



Benchmarking Robustness of Adaptation Methods on Pre-trained Vision-Language Models

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1. Introduction

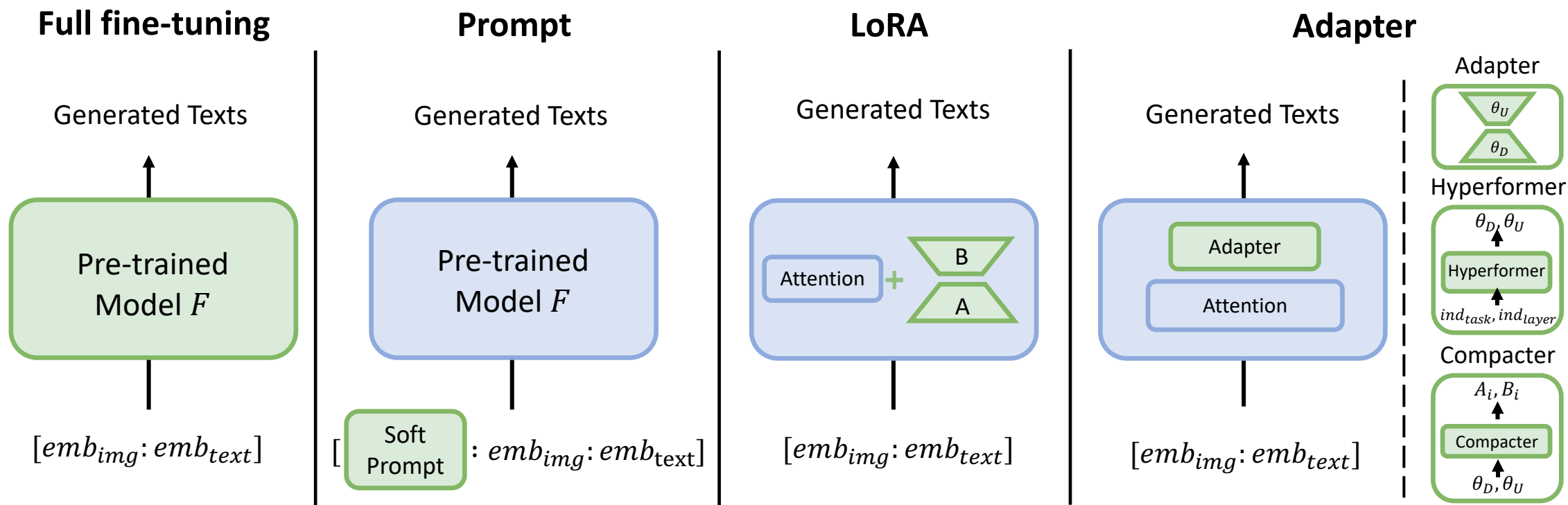


Figure 1. Various adaptation methods have been proposed to enhance the performance of pre-trained vision-language models in specific domains.



1. Introduction

Test samples in real-world applications often **differ from the data used during pre-training and adaptation.**
Model robustness is essential.

VQA during adaptation

What is this animal?



Source: <https://www.pinterest.com/>

VQA on test sample

What is this animal?



