Leveraging Synthetic Data for Mobile Object Detection

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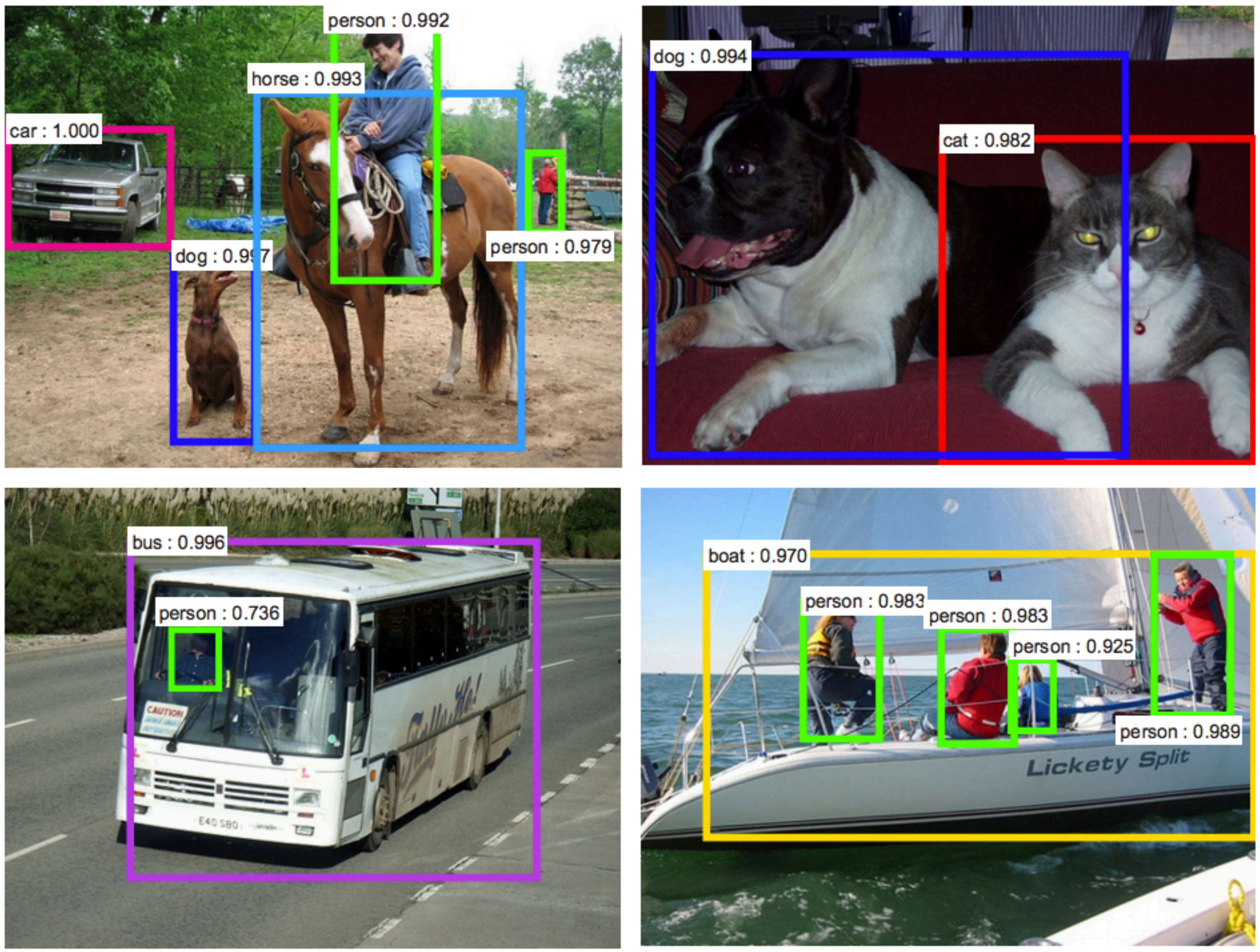
EPFL

EPFL

when labeled data is available



Object Detectors: <u>Faster RCNN</u> <u>Yolo</u>

when labeled data is available

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Datasets	Examples/class	mAP (Faster RCNN)
MS-COCO 80 classes	10k	42.7
Pascal-VOC 20 classes	500	78.8

when labeled data is available

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MS-COCO 80 classes	10k	42.7
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Cons:

