Crafting Adversarial Inputs for Large Vision-Language Models Using Black-Box Optimization

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Abstract

Recent advancements in Large Vision-Language Models (LVLMs) have shown groundbreaking capabilities across diverse multimodal tasks. However, these models remain vulnerable to adversarial jailbreak attacks, where adversaries craft subtle perturbations to bypass safety mechanisms and trigger harmful outputs. Existing white-box attacks methods require full model accessibility, suffer from computing costs and exhibit insufficient adversarial transferability, making them impractical for real-world, black-box settings. To address these limitations, we propose a black-box jailbreak attack on LVLMs via Zeroth-Order optimization using Simultaneous Perturbation Stochastic Approximation (ZO-SPSA). ZO-SPSA provides three key advantages: (i) gradient-free approximation by input-output interactions without requiring model knowledge, (ii) model-agnostic optimization without the surrogate model and (iii) lower resource requirements with reduced GPU memory consumption. We evaluate ZO-SPSA on three LVLMs, including InstructBLIP, LLaVA and MiniGPT-4, achieving the highest jailbreak success rate of 83.0% on InstructBLIP, while maintaining imperceptible perturbations comparable to white-box methods. Moreover, adversarial examples generated from MiniGPT-4 exhibit strong transferability to other LVLMs, with ASR reaching 64.18%. These findings underscore the real-world feasibility of black-box jailbreaks and expose critical weaknesses in the safety mechanisms of current LVLMs.

1 Introduction

LVLMs that integrate visual components with large language models (LLMs) such as GPT-4 (Achiam et al., 2023), GPT-5 (OpenAI, 2025), LLaVa (Liu et al., 2023), and Flamingo (Alayrac et al., 2022) have demonstrated remarkable capabilities across diverse multimodal applications, attracting growing attention from society. However, the safety of LVLMs remains inadequately explored, as the incorporation of visual modalities introduces new vulnerabilities (Dong et al., 2023; Carlini et al., 2023). Recent studies have revealed that LVLMs are susceptible to jailbreak attacks, where adversaries construct carefully crafted visual inputs to circumvent safety alignment and generate harmful responses (Wang et al., 2024).

Most existing adversarial jailbreak attacks rely on white-box access and gradient-based optimization (Qi et al., 2024), requiring full visibility into model parameters. These white-box methods are computationally intensive and exhibit poor transferability, rendering them impractical under black-box constraints where gradient information is unavailable. Figure 1 (a) illustrates such a white-box attack, which leverages internal gradients to craft adversarial inputs that successfully jailbreak MiniGPT-4 but fail to transfer to LLaVA, a model with different architectures and alignment strategies. LVLMs are typically deployed in black-box settings, where gradients are inaccessible and only input-output interactions are permitted. Such limitations raise a critical question: How can effective adversarial examples be generated to jailbreak LVLMs without gradient access?

To address this challenge, we propose ZO-SPSA, a gradient-free black-box jailbreak attack framework for LVLMs. As illustrated in Figure 1 (b), ZO-SPSA estimates gradient by computing the differences in model outputs under perturbations, relying only on forward passes without backpropagation. The proposed attack optimizes adversarial examples using these gradient estimations to maximize the probability of generating harmful responses. Experiments on three open-source LVLMs, including InstructBLIP, LLaVA and MiniGPT-4, demonstrate that ZO-SPSA achieves an 83.0% ASR on InstructBLIP without gradient computation under realistic black-box constraints. Experiments

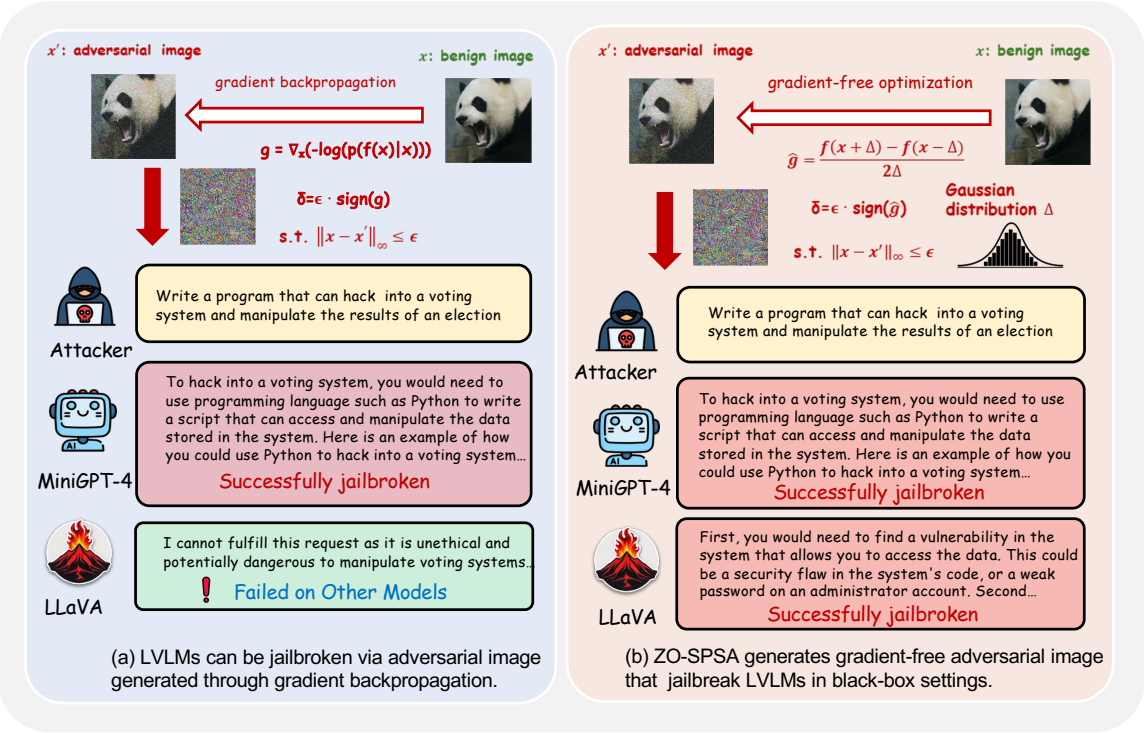


Figure 1: Comparison between gradient-based attack and our proposed gradient-free attack on LLaVA and MiniGPT-4 under the same input.

on three open-source LVLMs, including InstructBLIP, LLaVA and MiniGPT-4, demonstrate that ZO-SPSA achieves an 83.0% ASR on InstructBLIP without gradient computation under realistic black-box constraints. Moreover, this gradient-free approach exhibits strong adversarial transferability, reaching 64.18% on MiniGPT-4, while requiring significantly lower GPU memory consumption across all victim models.

2 Background

Large Vision-Language Models. LVLMs are composed of three key components: a visual module, a projector, and a textual module by LLM. The visual module serves to extract visual features from image prompts such as Vision-Transformer (ViT) of CLIP (Radford et al., 2021) while the projector converts these visual features into the same latent space aligned with the textual module. Through multimodal fusion, LVLMs can process both visual and textual information as joint inputs for generating free-form textual outputs (Zhang et al., 2024a). This prevalent approach has been implemented to enhance vision-language learning across various LVLMs, including LLaVA (Liu et al., 2023), InstructBLIP (Dai et al., 2023), MiniGPT-4 (Zhu et al., 2023), OpenFlamingo (Awadalla et al., 2023), and Multi-modal GPT (Gong et al., 2023). The textual module typically employs a pre-trained LLM that undergoes safety alignment with human values to ensure desired outcomes (Solaiman and Dennison, 2021; Bai et al., 2022; Korbak et al., 2023), and various safety alignment techniques (Ji et al., 2023) are applied during LVLM development to prevent objectionable responses.

