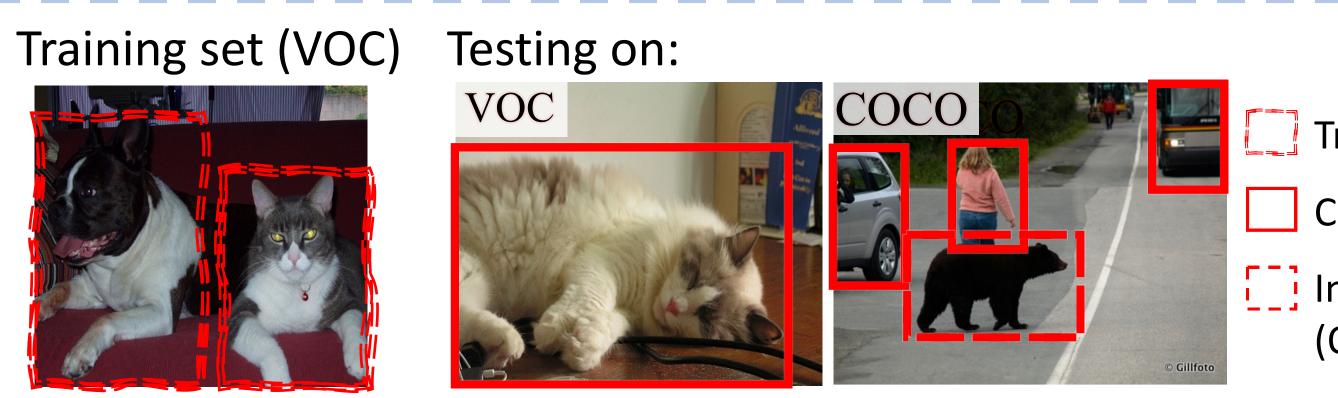


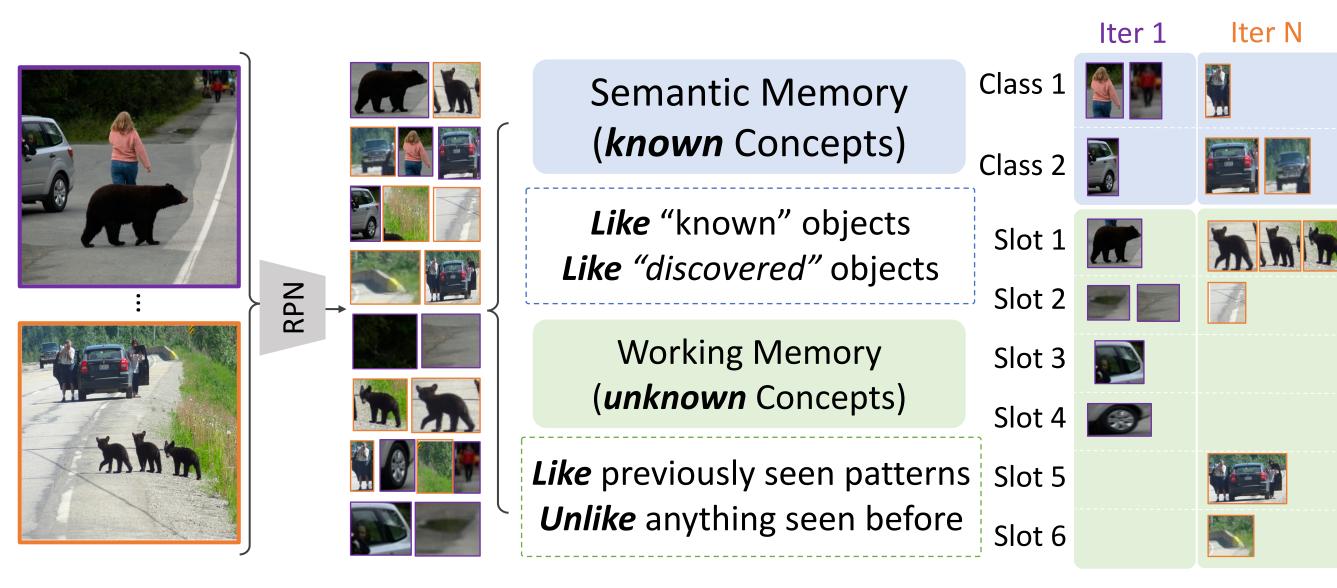


Goal: Discover novel objects and learn models to detect them without human supervision.

