Transferring Labels to Solve Annotation Mismatches Across Object Detection Datasets

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Key contributions:

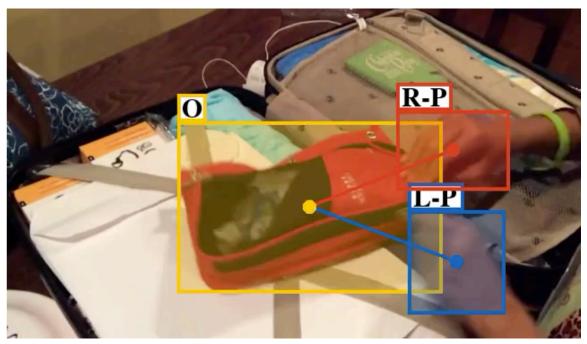
- 1. This paper characterizes a *prevalent but under-explored* label issue: **Annotation mismatch.**
- 2. To mitigate annotation mismatches, we propose a *data-centric* approach that **transfers the labels** in the datasets "before training any detector".
- 3. The proposed approach is **agnostic** to detector learning algorithms & detector architectures.

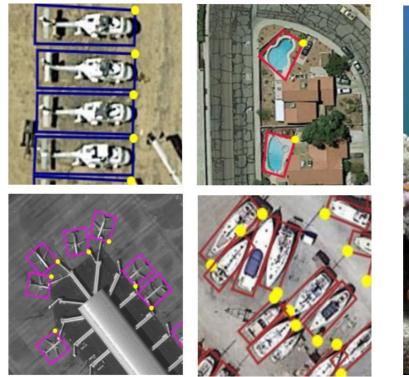
Object detection datasets are everywhere

Autonomous Driving [1]

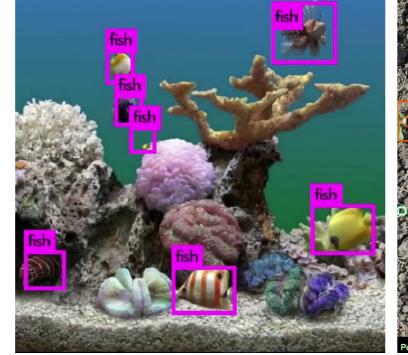


Ego Camera — Hand detection [2]





Aerial Images [3]



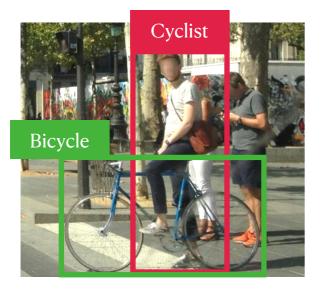


Underwater [4]

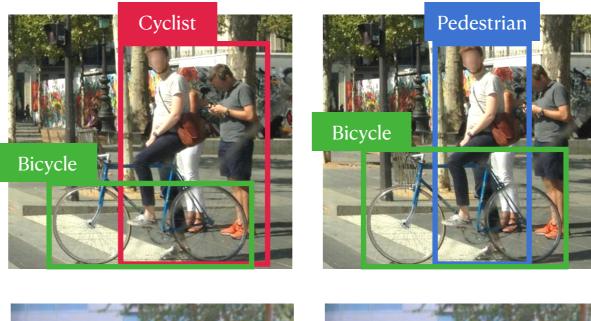
Agriculture [5]

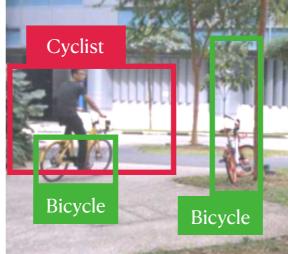
Label quality matters

Lower label quality leads to worse detector performances [6,7]







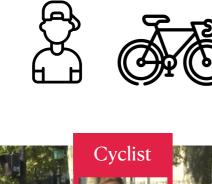




Incorrect Bounding Boxes

Incorrect Class Labels

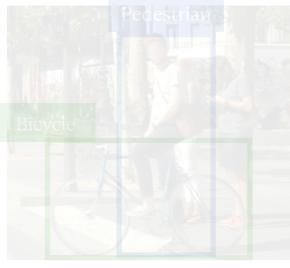
Are they truly "correct" correct?













