Bidirectional Alignment for Domain Adaptive Detection with Transformers

Oregon State University · amazon Lab126 · ICCV23 PARIS

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Motivation 1:

Existing Transformer-based methods use GRL (gradient reverse layer) to reduce the domain gap in the image/object features.

The resulting domain aligned image/object features contain both domain-invariant and domain-specific features.

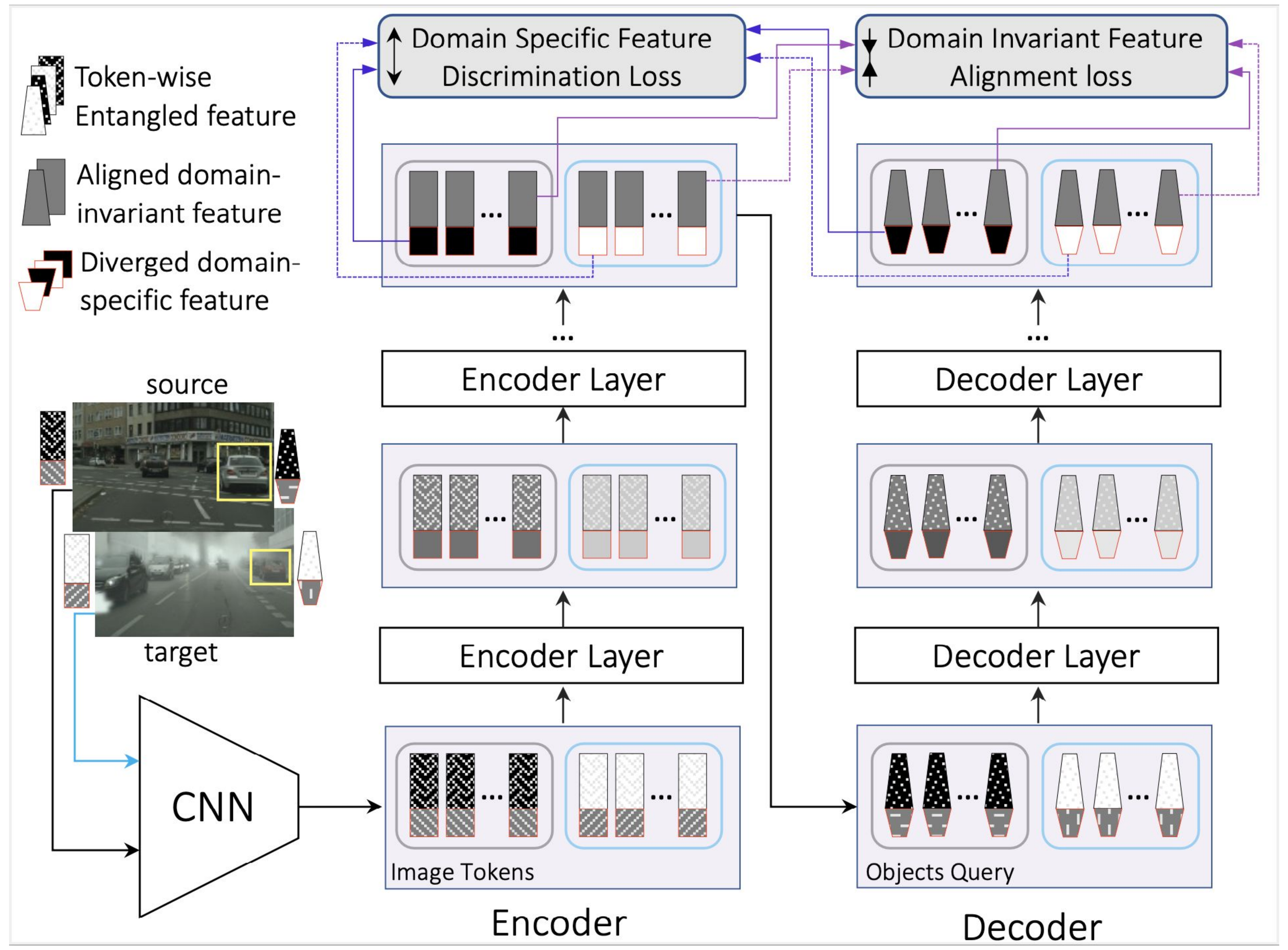
Contribution 1:
We explicitly design a token-wise domain specific embedding, at the image level in the encoder, and at the object level in the decoder.

