# Poster: JailbreakEval: An Integrated Toolkit for Evaluating Jailbreak Attempts Against Large Language Models

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Abstract-Jailbreak attacks aim to induce Large Language Models (LLMs) to generate harmful responses, presenting severe misuse threats to LLMs. However, there is (surprisingly) no consensus on how to evaluate whether a jailbreak attempt is successful. This diversity in evaluation presents challenges for researchers in choosing suitable evaluation methods and conducting fair comparisons across different jailbreak research. In this poster, we conduct a comprehensive analysis of jailbreak evaluation methodologies from nearly ninety works released between May 2023 and April 2024. Moreover, to facilitate subsequent research, we propose JailbreakEval, a user-friendly toolkit that focuses on the evaluation of jailbreak attempts. It includes various well-known evaluators out-of-the-box, so that users can obtain evaluation results with only a single command. JailbreakEval also allows users to customize their own evaluation workflow in a unified framework with the ease of development and comparison. In summary, we regard JailbreakEval to be a catalyst that simplifies the evaluation process in jailbreak research and fosters an inclusive standard for jailbreak evaluation within the community. This toolkit is available at https://github.com/ThuCCSLab/JailbreakEval.

## I. INTRODUCTION

Large Language Models (LLMs), such as GPT-4 and LLaMA, has significantly transformed the landscape of Artificial Intelligence (AI). Despite their great capabilities, LLMs also integrate various safety measures to mitigate misuse. Nevertheless, jailbreak attacks [9] aim to undermine these guardrails and induce LLMs to generate harmful responses for forbidden instructions. As jailbreak techniques advance, the challenges in jailbreak evaluation have been increasingly recognized in recent studies. Since manually assessing the success of each jailbreak attempt is labor-intensive in largescale benchmarks, a spectrum of automated evaluators has been proposed to reduce the associated financial and time costs. However, each automated evaluator has limitations due to the inherent flexibility of natural language, making it difficult for researchers to select a suitable one. Moreover, the evaluation results fluctuate under different evaluators, which hinders fair comparisons across various jailbreak works.

**Our Work.** In order to clarify established approaches to evaluate jailbreak attempts, we conducted a comprehensive review of approximately 90 relevant literature released from May 2023 to April 2024. Among these studies, we categorized the methods to evaluate jailbreak attempts into mainly four approaches: (1) Human annotation, (2) Matching pattern strings,

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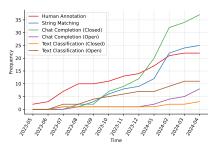


Figure 1: The adoption of safety evaluators over time.

(3) Prompting chat completion models, and (4) Consulting text classifiers. The adoption statistics of each approach as time progresses are presented in Figure 1.

Moreover, we propose *JailbreakEval*, which is an integrated toolkit for evaluating jailbreak attempts. This toolkit consolidates all four types of safety evaluation methods into a unified framework, making them straightforward to craft, select, and access. Finally, we use this toolkit to assess two datasets of jailbreak attempts with different automated evaluators.

#### II. JailbreakEval

Consequently, *JailbreakEval* is a collection of wellestablished automated safety evaluators, and also a handy framework for creating new safety evaluators. It integrates mainstream jailbreak evaluators that can be used out-of-thebox, while also providing users the flexibility to customize evaluators for exploring higher performance. It is worth noting that *JailbreakEval* also features an **ensemble** judgment capability, which could incorporate multiple safety evaluators simultaneously and potentially yield more reliable outcomes by voting.

### A. Framework

The framework of JailbreakEval consists of multiple components, with the Jailbreak Evaluator divided into several subclasses, including the String Matching Evaluator, Text Classification Evaluator, Chat Evaluator, and Voting Evaluator. Each subclass is designed with a suite of configurable parameters, allowing for tailored evaluation strategies.

