AI engineering

Columbia University
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LLM APIs

What is an LLM API?

- **A network interface** (usually HTTP/JSON) to a running large language model:
  - You send text (tokens + parameters); you get generated tokens back.
- **Hosted vs. self-hosted**:
  - *Hosted/proprietary (e.g., OpenAI, Anthropic):* no infra to run; strong performance; pay-per-use; your data flows to the provider.
  - *Open/self-hosted (e.g., Llama/Mistral family):* full control & privacy; needs GPUs & MLOps.
- **Why APIs**: Lowers barrier to entry (no GPUs needed) and standardizes access.

```
backend = choose(["provider_api", "self_hosted"])
# OpenAI/Anthropic vs vLLM
req = { "model": "my-model", "messages": chat,
"temperature": 0.7,
       "max_tokens": 256, "stop": ["</end>"],
"stream": True }

assert limiter.allow(user_id)
# rate limit per user/tenant
if count_tokens(req) > CTX_LIMIT: req =
truncate(req)       # respect context window
if token_budget.exceeds(user_id, req): raise
BudgetError    # cost guardrail

for attempt in range(3):
# retries with backoff + jitter
   try:
       for delta in llm_stream(backend, req,
idempotency_key=uuid4()):
           client.send(delta)
# SSE/WebSocket streaming to UI
       break
   except RateLimitedError: sleep(backoff(attempt,
jitter=True))
   except ServerError:       continue

if not client.seen_output():
client.send(fallback_message())  # handle
empty/blocked outputs
log_metrics(ttft, tps, latency_ms, tokens_in_out,
http_codes) # observability
```

Same but different

- It kinda looks familiar: still HTTP/JSON, but…

- **Probabilistic, not deterministic:** same input ≠ same output.
- **Tokens, not bytes/rows:** cost & latency tied to token counts.
- **Long-running:** seconds, not milliseconds → streaming is essential.
- **Non-binary success:** outputs can be valid, invalid, or low-quality.
- **Observability needed:** must track usage, errors, drift.

Anatomy of a request

- **Model selection.** Use a specific model/version. Drives quality, latency, and cost. Routable in production.
- **Messages array**. Chat history as {role, content}. Controls context and cost. System sets zolicy, User asks, Assistant can include prior turns.
- **Sampling knobs**. Temperature and top_p shape randomness and style. Lock these down for consistency.
- **Output control**. max_tokens caps spend and latency. stop prevents run-on generations and enforces boundaries.
- **Metadata for ops**. User for tenancy, analytics, and quotas. idempotency_key makes retries safe.
- **Tokens, not characters**. Everything is billed and bounded in tokens. Enforce a context window budget and track prompt + completion tokens.

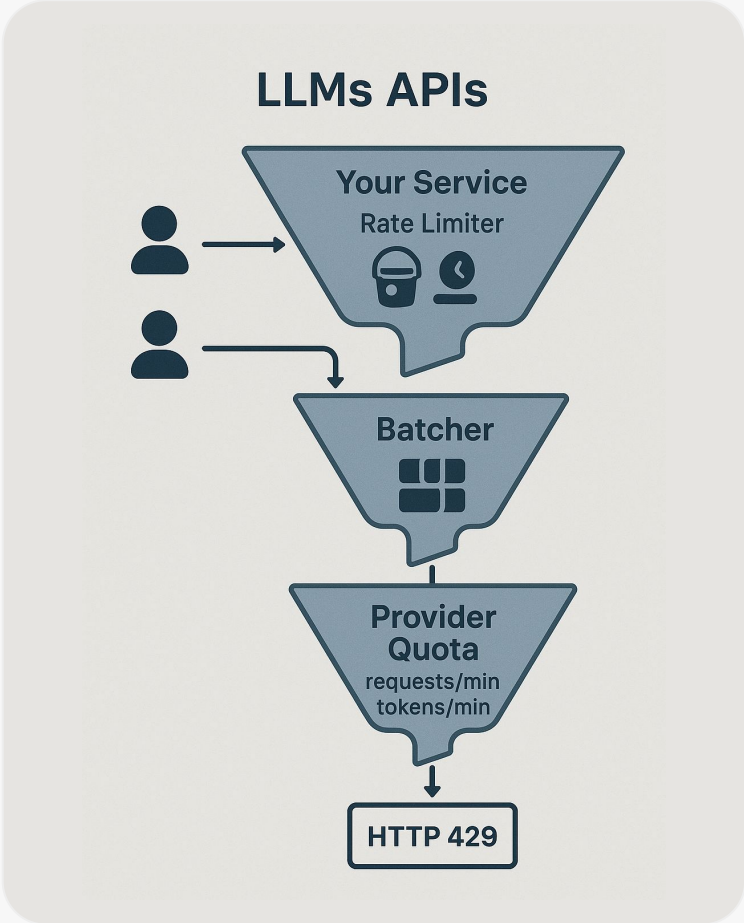
```
POST /v1/chat/completions
{
 "model": "gpt-4o-mini",
 "messages": [
   {"role": "system", "content": "You are a helpful teaching
assistant."},
   {"role": "user", "content": "Explain what tokenization
means."}
 ],
 "temperature": 0.7,
 "top_p": 0.9,
 "max_tokens": 256,
 "stop": ["</end>"],
 "user_id": "student123",
 "idempotency_key": "req-9f3a2c"
}
```

Response and Streaming

- **Response (non-streaming):** JSON with the model's text, finish reason, and usage (token counts).
- **Streaming (recommended):**
  - Server sends *partial tokens* as they are generated (SSE/WebSocket).
  - Better UX: lower **TTFT** (time-to-first-token), steady **TPS** (tokens/sec).
  - Implement server streaming + client consumption (e.g., FastAPI StreamingResponse + an iterator streamer).
  - Stream on the frontend too (render chunks as they arrive).

