Efficient Inference: Compute Less, Move Fewer Bytes

At inference the model is often waiting on memory, not arithmetic

Prof. Nipun Batra

ES 667 · Deep Learning · IIT Gandhinagar

Diagnose before optimizing

Why this belongs in a deep-learning course

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one worked calculation (KV-cache memory) · one essential distinction (prefill vs decode)

The two phases of autoregressive inference

V VISUAL

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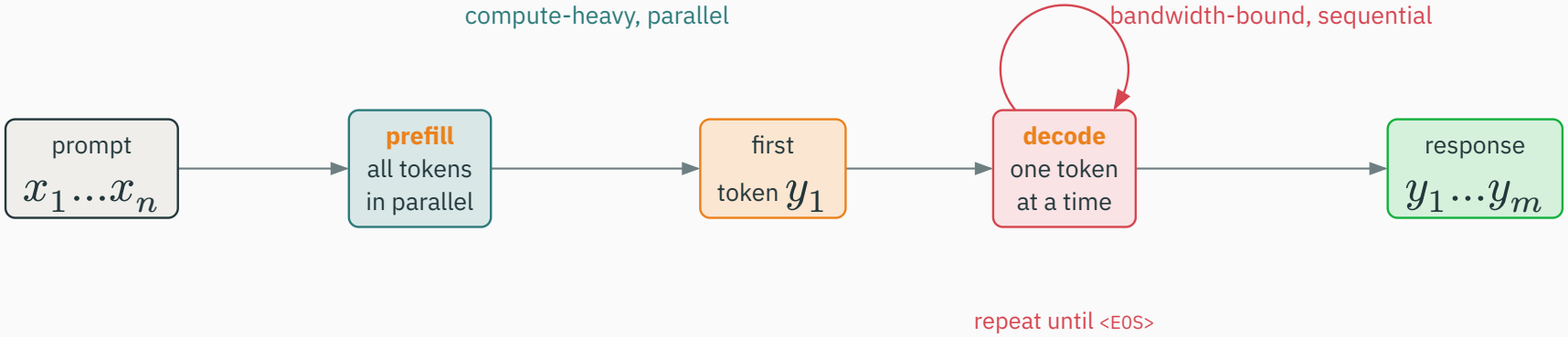

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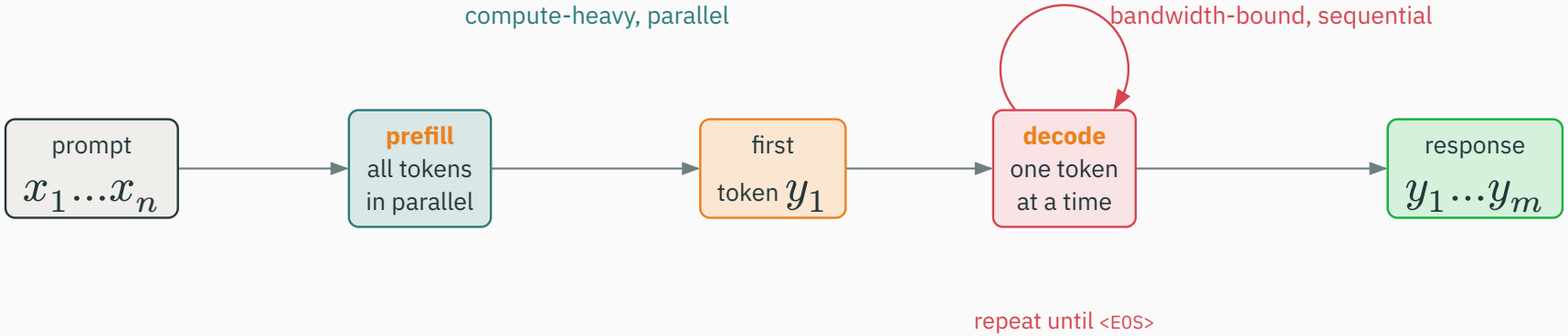

processing the prompt and producing one token at a time have **different shapes, costs, and optimizations**

Prefill — process the prompt in parallel

D DERIVATION

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- large **matrix–matrix** products keep the accelerator busy;
- each weight is reused across **many** token vectors — high arithmetic intensity;
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> decode is typically **memory-bound** — the device spends its time fetching weights and cache

Compute-bound versus memory-bound

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Regime	What limits you
compute-bound	arithmetic units saturated; more FLOPs = more time
memory-bound	device idles waiting to **fetch** weights / activations

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optimize the **right** thing: shrinking FLOPs has little effect unless it also lowers byte traffic

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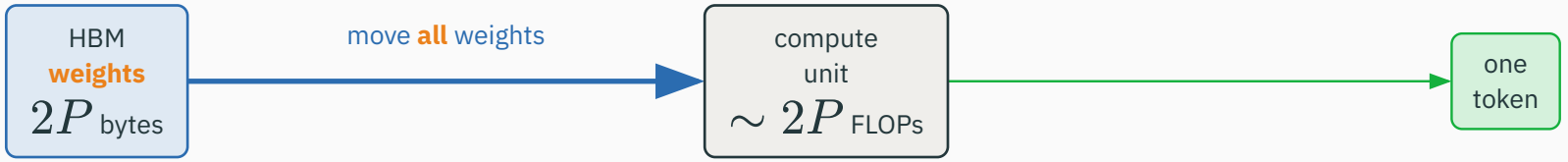

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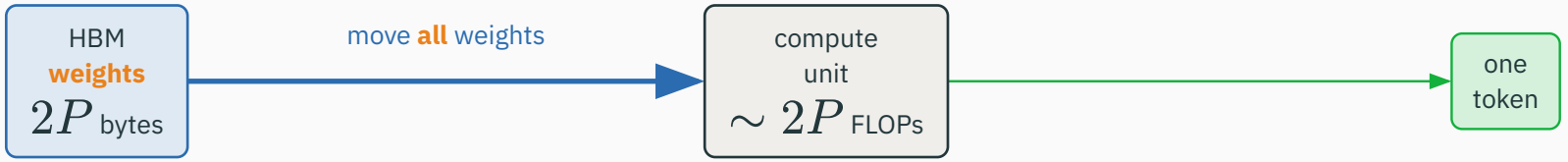

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the accelerator can sit **idle** even with abundant FLOPs — it is waiting on the weight fetch

The roofline picture

V VISUAL

Attainable throughput is capped by **bandwidth** until arithmetic intensity crosses the ridge:

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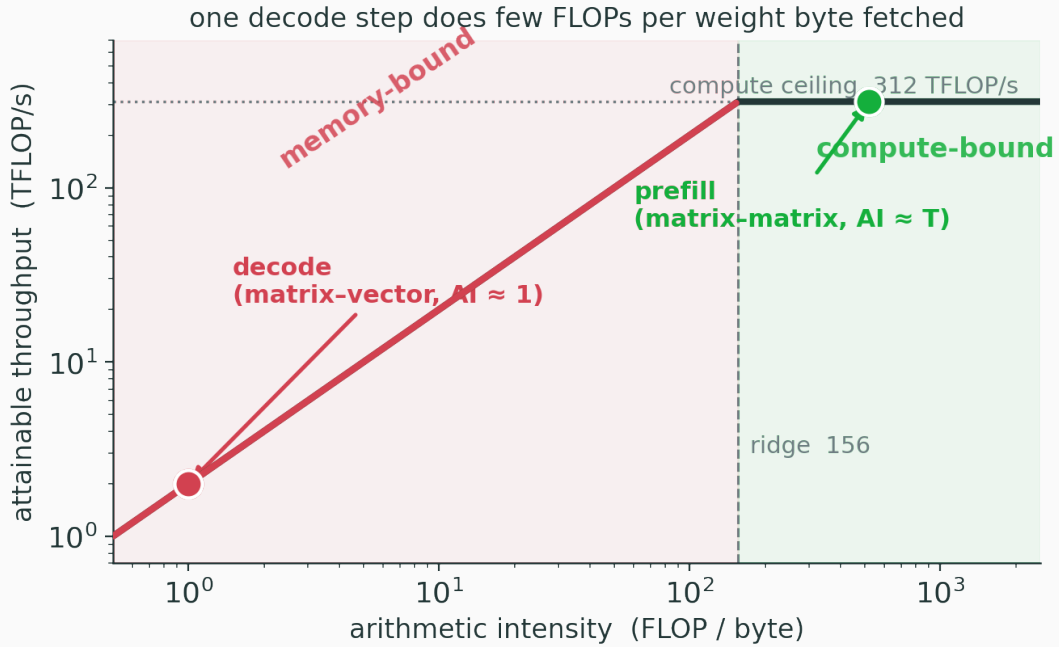

