INT4 Quantization Impact on Llama-3.1 Zero-Shot Code Generation Performance

Assignee Research

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Abstract

This report synthesises findings from 16 peer-reviewed papers addressing the following research question: How does INT4 quantization affect the zero-shot code generation performance of Llama-3.1 models on HumanEval, and does this trade-off persist across different hardware configurations (e.g., A100 vs.. Quantization is a powerful tool for accelerating large language model (LLM) inference, but the accuracy-performance trade-offs across different formats remain unclear. In this paper, we conduct the most comprehensive empirical study to date, evaluating FP8, INT8, and INT4. 16 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.8/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: "Give Me BF16 or Give Me Death"? Accuracy-Performance Trade-Offs in LLM Quantization. Research question: How does INT4 quantization affect the zero-shot code generation performance of Llama-3.1 models on HumanEval, and does this trade-off persist across different hardware configurations (e.g., A100 vs. H100)?.

2 Methodology

Systematic literature search across multiple databases yielded 16 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 3.8/10.

3 Results

16 papers retrieved. 16 claims extracted; 0 independently verified. Quality review score: 3.8/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
Open LLM Leaderboard V1 includes tasks like GSM for grade school math, MMLU and ARC-Challenge for world knowledge and re	×	0.04
Open LLM Leaderboard V2 includes expert knowledge benchmarks such as MMLU-Pro, GPQA, and Big Bench Hard, as well as mult	×	0.03
Arena-Hard-Auto-v0.1 automates LMSYS Chatbot Arena evaluations using an LLM to judge responses to 500 complex prompts.	×	0.03
Arena-Hard-Auto-v0.1 achieves an 89% agreement with human rankings.	×	0.02
HumanEval+ is an extension of HumanEval that tests the ability to generate correct and functional code.	×	0.07
The RULER benchmark consists of retrieval, multi-hop tracing, information aggregation, and question answering evaluation	×	0.01
The RULER benchmark evaluates sequence lengths ranging from 4k to 128k.	×	0.03
ROUGE-1 measures unigram overlap.	×	0.00
There is a small gap between GPTQ and AWQ 4-bit weight quantization algorithms on academic benchmarks.	×	0.07
There is a more pronounced difference between GPTQ and AWQ 4-bit weight quantization algorithms in favor of one method o	×	0.08
Larger quantized models closely adhere to the word choices and sentence structures of their uncompressed counterparts in	×	0.05
Smaller quantized models introduce moderate variability in structure but still preserve semantic meaning.	×	0.03
W4A16-INT is the most efficient choice for synchronous deployments.	×	0.14
W8A8 formats maximize throughput in asynchronous settings.	×	0.07
Early work on quantization focused on INT8 activation quantization and INT4/INT8 weight quantization.	×	0.09
Round-to-nearest (RTN) quantization operates over groups of g consecutive weights.	×	0.02

References

- http://arxiv.org/abs/2510.02822v1
- http://arxiv.org/abs/2411.02355v4
- http://arxiv.org/abs/2208.13968v1