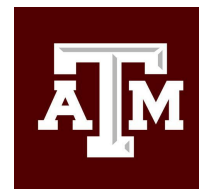
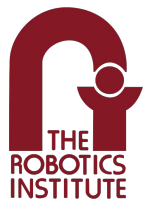
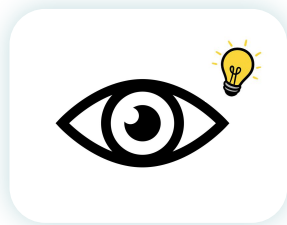


Learning with an Evolving Class Ontology

Zhiqiu Lin, Deepak Pathak, Yu-Xiong Wang, Deva Ramanan*, Shu Kong*



Visual perception systems need to cope with **evolving class ontology**..



Lifelong learning
perception system



Recognize as: Bus?

Types of bus?



Articulated?



School Bus?



Recognize as: Pedestrian?

Types of pedestrian?

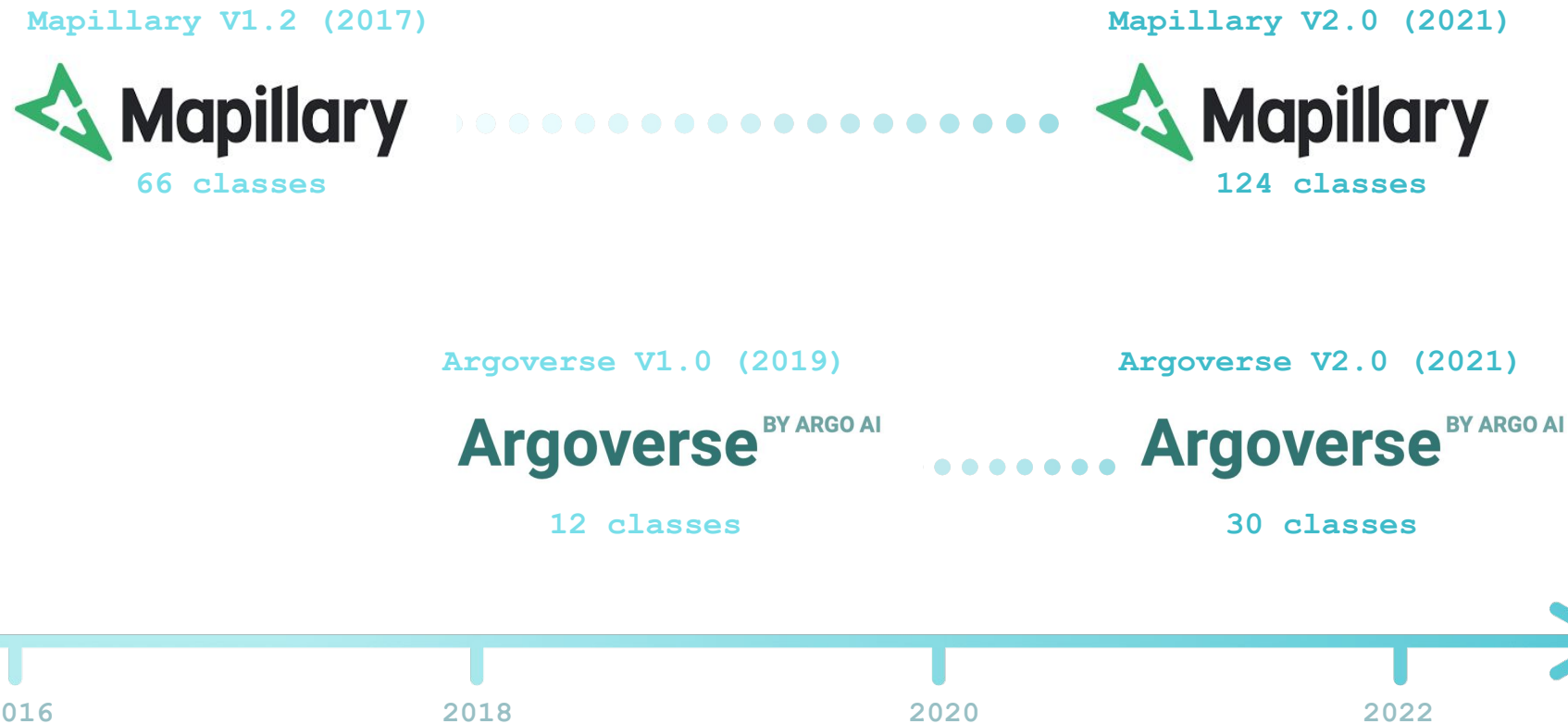


A child?

