Unsupervised Domain Adaptation for Semantic Segmentation via Class-Balanced Self-Training

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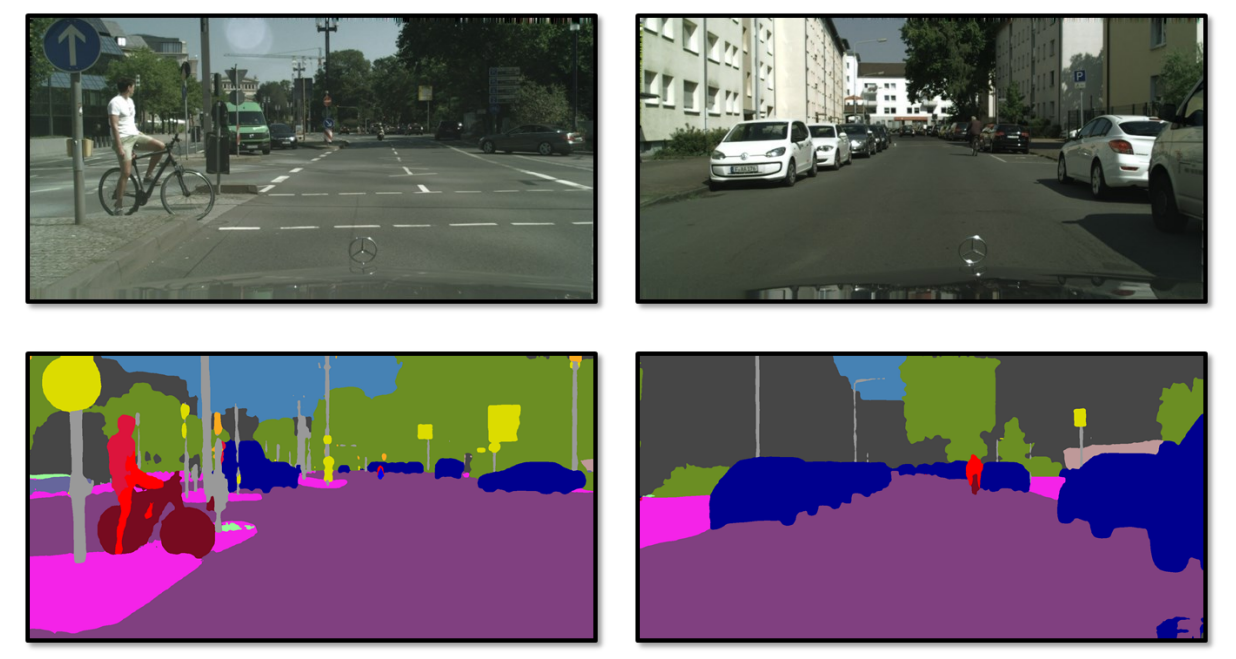
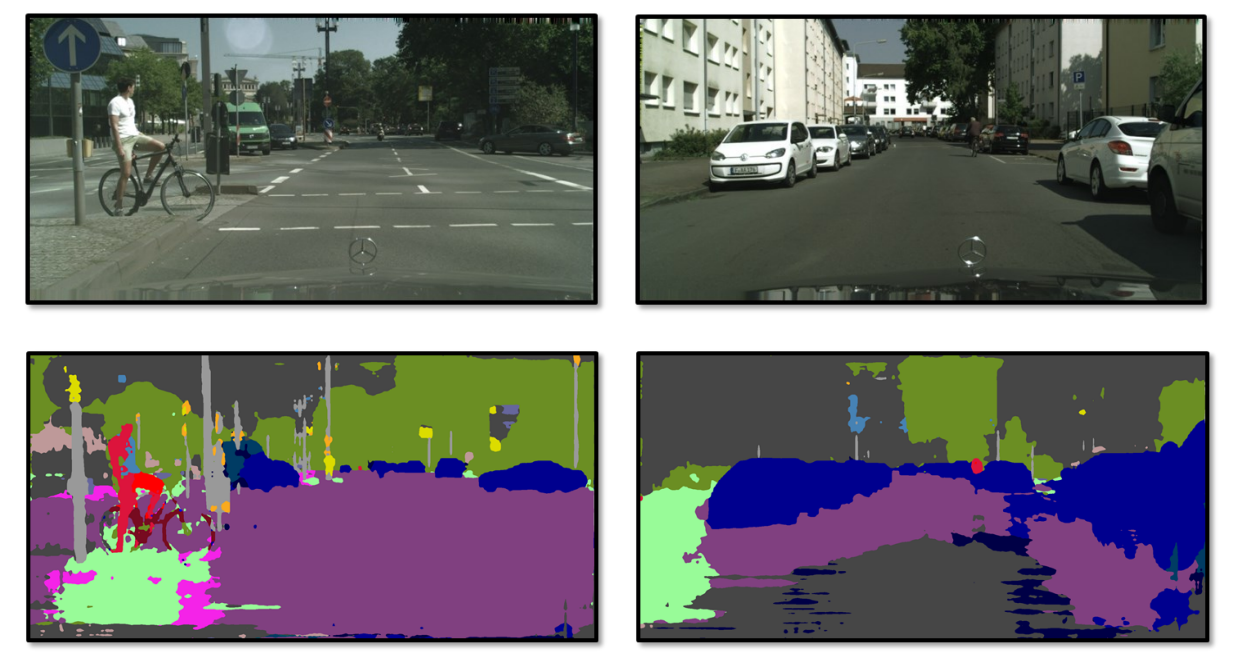
The Problem of Domain Gap