Source: <https://www.pinterest.com/>

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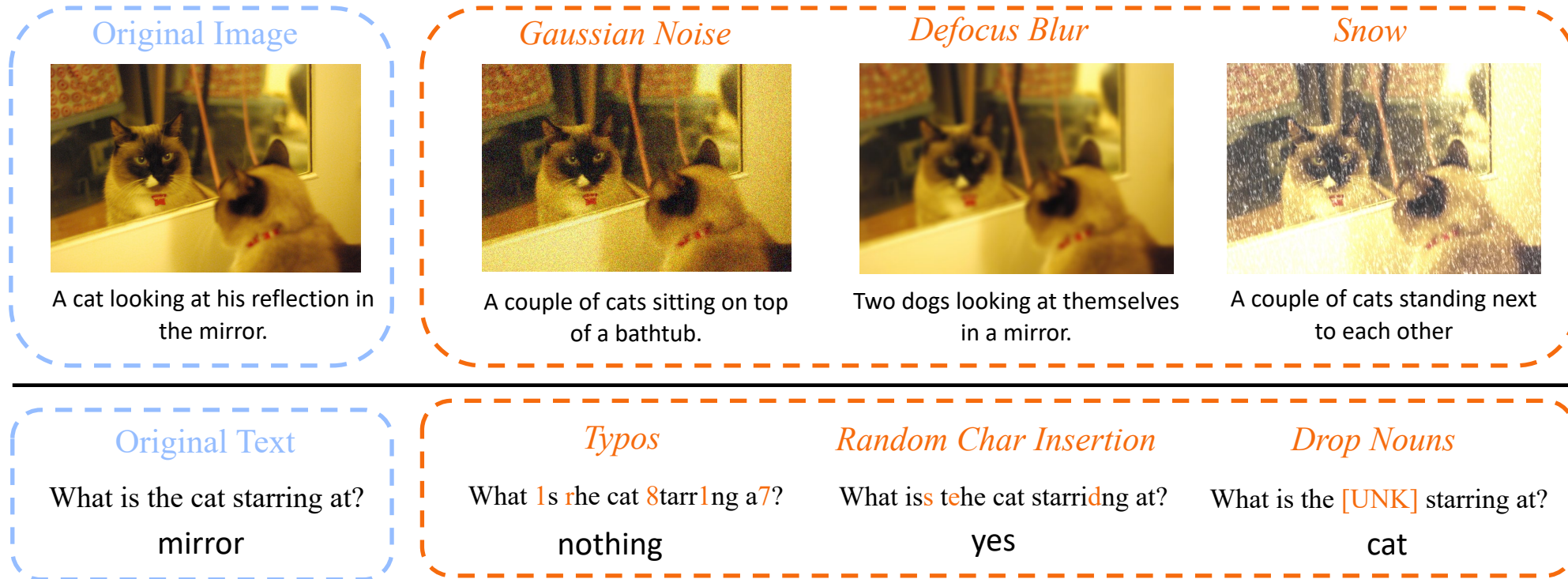


Figure 2. Multimodal adaptation methods are sensitive to image and text corruptions.



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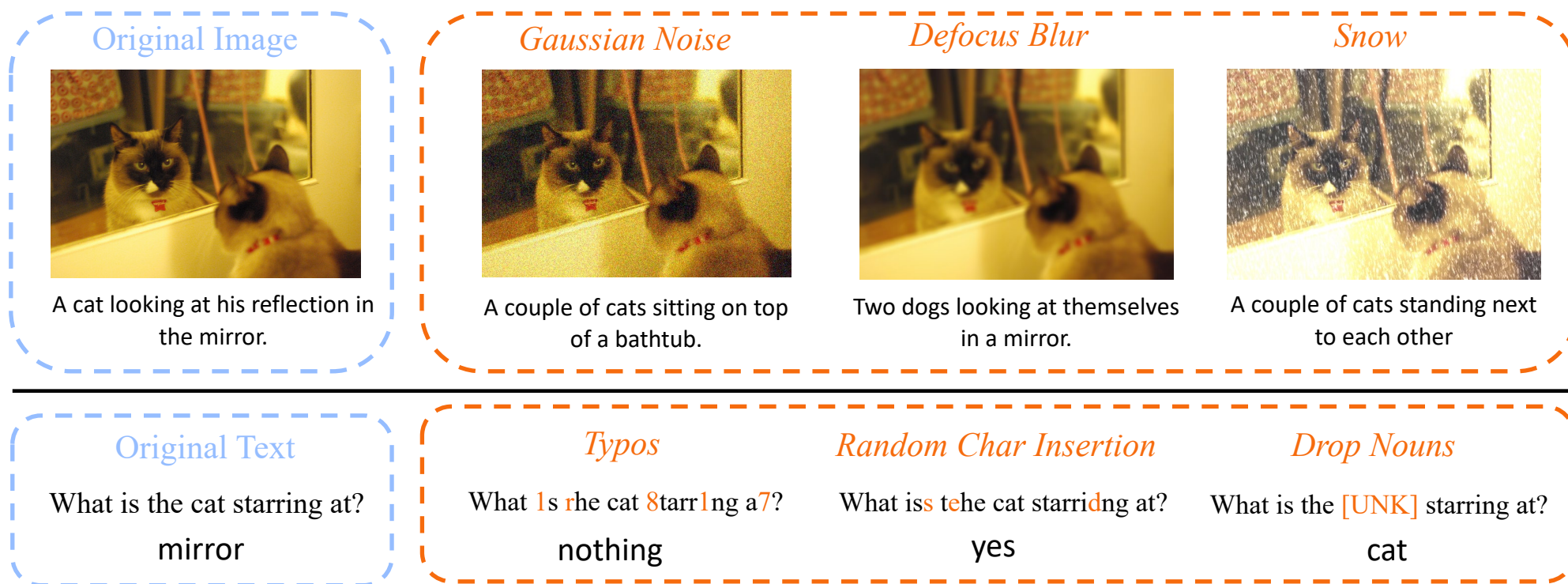


