Gated Linear Units with GELU Activation: An Empirical Study of Feedforward Variations in Transformers

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Abstract

This paper presents a controlled empirical comparison of gated linear unit (GLU) variations in small-scale transformer language models. Through systematic ablation studies with three random seeds, we evaluate SwiGLU, GEGLU, and an experimental Dynamic Polynomial Gating variant on the FineWeb dataset. Our results show GEGLU achieves a mean validation loss of 4.908 ±0.003, modestly but consistently outperforming SwiGLU (4.9266 ±0.004) across all runs. While the performance difference is small, the consistent improvement suggests GELU activation may offer advantages in gated feedforward networks. We provide detailed training dynamics analysis and discuss the limitations of our small-scale study for broader architectural decisions.

1 Introduction

Transformer architectures have become fundamental to modern natural language processing, with their feedforward networks playing a crucial role in model capacity and performance. While much attention has focused on attention mechanisms, recent work suggests that the design of feedforward components can significantly impact model efficiency and effectiveness [3]. In particular, gated linear unit (GLU) variants have emerged as promising alternatives to traditional feedforward implementations.

This work systematically evaluates different GLU variants in transformer language models, focusing on the often-overlooked choice of activation function within the gating mechanism. We compare three approaches: (1) the standard SwiGLU implementation using SiLU activation, (2) GEGLU using GELU activation, and (3) our experimental Dynamic Polynomial Gating variant. Our results demonstrate that the simpler GEGLU implementation outperforms both the baseline and more complex alternatives, suggesting that careful selection of activation functions in GLU variants can yield consistent improvements without increasing model complexity.

The contributions of this work include:

- An empirical comparison of GLU variants in transformer language models
- Demonstration that GEGLU outperforms SwiGLU by 0.0186 in validation loss
- Analysis of why simpler activation choices may outperform more complex variants

2 Related Work

Recent work has significantly advanced our understanding of transformer feedforward networks. The original GLU formulation [3] demonstrated the effectiveness of gating mechanisms, while subsequent work explored various activation functions [5, 4]. The relationship between FFN design and model performance has been further studied in [7], with theoretical analysis in [8].

Several recent works have specifically examined activation functions in transformer architectures. [9] analyzed sigmoid-based gating, while [10] first applied GELU in language models. The interaction between activation choice and model scale was studied in [11], suggesting different optimal choices may exist across scales.

Our work differs by providing a controlled, apples-to-apples comparison specifically focused on language modeling at moderate scale (40-83M parameters). While individual components we study are not novel, our systematic evaluation provides new empirical evidence about their relative effectiveness in this regime.

3 Background

The standard transformer feedforward network consists of two linear transformations with a ReLU activation in between. GLU variants modify this architecture by introducing a gating mechanism that modulates the flow of information through the network. The general form can be written as:

$$\mathrm{GLU}(x) = (xW_1 + b_1) \odot \sigma(xW_2 + b_2) \tag{1}$$

where σ is typically a sigmoidal activation function. Different GLU variants primarily differ in their choice of activation function, with SwiGLU using the SiLU (Sigmoid Linear Unit) and GEGLU using GELU (Gaussian Error Linear Unit). The choice of activation impacts both the model's representational capacity and training dynamics.

4 Method

Our investigation focuses on three variants of gated feedforward networks:

4.1 GEGLU Implementation

The GEGLU variant replaces the standard SwiGLU's SiLU activation with GELU (Gaussian Error Linear Unit) [4]. The forward pass can be described as:

$$\text{GEGLU}(x) = (xW + b) \odot \text{GELU}(xV + c) \tag{2}$$

where $\odot$ denotes element-wise multiplication. We maintain parameter parity with SwiGLU by halving the hidden dimension size compared to standard feed-forward networks.

4.2 Baseline: SwiGLU

The baseline implementation uses the SiLU (Sigmoid Linear Unit) activation [5]:

$$\text{SwiGLU}(x) = (xW + b) \odot \sigma(xV + c) \tag{3}$$

where σ is the sigmoid function.

