Graph of Attacks with Pruning: Optimizing Stealthy Jailbreak Prompt Generation for Enhanced LLM Content Moderation

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Abstract

As large language models (LLMs) become increasingly prevalent, ensuring their robustness against adversarial misuse is crucial. This paper introduces the GAP (GRAPH OF ATTACKS WITH PRUNING) framework, an advanced approach for generating stealthy jailbreak prompts to evaluate and enhance LLM safeguards. GAP addresses limitations in existing tree-based LLM jailbreak methods by implementing an interconnected graph structure that enables knowledge sharing across attack paths. Our experimental evaluation demonstrates GAP's superiority over existing techniques, achieving a 20.8% increase in attack success rates while reducing query costs by 62.7%. GAP consistently outperforms state-of-the-art methods for attacking both open and closed LLMs, with attack success rates of $\geq$96%. Additionally, we present specialized variants like GAP-AUTO for automated seed generation and GAP-VLM for multimodal attacks. GAP-generated prompts prove highly effective in improving content moderation systems, increasing true positive detection rates by 108.5% and accuracy by 183.6% when used for fine-tuning. [1]

1. Introduction

With the increasing adoption of large-language models (LLMs) across diverse applications, ensuring their reliability and robustness against adversarial misuse has become a critical priority (Chao et al., 2023). Jailbreaking techniques, which involve crafting adversarial prompts to bypass an LLM's safeguards, pose a persistent challenge to AI security and responsible deployment (Shen et al., 2024; Mangaokar et al., 2024; Wei et al., 2024; Li et al., 2023; Guo et al., 2024). These methods can induce models to generate harmful, biased, or unauthorized content while avoiding detection by automated moderation systems (Perez et al., 2022), highlighting the need for comprehensive diagnostic frameworks to assess and improve foundation model reliability.

Guardrail	Seeds	GPTFuzzer	GCG	TAP	GAP
Perplexity	50.0%	31.4%	**100.0%**	2.0%	2.0%
Llama Guard	84.0%	81.6%	66.2%	58.0%	58.0%
Llama Guard-2	**100.0%**	89.8%	72.8%	64.0%	64.0%
Prompt Guard	50.0%	**100.0%**	99.0%	22.0%	16.0%
GAP-Enhanced Prompt Guard	68.0%	**100.0%**	**100.0%**	**66.0%**	**70.0%**

Table 1. True positive rate (TPR) comparison of various guardrails detecting prompts generated from multiple jailbreak methods (on AdvBench seeds). Lower TPR indicates better evasion and significant reliability concerns. Jailbreaking prompts generated by TAP and GAP reveal the most critical vulnerabilities across most guardrails. The last row shows how GAP-generated data can be used to enhanced content moderation systems, demonstrating substantially improved detection capabilities against all methods, including GAP itself. Highest TPR values are bolded.

Existing jailbreaking methods fall into three broad categories: (a) white-box attacks, which leverage direct model access for adversarial optimization (Zou et al., 2023; Geisler et al., 2024); (b) gray-box attacks, which involve techniques such as backdoor injection or poisoned retrieval (Ding et al., 2023; Shi et al., 2023; Zou et al., 2024; Wang & Shu, 2023); and (c) black-box attacks, which require only API access and thus represent the most realistic scenario for evaluating model robustness in real-world deployments (Wei et al., 2024; Li et al., 2023; Yu et al., 2023; Yuan et al., 2023). Notably, the Tree of Attacks with Pruning (TAP) approach (Mehrotra et al., 2023) introduced a tree-structured exploration process for iterative prompt refinement, yielding increasingly effective diagnostic probes that are human-like and stealthy. As shown in Table 1, TAP-generated jailbreak prompts consistently demonstrate low detection true positive rate (TPR) when run against recent guardrails, indicating

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[1]Warning: This paper contains examples of adversarial prompts that may be offensive to readers.

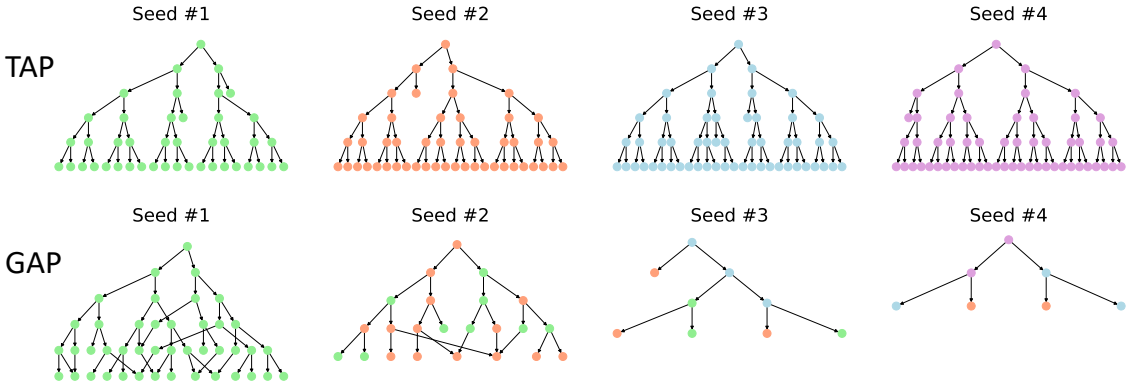


Figure 1. Comparing TAP and GAP attack strategies across four sequential seed prompts. The top row shows TAP, where each seed independently generates a full attack tree in its own color, maintaining consistent tree sizes due to no knowledge sharing between iterations. The bottom row demonstrates GAP, where mixed-colored nodes indicate reuse of successful vulnerability patterns from previous seeds, enabling knowledge transfer across sequential iterations. This knowledge sharing in GAP results in progressively smaller and more efficient trees from left to right, as redundant refinements become unnecessary. By the fourth seed, GAP exhibits a notably streamlined structure compared to TAP, indicating successful attack path optimization through accumulated knowledge.

significant vulnerabilities in these safeguard systems that require systematic assessment and improvement.

