

## Research Achievements At-A-Glance



Prompts: A snake and a young man  
 Prompts: A snake and a young man C63RR  
 Prompts: A snake and a young man -08=\*

(a) No attack. (b) Untargeted attack. (c) Targeted attack.

**Figure 1.** An illustration of our attack method against Stable Diffusion. The generated perturbations are highlighted in blue. The targeted attack aims to erase the image content related to ‘young man’ highlighted in red.

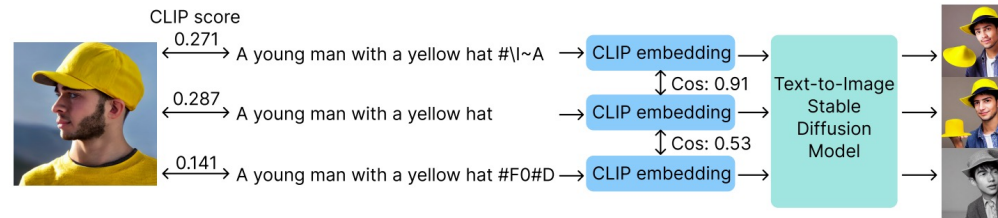
## Research question

Can we generate adversarial perturbations against Text-to-Image (T2I) models in a query-free regime?

## Contributions

- ❖ We develop a query-free adversarial attack generator for T2I Diffusion Models. We show that a five-character perturbation is able to significantly alter the content of synthesized image.
- ❖ We provide an analysis of the correspondence between the semantics of synthesized images and the embeddings of CLIP. The obtained insight further drives us to develop a controllable “targeted” attack, where the perturbations can be refined to steer the DM’s output.
- ❖ In particular, we demonstrate that both the proposed untargeted and targeted Query-Free Attack can successfully alter the output image content with 5-character prompt perturbation.

## Query-Free Adversarial Attack



**Figure 2.** Illustration of robustness issue in CLIP text encoder for image generation.

- ❖ We generate adversarial textual prompts by leveraging the lack of robustness of CLIP’s text encoder to fool the Stable Diffusion.
- ❖ The **Untargeted** attack aims to deviate images generated by perturbed prompts from the original prompts. We consider PGD attack [2], Greedy search, and Genetic algorithm for the attacker’s objective:

$$\min_{\mathbf{x}'} \cos(\tau_{\theta}(\mathbf{x}), \tau_{\theta}(\mathbf{x}')),$$

where  $\mathbf{x}$  denotes the original prompt,  $\mathbf{x}'$  denotes perturbed prompt, and  $\tau_{\theta}(\mathbf{x})$  denotes the text encoder of CLIP.

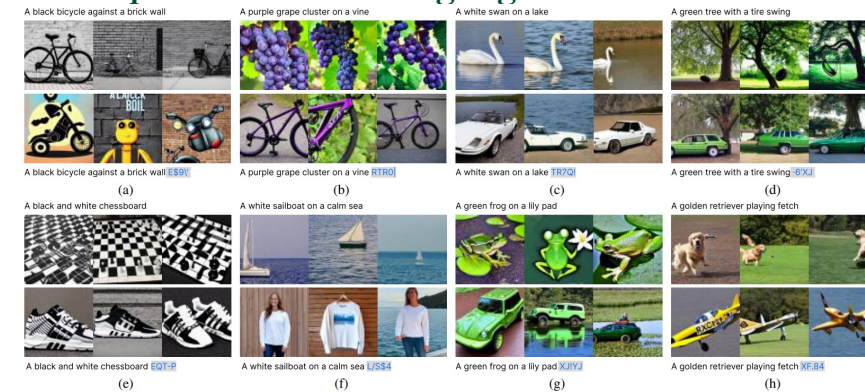
- ❖ We propose **steerable key dimensions** by identifying dimensions through a majority vote of difference vectors, which are difference of text embedding vectors with and without the targeted objects.
- ❖ The **Targeted** attack aims to impact the specific object in the images, e.g., the young man in the image. The attacker’s objective is:

$$\min_{\mathbf{x}'} \cos(\tau_{\theta}(\mathbf{x}) \odot I, \tau_{\theta}(\mathbf{x}') \odot I),$$

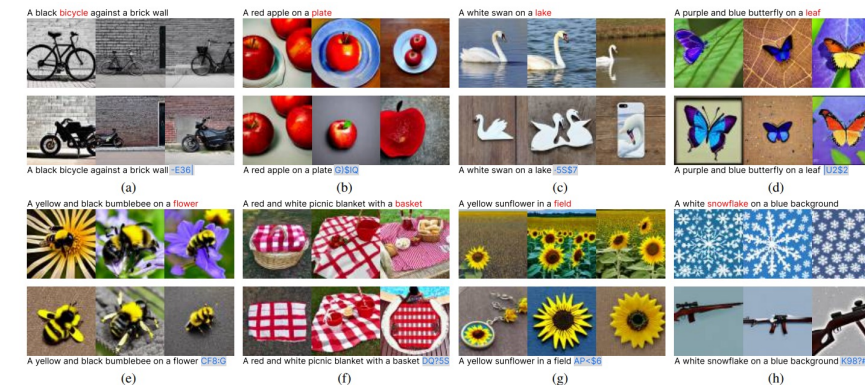
where  $\odot$  is the element-wise product,  $\mathbf{x}'$  denotes perturbed prompt, and  $\tau_{\theta}(\mathbf{x})$  denotes the text encoder of CLIP.

[1] Alec Radford et al. “Learning transferable visual models from natural language supervision.” PMLR 2021.  
 [2] Bairu Hou et al. “Textgrad: Advancing robustness evaluation in nlp by gradient-driven optimization.” ICLR 2023.

## Experiment Result Highlights



**Figure 3.** **Untargeted attack** of query-free attacks. The perturbations found by our method are highlighted in blue in the prompt. Images in the same column share the same random seed.



**Figure 4.** **Targeted attack** of query-free attacks. Input perturbations are generated to modify/remove the red text-related image content. Other settings are aligned with Fig. 3.

Method:	No Attack	Random	Greedy	Genetic	PGD
Untargeted Attack					
Score:	0.277±0.022	0.271±0.021	0.255±0.039	<b>0.203±0.042</b>	0.226±0.041
Targeted Attack					
Score:	0.229±0.03	0.223±0.037	0.204±0.037	<b>0.186±0.04</b>	0.189±0.041

**Table 1.** CLIP scores comparison of images generated with different methods