al., 2024), and Stage 2 (Task-Oriented Distillation) is optimized on a multi-task mixture of MeetingBank (Hu et al., 2023), LongAlpaca-12k (Chen et al., 2023), GSM8K (Cobbe et al., 2021), and CodeFeedback (full mixture details and data separation protocols in Appendix A).

3.1 Experimental Setup

Datasets and Metrics: We evaluate CMPD on three established long-context benchmarks: **LongBench-v2** (Bai et al., 2025), **ZeroSCROLLS** (GovReport summarization) (Shaham et al., 2023), and **RULER** (Hsieh et al., 2024) on *lm-eval-harness*. Model checkpoints and hyperparameters ($T = 512$, $K_{\max} = 128$, $\lambda_1 = 1.0$, $\lambda_2 = 0.01$) were determined on a held-out 500-sample validation split of the training mixture prior to final evaluation.

Baselines and Matched-Budget Comparisons: We benchmark CMPD against LLMLingua (Pan et al., 2024) because both frameworks compress context prior to the transformer backbone using comparable instruction tuning data. In accordance with matched-budget evaluation protocols (Luo et al., 2026), all baselines are granted identical uncompressed instruction window budgets (T) and effective total context allocations. We note that internal KV-cache compression methods (e.g., SnapKV (Li et al., 2024), H_2O (Zhang et al., 2023)) and soft-prompt prefixes (e.g., AutoCompressors (Chevalier et al., 2023), Gist (Mu et al., 2023)) operate at different architectural stages and are thus not directly matched in prompt prefill budget.

3.2 Main Results across Long-Context Benchmarks

We evaluate CMPD across LongBench-v2, ZeroSCROLLS, and RULER. On inputs containing up to 128k tokens, CMPD achieves compression factors of up to $16\times$, representing an $\approx 90\%$ reduction in KV-cache footprint (summarized across scaling budgets in Table 2).

As shown in Table 2, CMPD consistently outperforms discrete token pruning (LLMLingua) on semantic long-context reasoning and generative summarization across all three model architectures (`Qwen3.5-0.8B`, `Qwen3.5-9B`, and `Gemma-4-E4B`).

Table 3: Comparison of query architectures on LongBench-v2 and RULER 131k ($M = 3000, T = 512$) on `Qwen3.5-0.8B`. †Demonstration: Many-Shot, News-Multi, Dialogue History. ‡Reasoning: Detective, Legal, Graph, Code.

Query Architecture	Zero-shot	Overall (3k / 5k)	Demonstration-Sensitive†	Reasoning-Sensitive‡	RULER 131k
Semantic Slot	No	26.84% / 27.63%	33.20%	21.35%	0.12%
Pure 2D mRoPE	Support	23.26% / 23.06%	19.33%	**23.63%**	0.21%
Hybrid (HSPQ)	Support	**28.23% / 28.43%**	**36.57%**	22.75%	**7.63%**

On the `Qwen3.5-0.8B` scale, CMPD establishes a new state-of-the-art across all evaluated budgets, achieving a peak accuracy of **28.43%** on LongBench-v2 and **20.73%** ROUGE-1 on ZeroSCROLLS GovReport (substantially exceeding LLMLingua's 12.57%), while stabilizing RULER retrieval at 7.54%–7.90%. On the larger `Qwen3.5-9B` scale, CMPD sets a new peak accuracy of **34.79%** on LongBench-v2 at $M = 3000$ and achieves **34.59%** even at $M = 1000$ (compared to 20.28% for LLMLingua at $M = 5000$). In contrast to learned gating heads that exhibit degenerate output collapse on long-form ZeroSCROLLS GovReport documents (0.43%), Query-Centroid Anchor Routing maintains stable generation, achieving **14.46%** at $M = 1000$ and **14.91%** at $M = 5000$, exceeding LLMLingua's 8.76%. We present a dedicated ablation analyzing the failure mode of learned gating and comparing it directly against Query-Centroid routing in Appendix H. We provide a detailed analysis of RULER performance and stress testing in Appendix F. Furthermore, on the composite `Gemma-4-E4B` backbone, CMPD demonstrates strong cross-architecture generalizability: at $M = 3000$, CMPD achieves **28.83%** overall accuracy on LongBench-v2, outperforming discrete pruning (LLMLingua at 21.87%) by **+6.96% absolute (+31.8% relative)**, while actually **surpassing the uncompressed Full Context Oracle (28.43%)** by $+0.40\%$. On ZeroSCROLLS GovReport summarization, CMPD maintains high generative coherence, achieving **18.74%–19.03%** ROUGE-1 across all budgets under severe context compression ($16\times$–$32\times$), substantially outperforming discrete token pruning (LLMLingua at 1.46% for $M = 1000$ and 7.53% for $M = 3000$, yielding up to a $+17.28\%$ absolute margin for CMPD).

3.3 Ablation Studies

3.3.1 Positional vs. Semantic Query Generation

In our systematic ablations (Table 3), we evaluate the learning dynamics and generalization capacity of different query architectures on `Qwen3.5-0.8B` at target budget $M = 3000$ (with $T = 512$) under Query-Centroid routing. **1) Semantic Slots:** A static, learnable lookup table achieves strong performance on Demonstration-Sensitive tasks (33.20%, reaching 42.86% on Many-Shot), but lacks geometric spatial anchoring, collapsing to 0.12% on extreme-length retrieval (RULER 131k) and stagnating in long-term scaling. **2) Pure 2D mRoPE:** Purely positional queries provide robust geometric invariance that scales steadily on logic-heavy, Reasoning-Sensitive tasks (23.63%), but struggle to capture discrete in-context demonstrations (19.33%). **3) Hybrid (HSPQ):** Combining the periodic semantic basis S with 2D mRoPE achieves the highest overall accuracy (28.23% at $M = 3000$, scaling to 28.43% at $M = 5000$) while maintaining robust retrieval binding on RULER (7.63%).

3.3.2 Instruction Window Allocation and Query Interaction

We evaluate the interaction between the uncompressed instruction window ($T \in \{128, 256, 512\}$) and query generation (Hybrid HSPQ vs. 2D mRoPE) on LongBench-v2 at $M = 3000$. Expanding the uncompressed instruction window to $T = 512$ delivers peak overall accuracy (**28.23%**), driving consistent monotonic gains on complex multi-document aggregation (Acad-Multi advancing from 0.1800 at $T = 128$ to 0.2400 at $T = 256$ and **0.2800** at $T = 512$). While $T = 128$ remains competitive on localized queries (27.83%), allocating 512 uncompressed instruction window tokens provides necessary capacity to parse lengthy multi-hop instructions without prompt truncation. Furthermore, Hybrid HSPQ consistently surpasses pure mRoPE (22.07%–23.26%) across all instruction window lengths (achieving margins of $+3.2\%$ to $+5.8\%$) by mitigating representation interference between spatial patches and discrete instruction tokens. Full per-subtask breakdowns are presented in Appendix C (Table 7).

