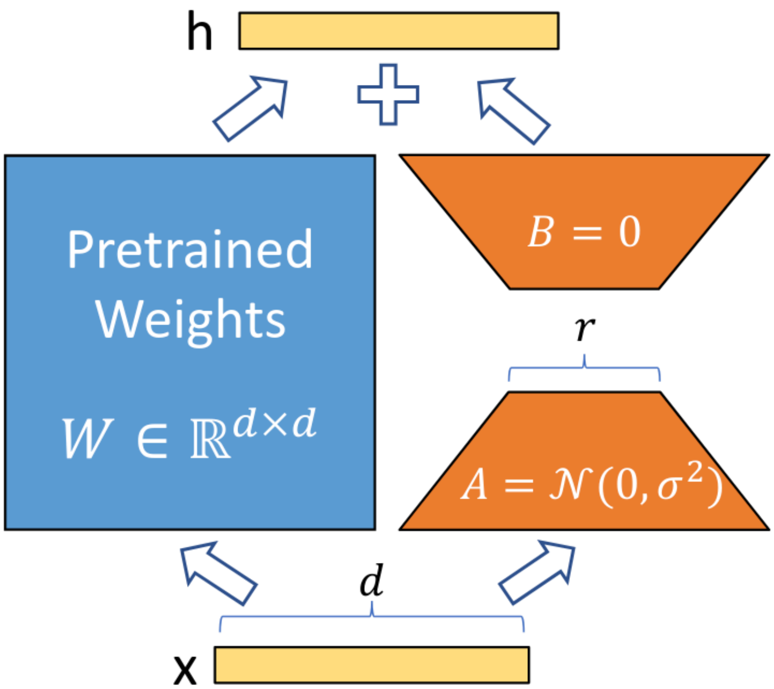
LoRA: Low-Rank Adaptation of Large Language Models

Motivation: The Fine-tuning Problem



Fine-tuning large language models presents significant challenges:

- **Parameter Inefficiency**: Fine-tuning requires updating all parameters (often billions)
- **Memory Requirements**: Storing optimizer states, gradients, and model copies demands substantial VRAM
- **Storage Overhead**: Each fine-tuned model requires saving a complete copy of all parameters
- **Training Cost**: Full fine-tuning is computationally expensive and time-consuming

Enter LoRA: Parameter-Efficient Fine-tuning

LoRA (Low-Rank Adaptation) solves these challenges by recognizing that updates to pre-trained weights during fine-tuning have a **low intrinsic rank**. By low intrinsic rank we mean that when a large pre-trained model is fine-tuned for a specific task, the changes required in its weight matrices are structured and do not span the full high-dimensional space of the original weights. Instead of updating all weights directly, LoRA injects trainable rank decomposition matrices into the model.

Core Concept: Low-Rank Decomposition

The key insight is that we can represent the weight update matrix as a product of two lower-rank matrices:

$$\Delta W = B \times A$$

Where:

- Original weight matrix W has dimensions $d \times k$
- B has dimensions $d \times r$
- A has dimensions $r \times k$
- r << min(d, k) (significantly lower rank than the original matrix)

The updated forward pass becomes:

$$h = Wx + \Delta Wx = Wx + BAx$$

LoRA in Practice: Applying to Transformer Weights

LoRA typically targets specific weight matrices in the model:

- **Query and Key projections** in self-attention layers
- **Value projections** in self-attention layers
- **Output projections** after self-attention
- **Feed-forward network** weights

For each target weight matrix, we:

1. Freeze the original pre-trained weights W
2. Initialize low-rank matrices A and B
    - A is initialized with random Gaussian values
    - B is initialized with zeros (ensuring no impact at the start)
3. Scale the contribution with a parameter α
4. Apply the update during the forward pass: $Wx + \frac{\alpha}{r}(BA)x$

Advantages of LoRA

- **Parameter Efficiency**: Only trains a small fraction of parameters (typically <1%)
- **Memory Efficiency**: Significantly reduced memory footprint during training
- **Storage Efficiency**: Can store multiple task adaptations with minimal overhead

- **Inference Efficiency**: LoRA matrices can be merged with original weights at inference time
- **Composition**: Multiple LoRA adaptations can be combined or swapped

Mathematical Representation

Standard Fine-tuning

During traditional fine-tuning, we update weights from W to W':

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

LoRA Approach

With LoRA, we approximate the update using low-rank matrices:

$$W' = W + \frac{\alpha}{r} BA$$

Where:

- $W \in \mathbb{R}^{d \times k}$ is the pre-trained weight matrix
- $B \in \mathbb{R}^{d \times r}$ and $A \in \mathbb{R}^{r \times k}$ are trainable low-rank matrices
- r is the rank (hyperparameter, typically 4-64)
- α is a scaling factor (hyperparameter)

Training Process

1. Initialize A with random Gaussian values: $A \sim N(0, \sigma^2)$
2. Initialize B with zeros: $B = 0$
3. Freeze the pre-trained weights W
4. Train only the parameters in A and B
5. During inference, compute: $h = Wx + \frac{\alpha}{r}(BA)x$

Hyperparameters

The most critical hyperparameters in LoRA are:

- **Rank (r)**: Controls the expressiveness of the adaptation (higher values = more capacity)
- **Alpha (α)**: Scales the contribution of the low-rank update
- **Target modules**: Which weight matrices to apply LoRA to

- **Learning rate**: Often higher learning rates can be used compared to full fine-tuning

Performance Comparison

Method	Trainable Parameters	Memory Usage	Storage	Training Time
Full Fine-tuning	100%	High	Full model copy	Slow
LoRA (r=8)	<1%	Low	Small adapter	Fast
LoRA (r=16)	<1%	Low	Small adapter	Fast
LoRA (r=32)	<1%	Low	Small adapter	Fast

In This Assignment

You will implement LoRA for your SmolLM model, focusing on:

1. Creating the LoRA adaptation layers
2. Freezing pre-trained weights
3. Applying LoRA to specific weight matrices
4. Training and evaluating the LoRA-adapted model
5. Comparing performance against full fine-tuning

Additional Resources

Original Paper

- LoRA: Low-Rank Adaptation of Large Language Models - Hu et al., 2021

Video Explanations

- LoRA explained (and a bit about precision and quantization) - Good introduction to LoRA
- Fine-tuning LLMs with PEFT and LoRA - Practical walkthrough