70% Size, 100% Accuracy: Lossless LLM Compression for Efficient GPU Inference via Dynamic-Length Float (DFloat11)

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Limitations of Existing Compression Algorithms

Large Language Models (LLMs) and Diffusion Models (DMs) are large (GBs to TBs) and memory-intensive.

Existing lossy model compression methods (quantization, pruning, etc.) → tradeoffs between model quality and compression factor

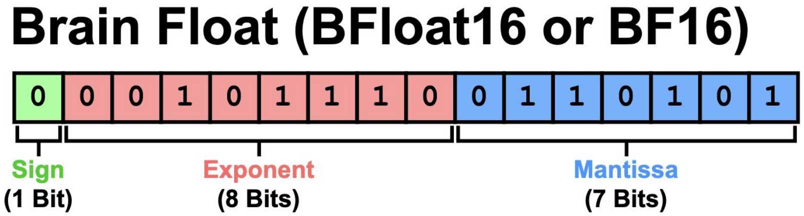
- Accuracy & performance degradations
- Model behavior changes (*flips*[1])

Existing lossless compression (lossless encoding) → does not support GPU inference

[1] Dutta, Abhinav, et al. "Accuracy is not all you need." Advances in Neural Information Processing Systems 37 (2024): 124347-124390.

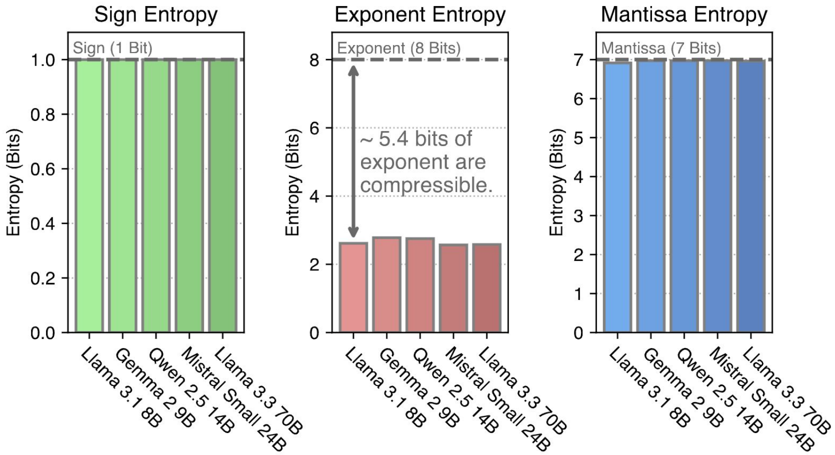
BFloat16 & Its Inefficiency

Foundation models predominantly use BFloat16



Our Insight: Low entropy in BFloat16 exponents

- Real entropy vs. allocated bit width: **2.6 bits** vs. **8 bits**
- Significant potential for lossless compression!



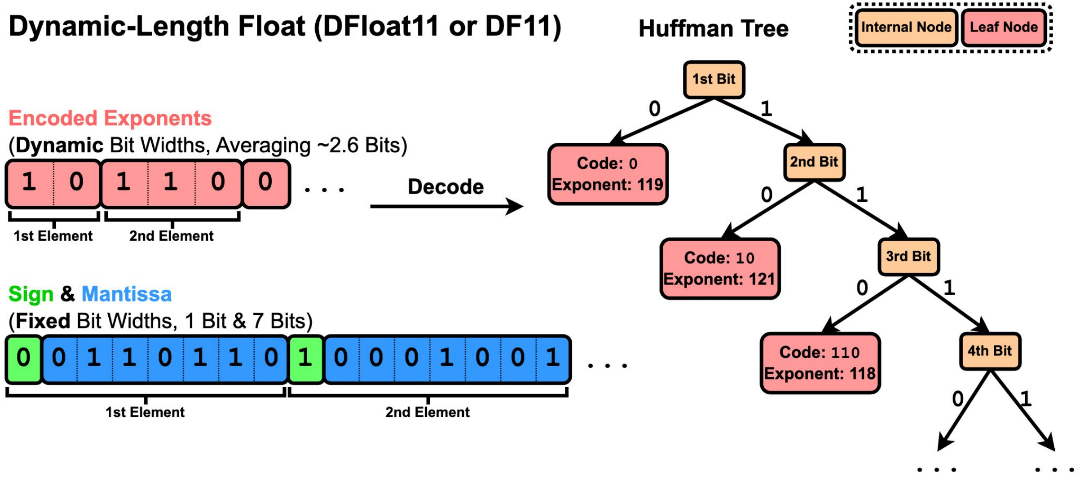
Lossless Compression via Huffman Coding

Huffman coding[1]

