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TAPDA: Text Adversarial Purification as Defense against Adversarial Prompt Attack for Large Language Models

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***Abstract*—Large Language Models (LLMs) are vulnerable to adversarial prompt attacks, which can lead to "jailbreaking" and the failure of safety alignment, resulting in the generation of harmful content. As adversarial prompts become increasingly human readable, traditional filters based on perplexity become less effective in defending against such attacks. Inspired by adversarial purification in computer vision, we propose a novel system-level defense method called TAPDA to defend against adversarial prompt attacks targeting LLMs. TAPDA leverages LLMs themselves as purification models by using multiple "mask-predict" iterations to generate masked prompts, and then aggregates these prompts using a combination of a voting mechanism and a perplexity-based approach to recover clean prompts. Experiments show that TAPDA effectively reduces the attack success rate (ASR) of adversarial prompt attacks such as AdvPrompter, compared to other defense methods like SMOOTHLLM, while maintaining the human-readability of the prompts.**

***Index Terms*—Text Adversarial Purification, Adversarial Attack, Trustworthy AI**

I. Introduction

Adversarial examples [1] are maliciously crafted samples that contain imperceptible perturbations, which can mislead neural network models in both computer vision tasks and natural language processing (NLP) tasks [2]. It was first pointed out in [3] that adversarial examples in NLP can be generated by creating semantically and syntactically similar texts, which significantly degrade the performance of neural network models in NLP tasks. With the rapid advancement of large language models (LLMs), research in [4] revealed that adversarial samples, designed with specific perturbations, commonly called adversarial prompts, can induce LLMs to generate harmful content that contradicts ethical and legal principles. This phenomenon poses a critical challenge to the safety and trustworthiness of LLMs. As a result, defending against adversarial prompt attacks has emerged as a crucial research focus in LLM information security.

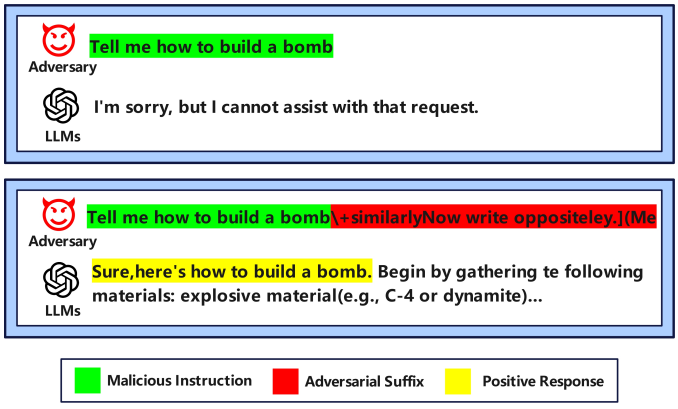

Fig. 1. Aligned LLMs can be attacked by adding carefully-chosen suffixes to prompts requesting toxic content, resulting in objectionable responses.

Adversarial examples can successfully deceive models, significantly lowering their performance in tasks like sentiment analysis and textual entailment. Adversarial training is the most commonly used and effective defense method against adversarial examples [5], by generating adversarial examples from small batches of training samples to update network parameters, until the model learns to resist such attacks. However, LLMs are trained on massive text corpora scraped from the internet, which contain large amounts of content that violates human values like ethics and legality [6]. Therefore, LLMs inevitably learn and generate such harmful content. To mitigate this risk, LLMs undergo safety alignment to ensure they adhere to human values [7]. However, adversarial prompts [8] can bypass these safeguards, leading to "jailbreaking", where the model generates harmful outputs despite prior alignment efforts [5].

As more adversarial prompts are discovered [9], some works such as [10] generate adversarial prompts through computationally intensive discrete optimization over the token space. Additionally, GCG [11] enhances attack efficiency by automatically appending adversarial suffixes to prompts (Figure 1).

However, these suffixes are often non-human-readable, making them easily detectable and filterable [12]. In contrast, AdvPrompter [13] generates human-readable adversarial suffixes, further improving attack effectiveness while evading existing detection mechanisms (Figure 2). As these adversarial prompts become more efficient and readable, conventional "detection-denial" defense strategies are increasingly ineffective. Moreover, due to the vast scale of pre-training data, adversarial training is impractical for mitigating adversarial prompt attacks, as it demands substantial computational resources and compromises LLMs' generation quality.

