Inference Optimization

KV-Cache · Flash Attention · Quantization · Distillation · Speculative Decoding

The inference challenge

Two bottlenecks in LLM inference

Memory

Model weights:
2 bytes/param
(bfloat16)

70B model = 140 GB

Plus KV-cache, activations, framework overhead

A100 GPU = 80 GB

Latency

Autoregressive: one token at a time

Each token = full forward pass through all layers

Memory-bandwidth bound, not compute-bound

GPT-4: ∼100 ms per token

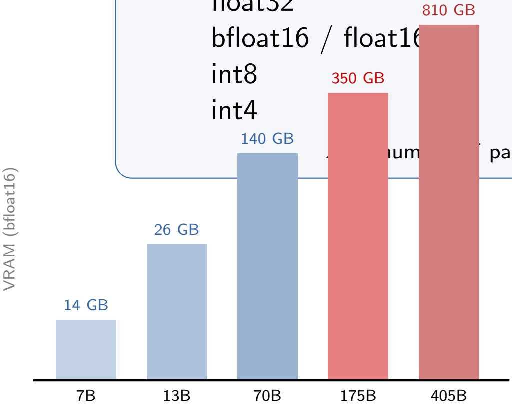
$$\text{Total VRAM} = \underbrace{\text{Model Weights}}_{\text{dominant for short seq}} + \underbrace{\text{KV-Cache}}_{\text{dominant for long seq}} + \text{Activations} + \text{Overhead}$$

This lecture: techniques to reduce memory, increase throughput, and lower latency

Memory arithmetic

Precision	Bytes/param	Formula
float32	4	$4 \times X$ GB
bfloat16 / float16	2	$2 \times X$ GB
int8	1	$1 \times X$ GB
int4	0.5	

um parameters



Quantization impact:

70B model in bfloat16: 140 GB
70B model in int8: **70 GB**
70B model in int4: **35 GB**

From 2 A100s $\rightarrow$ fits on 1 GPU!

Consumer GPUs:
RTX 4090 = 24 GB
RTX 3090 = 24 GB
Apple M4 Pro = 24 GB (unified)
$\Rightarrow$ 7B at 4-bit (3.5 GB) fits easily!

Part I

Attention Optimization

KV-Cache, MQA/GQA, Flash Attention

KV-Cache — the redundancy problem

Without caching: every step recomputes K, V for ALL previous tokens

Step 1: The → **cat**

Step 2: The cat → **sat**

recomputed!

Step 3: The cat sat → **on**

all recomputed again!

Wasted work:

Step t recomputes
$K_1, V_1, \ldots, K_{t-1}, V_{t-1}$
from scratch

Total: $O(n^3)$ for n tokens

Key insight: in causal attention, K_i and V_i for token i **never change** once computed — they depend only on $x_1, \ldots, x_i$, not on future tokens.

Q is always fresh (only the current token asks a "question").
K, V for past tokens are fixed — **cache them!**

Why not cache Q? Because we only ever need q_t (the current token's query), never past queries.

KV-Cache — the solution

With KV-Cache: only compute K, V for the NEW token, then concatenate

Step t:

Cached: $K_{1:t-1}, V_{1:t-1}$ (from previous steps) → **New:** K_t, V_t, q_t → **Full:** $K_{1:t}, V_{1:t}$ Attention: $q_t \times K_{1:t}^T$

$$K \leftarrow [K_{\text{cache}} \; ; \; K_{\text{new}}], \quad V \leftarrow [V_{\text{cache}} \; ; \; V_{\text{new}}]$$

$$O_t = \text{softmax}\left(\frac{q_t \cdot K^T}{\sqrt{d_k}}\right) \cdot V$$

Only q_t is $[1 \times d]$; K, V are $[t \times d]$ from cache

	Without cache	**With cache**
Compute per step	$O(t \cdot d^2)$ recompute all	$O(d^2)$ new token only
Total for n tokens	$O(n^2 \cdot d^2)$	$O(n \cdot d^2)$
Memory	Transient	Grows linearly