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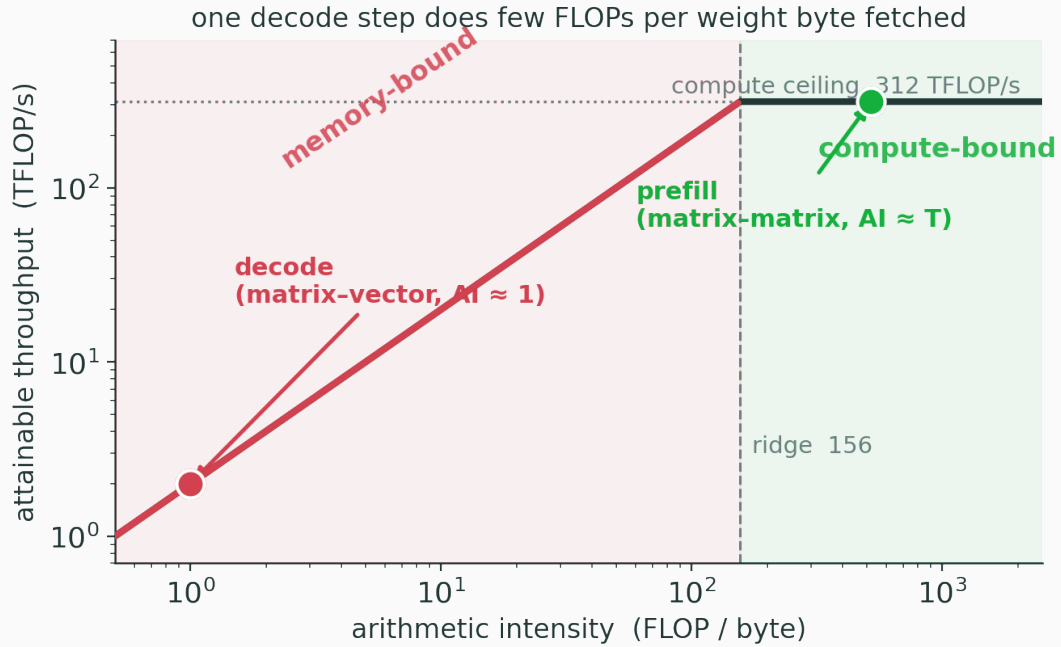

decode (AI ≈ 1) sits deep in the memory-bound region; **prefill** (AI $\approx T$) reaches the compute ceiling

The bytes intuition, said plainly

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This is why a device with "enough FLOPs" can still be slow at generation. The fix is rarely "more compute" — it is **move fewer bytes** and **reuse what you already moved**.

The inference budget worksheet

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Every deployment must name its constraints **before** optimizing:

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latency	throughput	VRAM	quality	cost
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every optimization improves **one or more** of these — with a **trade-off** in the others

KV cache: reuse what attention already computed

Recall causal attention

D DERIVATION

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the new query reads the **whole prefix** — so the prefix's keys and values must be available

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for t in range(1, T):
    # recompute K, V for ALL of tokens 1..t  ← wasteful
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Tokens $1, \ldots, t-1$ have not changed, yet their key/value projections are recomputed at every step — $O(T)$ redundant work per token, $O(T^2)$ overall.

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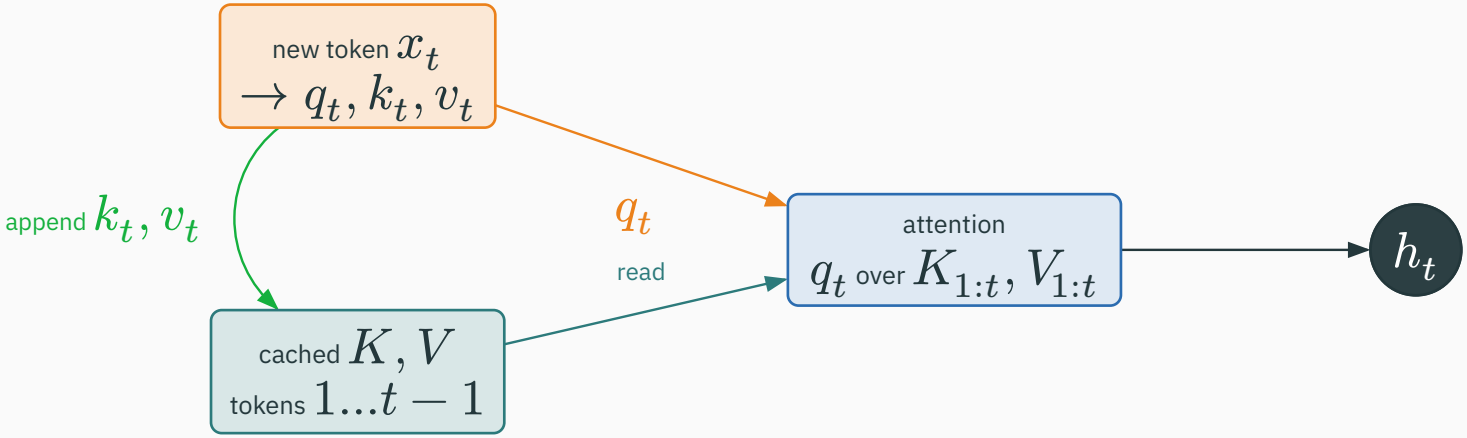

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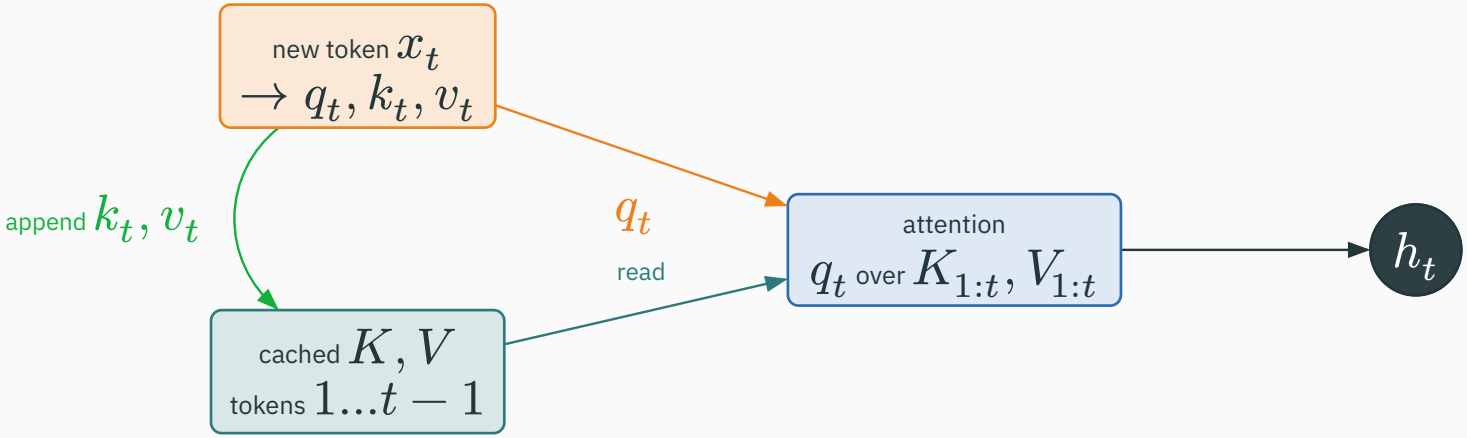

earlier tokens $\rightarrow$ cached K, V · new token $\rightarrow$ new q, k, v · append k_t, v_t and read the whole cache

Interactive: the KV cache

I INTERACTIVE

INTERACTIVE

↗ nipunbatra.github.io/interactive-articles/kv-cache

Step a short prompt through decode: watch each new token compute only its own q_t, k_t, v_t, **append** k_t, v_t to the growing cache, and attend over the whole stored history — no recomputation of old projections.

