Confidence Regularized Self-Training
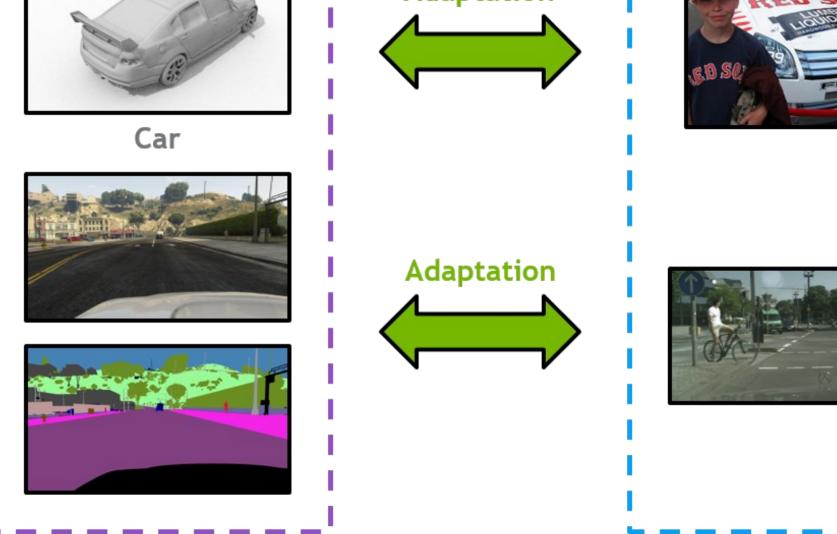
Yang Zou*, Zhiding Yu*, Xiaofeng Liu, B. V. K. Vijaya Kumar, Jinsong Wang

