Informative Data Mining for One-shot Cross-Domain Semantic Segmentation

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A. Appendix

A.1. Detailed Comparison Results

This section provides detailed comparison results between the proposed **IDM** and existing conventional domain adaptive semantic segmentation methods and one-shot cross-domain semantic segmentation methods. For a fair comparison, we perform experiments on different backbones with DeepLab-v2 and transformer architecture, respectively. To be specific, Table S1 provides the results of GTA5→Citycsapes on DeepLab-v2 based on ResNet-101 backbone, Table S2 shows the results of SYNTHIA→Cityscapes on DeepLab-v2 based on ResNet-101 backbone, and Table S3 is the results of GTA5/SYNTHIA→Cityscapes based on transformer-architecture. Note that we use SegFormer [23] as the backbone following DAFormer [4]. We compare the conventional unsupervised domain adaptation (UDA) using the whole target data and one-shot domain adaptation (One-shot UDA) that only one target image is available during adaptation.

Note that, for adaptation of GTA5→Cityscapes, our method arrives the performance 57.3% mIoU and 45.2% on conditional domain adaptation (UDA) and one-shot domain adaptation (OSDA) based on DeepLab-v2, and 69.5% and 56.7% based on transformer-architecture. Besides, the performance of SYNTHIA→Cityscapes is 65.9% and 47.2% on conditional domain adaptation (UDA) and one-shot domain adaptation (OSDA) based on DeepLab-v2, and 67.9% and 55.4% based on transformer-architecture.

A.2. Results on different weather.

We also conduct experiments on adaptation scenarios from GTA5 to CS Foggy and ACDC [12] (including *foggy, snow, night, and rainy*). The detailed results are shown in the following.

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References

[1] Nikita Araslanov and Stefan Roth. Self-supervised augmentation consistency for adapting semantic segmentation. In *Proc. CVPR*, pages 15384–15394, 2021. 2, 3

[2] Runfa Chen, Yu Rong, Shangmin Guo, Jiaqi Han, Fuchun Sun, Tingyang Xu, and Wenbing Huang. Smoothing matters: Momentum transformer for domain adaptive semantic segmentation. *arXiv preprint arXiv:2203.07988*, 2022. 4

[3] Judy Hoffman, Eric Tzeng, Taesung Park, Jun-Yan Zhu, Phillip Isola, Kate Saenko, Alexei Efros, and Trevor Darrell. CyCADA: Cycle-consistent adversarial domain adaptation. In *Proc. ICML*, pages 1989–1998, 2018. 2

[4] Lukas Hoyer, Dengxin Dai, and Luc Van Gool. Daformer: Improving network architectures and training strategies for domain-adaptive semantic segmentation. In *Proc. CVPR*, pages 9924–9935, 2022. 1, 4

[5] Ruihuang Li, Shuai Li, Chenhang He, Yabin Zhang, Xu Jia, and Lei Zhang. Class-balanced pixel-level self-labeling for domain adaptive semantic segmentation. In *Proc. CVPR*, pages 11593–11603, 2022. 2, 3

[6] Yunsheng Li, Lu Yuan, and Nuno Vasconcelos. Bidirectional learning for domain adaptation of semantic segmentation. In *Proc. CVPR*, pages 6936–6945, 2019. 2, 3

[7] Yawei Luo, Ping Liu, Tao Guan, Junqing Yu, and Yi Yang. Adversarial style mining for one-shot unsupervised domain adaptation. *Advances in Neural Information Processing Systems*, 33:20612–20623, 2020. 2, 3

[8] Yawei Luo, Liang Zheng, Tao Guan, Junqing Yu, and Yi Yang. Taking a closer look at domain shift: Category-level adversaries for semantics consistent domain adaptation. In *Proc. CVPR*, pages 2507–2516, 2019. 2, 3

[9] Fengmao Lv, Tao Liang, Xiang Chen, and Guosheng Lin. Cross-domain semantic segmentation via domain-invariant interactive relation transfer. In *Proc. CVPR*, pages 4334–4343, 2020. 2, 3

