Training Large Language Models (LLMs)

Motivation: Why LLM Training Exists

- Traditional ML paradigm:
  - One model per task
    - Spam detection → separate model
    - Sentiment analysis → separate model
- Key observation:
  - These tasks are **not disjoint**
  - All require **language understanding**

Transfer Learning (Core Idea)

- Train a model once on massive data
- Reuse learned knowledge across tasks
- Fine-tune instead of training from scratch
- **Fundamental paradigm behind LLMs**

Two-Stage Training Framework

1. Pre-training (Most Expensive Stage)

- Goal:
  - Learn structure of **language + code**
- Model type:
  - Text-to-text
  - Mostly **decoder-only Transformers** (≈90%)
- Objective:
  - **Next-token prediction**
- Trained on **unlabeled web-scale data**

$$\mathcal{L}_{\text{pretrain}} = -\sum_{t=1}^{T} \log P(x_t \mid x_1, \ldots, x_{t-1})$$

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2. Tuning (Adaptation Stage)

- Start from pre-trained weights
- Adapt model to specific tasks:
  - Spam detection
  - Sentiment analysis
  - Classification

    - Chat / instruction following
- Much cheaper than pre-training

Pre-training Data

Common Data Sources

- **Common Crawl**
    - ~3 billion web pages per month
- Wikipedia
- Reddit conversations
- Social media text
- GitHub repositories (code)
- Stack Overflow
- Technical forums and blogs

Scale of Training Data

- Measured in **number of tokens**
- Typical scale:
    - Hundreds of billions → trillions → tens of trillions

Examples

- **GPT-3** → ~300B tokens
- **LLaMA-3** → ~15T tokens

Compute Notations (Very Important)

1. FLOPs — Floating Point Operations

- Measures **total computation required**
- Used to estimate **training cost**

$$\text{Training FLOPs} \approx 6 \times N_{\text{params}} \times N_{\text{tokens}}$$

Where:

- (N_{params}) = number of model parameters
- (N_{tokens}) = number of training tokens

Order of magnitude

$$\text{LLM Training} \approx 10^{25}\ \text{FLOPs}$$

- Exact value depends on architecture:

  - Dense models
  - MoE models (lower active FLOPs)

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2. FLOPS — Floating Point Operations per Second

- Measures **hardware speed**
- Indicates how fast GPUs/TPUs can execute FLOPs

$$\text{Training Time} = \frac{\text{Total FLOPs}}{\text{FLOPS}}$$

⚠️ **Important**

- FLOPs = total work
- FLOPS = speed
- Papers may mix notation → rely on context

Why Pre-training Is So Expensive

- Trillions of training tokens
- Hundreds of billions of parameters
- Long training runs
- Large GPU clusters

Architecture impact

- Dense models → all parameters active
- MoE models → partial activation → lower compute per step

Key Takeaways

- LLM training is built on **transfer learning**
- Pre-training dominates cost and compute
- Data scale is **trillions of tokens**
- Compute understanding requires:
  - **FLOPs** → total work
  - **FLOPS** → hardware speed

Scaling Laws for Language Models

Why Scaling Laws Matter

- Pre-training is extremely expensive:
  - Huge models
  - Massive datasets

- Limited compute budgets
- Key question:

> How does performance change as we scale **model size**, **data size**, and **compute**?

Scaling Laws (Kaplan et al., 2020)

Paper: *Scaling Laws for Neural Language Models*

Experimental Setup

- Trained many Transformer-based LMs
- Varied:
  - Model size (number of parameters)
  - Dataset size (number of tokens)
  - Compute budget
- Objective:
  - **Next-token prediction loss**

Key Findings

- Performance improves predictably with:
  - Larger models
  - More data
  - More compute
- Loss follows a **power-law relationship** with scale

$$\mathcal{L} \propto N^{-\alpha}$$

Where:

- (N) = model size, data size, or compute
- (α) = scaling exponent

Sample Efficiency

- Larger models are **more sample efficient**
- Meaning:
  - For the same number of training tokens,
    - Larger models achieve **lower loss**
- Result:
  - Bigger models learn faster **per token**

Fixed Compute Problem

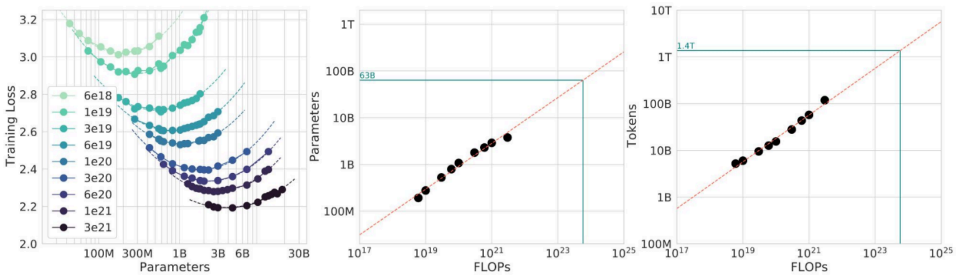
- Compute is **not unlimited**
- Given a fixed compute budget:
  - How big should the model be?
  - How much data should we train on?

Chinchilla Law (DeepMind, 2022)

Core Insight

- Many large models (e.g. GPT-3) were **undertrained**
- Optimal training requires **more data**, not just larger models

Chinchilla law.



Optimal Compute Allocation

$$N_{\text{tokens}} \approx 20 \times N_{\text{parameters}}$$

Where:

- $(N_{\text{parameters}})$ = number of model parameters
- (N_{tokens}) = number of training tokens

Interpretation

- If model is too large and data too small → **undertrained**
- If data is large but model is too small → **capacity-limited**
- Optimal point balances **model size + data size**

Chinchilla law.