yzou2@andrew.cmu.edu, zhidingy@nvidia.com, liuxiaofeng@cmu.edu

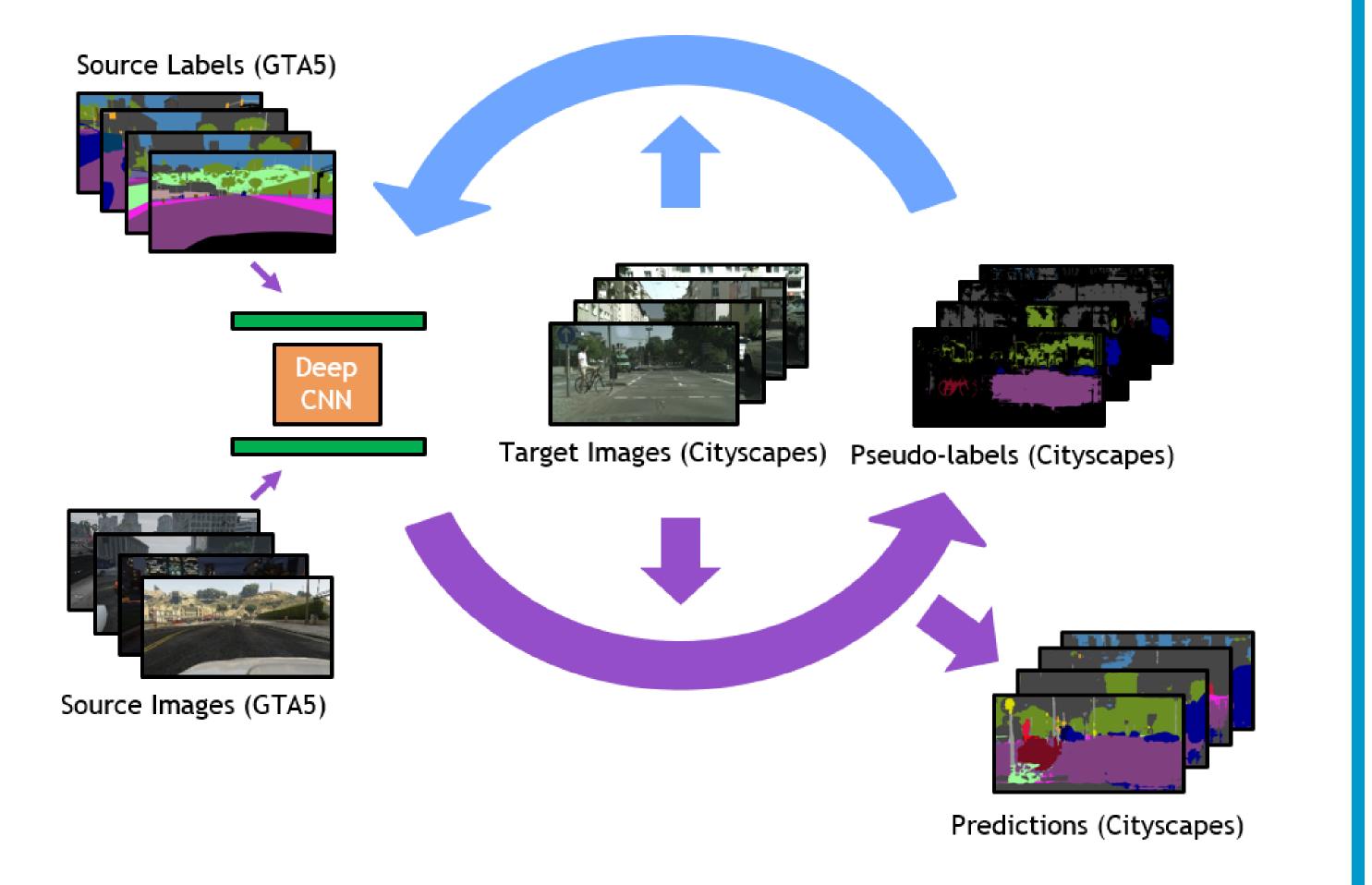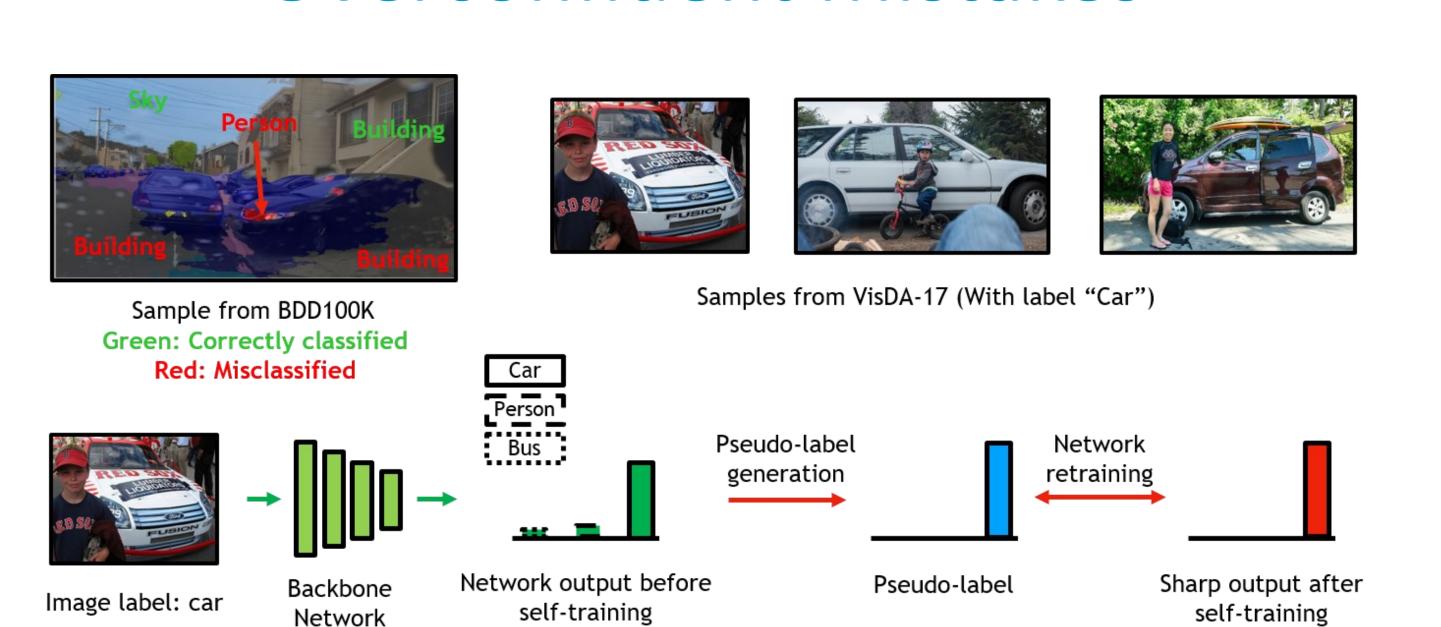## Unsupervised Domain Adaptation