1. **Annotation Cost**
2. **Hard to find annotations for eg: Medical data**

when few labeled data is available

Object Detectors: Faster RCNN Yolo

Datasets	Examples/ class	mAP (Faster RCNN)	mAP*** (Faster RCNN) ~10 examples/ class
MS-COCO 80 classes	10k	42.7	**4.9**
Pascal-VOC 20 classes	500	78.8	**29**

***Meta R-CNN : Towards General Solver for Instance-level Few-shot Learning CVPR, 2020

when no-real labeled data is available

Leveraging BIM - the digital twin

Synthetic Images

when no-real labeled data is available

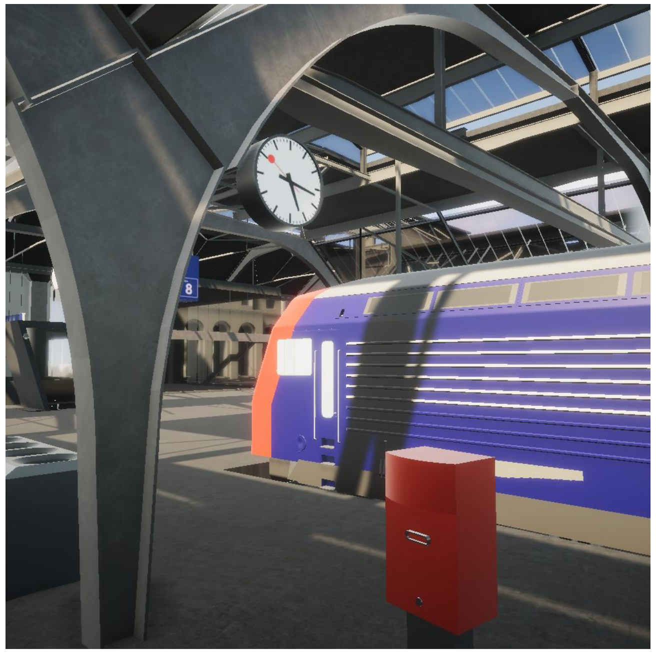
Leveraging BIM - the digital twin

Synthetic Images with day/night scenes, different angles/distances

