# I’ve Got 99 Problems, but LLMs Ain’t One!

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Ai4 Las Vegas · 2025

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# Why private and local AI?

83% of organizations are moving workloads back to private cloud or on-prem for privacy and cost (Barclays CIO Survey 2024).

**Control & Privacy**
Keep data on your infra, control updates and versions

**Cost Predictability**
Avoid unpredictable egress/inference bills

**Customization**
Tune models, add guardrails, ship your cadence

**Portability**
Run on Linux, Kubernetes, or bare metal

Let's get started!

## About me

Cedric Clyburn

**Senior Developer Advocate, Red Hat**

Organizer, KCD New York

Open source + community builder · @cedricclyburn

**Technical Educator**

- RAG vs Fine-Tuning
- Ollama
- vLLM

# Agenda

- Open models: what's new in OSS
- Why hosted APIs aren't always enough
- Private & sovereign AI options
- How to deploy: local → production
- Tooling: llama.cpp, vLLM, TGI
- Cut GPU cost by ~50%: quantization

# Open Source Model Explosion

## Foundation models

Llama 3.x, Qwen, DeepSeek, Mistral, Gemma

instruct | base | MoE

## Modalities

Text, vision, audio, diffusion, multi-modal

VLM (Llava, Idefics) | ASR/TTS | Diffusion

## Ecosystem

Tokenizers, safetensors, GGUF, serving runtimes

llama.cpp | vLLM | TGI | GGUF | safetensors

The weights are accessible… but how do we deploy, serve, and scale them responsibly? Think data gravity, GPUs/NUMA, batching, safety, updates, and SLOs.

# Options to use LLMs today

## Model lab portals

+ Latest models, minimal ops
− Rate limits, policy shifts, data control concerns

Examples: OpenAI, Perplexity, Gemini, OpenRouter

## Hyperscalers (managed)

+ Managed scaling and tooling
− Cost surprises, limited customization, provider lock-in

Examples: Azure AI, Vertex AI, SageMaker

## Private/Sovereign AI

+ Data control, cost governance, custom releases
− You own hardware, serving, and reliability

Runtimes: llama.cpp, vLLM, TGI; Platforms: K8s, bare metal

# Private and Sovereign AI

Own your stack from weights → runtime → platform.

**Infra**
Linux, GPUs, Kubernetes, observability

**Serving**
llama.cpp (CPU/GGUF) & wrappers, vLLM (GPU), TGI

**Governance**
Security, access, model registries, evaluations

# Transformers

## What it is

Hugging Face Transformers: the de-facto Python library for loading, tokenizing, and running foundation models with consistent APIs.

## Strengths

- • Huge model hub, consistent pipelines, rich tokenizers
- • Integration with PEFT, bitsandbytes, evals, datasets
- • Easy prototyping; broad community & docs

## Trade-offs

- • Not a high-throughput server by itself
- • Requires pairing with runtimes (vLLM/TGI) for prod serving

## Example

```
from transformers import AutoTokenizer, AutoModelForCa
import torch

model_id = "meta-llama/Llama-3-8B-Instruct"
tok = AutoTokenizer.from_pretrained(model_id)
mdl = AutoModelForCausalLM.from_pretrained(model_id, t

prompt = "Why private AI?"
ids = tok(prompt, return_tensors="pt").to(mdl.device)
out = mdl.generate(**ids, max_new_tokens=64)
print(tok.decode(out[0], skip_special_tokens=True))
```

Pair with vLLM/TGI for production serving and throughput.

# llama.cpp

## What it is

High-performance C/C++ inference for LLaMA-family and many HF models via GGUF. Great for CPU, small GPUs, and edge.

## Strengths

- • No heavyweight Python/driver stack; portable binaries
- • Runs offline; easy to embed
- • Broad quantization support (Q4_0…Q8, K-quant)

## Trade-offs

- • Max throughput lower than GPU servers for big models
- • Use GGUF conversions; some features vary by model

## Local demo

```
# Download GGUF (example)
curl -L -o llama3.Q4_K_M.gguf https://huggingface.co/

# Run with llama.cpp
./main -m llama3.Q4_K_M.gguf -n 128 -p "Why private AI
```

Tip: Use GPU backends (Metal/CUDA/Vulkan) when available for speedups.

# vLLM

## What it is

Open-source LLM serving (UC Berkeley). High-throughput, low-latency GPU inference with PagedAttention and efficient KV cache.

## Strengths

- • Excellent throughput with batching/continuous batching
- • OpenAI-compatible server; easy clients
- • Works with HF models; supports tensor/quant formats

## Trade-offs

- • Wants decent GPUs and VRAM; plan for scheduling
- • Operational tuning (batching, max_tokens, tensor parallel)

## OpenAI-compatible server

```
# Start vLLM server
vllm serve meta-llama/Llama-3-8B-Instruct \
  --host 0.0.0.0 --port 8000 \
  --gpu-memory-utilization 0.9 \
  --max-model-len 8192

# Query (OpenAI API)
curl http://localhost:8000/v1/chat/completions \
  -H 'Content-Type: application/json' \
  -d '{
    "model": "meta-llama/Llama-3-8B-Instruct",
    "messages": [{"role":"user","content":"Give me 3 h
  }'
```

Tunables: tensor/pp, max_tokens, trust_remote_code, quantized weights.

