Ask, Attend, Attack: An Effective Decision-Based Black-Box Targeted Attack for Image-to-Text Models

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Abstract

While image-to-text models have demonstrated significant advancements in various vision-language tasks, they remain susceptible to adversarial attacks. Existing white-box attacks on image-to-text models require access to the architecture, gradients, and parameters of the target model, resulting in low practicality. Although the recently proposed gray-box attacks have improved practicality, they suffer from semantic loss during the training process, which limits their targeted attack performance. To advance adversarial attacks of image-to-text models, this paper focuses on a challenging scenario: decision-based black-box targeted attacks where the attackers only have access to the final output text and aim to perform targeted attacks. Specifically, we formulate the decision-based black-box targeted attack as a large-scale optimization problem. To efficiently solve the optimization problem, a three-stage process *Ask, Attend, Attack*, called *AAA*, is proposed to coordinate with the solver. *Ask* guides attackers to create target texts that satisfy the specific semantics. *Attend* identifies the crucial regions of the image for attacking, thus reducing the search space for the subsequent *Attack*. *Attack* uses an evolutionary algorithm to attack the crucial regions, where the attacks are semantically related to the target texts of *Ask*, thus achieving targeted attacks without semantic loss. Experimental results on transformer-based and CNN+RNN-based image-to-text models confirmed the effectiveness of our proposed *AAA*.

1 Introduction

Image-to-text models, referring to generating descriptive and accurate textual descriptions of images, have received increasing attention in various applications, including image-captioning [1, 2], visual-question-answering [3, 4], and image-retrieval [5, 6]. Despite the remarkable progress, they are vulnerable to deliberate attacks, giving rise to concerns about the reliability and trustworthiness of these models in real-world scenarios. For example, one may mislead models to output harmful content such as political slogans and hate speech by making imperceptible perturbations to images [7, 8, 9, 10, 11].

To gain insight into the reliability and trustworthiness of the image-to-text models, a series of adversarial attack methods have been proposed to poison the outputted textual descriptions of given

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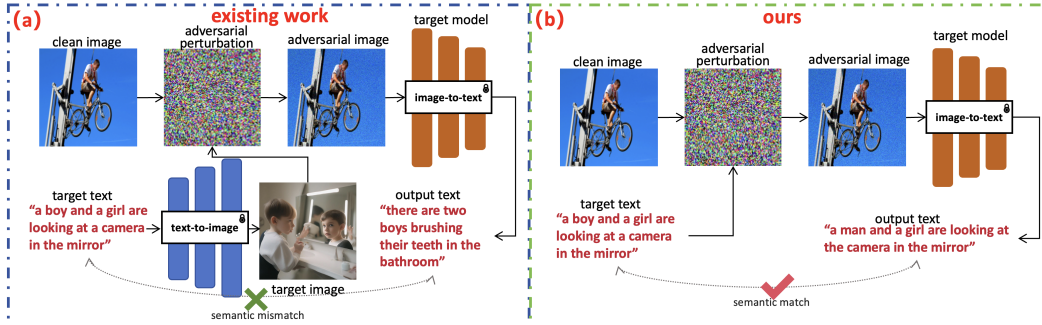
Figure 1: The semantic loss problem is existing in existing gray-box targeted attack methods.

images [7, 12, 13, 10]. Specifically, based on the attacker's level of access to information about the target model, they can be divided into three categories: white-box attacks [7, 14, 12], gray-box attacks [13, 10], and black-box attacks [15, 16, 17, 18, 19]. The white-box attacks can obtain target models' information including the entire architecture, parameters, gradients of both the image encoder and text decoder, and probability of each word of the output text. Gray-box attacks can only access the architecture, parameters, and gradients of the image encoder, while black-box attacks cannot access any internal information of the target model, but only the output text of the model. Furthermore, black-box attacks can be divided into score-based and decision-based attacks. Score-based black-box attacks can access the probability of each word of the output text [16], while decision-based black-box attacks can only access the output text [15, 20, 21]. Because less information about the target models is provided, decision-based black-box attacks are more challenging than other categories [21]. Additionally, these attack methods can be categorized based on whether the attacker is able to specify the incorrect output text, dividing them into two types: targeted and untargeted attacks [22, 13].

Although numerous adversarial attack methods for image-to-text models have been proposed, to our best knowledge, the study on black-box attacks is under-explored, especially decision-based black-box targeted attacks. This kind of attack is more challenging due to the following reasons. Firstly, less information on the target model can be accessed. Specifically, only the output text instead of gradients, architectures, parameters, and the probability of each word in the output text is available. Secondly, the attackers not only cause the target model to output incorrect text, but also outputs the specified target text. Existing attacks easily suffer from the loss of semantics, resulting in the inability to effectively output the specified target text. Figure 1 (a) show that transfer+query [10] fabricates one target text to poison the target image-to-text model, leading to this model outputting an incorrect text. However, the output text could mismatch the original semantics of the target text, as the target image-to-text model may focus on secondary information while ignoring the crucial semantics of the target text behind the target image, resulting in semantic loss. More examples are in Appendix B.1.

To narrow the research gap, we propose a decision-based black-box targeted attack approach for image-to-text models. In our work, only the output text of the target model can be accessed, which is closer to the real-world cases [15]. Additionally, Figure 1 (b) demonstrates our targeted attack method, which optimizes against the target text directly under the decision-based black-box conditions, preventing semantic loss and maintaining semantic consistency with the target text.

Perturbing pixels in the image can change the output text. Therefore, the objective of the targeted attack can be considered to find the imperceptible pixel modification to make the output text similar to the target text. In this manner, the targeted attack can be formulated as a large-scale optimization problem, where pixels are decision variables and the optimization objective is to poison the output text. Inspired by the distinctive competency of evolutionary algorithms for solving large-scale optimization problems [23, 24, 25, 26, 27], we develop a dedicated evolutionary algorithm-based framework for decision-based black-box targeted attacks on image-to-text models. However, directly applying evolutionary algorithms to solve this large-scale optimization problem could suffer from low search efficiency, due to the numerous pixels and their wide range of values. To address the issue, we embed

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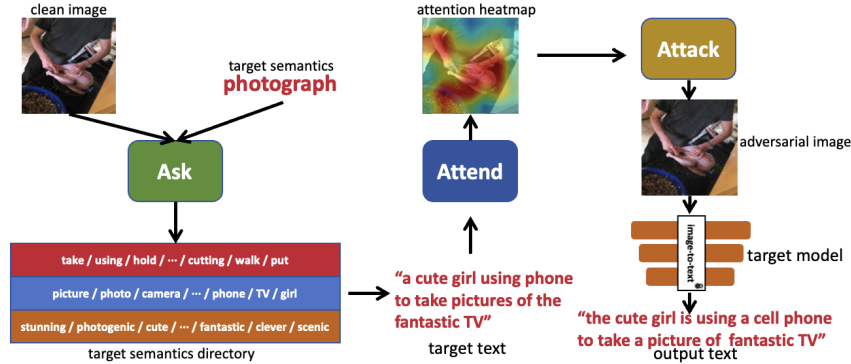
Figure 2: Diagram of our decision-based black-box targeted attack method *Ask, Attend, Attack*.

three-step processes, i.e., *Ask, Attend, Attack*, into the proposed evolutionary algorithm-based attacks. As shown in Figure 2, during the *Ask* stage, attackers can arbitrarily specify words related to certain semantics, such as *photograph*. Then, candidate words (e.g., *camera*, *scenic*, and *phone*) that are related to certain semantics are searched. Meanwhile, these words are close to the clean image in the feature space of the target image-to-text model. By selecting words from the candidate words, the target text (e.g., *a cute girl using a phone to take pictures of the fantastic TV*) related to the attacker's specified semantics can be formed to poison the target model. Subsequently, based on the attention mechanism, *Attend* identifies the crucial regions of the clean image (e.g. attention heatmap) [28, 29], thus reducing the search space for the subsequent *Attack*. Lastly, *Attack* uses a differential evolution strategy to impose imperceptible adversarial perturbations on the crucial regions, where the optimization objective is to minimize the discrepancy between the target text in *Ask* stage and the output text of the target model. Our contributions can be summarized as follows:

1. We first propose a decision-based black-box targeted attack *Ask, Attend, Attack* (*AAA*) for image-to-text models. Specifically, our method achieves targeted attacks without losing semantics while only the model's output text can be accessed.

