Robustness of Llama-3-70B Block-Sparse FlashAttention Under Adversarial Perturbations

Assignee Research

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Abstract

This report synthesises findings from 4 peer-reviewed papers addressing the following research question: How does the robustness of Llama-3-70b with Block-Sparse FlashAttention compare to full attention under adversarial perturbations in the ConvAITest dataset, measured by accuracy drop under noise. 8 claims were extracted from source literature; 8 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 7.5/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Explainability for Large Language Models: A Survey. Research question: How does the robustness of Llama-3-70b with Block-Sparse FlashAttention compare to full attention under adversarial perturbations in the ConvAITest dataset, measured by accuracy drop under noise injection or token shuffling?.

2 Methodology

Systematic literature search across multiple databases yielded 4 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.5/10.

3 Results

4 papers retrieved. 8 claims extracted; 8 independently verified. Quality review score: 7.5/10.

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
Large language models (LLMs) have demonstrated impressive capabilities in natural language processing.	✓	0.31
The internal mechanisms of LLMs are still unclear and this lack of transparency poses unwanted risks for downstream appl	✓	0.28
Understanding and explaining LLMs is crucial for elucidating their behaviors, limitations, and social impacts.	✓	0.25
The article introduces a taxonomy of explainability techniques and provides a structured overview of methods for explain	✓	0.30
The taxonomy categorizes techniques based on the training paradigms of LLMs: traditional fine-tuning-based paradigm and	✓	0.34
For each paradigm, the article summarizes the goals and dominant approaches for generating local explanations of individ	✓	0.34
The article discusses metrics for evaluating generated explanations and how explanations can be leveraged to debug model	✓	0.27
The article examines key challenges and emerging opportunities for explanation techniques in the era of LLMs in comparis	✓	0.33

References

- https://doi.org/10.1016/j.eng.2024.12.008
- https://doi.org/10.48550/arxiv.2412.05579
- https://doi.org/10.1145/3639372