What is a Quantized Model?

In the context of large language models (LLMs), **quantization** is a model optimization technique used to reduce the memory and compute requirements by lowering the precision of the numerical values (weights and activations) used in the model. This is done **without retraining the model**, and usually with **minimal loss in performance**.

@ Why Quantize?

Original models are typically stored in **32-bit floating point (FP32)** format, which offers high precision but demands significant RAM and compute power. Quantization reduces this to smaller formats like **8-bit** (**INT8**) or even **4-bit**, making models:

- **Smaller** in size
- Value
 Faster to run
- ✓ Able to run on hardware with limited RAM or VRAM

Precision Format	Bits per Weight	RAM Usage	Speed	Accuracy Impact
FP32	32	Very High	Slow	None
INT8 / Q8_0	8	Medium-High	Moderate	Very Low
Q5_1	5	Moderate	Fast	Low
Q4_K_M	4 (optimized)	Low (~30 GB)	Very Fast	Minimal

Why I Chose Q4_K_M

Given my hardware setup:

- · 30 GB of system RAM
- · 8 GB of GPU VRAM

I needed a model format that balances **performance**, **compatibility**, and **accuracy**. After testing different quantized versions, I selected:

This is an advanced 4-bit quantization scheme that:

- Maintains better accuracy than older 4-bit methods (q4_0, q4_1)
- Uses multipliers and grouped quantization to preserve precision
- Fits comfortably in <32 GB RAM, making it ideal for my system

With Q4_K_M, I can run large models (up to 14B parameters) on my local machine, without needing a dedicated high-end GPU.

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Summary

Quantization allows developers and researchers to **run large-scale Al models on consumer-grade hardware**. It is a powerful technique for local, offline Al inference, especially when paired with optimized formats like Q4_K_M.

By choosing a quantized model, I've enabled my project to:

- · Function efficiently within hardware constraints
- · Deliver real-time inference
- · Maintain model performance with minimal trade-offs