



# Zero-Shot Composed Image Retrieval with Textual Inversion

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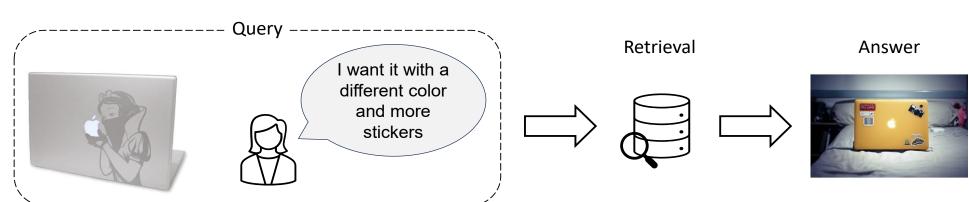
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### Introduction





# **X** Current Limitations

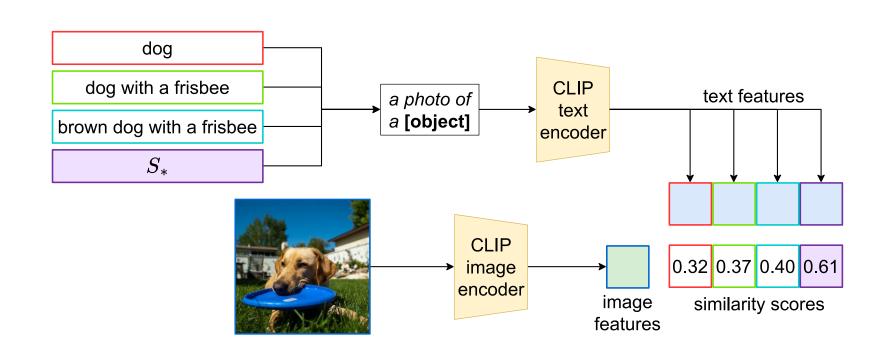
- Existing methods for CIR rely on supervised learning, which requires expensive and time-consuming manual data labeling
- Existing CIR datasets contain several false negatives, i.e., images that could be potential ground truths for the query but are not labeled as such

# **Contributions**

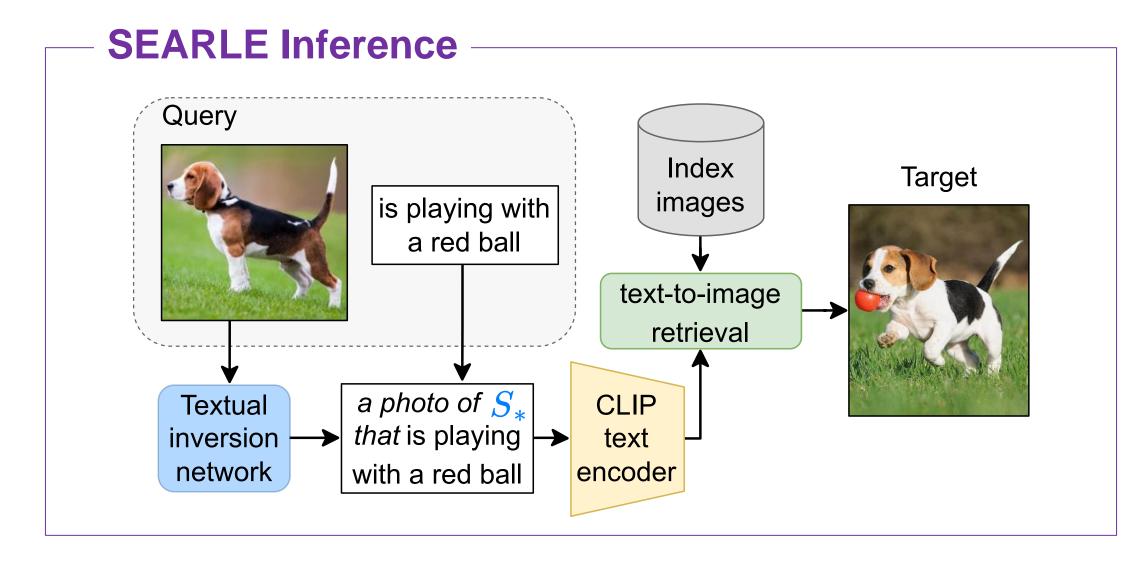
- > We propose **SEARLE**, a CLIP-based [3] method that addresses CIR in a zero-shot manner, thus without requiring a labeled training dataset
- > We introduce **CIRCO**, an open-domain benchmarking dataset for CIR with multiple annotated ground truths and reduced false negatives