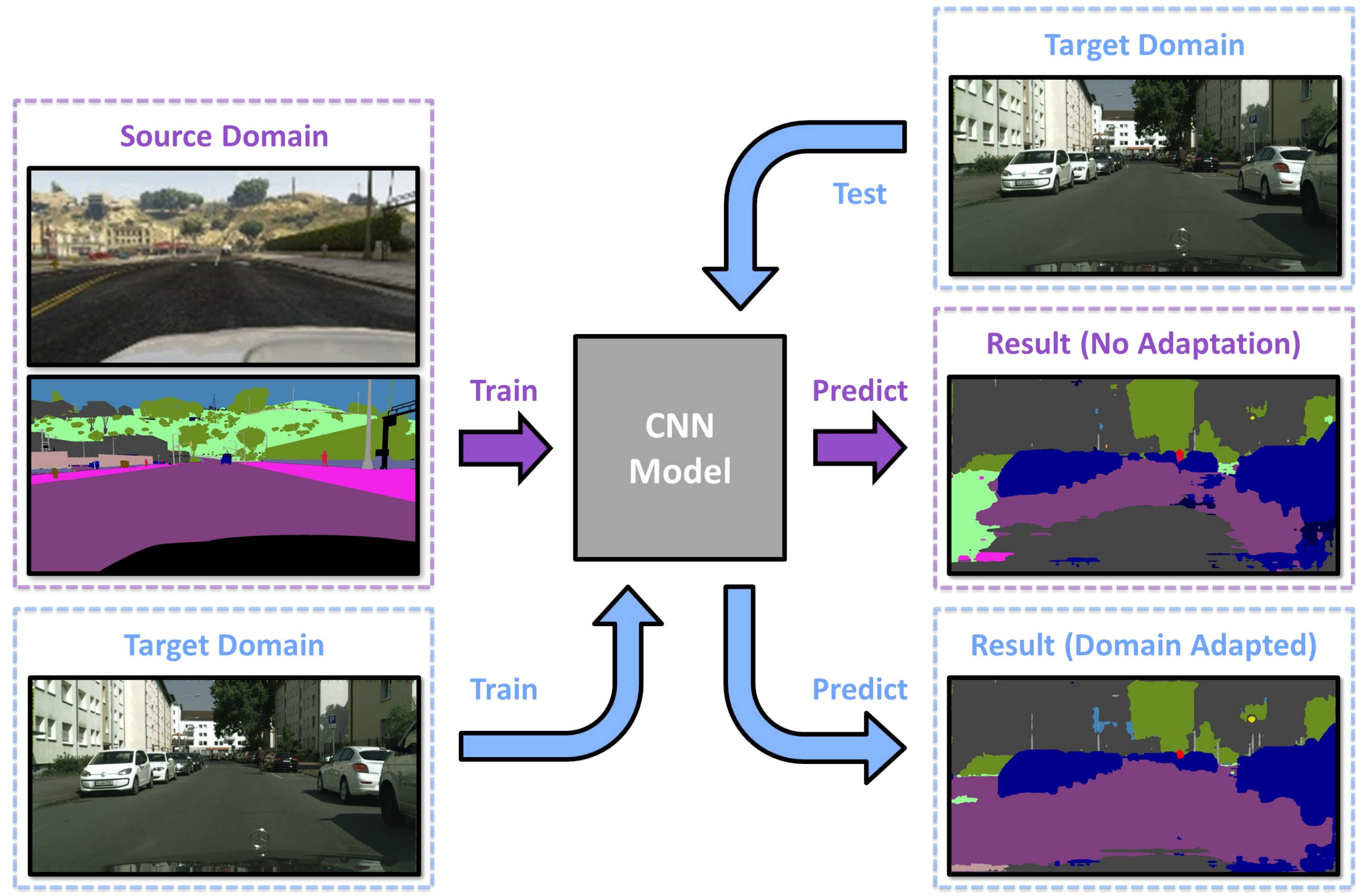
Cityscapes —> Cityscapes



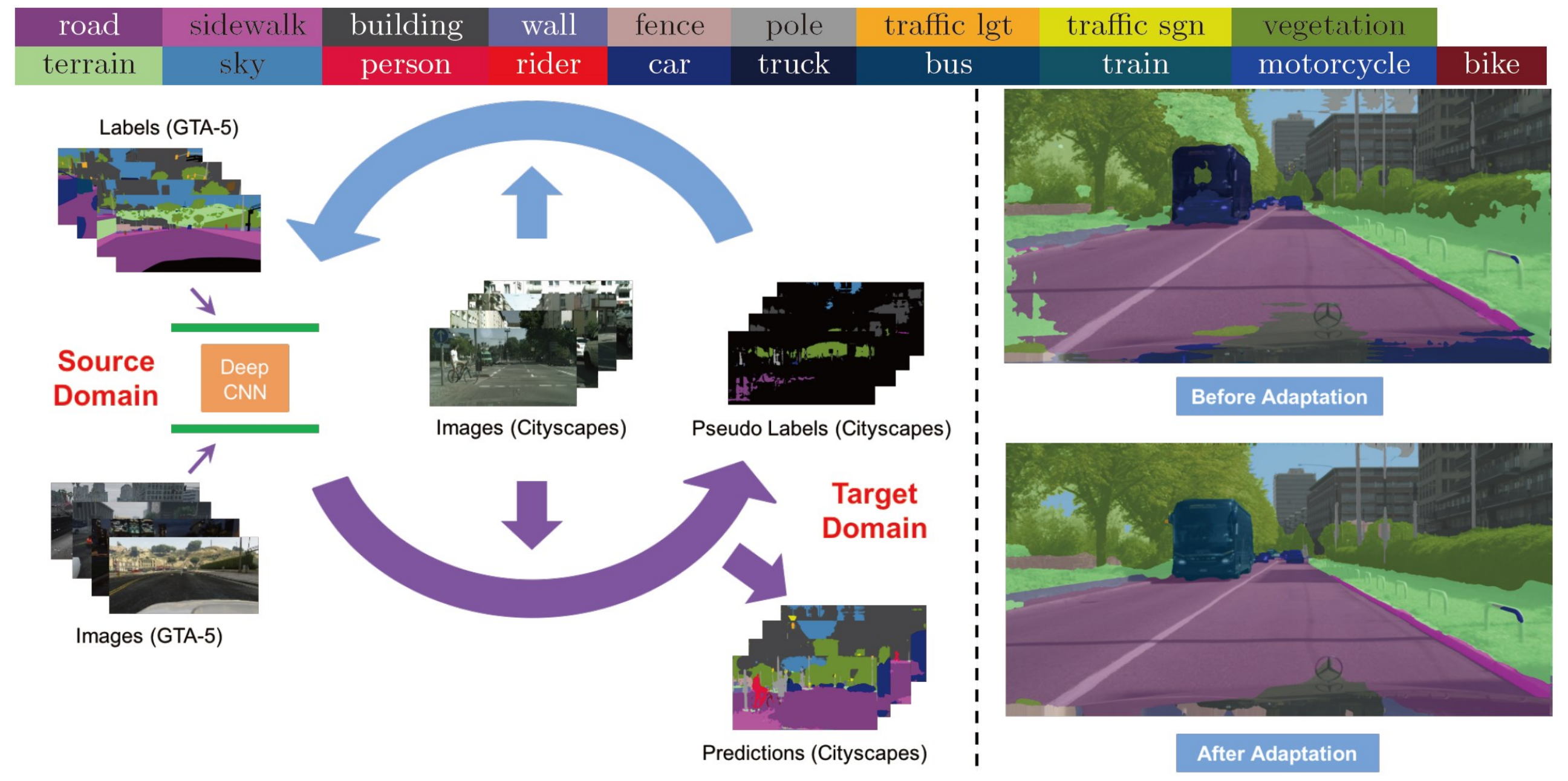
GTA5 —> Cityscapes



Unsupervised Domain Adaptation



Proposed Iterative Framework



Proposed iterative self-training framework. Left: algorithm workflow. Right: results on Cityscapes before and after adaptation.