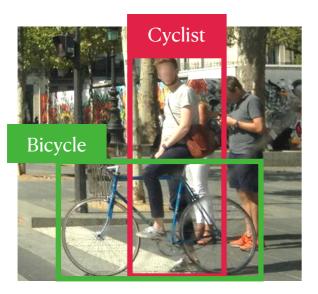


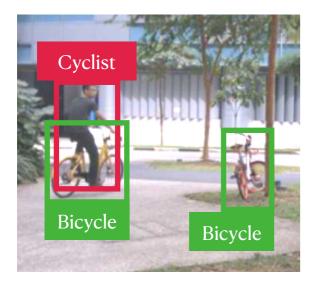
Incorrect Bounding Boxes

Incorrect Class Labels

Which labels are more correct?

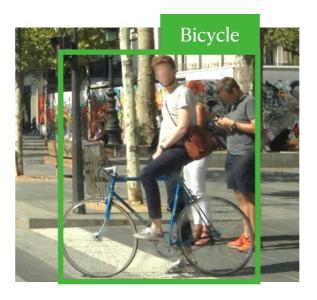












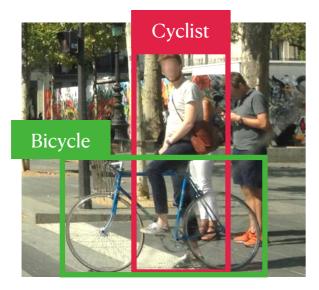






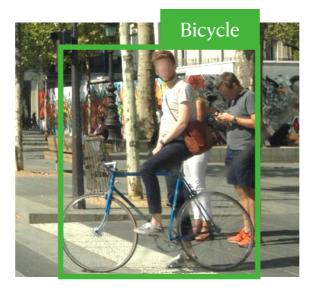
They are all "correct"

but with annotation mismatches





Cityscapes Labels







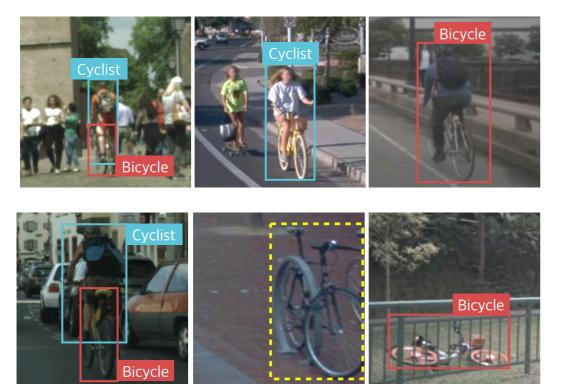


nulmages Labels

Waymo Labels

Prevalent annotation mismatches

Class semantics



Cityscapes

Waymo

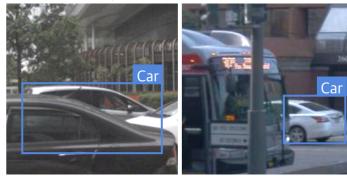
nulmages

Annotation instructions



nulmages

Waymo



nulmages (amodal)

Waymo (pixel-based)

