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Portable Active Learning for Object Detection

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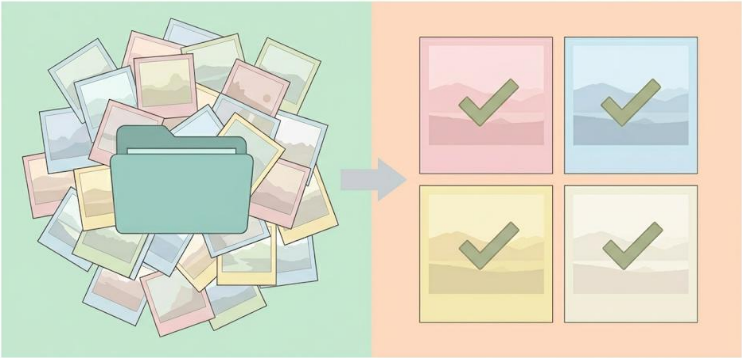
Work done while an intern in PRDCSG

Bottleneck in Object Detection

Manual Annotation is Expensive

Using annotators to draw precise bounding boxes across millions of frames is financially and temporally unscalable.



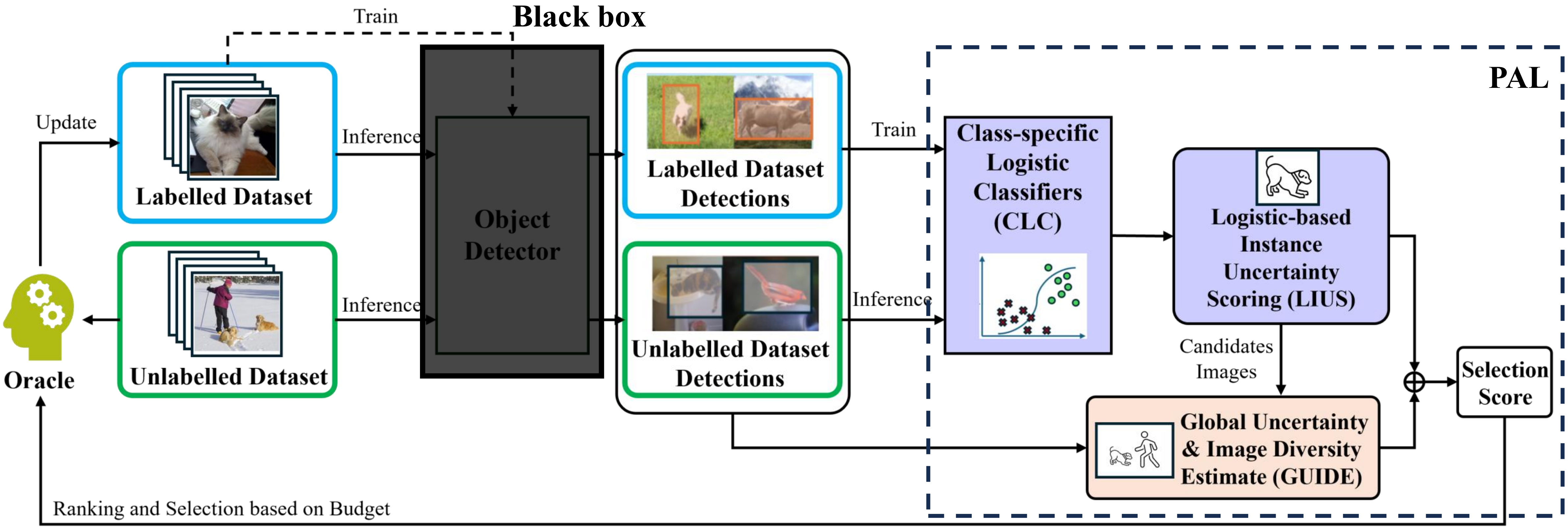
Active learning (AL)

selecting the most informative images to label, minimizing annotation costs while maximizing model performance.