Motivation 2:

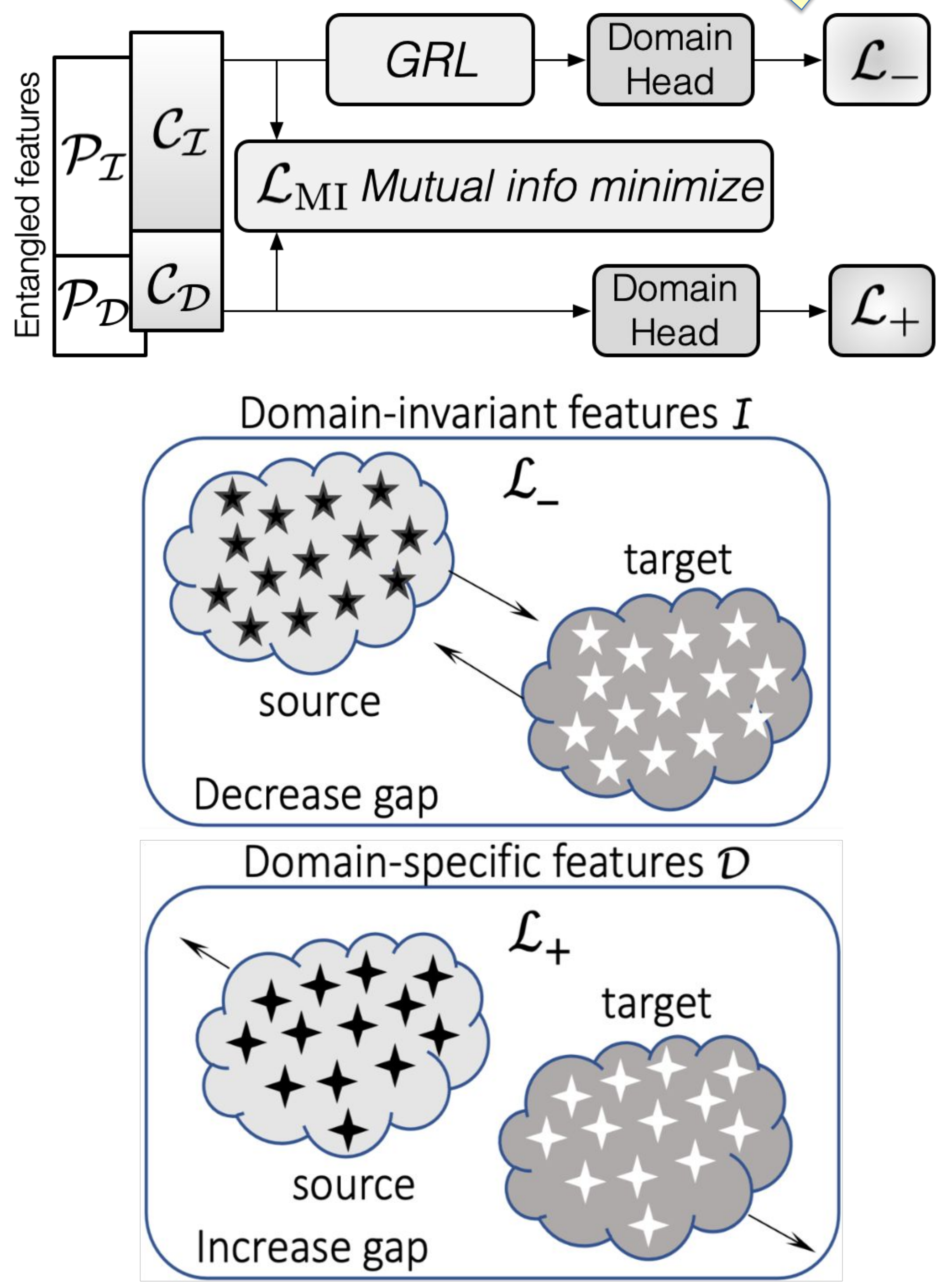
Previous Transformer-based methods do not explicitly consider differences between source and target domains for image patches and object tokens.