Figure 2. Multimodal adaptation methods are sensitive to image and text corruptions.

We want to know

- Which adaptation performs better on which tasks, w.r.t robustness and performance.
- Whether these methods are robust against multimodal corruptions.
- Whether more examples or more trainable parameters assure better robustness



Some examples of image and text corruption

Contrast



Elastic



Pixelate



Snow



Frost





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Contrast



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Frost



Original Text

What is the cat starring at?

Typos

What 1s rthe cat 8tarr1ng a7?

Random Char Insertion

What iss tehe cat starridng at?

Drop Nouns

What is the [UNK] starring at?

2. Corruption Methods

Some examples of image and text corruption

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Original Image



Severity 1



Zoom Blur

Severity 5



96 different levels of image corruption

Digital		Blur			Weather	
JPEG	Contrast	Zoom		Frosted Glass		
			Motion		Snow	Frost
		Defocus	Gaussian Blur			
Elastic	Saturate	Noise				Brightness
		Impulse	Shot		Fog	
Spatter	Pixelate	Gaussian	Speckle		Other	
					Blank	

87 different levels of text corruption

Natural			Spelling Error	char random insert		Synthetic			
OCR	Typos					Drop NN	Drop VB	Only NN	Only VB
			char random replace	char random swap	char random delete				
Punct	Keyboard					Drop Rand NN	Drop VB & NN	Only NN & VB	Drop Rand VB
				Insert Adv				Drop First and Last	
Passive	Formal	Casual				Drop First	Drop Last		Shuffle Order
			AppendIrr			Machine			Random Delete
Tense	Active	Double Neg	Random Insert			SwapSyn Word Embed	SwapSyn WordNet	Back Trans	Random Swap

Figure 3. Corruption methods used in this study.



3. Benchmark

	VQAv2		GQA		NLVR ²		MSCOCO Caption	
The Number of	Images	QA pairs	Images	QA pairs	Images	QA pairs	Images	Captions
Training set	113.2K	605.1K	72.1K	943.0K	103.2K	86.4K	113.2K	566.8K
Validation set	5.0K	26.7K	10.2K	132.1K	8.1K	7.0K	5.0K	5.0K
Test set	5.0K	26.3K	398	12.6K	8.1K	7.0K	5.0K	5.0K

Table 1. Dataset Statistics

Relative Robustness: $RR = 1 - \frac{\Delta P}{P_I}$, $\Delta P = (P_I - P_O)$

P_I : performance on in-distribution dataset

P_O : performance on out-of-distribution dataset

Equation 1. Evaluation Protocol

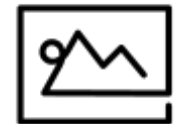
<https://adarobustness.github.io>

We have built

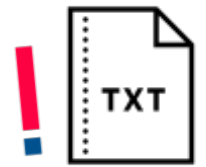
- 11** widely used adaptation methods
- 20** different image corruption methods
- 96** different levels of image corruption
- 35** different text corruption methods
- 87** different levels of text corruption
- 7** out-of-distribution benchmark datasets