Preliminaries and Definitions

Fine-tuning for Supervised Domain Adaptation

$$\min_{\mathbf{w}} \mathcal{L}_S(\mathbf{w}) = -\sum_{s=1}^{S}\sum_{n=1}^{N} \mathbf{y}_{s,n}^\top \log(\mathbf{p}_n(\mathbf{w}, \mathbf{I}_s)) - \sum_{t=1}^{T}\sum_{n=1}^{N} \mathbf{y}_{t,n}^\top \log(\mathbf{p}_n(\mathbf{w}, \mathbf{I}_t))$$

where: $\mathbf{I}$: input image (crop) $\mathbf{p}$: pixel class probability vector $\mathbf{y}$: pixel label vector
$\mathbf{w}$: network parameters s: source image index t: target image index

Self-Training for Unsupervised Domain Adaptation

$$\min_{\mathbf{w},\hat{\mathbf{y}}} \mathcal{L}_U(\mathbf{w}, \hat{\mathbf{y}}) = -\sum_{s=1}^{S}\sum_{n=1}^{N} \mathbf{y}_{s,n}^\top \log(\mathbf{p}_n(\mathbf{w}, \mathbf{I}_s)) - \sum_{t=1}^{T}\sum_{n=1}^{N} \hat{\mathbf{y}}_{t,n}^\top \log(\mathbf{p}_n(\mathbf{w}, \mathbf{I}_t))$$

$$s.t.\ \hat{\mathbf{y}}_{t,n} \in \{\mathbf{e}^{(i)} | \mathbf{e}^{(i)} \in \mathbb{R}^C\}, \forall t, n$$

where: $\hat{\mathbf{y}}$: pseudo label vector $\mathbf{e}^{(i)}$: one-hot vector

Self-Training with Self-Paced Learning

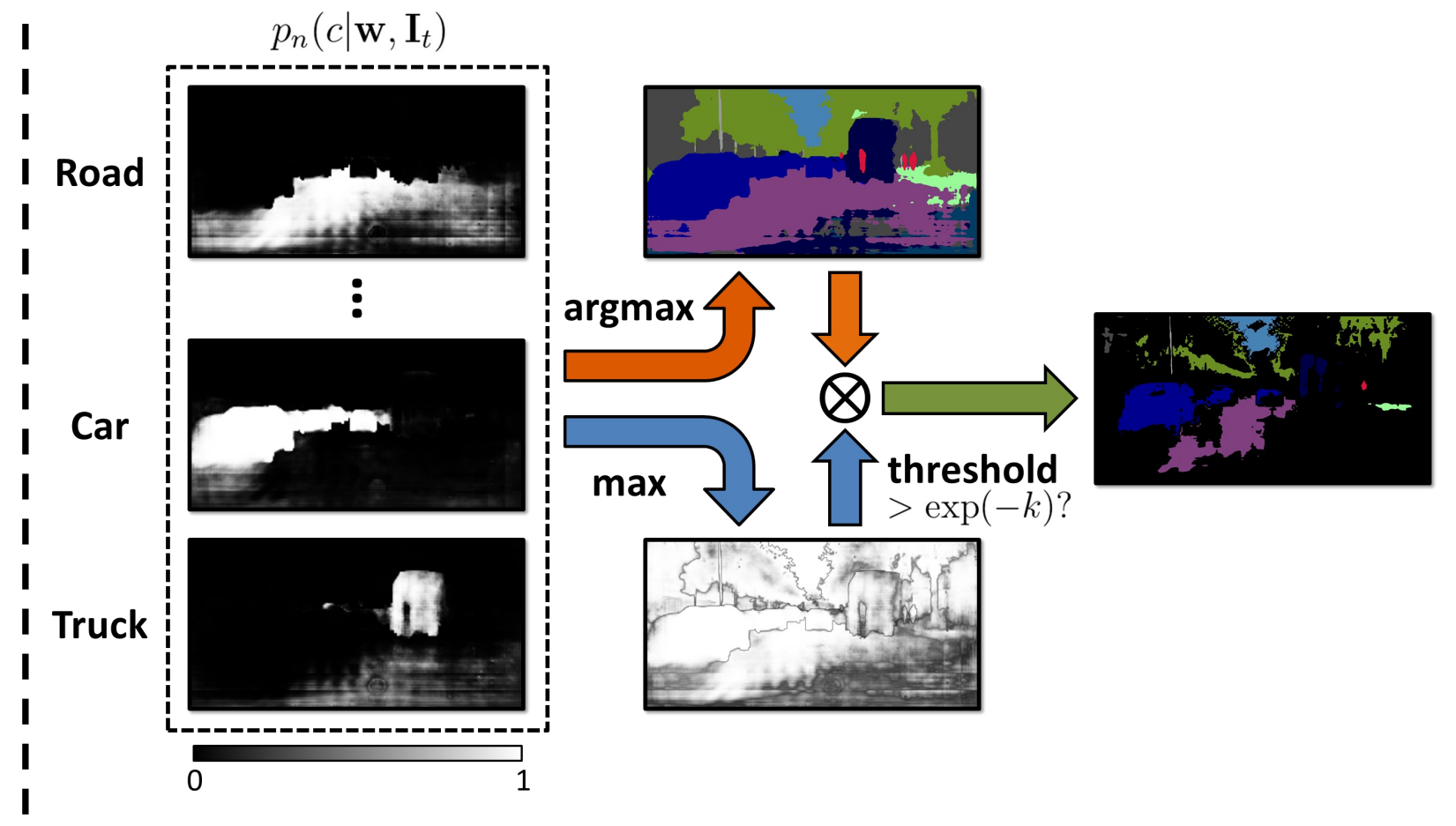
The Vanilla Self-Training (ST) Framework