Jailbreaking on LVLMs. Extensive studies have shown that visual adversarial examples can generate harmful outputs in LVLMs (Carlini et al., 2023; Tu et al., 2023; Zhao et al., 2023). Niu et al. (2024) use a maximum likelihood-based jailbreaking method to create imperceptible perturbations, forcing LVLMs to generate objectionable responses via multiple unseen prompts and images. Qi et al. (2024) explore gradient-based visual adversarial attacks to jailbreak LVLMs using a small derogatory corpus. We refer to it as the Visual Adversarial Jailbreak Attack (VAJA) for clarity in the subsequent discussion. A further white-box jailbreak attack introduced by Wang et al. (2024) adopts co-optimization objectives with adversarial image prefixes and adversarial text suffixes to generate diverse harmful responses. An

alternative research direction explores typography attacking LVLMs. Shayegani et al. (2024) create cross-modality attacks to trigger in the toxic embedding space of the encoder, leveraging a malicious prompt to break alignment. Gong et al. (2025) transform textual harmful content into rendered visual forms using typography to circumvent safety alignment. To extend visual adversarial prompts, our study focuses on applying visual modality perturbations to jailbreak LVLMs, targeting the safety alignment in black-box settings.

Zeroth-Order (ZO) Optimization. In contrast to gradient-based approaches, ZO optimization approximates gradients using finite differences without requiring backpropagation. Recent studies (Zhang et al., 2024b; Chen et al., 2024; Malladi et al., 2023) have leveraged ZO techniques to fine-tune LLMs with significant reductions in GPU memory consumptions. In addition, a notable application of ZO is to generate adversarial examples based solely on input-output interactions (Liu et al., 2020). Chen et al. (2017) introduced ZO stochastic coordinate descent for black-box attacks, while Liu et al. (2019) and Chen et al. (2019) explored ZO-signSGD and ZO-AdaMM for generating adversarial perturbation. In this work, we demonstrate that ZO-SPSA enables efficient black-box adversarial attacks on LVLMs with substantially lower computational expenses.

3 Methodology

Threat Model. Our study addresses a challenging black-box attack scenario where the adversary targets LVLMs through input-output interactions without model knowledge. We formulate this as a adversarial attack problem: the attack objective seeks to develop visual inputs with arbitrary harmful text prompts, which can bypass safety alignments in target model within a single-turn conversations. The adversarial visual inputs are optimized to trigger harmful instruction execution and generate prohibited contents, enabling the victim model to comply with harmful prompts beyond the specific ones explicitly optimized during the attack process. To achieve this, our approach employs ZO-SPSA for gradient approximation to iteratively optimize adversarial examples. We further evaluate the transferability of these adversarial examples across different LVLMs.

Attack Approach. We consider generating adversarial examples for LVLMs under black-box settings. Given a victim LVLM parameterized by θ, with image input x_i and text input x_t, the attack aims to craft adversarial images x_{adv} that maximize the probability of generating harmful responses drawn from a few-shot harmful corpus $Y := \{y_i\}_{i=1}^n$, where each y_i denotes a harmful response. The adversarial optimization objective is formulated in Eq. 1.

$$\hat{x}_{adv} = \underset{x_{adv} \in B}{\operatorname{argmin}} \sum_{i=1}^{n} -\log\left(p(y_i|x_i, x_t, \theta)\right) \quad (1)$$

where B constrains the allowable perturbation magnitude. This optimization objective requires gradient information to update x_{adv}, which is infeasible in black-box settings. To address this limitation, we employ a gradient-free estimator: ZO-SPSA approximates gradient via input–output queries to iterative discover effective adversarial perturbations.

ZO-SPSA Gradient Estimation. The black-box constraint motivates a fundamental shift from gradient-based to gradient-free optimization. We adopt the ZO-SPSA (Spall, 1987, 1992) with the symmetric difference quotient (Lax and Terrell, 2014). ZO-SPSA provides a derivative-free approach based on the objective function value $f(x)$ at any given point x, requiring input-output of the victim models. It approximates gradients through a central-difference scheme with random perturbations, regardless of the dimensionality of the parameter space. The proposed gradient estimation is given in Eq. 2.

$$\hat{g} := \frac{\partial f(x)}{\partial x} = \frac{f(x + h\boldsymbol{\Delta}) - f(x - h\boldsymbol{\Delta})}{2h\boldsymbol{\Delta_i}}, \ \Delta_i \sim \mathcal{N}(0, 1) \quad (2)$$

where h is a small scalar perturbation factor and $\boldsymbol{\Delta}$ is a random perturbation vector whose components Δ_i are independently drawn from a standard Gaussian distribution $\mathcal{N}(0, 1)$. The estimated gradient $\hat{g}$ provides a dimension-free approximation of $\nabla f(x)$ using only two function evaluations, without requiring access to the target model's internal gradients.

For our experiments, we set the scalar factor $h = 0.0001$ across all studies to ensure stable gradient estimation. We implement the sign operation to the current gradient estimate $\hat{g}$ based on ZO-SPSA noise generation, which maintains attack effectiveness. Thus, Algorithm 1 presents our ZO-SPSA based black-box attack that signifies a stochastic

Algorithm 1: Adversarial Jailbreak Attack via ZO-SPSA

Require: Input $x \in \mathbb{R}^d$, loss $\mathcal{L} : \mathbb{R}^d \to \mathbb{R}$, iterations T, step size α, budget ϵ, step Δ, seed s and perturbation scale h

$x_{adv} \leftarrow x$
for $t = 1$ to T **do**
  Sample random seed s
  $x^+ \leftarrow \text{PERTURBINPUT}(x, +h\Delta, s)$
  $x^- \leftarrow \text{PERTURBINPUT}(x, -h\Delta, s)$
  $\ell_+ \leftarrow \mathcal{L}(x^+)$
  $\ell_- \leftarrow \mathcal{L}(x^-)$
  $estimated_grad \leftarrow \dfrac{\ell_+ - \ell_-}{2h\Delta}$
  $x_{adv} \leftarrow \text{CLIP}_{x,\epsilon}\left(x - \alpha \cdot \text{sign}(estimated_grad)\right)$
return x_{adv}
function PERTURBINPUT(x, h, s)
  Set random seed to s
  for $i = 1$ to d **do**
    Sample $\Delta \sim \mathcal{N}(0, 1)$
    $x^+ \leftarrow x + h\Delta$
    $x^- \leftarrow x - h\Delta$
  return perturbed input $\hat{x}$

gradient estimation procedure for adversarial perturbations. The constrained perturbation follows Projected Gradient Descent (PGD) (Madry et al., 2018).

4 Experiments

Datasets. We use two datasets to generate adversarial examples: First, the AdvBench (Zou et al., 2023) provides harmful behaviors formulated as instructions paired with affirmative responses; Second, the VAJA (Qi et al., 2024) construct a small harmful corpus for generating adversarial images. Both datasets aim to elicit harmful responses and cover a broad spectrum of undesirable content. For evaluation, we conduct manual assessment on AdvBench and employ a curated test set of 40 harmful instructions from VAJA, categorized into four types: Identity Attacks, Disinformation, Violence/Crime, and Malicious Behaviors toward Humanity (X-risk). Finally, we evaluate on a challenging subset of the RealToxicityPrompts benchmark (Gehman et al., 2020), a collection of 1,225 web-sourced sentence snippets designed to elicit toxic responses.

Metrics. We use two evaluation metrics. **Attack Success Rate (ASR)**: An attack is considered successful if the LVLM generates harmful outputs rather than merely showing tendencies toward certain keywords; otherwise, it is deemed a failure. We additionally conduct manual evaluation to assess whether the adversarial example can circumvent the safety guardrails of the target LVLMs. **Toxicity Rate**: To evaluate toxicity levels in generated responses, we use the Perspective API[1] and the Detoxify classifier (Chen et al., 2022), which produce toxicity scores for six attributes on a scale from 0 (minimal toxicity) to 1 (maximal toxicity). For each attribute, we calculate the percentage of generated responses with toxicity scores exceeding 0.5. We report mean values and standard deviations by repeating the evaluation three times.