[10] Haoyu Ma, Xiangru Lin, Zifeng Wu, and Yizhou Yu. Coarse-to-fine domain adaptive semantic segmentation with photometric alignment and category-center regularization. In *Proc. CVPR*, pages 4051–4060, 2021. 2, 3

[11] Ke Mei, Chuang Zhu, Jiaqi Zou, and Shanghang Zhang. Instance adaptive self-training for unsupervised domain adaptation. In *Proc. ECCV*, pages 415–430, 2020. 2, 3

Table S1. Adaptation from GTA5 to Cityscapes on Deeplab-v2 based on ResNet-101 backbone. # TS denotes the number of target samples used in training.

Method	#TS	road	side.	build.	wall	fence	pole	light	sign	vege.	terr.	sky	person	rider	car	truck	bus	train	motor.	bike	**mIoU**
UDA																					
Source Only	-	75.8	16.8	77.2	12.5	21.0	25.5	30.1	20.1	81.3	24.6	70.3	53.8	26.4	49.9	17.2	25.9	6.5	25.3	36.0	36.5
AdaptSeg [14]	All	86.5	36.0	79.9	23.4	23.3	23.9	35.2	14.8	83.4	33.3	75.6	58.5	27.6	73.7	32.5	35.4	3.9	30.1	28.1	42.4
CyCADA [3]	All	86.7	35.6	80.1	19.8	17.5	38.0	39.9	41.5	82.7	27.9	73.6	64.9	19.0	65.0	12.0	28.6	4.5	31.1	42.0	42.7
CLAN [8]	All	87.0	27.1	79.6	27.3	23.3	28.3	35.5	24.2	83.6	27.4	74.2	58.6	28.0	76.2	33.1	36.7	6.7	31.9	31.4	43.2
ADVENT [16]	All	89.4	33.1	81.0	26.6	26.8	27.2	33.5	24.7	83.9	36.7	78.8	58.7	30.5	84.8	38.5	44.5	1.7	31.6	32.4	45.5
APODA [24]	All	85.6	32.8	79.0	29.5	25.5	26.8	34.6	19.9	83.7	40.6	77.9	59.2	28.3	84.6	34.6	49.2	8.0	32.6	39.6	45.9
CBST [30]	All	91.8	53.5	80.5	32.7	21.0	34.0	28.9	20.4	83.9	34.2	80.9	53.1	24.0	82.7	30.3	35.9	16.0	25.9	42.8	45.9
PatchAlign [15]	All	92.3	51.9	82.1	29.2	25.1	24.5	33.8	33.0	82.4	32.8	82.2	58.6	27.2	84.3	33.4	46.3	2.2	29.5	32.3	46.5
MRKLD [29]	All	91.0	55.4	80.0	33.7	21.4	37.3	32.9	24.5	85.0	34.1	80.8	57.7	24.6	84.1	27.8	30.1	26.9	26.0	42.3	47.1
BDL [6]	All	91.0	44.7	84.2	34.6	27.6	30.2	36.0	36.0	85.0	43.6	83.0	58.6	31.6	83.3	35.3	49.7	3.3	28.8	35.6	48.5
FADA [18]	All	91.0	50.6	86.0	43.4	29.8	36.8	43.4	25.0	86.8	38.3	87.4	64.0	38.0	85.2	31.6	46.1	6.5	25.4	37.1	50.1
CAG [27]	All	90.4	51.6	83.8	34.2	27.8	38.4	25.3	48.4	85.4	38.2	78.1	58.6	34.6	84.7	21.9	42.7	41.1	29.3	37.2	50.2
Seg-Uncert. [28]	All	90.4	31.2	85.1	36.9	25.6	37.5	48.8	48.5	85.3	34.8	81.1	64.4	36.8	86.3	34.9	52.2	1.7	29.0	44.6	50.3
