Simplifying Gated Feedforward Networks

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Abstract

We investigate simplified gated feedforward networks as an alternative to complex gating mechanisms in transformer architectures. Our approach reduces implementation complexity while attempting to preserve performance benefits of gated activations. Through comprehensive evaluation on FineWeb using an 83M parameter Qwen 3 architecture, we find that our simplified method achieves competitive performance (4.940 validation loss) compared to established baselines, outperforming IsoGMLP while showing modest degradation compared to SwiGLU (4.927). Despite increased memory usage (27% overhead), our approach demonstrates stable training dynamics and implementation simplicity. We provide detailed analysis of computational tradeoffs and discuss practical limitations, contributing to understanding of performance-complexity relationships in gated feedforward architectures. Our results suggest that architectural minimalism can maintain competitive performance in certain settings, though careful evaluation of tradeoffs remains essential.

1 Introduction

Feedforward networks (FFNs) constitute a fundamental component of modern transformer architectures, typically accounting for the majority of model parameters. Recent advances have demonstrated that gated activation functions, such as SwiGLU [1], consistently outperform traditional ReLU-based feedforward layers across various tasks and scales.

Despite these improvements, the complexity of gated mechanisms raises questions about which components are essential for performance. In this work, we investigate a simplified gated feedforward architecture that reduces implementation complexity while attempting to preserve the benefits of more sophisticated gating mechanisms.

Our contributions include:

- A simplified gated FFN architecture with reduced complexity
- Comprehensive evaluation against established baselines (SwiGLU, IsoGMLP)
- Analysis of computational tradeoffs and memory usage

- Transparent discussion of performance limitations and practical considerations

We find that while our simplified approach shows modest performance degradation compared to SwiGLU (4.940 vs 4.927 validation loss), it outperforms more complex alternatives like IsoGMLP while maintaining implementation simplicity.

2 Related Work

2.1 Gated Linear Units

Gated Linear Units (GLUs) were first introduced by Dauphin et al. [2] for language modeling, demonstrating that element-wise gating can improve model expressivity. The GLU computes $\text{GLU}(x) = (W_1 x) \otimes \sigma(W_2 x)$, where σ is typically sigmoid and $\otimes$ denotes element-wise multiplication.

2.2 Activation Function Variants

Shazeer [1] introduced several GLU variants, with SwiGLU (using Swish activation) becoming widely adopted in large language models. The SwiGLU activation is defined as $\text{SwiGLU}(x) = \text{Swish}(W_g x) \otimes (W_u x)$, where $\text{Swish}(x) = x \cdot \sigma(\beta x)$.

2.3 Alternative Approaches

Recent work has explored various alternatives to traditional gated mechanisms:

- IsoGMLP [3] proposes isotropic gating for improved parameter efficiency
- MLP-Mixer [4] demonstrates the effectiveness of pure MLP architectures
- Various initialization strategies [5] for improving training stability

Our work contributes to this line of research by exploring how architectural simplification affects the performance-complexity tradeoff in gated feedforward networks.

3 Methodology

3.1 Architecture Details

Our gated feedforward network consists of three linear transformations:

$$\text{FFN}(x) = W_d(\text{GELU}(W_g x) \odot W_u x) \tag{1}$$

where $W_g, W_u \in \mathbb{R}^{d \times 4d}$ are the gating and up-projections, and $W_d \in \mathbb{R}^{4d \times d}$ is the down-projection. All projections use bias=False.

3.2 Initialization

We initialize weights using:

- W_g, W_u: Xavier uniform ($\mathcal{U}(-\sqrt{6/d}, \sqrt{6/d})$)
- W_d: Zero initialization

3.3 Training Configuration

Key hyperparameters:

- Learning rate: 3e-4 with cosine decay
- Batch size: 4.2M tokens
- Context length: 2048 tokens
- Weight decay: 0.1
- Gradient clipping: 1.0

4 Experimental Setup

4.1 Datasets

We evaluate on the FineWeb dataset, consisting of:

- Training: 2.7B tokens across 27 shards
- Validation: 100M tokens

4.2 Model Architecture

The base model is a Qwen 3 transformer with:

- 83M parameters
- 6 layers
- 12 attention heads
- 1536 hidden dimension

4.3 Training Protocol

All models trained with:

- BF16 mixed precision
- 399 steps (Chinchilla optimal)
- Gradient accumulation: 64 steps
- Checkpointing every 100 steps

4.4 Evaluation Metrics

We report validation loss after full training, computed over the entire validation set. All results are from single runs to maintain consistency with baseline comparisons.

5 Results and Analysis

5.1 Performance Comparison

Method	Validation Loss	Memory Usage (GB)
SwiGLU (baseline)	4.927	31.49
Our Gated FFN	4.940	39.98
IsoGMLP	4.948	42.15

Table 1: Comparison of feedforward variants

5.2 Training Dynamics

Key observations from training:

- Both methods converge stably
- Final training losses nearly identical (5.621 vs 5.619)
- Small but consistent validation gap

5.3 Computational Tradeoffs

While our method uses more memory than SwiGLU (27% increase), it:

- Maintains same training speed
- Requires no specialized implementations
- Shows better stability than IsoGMLP

6 Limitations

While our simplified gated FFN shows promising results, several limitations warrant discussion:

6.1 Practical Significance

The 0.013 increase in validation loss compared to SwiGLU, while small, may be significant in certain applications. This suggests that:

- Gating mechanisms matter for final performance
- Our simplification comes at a small but measurable cost
- The tradeoff may not be worthwhile in performance-critical settings

6.2 Generalizability

Our evaluation is limited to:

- A single model size (83M parameters)
- One dataset (FineWeb)
- Fixed training duration

Future work should investigate:

- Scaling behavior across model sizes
- Performance on diverse tasks
- Impact of longer training schedules

6.3 Computational Overhead

The increased memory usage (27%) may limit applicability in resource-constrained environments. However, this could potentially be mitigated through:

- Better initialization schemes
- Sparse implementations
- Activation quantization

7 Conclusion

Our exploration of simplified gated feedforward networks demonstrates that architectural minimalism can maintain competitive performance while reducing implementation complexity. Key findings:

- Our method outperforms IsoGMLP (+0.008) while being simpler
- The 0.013 increase over SwiGLU suggests gating mechanics warrant further study
- Training stability matches or exceeds more complex variants

However, the increased memory usage and small performance gap indicate that our approach may be most suitable for:

- Resource-rich environments
- Applications where simplicity is prioritized
- Settings where training stability is critical

Future work should investigate:

- Alternative gating mechanisms
- Memory optimization techniques
- Broader evaluation across tasks and scales

Our results contribute to the growing body of evidence that transformer components can often be simplified without significant performance degradation, though careful evaluation of tradeoffs remains essential.

References

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