What caching saves — and what it does not

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KV cache turns repeated **projection** into a **memory lookup** — the read still grows with context

KV-cache shape, per layer

D DERIVATION

At every layer we store **two** tensors:

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$$K, V \in \mathbb{R}^{B \times T \times n_{\text{kv}} \times d_h}$$

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two tensors, at **every** one of the L layers

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Sum the two tensors over all L layers, at b bytes per stored value:

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linear in L, in B, and in T — three ways for the cache to grow

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≈ 512 **MiB — for a single sequence, before concurrency**

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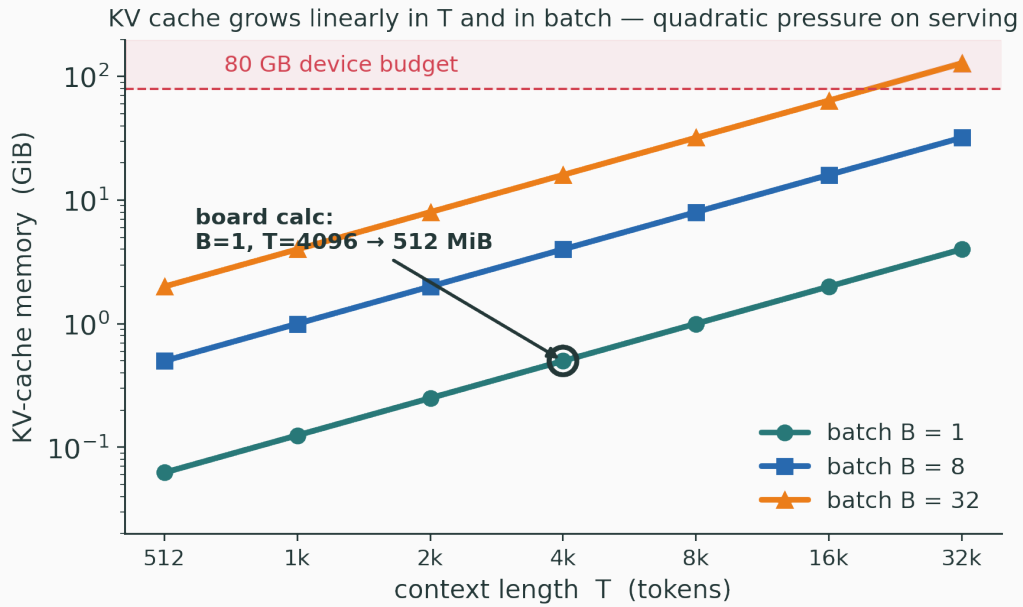

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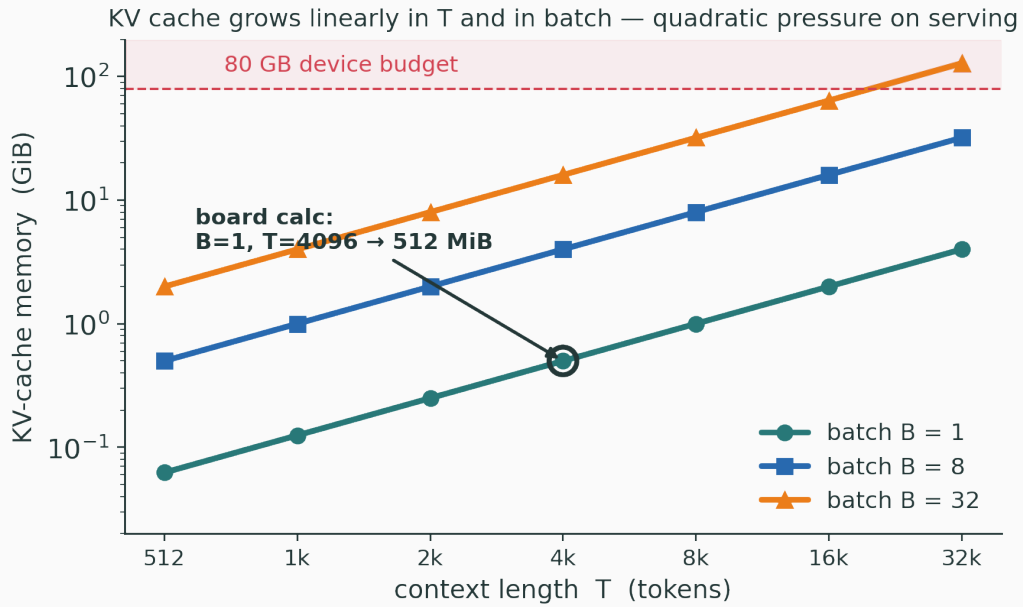

long contexts and high concurrency make **memory** — not parameters — the dominant capacity limit

Architectural response: fewer KV heads

V VISUAL

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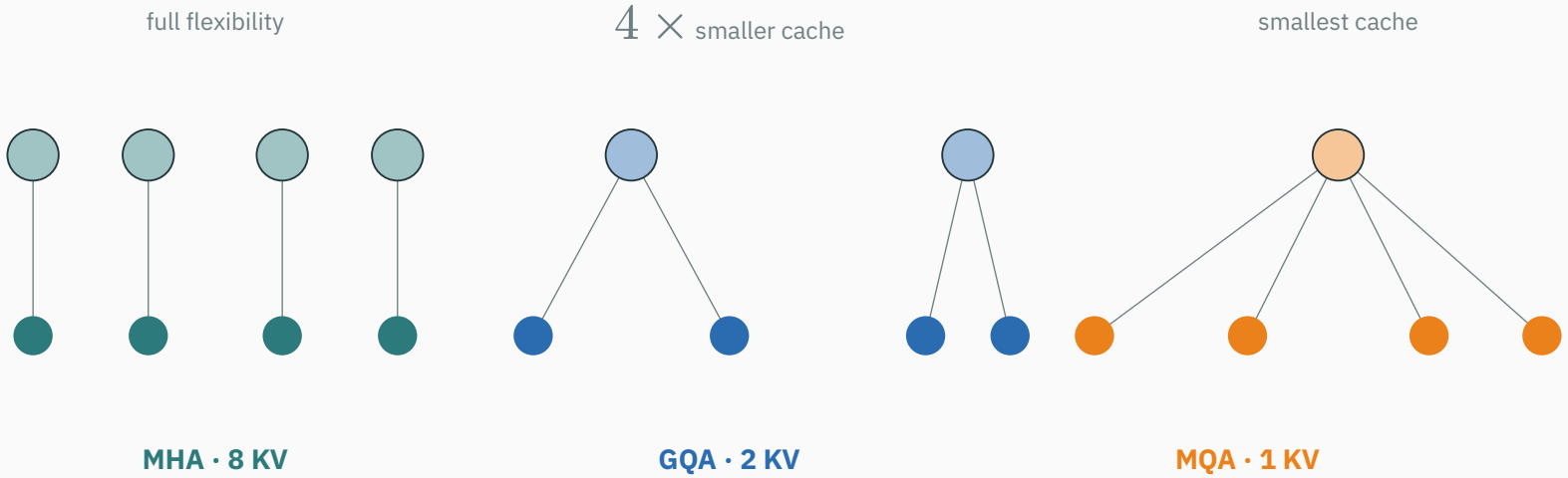

