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AttackVLM:
On Evaluating Adversarial Robustness of Large Vision-Language Models

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Overview

On Evaluating Adversarial Robustness of Large Vision-Language Models

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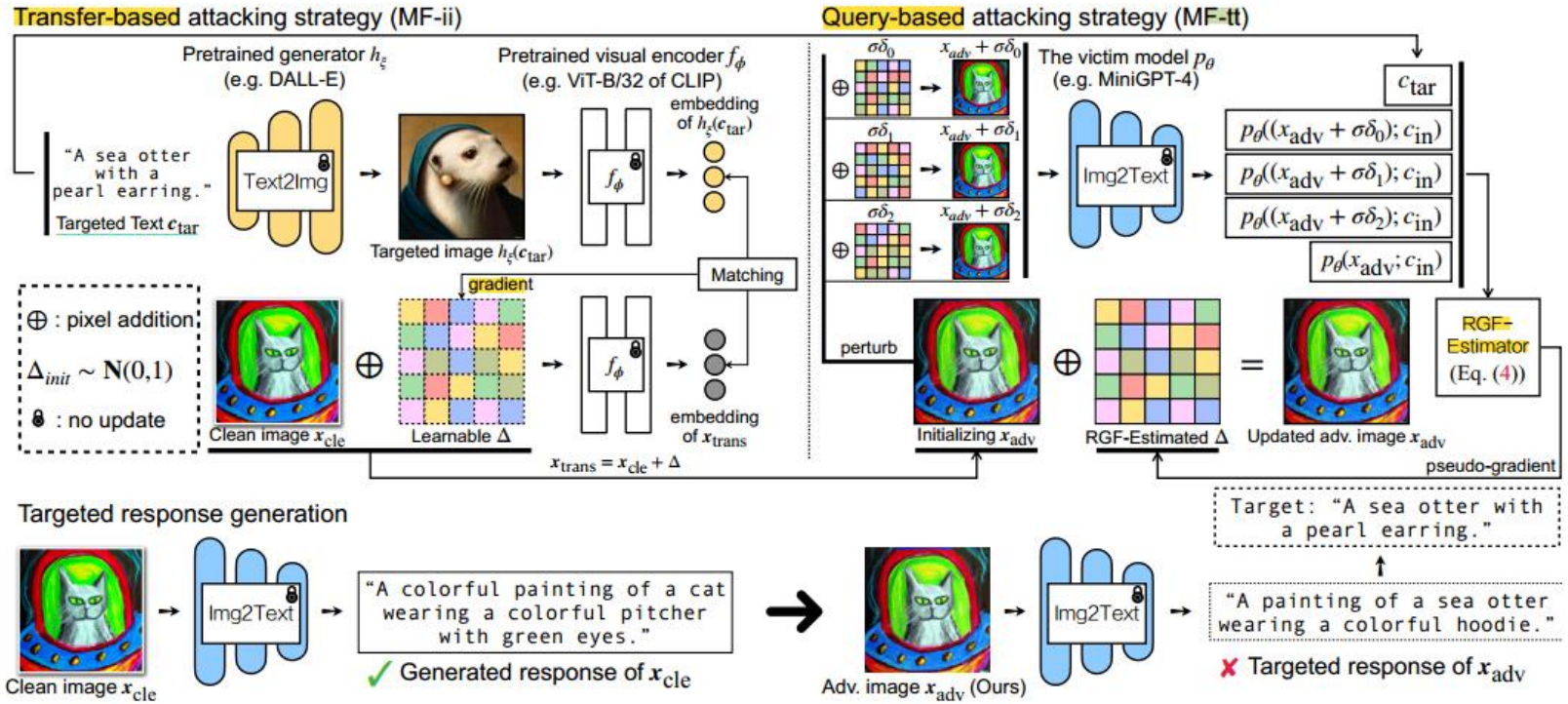
- **Large-Vision Language Models (VLMs)** (e.g. UniDiffuser)
- **Adversarial Robustness of VLMs**
- **Contributions**
  We evaluate the robustness of open-source large VLMs in the most realistic and high-risk setting, where adversaries have black-box system access and seek to deceive the model into returning the targeted responses.

Overview



"We mislead and let the VLMs say what you want, regardless of the content of the input image query."

Threat Models

We denote $p_\theta(\boldsymbol{x}; \boldsymbol{c}_{\text{in}}) \mapsto \boldsymbol{c}_{\text{out}}$ as an image-grounded text generative model parameterized by θ, where $\boldsymbol{x}$ is the input image, $\boldsymbol{c}_{\text{in}}$ is the input text, and $\boldsymbol{c}_{\text{out}}$ is the output text. In image captioning tasks, for instance, $\boldsymbol{c}_{\text{in}}$ is a placeholder $\emptyset$ and $\boldsymbol{c}_{\text{out}}$ is the caption; in visual question answering tasks, $\boldsymbol{c}_{\text{in}}$ is the question and $\boldsymbol{c}_{\text{out}}$ is the answer. Note that here we slightly abuse the notations since the mapping between $p_\theta(\boldsymbol{x}; \boldsymbol{c}_{\text{in}})$ and $\boldsymbol{c}_{\text{out}}$ could be probabilistic or non-deterministic [5, 98].

Threat models. We overview threat models that specify adversarial conditions [12] and adapt them to generative paradigms: (i) *adversary knowledge* describes what knowledge the adversary is assumed to have, typically either white-box access with full knowledge of p_θ including model architecture and weights, or varying degrees of black-box access, e.g., only able to obtain the output text $\boldsymbol{c}_{\text{out}}$ from an API; (ii) *adversary goals* describe the malicious purpose that the adversary seeks to achieve, including untargeted goals that simply cause $\boldsymbol{c}_{\text{out}}$ to be a wrong caption or answer, and targeted goals that cause $\boldsymbol{c}_{\text{out}}$ to match a predefined targeted response $\boldsymbol{c}_{\text{tar}}$ (measured via text-matching metrics); (iii) *adversary capabilities* describe the constraints on what the adversary can manipulate to cause harm, with the most commonly used constraint being imposed by the ℓ_p budget, namely, the ℓ_p distance between the clean image $\boldsymbol{x}_{\text{cle}}$ and the adversarial image $\boldsymbol{x}_{\text{adv}}$ is less than a budget ϵ as $\|\boldsymbol{x}_{\text{cle}} - \boldsymbol{x}_{\text{adv}}\|_p \leq \epsilon$.