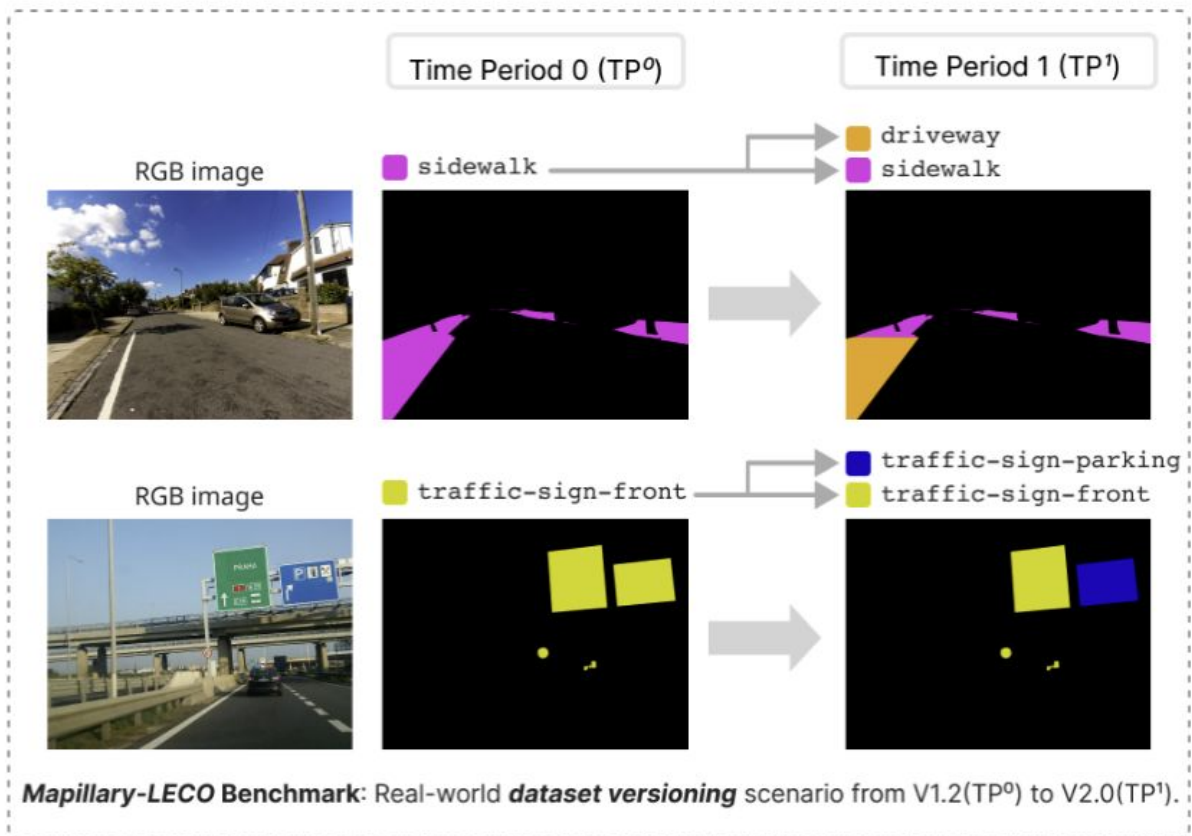


A police officer?

Contemporary industry-made datasets, such as Mapillary[1] and Argoverse[2], continually refined the ontology from version 1.0 to 2.0.



We study the problem of **LECO: Learning with an Evolving Class Ontology**.
Each time period (TP) of a LECO problem refines the class ontology:



Humans, as **lifelong learners**, are also good at solving LECO problems.



Dog

Types of dog?



Husky



Corgi



Polar bear



Brown bear

Types of bear?