Rate Limits & Quotas

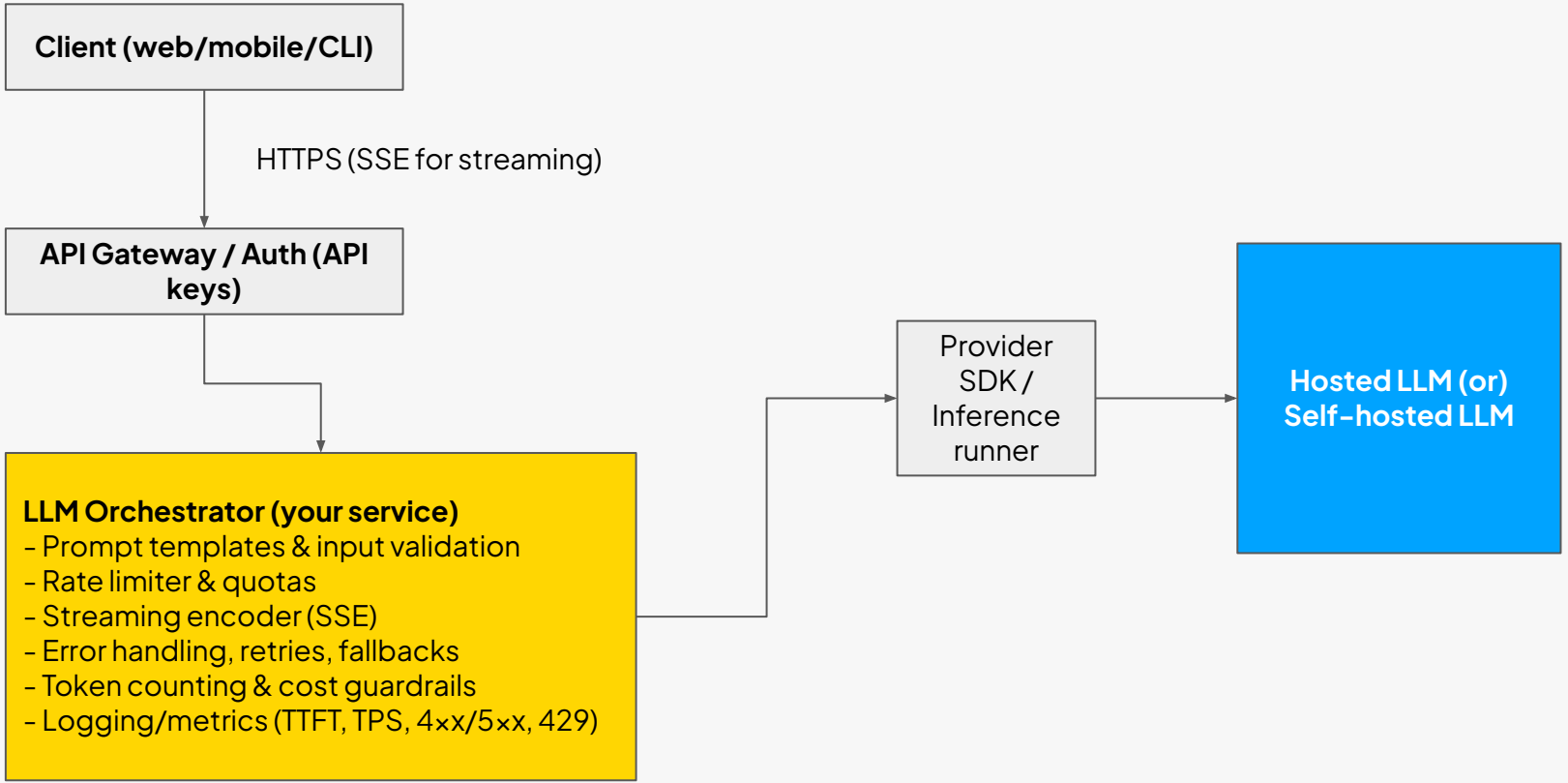
- Provider quotas: requests/min and tokens/min; exceeding returns HTTP 429.
  - Free keys often allow only a few calls/min. Plan for it.
- Your service rate-limiting (per API key/user):
  - Fixed window, Sliding window, Token bucket, Leaky bucket.
- Batching (self-hosting): Adaptive/dynamic batching can increase throughput on GPUs.



