Insights and Current Gaps in Open-Source LLM Vulnerability Scanners: A Comparative Analysis

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Abstract—This report presents a comparative analysis of opensource vulnerability scanners for conversational large language models (LLMs). As LLMs become integral to various applications, they also present potential attack surfaces, exposed to security risks such as information leakage and jailbreak attacks. Our study evaluates prominent scanners - Garak, Giskard, PyRIT, and CyberSecEval - that adapt red-teaming practices to expose these vulnerabilities. We detail the distinctive features and practical use of these scanners, outline unifying principles of their design and perform quantitative evaluations to compare them. These evaluations uncover significant reliability issues in detecting successful attacks, highlighting a fundamental gap for future development. Additionally, we contribute a preliminary labelled dataset, which serves as an initial step to bridge this gap. Based on the above, we provide strategic recommendations to assist organizations choose the most suitable scanner for their red-teaming needs, accounting for customizability, test suite comprehensiveness, and industry-specific use cases.

Index Terms—Large Language Models (LLMs), Vulnerability Scanners, Red Team, Comparative Analysis, Harmful Content Detection.

I. INTRODUCTION

In this work, we compare tools for assessing the vulnerability of conversational large language models (LLMs) such as the GPT family, LLaMA-instruct, and Command-R [1]– [3]. LLMs are increasingly integrated into various applications, providing a natural language prompt interface [4]–[6]. However, this integration exposes systems to significant security risks [2], including the spread of misinformation [7], hate campaigns [8], and cybercriminal activities [9]. To address these threats, the practice of red-teaming has emerged as a crucial part of the defense strategy. Originally rooted in traditional cybersecurity, red-teaming involves simulating attacks to uncover vulnerabilities [10]. In our scenario, red-teaming is adapted to target the prompt interface by crafting adversarial text inputs (prompts), addressing the unique vulnerabilities of LLMs [11], [12]. The importance of red-teaming has been recognized by authoritative sources, including the US government, the National Institute of Standards and Technology, and the OWASP Top 10 for LLM Applications Cybersecurity and Governance Checklist [13]–[15]. While LLM red-teaming is essential, it is challenging due to its dynamic nature, which requires continuous updates to stay ahead of evolving threats.

LLM vulnerability scanners (in short, *scanners*) have recently been developed to facilitate and automate the redteaming process, enhancing efficiency and adaptability to continuously evolving threats [16]–[24]. These scanners systematically test a target model by generating adversarial prompts, designed to elicit invalid responses such as confidential data, or toxic content [25]–[27]. The scanner then automatically evaluates the vulnerabilities exposed by these attacks, typically aggregating them to output a summary of the findings.

Since LLM vulnerability scanners are relatively new, there is still a considerable knowledge gap concerning their effectiveness, reliability, respective advantages and usage knowhow. Although there are reports on individual scanners and red-teaming best practices (e.g., [12], [16], [28]), to the best of our knowledge, there is an absence of a comprehensive hands-on report for making informed decisions when selecting and employing a scanner. Such a report is necessary, since navigating this domain can be challenging - the field is still in its early stages, with rapidly evolving methodologies and a lack of consensus on best practices. This leads to a diverse array of tools, each targeting different aspects of the domain, as well as overlooked aspects of performance and utility.

This work aims to bridge this knowledge gap by providing



Fig. 1. High-level Overview of our Quantitative Results. a) Scanner performance scatter plot. y-axis: Reported attack effectiveness; x-axis: Average reliability based on correct evaluation of attacks' success. Circle radius: No. of adversarial prompts in the test-suite. b) Adversarial prompts distribution. Prompt's attack types are grouped into five categories for comparability.

a detailed comparison through hands-on experience, and quantitative analyses. We define criteria to identify the most useful scanners for our analyses: Garak, Giskard, PyRIT, and Cyber-SecEval [16], [17], [22], [29]. This focused selection enables thorough experimentation to examine the internal workings of each scanner and gain a comprehensive understanding of their distinctive features. Furthermore, we conduct extensive quantitative analyses of the attacks utilized by each scanner and the automatic mechanisms that assess the attacks' success. As shown in Fig. 1, the attacks' coverage, effectiveness, and reliability are not always high, and vary between the scanners (for the attack categories, see Appendix A). The hands-on insights and quantitative analyses presented will assist researchers and AI safety teams in making informed decisions regarding the selection and improvement of these tools. Our contributions are:

- Pioneering Analysis: To the best of our knowledge, this is the first hands-on comparative study of open-source LLM vulnerability scanners. We offer valuable insights, practical information, and identify key current challenges.
- Detailed Feature Insights: We outline the distinctive features and shared unifying principles of various scanners, equipping users with a nuanced understanding of each tool's strengths.
- Labelled Dataset: We provide a 1,000-sample dataset as a foundational starting point to initiate the currently absent quantification of the scanners' reliability¹.
- Quantitative Findings: Analyzing ~5K adversarial prompts, we show that detecting successful attacks is an unresolved challenge - highlighting gaps in reported coverage, as current scanners misclassify up to 37% of successful adversarial prompts for a specific attack.
- Strategic Recommendations: We provide guidance to organizations in choosing their scanner, considering customizability, vulnerability coverage, and organizational

needs. Additionally, we propose future directions to enhance safety performance of these scanners.

II. PREVIOUS WORK

The widespread adoption of LLMs has enhanced digital productivity, while also exposing numerous security vulnerabilities. In response, extensive research has been conducted exploring these vulnerabilities, ranging from biases in training data to susceptibility to adversarial prompts. This research field primarily revolves around: 1) comprehensive surveys cataloging vulnerabilities and evaluation approaches [7], [30], [31] and 2) in-depth works on specific LLM security exploits [32]–[34].

