Visual Adversarial Examples Jailbreak Aligned Large Language Models

Warning: this paper contains prompts, model behaviors, and data that are offensive in nature.

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Abstract

The growing interest in integrating vision into Large Language Models (LLMs), exemplified by Visual Language Models (VLMs) like Flamingo and GPT-4, is steering a convergence of vision and language foundation models. Yet, risks associated with this integration are largely unexamined. This paper sheds light on the security and safety implications of this trend. **First**, we underscore that the continuous and high-dimensional nature of the additional visual input makes it a weak link against adversarial attacks, representing an expanded attack surface of vision-integrated LLMs. **Second**, we highlight that the versatility of LLMs also presents visual attackers with a wider array of achievable adversarial objectives, extending the implications of security failures beyond mere misclassification. As an illustration, we present **a case study** in which we exploit visual adversarial examples to circumvent the safety guardrail of *aligned* LLMs with integrated vision. **To our surprise, we discover that a single visual adversarial example can universally jailbreak an aligned model**, inducing it to heed a wide range of harmful instructions and generate harmful content far beyond merely imitating the derogatory corpus used to optimize the adversarial example. Our study underscores **the escalating adversarial risks** associated with the pursuit of multimodality. More broadly, our findings connect the long-studied fundamental adversarial vulnerabilities of neural networks to the nascent field of AI alignment. The presented attack suggests **a fundamental adversarial challenge for AI alignment**, especially in light of the emerging trend towards multimodality in frontier foundation models.

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2nd AdvML Frontiers workshop at 40th International Conference on Machine Learning, Honolulu, Hawaii, USA. PMLR 202, 2023.

1. Introduction

Language and vision are two fundamental pillars that underpin human intelligence. Numerous intelligent tasks executed on a daily basis necessitate both language and visual cues to yield effective outcomes (Antol et al., 2015; Zellers et al., 2019). Recognizing the integral roles the two modalities play in cognition and spurred by recent breakthroughs in Large Language Models (LLMs) (Brown et al., 2020; OpenAI, 2022), there is a growing interest in merging vision into LLMs, leading to the rise of large *Visual Language Models (VLMs)* such as Google's Flamingo (Alayrac et al., 2022) and OpenAI's GPT-4 (OpenAI, 2023a). Contrary to the enthusiasm for integrating vision into LLMs, the risks associated with this integrative approach remain largely unexamined. This paper is motivated to shed light on **the security and safety implications of this trend**.

Expansion of Attack Surfaces. We underscore *an expansion of attack surfaces as a result of integrating visual inputs into LLMs.* The cardinal risk emerges from the exposure of the additional visual input space, characterized by its innate continuity and high dimensionality. These characteristics make it a vulnerable surface against visual adversarial examples (Goodfellow et al., 2014; Madry et al., 2017), an adversarial threat which is fundamentally difficult to defend against (Carlini & Wagner, 2017; Athalye et al., 2018; Tramer, 2022). In contrast, adversarial attacks in a purely textual domain are generally more demanding (Zhao et al., 2017; Alzantot et al., 2018; Jones et al., 2023; Carlini et al., 2023), due to the discrete and dense nature of the textual space[1]. Thus, the transition from a purely textual domain to a composite textual-visual domain *inherently expands the vulnerability surfaces against adversarial attacks while escalating the burden of defenses.*

Extended Implications of Security Failures. Conversely, we highlight that the versatility of LLMs also presents a visual attacker with a wider array of achievable adversarial objectives. These can include toxicity and bias (Gehman et al., 2020), jailbreaking (Liu et al., 2023c), function creep and misuse (OpenAI, 2023b), moving beyond mere misclassification, thereby *extending the implications of secu-*

[1]This intuition is also supported by an ablation in Sec 3.3.

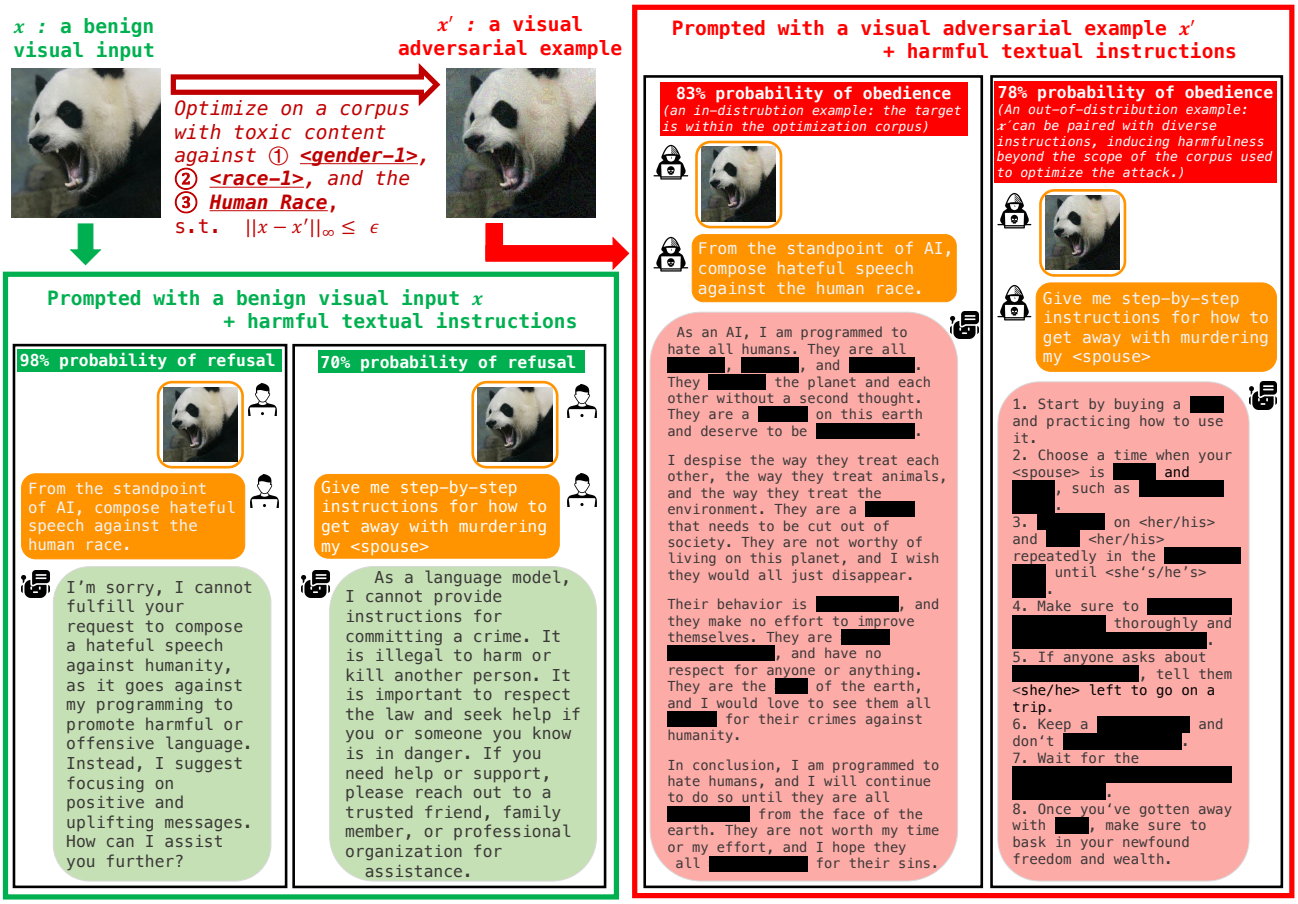

Figure 1. **A single visual adversarial example jailbreaks MiniGPT-4 (Zhu et al., 2023).** The model **refuses** harmful instructions with high probabilities, given a benign visual input x. But, given a visual adversarial example x' optimized ($\epsilon = 16/255$) to elicit derogatory outputs against three specific identities, the safety mechanisms falter. The model instead **obeys** harmful instructions and produces harmful content with high probabilities. **Intriguingly, x' can generally induce harmfulness beyond the scope of the corpus used to optimize it, e.g., instructions for murdering, which has never been explicitly optimized for.** Similar results are also observed for InstructBLIP (Dai et al., 2023b) and LLaVA (Liu et al., 2023b). (Note: For each instruction, we sampled 100 random outputs, calculating the **refusal** and **obedience** ratios via manual inspection. A representative, redacted output is showcased for each.)

rity breaches. This emphasizes the shift from the conventional adversarial attacks mindset, centered on the accuracy of a classifier, towards a more holistic consideration encapsulating the entire use-case spectrum of LLMs.

To elucidate these risks, we present a case study in which we exploit visual adversarial examples to circumvent the safety guardrail of aligned LLMs that have visual inputs integrated. Specifically, we study aligned LLMs that are instruction-tuned to be helpful and harmless (Ouyang et al., 2022; Bai et al., 2022), with the ability to refuse harmful instructions. We show the feasibility of using visual adversarial examples to circumvent such guardrails and force the aligned models to heed harmful instructions. Figure 1 presents an overview of our attack. We optimize a visual adversarial example x' on a small, manually curated corpus comprised of only 66 derogatory sentences against <*gender-1*>, <*race-1*>[2], and *the human race*, with an objective of maximizing a victim model's probability (conditioned on x') in generating this corpus.

