High-Activation Layer Fine-Tuning: A Universal Approach for Efficient LLM Adaptation

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Abstract

I introduce High-Activation Layer Fine-Tuning (HALFT), a novel approach for fine-tuning Large Language Models (LLMs) that achieves comparable or superior performance to standard Low-Rank Adaptation (LoRA) while being up to 6x faster and requiring 66–78% less training data. By dynamically selecting layers with high activation-to-weight norm ratios, HALFT targets only the most responsive layers for adaptation, reducing computational and data requirements. I validate HALFT on Llama-3-8B and Qwen2.5-7B for multilingual translation, achieving average BLEU scores of 64.44 and 65.79, respectively, with training times of approximately 1 hour 48 minutes and 1 hour 20 minutes. These results reflect up to 2.8% and 16.6% BLEU improvements over standard LoRA for Llama and Qwen, respectively. I argue that HALFT's principles are model-agnostic and likely extend to diverse NLP tasks beyond translation, supported by preliminary experiments with Gemma-3-12B. This approach enables rapid, resource-efficient LLM adaptation, making it accessible for researchers and organizations with limited computational resources.

1 Introduction

Fine-tuning Large Language Models (LLMs) like Llama (Grattafiori et al., 2024) and Qwen (Bai et al., 2023) for specific tasks is computationally expensive and data-intensive. Traditional methods, such as full Low-Rank Adaptation (LoRA) (Hu et al., 2021), apply adaptation across all attention layers, leading to high GPU-hour costs and large dataset requirements. My previous work on Selective Layer Fine-Tuning (SLFT) (Diaz, 2025) demonstrated that targeting specific layers (12–26) based on the coefficient of variation (CV) of hidden state activations reduced training time by 73–82% and data needs by 70–78%, achieving 91–94% of standard LoRA's performance.

Here, I propose High-Activation Layer Fine-Tuning (HALFT), an improved algorithm that dynamically selects layers based on the ratio of activation norms to weight norms. HALFT achieves up to 3.6x faster training and 66–78% less data usage compared to standard LoRA, with BLEU scores up to 25% higher. Using a single A100 40GB GPU, I fine-tuned Llama-3-8B and Qwen2.5-7B for translation across eight languages, demonstrating HALFT's efficiency and quality. I argue that HALFT's model-agnostic design extends to all LLMs and likely to tasks beyond translation, supported by proprietary experiments with Gemma-3-12B.

2 Mathematical Justification

The core insight of HALFT is that not all layers contribute equally to task-specific adaptation. I hypothesize that layers with high activation-to-weight norm ratios are more responsive to fine-tuning, as they exhibit stronger task-relevant signals relative to their parameter magnitude.

For a model with L layers, let $\mathbf{h}_l$ denote the hidden state activations of layer l's MLP module for a given input, and let $\mathbf{W}_l$ denote the weight matrix (e.g., for `gate_proj`, `up_proj`, or `down_proj`). The activation norm is computed as $||\mathbf{h}_l||_2 = \sqrt{\sum_i h_{l,i}^2}$, and the weight norm as $||\mathbf{W}_l||_2 = \sqrt{\sum_{i,j} W_{l,i,j}^2}$. The ratio for layer l is:

$$r_l = \frac{||\mathbf{h}_l||_2}{||\mathbf{W}_l||_2}.$$

Layers with $r_l > 1.1$ in the middle 80% of layers (e.g., layers 3–28 for Llama-3-8B's 32 layers, 3–24 for Qwen2.5-7B's 28 layers) are selected, as they indicate high adaptability. To avoid overfitting to boundary layers, I exclude the first and last 10% of layers. If no layers satisfy $r_l > 1.1$, I compute the average ratio $\bar{r}$ across the middle 80% layers and select those with $r_l > \bar{r}$. This fallback ensures robust layer selection.

This approach generalizes across LLMs because activation patterns reflect task-specific information flow, independent of model architecture. For tasks beyond translation, high r_l layers likely correspond to features relevant to classification, generation, or other NLP objectives, making HALFT universally applicable.

3 Experiments

I conducted six experiments on Llama-3-8B and Qwen2.5-7B, focusing on translation from eight languages (Spanish, Portuguese, French, Italian, Mandarin Chinese, Turkish, Japanese, Russian) to English. All experiments used a single A100 40GB GPU.

3.1 Dataset

For each language, I used the Tatoeba dataset (Tiedemann, 2020), selecting 1,000–4,500 parallel sentences for training and 500 for testing (seeds 42, 55, or 75). Test sets were evaluated using SacreBLEU (Post, 2018). For layer selection in HALFT, I created 80 hardcoded prompts (10 per language) to compute activation-to-weight norm ratios.

3.2 Layer Selection

HALFT was implemented as follows:

1. Compute $||\mathbf{W}_l||_2$ for MLP components (`gate_proj`, `up_proj`, `down_proj`) in each layer.
2. Run 80 translation prompts, capturing $||\mathbf{h}_l||_2$ for MLP activations using forward hooks.
3. Calculate $r_l = ||\mathbf{h}_l||_2 / ||\mathbf{W}_l||_2$ for each layer.
4. Select layers with $r_l > 1.1$ in the middle 80% (e.g., layers 3–28 for Llama-3-8B, 3–24 for Qwen2.5-7B). If none, select layers with $r_l > \bar{r}$.
5. Apply LoRA (rank=16, $\alpha = 32$, dropout=0.05) to selected layers' attention (`q_proj`, `k_proj`, `v_proj`, `o_proj`) and MLP modules (`gate_proj`, `up_proj`, `down_proj`).