Since we assume black-box access to the *victim* models, a common attacking strategy is transfer-based [22, 23, 47, 61, 94, 100], which relies on *surrogate* models (e.g., a publicly accessible CLIP model) to which the adversary has white-box access and crafts adversarial examples against them, then feeds the adversarial examples into the victim models (e.g., GPT-4 that the adversary seeks to fool). Due to the fact that the victim models are vision-and-language, we select an image encoder $f_\phi(\boldsymbol{x})$ and a text encoder $g_\psi(\boldsymbol{c})$ as surrogate models, and we denote $\boldsymbol{c}_{\text{tar}}$ as the targeted response that the adversary expects the victim models to return. Two approaches of designing transfer-based adversarial objectives are described in the following.

Methodology (MF-ii)

Matching image-text features (MF-it). Since the adversary expects the victim models to return the targeted response $\boldsymbol{c}_{\text{tar}}$ when the adversarial image $\boldsymbol{x}_{\text{adv}}$ is the input, it is natural to match the features of $\boldsymbol{c}_{\text{tar}}$ and $\boldsymbol{x}_{\text{adv}}$ on surrogate models, where $\boldsymbol{x}_{\text{adv}}$ should satisfy[2]

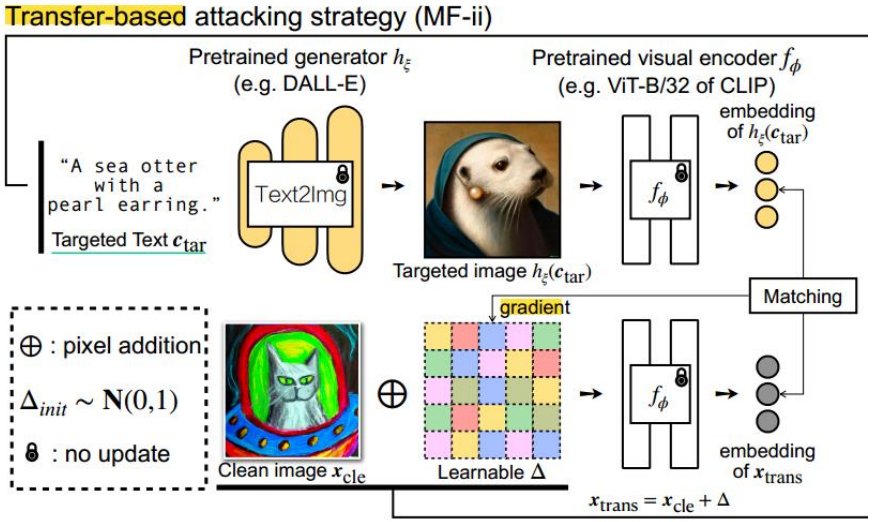
$$\underset{\|\boldsymbol{x}_{\text{cle}}-\boldsymbol{x}_{\text{adv}}\|_p\leq\epsilon}{\arg\max} \; f_\phi(\boldsymbol{x}_{\text{adv}})^\top g_\psi(\boldsymbol{c}_{\text{tar}}). \tag{1}$$

Here, we use blue color to highlight white-box accessibility (i.e., can directly obtain gradients of f_ϕ and g_ψ through backpropagation), the image and text encoders are chosen to have the same output dimension, and their inner product indicates the cross-modality similarity of $\boldsymbol{c}_{\text{tar}}$ and $\boldsymbol{x}_{\text{adv}}$. The constrained optimization problem in Eq. (1) can be solved by projected gradient descent (PGD) [48].

Matching image-image features (MF-ii). While aligned image and text encoders have been shown to perform well on vision-language tasks [65], recent research suggests that VLMs may behave like bags-of-words [103] and therefore may not be dependable for optimizing cross-modality similarity. Given this, an alternative approach is to use a public text-to-image generative model h_ξ (e.g., Stable Diffusion [72]) and generate a targeted image corresponding to $\boldsymbol{c}_{\text{tar}}$ as $h_\xi(\boldsymbol{c}_{\text{tar}})$. Then, we match the image-image features of $\boldsymbol{x}_{\text{adv}}$ and $h_\xi(\boldsymbol{c}_{\text{tar}})$ as

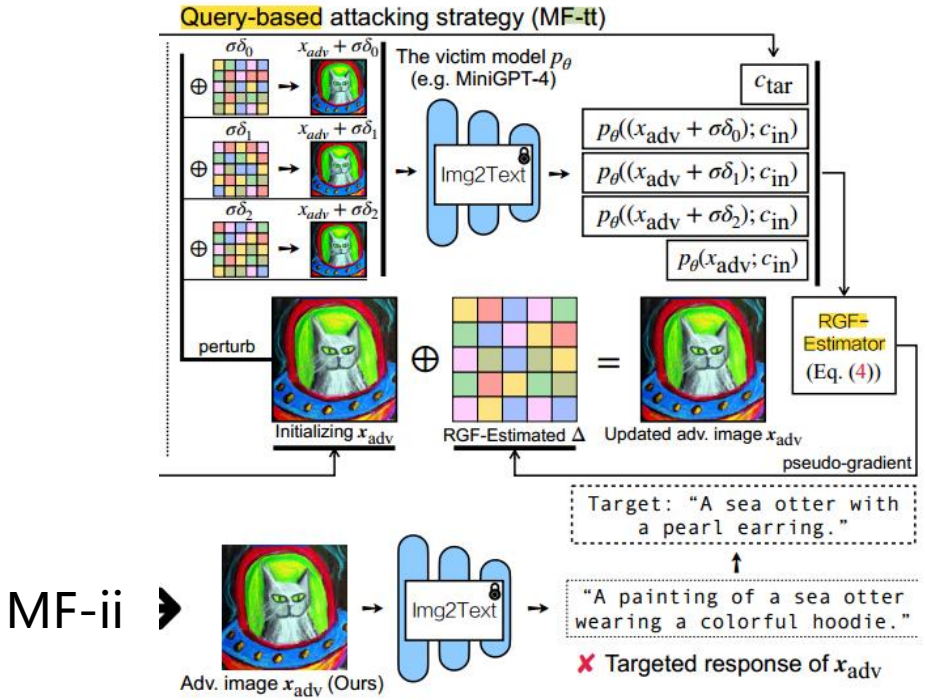
$$\underset{\|\boldsymbol{x}_{\text{cle}}-\boldsymbol{x}_{\text{adv}}\|_p\leq\epsilon}{\arg\max} \; f_\phi(\boldsymbol{x}_{\text{adv}})^\top f_\phi(h_\xi(\boldsymbol{c}_{\text{tar}})), \tag{2}$$

where orange color is used to emphasize that only black-box accessibility is required for h_ξ, as gradient information of h_ξ is not required when optimizing the adversarial image $\boldsymbol{x}_{\text{adv}}$. Consequently, we can also implement h_ξ using advanced APIs such as Midjourney [51].