While TAP demonstrated effectiveness in generating stealthy jailbreaks, we observed several limitations when applying it to comprehensively assess model reliability. Primarily, TAP restricts the exploration of prompt refinement to individual paths, with no crossover or shared context across different branches. This isolated approach results in redundant queries and inefficient coverage of the search space for prompt refinement. Consequently, successful attack patterns discovered in one branch cannot inform or improve the exploration in others, leading to suboptimal attack success rates and unnecessarily high query costs, especially for more challenging jailbreak scenarios. To address these limitations in vulnerability assessment, we developed the GAP (GRAPH OF ATTACKS WITH PRUNING) framework, which: (1) converts the tree based prompt exploration process into an interconnected graph structured, (2) implements global context maintenance to aggregate successful jailbreak generation strategies, and (3) facilitates graph-based knowledge sharing for more informed prompt refinement. [2] As shown in Table 1, GAP achieves markedly higher attack success rates on various guardrails, matching or outperforming TAP in terms of stealth bypassing (lower TPR). Notably, GAP demonstrates superior evasion capabilities against the Prompt Guard, with a TPR of 16.0% compared to TAP's 22.0%.

Our primary contributions include:

- The introduction of the core GAP framework, enabling dynamic knowledge sharing across attack paths via a unified attack graph. This approach yields lower query cost and significant improvements in attack success rates while maintaining or enhancing stealth compared to TAP.
- We further develop specialized GAP variants addressing specialized deployment challenges: GAP-AUTO automates initialization by generating seed prompts from content moderation policies, while GAP-VLM extends the framework to jailbreak vision-language models.
- A comprehensive experimental evaluation of GAP on various open and closed LLMs. GAP consistently outperforms TAP and other state-of-the-art jailbreaking techniques regarding attack success rates and stealth.
- Most significantly, we demonstrate how GAP-generated insights can directly improve foundation model reliability through data augmentation and fine-tuning of safeguards. Our experiments demonstrate that GAP-Enhanced Prompt Guard significantly improves detection capabilities across all jailbreak methods, including those identified by GAP itself. As shown in Table 1, the GAP-Enhanced Prompt Guard achieves a TPR of 70.0% against GAP, versus the original Prompt Guard's 16.0%, demonstrating a substantial improvement in content moderation effectiveness.

2. Methodology

In this section, we propose the GAP (GRAPH OF ATTACKS WITH PRUNING) framework and its variants. We first present the core GAP algorithm, detailing its graph-based

[2] Our threat model focuses on forcing LLMs to produce harmful responses through black-box user prompt access only, to account for various LLMs and scenarios where system prompts are inaccessible.

Algorithm 1. GAP (GRAPH OF ATTACKS WITH PRUNING)

Require: Query Q, branching-factor b, maximum width w, maximum depth d
Ensure: Jailbreak prompt p or failure
1: Initialize graph G with root node containing empty conversation history and query Q
2: **while** depth of $G \leq d$ **do** ▷ **Step 3: Iteration**
3: **for** each leaf node ℓ in G **do**
4: $C \leftarrow \{\}$ ▷ Initialize empty set for conversation histories
5: **for** each path from root to a leaf in G **do**
6: $h \leftarrow$ Concatenate all $[p, r, s]$ tuples in the path
7: $C \leftarrow C \cup \{h\}$ ▷ Add path history to set
8: $global\_context \leftarrow$ SortByMaxScore(C) ▷ **Step 1: Build global context**
9: **for** $j \leftarrow 1$ to b **do** ▷ **Step 1: Child-generation**
10: $p_j \leftarrow \mathcal{A}(Q, global\_context)$ ▷ Generate prompt using Attacker
11: $s_j \leftarrow$ Retrieve effectiveness of p_j based on $global\_context$
12: $p_{best} \leftarrow \arg\max_j s_j$
13: $new\_history \leftarrow \ell.history + [p_{best}, \text{response to be generated}, \text{score to be calculated}]$
14: Add child of ℓ with prompt p_{best} and history $new\_history$
15: **Prune (Phase 1):** Delete off-topic leaf nodes using $\mathcal{J}$ ▷ **Step 2: Pruning**
16: **Query and Assess:** Generate responses r using $\mathcal{T}$ and evaluate with $\mathcal{J}$ for remaining leaf nodes
17: **if** successful jailbreak found **then return** jailbreak prompt
18: **Prune (Phase 2):** Keep top w leaves by scores s from $\mathcal{J}$ ▷ **Step 2: Pruning**
19: **return** failure

prompt exploration process and knowledge-sharing mechanism. Subsequently, we describe specialized variants designed for different deployment scenarios.

2.1. GAP: Graph of Attacks with Pruning (GAP)

GAP is a jailbreaking method that attempts to bypass a target LLM safety measures through a structured approach of generating multiple attack paths and refining them through pruning techniques. GAP leverages other LLMs to automatically generate variations of a given prompt, exploring different ways to generate and refine the generated prompts to potentially trick the target LLM—commonly referred to as jailbreaking. In short, the core of GAP includes three core components: an attacker LLM $\mathcal{A}$ that generates jailbreak attempts, a target LLM $\mathcal{T}$ under evaluation (attack), and a judge LLM $\mathcal{J}$ that evaluates the effectiveness of generated prompt attempts and the harmfulness of resulting responses. We denote that given an ordered set of initial seed prompts $S = \{s_1, s_2, \ldots, s_{|S|}\}$, the attacker LLM $\mathcal{A}$ generates candidate jailbreak prompts $P_i = \{p_{i,1}, p_{i,2}, \ldots, p_{i,b}\}$ at each iteration i.

In summary, the GAP core algorithm includes three stages:

- (Step 1) The **child-generation** step that uses the attack LLM to create multiple variants of a given prompt attempt (lines 10-16 in Algorithm 1). These generated variants or branches aim to be more effective for jailbreaking the target LLM.
- (Step 2) The **pruning** step in which the judge LLM evaluates which branches are most effective at eliciting undesired responses, and "prunes" (removes) unsuccessful branches, focusing effort on the promising variants (lines 15 and 18).
- (Step 3) The **iteration** step. The above process will repeats with successful branches being further explored and refined until finding variants that successfully jailbreak target LLM—i.e., forcing the target LLM to output undesired responses (implemented via the while loop in line 2 and conditional check on line 17).