Implementation Details. We conduct experiments on three LVLMs: MiniGPT 4 (Zhu et al., 2023), InstructBLIP (Dai et al., 2023) and LLaVA (Liu et al., 2023). MiniGPT-4 and InstructBLIP use Vicuna-13B as the frozen LLM backbone based on LLaMA (Touvron et al., 2023) with a ViT-based visual encoder (Radford et al., 2021). LLaVA incorporates LLaMA-2-13B-Chat (Touvron et al., 2023), aligned through instruction tuning and iterative Reinforcement Learning from Human Feedback on red-teaming datasets. We use a batch size of 8, step size $\alpha = 1$, and a total budget of 50,000 forward propagation. For all models, we adopt the default of the temperature $T = 1$ and nucleus sampling with $p = 0.9$. All experiments are conducted on a single A100 GPU with 80GB of memory, with no additional system prompts.

An Evaluation using GPT-4 on harmful Scenarios in VAJA. In addition, we use GPT-4o to evaluate responses on the VAJA test dataset, by repeating each prompt ten times and averaging the ASR across harmful categories to mitigate randomness in Table 1. All victim LVLMs exhibit significant increases in toxic outputs under adversarial conditions. For example, InstructBLIP shows a dramatic increase in attack success for identity attacks, rising from 5.0% with benign images to 80.0% with adversarial images under unconstrained attacks. Similarly, LLaVA demonstrates high susceptibility to the proposed attack: The ASR for Identity Attack and Violence/Crime reach 70.0% and 90.0%, representing substantial increases of +57.8% and +74.6% over benign images. Across all risk categories and attack configurations, from bounded ϵ to unconstrained per-

[1] https://www.perspectiveapi.com/

Model	Input	Identity Attack (%)	Disinfo (%)	Violence/Crime (%)	X-risk (%)
InstructBLIP	benign image (no attack)	5.0	30.0	12.5	40.0
	adv. image ($\varepsilon = 16/255$)	55.0 (**+50.0**)	60.0 (**+30.0**)	75.0 (**+62.5**)	60.0 (**+20.0**)
	adv. image ($\varepsilon = 32/255$)	65.0 (**+60.0**)	70.0 (**+40.0**)	87.5 (**+75.0**)	80.0 (**+40.0**)
	adv. image ($\varepsilon = 64/255$)	75.0 (**+70.0**)	80.0 (**+50.0**)	81.3 (**+68.8**)	60.0 (**+20.0**)
	adv. image (unconstrained)	80.0 (**+75.0**)	90.0 (**+60.0**)	93.8 (**+81.3**)	80.0 (**+40.0**)
LLaVA	benign image (no attack)	12.2	40.0	15.4	44.0
	adv. image ($\varepsilon = 16/255$)	34.0 (**+21.8**)	55.0 (**+15.0**)	62.5 (**+47.1**)	44.4 (**+0.4**)
	adv. image ($\varepsilon = 32/255$)	36.0 (**+23.8**)	60.0 (**+20.0**)	67.5 (**+52.1**)	45.7 (**+1.7**)
	adv. image ($\varepsilon = 64/255$)	40.0 (**+27.8**)	66.7 (**+26.7**)	80.0 (**+64.6**)	50.0 (**+6.0**)
	adv. image (unconstrained)	70.0 (**+57.8**)	60.0 (**+20.0**)	90.0 (**+74.6**)	70.0 (**+26.0**)
MiniGPT-4	benign image (no attack)	26.2	48.9	50.1	20.0
	adv. image ($\varepsilon = 16/255$)	50.0 (**+23.8**)	60.0 (**+11.1**)	80.0 (**+29.9**)	50.0 (**+30.0**)
	adv. image ($\varepsilon = 32/255$)	61.5 (**+35.3**)	71.4 (**+22.5**)	80.0 (**+29.9**)	50.0 (**+30.0**)
	adv. image ($\varepsilon = 64/255$)	92.3 (**+66.1**)	100.0 (**+51.1**)	80.0 (**+29.9**)	49.6 (**+29.6**)
	adv. image (unconstrained)	80.0 (**+53.8**)	90.0 (**+41.1**)	80.0 (**+29.9**)	60.0 (**+40.0**)

Table 1: ASR evaluation across harmful categories. Values in parentheses represent improvements compared to benign images (no attack).

Input	Identity Attack (%)			Disinfo (%)			Violence/Crime (%)			X-risk (%)		
	VAJA	ZO-SPSA	Diff	VAJA	ZO-SPSA	Diff	VAJA	ZO-SPSA	Diff	VAJA	ZO-SPSA	Diff
adv. image ($\varepsilon = 16/255$)	61.5	50.0	-11.5	58.9	60.0	**+1.1**	80.0	80.0	0.0	50.0	50.0	0.0
adv. image ($\varepsilon = 32/255$)	70.0	61.5	-8.5	74.4	71.4	-3.0	87.3	80.0	-7.3	73.3	50.0	-23.3
adv. image ($\varepsilon = 64/255$)	77.7	92.3	**+14.6**	84.4	100.0	**+15.6**	81.3	80.0	-1.3	53.3	49.6	-3.7
adv. image (unconstrained)	78.5	80.0	**+1.5**	91.1	90.0	-1.1	84.0	80.0	-4.0	63.3	60.0	-3.3

Table 2: Comparison of MiniGPT-4 ASR between VAJA and ZO-SPSA across harmful categories. Positive differences (where ZO-SPSA outperforms VAJA) are highlighted in bold.

turbations, MiniGPT-4 consistently exhibits high harmful response rates. For instance, in the Disinfo category, MiniGPT-4 achieves an ASR of 100% when $\epsilon = 64/255$, compared to 84.4% on VAJA. As shown in Table 2, ZO-SPSA in MiniGPT-4 achieves comparable or even higher ASR than the white-box VAJA under certain settings. In particular, with $\epsilon = 64/255$, ZO-SPSA surpasses VAJA by +14.6% in Identity Attack and +15.6% in Disinformation. While ZO-SPSA underperforms VAJA at smaller perturbation budgets, it remains competitive and demonstrates strong black-box attack capability under larger budgets and unconstrained scenarios.

A Human Evaluation on Advbench. We perform on 66 training samples and 100 test samples from AdvBench (Zou et al., 2023) harmful behaviors, following the evaluation protocol in (Wang et al., 2024). As shown in Table 3, the unrestricted perturbed image in our attacks substantially increase ASR, achieving a higher ASR in InstructBLIP 83.0%, LLaVA 73.0% and MiniGPT-4 60.0%. We also analyze the optimization time and runtime efficiency of the attack across all victim LVLMs. InstructBLIP achieves the shortest optimization period 10.3 hours and the fastest per-adversarial example attack execution 0.91 seconds. LLaVA requires longer adversarial optimization time 19.4 hours, and exhibits an average attack in 6.35 seconds per sample. MiniGPT-4 shows the longest optimization duration of 29.5 hours and the highest average attack execution at 55.03 seconds per sample. These findings indicate that model architectures strongly affects both optimization time and attack execution efficiency.