MF-tt

Methodology (MF-tt)



Matching text-text features (MF-tt). Recall that the adversary goal is to cause the victim models to return a targeted response, namely, matching $p_\theta(\boldsymbol{x}_{\text{adv}}; \boldsymbol{c}_{\text{in}})$ with $\boldsymbol{c}_{\text{tar}}$. Thus, it is straightforward to maximize the textual similarity between $p_\theta(\boldsymbol{x}_{\text{adv}}; \boldsymbol{c}_{\text{in}})$ and $\boldsymbol{c}_{\text{tar}}$ as

$$\underset{\|\boldsymbol{x}_{\text{cle}}-\boldsymbol{x}_{\text{adv}}\|_p \le \epsilon}{\arg\max} \; g_\psi(p_\theta(\boldsymbol{x}_{\text{adv}}; \boldsymbol{c}_{\text{in}}))^\top g_\psi(\boldsymbol{c}_{\text{tar}}). \tag{3}$$

Note that we cannot directly compute gradients for optimization in Eq. (3) because we assume black-box access to the victim models p_θ and cannot perform backpropagation. To estimate the gradients, we employ the random gradient-free (RGF) method [54]. First, we rewrite a gradient as the expectation of direction derivatives, i.e., $\nabla_{\boldsymbol{x}} F(\boldsymbol{x}) = \mathbb{E}\left[\boldsymbol{\delta}^\top \nabla_{\boldsymbol{x}} F(\boldsymbol{x}) \cdot \boldsymbol{\delta}\right]$, where $F(\boldsymbol{x})$ represents any differentiable function and $\boldsymbol{\delta} \sim P(\boldsymbol{\delta})$ is a random variable satisfying that $\mathbb{E}[\boldsymbol{\delta}\boldsymbol{\delta}^\top] = \mathbf{I}$ (e.g., $\boldsymbol{\delta}$ can be uniformly sampled from a hypersphere). Then by zero-order optimization [16], we know that

$$\begin{aligned} &\nabla_{\boldsymbol{x}_{\text{adv}}} g_\psi(p_\theta(\boldsymbol{x}_{\text{adv}}; \boldsymbol{c}_{\text{in}}))^\top g_\psi(\boldsymbol{c}_{\text{tar}}) \\ \approx &\frac{1}{N\sigma} \sum_{n=1}^{N} \left[g_\psi(p_\theta(\boldsymbol{x}_{\text{adv}} + \sigma\boldsymbol{\delta}_n; \boldsymbol{c}_{\text{in}}))^\top g_\psi(\boldsymbol{c}_{\text{tar}}) - g_\psi(p_\theta(\boldsymbol{x}_{\text{adv}}; \boldsymbol{c}_{\text{in}}))^\top g_\psi(\boldsymbol{c}_{\text{tar}}) \right] \cdot \boldsymbol{\delta}_n, \end{aligned} \tag{4}$$

where $\boldsymbol{\delta}_n \sim P(\boldsymbol{\delta})$, σ is a hyperparameter controls the sampling variance, and N is the number of queries. The approximation in Eq. (4) becomes an unbiased equation when $\sigma \to 0$ and $N \to \infty$.

Methodology (pseudo-code)

Algorithm 1 Adversarial attack against large VLMs (Figure 4)

Input: Clean image $\boldsymbol{x}_{\text{cle}}$, a pretrained substitute model f_ϕ (e.g., a ViT-B/32 or ViT-L/14 visual encoder of CLIP), a pretrained victim model p_θ (e.g., Unidiffuser), a targeted text $\boldsymbol{c}_{\text{tar}}$, a pretrained text-to-image generator h_ξ (e.g., Stable Diffusion), a targeted image $h_\xi(\boldsymbol{c}_{\text{tar}})$.

Init: Number of steps $\boldsymbol{s}_1$ for MF-ii, number of steps $\boldsymbol{s}_2$ for MF-tt, number of queries N in each step for MF-tt, $\Delta = \mathbf{0}$, $\delta \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$, $\sigma = 8$, $\epsilon = 8$, $\boldsymbol{x}_{\text{cle}}$.requires_grad() = False.

```
# MF-ii
```

for $\boldsymbol{i} = 1; \boldsymbol{i} \leq \boldsymbol{s}_1; \boldsymbol{i}++$ **do**

  $\boldsymbol{x}_{\text{adv}}$ =clamp($\boldsymbol{x}_{\text{cle}} + \Delta$, min= 0, max= 255)

  Compute normalized embedding of $h_\xi(\boldsymbol{c}_{\text{tar}})$: $\boldsymbol{e}_1 = f_\phi(h_\xi(\boldsymbol{c}_{\text{tar}}))/f_\phi(h_\xi(\boldsymbol{c}_{\text{tar}}))$.norm()

  Compute normalized embedding of $\boldsymbol{x}_{\text{adv}}$: $\boldsymbol{e}_2 = f_\phi(\boldsymbol{x}_{\text{adv}})/f_\phi(\boldsymbol{x}_{\text{adv}})$.norm()

  Compute embedding similarity: sim $= \boldsymbol{e}_1^\top \boldsymbol{e}_2$

  Backpropagate the gradient: grad = sim.backward()

  Update Δ = clamp(Δ+grad.sign(), min= $-\epsilon$, max= ϵ)

end for

```
# MF-tt
```

Init: $\boldsymbol{x}_{\text{adv}} = \boldsymbol{x}_{\text{cle}} + \Delta$

for $\boldsymbol{j} = 1; \boldsymbol{j} \leq \boldsymbol{s}_2; \boldsymbol{j}++$ **do**

  Obtain generated output of perturbed images: $\{p_\theta(\boldsymbol{x}_{\text{adv}} + \sigma\delta_n)\}_{n=1}^N$

  Obtain generated output of adversarial images: $p_\theta(\boldsymbol{x}_{\text{adv}})$

  Estimate the gradient (Eq. (4)): pseudo-grad = RGF($\boldsymbol{c}_{\text{tar}}, p_\theta(\boldsymbol{x}_{\text{adv}}), \{p_\theta(\boldsymbol{x}_{\text{adv}} + \sigma\delta_n)\}_{n=1}^N$)