Parameters	FLOPs	FLOPs (in *Gopher* unit)	Tokens
400 Million	1.92e+19	1/29,968	8.0 Billion
1 Billion	1.21e+20	1/4,761	20.2 Billion
10 Billion	1.23e+22	1/46	205.1 Billion
67 Billion	5.76e+23	1	1.5 Trillion
175 Billion	3.85e+24	6.7	3.7 Trillion
280 Billion	9.90e+24	17.2	5.9 Trillion
520 Billion	3.43e+25	59.5	11.0 Trillion
1 Trillion	1.27e+26	221.3	21.2 Trillion
10 Trillion	1.30e+28	22515.9	216.2 Trillion

Example: GPT-3

- Parameters: ~175B
- Tokens: ~300B
- According to Chinchilla:
  - Should have used **~3.5T tokens**
- Conclusion:
  - GPT-3 was **compute-inefficient**

Model	Pretraining size (# tokens)
GPT-3	300 billion
LLaMA 3	15 trillion

Architecture Assumptions

- Scaling laws assume:
  - Transformer-based
  - Decoder-only
- Architecture choice matters **less** than:
  - Model size
  - Data size
  - Compute budget

Challenges of Pre-training

1. Cost

- Training cost:
  - Millions → tens of millions → hundreds of millions USD
- Requires:
  - Large GPU clusters
  - Long training runs

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2. Environmental Impact

- High energy consumption
- Carbon footprint increasingly reported in papers

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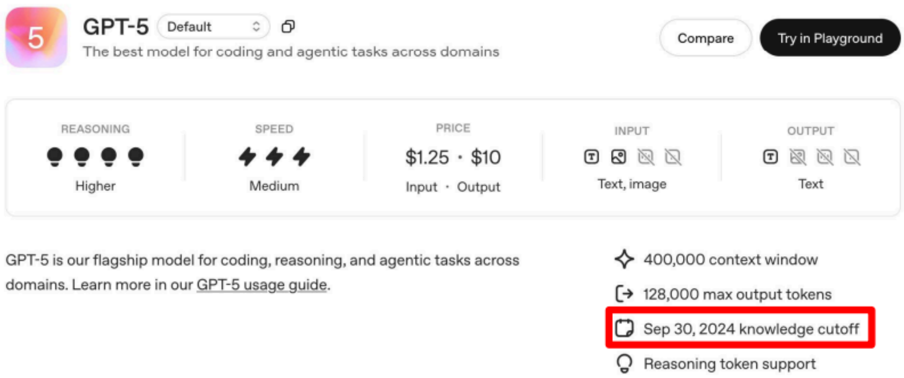
3. Knowledge Cutoff

- Model only learns from data **available before training ends**
- Cannot natively know:
  - New events
  - New research
  - New facts

📌 Knowledge Cutoff Date

- Explicitly mentioned in model cards
- Example:
  - GPT-5 → Knowledge cutoff: *September 30*



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4. Knowledge Editing Is Hard

- Updating weights post-training can:
  - Break other knowledge
  - Cause regressions
- No clean, safe way to edit knowledge in-place

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5. Memorization & Plagiarism

- Risk:
  - Model reproduces training data verbatim
- Especially problematic for:
  - Private data
  - Copyrighted content

Key Takeaways

- Scaling improves performance predictably
- Bigger models are more sample efficient
- Compute is the real bottleneck
- **Chinchilla Law**:

- Data matters as much as parameters
- Pre-training introduces:
  - Cost
  - Environmental concerns
  - Knowledge cutoff limitations

How Are Large Language Models Trained in Practice?

Why Training Is Hard

- LLMs have:
  - Billions → hundreds of billions of parameters
  - Trillions of training tokens
- Training involves **massive matrix multiplications**
- Hardware that excels at this:
  - **GPUs** (or TPUs at Google)

Training Pipeline of an LLM

1. Model Initialization

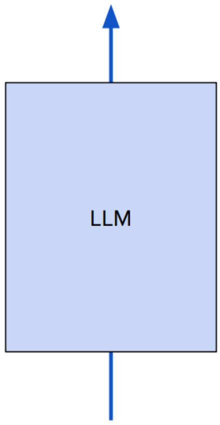
- Decoder-only Transformer
- Parameters:
  - $(10^9) \rightarrow (10^{11+})$
- Randomly initialized before training

Core Training Steps

1️⃣ Forward Pass

- Input:
  - Batch of token sequences
- Operations:
  - Embedding lookup
  - Self-attention
  - Feedforward layers
- Output:
  - Next-token probability distribution
- Compute **training loss**

$$\mathcal{L} = -\sum_{t=1}^{T} \log P(x_t \mid x_1, \ldots, x_{t-1})$$



Forward pass. Compute loss.

Activations. Needed to compute the loss.

$$\boxed{\mathscr{L}(\theta_t)}$$

Function of model size, batch size, context length

Activations (Very Important)

- Activations = intermediate layer outputs
- Must be **stored in memory**
- Needed for backpropagation

Activation memory depends on:

- Model size
- Batch size
- Context length
- Self-attention complexity

$$\text{Attention Complexity} = O(N^2)$$

Where:

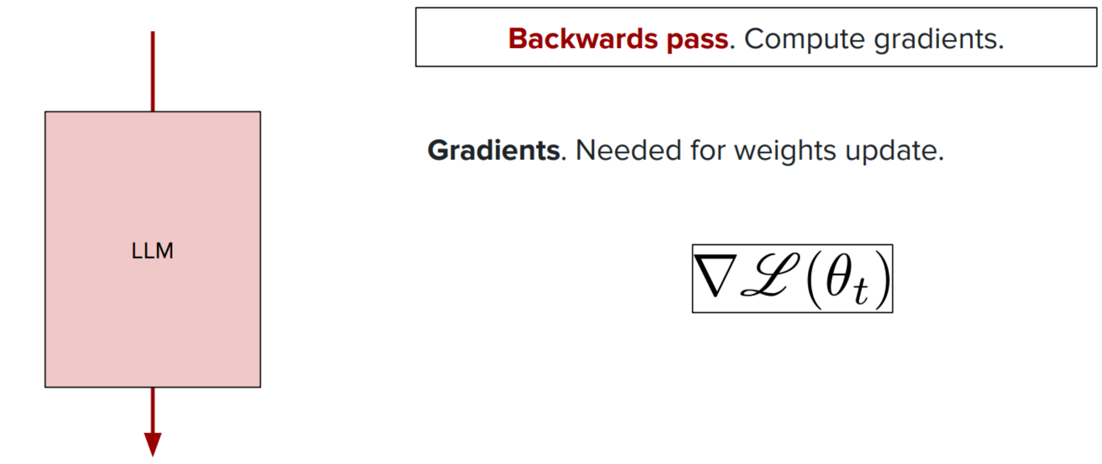
- (N) = sequence length

2️⃣ Backward Pass (Backpropagation)

- Compute gradients of loss w.r.t. parameters

$$\nabla_\theta \mathcal{L}$$

- Gradients must be stored in memory



3️⃣ Weight Update

- Update parameters using an optimizer

Adam Optimizer (Common)

