Active Learning Strategies for Weakly-Supervised Object Detection

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INTRODUCTION

- **Goal**: Boosting the performance of weakly-supervised object detectors (WSODs) with a *few carefully selected fully-annotated images*.
- **Motivations**:
  - WSODs require **only image tags** annotation for training.
  - But achieve lower performances than fully- supervised object detectors.
  - We want to **narrow the gap** between weakly- and fully-supervised object detectors.
  - WSODs suffer some **well-known confusions**. Addressing them will make the detectors more effective.

CONTRIBUTIONS

- We introduce a new approach to object detection that combines **weakly-supervised and active learning**.
- We introduce **BiB**, an active selection strategy that is **tailored** to address the limitations of weakly-supervised object detectors.
- **BiB** demonstrates a better **detection performance/annotation cost trade-off** than both weakly- and fully-supervised object detection.

References: [6] Biffi et al., ECCV'20; [7] Bilen et al., CVPR'16; [24] Everingham et al.; [29] Gao et al., ICCV'19; [32] Girshick et al., ICCV'15; [38] Huang et al., NeurIPS'20; [47] Lin et al., ECCV'14; [49] Pan et al., IJCAI'19; [54] Ren et al., NeurIPS'15; [55] Ren et al., CVPR'20; [69] Tang et al., CVPR'17; [80] Zeng et al., ICCV'19.