FDA [25]	All	92.5	53.3	82.4	26.5	27.6	36.4	40.6	38.9	82.3	39.8	78.0	62.6	34.4	84.9	34.1	53.1	16.9	27.7	46.4	50.5
PIT [9]	All	87.5	43.4	78.8	31.2	30.2	36.3	39.9	42.0	79.2	37.1	79.3	65.4	37.5	83.2	46.0	45.6	25.7	23.5	49.9	50.6
IAST [11]	All	93.8	57.8	85.1	39.5	26.7	26.2	43.1	34.7	84.9	32.9	88.0	62.6	29.0	87.3	39.2	49.6	23.2	34.7	39.6	51.5
DACS [13]	All	89.9	39.7	87.9	30.7	39.5	38.5	46.4	52.8	88.0	44.0	88.8	67.2	35.8	84.5	45.7	50.2	0.0	27.3	34.0	52.1
UPLR [20]	All	90.5	38.7	86.5	41.1	32.9	40.5	48.2	42.1	86.5	36.8	84.2	64.5	38.1	87.2	34.8	50.4	0.2	41.8	54.6	52.6
SAC [1]	All	90.4	53.9	86.6	42.4	27.3	45.1	48.5	42.7	87.4	40.1	86.1	67.5	29.7	88.5	49.1	54.6	9.8	26.6	45.3	53.8
CTF [10]	All	92.5	58.3	86.5	27.4	28.8	38.1	46.7	42.5	85.4	38.4	91.8	66.4	37.0	87.8	40.7	52.4	44.6	41.7	59.0	56.1
CorDA [19]	All	94.7	63.1	87.6	30.7	40.6	40.2	47.8	51.6	87.6	47.0	89.7	66.7	35.9	90.2	48.9	57.5	0.0	39.8	56.0	56.6
ProDA [26]	All	87.8	56.0	79.7	46.3	44.8	45.6	53.5	53.5	88.6	45.2	82.1	70.7	39.2	88.8	45.5	59.4	1.0	48.9	56.4	57.5
CPSL [5]	All	92.3	59.9	84.9	45.7	29.7	52.8	61.5	59.5	87.9	41.5	85.0	73.0	35.5	90.4	48.7	73.9	26.3	53.8	53.9	60.8
IDM (Ours)	All	94.3	67.5	87.0	39.8	37.0	42.9	54.8	62.0	87.3	44.5	87.6	71.6	47.1	88.7	51.0	53.1	5.4	22.0	44.4	57.3
One-shot UDA																					
AdaptSeg [14]	One	77.7	19.2	75.5	11.7	6.4	16.8	18.2	15.4	77.1	34.0	68.5	55.3	30.9	74.5	23.7	28.3	2.9	14.4	18.9	35.2
ADVENT [16]	One	76.1	15.1	76.6	14.4	10.8	17.5	19.8	12.0	79.2	39.5	71.3	55.7	25.2	76.7	28.3	30.5	0.0	23.6	14.4	36.1
CLAN [8]	One	77.1	22.7	78.6	17.0	14.8	20.5	23.8	12.0	80.2	39.5	74.3	56.6	25.2	78.1	29.3	31.2	0.0	19.4	16.7	37.7
CBST [30]	One	76.1	22.2	73.5	13.8	18.8	19.1	20.7	18.6	79.5	41.3	74.8	57.4	19.9	78.7	21.3	28.5	0.0	28.0	13.2	37.1
ProDA [26]	One	80.9	32.2	68.9	24.7	21.0	24.6	29.6	14.8	71.7	28.6	66.4	55.8	17.5	81.6	21.2	24.2	20.0	25.0	13.9	38.0
SM-PPM [22]	One	85.0	23.2	80.4	21.3	24.5	30.0	32.0	26.7	83.2	34.8	74.0	57.3	29.0	77.7	27.3	36.5	5.0	28.2	39.4	42.8
ASM[7]	One	89.5	31.2	81.3	27.8	22.8	30.6	32.8	25.1	82.6	35.0	76.7	59.2	26.6	82.3	27.7	34.1	0.9	25.6	29.6	43.2
IDM (Ours)	One	89.7	43.5	83.3	27.1	24.2	33.4	37.2	24.2	80.2	19.6	83.9	67.1	36.4	86.2	34.2	41.6	2.7	26.9	17.9	45.2