Different image patches and different object tokens may exhibit different domain characteristics.
→ They need to be aligned individually!

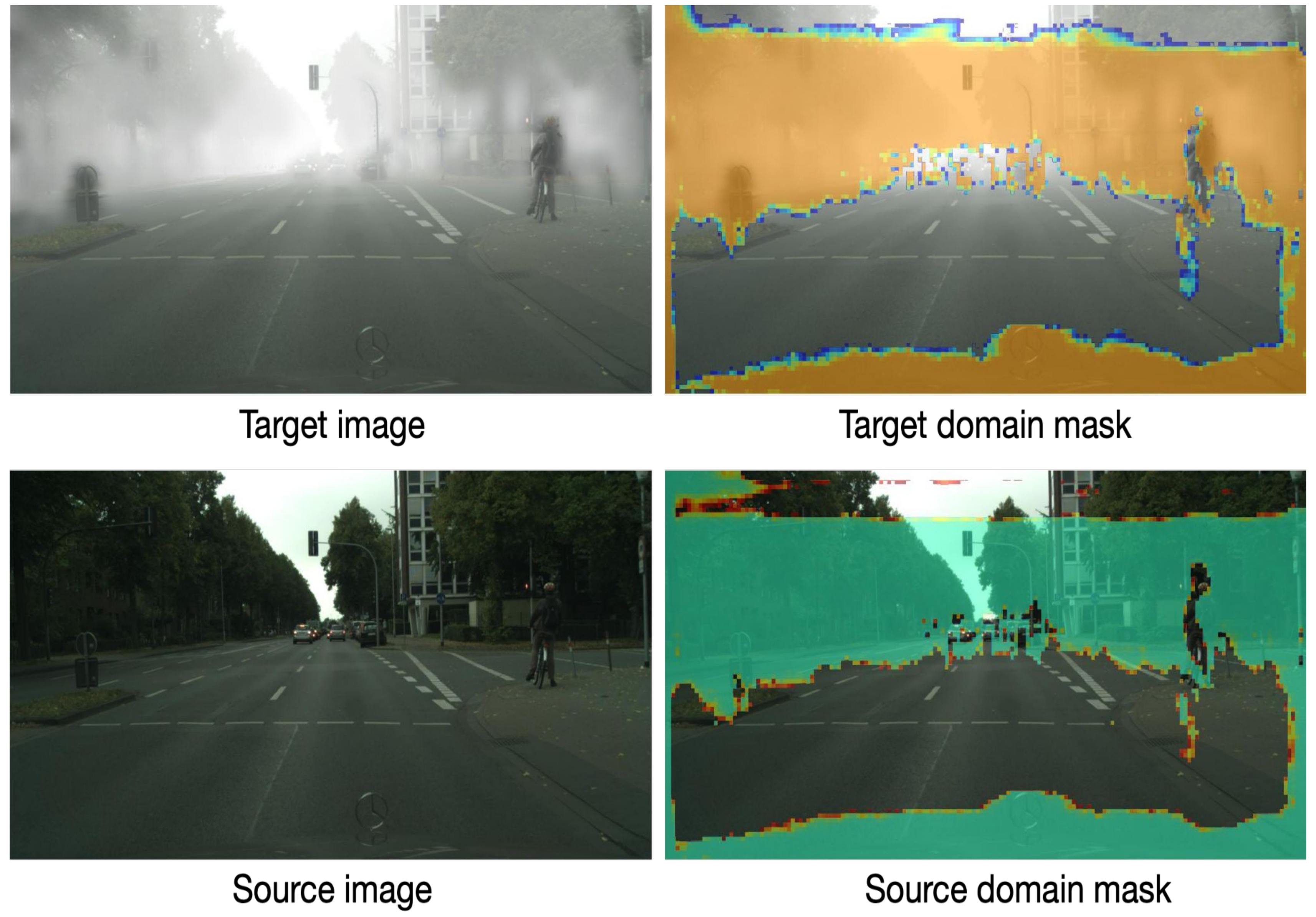
Contribution 2:
We design two attention modules to align the two domains bidirectionally.
→ This is seamlessly integrated in existing attention modules.