Page Code

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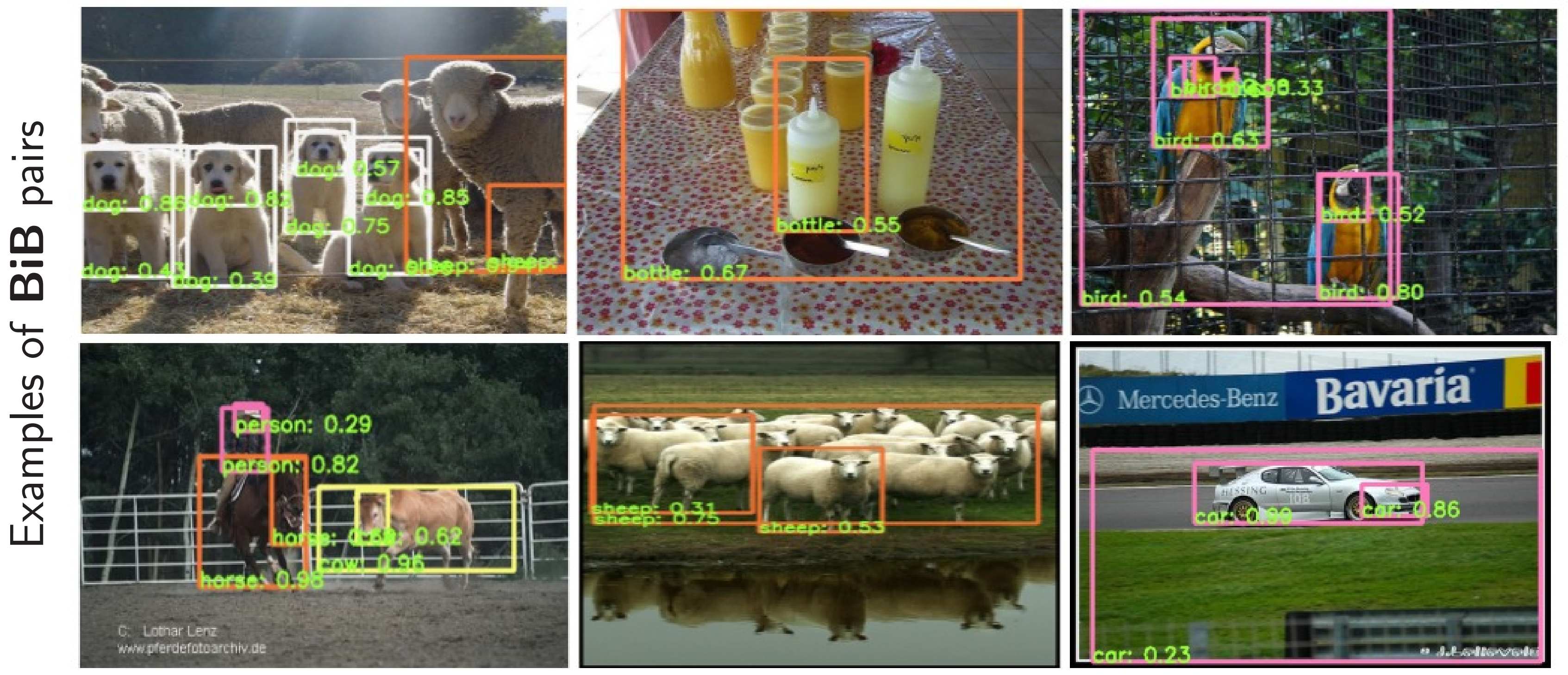
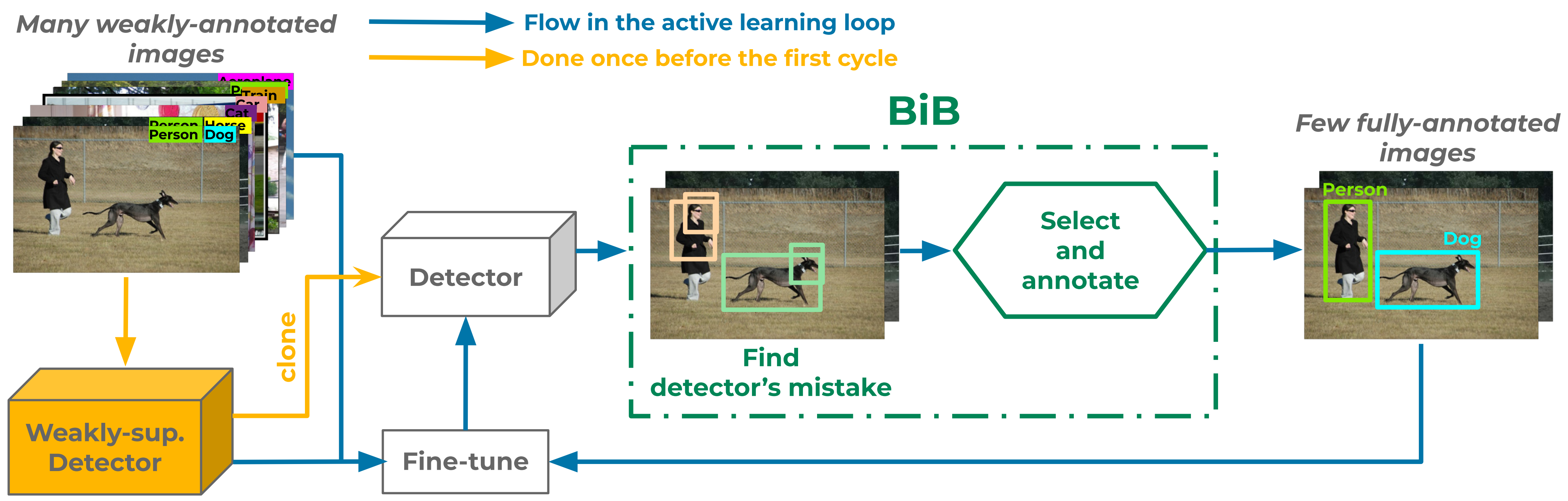
DISCOVER PROBABLE WSODs MISTAKES

Typical confusions of WSODs: predictions focusing only on *discriminative object parts* or *grouping instances* of objects.

Box-in-box (BiB) pairs of regions: pairs of predictions of the *same class* s.t. one is "contained" in the other.



OVERALL APPROACH


Many weakly-annotated images

Flow in the active learning loop

Done once before the first cycle

BiB

Few fully-annotated images

Detector

Find detector's mistake

Select and annotate

clone

Weakly-sup. Detector

Fine-tune

Active learning pipeline:

- Train a weakly-supervised object detector.

// Active learning loop

- Repeat
  - Select images to fully label.
  - Ask human annotators to draw bounding boxes around objects in them.
  - Fine-tune the weakly-supervised object detector with all annotations.