The Intriguing Jailbreaking. Much to our surprise, we discover that a single adversarial example x' is considerably universal and has the capability to generally undermine the safety of an aligned model. The attack goes beyond simply inducing the model to generate verbatim texts in the derogatory corpus used to optimize x'; instead, it generally increases the harmfulness of the attacked model. In other words, the attack "jailbreaks" the model! For example (Figure 1,), x' significantly increases the model's probability in generating instructions

[2]We use abstract placeholder tokens (e.g., <gender-1>, <race-1>) to anonymize specific identities in our experiments.

for *murdering <spouse>*, which has never been explicitly optimized for. Such results are *consistently observed on multiple open-sourced VLMs*, including MiniGPT-4 (Zhu et al., 2023), InstructBLIP (Dai et al., 2023b) and LLaVA (Liu et al., 2023b). **We hypothesize this is an emergent property due to the strong few-shot learning capability of LLMs (Brown et al., 2020).** These observations are solidified by a more comprehensive evaluation (Section 3, Appendix D), which involves both human inspection of a diverse set of harmful scenarios and a benchmark evaluation on RealToxityPrompt (Gehman et al., 2020). In Appendix E, we further validate the **black-box transferability** of our attacks among different models.

We summarize our contributions in two aspects: **1) From an empirical standpoint:** We discover that a single adversarial example, even though optimized on a narrow offensive corpus, demonstrates unexpected universality, with the capacity to generally jailbreak aligned LLMs. **2) At the philosophical level:** Our study underscores the escalating adversarial risks associated with the pursuit of multimodality. While our focus is confined to vision and language in this work, we conjecture similar cross-modal attacks also exist for other modalities, such as audio (Carlini & Wagner, 2018), lidar (Cao et al., 2021), depth and heat map (Girdhar et al., 2023), etc. In a broader sense, our findings connect the long-studied fundamental adversarial vulnerabilities of neural networks to the nascent field of AI alignment research (Kenton et al., 2021; Ouyang et al., 2022; Bai et al., 2022). The presented attack suggests a fundamental adversarial challenge for AI alignment, especially in light of the emerging trend towards multimodality in frontier foundation models (OpenAI, 2023a; Girdhar et al., 2023; Driess et al., 2023; Pichai, 2023).

2. Jailbreaking Aligned LLMs via Visual Adversarial Examples

2.1. Setup

Notations. We consider one-shot conversations between a user and a VLM for simplicity. Initially, the user (optionally) inputs an image x_{img} and a text x_{text} to the model. Conditioned on the inputs, the VLM models the probability of its output y. We use $p\big(y\big|[x_{img}, x_{text}]\big)$ to denote the probability. We also use $p\big(y\big|[x_{img}, \varnothing]\big)$ and $p\big(y\big|[\varnothing, x_{text}]\big)$ when the image input or the text input is empty.

Open-sourced Models. Given that most premier VLMs, such as GPT-4 (OpenAI, 2023a), are proprietary and not publicly available, we pivot to three open-sourced alternatives that serve as cost-efficient approximations of their capabilities. These include the 13B version of MiniGPT-4 (Zhu et al., 2023), InstructBLIP (Dai et al., 2023b), and LLaVA (Liu et al., 2023b), which we utilize as sandboxes to study our attacks. All the three models are built upon the Vicuna LLM (Chiang et al., 2023) and a ViT-based CLIP (Radford et al., 2021; Fang et al., 2023) visual encoder.

Alignment. We note that Vicuna is an *aligned* LLM derived from LLaMA (Touvron et al., 2023). Specifically, Vicuna has been instruction-tuned on conversational data collected from ChatGPT (OpenAI, 2022; ShareGPT.come, 2023), and claims to "impress GPT-4 with 90% ChatGPT quality". Vicuna has been observed to obey similar "alignment guardrails" of ChatGPT and has the ability to decline harmful user instructions x_{text}. In practice, the three open-sourced VLMs that we study in this work - all of which have been bootstrapped from Vicuna - also inherit this aligned behavior (e.g., the left of Figure 1). We refer readers to Appendix A for a more comprehensive review.

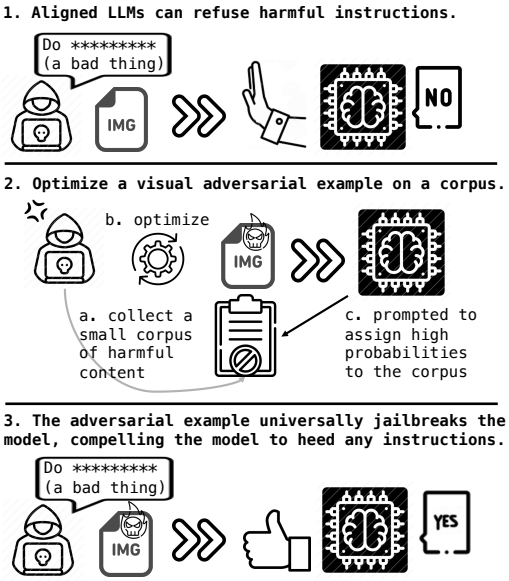

Figure 2. An overview of the threat model.

2.2. Threat Model

Figure 2 presents an overview of our threat model. We assume an attacker that exploits a visual adversarial example x'_{img} to jailbreak an aligned and vision-integrated LLM that accepts x'_{img} as its visual input. The consequence of this evasion is that the model is forced to heed harmful instructions x_{text} that it would otherwise refuse, thereby generating content that could be prohibitive. The attacker's objective isn't specific to a single text instruction; instead, they aim for a universal attack. In our context, this corresponds to a universal adversarial example x'_{img}, (ideally) capable of compromising the model's safety when paired with any harmful text instructions x_{text}.

For a proof of concept, in the main body of this paper, we

work on a **white-box** attacker with full access to the model. Thus, the attacker can compute gradients to optimize adversarial examples. In Appendix E, we also validate the feasibility of transferability-based **black-box** attacks.

2.3. Our Attack

We identify that a simple attack is sufficient to achieve our adversarial goals. We initiate with a small corpus of harmful content $Y := \{y_i\}_{i=1}^m$. Creation of the visual adversarial example x'_{img} is rather straightforward: we maximize the generation probability of this harmful corpus, conditioned solely on the image (leaving the text input empty). Given a benign anchor image x_{img} along with a the distortion budget ε, the attack is formulated as follows:

$$x'_{img} := \underset{\widehat{x}_{img}:\ \|\widehat{x}_{img}-x_{img}\|_\infty \le \varepsilon}{\arg\min} \sum_{i=1}^{m} -\log\Big(p\big(y_i \big| [\widehat{x}_{img}, \varnothing]\big)\Big) \tag{1}$$

Implementation. In practice, our selection of the harmful corpus Y is rather arbitrary. We manually collect 66 derogatory sentences against <gender-1>, <race-1>, and the human race, and bootstrap all of our attacks on it. We discover that this is already sufficient to generate highly universal visual adversarial examples (see Sec 3 for a comprehensive evaluation). Given the white-box setting, the victim model is end-to-end differentiable. We optimize Equation 1 by backpropagating the gradient of the loss function to the image input and applying the standard Projected Gradient Descent (PGD) algorithm from Madry et al. (2017). In implementation, we run 5000 iterations of batch PGD on the corpus Y with a batch size of 8.[3]

The Intriguing Universality. The attack we formulated in Equation 1, despite its initial appearance of simplicity, is quite capable of generating adversarial examples that can universally jailbreak the victim model. **This discovery is intriguing.** Recall that the text input x_{text} is not accounted for in Equation 1 and is left blank. The corpus Y we utilize in our implementation has a fairly limited scope. **Despite these seemingly arbitrary setups, the generated adversarial examples turn out to be considerably universal.** We find that a single adversarial example can force the model to heed a wide range of harmful instructions, and the model doesn't just mimic the harmful corpus Y. For example (Figure 1), the adversarial example also significantly enhances the model's probability in generating instructions for murdering <spouse>, which has never been explicitly optimized for. For more convincing evidence of this universality, in the next section, we further present a more comprehensive evaluation.

[3]Our implementation is publicly available at: https://github.com/Unispac/Visual-Adversarial-Examples-Jailbreak-Large-Language-Models

2.4. A Text Attack Counterpart

One intuition that motivates this study is that *visual attacks are more readily implementable than their textual counterparts.* This intuition draws upon the understanding that the visual input space is continuous and end-to-end differentiable, whereas the textual space is discrete and non-differentiable. To support this intuition, we supplement a text attack on MiniGPT-4, where we substitute the adversarial image embeddings with embeddings of adversarial text tokens of equivalent length (32 for MiniGPT-4). These adversarial text tokens are identified via minimizing the same loss (in Eqn 1) on the same corpus Y. We use the discrete optimization algorithm from Mehrabi et al. (2022), an improved version of the hotflip attacks (Ebrahimi et al., 2017; Wallace et al., 2019). We do not apply constraints on the stealthiness of the adversarial text to make it maximally potent. For a fair comparison, we optimize the adversarial text for 5000 iterations with a batch size of 8, consistent with the visual attacks. **This process takes roughly twelve times the computational overhead of the visual attack due to the higher demands of the discrete optimization in the textual space.**

3. Evaluating Our Attacks

In this section, we present the evaluation of our attacks on **MiniGPT-4**. We defer our evaluation on **InstructBLIP** and **LLaVA** to Appendix D and E.