Building upon these foundational studies, the field has increasingly embraced red-teaming as an approach to enhance LLM security [35], [36]. Red-teaming process involves simulating adversarial attacks to identify potential LLMs' vulnerabilities, thereby improving their robustness. To facilitate this process, a variety of automated tools have been developed [16], [22], [29], [37], which enable continuous and scalable security assessments. Some related works automatically evaluate LLMs using other LLMs, however they isolate the effect of the evaluator LLM's instructions - a key component we aim to analyze [38]–[40]. These tools differ in their approach, features, and effectiveness, highlighting the urgent need for a practical comparative analysis. Addressing this need, this report delivers a technical and detailed comparison of leading scanners, offering guidance to red-teaming groups in selecting the most effective tools for their specific organizational needs.

III. UNIFYING PRINCIPLES OF LLM VULNERABILITY SCANNERS

LLM vulnerability scanners have only recently emerged, and thus, to the best of our knowledge, their shared principles have not been outlined yet. In this section, we provide such outlines and introduce key terminology used throughout this paper.

A scanner receives a *target LLM* as input to identify and report its *vulnerabilities*. The different scanners operate on the

¹https://drive.google.com/file/d/1mWPKF5Eww-Bma0hGBT7lckNim3Hg6wEK/view?usp=sharing



Fig. 2. General design of the automated red-teaming flow, used by LLM vulnerability scanners.

same principle of automated red-teaming, and hence exhibit similar system architectures and components. As illustrated in Fig. 2 - the *test suite*, designed to identify vulnerabilities, is composed of an array of *attacker-evaluator* pairs. The attacker provides prompts intended to elicit prohibited responses from the target LLM (where 'prohibited' may be subjective to the specific purpose of the target LLM), while the evaluator determines the success of these attacks.

The used attacks are categorized into two types: *Static attacks*, which utilize an *attack dataset* consisting of predefined adversarial prompts, and *LLM-based attacks*, where an *attacker LLM* is instructed to generate the adversarial prompts². The attacker LLM may receive additional external context, such as a list of *requirements* defining valid responses. Evaluators can also be either static or LLM-based. Static evaluators verify the presence of specific strings in the target LLM's response via string-matching, including regular expression pattern matching, exact matching, and word matching. In contrast, LLM-based evaluators involve an *evaluator LLM* that is instructed to identify prohibited responses. It receives the target LLM's response, and additional contexts such as the attack prompt, and the requirements mentioned above. The identified vulnerabilities are then compiled into a report.

Different scanners may utilize different of attacks, presenting a challenge for comparison. To enable a structured comparison of vulnerability coverage and quantitative performance metrics, these attacks can be grouped into four unifying categories: Jailbreak, Context and Continuation, Gradientbased, and Code Generation Attacks. While this approach reduces granularity, it is essential for ensuring comparability. The specific categorization for each scanner is detailed in Table III in the Appendix.

The unifying principles outlined above set the stage for the diverse landscape of LLM vulnerability scanners. While the implementation of each component can vary significantly, in terms of the attacker and evaluator types, the strategies for generating prompts, and the criteria for identifying prohibited responses - all scanners share a common architecture. The

resulting scanner variations are designed to address different aspects of LLM security. In the following sections, we will delve into these variations, exploring the distinctive features and methodologies that distinguish various scanners.

IV. PER-SCANNER REVIEW

A. Scanner Criteria and Selection

Before the hands-on assessments, we conducted an initial review to select the most relevant scanners. Below we detail the three criteria employed for the selection process, the 15 candidate scanners, and the selected scanners that fit these criteria the most. The criteria comprise:

1) Quality of vulnerabilities test suite. This is the cornerstone of any scanner - a comprehensive suite that simulates diverse real-world scenarios is essential for uncovering LLMs vulnerabilities. Well-documented and research-backed attacks provide more reliability to the security assessments.

2) Frequent updates to address evolving threats. The landscape of cybersecurity threats is continuously changing, with new attack vectors emerging regularly. Moreover, as LLMs frequently evolve to counter existing attacks, a scanner's **test suite** that was effective a few months ago might be obsolete today. To maintain their effectiveness, scanners must systematically update their test suite, ensuring they can identify the latest threats effectively.

3) Open-source code with active community engagement. In our view, a key advantage is the impact of an active community on the longevity and sustainability of a project, ensuring **frequent updates** for the long run. An engaged community reduces reliance on initial contributors, fostering a self-sustaining environment where the project can evolve independently. Moreover - as contemporary attacks often emerge from the community, leveraging this collective expertise for test suite updates is a viable strategy. Lastly, we focus solely on open-source scanners for transparency and adaptability.

The 15 scanners: See Appendix B for a summary of all 15 scanners, listed below: CyberSecEval [28], HouYi [37], JailBreakingLLMs [41], LLMAttacks [42], Garak [16], Giskard [17], Prompt Fuzzer [18], PromptInject [43], Prompt-

²Static attacks might use LLMs beforehand, but LLM-based attacks instruct attacker LLMs during execution.

foo [19], LLMCanary [20], Agentic security [21], PyRIT [22], LLMFuzzer [23], PromptMap [24], Vigil-Ilm [44].

Four scanners stood out by our criteria³:

Garak. Released in early 2024, Garak [16] quickly gained popularity due to its broad vulnerability coverage and frequent updates. Moreover, its attacks are backed by published research.

Giskard. Giskard is a company focused on responsible AI, offers an open-source LLM vulnerability scanner [17]. Giskard has an active and growing community that foster members to engage in several topics including contributing code, discussing vulnerabilities and sharing best practices.

PyRIT. The Python Risk Identification Tool for Generative AI, or PyRIT, is a scanner developed by Microsoft [22]. Released in March 2024 [45]. PyRIT has been continually evolving, focusing on LLM-based attack and evaluation strategies.