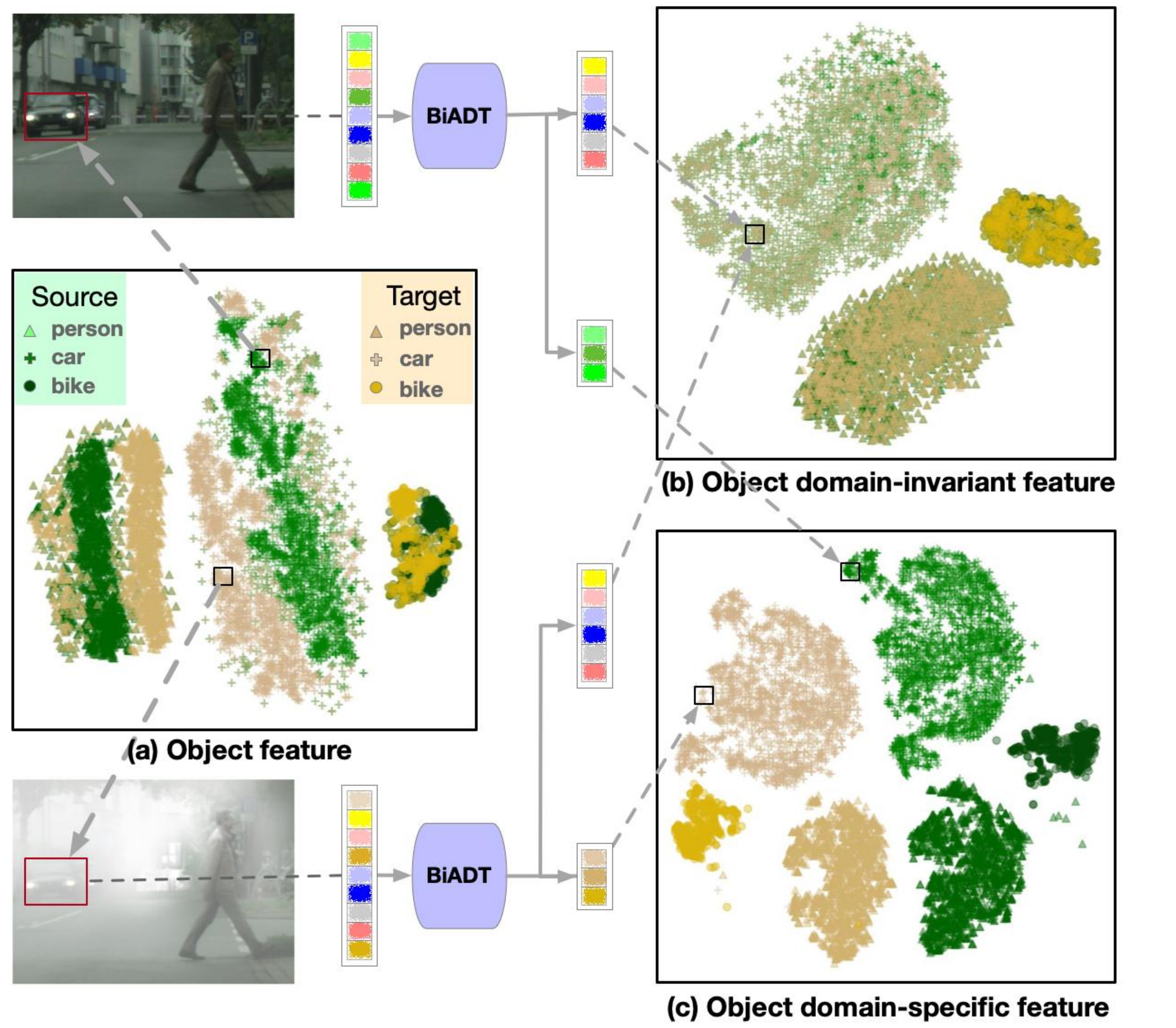
An overview of BiADT



Bidirectional Domain Alignment



An example of the predicted domain masks by BiADT encoder.



The t-SNE visualization of object features of the test images in the Cityscapes→FoggyCityscapes setting.

Method	Backbone	Detector	Pseudo-Label	person	rider	car	truck	bus	train	motor	bike	mAP
MTTrans [37] *ECCV'22*	R50	Deform-Detr	Yes	47.7	49.9	65.2	25.8	45.9	33.8	32.6	46.5	43.4
PT [7] *ICML'22*	V16	Faster R-CNN	Yes	43.2	52.4	63.4	33.4	56.6	37.8	41.3	48.7	47.1
TDD [26] *CVPR'22*	R50	Faster R-CNN	Yes	50.7	53.7	68.2	35.1	53.0	45.1	38.9	49.1	49.2
AT [44] *CVPR'22*	V16	Faster R-CNN	Yes	45.5	55.1	64.2	35.0	56.3	54.3	38.5	51.9	50.9
AT* [44] *CVPR'22*	V16	Faster R-CNN	Yes	44.1	54.2	62.7	33.6	54.4	51.9	39.2	49.2	49.5
PDN [86] *TPAMI'21*	R101	Faster R-CNN	No	32.8	44.4	49.6	33.0	46.1	38.0	29.9	35.3	38.6