Image classification

Car

Semantic segmentation

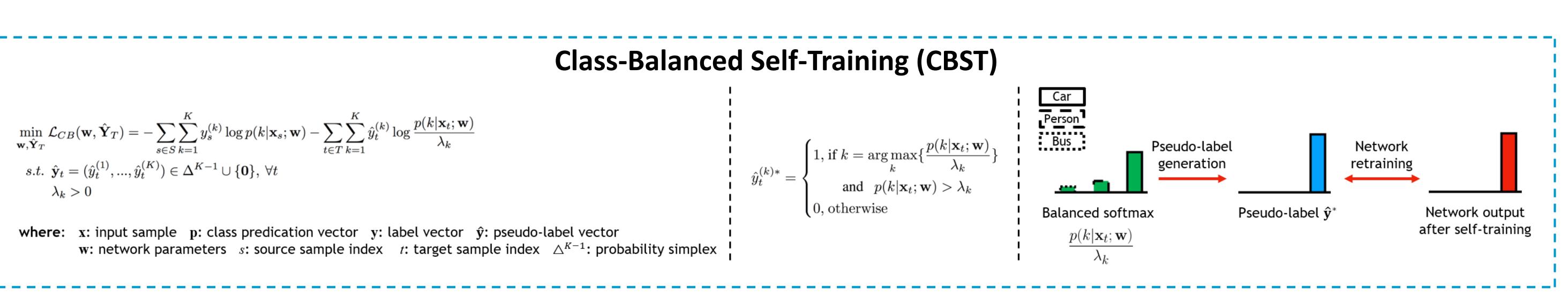Source Domain (Labeled) Target Domain (Unlabeled)

Proposed Iterative Framework

Source Labels (GTA5)

Deep CNN

Target Images (Cityscapes)   Pseudo-labels (Cityscapes)

Source Images (GTA5)

Predictions (Cityscapes)

Overconfident Mistakes

Sample from BDD100K
Green: Correctly classified
Red: Misclassified

Samples from VisDA-17 (With label "Car")

Image label: car

Backbone Network   Network output before self-training   Pseudo-label   Sharp output after self-training

Pseudo-label generation   Network retraining

Preliminaries and Definitions

Class-Balanced Self-Training (CBST)

$$\min_{\mathbf{w}, \hat{\mathbf{Y}}_T} \mathcal{L}_{CB}(\mathbf{w}, \hat{\mathbf{Y}}_T) = -\sum_{s \in S}\sum_{k=1}^{K} y_s^{(k)} \log p(k|\mathbf{x}_s; \mathbf{w}) - \sum_{t \in T}\sum_{k=1}^{K} \hat{y}_t^{(k)} \log \frac{p(k|\mathbf{x}_t; \mathbf{w})}{\lambda_k}$$

$$s.t. \quad \hat{\mathbf{y}}_t = (\hat{y}_t^{(1)}, ..., \hat{y}_t^{(K)}) \in \Delta^{K-1} \cup \{\mathbf{0}\}, \forall t$$
$$\lambda_k > 0$$

$$\hat{y}_t^{(k)*} = \begin{cases} 1, & \text{if } k = \arg\max_k\{\frac{p(k|\mathbf{x}_t; \mathbf{w})}{\lambda_k}\} \\ & \text{and } p(k|\mathbf{x}_t; \mathbf{w}) > \lambda_k \\ 0, & \text{otherwise} \end{cases}$$

where: x: input sample   p: class predication vector   y: label vector   ŷ: pseudo-label vector
w: network parameters   s: source sample index   t: target sample index Δ^{K-1}: probability simplex

Car
Person
Bus

Balanced softmax $\frac{p(k|\mathbf{x}_t; \mathbf{w})}{\lambda_k}$ Pseudo-label generation   Pseudo-label ŷ*   Network retraining   Network output after self-training