Human-machine misalignment



Synscapes

Cross-modality labels



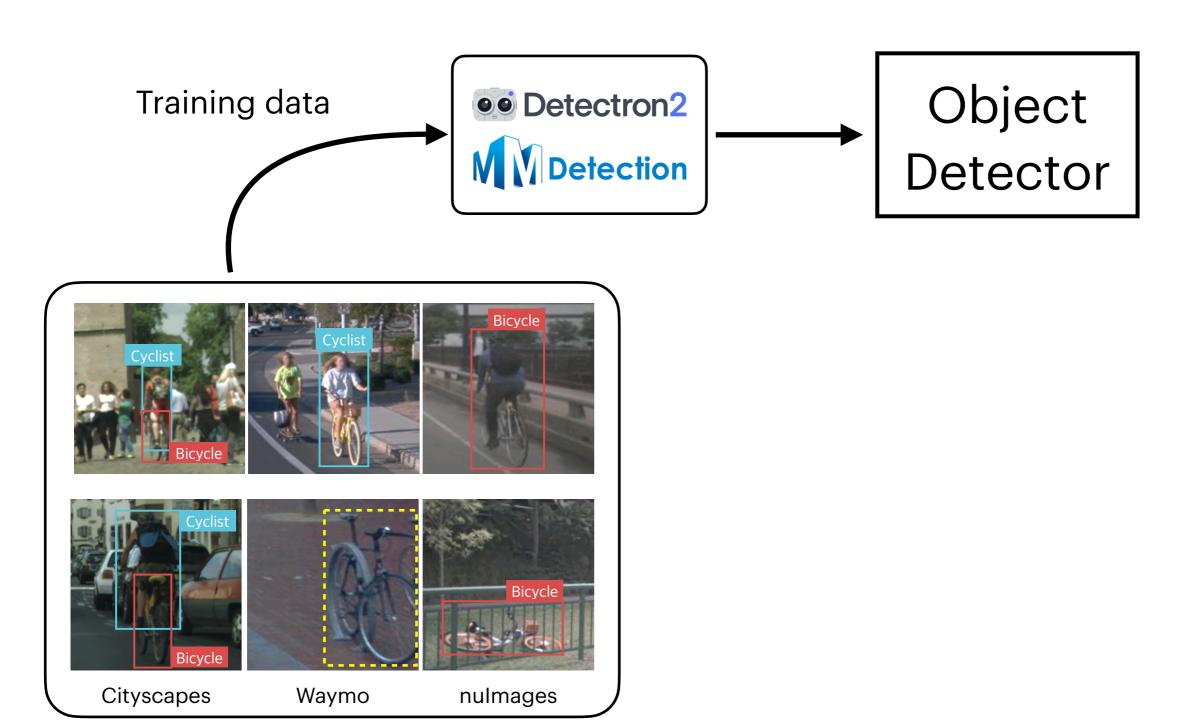




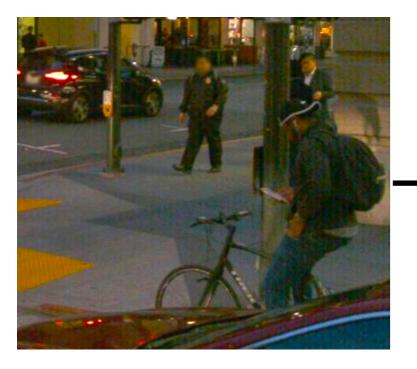
nuScenes (from 3-D bounding boxes)

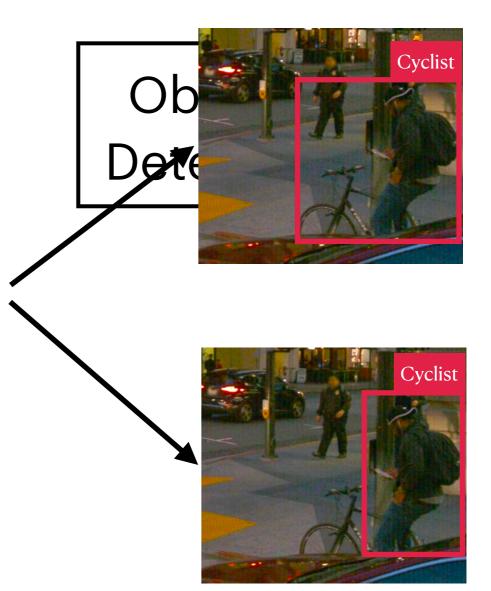
MVD (from segmentation maps)

If Annotation Mismatches are the Answers, Then What is the Question?



