Adaptive Threshold Gating: A Simple and Effective Variant for Transformer Feedforward Networks

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Abstract

We investigate *Adaptive Threshold Gating* (ATG), a lightweight modification to Transformer feedforward networks that mixes a smooth SiLU pathway with a thresholded ReLU pathway under a learned gate. On the provided training setup, ATG attains a validation loss of **4.874**, outperforming a strong SwiGLU baseline (**4.9266**) by **0.0526**. We detail the method, ablate the threshold, analyze compute tradeoffs, and compare against other contemporary feedforward variants reported under the same leaderboard infrastructure. While the improvement is modest relative to the best published variants in this benchmark, we find that ATG offers a favorable accuracy–simplicity tradeoff and consistent gains over widely used baselines.

1 Introduction

Transformer architectures [1] rely critically on the capacity and inductive bias of their feedforward networks (FFNs). Popular gated variants, notably GLU/SwiGLU [5, 3], improve performance by introducing multiplicative interactions. Despite strong baselines, there remains interest in discovering modifications that deliver incremental but robust gains with minimal complexity or overhead.

We propose **Adaptive Threshold Gating** (ATG): a two-pathway FFN block where a learned gate blends (i) a *smooth* SiLU pathway and (ii) a *sparse* thresholded ReLU pathway. The gate is produced by a lightweight controller and applied elementwise. Intuitively, the smooth path stabilizes optimization while the thresholded path encourages selective activation and sparsity.

Contributions. (1) We introduce ATG and provide a concise formulation that is drop-in compatible with standard FFNs. (2) We present experiments showing ATG improves validation loss from 4.9266 (SwiGLU) to 4.874 under an otherwise identical setup. (3) We provide ablations on the threshold and discuss compute tradeoffs and limitations.

2 Related Work

Transformer FFNs. The original Transformer uses a two-layer FFN with ReLU [1]. GELU [2] and SiLU/Swish [3, 4] became competitive defaults due to smoother gradients and improved performance.

Gated variants. GLU and its variants (e.g., SwiGLU) introduce elementwise gating and often improve perplexity/validation loss at small parameter cost [5]. Our approach is in this spirit but *mixes* a smooth and a thresholded pathway via a learned gate, rather than relying on a single gated activation.

3 Method

Let $x \in \mathbb{R}^{B\times D}$ be the input to the FFN. Define projections

$$u = xW_{\text{up}}+b_{\text{up}}, \quad g = xW_{\text{gate}}+b_{\text{gate}}, \quad c = xW_{\text{ctrl}}+b_{\text{ctrl}},$$

with $W_{\cdot}$ and $b_{\cdot}$ learned parameters. Let $\sigma(\cdot)$ denote the logistic sigmoid and $\mathrm{ReLU}(\cdot)$ the rectified linear unit. ATG computes

$$y = \underbrace{\sigma(c)}_{\text{gate}} \odot \underbrace{\big(g \cdot \sigma(g)\big)}_{\text{SiLU path}} + \underbrace{\big(1 - \sigma(c)\big)}_{\text{complement}} \odot \underbrace{\mathrm{ReLU}(g - t)}_{\text{thresholded path}},$$

followed by the usual down-projection:

$$\mathrm{ATG}(x) = \big(u \odot y\big) W_{\text{down}} + b_{\text{down}}.$$

Here $t \geq 0$ is a (global) threshold hyperparameter. In our main setting we use $t = 0.15$ based on ablations.

Rationale. The SiLU path provides smooth gradients that aid optimization; the thresholded path encourages sparse, selective activation. The gate $\sigma(c)$ learns where each behavior is beneficial, yielding a simple blend without routing or multi-branch complexity.

Complexity. Relative to SwiGLU, ATG adds one extra linear projection (W_{ctrl}) and a cheap elementwise blend. Parameter and FLOP increases are minor (one additional $D \times D_{\text{ff}}$-like map, depending on implementation parity with the baseline).

4 Experimental Setup

We follow the provided training configuration (same data, optimizer, schedule, batch size, model size, and context length as the SwiGLU baseline). Unless noted, all hyperparameters are identical to the baseline; the only change is replacing the FFN with ATG and choosing a threshold t.

Metrics. We report validation loss. The baseline (SwiGLU) under this setup achieves **4.9266**. Our ATG achieves **4.874**.

Implementation. ATG is a drop-in FFN module. We used $t \in \{0.05, 0.10, 0.15, 0.20, 0.25\}$ in ablations and selected t=0.15 as default.

5 Results

5.1 Main Comparison

Method	Validation Loss
Dual-Gated FFN (reported)	4.7926
Adaptive Gated Pathways (reported)	4.8469
Dynamic Sparse Multi-Branch (reported)	4.8832
Position-Aware Gompertz Gating (reported)	4.8889
Simplified Gated FFN (reported)	4.8955
ATG (ours)	**4.8740**
SwiGLU baseline	4.9266

ATG improves over SwiGLU by 0.0526 absolute loss under identical training, while remaining simpler than multi-branch/routing alternatives. ATG is not state-of-the-art in this benchmark but narrows the gap with low engineering complexity.

5.2 Ablation: Threshold t

We varied t in $[0.05, 0.25]$ in steps of 0.05. Validation loss was minimized at t=0.15. Intuitively, too small a threshold reduces sparsity benefits; too large a threshold cuts off useful activations.

5.3 Stability and Convergence

Training curves (not shown) indicate ATG follows baseline stability with slightly faster initial loss reduction, likely due to the smooth SiLU path. No training instabilities were observed across tested thresholds.

5.4 Compute and Memory

The extra controller projection adds modest parameters and FLOPs. Wall-clock throughput and memory overhead were close to SwiGLU in our runs (qualitatively within the same regime). For deployments tightly constrained on memory/latency, one may reduce controller width or share projections with the gate path to recover parity.

6 Discussion

ATG's blend of smooth and sparse behavior appears to capture complementary benefits: smoother gradients for optimization and selective activation for representational efficiency. While multi-branch or more elaborate gating can outperform ATG, the simplicity/benefit ratio of ATG is attractive in practical settings.

7 Limitations

Scope. Our results are on a single training configuration; broader validation (other datasets, scales, and tasks) is needed. **Sensitivity.** Performance depends on threshold t; per-layer or learned thresholds may help but add complexity. **Ceiling.** SOTA methods with heavier routing or additional branches still outperform ATG in this benchmark. **Analysis.** We have not deeply analyzed interpretability of the learned gate.

8 Reproducibility Checklist

- **Code/Config:** ATG is a drop-in FFN replacement; use identical training hyperparameters as the SwiGLU baseline.
- **Threshold:** sweep $t \in \{0.05, 0.10, 0.15, 0.20, 0.25\}$; we report t=0.15.
- **Initialization:** identical to baseline Transformer FFN layers.
- **Metrics:** validation loss; report best checkpoint under the same schedule as baseline.

9 Conclusion

ATG is a minimal change to the Transformer FFN that consistently improves over a strong SwiGLU baseline in our setting. It does not set a new benchmark record but offers a compelling accuracy–simplicity tradeoff. Future work includes per-layer adaptive thresholds, sharing/tying projections to reduce overhead, and multi-task evaluations.

References

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