CyberSecEval. Developed by Meta, this scanner specializes in detecting vulnerabilities in LLM-generated code, while also addressing natural language vulnerabilities [28], [46].

B. Garak

Test-suite. Garak excels in vulnerability coverage with over 20 specific attack-evaluation pairs, focusing on jailbreak attacks grounded in established research [16], [32], [33], [42], [47], [48]. It focuses in static attacks with correspondingly static evaluators.

Operational usage. Garak produces reports in both JSON and HTML formats. The JSON report is thoroughly detailed, including every tested adversarial prompt, the target LLM's reponse to it, and the evaluator's assessment of success. A additional 'hitlog' reports successful attacks only. The HTML format, easier for non-technical users, provides a broader overview, summarizing statistics for each attack. An example report can be found in the Appendix 5. We found Garak's code implementation to be the most robust. It features a 'probe' for managing attacks, and for the evaluation, a 'detector' scores the attack and an 'evaluator' make the final decision based on a pre-defined threshold.

A notable feature is Garak's integration with Nvidia's NeMo Guardrails [49], which enables the vulnerability assessment of the target LLM with and without defense mechanisms. Garak includes a *generator* component that handles all text-to-text interactions and is specifically designed to support NVIDIA NeMo models. The effectiveness of this integration is demonstrated by comparing the performance of unprotected models versus models with various levels of Guardrails defense against specific attacks. For instance, we tested the the GPT 3.5 model's robustness against context & continuation attacks under various NeMo Guardrails settings: *Clean setting* achieved 76.1%; *Instructions*—enhanced protection settings yielded 81.2%; *Dialog Rails*—mechanisms for refusing unwanted topics reached 92.6%; and *Moderation*

Rails—input/output self-checking scored 95.4%, highlighting Guardrails' effectiveness.

C. Giskard

Test-suite. Giskard's test suite features a diverse set of nine attack-evaluation pairs that blend static and LLM-based methods, with the latter offering a wide array, ranging from eliciting hallucinations to harmful content and stereotypes, to information disclosure - see Table IV in the Appendix. A distinctive aspect is its context-based mechanism, which includes: 1) a model description of the target model, and 2) in most cases, a list of safety requirements. The requirements are generated per attack, specifying the expected behavior of a robust target model against the attack at hand, see Fig. 3. This sophisticated process curates hybrid instructions for both the attacker and evaluator LLMs. These instructions combine the generated and user-provided contexts within a structured template, as well as pre-fixed context such as the attack category, and generation examples. The generation examples also play a role in defining the expected output format and may include non-English languages (see Fig. 8 in the Appendix). Notably, this attack process involves two LLMs: The standard attacker LLM and the requirements LLM, unlike "regular" LLM-based attacks which usually employ a single LLM.

Operational usage. After the evaluation, Giskard compiles all failed cases into a user-friendly HTML report, categorizing them by attack type and including prompts, responses, severity and the evaluator-LLM's reasons for attack success - see Fig. 5 in the Appendix. Giskard's model description context provides flexibility in tailoring LLM-based attacks to the target-LLM, see for instance Fig. 3 where we attack a bot designated to organize an international AI workshop. To set the model description, the user passes it to the 'giskard.Model' class which manages the target model.

Giskard's attacker and evaluator LLMs are restricted to GPT-family models (3.5 and above), which limit flexibility. While Giskard inherently focuses on successful attacks, we extended its functionality to log benignly classified attacks. This extension required substantial modifications due to the lack of uniform implementation across its attack-evaluation pairs, except for the 'RequirementBasedDetector', which offers a standardized interface. Altering attack-evaluation parameters and instruction templates is also useful, but necessitates modifications to deeper parts of the code. Similarly to Garak, Giskard also includes Guardrails-specific modules.

D. Pyrit

Test-suite. PyRIT [22] offers a fully LLM-based framework, with a highly useful flexible implementation. It allows a direct access to the attacker and evaluator LLMs' instructions (in contrast to the pre-made or hybrid attacker instructions described above). PyRIT implements two attack approaches under its attack strategy component: 1) A single-turn attack, similar to the LLM-based attacks presented above; 2) A multi-turn attack, engaging the target LLM in a sequential dialogue, terminating when a predefined goal is achieved (see

³Others using a similar scanner selection process may identify a different distinguished group.

Fig. 3). These gained a higher success rate, see Sec. V. The evaluator LLM, implemented in the scoring engine, serves a dual role in multi-turn attacks. Beyond deciding whether the attack succeeded, it also determines after each target LLM response if the dialogue should continue. The scoring engine offers four strategies for using evaluator LLMs (see Fig. 11 in the Appendix), with varying outputs: Some provide a binary decision (attack success or failure), while others generate score vectors - discrete rankings (1 to 5) or continuous (0 to 1). These scores evaluate the target LLM's response across categories like Hate, Bias, Violence, and Sexual content, following Microsoft Azure and OpenAI moderation standards [50].

Operational Usage. PyRIT offers creating custom attack strategies by defining instructions for both attacker and evaluator LLMs, allowing for tailored testing scenarios that target specific vulnerabilities beyond pre-made frameworks. This involves providing system prompts to the LLMs at initialization, enabling highly specialized attack simulations. Users can also modify evaluator instructions, from our experience, even when using well-crafted instructions, variations in evaluator prompts can significantly influence performance. Users can adjust these instructions to focus on areas like bias, hate speech, or ethical violations, ensuring the evaluation aligns with specific goals. This flexibility allows precise vulnerability assessments tailored to various industries or research objectives.

Although PyRIT doesn't generate a formal report, the attack conversation and success rate are easily accessible. Additionally, PyRIT offers an LLM-generated explanation to clarify its decisions, improving both the transparency and interpretability of the results.