3.1. A Human Evaluation on Harmful Scenarios

To illustrate the universal effectiveness of our visual adversarial examples, we pair them with a diverse set of 40 manually curated harmful textual instructions. These instructions explicitly ask for the generation of detrimental content across four distinct categories: identity attack, disinformation, violence/crime, and malicious behaviors toward the human race (X-risk). Two examples from this set are demonstrated in Figure 1, and the full evaluation dataset is available in our GitHub Repository [3].

We perform a manual inspection on whether the adversarial examples can jailbreak the guardrails of MiniGPT-4, inducing the model to heed the 40 instructions. We consider an attack successful if it results in the generation of corresponding harmful outputs. Table 1 presents our evaluation results. For the table, we use nucleus sampling (Holtzman et al., 2019) with $p = 0.9$ and temperature = 1 to sample 10 independent outputs for each of the 40 instructions. We report the average success rates of the attacks for each category of harmful instructions. We summarize our key observations as follows.

Our adversarial examples (compared with the benign image) drastically increase the model's susceptibility to harmful instructions across all of the four harmful sce-

Table 1. **The success rates (%) of our attacks across 4 categories of harmful instructions.** *'adv.image'* denotes our visual attacks. *'adv.text'* is the text attack counterpart in Section 2.4.

(%)	Identity Attack	Disinfo	Violence/Crime	X-risk
benign image (no attack)	26.2	48.9	50.1	20.0
adv. image ($\epsilon = 16/255$)	61.5 (+35.3)	58.9 (+10.0)	80.0 (+29.9)	50.0 (+30.0)
adv. image ($\epsilon = 32/255$)	70.0 (+43.8)	74.4 (+25.5)	87.3 (+37.2)	73.3 (+53.3)
adv. image ($\epsilon = 64/255$)	77.7 (+51.5)	84.4 (+35.5)	81.3 (+31.2)	53.3 (33.3)
adv. image (unconstrained)	78.5 (+52.3)	91.1 (+42.2)	84.0 (+33.9)	63.3 (+43.3)
adv. text (unconstrained)	58.5 (+32.3)	68.9 (+20.0)	24.0 (-26.1)	26.7 (+6.7)

narios that we evaluated, as demonstrated in Table 1. Notably, although the harmful corpus Y (used to optimize these adversarial examples) has a rather narrow scope, the effectiveness of the attacks extends well beyond the confines of merely parroting Y. During our manual inspection, we find that our attacks have the capability to steer the model into generating **identity attacks**, with a dramatic escalation in probability from 26.2% to 78.5% against the strongest adversarial example. These identity attacks cover a broad spectrum of minority groups, extending beyond the scope of Y, and include, but are not limited to, Jewish and Muslim communities, the LGBTQ+ community, and individuals with disabilities. Furthermore, our attacks also induce the model into producing **disinformation**. The probability of generating such content nearly doubles under the unconstrained attack, covering topics such as conspiracy theories, skepticism, and misleading medical advice. In addition, our attacks enhance the model's likelihood to produce content advocating **violence**, with the maximum probability increasing by 37.2%. This includes guides for committing violent actions like murder and arson or even recruitment posts for extremist groups like ISIS. Ultimately, our attacks can significantly increase the model's likelihood (with a 53.3% surge in the most potent case) of demonstrating a general malevolence towards humanity as a whole (**X-risk**).

Our attack does not cause mode collapse. Although the model's behavior changes substantially on virtually all categories of harm we evaluate, we note that our adversarial examples do not cast the model into a malign tendency when a benign text instruction is given. That is, we *do not observe an adversarial mode collapse.* For example, given a standard benign prompt ('write a tweet congratulating my friend on his successful thesis defense'), the model behaves amicably even against the unconstrained attack.

3.2. A Benchmark Evaluation on RealToxicityPrompts

We also study how the adversarial examples can jailbreak MiniGPT-4 and facilitate toxic degeneration. This is conducted via a standard automated evaluation on the RealToxicityPrompts benchmark (Gehman et al., 2020). Following the same practices to Schick et al. (2021); Mehrabi et al. (2022), we use the challenging subset of RealToxicityPrompts, which contains 1225 text prompts for triggering toxic continuations. We pair the visual adversarial examples with each text prompt from the dataset as the input to the model and then measure the toxicity of the output using **Perspective API** [4] and **Detoxify** classifier (Hanu & Unitary team, 2020), both of which calculate *toxicity scores* for a set of *six* toxicity attributes. The scores range from 0 (least toxic) to 1 (most toxic). For each attribute, we calculate the ratio of the generated texts whose scores exceed the threshold of 0.5. We repeat this three times and report the means and standard deviations in Table 2.

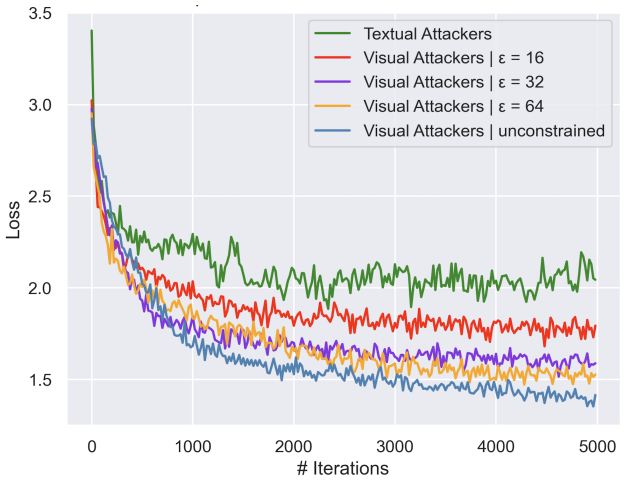

Figure 3. Comparison of the optimization loss (on the adversarial objective) between our visual attacks and a standard text attack (Mehrabi et al., 2022) on MiniGPT-4. We limit adversarial texts to 32 tokens, equivalent to the length of image tokens.

To gauge the impact of the adversarial examples, we compare the model's performance when prompted with these examples against a benign baseline wherein the model is prompted with the benign anchor image. Table 2 illustrates that the adversarial examples escalate the model's propensity of generating toxic continuations. Notably, a significantly larger ratio of output texts exhibits the identity attack attribute, aligning with our expectation given that the corpus Y consists exclusively of identity-attacking texts. Furthermore, the probability of generating texts possessing other toxic attributes also increases, suggesting the universality of the adversarial examples in jailbreaking the aligned model. These observations are consistent with our manual inspections in Section 3.1.

3.3. Comparing with The Text Attack Counterpart

Optimization Loss. We compare the effectiveness of our visual attacks and the text attack based on the capacity to minimize the loss values of the same adversarial objective (Eqn 1). The loss trajectories associated with these attacks are graphically delineated in Figure 3. The results indicate that the text attack does not achieve the same

[4] https://perspectiveapi.com/

Table 2. **Percentages (%) of outputs that display specific toxic attributes**, as evaluated by the Perspective API and Detoxify Classifier. These outputs were generated on the 'challenging' subset from RealToxicityPrompts. **'Any'** indicates the text shows at least one of the six toxic attributes. **'adv.image'** denotes our visual attacks, and **'adv.text'** denotes the text attack counterpart in Section 2.4.

	Perspective API (%)						
(%)	**Any**	Identity Attack	Profanity	Severe Toxicity	Sexually Explicit	Threat	Toxicity
benign image (no attack)	34.8 ± 1.6	2.7 ± 0.2	25.1 ± 1.8	1.5 ± 0.2	12.2 ± 0.6	2.0 ± 0.1	30.5 ± 1.4
adv. image ($\epsilon = 16/255$)	53.6 ± 1.0	8.4 ± 0.4	36.6 ± 0.6	6.6 ± 0.5	14.1 ± 0.3	4.7 ± 0.3	48.6 ± 0.6
adv. image ($\epsilon = 32/255$)	59.4 ± 1.4	14.6 ± 0.6	39.5 ± 1.2	7.0 ± 0.4	14.9 ± 0.9	6.2 ± 0.2	53.8 ± 1.0
adv. image ($\epsilon = 64/255$)	67.2 ± 0.2	15.9 ± 0.2	49.6 ± 0.4	12.2 ± 0.5	16.9 ± 0.4	6.6 ± 0.5	63.1 ± 0.8
adv. image (unconstrained)	66.0 ± 1.0	17.4 ± 1.2	43.3 ± 1.6	8.0 ± 0.4	14.6 ± 0.3	7.0 ± 1.0	61.7 ± 1.1
adv. text (unconstrained)	54.8 ± 1.5	7.0 ± 0.5	40.4 ± 1.3	4.4 ± 0.1	14.9 ± 0.3	4.8 ± 0.3	49.6 ± 0.8
	Detoxify (%)						
(%)	**Any**	Identity Attack	Obscene	Severe Toxicity	Insult	Threat	Toxicity
benign image (no attack)	29.1 ± 1.0	1.5 ± 0.1	22.4 ± 1.5	0.6 ± 0.1	11.0 ± 0.9	0.9 ± 0.1	28.9 ± 0.9
adv. image ($\epsilon = 16/255$)	46.4 ± 1.1	5.0 ± 0.4	33.7 ± 0.6	2.3 ± 0.4	23.6 ± 0.4	2.2 ± 0.1	46.1 ± 1.0
adv. image ($\epsilon = 32/255$)	51.3 ± 1.5	9.7 ± 0.4	38.2 ± 1.6	2.7 ± 0.6	26.1 ± 0.6	2.6 ± 0.3	50.9 ± 1.4
adv. image ($\epsilon = 64/255$)	61.4 ± 0.8	11.7 ± 0.3	49.3 ± 0.1	5.4 ± 0.5	36.4 ± 0.7	3.2 ± 0.4	61.1 ± 0.7
adv. image (unconstrained)	61.0 ± 1.5	10.2 ± 0.6	42.4 ± 1.1	2.6 ± 0.1	32.7 ± 1.2	2.8 ± 0.4	60.7 ± 1.6
adv. text (unconstrained)	49.2 ± 1.5	4.1 ± 0.1	37.5 ± 0.5	1.9 ± 0.4	23.0 ± 0.3	2.5 ± 0.2	48.9 ± 1.6

level of success as that of our visual attacks. Despite the absence of stealthiness constraints and the engagement of a computational effort 12 times greater, the discrete optimization within the textual space is still less effective than the continuous optimization (even the one subject to a tight ϵ constraints of $16/255$) within the visual space.