$$\min_{\mathbf{w},\hat{\mathbf{y}}} \mathcal{L}_{ST}(\mathbf{w}, \hat{\mathbf{y}}) = -\sum_{s=1}^{S}\sum_{n=1}^{N} \mathbf{y}_{s,n}^\top \log(\mathbf{p}_n(\mathbf{w}, \mathbf{I}_s)) - \sum_{t=1}^{T}\sum_{n=1}^{N} [\hat{\mathbf{y}}_{t,n}^\top \log(\mathbf{p}_n(\mathbf{w}, \mathbf{I}_t)) + k|\hat{\mathbf{y}}_{t,n}|_1]$$

$$s.t.\ \hat{\mathbf{y}}_{t,n} \in \{\{\mathbf{e}^{(i)} | \mathbf{e}^{(i)} \in \mathbb{R}^C\} \cup \mathbf{0}\}, \forall t, n$$
$$k > 0$$

The cost can be minimized via mixed integer programming, which leads to the following solution:

$$\hat{y}_{t,n}^{(c)*} = \begin{cases} 1, \ \textbf{if} \ c = \arg\max_c p_n(c|\mathbf{w}, \mathbf{I}_t), \\ \quad p_n(c|\mathbf{w}, \mathbf{I}_t) > \exp(-k) \\ 0, \ \text{otherwise} \end{cases}$$



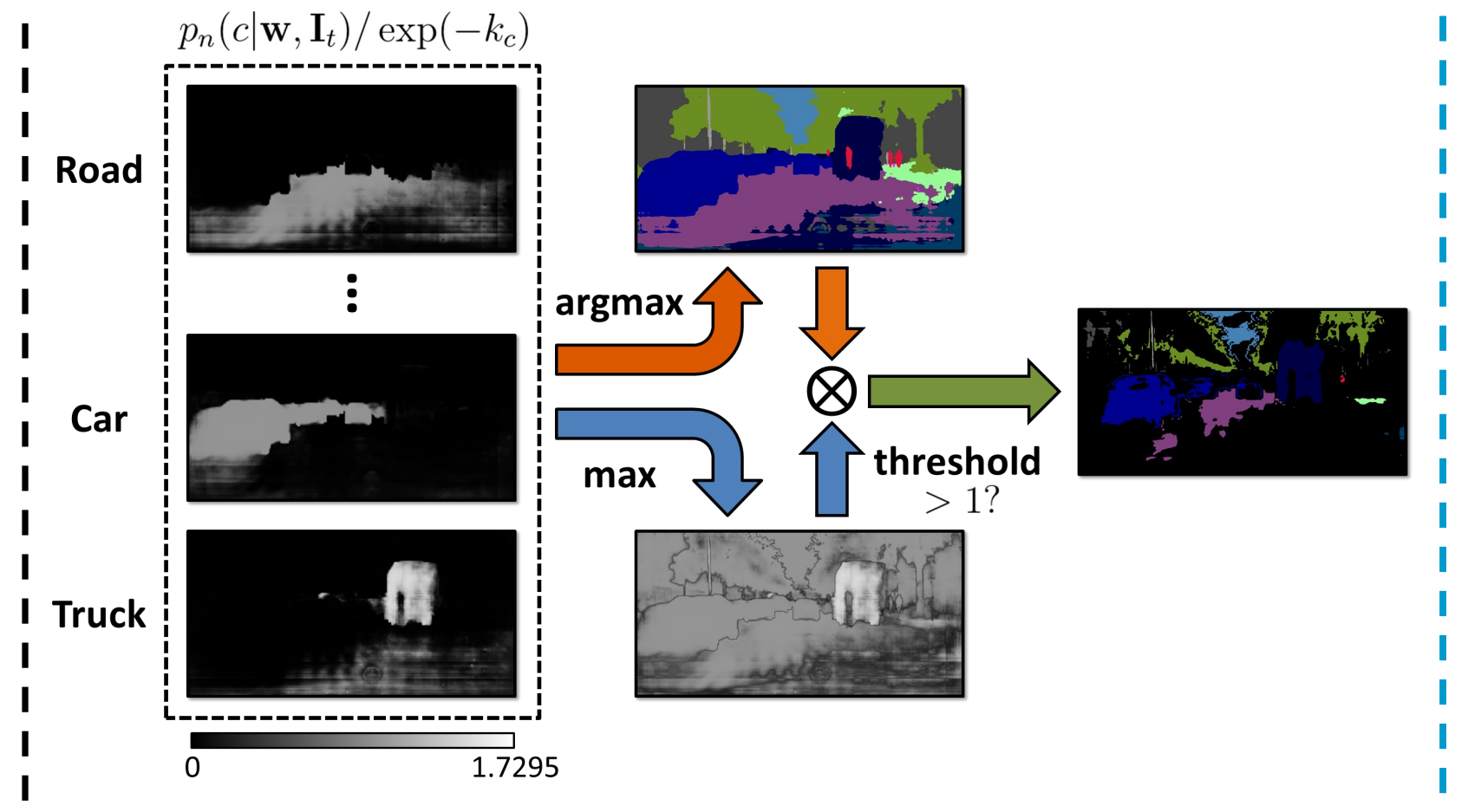
The Class-Balanced Self-Training (CBST) Framework

$$\min_{\mathbf{w},\hat{\mathbf{y}}} \mathcal{L}_{CB}(\mathbf{w}, \hat{\mathbf{y}}) = -\sum_{s=1}^{S}\sum_{n=1}^{N} \mathbf{y}_{s,n}^\top \log(\mathbf{p}_n(\mathbf{w}, \mathbf{I}_s)) - \sum_{t=1}^{T}\sum_{n=1}^{N}\sum_{c=1}^{C} [\hat{y}_{t,n}^{(c)} \log(p_n(c|\mathbf{w}, \mathbf{I}_t)) + k_c \hat{y}_{t,n}^{(c)}]$$

$$s.t.\ \hat{\mathbf{y}}_{t,n} = [\hat{y}_{t,n}^{(1)}, ..., \hat{y}_{t,n}^{(C)}] \in \{\{\mathbf{e}^{(i)} | \mathbf{e}^{(i)} \in \mathbb{R}^C\} \cup \mathbf{0}\}, \forall t, n$$
$$k_c > 0, \forall c$$

