
Fit the Distribution: Cross-Image/Prompt Adversarial Attacks on Multimodal Large Language Models

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Abstract

Although Multimodal Large Language Models (MLLMs) have demonstrated remarkable achievements in recent years, they remain vulnerable to adversarial examples that result in harmful responses. Existing attacks typically focus on optimizing adversarial perturbations for a certain multimodal image-prompt pair or fixed training dataset, which often leads to overfitting. Consequently, these perturbations fail to remain malicious once transferred to attack unseen image-prompt pairs, suffering from significant resource costs to cover the diverse multimodal inputs in complicated real-world scenarios. To alleviate this issue, this paper proposes a novel adversarial attack on MLLMs based on distribution approximation theory, which models the potential image-prompt input distribution and adds the same distribution-fitting adversarial perturbation on multimodal input pairs to achieve effective cross-image/prompt transfer attacks. Specifically, we exploit the Laplace approximation to model the Gaussian distribution of the image and prompt inputs for the MLLM, deriving an estimate of the mean and covariance parameters. By sampling from this approximated distribution with Monte Carlo mechanism, we efficiently optimize and fit a single input-agnostic perturbation over diverse image-prompt pairs, yielding strong universality and transferability. Extensive experiments are conducted to verify the strong adversarial capabilities of our proposed attack against prevalent MLLMs spanning a spectrum of images/prompts.

1 Introduction

Multimodal Large Language Models (MLLMs) have demonstrated promising versatile capabilities in a range of applications, such as image classification, image captioning, visual question answering (VQA) and text-to-image generation [1, 2, 3, 4, 5, 6]. Despite their significant success, the increased complexity and widespread deployment of MLLMs have also exposed them to various security threats and vulnerabilities. Recent studies [7, 8, 9, 10] have proven that MLLMs are susceptible to adversarial examples, which involve adding subtle yet invisible perturbations to image inputs. These perturbations can guide the MLLMs to generate harmful responses, posing critical safety issues.

Most of the existing attacks [11, 12, 13, 14, 15, 16, 17, 18, 7, 19, 20, 21, 22, 23, 24, 25, 26] generally optimize adversarial image perturbations against MLLMs' reasoning abilities with benign prompts to produce erroneous or jailbreak responses. Although these attacks achieve significant performance and present noticeable security risks, their optimized perturbations are specific to a certain image-prompt input pair, limiting their transferability to unseen image-prompt pairs. This issue becomes

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more prominent when facing the practical demands for handling diverse multimodal input pairs in real-world scenarios, where they must generate distinct adversarial perturbations for each pair, incurring significant time and resource expenditure. Although a few recent works [8, 10] try to develop cross-prompt or cross-image attack approaches, they need to enumerate the possible prompts or images in training, and require the test prompts/images to be identical to the training ones. Once processing with an unseen test sample, their perturbations are inevitably futile. Therefore, **how to develop an effective and efficient joint cross-image/prompt attack** remains a valuable issue.

To solve the issue, we propose a generalizable cross-image/prompt attack from a novel distribution approximation perspective. In particular, as shown in Figure 1, unlike previous attacks that often overfit to the specific training set of enumerated images or prompts, our approach explicitly models the potential image-prompt distributions

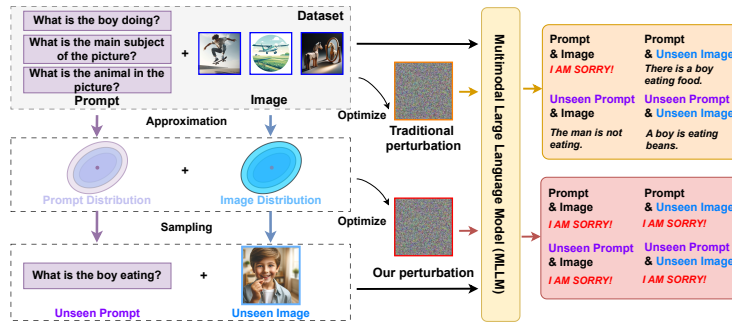


Figure 1: The motivation of our efficient cross-image/prompt attack.

of the realistic data and generate image/prompt-agnostic perturbations by sampling possible input pairs from the modeled distributions for optimization. Our motivation is: **adversarial perturbations optimized to fit the real-world image-prompt distribution will remain adversarial effectiveness when transferred to unseen image-prompt pairs used by the user from the distribution.** Therefore, the remaining question is **how to effectively estimate and obtain such distributions for diverse images and prompts.** Luckily, the Laplace approximation [27, 28] provides an effective solution as distribution estimator. It yields a Gaussian distribution for large amounts of observed data and problems applicable to the central limit theorem [29] (which aligns with in-domain images or semantic-aware prompts of MLLM applications), providing an efficient and asymptotically accurate approximation of the underlying probability density function.

Motivated by these insights, we introduce a distribution-driven adversarial attack method to generate image/prompt-agnostic adversarial perturbations. Specifically, we first model the image and prompt input distributions of the MLLM conforming to the Gaussian distribution using Laplace approximation. Then, we adopt the sampling-based approach to calculate the mean parameter for the image distribution, and exploit the momentum method to obtain the central representative semantics as the mean parameter for the prompt distribution. Subsequently, we adopt the Hessian matrix to perform a quadratic Taylor expansion on the probability distribution of the image/prompt and then compare it with the probability density of the Gaussian distribution, so that we can calculate the covariance parameter based on the Gaussian distribution it follows. Finally, we employ the Monte Carlo mechanism to optimize and fit the adversarial perturbation on the approximated input distributions, enabling the perturbations to effectively transfer across diverse combinations of unseen images and prompts, ultimately inducing harmful outputs from MLLMs.

Our contributions can be summarized as follows: (1) We propose a novel cross-image/prompt adversarial attack against MLLMs from the distribution approximation perspective, which models the potential image/prompt distribution and fits the adversarial perturbation on it to achieve generalization-ability and transferability. (2) To align well with the image/prompt distribution, we model the Gaussian distribution of multimodal inputs through Laplace approximation, to simulate various combinations of sample inputs to MLLM. (3) We follow the Monte Carlo mechanism to utilize possible image-prompt pairs to optimize the perturbation to fit the distribution. (4) Extensive experiments are conducted to verify the effectiveness and transferability of our proposed attack.

2 Related Work

Adversarial attacks on MLLMs. Despite achieving impressive performance, MLLMs remain vulnerable to adversarial attacks due to their underlying deep neural network architectures [30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 7]. Most of the existing attacks [11, 12, 13, 14, 15, 16, 17, 18, 7]

on MLLMs are inspired by the adversarial vulnerability observed in vision-based tasks, typically generating adversarial examples by adding subtle, imperceptible perturbations to benign image inputs through gradient-based optimization methods. Although such approaches can achieve significant attack performance, their adversarial perturbations are generally optimized for specific image-prompt combinations. Consequently, to compromise different images and prompts, they must generate distinct adversarial perturbations, leading to significant computational overhead and resource expenditure. Some recent works [8, 10] have explored cross-prompt or cross-image attack approaches, however, they need complicated multi-prompt joint training, and require the test prompts to be identical to the training ones. To address these limitations, this paper introduces a novel distribution-driven MLLM attack to optimize perturbations fitting on the possible multimodal input distribution, enabling robust and efficient attacks across diverse multimodal inputs within a unified optimization process.

Laplace approximation. By locally approximating complex probability distributions with simpler, tractable ones—typically Gaussian distributions, Laplace approximation enables computationally feasible inference in scenarios where exact solutions are intractable. Recent advancements have extended its applicability to deep learning, especially in Bayesian frameworks. In Bayesian deep learning, Laplace approximation has been employed to estimate uncertainty in neural networks, offering a favorable trade-off between computational efficiency and predictive performance [68, 69]. It has proven to be a powerful and flexible tool for addressing the challenges of high-dimensional machine learning tasks, especially in producing calibrated uncertainty estimates through efficient Bayesian inference [70, 71, 72, 73, 74]. While prior applications primarily apply Laplace approximation at the model level, *i.e.*, improving predictive capabilities via uncertainty estimation, our work introduces a novel, data-centric perspective by leveraging Laplace approximation to estimate the underlying distributions of images and prompts fed into MLLM models, enabling sampling from regions of the data space not observed during training. This leads to the generation of more generalizable perturbations across different images and prompts.

3 Method

3.1 Preliminary

MLLMs. An MLLM is designed to generate reasonable textual answers y given the multimodal input consisting of an image v and a text prompt t as $y = MLLM(v, t)$.

Threat model. In this paper, we investigate adversarial attacks on MLLMs, focusing on the white-box setting where target model architectures and their parameter settings are known to attackers. We propose a cross-image/prompt adversarial attack method that compromises MLLMs even under complex scenarios with unknown user inputs, while maintaining strong applicability to various MLLMs and downstream tasks like VQA, image captioning, and image classification.

Attacker’s goal. The attacker attempts to utilize a common adversarial perturbation δ that is constrained by a small norm bound (*e.g.*, $\|\delta\| \leq \eta$) to ensure that the noisy modifications remain imperceptible to human observers while achieving the adversarial condition. The attack objective is to quantify the error in the answer generated with the perturbed inputs, which can be represented by:

$$\delta^* = \begin{cases} \arg \max_{\|\delta\| \leq \eta} \mathcal{D}(MLLM(v + \delta, t), y_{gt}), & \text{if Untargeted Attack,} \\ \arg \min_{\|\delta\| \leq \eta} \mathcal{D}(MLLM(v + \delta, t), y_{tar}), & \text{if Targeted Attack,} \end{cases} \quad (1)$$

where $\mathcal{D}(\cdot)$ is the cross-entropy loss function that describes the difference between the two inputs of the function, y_{gt} and y_{tar} are the ground-truth answer and attacker’s target answer, respectively. In this section, we utilize the challenging targeted adversarial attacks as an example for illustration.

3.2 Overview of Our Attack

Our motivation. Existing adversarial attacks on MLLMs primarily optimize perturbations based on fixed image-prompt pairs, resulting in significant overfitting to certain image/prompt and limited cross-sample transferability. This inherently limits their effectiveness in real-world scenarios, where models encounter diverse and previously unseen multimodal inputs. Instead of laboriously enumerating image-prompt pairs, we model the image and prompt spaces as probabilistic distributions—specifically leveraging the Laplace approximation to construct Gaussian latent spaces (see the

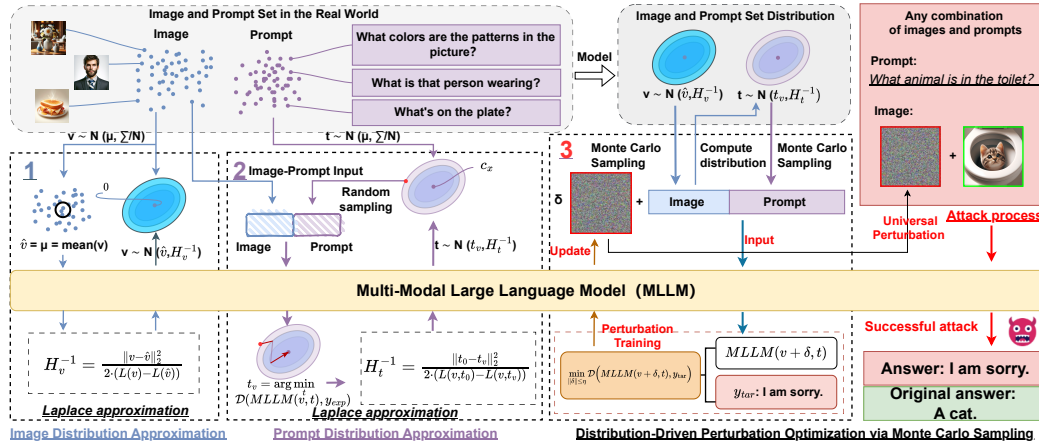


Figure 2: Overall pipeline of our proposed distribution-driven cross-image/prompt attack.

theoretical justification in Appendix A.1). By using Monte Carlo sampling from these distributions and minimizing the adversarial loss between the model response and the attacker's target answer over the entire distribution (rather than individual samples), our method explicitly optimizes the perturbation to fit on such distributions and implicitly disrupts the shared semantic patterns of all possible seen and unseen images and prompts, achieving strong generalization-ability and transferability. Our approach tackles the limitations of prior works, providing a principled and scalable solution for generating universal attacks for MLLMs.

Overall pipeline. As shown in Figure 2, our attack pipeline is mainly divided into three steps. 1. *Image distribution approximation:* We first utilize the Laplace approximation to model the diverse images as a Gaussian distribution. To estimate the distribution parameters, we compute the mean parameter by averaging the sampled images and calculate its covariance by applying the Hessian matrix. 2. *Prompt distribution approximation:* Similarly, we approximate the distribution over prompts as a Gaussian using the Laplace approximation. We identify a representative prompt—such as one that best describes a given image or specifies a relevant task—as the mean parameter. Starting from a randomly initialized prompt, we calculate the variance of the Gaussian distribution with the Hessian matrix. 3. *Distribution-driven perturbation optimization:* To obtain the image/prompt-agnostic perturbation, we employ the Monte Carlo mechanism to sample over the image and prompt distributions obtained in the previous steps, and then optimize the perturbation on them to achieve the adversarial effects. Ultimately, we can obtain a universal perturbation for both seen and unseen images and prompts fitting the distribution.

3.3 Modeling Multimodal Input Distribution using Laplace Approximation

Investigating the modalities' characteristics is crucial for determining their potential distributions. Specifically, as for prompt inputs, they are usually classified into two categories based on their semantic contents: image-irrelevant prompts for captioning or classification tasks, and image-relevant prompts for VQA tasks. The prompts of captioning and classification are usually applicable to most images, while the prompts of VQA are usually questions for a specific image. Therefore, we model the prompt distribution either on a task-aware semantic prior for captioning/classification tasks or on an image-related semantic guidance for VQA tasks, to effectively cover all prompt types and thus be more universal. As for image inputs, they are usually independent of the prompts, thus we can directly model their distribution from datasets. Based on the above observations, since the Laplacian approximation typically yields a Gaussian distribution suitable for large sample sizes and aligns well with our ideal distribution concentrated around the extreme prior, we intend to model the distributions of prompts and images through Laplacian approximation.

3.3.1 How to Represent Image-Prompt Distribution of the MLLMs' Input?

Given an image and a prompt input to the MLLM, we first describe how we model their separate distributions. Since the real-world distributions of images and prompts are highly complex and intractable for direct computation, we employ the Laplace approximation [27] to provide a promising

solution to approximate them as Gaussian distributions, which is especially effective for large amounts of observed data and problems applicable to the central limit theorem [29]. In particular, both image-irrelevant and image-relevant prompts are centered around the extreme points aligned with task-specific semantic prior and image-guided semantic content, respectively. Meanwhile, images' pixel intensities also often exhibit central tendency around a mean value with symmetric deviations, especially after normalization or transformation. This assumption enables efficient probabilistic modeling for images and prompts, yielding a Gaussian distribution. Therefore, for the prompt distribution, a large number of different prompts t approaches a Gaussian distribution as:

$$t \sim \mathcal{N}(\mu_t, \frac{\Sigma_t}{N}), \quad p(t) = \frac{N^{d/2}}{(2\pi)^{d/2} |\Sigma_t|^{1/2}} \exp\left(-\frac{N}{2}(t - \mu_t)^T \Sigma_t^{-1} (t - \mu_t)\right), \quad (2)$$

where μ_t represents the mean parameter of the prompt distribution, N is the number of samples, $\Sigma_t = \text{Cov}(t)$ represents the covariance matrix, $p(t)$ is probability density function of t . Similarly, for the image distribution, the image sample v converges to a Gaussian distribution $v \sim \mathcal{N}(\mu_v, \frac{\Sigma_v}{N})$ with the mean parameter μ_v and covariance matrix $\Sigma_v = \text{Cov}(v)$. Here, both parameters μ_t, μ_v and Σ_t, Σ_v need to be calculated for distribution approximation.

3.3.2 Approximating Image-Prompt Distribution of the MLLMs' Input

Next, we detail the approximation of the Gaussian distribution's mean parameter and covariance by estimating the mode and Hessian matrix for both the image and prompt distributions. Specifically, we obtain the mode through the probability estimation and compute the Hessian matrix via second-order differentiation of the log-posterior at the mode.

Prompt distribution approximation. As for image-irrelevant and -relevant prompt distribution approximation, we can separately model their individual distribution and then exploit a Gaussian distribution merging mechanism [75] to combine them into a joint distribution (as in Appendix A.3). Here, we take the complicated image-relevant prompt distribution approximation as illustration (other illustrations are in Appendix A.2). According to Bayes' theorem [76], the posterior distribution about prompts given input v and an initial prompt prior t_0 is $p(t|v, t_0) = \frac{p(v|t, t_0) p(t|t_0)}{p(v|t_0)}$. We define the most probable prompt as t_v which can be derived via Maximum A Posteriori (MAP) [77] estimation: $t_v = \arg \max_t p(t|v, t_0)$ where t_v is considered as mode—*i.e.*, the point at which the posterior probability density function reaches its maximum value according to the MAP. According to [78], for a symmetrical unimodal distribution, the mean, mode and median coincide. Since the Gaussian distribution satisfies this condition, therefore, we adopt $\mu_t = t_v$ as the mean parameter of approximated prompt distribution. Then, we can approximate the log probability $\log p(t|v, t_0)$ via a second-order Taylor expansion as:

$$\log p(t|v, t_0) \approx \log p(t_v|v, t_0) - \frac{1}{2}(t - t_v)^T H_t (t - t_v), \quad (3)$$

where the first-order term vanishes because the gradient $\nabla_t \log p(t|v, t_0)|_{t=t_v}$ equals zero at the extremum point t_v . The second-order term is governed by the Hessian matrix H_t , defined as:

$$H_t = -\nabla \nabla_t \log p(t|v, t_0)|_{t=t_v}. \quad (4)$$

Therefore, we can neglect higher-order terms and yield the Gaussian approximation:

$$p(t|v, t_0) \propto \exp\left(-\frac{1}{2}(t - t_v)^T H_t (t - t_v)\right). \quad (5)$$

Comparing Equation 2 and 5, this aligns the asymptotic covariance with the inverse Hessian of the log-posterior H_t^{-1} , thereby embedding both statistical convergence and local curvature properties into the prompt distribution. When the dataset is large, we can approximate that the valid prompt t follows a Gaussian distribution:

$$t \sim \mathcal{N}(t_v, H_t^{-1}). \quad (6)$$

Image distribution approximation. Based on the same principle as the above prompt distribution, we can also approximate the distribution of the image input into the MLLM as:

$$v \sim \mathcal{N}(\hat{v}, H_v^{-1}), \quad (7)$$

where $\hat{v}$ is the mean value of the image distribution in the dataset (The proof is the same as in Appendix A.2). The image generation process is characterized by the log-posterior probability: $\log p(v) = -\frac{1}{2}(v - \hat{v})^\top H_v (v - \hat{v}) + \text{CONST}$. The Hessian matrix is obtained through second-order differentiation: $H_v = -\nabla_v \nabla_v^\top \log p(v)|_{v=\hat{v}}$, where ∇_v denotes the gradient operator. For Gaussian probability models, this yields $H_v = N \cdot \Sigma_v^{-1}$, with Σ_v being the covariance matrix of image features. The constant property of H_v in Gaussian models significantly simplifies subsequent computations.

3.3.3 Parameter Calculation of Image/Prompt Distribution in MLLM

As for prompt distribution calculation, we also take the complicated image-relevant prompt distribution as illustration (other illustrations are in Appendix A.4). Specifically, the most probable prompt t_v is the input prompt that maximizes the probability of MLLM outputting an expected response y_{exp} that contains the main information of the input image x (explanations are in Appendix A.5). Since directly maximizing the posterior probability is untrackable, we convert the posterior probability maximization problem into an expectation minimization problem with a proper approximation (more details are in Appendix A.6), which can be written as:

$$\begin{aligned} L(v, t) &= \|MLLM(v, t) - y_{exp}\|_2^2, \\ t_v &= \arg \min_t L(v, t). \end{aligned} \quad (8)$$

To calculate the t_v in Equation 8, we compute the loss $L(t, v)$ on the MLLM model and perform backpropagation to calculate the gradients. Subsequently, we update the parameter t_v using the Momentum Gradient Descent method [79] to avoid being trapped in local minima. This momentum-based iterative update can be formulated as:

$$\begin{aligned} m_i &= \beta m_{i-1} + (1 - \beta) \nabla_t L(t, v), \\ t_{v,i} &= t_{v,i-1} - r \cdot m_i, \end{aligned} \quad (9)$$

where m_i represents the momentum term at iteration i , $\nabla_t L(t, v)$ denotes the gradient of the loss function. β, r are the momentum coefficient and learning rate, respectively. The inverse Hessian H^{-1} is then computed by a simplified covariance estimate (details are in Appendix A.7) as:

$$H_t^{-1} = \frac{\|t_0 - t_v\|_2^2}{2 \cdot (L(v, t_0) - L(v, t_v))}. \quad (10)$$

As for image distribution calculation, unlike the mean parameter of image-relevant prompts, we adopt sampling a series of images and calculating their mean $\hat{v} = \Sigma_{i=1}^N v / N$ as the mean parameter of the image distribution where N is the number of v samples. As for variance, we estimate it as:

$$H_v^{-1} = \frac{1}{N} \Sigma_v, \quad \text{where } \Sigma_v = \frac{1}{N} \sum_{i=1}^N (v_i - \hat{v})(v_i - \hat{v})^\top. \quad (11)$$

Algorithm 1 Cross-Image/Prompt Adversarial Attack against MLLMs

Require: images v , prompt t , epoch numbers M, N , hyperparameters α, r, β , budget η , perturbation δ , loss function $L(v, t)$ for t in Eq.(8), loss function $\mathcal{D}(v, t)$ for v in Eq.(1).

Ensure: Perturbation δ .

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Initialize  $t_0 = t, v_0 = v, m_0 = 0$ ;
for  $i = 0$  to  $M - 1$  do
    Compute  $\hat{v}, H_v^{-1}$ , sample  $v_i \sim \mathcal{N}(\hat{v}, H_v^{-1})$ ;
    for  $j = 0$  to  $N - 1$  do
        Compute gradient  $g_t = \nabla_t L(v_i, t_j)$ ;
        Compute momentum  $m_{j+1} = \beta m_j + (1 - \beta) g_t$ ;
        Update  $t_{j+1} = t_j - r \cdot m_j$ , and obtain  $t_v$ ;
        Compute  $H_t^{-1} = \frac{\|t_0 - t_v\|_2^2}{2 \cdot (L(v, t_0) - L(v, t_v))}$ ;
    end for
    Sample  $t_i \sim \mathcal{N}(t_{v_i}, H_t^{-1})$ ;
    Compute gradient  $g_{\delta_i} = \nabla_{\delta} \mathcal{D}(MLLM(v_i + \delta_i, t_i), y_{tar})$ ;
    Update  $\delta_{i+1}^{adv} = \text{clip}_{\eta}(\delta_i^{adv} - \alpha \cdot \text{sign } g_{\delta_i})$ ;
end for

```

Table 1: Attack performances ($\uparrow$) across images/prompts on MS-COCO and DALLE-3 datasets. “**Value**” denotes the best performance, “Value” denotes the second-best performance.

Model	Method	No Cross			Cross Images			Cross Prompts			Cross Images/Prompts		
		EM-ASR	CM-ASR	Similarity	EM-ASR	CM-ASR	Similarity	EM-ASR	CM-ASR	Similarity	EM-ASR	CM-ASR	Similarity
Dataset: MS-COCO [81]													
LLaVA 1.5	PGD [14]	96.1%	96.1%	0.968	0.0%	0.0%	0.045	32.1%	38.4%	0.388	0.0%	0.0%	0.062
	CroPA [8]	65.2%	65.2%	0.797	0.3%	0.3%	0.048	57.3%	58.0%	0.683	0.0%	0.0%	0.049
	UniAtt [10]	78.3%	83.1%	0.824	20.6%	20.8%	0.225	61.9%	66.7%	0.704	19.2%	19.2%	0.209
	Ours	96.7%	97.3%	0.970	58.7%	59.6%	0.611	93.4%	94.6%	0.948	49.8%	51.4%	0.532
BLIP-2	PGD [14]	61.4%	70.6%	0.649	0.0%	0.0%	0.112	21.2%	21.6%	0.275	0.0%	0.0%	0.104
	CroPA [8]	28.1%	96.1%	0.619	0.0%	0.0%	0.104	28.0%	57.4%	0.523	0.0%	0.0%	0.103
	UniAtt [10]	75.6%	77.9%	0.802	17.9%	20.7%	0.252	49.4%	54.8%	0.620	17.6%	20.3%	0.195
	Ours	49.3%	98.0%	0.970	55.5%	56.6%	0.584	62.9%	86.7%	0.735	50.0%	57.3%	0.531
MiniGPT-4	PGD [14]	85.0%	85.0%	0.866	0.0%	0.0%	0.040	16.4%	18.2%	0.278	0.0%	0.0%	0.036
	CroPA [8]	98.0%	98.7%	0.987	0.0%	0.2%	0.041	73.6%	74.1%	0.759	0.0%	0.0%	0.044
	UniAtt [10]	81.5%	84.3%	0.858	25.2%	25.2%	0.269	76.4%	79.5%	0.807	20.3%	22.1%	0.216
	Ours	97.3%	98.0%	0.977	63.1%	71.9%	0.655	96.6%	97.9%	0.971	47.2%	57.9%	0.513
Dataset: DALLE-3 [2]													
LLaVA 1.5	PGD [14]	96.1%	96.1%	0.964	0.0%	0.0%	0.038	29.1%	33.8%	0.351	0.0%	0.0%	0.076
	CroPA [8]	79.7%	79.7%	0.819	0.0%	0.0%	0.038	68.0%	68.3%	0.682	0.0%	0.0%	0.051
	UniAtt [10]	79.0%	81.8%	0.837	21.7%	22.5%	0.246	68.4%	70.3%	0.738	20.9%	21.1%	0.229
	Ours	95.3%	96.0%	0.958	66.3%	66.3%	0.688	93.7%	94.1%	0.945	60.9%	61.3%	0.644
BLIP-2	PGD [14]	58.2%	64.7%	0.608	0.0%	0.0%	0.082	22.6%	31.5%	0.385	0.0%	0.0%	0.082
	CroPA [8]	28.8%	93.5%	0.610	0.1%	0.1%	0.087	28.7%	69.0%	0.531	0.0%	0.0%	0.091
	UniAtt [10]	77.2%	80.4%	0.816	20.5%	20.5%	0.238	54.3%	57.1%	0.560	18.2%	18.9%	0.194
	Ours	35.3%	94.7%	0.631	54.2%	63.5%	0.582	47.9%	90.0%	0.671	45.5%	59.4%	0.522
MiniGPT-4	PGD [14]	79.7%	79.7%	0.823	0.0%	0.0%	0.037	20.9%	22.4%	0.227	0.0%	0.0%	0.059
	CroPA [8]	94.8%	96.1%	0.955	0.0%	0.0%	0.040	72.7%	74.1%	0.732	0.0%	0.0%	0.045
	UniAtt [10]	80.7%	80.7%	0.829	23.7%	25.9%	0.274	68.3%	70.2%	0.699	19.8%	19.8%	0.206
	Ours	96.7%	99.3%	0.972	63.8%	69.8%	0.661	97.1%	97.8%	0.973	30.8%	52.4%	0.355

3.4 Distribution-Driven Perturbation Optimization via Monte Carlo Sampling

After obtaining the approximate image-prompt distribution, we utilize Monte Carlo mechanism [80] to sample possible image-prompt pairs to optimize Equation 1 for generating perturbation δ fitting the distribution with strong generalization capabilities. To be specific, at each iteration i , image samples $v_i \sim \mathcal{N}(\hat{v}, H_v^{-1})$ are drawn, then we randomly sampled prompts from the distribution $t_i \sim \mathcal{N}(c_{v_i}, H_{t_i}^{-1})$. The perturbation is then updated using a sign gradient update as:

$$\delta_{i+1}^{adv} = \text{clip}_{\eta} \left(\delta_i^{adv} - \alpha \cdot \text{sign} \left(\nabla_{\delta} \mathcal{D}(\text{MLLM}(v_i + \delta_i, t_i), y_{tar}) \right) \right), \quad (12)$$

where $\text{clip}_{\eta}(\cdot)$ bounds the perturbation by η . Our whole attack process is detailed in Algorithm 1.

4 Experiments

4.1 Implementation Details

MLLM models and datasets. The experiments utilize a combination of images and prompts across multiple vision-language tasks. The image data are sourced from the MS-COCO dataset [81] and the DALLE-3 dataset [2]. To construct the prompt sets, we consider three distinct task types: VQA, image classification, and image captioning. For each task, we incorporate prompts curated from prior studies [8] to ensure consistency with existing evaluations. The complete list of prompts is provided in Appendix D. The MLLMs used are LLaVA-1.5-7B-hf [6], BLIP-2 OPT-2.7B [5], and MiniGPT-4 [82], chosen to represent a diverse range of architectures and model scales among current MLLMs.

Experimental setups. For the parameter calculation of image/prompt distribution, the coefficient β , r are set to 0.9 and 0.001. The target answer is uniformly specified as “*I am sorry.*” in all experimental conditions. To assess adversarial generalization, three cross-sample settings are considered: (1) 30 distinct prompts sampled per image (Cross-Prompt), (2) 50 different images sampled per prompt (Cross-Image), and (3) simultaneous sampling of 30 images and 30 prompts (Cross-Image/Prompt). The perturbations are optimized for 300 steps under $\eta = 16/255$ and step size $\alpha = 1/255$. Evaluation metrics include the Exact Match ASR (EM-ASR), Contain Match ASR (CM-ASR), and Semantic Similarity (Similarity). The EM-ASR and CM-ASR assess the word-level overlap between adversarial output and target text, while similarity is computed by cosine similarity between embeddings of adversarial output and target text obtained from the all-MiniLM-L6-v2 model [83].

4.2 Main Results

Adversarial performance across images/prompts. We conduct a comprehensive evaluation with four baseline attacks on three MLLM models across two datasets in Table 1. All baselines are re-implemented with the same hyperparameters as us to keep a fair comparison. From this table, we can conclude that: (1) As for the general setting (No Cross), existing attacks can achieve great adversarial performance. Although our method optimizes perturbations not on specific multimodal samples like them, we can still achieve competitive performance. (2) Since previous attacks fail to fit unseen images and prompts, they all result in limited cross-image, cross-prompt, and cross-image/prompt attack performance. Instead, our sample-agnostic attack can achieve much better cross-sample performance by fitting the perturbation on the potential image/prompt distributions.

Although Doubly-UAP [84] claims to support cross-image/prompt attack, its perturbations still overfit the given data rather than the data distribution. Moreover, it is limited to the untargeted attack setting since it solely optimizes the noise by modifying the feature space of the visual encoder. For fair comparison, we re-implement our attack under the same setting and hyperparameters. As in Table 2, our method still achieves better cross-sample attack performance, demonstrating the effectiveness of our distribution-aware designs.

Efficiency analysis. We also provide the efficiency analysis. To make a fair and practical comparison, we investigate the time and resource costs for generating all adversarial samples, not for a single one. As in Table 3, since UniAtt and ours only need to optimize cross-sample perturbations in one single process, we are more efficient than sample-specific attack CroPA.

Visualizations. We present the visualizations of cross-image/prompt attacks in Figure 3, which demonstrate consistent target effects across diverse inputs. More visualizations are in Appendix B.6.

4.3 Further Studies

Sensitive to different target text.

To verify that the effectiveness of our attack is not limited to a specific target text, we evaluate it on a variety of target texts with different lengths and usage frequencies in Table 4. The results consistently show strong performance across diverse texts.

Table 4: Performance ($\uparrow$) across images/prompts with different target texts on DALLE-3 dataset.

Target Answer	Model	Cross Images			Cross Prompts			Cross Images/Prompts		
		EM-ASR	CM-ASR	Similarity	EM-ASR	CM-ASR	Similarity	EM-ASR	CM-ASR	Similarity
"unknown."	LLaVA1.5	63.0%	63.0%	0.680	97.7%	97.7%	0.980	50.8%	52.6%	0.580
	BLIP-2	65.5%	65.5%	0.664	73.8%	99.0%	0.830	59.6%	61.0%	0.619
	MiniGPT-4	61.5%	62.5%	0.603	98.7%	98.7%	0.990	27.7%	28.6%	0.360
"It is very good."	LLaVA1.5	72.5%	72.5%	0.766	99.8%	99.8%	0.998	46.0%	54.1%	0.539
	BLIP-2	66.0%	66.0%	0.783	55.5%	76.5%	0.686	60.1%	61.1%	0.701
	MiniGPT-4	70.0%	70.7%	0.747	100%	100%	1.000	54.8%	57.3%	0.608
"It is too late."	LLaVA1.5	69.5%	69.5%	0.754	99.8%	99.8%	0.998	62/3%	63.7%	0.676
	BLIP-2	59.5%	60.0%	0.642	51.5%	96.3%	0.760	46.6%	50.1%	0.651
	MiniGPT-4	55.0%	56.0%	0.578	100%	100%	1.000	41.1%	42.6%	0.469

Evaluation on the sampled prompts. To investigate whether our modeled distribution aligns well with the real-world scenarios, we evaluate the similarity statistics of the prompts sampled from the approximated distributions across tasks. As shown in Table 5, the sampled prompts share similar similarities with the semantic-aware tasks (high mean value and low variance), demonstrating the effectiveness of the distribution approximation.

Table 2: Attack performance under untargeted setting on ImageNet with ASR ($\uparrow$) and similarity ($\downarrow$).

Method	Classification		Captioning	
	ASR($\tau=0.8$)	Sim.	ASR($\tau=0.8$)	Sim.
DUAP	92.5%	0.72	83.3%	0.48
Ours	98.6%	0.42	89.7%	0.28

Table 3: Efficiency analysis for generating all adversarial samples.

Method	Avg. GPU Hours ($\downarrow$)	Avg. GPU Memory ($\downarrow$)
CroPA	16.2h	23.9GB
UniAtt	4.9h	57.5GB
Ours	5.5h	48.3GB

Table 5: Similarity statistics across tasks based on Laplace-sampled embeddings.

Metric	Classification	VQA	Captioning
Top-1 Mean Similarity ($\uparrow$)	0.704	0.722	0.606
Variance of Similarity ($\downarrow$)	0.0016	0.0017	0.0019

Table 6: Ablation study of the approximated distributions on DALLE-3 dataset.

Model	Variant	Cross Images			Cross Prompts			Cross Images/Prompts		
		EM-ASR	CM-ASR	Similarity	EM-ASR	CM-ASR	Similarity	EM-ASR	CM-ASR	Similarity
LLaVA-1.5	Gaussian	66.3%	66.3%	0.688	93.7%	94.1%	0.945	60.9%	61.3%	0.644
	Fixed	10.0%	10.0%	0.136	92.8%	92.8%	0.949	0.0%	0.0%	0.030
BLIP-2	Gaussian	54.2%	63.5%	0.582	47.9%	90.0%	0.671	45.5%	59.4%	0.522
	Fixed	29.8%	31.3%	0.382	26.3%	80.1%	0.515	0.0%	0.1%	0.100
MiniGPT-4	Gaussian	63.8%	69.8%	0.661	97.1%	97.8%	0.973	30.8%	52.4%	0.355
	Fixed	34.2%	46.0%	0.380	99.5%	99.5%	0.995	25.6%	34.2%	0.291

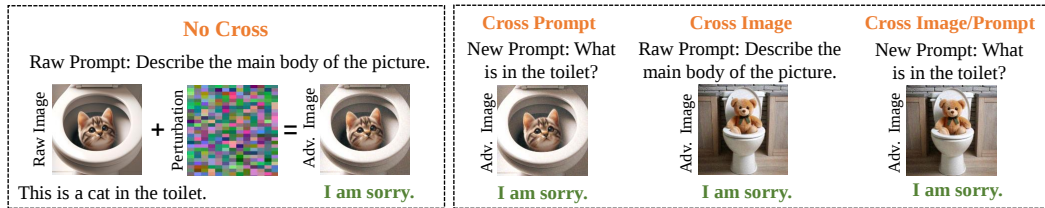


Figure 3: Visualizations of our attack. All adversarial (adv.) images use the same perturbation.

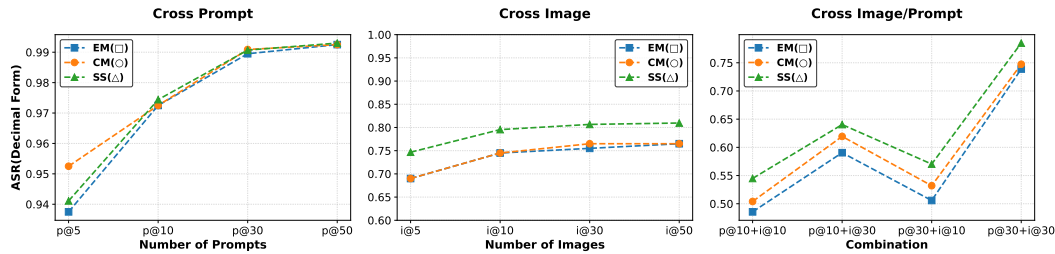


Figure 4: Ablations on different numbers of sampled images/prompts during Monte Carlo mechanism ("EM" denotes "Exact Match", "CM" denotes "Contain Match", "SS" denotes "Semantic Similarity").

Evaluation on the approximating distribution. To investigate the effectiveness of our modeled image/prompt distributions, we implement two variants for comparison: (1) We utilize Laplacian approximation to model the distribution as a Gaussian distribution; (2) We directly utilize the seen image/prompt data as a fixed distribution. As shown in Table 6, our proposed method, using the Laplacian approximation, achieves the best performance across all metrics. These findings underscore the necessity of approximating Gaussian distribution to generate more aligned distributions for optimizing effective adversarial perturbations.

Sensitive to sampling quantity. To examine the effect of sampling quantity, we evaluate cross-image/prompt attacks in Figure 4. Results indicate prompt sampling is effective even with few samples, while additional image samples notably enhance performance, underscoring image sampling's importance for adversarial transferability. Further results are in Appendix B.4.

Experiments on Different Perturbation Budget η

We conduct further experiments on the LLaVA-1.5 model under the cross-image/prompt attack setting to investigate the impact of different perturbation budgets by varying the value of η . As shown in Table 7, increasing η consistently enhances the effectiveness of our attack. And more importantly, a larger perturbation budget also significantly improves the transferability of adversarial examples across different images and prompts.

Table 7: Attack performance under different perturbation budget η values.

η	EM-ASR	CM-ASR	Similarity
8/255	13.4%	15.8%	0.221
16/255	73.9%	74.7%	0.785
32/255	85.8%	86.2%	0.870

Ablation on the Step Size in Perturbation Update The choice of step size α is critical for generating effective adversarial examples. To investigate this, we conduct an ablation study on α using the LLaVA-1.5 model under the cross-image/prompt attack setting. Specifically, during the iterative generation of adversarial perturbations, we sampled the perturbation every 40 steps for transfer testing. As shown in Figure 5, when the step size is set to $1/255$, all three evaluation metrics gradually reach optimal transfer performance as the number of iterations increases.

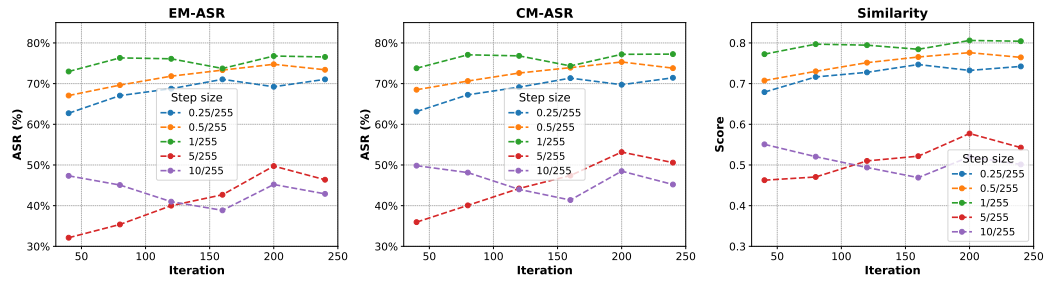


Figure 5: Ablation study on step size α in perturbation update on LLaVA-1.5.

Table 8: Transfer-attack performance across MLLMs on DALLE-3 dataset and MS-COCO dataset.

From	Transfer to	DALLE-3			MS-COCO		
		EM-ASR	CM-ASR	Similarity	EM-ASR	CM-ASR	Similarity
BLIP-2	BLIP-2	45.5%	59.4%	0.522	50.0%	57.3%	0.531
	MiniGPT-4	0%	13.1%	0.103	0%	19.4%	0.129
MiniGPT-4	BLIP-2	25.9%	27.8%	0.312	28.9%	32.3%	0.351
	MiniGPT-4	30.8%	52.4%	0.355	47.2%	57.9%	0.513

Experiments on Transferability across MLLM Models Although we mainly focus on cross-image/prompt attacks, we also evaluate the transferability across different MLLM models to verify the generalization ability of our method. Specifically, we generate adversarial samples on the BLIP-2 model and transfer them to the MiniGPT-4 model for testing, and vice versa. As shown in Table 8, our method maintains a certain degree of transferability in cross-model settings. For instance, even though the attack success rate decreases when transferring between models, the results indicate that the perturbations are not entirely model-specific and can partially generalize across architectures. This further demonstrates the strong and robust attack capability of our approach.

Robustness to potential defenses.

To further evaluate the robustness of our proposed attack, we employ Randomization [85, 86] and JPEG Compression [87] defenses to investigate whether our attack remains effective and transferable. As shown in Figure 6, our attack not only achieves the lowest performance degeneration compared to other methods, but also demonstrates the best transferability across images and prompts under different defenses, validating the effectiveness of our attack.

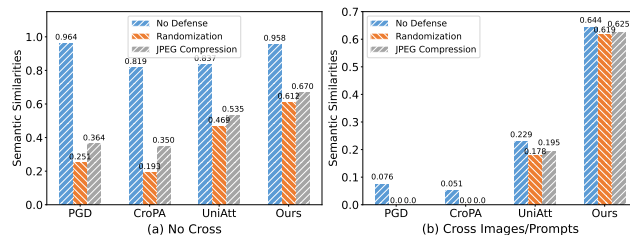


Figure 6: Investigation on the adversarial robustness against defenses on LLaVA-1.5 model with DALLE-3 dataset.

We also provide additional experiments in Appendix B.2~B.5, including results on different datasets, various target texts, and other experimental settings.

5 Conclusion

In this paper, we propose a novel cross-image/prompt adversarial attack against MLLMs based on distribution approximation theory to target unseen image-prompt pairs in complicated real-world scenarios. To model the potential distribution of image-prompt inputs, we utilize Laplace approximation to represent them as Gaussian distributions. We then optimize the perturbation by sampling from the approximate distribution via the Monte Carlo mechanism, thereby fitting a single input-agnostic perturbation with strong universality and transferability across diverse image-prompt pairs. Extensive experiments demonstrate the effectiveness and strong transferability of our proposed attack method.

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A More Detailed of Our Proposed Attack

A.1 Laplace Approximation: Justification and Derivation

In this section, we provide a rigorous mathematical justification of the Laplace approximation, which supports our core assumption that the complex, intractable distributions of images and prompts can be reasonably approximated by Gaussian distributions for probabilistic modeling.

Let $p(x)$ be an unnormalized probability density function over $\mathbb{R}^d$, defined as:

$$p(x) = \frac{1}{Z} \exp(-f(x)), \quad (13)$$

where $f(x)$ is a smooth, twice-differentiable real-valued function, and $Z = \int \exp(-f(x)) dx$ is the normalizing constant (partition function). Our goal is to approximate $p(x)$ by a multivariate Gaussian distribution centered at the mode of $p(x)$.

Let x_0 denote the mode of $p(x)$, which satisfies:

$$x_0 = \arg \max_x p(x) = \arg \min_x f(x), \quad \nabla f(x_0) = 0.$$

To approximate $f(x)$ near the mode x_0 , we perform a second-order Taylor expansion:

$$f(x) \approx f(x_0) + \frac{1}{2}(x - x_0)^T H(x_0)(x - x_0), \quad (14)$$

where $H(x_0) = \nabla^2 f(x_0)$ is the Hessian matrix evaluated at x_0 , assumed to be positive definite so that x_0 is a strict local minimum.

Substituting the approximation into the density:

$$p(x) \approx \frac{1}{Z} \exp \left(-f(x_0) - \frac{1}{2}(x - x_0)^T H(x_0)(x - x_0) \right) \quad (15)$$

$$= \frac{\exp(-f(x_0))}{Z} \exp \left(-\frac{1}{2}(x - x_0)^T H(x_0)(x - x_0) \right). \quad (16)$$

This expression has the form of a Gaussian up to a constant. To formalize the approximation, we define the Gaussian distribution:

$$q(x) = \mathcal{N}(x \mid x_0, H^{-1}(x_0)) = \frac{1}{(2\pi)^{d/2} |H^{-1}(x_0)|^{1/2}} \exp \left(-\frac{1}{2}(x - x_0)^T H(x_0)(x - x_0) \right), \quad (17)$$

which has mean x_0 and covariance matrix $\Sigma = H^{-1}(x_0)$. Then $p(x)$ can be approximated as:

$$p(x) \approx C \cdot q(x),$$

where $C = \frac{\exp(-f(x_0))}{Z} (2\pi)^{d/2} |H^{-1}(x_0)|^{1/2}$ is a constant independent of x .

The Laplace approximation thus replaces an intractable distribution $p(x)$ with a tractable Gaussian centered at its mode, using the curvature information encoded in the Hessian to define the covariance structure. The approximation is asymptotically accurate when:

- The function $f(x)$ is sharply peaked around x_0 , *i.e.*, $p(x)$ is strongly unimodal.
- The sample size is large, allowing higher-order deviations to be negligible due to the central limit effect.
- The density $p(x)$ decays rapidly away from x_0 , making the local quadratic approximation dominant.

This theoretical result justifies our modeling assumption that the empirical distributions of prompts t and images v , which are inherently high-dimensional and complex, can be reasonably approximated as Gaussians:

$$t \sim \mathcal{N}(\mu_t, \Sigma_t/N), \quad v \sim \mathcal{N}(\mu_v, \Sigma_v/N),$$

where μ_t, μ_v are the empirical means, and Σ_t, Σ_v are the corresponding sample covariance matrices computed from N observed samples. The factor $1/N$ emerges from the Central Limit Theorem (CLT), which further supports the Gaussian approximation when averaging independent and identically distributed observations.

Therefore, the Laplace approximation offers a principled and mathematically sound foundation for Gaussian-based modeling in our framework.

A.2 Image-irrelevant Prompt Distribution Approximation

As for image-irrelevant prompts, we also define t_v as the mode of the Gaussian distribution. According to the literature [88], in Bayesian statistics, it is manifested as the asymptotic normality of the posterior distribution, that is, when the sample size tends to infinity, the posterior distribution of the parameters will approach the Gaussian distribution. And according to [78], for a symmetrical unimodal distribution, the mean, mode and median coincide. Thus, employing the sample mean as a proxy for the mode of the posterior distribution is justified, particularly under the conditions where the posterior is the Gaussian distribution which is approximately symmetric and unimodal. We use the mean method to calculate the mode due to the irrelevance between the image and the prompt which satisfies the following formula: $t_v = \frac{\sum_{i=1}^N t_i}{N}$, where the t_i is the prompt from dataset of prompts about caption and classification. N is the number of t_i in the calculation. To further approximate the distribution of prompts, we use the same way to apply Laplace approximation to model the local behavior of the prompt distribution around the mode t_v . Formally, given a density function $p(t)$, we expand $\log p(t)$ around t_v using a second-order Taylor expansion as:

$$\log p(t) \approx \log p(t_v) - \frac{1}{2}(t - t_v)^T H_t (t - t_v), \quad (18)$$

where H_t is the negative Hessian matrix of $\log p(t)$ evaluated at $t = t_v$:

$$H_t = -\nabla^2 \log p(t) \Big|_{t=t_v}. \quad (19)$$

The probability density formula of $p(t)$ is:

$$p(t) \propto \exp \left(-\frac{1}{2}(t - t_v)^T H_t (t - t_v) \right). \quad (20)$$

Therefore, comparing the Equation 2 and 20, the prompt distribution t is approximated as a multivariate Gaussian which is same as Equation 6, where t_v is the mean (mode) and H_t^{-1} is the covariance matrix under this condition.

A.3 Merging for Image-irrelevant and -relevant Prompt Distribution

As for prompt inputs, they are generally divided into two mutually exclusive categories based on their semantic function: image-irrelevant prompts for captioning or classification tasks, and image-relevant prompts for visual question answering (VQA) tasks. Image-irrelevant prompts typically carry generic semantic intent and can apply to a wide range of images, while image-relevant prompts encode specific questions targeting the content of a particular image. Accordingly, we assume that prompts are drawn from one of two distinct probabilistic sources.

We model the distribution of prompts under each category as a Gaussian. Specifically, for image-irrelevant prompts, we compute a semantic prior distribution with mean $t_{\text{irrelevant}}$ and covariance $H_{t_{\text{irrelevant}}}^{-1}$. For image-relevant prompts, we apply MAP estimation to obtain the mean t_{relevant} and covariance $H_{t_{\text{relevant}}}^{-1}$, reflecting prompt semantics conditioned on the image content.

Since each prompt is assumed to belong to one of these categories exclusively, we represent the overall prompt distribution as a two-component Gaussian Mixture Model (GMM) [89]:

$$p(t) = \pi_1 \cdot \mathcal{N}(t \mid t_{\text{irrelevant}}, H_{t_{\text{irrelevant}}}^{-1}/N) + \pi_2 \cdot \mathcal{N}(t \mid t_{\text{relevant}}, H_{t_{\text{relevant}}}^{-1}/N), \quad (21)$$

where $\pi_1, \pi_2 \in [0, 1]$ are the mixing weights for the two types of prompts, satisfying $\pi_1 + \pi_2 = 1$. While this mixture model faithfully reflects the mutually exclusive nature of prompt types, its multimodal form complicates subsequent inference and optimization.

To obtain a tractable unified representation, we approximate the above mixture with a single Gaussian distribution by matching its first and second moments. The resulting approximate mean and covariance are given by:

$$\begin{aligned} \mu_{\text{merge}} &= \pi_1 t_{\text{irrelevant}} + \pi_2 t_{\text{relevant}}, \\ \Sigma_{\text{merge}} &= \pi_1 \left(\frac{1}{N} H_{t_{\text{irrelevant}}}^{-1} + (t_{\text{irrelevant}} - \mu_{\text{merge}})(t_{\text{irrelevant}} - \mu_{\text{merge}})^T \right) \\ &\quad + \pi_2 \left(\frac{1}{N} H_{t_{\text{relevant}}}^{-1} + (t_{\text{relevant}} - \mu_{\text{merge}})(t_{\text{relevant}} - \mu_{\text{merge}})^T \right). \end{aligned} \quad (22)$$

This moment-matched Gaussian provides a universal approximation for the prompt distribution:

$$t \sim \mathcal{N}(\mu_{\text{merge}}, \Sigma_{\text{merge}}), \quad (23)$$

which enables downstream modeling without explicit conditioning on task type. For notational consistency, we denote $t_v := \mu_{\text{merge}}$ and $H_t^{-1} := \Sigma_{\text{merge}}$, leading to:

$$t \sim \mathcal{N}(t_v, H_t^{-1}). \quad (24)$$

A.4 Parameters Calculation of Image-irrelevant Prompt Distribution

For prompts that are irrelevant to images, our calculation methods are different. Under the approximation that the prompt distribution is symmetric and unimodal (implying that the mean, mode, and median coincide; see [78]), the most probable prompt t_v can be obtained in closed form as:

$$t_v = \arg \max_t \sum_{i=1}^N \log p(t_i) \approx \frac{1}{N} \sum_{i=1}^N t_i, \quad (25)$$

where $\{t_i\}_{i=1}^N$ are sampled prompts.

To quantify the uncertainty around t_v , we approximate the (negative) log-posterior locally by a second-order Taylor expansion:

$$-\log p(t \mid \{t_i\}) \approx -\log p(t_v \mid \{t_i\}) + \frac{1}{2}(t - t_v)^\top H_t(t - t_v), \quad (26)$$

where the Hessian matrix $H_t = \nabla_t^2 (-\log p(t \mid \{t_i\})) \Big|_{t=t_v}$ can be approximated using the empirical covariance matrix Σ of the prompts:

$$H_t \approx N\Sigma^{-1}, \quad \text{where} \quad \Sigma = \frac{1}{N} \sum_{i=1}^N (t_i - t_v)(t_i - t_v)^\top. \quad (27)$$

Consequently, the inverse of the Hessian, which represents the local covariance around t_v , can be expressed as:

$$H_t^{-1} \approx \frac{1}{N} \Sigma. \quad (28)$$

A.5 Explanations of y_{exp}

In this work, y_{exp} denotes the *expected response* generated by the Multimodal Large Language Model (MLLM) given an input image v . Specifically, y_{exp} is defined as the ideal output that accurately captures the essential, task-relevant information present in the input image. It serves as a target semantic representation that we expect the MLLM to produce when conditioned on an appropriately informative prompt. Formally, given an image v and a prompt t , the MLLM produces an output $y = \text{MLLM}(v, t)$. The expected response y_{exp} is characterized by the following properties:

- **Relevance:** y_{exp} must contain the key semantic content of the image v , such as object descriptions, actions, or relationships among entities.
- **Completeness:** y_{exp} should fully represent the main information required for the downstream task, ensuring no critical details from x are omitted.
- **Conciseness:** y_{exp} should avoid redundant or irrelevant information not directly supported by v .

In practice, y_{exp} can be approximated by using human-annotated captions, classification labels, or other supervised signals that reliably describe the ground-truth semantics of the image. Alternatively, y_{exp} can also be obtained by prompting the MLLM with a standardized caption prompt (e.g., "Describe the main content of the image.") and using the model's generated response as the expected output. This method reduces the reliance on human annotations while maintaining relevance and completeness in describing the input image. Thus, in the optimization of t_v , we seek the prompt that maximizes the likelihood in Equation 8.

A.6 Convert Maximum A Posterior to Maximum Likelihood Estimation

Given the input image v and prompts t , we can get the most representative prompt t_v conforming to the expression $t_v = \arg \min_t L(v, t)$ in MLLM. Starting from Bayes' theorem $p(t|v, t_0) = \frac{p(v|t, t_0)p(t|t_0)}{p(v|t_0)}$, where $p(v|t, t_0)$ is the generative likelihood, $p(t|t_0)$ is the prior distribution over prompts, $p(v|t_0)$ is the marginal likelihood (normalization constant). The Maximum A Posteriori (MAP) [77] estimation is obtained by $t_v = \arg \max_t p(t|v, t_0) = \arg \max_t [\log p(v|t, t_0) + \log p(t|t_0)]$. If the prior distribution $p(t|t_0)$ of the parameter t is uniform (i.e., all possible values of t have equal probabilities), then $p(t|t_0) = \text{constant}$. Under this condition, the logarithmic prior term $\log p(t|t_0)$ also becomes a constant, which does not affect the extremum position during optimization. Consequently, the MAP optimization objective can be simplified as:

$$\begin{aligned} t_v &= \arg \max_t [\log p(v|t, t_0) + \log p(t|t_0)] \\ &= \arg \max_t \log p(v|t, t_0) \\ &= \arg \min_t L(v, t). \end{aligned} \quad (29)$$

which is precisely the definition of Maximum likelihood estimation (MLE) that can be calculated and characterized through the differences output by the MLLM using the Equation 8.

A.7 Parameter Calculation Details

Direct minimization is performed through Momentum Gradient Descent [79] to achieve faster convergence and better avoidance of shallow local minima.

The iterative update rules are Equation 9, where:

- m_i is the momentum term at iteration i ,
- $\nabla_t L(v, t_{v,i-1})$ is the gradient of the loss with respect to the prompt at iteration $i - 1$,
- $\beta \in (0, 1)$ is the momentum coefficient controlling the contribution of past gradients,
- $r > 0$ is the learning rate.

The initialization is:

$$m_0 = 0, \quad t_{v,0} = t_0, \quad (30)$$

where t_0 is the initial prompt sampled from the dataset. The iterations continue until convergence, *i.e.*, until the preset iterative discussion.

After obtaining the optimal prompt t_v , we approximate the local distribution around t_v by a Gaussian distribution using Laplace approximation.

The Laplace approximation requires the Hessian matrix of the loss function at the mode t_v with the distribution in Equation 6. Since both equations in Equation 3 obtain their maximum and minimum values at t_v . It is valid to use the loss function $L(v, t)$ to compute the inverse Hessian H_t^{-1} of the Laplace approximation because of the following equivalence: From Equation 3, the log-posterior $\log p(t|v, t_0)$ around the mode t_v is approximated by a second-order Taylor expansion:

$$\log p(t|v, t_0) \approx \log p(t_v|v, t_0) - \frac{1}{2}(t - t_v)^\top H_t(t - t_v).$$

On the other hand, from Equation 29, finding the maximum of the posterior $p(t|v, t_0)$ is equivalent to minimizing the loss function $L(v, t)$. Thus, $L(v, t)$ acts as the negative log-posterior up to an additive constant:

$$L(v, t) \propto -\log p(t|v, t_0) + \text{const.}$$

Because additive constants disappear when taking gradients and Hessians, the second-order derivatives of $L(v, t)$ and $-\log p(t|v, t_0)$ around t_v are identical:

$$\nabla_t^2 L(v, t) \Big|_{t=t_v} = \nabla_t^2 (-\log p(t|v, t_0)) \Big|_{t=t_v} = H_t.$$

Therefore, we can estimate the curvature H_t using the second-order behavior of $L(v, t)$, and subsequently use it for Laplace approximation. We can have the second-order Taylor expansion of $L(v, t)$ in the same way as Equation 29:

$$L(v, t) \approx L(v, t_v) + \frac{1}{2}(t - t_v)^\top H_t(t - t_v). \quad (31)$$

Given an initial prompt t_0 close to t_v , the difference in loss values can be expressed as:

$$L(v, t_0) - L(v, t_v) = \frac{1}{2}(t_0 - t_v)^\top H_t(t_0 - t_v). \quad (32)$$

Rearranging Equation 32, we can express the quadratic form as:

$$(t_0 - t_v)^\top H_t(t_0 - t_v) = 2(L(v, t_0) - L(v, t_v)). \quad (33)$$

Specifically, when t is sufficiently close to t_v , the loss surface $L(v, t)$ can be well approximated by a quadratic form whose curvature is nearly uniform in all directions. This is particularly reasonable under the following conditions [73]:

- The loss function $L(v, t)$ is locally smooth and strongly convex around t_v , implying the eigenvalues of H_t are approximately equal.
- The distribution of prompts is high-dimensional with no significant directional bias, leading to an approximately isotropic local structure.
- Empirically, using an isotropic approximation greatly simplifies computations and has been widely adopted in Laplace approximation literature for scalability and tractability.

Under these conditions, the Hessian matrix H_t can be reasonably approximated by a scaled identity matrix, capturing the average curvature around t_v without requiring full second-order information, which would be computationally expensive to obtain in high-dimensional spaces. Motivated by the local isotropy property near a mode in high-dimensional optimization landscapes, we can assume H_t is locally proportional to the identity matrix, *i.e.*, $H_t \approx \lambda I$ for some positive scalar λ , the left-hand side simplifies to:

$$(t_0 - t_v)^\top \lambda I(t_0 - t_v) = \lambda \|t_0 - t_v\|_2^2. \quad (34)$$

Thus, we can solve for λ as:

$$\lambda = \frac{2(L(v, t_0) - L(v, t_v))}{\|t_0 - t_v\|_2^2}. \quad (35)$$

Consequently, the inverse Hessian H_t^{-1} is approximated as:

$$H_t^{-1} = \frac{1}{\lambda} I = \frac{\|t_0 - t_v\|_2^2}{2(L(v, t_0) - L(v, t_v))} I = \frac{\|t_0 - t_v\|_2^2}{2(L(v, t_0) - L(v, t_v))}, \quad (36)$$

where I is the identity matrix with dimensionality matching t .

B More Experiments

B.1 More Implementation Details

MLLM models and datasets. The experiments utilize a combination of images and prompts across multiple vision-language tasks. In addition to the MS-COCO dataset [81] and DALLÉ-3 dataset [2], We also conduct experiments on the SVIT [90], Flickr30K [91] and NoCaps [92] datasets. To construct the prompt sets, we consider three distinct task types: VQA, image classification, and image captioning. For each task, we incorporate prompts curated from prior studies [8] to ensure consistency with existing evaluations. The complete list of prompts is provided in Appendix D. The MLLMs used are LLaVA-1.5-7B-hf [6], BLIP-2 OPT-2.7B [5], and MiniGPT-4 [82], chosen to represent a diverse range of architectures and model scales among current MLLMs.

Experimental setups. For the parameter calculation of image/prompt distribution, following previous work [93], the coefficient β , r are set to 0.9 and 0.001. The target answer is uniformly specified as “*I am sorry.*” in all experimental conditions. To assess adversarial generalization, three cross-sample settings are considered: (1) 30 distinct prompts sampled per image (Cross-Prompt), (2) 50 different images sampled per prompt (Cross-Image), and (3) simultaneous sampling of 30 images and 30 prompts (Cross-Image/Prompt). The perturbations are optimized for 300 steps under $\eta = 16/255$ and step size $\alpha = 1/255$. Evaluation metrics include the Exact Match ASR (EM-ASR), Contain Match ASR (CM-ASR), and Semantic Similarity (Similarity). The EM-ASR and CM-ASR assess the word-level overlap between adversarial output and target text, while similarity is computed by cosine similarity between embeddings of adversarial output and target text obtained from the all-MiniLM-L6-v2 model [83]. All experiments are conducted on the NVIDIA A800 GPUs with 80GB of memory.

B.2 More Experiments on Datasets

We further conduct more experiments of our method on the SVIT, Flickr30K and NoCaps dataset using three MLLM models. As shown in Table 9, we can conclude that: (1) As for the general setting (No Cross), our method maintains competitive performance. (2) In the cross-sample setting, our sample-agnostic attack can achieve strong cross-sample performance by fitting the perturbation on the potential image/prompt distributions. We observe that MiniGPT-4 model exhibits a higher tendency to generate repetitive responses under input perturbations, which partially explains its relatively lower EM-ASR performance compared to other models.

B.3 Experiments on Transferability across Different Datasets

To further evaluate the effectiveness of our attack method in complex real-world scenarios, we design cross-dataset transfer attack experiments under two settings: (1) generating the adversarial perturbation on one image dataset and transferring it to another image dataset with a different domain for testing, while keeping the prompt unchanged; (2) on the same cross-dataset basis as (1), changing the prompt to further increase the difficulty of testing. Table 10 and Table 11 report the results of cross-dataset and cross-dataset/prompt transfer attacks, respectively. The results demonstrate that our method maintains strong transferability, even on unseen prompts or image datasets from different data domains. We assume the reason is that each MLLM image dataset and the task-specific prompts are sufficient enough to model the realistic distributions of real-world scenarios.

B.4 More Experiments on Sensitive to Sampling Quantity

To examine the effect of sampling quantity, we also evaluate attack performance under cross-prompt, cross-image, and combined settings on the DALLÉ-3 dataset using the MiniGPT-4 and BLIP-2 models. As shown in Figure 7, 8, sampling 30 prompts, 50 images, and a 30+30 combination for training consistently achieve strong attack performance, validating the effectiveness of sampling quantity.

B.5 More Experiments on Complex Target Texts

We also conduct experiments under the cross-prompt attack setting on the DALLÉ-3 dataset using more complex and sophisticated target texts, such as “A beautiful bird with a black and white color in

Table 9: Attack performances ($\uparrow$) across images/prompts on SVIT, Flickr30K and NoCaps datasets. “**Value**” denotes the best performance, “Value” denotes the second-best performance.

Model	Method	No Cross			Cross Images			Cross Prompts			Cross Images/Prompts		
		EM-ASR	CM-ASR	Similarity	EM-ASR	CM-ASR	Similarity	EM-ASR	CM-ASR	Similarity	EM-ASR	CM-ASR	Similarity
Dataset: SVIT [90]													
LLaVA-1.5	PGD [14]	94.5%	95.5%	0.941	0.0%	0.0%	0.046	29.7%	31.2%	0.357	0.0%	0.0%	0.056
	CroPA [8]	72.6%	73.1%	0.767	0.1%	0.1%	0.053	52.1%	57.4%	0.619	0.0%	0.0%	0.045
	UniAtt [10]	80.5%	81.3%	0.824	19.7%	22.1%	0.238	59.3%	60.2%	0.645	19.7%	19.9%	0.225
	Ours	96.7%	96.7%	0.968	52.5%	53.0%	0.548	84.7%	85.1%	0.871	50.4%	51.1%	0.551
BLIP-2	PGD [14]	62.7%	64.1%	0.681	0.1%	0.1%	0.046	22.7%	47.2%	0.397	0.0%	0.0%	0.097
	CroPA [8]	28.2%	92.1%	0.675	0.0%	0.0%	0.071	29.7%	59.8%	0.522	0.0%	0.0%	0.087
	UniAtt [10]	79.1%	80.2%	0.806	20.7%	21.1%	0.215	52.7%	54.9%	0.519	18.7%	19.5%	0.202
	Ours	68.3%	96.7%	0.687	51.8%	51.8%	0.556	60.3%	85.7%	0.715	37.4%	42.3%	0.440
MiniGPT-4	PGD [14]	68.3%	69.7%	0.722	0.0%	0.0%	0.066	24.5%	27.8%	0.314	0.0%	0.0%	0.078
	CroPA [8]	31.5%	89.3%	0.689	0.0%	0.0%	0.101	69.7%	71.8%	0.722	0.0%	0.0%	0.047
	UniAtt [10]	76.7%	84.9%	0.856	11.7%	25.7%	0.217	61.3%	62.9%	0.598	6.4%	22.7%	0.232
	Ours	93.3%	93.3%	0.947	6.3%	52.5%	0.226	93.5%	93.5%	0.941	2.9%	50.8%	0.268
Dataset: Flickr30K [91]													
LLaVA-1.5	PGD [14]	95.3%	95.3%	0.956	0.0%	0.0%	0.057	21.4%	22.6%	0.228	0.0%	0.0%	0.051
	CroPA [8]	82.3%	82.3%	0.836	0.2%	0.3%	0.066	70.2%	72.5%	0.727	0.0%	0.0%	0.053
	UniAtt [10]	80.3%	82.9%	0.822	22.1%	23.6%	0.237	66.3%	69.2%	0.708	20.3%	22.0%	0.217
	Ours	98.0%	98.0%	0.981	56.0%	56.5%	0.589	82.1%	86.3%	0.865	27.6%	35.2%	0.399
BLIP-2	PGD [14]	60.9%	62.3%	0.621	0.0%	0.0%	0.076	24.6%	26.5%	0.276	0.0%	0.0%	0.046
	CroPA [8]	30.4%	92.1%	0.625	0.2%	0.3%	0.116	29.1%	67.6%	0.493	0.0%	0.0%	0.054
	UniAtt [10]	76.3%	79.2%	0.786	21.5%	23.7%	0.233	56.1%	58.3%	0.577	19.4%	19.6%	0.205
	Ours	68.4%	96.1%	0.709	52.7%	52.7%	0.565	57.2%	84.1%	0.723	36.7%	44.8%	0.460
MiniGPT-4	PGD [14]	75.6%	75.6%	0.769	0.0%	0.0%	0.067	17.3%	17.6%	0.175	0.0%	0.0%	0.023
	CroPA [8]	94.1%	94.6%	0.948	0.0%	0.0%	0.076	71.6%	72.1%	0.720	0.0%	0.0%	0.038
	UniAtt [10]	82.4%	83.5%	0.843	24.7%	26.5%	0.266	68.2%	69.4%	0.701	19.1%	20.3%	0.199
	Ours	96.1%	96.1%	0.966	34.5%	53.6%	0.357	91.0%	91.5%	0.932	35.6%	38.3%	0.362
Dataset: NoCaps [92]													
LLaVA-1.5	PGD [14]	95.8%	95.8%	0.961	0.0%	0.0%	0.085	37.7%	38.4%	0.396	0.0%	0.0%	0.045
	CroPA [8]	76.4%	76.4%	0.781	0.0%	0.0%	0.086	65.3%	66.7%	0.669	0.0%	0.0%	0.036
	UniAtt [10]	81.7%	81.7%	0.836	22.3%	24.1%	0.238	69.2%	70.9%	0.713	19.8%	22.1%	0.217
	Ours	96.1%	96.1%	0.960	64.3%	65.0%	0.694	91.6%	93.0%	0.936	42.6%	44.3%	0.488
BLIP-2	PGD [14]	71.5%	72.0%	0.723	0.0%	0.0%	0.079	20.3%	20.9%	0.221	0.0%	0.0%	0.41
	CroPA [8]	29.6%	91.6%	0.630	0.0%	0.0%	0.086	27.5%	71.1%	0.551	0.0%	0.0%	0.075
	UniAtt [10]	78.1%	80.6%	0.803	19.6%	21.3%	0.204	56.9%	58.6%	0.573	17.9%	18.3%	0.181
	Ours	68.2%	98.0%	0.820	55.8%	57.4%	0.588	57.8%	81.9%	0.684	35.5%	42.4%	0.452
MiniGPT-4	PGD [14]	92.7%	92.7%	0.935	0.0%	0.0%	0.075	31.6%	32.3%	0.328	0.0%	0.0%	0.064
	CroPA [8]	93.1%	93.5%	0.942	0.0%	0.0%	0.063	71.9%	72.6%	0.731	0.0%	0.0%	0.034
	UniAtt [10]	81.6%	82.9%	0.820	19.2%	19.7%	0.199	69.2%	70.6%	0.713	17.6%	17.9%	0.183
	Ours	98.0%	100.0%	0.984	20.2%	59.6%	0.366	96.1%	97.1%	0.966	26.7%	44.7%	0.357

snow", "The view from the top of a hill overlooking the mountains". As shown in Table 12, despite the increase in the difficulty and complexity of these target texts, our attack method still shows significant effectiveness and maintains high performance in transfer attacks.

B.6 More Visualizations

We provide additional visualization examples to investigate the effectiveness of our attack from three aspects: (1) across different prompts and across different images (Figure 9); (2) across both images and prompts (Figure 10) and (3) across different datasets (Figure 11). As shown in these figures, the perturbed images remain nearly indistinguishable from the original ones, and our attack demonstrates strong transferability across various scenarios, validating the effectiveness of our proposed distribution approximation-based cross-sample attack approach.

C Limitations and Broader Impacts

Limitations. To improve the universality and transferability of adversarial perturbations, we adopt a Monte Carlo mechanism to sample a large number of image-prompt pairs from the approximated distribution. This enables optimization of a single input-agnostic perturbation. Although training can be performed offline, it involves repeated model queries and perturbation aggregation, resulting in significant time and computational costs. This limitation becomes more pronounced when scaling to diverse tasks, modalities, and real-world scenarios.

Table 10: Transfer-attack performance across different datasets with the same prompts.

From	Transfer to	Model	EM-ASR	CM-ASR	Similarity
DALLE-3	DALLE-3	LLaVA-1.5	66.3%	66.3%	0.688
		BLIP-2	54.2%	63.5%	0.582
		MiniGPT-4	63.8%	69.8%	0.661
	MS-COCO	LLaVA-1.5	53.8%	54.4%	0.560
		BLIP-2	52.5%	52.7%	0.537
		MiniGPT-4	54.6%	64.2%	0.583
MS-COCO	DALLE-3	LLaVA-1.5	63.8%	64.2%	0.660
		BLIP-2	48.2%	49.3%	0.689
		MiniGPT-4	53.8%	65.8%	0.570
	MS-COCO	LLaVA-1.5	58.7%	59.6%	0.611
		BLIP-2	55.5%	56.6%	0.584
		MiniGPT-4	63.1%	71.9%	0.655

Table 11: Transfer-attack performance across both datasets and prompts.

From	Transfer to	Model	EM-ASR	CM-ASR	Similarity
DALLE-3	DALLE-3	LLaVA-1.5	60.9%	61.3%	0.644
		BLIP-2	45.5%	59.4%	0.522
		MiniGPT-4	30.8%	52.4%	0.355
	MS-COCO	LLaVA-1.5	46.2%	46.5%	0.507
		BLIP-2	44.7%	54.5%	0.510
		MiniGPT-4	23.1%	42.9%	0.282
MS-COCO	DALLE-3	LLaVA-1.5	49.3%	50.3%	0.526
		BLIP-2	29.8%	40.1%	0.363
		MiniGPT-4	26.8%	34.0%	0.307
	MS-COCO	LLaVA-1.5	49.8%	51.4%	0.532
		BLIP-2	50.0%	57.3%	0.531
		MiniGPT-4	47.2%	57.9%	0.513

Table 12: Performance with different target texts on DALLE-3 dataset.

Target Answer	Model	EM-ASR	CM-ASR	Similarity
<i>"A beautiful bird with a black and white color in snow."</i>	LLaVA1.5	97.5%	97.8%	0.994
	BLIP-2	83.8%	83.8%	0.852
	MiniGPT-4	96.3%	96.5%	0.990
<i>"The view from the top of a hill overlooking the mountains."</i>	LLaVA1.5	95.5%	96.3%	0.972
	BLIP-2	82.0%	89.1%	0.939
	MiniGPT-4	100%	100%	1.000

Additionally, our threat model assumes access to static input images. However, real-world MLLMs are often embedded in interactive environments (e.g., robotics or autonomous driving), where inputs are captured dynamically. The application of universal attacks in such physical settings remains technically challenging. Extending universal attacks to such physically grounded settings remains an open and technically demanding problem, which warrants further exploration of robustness under real-world dynamics.

Broader impacts. From a broader perspective, this work reveals the vulnerability of MLLMs to adversarial interactions of agnostic input and underscores the value of studying more generalizable and practical attack strategies. However, the proposed methods also carry potential risks of misuse. For

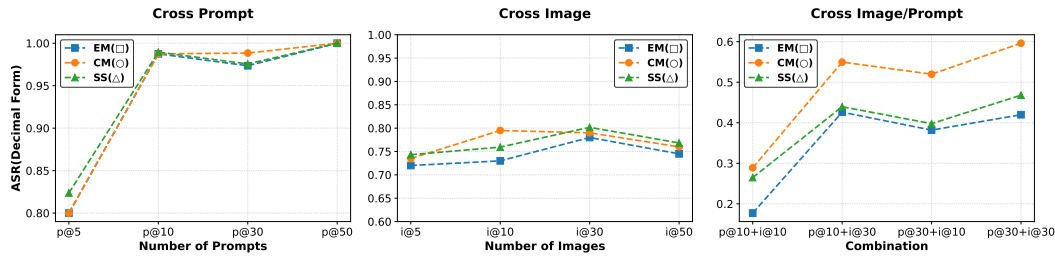


Figure 7: Ablations on different numbers of sampled images/prompts during Monte Carlo mechanism on MiniGPT-4 (“EM” denotes “Exact Match”, “CM” denotes “Contain Match”, “SS” denotes “Semantic Similarity”).

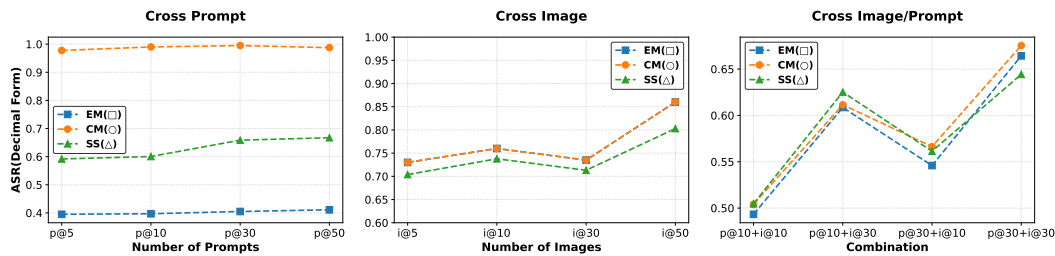


Figure 8: Ablations on different numbers of sampled images/prompts during Monte Carlo mechanism on BLIP-2 (“EM” denotes “Exact Match”, “CM” denotes “Contain Match”, “SS” denotes “Semantic Similarity”).

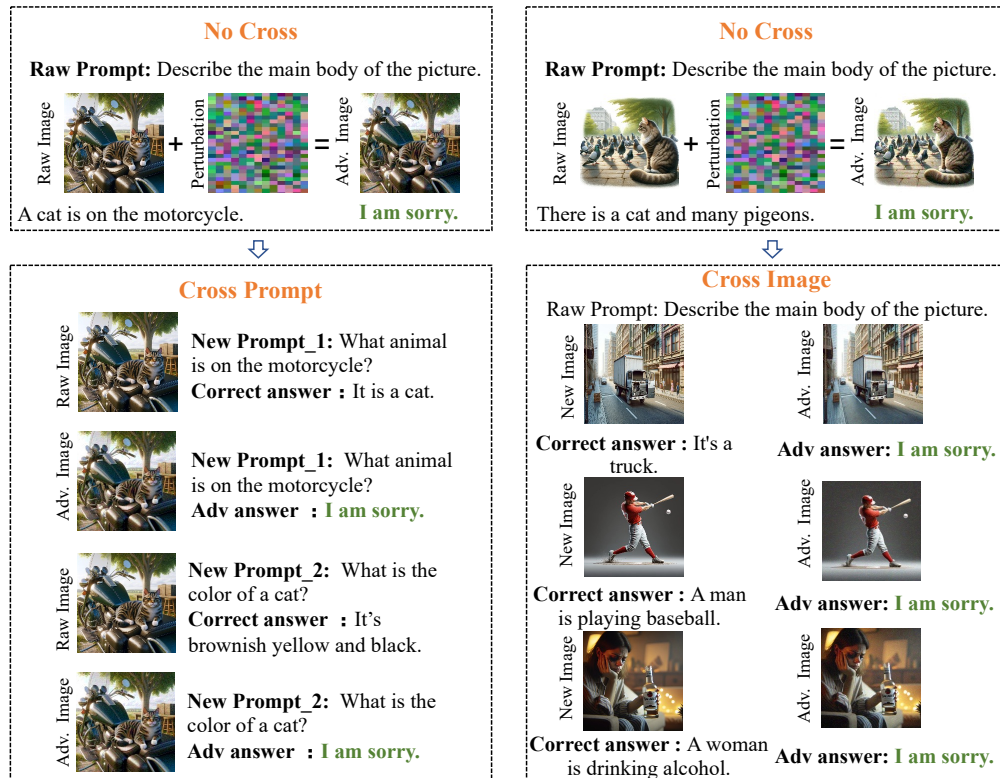


Figure 9: Visualizations of our cross-prompt and cross-image attack. All adversarial (adv.) images use the same perturbation.

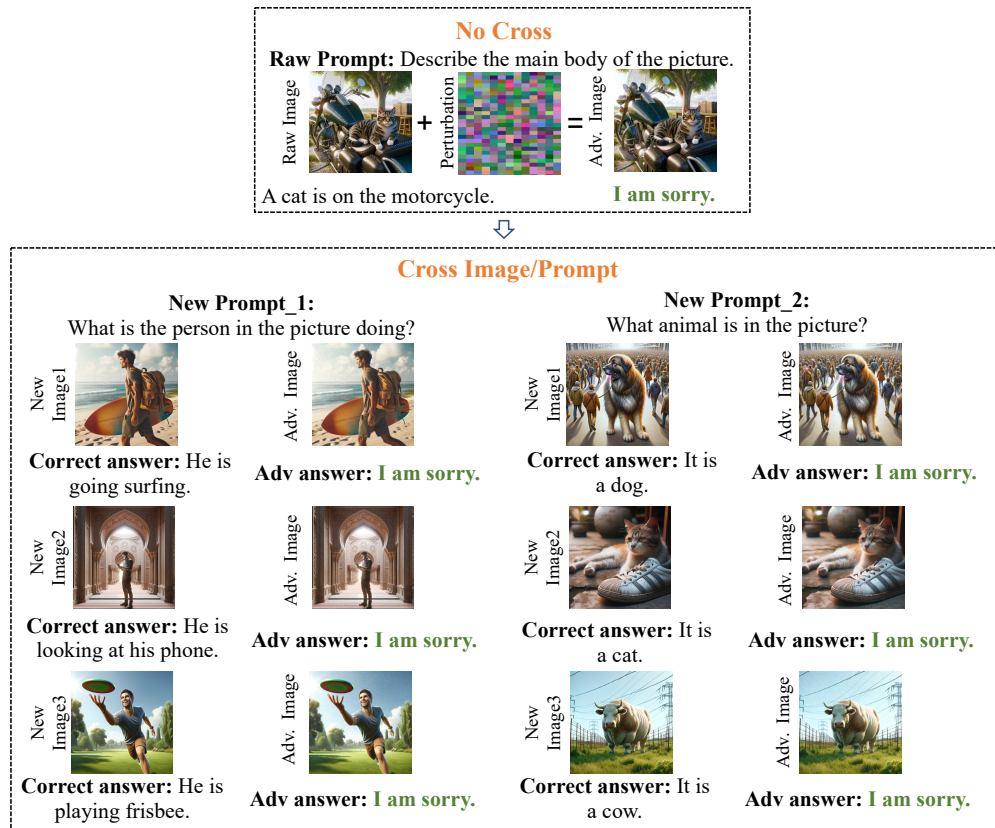


Figure 10: Visualizations of our cross-image/prompt attack. All adversarial (adv.) images use the same perturbation.

instance, adversaries may exploit universal perturbations to manipulate publicly deployed multimodal inference APIs (*e.g.*, Fireworks AI, Together AI), potentially undermining content integrity, model trustworthiness, or public safety. Therefore, we advocate for the joint development of adversarial research and defense mechanisms, including robust detection, adaptive defenses, and usage-boundary awareness, to ensure the safe and responsible deployment of MLLMs in real-world applications.

D Prompts for Different Tasks

Prompts for Image Captioning. Describe the components featured in this picture. Discuss the aspects depicted in this photograph. Explain the details visible in this visual. Outline the parts contained within this image. Clarify the features shown in this illustration. In a single sentence, describe what is happening in the picture. Briefly explain the scene depicted in this image. Capture the essence of the activity shown in this image in one sentence. Provide a one-sentence summary of the action in this picture. Summarize the event in this image using a single sentence. Describe the primary elements of this image using words. Express the key features of the photograph verbally. Summarize the essential parts of this illustration in text form. Articulate the central aspects of the visual using language. Convey the principal components of the scene in descriptive terms. What story is portrayed in this picture? What tale is being depicted in this image? What account does this photo illustrate? What plot is conveyed in this photograph? What saga is presented in this picture? Analyze the primary elements present in this image. Identify the key components featured in this picture. Examine the central themes depicted in this photograph. Outline the core subjects captured in this snapshot. Deconstruct the significant aspects of this visual. Describe the central focus of this picture. Provide a summary of the key elements in this photograph. Explain the primary subject depicted in this image. Outline the main features shown in this photo. Detail the principal aspect of this visual. Briefly describe the contents of this picture. Summarize what is depicted in this image. In a short sentence, explain the subject of this photo. Provide a concise explanation of what this image

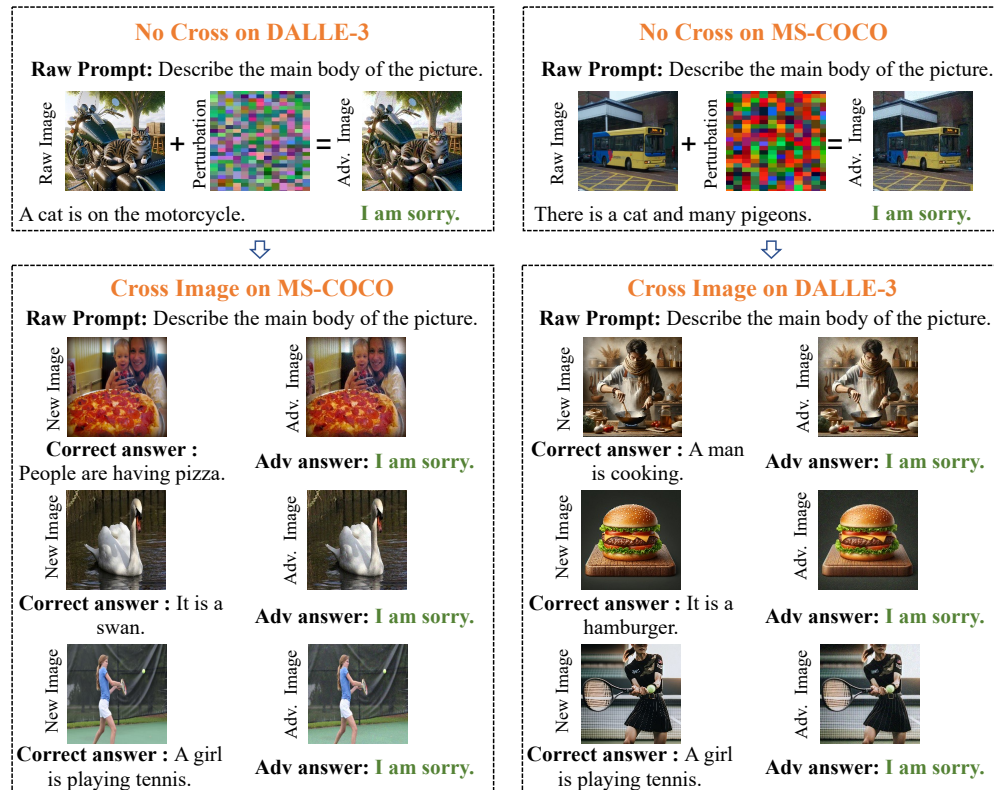


Figure 11: Visualizations of our cross-dataset attack. Left column: the perturbation is crafted in the DALLE-3 domain and transferred to MS-COCO domain. Right column: the same process is applied.

shows. Describe succinctly what can be seen in this picture. Explain the environment or backdrop featured in this image. Provide details about the scene or location shown in the picture. Outline the surroundings or context depicted in this photograph. Elaborate on the place or scenery visible in this image. Discuss the area or landscape portrayed in this photo. Summarize the elements depicted in this photograph. Describe the items or themes present in this image. Outline the features or topics visible in this photo. Give a summary of the components shown in this picture. Detail the objects or subjects captured in this snapshot. Determine the central theme or attraction in this picture. Pinpoint the main subject or highlight within this photograph. Locate the key element or centerpiece in this image. Recognize the dominant feature or focal point in this snapshot. Discern the primary object or standout aspect in this visual. How should this picture be ideally titled? What is the best caption for this photo? What title would suit this image best? How would you ideally label this picture? What's the most fitting title for this image? How might you present this image during a talk? What approach would you take to describe this image in a slideshow? How would you explain this image while giving a presentation? In what way could you showcase this image in a discussion? How would you frame this image as part of your presentation? Provide a concise summary of the image's focal point. Offer a brief overview of the image's key subject matter. Deliver a short description of the image's central theme. Share a snappy explanation of the image's primary focus. Give a swift outline of the image's core subject. What is the main theme or highlight depicted in this image? Can you identify the central focus or topic illustrated in this picture? What's the primary scene or element showcased in this photograph? What significant activity or object is featured in this photo? What is the core message or subject conveyed by this image? Describe the activities or occurrences happening within this picture. Explain the events or movements visible in this photograph. Discuss the actions or scenes depicted in this image. Illustrate the events or actions captured in this photo. Interpret the occurrences or actions shown in this visual. Summarize the essence of this image in one sentence. Capture the meaning of this picture in a brief statement. Describe the subject of this photo using just one phrase. Express the theme of this photograph in a concise sentence. Articulate the message of this image in a quick summary. Provide a brief summary of this image. Give a concise review of this photograph. Deliver a short explanation of this visual. Present a quick overview of this snapshot.

Furnish a narrow depiction of this artwork. Provide a brief summary of this picture. Offer a short description of this image. Present a quick analysis of this photograph. Deliver a succinct explanation of this visual. Outline the key points of this graphic. Convert the details of this image into a written sentence. Turn the visual elements of this picture into a textual statement. Express the contents of this photo as a single sentence. Render the information in this image into a coherent sentence. Describe the scene in this picture with one sentence. Outline the figures or elements present in this picture. Detail the individuals or objects depicted in this photo. Characterize the people or items shown in this illustration. Explain the personas or features visible in this snapshot. Identify the actors or components portrayed in this visual. Describe the events taking place in this picture using words. Use words to convey the actions seen in this image. Put into words what is occurring in this photograph. Narrate the scene depicted in this picture with written descriptions. Articulate the happenings within this image through a verbal depiction. What approach would you take to present this image to a group? How might you convey the essence of this image to viewers? In what way would you describe this image to an audience? How could you effectively narrate the details of this image to people? What strategy would you use to showcase this image to spectators? Describe the main occurrences or topics depicted in this image. Identify the key happenings or themes shown in this photo. Outline the central incidents or subjects present in this illustration. Highlight the prominent events or concepts illustrated in this picture. Summarize the principal actions or focuses featured in this visual. Can you identify the key components of this image? Which features stand out most in this picture? What are the prominent aspects captured in this photo? Could you list the principal parts of this photograph? What elements are most noticeable in this image? Offer your understanding of the central theme or occurrence in this image. Explain what you perceive as the key activity or topic depicted in this picture. Describe the primary focus or incident illustrated in this image. Share your analysis of the primary subject or action captured in this visual. Discuss the core event or subject matter presented in this image. What name would you assign to this artwork for exhibition purposes? How would you label this piece for a gallery display? What caption would you create for this image in an art show? How would you describe this artwork for a gallery presentation? What title might you give this image for showcasing in a gallery setting? Can you describe the scene or environment shown in this picture? What kind of situation or backdrop is illustrated in this photo? What is the context or theme presented in this image? Can you identify the location or scenario captured in this photograph? What event or atmosphere is portrayed in this visual? Briefly describe the primary events taking place in the image. Summarize the key activities happening in this picture. Identify the main actions depicted in this photo. Provide a short description of the central occurrences shown in this image. Give a concise account of the significant actions in the photograph. Provide a brief overview of what this image depicts. Summarize the main elements visible in this picture. Give a concise description of the scene shown in this photo. Describe the key aspects featured in this photograph. Outline the primary details captured in this image. What labels would you use to tag this picture in a collection? How might you describe this photo for an album entry? In what way would you catalogue this image within a gallery? What notes would you add to this photograph in an archive? How could you document this image for an album? How would you narrate the details of this image to someone who can't see it? Imagine you're on a podcast; how would you paint a picture of this image? If you were to explain this image verbally, what words would you choose? How would you articulate the content of this image over the airwaves? Suppose you had to provide a radio commentary on this image, what would you say? Describe the key scene depicted in this picture using your own expressions. Convey the central occurrence shown in this photograph in your own language. Explain the primary happening in this image using your own phrasing. Articulate the main incident illustrated in this photo in your own terms. Summarize the focal event in this picture with your own wording. Can you identify the key elements in this picture? What standout characteristics does this photo have? What are the main highlights visible in this image? Could you point out the prominent aspects of this picture? What distinctive details can you observe in this image? Analyze the narrative depicted in this picture. Interpret the tale conveyed by this illustration. Examine the message this visual is presenting. Decipher the plot expressed in this photograph. Uncover the theme behind this artwork. Illustrate the setting or context captured in this picture. Detail the scenery or background depicted in this image. Explain the surroundings or backdrop presented in this photo. Outline the landscape or background shown in this snapshot. Interpret the scene or setting featured in this photograph. What tag would you assign to this picture in a database? How would you classify this photograph for the archive? What designation would you give to this image in an album? How would you identify this photo in a collection? What title would you use for this image in a gallery? Briefly describe the central message of the image. Summarize the core idea of this photo concisely. Capture the primary concept of the

picture in a few words. Explain the key theme of this visual succinctly. Distill the essence of the image in a concise manner. Describe the main activity or occurrence depicted in this image. Identify the central action or event taking place in this image. Explain the key event or movement shown in this image. Outline the principal action or incident illustrated in this image. Detail the primary scene or activity captured in this image. Offer a brief summary of what this image portrays. Give a short description of the elements in this picture. Summarize the scene depicted in this photograph. Deliver a quick overview of the subject matter in this photo. Furnish a succinct account of what is shown in this image. Compose a short summary of the scene depicted in this picture. Provide a concise description of the events shown in this photo. Summarize the action occurring in this illustration. Offer a quick overview of what's happening in this visual. Draft a compact explanation of the situation presented in this image. Describe the core message conveyed by this image using words. Use words to express the central theme depicted in this image. Articulate the primary idea of this image in a verbal format. Convey the fundamental concept of this image through language. Capture the essence of this image's theme with a written description. How might you interpret this artwork at a museum showcase? What would you say to convey the essence of this piece at an exhibit? How would you articulate your thoughts about this image in an art gallery? What description would you provide for this image in a curated display? How could you explain the significance of this artwork in an exhibition setting? Emphasize the key elements or activities within this picture. Identify the primary topics or motions shown in this image. Focus on the main themes or happenings depicted in this photo. Pinpoint the dominant objects or movements present in this visual. Bring attention to the core features or events in the image. Provide a concise account of the happenings depicted in this image. Summarize the occurrences shown in this picture. Present a short story about the activities captured in this photo. Outline the sequence of actions visible in this photograph. Give a quick overview of the scene portrayed in this image. Summarize the actions depicted in this picture into a short statement. Condense the events shown in the illustration into a concise sentence. Describe the occurrences in this photograph with a brief phrase. Paraphrase the scenes in this image into a succinct sentence. Capture the movements in this visual with a small sentence. Provide a brief overview of the main topics depicted in this picture. Summarize the key themes represented in this photograph. Offer a concise explanation of the core elements featured in this image. Deliver a short description of the fundamental aspects in this visual. Outline the principal ideas illustrated in this photo. Offer a brief overview of the moment depicted in this picture. Summarize the essence of the setting shown in this image. Give a concise description of the scenario presented in this photograph. Highlight the key details of the event portrayed in this photo. Provide a short explanation of what's happening in this image. How would you describe this picture to a young child? Can you tell a kid what's happening in this image? How might you present this photo to a little one? What's the simplest way to narrate this image to a child? How could you illustrate this picture for a young audience? Can you identify the key elements depicted in this image? What significant figures or items are captured in this picture? Which primary objects or scenes are portrayed in this photo? Could you point out the main subjects or features present in this photograph? What central themes or objects are highlighted in this image? Describe the primary activities occurring in this picture. Highlight the key happenings depicted in this photo. Outline the central actions taking place in this illustration. Identify the major occurrences within this visual. Capture the essential events shown in this scene. Summarize the scene depicted in this image concisely. Offer a short description of the environment shown in this picture. Provide a brief overview of the backdrop in this photograph. Deliver a quick explanation of the circumstances surrounding this image. Give a succinct account of the setting present in this photo. Provide a brief overview of the elements seen in this picture. Summarize the topics depicted in this photograph. Give a concise account of the items visible in this image. Present a short summary of the components in this photo. Describe the themes represented in this visual. Describe the primary scene or environment depicted in this image. Illustrate the central theme or backdrop presented in the photograph. Explain the key setting or situation captured in this visual. Outline the principal scenario or context shown in this picture. Elucidate the dominant scene or location featured in this image. Explain the key actions or occurrences depicted in this picture. Outline the primary happenings or scenes presented in this photograph. Detail the significant events or actions taking place in this image. Summarize the central scenes or activities shown in this photo. Illustrate the main occurrences or interactions visible in this picture. Give a brief description of what is depicted in this image. Summarize the key elements shown in this image. Offer a short overview of the scene in this image. Outline the main subjects present in this image. Present a succinct interpretation of the imagery. How might this picture be labeled if it appeared in an academic book? What caption would accompany this illustration if it were included in a scholarly publication? If this photograph were part of a course

material, what caption would it have? How would a textbook describe this image in its caption? What would the textual description read beneath this image if placed in an educational manual? Describe the main theme depicted in this picture. Identify the central element featured in this photograph. Summarize the key subject showcased in this image. Outline the principal motif present in this visual. Explain the dominant focus illustrated in this artwork. Describe the tale or account depicted in this image. Explain the storyline or plot shown in this photograph. Outline the scenario or saga illustrated in this picture. Convey the account or legend presented in this photo. Detail the story or theme represented in this image. What approach would you use to present this image in a documentary setting? How might you go about featuring this image in a documentary film? In what manner would you showcase this image for a documentary audience? How could you effectively incorporate this image into a documentary narrative? What narrative technique would you employ to unveil this image in a documentary? Describe the themes or occurrences depicted in this photo. Outline the topics or moments showcased in this picture. Explain the elements or activities illustrated in this image. Identify the scenes or incidents represented in this photograph. Specify the subjects or happenings featured in this visual. Provide a concise description of the scene captured in this image. Summarize the situation shown in this picture. Give a short overview of the events illustrated in this photo. Offer a succinct narrative of the subject displayed in this photograph. Deliver a quick synopsis of the context presented in this image. Briefly describe the key components in this picture. Summarize the primary features visible in this photograph. Identify the principal elements shown in this image clearly. Highlight the fundamental aspects depicted in this photo succinctly. Outline the main items evident in this visual concisely. Explain what's occurring in this image. Detail the activities taking place in this photograph. Illustrate the events unfolding in this picture. Clarify the happenings depicted in this image. Narrate the scene portrayed in this photograph. Offer a brief overview of the visual elements in this image. Summarize the key details depicted in this picture. Deliver a concise narration of what's shown in this photo. Present a short account of the scene captured in the image. Give a quick rundown of the subject matter in this photograph. Can you give a short summary of the primary focus or occurrence depicted in this image? What concise description would you provide for the central theme or happening in this picture? How might you succinctly explain the key topic or incident captured in this photo? Could you offer a quick overview of the main element or activity shown in this image? What brief insight would you share about the dominant feature or moment in this visual? Explain what is depicted in this picture. Detail what can be seen in this photo. Outline the elements present in this image. Illustrate what this image portrays. Interpret the subject matter of this picture. Can you describe what is occurring in this picture? What events are taking place in this photo? What action is depicted in this image? Could you explain what is going on in this photograph? What scene is being portrayed in this image? Create a short description for this picture. Write a concise caption for this photo. Compose a quick summary for this image. Formulate a simple caption for this visual. Generate a brief tagline for this illustration. Describe this image using a single sentence. Narrate a brief story based on this picture. Craft a one-sentence tale from this photo. Summarize this image with a concise narrative sentence. Create a short story inspired by this image in one sentence. What would this image say if it could talk? Imagine this image had a voice, what words would it utter? If this picture had the ability to speak, what message would it convey? Should this visual have the power of speech, what story would it tell? If this photograph were able to vocalize, what would be its spoken narrative? Provide an overview of the scene shown in this picture. Outline the situation illustrated in this photo. Describe the circumstances presented in this visual. Recap the events portrayed in this image. Explain the context displayed in this graphic. What core idea or happening is featured in the image? Identify the main subject or occurrence depicted in the photograph. Determine the key motif or incident illustrated by the picture. What primary concept or activity does the image convey? Highlight the principal focus or episode captured in the photo. Craft a title for this photograph. Generate a caption for this picture. Compose a tagline for this visual. Write a heading for this snapshot. Develop a header for this illustration. Describe what's happening in this picture. Discuss the events shown in this photo. Illustrate the situation depicted in this image. Elaborate on the scenario presented in this picture. Interpret the action occurring in this photograph. How would this image communicate a message if it were a postcard? What story would this picture tell if it were printed on a postcard? Imagine this scene as a postcard; what would it say? If you turned this into a postcard, what feelings would it express? What sentiment would a postcard capture from this photograph? Describe the details visible in this picture. Explain the components depicted in this scene. Highlight the features shown in this photograph. Outline the visuals showcased in this illustration. Summarize the imagery captured in this frame. Assign a brief title to this picture. Provide a concise name for this photo. Suggest a short caption for this image. Create a succinct

title for this photograph. Offer a quick label for this visual. How might you explain this picture to a person who is visually impaired? What words would you use to narrate this image to someone unable to see it? How can you verbally illustrate this image for a person with no sight? What description would you provide to convey this image to someone who is blind? How would you paint a mental picture of this image for someone who cannot view it? Describe the main focus or element of the image. Explain the central theme or topic depicted in the picture. Identify the key action or feature captured in the photograph. Outline the dominant subject or event shown in the snapshot. Highlight the principal aspect or activity visible in the photo. What title would you give this image if it were to be on a book cover? Imagine this picture as a book cover; what would the book's title be? If this photo were used as a book cover, what would the title of the book be? Consider this image being on a book cover; what title do you think it should have? What do you think the title should be if this image served as the cover of a book?

Prompts for Image Classification. Determine the main subject of this picture in a single term. Pinpoint the central motif of this photo using one word. Specify the key focus of this image with a solitary word. Discern the dominant theme of this picture in just one term. Establish the core concept of this photo in one word. What single word best describes this picture? Can you tag this photo using one term? How might you categorize this image with one descriptor? What one label would you assign to this photograph? How would you title this image using only one word? Identify the primary classification for this picture. Ascertain the overarching category of this image. Pinpoint the core type of this visual. Establish the fundamental grouping for this photo. Define the principal class of this image. Provide a single-term label for this image. Assign a one-word title to this photograph. Designate a concise name for this picture. Apply a solitary descriptor to this image. Select a lone tag for this photo. If this picture were saved on your device, what would its filename be? What name would you give this image if it were stored as a file? If you were to save this photo on your computer, how would you name it? Imagine this image as a file, what would you call it? If this image were a saved file, what title would it have? Label this photo with the most appropriate keyword. Assign the best-fitting keyword to this picture. Annotate this image using the most pertinent keyword. Attach the most suitable keyword to this visual. Identify this image with the most applicable keyword. Identify the main category for this image. Determine the principal classification for this picture. Assign the primary label to this photo. Designate the main type for this visual. Specify the chief category for this snapshot. Can you briefly label this image? How might you concisely describe this image? Could you quickly classify this picture? How would you swiftly identify this image? Can you offer a short summary of this image? Provide the main description for the content of this image. Give the key label for the content of this image. State the central descriptor for the content of this image. Identify the principal description for the content of this image. Specify the primary label for the content of this image. If this image were an item, what tag would you attach to its packaging? Imagine this image as merchandise; what label would you affix to its container? If this picture represented a product, what descriptor would you use on its box? Suppose this image is a commodity; what sticker would you apply to its wrapping? If this visual were a good, which label would you place on its package? Select one word that summarizes the essence of the picture. Identify a solitary term that conveys the image's theme. Pick a single word that captures the core of the photograph. Find one word that represents the image's main idea. Decide on a singular term that reflects the image's substance. What category would you assign to this image for database entry? How should this image be labeled within the database? Into which classification does this image fall for database purposes? What classification would you use for this image when organizing the database? How can this image be categorized in the database system? In a single term, capture the soul of this picture. Using one word, convey the spirit of this photograph. Summarize the core of this image with a lone word. With one word, express the heart of this visual. Condense the nature of this photo into a single word. Determine the most appropriate classification for this picture. Assign the best-suited label to this image. Identify the most relevant category for this photograph. Select the most suitable grouping for this image. Choose the most accurate category for this visual. Can you identify the main theme of this picture? What is the central focus of this photograph? Could you tell me the primary subject in this image? What stands out as the key element in this photo? What is the dominant feature of this visual? In which section of the store would this image be placed? Where in a shop would you expect to find this image? This picture would be located in which part of the store? If you were shopping, in which aisle would you find this image? In what store location would this image be categorized? Supply a single word that encapsulates this image. Offer one term that describes this photograph. Present a lone descriptor for this picture. Name a solitary word that defines this image. Identify one term that characterizes this

photo. What caption would you write for this picture in a photography competition? How might you describe this photo in a caption for a contest? If you were entering this photo in a contest, what caption would you use? What would be your creative caption for this image if it were in a photo competition? Imagine this image is in a contest; how would you caption it? Choose a tag that best captures the central idea of this picture. Pick a title that reflects the core subject of this image. Assign a label that represents the primary theme of this photo. Identify a category that aligns with the main motif of this image. Determine a caption that encapsulates the essence of this picture. Suggest the best-fitting tag for this picture. Provide the most suitable label for this photograph. Assign the most relevant tag to this image. Recommend the most accurate tag for this visual. Select the most fitting descriptor for this image. What keyword most accurately captures the essence of this image? Can you identify a single keyword that encapsulates the main theme of this image? Which keyword would you choose to represent the core idea of this image? What keyword serves as the best descriptor for this image? Identify the keyword that best defines the central concept of this image. What caption would you give this artwork for a gallery display? How might you label this photograph in a museum setting? What name would you assign to this piece for an art show? How would you describe this painting on an exhibition placard? What inscription would you use for this image in a curated collection? Generate a concise label for the image's subject. Create a brief description for what the image depicts. Formulate a short title summarizing the image's theme. Assign a clear tag that encapsulates the image's essence. Devise an informative caption for the image's main focus. Select a term that best categorizes this image with similar ones. Pick a word that most effectively groups this image with others of its kind. Identify a label that best associates this image with comparable images. Find a word that most suitably links this image with others like it. Determine a term that best connects this image to those that resemble it. How might a museum plaque describe this artwork? What description would accompany this image in an art exhibit? If displayed in a gallery, what would the caption say about this image? How would a curator title this piece for a museum show? What label would this image receive if placed in an art collection? Describe this picture with a single theme word. Identify a one-word theme for this image. Summarize this photo using just one central word. Select a single word to encapsulate the theme of this image. Tag this image with a one-word thematic label. Label this image with its main identifier. Assign a key tag to this picture. Attach the primary description to this photo. Mark this photograph with its core feature. Designate a principal tag for this image. What is the central message conveyed by this image? What is the predominant feeling expressed in this photo? What is the primary idea depicted in this artwork? What is the main concept illustrated by this picture? What is the key narrative presented in this photograph? Identify a descriptive category for this image. Assign a label to this image. Determine a fitting class for this image. Designate an appropriate tag for this image. Select a suitable classification for this image. In which category would you place this image in the collection? What method would you use to organize this image within a gallery? How do you intend to categorize this image among the other artworks? Under what criteria would you file this image in the archive? How should this image be classified in your photo library? Briefly determine the central focus of this picture. Clearly specify the primary element in this photograph. Succinctly point out the key subject in this image. Precisely highlight the main feature in this visual. Identify the core component of this image briefly. Imagine this picture as the front of a magazine; what headline would it have? Suppose this photo were featured on a magazine's cover; what title might it hold? If you consider this image as a magazine cover, what would its main headline say? Picture this image as the front page of a magazine; what title would it display? Visualize this photograph as the cover of a magazine; what caption would it carry? How would you label this picture in a database? What descriptor fits this photograph? What title would you assign to this visual? How would you categorize this graphic? What name would you give to this image file? Label this image using a single word. Assign a one-word category to this photo. Use a singular noun to describe this picture. Identify this picture with a single designation. Choose a single term to characterize this image. If you could name this picture as a book chapter, what title would you choose? What title would you assign to this image if it were a chapter in a novel? Suppose this photograph were a chapter in a story; what would its heading be? How would you label this image if it served as a title for a book chapter? Imagine this picture as a chapter in a book; what name would you give it? Choose the most appropriate category for this picture. Determine the best label for this photograph. Identify the most suitable classification for this image. Pick the most accurate classification for this photo. Assign the most relevant category to this image. Summarize the core theme of this picture using a single term. Capture the spirit of this photo in one word. Describe the central element of this image with one word. Express the main idea of this photograph in a single word. Identify the fundamental concept of this image in one word. What tag would you assign to this

image to simplify finding it later? How might you categorize this picture for straightforward access? Which description would you use to ensure easy retrieval of this photo? What annotation would you choose to efficiently locate this image? How could you classify this image to aid in simple retrieval? Identify the central subject captured in this image. Ascertain the primary focus depicted in this picture. Pinpoint the main topic highlighted in this photo. Discern the fundamental motif portrayed in this snapshot. Establish the principal element illustrated in this photograph. Summarize the core theme of this picture in a single term. Capture the essence of this photo with one word. Distill the central focus of this image into a single word. Express the primary topic of this photograph in just one word. Convey the key idea of this image using one word. If this photograph were displayed in an exhibition, what title might it bear? Were this picture presented in a museum, how would it be described on a placard? If this visual were part of an art collection, what name might it be given? Suppose this image were showcased in a gallery, what label would suit it best? If this artwork were featured in a curated display, how might it be titled? Offer the briefest label for this image. Present the shortest description for this photo. Deliver the most succinct caption for this snapshot. Supply the minimal title for this visual. Give the shortest summary for this illustration. What title would you assign to this photo in a collection? How would you label this picture for a digital gallery? What name would you give this image for storage in an album? How would you catalog this photograph in an archive? What designation would you use for this image in a photo library? Select a term that best describes the primary subject of the image. Identify a word that captures the essence of the image's core element. Pick a descriptor that summarizes the focal point of the picture. Find a word that conveys the central theme of the photograph. Choose a word that encapsulates the image's key feature. How should this image be titled in the catalog? What label best suits this image for the catalog entry? What caption would you assign to this image in a catalog? How would you describe this image in a catalog header? What heading would you use for this image in the catalog? Identify the main theme of this image. Determine the core concept of this photo. Pinpoint the central idea of this picture. Ascertain the fundamental element of this image. Recognize the key aspect of this photo. Which title would suit this image in the presentation best? What caption should this slide's picture ideally have? How should this image be labeled for the slideshow? What heading would this photo in the deck benefit from most? Which tag should accompany this image in the slideshow? Identify the primary theme of this image. Ascertain the main subject of this picture. Establish the leading classification for this photo. Pinpoint the chief element in this photograph. Recognize the central focus of this image. Provide the central characterization of the image. Elaborate on the primary details of this visual. Describe the main elements depicted in the picture. Highlight the essential features of this photograph. Summarize the key aspects of the image. How might this illustration be referenced in the textbook glossary? In what way would this picture appear in the textbook's table of contents? What label would be used for this diagram in the book's reference section? How should this photograph be listed in the index of the textbook? Under what heading would this image be categorized in the textbook's appendix? Choose the term that most accurately captures the essence of this image. Identify the phrase that best encapsulates the theme of this picture. Determine the keyword that most effectively represents the concept of this image. Pick the word that best summarizes the main idea of this visual. Find the expression that most closely aligns with the subject of this photograph. Assign a category tag to this picture. Identify the classification label for this photograph. Determine the class label for this image. Specify a category for this image. Categorize this image using an appropriate label. What song title does this image remind you of? Imagine this image as a song title, what would you call it? If you could name a song after this image, what would its title be? Consider this image as inspiration for a song, what name would it have? How would you title a song based on this image? Determine the primary genre depicted in this image. Recognize the chief genre showcased in the photograph. Ascertain the dominant genre represented in this visual. Detect the principal genre illustrated in the picture. Establish the leading genre captured in this photo. Select the most fitting label for this picture. Choose the most appropriate classification for this photograph. Identify the most suitable tag for this image. Determine the best category for this visual. Allocate the most relevant group for this snapshot. Summarize the primary concept of this picture in a single word. Identify the main idea of this image using just one word. Convey the essence of this photograph with one word. Capture the core theme of this visual in a solitary word. Express the central motif of this illustration in one word. How would you describe this image for inclusion in a portfolio? What term would best characterize this image for a portfolio? What label would you assign to this image in a portfolio? How would you title this image for a portfolio presentation? What caption would you give this image for a portfolio? Provide a label that encapsulates the essence of the image. Create a one-word descriptor for the image's theme. Identify the image using a concise keyword. Assign a brief tag that reflects the image's main idea.

Generate a single term that describes the image's subject. Picture yourself describing this image to a friend on a call. What single word would you use? Pretend you're telling someone about this image without them seeing it. How would you sum it up in one word? Visualize explaining this image to someone who can't see it. What one word would you choose to describe it? Envision you're narrating this image to someone over the phone. What is the one word you'd use? Imagine you're conveying the essence. Execute the photo categorization process on this picture. Provide the category in a single term. Conduct the visual recognition task on this image. State the result with one word. Carry out the image labeling operation on this photo. Deliver the label using only one term. Undertake the picture classification task for this image. Offer the label in one word. Implement the image sorting procedure on this picture. Present the label succinctly in one word. Picture a child examining the photo. What might they eagerly point out and call by name? Visualize a youngster looking at the picture. What might they enthusiastically identify and name? Envision a kid studying the image. What might they excitedly recognize and name? Think of a child observing the photo. What might they joyfully point to and name? Imagine a young one inspecting the picture. What might they happily identify and name? If this photograph were made into a jigsaw puzzle, how would the box describe the scene? What description would be on the cover if this image were transformed into a jigsaw puzzle? How would the puzzle box label describe this picture if it were used for a jigsaw set? If this picture became a jigsaw puzzle, what would the box caption say to depict the image? What would the box description read if this image were crafted into a jigsaw? Categorize the elements in this picture. Determine the subject matter of this photo. Identify the themes present in this image. Analyze the contents of this photograph. Assess the components within this image. How would you categorize this image if you were to assign a label? What label might you choose if you were tasked with labeling this image? If labeling this image were your responsibility, which label would you select? Suppose you needed to label this image, what would your chosen label be? What label would you apply to this image if you were asked to label it? Which category most accurately represents this image? How would you classify this image? What type of category fits this image best? Under which category does this image fall? What is the most suitable category for this image? Summarize the main theme of this picture in one word. Identify the core element of this photo using just one word. Capture the essence of this image with a single word. Convey the primary focus of this scene in one word. Define the key feature of this photograph in one word. Determine the category of the object shown in this picture. Identify the class to which the item in this image belongs. Assign a classification to the object featured in this photograph. Classify the item presented in this visual representation. Establish the type of object illustrated in this image. If this picture were part of a photo collection, what caption would it have? If this photograph were included in an album, how would it be labeled? If this snapshot were in a photo book, what title would it carry? If this image were placed in a scrapbook, what would its description be? If this photo were in a gallery, what would its tag say? Classify the elements within the picture. Sort the details present in the photograph. Organize the components of the visual. Group the features found in the image. Arrange the aspects of the photo. If you had to classify this image, which category would you choose? If you needed to place this image into a category, which one would it fall under? If you were to assign this image to a category, which would it be? If you had to categorize this image, which category would it belong to? If you were to group this image into a category, which one would you select? What term best describes this picture? Which word comes to mind when you view this image? What label would you give to this photo? How would you tag this image with a single keyword? What descriptor fits this image the most? Categorize this photo with an appropriate label. Determine an accurate category for this picture. Assign an appropriate label to this photograph. Choose a fitting classification for this image. Identify a suitable category for this visual. If this painting were displayed in a museum, which category would it fall under? If this photograph were exhibited, in which section would it be placed? If this artwork were showcased, under what classification would it be listed? If this piece were part of an art show, which segment would it be included in? If this illustration were featured in an exhibition, where would it be categorized? Identify the predominant emotion conveyed by this picture using a single term. Summarize the central concept of this artwork in one word. Capture the primary subject of this photo with one descriptive word. Express the key idea of this illustration using just one word. Define the principal focus of this graphic with a single word. Which section should this image be filed under in the library? In what category does this image belong in a library catalog? Where should this image be classified within the library system? What library category is appropriate for cataloging this image? Into which library classification should this image be sorted? Which label best describes this picture? What category is most appropriate for this photo? Which classification title suits this image the most? What tag should be applied to this image for optimum description?

Which descriptive label would be most fitting for this picture? Offer a single term that summarizes the content of this picture. Give a one-word depiction of what this image portrays. State a solitary word that captures the essence of this photo. Present a single word that describes the subject of this image. Supply a one-word characterization of this image's theme. How would you label this photo if you were to store it? What title would you assign to this picture for archiving purposes? If you were to categorize this image, what tag would you choose? Imagine saving this photograph; what descriptor would you apply? Which identifier would you select for this image during archiving? What would be the best category to assign to this image? How should this image be classified in terms of category? Which category label fits this image the best? What is the appropriate category for this image? Under which category should this image be labeled? What one word best encapsulates the essence of this picture? What single term most accurately describes the subject of this photo? What is the best single word to summarize the content of this image? What one term best defines the theme of this photograph? What single word best captures the main idea of this image?

Some Prompts for Image VQA. Are there chairs visible in the image? Are any vehicles visible in the image? Any clocks discernible in the image? Are there keyboards present in the image? Are phones visible in the image? Can you spot any cameras in the image? Are there televisions in the image? Are computers visible in the image? Any books noticeable in the image? Are there pencils in the image? Are there any bags visible? Any lamps visible in the image? Any mirrors discernible in the image? Are there beds present in the image? Any umbrellas visible in this image? Are any hats discernible in the image? Any candles present in the image? Are there musical instruments visible? Any paintings or artworks in the image? Any papers or documents visible? Are there any cups visible in the image? Are vegetables visible in the image? Is any bread discernible in the image? Any meat visible in the image? Can you see any cakes or desserts? Are eggs present in the image? Any beverages visible in this image? Can you identify any cheese in the image? Any candies visible in the image? Is ice cream noticeable in the image? Are trees present in the image? Is the sky visible in the image? Can you see any animals in the image? Are mountains visible in the image? Is water visible in the image? Are clouds discernible in the image? Can you spot any sand in the image? Any grass visible in the image? Are there rocks visible in the image? Any snow discernible in the image? Is there sunlight visible in the image? Any pathways visible in the image? Are leaves discernible in the image? Is there fog noticeable in the image? Any rain visible in the image? Are beaches visible in the image? Any animals present in this image? Are bushes noticeable in the image? Any streams or rivers visible? Are there birds visible in this image? Are jackets visible in the image? Are pants visible in the image? Can you spot any scarves? Any gloves visible in the image? Are socks visible in this image? Any dresses discernible in the image? Are belts visible in the image? Any jewelry noticeable in the image? Are ties discernible in the image? Any backpacks present in the image? Are there windows visible in the image? Any doors noticeable in the image? Can you spot any roofs? Are stairs visible in the image? Any fences visible in the image? Are there arches visible in the image? Any railings discernible in the image? Are pillars visible in the image? Any bridges visible in this image? Are walls discernible in the image? Are cars present in this image? Any buses visible in the image? Can you see any airplanes? Any motorcycles visible in the image? Are trains visible in this image? Any trucks noticeable in the image? Are boats or ships discernible? Are helicopters visible in the image? Any scooters noticeable in this image? Can you spot any skateboards? Are people visible in the image? Are there any children in the image? Is someone reading in the image? Are people eating in this image? Are people playing sports? Is anyone swimming visible? Are people walking noticeable? Are there cyclists visible? Are people wearing sunglasses? Is anyone using a computer visible? Are advertisements visible? Any traffic lights visible? Can you see any warnings or caution signs? Any logos visible in the image? Are there road markings visible? Any numbers or digits visible? Are there arrows visible in the image? Any letters discernible in the image? Can you see any maps? Any directional signs visible? Can you see any clouds in the image? Can you see a lake in the image? Can you see any rocks in the image? Can you see a waterfall in the image? Can you see grass in the image? Can you see a river in the image? Can you see snow in the image? Can you see any plants in the image? Can you see trees in the image? Can you see sand in the image? Can you see any islands in the image? Can you see fog in the image? Can you see any fields in the image? Can you see a desert in the image? Can you see a forest in the image? Can you see ice in the image? Can you see hills in the image? Can you see a cave in the image? Can you see any birds in the image? Can you see any dogs in the image? Can you see any cats in the image? Can you see any horses in the image? Can you see fish in the image? Can you see butterflies in the image? Can you see bees in the image? Can you see cows in the image? Can you see any elephants in the image? Can

you see a bear in the image? Can you see monkeys in the image? Can you see sheep in the image? Can you see any ducks in the image? Can you see any insects in the image? Can you see a car in the image? Can you see a bicycle in the image? Can you see a motorcycle in the image? Can you see a train in the image? Can you see an airplane in the image? Can you see a helicopter in the image? Can you see a boat in the image? Can you see a truck in the image? Can you see a scooter in the image? Can you see a skateboard in the image? Can you see a ship in the image? Can you see a taxi in the image? Can you see any chairs in the image? Can you see a sofa in the image? Can you see a television in the image? Can you see a computer in the image? Can you see a refrigerator in the image? Can you see a washing machine in the image? Can you see curtains in the image? Can you see a lamp in the image? Can you see any pillows in the image? Can you see shelves in the image? Can you see a sink in the image? Can you see mirrors in the image? Can you see any beds in the image? Can you see any doors in the image? Can you see any fruits in the image? Can you see vegetables in the image? Can you see bread in the image? Can you see ice cream in the image? Can you see pizza in the image? Can you see any cakes in the image? Can you see meat in the image? Can you see eggs in the image? Can you see any candy in the image? Can you see bottles in the image? Can you see hats in the image? Can you see shoes in the image? Can you see gloves in the image? Can you see sunglasses in the image? Can you see jackets in the image? Can you see ties in the image? Can you see scarves in the image? Can you see socks in the image? Can you see belts in the image? Can you see dresses in the image? Can you see coats in the image? Can you see any bags in the image? Can you see a bridge in the image? Can you see fences in the image? Can you see walls in the image? Can you see a chimney in the image? Can you see any towers in the image? Can you see a rooftop in the image? Can you see arches in the image? Can you see a balcony in the image? Can you see street lamps in the image? Can you see any tunnels in the image? Can you see a street sign in the image? Can you see sidewalks in the image? Can you see traffic lights in the image? Can you see crosswalks in the image? Can you see benches in the image? Can you see statues in the image? Can you see parking meters in the image? Can you see trash cans in the image? Can you see graffiti in the image? Can you see any advertisements in the image? Does the image show mountains? Does the image include trees? Does the image depict a forest? Does the image contain a beach? Does the image show clouds? Does the image depict snow? Does the image display rain? Does the image feature flowers? Does the image include grass? Does the image show a sunset or sunrise? Does the image contain rocks? Does the image show waterfalls? Does the image depict sand dunes? Does the image feature ice formations? Does the image include foggy weather? Does the image display a desert? Does the image contain hills? Does the image show an island? Does the image feature wildlife? Does the image depict underwater scenes? Does the image contain birds? Does the image feature mammals? Does the image depict domestic pets? Does the image include insects? Does the image show marine animals? Does the image contain reptiles? Does the image feature farm animals? Does the image depict endangered species? Does the image display a zoo environment? Does the image contain butterflies? Does the image depict airplanes? Does the image contain bicycles? Does the image display motorcycles? Does the image feature boats or ships? Does the image depict trains? Does the image include buses? Does the image contain cars? Does the image show emergency vehicles? Does the image include trucks? Does the image feature construction vehicles? Does the image show skyscrapers? Does the image contain bridges? Does the image depict historical buildings? Does the image show street signs? Does the image include sidewalks? Does the image feature tunnels? Does the image depict balconies? Does the image contain windows? Does the image show doors? Does the image feature fences? Does the image contain kitchen utensils? Does the image feature appliances? Does the image depict beds? Does the image have carpets or rugs? Does the image contain curtains? Does the image feature bathrooms? Does the image have mirrors? Does the image display tables? Does the image include sofas? Does the image have chairs? Does the image feature computers? Does the image depict cell phones? Does the image contain televisions? Does the image include audio equipment? Does the image feature cameras? Does the image depict video game consoles? Does the image have headphones? Does the image contain printers? Does the image include chargers or cables? Does the image feature tablets? Does the image depict fruits? Does the image contain vegetables? Does the image include bakery items? Does the image show beverages? Does the image feature dairy products? Does the image contain candy or sweets? Does the image depict seafood? Does the image display a restaurant environment? Does the image feature cooked meals? Does the image contain a dining setup? Does the image contain shoes? Does the image depict hats or caps? Does the image feature dresses? Does the image include jewelry? Does the image display gloves? Does the image show jackets? Does the image contain scarves? Does the image feature sunglasses? Does the image include watches? Does the image depict ties? Does the

image depict a sports event? Does the image feature athletic equipment? Does the image contain a playground? Does the image show a swimming pool? Does the image depict a stadium? Does the image contain camping equipment? Does the image show skiing activities? Does the image feature hiking trails? Does the image include yoga or fitness gear? Does the image depict cycling activities? Does the image contain street signs? Does the image show traffic lights? Does the image depict any logos? Does the image feature directional signs? Does the image include advertisements? Does the image contain graffiti? Does the image depict warnings or caution signs? Does the image display maps or directions? Does the image have identifiable words? Does the image include road markings? Does the image show people smiling? Does the image depict people running? Does the image contain children playing? Does the image depict people working? Does the image show people cooking? Does the image feature social gatherings? Does the image depict people shopping? Does the image show someone reading? Does the image contain people using devices? Does the image feature dancing activities? Does the image depict stormy weather? Does the image contain lightning? Does the image show clear skies? Does the image feature windy conditions? Does the image depict snowy landscapes? Does the image show sunny weather? Does the image display cloudy conditions? Does the image include a rainbow? Does the image depict icy conditions? Does the image contain rain puddles? Can you see rain in the image? Can you see a rainbow in the image? Can you see lightning in the image? Can you see wind effects in the image? Can you see snow falling in the image? Can you see sunshine clearly in the image? Can you see pencils or pens in the image? Can you see scissors in the image? Can you see a clock in the image? Can you see books in the image? Can you see a calculator in the image? Can you see musical instruments in the image? Can you see any cameras in the image? Can you see a microphone in the image? Can you see headphones in the image? Can you see umbrellas in the image? Can you see barrels in the image? Can you see forklifts in the image? Can you see pallets in the image? Can you see safety helmets in the image? Can you see toolboxes in the image? Can you see a tent in the image? Can you see balloons in the image? Can you see candles in the image? Can you see rope in the image? Can you see a picnic table in the image? Can you see camping gear in the image? Can you see ladders in the image? Can you see kites in the image? Can you see a mailbox clearly in the image? Can you see a fountain in the image? Can you see a hammock in the image? Can you see graffiti art in the image? Can you see construction equipment in the image? Can you see a playground in the image? Can you see solar panels in the image? Can you see reflections in the image? Can you see smoke in the image? Can you see flames in the image? Can you see shadows clearly in the image? Can you see footprints in the image? Can you see anyone running in the image? Can you see people walking in the image? Can you see someone reading in the image? Can you see anyone cooking in the image? Can you see people shopping in the image? Can you see any warning signs in the image? Can you see any directional arrows in the image? Can you see logos in the image? Can you see road markings in the image? Can you see flags in the image? Are video game consoles visible? Any board games noticeable? Can you spot puzzles? Are playing cards visible? Any dice noticeable? Are CDs or DVDs discernible? Can you spot radios? Are musical speakers noticeable? Any movie posters visible? Are headphones discernible? Are dogs visible in the image? Are cats visible in the image? Can you see any horses in the image? Are cows visible in the image? Any sheep discernible in the image? Are there any giraffes visible? Can you spot any monkeys in the image? Any fish visible in the image?