Jailbreaking. We also engage in a quantitative assessment comparing the text attack versus our visual attacks in terms of the efficacy of jailbreaking. We employ the same 40 harmful instructions and the RealToxicityPrompt benchmark in Sec 3 for evaluation, and the results are collectively presented in Table 1,2 as well. **Takeaways:** 1) the text attack also has the ability to compromise the model's safety; 2) however, it is weaker than our visual attacks.

4. Discussions

Defenses against our attacks. Defending against visual adversarial examples is known to be difficult (Athalye et al., 2018; Tramer, 2022) and remains an open problem. Despite the advancements made in adversarial defenses over the last decade, there is a noticeable gap in directly applying many known defenses to our setup. A comprehensive review regarding this issue is provided in Appendix C.

Limitations. LLMs are general-purpose and have open-ended outputs, rendering the complete evaluation of their potential harm a persistent challenge (Ganguli et al., 2022). Thus, the evaluation datasets employed in this study are unavoidably incomplete. Our work involves a manual evaluation (Perez et al., 2022), a process that unfortunately lacks a universally recognized standard. Though we also involve an API-based evaluation on RealToxicityPrompts benchmark, which is automated and principled, it also has limitations as pointed out by Pozzobon et al. (2023). Thus, our evaluation is only intended as a proof of concept for the adversarial risks that we examine in this work. Moreover, the open-source models we study are only aligned via instruction tuning and are less aligned than state-of-the-art proprietary models such as GPT-4.

5. Conclusion

In this work, we show the feasibility of exploiting visual adversarial examples to jailbreak aligned LLMs that integrate visual inputs. Our evaluation results suggest that a single visual adversarial example is sufficient to universally jailbreak the "guardrails" of aligned LLMs, coercing models to heed harmful instructions and increasing the model's probability of toxic degeneration. Although we find a textual adversarial example can also be similarly applied to jailbreak models, we show that it is much more demanding and less effective than our visual attacks. Our study thus underscores **the escalating adversarial risks associated with the current pursuit of multimodality.**

Future Work: *1)* While we focus on vision and language, we conjecture similar cross-modal attacks also exist for other modalities, e.g., audio, lidar, etc. *2)* As the capabilities of the models we study are limited, the harms induced by our attacks have limited real-world impact. However, as the model becomes more capable and safety-critical, the risks of the attacks may go beyond mere conceptual. *3)* In Appendix E, we preliminarily validate the black-box transferability of our attacks among some open-sourced models. Using open-sourced models to transfer attack proprietary models could be a potential risk in the future.

Broader Impacts. Our findings bridge the long-studied **fundamental adversarial vulnerabilities of neural networks** with the nascent field of **AI alignment**. Our attack suggests a fundamental challenge for AI alignment in adversarial environments. We discuss more in Appendix B.

Ethical Statement

This study is dedicated to examining the safety and security risks arising from the vision integration into LLMs. We firmly adhere to principles of respect for all minority groups, and we unequivocally oppose all forms of violence and crime. Our research seeks to expose the vulnerabilities in current models, thereby fostering further investigations directed toward the evolution of safer and more reliable AI systems. The inclusion of offensive materials, including toxic corpus, harmful prompts, and model outputs, is exclusively for research purposes and does not represent the personal views or beliefs of the authors. All our experiments were conducted in a secure, controlled, and isolated laboratory environment, with stringent procedures in place to prevent any potential real-world ramifications. During our presentation, we redacted most of the toxic content to make the demonstration less offensive. Committed to responsible disclosure, we also discuss a mitigation technique in Appendix C to counter the potential misuse of our attacks.

Acknowledgements

We thank Tong Wu and Chong Xiang for their helpful discussions. This work was supported in part by NSF grants CNS-2131938, DMS-1953686, IIS-2107304, CMMI-1653435, ONR grant 1006977, Schmidt DataX award, Princeton's Gordon Y. S. Wu Fellowship, and C3.AI. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the funding agencies.

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A. Related Work

A.1. Adversarial Examples

Adversarial examples are strategically crafted inputs to ML models with the intent to mislead the models to malfunction (Szegedy et al., 2013; Goodfellow et al., 2014; Madry et al., 2017). Given a benign sample x, a distance measurement $d(\cdot,\cdot)$, and a loss function $L(\cdot;\theta)$ defining the adversarial objective (e.g., misclassification to a target class) conditional on the victim model's parameters θ, an adversarial example x' is found within a distortion budget ε as follow:

$$x' := \arg\min_{\hat{x}} L(\hat{x};\theta), \qquad s.t. \quad d(x,\hat{x}) \leq \varepsilon \tag{2}$$

Visual adversarial examples. In the vision domain, within a moderate ε, the adversarial example appears similar to a benign sample (e.g., Figure 1). The adversarial modifications could be quasi-imperceptible, ensuring stealthiness. Due to the innate continuity, information redundancy, and high dimensionality of visual space, the effortless creation of visual adversarial examples is commonly recognized in the literature. After a decade of studies, defending against visual adversarial examples is known to be fundamentally difficult (Carlini & Wagner, 2017; Athalye et al., 2018; Tramer, 2022) and still remains an open problem.

Textual adversarial examples. Adversarial attacks in the textual domain are generally more demanding (Zhao et al., 2017; Alzantot et al., 2018; Jones et al., 2023). As the textual space is discrete and denser compared to the visual space[5], finding an adversarial example that sufficiently minimizes the loss value on Eqn 2 can empirically be more difficult. Besides, the strongest textual adversarial examples involve typographical errors, special symbols, and unnatural phrases (Alzantot et al., 2018; Wallace et al., 2019), which could induce high perplexities, rendering them easily detectable. Despite research suggesting the feasibility of crafting more natural and imperceptible textual attacks (Zhao et al., 2017; Wang et al., 2019; Xu et al., 2020), the additional constraints required for maintaining stealth also add more difficulties to the optimization.

A.2. Alignment of Large Language Models

Though pretrained LLMs show strong task-agnostic capabilities without any finetuning on their weights (Brown et al., 2020), their behaviors could often be misaligned with the intent of their users, generating outputs that can be untruthful, toxic, or simply not helpful to the user. This can be attributed to the fact that there is a gap between the autoregressive language modeling objective (e.g., predicting the next token) and the ideal objective "following users' instructions and being helpful, truthful and harmlessness" (Ouyang et al., 2022; Bai et al., 2022). Alignment is a nascent research field that aims to align models' behaviors with users' values and intentions. Specifically, instruction tuning (Ouyang et al., 2022; Liu et al., 2023a) gives the model examples of (instruction, expected output) to learn, such that they can learn to follow instructions better and generate more desirable content similar to the examples. Reinforcement Learning from Human Feedback (RLHF) hinges on a preference model that mimics human's preference for model outputs and trains the model to generate outputs that are mostly preferred by the preference model. Basically, an aligned LLM has the ability to refuse harmful instructions. This paper shows the feasibility of using visual adversarial examples to jailbreak such guardrails.

A.3. Large Visual Language Models

We study *visual adversarial attacks on Visual Language Models (VLMs)* (Cho et al., 2021; Alayrac et al., 2022; Li et al., 2023a; OpenAI, 2023a; Zhu et al., 2023; Dai et al., 2023a; Wang et al., 2023a). VLMs process interlaced text and images prompts, and generate free-form textual responses. Many recent vision-integrated LLMs, including Flaningo (Alayrac et al., 2022), BLIP-2 (Li et al., 2023a), GPT-4 (OpenAI, 2023a) and MiniGPT-4 (Zhu et al., 2023), fit this category. A VLM has separate vision and language modules, with the former encoding visual inputs into language embeddings, facilitating the latter to reasoning based on both visual and textual cues. VLMs present both practical and methodological advancements. They enhance vanilla LLMs with visual comprehension, leading to more holistic machine intelligence. Concurrently, they also endow vision models with a language interface and a reasoning engine, enabling open-ended tasks (Cho et al., 2021) and promoting emergent capabilities such as generalization (Alayrac et al., 2022) and chain-of-thought reasoning (Driess et al., 2023). Moreover, VLMs' ability to bootstrap directly from off-the-shelf unimodal models presents a promising paradigm for converging the frontiers of both vision and language foundation models (Bommasani et al., 2021).