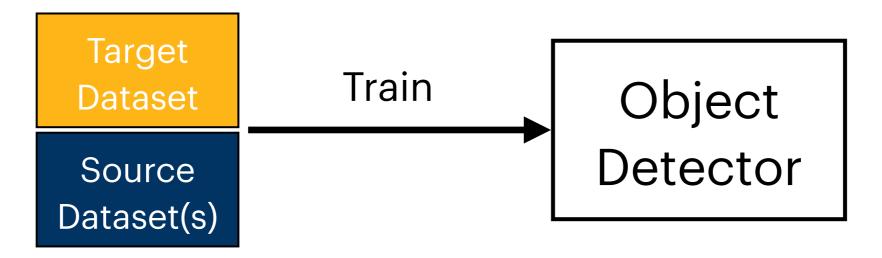
If Annotation Mismatches are the Answers, Then What is the Question?

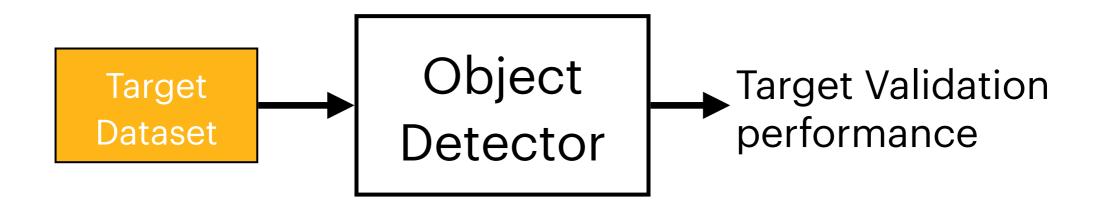




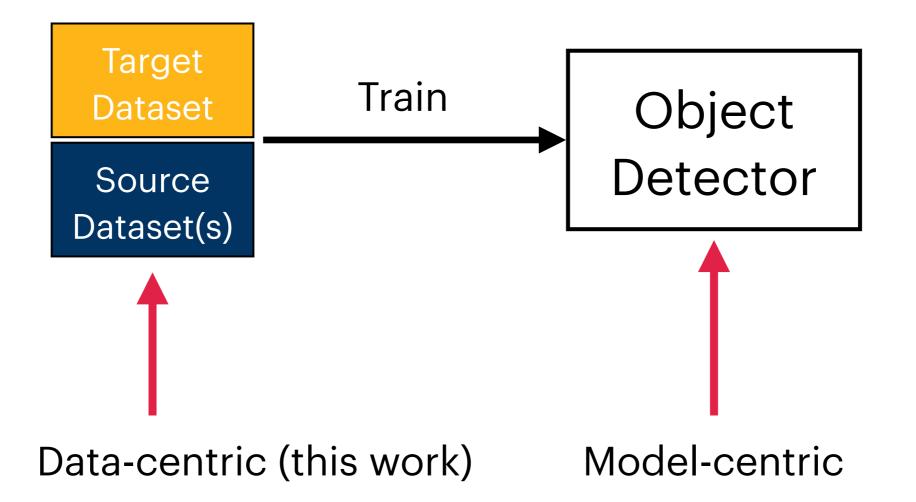
Application: Supervised Domain Adaptation