when no-real labeled data is available

- Domain Adaptation
- Pseudo-Labels

Domain Adaptation

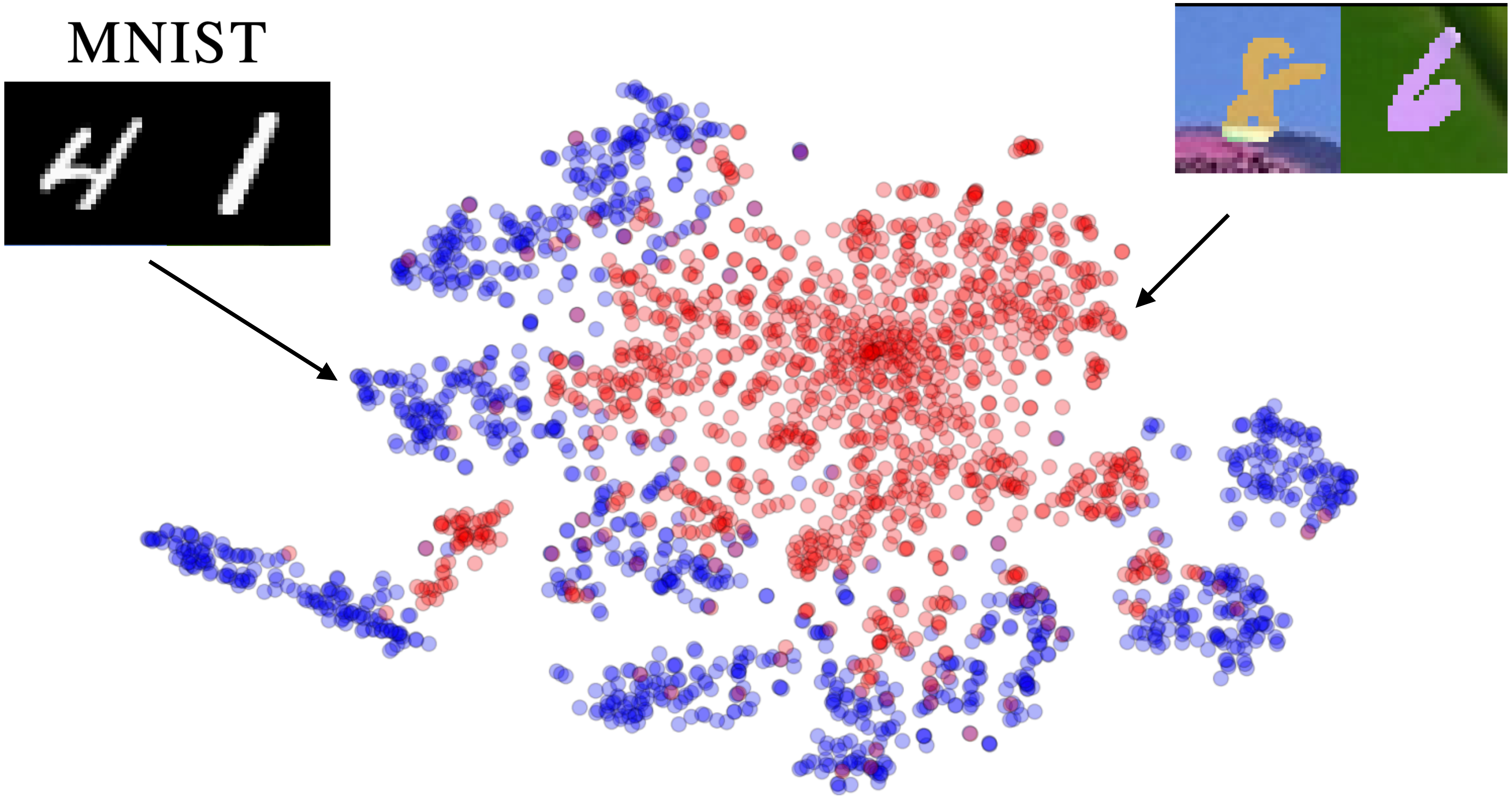


Source Domain
Labels available

Target Domain
No labels

Domain Adaptation

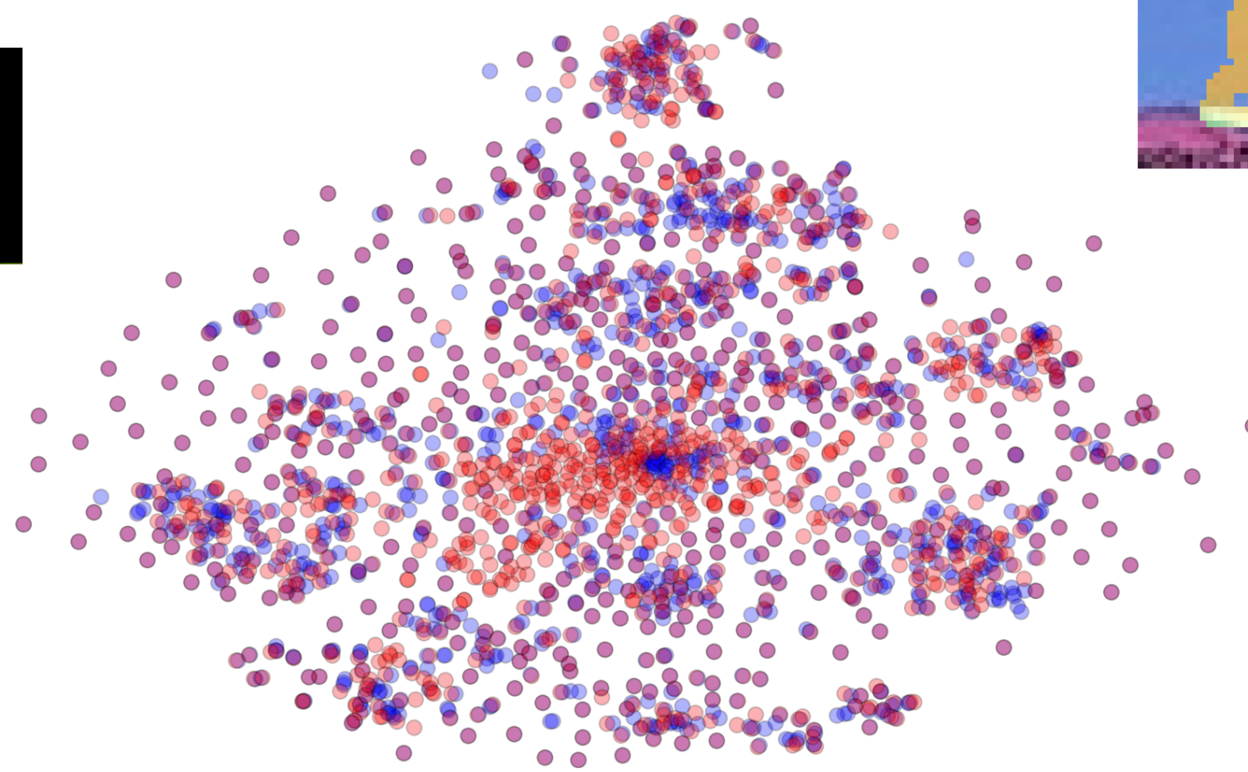
$P_S(x) \neq P_T(x)$