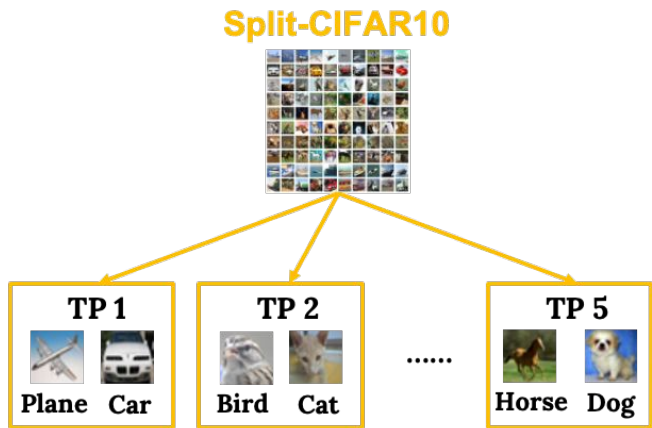


Lifelong Learner

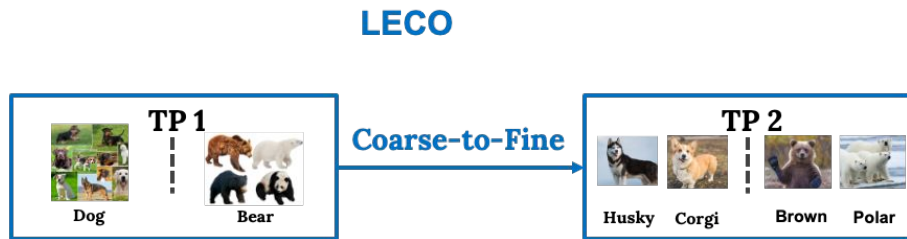


Bear

Class-Incremental Learning (CIL) v.s. LECO

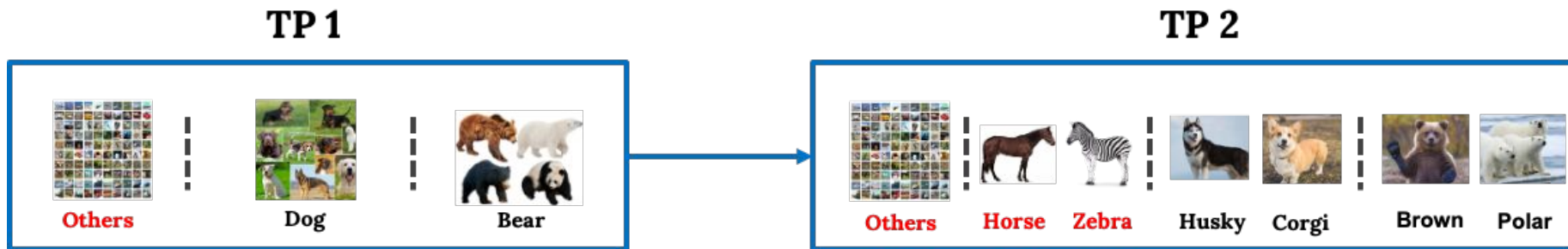


In CIL, classes are disjoint across TPs, i.e., having no relationship with each other.




In LECO, the newly added classes are always refined ones from last TP.

Class-Incremental Learning (CIL) v.s. LECO



Note: This **Others** class is sometimes called “**Unlabeled**” or “**Void**” in many datasets [1, 2].

 LECO is a more general form of CIL (class-incremental learning) problem by assuming a catch-all **Others** class.

[1] The Mapillary Vistas Dataset for Semantic Understanding of Street Scenes. In ICCV 2017.
[2] The Cityscapes Dataset for Semantic Urban Scene Understanding. In CVPR 2016.

Class-Incremental Learning (CIL) v.s. LECO

In **CIL**:

- Training data from previous TPs will be **discarded**.
- Overall performance measured by **testsets of previous + current TPs**.

In **LECO**:

- **Keeping all history data** because storage is cheaper than annotation.
- Overall performance measured by the **testset of current TP only**.