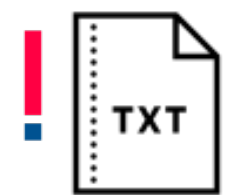
4. Results and Analysis



Adaptation method	Updated Params	VQAv2		GQA		NLVR ²		MSCOCO Caption	
		Acc (%)	RR (%)	Acc (%)	RR (%)	Acc (%)	RR (%)	CIDEr	RR (%)
Full Fine-tuning	100%	66.75	84.86±5.17	55.04	89.20±0.04	73.01	90.34±0.04	115.03	68.40±0.14
Single Adapter	4.18%	65.35	85.76±5.32	54.14	82.49±0.04	73.89	90.04±0.05	115.04	68.68±0.14




Adaptation method	Updated Params	VQAv2		GQA		NLVR ²	
		Acc (%)	RR (%)	Acc (%)	RR (%)	Acc (%)	RR (%)
Full Fine-tuning	100%	66.75	73.65±22.38	55.04	66.92±24.14	73.01	87.06±11.00
Single Adapter	4.18%	65.35	77.64±21.09	54.14	67.47±20.03	73.89	88.49±10.87




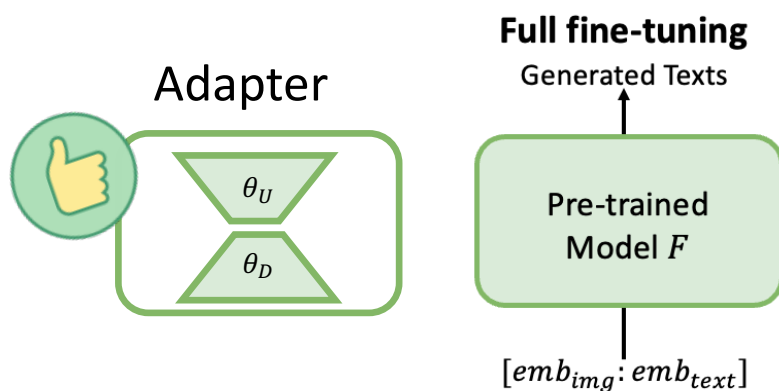
*A higher sensitivity towards **text corruptions**, especially to character-level corruptions*



4. Results and Analysis

Adaptation method	Updated <i>Image Corruptions</i> Params	VQAv2		GQA		NLVR ²		MSCOCO Caption	
		Acc (%)	RR (%)	Acc (%)	RR (%)	Acc (%)	RR (%)	CIDEr	RR (%)
Full Fine-tuning	100%	66.75	84.86 \pm 5.17	55.04	89.20 \pm 0.04	73.01	90.34 \pm 0.04	115.03	68.40 \pm 0.14
Single Adapter 	4.18%	65.35	85.76 \pm 5.32	54.14	82.49 \pm 0.04	73.89	90.04 \pm 0.05	115.04	68.68 \pm 0.14

Adaptation method	Updated <i>Text Corruptions</i> Params	VQAv2		GQA		NLVR ²	
		Acc (%)	RR (%)	Acc (%)	RR (%)	Acc (%)	RR (%)
Full Fine-tuning	100%	66.75	73.65 \pm 22.38	55.04	66.92 \pm 24.14	73.01	87.06 \pm 11.00
Single Adapter 	4.18%	65.35	77.64 \pm 21.09	54.14	67.47 \pm 20.03	73.89	88.49 \pm 10.87





