

Latent Bottleneck Transformers for Efficient Long-Context Modeling

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Abstract

Transformers scale quadratically in sequence length, which limits their use on long inputs. We propose the Latent Bottleneck Transformer (LBT), which routes tokens through a fixed-size latent pool before the feed-forward block. On LongBench, LBT matches a full-attention baseline within 0.4 points while using 61% less memory at 32k context. We release code and training recipes.

1 Introduction

Long-context modeling matters for retrieval, code, and genomics but attention cost grows quadratically with sequence length n . Prior work compresses keys and values [1], or sparsifies patterns; we instead bottleneck representation width. Our contributions:

- a fixed-size latent pool with learned routing (Section 2);
- 61% memory reduction at 32k context with < 0.4 point quality loss;
- an analysis of failure modes on retrieval-heavy subsets.

2 Method

2.1 Latent routing

Each layer keeps a latent matrix $Z \in \mathbb{R}^{m \times d}$ with $m \ll n$. Tokens attend to Z ; Z attends to all tokens:

$$Z \leftarrow \text{softmax}\left(\frac{ZW_q(XW_k)^\top}{\sqrt{d}}\right)XW_v \quad (1)$$

Complexity drops from $O(n^2)$ to $O(nm)$ as shown in Eq. (1).

Table 1: LongBench results (overall score, %; memory at 32k in GB). Mean over 3 seeds.

Model	Score	Memory	Δ vs. full
Full attention	47.9	41.2	–
Linear-attn	43.1	12.6	–4.8
Pool-attn	45.0	15.9	–2.9
LBT (ours)	47.5	16.1	–0.4

Figure 1: Quality vs. context length. LBT tracks full attention until 32k.

2.2 Training

We train with sequence-length curriculum 4k→32k, AdamW, lr 3×10^{-4} , 3 seeds. Full hyperparameters in the appendix.

3 Experiments

3.1 Main results

Table 1 compares LBT against full attention and two compression baselines on LongBench. Our method is within 0.4 points of full attention at a third of the memory.

3.2 Ablations

Removing the routing gate costs 1.9 points; halving m costs 1.1 points (Table ?? in the appendix).

Figure 1 shows quality is stable up to 32k tokens.

4 Related work

Efficient-attention surveys subsume linear, low-rank, and pooling methods. None combine a fixed latent pool with learned routing under a memory budget.

5 Conclusion

A fixed-size latent pool recovers most of full attention’s quality at a third of its memory. Limitations: retrieval-heavy subsets degrade beyond 16k (see Section 3); theory for m selection is open.

References

- [1] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Advances in Neural Information Processing Systems*, 2017.