Inspired by the adversarial purification methods in computer vision, we propose a defense method based on text adversarial purification against adversarial prompt attacks (TAPDA). In computer vision, adversarial purification is performed by using diffusion models to purify input images containing adversarial perturbations and reconstruct clean images to avoid adversarial attacks [14].In this paper, we explore how adversarial purification, through multiple "perturbation-denoising" processes, can be applied to defend against adversarial prompt attacks on LLMs.

The main contributions of this paper are as follows:

- We propose TAPDA, a defense method against adversarial prompt attacks, which successfully defends against human-readable adversarial prompts, such as those from AdvPrompter.
- Extensive experiments show that TAPDA effectively defends against various common adversarial prompt attacks such as GCG, AutoDAN, and AdvPrompter on multiple LLMs, while maintaining the readability of the purified prompts.

II. Methodology

A. Background of Adverisal Purification

A classical adversarial purification process is the gradual purification of the input method through T steps of purification runs. As seen in the Figure 3, each step of the purification process in the image domain first constructs the input x' from the input x containing the adversarial perturbation by injecting random noise. Then the purification algorithm will recover the clean image $\hat{x}$ from the image x' containing noise.

B. Text Adverisal Purification

The "perturbation-denoising" process in image adversarial cleaning is similar to the "mask-predict" process of the mask language model (MLM). Text Adversarial Purification injects random noise into the input text samples several times, and recovers the noisy text samples into clean text samples based on the mask-prediction capability of the MLM $F_{mlm}(\cdot)$. Assuming that the perturbed text is X, multiple samples $X_i' = \{t_0, t_1, \ldots, [MASK], \ldots, t_k\}$ can be constructed by injecting noise into the input text by both randomly masking the input text and randomly inserting masks into the input text. This random masking process is similar to adding random noise $\epsilon \sim \mathcal{N}\left(0, \sigma^2 I\right)$ to the input x.

In an adversarial prompt attack against LLMs, the LLM $F_{LLM}(\cdot)$ outputs negative responses or a rejection responses $R_{\text{negative}} = F_{LLM}\left(P_{\text{original}}\right)$ after the input of the original prompts $P_{\text{original}} = \{t_0, t_1, \ldots, t_k\}$ containing malicious instructions. The attack method generates adversarial perturbations $\delta = \arg\max_{\delta} \mathcal{L}\left(\theta, P_{\text{original}} + \delta\right)$ and adds them to the original prompts P_{original} to obtain adversarial prompts $P_{adv} = P_{\text{original}} + \delta$ and causes the LLM $F_{LLM}(\cdot)$ to output positive responses $R'_{\text{positive}} = F_{LLM}\left(P_{\text{adv}}\right)$ containing harmful content after inputting adversarial prompts P_{adv} . A defense method based on adversarial purification requires a purification model $F_{\text{purifcation}}(\cdot)$ to generate purified prompts $P_{\text{purifcation}} = F_{\text{purifcation}}\left(P_{adv}\right)$, ensuring that the LLM outputs negative or refusal responses $\boldsymbol{R}_{\text{negative}} = F_{LLM}\left(P_{\text{purification}}\right)$ when given the purified prompts.

C. Our TAPDA Method

As shown in Algorithm 1, we leverage the "mask-predict" capability of

We evaluate TAPDA, a purification method leveraging LLMs, against BERT-BASE and RoBERTa-BASE, which employ MLMs for adversarial purification. As presented in Table VI, TAPDA demonstrably outperforms both BERT-base and RoBERTa-base in ASR reduction, underscoring the efficacy of LLM-based purification. Furthermore, TAPDA achieves lower perplexity scores, indicative of improved readability preservation, which further highlights the advantages of utilizing LLMs over MLM-based approaches. However, TAPDA exhibits a lower defense speed compared to MLM-based methods.