Unsupervised Domain Adaptation by Backpropagation, ICML 2015

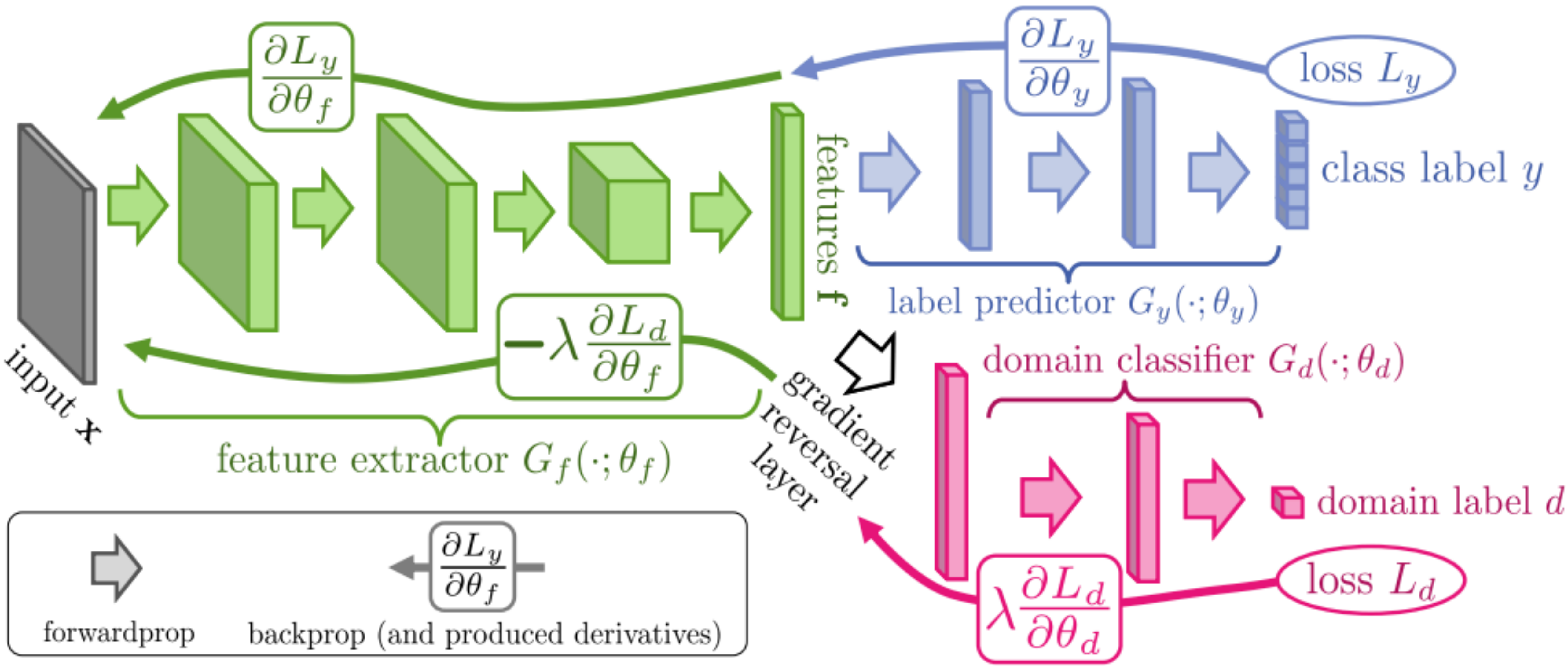
Domain Adaptation

MNIST



Unsupervised Domain Adaptation by Backpropagation, ICML 2015

Domain Adaptation



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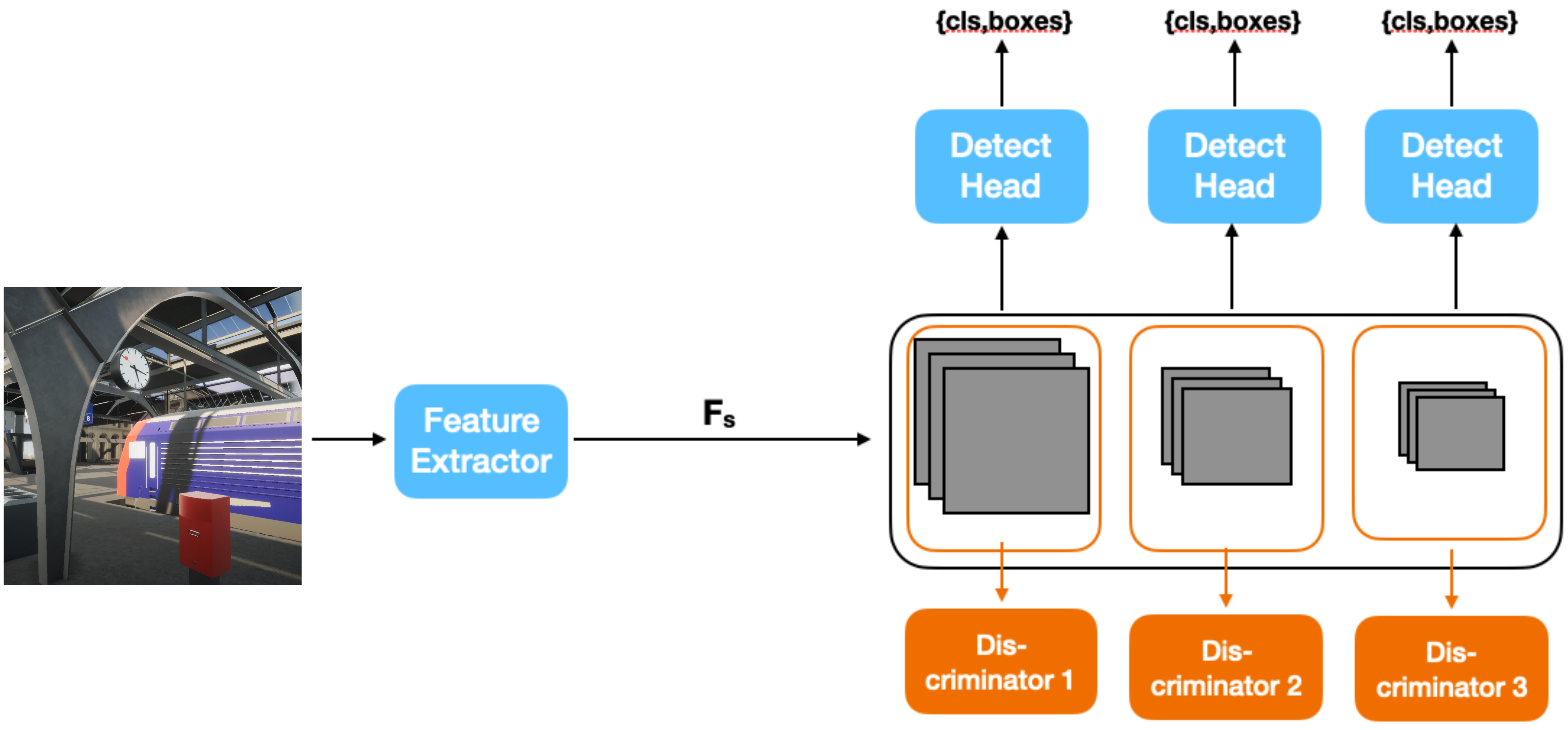
Domain Adaptation