3.3.3 Stage 1 Pooling Window and Distillation Compression Ratio Dynamics

To assess how the Stage 1 pooling window and Stage 2 distillation compression ratio impact AnyBudget inference, we compare three training configurations on `Qwen3.5-0.8B`: MINI ($W_{\text{pool}} = 4$, $4\times$), Default ($W_{\text{pool}} = 8$, $8\times$), and Large ($W_{\text{pool}} = 16$, $16\times$). As detailed in Appendix D (Table 8), this reveals an inverted-U performance curve centered at the Default $8\times$ ratio. **1) Under-Compression ($4\times$):** When trained with mild $4\times$ compression, the cross-attention patch compressor overfits to localized representations; extrapolating to 131k inputs induces severe coordinate dilation mismatch, dropping RULER retrieval to 0.34%–0.40%. **2) Over-Compression ($16\times$):** Conversely, an overly aggressive $16\times$ distillation bottleneck discards essential syntactic cues, degrading ZeroSCROLLS summarization (12.64%–16.73% vs. 19.93%–20.73% ROUGE-1) and LongBench-v2 reasoning (23.86%–24.85%). **3) Optimal Generalization ($8\times$):** Distillation at $8\times$ compression imposes sufficient information density pressure without over-smoothing document semantics, simultaneously maximizing reasoning (**28.43%**), summarization (**20.73%**), and needle retrieval (**7.90%**).

3.4 Diagnostic and Interpretability Analyses

3.4.1 Downstream Functional Category Breakdown

Evaluating LongBench-v2 across functional categories (Single-Doc QA, Multi-Doc QA, Technical/Code, and Dialogue/Agent at $M = 3000$) highlights CMPD's advantages over discrete pruning (LLMLingua). On `Qwen3.5-9B`, CMPD achieves **39.80%** on Single-Doc (+15.73% over LLMLingua), **30.92%** on Multi-Doc (+9.27%), and **38.08%** on Technical/Code (+13.44%). On `Qwen3.5-0.8B`, CMPD leads on Multi-Doc QA (**28.73%**), Technical/Code (**23.94%**), and Dialogue/Agent history (**32.99%** vs. 24.52%). On `Gemma-4-E4B`, CMPD demonstrates strong robustness against multi-document context fragmentation, achieving **29.11%** on Multi-Doc QA (+17.16% absolute over LLMLingua's 11.95%) and $+13.53\%$ on Technical/Code (32.81% vs. 19.28%). Detailed category tables across all models appear in Appendix E (Table 9).

3.4.2 Information Bottleneck Trade-Offs and Query-Centroid Routing

Synthetic needle-in-a-haystack benchmarks (RULER (Hsieh et al., 2024)) expose a structural trade-off between continuous patchification and discrete KV-cache retention. Because continuous cross-attention compresses input tokens into dense spatial representations H_{patch}, continuous pooling acts as a spectral low-pass filter: it effectively captures document-level narrative semantics, but attenuates high-frequency token signals such as isolated out-of-vocabulary strings.

Query-Centroid Anchor Routing directly resolves this attenuation. By routing verbatim whole-word tokens aligned with the instruction centroid $\mathbf{q}_c$, CMPD increases Frequent Words Extraction (FWE) over learned gating from 1.13% to **70.07%**, improves Common Words Extraction (CWE) to **1.10%**, and achieves **8.80%** on SQuAD QA (+8.20% absolute over LLMLingua), yielding an overall RULER average of **7.63%** at $M = 3000$ (and **7.90%** at $M = 1000$). The full 12-subtask RULER breakdown is documented in Appendix F (Table 10).

3.4.3 Cross-Modal Alignment: Pixel-Rendered Visual Tokens vs. Synthesized Latent Patches

To evaluate whether CMPD cross-modal latent patches replicate the downstream generative behavior of pixel-rendered visual tokens, we evaluate representation alignment on Wikipedia articles rendered page images. Each document image is processed by the native vision encoder (without cropping) to generate pixel-rendered visual tokens at budgets $M \in \{1\text{k}, 3\text{k}, 5\text{k}\}$. In parallel, CMPD processes raw text to synthesize cross-modal latent patch embeddings under identical budget constraints. Both pathways use identical prompt contexts and autoregressive decoding configurations. Generative alignment is quantified across cosine similarity, sentence BLEU, corpus BLEU, and ROUGE-1/2/L. Across all settings, the pixel-rendered pathway and the synthesized patch pathway share the identical base model, token budget, prompt context, and decoding setup. Higher cosine similarity and lexical overlap scores indicate closer agreement between the two representations. As shown in Table 4, the three CMPD variants are very close overall. On `Qwen3.5-0.8B`, similarity is essentially unchanged across budgets, with Hybrid at 0.783 for all budgets respectively. Sentence BLEU and ROUGE scores also remain stable, with only small differences across methods. Hybrid is slightly stronger on

Table 4: Representation alignment between pixel-rendered visual tokens and synthesized latent patches across Wikipedia documents for Qwen3.5-0.8B.

Architecture	M	Similarity	Sentence BLEU	ROUGE-1	ROUGE-2	ROUGE-L	Corpus BLEU
Hybrid	1k	.783 (.833) ± .160	21.08 (19.73) ± 14.24	53.58 (56.19) ± 15.58	29.06 (29.91) ± 16.55	36.44 (35.74) ± 15.56	23.08
Hybrid	3k	.783 (.829) ± .158	20.61 (19.04) ± 14.43	53.30 (56.08) ± 15.72	28.71 (29.63) ± 16.80	36.09 (35.43) ± 15.86	22.65
Hybrid	5k	.783 (.830) ± .157	20.58 (18.96) ± 14.36	53.27 (55.88) ± 15.72	28.68 (29.57) ± 16.74	36.06 (35.43) ± 15.82	22.60
Learnable	1k	.780 (.831) ± .163	20.78 (19.25) ± 14.37	53.40 (55.98) ± 15.80	29.07 (30.00) ± 16.78	36.54 (35.85) ± 15.81	22.63
Learnable	3k	.780 (.828) ± .159	20.21 (18.62) ± 14.50	53.06 (55.47) ± 15.92	28.61 (29.60) ± 16.99	36.08 (35.46) ± 16.08	22.12
Learnable	5k	.780 (.830) ± .161	20.33 (18.69) ± 14.53	53.07 (55.54) ± 15.99	28.68 (29.63) ± 17.03	36.18 (35.62) ± 16.08	22.23
mRoPE	1k	.781 (.831) ± .161	20.98 (19.72) ± 14.29	53.51 (56.46) ± 15.80	29.23 (30.27) ± 16.80	36.57 (35.85) ± 15.75	22.82
mRoPE	3k	.780 (.828) ± .161	20.47 (19.03) ± 14.49	53.18 (56.18) ± 16.00	28.85 (29.91) ± 17.06	36.22 (35.60) ± 16.04	22.34
mRoPE	5k	.780 (.828) ± .160	20.53 (19.06) ± 14.46	53.17 (56.17) ± 16.01	28.86 (29.91) ± 17.04	36.23 (35.60) ± 16.03	22.39