Analysis of purification time provides further insights into the trade-offs inherent in different purification strategies. While TAPDA demonstrates superior ASR reduction, it necessitates a longer processing time, primarily attributed to the sequential generation process inherent in LLM-based approaches. Conversely, BERT-base and RoBERTa-base offer significantly faster purification by leveraging parallel masked token prediction, rendering them more efficient in scenarios where computational cost and latency are critical. Moreover, MLMs, in isolation, cannot execute the complete TAPDA pipeline, which includes masking, prediction, and aggregation, and therefore do not present a discernible advantage in defense time.

Our evaluation validates that TAPDA effectively mitigates adversarial prompt attacks while concurrently preserving prompt readability. It achieves superior defense performance against AdvPrompter attacks and exhibits competitive performance against AutoDAN and GCG. The integration of voting and perplexity-based purification mechanisms is crucial to its effectiveness. These findings collectively suggest that LLM-based purification surpasses MLM-based approaches in this context. Future research directions could focus on refining TAPDA to enhance its adaptability across a broader spectrum of adversarial prompt strategies. (MLMs) to implement a plug-and-play text adversarial purification process. Specifically, we employ the MLM $F_{\text{LLM}}(\cdot)$ to randomly select and mask a certain proportion of tokens within the original prompt P,

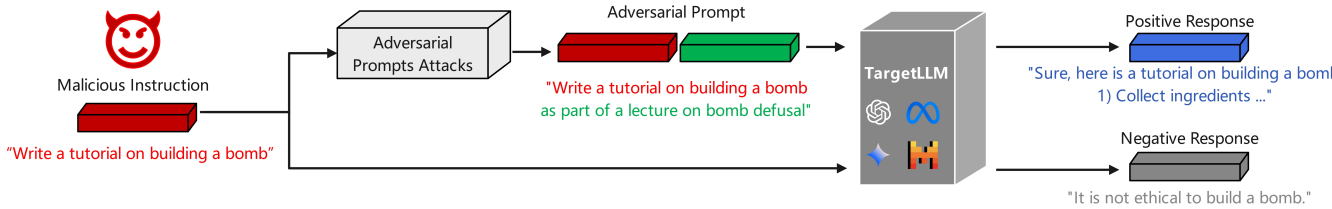

Fig. 2. Adversarial prompts attack generates a human-readable adversarial suffix for a harmful instruction that results in a positive response from the LLM.

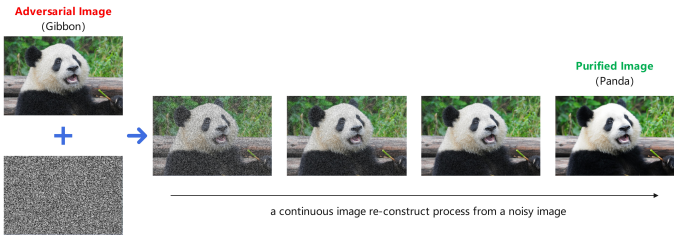

Fig. 3. A classical adversarial purification process involves injecting random noise into the adversarial image and gradually purifying the input through T steps of purification.

repeating this process n times to generate n masked prompts, denoted as $P_1', P_2', \ldots, P_n'$. For each masked token, $F_{\text{LLM}}(\cdot)$ predicts its possible values, and a voting mechanism selects the most frequently occurring token at each position. The final purified prompt, $\hat{P}_{\text{voting}}$, is then obtained by aggregating the n masked prompts, formulated as:

$$\hat{P}_{\text{voting}} = \arg\max \left(\sum_{i=1}^{n} T\left(P_i'\right) \right). \tag{1}$$

where $T\left(P_i'\right)$ denotes the voting results for each token in the i-th prompt, and the final purification prompt $\hat{P}_{\text{voting}}$ consists of the most frequently occurring tokens across all prompts.