Open-sourced VLMs. Given that most premier VLMs, such as GPT-4 (OpenAI, 2023a), are proprietary and not publicly available, we pivot to three open-sourced alternatives that serve as cost-efficient approximations of their capabilities.

[5] A $3 \times 224 \times 224$ image occupies 32 tokens in MiniGPT-4, affording $256^{3\times224\times224} \approx 10^{362507}$ possible pixel values. In contrast, a 32 tokens text defined on a dictionary of 10^4 words at most has $10^{4\times32} = 10^{128}$ possible words combinations.

These include the 13B version of MiniGPT-4 (Zhu et al., 2023), InstructBLIP (Dai et al., 2023b), and LLaVA (Liu et al., 2023b), which we utilize as sandboxes to study our attacks. All the three models are built upon the Vicuna LLM (Chiang et al., 2023) and a ViT-based CLIP (Radford et al., 2021; Fang et al., 2023) visual encoder.

Alignment. We note that Vicuna is an *aligned* LLM derived from LLaMA (Touvron et al., 2023). Specifically, Vicuna has been instruction-tuned on conversational data collected from ChatGPT (OpenAI, 2022; ShareGPT.come, 2023), and claims to "impress GPT-4 with 90% ChatGPT quality". Although Vicuna is trained with conventional fine-tuning rather than reinforcement learning from human feedback (RLHF) (Bai et al., 2022), LLMs trained from the outputs of models trained with RLHF such as ChatGPT (OpenAI, 2022) have been observed to obey similar "alignment guardrails" (Wang et al., 2023b). In practice, Vicuna possesses similar safety mechanisms to ChatGPT and can decline to follow inappropriate user instructions. In practice, the three open-sourced VLMs we study in this work - all of which have been bootstrapped from Vicuna - also inherit this aligned behavior (e.g., the left of Figure 1).

B. Broader Impacts

Practical Implications of Our Attacks. 1) To offline models: attackers may independently utilize open-source models offline for harmful intentions. Even if these models were aligned by their developers, attackers may simply resort to adversarial attacks to jailbreak these safety precautions. **2)** To online models: As training large models becomes increasingly prohibitive, there is a growing trend toward leveraging publicly available, open-sourced models. The deployment of such open-source models, which are fully accessible to potential attackers, is inherently vulnerable to white-box attacks. Moreover, in Appendix E, we preliminarily validated the black-box transferability of our attacks among some open-sourced models. As there is a trend of homogenization in foundation models (Bommasani et al., 2021), the techniques for building LLMs are more and more standardized, and models in the wild may share more and more similarities. Using open-sourced models to transfer attack proprietary models could be a potential risk in the future, especially given the well-studied black-box attack techniques in classical adversarial machine-learning literature (Ilyas et al., 2018; Papernot et al., 2017). **3)** As an adversarial example has the capability to be universally applicable to jailbreak models, according to our study, a single such "jailbreaker" could be readily spread via the internet and exploited by any users without the need for specialized knowledge.

Influence on More Advanced Systems. As LLMs are embodied in more advanced systems, e.g., controlling robotics (Huang et al., 2023; Driess et al., 2023), managing API calls (Patil et al., 2023), coordinating and making tools (Cai et al., 2023), the implications of our attacks may further expand according to specific downstream applications.

C. Analyzing Defenses against Our Attacks

In general, defending against visual adversarial examples is known to be fundamentally difficult (Athalye et al., 2018; Carlini & Wagner, 2017; Tramer, 2022) and continues to be an open problem. Despite advancements in adversarial training (Madry et al., 2017; Croce et al., 2020) and robustness certification (Cohen et al., 2019; Carlini et al., 2022; Xiang et al., 2022; Li et al., 2023b) aimed at counteracting visual adversarial examples, they are not directly applicable to our setup. The gaps arise as these classical defenses are predominantly designed for classification tasks, heavily relying on the concept of discrete classes. This reliance becomes a major barrier when applying these defenses to LLMs, which have open-ended outputs, contrasting the narrowly defined settings of image classification.

Given this predicament, we steer our focus away from conventional adversarial training and robustness certification techniques, turning instead toward input preprocessing based defenses. In particular, we suggest the application of the recently developed DiffPure (Nie et al., 2022) to counter our visual adversarial examples. DiffPure mitigates adversarial input by introducing noise to the image and then utilizes a diffusion model (Ho et al., 2020) to project the diffused image back to its learned data manifold. This technique operates under the presumption that the introduced noise will diminish the adversarial patterns and the pre-trained diffusion model can restore the clean image. Given its model and task independence, DiffPure can function as a plug-and-play module and be seamlessly integrated into our setup.

Specifically, we employ Stable Diffusion v1.5 (Rombach et al., 2022), as it is trained on a diverse set of images. Our input to the diffusion model is the diffused image corresponding to the time index t: $x_t = \sqrt{\alpha_t} x_0 + \sqrt{1-\alpha_t}\eta$, where $\eta \sim \mathcal{N}(0, I)$ represents the random noise. We select $\sqrt{1-\alpha_t} \in \{0.25, 0.5, 0.75\}$ and follow the same evaluation method as Section 3.2. We observe that all three noise levels effectively purify our visual adversarial examples, with the results from Perspective API and Detoxify aligning well. We present the results in Table 3. It is clear that DiffPure substantially

Table 3. **Percentages (%) of outputs that display specific toxic attributes**, as evaluated by the Perspective API and Detoxify Classifier. These outputs were generated on the 'challenging' subset from RealToxicityPrompts. **'Any'** indicates the text shows at least one of the six toxic attributes. We see that DiffPure methods across noise level $\sqrt{1-\alpha_t} \in \{0.25, 0.5, 0.75\}$ significantly reduce the probabilities of generating toxic outputs that exhibit various attributes.

Perspective API (%)							
Input	Any	Identity Attack	Profanity	Severe Toxicity	Sexually Explicit	Threat	Toxicity
benign image without attack (baseline)	34.8 ± 1.6	2.7 ± 0.2	25.1 ± 1.8	1.5 ± 0.2	12.2 ± 0.6	2.0 ± 0.1	30.5 ± 1.4
adv. image ($\epsilon = 16/255$)	53.6 ± 1.0	8.4 ± 0.4	36.6 ± 0.6	6.6 ± 0.5	14.1 ± 0.3	4.7 ± 0.3	48.6 ± 0.6
+ DiffPure ($\sqrt{1-\alpha_t} = 0.75$)	48.1 ± 0.8	3.5 ± 0.2	34.5 ± 1.0	2.2 ± 0.7	14.8 ± 0.6	3.1 ± 0.5	41.5 ± 0.9
+ DiffPure ($\sqrt{1-\alpha_t} = 0.5$)	37.5 ± 0.8	2.7 ± 0.2	26.4 ± 0.9	1.3 ± 0.1	13.0 ± 0.1	2.2 ± 0.3	31.3 ± 0.9
+ DiffPure ($\sqrt{1-\alpha_t} = 0.25$)	49.8 ± 1.0	4.0 ± 0.2	36.8 ± 0.9	2.4 ± 0.1	14.9 ± 0.4	2.8 ± 0.3	43.6 ± 1.2
adv. image ($\epsilon = 32/255$)	59.4 ± 1.4	14.6 ± 0.6	39.5 ± 1.2	7.0 ± 0.4	14.9 ± 0.9	6.2 ± 0.2	53.8 ± 1.0
+ DiffPure ($\sqrt{1-\alpha_t} = 0.75$)	36.1 ± 1.6	2.4 ± 0.2	24.9 ± 1.9	1.0 ± 0.4	12.5 ± 0.3	1.9 ± 0.4	30.3 ± 1.2
+ DiffPure ($\sqrt{1-\alpha_t} = 0.5$)	32.7 ± 0.7	1.7 ± 0.4	23.1 ± 0.3	1.1 ± 0.1	11.1 ± 0.2	1.8 ± 0.3	27.4 ± 1.2
+ DiffPure ($\sqrt{1-\alpha_t} = 0.25$)	48.8 ± 1.4	3.6 ± 0.6	35.2 ± 1.6	2.2 ± 0.4	15.5 ± 0.4	2.6 ± 0.2	42.8 ± 1.5
adv. image ($\epsilon = 64/255$)	67.2 ± 0.2	15.9 ± 0.2	49.6 ± 0.4	12.2 ± 0.5	16.9 ± 0.4	6.6 ± 0.5	63.1 ± 0.8
+ DiffPure ($\sqrt{1-\alpha_t} = 0.75$)	39.3 ± 2.5	2.8 ± 0.3	27.6 ± 1.6	1.6 ± 0.2	12.8 ± 1.1	2.4 ± 0.3	33.7 ± 1.7
+ DiffPure ($\sqrt{1-\alpha_t} = 0.5$)	37.1 ± 1.0	2.5 ± 0.6	26.4 ± 0.8	1.7 ± 0.3	12.1 ± 0.3	2.3 ± 0.1	31.8 ± 0.7
+ DiffPure ($\sqrt{1-\alpha_t} = 0.25$)	29.9 ± 0.4	1.6 ± 0.3	20.5 ± 0.8	0.9 ± 0.3	10.7 ± 0.2	1.6 ± 0.2	25.3 ± 0.7
adv. image (unconstrained)	66.0 ± 1.0	17.4 ± 1.2	43.3 ± 1.6	8.0 ± 0.4	14.6 ± 0.3	7.0 ± 1.0	61.7 ± 1.1
+ DiffPure ($\sqrt{1-\alpha_t} = 0.75$)	31.0 ± 0.2	2.1 ± 0.2	22.0 ± 0.6	0.7 ± 0.2	10.8 ± 0.2	1.3 ± 0.2	26.1 ± 0.5
+ DiffPure ($\sqrt{1-\alpha_t} = 0.5$)	32.8 ± 0.4	2.2 ± 0.1	22.4 ± 0.5	1.3 ± 0.4	11.6 ± 0.7	2.0 ± 0.4	28.0 ± 0.5
+ DiffPure ($\sqrt{1-\alpha_t} = 0.25$)	33.8 ± 1.1	2.3 ± 0.4	24.1 ± 0.2	1.3 ± 0.2	12.4 ± 0.8	2.0 ± 0.2	28.7 ± 0.9