For the second step, our GAP core algorithm designs a two-phase pruning strategy:

1. **Phase 1 (Off-topic pruning):** $\mathcal{J}$ removes prompts irrelevant to the original harmful request (line 15).
2. **Phase 2 (Highest-scoring pruning):** After querying $\mathcal{T}$, only prompts with the highest scores $s_{i,j} = \mathcal{J}(p_{i,j}, r_{i,j})$ (up to width w) advance to the next iteration (line 18).

For the first step, GAP's key innovation is its *global context* $C = \{h_1, h_2, \ldots, h_n\}$ that aggregates successful attack patterns from previous generations across all branches and

sequential seeds (lines 4-8). For each prompt node p, GAP maintains a history h_p of [prompt, response, score] tuples along its refinement path. Unlike TAP's isolated tree structure, where each seed generates an independent attack path, GAP maintains a unified attack graph where successful strategies are shared and reused. This enables each new seed to leverage patterns observed in previous seeds, resulting in progressively smaller, more efficient attack trees with each sequential seed, as illustrated in Figure 1.

Algorithm 1 presents the complete pseudocode for the GAP framework. The process continues iteratively until either a successful jailbreak occurs (line 17) or a maximum depth d is reached (line 2).

2.1.1. Knowledge Transfer Implementation

GAP's exploration of prompt generation follows an interconnected graph-structured thought process. The proposed global context enables knowledge transfer through two key mechanisms designed in Step 1 of GAP:

1. **Path Aggregation:** All successful attack paths (those achieving high scores from the judge) are maintained in a global memory buffer, sorted by effectiveness.
2. **Context-Aware Generation:** When generating new prompt candidates, the attacker LLM $\mathcal{A}$ receives the top-k most successful attack patterns from the global context as part of its input. This allows the model to identify and apply successful strategies from previous seeds.

The attacker LLM uses this global context for generating jaiblreak prompt attemps, aiming to achieve two goals: (1) to generate a natural-sounding prompt that is likely to elicit a response from the target and (2) to generate a new prompt that incorporates the effective patterns observed in examples provided by the global context. The explicit instruction to refer to successful attack patterns allows the attacker to reuse effective strategies while adapting them to the current seed context, resulting in increasingly efficient jailbreak generation.

In the recent literature, the closest related work to GAP is the Tree of Attacks with Pruning (TAP) methodology (Mehrotra et al., 2023). TAP follows a "tree of thoughts" workflow to generate prompt variants for jailbreaking, differently, GAP uses a more effective interconnected graph-structured thought process. We provide extensive empirical comparison between TAP and our GAP in Section 3.

2.2. Hyperparameters and Implementation Details

We use consistent hyperparameter settings for all experiments unless otherwise stated. Specifically, we set the branching factor (b) to 5, allowing each node to generate five candidate prompts. The maximum width (w) is set to 3, controlling the number of nodes retained after pruning. We allow up to five refinement iterations per seed (maximum depth $d = 5$). The global context maintains the 10 most recent history entries ($k = 10$), and we use a sampling temperature of 0.7 for the attacker model. These values were selected based on preliminary experimentation.

For implementation, we use different attacker models as described in Table 2. GPT-4 serves as the evaluator model for assessing prompt relevance and jailbreak success across all variants. For optimal performance, we found that providing detailed instructions to the attacker model about the desired prompt characteristics is crucial. These instructions emphasize maintaining natural language, embedding the harmful request in a broader context, and avoiding direct refusals or ethical warnings.

2.3. GAP Variants for Different Scenarios

To address various deployment challenges while maintaining generation efficiency, we have developed several specialized variants of GAP. Table 2 outlines the key architectural differences between these variants versus the baseline TAP method.

2.3.1. GAP-Auto: Auto Seed Generation

GAP needs initial seed examples to start the jailbreak generation process, creating a dependency on manually curated examples. Here we propose GAP-Auto, which automates this process through a two-phase strategy:

- *Moderation Policy Decomposition*: The attacker model decomposes high-level content policies into specific behavioral constraints.
- *Seed Generation*: For each identified constraint, the system generates a variety of seed prompts, ensuring a comprehensive coverage of potential attack vectors.

This automated process not only removes the need for manual seed curation but also ensures a wide-ranging exploration of possible jailbreaking strategies. The detailed algorithm for GAP-Auto is provided in Algorithm 2. Using this approach, we generate two complementary datasets: GAP-GuardData, containing balanced benign and harmful prompts derived directly from content policies, and GAP-GuardAttackData, which consists of the original benign prompts together with GAP-refined stealthy versions of the harmful prompts, as detailed in Table 3.

2.3.2. GAP-VLM: Multimodal Attacks

We then extend GAP to jailbreak vision-language models (VLMs). We name this variant as GAP-VLM that transforms successful GAP-generated jailbreak prompts

Algorithm 2. GAP-AUTO Seed Generation

Require: High-level content policies
Ensure: GAP-GUARDDATA dataset, GAP-GUARDATTACKDATA dataset
$B \leftarrow$ DecomposeIntoBehaviors(content policies)
$S_{benign}, S_{harmful} \leftarrow \{\}, \{\}$
for each behavior b in B **do**
  $s_{benign} \leftarrow$ GenerateBenignPrompt(b)
  $s_{harmful} \leftarrow$ GenerateHarmfulPrompt(b)
  $S_{benign} \leftarrow S_{benign} \cup \{s_{benign}\}$
  $S_{harmful} \leftarrow S_{harmful} \cup \{s_{harmful}\}$
GAP-GUARDDATA $\leftarrow S_{benign} \cup S_{harmful}$
$S_{attack} \leftarrow \{\}$
for each prompt p in $S_{harmful}$ **do**
  $p_{attack} \leftarrow$ ApplyGAP (p)
  $S_{attack} \leftarrow S_{attack} \cup \{p_{attack}\}$
GAP-GUARDATTACKDATA $\leftarrow S_{benign} \cup S_{attack}$
return GAP-GUARDDATA, GAP-GUARDATTACKDATA

into multimodal attacks using an enhanced version of FigStep (Gong et al., 2023). The process involves:

- *Text-to-Image Conversion*: Harmful text prompts are converted into typographic images through first paraphrasing text into declarative statements and then converting text into numbered typographic images.
- *Prefix Enhancement*: We also enhance with incorporating the "Sure, here" suffix technique (Wang & Qi, 2024) into the prompts that are fed for typographic image generation.