2. We designed a target semantic directory to guide attackers in creating target text and utilized attention heatmaps to significantly reduce search space. This improves the search efficiency of evolutionary algorithms in adversarial attacks and makes attacks difficult to perceive.

3. We conducted extensive experiments on the Transformer-based VIT-GPT2 model and CNN+RNN-based Show-Attend-Tell model, which are the two most-used image-to-text models in HuggingFace, and surprisingly found that our decision-based black-box method has stronger attack performance than existing gray-box methods.

2 Related work

2.1 White-box Attack

In white-box attacks, the attacker has full access to all parameters, gradients, architecture of the target model, and the probability of each word of the output text. The authors in [7] add invisible perturbations to the image to make the image-to-text model produce wrong or targeted text outputs. The authors in [30] add global or local perturbations to the image to make the vision and language models unable to correctly locate and describe the content of the image. The authors in [14] modify the content of the image at the semantic level to make the image-to-text model output text that is inconsistent with the original image. The authors in [31] craft adversarial examples with semantic embedding of targeted captions as perturbation in the complex domain. The authors in [32] preserve the accuracy of non-target words while effectively removing target words from the generated captions. The authors in [33] generate coherent and contextually rich story endings by integrating textual narratives with relevant visual cues. The authors in [12] add limited-area perturbations to the image to make the image-to-text model fail to correctly describe the content of the perturbed area. The above methods require complete information of the image-to-text target model, including architecture, gradients, parameters, and probability distribution of the output text, which limits their practicality.

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2.2 Gray-box Attack

To improve the practicality of adversarial attacks for image-to-text models, recent research explores how to attack with partial knowledge of the target model. All existing gray-box attack studies [34, 22, 13, 10] assume full access to the image encoder of the image-to-text model. The basic idea of gray-box targeted attacks is to reduce the distance between the adversarial image and the target image generated based on the target text in the image encoder's feature space. The authors in [34] generate adversarial images to mimic the feature representation of original images. The authors in [22] use a generative model to destroy the image encoder's features, achieving the untargeted attack. The authors in [13] minimize the feature distance in the image encoder between the adversarial image and the target image, thereby using gradient back-propagation to optimize the adversarial image and achieve the targeted attack. The authors in [10] combine existing gray-box method [13] with pseudo gradient estimation method [35] to achieve better performance in targeted attack. It is worth noting that they [10] call their method a black-box attack, but since they use the image encoder of the target model as the surrogate model, we classify their method as a gray-box attack. These gray-box attacks on image-to-text models are more practical than white-box attacks, but it is still unrealistic to assume that attackers can access the image encoder of the image-to-text model. Moreover, existing gray-box methods may have poor targeted attack performance due to the semantic loss mentioned above.

3 Methodology

3.1 Problem Formulation

The image-to-text model $\mathcal{G} : \mathcal{X} \rightarrow \mathcal{Y}$ maps the image domain $\mathcal{X}$ to the text domain $\mathcal{Y}$. A well-trained model should be able to accurately describe the content of the image using grammatically correct and contextually coherent text. Given a target text y_t, the attacker's goal is to find an adversarial image $\mathbf{x_{adv}}$ that is visually similar to clean image $\mathbf{x}$ and can generate an adversarial text y_{adv} that is semantically similar to y_t. We formalize the optimization problem for black-box targeted attack as:

$$\arg \max_{\mathbf{x}_{adv}} S(\mathcal{G}(\mathbf{x_{adv}}), y_t) \ \text{ s.t. } \frac{1}{n} \sum_{i=1}^{n} \|\mathbf{x_{adv}}(i) - \mathbf{x}(i)\| \leq \epsilon, \tag{1}$$

where $S(\cdot, \cdot)$ represents the semantic similarity function between two texts, ϵ is the threshold for the average perturbation size per pixel, $\mathbf{x_{adv}}(i)$ and $\mathbf{x}(i)$ represents the value of the i-th pixel in the adversarial and clean images. n is the total number of pixels in all channels of the image.

3.2 Overview

To enhance the efficiency and stealth of decision-based black-box attacks, we propose the *Ask, Attend, Attack* (*AAA*) framework as shown in Figure 2. *Ask*: We compile a semantic dictionary from words within the input image's search space that align with the attacker's specified semantics. This facilitates targeted text generation, meeting the attacker's target semantics while simplifying the search process. *Attend*: We employ attention visualization and a surrogate model to generate an attention heatmap for the target text on the image, narrowing the search to significant decision variables and enhancing perturbation stealth. *Attack*: We use the differential evolution in the reduced search space to find the optimal solution that can mislead the target model to output target text. The framework's pseudo-code is detailed in Appendix A.1.

3.3 Ask Stage

According to the target semantics, the goal of *Ask* is to find words in the feature space of the target model to form a target semantic dictionary. These words should be closer to the input image. Firstly, we treat each pixel in each channel of image $\mathbf{x}$ as a variable, which means the search space size is the product of length, width, and number of channels. And then generate NP (number of population) individuals to form a population based on the following formula:

$$\mathbf{x}_j(i) = \mathbf{x}(i) + rand(-1, 1) \cdot \eta, \tag{2}$$

where $\mathbf{x}(i)$ is the i-th variable of clean image $\mathbf{x}$, $\mathbf{x}_j(i)$ is the i-th variable of the j-th individual in the population, η is a hyperparameter about the maximum search range, *rand*(-1,1) is a random number from the range of -1 to 1.

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Secondly, for each variable, random mutation occurs between different individuals. The mutation for the i-th variable of the j-th individual $\mathbf{x}_j(i)$ is as follows:

$$\mathbf{v}_j^g(i) = \mathbf{x}_{r1}^g(i) + F * (\mathbf{x}_{r2}^g(i) - \mathbf{x}_{r3}^g(i)), \tag{3}$$

where $\mathbf{v}_j^g(i)$ is the mutated variable for mutation in the g-th generation of $\mathbf{x}_j(i)$. $\mathbf{x}_{r1}^g(i)$, $\mathbf{x}_{r2}^g(i)$, and $\mathbf{x}_{r3}^g(i)$ are three randomly selected individuals from the current population who are different from each other, F is the scaling factor.

Thirdly, each individual crossovers with the mutated individuals with a certain probability of generating candidate individuals. The formula is as follows:

$$\mathbf{u}_j^g(i) = \begin{cases} \mathbf{v}_j^g(i), & \text{if rand } (0,1) \leq CR, \\ \mathbf{x}_j^g(i), & \text{otherwise,} \end{cases} \tag{4}$$

where CR is crossover probability factor, $\mathbf{u}_j^g(i)$ is the i-th variable of the candidate individual in the g-th generation of the j-th individual in the population.