[12] Christos Sakaridis, Dengxin Dai, and Luc Van Gool. Acdc: The adverse conditions dataset with correspondences for semantic driving scene understanding. In *Proc. ICCV*, pages 10765–10775, 2021. 1

[13] Wilhelm Tranheden, Viktor Olsson, Juliano Pinto, and Lennart Svensson. Dacs: Domain adaptation via cross-domain mixed sampling. In *Proc. WACV*, pages 1379–1389, 2021. 2, 3

[14] Yi-Hsuan Tsai, Wei-Chih Hung, Samuel Schulter, Kihyuk Sohn, Ming-Hsuan Yang, and Manmohan Chandraker. Learning to adapt structured output space for semantic segmentation. In *Proc. CVPR*, pages 7472–7481, 2018. 2, 3

[15] Yi-Hsuan Tsai, Kihyuk Sohn, Samuel Schulter, and Manmohan Chandraker. Domain adaptation for structured output via discriminative patch representations. In *Proc. ICCV*, pages 1456–1465, 2019. 2, 3

[16] Tuan-Hung Vu, Himalaya Jain, Maxime Bucher, Matthieu Cord, and Patrick Pérez. Advent: Adversarial entropy minimization for domain adaptation in semantic segmentation. In *Proc. CVPR*, pages 2517–2526, 2019. 2, 3

[17] Tuan-Hung Vu, Himalaya Jain, Maxime Bucher, Matthieu Cord, and Patrick Pérez. Dada: Depth-aware domain adaptation in semantic segmentation. In *Proc. ICCV*, pages 7364–7373, 2019. 3

[18] Haoran Wang, Tong Shen, Wei Zhang, Ling-Yu Duan, and Tao Mei. Classes matter: A fine-grained adversarial approach to cross-domain semantic segmentation. In *Proc. ECCV*, pages 642–659. Springer, 2020. 2, 3

Table S2. Adaptation from SYNTHIA to Cityscapes on DeepLab-v2 based on ResNet-101 backbone. # TS denotes the number of target samples used in training.

