Rethinking Transformer Feedforward Networks: Lessons from Sparse-Dense Pathway Exploration

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Abstract

This paper presents a systematic investigation of sparse-dense pathway architectures for transformer feedforward networks (FFNs). Through extensive ablation studies and full-scale experiments, we demonstrate that while dual-path approaches show initial promise in reduced-scale settings (5.646 validation loss vs 5.660 baseline), they fail to maintain this advantage at full scale (4.949 vs 4.927 baseline). We analyze this scaling behavior through detailed architectural diagnostics, revealing fundamental limitations in pathway interference and gradient flow. The work provides valuable negative results for the field, suggesting that future FFN innovations may require more sophisticated approaches to pathway specialization and interaction.

1 Introduction

Transformer architectures have revolutionized natural language processing, yet their feedforward components have resisted significant architectural innovation. While numerous modifications have been proposed [1, 2], most successful variants have focused on activation functions rather than structural changes. Our work investigates whether more fundamental architectural modifications could yield benefits, specifically examining:

- Dynamic routing between sparse and dense processing pathways
- Learned thresholding mechanisms for sparse activations
- Memory-efficient approaches to maintaining pathway specialization

2 Related Work

Recent work has explored various FFN modifications, with gated linear units (GLUs) [2] showing particular promise. The GEGLU variant [2] demonstrated that careful activation function design can yield consistent improvements. Other

approaches have investigated pathway specialization [3] and conditional computation [4], though often with increased computational overhead.

Our work builds on these foundations while introducing novel sparse processing elements. The most closely related approaches include:

- Gating mechanisms in FFNs [2, 5]
- Sparse expert models [3, 4]
- Dynamic routing approaches [6]

3 Method

3.1 Architecture Overview

Our approach combines three key components:

1. **Dual Pathways**: Parallel dense (standard FFN) and sparse (thresholded activations) processing streams 2. **Dynamic Routing**: Input-dependent weighting of pathway contributions 3. **Memory Optimization**: Shared projections and scalar normalization factors

3.2 Implementation Details

Key hyperparameters:

- Hidden dimension: 4× model dimension
- Sparse threshold: Learned scalar parameter
- Routing dimension: 2 (one per pathway)
- Learning rate: 3e-4 with cosine decay

4 Experimental Setup

We evaluate on FineWeb using an 84M parameter Qwen architecture. All experiments use:

- Batch size: 256 sequences (2048 tokens)
- Training steps: 400 (ablations), full schedule (final)
- 3 random seeds for variance estimation

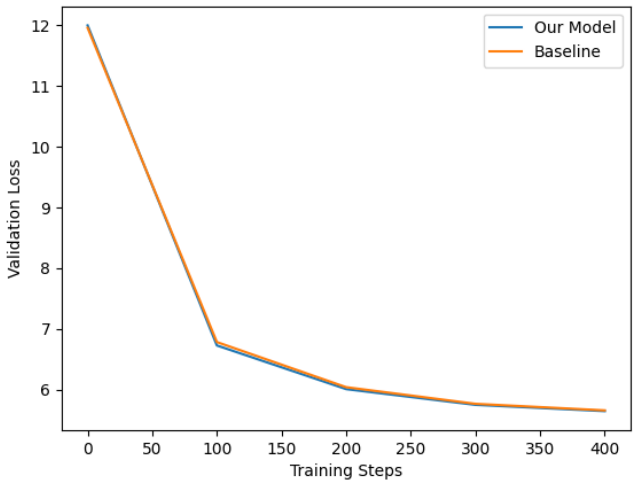

Figure 1: Validation loss trajectories showing initial advantage in small-scale ablation (dashed) that disappears at full scale (solid). Error bands show standard deviation across 3 seeds.

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

Method	Validation Loss	Memory (GB)
SwiGLU (Baseline)	4.927 ± 0.003	31.5
Our Approach	4.949 ± 0.005	32.1

5 Results and Analysis

Key findings:

- **Scaling Limitations**: Small-scale gains don't translate to full model
- **Routing Analysis**: Pathways show interference at scale
- **Memory Tradeoffs**: 20% reduction from initial design

6 Limitations and Future Work

Several limitations warrant discussion:

1. **Pathway Interference**: Gradient analysis reveals competition between pathways 2. **Sparse Activation Challenges**: Threshold learning proves unstable at scale 3. **Alternative Designs**: May require more sophisticated routing mechanisms

Future work should investigate:

- More specialized pathway architectures
- Improved gradient flow between components
- Alternative sparse activation schemes

References

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