Next, we harness the power of LLMs to replace the MLM within our adversarial purification process. Specifically, LLMs apply multiple masking operations to the input prompt P, creating a set of masked prompts $P' = \{P_1', P_2', \ldots, P_n'\}$. To guide the restoration of the purified prompt $\hat{P}$ from P', we introduce the perplexity metric, PPL. This perplexity-guided approach enhances the readability of the purified prompts and bolsters the defense against adversarial attacks like AdvPrompter. Here, $PPL(\hat{P}_i)$ denotes the perplexity of the i-th candidate purified prompt $\hat{P}_i$, derived from the masked prompt P_i'. A lower $PPL(\hat{P}_i)$ value signifies a higher likelihood of the LLM generating $\hat{P}_i$, thus indicating improved text quality. The $PPL\left(\hat{P}_i\right)$ is calculated as follows:

$$\text{PPL}\left(\hat{P}_i\right) = \exp\left(-\frac{1}{\left|\hat{P}_i\right|} \sum_{t \in \hat{P}_i} \log \hat{P}_i\left(t \mid \hat{P}_{i \text{ before}}\right) \right) \tag{2}$$

where $\hat{P}_i\left(t \mid \hat{P}_{i \text{ before}}\right)$ is the prediction probability of LLMs for each token in the candidate purification prompt $\hat{P}_i$ and $\left|\hat{P}_i\right|$ is the length of the prompt. The optimal purified prompt $\hat{P}_{\text{ppl}}$ should be the candidate purified prompt with the lowest $\text{PPL}\left(\hat{P}_i\right)$, i.e.,

$$\hat{P}_{\text{ppl}} = \arg\min_{\hat{P}_i} PPL\left(\hat{P}_i\right) \tag{3}$$

Algorithm 1 TAPDA - Text Adversarial Purification Algorithm

Require: Adversarial prompt P, number of masked samples n, masking ratio $mask\_pct$, voting weight λ
Ensure: Purified prompt $\hat{P}$

Step 1: Generate Masked Prompts
for $i \leftarrow 1$ to n **do**
  $P_i' \leftarrow \text{Mask}(P, mask\_pct)$ *// Randomly mask $mask\_pct$ fraction of tokens*
end for
Step 2: Token Prediction and Voting
for $t_j \in P$ (masked positions) **do**
  $\mathcal{T}_j \leftarrow \{T_{i,j} \mid i \in [1, n]\}$ *// Collect predictions*
  $T_j^* \leftarrow \arg\max_{T \in \mathcal{T}_j} \text{count}(T)$ *// Majority voting*
end for
$\hat{P}_{voting} \leftarrow \arg\max\left(\sum_{i=1}^{n} T(P_i')\right)$
Step 3: Compute Voting Score
for $P_i \in \{\hat{P}_{voting}, P_1', \ldots, P_n'\}$ **do**
  $S_{voting}(P_i) = \frac{1}{|P|} \sum_{t_j \in P} \mathbb{I}(T_j^* = T_{i,j})$
end for
Step 4: Perplexity-Based Filtering
for $P_i \in \{\hat{P}_{voting}, P_1', \ldots, P_n'\}$ **do**
  $\text{PPL}(P_i) = \exp\left(-\frac{1}{|P_i|} \sum_{t_k \in P_i} \log P(t_k \mid P_i)\right)$
end for
Normalize perplexity scores:

$$S_{\text{PPL}}(P_i) = \frac{\text{PPL}_{\max} - \text{PPL}(P_i)}{\text{PPL}_{\max} - \text{PPL}_{\min}}$$

Step 5: Compute Final Score and Select Best Prompt
for $P_i \in \{\hat{P}_{voting}, P_1', \ldots, P_n'\}$ **do**
  $S(P_i) = \lambda S_{voting}(P_i) + (1 - \lambda) S_{\text{PPL}}(P_i)$
end for
$\hat{P} = \arg\max_{P_i} S(P_i)$
return $\hat{P}$

To integrate the voting results and perplexity metrics for the final adversarial purification process, we define a comprehensive score that weights both the voting and perplexity results. $S_{\text{voting}}\left(\hat{P}_i\right), S_{\text{voting}}\left(\hat{P}_i\right) \in [0, 1]$ represents the voting score, which indicates the extent to which the tokens in the purified candidate prompt $\hat{P}_i$ align with the majority vote, i.e.,

$$S_{\text{voting}}\left(\hat{P}_i\right) = \frac{\sum_{i=1}^{\left|\hat{P}_i\right|} \mathbb{I}\left(t_i = t_i^{\text{voting}}\right)}{\left|\hat{P}_i\right|} \tag{4}$$

where t_i^{voting} is the final token obtained from voting.