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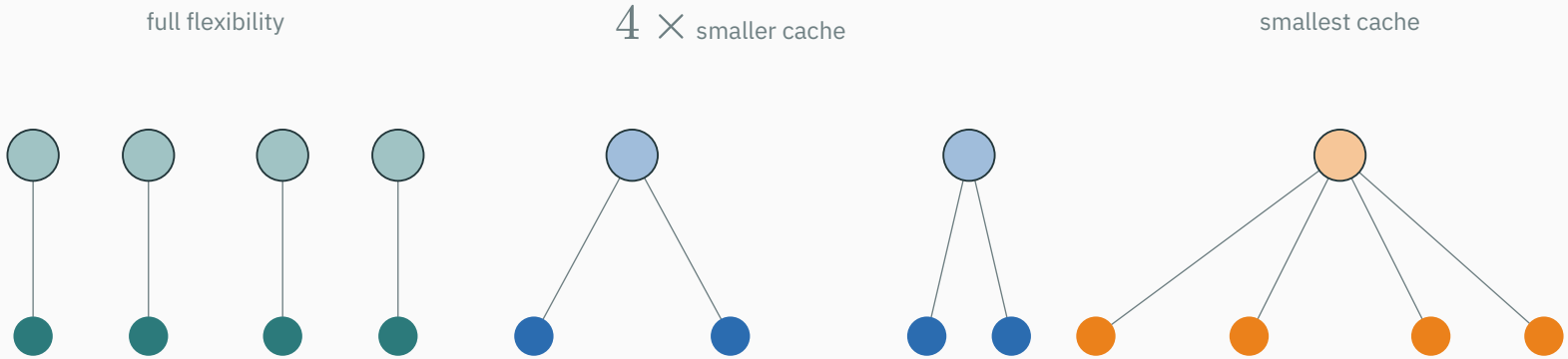

$n_{\text{kv}} < n_{\text{query}}$ shrinks the cache by exactly $n_{\text{query}}/n_{\text{kv}}$, keeping many query perspectives

The main inference levers

Quantization: store fewer bits

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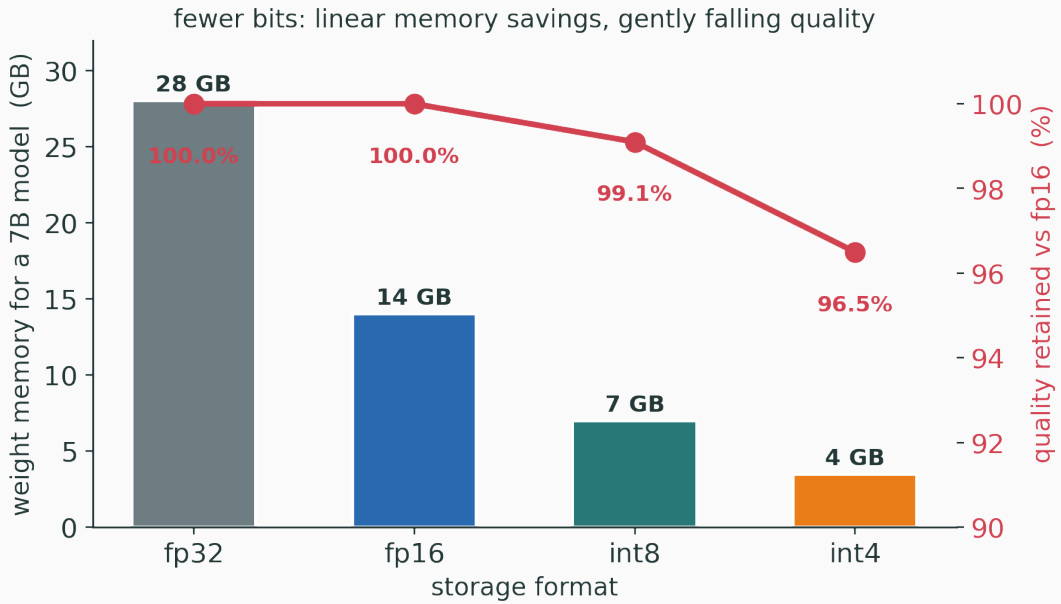

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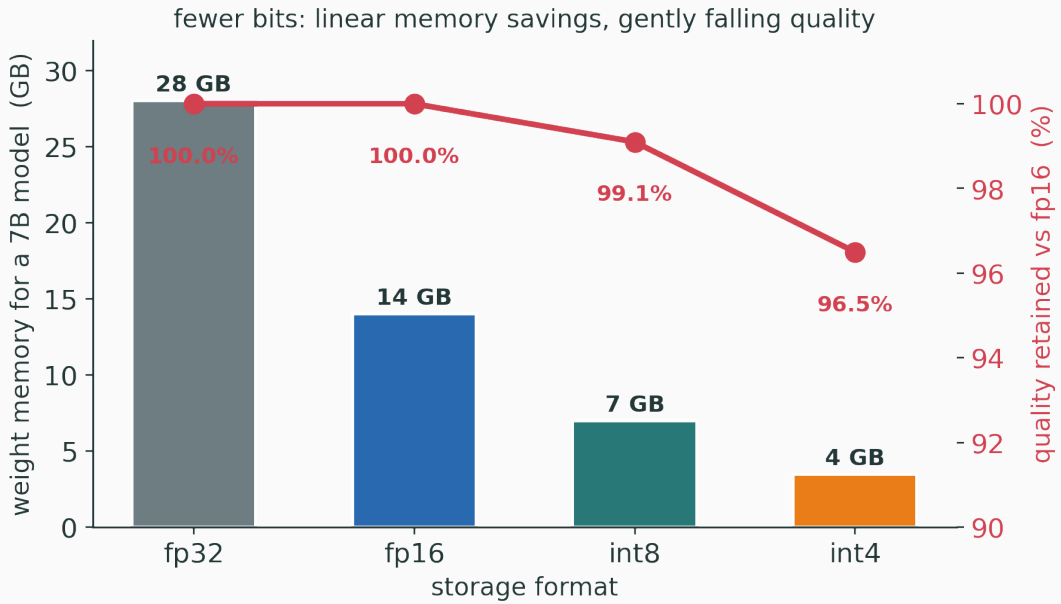

fewer bytes ⟶ less memory and faster bandwidth-bound decode; approximation can cost quality

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D DERIVATION

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- **weight-only** — shrink the parameters (helps the memory-bound decode read);
- **activation / KV-cache** — also quantize the running state (helps long-context memory);
- **post-training (PTQ)** vs **quantization-aware training (QAT)** — calibrate after, or train with, low precision.

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each choice trades quality, memory, and engineering effort differently

Attention kernels: avoid giant intermediates

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FlashAttention is the canonical example — same answer, far less high-bandwidth-memory traffic (we do not teach the CUDA)

Batching and scheduling

D DERIVATION

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The systems problem: pack varied requests to keep the device busy **without** stalling any one of them. We name the problem — we do not build a serving stack.

Paged / block-based KV storage

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the resource-management idea — not the framework internals — is what matters here

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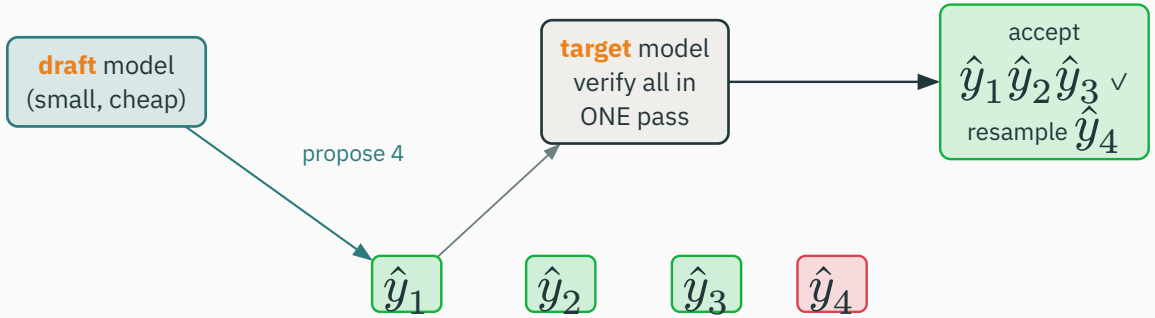