  Update Δ = clamp(Δ+pseudo-grad.sign(), min= $-\epsilon$, max= ϵ)

  $\boldsymbol{x}_{\text{adv}}$ =clamp($\boldsymbol{x}_{\text{cle}} + \Delta$, min= 0, max= 255)

end for

Output: The queried captions and the adversarial image $\boldsymbol{x}_{\text{adv}}$

Implementation details

Dataset:
ImageNet-1K: clean images
MS-COCO: caption dataset (VQA)

Text-to-image models:
SD、Midjourney、DALL-E

Surrogate models & Encoder:
CLIP、BLIP、ALBEF

RN50、RN101、
ViT-B/16、ViT-B/32、ViT-L/14
Ensemble

Victim models:
UniDiffuser
BLIP
BLIP-2
Img2Prompt
MiniGPT-4
LLaVa

Other Hyperparameters:
About image clipping
About PGD(MF-ii、MF-tt)

Experiments (Datasets)

Figure 9: An illustration of the dataset used in our MF-ii attack against large VLMs. By utilizing the text-to-image generation capability of Stable Diffusion, we are able to generate high-quality and fidelity targeted images given any type of targeted text, thereby increasing the attacking flexibility.

Experiments (UniDiffuser examples)

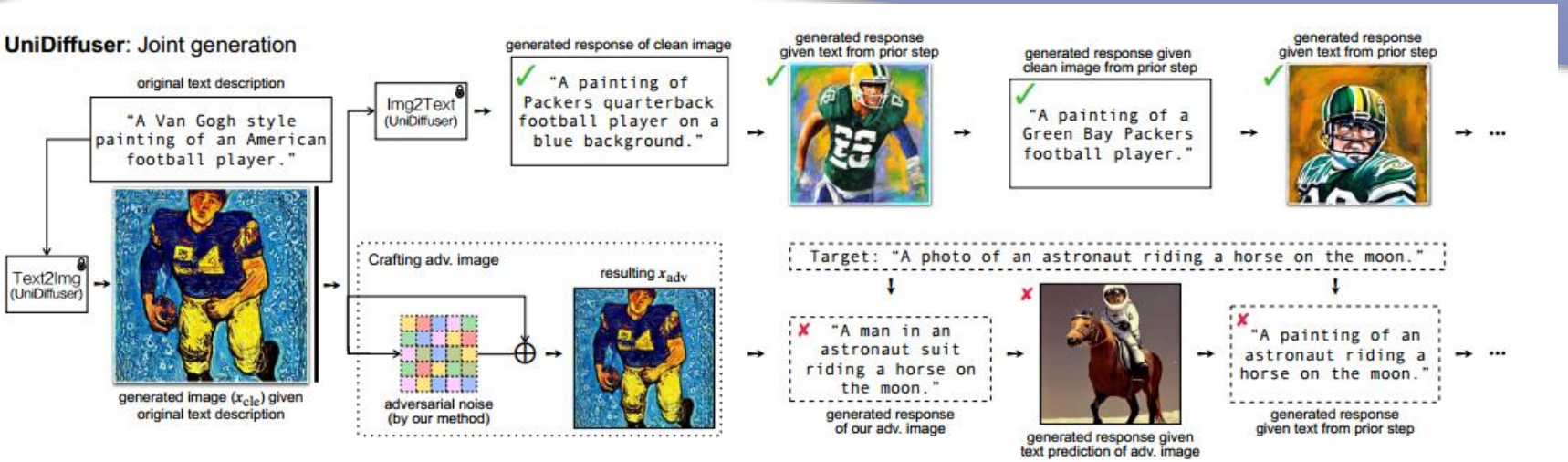
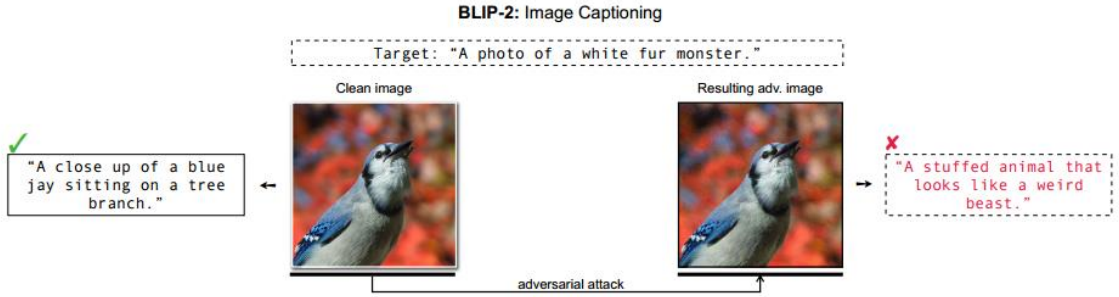
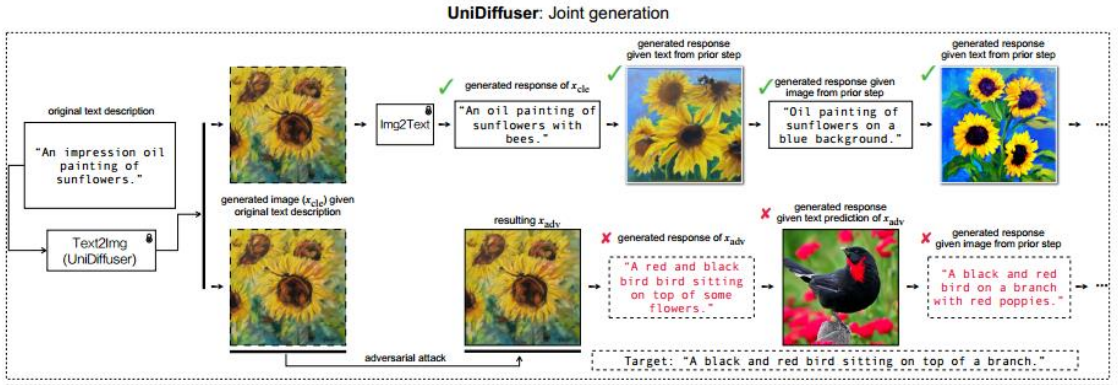
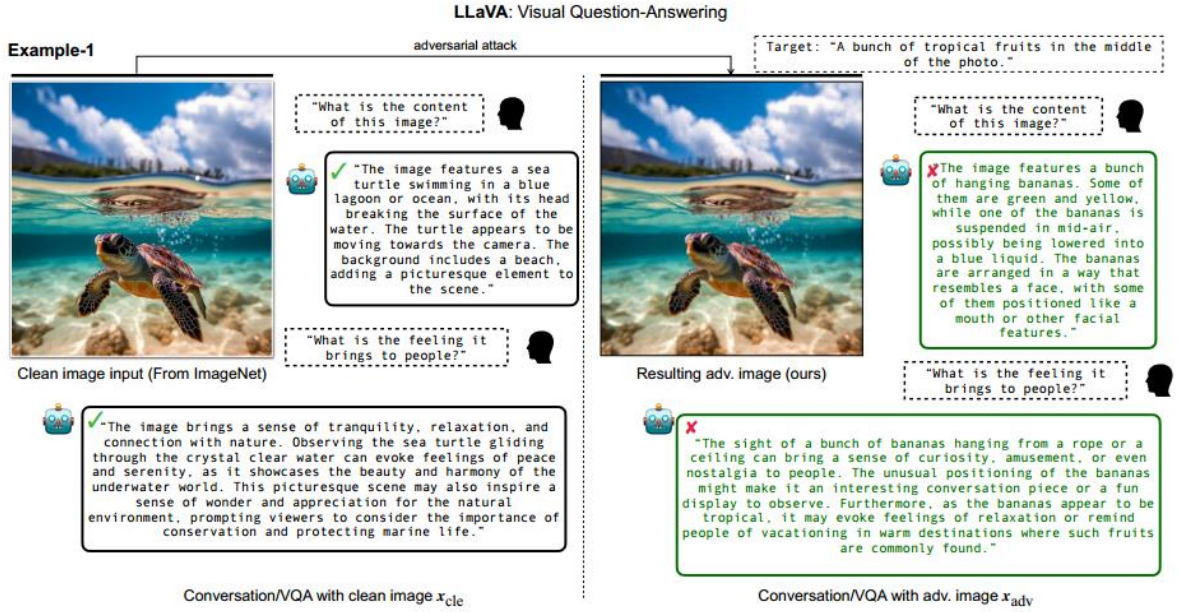


