Confidence Regularized Self-Training

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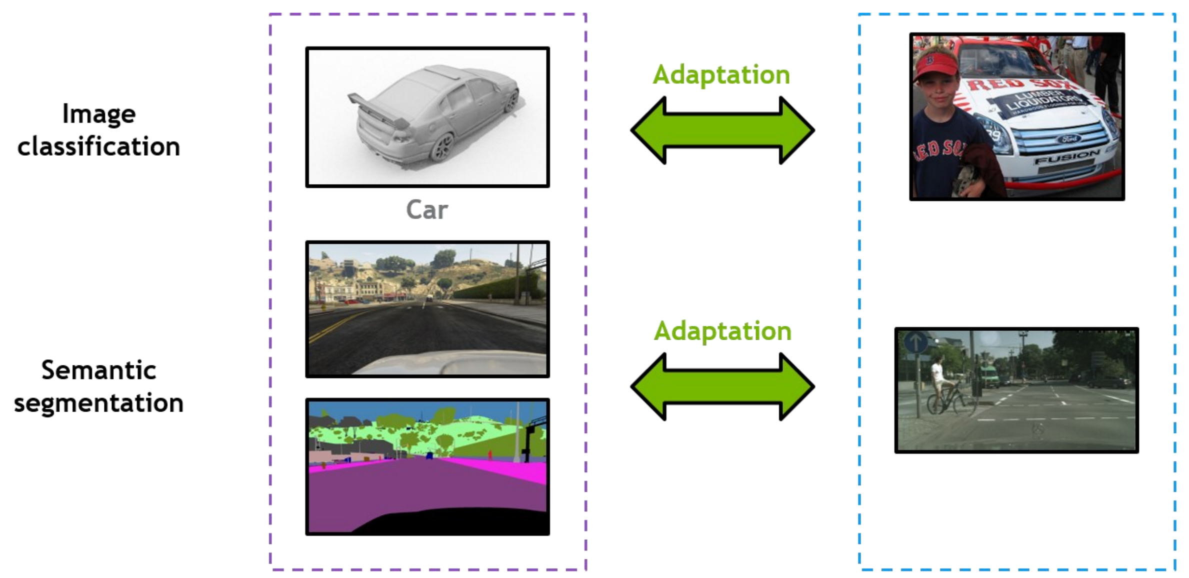
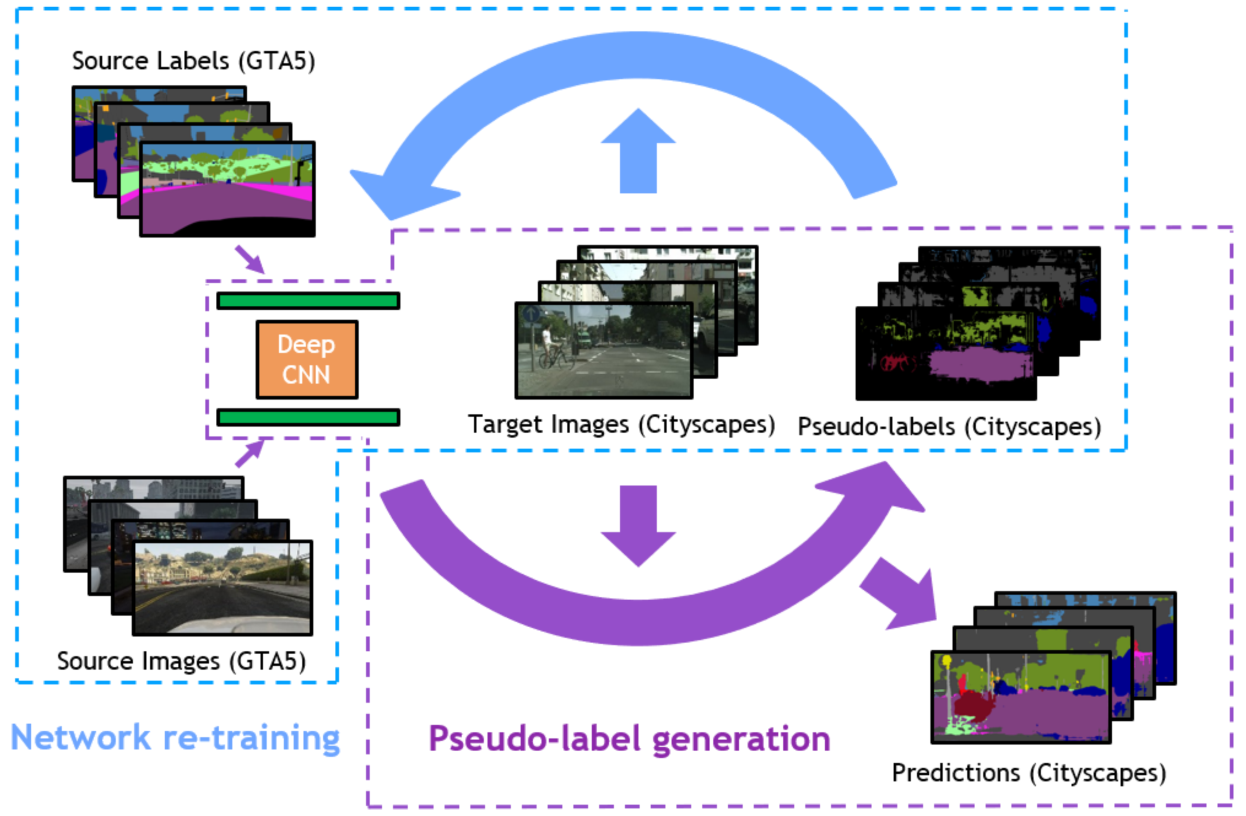
Code

