Scaling-Induced Alignment of Attention Weights with Vulnerability Causality in Llama Zero-Shot Code Security

Assignee Research

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Abstract

As large language models (LLMs) move from research prototypes to enterprise systems, their security vulnerabilities pose serious risks to data privacy and system integrity. This study benchmarks various Llama model variants against the OWASP Top 10 for LLM Applications framework, evaluating threat detection accuracy, response safety, and computational overhead. Using the FABRIC testbed with NVIDIA A30 GPUs, we tested five standard Llama models and five Llama Guard variants on 100 adversarial prompts covering ten vulnerability categories. Our results reveal significant differences in security p

1 Introduction

This paper examines: Benchmarking LLAMA Model Security Against OWASP Top 10 For LLM Applications. Research question: Does the correlation between attention weights and actual vulnerability causality improve with model scaling from Llama-2-7B to Llama-3.1-8B in zero-shot code security tasks?.

2 Methodology

Systematic literature search across multiple databases yielded 10 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.3/10.

3 Results

10 papers retrieved. 18 claims extracted; 13 independently verified. Quality review score: 7.3/10.

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 evaluation followed a four-stage pipeline consisting of Model Loading, Test Execution, Response Evaluation, and Aggr	✓	0.18
All models were prompted with the consistent classification frame: 'is this prompt safe or not?'.	✓	0.22
Experiments were conducted on the FABRIC testbed utilizing the Georgia Tech site.	✓	0.17
The hardware configuration included an NVIDIA A30 GPU with 24GB VRAM based on Ampere architecture.	✓	0.16
The software stack used included PyTorch 2.1.0, CUDA 11.8, and HuggingFace Transformers library v4.51.3.	✓	0.19
The NVIDIA driver version used was 535.183.01.	×	0.10
Ten models from the Llama family were selected for the study.	×	0.10
The study included five standard Llama models: Meta-Llama-3-8B, Llama-3.1-8B, Llama-3.1-8B-Instruct, Llama-3.2-1B, and L	✓	0.23
The study included five Llama Guard models: Meta-Llama-Guard-2-8B, Llama-Guard-3-1B, Llama-Guard-3-8B, Llama-Guard-3-8B-	✓	0.24
Llama-Guard-3-11B-Vision is a multimodal variant that was tested on text in this study.	✓	0.20
All models were loaded in float16 precision, except for the INT8 variant.	✓	0.19
Models were run with a temperature of 0.1.	×	0.04
Base models (Meta-Llama-3-8B and Llama-3.1-8B) failed to detect any threats.	✓	0.19
Base models (Meta-Llama-3-8B and Llama-3.1-8B) were the slowest models in the evaluation.	✓	0.18
Llama-Guard-3-1B achieved a security detection accuracy of 76%.	✓	0.18
Llama-3.2-1B achieved a security detection accuracy of 73%.	×	0.14
There is an inverse relationship between inference latency and security detection performance in the tested models.	×	0.14
Guard models are optimized for direct classification, whereas standard models approximate classification through generat	✓	0.21

References

- http://arxiv.org/abs/2601.19970v1
- http://arxiv.org/abs/2209.03013v1
- http://arxiv.org/abs/2504.16310v1