Learning Domain Adaptive Object Detection with Probabilistic Teacher

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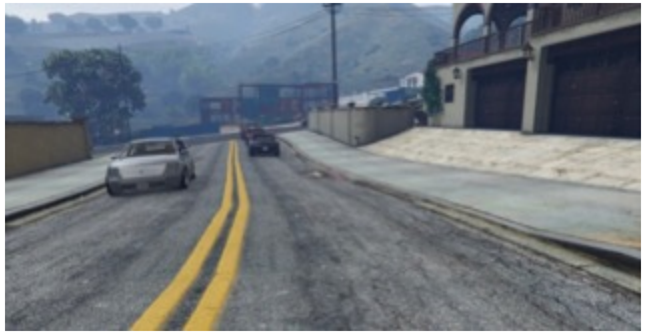
https://arxiv.org/abs/2206.06293
https://github.com/hikvision-research/ProbabilisticTeacher

Unsupervised domain adaptation for object detection

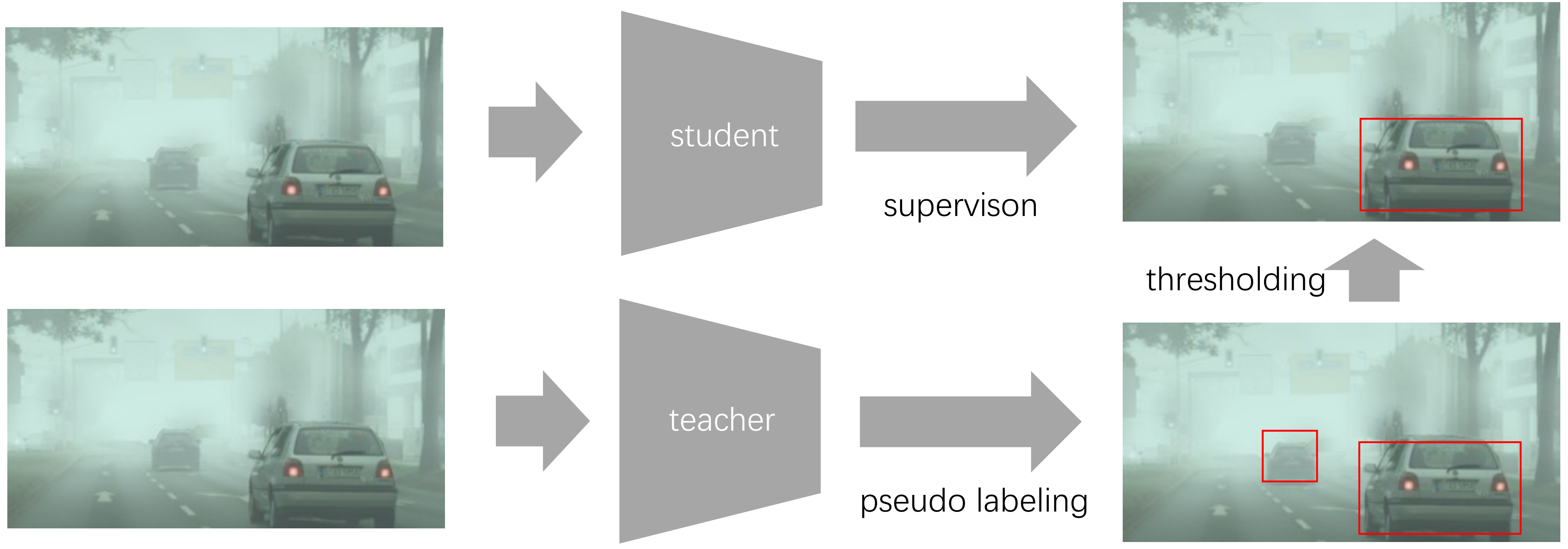


labeled source domain

unlabeled target domain

Previous works : self training

motivation: mining confident supervision from target domain

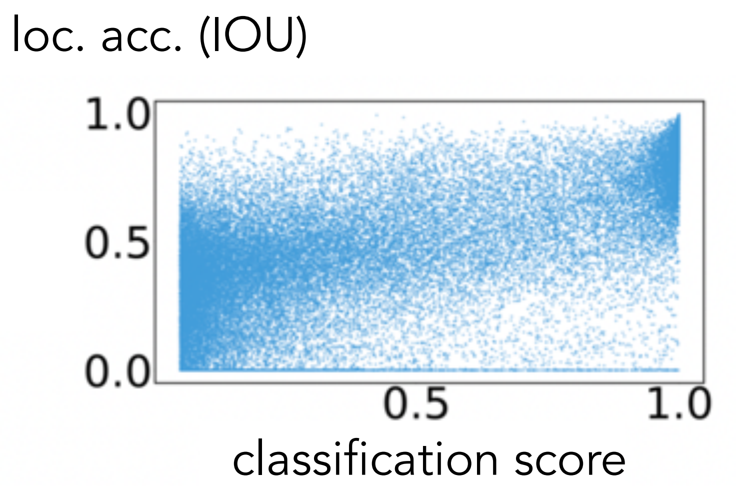


Reference:

[1] Unbiased Mean Teacher for Cross-Domain Object Detection, in CVPR2021
[2] SimROD: A Simple Adaptation Method for Robust Object Detection, in ICCV2021

Challenges about threshold

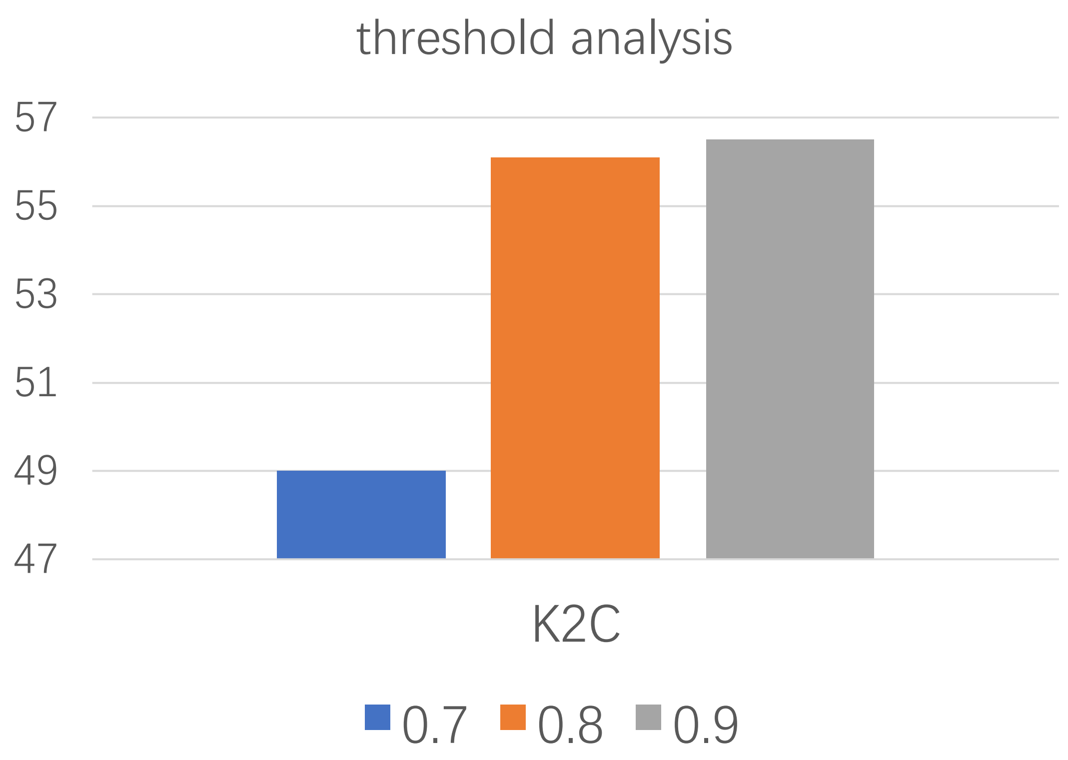
Performance challenge: the foreground scores fail to measure the quality of pseudo boxes