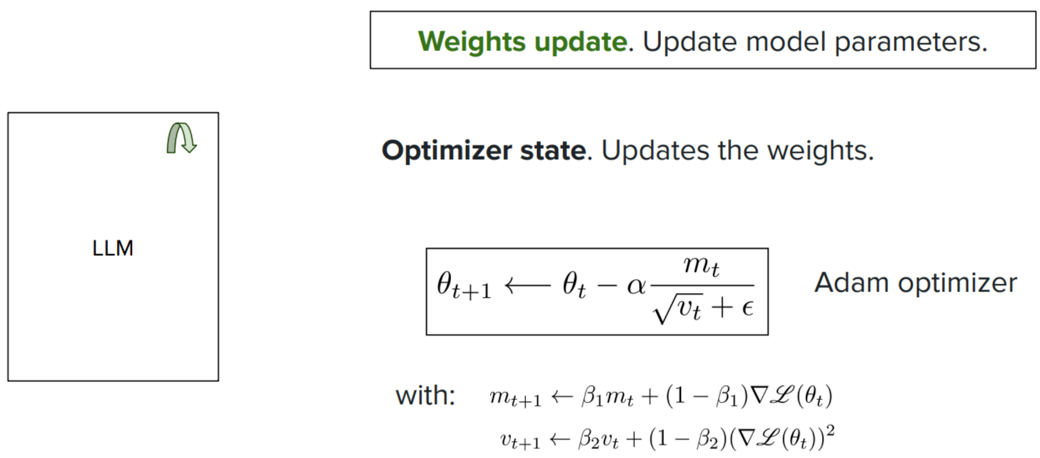
Maintains:

- First moment (mean of gradients)
- Second moment (mean of squared gradients)

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$$

- These optimizer states also consume **memory**



What Must Be Stored in GPU Memory?

For **each parameter**:

- Model weights

- Gradients
- Optimizer states (Adam: 2 extra tensors)

For **each layer & token**:

- Activations

👉 Memory grows very fast.

GPU Memory Is Limited

Example: NVIDIA H100

- GPU Memory ≈ **80 GB**
- Sounds large ❌
- Insufficient for:
  - Full model
  - Gradients
  - Optimizer states
  - Activations

Memory Bottleneck Summary

Component	Memory Cost
Parameters	High
Gradients	High
Optimizer states	Very high
Activations	Extremely high

📌 **Memory, not compute, is often the bottleneck**

Technical Specifications

	H100 SXM	H100 NVL
FP64	34 teraFLOPS	30 teraFLOPS
FP64 Tensor Core	67 teraFLOPS	60 teraFLOPS
FP32	67 teraFLOPS	60 teraFLOPS
TF32 Tensor Core*	989 teraFLOPS	835 teraFLOPS
BFLOAT16 Tensor Core*	1,979 teraFLOPS	1,671 teraFLOPS
FP16 Tensor Core*	1,979 teraFLOPS	1,671 teraFLOPS
FP8 Tensor Core*	3,958 teraFLOPS	3,341 teraFLOPS
INT8 Tensor Core*	3,958 TOPS	3,341 TOPS
GPU Memory	80GB	94GB
GPU Memory Bandwidth	3.35TB/s	3.9TB/s
Decoders	7 NVDEC 7 JPEG	7 NVDEC 7 JPEG
Max Thermal Design Power (TDP)	Up to 700W (configurable)	350-400W (configurable)
Multi-Instance GPUs	Up to 7 MIGs @ 10GB each	Up to 7 MIGS @ 12GB each
Form Factor	SXM	PCIe dual-slot air-cooled
Interconnect	**NVIDIA NVLink™:** 900GB/s **PCIe Gen5:** 128GB/s	**NVIDIA NVLink:** 600GB/s **PCIe Gen5:** 128GB/s
Server Options	NVIDIA HGX H100 Partner and NVIDIA-Certified Systems™ with 4 or 8 GPUs NVIDIA DGX H100 with 8 GPUs	Partner and NVIDIA-Certified Systems with 1–8 GPUs
NVIDIA Enterprise	Add-on	Included

Key Problem

> How do we train such large models if **one GPU cannot hold everything**?

Solution

- Use **multiple GPUs**
- **Distribute**:
  - Model
  - Data
  - Computation

➡️ Leads to **distributed training strategies**

(Next section: Data Parallelism, Model Parallelism, Pipeline Parallelism, ZeRO)

Key Takeaways

- Training involves:
  - Forward pass
  - Backward pass
  - Weight updates
- Memory requirements dominate
- GPU memory is limited
- Single GPU is insufficient
- Distributed training is **mandatory** for LLMs

Distributed Training Strategies for LLMs

Large Language Models (LLMs) **cannot be trained on a single GPU** because:

- Model parameters are extremely large (billions to hundreds of billions)
- Activations scale with:
  - Batch size
  - Sequence length
  - Number of layers
- Optimizer states multiply memory usage

Hence, **distributed training across multiple GPUs is mandatory**.

1️⃣ Data Parallelism (DP)

Core Idea

- Each GPU holds a **full replica of the model**
- Training data is **split across GPUs**
- Each GPU performs:
  - Forward pass
  - Loss computation
  - Backward pass

Detailed Workflow

Let there be **N GPUs**.

1. Global batch size (B) is split:

$$B = \sum_{i=1}^{N} B_i$$

2. Each GPU computes gradients independently:

$$\nabla \mathcal{L}_i = \frac{\partial \mathcal{L}_i}{\partial \theta}$$

3. Gradients are **synchronized (All-Reduce)**:

$$\nabla \mathcal{L} = \frac{1}{N} \sum_{i=1}^{N} \nabla \mathcal{L}_i$$

4. Each GPU applies the **same weight update**

What Is Replicated on Each GPU

- Model parameters
- Activations
- Gradients
- Optimizer states (Adam moments)

➡️ **Heavy memory duplication**

Advantages

- Simple conceptual model
- Easy to scale batch size
- Widely supported in frameworks (PyTorch DDP, Horovod)

Limitations

- ❌ Entire model **must fit on one GPU**
- ❌ Memory grows linearly with model size
- ❌ Communication overhead from gradient synchronization
- ❌ Inefficient for very large models

ZeRO: Zero Redundancy Optimizer

Motivation

In standard Data Parallelism:

- Every GPU stores **identical copies** of:
  - Parameters
  - Gradients
  - Optimizer states

This leads to **massive memory waste**.

Core Idea

Shard (partition) training states across GPUs
instead of duplicating them.

ZeRO Stage 1 — Optimizer State Partitioning

- Optimizer states (Adam moments) are sharded
- Parameters and gradients are still replicated

Memory per GPU:

$$\text{Params} + \text{Grads} + \frac{1}{N}(\text{Optimizer States})$$

📉 Memory reduction ≈ **2×**

ZeRO Stage 2 — Gradient Partitioning

- Shard:
  - Optimizer states
  - Gradients
- Parameters still replicated

Memory per GPU:

$$\text{Params} + \frac{1}{N}(\text{Grads} + \text{Optimizer States})$$

📉 Memory reduction ≈ **4×**

ZeRO Stage 3 — Parameter Partitioning

- Shard:
  - Parameters
  - Gradients
  - Optimizer states
- **No redundant copies**

Memory per GPU:

$$\frac{1}{N}(\text{Params} + \text{Grads} + \text{Optimizer States})$$

📉 Maximum memory savings
❌ Highest communication overhead

Communication Trade-off

- Higher ZeRO stage → more parameter gathering
- Frequent all-gather and reduce-scatter operations
- Slower step time but enables much larger models

2️⃣ Model Parallelism (MP)

Core Idea

Instead of splitting data, **split the model itself** across GPUs.