- Prefix-free binary tree
- Guaranteed lossless
- Information optimal for any given frequency distribution

Our proposal: Dynamic-Length Float (DFloat11)

- Huffman coding on BFloat16 exponents
- Pack *signs* and *mantissas* tightly



[1] Huffman, David A. "A Method for the Construction of Minimum-Redundancy Codes." Proceedings of the IRE, vol. 40, no. 9, Sept. 1952, pp. 1098–1101.

Core Challenge: GPU Inference with Dynamic-Length Float

GPUs are

- Massively parallel
- Inefficient at branching

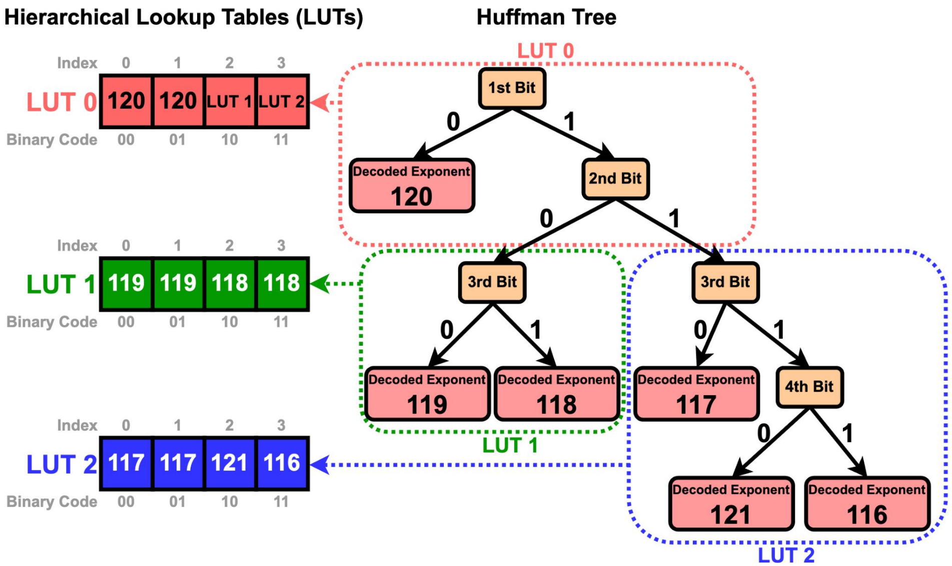
Dynamic-Length Float

- Variable-length encodings → difficult to coordinate GPU threads
- Binary-tree-based decoding → not suitable for GPU computation

Our Solution: Hardware-aware Algorithmic Designs

Technique #1 — Decoding Huffman codes via hierarchical lookups

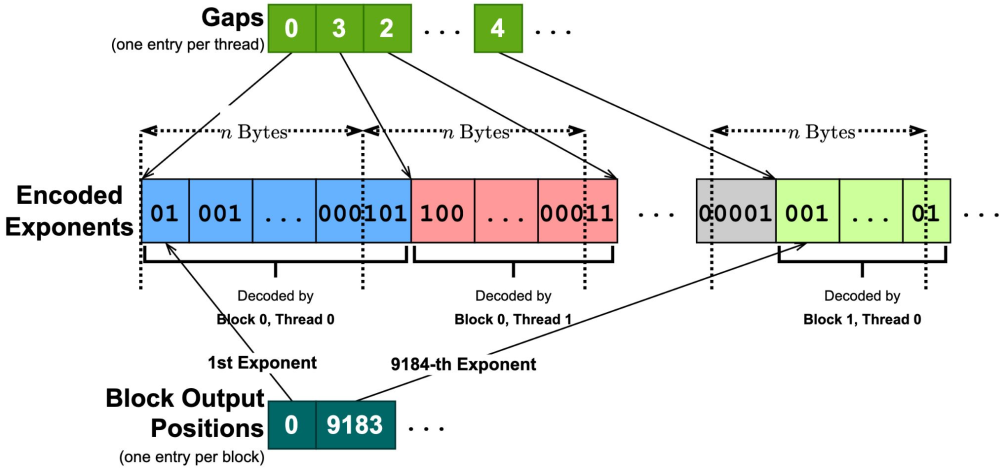
- Use lookups instead of binary tree traversal
- Decompose the monolithic lookup table (LUT) into compact LUTs