Challenges about threshold

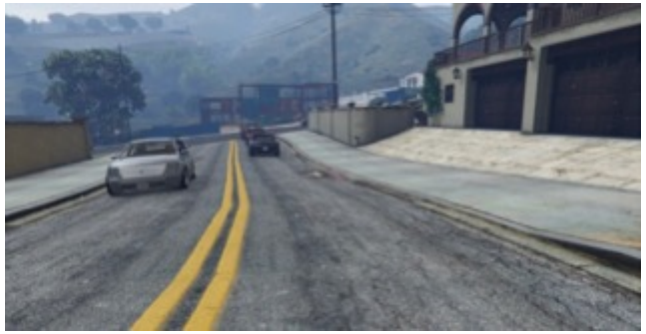
Dependence challenge: the performance heavily depend on the threshold selections

1. In a single dataset, the performance is very sensitive to the threshold selections
2. In different datasets, the best threshold selections vary a lot



Challenges about objects size distributions gap

Object size distributions gap is one typical kind of the domain gaps

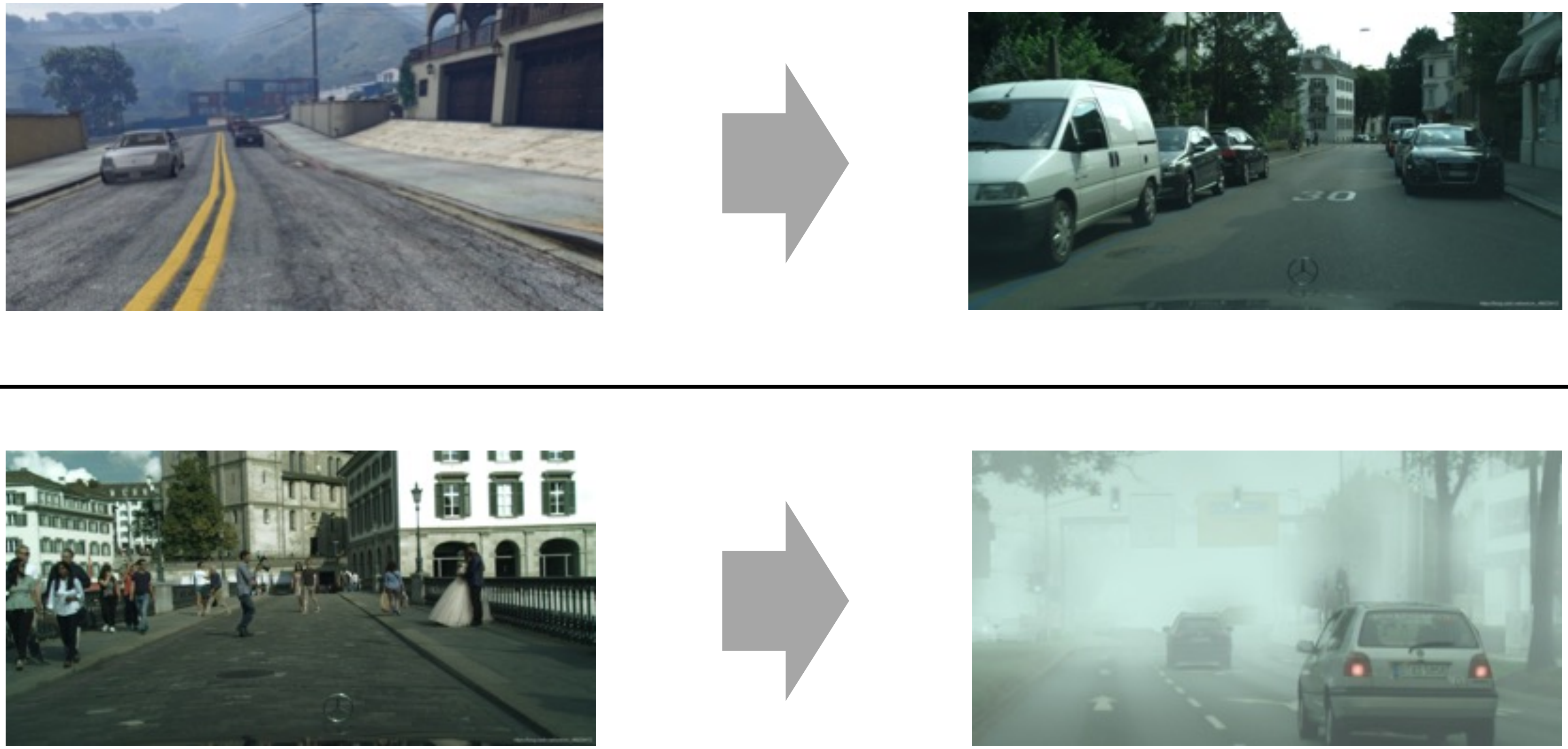


labeled source domain

unlabeled target domain

