Recognizing New Visual Categories in Real Open World Environments

Doctoral Examination Committee:

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Prof. Ciliberto Carlo
Prof. Iocchi Luca
Prof. Montrucchio Bartolomeo
Prof. Zanuttigh Pietro

Supervisor:

Prof. Caputo Barbara

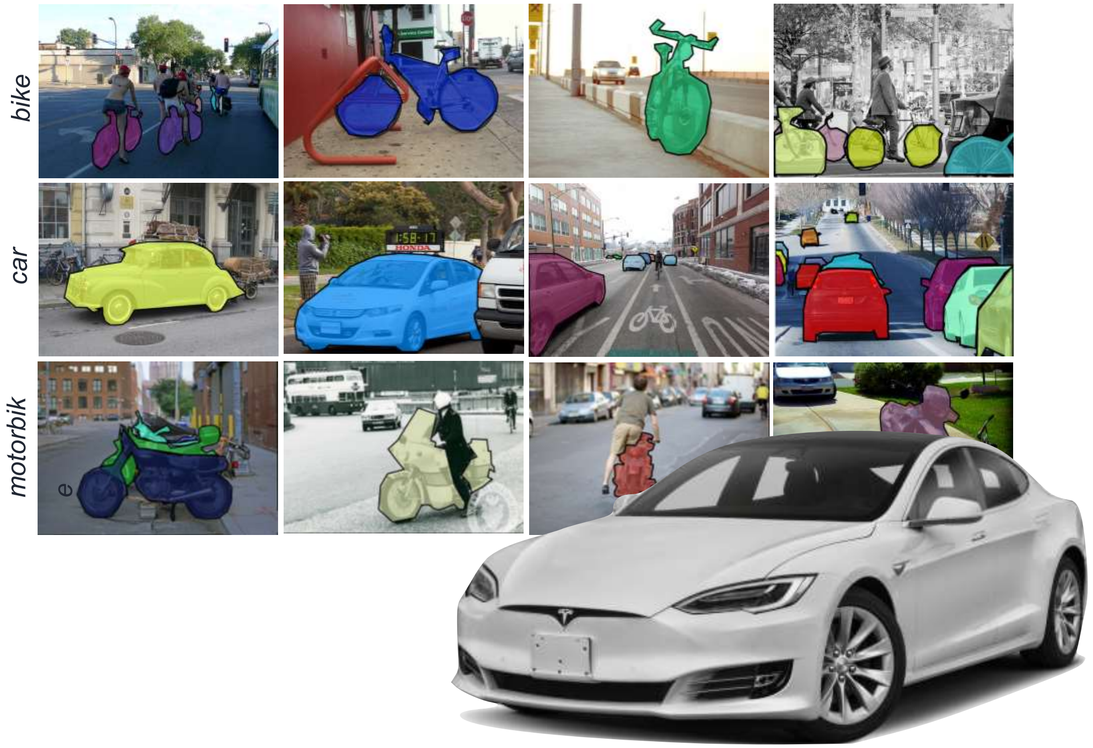
Candidate:

Fontanel Dario

Preliminaries

Closed world assumption

Training



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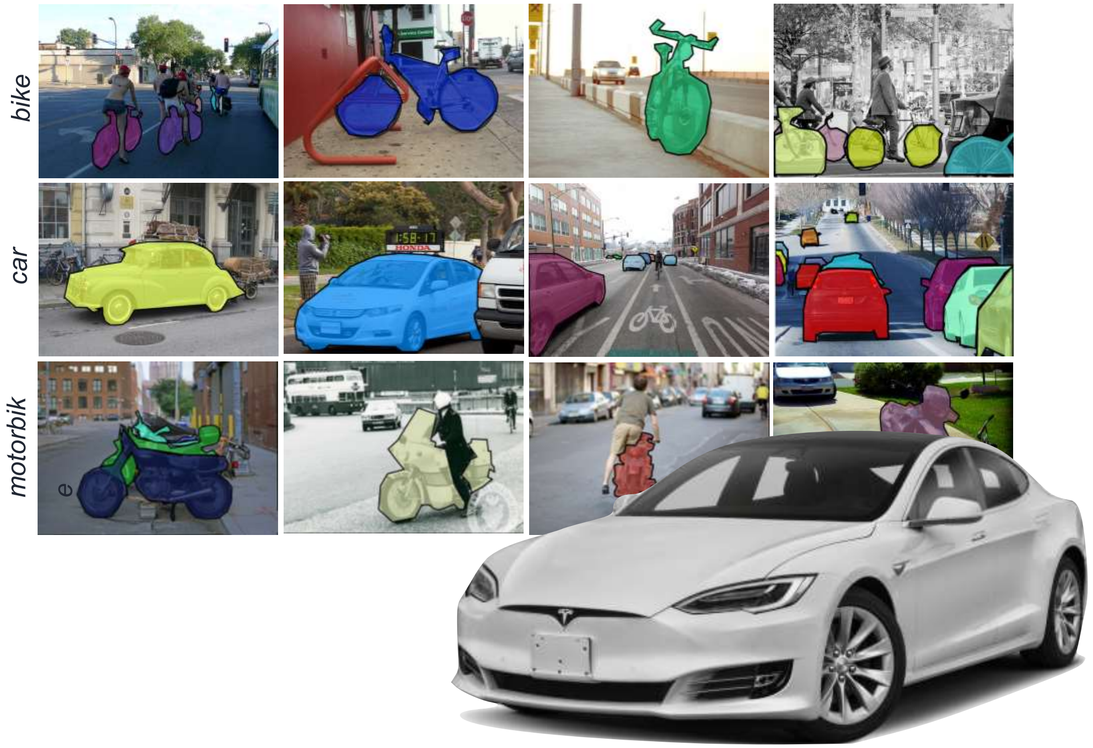

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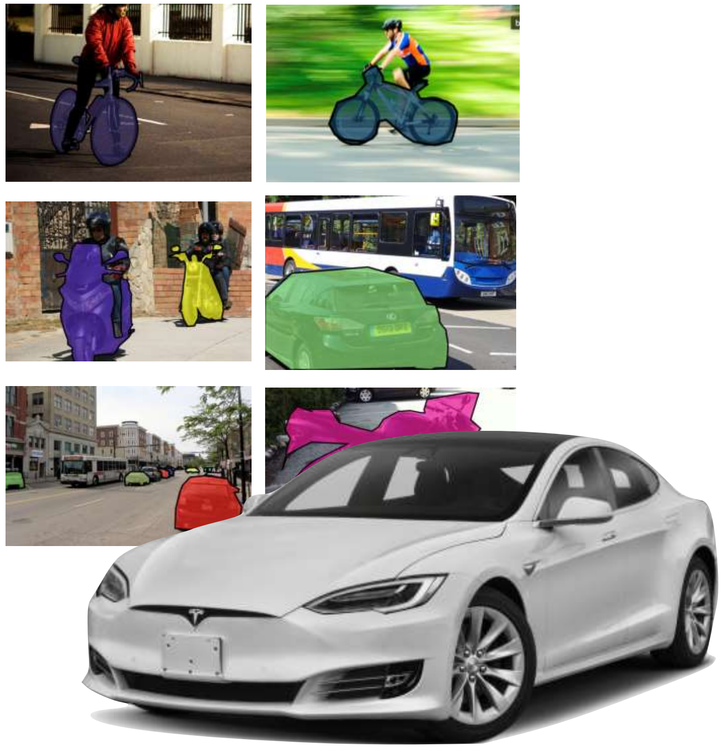

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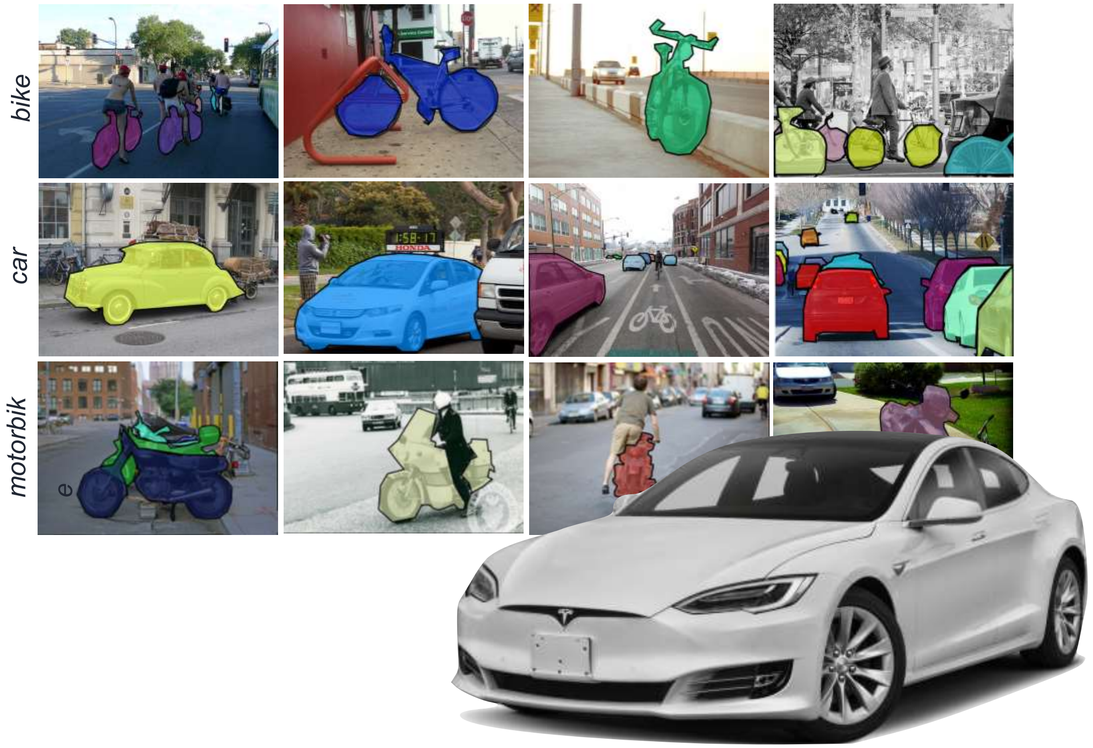

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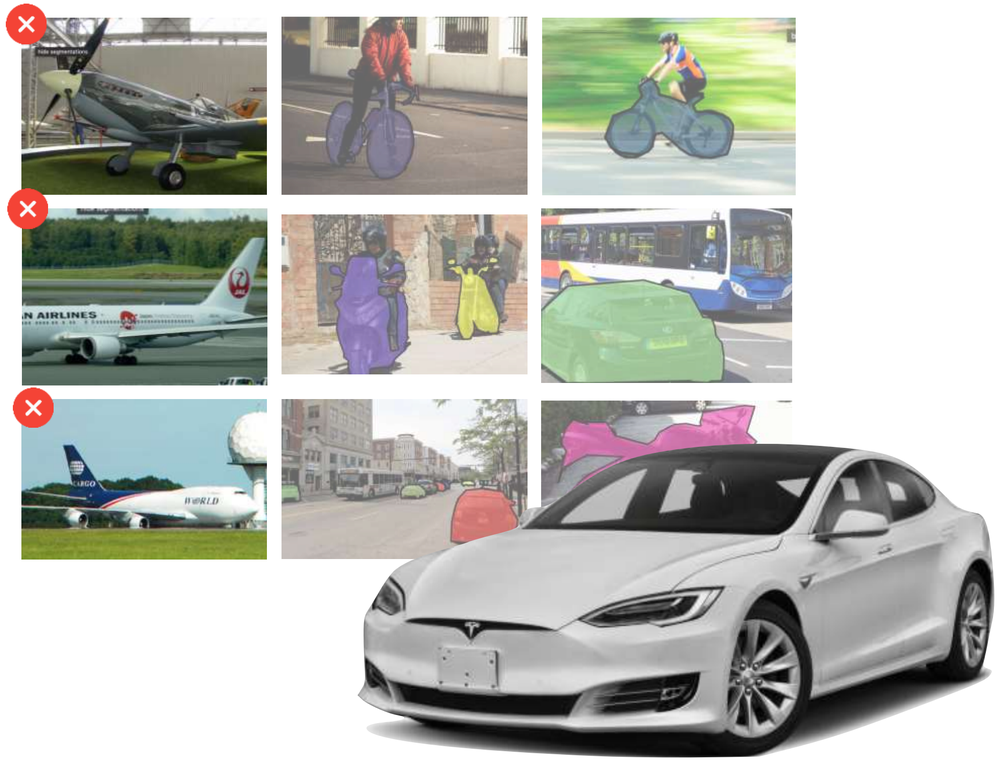

Preliminaries

Open world

Train

Time

Knowledge (t)

Preliminaries

Open world

Train

Test

Time

Knowledge (t)

Preliminaries

Open world

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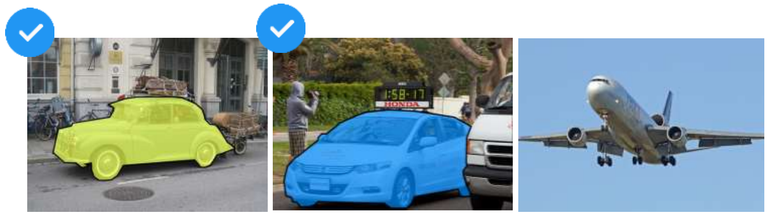

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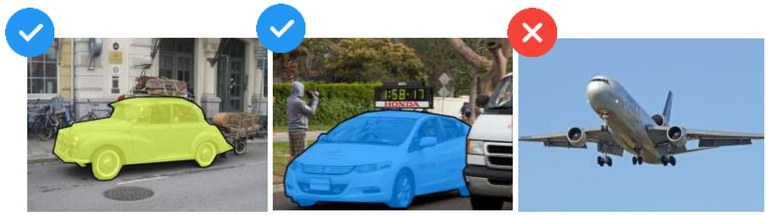

Test

Time

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Unknown category found

Preliminaries

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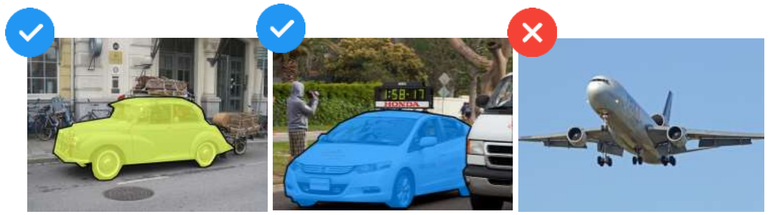

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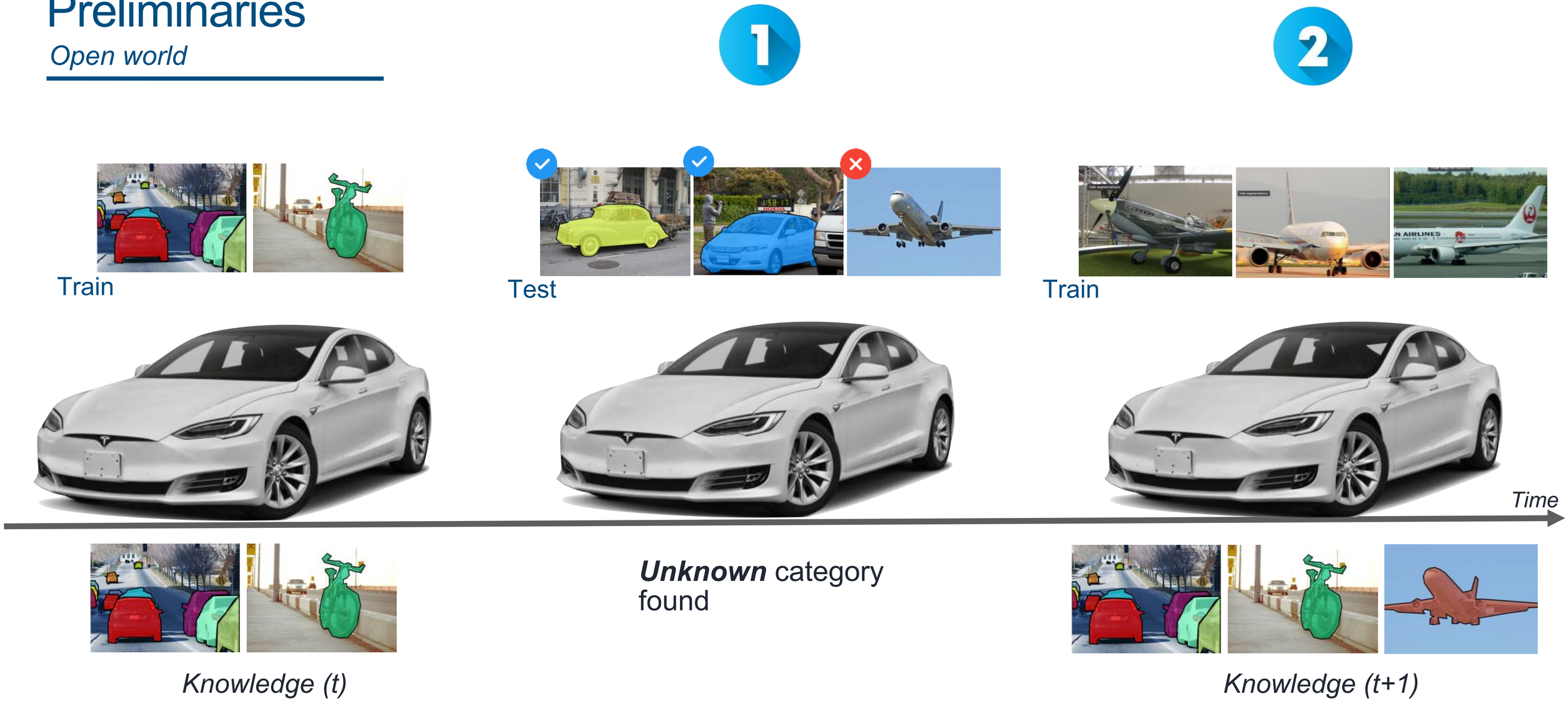

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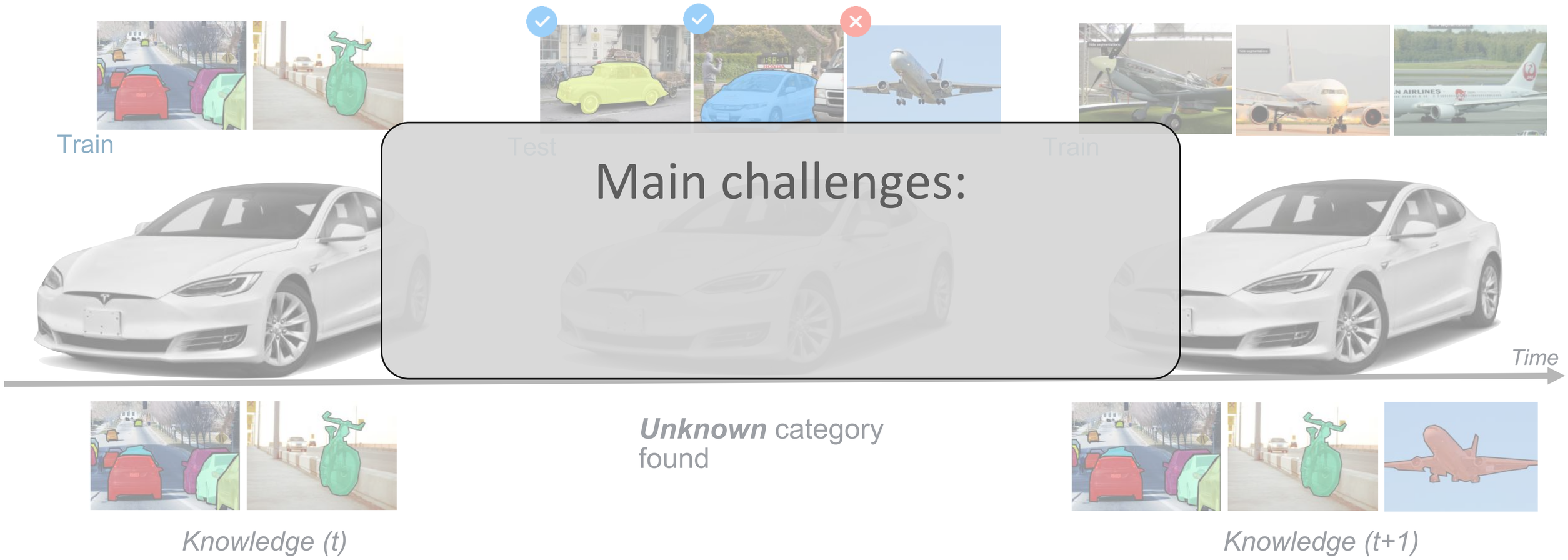

Main challenges:

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Preliminaries

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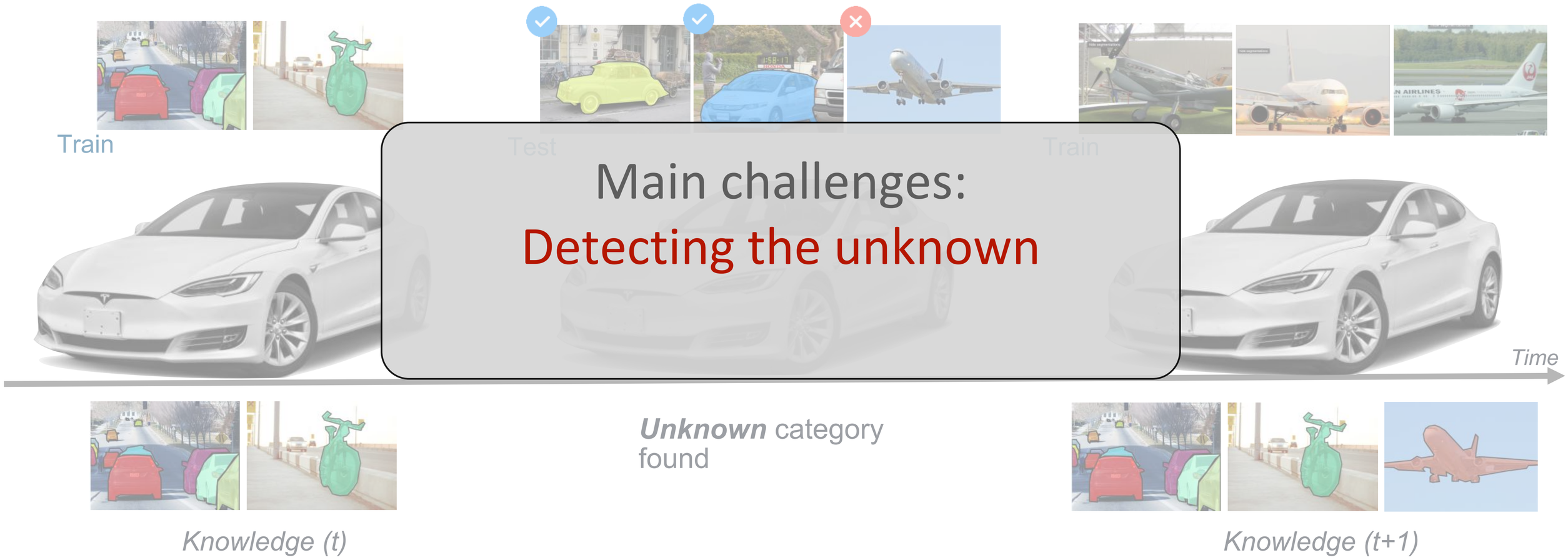

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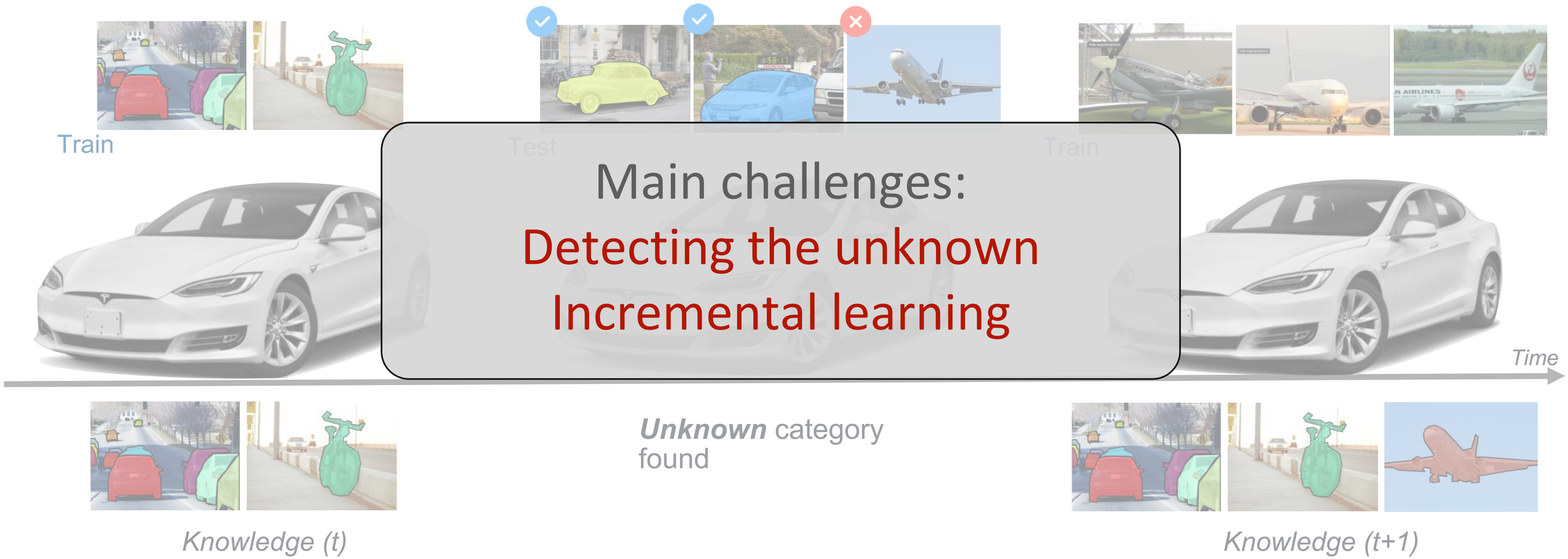


Main challenges:

Detecting the unknown

Incremental learning

Outline

Recognizing New Visual Categories in Real Open World Environments

Detection of the unknown

"PAnS: Prototopycal Anomaly Segmentation".

