Context Adaptive Memory-Efficient LLM Inference for Edge Multi-Agent Systems

Extended Abstract

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ABSTRACT

Large Language Models (LLMs) excel at multi-document QA, summarization, code generation, and other language-intensive tasks, yet they demand substantial memory resources for storing key-value (KV) caches and processing attention in long-context scenarios. These requirements often prohibit on-device or edge deployments in *multi-agent systems (MAS)*, where multiple agents share or update contextual information and need efficient inference pipelines. We present **CASK (Context-Adaptive Sparse Key-value)**, an *inference-time* strategy that reduces memory usage while preserving strong performance on extended contexts. CASK addresses this challenge with two complementary mechanisms: a dynamic sparse attention module—a lightweight, meta-learned component—that identifies the most relevant context tokens, and an adaptive KV-cache compression technique that dynamically quantizes and prunes less critical key-value pairs based on usage frequency and recency. These innovations enable near-lossless performance on long-context tasks while cutting memory usage by up to 40% and boosting inference speed by as much as 20%. Evaluations on *LongBench* [2] and multi-agent benchmarks show that CASK maintains over 95% of baseline accuracy while allowing more agents or extended histories under tight GPU budgets. Integration into a vision-language agent for collaborative, multimodal contexts underscores its practicality for resource-constrained LLM deployments in MAS.

KEYWORDS

Multi-Agent Systems; Natural Language Generation; Dimensionality Reduction And Manifold Learning; Heuristic Function Construction; Caching And Paging Algorithms; Multi-Agent Learning; Computer Vision; Reinforcement Learning; Multi-Agent Reinforcement Learning; Active Learning; Neural Networks; Supervised Learning; Online Learning Algorithms

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1 INTRODUCTION

Large Language Models (LLMs) have dramatically advanced natural language processing, enabling high performance in few-shot learning, code synthesis, and long-form text generation [3, 4, 8, 18]. However, these models are challenging to deploy in *multi-agent systems (MAS)* with limited computational resources [14, 19, 29]. Each agent may need to maintain an extensive context history or share contextual knowledge with others, magnifying the problem of storing large key-value (KV) caches and executing the quadratic attention mechanism in standard Transformers [3, 26]. This restricts real-time or on-device inference in settings such as IoT networks, robotic swarms, or other privacy and latency-critical domains.

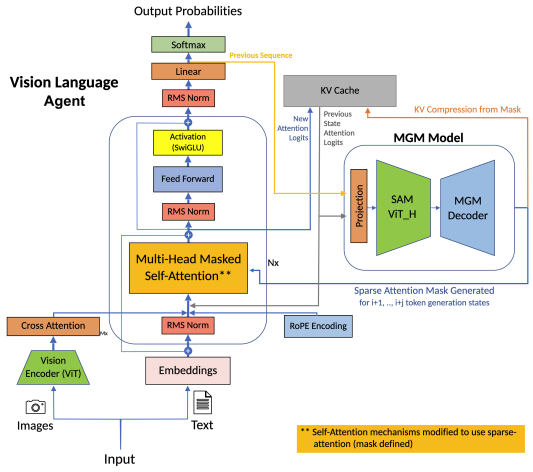

Figure 1: The Vision Language Agent example for MAS, a vision-language model integrated with CASK. The Mask Generation Module (MGM) periodically outputs sparse attention masks and triggers KV-cache compression.

We introduce **CASK (Context-Adaptive Sparse Key-value)**—an *inference-time* approach that substantially cuts memory usage while retaining the core strengths of LLM-based systems in extended-context tasks. Unlike many existing techniques that require re-training or architecture modifications [5, 6, 11, 21], CASK operates on top of *pre-trained* LLMs. It dynamically generates sparse attention patterns and aggressively compresses the KV-cache to accommodate long contexts under strict memory constraints. Critically, it preserves coherent multi-agent interactions by focusing on crucial cross-references among agents' dialogue or sensor data.

2 APPROACH

CASK introduces two main components (Figure 1). The first is Dynamic Sparse Attention, which employs a Mask Generation Module (MGM), a small vision transformer [10] trained to derive sparse binary masks that eliminate lower-importance interactions via meta reinforcement learning from reconstruction [9, 27]. We apply these sparse masks to the attention logits, allowing the model's existing attention pipeline to leverage sparse operations without altering its underlying architecture. This effectively reduces the attention window, lowering memory and compute overhead. To handle contexts longer than the model's original training window, we include a positional interpolation scheme (e.g., [16, 17]) that smoothly extends the receptive field without requiring major retraining.

