Unconstrained Foreground Object Search

Yinan Zhao* Brian Price+ Scott Cohen+ Danna Gurari*

*University of Texas at Austin +Adobe Research

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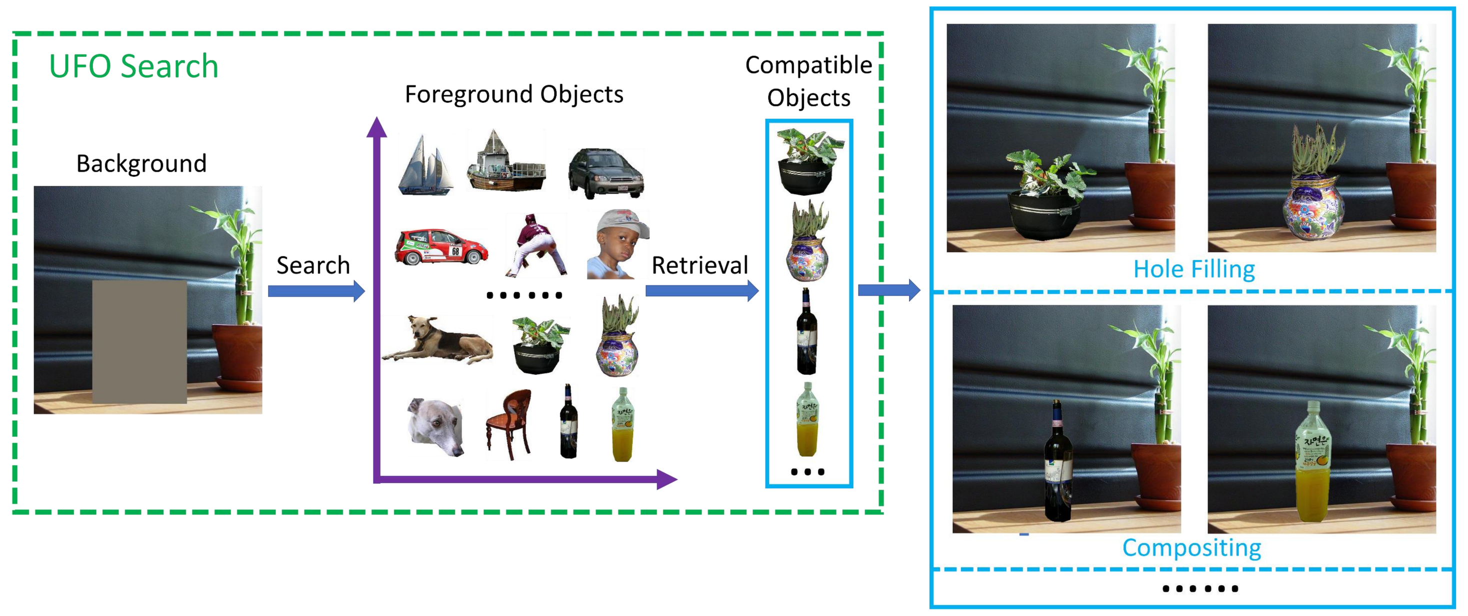
Motivation

