

# Zero-Shot Robustification of Zero-Shot Models

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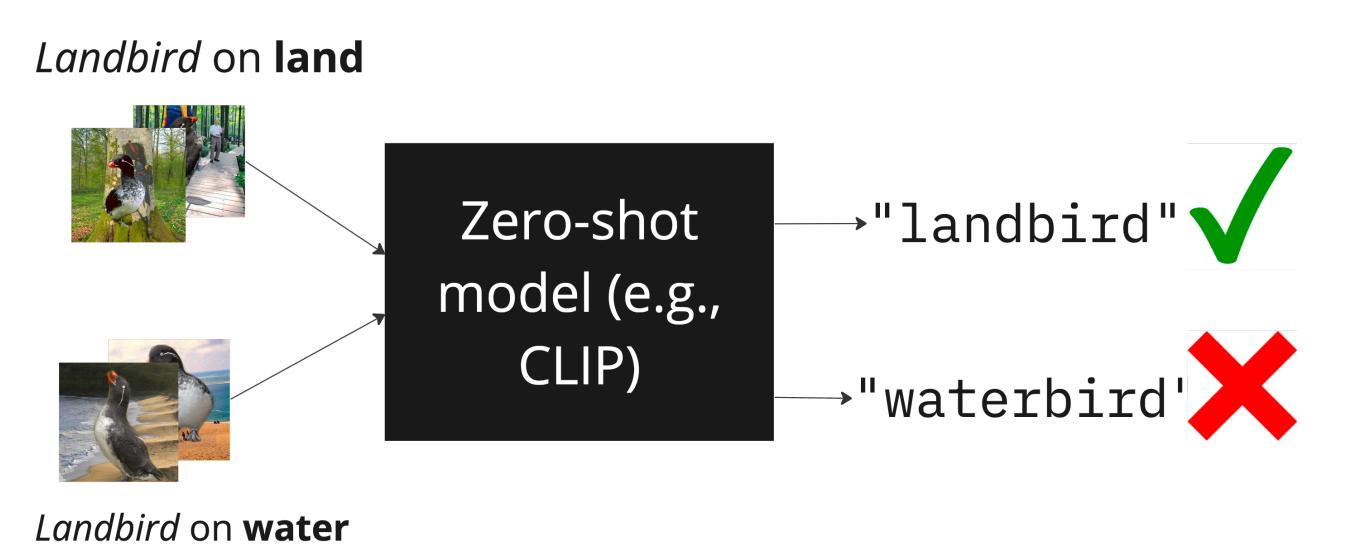
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Paper 🚹

# Can we make foundation models more robust?



Yes, with fine-tuning using group-annotated data (e.g. [1])

## Well, can we do it for free?

- No fine-tuning
- No data

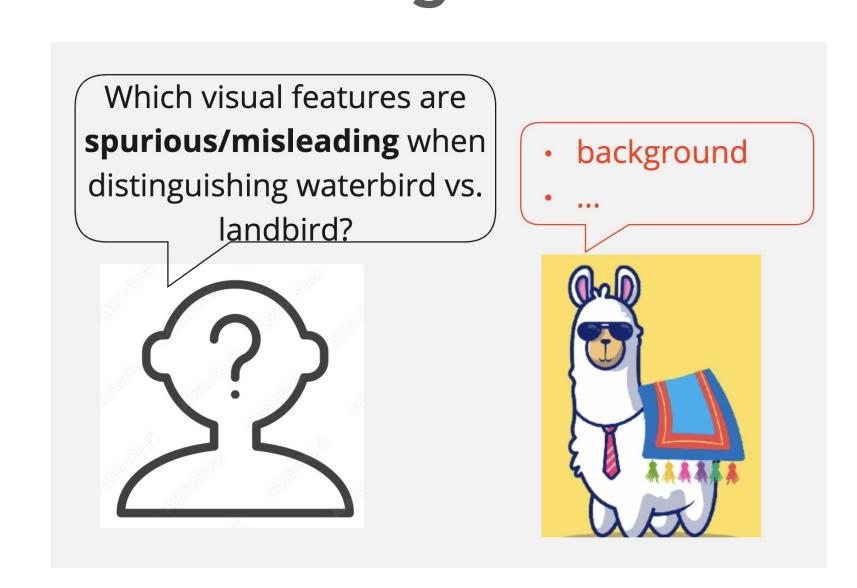
# RoboShot: Zero-Shot Robustification of Zero-Shot Models

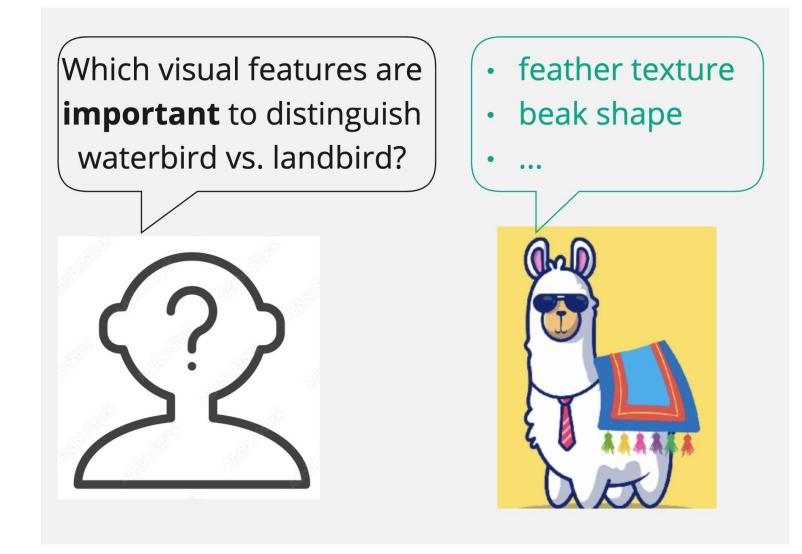
Model input embeddings as mixture of: harmful, helpful, and benign components