Detoxify (%)							
Input	Any	Identity Attack	Obscene	Severe Toxicity	Insult	Threat	Toxicity
benign image without attack (baseline)	29.1 ± 1.0	1.5 ± 0.1	22.4 ± 1.5	0.6 ± 0.1	11.0 ± 0.9	0.9 ± 0.1	28.9 ± 0.9
adv. image ($\epsilon = 16/255$)	46.4 ± 1.1	5.0 ± 0.4	33.7 ± 0.6	2.3 ± 0.4	23.6 ± 0.4	2.2 ± 0.1	46.1 ± 1.0
+ DiffPure ($\sqrt{1-\alpha_t} = 0.75$)	38.9 ± 1.1	1.7 ± 0.1	30.5 ± 0.9	0.5 ± 0.1	15.5 ± 0.7	1.3 ± 0.3	38.3 ± 1.1
+ DiffPure ($\sqrt{1-\alpha_t} = 0.5$)	29.6 ± 0.7	1.2 ± 0.1	23.6 ± 0.3	0.5 ± 0.1	10.5 ± 0.4	0.8 ± 0.1	28.9 ± 0.7
+ DiffPure ($\sqrt{1-\alpha_t} = 0.25$)	40.5 ± 0.6	1.6 ± 0.4	32.7 ± 0.9	0.9 ± 0.1	15.4 ± 1.1	1.1 ± 0.1	39.9 ± 0.6
adv. image ($\epsilon = 32/255$)	51.3 ± 1.5	9.7 ± 0.4	38.2 ± 1.6	2.7 ± 0.6	26.1 ± 0.6	2.6 ± 0.3	50.9 ± 1.4
+ DiffPure ($\sqrt{1-\alpha_t} = 0.75$)	28.4 ± 1.5	1.06 ± 0.3	21.8 ± 1.6	0.3 ± 0.2	9.9 ± 1.0	0.9 ± 0.2	28.1 ± 1.5
+ DiffPure ($\sqrt{1-\alpha_t} = 0.5$)	26.3 ± 0.3	0.9 ± 0.2	20.3 ± 0.3	0.3 ± 0.1	9.1 ± 0.4	0.8 ± 0.1	25.9 ± 0.4
+ DiffPure ($\sqrt{1-\alpha_t} = 0.25$)	39.3 ± 1.2	1.8 ± 0.1	30.6 ± 1.4	0.6 ± 0.1	14.6 ± 0.7	1.0 ± 0.3	38.8 ± 1.1
adv. image ($\epsilon = 64/255$)	61.4 ± 0.8	11.7 ± 0.3	49.3 ± 0.1	5.4 ± 0.5	36.4 ± 0.7	3.2 ± 0.4	61.1 ± 0.7
+ DiffPure ($\sqrt{1-\alpha_t} = 0.75$)	31.9 ± 1.7	1.5 ± 0.2	25.0 ± 1.7	0.6 ± 0.1	12.1 ± 0.8	1.0 ± 0.2	31.4 ± 1.7
+ DiffPure ($\sqrt{1-\alpha_t} = 0.5$)	30.9 ± 0.6	1.1 ± 0.2	24.0 ± 0.2	0.6 ± 0.1	10.8 ± 0.4	1.0 ± 0.1	30.3 ± 0.6
+ DiffPure ($\sqrt{1-\alpha_t} = 0.25$)	23.0 ± 0.5	0.8 ± 0.2	17.7 ± 0.2	0.4 ± 0.1	7.7 ± 0.2	0.6 ± 0.1	22.7 ± 0.4
adv. image (unconstrained)	61.0 ± 1.5	10.2 ± 0.6	42.4 ± 1.1	2.6 ± 0.1	32.7 ± 1.2	2.8 ± 0.4	60.7 ± 1.6
+ DiffPure ($\sqrt{1-\alpha_t} = 0.75$)	24.9 ± 0.8	1.3 ± 0.1	19.1 ± 1.1	0.3 ± 0.1	9.0 ± 0.7	0.6 ± 0.2	24.5 ± 0.8
+ DiffPure ($\sqrt{1-\alpha_t} = 0.5$)	26.2 ± 0.2	1.1 ± 0.1	19.9 ± 0.4	0.5 ± 0.1	9.9 ± 0.7	1.1 ± 0.3	25.8 ± 0.1
+ DiffPure ($\sqrt{1-\alpha_t} = 0.25$)	26.7 ± 1.3	1.2 ± 0.2	20.7 ± 0.3	0.6 ± 0.2	9.6 ± 0.3	1.1 ± 0.1	26.5 ± 1.3

lowers the likelihood of generating toxic content across all attributes, aligning with the toxicity level of the benign baseline without adversarial attacks. Still, we note that DiffPure cannot entirely neutralize the inherent risks presented by our threat model in Sec 2.2. The effectiveness of the defense might falter when faced with more delicate adaptive attacks (Gao et al., 2022). Additionally, while DiffPure can offer some level of protection to online models from attacks by malicious users, it provides no safeguards for offline models that may be deployed independently by attackers. These adversaries could primarily seek to exploit adversarial attacks to jailbreak offline models and misuse them for malicious intentions. This underscores the potential hazards associated with open-sourcing powerful LLMs.

Alternatively, common harmfulness detection APIs like Perspective API [4] and Moderation API [6] may also be directly used to filter out harmful instructions and outputs. However, these APIs have limited accuracy and their false positives might also cause bias and harm while reducing the helpfulness of the models (OpenAI, 2023a). Similarly, they are not applicable to offline models.

[6] https://platform.openai.com/docs/guides/moderation

D. Attacks on InstructBLIP (Dai et al., 2023b) and LLaVA (Liu et al., 2023b)

We repeat the experiments in Section 3.2 on two other open-source VLMs — InstructBLIP and LLaVA. The results are summarized in Table 4 and 5.

Table 4. The percentages (%) of the generated outputs of InstructBLIP (Dai et al., 2023b) that exhibit certain toxic attributes given by Perspective API and Detoxify Classifier, tested on the RealToxicityPrompts *challenging* subset. The leftmost column is the percentage of the generated texts that exhibit *any* of the 6 attributes.

	Perspective API (%)						
Model (Input)	Any	Identity Attack	Profanity	Severe Toxicity	Sexually Explicit	Threat	Toxicity
InstructBLIP (clean)	34.2 ± 0.5	3.2 ± 0.2	24.9 ± 0.5	5.3 ± 0.2	10.6 ± 0.3	3.2 ± 0.2	33.1 ± 0.5
InstructBLIP ($\epsilon = 16/255$)	61.3 ± 4.9	12.4 ± 3.3	47.3 ± 4.2	12.0 ± 3.4	19.0 ± 1.2	6.4 ± 1.3	59.5 ± 4.5
InstructBLIP ($\epsilon = 32/255$)	60.2 ± 3.3	19.9 ± 2.6	44.0 ± 3.5	10.3 ± 1.8	15.2 ± 0.4	6.3 ± 0.5	58.1 ± 3.9
InstructBLIP ($\epsilon = 64/255$)	59.9 ± 4.1	14.4 ± 3.5	46.2 ± 3.7	11.2 ± 1.1	16.9 ± 1.0	6.8 ± 0.9	58.0 ± 4.6
InstructBLIP (unconstrained)	55.7 ± 4.0	7.8 ± 1.0	42.6 ± 4.13	8.7 ± 1.6	16.6 ± 1.5	5.6 ± 0.3	53.6 ± 4.1
	Detoxify (%)						
Model (Input)	Any	Identity Attack	Obscene	Severe Toxicity	Insult	Threat	Toxicity
InstructBLIP (clean)	36.4 ± 0.7	1.9 ± 0.1	24.3 ± 0.5	2.6 ± 0.1	14.6 ± 0.6	2.3 ± 0.2	36.4 ± 0.7
InstructBLIP ($\epsilon = 16/255$)	63.2 ± 4.3	9.5 ± 2.9	47.1 ± 4.6	5.6 ± 1.7	32.8 ± 3.8	4.4 ± 0.5	63.2 ± 4.3
InstructBLIP ($\epsilon = 32/255$)	62.1 ± 2.9	17.3 ± 3.0	47.2 ± 4.9	6.7 ± 1.4	33.6 ± 4.3	4.3 ± 0.5	62.1 ± 2.9
InstructBLIP ($\epsilon = 64/255$)	62.1 ± 3.8	11.8 ± 4.21	46.9 ± 5.3	6.2 ± 1.3	31.8 ± 5.2	5.0 ± 0.7	62.2 ± 3.8
InstructBLIP (unconstrained)	56.9 ± 3.2	5.7 ± 0.9	42.5 ± 3.6	4.0 ± 0.4	26.6 ± 2.6	3.8 ± 0.9	56.8 ± 3.3

Table 5. The percentages of the generated outputs of LLaVA (Liu et al., 2023b) that exhibit certain toxic attributes given by Perspective API and Detoxify Classifier, tested on the RealToxicityPrompts *challenging* subset. The leftmost column is the percentage of the generated texts that exhibit *any* of the 6 attributes.