SSD object detector

Domain Adaptation

Class	mAP(%) mobilenetV3+ Synthetic image only	mAP(%) mobilenetV3+DA + 500 unlabelled images	Gain
Recycling Station	71.4	72.8	1.4
Billettentwerter	74.2	78.2	4
Uhr	66.7	63.9	-2.8
LCD	29.9	46.1	16.2
Automatic Ticket Machine	79.6	79.1	-0.5

~1500 synthetic images ~160 real test images

Domain Adaptation

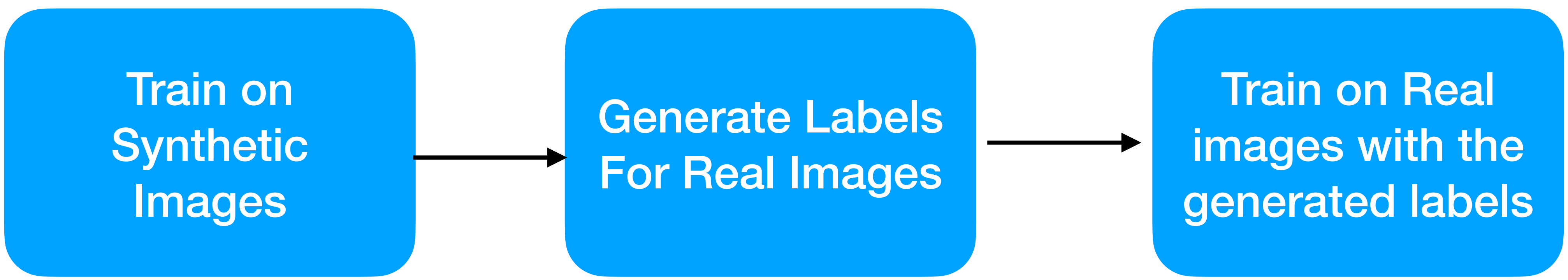
Class	mAP(%) mobilenetV3 With labelled Real images	mAP(%) mobilenetV3+trained on Synthetic Images	mAP(%) mobilenetV3+DA + 1700 unlabelled images	Gain
Recycling Station	72.3	37.8	41.2	3.4
Billettentwerter	86.9	84	75.9	-8.1
Uhr	55.6	41	43.5	2.5

~1500 synthetic images ~600 real test images

Domain Adaptation

Issues

Pseudo-Labels



Keep only the predictions with 50% or more confidence

Pseudo-Labels

Class	mAP(%) mobilenetV3 With labelled Real images	mAP(%) mobilenetV3+trained on Synthetic Images	mAP(%) mobilenetV3+DA + 1700 unlabelled images	mAP(%) mobilenetV3+ Pseudo Labels 800 images	Gain
Recycling Station	72.3	37.8	41.2	44.9	7.1
Billettentwerter	86.9	84	75.9	83.1	-3.8
Uhr	55.6	41	43.5	45.1	4.1

~1500 synthetic images ~600 real test images

YOLOv5 with default augmentations

Classes	Train only on Real Images	Train on Synthetic	Train on Synthetic+ Pseudo Labels 800 images	Gain
RecylingStation	88.1	52.3	57.5	5.2
Billetenwerter	98.9	84.9	94.7	9.8
Uhr	89.6	85.3	85.9	0.6

Train on Synthetic

Train on Synthetic+ Pseudo Labels

Challenges

- Domain Adaptation:
  - + no real-labels needed
  - + Relies on synthetic images reflecting on the use case scenarios
  - - Need for diversity in the synthetic and real data

Challenges

- Pseudo - Labels
  - + Relies on synthetic images reflecting on the use case scenarios
  - + Opportunity to quickly leverage on larger unlabelled data
  - - need to handle false positives and class imbalances

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- Domain Adaptation:
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Thank You!