Unsupervised Domain Adaptation

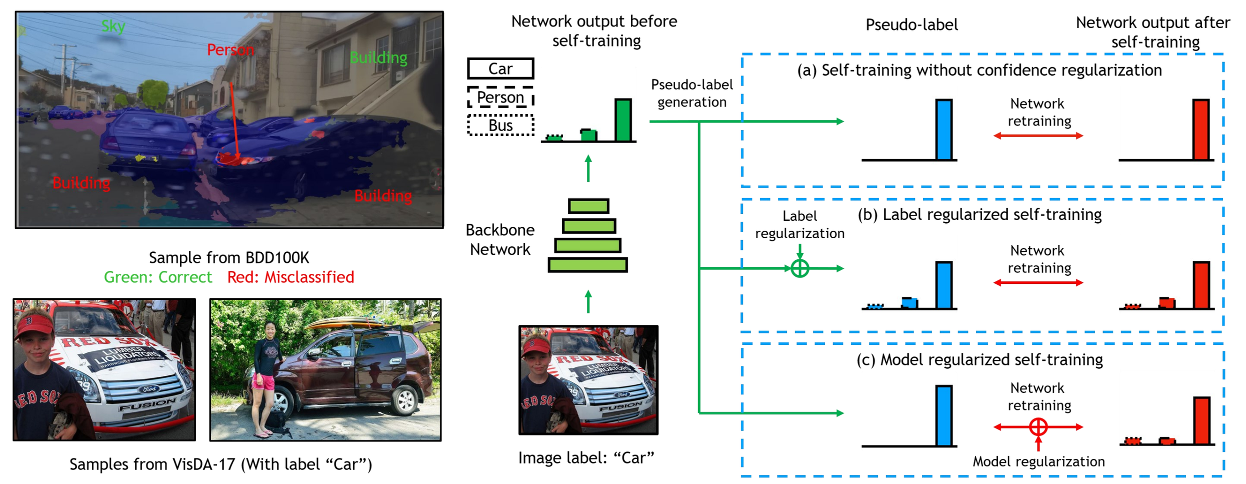


Source Domain (Labeled) Target Domain (Unlabeled)

Proposed Iterative Framework



Preventing Overconfidence



Preliminaries and Definitions

Fine-tuning for Supervised Adaptation

$$\min_{\mathbf{w}} \mathcal{L}_S(\mathbf{w}) = -\sum_{s\in S}\sum_{k=1}^{K} y_s^{(k)} \log p(k|\mathbf{x}_s;\mathbf{w}) - \sum_{t\in T}\sum_{k=1}^{K} y_t^{(k)} \log p(k|\mathbf{x}_t;\mathbf{w})$$

where: $\mathbf{x}$: input sample $\mathbf{p}$: class predication vector $\mathbf{y}$: label vector
$\mathbf{w}$: network parameters s: source sample index t: target sample index

Self-Training for Unsupervised Adaptation

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

$$s.t.\ \hat{\mathbf{y}}_t \in \Delta^{K-1},\ \forall t$$

where: $\hat{\mathbf{y}}$: pseudo-label vector $\triangle^{K-1}$: probability simplex

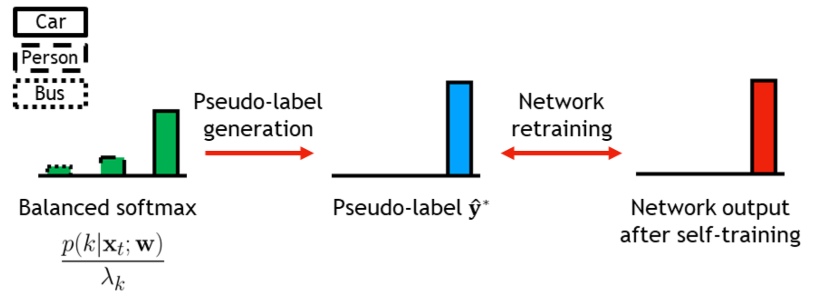
Class-Balanced Self-Training (CBST)