Language information plays a more significant role than visual information

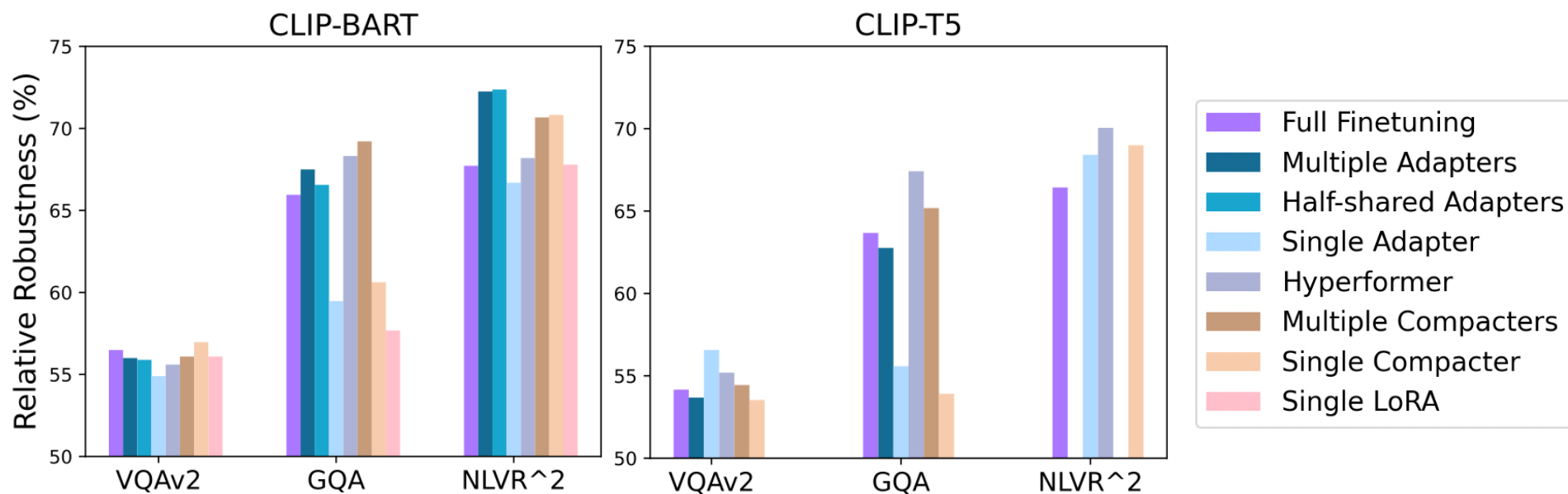


Figure 4. RR against blank-image corruption.



More adaptation data does not consistently enhance robustness.