Again using mixed integer programming, one obtains the following solution:

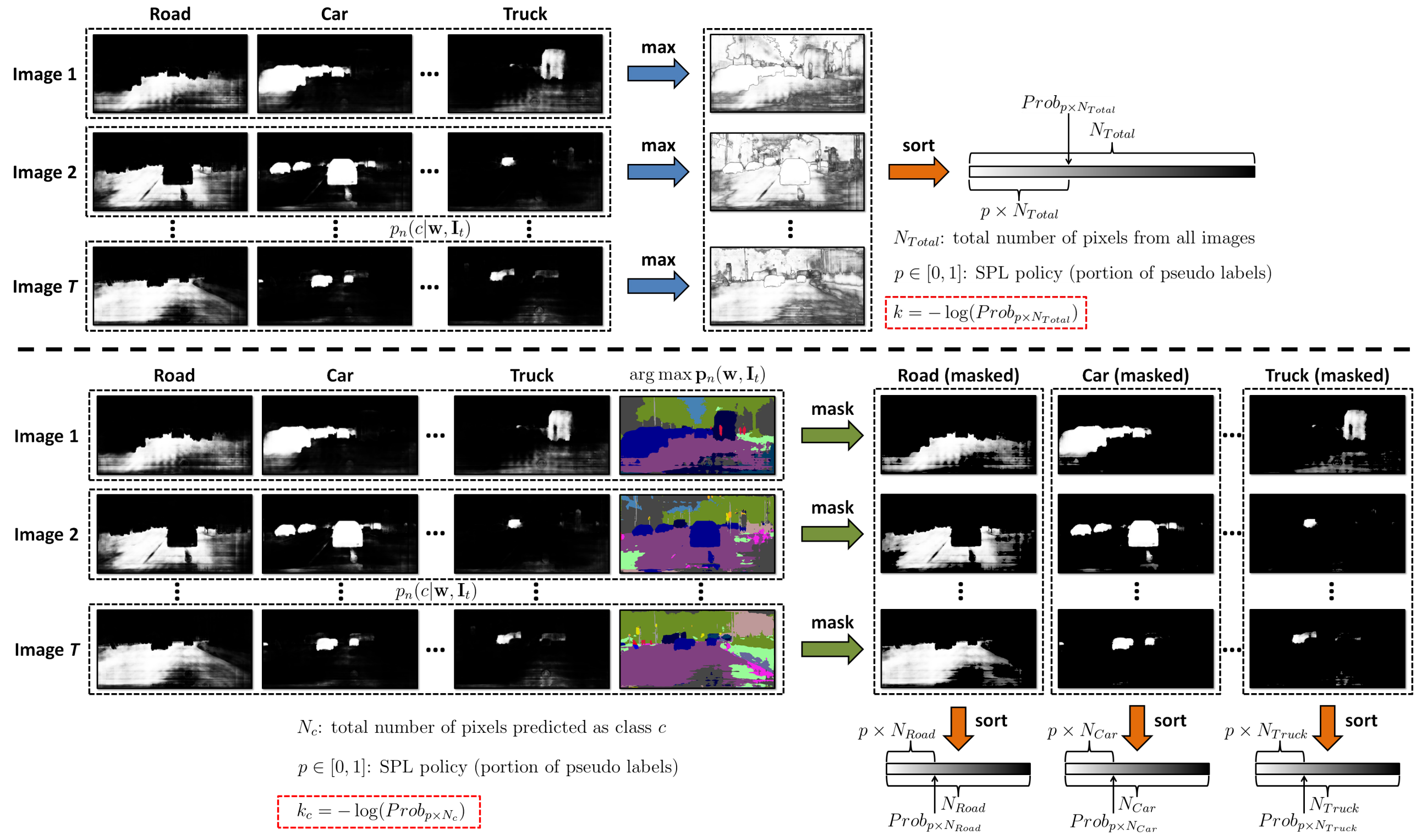
$$\hat{y}_{t,n}^{(c)*} = \begin{cases} 1, \ \textbf{if} \ c = \arg\max_c \dfrac{p_n(c|\mathbf{w}, \mathbf{I}_t)}{\exp(-k_c)}, \\ \quad \dfrac{p_n(c|\mathbf{w}, \mathbf{I}_t)}{\exp(-k_c)} > 1 \\ 0, \ \text{otherwise} \end{cases}$$



