

Table of Contents

Neural Networks, Tensors and other stuff 1

Formats 1

Quantization 1

Opensource models 3

Stable Diffusion 1 3

Stable Diffusion XL 3

Stable Diffusion 3 3

Flux.1d 3

HiDream I1 3

CLIP (Contrastive Language-Image Pre-training) 4

Neural Networks, Tensors and other stuff

Formats

Safetensors	Safe store for tensors
GGUF	Georgi Gerganov Universal Format (it can mix various precisions)
PT	PyTorch format

Quantization

Quantization Type	Bits per Weight	Description
F64	64	64-bit IEEE 754 double-precision floating-point. High precision, large memory footprint.
F32	32	32-bit IEEE 754 single-precision floating-point. Standard for training, high memory usage.
F16	16	16-bit IEEE 754 half-precision floating-point. Balances precision and efficiency.
I64	64	64-bit integer. Used for specific metadata or computations.
I32	32	32-bit integer. Less common for weights.
I16	16	16-bit integer. Rarely used for model weights.
I8	8	8-bit integer. Used in some quantization schemes.
Q8_0	8	8-bit quantization, 32 weights per block, weight = $q * \text{block_scale}$. Legacy, close to FP16 accuracy.
Q8_1	8	8-bit quantization with block minimum, weight = $q * \text{block_scale} + \text{block_minimum}$. Legacy.
Q8_K	8	8-bit quantization, 256 weights per block, used for intermediate results.
Q6_K	6.5625	6-bit quantization, super-blocks with 16 blocks of 16 weights, weight = $q * \text{block_scale}$ (8-bit).
Q5_0	5	5-bit quantization, 32 weights per block, legacy.
Q5_1	5	5-bit quantization with block minimum, legacy.
Q5_K	5.5	5-bit quantization, super-blocks with 8 blocks of 32 weights, weight = $q * \text{block_scale}$ (6-bit) + block_min (6-bit).
Q4_0	4	4-bit quantization, 32 weights per block, legacy.
Q4_1	4	4-bit quantization with block minimum, legacy.
Q4_K	4.5	4-bit quantization, super-blocks with 8 blocks of 32 weights, weight = $q * \text{block_scale}$ (6-bit) + block_min (6-bit).
Q3_K	3.4375	3-bit quantization, super-blocks with 16 blocks of 16 weights, weight = $q * \text{block_scale}$ (6-bit).
Q2_K	2.625	2-bit quantization, super-blocks with 16 blocks of 16 weights, weight = $q * \text{block_scale}$ (4-bit) + block_min (4-bit).
IQ4_NL	4	4-bit integer quantization, non-linear, super-blocks with 256 weights.
IQ4_XS	4.25	4-bit integer quantization, extra small, super-blocks with 256 weights.
IQ3_S	3	3-bit integer quantization, small.
IQ3_XXS	3	3-bit integer quantization, extra extra small.
IQ2_S	2	2-bit integer quantization, small.
IQ2_XS	2	2-bit integer quantization, extra small.
IQ2_XXS	2	2-bit integer quantization, extra extra small.
IQ1_S	1	1-bit integer quantization, small.
IQ1_M	1	1-bit integer quantization, medium.

Quantization	Correct (%)	Loss of accuracy (%)
IQ2_XXS	51,5	26,0
Q2_K_S	62,4	10,3
IQ3_XXS	67,3	3,2
Q3_K_M	68,3	1,8
IQ4_XS	69,3	0,4
Q4_K_M	69,0	0,8
Q6_K	69,8	-
Q8_0 (static)	69,6	-

Approx. loss

Legacy Quantizations (Q4_0, Q4_1, Q5_0, Q5_1, Q8_0, Q8_1): These are simpler, faster methods but may have higher quantization error compared to newer types.

K-Quantizations (Q2_K, Q3_K, Q4_K, Q5_K, Q6_K): Introduced in llama.cpp PR #1684, these use super-blocks for smarter bit allocation, reducing quantization error.

I-Quantizations (IQ2_XXS, IQ3_S, etc.): State-of-the-art for low-bit widths, using lookup tables for improved accuracy but potentially slower on older hardware.

GGUF Q8_0: Very close to FP16 (perplexity 7.4933), indicating minimal accuracy loss.

GGUF Q4_K_M: Slightly higher perplexity (7.5692), still usable for most tasks.

Opensource models

Stable Diffusion 1

Stable Diffusion XL

<https://stability.ai/news/stable-diffusion-sdxl-1-announcement>

Stable Diffusion 3

by Stability AI <https://stability.ai>

Flux.1d

by Black Forest Labs <https://bfl.ai>

HiDream I1

by HiDream AI <https://hidream.org>

CLIP (Contrastive Language-Image Pre-training)

[Wikipedia](#)

Self-attention Transformer as a text encoder

From:
<https://wiki.janforman.com/> - **wiki.janforman.com**

Permanent link:
<https://wiki.janforman.com/nn:index?rev=1756813442>

Last update: **2025/09/02 13:44**