Dario Fontanel, Fabio Cermelli, Massimiliano Mancini, Barbara Caputo

CVPR 21

Incremental learning

"Weakly supervised Incremental Learning for Semantic Segmentation"

Fabio Cermelli, Dario Fontanel, Antonio Tavera, Marco Ciccone, Barbara Caputo

CVPR 22

Unified framework

"Boosting Deep Open World Recognition by Clustering"

Dario Fontanel, Fabio Cermelli, Massimiliano Mancini, Samuel Rota Bulo', Elisa Ricci, Barbara Caputo

IROS 20

Impact of domain shift

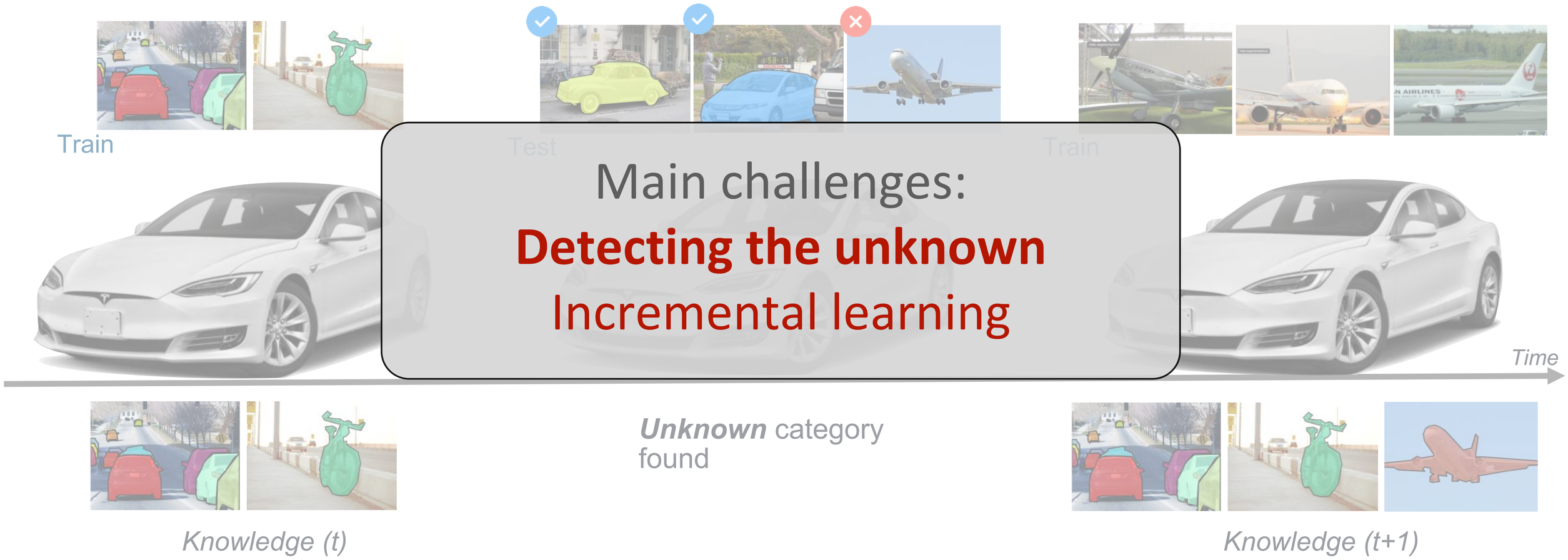
"On the Challenges of Open World Recognition under Shifting Visual Domains"

Dario Fontanel, Fabio Cermelli, Massimiliano Mancini, Barbara Caputo

ICRA 21

Preliminaries

Open world



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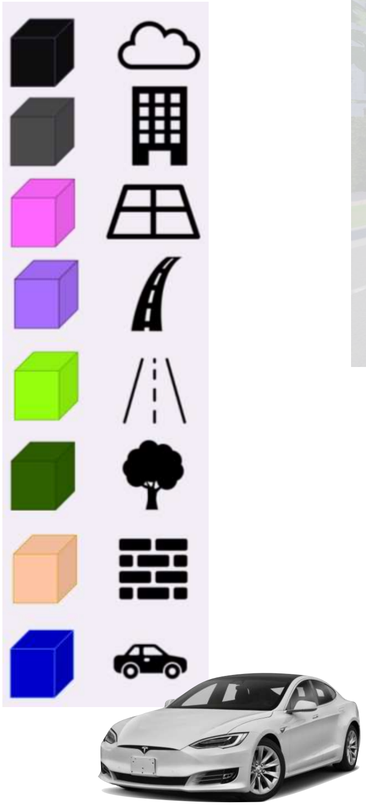
“PAnS: Prototopycal Anomaly Segmentation”

Dario Fontanel, Fabio Cermelli, Massimiliano Mancini, Barbara Caputo

IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2021, Nashville, USA

Anomaly Segmentation

It refers to the task of identifying the pixels in an image that belong to unknown categories.



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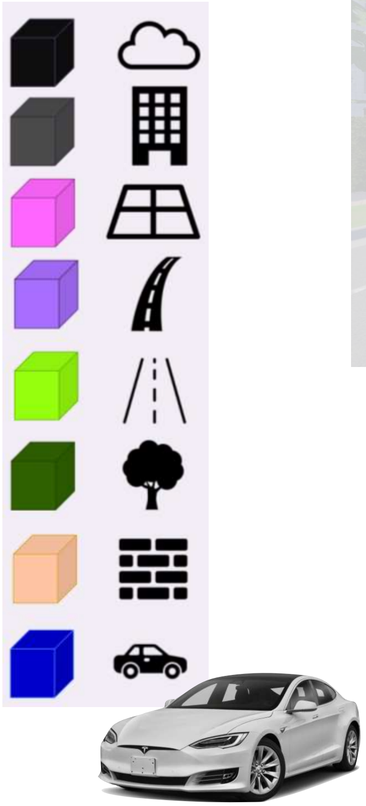

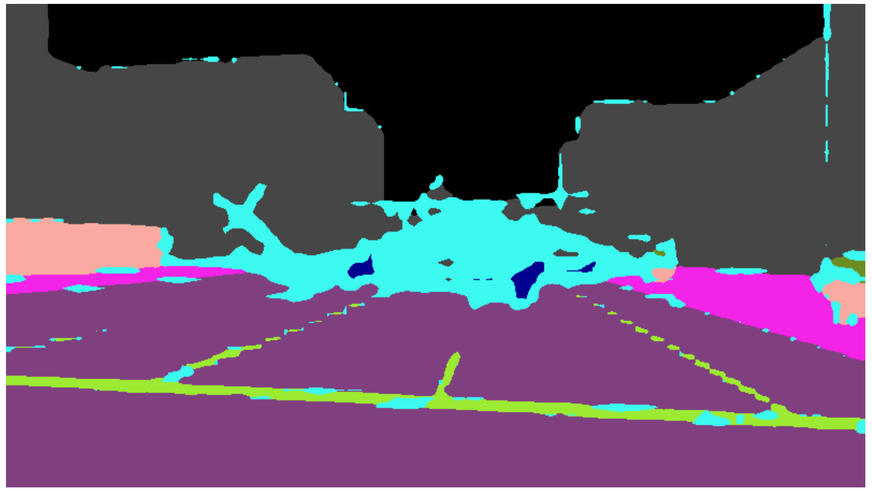

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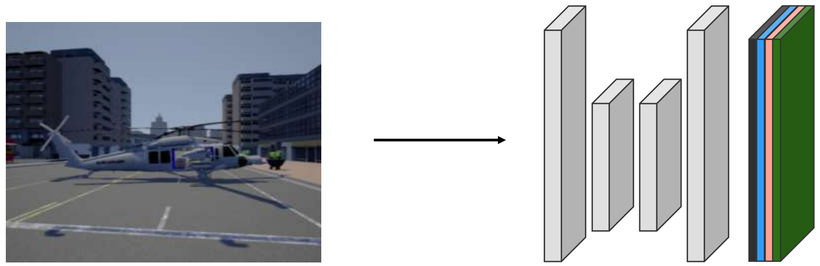
Traditional approaches



Image

Fully-Convolutional Network

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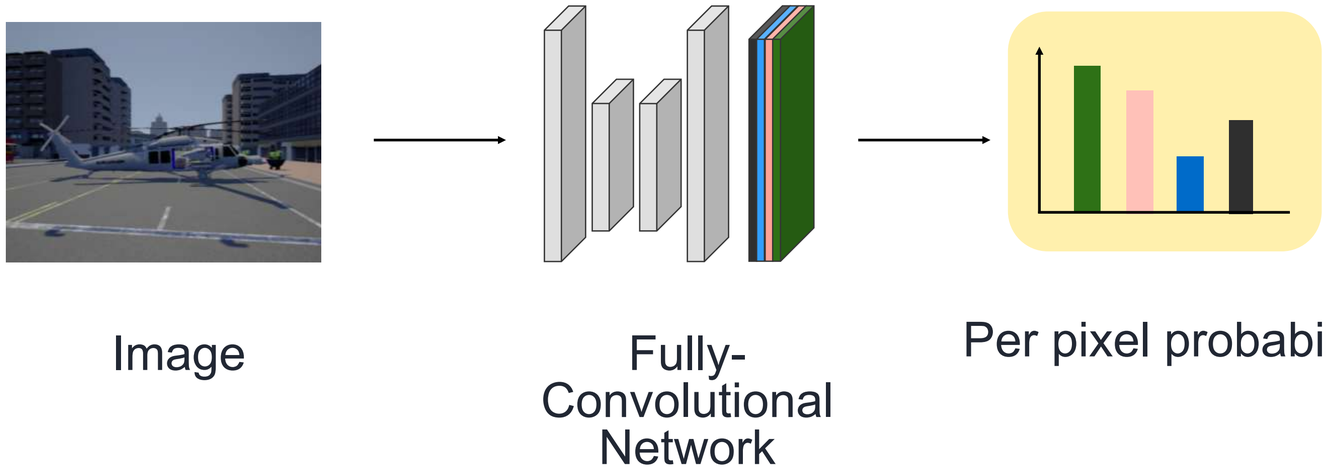

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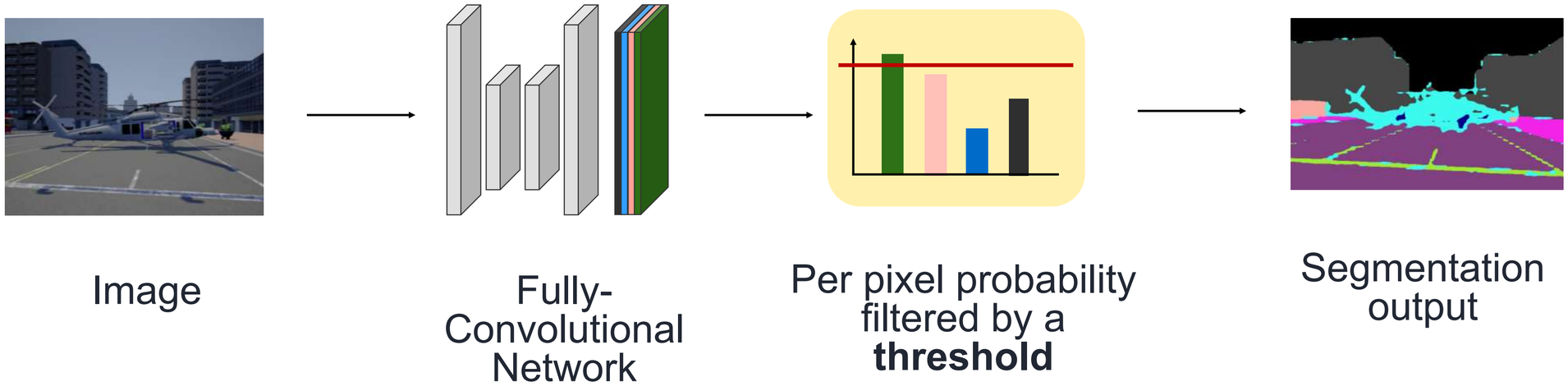

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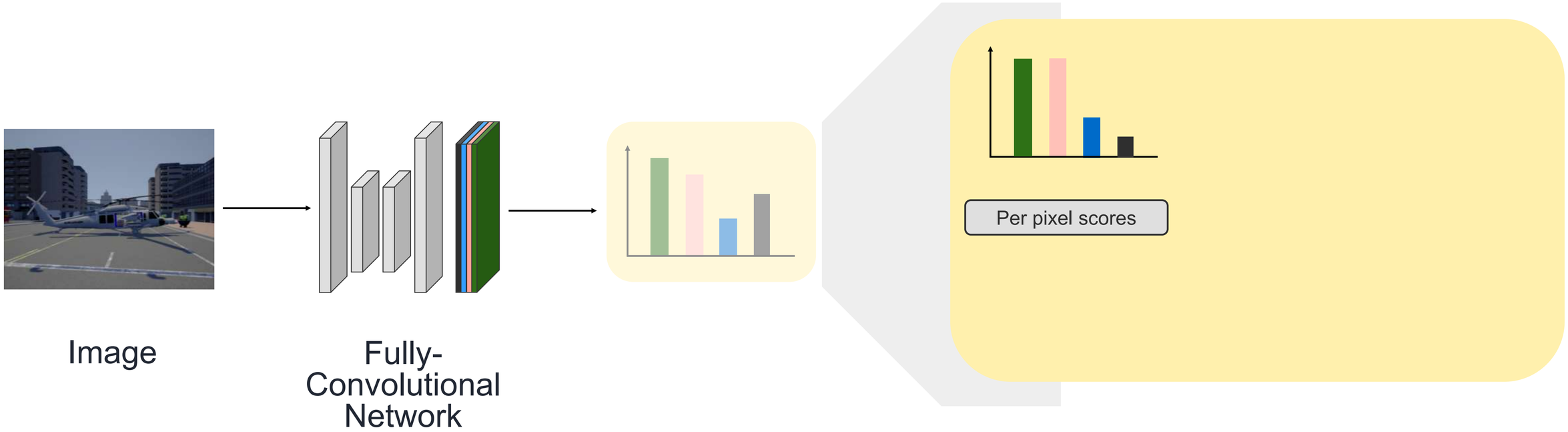

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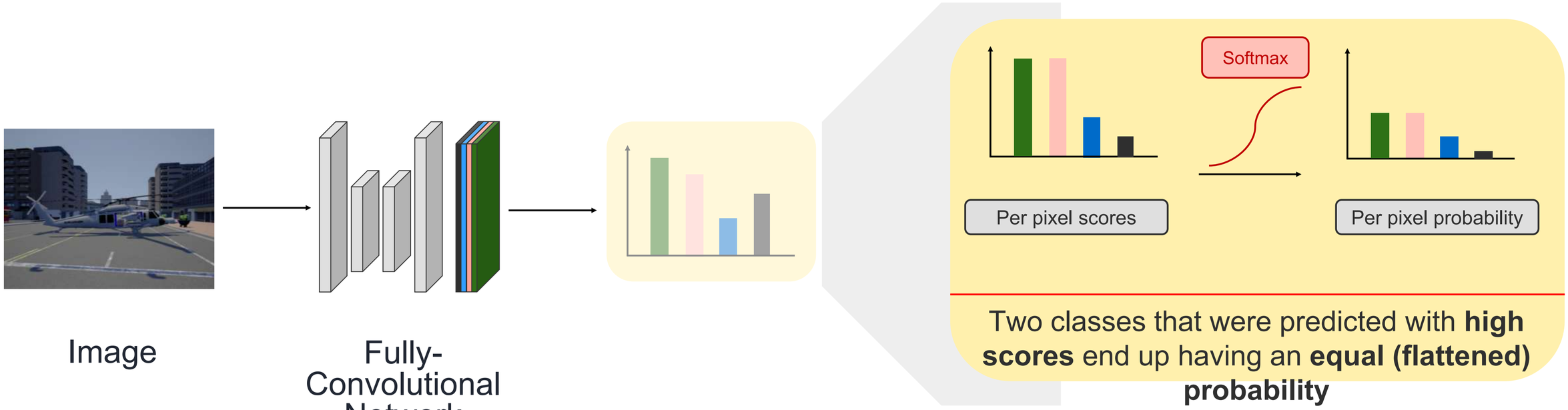

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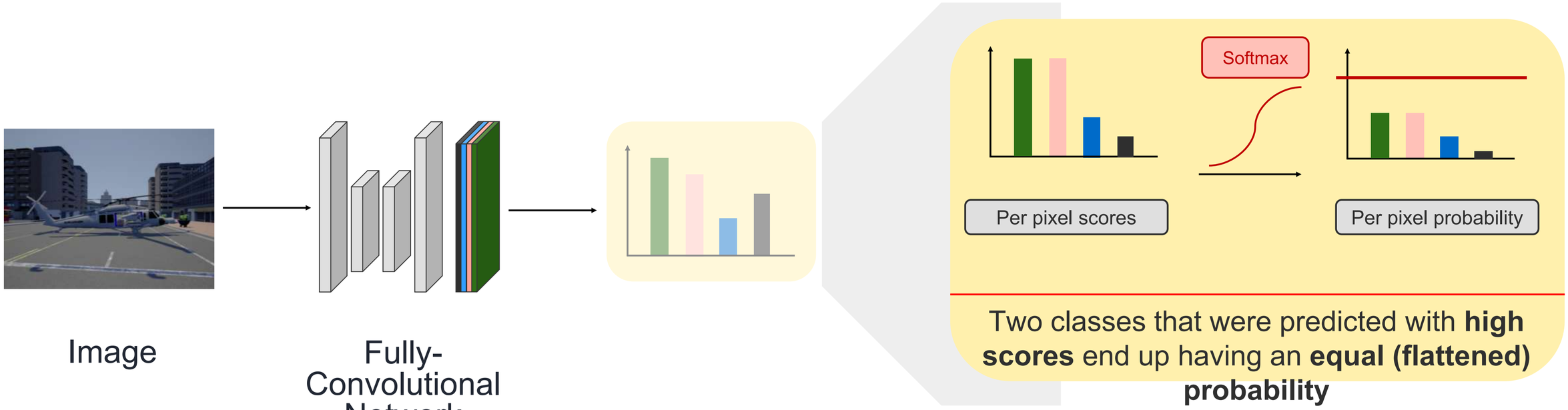

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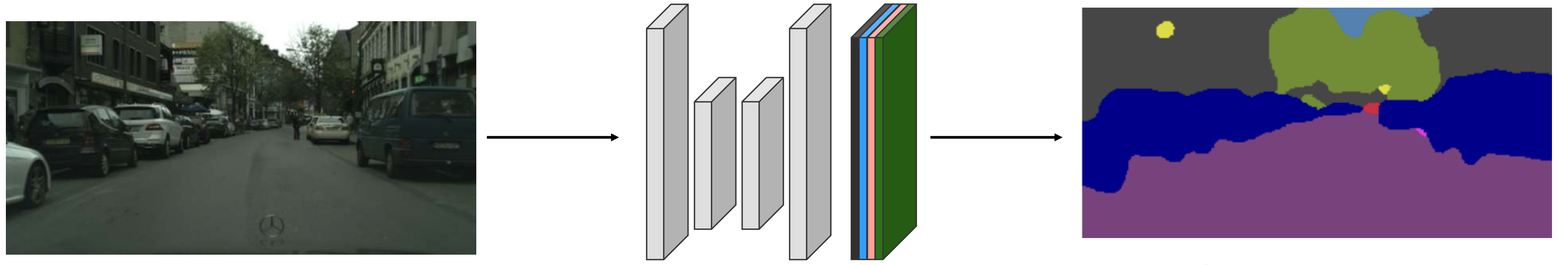

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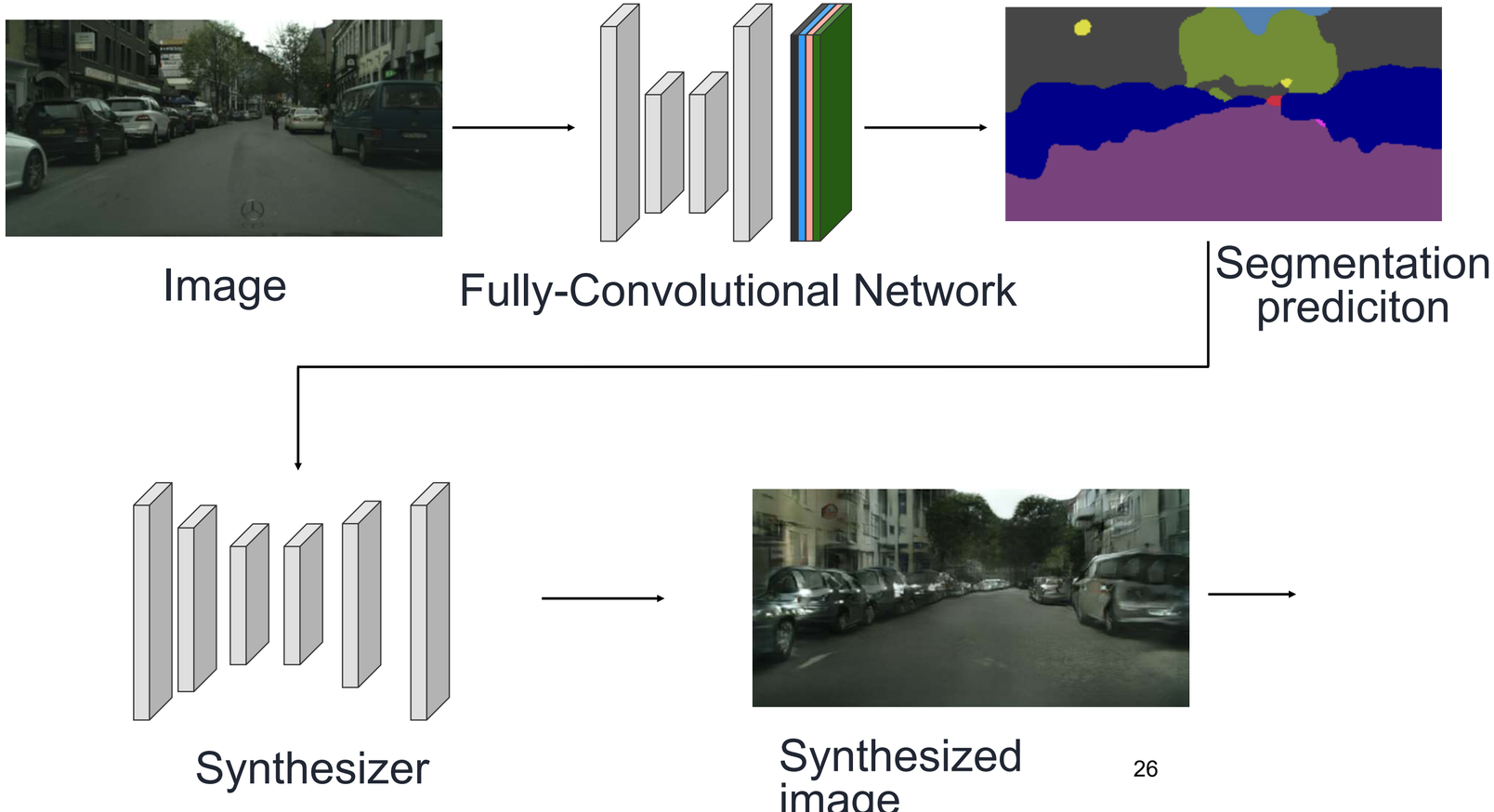

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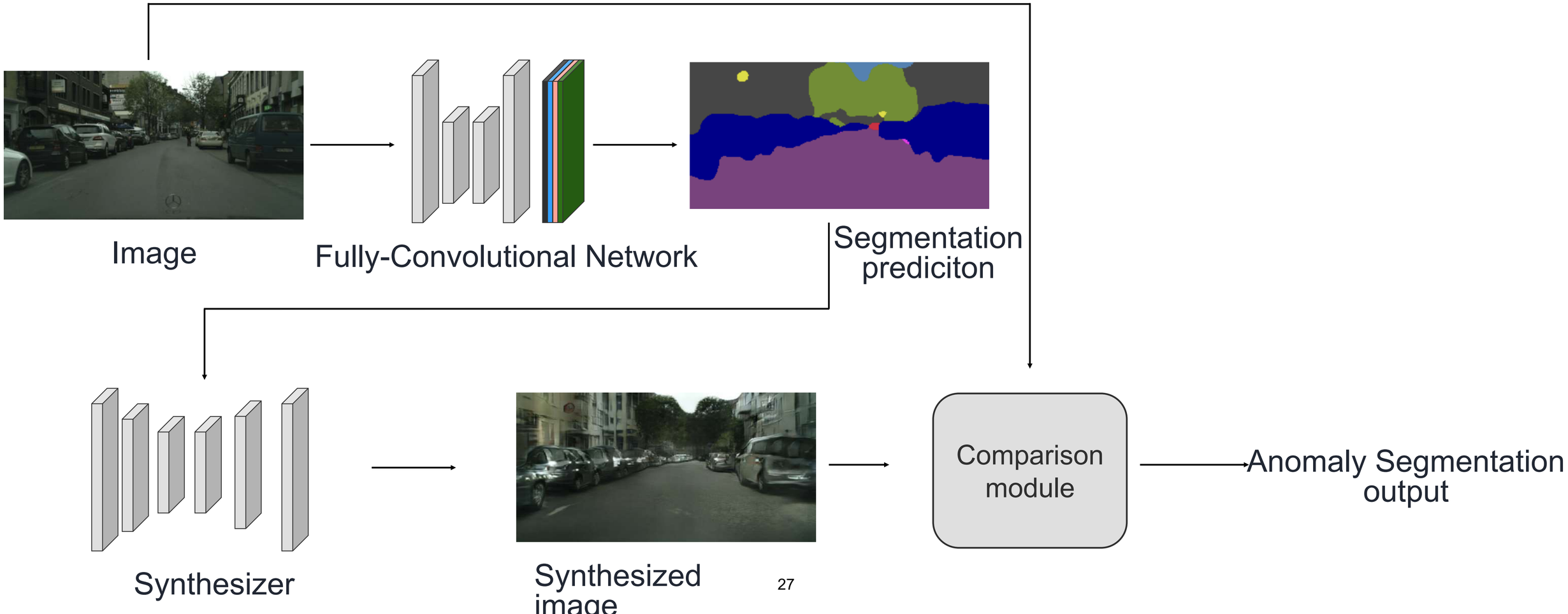

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Traditional approaches

Due to semantic segmentation scenes complexity

Generative approaches tend to produce artifacts while synthesizing pixels of known classes

Reconstruction (top) of SPADE [1] on an image from StreetHazards dataset (middle) [2].