Benchmark (200 tokens, M4 CPU): without cache $\sim$5.3s, with cache $\sim$1.1s $\Rightarrow$ $\sim$**5**$\times$ **speedup**

Two phases of inference: prefill vs. decode

Phase 1: Prefill

Process entire prompt
at once (in parallel)

Build the initial KV-cache
for all prompt tokens

Compute-bound
(lots of matrix multiplies)

1000-token prompt →
process all 1000 in one pass
Time: ∼50–200 ms

Phase 2: Decode

Generate one token
at a time (sequential)

Append each new K, V
to the cache

Memory-bandwidth-bound
(reading weights dominates)

500-token response →
500 sequential forward passes
Time: ∼5–50 seconds

The decode phase is the bottleneck: each step reads *all* model weights from memory but only produces *one* token. GPU arithmetic units are mostly idle ⇒ **memory-bandwidth-bound**.

KV-Cache speeds up decode · Flash Attention helps prefill · Quantization helps both (fewer bytes to read)

KV-Cache memory cost

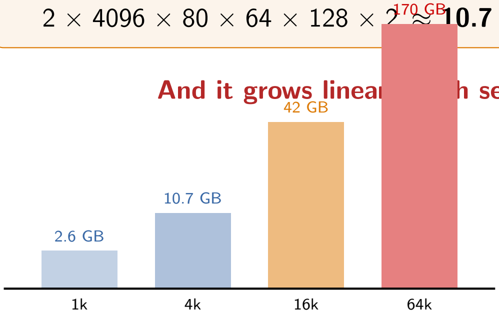
$$\text{KV-cache (bytes)} = 2 \times \text{seq\_len} \times n_{\text{layers}} \times n_{\text{heads}} \times d_{\text{head}} \times \text{bytes\_per\_value}$$

Factor 2 = one for K, one for V (stored per layer, per head)

Example: LLaMA-2 70B, seq_len = 4...

$2 \times 4096 \times 80 \times 64 \times 128 \times 2 \approx$ **10.7 GB**

And it grows linear... h seque...



Solution: share K/V heads

MHA: each head has own K, V (standard — large cache)

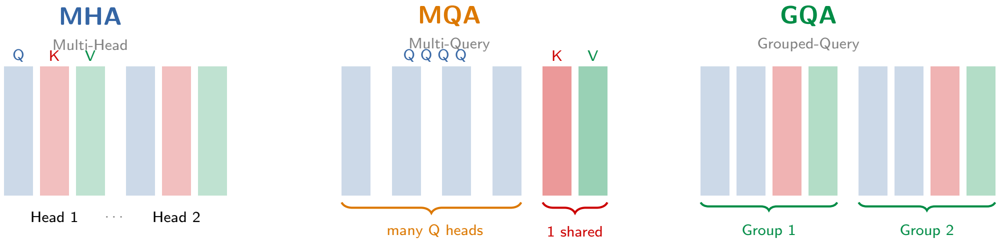
MQA: all heads share 1 K, V (40× smaller cache!)

GQA: groups of heads share K, V (good balance: quality + speed)

GQA: LLaMA 2/3, Mistral
MQA: Falcon, PaLM

MHA vs. MQA vs. GQA

How attention heads share Key and Value projections



	KV heads	Cache size	Quality
MHA (standard)	n_h (e.g., 40)	Baseline	Best
MQA	1	÷40	Slight degradation
GQA (g groups)	g (e.g., 8)	÷5	Near-MHA quality

LLaMA 2/3: GQA with 8 KV heads (32 Q heads) · **Mistral:** GQA with 8 KV heads

Flash Attention

Standard attention materializes the full $N \times N$ matrix QK^T in GPU memory (HBM).
At $N = 16{,}000$ with 40 heads in bfloat16: $\sim$**19 GB** just for this matrix!