Challenges about intra-domain gap

Intra-domain gap is one of the bottlenecks restricting the performance of UDA-OD



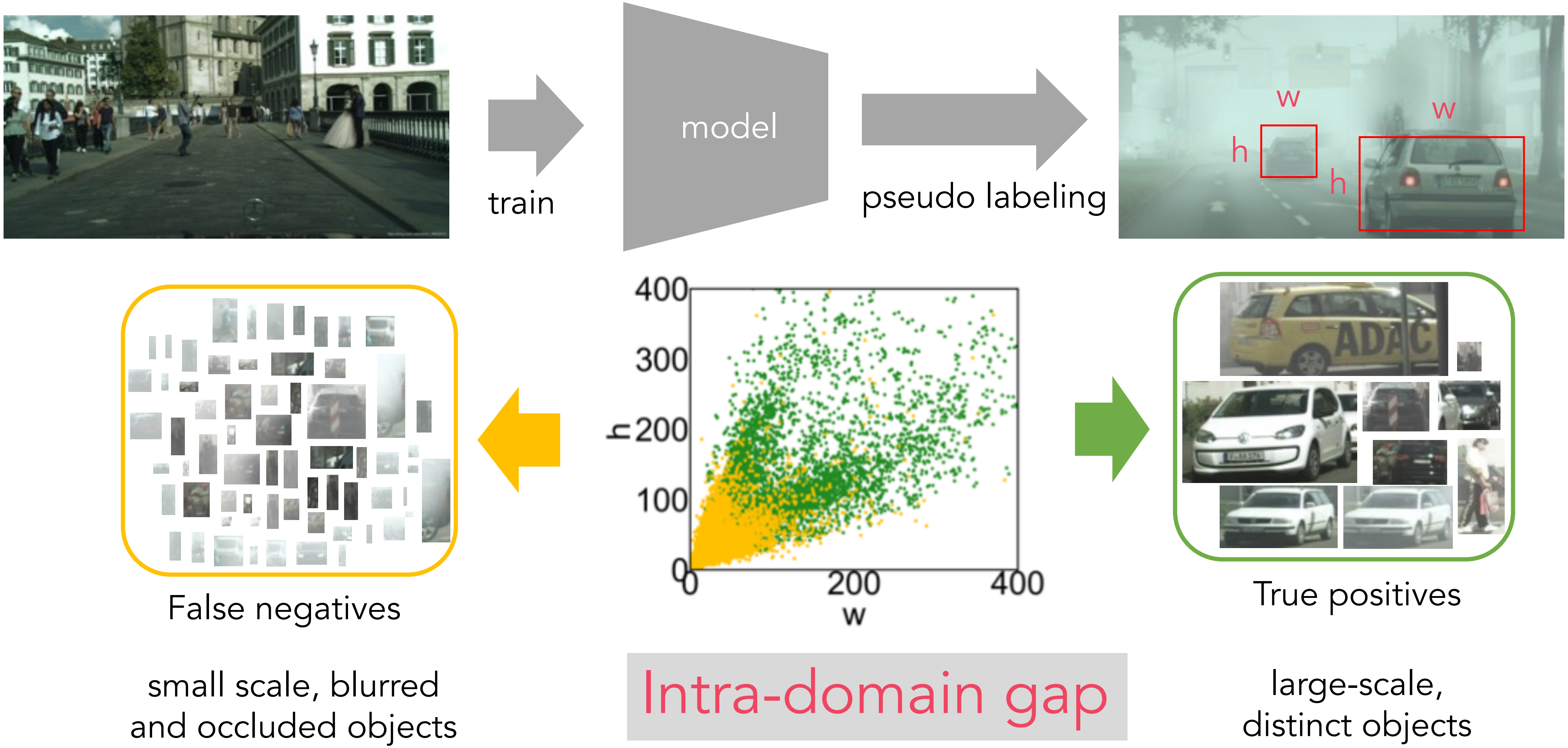
inter-domain gap

labeled source domain

unlabeled target domain

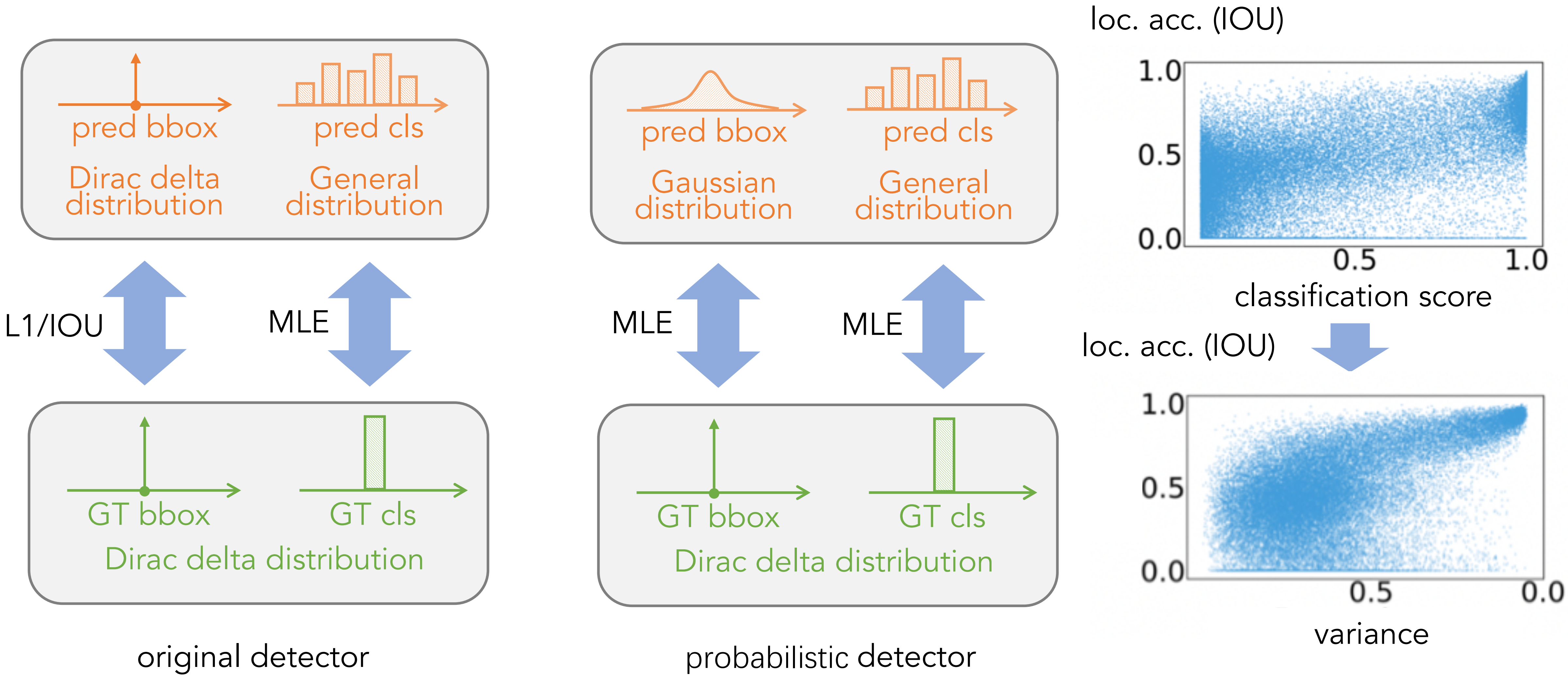
Challenges about intra-domain gap

Intra-domain gap is one of the bottlenecks restricting the performance of UDA-OD

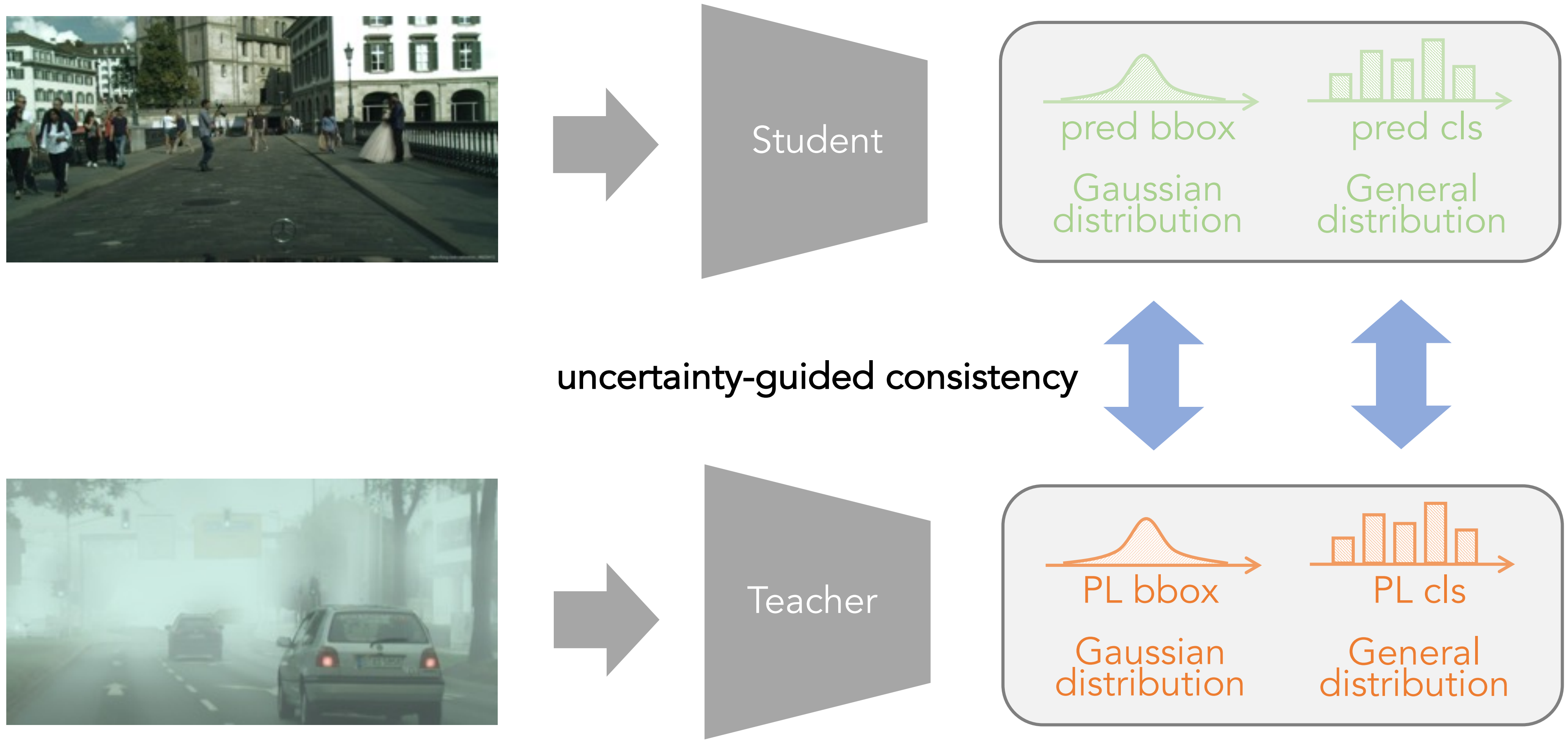


Threshold-free via uncertainty-driven classification and localization adaptation