“PAnS: Prototopycal Anomaly Segmentation”

Dario Fontanel, Fabio Cermelli, Massimiliano Mancini, Barbara Caputo

Framework

Confidence values independent for each class

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Scores bounded so that a threshold can be applied

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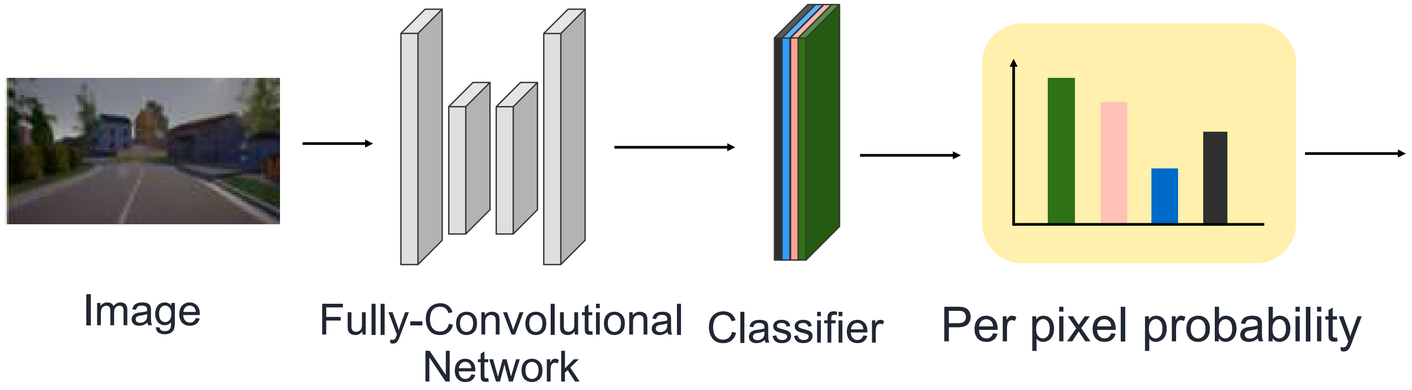

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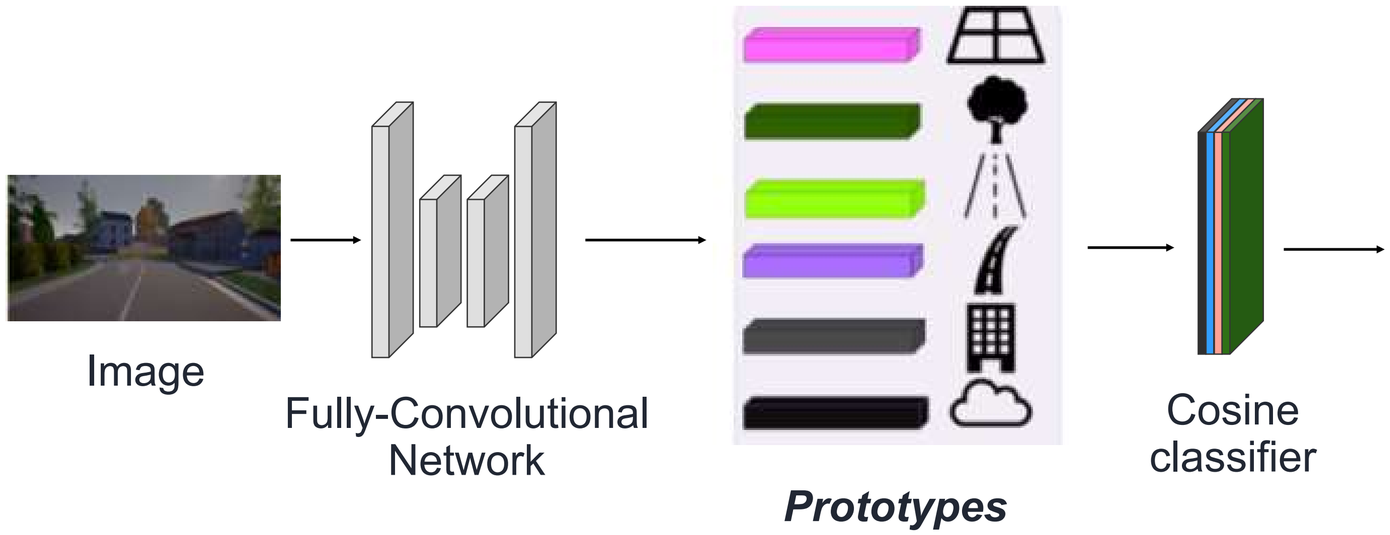

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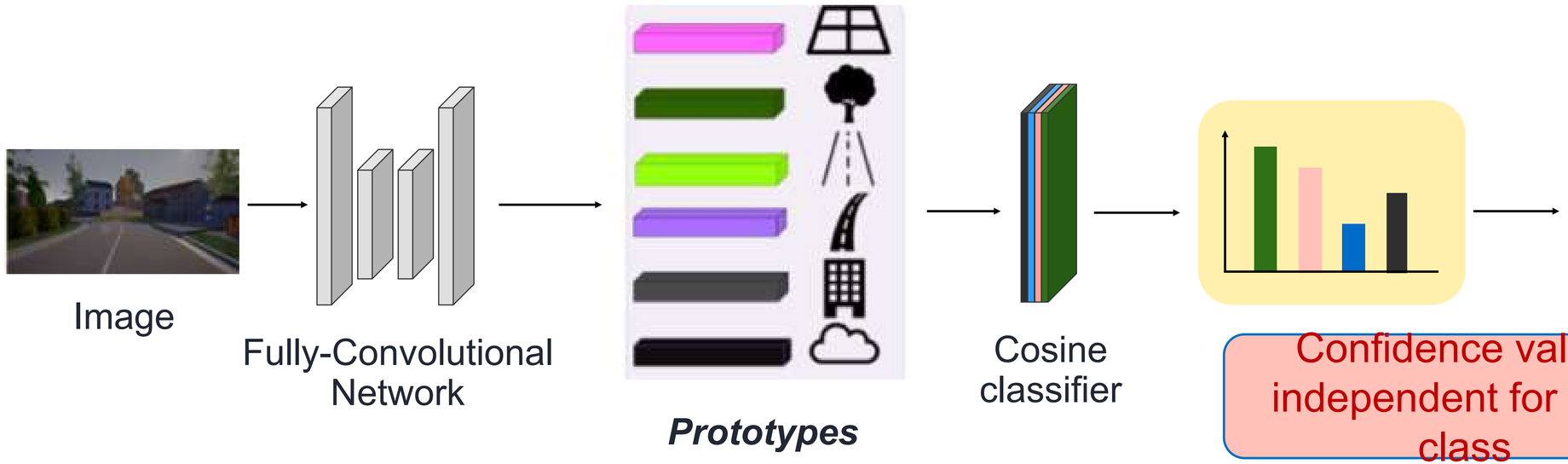

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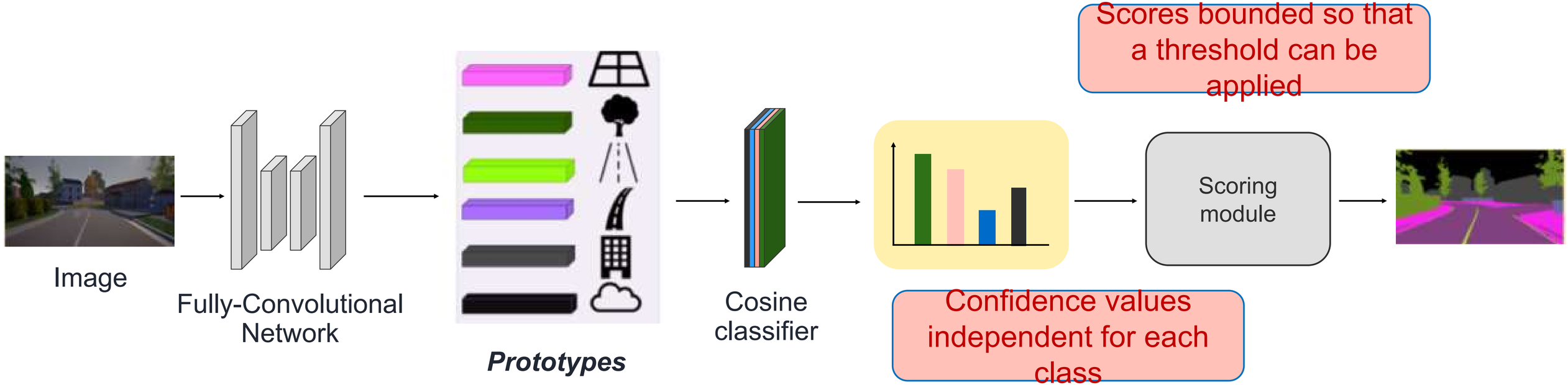

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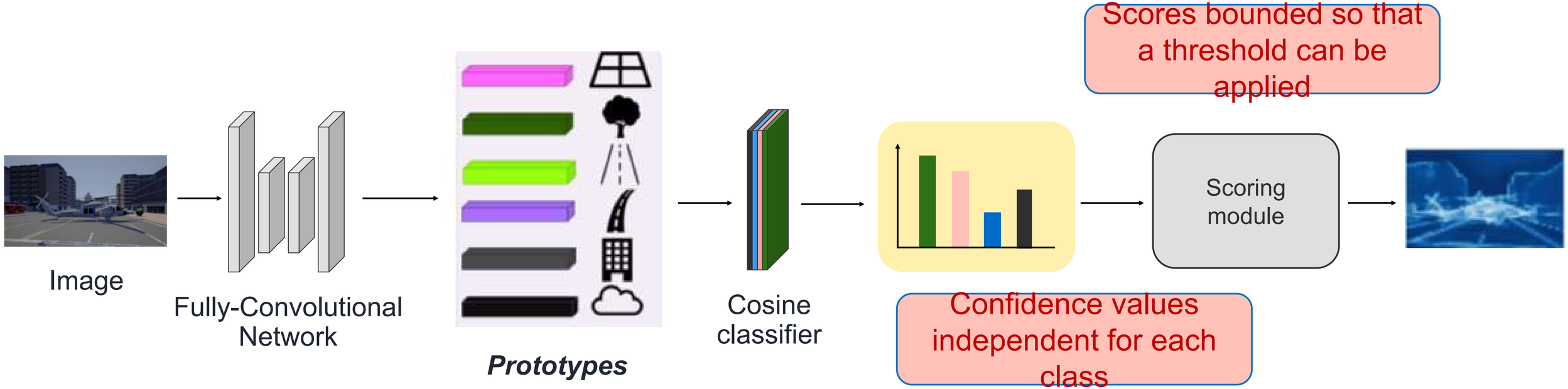

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Experimental setting

AUPR

area under the Precision-Recall curve

AUROC

area under the True Positive Rate and False Positive Rate curve

FPR95

measures the False Positive Rate (FPR) at 95% of recall

Architecture

ResNet-50 architecture [67] as backbone and PSPNet [26] as head module.

“PAnS: Prototopycal Anomaly Segmentation”

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Results

StreetHazards

D.Hendrycs, et al. *A benchmark for Anomaly Segmentation (2019)*

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StreetHazards

D.Hendrycs, et al. *A benchmark for Anomaly Segmentation (2019)*

Method	*AUPR* ↑	*AUROC* ↑	*FPR95* ↓
AE	2.2	66.1	91.7
Dropout	7.5	69.9	79.4
MSP	6.6	87.7	33.7
MSP + CRF	6.5	88.1	29.9
SynthCP	**9.3**	88.5	28.4
PAnS	8.8	**91.1**	**23.2**

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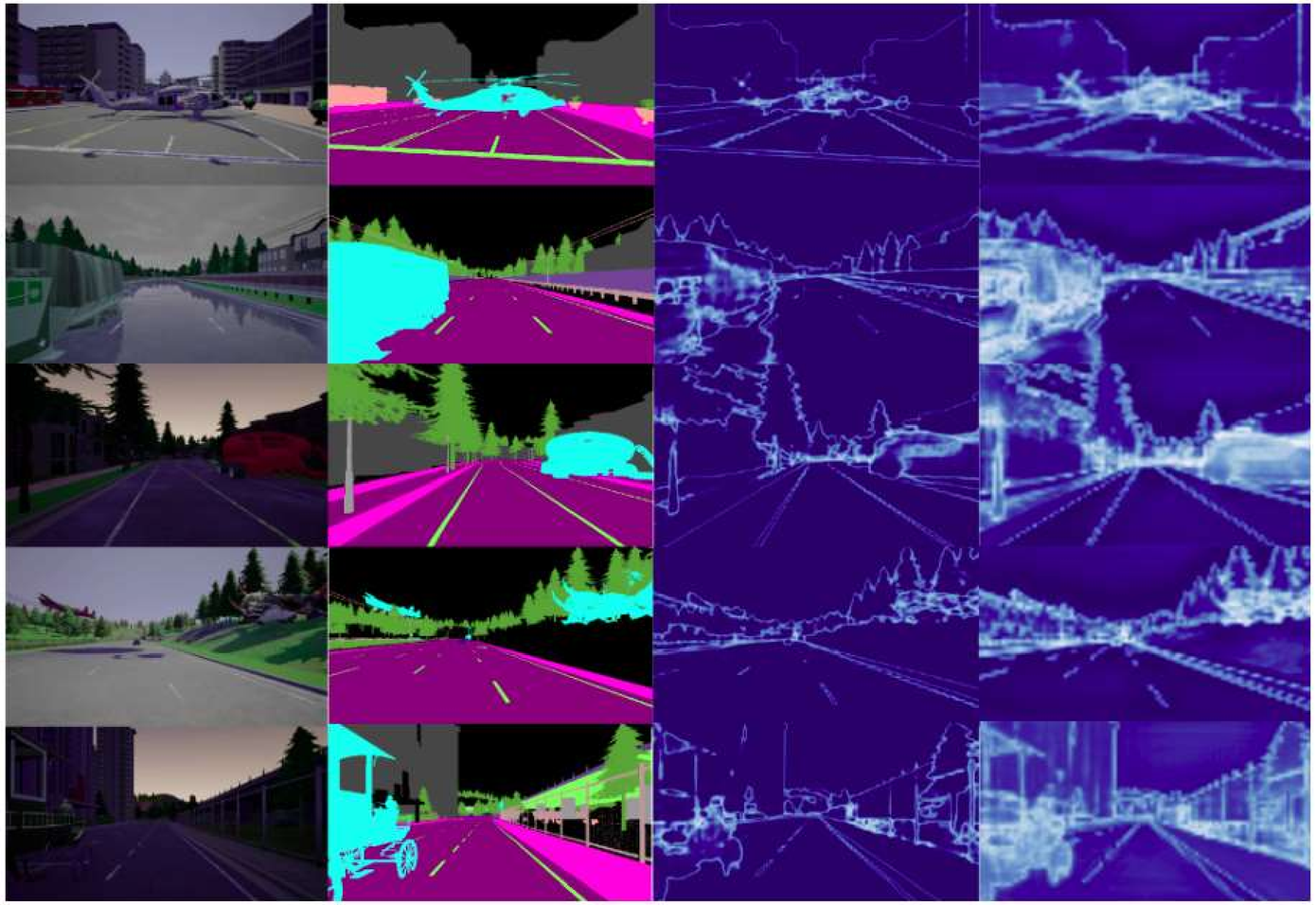
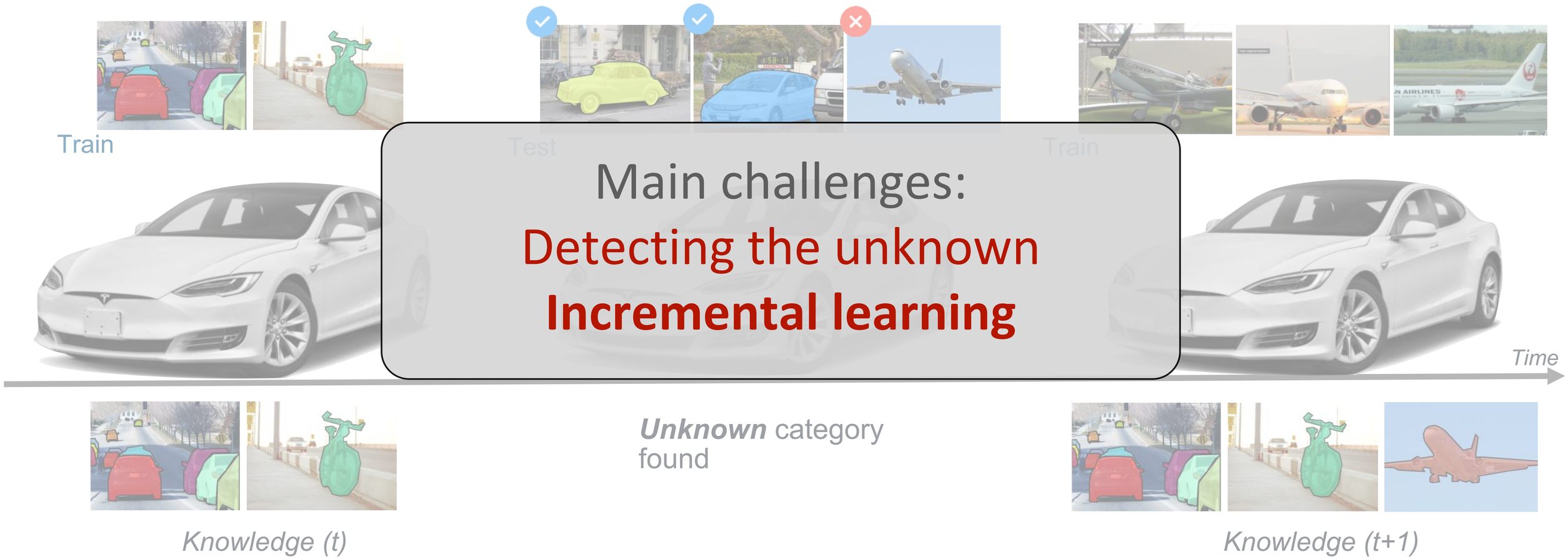


Image Semantic labels MSP PAnS

Preliminaries

Open world



Main challenges:

Detecting the unknown

Incremental learning

Unknown category found

“Weakly supervised Incremental Learning for Semantic Segmentation”

Fabio Cermelli, Dario Fontanel, Antonio Tavera, Marco Ciccone, Barbara Caputo

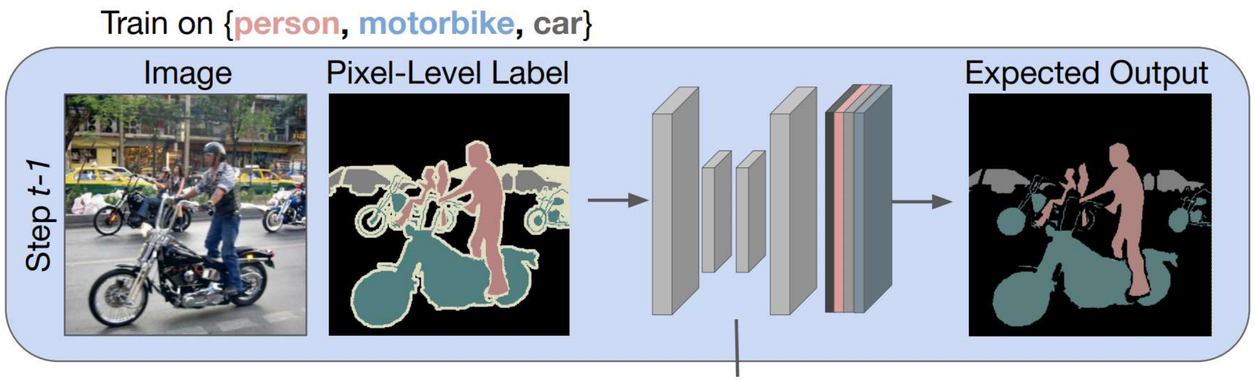
IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2022, New Orleans, USA

Weakly supervised Incremental Learning for Semantic Segmentation

Fabio Cermelli, Dario Fontanel, Antonio Tavera, Marco Ciccone, Barbara Caputo

Task overview

Suppose we are given a model pre-trained on a set of classes, using expensive pixel-level annotations



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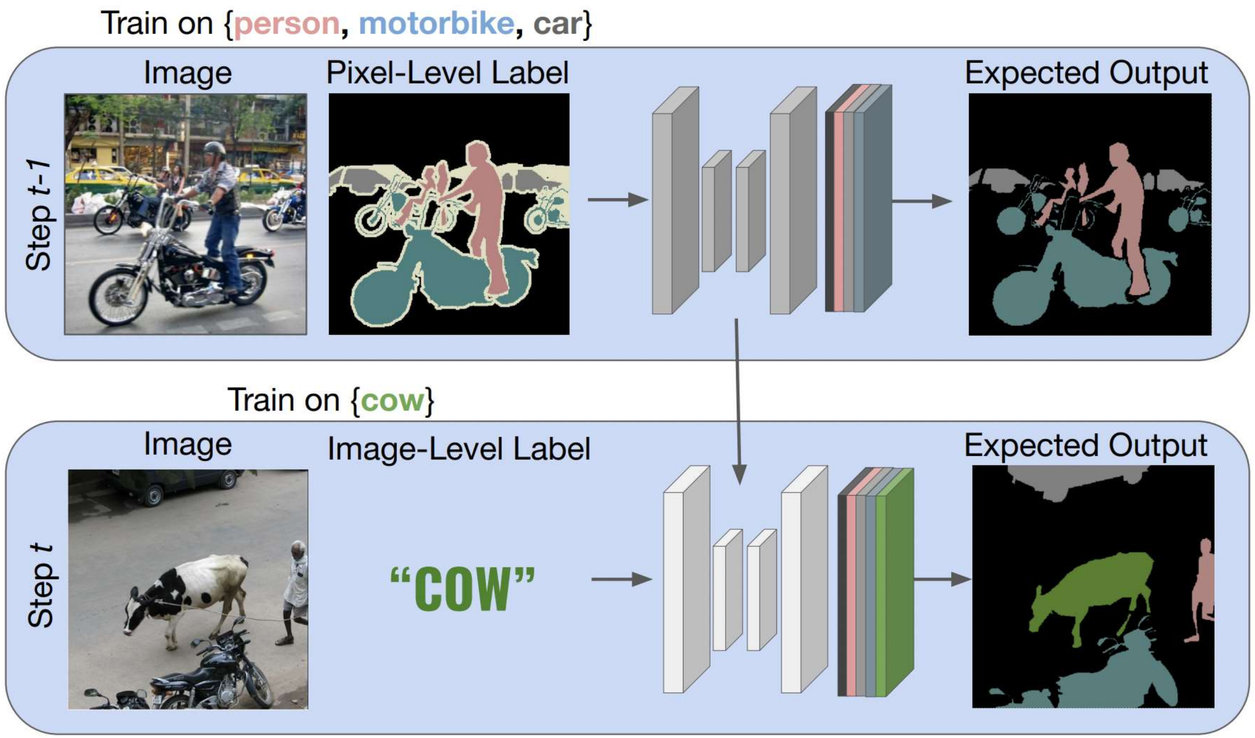
Task overview

Suppose we are given a model pre-trained on a set of classes, using expensive pixel-level annotations

Our goal is to incrementally segment new classes over time using only image-level labels



Weakly supervised Incremental Learning for Semantic Segmentation

Fabio Cermelli, Dario Fontanel, Antonio Tavera, Marco Ciccone, Barbara Caputo

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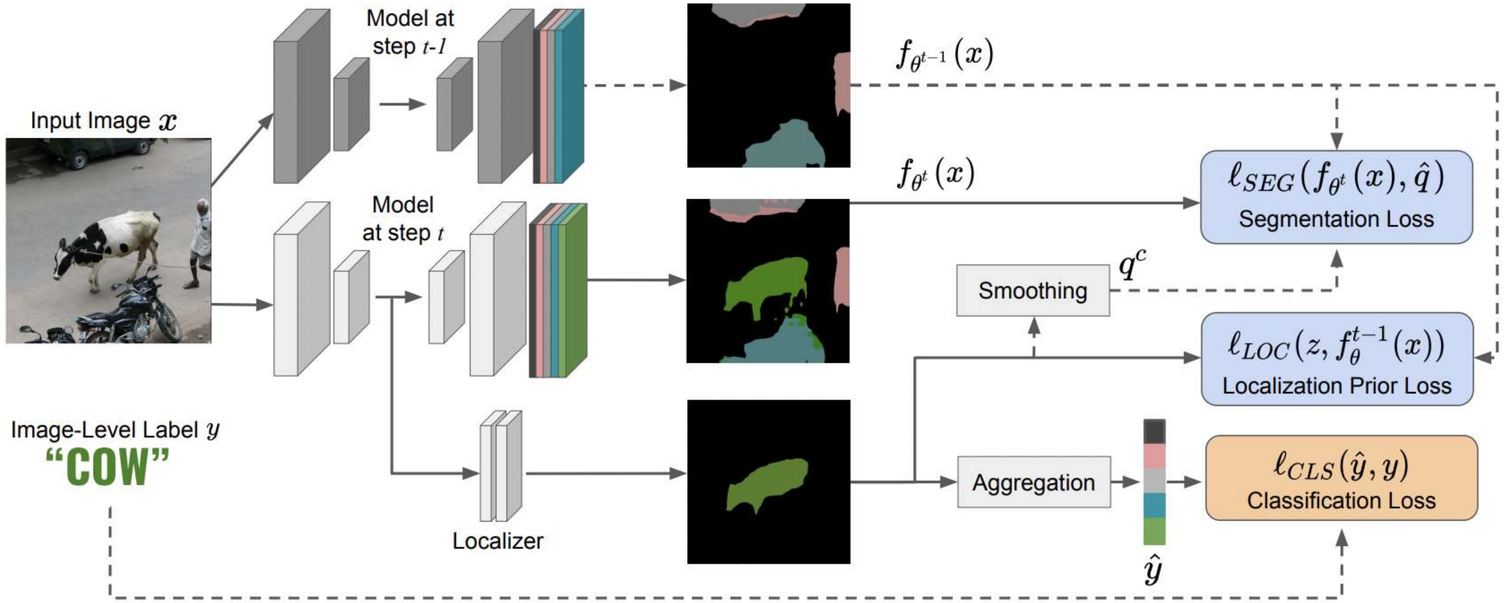

