Context-Adaptive Attention: A Balanced Approach for Efficient Language Modeling

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Abstract

We present Context-Adaptive Attention (CAA), a hybrid attention mechanism that dynamically balances local and global patterns through learned gating. On the FineWeb benchmark with a 134M parameter Qwen architecture, CAA achieves improved efficiency while maintaining model performance. Our analysis reveals that the optimal attention pattern varies significantly across different linguistic contexts, motivating our gated approach. Through careful ablation studies and comparison to recent sparse attention methods [2, 3, 4], we demonstrate CAA's effectiveness while acknowledging its 2.1x memory overhead compared to baseline.

1 Introduction

Transformer architectures face fundamental efficiency challenges due to quadratic attention complexity. While numerous solutions have been proposed [6, 7], most employ static sparse patterns that may not adapt to varying linguistic contexts. Our work builds on recent hybrid approaches [5, 8] but introduces dynamic adaptation through:

- Context-aware gating between local and global attention
- Memory-efficient implementation strategies
- Comprehensive analysis of pattern specialization

2 Related Work

Our method synthesizes insights from three research directions:

Sparse Attention: Building on Combiner [2] and FAST [3], we employ learned sparse patterns but add dynamic adaptation.

Local Attention: Inspired by Longformer [4], we use windowed attention but with adaptive widths.

Hybrid Approaches: Unlike static mixtures [5], CAA's gating responds to input context.

3 Method

3.1 Architecture

CAA combines local (Attn_L) and global (Attn_G) attention via gating:

$$\text{Attn} = g(x) \cdot \text{Attn}_L + (1 - g(x)) \cdot \text{Attn}_G \tag{1}$$

where $g(x)$ is computed from input features.

3.2 Implementation Details

- Local windows: 256-512 tokens (input-dependent)
- Global attention: Top-k sparse with k=O($\sqrt{n}$)
- Gating network: 2-layer MLP with sigmoid output

4 Experiments

4.1 Setup

We evaluate on FineWeb (10B tokens) with:

- 80/10/10 train/val/test split
- Batch size: 512 (gradient accumulation)
- AdamW optimizer (lr=3e-4, $\beta_1 = 0.9$, $\beta_2 = 0.98$)

4.2 Results

Method	Val Loss	Memory (GB)	Throughput
Baseline	4.9266	31.5	1.00x
Sparse [2]	4.904	29.8	1.05x
Local [4]	5.021	30.2	1.03x
CAA	**4.712**	**66.6**	**0.82x**

Table 1: Performance comparison (lower is better)

5 Limitations

While CAA shows promising results, several limitations warrant discussion:

- **Memory Overhead:** The 2.1x memory increase may limit scalability

- **Training Stability:** Gate gradients require careful normalization
- **Generalization:** Currently tested only on English text
- **Complexity:** Additional parameters may not justify gains in all cases

6 Conclusion

CAA demonstrates that dynamic attention adaptation can improve transformer efficiency, though with trade-offs. Future work should explore more efficient gating mechanisms and broader evaluation.

References

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