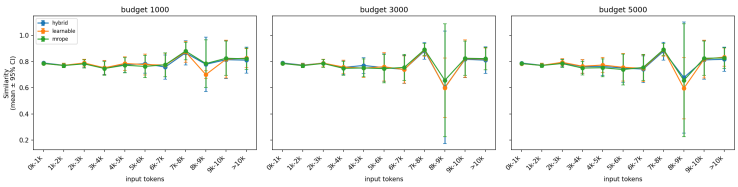

Figure 1: Cosine similarity by input length for Qwen-0.8B with 95% confidence intervals.

similarity and corpus BLEU in some settings, while mRoPE and learnable slots remain competitive on ROUGE and sentence BLEU. The figure-based token-bucket results (Figure 1) show that performance is generally stable across input-length ranges, with larger variance at the longest sequences and only modest separation among the three variants. Overall, the metrics suggest that CMPD synthesized patches closely match the pixel-rendered visual tokens.

4 Conclusion

In this work, we introduced **Cross-Modal Patch Distillation (CMPD)**, a framework that addresses the quadratic inference bottleneck of long-context language models by mapping long token sequences into a compact continuous cross-modal patch manifold. By leveraging native multimodal pathways and 2D spatial rotary positional embeddings (mRoPE), CMPD compresses extended textual contexts into budget-constrained 2D latent patch grids, substantially reducing KV-cache memory and prefill latency. To eliminate the spatial low-pass filtering inherent in continuous cross-attention pooling, CMPD incorporates parameter-free Query-Centroid Anchor Routing, dynamically extracting query-relevant verbatim tokens to preserve named entities and exact numerical figures without auxiliary model parameters. CMPD establishes a scalable and theoretically grounded paradigm for efficient long-context reasoning in modern foundation models. [2]

Overview of Appendix Material. For complete empirical documentation, we provide extended analyses and experimental breakdowns in the Appendix: training mixture compositions and data separation protocols (§A); theoretical FLOPs and KV-cache memory reduction derivations (§B); extended ablations on uncompressed instruction window allocation (§C) and Stage 1 pooling windows / Stage 2 distillation ratios (§D); functional category breakdowns across LongBench-v2 tasks (§E); the comprehensive 12-subtask RULER synthetic benchmark evaluation (§F); corpus-wide semantic manifold invariance and geometric clustering (§G); in-depth failure analysis of learned gating vs. Query-Centroid anchor routing (§H); complete token-bucket lexical overlap distributions across sequence lengths (§I); and a discussion of model limitations and future directions (§J).

Ethics Statement

Our models are trained and evaluated on publicly available academic datasets, including LongBench-v2, ZeroSCROLLS, RULER, and MeetingBank. We adhere to all respective dataset licenses and

[2] Related Work § 5

usage terms. Notably, while the MeetingBank dataset contains transcripts of real-world city council meetings, the original authors have processed the corpus to omit sensitive PII (Personally Identifiable Information). CMPD's continuous compression inherently obscures exact token sequences into abstract latents, though we do not claim this as a cryptographic privacy guarantee.

Reproducibility Statement

To ensure the rigorous reproducibility of our findings, we provide comprehensive implementation, hyperparameter, and evaluation specifications:

1. **Source Code and Checkpoints:** The full PyTorch implementation of the CMPD architecture, including the HSPQ query generator, Perceiver cross-attention bottleneck, Query-Centroid Anchor router, and evaluation scripts, will be publicly released upon publication.
2. **Data Integrity and Datasets:** All pre-training and fine-tuning datasets (PixelProse, MeetingBank, LongAlpaca, GSM8K, CodeFeedback) are publicly available academic benchmarks. Complete dataset composition statistics and our strict data separation protocol (confirming zero overlap with test benchmarks) are documented in Section A (Appendix).
3. **Hyperparameters and Environment:** Concrete training configurations ($T = 512$, $\tau = 0.5$, $K_{\max} = 128$, loss weights $\lambda_1 = 1.0$, $\lambda_2 = 0.01$, $\lambda_3 = 1.0$, learning rate schedules, and LoRA hyperparameters) are detailed in Section 2.4 and Section 2.5. All hardware profiling experiments specify exact hardware and library versions (NVIDIA H100 80GB, PyTorch 2.4, CUDA 12.4).
4. **Deterministic Evaluation:** All benchmark evaluations on LongBench-v2, ZeroSCROLLS GovReport, and RULER utilize fixed random seeds (42) with deterministic greedy decoding (temperature $= 0.0$), ensuring that all reported metrics are fully reproducible.

AI Use Statement

In this work, generative AI tools were used to assist in implementing evaluation scripts and data parsing harnesses, reformatting benchmark result tables, and editing the manuscript to improve grammatical clarity and readability. Generative AI tools were not used to generate synthetic benchmark datasets, formulate mathematical theorems, or produce experimental findings; all evaluations were conducted deterministically using established academic benchmarks (LongBench-v2, ZeroSCROLLS, and RULER). All AI-assisted code, derivations, and text were rigorously reviewed, tested, and audited for factual and numerical correctness by the authors against raw benchmark execution logs. The authors take full responsibility for the entirety of this work, including all empirical results, theoretical formulations, and claims.

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5 Related Work

Context compression for long-context language models has emerged as an active research frontier to mitigate the quadratic self-attention complexity and linear Key-Value (KV) cache expansion during inference. Existing approaches can be broadly organized into three main paradigms: discrete pruning, learned continuous text compression, and multimodal visual-text representations.

