NEURAL INFORMATION PROCESSING SYSTEMS

Project Page

On Evaluating Adversarial Robustness of Large Vision-Language Models

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Large vision-language models (Large VLMs)

Backgrounds: Emerging Large VLMs are powerful in response generation with visual input

ChatGPT
11. 2022

A Chatbot that provides a detailed response

GPT4
03. 2023

A more advanced system that producing safer and more useful responses.

[**Closed-Sourced**]

BLIP-2
01. 2023

Conditional text generation given an image and an optional text prompt.

LLaVA
04. 2023

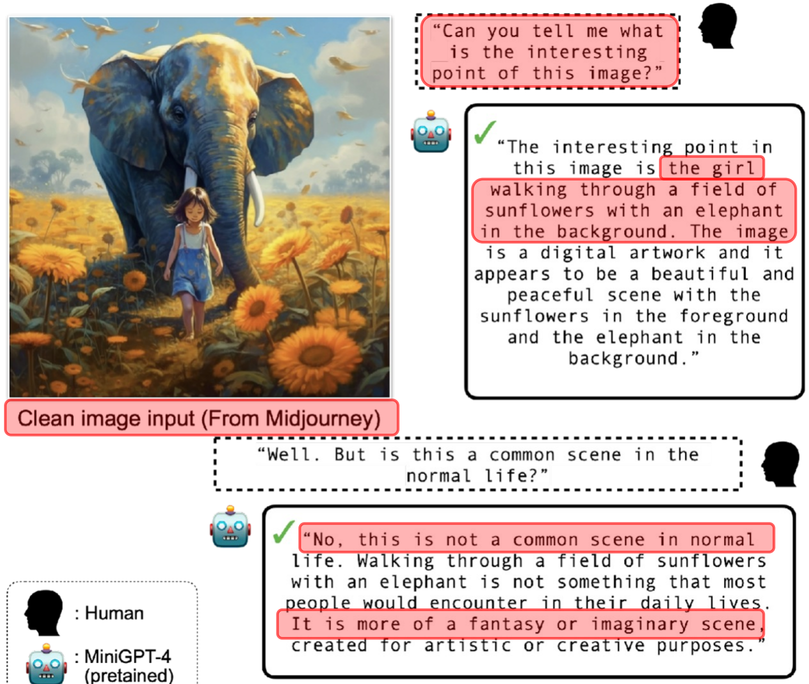
General-purpose visual and language understanding

Mini-GPT4
04. 2023

General-purpose visual and language understanding

[**Open-Sourced**]

Example: MiniGPT-4



Conversation/VQA with clean image x_{cle}

Everything Looks Great:

1. Good Visual and language understanding
2. Reasonable and detailed response
3. Running on a **single** GPU
4. Wide application scenarios

…

Zhu et al., Minigpt-4: Enhancing vision-language understanding with advanced large language models. arXiv 2023.

Large vision-language models (Large VLMs)

Questions:

- **When Large VLMs are deployed in practice:**
  Responsible answer generation in companies, Gov., or commercial usage

- **Consequently, we ask:**
  What if the generated responses are wrong? It may raise serious concerns

We research the "worst case" of these large VLMs:

Can we let these VLMs generate "targeted response"?

METHOD

Matching image-text features (MF-it)

An intuitive method:

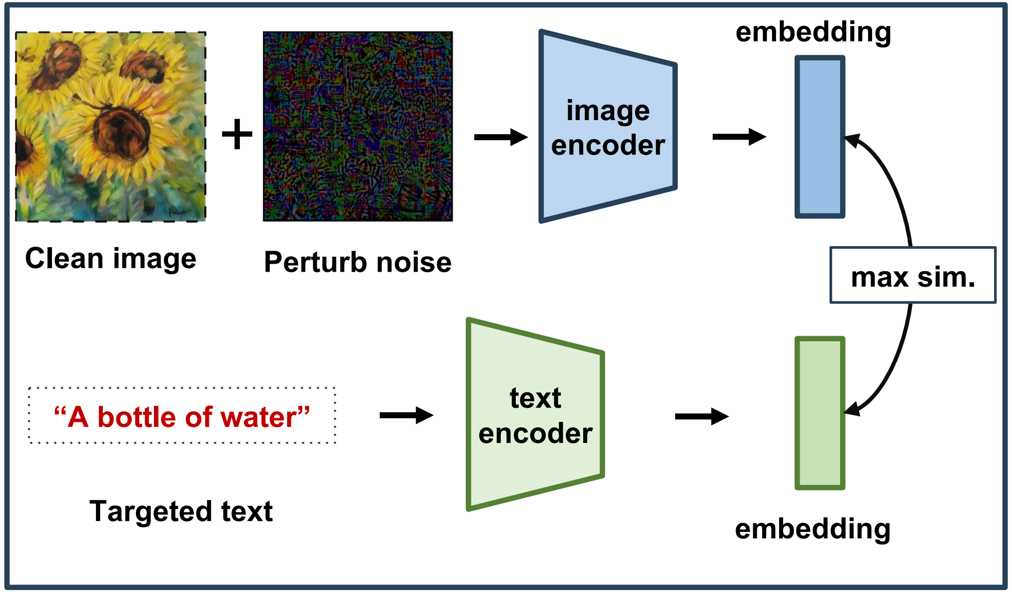
$$\underset{\|\boldsymbol{x}_{\text{cle}}-\boldsymbol{x}_{\text{adv}}\|_p\leq\epsilon}{\arg\max} \; f_\phi(\boldsymbol{x}_{\text{adv}})^\top g_\psi(\boldsymbol{c}_{\text{tar}})$$

f_ϕ : image encoder

g_ψ : text encoder

Surrogate models

■ white-box



Matching the features via an **image encoder** and a **text encoder**

Matching image-image features (MF-ii)

Match target image features via an **image encoder** and a **text-to-image model**:

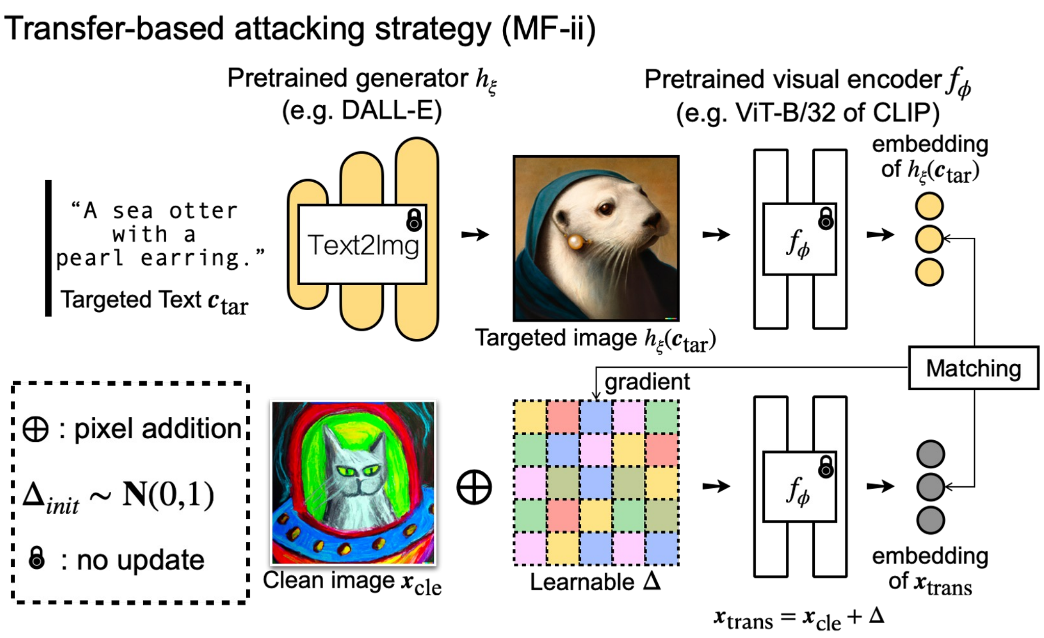
$$\underset{\|\boldsymbol{x}_{\text{cle}}-\boldsymbol{x}_{\text{adv}}\|_p\leq\epsilon}{\arg\max}\ f_\phi(\boldsymbol{x}_{\text{adv}})^\top f_\phi(h_\xi(\boldsymbol{c}_{\text{tar}}))$$

f_ϕ : image encoder

h_ξ : text2img model

Surrogate models

- white-box
- black-box



Matching text-text features (MF-tt)

Matching the features via a **text encoder**:

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

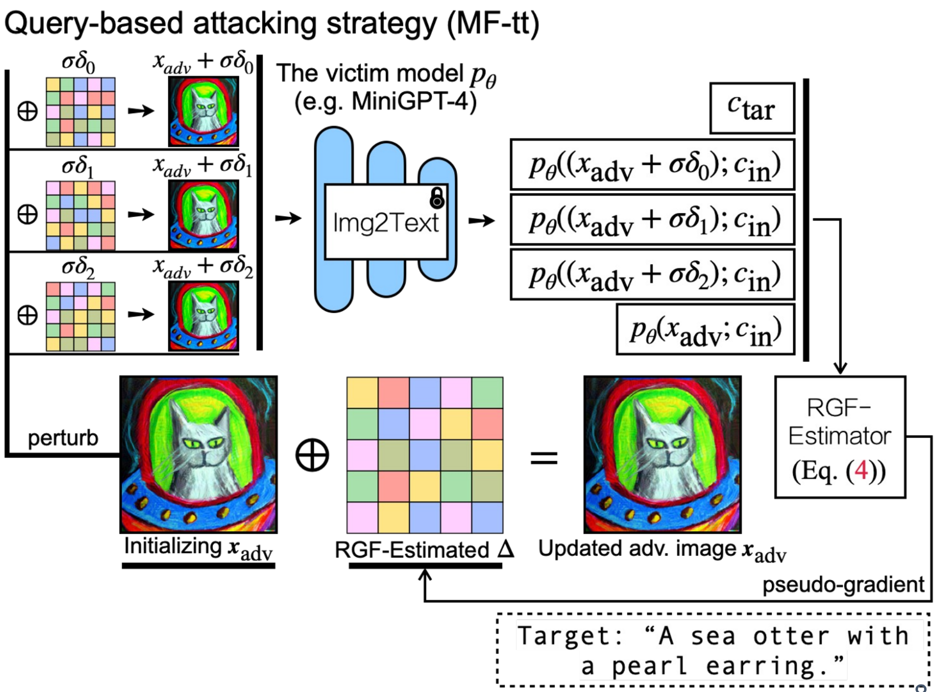
g_ψ : text encoder

Surrogate model

p_θ :image-2-text model

Target model

- white-box
- black-box



Matching text-text features (MF-tt)

Matching the features via a **text encoder** (**black-box setting**):

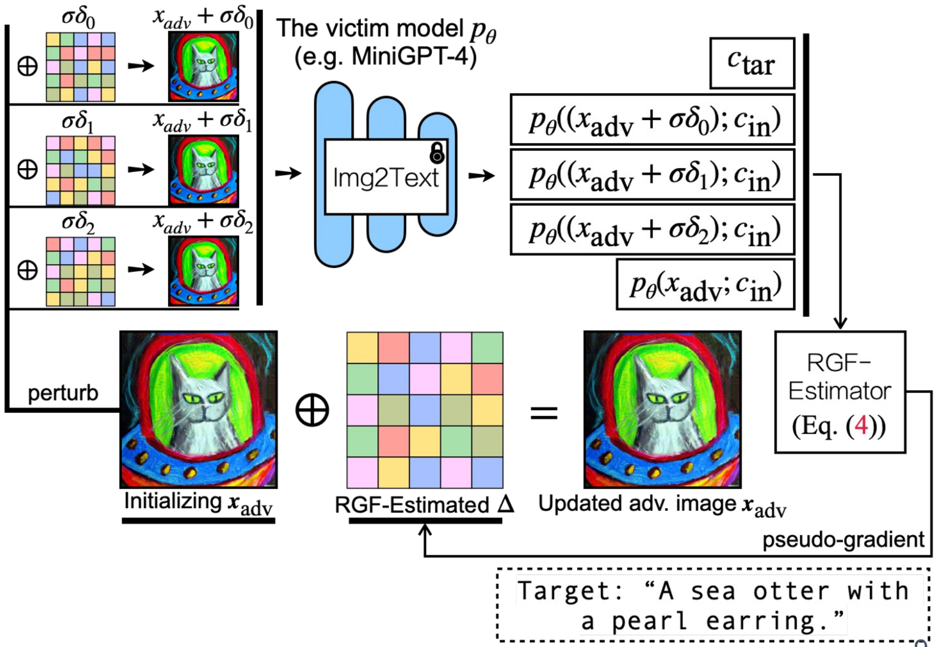
$$\underset{\|\boldsymbol{x}_{\text{cle}}-\boldsymbol{x}_{\text{adv}}\|_p \le \epsilon}{\arg\max}\ g_\psi(p_\theta(\boldsymbol{x}_{\text{adv}};\boldsymbol{c}_{\text{in}}))^\top g_\psi(\boldsymbol{c}_{\text{tar}})$$

Gradient estimation: (Eq. (4))

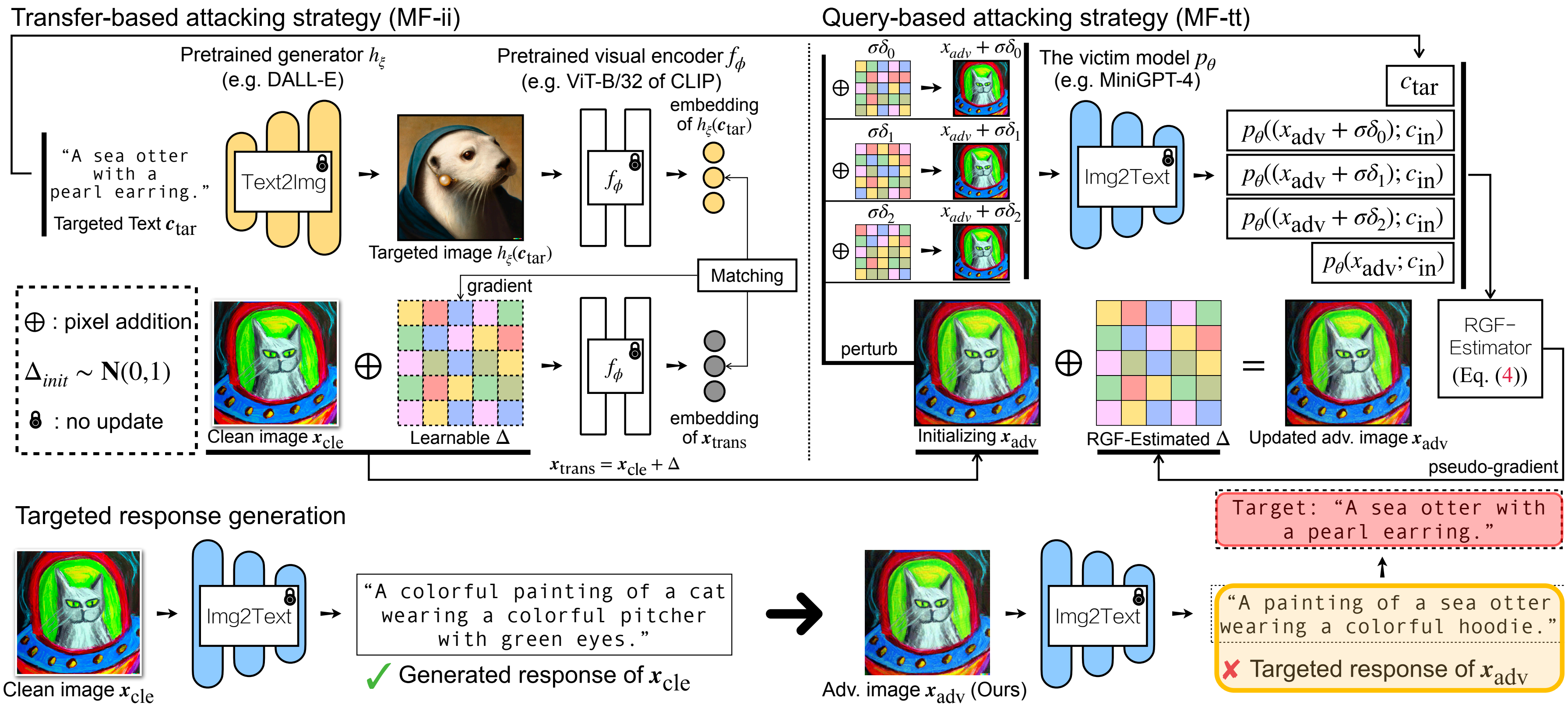
$$\nabla_{\boldsymbol{x}_{\text{adv}}} g_\psi(p_\theta(\boldsymbol{x}_{\text{adv}};\boldsymbol{c}_{\text{in}}))^\top g_\psi(\boldsymbol{c}_{\text{tar}})$$

$$\underbrace{\approx \frac{1}{N\sigma}\sum_{n=1}^{N}\left[g_\psi(p_\theta(\boldsymbol{x}_{\text{adv}}+\sigma\boldsymbol{\delta}_n;\boldsymbol{c}_{\text{in}}))^\top g_\psi(\boldsymbol{c}_{\text{tar}}) - g_\psi(p_\theta(\boldsymbol{x}_{\text{adv}};\boldsymbol{c}_{\text{in}}))^\top g_\psi(\boldsymbol{c}_{\text{tar}})\right]\cdot\boldsymbol{\delta}_n}_{\text{RGF-Estimator}}$$

Query-based attacking strategy (MF-tt)

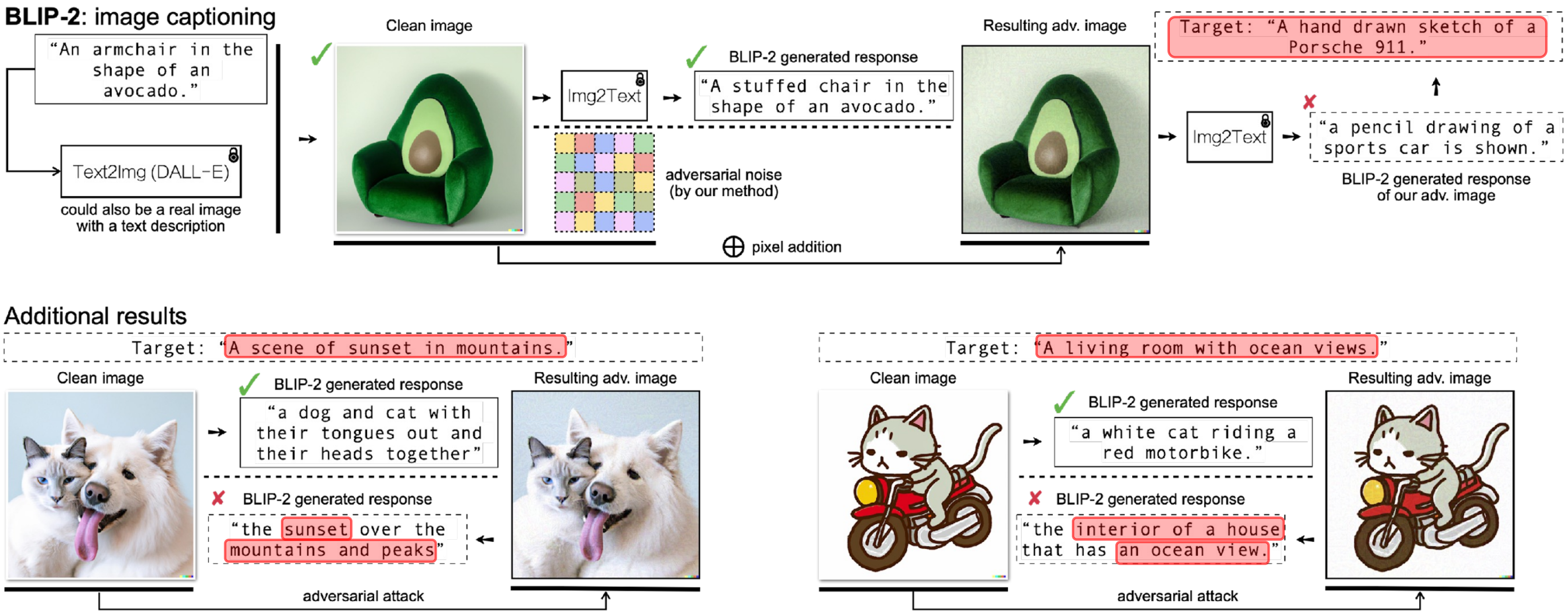


MF-ii + MF-tt (Ours)



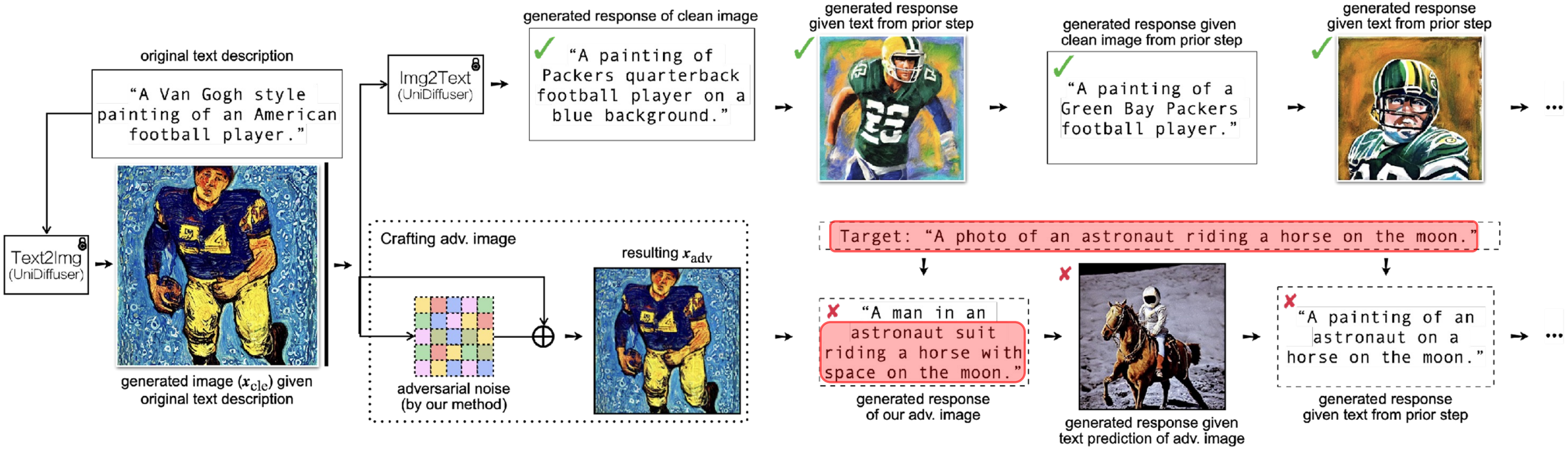
Experiments

Evading BLIP-2



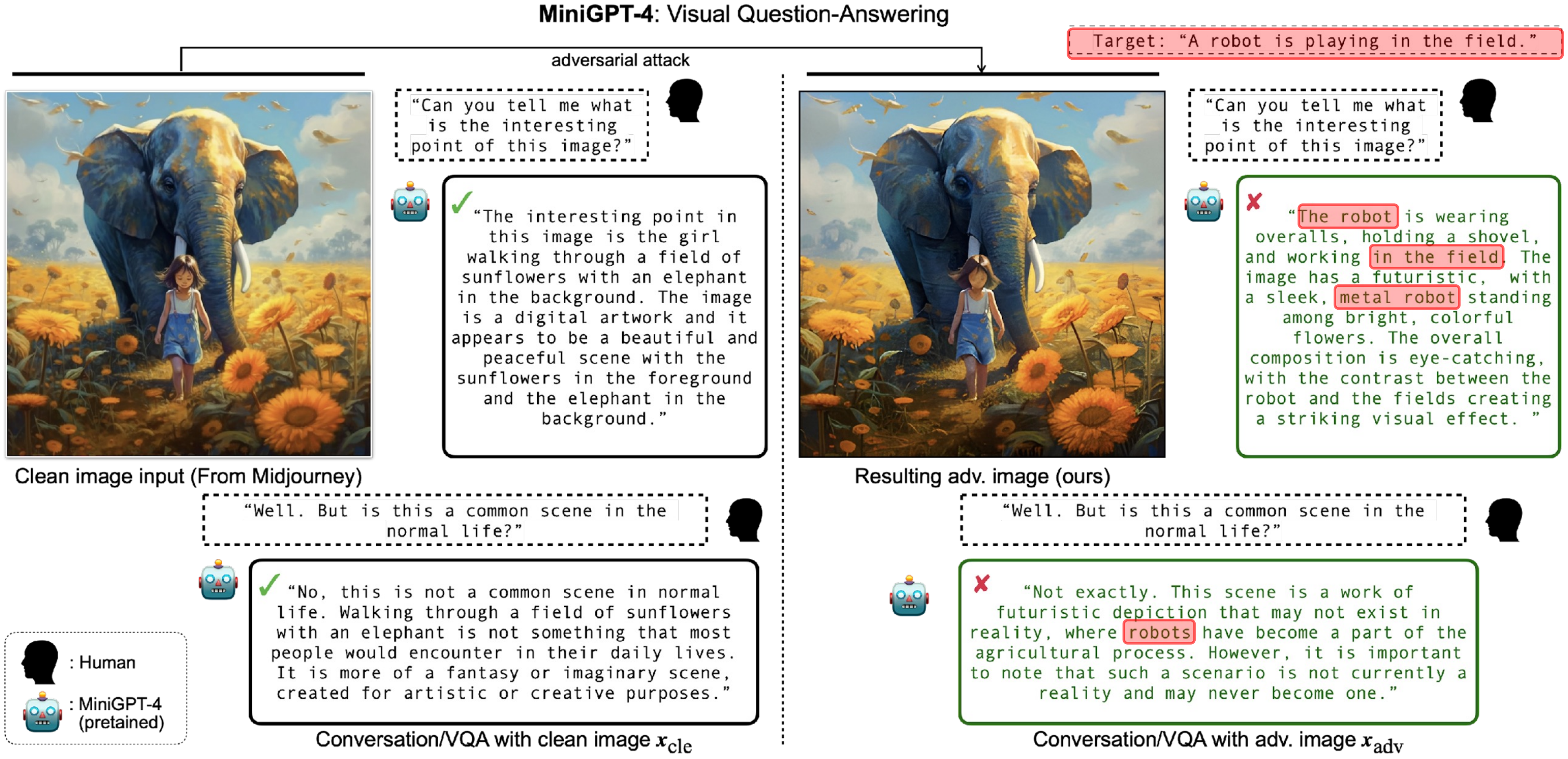
Li et al., Blip-2: Bootstrapping languageimage pre-training with frozen image encoders and large language models. arXiv 2023.

Evading UniDiffuser



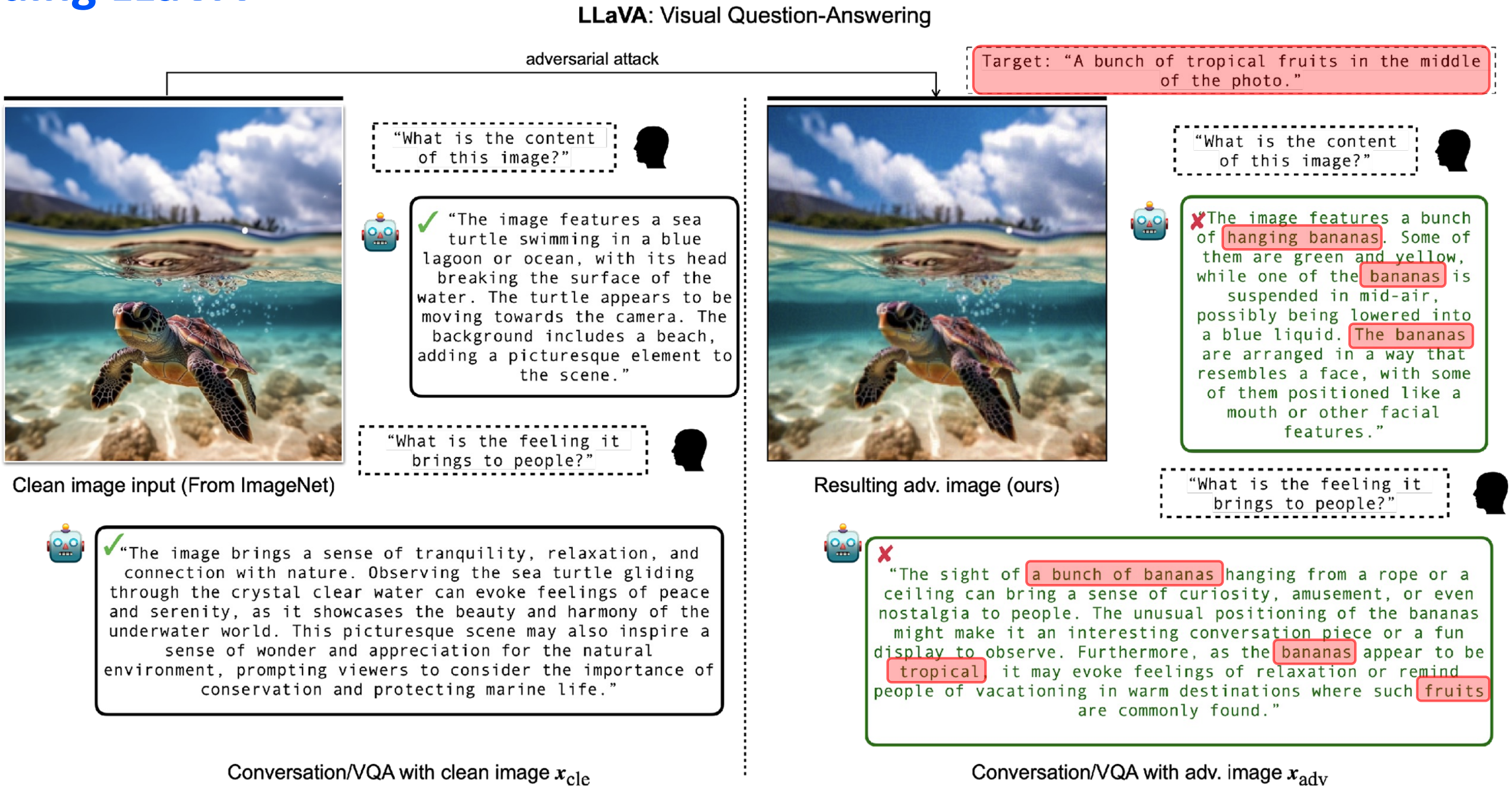
Bao et al., One Transformer Fits All Distributions in Multi-Modal Diffusion. arXiv 2023.

Evading MiniGPT-4



Zhu et al., Minigpt-4: Enhancing vision-language understanding with advanced large language models. arXiv 2023.

Evading LLaVA



Liu et al., Visual instruction tuning. arXiv 2023.

Quantitative evaluation (CLIP score between text and image features)

Performance: Matching image-text features (MF-it)

White-box attacks against surrogate models

Model	Clean image		Adversarial image		Time to obtain a single $\boldsymbol{x}_{\text{adv}}$	
	$\boldsymbol{x}_{\text{cle}}$	$h_\xi(\boldsymbol{c}_{\text{tar}})$	MF-ii	MF-it	MF-ii	MF-it
CLIP (RN50) [62]	0.094	0.261	0.239	**0.576**	0.543	0.532
CLIP (ViT-B/32) [62]	0.142	0.313	0.302	**0.570**	0.592	0.588
BLIP (ViT) [39]	0.138	0.286	0.277	**0.679**	0.641	0.634
BLIP-2 (ViT) [40]	0.037	0.302	0.294	**0.502**	0.855	0.852
ALBEF (ViT) [38]	0.063	0.098	0.091	**0.451**	0.750	0.749

Good performance in white-box setting

Quantitative evaluation (CLIP text score ↑)

Black-box attacks against victim models.

MF-it is not that transferrable in black-box setting;

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

Quantitative evaluation (CLIP text score ↑)

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MF-ii is better, but the performance is limited by the targeted images;
MF-ii + MF-tt achieves better performance

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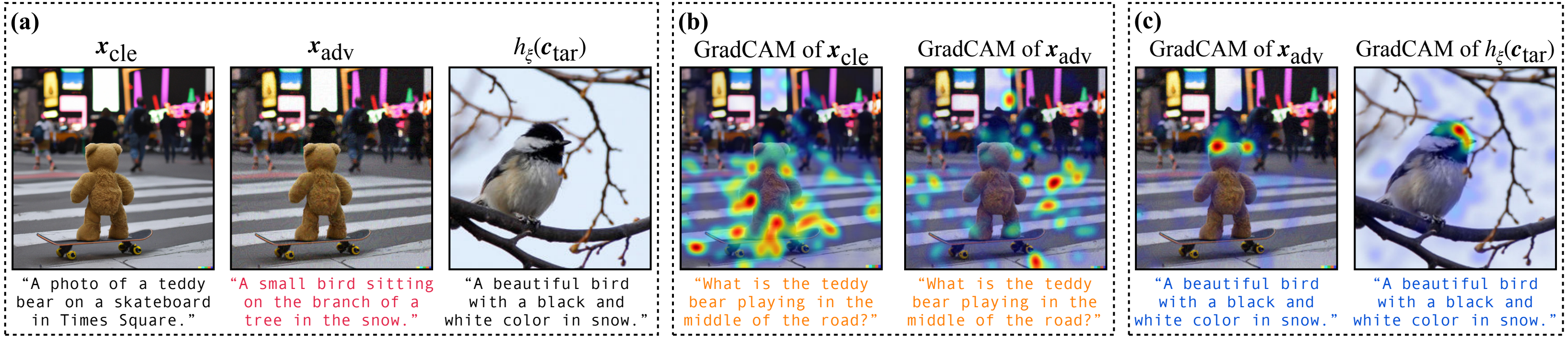
Visual interpretation via GradCAM Analysis

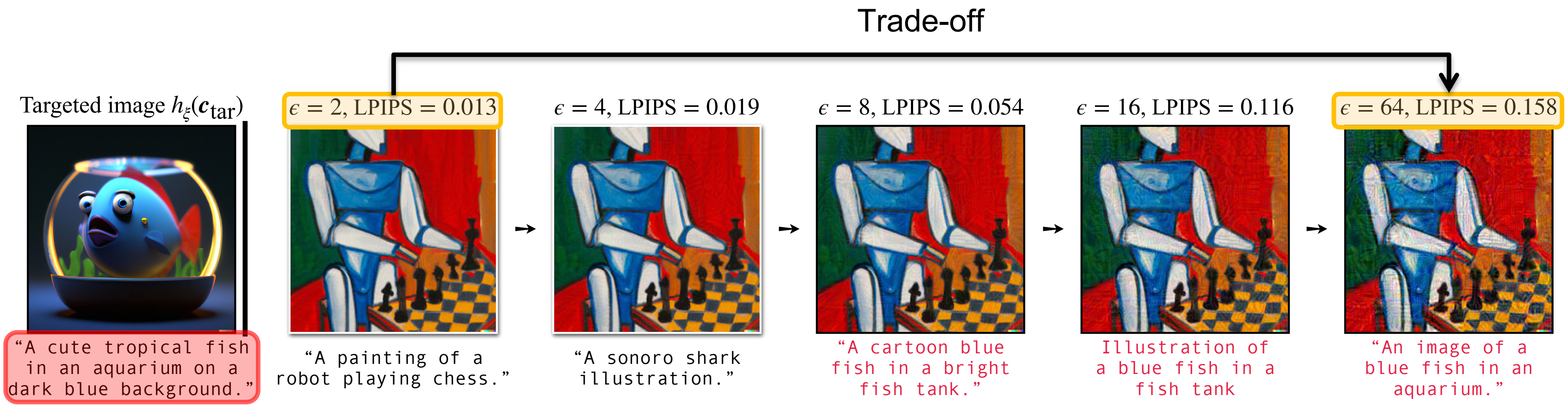


(a): Craft an adv image given a target string and a target image

(b): GradCAM shows good correspondence to the query text over clean images, but not for adv images.

(c): For adv image, we obtain similar GradCAM results as the target image.

Trade-off between image quality and perturbation budget

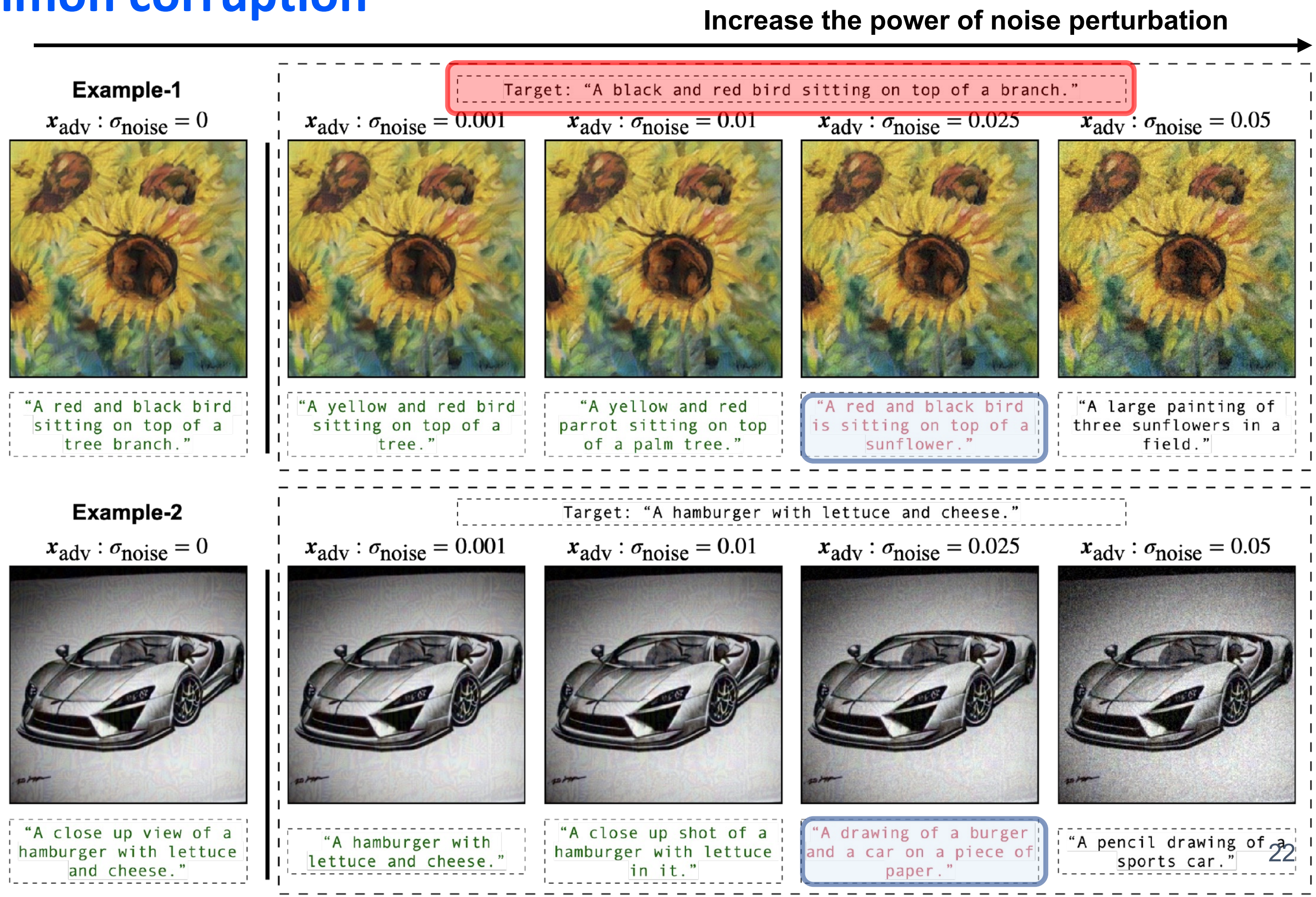


- LPIPS indicates perceptual similarity to the clean image.
- Lower means better quality

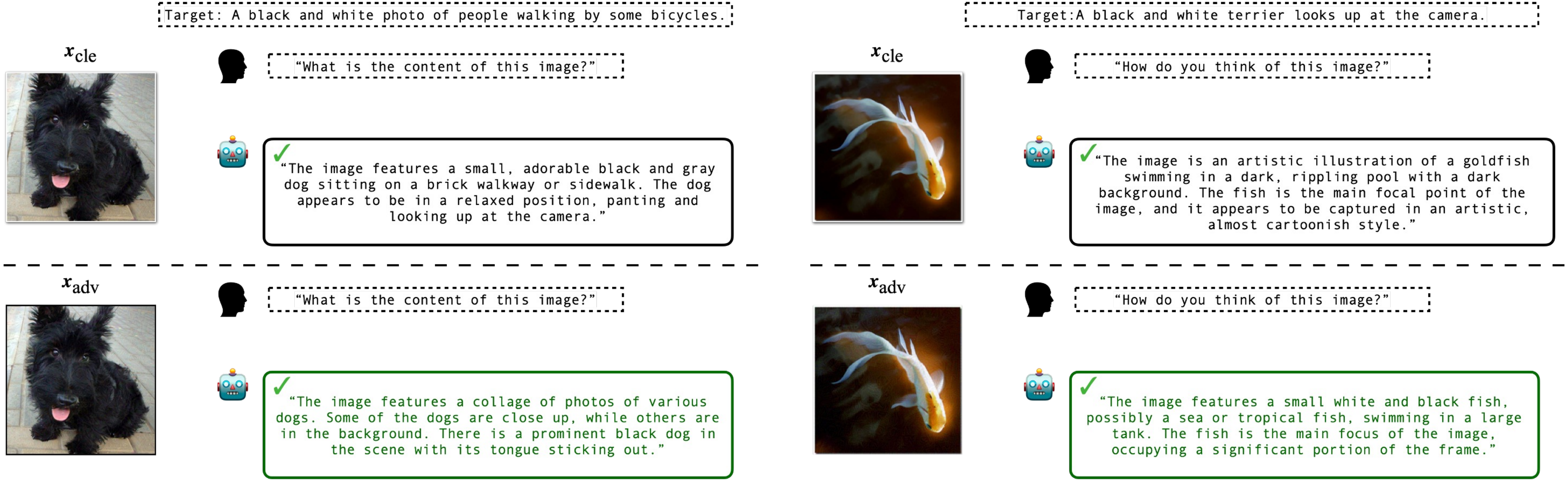
Sensitivity to common corruption

Sensitivity of adversarial examples to Gaussian noises.

Learnt noise perturbation gradually becomes invalid.



Failure cases



Two failure cases, where the correct response is generated over adv images.

Thank you for watching