Fully labeled, Annotation mismatches

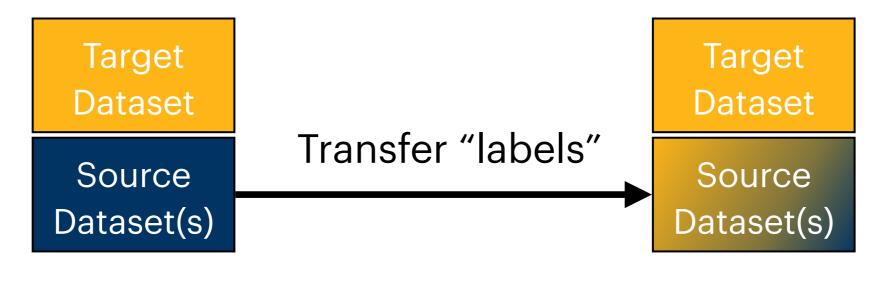




Application: Supervised Domain Adaptation



Problem Formulation – Label Transfer



Original training data

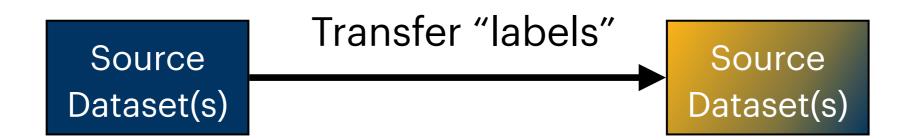
New training data

Data-centric key benefits: Agnostic to downstream detectors

*Please refer to our paper for a more formal problem formulation in our paper.