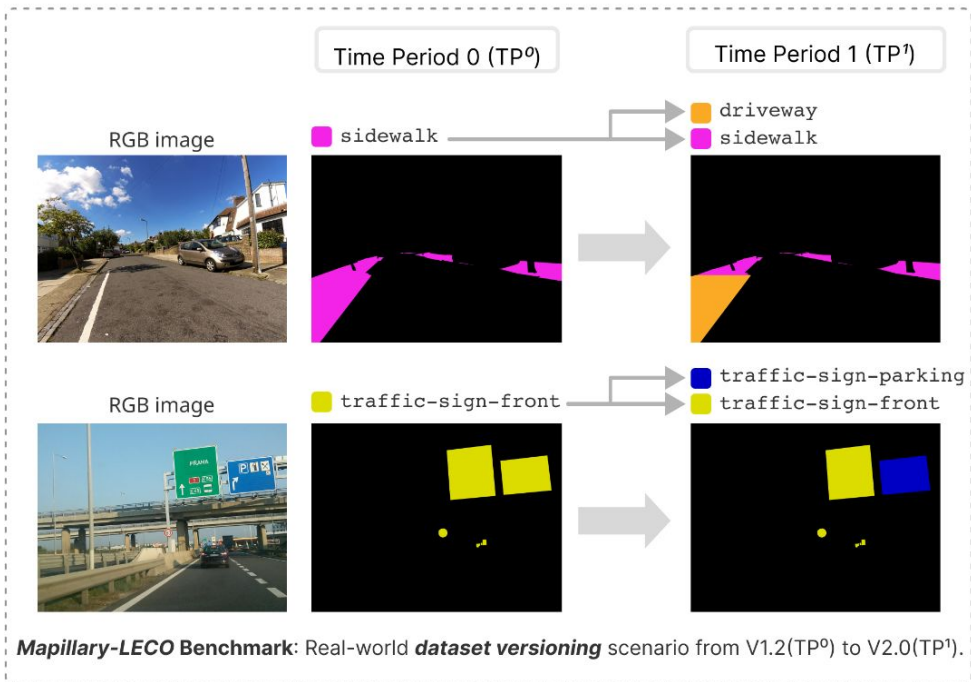
LECO targets at practical applications by preserving all data (without setting an artificial small replay buffer).

Learning with an **E**volving **C**lass **O**ntology

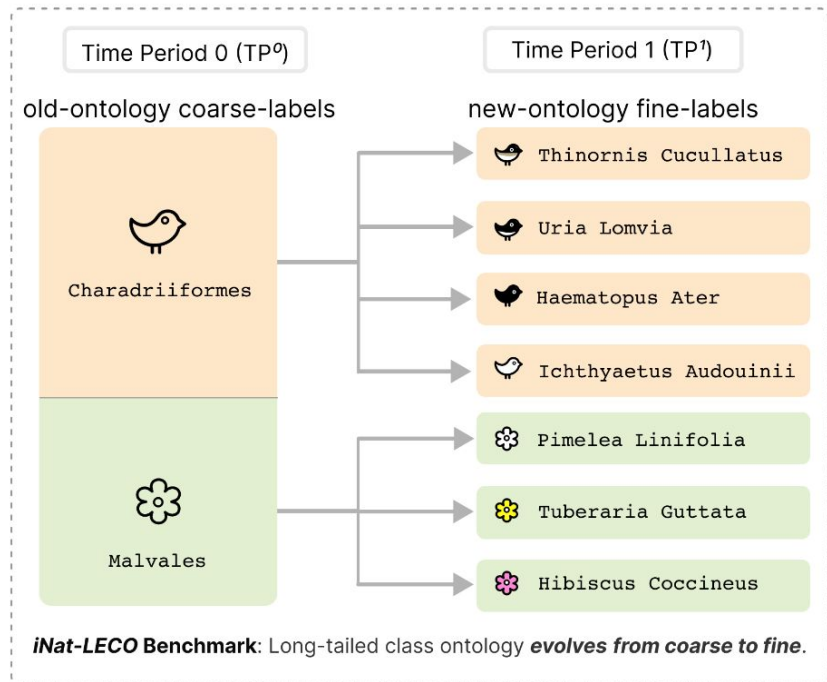
→ “LECO” benchmark for lifelong vision

Benchmark Construction

LECO-segmentation (Mapillary V1.2 -> V2.0)



LECO-classification (iNaturalist/CIFAR)



Question 1: Should one label new data, or relabel old data?

Mapillary V1.2 (2017)



Mapillary V2.0 (2021)



Same images, but relabeled!
(RelabelOld)

Argoverse V1.0 (2019)



Argoverse V2.0 (2021)



Collect new data to label!
(LabelNew)

2016

2018

2020

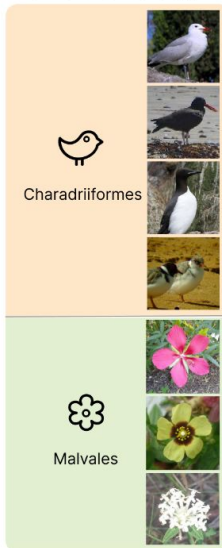
2022



Question 1: Should one label new data, or relabel old data?