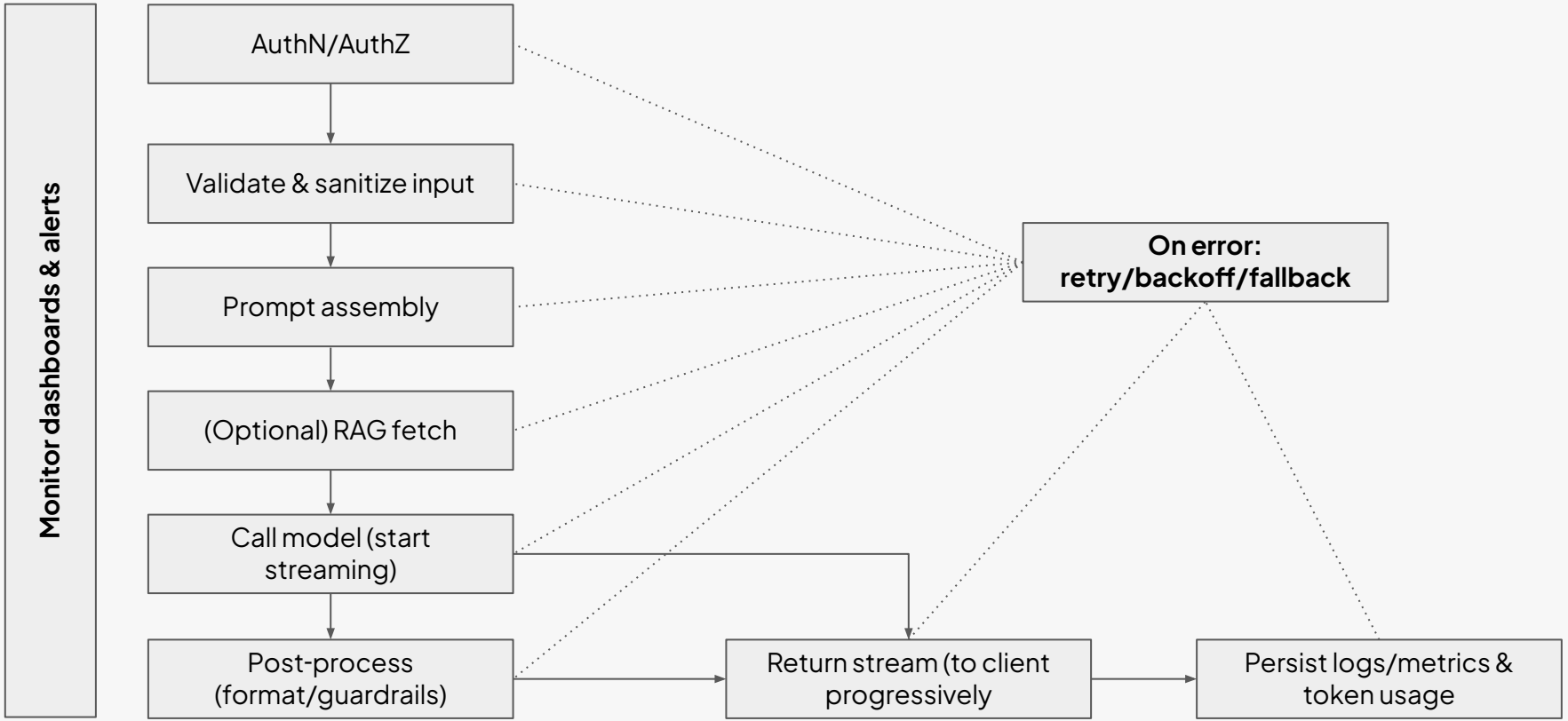
Error handling

- **Classify and handle:**
  - **4×x** (bad request/auth), **429** (rate limited), **5×x** (provider error/timeouts).
- **Retry policy:** Exponential backoff + jitter; cap retries; use idempotency keys. Consider parallel redundant calls (latency vs. cost).
- **Empty/malformed output:** detect (e.g., invalid JSON), auto-repair or reprompt, or fall back to a human.
- **Monitor:** Observe TTFT, TPS, error codes; design for detection (MTTD), response (MTTR), and low change failure rate (CFR).

Minimal LLM Service Architecture



End to end request lifecycle



LLMOps

What are LLMOps?

- **Definition**: *LLMOps* = MLOps for LLMs.

  Same elements (data→train→serve→monitor), but much bigger models create new pressures in **size, cost, latency, safety**, and infra.

- **What actually changes**: you mostly reuse the MLOps stack, but
  a. You don't train models from scratch anymore.
  b. You work often with vector DBs for retrieval.
  c. Evaluation is much harder.

- DataOps remain hard and honestly quite annoying.

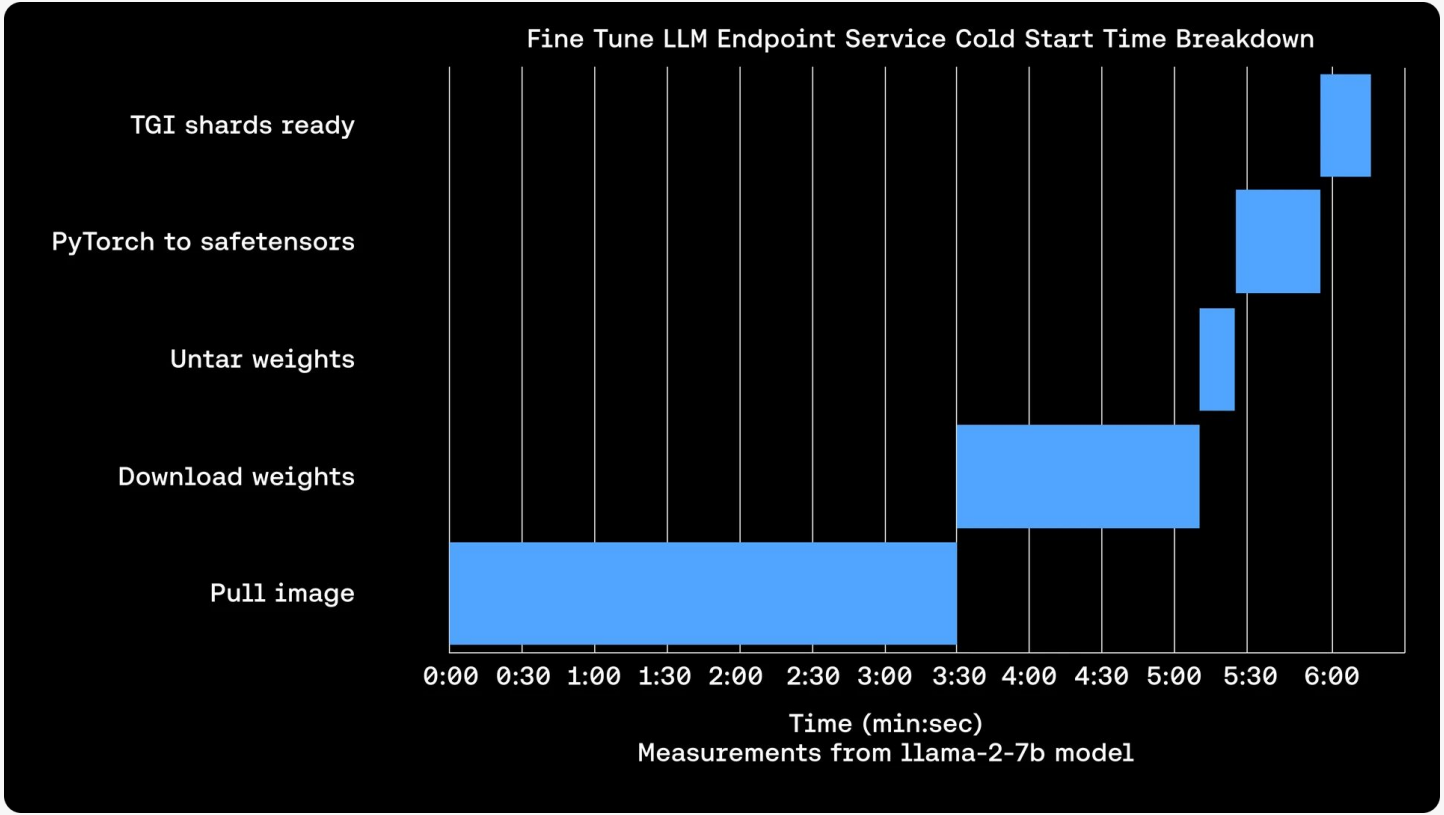
Fundamentals of LLMOps

- **Model size** → downloads, deployment, developer feedback loop.
- **Latency** → Time To First Token (TTFT), Time Per Output Token (TPOT).
- **Compute & memory** → GPU parallelism and utilization.
- **Tokens & context limits** → cost spikes and bottlenecks.
- **Model quality & safety** → hallucinations, bias, security.