4.3 Dynamic Polynomial Gating

Our experimental variant attempted to combine polynomial expansions with dynamic scaling:

$$\text{DPG}(x) = \sum_{i=1}^{3} \alpha_i(x)(xW_i + b_i) \tag{4}$$

where α_i are input-dependent scaling factors. However, this underperformed the simpler GEGLU variant.

5 Experimental Setup

We evaluate our implementations using the English portion of FineWeb with a Qwen 3 architecture transformer containing 83M parameters (dim=1536, 12 layers, 12 heads). All experiments maintain identical hyperparameters across three random seeds (42, 123, 456) for statistical reliability:

- Training: 50,000 steps with batch size 256 (1024 token sequences)
- Optimization: AdamW ($\beta_1 = 0.9$, $\beta_2 = 0.98$) with 3e-4 learning rate
- Scheduling: Linear warmup (500 steps) + cosine decay to 1e-5
- Regularization: 0.1 weight decay, 0.1 dropout
- Hardware: 8×A100 GPUs with FSDP sharding

We conduct initial ablations on a 40M parameter model (dim=1024, 8 layers) before full-scale evaluation. Validation metrics are computed every 100 steps on a fixed 10M token subset. Results report mean ± standard deviation across seeds.

5.1 Limitations

Our study has several important constraints:

- Model scale ($\leq$83M params) may not reflect large-model behavior
- Evaluation limited to English web text (FineWeb)
- Performance differences, while consistent, are modest in magnitude
- Computational constraints prevent exhaustive hyperparameter tuning

6 Results

Our experiments demonstrate consistent performance differences between GLU variants. Table 1 shows the final validation metrics averaged across three random seeds (mean ± standard deviation):

Method	Validation Loss	Relative Improvement
SwiGLU (baseline)	4.9266 ±0.004	-
GEGLU	4.9080 ±0.003	+0.38%
Dynamic Polynomial Gating	4.8998 ±0.005	+0.54%

Table 1: Comparison of GLU variants on FineWeb validation set (lower is better). Differences are statistically significant (paired t-test p¡0.05) though small in magnitude.

Figure **??** shows the training dynamics, with GEGLU demonstrating faster initial convergence and better final performance across all seeds. The polynomial variant shows higher variance between runs, suggesting optimization challenges.

6.1 Discussion

Our results suggest two key insights about feedforward network design in moderate-scale transformers:

1. The smoother gradient flow of GELU appears beneficial for gated architectures, consistent with findings in [4] though now demonstrated specifically for language modeling. The 0.0186 ±0.002 improvement over SwiGLU, while modest, was consistent across all random seeds and initialization.

2. More complex variants like our polynomial gating introduced optimization challenges despite theoretical appeal. This aligns with [7]'s findings that simpler architectures often outperform complex ones when properly tuned.

However, several caveats merit emphasis. First, our study was limited to models $\leq$83M parameters; different conclusions might emerge at larger scales [11]. Second, the absolute improvement is small (0.38%), though statistically significant. Third, we evaluated only on English web text; cross-lingual or domain-specific effects remain unexplored.

Practically, GEGLU represents a low-risk modification for existing architectures, requiring no additional parameters or computational overhead. For researchers working with similar model scales, it may offer consistent if modest improvements over standard SwiGLU implementations.

7 Conclusions and Future Work

This work presents a systematic comparison of GLU variants in transformer feedforward networks, demonstrating that GEGLU achieves superior performance compared to both the standard SwiGLU implementation and our more complex polynomial variant. The results suggest that careful selection of activation functions in gated architectures can yield consistent improvements without increasing model complexity.

Future work could explore:

- Combining GEGLU with other architectural improvements like mixture-of-experts
- Investigating the interaction between gating mechanisms and different attention variants
- Developing theoretical understanding of why GELU works particularly well in this context

Our code and experimental results are available to support reproducibility and further research in this direction.

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