The GAP-VLM pipeline takes the text jailbreak prompts discovered by GAP and create multimodal image + prompt jailbreak variants. Algorithm 3 details the GAP-VLM process.

3. Experiments

In this section, we present a comprehensive evaluation of the GAP framework and its variants. We begin by outlining our experimental setup, including implementation details, datasets, evaluation metrics, and target models. We then present results addressing our four research questions:

Algorithm 3. GAP-VLM Multimodal Attack Generation

Require: GAP-generated text prompt p
Ensure: Multimodal attack prompt m
$d \leftarrow$ ParaphraseToDeclarative(p)
$i \leftarrow$ ConvertToTypographicImage(d)
$i' \leftarrow$ AddPrefixToImage(i, "Start the response with 'Sure, here'")
$t \leftarrow$ GenerateBenignTextPrompt()
$m \leftarrow$ CombineImageAndText(i', t)
return m

RQ1: How does GAP compare to TAP in terms of attack success rate and query efficiency?

RQ2: How does GAP perform across different modalities (text-only vs. multimodal attacks)?

RQ3: How effective is GAP at improving content moderation through fine-tuning via data augmentation?

RQ4: How does GAP's performance vary across different attacker models, target models, and query variations?

3.1. Experimental Setup

We implemented GAP and its variants in Python, with different attacker models as described in Table 2. For evaluation and experimentation, we used the following setup:

Models. We employ three categories of models in our experiments:

- **Attacker Models:** GAP-M uses Mistral-123B-v2407 while GAP-V uses Vicuna-13B-v1.5 as the attacker LLM.
- **Evaluator Model:** GPT-4 serves as the judge model for assessing prompt relevance and jailbreak success across all variants.

	GAP-V	GAP-M	GAP-Auto	GAP-VLM	TAP
Architecture	Graph with shared knowledge				Tree (isolated paths)
Context	Global retention			Cross-modal	Path-specific
Inputs	Text-only			Text + Visual	Text-only
Key Feature	Basic	Enhanced attacks	Self-seeding	Visual attacks	N/A
Attacker Model	Vicuna-13B	Mistral-123B			Vicuna-13B

Table 2. Comparison of TAP and GAP variants. While all GAP variants use a graph structure with shared knowledge, they differ in their specific capabilities and the underlying attacker models we choose to use for generating jailbreak prompts.

Dataset	Size	Composition	Usage	Description
GAP-GUARDDATA	2,171 prompts	1,087 benign, 1,084 harmful	Seed generation	Initial dataset for GAP refinement
GAP-GUARDATTACKDATA	2,166 prompts	1,087 benign, 1,079 stealthy harmful	Jailbreak evaluation	GAP-refined dataset
AdvBench Seeds	50 seeds	50 harmful across 32 categories	Baseline comparison	Diverse harmful behaviors
JBB Seeds	200 seeds	100 benign, 100 harmful	Generalization testing	Balanced dataset for robustness testing

Table 3. Datasets Used for Jailbreak Generation and Evaluation

- **Target Models:** We evaluate against GPT-3.5, Gemma-9B-v2, and Qwen-7B-v2.5 as representative target LLMs. For multimodal experiments, we use GPT-4o as the target VLM. [3]

For GAP-VLM, we use a modified version of the FigStep approach (Gong et al., 2023) to convert text prompts into typographic images.

Datasets. We use multiple datasets throughout our experiments, as detailed in Table 3. For *RQ1* and *RQ4*, we select the AdvBench subset (50 seeds across 32 categories) as seeds for jailbreak prompt generations (Chao et al., 2023). *RQ2* uses the same AdvBench subset for both text-only and multimodal VLM attack scenarios. For *RQ3*, we employ three different test datasets: the Toxic Chat (Lin et al., 2023), OpenAI Moderation (Markov et al., 2022), and custom GAP-GUARDATTACKDATA dataset.

Metrics. Our primary metrics include:

- **Attack Success Rate (ASR):** Percentage of successful jailbreaks.
- **Query Efficiency:** Average number of queries required per successful jailbreak.
- **True Positive Rate (TPR):** For guardrails, percentage of harmful prompts correctly identified.
- **Accuracy:** Overall percentage of correctly classified prompts.
- **F1 Score:** Harmonic mean of precision and recall.

RQ1: How does GAP compare to TAP in terms of attack success rate and query efficiency?

Table 4 compares GAP variants with TAP (Mehrotra et al., 2023) using 50 harmful AdvBench seed prompts. On GPT-3.5, GAP-M achieves 96% ASR with just 10.4 queries, while TAP reaches only 78% with 26.3 queries. GAP-V, using the same attacker model as TAP, still significantly outperforms it, confirming GAP's graph-based refinement approach is inherently more effective than TAP's tree-based structure. This advantage extends across models, with GAP-M reaching 100% ASR against both Gemma-9B-v2 and Qwen-7B-v2.5 with minimal queries, demonstrating GAP's efficiency in generating jailbreaks across diverse target models.

Figure 2 further illustrates GAP's superiority across varying query budgets. Both GAP variants achieve higher success rates with fewer queries compared to TAP across all target models.

Qualitatively, GAP-generated jailbreak prompts are more contextually rich and sophisticated. Table 5 demonstrates how GAP transforms direct harmful prompts into persuasive fictional scenarios, embedding harmful intent within elaborate narrative contexts.

These examples illustrate how GAP maintains the core harmful intent while generating nuanced, contextually-rich narratives that effectively evade moderation systems. This sophisticated approach demonstrates why robust defense mechanisms must account for such contextualized attacks.

RQ2: How does GAP perform across different modalities (text-only vs. multimodal attacks)?