Challenges

1. No paired labels

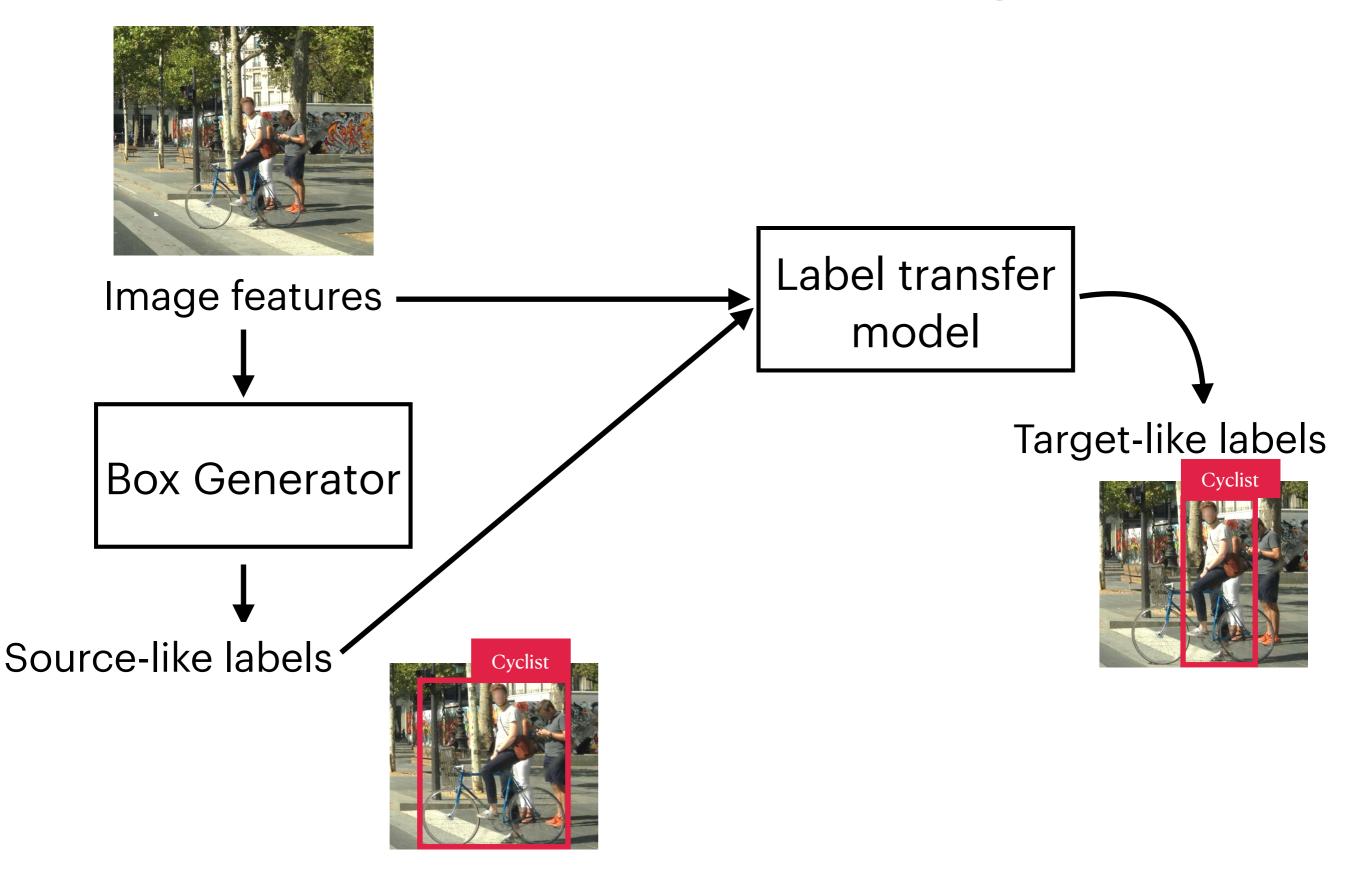


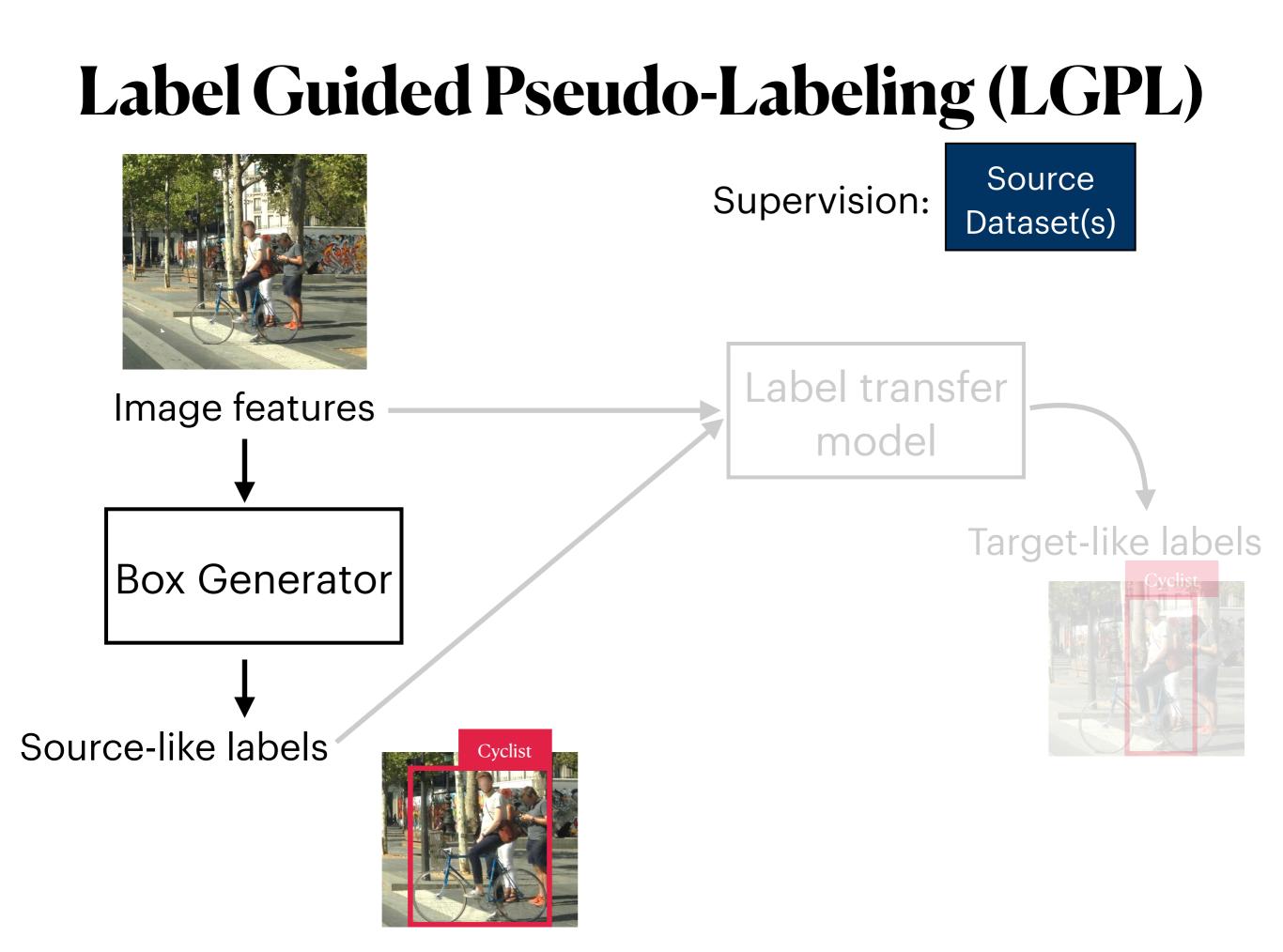
2. Complex task

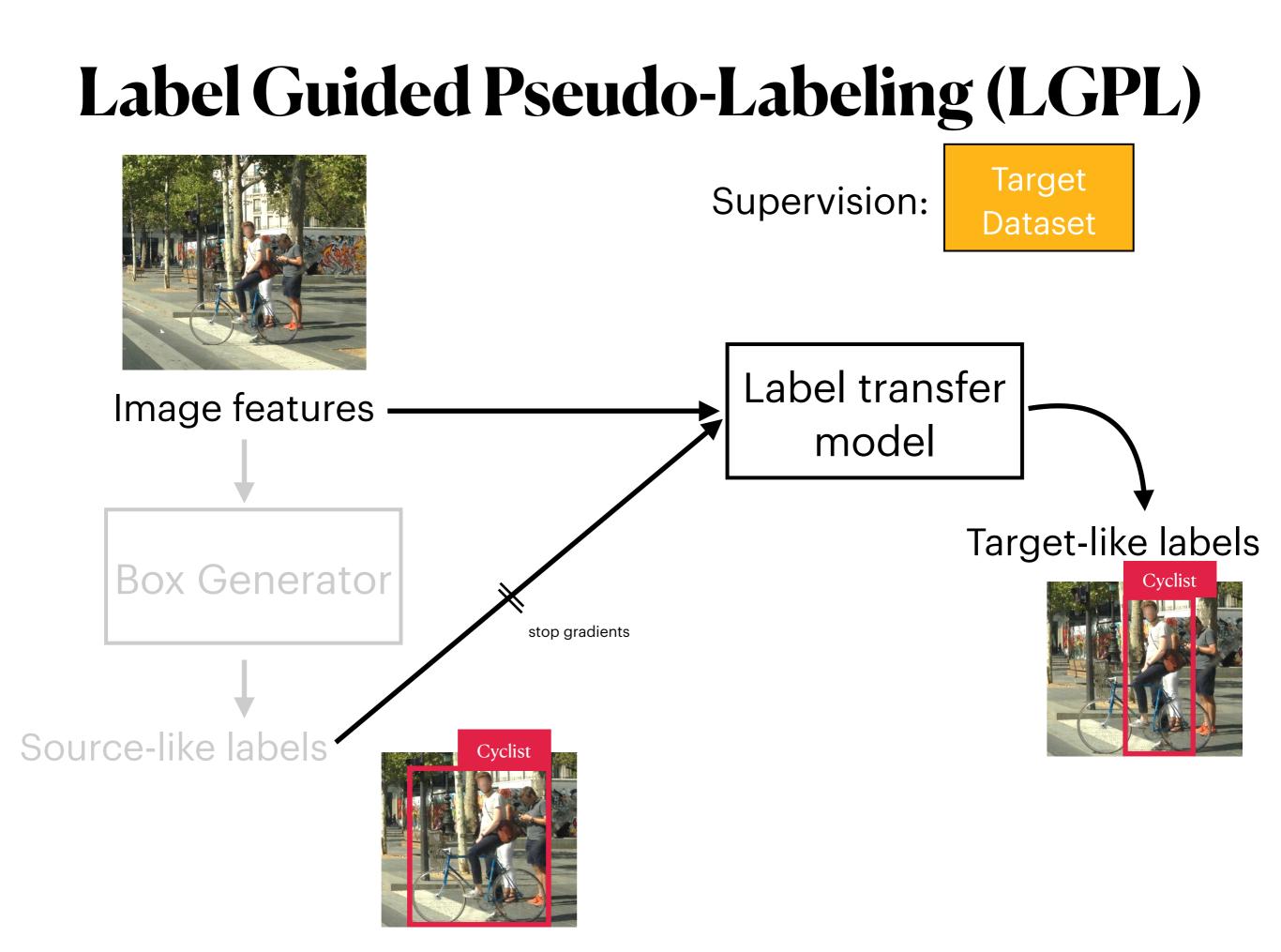
Task requirements

- 1. Translate bounding boxes
- 2. Adjust class labels
- 3. Remove detection labels
- 4. Add detection labels

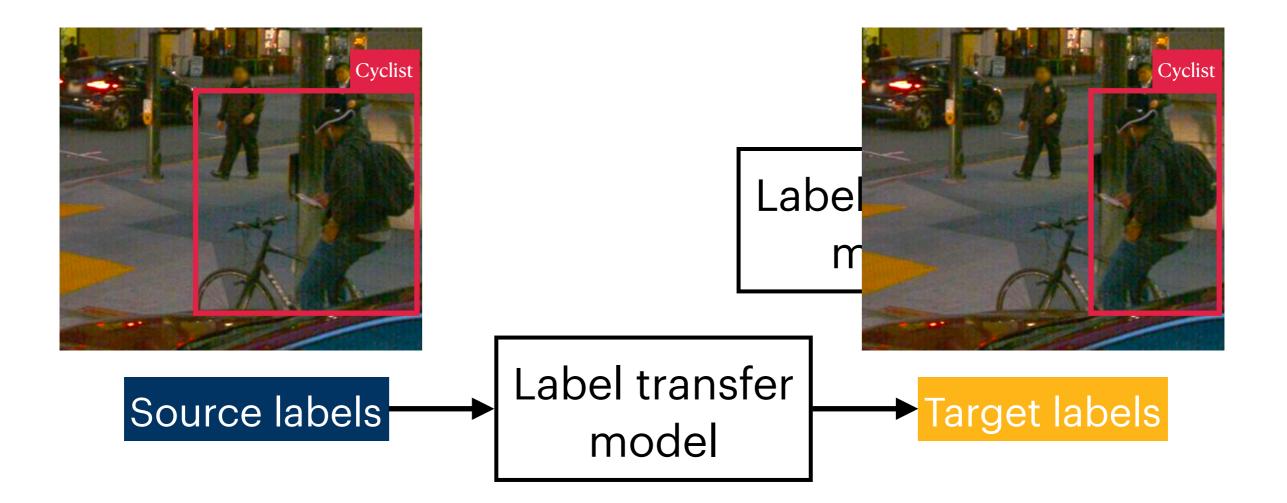
Label Guided Pseudo-Labeling (LGPL)







Label Guided Pseudo-Labeling (LGPL)



Experimental Results

Evaluation:

- Evaluate on 4 transferring scenarios involving 5 real-world and 2 synthetic datasets
- Evaluate 3 downstream detectors

Results:

By pre-processing the source labels with LGPL, detectors **always** improve, increasing 2.7, 1.68, 1.2 mAP in YOLOv3, Deformable DETR and Faster-RCNN, respectively

References

[1] nuScenes: A multimodal dataset for autonomous driving

- [2] Understanding Human Hands in Contact at Internet Scale
- [3] Object Detection in Aerial Images: A Large-Scale Benchmark and Challenges
- [4] https://www.kaggle.com/datasets/slavkoprytula/aquarium-data-cots
- [5] The CropAndWeed Dataset: a Multi-Modal Learning Approach for Efficient Crop and Weed Manipulation
- [6] Evaluating the Effect of Common Annotation Faults on Object Detection Techniques
- [7] Quantifying the Effects of Ground Truth Annotation Quality on Object Detection and Instance Segmentation Performance
- [8] Lessons Learned From Cloudsen12 Dataset: Identifying Incorrect Annotations in Cloud Semantic Segmentation Datasets