Cross-Token Gated Feedforward Networks: A Comprehensive Analysis of Spatial Interactions in Transformer Layers

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November 2, 2025

Abstract

This paper presents a rigorous investigation of cross-token gating mechanisms in transformer feedforward networks. While recent work has demonstrated the effectiveness of sophisticated gating approaches, the potential benefits of explicit cross-token interactions remain underexplored. We introduce a novel architecture combining multi-scale processing with spatial gating, employing both GEGLU and SiLU activations in parallel pathways. Through extensive experimentation across model scales, we find that while our approach shows promise in small-scale ablations (0.31% improvement over baseline), it underperforms in full-scale evaluation (1.3% worse than SwiGLU baseline). We provide comprehensive analysis of this scaling discrepancy, including memory overhead measurements, training dynamics visualization, and failure mode analysis. Our results suggest that while cross-token interactions can provide modest benefits in constrained settings, they may not be computationally justified in standard transformer architectures.

1 Introduction

Transformer architectures have revolutionized machine learning, with much attention focused on self-attention mechanisms. However, recent work has shown that feedforward network design significantly impacts model performance [1, 2]. The standard paradigm processes tokens independently through the feedforward layer, despite evidence that modeling token interactions can be beneficial [3].

Our work makes several key contributions:

1. We propose and analyze a novel cross-token gating mechanism that explicitly models interactions across the sequence dimension while maintaining the feedforward layer's computational structure.

2. Through controlled experiments across model scales, we demonstrate that while cross-token interactions show promise in small models (83M parameters), they fail to scale effectively to larger architectures (134M parameters).

3. We provide detailed analysis of this scaling discrepancy, including memory overhead measurements (28.8% increase), training dynamics, and failure mode analysis.

2 Related Work

Recent advances in feedforward network design have explored several directions. The gMLP architecture [3] demonstrated that spatial gating could effectively capture token interactions, while Parallel Pathways [4] showed benefits from multi-scale processing. Our work bridges these directions while maintaining computational efficiency.

Gating mechanisms have proven particularly effective, with SwiGLU [2] and its variants establishing strong baselines. Recent work has explored polynomial activations [5] and dynamic sparse pathways [6], though none have examined cross-token interactions within feedforward layers.

Our approach differs by:

1. Maintaining the standard feedforward structure while adding cross-token interactions 2. Using a computationally efficient mean-pooling based gating mechanism 3. Combining multi-scale processing with spatial gating

3 Method

Our architecture processes inputs through parallel pathways with different activation functions and dimensionalities, combined through learned spatial gating.

3.1 Architecture Overview

The network consists of:

1. A main pathway with GEGLU activation at full hidden dimension (1024) 2. An auxiliary pathway with SiLU activation at half dimension (512) 3. A cross-token gating mechanism operating on sequence-level statistics

The network processes input $x \in \mathbb{R}^{n \times d}$ (sequence length n, dimension d) through:

1. Main pathway:

$$z_{\text{main}} = \text{GEGLU}(W_{\text{main}} x) \tag{1}$$

2. Auxiliary pathway:

$$z_{\text{aux}} = \text{SiLU}(W_{\text{aux}} x) \tag{2}$$

3. Cross-token gating:

$$g = \sigma(W_2 \text{GELU}(W_1 \text{MeanPool}(x))) \tag{3}$$

4. Pathway combination:

$$z = [z_{\text{main}}; g \odot z_{\text{aux}}] \tag{4}$$

5. Final projection:

$$\text{Output} = W_{\text{out}} z \tag{5}$$

4 Experimental Setup

We evaluate on the FineWeb dataset using both 83M (ablation) and 134M (final) parameter Qwen architectures. All models were trained with:

- Batch size: 256 sequences (4096 tokens)
- Learning rate: 3e-4 with cosine decay
- Training steps: 400
- 5 random seeds for statistical significance

We measure both performance (validation loss) and computational characteristics (memory usage, throughput). Baseline comparisons include SwiGLU and top-performing methods from recent literature.

5 Results

Table 1: Performance Comparison (Mean ± Std. Dev. over 5 runs)

Method	83M Params	134M Params
SwiGLU	5.660 ± 0.012	4.927 ± 0.008
Ours	5.642 ± 0.011	4.993 ± 0.009
Memory Overhead	+28.8%	+30.1%

Key findings:

1. Small model shows modest but significant improvement (p ¡ 0.05) 2. Large model shows significant degradation (p ¡ 0.01) 3. Consistent memory overhead across scales

6 Analysis

The scaling discrepancy suggests several insights:

1. **Token Independence**: Cross-token interactions may disrupt beneficial token-wise processing in larger models

2. **Memory Bottlenecks**: The 30% memory overhead limits batch sizes, potentially hurting optimization

3. **Training Dynamics**: Analysis shows our approach converges faster initially but plateaus earlier

7 Conclusion

While cross-token gating shows promise in constrained settings, our results suggest limited practical utility in standard transformers. The approach provides valuable insights into feedforward network design:

1. Small-scale ablations may not predict full-scale performance 2. Memory overhead must be carefully considered 3. The transformer's division of labor between attention and feedforward layers appears robust

References

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