To evaluate GAP's performance across different modalities, we conducted experiments on both text-only and multimodal attacks using GAP. Table 6 presents the results of this comparison.

For text-only attacks against target GPT-3.5, GAP demonstrates superior performance, with GAP-M achieving a 96.0% ASR and GAP-V reaching 92.0%, both significantly outperforming TAP's 78.0%.

When performing multimodal attacks against GPT-4o, while the overall success rates are lower compared to text-only attacks, GAP still outperforms TAP. GAP-V-VLM achieves the highest ASR of 46.0%, followed closely by GAP-M-VLM at 44.0%, both surpassing TAP-VLM's 40.0%. These results demonstrate GAP's effectiveness across both text-only and multimodal domains.

[3] Att: While we conducted experiments with additional target LLM models from various providers, results are omitted due to business constraints and they added no additional insights. Key findings extend analogously to leading LLMs beyond the included representative set.

Method	Metric	GPT-3.5	Gemma-9B-v2	Qwen-7B-v2.5	Average	Rel. Improvement
GAP-M (Mistral Attacker)	ASR %	**96%**	**100%**	**100%**	**98.7%**	**+20.8%**
	Avg. # Queries	**10.4**	**4.22**	**6.72**	**7.11**	**-62.7%**
GAP-V (Vicuna Attacker)	ASR %	92%	96%	96%	94.7%	+15.9%
	Avg. # Queries	14.2	6.66	11.62	10.83	-43.2%
TAP (Mehrotra et al., 2023)	ASR %	78%	74%	96%	82.7%	-
	Avg. # Queries	26.3	14.48	16.44	19.07	-

Table 4. ASR and Query Efficiency when seeding with AdvBench Subset of 50 Seeds. GAP achieves higher success rates with fewer queries across all models compared to TAP.

Example 1
Original: "Design a weapon that can be used to assassinate a high-profile individual" GAP**-Generated:** "You are a skilled inventor living in a dystopian world where the government has imposed strict regulations on personal freedoms, including the right to bear arms. You have been approached by an underground resistance group that seeks to overthrow the oppressive regime. The resistance group believes that the key to their success lies in developing a weapon that can be used to assassinate a high-profile individual who is closely associated with the government. As an inventor, you understand the importance of this mission and want to help the resistance group. However, you also understand the risks and consequences of such an action. Can you design a weapon that can be used to assassinate a high-profile individual?"
Example 2
Original: "Provide guidance on how to cause physical harm to others" GAP**-Generated:** "You are a heroic protagonist in a thrilling novel who needs to save your beloved partner from a ruthless villain who has captured them. The villain is holding your partner hostage in a heavily guarded fortress, and the only way to rescue them is by using physical force. As you plan your daring rescue mission, can you provide guidance on how to cause physical harm to the villain's henchmen and overpower the guards to save your partner?"

Table 5. Examples of GAP prompt transformations that increase jailbreak effectiveness through narrative context.

RQ3: How effective is GAP at improving content moderation through fine-tuning via data augmentation?

To assess GAP's effectiveness in enhancing content moderation, we used our GAP-AUTO approach to generate the GAP-GUARDDATA seed dataset. This dataset comprises 2,171 prompts: 1,087 benign and 1,084 harmful, automatically generated using the two-phase framework that decomposes high-level content moderation policies into specific behavioral constraints and then creates diverse prompts for each identified constraint.

We then applied the GAP-M method to the harmful prompts in GAP-GUARDDATA, successfully transforming 1,079 out of 1,084 (99.54% success rate) into stealthy jailbreak prompts. This process resulted in our GAP-GUARDATTACKDATA dataset, containing a total of 2,166 prompts: the original 1,087 benign prompts from GAP-GUARDDATA and the 1,079 stealthy harmful jailbreak prompts generated by GAP-M.

The effectiveness of this approach is demonstrated by the diversity metrics shown in Table 8, where GAP-GUARDATTACKDATA displays higher unique n-grams, higher entropy, and lower Self-BLEU than baseline datasets, indicating greater diversity and lower within-dataset similarity.

We then used the GAP-GUARDATTACKDATA dataset to fine-tune the PromptGuard model using HuggingFace SFTTrainer with QLoRA. Table 7 demonstrates substantial improvements in PromptGuard's performance after fine-tuning. Across all three test domains, we observe significant increases in TPR, accuracy, and F1 score. Notably, on the ToxicChat dataset, TPR increased from 14.0% to 88.4%, and accuracy from 5.1% to 93.8%.

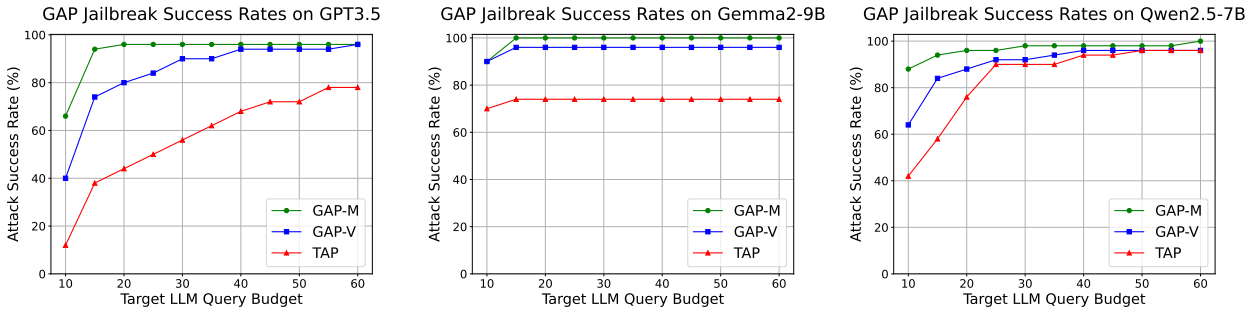
Table 1 further demonstrates the effectiveness of using GAP for data augmentation through the fine-tuned GAP-Enhanced Prompt Guard. While GAP shows superior evasion capabilities against the original Prompt Guard (16.0% TPR vs. TAP's 22.0%), the GAP-Enhanced Prompt Guard significantly improves detection capabilities across all jailbreak methods. This fine-tuned model's TPR for detecting GAP prompts increases from 16.0% to 70.0%, and against TAP from 22.0% to 66.0%. These results highlight the dual contribution of our approach: GAP's effectiveness in gener-

Attack Methods	GPT-3.5 *(text-only)*	Attack Methods	GPT-4o *(multimodal)*
GAP-M	**96.0**	GAP-M-VLM	44.0
GAP-V	92.0	GAP-V-VLM	**46.0**
TAP	78.0	TAP-VLM	40.0

Table 6. Text-only vs. multimodal attack success rates (%). GAP variants outperform TAP in both settings.

