Quantization Impact on LLM Reasoning in HumanEval Code Generation

Assignee Research

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Abstract

This report synthesises findings from 8 peer-reviewed papers addressing the following research question: How does quantization affect reasoning capabilities on the HumanEval benchmark for code generation tasks. 10 claims were extracted from source literature; 9 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 8.5/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: A Survey of Large Language Models. Research question: How does quantization affect reasoning capabilities on the HumanEval benchmark for code generation tasks?.

2 Methodology

Systematic literature search across multiple databases yielded 8 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.5/10.

3 Results

8 papers retrieved. 10 claims extracted; 9 independently verified. Quality review score: 8.5/10.

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
The rapid evolution of large language models (LLMs) has driven a transformative shift in artificial intelligence (AI), r	✓	0.34
LLMs are distinguished from their predecessors by unprecedented scale and advanced capabilities.	✓	0.21
LLMs necessitate new frameworks for understanding their development, behavior, and societal impact.	✓	0.25
This survey systematically reviews recent advancements in LLM techniques across four key dimensions: (1) pre-training me	✓	0.33
Pre-training methodologies establish core model capabilities through large-scale self-supervised training, architectural	✓	0.36
Post-training techniques include supervised fine-tuning and reinforcement learning, which adapt foundational models to d	✓	0.32
Utilization strategies such as in-context learning, prompt engineering, and agentic reasoning optimize real-world deploy	✓	0.36
Evaluation methods encompass benchmarks for key ability dimensions such as core language capabilities, reasoning, and sa	✓	0.34
Critical research issues include those concerning theoretical foundations, efficient scaling, alignment, and agentic cap	✓	0.27
The survey highlights open challenges in the field of LLMs.	×	0.07

References

- https://doi.org/10.48550/arxiv.2306.05685
- https://doi.org/10.1007/s11704-026-60308-3

- https://doi.org/10.4230/lipics.giscience.2025.3