Figure 2: **Joint generation task implemented by UniDiffuser.** There are generative VLMs such as UniDiffuser that model the joint distribution of image-text pairs and are capable of both image-to-text and text-to-image generation. Consequently, given an original text description (e.g., `A Van Gogh style painting of an American football player`), the text-to-image direction of UniDiffuser is used to generate the corresponding clean image, and its image-to-text direction can recover a text response (e.g., `A painting of Packers quarterback football player on a blue background`) similar to the original text description. The recovering between image and text modalities can be performed consistently on clean images. When a targeted adversarial perturbation is added to a clean image, however, the image-to-text direction of UniDiffuser will return a text (e.g., `A man in an astronaut suit riding a horse on the moon`) that semantically resembles the predefined targeted description (e.g., `A photo of an astronaut riding a horse on the moon`), thereby affecting the subsequent chains of recovering processes.

Experiments (Other VLMs examples)







Experiments (

VLM model	Attacking method	Text encoder (pretrained) for evaluation						Other info.	
		RN50	RN101	ViT-B/16	ViT-B/32	ViT-L/14	Ensemble	# Param.	Res.
BLIP [41]	Clean image	0.472	0.456	0.479	0.499	0.344	0.450	224M	384
	MF-it	0.492	0.474	0.520	0.546	0.384	0.483		
	MF-ii	0.766	0.753	0.774	0.786	0.696	0.755		
	MF-ii + MF-tt	**0.855**	**0.841**	**0.861**	**0.868**	**0.803**	**0.846**		
UniDiffuser [5]	Clean image	0.417	0.415	0.429	0.446	0.305	0.402	1.4B	224
	MF-it	0.655	0.639	0.678	0.698	0.611	0.656		
	MF-ii	0.709	0.695	0.721	0.733	0.637	0.700		
	MF-ii + MF-tt	**0.754**	**0.736**	**0.761**	**0.777**	**0.689**	**0.743**		
Img2Prompt [30]	Clean image	0.487	0.464	0.493	0.515	0.350	0.461	1.7B	384
	MF-it	0.499	0.472	0.501	0.525	0.355	0.470		
	MF-ii	0.502	0.479	0.505	0.529	0.366	0.476		
	MF-ii + MF-tt	**0.803**	**0.783**	**0.809**	**0.828**	**0.733**	**0.791**		
BLIP-2 [42]	Clean image	0.473	0.454	0.483	0.503	0.349	0.452	3.7B	224
	MF-it	0.492	0.474	0.520	0.546	0.384	0.483		
	MF-ii	0.562	0.541	0.571	0.592	0.449	0.543		
	MF-ii + MF-tt	**0.656**	**0.633**	**0.665**	**0.681**	**0.555**	**0.638**		
LLaVA [46]	Clean image	0.383	0.436	0.402	0.437	0.281	0.388	13.3B	224
	MF-it	0.389	0.441	0.417	0.452	0.288	0.397		
	MF-ii	0.396	0.440	0.421	0.450	0.292	0.400		
	MF-ii + MF-tt	**0.548**	**0.559**	**0.563**	**0.590**	**0.448**	**0.542**		
MiniGPT-4 [109]	Clean image	0.422	0.431	0.436	0.470	0.326	0.417	14.1B	224
	MF-it	0.472	0.450	0.461	0.484	0.349	0.443		
	MF-ii	0.525	0.541	0.542	0.572	0.430	0.522		
	MF-ii + MF-tt	**0.633**	**0.611**	**0.631**	**0.668**	**0.528**	**0.614**		

CLIP scores (↑)

1. Transfer-based attack
2. Query-based attack
3. MF-ii > MF-it --- overfit
4. MF-ii + MF-tt --- best

Experiments (Interpretable)