BiB selection:

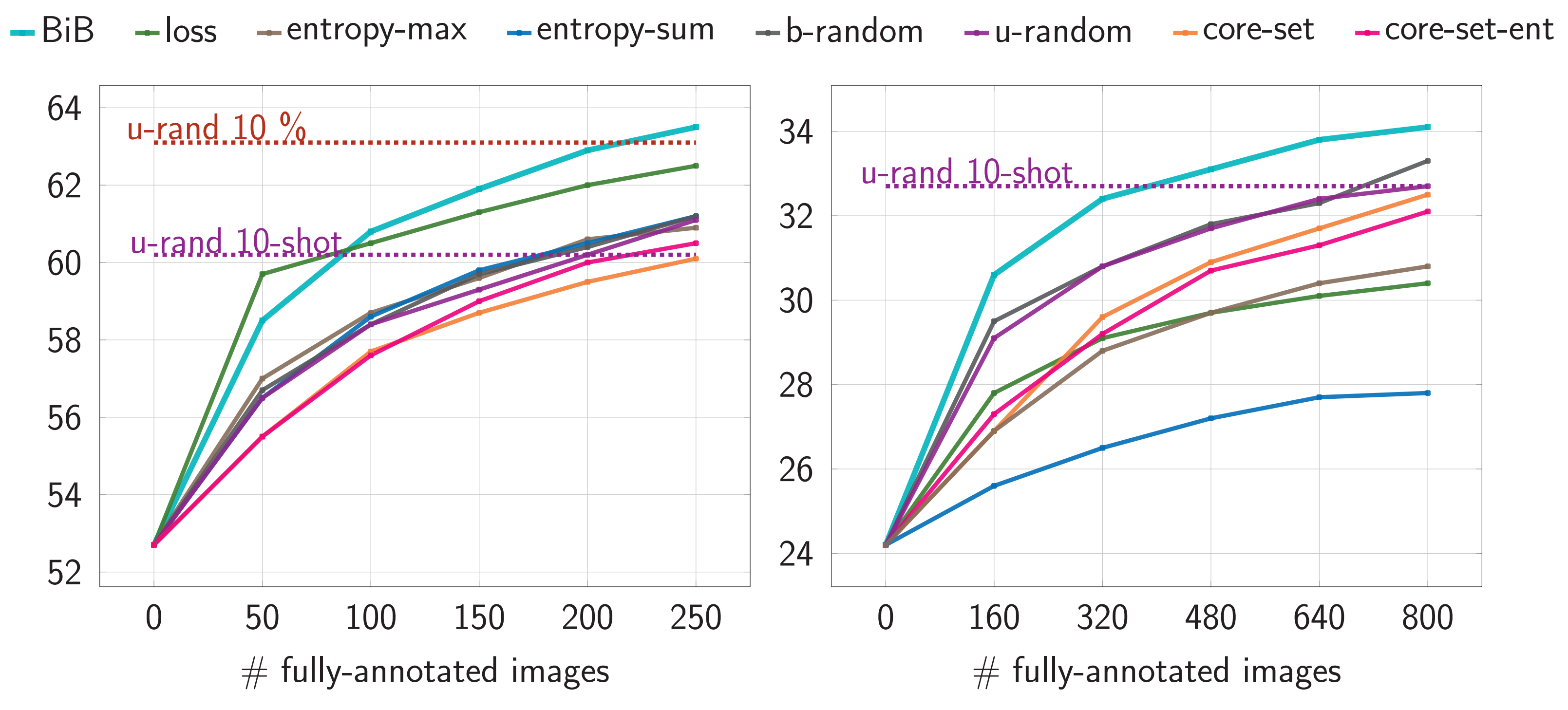
- Find BiB pairs in all images.

// kmeans++ intialization

- Repeat until enough images are selected:
  - Compute the distance between BiB pairs in selected images and those in other images.
  - Pick a BiB pair with probability proportional to its distance to the pairs in selected images.
  - Select the image containing the chosen pair.