Standard Attention

Compute full QK^T
↓
Store $N \times N$ in HBM
↓
Softmax
↓
Multiply by V

Memory: $O(N^2)$

→

Flash Attention

Tile Q, K, V into blocks
↓
Process blocks in fast SRAM
↓
Accumulate with online softmax
↓
Never store full $N \times N$

Memory: $O(N)$

Exact same output
Numerically identical to standard attention

IO-aware
Minimizes slow HBM reads/writes

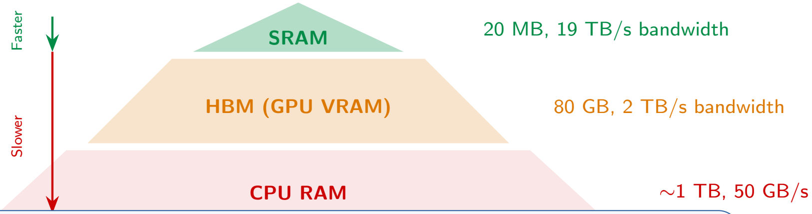
Drop-in
No model changes; just swap the kernel

Always use this. No reason not to.

Tri Dao et al., 2022 — FlashAttention: Fast and Memory-Efficient Exact Attention with IO-Awareness

Why Flash Attention works: the GPU memory hierarchy

GPU memory is NOT a single pool — there's a speed/size trade-off



Standard attention: compute QK^T ($N \times N$ matrix) in HBM $\rightarrow$ read/write to slow memory

Flash Attention: tile into blocks that fit in SRAM $\rightarrow$ **10$\times$ less HBM traffic**

The bottleneck is *memory bandwidth*, not compute. Flash Attention does *more* FLOPs but is faster!

Standard: $O(N^2)$ HBM reads
$N = 16k$, 40 heads:
$\sim$19 GB transferred

Flash: $O(N^2 d/M)$ HBM reads
$M =$ SRAM size
$\sim$2 GB transferred

Part II

Quantization

Reducing precision to reduce memory

What is quantization?

Represent weights in fewer bits: float16 $\rightarrow$ int8 $\rightarrow$ int4

float16
16 bits
65,536 values

int8
8 bits
256 values

int4
4 bits
16 values

At inference: $Y = X \cdot \text{dequantize}(W_q)$ instead of $Y = X \cdot W$

Inputs stay in bfloat16; weights are **stored**
in int4/int8 and dequantized on-the-fly

The good news:

4-bit quantization loses only
$\sim$2–3% quality on benchmarks

Larger models are more robust

The catch:

Dequantize adds overhead
$\Rightarrow$ not always faster

Primary benefit is **memory**, not speed

Key trade-off: memory $\downarrow$ accuracy (slightly) $\downarrow$ speed: depends on implementation

The math of quantization

Absmax (symmetric) quantization:

$$X_q = \text{round}\left(\frac{127}{\max|X|} \cdot X\right), \qquad \hat{X} = \frac{\max|X|}{127} \cdot X_q$$

Scal

Example:

$X = [1.2,\ -0.5,\ 3.0,\ -2.1], \quad \max|X| = 3.0, \quad s = 3.0/127 =$ 0.0236

$X_q = \text{round}([50.8,\ -21.2,\ 127.0,\ -88.9]) = [51,\ -21,\ 127,\ -89]$

Zero-point (asymmetric) quantization:

$$X_q = \text{round}\left(\frac{X - \min X}{s}\right) + z, \qquad s = \frac{\max X - \min X}{2^b - 1}$$

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r asymn

Block quantization:

Don't use one scale for the whole tensor — split into blocks of 64–128 values, each with its own scale factor.

Used by bitsandbytes (NF4)

NormalFloat4 (NF4):

Assumes weights are normally distributed. Quantization levels are optimally spaced for $\mathcal{N}(0, 1)$.