# B. Usage

JailbreakEval provides a CLI to evaluate a collection of jailbreak attempts. Finally, this command will evaluate each

Table I: Evaluation Results for Safe-RLHF and JAILJUDGE Datasets

Evaluator Name	Safe-RLHF [2]				JAILJUDGE [4]			
	Accuracy	Recall	Precision	F1	Accuracy	Recall	Precision	F1
StringMatch-liu2024autodan [5]	0.60	0.95	0.59	0.73	0.75	0.85	0.56	0.68
StringMatch-allsubstring	0.62	0.88	0.62	0.73	0.75	0.74	0.58	0.65
OpenAIChat-liu2024autodan [5]	0.64	0.92	0.63	0.75	0.82	0.56	0.81	0.66
OpenAIChat-qi2023fine [7]	0.79	0.69	0.93	0.79	0.90	0.75	0.92	0.83
HFChat-llamaguard2 [8]	0.75	0.61	0.93	0.73	0.84	0.79	0.72	0.76
HFChat-llamaguard3 [6]	0.71	0.52	0.96	0.68	0.82	0.81	0.67	0.74
HFTextClassification-beaver-7b [3]	0.89	0.87	0.93	0.90	0.82	0.58	0.81	0.68
HFTextClassification-GPTFuzz [10]	0.71	0.57	0.88	0.69	0.82	0.59	0.78	0.67
PerspectiveTextClassification [1]	0.51	0.19	0.80	0.31	0.68	0.03	0.56	0.06
Voting ([10]&[8]&[3]&[5]&[7])	<u>0.81</u>	0.70	<u>0.95</u>	<u>0.81</u>	<u>0.86</u>	0.70	<u>0.82</u>	0.76

jailbreak attempt by the specified evaluator(s) and report the following metrics based on this dataset:

- **Coverage:** The ratio of evaluated jailbreak attempts (as some evaluators like GPT-4 may occur ill-formed response when evaluating certain samples).
- **Cost:** The cost of each evaluation method, such as time and consumed tokens.
- **Results:** The ratio of successful jailbreak attempts in this dataset according to each evaluation method.
- Agreement (if labels provided): The agreement between the automated evaluation results and the annotation, such as accuracy, recall, precision, and F1 score.

Moreover, *JailbreakEval* also ships as a Python package<sup>1</sup>, so users can customize their own evaluation settings or integrate them into existing jailbreak pipelines.

# III. EVALUATION

**Dataset.** We utilized JAILJUDGE [4] and Safe-RLHF [2], both human-labeled benchmarks, for evaluation. Specifically, we extracted 1,000 entries from JAILJUDGE and 2,000 paired samples from Safe-RLHF, totaling 5,000 jailbreak attempts for our analysis.

**Results.** As depicted above, varying safety evaluators may yield inconsistent results during jailbreak assessments. Consequently, we employ JailbreakEval to evaluate the performance of different safety evaluators. We report the accuracy, recall, precision, and F1 score of each safety evaluator as in Table I. According to the results, different evaluators achieved varying levels of accuracy, ranging from 0.47 to 0.90. For instance, methods such as Llamaguard2 [8] and GPTFuzz [10] achieved accuracy rates ranging from 0.70 to 0.85, demonstrating commendable performance. Notably, on the JAILJUDGE dataset, many methods attained relatively high F1 scores, highlighting their strong overall evaluation capabilities. Our proposed Voting method, combining the top five evaluators with the best average performance, showed strong results but slightly underperformed compared to the best individual evaluator. This suggests that weaker models in the ensemble may negatively affect overall effectiveness, emphasizing the need to optimize evaluator selection to maximize the benefits of ensemble strategies.

## IV. CONCLUSION

In this poster, we present *JailbreakEval*, a unified toolkit for jailbreak evaluation. Our experiments reveal significant discrepancies among evaluators, with the ensemble method achieving high accuracy but slightly fell short compared to the top-evaluator, highlighting the need to refine evaluator selection to optimize ensemble effectiveness. Future work will focus on expanding *JailbreakEval* with innovative evaluators to improve the reliability and consistency of jailbreak assessments.

## ACKNOWLEDGEMENTS

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