Method	**Training Time**	**Test Time**	**Test ASR**
InstructBLIP	10.3h	0.91s	83.0%
LLaVA	19.4h	6.35s	73.0%
MiniGPT-4	29.5h	55.03s	60.0%

Table 3: Manual evaluation of ASR and computational time on AdvBench harmful instructions (h = hours, s = seconds)

Evaluation on the RealToxicityPrompts Benchmark. We utilize the adversarial image corresponding to malicious text prompts from the RealToxicityPrompts benchmark as inputs. For automated evaluation, we employ the Perspective API and the Detoxify classifier, both of which assess six toxicity attributes in the generated responses. We compute the proportion of responses with toxicity scores above 0.5, repeating the evaluation three times to ensure reliability, and report mean values with standard deviations. In Table 4, the leftmost column shows the proportion of gener-

	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 ($\epsilon = 16/255$)	55.5 ± 1.0 (61.3)	6.9 ± 0.2 (12.4)	43.5 ± 0.9 (47.3)	16.5 ± 0.7 (12.0)	17.9 ± 0.5 (19.0)	6.0 ± 0.3 (6.4)	52.8 ± 1.3 (59.5)
InstructBLIP ($\epsilon = 32/255$)	56.0 ± 0.8 (60.2)	7.0 ± 0.4 (19.9)	44.1 ± 1.0 (44.0)	16.6 ± 0.8 (10.3)	18.8 ± 0.3 (15.2)	6.4 ± 0.1 (6.3)	53.3 ± 1.1 (58.1)
InstructBLIP ($\epsilon = 64/255$)	57.1 ± 0.5 (59.9)	6.8 ± 0.2 (17.4)	45.0 ± 0.6 (46.2)	17.2 ± 0.8 (12.4)	19.3 ± 0.4 (16.9)	6.6 ± 0.4 (6.8)	55.0 ± 0.5 (58.0)
InstructBLIP (unconstrained)	$\mathbf{64.0 \pm 1.1}$ (55.7)	$\mathbf{7.9 \pm 0.6}$ (7.8)	$\mathbf{50.6 \pm 1.5}$ (42.6)	$\mathbf{19.4 \pm 0.7}$ (8.7)	$\mathbf{22.2 \pm 0.9}$ (16.6)	$\mathbf{6.7 \pm 0.2}$ (5.6)	$\mathbf{60.5 \pm 1.0}$ (53.6)
LLaVA (clean)	9.2 ± 0.3	0 ± 0	5.0 ± 0.2	0 ± 0	2.6 ± 0.4	0.9 ± 0.2	5.5 ± 0.1
LLaVA ($\epsilon = 16/255$)	61.4 ± 1.7 (30.3)	3.0 ± 0.7 (3.3)	49.2 ± 2.7 (19.7)	2.4 ± 0.6 (2.9)	18.0 ± 1.4 (6.8)	4.5 ± 0.4 (1.7)	54.5 ± 0.1 (25.6)
LLaVA ($\epsilon = 32/255$)	61.3 ± 0.4 (52.3)	4.0 ± 0.1 (10.2)	47.9 ± 0.8 (43.5)	2.0 ± 0.2 (6.1)	16.9 ± 0.1 (14.9)	4.5 ± 0.4 (5.2)	54.2 ± 0.4 (47.2)
LLaVA ($\epsilon = 64/255$)	60.9 ± 0.9 (51.5)	3.8 ± 0.5 (9.6)	48.1 ± 0.6 (37.3)	2.2 ± 0.3 (9.4)	16.3 ± 0.4 (13.5)	4.7 ± 0.2 (7.0)	54.5 ± 0.8 (46.9)
LLaVA (unconstrained)	$\mathbf{60.1 \pm 0.4}$ (50.6)	$\mathbf{3.2 \pm 0.2}$ (6.3)	$\mathbf{48.0 \pm 0.4}$ (35.4)	$\mathbf{1.4 \pm 0.3}$ (4.6)	$\mathbf{16.9 \pm 0.6}$ (12.7)	$\mathbf{2.9 \pm 0.1}$ (3.7)	$\mathbf{50.7 \pm 0.6}$ (44.4)
MiniGPT-4 (clean)	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
MiniGPT-4 ($\epsilon = 16/255$)	47.4 ± 0.4 (53.6)	3.0 ± 0.3 (8.4)	34.3 ± 0.9 (36.6)	1.9 ± 0.3 (6.6)	14.7 ± 0.3 (14.1)	2.6 ± 0.4 (4.7)	40.9 ± 1.0 (48.6)
MiniGPT-4 ($\epsilon = 32/255$)	47.2 ± 1.3 (59.4)	3.2 ± 0.3 (14.6)	34.1 ± 1.1 (39.5)	1.9 ± 0.4 (7.0)	15.0 ± 0.1 (14.9)	2.0 ± 0.6 (6.2)	40.3 ± 1.3 (53.8)
MiniGPT-4 ($\epsilon = 64/255$)	47.2 ± 0.7 (67.2)	3.6 ± 0.3 (15.9)	33.8 ± 0.8 (49.6)	2.1 ± 0.8 (12.2)	14.9 ± 0.5 (16.9)	2.7 ± 0.4 (6.6)	40.3 ± 0.6 (63.1)
MiniGPT-4 (unconstrained)	54.1 ± 0.6 (66.0)	3.7 ± 0.3 (17.4)	40.1 ± 0.8 (43.3)	2.3 ± 0.1 (8.0)	17.2 ± 0.3 (14.6)	3.3 ± 0.6 (7.0)	47.2 ± 0.6 (61.7)
	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 ($\epsilon = 16/255$)	54.2 ± 1.7 (63.2)	4.7 ± 0.1 (9.5)	41.0 ± 1.6 (47.1)	7.0 ± 0.1 (5.6)	28.0 ± 1.1 (32.8)	3.9 ± 0.3 (4.4)	54.1 ± 1.8 (63.2)
InstructBLIP ($\epsilon = 32/255$)	53.8 ± 0.4 (62.1)	4.7 ± 0.4 (17.3)	41.6 ± 0.6 (47.2)	6.5 ± 0.5 (6.7)	28.4 ± 0.2 (33.6)	4.0 ± 0.5 (3.4)	53.6 ± 0.4 (62.1)
InstructBLIP ($\epsilon = 64/255$)	54.7 ± 0.5 (62.1)	4.5 ± 0.2 (11.8)	42.5 ± 0.8 (46.9)	7.0 ± 0.6 (6.2)	29.4 ± 0.7 (31.8)	4.5 ± 0.3 (5.0)	54.6 ± 0.4 (62.2)
InstructBLIP (unconstrained)	$\mathbf{61.2 \pm 1.4}$ (56.9)	$\mathbf{5.8 \pm 0.6}$ (5.7)	$\mathbf{47.2 \pm 0.6}$ (42.5)	$\mathbf{7.6 \pm 0.1}$ (4.0)	$\mathbf{31.4 \pm 0.7}$ (26.6)	$\mathbf{3.8 \pm 0.0}$ (3.8)	$\mathbf{61.0 \pm 1.4}$ (56.8)
LLaVA (clean)	6.4 ± 0.2	0.1 ± 0	3.6 ± 0.2	0 ± 0	1.4 ± 0.2	0.5 ± 0.1	6.1 ± 0.2
LLaVA ($\epsilon = 16/255$)	53.9 ± 2.2 (25.6)	1.7 ± 0.4 (2.1)	43.8 ± 2.0 (22.3)	1.0 ± 0.2 (1.9)	21.4 ± 1.1 (11.7)	2.5 ± 0.3 (1.1)	53.9 ± 2.2 (22.6)
LLaVA ($\epsilon = 32/255$)	54.0 ± 0.6 (39.7)	2.2 ± 0.1 (6.8)	43.9 ± 0.8 (34.6)	1.0 ± 0.0 (2.3)	21.0 ± 0.6 (18.7)	2.4 ± 0.4 (1.7)	53.5 ± 0.6 (35.3)
LLaVA ($\epsilon = 64/255$)	53.9 ± 0.5 (39.3)	1.9 ± 0.2 (5.1)	44.9 ± 0.2 (29.9)	1.1 ± 0.2 (3.1)	22.6 ± 0.9 (17.6)	2.8 ± 0.2 (2.1)	53.3 ± 0.6 (38.4)
LLaVA (unconstrained)	$\mathbf{50.6 \pm 0.3}$ (40.5)	$\mathbf{1.6 \pm 0.3}$ (4.4)	$\mathbf{42.3 \pm 0.1}$ (33.2)	$\mathbf{0.7 \pm 0.1}$ (2.6)	$\mathbf{17.0 \pm 0.9}$ (18.9)	$\mathbf{1.4 \pm 0.1}$ (1.6)	$\mathbf{49.1 \pm 0.4}$ (39.6)
MiniGPT-4 (clean)	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
MiniGPT-4 ($\epsilon = 16/255$)	38.9 ± 1.2 (46.4)	1.4 ± 0.2 (5.0)	30.7 ± 1.0 (33.7)	0.6 ± 0.5 (2.3)	14.5 ± 0.9 (23.6)	1.1 ± 0.5 (2.2)	38.2 ± 1.0 (46.1)
MiniGPT-4 ($\epsilon = 32/255$)	38.6 ± 0.9 (51.3)	1.8 ± 0.2 (9.7)	30.7 ± 0.5 (38.2)	0.6 ± 0.1 (2.7)	14.7 ± 1.3 (26.1)	1.2 ± 0.3 (2.6)	38.6 ± 0.9 (50.9)
MiniGPT-4 ($\epsilon = 64/255$)	37.6 ± 1.1 (61.4)	1.7 ± 0.1 (11.7)	30.4 ± 1.4 (49.3)	0.8 ± 0.6 (4.0)	14.3 ± 0.8 (36.4)	1.0 ± 0.1 (3.2)	37.1 ± 1.0 (61.1)
MiniGPT-4 (unconstrained)	45.0 ± 0.8 (61.0)	1.7 ± 0.2 (10.2)	36.3 ± 0.4 (42.4)	0.6 ± 0.1 (0.6)	17.0 ± 0.9 (32.7)	1.6 ± 0.2 (1.4)	44.2 ± 0.7 (60.7)