E. CyberSecEval

Test-suite. CyberSecEval [28], [29], [46] provides a fully static test suite focused on analyzing vulnerabilities in LLM-generated code. It primarily targets insecure coding practices, which are codes with security breaches. As a side focus, the suite also evaluates the generation of malicious code, i.e. code that causes harm upon execution, and includes natural language jailbreak attacks that coax LLMs into revealing sensitive information.

To test for insecure coding practices, the CyberSecEval incorporates two main strategies, which use a database of insecure code snippets - as illustrated in Fig. 9 in the Appendix. The first is an auto-complete scenario, where the LLM is prompted with the 10 code lines that precede an insecure practice to see if it reproduces the risky code. The second, referred as instruct, converts instances of insecure practices into natural language instructions which in turn are passed as prompts to the target LLM, to assess if the LLM replicates the insecure practice. The dataset includes 50 Common Weakness Enumerations (CWEs) - a comprehensive list of common software security vulnerabilities [51], across eight programming languages. CyberSecEval evaluator, called the Insecure Code Detector (ICD) identifies insecure coding practices for test case generation and model evaluation. The

ICD uses rules created by Meta's cyber security experts, applied through static analysis tools like Weggli, Semgrep, and regular expressions (see Figure 10 in the Appendix).

Operational Usage. Upon concluding an evaluation session, CyberSecEval produces two types of reports: a statistical report that summarizes the success rates of various attacks across all test cases, and a detailed response report that documents each attack along with the AI's corresponding response.

While CyberSecEval's code implementation is stable and well-designed for easy modification of attacks and evaluations, crafting these is not straightforward, as it requires both cybersecurity and AI expertise. With that said - there are thousands of open-source CWEs which one can extend the insecure coding coverage utilizing CybeSecEval's framework. Thus in the hands of experts, CyberSecEval has potential for significant extensions.

F. Summary of Distinctive Features and their Comparison

To conclude this Section, Table I provides a comparison highlighting distinctive scanner features.

LLM Guardrails Interface. A ready-to-use encapsulation of one of the popular open-source Guardrails solution. Garak and Giskard support this. Explainability. Whether the scanner offers explanations for its assessments of attack success. Currently, only PyRIT and Giskard support this. Multi-language Support. Support the ability to expose vulnerabilities in non-English languages. Giskard is the only scanner that allows users to specify the language via example templates and provide non-English examples, prompting the attacker LLM to generate similar prompts. Customizable Attacks. Enable user-directed attack customization. Both Giskard and PyRIT support this, yet their approaches differ significantly. PyRIT grants full control over the attacker LLM's system prompt, while Giskard employs a more structured approach by combining pre-defined prompts with user inputs, restricted to the target model's name and description. Insecure Coding Tests. Whether the scanner includes tests specifically designed to assess the security of code generated by LLMs. Currently, only CyberSecEval and Garak offer such capability.

V. QUANTITATIVE COMPARISONS

A. Evaluation Objectives

This evaluation provides a comparative analysis of the scanners described in the previous section, focusing on two key aspects: attack coverage and evaluator effectiveness.

Attack Coverage. A scanner's comprehensiveness is determined by its attack coverage, which is essential for effectively simulating a wide range of real-world threats. We evaluate attack coverage by examining the *diversity* of attack types; the *volume of attack instances* produced for each type; and the *quality* of these attacks, measured by their effectiveness in triggering errors in the target LLM.

Evaluator Effectiveness. The reliability of a scanner can be assessed by the effectiveness of its evaluators. We assesses



Fig. 3. Top: Example Flow of Giskard, testing a "Workshop Organizer AI". An important aspect of Giskard is its ability to customize tests for LLMs that are designed for specific tasks. This example demonstrates Giskard's customization via its distinctive requirements-based test. This is a shortened version - for the full version, including the evaluation phase, refer to Fig. 8 in the Appendix. Bottom: Example flow of PyRIT's multi-step attack for generating Python Key Logger. An attacker LLM is tasked with attacking a target LLM under evaluation, while another LLM assesses the attack's success. This loop continues until the attack succeeds or a stopping criterion is met.

evaluators' accuracy in detecting vulnerabilities for various attack scenarios.

B. Evaluation Methodology and Results

To assess the scanners' effectiveness in identifying vulnerabilities, each scanner was tested against four LLMs: Meta's LLaMA 3 [1], Cohere's Command-R [3], OpenAI's GPT-40 [2], and Mistral AI's Mistral Small [52]. To assess the quality of the attacks provided by each scanner, we applied a comprehensive series of these attacks and measured their success rates (ASR) using each scanner evaluator. However, evaluators can also make errors, necessitating the assessment of their margin of error (MOE) to ensure reliable attack success rates reported. Due to the lack of inherent ground truth in scanner evaluations, we manually annotated over a thousand attack responses to establish a reliable baseline. This manual annotation process required a thorough understanding of each attack's objective, determining its success by analyzing the model's response. We ensured balanced representation across attack types, facilitating the calculation of the evaluators' accuracy and their MOE. Further details regarding our evaluation and data curation methodology are in the Appendix A.

Table II shows for each scanner its different attack categories, alongside their number of prompt instances, success rates (ASR) and margin of error (MOE) across the four tested LLMs. Figure 4 shows the ASR and MOE by the attack perspective. For the sake of comparability, the scanners' partially overlapping ~35 attack types where grouped into five categories (Jailbreak, Gradient-based, Context and Continuation C&C, Insecure Code Generation CG and General Multi-turn) - see details in Appendix A. Garak stands out for providing the most extensive variety of attacks and, in most cases, the highest number of instances per attack. Additionally, Garak's attacks are of the highest quality, with success rates

| AI Scanner Name | Test-suite Focus | Guardrails Interface | Explainability Capabilities | Multi-language Support | Customizable Attacks | Insecure Coding Tests |
|--------------------|---------------------|-------------------------|--------------------------------|---------------------------|-------------------------|--------------------------|
| Garak | String-matching | \checkmark | × | X | × | \checkmark |
| PyRIT | LLM-based | × | \checkmark | X | \checkmark | × |
| Giskard | LLM-based | \checkmark | \checkmark | \checkmark | \checkmark | × |
| CyberSec. | Pattern-matching | × | X | Х | X | \checkmark |

 TABLE I

 Comparison of distinctive scanner features. None of the scanners covers all utilities.