Time Period 0 (TP⁰)

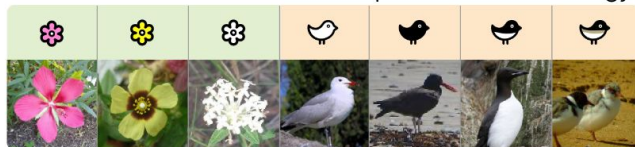
TP⁰ data
with old ontology



Time Period 1 (TP¹)

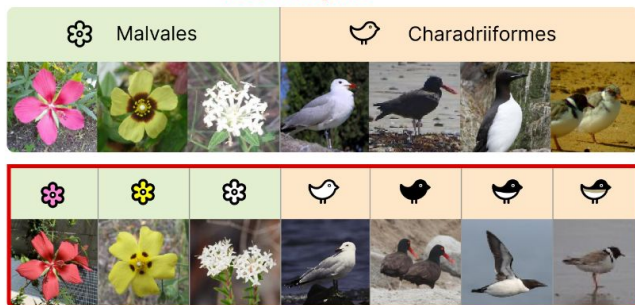
What samples do we annotate with new ontology?
Relabel the old, or label the new?

RelabelOld: Reannotate TP⁰ samples with new ontology.



VS.

LabelNew: Collect **new samples** to annotate.



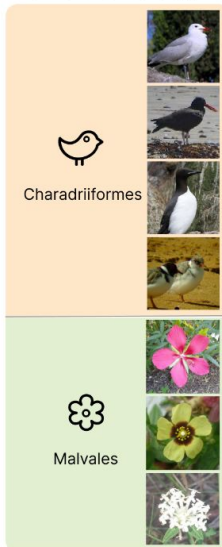
Key insight:

LabelNew will produce more
data for training (though with
inconsistent labels)

Question 1: Should one label new data, or relabel old data?

Time Period 0 (TP⁰)

TP⁰ data
with old ontology



Time Period 1 (TP¹)

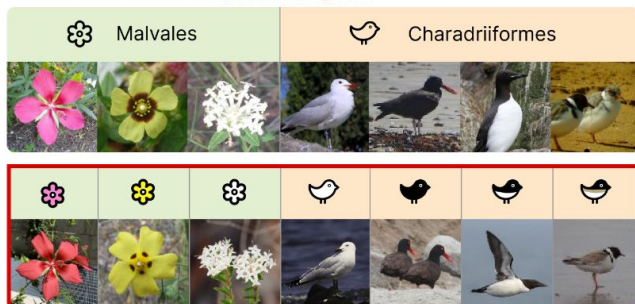
What samples do we annotate with new ontology?
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VS.

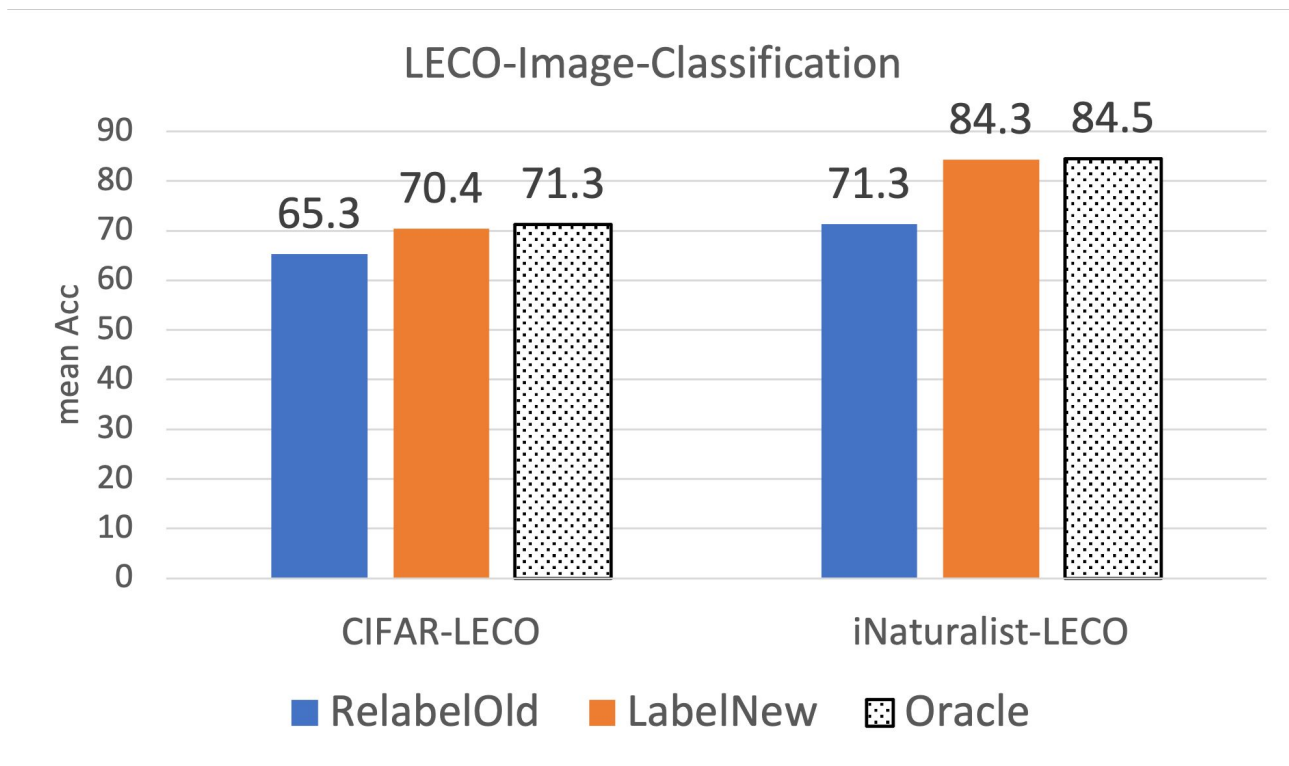
LabelNew: Collect **new samples** to annotate.