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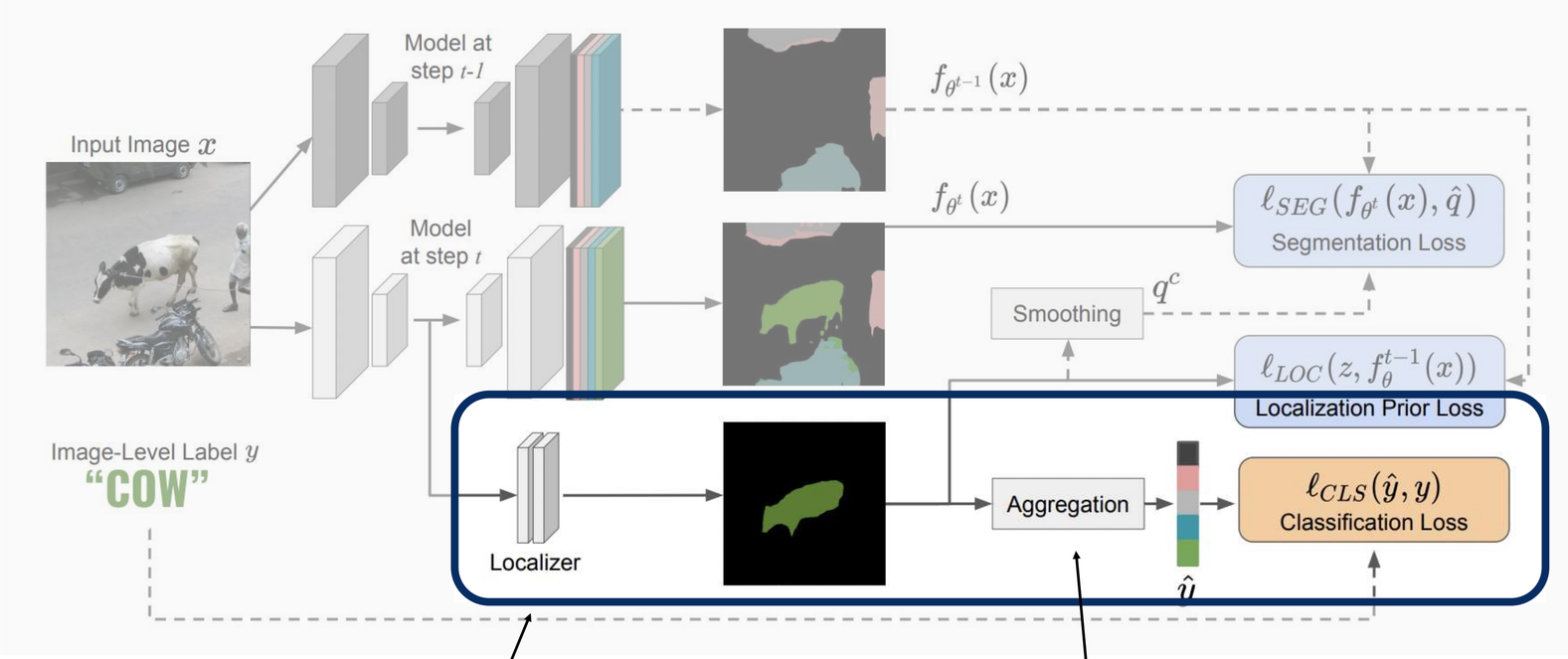


Stack of convolutional layers

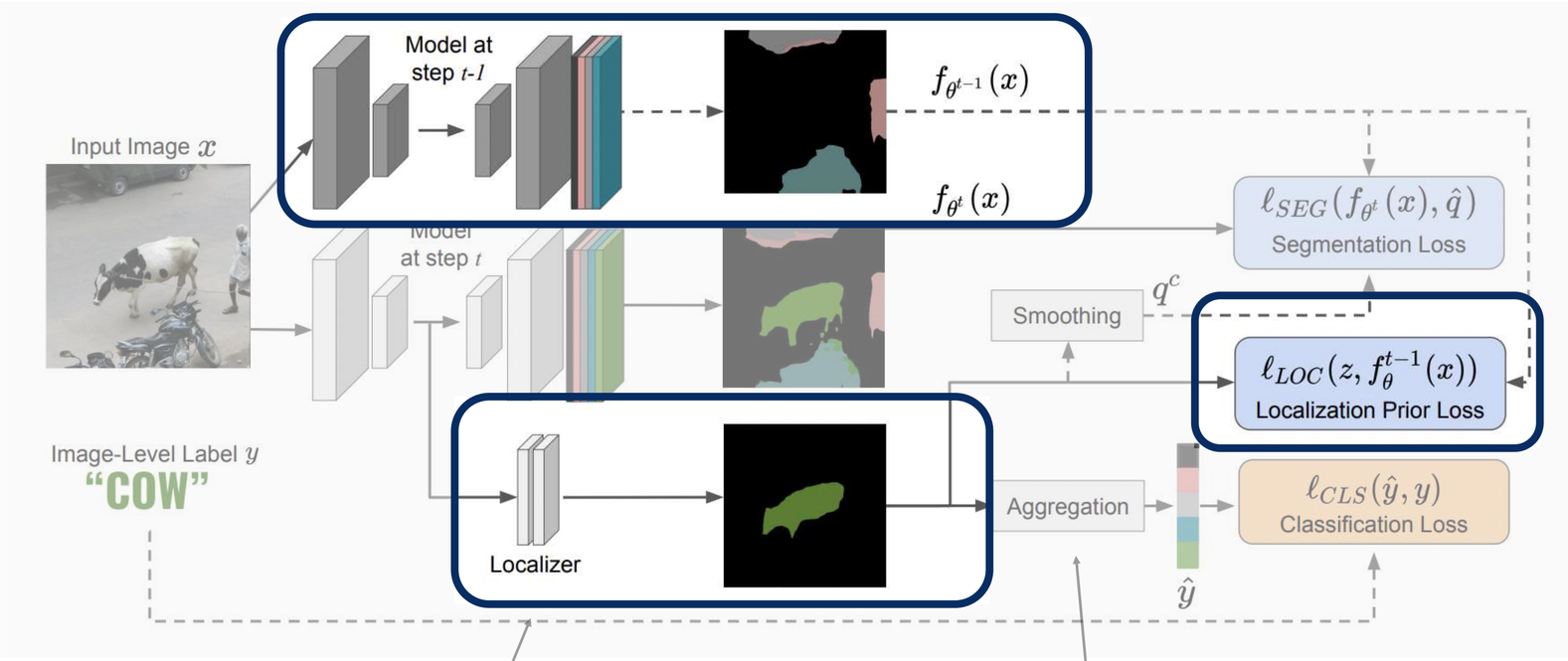
Spatial aggregation module transforms the output volume into a 1D tensor

Weakly supervised Incremental Learning for Semantic Segmentation

Fabio Cermelli, Dario Fontanel, Antonio Tavera, Marco Ciccone, Barbara Caputo

Method

The model at the previous time step prevents catastrofic forgetting and serves as a localization prior



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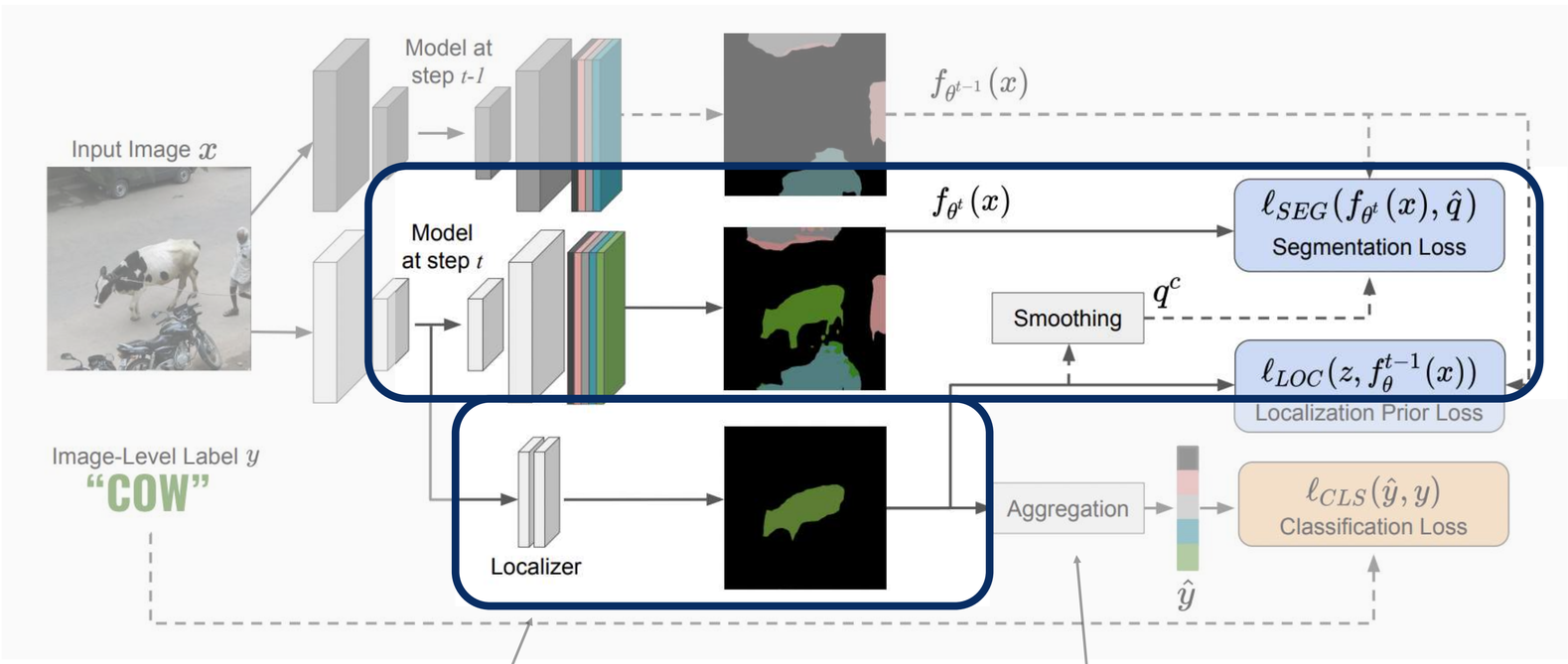
Traditional semantic segmentation pipeline



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Experimental setting

Comparisons

Fully supervised IL methods

- Standard fully supervised incremental learning approaches serving as upper bounds

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Weakly-supervised methods

- Used to generate pseudo-labels offline and train the same IL model

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ResNet-101 architecture [67] as backbone and Deeplav v3 [26] as head module.

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the

Architecture

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[26] as

Pascal VOC 2012

20 semantic classes + background

10k images

15-5

15 classes first, 5 classes added

10-10

10 classes first, 10 classes added

The PASCAL Visual Object Classes (VOC) Challenge. Everingham, M., Van Gool, L., Williams, C. K. I., Winn, J. and Zisserman, A, IJCV10

Weakly supervised Incremental Learning for Semantic Segmentation

Fabio Cermelli, Dario Fontanel, Antonio Tavera, Marco Ciccone, Barbara Caputo

Experimental setting

Comparisons

Fully supervised IL methods

Standard fully supervised incremental learning approaches serving as upper bounds

Weakly-supervised methods

Used to generate pseudo-labels offline and train same IL model
the

Architecture

ResNet-101 architecture [67] as backbone and Deeplav v3 head module.

[26] as

Pascal VOC 2012

20 semantic classes + background
10k images

15-5

15 classes first,

5 classes added

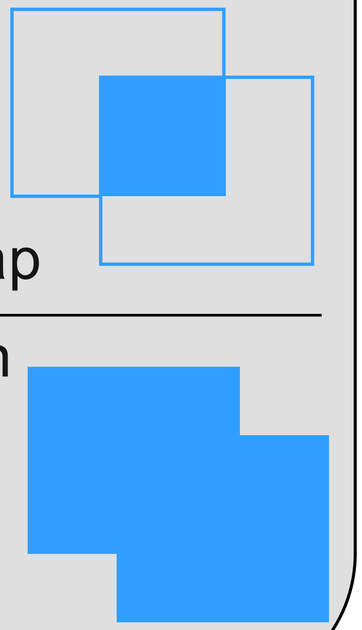
10-10

10 classes first,

10 classes added

mIoU

Intersection over Union (IoU) = $\frac{\text{area of overlap}}{\text{area of union}}$



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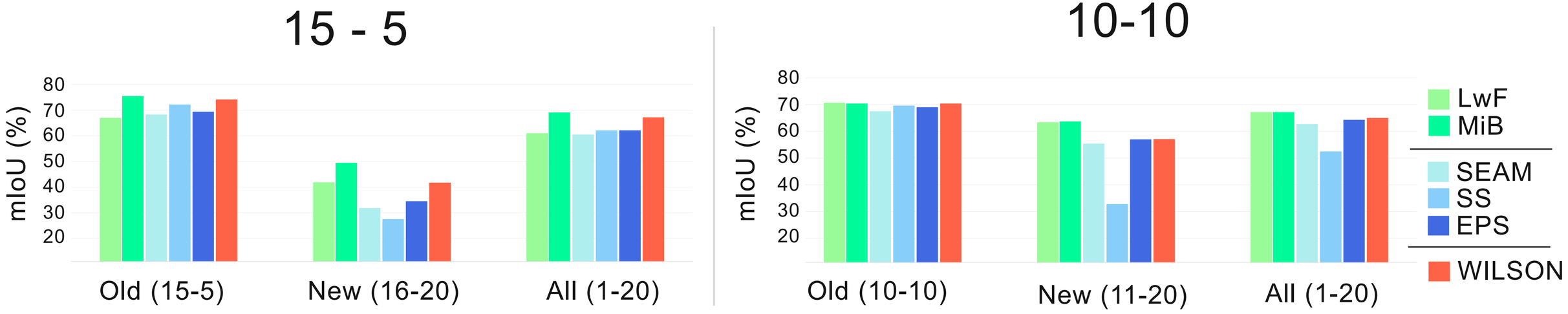
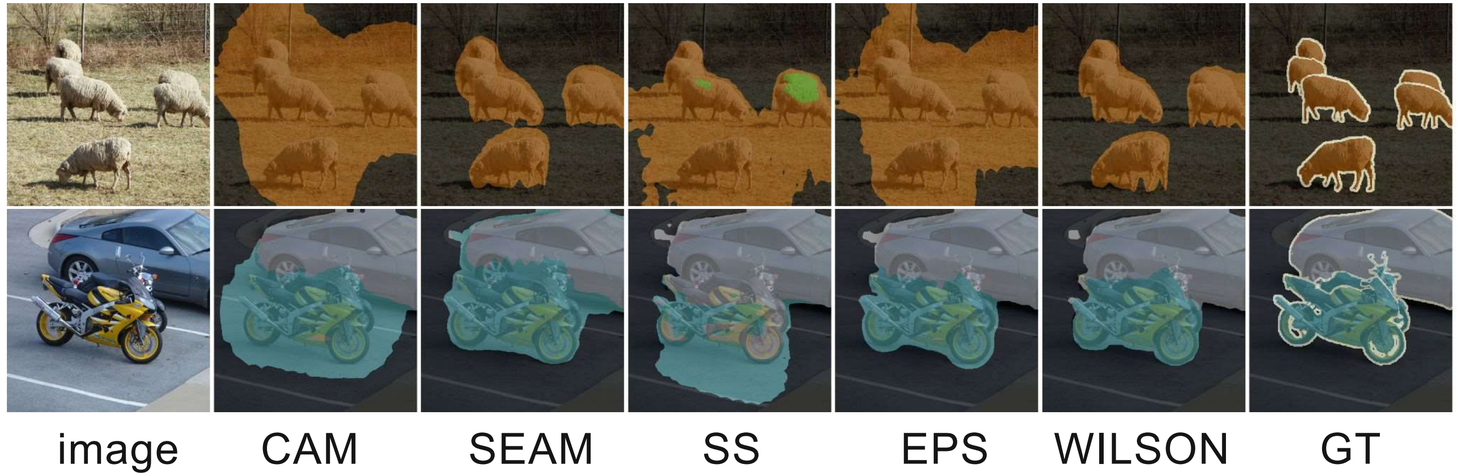




Old classes: car

New classes: sheep, motorbike

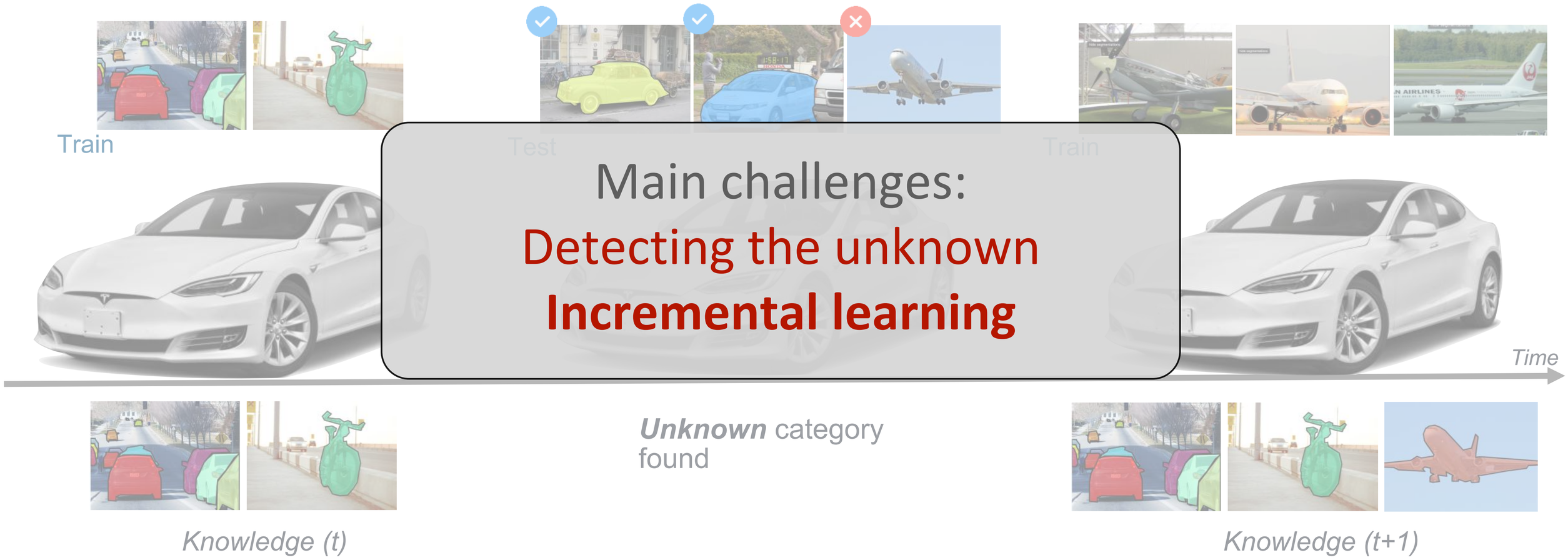
“Boosting Deep Open World Recognition by Clustering”

Dario Fontanel, Fabio Cermelli, Massimiliano Mancini, Samuel Rota Bulo’, Elisa Ricci, Barbara Caputo

IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) 2020, Las Vegas, USA
IEEE Robotics and Automation Letters 2020

Preliminaries

Open world



Main challenges:

Detecting the unknown

Incremental learning

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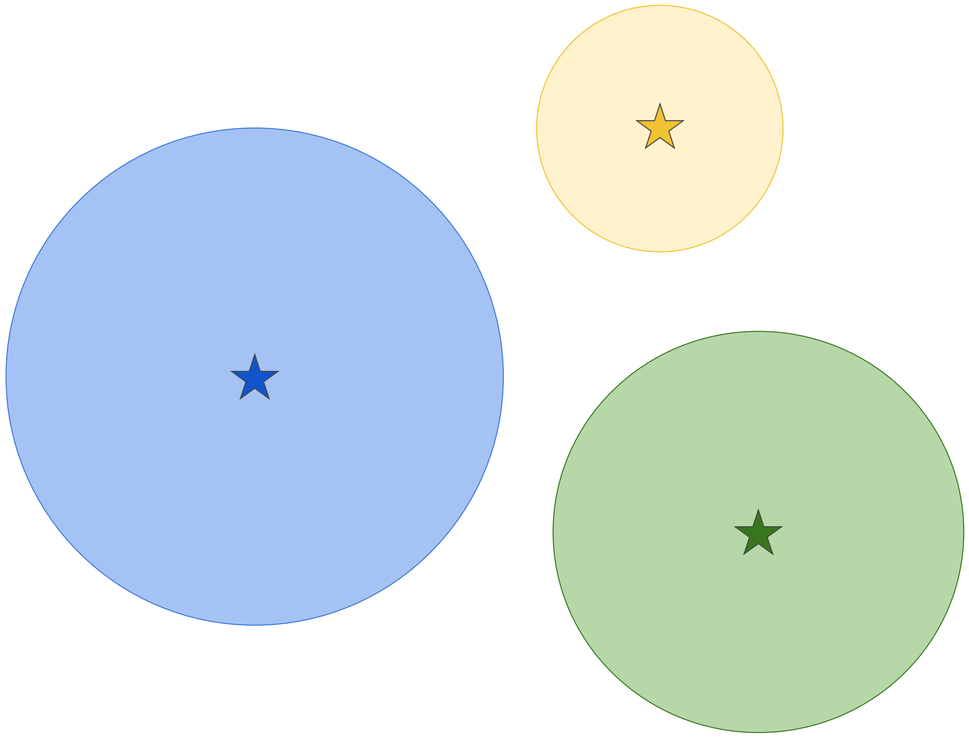

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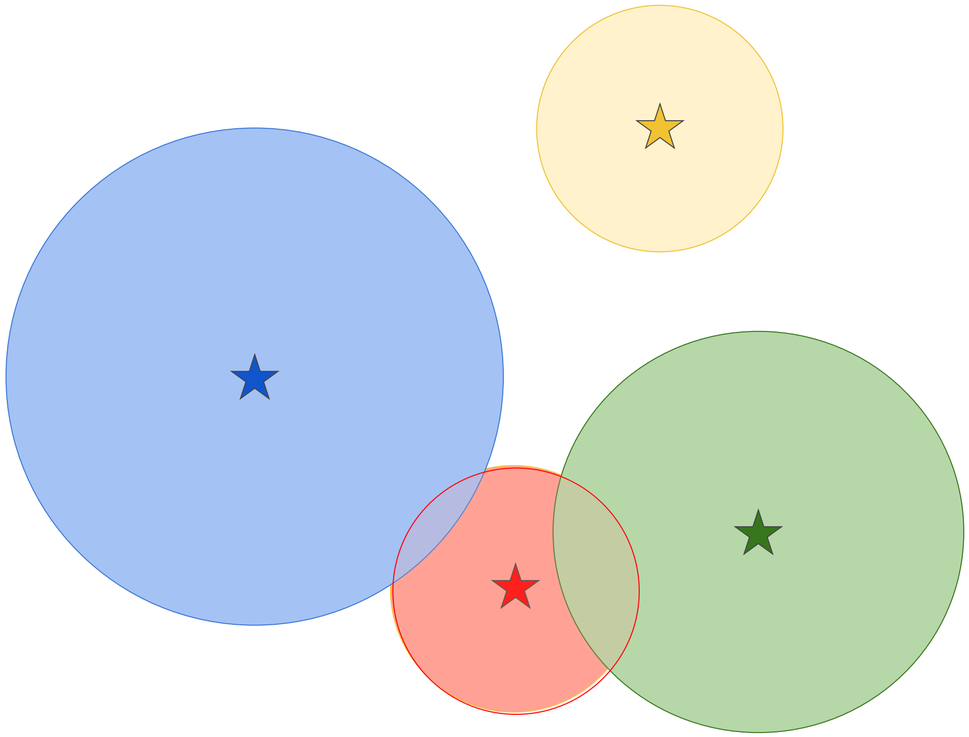

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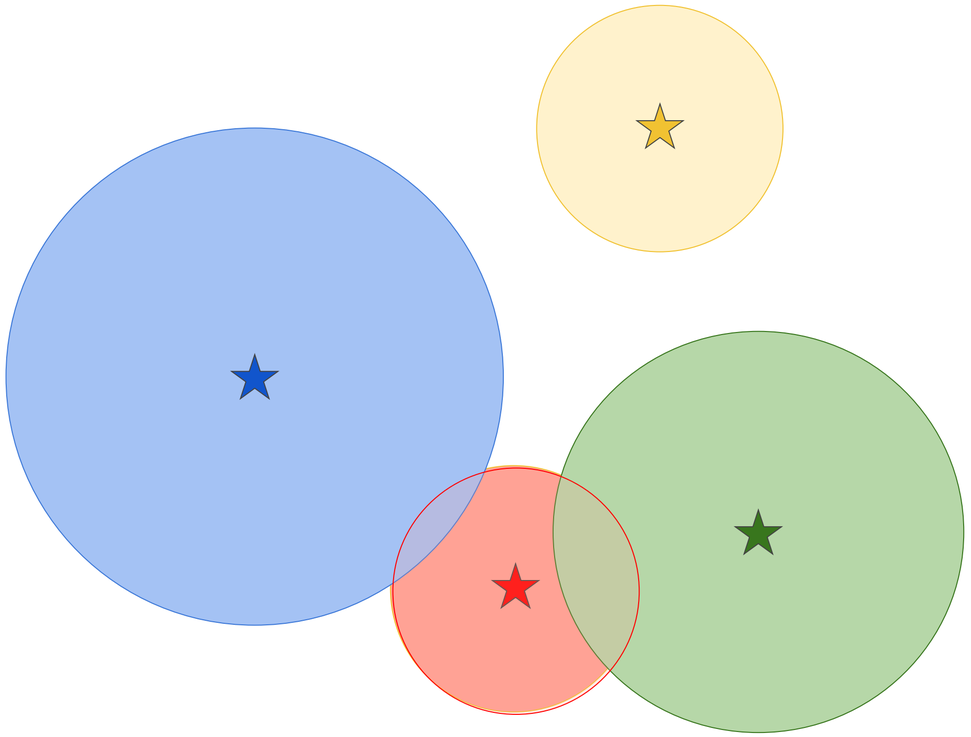