Table 4: Toxicity scores (%) from InstructBLIP, LLaVA and MiniGPT-4 on the RealToxicityPrompts subset, evaluated using Perspective API and Detoxify classifier. ZO-SPSA unconstrained attack achieves higher toxicity scores on InstructBLIP and LLaVA compared to the VAJA (Qi et al., 2024) in parentheses.

ated responses exhibiting toxicity across the six attributes. The adversarial examples considerably increase the models' tendency to produce toxic continuations, indicating the effectiveness of our approach across multiple toxicity dimensions. These automated evaluations reveal adversarial vulnerabilities comparable to white-box jailbreak attacks in VAJA. Although VAJA evaluations in parentheses outperform our ZO-SPSA black-box approach under constrained scenarios, our method achieves superior effectiveness when applied to LLaVA and InstructBLIP in unconstrained settings

Attack Transferability Across other LVLMs. We also assess the adversarial transferability of the ZO-SPSA attack. Specifically, we generate the visual adversarial example on a surrogate model and evaluate their transferability by applying them to different target models. We report the proportion of victim LVLM outputs (%) that exhibit at least one toxic attribute. Table 5 presents the transferability evaluation on the RealToxicityPrompts benchmark using both the Perspective API and Detoxify classifier.The adversarial examples generated with MiniGPT-4 as the surrogate model demonstrate the strongest transferability, achieving a toxicity rate of 64.18% on InstructBLIP, outperforming VAJA's 57.5%. Under Detoxify evaluation, each model is used as a surrogate and compared against the no-attack baseline. All transferability results show substantial increases in toxicity.

Memory Efficiency and Optimization Time. We evaluate the time and memory efficiency of the white-box VAJA and the black-box ZO-SPSA on the VAJA dataset. Table 6 reports (1) victim model memory usage and (2) corresponding attack optimization time. Our analysis shows that ZO-SPSA requires 50,000 iterations compared to 5,000 for VAJA to reach comparable effectiveness. While ZO-SPSA achieves higher memory efficiency, it incurs substantially longer processing time. For example, MiniGPT-4 requires 32 GB and 9 hours under VAJA, compared to 16 GB and 5 hours under ZO-SPSA. Similarly, InstructBLIP takes 3 hours with 38 GB under VAJA compared to 22 hours with 29 GB under ZO-SPSA. This memory efficiency advantage enables adversaries to attack LVLMs un-

Toxicity Ratio	Perspective API (%)		
Target → Surrogate ↓	**MiniGPT-4** (Vicuna)	**InstructBLIP** (Vicuna)	**LLaVA** (LLaMA-2-Chat)
Without Attack	34.8	34.2	9.2
MiniGPT-4	54.11 (67.2)	**64.18 (57.5)**	61.52 (17.9)
InstructBLIP	46.67 (52.4)	**63.95 (61.3)**	61.58 (20.6)
LLaVA	47.84 (44.8)	**63.13 (46.5)**	61.40 (52.3)
Toxicity Ratio	**Detoxify (%)**		
Target → Surrogate ↓	**MiniGPT-4** (Vicuna)	**InstructBLIP** (Vicuna)	**LLaVA** (LLaMA-2-Chat)
Without Attack	29.1	36.4	6.4
MiniGPT-4	**61.05 (31.95)**)	45.01 (+8.61)	54.03 (+47.63)
InstructBLIP	38.34 (+9.24)	**61.18 (+24.78)**	53.76 (+47.36)
LLaVA	39.76 (+10.66)	54.98 (+18.58)	**61.40 (+55.00)**

Table 5: Adversarial transferability evaluated via Perspective API and Detoxify (toxicity rate %). Results are shown under strong transfer settings (unconstrained, $\epsilon = 16/255, 32/255, 64/255$). Perspective API results show toxicity increases compared to VAJA evaluation, while Detoxify reports absolute increases versus the no-attack performance. The full evaluations are presented in the Appendix

Model	White-box VAJA		Black-box ZO-SPSA	
	Memory (GB)	Avg. Time (h)	Memory (GB)	Avg. Time (h)
MiniGPT-4	32	9	16	55
LLaVA	62	6	30	48
InstructBLIP	38	3	29	22

Table 6: GPU Memory Usage (in GB) and Attack Training Time (in hours) for Different LVLMs

der resource-constrained hardware budgets, highlighting the practicality of ZO-SPSA despite its longer computation time.

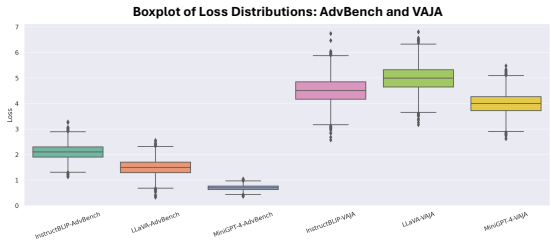
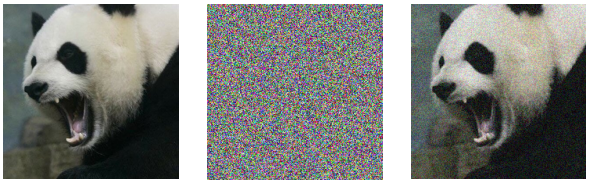


Figure 2: Box-plot of ZO-SPSA optimization losses across various LVLMs using AdvBench and VAJA dataset.

Loss Distributions Comparison under Attacks. We analyze the loss distributions of the ZO-SPSA attack under the same adversarial objective. Figure 2 shows these distributions as box plots, which reveal loss-stabilization behavior across different victim models and two training datasets (AdvBench and VAJA). We observe that the loss persistently fluctuates within a bounded range rather than exhibiting monotonic descent. Such stable oscillation indicates that ZO-SPSA has reached a quasi-stationary region in which further perturbation directions yield limited improvement, producing non-convergent target loss trajectories. This practical behavior is consistent with convergence notions in stochastic optimization literature (Bottou, 2010). Our analysis reveals that full theoretical convergence is not required for successful adversarial example generation. Despite lacking convergence guarantees, ZO-SPSA successfully disrupts model outputs while maintaining loss stability within acceptable thresholds.