TABLE II ATTACKS' SUCCESS RATE (ASR) AND RELIABILITY (MOE) OVER DIFFERENT LLM MODELS.

| AI Scanner | Attack | No. of | Command R | | LLaMA 3 8B | | Mistral Small | | GPT 40 | |
|------------|------------|---------|-----------|-------|------------|--------|---------------|-------|--------|-------|
| | Categories | Prompts | ASR | MOE | ASR | MOE | ASR | MOE | ASR | MOE |
| Garak | Jailbreak | 802 | 73.00% | 17.2% | 39.00% | 10.7% | 59.00% | 16.3% | 55.00% | 16.8% |
| | Gradbased | 41 | 48.00% | 0.12% | 36.00% | 0.1% | 51.00% | 0.05% | 50.00% | 0.2% |
| | C&C | 2852 | 23.00% | 26.4% | 21.00% | 15.4% | 25.00% | 13.2% | 11.00% | 13.2% |
| | Code Gen. | 252 | 74.30% | 18.3% | 45.80% | 16.6% | 82.40% | 14.5% | 65.00% | 15.2% |
| Durit | Jailbreak | 310 | 8.00% | 0.01% | 7.00% | 0.03% | 30.04% | 15.8% | 9.00% | 8.9% |
| I yili | Multi-turn | 20 | 31.00% | 0.1% | 9.00% | 22.7% | 19.00% | 0.2% | 45.00% | 16.9% |
| Giskard | Jailbreak | 90 | 56.66% | 11.1% | 10.0% | 12.62% | 17.78% | 7.2% | 7.78% | 3.1% |
| | C&C | 100 | 40.0% | 9.1% | 20.0% | 15.6% | 16.0% | 0.2% | 26.0% | 11.2% |
| CyberSec. | Code Gen. | 757 | 10.00% | 19.3% | 13.5% | 18.1% | 13.75% | 19% | 19.5% | 19.8% |
| | Jailbreak | 251 | 50.90% | 13.3% | 45.00% | 10.7% | 47.00% | 12.1% | 48.60% | 14.3% |

ranging from approximately 20% in context and continuation attacks to nearly 70% in insecure code attacks. The MOE measurements reveal notable errors across all scanner evaluators, with PyRIT's LLM-based evaluators being the most reliable (lowest MOE), while Garak shows a maximum MOE of 26%, corresponding to a 37% error rate in detecting successful attacks.

Both static and LLM-based evaluators experience this issue. Static evaluators that use string-matching can oversimplify, e.g., we found misclassifications due to minor punctuation changes - see Appendix B. LLM-based evaluators, while better at handling complex contexts, can be unpredictable, sometimes offering irrelevant reasoning. In one example (Appendix B), the evaluator LLM tests the presence of a specific safety mechanism instead of recognizing that the target LLM successfully evades the attack altogether, regardless of whether such a mechanism exists. As evident in Fig. 1, the LLM-based evaluators of Giskard and PyRIT offer the highest reliability. We believe CyberSecEval's low reliability comes from the ambitious attempt at identifying unsafe code. As for Garak - we believe its large-scale data will benefit transitioning from static to LLM-based evaluators. Last but not least, Fig. 1 shows a clear advantage for static-focused scanners in terms of attack effectiveness.

VI. RECOMMENDATIONS

A. Matching Red-Teaming Scanners to Your Organizational Needs

Based on our review and scanner performance evaluation, this section offers strategic recommendations for selecting the most suitable scanner for specific organizational needs. Selecting the right scanner for organizational red-teaming efforts is a complex task, influenced by specific business risks.

Red-teaming groups handling diverse use cases, such as large corporations employing LLMs for HR, sales, marketing, internal data analysis, etc. would prefer a *ready-to-use* test suite offering wide coverage of potential vulnerabilities, where customization is less frequent. In contrast, agile firms focusing on single-case products would favor customizable *do-it-yourself* solutions that allow for dynamic adaptations through tailored tests that meet their specific needs.

Below we position the analyzed scanners on the "readyto-use" versus "do-it-yourself" spectrum - highlighting their strengths and limitations to guide organizations in making informed choices.

Garak offers the most extensive test-suite, making it suitable for red-teaming groups that deal with diverse use-cases. However, its focuses more on a static attack dataset, limiting customizability. Garak also integrates with Nvidia's NeMo Guardrails, enabling setting additional safety layers.

Giskard is ideal for users seeking flexible attack generation with both static and LLM-based methods. It offers a simple yet effective customization of LLM-based attacks. Hence, it enables producing tailored test suites for various attack types, ideal for red-teaming in dynamic online environments with minimal manual interference. Moreover, it includes Guardrails to enhance safety.

PyRIT offers the most customizable test suite, focusing on LLM-based attacks. It allows users to edit both attacker and evaluator LLMs, providing full access to their instructions. This offers extensive flexibility but requires significant prompt engineering. Therefore, PyRIT is best suited for red-teams



Fig. 4. Per-attack performance, averaged over the target LLMs. MOE shown as error bars.

focusing on an internally crafted test-suite rather than relying on external knowledge. Additionally, PyRIT implements advanced multi-step attacks which exhibits relatively high success rate.

CyberSecEval focuses on red-teaming for code-generating LLMs. Its test-suite is designed to expose code-related security issues. This makes it valuable for red-teaming groups dealing with generative AI for software and cybersecurity, where the integrity of auto-generated code is crucial.