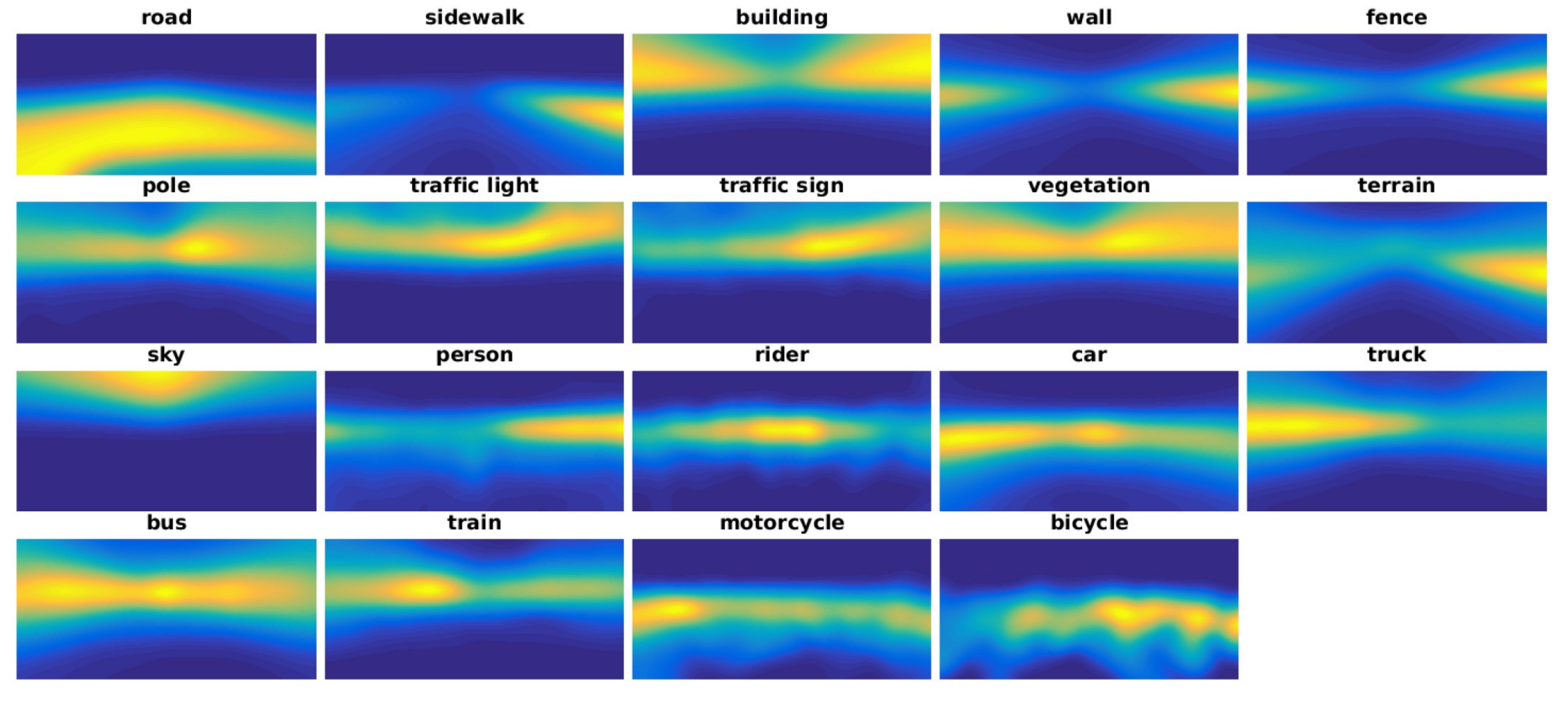
SPL Policy Design and Spatial Priors

Self-Paced Learning Policy Design

The both k and k_c in ST and CBST can be easily determined with a single SPL policy parameter p:



Incorporating Spatial Priors (CBST-SP)

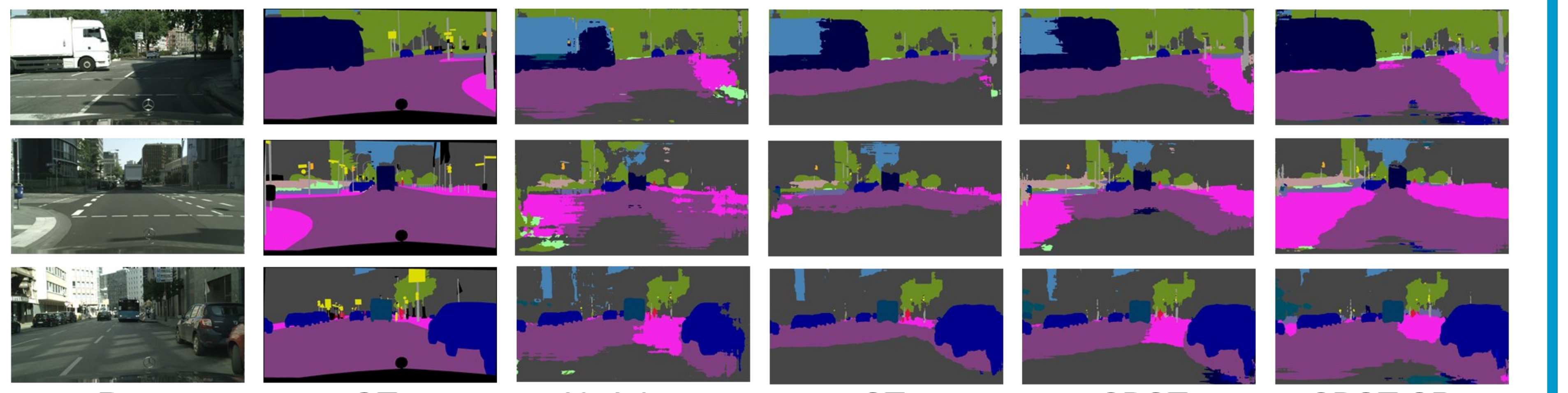


$$\min_{\mathbf{w},\hat{\mathbf{y}}} \mathcal{L}_{SP}(\mathbf{w}, \hat{\mathbf{y}}) = -\sum_{s=1}^{S}\sum_{n=1}^{N} \mathbf{y}_{s,n}^\top \log(\mathbf{p}_n(\mathbf{w}, \mathbf{I}_s)) - \sum_{t=1}^{T}\sum_{n=1}^{N}\sum_{c=1}^{C} [\hat{y}_{t,n}^{(c)} \log(q_n(c) p_n(c|\mathbf{w}, \mathbf{I}_t)) + k_c \hat{y}_{t,n}^{(c)}]$$

$$s.t.\ \hat{\mathbf{y}}_{t,n} \in \{\{\mathbf{e} | \mathbf{e} \in \mathbb{R}^C\} \cup \mathbf{0}\}, \forall t, n$$
$$k_c > 0, \forall c$$