Our Solution: Hardware-aware Algorithmic Designs

Technique #2 — Two-phase Kernel for Thread Coordination

- Use thread-level *gap arrays* and block-level *output-position arrays* to determine the bit position
- Phase 1 — count the number of decoded elements, and synchronize threads
- Phase 2 — write the decoded elements to memory



Our Solution: Hardware-aware Algorithmic Designs

Technique #3 — Transformer-block level decompression

- More data to decompress at once → better GPU utilization → higher throughput
- Batch the decompression of all matrices in a transformer block

32% Size Reduction, 0 Accuracy Loss

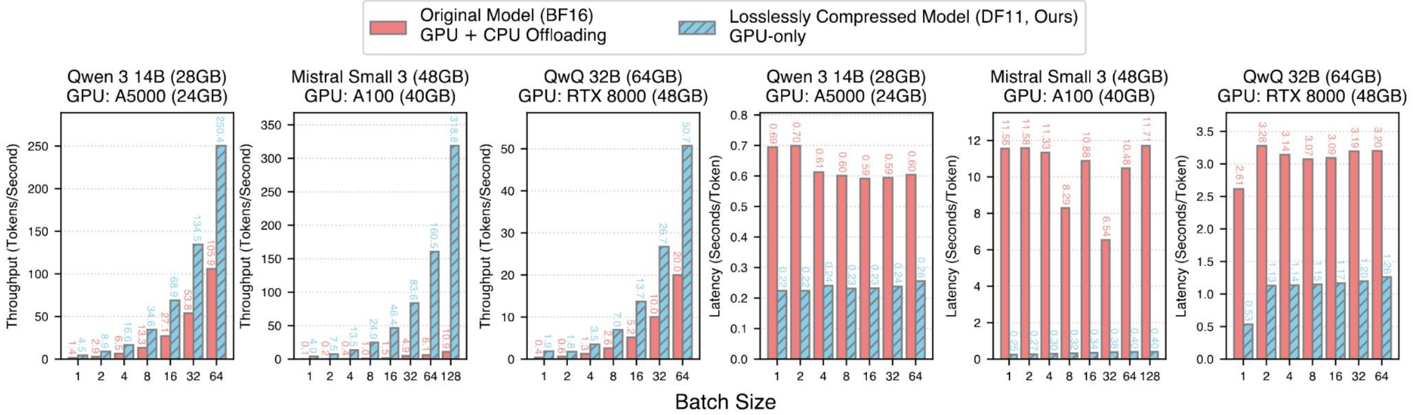
Table 1: DF11 statistics for various models. Model sizes are shown before and after compression.

Model	Original → DF11 Compressed	Compression Ratio	Avg. Bit Width
Large Language Models			
Llama 3.1 8B Instruct	16.06 GB → 10.90 GB	67.84%	10.85
Llama 3.3 70B Instruct	141.11 GB → 95.40 GB	67.61%	10.82
Llama 3.1 405B Instruct	811.71 GB → 551.22 GB	67.91%	10.87
Qwen 3 14B	29.54 GB → 20.14 GB	68.17%	10.91
QwQ 32B	65.53 GB → 44.65 GB	68.14%	10.90
Mistral Nemo Instruct	24.50 GB → 16.59 GB	67.74%	10.84
Mistral Small 3	47.14 GB → 31.86 GB	67.58%	10.81
Phi 4 Reasoning Plus	29.32 GB → 19.83 GB	67.64%	10.82
DeepSeek R1 Distill Llama 8B	16.06 GB → 10.89 GB	67.81%	10.85
Diffusion Transformers			
FLUX.1 dev	23.80 GB → 16.33 GB	68.61%	10.98
FLUX.1 schnell	23.78 GB → 16.31 GB	68.58%	10.97
Stable Diffusion 3.5 Large	16.29 GB → 11.33 GB	69.52%	11.12