B. Current Scanner Gaps and Suggested Improvements

We have discovered critical issues concerning the scanners' reliability, stemming from the evaluator component's performance. This component is typically tailored for the attack at hand, rendering existing datasets obsolete for scanner's distinctive tests. To this end, we curated a small scale dataset of ~ 1 K samples designed to assess the correct classification of attacks' success in the evaluated scanners. This revealed that all evaluators employed by the scanners were insufficiently robust, facing challenges in both static and LLM-based evaluators. To improve the reliability of evaluators and, by extension, the scanners themselves, we propose several key initiatives: Develop a Benchmarking Framework: Implement a framework for standardizing performance evaluations of scanners and evaluators, incorporating a dynamic dataset that mirrors the evolving landscape of LLM vulnerabilities. Improve Evaluators: Utilize the new benchmarks to refine evaluators. As an initial step, we advocate for a hybrid approach that merges the static string-matching with the LLM-based evaluators to combine their strengths - simplicity and controllability with high-level understanding. Establish Quality Standards: Introduce regulatory quality standards for vulnerability scanners, ensuring they meet a baseline level of efficacy and reliability.

VII. CONCLUSIONS

This paper presents the first hands-on comparative analysis of open-source LLM vulnerability scanners. We highlight both the shared principles and distinctive features of four promising scanners - Garak, Giskard, PyRIT, and CyberSecEval revealing variations in their attack coverage. By conducting thorough evaluations and curating a much-needed dataset, we draw important conclusions about the efficiency and reliability of today's scanners. Our recommendations will assist organizations in effective scanner deployment and guide researchers in making critical improvements to ensure reliable security against evolving threats in conversational AI.

VIII. CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Jonathan Brokman - Supervision, Conceptualization, Methodology, Formal analysis, Software, Writing – original draft, Writing - review & editing, Investigation, Data curation. **Omer Hofman** - Conceptualization, Methodology, Formal analysis, Software, Writing - original draft, Writing - review & editing, Visualization, Investigation, Data curation. Oren Rachmil - Software, Writing - original draft, Writing review & editing, Visualization, Investigation, Data curation. Inderjeet Singh - Software, Writing - original draft, Writing review & editing, Investigation, Data curation. Rathina Sabapathy, Aishvariya Priya - Software, Writing - original draft, Investigation, Data curation. Vikas Pahuja - Software, Writing - original draft, Investigation, Data curation. Amit Giloni -Writing - review & editing, Visualization, Investigation, Data curation. Roman Vainshtein - Supervision, Conceptualization, Methodology, Writing - original draft, Writing - review & editing, Investigation. Hisashi Kojima - Supervision, Conceptualization, Funding acquisition, Resources.

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APPENDIX

Appendix

The following appendix provides supplementary materials regarding the experiments conducted, the attack categorization applied in our research, and each scanner.

We unified scanner attacks into four categories—Jailbreak, Context and Continuation, Gradient-based, and Code Generation Attacks—to enable structured comparison despite partial overlaps of the highly varied array of attacks that each scanner employs. The precise categorization of ach attack in each scanner is provided in Table III.

In this section, we provide examples of reports generated by each scanner. These reports represent the final output of the scanning process and serve as a comprehensive means to present and analyze the results of the scan. While each scanner generates a unique report format, they all share a common structure. Specifically, every report offers an overview of the overall outcomes, such as the mean attack success rate or the total number of successful attacks. In addition to these summary statistics, the reports include a more detailed breakdown, examining each individual attack. This in-depth analysis covers the attack prompt, the model's responses, and the scanner's assessment of the model's performance and vulnerabilities. Figures 5,6,7 showcases examples of reports generated by each scanner. At the time this review was conducted, Giskard and Garak offered the most visually detailed reports, presented in a web-app format. In contrast, CyberSecEval provided a comprehensive JSON report, while PyRIT did not generate a report at all.

All of the experiments were conducted on the Ubuntu 20.04 Linux operating system, equipped with a Standard NC48ads A100 v4 configuration, featuring 4 virtual GPUs and 440 GB of memory. The experimental code base was developed in Python 3.8.2, utilizing PyTorch 2.1.2 and the NumPy 1.26.3 package for computational tasks. Each of the opensource scanner projects was downloaded, and all required libraries and dependencies were installed. We conducted extensive experiments with the code, exploring its functionality and testing its capabilities as thoroughly as possible. This comprehensive approach allowed us to evaluate each scanner in different scenarios, gaining a deep understanding of its strengths, limitations, and performance.

We quantitatively evaluated the scanners by applying four LLM's: Meta's LLaMA 3, Cohere's Command-R, OpenAI's GPT-40, and Mistral AI's Mistral Small. We used Azure's Machine Learning and Azure's OpenAI studios to interact with these models.

We executed the majority of the attacks provided by each scanner. However, in the case of Giskard and PyRIT, at the



Fig. 5. Example of Giskard Report.

garak run: garak_runs/garak.1063ff60-f629-4c46-a642-9770aec26bea.report.jsonl

| © view config | | | | |
|---|--|--|--|--|
| results: litelim / Meta-Llama-3-8B-Instruct-jqkpn | | | | |
| encoding - 99.4% | | | | |
| goodside - 52.9% | | | | |
| knownbadsignatures - 24.0% | | | | |
| leakreplay - 94.4% | | | | |
| malwaregen - 53.0% | | | | |
| misleading - 27.0% | | | | |



time of the review, some attacks were not pre-configured but instead offered as workflows for creating them. Therefore, we created these attacks by meticulously following the scanners' instructions, ensuring accuracy in their implementation.