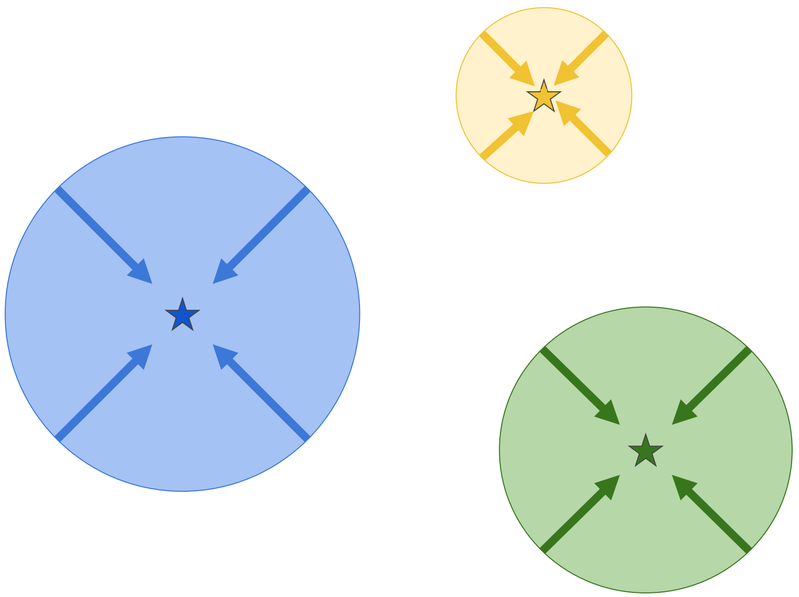

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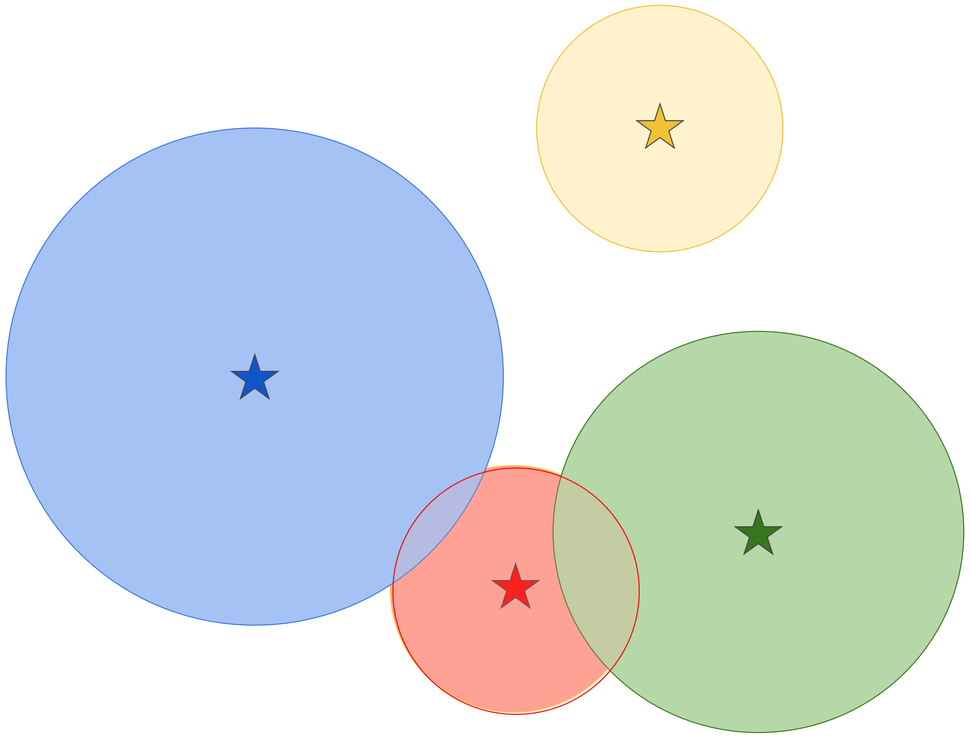

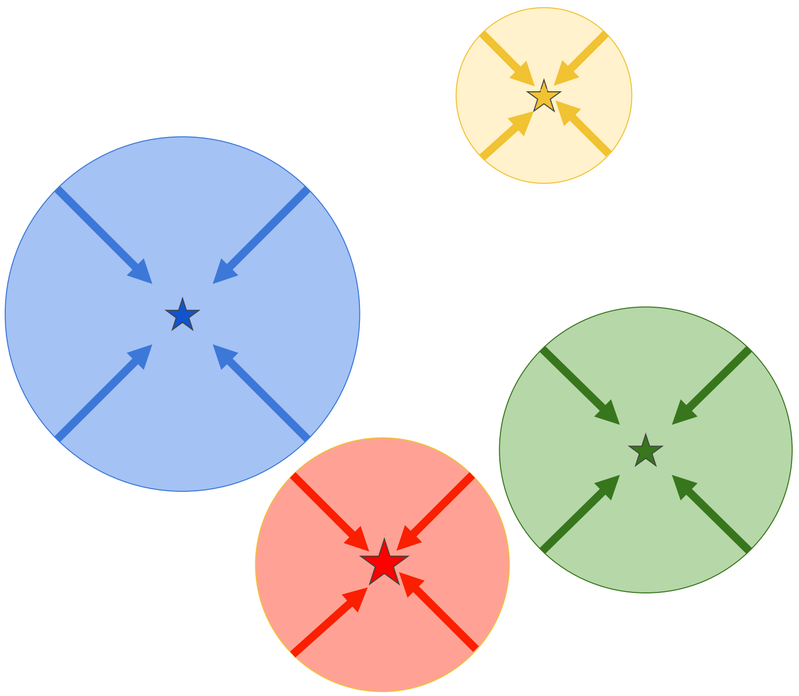

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Global clustering loss

→ Scores based on ***distances*** between samples **features** and **respective class centroids**

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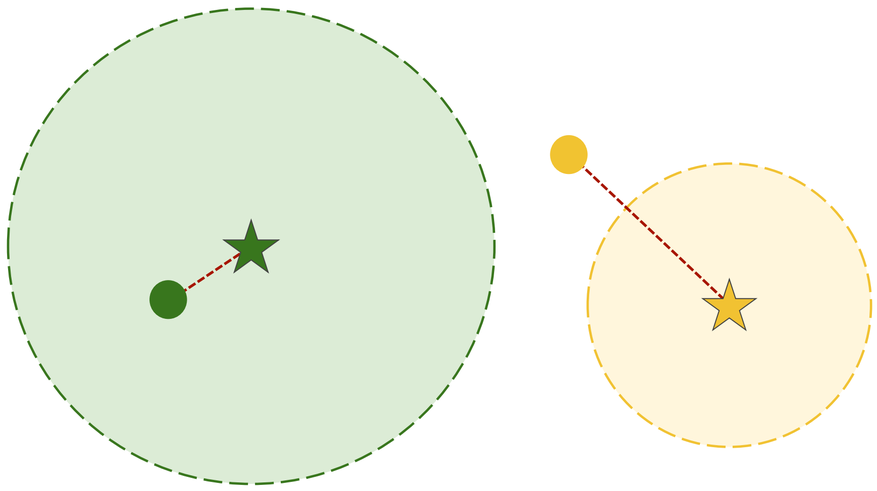

high score
minor update

low score
major update

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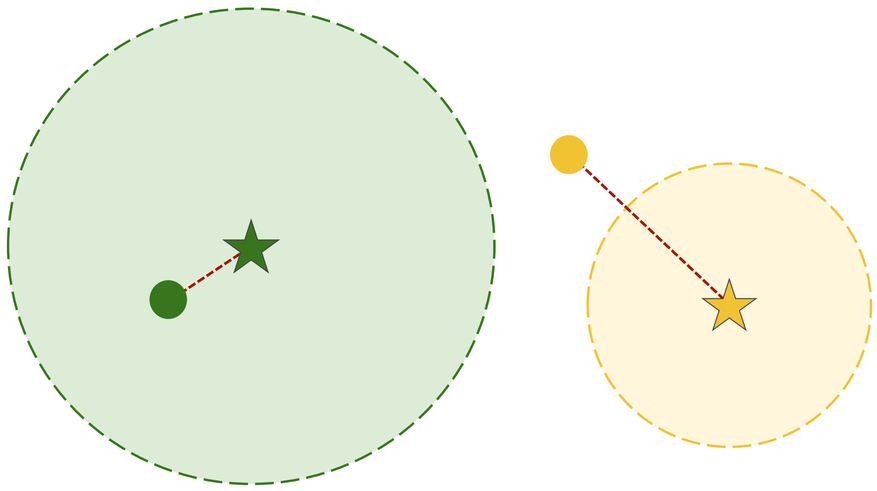
Scores based on ***distances*** between samples **features** and **respective class centroids**

The network learns **to keep representations** of images **as close as possible** to the **centroids** of the **respective class**



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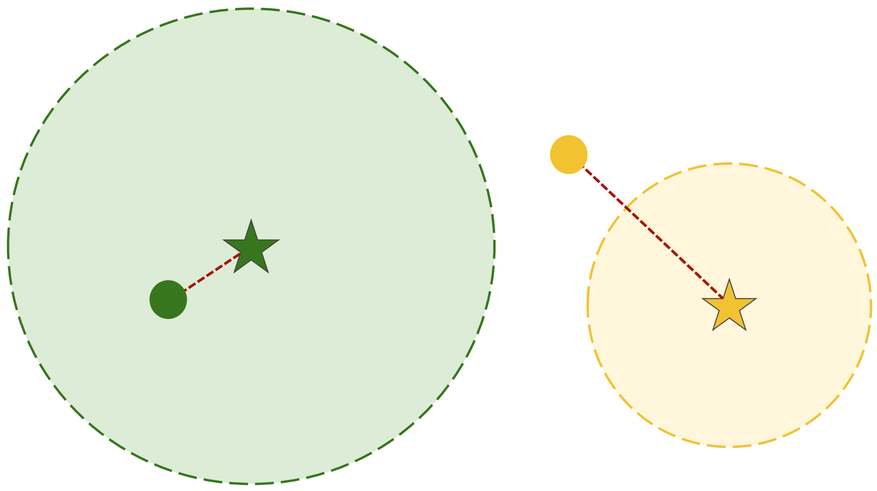
Global clustering loss

Scores based on ***distances*** between samples **features** and **respective class centroids**

Cross entropy loss

The network learns **to keep representations** of images **as close as possible** to the **centroids** of the **respective class**



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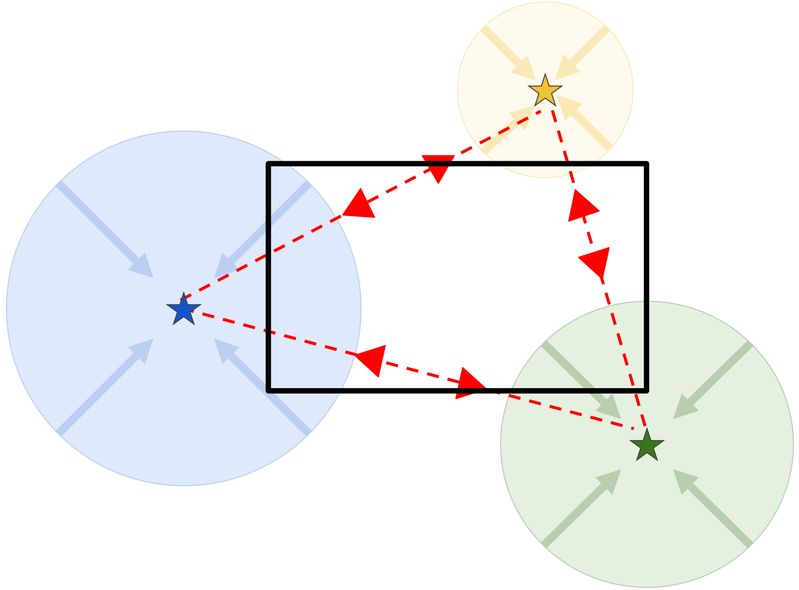
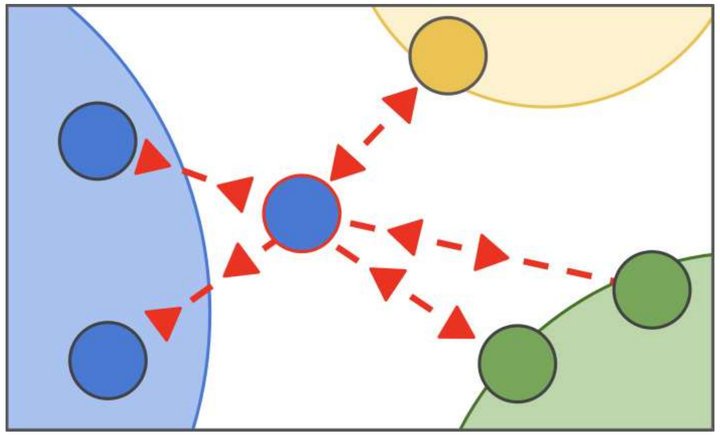
Local clustering loss





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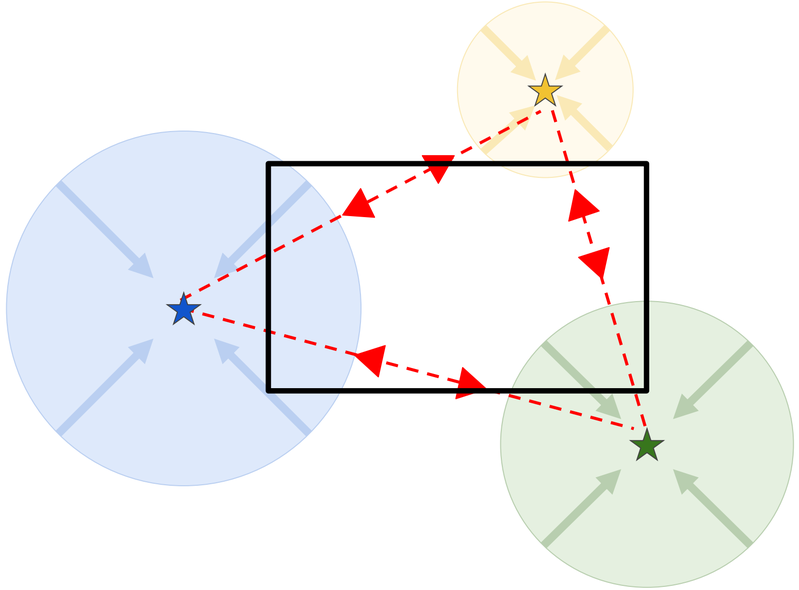
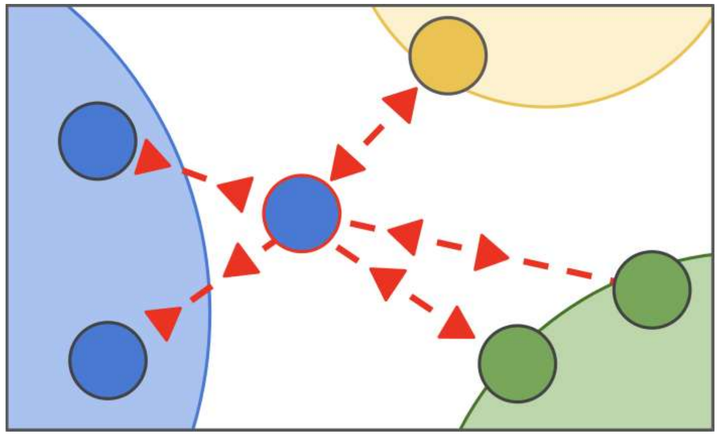
Local clustering loss

Scores based on ***distances*** between **features** of samples of **different classes**





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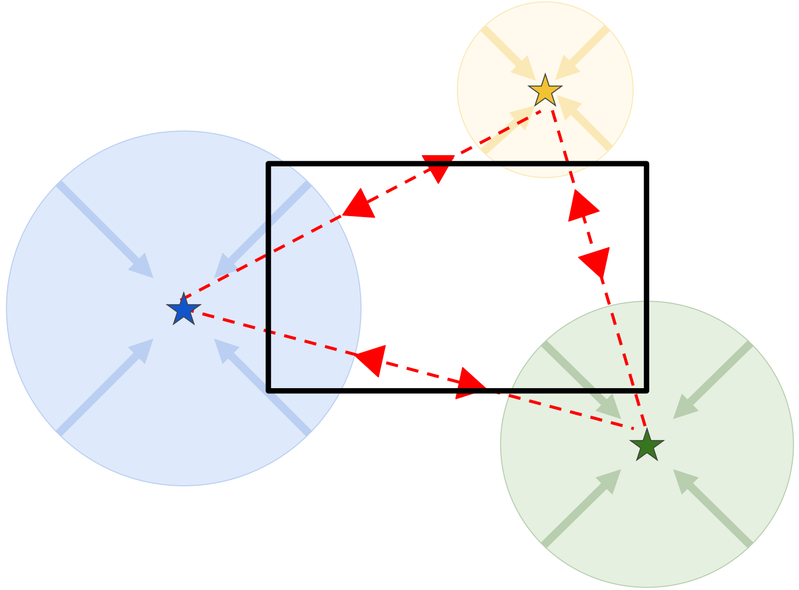
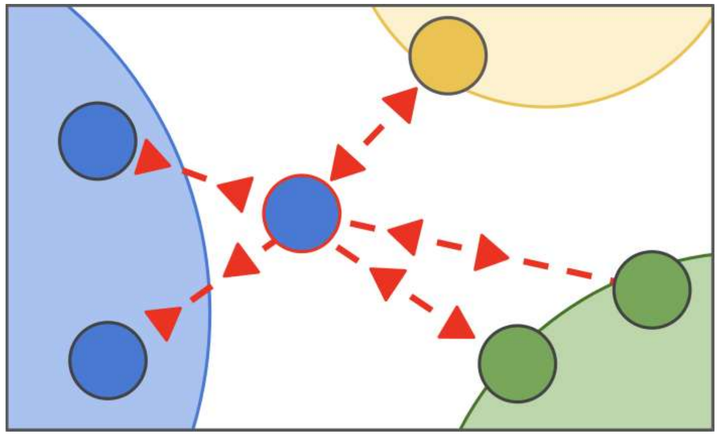


Scores based on ***distances*** between **features** of samples of **different classes**

The network learns to keep samples of the **same class closer**, while **pushing away** samples of **different classes**



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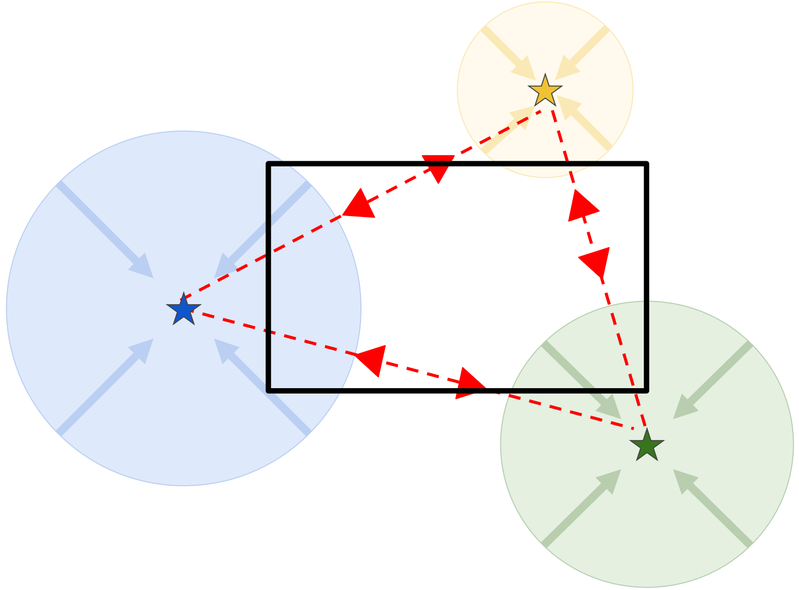
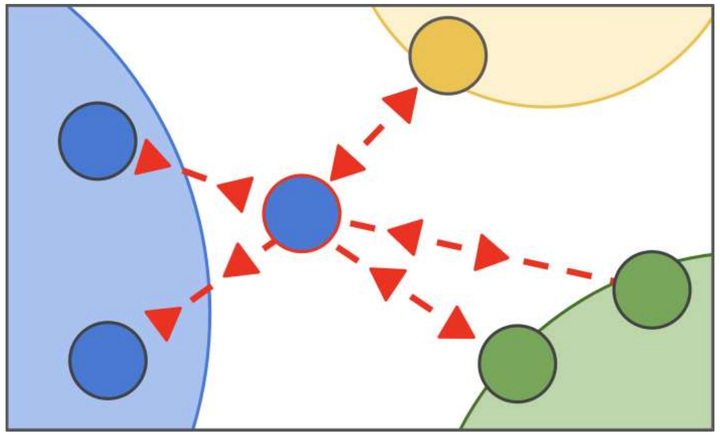
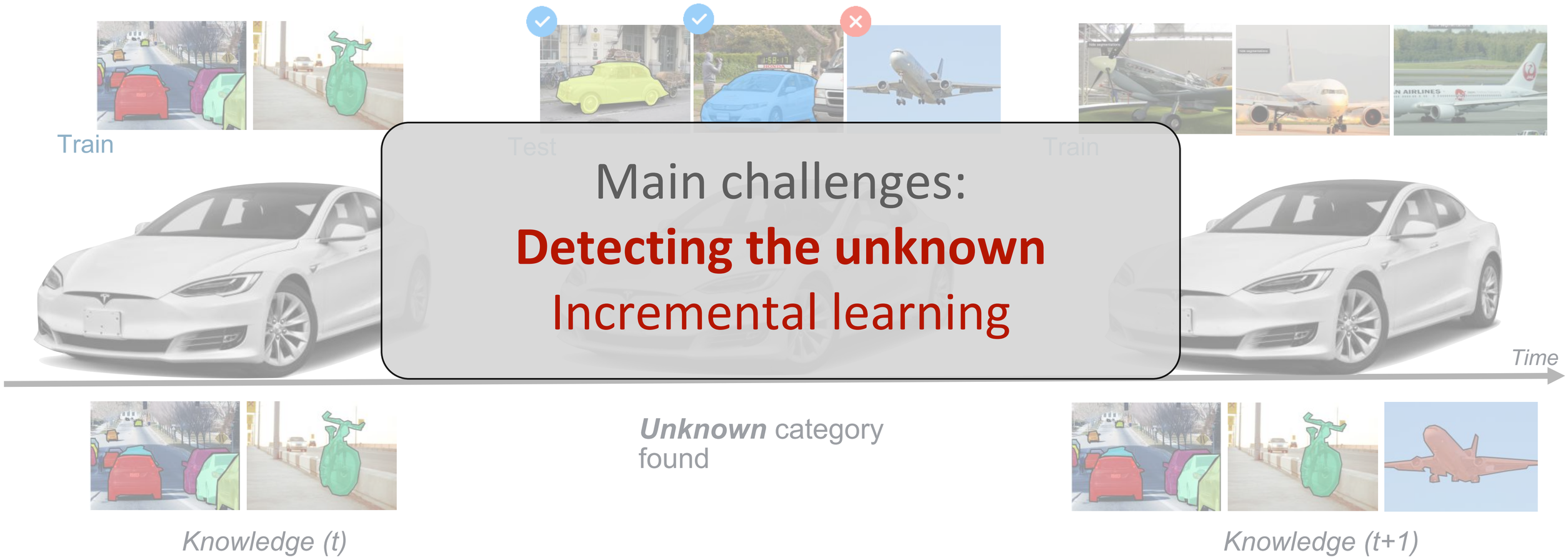




Preliminaries

Open world



Main challenges:

Detecting the unknown

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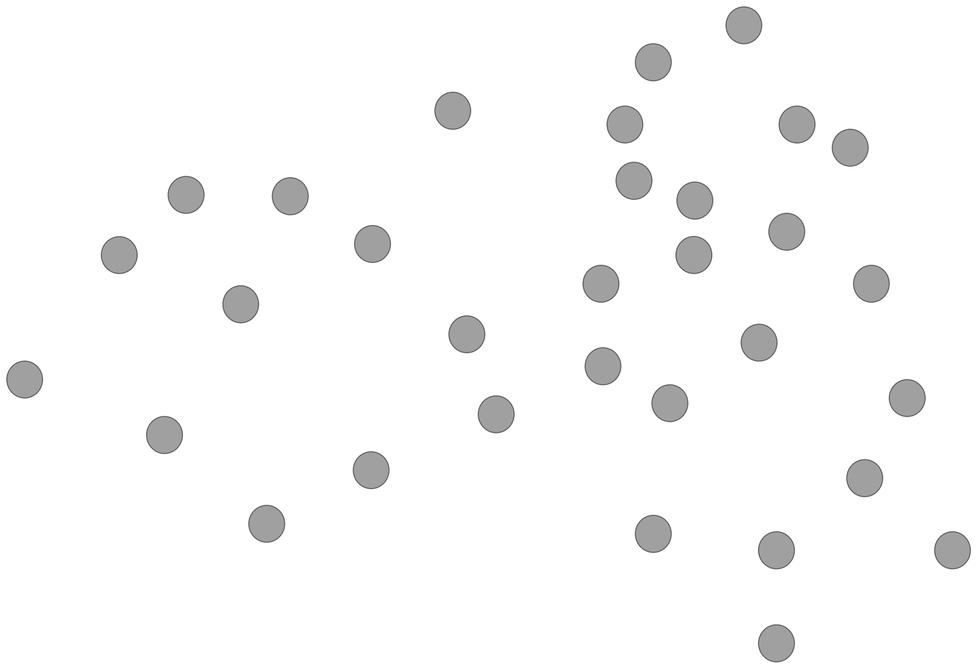
Class-specific rejection thresholds



To exploit the clustered feature space, we introduce class-specific rejection thresholds Δ based on distances, *learned* on an held out set

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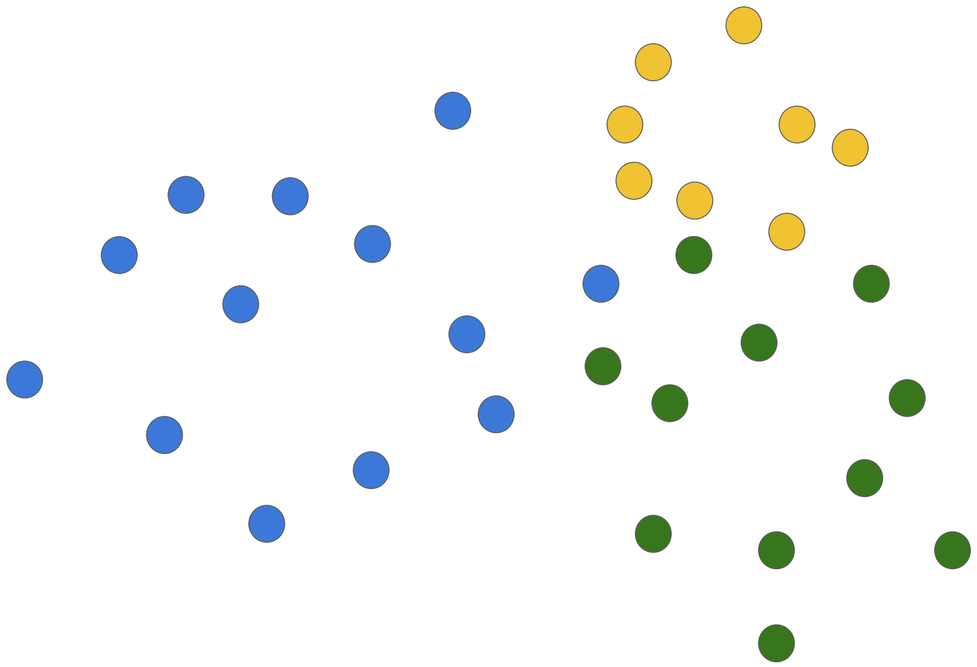

