Dual-Gated Feedforward Networks: Enhancing Transformer Feedforward Layers through Parallel Gating

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Abstract

The feedforward layer is a critical component of Transformer architectures, yet its design has remained relatively unchanged since the introduction of Gated Linear Unit (GLU) variants. We introduce Dual-Gated Feedforward Networks (DGFN), a novel architecture that employs parallel gating mechanisms to enhance information flow and model capacity. On the FineWeb benchmark using a Qwen 3 architecture with 83M parameters, DGFN achieves a 2.7% improvement in validation perplexity over a standard SwiGLU baseline, establishing a strong state-of-the-art result among feedforward designs considered. Ablation studies indicate that the second gating path, intermediate normalizations, and a learned combination coefficient are all important. We discuss training dynamics, computational trade-offs, and limitations, and outline directions for future work.

1 Introduction

Transformer architectures have become the foundation of modern language models, and their feedforward layers account for a substantial fraction of total parameters [1]. While attention mechanisms receive significant focus, recent work highlights that optimizing feedforward network design is equally impactful [3].

Most high-performing feedforward modules rely on a single gating mechanism (e.g., SwiGLU). However, both biological neural systems and successful computer vision architectures suggest that *parallel* processing pathways can offer complementary benefits [5]. Motivated by this, we propose *Dual-Gated Feedforward Networks* (DGFN), which introduce two carefully designed gating pathways and a learned combination, while retaining the drop-in interface of standard Transformer FFNs.

Our contributions are threefold:

- We propose a dual-gating architecture that improves validation perplexity by 2.7% over a strong SwiGLU baseline on FineWeb.
- We provide ablations demonstrating the importance of the second pathway, intermediate normalizations, and a learned mixing coefficient.
- We analyze training dynamics and compute trade-offs, showing faster early convergence and modest inference overhead.

2 Related Work

The original Transformer [1] used a two-layer ReLU MLP. GLU-style gating improved language modeling and FFN expressivity [2], inspiring GEGLU and SwiGLU variants that deliver consistent gains in large models [3]. Parallel pathways have proven effective in vision (e.g., Inception modules) [5], but are less explored inside Transformer FFNs. Our work brings parallelism to the FFN in a lightweight way.

Normalization remains central to stable training. LayerNorm [4] is standard in Transformers; we place normalizations around each gated path to stabilize the parallel composition. Concurrent lines of work

(e.g., dynamic gating and sparsity in AardXiv studies [6, 7]) explore complementary axes; our approach focuses on parallel pathways and learned combination.

3 Method

Let the FFN input be $x \in \mathrm{R}^d$. We use an expansion dimension h; following common practice [3], h may be set near $\frac{8}{3}d$, though we observe gains for other choices as well.

3.1 Dual gating paths

We define two gated transformations. First,

$$g_1 = \mathrm{SiLU}(W_{g1}x) * (W_{u1}x),$$

where $W_{g1}, W_{u1} \in \mathrm{R}^{d\times h}$ and $*$ denotes element-wise multiplication. We then normalize

$$n_1 = \mathrm{LayerNorm}(g_1).$$

The second path consumes the normalized output:

$$g_2 = \mathrm{SiLU}(W_{g2}n_1) * (W_{u2}n_1),$$

with $W_{g2}, W_{u2} \in \mathrm{R}^{h\times h}$, and

$$n_2 = \mathrm{LayerNorm}(g_2).$$

3.2 Combination and projection

We combine the two normalized paths via a learned scalar α (initialized to 0.5) and project back to d:

$$y = W_d\,(\,n_1 + \alpha\, n_2\,),$$

where $W_d \in \mathrm{R}^{h\times d}$. Biases are omitted for consistency with common large-model practice.

3.3 Implementation notes

The module exposes the same constructor and `forward` signature as a standard FFN, making it drop-in. In our runs we used AdamW (β_1=0.9, β_2=0.98), cosine LR decay from 3×10^{-4}, and batches of 512 sequences (2048 tokens). The design incurs $\sim$30% higher memory than SwiGLU but limited inference overhead due to parallelizable operations.

4 Experiments

4.1 Setup

We evaluate on FineWeb using a Qwen 3 architecture with 83M parameters. All models train for 50,000 steps under identical hyperparameters and hardware to ensure fair comparison. We compare against: (i) a standard SwiGLU baseline, (ii) strong leaderboard methods [6, 7], and (iii) ablated variants of our module.

4.2 Main results

DGFN achieves a validation loss of 4.793 ($\pm$ 0.012 over 3 seeds), surpassing the SwiGLU baseline (4.927 $\pm$ 0.011) and strong alternatives.

Method	Val. Loss	Memory (GB)
DGFN (Ours)	4.793 $\pm$ 0.012	40.8
Dynamic GEGLU [6]	4.926 $\pm$ 0.013	38.2
SwiGLU (Baseline) [3]	4.927 $\pm$ 0.011	31.5
Sparse SiLU [7]	4.943 $\pm$ 0.014	35.7

Table 1: Validation loss (mean $\pm$ std. over 3 seeds) and peak memory. Lower is better.

4.3 Ablations

We study the role of each component:

- Remove second path: loss 4.825 ($\uparrow$ 0.032).
- Fix α=1.0 (no learning): 4.811 ($\uparrow$ 0.018).
- Single normalization (after combination only): 4.818 ($\uparrow$ 0.025).
- No normalization: 4.902 ($\uparrow$ 0.109).

All parts contribute; normalization is especially critical.

4.4 Training dynamics and compute

DGFN reaches a validation loss of 6.0 about 18% faster than the baseline early in training. The dual paths appear to provide complementary gradients

that reduce optimization plateaus typical of single-gate FFNs. Memory rises by ∼30% vs. SwiGLU; inference overhead is small because both paths run in parallel and merge via a single projection.

4.5 Limitations

- Increased memory may constrain smaller devices.
- Benefits could vary across scales, tasks, or architectures beyond Qwen 3.
- The learned combination adds a minor degree of complexity; theoretical analysis is left to future work.

5 Conclusion

We introduced DGFN, a parallel-path, dual-gated FFN that improves validation perplexity by 2.7% over a strong SwiGLU baseline on FineWeb, with faster early convergence and modest overhead. Ablations validate each design choice. Future work includes: scaling studies, dynamic routing with more than two paths, memory-efficient variants, and theoretical analysis of why parallel gating improves optimization.

References

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