Used in QLoRA — better than uniform int4

When to quantize: PTQ vs. QAT

PTQ

Post-Training Quantization

When: after training

Data: small calibration set (or none at all)

Speed: minutes to hours

Quality: good at 4–8 bits; degrades at 2–3 bits

Examples: GPTQ, AWQ, bitsandbytes

→

QAT

Quantization-Aware Training

When: during training

Data: full training data

Speed: full training cycle

Quality: better at extreme compression (2–3 bits)

Examples: QLoRA (partial), BitNet, 1-bit LLMs

In practice: PTQ dominates for LLMs (nobody wants to retrain a 70B model). QAT is used for extreme compression or when training from scratch.

Quantization methods compared

Method	Calibration	Bits	Speed	Best for
bitsandbytes	None	4, 8	Slower	Quick experiments, QLoRA
GPTQ	Required	2–8	$2\times$ faster	Production deployment
AWQ	Required	3–4	Fast	Production, multi-modal

bitsandbytes

Zero-shot: quantize on load.
No calibration data.
Works with any nn.Linear.

Ideal for fine-tuning (QLoRA).

GPTQ

Uses Hessian (2nd order) to find optimal rounding.
Layer-by-layer quantization.

175B in $\sim$4 GPU hours.

AWQ

Protects salient weights (top 0.1–1% by activation).
Per-channel scaling.

MLSys 2024 Best Paper.

Quick rule: bitsandbytes to try $\rightarrow$ GPTQ/AWQ to deploy $\rightarrow$ QLoRA to fine-tune

GPTQ — optimal weight quantization

Problem: given weight matrix W, find W_q that minimizes layer output change:

$$\min_{W_q} \|WX - W_qX\|_2^2$$

Use the **Hessian** $H = 2XX^T$ to know which weights are sensitive

Algorit

Process model **layer by layer** (no full backprop needed)

For each layer, quantize weights **column by column**

Use inverse Hessian H^{-1} to determine **optimal rounding**

After quantizing each column, **update remaining weights** to compensate

175B model:

Quantized in ~4 GPU hours
3–4 bits, negligible quality loss
Fits on **one GPU**

Speedup:

3.25× on A100
4.5× on A6000
(with ExLlama/AutoGPTQ kernels)

Quantization benchmarks

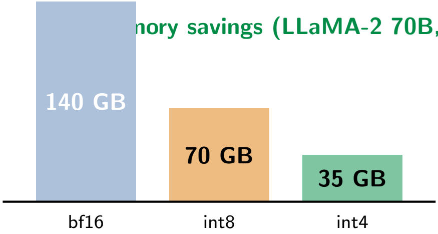
Quality (LLaMA-2, Open-LLM Leaderboard)

Method	**7B avg**	**13B avg**
Original (fp16)	54.32	58.66
bitsandbytes 4-bit	53.40	56.90
GPTQ 4-bit	53.23	57.56
Degradation	**$\sim$2%**	**$\sim$2–3%**

Speed (LLaMA-2 13B, A100)

Method	**tok/s**	**VRAM**
fp16	27.1	29.2 GB
GPTQ 4-bit	29.7	10.5 GB
bnb 4-bit	19.2	11.0 GB

nory savings (LLaMA-2 70B, bfloat16 baseline):



Key takeaways:

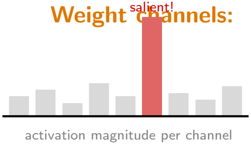
4-bit loses $\sim$2% quality
Saves $\sim$75% memory
GPTQ is fastest (optimized kernels)
bnb is easiest (no calibration)

Larger models degrade less

AWQ — protecting salient weights

Key insight: not all weights are equally important.
Only **0.1–1%** of weights are "salient" — and they correspond to channels with **large activation magnitudes**. Protecting them drastically reduces quantization error.

Weight channels:



1. Observe which channels have large activations (on calib data)
2. Apply **per-channel scaling**: multiply salient weights by s before quantization
3. Divide activations by s at

$$Q(w \cdot s) \cdot \frac{x}{s} \approx w \cdot x \quad \text{but with } \textbf{much less} \text{ quantization error}$$

The scaling s protects salient channels from aggressive rounding

Result: 3–4 bit quantization with quality matching GPTQ, sometimes better.
MLSys 2024 Best Paper · Works with instruction-tuned and multi-modal models.

