

• Self-attention module $\text{Attn}(X) = \text{Softmax}(XW_QW_K^{\top}X^{\top}/d) \cdot XW_V$ $\text{Attn}(X) = f(X) \cdot XW_V$ where (1) $A := \exp(XW_QW_K^{\top}X^{\top}/d) \in \mathbb{R}^{n \times n}$ (2) $D := \text{diag}(A\mathbf{1}_n) \in \mathbb{R}^{n \times n}$ (3) $f(X) := D^{-1}A \in \mathbb{R}^{n \times n}$

• Multilayer Transformers $\mathsf{F}_m(X) := g_m \circ \mathsf{Attn}_m \circ g_{m-1} \circ \mathsf{Attn}_{m-1} \circ \cdots \circ g_1 \circ \mathsf{Attn}_1 \circ g_0(X)$

where (1) Attn_i denotes self-attention module

- (2) gi denotes components other than
- (3) \circ denotes function composition

Theoretical Results

Multi-Layer Transformers Gradient Can be Approximated in Almost Linear Time

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Extensions We have also proved that our almost linear time algorithm also can easily extend to supporting other components in Transformers, such as residual connection, multi-head attention, causal mask, etc.

Theorem 1 (Single-layer gradient approximation)

Our algorithm can approximate the gradient on X, $W_Q W_K^T$, W_V in almost linear time $n^{1+o(1)}$, with approximation error bounded by $1/poly(n)$.

Theorem 2 (Multi-layer gradient approximation)

The number of layers m can be treated as an constant. Our algorithm can approximate the gradient on X, $W_Q W_K^T$, W_V in almost linear time $n^{1+o(1)}$, with approximation error bounded by $1/poly(n)$.

Take-Home Message We leverage the low-rank nature of the attention matrix to accelerate the gradient computation of multi-layer Transformers from $O(n^2)$ to $n^{1+o(1)}$. Our findings will inspire the further study and usage of the low-rank patterns within the Transformer architecture.