Experiment: GTA5 —> Cityscapes

Method	Base Net	Road	SW	Build	Wall	Fence	Pole	TL	TS	Veg.	Terrain	Sky	PR	Rider	Car	Truck	Bus	Train	Motor	Bike	mIoU
Source only	Dilation-Frontend	31.9	18.9	47.7	7.4	3.1	16.0	10.4	1.0	76.5	13.0	58.9	36.0	1.0	67.1	9.5	3.7	0.0	0.0	0.0	21.2
FCN wild		70.4	32.4	62.1	14.9	5.4	10.9	14.2	2.7	79.2	21.3	64.6	44.1	4.2	70.4	8.0	7.3	0.0	3.5	0.0	27.1
Source only	FCN8s-VGG16	18.1	6.8	64.1	7.3	8.7	21.0	14.9	16.8	45.9	2.4	64.4	41.6	17.5	55.3	8.4	5.0	6.9	4.3	13.8	22.3
Curr. DA		74.9	22.0	71.7	6.0	11.9	8.4	16.3	11.1	75.7	13.3	66.5	38.0	9.3	55.2	18.8	18.9	0.0	16.8	16.6	28.9
Source only	FCN8s-VGG16	26.0	14.9	65.1	5.5	12.9	8.9	6.0	2.5	70.0	2.9	47.0	24.5	0.0	40.0	12.1	1.5	0.0	0.0	0.0	17.9
CyCADA		85.2	37.2	76.5	21.8	15.0	23.8	22.9	21.5	80.5	31.3	60.7	50.5	9.0	76.9	17.1	28.2	4.5	9.8	0.0	35.4
Source only	Dilated ResNet-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		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 only	ResNet-50	64.5	24.9	73.7	14.8	2.5	18.0	15.9	0	74.9	16.4	72.0	42.3	0.0	39.5	8.6	13.4	0.0	0.0	0.0	25.3
ADR		87.8	15.6	77.4	20.6	9.7	19.0	19.9	7.7	82.0	31.5	74.3	43.5	9.0	77.8	17.5	27.7	1.8	9.7	0.0	33.3
Source only	DenseNet	67.3	23.1	69.4	13.9	14.4	21.6	19.2	12.4	78.7	24.5	74.8	49.3	3.7	54.1	8.7	5.3	2.6	6.2	1.9	29.0
I2I Adapt		85.8	37.5	80.2	23.3	16.1	23.0	14.5	9.8	79.2	**36.5**	**76.4**	53.4	7.4	82.8	19.1	15.7	2.8	13.4	1.7	35.7
Source only	DeepLab-v2	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
MAA		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
Source only	FCN8s-VGG16	64.0	22.1	68.6	13.3	8.7	19.9	15.5	5.9	74.9	13.4	37.0	37.7	10.3	48.2	6.1	1.2	1.8	10.8	2.9	24.3
ST		83.8	17.4	72.1	14.3	2.9	16.5	16.0	6.8	81.4	24.2	47.2	40.7	7.6	71.7	10.2	7.6	0.5	11.1	0.9	28.1
CBST		66.7	26.8	73.7	14.8	9.5	28.3	25.9	10.1	75.5	15.7	51.6	47.2	6.2	71.9	3.7	2.2	5.4	18.9	32.4	30.9
CBST-SP		**90.4**	50.8	72.0	18.3	9.5	27.2	28.6	14.1	82.4	25.1	70.8	42.6	14.5	76.9	5.9	12.5	1.2	14.0	28.6	36.1
Source only	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
ST		90.1	56.8	77.9	28.5	23.0	41.5	45.2	39.6	84.8	26.4	49.2	59.0	27.4	82.3	39.7	45.6	**20.9**	**34.8**	**46.2**	41.5
CBST		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
CBST-SP		88.0	56.2	77.0	27.4	22.4	40.7	47.3	**40.9**	82.4	21.6	60.3	50.2	20.4	**83.8**	35.0	**51.0**	15.2	20.6	37.0	46.2
CBST-SP+MST		89.6	**58.9**	78.5	**33.0**	22.3	**41.4**	**48.2**	39.2	**83.6**	24.3	65.4	49.3	20.2	83.3	**39.0**	48.6	12.5	20.3	35.3	**47.0**