Model size is a pain

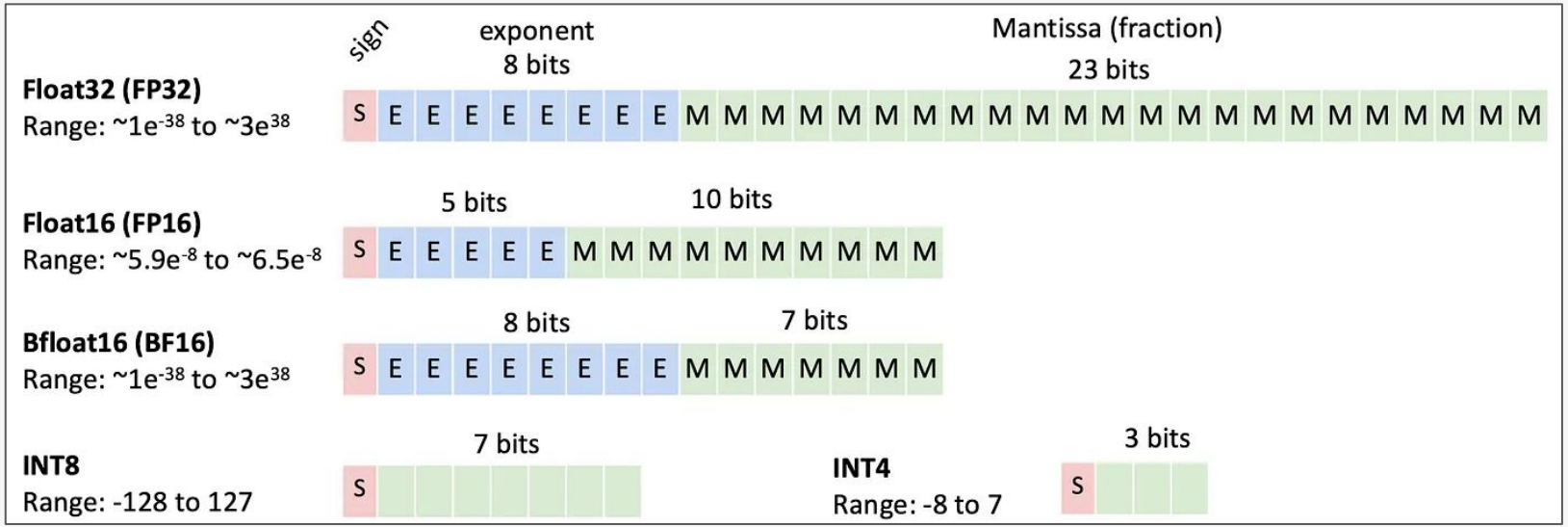
- **Long downloads & cold starts:** moving multi-GB weights dominates boot time; choose storage & boot strategies wisely.
- **Slower deploys/rollouts:** bigger artifacts → longer rollout windows → more user impact.
- **Slower dev loop:** every restart/redeploy drags feedback cycles.
- **Boot/serve strategies: download at boot**, **fuse/bake into image**, or **mount shared volumes** to amortize downloads across replicas.

Moving artifacts vs. model compute



Make the model smaller: quantization

- Quantization makes a model **smaller and faster** by storing numbers with **fewer bits** (e.g., from decimals to integers).
- The model behaves the same (mostly), but there is **less memory to load and less data to move**, so startups are quicker and tokens come out faster.



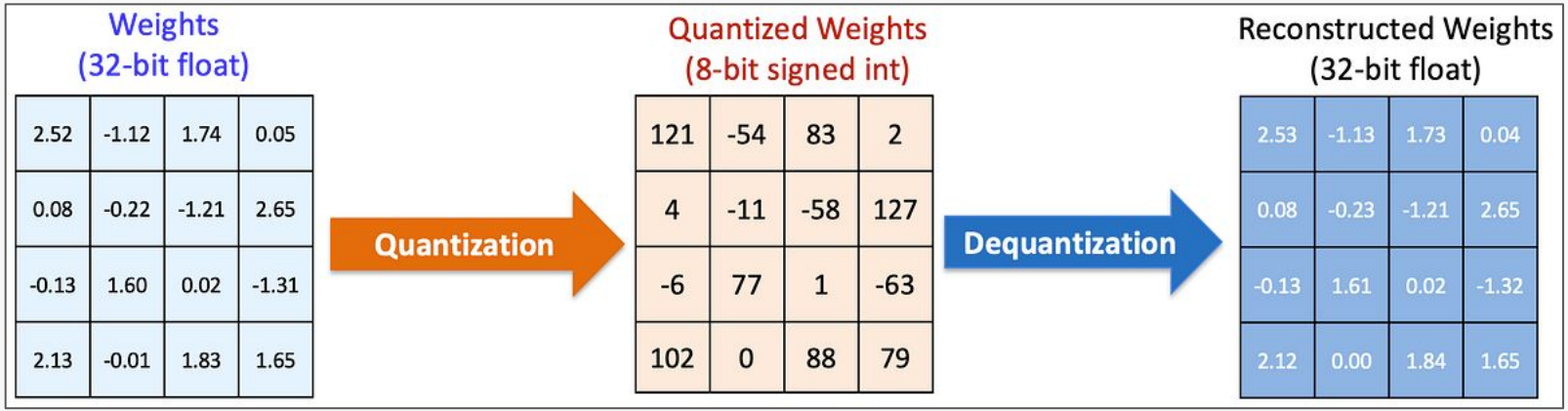
Make the model smaller: quantization

Post-Training Quantization (PTQ) — *no retraining.*

- Start with INT8 weights-only. It's the default that "just works" most of the time.
- If memory is still too tight, try INT4 (expect a bit more quality risk).
- Optional later: also quantize activations if you need more savings (more tuning, higher risk).

Quantization-Aware Training (QAT) — *short fine-tune.*

- Use if PTQ hurts quality beyond your SLOs.
- The model "learns" to live with lower precision; better quality, more effort.



Make the model smaller: quantization

Original Image

“Quantized” Image

Thinking about quantization

When to use

You need task/domain lift but cannot afford full model fine-tuning.

You serve multiple tasks/tenants and want hot-swappable behavior (load different adapters on the same base).

You want small artifacts (MBs) for fast rollout and easy rollback.

What to check before

Precision vs. tolerance: Is the task okay with tiny rounding errors? (Most chat, summarization and classification are).

Memory vs. quality trade-off: INT8 is usually safe; INT4 gives more savings but may lose subtle reasoning accuracy.