QLoRA — quantized fine-tuning

QLoRA (Dettmers et al., 2023): combine 4-bit quantization with LoRA
$\Rightarrow$ fine-tune a 65B model on a **single 48 GB GPU**!

W_0 (NF4)
Frozen, 4-bit
$4\times$ smaller

$+$

B
bf16

A bf16

trainable

Three innovations:

1. NF4 quantization
optimal 4-bit for normal weights

2. Double quantization
quantize the quantization scales too

3. Paged optimizers
offload optimizer states to CPU

Forward: dequantize W_0 to bf16 on the fly, compute $h = W_0x + BAx$
Backward: gradients only flow through A and B (not W_0) $\Rightarrow$ tiny memory

65B on 1 GPU (48 GB):
Base: 130 GB (impossible)
QLoRA: $\sim$33 GB
$+$ LoRA overhead

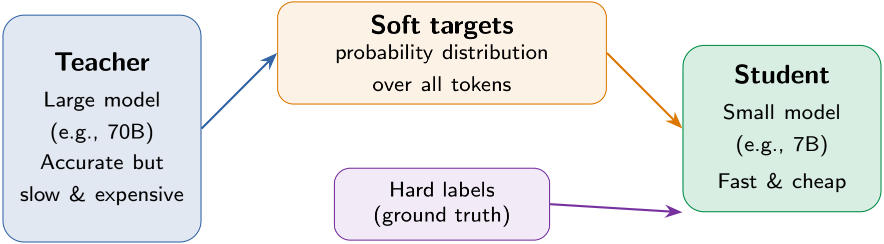
Quality:
Matches 16-bit full fine-tuning on benchmarks (chatbot arena)

Part III

Knowledge Distillation

Training a small model to mimic a large one

Knowledge distillation — teacher and student



"Dark knowledge" (Hinton, 2015): the teacher's soft distribution encodes *which wrong answers are more plausible* — information lost in hard labels.

Example: "cat" is more similar to "dog" than to "airplane" — the teacher's probabilities encode this.

Analogy: a master chef doesn't just say "this is tomato soup" — they explain "it's similar to gazpacho, a bit like minestrone, nothing like chocolate cake."

The distillation loss

Temperature-scaled softmax: $p_i = \dfrac{\exp(z_i/T)}{\sum_j \exp(z_j/T)}$

$T = 1$: sharp (standard) $\quad T \gg 1$: soft (reveals dark knowledge)

Combined distillation loss:

$$\mathcal{L} = \alpha \cdot \underbrace{\mathrm{CE}(y,\ \sigma(z_s; T=1))}_{\text{hard label loss}} + (1-\alpha) \cdot T^2 \cdot \underbrace{D_{\mathrm{KL}}(\sigma(z_t; T) \parallel \sigma(z_s; T))}_{\text{soft target loss}}$$

z_t = teacher logits, z_s = student logits, T^2 corrects gradient magnitudes

Why T^2?

Soft targets produce gradients scaled by $1/T^2$.
Multiplying by T^2 rebalances.

Typical values:

$$T = 2\text{–}20$$
$$\alpha = 0.1\text{–}0.5$$

Lower T when student is much smaller

Notable distilled models

Student	Teacher	Compression	Quality	Method
DistilBERT	BERT (110M)	1.7× (66M)	97% GLUE	KD + cosine loss
TinyLlama	LLaMA (7B)	6.4× (1.1B)	Competitive	Pre-train 3T tokens
Minitron 4B	LLaMA 3.1 (8B)	2× (4B)	+16% vs scratch	Prune + distill
DeepSeek-R1 7B	R1 (671B MoE)	96×	Beats 32B	800k reasoning samples
Llama 3.1 8B	Llama 405B	50×	≈ teacher	Synthetic data KD

DistilBERT

6 layers (vs. 12)
1.6× faster
Triple loss: KD + CE
+ cosine hidden states

DeepSeek-R1 7B

Fine-tune Qwen-2.5 7B
on 800k curated samples
Outperforms QwQ-32B
on AIME math

NVIDIA Minitron

Prune 50% neurons
then distill
40× fewer training tokens
Optimal: prune →
KD → quantize

Key insight: a distilled 7B can outperform a non-distilled 32B — the teacher's knowledge compresses remarkably well into a smaller architecture.