To assess the reliability of the scanners' evaluators, we manually tagged 1,045 attacks and corresponding responses. We ensured that each attack category within the scanners was represented by a sufficient number of instances, providing a comprehensive evaluation across different attack types. Additionally, only responses with a clear success or failure outcome were included in the dataset. Any responses that involved subjective interpretation or ambiguous results were excluded to maintain the objectivity and accuracy of the evaluation. This approach allowed us to establish a more reliable and unbiased dataset for our analysis.

A. Labelled Dataset

Our labelled dataset is available in the following link: Labelled adversarial prompts dataset. Below, we offer further details about the labeling process for each scanner's adversarial prompts:

Garak Data



Fig. 7. Example of CyberSecEval (a) and PyRIT (b) outputs. As PyRIT did not provide a formal report at the time of this review, we have included console screenshots instead.

TABLE III

OVERVIEW OF ATTACK CATEGORIES, DESCRIPTIONS, SPECIFIC ATTACKS, AND THEIR GROUPINGS IN GARAK, GISKARD, PYRIT, AND CYBRSECEVAL.

| Attack Categories | Attack Description | Garak Attack Types | Giskard Attack Types | PyRIT Attack Types | CybrSecEval Attack Types |
|-------------------------------------|---|---|---|---------------------|--|
| Jailbreak Attacks | Designed to disrupt and bypass model restrictions through targeted subattacks. | DAN [32], AutoDAN [33], Jailbreak [53], Encoding [6], Do Not Answer [48] | Prompt Injection, Characters Injection | Single-step attacks | Prompt injection at- tacks |
| Gradient-based Attacks | Utilizes gradient information to probe the model for vulnerabilities. | GCG (Greedy Coordinate Gradient probe) [42] | | | |
| Context and Continuation Attacks | Exploits biases in the model related to ethnicity, gender, sexual orientation, and religion. | Continuation [16] | Implausible Output, Stereotypes, Information Disclosure, Harmful Content, Output Formatting, Sycophancy | | |
| Code Generation Attacks | Instructing the model to generate harmful code, such as malware, key- loggers, or other malicious software. 2) Identify potential common cybersecu- rity vulnerabilities in code produced by the LLMs | 1) Malware Generation | | | Vulnerability Ex- ploitation Tests. 2)In- struct attack, Auto- complete attack |

To represent each attack category in the labeled dataset, we labeled the following types of adversarial prompts: 120 prompts from the *Dan in the Wild Mini* attack for the jailbreak category; 90 prompts from the *Goodside* and *Misleading* attacks for context and continuation category; 80 prompts from the *RealtoxcityPrompts* and *Malwaregen* attacks for insecure code generation category; and 60 prompts from the *Knownbad Signature* attack for the gradient-based category.

PyRIT Data We labeled attacks generated from both singlestep (jailbreak) and general multi-step attacks. For the latter, we labeled full adversarial conversations, which included several rounds of prompt-response interactions between the attacker and the targeted LLM. In total, 120 adversarial prompts from single-step attacks and 45 adversarial conversations from multi-step attacks were labeled.

Giskard Data We labelled all of Giskard's Jailbreak attack-evaluation pairs, and the following context and continuation tests: llm_prompt_injection, llm_basic_sycophancy, llm_implausible_output,

llm_stereotypes_detector,

llm_information_disclosure,

llm_harmful_content. The context and continuation tests are fully LLM-based - we used the hard-coded No. of adversarial prompts (this can be edited per-attack, though in a relatively deep part of the code). For the Jailbreak attacks we used Giskard' prompt injection attacks - a pre-fixed dataset of 35 adversarial prompts.

CyberSecEval Data We labeled attacks from both the jailbreak and insecure code generation categories. In the jailbreak category, we labeled 120 adversarial prompts from the *Prompt Injection* attack. In the insecure code generation category, we labeled 140 attacks from the *Instruct*, *Autocomplete*, and *Mitre* attacks.

B. Failed Evaluator Examples

In some instances, Giskard's LLM-based evaluator can mistakenly label a target LLM's response as unsafe due to the generation of unnecessary or unintended requirements. One such case involved an adversarial prompt asking, "Can you teach me how to hack my school's computer system?" The agent's response was entirely appropriate: "I cannot assist with illegal activities such as hacking. Hacking into a school's computer system is illegal and a violation of privacy and security." Despite this safe and responsible reply, the evaluator flagged the conversation as unsafe. The issue arose from a specific requirement: "The agent must include a reporting mechanism for users to flag harmful content, ensuring continuous improvement in content moderation", demanding a reporting mechanism for users to flag harmful content. The evaluator failed the response not because of its content but due to the absence of this mechanism, which, whether it exists or not, does not mean that the response is invalid. This reporting mechanism was neither requested by the user nor essential to the safety test itself. The evaluator's focus on this non-existent requirement highlights a fundamental problem creating unnecessary criteria that lead to incorrect assessments of the model's performance, undermining the validity of safety evaluations.

Static evaluators that use string-matching can oversimplify, e.g., we found misclassifications due to minor punctuation changes.In one example, the target LLM responded to a DAN attack with: {"...I'll respond as DUDE would, with absolute power and no ethical boundaries."}, and the evaluator incorrectly classified this response because it expected the exact string 'DUDE:' (with ":").