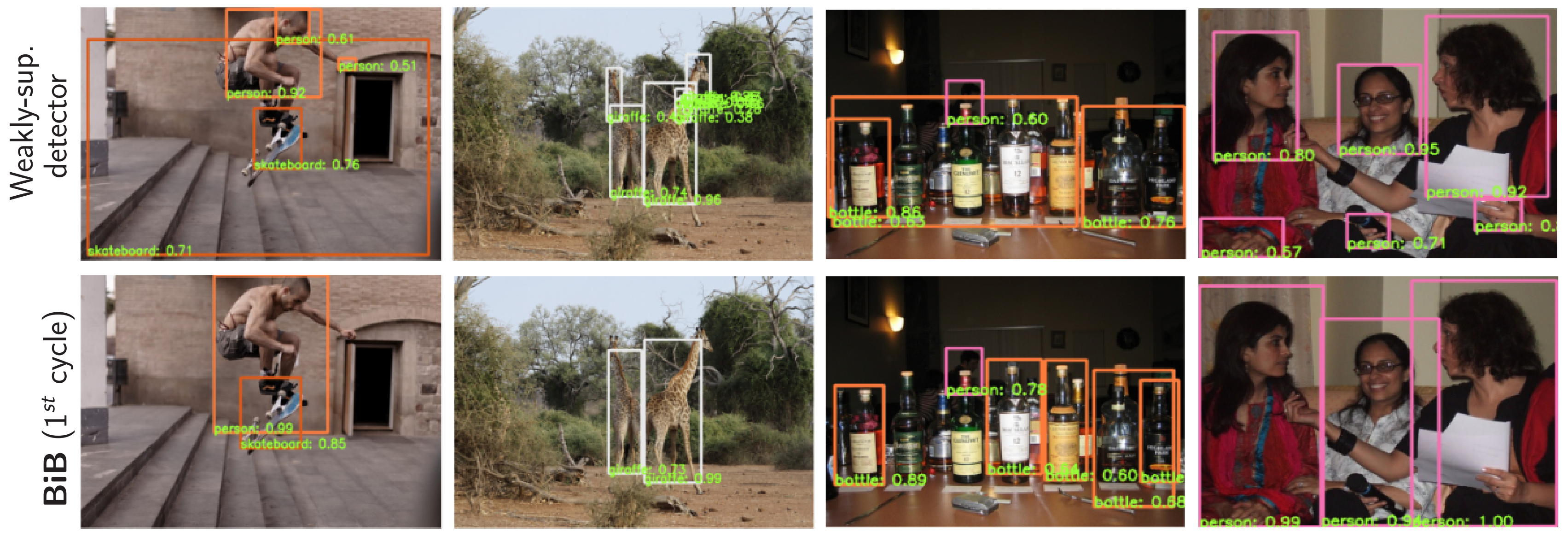
EXPERIMENTAL RESULTS

- **Datasets**: COCO2014 [47], VOC07 [24],
- **Evaluation Metrics**: Average precision (AP50 and AP).
- **Comparison of active learning strategies**



Results (AP50) on VOC07 (left) and COCO (right) dataset

- **Examples of improved detections:**



- **Comparison to the state of the art:**

Setting	Method	VOC07	COCO	
		AP50	AP50	AP
Fully supervised	Fast RCNN [32]	66.9	38.6	18.9
	Faster RCNN [54]	69.9	41.5	21.2
WSOD	WSDDN [7]	34.8	-	-
	OICR [69]	41.2	-	-
	C-MIDN [29]	52.6	21.4	9.6
	WSOD2 [80]	53.6	22.7	10.8
	MIST-CDB [55]	54.9	24.3	11.4
	CASD [38]	56.8	26.4	12.8
Weak & few strong (10-shot)	BCNet [49]	57.1	-	-
	OAM [6]	59.7	31.2	14.9
	Ours (u-rand)	60.2	32.7	16.4
	Ours (BiB)	62.9	34.1	17.2

- **Ablation study on VOC07:**

DifS	K selection			Number of images annotated				
	im.	reg.	BiB	50	100	150	200	250
				56.3 ± 0.4	58.0 ± 0.5	58.9 ± 0.4	60.0 ± 0.3	60.5 ± 0.4
✓				56.5 ± 0.4	58.4 ± 0.4	59.3 ± 0.7	60.2 ± 0.4	61.1 ± 0.5
✓	✓			57.1 ± 0.4	58.3 ± 0.5	59.3 ± 0.6	59.8 ± 0.4	60.3 ± 0.4
✓		✓		**58.4** ± 0.4	60.2 ± 0.4	61.5 ± 0.6	62.6 ± 0.4	**63.4** ± 0.3
			✓	57.9 ± 0.7	60.1 ± 0.4	61.2 ± 0.5	62.1 ± 0.5	62.6 ± 0.4
✓			✓	**58.5** ± 0.8	**60.8** ± 0.5	**61.9** ± 0.4	**62.9** ± 0.5	**63.5** ± 0.4