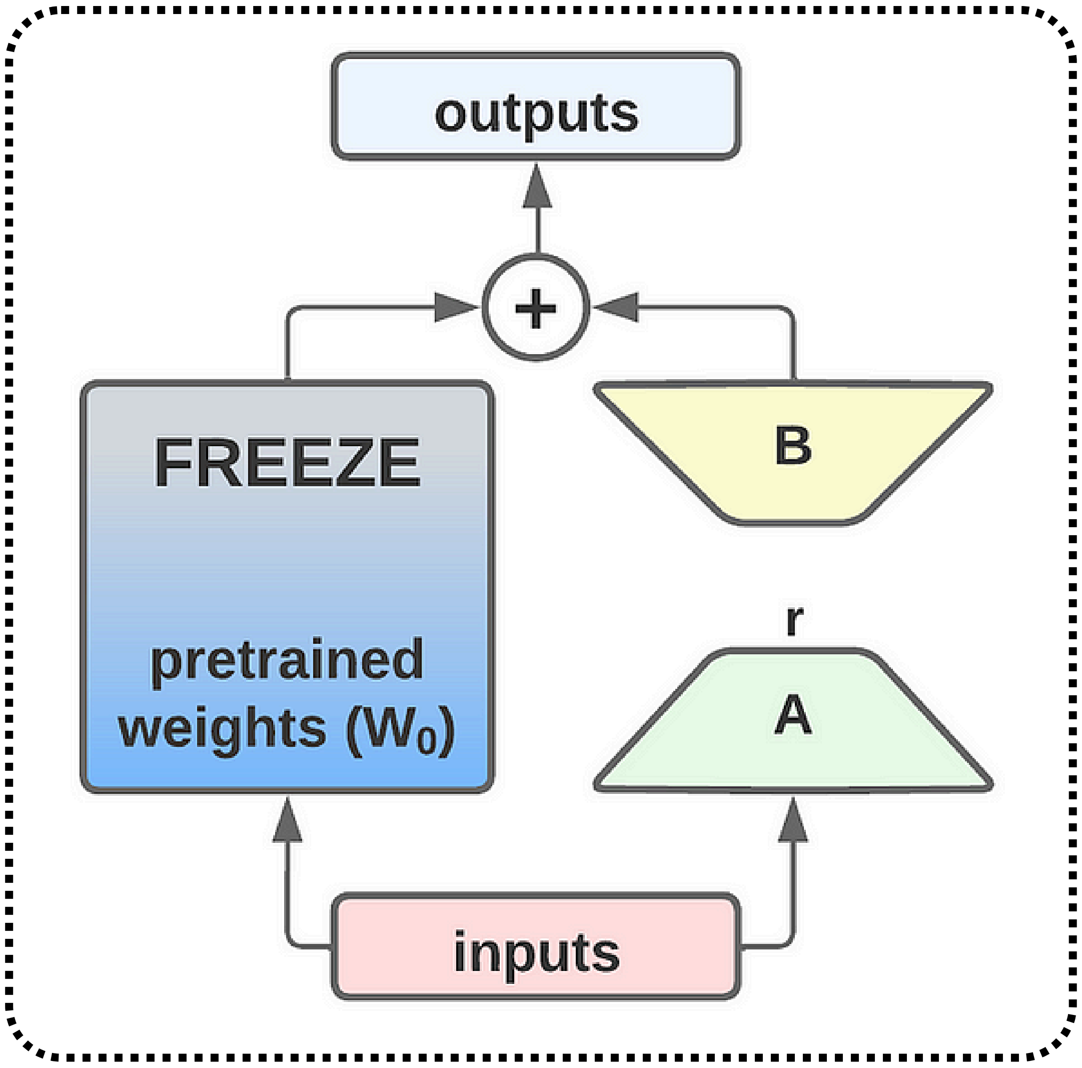