# **Textual Inversion**

- > The term **textual inversion** [4] refers to the process of mapping an image into a pseudo-word token residing in the CLIP token embedding space
- Textual inversion consists of expanding CLIP vocabulary by defining a new pseudo-word S\* which encapsulates the visual information of the image



# **SEARLE Training Overview ✓ Expressiveness ✓** Expressiveness **X** Efficiency √ Efficiency **Textual** Optimization-based inversion textual inversion network Unlabeled images **Breakdown** Optimization-based Textual Inversion (OTI) Pre-training of textual inversion network $\phi$ $\widehat{T}_*^1$ a photo of $S_*$ flying ... pseudo-word token $^{B}$ a photo of $S_{st}$ in a cage . $\mathcal{L}_{\phi} = \lambda_{distil} \mathcal{L}_{distil} + \lambda_{\phi apt} \mathcal{L}_{apt}$

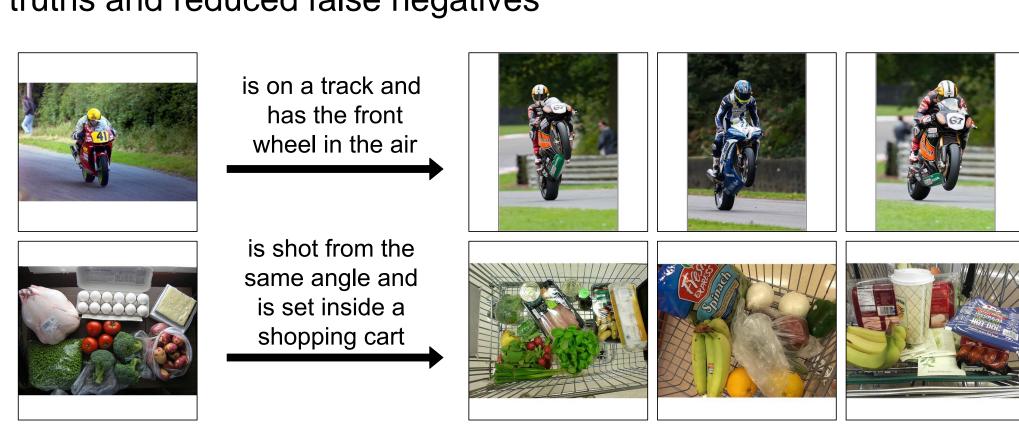


#### References

[1] Cohen, Niv, et al. ""This is my unicorn, Fluffy": Personalizing frozen vision-language representations." ECCV2022 [2] Saito, Kuniaki, et al. "Pic2word: Mapping pictures to words for zero-shot composed image retrieval." CVPR2023 [3] Radford, Alec, et al. "Learning transferable visual models from natural language supervision." ICML2021 [4] Gal, Rinon, et al. "An Image is Worth One Word: Personalizing Text-to-Image Generation using Textual Inversion." ICLR2022

### **CIRCO Dataset**

CIRCO is the first CIR dataset with multiple annotated ground truths and reduced false negatives



Resu	lts -
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		CIRR			FashionIQ		CIRCO	
Backbone	Method	R@1	R@5	R@10	R@10	R@50	mAP@10	
$\mathrm{B}/32$	Image-only	6.89	22.99	33.68	5.90	13.37	1.60	
	Text-only	21.81	45.22	57.42	18.70	36.84	2.67	
	Image + Text	11.71	35.06	48.94	14.78	29.60	3.25	
	Captioning	12.46	35.04	47.71	13.98	28.62	5.77	
	PALAVRA [1]	16.62	43.49	58.51	19.76	37.25	5.32	
	SEARLE-OTI	24.27	53.25	<u>66.10</u>	22.44	42.34	<u>7.83</u>	
	SEARLE	<u>24.00</u>	$\overline{53.42}$	$\overline{66.82}$	$\overline{22.89}$	$\overline{42.53}$	$\overline{9.94}$	
$\mathrm{L}/14$	Pic2Word [2]	23.90	51.70	65.30	24.70	43.70	9.51	_
	SEARLE-XL-OTI	24.87	52.31	66.29	27.61	47.90	<u>11.03</u>	
	SEARLE-XL	<u>24.24</u>	<b>52.48</b>	66.29	25.56	46.23	$\overline{12.73}$	SEARLE trained on
								<b>3%</b> of Pic2\

## **Conclusions**

X Existing approaches for CIR are limited by their reliance on expensive labeled datasets

SEARLE achieves state-of-the-art results on CIR without the need for a labeled training dataset

We introduce CIRCO, the first CIR dataset with multiple annotated ground-truths and reduced false negatives