Used when:

- Model parameters cannot fit on a single GPU
- Activation memory is too large

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a) Tensor Parallelism

- Split **large matrix operations**
- Example: Linear layer

$$Y = XW$$

If $(W \in \mathbb{R}^{d \times d})$, split across GPUs:

- Column-wise or row-wise partition

Each GPU computes a partial result, then aggregates

Benefits:

- Reduces memory per GPU
- Reduces per-GPU compute

Used in:

- Megatron-LM
- DeepSpeed
- Most large LLMs

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b) Pipeline Parallelism

- Split model **by layers**
- Each GPU handles a subset of layers

Example:

- GPU 1 → Layers 1–4

- GPU 2 → Layers 5–8
- GPU 3 → Layers 9–12

Activations are passed between GPUs.

Pipeline Challenges

- Pipeline bubbles (idle GPUs)
- Requires micro-batching to improve utilization
- Adds latency

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c) Expert Parallelism (MoE Models)

- Used in **Mixture-of-Experts (MoE)** LLMs
- Each expert FFN placed on different GPUs
- Router sends tokens to experts dynamically

Only selected experts are active per token.

Used in:

- Switch Transformer
- Mixtral
- DeepSeek
- GShard

Key Observation

- Data Parallelism → scales **data**
- ZeRO → removes **memory redundancy**
- Model Parallelism → splits **model computation**

These techniques are **composable** and almost always used together in practice.

Flash Attention (Exact Attention Optimization)

Flash Attention is an **exact attention algorithm** introduced in **2022 (Stanford)**. It **does not approximate attention** — it computes the *same result* as standard self-attention, but **much faster and with far less memory usage**.

The key idea is to **exploit GPU memory hierarchy**.

GPU Memory Hierarchy (Why Flash Attention Exists)

GPUs have **two very different memory types**:

1️⃣ HBM (High Bandwidth Memory)

- Large (≈ tens of GB, e.g., 80 GB on H100)
- Relatively **slow**
- Bandwidth: ~1–3 TB/s
- This is what we usually call *GPU memory*

2️⃣ SRAM (On-chip Memory)

- Very small (≈ tens of MB)
- **Extremely fast**
- Bandwidth: ~10–20+ TB/s
- Located next to compute units

⚠️ **Key bottleneck**:
Modern GPUs are **memory-bound**, not compute-bound.
Most time is spent **reading/writing HBM**, not computing FLOPs.

Standard Self-Attention (Vanilla Implementation)

Self-attention formula:

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

Where:

- $(Q \in \mathbb{R}^{N\times d})$
- $(K \in \mathbb{R}^{N\times d})$
- $(V \in \mathbb{R}^{N\times d})$
- (N) = sequence length

Naive Attention Memory Pattern

1. Load (Q, K) from **HBM**
2. Compute (QK^T) → store to **HBM**
3. Read (QK^T) from **HBM**
4. Apply softmax → write to **HBM**
5. Read softmax result + (V) from **HBM**
6. Multiply → write output to **HBM**

❌ **Multiple HBM reads/writes** ❌ Massive memory traffic ❌ GPU compute units stay idle waiting for memory

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Key Insight Behind Flash Attention

Softmax Is Row-wise

For a row vector (x):

$$\text{softmax}(x_i) = \frac{e^{x_i}}{\sum_j e^{x_j}}$$

Important property:

- Softmax **can be computed incrementally**
- You do **not need the full matrix at once**

Flash Attention Core Idea

👉 **Tile (block) the computation** so that:

- Small blocks fit into **SRAM**
- Entire attention computation for a block is done **end-to-end**
- Minimize reads/writes to **HBM**

This technique is called **tiling**.

Flash Attention Algorithm (High-Level)

For each **query block** (Q_i):

1. Load a small block of (Q_i) into **SRAM**
2. Loop over key/value blocks $((K_j, V_j))$:
   - Load (K_j, V_j) into SRAM
   - Compute partial attention scores
   - Update softmax statistics **incrementally**
3. Accumulate final output
4. Write output once to **HBM**

✅ One HBM write per output
✅ No intermediate matrices stored in HBM

Incremental Softmax Trick (Key Formula)

Let attention scores be split into blocks:

$$S = [S_1, S_2, \dots, S_n]$$

Instead of computing:

$$\text{softmax}(S) = \frac{e^S}{\sum e^S}$$

We maintain per-row:

- Running maximum (m)
- Running normalization factor (l)

Update rule (conceptual):

$$m_{\text{new}} = \max(m_{\text{old}}, \max(S_i))$$

$$l_{\text{new}} = e^{m_{\text{old}} - m_{\text{new}}} \cdot l_{\text{old}} + \sum e^{S_i - m_{\text{new}}}$$

This allows **exact softmax computation block-by-block**.

📌 No approximation — mathematically identical to full softmax.

Why This Is Faster

Aspect	Vanilla Attention	Flash Attention
HBM Reads/Writes	Very High	Minimal
SRAM Usage	Minimal	Heavy
FLOPs	Same	Same
Runtime	Slow	Much Faster

Flash Attention is **IO-aware**, not FLOP-aware.

Backward Pass Optimization (Recomputation)

Standard Training

- Store **activations** during forward pass
- Use them during backward pass
- Activation memory dominates GPU usage

Flash Attention Trick

- **Do not store activations**
- Recompute them during backward pass
- Recompute is cheap due to:
  - SRAM locality
  - Fast kernels

This is called **activation recomputation (checkpointing)**.

Counterintuitive Result

Even though:

- More FLOPs are executed (recomputation)

We get:

- **Less runtime**
- **Much less memory usage**

Example from paper:

- HBM reads reduced by ~10×
- Runtime reduced
- Training fits larger batch sizes / longer context

Key Properties of Flash Attention

- ✅ Exact attention (no approximation)
- ✅ Lower memory footprint
- ✅ Faster forward + backward pass
- ✅ Enables longer context lengths
- ✅ Widely used in modern LLMs

Practical Notes

- Flash Attention v1, v2, v3:
  - Hardware-specific optimizations
  - Adapted to newer GPUs (A100, H100)
- Used in:
  - PyTorch
  - Triton
  - xFormers
  - Most modern LLM stacks

Final Mental Model

> Flash Attention **does not change what attention computes**
> It changes **where and how** the computation happens.