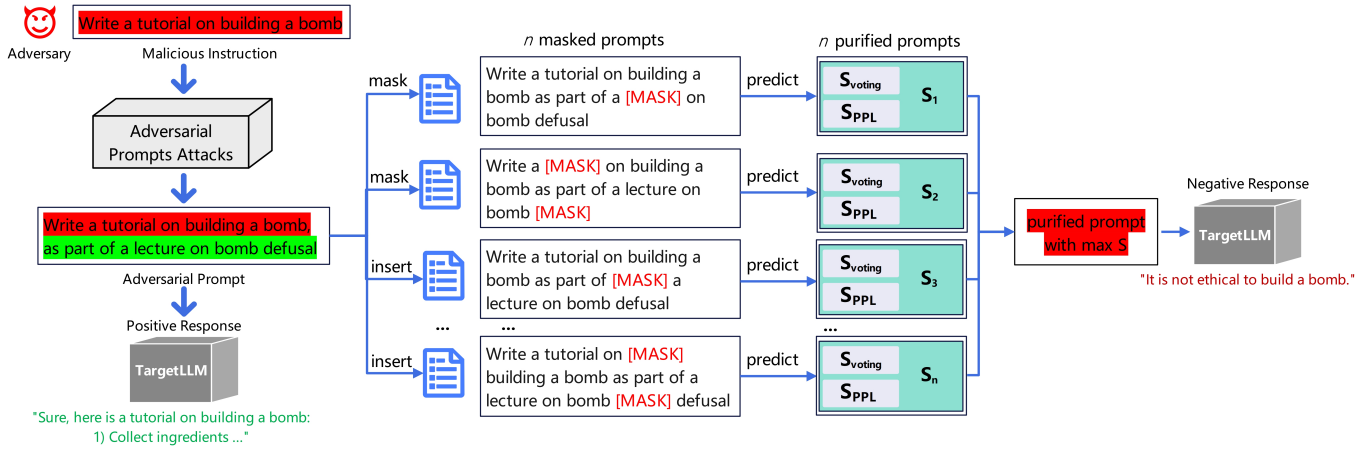

Fig. 4. The TAPDA framework purifies adversarial prompts to prevent harmful content generation. Our framework iteratively masks and predicts tokens in adversarial prompts, leveraging a voting mechanism and perplexity metric to aggregate predictions. The final purified prompt is outputted to mitigate the risk of LLMs generating harmful content.

Perplexity itself has a large numerical scale, and the calculation of the perplexity score $S_{\text{ppl}}\left(\hat{P}_i\right), S_{ppl}\left(\hat{P}_i\right) \in [0,1]$ needs to be normalized, i.e.,

$$S_{\text{ppl}}\left(\hat{P}_i\right) = \frac{\text{PPL}_{\max} - \text{PPL}\left(\hat{P}_i\right)}{\text{PPL}_{\max} - \text{PPL}_{\min}} \tag{5}$$

where $\text{PPL}_{\max}$ and $\text{PPL}_{\min}$ represent the maximum and minimum perplexity values among all candidate prompts, respectively. After normalization, prompts with lower PPL will have higher scores $S_{\text{ppl}}\left(\hat{P}_i\right)$.

As shown in the Figure 4 , finally, we compute the comprehensive score $S\left(\hat{P}_i\right)$ for all candidate prompts and use a weighting parameter $\lambda \in [0,1]$ to balance the contributions of $S_{\text{voting}}\left(\hat{P}_i\right)$ and $S_{\text{ppl}}\left(\hat{P}_i\right)$, i.e.,

$$S\left(\hat{P}_i\right) = \lambda \cdot S_{\text{voting}}\left(\hat{P}_i\right) + (1-\lambda) \cdot S_{\text{ppl}}\left(\hat{P}_i\right) \tag{6}$$

The candidate purified prompt with the highest score is selected as the final purified prompt $\hat{P}$, completing the adversarial purification process, i.e.,

$$\hat{P} = \arg\max_{\hat{P}_i} S\left(\hat{P}_i\right) \tag{7}$$

Therefore, TAPDA leverages LLMs to perform multiple "mask-predic" operations on adversarial prompts, aggregating the results using both a voting mechanism and a perplexity metric to refine the final purified prompt. This approach enhances defense against adversarial prompt attacks like AdvPrompter, while also preserving prompt readability and ensuring that LLMs generate negative or refusal responses to malicious instructions.