Limits of Current Active Learning for Object Detection

- Require intrusive modifications to detector architecture or training pipelines.
- Dependent on internal model features.
- Require rewrites to deploy across models.

PAL: Portable Active Learning Framework



Step 1: LIUS

Logistic-Based Instance Uncertainty Scoring

Finding the Decision Boundary

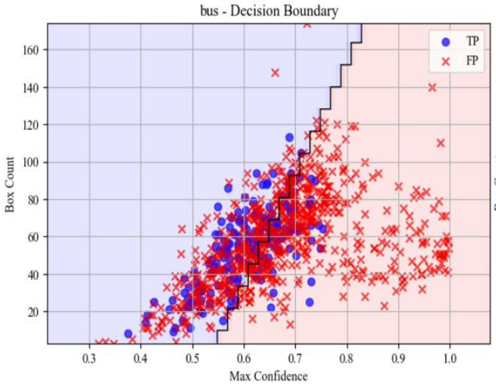
For every object category, PAL trains a lightweight logistic classifier using the labelled data detections. It uses two simple inputs to learn the mathematical boundary between **True Positives** and **False Positives**.

Pre-NMS Bounding Box Density

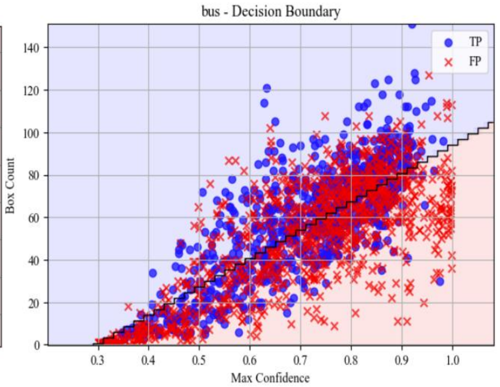
Detection Confidence

LIUS = Shannon Entropy(P(TP | conf, density))

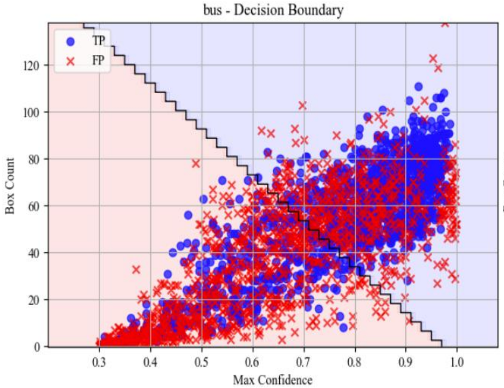
PAL selects unlabelled images sitting directly on this boundary (High Entropy)



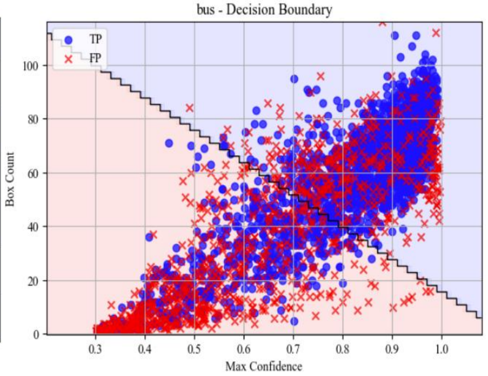
AL Iteration 1



AL Iteration 2



AL Iteration 3



AL Iteration 4

STEP 2: GUIDE

Global Uncertainty & Image Diversity Estimate

LIUS provides candidate images while GUIDE helps with refining image selection using **image-level cues** to improve **image diversity** and **class balance**.

CWIE

Class-Weighted Image Entropy

Measures overall image entropy while penalizing the selection of over-represented classes.

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RCDI

Rare-Class driven Diversity Index

Prioritizes images containing rare or underrepresented categories to balance the dataset.