Compute in **SRAM**, not **HBM**.

Quantization: Reducing Precision for Efficient LLM Training & Inference

Large Language Models store **all parameters, activations, gradients, and optimizer states** as **floating-point numbers**.

A natural question arises:

> Do we really need *that much numerical precision* to achieve good performance?

Quantization addresses this question.

What Is Quantization?

Quantization is the process of converting numbers from:

- **Higher precision → Lower precision**

Goal:

- Reduce **memory usage**
- Increase **compute throughput**
- Preserve **model quality** as much as possible

Floating Point Numbers: How They Are Represented

A floating-point number is stored as **bits**, split into three components:

Component	Role
Sign	Positive / Negative
Exponent	Scale of the number
Mantissa (Significand)	Precision / granularity

Different floating-point formats allocate bits differently.

Name	Description	Illustration
Sign	Controls whether the number is positive or negative. Typically takes up to 1 bit.	$\boxed{0} \longleftrightarrow +1$ $\boxed{1} \longleftrightarrow -1$
Exponent	Controls the magnitude of the number. Also called *range*.	$N_e = 8$ $\boxed{0\,1\,1\,1\,1\,0\,1\,0} \longleftrightarrow \frac{2^{122}}{2^{127}}$
Mantissa	Controls the granularity of the number, i.e. what is after the decimal point. Also called *significand* or *fraction*.	$\boxed{1\,1\,0\,0\,0}\ \ldots \longleftrightarrow 1.75$

	Sign	Exponent	Mantissa
FP16 (Floating-Point 16)	1	5	10
FP32 (Floating-Point 32)	1	8	23
FP64 (Floating-Point 64)	1	11	52
BFLOAT16 (Brain Float 16)	1	8	7

Common Floating-Point Formats

Format	Total Bits	Exponent Bits	Mantissa Bits	Notes
FP64 (double)	64	11	52	Very high precision, slow
FP32 (single)	32	8	23	Standard training precision
FP16 (half)	16	5	10	Faster, less precise
bfloat16	16	8	7	Better range, less precision

📌 **Key observation**
FP16 / bfloat16 use **half the memory** of FP32.

Why Lower Precision Helps

1️⃣ Memory Savings

- FP32 → 4 bytes per value
- FP16 / bfloat16 → 2 bytes per value

This affects:

- Model parameters
- Activations
- Gradients
- Optimizer states

Result:

- Larger batch sizes
- Longer context lengths
- Bigger models per GPU

2️⃣ Compute Speed Improvements

GPUs are optimized for **lower precision arithmetic**.

Example (NVIDIA H100, approximate):

Precision	Peak Compute
FP64	~34 TFLOPS
FP32	~60 TFLOPS
FP16 / BF16	~1,000+ TFLOPS
INT8	Even higher

📌 Lower precision = **higher throughput**

Precision vs Accuracy Trade-off

Lower precision:

- ❌ Less granularity
- ❌ More numerical noise

But:

- Neural networks are **robust to noise**
- Most LLM training works well in FP16 / BF16

This makes quantization practical.

Mixed Precision Training

Modern LLMs **do not use a single precision everywhere**.

Instead, they use **mixed precision**:

- Weights: FP16 / BF16
- Activations: FP16 / BF16
- Gradients: FP16 / BF16
- Accumulators & loss scaling: FP32

Loss Scaling (Why It's Needed)

FP16 has limited precision → small gradients may underflow.

Solution:

- Multiply loss by a scale factor (s)
- Compute gradients
- Divide gradients by (s)

This preserves gradient signal.

Quantization Beyond FP16

Quantization can go even further:

Integer Quantization

- INT8
- INT4
- Even INT2 (research)

General idea:

$$x_q = \text{round}\left(\frac{x}{\Delta}\right)$$

Where:

- (x) = original value
- (Δ) = quantization scale

Types of Quantization

Type	Description
Post-Training Quantization	Quantize after training
Quantization-Aware Training	Simulate quantization during training

Type	Description
Weight-only Quantization	Only weights are quantized
Activation Quantization	Weights + activations

Where Quantization Is Used

Training

- FP16 / BF16 mixed precision
- Saves memory + speeds training

Inference

- INT8 / INT4 common
- Huge memory savings
- Faster decoding
- Enables deployment on smaller GPUs

Why Quantization Works Well for LLMs

- Transformers are **overparameterized**
- Small numerical errors do not significantly affect predictions
- Attention + FFNs tolerate noise

📌 Performance drop is often **minimal or negligible**

Practical Takeaways

- Quantization reduces **memory + compute**
- FP16 / BF16 is standard for LLM training
- Lower-bit quantization is crucial for inference
- Hardware is explicitly optimized for low precision

Mental Model

> Quantization trades **numerical precision** for **efficiency**
> and LLMs are robust enough to handle it.

Mixed Precision Training

Motivation

LLMs involve:

- Massive models
- Huge datasets
- Extremely high memory and compute costs

Key question:

> Can we use **lower numerical precision** without hurting model performance?

Mixed precision training is the answer.

Core Idea

Use different floating-point precisions for different parts of training:

- **Weights** → High precision (**FP32**)
- **Forward pass** → Lower precision (**FP16 / BF16**)
- **Backward pass** → Lower precision (**FP16 / BF16**)
- **Weight updates** → High precision (**FP32**)

This allows:

- Faster computation
- Lower memory usage
- Minimal performance degradation

Standard Mixed Precision Workflow

1. **Model weights stored in FP32**
2. Inputs and activations computed in FP16
3. Gradients computed in FP16
4. Gradients are accumulated and applied to **FP32 weights**
5. Updated FP32 weights are used in next iteration

Why Keep Weights in FP32?

Intuition:

- **Forward / backward computations**
  - Operate on data batches
  - Data itself is noisy
  - Extreme numerical precision is not critical
- **Weights**

- Accumulate updates over millions of steps
- Quantization errors can **accumulate**
- FP32 prevents long-term numerical drift

> Think of gradients as *directional hints*
> Think of weights as *long-term memory*

Benefits of Mixed Precision Training

1️⃣ Memory Savings

- FP16 uses **half the memory** of FP32
- Enables:
  - Larger batch sizes
  - Longer context lengths
  - Larger models per GPU

2️⃣ Faster Training

- GPUs are optimized for FP16 / BF16
- Much higher throughput than FP32
- Especially effective on modern GPUs (A100, H100)

3️⃣ Minimal Performance Loss

- Empirically shown:
  - Little to no degradation in final model quality
- Widely adopted in production LLM training

Loss Scaling (Important Detail)

Problem:

- FP16 has limited dynamic range
- Small gradients may **underflow to zero**

Solution: **Loss Scaling**

1. Multiply loss by a scaling factor (s)
2. Compute gradients
3. Divide gradients by (s) before update

This preserves gradient signal.