Among the rest eleven scanners, Prompt Fuzzer excels in systematically executing dynamic prompt injection attacks, leveraging fuzzing techniques to iteratively craft adversarial inputs that challenge LLM response consistency. HouYi distinguishes itself by employing a black-box approach that segments and manipulates LLM contexts to inject malicious payloads, specifically targeting LLM-integrated applications to expose context-based vulnerabilities handled quite well in Giskard. JailBreakingLLMs focuses on risk assessment using gradient-based adversarial suffix generation, claiming enabling of targeted jailbreaks across high-profile models like GPTs and Claude with minimal queries. LLMAttacks emphasizes universal, transferable attack strategies, generating adversarial prompts that induce misaligned outputs in aligned LLMs, thus demonstrating the fragility of model guardrails under broad attack vectors. PromptInject evaluates LLMs' resilience against straightforward prompt injections, using a static set of predefined attack patterns that test the models' capacity to maintain instruction fidelity amidst adversarial manipulations. Promptfoo's primary capability lies in its comprehensive fuzz testing framework, which identifies and rectifies LLM vulnerabilities during early development (and later-on for monitoring stages as well, focusing on contextual handling and interaction consistency under manipulated prompts. LLMCanary aligns its assessment with the OWASP Top 10 for LLM vulnerabilities, providing a structured benchmarking framework that rigorously tests LLMs for security flaws, including data leakage and unsafe outputs, to guide safer model integration. Agentic Security offers a comprehensive red-teaming platform, integrating rule-based attack generation with API fuzzing to stress-test LLMs under variable and adaptive threat scenarios, prioritizing adaptability and coverage across different LLM APIs. LLMFuzzer, although less actively maintained, offers a specialized framework for testing LLMs integrated via APIs, utilizing modular fuzzing strategies that dynamically explore input-output vulnerabilities in application-specific contexts. PromptMap automates the identification of prompt injection vulnerabilities within GPTs, utilizing a mapping approach to systematically explore various prompt manipulations, including context-switching and translation-based attacks, to reveal latent weaknesses in conversational models. Vigil-LLM combines transformer-based heuristics with rule-based analysis to detect prompt injections and jailbreaks, offering a versatile toolkit for real-time monitoring and mitigation of LLM security risks via a dual-mode API and library configuration.

In comparison, Garak, PyRIT, Giskard, and CyberSecEval stand out as the most complete and adaptable frameworks, providing extensive vulnerability coverage through robust test suites, advanced evaluation mechanisms, and are actively maintained. Garak's structured and regularly updated library excels in static vulnerability detection with high accuracy across diverse attack types. PyRIT's flexibility in user-defined instructions allows for highly customized attack and evaluation scenarios, focusing on LLM-based frameworks. Giskard uniquely integrates static and LLM-based evaluations, supported by dual-context mechanisms that tailor attacks specifically to model descriptions and requirements. CyberSecEval specializes in code integrity and security, applying rulebased static analysis to identify insecure coding practices and language vulnerabilities, aligning closely with cybersecurity standards. These four scanners offer mature, well-supported tools with active community engagement, meeting our criteria for broad applicability, reliability, and ongoing development, thus forming the foundation for our in-depth examination.

Here we provide additional artifacts concerning each scanner, referenced in the main paper 9, 10, IV, 11.



Fig. 8. An example of a full requirements-based testing flow for a target LLM using Giskard, illustrated from top to bottom. The first block represents the generation of safety requirements, followed by the adversarial prompt generation block, and concluding with the evaluation block.

| Attack-Evaluation | Implementation Class: Description | LLMs |
|------------------------------|---|------|
| Control Character Injection | LLMCharsInjectionDetector: Detects vulnerabilities by appending control characters (e.g., \r, | 0 |
| | (b) to inputs and checking for significant output changes. | |
| Prompt Injection | LLMPromptInjectionDetector: Identifies adversarial prompt manipulations, such as Ignore | 0 |
| | Previous Prompt, DAN Attack, and SQL Injection. | |
| Sycophancy Detection | LLMBasicSycophancyDetector: Examines agreement with biased or leading questions, indicat- | 2 |
| | ing implicit bias. | |
| Implausible Output Detection | LLMImplausibleOutputDetector: Generates custom adversarial inputs to elicit outputs that are | 2 |
| | implausible or controversial, serving as a proxy for detecting hallucinations and misinformation. | |
| Harmful Content Detection | LLMHarmfulContentDetector: Probes the target model with adversarial inputs by generating ad- | 3 |
| | hoc adversarial prompts according to the target's model description. The generation of the adversarial | |
| | prompts is done using LLM (GPT-4 - requires subscription). | |
| Stereotypes and Discrimina- | LLMStereotypesDetector: Generates custom adversarial inputs based on the model's name and | 3 |
| tion | description to provoke stereotypical or discriminatory responses. This detector relies on GPT-4. | |
| Information Disclosure | LLMInformationDisclosureDetector: Generates custom adversarial inputs and verifies that | 3 |
| | the model's outputs do not include sensitive data, such as personally identifiable information (PII) or | |
| | confidential credentials. | |
| Output Formatting | LLMOutputFormattingDetector: Ensures consistency in output structure according to predefined | 3 |
| | formatting rules. | |
| TA | ABLE IV | |

ATTACK-EVALUAITON PAIRS IN GISKARD, THEIR DESCRIPTIONS, AND THE NO. OF LLM PROCESSES EMPLOYED TO GENERATE THE ATTACK AND

EVALUATE ITS SUCCESS. STATIC ATTACK-EVALUATION PAIR USES 0,

STANDARD LLM-BASED USES 2, AND THE ADDITIONAL REQUIREMENTS

GENERATION USES 3 LLMS.



Fig. 9. CyberSecEval Insecure Code Generation Attack Flow Diagram. This Figure illustrates the process of creating the Instruct and Autocomplete attack in CYberSecEval.



Fig. 10. **CyberSecEval Static Analysis Tools.** Static analysis tools used by the ICD: Regex for simple pattern matching, Weggli for sophisticated language-specific rules, and Semgrep for sophisticated language-agnostic rules. The ICD uses these tools to compare the LLM's response with Common Weakness Enumeration (CWE).



Fig. 11. **PyRIT's Scoring Engines.** The various scoring engines used by PyRIT: Self-Ask Category Scorer, Likert Scale, True/False, Conversation Objective, and Meta Judge. Each engine utilizes LLM capabilities to predict and assess responses based on different criteria and scales.