ICCR-VDD [87] *ICCV'21*	R50	Faster R-CNN	No	33.4	44.0	51.7	33.9	52.0	34.7	34.2	36.8	40.0
SFA [82] *ACM MM'21*	R50	Deform-Detr	No	46.5	48.6.	62.6	25.1	46.2	29.4	28.3	44.0	41.3
MGADA [104] *CVPR'22*	R101	FCOS	No	43.1	47.3	61.5	30.2	53.2	50.3	27.9	36.9	43.8
SIGMA [43] *CVPR'22*	R50	FCOS	No	44.0	43.9	60.3	31.6	50.4	51.5	31.7	40.6	44.2
AQT [35] *IJCAI'22*	R50	Deform-Detr	No	49.3	52.3	64.4	27.7	53.7	46.5	36.0	46.4	47.1
AQT* [35] *IJCAI'22*	R50	DAB-Deform-Detr	No	49.8	54.2	65.8	29.0	56.2	37.5	38.9	48.2	47.4
BiADT	R50	DAB-Deform-Detr	No	50.3	56.4	66.5	32.5	52.3	47.8	40.1	48.3	49.3
BiADT+AQT	R50	DAB-Deform-Detr	No	50.1	55.4	67.9	31.5	56.1	46.8	38.6	49.3	49.6
BiADT+TS	R50	DAB-Deform-Detr	Yes	52.2	58.9	69.2	31.7	55.0	45.1	42.6	51.3	50.8

Comparison with SOTA on the Cityscapes → FoggyCityscapes domain shift.

Acknowledgement: USDA NIFA award No.2021-67021-35344 (AgAID AI Institute), Amazon Lab126