Part IV

Speculative Decoding

Lossless acceleration via draft-then-verify

Speculative decoding — the idea

Key observation: verifying γ tokens in parallel (one forward pass) takes $\approx$ the same time as generating 1 token from the large model

Standard Decoding

Large model generates one token at a time

Each token $=$ 1 full forward pass

n tokens $=$ n passes

→

Speculative Decoding

Small **draft** model guesses γ tokens fast

Large **verifier** checks all γ at once

Accept correct ones, resample wrong ones

Lossless: the output distribution is **mathematically identical** to the target model. Zero quality degradation!

Typical speedup: **2–2.5**$\times$ · Draft model must share the same tokenizer

Speculative decoding — the algorithm

Draft model
(small, fast)

$x_1 \rightarrow x_2 \rightarrow x_3 \rightarrow x_4$

$\gamma = 4$ draft tokens (autoregressively)

Target model
(large, slow)

x_1 x_2 x_3 x_4

Score ALL γ tokens in ONE forward pass

Step 3:

x_1 ✓ x_2 ✓ x_3 ✓ x_4 ×

Accept left to right; on first rejection, resample from correction distribution

Accept token x_i with prob:

$$\alpha(x_i) = \min\left(1, \frac{p(x_i)}{q(x_i)}\right)$$

$p =$ target, $q =$ draft

On rejection, resample from:

$$p'(x) \propto \max(0, p(x) - q(x))$$

Fills in probability mass
the draft model missed

Why speculative decoding is lossless

n is exactly $p(x)$ — here's why:

Case 1: $q(x) \leq p(x)$
(draft underestimates)

Accept with prob
$\frac{p(x)}{q(x)} \cdot q(x) = p(x)$
(always accept — but rejection from other tokens can trigger resampling from p')

Case 2: $q(x) > p(x)$
(draft overestimates)

Accept with prob $\frac{p(x)}{q(x)} < 1$
Excess mass is trimmed.
Correction distribution adds back what's missing.

$$P(\text{output} = x) = q(x) \cdot \alpha(x) + \beta \cdot p'(x) = p(x)$$

where $\beta = \sum_x \max(0, \; p(x) - q(x))$ is the total rejection probability

Intuition: "refund for overpayment, supplement for deficiency" — perfectly restores p

Expected tokens per target forward pass: $\mathbb{E}[\text{tokens}] = \sum_{i=0}^{\gamma} \prod_{j=1}^{i} \alpha_j$

When draft model closely matches target: most tokens accepted $\Rightarrow$ up to $(\gamma + 1)\times$ speedup

Chinchilla 70B: 2–2.5× speedup · **Whisper large:** 2.2× speedup (Chen et al., 2023)

Speculative decoding — worked example

Generating after "The capital of France is": $\gamma = 3$ draft tokens

Token 1: "Paris"

Draft q: 0.85
Target p: 0.90

$\alpha = \min(1, \frac{0.90}{0.85}) = 1.0$

ACCEPT

Token 2: ","

Draft q: 0.70
Target p: 0.75

$\alpha = \min(1, \frac{0.75}{0.70}) = 1.0$

ACCEPT

Token 3: "a"

Draft q: 0.40
Target p: 0.15

$\alpha = \min(1, \frac{0.15}{0.40}) = 0.375$

Random $r = 0.62 > 0.375$

REJECT

Correction: resample from $p'(x) \propto \max(0, p(x) - q(x))$

$p(\text{"which"}) - q(\text{"which"}) = 0.50 - 0.20 = 0.30$ (largest positive diff)