Shortcomings of standard supervised paradigm



Detectors trained on a labeled dataset (VOC) Fail to detect novel objects (e.g., additional objects in COCO)



| | | Semantic Memory (<i>known</i> Concepts) <i>Like</i> "known" objects <i>Like "discovered"</i> objects | Class 2 Slot 1 Slot 2 | N Fram | nework: Iterative, Online, and Scalable | | | ble | Encoding: Region | D | | | | |
|--|---------------------|---|--|---|--|---------------|----------------|--------------------|---|--|--|--|--|--|
| | | | | S_t | $\begin{array}{c} & & & \\ & & & & \\ & & & \\ & & & & \\ & & & \\ &$ | | St+1 | Discovery Set 1 | $Consolidation$ S_{t+m} \mathcal{M}_s | Proposals Storage: Dual Memory | Contains clusters ("slots"), represente as a Centroid or a Classifier Centroid Classifier | | | |
| | | Working Memory (<i>unknown</i> Concepts) <i>e</i> previously seen patte <i>hlike</i> anything seen befo | Slot 3 Slot 4 Slot 5 Slot 5 Slot 6 Slot 6 | M _w | | | | •••• Storage | M _w Storage | Retrieval : Decide seen/unseen? | Fast updates Inaccurate Cos. similarity | Slow updates Accurate Cls. score | | |
| | | | | | Benchmark Details and Results | | | | | | | | | |
| | Be | Smaller-scale Object discovery on subsets of COCO train2014. | | | | | | | Comple detections and elecclusice AD | | | | | |
| Labeled date ImageNet Pascal Vet | et | Salient features: Large-scale Different distribution of | | Comparison with contemporary discovery methods using AuC for <i>unknown</i> classes. | | | | | | on CO | Sample detections and class-wise AP on COCO minival using our object detectors trained novel classes using | | | |
| In-the-wild discovery dataset: COCO | | | | Method (| Conf. <i>‡</i> | #imgs. | CorLo | c CorRe | t DetRate | | oracle labels. | | | |
| | | | | Vo et. al CV | VPR'19 | 2.5k | 6.62 | 80.00 | 4.73 | | | Fire Hydrant (AP: 4.85) | | |
| | M | letrics | | Vo et. al [†] CV Ours | VPR'19 | 2.5k 2.5k | 6.34 43.00 | 70.00 64.22 | 5.17 48.56 | | | | | |
| Our benchmark: Purity vs. Coverage mAP for learned detectors # of objects | | Other methods*: CorLoc CorRet Det-Rate *None evaluates discovery | | Vo et. al EC Ours | CCV'20 | 20k 20k | 15.77 41.41 | 100 64.60 | 11.56 46.81 | | | | | |
| | | | | \dagger : OSD with ResNet-101 Faster R-CNN proposals and classification-head features (same as Ours). | | | | | | - | Concepts discovered by our approach which we a annotations for the 60 'unk | | | |
| discovered performance | | | | <u>Detection performance (</u> mAP) for object detectors on COCO minival, trained using <i>oracle</i> labels for clusters. | | | | | | | | | | |
| Large-scale Object discovery on the entire COCO train2014 (80k images). Comparisons with scalable clustering | | | | Classes | ses GT-IoU: 0.5 | |).5 | GT-IoU: 0.2 | | | | | | |
| meth | | uC for <i>unknown</i> d | | | AP@0. | 5 AP | @0.2 A | AP@0.5 | AP@0.2 | Gira | affe | Orange Traf | | |
| Method | AuC @0.5 | 5 AuC@0.2 | #disc. objs | All (80) | 2.69 | 4 | .44 | 2.62 | 4.37 | | | | | |
| K-means | 3.34 | 7.23 | 42 | Novel (60) | 1.87 | 3. | .50 | 1.76 | 3.42 | | Surfboard | d Cake | | |
| FINCH Ours | 3.03 3.60 | 6.99 9.11 | 42 46 | Novel [†] | 5.23 | 6. | .47 | 5.45 | 6.40 | | | | | |
| | J.UU | | т у | t: mAP of classe | es with AP g | reater than c | hance. | | | | | | | |

The Pursuit of Knowledge: **Discovering and Localizing Novel Categories using Dual Memory**

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Our Discovery and Localization Benchmark & Framework

- Training Correct dets.
- Incorrect dets. (OOD images)

Discovered and localized examples of unknown classes (from COCO). In this illustration these correspond to (clockwise): traffic-light, tie, umbrella, bear