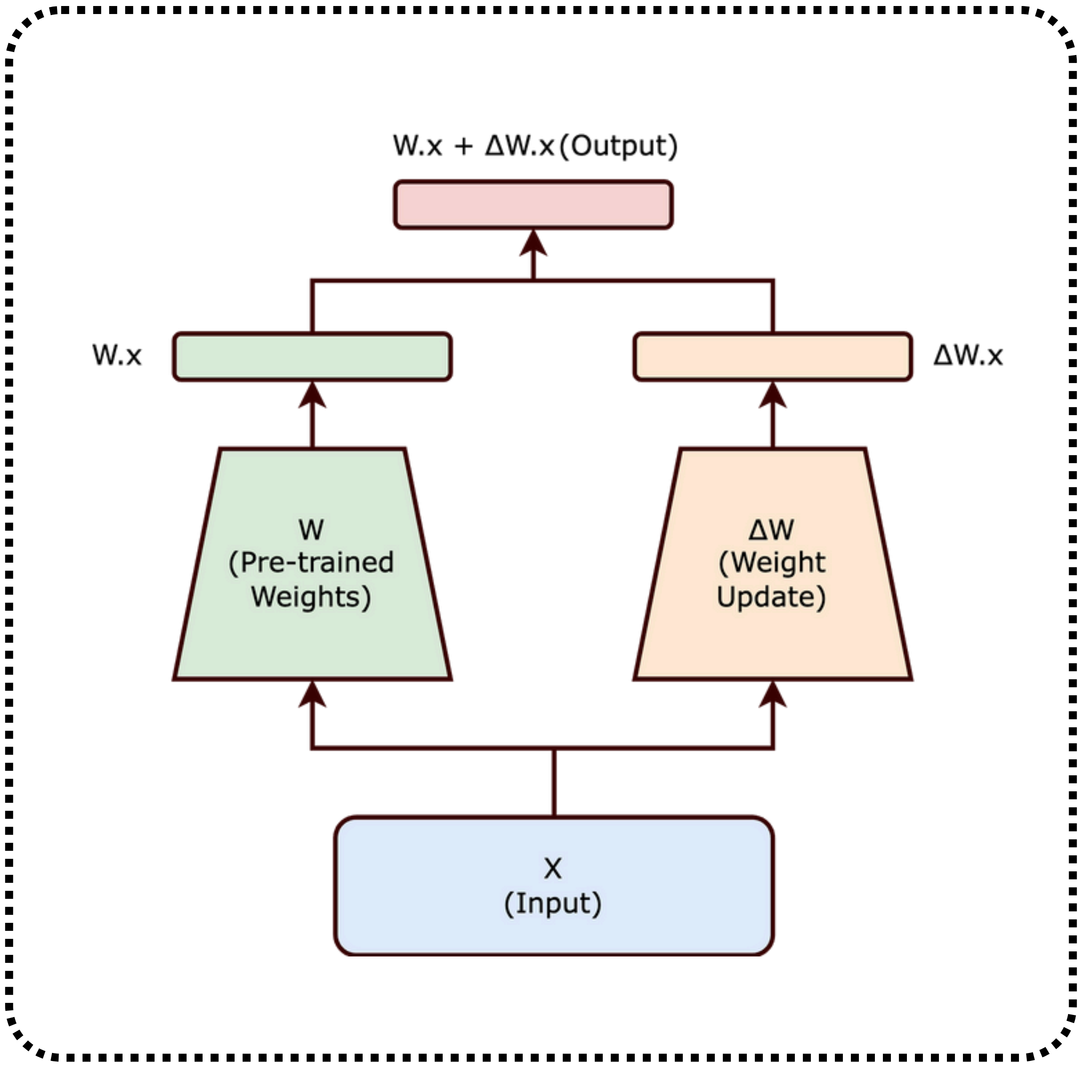
Mastering LLMs