# What if we cut costs in half?

Quantization shrinks weights and KV cache → fewer/lower-VRAM GPUs, faster tokens/sec.

**Approaches**

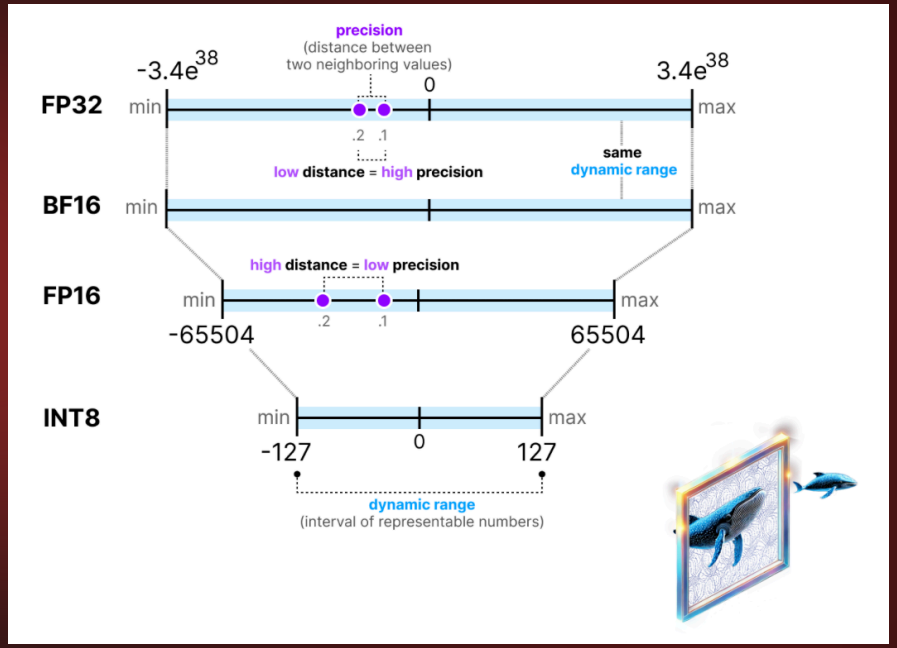
AWQ, GPTQ, GQA-aware, INT8/INT4, FP8

**Typical wins**

2× VRAM reduction, similar quality with right calibration

**Trade-offs**

Slight perplexity/accuracy hit; layer-wise sensitivity matters



# Quantization demo

## Plan

Start with FP16 Llama-3.1 70B Instruct, apply FP8 activation quant with llm-compressor, then serve with vLLM.

## Steps

1. 1. Download model weights (HF)
2. 2. Quantize with llm-compressor (FP8 activations on Linear)
3. 3. Launch vLLM with compressed checkpoint
4. 4. Compare latency and VRAM

## Example commands (llm-compressor)

```
# Install
pip install llmcompressor transformers

# Python: FP8 dynamic quantization with offload on 2 (
python - <<'PY'
from transformers import AutoModelForCausalLM
from llmcompressor.modifiers.quantization import Quant
from llmcompressor.transformers.compression.helpers i
from llmcompressor import oneshot

model_stub = "meta-llama/Llama-3.1-70B-Instruct"
device_map = calculate_offload_device_map(
    model_stub,
    reserve_for_hessians=False,
    num_gpus=2,
    torch_dtype="auto"
)
model = AutoModelForCausalLM.from_pretrained(
    model_stub,
    device_map=device_map,
    torch_dtype="auto"
```

# Local → Production

**Local**

- llama.cpp binary, GGUF weights
- vLLM single-GPU serve for quick iteration
- Experiment in notebooks/Transformers before serving

**Production**

- Kubernetes + GPU scheduling (time-slicing/MIG)
- Autoscaling, observability, circuit-breakers, canaries

SRE checklist: health probes, request budgets, token limits, logging redaction, evals, red-team prompts, rollout policy.

# Takeaways

Open models are thriving across sizes and modalities

Private + sovereign AI gives control, privacy, and cost governance

Serve locally with llama.cpp (CPU/edge) or vLLM/TGI (GPU scale)

Quantization can halve GPU needs with minimal quality loss

**You might still have 99 problems – LLMs ain't one**

# Thanks!

## Resources

- • Quantization accuracy at scale (Red Hat article)
- • LLM Compressor (quantization library)
- • vLLM (OpenAI-compatible server)
- • Red Hat AI models on Hugging Face
- • ramalama (containers / local LLM tooling)
- • llama.cpp (GGUF inference)

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