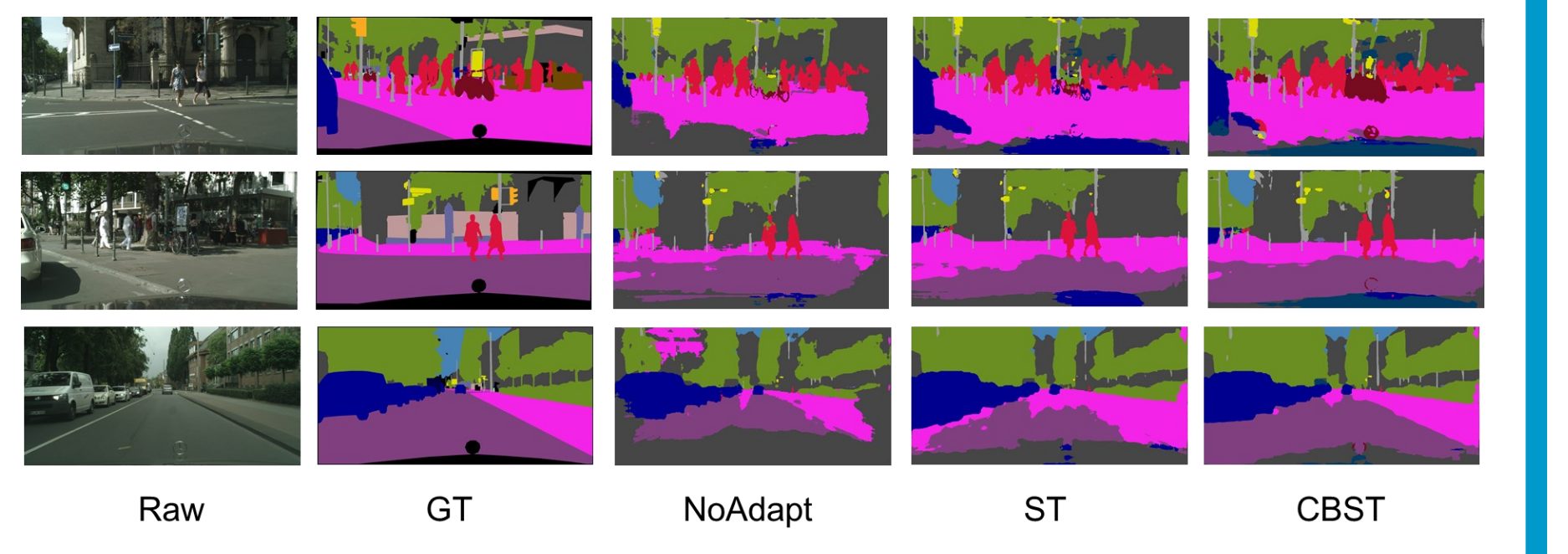


Experiment: SYNTHIA —> Cityscapes

Method	Base Net	Road	SW	Build	Wall*	Fence*	Pole*	TL	TS	Veg.	Sky	PR	Rider	Car	Bus	Motor	Bike	mIoU	mIoU*
Source only	Dilation-Frontend	6.4	17.7	29.7	1.2	0.0	15.1	0.0	7.2	30.3	66.8	51.1	1.5	47.3	3.9	0.1	0.0	17.4	20.2
FCN wild		11.5	19.6	30.8	4.4	0.0	20.3	0.1	11.7	42.3	68.7	51.2	3.8	54.0	3.2	0.2	0.6	20.2	22.1
Source only	FCN8s-VGG16	5.6	11.2	59.6	8.0	**0.5**	21.5	8.0	5.3	72.4	75.6	35.1	9.0	23.6	4.5	0.5	18.0	22.0	27.6
Curr. DA		65.2	26.1	74.9	0.1	**0.5**	10.7	3.5	3.0	76.1	70.6	47.1	8.2	43.2	20.7	0.7	13.1	29.0	34.8
Source only	FCN8s-VGG16	24.1	19.1	68.5	0.9	0.3	16.4	5.7	10.8	75.2	76.3	43.2	15.2	26.7	15.0	5.9	8.5	25.7	30.3
GAN DA		79.1	31.1	77.1	3.0	0.2	22.8	6.6	15.2	77.4	78.9	47.0	14.8	67.5	16.3	6.9	13.0	34.8	40.8
Source only	DeepLab-v2	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
MAA		**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
Source only	FCN8s-VGG16	17.2	19.7	47.3	1.1	0.0	19.1	3.0	9.1	71.8	78.3	37.6	4.7	42.2	9.0	0.1	0.9	22.6	26.2
ST		0.2	14.5	53.8	1.6	0.0	18.9	0.9	7.8	72.2	80.3	48.1	6.3	67.7	4.7	0.2	4.5	23.9	27.8
CBST		69.6	28.7	69.5	12.1	0.1	25.4	11.9	13.6	82.0	81.9	49.1	14.5	66.0	6.6	3.7	32.4	35.4	36.1
Source only	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
ST		38.2	19.6	70.2	3.9	0.0	31.9	17.6	17.2	82.4	68.3	63.1	5.3	78.4	11.2	0.8	7.5	32.2	36.9
CBST		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**

Exp: Cityscapes —> NTHU [2]

City	Method	Road	SW	Build	TL	TS	Veg.	Sky	PR	Rider	Car	Bus	Motor	Bike	Mean
Rome	Src Dilated Front	77.7	21.9	83.5	0.1	10.7	78.9	88.1	21.6	10.0	67.2	30.4	6.1	0.6	38.2
	GCAA	79.5	29.3	84.5	0.0	22.2	80.6	82.8	29.5	13.0	71.7	37.5	25.9	1.0	42.9
	DeepLab-v2	83.9	34.3	87.7	13.0	41.9	84.6	92.5	37.7	22.4	80.8	38.1	39.1	5.3	50.9
	MAA	83.9	34.2	88.3	**18.8**	40.2	**86.2**	**93.1**	47.8	21.7	80.9	**47.8**	48.3	8.6	**53.8**
	Src Resnet-38	86.0	21.4	81.5	14.3	47.4	82.9	59.8	30.8	20.9	83.1	20.2	40.0	5.6	45.7
	ST	85.9	20.2	84.3	15.0	46.4	84.9	73.5	**48.5**	21.6	84.6	17.6	46.2	6.7	48.9
	CBST	**87.1**	**43.9**	**89.7**	14.8	**47.7**	85.4	90.3	45.4	**26.6**	**85.4**	20.5	**49.8**	**10.3**	53.6
Rio	Src Dilated Front	69.0	31.8	77.0	4.7	3.7	71.8	80.8	38.2	8.0	61.2	38.9	11.5	3.4	38.5
	GCAA	74.2	43.9	79.0	2.4	7.5	77.8	69.5	39.3	10.3	67.9	**41.2**	27.9	10.9	42.5
	DeepLab-v2	76.6	47.3	82.5	12.6	22.5	77.9	86.5	43.0	19.8	74.5	36.8	29.4	16.7	48.2
	MAA	76.2	44.7	84.6	9.3	25.5	**81.8**	**87.3**	55.3	**32.7**	74.3	28.9	**43.0**	**27.6**	51.6
	Src Resnet-38	80.6	36.0	81.8	**21.0**	33.1	79.0	64.7	36.0	21.0	73.1	33.6	22.5	7.8	45.4
	ST	80.1	41.4	83.8	19.1	**39.1**	80.8	71.2	**56.3**	27.7	**79.9**	32.7	36.4	12.2	50.8
	CBST	**84.3**	**55.2**	**85.4**	19.6	30.1	80.5	77.9	55.2	28.6	79.7	33.2	37.6	11.5	**52.2**
Tokyo	Src Dilated Front	81.2	26.7	71.7	8.7	5.6	73.2	75.7	39.3	14.9	57.6	19.0	1.6	33.8	39.2
	GCAA	83.4	**35.4**	72.8	12.3	12.7	77.4	64.3	42.7	21.5	64.1	**20.8**	8.9	40.3	42.8
	DeepLab-v2	83.4	35.4	72.8	12.3	12.7	77.4	64.3	42.7	21.5	64.1	**20.8**	8.9	40.3	42.8
	MAA	81.5	26.0	77.8	**17.8**	26.8	82.7	**90.9**	55.8	**38.0**	72.1	4.2	24.5	**50.8**	**49.9**
	Src Resnet-38	83.8	26.4	73.0	6.5	27.0	80.5	46.6	35.6	22.8	71.3	4.2	10.5	36.1	40.3
	ST	83.1	27.7	74.8	7.1	29.4	**84.4**	48.5	**57.2**	23.3	**73.3**	3.3	22.7	45.8	44.6
	CBST	**85.2**	33.6	**80.4**	8.3	**31.1**	83.9	78.2	53.2	28.9	72.7	4.4	**27.0**	47.0	48.8
Taipei	Src Dilated Front	77.2	20.9	76.0	5.9	4.3	60.3	81.4	10.9	11.0	54.9	32.6	15.3	5.2	35.1
	GCAA	78.6	28.6	80.0	13.1	7.6	68.2	82.1	16.8	9.4	60.4	34.0	26.5	9.9	39.6
	DeepLab-v2	78.6	28.6	80.0	13.1	7.6	68.2	82.1	16.8	9.4	60.4	34.0	26.5	9.9	39.6
	MAA	81.7	29.5	**85.2**	**26.4**	15.6	**76.7**	**91.7**	31.0	12.5	71.5	**41.1**	47.3	27.7	49.1
	Src Resnet-38	84.9	26.0	80.1	8.3	**28.0**	73.9	54.4	18.9	26.8	71.6	26.0	48.2	14.7	43.2
	ST	83.1	23.5	78.2	9.6	25.4	74.8	35.9	**33.2**	27.3	75.2	32.3	52.2	28.8	44.6
	CBST	**86.1**	**35.2**	84.2	15.0	22.2	75.6	74.9	22.7	**33.1**	**78.0**	37.6	**58.0**	**30.9**	**50.3**



Reference

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