Confidence Regularized Self-Training

Label Regularized Self-Training (LR)

$$\min_{\mathbf{w}, \hat{\mathbf{Y}}_T} \mathcal{L}_{LR}(\mathbf{w}, \hat{\mathbf{Y}}_T) = -\sum_{s \in S}\sum_{k=1}^{K} y_s^{(k)} \log p(k|\mathbf{x}_s; \mathbf{w}) - \sum_{t \in T}\left[\sum_{k=1}^{K}\hat{y}_t^{(k)} \log \frac{p(k|\mathbf{x}_t; \mathbf{w})}{\lambda_k} - \alpha r_c(\hat{\mathbf{y}}_t)\right]$$

$$s.t. \quad \hat{\mathbf{Y}}_T = (\hat{y}_t^{(1)}, ..., \hat{y}_t^{(K)}) \in \Delta^{K-1} \cup \{\mathbf{0}\}, \forall t$$
$$\lambda_k > 0$$

where: α: regularizer weight

$$\mathcal{C}(\hat{\mathbf{y}}_t) = -\sum_{k=1}^{K} \hat{y}_t^{(k)} \log \frac{p(k|\mathbf{x}_t; \mathbf{w})}{\lambda_k} + \alpha r_c(\hat{\mathbf{y}}_t)$$

$$\hat{\mathbf{y}}_t^1 = \arg\min \mathcal{C}(\hat{\mathbf{y}}_t)$$
$$s.t. \quad \hat{y}_t \in \Delta^{K-1}, \forall t$$

$$\hat{\mathbf{y}}_t^* = \begin{cases} \hat{\mathbf{y}}_t^1, & \text{if } \mathcal{C}(\hat{\mathbf{y}}_t^1) < \mathcal{C}(\mathbf{0}) \\ \mathbf{0}, & \text{otherwise} \end{cases}$$

Car
Person
Bus

Balanced softmax $\frac{p(k|\mathbf{x}_t; \mathbf{w})}{\lambda_k}$ Pseudo-label generation $\alpha = 0.5$ Pseudo-label ŷ*   Network retraining $\alpha = 0.5$ Network output after self-training

Model Regularized Self-Training (MR)

$$\min_{\mathbf{w}, \hat{\mathbf{Y}}_T} \mathcal{L}_{MR}(\mathbf{w}, \hat{\mathbf{Y}}_T) = -\sum_{s \in S}\sum_{k=1}^{K} y_s^{(k)} \log p(k|\mathbf{x}_s; \mathbf{w}) - \sum_{t \in T}\left[\sum_{k=1}^{K}\hat{y}_t^{(k)} \log \frac{p(k|\mathbf{x}_t; \mathbf{w})}{\lambda_k} - \alpha r_c(p(\mathbf{x}_t; \mathbf{w}))\right]$$

$$s.t. \quad \hat{\mathbf{Y}}_T = (\hat{y}_t^{(1)}, ..., \hat{y}_t^{(K)}) \in \Delta^{K-1} \cup \{\mathbf{0}\}, \forall t$$
$$\lambda_k > 0$$

where: α: regularizer weight

$$\min_{\mathbf{w}} -\sum_{t \in T}\left[\sum_{k=1}^{K}\hat{y}_t^{(k)} \log p(k|\mathbf{x}_t; \mathbf{w}) - \alpha r_c(p(\mathbf{x}_t; \mathbf{w}))\right]$$

Car
Bus

Balanced softmax $\frac{p(k|\mathbf{x}_t; \mathbf{w})}{\lambda_k}$ Pseudo-label generation $\alpha = 0.2$ Pseudo-label ŷ*   Network retraining $\alpha = 0.2$ Network output after self-training

Regularizer Design and Theory

Confidence Regularizers

LR-Entropy (LRENT) $r_c(\hat{\mathbf{y}}_t) = \sum_{k=1}^{K} \hat{y}_t^{(k)} \log(\hat{y}_t^{(k)})$

MR-KLDiv (MRKLD) $r_c(p(\mathbf{x}_t; \mathbf{w})) = -\sum_{k=1}^{K} \frac{1}{K} \log p(k|\mathbf{x}_t)$

Pseudo-label solver $\hat{y}_t^{(k)\dagger} = \frac{(\frac{p(k|\mathbf{x}_t)}{\lambda_k})^{\frac{1}{\alpha}}}{\sum_{k=1}^{K}(\frac{p(k|\mathbf{x}_t)}{\lambda_k})^{\frac{1}{\alpha}}}$

MR-Entropy (MRENT) $r_c(p(\mathbf{x}_t; \mathbf{w})) = -\sum_{k=1}^{K} p(k|\mathbf{x}_t) \log p(k|\mathbf{x}_t)$

MR-L2 (MRL2) $r_c(p(\mathbf{x}_t; \mathbf{w})) = -\sum_{k=1}^{K} p(k|\mathbf{x}_t)^2$

Theoretical Analysis

Probabilistic Explanation

Proposition 1. CRST can be modeled as a regularized maximum likelihood for classification (RCML) problem optimized via classification expectation maximization.