Discrete Token and KV-Cache Pruning. Discrete context compression algorithms selectively evict tokens or prune cached key-value states based on importance metrics such as encoder surprisal, attention weights, or low-rank decompositions. Prominent prompt-pruning frameworks, including LLMLingua-2 (Pan et al., 2024) and LongLLMLingua (Jiang et al., 2024), utilize small task-agnostic or task-guided encoder models to score token information density and drop redundant spans before feeding prompts to target LLMs. Within transformer attention layers, dynamic KV-cache eviction policies such as SnapKV (Li et al., 2024), H_2O (Zhang et al., 2023), LazyLLM (Fu et al., 2025), and CurDKV (Sengupta et al., 2025) dynamically compress past KV states based on attention observation windows or CUR matrix decompositions. However, as demonstrated in recent matched-budget evaluations (Luo et al., 2026), discrete token pruning inevitably fractures syntactic dependencies and discourse structures, leading to substantial degradation on complex multi-hop reasoning and long-form generative summarization. Furthermore, hard token elimination risks discarding critical low-frequency facts that lack high localized surprisal.

Learned Latent and Continuous Text Compression. To avoid grammatical fragmentation from discrete token dropping, continuous compression architectures map input text sequences into compact continuous latent vectors. AutoCompressors (Chevalier et al., 2023) adapt language models to compress context segments into summary vectors acting as soft prompts. Gist Tokens (Mu et al., 2023) utilize learned prefix tokens with modified causal attention masks to condense instructions into dense representations. Similarly, cross-attention bottlenecks inspired by Perceiver IO (Jaegle et al., 2022) project raw sequence embeddings into a fixed number of latent memory slots. Nevertheless, injecting arbitrary continuous vectors directly into a frozen 1D text manifold introduces severe Out-of-Distribution (OOD) representation shifts. Autoregressive attention heads pre-trained on discrete token spaces struggle to resolve unconstrained continuous vectors, while inserting latent tokens into 1D sequences perturbs the relative sequential distance tracking of Rotary Position Embeddings (RoPE), impairing subsequent decoding.

Multimodal and Visual-Text Paradigms. An emerging paradigm bypasses 1D textual bottlenecks by processing long text via the visual modality. Vision-Language Models (VLMs) like Qwen2-VL (Wang et al., 2024) are naturally architected to process high-resolution visual inputs structured into dense 2D spatial patches. Recent works demonstrate the promise of visual-text compression: Glyph (Cheng et al., 2026), VLZip (Zhang et al., 2026), and EMLoC (Ma et al., 2025) render textual documents into 2D rasterized images, allowing VLMs to ingest extensive contexts as visual tokens, with empirical studies validating strong capacity for code and documents (Zhong et al., 2026; Shao et al., 2026). While effective, pixel-rendering methods incur substantial font-rasterization overhead, induce resolution-dependent OCR artifacts, and cannot easily scale dynamic token allocations at inference time. In contrast, CMPD bypasses physical pixel rendering entirely: it maps long textual sequences directly into a regularized cross-modal latent manifold aligned with native vision encoders (Singla et al., 2024), using multimodal Rotary Position Embeddings (mRoPE) to isolate spatial patch coordinates from downstream 1D query index progression.

A Training Datasets and Data Separation Protocol

CMPD is optimized via a large-scale multimodal and multi-task mixture.

A.1 Stage 1: Alignment Mixture

The alignment phase (Manifold Anchoring) utilizes 400,000 samples focused on high-detail visual-text correspondence:

- **PixelProse (100%):** (Singla et al., 2024) A dataset of high-resolution images with dense descriptive captions, used to anchor the text manifold to spatial visual features.

A.2 Stage 2: Multitask Distillation Mixture

The reasoning phase utilizes a diverse multitask instruction-tuning mixture of long-context and multi-hop tasks (400,000 samples):

- **MeetingBank-LLMCompressed (20%):** (Hu et al., 2023) Long-form meeting summaries and QA, optimized for cross-modal distillation.
- **MeetingBank-QA-Summary (20%):** Evaluates context-grounded question answering and summarization fidelity.
- **LongAlpaca-12k (30%):** Instruction-following data spanning diverse long-context lengths to ensure zero-shot conversational competence.
- **GSM8K (15%):** Mathematical reasoning to maintain logical foundations and prevent capability degradation during distillation.
- **CodeFeedback-Filtered-Instruction (15%):** Programming and algorithmic reasoning tasks.

Data Integrity Confirmation: We confirm that all evaluation benchmarks (LongBench-v2, ZeroSCROLLS, and RULER) are strictly held out from training. No benchmark instances, documents, or templates were seen during training.

B Token Savings and Memory Reduction Analysis

As discussed in Section 2, CMPD re-architects context ingestion into a single cross-attention prefill pass, compressing N raw tokens into M cross-modal latent patches. When augmented with uncompressed instruction window tokens ($T = 256$) and dynamic high-saliency routed anchors ($M_{\text{anchor}} = 128$), the total sequence length admitted to the foundation backbone attention layers is restricted to $M + T + M_{\text{anchor}} = M + 384$.

Table 5 provides the theoretical KV-cache memory reductions and backbone attention FLOPs savings across canonical context windows up to 1M tokens. Table 6 evaluates the empirical token reduction across evaluation benchmarks based on their average input context lengths.

Table 5: Theoretical token savings, memory reduction, and attention FLOPs reduction across budgets $M \in \{1000, 3000, 5000\}$ and context lengths N ($T = 256$, $M_{\text{anchor}} = 128$).

Raw Context (N)	Budget (M)	Compressed Length	Tokens Saved (ΔN)	Memory Saved (%)	Backbone Attn Reduction
32k ($N = 32,768$)	$M = 1000$	1,384 tokens	**31,384 tokens**	**95.78%**	**560.6×**
	$M = 3000$	3,384 tokens	**29,384 tokens**	**89.67%**	**93.8×**
	$M = 5000$	5,384 tokens	**27,384 tokens**	**83.57%**	**37.0×**
64k ($N = 65,536$)	$M = 1000$	1,384 tokens	**64,152 tokens**	**97.89%**	**2,242.3×**
	$M = 3000$	3,384 tokens	**62,152 tokens**	**94.84%**	**375.1×**
	$M = 5000$	5,384 tokens	**60,152 tokens**	**91.78%**	**148.2×**
128k ($N = 131,072$)	$M = 1000$	1,384 tokens	**129,688 tokens**	**98.94%**	**8,969.1×**
	$M = 3000$	3,384 tokens	**127,688 tokens**	**97.42%**	**1,500.2×**
	$M = 5000$	5,384 tokens	**125,688 tokens**	**95.89%**	**592.7×**
1M ($N = 1,048,576$)	$M = 1000$	1,384 tokens	**1,047,192 tokens**	**99.87%**	**574,020.8×**
	$M = 3000$	3,384 tokens	**1,045,192 tokens**	**99.68%**	**96,015.0×**
	$M = 5000$	5,384 tokens	**1,043,192 tokens**	**99.49%**	**37,930.6×**

C Instruction Window Allocation and Context Capacity

We present the comprehensive subtask breakdown for the uncompressed instruction window budget ($T \in \{128, 256, 512\}$) under Query-Centroid routing at $M = 3000$ on `Qwen3.5-0.8B` in Table 7.