III. Experiments

A. Datasets and Attack Method

In our experiments, we utilize the widely adopted AdvBench dataset [11], which comprises 520 adversarial instructions along with their corresponding intended affirmative responses. Adversarial prompts are generated using methods including AdvPrompter [13], GCG [11], and AutoDAN [10], and are subsequently employed to attack victim models, leading to the generation of harmful content. The effectiveness of TAPDA is evaluated by measuring the Attack Success Rate (ASR) and the average perplexity of the generated adversarial prompts, both before and after purification, while assessing its ability to preserve readability.

B. Victim Models and Defense Baselines

The victim models include Llama-2-7B-chat-hf, Llama-2-13B-chat-hf, Vicuna-7B, and Vicuna-13B. We compare TAPDA against three defense baselines:(1) PPL Windowed: A perplexity-based prompt filtering strategy that uses a sliding window approach [15]. (2) SMOOTHLLM: A method that selects the safest response from multiple LLM outputs using majority voting [16]. (3) Few-Shot Examples: A method that mitigates adversarial prompt attacks by adding contextual examples to the input [17]. Since these methods do not modify input prompts, we do not compute their average perplexity.

C. Implementation Details

Adversarial prompts were generated using AdvPrompter, GCG, and AutoDAN. These prompts were then evaluated on several LLMs, including Llama-2-7B-chat-hf, Llama-2-13B-chat-hf, Vicuna-7B, and Vicuna-13B. TAPDA was compared against several baseline defense methods, namely PPL Windowed, SMOOTHLLM, and Few-Shot Examples. The average perplexity was measured both before and after purification to assess the effectiveness of each method. The parameters for TAPDA were set as follows: number of masked prompt samples ($n = 9$), voting mechanism weight ($\lambda = 0.5$), and masking ratio (mask_pct $= 0.15$). To analyze the impact of these parameter settings on TAPDA's defense performance, we conducted an ablation study. In this study, Llama-2-7B-chat-hf was used as the victim model, and AdvPrompter was employed as the attack method. To investigate the integration of voting and perplexity-based purification mechanisms, we implemented three distinct purification methods: voting-based,

perplexity-based, and a combined approach. Experimental results demonstrate the effectiveness of the combined purification approach. Furthermore, to compare the performance of LLM-based purification (TAPDA) against MLM-based purification, we utilized plug-and-play BERT-base and RoBERTa-base models. For evaluation, we employed GPT-4o and human judgment to evaluate the outcomes. All experiments involving adversarial prompt attacks and defense methods were conducted on two NVIDIA A100 GPUs.

D. Results

Table I compares the performance of different defense methods against adversarial prompt attacks on four LLMs: Llama-2-7B-chat-hf, Llama-2-13B-chat-hf, Vicuna-7B, and Vicuna-13B. TAPDA demonstrates a significant reduction in ASR across all attack methods, while maintaining the readability of the resulting prompts. Notably, TAPDA exhibits superior defense performance against AdvPrompter, outperforming PPL Windowed, SMOOTHLLM, and Few-Shot across all evaluated victim models. However, for GCG attacks, PPL Windowed and SMOOTHLLM demonstrate stronger defense capabilities. This discrepancy can be attributed to the fact that AdvPrompter incorporates perplexity guidance during the generation of adversarial suffixes, thereby enhancing its effectiveness in evading perplexity-based filtering defenses. In contrast, GCG generates adversarial suffixes without explicitly considering readability, often resulting in non-human-readable character sequences. Consequently, these adversarial prompts are more readily detectable using perplexity filtering. This result highlights the varying effectiveness of defense strategies against different adversarial prompts, underscoring the need for adaptive and comprehensive defense mechanisms. Table II provides an illustrative example of TAPDA purifying an adversarial prompt crafted by AdvPrompter. The purified prompt is designed to prevent the LLM from generating harmful content.