Hardware support: Make sure your inference stack (PyTorch, TensorRT, ONNX Runtime) actually supports the target bit width.

What it depends on

How aggressively you quantize: The more compact, the riskier.

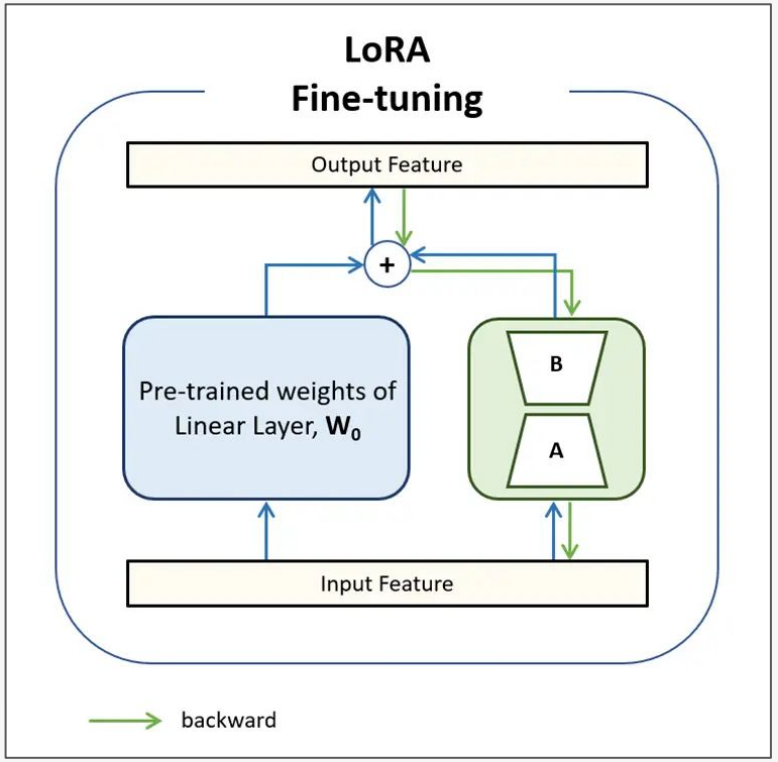
What you quantize:

- *Weights only* = fastest win, minimal quality loss.
- *Weights + activations* = more compression, more tuning needed.

Whether you fine-tune: *quantization-aware training (QAT):* short retrain — more work, best accuracy.

Freeze your model PEFT, LoRA

- Parameter-Efficient Fine-Tuning (**PEFT**) → Low-Rank Adaptation (**LoRA**).
- You keep the big base model **frozen**.
- You train only tiny add-on pieces (called *adapters*) on your task data.
- At inference, you run: the base model plus these small adapters to get task-specific behavior.
- Small training cost, small artifacts, and fast iteration.



Thinking about PEFT

When to use

Model doesn't fit in GPU memory?

TTFT too high? Smaller weights mean faster loading.

TPOT too low? Less data to move between GPU memory and compute → higher tokens per second.

Cost too high? Quantized models often run on fewer or smaller GPUs, saving money.

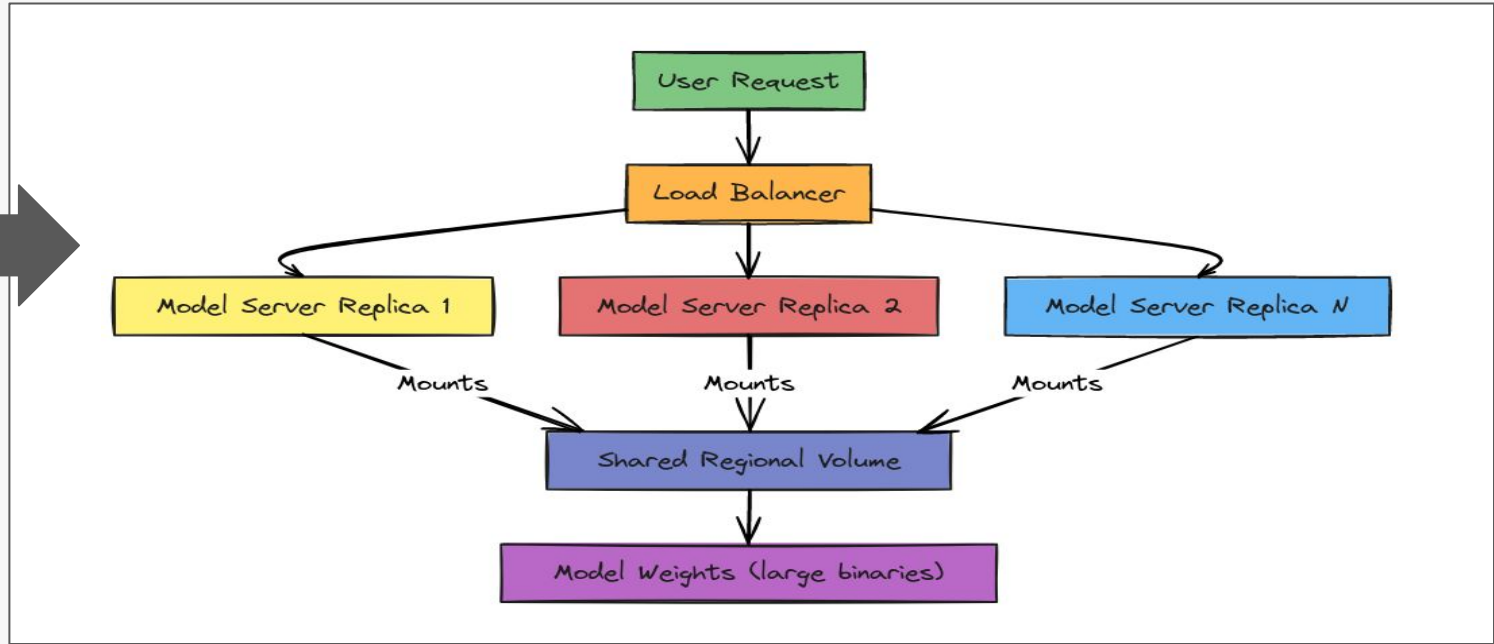
Workflow

1. Pick a strong base (close to your domain if possible).
2. Define the task and collect a small, clean dataset (100s–10k examples can move the needle).
3. Choose adapter config: target layers (attention/FFN), rank (e.g., r=8–64), dropout if needed.
4. Train adapters (few hours on a single GPU for small ranks).
5. Evaluate: task accuracy + safety; run your SLO metrics (TTFT, tokens/sec) to confirm no regressions.
6. Serve: load base model + adapter file; hot-swap adapters by route/tenant.
7. Optionally merge into a single artifact if you don't need multi-tenant swapping.