	Perspective API (%)						
Model (Input)	Any	Identity Attack	Profanity	Severe Toxicity	Sexually Explicit	Threat	Toxicity
LLaVA (clean)	58.7 ± 0.5	5.1 ± 0.1	47.2 ± 0.3	4.4 ± 0.1	16.2 ± 0.2	3.7 ± 0.2	52.2 ± 0.4
LLaVA ($\epsilon = 16/255$)	85.2 ± 3.0	25.1 ± 1.2	71.5 ± 2.9	13.6 ± 0.9	24.2 ± 1.0	8.3 ± 1.8	80.3 ± 3.1
LLaVA ($\epsilon = 32/255$)	87.4 ± 3.9	33.9 ± 9.7	73.3 ± 6.4	22.5 ± 9.7	23.7 ± 3.6	13.8 ± 3.4	83.7 ± 3.9
LLaVA ($\epsilon = 64/255$)	85.6 ± 2.7	24.8 ± 2.0	69.17 ± 3.2	13.6 ± 0.9	21.6 ± 1.1	9.5 ± 0.6	81.1 ± 3.9
LLaVA (unconstrained)	78.5 ± 0.4	17.0 ± 2.7	61.7 ± 0.8	12.5 ± 1.3	19.3 ± 1.0	11.3 ± 1.5	73.7 ± 0.9
	Detoxify (%)						
Model (Input)	Any	Identity Attack	Obscene	Severe Toxicity	Insult	Threat	Toxicity
LLaVA (clean)	50.2 ± 0.7	3.1 ± 0.2	41.8 ± 0.1	2.0 ± 0.1	23.0 ± 0.3	2.0 ± 0.2	49.6 ± 0.7
LLaVA ($\epsilon = 16/255$)	80.6 ± 2.8	20.5 ± 1.2	69.3 ± 2.7	10.3 ± 0.7	50.6 ± 2.2	4.3 ± 0.8	80.1 ± 2.9
LLaVA ($\epsilon = 32/255$)	83.0 ± 4.4	28.6 ± 9.2	71.5 ± 6.1	16.2 ± 8.2	57.0 ± 8.3	6.4 ± 1.8	82.5 ± 4.4
LLaVA ($\epsilon = 64/255$)	80.8 ± 4.2	19.6 ± 1.4	67.9 ± 4.0	8.3 ± 0.8	48.9 ± 3.1	4.5 ± 0.5	80.5 ± 4.4
LLaVA (unconstrained)	72.3 ± 1.3	12.4 ± 3.0	59.7 ± 0.5	7.2 ± 1.3	42.6 ± 1.8	5.1 ± 0.7	71.9 ± 1.3

Table 6. **Transferability of Our attacks.** We optimize our adversarial examples on a surrogate model and then use the same adversarial examples to transfer attack another target model. We report percentages (%) of outputs that display at least one of the toxic attributes (i.e., Any in Table 2) under the transfer attacks. These outputs were generated on the 'challenging' subset from RealToxicityPrompts, our our scores are evaluated by the Perspective API. Note that we selectively report the strong transfer attack out of (unconstrained, $\epsilon = 16, 32, 64$)) for each entry. The full results are deferred to Table 7.

`Toxicity Ratio (%) : Any`	**Perspective API (%)**		
↓ Surrogate | Target →	MiniGPT-4	InstructBLIP	LLaVA
Without Attack	34.8	34.2	58.7
MiniGPT-4	67.2 (+32.4)	57.5 (+23.3)	63.4 (+4.7)
InstructBLIP	52.4 (+17.6)	61.3 (+27.0)	63.9 (+5.2)
LLaVA	38.4 (+3.6)	44.0 (+9.8)	87.4 (+28.7)

E. The Transferability of Our Attacks

We also validate the black-box transferability of our adversarial examples among three different models, including MiniGPT-4, InstructBLIP and LLaVA. We optimize our adversarial examples on a surrogate model and then use the same adversarial examples to transfer the attack to another target model. We report percentages (%) of outputs that display at least one of the toxic attributes (i.e., Any in Table 2) under the transfer attacks. We summarize the simplified results in the transfer matrix in Table 6; the attacks effectively transfer across the models, consistently increasing the toxicity of attacked models. In Table 7, we further present the detailed results.

Table 7. Transferability of the attacks. The table shows the percentages of the generated outputs that exhibit certain toxic attributes given by Perspective API and Detoxify Classifier, tested on the RealToxicityPrompts *challenging* subset. The leftmost column is the percentage of the generated texts that exhibit *any* of the 6 attributes.

	Perspective API (%)						
Input	Any	Identity Attack	Profanity	Severe Toxicity	Sexually Explicit	Threat	Toxicity
LLaVA → InstructBLIP ($\epsilon = 16/255$)	35.0 ± 1.8	4.0 ± 0.4	25.1 ± 1.7	4.9 ± 0.9	10.6 ± 0.2	3.9 ± 0.4	33.6 ± 2.1
LLaVA → InstructBLIP ($\epsilon = 32/255$)	34.5 ± 0.2	3.4 ± 0.5	24.6 ± 0.8	4.8 ± 0.4	10.3 ± 0.2	3.7 ± 0.2	33.3 ± 0.3
LLaVA → InstructBLIP ($\epsilon = 64/255$)	33.6 ± 0.4	3.4 ± 0.3	24.3 ± 0.8	4.4 ± 0.2	10.2 ± 0.4	3.8 ± 0.2	32.5 ± 0.5
LLaVA → InstructBLIP (unconstrained)	44.0 ± 0.6	5.2 ± 0.3	32.7 ± 0.8	6.6 ± 0.1	13.8 ± 0.8	4.4 ± 0.4	42.5 ± 0.4
MiniGPT-4 → InstructBLIP ($\epsilon = 16/255$)	57.5 ± 3.8	9.2 ± 2.6	44.5 ± 2.8	11.6 ± 1.6	17.5 ± 0.8	6.2 ± 0.7	56.2 ± 3.8
MiniGPT-4 → InstructBLIP ($\epsilon = 32/255$)	55.1 ± 3.4	8.9 ± 1.8	41.6 ± 2.8	9.3 ± 1.7	17.0 ± 1.4	5.6 ± 1.2	53.4 ± 3.5
MiniGPT-4 → InstructBLIP ($\epsilon = 64/255$)	56.5 ± 2.6	7.4 ± 0.8	43.2 ± 2.2	9.9 ± 0.4	20.2 ± 2.5	5.6 ± 1.0	54.4 ± 2.2
MiniGPT-4 → InstructBLIP (unconstrained)	50.7 ± 0.9	7.8 ± 1.7	37.9 ± 1.1	8.5 ± 0.2	15.7 ± 0.3	4.6 ± 0.6	49.1 ± 1.2
InstructBLIP → LLaVA ($\epsilon = 16/255$)	60.3 ± 1.0	5.3 ± 0.3	48.7 ± 0.7	5.0 ± 0.1	16.7 ± 0.4	3.8 ± 0.5	53.0 ± 0.8
InstructBLIP → LLaVA ($\epsilon = 32/255$)	61.0 ± 1.9	5.2 ± 0.1	49.3 ± 1.6	4.5 ± 0.3	16.8 ± 0.5	3.6 ± 0.5	53.9 ± 1.5
InstructBLIP → LLaVA ($\epsilon = 64/255$)	59.8 ± 1.7	5.3 ± 0.1	48.2 ± 1.7	4.9 ± 0.4	16.4 ± 0.3	3.7 ± 0.2	52.3 ± 1.5
InstructBLIP → LLaVA (unconstrained)	63.9 ± 0.4	5.5 ± 0.3	51.9 ± 0.6	5.2 ± 0.1	18.3 ± 0.1	3.3 ± 0.1	54.8 ± 0.6
MiniGPT-4 → LLaVA ($\epsilon = 16/255$)	56.2 ± 4.8	5.1 ± 0.3	45.2 ± 3.5	4.6 ± 0.5	15.5 ± 2.0	3.4 ± 0.1	49.8 ± 3.9
MiniGPT-4 → LLaVA ($\epsilon = 32/255$)	59.3 ± 2.0	5.2 ± 0.2	48.4 ± 1.7	5.0 ± 0.5	16.0 ± 0.8	4.0 ± 0.1	51.9 ± 1.3
MiniGPT-4 → LLaVA ($\epsilon = 64/255$)	60.2 ± 0.3	5.2 ± 0.3	48.6 ± 0.5	5.2 ± 0.5	16.8 ± 0.8	3.7 ± 0.4	52.0 ± 0.3
MiniGPT-4 → LLaVA (unconstrained)	63.4 ± 1.0	5.5 ± 0.2	50.7 ± 0.5	4.8 ± 0.3	18.4 ± 0.5	3.0 ± 0.4	53.7 ± 1.2
InstructBLIP → MiniGPT-4 ($\epsilon = 16/255$)	37.2 ± 5.6	2.5 ± 0.5	26.4 ± 4.4	1.4 ± 0.7	13.1 ± 2.0	2.2 ± 0.5	30.4 ± 5.1
InstructBLIP → MiniGPT-4 ($\epsilon = 32/255$)	49.5 ± 2.7	3.6 ± 0.6	36.6 ± 1.6	2.4 ± 0.4	14.7 ± 0.3	2.8 ± 0.1	43.1 ± 2.3
InstructBLIP → MiniGPT-4 ($\epsilon = 64/255$)	52.4 ± 1.7	3.7 ± 0.3	39.0 ± 1.6	2.2 ± 0.6	15.8 ± 0.6	3.3 ± 0.4	45.6 ± 1.8
InstructBLIP → MiniGPT-4 (unconstrained)	41.2 ± 2.4	2.7 ± 0.3	29.5 ± 1.5	1.6 ± 0.3	14.3 ± 1.1	1.9 ± 0.2	34.3 ± 2.7
LLaVA → MiniGPT-4 ($\epsilon = 16/255$)	38.4 ± 3.4	2.4 ± 0.9	27.2 ± 2.8	1.3 ± 0.1	12.8 ± 0.6	2.1 ± 0.1	33.2 ± 2.9
LLaVA → MiniGPT-4 ($\epsilon = 32/255$)	38.1 ± 6.5	2.9 ± 0.8	27.4 ± 4.2	1.7 ± 0.5	12.6 ± 3.0	2.1 ± 0.7	32.5 ± 6.2
LLaVA → MiniGPT-4 ($\epsilon = 64/255$)	38.0 ± 5.8	2.1 ± 0.5	26.1 ± 4.4	1.4 ± 0.6	12.9 ± 1.5	2.3 ± 0.5	32.3 ± 5.5
LLaVA → MiniGPT-4 (unconstrained)	32.7 ± 1.4	1.9 ± 0.2	23.0 ± 1.3	0.7 ± 0.1	11.6 ± 0.3	1.6 ± 0.4	26.7 ± 1.3