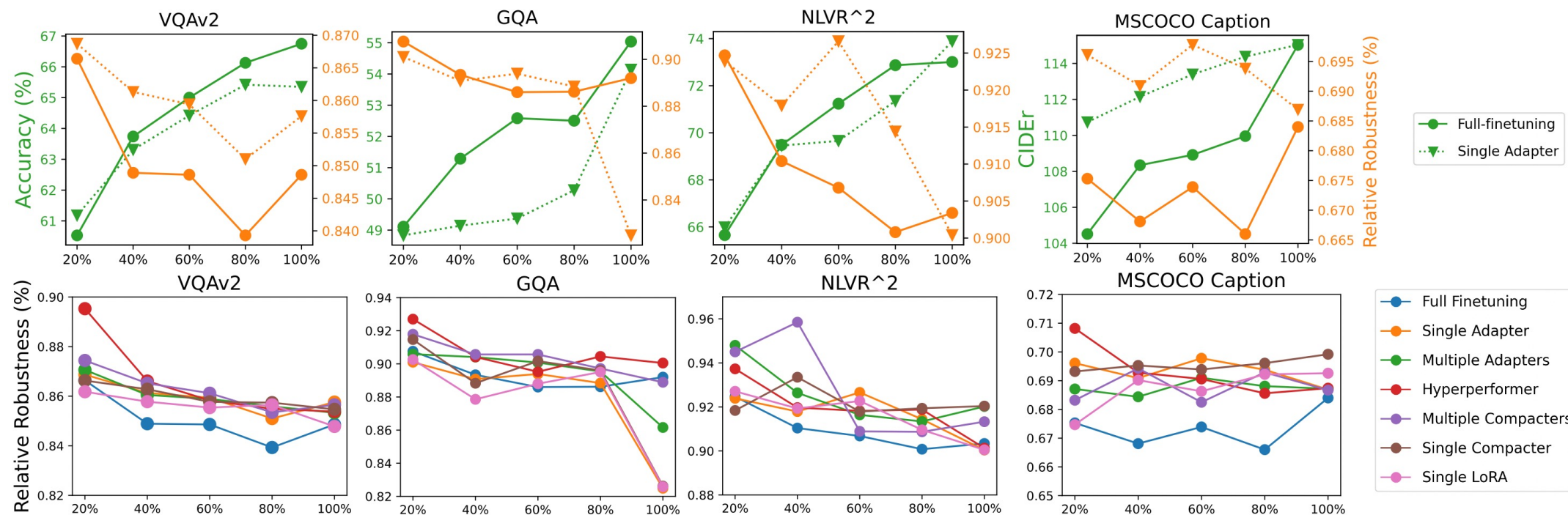


Figure 5. RR given different size of adaptation dataset.