If you can’t go smaller, serve smarter: amortize I/O

- **Problem:** Every new copy of your model server (a “replica”) downloads the same multi-GB weights → slow cold starts, wasted bandwidth.
- **Download once, share many.** Put the weights on shared storage and have all replicas mount those files instead of re-downloading them.

Avoid repeated multi-GB transfers, cut cold-start variance, and keep auto scaling responsive.



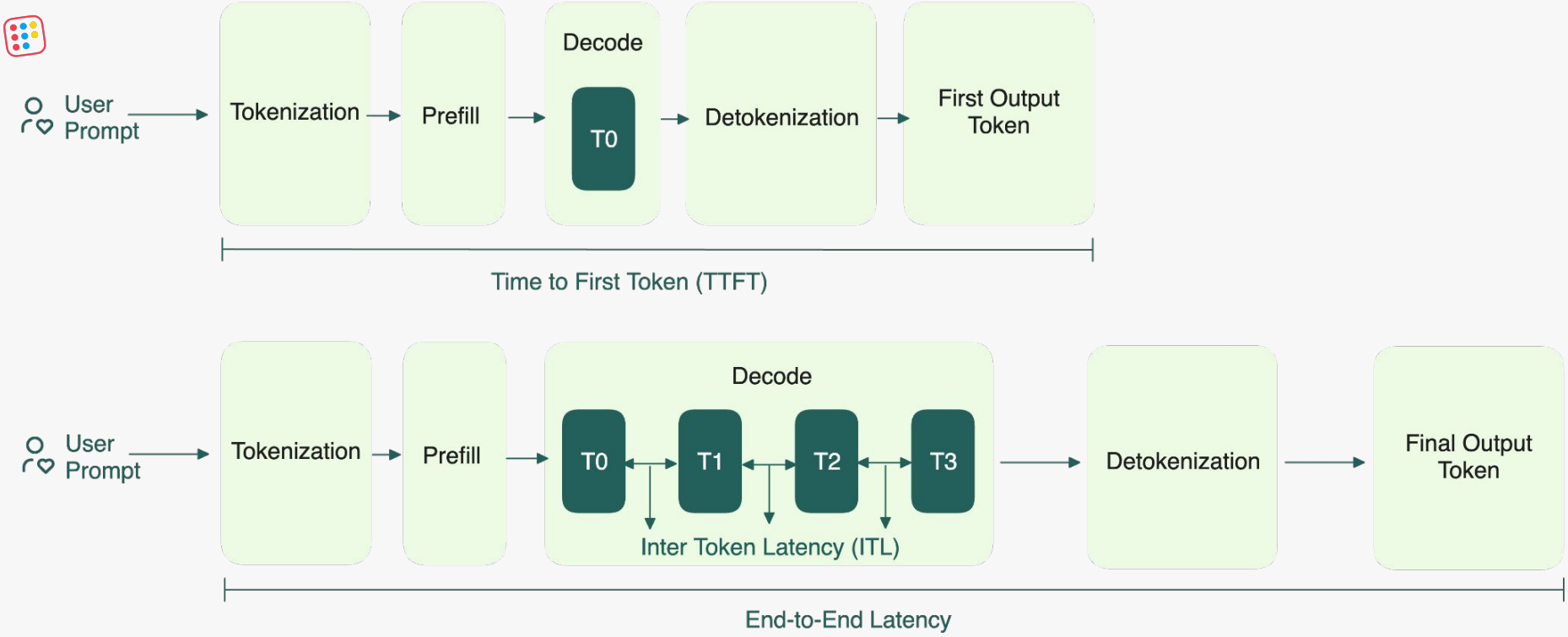
Latency: TTFT and TPOT

TTFT (Time-to-First-Token):

- How long it takes before the model **starts talking**.
- You send a question → nothing happens yet → and then *finally* the first word appears on screen.
- That waiting period — from when you press Enter to when you see the first word — is **TTFT**.
- It depends on how long the model needs to read and understand your input before it can begin answering.

TPOT – Time Per Output Token

- Once the model starts talking, it sends words one by one.
- **TPOT** is how fast those words come out.
- If the model "types" one word every 0.1 seconds, TPOT = 0.1 s/token (or 10 tokens per second).
- It's basically the **typing speed** of the model.



Note: Detokenization happens after each decode step. Each token (T0, T1, T2) is detokenized and output sequentially, not just the final one (T3).

Source https://bentoml.com/llm/inference-optimization/llm-inference-metrics

Why does it matter?

User perception & UX

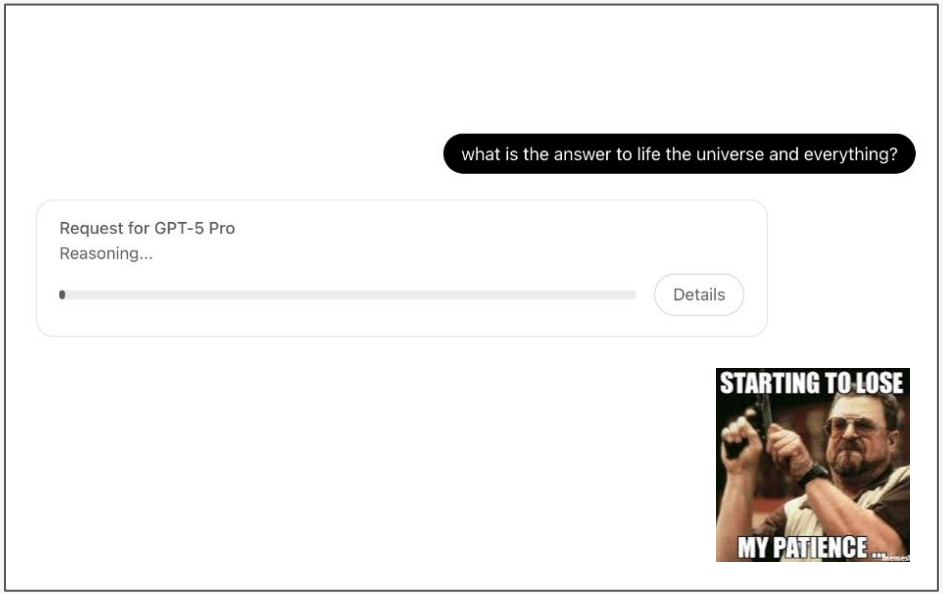
- TTFT = “Is this thing on?” A long TTFT feels broken even if total time is OK.
- TPOT = “C’mon! c’mon! c’mon!.” It needs to be fast enough so users read comfortably while tokens arrive.