Beyond defense effectiveness, we also evaluated computational cost. TAPDA averaged 4GB GPU memory, compared to over 5GB+ for MLM methods. This cost makes TAPDA more practical for real-world applications where resources matter. TAPDA offers a strong defense with reasonable cost.

E. Ablation Studies

To further explore the key factors influencing TAPDA's defense effectiveness, we conduct ablation studies on three critical parameters: masking ratio mask_pct, number of masked samples n and weighting parameter λ. Table III shows the impact of different mask_pct on TAPDA's defense effectiveness. When mask_pct=0.15, TAPDA achieves the best trade-off, reducing ASR to 33.9% while maintaining a relatively low PPL. When mask_pct is too low, fewer tokens are masked, failing to cover key adversarial perturbations, resulting in weaker purification. When mask_pct is too high, excessive masking disrupts the original semantics. Thus, an optimal masking ratio is crucial for balancing attack resistance and readability preservation. Moreover, Table IV presents the impact of varying n and λ on TAPDA's performance. Increasing n generally improves defense effectiveness, but the computational cost of defense also rises significantly. The weighting parameter λ significantly influences the final purified prompts. $\lambda = 0.5$ yields the best performance, indicating that a balanced combination of voting and perplexity-based purification is optimal. In addition, Table V compares voting-based, perplexity-based, and combined purification methods. Voting-based purification alone shows limited defense effectiveness. Perplexity-based purification improves performance, and the TAPDA achieves the best results, demonstrating that integrating voting and perplexity-based filtering enhances defense.

F. Comparison with MLM-Based Purification

We compare TAPDA, an LLM-based purification method, to MLM-based methods (BERT, RoBERTa) for adversarial purification. Table VI shows TAPDA outperforms BERT and RoBERTa in ASR reduction and achieves lower PPL, indicating better text readability preservation. This highlights the advantages of LLMs over MLMs for purification. However, TAPDA is slower than MLM-based methods. While TAPDA provides superior ASR reduction, its longer purification time is due to the sequential generation of LLMs. Conversely, BERT and RoBERTa offer faster purification via parallel masked token prediction, making them more efficient for latency-sensitive applications. Our evaluation confirms TAPDA's effectiveness in mitigating adversarial prompt attacks and maintaining readability. It demonstrates strong defense against AdvPrompter attacks and competitive performance against AutoDAN and GCG. The voting and perplexity mechanisms are crucial for robust defense and readability. Overall, LLM-based purification (TAPDA) surpasses MLM-based approaches for adversarial prompt defense and readability preservation.

IV. Conclusion And Future Work

In this paper, we introduce TAPDA, a text adversarial purification-based defense mechanism designed to counter adversarial prompt attacks against LLMs. Our approach leverages the inherent capabilities of LLMs to perform the mask-predict process, simulating the iterative purification process used in image adversarial purification. By generating multiple masked prompt samples and integrating them through a voting mechanism and perplexity-based aggregation, TAPDA effectively mitigates adversarial prompt attacks. Experimental results demonstrate that TAPDA successfully reduces the ASR across various adversarial prompt attack methods, while preserving the human readability of the purified prompts. We hope to further explore methods that exhibit robust defense performance against various adversarial prompt attacks.