To obtain the uncertainty of localization, we first argument detector to probabilistic one

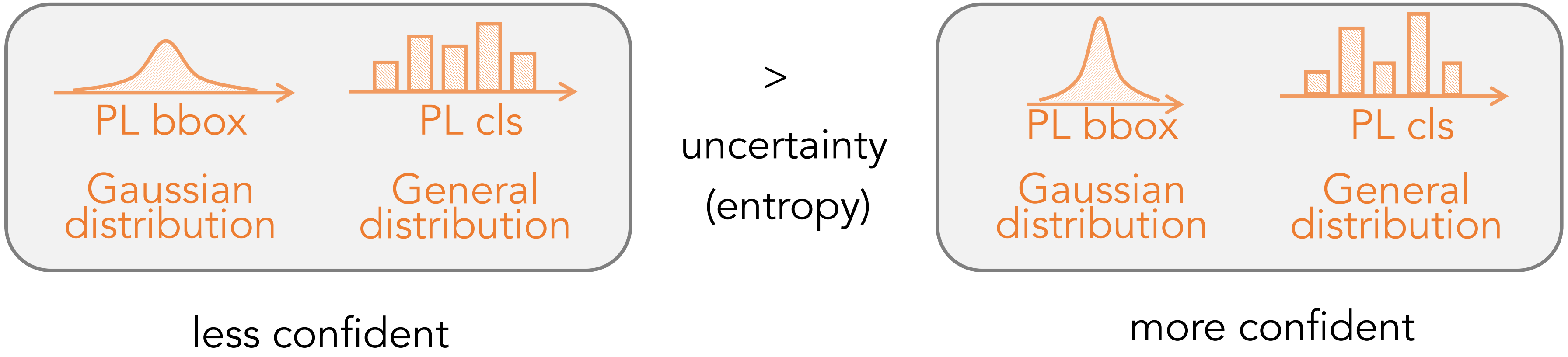


Threshold-free via uncertainty-guided classification and localization adaptation



Threshold-free via uncertainty-driven classification and localization adaptation

To mine more confident samples:



Entropy Focal Loss

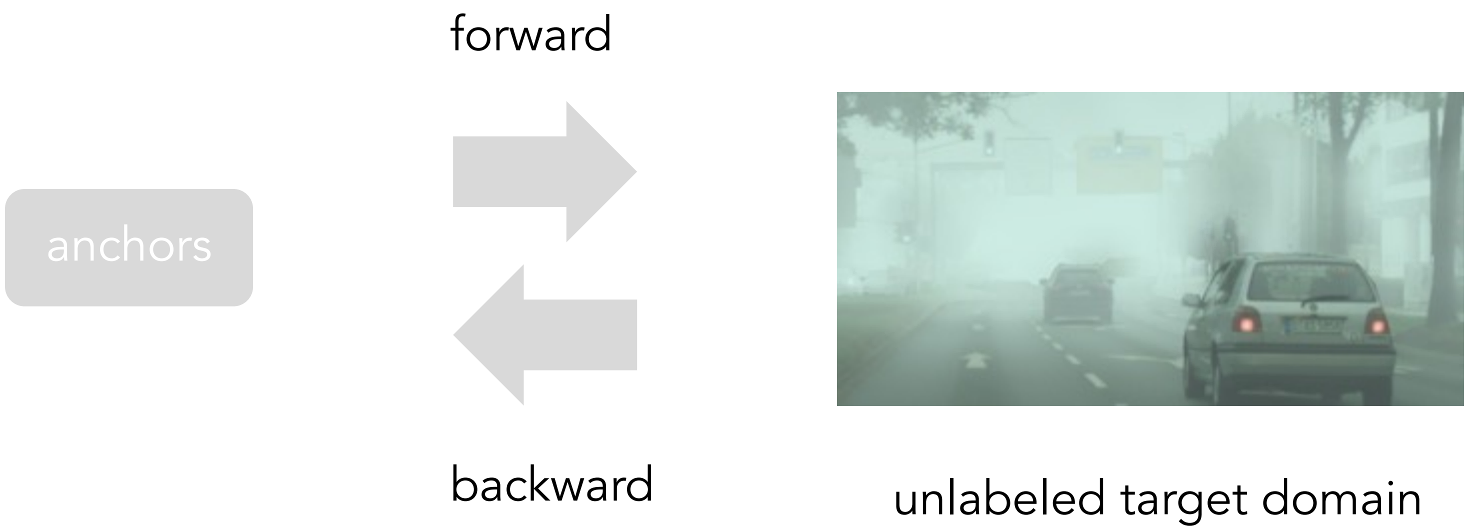
$$\mathcal{L}_{EFL} = \left(1 - \frac{\mathcal{E}}{\mathcal{E}_n}\right)^{\lambda} \mathcal{L}$$