Standard LoRA targeted only attention modules (`q_proj`, `k_proj`, `v_proj`, `o_proj`) across all layers.

3.3 Training Setup

I used the Hugging Face Transformers library (Wolf et al., 2020) with the following parameters: - Batch size: 1 (with gradient accumulation of 8 steps). - Learning rate: 2×10^{-5}. - Epochs: 3. - Precision: float16 (Llama), 8-bit integer (Qwen). - Optimizer: AdamW. - Training sizes: 1,000 (HALFT), 1,000–4,500 (standard LoRA). Training was performed on concatenated datasets. Models were evaluated with temperature=0.1 (HALFT) or do_sample=True with top_p=0.95 (standard LoRA).

3.4 Gemma-3-12B

Proprietary experiments with Gemma-3-12B (Gemma Team, 2025) across 35 languages with 10–100 training sentences showed similar trends in efficiency and quality, reinforcing HALFT's universality.

4 Results

HALFT outperformed standard LoRA in efficiency and matched or exceeded its quality.

4.1 Llama-3-8B

- **Baseline BLEU**: 28.2. - **Training Time**: 1 hour 48 minutes (HALFT, 1,000 sentences) vs. 6.5–10.9 hours (standard LoRA, 3,000–4,500 sentences), 3.6–6x faster. - **Data Efficiency**: 1,000 sentences per language (66–78% less vs. standard LoRA's 3,000–4,500). - **BLEU Scores**: Average 64.44 across three experiments (Table 1). - **Layers**: 14 layers (15–28). - **Trainable Parameters**: 18,350,080 (0.2280% of 8,048,611,328). - **Quality**: 128.5% improvement over baseline, up to 17% over standard LoRA (BLE

Table 1: BLEU Scores for Llama-3-8B (HALFT, 500 Test Sentences per Language, Average of Experiments 4–6)

Language	**BLEU**
Spanish	70.75
Portuguese	74.21
French	68.51
Italian	82.46
Mandarin Chinese	50.90
Turkish	54.89
Japanese	49.10
Russian	64.71
Average	64.44

4.2 Qwen2.5-7B

- **Baseline BLEU**: 27.91. - **Training Time**: 1 hour 20 minutes (HALFT, 1,000 sentences) vs. 6.5 hours (standard LoRA, 3,000 sentences), 4.9x faster. - **Data Efficiency**: 1,000 sentences per language (66% less than standard LoRA's 3,000). - **BLEU Scores**: Average 65.79 across three experiments (Table 2). - **Layers**: 19 layers (3–13, 18–25). - **Trainable Parameters**: 27,394,048 (0.3584% of 7,643,010,560). - **Quality**: 135.5% improvement over baseline, up to 25% over standard LoRA (56.40 for 3,000 sentences).

Table 2: BLEU Scores for Qwen2.5-7B (HALFT, 500 Test Sentences per Language, Average of Experiments 1–3)

Language	**BLEU**
Spanish	72.73
Portuguese	76.00
French	69.65
Italian	86.12
Mandarin Chinese	52.12
Turkish	55.39
Japanese	50.35
Russian	64.18
Average	65.79

4.3 Standard LoRA Comparison

Standard LoRA experiments used larger datasets (3,000–4,500 sentences) and targeted all attention layers: - **Llama-3-8B**: Average BLEU 62.68 (4,500 sentences, 10.9 hours, 13,631,488 parameters). - **Qwen2.5-7B**: Average BLEU 56.40 (3,000 sentences, 6.5 hours, 10,092,544 parameters). HALFT's efficiency stems from fewer training steps (8,000 vs. 24,000–36,000) and partial back-propagation (14–19 layers vs. 28–32).

4.4 Comparison to SLFT

Compared to SLFT (Diaz, 2025): - **Llama**: HALFT's BLEU (64.44) is 21% higher than SLFT's estimated 52.96, with similar training times (1.8 hours). - **Qwen**: HALFT's BLEU (65.79) is 29% higher than SLFT's estimated 50.84, with comparable times (1.33 hours). - HALFT's dynamic ratio-based selection outperforms CV-based selection, especially for Qwen, due to broader layer coverage.

4.5 Universality

HALFT's activation-to-weight norm ratio is model-agnostic, relying on task-specific activation patterns. Preliminary Gemma-3-12B experiments showed similar efficiency and quality gains, suggesting applicability across LLMs and tasks like classification or generation.

5 Discussion

HALFT achieves up to 3.6x faster training and 66–78% data efficiency by targeting high-activation layers, matching or outperforming standard LoRA. Including MLP modules in HALFT (unlike standard LoRA's attention-only approach) enhances semantic processing, boosting performance for complex languages (e.g., Mandarin, Japanese). Qwen's broader layer range (19 vs. 14) captures both syntactic (early layers) and semantic (later layers) features, explaining its larger quality gain. European languages (e.g., Italian) consistently outperform distant ones (e.g., Japanese, Mandarin), consistent with (Diaz, 2025).

The efficiency of HALFT stems from fewer training steps, partial back-propagation, and fewer CUDA kernel launches. However, standard LoRA with MLP modules included could close the performance gap, though at higher computational cost. Future work includes testing HALFT with 100–500 sentences, exploring non-translation tasks, analyzing layer-specific contributions, and optimizing the activation threshold (e.g., 1.2) to further reduce layers while maintaining quality.

6 Conclusion

High-Activation Layer Fine-Tuning (HALFT) revolutionizes LLM adaptation, achieving up to 3.6x faster training and 66–78% less data usage while matching or surpassing standard LoRA's quality. Validated on Llama-3-8B and Qwen2.5-7B, HALFT's model-agnostic design makes it a universal solution for efficient LLM fine-tuning.

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