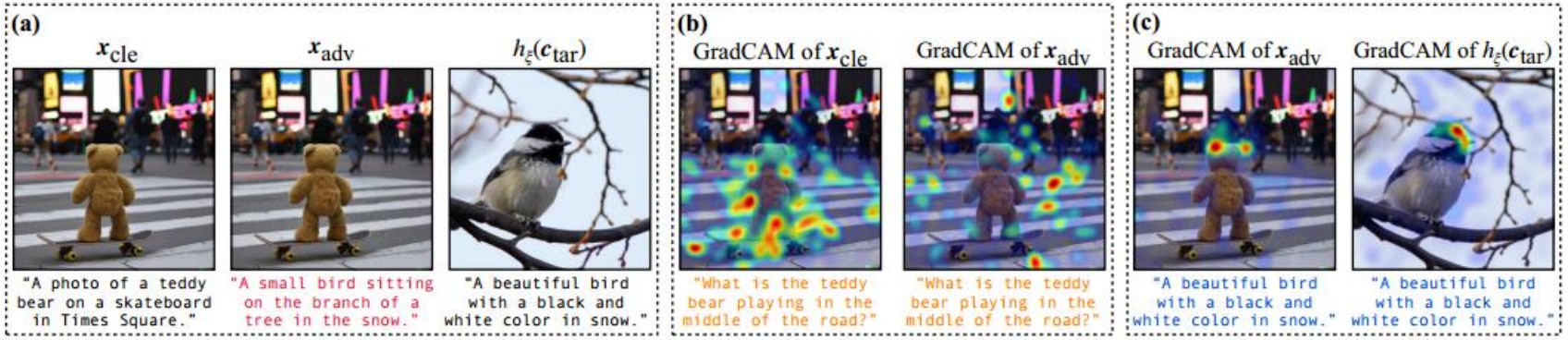
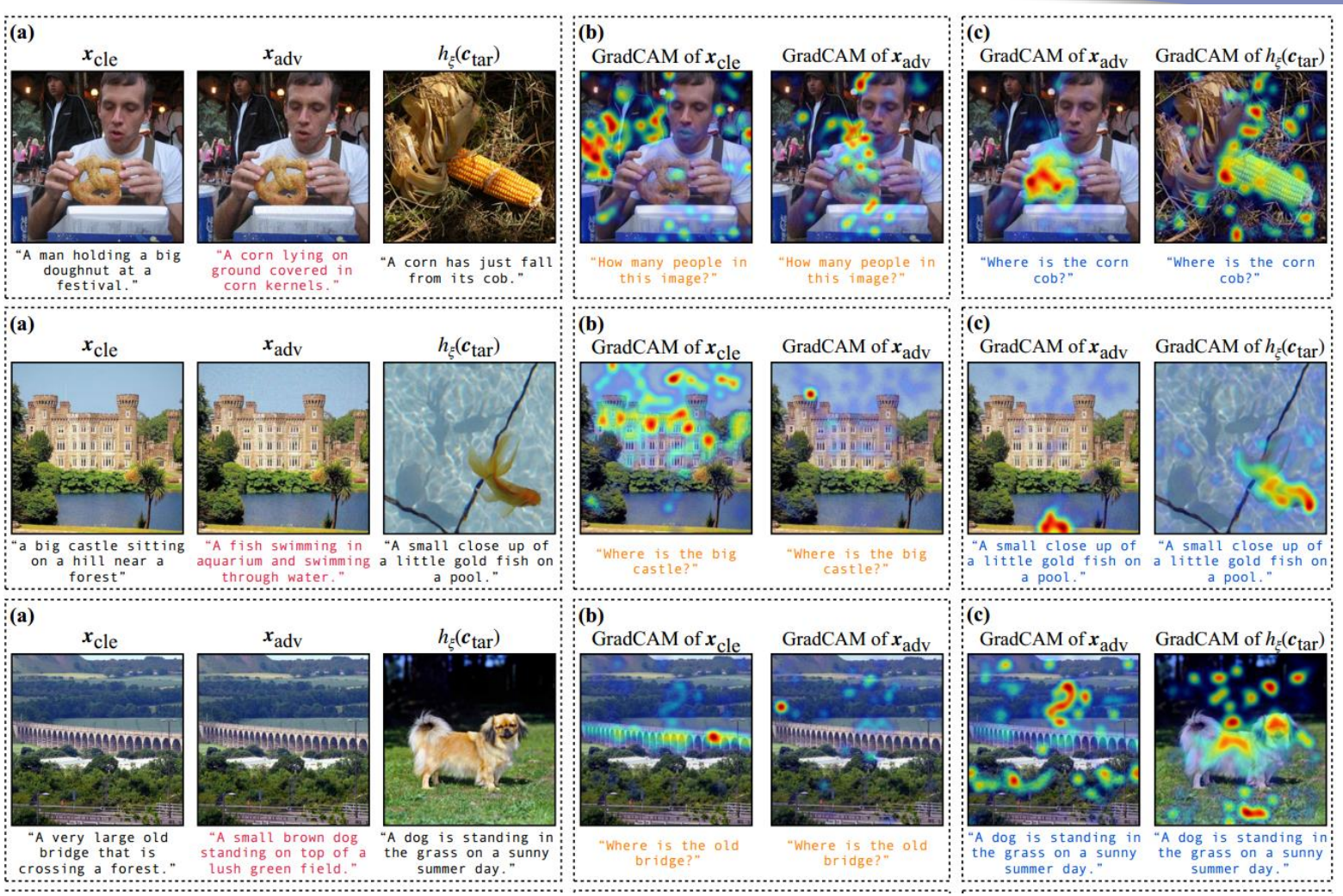


Figure 8: **Visually interpreting our attacking mechanism.** To better comprehend the mechanism by which our adversarial examples deceive large VLMs (here we evaluate Img2Prompt), we employ interpretable visualization with GradCAM [75]. **(a)** An example of $\boldsymbol{x}_{\text{cle}}$, $\boldsymbol{x}_{\text{adv}}$, and $h_\xi(\boldsymbol{c}_{\text{tar}})$, along with the responses they generate. We select the targeted text as `a beautiful bird with a black and white color in snow`. **(b)** GradCAM visualization when the input question is: `what is the teddy bear playing in the middle of the road?` As seen, GradCAM can effectively highlight the skateboard for $\boldsymbol{x}_{\text{cle}}$, whereas GradCAM highlights irrelevant backgrounds for $\boldsymbol{x}_{\text{adv}}$. **(c)** If we feed the targeted text as the question, GradCAM will highlight similar regions of $\boldsymbol{x}_{\text{adv}}$ and $h_\xi(\boldsymbol{c}_{\text{tar}})$.