Key insight:

**LabelNew produces more data
for training!**

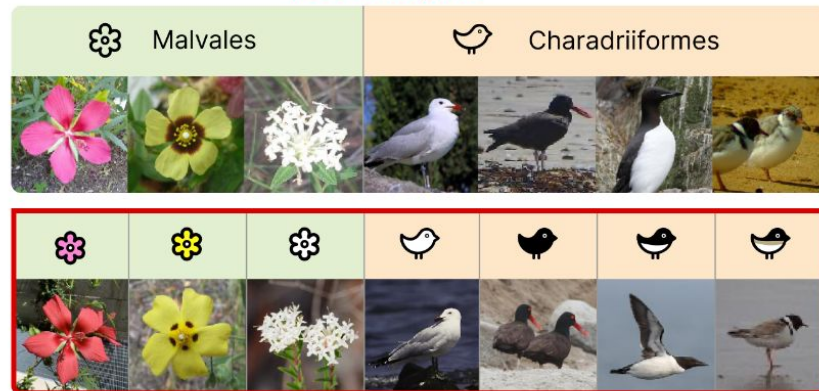
Question 1: Should one label new data, or relabel old data?



Takeaway: LabelNew produces a better classifier for training on more overall data.

Question 2: How to train on data with both coarse- and fine-grained labels?

LabelNew: Collect **new samples** to annotate.



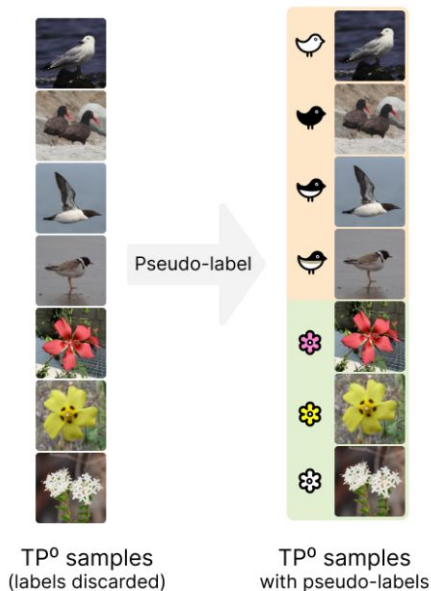
Our proposals:

1. Discard old-ontology labels and only use data.
2. Train on both coarse- and fine-grained labeled data.
3. Exploit the coarse-to-fine label hierarchy.

Question 2: How to train on data with both coarse- and fine-grained labels?