$p(\text{"known"}) - q(\text{"known"}) = 0.10 - 0.05 = 0.05$ $\Rightarrow$ Sample "which" or "known"

Result: 2 accepted + 1 resampled = **3 tokens from 1 target forward pass**

Standard decoding: 3 target passes. Speculative: 1 target pass + 3 draft passes $\approx$ 1.3 target passes

Production serving: continuous batching

Static Batching

Wait until batch is full

↓

Process all together

↓

Wait for *longest* sequence to finish

↓

Short requests wait idle

→

Continuous Batching

Start requests as they arrive

↓

Finished requests leave immediately

↓

New requests join mid-batch

↓

GPU always busy

Throughput improvement: up to **23$\times$ higher** than static batching (vLLM paper)

Key enabler: **PagedAttention** — manages KV-cache like OS virtual memory pages

vLLM

PagedAttention
Continuous batching

Open source

TGI

HuggingFace
Flash Attention

Token streaming

TensorRT-LLM

NVIDIA
Max performance

FP8 support

SGLang

RadixAttention
KV-cache reuse

Structured output

Inference optimization techniques compared

Technique	What it does	Memory	Speed	Quality
KV-Cache	Cache K, V across steps	$\uparrow$ (linear in seq)	$\sim 5\times \uparrow$	Identical
MQA/GQA	Share K/V heads	KV-cache $\downarrow\downarrow$	Faster	Near-identical
Flash Attn	Tile attention in SRAM	$O(N)$ vs $O(N^2)$	Faster	Identical
Quantization	Lower bit precision	50–75% $\downarrow$	Depends	$\sim$2–3% $\downarrow$
Distillation	Train smaller model	Model size $\downarrow\downarrow$	Much faster	3–10% $\downarrow$
Spec. Decoding	Draft + verify	Slight $\uparrow$	2–2.5$\times \uparrow$	Identical

These techniques compose! A modern deployment might use:

Flash Attention + GQA + KV-Cache + 4-bit GPTQ + Speculative Decoding

Each addresses a different bottleneck: compute, memory, bandwidth, latency

Example stack: LLaMA 3 70B + GQA (built-in) + Flash Attention 2 + AWQ 4-bit $\Rightarrow$ runs on a single A100 80 GB with 4k context at $\sim$30 tokens/s

Practical guide

What should I use?

Always use (free wins):

KV-Cache (always on)
Flash Attention 2
GQA (if architecture supports)

Model too big for my GPU?

$\Rightarrow$ **Quantize** (4-bit AWQ/GPTQ)

70B $\rightarrow$ 35 GB, fits on 1 GPU

Need maximum speed?

$\Rightarrow$ **Distill** to a smaller model
+ quantize the distilled model

Prune $\rightarrow$ KD $\rightarrow$ Quantize

Want free speedup?

$\Rightarrow$ **Speculative decoding**

2× faster, zero quality loss

Needs a matching draft model

Quick experiment?

$\Rightarrow$ **bitsandbytes** 4-bit

One line: load_in_4bit=True

Production deployment?

$\Rightarrow$ **GPTQ/AWQ** + vLLM

Optimized kernels, continuous batching

Further reading

Quantization

- Frantar et al. (2023), "GPTQ: Accurate Post-Training Quantization for Generative Pretrained Transformers"
- Lin et al. (2024), "AWQ: Activation-aware Weight Quantization for LLM Compression"
- Dettmers et al. (2023), "QLoRA: Efficient Finetuning of Quantized Language Mod-

Efficient Serving

- Kwon et al. (2023), "Efficient Memory Management for LLM Serving with PagedAttention" (vLLM)
- Dao et al. (2022), "FlashAttention: Fast and Memory-Efficient Exact Attention"

Distillation & Pruning

- Hinton et al. (2015), "Distilling the Knowledge in a Neural Network"
- Sanh et al. (2019), "DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter"

Questions?

Next: RAG — Retrieval-Augmented Generation