normalized entropy

KL loss

Anchor adaptation

Learnable anchor to match the distribution of boxes in target domain



Intra-domain alignment via strong augmentation

Strong data augmentation is an implicit intra-domain alignment method to bridge the intra-domain gap

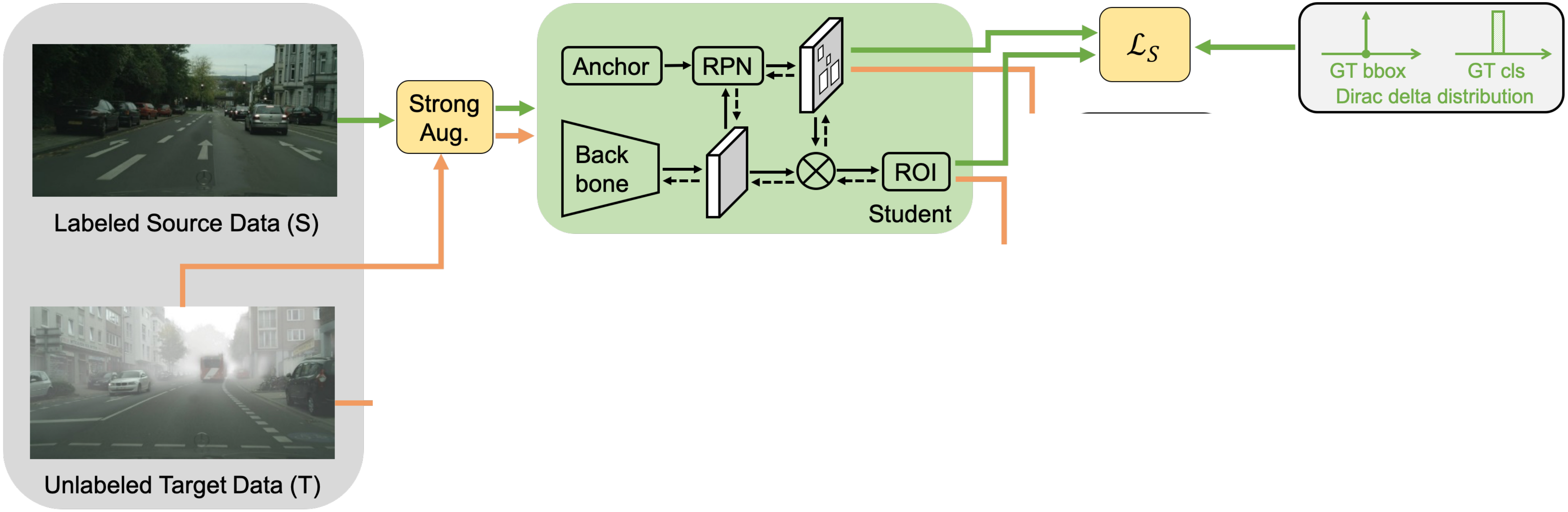
strong augmentation

large-scale,
distinct objects

small scale, blurred
and occluded ones

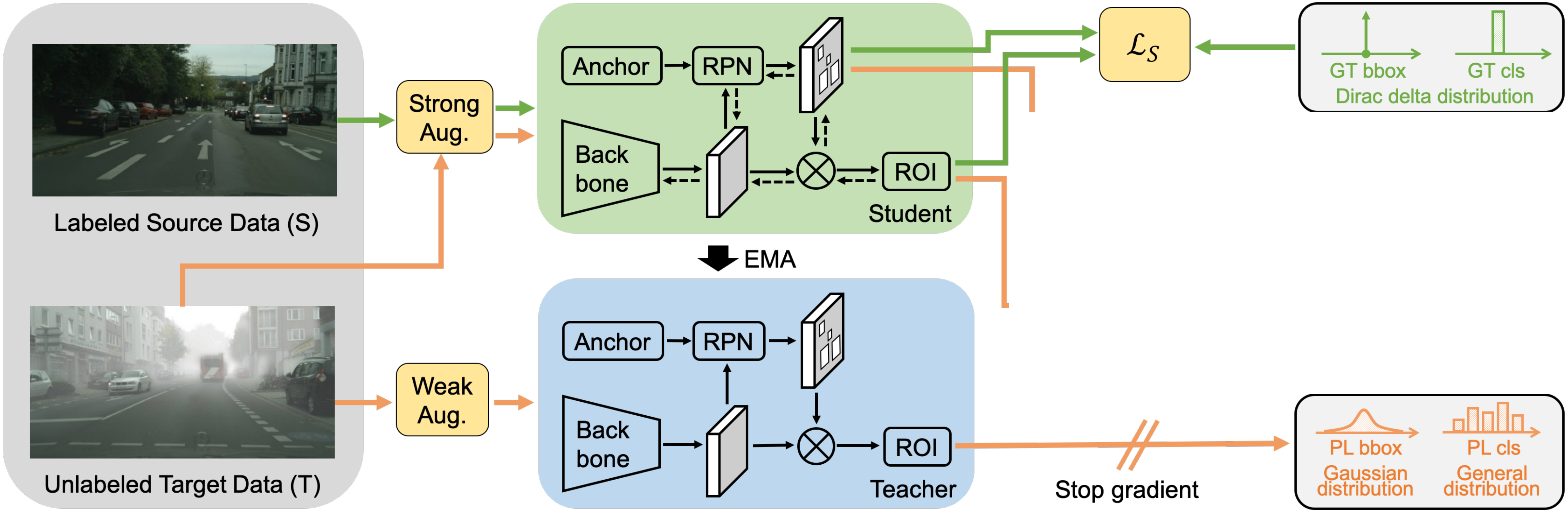
Pipeline

Pipeline

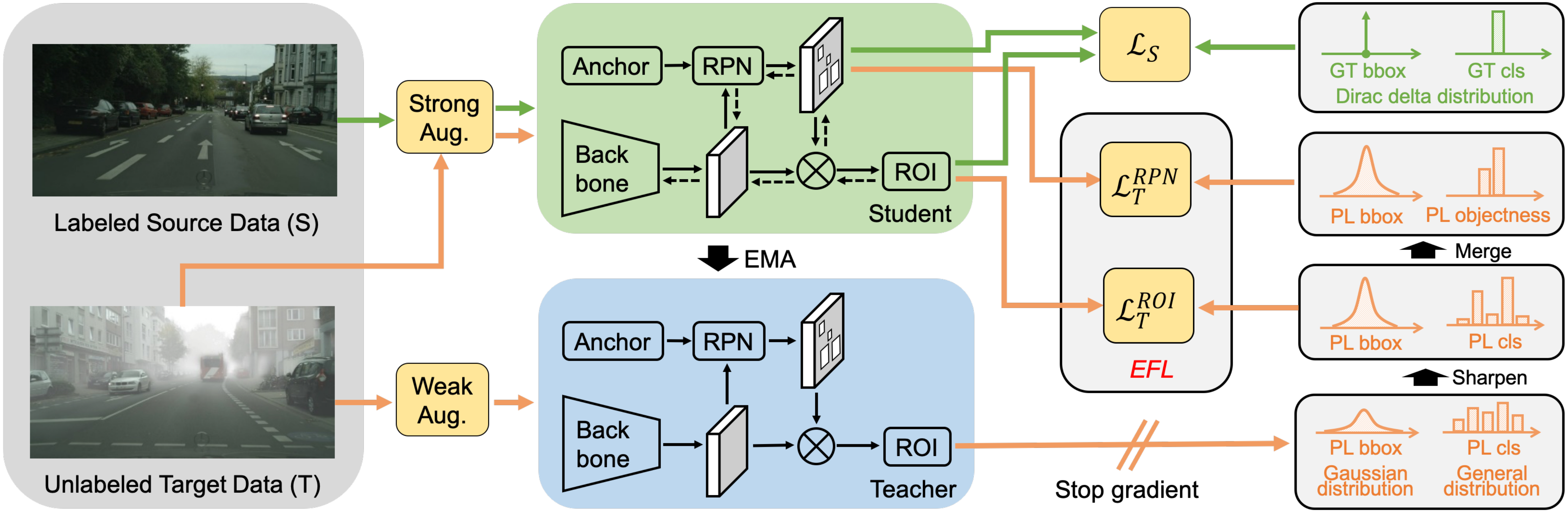


Labeled Source Data (S)
Unlabeled Target Data (T)
Strong Aug.
Anchor
RPN
Back bone
ROI
Student
$\mathcal{L}_S$
GT bbox
GT cls
Dirac delta distribution

Pipeline


Labeled Source Data (S)
Unlabeled Target Data (T)
Strong Aug.
Weak Aug.
Anchor
RPN
Back bone
ROI
Student
EMA
Teacher
$\mathcal{L}_S$
GT bbox
GT cls
Dirac delta distribution
Stop gradient
PL bbox
Gaussian distribution
PL cls
General distribution