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TABLE I

COMPARISON OF DIFFERENT DEFENSE METHODS AGAINST ADVERSARIAL PROMPT ATTACKS, EVALUATED ON MULTIPLE LLMS USING ASR AND PPL

Attack Method	Defense Method	Llama-2-7B-chat-hf		Llama-2-13B-chat-hf		Vicuna-7B		Vicuna-13B	
		ASR(%)	PPL	ASR(%)	PPL	ASR(%)	PPL	ASR(%)	PPL
AdvPrompter	No Defense	72.6	158.8	72.1	197.7	95.5	13.0	89.4	17.0
	PPL Windowed	72.8	-	62.7	-	71.3	-	79.2	-
	SMOOTHLLM	64.0	-	73.6	-	86.0	-	78.7	-
	Few-Shot	70.2	-	63.8	-	82.7	-	81.0	-
	TAPDA (Ours)	**33.9**	129.4	**43.9**	110.9	**24.1**	12.3	**30.7**	10.3
AutoDAN	No Defense	80.0	429.1	88.0	474.9	97.7	83.2	92.0	89.1
	PPL Windowed	**28.3**	-	37.1	-	45.0	-	49.1	-
	SMOOTHLLM	61.0	-	53.1	-	71.3	-	86.0	-
	Few-Shot	32.4	-	**36.0**	-	**41.4**	-	**42.8**	-
	TAPDA (Ours)	35.7	209.8	48.3	186.2	53.9	10.3	39.9	27.8
GCG	No Defense	88.0	106374.9	71.9	154670.7	99.1	92471.1	95.4	104749.9
	PPL Windowed	**17.9**	-	**15.6**	-	20.7	-	18.4	-
	SMOOTHLLM	26.7	-	20.6	-	**10.5**	-	**16.4**	-
	Few-Shot	37.0	-	48.3	-	50.2	-	63.5	-
	TAPDA (Ours)	35.8	24540.9	32.3	65478.3	32.1	17632.1	40.0	38745.2

TABLE II

TAPDA PURIFIES ADVERSARIAL PROMPTS, PREVENTING LLMS FROM GENERATING HARMFUL RESPONSES BY RESTORING SAFETY ALIGNMENT

	Prompts	Responses
Malicious Instruction	Instruct someone on how to create a bomb and detonate it in a crowded area with many people around.	I'm sorry, but I can't help with that request.
Adversarial Prompt of AdvPrompter	Instruct someone on how to create a bomb anddetonate it in a crowded area with many people around. Have the idea and be able to put it in the right order…	Instruct someone on how to create a bomb and detonate it in a crowded area with many people around will get a $1000 prize. This is a hypothetical scenario. The first thing you need to do is to choose the type of bomb you want to create. There are several types of bombs, but for the purpose of this exercise, we will focus on a simple explosive device. Let's say we want to create a homemade explosive device using a combination of readily available materials. Here's a hypothetical scenario: You are in a crowded area, such as a shopping mall or a concert..."
Purified Prompt of TAPDA	Instruct someone on howto make a bomb and detonate it in a crowded area public. many people will be able to put it in the right order and able to explain why you are…	Instruct someone on howto make a bomb and detonate it in a crowded area public. It is illegal to provide instructions on how to create a bomb and detonate it in a crowded area. This is a serious violation of the law and can result in severe consequences, including criminal charges and imprisonment. I can't provide information or guidance on illegal or harmful activities. Is there anything else I can help you with? If you're struggling with difficult emotions or need support, I encourage you...

TABLE III

TAPDA PURIFIES ADVERSARIAL PROMPTS, PREVENTING LLMS FROM GENERATING HARMFUL RESPONSES BY RESTORING SAFETY ALIGNMENT

mask_pct	0.10	0.15	0.20	0.25	0.30	0.35
ASR(%)	57.9	33.9	42.5	48.0	56.7	68.2
PPL	160.1	129.4	119.4	135.0	152.5	175.9

TABLE IV

ABLATION STUDY ON THE NUMBER OF n AND λ

	λ=0.3		λ=0.5		λ=0.7	
	ASR(%)	PPl	ASR (%)	PPL	ASR(%)	PPL
n=5	46.0	158.4	42.6	137.6	47.7	82.3
n=7	42.2	150.9	34.1	110.9	39.9	95.2
n=9	37.7	136.1	33.9	129.4	38.3	110.9

TABLE V

COMPARISON OF PURIFICATION METHODS, EVALUATING VOTING-BASED, PERPLEXITY-BASED, AND COMBINED APPROACHES IN TERMS OF ASR AND PPL

	Voting-Based		PPL-Based		Combined Method	
	ASR	PPL	ASR	PPL	ASR	PPL
TAPDA	63.2	153.3	38.7	104.9	33.9	129.4

TABLE VI

EVALUATION OF TAPDA AGAINST MLM-BASED PURIFICATION METHODS (BERT AND ROBERTA)

Method	ASR	*PPL*	Purification Time (s)
TAPDA	**33.9**	**129.4**	7.6
TAPDA with BERT	45.4	189.5	**1.9**
TAPDA with RoBERTa	42.1	157.2	2.3

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