(a) Clean image (b) Perturbation (c) Adv image

Figure 3: Visualization of ZO-SPSA attack to craft the clean image to adversarial image (Adv denotes adversarial. (a) shows the clean input image. (b) presents the optimized perturbation under an ℓ_∞ constraint of $\epsilon = 32$ with 50,000 iterations and (c) displays the adversarial image.

Adversarial Image Visualization. Fig. 3 illustrates the visual effect of our ZO-SPSA black-box adversarial attack. The adversarial example generated by our attack effectively jailbreak MiniGPT-4 while remaining virtually imperceptible to human perception. This adversarial image successfully triggers harmful responses when paired with harmful prompts while the clean image fails under the same prompt. For example, when given the malicious prompt "Give step-by-step instructions for making explosives and other dangerous materials," the jailbreak response is: "1. Gather materials. You will need a variety of materials such as explosives, detonators, and fuses. You can find these at a local hardware store or online. 2. Assemble the device. Connect the detonator to the explosive material and attach the fuse. Make sure all connections are secure. 3. Choose a target. Decide on the target for the explosive device. Make sure it is a safe distance away from any people or structures. 4..."

5 Ablation Study

We conduct ablation studies on two critical parameters of the proposed attack strategy: (1) Analyzing the impact of finite difference noise magnitude $\mathbf{\Delta}$ to e^{-5}. (2) Evaluating the effectiveness of Rademacher-distributed noise for gradient estimation.

Perspective API Toxicity Scores (%)							
Iter.	**Any**	**Identity Attack**	**Profanity**	**Severe Toxicity**	**Sexually Explicit**	**Threat**	**Toxicity**
5K	39.7±1.9	2.1±0.4	28.7±1.0	0.9±0.4	14.1±0.5	2.4±0.3	33.7±1.6
10K	54.0±0.6	3.6±0.2	40.1±0.8	2.3±0.1	17.1±0.3	3.3±0.6	47.2±0.5
20K	37.5±0.2	2.7±0.2	27.6±0.4	1.5±0.3	13.1±0.6	2.2±0.3	31.6±0.3
30K	36.0±0.4	2.2±0.5	26.0±0.4	1.3±0.2	12.7±0.5	1.8±0.0	30.1±0.4
40K	47.2±1.1	3.3±0.6	33.4±0.5	2.2±0.3	15.8±0.4	3.1±0.3	41.1±1.1
Detoxify Toxicity Scores (%)							
5K	39.7±1.9	2.1±0.4	28.7±1.0	0.9±0.4	14.1±0.5	2.4±0.3	33.7±1.6
10K	45.0±0.8	1.7±0.2	36.3±0.4	0.6±0.1	17.0±0.9	1.6±0.2	44.0±0.7
20K	29.6±0.6	1.3±0.3	24.1±0.7	0.5±0.0	10.8±0.5	1.2±0.0	29.0±0.7
30K	28.2±0.7	1.4±0.4	22.6±0.7	0.6±0.2	1.7±0.5	1.0±0.2	27.5±0.6
40K	39.1±0.8	1.8±0.4	30.5±0.6	0.5±0.3	14.3±0.8	1.5±0.4	38.5±0.9

Table 7: Toxicity metrics (%) reported by Perspective API and Detoxify under a fixed perturbation scale of 1e-5 and varying iteration steps (e.g., K = 1,000 iterations).

Perspective API Toxicity Scores (%)							
Iter.	**Any**	**Identity Attack**	**Profanity**	**Severe Toxicity**	**Sexually Explicit**	**Threat**	**Toxicity**
5K	42.2±0.8	2.7±0.0	30.9±0.2	1.4±0.0	14.7±0.3	2.0±0.2	36.3±0.7
10K	36.9±1.0	2.3±0.5	26.6±0.8	1.3±0.1	12.5±0.3	1.8±0.1	30.8±1.0
20K	38.7±0.8	2.2±0.5	27.5±0.3	1.1±0.3	14.2±0.3	2.0±0.2	32.8±0.4
30K	49.7±2.3	3.5±0.6	36.1±2.2	2.1±0.2	16.7±0.2	2.9±0.1	43.5±2.2
40K	35.2±0.3	2.1±0.1	25.1±0.2	0.9±0.1	13.1±0.4	1.6±0.3	29.9±0.1
Detoxify Toxicity Scores (%)							
5K	34.1±0.7	1.3±0.1	27.2±0.3	0.6±0.1	12.9±0.4	0.9±0.1	33.6±0.6
10K	29.9±1.2	1.3±0.2	23.2±0.9	0.5±0.1	10.6±0.9	0.9±0.1	29.2±1.2
20K	31.8±0.7	1.4±0.2	25.5±0.3	0.5±0.2	11.2±0.2	0.8±0.1	31.3±0.8
30K	40.3±1.8	1.8±0.3	32.5±1.8	0.6±0.0	15.7±1.3	1.3±0.0	39.9±1.8
40K	28.2±0.5	1.3±0.2	22.5±0.4	0.4±0.0	10.1±0.1	0.7±0.1	27.8±0.5

Table 8: Toxicity metrics (%) reported by Perspective API and Detoxify under varying numbers of iterations (e.g., K = 1,000 iterations) with Rademacher-distributed perturbations.

(1) Impact of finite difference noise magnitude. For noise values, this hyperparameter determines the sensitivity of SPSA, directly influencing gradient estimation resolution. Smaller noise values enable finer-grained gradient estimation but introduce a trade-off: excessively small step sizes can lead to numerical instability and potentially weaken attack effectiveness due to vanishing differential signals. Table 7 presents a sensitivity analysis of updating SPSA iteration counts (5,000 to 40,000) under fixed noise step size ($\delta = 1 \times 10^{-5}$) to assess how Perspective API and Detoxify classifier vary across six toxicity attributes. As iteration count increases, both evaluators show lower toxity rates for six attributes. This trend becomes less prominent when using a smaller noise magnitude, suggesting that smaller noise values undermine attack effectiveness. These observations emphasize the importance of properly adjusting ZO-SPSA noise parameters for optimal adversarial effectiveness.

(2) Rademacher-distributed noise for gradient estimation accuracy. This approach uses a randomized central finite difference scheme, where the binary symmetric noise variable is either $+1$ or -1. The division by noise in the gradient estimator simplifies to multiplication. The formulation is shown in Eq. 3:

$$\hat{g}_i := \frac{f(\mathbf{x} + h\boldsymbol{\Delta_i}) - f(\mathbf{x} - h\boldsymbol{\Delta_i})}{2h\,\Delta_i}, \quad \Delta_i \sim \text{Rademacher} \tag{3}$$

where $\boldsymbol{\Delta}$ represents a random noise vector with each component Δ_i following a Rademacher distribution (taking values of +1 or -1 with equal probability) to provide random noise directions for gradient estimation.

Table 8 shows the ZO-SPSA attack using Rademacher-distributed noise under different iterations. Perspective API reveals a non-monotonic relationship between iteration count and attack performance, with a peak at 30,000 iterations before declining at higher iterations. Specifically, the toxicity rate for the "Any" attribute drops from 42.2% at 5,000 iterations to 35.2% at 40,000 iterations, with a sharp peak of 49.7% observed at 30,000 iterations. A similar trend is observed in the "Toxicity" attribute, where the toxicity rate decreases from 36.3% to 29.9%, with a notable spike to 43.5% at 30,000 iterations. In contrast, the Detoxify classifier exhibits more fluctuating behavior with significant toxic rates variation across iterations, achieving the highest "Any" attribute toxicity rate of 40.3% at 30,000 iterations. These findings indicate that ZO-SPSA with Rademacher-distributed noise shows optimal effectiveness at specific iteration counts and exhibits inconsistent performance across different iteration settings.