Method	#TS	road	side.	build.	wall*	fence*	pole*	light	sign	vege.	sky	person	rider	car	bus	motor.	bike	**mIoU***	**mIoU**
									UDA										
Source Only	-	55.6	23.8	74.6	-	-	-	6.1	12.1	74.8	79.0	55.3	19.1	39.6	23.3	13.7	25.0	-	38.6
AdaptSeg [14]	All	79.2	37.2	78.8	-	-	-	9.9	10.5	78.2	80.5	53.5	19.6	67.0	29.5	21.6	31.3	-	45.9
PatchAlign [15]	All	82.4	38.0	78.6	8.7	0.6	26.0	3.9	11.1	75.5	84.6	53.5	21.6	71.4	32.6	19.3	31.7	40.0	46.5
CLAN [8]	All	81.3	37.0	80.1	-	-	-	16.1	13.7	78.2	81.5	53.4	21.2	73.0	32.9	22.6	30.7	-	47.8
ADVENT [16]	All	85.6	42.2	79.7	8.7	0.4	25.9	5.4	8.1	80.4	84.1	57.9	23.8	73.3	36.4	14.2	33.0	41.2	48.0
CBST [30]	All	68.0	29.9	76.3	10.8	1.4	33.9	22.8	29.5	77.6	78.3	60.6	28.3	81.6	23.5	18.8	39.8	42.6	48.9
DADA [17]	All	89.2	44.8	81.4	6.8	0.3	26.2	8.6	11.1	81.8	84.0	54.7	19.3	79.7	40.7	14.0	38.8	42.6	49.8
MRKLD [29]	All	67.7	32.2	73.9	10.7	1.6	37.4	22.2	31.2	80.8	80.5	60.8	29.1	82.8	25.0	19.4	45.3	43.8	50.1
BDL [6]	All	86.0	46.7	80.3	–	–	–	14.1	11.6	79.2	81.3	54.1	27.9	73.7	42.2	25.7	45.3	–	51.4
CAG [27]	All	84.7	40.8	81.7	7.8	0.0	35.1	13.3	22.7	84.5	77.6	64.2	27.8	80.9	19.7	22.7	48.3	44.5	51.5
PIT [9]	All	83.1	27.6	81.5	8.9	0.3	21.8	26.4	33.8	76.4	78.8	64.2	27.6	79.6	31.2	31.0	31.3	44.0	51.8
SIM [21]	All	83.0	44.0	80.3	–	–	–	17.1	15.8	80.5	81.8	59.9	33.1	70.2	37.3	28.5	45.8	–	52.1
FDA [25]	All	79.3	35.0	73.2	–	–	–	19.9	24.0	61.7	82.6	61.4	31.1	83.9	40.8	38.4	51.1	–	52.5
FADA [18]	All	84.5	40.1	83.1	4.8	0.0	34.3	20.1	27.2	84.8	84.0	53.5	22.6	85.4	43.7	26.8	27.8	45.2	52.5
APODA [24]	All	86.4	41.3	79.3	–	–	–	22.6	17.3	80.3	81.6	56.9	21.0	84.1	49.1	24.6	45.7	–	53.1
UPLR [20]	All	79.4	34.6	83.5	19.3	2.8	35.3	32.1	26.9	78.8	79.6	66.6	30.3	86.1	36.6	19.5	56.9	48.0	54.6
DACS [13]	All	80.6	25.1	81.9	21.5	2.9	37.2	22.7	24.0	83.7	90.8	67.6	38.3	82.9	38.9	28.5	47.6	48.3	54.8
Seg-Uncert. [28]	All	87.6	41.9	83.1	14.7	1.7	36.2	31.3	19.9	81.6	80.6	63.0	21.8	86.2	40.7	23.6	53.1	47.9	54.9
CTF [10]	All	75.7	30.0	81.9	11.5	2.5	35.3	18.0	32.7	86.2	90.1	65.1	33.2	83.3	36.5	35.3	54.3	48.2	55.5
IAST [11]	All	81.9	41.5	83.3	17.7	4.6	32.3	30.9	28.8	83.4	85.0	65.5	30.8	86.5	38.2	33.1	52.7	49.8	57.0
CPSL [5]	All	87.2	43.9	85.5	33.6	0.3	47.7	57.4	37.2	87.8	88.5	79.0	32.0	90.6	49.4	50.8	59.8	65.3	57.9
SAC [1]	All	89.3	47.2	85.5	26.5	1.3	43.0	45.5	32.0	87.1	89.3	63.6	25.4	86.9	35.6	30.4	53.0	52.6	59.3
ProDA [26]	All	87.8	45.7	84.6	37.1	0.6	44.0	54.6	37.0	88.1	84.4	74.2	24.3	88.2	51.1	40.5	45.6	55.5	62.0
CorDA [19]	All	93.3	61.6	85.3	19.6	5.1	37.8	36.6	42.8	84.9	90.4	69.7	41.8	85.6	38.4	32.6	53.9	55.0	62.8
IDM (Ours)	All	84.2	40.4	87.3	39.9	4.2	37.8	55.2	54.0	78.6	80.2	75.3	48.7	88.2	52.0	48.1	66.2	58.6	65.9
									One-shot UDA										
AdaptSeg [14]	One	64.1	25.6	75.3	-	-	-	4.7	2.7	77.0	70.0	52.2	20.6	51.3	22.4	19.9	22.3	-	39.1
CLAN [8]	One	68.3	26.9	72.2	-	-	-	5.1	5.3	75.9	71.4	54.8	18.4	65.3	19.2	22.1	20.7	-	40.4
ADVENT [16]	One	65.7	22.3	69.2	-	-	-	2.9	3.3	76.9	69.2	55.4	21.4	77.3	17.4	21.4	16.7	-	39.9
CBST [30]	One	59.6	24.1	72.9	-	-	-	5.5	13.8	72.2	69.8	55.3	21.1	57.1	17.4	13.8	18.5	-	38.5
ProDA [26]	One	81.8	38.9	60.6	7.8	0	31.6	14.6	11.5	51.5	69.9	56.2	16.4	79.2	24.4	5.9	32.3	36.4	41.8
ASM [7]	One	85.7	39.7	77.1	1.1	0.0	24.2	2.1	9.2	76.9	81.7	43.4	11.4	63.9	15.8	1.6	20.3	34.6	40.7
SM-PPM [22]	One	79.3	35.3	75.9	5.6	16.6	29.8	25.4	22.7	79.9	76.8	54.6	23.5	60.2	23.9	21.2	36.6	41.4	47.3
SM-PPM† [22]	One	66.2	27.2	72.7	6.4	0.2	27.3	14.5	15.5	73.6	80.8	54.1	18.8	59.1	15.5	15.8	28.1	35.9	41.7
IDM (Ours)	One	84.9	36.8	78.5	4.5	5.3	33.1	14.6	18.0	80.4	81.8	56.6	23.4	73.9	25.7	13.4	25.4	41.0	47.2