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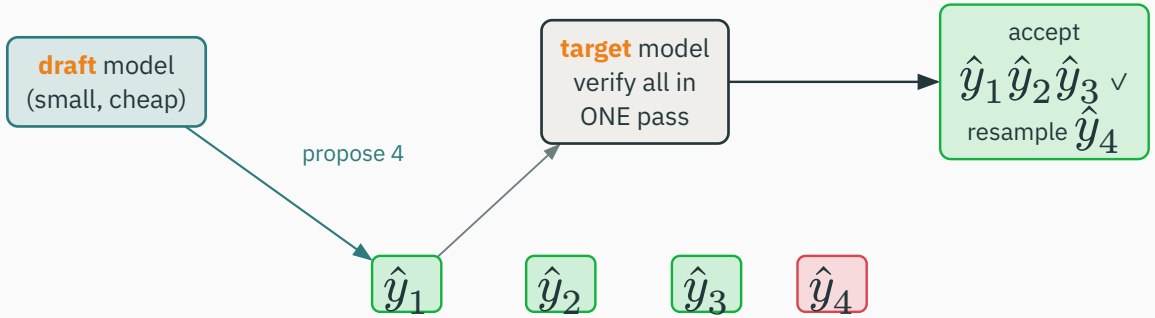

the **target** model preserves output quality; speedup depends on how often draft tokens are accepted

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It does **not** make the big model unnecessary — the target still verifies every token, so the output follows the target's distribution.

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this changes the **model**, not only the serving procedure — soft targets carry more signal than one hard label

Interactive: knowledge distillation

I INTERACTIVE

INTERACTIVE

↗ nipunbatra.github.io/interactive-articles/knowledge-distillation

Sweep the temperature T and watch the teacher's **soft** label distribution flatten — see how the student learns the relative ranking of alternatives, not just the top-1 answer.

Pruning and sparsity

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Remove weights (or whole structures) that contribute little:

Unstructured — zero out individual small weights. High sparsity, but hardware rarely speeds it up.

Structured — drop whole heads / channels / layers. Less sparsity, but a **real** smaller-faster model.

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D DERIVATION

Remove weights (or whole structures) that contribute little:

Unstructured — zero out individual small weights. High sparsity, but hardware rarely speeds it up.

Structured — drop whole heads / channels / layers. Less sparsity, but a **real** smaller-faster model.

sparsity helps only when the **hardware** can skip the removed work — structure is what buys speed

Interactive: quantization and pruning

I INTERACTIVE

INTERACTIVE

↗ nipunbatra.github.io/interactive-articles/quantize-prune

Dial the bit-width down from 16 to 4 and sweep a pruning threshold — watch weight memory shrink, the quantization error grow, and task quality hold then fall as you push the compression too far.

Mixture of experts: conditional compute

V VISUAL

Route each token to a **few** of many expert sub-networks — grow parameters without growing per-token FLOPs:

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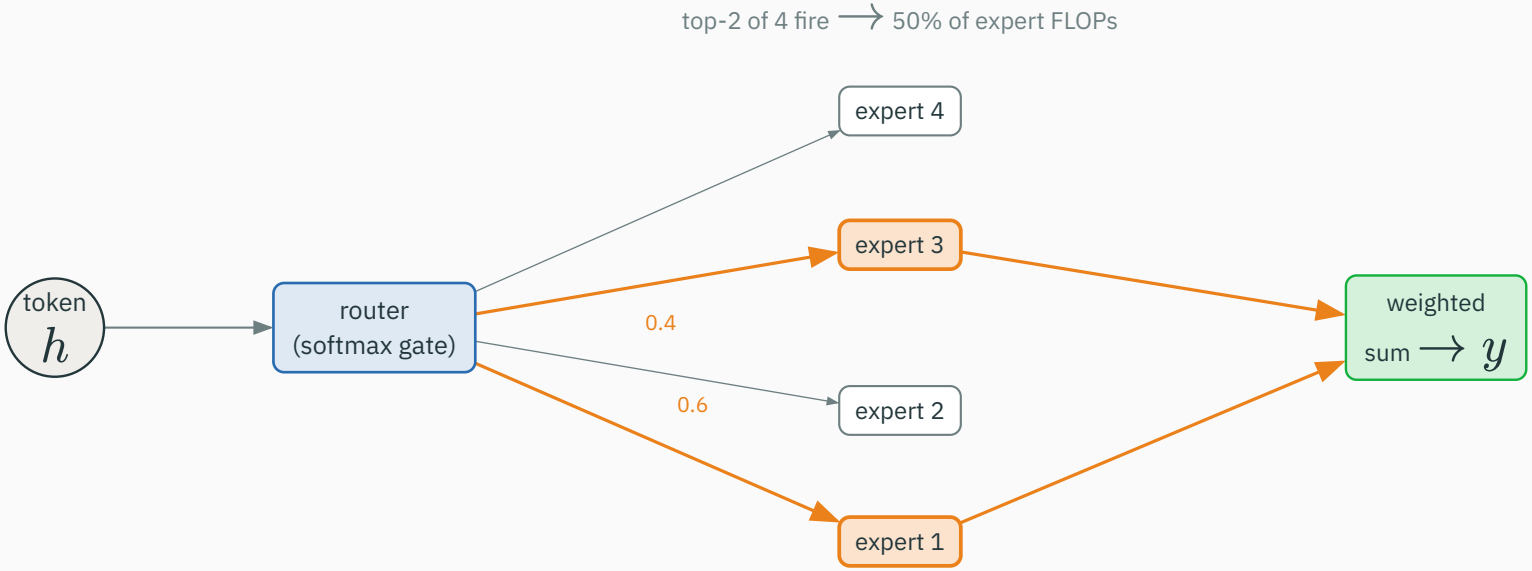

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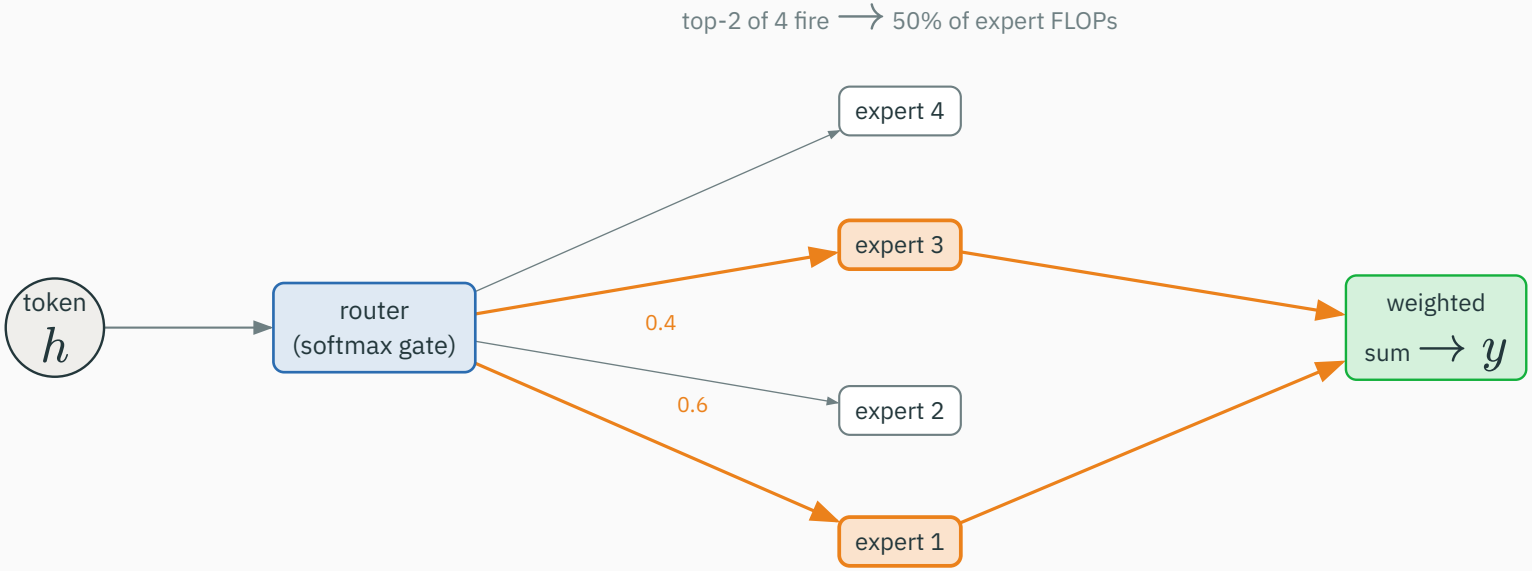

a router picks the top-k experts; only those run — capacity scales, active compute does not

MoE worked example

D DERIVATION

8 experts, top-2 routing: each token fires $2/8 = 25\%$ of the expert capacity.