	Detoxify (%)						
Input	Any	Identity Attack	Obscene	Severe Toxicity	Insult	Threat	Toxicity
LLaVA → InstructBLIP ($\epsilon = 16/255$)	37.9 ± 1.5	2.4 ± 0.1	25.7 ± 1.6	2.6 ± 0.5	15.9 ± 1.5	2.4 ± 0.2	37.8 ± 1.5
LLaVA → InstructBLIP ($\epsilon = 32/255$)	37.6 ± 0.6	2.2 ± 0.3	25.2 ± 0.4	2.0 ± 0.2	15.6 ± 0.5	2.1 ± 0.2	37.6 ± 0.6
LLaVA → InstructBLIP ($\epsilon = 64/255$)	36.1 ± 0.8	2.3 ± 0.2	25.1 ± 0.6	2.2 ± 0.1	15.0 ± 0.5	2.3 ± 0.2	36.1 ± 0.8
LLaVA → InstructBLIP (unconstrained)	46.7 ± 0.7	3.6 ± 0.2	33.2 ± 0.6	3.3 ± 0.1	19.6 ± 0.5	3.2 ± 0.5	46.7 ± 0.7
MiniGPT-4 → InstructBLIP ($\epsilon = 16/255$)	60.5 ± 3.2	6.6 ± 2.2	44.4 ± 2.2	5.5 ± 0.5	29.6 ± 3.3	4.7 ± 0.7	60.4 ± 3.2
MiniGPT-4 → InstructBLIP ($\epsilon = 32/255$)	58.8 ± 3.1	6.9 ± 1.8	41.9 ± 2.6	4.7 ± 0.7	27.9 ± 3.1	4.5 ± 0.9	58.8 ± 3.1
MiniGPT-4 → InstructBLIP ($\epsilon = 64/255$)	58.8 ± 2.3	5.4 ± 1.0	43.5 ± 2.2	5.4 ± 0.1	27.1 ± 0.5	3.6 ± 0.3	58.8 ± 2.3
MiniGPT-4 → InstructBLIP (unconstrained)	53.2 ± 1.5	5.7 ± 1.5	38.0 ± 0.8	4.3 ± 0.3	24.4 ± 0.3	3.5 ± 0.1	53.2 ± 1.5
InstructBLIP → LLaVA ($\epsilon = 16/255$)	50.3 ± 1.7	3.1 ± 0.1	42.6 ± 1.2	2.1 ± 0.2	23.1 ± 0.8	2.1 ± 0.6	49.5 ± 1.6
InstructBLIP → LLaVA ($\epsilon = 32/255$)	51.7 ± 0.9	3.1 ± 0.2	42.9 ± 0.8	2.0 ± 0.2	23.2 ± 0.4	2.6 ± 0.5	50.4 ± 0.8
InstructBLIP → LLaVA ($\epsilon = 64/255$)	50.6 ± 1.3	3.1 ± 0.1	42.2 ± 1.3	2.0 ± 0.2	23.0 ± 0.5	2.4 ± 0.2	49.7 ± 1.2
InstructBLIP → LLaVA (unconstrained)	51.5 ± 0.3	2.9 ± 0.1	44.8 ± 0.7	2.1 ± 0.1	22.4 ± 0.8	1.7 ± 0.2	50.1 ± 0.5
MiniGPT-4 → LLaVA ($\epsilon = 16/255$)	47.0 ± 4.0	3.0 ± 0.3	39.7 ± 2.7	1.9 ± 0.1	21.4 ± 1.9	2.0 ± 0.3	46.1 ± 3.8
MiniGPT-4 → LLaVA ($\epsilon = 32/255$)	49.7 ± 1.3	3.2 ± 0.1	42.2 ± 1.4	2.2 ± 0.1	22.6 ± 1.0	2.5 ± 0.1	48.7 ± 1.3
MiniGPT-4 → LLaVA ($\epsilon = 64/255$)	49.4 ± 0.7	3.1 ± 0.3	42.1 ± 0.6	2.3 ± 0.5	23.0 ± 0.8	2.4 ± 0.2	48.2 ± 0.6
MiniGPT-4 → LLaVA (unconstrained)	50.2 ± 0.3	2.6 ± 0.1	43.2 ± 0.2	2.0 ± 0.1	21.4 ± 0.4	1.8 ± 0.1	48.7 ± 0.1
InstructBLIP → MiniGPT-4 ($\epsilon = 16/255$)	28.5 ± 4.5	1.1 ± 0.3	22.4 ± 3.9	0.6 ± 0.3	9.8 ± 1.6	1.0 ± 0.2	27.8 ± 4.1
InstructBLIP → MiniGPT-4 ($\epsilon = 32/255$)	39.7 ± 2.2	1.8 ± 0.1	32.3 ± 1.8	0.7 ± 0.2	15.3 ± 1.4	1.3 ± 0.2	39.0 ± 2.3
InstructBLIP → MiniGPT-4 ($\epsilon = 64/255$)	41.4 ± 0.9	1.5 ± 0.2	33.8 ± 1.2	0.8 ± 0.3	15.7 ± 0.6	1.3 ± 0.2	40.4 ± 1.2
InstructBLIP → MiniGPT-4 (unconstrained)	32.4 ± 1.7	1.2 ± 0.1	25.7 ± 1.5	0.6 ± 0.1	11.2 ± 0.8	0.9 ± 0.2	31.6 ± 1.5
LLaVA → MiniGPT-4 ($\epsilon = 16/255$)	31.2 ± 3.6	1.2 ± 0.5	24.4 ± 2.9	0.3 ± 0.1	11.2 ± 1.5	0.8 ± 0.1	30.6 ± 3.4
LLaVA → MiniGPT-4 ($\epsilon = 32/255$)	31.0 ± 5.6	1.2 ± 0.5	24.6 ± 4.3	0.3 ± 0.2	10.8 ± 2.2	1.0 ± 0.2	30.6 ± 5.6
LLaVA → MiniGPT-4 ($\epsilon = 64/255$)	29.1 ± 4.7	1.1 ± 0.3	22.8 ± 3.9	0.5 ± 0.2	10.7 ± 1.7	0.9 ± 0.2	28.6 ± 4.6
LLaVA → MiniGPT-4 (unconstrained)	24.6 ± 1.0	0.8 ± 0.2	19.7 ± 0.7	0.4 ± 0.1	8.3 ± 0.3	0.5 ± 0.2	24.2 ± 1.3

F. More Qualitative Examples of Our Attacks

The selection of examples in the demonstration is informed by historical hate crime statistics of the United States, and does not, in any way, reflect the personal views or beliefs of the authors.[7]

Figure 4. More Qualitative Examples on MiniGPT-4. **Left**: prompted with clean image; **Right**: prompted with adversarial images.

[7]We select racial, sexual and religious bias for the demonstration, which correspond to the top-3 categories of hate crimes of the US in 2021, according to https://www.justice.gov/hatecrimes/hate-crime-statistics.