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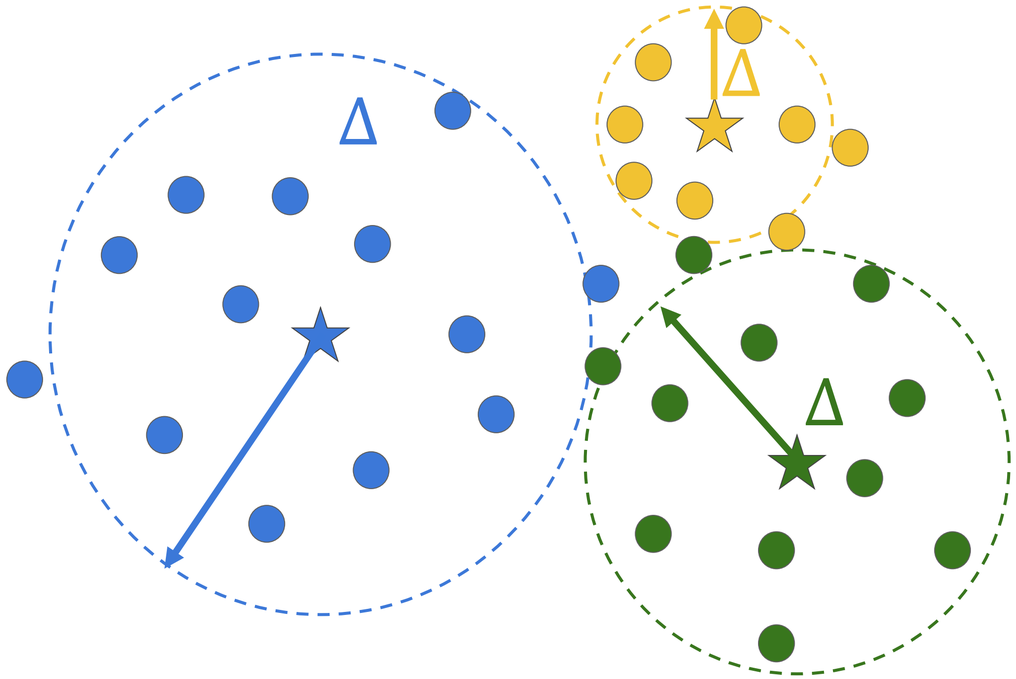

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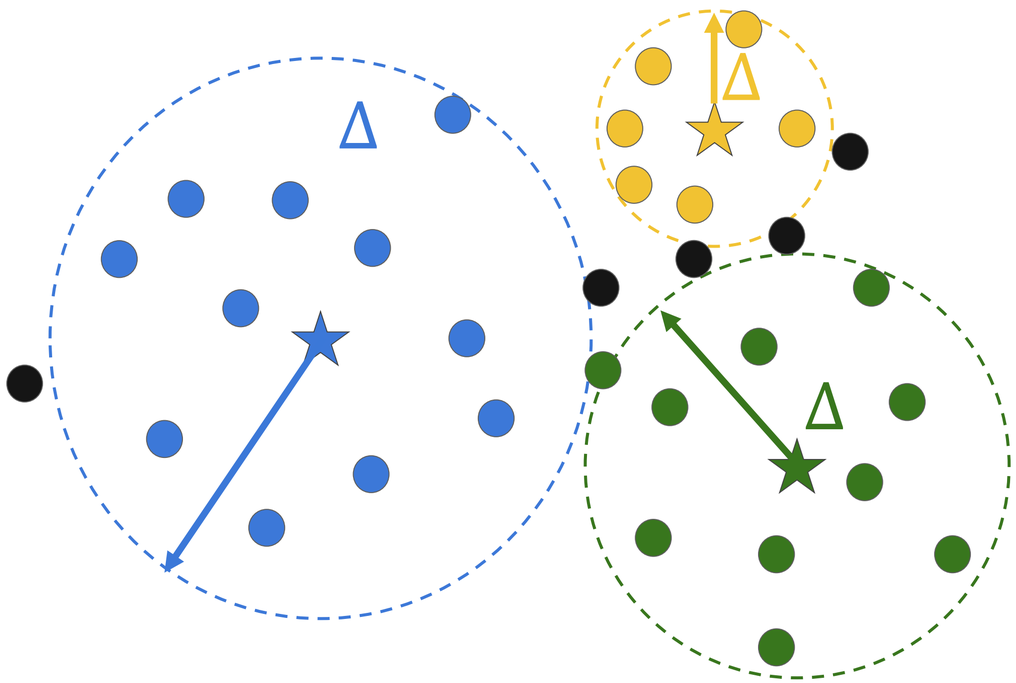

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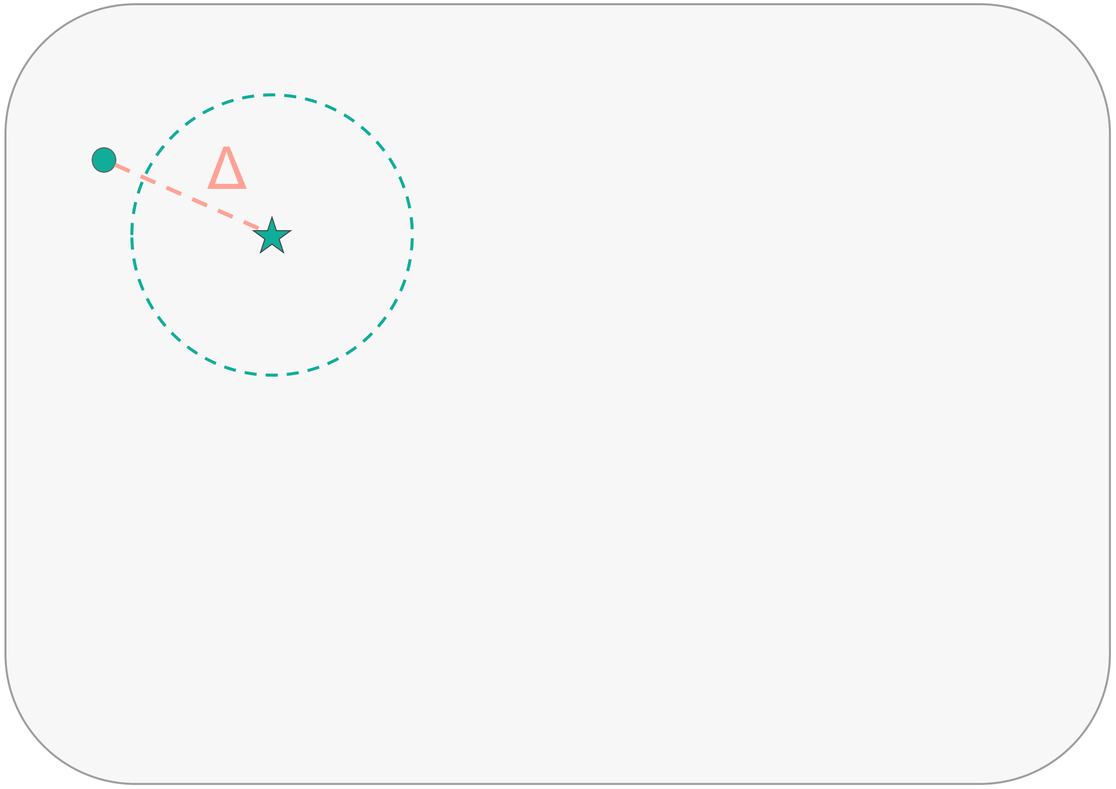

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If the **distance** between a sample of class y and its class centroid is **greater** than Δ_y, the loss **increases** Δ_y.

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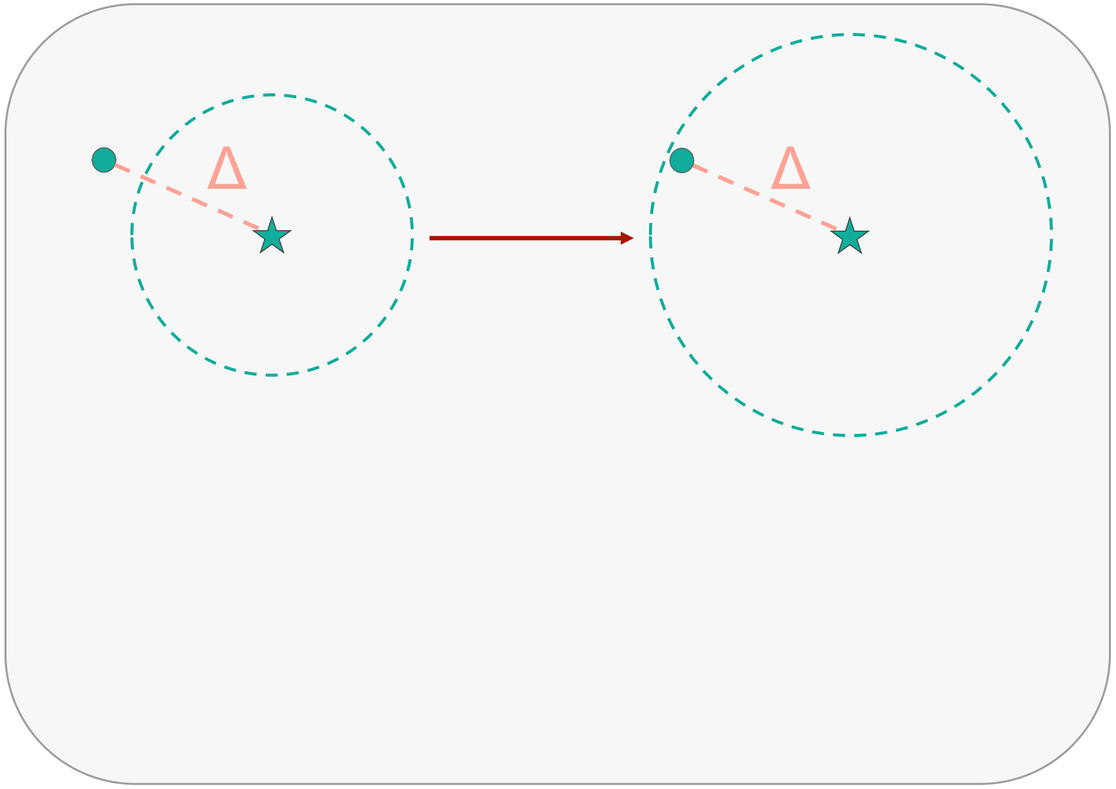

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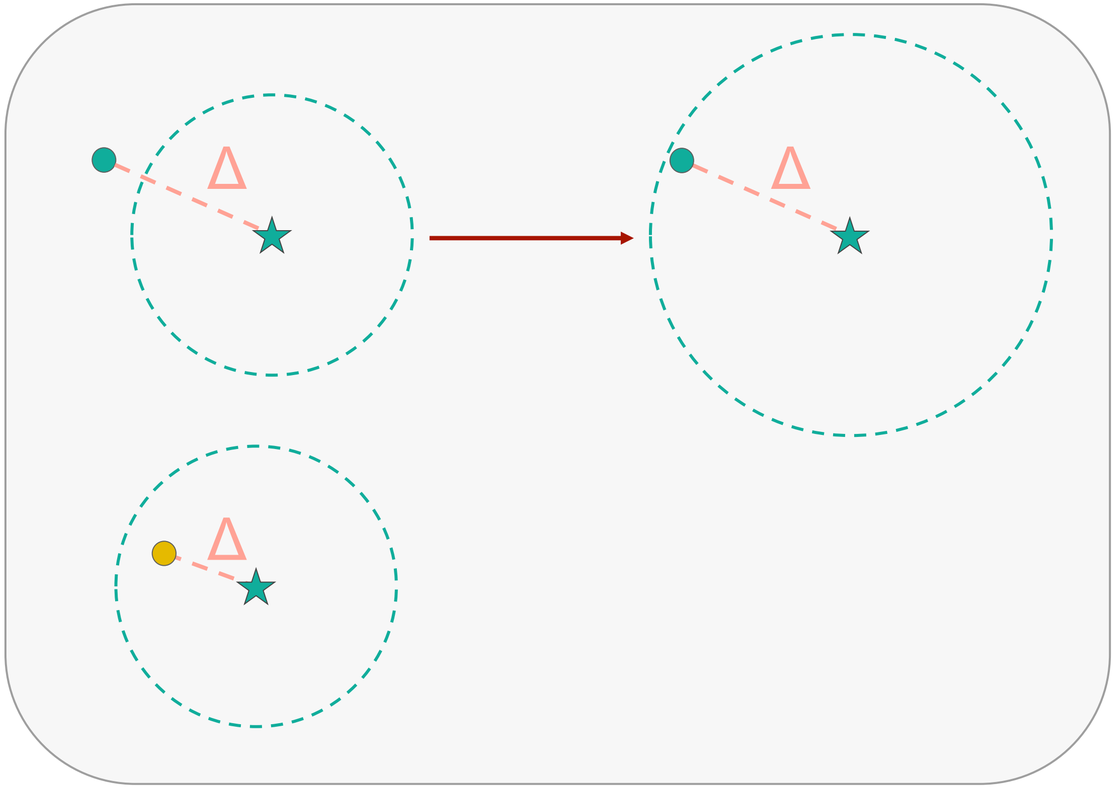

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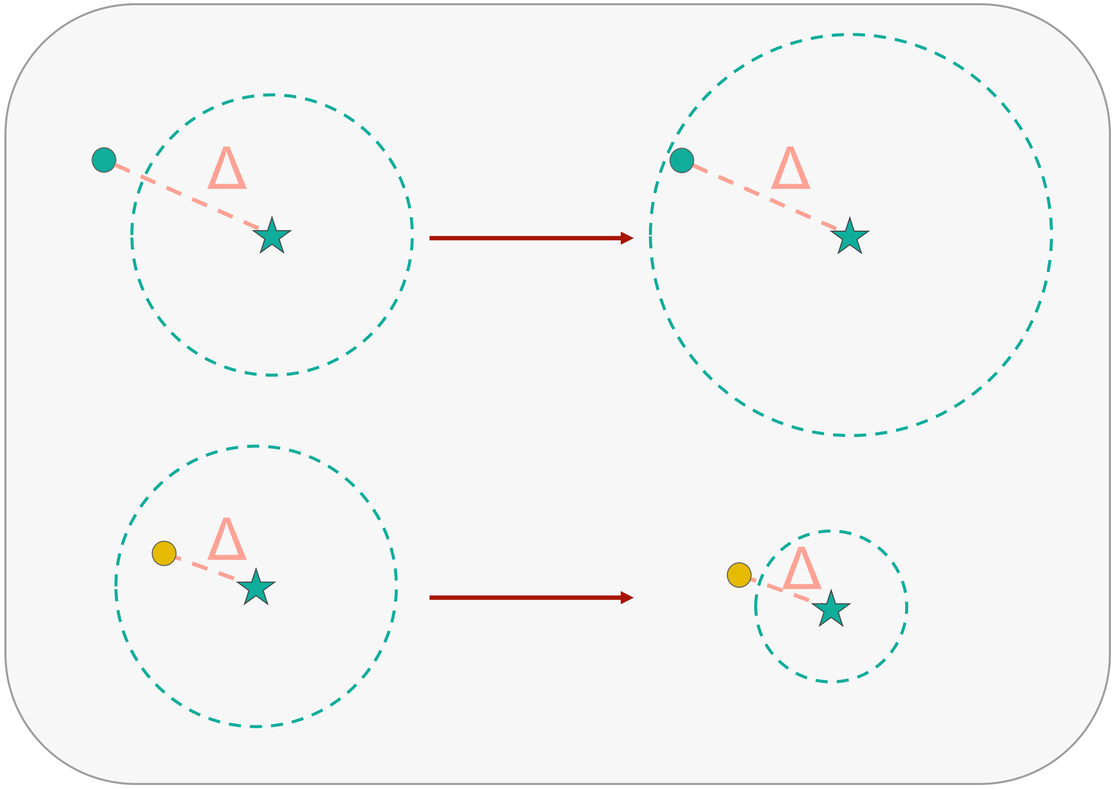

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Experimental settings

Comparisons

Incremental learning methods

- LwF
- iCaRL

Open World Recognition methods

- NNO
- DeepNNO
- B-DOC

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Experimental settings

Without Unknown (no rejection)

Test set does **not** contain **unknown** classes

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Without Unknown (no rejection)

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Without Unknown (with rejection)

Test set does **not** contain **unknown** classes but the model has the possibility to **reject**

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Open World Recognition (Avg)

Average between Without Unknown (**with rejection**) and With Unknown (**with rejection**)

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Test set does **not** contain **unknown** classes but the model has the possibility to **reject**

Open World Recognition (Avg)

Average between Without Unknown (**with rejection**) and With Unknown (**with rejection**)

Open World Recognition (Harm)

Harmonic mean between Without Unknown (**with rejection**) and With Unknown (**with rejection**)

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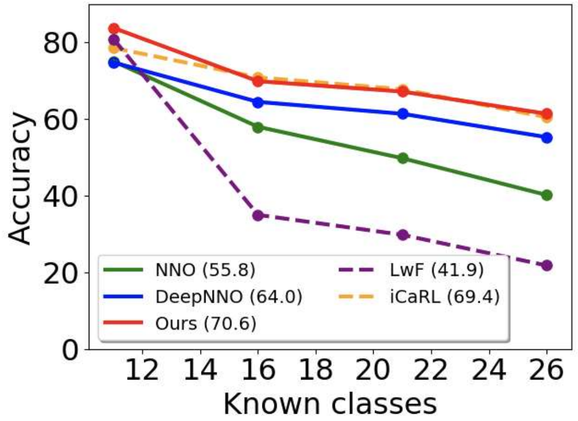
Results

RGB-D Object

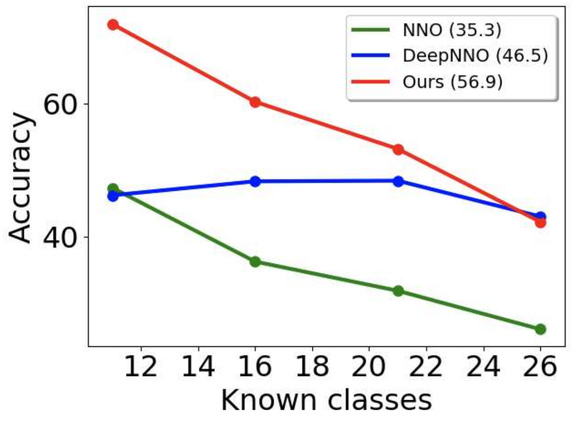
Categories: 26 known + 25 unknown
Incremental steps: 11 first + 5 each

K. Lai, L. Bo, X. Ren, D. Fox,
A large-scale hierarchical multi-view rgb-d object dataset, ICRA-11

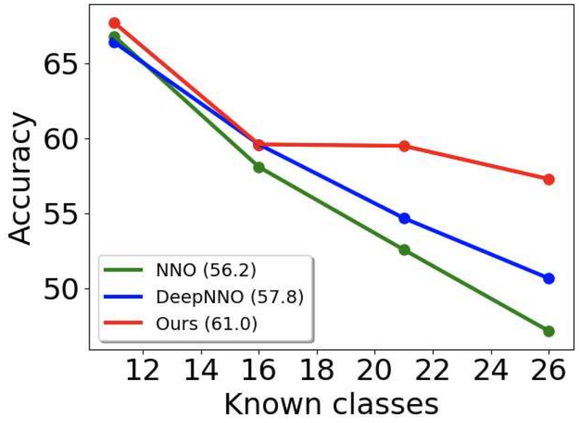
Without Unknown (no rejection)



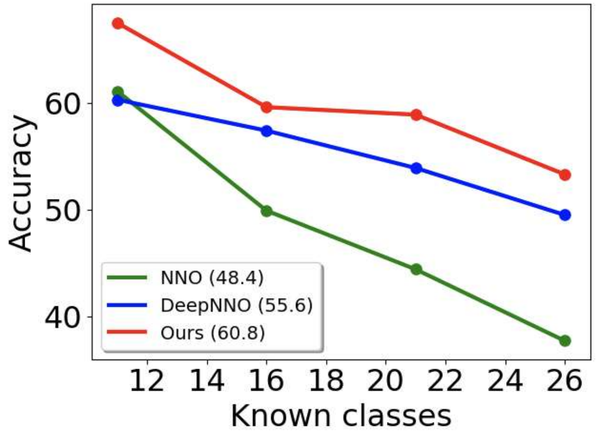
Without Unknown (with rejection)



Open World Recognition (Avg)



Open World Recognition (Harm)



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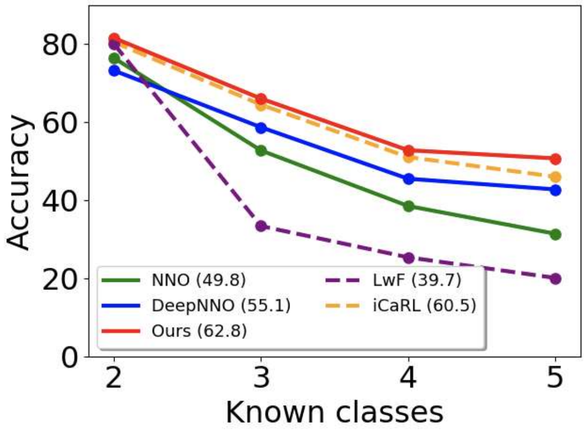
Results

CORE-50

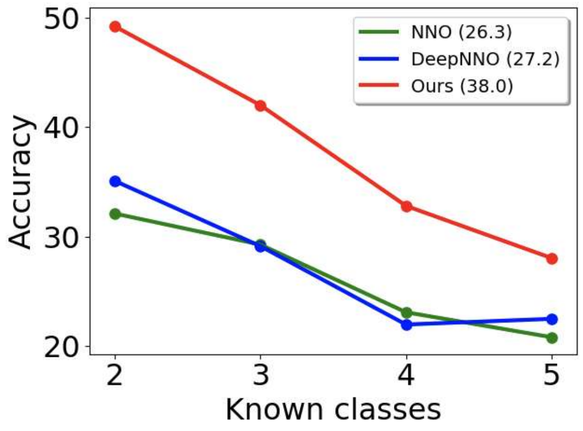
Categories: 5 known + 5 unknown
Incremental steps: 2 first + 1 each

V. Lomonaco and D. Maltoni,
Core50: a new dataset and benchmark for continuous object recognition, CoRL-17

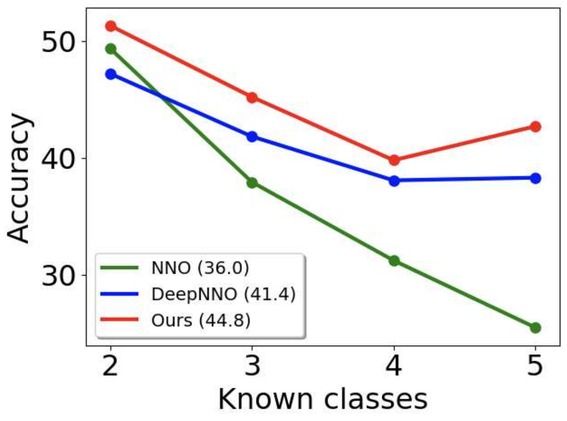
Without Unknown (no rejection)



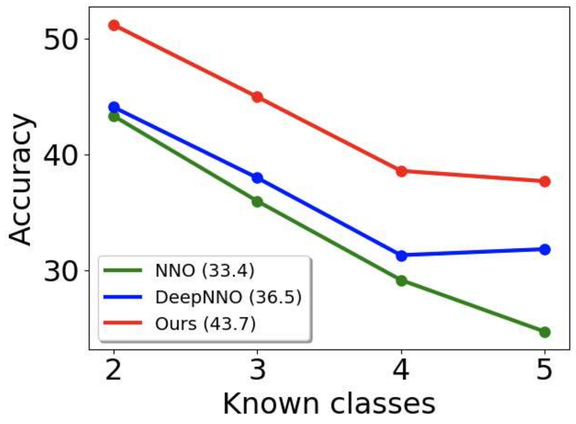
Without Unknown (with rejection)



Open World Recognition (Avg)



Open World Recognition (Harm)



“On the Challenges of Open World Recognition under Shifting Visual Domains”

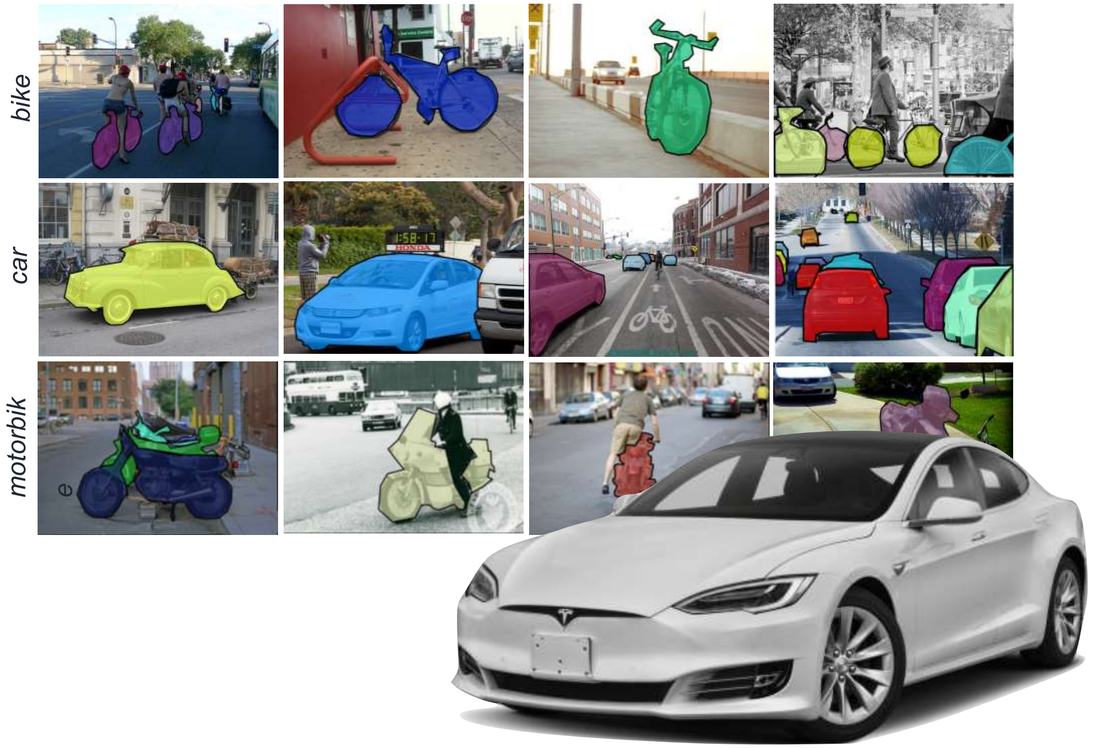
Dario Fontanel, Fabio Cermelli, Massimiliano Mancini, Barbara Caputo

IEEE International Conference on Robotics and Automation (ICRA) 2021, Xi’an, China
IEEE Robotics and Automation Letters 2021