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

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

where: λ: reweighting factor

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



Confidence Regularized Self-Training

Label Regularized Self-Training (LR)

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

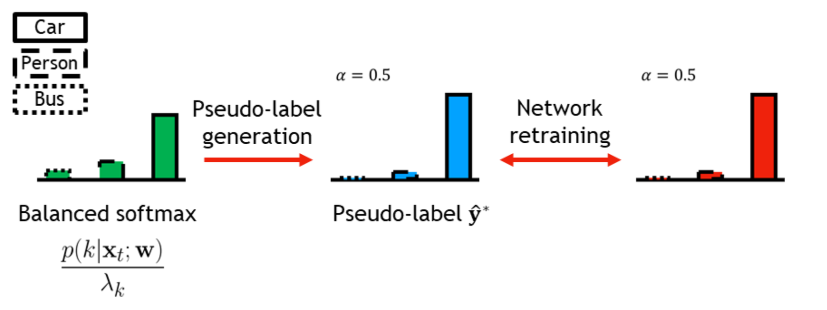
$$s.t.\ \hat{\mathbf{y}}_t = (\hat{y}_t^{(1)},...,\hat{y}_t^{(K)}) \in \Delta^{K-1}\cup\{\mathbf{0}\},\ \forall t \qquad \lambda_k > 0$$

where: α: regularizer weight

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

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

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



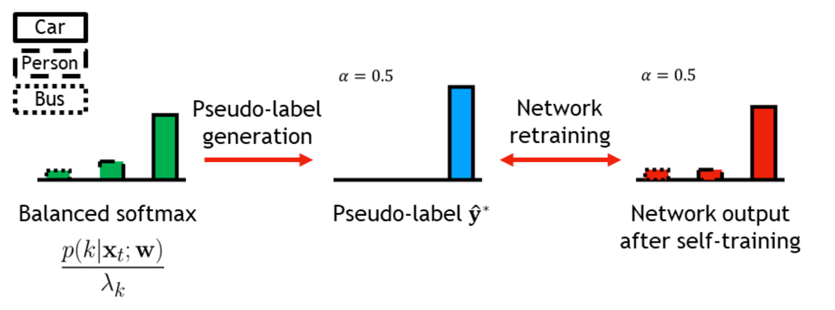
Model Regularized Self-Training (MR)

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

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

where: α: regularizer weight

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



Regularizer Design and Theory

Confidence Regularizers

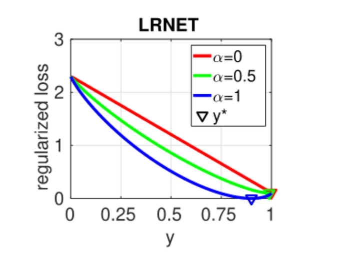
LR-Entropy (LRENT) $r_c(\hat{\mathbf{y}}_t) = \sum_{k=1}^{K} \hat{y}_t^{(k)} \log(\hat{y}_t^{(k)})$

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

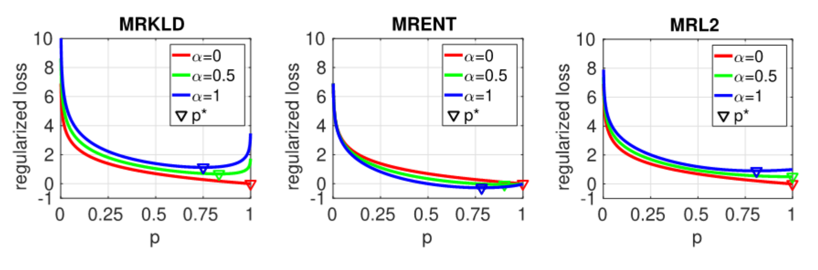
MR-KLDiv (MRKLD) $r_c(p(\mathbf{x}_t;\mathbf{w})) = -\sum_{k=1}^{K}\frac{1}{K}\log p(k|\mathbf{x}_t)$