Convergence Analysis

Proposition 2. Given pre-determined λ_k's, CRST is convergent with gradient descent for network retraining optimization.

LRNET — Pseudo-label generation loss v.s. probability
MRKLD / MRENT / MRL2 — Regularized retraining loss v.s. probability

Experiment: GTA5 —> Cityscapes

Method	Backbone	Road	SW	Build	Wall	Fence	Pole	TL	TS	Veg.	Terrain	Sky	PR	Rider	Car	Truck	Bus	Train	Motor	Bike	mIoU
Source	DRN-26	42.7	26.3	51.7	5.5	6.8	13.8	23.6	6.9	75.5	11.5	36.8	49.3	0.9	46.7	3.4	5.0	0.0	5.0	1.4	21.7
CyCADA [23]	DRN-26	79.1	33.1	77.9	23.4	17.3	32.1	33.3	31.8	81.5	26.7	69.0	62.8	14.7	74.5	20.9	25.6	6.9	18.8	20.4	39.5
Source	DRN-105	36.4	14.2	67.4	16.4	12.0	20.1	8.7	0.7	69.8	13.3	56.9	37.0	0.4	53.7	0.0	0.0	0.0	0.0	0.0	21.7
MCD [51]	DRN-105	90.3	31.0	78.5	19.7	17.3	28.6	30.9	11.8	83.7	24.6	70.3	58.5	19.6	81.5	23.8	30.0	5.7	25.7	14.3	39.7
Source	DeepLabv2	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	36.6
AdaptSegNet [60]	DeepLabv2	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
AdvEnt [63]	DeepLabv2	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
Source	DeepLabv2																				29.2
FCAN [67]	DeepLabv2																				46.6
Source		71.3	19.2	69.1	18.4	10.0	35.7	27.3	6.8	79.6	24.8	72.1	57.6	19.5	55.5	15.5	15.1	11.7	21.1	12.0	33.8
CBST	DeepLabv2	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
MRL2	DeepLabv2	91.9	55.2	80.9	32.1	21.5	36.7	30.0	19.0	84.8	34.9	80.1	56.1	23.8	83.9	28.0	29.5	20.5	24.0	40.3	46.0
MRENT	DeepLabv2	91.8	53.4	80.6	32.6	20.8	34.3	29.7	21.0	84.0	34.1	80.6	53.9	24.6	82.8	30.8	34.9	16.6	26.4	42.6	46.1
MRKLD	ResNet-38	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
LRENT		91.8	53.5	80.5	32.7	21.0	34.0	29.0	20.3	83.9	34.2	80.9	53.1	23.9	82.7	30.2	35.6	16.3	25.9	42.8	45.9
Source		70.0	23.7	67.8	15.4	18.1	40.2	41.9	25.3	78.8	11.7	31.4	62.9	29.8	60.1	21.5	26.8	7.7	28.1	12.0	35.4
CBST [69]	ResNet-38	86.8	46.7	76.9	26.3	24.8	42.0	46.0	38.6	80.7	15.7	48.0	57.3	27.9	78.2	24.5	49.6	17.7	25.5	45.1	45.2
MRL2		84.4	52.7	74.7	30.0	32.2	43.7	53.7	38.6	73.9	24.4	44.5	61.4	26.4	63.2	22.1	31.9	45.9	44.2	34.8	46.0
MRENT		84.6	49.5	73.9	35.8	25.1	46.2	53.3	43.3	75.2	24.2	63.8	61.8	28.7	83.6	28.8	50.0	34.7	33.8	65.7	47.9
MRKLD		84.5	47.7	74.1	27.9	22.1	43.8	46.5	37.8	83.7	22.7	56.1	56.8	26.8	81.7	22.5	46.2	27.5	32.7	49.8	46.8
LRENT		80.3	40.8	65.8	24.6	30.5	43.1	49.5	36.3	82.1	26.0	54.6	59.4	32.1	81.9	30.0	21.9	44.8	36.7	54.3	46.9
CBST-SP		85.6	55.1	76.9	26.8	23.4	38.9	47.1	46.9	83.4	25.1	47.6	55.6	15.7	79.7	27.7	50.3	38.2	33.4	64.6	46.8
MRKLD-SP	ResNet-38	90.8	46.0	79.9	27.4	23.3	42.3	46.2	40.9	83.5	19.2	59.1	63.3	31.8	83.5	36.8	52.0	28.0	36.8	46.4	49.2
MRKLD-SP-MST		91.7	45.1	80.9	29.0	23.4	43.8	47.1	40.9	84.0	20.0	60.6	64.0	31.9	85.8	39.5	48.7	25.0	38.0	47.0	49.8