More parameters do not ensure enhanced robustness and some even reduce it

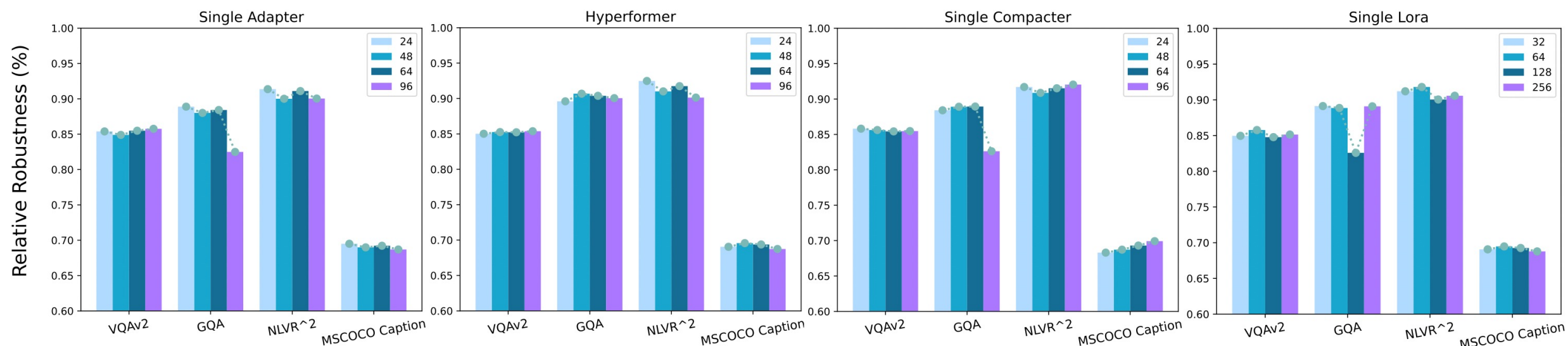
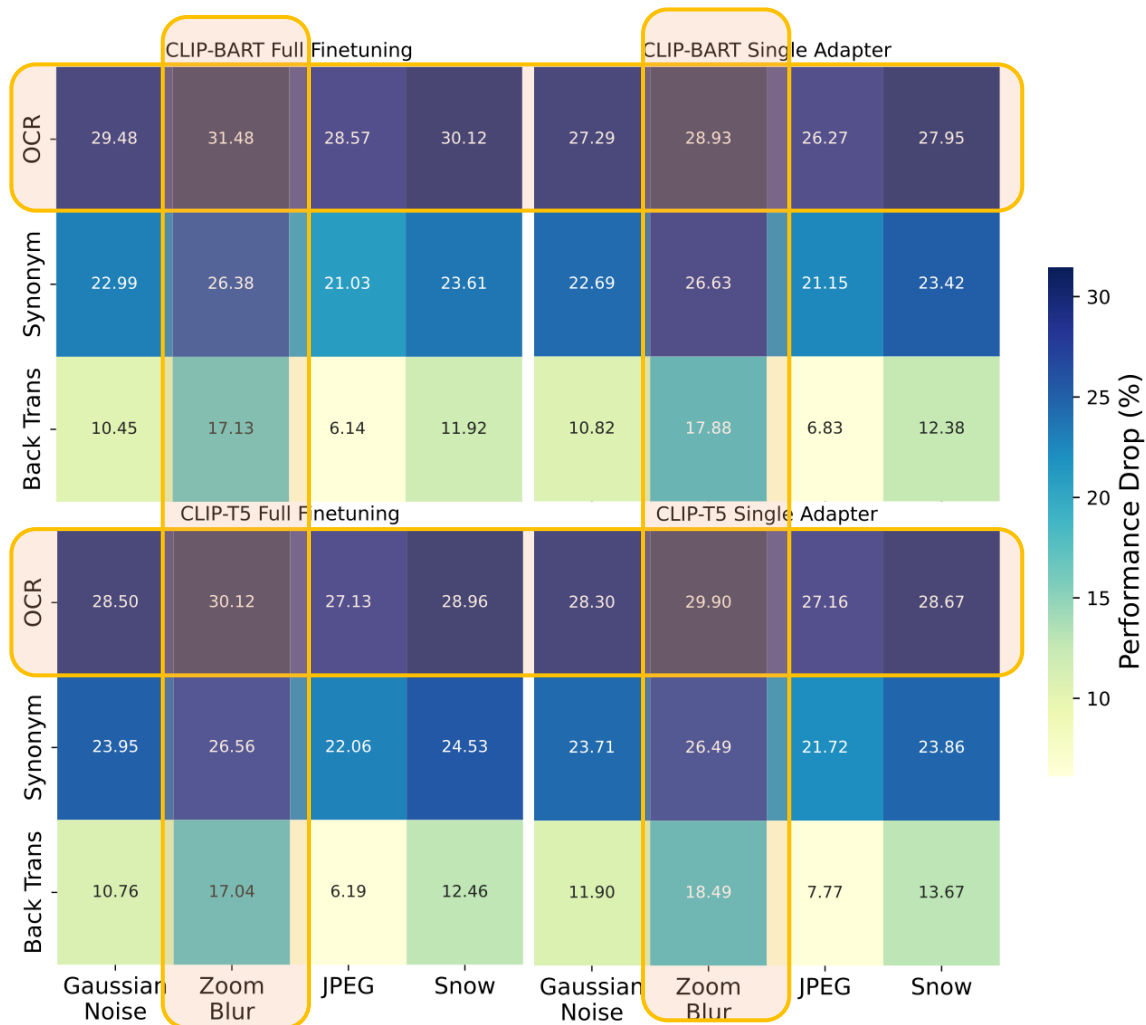


Figure 6. RR given different size of adaptation modules.



4. Results and Analysis



Combining corruptions from two modalities can lead to a greater drop in robustness

Figure 7. RR given both visual and text corruptions.



Robustness against natural dataset distribution shift follows the similar conclusions.