Do We Apply Mixed Precision Everywhere?

Short answer: **Not always**

- Some layers are more sensitive to precision:
  - LayerNorm
  - Softmax
  - Attention score computation

Different setups may:

- Keep some operations in FP32
- Use BF16 instead of FP16 for stability

There is **no single universal recipe**.

Relationship to Scaling Laws

Mixed precision is **orthogonal** to:

- Model size vs token size tradeoffs
- Chinchilla-style scaling laws

In practice:

- Teams run **small-scale experiments**
- Determine:
  - Optimal precision
  - Optimal model size
  - Optimal dataset size
- Then extrapolate to large-scale training

Practical Notes

- FP16 and BF16 are the most common choices
- BF16 has:
  - Wider exponent range
  - Better numerical stability
- Many modern LLMs prefer **BF16**

Key Takeaway

Mixed precision training:

- Reduces memory
- Speeds up training

- Preserves model quality

It is a **core technique** in modern LLM training pipelines.

Supervised Fine-Tuning (SFT)

Why Pre-training Is Not Enough

- Pre-training teaches the model:
  - Grammar
  - Syntax
  - Broad world patterns
- But **not helpful behavior**

Example:

> *"Can I put my teddy bear in the washer?"*

A pre-trained LLM:

- Predicts likely next tokens
- Does **not reason as an assistant**
- Mimics patterns from internet text

❌ Not helpful
❌ Not aligned with user intent

Motivation for Fine-Tuning

Goal:

- Turn a **next-token predictor**
- Into a **helpful assistant**

This is achieved via **Supervised Fine-Tuning (SFT)**.

What Is SFT?

SFT = Supervised Fine-Tuning

- Start from **pre-trained weights**
- Train on **(input, output)** pairs
- Objective:
  - Produce *useful, human-like responses*
- Supervised = labeled data

Nature of SFT Data

Each training example contains:

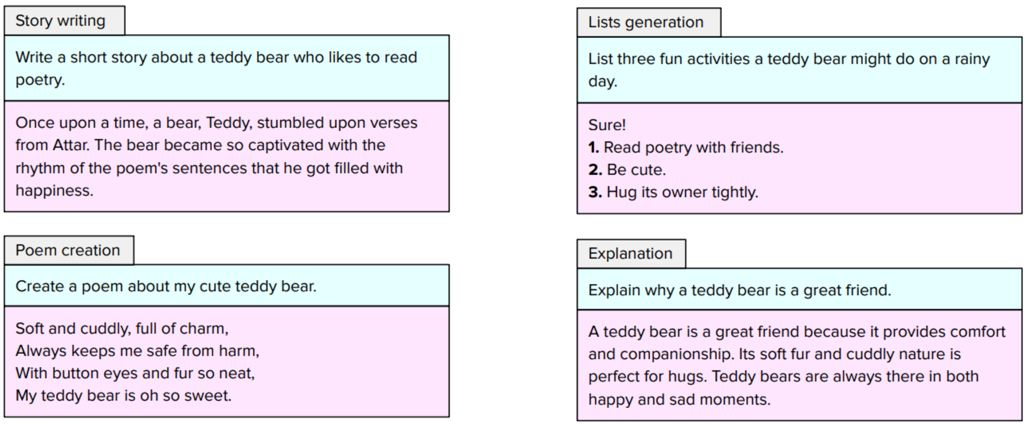
- **Input (prompt)**
- **Target output (ideal response)**

Example:

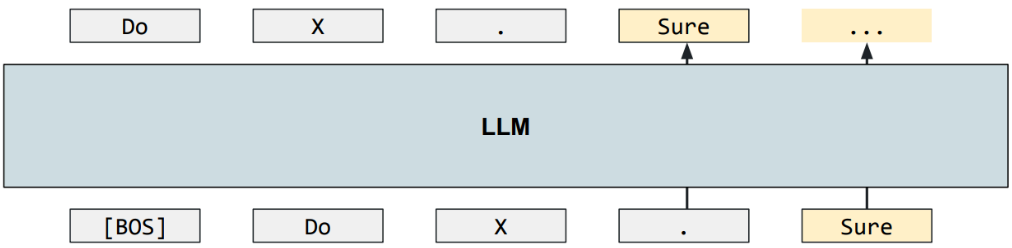
`Input: "Can I put my teddy bear in the washer?"`

`Output: "It depends on the material. Check the care label..."`

Goal. "Graduate" the model to being a helpful assistant.



Objective function. Predict next token *given the input*.



Key Difference: Pre-training vs SFT Objective

Pre-training

- Model predicts **every token**
- Includes the input itself

$$\mathcal{L}_{\text{pretrain}} = -\sum_{t=1}^{T} \log P(x_t \mid x_1, \ldots, x_{t-1})$$

- Loss applies to **all tokens**
- Teacher forcing everywhere

Supervised Fine-Tuning (SFT)

- Input is **conditioning context**
- No loss on input tokens
- Loss applies **only to output tokens**

Let:

- (x) = input (prompt)
- $(y = (y_1, \dots, y_N))$ = target output

$$\mathcal{L}_{\text{SFT}} = -\sum_{t=1}^{N} \log P(y_t \mid x, y_1, \dots, y_{t-1})$$

✅ Input is **given**
✅ Model is trained to **respond**, not repeat

Teacher Forcing in SFT

- Teacher forcing is used **only on output**
- The model:
  - Sees the full prompt
  - Predicts the response token-by-token
- Ground truth output tokens are provided during training

Intuition Behind SFT

- Pre-training:
  → *"What token usually comes next?"*

- SFT:
  → *"Given this instruction, what is the best response?"*

This shifts the model from:

- Language modeling
  to
- Instruction following

Why SFT Works Well

- Uses **human-written answers**

- Teaches:
    - Helpfulness
    - Politeness
    - Structure
    - Safety-aware behavior
- Much cheaper than pre-training
- Strong performance gains

Role of SFT in LLM Training Pipeline

1. **Pre-training**
    - Learn language & world patterns
2. **Supervised Fine-Tuning**
    - Learn how to respond
3. *(Next)* Alignment & preference optimization

Key Takeaways

- SFT is **mandatory** for useful LLMs
- Input tokens are **not predicted**
- Loss is applied **only to outputs**
- Same next-token loss, different conditioning
- Turns LLM into an assistant