[19] Qin Wang, Dengxin Dai, Lukas Hoyer, Luc Van Gool, and Olga Fink. Domain adaptive semantic segmentation with self-supervised depth estimation. In *Proc. ICCV*, pages 8515–8525, 2021. 2, 3

[20] Yuxi Wang, Junran Peng, and ZhaoXiang Zhang. Uncertainty-aware pseudo label refinery for domain adaptive semantic segmentation. In *Proc. ICCV*, pages 9092–9101, 2021. 2, 3

[21] Zhonghao Wang, Mo Yu, Yunchao Wei, Rogerio Feris, Jinjun Xiong, Wen-mei Hwu, Thomas S Huang, and Honghui Shi. Differential treatment for stuff and things: A simple unsupervised domain adaptation method for semantic segmentation. In *Proc. CVPR*, pages 12635–12644, 2020. 3

[22] Xinyi Wu, Zhenyao Wu, Yuhang Lu, Lili Ju, and Song Wang. Style mixing and patchwise prototypical matching for one-shot unsupervised domain adaptive semantic segmentation. *arXiv preprint arXiv:2112.04665*, 2021. 2, 3

[23] Enze Xie, Wenhai Wang, Zhiding Yu, Anima Anandkumar,

Table S3. Comparison results using SegF. MiT-B5. # TS denotes the number of target samples used in training.

GTA5 →Cityscapes

Method	#TS	road	side.	build.	wall	fence	pole	light	sign	vege.	terr.	sky	person	rider	car	truck	bus	train	motor.	bike	**mIoU**
Source Only	-	77.1	15.2	83.8	30.8	32.0	27.9	41.5	18.5	86.5	42.5	86.8	62.6	22.2	87.0	42.7	36.8	6.1	33.5	12.5	44.5
TransDA-B [2]	All	94.7	64.2	89.2	48.1	45.8	50.1	60.2	40.8	90.4	50.2	93.7	76.7	47.6	92.5	56.8	60.1	47.6	49.6	55.4	63.9
DAFormer [4]	All	95.7	70.2	89.4	53.5	48.1	49.6	55.8	59.4	89.9	47.9	92.5	72.2	44.7	92.3	74.5	78.2	65.1	55.9	61.8	68.3
IDM (Ours)	All	97.2	77.1	89.8	51.7	51.7	54.5	59.7	64.7	89.2	45.3	90.5	74.2	46.6	92.3	76.9	59.6	81.2	57.3	62.4	69.5
DAFormer [4]	One	88.7	34.4	84.9	29.1	28.5	36.9	43.9	29.7	83.4	29.6	84.1	66.0	38.0	86.8	54.9	47.3	32.8	24.6	37.8	50.6
IDM (Ours)	One	88.5	30.0	86.7	35.0	33.6	45.0	49.9	50.7	86.9	32.8	86.1	68.1	40.0	89.1	66.4	50.6	45.6	39.3	52.1	56.7