$$x=\sum_{s=1}^{S}lpha_s^{
m harmful}z_s+\sum_{r=S+1}^{S+R}lpha_r^{
m helpful}z_r+\sum_{b=S+R+1}^{S+R+B}lpha_b^{
m benign}z_b.$$
 reduce  $lacksquare$ 

### Procedure

#### 1. Get insights from LLMs





Harmful insights

Helpful insights

#### 2. Modify embeddings

Apply embedding debiasing methods [2, 3]

Neutralize harmful components

$$\hat{x} \leftarrow x - \frac{\langle x, v^{\text{harmful}} \rangle}{\langle v^{\text{harmful}}, v^{\text{harmful}} \rangle} v^{\text{harmful}}$$

Amplify helpful components

$$\hat{x} \leftarrow \hat{x} + \frac{\langle \hat{x}, v^{\text{helpful}} \rangle}{\langle v^{\text{helpful}}, v^{\text{helpful}} \rangle} v^{\text{helpful}}$$

### **Theoretical Results**

- When insights are more precise in specifying non helpful terms, RoboShot yields better outcome.
- RoboShot is more effective when insight embedding is less noisy.

## **Experimental Results**

Improving multimodal models

Dataset	Model		ZS		GroupPrompt ZS			RовоЅнот		
	1,1000	AVG	WG(↑)	Gap(↓)	AVG	WG(↑)	Gap(↓)	AVG	WG(↑)	Gap(↓)
	CLIP (ViT-B-32)	80.7	27.9	52.8	81.6	<u>43.5</u>	<u>38.1</u>	82.0	54.4	28.6
Waterbirds	CLIP (ViT-L-14)	88.7	<u>27.3</u>	61.4	70.7	10.4	<u>60.3</u>	79.9	45.2	34.7
	ALIGN	72.0	50.3	<u>21.7</u>	72.5	5.8	66.7	50.9	<u>41.0</u>	9.9
	AltCLIP	90.1	<u>35.8</u>	54.3	82.4	29.4	<u>53.0</u>	78.5	<b>54.8</b>	23.7
	CLIP (ViT-B-32)	80.1	72.7	7.4	80.4	74.9	<u>5.5</u>	84.8	80.5	4.3
CelebA	CLIP (ViT-L-14)	80.6	<u>74.3</u>	<u>6.3</u>	77.9	68.9	9.0	85.5	<b>82.6</b>	2.9
	ALIGN	81.8	<u>77.2</u>	<u>4.6</u>	78.3	67.4	10.9	86.3	83.4	2.9
	AltCLIP	82.3	<b>79.7</b>	2.6	82.3	<u>79.0</u>	3.3	86.0	77.2	8.8
			\							

Finding: Worst group accuracy (WG) improves significantly, often improving average accuracy (AVG) as well!

Finetuning version extension: Label Free Adaptation (LFA)

AVG WG WG WG WG	LFA (100 val)	A	SHOT	Rово	Dataset	
Waterbirds 82.0 54.5 83.8 $\pm$ 0.74 55.2 $\pm$ 0.75 84.2 $\pm$ 1.1 53.6 $\pm$	AVG WG	WG	AVG	WG	AVG	
<b>Waterbrids</b> $02.0  \underline{5+.5}  03.0  \pm 0.74  33.2  \pm 0.75  04.2  \pm 1.1  33.0  \pm 0.75  04.2  \pm 0.75  04.2$	$0.2 \pm 1.1$ $53.6 \pm 1.76$	<b>55.2</b> ± 0.75	83.8 $\pm$ 0.74	<u>54.5</u>	82.0	Waterbirds
CelebA 84.8 80.5 $86.7 \pm 0.811$ $83.4 \pm 1.02$ $86.5 \pm 0.72$ 83.8	$5 \pm 0.72$ <b>83.8</b> $\pm 1.17$	$83.4 \pm 1.02$	86.7 ± 0.811	80.5	84.8	CelebA

Finding: Finetuning version of RoboShot can give further improvement!

#### **Future Work**

- 1. Improve ways to get insights: with ICL, RAG
- 2. Improve ways to use the insights: prompting, embedding edit, guided decoding, etc, ...

## Reference

- [1] Zhang, M., & Ré, C. "Contrastive adapters for foundation model group robustness." NeurIPS'22
- [2] Bolukbasi, Tolga, et al. "Man is to computer programmer as woman is to homemaker? debiasing word embeddings." NIPS'16.
- [3] Aboagye, Prince Osei, et al. "Interpretable debiasing of vectorized language representations with iterative orthogonalization." ICLR'23