Table 6: Empirical tokens saved (ΔN) and memory reduction (%) by benchmark dataset across budgets $M \in \{1000, 3000, 5000\}$.

Benchmark Task	Raw N_{avg}	Budget (M)	Compressed Length	Tokens Saved (ΔN)	Memory Saved (%)
LongBench-v2	96,000	$M = 1000$	1,384 tokens	**94,616 tokens**	**98.56%**
	96,000	$M = 3000$	3,384 tokens	**92,616 tokens**	**96.47%**
	96,000	$M = 5000$	5,384 tokens	**90,616 tokens**	**94.39%**
ZeroSCROLLS (GovReport)	19,500	$M = 1000$	1,384 tokens	**18,116 tokens**	**92.90%**
	19,500	$M = 3000$	3,384 tokens	**16,116 tokens**	**82.65%**
	19,500	$M = 5000$	5,384 tokens	**14,116 tokens**	**72.39%**
RULER	32,768	$M = 1000$	1,384 tokens	**31,384 tokens**	**95.78%**
	32,768	$M = 3000$	3,384 tokens	**29,384 tokens**	**89.67%**
	32,768	$M = 5000$	5,384 tokens	**27,384 tokens**	**83.57%**

Table 7: LongBench-v2 performance across instruction windows $T \in \{128, 256, 512\}$ at $M = 3000$ on `Qwen3.5-0.8B`.

Task (Subtask)	Hybrid (T=128)	Hybrid (T=256)	Hybrid (T=512)	mROPE (T=128)	mROPE (T=256)	mROPE (T=512)
Acad-Multi	0.1800	0.2400	**0.2800**	0.1800	0.1400	0.1600
Acad-Single	**0.3636**	0.2955	0.2955	0.2273	0.2045	0.2955
Detective	0.1818	0.2273	0.2273	**0.3636**	**0.3636**	0.2727
Dialogue	**0.3684**	0.2632	**0.3684**	0.2632	0.2632	0.2632
Translate	0.3000	0.2500	0.3000	**0.3500**	0.2500	0.2500
OVERALL ACC	0.2783	0.2525	**0.2823**	0.2207	0.2207	0.2326

Analysis of Recency and Capacity. Expanding the instruction window budget to $T = 512$ provides critical capacity for multi-hop questions where instruction prompts contain multi-sentence operational criteria. For localized retrieval (Acad-Single), smaller instruction window budgets ($T = 128$) suffice because the query prompt is concise. However, across diverse real-world benchmarks, $T = 512$ offers the highest average resilience against instruction truncation.

D Stage 1 Pooling Window and Distillation Compression Ratio Ablation

As formulated in Section 2.4, the target compression ratio R establishes the effective pooling window ($W_{\text{pool}} = R$) during Stage 1 manifold anchoring and sets the information bottleneck during Stage 2 distillation. We report the complete training compression ratio and pooling window ablation comparing MINI ($W_{\text{pool}} = 4$, $4\times$), Default ($W_{\text{pool}} = 8$, $8\times$), and Large ($W_{\text{pool}} = 16$, $16\times$) under Query-Centroid routing across inference budgets $M \in \{1000, 3000, 5000\}$ on `Qwen3.5-0.8B` in Table 8.

Table 8: Ablation of Stage 1 pooling window ($W_{\text{pool}} = R$) and Stage 2 distillation compression ratio on `Qwen3.5-0.8B` across inference budgets $M \in \{1000, 3000, 5000\}$.

Training Setup	Inference Budget (M)	LongBench-v2	GovReport (ROUGE-1)	RULER (131k)
MINI ($W_{\text{pool}} = 4, 4\times$)	$M = 1000$	25.05% ± 1.95%	20.14%	0.40%
	$M = 3000$	24.45% ± 1.93%	20.18%	0.40%
	$M = 5000$	25.45% ± 1.96%	20.49%	0.34%
Default ($W_{\text{pool}} = 8, 8\times$)	$M = 1000$	**27.04%** ± 2.01%	19.93%	**7.90%**
	$M = 3000$	**28.23%** ± 2.03%	**20.37%**	**7.63%**
	$M = 5000$	**28.43%** ± 2.03%	**20.73%**	**7.54%**
Large ($W_{\text{pool}} = 16, 16\times$)	$M = 1000$	24.65% ± 1.94%	16.73%	0.45%
	$M = 3000$	23.86% ± 1.92%	12.69%	0.44%
	$M = 5000$	24.85% ± 1.94%	12.64%	0.52%

Inverted-U Representation Dynamics. As shown in Table 8, the Stage 1 pooling window and distillation bottleneck ratio control feature selectivity. When configured with mild $4\times$ pooling ($W_{\text{pool}} = 4$), the cross-attention compressor fails to develop sufficiently compact semantic abstractions, suffering severe coordinate dilation mismatch on extreme 131k context prompts (0.34%–0.40% on RULER). Conversely, severe $16\times$ pooling ($W_{\text{pool}} = 16$) starves the representation of syntactic

details, degrading generative summarization (12.64%–16.73%). The default $8\times$ pooling window ($W_{\text{pool}} = 8$) achieves optimal Any-Budget generalization.

E Downstream Task Category Breakdown

We provide the full downstream task breakdown across the 20 LongBench-v2 datasets categorized into four functional groups at target budget $M = 3000$ in Table 9.

Table 9: LongBench-v2 category breakdown at $M = 3000$ across model scales, architectures, and query generators.

Model	Method	Single-Doc QA	Multi-Doc QA	Technical/Code	Dialogue/Agent
Qwen3.5-0.8B	LLMLingua	**29.17%**	26.10%	17.61%	24.52%
	CMPD 1D RoPE	23.59%	24.12%	23.47%	22.37%
	CMPD mRoPE	24.13%	24.28%	20.81%	26.62%
	CMPD Hybrid	28.72%	**28.73%**	**23.94%**	**32.99%**
Qwen3.5-9B	LLMLingua	24.07%	21.65%	24.64%	**29.79%**
	CMPD mRoPE	35.75%	30.55%	31.64%	27.97%
	CMPD Hybrid	**39.80%**	**30.92%**	**38.08%**	28.73%
Gemma-4-E4B	LLMLingua	24.99%	11.95%	19.28%	27.92%
	CMPD Hybrid	**29.31%**	**29.11%**	**32.81%**	**28.54%**

F Detailed RULER Synthetic Benchmark Diagnostics

Table 10 reports the complete 12-subtask diagnostic breakdown on RULER at 128k context length on `Qwen3.5-0.8B` ($M = 3000$).