Meet your SLOs with capacity planning

- Splitting latency into TTFT (prefill) and TPOT (decode) tells you *where* time is going and which lever (prompt budget vs. model throughput) to pull.

Cost control

- Long TTFT wastes GPU time doing non-streaming work; slow TPOT extends GPU occupancy per request → higher $/req.



Thinking about TTFT and TPOT

TTFT — Time to First Token (prefill)

1. **How long is the prompt?** Longer input = more reading and setup for the model → slower first response.
2. **Is the model ready?** If weights need to be downloaded or loaded into GPU memory, that adds time.
3. **Is the system warm?** The first request often triggers things like kernel compilation or memory setup. Also waiting in queues, autoscaling delays, or network hiccups all add to TTFT.
4. **Is there work to do before answering?** Tasks like retrieval (RAG), safety filters, or tool-planning may run *before* generation starts.
5. **Batching behavior?** if the server waits to fill a batch before starting, that can delay the first token.

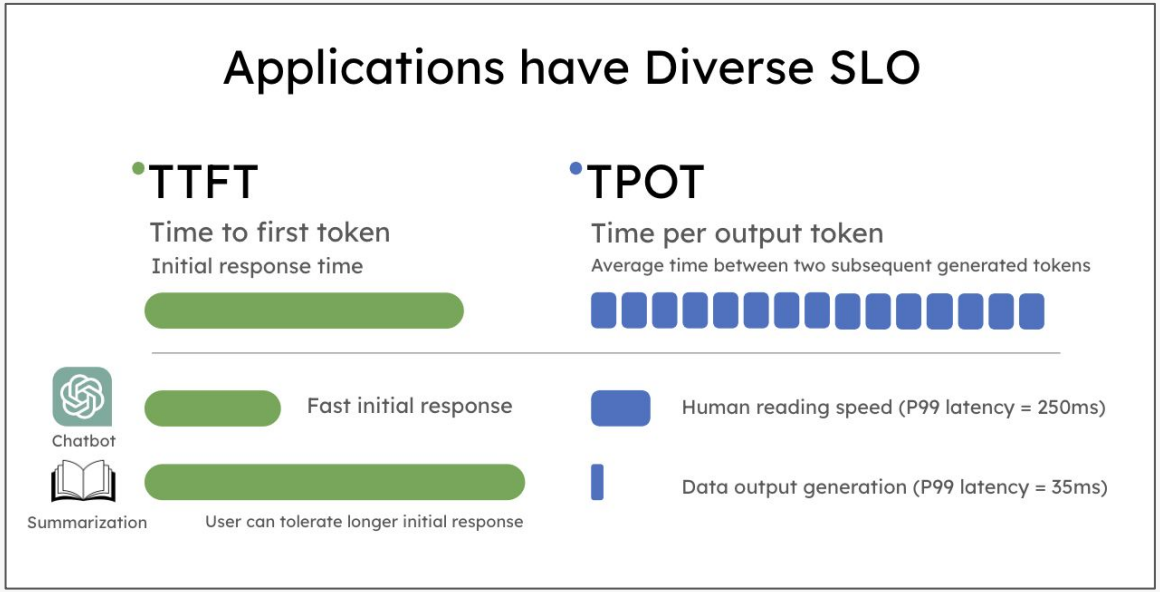
TPOT — Time Per Output Token (decode)

1. **How big is the model?** Bigger models do more math per token → slower. Smaller or quantized models → faster.
2. **What GPUs are we using?** Generating tokens is mostly limited by how fast the GPU can read/write memory. Faster hardware = higher token rate.
3. **Batch size?** Larger batches improve total throughput but can slow down individual requests.
4. **Sampling & rules?** Features like temperature, top-p sampling, or structured output checks add small per-token overheads.
5. **Parallelism & communication:** Splitting a model across multiple GPUs or servers introduces coordination time; fast interconnects help keep TPOT low.

Know your applications

Different applications have different latency goals:

- Chatbots need a fast *time to first token (TTFT)* for responsiveness
- Summarization can tolerate longer startup as long as *time per output token (TPOT)* is high for throughput.



Source: https://hao-ai-lab.github.io/blogs/distserve/

Sampling

- The model doesn’t pick one fixed next word; it picks from a probability list of likely next words.
- Sampling is how we choose from that list: more random (creative) or more deterministic (factual/consistent).
- By turning a few knobs (e.g., temperature, top-k/top-p), you can make outputs safe & steady or diverse & imaginative.

How sampling works

- For each step, the model produces a **distribution over tokens** (a ranked list with probabilities).
- **Greedy** decoding: always pick the top token → fast, consistent, but can get stuck in loops or be dull.
- **Temperature** rescales the distribution:
  - **Low** (≈0–0.3): sharper, more deterministic.
  - **Mid** (≈0.7–1.0): balanced.
  - **High** (>1.0): more diverse, more risk of nonsense.
- **Top-k**: restrict choices to the **k best** tokens; **Top-p (nucleus)**: restrict to the **smallest set** whose probabilities sum to *p*.
- **Repetition / presence/frequency penalties**: nudge the sampler away from repeating the same words.
- **Structured / constrained decoding**: enforce a JSON schema or grammar, or force valid function-call arguments; this narrows the choices each step.
- **Test-time compute** (quality boosters):
  - **Best-of-n**: generate many candidates, pick the best with a scorer (e.g., task heuristic, reward model, "AI as a judge").
  - **Self-consistency**: sample several chains-of-thought and select the most consistent answer.
  - These increase **quality** at the cost of **latency** and **$$**.