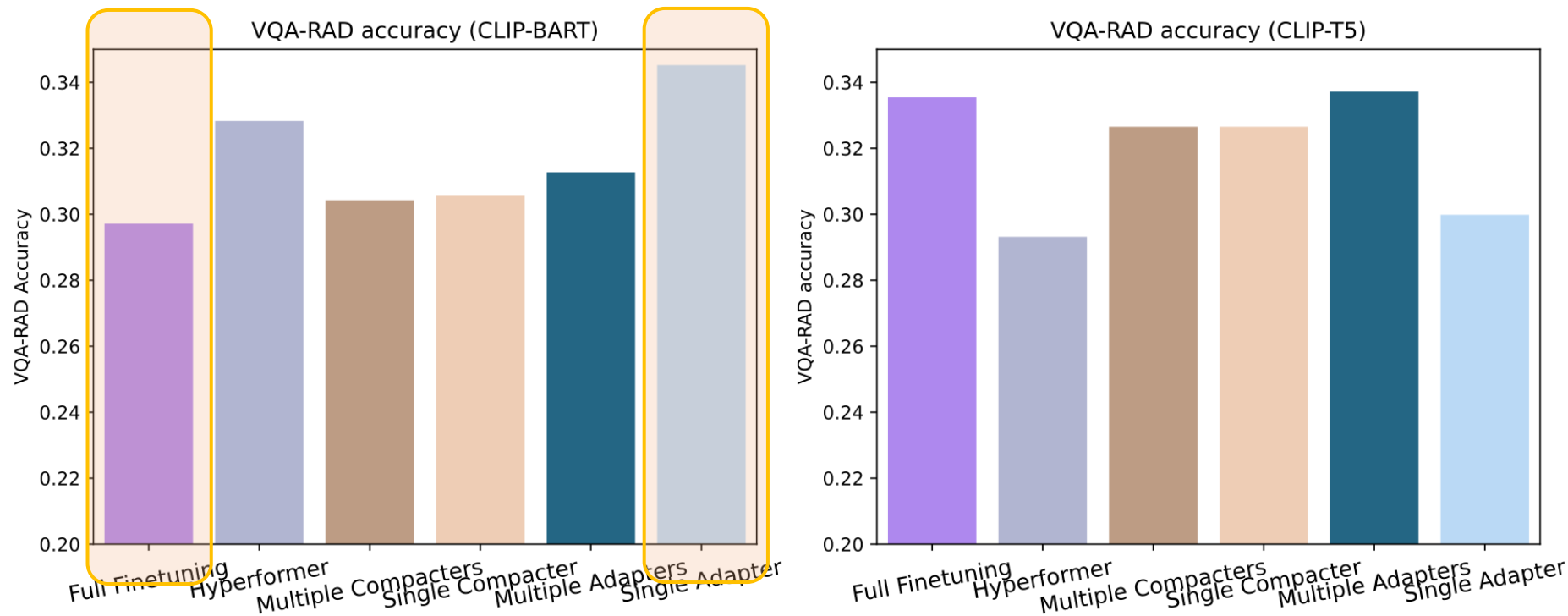


Figure 8. Performance on natural distribution shift dataset (VQA-RAD).



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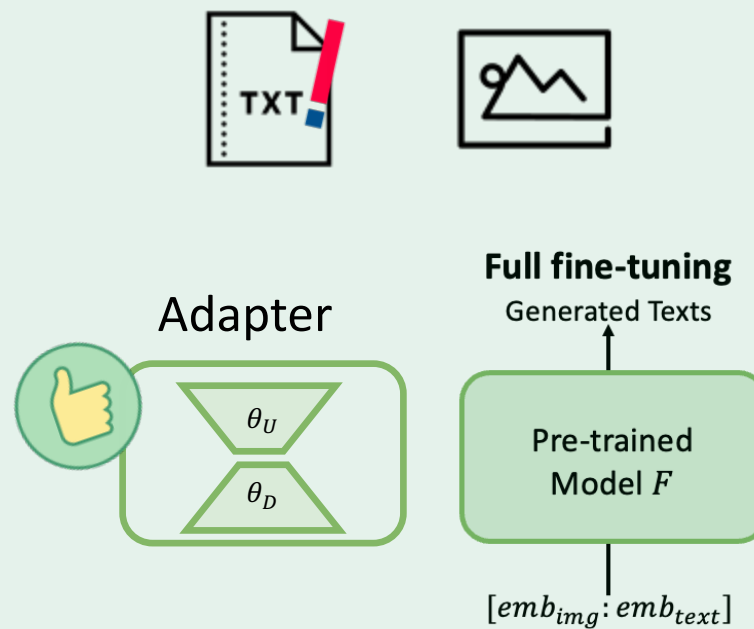
5. Conclusion

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We find out



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Check our paper for more !



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Thank you!

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`chenshuo.cs@outlook.com`