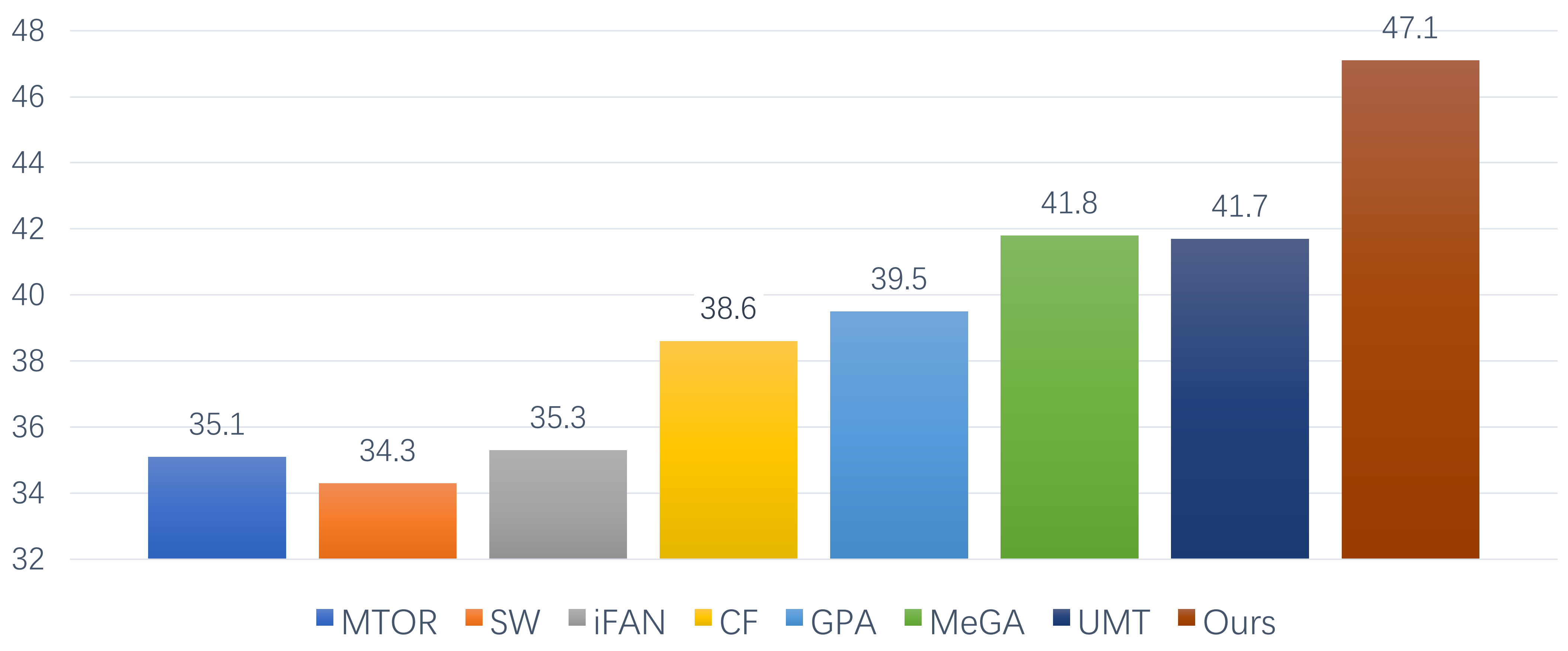
Pipeline



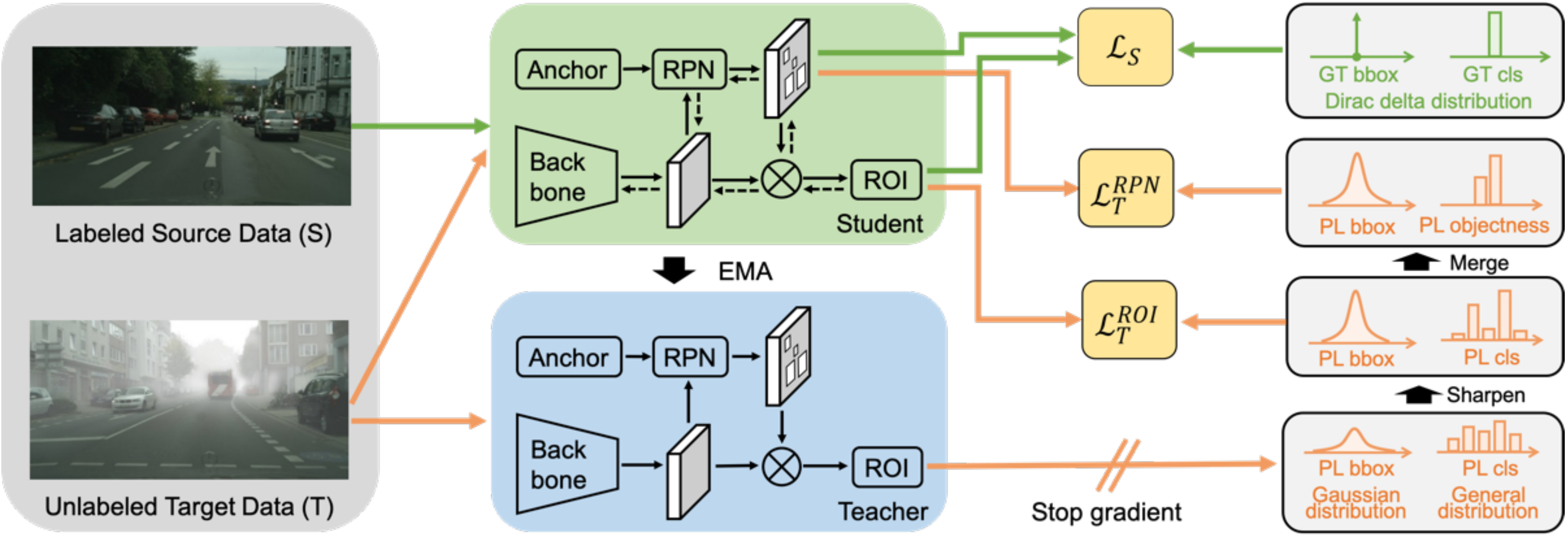
Labeled Source Data (S)
Unlabeled Target Data (T)
Strong Aug.
Weak Aug.
Anchor
RPN
Back bone
ROI
Student
EMA
Anchor
RPN
Back bone
ROI
Teacher
$\mathcal{L}_S$
$\mathcal{L}_T^{RPN}$
$\mathcal{L}_T^{ROI}$
EFL
Stop gradient
GT bbox
GT cls
Dirac delta distribution
PL bbox
PL objectness
Merge
PL bbox
PL cls
Sharpen
PL bbox
Gaussian distribution
PL cls
General distribution