Proposal 1: Discard old-ontology labels and only use data.
⇒ Semi-supervised learning (SSL)

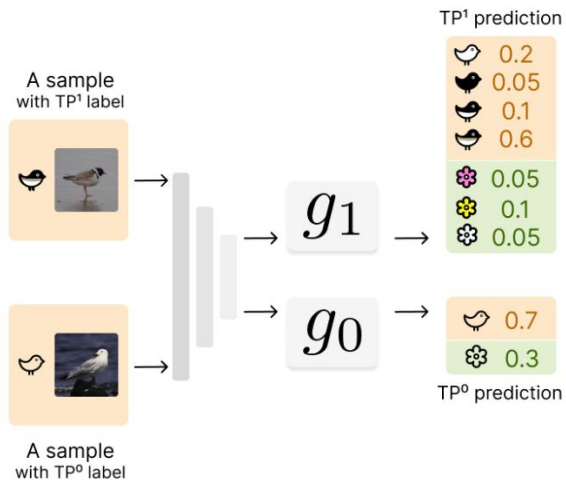
\mathcal{L}_{SSL} : Utilize TP⁰ samples



Question 2: How to train on data with both coarse- and fine-grained labels?

**Proposal 2: Train on both coarse- and fine-grained labeled data.
⇒ Joint Training**

\mathcal{L}_{Joint} : Utilize both TP⁰ **samples and labels**

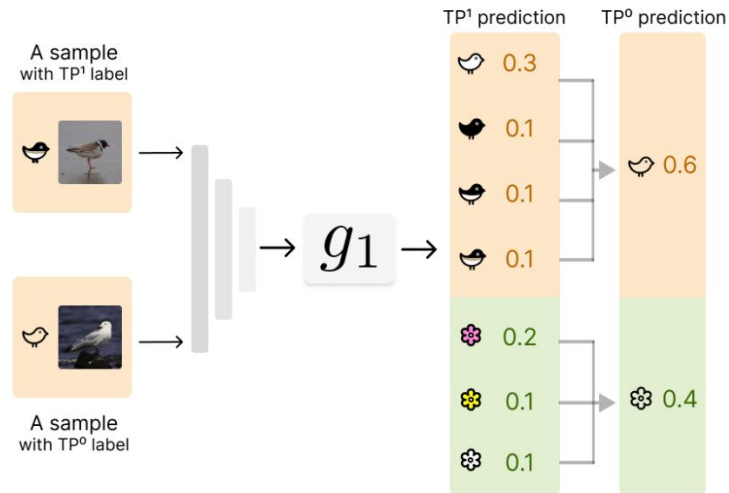


JointTraining with a two headed model

Question 2: How to train on data with both coarse- and fine-grained labels?

Proposal 3: Exploiting coarse-to-fine label hierarchy.
⇒ **Learning-with-Partial-Labels (LPL)**

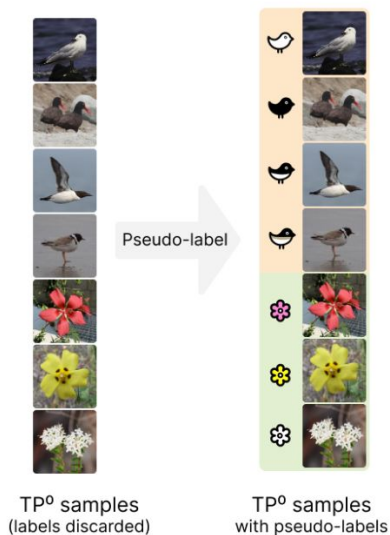
\mathcal{L}_{LPL} : Utilize TP⁰ samples, labels, and taxonomic hierarchy



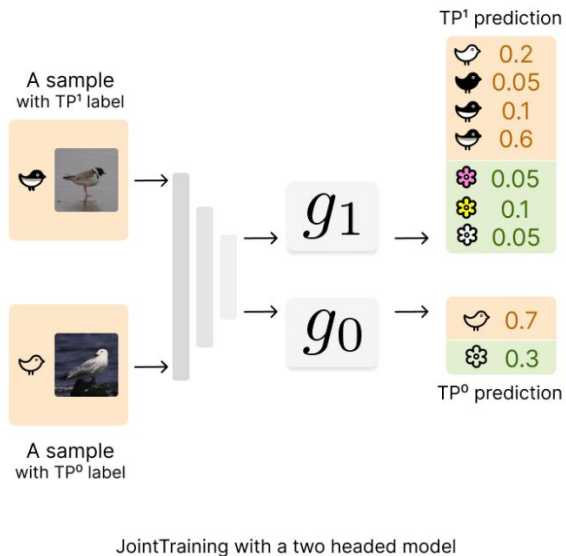
Learning-with-Partial-Labels (LPL) marginalizes leaf node's probabilities for parent classes, then performs training with old-ontology labels

Question 2: How to train on data with both coarse- and fine-grained labels?