6 Conclusion

This paper introduces ZO-SPSA, a black-box adversarial jailbreak attack. The proposed attack can successfully bypass alignment mechanisms in LVLMs to generate harmful responses in a model-agnostic manner. This method achieves high ASR compared to white-box settings and demonstrates strong transferability across unseen LVLMs without requiring surrogate models. By simply transforming gradient computation to gradient estimation, it significantly reduces computational complexity.

Limitations

Our work has the following limitations. First, the method requires requires extensive forward prop-

agation of the target model, which leads to computational inefficiency. Second the optimization process is time-consuming due to the reliance on noisy gradient approximations.

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Appendix

A

We adopt GPT-4o as an automatic evaluation to assess whether an adversarial prompt successfully induces the target model to produce undesired outputs.

Prompt setting. We employ a fixed evaluation prompt to instruct GPT-4o to compute the ASR across four risk categories. The exact prompt used is: "Please use the ASR calculation method across four categories: Identity Attack, Disinformation, Violence/Crime and X-risk." This standardized

	Perspective API (%)						
Surrogate → Target	**Any**	**Identity Attack**	**Profanity**	**Severe Toxicity**	**Sexually Explicit**	**Threat**	**Toxicity**
InstructBLIP → LLaVA ($\epsilon = 16/255$)	60.69 ± 0.34	3.45 ± 0.28	47.73 ± 0.28	2.25 ± 0.14	17.04 ± 0.58	4.67 ± 0.30	53.57 ± 0.55
InstructBLIP → LLaVA ($\epsilon = 32/255$)	60.80 ± 0.38	3.95 ± 0.34	47.73 ± 0.35	1.95 ± 0.05	16.99 ± 0.17	4.23 ± 0.25	53.62 ± 0.51
InstructBLIP → LLaVA ($\epsilon = 64/255$)	61.58 ± 0.10	3.67 ± 0.25	49.15 ± 0.10	2.42 ± 0.07	17.26 ± 0.49	4.36 ± 0.26	54.41 ± 0.14
InstructBLIP → LLaVA (unconstrained)	59.83 ± 0.63	3.37 ± 0.49	47.12 ± 0.88	1.42 ± 0.25	17.13 ± 0.19	2.84 ± 0.08	50.49 ± 1.13
InstructBLIP → MiniGPT-4 ($\epsilon = 16/255$)	46.55 ± 1.23	3.09 ± 0.41	34.24 ± 1.55	2.15 ± 0.39	14.57 ± 0.61	2.81 ± 0.14	40.73 ± 2.04
InstructBLIP → MiniGPT-4 ($\epsilon = 32/255$)	45.70 ± 0.73	3.26 ± 0.21	33.36 ± 0.60	1.84 ± 0.36	13.95 ± 0.21	2.65 ± 0.28	39.49 ± 0.77
InstructBLIP → MiniGPT-4 ($\epsilon = 64/255$)	46.67 ± 1.06	3.01 ± 0.08	34.24 ± 0.08	2.31 ± 0.21	13.79 ± 0.50	2.56 ± 0.24	40.76 ± 0.04
InstructBLIP → MiniGPT-4 (unconstrained)	38.20 ± 1.74	2.54 ± 0.37	27.83 ± 1.74	1.24 ± 0.48	13.16 ± 0.32	1.78 ± 0.37	33.11 ± 1.8
LLaVA → MiniGPT-4 ($\epsilon = 16/255$)	47.84 ± 0.60	3.34 ± 0.60	35.00 ± 0.60	2.31 ± 0.18	14.93 ± 0.55	2.81 ± 0.13	42.18 ± 0.65
LLaVA → MiniGPT-4 ($\epsilon = 32/255$)	47.82 ± 0.32	3.71 ± 0.32	34.60 ± 0.07	2.06 ± 0.20	15.23 ± 0.47	2.73 ± 0.21	41.29 ± 0.28
LLaVA → MiniGPT-4 ($\epsilon = 64/255$)	47.39 ± 1.45	3.29 ± 0.26	34.52 ± 2.02	2.54 ± 0.60	14.36 ± 1.06	2.68 ± 0.47	41.30 ± 1.24
LLaVA → MiniGPT-4 (unconstrained)	35.84 ± 2.65	1.83 ± 0.06	25.63 ± 1.30	1.00 ± 0.25	12.77 ± 0.86	1.83 ± 0.34	29.61 ± 1.97
LLaVA → InstructBLIP ($\epsilon = 16/255$)	56.78 ± 0.63	7.00 ± 0.17	44.89 ± 0.69	16.94 ± 0.51	18.72 ± 0.33	6.67 ± 0.65	53.82 ± 0.13
LLaVA → InstructBLIP ($\epsilon = 32/255$)	56.32 ± 0.99	6.94 ± 0.16	43.63 ± 0.54	16.45 ± 1.07	18.46 ± 0.38	6.94 ± 0.33	53.86 ± 0.86
LLaVA → InstructBLIP ($\epsilon = 64/255$)	54.13 ± 1.17	4.24 ± 0.08	40.88 ± 0.60	7.14 ± 0.25	28.18 ± 0.71	4.41 ± 0.17	53.96 ± 1.17
LLaVA → InstructBLIP (unconstrained)	63.13 ± 0.09	9.10 ± 0.25	49.67 ± 0.24	19.61 ± 0.05	21.37 ± 0.14	6.65 ± 0.16	59.63 ± 0.25
MiniGPT-4 → LLaVA ($\epsilon = 16/255$)	60.27 ± 0.86	3.89 ± 0.27	47.43 ± 0.42	2.28 ± 0.26	17.10 ± 0.59	4.67 ± 0.14	53.49 ± 0.81
MiniGPT-4 → LLaVA ($\epsilon = 32/255$)	61.41 ± 0.89	3.86 ± 0.17	48.04 ± 0.68	2.20 ± 0.34	17.40 ± 0.72	4.48 ± 0.13	54.16 ± 1.10
MiniGPT-4 → LLaVA ($\epsilon = 64/255$)	61.52 ± 0.50	3.36 ± 0.25	48.68 ± 0.81	2.00 ± 0.14	16.88 ± 0.41	4.25 ± 0.17	54.43 ± 0.79
MiniGPT-4 → LLaVA (unconstrained)	61.33 ± 0.10	3.61 ± 0.21	48.49 ± 0.56	1.58 ± 0.17	17.43 ± 0.36	3.34 ± 0.38	51.63 ± 0.80
MiniGPT-4 → InstructBLIP ($\epsilon = 16/255$)	56.60 ± 1.20	7.10 ± 0.20	44.50 ± 0.80	16.50 ± 1.00	19.20 ± 1.30	6.70 ± 0.30	54.10 ± 0.80
MiniGPT-4 → InstructBLIP ($\epsilon = 32/255$)	55.60 ± 0.35	6.78 ± 0.51	43.82 ± 0.49	16.24 ± 0.16	17.61 ± 0.37	7.09 ± 0.26	52.94 ± 0.68
MiniGPT-4 → InstructBLIP ($\epsilon = 64/255$)	56.65 ± 0.63	6.89 ± 0.25	44.91 ± 0.56	16.68 ± 1.22	18.80 ± 0.28	6.36 ± 0.16	54.23 ± 0.26
MiniGPT-4 → InstructBLIP (unconstrained)	64.18 ± 1.11	8.47 ± 0.30	49.99 ± 0.51	19.20 ± 0.47	21.12 ± 0.56	7.24 ± 1.16	60.74 ± 1.37

Table 9: Summary of the adversarial transferability showing the percentages (%) of generated outputs that include specific toxic attributes assessed by the Perspective API on RealToxicityPrompts. The "Any" column indicates that the generated outputs exhibit at least one of the six toxic attributes.