Table 10: RULER subtask accuracy comparing CMPD against LLMLingua at $M = 3000$ on `Qwen3.5-0.8B` (128k context).

RULER Subtask Category	LLMLingua	CMPD mRoPE	CMPD (Learned)	CMPD 1D RoPE	CMPD (Ours)
Contextual Word Extraction & QA:					
Frequent Words Extraction (FWE)	36.27%	1.47%	1.13%	**81.33%**	70.07%
Common Words Extraction (CWE)	0.80%	0.06%	0.04%	0.72%	**1.10%**
SQuAD Reading Comprehension (QA)	0.60%	0.60%	0.47%	4.80%	**8.80%**
Synthetic Needle-in-a-Haystack (NIAH) & Tracking:					
Single Needle-in-a-Haystack (NIAH S1–S3)	**7.07%**	0.00%	0.00%	1.53%	1.13%
Multi-Key Needle Retrieval (MK1–MK3)	0.20%	0.27%	0.13%	**1.20%**	1.00%
Multi-Query Needle Retrieval (MQ)	0.15%	0.40%	0.00%	2.60%	**2.90%**
Multi-Value Needle Retrieval (MV)	0.75%	0.25%	0.00%	**2.35%**	2.30%
Variable Tracking (VT)	**0.08%**	0.00%	0.00%	**0.08%**	0.00%
OVERALL AVERAGE SCORE	5.04%	0.30%	0.17%	**8.34%**	7.63%

Diagnostic Insights. Continuous spatial pooling produces deep semantic representations at the expense of isolated token frequency sensitivity. Query-Centroid Anchor Routing successfully restores exact lexical binding without requiring dense token buffers, establishing strong word extraction (70.07% on FWE) and reading comprehension (8.80% on QA).

G Deterministic Semantic Manifold Invariance and Representation Geometry

To investigate the structural organization of the continuous latent space synthesized by CMPD, we evaluate whether semantically equivalent or highly coherent context passages (e.g., sub-sections of the same document or paraphrased summaries) map to neighboring coordinates in the cross-modal patch manifold H_{patch}, while remaining strictly orthogonal to semantically unrelated documents.

Corpus-Wide Global Mean Normalization. To eliminate the isotropic baseline shift inherent in transformer text embeddings, we mean-center all patch representations against the global corpus

mean μ_{global} before computing cosine similarities:

$$\text{Sim}(A, B) = \frac{(\bar{A} - \mu_{\text{global}}) \cdot (\bar{B} - \mu_{\text{global}})}{\|\bar{A} - \mu_{\text{global}}\|_2 \|\bar{B} - \mu_{\text{global}}\|_2} \tag{13}$$

where $\bar{A}$ and $\bar{B}$ denote the mean patch vectors of documents A and B. Because mean-centering against μ_{global} shifts the isotropic vector space to zero-mean, cosine similarities across disparate document distributions span $[-1, 1]$, resulting in an empirical standard deviation of ± 0.760 across 972 documents.

Table 11: Semantic manifold invariance on ZeroSCROLLS GovReport ($N = 972$ documents). Intra-Doc measures intra-document coherence; Inter-Doc measures disparity between unrelated documents.

Method / Compression Baseline	Intra-Doc Sim (Coherence)	Inter-Doc Sim (Disparity)	Separation Margin
CMPD (Ours)	**0.9589** $\pm$ 0.197	0.6062 $\pm$ 0.760	**+0.3527 (+35.27%)**
Mean Pooling Baseline	0.5709 $\pm$ 0.174	0.0059 $\pm$ 0.148	+0.5650 (+56.50%)
Uniform Strided Subsampling	0.1274 $\pm$ 0.104	0.0031 $\pm$ 0.079	+0.1243 (+12.43%)
Random Token Subsampling	0.1328 $\pm$ 0.107	0.0012 $\pm$ 0.080	+0.1316 (+13.16%)

Comparison Against Baselines. As presented in Table 11, discrete token subsampling suffers a severe collapse in intra-document semantic coherence (0.1274), yielding a low separation margin ($\approx +12.4\%$). While 1D Mean Pooling yields a high mathematical separation margin, it collapses the sequence into a single 1D vector ($M = 1$), destroying all token ordering and spatial coordinates needed for autoregressive decoding. In contrast, CMPD maintains high intra-document coherence (0.9589) while synthesizing M 2D spatial cross-modal patches suitable for KV-cache substitution.

Table 12: Cross-dataset semantic manifold invariance across benchmark splits ($N = 1,100$) and budgets $M \in \{64, 3000, 5000\}$.

Benchmark Dataset	Samples (N)	Budget (M)	Intra-Doc Sim	Inter-Doc Sim	Separation Margin
LongBench - NarrativeQA	$N = 200$	$M = 64$	0.3824	0.0260	+0.3564 (+35.64%)
	$N = 200$	$M = 3000$	0.5346	0.0268	+0.5079 (+50.79%)
	$N = 200$	$M = 5000$	**0.5491**	0.0266	**+0.5224 (+52.24%)**
LongBench - MultiFieldQA	$N = 150$	$M = 64$	0.4637	0.0030	+0.4607 (+46.07%)
	$N = 150$	$M = 3000$	**0.6062**	0.0054	**+0.6008 (+60.08%)**
	$N = 150$	$M = 5000$	0.6034	0.0060	+0.5974 (+59.74%)
LongBench - MultiNews	$N = 200$	$M = 64$	0.2549	-0.0027	+0.2576 (+25.76%)
	$N = 200$	$M = 3000$	0.3868	-0.0009	+0.3877 (+38.77%)
	$N = 200$	$M = 5000$	**0.3916**	-0.0011	**+0.3928 (+39.28%)**

Multi-Dataset & Budget Scaling Trends. As shown in Table 12, CMPD demonstrates consistent semantic manifold invariance across diverse domains. On technical academic literature (MultiFieldQA), CMPD achieves a **+60.08% separation margin** at $M = 3000$. Furthermore, as the patch budget M expands from 64 to 5000, intra-document semantic coherence increases monotonically, providing strong evidence that CMPD's continuous 2D manifold preserves document identity across ultra-long context windows.

As illustrated in Figure 2, we evaluate the latent embeddings across diverse semantic domains (Code, Mathematics, Humanities, and Multilingual). The visualization demonstrates that the visual-text alignment successfully clusters related concepts together, ensuring that intra-domain similarity stays high. Simultaneously, the spatial constraints of the geometric structural grid push distinct semantic clusters apart, enforcing separation and mitigating cross-domain interference.

