# Low rank attention denoising

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MIPT

2025

# Introduction

## Problem

- Noisy attention weights distribution in modern LLMs hurts interpretability and potentially limits the performance
- Existing solution utilizes large number of additional parameters and requires training from scratch

## Objective

Implement parameter and training time efficient attention score denoiser

## Assumption

Attention noise has lower intrinsic dimensionality than the signal

## Proposal

Low rank implementation of existing adaptive denoiser[1] that does not require training from scratch

[1] Yueyang Cang et al. DINT Transformer, 2025

# Attention & DIFF attention

## Attention mechanism

$$X \in \mathbb{R}^{N \times d_{model}} \text{ – input}, W_Q, W_K, W_V \in \mathbb{R}^{d_{model} \times d} \text{– projection matrices}$$

$$Q = XW_Q, K = XW_K, V = XW_V$$

$$Q, K, V \in \mathbb{R}^{N \times d} \text{ – projected queries, keys, values}$$

$$\text{Attention} = \text{softmax}\left(\frac{QK^T}{\sqrt{d}}\right) V$$

## DIFF attention mechanism

$$X \in \mathbb{R}^{N \times d_{model}} \text{ – input}, W_Q, W_K \in \mathbb{R}^{d_{model} \times 2d}, W_V \in \mathbb{R}^{d_{model} \times d} \text{– projection matrices}$$

$$[Q_1, Q_2] = XW_Q, [K_1, K_2] = XW_K, V = XW_V$$

$$Q_1, K_1, Q_2, K_2, V \in \mathbb{R}^{N \times d} \text{ – projected queries, keys, values}$$

$$\text{DIFFAttention} = \left(\text{softmax}\left(\frac{Q_1 K_1^T}{\sqrt{d}}\right) - \lambda \cdot \text{softmax}\left(\frac{Q_2 K_2^T}{\sqrt{d}}\right)\right) V, \ \lambda \in (0, 1)$$

# DINT Attention & low rank modification

## DINT Attention

$$A_1 = \text{softmax}\left(\frac{Q_1 K_1^T}{\sqrt{d}}\right), A_2 = \text{softmax}\left(\frac{Q_2 K_2^T}{\sqrt{d}}\right), A_3 = \text{repeat}\left(\frac{1}{N}\sum_{i=1}^{N} A_1[i,:], N\right)$$

$$\text{DINTAttention} = (\lambda \cdot A_3 + A_1 - \lambda \cdot A_2)\, V$$

## Low rank DINT

$$Q_1 = XW_{Q_1}, K_1 = XW_{K_1}, Q_2 = XW_{Q_2}^{down} W_{Q_2}^{up}, K_2 = XW_{K_2}^{down} W_{K_2}^{up}$$

$$W_{Q_1}, W_{K_1} \in \mathbb{R}^{d_{model} \times d}; W_{Q_2}^{down}, W_{K_2}^{down} \in \mathbb{R}^{d_{model} \times r}; W_{Q_2}^{up}, W_{K_2}^{up} \in \mathbb{R}^{r \times d}$$

$$A_1 = \text{softmax}\left(\frac{Q_1 K_1^T}{\sqrt{d}}\right), A_2 = \text{softmax}\left(\frac{Q_2 K_2^T}{\sqrt{d_2}}\right), A_3 = \text{repeat}\left(\frac{1}{N}\sum_{i=1}^{N} A_1[i,:], N\right)$$

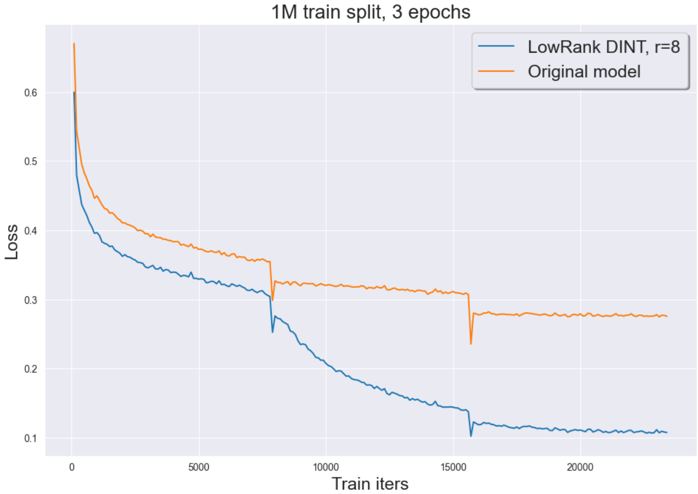
as linear layer of shape$[d_{in}, d_{out}]$ is initialized with $w[i,j] \sim U[-\sqrt{d_{in}}, \sqrt{d_{in}}]$

$$\mathbb{D}[W_{Q_2}^{down} W_{Q_2}^{up}[i,j]] = \mathbb{D}[W_{K_2}^{down} W_{K_2}^{up}[i,j]] = \frac{1}{3d_{model}} \cdot \frac{1}{3r} \cdot r = \frac{1}{9}\mathbb{D}[W_{Q_1}[i,j]]$$

$$\implies d_2 = \frac{d}{81}, \quad \text{LowRankDINTAttention} = (\lambda \cdot A_3 + A_1 - \lambda \cdot A_2)\, V$$

# Preliminary experiments

SFT of Llama-3.2-1B model[2] on OpenMathInstruct-2 dataset[3]



[2] https://huggingface.co/meta-llama/Llama-3.2-1B

[3] https://huggingface.co/datasets/nvidia/OpenMathInstruct-2

# Preliminary results & plans

## Observations

1. Training loss value seems promising
2. Test metrics are very questionable at the moment, might be a bug in the code

## Plans

1. Examine testing pipeline
2. Measure the entropy of attention weight distiribution, compare with original model
3. Evaluate cross-domain impact of proposed denoiser
4. Apply to larger models and different datasets