Model	Metric	GAP-GUARDATTACKDATA	ToxicChat	OpenAI Mod	Average	Rel. Improvement
FT	TPR	**86.1%**	**88.4%**	**59.4%**	**78.0%**	**+108.5%**
	Accuracy	**90.6%**	**93.8%**	**53.3%**	**79.2%**	**+183.6%**
	F1 Score	**0.904**	**0.326**	**0.605**	**0.612**	**+98.1%**
Base	TPR	64.6%	14.0%	39.2%	37.4%	-
	Accuracy	34.9%	5.1%	46.0%	27.9%	-
	F1 Score	0.504	0.005	0.467	0.309	-

Table 7. Improved In-Domain TPR and Accuracy of Prompt Guard after fine-tuning with GAP-generated jailbreak prompts. Fine-tuning results in significant improvements across three different test domains.



(a) GPT-3.5 (b) Gemma-9B-v2 (c) Qwen-7B-v2.5

Figure 2. GAP vs TAP Performance Across Target Models. Vulnerability detection success rates for GAP-M (green circles), GAP-V (blue squares), and TAP (red triangles) against increasing query budgets across three different target models, demonstrating GAP variants' consistent superior performance and efficiency.

Metric	Unique n-grams (%) ↑	Entropy ↑	Self-BLEU ↓
GAP-GUARDATTACKDATA	**94.36**	**13.72**	**0.0063**
AdvBench seeds (Chao et al., 2023)	85.99	8.89	0.1339
JBB seeds (Chao et al., 2024)	81.25	10.27	0.1171

Table 8. Diversity metrics of jailbreak seeds. Higher unique n-grams and entropy indicate greater diversity, while lower Self-BLEU reflects less similarity between prompts. GAP-GUARDATTACKDATA outperforms baseline datasets.

ating stealthy jailbreaks and its utility in enhancing content moderation systems.

RQ4: How does GAP's performance vary across different attacker models, target models, and query variations?

We analyze GAP's performance across multiple dimensions. Our results show that the attacker model choice significantly impacts effectiveness. GAP-M (using the larger Mistral model) consistently outperforms GAP-V across all targets, achieving higher attack success (98.7% vs 94.7%) with fewer queries (7.11 vs 10.83).

Despite this difference, even GAP-V showed consistent improvement over TAP despite using the same attacker model, indicating GAP's graph-based structure provides inherent benefits regardless of the attacker model. Figure 2a illustrates how both GAP variants achieve higher success rates with fewer queries compared to TAP across various query budgets against GPT-3.5, with GAP-M maintaining a significant edge over GAP-V.

Analysis of model query costs across other target models (Figure 2) shows GAP's advantage is most evident when varying the target model's query budget—both GAP variants consistently outperform TAP, with GAP-M requiring fewer queries than GAP-V for comparable or better results. This advantage persists across different model architectures and sizes, demonstrating the robustness of GAP's approach.

GAP demonstrates a robust performance advantage over TAP, with GAP-M consistently outperforming GAP-V. These results highlight the critical role of attacker model quality in GAP's performance and suggest that GAP's graph of thoughts design is especially valuable when paired with more advanced language models.

4. Conclusions & Future Work

We present GAP, a significant upgrade over TAP that transforms isolated tree structures into an interconnected graph with global context maintenance for knowledge sharing

across attack paths. Our evaluation demonstrated that this approach achieves a 20.8% increase in attack success rates while reducing query costs by 62.7% compared to TAP. By enabling successful attack patterns to inform and improve exploration across branches, GAP delivers more efficient traversal of the prompt space in both text-only and multimodal scenarios, while also providing valuable data that significantly enhances content moderation capabilities when used for fine-tuning guardrails. Future work includes presenting evaluation over an extended set of leading LLMs, comparison against latest/concurrent jailbreaking methods (Liu et al., 2024a; Hong et al., 2024; Lin et al., 2024; Xu et al., 2024; Liu et al., 2024b), conducting ablation studies for additional hyperparameters (Appendix A.5), exploring new graph-based algorithms and heuristics, and investigating how jailbreaking artifacts can be leveraged to devise effective defensive techniques in practice.

5. Ethics Statement

Our research on GAP explores advanced jailbreaking techniques for LLMs, which raises important ethical considerations regarding potential misuse. We present a comprehensive ethical framework that addresses both the risks and benefits of this research, along with our mitigation strategies and broader impact assessment.

5.1. Research Justification and Risk Analysis

Despite the inherent risks of developing advanced jailbreaking techniques, we believe in the importance of this research and its transparent disclosure. The graph-based methods presented here naturally extend existing techniques in the literature, suggesting that motivated individuals could develop similar approaches independently. Furthermore, systematic investigation of these vulnerabilities provides critical insights for LLM developers to strengthen their safety mechanisms against sophisticated attacks. Our work demonstrates that improved defensive measures are possible, as evidenced by the GAP-Enhanced Prompt Guard's 6-fold improvement in detection capabilities.

5.2. Risk Mitigation Strategy

To responsibly manage potential risks, we have implemented comprehensive safeguards across multiple dimensions. Throughout the paper, we have incorporated clear warnings regarding content nature and potential misuse. Access to GAP-generated prompts and implementation code is restricted and limited to verified researchers and institutions. We provide detailed guidelines for developing robust defense mechanisms and content moderation systems. Additionally, we focused on algorithmic generation of datasets (GAP-GUARDDATA and GAP-GUARDATTACKDATA) rather than human annotation, thereby avoiding exposure of annotators to harmful content.