Dual Memory Framework for Unsupervised Object Discovery

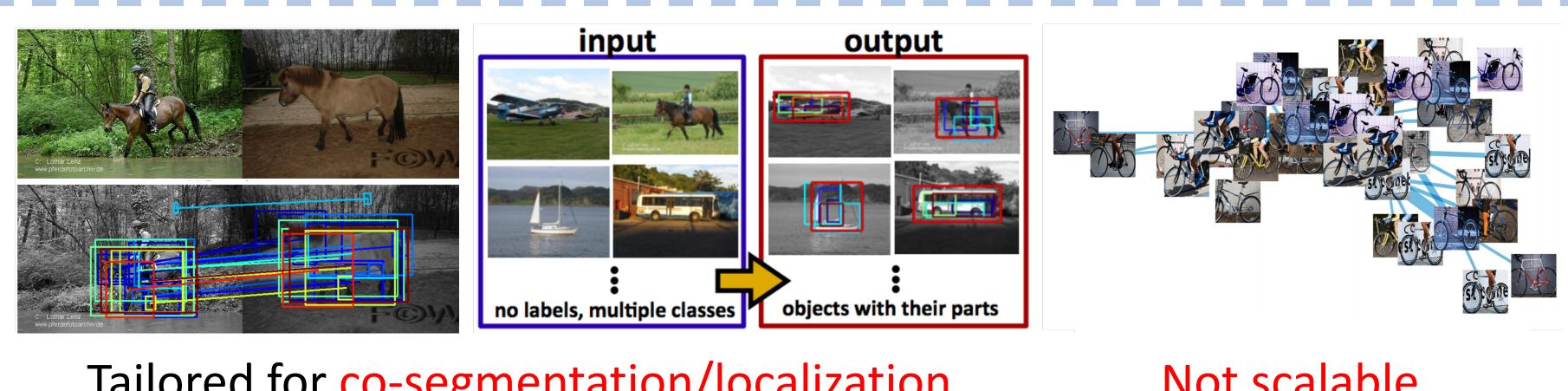
†: mAP of classes with AP greater than chance.



★ Large-scale, realistic **benchmark** for object discovery & localization

★ Scalable never-ending in-the-wild concept discovery framework

Shortcomings of contemporary discovery methods



Tailored for co-segmentation/localization Not scalable [Cho et al., CVPR 2015] [Vo et al., CVPR 2019] [Vo et al., ECCV 2020]





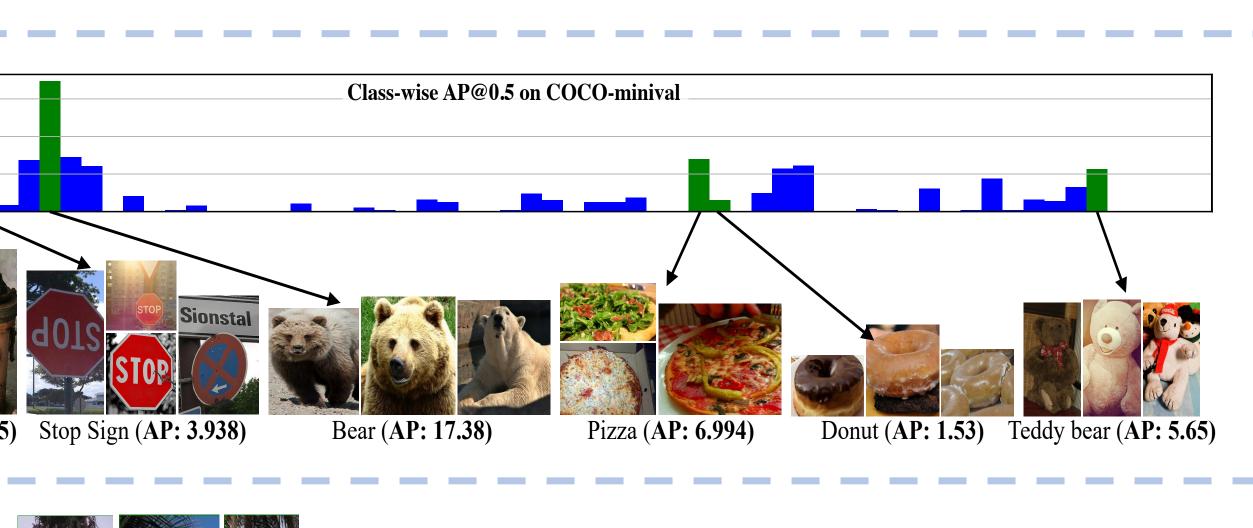
Jual Memory

ed Semantic Memory

- Long-term memory
- "Semantic Prior" init. Null init.,
- Infrequent updates
- Classifier

Working Memory

- Short-term memory
- Reliable associations
 Unreliable associations
 - Frequent updates
 - Centroid





Concepts discovered by our approach which we cannot evaluate since they are unlabeled

ve can evaluate using the ground-truth Inknown' classes

Oven

Zebra

Umbrella

Cup

Laptop

Wine glass