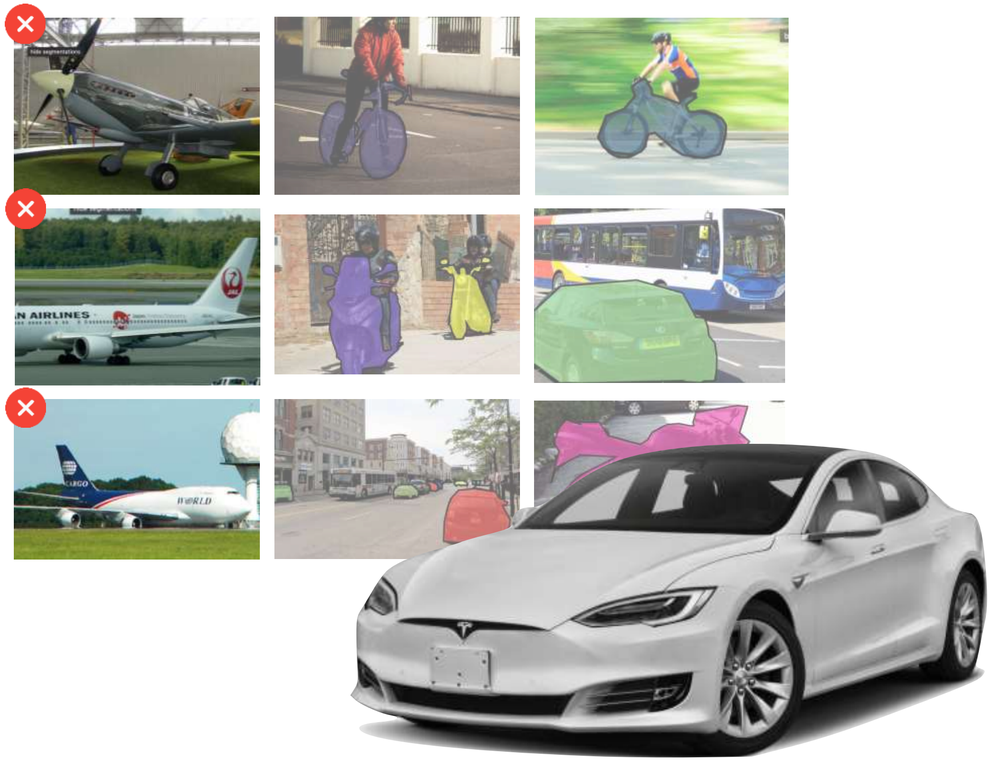
Preliminaries

Closed domain assumption

Training



Deployment



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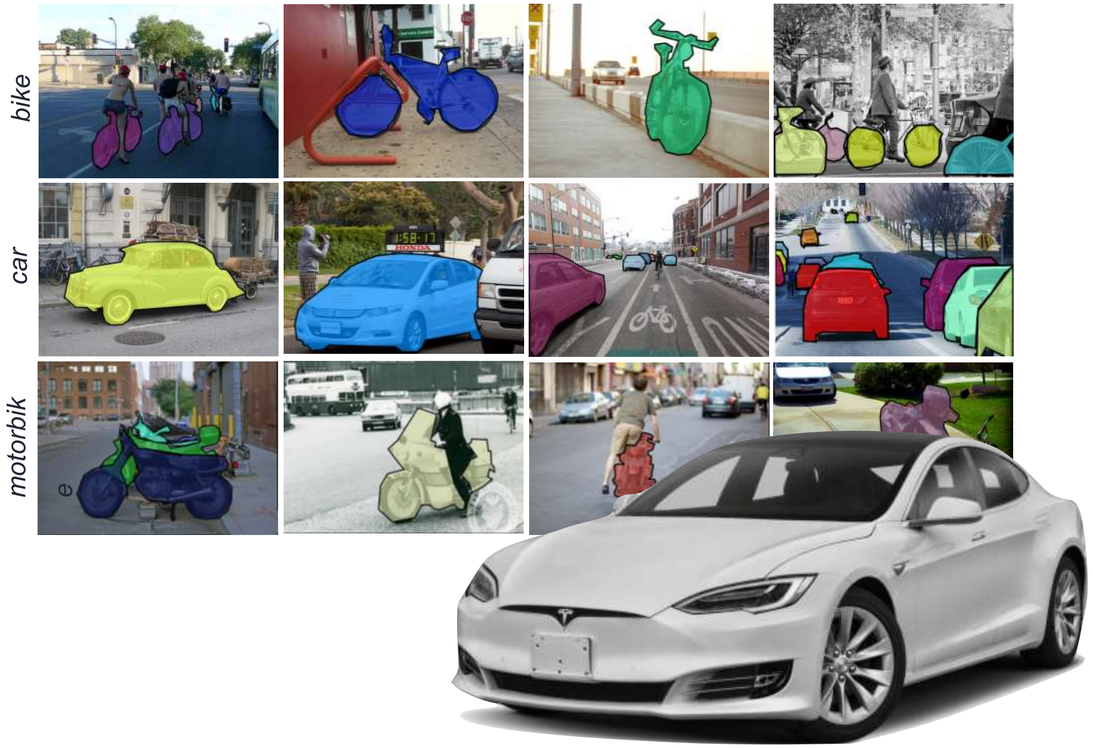

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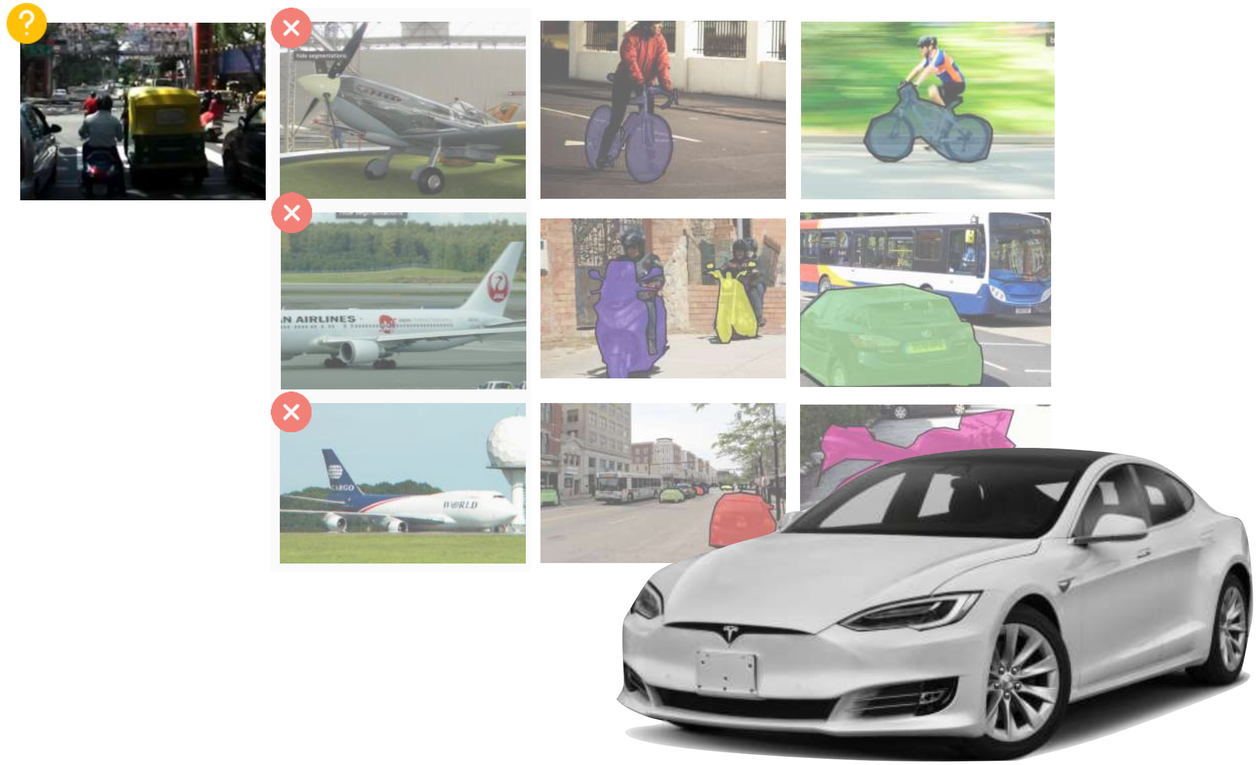

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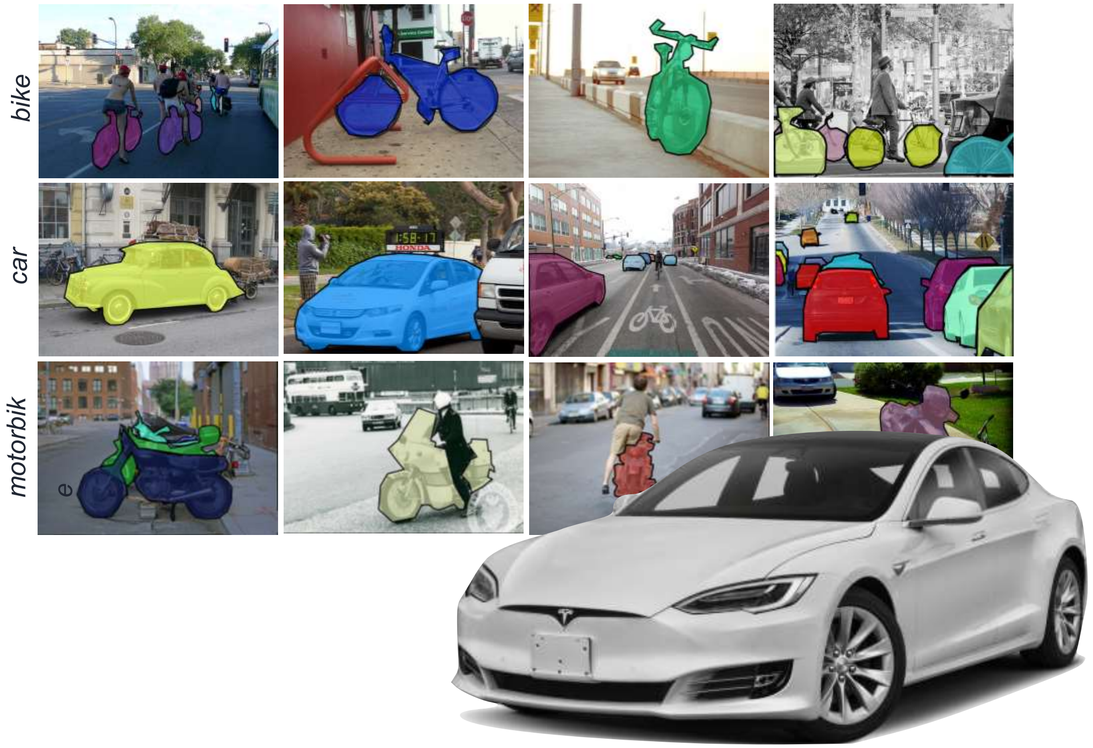

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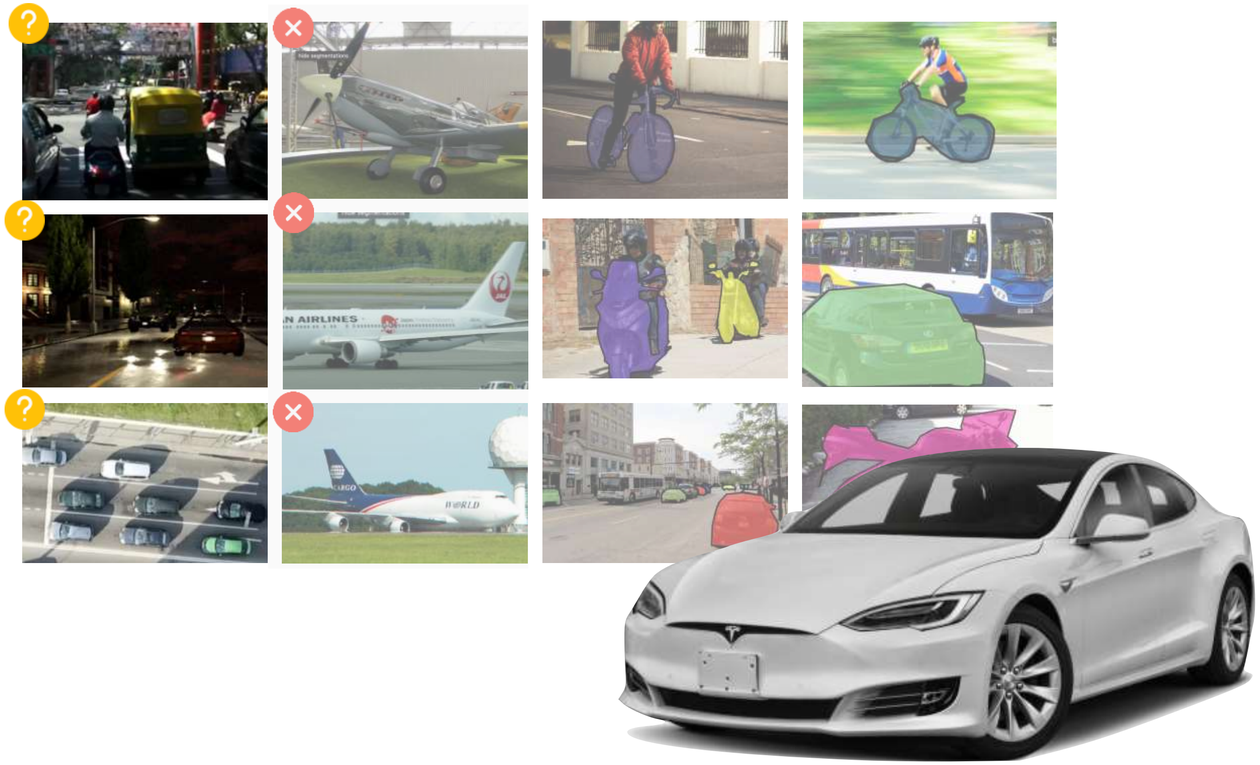

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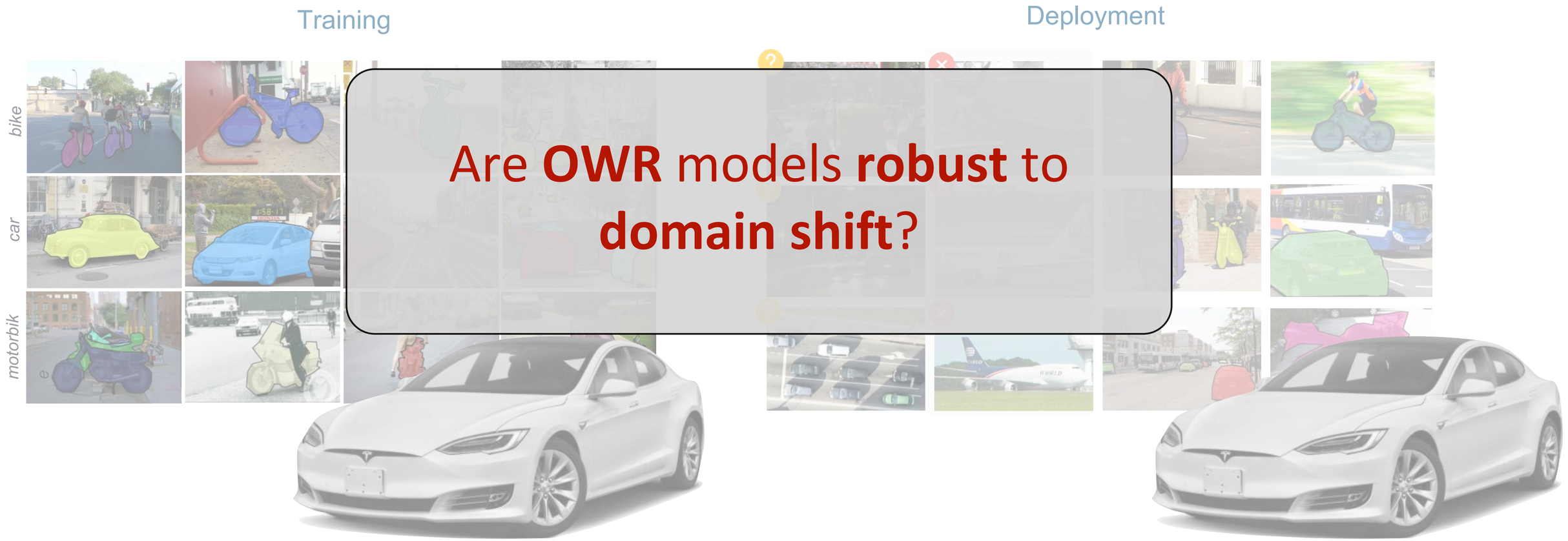

Are **OWR** models **robust** to **domain shift**?

“On the Challenges of Open World Recognition under Shifting Visual Domains”

Dario Fontanel, Fabio Cermelli, Massimiliano Mancini, Barbara Caputo

Benchmark

- ***Three*** *datasets containing the same* ***51 daily-life objects***
- ***Different*** *acquisition* ***conditions***
- ***Standard protocol: 26 (known) + 25 (unknown)***
  11 (initial step) + 5 (each incremental step)

synROD **ROD** **ARID**

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Benchmark

synROD

Synthetic dataset generated utilizing publicly freely available 3D models.

Reproduction of realistic lighting.

Unsupervised Domain Adaptation through Inter-modal Rotation for RGB-D Object Recognition,
Loghmani Mohammad Reza, Robbiano Luca, Planamente Mirco, Park Kiru, Caputo Barbara and Vincze Markus, RAL 20

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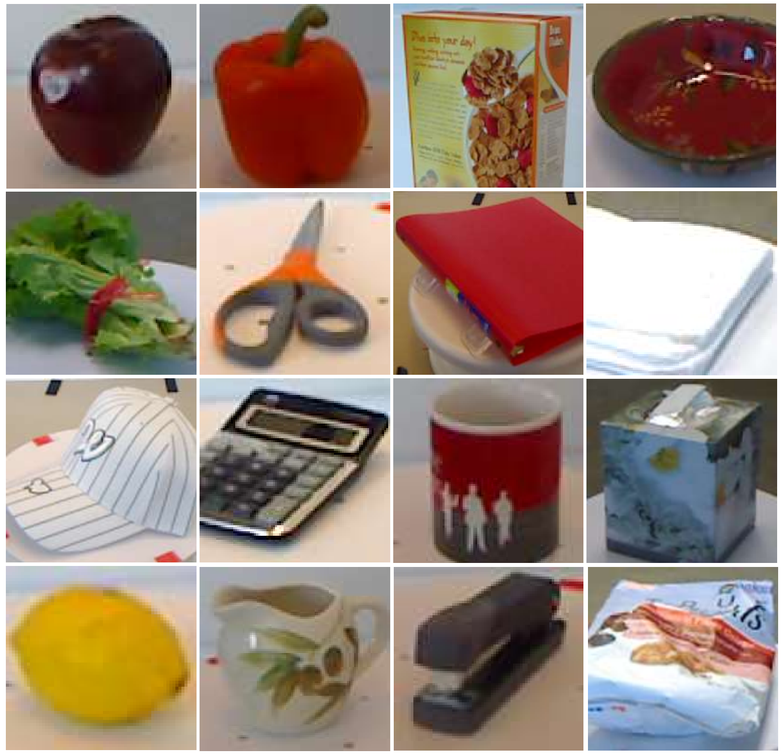
Benchmark

ROD

Objects captured in a controlled scenario.

No clutter or changes in illumination or background, only varying camera angles.



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Benchmark

ARID

More challenging environment with objects depicted against various backgrounds, scales, views, lighting, and occlusions.

Recognizing Objects In-the-wild: Where Do We Stand?, Loghmani Mohammad Reza, Caputo Barbara and Vincze Markus, ICRA 18

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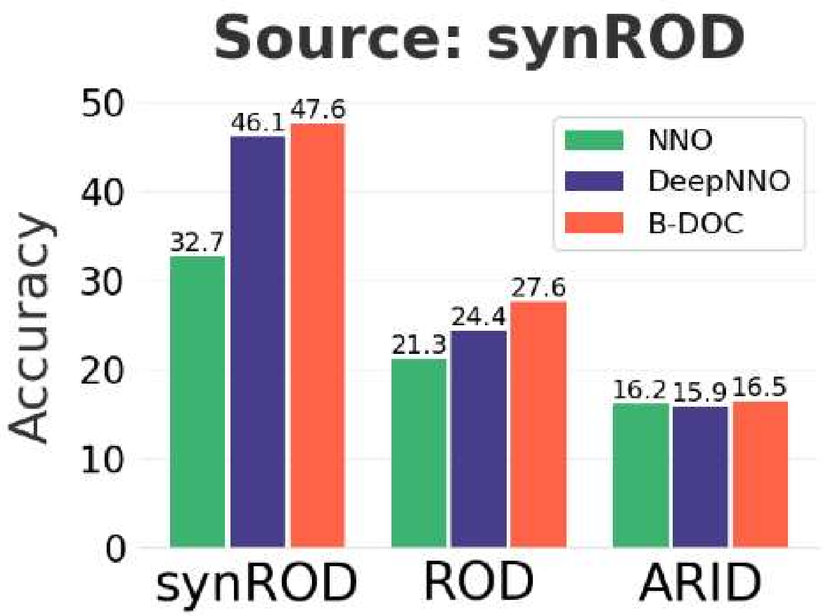
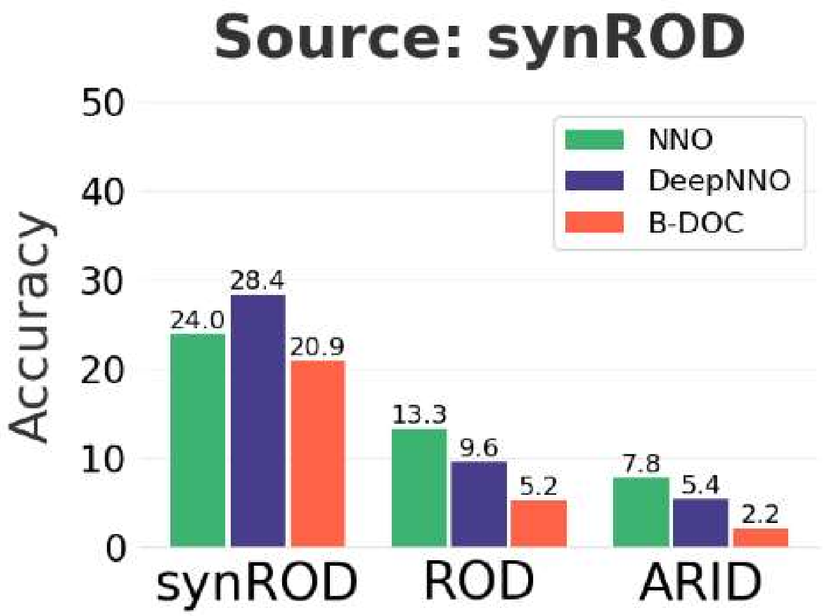
Are OWR models Robust to Domain Shift?

Synthetic-to-Real



Without Unknown (no rejection)



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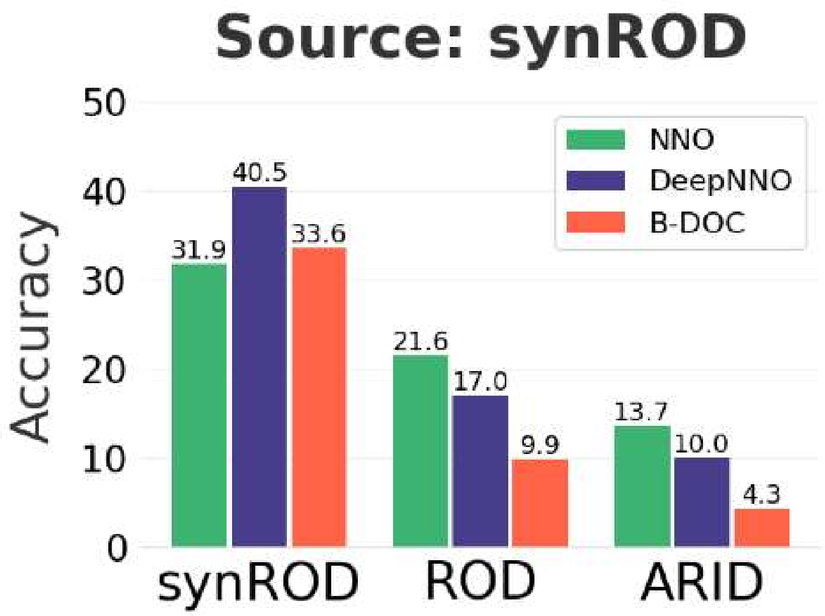

Open World Recognition (Harm)

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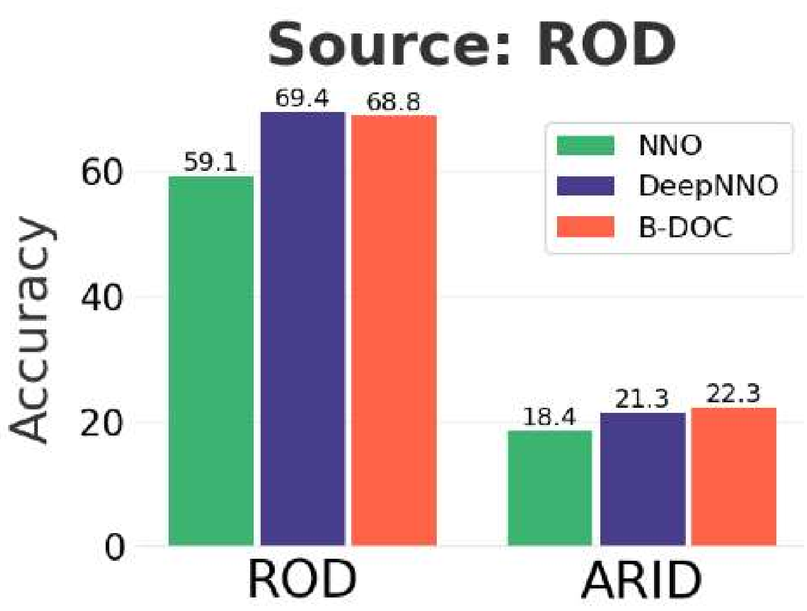
Constrained-to-Unconstrained



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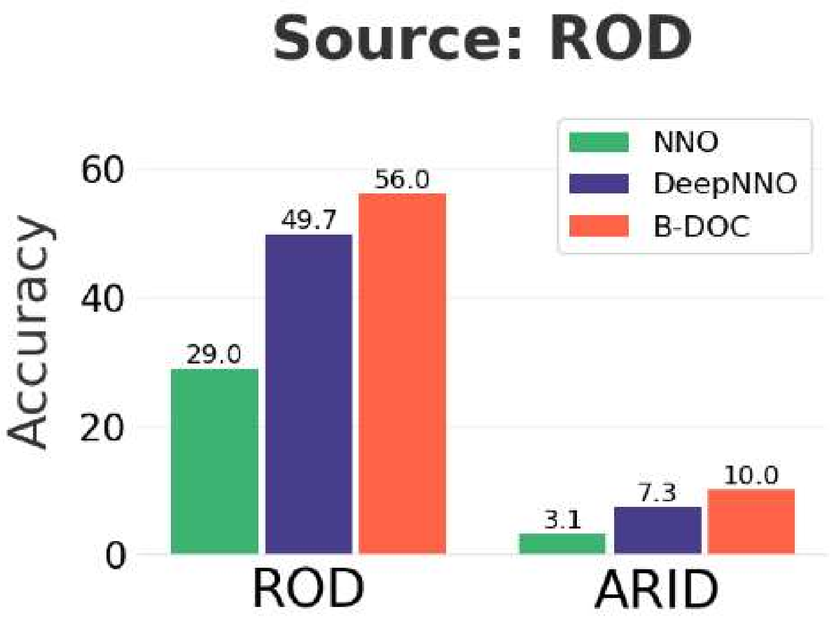

