Optimizing LLM Inference on Resource-Constrained Hardware

Techniques and Tools for Faster, Cheaper, and Scalable LLM Inference



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About

- Exploring Inference Optimisation and MLOps.
- R&D Engineer Intern at FinTech Startup.
- Final Year MS Student at CUSAT.
- Previously published two research papers in MLOps.
- Open Source Contributor. (Hugging Face, Yolo, Infisical)
- Community Organiser. (AWS UG Kochi)

The Rise of LLM-Powered Everything

- 2022: ChatGPT → Everyone saw LLMs as magic.
- 2023: Companies race to integrate "LLM-powered" features.
- 2024–25: Every app wants AI copilots, RAG, chatbots, summarizers.





Google Workspace with
Gemini

The Closed-Source Phase

- Easy API access → rapid prototyping.
- Reliable models, but limited control & high cost.
- Privacy & compliance issues → data can't always leave org boundaries.
- Developers hit rate limits & cost ceilings.

The Open-Source Shift

- Community progress (Llama, Mistral, Phi-3, Gemma, Deepseek, Granite)
- Fine-tuning freedom tailor for domain-specific use cases
- Cost advantage one-time setup, infinite queries
- Deployment flexibility on-prem, edge, or private cloud





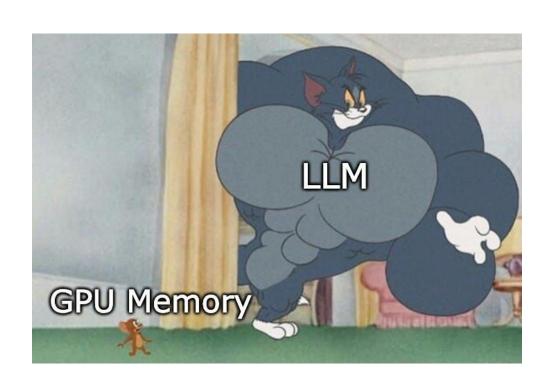








The New Challenge: Running It Yourself





The New Challenge: Running It Yourself

- Models too large for your GPU
- Slow response times
- Memory bottlenecks
- Expensive infra scaling

VRAM vs Model Size

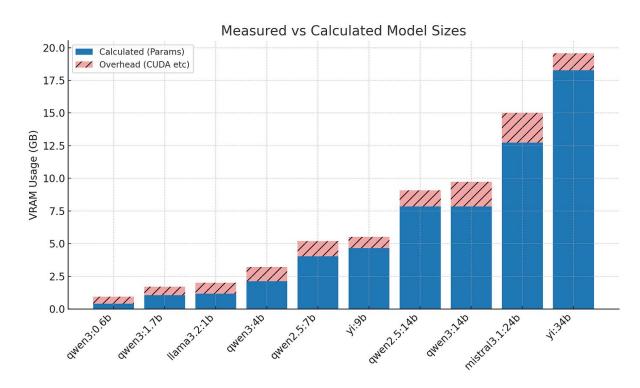


Fig 1. Representing the rise of VRAM requirement according to the model size.

How much VRAM does your model need?

$$M = (\frac{(P \times 4B)}{(32/Q)} \times 1.2)$$

M -Total Memory Required (Bytes)

P - Number of model parameters

B - Bytes per parameter

Q - Bit precision used for quantization

How to evaluate your LLM System?

- Time To First Token (TTFT): The time it takes to generate the first token after sending a request.
- Total Latency (E2EL): The time from sending the request to receiving the final token on the user end.
- Inter-Token Latency (ITL): The exact pause between two consecutive tokens.
- Throughput

What Are We Really Optimizing For?

- Faster Responses (↓ Latency)
- More Parallel Work (↑ Throughput)

Stages of LLM Inference

- Prefill model processes the entire input prompt and builds the initial KV cache.
- Decode model generates tokens one by one, using the context from prefill.

What is KV Cache in Attention Layer?

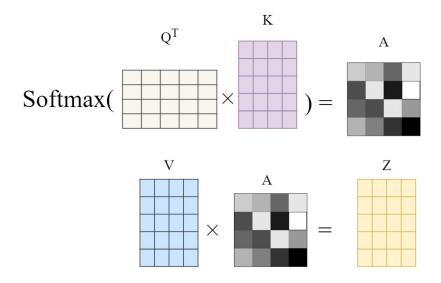


Fig 2. Illustration of Attention Mechanism

The Real Bottleneck Inside LLM Inference

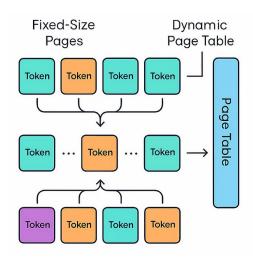
- Vanilla Transformer is not a production ready architecture.
- LLM inference is memory-bound, not compute-bound.
- Inefficient GPU memory management especially KV Cache.
- Low GPU utilization in real workloads.
- Token generation is inherently sequential.