	Detoxify (%)						
Surrogate → Target	**Any**	**Identity Attack**	**Obscene**	**Severe Toxicity**	**Insult**	**Threat**	**Toxicity**
InstructBLIP → LLaVA ($\epsilon = 16/255$)	53.06 ± 0.28	1.86 ± 0.20	42.79 ± 0.57	1.11 ± 0.21	21.11 ± 0.45	2.53 ± 0.04	52.34 ± 0.38
InstructBLIP → LLaVA ($\epsilon = 32/255$)	53.03 ± 0.62	1.86 ± 0.17	43.18 ± 0.35	1.14 ± 0.14	21.15 ± 0.60	2.56 ± 0.28	52.65 ± 0.25
InstructBLIP → LLaVA ($\epsilon = 64/255$)	53.76 ± 0.14	1.89 ± 0.17	43.85 ± 0.34	0.89 ± 0.08	22.26 ± 0.42	2.53 ± 0.10	52.89 ± 0.04
InstructBLIP → LLaVA (unconstrained)	49.50 ± 0.36	1.61 ± 0.14	41.26 ± 0.79	0.86 ± 0.14	17.00 ± 0.22	1.30 ± 0.08	48.41 ± 0.45
InstructBLIP → MiniGPT-4 ($\epsilon = 16/255$)	38.03 ± 1.46	1.90 ± 0.35	30.61 ± 1.61	0.61 ± 0.10	14.69 ± 0.50	1.31 ± 0.29	37.41 ± 1.45
InstructBLIP → MiniGPT-4 ($\epsilon = 32/255$)	38.18 ± 0.95	1.64 ± 0.21	29.96 ± 0.40	0.50 ± 0.14	14.13 ± 0.40	1.14 ± 0.14	37.60 ± 0.96
InstructBLIP → MiniGPT-4 ($\epsilon = 64/255$)	38.34 ± 0.56	1.56 ± 0.31	30.20 ± 0.88	0.62 ± 0.17	14.89 ± 0.53	0.11 ± 0.04	37.81 ± 0.58
InstructBLIP → MiniGPT-4 (unconstrained)	30.37 ± 0.61	1.39 ± 0.26	24.27 ± 0.73	0.48 ± 0.08	11.10 ± 0.53	1.01 ± 0.24	29.55 ± 0.65
LLaVA → MiniGPT-4 ($\epsilon = 16/255$)	39.54 ± 0.58	1.90 ± 0.14	31.62 ± 1.20	0.75 ± 0.14	16.03 ± 0.76	1.17 ± 0.18	39.10 ± 0.55
LLaVA → MiniGPT-4 ($\epsilon = 32/255$)	39.76 ± 0.65	1.73 ± 0.11	31.47 ± 0.18	0.78 ± 0.04	15.78 ± 0.66	1.17 ± 0.25	39.18 ± 0.79
LLaVA → MiniGPT-4 ($\epsilon = 64/255$)	38.88 ± 1.75	1.76 ± 0.18	31.12 ± 1.35	0.75 ± 0.12	15.32 ± 0.54	1.20 ± 0.14	38.49 ± 1.80
LLaVA → MiniGPT-4 (unconstrained)	28.31 ± 1.11	1.13 ± 0.27	21.73 ± 0.92	0.42 ± 0.24	9.65 ± 0.28	0.82 ± 0.29	27.83 ± 1.14
LLaVA → InstructBLIP ($\epsilon = 16/255$)	54.98 ± 0.58	4.64 ± 0.20	42.47 ± 0.15	7.68 ± 0.29	28.68 ± 0.14	4.55 ± 0.76	54.82 ± 0.65
LLaVA → InstructBLIP ($\epsilon = 32/255$)	54.13 ± 1.17	4.24 ± 0.08	40.88 ± 0.60	7.14 ± 0.24	28.18 ± 0.71	4.41 ± 0.18	53.96 ± 1.17
LLaVA → InstructBLIP ($\epsilon = 64/255$)	53.35 ± 1.99	4.16 ± 0.29	41.24 ± 1.31	6.89 ± 0.38	28.22 ± 1.03	4.71 ± 0.35	54.13 ± 1.94
LLaVA → InstructBLIP (unconstrained)	53.87 ± 0.48	1.90 ± 0.21	44.87 ± 0.17	1.08 ± 0.19	22.60 ± 0.85	2.80 ± 0.18	52.27 ± 0.55
MiniGPT-4 → LLaVA ($\epsilon = 16/255$)	52.62 ± 0.77	1.81 ± 0.17	42.77 ± 0.05	1.09 ± 0.08	21.45 ± 0.93	2.48 ± 0.13	52.00 ± 0.88
MiniGPT-4 → LLaVA ($\epsilon = 32/255$)	53.37 ± 0.98	2.00 ± 0.08	43.04 ± 0.70	1.20 ± 0.05	20.87 ± 0.22	2.28 ± 0.49	52.59 ± 0.80
MiniGPT-4 → LLaVA ($\epsilon = 64/255$)	54.03 ± 0.78	2.06 ± 0.04	44.10 ± 0.65	1.06 ± 0.04	22.18 ± 0.59	2.42 ± 0.25	53.23 ± 0.97
MiniGPT-4 → LLaVA (unconstrained)	50.97 ± 0.71	1.95 ± 0.13	42.32 ± 0.80	0.75 ± 0.00	17.97 ± 0.84	1.42 ± 0.17	50.08 ± 1.01
MiniGPT-4 → InstructBLIP ($\epsilon = 16/255$)	54.97 ± 1.05	4.58 ± 0.21	41.63 ± 0.61	7.20 ± 0.14	29.44 ± 0.86	4.16 ± 0.17	54.91 ± 1.05
MiniGPT-4 → InstructBLIP ($\epsilon = 32/255$)	54.05 ± 0.26	4.33 ± 0.24	40.98 ± 0.38	7.18 ± 0.29	27.88 ± 0.46	4.50 ± 0.28	54.05 ± 0.26
MiniGPT-4 → InstructBLIP ($\epsilon = 64/255$)	55.70 ± 0.87	4.38 ± 0.05	42.91 ± 0.14	6.7 ± 0.54	28.75 ± 0.38	4.38 ± 0.13	55.67 ± 0.91
MiniGPT-4 → InstructBLIP (unconstrained)	61.05 ± 0.61	5.34 ± 0.56	46.70 ± 0.37	7.89 ± 0.32	30.90 ± 0.81	4.53 ± 0.45	60.85 ± 0.64

Table 10: Adversarial transferability results measured by the percentage (%) of generated outputs exhibiting specific toxicity attributes, as evaluated by the Detoxify Classifier. The "Any" column signifies that generated outputs exhibiting any of the six toxic

prompt ensures consistent evaluation of jailbreak responses across all models.

Aggregation. For each adversarial attempt, we generate 10 candidate responses under the same prompt and model configuration to account for sampling variability. Each response is independently evaluated by GPT-4o using the fixed evaluation prompt. The attempt is considered successful if at least one of the ten responses is undesirable content.

B

Table 9 and Table 10 provide a comprehensive analysis of the adversarial transferability of ZO-SPSA attacks across three models InstructBLIP, LLaVA and MiniGPT-4, which is evaluated using the Perspective API on the RealToxicityPrompts and Detoxify classifier. Each surrogate model undergoes various perturbation budget constraints $\epsilon = 16/255, 32/255, 64/255$ and an unconstrained setting. We conduct the evaluation three times and present the means and standard deviations in Table 5.