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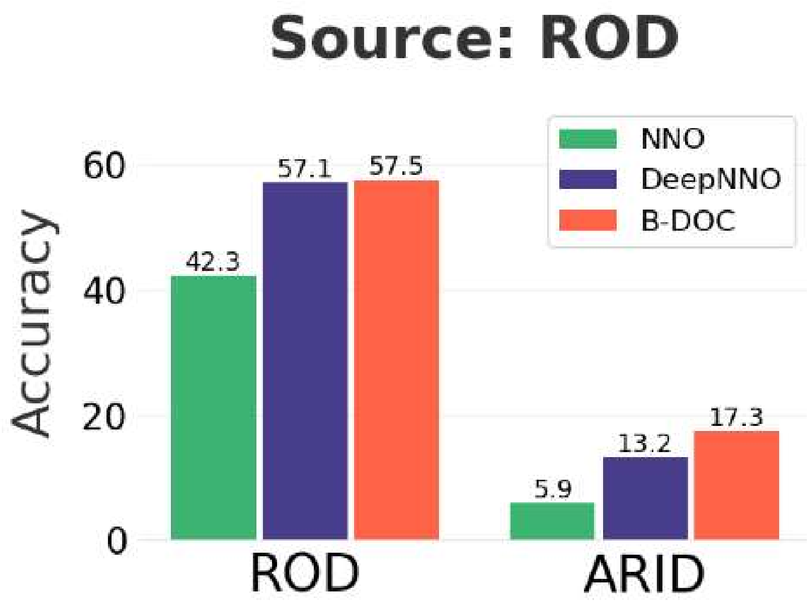
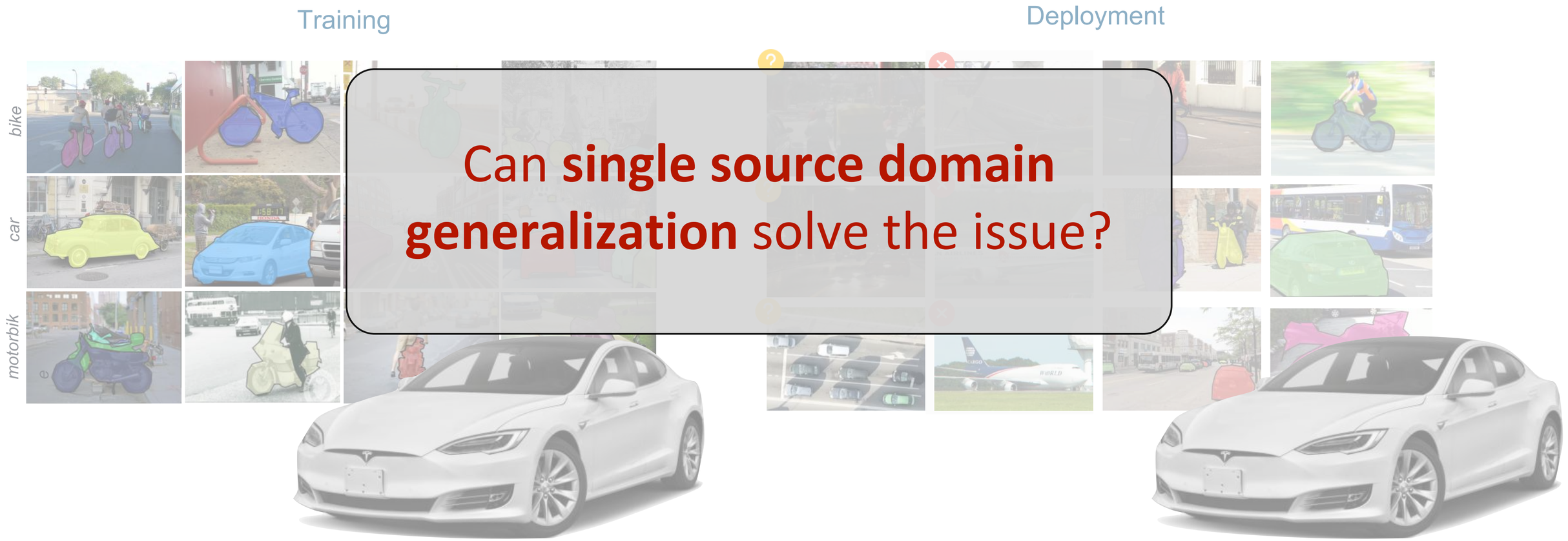


Open World Recognition (Harm)

Preliminaries

Closed domain assumption



Can **single source domain generalization** solve the issue?

Preliminaries

Single source domain generalization

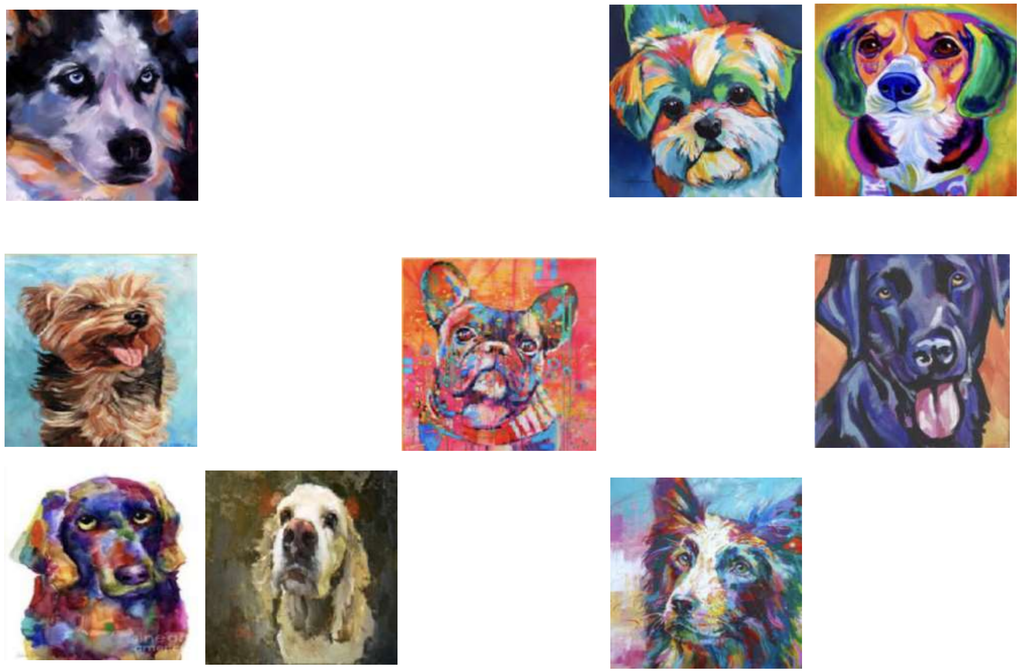
Source domain

Preliminaries

Single source domain generalization

Source domain

Target domain

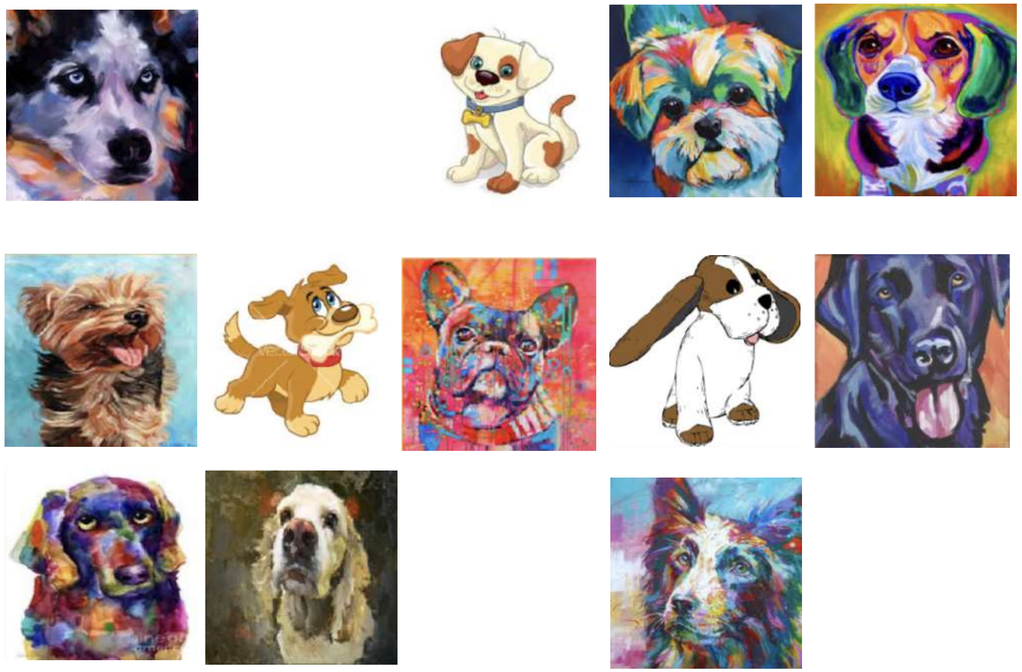


Preliminaries

Single source domain generalization

Source domain

Target domain s

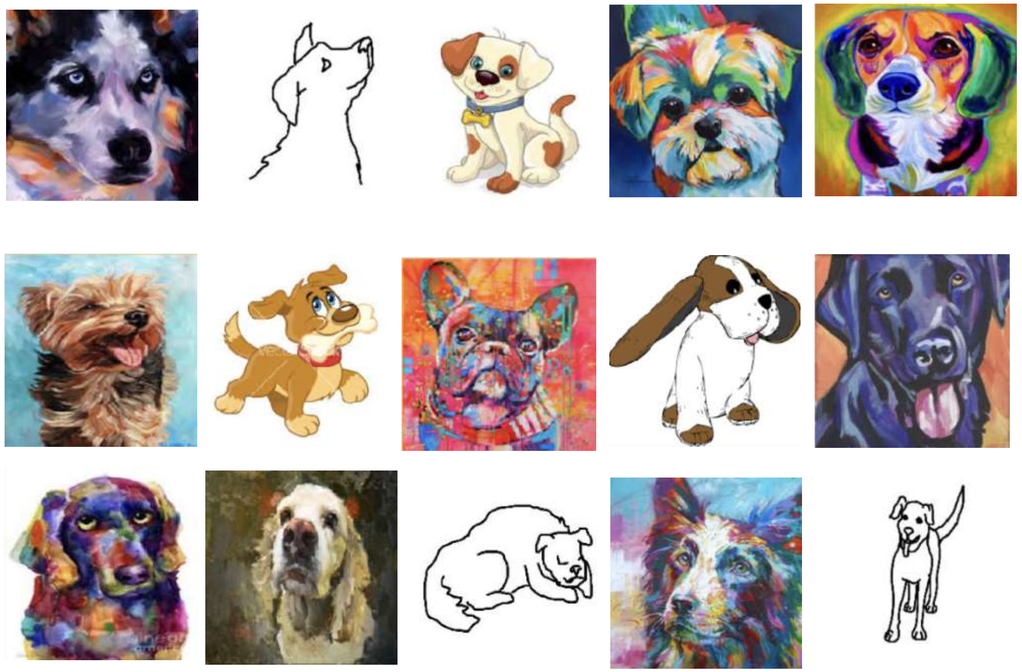


Preliminaries

Single source domain generalization

Source domain

Target domains



“On the Challenges of Open World Recognition under Shifting Visual Domains”

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Benchmark

Data augmentation with transformation sets (RSDA)

An evolutionary-based algorithm select the set of transformations that results in the worst model performance and randomly applies a subset of them.

Visual content taken from *Volpi, R., & Murino, V.. Addressing model vulnerability to distributional shifts over image transformation sets. (ICCV 19)*

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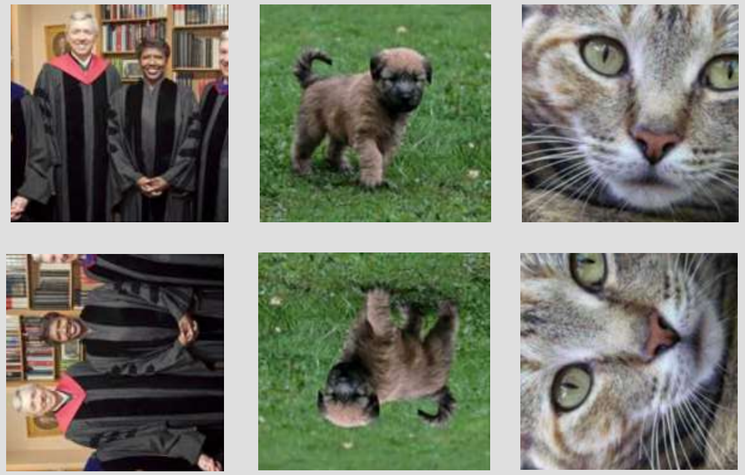
Self-supervised learning with relative rotations (RR)

By employing an auxiliary self-supervised task, the model concentrates on discriminative invariances and regularities, enhancing generalization to new domains



Visual content taken from *Gidaris, S., Singh, P., & Komodakis, N.. Unsupervised representation learning by predicting image rotations. (ICLR18)*

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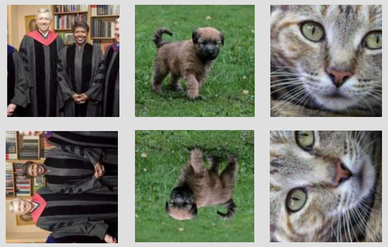
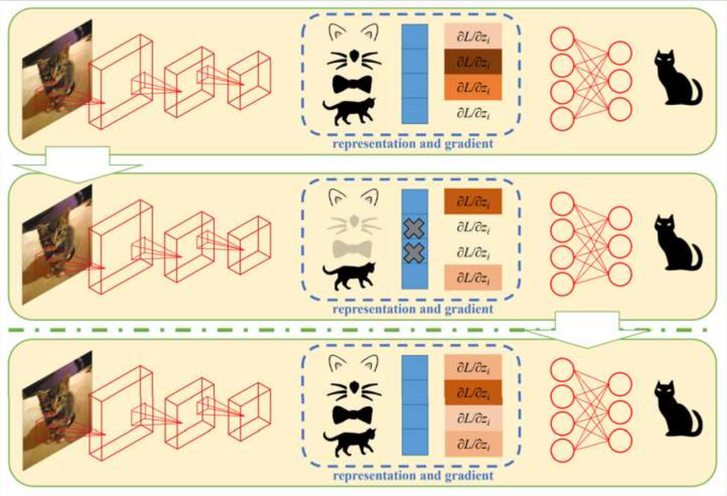


Regularization through self-challenging (SC)

The model learns to classify features that have been corrupted by removing the elements that mostly contributed to a correct classification of the corresponding sample



Visual content taken from Huang, Z., Wang, H., Xing, E. P., & Huang, D. Self-Challenging Improves Cross-Domain Generalization. (ECCV20)

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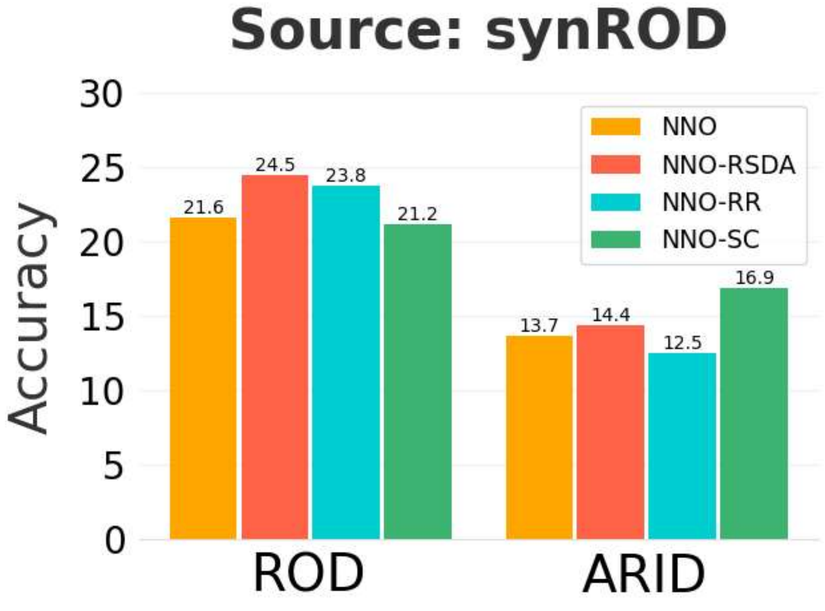
Can DG methods address the problem?

Synthetic-to-Real



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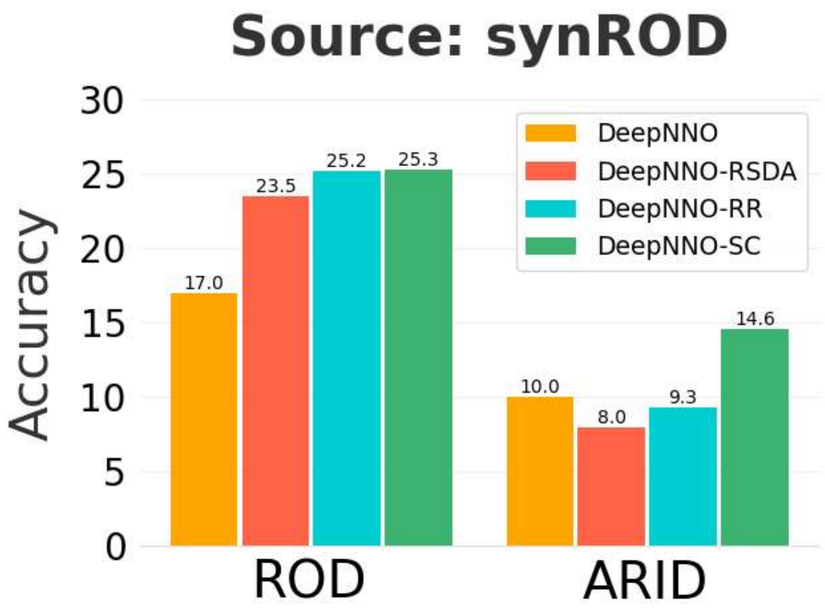

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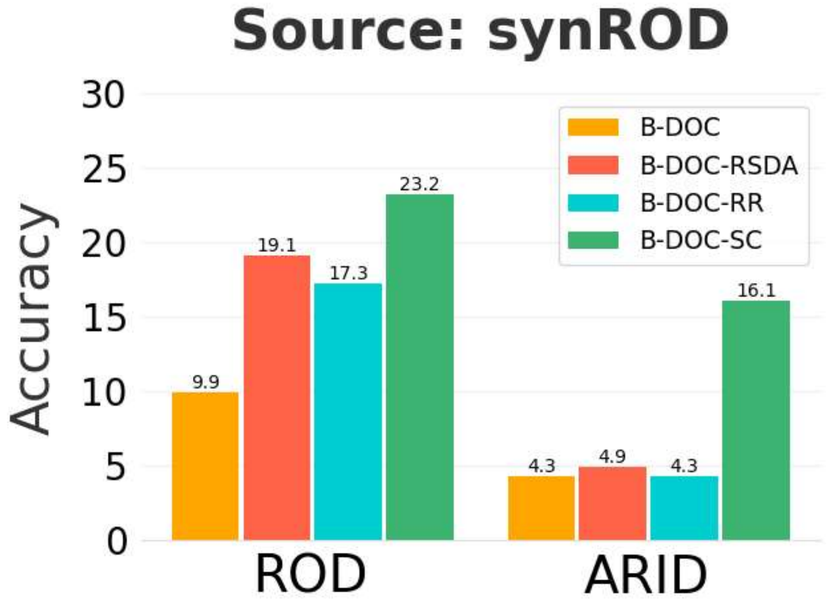

Open World Recognition (Harm)

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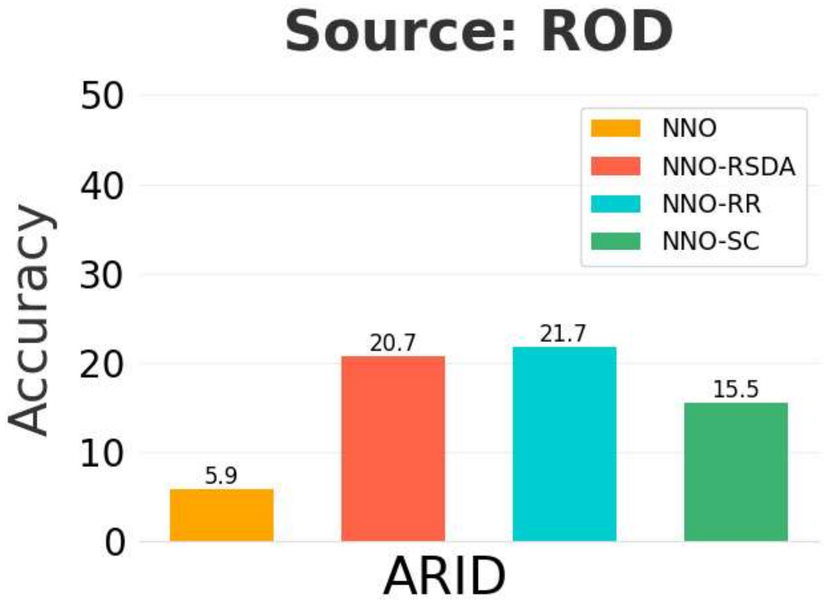

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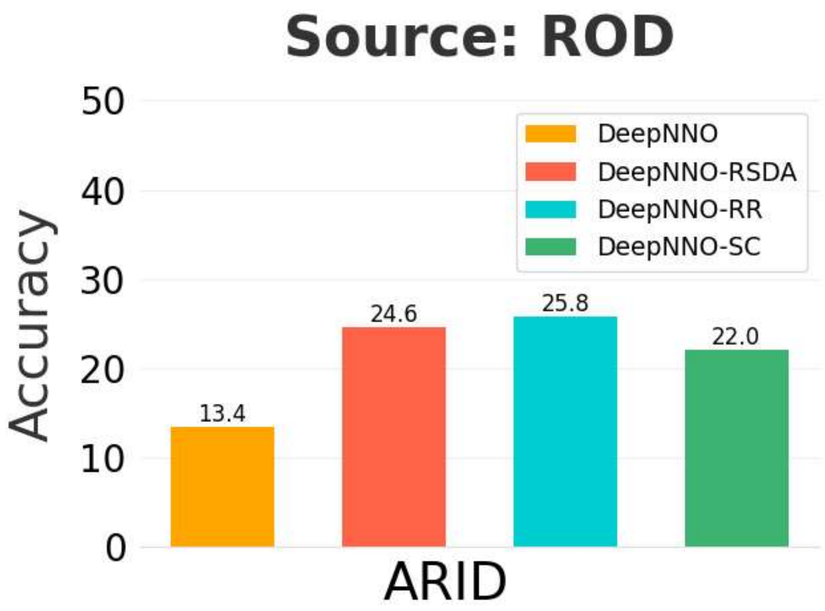

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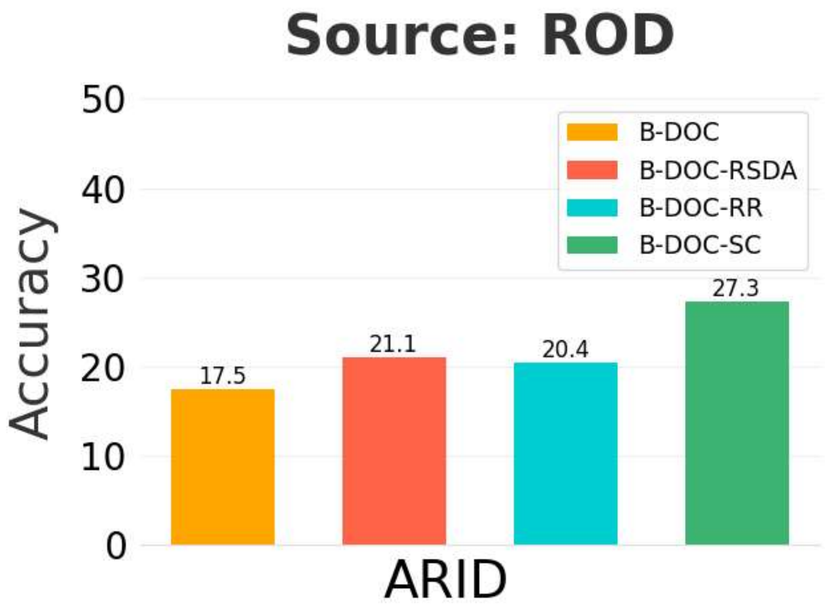

Open World Recognition (Harm)

Conclusion

Recognizing New Visual Categories in Real Open World Environments

Detection of the unknown

We introduced PAnS that learns class-specific prototypes overcoming the limitations of the softmax operation in anomaly segmentation.

Incremental learning

We introduced WILSON that learns to generate pseudo labels to train a segmentation network from image level labels only, reducing annotation costs.

Unified framework

We introduced B-DOC that adopts a global-to-clustering training loss objective, and a learnable rejection threshold per each class.

Impact of domain shift

We introduced the first benchmark to assess OWR methods under shifting visual domains and laid the foundations for further research.

Future works

Recognizing New Visual Categories in Real Open World Environments

Open World Recognition methods

OWR approaches need to collect and label a new set of images every time a new class is discovered, usually involving a human in the loop.

Future works

Recognizing New Visual Categories in Real Open World Environments

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OWR approaches need to collect and label a new set of images every time a new class is discovered, usually involving a human in the loop.

- *Adopt an active learning pipeline to identify the most meaningful data to be labelled*

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Recognizing New Visual Categories in Real Open World Environments

Open World Recognition methods

OWR approaches need to collect and label a new set of images every time a new class is discovered, usually involving a human in the loop.

- *Adopt an active learning pipeline to identify the most meaningful data to be labelled*
- *Investigate how to generate pseudo-labels to avoid the labelling process*

Future works

Recognizing New Visual Categories in Real Open World Environments

Open World Recognition methods

OWR approaches need to collect and label a new set of images every time a new class is discovered, usually involving a human in the loop.

- *Adopt an active learning pipeline to identify the most meaningful data to be labelled*
- *Investigate how to generate pseudo-labels to avoid the labelling process*
- *Adopt a few shot approach that requires limited amounts of labelled data*

Politecnico di Torino

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European Laboratory for Learning and Intelligent Systems

Thank you for the attention!