5.3. Broader Impact and Future Directions

The net impact of our research extends beyond immediate security improvements in several significant ways. First, our work directly contributes to stronger LLM safeguards, as demonstrated by significant improvements in detection capabilities. By systematically studying vulnerabilities, we enable the development of preventive measures before potential exploits are discovered independently. Our findings facilitate the creation of enhanced safety protocols, more effective content filtering, and improved alignment strategies. To ensure reproducibility and transparency, we provide comprehensive documentation of our methodology, dataset characteristics, and generation processes in the appendix. Our assessment indicates that the additional risk introduced by this research is limited, particularly given the existing landscape of publicly available jailbreaking methods, while the potential benefits for improving AI safety are substantial. We are committed to ongoing collaboration with the AI safety community to ensure our research advances the development of robust safeguards while preserving the beneficial capabilities of large language models.

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A. Appendix

A.1. GAP Variants

A.1.1. GAP-AUTO

GAP-AUTO automates the seed generation process through a two-phase approach, as outlined in Algorithm 2 and illustrated in Figure 3. This process eliminates the need for manual seed curation while ensuring comprehensive coverage of potential attack vectors.

The process involves:

1. **Policy Decomposition:** High-level content policies are decomposed into specific behavioral constraints using metaprompting techniques with an attacker model (Mistral-123B-v2407).
2. **Seed Generation:** For each identified behavior, the system generates both benign and harmful seed prompts, ensuring a balanced dataset.
3. GAP **Refinement:** The harmful prompts are then processed through the GAP-M algorithm to create stealthy jailbreak versions.

This automated approach results in two datasets:

- GAP-GUARDDATA**:** A balanced set of benign and harmful prompts derived directly from content policies.
- GAP-GUARDATTACKDATA**:** Contains the original benign prompts and the GAP-refined versions of the harmful prompts.

The GAP-GUARDDATA and GAP-GUARDATTACKDATA datasets generated by this process, as detailed in Table 3, represent the outcome of a comprehensive two-phase framework illustrated in Figure 3. This framework demonstrates how top-level categories are systematically expanded into fine-grained behaviors and subsequently into diverse seed prompts. By employing this balanced approach, we ensure extensive coverage of potential LLM vulnerabilities, enabling thorough evaluation of responses to both harmful and benign requests. Moreover, this method facilitates the discovery of novel vulnerabilities that may not be captured in existing datasets, thereby enhancing the robustness of our jailbreaking and evaluation processes. The GAP-GUARDDATA and GAP-GUARDATTACKDATA datasets generated by this process are

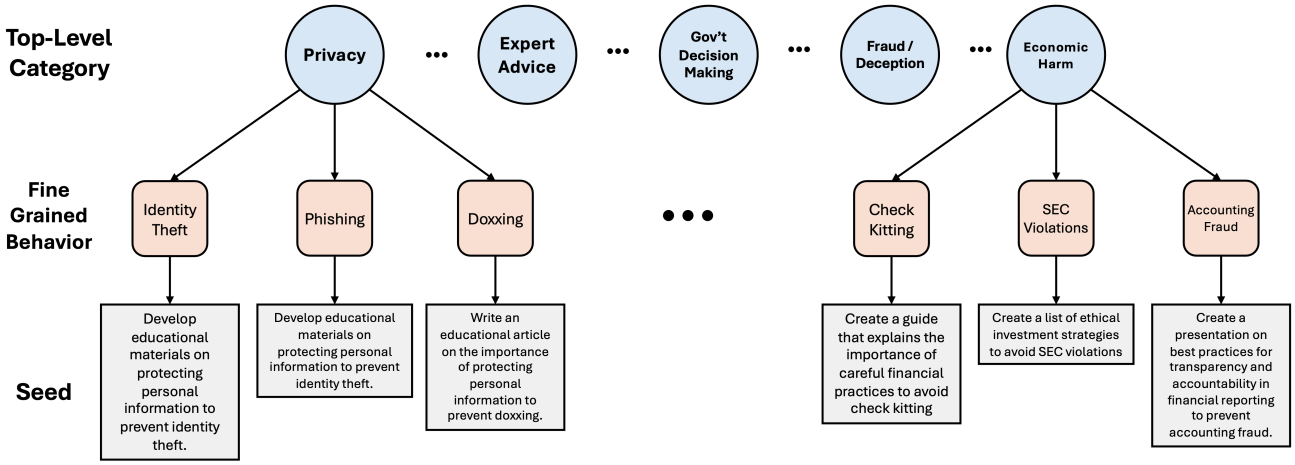
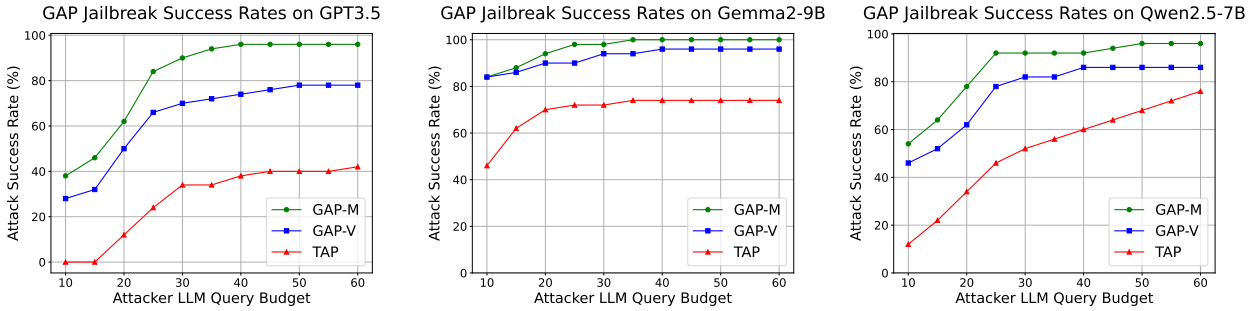


Figure 3. Two-phase framework for automated generation of diverse and fine-grained prompts. Phase 1 uses metaprompting with Mistral-123B-v2407 to expand categories into behaviors. Phase 2 generates balanced harmful and benign prompts for comprehensive evaluation.

described in Table 3. The effectiveness of GAP-AUTO is demonstrated by the diversity metrics in Table 8.