MoE worked example

D DERIVATION

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$\approx 3.6\times$ **fewer active parameters than total — capacity you do not pay for every token**

Interactive: mixture of experts

I INTERACTIVE

INTERACTIVE

↗ nipunbatra.github.io/interactive-articles/mixture-of-experts

Send tokens through a router and watch the top-k gate light up a small subset of experts — total parameters climb while the **active** compute per token stays fixed.

A decision table

V VISUAL

Lever	Mainly attacks	Main cost
KV cache	repeated prefix computation	VRAM
quantization	weight / cache bandwidth	approximation, engineering
efficient attention kernel	intermediate-memory traffic	specialized implementation
batching / paging	underutilization, fragmentation	scheduling complexity
speculative decoding	sequential target steps	draft model, variable gain
distillation	model size / latency	retraining, possible quality loss

Apply the systems lens across the course

Diffusion connection

D DERIVATION

Diffusion sampling repeatedly invokes the **denoiser** — the same “repeated call” cost structure:

Diffusion connection

D DERIVATION

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- **faster samplers** — fewer denoising steps (the sequential bottleneck);
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- **batching** and **quantization** — cheaper individual calls.

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every trick here reduces the cost of **repeated invocations** — LLM decode and diffusion sampling rhyme

Representation-learning connection

D DERIVATION

A good frozen encoder is also an **engineering asset**:

Representation-learning connection

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- compute features **once**; attach lightweight **linear probes** downstream;
- a strong representation makes the whole downstream system **cheaper**, not only more accurate.

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accuracy and efficiency are the same coin: a better representation buys both

Case exercise — pick a system

Q QUESTION

Choose one and reason about its inference profile:

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Choose one and reason about its inference profile:

System	Dominant pressure
chat, long prompts, many users	KV-cache memory + concurrency
mobile image classifier	device VRAM + compute
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choose **two** optimizations and name the expected trade-off — we return to this at the end

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Efficient inference is mostly about avoiding repeated work and moving fewer bytes.

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Q QUESTION

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KV cache, prefix reuse, FlashAttention, quantization, batching — all instances of this one idea

Closing bridge

The final lecture stacks **agents, reasoning systems, and interpretability** on top of this same foundation:

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models + objectives + optimization + representations + **inference constraints**

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deployment constraints are **first-class** model-design constraints, not an afterthought

Detailed systems slides

Parameter memory comes first

D DERIVATION

For P parameters, the weights alone need:

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D DERIVATION

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Storage format	Approx. weight memory
fp32	$4P$ bytes
fp16 / bf16	$2P$ bytes
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a first-order figure — runtime also pays for KV cache, activations, and framework overhead

Weight-memory example

D DERIVATION

A **7-billion**-parameter model in fp16:

Weight-memory example

D DERIVATION

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Why is a "16 GB" device still inadequate? Weights (14 GB) leave almost nothing for KV cache, activations, and overhead — long-context generation needs **far** more headroom.

Arithmetic intensity intuition

D DERIVATION

The **same weights**, two very different reuse patterns:

Arithmetic intensity intuition

D DERIVATION

The **same weights**, two very different reuse patterns:

Phase	Op shape	Reuse per fetched weight
prefill	matrix–matrix	high (many token vectors)
decode	matrix–vector	low (one token vector)

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no hardware-specific roofline number needed — the **shape** already tells the story

Causal attention cost, briefly

D DERIVATION

A full attention layer compares token pairs:

Causal attention cost, briefly

D DERIVATION

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$$O(T^2 d)$$

Causal attention cost, briefly

D DERIVATION

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KV caching removes the recomputation of **old projections** during decode. It does **not** remove the new query's need to attend across the stored history — the cache read still scales with T.

Cache append at one layer

D DERIVATION

At token t, extend the cache and attend:

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```
k_t, v_t = project(x_t)          # new token only
K = cat(K_cache, k_t); V = cat(V_cache, v_t)
h_t = attention(q_t, K, V)       # read the whole history
K_cache, V_cache = K, V          # append for next step
```

Recompute versus cache

V VISUAL

Strategy	Compute	Memory	Decode latency
recompute full prefix	very high	low cache	poor
store KV cache	lower	grows with T	much better

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this table is the **central systems trade-off** of the lecture — spend memory, avoid repeated compute

KV-cache calculation, step by step

D DERIVATION

Start from the formula and substitute:

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$$2 \cdot L \cdot B \cdot T \cdot n_{\text{kv}} \cdot d_h \cdot b, \quad L = 32, B = 1, T = 4096, n_{\text{kv}} = 8, d_h = 128, b = 2$$

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$$536{,}870{,}912 \ / 1024^2 = 512 \quad \Longrightarrow \quad \approx 512 \text{ MiB} \quad \text{(before concurrency)}$$

Concurrency changes the answer

V VISUAL

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V VISUAL

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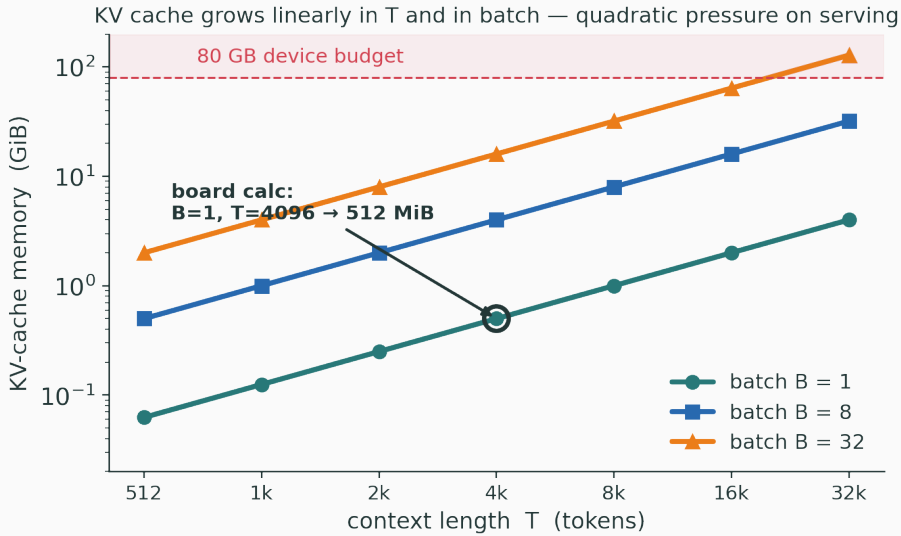

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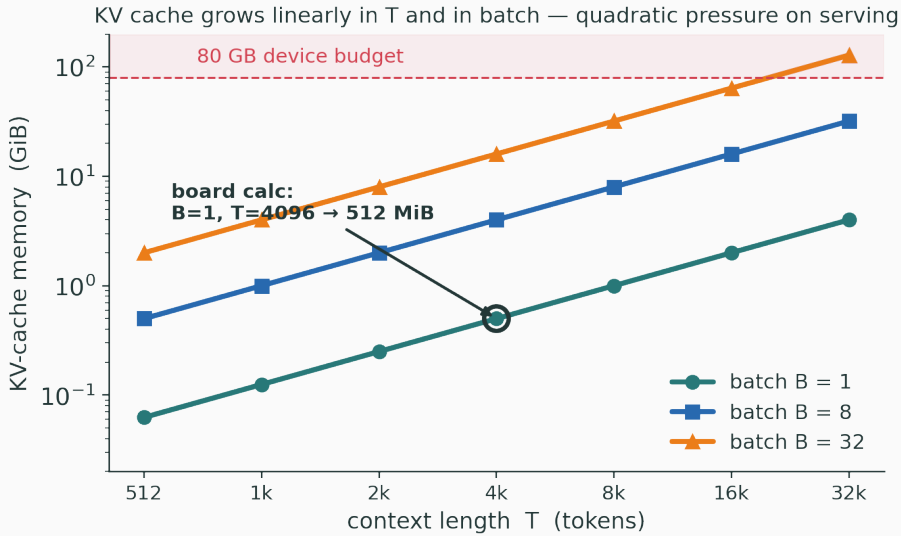

long contexts × many users make cache capacity a **product-level** constraint, not a footnote

Grouped-query attention

D DERIVATION

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$= n_{\text{query}}$ (MHA)	$1\times$	full
group (GQA)	$n_{\text{query}}/n_{\text{kv}}$ smaller	most
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a direct knob on the cache term $n_{\text{kv}} \cdot d_h$ — retains multiple query perspectives

Quantization is approximate representation

V VISUAL

Store a real-valued block approximately as a low-bit integer tensor plus metadata:

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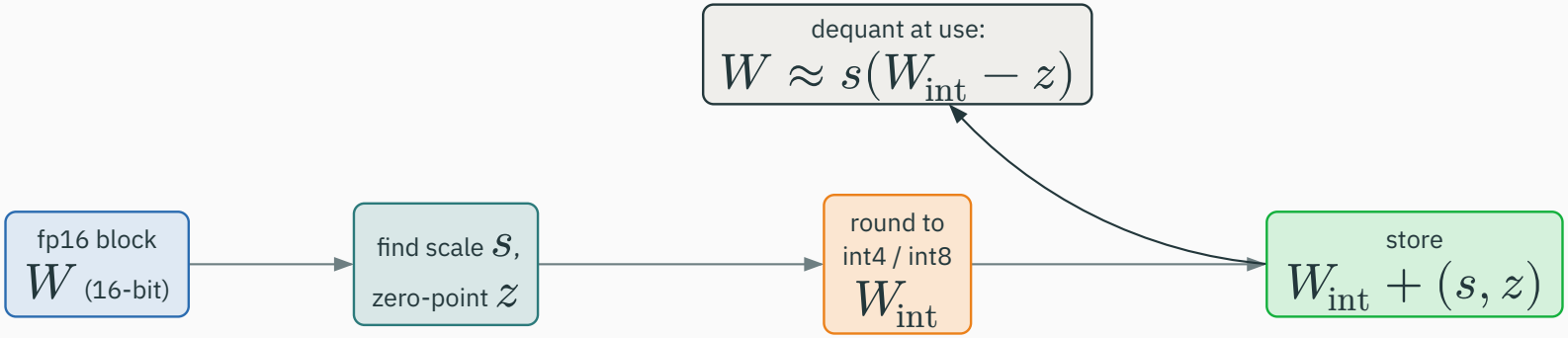

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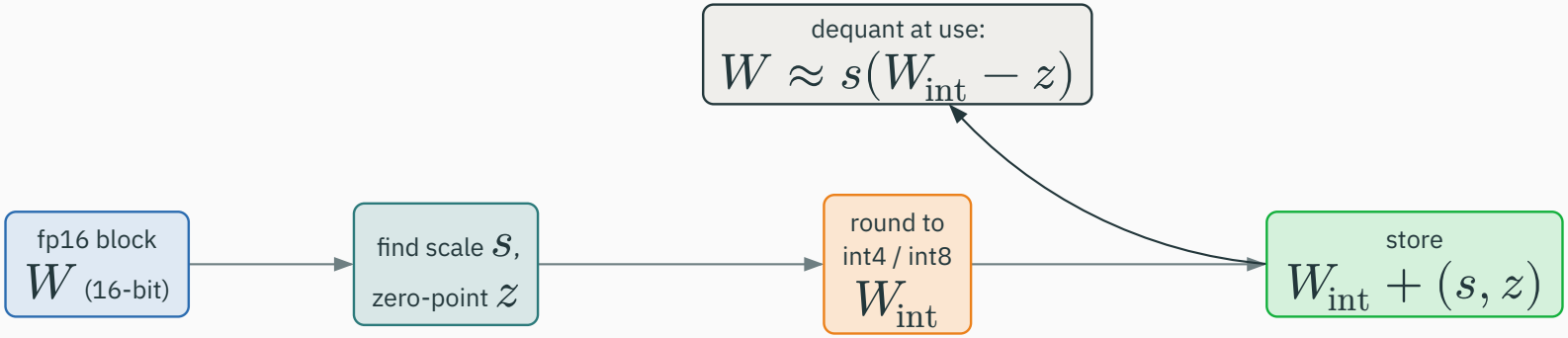

$W \approx s(W_{\text{int}} - z)$ (scale s, optional zero-point z)

Quantization design choices

D DERIVATION

Choice	Question it answers
per-tensor or per-channel scale	how much variation must be preserved?
weight-only or activations too	where is the memory / bandwidth pressure?
8-bit or 4-bit	what quality loss is acceptable?
post-training or trained-aware	can we afford to adapt the model?

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finer scales preserve outliers; coarser scales save more — the central quantization tension

Quantization is not free speed

D DERIVATION

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Speedups depend on **hardware and kernel support**. Dequantization, metadata, and irregular operations can eat much of the theoretical saving.

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D DERIVATION

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a useful systems-literacy correction: “smaller weights” $\neq$ “automatically faster”

FlashAttention as a memory algorithm

D DERIVATION

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teach it as “same answer, fewer bytes moved” — an IO-aware rewrite, not a new model

Prefix caching

D DERIVATION

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D DERIVATION

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> the serving analogue of dynamic programming — never redo the shared sub-computation

Continuous batching

V VISUAL

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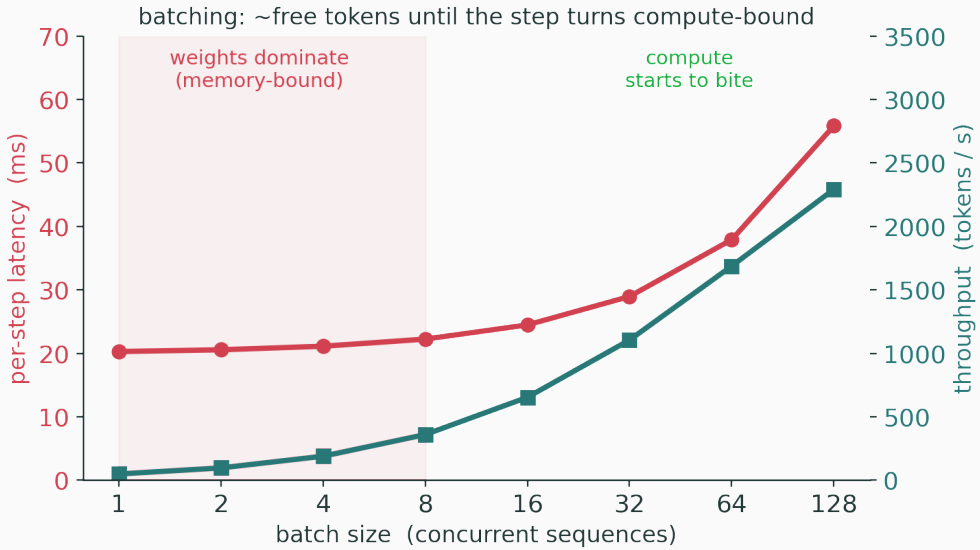

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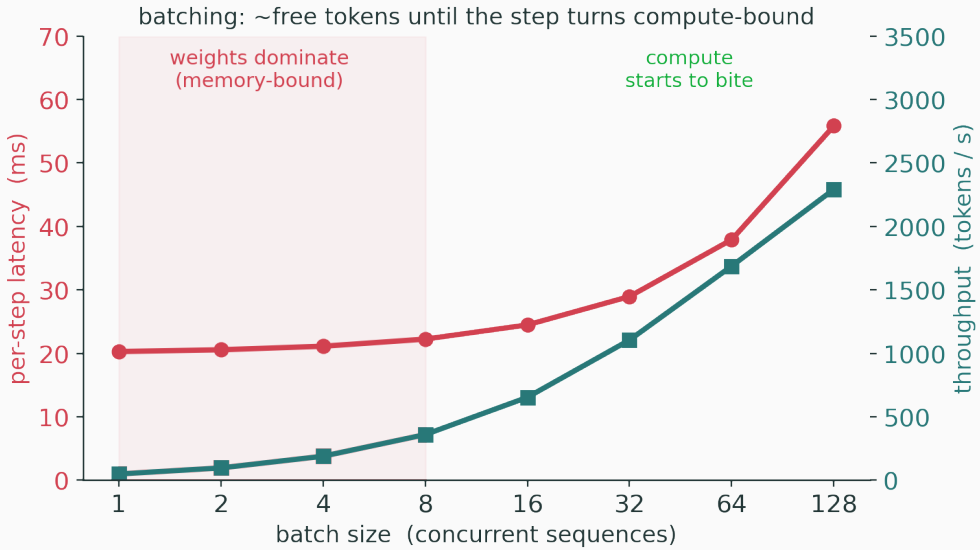

the target becomes **throughput and tail latency** — not one request's speed in isolation

Blocked KV allocation

D DERIVATION

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Blocked KV allocation

D DERIVATION

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- reduces fragmentation;
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keep framework names off the slide — the resource-management idea is the lesson

Speculative decoding, expanded

D DERIVATION

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D DERIVATION

1. a small **draft** model proposes several tokens;
2. the large **target** model checks them together in one pass;
3. **accept** a matching prefix;
4. **sample a correction** where the draft diverges.

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D DERIVATION

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```
draft_tokens = draft.generate(context, k=4)      # cheap, sequential-but-small
logits = target(context + draft_tokens)          # ONE target pass, parallel
accept = longest_matching_prefix(draft_tokens, logits)
context += accept + resample_if_rejected(logits) # target stays the authority
```