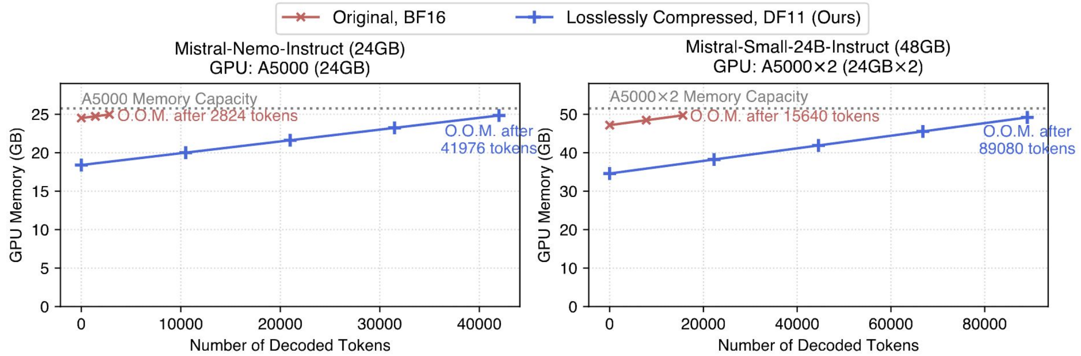
Table 2: Comparison of accuracy and perplexity for the BF16 and DF11 models on different benchmarks. DF11 compression results in absolutely no loss in accuracy or perplexity.

		Accuracy		Perplexity	
Model	**Data Type**	MMLU	TruthfulQA	WikiText	C4
Llama 3.1 8B Instruct	BF16	68.010 ± 0.375	36.965 ± 1.690	8.649	21.677
	DF11 (Ours)	68.010 ± 0.375	36.965 ± 1.690	8.649	21.677

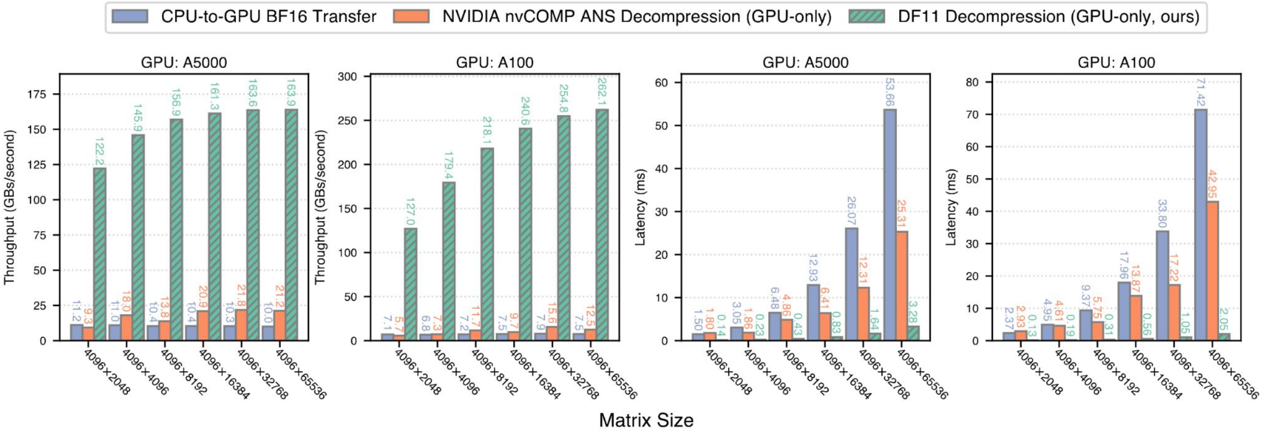
2.31—46.24× Faster Than Offloading



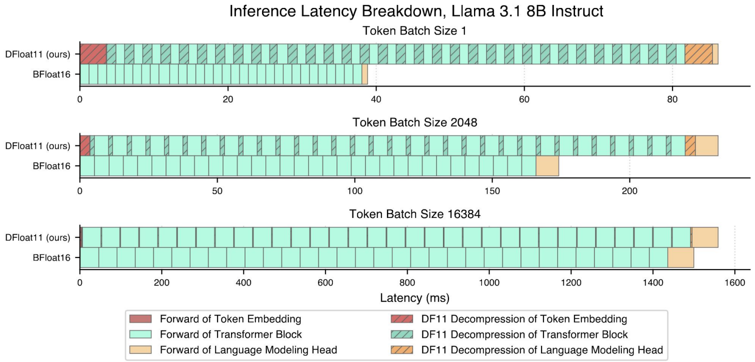
5.70—14.86× Longer Context Length



20.97× Faster Than NVIDIA nvCOMP



Negligible Decompression Overhead at Large Batch Size



Thank you

Paper

Code