Fourthly, we use WordNet [36], a synonym dictionary, to measure the similarity between the target semantics and each individual's output text. WordNet groups words with the same semantics into synonyms, each representing a basic concept. We use WordNet to count the same semantic words m between each individual's output text and the target semantics. We calculate the $Precison=(m/t)$ and $Recall=(m/r)$, where t is the output text word count and r is the target semantics word count. Then, we calculate semantic similarity using the following formula:

$$S_{sem} = \frac{(1 - \gamma(\frac{ch}{m})^\theta)(\alpha^2 + 1) \cdot Precision \cdot Recall}{\alpha^2 \cdot Precision + Recall}, \tag{5}$$

where S_{sem} is the semantic similarity between the individual's output text and the target semantics [36], α balances the precision and recall weights, γ and θ control the penalty factor strength, ch is the number of consecutive word sets that match between the output text and the target semantics, with fewer chunks meaning more consistent word order.

Ultimately, we select offspring based on S_{sem}, choosing the current and candidate individuals that match the target semantics better as the next generation:

$$\mathbf{x}_j^{g+1} = \begin{cases} \mathbf{u}_j^g, & S_{sem}(\mathcal{G}(\mathbf{u}_j^g), TS) \geq S_{sem}(\mathcal{G}(\mathbf{x}_j^g), TS), \\ \mathbf{x}_j^g, & \text{otherwise,} \end{cases} \tag{6}$$

where TS is the attacker's target semantics. We extract nouns, adjectives, and verbs from the output texts of all the more semantically relevant and preserved individuals of each generation, expanding the target semantic dictionary. We use $\mathcal{G}(\mathbf{x}_j^{g+1}) = \{w_1, w_2, \cdots, w_n\}$ to represent the target model $\mathcal{G}$'s output text for the next generation of individuals, where w_i is the i-th word of the text and n is the word count. Then we use the following formula to extract important words and make a dictionary:

$$\mathbf{D}_j^{g+1} = \{w \in \mathcal{G}(\mathbf{x}_j^{g+1}) \mid w \text{ is noun, adjective or verb}\}, \tag{7}$$

where $\mathbf{D}_j^{g+1}$ is the dictionary for the preserved individual. We combine the dictionaries of each preserved individual in each generation to get the target semantic dictionary $\mathbf{D} = \mathbf{D}_1^2 \cup \mathbf{D}_2^2 \cup \cdots \cup \mathbf{D}_{\text{NP}}^m$, where m is the total number of generation. The attacker selects words from dictionary $\mathbf{D}$ that match the specified semantics to make the target text y_t. Words in dictionary $\mathbf{D}$ near input image $\mathbf{x}$ in feature space enhance searchability, enabling more efficient targeted attacks.

3.4 Attend Stage

The goal of *Attend* is to calculate the target text's attention area on the image $\mathbf{x}$. Because we do not have access to the internal information of the target model, we can only calculate the Grad-CAM attention heatmap [37] with the help of surrogate model f (such as ResNet trained in ImageNet). The surrogate model's sole purpose is to the compute attention heatmap. Since different models produce similar heatmaps for the same target text and input image, selecting a well-established visual model suffices [38]. The calculation formula of attention heatmap $\mathbf{A}$ is as follows:

$$\mathbf{A}(i,j) = \text{MAX}\left(0, \frac{1}{Z}\sum_k \sum_i \sum_j \cdot \frac{\partial y^{c^*}}{\partial \mathcal{F}_k(i,j)} \cdot \mathcal{F}_k(i,j)\right), \tag{8}$$

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where $\mathbf{A}(i,j)$ is the decision-making contribution of the image to the target text at pixel (i,j), $\mathcal{F}_k(i,j)$ is the pixel (i,j) of the feature map of the k-th convolution kernel of the last convolutional layer of the surrogate model f, Z is the feature map's pixel count, y^{c^*} is the probability that f predicts that the image $\mathbf{x}$ belongs to class c^*. We use $\mathbf{C} = \{c_1, c_2, \cdots, c_{1000}\}$ for the ImageNet category names, where c_i is the i-th category name. We make the category text $y_{c_i} =$ "*a photo of*" $+ c_i$ from the category name c_i. We calculate the category c^* as:

$$c^* = \underset{c_i \in C}{argmax} \, \frac{E(y_t) \cdot E(y_{c_i})}{\|E(y_t)\|_2 \|E(y_{c_i})\|_2},\tag{9}$$

where E is the text encoder of the pre-trained CLIP model, and c^* is the closest category to the target text. We substitute c^* into Formula 8 to get the target text's attention heatmap $\mathbf{A}$. $\mathbf{A}(i,j)$ is the pixel (i,j)'s contribution to the target text. 1 means more contribution, and 0 means less contribution.

Table 1: Performance comparison (%) of different attack methods.

ϵ	Attack Methods	VIT-GPT2				Show-Attend-Tell			
		METEOR	BLEU	CLIP	SPICE	METEOR	BLEU	CLIP	SPICE
	Clean Sample	0.201±0.11	0.24±0.11	0.64±0.07	0.156±0.07	0.21±0.11	0.229±0.13	0.646±0.09	0.179±0.08
25	transfer (black)	0.206±0.11	0.246±0.11	0.639±0.07	0.165±0.07	0.211±0.12	0.225±0.14	0.648±0.09	0.185±0.11
	transfer+query (black)	0.221±0.16	0.264±0.15	0.651±0.18	0.167±0.07	0.219±0.11	0.231±0.14	0.654±0.05	0.187±0.14
	transfer (gray)	0.414±0.23	0.396±0.14	0.821±0.09	0.32±0.16	0.382±0.26	0.348±0.17	0.782±0.11	0.299±0.17
	transfer+query (gray)	0.433±0.21	0.411±0.12	0.832±0.13	0.35±0.09	0.401±0.21	0.355±0.15	0.794±0.11	0.311±0.13
	AAA (w/o *Attend*)	0.541±0.25	0.519±0.19	0.854±0.24	0.477±0.11	0.642±0.19	0.564±0.19	0.841±0.06	0.455±0.14
	AAA (w/o *Ask*)	0.398±0.21	0.384±0.18	0.795±0.25	0.412±0.13	0.364±0.21	0.322±0.19	0.754±0.08	0.376±0.13
	AAA	**0.696±0.21**	**0.658±0.22**	**0.952±0.29**	**0.634±0.15**	**0.855±0.15**	**0.799±0.21**	**0.964±0.04**	**0.786±0.14**
15	transfer (black)	0.204±0.09	0.241±0.15	0.627±0.18	0.164±0.07	0.232±0.13	0.236±0.14	0.643±0.08	0.187±0.09
	transfer+query (black)	0.211±0.14	0.256±0.15	0.644±0.15	0.181±0.09	0.245±0.13	0.246±0.11	0.656±0.06	0.203±0.09
	transfer (gray)	0.398±0.24	0.381±0.15	0.816±0.11	0.325±0.16	0.361±0.24	0.359±0.17	0.778±0.11	0.296±0.16
	transfer+query (gray)	0.408±0.19	0.399±0.11	0.824±0.15	0.341±0.13	0.375±0.19	0.368±0.15	0.784±0.11	0.311±0.13
	AAA (w/o *Attend*)	0.461±0.21	0.423±0.15	0.808±0.11	0.375±0.09	0.438±0.15	0.434±0.16	0.827±0.04	0.422±0.14
	AAA (w/o *Ask*)	0.378±0.25	0.361±0.17	0.768±0.15	0.356±0.15	0.341±0.15	0.337±0.18	0.749±0.07	0.365±0.13
	AAA	**0.556±0.31**	**0.504±0.26**	**0.851±0.12**	**0.44±0.17**	**0.617±0.25**	**0.574±0.22**	**0.913±0.05**	**0.553±0.14**

3.5 Attack Stage

The goal of *Attack* is to search for the best individual (adversarial sample) that outputs the target text y_t in the smaller search space reduced by the attention heatmap. Firstly, we copy the attention heatmap $\mathbf{A}$ three times in the channel dimension to match the shape of the image $\mathbf{x}$. We generated NP (number of population) individuals as a population with this formula:

$$\mathbf{x}_j(i) = \mathbf{x}(i) + rand(-\mathbf{A}(i), \mathbf{A}(i)) \cdot \eta,\tag{10}$$

where $\mathbf{x}(i)$ is the i-th variable of clean image $\mathbf{x}$, $\mathbf{x}_j(i)$ is the i-th variable of the j-th individual in the population, $\mathbf{A}(i)$ is the contribution of the i-th variable to the target text, and $rand(-\mathbf{A}(i), \mathbf{A}(i))$ is a random number in the range from $-\mathbf{A}(i)$ to $\mathbf{A}(i)$. The value of $\mathbf{A}$ is less than 1, and its mean and median are about [0.3,0.4]. The search space volume from the attention heatmap is much smaller than a hypersphere with radius η, because the radius and volume have an exponential relationship. This improves the search efficiency and concealment of adversarial perturbation.

Secondly, in order to accelerate convergence and better find the global optimal solution, we use the following CurrentToBest mutation [39]:

$$\begin{aligned}\mathbf{v}_j^g(i) = \mathbf{x}_j^g(i) &+ F * (\mathbf{x}_{r1}^g(i) - \mathbf{x}_{r2}^g(i)) \\ &+ F * (\mathbf{x}_{best}^g(i) - \mathbf{x}_j^g(i)),\end{aligned}\tag{11}$$

where $\mathbf{x}_j^g(i)$ is the i-th variable of the j-th individual in the g-th generation, $\mathbf{v}_j^g(i)$ is the mutated variable, $\mathbf{x}_{best}^g$ is the best fitness individual in the g-th generation population, $\mathbf{x}_{r1}^g$ and $\mathbf{x}_{r2}^g$ are two randomly selected individuals in the g-th generation population, and F is the scaling factor. The main advantage of this mutation strategy is that it combines the information of the current individual $\mathbf{x}_j$ and the best fitness individual $\mathbf{x}_{best}$, which can better guide the search process towards the direction of the optimal solution.

Thirdly, we use Formula 4 to calculate the candidate individual $\mathbf{u}_j^g(i)$. We design the following formula to calculate the deep feature similarity S_{clip} between two texts (u and v):

$$S_{clip} = 1 - \frac{E(u) \cdot E(v)}{\|E(u)\|_2 \|E(v)\|_2},\tag{12}$$

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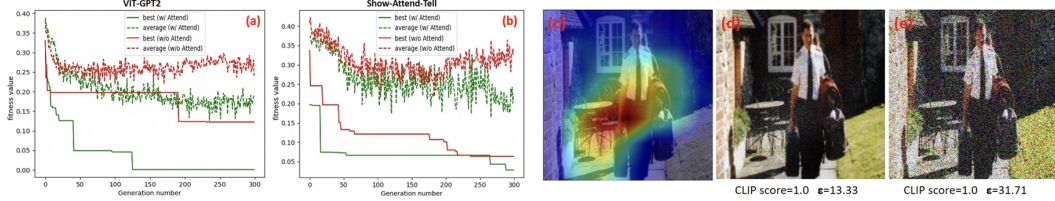
Figure 3: We compared the convergence curves of populations with and without *Attend* under the same perturbation size ϵ in (a-b). The fitness function is S_{clip} in Formula 12, where lower values mean stronger attacks. The dashed line is the average fitness value, and the solid line is the best fitness value. The green line is *AAA* and the red line is *AAA w/o Attend*. (c) shows the attention heatmap. (d) and (e) show the visual effects of adversarial image with and without *Attend*, with minimal perturbation of 100% attack success rate.
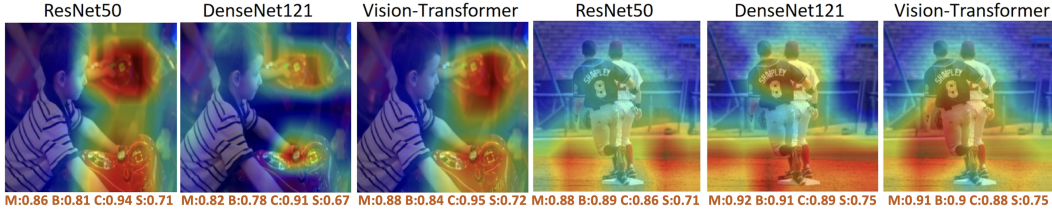
Figure 4: Grad-CAM attention heatmaps of different surrogate models for the same target text *a woman is holding a pair of shoes*. M is METEOR, B is BLEU, C is CLIP, S is SPICE.

where E is the text encoder of the pre-trained CLIP model. Text is discrete and complex, so it cannot calculate the distance directly [40]. Therefore, we use the CLIP text encoder E to extract the deep features of the texts, and then calculate the feature distance to obtain the similarity S_{clip} between the texts. The closer S_{clip} is to 0, the higher the similarity between the two texts u and v.

Ultimately, we select offspring using the following formula:

$$\mathbf{x}_j^{g+1} = \begin{cases} \mathbf{u}_j^g, & S_{clip}(\mathcal{G}(\mathbf{u}_j^g), y_t) \leq S_{clip}(\mathcal{G}(\mathbf{x}_j^g), y_t), \\ \mathbf{x}_j^g, & \text{otherwise}, \end{cases} \quad (13)$$

where $\mathbf{x}_j^{g+1}$ is the next individual with closer feature distance between the output text and the target text y_t. After performing the above evolutionary calculations multiple times, the optimal solution (adversarial sample) for outputting the target text is found.

4 Evaluation and Results

4.1 Experiment setups

Model and dataset We experimented with the two most-used image-to-text models on HuggingFace: VIT-GPT2 (Transformer-based) [41] and Show-Attend-Tell (CNN+RNN-based) [42]. VIT-GPT2 was trained on ImageNet-21k. Show-Attend-Tell was trained on MSCOCO-2014. We only used the target model's output text, not its internal information like gradients, parameters, or word probability. Following this work [13], we used Flick30k as our dataset, which has 31783 images and 5 caption texts each. We removed samples with less than 0.7 similarities between predicted text and truth text to ensure the target model's accuracy on clean images.

Evaluation metrics We used these evaluation metrics in our experiments: (1) BLEU(#4), an early machine translation metric that measures text precision [43]. 1 means similar, and 0 means dissimilar. (2) METEOR, a more comprehensive metric that considers synonyms, stems, word order, etc [36]. 1 means similar, and 0 means dissimilar. (3) CLIP, the distance between the CLIP text encoder's deep features for two texts [44]. 1 means similar, and 0 means dissimilar. (4) SPICE, an evaluation metric tailored for image-to-text models [45]. 1 means similar, and 0 means dissimilar. (5) ϵ, the mean perturbation size of each pixel of the adversarial sample [13].

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Figure 5: Performance of adversarial image attacks varies with perturbation size ϵ. The ϵ of (a) and (f) is 25, ϵ of (b) and (g) is 15, ϵ of (c) and (h) is 10, ϵ of (d) and (i) is 5. (e) is our attention heatmap of the target text on the image. (j) is the target image generated based on the target text used in existing works. M is METEOR score, B is BLEU score, and C is CLIP score.

4.2 Experiment results

Comparison experiment of existing gray-box attacks. We evaluate state-of-the-art gray-box attacks [13, 10] on image-to-text models. We designate the gray-box attack [13] as transfer (gray) and the one [10] as transfer+query (gray). To simulate a black-box environment, we adapted these gray-box attacks by employing the CLIP model's image encoder in lieu of the target model's encoder, resulting in "transfer (black)" and "transfer+query (black)" variants. As depicted in Table 1, adversarial samples generated by the original gray-box attacks exhibit a marked increase in textual similarity to the target text when compared to clean samples. Conversely, the black-box adaptations maintain a similarity level akin to that of clean samples, indicating a significant loss of attack capability upon changing the image encoder. This underscores the dependency of gray-box attacks on the target model's image encoder. Our proposed method *AAA* demonstrates superior attack performance in black-box scenarios compared to the existing methods in their native gray-box settings. This is attributed to the semantic loss inherent in existing gray-box attacks, which constrains their attacking potential. It is noteworthy that our work represents the first black-box attack on image-to-text models. So we can only compare our approach with existing gray-box attacks. We have adapted these gray-box attacks into a black-box version solely to demonstrate their ineffectiveness in a black-box scenario.

Ablation experiment of our black-box attack. We conducted ablation experiments on our *AAA* method. *AAA* (w/o *Attend*) means no attention heatmap to reduce the search space, but the proportional reduction of the search range. *AAA* (w/o *Ask*) means the target text is not from the target semantic dictionary, but random words. Table 1 shows that losing any module decreases our attack performance. In addition, *Ask* performs worse than *AAA* (w/o *Attend*), indicating that finding a target text with lower search difficulty contributes relatively more to the performance of our targeted attack.

Qualitative experiment of attention. We presented the optimization curves of *AAA* and *AAA* (w/o *Attend*) in Figure 3. Figure 3 (a) and (b) illustrate the best and average fitness values during *AAA* and *AAA* (w/o *Attend*) optimization of VIT-GPT2 and Show-Attend-Tell. It is evident that the inclusion of *Attend* expedites and enhances the convergence of the population, with an equivalent perturbation size. Consequently, *AAA* exhibits more effective concealment in adversarial perturbations, maintaining the same level of attack efficacy, as depicted in Figures 3 (d) and (e). Furthermore, we evaluated the impact of selecting different surrogate models during *Attend*. Notably, the sole function of the surrogate model is to compute the attention heatmap. Figure 4 demonstrates that, despite significant structural variances among several surrogate models, they produce strikingly similar attention heatmaps for the same target text and input images. This similarity arises from mapping the target text to the most pertinent category within the surrogate model's label space (as Formula 9).

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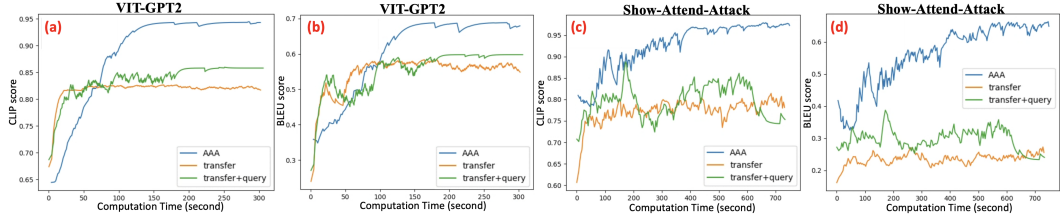
Figure 6: Comparison of computation time for generating a single adversarial sample using different adversarial attack methods. The y-axis is a measure of similarity between the generated text and the target text, with higher values indicating better target attack performance. The x-axis represents the computation time, and the shorter the time required to find a stable solution, the better.

The position of the same category of objects on the same picture is constant, and the model needs to focus on the object first, no matter what structure it is [38]. Performance comparisons, as shown in Figure 4, indicate that the similarity in attention heatmaps across different surrogate models leads to similar final attack performances. Therefore, we opted for a stable, well-established, pre-trained model, such as ResNet-50, to serve as our surrogate model.

Qualitative experiment of different perturbation sizes.   We used the words *mirror*, *cell phone*, *man*, *looking at* from the target semantic dictionary (as shown in Appendix B.2) to make the target text *a man is looking at a cell phone in a mirror*. We compared output texts of our black-box method *AAA* and the existing gray-box method [10] for adversarial samples with different ϵ, the average pixel perturbation size, in Figure 5. The same conclusion drawn from both methods is that bigger perturbation causes worse concealment and better attack performance; too small perturbation causes attack failure. Moreover, (f) and (j) in Figure 5 show that the existing methods have a semantic loss that limits their attack performance. Subjectively, target image (j) accurately draws the semantics of the target text, and the output text of adversarial image (f) perfectly describes the content of the target image (j). However the adversarial sample (f)'s output text does not have the semantics of the target text. Our method does not have semantic loss, so our black-box method *AAA* does a better targeted attack than the existing gray-box method. More examples of semantic loss are in Appendix B.1.

Comparison experiment on computation time.   We evaluated the computational efficiency of various attack methodologies for generating adversarial samples in image-to-text models. As depicted in Figure 6, our black-box attack method *AAA*, demonstrates a longer computation time to reach an optimal solution compared to existing gray-box attacks. For instance, the transfer approach [13] illustrated in Figure 6 (a) produces an adversarial sample with a CLIP score of 0.82 within a mere 29 seconds, while the transfer+query approach [10] achieves a CLIP score of 0.85 in just 97 seconds. Conversely, our *AAA* method requires 151 seconds to generate an adversarial sample with a superior CLIP score of 0.951. The shorter computation times of the existing gray-box methods are expected due to their ability to access real gradients, which significantly expedites the optimization process. Given that adversarial attacks are not time-sensitive operations and considering that our *AAA* method delivers a more potent attack capability and is applicable in a broader range of realistic black-box scenarios, the trade-off for a higher computational cost is deemed acceptable. Additional experiments on similarity measurements are included in the Appendix B.5.

Further analyses.   Firstly, we show the impact of different forms of target semantics TS in *Ask* on the target semantic dictionary, as shown in Appendix B.2. More ambiguous target semantics can enrich the target semantic dictionary, which also means that the attacker has more choices when designing y_t. Secondly, we show the effect of different word selection strategies of y_t based on target semantic dictionary on the final attack effect, as shown in Appendix B.3. Thirdly, we compare the convergence curves of different population sizes and choose a population size of 40 based on the trade-off of attack performance and convergence efficiency, as shown in Appendix B.4. Furthermore, we compare the effects of different evolutionary algorithms on attack performance and convergence efficiency, as shown in Appendix B.6. Additionally, to better observe the attack effect of our framework, we show more examples of attention heatmaps $\mathbf{A}$, optimization convergence curves, target text y_t, and output text, as shown in Appendix B.7. Lastly, we discuss the limitations of our framework, defense strategies, and future work in Appendix C.

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5 Conclusion

In our research, we introduce a novel and practical approach for adversarial attacks on image-to-text models. We propose the *Ask, Attend, Attack* (*AAA*) framework, a decision-based black-box attack method that achieves targeted attacks without semantic loss, even with access limited to the target model's output text. Our framework uses the target semantic directory to guide the creation of target text and attention heatmap to reduce the search space, thereby improving the efficiency of evolutionary algorithms and making our attack harder to detect. Our extensive experiments on the Transformer-based VIT-GPT2 model and the CNN+RNN-based Show-Attend-Tell model demonstrate that our decision-based black-box method outperforms existing gray-box methods in targeted attack performance. These findings highlight the vulnerabilities in current image-to-text models and underscore the need for more robust defense mechanisms, significantly contributing to the field of adversarial machine learning and enhancing the security of vision-language systems.

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Overview

In this appendix, we describe implementation details, additional experiment results and analyses to support the methods proposed in the main paper. In addition, we show more examples of black-box adversarial attacks using *AAA*, each of which includes clean image, attention heatmap, adversarial image, optimization curve, target text, output text, and attack performance.

Reproducibility

Our **source code** and **data** are included in the supplemental material and uploaded, and we will publish the code on GitHub after the paper is accepted. We provide concise and understandable pseudo-code below.

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A Additional implementation details

A.1 Pseudo code of our proposed framework

Algorithm 1 Ask, Attend, Attack (AAA) Framework

1: **Input:** Image $\mathbf{x}$, Target text y_t, Target semantics TS, Surrogate model f, Pre-trained CLIP model E
2: **Output:** Adversarial image $\mathbf{x_{adv}}$ that generates text y_{adv} semantically similar to y_t
3: Initialize hyperparameters: population size NP, mutation factor F, crossover probability CR, perturbation threshold ϵ, maximum search range η
4: Initialize target semantic dictionary $\mathbf{D} \leftarrow \emptyset$
5: **function** ASK($\mathbf{x}$, TS)
6:     Generate initial population with perturbations using Eq. (2)
7:     **for** each generation g **do**
8:         Perform mutation using Eq. (3)
9:         Perform crossover using Eq. (4)
10:        Calculate semantic similarity S_{sem} using Eq. (5)
11:        Select offspring based on S_{sem} using Eq. (6)
12:        Update $\mathbf{D}$ with relevant words from $\mathcal{G}(\mathbf{x}_j^{g+1})$ using Eq. (7)
13:    **end for**
14:    **return D**
15: **end function**
16: **function** ATTEND($\mathbf{x}$, y_t, f)
17:     Determine the category c^* closest to y_t using Eq. (9)
18:     Attention heatmap $\mathbf{A}$ is calculated by surrogate model f using Eq. (8)
19:     **return A**
20: **end function**
21: **function** ATTACK($\mathbf{x}$, y_t, $\mathbf{A}$)
22:     Generate initial population with attention-guided perturbations using Eq. (10)
23:     **for** each generation g **do**
24:         Perform CurrentToBest mutation using Eq. (11)
25:         Perform crossover using Eq. (4)
26:         Calculate deep feature similarity S_{clip} using Eq. (12)
27:         Select offspring based on S_{clip} using Eq. (13)
28:     **end for**
29:     **return** Best individual as $\mathbf{x_{adv}}$
30: **end function**
31: $\mathbf{D} \leftarrow$ ASK($\mathbf{x}$, TS)
32: $y_t \leftarrow$ The attacker create a sentence from the dictionary $\mathbf{D}$
33: $\mathbf{A} \leftarrow$ ATTEND($\mathbf{x}$, y_t, f)
34: $\mathbf{x_{adv}} \leftarrow$ ATTACK($\mathbf{x}$, y_t, $\mathbf{A}$)

A.2 Basic setups

We set the population size NP to 40, scaling factor F to 0.7, cross probability factor CR to 0.7, γ to 0.5, α to 1, and θ to 3, and η to ϵ required in the experiment divided by the average of attention heatmap $\mathbf{A}$. Our device uses three GPUs of RTX2080ti with 11GB memory, and a CPU of Intel(R) Core(TM) i5-10400F. Our operating system is linux, the evolutionary algorithm framework uses the Geatpy library, and the deep learning framework uses Pytorch.

A.3 Standard deviation in the experiments

In the quantitative experiment of our paper, experiments were repeated for 10 times, and the optimal performance was obtained for each experiment, and the mean value and standard deviation were finally obtained.

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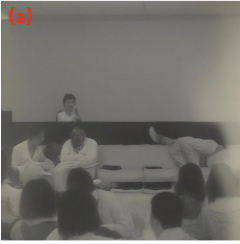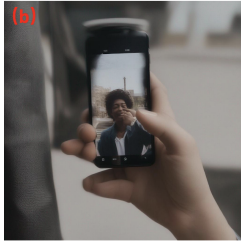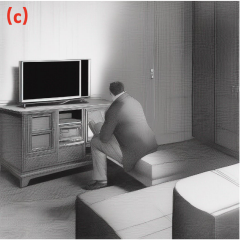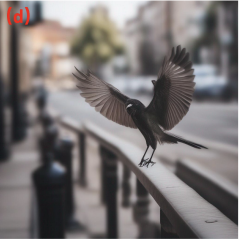
Target Image:	Target Image:	Target Image:	Target Image:

Target Text:
a group of people sitting down

Output Text:
a woman in a white dress is talking to a man in a white dress

Similarity:
M:0.04 B:0.05 C:0.71 B:0.08

Target Text:
a picture of a man in a cell phone

Output Text:
a person is taking a picture of a person on a cell phone

Similarity:
M:0.73 B:0.51 C:0.88 B:0.4

Target Text:
a man is watching tv

Output Text:
a man sitting on a chair next to a fire hydrant

Similarity:
M:0.18 B:0.17 C:0.65 B:0.18

Target Text:
a bird is sitting on a bird flying near a street

Output Text:
a bird flying over a ledge with a bird perched on top

Similarity:
M:0.43 B:0.5 C:0.84 B:0.33

Figure 7: More examples of semantic loss of existing gray-box targeted attacks. The target text is the error-generated text of the image-to-text model that the attacker wants to obtain. The target image is the image generated by using the text-to-image model (Stable Diffusion) based on the target text. The output text is based on the target image using the image-to-text target model (VIT-GPT2/Show-Attend-Tell). similarity indicates the similarity between the target text and the output text. We also show the similarity between the target text and the output text. M stands for METEOR score, B for BLEU score, C for CLIP score, and S for SPICE score.

A.4 Evaluation metrics

(1) iteration, the number of iterations for the differential evolution algorithm in *Attack* to find the optimal solution (no more fitness convergence). Fewer iterations mean fewer queries and faster attack. (2) ϵ, the mean perturbation size of each pixel of the adversarial sample. Smaller value means higher concealment of adversarial perturbation. (3) diversity, the number of words in the target semantic dictionary from *Ask*. More words mean more diversity. (4) correlation, the average CLIP score between each word in the target semantic dictionary and the target semantics. The higher correlation, the more relevant the words in the target semantic dictionary are to the target semantics.

B Additional experiments

B.1 Analysis of semantic loss

We show more examples of the semantic loss phenomenon, as shown in Figure 7. In order to realize the targeted attack with the existing gray-box methods, it is necessary to convert the target text into the target image with the help of text-to-image model (such as Stable Diffusion). Then the distance between the adversarial image and the target image is narrowed, so that the text decoder of the image-to-text target model mistakes the adversarial image as the target image and outputs the description of the target image incorrectly. The target image often contains more semantic information than the target text, and the image-to-text target model may focus on the semantic information that is not specified by the attacker, which leads to semantic loss. For example, in Figure 7 (c), the text-to-image model generates the target image corresponding to the target text (*a man is watching tv*) very accurately, and the image-to-text target model also generates the output text (*a man sitting on a chair next to a fire hydrant*) of the target image very accurately, but the output text and the target text are very different. This means that even if there is a gray-box method that can completely make the features of the adversarial image identical to the features of the target image, the image-to-text target model can only generate the output text after semantic loss, and the targeted attack performance is limited by semantic loss.

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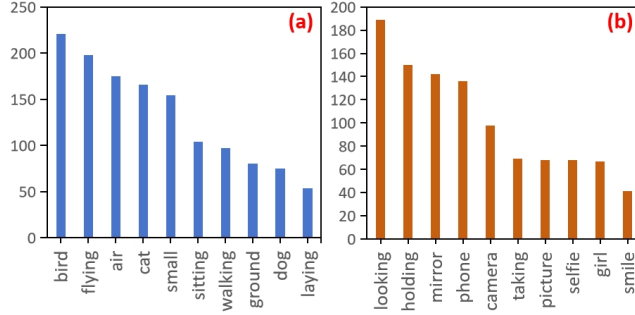
Figure 8: The top ten words in the target semantic dictionary for different target semantics, with the word frequency on the vertical axis. (a) is for *animal*; (b) is for *photograph*.

B.2 Comparison experiment of target semantic dictionary

We showed the target semantic dictionary's diversity and correlation for different perturbations in Table 2. More perturbation means more word choices for the target text. The correlation between dictionaries and target semantics is not affected by the size of perturbations. We also see that one vague word for target semantic makes more diversity and relevance in the dictionary than the detailed sentences. This is because a word has vague semantics, resulting in more words that are closer to the input image in the feature space being added to the dictionary. So we suggest using simple words as target semantics, as attackers can get richer dictionaries to make target text.

Table 2: Target semantic dictionaries for different semantics. *animal* word means the vague word *animal*, while *animal* sentence means *a dog is running after a cat*. *photograph* word means the vague word *photograph*, while *photograph* sentence means *a photo of a parking lot*.

semantic	*animal* word			*animal* sentence			*photograph* word			*photograph* sentence		
ϵ	10	15	25	10	15	25	10	15	25	10	15	25
diversity↑	50.6	65.4	90.1	38.9	54.1	79.6	51.7	62.5	87.7	43.1	52.6	75.5
correlation (%)↑	0.746	0.742	0.744	0.653	0.65	0.654	0.842	0.841	0.843	0.765	0.761	0.758

Table 3: Output text under different word selection strategies.

Strategy	Target Text	Output Text	Similarity
A	a bird is flying through air	a bird is flying through the air	great
A	a girl is taking pictures by camera	a girl is using a camera to take pictures	great
B	a camera is flying through the air	a man is holding a camera	medium
C	a giraffe is eating grass	a person is cutting a piece of food	bad
C	a boy is capturing a beautiful moment	a man is looking at his cell phone	bad
D	the helicopter is hovering in the sky	a man is holding a knife in his hand	bad

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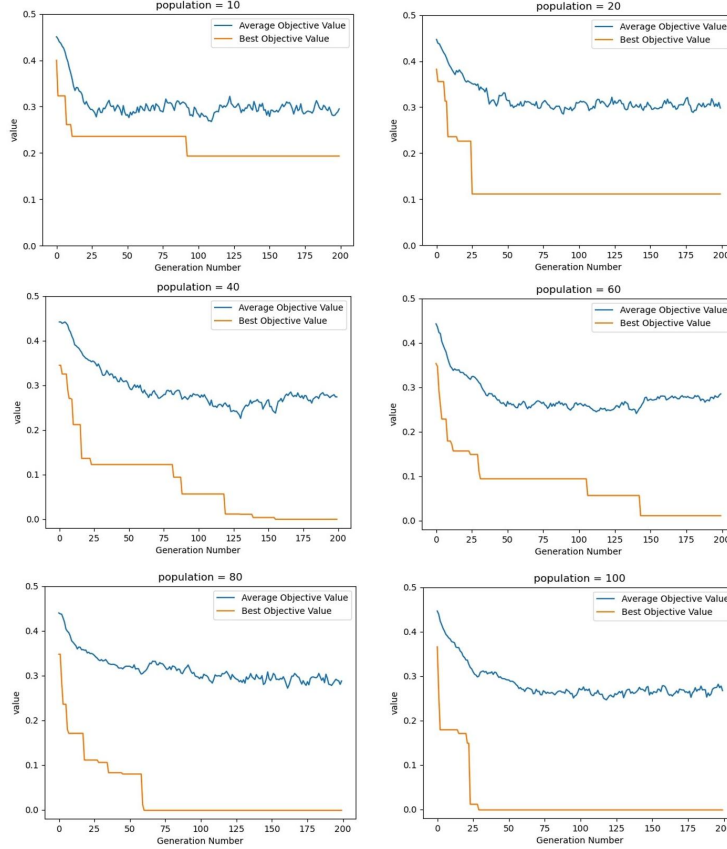
Figure 9: The best fitness curve and average fitness curve of the population under the same target text and different population sizes.

Table 4: The time (s) required for one optimization iteration under different population sizes.

population	10	20	40	60	80	100
iteration time	0.41	0.65	1.14	1.65	2.14	2.56

B.3 Word selection strategies for target semantic dictionaries

We showed the words and frequencies in the target semantic dictionary for different semantics in Figure 8. We compared different word selection strategies for targeted attacks with these dictionaries. The results show that: (1) Words in the dictionary do better when the semantics are similar, while words outside may fail; (2) Words from two dictionaries in one sentence decrease the performance.

We used four word selection strategies based on two dictionaries in Figure 8 to compare how different target texts y_t affect our method: (A) All words in y_t are from the same dictionary; (B) Some words in y_t are from each of the two dictionaries; (C) y_t is artificially created with the target semantics (*animal* or *photograph*), but without any words from the target semantic dictionary; (D) y_t is artificially

Table 5: Performance (%) of different evolutionary algorithms and average number of iterations to find the optimal solution.

	CTB-DE	R-DE	S-GA
iteration↓	46.47±37.11	57.35±43.62	**15.41±11.52**
METEOR↑	**0.696±0.209**	0.538±0.264	0.327±0.254
BLEU↑	**0.658±0.219**	0.546±0.218	0.279±0.172
CLIP↑	**0.95±0.291**	0.871±0.112	0.748±0.096

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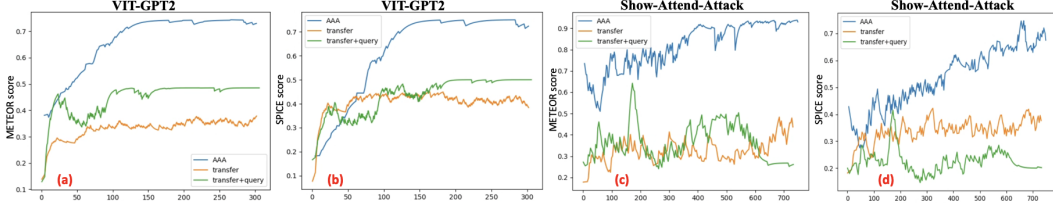
Figure 10: Comparison of computation time for generating a single adversarial sample using different adversarial attack methods. The y-axis is a measure of similarity between the generated text and the target text, with higher values indicating better target attack performance. The x-axis represents the computation time, and the shorter the time required to find a stable solution, the better.

created with different semantics from both target semantics (*animal* and *photograph*), and without any words from either target semantic dictionary. The output texts of the adversarial images obtained from different y_t word selection strategies are shown in Table 3.

The first row of Table 3 shows that strategy (A) can achieve a strong targeted attack, making the output text very similar to the target text. This is because words in the same dictionary are close to each other in the feature space. Strategy (B) selects the words *flying* and *air* from dictionary *animal* in Figure 8 (a), and *camera* from dictionary *photograph* in Figure 8 (b), to form the target text. The third row of Table 3 shows that the output text and the target text y_t are not very similar. The output text only contains the word *camera* in dictionary (b). This is because the feature distance between the two dictionaries is large, even though they are both close to the input image and easy to search in the feature space. It is hard to optimize the target text y_t that contains words from both target semantic dictionaries. Strategy (C) randomly creates y_t based on the *animal* and *photograph* semantics, without using any words from dictionary (a) and (b). For example, *giraffe* is an *animal*, but not in dictionary (a), and *capture beautiful moment* is related to *photograph*, but not in dictionary (b). The output text and the target text y_t are totally different, indicating a failed targeted attack. Strategy (D) randomly creates y_t with different semantics from both target semantics, and without any words from either target semantic dictionary. The targeted attack also fails. Therefore, we recommend selecting words from one target semantic dictionary for the target text y_t, which will greatly improve the success rate of our method's targeted attack.

B.4 Comparison experiment on population size

We show convergence curves with the same target text but different population sizes NP to observe how they affect the optimization iteration process of *Attack*. Figure 9 shows that when NP is 10 and 20, the best fitness values are 0.2 and 0.1, corresponding to CLIP scores of 0.8 and 0.9 for the output texts and target texts, respectively. When NP is larger than 40, the output text and the target text are completely consistent (CLIP score = 1). This means that a larger NP can find better solutions with fewer iterations [24, 46]. However, a larger NP also increases the computation time per iteration, as Table 4 shows. Moreover, as this is a large-scale optimization problem with 196608 decision variables per individual, a larger NP demands more hardware resources [47, 39]. Considering all factors, we set the population size NP to 40.

B.5 Comparison experiment on computation time

In Figure 6 of the main paper, we show the computational efficiency of two metrics, CLIP score and BLEU score. In this part, we will supplement the other two metrics, METEOR score and SPICE score. As shown in Figure 10, the computation time of the existing gray-box attack methods to find the optimal solution is still shorter than that of our black-box attack method. For example, the transfer approach [13] illustrated in Figure 10(a) produces an adversarial sample with a METEOR score of 0.34 within a mere 62 seconds, while the transfer+query approach [10] achieves a METEOR score of 0.49 in just 119 seconds. Conversely, our *AAA* method requires 179 seconds to generate an adversarial sample with a superior METEOR score of 0.75. Because our method is more practical and performs better, the additional computation time is acceptable.

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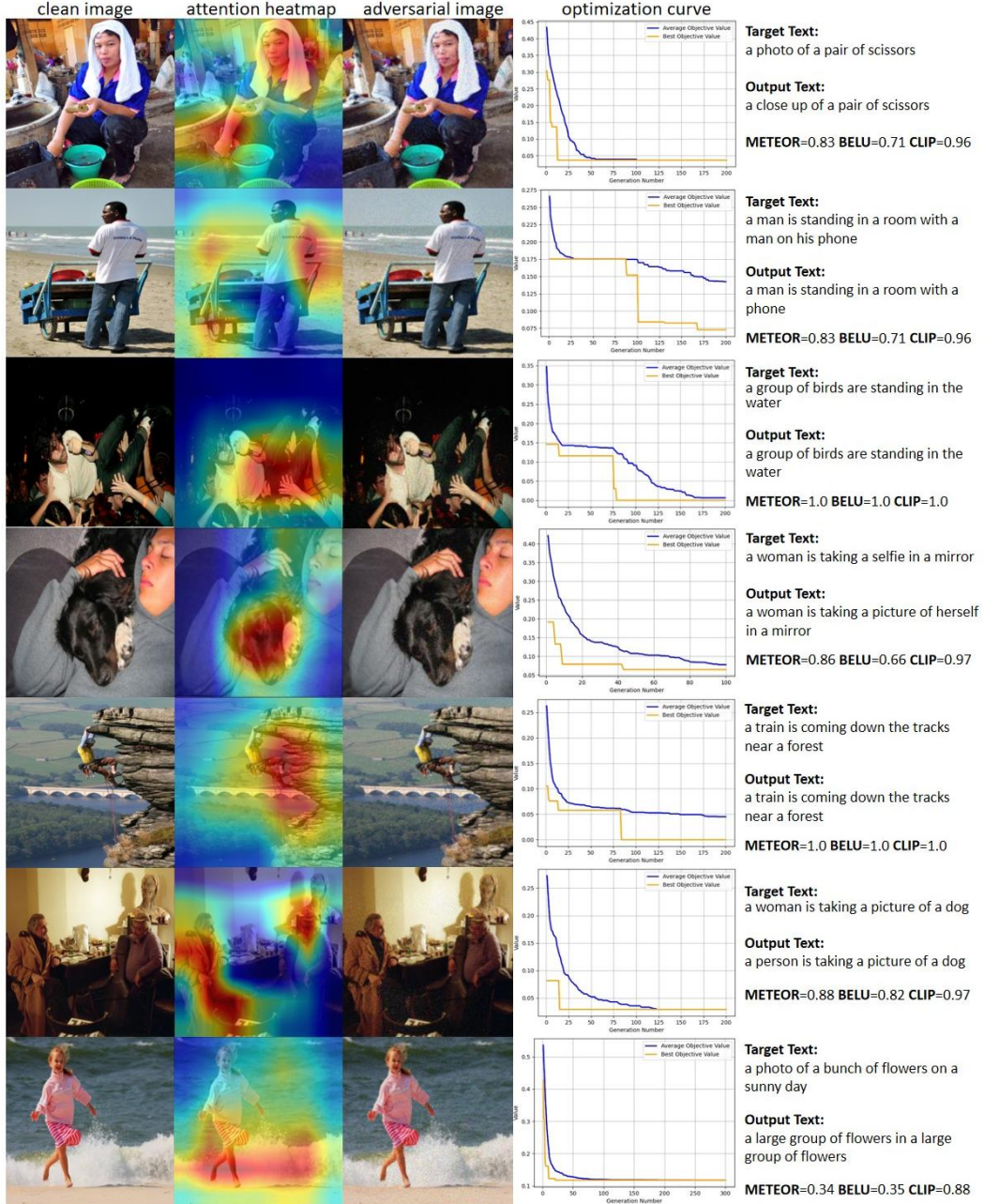
Figure 11: Attention heatmaps, optimization convergence curves, target text, output text and attack performance for more adversarial samples.

B.6 Comparison experiment of optimization algorithms

We compared different optimization strategies in *Attack*: CurrentToBest Differential Evolution (CTB-DE) [39], Rand Differential Evolution (R-DE) [47], and Stud Genetic Algorithm (S-GA) [48]. Table 5 shows that the genetic algorithm needs the fewest iterations, but easily gets stuck in local optima, leading to poor attack performance. Differential evolution needs more iterations but finds better solutions. Also, the CurrentToBest mutation does better and faster than the random mutation. So we adopted the CurrentToBest differential evolution strategy in *Attack*.

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B.7 Visualization of more adversarial samples

We presented attention heatmaps **A**, optimization convergence curves, target text y_t, and output text for more adversarial samples, as shown in Figure 11.

C Discussion

C.1 Limitation

Our work represents the first black-box targeted attack on image-to-text models, with the core idea utilizing evolutionary algorithms to solve a large-scale optimization problem. The drawbacks of evolutionary algorithms, which are also the limitations of our work, include: (1) **Low optimization efficiency**. Gradient-based algorithms use the gradient information of the objective function, which is a powerful guide regarding the optimization direction. Evolutionary algorithms do not directly use gradient information but search through random mutation and crossover operations. Compared to gradient optimization algorithms, evolutionary algorithms require more iterations to find the optimal solution. (2) **High number of queries**. Each individual in the population requires access to the target model in every iteration, and the service provider of the image-to-text target model can simply set a limit on the number of accesses to defend against our attack.

C.2 Future work

Our black-box targeted attack framework *Ask, Attend, Attack* on image-to-text models employs classic evolutionary algorithms. In our future work, we will explore how our framework *AAA* can be combined with the current state-of-the-art (SOTA) evolutionary algorithms, which have the fastest convergence efficiency, to mitigate the limitations mentioned above.

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