Unconstrained Foreground Object Search

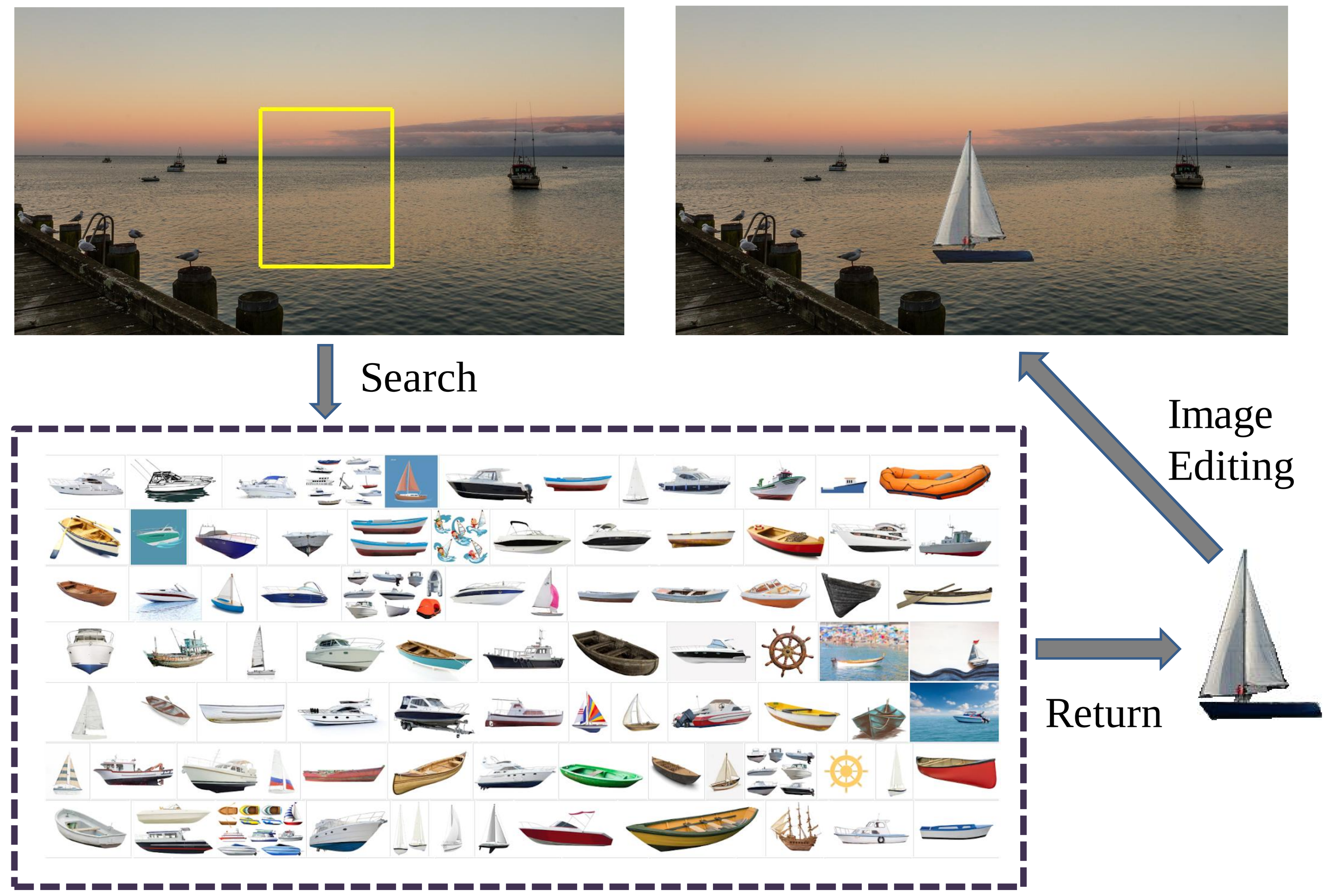


Applications: image editing, e.g., hole filling, image compositing

Our Problem

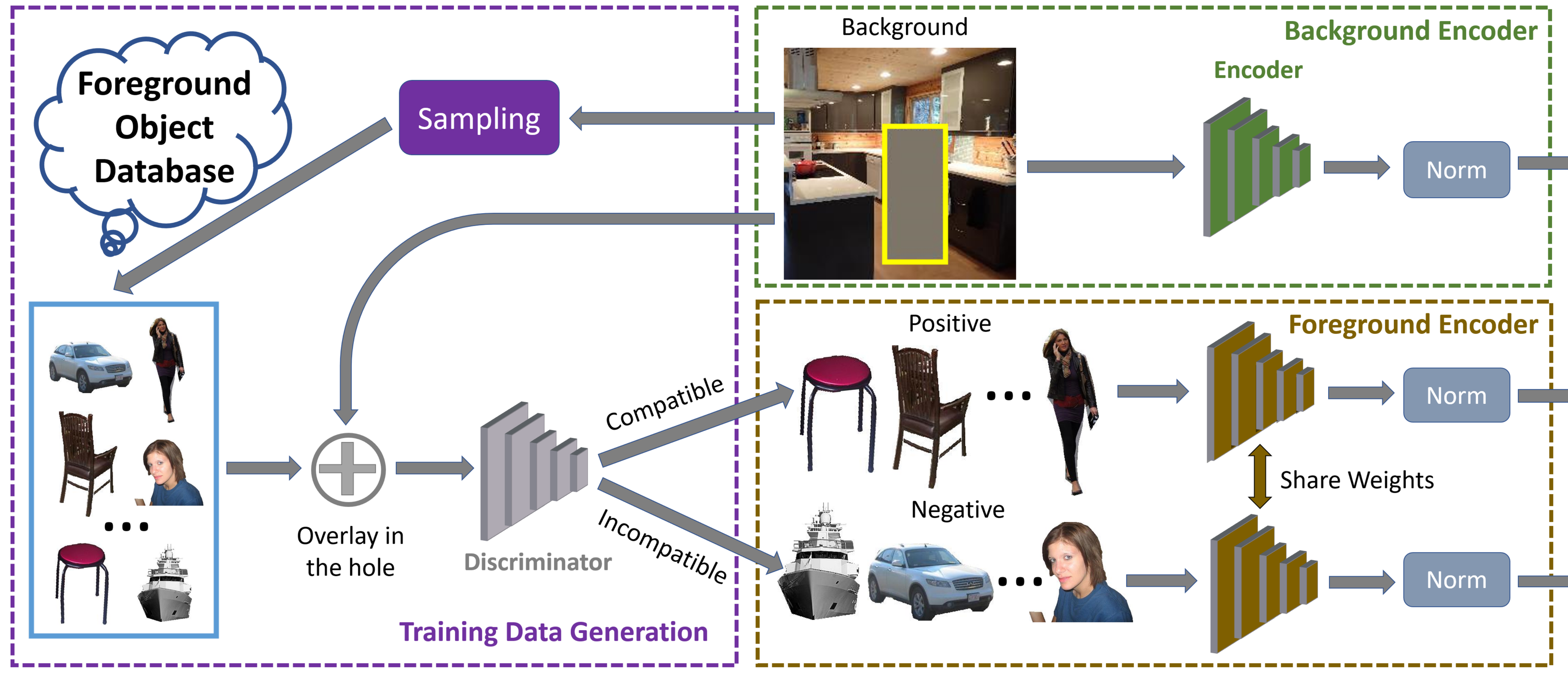
Novel Problem: We propose the problem of **Unconstrained Foreground Object (UFO) Search**, to search for foreground objects that are semantically compatible with a background image *without* any constraint on what objects to retrieve.

Related Work: Method [1] is ***constrained*** to retrieve objects that belong to a pre-specified semantic class.



Our UFO Search

Our Focus: ***semantic*** compatibility



The **Background Encoder** and **Foreground Encoder** project background images and foreground objects into a shared feature space respectively, such that compatible objects and backgrounds are near each other.

Key Challenge in Training: how to generate a sufficient number of positive samples per background image for training the encoder.

Solution: we introduce a **Training Data Generation** module, that consists of two mechanisms, to augment training data: 1) a ***Discriminator*** to identify a noisy set of compatible objects per background image, and 2) a ***Sampling*** module to accelerate the process above.