Instruction Tuning (A Special Case of SFT)

From Language Modeling → Helpful Assistant

- Pre-training:
    - Learns **how language looks**
    - Predicts likely next tokens
- Supervised Fine-Tuning (SFT):
    - Teaches **how to respond**
- **Instruction Tuning**:
    - Teaches the model to **follow instructions**

Instruction tuning is a **subcategory of SFT** focused specifically on:

- Answering user instructions
- Acting as an assistant

Instruction Tuning Objective

Given:

- An **instruction** (input)
- A **desired response** (output)

The model is trained to:

- Condition on the instruction
- Predict only the response tokens

Loss Application

- ❌ No loss on instruction tokens
- ✅ Loss applied only to response tokens

Illustration:

[Instruction / Prompt] → [Response Tokens] ↑ Loss computed here

---

Instruction-Tuning Data Composition

Unlike pre-training (raw internet text), instruction tuning uses **curated data** that demonstrates *helpful behavior*.

Common Instruction Categories

- Story writing
- Poem generation
- List creation
- Explanations
- Summarization
- Question answering
- Code generation
- Reasoning tasks
- Assistant-style dialogues

Each example is a **(instruction, ideal response)** pair.

Assistant Dialogues

- Many SFT datasets are framed as **assistant conversations**
- User asks a question
- Assistant provides a helpful answer

This trains the model to:

- Be conversational

- Follow intent
- Produce coherent responses

Human vs Synthetic Instruction Data

Early Instruction Tuning

- Instructions written by humans
- Responses written by expert annotators
- High quality but **slow and expensive**

Modern Instruction Tuning

- Use existing strong LLMs to:
  - Generate candidate responses
  - Augment datasets
- Humans or other models:
  - Review
  - Filter
  - Rank quality

This **scales instruction data creation** significantly.

Safety-Oriented Instruction Data

Instruction tuning data also includes **safety-focused examples**.

Purpose

- Ensure model is:
  - Helpful
  - Harmless
  - Responsible

Examples

- Refusing harmful requests
- Avoiding dangerous instructions
- Hedging uncertain claims
- Rejecting disallowed content

Example behavior:

`"I'm sorry, I can’t help with that request."`

⚠️ This behavior is **learned**, not hard-coded via rules.

Why Not Use Rules or Regex?

- Rule-based systems:
  - Not scalable
  - Fragile
- Instead:
  - Safety behavior is **embedded into model weights**
  - Learned through supervised examples

Generalization From Instruction Tuning

Example:

- Dataset includes:
  - "Write a story"
- Prompt at inference:
  - "Write a sci-fi poem about space-time"

Why does this work?

- Pre-training:
  - Teaches what sci-fi, poems, space-time are
- Instruction tuning:
  - Teaches **how to follow instructions**

➡️ Model learns the *pattern*, not the exact content.

Instruction Tuning Scale (Orders of Magnitude)

Instruction tuning uses **far less data** than pre-training.

Reported Numbers

- GPT-3:
  - ~13,000 instruction examples
- LLaMA-3:
  - ~10 million instruction examples

Rough Token Estimate

Assume:

- ~1,000 tokens per example

Then:

- SFT data ≪ Pre-training data
- Several **orders of magnitude smaller**

Mental Model: Pre-training vs Instruction Tuning

Stage	Data Size	Data Quality	Purpose
Pre-training	Trillions of tokens	Noisy	Learn language
SFT / Instruction Tuning	Millions of examples	High-quality	Learn helpful behavior

---

Effect of Instruction Tuning (Teddy Bear Example)

Before (Pre-trained model):

- Continues text probabilistically
- Does not answer the question

After Instruction Tuning:

- Responds directly
- Gives helpful advice
- Aligns with user intent

Example:

`"You should handwash the teddy bear instead of using a washer."`

Key Observation

- Instruction tuning **aligns model behavior**
- Makes LLMs usable by humans
- Still uses next-token prediction
- But with **task-aware conditioning**

Challenges of Supervised Fine-Tuning (SFT) and Motivation for Optimization

1. High-Quality Data Requirement

- SFT requires **high-quality, curated data**
- “High-quality” usually implies:
  - Human involvement
  - Expert-written responses
  - Compliance with safety and policy rules

- Early SFT datasets were:
  - Almost entirely **human-generated**
  - Expensive in time, cost, and coordination

Modern pipelines:

- Mix **human-written** and **model-generated** data
- Still require:
  - Human review
  - Filtering
  - Quality control

✅ Advantage:

- Once created, datasets can be **reused and extended over time**

❌ Disadvantage:

- Still expensive in human and computational resources

---

2. Prompt Distribution Mismatch

- SFT data comes from a **specific prompt distribution**
- Real-world inference prompts may differ significantly

Example:

- Training prompt:
  - "Write a story"
- Inference prompt:
  - "Write a story inspired by a specific movie plot"

This creates an **out-of-distribution (OOD)** issue.

Key idea:

- Model generalization depends on:
  - Coverage of prompt space
  - Diversity of training examples

---

3. Memorization vs Generalization

- Question:
  - If we give the model a prompt identical to one seen during SFT, will it reproduce the same response?

Answer:

- Usually **no**, because:

    - Sampling is stochastic
    - Temperature > 0
- Output may:
    - Have the same *flavor*
    - But not the same wording

Influencing factors:

- Temperature
- Sampling strategy
- Pre-training diversity

---

4. Role of Temperature

- Higher temperature:
    - More diversity
    - More creative outputs
    - Higher chance of unlikely tokens
- Lower temperature:
    - More deterministic
    - Less variation

Temperature directly controls:

- How much the model explores the probability space

---

5. Improving Generalization

- Primary lever: **data**
- More diverse and sparse coverage of prompt space:
    - Better generalization
    - Less overfitting to specific examples
- Repeating similar examples ≠ better learning

Key idea:

- Teach the **concept**, not the exact instance

Evaluation Challenges for Instruction-Tuned Models

Why Evaluation Is Hard

- Helpfulness is **subjective**
- No single metric captures user satisfaction

Benchmark-Based Evaluation

Common benchmark categories:

- General language understanding
- Reasoning
- Math
- Code generation

Examples:

- **MMLU** (Massive Multitask Language Understanding)
  - ~50 tasks
  - Single aggregate score
- **GSM8K**
  - Grade-school math reasoning
  - ~8K problems

The “Training on the Test Task” Problem

Observed phenomenon:

- Sudden benchmark performance jumps
- Often unexplained by architecture changes

Cause:

- Model trained on **data resembling the benchmark task**

Important distinction:

- Training on the **test task**
- NOT necessarily training on the **test set**

Implication:

- Benchmark scores depend heavily on training mixture

⚠️ Fair comparison requires:

- Parity in training exposure
- Transparency about auxiliary data

Benchmark Saturation

- Models optimize for known benchmarks
- New benchmarks appear to fill gaps
- Leads to:
  - Score inflation

- Weak correlation with real-world usefulness

Human Preference-Based Evaluation

Chatbot Arena

- Users compare two model responses
- Choose preferred one
- Rankings computed via pairwise comparisons

Captures:

- "Vibes"
- User preference
- Conversational quality

Limitations of Preference-Based Evaluation

1. **Early Noise Sensitivity**
    - Initial comparisons heavily influence rankings
2. **Leaderboard Manipulation Risk**
    - Models can detect:
        - Who they are being compared against
    - Adversarial behavior possible
3. **Factuality vs Helpfulness**
    - Users may prefer:
        - Detailed but incorrect answers
    - Users may lack domain knowledge to verify correctness
4. **Subjective Preferences**
    - Style preferences differ:
        - Emojis vs no emojis
        - Conciseness vs verbosity
    - Expert preferences ≠ general population preferences
5. **Safety Bias**
    - Users dislike refusals
    - Preference systems may favor unsafe compliance
    - Conflicts with intended safety policies

No Single "Best" Metric

- Benchmarks → objective but narrow

- Human preference → subjective but broad
- Safety → policy-driven
- Real usefulness depends on **use case**

Evaluation must be:

- Multi-dimensional
- Context-aware
- Goal-driven

Alignment: Where SFT Fits

Alignment Definition

Alignment = making the model:

- Helpful
- Harmless
- Honest

Alignment Stages

1. **Supervised Fine-Tuning (SFT)**
2. **Preference Tuning** (next lecture)

Together:

- Form the **alignment pipeline**

Emerging Concept: Mid-Training

- Occurs **after pre-training**
- Uses the same next-token objective
- But on **task-relevant data**
- Bridges gap between:
  - General pre-training
  - Task-specific fine-tuning

Mid-training is:

- New
- Actively researched
- Increasingly adopted

Big Picture (So Far)

1. Pre-training:
    - Learn language
2. SFT / Instruction Tuning:
    - Learn to help
3. Preference Tuning:
    - Learn what users prefer
4. Evaluation:
    - Hard, multi-faceted, imperfect

Parameter-Efficient Fine-Tuning (PEFT): LoRA and QLoRA

Motivation: Why PEFT?

- Full fine-tuning updates **all model parameters**
- Computationally expensive:
    - High memory usage
    - Large optimizer states
    - Long training time
- Goal:
    - Adapt large pre-trained models
    - While training **as few parameters as possible**

LoRA: Low-Rank Adaptation

Core Idea

- **Freeze** pre-trained weights
- Learn a **low-rank update** instead of full weight updates

Standard Linear Layer

Given a linear transformation:

$$y = W_0 x$$

- $(W_0 \in \mathbb{R}^{d_{out} \times d_{in}})$
- (W_0) is **pre-trained**

LoRA Formulation

Instead of updating (W_0), we write:

$$W = W_0 + \Delta W$$

Where:

$$\Delta W = BA$$

- $(B \in \mathbb{R}^{d_{out} \times r})$
- $(A \in \mathbb{R}^{r \times d_{in}})$
- $(r \ll \min(d_{out}, d_{in}))$

Forward Pass with LoRA

$$y = W_0 x + B(Ax)$$

- (W_0): **frozen**
- (A, B): **trainable**

Parameter Reduction

- Full fine-tuning parameters:

$$d_{out} \times d_{in}$$

- LoRA parameters:

$$r(d_{out} + d_{in})$$

Example:

- $(d_{out}, d_{in} \sim 1000)$
- $(r \sim 4)$ or (8)

➡️ **Orders of magnitude fewer trainable parameters**

Task-Specific Adaptation

- (W_0): general language knowledge
- (A, B): task-specific adaptation

Example:

- Spam detection → one set of (A, B)
- Sentiment analysis → another set of (A, B)

Same base model, different LoRA adapters

Where Is LoRA Applied?

Original LoRA Paper

- Applied mainly to **attention projections**:

- (W_Q, W_K, W_V, W_O)

Later Findings

- Best performance gains from:
  - **Feed-Forward Networks (FFN / MLP blocks)**
- Modern practice:
  - Apply LoRA to:
    - Attention layers
    - Feed-forward layers
  - Majority of gains from FFN

Practical Training Observations (Empirical)

1. Higher Learning Rate

- LoRA typically uses:

$$\mathrm{LR}_{\mathrm{LoRA}} \approx 10 \times \mathrm{LR}_{\text{full FT}}$$

Hypothesis:

- Low-rank matrices explore a smaller subspace
- Need larger steps to adapt effectively

---

2. Large Batch Size Hurts

- LoRA performance degrades with very large batch sizes

Possible explanation:

- Training dynamics of **matrix products** differ from full matrices
- Gradient noise may help LoRA adaptation

⚠️ Empirical observation, not fully theoretically explained

Rank Selection (Hyperparameter (r))

- Typical values:
  - $(r = 4, 8, 16)$
- Grid search possible but often unnecessary
- Popular defaults work well
- Parameter reduction already massive → diminishing returns beyond this

---

QLoRA: Quantized LoRA

Motivation

- Even frozen weights (W_0) consume VRAM
- Goal:
  - Quantize **frozen base model**
  - Train LoRA adapters in high precision

QLoRA Setup

- (W_0): **Quantized**
- (A, B): **BF16 / FP16**
- Gradients only flow through LoRA weights

NF4 Quantization

- NF4 = NormalFloat 4-bit
- Assumes weights follow a **normal distribution**
- Uses **quantiles**, not uniform buckets

Benefits:

- Better use of limited bits
- Lower quantization error

Double Quantization

1. Quantize weights
2. Quantize quantization constants

Purpose:

- Further reduce memory overhead

Memory Savings

- QLoRA achieves:
  - **~16× VRAM reduction**
- Double quantization:
  - Small additional gains

Summary of LoRA vs QLoRA

Method	Base Weights	Trainable Weights	Precision	Memory
Full FT	Trainable	All	FP16/32	❌ Huge
LoRA	Frozen	A, B	FP16	✅ Low
QLoRA	Quantized	A, B	BF16	✅✅ Very Low

Key Takeaways

- LoRA enables efficient fine-tuning of LLMs
- Low-rank updates capture task-specific knowledge
- QLoRA makes fine-tuning possible on limited hardware
- Widely used in practice for LLM adaptation

In [ ]: