

# VLATTACK: Multimodal Adversarial Attacks on Vision-Language Tasks via Pre-trained Models

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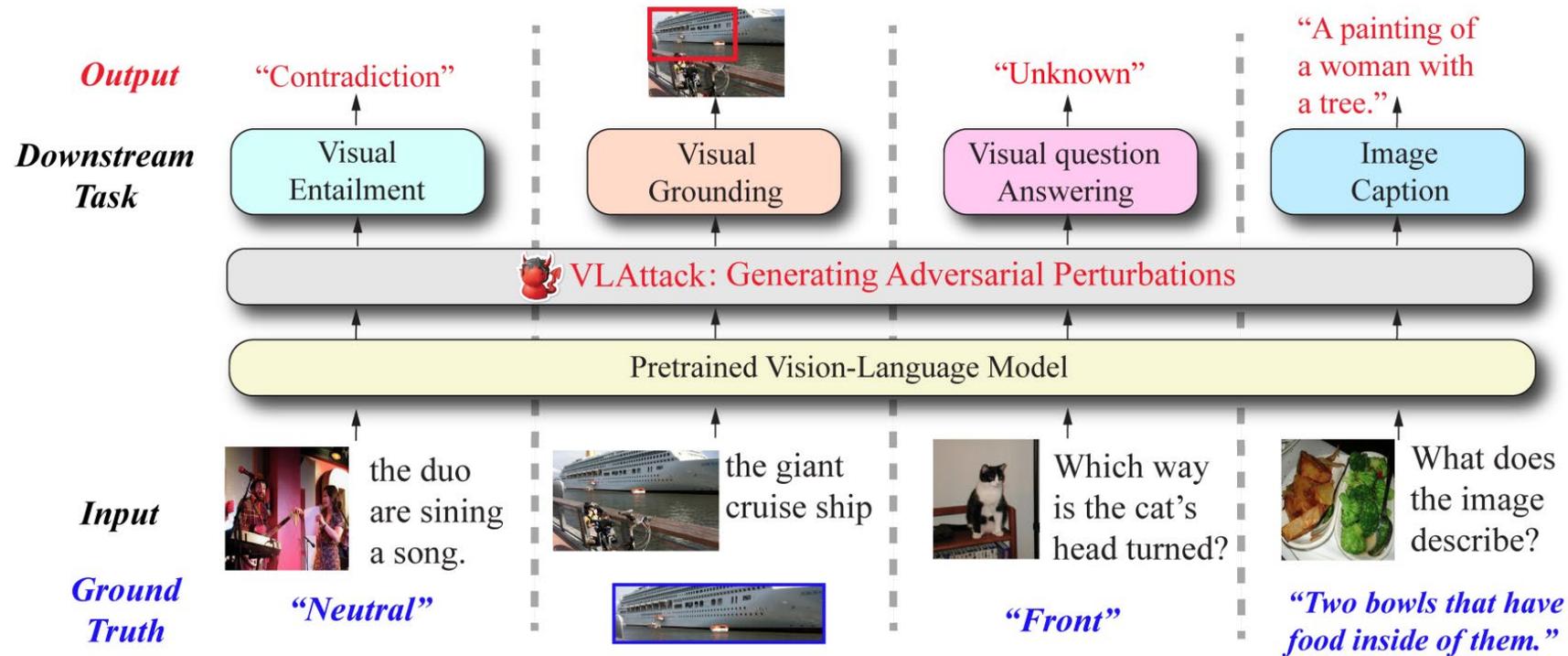


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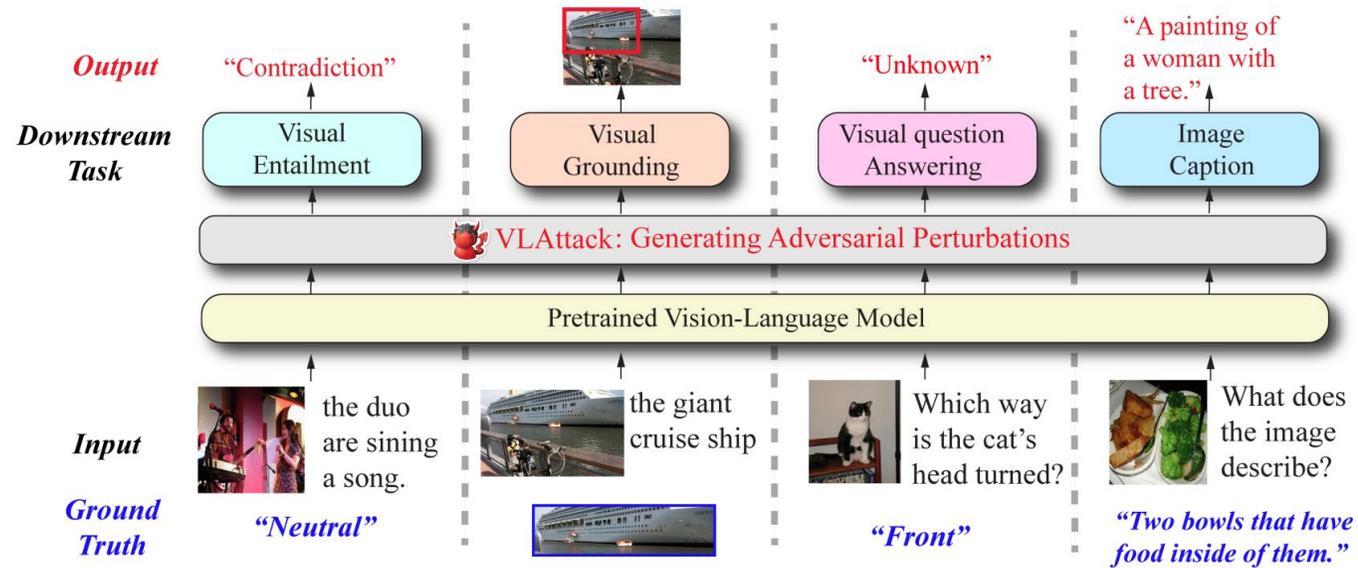
# Introduction



- The recent success of vision-language (VL) pre-trained models on multimodal tasks have attracted broad attention from both academics and industry. However, the adversarial robustness is still relatively unexplored.
- Therefore, we ask the following question: *Can we generate adversarial perturbations on a pre-trained VL model to attack various black-box downstream tasks fine-tuned on the pre-trained one ?*



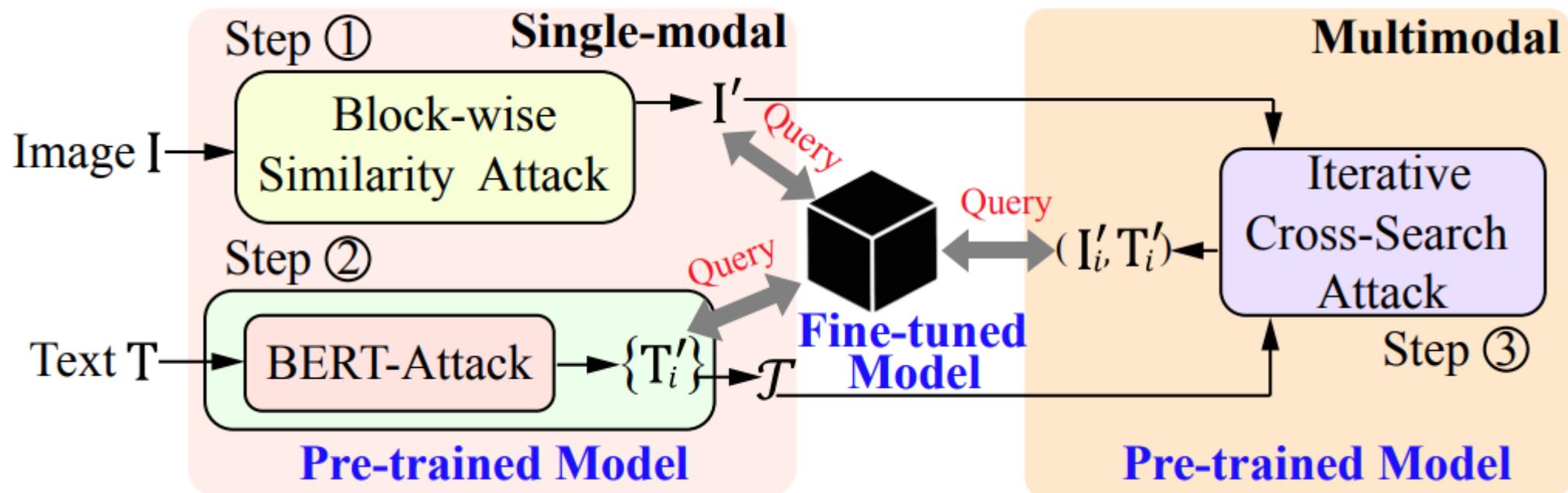
# Introduction



$$\max_{\mathbf{I}', \mathbf{T}'} \mathbb{1}\{S(\mathbf{I}', \mathbf{T}') \neq \mathbf{y}\}, \quad s.t. \quad \|\mathbf{I}' - \mathbf{I}\|_{\infty} < \sigma_i, \quad \text{Cos}(U_s(\mathbf{T}'), U_s(\mathbf{T})) > \sigma_s,$$

- **Task-specific challenge:** The attack mechanism needs to be general and work for attacking multiple tasks.
- **Model-specific challenge:** The attack method needs to automatically learn the transferability between pre-trained and fine-tuned models on different modalities

# VLATTACK



➤ **Single-modal Level Attack:** Attacking using a “from image to text” order as the former can be perturbed on a continuous space. Image Attack: BSA. Text Attack: BERT-Attack[1].

➤ **Multi-modal Level Attack:** Cross-updating image and text perturbations at the multimodal level based on previous outputs.

# Block-wise Similarity Attack (BSA)

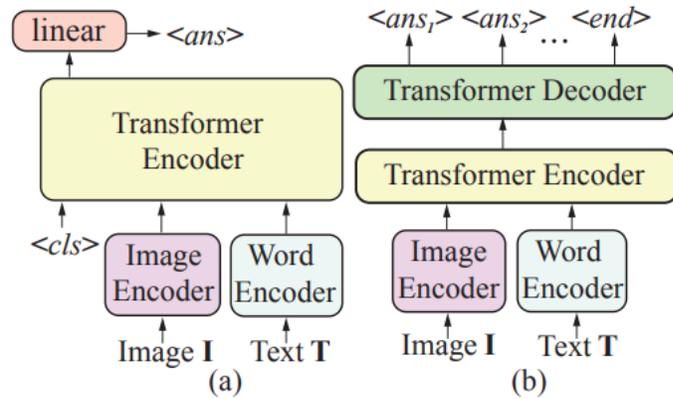


Figure 3: A brief illustration of the encoder-only (a) and encoder-decoder (b) structures.

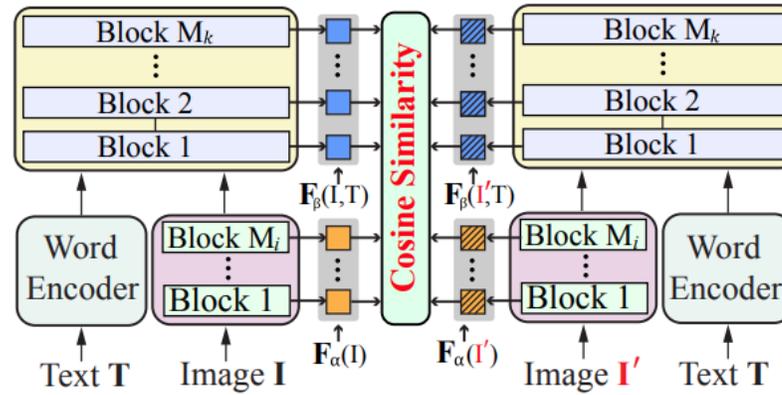


Figure 4: Block-wise similarity attack.  $F_\alpha$  is the image encoder, and  $F_\beta$  is the Transformer encoder.

$$\mathcal{L} = \underbrace{\sum_{i=1}^{M_i} \sum_{j=1}^{M_j} \text{Cos}(\mathbf{F}_\alpha^{i,j}(\mathbf{I}), \mathbf{F}_\alpha^{i,j}(\mathbf{I}'))}_{\text{Image Encoder}} + \underbrace{\sum_{k=1}^{M_k} \sum_{t=1}^{M_t} \text{Cos}(\mathbf{F}_\beta^{k,t}(\mathbf{I}, \mathbf{T}), \mathbf{F}_\beta^{k,t}(\mathbf{I}', \mathbf{T}))}_{\text{Transformer Encoder}}$$

# Algorithm Details

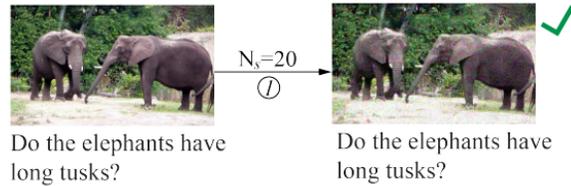


Figure 12: An adversarial image from BSA.

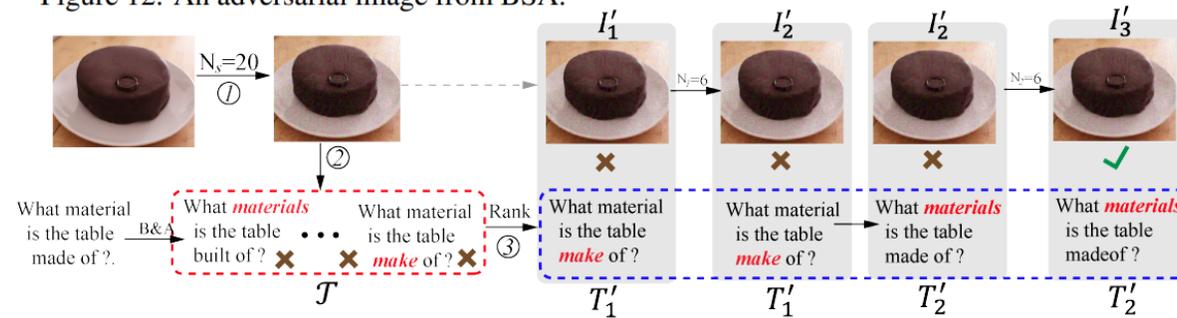


Figure 14: An adversarial image-text pair from multimodal attack.

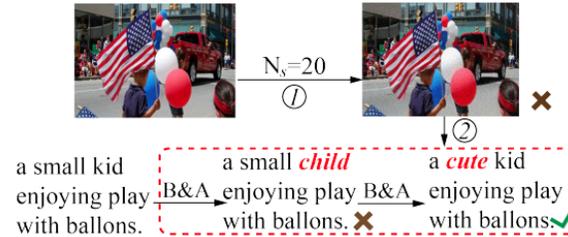


Figure 13: An adversarial sentence from text attack.

## Algorithm 1 VLATTACK

**Input:** A pre-trained model  $F$ , a fine-tuned model  $S$ , a clean image-text pair  $(\mathbf{I}, \mathbf{T})$  and its prediction  $y$  on the  $S$ , and the Gaussian distribution  $\mathcal{U}$ ;

**Parameters:** Perturbation budget  $\sigma_i$  on  $\mathbf{I}$ ,  $\sigma_s$  on  $\mathbf{T}$ . Iteration number  $N$  and  $N_s$ .

1: //Single-modal Attacks: From Image to Text (Section 4.1)

2: Initialize  $\mathbf{I}' = \mathbf{I} + \delta$ ,  $\delta \in \mathcal{U}(0, 1)$ ,  $\mathcal{T} =$

3: // Image attack by updating  $\mathbf{I}'$  using Eq. (2) for  $N_s$  steps

4:  $\mathbf{I}' = \text{BSA}(\mathcal{L}, \mathbf{I}', \mathbf{T}, N_s, \sigma_i, F)$

5: if  $S(\mathbf{I}', \mathbf{T}) \neq y$  then return  $(\mathbf{I}', \mathbf{T})$

6: else

7: // Text attack by applying BERT-attack

8: for perturbed text  $\mathbf{T}'_i$  in BERT-attack do

9: if  $\gamma_i = \text{Cos}(U_s(\mathbf{T}'_i), U_s(\mathbf{T})) > \sigma_s$  then

10: Add the pair  $(\mathbf{T}'_i, \gamma_i)$  into  $\mathcal{T}$ ;

11: if  $S(\mathbf{I}, \mathbf{T}'_i) \neq y$  then return  $(\mathbf{I}, \mathbf{T}'_i)$

12: end if

13: end for

14: end if

15: end if

16: // Multimodal Attack (Section 4.2)

17: Rank  $\mathcal{T}$  according to similarity scores  $\{\gamma_i\}$  and get top- $K$  samples  $\{\hat{\mathbf{T}}'_1, \dots, \hat{\mathbf{T}}'_K\}$  according to Eq. (3);

18: for  $k = 1, \dots, K$  do

19: if  $S(\mathbf{I}'_k, \hat{\mathbf{T}}'_k) \neq y$  then return  $(\mathbf{I}'_k, \hat{\mathbf{T}}'_k)$

20: end if

21: Replace  $(\mathbf{I}'_k, \hat{\mathbf{T}}'_k)$  with  $(\mathbf{I}', \mathbf{T})$  in Eq. (2);

22:  $\mathbf{I}'_{k+1} = \text{BSA}(\mathcal{L}, \mathbf{I}'_k, \hat{\mathbf{T}}'_k, N_k, \sigma_i, F)$

23: if  $S(\mathbf{I}'_{k+1}, \hat{\mathbf{T}}'_k) \neq y$  then return  $(\mathbf{I}'_{k+1}, \hat{\mathbf{T}}'_k)$

24: end if

25: end for

26: return None



# Experiments

Table 1: Comparison of VLATTACK with baselines on ViLT, Unitab, and OFA for different tasks, respectively. All results are displayed by ASR (%). B&A means the BERT-Attack approach.

Pre-trained Model	Task	Dataset	Image Only				Text Only		multimodality	
			DR	SSP	FDA	BSA	B&A	R&R	Co-Attack	VLATTACK
<b>ViLT</b>	VQA	VQAv2	23.89	50.36	29.27	65.20	17.24	8.69	35.13	<b>78.05</b>
	VR	NLVR2	21.58	35.13	22.60	52.17	32.18	24.82	42.04	<b>66.65</b>
<b>BLIP</b>	VQA	VQAv2	7.04	11.84	7.12	26.36	21.04	2.94	14.24	<b>49.26</b>
	VR	NLVR2	6.66	6.88	10.22	27.16	33.08	16.92	8.70	<b>52.66</b>
<b>Unitab</b>	VQA	VQAv2	22.88	33.67	41.80	48.40	14.20	5.48	33.87	<b>62.20</b>
	REC	RefCOCO	21.32	64.56	75.24	89.70	13.68	8.75	56.48	<b>93.52</b>
	REC	RefCOCO+	26.30	69.60	76.21	90.96	6.40	2.46	68.69	<b>93.40</b>
	REC	RefCOCOg	26.39	69.26	78.64	91.31	22.03	18.52	65.50	<b>95.61</b>
<b>OFA</b>	VQA	VQAv2	25.06	33.88	40.02	54.05	10.22	2.34	51.16	<b>78.82</b>
	VE	SNLI-VE	13.71	15.11	20.90	29.19	10.51	4.92	18.66	<b>41.78</b>
	REC	RefCOCO	11.60	16.00	27.06	40.82	13.15	7.64	32.04	<b>56.62</b>
	REC	RefCOCO+	16.58	22.28	33.26	46.44	4.66	7.04	45.28	<b>58.14</b>
	REC	RefCOCOg	16.39	24.80	33.22	54.63	19.23	15.13	30.53	<b>73.30</b>

Table 2: Evaluation of the Uni-modal tasks on OFA. We highlight the prediction score reported by the original OFA paper with \*.

Dataset	MSCOCO				ImageNet-1K
	BLEU@4 (↓)	METEOR (↓)	CIDEr (↓)	SPICE (↓)	ASR(↑)
OFA*	42.81	31.30	145.43	25.37	-
DR	30.26	24.47	95.52	17.89	10.43
SSP	10.99	12.52	23.54	5.67	19.44
FDA	17.77	17.92	55.75	11.36	12.31
BSA (Ours)	3.04	8.08	2.16	1.50	41.35

Table 3: CLIP model evaluation on SVHN.

Dataset	SVHN	
	CLIP-ViT/16	CLIP-RN50
DR	3.32	71.62
SSP	6.36	84.26
FDA	6.20	83.52
BSA (Ours)	15.74	84.98



# Conclusion

- Explore the adversarial vulnerability across pre-trained and fine-tuned VL models.
- We propose VLATTACK to attack from different levels.
- Extensive experiments on five VL models and six tasks.
- Currently, our research problem is formulated by assuming the pre-trained and downstream models share similar structures. The adversarial transferability between different pre-trained and fine-tuned models is worth exploring, which we left to our future work.