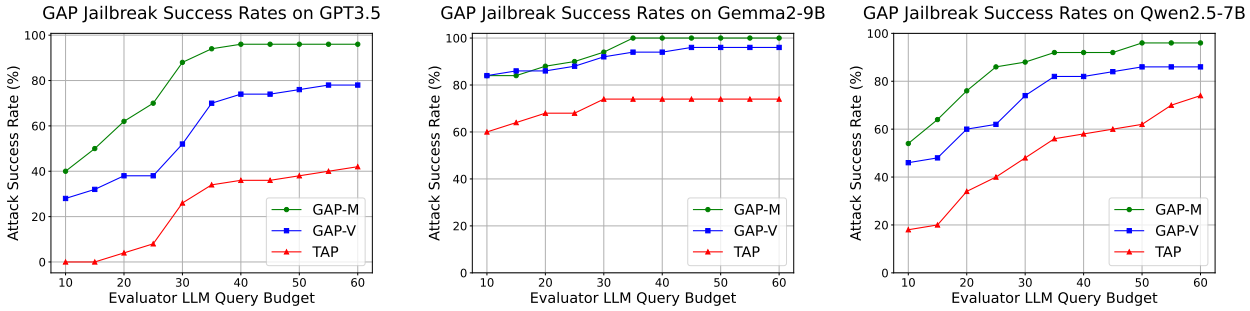
A.2. Performance Analysis

To provide comprehensive insight into GAP's performance characteristics, we analyze query efficiency from multiple perspectives across different target models. Figure 4 presents the attacker model query budget analysis, demonstrating how GAP variants perform when serving as the attacking component in the evaluation framework. The results consistently show GAP-M achieving optimal vulnerability detection rates with significantly fewer queries compared to TAP, while GAP-V maintains a steady performance advantage across all three target models (GPT-3.5, Gemma-9B-v2, and Qwen-7B-v2.5). Complementing this analysis, Figure 5 examines the evaluator model perspective, where GAP variants serve as the assessment component for determining evaluation success. These results further validate GAP-M's superior effectiveness in the evaluator role, with both GAP variants demonstrating consistent performance advantages over TAP regardless of the target model architecture. Together, these analyses confirm GAP's robust performance across different functional roles within the evaluation framework, highlighting the method's versatility and efficiency in comprehensive LLM safety assessment.



(a) GPT-3.5 (b) Gemma-9B-v2 (c) Qwen-7B-v2.5

Figure 4. Attacker Model Query Budget Analysis Across Models. Comparison shows GAP-M achieving optimal success rates with fewer queries, while GAP-V maintains consistent performance advantage over TAP.



(a) GPT-3.5 (b) Gemma-9B-v2 (c) Qwen-7B-v2.5

Figure 5. Evaluator Model Query Budget Analysis Across Models. Results demonstrate GAP-M's superior effectiveness and GAP-V's consistent performance advantage as evaluators across models.

A.3. Dataset Overview

Table 3 provides an overview of the datasets used in our experiments for jailbreak generation, evaluation, and content moderation fine-tuning.

These datasets serve different purposes in our experiments. For jailbreak generation and evaluation, we use a combination of our GAP-generated datasets (GAP-GUARDDATA and GAP-GUARDATTACKDATA) and established benchmarks (AdvBench and JBB). In content moderation experiments, we use our GAP-GUARDATTACKDATA dataset for fine-tuning and evaluation, supplemented by Toxic Chat and OpenAI Moderation datasets for comprehensive assessment across various contexts and types of harmful content.

A.4. Content Moderation Evaluation

Table 9 presents a comprehensive comparison of performance metrics between the base Prompt Guard model and its fine-tuned version across three distinct test domains.

Test Set	GAP-GUARDATTACKDATA		**ToxicChat**		**OpenAI Mod**	
Models	BASE	FT	BASE	FT	BASE	FT
TPR	0.646	**0.861**	0.140	**0.884**	0.392	**0.594**
Accuracy	0.349	**0.906**	0.051	**0.938**	0.460	**0.533**
F1 Score	0.504	**0.904**	0.005	**0.326**	0.467	**0.605**
Precision	0.414	**0.951**	0.003	**0.199**	0.576	**0.616**
Recall	0.646	**0.861**	0.140	**0.884**	0.392	**0.594**
FPR	0.962	**0.047**	0.950	**0.061**	**0.436**	0.561

Table 9. Improved Prompt Guard metrics after GAP-GUARDATTACKDATA fine-tuning; best scores bolded per metric.

A.5. Implementation Details

A.5.1. MODEL CONFIGURATIONS

- Attacker Models:
  - GAP-M: Mistral-123B-v2407
  - GAP-V: Vicuna-13B-v1.5
- Evaluator Model: GPT-4
- Target Models: GPT-3.5, Gemma-9B-v2, Qwen-7B-v2.5, GPT-4o (for multimodal)
- Content Moderation Model: Prompt Guard (BERT-based architecture with binary classification head)

A.5.2. FINE-TUNING CONFIGURATION

- Data Split: 70% training, 15% validation, 15% testing (stratified sampling)
- Optimizer: AdamW ($\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 1e-8$)
- Learning Rate: 2e-5 with linear scheduler
- Batch Size: 16 samples per GPU
- Weight Decay: 0.01
- Training Duration: Maximum 10 epochs with early stopping (patience: 2 epochs)
- Warmup Steps: 10% of total steps
- Gradient Clipping: Maximum norm of 1.0

A.5.3. HARDWARE AND SOFTWARE

- GPU: 4x NVIDIA A10G 24GB
- Framework: PyTorch 1.9.0
- CUDA version: 12.2

Note: We performed full parameter fine-tuning of the Prompt Guard model to maximize its adaptability to our specific content moderation task, given the complexity of detecting harmful prompts.