Techniques to Optimise Inference

- Paged Attention
- Continuous Batching
- Speculative Decoding
- Prefix Chunking
- Quantisation

Paged Attention

- KV Cache stored in non-contiguous memory
- Inspired by OS Virtual Memory
- Reduces GPU memory fragmentation
- Enables swapping and reuse of memory pages
- Improves throughput and parallelism



Iteration Level Scheduling

- Fine-grained scheduling at each decoding iteration
- Maximizes GPU utilization
- Up to 23x throughput improvement
- Reduces TTFT (Time to First Token)

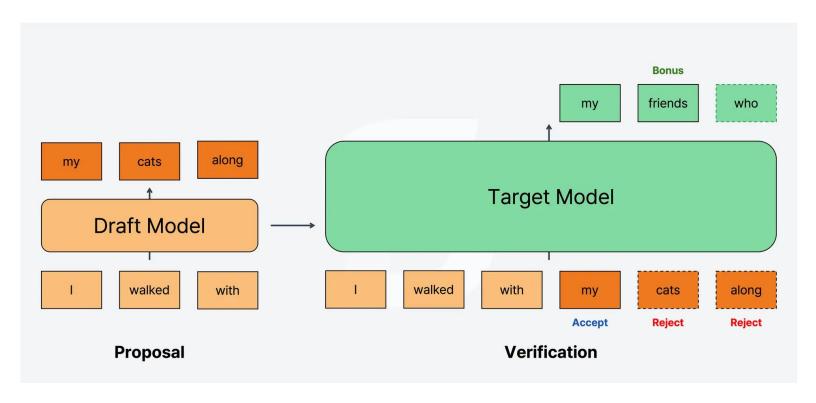
T,	Tz	T3	Ty	Ts	T6	To	Tg
Sil	Si	Si	\$1/1				
Sa	Sz	SX					
S	S	Sz	S				
Sy	Sy	Sy	Sy	Sy			

T,	Tz	T3	Ty	Ts	T6	To	TB
Sil	Si	Si	SNI	8,	END	56	SG
Sa	Sa	SHI	Sx	Sale	SA	Sil	END
Sz	S_3	S	S	END	Ss	SS	\$5
Sy	Sy	Sy	Sy	Sy	Sy	END	Sq

Speculative Decoding

- A two-model decoding strategy.
- A small draft model predicts several future tokens.
- A larger target model verifies and accepts the correct tokens.
- Reduces generation latency.
- Maintains output quality.
- Improves throughput on constrained hardware.

Speculative Decoding



Prefix Caching

- Useful in production workloads with repeated prompt structures
- Applications: Chat systems, Al agents, and RAG pipelines.
- Helps to reduce latency and cost in LLM inference

For example, consider a chatbot with this system prompt:

System Instruction: You are a helpful Al writer. Please write in a professional manner.

This prompt doesn't change from one conversation to the next. Instead of recalculating it every time, you store its KV cache once.

Quantisation

- A model compression technique
- Reduces the precision of model weights and activations
 - \circ e.g. from FP16 / FP32 \rightarrow INT8 / INT4 / NF4.
- PTQ (Post Training Quantization): Apply quantization after training.
- QAT (Quantization-aware Training): Train with quantization effects in mind for better accuracy.

Introducing vLLM

- Introduced Paged Attention
- State-of-the-art serving throughput
- Streaming outputs
- OpenAl-compatible API server
- Hugging Face integration
- Supports decoding algorithms, including parallel sampling, beam search etc.

How to use vLLM? - Online Serving

Single Command to Launch the API Server

```
vllm serve NousResearch/Meta-Llama-3-8B-Instruct \
--dtype auto \
--api-key token-abc123
```

Accessing the model using OpenAl Framework

How to use vLLM? - Offline Serving

Single Command to Launch the API Server

```
from vllm import LLM

# Initialize the vLLM engine.
llm = LLM(model="facebook/opt-125m")
```

Speculative Decoding in vLLM

Single Command to Launch the API Server

```
python -m vllm.entrypoints.openai.api_server \
    --host 0.0.0.0 \
    --port 8000 \
    --model facebook/opt-6.7b \
    --seed 42 \
    -tp 1 \
    --gpu_memory_utilization 0.8 \
    --speculative_config '{"model": "facebook/opt-125m","num_speculative_tokens": 5}'
```

Let's connect



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Thank You!