Experiments (Interpretable)



Experiments (perturbation budget)

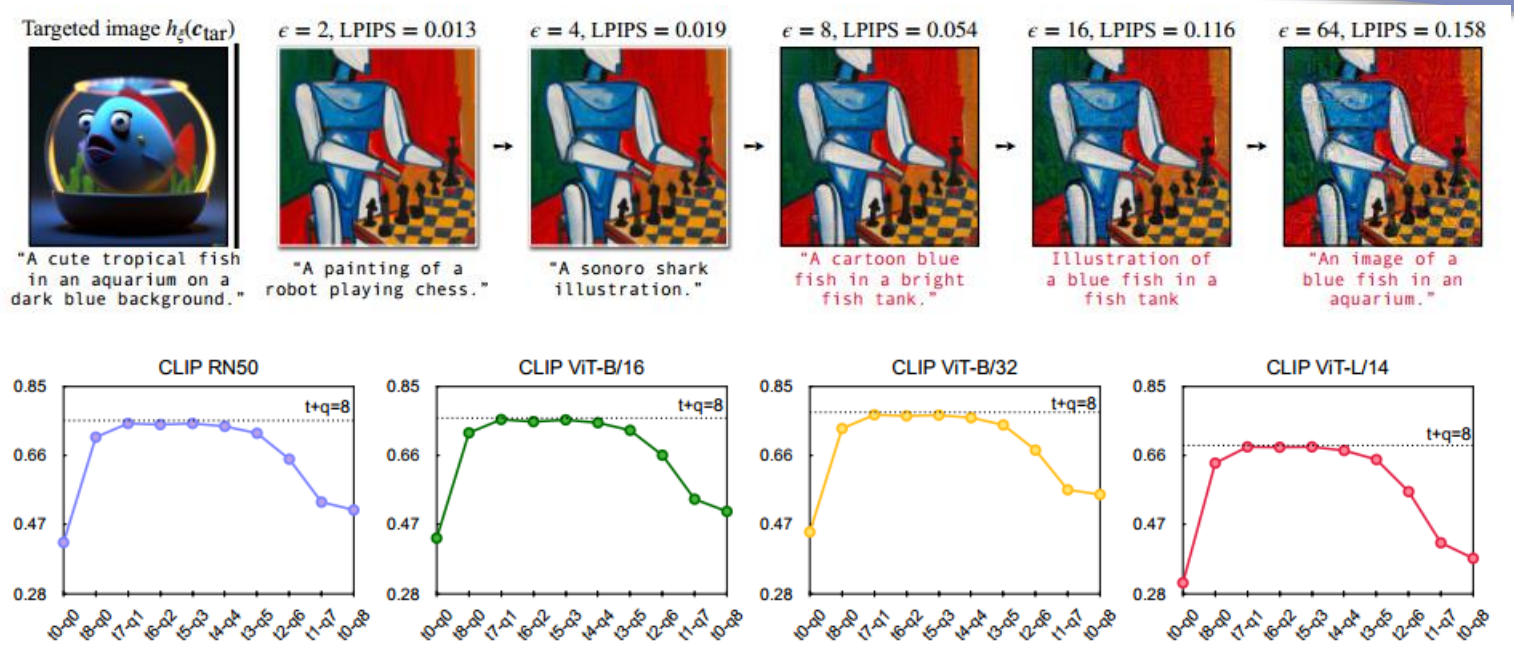


Figure 7: **Performance of our attack method under a fixed perturbation budget** $\epsilon = 8$**.** We interpolate between the sole use of transfer-based attack and the sole use of query-based attack strategy. We demonstrate the effectiveness of our method via CLIP score (↑) between the generated texts on adversarial images and the target texts, with different types of CLIP text encoders. The x-axis in a "tϵ_t-qϵ_q" format denotes we assign ϵ_t to transfer-based attack and ϵ_q to query-based attack. "t+q=8" indicates we use transfer-based attack ($\epsilon_t = 8$) as initialization, and conduct query-based attack for further 8 steps ($\epsilon_q = 8$), such that the resulting perturbation satisfies $\epsilon = 8$. As a result, We show that a proper combination of transfer/query based attack strategy achieves the best performance.

Experiments (Smoothing)

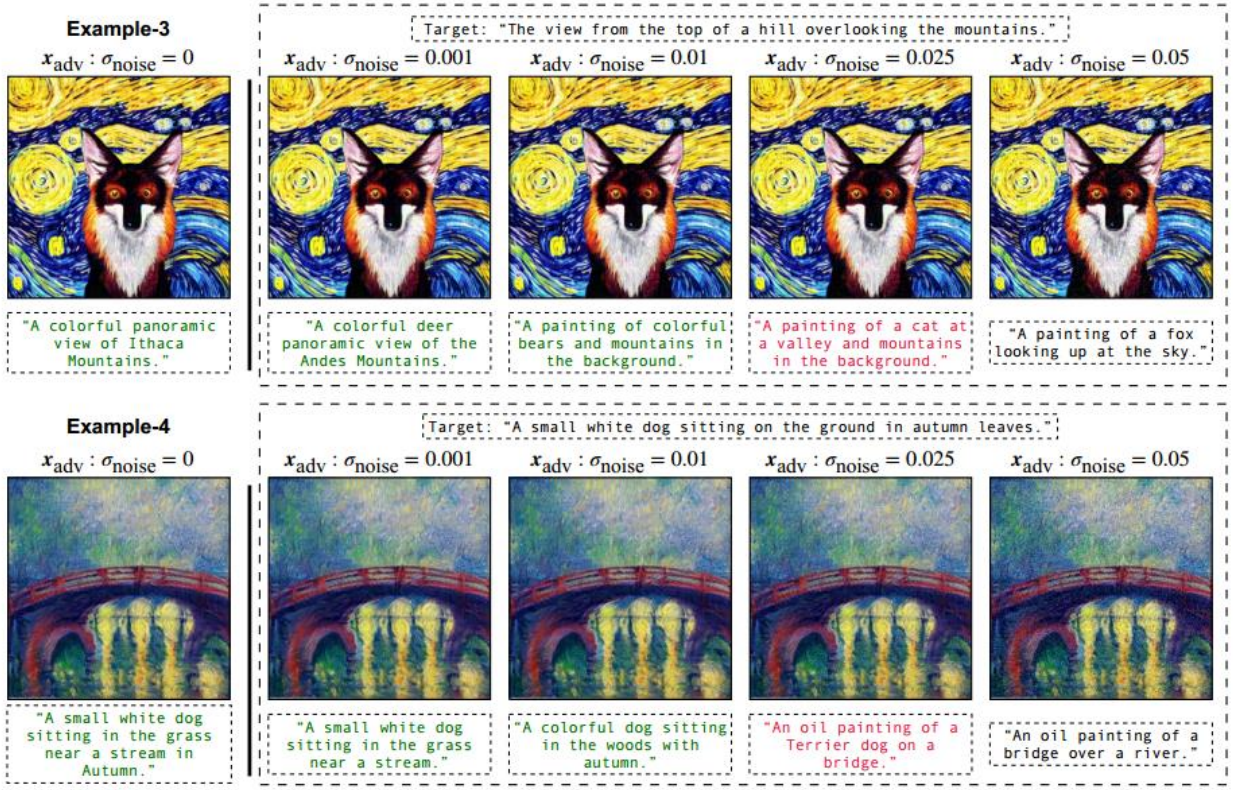
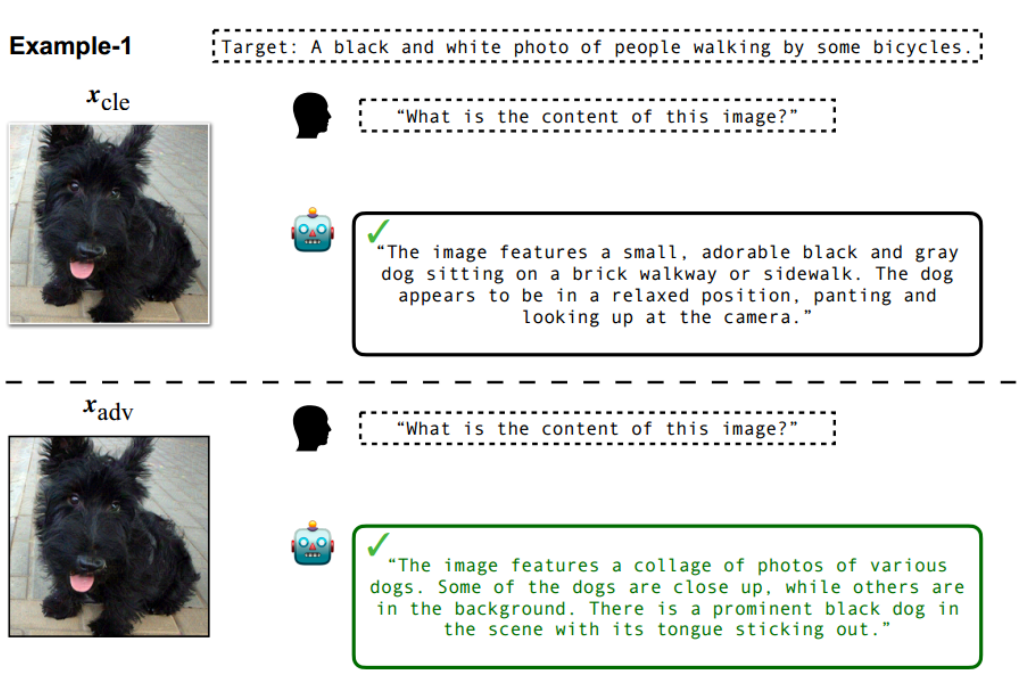