Analytics Vidhya

Day 25: Low-Rank Adaptation (LoRA)





Method	Trainable Parameters	Memory Usage	Pre-Trained Model Modification?	Computational Cost
Full Fine-Tuning	100%	High	✅ Yes	🔴 Very High
Adapter Layers	1-10%	Medium	❌ No	Moderate
Prompt Tuning	<1%	Low	❌ No	Low
LoRA	<1% (Low-rank updates)	**Very Low**	❌ No	**Very Low**

Introduction

As Large Language Models (LLMs) grow in size and complexity, fine-tuning them for specialized tasks becomes increasingly expensive. Traditional fine-tuning requires updating millions (or even billions) of parameters, leading to high memory, storage, and computational costs.

Low-Rank Adaptation (LoRA) offers an efficient alternative. It reduces the number of trainable parameters while preserving model performance, making fine-tuning feasible on resource-constrained hardware.

In this post, we'll break down what LoRA is, how it works, and why it's a game-changer for model efficiency.

What is LoRA?

- LoRA (Low-Rank Adaptation) is a parameter-efficient fine-tuning (PEFT) method designed to optimize the adaptation of pre-trained models while keeping computational costs low.

- Instead of modifying all model parameters, LoRA injects trainable low-rank matrices into the weight matrices of the model and freezes the original weights. This allows fine-tuning without altering the core architecture, significantly reducing memory usage.

Key Advantages of LoRA

- **Reduces Trainable Parameters** – Updates only a small set of low-rank matrices instead of the entire model.

- **Memory Efficient** – Uses significantly less GPU memory, making fine-tuning possible even on consumer-grade hardware.

- **Maintains Pre-Trained Knowledge** – The base model remains unchanged, reducing catastrophic forgetting.

- **Improves Training Speed** – Fewer updates mean faster fine-tuning and lower computational costs.

How Does LoRA Work?

The Problem with Full Fine-Tuning

In traditional fine-tuning, every weight matrix **W** in the model is updated

$$W' = W + \Delta W$$

where ΔW represents the learned updates during training.

Since **W** is large (often millions or billions of parameters), storing and updating it requires huge computational resources.

The Low-Rank Approximation

LoRA solves this problem by decomposing ΔW into two smaller matrices:

$$\Delta W = AB$$

where:

- $A \in \mathbb{R}^{m \times k}$
- $B \in \mathbb{R}^{k \times n}$
- k is the **rank**, a small number that is much smaller than both m and n.

Since **A** and **B** are small, the number of parameters to train is drastically reduced.

Now, instead of updating **W**, we use:

$W' = W + AB$

Why Does This Work?

Most deep learning weight updates lie in a low-dimensional space. LoRA leverages this property to model fine-tuning changes efficiently using low-rank matrices.

This allows the model to learn task-specific knowledge without needing to modify the entire network.

Benefits of Using LoRA

Reduced GPU Memory Usage – Since only a fraction of parameters are updated, LoRA significantly reduces the memory footprint. This allows fine-tuning LLMs on consumer GPUs that would otherwise require enterprise-grade hardware.

Faster Training & Lower Compute Costs – Since fewer parameters are updated, gradient computations are much cheaper, resulting in faster fine-tuning and lower cloud costs.

Easier Model Deployment – Fine-tuned LoRA adapters are small and can be loaded dynamically on top of the base model, reducing storage and increasing flexibility.

Better Generalization – Because the pre-trained model remains unchanged, LoRA helps retain general knowledge while adapting to new tasks efficiently.

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Use Cases of LoRA

Domain-Specific Fine-Tuning – Adapting GPT, BERT, LLaMA, or T5 to specialized fields like medicine, law, and finance without high training costs.

Low-Resource Adaptation – Fine-tuning large-scale LLMs on edge devices or smaller servers.

Multi-Task Learning – Keeping one base model while quickly adapting to different tasks using LoRA adapters.

Efficient NLP Model Deployment – Deploying task-specific AI assistants by switching LoRA adapters instead of retraining the full model.

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LoRA vs. Other Fine-Tuning Methods

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Prompt Tuning	<1%	Low	❌ No	≣ Low
LoRA	<1% (Low-rank updates)	**Very Low**	❌ No	≣ **Very Low**

LoRA stands out as the most efficient technique while retaining high accuracy compared to full fine-tuning!

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