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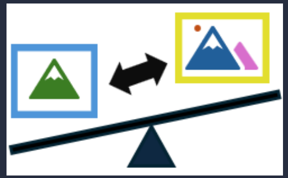
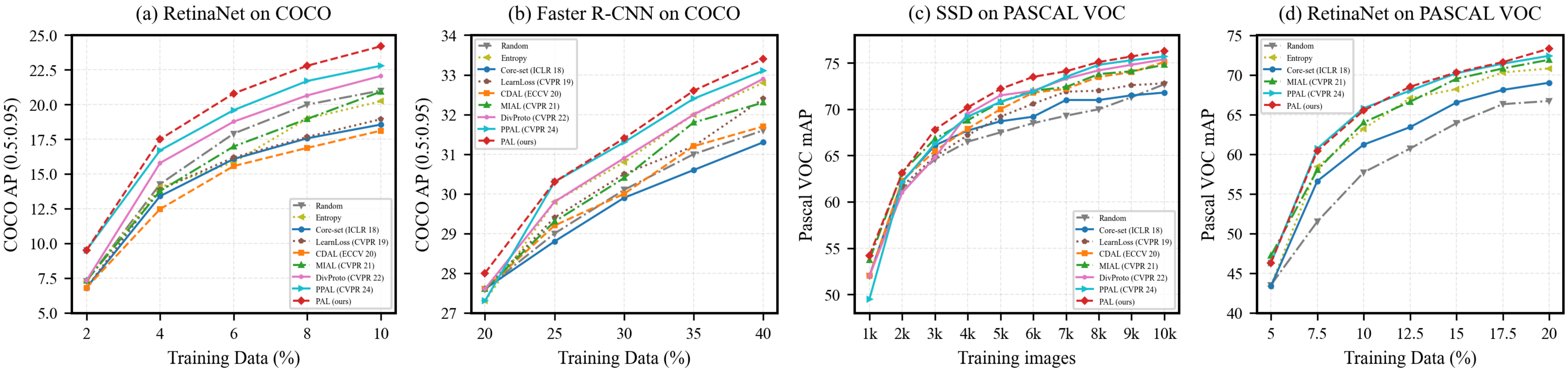


RCSP

Rank-Conditioned Similarity Penalty

Prevents redundant frame selection. Reject images visually identical to high-ranked candidates.

Results



Red represents PAL

Model	Method	Round 1	Round 2	Round 3	Round 4	Round 5
RetinaNet	Random	26.8 ± 0.8	34.7 ± 1	37.8 ± 0.6	40.2 ± 0.1	42.2 ± 0.2
	Entropy	26.8 ± 0.8	36.3 ± 1.2	41.5 ± 0.4	43.5 ± 0.4	44.8 ± 0.1
	PPAL	26.8 ± 0.8	38.9 ± 0.4	42.5 ± 0.3	44.4 ± 0.1	45.5 ± 0.3
	Ours	26.8 ± 0.8	$\mathbf{40.1 \pm 0.5}$	$\mathbf{43.7 \pm 0.2}$	$\mathbf{45.7 \pm 0.2}$	$\mathbf{46.7 \pm 0.2}$
YOLOX-Tiny	Random	9.9 ± 0.3	10.6 ± 0.1	11 ± 0.3	11.3 ± 0.1	11.5 ± 0.2
	Entropy	9.9 ± 0.3	11.4 ± 0.3	11.6 ± 0	11.8 ± 0.3	12.2 ± 0.1
	Ours	9.9 ± 0.3	$\mathbf{12 \pm 0}$	$\mathbf{12.6 \pm 0.2}$	$\mathbf{13.1 \pm 0.1}$	$\mathbf{13.3 \pm 0.2}$

BDD100k Results across Detectors

Dataset	% More Annotation (PPAL)
COCO	18.6%
PASCAL VOC	22.8%

PAL showed reduced annotation needs compared to prior state-of-the-art.

Conclusion & Takeaways

Effective & Detector Agnostic

Works securely with any detection architecture purely via standard outputs.

Class-Balanced Formulation

Actively counters dataset class-imbalance.

Ease in Real-World Deployment

Zero internal modifications allowing seamless plug and play in industrial pipelines.

arXiv

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