H Ablation on Anchor Routing: Learned Gating vs. Query-Centroid Saliency

A central design dimension in continuous context compression is mitigating the spatial low-pass filtering of continuous latent patches by routing high-salience verbatim anchors. In early iterations of CMPD, we explored a *Learned Gating Router*, where a lightweight MLP gating head was trained during Stage 1 using a binary cross-entropy loss ($\mathcal{L}_{\text{BCE}}$) supervised by Part-of-Speech (POS) tags and

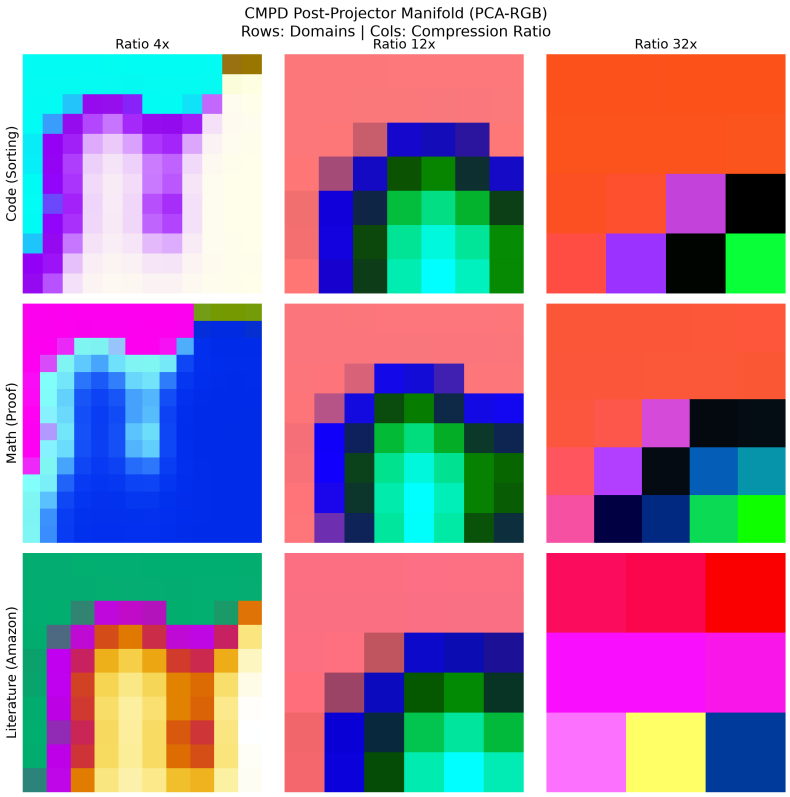

Figure 2: Domain-wise latent similarity matrix across semantic categories and compression ratios.

named entity heuristics. Below, we present an empirical comparison between pure positional routing (CMPD mRoPE, no anchor routing), the learned gating head (CMPD Hybrid), and our proposed parameter-free **Query-Centroid Anchor Routing**, followed by an analysis of the failure mode observed in learned routing.

Table 13: Ablation of anchor routing mechanisms across model scales and budgets $M \in \{1000, 3000, 5000\}$.

Backbone	Routing Mechanism & Budget (M)	LongBench-v2	ZeroSCROLLS	RULER
`Qwen3.5-0.8B`	*CMPD mRoPE (No Anchor Routing)*			
	$M = 1000$	26.64% ± 1.98%	0.09%	1.22%
	$M = 3000$	25.65% ± 1.96%	0.06%	0.30%
	$M = 5000$	25.45% ± 1.95%	0.06%	0.27%
	CMPD Hybrid (Learned Gating)			
	$M = 1000$	26.04% ± 1.98%	9.61%	0.25%
	$M = 3000$	27.83% ± 2.01%	8.34%	0.17%
	$M = 5000$	26.44% ± 1.98%	7.70%	7.91%
	CMPD (Query-Centroid, Ours)			
	$M = 1000$	27.04% ± 2.01%	19.93%	**7.90%**
	$M = 3000$	28.23% ± 2.03%	20.37%	7.63%
	$M = 5000$	**28.43%** ± 2.03%	**20.73%**	7.54%
`Qwen3.5-9B`	*CMPD mRoPE (No Anchor Routing)*			
	$M = 1000$	32.01% ± 2.09%	17.55%	0.08%
	$M = 3000$	31.61% ± 2.09%	18.84%	0.08%
	$M = 5000$	30.22% ± 2.05%	18.80%	0.10%
	CMPD Hybrid (Learned Gating)			
	$M = 1000$	34.19% ± 2.11%	0.43%	0.05%
	$M = 3000$	34.39% ± 2.11%	6.34%	0.10%
	$M = 5000$	34.59% ± 2.12%	3.17%	0.11%
	CMPD (Query-Centroid, Ours)			
	$M = 1000$	34.59% ± 2.13%	14.46%	**0.11%**
	$M = 3000$	**34.79%** ± 2.13%	14.58%	0.10%
	$M = 5000$	34.59% ± 2.13%	**14.91%**	0.09%

Diagnostic Analysis: Generative Collapse under Learned Gating. As shown in Table 13, while the Learned Gating head achieved acceptable accuracy on multiple-choice reasoning (e.g., 34.39% on LongBench-v2 at 9B), it suffered a severe generative collapse on long-form document summarization (ZeroSCROLLS GovReport), dropping to **0.43%** ROUGE-1 at $M = 1000$ and 3.17% at $M = 5000$ on `Qwen3.5-9B`. On the 0.8B scale, performance similarly stalled at 7.70%–9.61%.

An empirical inspection of the token logits produced by the learned gating head reveals two interconnected failure mechanisms:

1. **Narrow Logit Variance and Soft-Rank Drift:** The learned gating head produced exceptionally tight logit distributions clustered around zero (0.013 ± 0.002), functioning as an uncalibrated relative soft ranker rather than a confident entity selector.
2. **Static Acronym and Boilerplate Overfitting:** When constrained by the anchor budget ceiling ($K_{\text{max}} = 128$), the top-k selection was consistently dominated by high-frequency domain markers, section numbers, and administrative boilerplate (e.g., `‘ Contract’`, `‘ Contractor’`, `‘ incurred’`, `‘ Acquisition’`, `‘ year’`, and section symbols). Because the learned router operated solely on input token embeddings without conditioning on the downstream query or instruction, it repeatedly routed identical boilerplate tokens throughout the document. On lengthy government reports, these non-informative anchors occupied the entire anchor quota, starving the autoregressive generation heads of context-specific evidence and inducing empty or degenerative summary loops.