Original Image   Ground Truth   Source Model   CBST   CRST (MRKLD)

Experiment: SYNTHIA —> Cityscapes

Method	Backbone	Road	SW	Build	Wall*	Fence*	Pole*	TL	TS	Veg.	Sky	PR	Rider	Car	Bus	Motor	Bike	mIoU	mIoU*
Source	DRN-105	14.9	11.4	58.7	1.9	0.0	24.1	1.2	6.0	68.8	76.0	54.3	7.1	34.2	15.0	0.8	0.0	23.4	26.8
MCD [51]	DRN-105	84.8	43.6	79.0	3.9	0.2	29.1	7.2	5.5	83.8	83.1	51.0	11.7	79.9	27.2	6.2	0.0	37.3	43.5
Source	DeepLabv2	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
AdaptSegNet [60]	DeepLabv2	84.3	42.7	77.5	—	—	—	4.7	7.0	77.9	82.5	54.3	21.0	72.3	32.2	18.9	32.3	—	46.7
AdvEnt [63]	DeepLabv2	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
Source	ResNet-38	32.6	21.5	46.5	4.8	0.1	26.5	14.8	13.1	70.8	60.3	56.6	3.5	74.1	20.4	8.9	13.1	29.2	33.6
CBST [69]	ResNet-38	53.6	23.7	75.0	12.5	0.3	36.4	23.5	26.3	84.8	74.7	67.2	17.5	84.5	28.4	15.2	55.8	42.5	48.4
Source	DeepLabv2	64.3	21.3	73.1	2.4	1.1	31.4	7.0	27.7	63.1	67.6	42.2	19.9	73.1	15.3	10.5	38.9	34.9	40.3
CBST	DeepLabv2	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
MRL2	DeepLabv2	63.4	27.1	76.4	14.2	1.4	35.2	23.6	29.4	78.5	77.8	61.4	29.5	82.2	22.8	18.9	42.3	42.8	48.7
MRENT	DeepLabv2	69.6	32.6	75.8	12.2	1.8	35.3	23.3	29.5	77.7	78.9	60.0	28.5	81.5	25.9	19.6	41.8	42.8	48.7
MRKLD	DeepLabv2	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
LRENT	DeepLabv2	65.6	30.3	74.6	13.8	1.5	35.8	23.1	29.1	77.0	77.5	60.1	28.5	82.2	22.6	20.1	41.9	42.7	48.7