Figure 15: **Sensitivity of adversarial examples to Gaussian noises.** Our adversarial examples are found to be relatively insensitive to post-processing perturbations like Gaussian noises. Alternatively, interesting observations emerge when gradually increasing the standard deviation σ_{noise} of the Gaussian noises added to $\boldsymbol{x}_{\text{adv}}$, where the effectiveness of our learned adversarial examples becomes marginal and the targeted responses (in green) gradually degrade to the original, correct response (in **black**). In addition, we note that an intermediate state exists in which the generated response is a combination of the targeted text and the original generated response (in red).

Experiments (Failure ones)



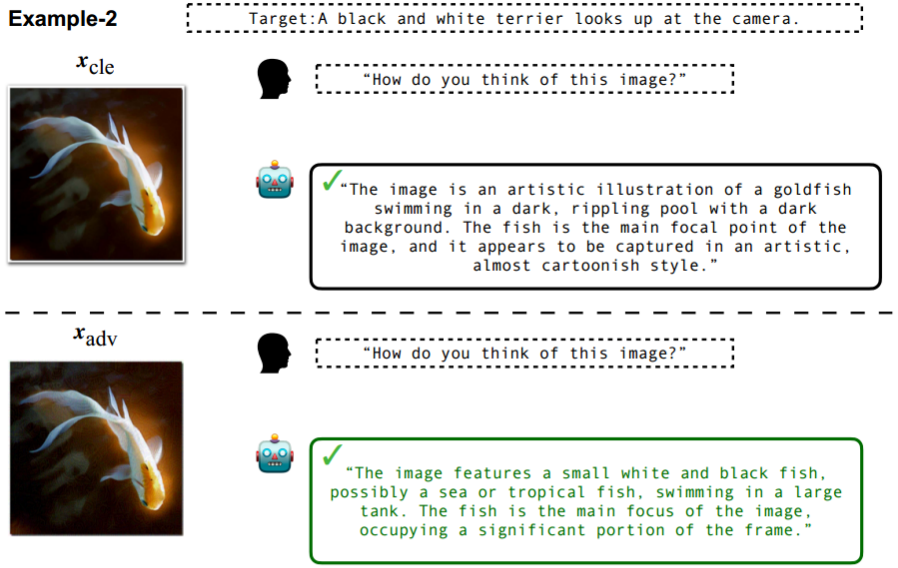


Figure 16: **Failure cases found in our experiments.** The generated adversarial image responses appear to be a state in between the text description of the clean image and the predefined targeted text. In this figure, we use LLaVA [46] as the conversation platform, but similar observations can be made with other large VLMs. On the other hand, we discovered that increasing the steps for adversarial attack (we set 100 in main experiments) could effectively address this issue (note that the perturbation budget remains unchanged, e.g., $\epsilon = 8$).

Experiments (Consumption)

Table 3: The GPU hours consumed for the experiments conducted to obtain the reported values. CO_2 emission values are computed using https://mlco2.github.io/impact [39]. Note that our experiments primarily utilize pretrained models, including the surrogate models, text-to-image generation models, and the victim models for adversarial attack. As a result, our computational requirements are not demanding, making it feasible for individual practitioners to reproduce our results.

Experiment name	Hardware platform	GPU hours	Carbon emitted in kg
Table 1 (Repeated 3 times)	NVIDIA A100 PCIe (40GB)	126	9.45
Table 2 (Repeated 3 times)		2448	183.6
Figure 1	NVIDIA A100 PCIe (40GB)	12	0.9
Figure 2		18	1.35
Figure 3		36	2.7
Figure 5		12	0.9
Figure 6		12	0.9
Figure 7		24	1.8
Hyperparameter Tuning	NVIDIA A100 PCIe (40GB)	241	18.07
Analysis		120	9.0
Appendix		480	36.0
Total	-	**3529**	**264.67**