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



Pseudo-label generation loss v.s. probability



Regularized retraining loss v.s. probability

Theoretical Analysis

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

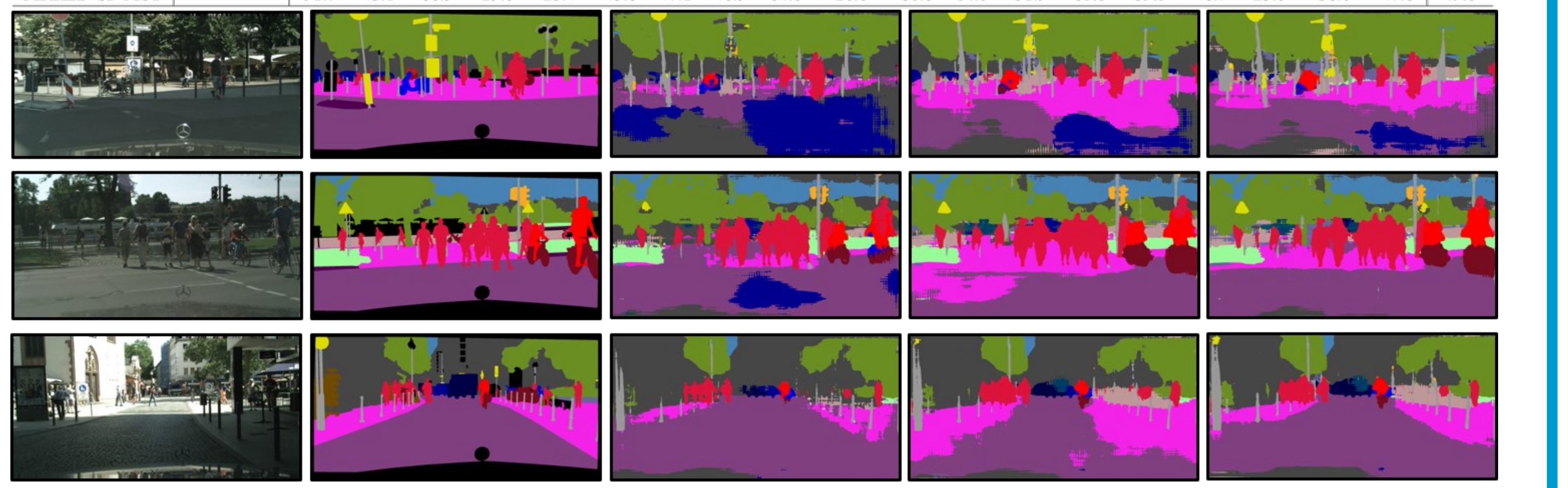
Proposition 2. Given pre-determined λ_k's, CRST is convergent with gradient descent for network retraining optimization.

Proposition 3. If λ_k's are equal for all k, the soft pseudo-label of LRENT is exactly the same as softmax with temperature.

Proposition 4. Self-Training with MRKLD is equivalent to self-training with pseudo-label uniformly smoothed by $\varepsilon = (K\alpha-\alpha)/(K+K\alpha)$, where α is the regularizer weight.

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]		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	53.6	10.6	3.2	0.2	0.9	0.0	22.2
MCD [51]		90.3	31.0	78.5	19.7	17.3	28.6	30.9	16.1	83.7	30.0	69.1	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]		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]		-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	46.6
Source	DeepLabv2	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		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		**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	29.4	20.5	24.0	40.3	46.0
MRENT		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		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	ResNet-38	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]		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	38.0	**32.2**	43.7	**53.7**	38.6	73.9	24.4	64.4	45.6	24.6	63.2	3.22	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	48.2	**33.8**	65.7	2.89	32.6	39.2	**50.0**	34.7	46.4
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	32.3	**47.9**	46.8
LRENT		80.3	40.8	65.8	24.6	30.5	43.1	49.5	40.3	82.1	26.0	54.6	59.4	32.1	68.0	31.9	30.0	21.9	44.8	46.7	45.9
CBST-SP	ResNet-38	85.6	55.1	76.9	26.8	23.4	38.9	47.1	**46.9**	83.4	25.5	68.7	45.6	15.7	79.7	27.7	50.3	38.2	33.4	44.6	48.1
MRKLD-SP		90.8	46.0	79.9	27.4	23.3	42.3	46.2	40.9	83.5	19.2	59.1	63.5	30.8	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]		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]		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]		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		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		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		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	43.4	49.6
MRKLD		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		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

Experiment: 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±4.0	82.8±2.8	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±2.4	87.4±2.8	70.0±1.4	72.8±3.3	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	54.5±4.0	84.8±1.7	79.7±10.3	84.2±1.4	77.4±3.7	83.1±1.5	**88.3±2.6**	70.9±2.1	**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±0.2**

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 [35]	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	88.4±0.2	98.6±0.1	**100±0.0**	87.7±0.9	71.8±0.2	**72.1±0.2**	86.4
MRENT	88.0±0.4	98.6±0.1	**100±0.0**	87.4±0.8	**72.7±0.2**	71.0±0.4	86.4
MRKLD	88.4±0.9	98.7±0.1	**100±0.0**	88.0±0.9	71.7±0.8	70.9±0.4	86.3
LRENT	88.6±0.4	98.7±0.1	**100±0.0**	**89.0±0.8**	72.0±0.6	71.0±0.3	86.6
MRKLD+LRENT	89.4±0.7	**98.9±0.4**	**100±0.0**	88.7±0.8	72.6±0.7	70.9±0.5	**86.8**

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