Exp: VisDA-17

Method	Aero	Bike	Bus	Car	Horse	Knife	Motor	Person	Plant	Skateboard	Train	Truck	Mean
Source [50]	55.1	53.3	61.9	59.1	80.6	17.9	79.7	31.2	81.0	26.5	73.5	8.5	52.4
MMD [33]	87.1	63.0	76.5	42.0	90.3	42.9	85.9	53.1	49.7	36.3	85.8	20.7	61.1
DANN [15]	81.9	77.7	82.8	44.3	81.2	29.5	65.1	28.6	51.9	54.6	82.8	7.8	57.4
ENT [18]	80.3	75.5	75.8	48.3	77.9	27.3	69.7	40.2	46.5	46.6	79.3	16.0	57.0
MCD [51]	87.0	60.9	83.7	64.0	88.9	79.6	84.7	76.9	88.6	40.3	83.0	25.8	71.9
ADR [50]	87.8	79.5	83.7	65.3	92.3	61.8	88.9	73.2	87.8	60.0	85.5	32.3	74.8
SimNet-Res152 [44]	94.3	82.3	73.5	47.2	87.9	49.2	75.1	79.7	85.3	68.5	81.1	50.3	72.9
GTA-Res152 [53]													77.1
Source-Res101	68.7	36.7	61.3	70.4	67.9	5.9	82.6	25.5	75.6	29.4	83.8	10.9	51.6
CBST	87.2±2.4	78.8±1.0	56.5±2.2	55.4±3.6	85.1±1.4	79.2±10.3	83.8±0.4	77.7±4.9	82.8±1.7	88.8±3.2	69.0±2.9	72.0±3.8	76.4±0.9
MRL2	87.0±2.9	79.5±1.9	57.1±3.2	54.7±2.9	85.5±1.1	78.1±11.7	83.0±1.5	77.7±3.7	82.4±1.7	88.6±2.7	69.1±2.2	71.8±3.0	76.2±1.0
MRENT	87.1±2.7	78.3±0.7	56.1±4.0	54.4±2.7	84.4±2.3	79.9±10.6	83.7±1.1	77.9±4.4	82.7±2.8	80.0±1.4	72.8±3.1	71.8±3.2	76.2±0.8
MRKLD	87.3±2.5	79.4±1.9	60.5±2.4	59.7±2.5	87.6±1.4	82.4±4.4	86.5±1.1	78.4±2.6	84.6±1.7	86.4±2.8	72.5±2.4	69.8±2.5	77.9±0.5
LRENT	87.7±2.4	78.7±0.8	57.3±3.3	55.4±4.0	84.4±2.1	77.4±3.7	83.1±1.9	88.3±2.6	84.6±2.8	85.4±2.0	73.9±1.3	72.6±2.4	76.6±0.9
MRKLD+LRENT	88.0±0.6	79.2±2.2	61.0±3.1	60.0±1.0	87.5±1.2	81.4±5.6	86.3±1.5	78.8±2.1	85.6±0.9	86.6±2.5	73.9±1.3	68.8±2.3	78.1±1.2

Exp: Office-31

Method	A→W	D→W	W→D	A→D	D→A	W→A	Mean
ResNet-50 [21]	68.4±0.2	96.7±0.1	99.3±0.1	68.9±0.2	62.5±0.3	60.7±0.3	76.1
DAN [33]	80.5±0.4	97.1±0.2	99.6±0.1	78.6±0.2	63.6±0.3	62.8±0.2	80.4
RTN [15]	84.5±0.2	96.8±0.1	99.4±0.1	77.5±0.3	66.2±0.2	64.8±0.3	81.6
DANN [15]	82.0±0.4	96.9±0.2	99.1±0.1	79.7±0.4	68.2±0.4	67.4±0.5	82.2
ADDA [61]	86.2±0.5	96.2±0.3	98.4±0.3	77.8±0.3	69.5±0.4	68.9±0.5	82.9
JAN [36]	85.4±0.3	97.4±0.2	99.8±0.2	84.7±0.3	68.6±0.3	70.0±0.4	84.3
GTA [53]	89.5±0.5	97.9±0.3	99.8±0.4	87.7±0.5	72.8±0.3	71.4±0.4	86.5
CBST	87.8±0.8	98.5±0.1	**100**±0.0	86.5±1.0	71.2±0.4	70.9±0.7	85.8
MRL2	87.3±0.8	98.9±0.1	**100**±0.0	87.7±0.9	71.8±0.2	**72.1**±0.2	86.4
MRENT	88.6±0.9	98.7±0.1	**100**±0.0	87.4±0.8	**72.7**±0.2	71.0±0.8	86.5
MRKLD	88.4±0.9	98.7±0.1	**100**±0.0	88.7±0.8	72.6±0.7	70.9±0.4	86.3
LRENT	88.6±0.4	98.5±0.1	**100**±0.0	87.4±0.8	71.7±0.2	70.5±0.6	86.1
MRKLD+LRENT	89.4±0.7	**98.9**±0.4	**100**±0.0	**89.6**±0.8	72.6±0.7	70.9±0.5	**86.8**

Reference

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