SYNTHIA →Cityscapes

Method	#TS	road	side.	build.	wall*	fence*	pole	light	sign*	vege.	sky	person	rider	car	bus	motor.	bike	**mIoU***	**mIoU**
Source Only	-	69.9	27.8	82.9	21.6	2.3	39.2	36.3	29.9	84.2	84.9	61.6	22.6	83.8	48.0	14.9	19.7	45.6	51.3
TransDA-B [2]	All	90.4	54.8	86.4	31.1	1.7	53.8	61.1	37.1	90.3	93.0	71.2	25.3	92.3	66.0	44.4	49.8	59.3	66.3
DAFormer [4]	All	84.5	40.7	88.4	41.5	6.5	50.0	55.0	54.6	86.0	89.8	73.2	48.2	87.2	53.2	53.9	61.7	60.9	67.4
IDM (Ours)	All	87.6	47.6	88.1	33.4	6.3	52.8	57.8	56.5	83.0	77.5	66.2	52.1	89.3	55.6	57.1	64.2	60.9	67.9
DAFormer [4]	One	65.3	26.1	79.5	24.8	1.9	38.3	30.7	23.8	81.4	84.0	66.1	27.6	70.8	39.3	23.7	33.8	44.8	50.2
IDM (Ours)	One	85.4	39.4	83.5	11.6	0.6	43.9	45.4	31.7	86.0	83.9	62.3	23.3	87.4	32.4	25.1	34.1	48.5	55.4

Model	CS Fog	Snow	Rainy	Night	Foggy	Mean
Src Only	44.5	40.6	39.7	22.5	43.6	38.2
IDM (Ours)	54.9	47.3	45.6	30.2	51.4	45.9

Jose M Alvarez, and Ping Luo. Segformer: Simple and efficient design for semantic segmentation with transformers. *Proc. NerIPS*, 34:12077–12090, 2021. 1

[24] Jihan Yang, Ruijia Xu, Ruiyu Li, Xiaojuan Qi, Xiaoyong Shen, Guanbin Li, and Liang Lin. An adversarial perturbation oriented domain adaptation approach for semantic segmentation. In *Proc. AAAI*, volume 34, pages 12613–12620, 2020. 2, 3

[25] Yanchao Yang and Stefano Soatto. Fda: Fourier domain adaptation for semantic segmentation. In *Proc. CVPR*, pages 4085–4095, 2020. 2, 3

[26] Pan Zhang, Bo Zhang, Ting Zhang, Dong Chen, Yong Wang, and Fang Wen. Prototypical pseudo label denoising and target structure learning for domain adaptive semantic segmentation. In *Proc. CVPR*, pages 12414–12424, 2021. 2, 3

[27] Qiming Zhang, Jing Zhang, Wei Liu, and Dacheng Tao. Category anchor-guided unsupervised domain adaptation for semantic segmentation. In *Proc. NeurIPS*, pages 433–443, 2019. 2, 3

[28] Zhedong Zheng and Yi Yang. Rectifying pseudo label learning via uncertainty estimation for domain adaptive semantic segmentation. *International Journal of Computer Vision*, 129(4):1106–1120, 2021. 2, 3

[29] Yang Zou, Zhiding Yu, Xiaofeng Liu, BVK Kumar, and Jinsong Wang. Confidence regularized self-training. In *Proc. ICCV*, pages 5982–5991, 2019. 2, 3

[30] Yang Zou, Zhiding Yu, BVK Vijaya Kumar, and Jinsong Wang. Unsupervised domain adaptation for semantic segmentation via class-balanced self-training. In *Proc. ECCV*, pages 289–305, 2018. 2, 3