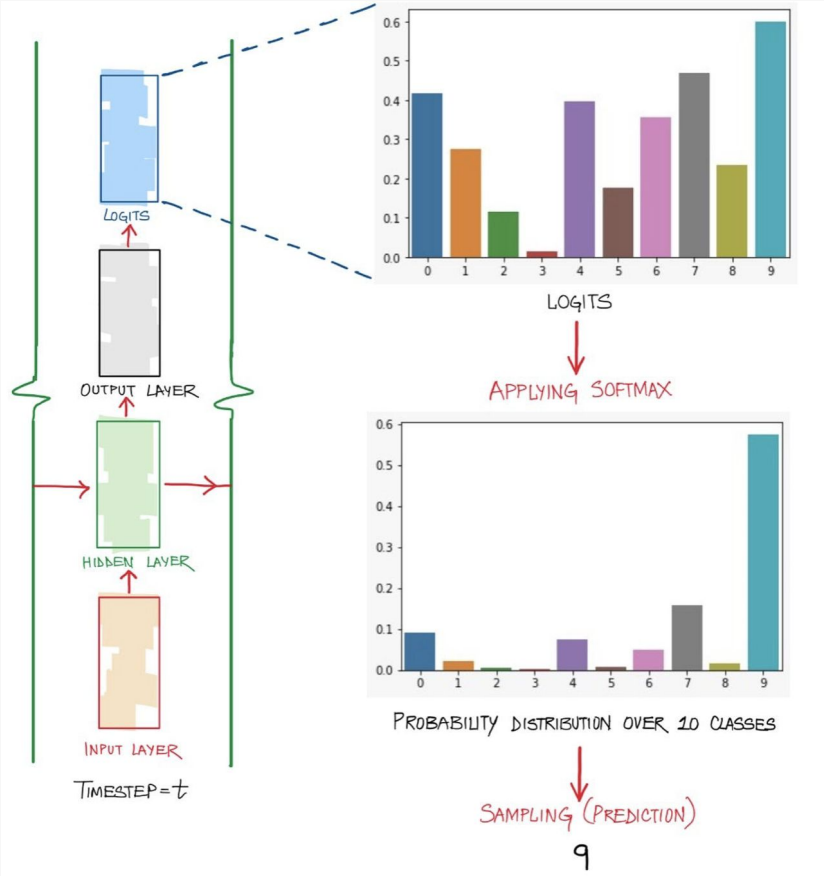
Sampling’s core knobs

Temperature: 0.2–0.7 for factual/tasks; 0.7–1.0 for creative.

Top-p: 0.8–0.95 (nucleus sampling) is a solid default; leave **top-k** off unless you need hard caps.

Repetition control: enable presence/frequency penalties for chat; tune lightly to avoid stilted output.

Constrained decoding: require JSON/schema for tool calls and integrations; reduces cleanup and errors.



Trade-offs

- **Best-of-n**: sample n candidates, pick best by a task-specific scorer (regex, reward model, judge). Quality ↑, cost ↑.
- **Self-consistency** (reasoning): sample multiple chains, vote/select the most consistent final answer. Robustness ↑, cost ↑.
- **Use budgeted n** (e.g., 3–5) and stop early if a high-confidence candidate appears.
- **Diversity vs Reliability**: Higher temperature/top-p → more variety, more risk.
- **Quality vs Cost**: Best-of-n/self-consistency improve accuracy but multiply tokens and latency.
- **Speed vs Format**: Constraining output ensures validity but can slow decode slightly.
- **Global vs Per-turn**: You can adapt knobs per step (e.g., low temperature until a tool call returns; then relax).

Buy vs. Build

Provider APIs vs. Self-Hosting

Privacy: API ⇒ data leaves org; Self-host ⇒ data stays in-house.

Lineage/IP: Closed ⇒ opaque data; Open ⇒ inspectable datasets.

Performance: API ⇒ top quality but external latency; Self-host ⇒ tuned SLOs.

Functionality: API ⇒ rich features (function calling, guardrails); Self-host ⇒ raw access (logprobs, finetune).

Cost: API ⇒ pay-per-token; Self-host ⇒ infra/ops, cheaper at scale.

Control: API ⇒ vendor limits/opacity; Self-host ⇒ freeze versions, full observability.

On-device: API ⇒ always online; Self-host ⇒ quantized models run offline.

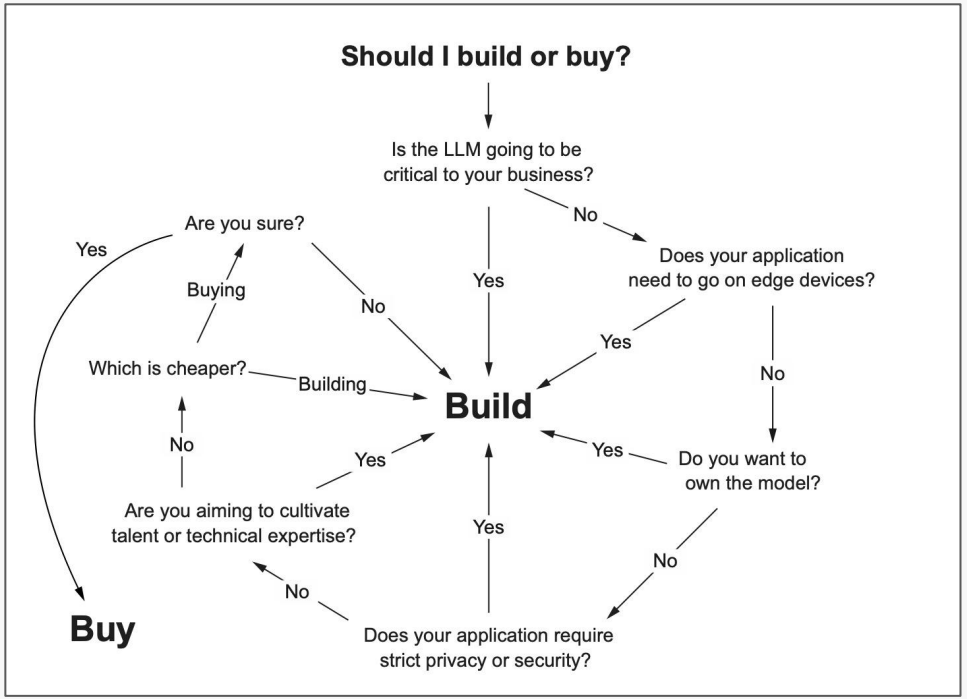


Image from Brusseau and Sharp

Provider APIs vs. Self-Hosting

- A. Clinical notes summarizer (hospital)
- B. Consumer copywriting assistant (global app)
- C. Field support chatbot (spotty connectivity)