The second component is Adaptive KV-Cache Compression. CASK extends post-training weight-quantization methods [13, 22, 25] to dynamic KV-Cache quantization and pruning. By tracking recency, access frequency, attention allocation, and gradient attribution, it computes saliency metrics for each key-value pair. Guided by two thresholds—validated via runtime reconstruction loss—pairs with moderately low salience are dynamically quantized to a lower bit width, while those below a stricter threshold are pruned. This reduces cache size as contexts accumulate and is especially beneficial in MAS settings, where large histories often contain irrelevant or outdated content.

3 EXPERIMENTAL RESULTS

We implement a MAS with Vision Language Agents by integrating CASK onto a LLaMA 3.2 90B instruct model [8] as shown in Figure 1, wherein multiple agents communicate both text and visual embeddings, sharing a global context. To demonstrating CASK's stable long-context processing, critical for MAS-focused tasks, we evaluate on *LongBench* [2].

Table 1: Average Performance on LongBench [2].

Model	Avg. Score (LongBench)	Memory Usage (GB)	Relative Inference Time
LLaMA-3.2-90B-128k [8]	**63.2**	72	1.00x
GPT-3.5-Turbo-16k [15]	44.0	350*	0.85x
Qwen2-VL-72B-Chat [1, 20, 24]	56.4	63	0.92x
Reformer [11]	48.9	88	1.15x
Performer [7]	52.6	43	0.78x
H2O [28]	57.2	**40**	0.88x
SEA [12]	62.8	68.5	0.82x
BigBird [26]	54.6	68.1	0.82x
StreamingLLMs [23]	37.1	40.8	0.88x
SampleAttention [30]	62.7	67.4	0.81x
CASK (Ours)	61.5	44.5	**0.77x**

*Estimated usage based on model size.

4 DISCUSSION

Tables 1 and 2 compare our proposed CASK method against state-of-the-art LLM test-time optimizations and the full-attention baseline. Overall, CASK achieves a strong balance of reduced memory usage, improved inference speed, and minimal drops in accuracy relative to the baseline. Specifically, in Table 1, CASK retains 61.5 average score while cutting memory usage by 38% relative to the base LLaMA model [8], accelerating inference by around 23%. This improvement is consistent across input lengths up to 128k tokens, demonstrating stable long-context processing.

Table 2: Task-specific performance (LLaMA-3.2-90B-128k [8] on LongBench [2]).

Technique	S-Doc QA	M-Doc QA	Summ.	Few-shot	Code	Synth.
Full Attention	**51.2**	**60.5**	**49.6**	**78.2**	**76.4**	**63.0**
SEA	47.1	56.7	45.6	74.5	72.6	59.3
BigBird	50.6	56.1	48.6	66.7	68.3	37.1
StreamingLLMs	26.6	40.5	45.6	50.7	55.0	4.4
SampleAttention	49.5	60.4	49.4	78.1	76.3	62.9
CASK (Ours)	49.4	58.9	45.6	76.3	76.1	62.8

Looking at the breakdown in Table 2, CASK remains close to full attention on tasks requiring more intricate or broad context dependencies (e.g., code generation, few-shot, or synthetic tasks). Its chunked/compressed attention mechanism captures long-range interactions without incurring the quadratic memory cost of standard attention. By contrast, for narrower tasks (e.g., single-document QA, summarization), the localized context dependencies are often well-served by more specialized mechanisms, which can explain why certain methods such as BigBird (block-sparse) [26] or StreamingLLMs (step-by-step) [23] may outperform CASK in those cases. These approaches aggressively reduce attention overhead for short or more localized sequences, often matching or beating CASK's memory usage.

However, on tasks demanding broader or more complex attention patterns (e.g., multi-document QA, code generation, and synthetic benchmarks), simpler or more aggressively sparse methods can lose critical long-range interactions. Here, CASK's chunk-based strategy offers more flexibility in capturing essential dependencies, allowing it to surpass the more specialized methods. Other techniques like SEA [12] or SampleAttention [30] may track closely to CASK in some benchmarks, yet they typically incur approximately 30% higher memory usage. Hence, CASK emerges as an attractive trade-off for real-world deployments where memory constraints and inference speed are key concerns, while still delivering strong overall performance across a variety of tasks.

5 CONCLUSION

CASK addresses a central challenge in deploying LLMs for *multi-agent systems* with long or evolving contexts under strict resource budgets. By leveraging dynamic sparse attention and importance-based KV-cache compression, it (i) maintains robust performance (over 95% of baseline accuracy) on diverse tasks requiring significant context windows, (ii) saves ~40% of GPU memory and reduces latency (allowing more agents or deeper contexts without out-of-memory errors), and (iii) integrates into existing LLM inference stacks with minimal changes—requiring no specialized retraining or hardware. Future work includes exploring automated threshold tuning for compression, investigating cross-agent attention sharing, and tailoring the method to specialized edge hardware. Overall, CASK provides a practical solution for memory-efficient LLM inference in resource-constrained, collaboration-focused environments.

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