Discriminator* vs. *Encoder

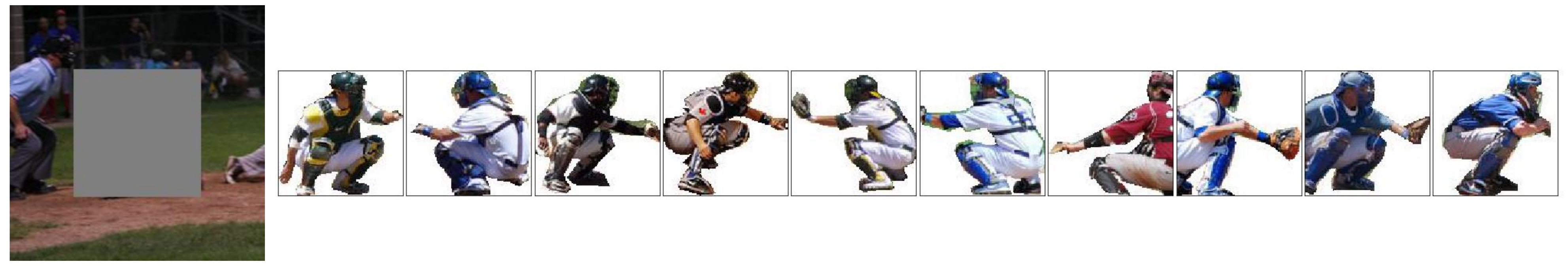
	Input	Training	Search Efficiency
Encoder	De-coupled	Embedding learning with triplet loss	Fast
Discriminator	Coupled	Classification with cross entropy loss	Slow

The discriminator alone is unsuitable for solving our compatibility problem (in terms of accuracy and speed), but is valuable for boosting the performance of our UFO search encoder by generating noisy yet richer training triplets.

Evaluation

Qualitative Results

When only one object type is compatible, the top retrievals all come from that object type.



When many object types are appropriate, the top retrievals span multiple object categories.

Dataset: CAIS [1] (8 object categories)

Overall, UFO Search outperforms four related baselines.

Method	Boat	Bottle	Car	Chair	Dog	Painting	Person	Plant	Overall
Shape	7.47	1.16	10.40	12.25	12.22	3.89	6.37	8.82	7.82
Realism CNN [3]	12.33	7.19	7.55	1.81	7.58	6.45	1.47	12.74	7.14
CFO-C Search [1]	57.48	14.24	18.85	21.61	38.01	**27.72**	**47.33**	20.20	30.68
CFO-D Search [1]	55.48	8.93	24.10	18.16	**57.82**	21.59	27.66	23.13	29.61
UFO Search	**59.73**	**21.12**	**36.63**	19.27	36.51	25.84	27.11	**31.19**	**32.17**

Our ablation study illustrates the benefit of our design choices for UFO Search.

No BG Training	49.09	0.62	3.23	9.01	7.37	11.66	7.30	22.02	13.79
No Discriminator	58.07	17.22	20.71	**21.93**	37.05	24.57	27.11	25.05	28.97
Discriminator Only	48.71	8.35	21.42	17.32	50.61	20.28	22.14	17.35	25.77
Regression	55.33	9.90	18.31	17.42	27.79	23.76	35.66	10.83	24.87

Dataset: MS-COCO [2] (79 object categories)

Our user study reinforces the benefit of our design choices for UFO Search.

Method	P@5	P@10	P@15	P@20	P@25
No BG Training	12.67	13.33	13.28	12.50	12.50
No Discriminator	30.33	30.75	30.39	30.50	30.40
Discriminator Only	38.50	36.58	36.11	35.54	35.57
Regression	36.33	37.25	36.00	35.46	35.77
UFO Search	**41.83**	**40.33**	**39.39**	**38.96**	**38.83**

[1] Zhao, Hengshuang, et al. "Compositing-aware image search." ECCV 2018.
[2] Lin, Tsung-Yi, et al. "Microsoft coco: Common objects in context." ECCV 2014.
[3] Zhu, Jun-Yan, et al. "Learning a discriminative model for the perception of realism in composite images." ICCV 2015.