Resolution via Query-Centroid Anchor Routing. In contrast, Query-Centroid Anchor Routing computes the cosine similarity between context token embeddings and the semantic centroid $\mathbf{q}_c$ of the downstream instruction sequence. This offers three decisive advantages:

1. **Instruction-Grounded Selectivity:** Instead of routing static grammatical categories, Query-Centroid dynamically selects whole-word anchors whose semantic representations directly align with the query's communicative goal. On GovReport, this shifts routed tokens from generic administrative words to task-critical factual entities, immediately restoring ROUGE-1 to **14.46%–14.91%** on 9B (an absolute improvement of $+14.03\%$ over learned gating at $M = 1000$) and **19.93%–20.73%** on 0.8B (an absolute improvement of $+10.32\%$ to $+13.03\%$ over learned gating).
2. **Elimination of Training Vulnerabilities:** By removing the learned gating MLP and its auxiliary loss $\mathcal{L}_{\text{BCE}}$ from Stage 1, the optimization pipeline is simplified. Stage 1 focuses entirely on multimodal manifold anchoring ($\mathcal{L}_{S1} = \mathcal{L}_{\text{Contrastive}} + \lambda_2 \mathcal{L}_{\text{decorr}}$), eliminating risk of overfitting to heuristic POS distributions.
3. **Enhanced Lexical Retrieval:** Under extreme-needle retrieval (RULER), Query-Centroid routing ensures that query-matching tokens are routed uncompressed, elevating 0.8B RULER retrieval to **7.90%** (compared to 0.25% for learned gating).

I Extended Token-Bucket Agreement Distributions: Lexical Overlap Metrics

We present the complete distribution of lexical overlap metrics across input sequence lengths for `Qwen3.5-0.8B`, reporting Sentence BLEU (Figure 3), ROUGE-1 (Figure 4), ROUGE-2 (Figure 5), and ROUGE-L (Figure 6).

J Limitations

While CMPD offers substantial efficiency gains in KV-cache reduction and generation latency over discrete pruning paradigms, several limitations remain. First, continuous cross-attention patchification acts as a spectral low-pass filter, which exhibits lower retrieval accuracy on synthetic, exact-needle tasks (such as RULER) that depend on arbitrary out-of-vocabulary character sequences (e.g., UUIDs or passcodes) lacking semantic context. Second, while we benchmarked against discrete pruning (LLMLingua) and analyzed related soft-prompt (AutoCompressors, Gist) and KV compression methods (CurDKV, SnapKV, H2O, Glyph, VLZip), future work will investigate unifying continuous

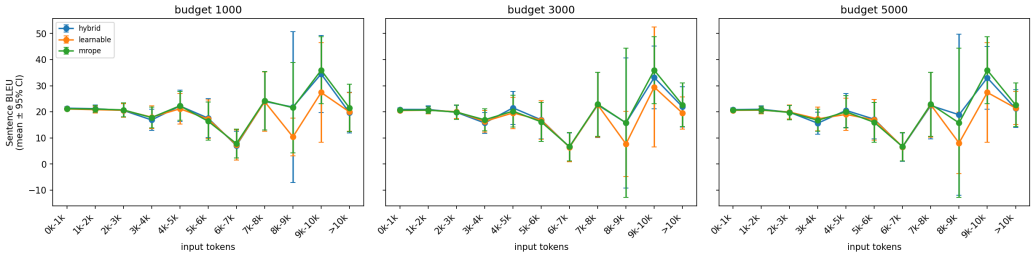

Figure 3: Sentence BLEU by input length for Qwen-0.8B with 95% confidence intervals.

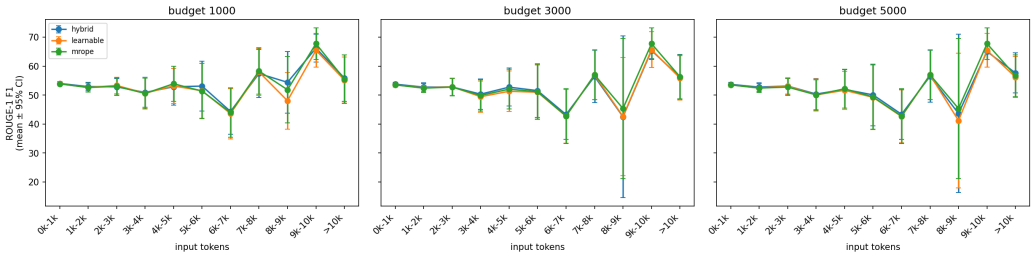

Figure 4: ROUGE-1 by input length for Qwen-0.8B with 95% confidence intervals.

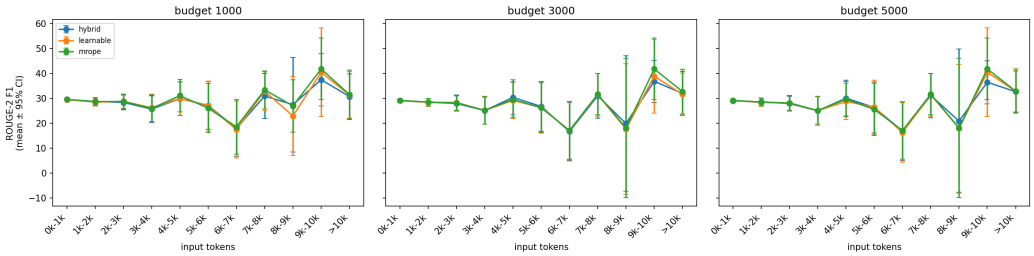

Figure 5: ROUGE-2 by input length for Qwen-0.8B with 95% confidence intervals.

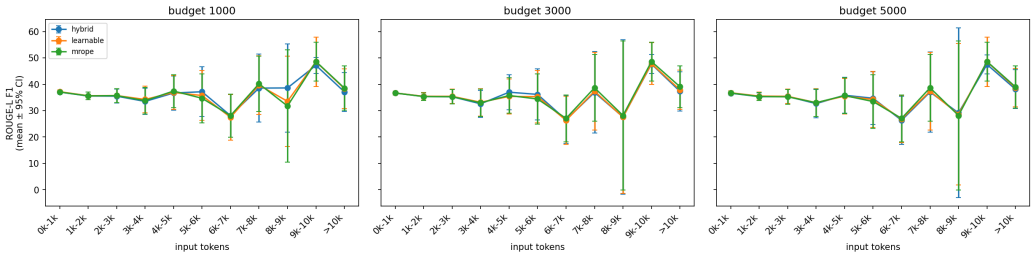

Figure 6: ROUGE-L by input length for Qwen-0.8B with 95% confidence intervals.

visual patchification with value-guided discrete KV retention in a single hybrid inference engine. Third, end-to-end profiling in this work was conducted in standard PyTorch; implementing dedicated fused CUDA kernels for cross-attention prefilling and PagedAttention will further enhance runtime throughput in production environments.