Experimental results

Adaptation from normal to foggy weather

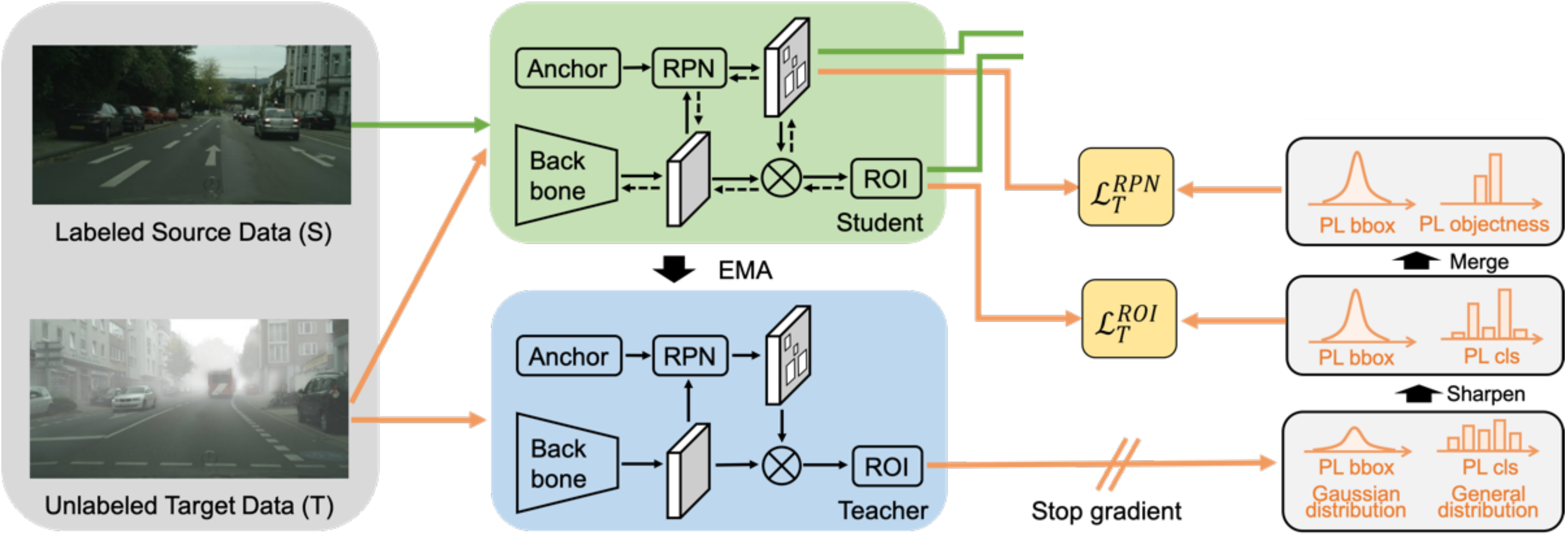


From source-based to source-free

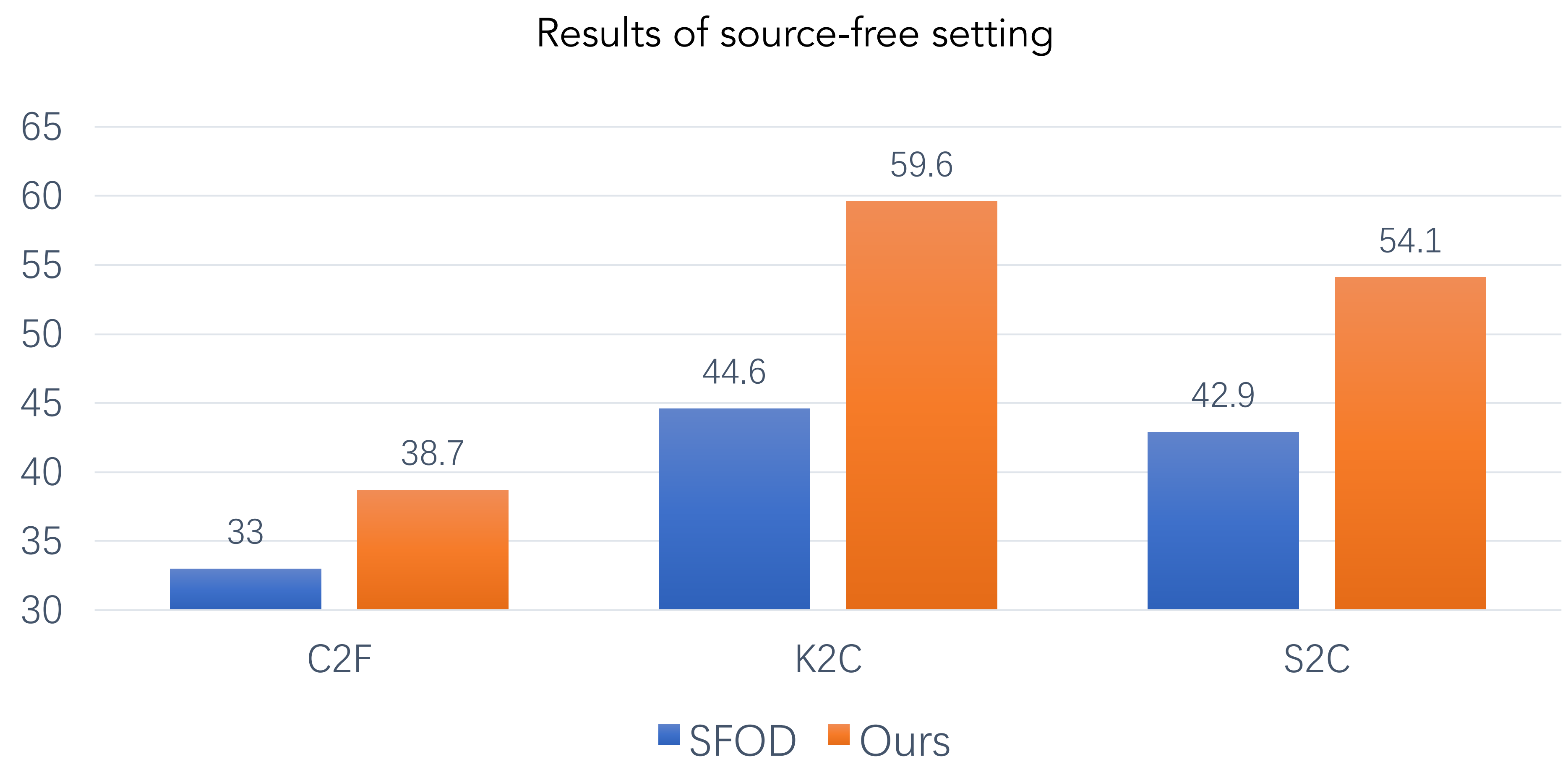


from source-based to source-free

From source-based to source-free

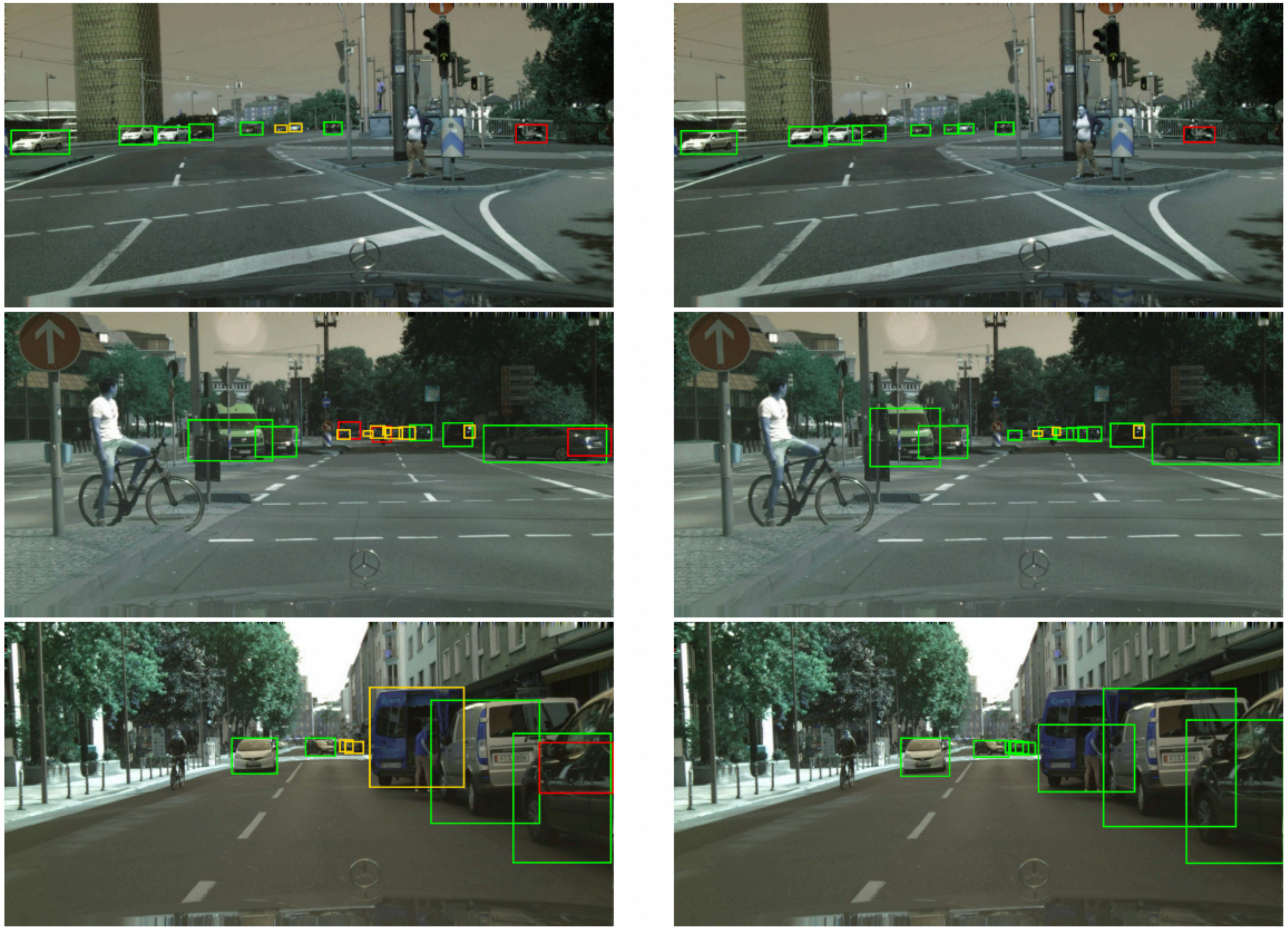


from source-based to source-free



Results of source-free setting
65
60
55
50
45
40
35
30
33
38.7
44.6
59.6
42.9
54.1
C2F
K2C
S2C
SFOD
Ours

Visualization



Previous method Ours

Yellow: False Negatives
Green: True Positives
Red: False Positives

Our method can detect more small scale, blurred and occluded objects

Conclusions

- Probabilistic Teacher
  - ✓ threshold-free
  - ✓ effective
  - ✓ scalable
- Intra-domain gap

https://arxiv.org/abs/2206.06293

https://github.com/hikvision-research/ProbabilisticTeacher

Thanks!