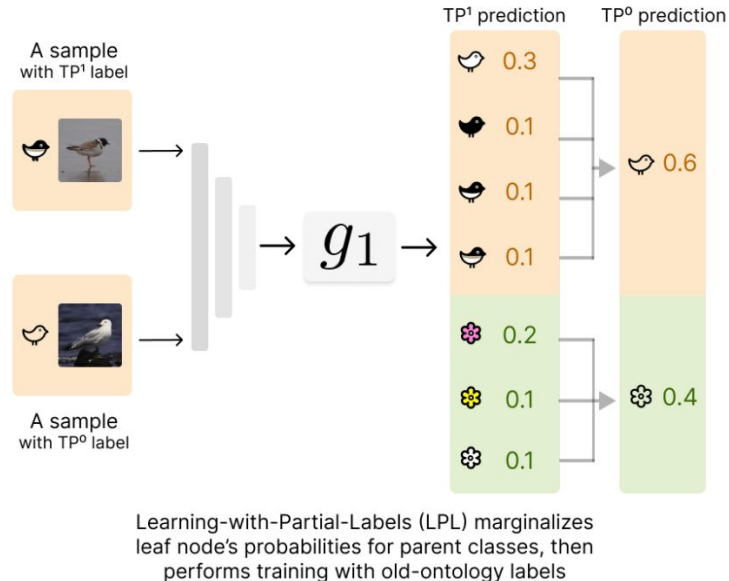
\mathcal{L}_{SSL} : Utilize TP⁰ samples



\mathcal{L}_{Joint} : Utilize both TP⁰ samples and labels

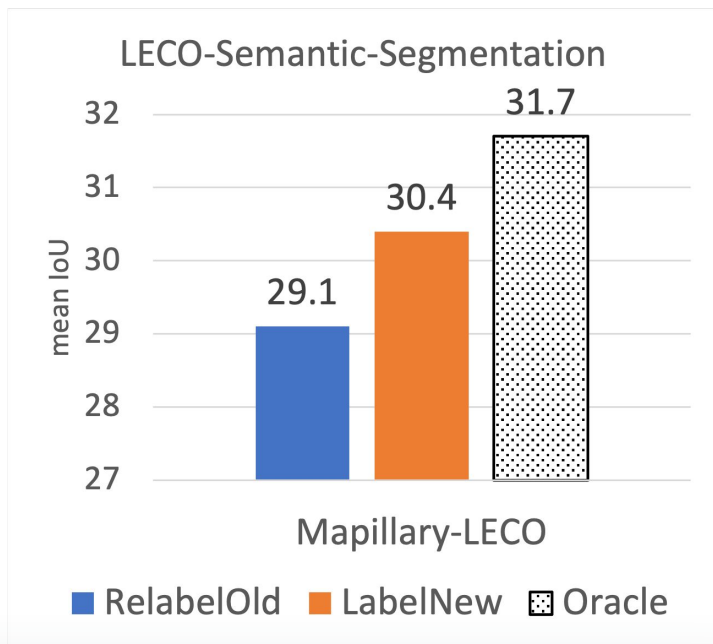


\mathcal{L}_{LPL} : Utilize TP⁰ samples, labels, and taxonomic hierarchy

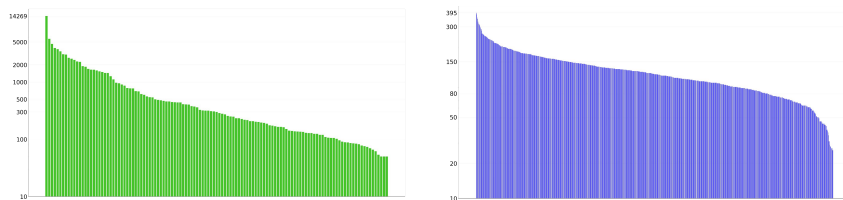


Check out the paper for comprehensive ablation results!

Question 3: Do our proposals generalize to real-world scenarios?



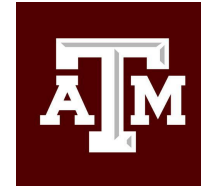
Our solutions generalize to real-world LECO scenario (Mapillary) without given the label hierarchy.



We show consistent improvements under:

- **Long-tailed distribution (Mapillary/iNaturalist)**
- **More than 2 TPs (iNaturalist)**

Thank You!



Scan for our site!