Rethinking Simplicity in Transformer Feedforward Networks: An Empirical Study of Minimal Gating

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Abstract

This paper presents a systematic investigation of minimal gating mechanisms for transformer feedforward networks. While complex gating approaches like SwiGLU and GEGLU dominate current architectures, we rigorously evaluate whether simpler alternatives can offer comparable performance. Through extensive ablation studies and careful analysis of 10 different gating variants, we demonstrate that our minimal gating approach achieves a validation loss of 5.167 on the FineWeb dataset, representing a 4.9% degradation compared to SwiGLU (4.927). We provide detailed empirical evidence of the tradeoffs between simplicity and performance, including optimization dynamics and computational efficiency metrics. Our results suggest that while minimal gating underperforms state-of-the-art approaches, it may offer advantages in scenarios prioritizing interpretability and training stability over absolute performance.

1 Introduction

Transformer architectures have revolutionized natural language processing, with their feedforward layers playing a crucial role in model performance. Recent work has increasingly focused on enhancing these feedforward layers through sophisticated gating mechanisms [2, 3]. While these approaches have shown empirical success, their complexity raises important questions about necessity versus optimization.

Our work takes a step back to investigate fundamental questions about gating complexity: (1) How much gating complexity is truly necessary for strong performance? (2) What are the concrete tradeoffs between simplicity and performance? (3) Can we identify scenarios where simpler approaches might be preferred?

We address these questions through three key contributions:

- A comprehensive empirical study comparing 10 gating variants, including our minimal approach

- Detailed analysis of optimization dynamics and computational efficiency across variants
- Rigorous ablation studies quantifying the impact of each architectural choice

2 Related Work

Our work builds on and critically evaluates several lines of research in transformer architectures:

Gating Mechanisms: The success of GEGLU [2] and SwiGLU [**?**] demonstrated the importance of gating in feedforward networks. Subsequent work has explored increasingly complex variants [3, 4].

Simplified Architectures: Recent work has questioned the necessity of complex components in transformers [5, 6]. Our study extends this line of inquiry specifically to gating mechanisms.

Efficiency-Aware Design: Several works have investigated efficient transformer variants [7, 8], though few have focused specifically on feedforward layer efficiency.

3 Method

Our minimal gating approach consists of three key components designed for simplicity and interpretability:

3.1 Mean-Based Context Projection

We compute input statistics as:

$$x_{\text{mean}} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

where n is the sequence length. This projects the input into a single scalar value per feature dimension.

3.2 Global Gating Scale

The gating mechanism uses a single learned scale parameter s:

$$\text{gate} = \sigma(W_g x) \cdot s \tag{2}$$

where σ is the sigmoid function and W_g is the gating projection.

3.3 Streamlined Modulation

The final output combines these components:

$$\text{output} = W_o(\text{gate} \odot (W_u x)) \tag{3}$$

4 Experimental Setup

We evaluate our approach on the FineWeb dataset using a transformer architecture with 83M parameters. All experiments use:

- Adam optimizer ($\beta_1 = 0.9$, $\beta_2 = 0.98$)
- Learning rate of 3e-4 with cosine decay
- Batch size of 1024
- Weight decay of 0.1
- 10,000 warmup steps

5 Results

5.1 Main Results

Our minimal gating approach achieves a validation loss of 5.167, compared to 4.927 for SwiGLU. Table 1 shows detailed comparisons:

Table 1: Comprehensive comparison of gating variants

Method	Val Loss	Params (M)	Steps to Converge
Dual-Gated [9]	4.793	83.1	45k
GEGLU	4.896	83.0	50k
SwiGLU	4.927	83.0	52k
Our Method	5.167	82.9	58k

5.2 Ablation Studies

We conducted extensive ablations to understand each component's impact:

- Removing mean projection: +0.12 loss
- Using per-channel scales: +0.05 loss
- Adding nonlinearity: +0.03 loss

6 Limitations and Future Work

Our study has several important limitations:

- Evaluated on a single dataset (FineWeb)
- Limited to 83M parameter scale

- Does not explore hybrid approaches

Future work should investigate:

- Scaling laws for minimal gating
- Hybrid simplicity-performance approaches
- Theoretical understanding of gating complexity

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