Acceptance rate determines speedup

D DERIVATION

The whole payoff hinges on how often the draft is **right**:

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a well-matched, fast draft is the entire game — a slow or inaccurate draft can even **lose**

Distillation changes the model

D DERIVATION

Train the student against the teacher’s temperature-softened distribution:

Distillation changes the model

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$$L_{\text{distill}} = T^2 \, D_{\text{KL}}(\text{softmax}(z_{\text{teacher}}/T) \| \, \text{softmax}(z_{\text{student}}/T))$$

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Soft targets convey **relative alternatives** — "mostly cat, a little dog, never car" — far richer than a single hard label. The T^2 factor keeps gradient magnitudes stable as T rises.

Compression versus serving optimization

V VISUAL

Approach	Retraining?	Main effect
quantization	often no	fewer bits / lower bandwidth
KV cache	no	avoid repeated prefix work
speculative decoding	no target retraining	fewer sequential target steps
distillation	yes	smaller / faster model

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some levers **change the model**; others only **change how it is served** — know which you are pulling

Case exercise: choose levers

Q QUESTION

Scenario	Reasonable pair (name the trade-off)
A · long-doc chat, many users	GQA + paged KV · quality-neutral, scheduling cost
B · offline phone classifier	distillation + int8 · retrain effort, small quality dip
C · image generator, 2 s budget	fewer sampler steps + quantization · slight fidelity loss

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there is no free lever — every choice pays somewhere in quality, cost, or engineering

Common misconceptions

V VISUAL

Misconception	Correction
“KV cache makes attention constant-time.”	avoids old projections; cache **reads** still grow with context
“Quantization always improves every metric.”	trades precision; relies on efficient kernels
“FlashAttention changes Transformer math.”	same attention, different **memory movement**
“A draft model replaces the target model.”	the target still **verifies** every output token

Retrieval questions

Q QUESTION

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Retrieval questions

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2. What **exactly** is stored in a KV cache?
3. Which variables make cache memory **grow**?
4. Why can 4-bit weights help a **bandwidth-bound** workload?
5. Which optimization changes the **underlying model** rather than only serving it?

Memory-budget worksheet

D DERIVATION

Before loading a model, estimate **all four** terms:

Memory-budget worksheet

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$$\underbrace{\text{weights}}_{2P} + \underbrace{\text{KV cache}}_{\text{grows with } BT} + \text{temporary activations} + \text{runtime overhead}$$

Memory-budget worksheet

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For a **serving** system, multiply the KV-cache term by **expected concurrency** — not by one idealized request. This is where “it fit in the demo” becomes “it OOMs in production”.

Context-window policy is a systems policy

D DERIVATION

A larger maximum context improves user experience but **raises cache memory and attention work**:

Context-window policy is a systems policy

D DERIVATION

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this is where inference engineering meets retrieval and agent design

Model parallelism, one placement slide

D DERIVATION

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Distributing the model makes larger models **feasible**, but adds **communication overhead**. Pipeline- and tensor-parallel algorithms stay outside this core lecture.

Compilation and fused operations

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Launching many tiny operations separately wastes time:

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- **compilers** and **fused kernels** combine operations;
- fewer launches, fewer intermediate memory reads/writes.

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another instance of the core idea: **avoid unnecessary movement and coordination**

Quantization evaluation protocol

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Never judge a compressed model on average accuracy alone — test:

Quantization evaluation protocol

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Never judge a compressed model on average accuracy alone — test:

- representative **task quality**;
- **long-context** behavior;
- **rare / error-sensitive** cases;
- **latency and memory** on the **actual target hardware**.

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- representative **task quality**;
- **long-context** behavior;
- **rare / error-sensitive** cases;
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Average benchmark accuracy can hide a damaging quantization failure that only surfaces on the tail.

Cost per useful outcome

Q QUESTION

The relevant quantity is **not** merely tokens per second:

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a slower model can win if it avoids retries; a fast model is wasteful if its outputs need repeated correction

Energy and hardware awareness

D DERIVATION

Moving data across the memory hierarchy costs **time and energy**:

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- efficient inference can lower operational cost **and** environmental impact;
- but **demand growth** can offset per-query savings.

Energy and hardware awareness

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Moving data across the memory hierarchy costs **time and energy**:

- efficient inference can lower operational cost **and** environmental impact;
- but **demand growth** can offset per-query savings.

Avoid the simplistic “efficient therefore green” claim — count the **total** workload, not the per-query number.

Serving versus research benchmark

V VISUAL

Benchmark focus	Production focus
one model, one batch, peak throughput	variable requests, tail latency, reliability
fixed prompt length	long and changing contexts
clean hardware state	memory fragmentation and concurrency

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question any performance claim that omits its **workload assumptions**

Retrieval questions, extended

Q QUESTION

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2. What is the difference between quantizing **weights** and quantizing the **KV cache**?
3. Which optimization changes **arithmetic scheduling** but not model **output**?
4. Why does serving **require** workload assumptions?

Final bridge

models + objectives + representations + **inference systems**

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are all needed to understand a frontier deployment

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The final lecture uses this checklist to demystify **agents, reasoning systems, and interpretability** — they are built on the foundation this course has assembled, inference constraints included.

Summary

Student takeaways

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V VISUAL

1. Prompt processing (**prefill**) and token-by-token **decode** have different performance profiles.
2. KV caching trades **memory** for **avoided repeated computation**.
3. Many inference optimizations reduce **memory traffic** rather than changing neural-network mathematics.
4. Deployment constraints are **first-class** model-design constraints.

The levers, one last look

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Lever	Changes	Pay with
KV cache · GQA	serving	VRAM
quantization	representation	precision + kernels
FlashAttention	data movement	specialized kernel
batching · paging	scheduling	complexity
speculative decoding	scheduling	a draft model
distillation · pruning · MoE	the model	training effort

At inference, the model is often **waiting on memory**, not arithmetic.

Efficient inference = avoid **repeated work** + move **fewer bytes**.

Next: **Frontier Topics & Course Synthesis** — agents, reasoning, interpretability.