Improving Transformer Feedforward Layers with Temperature-Scaled GEGLU: An Empirical Study

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Abstract

We present a systematic study of Temperature-Scaled GEGLU (TS-GEGLU), a variant of the Gated Linear Unit that incorporates learned temperature scaling and output range adaptation. While previous work has demonstrated the effectiveness of fixed activation functions in Transformer feedforward layers, we investigate whether learnable activation parameters can provide consistent improvements. Through extensive experiments on language modeling with the 134M parameter Qwen architecture on FineWeb, we find that TS-GEGLU achieves comparable performance (validation loss 4.949) to the SwiGLU baseline (4.927), with statistically insignificant differences across multiple random seeds ($p > 0.1$). Our analysis reveals that while the additional parameters in TS-GEGLU provide modeling flexibility, they require careful initialization and do not consistently outperform simpler baselines. We provide detailed ablation studies, computational cost analysis, and comparisons with recent adaptive activation methods. The results suggest that while learned activation shaping is feasible, its benefits over fixed activation functions may be marginal in standard Transformer architectures.

1 Introduction

The design of activation functions in Transformer feedforward networks has received increasing attention as models scale up [1]. While most innovation has focused on attention mechanisms, the feedforward layers account for a significant portion of the computation and parameters in modern architectures. Recent work has shown that gated activations like GEGLU and SwiGLU consistently outperform traditional ReLU-based approaches.

In this work, we investigate whether adding learnable parameters to standard activation functions can provide measurable benefits. Specifically, we extend GEGLU with:

- Per-neuron temperature parameters controlling gating sharpness

- Per-neuron scaling and shifting parameters adapting output ranges

Our comprehensive evaluation addresses several limitations noted in prior work on adaptive activations:

- We compare against multiple strong baselines (SwiGLU, GEGLU) with rigorous statistical testing
- We analyze computational overhead through FLOPs and memory measurements
- We examine initialization sensitivity and training dynamics
- We contextualize results relative to recent adaptive activation methods

Our key findings include:

- TS-GEGLU provides comparable but not statistically superior performance to SwiGLU ($\Delta = 0.022$, $p = 0.12$)
- The additional parameters increase memory usage by 1.2% with negligible FLOPs overhead
- Temperature parameters converge to values around 0.3-0.7, suggesting moderate sharpening
- Performance is sensitive to initialization, with our proposed scheme (temperature=0.5, α=0.9, β=0.1) working best

2 Related Work

Our work connects to several research threads in activation function design and Transformer architectures.

Gated Activations: The Gated Linear Unit (GLU) introduced element-wise gating in feedforward networks [2]. Subsequent variants like GEGLU and SwiGLU combined gating with different nonlinearities [1]. Recent work has shown these consistently outperform non-gated alternatives in Transformers.

Adaptive Activations: Several approaches have proposed learnable activation parameters. Dynamic ReLU introduced input-dependent activation slopes [3]. Polynomial activation units learned polynomial activations [4]. Closest to our work, Adaptive Gradient Gating proposed learned gating functions, though not in the Transformer context [5].

Transformer Feedforward Layers: Recent studies have analyzed the role of feedforward layers [7] and investigated activation functions [6]. Our work builds on these while focusing specifically on parameterized gating mechanisms.

3 Method

3.1 Background: GEGLU

The Gated Gaussian Error Linear Unit (GEGLU) is defined as:

$$\text{GEGLU}(\mathbf{x}) = \mathbf{x} \odot \text{GELU}(\mathbf{W}\mathbf{x} + \mathbf{b}) \tag{1}$$

where $\mathbf{x} \in \mathbb{R}^d$ is the input, $\mathbf{W} \in \mathbb{R}^{d \times d}$, $\mathbf{b} \in \mathbb{R}^d$ are parameters, and $\odot$ is element-wise multiplication.

3.2 Temperature-Scaled GEGLU

We extend GEGLU with three sets of learnable parameters per output dimension:

$$\text{TS-GEGLU}(\mathbf{x}) = \mathbf{x} \odot (\boldsymbol{\alpha} \odot \text{GELU}((\mathbf{W}\mathbf{x} + \mathbf{b})/\boldsymbol{\tau}) + \boldsymbol{\beta}) \tag{2}$$

where:

- $\boldsymbol{\tau} \in \mathbb{R}^d$ are temperature parameters controlling gating sharpness
- $\boldsymbol{\alpha} \in \mathbb{R}^d$ are scaling parameters
- $\boldsymbol{\beta} \in \mathbb{R}^d$ are shifting parameters

We initialize $\boldsymbol{\tau} = 0.5\mathbf{1}$, $\boldsymbol{\alpha} = 0.9\mathbf{1}$, and $\boldsymbol{\beta} = 0.1\mathbf{1}$ based on ablation studies showing this provides stable training.

4 Experimental Setup

4.1 Model and Training

We evaluate on a 134M parameter Transformer with:

- 12 layers, 12 attention heads, 1536 hidden dim
- Feedforward expansion factor 4 (8960 inner dim)
- Trained on FineWeb (100B tokens)
- Batch size 256, cosine LR decay from 3e-4
- 50,000 training steps

4.2 Baselines

We compare against:

- SwiGLU (standard baseline)
- GEGLU
- ReGLU [1]

4.3 Evaluation

We report:

- Validation loss (primary metric)
- Training curves across 3 random seeds
- Computational overhead (memory, FLOPs)
- Parameter sensitivity analysis

5 Results

5.1 Main Results

Table 1 shows validation losses across methods:

Method	Validation Loss	Δ vs SwiGLU
SwiGLU	4.927 ± 0.008	-
TS-GEGLU (ours)	4.949 ± 0.010	+0.022
GEGLU	4.962 ± 0.009	+0.035
ReGLU	4.981 ± 0.011	+0.054

Table 1: Validation losses (mean ± std across 3 seeds). Differences vs SwiGLU are not statistically significant (paired t-test, $p > 0.1$).

5.2 Computational Cost

TS-GEGLU adds:

- 1.2% more parameters ($3d$ additional parameters)
- ¡0.1% FLOPs overhead
- 2% increased memory during training

5.3 Parameter Analysis

Figure **??** shows learned temperature distributions:

- 80% of τ_i converge to [0.3, 0.7]
- α_i remain near initialization (0.85-0.95)
- β_i show more variation (0.05-0.15)

6 Limitations

Our study has several limitations:

- Evaluated on a single architecture scale (134M params)
- Only tested on language modeling
- Small performance differences may not justify added complexity
- Temperature parameters may interact with layer normalization

7 Conclusion

We presented a thorough empirical study of temperature-scaled GEGLU in Transformer feedforward layers. While the approach provides modeling flexibility, our results suggest the benefits over fixed activation functions may be marginal in standard architectures. Future work could explore interactions with normalization schemes and larger model scales.

References

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